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# Deconstructing Constructed Languages

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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 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 $12^{\text{th}}$ 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 $14^{\text{th}}$ 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 $17^{\text{th}}$ 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 19$^{th}$ and 20$^{th}$ 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 20$^{th}$ century.

While all share the defining characteristic of having been purposefully cre-

ated, 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.

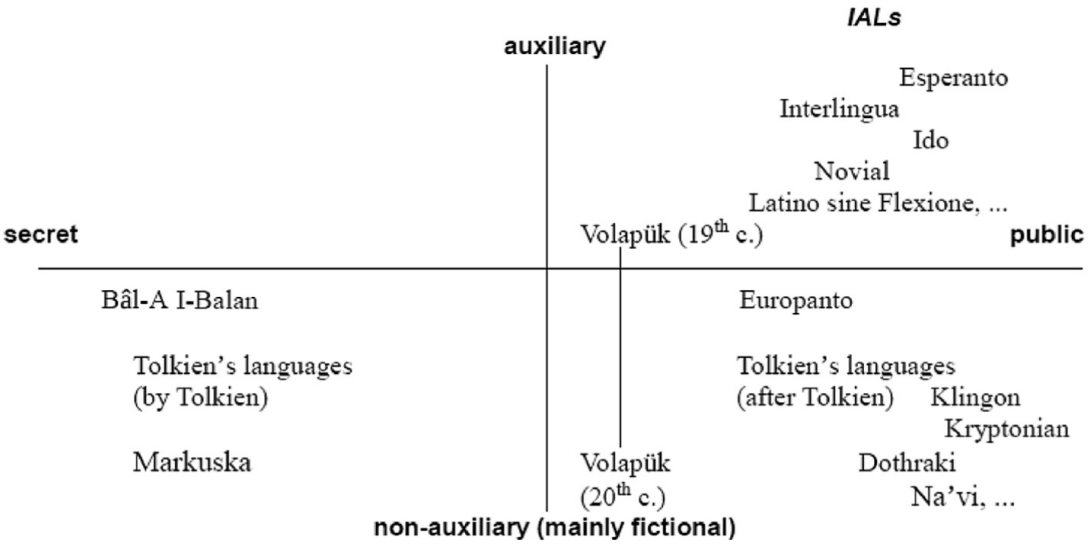



Figure 2.2: A taxonomy of constructed languages (Gobbo 2016).

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 other measurements which are commonplace to calculating linguistic complexity, and thus seemed appropriate to also include. 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. 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 and morphology. 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). Like most of the remaining constructed languages to be discussed in this section—with the exception of Volapük—Ido has small but a dedicated community of speakers and enthusiasts.

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), 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 $11^{\text{th}}$ to $18^{\text{th}}$ 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 $4^{\text{th}}$ 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.

Finally, 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 be visible in the results. This will be explored in greater detail later in Chapter 5.

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.

### 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).

In terms of typological features, these languages differ in their morphological systems. For example, Finnish, Hungarian, and Turkish are highly agglutinative, whereas Vietnamese, an isolating language, is an extreme opposite. German, Icelandic, Polish, and the Romance languages have fusional morphologies.

| **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 | |
| Icelandic | Indo-European, Germanic | |
| English | Indo-European, Germanic | A / F / I |
| Spanish | Indo-European, Romance | F |
| French | Indo-European, Romance | F |
| Occitan | Indo-European, Romance | |
| Italian | Indo-European, Romance | F |
| Polish | Indo-European, Slavic | |
| Vietnamese | Austroasiatic | I |
| Indonesian | Austronesian | |
| Tagalog | Austronesian | A / I |
| Turkish | Turkic | A |
| Hungarian | Uralic | A / F |
| Finnish | Uralic | |

Table 3.2: Natural languages in the dataset together with their respective language families and morphological systems.

Furthermore, Occitan is a unique case.

### 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 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 then made all lowercase and split by the periods—while also attempting to account for abbreviations—to make separate sentences. This was done mainly

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

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 visual-

izing 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 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:

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

where |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 segments 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, and the result was again multiplied by 100. Computing the average number of segments 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, reversed 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.

| **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

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

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

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 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. Reversed 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 reversed 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 $\mu$ is the mean and $\sigma$ 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 F1-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 F1-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. 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 determined by them.

