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Tools to Aid OCR of Hebrew Character Manuscripts

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Abstract

Digitalization of historical and cultural documents can provide researchers with new options for conducting research on a variety of subjects. Although OCR systems are the common method for digitalization processes, they are sometimes not enough due to the poor performance of those systems on documents that are handwritten, have low contrast, include shifts in writing style, and have various other typical characteristics of manuscripts. For such documents, OCR needs to be post-processed to allow successful utilization of the data contained in the documents.

This thesis proposes various methods for such post-processing, using techniques from the fields of natural language processing and statistical language modeling. Methods are proposed for language classification, document segmentation and text searching. These methods are designed to handle very noisy texts and are tuned to work on the Hebrew language. In this way, the methods can be of use in the project of digitalization of the Cairo Genizah – a collection of ancient and medieval Jewish works. Our methods have been evaluated on both real and artificially produced documents.

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CHAPTER 1

INTRODUCTION

The Cairo Genizah is a combination of important scholarly works, community records and ledgers, business and marriage contracts, personal letters and more. Among these documents are original manuscripts in the hand of famous scholars and personalities of that era. The digitalization of those manuscripts can open various research possibilities for cultural and historical researchers. Nonetheless, this process poses challenges to the traditional digitalization processes of scanning and recognition of text by an OCR engine. The fact that the manuscripts are handwritten, when handwriting can vary in style and clearance, even the fraction of documents written in Hebrew script present a big challenge to OCR systems. Other properties of the documents, such as low quality of the manuscripts, various languages, incomplete pages and other challenges make it impossible for an OCR engine to produce results that can satisfy the lowest demand needed for any research. The common method for handling noisy texts is using some statistical, language oriented post-process on the result to increase accuracy.

The post-processing of the text relies on properties of the language the text is written it. The tools present a scale up in the level of processing of the text, from geometric features of written figures to the linguistic meanings of those characters as building blocks for words. It is common, for example, to correct erroneous words by matching them to some known words in a known vocabulary or to measure the probability of some character combination in a language. Identification of the text language is a preliminarily for those methods, in case the language is not given and cannot be implied from the script/encoding of the characters. In the case of the Cairo Genizah, the texts appear in a variety of Hebrew-script languages such as Aramaic, Hebrew, Judeo-Arabic, Ladino and more. The similarity between those languages also vary from languages similar in style like Hebrew and Aramaic, to language that share only script with the others, like Judeo-Arabic. Moreover, many of the documents are mixtures of paragraphs in different languages, presenting further challenge for the application of a post-processing tool on them since a straight forward classification of language cannot be used.

Even after successful identification of the language of every part of the text, the application of traditional correcting methods in not straight forward. Due to the low accuracy of the results produced by the OCR process, correction of text using single word lookup is not satisfying. On the other hand, a significant part of the Genizah documents are transcriptions of some known Jewish texts, which we can look in pre-prepared repositories. Therefore, an application of approximate string matching techniques for searching the noisy text in this repository can be useful for such post-processing.

For the post-processing of OCR on Cairo Genizah documents we present a multi stage scheme

1. Identification of the document language
2. Segmenting the document to monolingual fragments in the case of a multi lingual document
3. Searching the text in a corpus according to language recognized.

1.1 The Cairo Genizah

The Cairo Genizah is a collection of over 300,000 Jewish manuscripts found in the loft of the ancient Ben Ezra Synagogue in Fustat medieval Cairo, to the south-west of the modern city between the 11th and 19th centuries. The dark, sealed, room in the arid Egyptian climate contributed to the preservation of the documents, the earliest of which may go back to the eighth and ninth centuries. The Genizah texts are written in various languages especially Hebrew, Arabic and Aramaic mainly on vellum and paper, but also on papyrus and cloth. They represent the most important discovery of new material for every aspect of scientific Hebrew and Jewish studies in the middle ages. In addition to containing Jewish religious texts such as Biblical, Talmudic and later Rabbinic works (some in the original hands of the authors), the Genizah gives a detailed picture of the economic and cultural life of the North African and Eastern Mediterranean regions, especially during the 10th to 13th centuries. Its documents reveal a wealth of information about this previously little known period in Jewish history. Today, a large portion of the Genizah's documents are available at Cambridge University Library and at the Jewish Theological Seminary in New York. Smaller collections are spread out in university library collections across the globe, among them London, Oxford, Manchester, Paris, Geneva, Vienna, Budapest, St. Petersburg, New York, Philadelphia, Washington and Jerusalem. Some are housed in private collections.

1.2. Corpora Collection

The algorithms proposed further use statistical properties of the languages. A significant work was made for collecting statistics on those languages, which are not commonly used in nowadays, and digital copies of documents in those languages are not widespread. The corpora collected for Hebrew contains the "Torah" – the Pentateuch and the Mishnah - the first major written redaction of the Jewish oral traditions called the "Oral Torah" which is also the first major work of Rabbinic Judaism. For Aramaic, the corpus contains the Jerusalem Talmud - a collection of rabbinic notes on the Mishnah which was compiled in the Land of Israel during the 4th-5th century. The Talmud, as a commentary on the Mishnah, contains significant number of Hebrew quotes, so it is not pure Aramaic. Another Aramaic book is "Targum Onkelos", an official Aramaic translation of the Torah. For Judeo-Arabic, later work was collected such as "More

Nevuchim" (The guide for the perplexed) by Maimonides, the "Kuzari" by Rabi Yehuda Halevy, and "Hamaspik Ovdey Hashem" by Maimonides son.

Other collection were obtained for further experiments, among which are the "Hazohar" in Aramaic, which is the foundational work in the literature of Jewish mystical thought known as Kabbalah, Hebrew "Shulhan Aruch" which is the most authoritative legal code of Judaism and other Jewish religious work. A full list of the corpus is listed in appendix 1.

For the use of the collection as a statistical reference it was processed to be cleaned of irrelevant characters, unneeded lines and various punctuation. It was then tokenized and several n-gram statistics were collected.

1.3 Related work

Much work have been conducted in the field of OCR postprocessing, most of them using statistical approaches over N-grams or vocabularies. The methods over vocabularies contain approximate string matching techniques for searching lists of all known words of a language such as proposed by Chen et al.(2010). Statistical methods use probabilities over character combinations for correcting the OCR errors, combined with confusion matrices (Kukish, 1992). Kolak and Resnik (2005) advice the use of statistic methods in the case of low density languages, where massive document sets for producing vocabulary are not available. Methods for using words n-gram for such process were also introduced. However, little work has been done on using those methods on multilingual documents. Approximate string matching methods of strings against corpora were surveyed by Navarro (2001) and include dynamic programming algorithms, filtering techniques and approaches using final automata.

Work on language classification has been widely learned (Hughes et al, 2006), mostly as a classification problem. Two approaches dominate the works in the area, word based and character based. Word based approaches represent the text as vector of words and use supervised classification techniques for the identification of language. The character based approaches do this by comparing n-gram probability distributions over each language and the text (Hakkinen and Tian 2001).

The processing of multilingual documents was addressed by Giguet (1996), which addressed the problem using grammatical words and end of word characters. The processing was sentence wise, and actually the segmentation process was not issued. Related work on segmentation of text, usually of semantic nature, was pioneered by Hearst (1993) and used sliding window techniques. Following work utilized lexical chains techniques, clustering, dynamic programming and other techniques (Choi, 2000).

1.4 Structure

The rest of the thesis is structured as follows: Chapter 2 describes the method for language classification of documents. Chapter 3 describes the extension of the method for segmenting multi-lingual documents to monolingual fragments. Chapter 4, presents the algorithm for searching noisy texts in a corpus. Each of those chapters includes a short background, description of the algorithm and experiments made for testing. Chapter 5 contains conclusions and discusses further possible research directions.

CHAPTER 2

LANGUAGE CLASSIFICATION

An important step in the digitalization process of manuscripts is language identification. Apart from using the language to efficiently catalogue the manuscripts, recognizing the language is a crucial part for OCR processes. An OCR post-processing algorithm (described in further in this work) assumes knowledge of the language of the manuscript for choosing the appropriate corpus to scan.

2.1 N-Gram approach

An obvious fact is that different languages, even if containing the same character set, have different distribution of the letters appearances. Therefore, gathering statistics on the typical distribution of letters in each language may lead us to reveal the language of a manuscript by comparing its letter distribution to the distributions we know. A simple distribution of the letters may not be enough, so a common technique in NLP is using n-grams which mean computing the distributions of all possible combinations of n letters. Obviously, the number of possible combinations grows exponentially with n, so usually the value of n does not exceed 4.

The classification can be described by the following procedure

1. Collect N-Gram statistics on all possible languages
2. Compute N-Gram distribution on the manuscript
3. Compute the distance of the manuscript's distribution to each language using some distance function
4. Classify the manuscript as the language with the minimal distance

The first task in computing the n-gram distributions is choosing the n. In our experiments we tried unigram, bigram and trigram. The characters we considered were all Hebrew alphabet letters, including “sofiot” (variants of letters that appear at the end of the words). The only additional character used was the space character (‘ ‘), under the assumption that different languages can have different word lengths (for languages with shorter words the space character will have higher appearance count) and that different languages tend to have different letters ending a word (and then bigrams or trigrams containing those letters followed by space will appear more). Specifically, when a human tries to identify Aramaic texts, he may do it by looking for words ending by Alef ('א'), a property strongly correlated with this language. The probability function for an n-gram i is given by

$$P(i) = \frac{Count(i)}{\sum_{j \in all\ Ngrams} Count(j)}$$

It is easy to see that the denominator, which is the sum of all appearances of all n-grams in the text, is just the length of the text (minus n). The formula implies that an n-gram that was not spotted in the text has a zero probability, a fact that can be true for some n-grams (for example n-gram which contains a letter that appears only at the end of the word followed by a character which is not space), but is not generally correct. There are techniques that smooth the distribution function, giving unseen n-grams a probability larger than zero, but we chose not to address this problem by smoothing but by adapting the distance function to handle such distributions.

The second missing detail in the algorithm is the distance function. Since the distribution function is discrete, we can actually represent it as a vector of probabilities, and transform the problem to vector distance problem. We tried the following three distance functions:

- **Cosine similarity** – this function is basically the cosines of the angle between two vectors, measuring how similar are the directions of the two vectors. The value is computed using

$$Cosine(d1,d2) = \frac{d1 \cdot d2}{\|d1\| * \|d2\|} = \frac{\sum_{i \in allNgrams}(P_{d1}(i) * P_{d2}(i))}{\sqrt{\sum_{i \in allNgrams}(P_{d1}(i))} * \sqrt{\sum_{i \in allNgrams}(P_{d2}(i))}}$$

The function is a similarity measure rather than a distance measure, therefore when classifying a manuscript, the language with the highest similarity value is taken (opposed to the minimal distance for other functions). It is also symmetric and normalized to values between zero and one.

- **KL Divergence** [] - the Kullback–Leibler divergence, often referenced as information gain, is a measure between two distributions, originated from information theory. The function is defined as following

$$\mathbf{KL(d1,d2)} = \sum_{i \in allNgrams} \left(P_{d1}(i) * \ln\left(\frac{P_{d1}(i)}{P_{d\square}(i)}\right)\right)$$

Note that there are several problems using this measure for classification purposes. First, the function is not symmetric therefore we need to choose whether d1 is the language corpus distribution or the manuscript distribution. It is common to look at the KL divergence as a measure to how much a sample distribution d2 differs from the "true" distribution therefore we used (after some testing) d1 as the corpus distribution. Another challenge is the presence of zero probabilities. If $P_{d1}(i) = 0$ or $P_{d2}(i) = 0$ then $\ln\left(\frac{P_{d1}(i)}{P_{d2}(i)}\right)$ is undefined. We chose to skip all n-grams not present in one of the distributions, what can of course distort the distance (for example if the manuscript and language has no n-gram in common the distance will be zero although it should be infinity) but simplifies the function to match our needs.

