Automatic Language Identification in Texts: A Survey

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Abstract

Language identification (LI) is the problem of determining the natural language that a document or part thereof is written in. Automatic LI has been extensively researched for over fifty years. Today, LI is a key part of many text processing pipelines, as text processing techniques generally assume that the language of the input text is known. Research in this area has recently been especially active. This article provides a brief history of LI research, and an extensive survey of the features and methods used so far in the LI literature. For describing the features and methods we introduce a unified notation. We discuss evaluation methods, applications of LI, as well as off-the-shelf LI systems that do not require training by the end user. Finally, we identify open issues, survey the work to date on each issue, and propose future directions for research in LI.

1. Introduction

Language identification (LI) is the task of determining the natural language that a document or part thereof is written in. Recognizing text in a specific language comes naturally to a human reader familiar with the language. Table 1 presents excerpts from Wikipedia articles in different languages on the topic of natural language processing (NLP), labeled according to the language they are written in. Without referring to the labels, readers of this article will certainly have recognized at least one language in Table 1, and many are likely to be able to identify all the languages therein.
Research into LI aims to mimic this human ability to recognize specific languages. Over the years, a number of computational approaches have been developed that, through the use of specially-designed algorithms and data structures, are able to infer the language being used without the need for human intervention. The capability of such systems could be described as super-human: an average person may be able to identify a handful of languages, and a trained linguist or translator may be familiar with dozens, but most of us will have, at some point, encountered written texts in languages they cannot place. However, LI research aims to develop systems that are able to identify any human language, a set which numbers in the thousands (Simons & Fennig, 2017).

<table>
<thead>
<tr>
<th>English</th>
<th>Natural language processing is a field of computer science, artificial intelligence, and linguistics concerned with the interactions between computers and human (natural) languages.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Italian</td>
<td>L’Elaborazione del linguaggio naturale è il processo di trattamento automatico mediante un calcolatore elettronico delle informazioni scritte o parlate nel linguaggio umano o naturale.</td>
</tr>
<tr>
<td>Chinese</td>
<td>自然语言处理是人工智能和语言学领域的分支学科。</td>
</tr>
<tr>
<td>Japanese</td>
<td>自然言語処理は、人間が日常的に使っている自然言語をコンピュータに処理させる一連の技術であり、人工知能と言語学の一分野である。</td>
</tr>
</tbody>
</table>

Table 1: Excerpts from Wikipedia articles on NLP in different languages.

In a broad sense, LI applies to any modality of language, including speech, sign language, and handwritten text, and is relevant for all means of information storage that involve language, digital or otherwise. However, in this survey we limit the scope of our discussion to LI of written text stored in a digitally-encoded form.

Research to date on LI has traditionally focused on monolingual documents (Hughes, Baldwin, Bird, Nicholson, & MacKinlay, 2006) (we discuss LI for multilingual documents in Section 10.6). In monolingual LI, the task is to assign each document a unique language label. Some work has reported near-perfect accuracy for LI of large documents in a small number of languages, prompting some researchers to label it a “solved task” (McNamee, 2005). However, in order to attain such accuracy, simplifying assumptions have to be made, such as the aforementioned monolinguality of each document, as well as assumptions about the type and quantity of data, and the number of languages considered.

The ability to accurately detect the language that a document is written in is an enabling technology that increases accessibility of data and has a wide variety of applications. For example, presenting information in a user’s native language has been found to be a critical factor in attracting website visitors (Kralisch & Mandl, 2006). Text processing techniques developed in natural language processing and information retrieval (IR) generally presuppose that the language of the input text is known, and many techniques assume that all documents are in the same language. In order to apply text processing techniques to real-world data, automatic LI is used to ensure that only documents in relevant languages are subjected to further processing. In information storage and retrieval, it is common to
index documents in a multilingual collection by the language that they are written in, and LI is necessary for document collections where the languages of documents are not known a-priori, such as for data crawled from the World Wide Web. Another application of LI that predates computational methods is the detection of the language of a document for routing to a suitable translator. This application has become even more prominent due to the advent of machine translation (MT) methods: in order for MT to be applied to translate a document to a target language, it is generally necessary to determine the source language of the document, and this is the task of LI. LI also plays a part in helping to bridge an increasing “digital divide” by providing support for the documentation and use of low-resource languages. One area where LI is frequently used in this regard is in linguistic corpus creation, where LI is used to process targeted web crawls to collect text resources for low-resource languages.

A large part of the motivation for this article is the observation that LI lacks a “home discipline”, and as such, the literature is fragmented across a number of fields, including NLP, IR, machine learning, data mining, social medial analysis, computer science education, and systems science. This has hampered the field, in that there have been many instances of research being carried out with only partial knowledge of other work on the topic, and the myriad of published systems and datasets.

Finally, it should be noted that this survey does not make a distinction between languages, language varieties, and dialects. We consider a set of dialects or a set of languages classes that a LI system is trained to identify. Of course, the more similar two classes are the more challenging it is for a LI system to discriminate between them. Training a system to discriminate between similar languages such as Croatian and Serbian (Ljubešić & Kranjčić, 2014), language varieties like Brazilian and European Portuguese (Zampieri & Gebre, 2012), or a set of Arabic dialects (Zampieri, Tan, Ljubešić, Tiedemann, & Nakov, 2015) is more challenging than training systems to discriminate between, for example, Japanese and Finnish. Even so, as evidenced in this article, from a computational perspective, the algorithms and features used to discriminate between languages, language varieties, and dialects are identical.

2. LI as Text Categorization

LI is in some ways a special case of text categorization, and previous research has examined applying the same methods to LI as well as other text categorization tasks (Cavnar & Trenkle, 1994; Elworthy, 1998).

Sebastiani (2002, Section 2.1) gives a definition of text categorization, which can be summarized as the task of mapping a document onto a pre-determined set of classes. This is a very broad definition, and indeed one that is applicable to a wide variety of tasks, amongst which falls modern LI. The archetypal text categorization task is perhaps the classification of newswire articles according to the topics that they discuss, exemplified by the Reuters-21578 dataset (Debole & Sebastiani, 2005). However, LI has particular characteristics that make it different from typical text categorization tasks:

1. Text categorization tends to use statistics about the frequency of words to model documents, but for LI purposes there is no universal notion of a word: LI must cater for languages where whitespace is not used to denote word boundaries. Furthermore,
the determination of the appropriate word tokenization strategy for a given document presupposes knowledge of the language the document is written in, which is exactly what we assume we don’t have access to in LI.

2. In text categorization tasks, the set of labels usually only applies to a particular dataset. For example, it is not meaningful to ask which of the Reuters-21578 labels is applicable to the abstract of a biomedical journal article. However, in LI there is a clear notion of language that is independent of domain: it is possible to recognize that a text is in English regardless of whether it is from a biomedical journal, a microblog post or a newspaper article.

3. In LI, classes can be somewhat multi-modal, in that text in the same language can sometimes be written with different orthographies and stored in different encodings.

4. In LI, labels are non-overlapping and mutually exclusive, meaning that a text can only be written in one language. This does not preclude the existence of multilingual documents, which contain text in more than one language, but when this is the case, the document can always be uniquely divided into monolingual segments. This is in contrast to text categorization involving multi-labeled documents, where it is not necessarily possible to associate specific segments of the document with specific labels.

These distinguishing characteristics present unique challenges and offer particular opportunities, so much so that research in LI has generally proceeded independently of text categorization research. In this survey, we will examine the common themes and ideas that underpin research in LI. We begin with a brief history of research that has led to modern LI (Section 3), and then proceed to review the literature, first introducing the mathematical notation used in the article (Section 4), and then providing synthesis and analysis of existing research, focusing specifically on the representation of text (Section 5) and the learning algorithms used (Section 6). We examine the methods for evaluating the quality of the systems (Section 7) as well as the areas where LI has been applied (Section 8), and then provide an overview of “off-the-shelf” LI systems (Section 9). We conclude the survey with a discussion of the open issues in LI (Section 10), enumerating issues and existing efforts to address them, as well as charting the main directions where further research in LI is required.

2.1 Previous Surveys

Although there are some dedicated survey articles, these tend to be relatively short; there has not been any comprehensive surveys of research in automated LI of text to date. The largest survey so far can be found in the literature review of Lui (2014) PhD thesis and it served as an early draft and starting point for the current article. Zampieri (2016) provides a historical overview of language identification focusing on the use of n-gram language models. Qafmolla (2017) gives a brief overview of some of the methods used for LI. Garg, Gupta, and Jindal (2014) have made a brief preview of some of the techniques and applications used previously. Shashirekha (2014) gives a short overview of some of the challenges, algorithms and available tools for LI. Juola (2006) provides a brief summary of LI, how it relates to
other research areas and some outstanding challenges, but only does so in general terms and does not go into any detail about existing work in the area. Another brief article about LI is Muthusamy and Spitz (1997), which covers LI both of spoken language as well as of written documents, and also discusses LI of documents stored as images rather than digitally-encoded text.

3. A Brief History of LI

LI as a task predates computational methods – the earliest interest in the area was motivated by the needs of translators, and simple manual methods were developed to quickly identify documents in specific languages. The earliest known work to describe a functional LI program for text is by Mustonen (1965), a statistician, who used multiple discriminant analysis to teach a computer how to distinguish, on a word level, between English, Swedish and Finnish. Mustonen compiled a list of linguistically motivated character-based features and gave his language identifier 300 words from a dictionary for each of the three languages to be used as training data. The training procedure created two discriminant functions, which were tested with 100 words for each language. The experiment resulted in 76% of the words being correctly classified; even by current standards this percentage would be seen as acceptable given the small amount of training material.

In the early 1970s, Nakamura (1971) considered the problem of automatic LI. According to Rau (1974), and the available abstract of Nakamura’s article, his language identifier was able to distinguish between 25 languages written in Latin characters. As features for LI, the method used the occurrence rates of characters and words in each language. From the abstract it seems that, in addition to the frequencies, he used some of the negative and positive Boolean type deductions about the binary presence/absence of particular characters or words, utilized with manual LI.

Rau (1974) wrote his master’s thesis “Language Identification by Statistical Analysis” for the Naval Postgraduate School at Monterey, California. The continued interest and the need to use LI of text in military intelligence settings is evidenced by the recent articles of, for example, Rafidha Rehiman, Keerthy, Lakshmi, and Sreekumar (2013), Rowe, Schwamm, and Garfinkel (2013), Tratz (2014), and Voss, Tratz, Laoudi, and Briesch (2014). As features for LI, Rau (1974) used the relative frequencies of characters and character bigrams, among others. With a majority vote classifier ensemble of seven classifiers using Kolmogor-Smirnov’s Test of Goodness of Fit and Yule’s characteristic (K) he managed to achieve 89% accuracy for 53 characters when distinguishing between English and Spanish. His thesis actually includes the identifier program code (for the IBM System/360 Model 67 mainframe) and even the language models used in printed form.

Much of the earliest work on automatic LI was focused on identification of spoken language, or did not make a distinction between written and spoken language. As for example the work of House and Neuburg (1977), which is primarily focused on LI of a spoken utterance, but makes a broader contribution in demonstrating the feasibility of LI on the basis of a statistical model of broad phonetic information. However, their experiments do not use actual speech data, but rather “synthetic” data in the form of phonetic transcriptions derived from written text.
Another subfield of speech technology, speech synthesis, has also generated a considerable amount of research in the LI of text starting already from the 1980s. In speech synthesis, the need to know the origin language of individual words is crucial in determining how they should be pronounced. Church (1985) uses the relative frequencies of character trigrams as probabilities and determines the language of words using a Bayesian argument. Church explains the method, that has since been widely used in LI, as a small part of an article concentrating on many aspects of letter stress assignment in speech synthesis, which is probably why Beesley (1988) is usually attributed to being the one to have introduced the aforementioned method to LI of text. As Beesley’s article concentrated solely on the problem of LI, this single focus probably enabled his research to have greater visibility. The role of the program implementing his method was to route documents to MT systems, and Beesley’s paper more clearly describes what has later come to be known as a character n-gram model. The fact that the distribution of characters is relatively consistent for a given language was already well known.

The highest-cited early work, or any work, on automatic LI is Cavnar and Trenkle (1994). Cavnar and Trenkle’s method (which we describe in detail in Section 6.5) builds up per-document and per-language profiles, and classify a document according to which language profile it is most similar to, using a rank-order similarity metric. They evaluate their system on 3478 documents in eight languages obtained from USENET newsgroups, reporting a best overall LI accuracy of 99.8%. Gertjan van Noord produced an implementation of the method of Cavnar and Trenkle named TextCat, which has become eponymous with the method itself. TextCat is packaged with pre-trained models for a number of languages, and so it is likely that the strong result reported by Cavnar and Trenkle, combined with the ready availability of an “off-the-shelf” implementation, has resulted in the exceptional popularity of this particular method. Cavnar and Trenkle (1994) can be considered a milestone in automatic LI, as it popularized the use of automatic methods on character n-gram models for LI, and to date the method is still considered a benchmark for automatic LI.

4. On notation

This section introduces the unified notation used throughout this article. The notations used in the original articles vary from written explanations or pseudocode to detailed mathematical notation. The unified notation makes it easier to see the similarities and differences between the LI methods presented in the literature. The formulas presented could be used to implement language identifiers and re-evaluate the studies they were originally presented in.

A corpus \( C \) consists of individual tokens \( u \) which may be bytes, characters or words. A corpus \( C \) is a finite sequence of individual tokens, \( u_1, ..., u_l \). The total count of all individual tokens \( u \) in the corpus \( C \) is denoted by \( l_C \). In a corpus \( C \) with non-overlapping segments \( S \), each segment is referred to as \( C_s \), which may be a short document or a word or some other way of segmenting the corpus. The number of segments is denoted as \( l_S \).

A feature \( f \) is some countable characteristic of the corpus \( C \). When referring to all features \( F \) in a corpus \( C \), we use \( C^F \) and the count of all features is denoted by \( l_{CF} \). A set of unique features in a corpus \( C \) is denoted by \( U(C) \). The number of unique features is referred to as \( |U(C)| \). The count of a feature \( f \) in the corpus \( C \) is referred to as \( c(C, f) \).
If a corpus is divided into segments $S$, the count of a feature $f$ in $C$ is defined as the sum of counts over the segments of the corpus, i.e. $c(C, f) = \sum_{s=1}^{l_S} c(C_s, f)$. Note that the segmentation may affect the count of a feature in $C$ as features do not cross segment borders.

A frequently used feature is an $n$-gram, which consists of a sequence of $n$ individual tokens. An $n$-gram starting at position $i$ in a corpus segment is denoted $u_i, \ldots, i+1+n$, where positions $i+1, \ldots, i-1+n$ remain within the same segment of the corpus as $i$. If $n = 1$, $f$ is an individual token. When referring to all $n$-grams of length $n$ in a corpus $C$, we use $C^n$ and the count of all such $n$-grams is denoted by $l_{C^n}$. The count of an $n$-gram $f$ in a corpus segment $C_s$ is referred to as $c(C_s, f)$ and is defined by Equation 1.

$$c(C_s, f) = \sum_{i=1}^{l_{C_s}+1-n} \begin{cases} 1, & \text{if } f = u_i, \ldots, i-1+n \\ 0, & \text{otherwise} \end{cases}$$ (1)

The set of languages is $G$, and $l_G$ denotes the number of languages. A corpus $C$ in language $g$ is denoted by $C_g$. A language model $O$ based on $C_g$ is denoted by $O(C_g)$. The features given values by the model $O(C_g)$ are the domain $\text{dom}(O(C_g))$ of the model. In a language model, a value $v$ for the feature $f$ is denoted by $v_{C_g}(f)$. For each potential language $g$ of a corpus $C$ in an unknown language, a resulting score $R(g, C)$ is calculated. A corpus in an unknown language is also referred to as a mystery text.

4.1 An archetypal language identifier

The design of a supervised language identifier can generally be deconstructed into four key steps:

1. A representation of text is selected
2. A model for each language is derived from corpora where the languages are known
3. A function is defined that determines the similarity between text and each language
4. The highest-scoring model determines the language of the text predicted by the system

Early similar descriptions of the process can be found in House and Neuburg (1977), as well as Ueda and Nakagawa (1990), and in a broad sense this describes a general supervised machine learning approach.

5. Features

In this section, an extensive list of features is presented in order to remind the interested reader of all the possibilities at hand, some of which are not self-evident. The equations written in the unified notation defined earlier show how the values $v$ used in the language models are calculated from the tokens $u$. It is not trivial to draw the line between the ways of calculating features and the ways methods use them. As a general rule the features are something that are or can be calculated from a training corpus. For each feature type we generally introduce the first article using the feature, as well as some of the more recent articles where the feature type has been considered.
5.1 Bytes and encodings

In LI, text is typically modeled as a stream of characters. However, there is a slight mismatch between this view and how text is actually stored: documents are digitized using a particular encoding, which is a mapping from characters (e.g. a character in the alphabet, or a Chinese ideogram), onto the actual sequence of bytes that is stored and transmitted by computers. Encodings vary in how many bytes they use to represent each character. Some encodings use a fixed number of bytes for each character (e.g. ASCII), whereas others use a variable-length encoding (e.g. UTF-8). Some encodings are specific to a given language (e.g. GuoBiao 18030 or Big5 for Chinese), whereas others are specifically designed to represent as many languages as possible (e.g. the Unicode family of encodings). Languages can often be represented in a number of different encodings (e.g. UTF-8 and Shift-JIS for Japanese), and sometimes encodings are specifically designed to share certain codepoints (e.g. all single-byte UTF-8 codepoints are exactly the same as ASCII). All of this variation in the concrete representation of text poses unique challenges for practical LI applications, where we must take into account the variety of possible encodings in modeling a language.

Some LI research has included an explicit encoding detection step to resolve bytes to the characters they represent (Kikui, 1996), effectively transcoding the document into a standardized encoding before attempting to identify the language. However, transcoding is computationally expensive, and other research suggests that it may be possible to ignore encoding and build a single per-language model covering multiple encodings simultaneously (Kruengkrai, Srichaivattana, Sornlertlamvanich, & Isahara, 2005; Baldwin & Lui, 2010a). Another solution is to treat each language-encoding pair as a separate category (Cowie, Ludovik, & Zacharski, 1999; Suzuki, Mikami, Ohsato, & Chubachi, 2002; Singh & Gorla, 2007; Brown, 2012). The disadvantage of this is that it increases computational costs by modeling a larger number of classes. Most of the research has avoided issues of encoding entirely by assuming that all the documents to be processed use the same encoding (Mandl, Shramko, Tartakovski, & Womser-Hacker, 2006). This may be a reasonable assumption in some settings, such as when processing data from a single source (e.g. all data from Twitter and Wikipedia is UTF-8 encoded). Assuming a fixed encoding separates the problem of LI from the problem of encoding detection. In practice, a disadvantage of this approach may be that some encodings are only applicable to certain languages (e.g. EUC-JP for Japanese and Big5 for Chinese), so knowing that a document is in a particular encoding can provide information that would be lost if the document is transcoded to a universal encoding such as UTF-8. Li and Momoi (2001) used a parallel state machine to detect which encoding scheme a file could potentially have been encoded with. The knowledge of the encoding, if detected, is then used to narrow down the possible languages.

As such, detecting the encoding can be considered a separate task from LI. When the encoding is known, the byte sequences can be translated into sequences of characters. Most of the features or methods do not make a distinction whether they use bytes or characters and because of this we are using the word character in the following feature and method descriptions even if bytes were actually used.

