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N-gram based Text Categorization

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By this, I declare that I wrote this diploma thesis by oneself, only with the help of the referenced literature, under the careful supervision of my thesis advisor.

Bratislava, 2005 Peter Náther

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Contents

Chapter 1

Introduction

We live in the world where information have a great value and the amount of available information (mostly on internet) has been expansively growing during last years. There are so much information around us, that it becomes a problem to find those that are relevant for us. Because of this, there are many databases and catalogues of information divided into categories, helping the user to navigate to the information he would like to obtain. Most of these information are texts and here the text categorization comes to the scene. Text categorization is the problem of choosing a category from the catalogue or database that has common characteristics with the selected text. Usually these catalogs are made by people. However, creating such a database consumes a lot of time, because you have to read each text (or its part) to assign a correct category to it. That is why there is a lot of research in the area of automatic text categorization. Usually text categorization tries to categorize documents according to two characteristics - the language and the subject (or topic) of the text.

These tasks are usually solved within the machine learning framework. Such a learning algorithm is trained on the set of texts with assigned categories. Trained system we can use to assign category(ies) to the previously unseen documents. Used methods vary from simple methods to very complex ones. Usually the text is represented as the sequence of words and to find a correct category for it you have to use a lot of information about the text (number of words, relations between them, etc.). Because of this, the automatic text categorization is a hard problem, which consumes a lot of resources and computational time and the results are often not so good to be used.

The inspiration for this work comes from the article *N-gram Based Text Categorization* by J. Trenkle and W. Cavnar [1]. They introduced a very simple method based on statistical principles, with the usage of sequences of characters. Usually whole words or sequences of words are used in text categorization. First, this method was designed for categorization by a language, and solved this problem with the accuracy of 99.8%. This is an excellent number and I think that it is easy to increase it even more. They tested it also on the problem of categorization by a subject, but with lower achievement and some other restrictions. The main problem of the designed system was

that it was working only for short texts. I wanted to find a way to improve this method to make it more general and obtain better results. Especially to change this system in the way that it will be working well for long texts.

As I have written, text categorization used to be solved with learning methods. In addition, the one introduced in [1] is not an exception, even if the "learning phase" is so simple that we can say there is almost no learning. Nevertheless, we need the mentioned training set. What I needed was the database of documents (articles, books ...) with the categories assigned to each of these documents. To provide sufficient experiments we needed a large set of long documents. This means articles or books. I asked forthe Reuter's corpus, which is often used for training and testing automatic text categorization, unfortunately I got no answer. I have tried many other resources and finally I tried to build up my own database from the books (E-texts) available on the Project Gutenberg's site [1] with the help of the database of publication on the database located on the web site of the Library of Congress [2], where the numbers of Dewey Decimal Classification for some publications were. This Classification was developed early, in 1873, and has more levels of categories. Therefore, I extracted names of authors and titles from the E-texts. Than I tried to match them with the entries in this database, but this also does not work well enough to build and categorized database.

After all these unsuccessful attempts, I gave it up and decided to build my database automatically. It means that before the text categorization I have to perform a *text clusterization*. This means to divide the training set (in this case E-texts) into the groups according to some common characteristics of the documents in one of such groups. Of course, these categories may not correspond to categories that people use, but it is a nice experiment, which can tell us whether the documents in the categories we used had something common. In my work, I suggested a method for the text clusterization and I have made some implementation to be able to run some tests of clusterization and categorization.[3]

[1] *http://www.gutebberg.org*

[2] *http://www.loc.gov*

[3] In this thesis I use some standard terminology from the graph theory. You can find all definitions in the book - Diestel, R. Graph Theory, Springer-Verlag New York 1997.

Chapter 2

Text Categorization

Text categorization or *classification* can be defined as a *content-based* assignment of one or more *predefined categories* to free texts. In the 80's mainly knowledge-based systems were implemented and used for the text categorization. Nowadays statistical pattern recognition and neural networks are used to construct text classifiers. The goal of a classifier is to assign a category(ies) to given documents. Of course, each classifier needs some set of data as an input for each single computation. The most frequently used input is the vector of weighted characteristics. Often very complicated and sophisticated methods are used to construct these inputs, also called *feature vectors*.

Text categorization or the process of learning to classify texts can be divided into two main tasks: *Feature Construction and Feature Selection* 2.1, *Learning Phase* 2.2. The first one serves to prepare data for learning machines, in the second task we train the classification machine on *features* (*feature vectors*) obtained from documents from the training data set. Usually each text categorization system is then tested according to texts from outside of the training set. The best would be to make various measurements of performance and compare them to the results of other systems. Unfortunately, there were made only few such comparisons. The problem is that many authors used their own measures, and almost each system was tested with different data sets. However, for more complete overview in section 2.3, I described mainly used performance measures.

2.1 Feature Construction and Feature Selection

As I have mentioned above, learning and classification techniques work with vectors or sets of features. The reason is that classifiers use some computations algorithms and these work with some measurable characteristics and not the plain text. Therefore, we have to extract some features from the document, which will represent it. Some of already used features are simple words (or strings separated by blanks) with the number of occurrences in documents as the value of the feature. Other possibilities are the *context* of word w - set of words, that must co occur in the document with w(used in RIPPER [2]) or *spare phrases*, which is a sequence of nearby, not necessarily

consecutive words (used in Sleeping Experts [2]). Also word N-grams (ordered sequences of words)[3] and morphemes [4] were used. Last but not least I have to mention *character N-grams* that are very efficient and easy to be used in various text categorization tasks [1] [4] [5]. Let me note, that all these features where parts of the given text. Nevertheless, the feature of the document can be any characteristics you can observe and describe (e.g. the length of the text). However, I have not seen any solution that would use anything else as parts of the text.

All these features have a common disadvantage. The dimension of the features is very high, what can lead to overfitting of classification machine. For this reason, the feature selection plays an important reason in the text categorization. Feature selection methods are designed to reduce the dimension of the feature, with the smallest possible influence on the information represented by feature vector. There are many methods for dimensionality reduction in statistical literature. Usually the simple threshold cut off method is used. In this case, there are some possibilities of term-goodness criteria, examined in more details in [6]. These are: *document frequency* - number of documents in which a feature occurs, *information gain* - measures the number of bits of information obtained from category prediction by knowing the presence or absence of a feature in a document, χ^2 - statistic measure of the lack of independence between the *term* and the *category*, *term strength* - measures how commonly a term is likely to appear in "closely related" documents. In addition, some other feature selection methods were designed. E.g. *FuCe* and *Autofeatures* [4]. These work with previous results of classification machines. Generally, all these selections have a positive impact on the performance of text categorization.