- **Euclidean distance** – really the straight forward approach for measuring distances between vectors. $Dist(d1, d2) = \sqrt{\sum_{i \in allNgrams} (P_{d1}(i) * P_{d2}(i))^2}$

2.1.1 Unknown Classification

For shorter documents we can expect performance to be poor. To address this, we can allow the "Unknown" classification, using which we can reduce the error rate. To determine when the classification can be set to "Unknown" we need some certainty measure of the classification. We can then set some threshold and classifications with certainty above the threshold we be considered certain and below threshold will be considered uncertain or "unknown". This can be helpful in many cases, especially when the classification precision is of high importance. Using this method, "unknown" fragments can be further analyzed (maybe manually) and the classified fragments are only those of very high certainty.

To get this certainty measure we can look at the cosine similarities of fragments to their closest language. We obviously expect them to grow as the fragment length grows. For extracting the certainty measure we can use two methods:

Absolute distance – If the distance of the fragment to the classified language is very high, we can be more certain of the classification. Here we assume that mistakenly classified fragments will have lower similarity than the correct ones as presented in Figure 1. We then use regression to learn a function of the threshold dependency on the length. We tried establishing linear logarithmic function of the form $threshold = a + b * \ln(c * length + d)$ where a, b, c and d are parameters to be determined by regression.

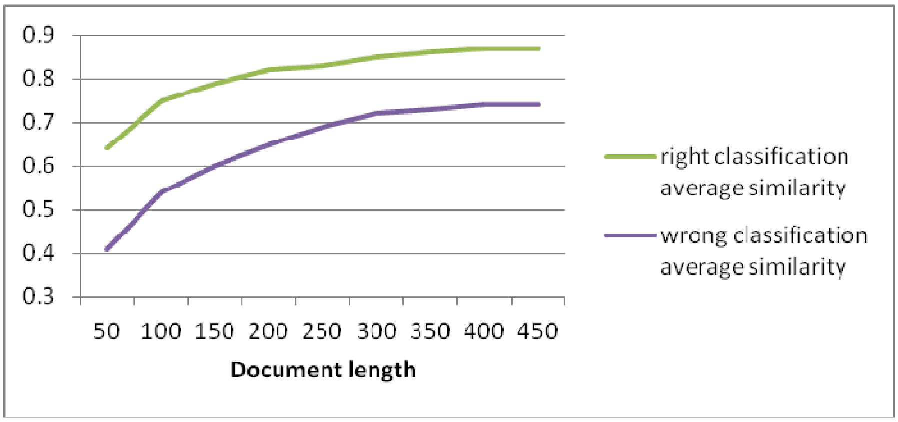


Figure 1: The difference between the average cosine distance of correctly classified texts and mistakenly classified texts

We can see in Figure 1 that the accurately classified texts are classified with much higher similarity then the mistaken ones so it looks possible to compute some threshold under which we can say the classification is not clear.

Relative distance – Here we rely on the intuition that when a document is classified correctly, its cosine similarity to the right language is much higher than the similarity to other languages. We can define a variable *offset* which will stand for the difference between the cosine similarity of the fragment to the closest language and the document's average similarity to all considered languages. More formally,

$$offset = \max_{l \in languages} Cosine(l, document) - \mathbf{Average}_{l \in languages} Cosine(l, document)$$

Figure 2 shows that *offset* indeed is significantly larger when the classification is correct, so we can use it as the certainty threshold as we can see that for wrongly classified documents the offset is always in the range of 0.04-0.05

Here we will not set the threshold as a function of the length, and use the variance of the similarity distances. For each document we can compute the standard deviation *std(document)* of the cosine distances from each language. We will say that the classification is certain if *offset>a*std.*

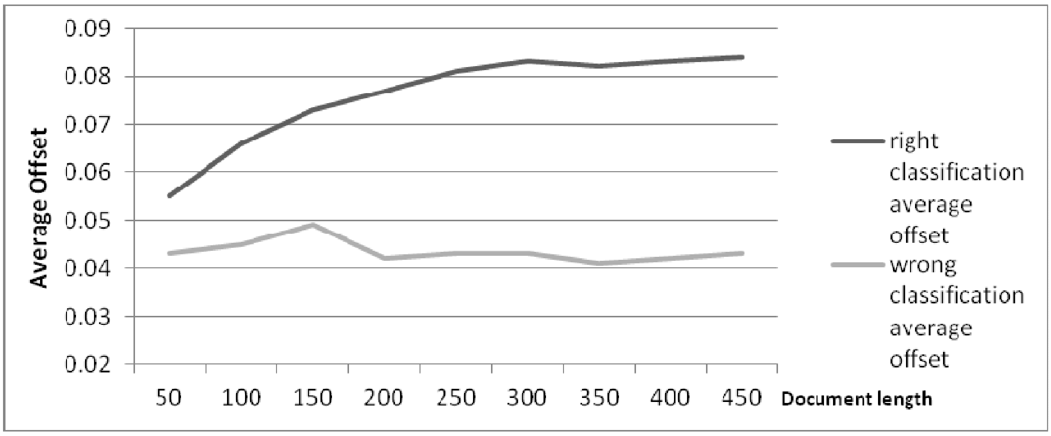


Figure 2: The average of the offset variable (the difference between the maximum similarities to the average similarity) of correctly and mistakenly classified documents.

2.1.2 SMALL AND NOISY DOCUMENTS

Classifying OCR processed manuscripts have several unique challenges, not encountered when handling traditional language classification of documents. One of these challenges is handling significant amount of noise characterizing OCR outputs. Another challenge is the frequency of extremely small texts, some less than 50 characters long (maybe two sentences). The significance of small documents classification rises when handling the problem of multilingual document segmentation described further. The length of the documents and the noise rates can make some statistic measures less efficient due to distorted distributions or insignificance of statistics on small samples.

Several methods (Kukich, 1992) have been proposed for error correction using N-grams, using transition probabilities – the probabilities of a letter following another. Here, we are not interested in error correction, but in the adjustment of the classifying procedure to handle noisy texts. For noise representation we introduce the *"$"* character which stands for an unrecognized character by the OCR. We do not discuss error recognition here and assume that errors are recognized and represented by the *"$"* sign. A conservative OCR system can only output characters which have high probability of correctness and output the rest as "$", so all misidentification mistakes can be reduced to this notion. There is also no assumption that the word boundaries will not be misidentified, so a "$" sign can be produced instead of a space character.

Several methods are proposed

Ignoring unrecognized n-grams – here we do not account the n-gram containing the "$" character in the cosine similarity measures. This requires no change from the regular pattern since those n-grams do not appear in the language model anyway. Here we assume there is enough bigrams left in the text to successfully identify its language with the remaining n-grams.

Remove unrecognized characters – we can also remove the "$" fragment from the text before starting any analysis. On one hand, it looks natural to ignore all noise, but on the other hand we lose the information that noise was indeed produced. Therefore 'א$ב' will transform to 'אב' which may distort the n-gram distributions

Error correction – Given unknown character we can try correcting it using trigrams. When observing the $ signed surrounded by a character *l1* on its left and *l2* on its right, we can look for the most common trigram in each language containing *l1* in the beginning and *l2* at the end. It looks natural to do it and enhances the statistical power of the n-gram distribution. On the other hand it does not scale well for high noise rate since there is no solution for two or more consecutive *"$"* characters.

Averaging n-gram probabilities – When encountering "$" we can use averaging to estimate the probability of the n-gram containing it. For instance the probability of the bigram 'א$' will be the average probability of all bigrams starting with 'א' in a certain language. This can of course scale to higher n-grams and integrates the noisy information into the computation.

**Replacing the '$' –** We can try to replace the '$' by some other character without relying on the language model. We do that by looking at the character before it, noting it as *l*, and searching the given text for another appearance of it. The character appearing after *l* in the closest appearance to the '$' character will be the one we will choose to replace it with. This is a rather heuristic and not statistic error correction, relying that replacing an unknown bigram can be predicted using similar bigrams close to it in the text.

Top n-grams – when looking at noisy text we can say that more weight should be given to the corpus statistics since it is error free. Moreover, since text is short we expect to see only a small portion of the n-grams in the text. Therefore we can look and compute distributions only on the n most common n-grams in the corpus, assuming that they must appear in the text regarding noise and length.

Higher or lower n-gram space – So far we used bigram which showed superior performance. When error rate rises and text length drops, the more distinctive n-gram such as trigrams may produce higher success rate. On the opposite, unigrams need shorter text sample for robust statistics so are also reconsidered.

2.2 Experiments and results

2.2.1 TEST SETTINGS

The success of language classification can heavily depend on the properties of the test set. For the task of classifying manuscripts, there are several properties to be considered:

Text length – manuscripts can be of different lengths, from a small number of sentences up to a whole page that contains multiple paragraphs. It is clear that the variance of the distributions of smaller texts is much higher, so the probability of a statistic model extracted from short text to differ from the language statistic model is higher. Therefore, we can expect lower accuracy rate on shorter texts. For our experiments we tested various text lengths to measure the influence of this parameter.

OCR error rate – Assuming that the classified text is a result of some noisy process, we expect that high rate of noise will reduce the classification success rate. This parameter was also tested and we present how we address highly erroneous documents.

Language set – Even when languages share the same character set, they can still significantly differ from one another. For example Hebrew and Judeo-Arabic are completely different, with little chance that a Hebrew speaker will understand Judeo-Arabic even a little. On the other hand, some languages can share the same character set due to common origins, which will resemble in the high similarity between them that can make the classification task more difficult. Such are Hebrew and Aramaic that have a lot of similar words or a word in one language that is some variant or descendant of a word of the other language. Needless to say that as the set of languages grows the classification task becomes more difficult.

2.2.2 Test Results

To test the distance function we begin by selecting 300 documents, 100 of each language and try to classify those using bigrams with each of the mentioned distance functions. For this purpose we use prepared texts with no errors. Each document is 300 characters long.

	Cosine	KL	Euclidian
Overall	0.94	0.81	0.94
Hebrew	0.93	0.78	0.94
Aramaic	0.89	0.72	0.89
Judeo-Arabic	1	0.94	1

Table 1: Classification accuarcy of distance function

From the results two facts arise clearly: The cosine and Euclidean functions have higher accuracy then KL and Judeo-Arabic language is much easier to spot then Hebrew and Aramaic.

300 characters are about four sentences which is a pretty short text. For similar languages like Hebrew and Aramaic it may be too short to get a good classification. We also want to try out trigrams in order to gain better statistics. To test this, we classified texts of various lengths, using unigrams, bigrams and trigrams. We tried it only on Hebrew and Aramaic since we saw that Judeo-Arabic is distinguishable pretty easily.