5.2 Characters

In this section, we review how individual characters have been used as features in LI.
**Non-alphabetic or non-ideographic characters**  Ranaivo-Malançon and Ng (2005) used the formatting of numbers when distinguishing between Malay and Indonesian. King and Abney (2013) used the presence of non-alphabetic characters between the current word and the words before and after as features. Elfardy and Diab (2013) used emoticons (or emojis) in Arabic dialect identification with Naive Bayes (NB, see Section 6.4). In 2017, non-alphabetic characters have also been used by Basile, Dwyer, Medvedeva, Rawee, Haagsma, and Nissim (2017), Bestgen (2017), Samih (2017), and Simaki, Simakis, Paradis, and Kerren (2017).

**Alphabets**  Henrich (1989) used the knowledge of alphabets to exclude languages where the unique characters did not appear. Giguet (1995) used alphabets collected from dictionaries to check if a word might belong to a language. Hanif, Latif, and Khiyal (2007) used the Unicode database to get the possible languages of unicode characters. Lately, the knowledge of relevant alphabets has been used for LI also by Hasimu and Silamu (2017) and Simih (2017).

**Capitalization**  Capitalization is mostly taken into account when calculating character or character n-gram frequencies. Many times it is ignored by lowercasing in order to provide more samples. In 2017, capitalization has been used as a special feature for LI by Basile et al. (2017), Bestgen (2017), and Simaki et al. (2017).

**The number of characters in words and word combinations**  Langer (2001) was the first to use the length of words in LI. Nobesawa and Tahara (2005) used the length of full person names comprising several words. Lately, the number of characters in words has been used for LI by Dongen (2017), van der Lee and Bosch (2017), Samih (2017), and Simaki et al. (2017). Dongen (2017) also used the length of the two previous words.

**The frequency or probability of each character**  Kerwin (2006) used character frequencies as feature vectors. In a feature vector, each feature $f$ has its own integer value. The raw frequency, also called term frequency (TF), is calculated for each language $g$ as in Equation 2.

$$v_{C_g}(f) = c(C_g, f)$$  \hspace{1cm} (2)

Rau (1974) was the first to use the probability of characters. He calculated the probabilities as relative frequencies. Relative frequencies are calculated by dividing the frequency of a feature found in the corpus by the total count of features of the same type in the corpus. When the relative frequency of a feature $f$ is used as a value, it is calculated for each language $g$, as in Equation 3.

$$v_{C_g}(f) = \frac{c(C_g, f)}{l_{C_g}}$$  \hspace{1cm} (3)

Tran and Sharma (2005) calculated the relative frequencies of the first characters of words and Windisch and Csink (2005) did the same for the last characters of words.

Ng and Selamat (2009) calculated the character frequency document frequency (LFDF) values. Takçı and Güngör (2012) compared their own inverse class frequency (ICF) method...
with the arithmetic average centroid (AAC) and the class feature centroid (CFC) feature vector updating methods. In ICF a character appearing frequently only in some language gets more positive weight for that language. The values differ from inverse document frequency (IDF, Equation 8), as they are calculated using also the frequencies of characters in other languages. Their ICF-based vectors generally performed better than those based on AAC or CFC. Takçı and Ekinci (2012) explored using the relative frequencies of characters with similar discriminating weights. Takçı and Güngör (2012) also used mutual information (MI) and chi-square weighting schemes with characters.

Baldwin and Lui (2010a) compared the identification results of single characters with the use of character bigrams and trigrams when choosing between 67 languages. Both bigrams and trigrams generally performed better than unigrams. Jauhiainen (2010) also found that the identification results from identifiers using just characters are generally worse than those using character sequences.

5.3 Character combinations

In this section we consider the different combinations of characters used in the literature. Character n-grams mostly consist of all possible characters in a given encoding, but can also consist of only alphabetic or ideographic characters.

Co-occurrence ratios Windisch and Csink (2005) calculated the co-occurrence ratios of any two characters, as well as the ratio of consonant clusters of different sizes to the total number of consonants. Sterneberg (2012) used the combination of every bigram and their counts in words. van der Lee and Bosch (2017) used the proportions of question and exclamation marks to the total number of the end of sentence punctuation as features with several machine learning algorithms.

Vowel-consonant relationship Rau (1974) used the relative frequencies of vowels following vowels, consonants following vowels, vowels following consonants and consonants following consonants. Dongen (2017) used vowel-consonant ratios as one of the features with Support Vector Machines (SVM, Section 6.7), Decision Trees (DT, Section 6.9), and Conditional Random Fields (CRF, Section 10.7).

Character repetition Elfardy and Diab (2013) used the existence of word lengthening effects and repeated punctuation as features with NB. Banerjee, Roy, Kuila, Naskar, Bandyopadhyay, and Rosso (2014) used the presence of characters repeating more than twice in a row as a feature with simple scoring (Equation 17). Barman, Das, Wagner, and Foster (2014a) used more complicated repetition identified by regular expressions. Sikdar and Gambäck (2016) used letter and character bigram repetition with CRF. Martinc, Škrjanec, Zupan, and Pollak (2017) used the count of character sequences with three or more identical characters with several machine learning algorithms.

n-grams of characters of the same size Character n-grams are continuous sequences of characters of length n. They can be either consecutive or overlapping. Consecutive character bigrams created from the four character sequence “door” are “do” and “or”, whereas the overlapping bigrams are “do”, “oo”, and “or”. Overlapping n-grams are most often used in the literature. Overlapping produces a greater number and variety of n-grams from the same amount of text.
Table 2: List of articles (2013-2017) where relative frequencies of character \( n \)-grams have been used as features. The columns indicate the length of the \( n \)-grams used. \( X \) indicates the best and \( X \) the second best \( n \)-gram length as evaluated in the article in question. Plain \( X \) indicates that there was no clear order of efficiency or that the order was not presented in the article.

Rau (1974) was the first to use combinations of any two characters. He calculated the relative frequency of each bigram. Table 2 lists more recent articles where relative frequencies of \( n \)-grams of characters have been used. Rau (1974) also used the relative frequencies of two character combinations which had one unknown character between them, also known as skipgrams. Seifart and Mundry (2015) used a modified relative frequency of character unigrams and bigrams.

Character trigram frequencies relative to the word count was used by Vega and Bressan (2001a), who calculated the values \( v_C(f) \) as in Equation 4. Let \( T \) be the word-tokenized segmentation of the corpus \( C \) of character tokens:

\[
v_C(f) = \frac{c(C, f)}{l_T}
\]  

(4)

where \( c(C, f) \) is the count of character trigrams \( f \) in the corpus \( C \) and \( l_T \) the total word count in the corpus. Later \( n \)-gram frequencies relative to the word count were used by Hamzah (2010) for character bigrams and trigrams.

House and Neuburg (1977) divided characters into five phonetic groups and used a Markovian method to calculate the probability of each bigram consisting of these phonetic
Table 3: List of articles where Markovian character \( n \)-grams have been used as features.

The columns indicate the length of the \( n \)-grams used. \( \text{X} \) indicates the best and \( \text{X} \) the second best \( n \)-gram length as evaluated in the article in question. Plain \( \text{X} \) indicates that there was no clear order of efficiency or that the order was not presented in the article.

In Markovian methods the probability \( P \) is calculated so that the probabilities of a given character \( u_i \) following any character sequence \( u_{i-n+1}, \ldots, u_{i-1} \) in corpus \( C \) add up to one, as in Equation 5:

\[
P(u_i|u_{i-n+1}, \ldots, u_{i-1}) = \frac{c(C, u_{i-n+1}, \ldots, u_i)}{c(C, u_{i-n+1}, \ldots, u_{i-1})} \tag{5}
\]

where \( u_{i-n+1}, \ldots, u_{i-1} \) is an \( n \)-gram of the length \( n - 1 \) from the beginning of \( u_{i-n+1}, \ldots, u_i \). In this case, the probability \( P(u_i|u_{i-n+1}, \ldots, u_{i-1}) \) is the value \( v_C(f) \), where \( f = u_{i-n+1}, \ldots, u_i \), in the model \( O(C) \). Ludovik and Zacharski (1999) used 4-grams with recognition weights which were derived from Markovian probabilities. Table 3 lists some of the more recent articles where Markovian character \( n \)-grams have been used.

Vitale (1991) was the first author to consider the probabilistic theory behind his language identifier in detail. He defines the probability of a trigram \( f \) being written in the language \( g \), as in Equation 6.

\[
P(g|f) = \frac{P(f|g)P(g)}{\sum_{h \in G} P(f|h)P(h)} \tag{6}
\]

He considers the a priori probabilities of the languages \( P(g) \) to be equal, which leads to Equation 7.

\[
P(g|f) = \frac{P(f|g)}{\sum_{h \in G} P(f|h)} \tag{7}
\]
<table>
<thead>
<tr>
<th>Article</th>
<th>1</th>
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<th>3</th>
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<th>5</th>
<th>6</th>
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<td>X</td>
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</table>

Table 4: References (2016-) where the frequency of character $n$-grams has been used as feature vectors. The columns indicate the length of the $n$-grams used and the method or methods used with the features. The relevant section numbers are mentioned in parentheses.

Vitale (1991) used the probabilities $P(g|f)$ as the values $v_{C_g}(f)$ in the language models.

MacNamara, Cunningham, and Byrne (1998) used a list of the most frequent bi- and trigrams with logarithmic weighting. Prager (1999) was the first to use direct frequencies of character $n$-grams as feature vectors. Vinosch Babu and Baskaran (2005) used Principal Component Analysis (PCA) to select only the most discriminating bigrams in the feature vectors representing languages. Murthy and Kumar (2006) used the most frequent and discriminating byte uni-, bi-, and trigrams as part of feature functions. They define the most discriminating features as those which have the most differing relative frequencies between the models of the different languages. Gottron and Lipka (2010) tested $n$-grams from two to five using frequencies as feature vectors, frequency ordered lists, relative frequencies, and Markovian probabilities. Table 4 lists the more recent articles where the frequency of character $n$-grams has been used as features. In the method column, RF refers to Random Forest (cf. 6.9), LR to Logistic Regression (Section 6.6), KRR to Kernel Ridge Regression (Section 6.5), KDA to Kernel Discriminant Analysis (Section 6.5), and NN to Neural Networks (Section 6.8).

Giguet (1995) used the last two and three characters of non-grammatical words. Suzuki et al. (2002) used an unordered list of distinct trigrams with the simple scoring method (Section 6.2). Hayati (2004) used Fishers discriminant function to choose the 1000 most discriminating trigrams. Bilcu and Astola (2006) used 4-grams with a Boolean method (Section 6.1). Ozbek, Rosenn, and Yeh (2006) used the frequencies of bi- and trigrams in
words unique to a language. Milne, O’Keefe, and Trotman (2012) used lists of the most frequent trigrams.

Li and Momoi (2001) divided character bigrams into common and uncommon groups based on their frequency. Xafopoulos, Kotropoulos, Almpanidis, and Pitas (2004) used the value of the difference between the ISO Latin-1 code value of two consecutive characters as well as two characters separated by another character, also known as gapped character bigrams.

Artemenko and Shramko (2005) used the IDF and the transition probability of trigrams. They calculated the IDF values $v_{C_g}(f)$ of trigrams $f$ for each language $g$, as in Equation 8, where $c(C_g, u)$ is the number of trigrams $f$ in the corpus of the language $g$ and $df(C_G, f)$ is the number of languages in which the trigram $f$ is found, when $C_G$ is the language segmented training corpus with each language in a single segment.

$$v_{C_g}(f) = \frac{c(C_g, f)}{df(C_G, f)} \quad (8)$$

$df()$ is defined as in Equation 9.

$$df(C_G, f) = \sum_{g \in G} \begin{cases} 1 & \text{if } c(C_g, f) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

Malmasi, Refaee, and Dras (2015) used n-grams from one to four, which were weighted with TF-IDF (term frequency-inverse document frequency). TF-IDF can be calculated as in Equation 10.

$$v_{C_g}(f) = c(C_g, f) \log \frac{l_G}{df(C_G, f)} \quad (10)$$

TF-IDF weighting or a close variation has been widely used for LI. Thomas and Verma (2007) used CF-IOF (class frequency-inverse overall frequency) weighted 3- and 4-grams.

Jhamtani, Bhogi, and Raychoudhury (2014) used the logarithm of the division of the counts of character bigrams and trigrams in the English and Hindi dictionaries. Zamora, Bruzón, and Bueno (2014) used a feature weighting scheme based on MI. They also tried weighting schemes based on the GSS (Galavotti, Sebastiani, and Simi) and NGL (Ng, Goh, and Low) coefficients, but using the MI-based weighting scheme proved clearly the best in their evaluations where they used the sum of values method (Equation 18). Martinc et al. (2017) used punctuation trigrams, where the first character has to be a punctuation mark. Saharia (2017) used consonant bi- and trigrams which were generated from words after the vowels had been removed.

**Character n-grams of differing sizes** The language models mentioned earlier consisted only of n-grams of the same size $n$. If $n$-grams from one to four were used, then there were four separate language models. Cavnar and Trenkle (1994) created ordered lists of the most frequent $n$-grams for each language. Singh and Goyal (2014) used similar $n$-gram lists with symmetric cross entropy. Russell and Lapalme (2003) used a Markovian method to calculate the probability of byte trigrams interpolated with byte unigrams. Vatanen, Väyrynen, and Virpioja (2010) created a language identifier which included 281 languages and obtained
an identification accuracy of 62.8% for extremely short samples (5-9 characters). Their language identifier was used or evaluated by Rodrigues (2012), Maier and Gómez-Rodríguez (2014), and Jauhiainen, Lindén, and Jauhiainen (2017b). Rodrigues (2012) managed to improve the identification results by feeding the raw language distance calculations into a separate SVM.

Table 5 lists recent articles where character n-grams of differing sizes have been used. ME in the methods column refer to Maximum Entropy (Section 6.5), LSTM RNN to Long Short-Term Memory Recurrent Neural Networks (Section 6.8), and DAN to Deep Averaging Networks (Section 6.8). Kikui (1996) used up to the four last characters of words and calculated their relative frequencies. Ahmed, Cha, and Tappert (2004) used frequencies of 2-7-grams in relation to the total number of n-grams in all the language models as well as in the current language model. Jauhiainen (2010) compared the use of different sizes of n-grams with some of their combinations and found that combining n-grams of differing sizes resulted in better identification scores. Lui and Baldwin (2011, 2012, 2014) used mixed length domain independent language models of byte n-grams from one to three or four.
<table>
<thead>
<tr>
<th>Article</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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<th>7</th>
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Table 5: List of articles (2016-) where character $n$-grams of differing sizes have been used as features. The numbered columns indicate the length of the $n$-grams used. The method column indicates the method used with the $n$-grams. The relevant section numbers are mentioned in parentheses.
Mixed length language models were also generated by Brown (2012), who used the most frequent and discriminating n-grams longer than two bytes and later by Brown (2013, 2014), where he used the most frequent and discriminating byte n-grams from two to 12, calculating their weighted relative frequencies. $K$ of the most frequent n-grams were extracted from training corpora for each language and their relative frequencies were calculated. In the tests reported in (Brown, 2013), $K$ varied from 200 to 3,500 n-grams. Later also Sanchez-Perez et al. (2017) evaluated different combinations of character n-grams as well as their combinations with words.

Stensby, Oomen, and Granmo (2010) used the mixed-order n-grams frequency relative to the total number of n-grams in the language model. Sterneberg (2012) used frequencies of n-grams from one to five and gapped 3- and 4-grams as features with SVM. As an example, some gapped 4-grams from the word “Sterneberg” would be “Senb”, “tree”, “enbr”, and “reeg”. King, Baucom, Gilmanov, Kübler, Whyatt, Maier, and Rodrigues (2014) used character n-grams as a backoff from Markovian word n-grams. Shrestha (2014) used the frequencies of word initial n-grams ranging from 3 to the length of the word minus 1. Ács, Grad-Gyenge, Bruno, and Oliveira (2015) used the most relevant n-grams selected using the absolute value of the Pearson correlation. Mandal, Banerjee, Naskar, Rosso, and Bandyopadhyay (2015) used only the first 10 characters from a longer word to generate the n-grams, while the rest were ignored. Qiao and Lévy (2015) used only those n-grams which had the highest TF-IDF scores. Bestgen (2017) used character n-grams weighted by means of the BM25 (Best Match 25) weighting scheme. Hanani et al. (2017) used byte n-grams up to the length of 25.

Consonant or vowel sequences  Sterneberg (2012) used consonant sequences generated from words. Anand (2014) used the presence of vowel sequences as a feature with a NB classifier (see Section 6.4) when distinguishing between English and transliterated Indian languages.

N-gram dictionary  Chanda, Das, and Mazumdar (2016b) used a basic dictionary (Sec. 5.5) composed of the 400 most common character 4-grams.

Unique character combinations  Henrich (1989) and Vitale (1991) used character combinations (of different sizes) that either existed in only one language or did not exist in one or more languages.

5.4 Morphemes, syllables and chunks

Table 6: References (2016–) where prefixes and suffixes collected from a training corpus has been used for LI. The columns indicate the length of the prefixes and suffixes. The method column indicates the method used. The relevant section numbers are mentioned in parentheses.

<table>
<thead>
<tr>
<th>Reference</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Method</th>
</tr>
</thead>
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<td>SVM, LR, RF (cf. 6.9), ...</td>
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accuracy while the $n$-grams reached 82.7%. Yeong and Tan (2010) stripped Malay affixation from words in order to get the base forms. Lu and Mohamed (2011) used a morphological analyzer of Arabic. Zampieri et al. (2013) used morphological information from a part-of-speech (POS) tagger. Anand (2014) and Banerjee et al. (2014) used manually selected suffixes as features. Bekavac, Kocijan, and Tadić (2014) created morphological grammars to distinguish between Croatian and Serbian. Darwish, Sajjad, and Mubarak (2014) used morphemes created by Morfessor, but they also used manually created morphological rules. Gamallo et al. (2014) used a suffix module containing the most frequent suffixes. Dutta, Saha, Banerjee, and Naskar (2015) and Mandal et al. (2015) used word suffixes as features with CRFs. Barbaresi (2016) used an unsupervised method to learn morphological features from training data. Gómez-Adorno et al. (2017) used typed character $n$-grams. Table 6 lists some of the more recent articles where prefixes and suffixes collected from a training corpus has been used for LI.

**Syllables and syllable $n$-grams** Chen, You, Chu, Zhao, and Wang (2006) used trigrams composed of syllables. Yeong and Tan (2010) used Markovian syllable bigrams for LI between Malay and English. Later Yeong and Tan (2011) also experimented with syllable uni- and trigrams. Murthy and Kumar (2006) used the most frequent as well as the most discriminating Indian script syllables called aksharas. They used single aksharas, akshara bigrams, and akshara trigrams. Syllables would seem to be especially usable in situations where distinction needs to be made between two closely related languages.

**Chunks, chunk $n$-grams and $n$-grams of $n$-grams** You et al. (2008) used the trigrams of non-syllable chunks that were based on MI. Yeong and Tan (2010) experimented also with Markovian bigrams using both character and grapheme bigrams, but the syllable bigrams proved to work better. Graphemes in this case are the minimal units of the writing system, which may consist of several characters. Later, Yeong and Tan (2011) also used grapheme uni- and trigrams. Yeong and Tan (2011) achieved their best results combining word unigrams and syllable bigrams with a grapheme back-off. Elfardy, Al-Badrashiny, and
Diab (2014) used the MADAMIRA toolkit for D3 decliticization and then used D3-token 5-grams. D3 decliticization is a way to preprocess Arabic words.

Graphones are sequences of characters linked to sequences of corresponding phonemes. They are automatically deduced from a “bilingual” corpus which consists of words and their correct pronunciations using Joint Sequence Models (JSM). Giwa and Davel (2014) replaced the phonemes with languages when generating the graphones and then used Markovian graphone $n$-grams from 1 to 8 in LI.

5.5 Words

Position of words Kumar, Kumar, and Soman (2015) used the position of the current word in word level LI. Position of words in sentences has been used as a feature in code-switching detection also by Dongen (2017). It had predictive power greater than the language label or length of a word before the last.