2.2 Learning Phase

We can divide classifiers into two main types. These are binary classifiers and m-ary ($m > 2$) classifiers. The difference between these two types is following. Binary classifiers assign YES/NO for a given category and document, independently from its decisions on other categories. m-ary classifiers use the same classifier for all categories and produce a ranked list of candidate categories for each document, with a confidence score for each candidate. Per-category binary decisions can be obtained by thresholding on ranks or scores of candidate categories. There are several algorithms for converting m-ary classification output into per-category binary decisions. See [7] for details. In principle, to use independent binary classifier to produce category ranking is also possible, but it is still not well understood and can be an object of future research. Usually, algorithms of classifiers are closely related to machine learning algorithms, used for their training. Now I will shortly describe some classifiers and machine learning frameworks, which are commonly used in the text categorization. Some experiments and more details about most of the following can be found in [8].

Distances of vectors are the simplest classifiers. For each category and document represen-

tative vectors are produced. Some measure of the distance must be defined. We count all these distances between vectors of categories and a document's vector and the category closest to the document is chosen. Often the dot product cosin value of vectors is used instead of the distance.

Decision Trees are algorithms that are used to select informative words based on an information gain criterion and predict categories of document according to occurrences of word combinations

Naive Bayes are probabilistic classifiers using joint probabilities of words and categories to calculate the category of a given document. Naive Bayes approach is far more efficient than many other approaches with the exponential complexity. Naive Bayes based systems are probably the most frequently used systems in text categorization.

kNN is the k-nearest neighbors classification. This system ranks k-nearest documents from the training set and use categories of these documents to predict a category of a given document. kNN belongs to m-ary classifiers

Rocchio algorithm uses vector-space model for document classification. The basic idea uses summing vectors of document and categories with positive or negative weights, which depends on belonging of a document to a given category. The weakness of this method is the assumption of one centroid (a group of vectors) per category. This brings problems, when documents with very different vectors belong to the same category.

RIPPER is a nonlinear rule learning algorithm. It uses a statistical data to create simple rules for each category and then uses conjunctions of these rules do determine whether the given document belongs to the given category [2].

Sleeping experts are based on the idea of combining predictions of several classifiers. It is important to obtain a good classifier, the master algorithm, which combines results of these classifiers. Empirical evidence shows, that multiplicative updates of weights of classifiers are the most efficient [2].

Neural networks were also used to solve this task. Simple more-layered networks were designed and tested.

Support Vector Machines(SVM) is a learning method introduced by Vapnik [9]. This method is based on the Structural Risk Minimization principle and mapping of input vectors in high-dimensional feature space. Experimental results show, that SVM is good method for text catego-

rization. It reaches very good results in the high-dimensional feature space, avoids overfitting and does not need a *feature selection*. SVM method has also one of best results in efficiency of text categorization [10].

Similarity Measure

All these techniques are well-known machine learning algorithms that can be used to solve many other problems. However, the essential part of the text categorization is the "similarity measure" of two documents or a document and a category. To count this measure the feature sets or vectors are used. There are many possibilities how to define such a measure. Often the probability measure is used. Some systems work also with the dot product of some feature vectors. The goal of the machine learning is then to train all parameters and thresholds of the algorithm to obtain best similarities for documents that belong to the same category.

2.3 Performance Measures

Now I would like to show some measures that are used to evaluate classifiers. Again, we can divide measures for category ranking and binary classification. Two basic measures for a given document, in ranking based systems, are recall and precision. These are computed as follows:

$$recall = \frac{categoriesfoundandcorrect}{totalcategoriescorrect}$$

$$precision = \frac{categoriesfoundandcorrect}{totalcategoriesfound}$$

Very popular method for global evaluation of a classifier is an *11-point average precision* measure. It can be computed using following algorithm:

- For each document, compute the recall and precision at each position for the ranked list.
- For each interval between recall values (0%-10%,10%-20%,...,90%-100% - therefore 11-point), use the highest precision value as the representative precision.
- For each interval between recall values compute average precision over all test documents.
- Average eleven precision obtained from previous step to obtain a single number - *11-point average precision*.

For evaluation of binary classifiers four are values important (for a given category):

a - number of documents correctly assigned to the category.

b - number of documents incorrectly assigned to the category.

c - number of documents incorrectly rejected from the category.

d - number of documents correctly rejected from the category.

Following performance measures are defined and computed from these values:

recall $r = a/(a + c)$

precision $p = a/(a + b)$

fallout $f = b/(b + d)$

accuracy $Acc = (a + d)/n$ where $n = a + b + c + d$

error $Err = (b + c)/n$ where $n = a + b + c + d$

For evaluation of average performance over categories, there are two methods, *macro-averaging* and *micro-averaging*. The first one are computed as average from per-category values, in micro-averaging values a, b, c, d are computed first over all categories and then the performance measures are computed. Macro-average gives equal weights to categories; micro-average gives it to the document.

Some of performance measures may be misleading when examined alone. Therefore, two new measures are of importance. The first one is *break-even point* (BEP) of the system, the second is F-measure. BEP is a value, when the recall and precision are equal. F-measure was also designed to balance weights of recall and precision. The F-measure is defined as:

$$F_\beta(r, p) = \frac{(\beta^2+1)pr}{\beta^2 p+r}$$

Last two measures are most often used to compare the performance of classifiers.

Chapter 3

N-gram based Text Categorization

From all possible features presented in the previous chapter, I chose the solution based on N-grams. I would like to explore possible improvements of methods described in [1] and [5]. In the second article, some improvements were introduced, but used methods are also more complicated. In this chapter, I would like to more deeply introduce these works.