## 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 the type of language distinguishable by marker and color.

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 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 feature distributions. 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.

The three measures for lexical complexity, 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

| 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 | 14.89 | 0.825 | 278.888 | 6.639 | 1.894 | 3.709 | 4.553 | 12.905 | 5.072 | 5.611 | 5.898 |
| **French** | nat | 5.16 | 23.12 | 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 | 1.77 | 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 | 18.66 | 7.185 | 0.715 | 87.187 | 7.674 | 1.793 | 2.805 | 4.173 | 10.546 | 3.53 | 6.741 | 7.118 |
| **English** | nat | 5.087 | 21.301 | 6.079 | 0.697 | 77.659 | 10.049 | 1.661 | 2.36 | 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 | 5.05 | 19.547 | 6.88 | 0.607 | 49.015 | 8.904 | 1.75 | 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 | 4.83 | 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 | 6.24 | 2.0 | 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 | 11.83 | 1.717 | 2.563 | 3.895 | 9.991 | 4.374 | 6.803 | 7.04 |
| **Turkish** | nat | 6.63 | 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 | 4.23 | 11.601 | 4.53 | 5.323 | 5.743 |
| **Kotava** | con | 5.06 | 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.

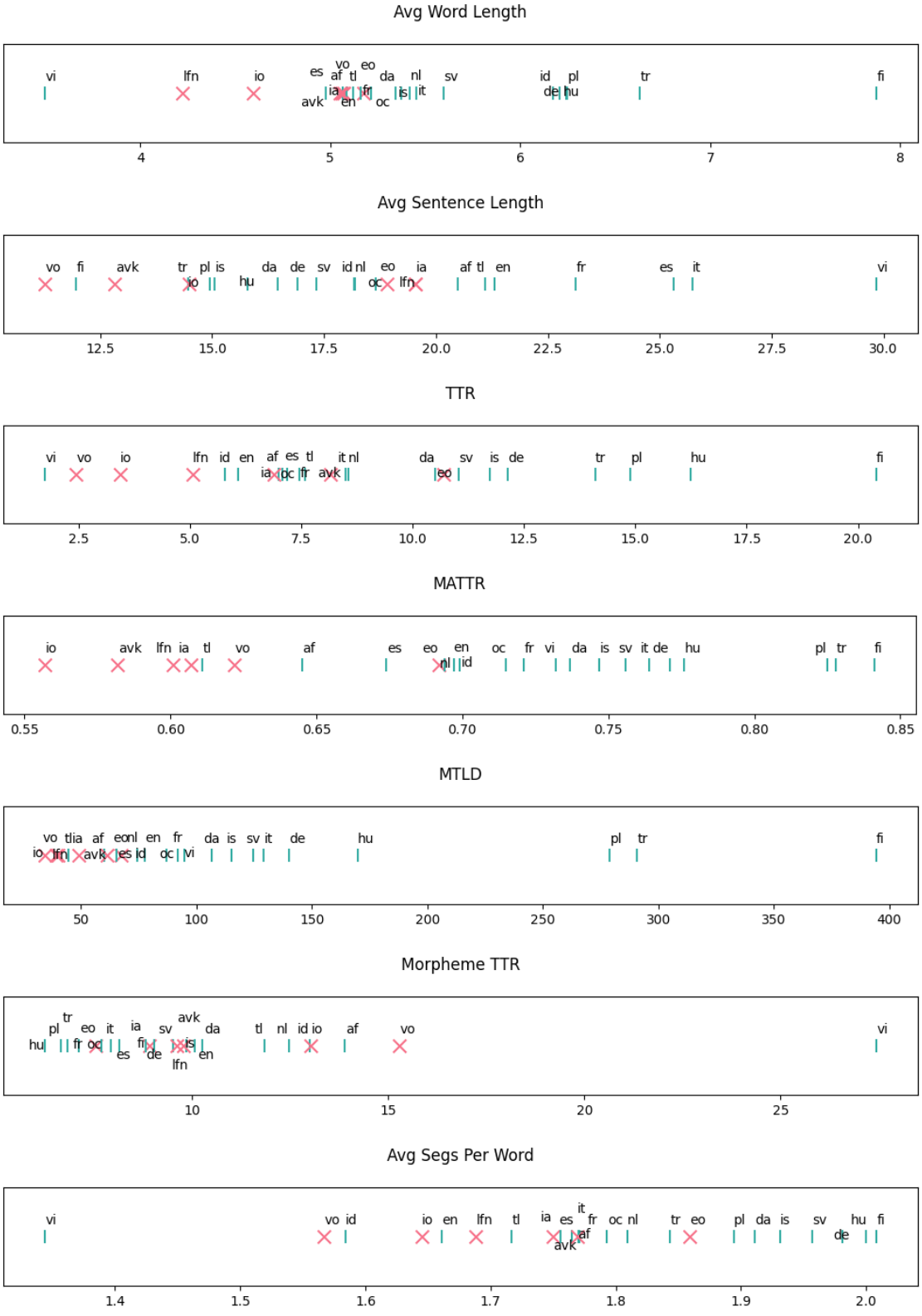
both TTR and MATTR. MATTR in particular also shows an almost complete divide between constructed and natural languages in the distribution, with the exception of Tagalog and Esperanto. Additionally, the distribution for MTLD reveals a cluster on the furthermost left side, with all six constructed languages 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 characters that comprise its corpora), 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. On the other end of the spectrum is Tagalog with the lowest character distribution entropy, followed closely by Lingua Franca Nova.