The characteristics of words Mustonen (1965) used the characteristics of words as parts of discriminating functions. Barman, Wagner, Chrupala, and Foster (2014b) used the string edit distance and $n$-gram overlap between the word to be identified and words in dictionaries. Similarly Jhamtani et al. (2014) used a modified edit distance, which considers the common spelling substitutions when Hindi is written using latin characters. Das and Gambäck (2013) used the Minimum Edit Distance (MED).

Basic dictionary Basic dictionaries are unordered lists of words belonging to a language. Basic dictionaries do not include knowledge of word frequency and are independent of the dictionaries of other languages. Vitale (1991) used a dictionary for LI as a part of his speech synthesizer. Each word in a dictionary had only one possible “language”, or pronunciation category. Lately, a basic dictionary has been used for LI by Adouane and Dobnik (2017), Dongen (2017), and Duvenhage et al. (2017).

Dictionary of unique words Unique word dictionaries include only those words of the language, that do not belong to the other languages used by the language identifier. Kulikowski (1991) used unique short words (from one to three characters) to differentiate between languages. Recently, a dictionary of unique words has been used for LI by Adouane (2016), Guellil and Azouaou (2016), and Martinc et al. (2017).

Specific classes of words Giguet (1995) used exhaustive lists of grammatical words collected from dictionaries. Wechsler, Páraic, and Schäuble (1997) used stop words, that is words that did not represent the content of document used as corpus. Lins and Gonçalves (2004) used words from closed word classes. Stupar et al. (2011) used lists of function words. Al-Badrashiny, Elfardy, and Diab (2015) used a lexicon of Arabic words and phrases that convey modality. Common to these features is that they are collected using linguistic knowledge.

Discriminating words Pham and Tran (2003) used an LBG-VQ (Linde, Buzo & Gray algorithm for Vector Quantization) approach to design a codebook for each language. The codebook contained vectors which were words converted to a sequence of numbers. Rehůřek and Kolkus (2009) used the most relevant words for each language. Babu and Kumar (2010)
The most common words Souter, Churcher, Hayes, Hughes, and Johnson (1994) made an (unordered) list of the most common words for each language, as did lately Cazamias, Dixit, and Marek (2015), Panich (2015), and Abainia et al. (2016). Pavan, Tandon, and Varma (2010) encoded the most common words to root forms with the Soundex algorithm.

The frequency of words Mather (1998) collected the frequencies of words into feature vectors. Prager (1999) compared the use of character \( n \)-grams from 2 to 5 with the use of words. Using words resulted in better identification results than using character bigrams in tests (mystery text sizes of 20, 50, 100 or 200 characters), but always worse than character 3-, 4- or 5-grams. However, the combined use of words and character 4-grams gave the best results of all tested combinations, obtaining 95.6% accuracy for 50 character sequences when choosing between 13 languages. Ács et al. (2015) used TF-IDF scores of words to distinguish between language groups. Recently, the frequency of words has been used for LI also by Clematide and Makarov (2017), Gómez-Adorno et al. (2017), Plaza Cagigós (2017), and Saharia (2017).

The relative frequency of words Nakayama and Spitz (1993) manually selected one representative word-shape token (characters were collapsed into 12 categories called character-shapes) for each language. The relative frequencies of these tokens were calculated for every language. As did Prager (1999) for word frequencies, also Jauhiainen (2010) found that combining the use of character \( n \)-grams with the use of words provided the best results. His language identifier obtained 99.8% average recall for 50 character sequences for the 10 evaluated languages (choosing between the 13 languages known by the language identifier) when using character \( n \)-grams from 1 to 6 combined with words. Tiedemann and Ljubešić (2012) calculated the relative frequency of words over all the languages. Artemenko and Shramko (2005) calculated the IDF of words the same way as trigrams of characters in Equation 8. Xu et al. (2016) calculated the Pointwise Mutual Information (PMI) for words and used it to group words to Chinese dialects or dialect groups. Recently, the relative frequency of words has been used for LI also by Jauhiainen et al. (2017a, 2017b) and Jourlin (2017).

Short words Grefenstette (1995) used the relative frequency of words with less than six characters. Recently, also Panich (2015) used short words, as did Simaki et al. (2017).

Search engine queries Alex (2005) used the relative frequency calculated from the Google lookup module search hits. Google was later also used by You et al. (2008) and Yang and Liang (2010).

Word probability maps Scherrer and Rambow (2010) created probability maps for words for German dialect identification. Probability maps were derived from automatically induced dialect lexicons.

Morphological analyzers and spellchecking Pienaar and Snyman (2010) used commercial spelling checkers, which utilized lexicons and morphological analyzers. The language identifier of Pienaar and Snyman (2010) obtained 97.9% accuracy when classifying one line texts between 11 official South African languages. Elfardy and Diab (2012) used
ALMORGEANA analyzer to check if the word had an analysis in modern standard Arabic. They also used sound change rules to use possible phonological variants with the analyzer. Joshi, Bhatt, and Patel (2013) used spellchecking and morphological analyzers to detect English words form Hindi-English mixed search queries. Akosu and Selamat (2014) used spelling checkers to distinguish between 15 languages, extending the work of Pienaar and Snyman (2010) with dynamic model selection in order to gain better performance. Shrestha (2014) used a similarity count to find if mystery words were misspelled versions of the words in his dictionary.

5.6 Word combinations

Sentence length Elfardy and Diab (2013) used the number of words in a sentence with NB. van der Lee and Bosch (2017) and Simaki et al. (2017) used the sentence length calculated in both words and characters with several machine learning algorithms.

Statistics of words van der Lee and Bosch (2017) used the ratios of different words, once-occurring words, twice-occurring words, short words, long words, function words, adjectives and adverbs, personal pronouns, and question words to the total number of words. They also used the word-length distribution for words of 1-20 characters.

Word n-grams Marcadet et al. (2005) used at least the previous and next words with manual rules in word level LI for text-to-speech synthesis. Rosner and Farrugia (2007) used Markovian word n-grams with a Hidden Markov Model (HMM) tagger (Section 6.10). Table 7 lists more recent articles where word n-grams or similar constructs have been used. PPM in the methods column refer to Prediction by Partial Matching (Section 5.7) and kNN to k Nearest Neighbors (Section 6.11). Singh (2006) used the word trigrams simultaneously with character 4-grams. He concluded that the word-based models can be used to augment the results from character n-grams when they are not providing reliable identification results. Table 8 lists the articles where both character and word n-grams have been used together. CBOW in the methods column refer to Continuous Bag of Word (Section 6.8) and MIRA to Margin Infused Relaxed Algorithm (Section 6.7). Sanchez-Perez et al. (2017) evaluated different combinations of word and character n-grams with SVMs. The best combination for language variety identification was using all the features simultaneously. Tellez et al. (2017) used normal and gapped word n-grams and character n-grams simultaneously.

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Table 7: References (2015-) where word n-grams have been used as features. The numbered columns indicate the length of the n-grams used. X indicates the best and X the second best n-gram length as evaluated in the article in question. Plain X indicates that there was no clear order of efficiency or that the order was not presented in the article. The method column indicates the method used. The relevant section numbers are mentioned in parentheses.
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<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>2-4</td>
<td>CRF</td>
</tr>
<tr>
<td>Malmasi and Dras (2015a)</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1-3</td>
<td>SVM</td>
</tr>
<tr>
<td>Malmasi and Dras (2015b)</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1-6</td>
<td>SVM</td>
</tr>
<tr>
<td>Malmasi et al. (2015)</td>
<td>X</td>
<td>X</td>
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<td></td>
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<td></td>
<td>1-4</td>
<td>SVM</td>
</tr>
<tr>
<td>Castro et al. (2016)</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2-7</td>
<td>Product (cf. 6.4)</td>
</tr>
<tr>
<td>Zirikly, Desmet, and Diab (2016)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1-6</td>
<td>LR</td>
</tr>
<tr>
<td>Basile et al. (2017)</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3-6</td>
<td>SVM</td>
</tr>
<tr>
<td>Castro et al. (2017)</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2-7</td>
<td>NB, LR, SVM, RF</td>
</tr>
<tr>
<td>Ciobanu, Zampieri, Malmasi, and Dinu (2017)</td>
<td>X</td>
<td>X</td>
<td></td>
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<td></td>
<td></td>
<td>1-6</td>
<td>SVM</td>
</tr>
<tr>
<td>Çöltekin and Rama (2017)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1-7+</td>
<td>SVM</td>
</tr>
<tr>
<td>Markov, Gómez-Adorno, and Sidorov (2017)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3-7</td>
<td>SVM, NB</td>
</tr>
<tr>
<td>Martinc et al. (2017)</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4</td>
<td>SVM, LR, RF, ...</td>
</tr>
<tr>
<td>Medvedeva, Kroon, and Plank (2017)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>1-6</td>
<td>SVM, CBOW (cf. 6.8)</td>
</tr>
<tr>
<td>Mendoza and Mendelsohn (2017)</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td>1-6</td>
<td>SVM</td>
</tr>
<tr>
<td>Pla and Hurtado (2017)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1-6</td>
<td>SVM</td>
</tr>
<tr>
<td>Williams and Dagli (2017)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>1-5</td>
<td>MIRA (cf. 6.7)</td>
</tr>
</tbody>
</table>

Table 8: List of articles where word and character n-grams have been used as features. The numbered columns indicate the length of the word n-grams and char-column the length of character n-grams used. The method column indicates the method used. The relevant section numbers are mentioned in parentheses.
**Syntax and part-of-speech (POS) tags** Alex (2005) evaluated methods for detecting foreign language inclusions and experimented with a Conditional Markov Model (CMM) tagger, which had performed well on Named Entity Recognition (NER). Alex (2005) was able to produce the best results by incorporating her own English inclusion classifiers decision as a feature for the tagger and not using the taggers POS tags. Romsdorfer and Pfister (2007) used syntactic parsers together with dictionaries and morpheme lexicons. Lui and Cook (2013) used $n$-grams composed of POS tags and function words. Piergallini et al. (2016a) used labels from a NER system, Brown clusters and cluster prefixes. Adouane and Dobnik (2017) used POS tag $n$-grams from one to three and Bestgen (2017) from one to five, and Martine et al. (2017) POS tag trigrams with TF-IDF weighting. Schulz and Keller (2016), Basile et al. (2017), van der Lee and Bosch (2017), and Simaki et al. (2017) also have recently used POS tags. Franco-Salvador et al. (2015a) used POS tags with Emotion-labeled Graphs. Elfardy et al. (2014) used the MADAMIRA tool for morphological analysis disambiguation. Romsdorfer and Pfister (2007) and Franco-Salvador et al. (2015a) used syntactic analyzers. Noh, Talib, Ahmad, Halim, and Mohamed (2009) converted sentences into word-class patterns. Laboreiro, Bošnjak, Sarmento, Rodrigues, and Oliveira (2013) used Jspell to detect differences in the grammar of Portuguese variants. Bekavac et al. (2014) created syntactic grammars to distinguish between Croatian and Serbian.

**Languages identified for the surrounding words in word level LI** Marcadet et al. (2005) used the weighted LI scores of the words to the left and right of the word to be classified. Rosner and Farrugia (2007) used language labels with HMM. Akhil and Abhishek (2014) used the language labels of other words in the same sentence to determine the language of the ambiguous word. The languages of the other words had been determined by the positive Boolean method (Section 6.1) using dictionaries of unique words when possible. Das and Gambäck (2014, 2013) used the language tags of the previous three words with SVM. Mukherjee, Ravi, and Datta (2014) used language labels of surrounding words with NB. King et al. (2015) used the language probabilities of the previous word for determining weights for languages. King et al. (2014) used unigram, bigram and trigram language label transition probabilities. Papalexakis, Nguyen, and Dogruöz (2014) used the language labels for the two previous words as well as the knowledge of whether code-switching had already been detected or not. Raj and Karfa (2014) used the language label of the previous word to determine the language of an ambiguous word. Sinha and Srinivasa (2014) also used the language label of the previous word. Chanda, Das, and Mazumdar (2016a) used the language identifications of 2-4 surrounding words for post identification correction in word level LI. Samih and Maier (2016) used language labels with CRF. Dongen (2017) used language labels of the current and two previous words in code-switching point prediction. Their predictive strength were bested by the count of code-switches so far, but they were better than the length or position of the word. All of the features were used together with NB, DT and SVM. Guzmán, Ricard, Serigos, Bullock, and Toribio (2017) used language label bigrams with HMM. Elfardy and Diab (2013) used the word-level language labels obtained with the approach of Elfardy, Al-Badrashiny, and Diab (2013) on sentence-level dialect identification.
5.7 Feature smoothing

Feature smoothing is required in order to handle the cases where not all features \( f_i \) from the mystery text have been attested in the training corpora. Thus, it is used especially when the count of used features is high and/or when the amount of training data is low. Smoothing is usually handled as part of the method, and not pre-calculated into the language models. Most of the smoothing methods evaluated by Chen and Goodman (1999) have been used in LI and we follow the order of introduction from that article.

Additive smoothing (Laplace, Lidstone) In Laplace smoothing an extra number of instances are added to every possible feature in the language models. Dunning (1994) used Laplace’s sample size correction (add-one smoothing) with the product of Markovian probabilities. Adams and Resnik (1997) experimented with additive smoothing of 0.5 and notes that it was almost as good as the Good-Turing smoothing he ended up using later in the tests. Chen and Goodman (1999) calculate the values for each \( n \)-gram as in Equation 11,

\[
v_{C_g}(f) = \frac{c(C_g, f) + \lambda}{l_{C_g} + |U(C_g^n)| \lambda}
\]  

(11)

where \( v_{C_g}(f) \) is the probability estimate of \( n \)-gram \( f \) in the model and \( c(C_g, f) \) its frequency in the training corpus. \( l_{C_g} \) is the total number of \( n \)-grams of length \( n \) and \( |U(C_g^n)| \) the number of distinct \( n \)-grams in the training corpus. \( \lambda \) is the Lidstone smoothing parameter. When using Laplace smoothing, the \( \lambda \) is equal to 1 and with Lidstone smoothing, the \( \lambda \) is usually set between 0 and 1.

The penalty values used by Jauhiainen et al. (2016) with the HeLI method function as a form of additive smoothing. Vatanen et al. (2010) evaluated additive, Katz, absolute discounting, and Kneser-Ney smoothings. Additive smoothing produced the least accurate results of the four methods. Cann (2015) and Franco-Penya and Sanchez (2016) evaluated NB with several different Lidstone smoothing values. Cianflone and Kosseim (2016) used additive smoothing with character \( n \)-grams as a baseline classifier, which they then were unable to beat with Convolutional Neural Networks (CNN).

Good-Turing Discounting Adams and Resnik (1997) used Good-Turing smoothing with the product of Markovian probabilities. Chen and Goodman (1999) define the Good-Turing smoothed count \( c_{GT}(C, f) \) as in Equation 12,

\[
c_{GT}(C_g, f) = (c(C_g, f) + 1) \frac{r_c(C_g, f) + 1}{r_c(C_g, f)}
\]  

(12)

where \( r_c(C_g, f) \) is the number of features occurring exactly \( c(C_g, f) \) times in the corpus \( C_g \). Lately Good-Turing smoothing has been used by Gamallo, Pichel, Alegria, and Agirre (2016) and Giwa (2016).

Jelinek-Mercer Rehůřek and Kolkus (2009) used Jelinek-Mercer smoothing correction with the relative frequencies of words. They calculated the smoothing as in Equation 13,

\[
v_{C_g}(f) = \lambda \frac{c(C_g, f)}{l_{C_g}} + (1 - \lambda) \frac{c(C_g, f)}{l_{C_g}}
\]  

(13)

25
where $\lambda$ is the smoothing parameter which is usually some small value like 0.1. Mendizabal et al. (2014) used character 1-8 grams with Jelinek-Mercer smoothing. Their language identifier using character 5-grams achieved 3rd place (out of 12) in the TweetLID shared task constrained track.

**Katz** Ramisch (2008) and Vatanen et al. (2010) used the Katz back-off smoothing (Katz, 1987) from the SRILM toolkit with perplexity. Katz smoothing is an extension of Good-Turing discounting. The probability mass left over from the discounted $n$-grams is then distributed over unseen $n$-grams via a smoothing factor. In the smoothing evaluations by Vatanen et al. (2010), the Katz smoothing performed almost as well as the absolute discounting, which produced the best results. Giwa and Davel (2013) evaluated Witten-Bell, Katz, and absolute discounting smoothing methods. Witten-Bell got 87.7%, Katz 87.5%, and absolute discounting 87.4% accuracy with character 4-grams.

**Prediction by Partial Matching (PPM/Witten-Bell)** Teahan (2000) used the PPM-C algorithm for LI. PPM-C is basically a product of Markovian probabilities with an escape scheme. If an unseen context is encountered for the character being processed, the escape probability is used together with a lower order model probability. In PPM-C the escape probability is the sum of the seen contexts in the language model. PPM-C was lately used by Adouane et al. (2016d). The PPM-D+ algorithm was used by Celikel (2005). Bergsma, McNamee, Bagdouri, Fink, and Wilson (2012) and McNamee (2016) used a PPM-A variant. Also Yamaguchi and Tanaka-Ishii (2012) used PPM. The language identifier of Yamaguchi and Tanaka-Ishii (2012) obtained 91.4% accuracy when classifying 100 character texts between 277 languages. Jaech, Mulcaire, Hathi, Ostendorf, and Smith (2016b) used Witten-Bell smoothing with perplexity.

**Absolute discounting** Vatanen et al. (2010) used several smoothing techniques with Markovian probabilities. Absolute discounting from the VariKN toolkit performed the best. Vatanen et al. (2010) define the smoothing as follows: a constant $D$ is subtracted from the counts $c(C_g, u_{i-n+1},...,i)$ of all observed $n$-grams $u_{i-n+1},...,i$ and the left-out probability mass is distributed between the unseen $n$-grams in relation to the probabilities of lower order $n$-grams $P_g(u_i|u_{i-n+2},...,i-1)$, as in Equation 14:

$$P_{C_g}(u_i|u_{i-n+1},...,i-1) = \frac{c(C_g, u_{i-n+1},...,i)}{c(C_g, u_{i-n+2},...,i-1)} + \lambda_{u_{i-n+1},...,i-1} P_{C_g}(u_i|u_{i-n+2},...,i-1)$$  (14)

where $\lambda_{u_{i-n+1},...,i-1}$ is a scaling factor that makes the conditional distribution sum to one. Absolute discounting with Markovian probabilities from the VariKN toolkit was later also used by Rodrigues (2012), Maier and Gómez-Rodríguez (2014), and Jauhiainen et al. (2017b).

**Kneser-Ney smoothing** Kneser-Ney is based on absolute discounting. Chen and Mai-son (2003) used the Markovian probabilities with Witten-Bell and modified Kneser-Ney smoothings. Giwa (2016), Balazević et al. (2016), and Rijhwani et al. (2017) also recently used the modified Kneser-Ney discounting. Barbaresi (2016) used both original and the
modified Kneser-Ney smoothing. In the evaluations of Vatanen et al. (2010), the Kneser-Ney smoothing fared clearly better than additive, but somewhat worse than the Katz and absolute discounting smoothings. Lately also Samih and Maier (2016) used Kneser-Ney smoothing.

Castro et al. (2016, 2017) evaluated several smoothing techniques with character and word n-grams: Laplace/Lidstone, Witten-Bell, Good-Turing, and Kneser-Ney. In their evaluations additive smoothing with 0.1 provided the best results. Good-Turing was not as good as additive smoothing, but better than Witten-Bell or Kneser-Ney smoothings. Witten-Bell proved to be clearly better than Kneser-Ney.

