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in Computational Linguistics

Deconstructing Constructed Languages

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Abstract

This thesis investigates the distinction between constructed and natural languages through empirical analysis of various linguistic features and the use of machine learning methods. Constructed languages typically are designed in specific ways that reflect their intended purpose, such as for use in fictional media or as an international auxiliary language. At the same time though, they are also usually inspired or influenced by various natural languages. To analyze the extent that the two may be similar, linguistic features corresponding to measurements of text complexity, lexical diversity, morphological complexity, and entropy were calculated for twenty-four languages (six constructed and eighteen natural). Models were then trained on these features for supervised binary classification and unsupervised anomaly detection, after which they were further analyzed using SHAP. The results suggest that some constructed languages, particularly Esperanto, have measurable similarities to natural languages with regard to certain features, while others are more distinct. These findings provide further insight into the linguistic properties of constructed languages, as well as the broader debate of what constitutes a language.

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List of Abbreviations

API	Application Programming Interface
NLP	Natural Language Processing
PCA	Principal Component Analysis
TF-IDF	Term Frequency - Inverse Document Frequency
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
SVM	Support Vector Machine
XML	eXtensible Markup Language
TTR	Type-Token Ratio
MATTR	Moving-Average Type-Token Ratio
MTLD	Measurement of Textual Lexical Diversity
IAL	International Auxiliary Language
SVO	Subject-Verb-Object
SOV	Subject-Object-Verb
IALA	International Auxiliary Language Association
LFN	Lingua Franca Nova
CSV	Comma-Separated Values
MAP	Maximum a Posteriori
MSE	Mean Squared Error
MDI	Mean Decrease in Impurity
MDA	Mean Decrease in Accuracy
AUC	Area Under the Curve
ROC	Receiving Operating Characteristic
PRC	Precision-Recall Curve
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
SHAP	SHapley Additive exPlanations
LIME	Local Interpretable Model-agnostic Explanations

1 Introduction & Motivation

Constructed languages—also called artificial languages, invented languages, planned languages, engineering languages, glossopoeia, or more simply as "conlangs" (Ball 2015)—are languages that are consciously and purposefully created for some intended use, usually being defined in antithesis to the spontaneous and organic method in which natural languages arise and develop (Sanders 2016). These variations of the term are often, but not always, used interchangeably, as linguists do not all agree upon a core term due to personal preferences (Adelman 2014), and there are sometimes differences in nuance depending on the context in which they appear. This thesis will mainly refer to them as constructed languages for simplicity.

The intended uses for which they are created can range broadly. Some are made specifically for fictional media, often seen in the genres of fantasy or science-fiction, with some more well-known examples being J. R. R. Tolkien's Elvish languages (e.g., Quenya, Sindarin, Nandorin) found in the world of Middle-earth in his writings, Marc Okrand's Klingon language from the Star Trek universe, and David J. Peter's Dothraki language used in George R. R. Martin's A Song of Ice and Fire novels along with their television adaptation, Game of Thrones (Punske, Sanders, and Fountain 2020). Others are created to function as international auxiliary languages (IALs)—languages planned for the use of international and cross-cultural communication (Gobbo 2016). The most well-known example (based on estimated number of speakers) of these is Esperanto, created in the 19$^{\text{th}}$ Century by L. L. Zamenhof. Typically, constructed languages are distinguished and categorized based on these communicative functions. This will be discussed more comprehensively in Chapter 2.

Despite being defined in contrast to one another, however, constructed and natural languages are not necessarily opposite to one another characteristically. Aside from their origins, the boundaries between the two are not always clear when analyzed in greater detail (Goodall 2022). For example, K. Schubert (1989) argues that some languages which are considered "natural" have some degree of artificiality, such as standardized written German and English differing from their spoken forms, and that the reverse is also true of some languages which are considered "artificial" because they draw from aspects of natural languages. As such, he believes human languages exist on a continuum of the two labels, rather than in the binary distinction—a view echoed by other linguists as well (Novikov 2022).

In many ways, the investigation into the disparity between the these two kinds of languages overlaps with the broader debate regarding what constitutes a language. Central to this debate is the search for linguistic universals—

properties shared by all languages (Mairal and Gil 2006). The concept of universals in language is recognized as one of the most important areas of research in linguistics (Christiansen, Collins, and Edelman 2009) and has served as a foundation for much linguistic theory, especially in more recent history, stemming largely from the influential theories and works of Greenberg (Greenberg 1970) and Chomsky (Chomsky 1957; Cook and Newson 2007).

Analyzing their surface structures can reveal whether or not constructed languages adhere to the same linguistic conventions as their natural counterparts. If machine learning models fail to successfully distinguish between the two, it may reinforce the notion that these universals are present in all languages, regardless of origin. Conversely, the models succeeding may suggest the opposite. In short, the primary motivation behind this thesis is to contribute to this ongoing debate through the application of machine learning, and a desire to learn more about the fascinating genre of constructed languages.

1.1 Scope of Study & Research Question

The present work analyzes various linguistic features and seeks to successfully discriminate a language as being either natural or constructed based on these. More specifically, the scope of this study includes both supervised binary classification and unsupervised anomaly detection, with the models being trained on a set of selected features rather than raw text data.

Because of the wide-ranging nature of conducting such a broad analysis, there are of course many features left unconsidered or excluded, intentionally or otherwise. With this in mind and following the precedent set by other related research on this topic, the main focus for linguistic features relate to text complexity, entropy, morphological complexity, and overall lexical diversity.

The following is a breakdown of the structure of this thesis from here onward: the next chapter provides relevant background information, including an overview on constructed languages and a comprehensive review of related literature that examines the prior theoretical groundwork laid for exploring linguistic similarities and differences between constructed and natural languages; Chapter 3 covers in detail the methodology taken in this research, from an explanation of the data used to the various experiments performed; Chapter 4 presents the results of the study and discussion of these follows in Chapter 5; lastly, Chapter 6 consists of a conclusion as well as elaboration for possible future work.

2 Background

The vast landscape of linguistic research comprises a myriad of literature delving into the intricacies of languages, both natural and constructed. As this thesis is concerned with constructed languages in particular and possible distinctive properties they may have, this section begins with a brief overview of their history and development, which provides some relevant context. Following this is an overview of some related literature, which is relevant to understanding the motivation behind the various computational approaches I employ in my experiments.

2.1 History of Constructed Languages

Okrent (2009) states, "The history of invented languages is, for the most part, a history of failure." She may be justified in saying this, depending on one's definition of failure in this context. From past to present, the total number of constructed languages may be as high as a thousand (Libert 2016; K. Schubert 1989; K. Schubert et al. 2001), with hundreds proposed for the purpose of being IALs in Europe alone (K. Schubert et al. 2001). Yet of these, only Esperanto is commonly considered to be successful in achieving its creator's intended goal of world-wide use as an auxiliary language (or rather that it is by far the most successful), with very few others even coming close, having a conservative estimation of two million speakers (Okrent 2009).

While the construction of languages is possibly as old as human history, they typically were not written down and were limited to in-group communication (Gobbo 2016). The first documented endeavors came out of religious contexts and were likely used as secret languages, intentionally obscured and incomprehensible to lay people. In the 12th century, abbess Hildegard of Bingen described and recorded a lexicon for Lingua Ignota, a Latin name meaning "unknown language". While extensive documentation of it (i.e., a grammar) was never found, it possessed a semiotic system based on Latin, German, and Greek. Later in the 14th century, a group of Sufi mystics created Balaibalan, a language written in the Ottoman Turkish alphabet and which incorporated features of Persian, Turkish, and Arabic languages (Novikov 2022).

Interest in creating such languages picked up in the 17th century with the rise of so-called philosophical languages. In contrast to the last two, these languages were made to be more precise, less ambiguous, and better allow for philosophical reasoning (compared to natural language), such as by organizing world knowledge into hierarchies (Goodall 2022). Notable figures involved in making these include Francis Lodwick, Gottfried Leibniz, and John Wilkins, the latter of whose being arguably the most well-known and influ-

(1) **special > creature > distributively > substances > animate > species > sensitive > sanguineous > beasts > viviparous > clawed > rapacious > oblong-headed > European > terrestrial > big > docile**

Figure 2.1: Wilson's expression of "dog" in his philosophical language (Goodall 2022).

ential. Wilkins created a system of semantic categorization, cataloging all concepts in the universe (Okrent 2009), and then published his proposed language (Wilkins 1968). An example of this hierarchal categorization can be seen in Figure 2.1.

In the 19th and 20th centuries the focus for language construction, especially in Europe, shifted to that of making international auxiliary languages (IALs) intended to better enable communication across language barriers, i.e., people who do not share a similar language (Goodall 2022). Notably, this means they were generally (though not always) designed to resemble natural language, with choice exceptions being the simplification of certain linguistic features. The surge in need for IALs correlated with the increase in prevalence and accessibility regarding international travel and communication at the time. Such languages were also described as "neutral" (Large 1985), in the sense that individual advantages amongst speakers and learners would, theoretically, not exist due to IALs being second languages to everyone (Gobbo 2016). That being said, many of the most prominent examples (e.g., Volapük, Interlingua, Esperanto, Ido) are derived from the Indo-European language family (Novikov 2022; Goodall 2022), so such a description might not be apt. Overall, IALs can be viewed as an intended rival to natural languages, which is one reason why all of the constructed languages analyzed in the present work are IALs. A more detailed explanation of each is provided in Section 3.1

Lastly, there exist constructed languages that have been made for experimental, artistic, literary, or fictional purposes. In contrast to IALs, these languages are not made with the intention of replacing existing languages for everyday communication. Instead, their creators want to push the boundaries of language, test scientific hypotheses like linguistic relativity, or create a world, as is the case for the fictional examples provided in Chapter 1. Some other examples in this category include Solresol, a language that uses musical notes; Láadan, a language designed to be inherently feminist (i.e. more capable of expressing the female experience); and Loglan, a self-described "logical" language whose morphology and syntax are based on predicate logic (Adelman 2014). Though it would be inaccurate to describe such languages as being only a recent invention, popularity in their conceptualization largely grew in the later part of the 20th century.

While all share the defining characteristic of having been purposefully created, the linguistic features of constructed languages (e.g., phonetic, morphological, syntactical, lexical, orthographic) can vary immensely depending on factors such as their intended purpose for use or the other languages they draw from. An example of this was observed by Gobbo (2016) in secret languages, specifically their tendency to have more complicated features, such as morphological irregularities, "in order to preserve their secrecy." Contrast to this are IALs, which have the opposite tendency for the sake of ease of communication and second-language acquisition, reflected in commonly assigned features such as SVO word orders, head-initial relative clauses, fronted *wh*-phrases, and morphological regularity (Goodall 2022; Gobbo 2016). Section 2.2 further examines research focused on linguistic features of these languages.

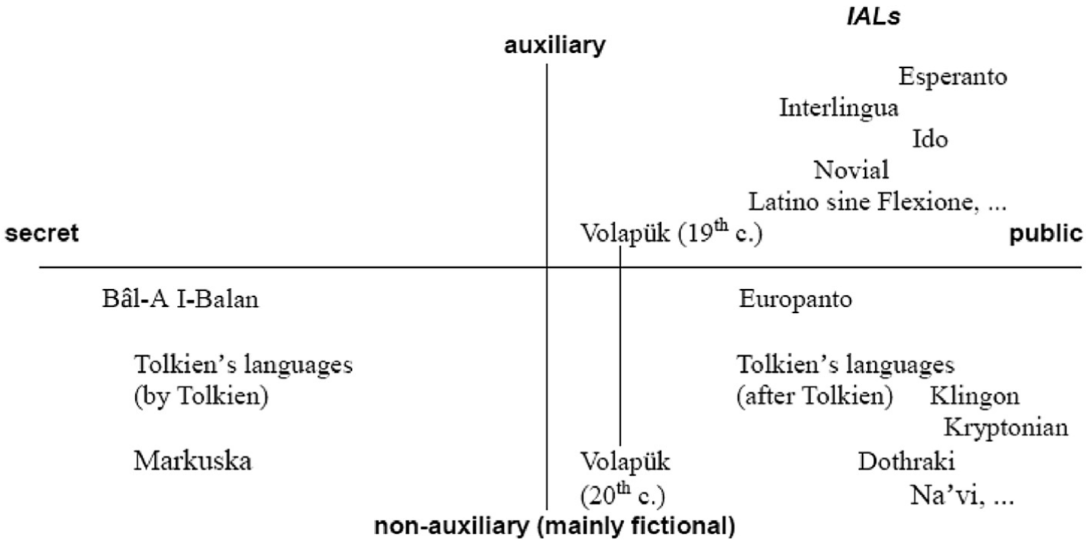


Figure 2.2: A taxonomy of constructed languages (Gobbo 2016).

In addition to this classification based on their intended communicative functions, i.e. as philosophical or international auxiliary languages, there are also taxonomies based on other criterion. For example, another frequently used distinction is that of *a priori* and *a posteriori* (Schreyer and Adger 2021; Gobbo 2008; K. Schubert 1989; K. Schubert et al. 2001; Novikov 2022; Adelman 2014; Tonkin 2015). Languages described as being *a priori* are structurally entirely new (Tonkin 2015) and not based on existing languages, whereas so-called *a posteriori* languages are the opposite, drawing from aspects of specific natural languages (Schreyer and Adger 2021). Gobbo (2008) also proposed the dichotomy of *exoteric* (secret) and *esoteric* (public) languages, derived from Bausani (1974). Similar to critiques regarding the distinction between constructed and natural, such dichotomies for categorizing constructed languages are also argued by some linguists to be more accurately described as scales instead, with many languages falling somewhere in the middle (Novikov 2022). A final noteworthy classification scheme often cited by other linguists comes from BLANKE (1989) in the form of three classes: project, semi-planned, and planned. In short, these correspond to a set of steps that a constructed language must go through before it can be considered a "real" language (K. Schubert et al. 2001).

A two-dimensional taxonomy for constructed languages containing several notables examples is shown in Figure 2.2 (Gobbo 2016).

2.2 Prior Studies

In contrast to the abundance in literature and cross-linguistic analyses done on natural languages, similar research which also includes constructed languages is relatively sparse. In particular, while there is research that analyzes specific instances of linguistic differences between certain natural and constructed languages, large-scale cross-linguistic studies which utilize computational methods to classify the two based on linguistic features are practically nonexistent. Consequently, the present study is a somewhat novel approach. However, there is precedent for this research and the specific features examined, as well as computational approaches used, which this section will describe.

As noted in the previous section, the creation of IALs often involved the intentional simplification of particular linguistic features to facilitate language acquisition, for instance having more regularity in their morphological systems. Intuitively, then, one would assume this translates to measurable differences in various aspects of linguistic complexity when compared to natural languages, which often have irregularities as a result of their development and evolution. When comparing Volapük and English, Gobbo (2016) concluded that

Much of the literature on constructed languages focuses on Esperanto specifically.