In contrast to this feature distribution, 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—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.


Avg Word Length
vi lfn io es vo eo af tl da nl sv id pl tr fi
ia fr is it de hu
avk en oc
4 5 6 7 8
Avg Sentence Length
vo fi avk tr pl is da de sv id nl eo ia af tl en fr es it vi
io hu qc lfn
12.5 15.0 17.5 20.0 22.5 25.0 27.5 30.0
TTR
vi vo io lfn id en af es tl it nl da sv is de tr pl hu fi
ia qc fr avk eo
2.5 5.0 7.5 10.0 12.5 15.0 17.5 20.0
MATTR
io avk lfn ia tl vo af es eo en oc fr vi da is sv it de hu pl tr fi
nl id
0.55 0.60 0.65 0.70 0.75 0.80 0.85
MTLD
vo tl ia af eo nl en fr da is sv it de hu pl tr fi
io lfn avk es id qc vi
50 100 150 200 250 300 350 400
Morpheme TTR
tr pl eo it ia sv avk da tl nl id io af vo vi
hu fr oc es fi de is en lfn
10 15 20 25
Avg Segs Per Word
vi vo id io en lfn tl ia it es fr oc nl tr eo pl da is sv hu fi
af avk de
1.4 1.5 1.6 1.7 1.8 1.9 2.0