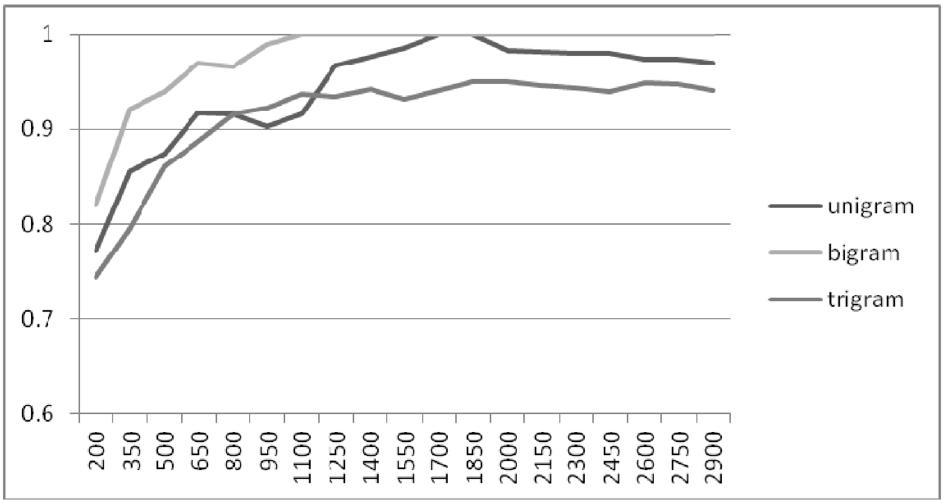


Figure 3: Classification accuracy of different n-grams

From figure 3 we can see that generally bigrams are the best method on all lengths. For texts longer than 1000 characters the performance is perfect. On short texts trigrams have low performance which rises as the text size grows, but does not reach the bigram performance even on long texts. Perhaps on really long texts, the statistic power of trigrams can be more significant but on page sized texts it is inferior. Unigram have poorer performance then bigrams even on the shortest texts.

2.2.3 "UNKNOWN" CLASSIFICATION TESTS

By allowing classification to return an "unknown" result, we obviously reduce the error rate. On the other hand, since the "unknown" classification is not a correct classification, it also reduces the success rate. To establish a fair measure, we can score a successful classification as 1, an unknown classification by 0 and wrong classification by -1. It is a "neutral" score since right and wrong classifications weigh the same. For error sensitive classification the weight of the error should increase.

For absolute threshold we estimated the threshold function as

$threshold = a + b * \ln(c * length + d)$ where

a = 5.31E-02;

b = 1.29E-01;

c = 8.27E-01;

d = -1.18E+01;

Increasing *a* will make classification more error sensitive (lower error rate and lower success rate) and decreasing it will give higher success rate (and error rate).

For relative threshold we set $threshold = a * std$ where *a=0.8.* As *a* grows, the classification is more error sensitive (lower error rate), and as *a* reduces the success rate grows.

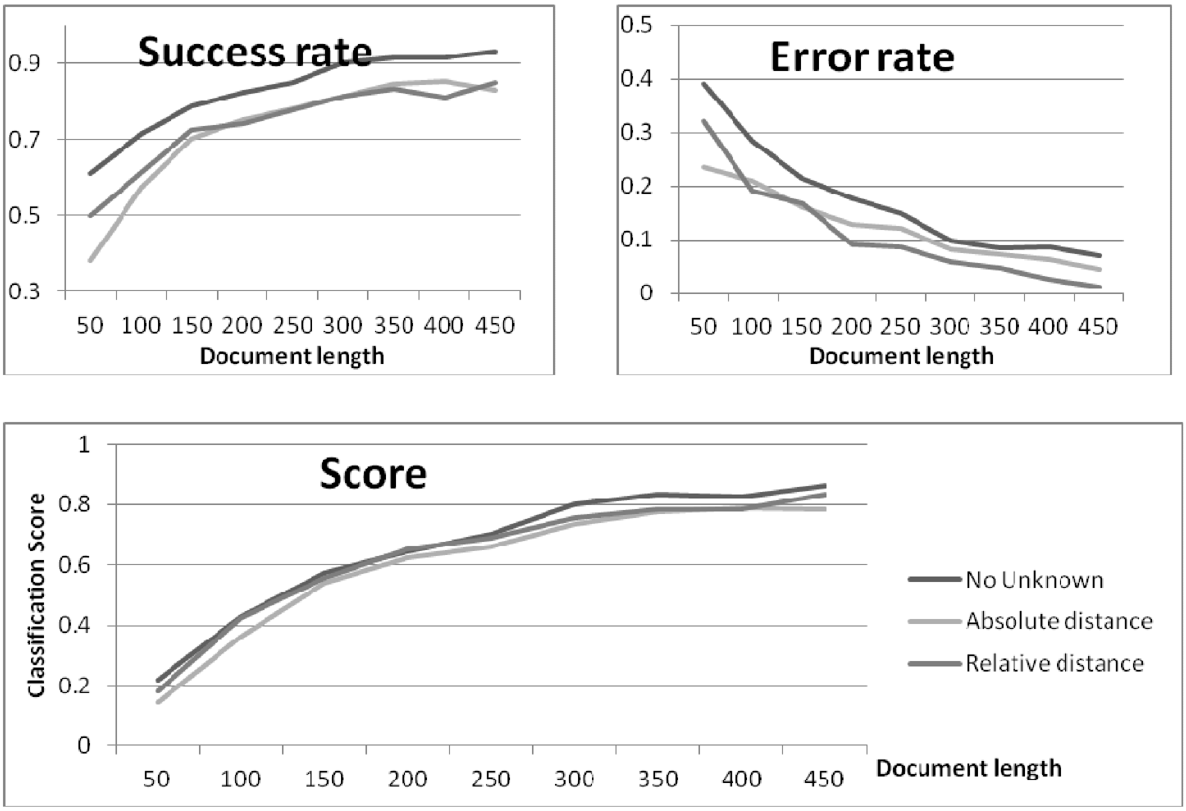


Figure 4: The success rate, the error rate and the classification score of every method of"unknown" classification

Naturally, "unknown" classification methods reduce both the error rate and success rate. We can see that the relative distance method is superior to the absolute distance, with significantly lower error rates on almost every length and equal success rate. We can also notice that for neutral classification score, the regular classification is superior to all methods. Only when we measure the classification with error sensitive score, the "unknown" classification methods become relevant.

2.2.4 NOISY TEXTS

A test to measure the performance of all noise reduction methods was done on several (but small) document lengths. The error rate was simulated using the '$' character, that randomly replaced text characters according to some error rate.

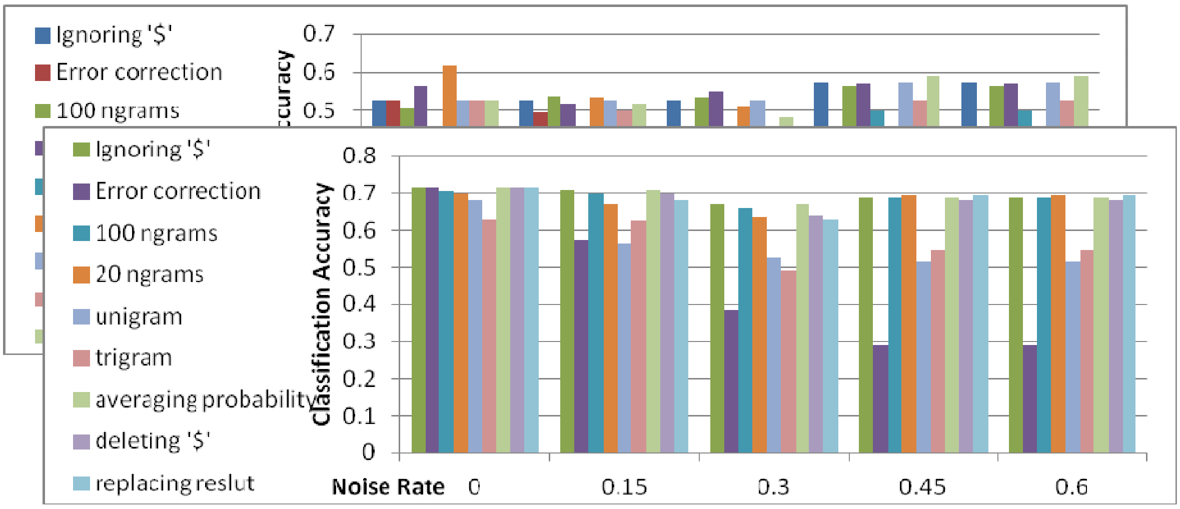


Figure 5: The performance of all noise reduction methods on 40 character length documents

Figure 6: The performance of all noise reduction methods on 100 character length documents

From Figures 5 and 6 we can see that usually, just ignoring the unrecognized character, relying on the statistics of the recognized text is the straight forward and best result. Trigrams perform well only on short noise free texts, and reducing the bigram to the top 100 performs good also, usually not very different from the ignoring methods. Top 20 bigrams performs well only on very noisy texts as we can expect, presenting poorer performance on other cases and looks suitable only when the amount of noise is extremely high. Error correction methods do not perform well, while replacing '$' with a character of neighboring bigram which looks like a useful feature in high noise rates.

CHAPTER 3

SPLITTING BI-LINGUAL TEXTS

In the previous chapter we showed methods for language classification of manuscripts. The methods work under the assumption that each manuscript is monolingual, and their behavior on multilingual texts is unexpected. As stated before, Genizah manuscripts contain many mixed texts which cannot be strictly classified to some language. When we look at texts of Jewish biblical philosophy or interpretation, we will usually find Aramaic texts with a lot of quotations in Hebrew. Classifying such texts to one language is rather useless so instead of classification we are interested in a more general problem of splitting the text into monolingual fragments, classifying each fragment to its language.

3.1 Background

The problem of fragmenting multilingual texts to monolingual fragments was not addressed much, although it is a natural generalization of the language classification problem (Hughes 2006). Several related methods can be useful for this type of problems. The notion of structured learning is the generalization of the classification task (Daume and Marcu, 2005) to extend the target to complex structures such as sequences or trees. Theoretical general methods use Markov models or support vector machines for such predictions, usually using massive datasets for learning. Segmentation problem, as a simple case of structured learning that results classification sequences can be addressed using those very general methods.

More specific methods deal with segmentation of text, such as automatic paragraph detection. All such methods use two modules, one classification model and another segment boundary searching model. The most popular approach is the sliding window technique that looks for the most rapid change in classification scores for detecting boundaries. The general scheme of the designed algorithm should not be affected by noise unlike some sliding window approaches which apply classification on very short windows, a technique shown as not efficient for classification of noisy documents.

3.2 Algorithm Outline

For the splitting task we assume that no dictionary is available and only n-gram statistics of each language is known. For want the algorithm to work even if the language shifts every few sentences so we do not assume anything on the length of each fragment (we of course cannot count several words as a language shift). In the general case of the algorithm there is also no assumption that the sentences in the text are marked, so it can be a one long sentence as well. The algorithm has 4 major steps

1. Split the text to fragments
2. Calculate characteristics for each fragment
3. Classify each fragment
4. Refine classification result and output final results

3.2.1 SPLITTING THE TEXT

As stated, we do not assume the documents are split into sentences or paragraphs. So the splitting is done in the naïve way of segmenting the text into fixed size fragments. Obviously, language cannot shift in the middle of a word so we do perform adjustment of the fragments sizes to fall between words. If sentences are marked in the text and we assume that language cannot shift in the middle of the sentence, then the adjustment described is done for sentence granularity.

The selection of the fragment size should depend on the language shift frequency. Nonetheless, each fragment is classified using statistical properties so it has to be long enough to have some statistic significance. On the other hand, if it is too long the language transition will be spotted less accurately, and if a fragment contains two language shifts the algorithm will not be able to classify the inner fragment (for example if a fragment starts with Hebrew, shifts to Aramaic and end in Hebrew, the algorithm can classify it as Aramaic or Hebrew, or split it to two languages in the post-processing but cannot spot all three fragments). Moreover, the post-processing phase is computationally more expensive, and it's complexity grows proportionally to the fragment length so we cannot choose a long fragment size.

3.2.2 Feature extraction

The core of the algorithm is classification of the fragments produced by the first step of the algorithm. Classification problems are usually reduced to vector classification, so there has to be a process of representing each fragment as a vector of features. Naturally, the selection of features is critical for successful classification, regardless of the classification algorithm.

