Detection of Translator Stylometry using Pair-wise Comparative Classification and Network Motif Mining

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Abstract

Stylometry is the study of the unique linguistic styles and writing behaviours of individuals. The identification of translator stylometry has many contributions in fields such as intellectual-property, education, and forensic linguistics. Despite the research proliferation on the wider research field of authorship attribution using computational linguistics techniques, the translator stylometry problem is more challenging and there is no sufficient machine learning literature on the topic. Some authors even claimed that detecting who translated a piece of text is a problem with no solution; a claim we will challenge in this thesis.

In this thesis, we evaluated the use of existing lexical measures for the translator stylometry problem. It was found that vocabulary richness could not identify translator stylometry. This encouraged us to look for non-traditional representations to discover new features to unfold translator stylometry. Network motifs are small sub-graphs that aim at capturing the local structure of a real network. We designed an approach that transforms the text into a network then identifies the distinctive patterns of a translator by employing network motif mining.

During our investigations, we redefined the problem of translator stylometry identification as a new type of classification problems that we call Comparative Classification Problem (CCP). In the pair-wise CCP (PWCCP), data are collected on two subjects. The classification problem is to decide given a piece of evidence, which of the two subjects is responsible for it. The key difference between PWCCP and traditional binary problems is that hidden patterns can only be unmasked by comparing the instances as pairs. A modified C4.5 decision tree classifier, we call PWC4.5, is then proposed for PWCCP.

A comparison between the two cases of detecting the translator using traditional classification and PWCCP demonstrated a remarkable ability for PWCCP to discriminate between translators.

The contributions of the thesis are: (1) providing an empirical study to evaluate the use of stylistic based features for the problem of translator stylometry identification; (2) introducing network motif mining as an effective approach to detect translator stylometry; (3) proposing a modified C4.5 methodology for pairwise comparative classification.

keywords

Stylometry Analysis; Translator Stylometry Identification; Parallel Translations; Computational Linguistics; Social Network Analysis; Network Motifs; Machine learning; Pattern Recognition; Classification Algorithms; Paired Classification; C4.5; Decision Trees.

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Originality Statement

'I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at UNSW or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by colleagues, with whom I have worked at UNSW or elsewhere, during my candidature, is fully acknowledged.

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List of Acronyms

AAAC	Ad-hoc Authorship Attribution Competition
ADA	AdaboostM1
BMR	Bayesian Multinomial Regression
BNC	British National Corpus
C4.5	C4.5 Decision Tree Algorithm
CCP	Comparative Classification Problems
CL-CNG	Cross-language Character n-Grams
CW	Content Words
FLR	Fuzzy Lattice Reasoning Classifier
FT	Functional Tree
FURIA	Fuzzy Unordered Rule Induction algorithm
FW	Function Words
ICLE	International Corpus of Learner English
ILP	Inductive logic programming
IR	Information Retrieval
JRIP	Rule-based Learners
KNN	k-Nearest Neighbours
LR	Linear Regression
M5D	M5 Decision Tree
M5R	M5 Regression Tree
MFW	Most Frequent Words
MVA	Multivariate Analysis
NB	Naïve Bayes
NCG	Nearest Shrunken Centroids
POS	Part-of-Speech
PPM	Prediction by Partial Matching Compression Algorithm
PWCCP	Pair-Wise Comparative Classification Problem
RDA	Regularized Discriminant Analysis
REP-T	REP-Tree Decision Tree
SMO	Support Vector Machines using Sequential Minimal Optimization
SNA	Social Network Analysis
SVM	Support Vector Machine
TiMBL	Tilburg Memory-Based Learner
VR	Vocabulary richness

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List of Publications

Journal Publications

- Heba El-Fiqi, Eleni Petraki, and Hussein Abbass
  "Network Motifs for Translator Stylometry Identification"
  A manuscript submitted to a peer-reviewed journal.

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  "Pairwise Comparative Classification Problems for Computational Linguistics"
  A manuscript submitted to a peer-reviewed journal.

Conference Publications

- Heba El-Fiqi, Eleni Petraki, and Hussein Abbass, 2011
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Chapter 1

Introduction

1.1 Overview

Translation is a challenging task, as it involves understanding of the meaning and function of language of the original author. Successful translation necessitates that the translator communicates the same mental picture as the original author of the text.

The art of translation is a complex process. Good translation does not stop at the level of mapping words; rather, it extends to mapping meaning, mental pictures, imagination, and feelings. During the translation process, the translator is trying to maintain the spirit of the original work. Nevertheless, the translator also has to make many personal decisions including the choice of words, discourse markers, modal verb selection, length of sentences, frames, and his/her own understanding of the original text. Such decisions constitute the translator's own distinctive style. Using these distinctive markers to identify the translator is the aim of this translator stylometry study. This is defined as the "loyalty" dilemma, and there is extensive literature on the importance of maintaining the spirit of the original work.

In 1995, Venuti discussed translator invisibility [185]. He echoes the aim of a good translation that was originally introduced by Shapiro "A good translation is like a pane of glass. You only notice that it's there when there are little

imperfections - scratches, bubbles. Ideally, there shouldn't be any. It should never call attention to itself." [185]. This concept ignores the effect of the translator's own identity on the translation process. Publishers and readers are satisfied with translator's invisibility, which makes the translation considered as derivative rather than innovative process. Baker described the implication of that view to translator stylometry as "... the translator cannot have, indeed *should not* have, a style of his or her own, the translator's task being simply to reproduce as closely as possible the style of the original."[19]

Translator invisibility is a tricky concept that has been criticized in the linguistics literature [61, 143]. Baker and Xiumei independently point out the translators' difficulty of excluding their personal views and attitudes when translating a text [19, 197]. Baker suggested the existence of translator fingerprints, and she pioneered the research in this area and tried to identify a possible signatures for translators in their translations [19]. Although Baker's study demonstrated the existence of translator stylometry, her study was limited in terms of computational linguistics analysis. Baker used in her study translations of different languages and for different text. The first translator translated from Portuguese and Spanish to English, while the second translator translated from Arabic to English. Furthermore, these translations are not for the same original texts. Such analysis left many open questions in terms of the translators' differences. These would be assigned to translating from different original languages, or maybe because they came from different original texts.

Translator stylometry is an under-researched area in the field of computational linguistics. It refers to the identification of stylistic differences that distinguish the writing style of different translators. In fact, it was treated as a noise affecting the original text [62]; Hedegaard and Simonsen originally considered the translator effect in the text as a noise that challenged identifying the author of the text rather than considering the translator's intellectual contribution to the work. Based on our knowledge, very limited research was found in this field. Mikhailov and Villikka's study is one of the few studies that suggested that translator stylometry cannot be detected using computational linguistics [121].

Again, this claim is supported by Rybicki [154], when he questioned the translator stylometry identification using clustering analysis.

1.2 Research Motivation

Detecting the translator of a text is an important problem and can serve a range of functions. In the legal domain, it can be used in resolving intellectual property cases [44]. In education, it can be used for detecting plagiarism in translation classes, or addressing differences between experts and learners [33].

1.2.1 Author, Translator, and the Intellectual property

In the beginning of the 90s, Lenita Esteves, a Brazilian translator was invited by a Brazilian publishing house to translate "The Lord of the Rings", the famous fantasy novel. That agreement was before the release of the first film in 2001, when the book turned to be a bestseller. Esteves sued the publishing house claiming for her share in the profit of book sales. Then, she discovered that all the subtitles in the Brazilian version of the film had been taken from her translation, including the names and some lines of poems. So, she sued the distributor of the film as well; but the distributor of the film offered her out of court agreement, and she accepted that offer and got paid by them. On the other hand, the publishing house rejected that claim because according to market practices the translators are not paid for copyright but for the task of translation; which means that they are paid once for whatever the book have been sold. The first judgment ended with the claim being accepted, and the publisher had to pay 5% of the price of each book sold to the translator, but the publishing house appealed that decision. We couldn't gain any information about the final judge decision. But the publishing house took a protective step by announcing about future translations for this book to stop the translators from gaining any further profit in case of wining the claim. The translator wrote an article about her story [44], in which she is arguing about her intellectual property rights; she also argued

about the translated names that she used to introduce the novel characters to the Brazilian readers. If the new translation used them, she claims that this is plagiarism, if they changed them, then readers need to be reeducated about the new characters' names!!!

What is important in this story is how market practice ignored the intellectual property of the translator. In fact, this suggests that translators want their own voice and identity in the field. This offers a strong justification and support for pursuing the topic of translator stylometry. This poses the question: Can we prove that the translator has a signature in the translated text? if so, how can we define the stylometric characteristics that can be used for such claim?

1.2.2 The Linguistic Challenge: Fidelity and transparency (from theory to practise)

Venuti described the practice of the translators in society and in their translations themselves with the term invisibility. He claimed that this is what readers and publishers expect from the translator. Shapiro asked translators to confine themselves to transparency [185]. Although Venuti called the translators to be more visible in terms of claiming intellectual property, he still argued that high quality translations are associated with fidelity, with loyalty to the original text, and again with being invisible in the text. Both terms of fidelity and transparency affected translation theories in the last decades, but both of them are too ideal to be attained in practice. Moving from theory to practice, we see how the translators are highly affected by their beliefs, backgrounds, understanding, and cultural boundaries. Their identities affect their translations [60].

The literature in many fields discussed the existence of translator styles. For example, in 2000, Baker discussed the existence of translator style in saying: "it is as impossible to produce a stretch of language in a totally impersonal way as it is to handle an object without leaving one's fingerprints on it" [19]. She suggested to study translator styles using forensic stylistics (unconscious linguistic habits) rather than literary stylistics (conscious linguistic choices).

Xiumei used relevance theory to explain the translator's style [197]. The findings from Xiumei research demonstrated that, while the translator tries to balance between the original author's communicative intentions and the target reader's cognitive environment, s/he is still influenced by his/her own preferences and abilities; the outcome of all of that introduces his/her style.

In 2010, Winters discussed how a translator's attitude influences his/her translation [194]. Winters, who used two German translations of the original novel "The Beautiful and Damned" (1922) written by F. Scott Fitzgerald, showed that different translators' views affect the macro level of the novel. Furthermore, he discussed how this from his point of view extended to influence the readers' attitude.

Scholars used different linguistics approaches to detect translator styles. While Winters used loan words, code switches [191] and speech-act report verbs [192], Kamenická explored how explicitations contributed to translators' style [84]. Wang and Li looked for translator's fingerprints in two parallel Chinese translations of Ulysses using keywords lists. They identified different preferences in choosing keywords by different translators. They also found differences on the syntactic level by analysing the decision on clause positions in the sentences [187]. This research confirmed the existence of stylistic features identifying different translators.

In translation studies in the field of linguistics, the researcher would rely on a very small sample of translators and text, mostly in the order of two translators and a few pieces of text. This manual process, while constrained in the sample size, relies on the researchers' solid linguistic expertise.

This poses the question whether this manual subjective process can be replaced with a computational and objective way.

1.2.3 The Computational Linguistic Challenge

The sample of papers reviewed above and others [194, 197, 9] showed that linguistics offers evidence for the existence of stylometric differences between translators

in a way that affect the translated texts. However, the area of automatic identification and feature extraction of translator stylometric features has not seen an equivalent breed of research.

We found very limited attempts which employ computational linguistics in translator identification. The first one was by Baker as discussed earlier [19]. Later on, in 2001, another study by Mikhailov and Villikka [121]. They tried to find "stylistic fingerprints" for a translator by extracting three lexical features : "Vocabulary richness", "Most frequent words" and "Favourite words". Their experiment was done on Russian fiction texts in addition to their Finnish translations. The lexical features that they used in the research failed to find stylistic fingerprints for different translators. Their conclusion was summed up in their title; that it is not possible to differentiate between translators. While this conclusion is inconsistent with traditional linguistic studies, another research by Burrow in 2002 using delta analysis on most frequent words supported these findings by concluding unclear results in translators' identification [29]. It seems that it was sufficient to turn away researchers from this line of research for almost 10 years. Recently, in 2011, Rybicki revisited the question of translators invisibility using cluster analysis, principal component analysis and bootstrap consensus tree graphs based on Burrows' Delta in three related studies [153, 63, 154]. Rybicki aimed to cluster translations into groups based on this method. He expected that the clustering will be according to their translators [154]. Unfortunately, his approach clustered the translators into their original authors rather than translators. He emphasises the shadowy existence of translators, and supported the vision of Venuti that of translators receiving minimal recognition for their work. Not only in fame, fortune and law, but in stylistically based statistics [154].

The limited number of research studies that we found and the findings from these elevated the need for further studies in employing computational linguistics for translator stylometry identification. Figure 1.1 illustrates how the research interest is distributed in the area of Stylometry Analysis. The listed research studies are only samples of the existing literature in the stylometry analysis subproblems. More details will be discussed later in the background chapter (Chapter 2). As

we can see, authorship attribution gained most interest amongst researchers. The sub-area of translator identification gain the least interest. Furthermore, social network analysis has not been investigated for the purpose of stylometry analysis.

While linguistic studies highlighted the existence of translator differences, computational research has not explored this issue in depth. In this thesis we are readdressing this question of the existence of translator stylometry considering the development of authorship techniques in the last few years. We also examine the features that can be used to distinguish different translators.

1.3 Research Question and hypothesis

If we compare author attributions to translator attributions, we find that the former is expected to have more signatures or discriminatory factors representing the choices made by the authors. Authors have many more degrees of freedom, where they can build their own identity as authors. Translators have less. Their objective is to transparently transmit the mental picture contained in the original text to the target language. Addressing the transparency factor limits translators' linguistic choices compared to an author who has more linguistic choices to draw his/her own mental picture from. Being constrained with the original text is a non-trivial limitation. This feature alone makes translator attributions a more difficult problem than author attributions. Nevertheless, we conjecture that translators attempt to have their own touch, signatures that can be used to detect who translated what.

The scope of this thesis is the study of translator stylometry identification using a computational linguistic approach. The study in this thesis aims at answering the following research question:

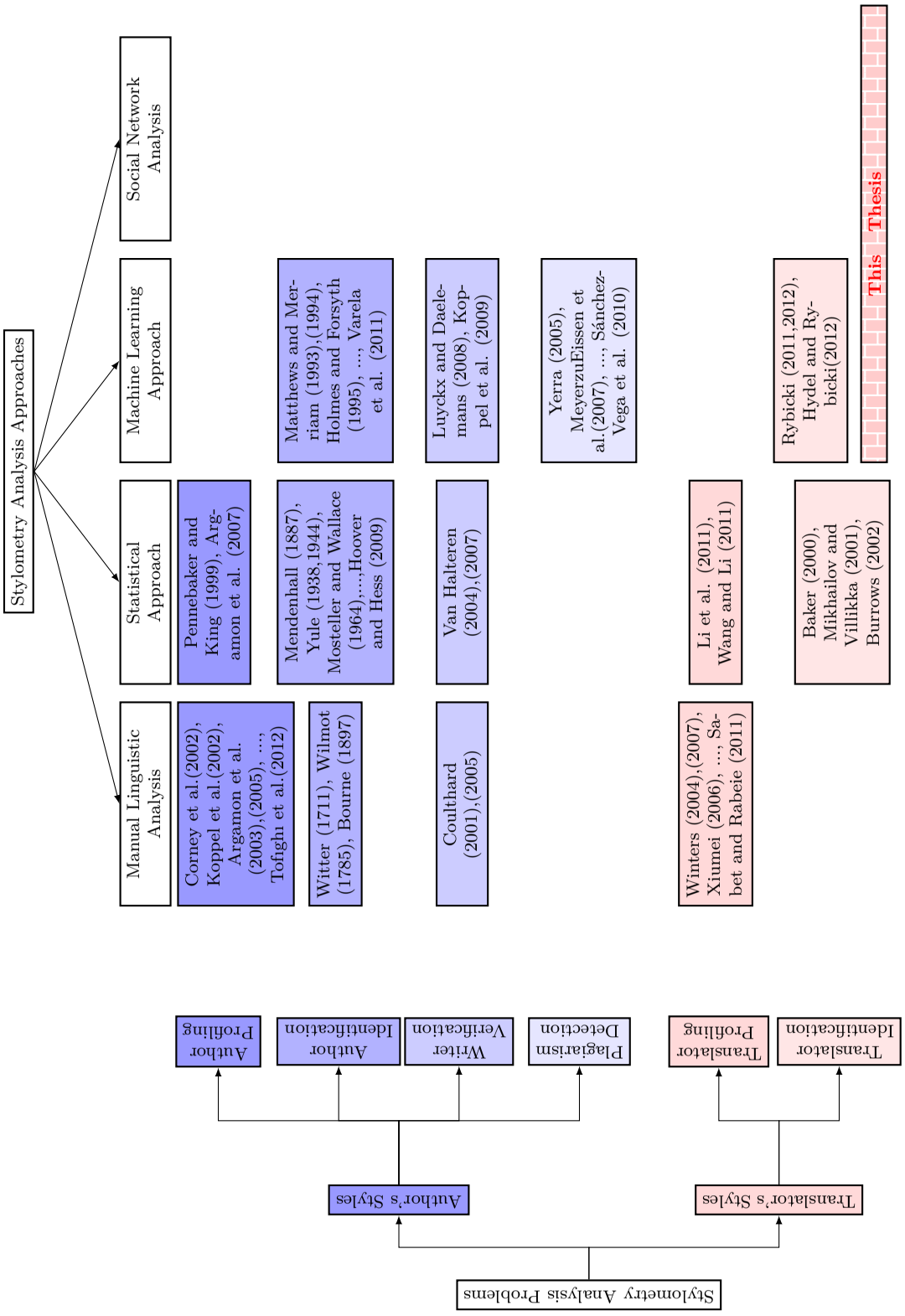

Figure 1.1: The Thesis Scope

? Main Research Question

" Can a computational linguistics framework meet the challenges of translators' stylometry identification problem?"

This research question can be broken down into several sub-questions to investigate and identify possible features and method as follows:

- The first sub-question we attempt to answer is: **"Which of the stylistic features to use to unfold a translator's stylometry?"**.
  In order to investigate an appropriate feature set for translator stylometry identification, we need to investigate the employment of network motifs, which is a novel feature in the area of stylometric analysis. It has not been used for the purpose of stylometry identification previously.

- The promising results that we found when we researched the first question encouraged us to evaluate the use of network motifs in comparing other features for the problem of translator stylometry identification. This raised the second sub-question **"What is the performance of network motifs approach compared to other approaches?"**. To answer this sub-question, we needed to evaluate the different features using the same dataset. We first investigated the performance of existing methods. Then, we evaluated the use of global network features as stylometry identification features. Furthermore, we explored the performance of both motif size three and size four using the same dataset. The accuracy obtained when we researched the performance of network motifs went lower than the accuracy we found while answering the first sub-question. We investigated the cause of that drop in accuracy. The details of that investigation are discussed in Chapter 4. That problem raised another issue: the effect of using different representations of the frequencies of network motifs in handling the change in text size.

- Researching the last element in the second sub-question revealed the existence of a hidden pattern that can only be uncovered by comparing paired

instances that represent the parallel translations that we examine. This investigation led us to define a new type of classification problems that we call Comparative Classification Problems (CCP)- where a data record is a block of instances. In CCP, given a single data record with n instances for n classes, the problem is to map each instance to a unique class. The interdependency in the data poses challenges for techniques relying on the independent and identically distributed assumption. In the Pair-Wise CCP (PWCCP), two different measurements - each belonging to one of the two classes - are grouped together. The key difference between PWCCP and traditional binary problems is that hidden patterns can only be unmasked by comparing the instances as pairs. That raised the third sub-question of this thesis, which is **"What is an appropriate classification algorithm that can handle *Pair-Wise Comparative Classification Problem* (PWCPP) ?"**.

1.4 Original contributions

The main contribution of this thesis is the support of our claim that a computational linguistics framework can meet the challenges of translators' stylometry identification problem. In general, the contributions of the thesis can be summarised as follows:

1. Providing an empirical study to support the use of computational linguistics and specifically stylistic features to support the identification of translator stylometry. This contradicts previous studies which were unable to provide evidence of translator stylometry.

2. The effectiveness of network motifs in detecting translator stylometry.

3. It introduces a new model that can handle Pair-Wise Comparative Classification Problem which assists the identification of translator stylometry by comparing their parallel translations.

1.5 Organization of the thesis

The remainder of the thesis is organized in six chapters as follows:

- Chapter 2 - Background :
  This chapter provides literature review on the different aspect of stylometry analysis problem, and how the sub-problem of translator stylometry identification is addressed in the literature . Furthermore, how we can see the problem of translator stylometry identification from a data mining perspective.

- Chapter 3 - Data and Evaluation of Existing Methods:
  The choice and design of the dataset used in this study is discussed in this chapter. Then, we evaluate the performance of existing computational linguistics methods for the problem of translator stylometry using the defined dataset.

- Chapter 4 - Identifying Translator Stylometry Using Network Motifs:
  This chapter aims at answering both first and second sub-questions of the thesis through two main experiments. In the first experiment, it investigates the possibility of using a computational based features for the problem of translator stylometry identification. That includes exploring the effect of: data normalization, sample size, and class imbalance on this problem. The aim of the second experiment is to answer the second sub-question of the thesis. Furthermore, it investigates the possibility of introducing different representation of the data as a response to variation in text size issue.

- Chapter 5 - Translator Identification Problem Redefined as Pair-Wise Comparative Classification Problem:
  The aim of this chapter is to address the third sub-question of the thesis. In this chapter, the Translator identification problem is redefined as a Pair-Wise Comparative Classification Problem. Then, a new model is proposed based on C4.5 decision tree algorithm to address this specific problem of classification.

- Chapter 6 - Conclusion and Future Work:

  This chapter summarises the contributions of the research, and discusses the future directions that stem from this work.

Chapter 2

Background

2.1 Introduction

Translator Stylometry is a small but growing area of research in computational linguistics. Despite the research proliferation on the wider research field of stylometry analysis for authors, the translator stylometry identification problem is a challenging one and there is no sufficient literature on the topic. Stylometry, which is the study of literary style, focus on the way of writing rather than the contents of the writings. Over the last decades, authorship attribution and profiling gained most of the attention in the area of stylometry analysis. The importance of and applications of stylometry analysis will be explored in detail in the next section.

These problems benefited from the development of computational linguistics and machine learning techniques, as translator stylometry analysis was limited to literary style analysis. In order to identify an appropriate approach for translator stylometry identification, we need not only understand the literary style analysis that has been used for identifying differences in translator's writing styles, but to extend our knowledge to the wider area of stylometry analysis, which involves both authors and translators. We should note that stylometry analysis for both authors and translators are related. In both cases we are analysing writing styles by identifying measurable features in the writing. However, it is important to

note there is additional difficulties for the translator identification problem due to the limited choices that the translator makes while translating in comparison to the freedom that an author has while he is writing.

In this chapter, we are going to explore the literature of the stylometry analysis area. We will start with the analysis of author styles before translator styles for two reasons. The first reason is that a significant proportion of the work in the stylometry analysis area started from author identification analysis. The second reason is to be able to see what type of features and approaches employed in the authorship analysis literature that can be applied to translator stylometry analysis. For both authors and translators stylometry analysis, we are going to identify the different types of problems, and discuss the methods and approaches that have been used for that purpose. Figure 2.1 in conjunction with Table 2.1 provides a road map to the literature surveyed in this chapter.

2.2 Stylometry Analysis

Stylometry is the study of the unique linguistic styles and writing behaviours of individuals. Kestemont defined it as the quantitative study of (literary) style, nowadays often by means of computation [91]. Stylometry can be thought as a measure of the style. So, what is a style?

"*Style* is the variable element of human behaviour" [115]. Typical human activities may look like being similar. How people get dressed, eat, or drive are generally invariant, but also they slightly vary from one person to another. The procedure along with the outcomes of these kind of activities are usually pretty much the same for everybody, yet the way an individual goes about this course of action in order to get the outcome will vary noticeably from one person to another.

Style in written language is generated by the repeated choices that the writer tends to make. These repeated choices are hypothesised to reflect his unconscious behaviour or preference of some writing pattern than others to represent the same

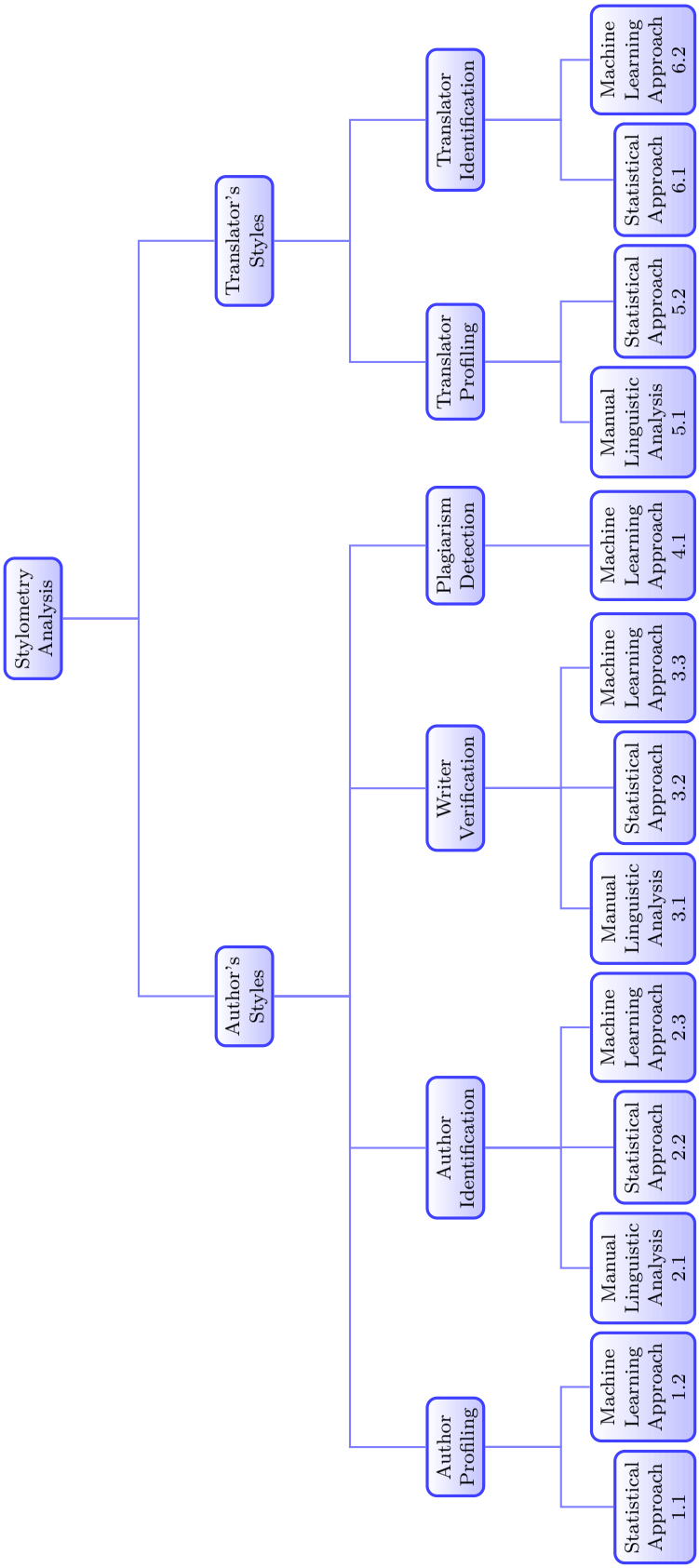

Figure 2.1: Road-Map to Research on Stylometry Analysis. Numerical Tags Correspond to Entries in Table 2.1

Table 2.1: Summary of Literature Survey on Stylometry Analysis. Numbered References Refer to the Numerical Tags Assigned in Figure 2.1.

Ref	Year	Authors	Method	Features	Corpus
1.1	1999	Pennebaker and King [136]	Distance	CW, and FW	Diaries, students assignments, journal abstracts
	2007	Argamon et al. [14]	Factor analysis and correlations	CW, and FW	Web blogs
	2002	Corney et al. [38]	SVM	Lexical, character, and structural features	E-mail texts
	2002	Koppel et al. [94]	Winnow-like algorithm	FW , and POS	BNC
	2003	Argamon et al. [13]	Balanced Winnow algorithm	FW, POS, and n-grams	BNC
1.2	2005	Argamon et al. [12]	SMO	FW, and CW	Students essays
	2005	Koppel et al. [97]	SVM	FW, chr n-grams, misspellings, and syntactic errors	ICLE

Continued on next page

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***Features*: CW**: Content words, **FW**: Function Words, **MFW**: Most Frequent Words, **VR**: Vocabulary richness, **POS**: Part-of-Speech
***Corpus*: AAAC** : Ad-hoc Authorship Attribution Competition , **BNC**: British National Corpus , **ICLE**: International Corpus of Learner English

Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
	2006	Mairesse and Walker [110]	LR, M5R, M5d, REP-T, C4.5, KNN, NB, JRIP, ADA, and SMO	CW	Students essays, conversation transcripts
	2006	Oberlander and Nowson [131]	SVM, NB	word n-grams	Web blogs
	2006	Schler et al. [158]	Multi-Class Real Winnow	FW	Web blogs
	2007	Estival [45]	C4.5, Random Forest, Lazy learner, JRIP, SMO SVM , Bagging, and ADA	Character, lexical, and structural features	English email messages
1.2	2007	Tsur and Rappoport [179]	SVM	Character n-grams, and FW	ICLE
	2008	Estival [46]	C4.5, Random Forest, Lazy learner, JRIP, SMO SVM , Bagging, and ADA	Character, lexical, and structural features	English and Arabic email messages
	2009	Argamon et al. [15]	BMR	FW, POS and CW	English blog posts and students essays

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Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
	2009	Tam and Martell [174]	NB,and SVM	n-grams	NPS Chat Corpus
	2009	Wong and Dras [196]	SVM	Lexical (FW, character n-grams, and POS n-grams) and Syntactic errors	ICLE
	2011	Rosenthal and McKeown [149]	Logistic regression and SVM	Lexical, stylistic, content features, and online behaviour	Web blogs
	2012	Tofighı et al. [177]	C4.5, SVM, and NB	Lexical, syntactic, structural, and content-specific features	online news texts
2.1	1711	H.B Witter [132]		Lexical	Bible
	1785	Wilmot [132]			Shakespeare plays
	1897	Bourne [23]	Similarities	lexical	Federalist papers
	1887	Mendenhall [117]	Distance	Sentence length, word length	Bacon/Marlowe/Shakespeare
	1938	Yule [200]	Distance	Sentence length	de Gerson
	1944	Yule [199]	Distance	VR (K-measure)	de Gerson

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Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
2.2	1964	Mosteller and Wallace [127]	Bayesian statistical inference	FW	Federalist papers
	1965	Morton [125]	Distance	sentence length	Ancient Greek Prose
	1987	Burrows [31]	MVA, and PCA	Lexical (FW)	English novels (Austen, S.Fielding, and H.Fielding)
	1989	Burrows [28]	PCA	Lexical (FW)	English novels (Austen, S.Fielding, and H.Fielding)
	1990	Morton and Michaelson [126]	CUSUM		
	1996	Baayen et al. [18]	PCA and Distance	Syntactic (frequencies of rewriting rules) lexical (VR and MFW)	Federalist papers
	1996	Merriam [119]	MVA, and PCA	FW	Shakespeare
2.2	1999	Binongo and Smith [21]	MVA, and PCA	FW	Shakespeare
	2001	Holmes et al. [67]	MVA, and PCA	FW	Pickett letters

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Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
	2002	Burrows [29]	Delta analsyis (MVA+PCA)	MFW	Restoration-era poets
	2003	Binongo [22]	MVA, and PCA	FW	the 15th Book of Oz
	2003	Hoover [70]	MVA (Cluster analysis and PCA)	MFW, word n-grams	novels and articles
	2003	Hoover [71]	MVA (Cluster analysis and PCA)	MFW, word n-grams	Orwell/Golding/Wilde
	2004	Hoover [73]	Delta analysis	MFW	American novels
	2004	Hoover [72]	Delta analysis	MFW	novels and articles
	2006	McCarthy et al. [138]	Discriminant function analysis	Coh-Metrix (lexical, syntactic, and semantic features)	English novels and articles (Rudyard Kipling, Charles Dickens, and P.G. Wodehouse)
2.2	2007	Burrows [30]	MVA& zeta	MFW	Restoration poets
	2008	Abbasi and Chen [3]	Writeprints Technique, PCA, K-L transforms, SMO, SVM Ensemble	characters, FW, syntax,VR, various	emails, online comments, chats

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Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
	2009	Hoover and Hess [74]	Delta analysis, t-testing, PCA, and Cluster analysis,	Lexical (MFW)	English Novel (Female Life Among the Mormons)
2.3	1993	Matthews and Merriam [114]	ANN	FW	Shakespeare/Fletcher
	1994	Merriam and Matthews [118]	ANN	FW	Shakespeare/Marlowe
	1995	Homes and Forsyth [65]	MVA, and Genetic algorithm	VR, FW	Federalist papers
	1996	Tweedie et al. [180]	ANN	FW	Federalist Papers
	2001	de Vel et al. [41]	SVM	Lexical (VR, word and sentences length,..) and structural features (greetings, signature, html tags)	emails
2.3	2004	Gamon [54]	SVM	Lexical (length, word n-grams, FW), syntactic (POS, context-free grammar), and semantic (Semantic dependency graphs)	Five English Novels for three authors

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Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
	2005	Abbasi and Chen [1]	SVM, C4.5	Lexical,, syntactic, structural and content specific features	Arabic forum posts
	2005	Abbasi and Chen [2]	SVM, C4.5	Characters, words, VR, various	Arabic forum posts
	2006	Zheng et al. [203]	SVM , ANN, C4.5	Lexical, syntactic, structural, and content-specific features	English and Chinese online-newsgroup
	2008	Stamatatos [167]	SVM	Character n-grams	English and Arabic news
	2008	Tearle et al. [176]	ANN	Lexical features (sentence length, FW, VR) character features (punctuation usage)	Shakespeare and Marlowe writings, and the federalist papers
	2009	Pavelec et al. [134]	PPM, and SVM	FW (Conjunctions), and CW(adverbs)	Portuguese articles from online Brazilian newspapers
2.3	2010	Jockers and Witten [82]	Delta , KNN, SVM, NSC , and RDA	Words, and words bigrams	Federalist papers
	2010	Tsimboukakis and Tambouratzis [178]	ANN, SVM	CW, FW, POS, word length	The minutes of the Greek parliament

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Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
	2011	Hedegaard and Simonsen [62]	SVM	MFW, chr N-grams, Semantics Frames	The Federalist Papers, and English translations of 19th century Russian romantic Literature.
	2011	Layton et al. [99]	Recentred local profiles	n-grams	AAAC
	2011	Luyckx and Daelemans [107]	TiMBL, in comparison to JRIP, SMO, NB, and C4.5.	Lexical, character, and syntactic features	AAAC (problem A), ABC-NL1 (Dutch Authorship Benchmark corpus) , Personae corpus (Student essays)
	2011	Varela et al. [184]	SVM, multi-objective genetic algorithm	FW (conjunctions, pronouns), and CW (adverbs, verbs)	Portuguese short articles
3.1	2001	Malcolm Coulthard [39] page 508		lexical	Danielle Jones disappearance case (text messages from cell phone)

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Ref	Year	Authors	Method	Features	Corpus
	2005	Malcolm Coulthard [39] page 508		lexical	Jenny Nicholl disappearance case (text messages from cell phone)
3.2	2004	Van Halteren [182]	Distance	Word n-grams, syntax	ABC-NL1
	2007	Van Halteren [183]	Distance (correction factor is added)	Word n-grams, syntax	ABC-NL1
3.3	2008	Luyckx and Daelemans [106]	TiMBL, and SMO	Words n-grams, POS, and FW, VR	Personae corpus (Student essays)
	2009	Koppel et al. [95]	SVM	FW, character n-grams	classic nineteenth and early twentieth century books
	2005	Yerra [198]	least-frequent n-grams, and fuzzy-set IR	sentence-based	Web documents
	2007	MeyerzuEissen et al. [120]	SVM	Lexical, POS, and VR features	Corpus constructed based on computer science articles from The ACM digital library

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Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
	2008	Elhadi and Al-Tobi [42]	Sequence alignment	Syntactic (POS tags)	David Gardner's plagiarism prevention samples
4.1	2009	Elhadi and Al-Tobi [43]	Improved Longest Common Subsequence	Syntactic (POS tags)	A set of documents that resulted of submitting the phrase of "Perl Tutorial" to AltaVista search engine
	2010	Barrón-Cedeno et al. [20]	CL-CNG, alignment based similarity analysis, and Translation with Monolingual Analysis	Distant Language Pairs	en-eu translation parallel corpora
	2010	Sánchez-Vega et al. [157]	NB	n-grams, Fragmentation features, Relevance features	METER corpus (from journalism domain designed to evaluate text reuse)
	2004	Winters [191]		Loan words and code switches	Two German translations of English novel

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Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
	2006	Xiumei [197]	Relevance-theoretic approach	Semantic level	Different samples of Chinese to English translations
	2006	Rybicki [152]	Delta analysis	MFW	Henryk Sienkiewicz's Trilogy and two English translations of them
	2007	Leonardi [100]		Textual, Lexical , grammatical and syntactic level, pragmatic and semantic level	Italian into English translation
	2007	Winters [192]		speech-act report verbs	Two German translations of English novel
	2008	KAMENICKÁ [84]	Explicitation profile	Lexical and Semantic level (explication and implication)	Czech translations of two English novels
	2009	Castagnoli [33]		Conjunctions, explications, and conjunctive explicitation	English to Italian and French to Italian student translations Corpus

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***Methods*: SVM**: Support Vector Machine, **SMO**: Support Vector Machines using Sequential Minimal Optimization, **C4.5**: C4.5 Decision Tree algorithm, **LR**: Linear regression, **M5R**: M5 regression tree , **M5D**: M5 decision tree , **REP-T**: REP-Tree decision tree, **NB**: Naïve Bayes, **JRIP**: rule-based learners, **ADA**: AdaboostM1, **KNN**: k-nearest neighbours, **NCG**: nearest shrunken centroids, **RDA**: regularized discriminant analysis. **PPM**: Prediction by Partial Matching Compression Algorithm, **TiMBL** : Tilburg Memory-Based Learner, **BMR**: Bayesian Multinomial Regression, **IR**: Information Retrieval, **CL-CNG** : Cross-language Character n-Grams, **MVA**:Multivariate analysis
***Features*: CW**: Content words, **FW**: Function Words, **MFW**: Most Frequent Words, **VR**: Vocabulary richness, **POS**: Part-of-Speech
Corpus: **AAAC** : Ad-hoc Authorship Attribution Competition , **BNC**: British National Corpus , **ICLE**: International Corpus of Learner English

Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
	2009	Winters [193]		Modal particles	Two German translations of English novel
	2010	Winters [194]		Semantic features	Two German translations of English novel
	2011	Sabet and Rabeie [156]		Character description level, and lexical level	Two Persian translations of the English Novel (Emily Bronte's Wuthering Heights)
5.2	2011	Li et al. [101]		Type/token ratios, Sentence length, and VR	two English translations of a classic Chinese novel
	2011	Wang and Li [187]		Keywords lists, clauses positions in the sentences	two parallel Chinese translations of Ulysses
6.1	2000	Baker [19]		Type-token ratio, mean sentence length, and frequency of using different formats of the reporting verb "Say"	Portuguese and Spanish to English translations for one translator, and Arabic to English translations for the second translator.

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***Methods*: SVM**: Support Vector Machine, **SMO**: Support Vector Machines using Sequential Minimal Optimization, **C4.5**: C4.5 Decision Tree algorithm, **LR**: Linear regression, **M5R**: M5 regression tree , **M5D**: M5 decision tree , **REP-T**: REP-Tree decision tree, **NB**: Naïve Bayes, **JRIP**: rule-based learners, **ADA**: AdaboostM1, **KNN**: k-nearest neighbours, **NCG**: nearest shrunken centroids, **RDA**: regularized discriminant analysis. **PPM**: Prediction by Partial Matching Compression Algorithm, **TiMBL** : Tilburg Memory-Based Learner, **BMR**: Bayesian Multinomial Regression, **IR**: Information Retrieval, **CL-CNG** : Cross-language Character n-Grams, **MVA**:Multivariate analysis
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Corpus: **AAAC** : Ad-hoc Authorship Attribution Competition , **BNC**: British National Corpus , **ICLE**: International Corpus of Learner English

Table 2.1 – continued from previous page

Ref	Year	Authors	Method	Features	Corpus
	2001	Mikhailov and Villikka [121]		VR, MFW, and Favourite words	Parallel corpus of Russian fiction texts and their translations into Finnish
	2002	Burrows [29]	Delta analsyis (MVA+PCA)	MFW	English Restoration poetry & 15 translations of Juvenal's tenth satire
6.2	2011	Rybicki [153]	Burrows's Delta, PCA, Clustering	MFW	works by Curtin (12 originals) and (21 translations)
	2012	Rybicki [154]	Burrows's Delta, PCA, Clustering	MFW	Multiple language translations: Polish, English, French, and Italian translations
	2012	Heydel and Rybicki [63]	Burrows's Delta, PCA, Clustering	MFW	Virginia Woolf's Night and Day

thing. Group and individual variation in written language can be manifested in examination of the style. Linguistic group variation can be observed for example using sociolinguistics and discourse studies, which examine the use of language in various context or the effect of social factors such as age or gender on the use of language [69, 188]. For example, a sociolinguistic study by Argamon et.al showed that males tend to use determiners (a, the, that, these) and quantifiers (one, two, more, some) more than females. On the other hand, females use pronouns (I, you, she, her, their, myself, yourself, herself) more frequently than males [13]. Additional Examples of sociolinguistics include the examination of linguistics characteristics between teenagers and elderly people, and the observation of the use of the English language by Chinese Australians and Italian Australians. Linguistic variation is affected by different factors such as age, culture, race, geography, social class, gender, education level, and specialisation. Despite the existence of similarities in speaking or writing of specific groups of language users, there can be individual characteristics which can contribute to individual distinctive styles. With respect to writing, individual variation is created by the writer's decision to pick up one particular form out of the assortment of all different possible forms. These variations can be within the norm, which are different correct ways of expressing the same thing, or deviation from a norm which may be mistakes, or Idiosyncrasy behaviour of the writer. An example by McMenamin [115] to describe grammatically correct variations within the norm is: if the norm is "I am going now", while variation within the norm can be "I'm going now", deviation from the norm "I be goin' now". Another example which describes socially an appropriate variation to the norm "I'm afraid you're too late" is "Sorry, the shop is closed". In this case, a deviation may be "Get the hell out of here!". As the style constitutes distinctiveness, identifying the writer's distinctive markers is the key to identifying their style. Analysis of the variation is the first step towards identification of style-markers.