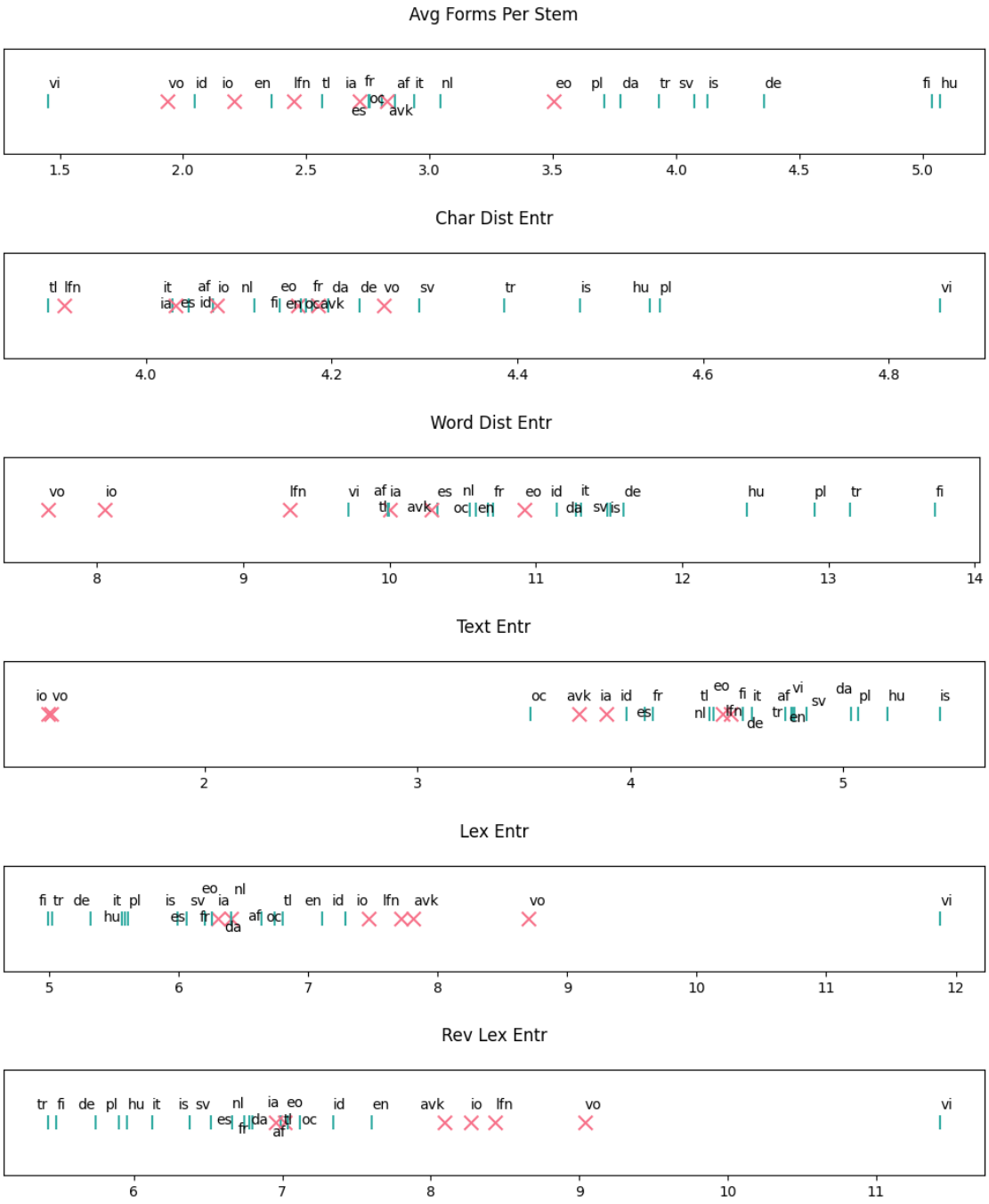
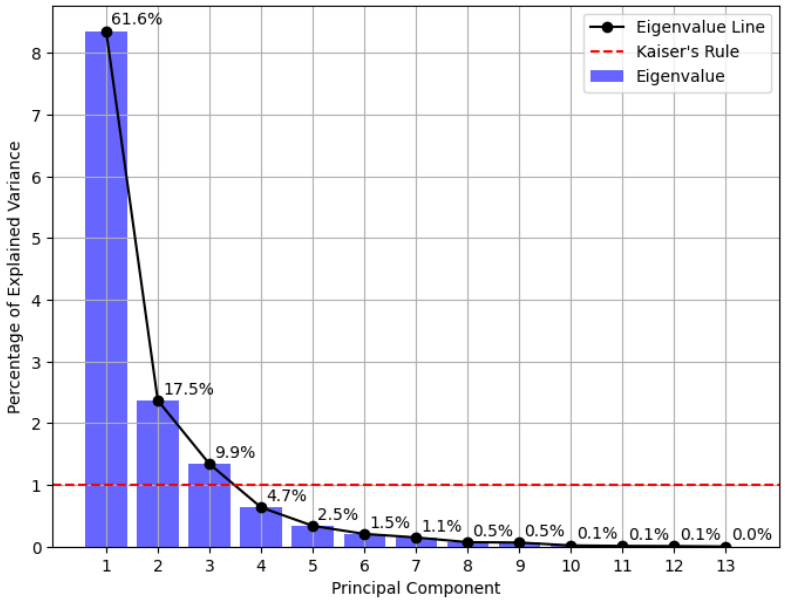



Figure 4.1: One-Dimensional Plots for Feature Distributions

## 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.

| | **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.

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 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.