2.2.1 Studies in Morphological Complexity

2.2.2 Studies in Entropy

Another feature examined is entropy. Originating from information science, entropy was introduced by Shannon (1949) as a measurement of uncertainty or surprisal for an event, with high surprisal being inversely proportionate to the amount of information conveyed by the event's occurrence. In NLP,

Many studies into the entropy of natural languages have been conducted, but less so regarding constructed languages. Smaha and Fellbaum (2015) investigated and compared two constructed languages (Lojban and Klingon) with several natural languages and other artificial languages (e.g., Fortran, a programming language) using calculations of block entropy (Shannon's entropy generalized to n-grams). While broad observation of the results found both Klingon and Lojban to have comparable entropies to the natural languages, closer analysis revealed them to actually be closer to Fortran instead.

2.2.3 Computational Approaches

Oktafiani, Hermawan, and Avianto (2024)

3 Methodology

In this section, I introduce the dataset for this thesis and discuss the steps taken for preprocessing it, followed by discussing in detail the features examined along with the different methods involved in extracting them from the data, and finally the classifiers employed on the feature set. A brief description of the various APIs and libraries used is also included in 3.3.

Since this study involves many different experiments and elements being performed and analyzed, I will begin by explaining an overview of what all was done. The number of possible features and measurements of linguistic complexity which could be analyzed in such a study is extensive to say the least; however, the scope of this thesis focuses mainly on empirical measurements relating to lexical diversity, morphological complexity, and entropy, along with some more simplistic measurements of text complexity. More specifically, the features investigated are average word length, average sentence length, type-token ratio (TTR) of morphemes, average number of segmentations in a word, average number of forms per lemma, lexical TTR, moving-average type-token ratio (MATTR), measurement of textual lexical diversity (MTLD), lexical entropy, reverse lexical entropy, text entropy, and character and word distribution entropies. Once the values of these were calculated for each language, the task became that of supervised binary classification and unsupervised anomaly detection with five machine learning models: a one-class support vector machine (SVM), local outlier factor, random forest, isolation forest, and decision tree. Principal Component Analysis (PCA) was also performed on the feature set to identify and visualize potential trends in the data. Lastly, the methods for evaluating the performances of these models and interpreting them based on feature importance are discussed.

3.1 Data

In total, twenty-four languages are analyzed in this study. Six of these are constructed languages: Esperanto, Ido, Interlingua, Lingua Franca Nova, Volapük, and Kotava. The remaining eighteen are natural: German, English, Spanish, Polish, Vietnamese, Indonesian, Turkish, Tagalog, Hungarian, French, Finnish, Italian, Dutch, Occitan, Danish, Swedish, Afrikaans, and Icelandic. The rationale behind this particular selection of languages will be discussed in further detail throughout this section, but the primary focus was on having diverse typological linguistic features represented in the data.

For consistency, only languages which are written using the Latin alphabet (including the use of diacritics) were chosen. This is mainly because the constructed languages in the dataset all use Latin alphabets, so the selection of natural languages followed the same criteria. Moreover, it allows for more uniform cross-linguistic analysis of features which may be sensitive (e.g. in the case of character entropy) to writing systems.

3.1.1 Constructed Languages in the Dataset

All of the constructed languages in the dataset are IALs, with most of them resembling natural (particularly various European) languages. I will briefly introduce each of them in this section, explaining where they come from, some notable typological features they have, and how they compare to both one another other and their natural counterparts.

Esperanto, the most widely-spoken constructed language and considered by many to be the most successful (Gobbo 2008), was created in 1887 by Polish ophthalmologist L. L. Zamenhof. Zamenhof's goal was to create a neutral, easy-to-learn language that would facilitate international communication. Esperanto is a highly regular language, with consistent grammar and a simplified, phonetic spelling system. It draws its lexical roots and syntax primarily from Romance, Germanic, and Slavic languages (Gobbo 2008; Gobbo 2011), making it recognizable and familiar to speakers of many European languages, while also intentionally being made to have a comparatively simpler grammar that avoids some complexities found in natural languages, such as irregular verbs or noun cases. Its morphological system is considered to be one of its more interesting aspects due to its classification being a source of debate amongst linguists (Reagan 2019). It also has a strong global community with speakers around the world, an array of written literature, and even a number of native speakers who learn it from birth—a distinguishing trait which sets it apart from other constructed languages (Goodall 2022). As a result of its success, Esperanto also serves as a direct influence for many other constructed languages that have come after it, one being Ido.

Ido is a reform of Esperanto that was proposed in 1907 by a group of linguists led by Louis Couturat, a French philosopher and mathematician, and in fact is an Esperanto word meaning "offspring" (K. Schubert et al. 2001). Its creators sought to address what they saw as imperfections in Esperanto, particularly those related to orthography, morphology, and lexicography (Novikov 2022). For instance, Ido avoids the use of the accusative case and reforms some Esperanto words to make them more universally recognizable. Overall, though, Ido still retains much of Esperanto's vocabulary and basic structure, and the two are mutually intelligible to a large extend (Goodall 2022; K. Schubert et al. 2001).

Interlingua was developed by the International Auxiliary Language Association (IALA) with the assistance of linguist Alexander Gode, officially being published in 1951. A central idea to its creation was that it would be most recognizable to the greatest number of people without requiring prior study (Goodall 2022), particularly in regards to its lexicon. The IALA's stated goal was to not so much create a new international language, but rather present a standardized international vocabulary (Large 1985) ("international" here basically referring to Western Europe). It is largely derived from and resembles Romance languages (with lesser influence from Greek and Germanic languages) (K. Schubert et al. 2001). In fact, this intentional resemblance extends even to morphological irregularities such as allomorphy, with other irregularities also being introduced to the language to make it appear more natural (Goodall 2022; K. Schubert 1993), a contrast to other IALs like Esperanto (Gobbo 2016).

Volapük was created in 1879 by Johann Martin Schleyer, a German Catholic priest who believed the language had been given to him by God. It features highly agglutinative structure and regular, yet complex, morphology (Reagan 2019). While being derived mainly from English, German, and Latin, roots in Volapük differ significantly to the point of being unrecognizable to speakers of these languages (Goodall 2022). Despite being argued to be the first successful constructed language due to its rise in popularity, having amassed a large number of supporters worldwide along with the formation of clubs and societies (Gobbo 2016), various issues regarding its complexity led to a rapid decline and eventual fall from usage in favor of Esperanto.

Lingua Franca Nova, also abbreviated as LFN, is a relatively recent constructed language created by linguist C. George Boeree in 1998. Its lexicon is based mainly on Romance languages, specifically French, Italian, Portuguese, Spanish, and Catalan, while its grammar is based on Romance creole languages (Pawlas and Paradowski 2020). In particular, inspiration came from the similarly-named Mediterranean Lingua Franca, a pidgin that developed for trade in the Mediterranean basin and was used from the 11th to 18th centuries, as well as from other creoles, such as Haitian Creole. It can be written in both Latin and Cyrillic scripts, though this dataset only contains the former.

The last constructed language used is Kotava. Created by Staren Fetcey in 1978, Kotava stands out in this dataset as being an attempt at creating a culturally neutral *a priori* language, free from any biases or influences of existing languages and based on a philosophy of linguistic egalitarianism. This intentionally designed uniqueness is apparent in several of its linguistic systems, from morphology to syntax. For example, though word order in Kotava is not imposed, the most frequently used one is OSV, which is exceedingly rare in natural languages in contrast. Other unique features include a 4th person plural, object complements being introduced by a transitive preposition, and a lack of declension (Fetcey and Comité Linguistique Kotava 2013).

Language	Source Languages/Families
Esperanto	Romance, Germanic, Slavic
Interlingua	Romance
Lingua Franca Nova	Romance
Volapük	Germanic
Kotava	N/A
Ido	Romance, Germanic, Slavic

Table 3.1: Constructed languages in the dataset together with their main respective source languages from which they were designed.

Table 3.1 shows the dataset's constructed languages together with the main source languages they draw from by design (with *N/A* for Kotava meaning *not applicable*). Note, however, that this is not an exhaustive list of all of their language influences. Lastly, it is worth drawing attention to the fact that each of these languages were created based on various European languages, with the exception of Kotava. Consequently, this may influence the models used in the experiments and also be visible in the results. This will be explored in greater detail later in Chapter 5.

3.1.2 Natural Languages in the Dataset

The natural languages included in this study comprise a variety of language families, geographic regions, and typological features. Although this representation is not necessarily equal in distribution, it is meant to serve as a contrast to the constructed languages in the dataset, which lack a similar extent of variety due to largely being based on the same handful of European languages, with only one exception. However, rather than delving into the same level of details for each of the eighteen languages here as was done in Section 3.1.1, they will instead be introduced by focusing mostly on their collective significance within the dataset and summarizing some of their typological traits which are relevant to the scope of this investigation.

In total, five major language families are represented. The largest of these—based on number of speakers worldwide as well as the number of languages in the dataset (twelve)—is Indo-European, with several of its branches being included. English, German, Dutch, Afrikaans, Swedish, Icelandic, and Danish all belong to the Germanic branch. Similarly, Italian, Spanish, French, and Occitan are part of the Romance branch, all being descendants of Latin. Polish is an outlier as the only represented language from the Slavic branch.

The other four families span less representation in the dataset in comparison, but were nevertheless included so as to have more variety in linguistic features across a broader phylogenetic spectrum. These include the Uralic languages, consisting of Hungarian and Finnish, which are the most widely-spoken and thus representative of their group, as well as Austronesian (Tagalog and Indonesian), Austroasiatic (Vietnamese), and Turkic (Turkish).

The main relevant typological feature of these languages is their morphological systems, for which there is also a range of representation. This typology is defined along the scale of agglutinative, fusional, and isolating systems, with many languages often exhibiting varying degrees of more than one. Thus, without exhaustive explanation for each language's morphology indid For example, Finnish, Hungarian, and Turkish are highly agglutinative, whereas Vietnamese, an isolating language, is an extreme opposite. The Indo-European languages included in this thesis have fusional morphologies, with the Germanic languages also

Language	**Language Family**	**Morphology**
German	Indo-European, Germanic	A / F / I
Dutch	Indo-European, Germanic	A / F / I
Afrikaans	Indo-European, Germanic	A / F / I
Swedish	Indo-European, Germanic	A / F / I
Danish	Indo-European, Germanic	A / F / I
Icelandic	Indo-European, Germanic	A / F / I
English	Indo-European, Germanic	A / F / I
Spanish	Indo-European, Romance	F
French	Indo-European, Romance	F
Occitan	Indo-European, Romance	F
Italian	Indo-European, Romance	F
Polish	Indo-European, Slavic	F / I
Vietnamese	Austroasiatic	I
Indonesian	Austronesian	A
Tagalog	Austronesian	A / I
Turkish	Turkic	A
Hungarian	Uralic	A / F
Finnish	Uralic	A / F

Table 3.2: Natural languages in the dataset together with their respective language families and morphological systems, adapted from Desjardins (2023).

3.1.3 Wikimedia

The data for this thesis comes from Wikimedia dump files. Wikimedia is a global movement and community founded on shared values, whose goal is to provide free and openly accessible information to everyone in the form of massive collaborative projects (which include, among others, the widely-used Wikipedia and Wiktionary). For a large, cross-linguistic study, massive databases with open-access make for an ideal source for corpora. Most importantly, the projects are multilingual, meaning data is available in a considerable number of different languages—including several constructed ones. This allows for composing a set of corpora which is adequately parallel to each other and from the same domain. Additional constructed languages which are also available from the dumps—but were not included in the present study due to having a much smaller amount of data—are Novial, Interlingue, and Lojban.

The dump files provide detailed, archived snapshots of the content from Wiki repositories for a specified point in time and are available in different formats. All dumps used were XML-formatted and from the 2024-07-01 archive, containing articles together with their metadata.[1] It is also worth mentioning here that there are some drawbacks to using these dumps for the present study. The files sizes vary considerably depending on the language, with the largest being roughly 22 gigabytes (English) and the smallest around 4 megabytes (Lingua Franca Nova), meaning all files do not contain the exact same articles. Additionally, the open and collaborative nature of Wikimedia means the articles are often authored by a multitude of different people, which can result in inconsistencies in the texts, such as with writing style. Similarly, it may also produce an imbalance in the amount of information provided across languages, with the same article in one language being considerably more detailed than in another, and inconsistent or low-quality machine translations, as Novikov (2022) noted to be the case for Wikipedia articles in Volapük. Thus, while Wikimedia was decided as the best available option for the task at hand, there are some unfavorable aspects of using it which may influence the results; this will be discussed more in Chapter 5.

3.2 Data Preprocessing

Preprocessing text data is essential for natural language processing (NLP) tasks, so meticulous effort was made to thoroughly clean all of the texts and obtain as close to a set of parallel data as possible.

Text data was first extracted from the Wikimedia XML-formatted dump files with the use of WikiExtractor,[2] a Python script (Attardi 2015) that I adapted by adding a limit to the number of articles in order to make extraction of the largest of the files (English in particular) less demanding and quicker. The output is a simple text file, which is a much easier format to clean and work with.

I then used several regular expressions to remove general, unnecessary text from each file such as page titles, section headers, links, fragments, HTML tags, braces, and all other non-alphabet symbols aside from periods. This also includes the removal of parantheses and their contents. The text was

[1] `https://dumps.wikimedia.org/backup-index.html`
[2] GitHub repository for WikiExtractor: `https://github.com/attardi/wikiextractor`

then made all lowercase and split by the periods—while also attempting to account for abbreviations—to make separate sentences. This was done mainly to enable more accurate measurement of entropy later.

Following this, foreign symbols (i.e., characters not part of a particular language's alphabet) were removed for each text/language, as occasionally proper nouns, loanwords, etc. would appear in the text, which would also affect measurements of entropy, in addition to morphological segmentation and analysis. To give an example of how this was done, there is no letter *h* in Kotava, but this would sometimes be used in proper nouns such as *Hiroshima*. After the text was cleaned, the result that remained was *irosima*.

Finally, each text file was truncated according to the file size of the smallest corpus, LFN, so as to have similar lengths. This was calculated based on number of words, with the limit being 630000 (since this is roughly the number of words remaining in the LFN text file after cleaning), and while preserving complete sentences. Sentences containing only one word were also removed. The end result of pre-processing was a single text file for each language, with every line in the file being a single sentence (split using a regular expression). The corpora with the smallest and largest number of words are Kotava and Danish/Volapük at 617400 and 629999 words, respectively. For number of sentences, the smallest and largest corpora are Vietnamese and Volapük at 21115 and 55920 sentences, respectively. For a full breakdown of these size for each language's text after pre-processing, refer to Table 8.1.