6. Methods

In recent years there has been a tendency towards attempting to combine several different types of features into one classifier or classifier ensemble. Many recent studies use readily available classifier implementations and simply report how well they worked with the feature set used in the context of their study. There are many methods presented in this article that are still not available as out of the box implementations. It appears that there are many studies which have not been re-evaluated at all, going as far back as Mustonen (1965). Our hope is that this article will inspire new studies and many previously unseen ways of combining features and methods. In the following subsections the reviewed articles are grouped by the methods used for LI.

6.1 Boolean method

Henrich (1989) used a positive Boolean method with unique characters and character n-grams, that is, if a unique character or character n-gram was found, the language was identified. The positive Boolean method (unique features) for the mystery text $M$ and the training corpus $C_g$ can be formulated as in Equation 15.

$$R_{\text{Boolean}^+}(g, M) = \begin{cases} 1, & \text{if } \exists f \in U(M) : c(C_g, f) > 0 \land c(C_j, u) = 0 \land g \neq j \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

where $C_g$ is the corpus for language $g$ and $C_j$ is a corpus of any other language $j$. The positive Boolean method can also be used with non-unique features when the decisions are made in a certain order. For example, Dongen (2017) presents the pseudo code for her dictionary lookup tool, where these kind of decisions are part of an if-then-else statement block. Her (manual) rule-based dictionary lookup tool actually works better for Dutch-English code-switching detection than the evaluated SVM, DT, or CRF methods. The positive Boolean method has also been used recently by Abainia et al. (2016), Chanda et al. (2016b, 2016a), Guellil and Azouaou (2016), Gupta, Bhatt, and Mittal (2016), He et al. (2016), and Adouane and Dobnik (2017).

In the negative Boolean method, if a character or character combination that was found in $M$ does not exist in a particular language, that language is omitted from further identification. The negative Boolean method can be expressed with Equation 16:

$$R_{\text{Boolean}^-}(g, M) = \begin{cases} 1, & \text{if } \exists f \in U(M) : c(C_g, f) > 0 \land c(C_j, u) = 0 \land g \neq j \\ 0, & \text{otherwise} \end{cases} \quad (16)$$
\[ R_{\text{Boolean}}^{-}(g, M) = \begin{cases} 0, & \text{if } \exists f \in U(M) : c(C_g, f) = 0 \\ 1, & \text{otherwise} \end{cases} \] (16)

where \( C_g \) is the corpus for language \( g \). The negative Boolean method was first used by Giguet (1995).

In isolation Boolean methods tend not to scale well to larger numbers of languages (or very short mystery texts), and are thus mostly used in combination with other LI methods.

### 6.2 Simple scoring

In simple scoring, each feature in the mystery text is checked against the language models and languages of models containing the feature are given a point, as in Equation 17:

\[ R_{\text{simple}}(g, M) = \sum_{i=1}^{t_{MF}} \begin{cases} 1, & \text{if } f_i \in \text{dom}(O(C_g)) \\ 0, & \text{otherwise} \end{cases} \] (17)

where \( f_i \) is the \( i \)th feature found in the mystery text \( M \). The language scoring the most points is the winner. Simple scoring is still a good alternative when facing an easy problem such as preliminary language group identification. It was recently used for this purpose by Franco-Salvador, Rosso, and Rangel (2015b) with a basic dictionary. They achieved 99.8% accuracy when identifying between 6 language groups. Kadri and Moussaoui (2013) use a version of simple scoring as a distance measure giving a penalty value to the features not found in a model. In this version, the language scoring the least amount of points is the winner. Their language identifier obtained 100% success rate with 4-grams of characters when classifying document-sized texts (from 1 to 3 kilobytes), between 10 languages. Simple scoring was also used lately by Balažević et al. (2016), Selamat and Akosu (2016), and Duvenhage et al. (2017).

### 6.3 Sum or average of values

The sum of values can be expressed as in Equation 18.

\[ R_{\text{sum}}(g, M) = \sum_{i=1}^{t_{MF}} v_{C_g}(f_i) \] (18)

where \( f_i \) is the \( i \)th feature found in the mystery text \( M \) and \( v_{C_g}(f_i) \) is the value for the feature in the language model of the language \( g \). The language with the highest score is the winner.

The simplest case of Equation 18 is when the text to be identified contains only one feature. An example of this is Shrestha (2014) who used the frequencies of short words as values in word level identification. For longer words he summed up the frequencies of different sized \( n \)-grams found in the word to be identified. Giwa and Davel (2014) first calculated the language corresponding to each graphone. They then summed up the predicted languages and the language scoring the highest was the winner. When a tie
occurred they used the product of the Markovian graphone \( n \)-grams. Their method managed to outperform SVMs in their tests.

Henrich (1989) used the average of all the relative frequencies of the \( n \)-grams in the text to be identified. Vogel and Tresner-Kirsch (2012) evaluated several variations of the LIGA algorithm introduced by Tromp and Pechenizkiy (2011). Moodley (2016) and Jauhiainen et al. (2017b) also used LIGA and logLIGA methods. The average or sum of relative frequencies was also used recently by Abainia et al. (2016) and Martadinata et al. (2016).

Ng and Selamat (2009) summed up their LFDF values obtaining 99.75% accuracy when classifying document sized texts between four languages using Arabic script. Vitale (1991) calculates the score of the language for the mystery text \( M \) as the average of the probability estimates of the features, as in Equation 19.

\[
R_{\text{avg}}(g, M) = \frac{\sum_{i=1}^{l_{MF}} v_{C_{g}}(f_i)}{l_{MF}} \quad (19)
\]

where \( l_{MF} \) is the number of features in the mystery text \( M \). Brown (2013) summed weighted relative frequencies of character \( n \)-grams and the score was then normalized dividing by the length (in characters) of the mystery text. Taking the average of the terms in the sums does not change the order of the scored languages, but it gives comparable results between different lengths of mystery texts.

Vega and Bressan (2001a, 2001b) summed up their weights and divided them by the number of words in the mystery text in order to set a threshold to detect unknown languages. Their language identifier obtained 88.88% precision and a 94% recall when classifying documents between five languages. El-Shishiny et al. (2004) used a weighting method combining alphabets, prefixes, suffixes and words. Elfardy and Diab (2012) summed up values from word trigram ranking, basic dictionary and morphological analyzer lookup. Akhil and Abhishek (2014) summed up language labels of the surrounding words to identify the language of the current word. Bekavac et al. (2014) summed up points awarded by the presence of morphological and syntactic features. Gamallo et al. (2014) used inverse rank positions as values. Ács et al. (2015) computed the sum of keywords weighted with TF-IDF. Fabra-Boluda, Rangel, and Rosso (2015) summed up the TF-IDF derived probabilities of words.

6.4 Product of values

The product of values can be expressed as in Equation 20.

\[
R_{\text{prod}}(g, M) = \prod_{i} v_{C_{g}}(f_i) \quad (20)
\]

where \( f_i \) is the \( i \)th feature found in the mystery text \( M \) and \( v_{C_{g}}(f_i) \) is the value for the feature in the language model of the language \( g \). The language with the highest score is the winner. Some form of feature smoothing is usually required with the product of values method to avoid multiplying by zero.
**Product of relative frequencies** Church (1985) was the first to use the product of relative frequencies and it has been widely used ever since, recent examples include Castro et al. (2016, 2017), Hanani et al. (2017), and Jauhiainen et al. (2017b). Some of the authors use the summing of logarithms instead of multiplying the relative frequencies, but the two methods yield the same relative ordering and optimum, with the proviso that the maximum of multiplying numbers between 0 and 1 becomes the minimum of summing their negative logarithms as can be inferred from Equation 21.

\[
R_{\logsum}(g, M) = -\log(R_{\text{prod}}(g, M)) = -\log \prod_{i=1}^{l_{MF}} v_{C_{g}}(f_i) = \sum_{i=1}^{l_{MF}} -\log(v_{C_{g}}(f_i))
\]  

(21)

**Naive Bayes (NB)** When (multinomial\(^1\)) NB is used in LI, each feature used has a probability to indicate each language. The probabilities of all features found in the mystery text are multiplied for each language and the language with the highest probability is selected as in Equation 20. Theoretically the features are assumed to be independent of each other, but in practice using features that are functionally dependent can improve classification accuracy (Peng & Schuurmans, 2003).

NB implementations have been widely used for LI, usually with a more varied set of features than simple character or word \(n\)-grams of the same type and length. The features are typically represented as feature vectors given to a NB classifier. Mukherjee et al. (2014) trained the NB classifier with language labels of surrounding words to help predict the language of ambiguous words first identified using SVM. The language identifier used by Tan et al. (2014) obtained 99.97% accuracy with 5-grams of characters when classifying sentence sized texts between six language groups. Goutte et al. (2014) used a probabilistic model similar to NB. Bhattu and Ravi (2015) used NB and Naive Bayes EM, which uses an Expectation-Maximization (EM) algorithm for improving accuracy. Ljubešić and Kranjčić (2014) used Gaussian Naive Bayes (GNB) from scikit-learn.

**Bayesian Network Classifiers** In contrast to NB, in Bayesian networks the features are not assumed to be independent from each other. The network learns the dependencies between features in a training phase. Fabra-Boluda et al. (2015) used a Bayesian Net classifier from Weka in a two-staged (group first) LI on the open track of the Discriminating between Similar Languages (DSL) 2015 shared task. Rangel et al. (2017a) evaluated BayesNet from the Weka package, which performed worst across the 12 algorithms tested.

**Product of Markovian probabilities** House and Neuburg (1977) used the product of the Markovian probabilities of bigrams of characters. The language identifier created by Brown (2013, 2014), “whatlang”, obtains 99.2% classification accuracy with smoothing for 65 character test strings, when distinguishing between 1,100 languages. The product of Markovian probabilities has recently also been used by Samih and Maier (2016) and Mendoza and Mendelsohn (2017).

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1. To the best of our knowledge, the multivariate Bernoulli version of NB has never been used for LI. See (Giwa, 2016) for explanations.
HeLI  Jauhiainen et al. (2016) use a word-based backoff method called HeLI. In the method, each language is represented by several different language models, only one of these models is used for every word found in the mystery text. The language models for each language are: a model based on words, and one or more models based on character $n$-grams from one to $n_{\text{max}}$. When a word that is not included in the model based on words is encountered in the mystery text, the method backs off to using the $n$-grams of the size $n_{\text{max}}$. If it is not possible to apply the $n$-grams of the size $n_{\text{max}}$, the method backs off to lower order $n$-grams and continues backing off until character unigrams, if needed. The LI system by Jauhiainen et al. (2016) implementing the HeLI method attained the shared first place in the closed track of the DSL 2016 shared task (Malmasi, Zampieri, Ljubešić, Nakov, Ali, & Tiedemann, 2016), and was the best method tested by Jauhiainen et al. (2017b) for mystery texts longer than 30 characters.

6.5 Similarity measures

Out-of-place method  The method by Cavnar and Trenkle (1994) uses overlapping character $n$-grams of varying size calculated from words. The language models are created by tokenizing the training texts for each language $g$ into words, and then padding each word with spaces, one before and four after. Each padded word is then divided into overlapping character $n$-grams of sizes from 1 to 5 and the counts of every unique $n$-gram are calculated over the whole corpus. The $n$-grams are ordered by frequency and $k$ of the most frequent $n$-grams, $f_1, \ldots, f_k$, are used as the domain of the language model $O(C_g)$ for the language $g$. The rank of an $n$-gram $f$ in language $g$ is determined by the $n$-gram frequency in the training corpus $C_g$ and denoted $\text{rank}_{C_g}(f)$.

During LI, the mystery text $M$ is treated in a similar way and a corresponding model $O(M)$ of the $K$ most frequent $n$-grams is created. Then a distance score is calculated between the model of the mystery text and each of the language models. The value $v_{C_g}(f)$ is calculated as the difference in ranks between $\text{rank}_{M}(f)$ and $\text{rank}_{C_g}(f)$ of the $n$-gram $f$ in the domain $\text{dom}(O(M))$ of the model of the mystery text. If an $n$-gram is not found in a language model, a special penalty value $p$ is added to the total score of the language for each missing $n$-gram. The penalty value should be higher than the maximum possible distance between ranks.

$$v_{C_g}(f) = \begin{cases} |\text{rank}_{M}(f) - \text{rank}_{C_g}(f)| & \text{if } f \in \text{dom}(O(C_g)) \\ p & \text{if } f \notin \text{dom}(O(C_g)) \end{cases} \quad (22)$$

The score $R_{CT}(g)$ for each language $g$ is the sum of values as in Equation 18. The language having the lowest score $R_{CT}(g)$ is selected as the identified language. The method is equal to Spearman’s measure of disarray (Diaconis & Graham, 1977). The out-of-place method has been widely used in LI literature as a baseline. In the evaluations of Jauhiainen et al. (2017b) for 285 languages, the out-of-place method achieved an F-score of 95% at 35 character mystery text size. It was the fourth best of the seven evaluated methods at mystery text lengths over 20 characters.

Local Rank Distance  Ionescu and Popescu (2016) and Ionescu and Butnaru (2017) used Local Rank Distance (Ionescu, 2013), with a Radial Basis Function (RBF) kernel
(see Section 6.7). For learning they experimented with both Kernel Discriminant Analysis (KDA), and Kernel Ridge Regression (KRR). Franco-Salvador, Kondrak, and Rosso (2017a) also used KDA.

**Levenshtein distance** Pavan et al. (2010) compared the most frequent words using the Levenshtein distance. Their language identifier obtained 97.7% precision when classifying texts from two to four words between five languages. Later Guellil and Azouaou (2016) used Levenshtein distance for Algerian dialect identification and Gupta et al. (2016) for query word identification.

**Probability difference** Botha, Zimu, and Barnard (2007) calculated the difference between probabilities. Singh (2006, 2010) used the log probability difference and the absolute log probability difference. The log probability difference proved slightly better obtaining a precision of 94.31% using both character and word n-grams when classifying 100 character texts between 53 language-encoding pairs.

**Vectors** Depending on the mathematical way used to represent the algorithm it is often easier to view the language models as vectors. In the following methods each language is represented by one or more feature vectors. Methods where each language is represented by only one feature vector are also referred to as centroid-based methods (Takçi & Güngör, 2012). The distance measures are generally calculated over all the features included in the feature vectors.

Kruengkrai et al. (2005) calculated the squared Euclidean distance between feature vectors. The Squared Euclidean distance can be calculated as in Equation 23.

$$R_{\text{euc}}^2(g, M) = \sum_i (v_M(f_i) - v_C(g, f_i))^2 \quad (23)$$

Hamzah (2010) used the simQ similarity measure, which is closely related to the Squared Euclidean distance. Stensby et al. (2010) updated the feature vector representing the mystery text $M$ using a Stochastic Learning Weak Estimator (SLWE) method for word level LI. This method uses a feature vector that includes all possible units from the language models, in their case mixed-order n-grams from one to four. The mystery text is processed one word at a time and the vector is updated using the SLWE updating scheme for each unit found in the current word. After each word the distance to the probability distributions of languages is calculated, and the language nearest is chosen as the language of the previous word. Their language identifier obtained 96.0% accuracy when classifying sentences with ten words between three languages. They used the Euclidean distance as the distance measure as in Equation 24.

$$R_{\text{euc}}(g, M) = \sqrt{R_{\text{euc}}^2(g, M)} \quad (24)$$

Tomović and Janičić (2007) compared the use of the Euclidean distance with their own similarity functions. Prager (1999) calculated the cosine angle between the feature vector of the mystery text and the feature vectors acting as language models. This is also called the cosine similarity and is calculated as in Equation 25.
\[ R_{\cos}(g, M) = \frac{\sum_i v_M(f_i)v_C(g)(f_i)}{\sqrt{\sum_i v_M(f_i)^2} \sqrt{\sum_i v_C(g)(f_i)^2}} \] (25)

The method of Prager (1999) was evaluated by Lui, Lau, and Baldwin (2014a). The cosine similarity has been recently used by Schaetti (2017). Brown (2012) used the dot product in Equation 26, as the feature values in the language models were already normalized.

\[ R_{\text{dotprod}}(g, M) = \sum_i v_M(f_i)v_C(g)(f_i) \] (26)

Jauhiainen (2010) used the chi-squared distance. He calculated the distance as in Equation 27.

\[ R_{\text{chi-square}}(g, M) = \sum_i \left(\frac{v_C(g)(f_i) - v_M(f_i)}{v_M(f_i)}\right)^2 \] (27)

Abainia et al. (2016) evaluated the Manhattan, Bhattacharyya, chi-2, canberra, Bray Curtis, histograms intersection, and correlation distances. The most accurate method evaluated by Abainia et al. (2016) was the out-of-place method.

**Entropy** Singh (2006, 2010) used cross-entropy and symmetric cross-entropy. Cross-entropy is calculated as in Equation 28 when \( v_M(f_i) \) and \( v_C(g)(f_i) \) are the probabilities of the feature \( f_i \) in the the mystery text \( M \) and the corpus \( C_g \).

\[ R_{\text{cross-entropy}}(g, M) = \sum_i v_M(f_i) \log v_C(g)(f_i) \] (28)

Symmetric cross-entropy is calculated as in Equation 29.

\[ R_{\text{sym-cross-entropy}}(g, M) = \sum_i v_M(f_i) \log v_C(g)(f_i) + v_C(g)(f_i) \log v_M(f_i) \] (29)

Cross-entropy was used recently by Hanani et al. (2017). Yamaguchi and Tanaka-Ishii (2012) used a cross-entropy-based method called Mean of Matching Statistics (MMS).

Sibun and Reynar (1996) calculated the relative entropy between the language models and the mystery text, as in Equation 30.

\[ R_{\text{rel-entropy}}(g, M) = \sum_i v_M(f_i) \log \frac{v_M(f_i)}{v_C(g)(f_i)} \] (30)

This equation can also be referred to as a Kullback-Leibler (KL) distance (Singh, 2006). Jauhiainen (2010) compared relative entropy with the product of the relative frequencies for different size character \( n \)-grams. They found that relative entropy was only competitive when used with bigrams of characters. The product of relative frequencies was clearly more efficient with higher order \( n \)-grams.
Jauhiainen, Lui, Zampieri, Baldwin, & Lindén

Singh (2006, 2010) also used the RE and MRE measures, which are based on relative entropy. The RE measure is calculated as in Equation 31. In the tests performed by Singh (2006, 2010), the RE measure with character n-grams outperformed other tested methods obtaining 98.51% precision when classifying 100 character texts between 53 language-encoding pairs.

\[
R_{RE}(g, M) = \sum_i v_M(f_i) \frac{\log v_M(f_i)}{\log v_C(f_i)}
\]  

(31)

MRE is the symmetric version of the same measure. Baldwin and Lui (2010a) used a variant of the KL divergence called skew divergence.


\[
R_{ME}(g, M) = \frac{1}{Z} \exp \left( \sum_j l_{MT} \sum_i v_C(f_i), \text{if } \exists f_i \in U(M^T) \right)
\]  

(32)

where \( Z \) is a normalization factor and \( l_{MT} \) is word count in the word-tokenized mystery text. Ács et al. (2015) used ME-classifier from the scikit-learn instead of SVM, as it was considerably faster with comparable results. Their ME-classifier ranked 6 out of 9 on the closed submission track of the DSL 2015 shared task.

**Perplexity** Ramisch (2008) was the first to use perplexity for LI. Perplexity is calculated using the Markovian probabilities \( P_g(u_i|u_{i-n+1,...,i-1}) \) for the mystery text \( M \) as in Equations 33 and 34.

\[
H_g(M) = -\frac{1}{c(M,f)} \prod_i \log_2 P_g(u_i|u_{i-n+1,...,i-1})
\]  

(33)

\[
R_{perplexity}(g, M) = 2^{H_g(M)}
\]  

(34)

where \( f = u_{i-n+1,...,i} \). Rodrigues (2012) and Jauhiainen et al. (2017b) evaluated the best performing method used by Vatanen et al. (2010). Perplexity was the best method for extremely short texts in the evaluations of Jauhiainen et al. (2017b), but for longer sequences the methods of Brown (2012) and Jauhiainen (2010) proved to be better. Lately, Gamallo et al. (2017) also used perplexity.