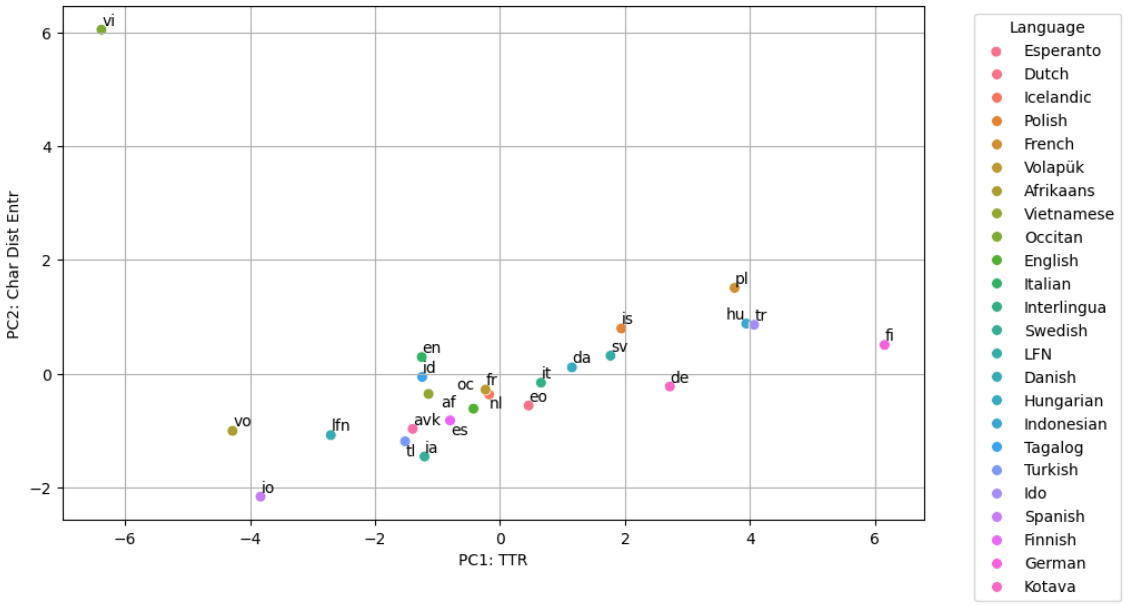



Figure 4.3 shows the results of the dimensionality reduction performed on the data using PCA.[4] Note that since this is a two-dimensional diagram, it depicts only the top two principal components. The values along both axes denote the principal component scores. Additionally, the top influential feature 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.

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

## 4.3 Results of Supervised Classification

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

| Model | $F_1$-score | Precision | Recall |
|---|---|---|---|
| Decision Tree | 0.83 | 0.83 | 0.83 |
| Random Forest | 0.83 | 0.83 | 0.83 |

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 several possible underlying reasons for this will be discussed in greater detail in Chapter 5.

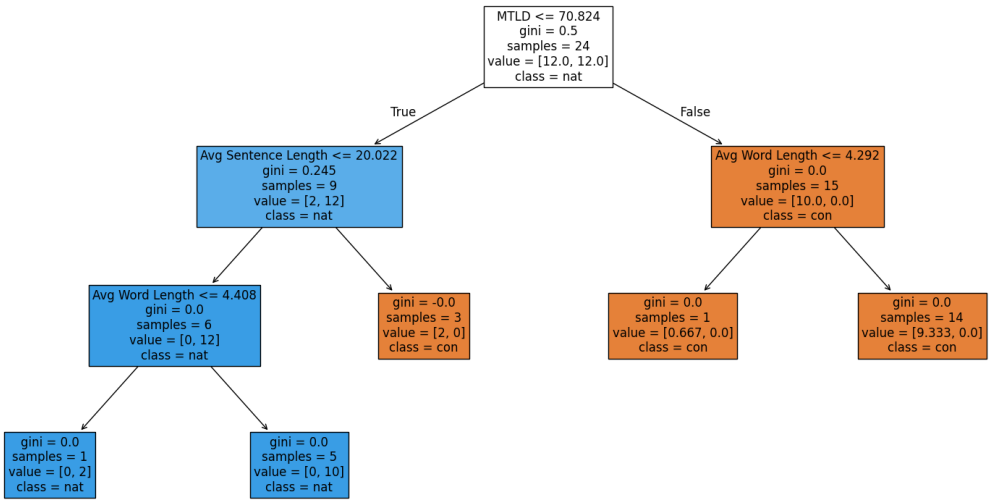



Figure 4.4: Tree structure diagram for decision tree classifier

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.