3.3 Libraries and APIs

Several libraries and APIs were used in both the feature engineering and classification steps of the experiment, and the most important of these will be briefly introduced here. In the field of machine learning, two of the most popular model frameworks used are PyTorch(Paszke et al. 2017) and TensorFlow(Chollet et al. 2015), which are interacted with via the torch and Keras APIs, respectively. Aside from some relatively minor differences (e.g., the syntax of their code and performance optimization), they share a lot of similarities and are typically used according to personal preference. In the context of this thesis, these frameworks are used for calculating some of the entropy values from the corpora. Other machine learning models used were for morphological segmentation via Morfessor 2.0(Virpioja et al. 2013; Creutz and Lagus 2002), a family of unsupervised, generative probabilistic models.

In addition to libraries used for constructing the model architectures, there are also ones used for the data itself. Arguably the most fundamental for this is NumPy(Harris et al. 2020), which stands for Numerical Python and is used to accomplish extremely fast and efficient computation of arrays. Other essential libraries include PANDAS(team 2020; McKinney 2010), used for data manipulation and analysis, and MATPLOTLIB(Hunter 2007), used for visualizing data and plotting model results. Lastly, SCIKIT-LEARN(Pedregosa et al. 2011) provides a wide range of tools for machine learning algorithms, data preprocessing, and model evaluation—as well as computation, thanks to it being built on top of NUMPY. The models I used for classification and anomaly detection (i.e., One-Class SVM, Isolation Forest, Local Outlier Factor, Random Forest, Decision Tree) as well as PCA come from this library. Altogether, these libraries are often used in tandem in NLP tasks due to integrating so well with one another.

Lastly, for analyzing and visualizing global and local feature importances as determined by the different models, the SHAP library was used (Lundberg and Lee 2017).

3.4 Feature Engineering

Before classification or anomaly detection can be done with the data, an initial step of feature engineering is performed. Put simply, feature engineering is the process of transforming raw text data into a more structured and comprehensible format for machine learning models through the specific selection of its most informative and relevant features, typically through some empirical measurements, thereby increasing the model's effectiveness.

The exact methods and measurements involved in this process depend on, among other factors, the task and data. For the scope of this thesis, some were only simple calculations, the simplest of these being the measurements for text complexity: the average word length and average sentence length of each text. For the rest of the linguistic features (i.e. lexical diversity, morphological complexity, entropy) analyzed, however, this process involved the use of more sophisticated algorithms and various machine learning models to derive measurements from.

The complete set of the analyzed features for each language and their computed values is shown in Chapter 4 in Table 4.1.

3.4.1 Lexical Diversity

A common way of measuring the lexical diversity of a text is with TTR, with a high value indicating that a given text contains a large amount of lexical variation. This is calculated using the formula:

$$\mathrm{TTR} = \frac{|\mathrm{V}|}{|\mathrm{N}|}$$

where $|\mathrm{V}|$ denotes the vocabulary size as the number of unique words, or types, and |N| denotes the text length as the total number of words, or tokens. I then multiply this by 100 to get a percentage.

A big issue with TTR, though, is that it does not always provide an accurate assessment due to its sensitivity to text length; the longer a particular text, the higher the likelihood of repetition in words occurring, consequently affecting the calculation. To remedy this, I also calculate the MATTR, a variation of TTR proposed by Covington and McFall (2010) that uses a sliding window of a fixed-length over the text and calculates the TTR at each length of the window, which is then averaged together. This is denoted by the formula:

$$\text{MATTR}_i = \frac{1}{N-i+1}\sum_{j=1}^{N-i+1}\frac{|\text{Types}_{j,j+i-1}|}{|\text{Tokens}_{j,j+i-1}|}$$

where N is the total number of tokens in the text, i is the window size, $|\text{Types}_{j,j+i-1}|$ is the number of unique words (types) in the window, and $|\text{Tokens}_{j,j+i-1}|$ is the total number of words (tokens) in the window.

While resistant to variation in overall text length, calculations for MATTR do vary based on the window size, and deciding which value to use depends on the task. Here, a length of $i = 100$ tokens was used.

Another alternative to the standard measurement of TTR is the Measurement of Textual Lexical Diversity (MTLD), which calculates the average length of sequential word strings that maintains a TTR above a specified threshold (Bestgen 2024). This was done by incrementally adding the words of a given text to a sequence and calculating the TTR at each increment. Each time the TTR fell below the threshold (here, the standard threshold of 0.720 (McCarthy and Jarvis 2010; Fergadiotis, Wright, and West 2013) was used), a counter—called a factor count—was increased by 1, and both the TTR evaluations and sequence were reset. This continued until the end of the text is reached, after which the text's total number of words is divided by the total factor count to get a value for MTLD. Then the text was reversed and the same process was repeated. The two resulting values were averaged to get the final MTLD.

Typically, there are remaining words at the end of a text that are referred to as partial factors, due to not making a full one. To still include these partial factors in the overall calculation, the TTR of the remaining words was divided by 0.280 (TTR threshold subtracted from the TTR upper-bound of 1), and the result was added to the factor count.

3.4.2 Morphological Complexity

Morphological complexity was analyzed as three features: morpheme TTR, the average number of segmentations per word, and the average number of forms per stem. To calculate these, the text data of a given corpus was first split and restructured into a list of words to then be fed to corresponding model for segmentation.

Baseline models, one for each corpus, were initiated using default parameters. The word lists were then loaded into the models, again with default parameters except for `count_modifier`, which was set to a specified logarithmic equation, expressed as:

$$\lfloor \log_2(x+1) \rfloor$$

Where x is the raw frequency count of the compound (i.e. the word being segmented), and the surrounding brackets $\lfloor\ \rfloor$ denote rounding to the nearest integer. This equation was used in order to dampen the frequency of the count of a given compound, which in turn allows the model to generalize better rather than focusing more on the compounds that occur at a higher frequency.

Finally, the models were trained with default parameters, including the recursive algorithm used for splitting the compounds. To briefly explain how this works without delving too deep into the math behind these segmentation models—as doing so would be beyond the scope of this thesis—training one epoch involves trying all viable two-part segmentations for every compound in the data, recursively attempting further segmentation based on the lowest cost (derived using maximum a posteriori (MAP) estimation) yielded each time and stopping once this cost falls below a given threshold (Smit et al. 2014).

Once all of the texts' compounds were segmented, the aforementioned features were computed. As an approximation, the stem of the compound was assumed to be the largest resulting segment that appeared first (in order of left to right). Remaining segments, if there were any, were thus considered morphemes. Morpheme TTR was then calculated using the same formula as lexical TTR (i.e., the ratio of unique to total morphemes), and the result was again multiplied by 100. Computing the average number of segmentations per word was simply each compound's number of segmentations summed together and then divided by the total number of compounds. Lastly, the average number of forms per stem was derived from the total number of morphemes for each unique stem (adding 1 to account for the stem itself) divided by total number of unique stems.

The preference for using mostly default parameters for the functions and models here, as well as the method for identifying the stem of a segmented compound, was to ensure uniformity, so that the results would be comparable for cross-linguistic analysis. The implications of this and possible alternative approaches will be further discussed in Chapter 5.

3.4.3 Entropy

In total, five values of entropy were measured: text, lexical, reverse lexical, character distribution, and word distribution. The latter two were calculated without the use of a model, simply with the formula for Shannon's entropy for a given text:

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i)$$

Where X refers to the random variable (e.g. the word or character distribution of a text), n is the number of distinct values (i.e. types) in the distribution, $p(x_i)$ shows the probability p of each type x_i occurring and is calculated by its relative frequency, and $-\log_2 p(x_i)$ represents the self-information for each type. Put together, $\log_2 p(x_i)$ represents the surprisal associated with a given type, and the average of all of these is the entropy.

Text entropy was calculated using a character-level Long Short-Term Memory (LSTM) model built for text generation.[3] LSTMs are a type of Recurrent Neural Network (RNN) that are typically better at handling long-term dependencies in sequential data due to their gating mechanisms for retaining only the information deemed useful, consequently making them better suited for generative tasks (Dhandapani et al. 2023).

Using this model required first creating a dictionary of the input text's characters and one-hot encoding (converting into binary vector representations) their numerical representations. The text was then split into mini-batches for training, which are essentially sliding windows in the shape of an $N \cdot M$ array of characters, where N is the number of sequences (equivalent to a batch size) and M is the number of steps, or length of the window. Additionally, this means the input must be divisible into full batches, so remainder text that is insufficient in size is discarded.

Table 3.3 shows the model's main parameters alongside their associated values as used here. All other parameters were left as the default values. The architecture comprises 2 hidden layers (`n_layers`), a dropout layer, and a fully-connected output layer. Both `n_layers` contain 256 hidden units (`n_hidden`), which are used to store information from the input and essentially act as the memory of the LSTM. Default values for learning rate, dropout rate, and gradient clipping were used, and training was done over 20 epochs. Minimal fine-tuning was performed overall, and primarily just for the `n_seqs` and `n_steps` hyperparameters.

Additionally, a fraction (0.1) of the initial input data was set aside to be used for validation, from which the model's perplexity—a measure related to

[3] Model adapted from `https://github.com/LeanManager/NLP-PyTorch/blob/master/Character-Level%20LSTM%20with%20PyTorch.ipynb`

LSTM For Calculating Text Entropy	
Parameters	**Values**
Number of epochs	20
Number of sequences (`n_seqs`)	128
Number of steps (`n_steps`)	100
Number of hidden layers (`n_layers`)	2
Number of hidden units (`n_hidden`)	256
Learning rate	0.001
Dropout rate	0.5
Optimizer	Adam
Criterion	Cross-Entropy Loss
Fraction of data for validation	0.1
Gradient clipping	5

Table 3.3: Parameters of PyTorch LSTM used to calculate text entropy

entropy—is derived. To arrive at this measurement though, the validation loss is first evaluated using (multi-class) cross-entropy. Cross-entropy is an extension of Shannon's entropy, but measures instead the difference between a model's predicted probability distribution and the true one. More formally, this is represented as:

$$H(p,q) = -\sum_{x=i} p(x)\log q(x)$$

Where p and q represent the discrete predicted and true probability distributions, respectively, and with the natural logarithm $\log_e$, as is commonplace in machine learning. As the predicted distribution gets closer to the true one, the resulting cross-entropy becomes lower. Entropy $H(q)$ is thus a lower bound of cross-entropy $H(p,q)$.

The validation loss was repeatedly assessed throughout training, and the mean of these was used to calculate the perplexity. Expressed mathematically, perplexity PP is simply an exponentiation of cross-entropy and can be denoted by the equation:

$$\begin{aligned} PP &= \mathrm{e}^{H(p,q)} \\ &= \mathrm{e}^{-\sum_{x=i} p(x)\log_q(x)} \end{aligned} \tag{1}$$

Therefore, the final value arrived at is the text's perplexity. This is used to represent the text entropy instead, however, due to being more interpretable while still conveying the same information about the text.

Finally, lexical entropy—at the character-level—is a measure of uncertainty in predicting the subsequent character in a given sequence, in this case a word. Reverse lexical entropy is the same thing applied to a sequence that has been reversed, which may be an informative feature for distinguishing languages whose lexicons, for example, present more prevalence in prefix or suffix constructions.

For calculating both of these features, LSTMs were again used. Similar to before, the text data was first encoded into integers via dictionaries containing the vocabulary (alphabet) of each text. In contrast to the model for calculating text entropy, however, both of these models analyze the data as individual sequences of words. This means the additional use of beginning of sequence ('<') and end of sequence ('>') characters, and each sequence being padded to the same length for uniformity.

The only significant change in the process for computing both entropies occurred in the text encoding step; for the reverse lexical entropy, the sequence was reversed prior to padding. An example of forward-facing sequences (2) and their reversed forms (3) from the English corpus is illustrated here:

'<misinterpreted>', '<filaments>', '<assisting>' (2)

'<deterpretnisim>', '<stnemalif>', '<gnitsissa>' (3)

The architecture of both models is identical. First is an embedding layer with an `input_dim` equal to one more than the size of the vocabulary, an `output_dim` of 128, and `mask_zero` set to `True` (due to padding the sequences previously). This is followed by an LSTM layer, dropout layer, and finally the output layer with a softmax activation function. Additionally, early stopping was implemented based on the validation loss and with a `patience` of 2. Table 3.4 shows an overview of the most relevant parameters of the model, for which a small degree of fine-tuning was also done. All other parameters were the default values.

LSTMs For Calculating Lexical & Reverse Lexical Entropy

Parameters	**Values**
Number of epochs	100
Batch size	32
Learning rate	0.001
Dropout	0.2
Optimizer	Adam
Criterion	Sparse Categorical Cross-Entropy Loss
Fraction of data for validation	0.2
Metrics	Sparse Categorical Accuracy

Table 3.4: Parameters of TensorFlow LSTMs used to calculate lexical and reverse lexical entropy.

A fraction (0.2) of the data was again set aside for use as the validation set. Perplexity of both models was then calculated the same way as before: an exponentiation of the cross-entropy derived from the average validation loss, using Equation 1.

3.4.4 Dimensionality Reduction of Features

PCA was performed in order to identify the specific linguistic features which convey the most meaningful information in the data. PCA is an unsupervised method for linear dimensionality reduction that transforms data from a high-dimensional space to a lower one while preserving as much variance or essential information in the data as possible (Deng et al. 2024).

There are different techniques for determining the optimal number of components to retain. Here, a common one called the Kaiser criterion was applied, which drops components with eigenvalues less than 1. Additionally, in the interest of easy visual interpretation to identify possible outliers in the data, reduction to two dimensions (two principal components) was also applied.

Before conducting the PCA, standardization (also called Z-score normalization) was performed on the data first, given by the formula:

$$Z = \frac{x_i - \mu}{\sigma} \tag{4}$$

where μ is the mean and σ is the standard deviation from the mean. This process scales the data to fit a standard normal distribution, thus the resulting transformed data has a mean of 0 and standard deviation of 1.

3.5 Classification

After computing the complete set of features, two models were trained for supervised binary classification, predicting a language in the dataset to be either natural or constructed according to said numerical features. Feature scaling (e.g. normalization, standardization) was not performed for this, as neither kind of model is sensitive to variance in the data, meaning it would have no effect.

Fine-tuning to find optimal parameters was done using the grid search method, which constructs estimators to exhaust all possible combinations of a specified set of values and evaluates each of these estimators to find the best performing one. Leave-one-out cross-validation was used in order to prevent overfitting on the small and imbalanced dataset. This approach trains a model on all the data except for one (left out) sample, which is used as the testing set to make a prediction, and repeats this process for all samples.

Additionally, to prevent bias towards the majority class, balanced class weights were used for both models; this adjusts the misclassification cost for each class with weights that are inversely proportionate to their frequency in the data (Han, Williamson, and Fong 2021).

3.5.1 Decision Tree

Decision Tree is a predictive analysis model structured as a hierarchy of nodes and connecting branches, constructed using binary splits. The optimal hyperparameters found from fine-tuning are shown in Table 3.5. For the rest of the model's parameters not shown here, the default values were used.