**Other similarity measures** Rau (1974) used Yule’s characteristic K and the Kolmogorov-Smirnov goodness of fit test to categorize languages. Kolmogorov-Smirnov proved to be the better of the two, obtaining 89% recall for 53 characters (one punch card) of text when choosing between two languages. In the goodness of fit test the ranks of features in the models of the languages and the mystery text are compared. Martins and Silva (2005) experimented with the Jiang and Conrath’s (JC) distance and Lin’s similarity measures, as well as the out-of-place method. They conclude that Lin’s similarity measure was consistently the most accurate of the three. JC-distance measure was later evaluated by Singh.
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(2006, 2010), and was outperformed by the RE measure. Ranaivo-Malançon and Ng (2005) and Ranaivo-Malançon (2006) calculated special ratios from the number of trigrams in the language models when compared with the text to be identified. da Silva and Lopes (2006a, 2006b, 2007) used the quadratic discrimination score to create the feature vectors representing the languages and the mystery text. They then calculated the Mahalanobis distance between the languages and the mystery text. Their language identifier obtained a 98.9% precision when classifying texts of four “screen lines” between 19 languages. Bayrak, Takçi, and Eminli (2012) and Hayta, Takçi, and Eminli (2013) used k-means clustering. Nguyen and Cornips (2016) used odds ratio to identify the language of parts of words.

6.6 Discriminant functions

The differences between languages can be stored in discriminant functions. The functions are then used to map the mystery text into an n-dimensional space. The distance of the mystery text to the languages known by the language identifier is calculated and the nearest language is selected.

Murthy and Kumar (2006) used multiple linear regression to calculate discriminant functions for two-way LI for Indian languages. Bhargava, Sharma, Sharma, and Baid (2015) compared linear regression, NB, and LR. The precisions of the three methods were very similar, linear regression being the second in precision after LR.

Multiple discriminant analysis was used for LI by Mustonen (1965). He used two functions, the first separated Finnish from English and Swedish, and the second separated English and Swedish from each other. He used Mahalanobis’ $D^2$ as a distance measure. Nakayama and Spitz (1993) used linear discriminant analysis. Takçi and Ekinci (2012) compared discriminant analysis with SVM and NN using characters as features and they conclude that SVM was the most suitable algorithm tested. Mather (1998) used linear algebra to first identify the words that discriminate between languages and then to calculate the best language to fit the mystery text.

Lu and Mohamed (2011) were the first to use Logistic Regression (LR) in LI. They used Adaptive Logistic Regression, a boosting method for LR, from the Apache Mahout package. LR is a binary classifier, but the Mahout package automatically handles the generation of one-vs-all classifiers for each language in a multiclass situation. In recent years LR has been widely used for LI.

King and Abney (2013) experimented with the Winnow 2 algorithm, but the method was outperformed by other methods they tested. Vinosh Babu and Baskaran (2005) used Principal Component Analysis (PCA) in LI. Espichán-Linares and Oncevay-Marcos (2017, 2018) evaluated the Stochastic Gradient Descent (SGD) algorithm from scikit-learn, but SVM gave better results.

6.7 Support vector machines (SVM)

The SVM algorithm creates a model that categorizes samples into two categories. It can be used for multiple categories (in our case, languages) by training several SVMs in a one-vs-the rest manner. In the following paragraphs we list the different kernels used with SVMs for LI.
Linear kernel In LI the SVMs have mostly been used with a linear kernel. The first to use SVM with a linear kernel were Kim and Park (2007). The linear kernel model has a weight vector $v_{g}(f)$ and the classification of a feature vector $v_{M}(f)$, representing the mystery text $M$, is calculated as in Equation 35.

$$R_{svm-lin}(g, M) = (\sum_{i} v_{M}(f_{i})v_{g}(f_{i})) + b \quad (35)$$

where $b$ is the bias, which is the only difference to the dot product. If $R_{svm-lin}$ is equal to or greater than zero, $M$ is categorized as $g$. SVM with a linear kernel has been widely used for LI, and to date has proven to be one of the best LI methods available in the relevant shared tasks.

Polynomial kernel Bar and Dershowitz (2014) were the first to test LI with a polynomial kernel. With a polynomial kernel the $R_{svm-pol}$ can be calculated as in Equation 36.

$$R_{svm-pol}(g, M) = ((\sum_{i} v_{M}(f_{i})v_{g}(f_{i})) + b)^{d} \quad (36)$$

where $d$ is the degree used.

Radial Basis Function (RBF) kernel RBF is also known as a Gaussian kernel or a Squared Exponential kernel. Botha et al. (2007) were the first to use SVM with an RBF kernel for LI. With an RBF kernel the $R_{svm-rbf}$ is calculated as in Equation 37.

$$R_{svm-rbf}(g, M) = exp\left(-\frac{(\sum_{i} |v_{M}(f_{i}) - v_{g}(f_{i})|)^{2}}{2\sigma^{2}}\right) \quad (37)$$

where $\sigma$ is a tunable parameter.

Sigmoid kernel Bhargava and Kondrak (2010) used a sigmoid kernel with SVM for LI. The sigmoid kernel is also known the Hyperbolic Tangent. With a sigmoid kernel the $R_{svm-sig}$ can be calculated as in Equation 38.

$$R_{svm-sig}(g, M) = tanh((\sum_{i} v_{M}(f_{i})v_{g}(f_{i})) + b) \quad (38)$$

Later an SVM using a sigmoid kernel from the e1071 package for R was evaluated by Majliš (2012). The SVM performed better than NB, Classification and Regression Tree (CART), and the two algorithms he presented.

Other kernels Alrifai et al. (2017) used an exponential kernel with SVM for LI. Porta (2014) used a rational kernel with SVM for LI. Porta (2014) participated in the TweetLID shared task and his SVM-based system was third out of seven participating teams. Kunengkrai et al. (2005) were the first to use SVMs in LI. They created their string kernels using Ukkonen’s algorithm and used the LIBSVM library. The same string kernels were used with the Euclidean distance, and did not perform as well as with the SVM. Both performed better than TextCat which was used as a baseline classifier. Castro et al. (2017) compared SVMs with linear and on-line passive-aggressive kernels on LI. Passive-aggressive
kernel performed better than the linear, but both SVMs were outperformed by NB and
the Log-Likelihood Ratio (sum of logarithms of probabilities). Kim and Park (2007) ex-
perimented with their own implementation of the Sequential Minimal Optimiza-
tion (SMO) algorithm, but reverted to using a linear kernel SVM from the LIBSVM library as it outper-
formed their own implementation. Alshutayri et al. (2016) achieved their best results using
the SMO algorithm. Lamabam and Chakma (2016) used SMO from the Weka package,
but found that CRFs worked better. Alrifai et al. (2017) found that SMO was better than
SVM with linear, exponential or polynomial kernels in Arabic Tweets gender and dialect
description.

Table 9 lists articles where several kernels have been tested with SVM. Goutte, Léger,
Malmasi, and Zampieri (2016) evaluated three different SVM approaches using datasets
from different DSL shared tasks. The SVM-based approaches were the top performing
systems of the 2014 and 2015 shared tasks.

<table>
<thead>
<tr>
<th>Reference</th>
<th>linear</th>
<th>string</th>
<th>RBF</th>
<th>sigmoid</th>
<th>$d^n$</th>
<th>exponential</th>
<th>pas. aggr.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bhargava and Kondrak (2010)</td>
<td>X</td>
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<td>Takçı and Güngör (2012)</td>
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<td>Giwa and Davel (2013), Giwa (2016)</td>
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<td>Hurtado et al. (2014)</td>
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<tr>
<td>Eldesouki et al. (2016)</td>
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<td>Hanani et al. (2016)</td>
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<td>Xu et al. (2016)</td>
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<td>Alrifai et al. (2017)</td>
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<tr>
<td>Castro et al. (2017)</td>
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<tr>
<td>Franco-Salvador et al. (2017a)</td>
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</table>

Table 9: List of references where SVMs has been tested with different kernels. The columns indicate
the kernels used. “$d^n$” stands for polynomial kernel.

**Margin Infused Relaxed Algorithm (MIRA)** Williams and Dagli (2017) used Margin
Infused Relaxed Algorithm, which is similar to SVMs, but without batch training. In their
evaluations this method achieved better results than langid.py with off-the-shelf language
models.

**6.8 Neural Networks (NN)**

Batchelder (1992) was the first to use Neural Networks (NN) in LI. She used a commercial
program, BrainMaker, which implemented a Backpropagation Neural Network (BPNN)
(Hecht-Nielsen, 1989). BPNN consists of an input layer, output layer, and one or more
hidden layers. The network is trained by feeding it a series of correct input-output vector
pairs, one or more times. Processing of an input-output pair includes a forward pass and a
backward pass. In the forward pass the weighted functions of the hidden layers are used to
map the input vector to an output vector. The output vector is compared with the correct
vector and in the backward pass the weights are adjusted so that they would produce an
outcome closer to the correct vector. Tian, Häkkinen, Riis, and Jensen (2002), Tian and
Babu and Kumar (2010) compared NNs with the out-of-place method. Their results show that the latter obtains significantly higher identification accuracy when dealing with mystery texts shorter than 400 characters.

MacNamara et al. (1998) were the first to use a Recurrent Neural Network (RNN) for LI. Their evaluation came to the conclusion that the RNN was unable to identify languages as well as the sum of logarithms of counts of character bi- or trigrams. RNN’s were more successfully used later by Barman et al. (2014b), Chang and Lin (2014), Hanani et al. (2016), and Samih et al. (2016). Cazamias et al. (2015) were the first to use Long Short-Term Memory (LSTM) for LI. Several articles were published in 2016 where LSTM RNN was used for LI. Medvedeva et al. (2017) used models based on Continuous Bag of Word (CBOW), which gave better results in the development set of DSL 2017 than RNN/LSTM neural networks.

During 2016 and 2017 many experiments in LI were made using Convolutional Neural Networks (CNN), most successfully by Jaech et al. (2016b), Jaech, Mulcaire, Hathi, Ostendorf, and Smith (2016a). Bjerva (2016) used Gated Recurrent Unit Networks (GRU) and Deep Residual Networks (ResNet) at DSL 2016. During 2017, GRU was successfully used by Jurgens, Tsvetkov, and Jufašky (2017) and Kocić and Bojar (2017).

Jalam and Teytaud (2001b, 2001a) and Jalam (2003) used radial basis function (RBF) networks for LI. Selamat, Ng, and Mikami (2007) were the first to use Adaptive Resonance Learning (ART) neural networks for LI. Abainia et al. (2016) used Neural Text Categorizer (NTC). Franco-Salvador et al. (2017b) used Deep Averaging Networks (DAN) with word embeddings in language variety identification.

6.9 Tree-based approaches
Häkkinen and Tian (2001) were the earliest users of Decision Trees (DT) in LI. They used DT based on characters and their context without any frequency information. In training the DT, each node is split into child nodes according to an information theoretic optimization criterion. For each node a feature is chosen, which maximizes the information gain at that node. The information gain is calculated for each feature and the feature with the highest gain is selected for the node. In the identification phase, the nodes are traversed until only one language is left (leaf node). Later, Ceylan and Kim (2009), Eskander, Al-Badrashiny, Habash, and Rambow (2014), and Moodley (2016) have been especially successful in using DTs.

Random Forest (RF) is an ensemble classifier generating many DTs. It has been successfully used in LI by Jhamtani et al. (2014), Darwish et al. (2014), Ranjan, Raja, Priyadharshini, and Balabantaray (2016), and Malmasi and Zampieri (2017a, 2017b).

6.10 Other methods
Simaki et al. (2017) used the decision table majority classifier algorithm from the Weka toolkit in English variety detection. The bagging algorithm using DTs was the best method they evaluated (73.86% accuracy), the decision table followed closely with 73.07% accuracy.

Ueda and Nakagawa (1990) were the first to generate Hidden Markov Models (HMM) for LI. More recently HMM’s have been used by Adouane and Dobnik (2017), Guzmán et al. (2017), and Rijhwani et al. (2017). Binas (2005) generated aggregate Markov models,
which resulted in the best results for ten character tests for six languages, obtaining 74% accuracy. Xia, Lewis, and Poon (2009) used Markov logic networks. King et al. (2014) used an extended Markov Model (eMM), which was essentially a standard HMM with modified emission probabilities. Their eMM used manually optimized weights to combine four n-gram scores (products of relative frequencies) into one n-gram score.

Bayrak et al. (2012) evaluated the Fuzzy C Means algorithm (FCM), but a centroid classifier based on the cosine similarity obtained the best results (93% vs. 77% accuracy).

Barbaresi (2016) and Martinc et al. (2017) evaluated the extreme gradient boosting (XGBoost) method. Barbaresi (2016) found that gradient boosting gave better results than RFs, conversely Martinc et al. (2017), found that LR gave better results than gradient boosting.

Benedetto, Caglioti, and Loreto (2002) used existing compression programs for LI. When compression programs are used for LI the mystery text to be identified is added to the training text of each language. The language with the smallest difference (after compression) between the sizes of the original training text file and the combined training and mystery text files is chosen. Haţegan, Bârligă, and Tăbuş (2009) built a maximal tree machine (MTM), which was originally introduced for data compression purposes. Bush (2014) used LZW-based compression. His language identifier obtained 80% accuracy when classifying tweets between five languages.

Alshutayri et al. (2016) evaluated the JRIP algorithm. JRIP is an implementation of the propositional rule learner. It was found to be inferior to the SVM, NB and DT algorithms.

Çöltekim and Rama (2016) evaluated the FastText method on the DSL 2016 shared task test set, where it reached low accuracy when compared with the other methods. Xia (2016) used FastText in codeswitching detection.

Very popular in text categorization and topic modeling, Voss et al. (2014) and Zhang, Clark, Wang, and Li (2016) used Latent Dirichlet Allocation (LDA) in unsupervised LI. Wan (2016) used a Dirichlet Process Gaussian Mixture Model (DPGMM) to automatically determine the number of clusters in unsupervised learning. Tratz (2014) used LDA-based features in Arabic dialect classification.

Poulston et al. (2017) used a Gaussian Process classifier with an RBF kernel in an ensemble with an LR classifier. Their ensemble achieved only ninth place in the PAN (Plagiarism Analysis, Authorship Identification, and Near-Duplicate Detection workshop) Author Profiling language variety shared task and did not reach the results of the baseline approach provided by the organizers.

Espichán-Linares and Oncevay-Marcos (2017, 2018) used a Passive Aggressive Classifier, which proved to be almost as good as the SVMs in their evaluations between five different machine learning algorithms.

### 6.11 Boosting methods

Boosting methods are methods developed to be able to enhance the results of more than one of the previously presented classification methods.

#### Adaptive Boosting (AdaBoost)

The AdaBoost algorithm examines the performance of the base classifiers on the evaluation set and iteratively boosts the significance of the misclassified cases. Adaboost was the best of the five machine learning techniques evaluated
by van der Lee and Bosch (2017), faring better than C4.5, NB, RF, and Linear SVM. Rangel et al. (2017a) used the LogitBoost variation of AdaBoost. It obtained 67.0% accuracy, attaining third place among the twelve methods evaluated.

**k-Nearest Neighbors (kNN)** In kNN, several models are created for each language $g$ by dividing the corpus $C_g$ into separate samples. The score $R(C_g, M)$ is calculated for each model. Plurality voting between the languages $g$ of the models with k-best scores is used to decide the language for the mystery text $M$. Jalam and Teytaud (2001a) evaluated the kNN with $k = 1$ (nearest neighbor, 1NN) with several similarity measures. Kerwin (2006) compared $k = 10$ and $k = 50$ and concludes that there was no major difference in accuracy when distinguishing between six languages (100 character test set). Baykan, Henzinger, and Weber (2008) experimented with kNN classifiers, but they gave clearly worse results than the other classifiers they evaluated. Barman et al. (2014b) used kNN in two phases, first selecting $k_1 = 800$ closest neighbors with simple similarity, and then using $k_2 = 16$ with more advanced similarity ranking.

**Bootstrap Aggregating (Bagging)** In Bagging the text is randomly divided into several parts, which are identified separately and then plurality voting is applied to the outcome of separate classifications. Martinc et al. (2017) used LR Bagging. Sierra, Montes-y Gómez, Solorio, and González (2017) used Bagging with Word Convolutional Neural Networks (W-CNN). Simaki et al. (2017) used Bagging with DTs in English national variety detection. The DT-based Bagging was the best method evaluated by Simaki et al. (2017) when all features were used, but it was the worst with only the highest ranking features.

**Rotation Forest** Rangel et al. (2017a) evaluated the Rotation Forest meta classifier for DTs. The method randomly splits the used features into a pre-determined number of subsets and then uses PCA for each subset. It obtained 66.6% accuracy, attaining fifth place among the twelve methods evaluated.

### 6.12 Ensemble methods

Ensemble methods are meta-classifying methods capable of combining two or more previously presented methods used for LI.

**Majority or Plurality Voting** Rau (1974) used majority voting to combine classifiers using different features and methods. In majority voting the language of the mystery text is identified if a majority ($> \frac{1}{2}$) of the classifiers in the ensemble vote for the same language. In plurality voting the language with most votes is chosen as in the simple scoring method (Equation 17). Some authors may also refer to plurality voting as majority voting.

Carter, Weerkamp, and Tsagkias (2013) used majority voting in tweet LI. Giwa and Davel (2014) used majority voting with JSM classifiers. Goutte et al. (2014) and Malmasi and Dras (2015a) used majority voting between SVM classifiers trained with different features. Gupta et al. (2014) used majority voting to combine four classifiers: RF, random tree, SVM, and DT. Doval, Vilares, and Vilares (2014) and Lui and Baldwin (2014) used majority voting between three off-the-shelf language identifiers. Leidig (2014) used majority voting between perplexity-based and other classifiers. Zamora et al. (2014) used majority voting between three sum of relative frequencies-based classifiers where values were
weighted with different weighting schemes. Malmasi and Dras (2015b, 2017), Malmasi and Zampieri (2016, 2017a, 2017b), and Mendoza and Mendelsohn (2017) used plurality voting with SVMs.

Gamallo et al. (2017) used voting between several perplexity-based classifiers with different features at the 2017 DSL shared task. A voting ensemble gave better results on the closed track than a singular word-based perplexity classifier (0.9025 weighted F1-score over 0.9013), but worse results on the open track (0.9016 with ensemble and 0.9065 without).

**Highest probability ensemble** In highest probability ensemble the winner is simply the language which is given the highest probability by any of the classifiers in the ensemble. You et al. (2008) used Gaussian Mixture Models (GMM) to give probabilities to the outputs of classifiers using different features. Doval et al. (2014) used higher confidence between two off-the-shelf language identifiers. Goutte et al. (2014) used GMM to transform SVM prediction scores into probabilities. Malmasi and Dras (2015b, 2017) used highest confidence with SVMs. Malmasi and Dras (2017) used an ensemble composed of low-dimension hash-based classifiers. According to their experiments hashing provided up to 86% dimensionality reductions without negatively affecting performance. Their probability-based ensemble obtained 89.2% accuracy, while the voting ensemble got 88.7%. Balažević et al. (2016) combined an SVM and a LR classifier.

**Mean Probability Rule** A mean probability ensemble can be used to combine classifiers that produce probabilities (or other mutually comparable values) for languages. The average of values for each language over the classifier results is used to determine the winner and the results are equal to the sum of values method (Equation 18). Malmasi and Dras (2015b) evaluated several ensemble methods and found that the mean probability ensemble attained better results than plurality voting, median probability, product, highest confidence or Borda count ensembles.