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

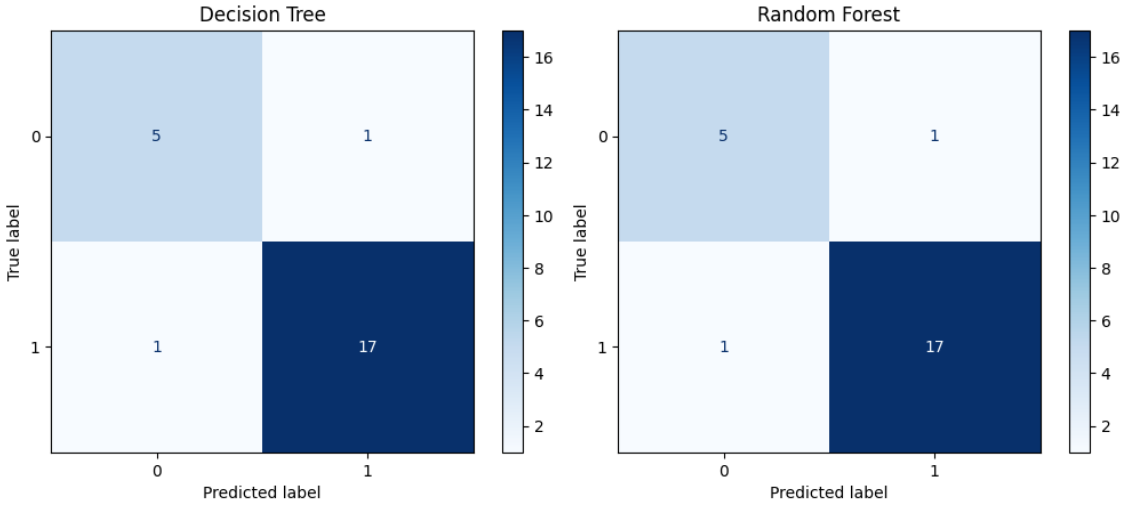



Figure 4.5: Confusion matrices for the fine-tuned supervised binary classifiers: decision tree (left) and random forest (right).

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

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

| 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 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, with 0 and 1 representing the constructed and natural language samples, respectively.