3.1 N-grams

N-gram is a sequence of terms, with the length of N. Mostly words are taken as terms. Nevertheless, Trenkle and Cavnar chose N-grams based on characters for their work. In literature, you can find the definition of N-gram as any co-occurring set of terms, but for this work, only contiguous sequences were used. One word from the document was represented as the set of overlapping N-grams. Here also leading and trailing spaces were considered as the part of the word. For example, the word "TEXT" would be composed of following N-grams:

bi-grams _T, TE, EX, XT, T_

tri-grams _TE, TEX, EXT, XT_, T__

quad-grams _TEX, TEXT, EXT_, XT__, T___

In the first of the mentioned texts, N-grams with various lengths were used (from 1 to 5-grams). In the second one only N-grams of the length of four were used. We can build such N-gram representation for the whole document. This representation is then used for comparing documents. The benefit of the N-gram based matching is derived form its nature. Every string is decomposed into small parts, so any errors that are presented, affects only a limited number of N-grams, leaving the remainder intact. The measure, counted as the number of N-grams, that are common for two strings, is resistant to various textual errors.

3.2 N-gram frequency statistics

Each word occurs in human languages with a different frequency. The most common observation of some regularity is known as Zipf's Law. If f is the frequency of the word and r is the rank of the word in the list ordered by the frequency, Zipf's Law states, that:

$$f = \frac{k}{r} \tag{3.1}$$

Later some modifications, were suggested, but they are only small deviations from original Zipf's observations. From this we get, that there is always a set of words, which dominates most of the other words, in terms of frequency of use. This is true for languages, but also for words, that are specific for the particular subject. As N-grams are components, which carry meanings, the idea of Zipf's law can be applicable also on frequencies of N-grams. The main idea of the categorization used by Trenkle and Cavnar is that if we are comparing documents from the same category, they should have similar N-gram frequency distribution [1].

In [5] Cavnar uses another helpful characterization and that is the inverse document frequency (IDF). IDF was used to help to choose most significant N-grams for the subject identification. The IDF for a specific N-gram is counted as the ratio of documents in the collection to the number of documents in which the given N-gram occurs. IDF strongly corresponds to the importance of the N-gram for the text categorization. If N-gram can be founded in all documents, it gives us no information about difference between contexts, on the other side, if it will occur only in part of the documents, these have something incommon (at least this N-gram).

3.3 Document representation

In the first article, documents were represented, by their N-gram frequency profiles. It is the list of N-grams ordered by the number of occurrences in the given document. It simply describes the Zipfian distribution of N-grams in the document. For the categorization by subject, N-grams starting at rank 300 were used. This number was obtained by several experiments.

In the second article, they used representation that was more sophisticated. Each document was represented as a vector, with values of term weights for each N-gram. As the vectors for each document would have a very high dimension and would be very sparse, IDF was used to reduce the dimension of the vector space. The weight for the terms was defined like:

$$w_j = \frac{(\log_2(tf_j) + 1) \cdot IDF_j}{\sqrt{\sum_i w_i}} \tag{3.2}$$

where tf_j is the term frequency and the IDF_j is the inverse document frequency of the jth N-gram in the document.

In both cases, the same representation as for documents was used also for categories.

3.4 Comparing

For the comparison of the two profiles, a very simple method was used, in the first work. The similarity measure of two profiles was defined as a sum of differences between the rank of the N-grams in one profile and the rank in the other profile. If an N-gram was not present in one of the profiles, a maximum value was used.

In the second article, the similarity of two documents or categories was defined as the angle between the representation vectors. Cosine of this angle can be computed as a dot product of these two vectors.

When we want to choose a category for the document, we have to count distances (angles) from all the categories profiles. Than we choose the category with the smallest distance (angle) from the document profile. As we have the list of distances from all categories, we can order them and with the help of some threshold, we can choose most relevant categories for the given document. This means that the suggested classifier belongs to m-ary classifiers. In their work, they used only the first category as the winner, so they assigned exactly one category to each document.

3.5 Observations

In the first case, categorization was tested on the Usenet newsgroups. They have chosen five closely related categories, from the computer science. For counting profiles of categories, they used the FAQs of the given newsgroups. They used 778 articles from the Usenet and tested them again the 7 selected FAQs. Their system achieved 80% correct classification rate. I tried to make same computation of recall and precision (Cavnar and Trenkle have mentioned only the numbers of documents correctly/incorrectly assigned) and from these computation I assumed that recall and precision of this system are both about 60%. It is not a very high number, but I think, that this classifier would obtain a pretty good score in the BEP measure.

Unfortunately, Usenet newsgroups messages articles are quite short and the system was not giving such a good results for longer texts. The problem is, that in short texts, N-grams in first 300 ranks are mostly language specific, and from the rank of 300, they are more subject specific, so we can use them to determine the subject of the text. The problem of longer texts is that there is a higher amount of language specific N-grams in the text and these have usually high frequencies. This leads to the fact that subject specific N-grams start on higher ranks than 300.

In the newer article, to eliminate this problem, inverse document frequency was used. This helped to reduce the dimension of N-gram vectors and thus increase the speed of computation, only with a low loss of performance. The system was tested on the TREC competition, against different data sets. Very popular performance measures like Average Precision, Precision @ 100

docs and R-precision were used, to see how good the results are. The values of all measures were somewhat lower, than median performance of all system in the TREC93 competition.

Both articles show, that it is possible to implement an N-gram based retrieval system. Such a system has some very nice advantages.

As it was already mentioned, it is resistant to various textual errors. Of course, we suppose that the same errors occur with a low probability. So such an error does not affect final results, because the frequency of such an "invalid" N-gram will be so low that we will never calculate with it.

The suggested systems are language independent, without any additional effort, because we do not do any linguistic computation on the data. Language independence was also verified on a set of Spanish documents.

Other advantage, but I think a very important one, is the simplicity of suggested methods. It is easy to implement them. We can say that the "learning phase" of these systems does not exist (all you need to do is to count the profiles of categories and they can be easily updated). The first system also consumes very little resources. The other one has a little problem with the table of IDF's.

3.6 Possible improvements

There are some possibilities, how to improve the systems suggested in these works. We can use more sophisticated term weighting, larger amount of N-grams to represent the text, use N-grams with larger N, find a clever function to appoint the correct number to replace the magical '300', with a most precise value for a various documents, etc.