N-gram distance – The first and obvious feature is the classification of the fragment using the methods described in chapter 2. However, the fragments are significantly smaller then the texts that were classified in the previous chapter so we can expect the accuracy be lower. The features in this case will be the cosine distance from each language model rather than a single feature with the result language. This is rather natural since we want to preserve the distances from each language model in order to combine it with other features further on. For each fragment *f* and language *l* we can compute $Distance_l = Dist(l, f)$ where $Dist(l, f)$ represents the cosine distance of the bigram distributions of *l* and *f*

Neighboring fragments language – We expect that languages in a document are not shifting too frequently. It is a reasonable assumption, since usually paragraphs tend to be monolingual and at least several sentences in a row are in the same language to present some idea. Therefore, if we are sure that a fragment is in some language, there is a high chance that the next fragment will be in the same language as well. One way to express such dependency is by post-processing the results to reduce noise. Other way is by combining the classification results of neighboring fragments as features in the classification of the fragment. Of course, not only neighboring fragments can be considered, and all fragments under some distance from the fragment can help in classification. For example if we have a classification results of HHHAHHH (where H stands for Hebrew fragment and A for Aramaic fragment), it looks possible that the A is noise and should be H. On the other hand, if the result is HAHAHAH, there is no intuition to turn the middle A to H. Some parameter should be estimated to be the threshold for the distance between fragments under which they will be considered neighbors. We denote Neighbor(f,i) = if i is positive then the i'th fragment after f. If i is negative the i'th fragment before f. If i=0 Neighbor(f,i) = f. So for each fragment *f* and language *l* we can compute $NeighborDist_{l,f}(i) = Dist(l, Neighbor(f, i))$

Whole document language - another feature to be considered is the cosine distance of the whole document from each language model. This feature tends to smooth and reduce noise from the classification output. Note that for a monolingual document the algorithm is expected to output a single fragment (the whole document) classified to the right language. So for each language *l* we calculate $DocumentDist_l = Dist(l, text)$

Clustering – a major drawback of the features presented so far is the fact that they resemble statistic similarity between language models and very short text fragments. To increase classification accuracy we would like to classify longer texts. In order to do so we can cluster similar fragments together and then classify the whole cluster as a single unit. It will obviously be longer than a single fragment, so the classification will be more accurate, but there is no guarantee that the clustered fragments will be actually monolingual.

The clustering is done using complete linkage hierarchical clustering. The idea is to perform iterative process where each iteration we unify the two closest clusters.

Initially, all fragments are clusters containing only one fragment. Every iteration we unify the two closest clusters, where complete linkage stands for the metric used for calculating distance between two clusters. The distance between clustering is the maximal distance between any elements in the two clusters. More formally $Dist(C1, C2) = Max_{f1\epsilon C1, f2\epsilon C2}(Dist(f1, f2))$ where $c1\epsilon C1$ stands for fragment *f1* belong to cluster *C1*. We end this iterative process when the minimal distance between two clusters rises above some threshold *T* (which in turn means there are two fragments that the distance between them exceeds the threshold). In the end of the process we can compute the distance between each cluster and each language model. For a fragment *f* we denote the cluster that contains *f* as *Clus(f)* and for each fragment *f* and language *l* we can calculate features $Clus_l = Dist(l, Clus(f))$. The threshold *T* for stopping the clustering process represents the threshold between gaining bigger clusters which can be better classified on one hand and risking to get clusters which are not monolingual on the other hand and is established empirically,

Since the point of clustering is to get longer text for classification, then as bigger the cluster gets the more positive we are in its classification. Therefore the size of the cluster is another feature we want to consider in order to give more significance to the $Clus_l$ features for longer clusters. So for each fragment *f* we denote $ClusSize = |Clus(f)|$ the number of fragments clustered to the same cluster as *f*.

3.2.3 Classification phase

After the features have been extracted, the classification step is rather straight forward. We can either use some known supervised learning method such as to learn the problem on a test set and produce a classifier or we can try establishing some manual scoring formula using the features and classify by the language getting the highest score.

3.2.4 POS- PROCESSING

We now want to refine the fragment splitting procedure. We do it the following way: We look at the results of the splitting procedure and recognize all language shifts. For each shift we try to find the position where the shift takes place (in words granularity). We unify the two fragments and then try to re-split the fragment in N points. For every such point we look at cosine distance of the words before the point from the language the first fragment was classified to and the cosine distance of the words after the point to the language the second fragment was classified to. For example suppose the fragment *A1….An* was classified as Hebrew and the fragment *B1….Bm* which appeared right after it in the text was classified as Aramaic. We look at the text *A1…An,B1…Bm* and try to split it in N points (say N =3). So we try to split it *to F1=A1…A(n+m)/3* and *to F2=A(n+m)/3…Bm* (suppose ((n+m)/3)<n). We look at cosine distance of *F1* to Hebrew and *F2* to Aramaic since those were the languages the fragments were originally classified to. Then we try to look on *F1 = A1…A(2*(n+m)/3)* and *F2 = A(2*(n+m)/3)…Bm* and so on. We take the split point with the lowest cosine distance multiplicative of the two values. The N value is a tradeoff between accuracy and computation efficiency. When N is higher we check more transition points, but for large fragments it can be computationally expensive.

3.3 Noise Reduction

As for language classification, the segmentation algorithm can be extended to handle noisy documents. As the splitting and shift recognition phases are not expected to be noise sensitive, the classification phase of each segment is the stage to handle noise. We test the segmentation success rate on all noise correction methods presented in the noise handling section for classification.

3.4 Experiments and results

3.4.1 TEST SETTINGS

We want to test the algorithm with a well defined parameters and evaluation factors. For this purpose we will create artificially mixed documents, containing fragments from two different languages (we can do it using Hebrew and Aramaic which are difficult to distinguish, Hebrew and Judeo-Arabic where classification is easy and the fragmentation is the main challenge or do it on three languages). The fragments will be produced using a procedure that accepts two parameters: The desired document length *d* and the average fragment length *l* – where fragment is a continuous text block of only one language. Obviously $\mathbf{l} < \square$. The procedure will iteratively randomize a number in the range *[l-20,l+20]* and will take a substring in this size from a corpus of one language. The substring will be adjusted to contain whole words only. It will repeat this on all corpora of all other languages and then will restart with the first language until the whole text will reach the size of *d*.

Obviously *l* and *d* are of significance. For a very small *l*, it will be very difficult to fragment the document exactly since the text blocks will not be long enough for statistic tests. As for *d*, it is clear that the average number of fragments inside the document is $\mathbf{n} = \frac{\mathbf{d}}{\square}$. As *n* grows larger it is more difficult for the splitting algorithm to be right in all fragments and since *n* grows with *d* we will expect to see a higher absolute error rate.

3.4.2 SUCCESS MEASURES

Obviously the splitting procedure will not be perfect and we cannot expect it to precisely split the document to the original fragments. Given that, we want to establish some measures for the quality of the splitting result. We would like the measure to produce some kind of score to the algorithm output, using which we can indicate whether a certain feature or parameter in the algorithm improves it or not. However, the result quality is not well defined since it is not clear what is more important: detecting the fragment's boundaries accurately, classifying each fragment correctly or even split the document to the exact number of fragments. For example, given a long document in Hebrew with a small fragment in Aramaic, is it better to return that it actually is a long document in Hebrew with Aramaic fragment but misidentify the fragment's location or rather recognize the Aramaic fragment perfectly but classify it as Judeo-Arabic.

We established three evaluation measures, using which we test the algorithm accuracy:

Correct word percentage – the most intuitive measure is simply measuring the percentage of words classified correctly. Since the "atomic" block of the text is words (or sentences in some cases described further), which are certainly monolingual, this measure will resemble the algorithm accuracy pretty good for most cases. It is however not enough, since in some cases it does not reflect the quality of the splitting. Assume a long Hebrew document with several short sentences in Aramaic. If the Hebrew is 95% of the text, a result that classifies the whole text as Hebrew will get 95% but it is actually pretty useless result and we may prefer a result that identifies the Aramaic fragments but errors on more words (say classifies the two Hebrew sentences before and after the Aramaic sentence as Aramaic also).

Fragment count ratio (FCR) **–** The measure estimates the algorithm sensitivity to language shifts. It counts the difference between the real fragments number to the fragments number returned by the algorithm. To normalize it is divided by the number of real fragments. Obviously $\mathbf{FCR} \in [-\square \ldots \mathbf{1}]$. It will indeed resemble the problem previously described, since if the entire document will be classified as Hebrew the FCR score will be very low as the actual fragments number is much higher than one.

Splitting edit-distance (ED) – Counting the fragments number (FCR) will allow evaluating the sensitivity of the splitting in the algorithm. However it does not resemble the quality of the classification stage output. Going back to the same example, the FCR will return the same result even if the algorithm will recognize the Aramaic fragment as Judeo-Arabic. In order to evaluate if the algorithm classifies right, we will define the following measure: If we label each language in the language set by 1…n. such that each document can be represented by a vector representing the languages of its fragments. The ED will be the edit-distance between the vectors of the actual fragment decomposition to the vector produced by the split of the algorithm (this measure is not normalized so it supposed to grow with *d/l*) .For instance, given a document which contains Hebrew text, then Aramaic then Hebrew and the Judeo-Arabic will be presented as *HAHJ*. If the algorithm misidentified the Aramaic fragment it will return *HJ* so the ED will be the edit distance between *HAHJ* and *HJ* which is 2. If it will misclassify the Judeo-Arabic as Aramaic and produce *HAHA* the ED will be 1. We can notice that if the language set contains only two languages, there is no point to the ED measure since it will return the absolute value of the FCR measure. Due to the fact that each character in the classification language vector is different from the character following it (if they are the same they would be unified to the same character) the edit distance on binary vectors is just the length difference up to ±1.

Therefore we will only use this measure when the language set contains more than two languages.

3.4.3 Naïve splitting

To get a reference on each feature of the algorithm we will run a naïve algorithm on the documents. The basic algorithm will simply split the document, classify each fragment in the way documents are classified and output the result. We want to test how d and l affect each classification parameter using this naïve scheme.

d	l	d/l	Correct words	FCR	ED
500	50	10.00	0.729	1.24	1.36
500	100	5.00	0.827	-0.48	0.56
500	150	3.33	0.847	-1.33	1.33
500	200	2.50	0.869	-1.77	1.77
500	250	2.00	0.902	1.45	1.45
1000	50	20.00	0.729	-2.64	2.68
1000	100	10.00	0.824	-0.62	0.9
1000	150	6.67	0.856	-1.52	1.56
1000	200	5.00	0.85	-2.75	2.79
1000	250	4.00	0.88	-2.61	2.61
1500	50	30.00	0.718	4.4	4.48
1500	100	15.00	0.813	-1.1	1.42
1500	150	10.00	0.841	-2.21	2.33
1500	200	7.50	0.859	-3.67	3.69
1500	250	6.00	0.882	-3.46	3.5
2000	50	40.00	0.716	5.93	5.95
2000	100	20.00	0.818	-0.82	1.54
2000	150	13.33	0.838	-3.28	3.36
2000	200	10.00	0.86	-4.47	4.49
2000	250	8.00	0.874	-4.63	4.63

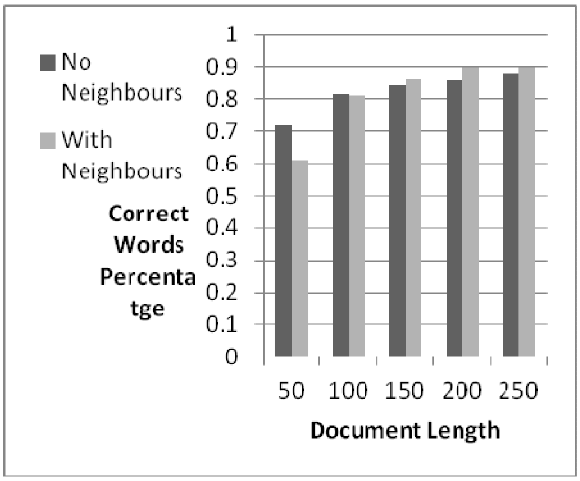
Table 2: The splitting results of artificially mixed texts from three languages. The *d* and *l* parameters are the length of the document and the fragment respectively, and *d/l* is the average number of fragments in a document. For each *d* and *l* we calculated the average evaluation measures.