In the following section, we are going to discuss the different problems addressed using Stylometric analysis: how stylometry analysis is used to profile an author or translator, identification of authors and translators based on their

writing style, verification of an author of text as used in forensic linguistics, and finally the use of stylometry analysis for plagiarism detection.

2.2.1 Authors Stylometric Analysis (Problem Definitions)

The development of computational tools, and the growing interest in forensic analysis, humanities scholarship, and electronic commerce led to the growing interest in the authorship attribution problem. This general problem was subdivided into more specific sub-problems: The first one is Author Profiling, which involves making inferences about the gender, age group, or origin of the author on the basis of their writing style [168, 97]. Another form of the problem is Author Identification, which includes identifying who wrote a piece of text from a set of candidate authors by analysing their writing styles. Attributing authorship of an anonymous text comprises the identification of stylistic similarities relating to previously known texts belonging to the candidate authors. Author Verification is another sub-problem, where the objective is to answer if this text is written by the claimed author. The fourth sub-problem is Plagiarism detection which attempts to identify the plagiarism by analysing the similarity between two pieces of texts.

2.2.1.1 Author profiling

Writer profiling is a stylometry analysis sub problem which is concerned with extracting as much information as possible about an unknown author by analysing his/her writing. This information may include his gender, personality, cultural background, etc... .

Researchers addressed author profiling and translator profiling in different ways. For author profiling, the focus is on observing sociolinguistic behaviour. Researchers analyse how a particular group of people use the language differently than other groups. These observations can be collected by grouping people based on gender [13], age [158], native language [97], or personality [137]. Then, these

observations can be used in similar unknown text to extract information about this text author.

The importance of the author profiling problem is growing with the recent development in forensic linguistics, security applications, and commercial marketing. An example of such importance in the area of forensic linguistics is giving the police the chance to identify the characteristics of the person behind the crime under investigation.

An example in the area of marketing includes analysing weblogs and product reviews websites. Author profiling can help in identifying the characteristics of groups of customers who do not like particular products. Then, the proposed company undergoing the renew can use these identified characteristics to help in the development of a marketing strategy to match the needs of the unsatisfied customers.

Gender based stylistics

Extracting the gender of the author of a text has been studied using different corpora in the literature. Corney et al. addressed the problem of author gender profiling of e-mail text documents based on the gender-preferential language used by the email writer [38]. Koppel et al. found out that male authors use determiners much more than female authors, while female authors tend to use pronouns and negation more than male authors [94]. This research was followed by another experiment by Argamon et.al to further investigate the employment of pronouns and certain types of noun modifiers that vary significantly when comparing documents belonging to male authors and female authors to determine the author gender [13].

In 2007, Argamon et al. analysed web blog data to explore what types of features can be used to determine the gender and the age of the authors [14].

They found that the *Articles* and *Prepositions* are used significantly more by male bloggers, while *Personal Pronouns*, *Conjunctions*, and *Auxiliary Verb*s are used significantly more by female bloggers [14].

Age stylistic features

Age specific characteristics was also studied by Argamon et al. in 2007 in the same research mentioned earlier [14]. Argamon et al. found that the usage of words associated with *Family*, *Religion*, *Politics*, *Business*, and *Internet* increases with age, while usage of words associated with *Conversation*, *AtHome*, *Fun*, *Romance*, *Music*, *School*, and *Swearing* decreases significantly with age. Another observation of that experiment is that the use of *Personal Pronouns*, *Conjunctions*, and *Auxiliary Verbs* decreases significantly with age, while the usage of the *Articles* and *Prepositions* increases significantly with age. More studies that have found age linked differences include research conducted by Schler et al. [158], and also Argamon et al. in 2009 [15].

Another research attempt is introduced by Tam and Martell to determine if the text writer belongs to teenagers or other ages using NPS Chat Corpus. This research demonstrates n-grams are useful with regard to sensing the age in addition to demonstrating the challenge of distinction between consecutive groups such as teens and 20s [174]. In 2011, Rosenthal et al. used lexical stylistic features, content and online behaviour to predict the age of bloggers of virtual community Live Journal using logistic regression and support vector machine [149].

Native language

To identify the native language of an author, researchers have used international Corpus of Learner English (ICLE) which contains essays written by intermediate to advanced learners of English. Koppel et al. used a set of function words and character n-grams as features, in addition to 185 error types, including

misspellings and syntactic errors such as repeated letter, letter substitution, letter inversion, and conflated words [97]. These features were used to identify five native languages for the writers: Bulgarian, Czech, Russian, French and Spanish. After that, Tsur and Rappoport formed the hypothesis that the choice of words people make when writing in a foreign language is strongly influenced by the phonology of their native language [179]. Thus, they only used character n-grams to identify the native language of the text author. The accuracy of 65.6% that achieved by their approach was enough to validate their hypothesis where the baseline was 20%, but it was less than the 80.2% accuracy that was achieved by Koppel et al. using a different combination of features on the same dataset [97].

Another research that supports the use of syntactic errors as a clue for author's native language identification is produced by Wong and Dras in 2009 [196]. They structured their approach based on the contrastive analysis hypothesis, where the common errors that a learner of a language makes can be explained by observing differences between that learner's native language and the learned language.

In 2012, Tofıghı et al. used online news texts as a corpus to identify the author's native language for four languages: English, Persian, Turkish and German [177]. They used a combination of lexical, syntactic, structural, and content-specific features for that purpose and demonstrated that this combination was able to identify the author's native language with an accuracy ranged from 70% to 80% using SVM.

Personality

Human personality is usually described in terms of the well known Big Five personality dimensions: Openness to experience (Imagination, Creativity vs. Conventionality), Conscientiousness (Need for achievement, organization vs. Impulsiveness), Extraversion (Sociability, Assertiveness vs. Quietness), Agree-

ableness (Kindness vs. Unfriendliness), and Neuroticism (Calmness and Emotions Stability vs. Self-conscious and Anxious)[113].

Pennebaker and King identified modest nevertheless dependable effects associated with individuality on word choices by analysing numerous text samples of students [136]. The correlations ranged between 0.10 and 0.16. Neuroticism was positively correlated with using negative feeling text as well as negatively with positive feeling text. Examples of positive feeling texts include *happy, love, beautiful, nice, exciting, win, ...etc.* On the other hand, negative feelings texts include : *ugly, hurt, anxiety, fear, anger, sadness, depression,...etc.* Extraversion correlated positively with positive feeling text as well as text associated with social processes. Agreeableness seemed to be positively linked to positive feeling as well as negatively to negative feeling text. Furthermore, Neuroticism seemed to be seen as an even more regular by using first person singular. After that, a further study by Pennebaker et al. was conducted to identify the Neuroticism level of text writers in 2003 [137]. They used Particles (pronouns, articles, prepositions, conjunctives, and auxiliary words) and function words for that purpose. They found that more frequent use of first person pronouns is associated with high degree of self involvement.

Argamon et al. used four lexical feature sets to identify Neuroticism and Extraversion in 2005 [12]. These features are a standard function word list, conjunctive phrases, modality indicators, and appraisal adjectives and modifiers [12]. They found that appraisal lexical (text choise that reflect appreciation, affect, or judgment) is effective in identifying Neuroticism level, and function words are more appropriate for identifying Extraversion.

In 2006, Mairesse and Walker used machine learning algorithms in order to model the five big personality aspects [110]. Their research findings showed that Extraversion, Neuroticism and Conscientiousness are easier to model than Openness and Agreeableness. Also, analysing the text using the constructed recognition models outperformed the results of self-reports based models [110].

Another research on analysing languages to predict personality traits is con-

ducted in the same year by Oberlander and Nowson. They used word bi and trigrams as features to analyse web blogs in order to predict four psychometric aspects: Neuroticism, Agreeableness, Extraversion and Conscientiousness [131].

After that, Estival et al extracted character, lexical, and structural features from Email messages in English [45] and Arabic [46] in order to profile five authors demographic characteristics: gender, age, geographic origin, level of education and native language, and the big five personality aspects as well. In 2009, Argamon et al. used content-based features and style-based features to profile gender, age, language, and neuroticism in English blog posts and students essays [15].

All of these discussed research studies demonstrate how the use of language varies significantly according to these different factors. Also, these research findings underline the use of computational linguistics in identifying stylistic features of texts.

2.2.1.2 Author Identification

The authorship attribution problem is not a recent research area. There are some Biblical authorship disputes traced back to 1711 by H.B Witter [132]. In 1785, the authorship of Shakespeare plays have been disputed. Wilmot raised the claim that Bacon is the real author of the Shakespeare plays [132]. Another study on the plays of Shakespeare was conducted by Mendenhall in 1887 using word length distribution. This was criticised later due to the expected differences between poetry and prose rather than being related to the author style [162]. Later on, Multiple researchers targeted authorship attribution dispute of Shakespeare plays: Matthews and Merriam in 1993 [114] and 1994 [118], Merriam in 1996 [119], Binongo and Smith in 1999 [21] ,and recently, Zhao and Zobel in 2007 [202].

Another famous authorship dispute is the Federalist papers, which is one of the most studied problems in this research area [23] [127] [151] [82]. These articles appeared New York newspapers under the pseudonym “Publius”. Twelve out of the 85 essays were claimed by both Hamilton and Madison. These twelve

disputed papers attracted many authorship attribution research studies in the last decades. The first research to my knowledge was introduced in 1897 [23]. Then it was followed by many research studies but the most popular was the one conducted by Frederick Mosteller and David Wallace in 1964 [127], which is described by Rudman [151] as the "most statistically sophisticated non-traditional study ever carried out". That research was cited hundreds of times by researchers who were interested in their statistical techniques, authorship attribution, and the federalist political beliefs themselves. Since that time, the Federalist papers were used by researchers who want to test their new method or hypothesis in authorship attribution. Example of some recent research includes Hedegaard and Simonsen in 2011 [62], who used the federalist to prove the validity of their authorship methods. Additionally in 2010, Jockers and Witten used the federalist papers as the corpus for their comparative analysis of five authorship attribution method [82].

In 2004, Patrick Juola invited authorship attribution scholars to participate in an authorship attribution competition as a part of the 2004 Joint International Conference of the Association for Literary and Linguistic Computing and the Association for Computers and the Humanities (ALLC/ACH 2004). The purpose of this competition was to conduct a benchmark study of the new methods that the researchers introduced recently. This competition attracted 12 teams to participate in it [83]. This dataset attracted some of the researchers after the competition as well, who were interested to test their methods in comparison to others. An example of recent research that used the same dataset is Layton and others in 2011 [99] for the purpose of authorship attribution. In their research, they generated authors' profiles, and then classified text into authors based on the best match author profile. Another example of using this dataset in authorship attribution is Luyckx [107] who used part of this data in 2011 aiming to identify the effect of data set size on the attribution problem.

More examples of authorship attribution problem will be discussed later in this chapter through the discussion of the stylometric features and methods.

2.2.1.3 Writer Verification

McMenamin highlights the existence of individual writer variation: "No two individuals use and perceive language in exactly the same way, so there will always be at least small differences in the grammar each person has internalized to speak, write, and respond to other speakers and writers" [115].

Given examples of the writing of a single author, the authorship verification task aims to determine if given texts were or were not written by this author [182]. It can be seen as a categorization problem or one class classification problem from the point of view of machine learning. Some of the research studies in this area who used authorship attribution techniques are Halteren [182] [183], Koppel et al. [95], and Luyckx and Daelemans [106]. Most of the research related to writer verification is conducted from forensic linguistics prospective.

Although the authorship attribution is not a new research area, the forensic linguistics research area is considered new. The first appearance of the phrase "Forensic Linguistics" was at 1968 by Jan Svartvik in an analysis of statements by Timothy John Evans [132]. After that, the growth of the Forensic linguistics was slow until the beginning of the 1990s, when a new wave in the development of Forensic Linguistics field came with 1989's murder trial at the Old Bailey. The first expert linguistic evidence was used in the court [132]. The International Association of Forensic Linguists was then founded in 1992; then the *International Journal of Speech, Language and the Law*, was founded in 1994.

Forensic linguistics is defined as the scientific study of language as applied to forensic purposes and contexts [115]. Forensic linguistics doesn't focus on hand writing recognition or the source of the suicide note paper or how old is it. Forensic Linguistic is concerned with author identification and stylometric analysis [41, 167, 135, 95, 134], Author Profiling [182, 94], Discourse Analysis [78], Forensic phonetics [81, 32], and significantly contributes to crime investigations.

One of the most prominent examples of the importance of forensic linguistics is seen in the case of "Jenny Nicholl", a nineteen year old girl who went missing in 30th of July 2005. After her disappearance, some text messages were sent from

her mobile to her family and friends. These messages were suspected of being not sent by her. That is why these messages were been analysed linguistically to find if she is the author of these messages or not. Some linguistics differences were identified in her writing like using ME/MESELF rather than MY/MYSELF; that is how she used to write them. Examples for other couples of words that was encountered in the analysis (IM / I AM), (OFF / OF), (CU /CYA), (FONE / PHONE), and (SHIT / SHITE). David Hodgson; her ex-lover was convicted for Nicholl's murder in Feb 2008 with the aid of these linguistic evidences [39].

2.2.1.4 Plagiarism Detection

Another related area to the field of translator stylometry is plagiarism detection. There are many types of plagiarism. It can start from the level of copying an idea, and it may extend to the text operation levels such as exact copy, or through translation from one language to another. It may also go to the level of the sentence, such as merging, splitting or paraphrasing of the text. Plagiarism on the word level may include addition, deletion, or substitution.

Plagiarism detection is divided into two main types: extrinsic analysis and intrinsic analysis. In the extrinsic case, we need to diagnose plagiarism by discovering near-matches of some text message in a database of texts. The extrinsic detection problem is addressed by different researchers in the last years [198, 20, 42, 157, 43]. In intrinsic detection, we analyse the possible suspicious document in isolation to show that various areas of a single author document could not have been authored by that identical writer. Intrinsic plagiarism analysis can be detected through stylistic inconsistencies within the explored text. Notably, that is similar to the problem of authorship verification, except that in the authorship verification problem; the tested corpus is not only a single document. Therefore, Intrinsic plagiarism can be seen as a generalization of the authorship verification problem [8]. Research targeted intrinsic detection includes [169, 171, 172, 120]. For further information, we refer the readers to plagiarism

detection surveys by Stamatatos and Koppel [169], Osman et al. [133], and Ali et al.[6].

2.2.2 Translators Stylometric Analysis (Problem Definitions)

2.2.2.1 Translator profiling

The translator profiling problem was dealt with differently to the author profiling. The focus of the conducted research in the literature is how the gender [100, 156], proficiency level [33], social [101], and cultural backgrounds [101] affected their translations. Most of the research in this area analysed two different parallel translations of the same original text by different translators to address how their identities might have affected the choices that they made throughout the process of the text translation.

Translator background has been shown to affect the translators' style. Most of the translation analysis studies in the literature targeted this area of research. Researchers were interested in analysing how two translations of the same text by two translators (which we will refer to it as parallel translations) differed in delivering different meaning and mental pictures based on their translators' identities. This includes their cultural background, social, and political views.

Scholars used different linguistic approaches to detect translator styles. Xiumei used relevance theory to explain the translator's style [197]. The findings from Xiumei's research demonstrated that: while the translator tries to balance between the original author's communicative intentions and the target reader's cognitive environment, s/he is still influenced by his/her own preferences and abilities; the outcome of all of that introduces her style [197].

Rybicki used Burrow's Delta to investigate character Idiolects in two English translations of Henryk Sienkiewicz's Trilogy in terms of major characters, old friends, nationality, characters in love, and idiolects of female characters. That study found that character's idiolects were preserved in translations. Burrow's

Delta was able to capture similar distances between characters in both the original text and the translations [152].

Kamenická explored how Explicitations contributes to translators' style in two parallel English to Czech translations of "Small World" by David Lodge and "Falconer" by John Cheever in 2008 [84]. Explicitation happens when the translator transfers a message that was hidden (but can be understood from the context) in the original text to the reader explicitly using the target language. Implicitation, on the other hand, occurs when the translator use the target language to conceal some details that were mentioned explicitly using the source language. Kamenická findings conclude that the two translators use experiential and interpersonal explicitation and implicitation in textual segments differently.

In terms of identifying the gender of a translator as in author profiling, there are some research studies that addressed this problem. In 2007, Leonardi conducted Contrastive Analysis of Italian to English translation corpus to address the question of how gender and ideology affect translation [100]. The same question was addressed again in 2011 by Sabet and Rabeie [156]. They studied the effect of gender ideology of the translators on their translation using two Persian translations of the English Novel "Wuthering Heights" by Emily Brontë, one of them by a male translator and the other by a female translator.

In 2009, Castagnoli investigated the possibility of a relationship between the occurrence of specific phenomena and translator competence [33]. For that investigation, she used a corpus consisting of student translations (from English to Italian) and (from French to Italian). That corpus provides the availability of multiple parallel translations of the same original text and availability of different levels of translation competency.

Winters conducted multiple studies on how a translator's attitude influences his/her translation [191, 192, 193, 194]. In all of these studies, Winters used two German translations of the original novel "The Beautiful and Damned" (1922) written by F. Scott Fitzgerald. In 2004, Winters used loan words and code switches to differentiate between translators' styles [191]. The analysis showed

that one of the translators tends to transfer English words from the source text into the translation where possible, while the other translator tends to Germanize the words to transfer the source text culture towards the target language reader. Later on in 2007, Winters used speech-act report verbs [192] to investigate their usefulness as potential elements of translator's individual style. Although the original text used repetition of some words, one of the translator transferred that repetition to the translation, but the other translator avoided that, and used different words to reflect different situations. In a 2009 study, Winters conducted a quantitative analysis to analyse the use of modal particles by the translators. That research showed that despite the overall similarities in using modal particles, there was a significant difference in the translation' choice and use of individual modal particles [193]. In 2010, Winters' study showed that different translators' views affect the macro level of the novel, in which, the main message delivered by the translations of the novel is different. The focus of one translator was to provide a character study while the other focused on societal issues. Furthermore, Winters discussed how that may extend to influence the readers' attitude as well [194].

Li et.al [101] tried to capture differences in the translation styles of two English translations of a classic Chinese novel "Hongloumeng". They calculated Type/token ratios, sentence length, and vocabulary. The analysis in that study aimed at differentiating between the styles regards translators' social, political, and ideological context of the translations. They also explored the effect of the translator's native language on their translation style as one of the translator was a Chinese native speaker, and the other was a British scholar. They found that the two translators used two different strategies in translation. They contributed that variations to be affected by their social, political, ideological preferences, as well as their primary purpose of the translations.

Wang and Li looked for translators' fingerprints in two parallel Chinese translations of Ulysses using keywords lists. They identified different preferences in choosing keywords by different translators. They also found differences on the syntactic level by analysing the decision of clauses positions in the sentences [187].

Additionally, their findings affirmed a hypothesis that they made in their study that a writer's preferences of linguistic expression is demonstrated in free writing.

All the above studies can be used as an evidence for the existence of translators' fingerprints in their translations. It also provides substantial background for this research. Although the variations in the linguistics approaches that these research studies introduced, none of these research studies employed data mining and machine learning, even the quantitative studies.

2.2.2.2 Translator Identification

Previously, in translator profiling section, we discussed the literature related to the analysis of variation in translations by different translators. These mentioned studies revealed how the translators as individuals use linguistic features differently to deliver the same original text. Their identities are reflected in the choices that they make while translating. Analysing their translations demonstrates the variation in their choices, which constitute their own translation styles.

In 2000, Baker discussed the existence of translator style: "it is as impossible to produce a stretch of language in a totally impersonal way as it is to handle an object without leaving one's fingerprints on it" [19]; Baker suggested studying translator styles using forensic stylistics rather than literary stylistics [19]. According to Baker description, literary stylistics are generated by the choices that translators make consciously. On the other hand, Forensic stylistics reflects unconscious linguistic habits, in which translators do not realise such linguistic preferences.

The identification of the translator of a piece of text didn't attract the researchers because some research produced conflicting results. Furthermore, there was a research study in 2011 which considered attributing the translated text to their original author rather than the translator, where they looked at the translator's contribution to the text as a noise [62]. Their study investigated the use of semantic features to investigate authorship attribution of translated texts. They based their study on the expectation that the most significant effect of the trans-

lator is seen on the lexical and syntactic level, while the strongest influence of the author is on the semantic level. In other words, there was as expectation that translations and originals share the same semantic content.

In 2001, Mikhailov and Villikka questioned the existence of translators' stylistic fingerprints [121]. That research is based on a parallel corpus of Russian fiction texts and their translations into Finnish. They used vocabulary richness, word frequencies, and favourite words. Their analysis shows that the language of different translations of the same text performed by different people is closer than that of the different translation by the same translator. Their finding concludes that despite the existence of some translators' preference patterns, authorship existing techniques (which they evaluated) failed to identify translator's styles. Using their words, "it appeared as if translators did not have a language of their own" [121]. Their conclusion was summed up in their title; "Is there such a thing as a translator's style?".

In 2002, Burrows proposed Delta analysis for authorship attribution. In his first trial, he worked on translations as well. In that study, Burrows examined fifteen translations of Juvenal's tenth satire with a number of English restoration poetry. With Delta distance, the output is a table containing authors ranked from the most possible author to the least possible author. Interestingly, Dryden's rank on his translation was 9th out of 25. While Johnson style was correctly identified by Delta, Vaughan and Shadwell appeared significantly down the rank of their own translations.

Recently, in a number of studies by Rybicki and others in 2011 and 2012 [153, 154, 63], they investigated the problem of translator stylometry attribution by employing a well known technique for authorship attribution called Burrows's Delta [29], which is based on the z-score of the word frequencies. Burrows's Delta used successfully for authorship attribution in multiple studies [72, 73, 55, 11, 163]. A brief discussion about Burrows's Delta is discussed in section 2.2.3.2. They submit the calculated z-score to Cluster Analysis to produce tree diagrams for a given set of parameters, such as number of MFWs studied, pronoun deletion, and culling rate. Based on that culling rate, a decision is made to include a

specific word in the analysis. Then, these results that produced a great variety of parameter combinations are used as input for a bootstrap procedure. Based on the generated tree, they analysed how these translations were grouped in the same branches.

In the first study, Rybicki employed this method for the investigation of the translator Jeremiah Curtin and his wife Alma Cardell contribution to his translations. Rybicki discussed the literature that shows that *Memoirs of Jeremiah Curtin (1940)* is proven to be the work of his wife. In Rybicki's investigation, that memoirs was clustered in a different branch with some other suspected literary works. The second study was by Heydel and Rybicki, they employed the same method to investigate if it can differentiate the collaborations between translators on a single literary work. The case that they investigated was for Virginia Woolf's *Night and Day*, which consists of 36 chapters. The first translator, Anna Kołyszko, died after translating the first 26 chapters, then another translator, Heydel, translated the remaining chapters. Their proposed method succeeded in clustering the translations according to their translators. Hydel and Rybicki highlighted that despite the success of these investigations, the detected translator signature may be lost if investigated in context of various corpus. In 2012, in another trial for translator stylometry attribution, Rybicki conducted a research study under the title of "The Great Mystery of the (Almost) Invisible Translator: Stylometry in Translation" [154]. The title reveals the challenge of identifying the translator of a piece of text. Rybicki's approach failed to attribute texts to their translators using machine learning techniques and the use of most frequent words. He concluded that except for some few highly adaptative translations, the investigated method failed to identify the translator of the text, but it identified the author instead. Rybicki found that in most of the cases, the translations were grouped based on the original author rather than the translators. For that study, he used a corpus of multiple language translations: Polish, English, French, and Italian translations. He tested each corpus translations group separately. Rybicki emphasises that his study supports Venuti's observation on translator's invisibility, and concluded that multivariate analysis of most-frequent-word condemns

translators to Stylometric invisibility in the case of a large corpus of translations [154].

2.2.3 Methods of Stylometric Analysis

The most important function of language is communication and understanding the message produced during this communication. It has become the subject of different fields. Linguistics is the scientific study of language and explores the language system at different levels: Phonetics, Phonology, Morphology, Lexicon, Syntax, and Semantics. Observing the variation through these different levels shows the linguistic variations that may occur between different groups as well as between individuals. These variations may appear in the pronunciation as a variation in the accent, word choice as a variation in (lexicon, word spelling, or morphology), punctuation choices, or grammar rules' preferences. McMenamin [115] gave an interesting example about written variation and included 23 different forms of the same word "strawberry" on different signs in the road in one state. The analysis of variation is the first step of the identification of style-markers as the style is about the distinctiveness.

Linguistic variation is observed between groups and between individuals. For example, sociolinguistics studies the language of social groups such as teenagers, or cultural groups. Group variation is affected by factors such as age, culture, race, geography, social class, education level, and specialisation. Despite the existence of similarities in writing produced by specific groups of language users, there are still some individual decisions made by the writer which can contribute to the study of individual distinctive markers. These distinctive markers can be used to identify stylometry. In the next subsection, we are going to discuss which type of features have been used for stylometry analysis. In the later subsection, the different approaches and methods are discussed in details.

2.2.3.1 Features

Researchers used many stylistic features for attributing authorship. These features can be categorized into five main groups: Lexical, Character, Syntactic, Semantic, and Application-specific features.

Lexical features include all the features that are associated with analysing the sentence as a sequence of tokens or words, such as: word length [117], sentence length [125], word frequencies, word n-grams, vocabulary richness, and typo-errors.

Character features constitute a stylistic variation when the text is being analysed as a sequence of characters. For example: counting character types as letters, digits, or punctuation. Another example is counting character n-grams either fixed or variable length. Using compression methods for authorship attributions analyse the text as a sequence of characters as well.

Syntactic Features are being used when the analysis is done on the syntactical level where a similar syntactic pattern can be captured. This group includes frequencies of Part-of-speech (POS) and chunks, sentence and phrase structure, frequencies of rewriting rules [18], and function words. These features are extracted using Natural Language Processing (NLP) tools such as: Tokenizers, Sentence splitters, POS taggers, Text chunkers, Partial and full parsers [168].

Semantic Features need deeper analysis to capture. Semantic dependency graphs were used by Gamon [54] for author identification. McCarthy et al. [138] used the synonyms and hypernyms of words to extract semantic measures. Defining a set of functional features that associate certain words or phrases with semantic information was another approach introduced by Argamon [16].

Application-specific Features is important if the attribution is related to a specific application. This includes: attributing the author of an e-mail message or the writer in online-forums. In such cases, features associated with the text organization and layout are important like font colour count, font size count, the use of indentation, and paragraph length [1, 2] . Furthermore, some structural

features are important such as greetings and farewells in messages, the types of signatures that are being used.

2.2.3.2 Approaches

1. **Manual linguistic analysis**

   Early authorship disputes cases like biblical authorship disputes and plays of Shakespeare were first analysed by Human linguistic experts. All of that changed since 1964, when Mosteller and Wallace employed Bayesian statistical analysis for the problem of authorship attribution of "The Federalist Papers". Although the shift in direction of authorship attribution studies from human to computational models for the analysis, the forensic linguistics area still prefer the human expert based methods [132]. Olsson aruges this is an appropriate method because: First, most of the exiting computational methods are based on availability of a large amount of data, while the forensic linguists face the challenge of very limited samples of data in real cases scenarios. So, the linguist expert needs to identify the possible stylometry marker according to the available text, and the type of this text. Secondly: forensic linguists do not see the goal of automating authorship attribution as an important forensic aim. On the other hand, they may find it a dangerous practice that may mislead them. Thirdly, in court, linguists need to deliver and explain their opinion for the court. Their judgement as experts is part of the process [132]. Different forensic interesting cases where linguists analysed writers style either for authorship attribution, verification, and profiling are presented in a number of forensic linguistics books [132, 77, 39] .

   As for translator stylometry analysis, a number of studies were conducted by linguists. Translator's attitude toward the novel characters and how this extends to affect the readers are studies by Winters [194]. Another example is a study by Xiumei which examined translator's style in terms of Relevance theory [197]. Another linguistic study is introduced by Sabet

and Rabeie to explore the effect of gender ideology on translation style [156].

2. **Statistical approach**

Univariate analysis approach is the simplest one; where the analysis is done based on one feature or attribute, such as average word length, vocabulary size, occurrences of vowel-initial words, or 2-3 letter words. One of the well-known techniques in forensic linguistics is the CUSUM (abbreviation for cumulative sum) technique, which is introduced by Morton and Michaelson in 1990 [126]. In this method, the cumulative sum of the deviations of the measured variable is calculated and plotted in a graph to compare different author's styles. Although this method was used by forensic experts and was accepted by the court, Holmes [68] criticized this method as being unreliable in regard to its stability when evaluated with multiple topics.

Dealing with one feature at a time is a limitation of the univariate methods that cannot be ignored; that has led to the need of multivariate analysis. Principal component analysis (PCA) is a good example for multivariate analysis approach. PCA first usage in this research area was by Burrows in 1987 with a set of 50 highest frequency words for the analysis of "The Federalist Papers" [31, 28]. It showed high level of accuracy in the authorship attribution field over the years [67, 29, 22, 3, 74]. Burrows' Delta was interpreted by Argamon [11] as being an equivalent to an approximate probabilistic ranking based on a multidimensional Laplacian distribution over frequently appearing words. In 2004, Hoover suggested some modifications in the way of calculating Delta and also introduced alternatives of the way of transforming Delta that improved the performance of the method. Hoover variation was introduced under the name of Delta Prime [72].

In a work by Rybicki and Eder [155] to investigate the performance of Burrow's Delta in authorship attribution in different languages, they examined a number of corpora in English, Polish, Frensh, Latin, Hungarian, German, and Italian. Among these languages, English and Germen were the easier

languages for attribution by Delta method. On the other hand, Polish or Latin showed poor results. Rybicki and Eder suggested that degree of inflection as a possible factor that may affect authorship attribution in these languages. In linguistics, inflection is referring to the alteration of word forms to show its grammatical role in the sentence [147]. For example, in English, the use of suffix –s to represent singular and plural forms of the same lexemes is an example of inflection. Another example is the –o ending of Latin 'amo' 'I love' represents: first person singular, present test, active, and indicative [40]. In the topological classification of languages, languages are inflecting, synthetic, or fusional languages if they have some degree of inflection. Latin, Greek, and Arabic are highly inflected languages, while English is weakly inflected language.

The explanation that Rybicki and Eder provided for the reason of the effect of the degree of inflection on the authorship attribution method that they investigated in their research was: "The relatively poorer results for Latin and Polish—both highly inflected in comparison with English and German—suggests the degree of inflection as a possible factor. This would make sense in that the top strata of word frequency lists for languages with low inflection contain more uniform words, especially function words; as a result, the most frequent words in languages such as English are relatively more frequent than the most frequent words in agglutinative languages such as Latin" [155].

3. **Machine learning approach**

The third group includes the approaches that used machine learning methods to construct classifiers. These include: Support Vector Machine (SVM) [167, 3, 184, 41, 203], neural network [180, 203, 170, 176, 134, 178], and decision trees [203]. The benefit of their scalability allows for handling more features smoothly in addition to the fact that they are less susceptible to noisy data [96, 166, 109].

The interest in machine learning algorithms for this research area led to

multiple comparative studies between these methods. One of these studies was introduced by Zheng in 2006 [203] between decision trees, back propagation neural network, and support vector machines using four groups of stylistic features that include lexical, syntactic, structural, and content-specific features. Support vector machine introduced the higher accuracy than both decision tree and neural network in Zheng's study. Pavelec, et al. conducted a comparison between compression algorithm called PPM and Support Vector Machine classifier [134]. Results using the same testing protocol show that both strategies produce very similar results, but with different confusion matrices.

In 2010, Tsimboukakis and Tambouratzis [178] conducted a comparative study between both neural network and support vector machines. Their study resulted in introducing higher accuracy by the proposed neural network approach (multilayer perceptron MLP-based) in addition to that it need a smaller set of parameters. Another example is the comparative study conducted by Jockers and Witten in 2010 [82]. They evaluated five classification methods: Delta [11, 29], k-nearest neighbours, support vector machine, nearest shrunken centroids, and regularized discriminate analysis. This study suggested that both nearest shrunken centroids and regularized discriminate analysis outperformed the other classification methods.

Cluster analysis was examined by Hoover on different data sets with different features [70, 71, 72, 73], and [74].

Hoover compared the raw frequencies of the n most frequent words simultaneously using cluster analysis to determine the similarity of two pieces of text to each other. The process continues with the next most similar pair or group. This process had been repeated until all the texts are grouped into a single cluster. Hoover found that the best clustering was achieved over a range of (the 500 to 800 most frequent words) when the novels were divided into section of size of 5000 words [71]. Hoover also found that using clustering analysis to compare the texts based on the frequencies of frequent sequences of words (Frequent Collocations) outperformed the frequencies of

the most frequent words for authorship stylistic analysis [70]. In another study by Hoover to investigate the use of clustering analysis with Burrows' Delta, he found that the best accuracy was achieved at a choice of the most frequent words to be over 500 words [73]. If 70% of the occurrence of personal pronouns and words falls within the same piece of text, the analysis eliminates these pronouns and words. This resulted in a significant increase in accuracy [73]. An investigation of other variations of Burrow's Delta using Cluster Analysis had been introduced in another study by Hoover but no significant improvement over the original Delta method had been achieved [72]. In 2009, Hoover examined a case study of a real life authorship problem for a novel called *"Female Life Among the Mormons"* using cluster analysis, Delta analysis, t-testing, and PCA, and he recommended that Mrs Ferris is not the real author of this novel based on his investigation [74].

4. **Social Network Analysis**

Since everything is connected: individuals, information, activities, as well as locations, a sensible strategy for generating perception of such mass of connections is to analyse them as networks. Social network analysis (***SNA***) is the mapping and measuring of relationships and flows between the studied entities.

To the best of our knowledge, Social network analysis was not employed by researchers for the purpose of stylometry analysis. However, it was combined with authorship identification for a number of forensic email investigations studies to explore suspected collaborators and suspicious activities, and behavioural profiles [173, 58, 108]. None of these researchers analysed the actual contents of the email using social network analysis for the purpose of stylometry analysis. This thesis proposes that the development of this method may offer an additional approach to the field.

2.3 Translator Identification: A Data Mining Perspective

The Data mining term is used interchangeably with Knowledge discovery. Frawley et al. defined ***Data mining*** as "*the nontrivial extraction of implicit, previously unknown, and potentially useful information from data*" [50].

The key reason for the captivated interest in data mining is the huge amount of available data that is caused by information explosion that necessitate the need to convert this data into useful information and knowledge. The data mining importance can be explained under the perception of "we are data rich but information poor". [59]

Fayyad et al. defined the high level goals of data mining to be predictive, descriptive, or a combination of predictive and descriptive [48]. The particular objectives associated with prediction and description are targeted by different data mining tasks. Among the different tasks, the major principal data mining tasks are: Classification, Regression, Clustering, Summarization, Dependency modelling, and Link analysis.

2.3.1 Classification for Translator Identification

Translator identification using stylometry analysis can be seen as a data mining task, which investigates (an) *interesting pattern*(s) that can be used to distinguish between two Translators' styles.

Among the different data mining tasks, Classification and Clustering are considered as the most important tasks that can help in the task of identifying the translator stylometry as in both cases, the problem can be seen as grouping the documents into appropriate classes, which are the translators. Clustering has been used in 2012 for the purpose of attributing translator's style [154]. Though, classification is more appropriate for stylometry identification or attributing problem. Clustering is an unsupervised learning approach in which the

groups are unlabelled. Stylistic markers are used by the clustering technique to group the documents based on the similarities. With Clustering, there is no predefined classes. The Clustering technique may group these translations based on an interesting pattern or similarity different than translator's styles. Rybicki's research is a good example for that [154]. The objective of Rybicki's research was translator stylometry attribution. Rybicki used clustering techniques for that purpose. Documents were grouped based on their original authors rather that their translators.

Translator identification problem, which may be referred to as "Translator Attributing Problem" as well, is the task of identifying the translator of a given text[175]. Generally, it can be considered as a typical classification problem, in which a set of documents with a known translator are used for training and the aim is to automatically determine the corresponding translator of an anonymous text. Classification techniques have been used to support the decision making processes in different applications areas [35].

The first challenge in this classification problem is in identifying the appropriate features to be used in translator identification. This question is raised due to the variation of features used by different research studies. Consequently, the main concern of computer-assisted translator identification problem is to define the appropriate features that are able to capture the writing style of a translator. For that purpose, we need to explore what type of features are suitable for translator identification problem from a data mining perspective.

2.3.2 Stylometric Features for Translator Stylometry Identification

Stylometric features are grouped into five categories as mentioned earlier in this chapter: Lexical, Character, Syntactic, Semantic, and Application-specific Features. Among these different categories, there is a need to identify what type of features may be suitable for translator stylometry identification.

A study by Hedegaard and Simonsen examining authorship attribution of

a translated text, Hedegaard and Simonsen used the semantic level for authors attribution [62]. They hypothesise their research on the perception that the author's fingerprint on the lexical level and syntactic levels are defaced by the translation process, and that the traditional lexical markers are highly affected by the translator fingerprints. They found that semantic features outperformed the baseline of random chance accuracy. Despite their findings that function words-, which is a lexical measure, -based classifier was influenced by translator rather than author, they found that combining semantic features with the traditional lexical approach introduced better results than semantic features alone.

This perception of the translator fingerprint being the highest on the lexical level, followed by the influence on the syntactic level are also demonstrated through the choices made by the translator stylometry analysis conducted previously.

Baker conducted a comparative study in 2000 looking for "translator's fingerprints" [19]. Baker analysed the text on the lexical level using three features: type-token ratio, mean sentence length, and frequency of using different formats of the reporting verb "Say". The comparative study for the two translators Peter Clark and Peter Bush showed differences in the evaluated features [19]. However, we need to highlight here that these translations were not of the same source text neither for the same source language. This is a limitation in such a comparative study. It is not clear if the reported differences are caused by variation in translation styles, or by variation in the source texts or variation between source languages.

As discussed in previously in section 2.2.2.2, Mikhailov and Villikka evaluated three lexical features to examine the existence of translator's styles . These three lexical features are: vocabulary richness, word frequency, and favourite words [121]. In this study, they used Russian to Finnish translations of different texts performed by the same translator and, in one case, translations of the same text performed by different translators. In that study, they found that comparing translations to originals by the same translators may give some similar ratios for number of words in original / number of words in translation, number of sentences

in original / number of sentences in translation ratio, and number of paragraphs in original / number of paragraphs in translation. However, they attributed those similarities to the translator's attitude to the structure of the original rather than translator's individual writing styles. Mikhailov and Villikka concluded that the language of different translations of the same text performed by different people is closer than that of the different translations by the same translator [121].

Wang and Li in 2011 focused on investigating the translator's fingerprints based on English to Chinese translations of Ulysses, they explored both lexical and syntactic features [187]. On the lexical level, verbal keywords and emotional particles keyword are compared for the two translations. On the syntactic level, frequency and percentage of post-positioned adverbial clauses in the translated texts are also compared. Wang and Li discussed the variations that they found between the two translations[187]. This study was only conducted on one pair of translations that included two translators Xiao Qian and Jin. They found differences on the syntactic level in frequency and percentage of post-positioned adverbial clauses between the two translations. That study also included some original writings of Xiao in Chinese language to investigate if there are similarities between the way of composing text while writing or translating. That investigation on the lexical level showed that Xiao has some lexical idiosyncrasy that exists in both his own writing as well as his translations.

Wang and Li did not mention in this study that the Ulysses translation by Qian was translated by both Xiao Qian and his wife Wen Jieruo [201, 186]. This information of shared contribution to the translation by two translators may have significantly affected the results of this translator stylometry study.

Rybicki's study on translator's stylometry relied on the lexical level [154]. Rybicki used Burrows's Delta to measure the similarities/distances between two pieces of text. For that study, Polish, English, French, and Italian translations are evaluated for different translators. Using clustering, the translations in most of the cases were grouped based on their original author rather than their translators.

As highlighted in the literature, there is limited number of research studies in using computational linguistics for translator stylometry identification, which revealed contradictory findings. Some of these studies had limitations in terms of the chosen corpus like Baker's study and Wang and Li study as highlighted earlier. Although the recent development in machine learning and data mining techniques helped in similar stylometry identification problems like authorship attribution, except from Rybicki's study [154], neither of these translator stylometry analyses employed data mining techniques to evaluate the features that they studied. Despite the high expectation of employing the lexical features for translator identification, existing lexical features failed to identify translator stylometry as shown in Mikhailov and Villikka and Rybicki studies. Thus, there is a need to explore other methods that can be used for translator stylometry identification problem. The support of translator stylometry signature that has been demonstrated in our previous discussion of the literary analysis of translator styles encouraged us to explore another possible approach to identify translator stylometry. This new approach will be based on employing the use of social network analysis and data mining techniques.

2.3.3 Social Network Analysis

Newman [129] defined a Network as "a collection of points joined together in pairs by lines"; these points are referred to as vertices or nodes and the lines are referred to as edges. Networks are everywhere; almost any system can be represented as a network. The traditional definition of a system is that it is a group of components interacting together for a purpose; this is a definition whereby a network representation is paramount (components are nodes and interactions are through links). Many tools exist in the literature for analysing networks [189]. These tools vary from mathematical, computational, to statistical tools.

Social network analysis has gained researchers' interest because of its ability to represent relationships among social entities in a way that enable further analysis of the relationship patterns and their implication. There were many research

studies that have benefited from using social network analysis, such as, studies in occupational mobility, community, group problem solving, social support, world political and economic system, markets, etc $\cdots$ [189].

Social network analysis is the mapping and measuring of relationships and flows between people, groups, organizations, computers or other information/knowledge processing entities. Social network analysis measures and represents the regularities in the patterns of relations among entities.

From social network analysis perspective, the network has two types of components: Actors, and Relations. Actors, which are also known as: Nodes, Points, and Vertices, represent the entities. These entities may be individuals, organizations, or events. Relations, which are also known as (lines, arcs, edges, and ties), represent the connections between pairs of actors. Social relations vary along three dimensions: direction, strength, content. The directions are either directed (asymmetric) or undirected (symmetric). Strength represents the intensity or frequency of interaction. Strength in its simplest way is binary and represents the existence or absence of the relation. In other cases, discrete or continuous numerical values are used to represent the weight of these relations. The third factor, content, is used to represent a specific substantive connection among actors. Relations are multiplex when actors are connected by more than one type of tie (e.g., friendship and business).

Important observations in regards to social network analysis definitions that can be linked to stylometry analysis to translator identification problems are:

- "... Social network analysis is based on an assumption of the importance of relationships among interacting units" [189].
- "... The unit of analysis in network analysis is not the individual, but an entity consisting of a collection of individuals and the linkages among them" [189]
- The main goal of social network analysis is detecting and interpreting patterns of relations among actors [130].

- "Actors and their actions are viewed as interdependent rather than independent, autonomous units". [189].