Decision Tree Classifier	
Parameters	**Values**
criterion	gini
splitter	best
max_depth	None
max_features	None
min_samples_leaf	1
min_samples_split	2

Table 3.5: Fine-tuned hyperparameters for Decision Tree.

The `criterion` parameter refers to the algorithm used to determine the optimal splits for the tree, which in this case was the Gini impurity; in short, this measures the probability of incorrect classification of a random datapoint in the data. The other parameters relate to limiting the structure of the tree in various ways (i.e., the number of nodes, splits, or layers).

3.5.2 Random Forest

Random Forest is an ensemble method that combines many decision tree classifiers and outputs the mode of their predictions as the final classification (Oktafiani, Hermawan, and Avianto 2024). Each tree is built using different random subsets of samples and features from the data using bagging techniques, thereby decreasing the risk of overfitting and increasing accuracy for classification (Salman and Al-Jawher 2024; Oktafiani, Hermawan, and Avianto 2024). This gives them an advantage over simple decision trees, albeit usually in the context of bigger datasets than the one used here.

The fine-tuned hyperparameters along with their respective optimal values, as determined by the estimator, are shown in Table 3.6. Default values were again used for remainder parameters not shown.

In addition to the same Decision Tree parameters is `n_estimators`, the number of trees, and `bootstrap`, which refers to the use of bootstrap sampling (random sampling from the data for each tree (Oktafiani, Hermawan, and Avianto 2024)).

Random Forest Classifier	
Parameters	**Values**
n_estimators	50
max_features	sqrt
max_depth	None
min_samples_split	7
min_samples_leaf	3
criterion	entropy
bootstrap	True

Table 3.6: Fine-tuned hyperparameters for Random Forest.

3.6 Anomaly Detection

The engineered feature set was also used for unsupervised anomaly detection (also called outlier detection), a task for identifying outliers (and inliers, by extension) in a given dataset. This means the models train and predict on the same data to determine possible outliers; although similar, it differs slightly from the task of novelty detection, which detects outliers in new, previously unseen data.

For these methods, fine-tuning was again performed using a grid search approach. A notable difference with these models from the previously discussed supervised classifiers in Section 3.5, however, is the lack of use of weighted classes to balance the dataset, since anomaly detection inherently assumes an imbalanced distribution of classes. Leave-one-out cross-validation was also not performed, since a testing set was not used.

3.6.1 Isolation Forest

Isolation Forest is similar to Random Forest, but with a few key differences that specialize it for the domain of anomaly detection instead. Proposed by Liu, Ting, and Zhou (2009), it is also an ensemble algorithm which constructs trees, here called "isolation trees", through iterative branching and partitioning the data with randomly selected features and random split values until the data points are isolated (Xu et al. 2023). Unique to this model, though, is the use of anomaly scores, which are calculated based on the average path length (i.e., from the root node until the isolated point) of all the isolation trees (Rosenhahn and Hirche 2024). It is shown to perform well with high-dimensional data (M. Naser and A. Z. Naser 2024) and thus is included here.

Just like the classification with Random Forest, feature scaling is not required for Isolation Forest, and doing so has no effect. Table 3.7 shows the hyperparameters that were fine-tuned along with the optimal values found for each. All others were left as their default values.

Isolation Forest	
Parameters	**Values**
max_samples	0.5
max_features	1.0
contamination	0.25
n_estimators	5
bootstrap	False

Table 3.7: Fine-tuned hyperparameters for Isolation Forest.

A notable parameter here not introduced yet by previous models—due to being unique to anomaly detection—is `contamination`, which reflects the proportion of outliers in the dataset.

3.6.2 One-Class SVM

A One-Class SVM is an unsupervised SVM used in the domain of anomaly detection which projects data into a higher-dimensional space and finds the hyperplane that maximally separates this data from the origin of said space (Boiar, Liebig, and E. Schubert 2022). Various kernel functions are utilized for this projection, and the resulting decision boundary encompasses inliers, with datapoints outside of it being considered outliers.

An initial step of standardization was performed on the data (Equation 4), and then the model was then fine-tuned to find the optimal parameters, shown in Table 3.8.

One-Class SVM	
Parameters	**Values**
kernel	poly
degree	2
coef0	0.3
gamma	0.0001
nu	0.5

Table 3.8: Fine-tuned hyperparameters for One-Class SVM.

Here, `nu` is essentially the same as the `contamination` parameter that other anomaly detection models have, the fraction of the data which comprises outliers, while `gamma` relates to the complexity of the model's decision boundary. Also of note is the use of a polynomial kernel, which handles non-linearity in the data and is influenced by `degree` (of the polynomial function, here being quadratic) and `coef0`.

3.6.3 Local Outlier Factor

Local Outlier Factor (LOF), first proposed in 2000 by Breunig et al. (2000), is a proximity-based clustering algorithm used for anomaly detection that is based on k-nearest neighbors, but additionally utilizes a concept called local density to identify potential outliers. In brief, the lower the calculated density between a given data point and its neighbors, the higher the likelihood of it being an outlier (Cheng, Zou, and Dong 2019).

Data was again scaled using standardization. Table 3.9 shows the model's hyperparameters that were fine-tuned; the rest were left as their defaults.

Local Outlier Factor	
Parameters	**Values**
n_neighbors	7
algorithm	kd_tree
leaf_size	3
metric	minkowski
p	1.5
contamination	0.25

Table 3.9: Fine-tuned hyperparameters for Local Outlier Factor.

For this model, the `n_neighbors` parameter refers to the number of nearest neighbors being considered, which were then identified using a KD-tree (k-dimensional tree) `algorithm`. Although a deeper explanation for this algorithm is beyond the scope of this thesis, it tends to be efficient for relatively small and low-dimensional data.

The other parameters worth mentioning here, as they are specific to this kind of model and related to one another, are `metric` and `p`. The former is the metric used for computing distances to the nearest neighbors, for which the Minkowski distance—a generalization of both the Euclidean and Manhattan distances—was used. The order of the Minkowski distance is represented by `p`, with a value of 1 or 2 corresponding to the Manhattan or Euclidean distance, respectively. The optimal value for this was found to be 1.5, which is effectively a balance between both.

3.7 Model Evaluation

To evaluate all five models, precision, recall, and F_1-score was calculated, given by Equations 5, 6, and 7, respectively. These are standard metrics which are commonly used in machine learning tasks, including for supervised classification and unsupervised anomaly detection (Agyemang 2024; Braei and Wagner 2020; Maya, Ueno, and Nishikawa 2019; Elmrabit et al. 2020; Oktafiani, Hermawan, and Avianto 2024), making them a reasonable choice. For anomaly detection, these measure the models' ability to correctly predict the target class, here being the constructed languages.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{6}$$

$$F_1\text{-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{7}$$

For evaluation of the supervised classifiers, the numbers of True Positive (TP), True Negative (NP), False Positive (FP), and False Negative (FN) predictions from all iterations of the leave-one-out cross-validation process during fine-tuning were aggregated together. The aggregated counts for each estimator (combination of parameters) were then used to calculate the metrics.

Due to training and predicting on the entire dataset, though, evaluating the unsupervised anomaly detection models was done by simply calculating the metrics for each estimator's overall predictions during fine-tuning.

In both tasks, the estimator which achieved the highest F_1-score was determined as having the optimal parameters for the respective model. It is important to note, however, that because of the limited size of the dataset, evaluation of these models proved challenging, as there was not enough data to create holdout sets for testing. As a result, the scores measuring their performance do not sufficiently indicate their ability to make predictions on new, unseen data.

3.8 Feature Importance with SHAP

In order to further analyze the selected linguistic features, their importances were also calculated. Feature importance is a measurement of the extent that each feature contributes to model prediction, consequently indicating how relevant or useful a particular feature is (or is not). In the context of this investigation, calculating these can provide insight into the discriminative ability that some language features may provide over others for being classified as belonging to either a constructed or natural language. It is necessary to note, however, that this is principally an interpretation of the models, from which analysis of the features can be tentatively inferred.

There are several ways of measuring feature importances, with two of the most commonly used methods being impurity-based and permutation-based. However, for the purposes of this thesis, the SHapley Additive exPlanation (SHAP) framework, which is derived from cooperative game theory, was used instead. A key advantage of using SHAP over other approaches is that it contains a method which is model-agnostic, meaning it can be utilized to interpret any model. Specifically, the Kernel SHAP method was used for both of the supervised and two of the unsupervised models: Isolation Forest and One-Class SVM. In brief, Kernel SHAP is an adaption of linear Local Interpretable Model-agnostic Explanations (LIME) which employs a weighted linear regression to estimate SHAP values, the computed output (Lundberg and Lee 2017). These SHAP values can then be used for global interpretation of feature importance for a model, as well as comparison across different models.

In all instances, the entire dataset was used to make predictions and derive the corresponding SHAP values, which consequently meant the local outlier factor model was not included here as it requires being used in a semi-supervised setting and detecting novelty anomalies in new data rather than unsupervised anomaly detection, which is beyond the scope of this thesis.

4 Results

This section starts by reporting the results of the methods implemented for, and the measurements derived from, the applied step of feature engineering. Each individual feature is also visualized in the format of a one-dimensional graph containing the distribution of languages and their corresponding values for said feature, in order to better interpret the empirical data, as well as to identify potential trends more easily. Initial, surface-level interpretation of these distributions will be addressed here, with deeper discussion and analysis continued in Chapter 5 that delves into possible explanations for the various observations.

Following this are the results of dimensionality reduction on the data using PCA, visualized in two-dimensional space. Then, the results of each of the fine-tuned models used for supervised classification and unsupervised anomaly detection are shown and compared. Lastly, the findings of the SHAP analysis for each model (except for local outlier factor) are reported, providing a better explanation of the models and examining global feature importances.

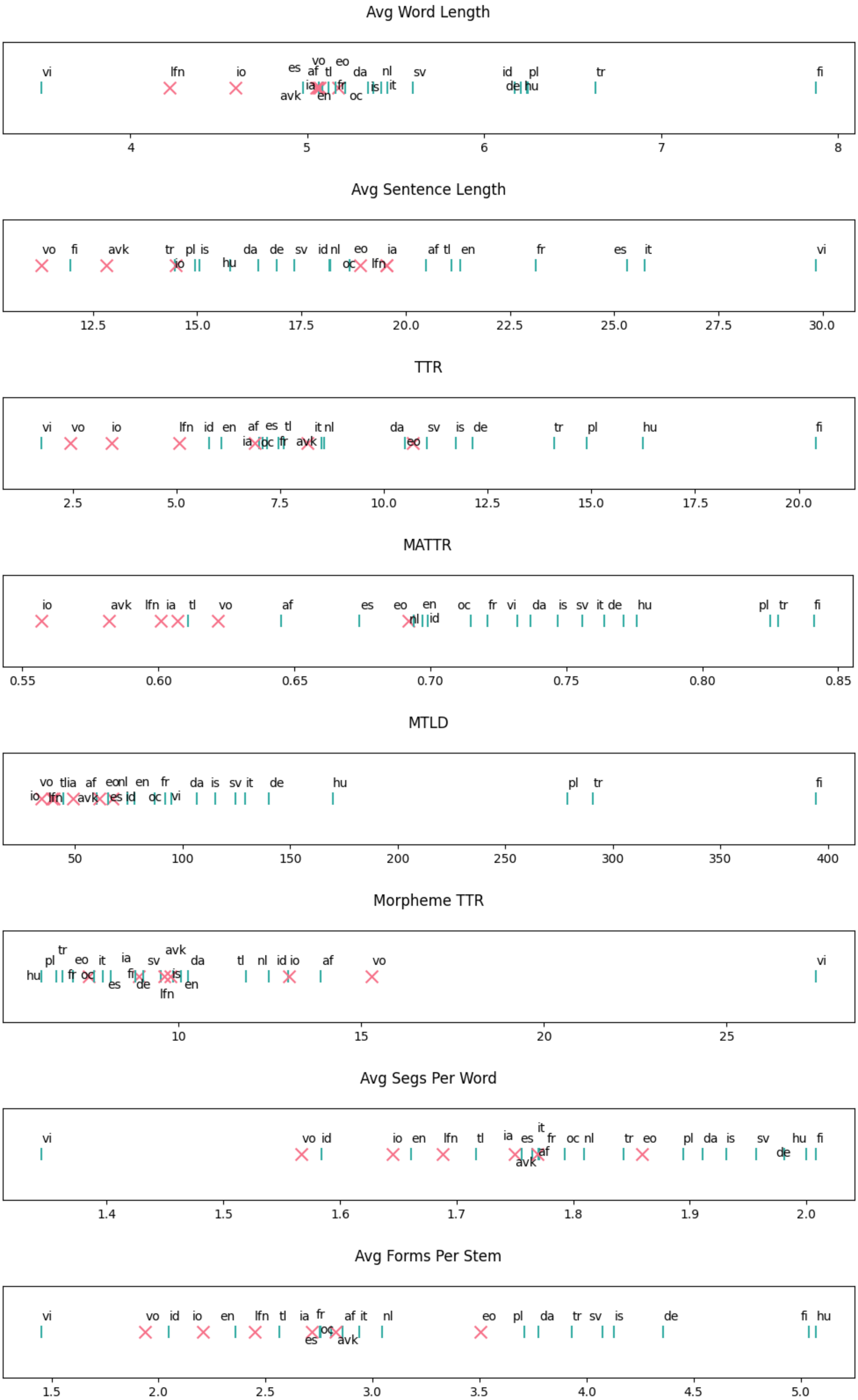
As a reminder, these findings correspond to a relatively small dataset of only 24 languages. This detail will also be relevant later in this chapter when the scores for the supervised and unsupervised models are reported, as only one difference in a model's predictions change the score more considerably than what would happen with a larger dataset. Additionally, the results of the two supervised models, decision tree and random forest, correspond to the leave-one-out experiments performed for fine-tuning, and thus were derived from the best-performing model.

4.1 Results of Feature Engineering

Table 4.1 shows the full set of features for each language of the dataset and their respective measurements rounded to three decimals places. Additionally, the column *Type* shows their labels as either constructed or natural languages (*con* or *nat*, respectively). The corresponding one-dimensional plots for the features can be seen in Figure 4.1, with each language represented by its ISO code and the type of language distinguishable based on the marker and color (red X's correspond to constructed languages, and green vertical lines correspond to natural languages).