From table 2 we can see how the measures behave on various document and fragment lengths. First of all, it is easy to see that as *l* grows, the correct word percentage grow as well regardless of document length. This is rather intuitive since longer fragments are easier to recognize and classify. The FCR is obviously strongly dependant on the number of fragments, and if the number of fragments in a document grows it is harder to accurately estimate it. We can notice that although the algorithm splits the document to fragment of 40 characters, if the average fragment length is 50 characters the algorithm underestimates the number of fragments (splits it to fewer fragments than needed). When the average fragment length is 100 and more the algorithm overestimates the number of fragments. The last observation is that ED is very close to the FCR, probably due to low rate of misclassification, so further test will consider only the correct words percentage and the fragment count ratio.

3.4.4 FEATURE EVALUATION

3.4.4.1 Neighboring fragments

The first enhancement to consider is the way fragment's classification is affected by neighboring fragments. To do that we begin by checking if adding the cosine distance of the closest fragments will enhance the algorithm performance. We define $Score_{f,l} = Dist(l,f) + a * \left(NeighborDist_{l,f}(1) + NeighborDist_{l,f}(-1)\right)$. For the test we set *a=0.4*



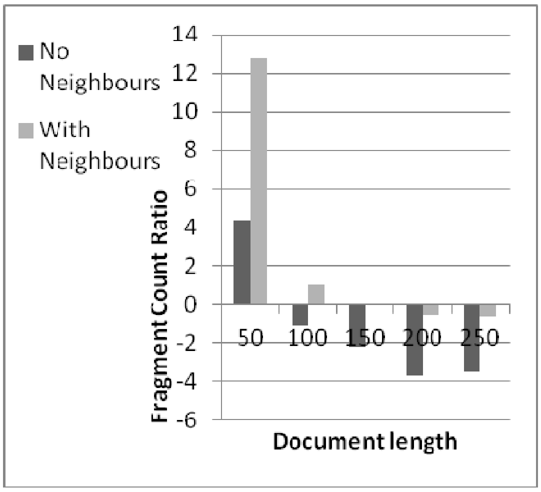


Figure 7: The word percentage of the algorithm with considering neighbors and without them as a function of l (d was chosen to 1500).

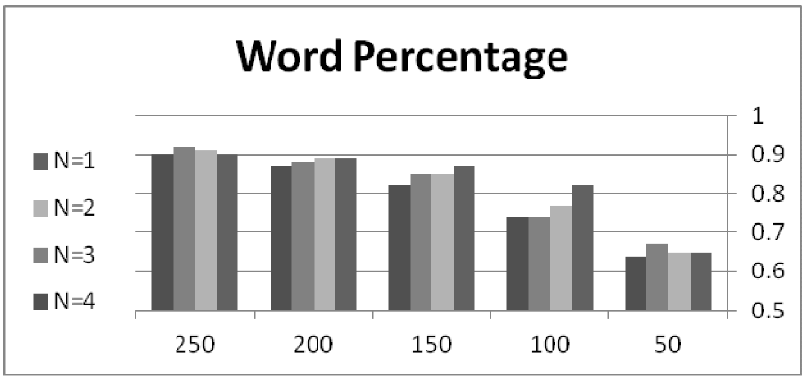
Figure 8: The fragment count ratio of the algorithm with considering neighbors and without them as a function of l (d was chosen to 1500).

We can see that on long fragment lengths the neighboring fragments improve classification, while on shorter ones classification without the neighbors was superior. It is not surprising that by using neighbors the splitting procedure tends to split the text to longer fragments, which has good effect only if fragments actually are longer. We can also see from Fig 8 that the FCR is now positive with *l=100* which means the algorithm underestimates the number of fragment even when each fragment is 100 characters long. By further experiments we can see that the *a* parameter is not significant, and we fix it on 0.3.

As expected, looking at neighboring fragment can improve results in most cases. The next question to be asked is if farther neighbors can improve it also. We try the following scoring function:

$$Score_{f,l} = Dist(l,f) + \sum_{k=1}^{N} \left(\frac{a}{k}\right)\left(NeighborDist_{l,f}(k\mathbf{1}) + NeighborDist_{l,f}(-k)\right)$$

. N stands



for the longest distance of neighbors to consider in the score. The *a* is set to 0.3.

Figure 9: the word percentage of the classification for different values of N

We can see that increasing N does not have a significant impact on the algorithm performance, and on shorter fragment lengths performance drops with N. We conclude that there is no advantage at looking on far neighbors and looking on the closest fragments is enough.

3.4.4.2 Clustering

Next thing we test is how the clustering method described above can enhance the algorithm. As stated before, the clustering refines fragment's classification by classifying similar fragments in the same document together which can allow more accurate classification since texts are longer. There are several parameters to consider: since the clustering method is hierarchical, there needs to be some similarity score under which we stop clustering. We set this similarity to 0.55, meaning two fragments which have lower similarity then 0.55 cannot be clustered together.

Fragment 1	Fragment 2	Cosine similarity
לעני אלהים סח יב אדני יתן אמר המבשרות צבא	*את תמר אחתו יג לג ועתה אל ישם אדני המלך*	0.56
אישתא עלתא הוא קורבן דמתקבל ברעווא קודם	*למדבחא עלתא הוא קודם לאתקבלא ברעווא קורבנא*	0.78
לבדו מת כי על פי אבשלום היתה שומה מיום ענתו	*על אדמת עמי קוץ שמיר תעלה כי על כל בתי משוש*	0.52
לעיני בני עמי יהבתה לך קבר מיתך וסגיד אברהם	*כספא דמי חקלא סב מיני ואקבר ית מיתי תמן*	0.49
אל בית ישראל ואפתח את פי ויאכילני את המגלה	*את המגלה הזאת אשר אני נתן אליך ואכלה ותהי*	0.61

Table 3: Fragments couples and their cosine similarity

To get some perspective Table 3 demonstrates fragments couples with their cosine similarities. We can see that fragments with over 0.6 similarity usually have common words (even long ones), a fact that makes it reasonable to assume they are in the same language. When similarity drops, the fragments look more random and we do not want to cluster them together for classification.

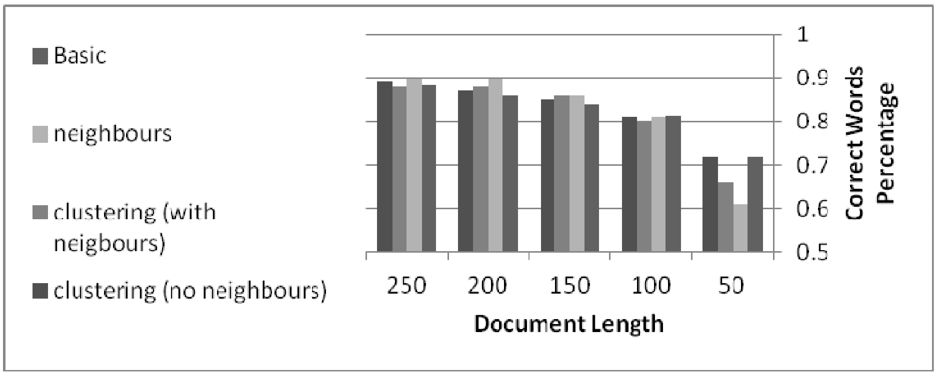


Figure 10: The word percentage rate of the algorithm with and withuot a clustering phase.

As seen in Figure 10 the clustering phase does not modify results dramatically, regarding the other features of the algorithm. It can be explained by the fact that clustered fragments were already correctly classified where the mistaken fragments that needed their classification corrected were not clustered because of their anomaly.

3.4.4.2 Post-Processing

Another thing we test is the post-processing of the splitting results to refine the initial fragment choice. We try to move the transition point from the original position to a more accurate position using the technique described above. We note it cannot affect the FCR measure since we only move the transition points without changing the classification. As shown in Figure 4.5 it does improve the performance for every value of l

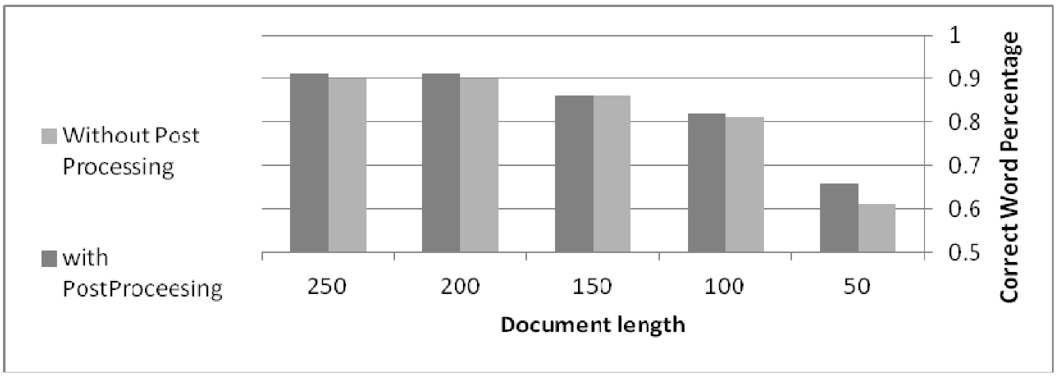


Figure 11: The correct words percentage of the algorithm with and without post-processing (the N value was set to N=5) as a function of l

3.4.5. SENTENCE ACCURACY

To test the success rate on sentences, we do the same procedure as for words, but the classification and mixed fragment creation works in sentence granularity. For simplicity, we mark 8 consecutive words of the same language as a sentence and mark the end of it by '.'. In the artificial creation phase, each fragment contains several language of each language (instead of creating fragments by the number of characters, we now create it by number of sentences). In the splitting phase we do not split it at arbitrary word, since it is certain that each sentence is monolingual. Therefore, we skip the refinement stage at the end of the algorithm and test how good is the sentence rate classification (what percentage of the sentences were recognized correctly), and the improvement of the algorithm using neighboring fragment data. We denote that for short fragment length documents each fragment contains only one sentence, so the most we can expect on those documents is the accuracy of language classification on sentence length (about 30 characters) texts. The results are in table 4 and we can see that for low *l* values the success rate is even lower than the word percentage, since it uses only language classification of sentences (the neighboring data only decreases accuracy in this case since neighbors are surely have different language). For longer fragments the classification rises above the words percentage

l	Correct words percentage	Correct sentence percentage (no neighbors)	Correct sentence percentage (with neighbors)
50	0.72	0.68	0.59
100	0.81	0.84	0.81
150	0.84	0.87	0.88
200	0.86	0.87	0.92
250	0.88	0.88	0.93

Table 4: The percentage of the sentences correctly identified by the algorithm, with and without neighboring fragments data, compared to the percentage of correct words percentage.

3.4.6. NOISE REDUCTION

To test the noise reduction we artificially noise the text by randomly replace some letters with the *"$"* character. We denote the desired noise rate as *P* and for each letter independently replace it with the "$" character with probability *P*. Since the replacement of each character of the text is mutually independent, we can expect normal distribution of the error positions in the text and the correction phase described above does not assume anything about the error creation process. The error creation does not assign different probabilities for different characters in the text unlike natural OCR systems or other noisy processing.