The question that arises here is: The question that arises here is: "Why has social network analysis be chosen for investigation rather than a non-network explanation?" The answer to this question relies on the understanding of the following idea: While the main focus in a non-network explanations targets one or all of the followings features of the individual entities, the associations of these features, and the convenience of using one or more feature to predict another feature [189], the social network analysis refers to the set of entities and the relations among them. In social network analysis, relations come first, and then the features of the entities come later.

Traditional Stylometric features discussed in the literature are represented by the non-network explanation that we discussed here, and we know that it failed in identifying translator stylometry. That raises another question; which is, Can we benefit from the social network analysis in stylometry analysis field? As mentioned earlier in this section, networks can represent most of the complex structure in our life. What about texts?

Network Text Analysis is one method for encoding the relationships between words in a text and constructing a network of the linked words by Popping in 2000 [140]. The technique is based on the assumption that language and knowledge can be modelled as networks of words and the relations between them as introduced by Sowa in 1984 [164]. Text was also modelled as a network for Centring resonance analysis by Corman et al. [37] and Willis and Miertschin [190] . Foster et al. analysed word-adjacency networks in a study that investigate the effect of edge direction on the networks structure. In Foster's study, the edges point from each word to any word that immediately follows it in a selected text [49]. Another example of word adjacency network is a study by Grabska-Gradzinska et al. of literary and scientific texts written in English and Polish [57].

Analysing texts as networks goes way beyond traditional text analysis tools. We are not interested in the usage of part-of-speeches tags, or finding the most

frequent words. Instead, we can analyse the actual relations, the process that aligns the words in a specific way, rather than the terms themselves.

2.3.4 Analysing Local and Global Features of Networks

To analyse and compare two networks, we can use their global statistical features; these include Shortest-path length, global centrality, clustering coefficient, etc $\cdots$, or their structural design principles like the network motifs.

2.3.4.1 Global Features

To evaluate global network features, we choose some of the common features like degree average, density, clustering coefficient, transitivity, modularity, betweenness, characteristic path length, and diameter.

- Degree average

  The degree of a node is the number of links that are attached to it, which is also the number of nodes adjacent to it. In directed networks, the indegree is the number of inward links and the outdegree is the number of outward links. The degree of a node is a measure of the "activity" of the actor it represents, and is the basis for one of the centrality measures [189]. The average of degree of a node i is the average of weighted degree which is calculated using the following equation

  $$k_i{}^w = \sum_{j \epsilon N} w_{ij} \tag{2.1}$$

  where N is the set of all nodes in the network, (i, j) is a link between nodes i and j where $(i, j \epsilon N)$, and w_{ij} is the connection weight associated with the link (i, j).

- Density

  The density of a network is the proportion of possible links that are actually present in the network. It is the ratio of the number of links present to

the maximum possible links in this network [189]. Connection weights are ignored in calculations. This measure is used to evaluate the cohesiveness of subgroups.

- Diameter

  The diameter of a connected graph is the length of the largest geodesic between any pair of nodes [189]. The diameter represents the maximum eccentricity. The diameter of a graph is important because it quantifies how far apart the farthest two nodes in the graph are.

- Assortativity

  The assortativity coefficient is a correlation coefficient between the degrees of all nodes on two opposite ends of a link. A positive assortativity coefficient indicates that nodes tend to link to other nodes with the same or similar degree.

- Clustering coefficient

  The clustering coefficient is the fraction of triangles around a node. It is equivalent to the fraction of node's neighbours that are neighbours of each other. Clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together.

- Transitivity

  The transitivity is the ratio of "triangles to triplets" in the network (an alternative version of the clustering coefficient).

- Modularity

  The modularity is a statistic measure that is used to quantify how the network can be divided into optimal community structure, which is the subdivision of the network into non- overlapping groups of nodes in a way that maximizes the number of within-group edges, and minimizes the number of between-group edges.

- Betweenness

  Node betweenness centrality is the fraction of all shortest paths in the network that contain a given node. Nodes with high values of betweenness centrality participate in a large number of shortest paths.

- Characteristic path length

  The characteristic path length is the average shortest path length in the network.

2.3.4.2 Local Features

Local measures attempt to capture the global features of the network using the local constructs. A widely used local measure is network motifs. Network motifs which are initially introduced by Milo et al. [122] are patterns (represented by small sub graphs) that are repeated in a real network more often than randomly generated networks. They are used to uncover network structural design principles [7]. The motifs usually consist of three, four or five nodes. Network motifs have been successfully used by different researchers in biology [165, 142], game theory [56], evolutionary algorithms [103], electronic circuits [79], and software [181].

2.4 Chapter Summary

This chapter has provided a brief summary of the stylometry analysis problem. It discussed the extensive literature of writer stylometric analysis and its subtopics: writer profiling, writer attribution, writer verification, and plagiarism detection. It also discussed the varied methodology employed in this topic. The different nominated features and approaches used to solve this problem are also presented.

The challenge of identifying translator stylometry is discussed in both literary studies and computational linguistic studies. Failure of attributing translation to their translators led to the need of identifying Stylometric features that are able

to capture the translators' individual styles. For that purpose, we explored how we can redefine the problem of translator stylometry identification as a classification problem, and how we can employ social network analysis to identify hidden Stylometric features.

There is limited research in stylometry analysis with identified problems. This study addressed the gap in the literature by combining a mixed methodology that employ features extracted from social network analysis as attributes for machine learning classification. The aim of this study is to introduce a computational framework that is able to identify translator stylometry.

Chapter 3

Data and Evaluation of Existing Methods

3.1 Overview

In this study, we follow Baker's definition of "Translator styles": " a study of a translator's style must focus on the manner of expression that is typical of a translator, rather than simply instances of open intervention. It must attempt to capture the translator's characteristic use of language, his or her individual profile of linguistic habits, compared to other translators" [19]. Her definition of the style as a matter of patterning of linguistic behaviour is what we targeted in this research. That guided us through the design and choice of our data corpus.

Based on Baker's definition, we find that the best way to identify translator stylometry is to compare translations of the same original text by different translators from the same source language to the same target language. That will minimize the variations that may be caused by factors other than translators individual style, such as: variations of the source text types or contents, or variations caused by different languages characteristics.

For that purpose, we are going to use for this study parallel Arabic to English translations of the "Holy Qura'an". In this chapter, we are going to clarify the

reason for our choices of the source and target languages of translation, the nature of the source text, and the structure of our dataset. After that, we are going to evaluate some of the existing methods that have been used in the literature for translator stylometry identification problem on our data corpus.

3.2 Why Arabic to English translations?

This study is focusing on translations from Arabic to English. Arabic Language is the third most official language in the world after English and French; where it is the official language for 26 countries [1] with approximately 280 million native speakers in the world [141].

Second language learners face difficulties when they learn a language that is derived from a different language family. For example, learning German language for a native English speaker is not as difficult as learning Arabic Language. German and English languages belong to the same branch and subgroup of the language families' taxonomy. Both of them belong to Western branch from Germanic subgroup from Indeo-Eurpoean family [88], while Arabic belongs to Semitic subgroup from Afro-Asiatic family [88]. Translating may pose similar difficulties between languages that belong to different language families; spaces of choices while mapping increase in this case.

The importance of the Arabic language can be understood because of its socio-political role, but it extends to its religious role. Approximately 1.57 billion Muslims of all ages live in the world today [148] who read Qur'an on a daily basis as a part of their religious activities, which explains the reason for having millions of Muslims seeking to learn Arabic, the language of "The Holy Qur'an" which is the main religious text of Islam.

[1] As in World Atlas website http://www.worldatlas.com/ on 28th of January 2011

3.3 Why the "Holy Qur'an"? Is the proposed approach restricted to Holy Qur'an?

From the above figure, less than 17.83% of Muslims are Arabic native speakers, and all the others need to look for interpretation and translations of the meaning of "The Holy Qur'an". Hence, there is a need to translate Qur'an meanings accurately to reflect and respect the original meaning. Despite the existence of many translations of this text, there is a considerable dispute about the loss in the translation of Qur'an meanings due to the uniqueness of its textual characteristics. Therefore, we chose to use the translation of the meanings of "The Holy Qur'an" as our corpus for this study. Another important consideration for the choice of this text was the expectation that given its religious significance, there would be minimal difference in the translations; thus, it would be a tough translator stylometry challenge.

Additionally, the availability of many translations for the same text provided a good source for evaluating the challenge of increasing the number of translators while trying to detect their translation stylometry. The study introduced in this thesis is not limited to the Holy Qur'an. Given the strength of this Holy book in its use of the Arabic language – in fact it is considered as the most powerful use of formal Arabic – we believe that it is the type of translation that can challenge most translators. We expected the translators to be as transparent as possible. Introducing a methodology that is able to handle such a challenge in a parallel translation leads to the expectation of higher accuracy when applied to different type of datasets. We obtained our corpus data from tanzil.net [2] website. This website offers translations in different languages for the meanings of Holy Qur'an. We chose seven translations for this study: Translations by: *Ahmed Raza Khan*, *Muhammad Asad*, *Abdul Majid Daryabadi*, *Abul Ala Maududi*, *Mohammed Marmaduke William Pickthall*, *Muhammad Sarwar*, and *Abdullah Yusuf Ali*. Table 3.1 provides brief information about these translators.

[2]Tanzil is a quranic project launched in early 2007 to produce a highly verified unicode Quran text to be used in quranic websites and applications. www.tanzil.net

In the following example: Figure 3.1 shows two verses from chapter 78 of the Holy Qur'an "An-Naba'"". Then, we provided the parallel English translations of the seven translators of these two versus. We can see the variation in the translations of two sentences; which causes variation in the delivered mental pictures to the reader.

Figure 3.1: In the Holy Qur'an 78(6-7)- Color Coding Represents Variations of Lexical Uses

Translation of *"Ahmed Raza Khan"*

"*Did We not make the earth a bed? (6) And the mountains as pegs? (7)*"

Translation of *"Muhammad Asad"*

"*HAVE WE NOT made the earth a resting-place [for you],(6) and the mountains [its] pegs?(7)*"

Translation of *"Abdul Majid Daryabadi"*

"*Have We not made the earth an expanse. (6) And the mountains as stakes?(7)*"

Translation of *"Abul Ala Maududi"*

"*Have We not spread the earth like a bed,(6) and fixed the mountains like pegs,(7)*"

Translation of *"Mohammed Marmaduke William Pickthall"*

"*Have We not made the earth an expanse,(6) And the high hills bulwarks?(7)*"

Translation of *"Muhammad Sarwar"*

"*Have We not made the earth as a place to rest (6) and the mountains as pegs (to anchor the earth)? (7)*"

Translation of *"Abdullah Yusuf Ali"*

"*Have We not made the earth as a wide expanse, (6) And the mountains as pegs? (7)*"

Another example is verse 14 of chapter 23 of the Holy Qur'an "Al-Mu'minun", which is shown in Figure 3.2. The translations of this verse by the seven translator is shown afterward. The availability of different parallel translations of the same text provide us with the required data to compare translator's individual styles. These two examples that we provided support our choice of the dataset in term of availability of a number of parallel translations as well as aiming that translators were trying to minimize their individual reflect in the text because of its religious type.

ثُمَّ خَلَقْنَا ٱلنُّطْفَةَ عَلَقَةً فَخَلَقْنَا ٱلْعَلَقَةَ مُضْغَةً فَخَلَقْنَا
ٱلْمُضْغَةَ عِظَٰمًا فَكَسَوْنَا ٱلْعِظَٰمَ لَحْمًا ثُمَّ أَنشَأْنَٰهُ خَلْقًا ءَاخَرَ ۚ
فَتَبَارَكَ ٱللَّهُ أَحْسَنُ ٱلْخَٰلِقِينَ ١٤

Figure 3.2: In the Holy Qur'an 23(14) - Color Coding Represents Variations of Lexical Uses

Translation of *"Ahmed Raza Khan"*

"*We then turned the drop of fluid into a clot of blood, then the clot into a small lump of flesh, then the lump into bones, then covered the bones with flesh; then developed it in a different mould; therefore Most Auspicious is Allah, the Best Creator.(14)*"

Translation of *"Muhammad Asad"*

"*... and then We create out of the drop of sperma germ-cell, and then We create out of the germ-cell an embryonic lump, and then We create within the embryonic lump bones, and then We clothe the bones with flesh - and then We bring [all] this into being as a new creation: hallowed, therefore, is God, the best of artisans!(14)*"

Translation of *"Abdul Majid Daryabadi"*

"*Thereafter We created the sperm a clot; then We created the clot a lump of flesh; then We created the lump of flesh bones; then We clothed the bones with flesh: thereafter textcolorvioletWe brought him forth as another creature. Blest then be Allah, the Best of creators!(14)*"

Translation of *"Abul Ala Maududi"*

"*then We made this drop into a clot, then We made the clot into a lump, then We made the lump into bones, then We clothed the bones with flesh, and then We caused it to grow into another creation. Thus Most Blessed is Allah, the Best of all those that create.(14)*"

Translation of *"Mohammed Marmaduke William Pickthall"*

> "*Then fashioned We the drop a clot, then fashioned We the clot alittle lump, then fashioned We the little lump bones, then clothed the bones with flesh, and then produced it as another creation. So blessed be Allah, the Best of creators! (14)*"

Translation of *"Muhammad Sarwar"*

> "*The living germ, then, was turned into a shapeless lump of flesh from which bones were formed. The bones, then, were covered with flesh. At this stage, We caused it to become another creature. All blessings belong to God, the best Creator.(14)*"

Translation of *"Abdullah Yusuf Ali"*

> "*Then We made the sperm into a clot of congealed blood; then of that clot We made a (foetus) lump; then we made out of that lump bones and clothed the bones with flesh; then we developed out of it another creature. So blessed be Allah, the best to create! (14)*"

3.4 How the dataset is structured?

The holy Qur'an is divided mainly into 114 surah (pl. suwar) which is also known by some as chapters, although they are not equal in length. The length of the surah varies from three ayat (verses) to 286 ayat. We will refer to them as chapters and verses in this study. Some Islamic scientists divided the Holy Qur'an into 30 parts (Juz') which are roughly equal in length for easier citation and memorizing during the month.

In this study, we are going to use parallel translations of the meanings of

Table 3.1: Translators' Demography

Translator	**Life interval**	**Birth place**	**Nationality**	**First language**	**Second language(s)**	**Translation appeared on**
Ahmed Raza Khan	1856-1921	Bareilly, India	Indian	Urdu	N/A	1912
Muhammad Asad	1900-1992	Lvov, Poland	Pakistani (Originally Polish)	Polish	Arabic, Hebrew, French, German, and English	1980
Abdul Majid Daryabadi	1892-1977	India	Indian	Urdu	English	1957
Abul Ala Maududi	1903-1979	Aurangabad, India	Indian	Urdu	Arabic, English	N/A
Mohammed Marmaduke William Pickthall	1875-1936	Harrow, London	British	English	Arabic, Turkish, and Urdu	1930
Muhammad Sarwar	1938- still alive	Quetta - Pakistan	Pakistani	N/A	N/A	1981
Abdullah Yusuf Ali	1872-1953	Bombay, India	Indian	Urdo	English, Arabic	1934

the last six parts of the Holy Qur'an. These six parts represent 74 chapters. The reason that we limited our dataset corpus to seven translations of six parts is due to the computation limitation. Additionally, we see that this amount of data will be enough to address our problem of translator stylometry identification in terms of data size and number of classes. The size of each part for each translator is shown in Table 3.2.

Table 3.2: Number of Words in the Dataset for Each Translator

Translator Name	**Part25**	**Part26**	**Part27**	**Part28**	**Part29**	**Part30**
khan	7427	4476	5974	5600	6182	5690
Asad	7326	7136	7261	7025	7499	6619
Daryabadi	6659	4105	5403	5100	5492	4942
Maududi	7310	4370	6255	5588	6291	5356
Pickthall	5340	4759	5384	5188	5477	4759
Sarwar	6831	4034	5654	5181	5784	5332
Yousif Ali	5950	5795	6019	5665	6265	5633

3.5 Evaluating Existing Methods

3.5.1 Is there such a thing as a translator's style

In 2001 a paper published by Mikhailov and Villikka [121] claimed that translators didn't have a language and a style of their own. In their research, they used vocabulary richness, most frequent words and favourite words as they are typical authorship attribution features to prove their claim. In response to this paper, and as a first step, we reapplied the same method and features that they used for their claim on our dataset.

3.5.1.1 Method I

1. Vocabulary Richness

   Vocabulary richness can be evaluated using different methods. Mikhailov and Villikka [121] used three different measures of Vocabulary richness from a multivariate approach to measure vocabulary richness that were originally introduced by Holmes in 1991 [66] then modified by Holmes and Forsyth in 1995 [65] for analyzing the federalist papers. These three measures are:

   (a) R-index is a measure suggested by Honore (1979). This measure targets (hapax legomena) which means words that used only once in the text. The higher number of words used only once in the text, the higher the R value.

   $$R = \frac{100LogN}{1 - \frac{V1}{V}} \tag{3.1}$$

   where N is the text length of N words, and V is the number of different words;

   (b) K-index is a measure that was proposed by Yule (1944). The measure monotonically increases as the high-frequency words in the text increases.

$$K = \frac{10^4(\sum_{i=1}^{\infty} i^2 V_i - N)}{N^2} \tag{3.2}$$

where $V_i(i=1,2,\dots)$ is the number of words used exactly i times in the text.

(c) W-index is originally proposed by Brunet (1978), who claimed that this measure is not affected by text length, and it is author specific. W-index increases as number of different words increases.

$$W = N^{V-a} \tag{3.3}$$

where a is a constant ranges from 0.165 to 0.172. As we couldn't find the methodology of choosing the value of (a), we used the value of 0.172 which was used by Mikhailov and Villikka [121] in their research.

2. Most Frequent Words

F-Index is used to measure the closeness of most frequent words as it reflects a correlation between two pieces of texts. The two targeted texts are compared by selecting the 40 most frequent words from their word lists. Then, the F-Index is calculated by adding three points for each word with close relative frequency, two points for each word with different relative frequency, and one point for each word with quite different relative frequency. One point is deduced for each word absent in the other list. We applied this method on lemmatized word lists for each text in our dataset.

To calculate the F-Index, we needed to define threshold for close relative frequency, different relative frequency, and quite different relative frequency, which were not defined in Mikhailov and Villikka research [121]. To do that, we divided the distance between the minimum frequency and maximum frequency to three equal parts, the first section represent low difference area, the middle two sections represent medium difference, and the last section represent high difference area. If the difference between the frequency of the same words in the two text occur in the low difference area, that means

they are relatively close to each other, and F-index is incremented by three. If the difference occurs in the medium difference area, it is considered as being quite different, and the F-Index is incremented by two. Otherwise, the F-Index is incremented by one. This process of calculation is illustrated in Figure 3.3.

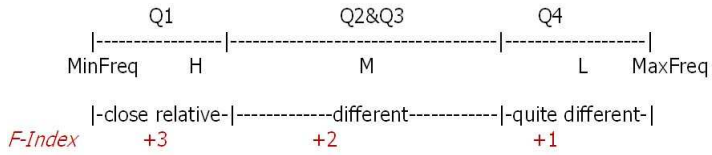


Figure 3.3: Calculating Thresholds for F-Index

3. Favorite Words

   To calculate the Favorite words: Firstly, the relative frequency for each word is calculated for the whole corpus. Relative frequency is the number of observations of a single word divided by the total number of words in the text. The output for this step is a table that has the word and the corresponding relative frequency. Secondly, for each tested text, we calculated the relative frequency for each word in that text, and we have similar output to the first step. Then, we compare the output of these two steps. After that, we have a filtered list that contains the favorite words for that author in that translation. The criterion for filtering is to have a much higher frequency than in the corpus, we denote this by alpha. Alpha is not defined by value, and therefore, we tested it with different values as we will describe later.

   We then re-applied the same method for F-Index, which was described in the Most frequent words subsection to compare the two obtained filtered lists for the two texts that we want to compare. Although the list size in the most frequent words method is predefined with the top 40 most frequent words, for FW-Index the size changes based on changing alpha. To define a threshold for the condition "where word freq in a text is much higher than in the corpus" [121], we have $Fc(w_1)$ representing the frequency of $word_1$ in the corpus, $F_i(w_1)$ represents frequency of word w_1 in $text_i$. If

$(Fi(w1_)/Fc(w_1))$ is greater than alpha, then its frequency is much higher than in the corpus.

To define an appropriate value for alpha, we used for this test two parts translated by two different translators; where we have part 25 translated by Ahmed Raza and Pickthall, and part 27 is translated by sarwer and yousifali. Table 3.3, with its subtables (a) and (b), shows that choosing alpha as twice or three times the relative frequencies introduces acceptable number of words in the list and FW-Index. So, we chose alpha as 3, as it complies more than 2 for the condition "where word freq in a text is much higher than in the corpus" that had been described in Mikhailov and Villikka [121].

Table 3.3: Affection of choosing alpha on the number of words in the coincidences Lists of FW-Index for two tested texts

(a) Number of Words in the Coincidences List of "Part 25"

Alpha	Khan (7427 words)	Pickthall (5340 words)	FW-Index
4	337	328	44
3	396	408	70
2	531	510	128
1.5	615	613	174

(b) Number of Words in the Coincidences List of "Part 27"

Alpha	Sarwer (5654 words)	Youasif ali (6019 words)	FW-Index
4	347	467	75
3	448	538	103
2	573	694	167
1.5	691	802	227

3.5.1.2 Experiment I

In this experiment, we are going to evaluate Mikhailov and Villikka approach using our dataset [121]. We found that "chapters" will be too small to be used with these measures, as some of them have the limitation of working with text size of 1000 words or more. So, we worked with the level of parts of the Holy Qur'an. More details about the possible divisions of the Holy Qur'an were explained earlier

in the data section. Therefore, we used seven translations for six parts of the Holy Qur'an in this experiment.

For vocabulary richness: R-Index, K-Index, and W-Index were calculated for each text. Then the results for these calculations were used to compare and analyze the similarities and differences between translations by the same translator with translations for the same text. The objective of this experiment is to identify if vocabulary richness for the same translator is the same for different translations, or it is only affected by the original text.

For the most frequent and most favourite words, we cannot evaluate a single text each time; as the proposed measures are used to measure similarities between two texts. Therefore, for the most frequent words, we calculated these measures for all possible combinations for the existing dataset. First, we calculated all the pairs of translations by the same translator. For example, for translator Asad, we calculated the most frequent words measure, F-Index, for (part25-part26), then for (part25-part27), then for (part 25-part 28),...etc. After measuring these for all translators, we evaluated the F-Index for different translators for the same original text. For example, for Part25, we calculated F-Index for (Asad-Daraybadi), (Asad,Maududi), (Asad-Pickthall),...etc. Then, all of these results were used to analyze if the most frequent words measure is more affected by the translator style or the original text. The same procedure is used for evaluating the favorite words measure.

3.5.1.3 Results and Discussion of Experiment I

For Vocabulary Richness, the three used measures are highly affected by the original text as seen in Figures 3.4(a), 3.4(b), and 3.4(c). The R-Index didn't reflect an individual translator's style; It is affected by the original text. Despite that all orginial text to come from the same language, both of K-Index and W-Index also didn't reflect individual translator styles. However, Asad had lower K-index for all translations, and Khan had the highest W-index values for all translations. This implies that both of K-Index and W-Index can show individual

styles for some special cases, which required further analysis so as to find the limitations for such cases. Detailed results for R-Index, K-Index and W-Index are shown in Table 3.5.

For Most Frequent Words, Table 3.6 shows F-Index for translations of **the same text**. These numbers (F-Index) reflect how close the most 40 frequent words are in each of these translations, while Table 3.4 shows F-Index for two translations for **the same translator**.

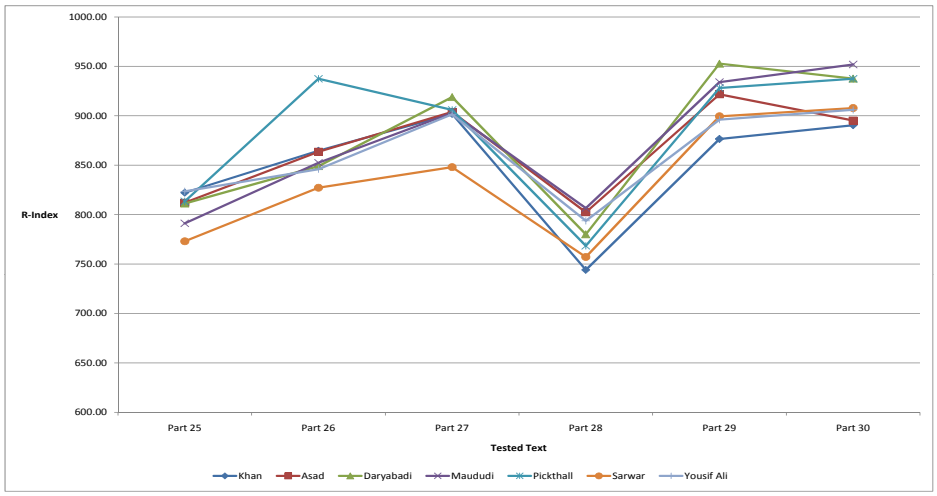
The average of F-Index for translations for the same text is 80.19 with a STD of 10.01 while the average for F-Index for translations for the same translator is 86.94 with a STD of 9.85.

Table 3.4: Most Frequent Words Index - for the Same Translator

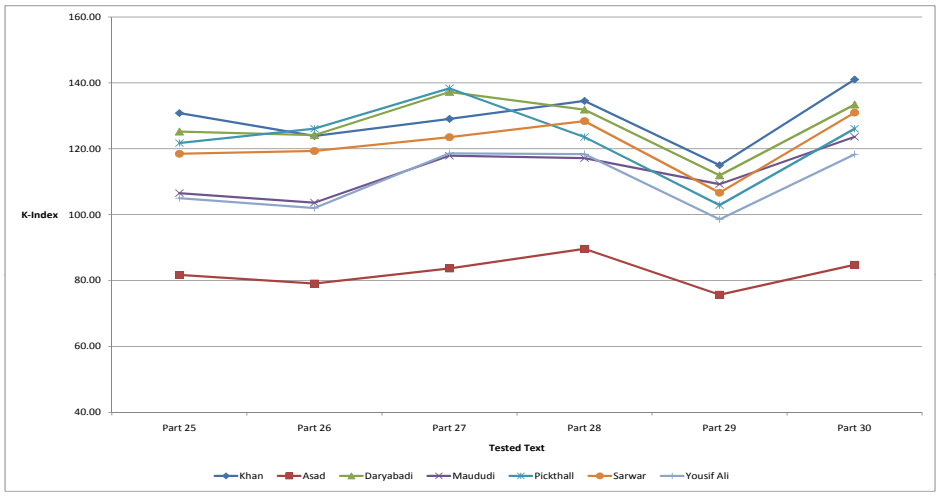
Translator Name	Part25-Part26	Part25-Part27	Part25-Part28	Part25-Part29	Part25-Part30	Part26-Part27	Part26-Part28	Part26-Part29	Part26-Part30	Part27-Part28	Part27-Part29	Part27-Part30	Part28-Part29	Part28-Part30	Part29-Part30
Asad	100	85	89	105	85	90	100	100	80	84	85	75	89	73	85
Pickthall	90	95	79	100	75	90	100	95	70	79	99	75	84	64	95
Yousif Ali	85	85	74	80	80	89	100	75	70	84	85	80	69	64	90
Khan	100	85	74	105	85	85	90	100	85	64	90	75	74	74	90
Daryabadi	100	100	94	100	85	95	105	100	85	89	90	75	94	80	100
Maududi	95	85	79	95	85	80	100	90	85	79	85	75	84	83	100
Sarwar	90	80	84	85	90	80	95	90	90	79	95	85	89	99	105

For Favourite Words, Table 3.7 shows FW-Index for translations of **the same text**, where FW-Index reflects how close the favourite words lists in a binary comparison of translations. Table 3.8 shows FW-Index for translations for **the same traslator**. The results showed that the average of FW-Index for translations of the same text is 110.93 with a STD of 31.28 while the average for FW-Index for translations for the same translator is 71.61 with a STD of 16.70. These tables show that favourite words list doesn't reflect a translator signature. It is more affected by original text than translator individual styles.

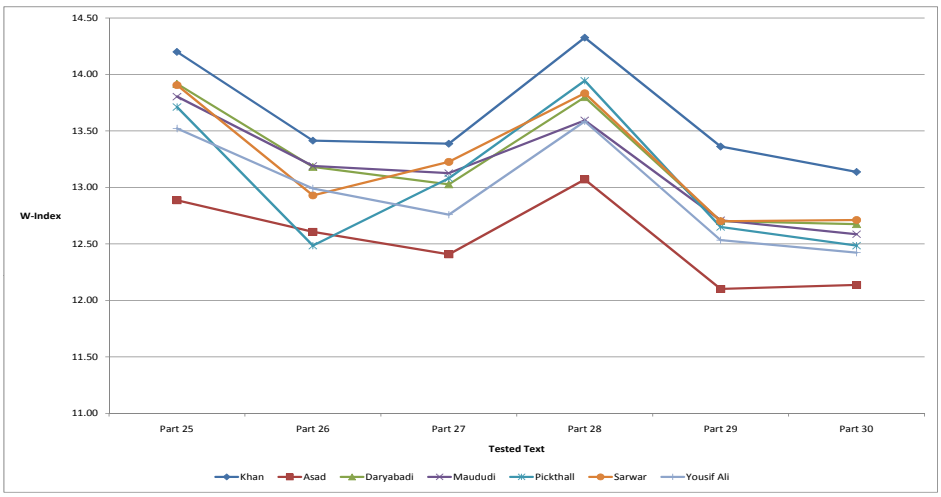
To obtain meaningful information from Tables 3.4 and 3.6 we extracted val-



(a) R-Index



(b) K-Index



(c) W-Index

Figure 3.4: Vocabulary Richness Measures

Table 3.5: Vocabulary Richness Measures

Translator Name	R-Index						K-Index						W-Index					
	Part25	Part26	Part27	Part28	Part29	Part30	Part25	Part26	Part27	Part28	Part29	Part30	Part25	Part26	Part27	Part28	Part29	Part30
khan	822.19	864.64	901.84	744.06	876.56	890.48	130.82	123.86	129.06	134.52	115.02	141.02	14.20	13.41	13.39	14.33	13.36	13.14
Asad	812.08	863.62	903.85	802.34	921.75	895.26	81.70	79.09	83.67	89.62	75.67	84.77	12.89	12.61	12.41	13.07	12.10	12.14
Daryabadi	811.20	849.03	918.87	780.07	952.72	937.62	125.21	124.14	137.23	131.87	111.91	133.41	13.92	13.18	13.03	13.80	12.70	12.67
Maududi	791.12	852.45	902.81	806.51	934.09	951.88	106.52	103.64	117.89	117.14	109.25	123.63	13.80	13.19	13.13	13.59	12.71	12.59
Pickthall	813.36	937.52	905.89	768.45	928.14	937.52	121.72	126.09	138.34	123.55	102.87	126.09	13.71	12.48	13.08	13.94	12.65	12.48
Sarwar	773.02	827.20	848.06	757.14	899.48	907.85	118.48	119.31	123.51	128.40	106.65	130.98	13.91	12.93	13.23	13.83	12.70	12.71
Yousif Ali	823.53	845.97	901.53	793.74	896.07	906.08	105.01	102.00	118.59	118.37	98.57	118.29	13.52	12.99	12.76	13.58	12.53	12.42

Table 3.6: Most Frequent Words Index - for the Same Part

Part number	**Asad-Daryabadi**	**Asad-Maududi**	**Asad-Pickthall**	**Asad-Khan**	**Asad-Sarwar**	**Asad-Yousif Ali**	**Daryabadi-Maududi**	**Daryabadi-Pickthall**	**Daryabadi-Khan**	**Daryabadi-Sarwar**	**Daryabadi-Yousif Ali**	**Maududi-Pickthall**	**Maududi-Khan**	**Maududi-Sarwar**	**Maududi-Yousif Ali**	**Pickthall-Khan**	**Pickthall-Sarwar**	**Pickthall-Yousif Ali**	**Khan-Sarwar**	**Khan-Yousif Ali**	**Sarwar-Yousif Ali**
Part25	69	90	70	69	74	85	73	95	70	59	79	78	94	85	95	70	64	89	69	80	80
Part26	64	85	75	84	79	80	67	100	70	72	80	72	94	80	99	75	73	85	84	90	84
Part27	59	80	69	59	74	80	79	95	70	65	80	79	85	75	89	85	75	100	70	85	85
Part28	63	80	70	69	74	80	73	95	70	67	79	78	95	85	89	85	84	100	84	89	84
Part29	69	79	74	74	74	70	89	105	75	74	89	89	95	85	100	80	75	95	80	85	70
Part30	75	80	80	69	84	80	75	95	70	70	95	85	100	85	85	80	75	95	90	75	75

ues for one translator, Asad, to compare the closeness between his own writing with translations that are written by others for the same original text. This comparison is shown in Figure 3.5(a). The first six columns represent the F-Index for the most frequent words for the six translators, while the last column represent the average of F-Index for Asad writings. For example, for Text "Part 25", we calculate the average of F-Index for "Part 25 and Part 26", "Part 25 and Part 27", "Part 25 and Part 28", "Part 25 and Part 29", and "Part 25 and Part 30". The same method is repeated for all other texts. Although Figure 3.5(a) shows that the F-index for Asad-to-himself is higher than Asad-to-others, by repeating the same analysis on another translator, Pickthall, we found the F-Index for Pickthall-to-himself is in average compared to Pickthall-to-others F-index as shown in Figure 3.5(b).

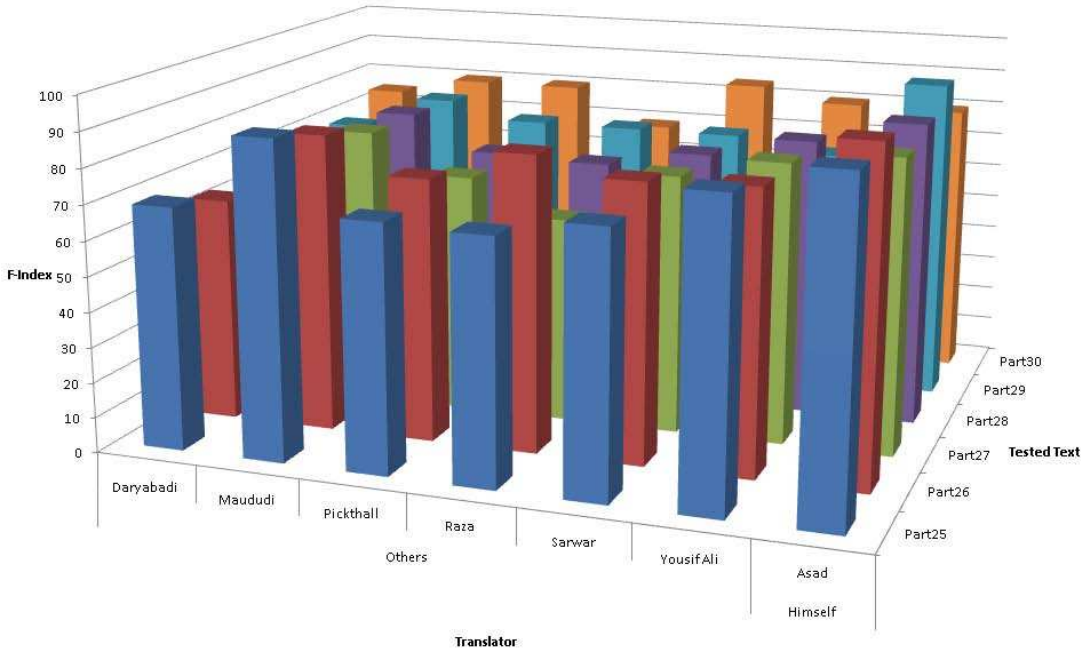
We used the same way of analysis like in most frequent words to extract meaningful information from Tables 3.8 and 3.7; We analyzed the results for translators Asad and Pickthall. Figures 3.6(a) and 3.6(b) show that FW-Index translators-to-their selves is considered slightly lower than FW-Index of translators-to-others. In conclusion, the Favorite words list cannot be used to identify translators' individual styles; the translation is affected by the original text rather than the translator's choices.

Table 3.7: Favorite Words Index - for the Same Translator

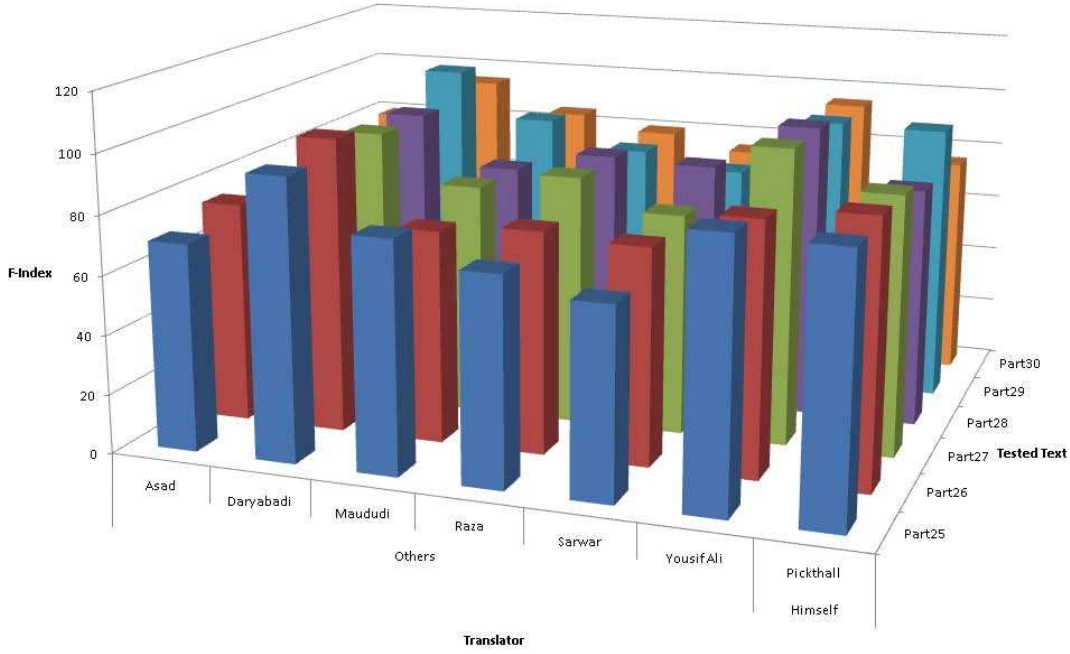
Translator Name	Part25-Part26	Part25-Part27	Part25-Part28	Part25-Part29	Part25-Part30	Part26-Part27	Part26-Part28	Part26-Part29	Part26-Part30	Part27-Part28	Part27-Part29	Part27-Part30	Part28-Part29	Part28-Part30	Part29-Part30
Asad	97	80	86	94	79	75	88	64	67	71	91	98	65	66	67
Pickthall	87	76	56	70	58	66	80	71	57	55	82	73	58	60	81
Yousif Ali	54	50	52	61	41	51	64	61	61	54	94	78	46	53	96
Khan	93	74	67	83	61	77	82	92	87	76	94	82	63	62	106
Daryabadi	94	89	71	86	73	84	103	78	83	77	98	91	68	65	100
Maududi	50	55	43	58	37	50	49	55	44	35	73	53	42	43	69
Sarwar	99	81	75	84	69	78	76	80	76	63	95	76	67	55	96

Table 3.8: Favorite Words Index - for the Same Part

Part number	**Part25**	**Part26**	**Part27**	**Part28**	**Part29**	**Part30**
Asad-Daryabadi	55	69	88	82	97	124
Asad-Maududi	98	120	139	135	146	158
Asad-Pickthall	67	88	101	98	97	142
Asad-Khan	64	88	101	98	97	142
Asad-Sarwar	57	82	81	92	93	109
Asad-Yousif Ali	88	83	95	113	125	137
Daryabadi-Maududi	84	117	127	128	165	171
Daryabadi-Pickthall	140	183	182	147	199	224
Daryabadi-Khan	61	74	85	87	80	117
Daryabadi-Sarwar	56	77	90	79	110	131
Daryabadi-Yousif Ali	79	117	109	117	165	157
Maududi-Pickthall	66	112	118	108	125	166
Maududi-Khan	83	109	112	114	119	134
Maududi-Sarwar	82	115	111	122	141	153
Maududi-Yousif Ali	109	115	122	132	152	176
Pickthall-Khan	70	88	107	104	110	136
Pickthall-Sarwar	65	89	85	94	130	145
Pickthall-Yousif Ali	70	108	110	106	135	152
Khan-Sarwar	87	104	92	115	123	127
Khan-Yousif Ali	76	88	97	102	100	120
Sarwar-Yousif Ali	67	91	103	115	123	140

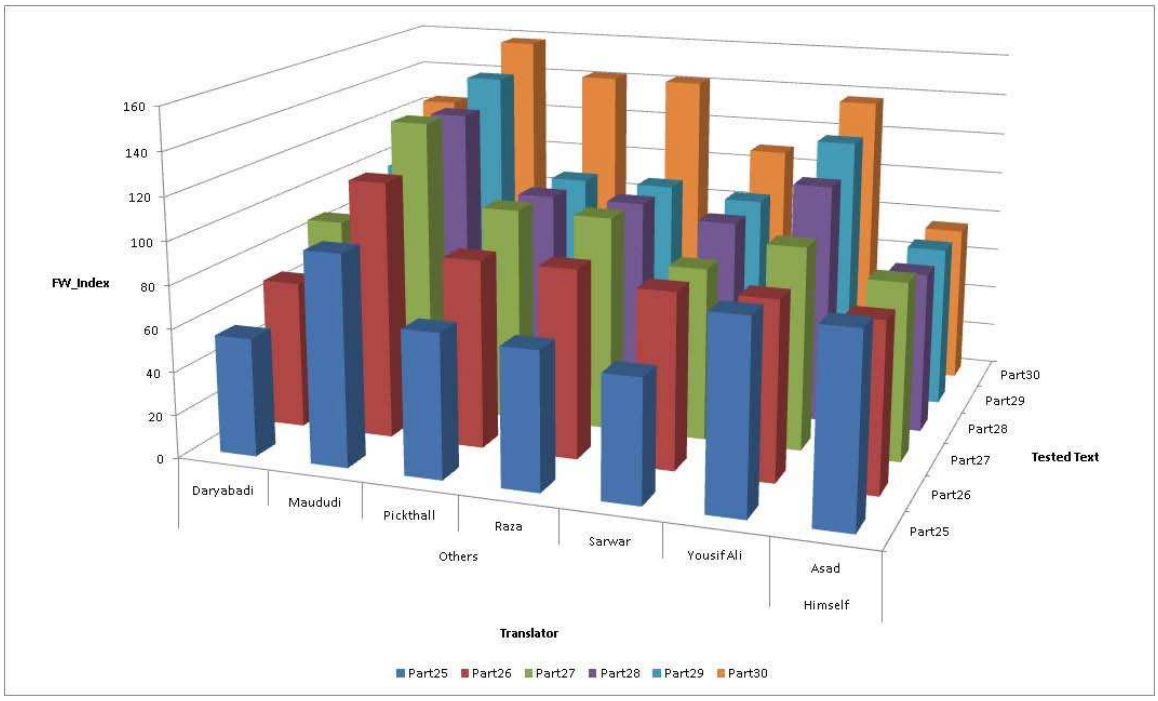


(a) Most Frequent Words for Translator Asad

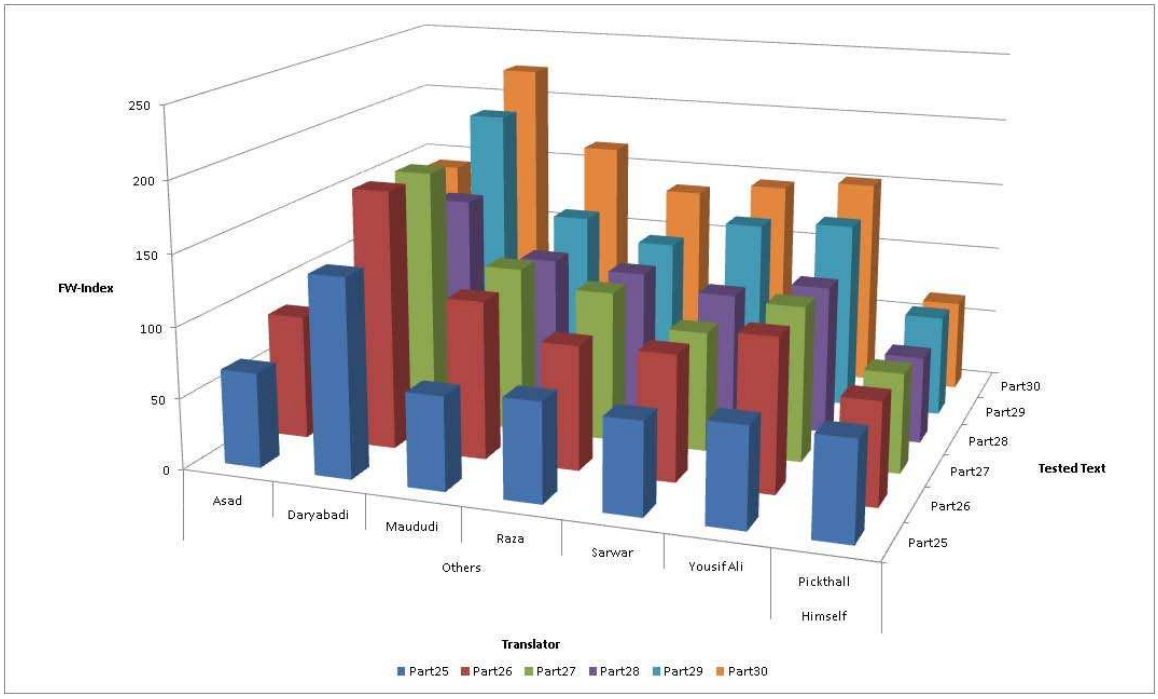


(b) Most Frequent Words for Translator Pickthall

Figure 3.5: Comparison between Most Frequent Words Index for Translators Asad and Pickthall



(a) Favorite Words Index for Translator Asad



(b) Favorite Words Index for Translator Pickthall

Figure 3.6: Comparison between Favorite Words Index for Translators Asad and Pickthall

In conclusion, changes in vocabulary richness measures were mostly affected by the original text rather than being affected by the differences of the translators. Except for Asad, who has a distinct style, most frequent words and favourite words measures used in this section were not able to discriminate different translators.