In my work, I would like to explore some of these possibilities, to find some way how to apply these methods to large texts, but I would like to keep it as simple as possible, because I think, it is a very important benefit of these systems.

Chapter 4

Clusterization and Categorization of Long Texts

The first inspiration to this project was the article [1]. The suggested system is very easy and has good results. As the main problem of this system is the fact, that in the way it was described in [1] it can be used only for short texts (Usenet newsgroups articles). I wanted to find some way how to improve this system to obtain better results also for longer texts, to make it more general. In their experiment they say, that in the sequence of N-grams ranked by the number of occurrences, the subject specific N-grams are starting at the rank of 300. The first idea was to try to find such a function, that will for each text return the most precise starting rank of the subject specific N-grams. Nevertheless, I wanted to find some relationship between the length of the text and this special rank. To do this, I needed a train set of long texts with assigned categories. Unfortunately, I did find any resource of this kind.

But I still wanted to discover the power of N-grams, so I decided to build categories by my own. Before the text categorization, I had to deal with the *text clusterization*. I decided to use the information given by comparing two texts - *"similarity"*, to build up clusters of documents, from the unknown set of documents (we can look at this as on the reinforcement learning). This means I will try automatically to divide the set of documents, to subsets according some common signs, in this case N-grams. I hoped that created subsets would have common subjects and would correspond to categories, as a man would set up. For this purposes I used the collection of books form Project Gutenberg [1]. It is a large collection of free books (almost 10 000) and it was easy to get it.

I made following tests: I chouse the train and the test set from the whole collection. Then I counted profiles of all documents. Next step was the clusterization phase, in which I selected

[1] *http://www.gutebberg.org*

documents to categories and counted profiles for them. The last phase was categorization phase. In this part, I compared documents from the test set to profiles of categories and chose one category for each document. These tests are described in the chapter 5. Now I will describe the suggested methods.

4.1 Feature Selection

In the first article [1], N-grams with the length from 1 to 5 were used, in the second article [5], quad-grams were used. In the first article the N-grams selected as features, were determined by its rank, in the second article, IDF (see 3.2) was used to determine appropriate N-grams. As I have already written, to determine the correct rank of important N-grams we need a categorized database of documents. I did not have it, so I also used IDF to select representative N-grams.

4.1.1 N-gram Selection

As I had already written, I used the N-gram with the length of 4. As an input, I took a plain text with a single space between words, without tabulators or new line characters. In [5] they worked with each word separately, so they did not take a care about N-grams, overlapping two words. I think this has two disadvantages. N-grams that interfere with two words, give us some information about relations between these words. For example, N-grams "ew Y" and "w Yo" fror words "New York", will be often together. The second disadvantage against the system, that completely treats input as a single word is, that we have to search for word boundaries, to split the text to words. Because of this, I decided to use also N-grams that interfere with more than one word. I was working with the text as one single word and include spaces between words into N-grams.

4.1.2 IDF table

The first task was to build up the table of inverse document frequencies. For each N-gram, I counted the number of documents, in which it occurs. The IDF of an N-gram t is defined as

$$IDF(t) = \frac{n_t}{N} \tag{4.1}$$

where n_t is the number of documents in which the N-gram t occurs and N is the number of all documents in the collection.

The table was very huge, so I decided to use N-grams with the length of 4, in tests. Even after this, the table was too huge to store in memory so I threw out N-grams with lowest frequencies. In this, I suppose these were mistakes, or it were very specific N-grams, that would give us no help by categorization. Zipf's law (see 3.1) helps us see that we can cut off quite a large part of N-grams with a low influence on the final distribution. From (3.1) we have $r = \frac{k}{f}$, where r is the rank of N-gram, f is its frequency and k is constant. Let a be N-gram with the lowest rank (r_a)

from N-grams with the frequency β (number of documents in witch it is present) and b the N-gram with the lowest rank (r_b) from N-grams with the frequency $\beta + 1$. Than the number of N-grams with the frequency β is:

$$r_a - r_b \approx \frac{k}{\beta} - \frac{k}{(\beta+1)} = \frac{k}{\beta(\beta+1)} \tag{4.2}$$

The highest rank of an N-gram in the collection is approximately:

$$r_{max} \approx \frac{k}{1} = k \tag{4.3}$$

Now if we want to determine the fraction of N-grams with the frequency of β we have $\frac{1}{\beta(\beta+1)}$. From this, the portion of N-grams, which occurs only once, is $\frac{1}{2}$. Clearly, such N-grams have no influence on the categorization, but we can highly reduce the number of N-grams we have to hold in the table (If an N-gram is not in the table, it means it was only in few documents, so do not use him for representation).

4.2 Document and Category Representation

From the list created like in previous section I chose 1000 N-grams with the highest frequency (number of occurrences), to represent the document. Because of that, I used two ways of comparing documents (see next section) and I used also two kinds of document profiles. The first method is the representation of the document as a list of selected N-grams, ordered by frequencies. Here the N-grams with the highest frequencies were at first ranks. For the second method, I used the vector representation, In which the weight w_t assigned to N-gram t was defined as

$$w_t = \frac{f_t}{\sqrt{\sum_i w_i}} \tag{4.4}$$

where f_t is the frequency of the N-gram t and w_i is the weight of N-gram i.

After comparing these representations in the clusterization problem, I decided to use only the first style of representation, while it was more successful than the vector representation. Because an intuitive way how to create an ordered list of N-grams for a category would be to take all the documents from the category as one text and to count its profile, but I used a slightly different strategy. I took profiles of all documents in the category and counted the reverse order of N-grams in the profile. This would assign the highest ranks to the N-grams with the highest frequencies. Then I counted a sum of ranks from all profiles for each N-gram. I used these sums to order N-grams into the final list of N-grams. This list I used to represent the category. I made this to prevent N-grams that have very high frequencies in few documents to be on high ranks in the final list. This representation has a great advantage. It is very easy to update the category profile, if you want to add a new document to the category.

From now, I will usually write only a document or a category in spite of the document or category profile (whether it will be a list or a vector).