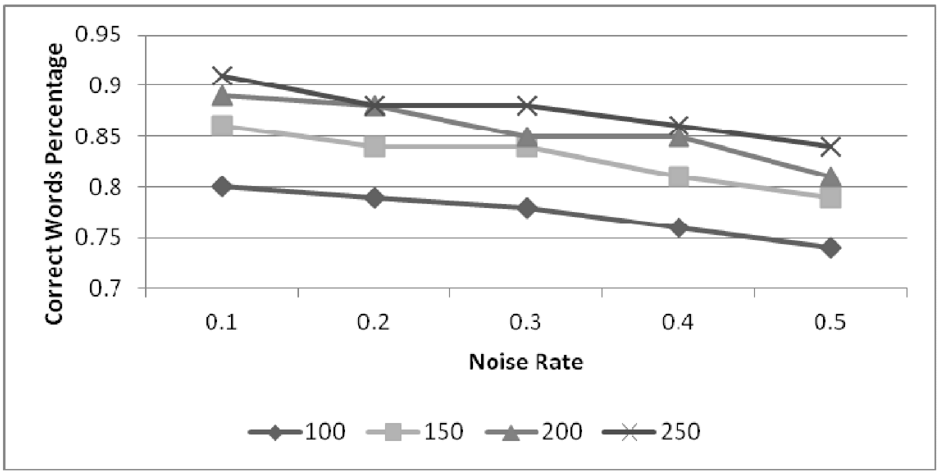


Figure 12: : The algorithm word accuracy as a function of the noise rate P. Each line shows the reduce in accuracy for every fragment length

Not surprisingly Figure 12 illustrates that the accuracy reduces as the error rate rises. However, it does not significantly drop even for very high error rate, and obviously we cannot expect the error reducing process will perform better then the algorithm performs on errorless text.

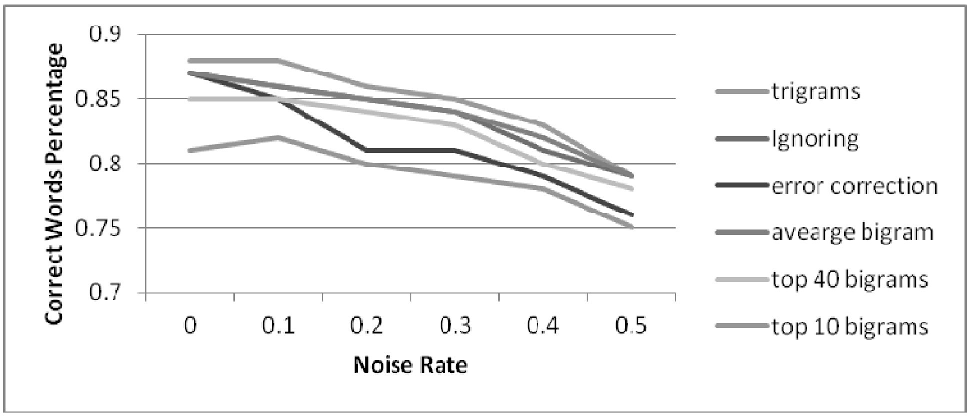


Figure 13: The performance of the correction methods above as for each error rate.

Figure 13 illustrates the performance of each method. It looks like looking at most common n-grams does not help and so is correcting the unrecognized character. Ignoring the unrecognized character, using either bigrams or trigrams, or estimating the missing unrecognized bigram probability show the best and pretty similar results.

4.3.5

CHAPTER 4

CORPUS SEARCHING ERROR CORRECTION

The identification of the language opens possibilities for creating simple catalogues and enhances search options over digitalized documents. As for text produced by an OCR process, it opens the option of post-process the text to enhance OCR accuracy. This is especially important for extremely noisy OCR processes, where the produced text cannot be used without further improvement.

A common technique in OCR post-processing is approximate string matching. We assume the text is a part of some big known corpus, and the problem is reduced to finding the correct sub-text in the corpus that corresponds to the processed document. In processing Hebrew manuscripts, it highly likely that the manuscript is a part of some known book and searching it can reveal the text that the OCR could not accurately recognize. Assuming we identified the language using the techniques from the previous chapters, we can use those language models also to improve the OCR result. This is relevant for extremely noisy texts, for which searching for approximation in the corpus may not provide with good results.

4.1 Background

String searching is a well studied problem in computer science with many established algorithms and strong theoretical background. The basic problem of finding a string in a long text has well known solutions such as Knuth-Morris-Pratt (KMP) and Rabin-Karp algorithms, which are linear in the text size. The problem of approximate string matching is a generalization of this problem, where the goal is to find a substring of the text that best matches some search pattern, where matches are ranked using some distance functions. The approximate string matching has applications in variety of fields in computer science especially computational biology, information retrieval, spell checking and more.

4.1.1 EDIT-DISTANCE

To deal with approximate matching, we first need to define what an approximate match is. This of course depends on the application, but one of the most popular similarity measures of string is Edit-Distance, also known as Levenstein distance. The edit distance between two strings is defined by the minimal number of edit operations needed to be performed on one string for it to exactly match the other. The edit operations allowed in the basic form of edit distance are insertion, deletion and substitution of letters. For example, given the words "train" and "ruins" we can perform 3 edit operations: deleting the 't' letter (getting rain), substitution of 'a' by 'u' (getting ruin) and inserting the 's' character at the end to get "ruins". Hence, the edit distance is 3.

Edit distance is highly suitable for OCR correction purposes, since the allowed edit operations are pretty consistent with the errors an OCR engine may perform. It is frequent for an OCR to skip a character or to recognize some irrelevant symbol as a letter (insertion and deletion operations), and of course confuse one character with another (substitution). We can use edit distance to approximate the probability the OCR engine will produce one string from the other, in the sense that the lower the edit distance is , the higher the probability for the OCR to produce one string as an output on the second string. A generalized version of the edit distance problem, assigns different weights for insertion of each character, deletion of each character and substitution of each character with each other character. This can match the different probabilities of mistakes made by the OCR engine (it is more likely for the OCR to replace two characters that have geometric similarity or to insert a character with simple geometric shape). Other string distance functions do not reflect the nature of OCR engines. The popular Hamming distance allows only substitution of letters, but gives infinite distance to two strings with different lengths which will assign zero probability for an OCR to miscalculate the length of its input (which is way above zero obviously). The generalization of Levenstein distance, Damerau-Levenstein is popular in spell correction because of the additional edit operation of substitution of two letters. As oppose to human typing, which have high probability of confusing the characters order, an OCR is an automatic procedure that scans the text linearly, so this function does not suit our requirements also. Other string distance function popular in natural language processing usually use phonetic or semantic word properties while OCR usually uses geometric properties of the characters.

The edit distance between two strings is usually computed using a dynamic programming procedure. The computation complexity is *O(n*m)* where *n* and *m* are the lengths of the two strings.

4.1.2 APPROXIMATE STRING MATCHING METHODS

There are several approaches to the approximate string matching problem. Some of them are mainly theoretical in nature, where the practical ones are dynamic programming, filtering and indexing.

Dynamic programming techniques are a search generalization of the distance computation method, by trying to compute distance from every possible starting point in the text. The run time of those methods is usually close to O(n*m) where n is the text length and m is the pattern length. Main drawback of those methods is the large space requirements due to the dynamic programming matrices needed to be managed. For large corpora this can make it inapplicable since there are searches of patterns of thousands of characters in texts of tens of millions of characters.

Filtering methods use heuristics to eliminate indexes in the text that cannot be the best solution. There is usually some fast scanning of the text which will make the search phase more efficient. The search phase usually makes use of dynamic programming techniques, so worst case scenarios will be similar to the dynamic programming complexity. Those methods are much more convenient for our purpose.

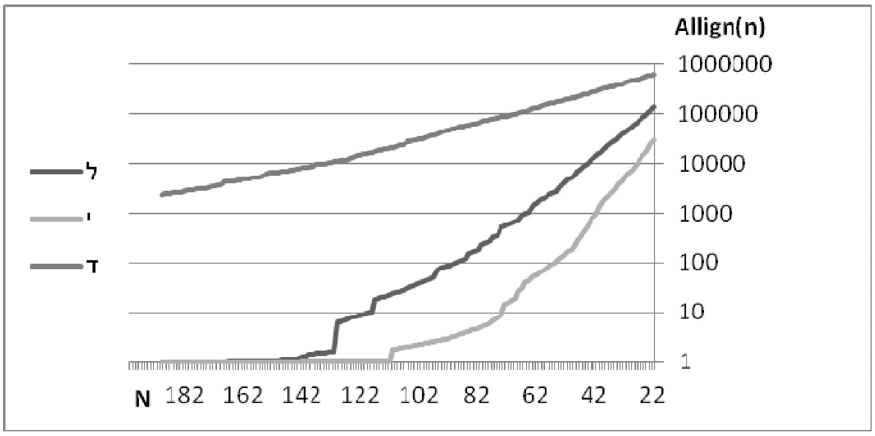
Indexing methods preprocess the text, which in turn enhances the matching procedure. Those methods are suitable for applications that perform multiple searches on the same text. The indexing is usually computationally expensive and has high memory consumption and the search algorithms are complex and difficult to modify.

4.2 Error rate estimation

Applying string matching techniques for correction of OCR process has unique properties, due to the unknown accuracy of the OCR process. Although edit-distance is suitable for estimating the probability of a string being produced by the OCR, there is still no guarantee that the closest substring in a text in terms of edit distance is the actual string. In other words we want to estimate how efficient will application of string matching techniques to OCR correction problem and what OCR accuracy is needed for it to be efficient.

4.2.1 SINGLE LETTER ALIGNMENT

The first thing we test is the application of string matching techniques, under the assumption the OCR can accurately recognize only one character of the alphabet. We first try exact matching, meaning we assume the OCR recognizes the letter perfectly. For this purpose we choose an arbitrary string in the text, mask it in the sense we leave only one letter in the string and turn all other characters to the '$' sign, and search it back in the text. We denote as $Allign_l(n)$ the average number of alignments for substrings of length n over 500 random strings which was masked to contain only the letter l. The use



the bible, which is 1505034 characters long, as the text to search in. We expect the number of alignments to rise as the text grows

Figure 14: The number of possible matches for string masked by three different letters, as a function of the string length.

As shown in Figure 5.1, we can see that for frequent letter (such as ‘י’ which has 10% frequency), the search yields a single match on strings longer than 110 characters. For rare characters, even on 200 character strings, it still has over 1000 correct matching, making the search irrelevant, so if OCR recognizes only rare characters we demand much longer documents.

4.2.1.1 Single letter with errors

After approaching the straight forward approach of exact matching, we will try to extend it to inexact substrings. We still assume the availability of only one letter. Suppose the substring is a copy of some fragment of the original text, while errors can be taken place in the copying process. We can look at a probability matrix of copy errors. Suppose we have a probability of $P_{\square}$ to get a letter *l* in the copy even when the original text contained something else. It means that we have a probability of only $1 - P_{\square}$ to get non *l* character (denote it by *$*) in the copy when there appeared *$* in the original text. Symmetrically, we define by $P_{\square}$ the probability of getting *$* in the copy when the original text contained *l* and it means we only have $1 - P_{\square}$ probability to copy the letter *l* correctly.

For the test we set *P1=0* and *P2=0.05*. This means that the OCR does not produce “false positives” and identify *l* where it did not appear. It does have a 0.05 probability to miss a character *l* and produce something else. For example given a string “אדאבדאהדאבדא” which contains 4 appearances of the character 'ד', the probability of getting “$ד$$ד$$ד$$ד$” (exactly correct OCR) is 0.95^4 , since the probability of correct recognition of the letter is 0.95. The probability for “$$$$ד$$ד$$ד$” is $0.95^3 * 0.05$ (3 correct identifications and one mistake). This can be the nature of a very conservative OCR, that identifies some character only when there is very high probability it is actually it and therefore does not produce false positives.