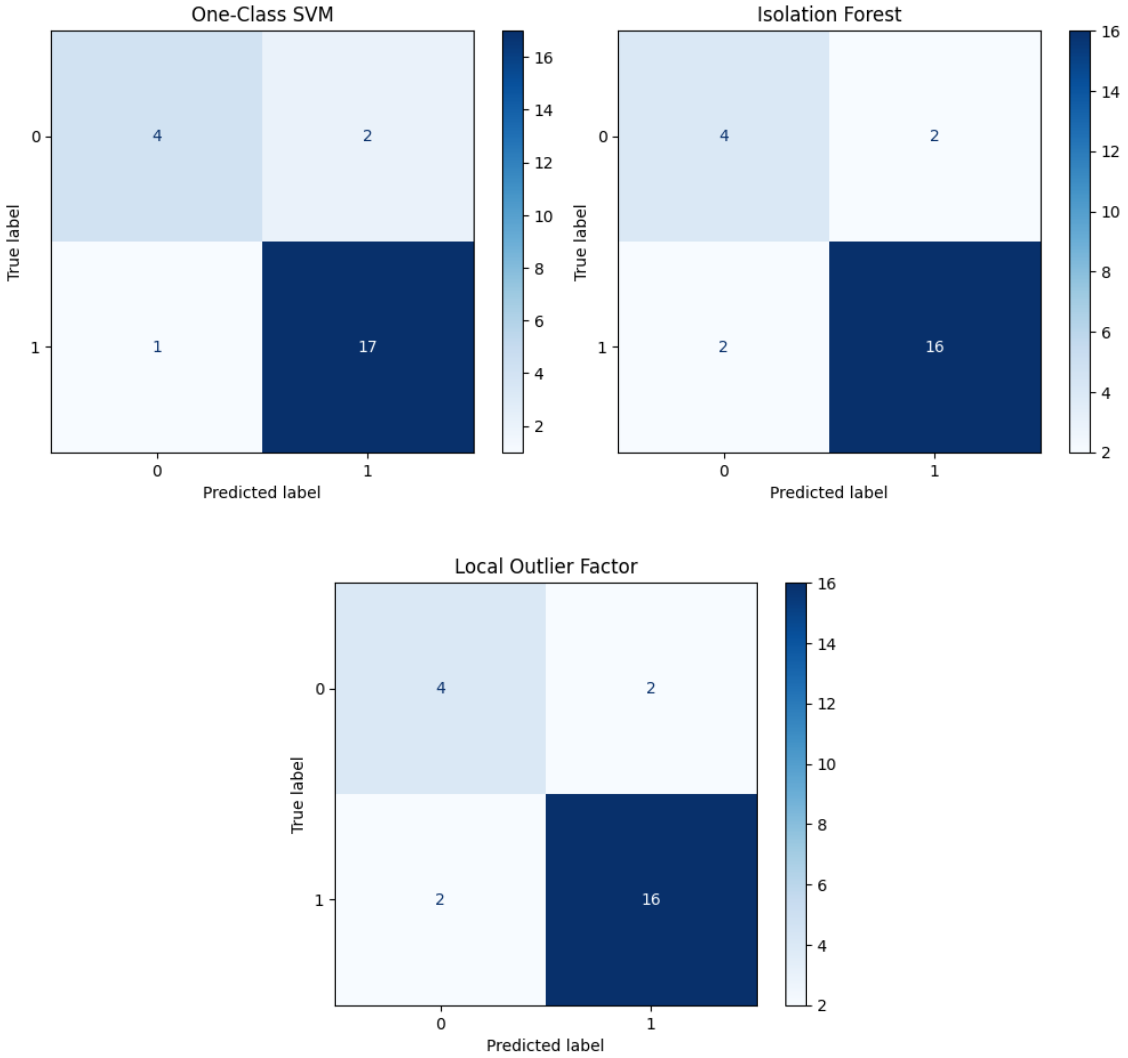



Figure 4.6: Confusion matrices for the fine-tuned unsupervised anomaly detection models: one-class SVM (top left), isolation forest (top right), and local outlier factor (bottom).

Overall, the unsupervised models performed comparable to one another, with all three correctly predicting 4 positive instances. Regarding their erroneous predictions, the One-Class SVM falsely considered Esperanto and Interlingua to be negative, or natural languages, and Vietnamese as positive, 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 a positive 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.

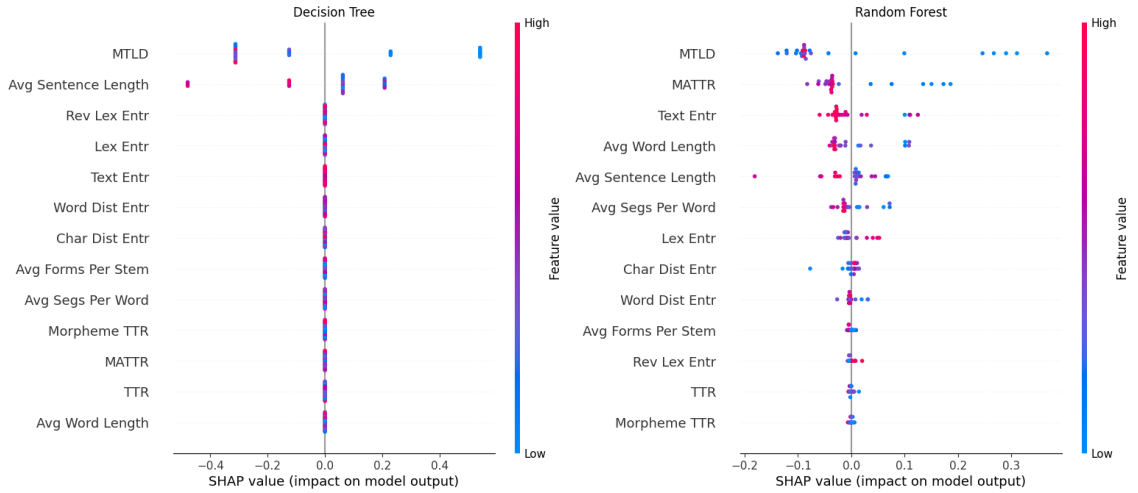



Figure 4.7: Beeswarm plots for SHAP results on fine-tuned supervised models: decision tree (left) and random forest (right).