**Median Probability Rule** In median probability ensemble the medians over the probabilities given by the individual classifiers are calculated for each language. Malmasi and Dras (2015b) and Malmasi and Zampieri (2016) used Median Probability Rule with SVM classifiers. Confirming the evaluations by Malmasi and Dras (2015b), Malmasi and Zampieri (2016) found that mean ensemble was better than median ensemble, attaining 68% accuracy over the 67.82% of the median ensemble.

**Product Rule** Product rule can be used with classifiers which produce probabilities for languages. Probabilities are then multiplied or their logarithms summed as in Equation 20. Giwa and Davel (2014) used log probability voting with JSM classifiers. Giwa and Davel (2014) observed a small increase in average accuracy using the product ensemble over a majority voting ensemble.

**Stacked generalization (Stacking)** In Stacking a higher level classifier is trained on the output and results of several base classifiers. You et al. (2008) used AdaBoost.ECC and CART to combine classifiers using different features. More recently, Mathur et al. (2017) used LR to combine the results of five RNNs. As an ensemble they produced better results than NB and LR, which were better than the individual RNNs. Also in 2017, Malmasi and Zampieri (2017a, 2017b) used RF to combine several linear SVMs with different features.
The system used by Malmasi and Zampieri (2017b) ranked first in the German dialect identification shared task, and the system by Malmasi and Zampieri (2017a) came second (71.65% accuracy) in the Arabic dialect identification shared task.

7. Empirical Evaluation

In the previous two sections, we have alluded to issues of evaluation in LI research to date. In this section, we examine the literature more closely, providing a broad overview of the metrics that have been used, as well as the experimental settings in which LI research has been evaluated.

7.1 Standardized evaluation for LI

The most common approach is to treat the task as a document-level classification problem. Given a set of evaluation documents, each having a known correct label from a closed set of labels (often referred to as the “gold-standard”), and a predicted label for each document from the same set, the document-level accuracy is the proportion of documents that are correctly labeled over the entire evaluation collection. This is the most frequently reported metric and conveys the same information as the error rate, which is simply the proportion of documents that are incorrectly labeled (i.e. $1 - \text{accuracy}$).

Authors sometimes provide a per-language breakdown of results. There are two distinct ways in which results are generally summarized per-language: (1) precision, in which documents are grouped according to their predicted language; and (2) recall, in which documents are grouped according to what language they are actually written in. Earlier work has tended to only provide a breakdown based on the correct label (i.e. only reporting per-language recall). This gives us a sense of how likely a document in any given language is to be classified correctly, but does not give an indication of how likely a prediction for a given language is of being correct. Under the monolingual assumption (i.e. each document is written in exactly one language), this is not too much of a problem, as a false negative for one language must also be a false positive for another language, so precision and recall are closely linked. Nonetheless, later authors have tended to explicitly state both precision and recall for clarity. It is also common practice to report an F-score $F$, which is the harmonic mean of precision and recall. The F-score (also sometimes called F-measure) was developed in IR to measure the effectiveness of retrieval with respect to a user who attaches different relative importance to precision and recall (van Rijsbergen, 1979). When used as an evaluation metric for classification tasks, it is common to place equal weight on precision and recall.

In addition to evaluating performance for each individual language, authors have also sought to convey the relationship between classification errors and specific sets of languages. Errors in LI systems are generally not random; rather, certain sets of languages are much more likely to be confused. The typical method of conveying this information is through the use of a confusion matrix, a tabulation of the distribution of (predicted language, actual language) pairs.

Presenting full confusion matrices becomes problematic as the number of languages considered increases, and as a result has become relatively uncommon in work that covers a broader range of languages. Per-language results are also harder to interpret as the
number of languages increases, and so it is common to present only collection-level summary statistics. There are two methods for summarizing across a whole collection: (1) giving each document equal weight; and (2) giving each class (i.e. language) equal weight. (1) is referred to as a micro-average, and (2) as a macro-average. For LI under the monolingual assumption, micro-averaged precision and recall are the same, since each instance of a false positive for one language must also be a false negative for another language. In other words, micro-averaged precision and recall are both simply the collection-level accuracy. On the other hand, macro-averaged precision and recall give equal weight to each language. In datasets where the number of documents per language is the same, this again works out to being the collection-level average. However, LI research has frequently dealt with datasets where there is a substantial skew between classes. In such cases, the collection-level accuracy is strongly biased towards more heavily-represented languages. To address this issue, in work on skewed document collections, authors tend to report both the collection-level accuracy and the macro-averaged precision/recall/F-score, in order to give a more complete picture of the characteristics of the method being studied.

Whereas the notions of macro-averaged precision and recall are clearly defined, there are two possible methods to calculate the macro-averaged F-score. The first is to calculate it as the harmonic mean of the macro-averaged precision and recall, and the second is to calculate it as the arithmetic mean of the per-class F-score.

The comparability of published results is also limited by the variation in size and source of the data used for evaluation. In work to date, authors have used data from a variety of different sources to evaluate the performance of proposed solutions. Typically, data for a number of languages is collected from a single source, and the number of languages considered varies widely. Earlier work tended to focus on a smaller number of Western European languages. Later work has shifted focus to supporting larger numbers of languages simultaneously, with the work of Brown (2014) pushing the upper bound, reporting a language identifier that supports over 1300 languages. The increased size of the language set considered is partly due to the increased availability of language-labeled documents from novel sources such as Wikipedia and Twitter. This supplements existing data from translations of the Universal Declaration of Human Rights, Bible translations, as well as parallel texts from MT datasets such as OPUS and SETimes, and European Government data such as JRC-Acquis. These factors have led to a shift away from proprietary datasets such as the ECI multilingual corpus that were commonly used in earlier research. As more languages are considered simultaneously, the accuracy of LI systems decreases. A particularly striking illustration of this is the evaluation results by Jauhiainen et al. (2017b) for the logLIGA method (Vogel & Tresner-Kirsch, 2012). Vogel and Tresner-Kirsch (2012) report an accuracy of 99.8% over tweets (averaging 80 characters) in six European languages as opposed to the 97.9% from the original LIGA method. The LIGA and logLIGA implementations by Jauhiainen et al. (2017b) have comparable accuracy for six languages, but the accuracy for 285 languages (with 70 character test length) is only slightly over 60% for logLIGA and the original LIGA method is at almost 85%. Many evaluations are not directly comparable as the test sizes, language sets and used parameters differ from each other. A particularly good example is the method of Cavnar and Trenkle (1994). The original paper reports an accuracy of 99.8% over eight European languages (>300 bytes test size). Lui and Baldwin (2011) report an accuracy of 68.6% over a dataset of 67 languages (500 byte test size), and
Jauhiainen et al. (2017b) report an accuracy of over 90% for 285 languages (25 character test size).

Separate to the question of the number and variety of languages included are issues regarding the quantity of training data used. A number of studies have examined the relationship between LI accuracy and quantity of training data through the use of learning curves. The general finding is that LI accuracy increases with more training data, though there are some authors that report an optimal amount of training data, where adding more training data decreases accuracy thereafter (Combrinck & Botha, 1995; Ljubešić, Mikelić, & Boras, 2007). Overall, it is not clear whether there is a universal quantity of data that is “enough” for any language, rather this amount appears to be affected by the particular set of languages as well as the domain of the data. The breakdown presented by Baldwin and Lui (2010a) shows that with less than 100KB per language, there are some languages where classification accuracy is near perfect, whereas there are others where it is very poor.

Another aspect that is frequently reported on is how long a sample of text needs to be before its language can be correctly detected. Unsurprisingly, the general consensus is that longer samples are easier to classify correctly. There is a strong interest in classifying short segments of text, as certain applications naturally involve short text documents, such as LI of microblog messages or search engine queries. Another area where LI of texts as short as one word has been investigated is in the context of dealing with documents that contain text in more than one language, where word-level LI has been proposed as a possible solution (see Section 10.6). These outstanding challenges have led to research focused specifically on LI of shorter segments of text, which we discuss in more detail in Section 10.7.

From a practical perspective, knowing the rate at which a LI system can process and classify documents is useful as it allows a practitioner to predict the time required to process a document collection given certain computational resources. However, so many factors influence the rate at which documents are processed that comparison of absolute values across publications is largely meaningless. Instead, it is more valuable to consider publications that compare multiple systems under controlled conditions (same computer hardware, same evaluation data, etc.). The most common observations are that classification times between different algorithms can differ by orders of magnitude and that the fastest methods are not always the most accurate. Beyond that, the diversity of systems tested and the variety in the test data make it difficult to draw further conclusions about the relative speed of algorithms.

Where feature selection is used, the number of features retained is a parameter of interest, as it affects both the memory requirements of the LI system and its classification rate. In general, a smaller feature set results in a faster and more lightweight identifier. Relatively few authors give specific details of the relationship between the number of features selected and accuracy. A potential reason for this is that the improvement in accuracy plateaus with increasing feature count, though the exact number of features required varies substantially with the method and the data used. At the lower end of the scale, Cavnar and Trenkle (1994) report that 300–400 features per language is sufficient. Conversely Jauhiainen et al. (2017b) found that, for the same method, the best results for the evaluation set were attained with 20,000 features per language.
7.2 Corpora used for LI evaluation

As we discussed in Section 7.1, the objective comparison of different methods for LI is difficult due to the variation in the data that different authors have used to evaluate LI methods. Baldwin and Lui (2010a) emphasize this by demonstrating how the performance of a system can vary according to the data used for evaluation. This implies that comparisons of results reported by different authors may not be meaningful, as a strong result in one paper may not translate into a strong result on the dataset used in a different paper. In other areas of research, authors have proposed standardized corpora to allow for the objective comparison of different methods.

Some authors have released datasets to accompany their work, to allow for direct replication of their experiments and encourage comparison and standardization. Table 10 lists a number of datasets that have been released to accompany specific LI publications. In this list, we only include corpora that were prepared specifically for LI research, and that include the full text of documents. Corpora of language-labelled Twitter messages that only provide document identifiers are also available, but reproducing the full original corpus may be an issue as the original Twitter messages are deleted or made otherwise unavailable.

One challenge in standardizing datasets for LI is that the codes used to label languages are not fully standardized, and a large proportion of labeling systems only cover a minor portion of the languages used in the world today (Constable & Simons, 2000). Xia, Lewis, and Lewis (2010) discuss this problem in detail, listing different language code sets, as well as the internal structure exhibited by some of the code sets. Some standards consider certain groups of “languages” as varieties of a single macro-language, whereas others consider them to be discrete languages. An example of this is found in South Slavic languages, where some language code sets refer to Serbo-Croatian, whereas others make distinctions between Bosnian, Serbian and Croatian (Tiedemann & Ljubešić, 2012). The unclear boundaries between such languages make it difficult to build a reference corpus of documents for each language, or to compare language-specific results across datasets.

Another challenge in standardizing datasets for LI is the great deal of variation that can exist between data in the same language. We examine this in greater detail in Section 10.2, where we discuss how the same language can use a number of different orthographies, can be digitized using a number of different encodings, and may also exist in transliterated forms. The issue of variation within a language complicates the development of standardized datasets, due to challenges in determining which variants of a language should be included. Since we have seen that the performance of LI systems can vary per-domain (Baldwin & Lui, 2010a), that LI research is often motivated by target applications (see Section 8), and that domain-specific information can be used to improve accuracy (see Section 10.9), it would frequently be nonsensical to use a generic LI dataset to develop a language identifier for a particular domain.

A third challenge in standardizing datasets for LI is the cost of obtaining correctly-labeled data. Manual labeling of data is usually prohibitively expensive, as it requires access to native speakers of all languages that the dataset aims to include. Large quantities of raw text data are available from sources such as web crawls or Wikipedia, but this data is frequently mislabeled (e.g. most non-English Wikipedias still include some English-language documents). In constructing corpora from such resources, it is common to use some form
of automatic LI, but this makes such corpora unsuitable for evaluation purposes as they are biased towards documents that can be correctly identified by automatic systems (Lui & Baldwin, 2014). Future work in this area could investigate other means of ensuring correct gold-standard labels while minimizing the annotation costs.

Despite these challenges, standardized datasets would be very useful for promoting replicable and comparable research in LI. Where a subset of data is used from a larger collection, researchers should include details of the specific subset, including any breakdown into training and test data or partitions for cross-validation. Where data from a new source is used, justification should be given for its inclusion, as well as some means for other researchers to replicate experiments on the same dataset.

7.3 LI Shared Tasks

To address specific sub-problems in LI, a number of shared tasks have been organized on problems such as LI in multilingual documents (Baldwin & Lui, 2010b), code-switched
data (Solorio, Blair, Maharjan, Bethard, Diab, Gohneim, Hawwari, AlGhamdi, Hirschberg, Chang, & Fung, 2014), discriminating between closely related languages (Zampieri, Tan, Ljubešić, & Tiedemann, 2014), and dialect and language variety identification in various languages (Grouin, Forest, Da Sylva, Paroubek, & Zweigenbaum, 2011; Zampieri, Malmasi, Ljubešic, Nakov, Ali, Tiedemann, Scherrer, & Aepli, 2017; Rangel, Rosso, Potthast, & Stein, 2017b; Ali, Vogel, & Renals, 2017). Shared tasks are important for LI because they provide datasets and standardized evaluation methods that serve as benchmark for the LI community. We summarize all LI shared tasks organized to date in Table 11.

Generally datasets for shared tasks have been made publicly available after the conclusion of the task, and are a good source of standardized evaluation data. However, the shared tasks to date have tended to target specific sub-problems in LI, and no general, broad-coverage LI datasets have been compiled. Widespread interest in LI over closely-related languages has resulted in a number of shared tasks that specifically tackle the issue. Some tasks have focused on varieties of a specific language. For example, the DEFT2010 shared task (Grouin et al., 2011) examined varieties of French, requiring participants to classify French documents with respect to their geographical source, in addition to the decade in which they were published. Another example is the Arabic Dialect Identification (ADI) shared task at the VarDial workshop (Malmasi, 2017; Zampieri et al., 2017), and the Arabic Multi-Genre Broadcast (MGB) Challenge (Ali et al., 2017).

Two shared tasks focused on a narrow group of languages using Twitter data. The first was TweetLID, a shared task on LI of Twitter messages according to six languages in common use in Spain, namely: Spanish, Portuguese, Catalan, English, Galician and Basque (in order of the number of documents in the dataset) (Zubiaga, San Vicente, Gamallo, Pichel, Alegria, Aranberri, Ezeiza, & Fresno, 2014; Zubiaga, Vicente, Gamallo, Pichel, Alegria, Aranberri, Ezeiza, & Fresno, 2016). The organizers provided almost 35,000 Twitter messages, and in addition to the six monolingual tags, supported four additional categories: undetermined, multilingual (i.e. the message contains more than one language, without requiring the system to specify the component languages), ambiguous (i.e. the message is ambiguous between two or more of the six target languages), and other (i.e. the message is in a language other than the six target languages). The second shared task was the PAN lab on authorship profiling 2017 (Rangel et al., 2017b). The PAN lab on authorship profiling is held annually and historically has focused on age, gender, and personality traits prediction in social media. In 2017 the competition introduced the inclusion of language varieties and dialects of Arabic, English, Spanish, and Portuguese.

More ambitiously, the four editions of the Discriminating between Similar Languages (DSL) (Zampieri et al., 2014, 2015; Malmasi et al., 2016; Zampieri et al., 2017) shared tasks required participants to discriminate between a set of twelve and fourteen languages in several language groups, each consisting of highly-similar languages or national varieties of that language. The dataset, entitled DSL Corpus Collection (DSLCC) (Tan et al., 2014), and the languages included are summarized in Table 12. Historically the majority of the best-performing systems (Goutte et al., 2014; Lui, Letcher, Adams, Duong, Cook, & Baldwin, 2014b; Bestgen, 2017) approached the task via hierarchical classification, first predicting the language group, then the language within that group.
8. Application areas

There are various reasons to investigate LI. Studies in LI approach the task from different perspectives and with different motivations and application goals in mind. In this section, we briefly summarize what these motivations are, and how their specific needs differ.

The oldest motivation for automatic LI is perhaps in conjunction with translation (Beesley, 1988). Automatic LI is used as a pre-processing step to determine what translation system to apply to an input text, whether it be by routing to a specific human translator or by applying MT. Such a use case is still very common, and can be seen in the Google Chrome web browser,\(^\text{2}\) where an built-in LI module is used to offer MT services to the user when the detected language of the web page being visited differs from the user’s language settings.

NLP components such as POS taggers and parsers tend to make a strong assumption that the input text is monolingual in a given language. Similarly to the translation case,

\(^\text{2}\) http://www.google.com/chrome

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Table 11: List of LI shared tasks.
LI can play an obvious role in routing documents written in different languages to NLP components tailored to those languages. More subtle is the case of documents with mixed multilingual content, the most commonly-occurring instance of which is foreign inclusion, where a document is predominantly in a single language (e.g., German or Japanese) but is interspersed with words and phrases (often technical terms) from a language such as English. For example, Alex, Dubey, and Keller (2007) found that around 6% of word tokens in German text sourced from the Internet are English inclusions. In the context of POS tagging, one strategy for dealing with inclusions is to have a dedicated POS for all foreign words, and force the POS tagger to perform both foreign inclusion detection and POS tagging of those words in the target language; this is the approach taken in the Penn POS tagset, for example (Marcus, Santorini, & Marcinkiewicz, 1993). An alternative strategy is to have an explicit foreign inclusion detection pre-processor, and some special handling of foreign inclusions. For example, in the context of German parsing, Alex et al. (2007) used foreign inclusion predictions to restrict the set of (German) POS tags used to form a parse tree, and found that this approach substantially improved parser accuracy.

Another commonly-mentioned use case is for multilingual document storage and retrieval. A document retrieval system (such as, but not limited to, a web search engine) may be required to index documents in multiple languages. In such a setting, it is common to apply LI at two points: (1) to the documents being indexed; and (2) to the queries being executed on the collection. Simple keyword matching techniques can be problematic in text-based document retrieval, because the same word can be valid in multiple languages.

Table 12: DSLCC: the languages included in each version of the corpus collection grouped by similarity.
A classic example of such words (known as “false friends”) includes gift, which in German means “poison”. Performing LI on both the document and the query helps to avoid confusion between such terms, by taking advantage of the context in which it appears in order to infer the language. This has resulted in specific work in LI of web pages, as well as search engine queries. Roy, Choudhury, Majumder, and Agarwal (2013) and Sequeira, Choudhury, Gupta, Rosso, Kumar, Banerjee, Naskar, Bandyopadhyay, Chittaranjan, Das, and Chakma (2015) give overviews of shared tasks specifically concentrating on language labeling of individual search query words. Having said this, in many cases, the search query itself does a sufficiently good job of selecting documents in a particular language, and overt LI is often not performed in mixed multilingual search contexts.

Automatic LI has also been used to facilitate linguistic and other text-based research. Suzuki et al. (2002) report that their motivation for developing a language identifier was “to find out how many web pages are written in a particular language”. Automatic LI has been used in constructing web-based corpora. The Crúbadán project (Scannell, 2007) and the Finno-Ugric Languages and the Internet project (Jauhiainen, Jauhiainen, & Lindén, 2015) make use of automated LI techniques to gather linguistic resources for under-resourced languages. Similarly, the Online Database of INterlinear text (ODIN) (Lewis & Xia, 2010) uses automated LI as one of the steps in collecting interlinear glossed text from the web for purposes of linguistic search and bootstrapping NLP tools.