4.3 Measure of Similarity

To make a clusterization or categorization we have to define some measure of similarity between the two documents or the category and the document. The measures I used are normalized to the interval $\langle 0, 1\rangle$, and are build in such a way, that the lower values mean higher similarity. First is the mentioned "out-of-place" measure. To count this measure we need the ordered list of N-grams. Now I will define this measure. Let v and w be lists of N-grams, with the same length l. The "out-of-place" measure $s(v, w)$ can be defined as following:

$$s(v,w) = 1 - \frac{\sum_a d(a) + \sum_b d(b) +}{2 \cdot l^2} \tag{4.5}$$

where a (b) goes through all N-grams from v (w) and $d(i, j)$ is defined as

$$d(x) = \begin{cases} |r_{vx} - r_{wx}| & x \in v \wedge x \in w \\ l & x \notin v \vee x \notin w \end{cases} \tag{4.6}$$

where r_{vx} is the rank of the N-gram x in the list v and r_{wx} is the rank in list w. This measure gains values from the interval $\langle 0, 1\rangle$. When we have this measure, we say that the similarity of two documents or categories v and w increases with increasing value of $s(v, w)$.

The second measure uses the dot product of two vectors. I used this measure for the second type of the document profile. As we know, the dot product of two vectors corresponds to the cosine value of the angle between these two vectors. This gives us the number from the interval$\langle -1, 1\rangle$. After this, I used a transformation to get values into the interval $\langle 0, 1\rangle$.

I compared both methods for comparing documents ("out-of-place" measure [1] and the vector processing [5]). Surprisingly, results of the first method were better. It seems like the "out-of-place" measure is creating categories that are more similar to categories created by people). This is why I did not use the vector processing method for the text categorization.

4.4 Clusterization

The task of clusterization is to divide the set of documents to groups (clusters), so that similar documents will be in the same group (cluster). If we want to define this problem, we can say that the measure, defined in the previous section between two documents from the same group will be higher, than similarities between these documents and any other document outside this group. More formally:

Let T be the set of all documents. $C \subset S$ is the cluster of similar documents, if and only if holds, that for any $a, b \in C$ and $c \in T \wedge c \notin C$ $s(a, b) > s(a, c)$.

So I had the set of N documents and the table of $N \times N$ with values of similarity measures between all these documents (we do not need the whole table, the upper triangle is sufficient,

because $s(v, w) = s(w, v)$). We can look at this table as at the complete graph, where documents can be mapped to nodes and the weight of an edge between nodes v and w is $s(v, w)$. Now we can transform our problem to split components of this graph, so that weights of edges inside of these components will be bigger than outgoing edges of these components. To do this, we need to set up a threshold, which says that edges with the lower weight than this threshold will be outgoing edges of components. This will split up the graph to "unconnected" components (it is something like deleting these edges from the graph). In the meaning of similarity, this threshold is saying that documents with the lower similarity should not be in the same cluster. This does not mean they will really be in different clusters, because they both can be similar to the third document, which will bind them together.

I made some experiments with clusterization and I came to the problem. The split graph looked like one big component of many independent documents and few small components that could be considered as categories. With increasing of the threshold, new components were cut form the big one, but the previous small components felt apart to single documents (or very small components from two or three documents). I was really disappointed, but now it seems, that I have found the solution. The problem was that the similarity of documents in one category (or cluster) was different and could be much higher or lower than the similarity of documents in other category. The idea of the improving the clusterization was as followed:

1. Set up an low threshold t
2. Split the graph using this threshold
3. If the clusters with the "good" size are present, mark them as clusters and remove them from the graph. The "good" size depends on the size of the graph and on your belief in your similarity measurement (if it is very good, then two documents can be a base for a cluster).
4. Increase t and repeat from the step 1., until there is a component with more than t nodes.

With this system, I was able to create clusters from the training set. There was quite a big junk - the clusters of a very small size or single documents, but some of created categories were "man-like" (see 5.3 for more details).

4.5 Categorization

The main goal was to find a good method for text categorization. The task of categorization assumes that we have the profile of the document we would like to categorize and the profiles of categories from which we chose the one that is most suitable to be the category of the document. Creating profiles of documents and categories was discussed in 4.2. The algorithm of the categorization is very simple and has only two steps.

1. First, count similarities (4.5) between the selected document and all categories.

2. Than choose the category with the highest similarity as the category of the document.

In reality, one document can be a member of more categories and this method of categorization (but not the clusterization from previous section) can handle this. All we need to do is to order the categories according to similarities with the document and then the categories with the highest similarity are the most probable categories of this document. For this work, I used only the first one as the category of the document.

Now if our test set contained documents with assigned categories, we can compare it with the chosen category and use it to tune up the system (all thresholds, sizes, etc. ...). Unfortunately, I do not have it. I checked results manually and made some statistical observations. They are described in chapter 5.

Chapter 5

Experiments

5.1 Corpus

For the training and testing text categorization, we need a corpus. As I have already written, I was not able to get a corpus sorted into categories. The set of documents, which I used in experiments with suggested methods of text clusterization and categorization, were E-texts of books freely available on the website of the Project Gutenberg[1]. The whole collection contains about 11 000 books. I did not use the whole collection, because my implementation was not able to work with such a great amount of data. I used only plain text files smaller than 2MB's (because of memory consumption). Of course I cut off headers of E-texts.

5.2 IDF's Threshold

First, I counted the table of IDF's. For this, I used the set of 8189 documents and the final table (without the N-grams with the lowest frequencies - see section 4.1.2) contained 346 305 unique N-grams.

I started measuring the similarity on a small set of 30 documents. I knew the subjects of these documents, so I was able to say whether the results are clever or not. Later I made some tests with 500 documents. I came to the threshold of 2.75. I do not say that it is the best value, but obtained results were giving best results. There is something strange about this value. In [5] they also used the value 2.75 as a threshold for IDF, but they defined IDF as $\log_2(\frac{N}{n_t}$ but I defined it without a logarithm. So this threshold corresponds to the threshold of 1.46 in their system. Their threshold corresponds to the threshold of 6,72 in my system. In spite of this, it looks like that the threshold of 2.75 gives much better results. I think this can be due to different creation of N-grams in their and my system (see 4.1.1).