Language	Type	Avg Word Length	Avg Sentence Length	TTR	MATTR	MTLD	Morpheme TTR	Avg Segs Per Word	Avg Forms Per Stem	Char Dist Entr	Word Dist Entr	Text Entr	Lex Entr	Rev Lex Entr
Esperanto	con	5.175	18.909	10.708	0.692	67.482	7.535	1.859	3.506	4.164	10.923	4.435	6.303	7.016
Dutch	nat	5.419	18.194	8.559	0.694	74.165	12.467	1.809	3.044	4.117	10.593	4.389	6.407	6.746
Icelandic	nat	5.375	15.055	11.727	0.747	115.342	9.847	1.931	4.128	4.468	11.512	5.455	5.993	6.376
Polish	nat	6.248	14.951	14.890	0.825	278.888	6.639	1.894	3.709	4.553	12.905	5.072	5.611	5.898
French	nat	5.160	23.120	7.461	0.721	91.865	7.109	1.771	2.759	4.179	10.711	4.104	6.256	6.779
Volapük	con	5.072	11.266	2.455	0.622	39.447	15.287	1.567	1.938	4.256	7.666	1.281	8.702	9.037
Afrikaans	nat	5.067	20.496	6.987	0.645	59.938	13.894	1.770	2.861	4.072	9.993	4.757	6.639	6.986
Vietnamese	nat	3.498	29.835	1.749	0.732	94.751	27.439	1.344	1.453	4.855	9.717	4.768	11.878	11.432
Occitan	nat	5.215	18.660	7.185	0.715	87.187	7.674	1.793	2.805	4.173	10.546	3.530	6.741	7.118
English	nat	5.087	21.301	6.079	0.697	77.659	10.049	1.661	2.360	4.167	10.673	4.771	7.106	7.601
Italian	nat	5.455	25.727	8.505	0.764	129.111	7.919	1.765	2.939	4.029	11.308	4.573	5.563	6.123
Interlingua	con	5.050	19.547	6.880	0.607	49.015	8.904	1.750	2.715	4.032	10.005	3.886	6.406	6.958
Swedish	nat	5.597	17.322	11.031	0.756	124.469	9.496	1.957	4.074	4.294	11.488	4.830	6.207	6.517
LFN	con	4.221	19.532	5.063	0.601	40.079	9.769	1.688	2.448	3.912	9.316	4.471	7.716	8.436
Danish	nat	5.346	16.466	10.517	0.737	106.412	10.259	1.911	3.776	4.197	11.274	5.037	6.408	6.796
Hungarian	nat	6.242	15.782	16.234	0.776	169.833	6.240	2.000	5.071	4.543	12.443	5.208	5.584	5.951
Indonesian	nat	6.173	18.164	5.782	0.699	74.365	12.993	1.584	2.048	4.072	11.142	3.982	7.285	7.342
Tagalog	nat	5.119	21.102	7.593	0.611	44.385	11.830	1.717	2.563	3.895	9.991	4.374	6.803	7.040
Turkish	nat	6.630	14.458	14.097	0.828	290.829	6.805	1.843	3.932	4.386	13.151	4.729	5.028	5.422
Ido	con	4.594	14.484	3.433	0.557	34.395	13.024	1.645	2.208	4.077	8.055	1.266	7.471	8.267
Spanish	nat	4.978	25.315	7.085	0.674	65.538	8.131	1.756	2.752	4.046	10.327	4.066	6.059	6.664
Finnish	nat	7.874	11.969	20.409	0.841	394.346	8.806	2.008	5.037	4.144	13.729	4.529	4.994	5.479
German	nat	6.206	16.907	12.128	0.771	139.978	9.026	1.981	4.356	4.230	11.601	4.530	5.323	5.743
Kotava	con	5.060	12.824	8.153	0.582	61.499	9.611	1.769	2.827	4.186	10.287	3.759	7.809	8.096

Table 4.1: Complete set of all 13 features for every language in the data, as well as each language's label (*Type*), which denote constructed or natural language as *con* or *nat*, respectively. Each feature's value is rounded to 3 decimal places.


Avg Word Length
4
5
6
7
8
Avg Sentence Length
12.5
15.0
17.5
20.0
22.5
25.0
27.5
30.0
TTR
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
MATTR
0.55
0.60
0.65
0.70
0.75
0.80
0.85
MTLD
50
100
150
200
250
300
350
400
Morpheme TTR
10
15
20
25
Avg Segs Per Word
1.4
1.5
1.6
1.7
1.8
1.9
2.0
Avg Forms Per Stem
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

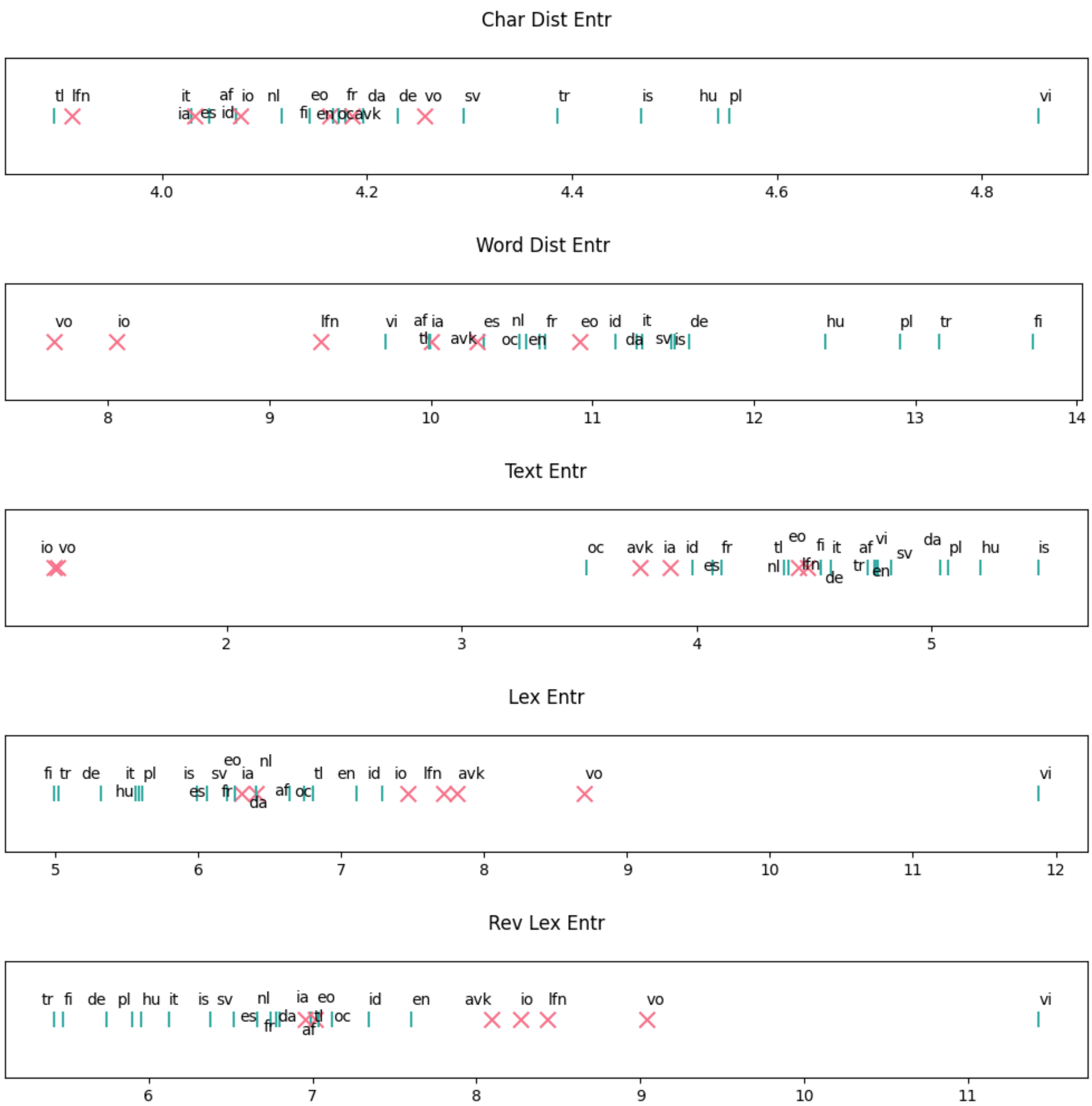


Figure 4.1: One-Dimensional Plots for Feature Distributions

Looking at the two features measuring text complexity first, average word length and average sentence length, one can see clustering left of the center in the former and, in comparison, a slightly more uniform distribution in the latter. Regarding average word length, Vietnamese and Finnish being at opposite extremities of shortest and longest lengths, respectively, aligns with expectations given the nature of their morphological systems. This pattern of both languages being at either end of the distribution appears again for average sentence length, and in fact is noticeable in many of the other feature distributions as well. Notably, all six constructed languages in the dataset appear on the left side of both distributions, left of the median values, and Volapük has the shortest average sentence length of all languages. While having some level of correlation to specific features (e.g., morphology) of the languages, both of these measures are also very influenced by the quality and content of the text data itself, such as its domain and the writing style of its authors.

The three measures for lexical diversity, TTR, MATTR, and MTLD, again show Finnish to be an extreme instance, with the highest values for all three. Likewise, all of the constructed languages again appear on the left side of the distributions; interestingly, of these, Esperanto is closest to center for both TTR and MATTR. MATTR in particular also shows an almost complete divide between constructed and natural languages in the distribution, with the exception of Tagalog and Esperanto. Additionally, the distribution for MTLD reveals a cluster on the furthermost left side, with all six constructed languages having extremely low values and Polish, Turkish, and Finnish appearing as on the opposite end with significantly higher values.

Similar clustering behavior can be observed in the distributions for the three measures of morphological complexity, particularly the first two which are imbalanced. In all, however, Vietnamese again appears as an extreme case, and this is especially apparent in the distributions for morpheme TTR and average segmentations per word, where it is significantly isolated from the rest—likely a reflection of its isolating morphology. When comparing these to the distributions for the lexical and text complexity features, constructed and natural languages appear to overlap more, suggesting that morphology complexity may not be as much of a discriminative linguistic feature between the two.

In the last group of features, corresponding to the five measurements of entropy, interesting patterns of clustering and imbalanced distributions again emerge in the findings. For character distribution entropy, the constructed languages are again grouped together on the left side. Perhaps unsurprisingly, given the exceedingly large size of its alphabet (i.e., the 93 lowercase alphabetical characters that comprise its corpora, a number which includes all variations of diacritics), Vietnamese is the highest value. Interestingly, though, this is followed next by Polish, despite having an alphabet size that is lower than several other languages in the study, suggesting the influence of other factors as well (e.g., orthography). On the other end of the spectrum is Tagalog with the lowest character distribution entropy, followed closely by Lingua Franca Nova.

In contrast, the measurements for word distribution entropy and text entropy both produced rather different results; rather than having a cluster on the left side, one appears in the center and right side, respectively. In both cases, Volapük and Ido have the lowest values, and in the latter case for text entropy, they are significantly lower than those of the other languages. As entropy is essentially a measure of predictability, this may be surmised as reflecting Volapük's intentional design of high regularity, especially with regard to morphology. The same can be said of Ido, though this along with comparison to the findings of the other constructed languages will be explored further in Chapter 5.

Last are the measures for lexical and reverse lexical entropy, which have very similar distributions. Vietnamese again emerged at one end of the spectrum with the highest entropy value, while agglutinative languages such as Finnish and Turkish appear at the opposite end with the lowest. Perhaps the most interesting finding here, however, is the cluster of constructed languages near the center of both distributions—with the notable absence of Interlingua and Esperanto, who instead appear in the midst of the natural languages on the left side in both cases. On the surface, both of these measures for entropy seem to be significantly discriminative compared to the majority of the other features.

4.2 Results of PCA

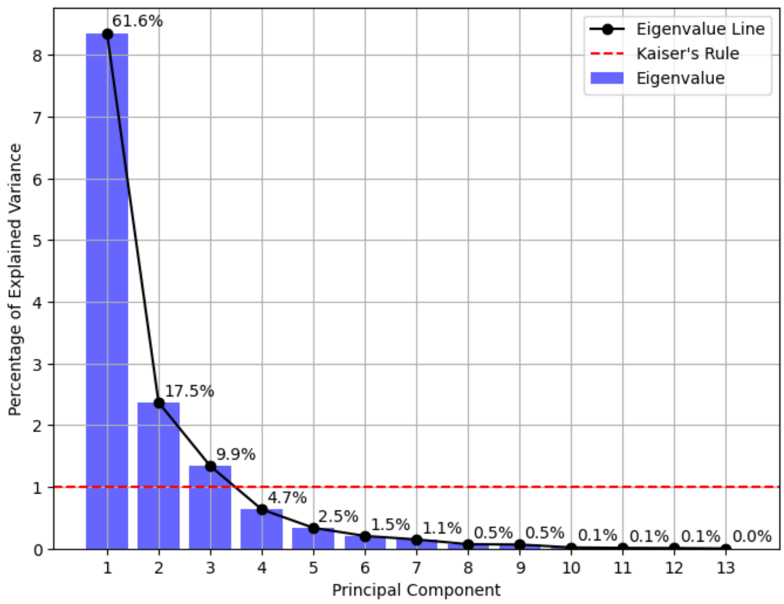


Figure 4.2: PCA Variance Screeplot - Kaiser Criterion

The result of applying the Kaiser criterion, shown in Figure 4.2, identified three principal components which have eigenvalues greater than 1 and thus capture the most significant portion of the variance, which correspond to contributing to 61.6%, 17.5%, and 9.9% of the total variance.

To interpret the degree to which each of the features in the data contributed to the formation of these dimensionally-reduced principal components, and therefore also determine the features that were the most influential (denoted in bold), the loadings are provided in Table 4.2. Each loading indicates the magnitude of contribution to a feature, with positive or negative signs denoting the direction of influence (i.e., a positive loading means a positive correlation to

	Avg Word Length	Avg Sentence Length	TTR	MATTR	MTLD	Morpheme TTR	Avg Segs Per Word	Avg Forms Per Stem	Char Dist Entr	Word Dist Entr	Text Entr	Lex Entr	Rev Lex Entr
PC1	0.312	-0.152	**0.343**	0.271	0.284	-0.25	0.318	0.328	0.042	0.323	0.19	-0.305	-0.319
PC2	-0.048	0.243	0.062	0.364	0.239	0.365	-0.154	0.017	**0.561**	0.214	0.318	0.283	0.214
PC3	-0.232	**0.671**	-0.075	0.02	-0.237	-0.175	0.045	-0.06	-0.263	0.099	0.511	-0.171	-0.168

Table 4.2: Loadings for the top three principal components, with the most influential feature for each in bold.

the principal component, and vice versa). Thus, for example, the first principal component *PC1* was most positively influenced by TTR and most negatively influenced by reverse lexical entropy, which have loadings of 0.343 and -0.319, respectively, and the next two overall most influential features following TTR were average forms per stem (0.328) and word distribution entropy (0.323). Similarly, for *PC2*, the top contributing features were character distribution entropy (0.561), followed by morpheme TTR (0.365) and MATTR (0.364); for *PC3*, these were average sentence length (0.671), text entropy (0.511), then character distribution entropy (-0.263).