One challenge in collecting linguistic resources from the web is that documents can be multilingual (i.e. contain text in more than one language). This is problematic for standard LI methods, which assume that a document is written in a single language, and has prompted research into segmenting text by language, as well as word-level LI, to enable extraction of linguistic resources from multilingual documents. A number of LI shared tasks discussed in detail in Section 7.3 included data from social media. Examples are the TweetLID shared task on tweet LI held at SEPLN 2014 (Zubiaga et al., 2014, 2016), the data sets used in the first and second shared tasks on LI in code-switched data which were partially taken from Twitter (Solorio et al., 2014; Molina, Rey-Villamizar, Solorio, AlGhamdi, Ghoneim, Hawwari, & Diab, 2016), and the third edition of the DSL shared task which contained two out-of-domain test sets consisting of tweets (Malmasi et al., 2016). The 5th edition of the PAN at CLEF author profiling task included language variety identification for tweets (Rangel et al., 2017b). There has also been research on identifying the language of private messages between eBay users (Mayer, 2012), presumably as a filtering step prior to more in-depth data analysis.

9. Off-the-Shelf Language Identifiers

In this context, “off-the-shelf” implies that the software is distributed with pre-trained models for a number of languages so that a user is not required to provide training data before using the system. Such a setup is highly attractive to many end-users of automatic LI whose main interest is in utilizing the output of a language identifier rather than implementing and developing the technique. To this end, a number of off-the-shelf language identifiers have been released over time. Many authors have evaluated these off-the-shelf identifiers, including a recent evaluation involving 13 language identifiers which was carried out by Pawelka and Jürgens (2015). In this section, we provide a brief summary of open-source or
otherwise free systems that are available, as well as the key characteristics of each system. We have also included dates of when the software has been last updated as of January 2018.

**TextCat** is the most well-known implementation of the out-of-place method, it lists models for 76 languages in its off-the-shelf configuration. The program is not actively maintained. **TextCat** is not the only example of an off-the-shelf implementation of the out-of-place method; other implementations include **libtextcat** with 76 language models, **JTCL** with 15 languages and **mguesser** with 104 models for different language-encoding pairs. The main issue addressed by later implementations is classification speed: **TextCat** is implemented in Perl and is not optimized for speed, whereas implementations such as **libtextcat** and **mguesser** have been specifically written to be fast and efficient. **whatlang-rs** uses an algorithm based on character trigrams and refers the user to the Cavnar and Trenkle (1994) article. It comes pre-trained with 83 languages.

**ChromeCLD** is the language identifier embedded in the Google Chrome web browser. It uses a NB classifier, and script-specific classification strategies. **ChromeCLD** assumes that all the input is in UTF-8, and assigns the responsibility of encoding detection and transcoding to the user. **ChromeCLD** uses Unicode information to determine the script of the input. **ChromeCLD** also implements a number of pre-processing heuristics to help boost performance on its target domain (web pages), such as stripping character sequences like `.jpg`. The standard implementation supports 83 languages, and an extended model is also available, that supports 160 languages.

**LangDetect** is a Java library that implements a language identifier based on a NB classifier trained over character n-grams. The software comes with pre-trained models for 53 languages, using data from Wikipedia. **LangDetect** makes use of a range of normalization heuristics to improve the performance on particular languages. These include: (1) clustering of Chinese/Japanese/Korean characters to reduce sparseness; (2) removal of “language-independent” characters, and other text normalization; and (3) normalization of Arabic characters.

**langid.py** is a Python implementation of the method described by Lui and Baldwin (2011), which exploits training data for the same language across multiple different sources of text to identify sequences of characters that are strongly predictive of a given language, regardless of the source of the text. This feature set is combined with a NB classifier, and is distributed with a pre-trained model for 97 languages prepared using data from 5 different text sources. Lui and Baldwin (2012) provide an empirical comparison of **langid.py** to **TextCat**, **LangDetect** and **ChromeCLD** and find that it compares favorably both in terms of

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accuracy and classification speed. There are also implementations of the classifier portion (but not the training portion) of langid.py in Java 12, C 13 and JavaScript 14.

whatlang (Brown, 2013) uses a vector-space model with per-feature weighting on character n-gram sequences. One particular feature of whatlang is that it uses discriminative training in selecting features, i.e. it specifically makes use of features that are strong evidence against a particular language, which is generally not captured by NB models. Another feature of whatlang is that it uses inter-string smoothing to exploit sentence-level locality in making language predictions, under the assumption that adjacent sentences are likely to be in the same language. Brown (2013) reports that this substantially improves the accuracy of the identifier. Another distinguishing feature of whatlang is that it comes pre-trained with data for 1400 languages, which is the highest number by a large margin of any off-the-shelf system 15.

whatthelang is a recent language identifier written in Python, which utilizes the FastText algorithm. It supports 176 languages 16.

YALI implements an off-the-shelf classifier trained using Wikipedia data, covering 122 languages 17. Although not described as such, the actual classification algorithm used is a linear model, and is thus closely related to both NB and a cosine-based vector space model.

In addition to the above-mentioned general-purpose language identifiers, there have also been efforts to produce pre-trained language identifiers targeted specifically at Twitter messages. LDIG is a Twitter-specific LI tool with built-in models for 19 languages 18. It uses a document representation based on tries (Okanohara & Tsujii, 2009). The algorithm is a LR classifier using all possible substrings of the data. The use of all possible substrings is important to maximize the available information from the relatively short Twitter messages.

Lui and Baldwin (2014) provides a comparison of 8 off-the-shelf language identifiers applied without re-training to Twitter messages. One issue they report is that comparing the accuracy of off-the-shelf systems is difficult because of the different subset of languages supported by each system, which may also not fully cover the languages present in the target data. The authors choose to compare accuracy over the full set of languages, arguing that this best reflects the likely use-case of applying an off-the-shelf LI system to new data. They find that the best individual systems are ChromeCLD, langid.py and LangDetect, but that slightly higher accuracy can be attained by a simple voting-based ensemble classifier involving these three systems.

In addition to this, commercial or other closed-source language identifiers and language identifier services exist, of which we name a few. The Polyglot 3000 19 and Lextek Language Identifier 20 are stand alone language identifiers for Windows. Open Xerox Language Identifier 21 is a web service with available REST and SOAP APIs.

13. https://github.com/saffsd/langid.c
15. https://sourceforge.net/projects/la-strings/ (last updated on May 2016)
17. https://github.com/martin-majlis/YALI (last updated on May 2014)
18. https://github.com/shuyo/ldig (last updated on July 2013)
10. Research Directions and Open Issues in LI

Several papers have catalogued open issues in LI (Sibun & Reynar, 1996; Xia et al., 2010; Hughes et al., 2006; da Silva & Lopes, 2006b; Baldwin & Lui, 2010a; Botha & Barnard, 2012; Malmasi et al., 2016). Some of the issues, such as text representation (Section 5) and choice of algorithm (Section 6), have already been covered in detail in this survey. In this section, we synthesize the remaining issues into a single section, and also add new issues that have not been discussed in previous work. For each issue, we review related work and suggest promising directions for future work.

10.1 Text Preprocessing

Text preprocessing (also known as normalization) is an umbrella term for techniques where an automatic transformation is applied to text before it is presented to a classifier. The aim of such a process is to eliminate sources of variation that are expected to be confounding factors with respect to the target task. Text preprocessing is slightly different from data cleaning, as data cleaning is a transformation applied only to training data, whereas normalization is applied to both training and test data. Hughes et al. (2006) raise text preprocessing as an outstanding issue in LI, arguing that its effects on the task have not been sufficiently investigated. In this section, we summarize the normalization strategies that have been proposed in the LI literature.

Case folding is the elimination of capitalization, replacing characters in a text with either their lower-case or upper-case forms. Basic approaches generally map between a-z and A-Z in the ASCII encoding, but this approach is insufficient for extended Latin encodings, where diacritics must also be appropriately handled. A resource that makes this possible is the Unicode Character Database (UCD)\(^{22}\) which defines uppercase, lowercase and titlecase properties for each character, enabling automatic case folding for documents in a Unicode encoding such as UTF-8.

Range compression is the grouping of a range of characters into a single logical set for counting purposes, and is a technique that is commonly used to deal with the sparsity that results from character sets for ideographic languages, such as Chinese, that may have thousands of unique “characters”, each of which is observed with relatively low frequency. Simões, Almeida, and Byers (2014) use such a technique where all characters in a given range are mapped into a single “bucket”, and the frequency of items in each bucket is used as a feature to represent the document. Byte-level representations of encodings that use multi-byte sequences to represent codepoints achieve a similar effect by “splitting” codepoints. In encodings such as UTF-8, the codepoints used by a single language are usually grouped together in “code planes”, where each codepoint in a given code plane shares the same upper byte. Thus, even though the distribution over codepoints may be quite sparse, when the byte-level representation uses byte sequences that are shorter than the multi-byte sequence of a codepoint, the shared upper byte will be predictive of specific languages.

Cleaning may also be applied, where heuristic rules are used to remove some data that is perceived to hinder the accuracy of the language identifier. For example, Suzuki et al. (2002) identify HTML entities as a candidate for removal in document cleaning, on the basis

\(^{22}\) http://www.unicode.org/ucd/
that classifiers trained on data which does not include such entities may drop in accuracy when applied to raw HTML documents. ChromeCLD includes heuristics such as expanding HTML entities, deleting digits and punctuation, and removing SGML-like tags. Similarly, LangDetect also removes “language-independent characters” such as numbers, symbols, URLs and mail addresses. It also removes words that are all-caps and tries to remove other acronyms and proper names, though how this is done is not specified (Nakatani, 2010).

In the domain of Twitter messages, Tromp and Pechenizkiy (2011) remove links, usernames, smilies and hashtags (a Twitter-specific “tagging” feature), arguing that these entities are language independent and thus should not feature in the model. Xafopoulos et al. (2004) address LI of web pages, and report removing HTML formatting, and applying stopping using a small stopword list. Takçı and Ekinci (2012) carry out LI experiments on the ECI multilingual corpus and report removing punctuation, space characters and digits.

The idea of preprocessing text to eliminate domain-specific “noise” is closely related to the idea of learning domain-independent characteristics of a language (Lui & Baldwin, 2011). One difference is that normalization is normally heuristic-driven, where a manually-specified set of rules is used to eliminate unwanted elements of the text, whereas domain-independent text representations are data-driven, where text from different sources is used to identify the characteristics that a language shares between different sources. Both approaches share conceptual similarities with problems such as content extraction for web pages. In essence, the aim is to isolate the components of the text that actually represent language, and suppress the components that carry other information. One application is the language-aware extraction of text strings embedded in binary files, which has been shown to perform better than conventional heuristic approaches (Brown, 2012). Future work in this area could focus specifically on the application of language-aware techniques to content extraction, using models of language to segment documents into textual and non-textual components. Such methods could also be used to iteratively improve LI itself by improving the quality of training data.

10.2 Orthography and Transliteration

LI is further complicated when we consider that some languages can be written in different orthographies (e.g. Bosnian and Serbian can be written in both Latin and Cyrillic script). Transliteration is another phenomenon that has a similar effect, whereby phonetic transcriptions in another script are produced for particular languages. These transcriptions can either be standardized and officially sanctioned, such as the use of Hanyu Pinyin for Chinese, or may also emerge irregularly and organically as in the case of arabizi for Arabic (Yaghać, 2008). Hughes et al. (2006) identify variation in the encodings and scripts used by a given language as an open issue in LI, pointing out that early work tended to focus on languages written using a romanized script, and suggesting that dealing with issues of encoding and orthography adds substantial complexity to the task. Suzuki et al. (2002) discuss the relative difficulties of discriminating between languages that vary in any combination of encoding, script and language family, and give examples of pairs of languages that fall into each category.
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LI across orthographies and transliteration is an area that has not received much attention in work to date, but presents unique and interesting challenges that are suitable targets for future research. An interesting and unexplored question is whether it is possible to detect that documents in different encodings or scripts are written in the same language, or what language a text is transliterated from, without any a-priori knowledge of the encoding or scripts used. One possible approach to this could be to take advantage of standard orderings of alphabets in a language – the pattern of differences between adjacent characters should be consistent across encodings, though whether this is characteristic of any given language remains to be explored.

10.3 Supporting Low-Resource Languages

Hughes et al. (2006) paint a fairly bleak picture of the support for low-resource languages in automatic LI. This is supported by the arguments of Xia et al. (2010) who detail specific issues in building hugely multilingual datasets. Abney and Bird (2010) also specifically called for research into automatic LI for low-density languages. Ethnologue (Simons & Fennig, 2017) lists a total of 7099 languages. Xia et al. (2010) describe the Ethnologue in more detail, and discuss the role that LI plays in other aspects of supporting minority languages, including detecting and cataloging resources. The problem is circular: LI methods are typically supervised, and need training data for each language to be covered, but the most efficient way to recover such data is through LI methods.

A number of projects are ongoing with the specific aim of gathering linguistic data from the web, targeting as broad a set of languages as possible. One such project is the aforementioned ODIN (Xia et al., 2009; Lewis & Xia, 2010), which aims to collect parallel snippets of text from Linguistics articles published on the web. ODIN specifically targets articles containing Interlinear Glossed Text (IGT), a semi-structured format for presenting text and a corresponding gloss that is commonly used in Linguistics.

Other projects that exist with the aim of creating text corpora for under-resourced languages by crawling the web are the Crúbadán project (Scannell, 2007) and SeedLing (Emerson, Tan, Fertmann, Palmer, & Regneri, 2014). The Crúbadán crawler uses seed data in a target language to generate word lists that in turn are used as queries for a search engine. The returned documents are then compared with the seed resource via an automatic language identifier, which is used to eliminate false positives. Scannell (2007) reports that corpora for over 400 languages have been built using this method. The SeedLing project crawls texts from several web sources which has resulted in a total of 1451 languages from 105 language families. According to the authors, this represents 19% of the world’s languages.

Much recent work on multilingual documents (Section 10.6) has been done with support for minority languages as a key goal. One of the common problems with gathering linguistic data from the web is that the data in the target language is often embedded in a document containing data in another language. This has spurred recent developments in text segmentation by language and word-level LI. Lui et al. (2014a) present a method to detect documents that contain text in more than one language and identify the languages present with their relative proportions in the document. The method is evaluated on real-world data from a web crawl targeted to collect documents for specific low-density languages.
LI for low-resource languages is a promising area for future work. One of the key questions that has not been clearly answered is how much data is needed to accurately model a language for purposes of LI. Work to date suggests that there may not be a simple answer to this question as accuracy varies according to the number and variety of languages modeled (Baldwin & Lui, 2010a), as well as the diversity of data available to model a specific language (Lui & Baldwin, 2011).

10.4 Number of Languages

Early research in LI tended to focus on a very limited number of languages (sometimes as few as 2). This situation has improved somewhat with many current off-the-shelf language identifiers supporting on the order of 50–100 languages (Section 9). The standout in this regard is Brown (2014), supporting 1311 languages in its default configuration. However, evaluation of the identifier of Brown (2013) on a different domain found that the system suffered in terms of accuracy because it detected many languages that were not present in the test data (Lui & Baldwin, 2014).

Lewis and Xia (2010) describe the construction of web crawlers specifically targeting IGT, as well as the identification of the languages represented in the IGT snippets. LI for thousands of languages from very small quantities of text is one of the issues that they have had to tackle. They list four specific challenges for LI in ODIN: (1) the large number of languages; (2) “unseen” languages that appear in the test data but not in training data; (3) short target sentences; and (4) (sometimes inconsistent) transliteration into Latin text. Their solution to this task is to take advantage of a domain-specific feature: they assume that the name of the language that they are extracting must appear in the document containing the IGT, and hence treat this as a co-reference resolution problem. They report that this approach significantly outperforms the text-based LI approach in this particular problem setting.

An interesting area to explore is the trade-off between the number of languages supported and the accuracy per-language. From existing results it is not clear if it is possible to continue increasing the number of languages supported without adversely affecting the average accuracy, but it would be useful to quantify if this is actually the case across a broad range of text sources. Table 13 lists the articles where the LI with more than 30 languages has been investigated.
10.5 “Unseen” Languages and Unsupervised LI

“Unseen” languages are languages that we do not have training data for that may nonetheless be encountered by a LI system being applied to real-world data. Dealing with languages for which we do not have training data has been identified as an issue by Hughes et al. (2006) and has also been mentioned by Xia et al. (2009) as a specific challenge in harvesting linguistic data from the web. Elfardy and Diab (2012) use an unlabeled training set with a labeled evaluation set in token level code switching identification between Modern Standard Arabic (MSA) and dialectal Arabic. They utilize existing dictionaries and also a morphological analyzer for MSA so the system has extensive external knowledge sources. The possibility to use unannotated training material is nonetheless a very useful feature.

Some authors have attempted to tackle the unseen language problem through attempts at unsupervised labeling of text by language. Biemann and Teresiak (2005) present such an approach, building graphs of co-occurrences of words in sentences, and then partitioning the graph using a custom graph-clustering algorithm which labels each word in the cluster with a single label. The number of labels is initialized to be the same as the number of words, and decreases as the algorithm is recursively applied. After a small number of iterations (the authors report 20), the labels become relatively stable and can be interpreted as cluster labels. Smaller clusters are then discarded, and the remaining clusters are interpreted as groups of words for each language. Shiells and Pham (2010) compared the Chinese Whispers algorithm of Biemann and Teresiak (2005) and Graclus clustering on unsupervised Tweet LI. They conclude that the Chinese Whispers is better suited to LI.

Mather (1998) uses an unsupervised clustering algorithm to separate a multilingual corpus into groups corresponding to languages. The separate linear algebra based LI algorithm (Section 6.6) used does not always classify the analyzed documents into any of the existing groups. Selamat and Ng (2008) used Fuzzy ART NNs in unsupervised language clustering

<table>
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<tr>
<th>Reference</th>
<th># Lang</th>
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<tbody>
<tr>
<td>Brown (2012)</td>
<td>923</td>
<td>Xia et al. (2009)</td>
<td>c. 600</td>
</tr>
<tr>
<td>Jauhiainen, Lindén, and Jauhiainen (2015b)</td>
<td>285</td>
<td>Jauhiainen et al. (2017b)</td>
<td>285</td>
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<tr>
<td>Cazamias et al. (2015)</td>
<td>200</td>
<td>Chew, Mikami, and Nagano (2011)</td>
<td>182</td>
</tr>
<tr>
<td>Lui (2014)</td>
<td>143</td>
<td>Kocmi and Bojar (2017)</td>
<td>136</td>
</tr>
<tr>
<td>Majliš (2011)</td>
<td>122</td>
<td>Jauhiainen (2010)</td>
<td>103</td>
</tr>
<tr>
<td>Majliš (2012)</td>
<td>90</td>
<td>Lui and Baldwin (2011)</td>
<td>89</td>
</tr>
<tr>
<td>Baldwin and Lui (2010b)</td>
<td>74</td>
<td>Chew, Mikami, Marasinghe, and Nandasara (2009)</td>
<td>68</td>
</tr>
<tr>
<td>Lui and Baldwin (2014)</td>
<td>65</td>
<td>Goldszmidt et al. (2013)</td>
<td>52</td>
</tr>
<tr>
<td>Chen and Maison (2003)</td>
<td>48</td>
<td>Lui et al. (2014a)</td>
<td>44</td>
</tr>
<tr>
<td>Absinina, Ouamour, and Sayoud (2014)</td>
<td>32</td>
<td>King and Abney (2013)</td>
<td>31</td>
</tr>
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</table>

Table 13: Empirical evaluations with more than 30 languages.
In Fuzzy ART, the clusters are also dynamically updated during the identification process.

Amine, Elberrichi, and Simonet (2010) also tackle the unseen language problem through clustering. They use a character n-gram representation for text, and a clustering algorithm that consists of an initial k-means phase, followed by particle-swarm optimization. This produces a large number of small clusters, which are then labeled by language through a separate step. Lately, Poulston et al. (2017) also used k-means clustering. Alfter (2015) used the z-means clustering algorithm in a custom framework. Lin et al. (2014) utilized unlabeled data to improve their LI system by using the CRF autoencoder framework, unsupervised word embeddings, and word lists.