3.5.2 Vocabulary Richness Measures as Translator Stylometry Features

The main objective of this experiment is to investigate the ability of vocabulary richness measures to discriminate between translators. To evaluate the effectiveness of vocabulary richness as translator stylometry features, we used the idea of classifying texts (as instances) into their translators (as classes) based on vocabulary richness (as attributes). Working on the level of parts for the Holy Qur'an as the instances give us only 6 instances (parts)/ per class (translator). For that reason, we chose to work on chapters' level as that gives us 74 instances/class.

3.5.2.1 Method II

For this experiment, we used five vocabulary richness measures as attributes: which are N, V, R-Index, K-index, and W-Index. Their description is discussed in section 3.5.1.1.

3.5.2.2 Experiment II

We use two of the most studied classification algorithms in the literature: these are the decision tree C4.5 and support vector machine (SVM). We used their implementation in WEKA "data mining software". For C4.5, which is a decision tree based classification algorithm developed by Quinlan in 1993 [144], we used pruned weka.classifiers.trees.J48. For SVM, we used weka.classifiers.functions.SMO; which is based on the Sequential Minimal Optimization algorithm for support vector machine [139] [89].

As we have seven translators, we worked with them in pairs using binary classifiers. We used ten- fold cross-validation to evaluate the classifiers. Ten-fold cross-validation is a common statistical method of measuring the predictive performance of a model, in which, data is partitioned into ten non-overlapping sets. Then, each of these partitions is being held once for testing while the other nine partitions are used for training the model. The average accuracy of the ten iterations is calculated to estimate the average accuracy of the model. The advantages of this cross-validation technique include the non-overlapping nature of the training and testing data and the provision of a chance for each instance in the data to appear in the testing dataset once. Additionally cross-validation is recommended when the available data for training and testing is limited [195].

3.5.2.3 Results and Discussion of Experiment II

In this thesis, we are evaluating binary classification for each pair of translators where training and testing data are balanced (i.e. equal class distribution) between the two translators. For such case, a baseline for the classifier is the random case of 50% chance of labelling the correct class. Anything above 50% is better than the random chance. Therefore, we choose 2/3, which is 66.67% as a threshold to achieve significantly better than the random baseline accuracy of 50%.

Considering a classifier is being acceptable if it is able to correctly classify 2/3 of tested instances, among the 21 studied cases, only 6/21 was acceptable using each of C4.5 and SVM as shown in Table 3.9 using vocabulary richness. All these 6 cases are easy to classify because they have Asad in common. As shown in Figure 3.4(b), Asad has very distinct translation style compared to all others.

Vocabulary richness measures did not introduce acceptable results neither using C4.5 nor SVM. The overall average accuracy was 55.12% using C4.5 and 54.31% using SVM.

Table 3.9: Classification Results for Vocabulary Richness Measures as Translator Stylometry Features

The Translators' Names	C4.5	SVM
Asad-Daryabadi	76.35%	77.70%
Asad-Maududi	71.62%	74.32%
Asad-Pickthall	81.76%	70.95%
Asad-Raza	76.35%	82.43%
Asad-Sarwar	72.30%	67.57%
Asad-Yousif Ali	68.92%	66.89%
Daryabadi-Maududi	50.00%	50.00%
Daryabadi-Pickthall	47.30%	39.19%
Daryabadi-Raza	47.30%	49.32%
Daryabadi-Sarwar	46.62%	50.68%
Daryabadi-Yousif Ali	51.35%	53.38%
Maududi-Pickthall	43.92%	46.62%
Maududi-Raza	45.27%	45.27%
Maududi-Sarwar	47.30%	45.95%
Maududi-Yousif Ali	47.30%	40.54%
Pickthall-Raza	46.62%	45.95%
Pickthall-Sarwar	46.62%	48.65%
Pickthall-Yousif Ali	45.95%	47.30%
Raza-Sarwar	49.32%	47%
Raza-Yousif Ali	47.97%	47.97%
Sarwar-Yousif Ali	47.30%	43.24%
Average	55.12%	54.31%
STD	0.1258	0.1274

3.6 Chapter Summary

In this chapter, we described the choice and design of our dataset. We justified our choice for that corpus. Then we examined our dataset using the same approach evaluated by Mikhailov and Villikka, which included vocabulary richness, most frequent words and favorite words. Then, we evaluated the use of vocabulary richness measures as attribution features for translator identification, as they are commonly used in authorship attribution area which is the closest area in computational linguistics to our problem. Vocabulary richness did not introduce acceptable results. Hence, there is a need to find an appropriate approach to identify translators' stylometry.

Chapter 4

Identifying Translator Stylometry Using Network Motifs

4.1 Overview

We started our journey to identify appropriate features to detect translators by our first experiment that we discussed in chapter 3, in which we evaluated Vocabulary Richness measures as translator stylometry features. The findings from that experiment encouraged us to evaluate the use of network motifs search for the purpose of translator stylometry identification. Therefore, the objective of this chapter is to introduce the methodology of using network motifs search for translator stylometry identification. The second objective of this chapter is to evaluate the performance of network motifs approach in comparison with other approaches.

In this chapter, we are going to describe two experiments that we conducted to evaluate the feasibility and performance of network motifs search as translator stylometry features. The first experiment is a preliminary experiment, in which we applied the network motifs search to a subset of the dataset which contains 30 samples for two translators. The promising results of the first experiment encouraged us to evaluate the proposed features on the entire dataset for the seven translators. Furthermore, we expanded the social network analysis with a

group of features that include global network features and two groups of local network features, where one group included all possible motifs of size three and the second group included all motifs of size four.

The accuracy levels obtained by these experiments were much lower than expected. We carefully investigated the problem and identified that the propositional nature of the classifier we used was the cause of the problem. This problem is overcome with a transformation that we performed on the data to still use the propositional classifier. We changed the data representation that was used to feed the classifier by replacing the discrete values of motifs frequency by their ranking. This transformation improved the results dramatically where we obtained an average accuracy of 79.02%.

The details of the study are explained in the rest of this chapter. The following section describes the expansion of the dataset used for this analysis. The next section explains the methodology that we used to apply social network analysis techniques for the problem of translator stylometry.Section 4.3 provides brief information in regards to the classifiers used in the experiments conducted in this chapter. Section 4.4 discusses the design and the findings of the first experiments. The second experiment design and results are described in Section 4.5. After that, section 4.6 describes the data transformation that we performed in order to introduce different representation of the data. Finally the last section concludes the chapter with a reflection on the initial problem of translator stylometry and the use of network analysis for identifying translator stylometry followed by suggestions for future research in the field.

4.2 Methodology

In this section, we are going to describe how social network analysis can be applied to the problem of translator stylometry identification. That includes how text can be transformed into network, how network motifs can be extracted, how to compute other network analysis measures like global network features.

4.2.1 Data Pre-processing

For the data pre-processing step, Natural Language Tool Kit NLTK of Python programming language had been used. First the text had been cleaned from anything rather than alphanumeric and any decimal digits. Then, each sentence had been tokenized into words. After that, these words had been lemmatized to their lemmas. "Lemmatization is the process of reducing a word into its base form" [10]. Then, each lemma of these words has been lowercased. By completing this data pre-processing stage, all of the occurrences of the same word (including their inflections) can be identified and grouped together during the formation of the word adjacency network.

4.2.2 Network Formation

To establish the word-adjacency network from the dataset, we worked on Ayah (verse) level. Each word is represented by a node, and each ordered word adjacency is represented by an edge (a link that connects two nodes) going from the first occurring word to the following word. The frequency of two word adjacencies is counted and represented by edge labels. The edges here represent an "occurring- before" binary relationship.

4.2.3 Features identification

By looking in the linguistics literature on translator stylometry, we found that we should primarily target the lexical level as this is the level that can be affected most by translators if compared to the syntactical and even to much lesser extent the semantic levels (considering translator invisibility assumption) .

Working on the lexical level, there are different features that can be extracted like word n-gram, vocabulary richness, word frequencies, and token-based [2]. We are trying to find the linkage between the words and how frequently they are used by different translators. We also attempt to extract the frequency of occurrence of patterns of ordered words –known in linguistics as 'lexical chunks'- in the text.

4.2.4 Motif extraction

To analyze and compare two networks, we can use their global statistical features; these include Shortest-path length, global centrality, clustering coefficient, etc.., or their structural design principles like the network motifs. Network motifs which are initially introduced by Ron Milo et al. [122] are patterns (represented by small subgraphs) that are repeated in a real network more often than randomly generated networks.

The motifs are small subgraphs, usually 3, 4 or 5 nodes. For a subgraph with three connected nodes, we have only 13 distinguished possible subgraphs as shown in Figure 4.2. For four connected nodes, we have 199 distinguished possible subgraphs, and 9364 possible subgraphs for five nodes. This study stopped at investigating motifs of size four because increasing the size of the motif results in an exponential increase in the number of features.

To illustrate how we can extract these 13 motifs, we give an example of a network generated using a sample translation by "Yousif Ali" for chapter 112 in the Holy Qura'n. The sample text is *"Say: He is Allah, the One and Only; (1) Allah, the Eternal, Absolute; (2) He begetteth not, nor is He begotten; (3) And there is none like unto Him. (4)"*.

The network formed to represent this sample text is shown in Figure 4.1, and examples of the extracted motifs are shown in Figure 4.2

For example, motif 7 (M7) represent the relationship between three nodes; two way relationship between the left and upper nodes, and one way relationship between the right and upper nodes. The first relationship is represented by the ordered appearance of words "is" and "He" in Aya (3), and the other direction where "He" before "is" in Aya (1). The second relationship is represented by the ordered appearance of words "nor" and "He" in Aya (3).

In motif 8 (M8), the first relationship that appeared in motif 7 is the same, while we have another two way relationship between the upper and right nodes, represented in Aya (3) where the word "He" appeared once before "not" and the second time after it.

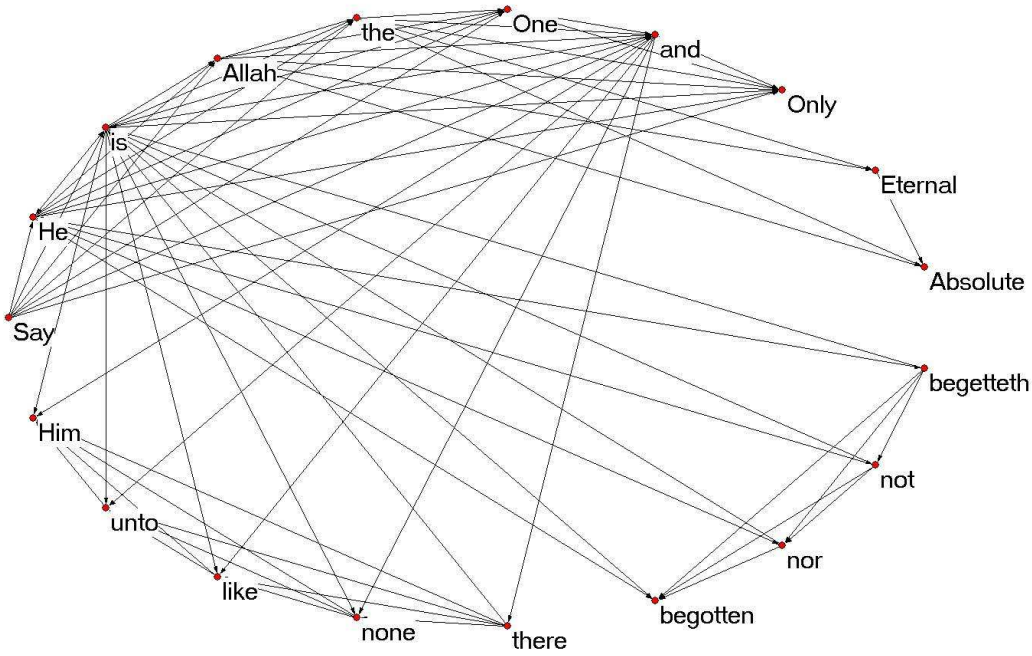


Figure 4.1: Network Example

We scanned the network for all of these possible subgraphs and counted each of them. As we illustrated earlier, we are going to conduct two different experiments in this chapter. For the first experiment, we used a tool of network motifs detection called ***MAVisto*** [160]. The first experiment contained only a subset of our dataset corpus. ***MAVisto*** tool scans the network for all possible network motifs subgraphs and count them, even if they are overlapping. It uses ***Frequent Pattern Finder (FPF)*** algorithm, which searches the network for the occurrence of target size patterns under a given frequency concept [159]. After that, in our second experiment which included the entire dataset, ***MAVisto*** showed very slow performance for counting network motifs for two reasons. First, in the second experiment, we were looking for both motifs of size three and size four, while in the first experiment we were looking for motifs of size three only. The second reason is related to the sample size. As for the second experiment, which contains the entire dataset, the text size of some chapters is significantly larger than the chapters that were included in the first experiment. Details regarding the sample size of the text are available in the appendix. To overcome the slow

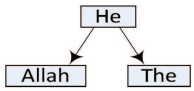
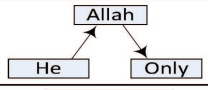
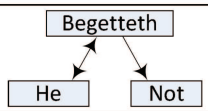
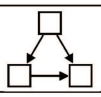
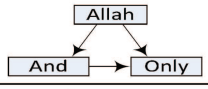
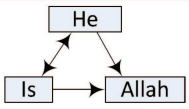
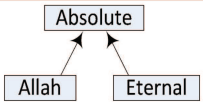
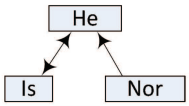
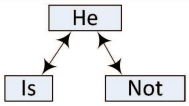
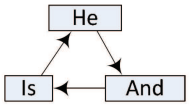
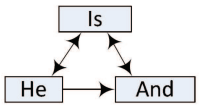
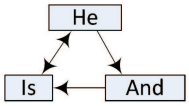
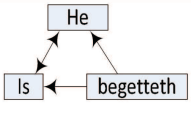
M1		Aya (1): "Say: **He** is **Allah**, **the** One and Only"	
M2		Aya (1): "Say: **He** is **Allah**, the One and **Only**;"	
M3		Aya (3): "**He begetteth not**, nor is **He** begotten;"	
M4		Aya (1):"Say: He is **Allah**, the One **and Only**;"	
M5		Aya(1): "Say: **He is Allah**, the One and Only". Aya(3): "He begetteth not, nor **is He** begotten;"	
M6		Aya(2):" **Allah**, the **Eternal**, **Absolute**	
M7		Aya(1): "Say: **He is** Allah, the One and Only" Aya(3): "He begetteth not, **nor is He** begotten;"	
M8		Aya(1):" Say: **He is** Allah, the One and Only" Aya(3):" **He** begetteth **not**, nor **is He** begotten;"	
M9		Aya(3):"He begetteth not, nor **is He** begotten;" Aya(1):"Say: **He** is Allah, the One **and** Only;" Aya(4):"**And** there **is** none like unto Him"	
M10		Aya(3):" He begetteth not, nor **is He** begotten;" Aya(1):" Say: **He is** Allah, the One **and** Only;" Aya(4):" **And** there **is** none like unto Him"	
M11		Aya(3): "He begetteth not, nor **is He** begotten;" Aya(1): " Say: **He is** Allah, the One **and** Only;" Aya(4): "**And** there **is** none like unto Him"	
M12		Aya(3): "**He begetteth** not, nor **is He** begotten;" Aya(1): "Say: **He is** Allah, the One and Only;"	
M13		Not applicable for this sample text	

Figure 4.2: All Possible 3-Nodes Connected Subgraph

performance of ***MAVisto***, we used another motifs detection tool called ***Mfinder*** [86] for our second experiment. ***Mfinder*** uses an algorithm that is explained in details in Kashtan et al research in 2004 [85].

Comparing Figures 4.1 and 4.3 shows variations in network complexity due to changes in network size. While the size of the text represented in the first network is 26 words, the second network, represents translation of chapter 80 by "Yousif Ali", is for text of size 359 words.

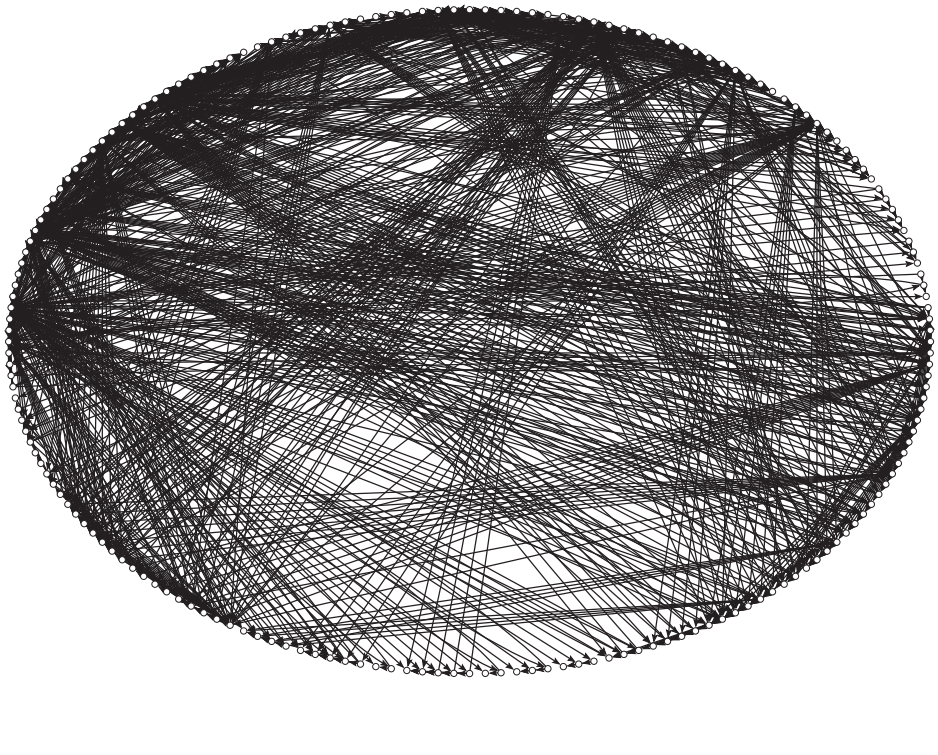


Figure 4.3: Network of Chapter 80 by "Yousif Ali"

4.2.5 Randomization

To randomize the network, a random local rewiring algorithm is used. This algorithm keeps the degrees of the vertices constant. This is done by reshuffling the links: If A is connected to B ($A \Rightarrow B$), and C is connected to D ($C \Rightarrow D$).

Then, it makes a link from A to D and from C to B instead of the old links. But before applying the new links, it checks if these links already exist in

the network. If so, this process is skipped and the algorithm attempts to find other links. This check is necessary to prevent having multiple links connecting the same vertices [111]. This process is repeated several times in excess of the total number of edges in the system to generate a randomized network [112]. We considered 500 randomized networks for each sample when conducting our experiments.

4.2.6 Significance test

To calculate Z-score, we need to calculate the average and standard deviation of occurrences of a motif in all randomized networks. The z-score is calculated as the difference between the frequency of this motif in the target network and the mean frequency of the generated randomized networks divided by the standard deviation of the frequency values for these randomized networks.

Since we are testing for confidence level %95, the z normal range is from -1.96 to +1.96. If the z-score is outside this range, it is significant.

4.2.7 Global Network Features

Among the different global network features, we choose the nine most common ones to be the classification attributes: Average of degree, density, clustering coefficient, transitivity, modularity, betweenness, characteristic path length, and diameter. All of these measures were evaluated using *brain connectivity toolbox* [150]. Their definitions are described in section 2.3.4.1 in the background chapter.

4.3 Classifiers

In order to evaluate frequency of network motifs as stylometry features using existing classification algorithms, we are going to apply a number of well known classifiers. The reason of starting with this number of classifiers is to overcome

possible limitations of individual classifiers that may mislead our investigations. These classifiers are:

1. **FT**: Functional Tree (FT) is a classifier that was introduced by João in 2004 [53]. This classifier uses decision tests based on a combination of attributes. FT is used with its default parameters using WEKA where the minimum number of instances at which a node is considered for splitting is set to 15, and the number of fixed LogitBoost iterations is set to 15 with no weight trimming.

2. **NBTree**: This decision tree uses Naive Bayes classifiers at the leaves. This hyperid classifier is firstly presented by Kohavi in 1996 [93].

3. **Random Forest**: This classifier generates a random number of decision trees that represent a forest to be used for classification [24]. We used this classifier with no constraints on the maximum depth of the trees and the number of attributes to be used, while the number of trees in limited to 10.

4. **Random Tree**: While constructing decision trees, a random number of attributes is chosen at each node to introduce a Random Tree classifier. We used the defaults parameters for this classifier which includes no backfitting or pruning.

5. **FURIA**: Fuzzy Unordered Rule Induction algorithm (FURIA) is an extension to the well-known RIPPER algorithm [36] but using fuzzy rather than conventional rules. This algorithm is introduced in 2009 by Hühn and demonstrated promising results in some types of classification problems [64, 76]. The parameters for applying this algorithm includes setting the minimum total weight of the instances in a rule to two, with two runs of an optimization procedure, and to use check for error rate that ≥ 0.5 for the stopping criterion.

6. **FLR**: Fuzzy Lattice Reasoning Classifier (FLR) is initially introduced by Athanasiadis in 2003 [17]. This classifier uses the Fuzzy Lattices to create

a Reasoning Environment. The rules are induced in a mathematical lattice data domain. FLR has the advantage that it can be incremental. It is also able to deal with missing data [80]. The vigilance parameter value is set to 0.5 while running our experiments.

7. **Logistic Classifier**: This classifier uses a multinomial logistic regression model with a ridge estimator. This classifier is based on le Cessie and Houwelingen model [34].

4.4 Experiment I

The purpose of this preliminary experiment is to explore the feasibility of using network motifs as a stylometric feature. For that reason, we choose to start with the last 30 chapters from the 74 chapters that we have in our dataset. Another reason for choosing these chapters is that they are also the smallest chapters; thus, the pilot study can identify efficiency of the methods on a limited corpus. We also limited the number of classes into two classes. Therefore, we choose two parallel translations in addition to their original texts: the first one is by Muhammad Marmaduke Pickthall and the second one is by Abdullah Yusuf Ali. These two translations are among the few translations that have been assessed by Khaleel Mohammed in 2005 [124] as being among the most accurate translations.

First: to address the normalization problem, we conduct 5 different tests considering the parameters as in Table 4.1: In the first test, we consider absolute values: The attributes of motifs represent $f(x_i)$ and $f(y_i)$. So, we have 13 attributes representing the 13 motifs and one attribute representing class label for 40 samples for training and 20 samples for testing considering class balance. The second test, using the same configuration of the first test but we tried to minimise the translator bias to her own writing; thus, we used the attributes of motifs to represent $f(x_i)/\sum(f(x_i))$ for the first translator, and $f(y_i)/\sum(f(y_i))$ for the second translator. In the third test: The attributes of motifs represent $f(x_i)/f(z_i)$ and $f(y_i)/f(z_i)$. The conjecture behind this is to minimise the bias

regarding the original text. While in the fourth test; we used the attributes of motifs to represent $f(x)/(\sum((f(x_i) * f(z_i))$ as a conjecture for minimising both the original text bias and translator bias. For tests 3 and 4, we need to divide by the frequency of Arabic motifs, which is sometimes zero, so we increment the number of motifs for Arabic text by 1. In the fifth test, we used 16 attributes which are the 13 motifs in addition to the number of nodes and edges and one attribute for class label. These five test are collected into one experiment, which we will denoted by Experiment I(a).

Table 4.1: Experiment I Parameters

$f(x_i)$	is the frequency of each motif in a sample i for the first translator.
$\sum f(x_i)$	is the summation of all frequencies of motifs in a sample i for the first translator.
$f(y_i)$	is the frequency of each motif in a sample i for the second translator.
$\sum f(y_i)$	is the summation of all frequencies of motifs in a sample i for the second translator.
$f(z_i)$	is the frequency of each motif in a sample i for the original Arabic text.

Second: to address the sample size problem, we repeated the previous experiments with 10 sample chapters for each translator for training and 10 samples for testing, and compared these results to their corresponding results from the Experiment I(a). The comparison is between an experiment with 10 samples as the training size and the other with 20 samples for the training size. In both cases, we maintained the test sample constant to have a fair comparison. The test size is 10 sample chapters, forming a total of 20 chapters covering both translators. We will denote this second experiment as Experiment I(b).

The third question was about class balance. To address such question we conducted Experiment I(c), in which we repeated the first experiment but considered randomizing the choice of the classes for training and testing purposes, and compared the results to the balanced experiment. Since we have 30 samples which introduce 60 (30x2) instances, and we are considering an imbalance problem, we choose randomly 40 out of the 60 instances for training and the rest are used for testing.

4.4.1 Results and analysis of Experiment I

Looking at Figure 4.4; when we calculated the means of the 30 sample that we have for each translator, we found that the appearance of the motifs is different for each author. The second translator has the highest average for all motifs.

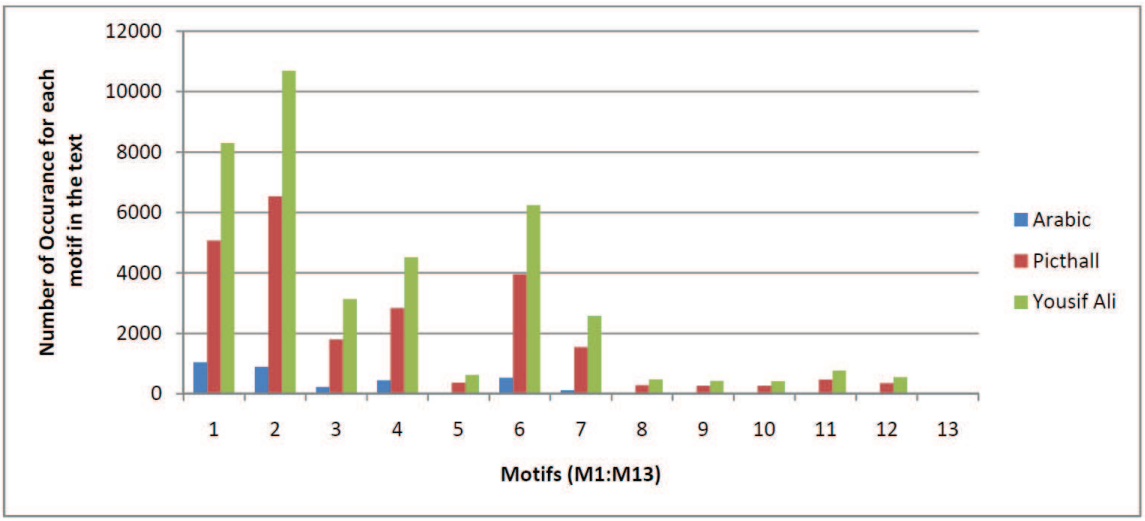


Figure 4.4: Comparison between the Average of the 13 Motifs for the Arabic, First English Translation, Second Translation

4.4.1.1 Paired T-test

We applied paired t-test on the frequencies of motifs for each paired sample text, where the pair here represents two translations of the same original text. Two tail t-critical for alpha=0.05 and sample size of 30 is 2.04523.

Table 4.2 displays the t-calculated for each motif. All of them show that the differences between the frequencies for the two translators are significant.

4.4.1.2 Correlation between motifs

We calculated the Pearson correlation coefficient between the motifs for each translator to find how often these motifs appeared concurrently, and then compared them to each other. We summarized the important differences in Table 4.3. Since these motifs represent links between words in the text, and the correlation

Table 4.2: Paired T-Test between Frequencies of Motifs for the Two Translators

Motif	t-test
M1	-5.21757
M2	-5.36426
M3	-4.71189
M4	-5.48586
M5	-4.39642
M6	-5.46861
M7	-5.28081
M8	-4.65985
M9	-4.42133
M10	-3.93762
M11	-4.36377
M12	-4.94248
M13	-2.75729

represents how often these motifs occur together, the difference between these correlations indicates difference in translator's style.

Table 4.3: Correlation between Frequencies of Motifs

Motifs	First Translator "Pickthall"	Second Translator "Yousif Ali"
(M2, M13)	0.768	0.523
(M4 , M13)	0.910	0.550
(M6, M13)	0.816	0.495
(M7, M13)	0.911	0.640
(M9, M13)	0.946	0.711
(M11, M13)	0.978	0.751
(M12, M13)	0.975	0.752

4.4.1.3 Experiment I(a)

For Experiment I(a); as Table 4.4 shows the best results are obtained using the Functional Tree classifier and Logistic classifier with test 5 which includes the number of nodes and edges with the motif frequency as inputs. The accuracy of these classifiers is 70%, which is the same accuracy of NBTree and FLR when applied to test 3, where the data is normalised against the original text bias.

Table 4.4: Accuracy of the Different Classifiers for Experiment I(a)

Classifier	Functional Tree	NBTree	Random Tree	Random Forest	FURIA	FLR	Logistic
Test1	60%	50%	55%	25%	50%	50%	55%
Test2	65%	50%	65%	65%	50%	60%	45%
Test3	65%	**70%**	45%	60%	55%	**70%**	60%
Test4	50%	50%	50%	50%	55%	60%	45%
Test5	**70%**	50%	60%	50%	50%	50%	**70%**

4.4.1.4 Experiment I(b)

For Experiment I(b), we test using smaller training sample size, which are 10 for each translator. We noticed that the results for the Logistic classifier are enhanced compared to the Experiment I(a), while the functional tree accuracy decreased. The best accuracy obtained for this experiment remained at 70% as shown in Table 4.5. This level of accuracy is obtained using Random Tree classifier and FLR classifier for test2 where the data is normalized against the translator bias. It is also obtained by the Logistic classifier with test5 which is the same result for this classifier in the first experiment.

Table 4.5: Accuracy of the Different Classifiers for Experiment I(b)

Classifier	Functional Tree	NBTree	Random Tree	Random Forest	FURIA	FLR	Logistic
Test1	50%	50%	60%	55%	50%	50%	65%
Test2	50%	50%	**70%**	60%	60%	**70%**	60%
Test3	50%	50%	60%	65%	55%	65%	60%
Test4	50%	50%	60%	45%	50%	55%	60%
Test5	50%	50%	50%	65%	60%	50%	**70%**

4.4.1.5 Experiment I(c)

In the third experiment, Experiment I(c), we addressed the imbalance class problem. We used the 40 instances for training as 24 instances for the first translator

"Pickthall" and 16 instances for the second translator "Yousif Ali". For testing, we used 20 instances, where 6 instances for "Pickthall" and 14 for "Yousif Ali".

While measures such as Kruppa measure and AUC (area under the curve) are more suitable for imbalanced classes, the degree of imbalance classes in the thesis is not large; thus the use of accuracy as a measure of performance is still relevant.

We noticed that most of the obtained accuracies were only 30% as shown in Table 4.6 where the classifiers classified all the instances to belong to the first translator. The only classifier that gives acceptable results was FLR, where we got 70% accuracy for test 3 where data is normalized against the original text. In general, the Random Forest classifier and FURIA consistently failed to detect

Table 4.6: Accuracy of the Different Classifiers for Experiment I(c)

Classifier	Functional Tree	NBTree	Random Tree	Random Forest	FURIA	FLR	Logistic
Test1	45%	30%	25%	60%	30%	30%	40%
Test2	60%	30%	30%	20%	30%	30%	50%
Test3	45%	45%	45%	50%	55%	**70%**	35%
Test4	30%	30%	40%	30%	45%	40%	40%
Test5	45%	30%	50%	35%	30%	30%	45%

the differences between translator's styles. On the other hand, the FLR classifier introduced acceptable results in the three experiments. Test 1 and test 4 failed to identify the translator's style, where in test 1 the data is not normalized, and in test 4 it is normalized against both the translator bias and the original text bias.

Both test 3 and test 5 introduced acceptable classifiers three times in the overall experiments. That indicates the importance of normalizing the data against its original text bias and the importance of including the number of nodes and edges into the attributes as it may help the classifier to normalize the data implicitly.

Overall Experiment I, an accuracy of 70% was achieved multiple times while investigating the performance of network motifs for the translator stylometry

identification problem. Among the seven classifiers that have been used, Fuzzy Lattice Reasoning Classifier (FLR) had the best performance. Additionally, normalizing the translated text against its original source outperformed the other normalization methods that were investigated in this experiment.

4.5 Experiment II

In this experiment, we are going to use the entire dataset to expand our investigation. We are going also to evaluate the global network features in addition to the local network features which are represented by the motifs. Furthermore, for the motifs search, we are going to consider motifs of size four in addition to motifs of size three that we considered in the previous experiment.

In this experiment, we have three groups of features: the first one is 13 attributes which are all possible network motifs of size three, the second group is 199 attributes which are all the possible network motifs of size four, and the third group is nine attributes, which are the selected global network features that we used. All of these three groups of features were used as attributes for the same classifiers that we used in Experiment I in addition to C4.5 and SVM, which we discussed earlier in Chapter 3. We feed these classifiers with 74 instances, chapters, for each of the seven translators. We used ten folds cross-validation for evaluation.

4.5.1 Results and Discussion of Experiment II

When we ran the experiment, we expected network motifs to introduce good results. This expectation was based on the findings of Experiment I, where we attempted to classify two translators using network motifs of size three. However, here we are attempting to use seven translators. The results were beyond our expectation. Both Network motifs and network global features failed to identify translator stylometry as shown in Tables 4.7, 4.8, and 4.9. For global features, Table 4.7 shows that the best average accuracy obtained was by FT classifier.

That was 52.57%, which means that global features can not be used to identify translators stylometry. Although network motifs of size three showed promising results in the previous experiment, it failed in this experiment to identify translator stylometry. The best average accuracy we obtained was also 52.06% using Logistic classifier as shown in Table 4.8. Furthermore, Motifs of size four produced similar results, with maximum average accuracy of 52.43% obtained using Logistic classifier. The detailed results of using motifs of size four as stylometry features are displayed in Table 4.9.

We tried to identify repeated patterns, that is lexical chunks which are repeated by one translator more often than others. Network motifs are also used to detect subgraphs that happen more frequently in a network than in random networks. Therefore theoretically, network motifs should work to identify different translators.

We found that as the size of the network varied in a wide range between instances and between each other, and the number of the subgraphs may vary widely as well. In our dataset, the network sizes varied from 19 nodes (as in Pickthall:Chapter109, Sarwar:Chapter112, Yousif Ali:Chapter112) to 597 (as in Asad: Chapter42), and the number of edges varied from 64 (as in Sarwar: Chapter112) to 29851 (as in Asad:Chapter42). As the number of subgraphs is highly affected by the network size, using the values of motifs count directly mislead the classifiers. The classifiers failed to detect a relation such as M3(A1) >M3(A7); which means translator A1 uses the pattern of motif id3 more than translator A7 does. On the other hand, a decision tree classifier can identify the relation of M3(A1)>100. Since we were interested in the first type of relation, where we can identify a translator preferred pattern, we needed to find a way to solve this problem.