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 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 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. Therefore, the plots show that MATTR was the most important feature for both models, with mid to

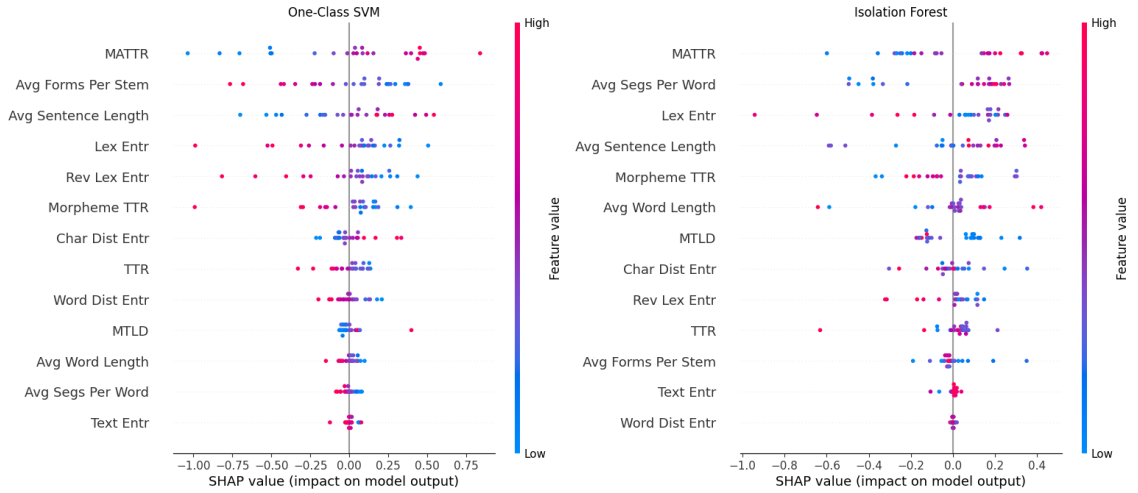



Figure 4.8: Beeswarm plots for SHAP results on fine-tuned unsupervised models: one-class SVM (left) and isolation forest (right).

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 results with the feature distributions shown in Figure 4.1, a few interesting questions arise. For instance, for the second most influential feature for the one-class SVM, average forms per stem, high feature values were seemingly indicative of an instance being a constructed language—something that is not at all reflected in the feature dataset. This will be further scrutinized in Chapter 5.

# 5 Discussion

This section begins by revisiting the results of the feature engineering more in-depth, particularly 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 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.

Revisiting the feature distribution plots first,

Ido was designed to be highly regular in terms of grammar, orthography, and lexicography, "correcting" perceived flaws of Esperanto (Novikov 2022).

## 5.1 Supervised Classifiers vs. Unsupervised Anomaly Detection Models

# 6 Conclusion

## 6.1 Future Work

The research presented in this thesis is far from encompassing all there is to the topic of defining language, and distinguishing between constructed and natural language. At present, this is an area of research with ample room for potential development.

Limiting factors: number of languages and which languages/language families, lack of real parallel corpora, problems associated with low-resource languages, relatively narrow scope of experimentation,

# 7 Acknowledgments

I would first and foremost like to thank my main supervisor, Dr. Çağrı Çöltekin, for all of his patience and support regarding this thesis, as well as my overall studies. All of his help and guidance has been invaluable to me, and I would not have been able to complete this otherwise. The same gratitude also extends to my other supervisor, Dr. Christian Bentz, for his interest and support regarding my research. Both of these incredible people were sources of encouragement for me when I most needed it, and for that I am extremely grateful.

Additionally, I want to thank my friends and family who helped me at every step. Though I would not be able to name all of them here, I am especially grateful for the support from my good friends Fidan, Leixin, Selene, Linhong, Pascal, and Lisa, as well as from my siblings, parents, grandparents, and aunt.

Though it may be less conventional, I also would like to thank my therapist and psychiatrist for all of their support and help too, not only with my thesis, but regarding all of my studies since I came here to Germany. It would not be an exaggeration to say that I was able to get this far because of them.

Last but not least, I want to sincerely thank my amazing girlfriend, Momoho, for her endless support, patience, care, and reassurance. She was a guiding light for me during this time, and I owe her a lifetime of gratitude for it.

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# 8 Appendices

Here I...

## 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

Morfessor

| **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.