[1] *http://www.gutebberg.org*

5.3 Clusterization

Dividing documents into categories depends on their similarity, the size of cluster we want and of course the clusterization algorithm. As clusters are created in iterations, it is possible, that the last created cluster will be only the rest of documents that had not fit anywhere but are slightly similar. First tests with clusterization were made on a set of 500 books randomly chosen from the set of 11 0000 books I had.[2] I was satisfied with these results. Only 246 books where used to create categories, so there was a big junk (60%). This set of 197 books was divided into 9 categories. Each category has the size from 10 to 35 documents. The best thing about these tests was that some of the created categories where "man-like". In *category1* were memories of people, in *category2* poems and theatre, in *category5* political documents. I do not know whether documents in other categories would be in similar categories as in the "man-like" categorization, because they were created from more "common books" and I had not read all these books to determine their subjects. In table A.1 are some examples of categories and documents from which they were created. In figure 5.1 you can se how 197 books were divided into categories.

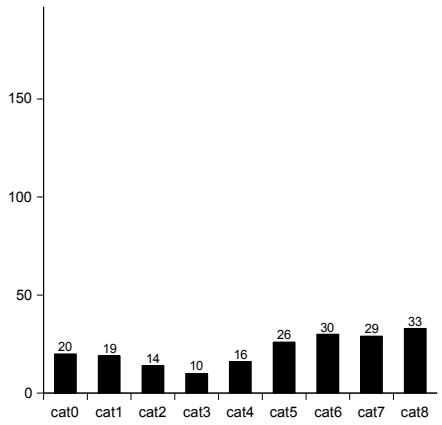


Figure 5.1: Distribution of documents among categories. "500 test", only 197 were divided into categories

I ran next test with the set of 3,000 documents. [3] I was expecting that if in the previous test categories had the size between 10 and 30, here I chose the size from 50 to 200. The results were following: 739 books were divided into 7 categories. But the junk was very big (75.3%). In the figure 5.2 you can see the distribution of books among categories. I think that one the reasons for this may be that the threshold for IDF with the value 2.75 is too high. The effect of this is that similar measures between documents are very low (it is under 0.2) and so only very similar documents create categories. Here I must say that there is nothing wrong with the fact that

[2] I will refer to all tests connected with this set of documents as the "500 test"

[3] I will refer to all tests connected with this set of documents as the "3,000 test"

distributions in figures 5.2 and 5.1 are completely different. There were used different train sets and numbers of categories does not say that these must have something common.

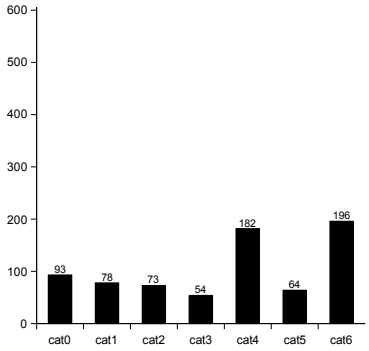


Figure 5.2: Distribution of documents among categories. “3,000 test”, only 739 were divided into categories

The problem in clusterization is that I assigned one or none category to each document. But in reality, each document can belongs to many categories, an so there are connections between categories which abuses the clusterization. This could be solved with more complicated algorithms that will split the graph, also when there is a small set off documents creating a cut between two sets of documents, but for the tests I used only a simple version, that was creating categories from standalone components, that had no connections to the rest of the graph.

In spite of all these problems, the results are quite interesting. First, in spite of the fact, that I threw out all frequent N-grams (this is because of usage IDF) documents from other languages than English created their own categories. For example in the “500 test” German books where in *category0*, in the “3,000 test” they where in *category4*. French books created *catgory1* in the “3,000 test”. Furthermore, I was able to describe some other categories too, e.g. in the “500 test”:

category1 - contained books somehow connected with Netherlands

category2 - books about theology and psychology

category3 - some philosophical books about people, their knowledge and senses

category4 - memories, diaries and life stories of famous people mainly from England and the USA

category5 - memories of famous French people from the times of Napoleon, together with novels from A. Dumas and H. Balzac (both were writing about these times)

category8 - theatre - plays

About categories from the “3,000 test”:

category0 - mainly some scientific books

category2 - memories and books about famous French people from the times of Napoleon

category3 - theatre - plays - except two, all by Shakespeare.

category4 - German literature, together with books about Greek mythology and antic times - maybe the reason is that some of German’s books were also from Greek mythology.

category5 - poetry

As you can see, I was not able to say anything about categories *6* and *7* from the first test and *category6* from the second test. One of the reasons can be following. The clusterization, in the way I implemented cutting components from one large graph. At the end there is a component, which is the rest of the graph, but it is enough small to fulfill the conditions to become a category. This can lead to categories that are giving no sense.

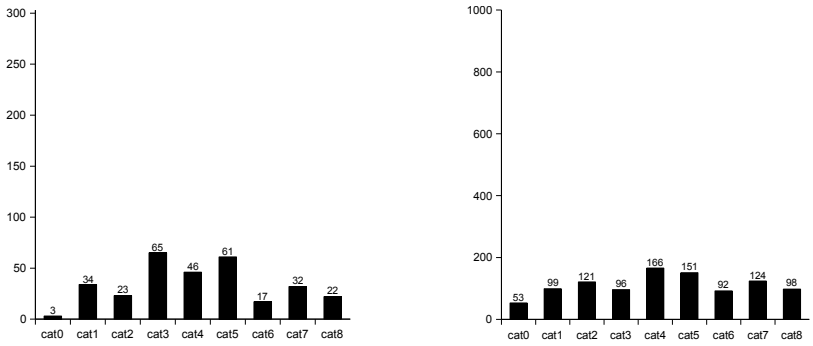
5.4 Categorization

The categorization tests consist of comparing set of documents with created categories. Results are lists of documents assigned to each category and the count of documents assigned to each category. With both sets of categories, I made two such tests. In the first test, I took the “junk files” - the files from train set that were not chosen to any category and ran the categorization test on them. In the second test I randomly chose 1,000 documents from the Project Gutenberg’s books (different from the train set). You can see the distribution of documents among categories in figures 5.3 and 5.4. Slightly disappointing is that these distributions do not correspond to the distribution of categories (fig 5.1, 5.2), but it is easy to see that distributions in figure 5.4 are similar. This can mean that there is a characteristics of this collection of books, which divides the whole collection to created categories. But this means that these categories are feasible, what would be a great success of the suggested method. This means that they really describe the whole collection of books.