Table 4.7: Classification Results for Network Global Features as Translator Stylometry Features

Translators' Names	C4.5	SVM	FT	NBTree	Random Forest	Random Tree	FURIA	FLR	Logistic
Asad-Daryabadi	50.68%	60.14%	64.86%	45.27%	55.41%	56.76%	51.35%	50.68%	**70.95%**
Asad-Maududi	47.97%	50%	54.73%	47.97%	45.27%	50%	45.27%	45.95%	**59.46%**
Asad-Pickthall	52.03%	60.81%	60.81%	50%	58.78%	50.68%	52.03%	50.68%	**67.57%**
Asad-Raza	54.05%	55.41%	65.54%	52.70%	53.38%	53.38%	46.62%	48.65%	**66.22%**
Asad-Sarwar	50.68%	54.73%	59.46%	54.73%	54.73%	47.30%	43.92%	55.41%	**62.16%**
Asad-Yousif Ali	45.27%	53.38%	**59.46%**	45.27%	44.59%	46.62%	45.95%	49.32%	57.43%
Daryabadi-Maududi	47.30%	46.62%	51.35%	47.30%	38.51%	39.19%	45.27%	47.97%	**53.38%**
Daryabadi-Pickthall	47.30%	43.92%	45.95%	47.30%	29.73%	34.46%	47.30%	45.27%	**52.03%**
Daryabadi-Raza	**61.49%**	51.35%	54.05%	58.78%	47.97%	52.03%	60.14%	45.95%	55.41%
Daryabadi-Sarwar	47.30%	43.24%	47.97%	47.30%	33.78%	40.54%	46.62%	**50%**	49.32%
Daryabadi-Yousif Ali	47.30%	50.68%	49.32%	47.30%	39.86%	39.86%	40.54%	48.65%	**52.03%**
Maududi-Pickthall	45.95%	**48.65%**	45.27%	46.62%	35.81%	43.92%	43.24%	47.97%	47.30%
Maududi-Raza	54.73%	50.68%	52.03%	**55.41%**	49.32%	53.38%	47.97%	47.30%	47.30%
Maududi-Sarwar	47.30%	43.92%	47.30%	47.30%	37.84%	43.24%	45.27%	**49.32%**	38.51%
Maududi-Yousif Ali	46.62%	35.14%	47.30%	46.62%	35.81%	43.92%	45.95%	**49.32%**	44.59%
Pickthall-Raza	67.57%	53.38%	66.22%	**68.24%**	58.11%	61.49%	62.84%	47.30%	47.30%
Pickthall-Sarwar	47.30%	43.24%	45.27%	47.30%	37.16%	44.59%	43.92%	**48.65%**	41.89%
Pickthall-Yousif Ali	47.30%	48.65%	51.35%	47.30%	35.14%	41.22%	45.27%	50.68%	**53.38%**
Raza-Sarwar	55.41%	52.70%	43.24%	**56.08%**	45.95%	47.30%	48.65%	50.68%	39.19%
Raza-Yousif Ali	58.78%	47.97%	44.59%	**59.46%**	44.59%	51.35%	54.05%	45.27%	48.65%
Sarwar-Yousif Ali	47.30%	43.92%	47.97%	47.30%	38.51%	44.59%	41.89%	**50%**	46.62%
Average	50.93%	49.45%	**52.57%**	50.74%	43.82%	46.94%	47.81%	48.81%	52.41%
STD	0.0585	0.0608	0.0738	0.0597	0.0861	0.0649	0.0558	0.0233	0.0900

Table 4.8: Classification Results for Network Motifs of Size Three as Translator Stylometry Features

Translators' Names	C4.5	SVM	FT	NBTree	Random Forest	Random Tree	FURIA	FLR	Logistic
Asad-Daryabadi	57.43%	54.05%	54.73%	56.08%	50.68%	57.43%	60.14%	52.03%	**61.49%**
Asad-Maududi	**55.41%**	52.70%	46.62%	54.73%	44.59%	53%	53.38%	52.03%	**55.41%**
Asad-Pickthall	52.03%	52.70%	52.03%	51.35%	52.03%	**57.43%**	54.73%	52.03%	53.38%
Asad-Raza	54.73%	54.05%	51.35%	53.38%	52.03%	50%	46.62%	49.32%	**56.08%**
Asad-Sarwar	**58.11%**	52.70%	45.95%	54.05%	55.41%	56.08%	56.76%	53.38%	53.38%
Asad-Yousif Ali	54.73%	52.70%	47.97%	52.70%	56.08%	56.08%	51.35%	49.32%	**56.76%**
Daryabadi-Maududi	47.30%	49.32%	48.65%	47.30%	40.54%	43.92%	45.27%	49.32%	**53.38%**
Daryabadi-Pickthall	47.30%	41.89%	47.30%	47.30%	25%	34.46%	46.62%	**48.65%**	47.97%
Daryabadi-Raza	45.95%	50.68%	51.35%	45.95%	47.30%	47.97%	47.30%	50.68%	**56.08%**
Daryabadi-Sarwar	47.30%	42.57%	47.30%	47.30%	41.89%	50%	48.65%	51%	**58.11%**
Daryabadi-Yousif Ali	47.97%	50%	47.97%	47.97%	44.59%	41.89%	43.24%	**53.38%**	49.32%
Maududi-Pickthall	47.30%	50.68%	47.30%	47.30%	37.84%	43.92%	45.27%	50%	**51.35%**
Maududi-Raza	47.30%	50.68%	49.32%	47.30%	42.57%	47.30%	43.92%	47.97%	**52.70%**
Maududi-Sarwar	47.30%	50%	47.30%	47.30%	41.89%	43.92%	44.59%	**51.35%**	41.89%
Maududi-Yousif Ali	47.30%	46.62%	47.30%	47.30%	28.38%	37.84%	45.27%	45.95%	**48.65%**
Pickthall-Raza	47.97%	50%	45.27%	46.62%	48.65%	41.22%	**51.35%**	**51.35%**	45.27%
Pickthall-Sarwar	47.30%	44.59%	47.30%	47.30%	39.19%	43.24%	47.30%	47.30%	**47.97%**
Pickthall-Yousif Ali	50.68%	**52.70%**	44.59%	50.68%	49.32%	45.95%	47.30%	47.97%	50.68%
Raza-Sarwar	46.62%	45.27%	47.97%	46.62%	46.62%	49.32%	50%	**51.35%**	49.32%
Raza-Yousif Ali	47.30%	51.35%	48.65%	47.30%	52.03%	43.92%	40.54%	47.30%	**54.73%**
Sarwar-Yousif Ali	49.32%	50.68%	47.30%	48.65%	44.59%	50%	43.24%	**53%**	49.32%
Average	49.84%	49.81%	48.26%	49.26%	44.82%	47.39%	48.23%	50.23%	**52.06%**
STD	0.0388	0.0358	0.0239	0.0313	0.0793	0.0635	0.0490	0.0214	0.0460

Table 4.9: Classification Results for Network Motifs of Size Four as Translator Stylometry Features

Translators' Names	C4.5	SVM	FT	NBTree	Random Forest	Random Tree	FURIA	FLR	Logistic
Asad-Daryabadi	58.11 %	52.70 %	58.78 %	54.05 %	54.73 %	47.97 %	52.03 %	52.03 %	**60.14 %**
Asad-Maududi	53.38 %	50.68 %	43.92 %	**54.05 %**	48.65 %	51 %	46.62 %	51.35 %	50.00 %
Asad-Pickthall	51.35 %	52.70 %	**57.43 %**	54.73 %	48.65 %	50.68 %	50.00 %	53.38 %	54.05 %
Asad-Raza	52.03 %	52.70 %	**58.78 %**	52.70 %	50.68 %	47.97 %	51.35 %	48.65 %	55.41 %
Asad-Sarwar	54.73 %	51.35 %	47.30 %	53.38 %	54.05 %	58.11 %	**58.78 %**	54.05 %	49.32 %
Asad-Yousif Ali	54.05 %	51.35 %	48.65 %	47.97 %	50.68 %	47.30 %	53.38 %	49.32 %	**54.05 %**
Daryabadi-Maududi	46.62 %	47.97 %	47.97 %	46.62 %	39.86 %	39.86 %	39.86 %	48.65 %	**58.78 %**
Daryabadi-Pickthall	47.30 %	44.59 %	41.22 %	47.30 %	29.73 %	37.84 %	41.89 %	**47.97 %**	45.95 %
Daryabadi-Raza	46.26 %	53.06 %	59.18 %	46.94 %	46.94 %	52.38 %	48.30 %	52.38 %	**59.86 %**
Daryabadi-Sarwar	47.30 %	54.05 %	47.97 %	47.30 %	41.22 %	52.70 %	48.65 %	51 %	**61.49 %**
Daryabadi-Yousif Ali	50.00 %	43.92 %	43.24 %	50.00 %	44.59 %	52.70 %	46.62 %	51.35 %	**54.05 %**
Maududi-Pickthall	45.95 %	49.32 %	48.65 %	45.95 %	33.78 %	45.27 %	37.16 %	**50.00 %**	46.62 %
Maududi-Raza	47.30 %	54.73 %	**58.11 %**	47.30 %	42.57 %	34.46 %	42.57 %	49.32 %	52.70 %
Maududi-Sarwar	47.30 %	42.57 %	45.95 %	47.30 %	44.59 %	47.30 %	43.24 %	**50.68 %**	47.97 %
Maududi-Yousif Ali	47.30 %	43.24 %	**51.35 %**	47.30 %	37.16 %	38.51 %	44.59 %	47.30 %	47.30 %
Pickthall-Raza	49.32 %	45.27 %	44.59 %	45.27 %	39.86 %	41.89 %	50.00 %	**51.35 %**	43.92 %
Pickthall-Sarwar	47.30 %	**48.65 %**	37.16 %	47.30 %	37.84 %	39.86 %	41.22 %	47.30 %	45.95 %
Pickthall-Yousif Ali	47.97 %	**52.03 %**	43.24 %	47.97 %	47.97 %	46.62 %	46.62 %	**52.03 %**	51.35 %
Raza-Sarwar	47.30 %	51.35 %	50.00 %	46.62 %	42.57 %	41.89 %	50.68 %	50.68 %	**54.73 %**
Raza-Yousif Ali	46.62 %	51.35 %	50.68 %	45.95 %	39.19 %	47.97 %	41.22 %	48.65 %	**56.08 %**
Sarwar-Yousif Ali	49.32 %	47.97 %	50.68 %	49.32 %	47.30 %	46.62 %	**58.11 %**	52 %	51.35 %
Average	49.37 %	49.60 %	49.28 %	48.82 %	43.93 %	46.16 %	47.28 %	50.47 %	**52.43 %**
STD	0.0334	0.0373	0.0627	0.0304	0.0651	0.0595	0.0575	0.0193	0.0513

4.6 Different Representations of Network Motifs for Detecting Translator Stylometry

The finding from the previous experiment triggered the need for another way of representing the data before using classification. The previous representation was considered as univariate approach where the decision was based on single variable as seen in the example M3(A1)>100, but we needed a multivariate approach that can identify two variables as in M3(A1) >M3(A7), which can be expressed as M3(A1) - M3(A7)>0. This is not a traditional multivariate classifier since the comparison is not between different attributes, but the same attribute for different translators.

In this section, we are introducing another representation of the data in a way that simplified this multivariate approach to single values, which can be used by the classifiers.

4.6.1 Method III

To express the discussed relationship, we grouped the translated text based on their original sources; the seven translations of chapter 41 are grouped in the first group, the seven translations of chapter 42 are grouped in the second group, and so on. Then, within each group, we compared motif id "1" for all translators, and replaced the frequency with rank of the translator. For example, if for a piece of text M3 if 10 for Author A1, 20 for Author A2, 30 for Author A3, we replace these frequencies with "3" for Author A1, "2" for Author A2 and "1" for Author A3. Here "1" for Author A3 means that Author A3 ranks on M3 for this piece of text is the highest.

4.6.2 Experiment III

We applied the proposed method for both motifs size three and motifs size four. We also used the same classification algorithms and dataset as in the previous

experiment. We evaluated the attributes in five groups. The first group contains 13 attributes (all the possible 13 motifs of size three). The second group contains 15 attributes, which are the same as the first group in addition to the number of nodes and edges for each instance. The third group contains 199 attributes (all the possible 199 motifs of size four). The fourth group contains 201 attributes which are the 199 attributes of the third group in addition to the number of nodes and edges. The fifth group contains 214 attributes which are all the possible motifs of size three and size four in addition to the number of nodes and edges.

4.6.3 Results and Discussion of Experiment III

The average of the classifiers that was built using the five group of attributes introduced acceptable results as shown in 4.10. They ranged from 75% to 79.02%. Moreover, some of the individual classifiers performed very well up to 97.97% accuracy as in the case of translators (Asad-Daryabadi) and (Asad-Pickthall). On the other hand, some pairs of translators couldn't be distinguished from one another. The five groups of attributes failed to differentiate between them. This case happened with three pairs of translators (Daryabadi-Pickthall), (Maududi-Yousif Ali), and (Maududi-Sarwar). Generally, SVM classification algorithm outperformed C4.5 decision tree. Comparing the five groups of attributes to each other, we found that the best accuracy was achieved by the fifth group (all the motifs of size three and four and the number of nodes and edges) using SVM classifier. However, this accuracy was not much higher than in all the other features groups in the case of SVM. In the best cases, 16 out of the 21 translator pairs introduced acceptable classifiers using the same group of features.

Such accuracy of 79% is enough to say that translators do have styles on their own. These styles, which are the results of individual behaviour, can be used to identify them. In this way, we were able to answer our first question on the existence of translators' styles. Our results provided evidence that translators can be identified through individual styles. This research also discussed possible features that can be used to distinguish translator stylometry. The use of network motifs in this research can be seen as capturing patterns on the lexical level while

been affected slightly by syntactic level. That may direct the research in translator stylometry to investigate more features on the lexical and syntactic level. Finally, this accuracy suggests that network motifs can be used for identifying translator stylometry.

4.7 Chapter Summary

Studying "Translator Stylometry" is a non-trivial task. While there has been research in linguistics and social sciences discussing the characteristics of each translator, this line of research is limited in computational linguistics. Contrary to previous findings that this problem does not have an automatic solution, this chapter presented a first attempt to counteract this belief. We demonstrated that translators cannot disappear under the skin of the original authors; they have their own identities. Different translators represent the same idea in different ways. Although some existing authorship attributions could not capture these differences [121, 154], this work shows that we can use social network analysis to differentiate between translators' styles. Detecting network motifs shows that each author is using certain patterns while writing.

In the first experiment, the proposed method introduced a classifier that can classify translated texts into their translators with accuracy of 70%. Fuzzy Lattice Reasoning Classifier (FLR) introduces the best results among seven tested classifiers. Normalising the data against its original text and the network size offers promising results. Further analysis is needed to explore this research area.

Although using network motifs as stylometry features failed to identify translators in the second Experiment, representing the data using ranking to express the relationship between different usages of the same pattern in comparison to different translators introduced promising results in the third Experiment. Some of the generated classifiers achieved accuracy of 97.97%, while the overall average of accuracy reached 79.02%.

The first contribution of this chapter is in providing further evidence for

the existence of translator stylometry using computational linguistics and data mining. The second contribution is the effectiveness of network motifs in detecting translator stylometry. Both of these contributions encourage further studies in translator stylometry identifications. Future research could continue on the use of network motifs with other linguistic features such as searching for some syntactic structures in word adjacency networks, or looking for network motifs in networks formed on the syntactic level.

Table 4.10: Classification Results for Using Motifs Size Three and Motifs Size Four with Ranking as Translator Stylometry Features

Translators' Names	Motifs Size Three		Motifs Size Three with Nodes and Edges		Motifs Size Four		Motifs Size Four with Nodes and Edges		Motifs Size Three and Size Four with Nodes and Edges	
	C4.5	SVM	C4.5	SVM	C4.5	SVM	C4.5	SVM	C4.5	SVM
Asad-Daryabadi	96.62%	97.30%	96.62%	97.30%	96.62%	96.62%	96.62%	96.62%	93.92%	97.30%
Asad-Maududi	89.86%	85.81%	88.51%	91.22%	85.81%	87.16%	85.81%	87.16%	88.51%	87.16%
Asad-Pickthall	97.97%	97.30%	97.97%	97.30%	91.22%	95.95%	91.22%	95.95%	97.30%	95.95%
Asad-Raza	79.73%	86.49%	81.76%	86.49%	81.08%	82.43%	82.43%	81.76%	81.08%	82.43%
Asad-Sarwar	87.84%	91.89%	91.22%	92.57%	89.86%	85.81%	89.86%	86.49%	89.19%	87.16%
Asad-Yousif Ali	85.14%	87.84%	85.14%	91.89%	86.49%	88.51%	86.49%	89.19%	86.49%	87.84%
Daryabadi-Maududi	80.41%	86.49%	81.08%	85.81%	74.32%	82.43%	74.32%	81.76%	77.03%	83.78%
Daryabadi-Pickthall	53.38%	55.41%	54.05%	54.05%	52.70%	64.19%	52.70%	64.19%	50%	62.84%
Daryabadi-Raza	83.78%	83.11%	83.78%	85.14%	87.16%	75.68%	75%	85.14%	84.46%	89.19%
Daryabadi-Sarwar	66.89%	72.97%	66.89%	70.27%	66.89%	77.03%	65.54%	75%	68.92%	75.68%
Daryabadi-Yousif Ali	89.86%	91.22%	89.86%	91.22%	88.51%	93.92%	88.51%	93.92%	87.84%	92.57%
Maududi-Pickthall	72.97%	85.14%	75%	83.78%	81.08%	80.41%	84.46%	79.73%	82.43%	79.05%
Maududi-Raza	57.43%	62.84%	57.43%	62.84%	65.54%	64.19%	65.54%	62.84%	64.86%	67.57%
Maududi-Sarwar	60.81%	67.57%	64.19%	66.89%	54.73%	61.49%	55.41%	63.51%	53.38%	63.51%
Maududi-Yousif Ali	52.70%	55.41%	57.43%	56.08%	59.46%	63.51%	59.46%	61.49%	64.86%	59.46%
Pickthall-Raza	81.76%	82.43%	80.41%	81.76%	79.05%	77.70%	80.41%	78.38%	79.05%	81.76%
Pickthall-Sarwar	63.51%	66.22%	64.86%	64.86%	58.78%	65.54%	58.78%	65.54%	60.81%	64.19%
Pickthall-Yousif Ali	87.84%	89.86%	87.84%	89.86%	83.11%	87.84%	83.11%	87.16%	82.43%	86.49%
Raza-Sarwar	63.51%	62.16%	64.19%	64.19%	65.54%	64.19%	66.22%	63.51%	66.89%	62.84%
Raza-Yousif Ali	64.86%	71.62%	65.54%	70.27%	64.86%	72.97%	64.86%	73.65%	66.22%	75.68%
Sarwar-Yousif Ali	78.38%	72.97%	78.38%	74.32%	68.24%	76.35%	68.24%	75%	70.27%	77.03%
Average	75.97%	78.67%	76.77%	78.96%	75.29%	78.28%	75%	78.47%	76%	79.02%
STD	0.1371	0.1288	0.1311	0.1337	0.1289	0.1105	0.1275	0.1128	0.1286	0.1142
Accuracy >66.67%	14/21	16/21	14/21	16/21	14/21	15/21	13/21	15/21	15/21	16/21

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Chapter 5

Translator Identification as a Pair-Wise Comparative Classification Problem

5.1 Overview

In this chapter, we present a new type of classification problems - we call it Comparative Classification Problems (CCP), where we use the term data record to refer to a block of instances. However, we acknowledge that in the wider literature, there might be a distinction between the two terms “records" and “instances". Given a single data record with n instances for n classes, the CCP problem is to map each instance to a unique class. This problem occurs in a wide range of applications where the independent and identically distribute assumption is broken down. The interdependency in the data poses challenges if the problem is handled as a traditional classification problem.

In the Pair-Wise CCP (PWCCP), two different measurements - each belonging to one of the two classes - are grouped together. The classification problem is to decide given these two measurements, which measurement belongs to which class. The key difference between PWCCP and traditional binary problems is that hidden patterns can only be unmasked by comparing the instances as pairs.

Paired data sets contain repeated measurements of the same attribute. The changes in the values of the paired instances hold pertinent information to the data mining process.

In this chapter, We introduce a new algorithm PWC4.5, which is based on the traditional C4.5 decision tree classifier, to manage PWCCP by dynamically inducing relationships between paired instances. We evaluated PWC4.5 using synthetic datasets to understand the performance of the algorithm.

In the next section, we discuss existing classification algorithms, and how these algorithms take into account the relationship between the attributes while ignoring the relationship between instances. We use examples to demonstrate these differences. In section 5.3, PWC4.5 is discussed in details. Experimental design and results are discussed in section 5.4.

5.2 From Classification to Comparative Classification

Repeated measurements are observations taken from the same subjects or different subjects on the same phenomenon over time or in different circumstances. Examples of repeated measurements for the same subject in the medical domain would be weight loss or reaction to a drug over time. Another example may include some blood test results for the same patient in a progressive disease.

Limited research exists on classification problems for paired data. Brenning and Lausen [26] and Adler et al. [4] [5] focused on the medical domain. Their research emphasized the need to use repeated measurements for a subject when the data is limited. They used different resampling-based methods. Brenning and Lausen [26] used an ensemble of k decision tree classifiers, while Adler et al. [4] [5] used k fold cross validation to resample the k number of observations that are taken from the same subject.

The above literature still treats instances independently despite that the

underlying measurements may come from the same subject; therefore a level of dependency is expected. In some applications, as in forensic sciences, the dependency in the data may be leveraged to improve detection rate. In this study, we focus on computational linguistics, whereby we may have some linguistics measurements for a parallel translation of the same text. Such type of "Paired Data" breaks away from the independent and identically distributed assumption that lies underneath many classifiers.

Let us now define our problem using this example. We will later on provide a general formal definition of the problem. Assume chapters $o_1 \dots o_m$, with m represents the number of chapters, represent the original text in the Arabic language. Let $\vec{v^1} \dots \vec{v^m}$ be the corresponding translations, with the cardinality of the vector $\vec{v}$, $|\vec{v}| = n$, representing the number of translators for each chapter. Let us also assume that we know the translators and as such, the order of elements in $\vec{v}$ follows the orders of translators $c_1 \dots c_n$.

Given $V^{m+1} \dots V^{m+u}$ additional translations, where V is now a set (i.e. the elements are unordered), the problem is how to map every element in V to the corresponding translator c_i. This can be seen as ordering V into $\vec{V}$ or simply having a bijection from V onto the set of translators $c_1 \dots c_n$. We will call this class of problems as CCP and when $n = 2$, we will call it PWCCP.

In CCP, the data is clearly not independent. While in the above example each translator independently translated the text, they all translated the same piece of text. Traditional classification trees and relational learning techniques are not designed to solve this problem.

Data mining searches for the existence of hidden patterns in the examined dataset using supervised, unsupervised, or semi-supervised machine learning techniques. Supervised machine learning methods can be used to generate a model that represents relationship between input attributes (independent variables) and target attribute (dependent variable). Supervised machine learning methods include: Classification models in case of a nominal or a categorical target attribute, and regression models in case of a continuous numeric target attribute. Classi-

fication has been widely used to assist the decision making processes in various applications. Among the many classification techniques that exist in the literature, decision tree algorithms are considered to be the most widely used learning algorithms in practice [123].

Decision trees are inductive inference algorithms that approximate discrete valued functions as trees. An algorithm in this class is based on the assumption that a concept is a disjunction of the conjunctions of attribute-values. It uses the observed examples to generate rules that can be generalized to unobserved examples. Decision tree learning normally relies on a heuristic, one-step, non-backtracking search through the space. The general idea behind the construction of Decision Trees is to use a divide and conquer strategy that divides a training dataset into homogeneous subgroups according to attribute based logical tests in a greedy top-down approach.

Decision trees consist of nodes and branches. Nodes in decision trees are of two types: either a leaf node which holds class/label value or a decision node that holds selected attribute for splitting the data into subgroups. The decision value of this attribute based logical test is represented on the branches that comes from this decision node. Decision trees are considered as deterministic algorithms as they use sharp boundaries with no consideration of degree of membership like other learning algorithms. As the divide and conquer algorithm partitions the data until every leaf contains cases of a single class, or until further partitioning is impossible, if there are no conflicting cases, the decision tree will correctly classify all training cases. This so-called overfitting is generally thought to lead to a loss of predictive accuracy in most applications [145].

Overfitting can be avoided by a stopping criterion that prevents some sets of training cases from being subdivided, or by removing some of the structure of the decision tree after it has been produced; a process known as pruning. Different pruning strategies are used by decision tree algorithms to overcome overfitting the training data; adding robustness to the algorithms. This robustness in addition to the intuitive representation and ease of interpretation of decision trees attracted many data mining researchers as well as non technical experts to use

them in a wide areas of applications. Not all of decision tree algorithms have the ability to handle continuous values. Thus, a discretization process of the continuous attribute is used before applying such algorithm on a classification problem with continues attribute(s), in which the continuous attribute values is transformed into intervals. Examples of discretization algorithms includes ChiMerge [90], Entropy-MDLC [47], and Heter-Disc [104].

There are many decision tree algorithms that are well known in the area of data mining. These include the three algorithms introduced by Quinlan : ID3 (Iterative Dichotomiser 3) in 1986 [145], and its successor C4.5 in 1993 [144], which was improved to produce a better memory efficient commercial system C5.0. Other decision tree algorithms includes (Chisquare Automatic Interaction Detection) algorithm known as CHAID developed by Kass in 1980 [87], CART (Classification And Regression Tree) developed by Breiman et al. in 1984 [25], LMDT by Brodley and Utgoff in 1995 [27], SPRINT by Shafer et al. in 1996 [161] , SLIQ by Mehta et al. in 1996 [116], and QUEST (Quick, Unbiased, Efficient, Statistical Tree) algorithm by Loh and Shih in 1997 [105].

Different splitting selection criteria have been used in decision tree algorithms. Splitting criterion can be characterized either according to their origin of measure such as information theory, dependence, and distance, or according to their measure structure such as impurity based criteria, normalized impurity criteria and binary criteria. ID3 algorithm uses an impurity-based criterion called Information gain which is based on the concept of entropy. Another impurity-based criterion is Gini index, which measures the divergences between the probability distributions of the target attribute‘s values. The CART algorithm uses Gini index as splitting criterion. An impurity based criterion is biased towards input attributes with many outcomes. Although this attribute would get the highest information gain, it may result in poor accuracy when generalized. Thus, a normalized impurity measure criteria called Gain ratio was introduced by Quinlan in C4.5 algorithm. Rank Mutual Information (RMI) is a recent split-

ting criterion that was developed in 2012 by Hu et al. [75]. RMI based decision trees are designed for special type of classification problems known as Monotonic classification through merging the robustness of Shannon's entropy with rough sets.

5.2.1 Inner vs Outer Classification

Classification algorithms can be categorized into two categories: outer algorithms and inner algorithms [92]. The first category (outer algorithms) contains algorithms that use a certain function or approach to approximate the boundaries of each class. Examples of this group of algorithms include neural networks, decision trees, and classification rules. The second category (inner algorithms) contains algorithms that have the objective of clustering data into classes groups. The boundary of each group is defined by a certain measure like a mean or median. Then, a new instance is classified into the class of the nearest group [92]. K-Nearest Neighbours algorithm is an example of inner classification algorithms. Figures 5.1 and 5.2 show the differences between outer and inner classification approaches.

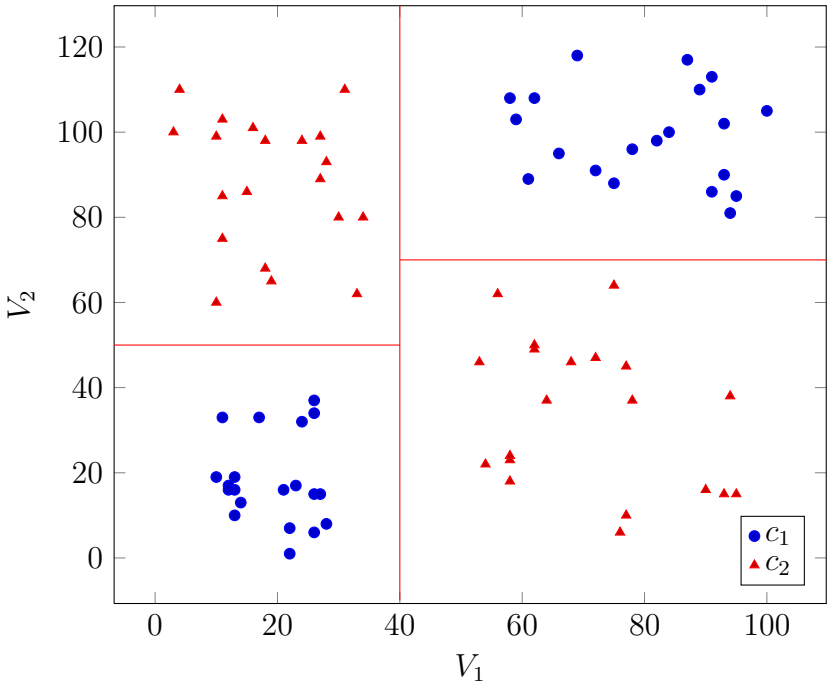


Figure 5.1: Outer Classification

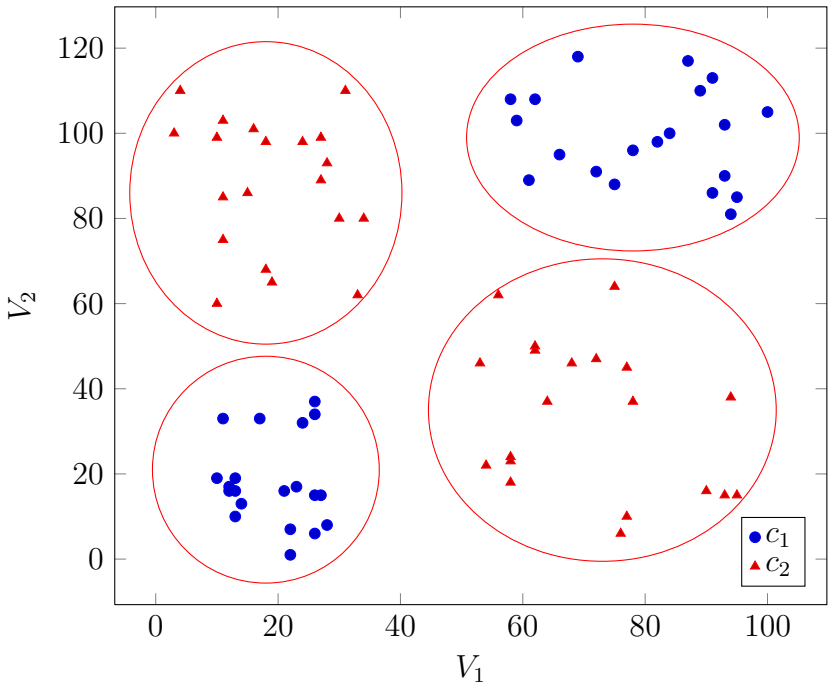


Figure 5.2: Inner Classification

5.2.2 Univariate Vs. Multivariate Decision Trees

The splitting functions in decision trees are usually univariate. Univariate means that splitting at each node is performed based on the values of a single selected attribute. That leads to axis-aligned splits. Though, there are some decision tree algorithms that are multivariate. In a linear multivariate decision tree, each decision node is based on multiple attributes. A linear multivariate decision tree selects the best linear combination of the attribute that divides the input space into two with an arbitrary hyperplane leading to oblique splits. Examples of linear multivariate decision trees include CART [51] and OC1 (Oblique Classifier 1)[128].

In 1998, Zheng proposed a new algorithm that dynamically constructs new binary attributes by performing a search over a path of a tree [204]. Zheng‘s algorithm constructs logical operations on conditions such as conjunction, negation , and disjunction of conditions. In 2000, Zheng extends his algorithm to construct nominal and numerical attributes [205]. Zheng proposed a constructive operation X-of-N , to be used in the decision tree learning algorithm that constructs new

attributes in the form of X-of-N representations. For a given instance, the value of at-least M-of-N representation is true if at least M of its conditions is true of the instance, otherwise it is false. Another constructive induction multivariate decision tree called linear tree was proposed by Gama and Brazdil [52] in 1999. Linear tree combines decision tree algorithms with linear discrimination to define decision surfaces in both orthogonal and oblique to the axes defined by the attributes of the input space. Gama, then, introduced the “Functional trees" algorithm which is a multivariate tree learning algorithm that combines univariate decision trees with a discriminant function by means of constructive induction [51].

A conceptual diagram demonstrating how a decision tree algorithm works by comparing a split on a variable and its impact on the class is presented in Figure 5.3(a) with an example of a traditional decision tree output in Figure 5.3(b).

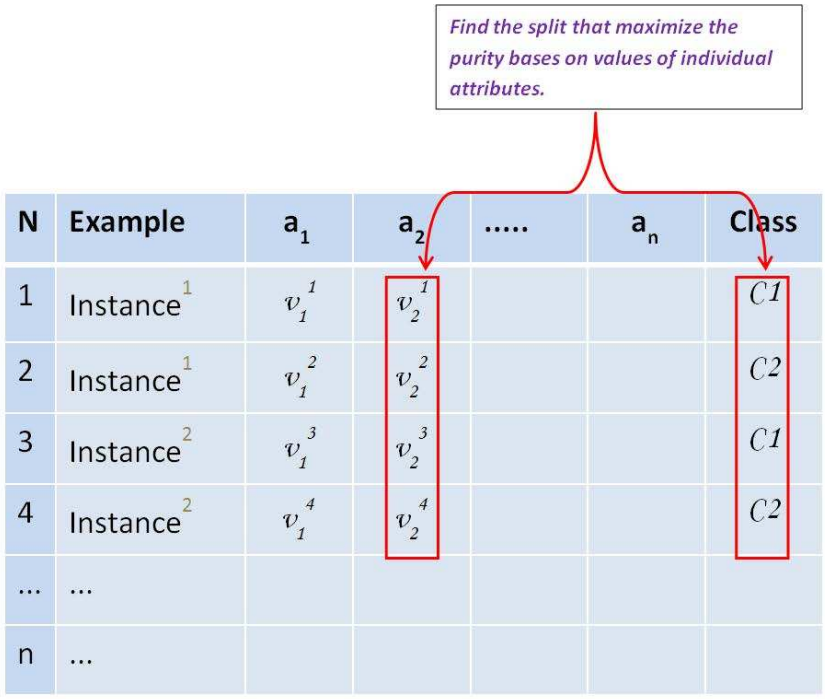
5.2.3 C4.5

C4.5 is an extension of the basic ID3 algorithm to overcome its limitations. C4.5 avoids overfitting the data by determining how deeply to grow a decision tree. Its advantages include its ability to handle missing values and numeric attributes. In a study that compared decision trees and other learning algorithms by Tjen-Sien et al. [102], C4.5 was found to have a very good combination of error rate and speed.

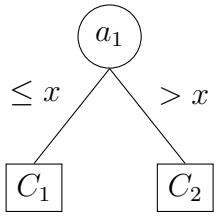
The selection criterion in C4.5 is based on either Information Gain or Gain Ratio. Both of these measures are based on another basic measure in information theory called Entropy. The Entropy measure is used to characterize the impurity of a collection of examples.

$$Entropy(S) = \sum_{i=1}^{c} -p_i \; log_2 \; p_i \tag{5.1}$$

Given S is any set of samples that belongs to k number of classes $C : C_i$,



(a) Framework



(b) Output

Figure 5.3: Traditional Decision Tree

where $Freq(C_i, S)$ = the number of instances in S belongs to C_i and $|S|$= total number of instances in S. Entropy can be calculated as:

$$Info(S) = -\sum_{i=1}^{k} \frac{freq(C_i, S)}{|S|} \, log_2 \left(\frac{freq(C_i, S))}{|S|} \right) \tag{5.2}$$

For T training set, that can be divided into subsets $\{T_1, T_2, \cdots, T_n\}$ based on test x : The total information content after T is partitioned is:

$$Info_x(T) = \sum_{i=1}^{n} \frac{|T_i|}{|T|} \, Info(T_i) \tag{5.3}$$

The quantity

$$Gain(x) = Info(T) - Info_x(T) \tag{5.4}$$

measures the information that is gained by partitioning T according to test x. The selection criterion is to select test x to maximize $Gain(x)$.

The information gain criterion has deficiency: it has a strong bias in favor of tests with a lot of outcomes. To solve this problem, Split-Info(x) is calculated as

$$Split - Info(x) = -\sum_{i=1}^{n} \frac{|T_i|}{|T|} \, log_2 \left(\frac{|T_i|}{|T|} \right) \tag{5.5}$$

This represents the potential information generated by dividing set T into n subsets T_i. Gain Ratio measure expresses the proportion of information generated by splitting of samples using test x. Gain-Ratio is robust, it gives consistently better choice of a test than Information Gain. Algorithm 1 list the Pseudocode of C4.5 decision tree.

$$Gain - Ratio(x) = \frac{Gain(x)}{Split - Info(x)} \tag{5.6}$$

Algorithm 1: Pseudocode of C4.5

1. Grow initial tree (divide and conquer): Tree (S)

- Test for leaf node;
  - ◇ ***if*** All cases in S belong to same class, ***then*** return leaf node with this class.
  - ◇ ***if*** Attributes is empty, ***then*** return leaf node with the majority class.
- Otherwise decision node:
  - ◇ Search for the best decision attribute based on gain ratio:
    For a nominal attribute a_i with values $\{v_1, v_2, v_3, \cdots\}$,One outcome for each value v_i
    For a numerical attribute a_i, a threshold z for splitting $a_i \leq z$ and $a_i > z$: Choose z to maximise test criterion (gain or gain ratio)
  - ◇ Select this single attribute a_i with outcomes $\{o_1, o_2, o_3, \cdots\}$
    Partition S into $\{S_1, S_2, S_3, \cdots\}$ according to outcomes
    Apply recursively to subsets, $Tree(S_1), Tree(S_2), Tree(S_3), \cdots$

2. Prune to avoid over fitting

5.2.4 Relational Learning

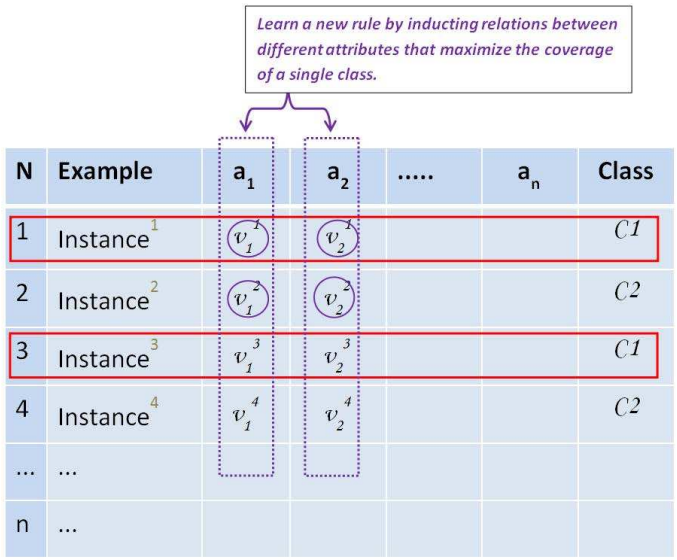
Unlike Decision trees, which are classified as propositional (variable free, or feature-value) learning techniques, relational learning looks for relational patterns among the variables.

Inductive logic programming (ILP) uses (first order predicate logic rules) to represent the detected relations among the variables. ILP based classifiers target one class at a time, trying to maximize the coverage of this class [98]. In ILP systems, the approach of generating the rules go through two loops: outer and inner. The purpose of the outer loop is to construct a clause that explains some of the positive examples, then adding this clause to the hypothesis. After that, the positive examples are removed, and the process is repeated until all the examples are represented through clauses. That means the hypothesis is complete. The inner loop is used to generate the individual clauses by searching the space for all possible clauses. This process starts with no conditions (general), then proceeds to add conditions until it only covers the positive examples. These generated clauses are used by the outer loop to select the one that has the maximum number of instances in order to maximize the coverage [98]. ILP learners have the privilege

of utilizing existing background knowledge through rules to guide the induction of new hypothesis.

In 1995, Quinlan introduced the FOIL classification algorithm which learns a set of first order rules for the purpose of predicting the class label [146]. FOIL uses general to specific search by adding single literal/condition to the preconditions list at each step. FOIL algorithm uses FOIL-Gain to select the best literal. One of the privileges of FOIL algorithm is its ability to learn recursive rules.

A conceptual diagram demonstrating how an ILP algorithm works by inducing a rule among different attributes to maximize the coverage of a single class is presented in Figure 5.4(a) with an example of an ILP learner in Figure 5.4(b).



(a) Framework

$$Class(Example, C1) \leftarrow a_1(Example, x), a_2(Example, y)$$

(b) Output

Figure 5.4: ILP Classifier

5.2.5 Classification vs Comparative Classification

For a general classification problem, A bag of instances that provides the description of the attributes and their domains can be denoted by $B(A \cup C)$, where A denotes the set of n input attributes $A = \{a_1, \cdots, a_i, \cdots, a_n\}$, and C represents

the set of k classes variable (target attribute) $C = \{c_1, \cdots, c_i, \cdots, c_k\}$.

A training set is defined as a collection of instances (also known as records, rows or tuples) that may contain duplicates. Each instance is an individual, independent example of the concept to be learned. These instances are characterized by a vector of predetermined attribute values as:

$$\begin{bmatrix} v_1^1, & \cdots, & v_n^1 \\ \vdots & \vdots & \vdots \\ v_1^m, & \cdots, & v_n^m \end{bmatrix} \tag{5.7}$$

where, v_i^j is the value of attribute j in instance i, n is the number of attributes and m is the number of instances.

A traditional classification problem can be defined as: Given a training set S with input attributes set $A = \{a_1, \cdots, a_i, \cdots, a_n\}$ and a nominal target attribute C, the goal is to find a model/classifier that can map previously unseen instances to the appropriate class that belongs to the target attribute $c \in C$ as accurate as possible.

PWCCP is a special type of binary classification problems. The goal of PWCCP is to find a model that maps unseen instances to the appropriate predefined classes in one-to-one correspondence for each pair of instances. Instances are paired in both training and testing data set, where each pair consists exclusively of classes instances; one instance per class. Thus, if one instance in this pair is misclassified, the other instance will be misclassified as well. Values of the same attribute for the paired instances are collected into a single vector as $\overrightarrow{v_i^j} = [v_i^j(c_1), \cdots, v_i^j(c_k)]$, where i represents the instance id, j represents the attribute id, and $|v_j^i| = k$

Instances in PWCCP can be represented as :

$$\begin{bmatrix} \overrightarrow{v_1^1}, & \cdots, & \overrightarrow{v_n^1} \\ \vdots & \vdots & \vdots \\ \overrightarrow{v_1^m}, & \cdots, & \overrightarrow{v_n^m} \end{bmatrix} \tag{5.8}$$

Based on this description, the definition of PWCCP becomes: Given a training set S with input attributes set $A = \{a_1, \cdots, a_i, \cdots, a_n\}$ and a nominal target attribute C, and a test set of instances $V = \{V^{m+1}, \ldots, V_{m+u}\}$, u is the size of the test set, the goal is to find a bijection mapping from every element in each V^i to the corresponding class or target attribute $c \in C$ as accurate as possible.

To avoid the confusion from switching between a vector representation for the training set and a set representation for the test set, we will adopt the notation $V_i(p_j)$ to represent the value of attribute i. We use p_j as an index for the order of the measurement. For example, in a PWCCP, $j = 2$, and $V_1(p_1)$ denotes the value of the first attribute for the first instance of the pairs. We will use the notation $p_1 \rightarrow c_1, p_2 \rightarrow c_2$ to denote that the first instance in the pairs are classified as class c_1, while the second instance is classified as class c_2. In a paired classification, the only other alternative would be $p_1 \rightarrow c_2, p_2 \rightarrow c_1$.

We will also use the following functions and notations to establish a relationship between the two instances in a pair.

1. $(R(V_1(p_1), \{V_1(p_1), V_2(p_2)\}) = min)$ to signify that the value of V_1 in the first instance of the pairs is the minimum value among the two values of V_1 in that pair.

2. $(R(V_1(p_1), \{V_1(p_1), V_2(p_2)\}) = max)$ to signify that the value of V_1 in the first instance of the pairs is the maximum value among the two values of V_1 in that pair.

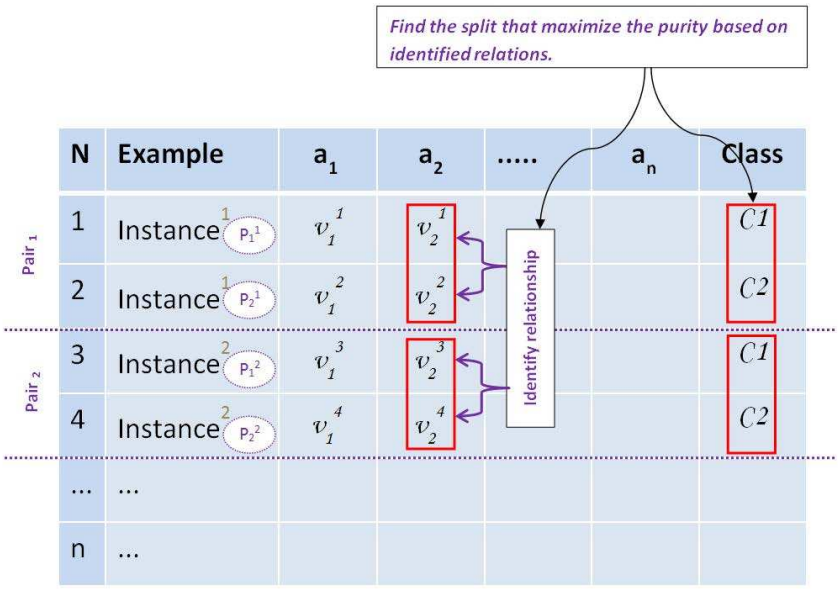
3. $(R(V_1(p_1), \{V_1(p_1), V_2(p_2)\}) = Eq)$ to signify that the values of V_1 in both instances in the pair are equal.

Figure 5.5(a) shows how PWC4.5 targets the relationship between paired instances within one variable at a time, and Figure 5.5(b) shows the output for that framework.