The test we produce is selecting an arbitrary string, leave only a character l in the string, while in probability *P2* we replace the appearances of *l* to *$*. Then the new patter is searched in the text and the match with the highest probability (as defined above) is returned. We are interested when the returned match is actually the string that was selected and masked. We use the character 'ל' as *l* which is an average letter with 0.05% percent appearance.

Pattern length	Percentage of correct matches	Average rank of original string
500	1	1
350	1	1
250	0.995	1.025
200	1	1

160	0.985	1.015
120	0.945	14.385
100	0.86	21.61
80	0.675	514.93
60	0.375	1760.85

Table 5: The percentage of correct matches of the patterns with errors searched in the bible. The second rows shows the average rank (in probability terms) of the correct string

As shown in table 5 for fragments of 200 characters and longer, there is high probability for the best match to actually be the correct fragment. For fragments longer than 100 the results are reasonable, below that results are poor, so we cannot expect string matching to show good performance. When the error rate raises the success rate drops as shown in figure 15. The performance is reasonable for error rates below 25%.

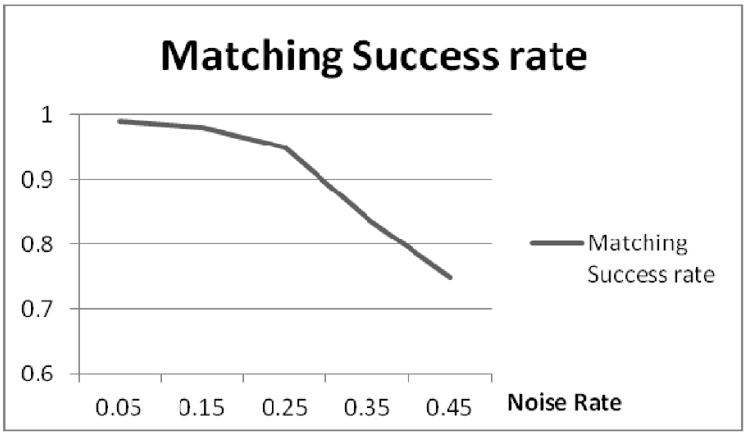


Figure 15: The percentage of correct matches of the patterns with errors searched in the bible as a function of the OCR error rate. The patterns are 200 characters long

4.2.2 MULTI LETTER ALIGNMENT

When scaling to several letters, we obviously expect the searching success rate to increase. It is obvious due to the higher rate of recognized characters but also due the veracity of symbols needed to be matched. Figure 16 illustrates the success rate for matching patterns containing various amounts of different letters, and we can see accuracy increases with the increase with number of letters.

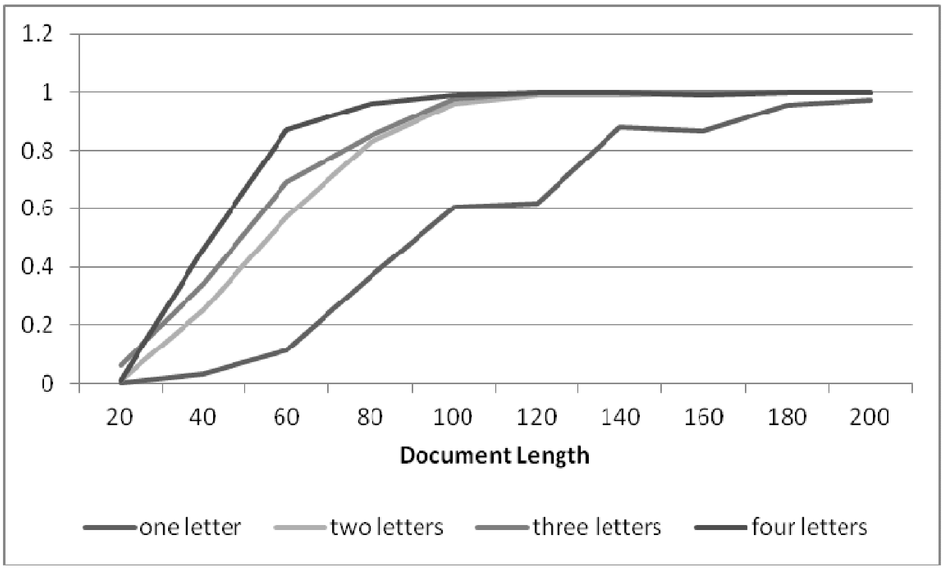


Figure 16: The percentage of a single match rates for a pattern in for various available letter numbers as a function of fragment length.

4.3 Proposed Algorithm

We propose an algorithm for post-process of OCR results by approximately searching a corpus of text. The algorithm has to deal with relatively large patterns and corpora, and the fact that the pattern is extremely noisy, so the search result may be considerably different from the pattern

4.3.1 THE INPUT

The corpus is a big text (several millions of characters denoted by T. The OCR results are given by the following: for each character in the OCR'ed text, denote it by $P_{\square}$ we get a set of characters $C_{i1} \ldots C_{\square,k}$ and a set of probabilities $P(C_{i,1}) \ldots P(C_{i,k})$ which stand for the probability that the character I of the pattern (the scanned text) is $C_{i,\square}$. Notice that the $\sum_{n=1}^{k} P(C_{\square,n})$ do not necessary add to 1, since some of the probabilities are neglected. For most characters only one option $C_{i,\square}$ is given.

We assume that the accuracy of the OCR is pretty low, which means that only about half of the top scored letters produced by the OCR are correct. The probabilities of each character are not high (most of them below 0.5 which is just a good guess), and in addition insertions and deletions of characters can occur frequently. On the other hand, the pattern is assumed to be quite long so we can use that fact to make more accurate search.

4.3.2 THE ALGORITHM

The proposed algorithm is actually a filter algorithm, where the filtering is heuristic, and uses substring of the pattern. The length of the corpus and fragment makes it very difficult to run a classic dynamic programming algorithm. The fact that the input is so noisy will make most of the filter algorithm inefficient.

The algorithm proposed follows the following scheme:

1. Clear the corpus and the pattern from characters that are poorly recognized
2. Iteratively choose a substring of the pattern and search it in the corpus
3. Combine the results to the one best result

The first stage handles the cleaning of the pattern from the noisy characters. We estimate the probability of each character as the average of the probabilities attached to the character at all its appearances. More formally, $\mathbf{P(l) = Average_{l}i \ \ P(C_1(i,k))|P(C_1(i,k)) > 0} \ \textit{and} \ \mathbf{C_1(i,k) = l}$. If the OCR engine proposed the character l as an option for the I'th place of the pattern, we consider it in the average of the probabilities of l. The estimation P(l) is an approximation for how accurate the engine handles the character l. The estimation is a combination for the OCR recall and precision on the character. After the estimation of accuracies for all character we pick a threshold under which all letters with lower accuracy will be neglected. The threshold should be estimated empirically and depends on the accuracy of the OCR. As shown in the previous section, even one character with reasonable error rate can be enough for searching a fragment of even medium length. Therefore the threshold should be set high enough for the extra recognized characters will increase rather than decrease the success of the search. All characters below the threshold are replaced by an "unknown" character both in the pattern and the corpus.

The second step is iterative search. In each iteration, we select a substring of the pattern and search it in the corpus. The length of the substring should be the shortest possible, such that using the characters chosen in step 1, the search is expected to return one result only. In other words, we would like to search a sub-pattern long enough so the search will return it's match (or matches) in the corpus with high probability. When searching, we search using the dynamic programming technique, assuming the sub-pattern is relatively short for efficient search. The result of each search is an interval [a..b] where a and b are the starting and ending indexes of the match in the corpus. We define the following variables:

l- the sub-pattern length, **L**- pattern length

r – the index of the sub-pattern in the pattern

a,b – the indexes in the corpus that define the match of the sub-pattern

Insert ratio - a parameter estimating the frequency of insertion mistakes made by the OCR engine.

From a, b we define an interval [i1..i2] which will estimate the position of the whole pattern in the string. Since the sub-pattern is in indexes [a..b] we naturally would expect to find the whole pattern at indexes [a-r…b+(L-(r+l))], by extending the match of the interval for by the distance of the sub-pattern form the pattern boundaries. Since we expect an amount of insertion mistakes we extend the interval to [a-(1+*InsertRatio)**r…b+(1+*InsertRatio*)(L-(r+l))] to estimate the alignment of the pattern with the mistakes. The estimated interval is the result of each search iteration.

In the third step we combine all intervals to a single result. The combination algorithm is as following:

1. *Initialize* $IntervalsList \leftarrow \emptyset$
2. *For each [i1,..i2] in Results*
   2.1. *If* $IntervalsList$ *contains Interval such that* $Interval.union \cap [i1..i2] \neq \emptyset$
      2.1.1. $Interval.union \leftarrow Interval.union \cup [i1 \dots i2]$
      2.1.2. $Interval.intersection \leftarrow Interval.intersection \cap [i1 \dots i2]$
      2.1.3. $Interval.count \leftarrow Interval.count + 1$
   2.2. Else
      2.2.1.
3.
4. *[a..b] = The search of pattern in Intmax.Intersection*
5. *Return [a..b]*

The combination algorithm is based on the fact the corpus is significantly longer than the pattern. We assume that given an interval returned we compare it to all other intervals returned by other searches. If two intervals intersect they are considered to be the same interval that is shifted. If an interval does not intersect with others it is considered new. The algorithm tries to unify all intervals and counts the number of intervals joined in each union and we expect for only one interval to be counted significant number of times and classify all others as noise. We then search the fragment back in the interval to return the final result.

4.4 Testing

The testing was made on several outputs of an OCR system operated on Genizah fragments. The input was as described in the previous chapter, where the number of iterations was 20 and the sub-pattern length was 50. The minimum accuracy, under which characters were omitted, was set to 0.5.