I checked these results also manually. It seems, that almost all documents that should belong to some category, where assigned to this category. However, to each category, there where assigned also documents that do not belong to it. Except the failure, the reason can be the fact, that this document should not belong to any of created categories, but the chosen category had the most similar characteristics. Tests with “junk files” are giving interesting results. Many of these files had something common with the categories in which they were assigned and I did not know why they do not become part of this category during clusterization.

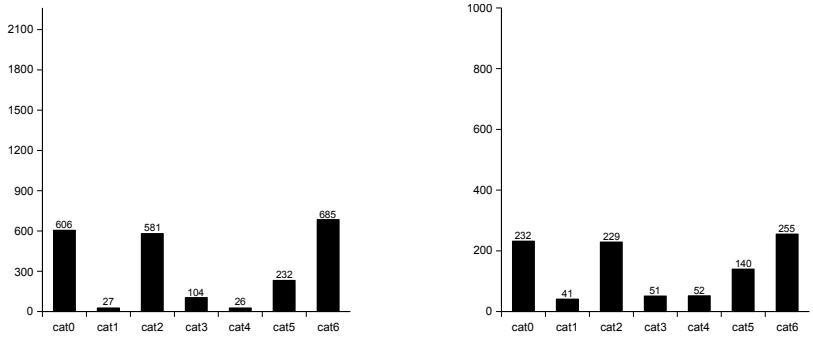
There is also an example, that it is possible that this method will reach good results with only few documents in a category (some categories had only ten documents), but also when these documents are very similar. To be more concrete, *category3* from the "3,000 test" consists of the plays written by Shakespeare (only two texts where by other authors). Then in the tests with "junk files" and the 1,000 randomly chosen files, much other theatre plays by various authors were assigned to this category.

Unfortunately, I was not able to make any classical measurements, because I did not have the set of correctly and incorrectly categorized documents as it used to be common.



"junk" 1,000 documents

Figure 5.3: Distributions of documents in "500 tests"



"junk" 1,000 documents

Figure 5.4: Distributions of documents in "3,000 tests"

Chapter 6

Conclusions and Further Work

In this work, I have implemented the system for text categorization. Used ideas are mainly the mixture of ideas from articles [1] and [5]. Unfortunately, I did not have the necessary database to train this method with some classical machine-learning algorithm. That was the reason I did not fulfill the goal stated at the beginning of the work completely.

Nevertheless, I had found a method for the text clusterization. It is a method, which helps us to build categories from the set of documents, without previous knowledge of given texts. We can look at text clusterization as at the reinforcement learning method of text categorization, because we do not know whether created categories are feasible or not. Obtained results are not so good that I could use this system to solve some real problems, but they are not so bad and we should not throw them into the bin. I was able to find some "real" similarities among documents in created categories and I do not say that there is no similarity among books from other categories, but I do not know every book, so I did not find it. The implemented system showed also some ability of generalization, when it correctly categorized previously unseen documents. I think that the system with a good ability of text clusterization in unknown environment will be very valuable for problems of information retrieval. Other very useful advantage of N-gram based systems, mentioned already by Trenkle and Cavnar [1] is the language independency. Of course, it is possible to make many improvements, which will for sure bring much better results, but I think that now we can see, that the N-gram based system has its meaning and it can be valuable for future research.

Here I would like to sketch some possible suggestions for improvements. The first thing what should be done is to find some database of categorized texts. With such a database, we can tune up the system for much better results. This would especially help to find better threshold for IDF's values. Furthermore, I believe that it is possible that with such a database we will be able to find *"ranks of important N-grams"* in the complete list of N-grams from a document without the help of IDF values. This would help us to reduce computational resources we need.

As I said, the text clusterization can be very useful and there are some possibillities how to

make it better. One problem of the implemented method was that each document was assigned only to one category. The suggested improvement is the question of algorithms in the graph of documents and their similarities. The idea is not to split the graph only when there are unconnected components. We can split the graph also when there are two sets of nodes, with the cut containing only few documents. In this case, we have to include these nodes in both sets. This will ensures that one document can be in more categories.

The last improvement is a slightly different view of the problem. If you think how the people do the text categorization, they usually do not read the whole book to determine its subject. They usually read only short parts. This means that these parts must contain the sufficient information for the text categorization. But we have the text categorization of short texts that reaches quite good results [1]. So why not split the long text into small parts, categorize them and from the results choose the category of the whole document? For the last part, the k-NN algorithm can be useful.

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Appendix A

Tables

Following tables show results of my experiments. There are lists of books from each category. This is no a complete list. All titles and authors were retrieved from the books by a small utility I made and some of them where not parsed correctly.