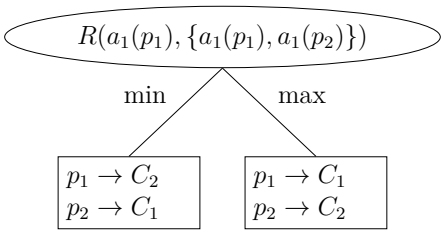
We can now define a synthetic problem to demonstrate the concept of PWCCP. Assume $V_1(p_1)$ is always the minimum of $\{V_1(p_1)\ , V_1(p_2)\}$ in a set of data as shown in Figure 5.6. It is clear that V_1 is the key variable to discriminate between the two classes while V_2 is not a useful feature. On the one hand, a traditional decision tree such as $C4.5$ couldn't identify the existing relationship among paired instances based on V_1. $C4.5$ classifies the instances based on feature values as shown in Figure 5.7. That resulted in poor accuracy of classification. On the other hand, PWC4.5 is a classifier that can detect the relationship and produces a decision tree that represents this relationship as in Figure 5.8. If we extend the previous example to two dimensions, "Example 2" presents this case. In Example 2 shown in Figure 5.9, there is a relationship based on both variables V_1 and V_2, in which the relationships are p_1 is labelled as C_1 if $V_1(p_1)$ is the minimum of $\{V_1(p_1), V_1(p_2)\}$ and $V_2(p_1)$ is the minimum of $\{V_2(p_1), V_2(p_2)\}$, or in case of $V_1(p_1)$ is the maximum of $\{V_1(p_1), V_1(p_2)\}$ and $V_2(p_1)$ is the maximum of $\{V_2(p_1), V_2(p_2)\}$. Other wise p_1 is labelled as C_2. Again, C4.5 failed to identify these relationships and put all of the instances into one leaf as shown in Figure 5.10, and Figure 5.11 shows the prospective decision tree that can represent these relationships.

5.3 PWC4.5 Decision Tree Algorithm

To uncover the hidden patterns or phenomena that may exist between each pair of instances, we need to consider the values of the attributes for these instances at the same time rather than working with each of them individually. Numerical attributes may hold hidden information that can be seen by comparing the



(a) Framework



(b) Output

Figure 5.5: PWC4.5

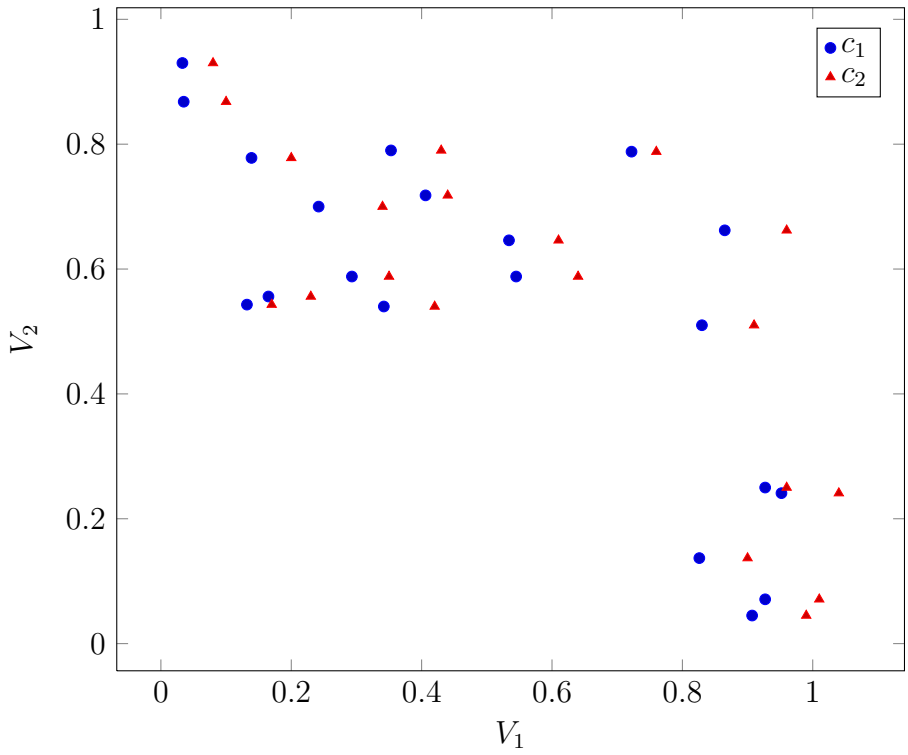


Figure 5.6: Example 1: Pair-Wise Relationship Based on Variable V_1

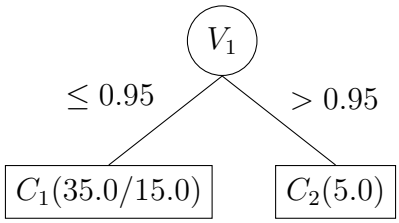


Figure 5.7: C4.5 Decision Tree of Example 1

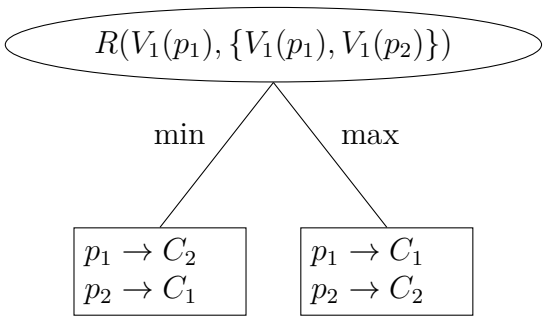


Figure 5.8: PWC4.5 Decision Tree of Example 1

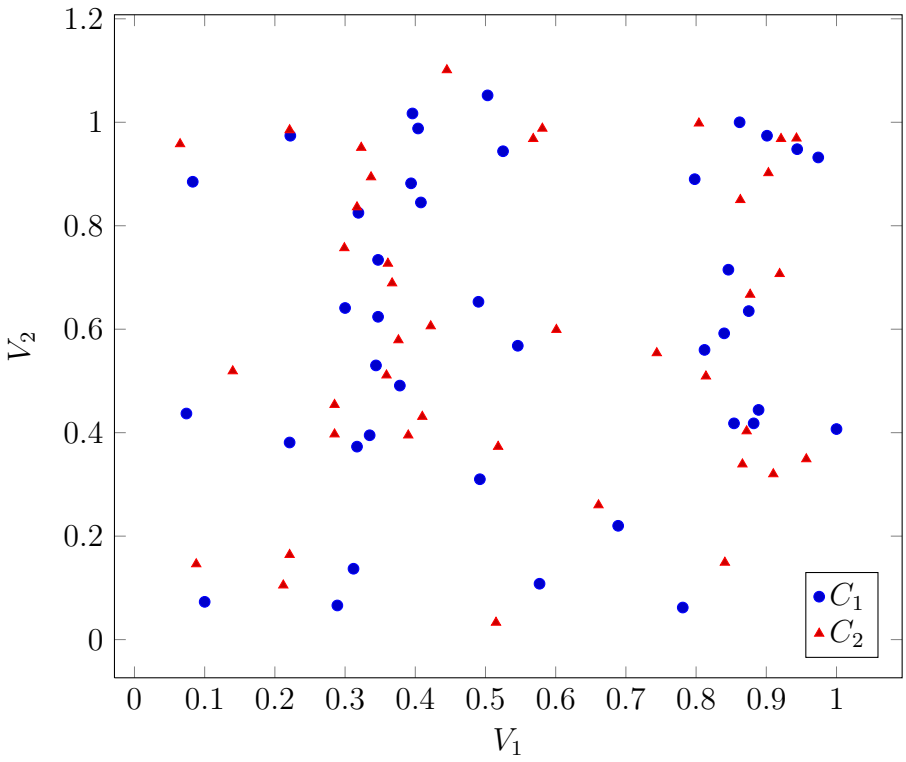


Figure 5.9: Example 2: Pair-Wise Relationship Based on Variables V_1 and V_2

$C_1(40.0/20.0)$

Figure 5.10: C4.5 Decision Tree of Example 2

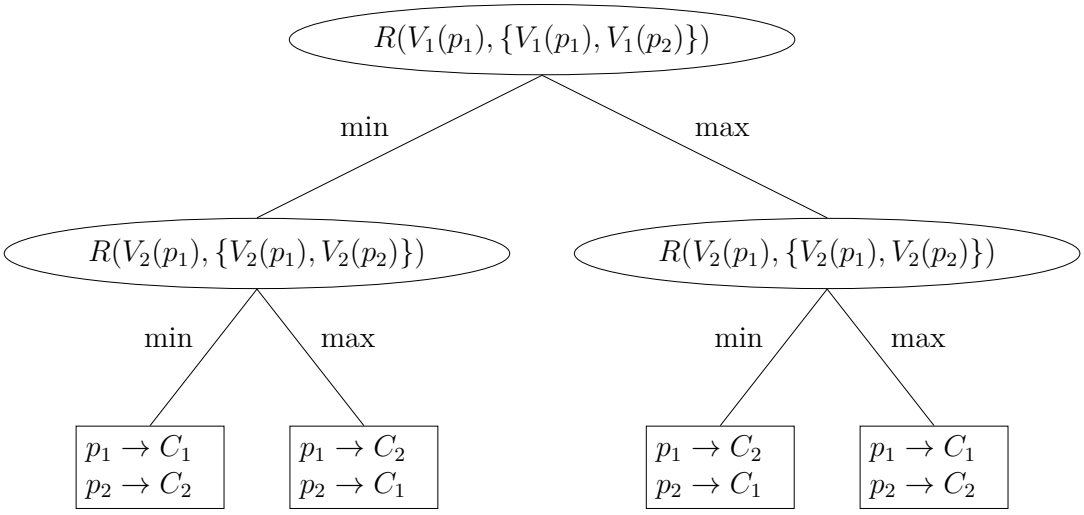


Figure 5.11: PWC4.5 Decision Tree of Example 2

values of each pair together. For example: we may find that $a_i(C_1)$ is usually the minimum of $\{a_1(C_1), a_1(C_2)\}$ for any pair of instances. We may find this relationship occurring regardless of the actual values of attribute a_i. The hidden pattern in this case will be $a_i(C_1) = min(\{a_1(C_1), a_1(C_2)\})$ or in our notation $R(a_i(p_1), (\{a_1(p_1), a_1(p_2)\}) = min, p_1 \rightarrow c_1, p_2 \rightarrow c_2$.

We need a special classifier that is able to capture the relationship between the values of the same attribute for the two parallel translations. It should be able to see the two instances as one pair that holds hidden information in their relations to each other. As we need to capture the hidden pattern in the relationship between the attribute values of the paired instances, we need to evaluate this relationship. Thus, for each numerical attribute, rather than using the traditional method of searching the best split point that C4.5 uses, a new method of search is used. In this method, we consider the new vector that holds information for the two items that represent a single pair. Values of the evaluated attributes for both items are compared together to induce the relationship. This relationship is used as a possible outcome for the relationship condition. Then, gain ratio is calculated based on the new outcomes. The attribute based relationship that introduces the highest gain ratio is then selected as the best split attribute.

PWC4.5 to solve this problem is based on C4.5 decision tree algorithm. We choose C4.5 as a well-known decision tree algorithm that uses information gain ratio to nominate preferred attributes for building the classifier. Advantages and limitation of C4.5 are discussed earlier in the background section. Pseudocode of PWC4.5 algorithm is presented in algorithm 2

5.4 Experiment

5.4.1 Artificial Data

In order to evaluate the performance of PWC4.5 in solving pair-wise comparative classification problem; we generated artificial datasets that have pair-wise relationships. For that purpose, we generated two types of datasets: the first dataset

Algorithm 2: Pseudocode of PWC4.5 Algorithm

1. Pairing: Transform S instances vector into PWCCP

- For each paired instances p_1, p_2, where:
  p_1 is represented by $V_1(p_1), V_2(p_1), \cdots, V_n(p_1)$ and
  p_2 is represented by $V_1(p_2), V_2(p_2), \cdots, V_n(p_2)$;
  A new vector PS that represent PWCCP is generated
  $PS(p_1, p_2) = \overrightarrow{V_1}, \overrightarrow{V_2}, \cdots, \overrightarrow{V_n}$, where:
  $\overrightarrow{V_1} = \{V_1(p_1), V_1(p_2)\}$,
  $\overrightarrow{V_2} = \{V_2(p_1), V_2(p_2)\}$,$\cdots$, and
  $\overrightarrow{V_n} = \{V_n(p_1), V_n(p_2)\}$
- For class balancing between the two paired instances, labeling them as p_1 and p_2 are generated randomly.
- ***If*** $(C(p_1) = c_1$, and $C(p_2) = c_2)$
  then: $\overrightarrow{C(p_1, p_2)} = \{p_1 \to c_1, p_2 \to c_2\}$,
  else: $\overrightarrow{C(p_1, p_2)} = \{p_1 \to c_2, p_2 \to c_1\}$

2. Grow initial tree (divide and conquer): Tree (PS)

- Test for leaf node;
  ◇ ***if*** $\overrightarrow{C(p_1, p_2)}$ for all cases in PS are the same, ***then*** return leaf node that represents this particular $\overrightarrow{C(p_1, p_2)}$.
  ◇ ***if*** Attributes is empty, ***then*** return a leaf node with majority class.
- Otherwise decision node:
  ◇ Search for the best decision attribute that has the highest gain ratio based on Pair-wise relationship. For each numerical attribute V_i:
  1. Create three possible nominal outcomes "Min","Eq","Max"
  2. Create three empty groups of samples for each of these new outcomes $S_{Min} = \phi$, $S_{Eq} = \phi$ and $S_{Max} = \phi$
  3. Induce the relationship by comparing $V_i(p_1)$ to the values of $\overrightarrow{V_i}$
     Loop*: For each** $PS_j = (p_1, p_2) \epsilon PS$ ***if $min(\overrightarrow{V_i^j}) = max(\overrightarrow{V_i^j})$
     then $S_{Eq} \leftarrow S_{Eq} \cup \{PS_j\}$
     else if $V_i(p_1) = min(\overrightarrow{V_i^j})$
     then $S_{Min} \leftarrow S_{Min} \cup \{PS_j\}$
     else $S_{Max} \leftarrow S_{Max} \cup \{PS_j\}$
  4. Calculate the gain ratio based on splitting PS into $\{S_{Min}, S_{Eq}, S_{Max}\}$
  ◇ Select the single attribute associated with the best decision. Partition PS into $\{PS_{Min}, PS_{Eq}, PS_{Max}\}$ according to its outcomes$\{S_{Min}, S_{Eq}, S_{Max}\}$
  ◇ Apply recursively to subsets, $Tree(PS_{Min}), Tree(PS_{Eq})$, and $Tree(PS_{Max})$

3. Prune to avoid over fitting

contains two attributes (2D), and the second dataset contains five attributes (5D). In each case, we first generated 10 noise free datasets for each problem, then generated from these noise free datasets other datasets with different levels of noise.

5.4.1.1 Artificial Data Generation

The data were generated using an XOR function over the predicate that $V_j(p_1)$ is the minimum between $V_j(p_1)$ and $V_j(p_2)$ as follows

if $\otimes_j(R(V_j(p_1), \{V_j(p_1), V_j(p_2)\}) = min)$***then*** $p_1 \rightarrow +$, $p_2 \rightarrow -$

We can see that in these rules, p_1 is labeled by + if the number of minimum relations is even, otherwise it is negative. For the case of 2D, 200 pairs were generated for training and 100 for testing. For the case of 5D, we increased the number of the pairs to 500 pairs for training, and 200 for testing to cover the larger space.

We experimented with 7 levels of noise in addition to the noise free baseline case. The test sets were always noise free. To explore the performance of PWC4.5 in case of noise, we added the following level of noise. Each of the eight cases (7 datasets with noise and one without) in each of the two problems (2D and 5D), 10 datasets were independently sampled using the above XOR relationship. These results were then collected to perform t-test analysis for the performance of C4.5 and PWC4.5 in each level of noise. A one tail paired T-Test with confidence level of 95% (alpha=0.05) was carried out. The proposed hypothesis is "The average accuracy of PWC4.5 is better than traditional C4.5 ". This can be expressed using:

$$H0 : \mu(PWC4.5) \leq \mu(C4.5)$$
$$H1 : \mu(PWC4.5) > \mu(C4.5)$$

5.4.1.2 Results

For 2D Experiment, PWC4.5 achieved average accuracy of 100% using noise free data. This accuracy was not affected by exposing the training data to noise of levels 1%, 2.5%, 5%, 10%, and 15%. At noise level of 20% the average accuracy dropped to 98.20%. The minimum average accuracy achieved was at the level of 25% noise, which was 82.90%. Meanwhile, C4.5 average accuracy ranged from 50.55% to 55.60% for the same samples. Details of the results are summarised in Table 5.1. For each level of noise, t-Test analysis was conducted to compare C4.5 accuracy to PWC4.5 as discussed in the experimental design. For the eight different levels of noise, H_0 is always rejected, and the alternative hypothesis is accepted, which concludes that $\mu(PWC4.5) > \mu(C4.5)$.

Similarly, the same experiment is applied to 5D dataset. The findings of this experiment is similar to 2D results. PWC4.5 always outperformed C4.5. The average accuracy for PWC4.5 was 100% for noise free data, and with noise levels of 1%, 2.5%, and 5%. For level of noise of 10%, 15%, 20%, the average accuracy achieved was 99.20%, 94.25%, and 82.80% respectively. The lowest average accuracy achieved was 63.65% at the noise level of 25%. As for C4.5, the average accuracy ranged from 48.53% to 51.35%. Additionally, the null hypothesis was rejected for all levels of noise.

Figure 5.12 shows a comparison between the accuracy obtained by PWC4.5 and C4.5 when exposed to different levels of noise. PWC4.5 demonstrated stability with different levels of noise up to 20%. Meanwhile, C4.5 was always around 50%. On the 5D dataset, Accuracy of PWC4.5 was more sensitive to the noise starting from noise level of 15% as shown in Figure 5.13.

In order to visualize the pairwise relationship in the 2D artificial dataset, we used first sample (Exp1) of each 10 samples at each level of noise. Then we show the two decision trees obtained by C4.5 and PWC4.5. These visualizations are collected in Figures 5.14 to 5.29. Additionally, we summarized the true positive, true negative, false positive, and false negative rates for each of these samples in Tables 5.3 and 5.4.

Table 5.1: Summary of the Results of One-Tail Paired T-Tests between the Accuracy of C4.5 and the Accuracy of PWC4.5 on 2D Artificial Data Where (Alpha=0.05) and (Degree of Freedom=9)

Noise level	**0%**		**1%**		**2.5%**		**5%**		**10%**		**15%**		**20%**		**25%**	
Methodology	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**
Exp_1	50%	100%	50%	100%	50%	100%	50%	100%	50%	100%	55%	100%	55%	100%	58%	88.00%
Exp_2	50%	100%	50%	100%	50%	100%	51.50%	100%	55%	100%	51.50%	100%	55.50%	100%	52%	67.00%
Exp_3	50%	100%	53.50%	100%	48.50%	100%	49.50%	100%	54.50%	100%	50%	100%	54.50%	100%	54.50%	88.00%
Exp_4	51.50%	100%	63%	100%	50%	100%	57%	100%	50%	100%	58%	100%	55.50%	82%	60.50%	69.00%
Exp_5	55.50%	100%	50%	100%	56%	100%	50%	100%	54.50%	100%	61.50%	100%	50%	100%	52%	100.00%
Exp_6	50%	100%	50%	100%	51%	100%	50%	100%	50%	100%	58.50%	100%	51.50%	100%	52%	100.00%
Exp_7	50%	100%	51.50%	100%	50%	100%	59%	100%	50%	100%	58%	100%	55.50%	100%	52.50%	63.00%
Exp_8	54.50%	100%	52%	100%	50%	100%	50%	100%	57%	100%	54%	100%	55.50%	100%	58.50%	86.00%
Exp_9	52%	100%	53%	100%	50%	100%	50%	100%	56%	100%	56.50%	100%	52.50%	100%	53%	100.00%
Exp_{10}	50%	100%	50%	100%	50%	100%	50%	100%	57%	100%	53%	100%	56.50%	100%	56%	68.00%
Average	51.35%	100%	52.30%	100%	50.55%	100%	51.70%	100%	53.40%	100%	55.60%	100%	54.20%	98.20%	54.90%	82.90%
STD	2.07%	0%	3.99%	0%	2.01%	0%	3.39%	0%	3.05%	0%	3.55%	0%	2.12%	5.69%	3.16%	14.92%
$P(T \leq t)$ one-tail	3.64E-14		1.59E-11		2.38E-14		3.29E-12		1.76E-12		1.05E-11		2.46E-09		1.83E-04	
t_{Stat}	-74.36		-37.76		-77.94		-45.02		-48.26		-39.55		-21.44		-5.53	
Hypothesis	P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected	

Table 5.2: Summary of the Results of One-Tail Paired T-Tests between the Accuracy of C4.5 and the Accuracy of PWC4.5 on 5D Artificial Data Where (Alpha=0.05) and (Degree of Freedom=9)

Noise level	**0%**		**1%**		**2.5%**		**5%**		**10%**		**15%**		**20%**		**25%**	
Methodology	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**	**C4.5**	**PWC4.5**
Exp_1	50%	100%	50%	100%	50%	100%	50%	100%	50%	100%	45%	89%	47.25%	92%	44.50%	44%
Exp_2	50%	100%	50%	100%	50%	100%	50%	100%	50%	100%	49.75%	98.50%	46.50%	57%	45.25%	87%
Exp_3	53%	100%	51.50%	100%	50%	100%	50%	100%	49.50%	100%	50%	94.50%	48.75%	90%	46.75%	47.50%
Exp_4	54.25%	100%	50%	100%	50%	100%	50%	100%	52.75%	99%	50%	93.50%	51%	73.50%	48%	51%
Exp_5	55.25%	100%	50%	100%	50%	100%	50%	100%	50%	100%	52%	92%	48.25%	83.50%	43.25%	40%
Exp_6	50%	100%	50%	100%	51.25%	100%	50%	100%	50%	99%	50.50%	95%	47.75%	85.50%	50.25%	76%
Exp_7	51%	100%	50%	100%	50%	100%	52%	100%	50%	100%	50%	94.50%	55%	78%	50.25%	74.50%
Exp_8	50%	100%	50%	100%	50%	100%	51.25%	100%	50%	97%	49.25%	94.50%	51.25%	92%	54.75%	82%
Exp_9	50%	100%	53.25%	100%	50%	100%	53.50%	100%	50%	97%	55.25%	98%	52.25%	87%	49.75%	79.50%
Exp_{10}	50%	100%	50.25%	100%	50%	100%	55.25%	100%	50%	100%	51.25%	93%	53%	89.50%	52.50%	55%
Average	51.35%	100%	50.50%	100%	50.13%	100%	51.20%	100%	50.23%	99.20%	50.30%	94.25%	50.10%	82.80%	48.53%	63.65%
STD	2.04%	0%	1.07%	0%	0.40%	0%	1.86%	0%	0.90%	1.23%	2.54%	2.74%	2.81%	10.89%	3.65%	17.78%
$P(T \leq t)$ one-tail	3.19E-14		8.54E-17		9.93E-21		1.33E-14		3.25E-15		2.37E-13		2.32E-06		8.07E-03	
t_{Stat}	-75.47		-145.79		-399.00		-83.18		-97.29		-60.35		-9.69		-2.95	
Hypothesis	P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected		P<0.05, then H_0 is rejected	

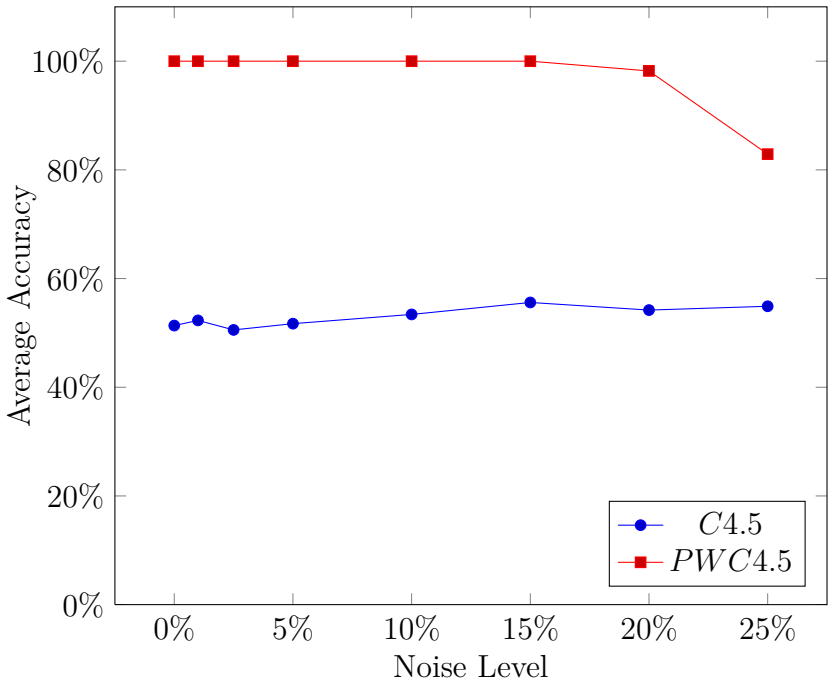


Figure 5.12: Average Accuracy for C4.5 and PWC4.5 for 2D Dataset

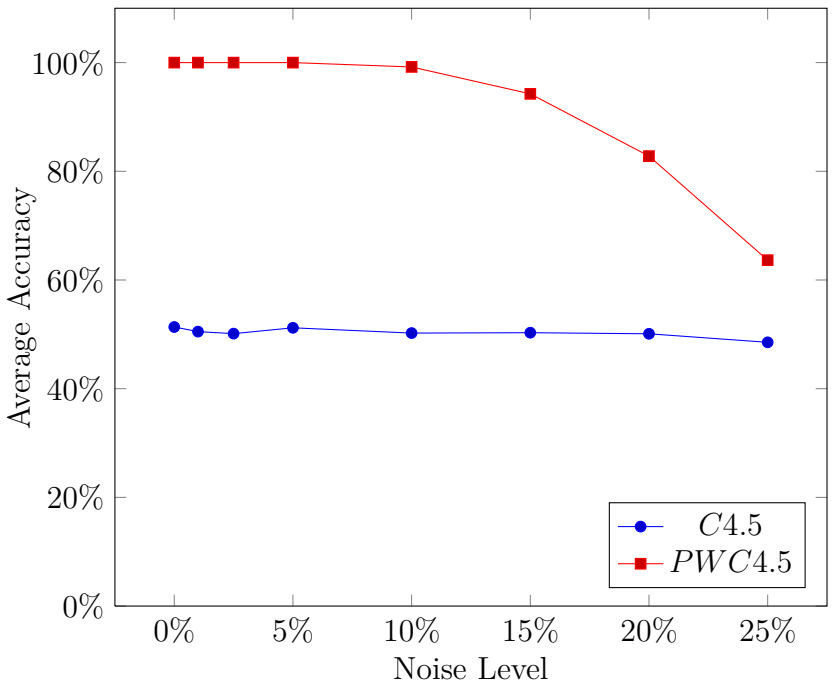


Figure 5.13: Average Accuracy for C4.5 and PWC4.5 for 5D Dataset

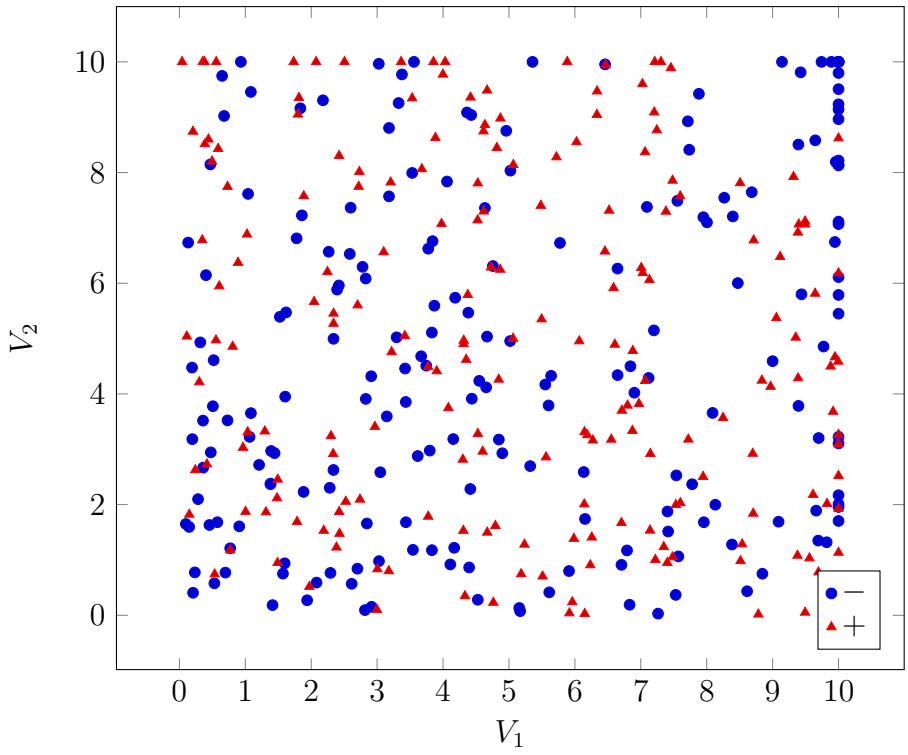
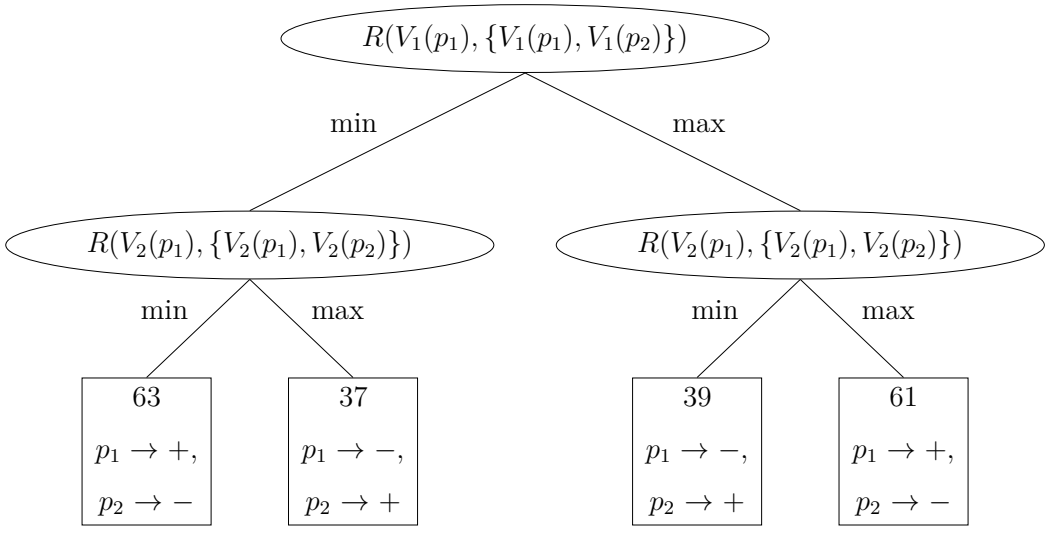
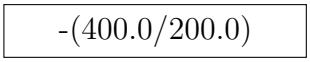


Figure 5.14: Pair-Wise Relationship of Noise Free 2D(Exp_1)



(a) PWC4.5 Decision Tree



(b) C4.5 Decision Tree

Figure 5.15: Decision Tree for Noise Free 2D(Exp_1)

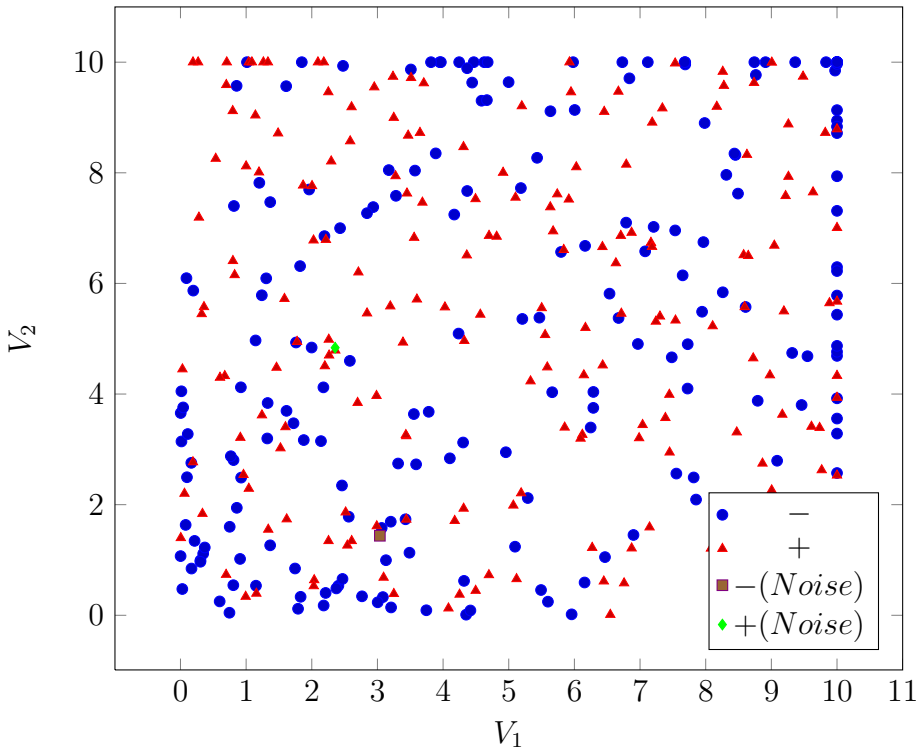
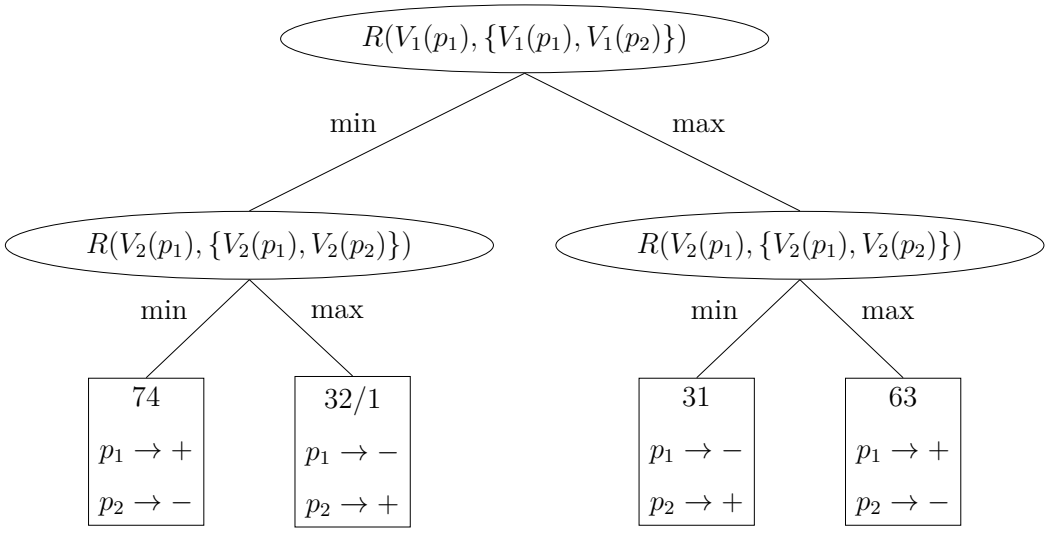


Figure 5.16: Pair-Wise Relationship of 2D(EXP_1) with Noise Level of 1%



(a) PWC4.5 Decision Tree

-(400.0/200.0)

(b) C4.5 Decision Tree

Figure 5.17: Decision Tree for 2D(EXP_1) with Noise Level of 1%

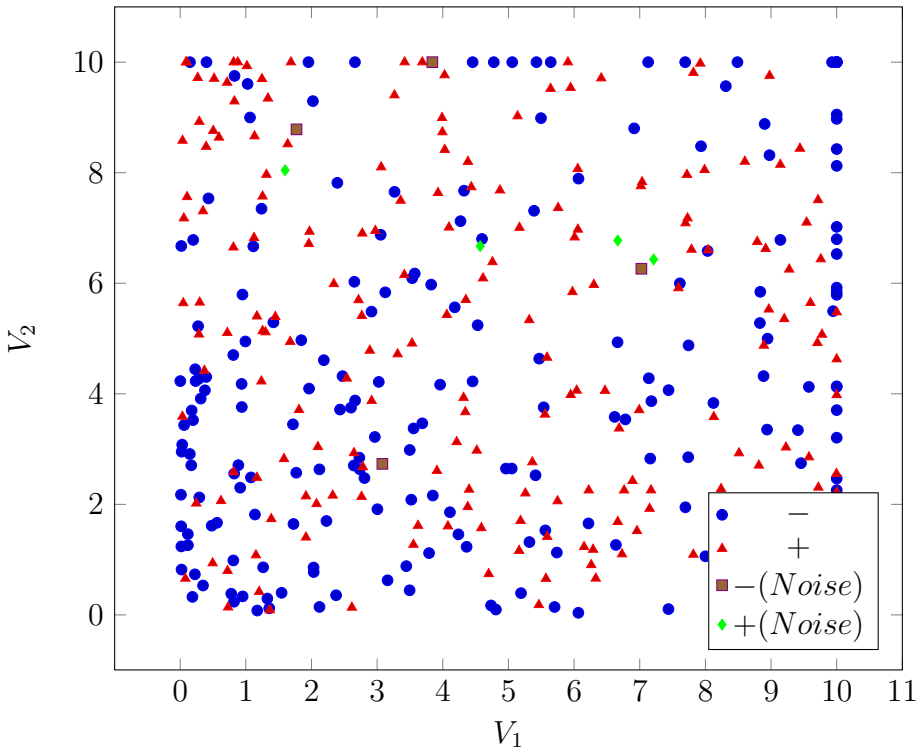
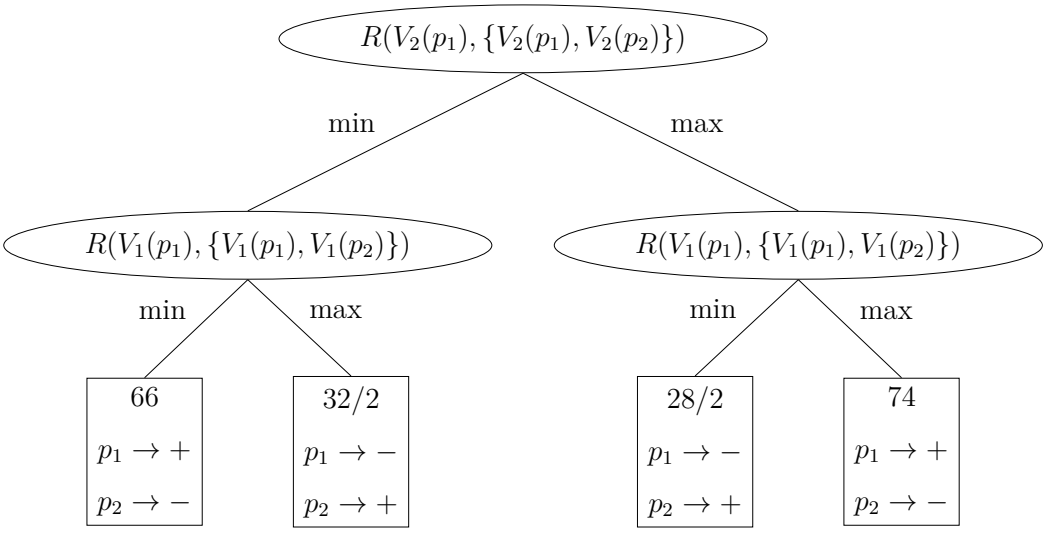
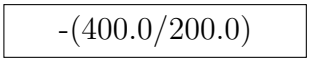


Figure 5.18: Pair-Wise Relationship of 2D(EXP_1) with Noise Level of 2.5%



(a) PWC4.5 Decision Tree



(b) C4.5 Decision Tree

Figure 5.19: Decision Tree for 2D(EXP_1) with Noise Level of 2.5%

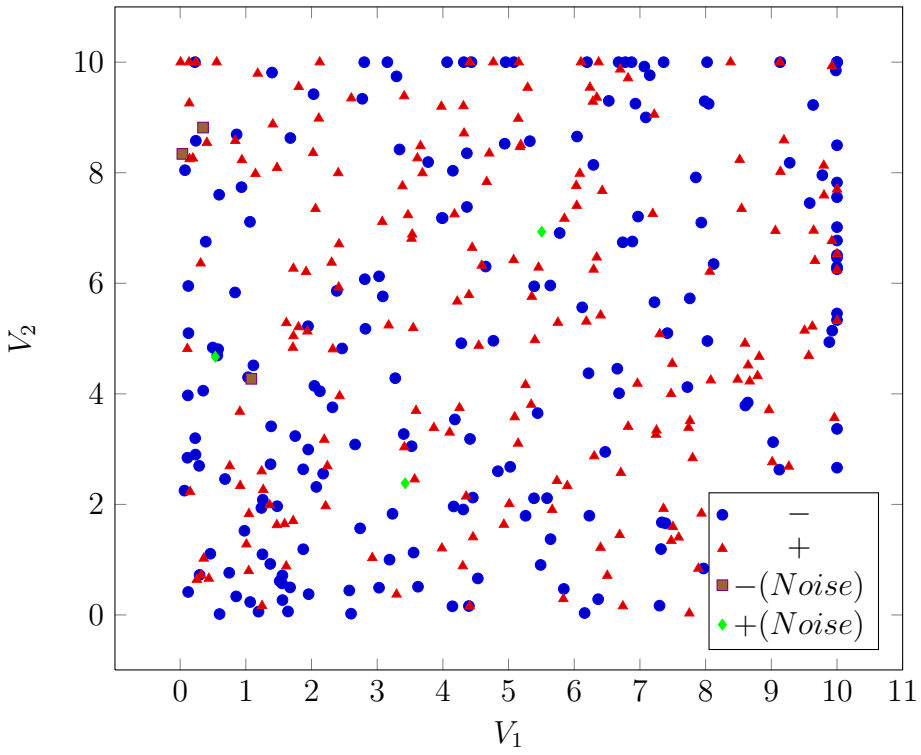
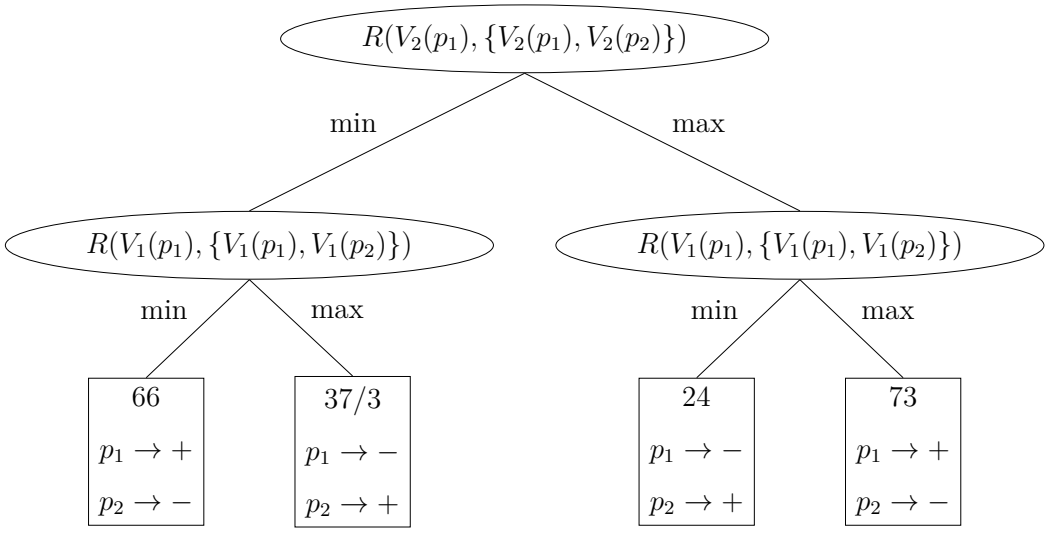