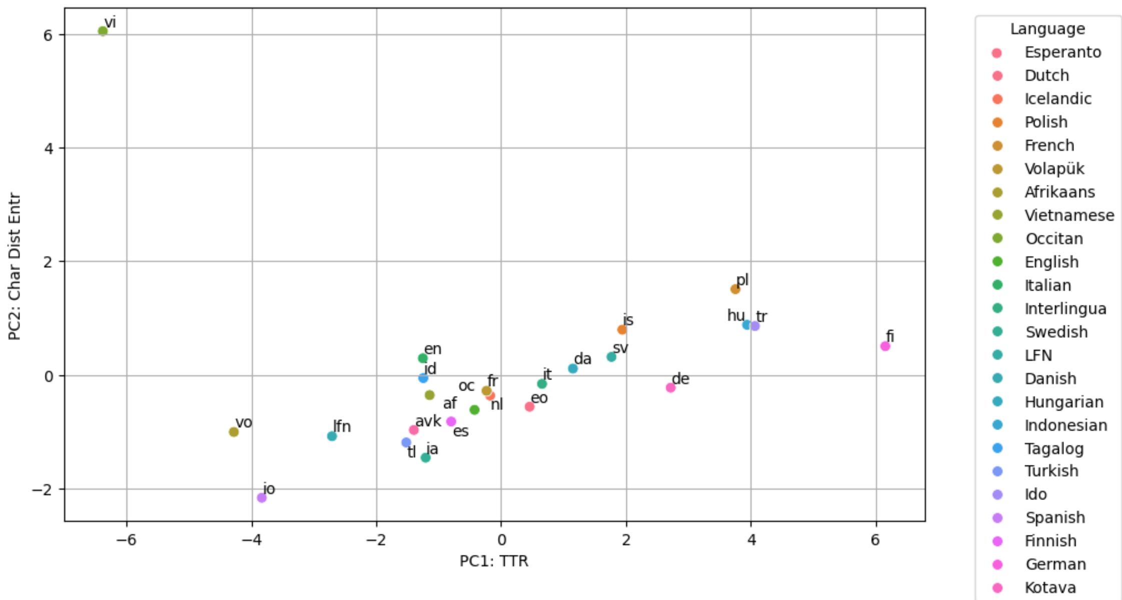


Figure 4.3: Principal component analysis of the features using 2 principal components.

Figure 4.3 shows the results of the dimensionality reduction performed on the data using PCA.[4] Note that since this is a two-dimensional diagram, it

[4] A script was used to increase the readability of the annotations in the graph: https://github.com/Phlya/adjustText

depicts only the top two principal components. The values along both axes denote the principal component scores. Additionally, the top influential feature for each, TTR and character distribution entropy, are also included in the axis labels for easier interpretation.

Immediately noticeable in the diagram is the isolated position of Vietnamese at the top left, having the highest *PC2* score and lowest *PC1* score. Another interesting observation can be seen in the tight cluster of languages at the bottom center, to the left of which Volapük, Ido, and Lingua Franca Nova appear relatively close together. Another small cluster comprised of Polish, Hungarian, and Turkish is visible right of center, with Finnish appearing farthest on the right side. Overall, these findings—combined with the loadings shown in Table 4.2—reiterate the previously discussed results in Section 4.1. However, the relatively small degree of separation that Volapük, Ido, and Lingua Franca Nova from all the other languages, together with the very adjacent positions that Esperanto, Interlingua, and Kotava have to so many of the natural languages, is much more visible in this format.

4.3 Results of Supervised Classification

Model	**F_1-score**	**Precision**	**Recall**
Decision Tree	0.83	0.83	0.83
Random Forest	0.83	0.83	0.83

Table 4.3: Precision, recall, and F1-scores of the fine-tuned supervised binary classification models.

As Table 4.3 shows, both classifiers achieved exactly the same precision, recall, and F_1-scores. This comes as a bit of a surprise, since Random Forest is a comparatively more advanced model, but possible underlying reasons for this will be discussed in Chapter 5.

Figure 4.4 shows the resulting structure of the fine-tuned decision tree. To briefly explain how this is interpreted, for each node of the tree except the terminal ones, the top line is the condition for the subsequent split, and each split is a binary partition of the remaining number of samples. For example, the condition for the root node is *MTLD* less than or equal to 70.824, which is true for 9 samples and false for the other 15. In addition, *value* shows the weighted counts for both classes, with *class* being equal to the majority class at that split, and *gini* ranges from 0.0 (the samples all belong to one class) to 0.5 (the samples are evenly distributed, referred to as maximum impurity). Thus, the diagram indicates that the features MTLD, average sentence length, and average word length were the most discriminating features for this model's predictions.

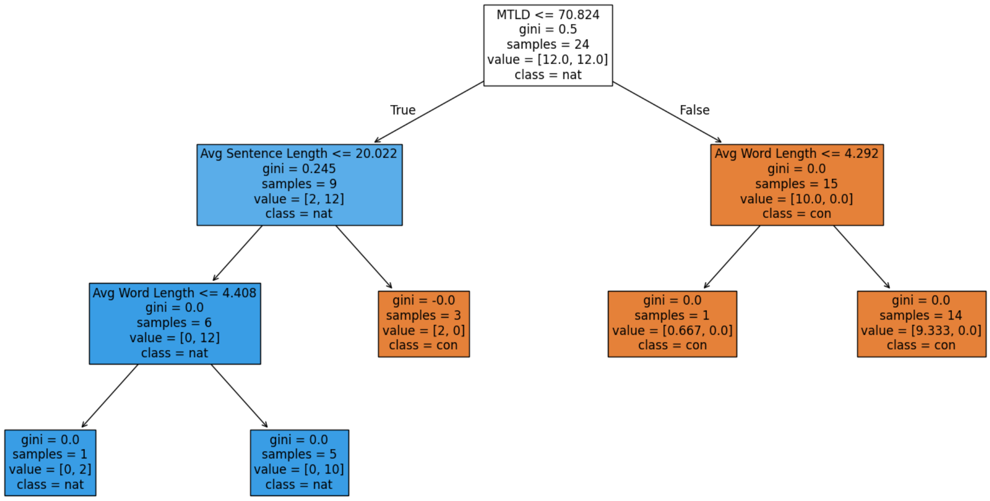


Figure 4.4: Tree structure diagram for decision tree classifier

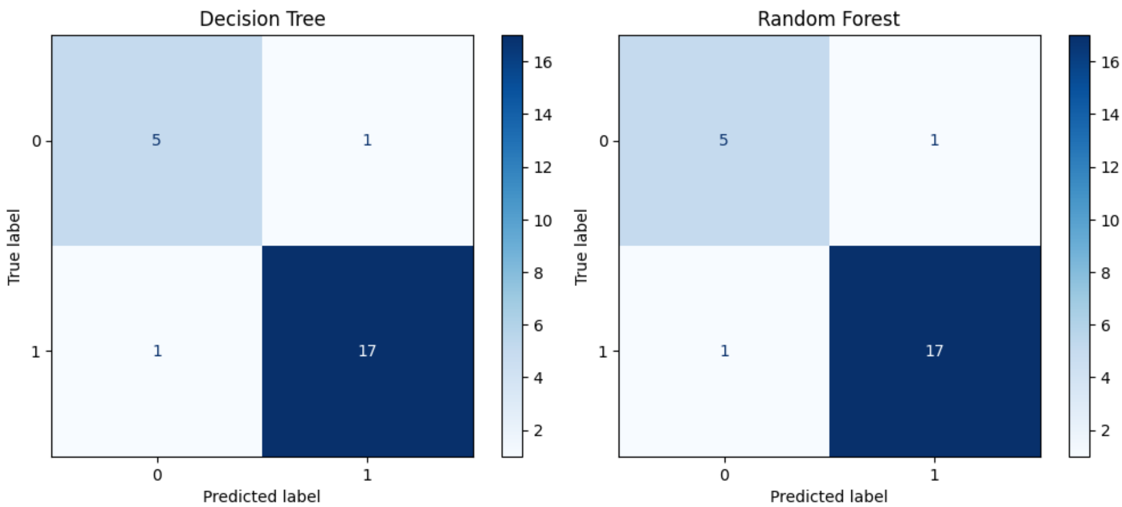


Figure 4.5: Confusion matrices for the fine-tuned supervised binary classifiers: decision tree (left) and random forest (right).

In the resulting confusion matrices for the fine-tuned supervised binary classifiers seen in Figure 4.5, the classes for *constructed* and *natural* correspond to 0 and 1, respectively, with constructed languages being the positive class. Both models made the same number of True Positive, False Positive, False Negative, and True Negative predictions. For the decision tree (left), Esperanto was incorrectly predicted as negative and Dutch incorrectly as positive. Similarly, the random forest (right) erroneously predicted Esperanto as negative too, but with Tagalog incorrectly as positive. This means, then, that both models mistakenly classified Esperanto as a natural language.

4.4 Results of Unsupervised Anomaly Detection

Model	F_1-score	Precision	Recall
Isolation Forest	0.67	0.67	0.67
One-Class SVM	0.73	0.80	0.67
Local Outlier Factor	0.67	0.67	0.67

Table 4.4: Precision, recall, and F_1-scores of the fine-tuned unsupervised anomaly detection models.

Table 4.4 shows the precision, recall, and F_1-scores for the unsupervised anomaly detection models. The isolation forest and local outlier factor achieved identical performance for precision, recall, and F_1-scores, all of which were 0.67. On the other hand, despite also achieving the same score for recall, one-class SVM performed slightly better in terms of precision and F_1-score, with a score of 0.80 and 0.73, respectively.

The resulting confusion matrices for all three unsupervised models are provided in Figure 4.6. Here again, constructed languages are the positive class being predicted (positive equating to an anomaly), with 0 and 1 representing the constructed and natural language samples, respectively.

Overall, the unsupervised models performed comparable to one another, with all three correctly predicting 4 instances of anomalies. Regarding their erroneous predictions, the one-class SVM falsely considered Esperanto and Interlingua to be non-anomalies, or natural languages, and Vietnamese as an anomaly, or a constructed language. Interestingly, both the isolation forest and local outlier factor models made exactly the same errors, with the addition of incorrectly predicting Finnish to be an anomaly instance in both cases too.

4.5 Results of SHAP

The results of the Kernel SHAP method are visualized in beeswarm plots for global analysis, which are explained how to read here. The features, ranked in descending order according to their importance, comprise the y-axis. The x-axis, centered on zero (0.0), corresponds to SHAP values—measurements of the impact that a particular instance had on model prediction, represented in terms of magnitude and either positive or negative. Finally, the color coding spectrum represents the value of that instance, with the highest values denoted by red and the lowest ones denoted by blue.

Figure 4.7 shows the two beeswarm plots corresponding to the supervised classifiers. Positive SHAP values correlate to constructed languages, and negative SHAP values correlate to natural languages. For the decision tree, only two features had any impact on the model's predictions: MTLD and average

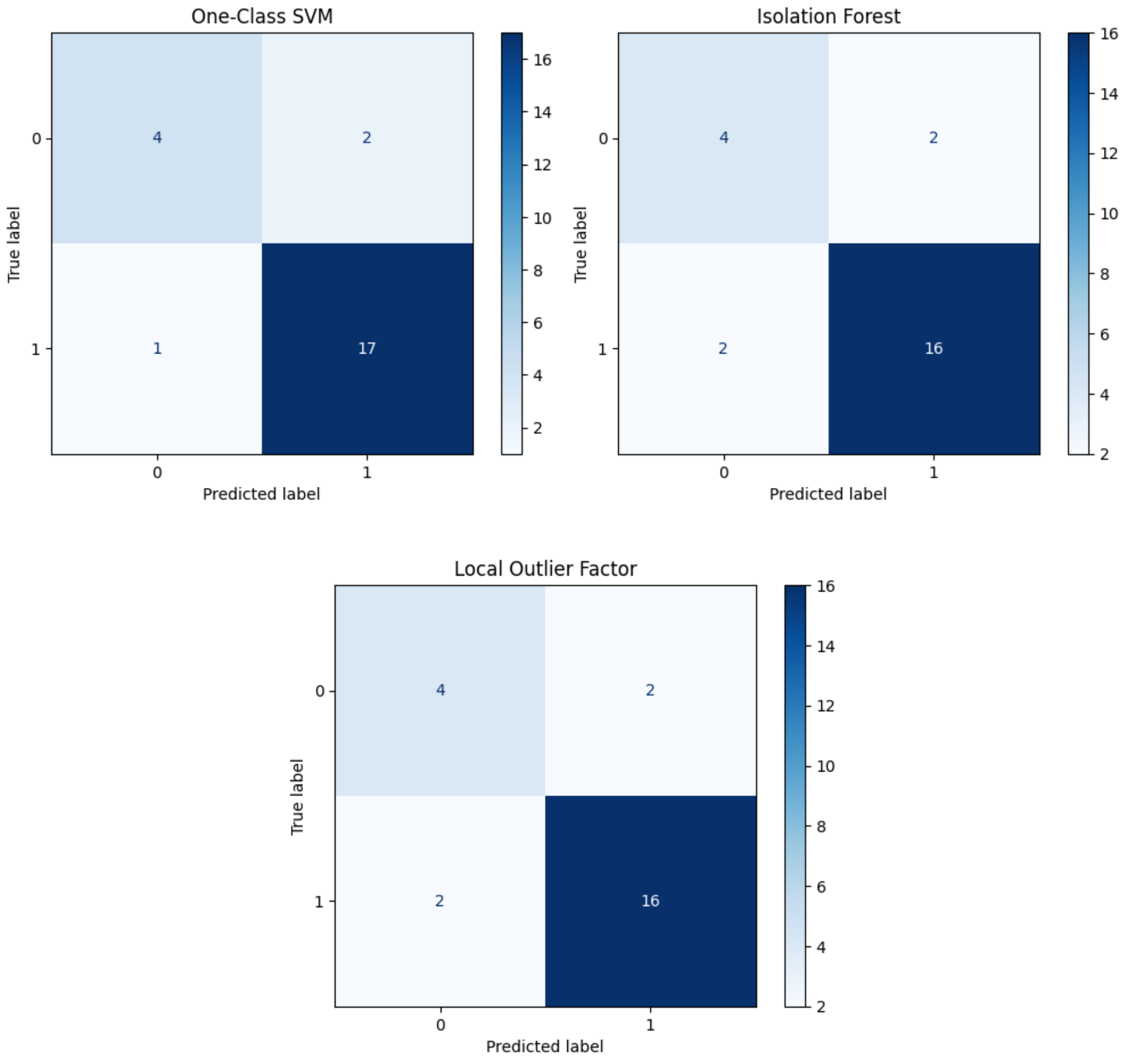


Figure 4.6: Confusion matrices for the fine-tuned unsupervised anomaly detection models: one-class SVM (top left), isolation forest (top right), and local outlier factor (bottom).

sentence length. Low values of the former correlated to a stronger positive impact, while high values of the latter correlated to a stronger negative impact. Notably, this also coincides with the findings shown by the tree structure diagram in Figure 4.4. For the random forest, MTLD was again the most important, with lower values again correlating to having a stronger positive impact, followed by MATTR with the same correlation to a lesser extent. In contrast to the decision tree though, average word length was a less important feature here, and the random forest utilized a broader selection of features for its predictions overall. However, the clustering around zero shown by impacts for word distribution entropy, average forms per stem, reverse lexical entropy, TTR, and morpheme TTR suggest these features had very little influence on the random forest's predictions.