Original Text	OCR result	OCR output with prob > 0.5	Algorithm Output	Best Match
שמיםליהוהוהארץנתןלבנ יאדםלאהמתיםיהללויהול אכלירדידומהואנחנונברך המעתהועדעולםהללויהא הבתיכיישמעיהוהאתקולי תחנוניכיהטהאזנוליובימי אקראאפפוניחבלימותומצ רישאולמצאוניצרהויגוןאמ צאובשםיהוהאקראאנהיהו המלטהנפשיחנוןיהוהוצדי קואלהינומרחםשמרפתאי םיהוהדלתיולייהושיעשובי נפשילמנוחיכיכייהוהגמלע ליכיכיחלצתנפשיממותאת עינימןדמעהאתרגלימדחי אתהלךלפנייהוהבארצות החייםהאמנתיכיאדבראני	שסיסלידודארץכעןלבני אדסלאדתיילוידולאכליו רדידומואשנונברךידעת דעולסדלוידאדזבעיכיש עידודארוליעחנוניכידסר אזנויוביסיארראאוניחבל ישתומצרישאולצאוניצדו גוןאמצאובשםידואררא אנאידודלטכשינוןידודוצ דידואדינוסרחםשוערת איסיזוזדלייילייזדושיעשו בינשילסנוחיכיכיידודגמ לעיכיכיחלצתנשימסועא עיניסדסעדאערגליאע דלךלניידודבארדחייפד אסנעיכיאדבראניגליאע דל	ש$י$$ידוד$רץ$$ן$ב $יאדס$אד$יי$וידולא כליורדידו$ו$$נו$$$ך יד$$ד$$לוסדלוידאד$ ב$יכי$$ידוד$$ו$י$ח נו$י$יד$ראזנויו$י$יא ר$או$י$בלי$$ו$$ר יש$ו$צאוני$דוגו$א$ $א$$שםי$וא$ראא$ אידודל$$שי$$ןידודו $די$ואדינו$רחסשו$ ר$$י$י$ו$ד$י$יי$יידו שיעשובי$$י$$נוחיכי כיידוד$$לעיכי$יחל$ $$שי$$ו$א$עינ$$ד $$דא$רג$יא$דלךל$ יידו$$$רד$י$פדא$$ $יכי$דברא$יג$יאד ל$	והארץנתןלבניאדםל אהמתיםיהללויהולא כלירדידומהואנחנונ ברךיהמעתהועדעול םהללויהאהבתיכיי שמעיהוהאתקולית חנוניכיהטהאזנוליוב ימיאקראאפפוניחבל ימותומצרישאולמצא וניצרהויגוןאמצאוב שםיהוהאקראאנהי הוהמלטהנפשיחנוןי הוהוצדיקואלהינומר חםשמרפתאיםיהוה דלתיולייהושיעשובי נפשילמנוחיכייהוה גמלעליכיכיחלצתנפ שיממותאתעינימןד מעהאתרגלימדחיא תהלךלפנייהוהבאר צותהחייםהאמנתיכי אדבראני	ליהוה והארץ נתן לבני אדם לא המתים יהללו יה ולא כל ירדי דומה ואנחנו נברך יה מעתה ועד עולם הללו יה אהבתי כי ישמע יהוה את קולי תחנוני כי הטה אזנו לי ובימי אקרא אפפוני חבלי מות ומצרי שאול מצאוני צרה ויגון אמצא ובשם יהוה אקרא אנה יהוה מלטה נפשי חנון יהוה וצדיק ואלהינו מרחם שמר פתאים יהוה דלתי ולי יהושיע שובי נפשי למנוחיכי כי יהוה גמל עליכי כי חלצת נפשי ממות את עיני מן דמעה את רגלי מדחי אתהלך לפני י
עניתימאדאניאמרתיבחפז יכלהאדםכזבמהאשיבליהו הכלתגמולוהיעליכוסישועו תאשאובשםיהוהאקראנד ריליהוהאשלםנגדהנאלכל עמויקרבעינייהוההמותהל חסידיואנהיהוהכיאניעבדך אניעבדךבןאמתךפתחתל מוסרילךאזבחזבחתודהוב שםיהוהאקראנדריליהוהא שלםנגדהנאלכלעמובחצר ותביתיהוהבתוככיירושלם הללויההללואתיהוהכלגוי םשבחוהוכלהאמיםכיגבר עלינוחסדוואמתיהוהלעול םהללויההודוליהוהכיטובכ	עניסאדאניאסדעיבהזיכלד אדסכוזככלדזאדסכוזכללד אשדודכלעגמולודיעליכוסי שועועאשאובשסידזודזאד ראכדרילידודאשלנגדדנאל כלעמויבעינייזודדמותדלחי דיואנידודכיאניעכדךאניעב דךבןאמתךעחתלוסרילדא זבחזבהתודדובשסידודאד זראנדרילידודאשלנגדדלכ לעובהותביתידודבעוככייו שלסבתלדזודזבעככושלס דללוידדללזאעידודכלגוידז ללזאעלוזכלגושכחזדוכלד אומיסכיגכעליוחסדוואעעיו עולסדללויד□וכלדאומיסכי	$$ י$$ד$נ$א$$$יב$ז$ כ$ד$דסכוז$כ$דז$ד סכוז$$$ד$שדודכ$$ $$ו$ודי$$יכוסישו$ו$ אשאובש$יד$וד$א$$ $$$רי$י$וד$ש$נ$ד ד$$לכל$$ויבעי$יידוד ד$ו$דל$ידיוא$ידודכי א$י$כדךאני$בדךבן$ $$ך$$$לו$ריל$$זב $$ב$$ודדו$שסי$ו$ א$$ר$$ד$ילידודאש ל$$דדלכ$$וב$ו$בי$ $דוד$$וככייוש$$ב$ $ד$וד$$$ככוש$$ד$	יתימאדאניאמרתיב חפזיכלהאדםכזבמ האשיבליהוהכלתגמ ולוהיעליכוסישועות אשאובשםיהוהאקר אנדריליהוהאשלםנג דהנאלכלעמויקרבעי נייהוההמותהלחסיד יואנהיהוהכיאניעבד ךאניעבדךבןאמתךפ תחתלמוסרילךאזב חזבחתודהובשםיהו האקראנדריליהוהא שלםנגדהנאלכלעמו בחצרותביתיהוהבת וככיירושלםהללויהה	אני אמרתי בחפזי כל האדם כזב מה אשיב ליהוה כל תגמולוהי עלי כוס ישועות אשא ובשם יהוה אקרא נדרי ליהוה אשלם נגדה נא לכל עמו יקר בעיני יהוה המותה לחסידיו אנה יהוה כי אני עבדך אני עבדך בן אמתך פתחת למוסרי לך אזבח זבח תודה ובשם יהוה אקרא נדרי ליהוה אשלם נגדה נא לכל עמו בחצרות

ילעולם	$גכעליוחסדווא	$וידדלל$$$י$ודכ$$ו ידזלל$$$לו$כ$$וש$ $$דוכלד$ו$י$כיג$$ל יו$$דווא$$יו$ולסד$ל וי$□וכלד$ו$י$כיג$$ $ליו$$דווא	ללואתיהוהכלגוימש בחוהוכלהאמיםכיגב רעלינוחסדוואמתיהו הלעולםהללויההודו ליהוהכיטובכילעולם חסדויא	בית יהוה בתוככי ירושלם הללו יה הללו את יהוה כל גוים שבחוהו כל האמים כי גבר עלינו חסדו ואמת יהוה לעולם הללו יה הודו
כבשיביאקרבנולחטאתנק בהתמימהיביאנהוסמךאת ידועלראשהחטאתושחטא תהלחטאתבמקוםאשריש חטאתהעלהולקחהכהןמד םהחטאתבאצבעוונתןעלק רנתמזבחהעלהואתכלדמ הישפךאליסודהמזבחואת כלחלבהיסירכאשריוסר	לישייאררונרזתמיריביוןרעי העלרשןרמושמאררחמברו שרישמדעלרייוןדןחרןרעב אצכיוזעלידמנץרלרואכדמ רזושרליסזדורמזבחואכלח לסישיומרו	$$$ יי$$ר$נר$$$י$$ביןו $$$ו$$רשן$ע$$$$ $$$$$$$$ו$$$$$$ $$$$$$ן$$ן$$ן$$י$ $ו$$$$$$$$$$$ו$ $$$$$$$$$$$$$$ שיו$$$$$$$ו$$ז$$ $$$	לואחותתובלקיןנעמ הויאמרלמךלנשיועד הוצלהשמעןקולינשי למךהאזנהאמרתיכי אישהר	להויאמרואליואישבע לשערואזורעוראזורב מתניוויאמראליההת שביהוואישלחאליו
החטאתבמקוםהעלהולקח הכהןמדמהבאצבעוונתןעל קרנתמזבחהעלהואתכלד מהישפךאליסודהמזבחוא תכלחלבהיסירכאשרהוסר חלבמעלזבחהשלמיםוהק טירהכהןהמזבחהלריחניח חליהוהוכפרעליוהכהןונסל חלוואם	ריחטאבץזרעליוררכדןמד מריבבעוןעלרריזברערזאי דכלדמריישראליסורזבחיו רכלרלבריסיבשרזסלבמזז רשיוררמירררכרמזבדלחגי ההיבירג	$$$$$$$$$$ יו$ר$$ן$$$$$$$עוו $$$$$$$$ז$ר$$$$ $$$$$שך$$$$$$$ $$$$$$$ר$$$$$$ שי$ז$$$$$$$ש$י$ $$$$$$$$$י$ר$$$ י$$$$$$$	מיםאשרמעללרקיעו יהיכןויקראאלהיםלר קיעשמיםויהיערבוי היבקריוםשניויאמר אלהים'	גידביזרעאלוירכביהו אוילךיזרעאלהכייורם שכבשמהואחזיהמלך יהודהיר
והקטירהמזבחהעלאשייה והחטאתהואוכפרעליוהכה ןעלחטאתואשרחטאמאח תמאלהונסלחלווהיתהלכ הןכמנחהוידבריהוהאלמש הלאמרנפשכיתמעלמעלו חטאהבשגגהמקדשייהוהו הביאאתאשמוליהוהאיל	ורירזסרדימזרשייחטריזבר עליורדןעמעורחזמאיחמלר ונלוורירלככהנחרןוידביאמי רןאמנכישכירסלמעלוזץטא רבמרייורבירזזיויל	$יי$$$$$$$$$$$ו $$ן$$$$$ע$$$י$$ ו$$$$$$$$$$$$ור$ $$$ו$$$נ$$$$י$ר$$ $$י$יש$$$$$$$$$י יו$$$רב$$$$$$ע$$ וי$ז$$י$ב$$	והארץהיתהתהווהבה ווחשךעלפניתהוםור וחאלהיםמרחפתעל פניהמיםויאמראלהי םיהיאורויהיאורויהא אל	ויעלמשםבארשבעויר אאליויהוהבלילהההו אויאמראנכיאלהיאבר המאביךאל

Table 6: The algorithm results for several fragments. The columns show the original text, the text as transcripted by the OCR, the transcript after the character omission, the algorithm results and the best edit distance match of the string to the corpus.

As seen in Table 6, the algorithm presents good results and approximates the original fragment well for reasonable OCR performance. The results are similar to the best edit distance matching. For extremely noisy OCR output, the results are not accurate, since edit distance cannot be a good approximation for the result and other methods need to ne applied.

CHAPTER 5

CONCLUSIONS AND FURTHER RESEARCH

5.1 Conclusions

The thesis presented methods for three slightly different but connected problems. A statistical algorithm for language classification of Hebrew script documents was presented, using bigram distributions. The algorithm showed over 95% accuracy for most of the documents, rising to perfect 100% performance on documents longer than 800 characters. It also showed a method for higher precision the error rate by allowing the classification algorithm to return an unknown result.

An algorithm for segmenting multilingual documents to monolingual fragments was introduced, reaching about 90% percent accuracy on 100-200 character length language shifts. The accuracy for more frequent language shifts was about 70%. Several methods were presented and compared for generalizing the method to handle noisy texts.

Finally, a heuristic filter algorithm for approximate string matching was described. It showed good accuracy results, running significantly faster than classic edit distance algorithms.

5.2 Further research

While the language classification problem has well established methods, the language segmentation has many open questions. The algorithm proposed was extremely sensitive to the language shift rate, so a method for approximating this rate can significantly increase performance by smarter parameter tuning. Another method for increasing performance can be a machine learning approach for parameter estimation, a method that was not tried thoroughly enough in this work. A different direction can be revise the shift smoothing process, by trying different way than trying constant shift points.

The probabilistic approximate search algorithm needs to be further tested on larger datasets, with patterns of various lengths and noise rates. A more accurate selection of the sub-patterns can be considered. Another direction can be an OCR ad hoc tuning such as considering specific substitution matrixes and error rates and test the change in performance.

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Appendix 1 – collected corpora

English name	Hebrew name	Language
Targum Onkelus, Targum Unkelus	תרגום אונקלוס	Aramaic
Jerusalem Talmud, Talmud Yerushalmi	תלמוד ירושלמי	Aramaic
Torah, Pentateuch, Five books of Moses	תורה, חומש	Hebrew
Mishnah	משנה	Hebrew
The Guide for the Perplexed, Moreh Nevukhim	מורה נבוכים	Judeo-Arabic
Kozari	הכוזרי	Judeo-Arabic
Maspik Ovdei Hashem, A Comprehensive Guide for the Servants of God	המספיק לעובדי השם	Judeo-Arabic
Ibn Ezra Commentaries (short and long)	אבן עזרא הקדמה לתורה (קצרה וארוכה)	Hebrew
Abarbanel Commenaries	אברבאנל, פירוש לתנך	Hebrew