Figure 5.20: Pair-Wise Relationship of 2D(EXP_1) with Noise Level of 5%



(a) PWC4.5 Decision Tree

-(400.0/200.0)

(b) C4.5 Decision Tree

Figure 5.21: Decision Tree for 2D(EXP_1) with Noise Level of 5%

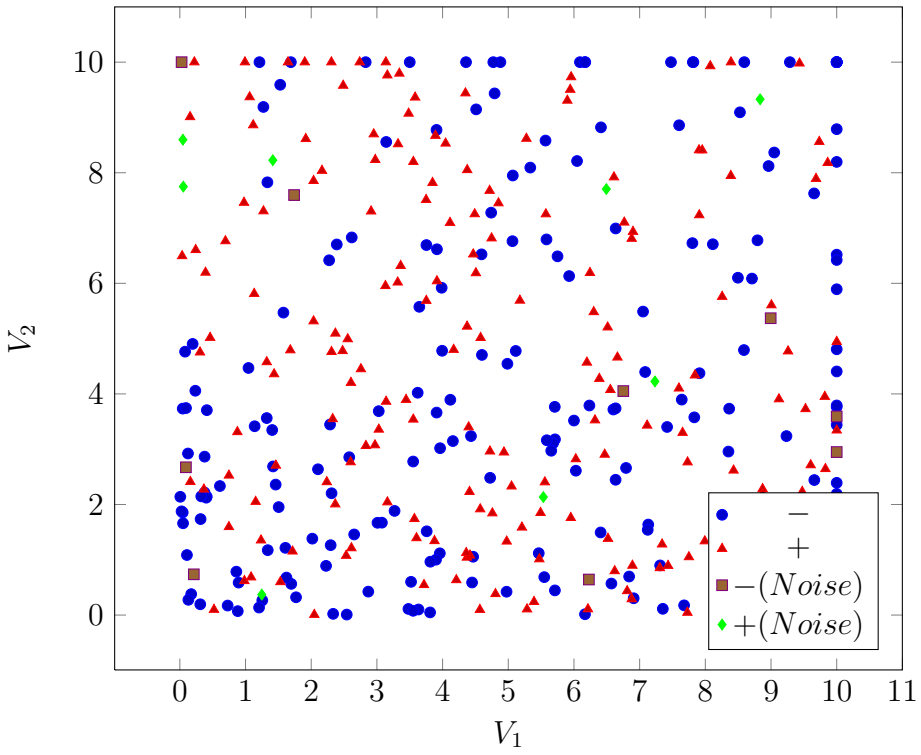
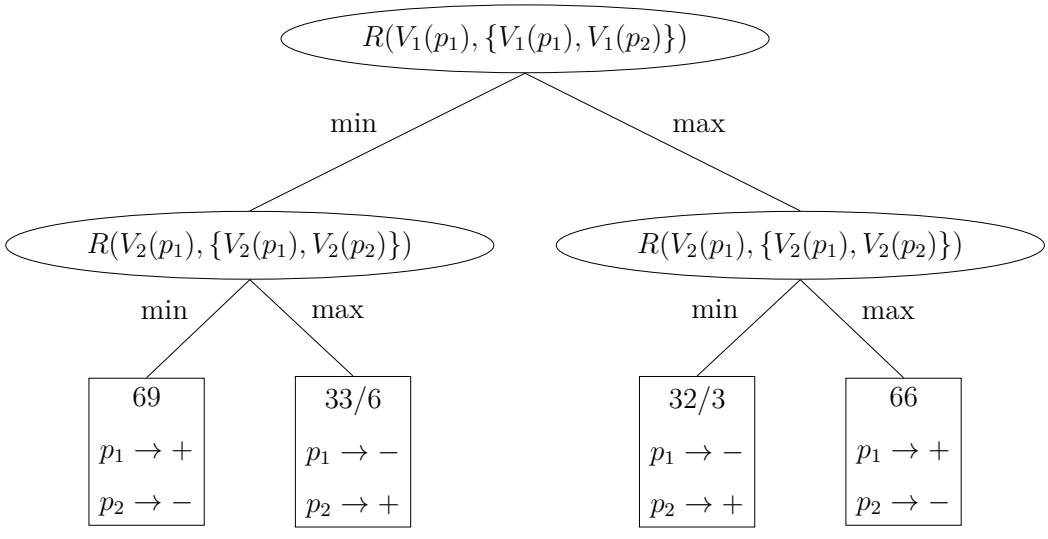
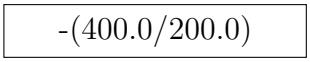


Figure 5.22: Pair-Wise Relationship of 2D(EXP_1) with Noise Level of 10%



(a) PWC4.5 Decision Tree



(b) C4.5 Decision Tree

Figure 5.23: Decision Tree for 2D(EXP_1) with Noise Level of 10%

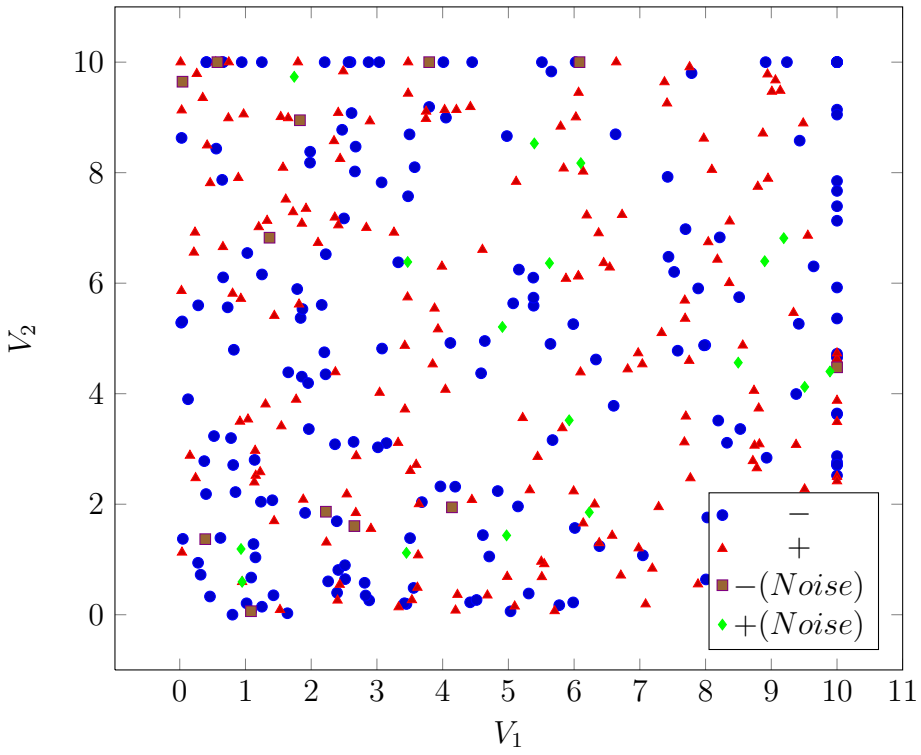
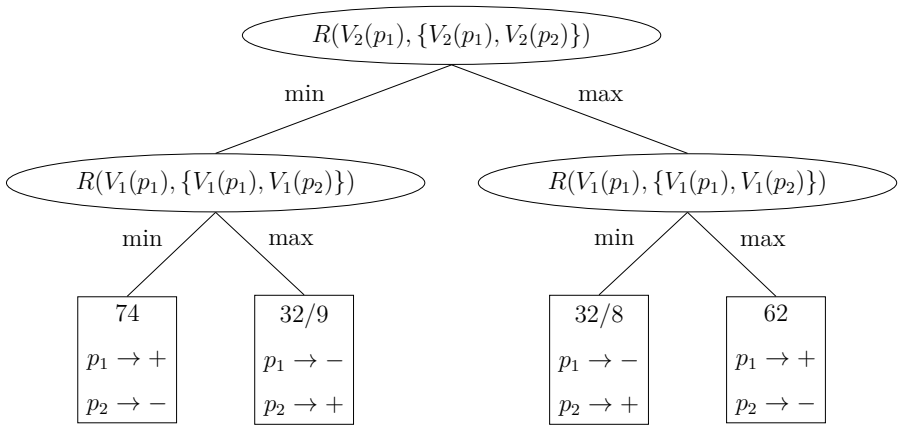
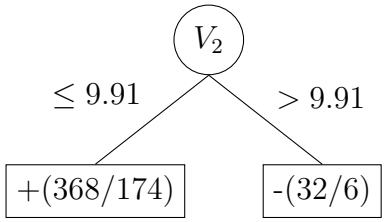


Figure 5.24: Pair-Wise Relationship of 2D(EXP_1) with Noise Level of 15%



(a) PWC4.5 Decision Tree



(b) C4.5 Decision Tree

Figure 5.25: Decision Tree for 2D(EXP_1) with Noise Level of 15%

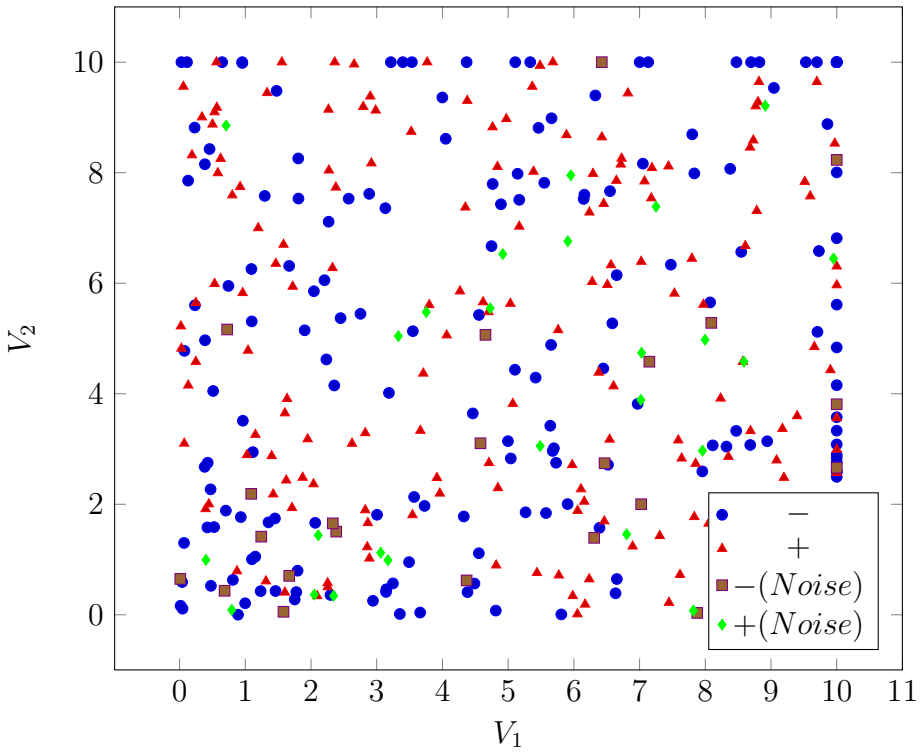
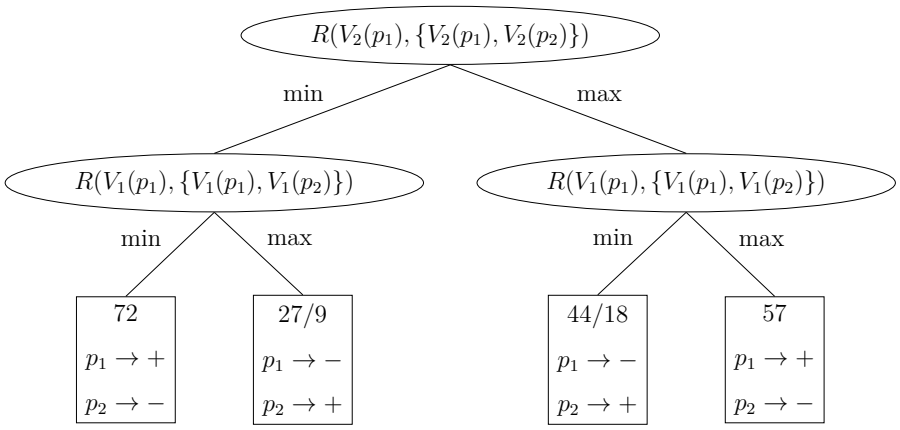
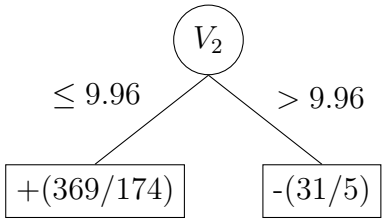


Figure 5.26: Pair-Wise Relationship of 2D(EXP_1) with Noise Level of 20%



(a) PWC4.5 Decision Tree



(b) C4.5 Decision Tree

Figure 5.27: Decision Tree for 2D(EXP_1) with Noise Level of 20%

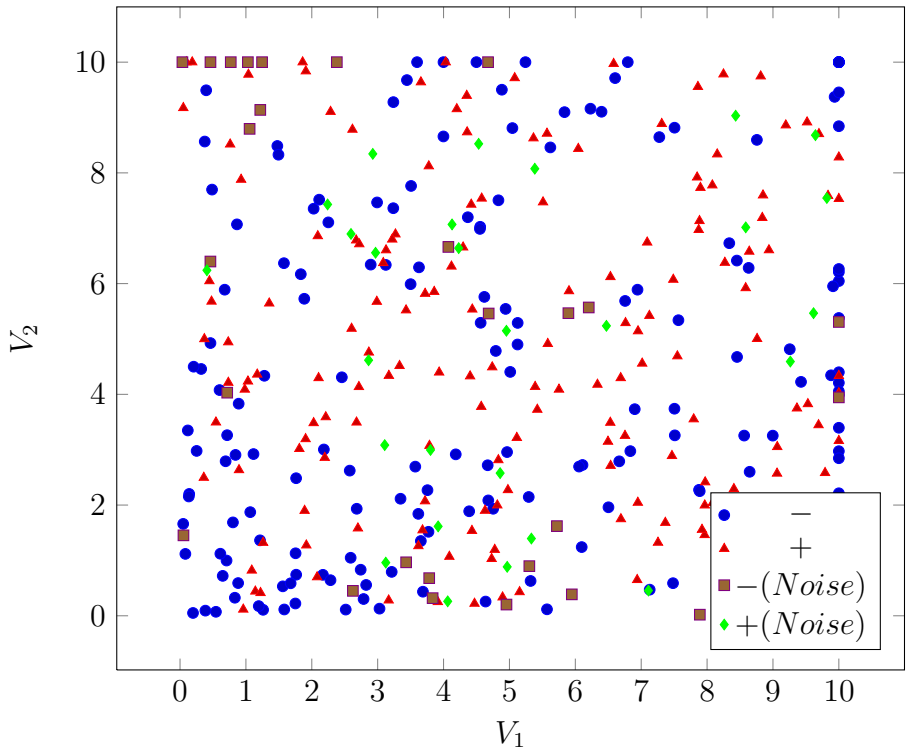
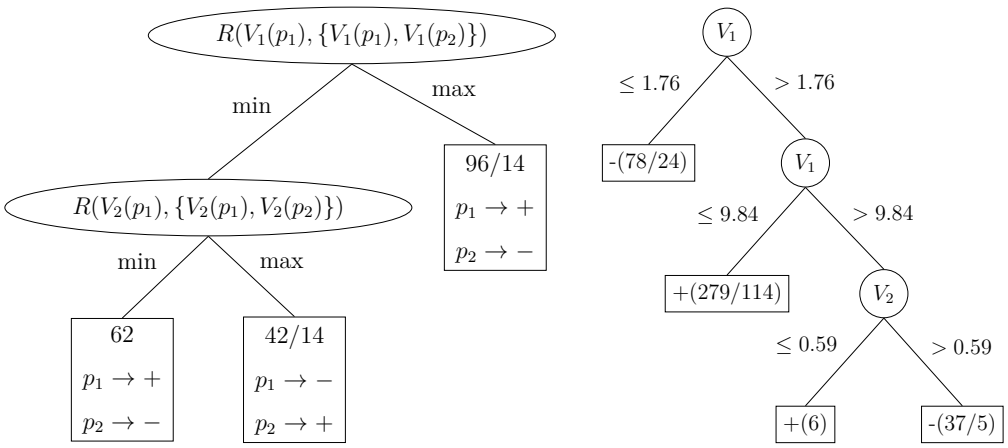


Figure 5.28: Pair-Wise Relationship of 2D(EXP_1) with Noise Level of 25%



(a) PWC4.5 Decision Tree

(b) C4.5 Decision Tree

Figure 5.29: Decision Tree for 2D(EXP_1) with Noise Level of 25%

Table 5.3: Accuracy by Class of Exp1(2D) for All Noises Levels

Noise Level	C4.5								PWC4.5							
	Training Data				Testing Data				Training Data				Testing Data			
	TP	TN	FP	FN	TP	TN	FP	FN	TP	TN	FP	FN	TP	TN	FP	FN
0%	0%	50%	0%	50%	0%	50%	0%	50%	62%	38%	0%	0%	69%	31%	0%	0%
1%	0%	50%	0%	50%	0%	50%	0%	50%	68.5%	31%	0%	0.5%	69%	31%	0%	0%
2.5%	0%	50%	0%	50%	0%	50%	0%	50%	70%	28%	0%	2%	69%	31%	0%	0%
5%	0%	50%	0%	50%	0%	50%	0%	50%	69.5%	29%	0%	1.5%	69%	31%	0%	0%
10%	0%	50%	0%	50%	0%	50%	0%	50%	67.5%	28%	0%	4.5%	69%	31%	0%	0%
15%	48.5%	6.5%	43.5%	1.5%	49.5%	5.5%	44.5%	0.5%	59.91%	32.6%	0%	7.49%	69%	31%	0%	0%
20%	48.75%	6.5%	43.5%	1.25%	49.5%	5.5%	44.5%	0.5%	64.5%	22%	0%	13.5%	69%	31%	0%	0%
25%	42.75%	21.5%	28.5%	7.25%	37%	21%	29%	13%	72%	14%	7%	7%	69%	19%	12%	0%

Table 5.4: Accuracy by Class of Exp1(5D) for All Noises Levels

Noise Level	C4.5								PWC4.5							
	Training Data				Testing Data				Training Data				Testing Data			
	TP	TN	FP	FN	TP	TN	FP	FN	TP	TN	FP	FN	TP	TN	FP	FN
0%	0%	50%	0%	50%	0%	50%	0%	50%	51.6%	48.4%	0%	0%	44%	56%	0%	0%
1%	0%	50%	0%	50%	0%	50%	0%	50%	49.4%	49.8%	0%	0.8%	44%	56%	0%	0%
2.5%	0%	50%	0%	50%	0%	50%	0%	50%	52.4%	44.4%	0%	3.2%	44%	56%	0%	0%
5%	0%	50%	0%	50%	0%	50%	0%	50%	50.6%	44.8%	0%	4.6%	44%	56%	0%	0%
10%	0%	50%	0%	50%	0%	50%	0%	50%	52.6%	38.2%	0%	9.2%	44%	56%	0%	0%
15%	25.2%	33.7%	16.3%	24.8%	19%	26%	24%	31%	55.2%	27.6%	5%	12.2%	44%	45%	11%	0%
20%	43.3%	14.2%	35.8%	6.7%	39.25%	8%	42%	10.75%	50.4%	28.8%	2.8%	18%	44%	48%	8%	0%
25%	44.2%	24.3%	25.7%	5.8%	30.75%	13.75%	36.25%	19.25%	78%	0%	22%	0%	44%	0%	56%	0%

5.4.2 Translator Stylometry Identification Problem

5.4.2.1 Using T Test to compare PWC4.5 to C4.5

For this experiment, 213 attributes are used (13 attributes as all possible motifs of size 3 in addition to 199 attributes as all possible motifs of size 4. The data set contains 74 parallel translations for seven translators. There are 21 possible combinations of these seven translators. We used all of these 21 possible combinations. For each pair of translator, we have (74x2) instances: 74 parallel translations. To evaluate the effectiveness of the algorithm without being affected by how these 74 pairs will be split, we decided to generate 10 different sets using these 74 sample pairs. The planned ratio of splitting for the data is (2/3) training and (1/3) testing. To generate these 10 different splits; we loop on the nominated pair of translator 10 times:

- For each pair of parallel translation, a random number is generated between 0 to 1.
- If this number belongs to the interval [0,0.667], then this pair go to the training dataset, otherwise, it is considered for testing dataset.

These 10 generated dataset are evaluated by C4.5 and then by PWC4.5 to compare the accuracy in each case. A one tail paired T-Test with confidence level of 95% (alpha=0.05) was carried out to evaluate if the accuracy of PWC4.5 is significantly better than the accuracy of $C4.5$. The question that we address in this experiment is "Can classification accuracy for paired data be enhanced by extracting information that represents paired instances relationship?". Thus, the proposed hypothesis will be "The average accuracy of PWC4.5 is better than traditional C4.5 ". This can be expressed using:

$$H0 : \mu(PWC4.5) \leq \mu(C4.5)$$
$$H1 : \mu(PWC4.5) > \mu(C4.5)$$

As described in PWC4.5 Pseudocode, labeling the two paired instances as p_1 and p_2 are generated randomly for equal opportunity between the two instances.

Therefore, this randomness may cause some variation in the generated decision tree. For the validation purpose of this experiment, we are going to run each experiment ten times, and take the mean of the accuracy to represent this single experiment's accuracy.

5.4.2.2 Results and analysis

Table 5.5 shows that the accuracy obtained by evaluating the 10 generated data sets using C4.5 and PWC4.5 for translators "Asad-Daryabadi". While the average accuracy of C4.5 is 56.24% ± 0.15%, PWC4.5 produced an average accuracy of 98.31% ±0.08%. After that, paired one-tail t-test is conducted for the average accuracy of the two algorithms using the 10 generated datasets. Results of this t-test are shown in Table 5.7. For this t-test, $t_{Critical}(9) = 1.833$, and alpha=0.05. Since $P(T \leq t) = 7.59E - 11$, P <0.05, then the test revealed that there was a statistical significance difference between PWC4.5 and C4.5

Although the variations between the ten runs of the experiment is not shown for the case of "Asad-Daryabadi", another example, for translators "Asad-Raza", shows these variations in Table 5.6. For example, accuracy of Exp_1 for '"Asad-Raza" varied from 70.37% to 92.598% with average of 82.96% ±6.58%. Therefore, we used the average to represent the accuracy of PWC4.5. Then, we applied t-test to compare between C4.5 and PWC4.5. $P(T \leq t) = 2.90E - 7$, P <0.05 as illustrated in Table 5.8. Therefore, the null hypothesis was rejected, and the alternative hypothesis $H1 : \mu(PWC4.5) > \mu(C4.5)$ is accepted.

We followed the same steps for each pair of translators. For all of the 21 pairs of translators, the null hypothesis was rejected, and the alternative hypothesis of μ(PWC4.5) >μ(C4.5) was always accepted. Results of T-tests are summarized in Table 5.9. These results demonstrates that PWC4.5 always outperformed C4.5 in this experiment.

The overall average of the accuracy of PWC4.5 is 78.81% in comparison to

Table 5.5: Classification Accuracy of C4.5 and PWC4.5 for Translators Asad-Daryabadi

Exp_n	C4.5	PWC4.5											
		1^{st} run	2^{nd} run	3^{rd} run	4^{th} run	5^{th}run	6^{th} run	7^{th} run	8^{th} run	9^{th} run	10^{th}run	Mean	STD
Exp_1	54.17%	95.83%	95.83%	95.83%	95.83%	95.83%	95.83%	95.83%	95.83%	95.83%	95.83%	95.83%	0.00%
Exp_2	60.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
Exp_3	51.92%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
Exp_4	62.50%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
Exp_5	58.93%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
Exp_6	55.36%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
Exp_7	51.92%	92.31%	92.31%	92.31%	92.31%	92.31%	92.31%	92.31%	92.31%	92.31%	92.31%	92.31%	0.00%
Exp_8	52.63%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
Exp_9	55.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%
Exp_{10}	60.00%	95.00%	95.00%	95.00%	95.00%	95.00%	95.00%	95.00%	95.00%	95.00%	95.00%	95.00%	0.00%
Average	56.24% ± 0.15%											98.31% ±0.08%	

Table 5.6: Classification Accuracy of C4.5 and PWC4.5 for Translators Asad-Raza

Exp_n	C4.5	PWC4.5											
		1^{st} run	2^{nd} run	3^{rd} run	4^{th} run	5^{th}run	6^{th} run	7^{th} run	8^{th} run	9^{th} run	10^{th}run	Mean	STD
Exp_1	51.85%	92.59%	88.89%	85.19%	81.48%	88.89%	77.78%	77.78%	81.48%	85.19%	70.37%	82.96%	6.58%
Exp_2	57.41%	85.19%	77.78%	70.37%	70.37%	66.67%	77.78%	85.19%	74.07%	77.78%	74.07%	75.93%	6.11%
Exp_3	51.79%	82.14%	82.14%	82.14%	82.14%	85.71%	82.14%	82.14%	82.14%	82.14%	82.14%	82.50%	1.13%
Exp_4	57.89%	68.42%	78.95%	73.68%	73.68%	84.21%	84.21%	89.47%	78.95%	78.95%	68.42%	77.89%	6.93%
Exp_5	56.67%	90.00%	73.33%	80.00%	83.33%	76.67%	80.00%	80.00%	86.67%	83.33%	80.00%	81.33%	4.77%
Exp_6	52.27%	90.91%	90.91%	90.91%	77.27%	77.27%	90.91%	86.36%	77.27%	72.73%	68.18%	82.27%	8.69%
Exp_7	47.06%	88.24%	76.47%	82.35%	82.35%	70.59%	82.35%	88.24%	76.47%	82.35%	76.47%	80.59%	5.58%
Exp_8	53.57%	89.29%	89.29%	92.86%	85.71%	92.86%	89.29%	85.71%	89.29%	92.86%	89.29%	89.64%	2.64%
Exp_9	71.74%	95.65%	78.26%	78.26%	86.96%	86.96%	86.96%	91.30%	86.96%	91.30%	91.30%	87.39%	5.59%
Exp_{10}	54.55%	81.82%	81.82%	86.36%	81.82%	81.82%	81.82%	81.82%	81.82%	81.82%	81.82%	82.27%	1.44%
Average	55.48% ± 0.43%											82.28% ±0.16%	

Table 5.7: T-Test: Paired Two Sample for Means of C4.5 and PWC4.5 for Classification Problem of Identifying Translators Asad-Daryabadi

	C4.5	PWC4.5
Mean	56.24%	98.31%
Variance	0.15%	0.08%
Observations	10	10
Pearson Correlation	0.235	
Hypothesized Mean Difference	0	
df	9	
t Stat	-31.701	
$P(T \leq t)\ one-tail$	7.59E-11	
t Critical one-tail	1.833	
$P(T \leq t)\ two-tail$	1.52E-10	
t Critical two-tail	2.262	

Table 5.8: T-Test: Paired Two Sample for Means of C4.5 and PWC4.5 for Classification Problem of Identifying Translators Asad-Raza

	C4.5	PWC4.5
Mean	55.48%	82.28%
Variance	0.43%	0.16%
Observations	10	10
Pearson Correlation	0.237	
Hypothesized Mean Difference	0	
df	9	
t Stat	-12.407	
$P(T \leq t)\ one-tail$	2.90E-7	
t Critical one-tail	1.833	
$P(T \leq t)\ two-tail$	5.79E-7	
t Critical two-tail	2.262	

average accuracy of 52.12% for C4.5. Four cases out of 21 achieved accuracy more than 95% in the case of PWC4.5. These were the cases of (Asad-Daryabadi, Asad-Maududi, Asad-Pickthall, and Asad-Sarwar). This may tell us that Translator Asad has a distinguished writing style than other translators. Though, C4.5 failed to capture this style for these four cases, where the accuracy of C4.5 were 56.24%, 52.99%,57.42%, and 54.92% for the four cases respectively. If we consider that any classifier that is able to correctly classify more than 66.67% of the testing data is acceptable as being able to capture differences between classes. Then, we can conclude that PWC4.5 is able to distinguish between 15 pairs of translators out of 21 cases, while C4.5 failed for distinguish between any pair out of the 21 studied cases. We included a number of Examples of decision trees generated by PWC4.5 in Figures 5.30 to 5.37.

The two experiments that we conducted for PWCCP show that for some type of data, traditional classification algorithms lake the ability to see the hidden relationship between the paired instances. There is a need for an algorithm that is able to capture such relationship. The findings of these two experiments demonstrate the ability of PWC4.5 to discover this relationship, and being able to use it for identifying the patterns in the dataset to distinguish between different classes. The promising results from this experiment would encourage the researchers to investigate this type of classification problems. Such problem may help in identifying diseases or drug reaction in the medical area, where repeated measurements are usually considered for the same subject overtime. While traditional method would be only able to identify a single measurement that is passing a threshold, PWC4.5 is able to use the increase or decrease in this measurement as indicator.

Table 5.9: Summary of the Results of One-Tail Paired T-Tests between the Accuracy of C4.5 and the Accuracy of PWC4.5 Where (Alpha=0.05) and (Degree of Freedom=9)

Translator Pair	C45		PWC4.5		T-Test Results		Null Hypothesis
	Mean	Variance	Mean	Variance	t_{stat}	$P(T \leq t)$ one tail	
Asad-Daryabadi	56.24%	1.46E-03	98.31%	8.12E-04	-31.70	7.59E-11	P<0.05, then H_0 is rejected
Asad-Maududi	52.99%	6.74E-04	98.44%	8.75E-04	-28.22	2.14E-10	P<0.05, then H_0 is rejected
Asad-Pickthall	57.42%	2.96E-03	95.46%	1.15E-03	-19.38	6.00E-09	P<0.05, then H_0 is rejected
Asad-Raza	55.48%	4.31E-03	82.28%	1.60E-03	-12.41	2.90E-07	P<0.05, then H_0 is rejected
Asad-Sarwar	54.92%	6.33E-03	95.04%	7.42E-04	-16.19	2.91E-08	P<0.05, then H_0 is rejected
Asad-Yousif Ali	55.63%	2.78E-03	93.09%	5.47E-04	-19.78	5.00E-09	P<0.05, then H_0 is rejected
Daryabadi-Maududi	50.00%	0	85.07%	1.32E-03	-30.57	1.05E-10	P<0.05, then H_0 is rejected
Daryabadi-Pickthall	50.00%	0	59.16%	1.67E-03	-7.09	2.86E-05	P<0.05, then H_0 is rejected
Daryabadi-Raza	52.94%	1.13E-03	80.66%	7.90E-03	-9.26	3.37E-06	P<0.05, then H_0 is rejected
Daryabadi-Sarwar	50.00%	0	76.82%	2.23E-03	-17.97	1.16E-08	P<0.05, then H_0 is rejected
Daryabadi-Yousif Ali	51.67%	2.52E-04	91.09%	4.79E-04	-59.29	2.78E-13	P<0.05, then H_0 is rejected
Maududi-Pickthall	50.00%	0	79.45%	5.45E-03	-12.61	2.52E-07	P<0.05, then H_0 is rejected
Maududi-Raza	50.79%	1.09E-03	55.73%	3.36E-03	-2.80	1.04E-02	P<0.05, then H_0 is rejected
Maududi-Sarwar	49.81%	3.43E-05	63.77%	1.50E-03	-11.49	5.55E-07	P<0.05, then H_0 is rejected
Maududi-Yousif Ali	50.00%	0	56.73%	1.68E-03	-5.19	2.85E-04	P<0.05, then H_0 is rejected
Pickthall-Raza	52.46%	7.80E-04	81.96%	2.36E-03	-16.37	2.63E-08	P<0.05, then H_0 is rejected
Pickthall-Sarwar	49.78%	4.73E-05	67.99%	1.84E-03	-13.94	1.07E-07	P<0.05, then H_0 is rejected
Pickthall-Yousif Ali	51.34%	1.23E-03	92.44%	7.93E-04	-30.49	1.07E-10	P<0.05, then H_0 is rejected
Raza-Sarwar	50.66%	2.29E-04	60.89%	1.13E-03	-8.32	8.05E-06	P<0.05, then H_0 is rejected
Raza-Yousif Ali	49.64%	5.93E-05	65.97%	4.27E-03	-8.22	8.87E-06	P<0.05, then H_0 is rejected
Sarwar-Yousif Ali	52.72%	1.04E-03	74.71%	2.24E-03	-11.12	7.32E-07	P<0.05, then H_0 is rejected
Average	52.12%± 6.13E-04		78.81% ± 2.08E-02				H_0 was always rejected

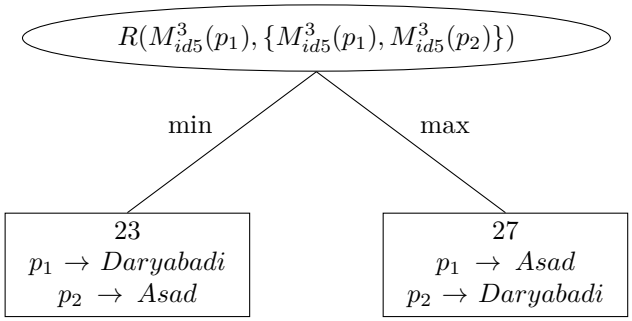


Figure 5.30: PWC4.5 Decision Tree for $1_{st}run(Exp_1)$ Asad-Daryabadi

5.5 Chapter summary

This chapter studied classification problems of paired data while considering the relationships between the paired instances. Traditional Classification methods ignore such relationship, and learn the instances individually. Thus, there is a loss in the information that can be mined if such relationship is not considered. In this chapter, we proposed a definition of *Pair-Wise Comparative Classification Problem*. We also proposed a new model, PWC4.5, that can address this problem. We conducted two experiments to evaluate PWC4.5 in comparison to traditional C4.5: using artificial data and real life problem. Our results demonstrated that considering these hidden relationships can aid the classification algorithm toward better classification for pair-wise comparative dataset. These results encourage for further investigation in the area of PWCCP. PWC4.5 can be applied further for different type of paired data, such as those occurring in forensic science and the medical domain.

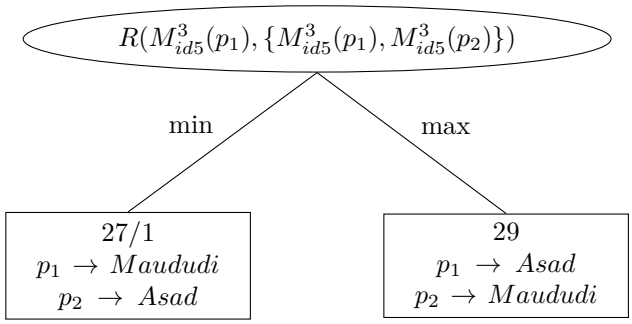


Figure 5.31: PWC4.5 Decision Tree for $1_{st}run(Exp_1)$ Asad-Maududi

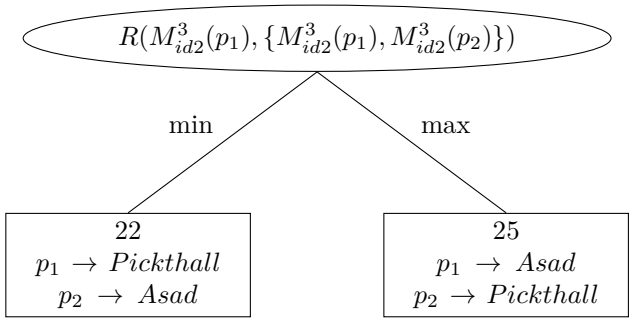


Figure 5.32: PWC4.5 Decision Tree for $1_{st}run(Exp_1)$ Asad-Pickthall

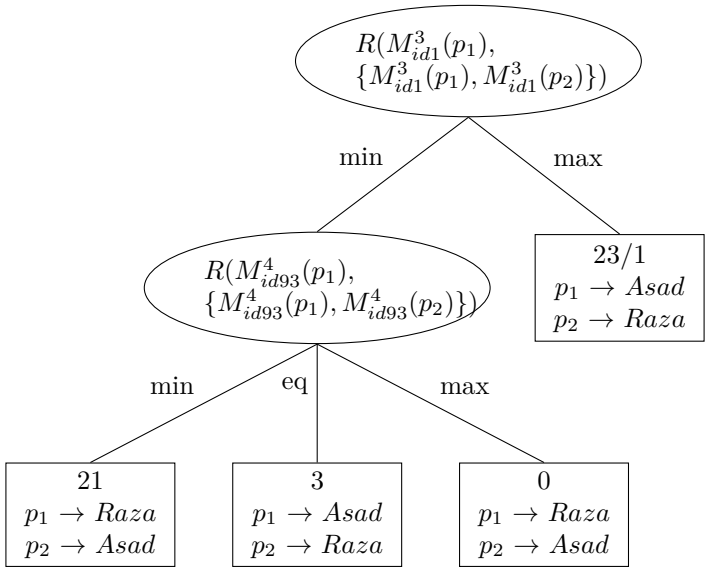


Figure 5.33: PWC4.5 Decision Tree for $1_{st}run(Exp_1)$ Asad-Raza

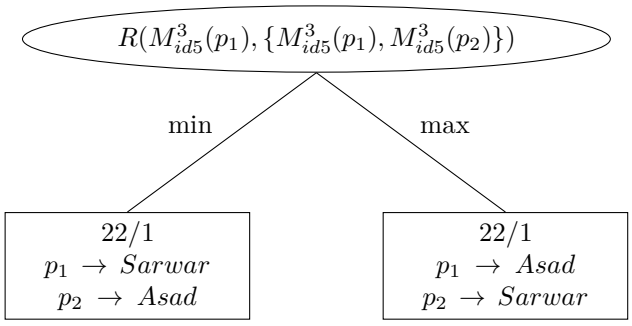


Figure 5.34: PWC4.5 Decision Tree for $1_{st} run(Exp_1)$ Asad-Sarwar

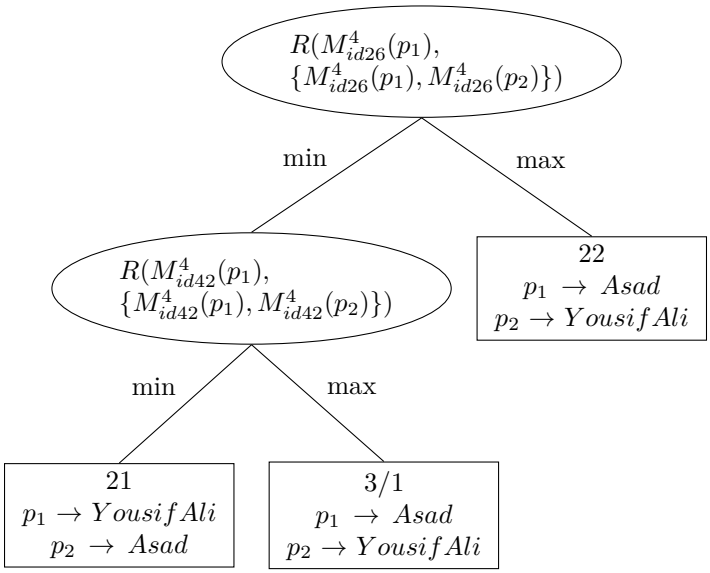


Figure 5.35: PWC4.5 Decision Tree for $1_{st} run(Exp_1)$ Asad-YousifAli

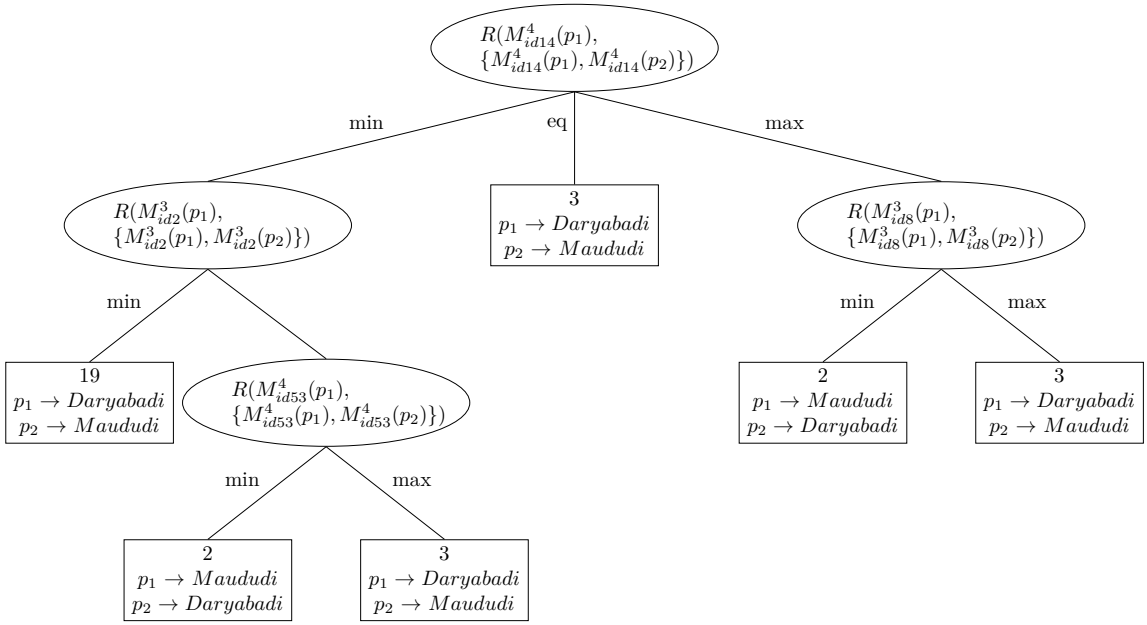


Figure 5.36: PWC4.5 Decision Tree for $1_{st} run(Exp_1)$ Daryabadi-Maududi

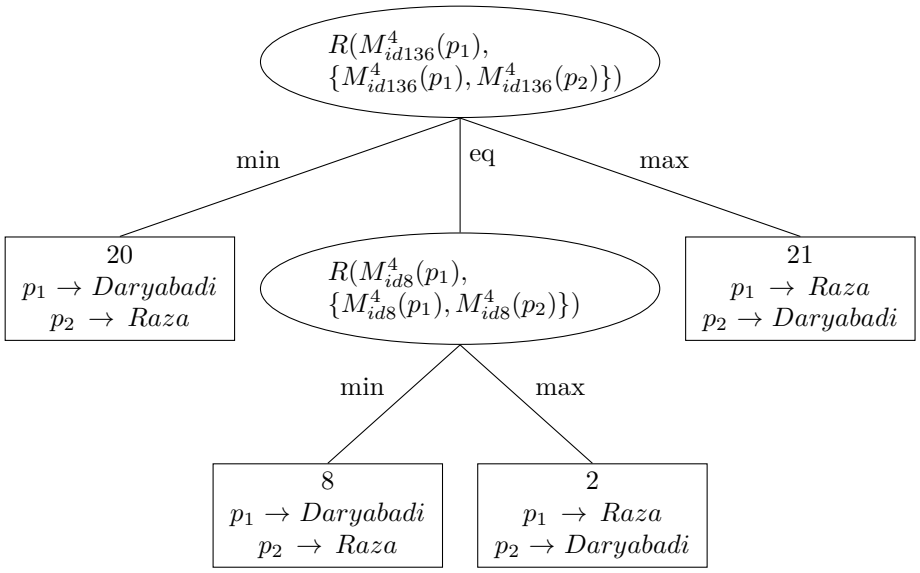


Figure 5.37: PWC4.5 Decision Tree for $1_{st}run(Exp_1)$ Raza-Daryabadi

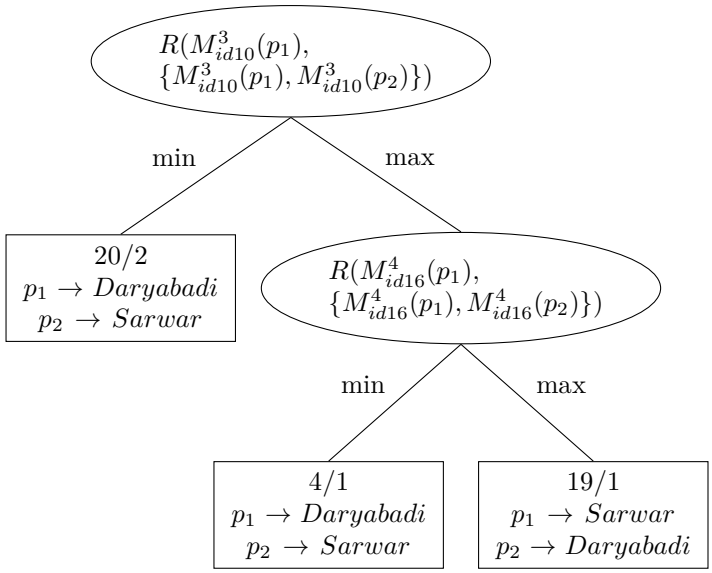


Figure 5.38: PWC4.5 Decision Tree for $1_{st}run(Exp_1)$ Daryabadi-Sarwar

Chapter 6

Conclusions and Future Research

6.1 Summary of Results

This thesis presented a study of the problem of translator stylometry identification using a computational linguistic framework. The problem of translator stylometry identification is understudied in the machine learning literature in comparison with other types of stylometry analysis problems such as authorship attribution, writer verification, and plagiarism detection. Research in linguistics has identified features of translator stylometry but in the computational linguistics field research is non-existent.