The beeswarm plots for the two analyzed unsupervised models are shown

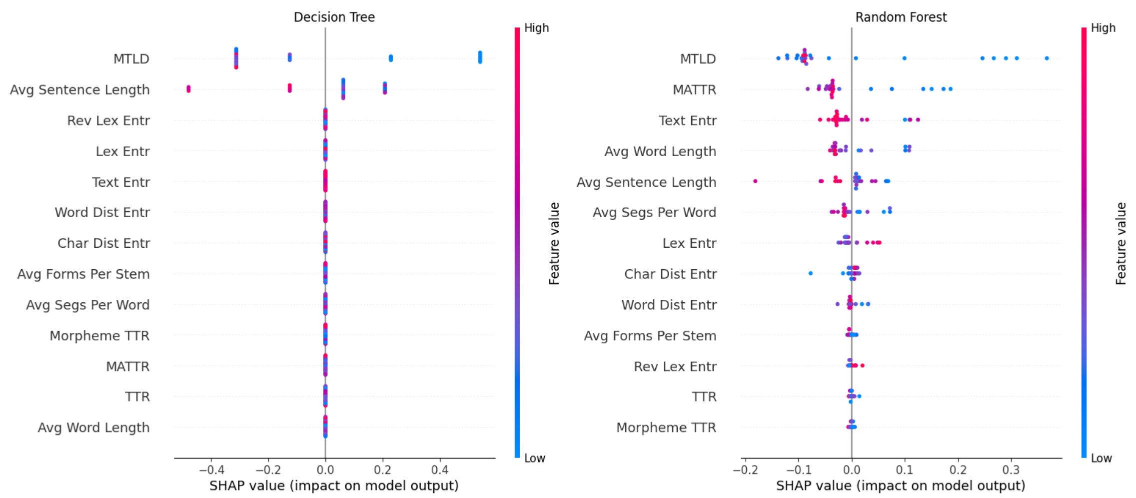


Figure 4.7: Beeswarm plots for SHAP results on fine-tuned supervised models: decision tree (left) and random forest (right).

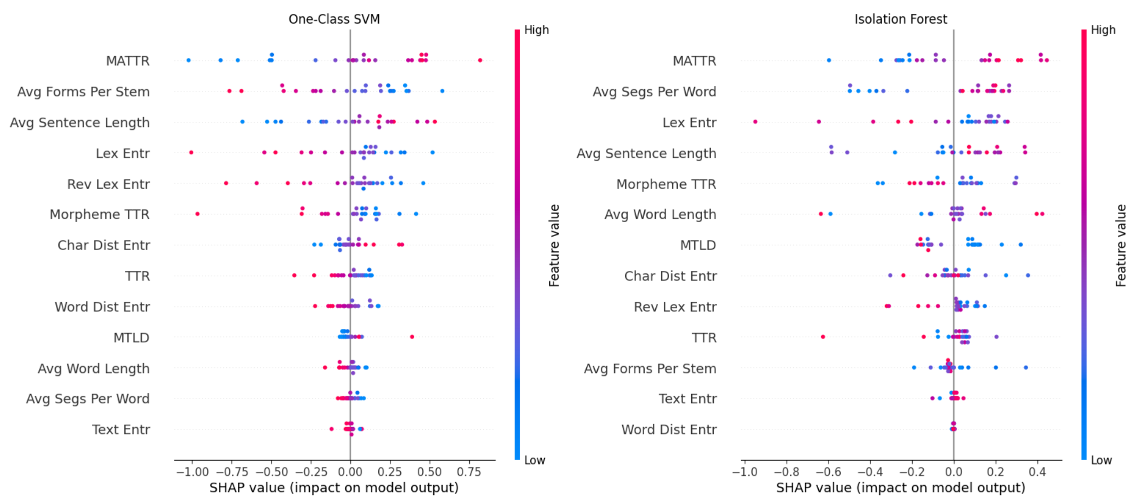


Figure 4.8: Beeswarm plots for SHAP results on fine-tuned unsupervised models: one-class SVM (left) and isolation forest (right).

in Figure 4.8. As these correspond to anomaly detection, their interpretation is slightly different due to the way the models make predictions. A negative anomaly score indicates a predicted anomaly (constructed language); likewise, a negative SHAP value indicates the same, and a positive SHAP value indicates a natural language. Therefore, the plots show that MATTR was the most important feature for both models, with mid to low feature values being predicted as anomalies, suggesting that this was the strongest indicator for detecting anomalies in the dataset. Additionally, average sentence length and lexical entropy were highly influential for both models as well, with low values for the former and high values for the latter indicating anomalies. However, when comparing these with the feature results in Table 4.1 and their corresponding distributions shown in Figure 4.1, some possible discrepancies also appear at first glance. For instance, the second most influential feature for the one-class

SVM, average forms per stem, shows that high feature values were seemingly indicative of an instance being a constructed language—contradictory to what the feature results shows. MTLD's influence on the isolation forest shows something similar, with a cluster of several mid to high values apparently indicating a constructed language to the model; if we compare this to the plot for random forest, we see a similar cluster of mid to high values on the left side too, but in this case these instances correspond to predictions for natural language, opposite to the cluster for the isolation forest. This shows an interesting contrast between the two models, where the same feature can influence the models in different ways.

5 Discussion

This section begins by revisiting the results of the feature engineering more in-depth, specifically the feature distribution plots from Figure 4.1, and then connecting these to the findings of the PCA, supervised classifiers, unsupervised anomaly detection models, and SHAP analysis to holistically address the primary focus of this thesis—comparing constructed and natural language—as well as address whether or not these findings align with initial expectations. In doing so, the potential linguistic implications of the results will be examined, along with possible explanations for observed patterns and discrepancies. Furthermore, some methodological shortcomings in the approaches used, and how these may have also impacted the final results, will also be noted.

Analyzing the feature distributions plots shown in Figure 4.1 again, it is evident that, out of all languages in the dataset—both constructed and natural—Vietnamese and Finnish consistently appear as the most extreme instances for many of the linguistic features measured, often having either the lowest or highest values. There are some notable exceptions to this, though; for instance regarding lexical diversity, while Vietnamese has the lowest value for TTR, it is closer to the median of the distributions for MATTR and MTLD. In comparison, Ido has a low value for TTR as well, being only slightly higher that of Vietnamese (and Volapük). However, Ido has the lowest MATTR and MTLD values; in fact, all of the constructed languages have lower values for MATTR and MTLD than not only Vietnamese, but most of the other natural languages in the dataset too, outside of a few exceptions—a point we will return to when discussing the classification and anomaly detection. As noted previously, in the case of Vietnamese, having the lowest TTR (and indeed, having the lowest or highest values for other features too) might be explained simply by way of its highly isolating and monosyllabic morphology—being an extremity in the dataset in that regard—which consequently tends to result in more frequent repetition of certain vocabulary, such as when forming compound words. In contrast to TTR, MATTR and MTLD are able to capture more changes in lexical variation throughout a text (and are irrespective of overall text length) due to how they are calculated. Thus, they are less affected by lower counts of unique words (types) for an entire text. In a similar vein, this could also explain why the same drastic change in position within these distributions is not observed for many of the other natural languages in the dataset that have more complex morphologies in comparison (e.g., Swedish, Icelandic, German, Hungarian, Polish, Turkish, and Finnish), and thus a general tendency for less repetition and more unique word formation, as any lexical richness captured using the simple metric of TTR would likely still be observable even at a more granular level with MATTR and MTLD.

Regarding constructed languages within these three distributions for lexical diversity, there is a clear general pattern of having lower values compared to the natural languages, which could be attributed to several different underlying reasons. The first—which is actually more widely applicable to all of the language data and will be a recurring notion throughout this chapter—is the quality of the text data itself. In addition to the apparent prevalence of low-quality machine translations for, at the very least, Volapük's Wikipedia entries that was already noted in Section 3.1.3, the often niche communities of speakers of constructed languages means it is likely that much of the Wikipedia data for them was written by a small number of people. Consequently, this can limit lexical diversity. Another possible explanation, and indeed the focal point of this thesis's investigation, stems from the design of the constructed languages themselves. Being IALs, they were, generally speaking, created to be more regular in various linguistic aspects than their natural counterparts—some even more so than others. For instance, Ido's design as essentially a more regular version of Esperanto, including lexically, may explain it having much lower values for lexical diversity compared to Esperanto despite being directly derived from it. Similarly, having a relatively fixed lexicon—that is, a vocabulary that is not changing much over time, as is instead usually the case for natural languages—may be a factor here as well.

In the case of Finnish, a notable exception to this pattern of appearing as an extreme instance for the different feature values is, maybe surprisingly, in the distribution for morpheme TTR. Whereas it is one of the highest values for both of the other two measurements of morphological complexity, it instead appears closer to the median for this one, with Hungarian—who is from the same language family (Uralic) as Finnish—having the lowest. Even more shockingly, Finnish has an even higher morpheme TTR than Esperanto. Since this measurement is the ratio of unique morphemes to total morphemes in a text, one might infer then that Finnish tends to utilize a greater number of unique morphemes in its constructions than other languages like Hungarian. Another possible explanation for this discrepancy may also be from the unsupervised segmentation models used for calculating morphological complexity; due to limitations (such as the inclusion of many low-resource languages in the dataset), the precision and recall of the models' segmentations for each language could not be adequately evaluated with ease. Therefore, this could also merely be an error in the segmentations for Finnish. Conversely, it could be that the measurement for Finnish is correct and those of the other languages are erroneous instead; the segmentation model that was used is an implementation written by researchers in Finland, Smit et al. (2014), which lends credence to this possibility to some degree. However, determining the exact cause with more certainty would require deeper investigation.

Additional points worth mentioning include the extreme similarity of the other two feature distributions (more specifically, the order of the languages) for morphological complexity, average number of segmentations per word and average number of forms per stem. As they are both essentially measuring the same underlying morphological processes, just in slightly different ways, this resemblance is not a complete surprise, and it may point towards the inclusion of both features being a bit redundant; on the other hand, though, the results of the SHAP analysis suggest the opposite. Lastly, when specifically examining the constructed languages within the three distributions, they appear to have less of an overall separation from the natural languages compared to other features like MATTR, MTLD, or lexical entropy. That being said, there are also some consistent and familiar patterns; Esperanto again appears as the most extreme case out of the constructed languages, having the lowest morpheme TTR and highest average number of forms per stem and average number of segmentations per word of the six—values which are relatively comparable to many of the natural languages. Furthermore, Volapük was consistently on the opposite end of the spectrum from Esperanto each time (closely followed again by Ido); it is difficult to say, though, the degree to which this accurately reflects expectations based on prior research and understanding of Volapük's morphological structure, or is in fact another possible discrepancy in the results. According to Reagan (2019), Volapük is an agglutinative language described as being grammatically and morphologically complex, a description that seems understated in the face of claims of having upwards of 1,584 ways to conjugate a verb (Reagan 2019; Rogers 2011). As such, its high morpheme TTR would suggest this complexity is expressed using a relatively high number of unique morphemes. At the same time, though, the low values for average number of segmentations per word and average number of forms per stem arguably appear, on the surface, contradictory to this characterization, especially when compared to strongly agglutinative languages in the dataset like Hungarian and Finnish.

As was already mentioned in Section 4.1 regarding character distribution entropy, at first glance it appears to have some degree of correlation to the number of unique alphabetical characters in a given language's corpus, as would be expected. Intuitively, the other likely biggest contributing factor is orthography. Tagalog, for example, has the lowest entropy value of all the languages, which could be due to its frequent use of consonant-vowel patterns, as seen in words like *tarayan* (to be rude to someone), *baka* (cow), and *sala* (living room). Lingua Franca Nova being the lowest of the constructed languages could be in part explainable as reflecting its intended strict adherence to phonetic spelling; on the other hand, the same is also true for Kotava and (for the most part) Ido, yet these results show Esperanto's entropy to be lower than Kotava's, and Interlingua lower than all three, so this interpretation is left inconclusive. As a whole, the relatively similar character distribution entropies of some of the constructed languages (namely Interlingua, Esperanto, Lingua Franca Nova, and Ido) and their close proximity with the Romance languages in the distribution fits prior expectations, though, given their very closely-related and similar alphabets and orthographies.

The remaining four measures of entropy all show very interesting results as well, albeit in different ways. For word distribution entropy and text entropy, Volapük and Ido appear to be significantly more separated from the rest of the languages, especially for text entropy, where they have almost identical values. While their highly regular grammars and morphologies could again serve as some explanation for their low values for entropy, the clustering and variation of both features' distributions potentially suggest the presence of other underlying factors here as well. Also of note is the appearance of Vietnamese closer to the middle of both distributions, rather than being at one end. While, in the case of word distribution entropy, its still-relatively low value could again intuitively be explained by its high isolating and monosyllabic morphology, having a higher value than that of Lingua Franca Nova, Ido, and Volapük is more challenging to explain in this way, as their morphological systems are quite different. It is possible limitations from the corpus data itself are again an influence here. Additionally, in the case of text entropy, limitations regarding the LSTM model that was used for calculating it could be another contributing factor to the results. For instance, more fine-tuning of the model may impact the final text entropy measurements.

Lastly, regarding lexical and reverse lexical entropies, some interesting observations were already noted in Section 4.1, with the biggest of these arguably being the clear distinction between four of the constructed languages (Kotava, Ido, Lingua Franca Nova, and Volapük) from the rest of the languages. This would suggest both measurements of entropy are discriminative to at least some degree. Another interesting observation is that, while both distributions appear to be extremely similar, there are many instances of two adjacent languages being switched with one another. For example, in the lexical entropy distribution the lowest value is Finnish, with Turkish right next to it. In contrast, Turkish is the lowest value in the reverse lexical entropy distribution, with Finnish right next to it. This appears many other times as well, and it may be reflective of differences in affixation affecting entropy, as was originally hypothesized. Interestingly, however, this effect appears to be very subtle, and does not even change the separation of constructed and natural languages in the distribution. Though it is also worth mentioning that model limitations could again be influencing these results somehow, similar to the measurements for text entropy.

Additionally, Kotava's results are somewhat surprising here. Despite its intended *a priori* design, it does not stand out in any of the feature distributions. In fact, out of all six constructed languages, it never appears as having the highest or lowest value for a feature, instead always being somewhere in the middle. While the quality of the corpus data could likely be the main underlying reason for these results, with most or all of it probably being written by a very small number of people—considering how niche the language is—it would also be interesting to see how much is actually due to the language itself. That is to say, if such dissimilarity to all other human languages is actually not as noticeable empirically when measured for morphological diversity, lexical diversity, or entropy.