A different partial solution to the issue of unseen languages is to design the classifier to be able to output “unknown” as a prediction for language. This helps to alleviate one of the problems commonly associated with the presence of unseen languages – classifiers without an “unknown” facility are forced to pick a language for each document, and in the case of unseen languages, the choice may be arbitrary and unpredictable (Biemann & Teresniak, 2005). When LI is used for filtering purposes, i.e. to select documents in a single language, this mislabeling can introduce substantial noise into the data extracted; furthermore, it does not matter what or how many unseen languages there are, as long as they are consistently rejected. Therefore the “unknown” output provides an adequate solution to the unseen language problem for purposes of filtering.

The easiest way to implement unknown language detection is through thresholding. Most systems internally compute a score for each language for an unknown text, so thresholding can be applied either with a global threshold (Cowie et al., 1999), a per-language threshold (Suzuki et al., 2002), or by comparing the score for the top-scoring N-languages. The problem of unseen languages and open-set recognition was also considered by Malmasi and Dras (2015b), Zampieri et al. (2015), and Malmasi (2017). Malmasi (2017) experiments with one-class classification (OCC) and reaches an F-score on 98.9 using OC-SVMs (SVMs trained only with data from one language) to discriminate between 10 languages.

Another possible method for unknown language detection that has not been explored extensively in the literature, is the use of non-parametric mixture models based on Hierarchical Dirichlet Processes (HDP). Such models have been successful in topic modeling, where an outstanding issue with the popular LDA model is the need to specify the number of topics in advance. Lui et al. (2014a) introduced an approach to detecting multilingual documents that uses a model very similar to LDA, where languages are analogous to topics in the LDA model. Using a similar analogy, an HDP-based model may be able to detect documents that are written in a language that is not currently modeled by the system. Voss et al. (2014) used LDA to cluster unannotated tweets. Recently Zhang et al. (2016) has also used LDA for LI.

Filtering, a task that we mentioned earlier in this section, is a very common application of LI, and it is therefore surprising that there is little research on filtering for specific languages. Filtering is a limit case of LI with unseen languages, where all languages but one can be considered unknown. Future work could examine how useful different types of negative evidence are for filtering – if we want to detect English documents, e.g., is it useful to have distinct models of Italian and German, or can we group them all together in a single
“negative” class? Are we better off including as many languages as possible in the negative class, or can we safely exclude some?

10.6 Multilingual Documents

Multilingual documents are documents that contain text in more than one language. In constructing the hrWac corpus, Stupar et al. (2011) found that 4% of the documents they collected contained text in more than one language. Martins and Silva (2005) report that web pages in many languages contain formulaic strings in English that do not actually contribute to the content of the page, but may nonetheless confound attempts to identify multilingual documents. Recent research has investigated how to make use of multilingual documents from sources such as web crawls (King & Abney, 2013), forum posts (Nguyen & Dogruöz, 2013), and microblog messages (Ling, Xiang, Dyer, Black, & Trancoso, 2013). However, most LI methods assume that a document contains text from a single language, and so are not directly applicable to multilingual documents.

Handling of multilingual documents has been named as an open research question (Hughes et al., 2006). Most NLP techniques presuppose monolingual input data, so inclusion of data in foreign languages introduces noise, and can degrade the performance of NLP systems. Automatic detection of multilingual documents can be used as a pre-filtering step to improve the quality of input data. Detecting multilingual documents is also important for acquiring linguistic data from the web, and has applications in mining bilingual texts for statistical MT from online resources (Ling et al., 2013), or to study code-switching phenomena in online communications. There has also been interest in extracting text resources for low-density languages from multilingual web pages containing both the low-density language and another language such as English.

The need to handle multilingual documents has prompted researchers to revisit the granularity of LI. Many researchers consider document-level LI to be relatively easy, and that sentence-level and word-level LI are more suitable targets for further research. However, word-level and sentence-level tokenization are not language-independent tasks, and for some languages are substantially harder than others (Peng, Feng, & McCallum, 2004).

Linguini (Prager, 1999) is a language identifier that supports identification of multilingual documents. The system is based on a vector space model using cosine similarity. LI for multilingual documents is performed through the use of virtual mixed languages. Prager (1999) shows how to construct vectors representative of particular combinations of languages independent of the relative proportions, and proposes a method for choosing combinations of languages to consider for any given document. One weakness of this approach is that for exhaustive coverage, this method is factorial in the number of languages, and as such intractable for a large set of languages. Furthermore, calculating the parameters for the virtual mixed languages becomes infeasibly complex for mixtures of more than 3 languages.

As mentioned previously, Lui et al. (2014a) propose an LDA-inspired LI method for multilingual documents that is able to identify that a document is multilingual, identify the languages present and estimate the relative proportions of the document written in each language. To remove the need to specify the number of topics (or in this case, languages) in advance, Lui et al. (2014a) use a greedy heuristic that attempts to find the subset of
languages that maximizes the posterior probability of a target document. One advantage of this approach is that it is not constrained to 3-language combinations like the method of Prager (1999). Language set identification has also been considered by Suzuki et al. (2002), Jauhiainen et al. (2015b), and Pla and Hurtado (2015, 2017).

To encourage further research on LI for multilingual documents, in the aforementioned shared task hosted by the Australasian Language Technology Workshop 2010, discussed in 7.3, participants were required to predict the language(s) present in a held-out test set containing monolingual and bilingual documents (Baldwin & Lui, 2010b). The dataset was prepared using data from Wikipedia, and bilingual documents were produced using a segment from an article in one language and a segment from the equivalent article in another language. Equivalence between articles was determined using the cross-language links embedded within each Wikipedia article.\(^{23}\) The winning entry (Tran, Nguyen, & Kieu, 2010) first built monolingual models from multilingual training data, and then applied them to a chunked version of the test data, making the final prediction a function of the prediction over chunks.

Another approach to handling multilingual documents is to attempt to segment them into contiguous monolingual segments. In addition to identifying the languages present, this requires identifying the locations of boundaries in the text which mark the transition from one language to another. Several methods for supervised language segmentation have been proposed. Cowie et al. (1999) generalized a LI algorithm for monolingual documents by adding a dynamic programming algorithm based on a simple Markov model of multilingual documents. More recently, multilingual LI algorithms have also been presented by Jhamtani et al. (2014), Minocha and Tyers (2014), Pethő and Mózes (2014), Ullman (2014), and King et al. (2015).

### 10.7 Short Texts

LI of short strings is known to be challenging for existing LI techniques. Mandl et al. (2006) find that the method of Cavnar and Trenkle (1994) has an error rate of 7%. Mandl et al. (2006) test four different classification methods, and find that all of them have substantially lower accuracy when applied to texts of 25 characters compared with texts of 125 characters. Hammarström (2007) describes a method specifically targeted at short texts that augments a dictionary with an affix table, which was tested over synthetic data derived from a parallel bible corpus. Vatanen et al. (2010) focus on messages of 5–21 characters, using n-gram language models over data drawn from Universal Declaration of Human Rights (UDHR).

We would expect that generic methods for LI of short texts should be effective in any domain where short texts are found, such as search engine queries or microblog messages. However, Hammarström (2007) and Vatanen et al. (2010) both only test their systems in a single domain, Bible texts in the former case and texts from the UDHR in the latter case. Other research has shown that LI results do not trivially generalize across domains (Baldwin & Lui, 2010a), and found that LI in UDHR documents is relatively easy (Yamaguchi & Tanaka-Ishii, 2012). For both Bible and UDHR data, we expect that the linguistic content is relatively grammatical and well-formed, an expectation that does not carry across to

\(^{23}\) Note that such articles are not necessarily direct translations but rather articles about the same topic written in different languages.

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domains such as search engine queries and microblogs. Another “short text” domain where LI has been studied is LI of proper names. Häkkinen and Tian (2001) identify this as an issue. Konstantopoulos (2007) found that LI of names is more accurate than LI of generic words of equivalent length.

Bergsma et al. (2012) raise an important criticism of LI work on Twitter messages to date: only a small number of European languages has been considered. Bergsma et al. (2012) expand the scope of LI for Twitter, covering nine languages across Cyrillic, Arabic and Devanagari scripts. Lui and Baldwin (2014) expand the evaluation further, introducing a dataset of language-labeled Twitter messages across 65 languages constructed using a mostly-automatic method that leverages user identity to avoid inducing a bias in the evaluation set towards messages that existing systems are able to identify correctly. Lui and Baldwin (2014) also test a 1300-language model based on Brown (2013), but find that it performs relatively poorly in the target domain due to a tendency to over-predict low-resource languages.

Work has also been done on LI of single words in a document, where the task is to label each word in the document with a specific language. Work to date in this area has assumed that word tokenization can be carried out on the basis of whitespace. Singh and Gorla (2007) explore word-level LI in the context of segmenting a multilingual document into monolingual segments. Other work has assumed that the languages present in the document are known in advance.

Conditional Random Fields (CRF) (Lafferty, McCallum, & Pereira, 2001) is a sequence labeling method most often used in LI for labeling the language of individual words in a multilingual text. CRF can be thought of as a finite state model (FST) with unnormalized transition probabilities. It can use any observations made from the mystery text as features, including language labels given by monolingual language identifiers for words. King and Abney (2013) used CRF trained with generalized expectation criteria and the CRF was the most accurate of all the methods (NB, LR, HMM, CRF) tested on word-level LI. King and Abney (2013) introduce a technique to estimate the parameters using only monolingual data, an important consideration as there is no readily-available collection of manually-labeled multilingual documents with word-level annotations. Nguyen and Dogruöz (2013) present a two-pass approach to processing Turkish-Dutch bilingual documents, where the first pass labels each word independently and the second pass uses the local context of a word to further refine the predictions. Nguyen and Dogruöz (2013) achieved 97.6% accuracy on distinguishing between the two languages using linear-chain CRF from the scikit-learn package. Clematide and Makarov (2017) are the only ones so far to use CRF for LI of monolingual texts. With CRF, they attained better F-score in German dialect identification than NB or an ensemble consisting of NB, CRF, and SVM. Lately CRF was also used for LI by Dongen (2017) and Samih (2017). Giwa and Davel (2013) investigate LI of individual words in the context of research on code switching. They find that smoothing of n-gram models substantially improves accuracy of a language identifier based on a NB classifier when applied to individual words.
10.8 Similar Languages, Language Varieties, and Dialects

While one line of research into LI has focused on pushing the boundaries of how many languages are supported simultaneously by a single system (Xia et al., 2010; Brown, 2012, 2013), another has taken a complementary path and focused on LI in groups of similar languages. Research in this area typically does not make a distinction between languages, varieties and dialects, because such terminological differences tend to be politically rather than linguistically motivated (Clyne, 1992; Xia et al., 2010; Zampieri & Gebre, 2012), and from an NLP perspective the challenges faced are very similar.

LI for closely-related languages, language varieties, and dialects has been studied for Malay–Indonesian (Ranaivo-Malançon, 2006), Indian languages (Murthy & Kumar, 2006), South Slavic languages (Ljubešić et al., 2007; Tiedemann & Ljubešić, 2012; Ljubešić & Kranjčić, 2014, 2015), Serbo-Croatian dialects (Zecevic & Vujicic-Stankovic, 2013), English varieties (Lui & Cook, 2013; Simaki et al., 2017), Dutch–Flemish (van der Lee & Bosch, 2017), Dutch dialects (including a temporal dimension) (Trieschnigg, Hienstra, Theune, de Jong, & Meder, 2012), German Dialects (Hollenstein & Aepli, 2015) Mainland–Singaporean–Taiwanese Chinese (Huang & Lee, 2008), Portuguese varieties (Zampieri & Gebre, 2012; Zampieri et al., 2016), Spanish varieties (Zampieri et al., 2013; Maia & Gómez-Rodríguez, 2014), French varieties (Mokhov, 2010b, 2010a; Diwersy, Evert, & Neumann, 2014), languages of the Iberian Peninsula (Zubiaga et al., 2014), Romanian dialects (Ciobanu & Dim, 2016), and Arabic dialects (Elfardy & Diab, 2013; Zaidan & Callison-Burch, 2014; Tillmann, Al-Onaizan, & Mansour, 2014; Sadat et al., 2014a; Wray, 2018), the last of which we discuss in more detail in this section. As to off-the-shelf tools which can identify closely-related languages, Zampieri and Gebre (2014) released a LI system trained to identify 27 languages, including 10 language varieties. Closely-related languages, language varieties, and dialects have also been the focus of a number of shared tasks in recent years as discussed in Section 7.3.

Similar languages are a known problem for existing language identifiers (Ranaivo-Malançon, 2006; Zampieri, 2013). Suzuki et al. (2002) identify language pairs from the same language family that also share a common script and the same encoding, as the most difficult to discriminate. Tiedemann and Ljubešić (2012) report that TextCat achieves only 45% accuracy when trained and tested on 3-way Bosnian/Serbian/Croatian dataset. Lui and Cook (2013) found that LI methods are not competitive with conventional word-based document categorization methods in distinguishing between national varieties of English. Ranaivo-Malançon (2006) reports that a character trigram model is able to distinguish Malay/Indonesian from English, French, German, and Dutch, but handcrafted rules are needed to distinguish between Malay and Indonesian. One kind of rule is the use of “exclusive words” that are known to occur in only one of the languages. A similar idea is used by Tiedemann and Ljubešić (2012), in automatically learning a “blacklist” of words that have a strong negative correlation with a language – i.e. their presence implies that the text is not written in a particular language. In doing so, they achieve an overall accuracy of 98%, far surpassing the 45% of TextCat. Brown (2013) also adopts such “discriminative training” to make use of negative evidence in LI.

Zampieri (2013) observed that general-purpose approaches to LI typically use a character n-gram representation of text, but successful approaches for closely-related languages,
varieties, and dialects seem to favor a word-based representation or higher-order n-grams (e.g. 4-grams, 5-grams, and even 6-grams) that often cover whole words (Huang & Lee, 2008; Tiedemann & Ljubešić, 2012; Lui & Cook, 2013; Goutte et al., 2016). The study compared character n-grams with word-based representations for LI over varieties of Spanish, Portuguese and French, and found that word-level models performed better for varieties of Spanish, but character n-gram models perform better in the case of Portuguese and French.

To train accurate and robust LI systems that discriminate between language varieties or similar languages, models should ideally be able to capture not only lexical but more abstract systemic differences between languages. One way to achieve this, is by using features that use de-lexicalized text representations (e.g. by substituting named entities or content words by placeholders), or at a higher level of abstraction, using POS tags or other morphosyntactic information (Zampieri et al., 2013; Lui et al., 2014b; Bestgen, 2017). Finally, an interesting research direction could be to combine work on closely-related languages with the analysis of regional or dialectal differences in language use (Peirsman, Geeraerts, & Speelman, 2010; Anstein, 2013; Doyle, 2014; Diwersy et al., 2014).

In recent years, there has been a significant increase of interest in the computational processing of Arabic. This is evidenced by a number of research papers in several NLP tasks and applications including the identification/discrimination of Arabic dialects (Elfardy & Diab, 2013; Zaidan & Callison-Burch, 2014). Arabic is particularly interesting for researchers interested in language variation due to the fact that the language is often in a diglossic situation, in which the standard form (Modern Standard Arabic or “MSA”) coexists with several regional dialects which are used in everyday communication.

Among the studies published on the topic of Arabic LI, Elfardy and Diab (2013) proposed a supervised approach to distinguish between Modern Standard Arabic (MSA) and Egyptian Arabic at the sentence level, and achieved up to 85.5% accuracy over an Arabic online commentary dataset (Zaidan & Callison-Burch, 2011). Tillmann et al. (2014) achieved higher results over the same dataset using a linear-kernel SVM classifier.

Zaidan and Callison-Burch (2014) compiled a dataset containing Modern Standard Arabic, Egyptian Arabic, Gulf Arabic and Levantine Arabic, and used it to investigate three classification tasks 1) MSA and dialectal Arabic, 2) four-way classification: MSA, Egyptian Arabic, Gulf Arabic, and Levantine Arabic, 3) three-way: Egyptian Arabic, Gulf Arabic, and Levantine Arabic.

Salloum, Elfardy, Alamir-Salloum, Habash, and Diab (2014) explores the use of sentence-level Arabic dialect identification as a pre-processor for MT, in customizing the selection of the MT model used to translate a given sentence to the dialect it uses. In performing dialect-specific MT, the authors achieve an improvement of 1.0% BLEU score compared with a baseline system which does not differentiate between Arabic dialects.

Finally, in addition to the above-mentioned dataset of Zaidan and Callison-Burch (2011), there are a number of notable multi-dialect corpora of Arabic: a multi-dialect corpus of broadcast speeches used in the ADI shared task (Ali, Dehak, Cardinal, Khurana, Yella, Glass, Bell, & Renals, 2016), a multi-dialect corpus of (informal) written Arabic containing newspaper comments and Twitter data (Cotterell & Callison-Burch, 2014), a parallel corpus of 2,000 sentences in MSA, Egyptian Arabic, Tunisian Arabic, Jordanian Arabic, Palestinian Arabic and Syrian Arabic, in addition to English (Bouamor, Habash, & Oflazer, 2014), a corpus of sentences in 18 Arabic dialects (corresponding to 18 different Arabic-speaking
countries) based on data manually sourced from web forums (Sadat et al., 2014a), and finally two recently compiled multi-dialect corpora containing microblog posts from Twitter (Elgabou & Kazakov, 2017; Alshutayri & Atwell, 2017).

10.9 Domain-specific LI

One approach to LI is to build a generic language identifier that aims to correctly identify the language of a text without any information about the source of the text. Some work has specifically targeted LI across multiple domains, learning characteristics of languages that are consistent between different sources of text (Lui & Baldwin, 2011). However, there are often domain-specific features that are useful for identifying the language of a text. In this survey, our primary focus has been on LI of digitally-encoded text, using only the text itself as evidence on which to base the prediction of the language. Within a text, there can sometimes be domain-specific peculiarities that can be used for LI. For example, Mayer (2012) investigates LI of user-to-user messages in the eBay e-commerce portal. He finds that using only the first two and last two words of a message is sufficient for identifying the language of a message.

11. Conclusions

This article has presented a comprehensive survey on language identification of digitally-encoded text. We have shown that LI is a rich, complex, and multi-faceted problem that has engaged a wide variety of research communities. LI accuracy is critical as it is often the first step in longer text processing pipelines, so errors made in LI will propagate and degrade the performance of later stages. Under controlled conditions, such as limiting the number of languages to a small set of Western European languages and using long, grammatical and structured text such as government documents as training data, it is possible to achieve near-perfect accuracy. This led many researchers to consider LI a solved problem in the 2000’s as argued by McNamee (2005). However, LI becomes much harder when taking into account the peculiarities of real-world data, such as very short documents (e.g. search engine queries), non-linguistic “noise” (e.g. HTML markup), non-standard use of language (e.g. Twitter messages), and mixed-language documents (e.g. forum posts in multilingual web forums).

Modern approaches to LI are generally data-driven and are based on comparing new documents with models of each target language learned from data. The types of models as well as the sources of training data used in the literature are diverse, and work to date has not compared and evaluated these in a systematic manner, making it difficult to draw broader conclusions about what the “best” method for LI actually is. We have attempted to synthesize results to date to identify a set of LI “best practices”, but these should be treated as guidelines and should always be considered in the broader context of a target application.

Existing work on LI serves to illustrate that the scope and depth of the problem are much greater than they may first appear. In Section 10, we discussed open issues in LI, identifying the key challenges, and outlining opportunities for future research. Far from being a solved problem, aspects of LI make it an archetypal learning task with subtleties that could be tackled by future work on supervised learning, representation learning, multi-
task learning, domain adaptation, multi-label classification and other subfields of machine learning. We hope that this paper can serve as a reference point for future work in the area, both for providing insight into work to date, as well as pointing towards the key aspects that merit further investigation.

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