In this study, we first evaluated the performance of existing stylometry identification methods to identify translators based on their translations. These methods could not differentiate between different translators. Therefore, there was a need to identify another stylometric feature that may have potential usefulness for this specific problem. By studying and analysing the problem of translator's stylometry analysis, we found a similarity between the process of identifying writers interesting patterns and network motifs in social network analyses. We studied the possibility of using network motifs search for the problem of translator stylometry identification.

Another interesting pattern that we discovered while analysing our dataset is

the existence of relationship that can only be seen if we compared paired parallel translations rather than examining each translation individually.

This interesting pattern cannot be detected using traditional classifiers. Therefore, we studied this type of relationship carefully, and proposed a new classifier -PWC4.5- based on C4.5 decision tree algorithm. After that, we evaluated this new classifier using different dataset.

In section 1.3 of the thesis, we specified the main research question that this thesis aims to answer, which is "Can a computational linguistics framework meet the challenges of translators' stylometry identification problem?". Furthermore, we divided this question into sub-questions that we identified in order to address the main question of the thesis.

The first sub-question was "Which of the stylistic features to use to unfold a translator's stylometry?". To answer this question, we evaluated the existing methods for the problem of translator stylometry identification in Chapter 3 of this thesis and we found that they failed to discriminate translators based on their stylometry. Then, we evaluated network motifs for the same problem as stylometric features in Chapter 4, and they introduced promising results for a subset of the studied dataset of accuracy up to 70% by different classifiers. Network formation, extracting features such as network motifs and global network features had been detailed in Chapter 4 as well.

The second sub-question that had been investigated in this thesis was "What is the performance of network motifs approach compared to other approaches?". This question has been addressed in Chapter 4 by conducting a comparison between network motifs and other features on the complete dataset. The task was to evaluate the performance of each feature set in discriminating 21 pairs of translators using 74 parallel translations for each pair of translators. All the evaluated features did not introduce acceptable results including network motifs. We investigated the reason for that dropping in accuracy of the performance of network motifs, and we found that the variation in text size of the originals and translations affected the network size and network motifs frequencies. Therefore,

we replaced the network motifs frequencies by their rank in order to overcome the variation of text size problem. That method enhanced the accuracy significantly for network motifs as translator stylometric features.

The third sub-question was a result of the relation that we identified while addressing the last question, when we found a hidden pattern that can be uncovered by comparing the frequencies of network motifs for each pair of translators. We identified that this relation is happening regardless the change in the text size. Therefore, we defined a new problem that we call as Pair-Wise Comparative Classification Problem (PWCPP). In Chapter 5, we defined PWCPP problem and answer the sub-question of "What is an appropriate classification algorithm that can handle Pair-Wise Comparative Classification Problem (PWCPP) ?". The design of a new algorithm that we call PWC4.5 had been detailed in Chapter 5 in addition to two experiments to evaluate its performance in addressing PWCPP in comparison to traditional classifiers. We found that PWC4.5 outperformed other traditional classifiers for the two samples of PWCPP that we investigated in Chapter 5 which were artificial dataset problem and Translator stylometric identification problem.

The contributions of this thesis can be recapped as follows:

1. Evaluating existing methods such as vocabulary richness, most frequent words, and favourite words as stylometric features for the problem of translator stylometry identification showed that these features do not have the discriminative power for identifying translators' signature. Changes in the values of the different measures were affected by changes in the original text rather than by different translator's styles.

2. Contrary to previous findings that this problem does not have an automatic solution, Experiment I in Chapter 4 presented a first attempt to counteract this belief. We demonstrated that translators cannot disappear under the skin of the original authors; they have their own identities. Different translators represent the same idea in different ways. Although some existing

authorship attributions could not capture these differences [121] and [154], this study shows that we can use a computational linguistics approach to differentiate between translator's styles.

3. Network motifs frequencies showed promising usefulness as stylometric methods for the problem of translator stylometry identification using a subset of the corpus. Classifying translations into their translators based on network motifs frequencies achieved 70% accuracy in multiple tests in Experiment I.

4. In Experiment II, in which the entire corpus was used to evaluate the performance of network motifs in comparison with other features, network motifs did not achieve acceptable accuracy. An investigation that we conducted for the cause of that change in the results showed that frequencies of network motifs were affected by variations of the original text size. Short text was represented in small size network. Thus, a count of an interesting network motif that is associated with a specific translator in this network is different than a count of the same network motif in a network that represents large size text. The relationship that was identified by that investigation was that frequencies of Mx(translator A) was frequently the minimum of frequencies of Mx(translator A),Mx(translator B) regardless of the original text size. To address this relationship, we replaced frequencies of network motifs by their ranking, and then we fed this new representation to the same classifiers. That new representation achieved significant change in the results and the overall average accuracy achieved was 79.02%.

5. Another contribution of Experiment II is that it demonstrated that global network features are not useful as translator Stylometric features. Evaluating the accuracy of classifiers based on global network features showed an average accuracy that ranged from 43.82% to 52.57% using different classifiers.

6. The interesting phenomena that was identified throughout the analysis of Experiment II guided us to a new definition of the problem of translator stylometry identification as a comparative classification problem, where each

parallel translations are considered as paired instances. Traditional classifiers could not handle this type of problems, as the interesting pattern can only be seen if we examined the relationship between paired instances. In Chapter 5, we proposed a new classifier that can handle this type of problem. The proposed classifier is based on C4.5 decision tree algorithm. The difference between C4.5 algorithm and PWC4.5 algorithm is in handling numerical attributes. While C4.5 tried to find the split that maximizes the purity of examples splitting, the proposed algorithm identified the potential propositional relationship between instances, and split them based on this identified relationship. The proposed classifier achieved high accuracy in comparison to C4.5, which failed to differentiate between the paired instances with an average accuracy of C4.5 of 52.12%. In that experiment, which included 21 pairs of translators, the proposed classifier achieved average accuracy of 78.81%. A t-test was conducted to compare the accuracy for the two classifiers for each of these 21 pairs. The findings from this experiment, was that the proposed classifier achieved significantly higher accuracy for each of these 21 pairs tests.

In conclusion, this thesis identified new stylometric features that can be used successfully for the problem of translator stylometry identification. It also proposed a new classifier that is able to handle comparative classification problems.

6.2 Future Research

This section introduces some research directions in which this work may be extended in future investigations in the field of translator stylometry.

One future direction for this study is in regards to features identification. That includes investigating the smallest text size that network motifs search can be applied to, investigating the performance of network motifs search when applied to multiple translators, and the efficiency of network motifs search for other type of stylometric analysis.

Another future direction is related to the proposed methodology. In this study, we are considering the relationship between instances. Splitting data based on a given nominal attribute is not considered yet, as it requires maintaining long distance relationship between paired instances if split. Modifying the algorithm to consider such issue is expected to enhance the classification accuracy.

Additionally, the promising results that we achieved using the proposed classifier could be used to investigate other types of real life comparative classification problems that can be handled in similar contexts, such as repeated diagnostic measures in the medical domain.

Appendix A

Dataset Description

Table A.1: Summary of Dataset Description

Chapter		Original Text (Arabic) Description		Number of Words in English Translations of ..						
Chapter Number	**Chapter Title**	**Number of Verses (Ayat)**	**Number of Words**	**Asad**	**Daryabadi**	**Maududi**	**Pickthall**	**Sarwar**	**Raza**	**Yousif Ali**
Chapter 41	(Fussilat)	54	796	2196	1660	1706	1606	1543	1706	1781
Chapter 42	(Ash-Shura)	53	860	2217	1672	1778	1635	1659	1824	1830
Chapter 43	(Az-Zukhruf)	89	837	2421	1736	1909	1749	1862	1934	1953
Chapter 44	(Ad-Dukhan)	59	346	971	685	773	702	754	764	775
Chapter 45	(Al-Jathiya)	37	488	1288	984	1070	986	970	1059	1068
Chapter 46	(Al-Ahqaf)	35	646	1702	1288	1419	1288	1308	1392	1397
Chapter 47	(Muhammad)	38	542	1543	1149	1217	1126	1094	1194	1224
Chapter 48	(Al-Fath)	29	560	1497	1196	1229	1157	1109	1248	1206
Chapter 49	(Al-Hujurat)	18	353	851	650	687	656	663	777	716
Chapter 50	(Qaf)	45	373	1033	785	849	794	798	808	860
Chapter 51	(Adh-Dhariyat)	60	360	1049	743	832	782	796	804	857
Chapter 52	(At-Tur)	49	312	991	638	782	692	664	693	752
Chapter 53	(An-Najm)	62	359	964	724	797	713	730	841	762
Chapter 54	(Al-Qamar)	55	342	1067	788	871	764	846	789	877
Chapter 55	(Ar-Rahman)	78	352	924	861	1026	823	938	956	905

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Table A.1 – continued from previous page

Chapter		Original Text (Arabic) Description		Number of Words in English Translations of ..						
Chapter Number	Chapter Title	Number of Verses (Ayat)	Number of Words	Asad	Daryabadi	Maududi	Pickthall	Sarwar	Raza	Yousif Ali
Chapter 56	(Al-Waqi'a)	96	379	1159	802	959	795	894	902	991
Chapter 57	(Al-Hadid)	29	575	1518	1172	1252	1162	1156	1252	1314
Chapter 58	(Al-Mujadila)	22	475	1230	915	937	909	964	959	998
Chapter 59	(Al-Hashr)	24	447	1215	883	946	915	894	954	971
Chapter 60	(Al-Mumtahina)	13	352	946	691	764	705	673	733	795
Chapter 61	(As-Saff)	14	226	604	409	446	413	416	444	449
Chapter 62	(Al-Jumu'a)	11	177	449	336	358	336	313	348	384
Chapter 63	(Al-Munafiqun)	11	180	483	350	389	354	361	380	398
Chapter 64	(At-Taghabun)	18	242	688	501	568	512	514	550	561
Chapter 65	(At-Talaq)	12	279	751	541	602	560	544	605	606
Chapter 66	(At-Tahrim)	12	254	699	474	542	492	502	544	533
Chapter 67	(Al-Mulk)	30	337	920	659	707	667	656	693	755
Chapter 68	(Al-Qalam)	52	301	916	637	771	642	725	728	742
Chapter 69	(Al-Haqqa)	52	261	767	580	646	558	584	600	648
Chapter 70	(Al-Ma'arij)	44	217	617	457	499	442	464	479	503
Chapter 71	(Nuh)	28	227	575	441	470	445	422	486	489

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Table A.1 – continued from previous page

Chapter		Original Text (Arabic) Description		Number of Words in English Translations of ..						
Chapter Number	Chapter Title	Number of Verses (Ayat)	Number of Words	Asad	Daryabadi	Maududi	Pickthall	Sarwar	Raza	Yousif Ali
Chapter 72	(Al-Jinn)	28	286	823	546	634	582	551	663	624
Chapter 73	(Al-Muzzammil)	20	200	513	404	465	410	434	438	463
Chapter 74	(Al-Muddathir)	56	256	727	527	586	503	555	561	576
Chapter 75	(Al-Qiyama)	40	164	489	333	414	335	420	420	415
Chapter 76	(Al-Insan)	31	243	655	504	537	480	463	509	545
Chapter 77	(Al-Mursalat)	50	181	580	404	518	413	510	453	505
Chapter 78	(An-Naba')	40	174	517	384	401	360	412	420	414
Chapter 79	(An-Nazi'at)	46	179	591	419	458	402	453	435	492
Chapter 80	(Abasa)	42	133	386	297	322	287	293	330	359
Chapter 81	(At-Takwir)	29	104	299	235	237	217	248	282	255
Chapter 82	(Al-Infitar)	19	81	236	175	172	163	182	182	199
Chapter 83	(Al-Mutaffifin)	36	169	516	359	374	337	372	364	389
Chapter 84	(Al-Inshiqaq)	25	108	306	233	231	221	269	257	260
Chapter 85	(Al-Buruj)	22	109	288	209	216	213	217	250	242
Chapter 86	(At-Tariq)	17	61	187	129	140	144	139	145	159
Chapter 87	(Al-A'la)	19	72	248	153	155	148	172	168	183

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Table A.1 – continued from previous page

Chapter		Original Text (Arabic) Description		Number of Words in English Translations of ..						
Chapter Number	Chapter Title	Number of Verses (Ayat)	Number of Words	Asad	Daryabadi	Maududi	Pickthall	Sarwar	Raza	Yousif Ali
Chapter 88	(Al-Ghashiya)	26	92	227	177	200	160	205	200	200
Chapter 89	(Al-Fajr)	30	139	385	283	303	271	352	309	323
Chapter 90	(Al-Balad)	20	82	211	157	187	166	191	192	187
Chapter 91	(Ash-Shams)	15	54	195	140	160	147	172	189	165
Chapter 92	(Al-Lail)	21	71	237	171	201	165	187	189	211
Chapter 93	(Ad-Dhuha)	11	40	118	107	117	99	108	116	105
Chapter 94	(Ash-Sharh)	8	27	59	57	57	47	59	50	64
Chapter 95	(At-Tin)	8	34	74	63	78	68	67	78	73
Chapter 96	(Al-Alaq)	19	72	184	145	158	139	178	172	168
Chapter 97	(Al-Qadr)	5	30	66	64	61	57	65	57	54
Chapter 98	(Al-Bayyina)	8	94	273	178	204	165	157	190	183
Chapter 99	(Az-Zalzala)	8	36	93	77	88	68	99	93	91
Chapter 100	(Al-Adiyat)	11	40	105	89	93	89	92	99	105
Chapter 101	(Al-Qari'a)	11	36	98	76	75	79	75	87	103
Chapter 102	(At-Takathur)	8	28	95	60	96	60	79	67	77
Chapter 103	(Al-Asr)	3	14	42	31	36	31	31	47	36

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Table A.1 – continued from previous page

Chapter		Original Text (Arabic) Description		Number of Words in English Translations of ..						
Chapter Number	**Chapter Title**	**Number of Verses (Ayat)**	**Number of Words**	**Asad**	**Daryabadi**	**Maududi**	**Pickthall**	**Sarwar**	**Raza**	**Yousif Ali**
Chapter 104	(Al-Humaza)	9	33	77	64	68	71	59	71	87
Chapter 105	(Al-Fil)	5	23	62	45	47	47	51	59	58
Chapter 106	(Quraysh)	4	17	36	39	32	41	37	46	41
Chapter 107	(Al-Ma'un)	7	25	67	47	62	42	49	57	55
Chapter 108	(Al-Kawthar)	3	10	35	25	31	25	22	58	31
Chapter 109	(Al-Kafirun)	6	27	55	56	48	43	42	53	51
Chapter 110	(An-Nasr)	3	19	36	38	41	38	33	42	39
Chapter 111	(Al-Masad)	5	29	59	45	49	42	55	56	53
Chapter 112	(Al-Ikhlas)	4	15	33	27	36	25	24	44	26
Chapter 113	(Al-Falaq)	5	23	54	50	49	45	46	64	45
Chapter 114	(An-Nas)	6	20	45	38	46	37	40	65	50

Appendix B

Most Frequent Words

Table B.1: Relative Frequency for the 40th Most Frequent Words for Each Translator for the Entire Corpus

	Asad		Daryabadi		Maududi		Pickthall		Sarwar		Raza		Yousif Ali	
Rank	Word	Relative Frequency	Word	Relative Frequency	Word	Relative Frequency	Word	Relative Frequency	Word	Relative Frequency	Word	Relative Frequency	Word	Relative Frequency
1st	and	0.0427	the	0.0573	the	0.0541	the	0.0547	the	0.0646	the	0.0622	the	0.0520
2nd	the	0.0399	and	0.0571	and	0.0426	and	0.0535	and	0.0342	and	0.0551	and	0.0451
3rd	of	0.0313	of	0.0283	to	0.0280	of	0.0309	of	0.0321	of	0.0263	of	0.0326
4th	to	0.0281	is	0.0215	of	0.0273	is	0.0240	to	0.0262	is	0.0243	to	0.0257
5th	a	0.0209	a	0.0197	you	0.0245	a	0.0185	you	0.0245	you	0.0233	a	0.0196
6th	in	0.0181	they	0.0178	a	0.0193	that	0.0173	will	0.0225	to	0.0184	in	0.0182
7th	that	0.0166	that	0.0169	is	0.0183	they	0.0166	god	0.0176	will	0.0153	is	0.0182
8th	is	0.0165	he	0.0166	that	0.0164	allah	0.0156	is	0.0167	in	0.0152	will	0.0167
9th	you	0.0162	allah	0.0140	they	0.0158	he	0.0155	a	0.0165	allah	0.0151	that	0.0155
10th	who	0.0147	them	0.0135	allah	0.0147	them	0.0143	they	0.0156	they	0.0151	they	0.0155
11th	they	0.0146	in	0.0125	in	0.0144	in	0.0136	have	0.0136	a	0.0148	allah	0.0155
12th	it	0.0133	who	0.0125	will	0.0138	who	0.0131	in	0.0133	it	0.0135	he	0.0137
13th	god	0.0131	shall	0.0123	he	0.0135	will	0.0129	them	0.0122	them	0.0132	for	0.0133
14th	will	0.0126	be	0.0123	them	0.0132	it	0.0126	who	0.0118	he	0.0116	ye	0.0129
15th	for	0.0120	unto	0.0122	it	0.0127	ye	0.0123	be	0.0114	for	0.0116	them	0.0127
16th	he	0.0115	we	0.0120	who	0.0116	to	0.0120	he	0.0114	who	0.0115	it	0.0113

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Table B.1 – continued from previous page

Rank	Asad		Daryabadi		Maududi		Pickthall		Sarwar		Raza		Yousif Ali	
	Word	**Relative Frequency**	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**
17th	all	0.0107	ye	0.0119	be	0.0110	for	0.0117	it	0.0104	not	0.0103	who	0.0106
18th	them	0.0104	not	0.0112	we	0.0097	unto	0.0113	for	0.0101	so	0.0099	be	0.0100
19th	be	0.0099	will	0.0108	shall	0.0091	we	0.0103	that	0.0101	that	0.0097	we	0.0095
20th	have	0.0095	it	0.0106	their	0.0088	are	0.0103	their	0.0101	indeed	0.0095	but	0.0093
21st	on	0.0085	verily	0.0097	are	0.0086	not	0.0096	not	0.0099	are	0.0090	their	0.0091
22nd	with	0.0084	are	0.0091	for	0.0086	lo	0.0090	we	0.0099	we	0.0089	not	0.0080
23rd	their	0.0084	to	0.0085	not	0.0086	him	0.0082	all	0.0080	him	0.0087	with	0.0071
24th	but	0.0082	then	0.0085	have	0.0077	you	0.0081	your	0.0080	be	0.0086	you	0.0071
25th	we	0.0080	have	0.0085	your	0.0076	their	0.0078	are	0.0076	their	0.0075	have	0.0069
26th	are	0.0079	him	0.0081	with	0.0075	those	0.0076	lord	0.0073	your	0.0074	those	0.0069
27th	his	0.0067	for	0.0080	lord	0.0068	lord	0.0073	from	0.0072	from	0.0072	are	0.0067
28th	not	0.0062	you	0.0079	those	0.0068	but	0.0071	his	0.0063	have	0.0068	from	0.0066
29th	him	0.0062	which	0.0077	him	0.0066	be	0.0069	do	0.0062	lord	0.0065	lord	0.0065
30th	this	0.0062	their	0.0072	his	0.0066	have	0.0069	which	0.0062	what	0.0063	him	0.0065
31st	from	0.0060	those	0.0071	all	0.0062	when	0.0068	people	0.0060	his	0.0063	his	0.0064
32nd	ha	0.0059	lord	0.0071	from	0.0059	his	0.0065	ha	0.0059	with	0.0061	then	0.0059
33rd	those	0.0057	with	0.0070	on	0.0059	which	0.0064	with	0.0057	this	0.0060	on	0.0056
34th	unto	0.0053	thou	0.0066	then	0.0058	with	0.0062	him	0.0056	upon	0.0060	all	0.0053

Continued on next page

Table B.1 – continued from previous page

	Asad		Daryabadi		Maududi		Pickthall		Sarwar		Raza		Yousif Ali	
Rank	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**	**Word**	**Relative Frequency**
35th	s	0.0053	his	0.0065	so	0.0057	from	0.0062	this	0.0055	all	0.0060	which	0.0049
36th	truth	0.0051	hath	0.0063	do	0.0056	then	0.0054	on	0.0054	when	0.0059	day	0.0048
37th	shall	0.0050	from	0.0058	when	0.0054	day	0.0054	day	0.0054	those	0.0058	your	0.0046
38th	sustainer	0.0049	on	0.0052	but	0.0050	hath	0.0054	those	0.0053	day	0.0056	when	0.0045
39th	your	0.0048	when	0.0052	ha	0.0048	your	0.0050	one	0.0051	do	0.0054	by	0.0044
40th	what	0.0046	day	0.0051	day	0.0047	on	0.0048	by	0.0049	o	0.0045	what	0.0043

Appendix C

5D Decision Trees Analysis

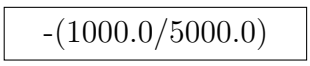

Figure C.1: C4.5 Decision Tree for Noise Free 5D(EXP_1)

$R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min:$
| $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min:$
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (73.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (15.0)
| | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (16.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (11.0)
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max:$
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (17.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (5.0)
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max:$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (8.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (10.0)
| $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max:$
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$

| | | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = min: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (20.0)
| | | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = max: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (7.0)
| | | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = max:$
| | | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = min: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (9.0)
| | | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = max: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (11.0)
| | | $R(V_1(p_1),\{V_1(p_1),V_1(p_2)\} = max:$

| | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = min:$
| | | | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = min: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (8.0)
| | | | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = max: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (9.0)
| | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = max:$
| | | | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = min: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (8.0)
| | | | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = max: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (27.0)
$R(V_2(p_1),\{V_2(p_1),V_2(p_2)\} = max:$
| $R(V_1(p_1),\{V_1(p_1),V_1(p_2)\} = min:$
| | $R(V_5(p_1),\{V_5(p_1),V_5(p_2)\} = min:$
| | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = min:$
| | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = min: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (24.0)
| | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = max: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (10.0)
| | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = max:$
| | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = min: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (12.0)
| | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = max: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (11.0)
| | $R(V_5(p_1),\{V_5(p_1),V_5(p_2)\} = max:$
| | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = min:$
| | | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = min: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (8.0)
| | | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = max: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (7.0)
| | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = max:$
| | | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = min: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (3.0)
| | | | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = max: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (17.0)
| $R(V_1(p_1),\{V_1(p_1),V_1(p_2)\} = max:$
| | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = min:$
| | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = min:$
| | | | $R(V_5(p_1),\{V_5(p_1),V_5(p_2)\} = min: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (7.0)
| | | | $R(V_5(p_1),\{V_5(p_1),V_5(p_2)\} = max: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (9.0)
| | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = max:$
| | | | $R(V_5(p_1),\{V_5(p_1),V_5(p_2)\} = min: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (8.0)
| | | | $R(V_5(p_1),\{V_5(p_1),V_5(p_2)\} = max: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (15.0)
| | $R(V_4(p_1),\{V_4(p_1),V_4(p_2)\} = max:$
| | | $R(V_5(p_1),\{V_5(p_1),V_5(p_2)\} = min:$
| | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = min: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (8.0)
| | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = max: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (14.0)
| | | $R(V_5(p_1),\{V_5(p_1),V_5(p_2)\} = max:$
| | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = min: \ p_1 \rightarrow -, \ p_2 \rightarrow +$ (11.0)
| | | | $R(V_3(p_1),\{V_3(p_1),V_3(p_2)\} = max: \ p_1 \rightarrow +, \ p_2 \rightarrow -$ (82.0)

Figure C.2: PWC4.5 Decision Tree for Noise Free 5D(EXP_1)

-(1000.0/5000.0)

Figure C.3: C4.5 Decision Tree for 5D(EXP_1) with Noise Level of 1%

$R(V_3(p_1), \{V_3(p_1), V_3(p_2)\}) = min:$
| $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = min:$
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\}) = min:$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = min:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min: p_1 \rightarrow -, p_2 \rightarrow +$ (79.0/2.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max: p_1 \rightarrow +, p_2 \rightarrow -$ (11.0)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = max:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min: p_1 \rightarrow +, p_2 \rightarrow -$ (16.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max: p_1 \rightarrow -, p_2 \rightarrow +$ (10.0)
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\}) = max:$
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = 1: p_1 \rightarrow +, p_2 \rightarrow -$ (0.0)
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = min: p_1 \rightarrow +, p_2 \rightarrow -$ (20.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = max: p_1 \rightarrow -, p_2 \rightarrow +$ (8.0)
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = min: p_1 \rightarrow -, p_2 \rightarrow +$ (11.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = max: p_1 \rightarrow +, p_2 \rightarrow -$ (7.0)
| $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = max:$
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\}) = min:$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = min:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min: p_1 \rightarrow +, p_2 \rightarrow -$ (19.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max: p_1 \rightarrow -, p_2 \rightarrow +$ (5.0)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = max:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min: p_1 \rightarrow -, p_2 \rightarrow +$ (8.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max: p_1 \rightarrow +, p_2 \rightarrow -$ (11.0)
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\}) = max:$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = min:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min: p_1 \rightarrow -, p_2 \rightarrow +$ (8.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max: p_1 \rightarrow +, p_2 \rightarrow -$ (10.0)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = max:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min: p_1 \rightarrow +, p_2 \rightarrow -$ (4.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max: p_1 \rightarrow -, p_2 \rightarrow +$ (17.0)
$R(V_3(p_1), \{V_3(p_1), V_3(p_2)\}) = max:$
| $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\}) = min:$
| | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = min:$
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = min: p_1 \rightarrow +, p_2 \rightarrow -$ (26.0)

| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = max : p_1 \rightarrow -, p_2 \rightarrow +$ (9.0/1.0)
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max :$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = min : p_1 \rightarrow -, p_2 \rightarrow +$ (8.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = max : p_1 \rightarrow +, p_2 \rightarrow -$ (12.0)
| | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = max :$
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min :$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = min : p_1 \rightarrow -, p_2 \rightarrow +$ (12.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = max : p_1 \rightarrow +, p_2 \rightarrow -$ (8.0)
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max :$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = min : p_1 \rightarrow +, p_2 \rightarrow -$ (8.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = max : p_1 \rightarrow -, p_2 \rightarrow +$ (22.0)
| $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\}) = max :$
| | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = min :$
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = min :$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min : p_1 \rightarrow -, p_2 \rightarrow +$ (9.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max : p_1 \rightarrow +, p_2 \rightarrow -$ (11.0)
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = max :$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min : p_1 \rightarrow +, p_2 \rightarrow -$ (8.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max : p_1 \rightarrow -, p_2 \rightarrow +$ (16.0)
| | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\}) = max :$
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = min :$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = min : p_1 \rightarrow +, p_2 \rightarrow -$ (10.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = max : p_1 \rightarrow -, p_2 \rightarrow +$ (15.0)
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\}) = max :$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = min : p_1 \rightarrow -, p_2 \rightarrow +$ (16.0/1.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\}) = max : p_1 \rightarrow +, p_2 \rightarrow -$ (66.0)

Figure C.4: PWC4.5 Decision Tree for 5D(EXP_1) with Noise Level of 1%

-(1000.0/5000.0)

Figure C.5: C4.5 Decision Tree for 5D(EXP_1) with Noise Level of 2.5%

$R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min:$
| $V1 = min:$
| | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min:$
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (75.0/2.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (12.0)
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max:$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (14.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (8.0/1.0)
| | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max:$
| | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (19.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (7.0/1.0)
| | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (15.0/2.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (6.0)
| $V1 = max:$
| | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min:$
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (31.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (7.0/1.0)
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (7.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (9.0)
| | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max:$
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (8.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (8.0)
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (7.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (19.0)
$R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max:$
| $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min:$
| | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | | $V1 = min:$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (11.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (4.0)
| | | $V1 = max:$

| | | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow -, p_2 \rightarrow +$ (8.0/2.0)
| | | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow +, p_2 \rightarrow -$ (9.0)
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max :$
| | | | $V1 = min :$
| | | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow -, p_2 \rightarrow +$ (8.0/1.0)
| | | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow +, p_2 \rightarrow -$ (11.0)
| | | | $V1 = max :$
| | | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow -$ (10.0)
| | | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow -, p_2 \rightarrow +$ (23.0/3.0)
| $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max :$
| | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min :$
| | | $V1 = min :$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow -, p_2 \rightarrow +$ (4.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow +, p_2 \rightarrow -$ (10.0)
| | | $V1 = max :$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow -$ (7.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow -, p_2 \rightarrow +$ (17.0)
| | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max :$
| | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min :$
| | | | $V1 = min : p_1 \rightarrow +, p_2 \rightarrow -$ (15.0)
| | | | $V1 = max : p_1 \rightarrow -, p_2 \rightarrow +$ (16.0/2.0)
| | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max :$
| | | | $V1 = min : p_1 \rightarrow -, p_2 \rightarrow +$ (12.0/1.0)
| | | | $V1 = max : p_1 \rightarrow +, p_2 \rightarrow -$ (83.0)

Figure C.6: PWC4.5 Decision Tree for 5D(EXP_1) with Noise Level of 2.5%

-(1000.0/5000.0)

Figure C.7: C4.5 Decision Tree for 5D(EXP_1) with Noise Level of 5%

$R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min:$
| $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min:$
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (85.0/11.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (14.0)
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (21.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (13.0/1.0)
| | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max:$
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (19.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (6.0/1.0)
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (12.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (7.0)
| $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max:$
| | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min:$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min:$
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (29.0)
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (7.0/1.0)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max:$
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (9.0/1.0)
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (9.0)
| | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max:$
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (7.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (9.0)
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (8.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (20.0/2.0)
$R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max:$
| $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min:$
| | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (19.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (4.0)

| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max:$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (7.0/1.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (9.0)
| | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max:$
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (7.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (8.0)
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max:$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (5.0)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (19.0)
| $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max:$
| | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min:$
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (9.0/3.0)
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (9.0)
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max:$
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (5.0)
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (17.0/1.0)
| | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max:$
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = 1: p_1 \rightarrow +, p_2 \rightarrow -$ (0.0)
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (8.0)
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (12.0)
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max:$
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (13.0/1.0)
| | | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (74.0)

Figure C.8: PWC4.5 Decision Tree for 5D(EXP_1) with Noise Level of 5%

-(1000.0/5000.0)

Figure C.9: C4.5 Decision Tree for 5D(EXP_1) with Noise Level of 10%

$R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min:$
| $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (75.0/18.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (11.0)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (16.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (6.0/1.0)
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max:$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (17.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (10.0/3.0)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (8.0/1.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (5.0)
| $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max:$
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (22.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (4.0)
| | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (12.0/3.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (9.0)
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max:$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (9.0/1.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (11.0)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max:$
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (7.0)
| | | | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (20.0/5.0)
$R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max:$
| $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min:$
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (20.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (7.0/1.0)
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max:$

| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (8.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (11.0)
| | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max:$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow$
+ (10.0/2.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (9.0)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max:$
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (8.0)
| | | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow$
+ (17.0/2.0)
| $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max:$
| | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min:$
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow$
+ (4.0/1.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (11.0)
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (6.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow$
+ (21.0/3.0)
| | $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max:$
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (11.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow$
+ (17.0/4.0)
| | | $R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow$
+ (9.0/1.0)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (89.0)

Figure C.10: PWC4.5 Decision Tree for 5D(EXP_1) with Noise Level of 10%

$V4 <= 4.07981 : - (443.0/189.0)$
$V4 > 4.07981 :$
$| \quad V4 <= 8.99737 : + (415.0/163.0)$
$| \quad V4 > 8.99737 : - (142.0/59.0)$

Figure C.11: C4.5 Decision Tree for 5D(EXP_1) with Noise Level of 15%

$R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min :$
$| \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min :$
$| \quad | \quad R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min :$
$| \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min :$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min : p_1 \rightarrow -, p_2 \rightarrow + (93.0/30.6)$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max : p_1 \rightarrow +, p_2 \rightarrow - (11.0/1.3)$
$| \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max :$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow - (20.0/1.3)$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max : p_1 \rightarrow -, p_2 \rightarrow + (8.0/2.4)$
$| \quad | \quad R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max :$
$| \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow - (25.0/4.9)$
$| \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max :$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min : p_1 \rightarrow -, p_2 \rightarrow + (5.0/2.3)$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max : p_1 \rightarrow +, p_2 \rightarrow - (9.0/1.3)$
$| \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max :$
$| \quad | \quad R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow - (47.0/12.6)$
$| \quad | \quad R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max :$
$| \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min :$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min : p_1 \rightarrow -, p_2 \rightarrow + (7.0/3.4)$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max : p_1 \rightarrow +, p_2 \rightarrow - (10.0/1.3)$
$| \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max :$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow - (9.0/1.3)$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max : p_1 \rightarrow -, p_2 \rightarrow + (19.0/5.9)$
$R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max :$
$| \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min :$
$| \quad | \quad R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow - (51.0/12.6)$
$| \quad | \quad R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max :$
$| \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min :$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min : p_1 \rightarrow -, p_2 \rightarrow + (11.0/5.6)$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max : p_1 \rightarrow +, p_2 \rightarrow - (11.0/1.3)$
$| \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max :$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow - (4.0/1.2)$
$| \quad | \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max : p_1 \rightarrow -, p_2 \rightarrow + (16.0/7.9)$
$| \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max :$

| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min:$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (16.0/3.7)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max:$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (6.0/1.2)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (16.0/7.9)
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max:$
| | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow +, p_2 \rightarrow -$ (7.0/1.3)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow -, p_2 \rightarrow +$ (12.0/6.7)
| | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max:$
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min: p_1 \rightarrow -, p_2 \rightarrow +$ (12.0/6.7)
| | | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max: p_1 \rightarrow +, p_2 \rightarrow -$ (75.0/1.4)

Figure C.12: PWC4.5 Decision Tree for 5D(EXP_1) with Noise Level of 15%

$V5 > 9.94342 : - (88.0/27.0)$
$V5 <= 9.94342 :$
$| \quad V5 > 8.14662 : + (135.0/39.0)$
$| \quad V5 <= 8.14662 :$
$| \quad | \quad V1 <= 0.847003 : - (121.0/40.0)$
$| \quad | \quad V1 > 0.847003 : + (656.0/319.0)$

Figure C.13: C4.5 Decision Tree for 5D(EXP_1) with Noise Level of 20%

$R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = min :$
$| \quad R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min :$
$| \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min :$
$| \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min :$
$| \quad | \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min : p_1 \to -, p_2 \to + (82.0/38.6)$
$| \quad | \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max : p_1 \to +, p_2 \to - (13.0/1.3)$
$| \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max :$
$| \quad | \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min : p_1 \to +, p_2 \to - (15.0/1.3)$
$| \quad | \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max : p_1 \to -, p_2 \to + (10.0/4.6)$
$| \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max :$
$| \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min :$
$| \quad | \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min : p_1 \to +, p_2 \to - (18.0/1.3)$
$| \quad | \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max : p_1 \to -, p_2 \to + (10.0/5.6)$
$| \quad | \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max :$
$| \quad | \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min : p_1 \to -, p_2 \to + (14.0/7.8)$
$| \quad | \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max : p_1 \to +, p_2 \to - (6.0/1.2)$
$| \quad R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max :$
$| \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min : p_1 \to +, p_2 \to - (46.0/12.6)$
$| \quad | \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max :$
$| \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min :$
$| \quad | \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min : p_1 \to -, p_2 \to + (8.0/3.5)$
$| \quad | \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max : p_1 \to +, p_2 \to - (8.0/1.3)$
$| \quad | \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max :$
$| \quad | \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min : p_1 \to +, p_2 \to - (7.0/1.3)$
$| \quad | \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max : p_1 \to -, p_2 \to + (15.0/5.8)$
$R(V_4(p_1), \{V_4(p_1), V_4(p_2)\} = max :$
$| \quad R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = min :$
$| \quad | \quad R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min :$
$| \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min :$
$| \quad | \quad | \quad | \quad R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \to +, p_2 \to - (17.0/1.3)$
$| \quad | \quad | \quad | \quad R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \to -, p_2 \to + (11.0/6.6)$
$| \quad | \quad | \quad R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max :$

| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow -, p_2 \rightarrow +$ (6.0/1.2)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow +, p_2 \rightarrow -$ (9.0/1.3)
| | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max :$
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min :$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow -, p_2 \rightarrow +$ (11.0/5.6)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow +, p_2 \rightarrow -$ (6.0/1.2)
| | | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max :$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow -$ (6.0/1.2)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow -, p_2 \rightarrow +$ (17.0/8.9)
| $R(V_2(p_1), \{V_2(p_1), V_2(p_2)\} = max :$
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = min :$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow -$ (17.0/5.9)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max :$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow -$ (6.0/1.2)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow -, p_2 \rightarrow +$ (19.0/9.0)
| | $R(V_1(p_1), \{V_1(p_1), V_1(p_2)\} = max :$
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = min :$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow +, p_2 \rightarrow -$ (15.0/1.3)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow -, p_2 \rightarrow +$ (15.0/7.8)
| | | $R(V_5(p_1), \{V_5(p_1), V_5(p_2)\} = max :$
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = min : p_1 \rightarrow -, p_2 \rightarrow +$ (16.0/8.9)
| | | | $R(V_3(p_1), \{V_3(p_1), V_3(p_2)\} = max : p_1 \rightarrow +, p_2 \rightarrow -$ (77.0/1.4)

Figure C.14: PWC4.5 Decision Tree for 5D(EXP_1) with Noise Level of 20%

```
V4 > 9.99127 : − (80.0/17.0)
V4 <= 9.99127 :
|  V2 > 9.94972 : − (61.0/14.0)
|  V2 <= 9.94972 :
|  |  V5 <= 9.96533 :
|  |  |  V4 <= 7.14541 :
|  |  |  |  V2 > 3.20644 : + (359.0/143.0)
|  |  |  |  V2 <= 3.20644 :
|  |  |  |  |  V1 > 2.95696 : + (171.0/82.0)
|  |  |  |  |  V1 <= 2.95696 :
|  |  |  |  |  |  V5 <= 8.05347 : − (104.0/21.0)
|  |  |  |  |  |  V5 > 8.05347 :
|  |  |  |  |  |  |  V3 > 4.51836 : + (6.0)
|  |  |  |  |  |  |  V3 <= 4.51836 :
|  |  |  |  |  |  |  |  V1 <= 0.837071 : + (2.0)
|  |  |  |  |  |  |  |  V1 > 0.837071 : − (5.0/1.0)
|  |  |  V4 > 7.14541 :
|  |  |  |  V1 <= 9.20491 : + (149.0/32.0)
|  |  |  |  V1 > 9.20491 :
|  |  |  |  |  V1 > 9.93512 : − (5.0)
|  |  |  |  |  V1 <= 9.93512 :
|  |  |  |  |  |  V3 > 7.25632 : − (4.0)
|  |  |  |  |  |  V3 <= 7.25632 :
|  |  |  |  |  |  |  V3 <= 2.35355 : − (3.0/1.0)
|  |  |  |  |  |  |  V3 > 2.35355 : + (6.0)
|  |  V5 > 9.96533 :
|  |  |  V2 > 1.0078 : − (29.0/2.0)
|  |  |  V2 <= 1.0078 :
|  |  |  |  V1 <= 3.55234 : − (7.0/1.0)
|  |  |  |  V1 > 3.55234 :
|  |  |  |  |  V4 <= 3.03018 : − (3.0/1.0)
|  |  |  |  |  V4 > 3.03018 : + (6.0)
```

Figure C.15: C4.5 Decision Tree for 5D(EXP_1) with Noise Level of 25%

$p_1 \rightarrow +$

$p_2 \rightarrow -$

(500.0/117.1)

Figure C.16: PWC4.5 Decision Tree for 5D(EXP_1) with Noise Level of 25%

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