Broadly speaking, the constructed languages most of the time do not appear as distinct from the natural languages for the resulting features as might have been initially expected, and in fact some natural languages—namely Vietnamese and Finnish—consistently stood out more significantly in comparison. This general observation was also illustrated in the PCA performed on the data that was shown in Figure 4.3. Despite not being to the extent that was expected, however, there is still some overall level of distinction between the two types that can be observed in both the feature distribution plots and the PCA, and that is also seemingly recognizable by the supervised and unsupervised models.

5.1 Models & Feature Importance

It bears repeating that due to the relatively small size of the dataset being used, conclusions derived from the results of the models are only tentative and in fact may not be exactly the same in the case of a larger dataset. For example, the measured precision, recall, and F_1-scores of the models, while still providing useful insights, are not sufficient to conclusively determine broader implications about their overall level of success and are mostly not different enough from one another to analyze in more detail either beyond speculation. This can be seen in the case of the decision tree and random forest classifiers, which both have the same score for all three metrics despite model differences. With more data, such as the inclusion of more languages, these scores would likely be more informative. However, there were still some noteworthy observations from the models, as well as the applied SHAP analysis, that are of interest here.

The biggest of these was the reinforcement of the same aforementioned trends from the feature distributions in both the supervised classification and unsupervised anomaly detection, with Esperanto consistently failing to be considered a constructed language by all five models, and—in the case of anomaly detection specifically—difficulties with Vietnamese and Finnish as well. Even more interestingly, all three anomaly detection models also considered Interlingua to be a natural language. As Interlingua was designed to be closely resembling natural languages (specifically Romance languages) even to the point of intentionally introducing irregularities, as discussed in Section 3.1.1, this misclassification may be seen as its creators' goals having been successfully achieved. However, it is not exactly clear why this finding would appear for the anomaly detection models but not the random forest or decision tree. Likewise, the discrepancy between the one-class SVM correctly considering Finnish to be a natural language and the local outlier factor and isolation forest models mistakenly considering it constructed is also not immediately clear, although it could be inferred to potentially stem from the way the one-class SVM determines its decision boundary.

Delving a bit deeper into analyzing the SHAP global feature importances shown in Figures 4.7 and 4.8, lexical diversity was most discriminative for the four models analyzed in determining between natural and constructed languages, based on MTLD being the top influential feature for the supervised classifiers (decision tree and random forest) and MATTR being the top influential feature for the unsupervised anomaly detection models (isolation forest and one-class SVM). Measures of morphological complexity and entropy were also influential to different degrees, though varying widely across all models. For example, for the two anomaly detection models, lexical (and reverse lexical, in the case of the one-class SVM) entropy was the most influential of the entropy measurements. This is supportive of the respective distribution plots in Figure 4.1, which indeed show a clear separation between the constructed and natural languages—with the exception of Esperanto and Interlingua. However, these same two entropy features had very little influence on the random forest and essentially zero influence on the decision tree, potentially suggesting a difference in what are considered discriminative features for supervised classification versus unsupervised anomaly detection. Another possible explanation though could simply be that such differences are model-specific, and not actually reflective of the features themselves. As for measures of morphological complexity, the one-class SVM and isolation forest show the average number of forms per stem and average number of segmentations per word to be the second most important features, respectively. Finally, it is worth noting that in the case of the decision tree specifically, MTLD and average sentence length appear as the only two features which influenced model predictions, and they also appear as the two biggest features (followed by average word length) selected for splitting the tree as shown in Figure 4.4. This again might suggest a correlation between these two specific features and the discernibility between natural and constructed languages in the data, or it could be more model-specific criteria that merely reflects the differences in the ways both models work.

As a last bit of feature analysis using SHAP, feature importance at the local context with individual observations was examined for the isolation forest, shown in the force plots in Figure 5.4. These plots provide an additive view of each feature and how it influences the final prediction of the model, and although they could be analyzed rather extensively, only a specific focus is used for this discussion. Two natural (Finnish and English) and two constructed languages (Esperanto and Volapük) are given to illustrate one correct and incorrect model prediction for each.

From these, additional interesting information that was not shown in the results of the beeswarm plots becomes visible. Notably, each feature that influenced the model's final prediction are shown together with their associated magnitudes as the lengths of the bars. Looking at the instance for Esperanto, one can see the only feature to push it into predicting an anomaly was TTR, which clearly was not enough to lead the model to the correct prediction. Interestingly, TTR was also the biggest influence that pushed the model to (incorrectly) predict Finnish as an anomaly. English and Volapük were also influenced by TTR, but in both cases this influence was correlated with the model making a correct final prediction. When comparing these results to the feature distribution plot for TTR in Figure 4.1, however, it seems unclear why this feature would correspond to so much variance in prediction and influence for this particular model, as well as why it would be the only feature out of all thirteen to push the model towards correctly identifying Esperanto as an anomaly.

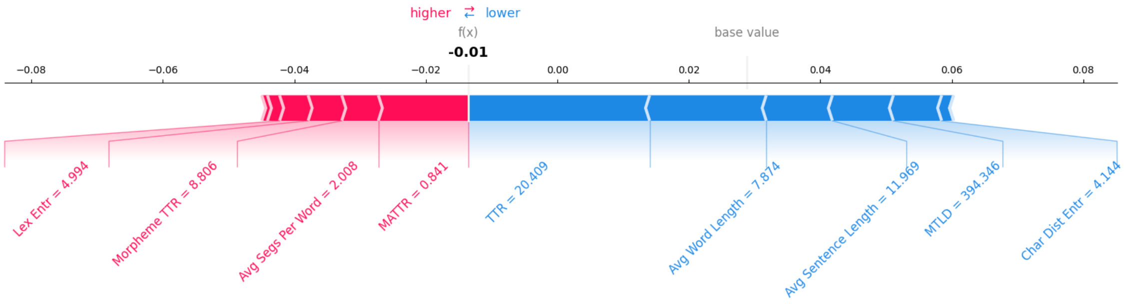


Figure 5.1: Isolation Forest - SHAP force plot for Finnish

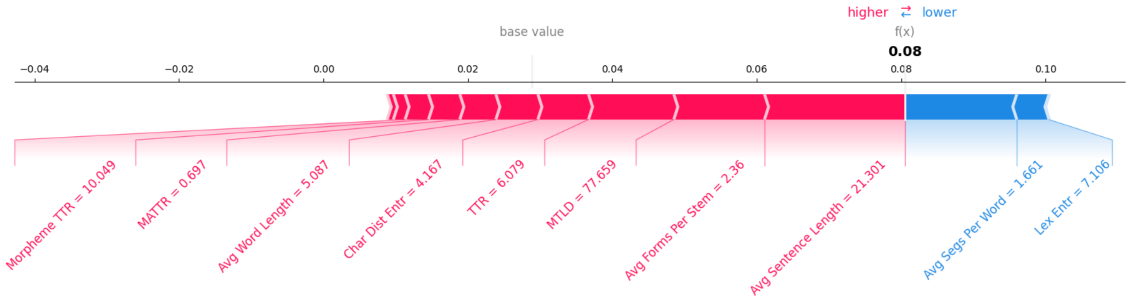


Figure 5.2: Isolation Forest - SHAP force plot for English

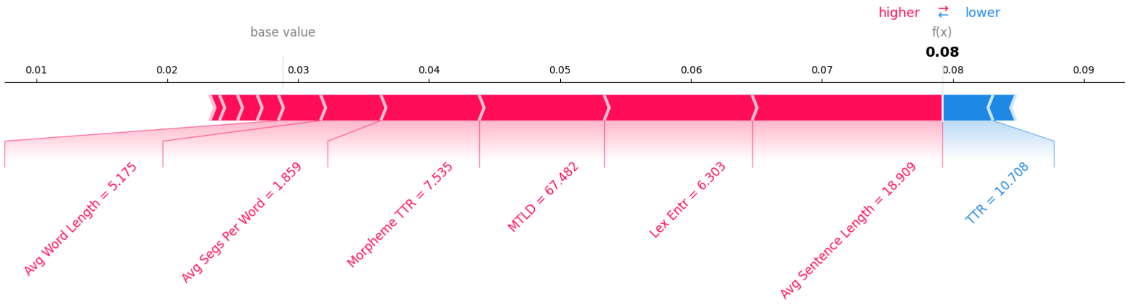


Figure 5.3: Isolation Forest - SHAP force plot for Esperanto

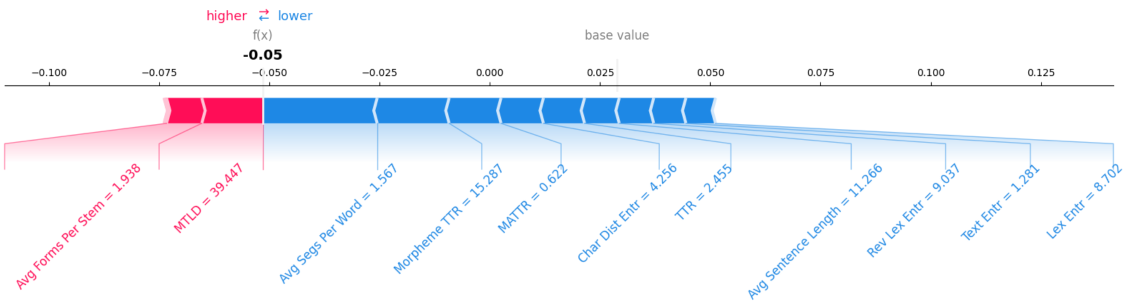


Figure 5.4: Isolation Forest - SHAP force plot for Volapük

6 Conclusion

This thesis sought to compare constructed and natural languages based on empirical measurements of various linguistic features, specifically those corresponding to text complexity, lexical diversity, morphological complexity, and entropy. A total of thirteen of such features were calculated for twenty-four languages (six constructed and eighteen natural), which involved the use of unsupervised segmenter models and several character-level LSTMs. The resulting feature dataset was subsequently examined using PCA and used for supervised binary classification with a decision tree and random forest, as well as unsupervised anomaly detection with a one-class SVM, local outlier factor, and isolation forest. Finally, four of the five models were further analyzed using SHAP to examine feature importances.

A few consistent patterns emerged from the results of the feature calculations, which were apparent in many of their corresponding distribution plots. Two of the natural languages, Finnish and Vietnamese, were often extremities in the distributions, having either the highest or lowest values for a given feature out of all languages. This is theorized to in large part be due to their respective morphological systems, Vietnamese's highly isolating and monosyllabic morphology and Finnish's highly agglutinative morphology, both of which are relatively extreme compared to most of the other languages in the data.

Notably, this also means the constructed languages were often not extremities in the feature distributions—aside from a few instances—and in fact frequently had values comparable to many of the natural languages. Some conclusions could therefore be tentatively made of having some level of linguistic similarity with natural languages, depending on the feature being examined, based on these results. Additionally, the supervised classification and unsupervised anomaly detection also consistently showed this lack of distinction between the two types of languages, specifically in the case of Esperanto—as well as Interlingua, to a lesser extent.

Overall, the findings for this thesis show some promising contributions to the debate of what defines a language. Although several of the constructed languages produced at times surprising results (e.g., Kotava's noticeable lack of distinctiveness), perhaps the most interesting findings pertained to Esperanto. Esperanto often appeared to be comparable to many of the natural languages—a phenomenon that was seen again during the classification and anomaly detection too—and even more so than its peers in many cases. Whether this is a reflection of some aspects of Esperanto's original design resembling natural language, an indication of undergoing linguistic evolution and development which in turn produces more "natural" qualities, a result of having a larger community of speakers and thus more variety of contributors to Wikipedia to create a more robust corpus, or still other reasons not considered here, it is difficult to conclude more concretely without further experimentation and data. However, these results are already encouraging to the idea that at least some constructed languages are quite similar to natural languages in measurable ways.

6.1 Future Work

The research presented here is far from encompassing all there is to the investigation into comparing constructed and natural languages, as well as the broader debate of defining what makes something a language. There were several methodological limitations of this thesis which could be improved upon in future studies, and open-ended questions remaining from the results here that could potentially be answered with more investigation and data.

Some of the biggest limitations of the study stem from the data. For one, the overall relatively small number of languages examined and lack of balanced representation of language families (and in the case of constructed languages, source languages) makes it difficult to extrapolate from the results regarding broader linguistic implications, as well as difficult to accurately assess the performance of the models. Furthermore, the corpora coming from Wikidumps means the quality of the text would vary widely from language to language, especially in the case of the constructed languages, which presumably had far fewer authors and were written by non-native speakers (Esperanto could be a possible exception). Using more robust corpora comprised of a much larger number (and variety) of languages could thus produce more conclusive findings and analysis. Lastly, another source of limitations also came from some of the processes for calculating the features, such as the lack of resources to evaluate the veracity of the unsupervised segmentations for all languages and lack of more thorough fine-tuning for the LSTMs calculating entropy. Future studies could try to address these, thereby making the resulting measurements more certain.

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8 Appendices

Here, I include additional information regarding the corpora following pre-processing, as well as the parameters for the `Morfessor` methods and models used for producing the segmentations.

8.1 Corpora

Language	**Number of Words**	**Number of sentences**	**Alphabet Size**
Icelandic	629995	41847	32
German	629987	37261	30
Polish	629997	42138	35
Ido	629990	43496	26
Afrikaans	629994	30737	43
Kotava	617400	48145	29
Hungarian	629946	39916	54
Lingua Franca Nova	628683	32188	26
Danish	629999	38260	29
Spanish	629978	24886	27
Interlingua	629996	32229	26
French	629983	27248	41
Occitan	629998	33762	37
Esperanto	629994	33317	28
Dutch	629997	34627	26
Turkish	629995	43573	29
English	629958	29574	26
Tagalog	629989	29855	27
Swedish	629998	36370	29
Vietnamese	629958	21115	93
Italian	629987	24487	26
Volapük	629999	55920	27
Indonesian	629997	34683	26
Finnish	629994	52637	31

Table 8.1: Lengths of each language's text after pre-processing, by number of words and sentences. The size of each language's alphabet is also shown, corresponding to only lowercase characters and excluding periods, which were also kept in the corpora.

8.2 Morfessor Methods & Models

Baseline Model	
Parameters	**Values**
forcesplit_list	None
corpusweight	None
use_skips	False
nosplit_re	None

Table 8.2: Parameters for Morfessor Baseline Model.

Morfessor Load Data Function	
Parameters	**Values**
freqthreshold	1
init_rand_split	None
count_modifier	$\lfloor \log_2(x+1) \rfloor$

Table 8.3: Parameters for Morfessor's Load Data Function.

Morfessor Train Batch Function	
Parameters	**Values**
algorithm	recursive
algorithm_params	()
finish_threshold	0.005
max_epochs	None

Table 8.4: Parameters for Morfessor's Train Batch Function.