category0	Wilhelm Busch , Hans Huckebein; Johann Wolfgang Goethe, Wilhelm Meisters Lehrjahre–Buch 2; Johann Wolfgang von Goethe, Reineke Fuchs; Heinrich Heine, Buch der Lieder; Theodor Mommsen, Römische Geschichte Book 8; Meyer, Die Versuchung des Pescara; Ferdinand Raimund, Der Verschwender; Jacob Michael Reinhold Lenz, Der Hofmeister; Friedrich Schiller, Kabale und Liebe; Johanna Spyri
category1	G. A. Henty, By England's Aid; Schiller, Book I., IV, Revolt of Netherlands; Georg Ebers, Vol. 1.,6.,9., Barbara Blomberg; Georg Ebers, v4, The Bride of the Nile; John Lothrop Motley, Rise of the Dutch Republic, 1564-65, 1573-1574; John Lothrop Motley, History of the United Netherlands, The Life of John of Barneveld,
category2	Michel de Montaigne, The Essays of Montaigne, V4; J. J. Thomas, Froudacity; Walter Pater, Marius the Epicurean, Vol. I; John Edgar McFadyen, Introduction to the Old Testament; Charlotte Mary Yonge, The Chosen People; Ethel D. Puffer, The Psychology of Beauty; Spinoza A Theologico-Political Treatise; William James, The Varieties of Religious Experience; Abraham Myerson, The Foundations of Personality
category3	Speeches and Writings of Edmund Burke; Joseph Butler, Human Nature & Other Sermons; William James, The Meaning of Truth Thomas Paine, Common Sense; Henry Handel Richardson, The Getting of Wisdom; James Gillman, The Life of Samuel Taylor Coleridge; D. Jerrold, Mrs. Caudle's Curtain Lectures; George Berkeley, A Treatise Concerning the Principles of Human Knowledge;
category4	General Philip Henry Sheridan, Memoirs of General P. H. Sheridan, v1; William T. Sherman, Memoirs of General W. T. Sherman, v1; Gardner, The Life of Stephen A. Douglas; David Widger, Quotations from Diary of Samuel Pepys; Matthew L. Davis, Memoirs of Aaron Burr; Stephen Gwynn, The Life of the Rt. Hon. Sir Charles W. Pepys The Diary of Samuel Pepys; Jacques Casanova, Old Age and Death;
category5	Tommaso Campanells, The City of the Sun; Louis Antoine Fauvelet de Bourrienne, the Memoirs of Napoleon; Constant, the Private Life of Napoleon La Marquise De Montespan, The Memoirs of Madame de Montespan; Elizabeth-Charlotte, Duchesse d'Orleans, Memoirs of Louis XIV. and the Regency Jean Jacques Rousseau, The Confessions of J. J. Rousseau; Charles Eastman, Indian Boyhood; Honore de Balzac, The Deputy of Arcis;
category6	Anthony Trollope, The Prime Minister; Irving Bacheller, Eben Holden; Charlotte M. Yonge, The Heir of Redclyffe; Guy de Maupassant Original Maupassant Short Stories.; Louisa May Alcott , Jo's Boys; Kate Douglas Wiggin, A Summer in a Canyon; Anonymous, The Book Of The Thousand Nights And One Night, I-III; Charles Dickens, A Christmas Carol; George Meredith, v6, Beauchamps Career;
category7	Trevelyan, Life and Letters of Lord Macaulay; The Earl of Chesterfield, Letters to His Son; Voltaire, Le Blanc et le Noir; Emile Zola, La Bete Humaine; Victor Hugo, L'homme qui rit; Thomas de Quincey, Memorials and Other Papers; Frederick Niecks, Frederick Chopin as a Man and Musician; Mary Schweidler, The Amber Witch; Emile Zola, Nana; Jean-Baptiste Poquelin, L'Avare; Arsene Houssaye, Les grandes dames;
category8	John Galsworthy , The Pigeon; Shakespeare, The Merchant of Venice; Upton Sinclair, The Second-Story Man; Bernard Shaw, Augustus Does His Bit; George Bernard Shaw, Heartbreak House; Tom Taylor, Our American Cousin Voltaire, Candido, o El Optimismo; Richard Hakluyt, The Principal Navigations, Voyages; Leonardo Da Vinci, The Notebooks of Leonardo Da Vinci ongreve, The Way of the World; Tullia d'Aragona, Rime;Ben Jonson., The Alchemist; James M. Barrie, What Every Woman Knows Dante Alighieri, "Divina Commedia di Dante: Inferno"; Dante Alighieri, Dante's Inferno; Shakespeare, Love's Labour's Lost;

Table A.1: Categories and assigned documents. "500 test"

category0	Trollope, The Courtship of Susan Bell; Trollope, George Walker At Suez; John Burroughs, Time and Change; Trollope, The House of Heine Brothers; Robert Chambers, Vestiges of the Natural History of Creation; Trollope, O'Conors of Castle Conor; Simon Newcomb, Side-Lights On Astronomy; Thomas Henry Huxley, The Rise and Progress of Palaeontology; Charles Darwin, Literary Archive Foundation; Huxley, Lectures on Evolution; Elizabeth Gaskell, Doom of the Griffiths; Andrew Lang, How to Fail in Literature Elizabeth Gaskell, The Half-Brothers; James Joyce , Chamber Music; Williams, A History of Science; Darwin, On the Origin of Species; Darwin, The Voyage of the Beagle; Stallman, The Right to Read;
category1	Hippolyte A. Taine, The Origins of Contemporary France; Marcel Proust, A L'Ombre Des Jeunes Filles en Fleur; Alexandre Dumas, Henri III et sa Cour; Jules Verne, Tour Du Mond 80 Jours ; Huguette Bertrand, Espace perdu, poesie; Pierre Loti, Pecheur d'Islande; Jules Renard, Poil De Carotte; Jules Verne, Voyage au Centre de la Terre; Huguette Bertrand, Les Visages du temps, poesie; Moliere , L'Etourdi, par Moliere; Voltaire, Candide; Emile Zola, La Bete Humaine; Robert de Boron, Li Romanz de l'estoire dou Graal; Victor Hugo, Le Dernier Jour d'un Condamne; Boileau, Le Lutrin; Frederic Mistral, Mes Origines. Memoires et Recits; Anatole France, Thais; Victor Hugo, Actes et Paroles; Alexandre Dumas, Les Quarante-Cinq
category2	The Duc de Saint-Simon, Memoirs Louis XIV, Madame Hausset, Memoirs of Louis XV./XVI; Louise Muhlbach, Napoleon And Blucher; S. Baring-Gould, In Troubador-Land; Dumas, The Man in the Iron Mask; Dumas, Louise de la Valliere; John K. Bangs, Mr. Bonaparte of Corsica; Eugene Sue, The Wandering Jew; Muhlbach, Frederick The Great And His Family; Constant, Private Life of Napoleon; Madam Campan, Memoirs of Marie Antoinette; Stewarton, Gentleman at Paris, to Nobleman in London; Alfred de Vigny, Cinq Mars; Eugene Sue, The Mysteries of Paris; Dumas, The Three Musketeers; Dumas, Twenty Years After; Honore de Balzac, Catherine de Medici
category3	William Shakespeare, The Merry Devil; Schiller, The Maid of Orleans (play); William Hazlitt, Characters of Shakespeare's Plays; Thomas Kyd, The Spanish Tragedie; Shakespeare, King Henry VI, Part 1; Shakespeare, Titus Andronicus; Shakespeare, The Two Gentlemen of Verona; Shakespeare, King John ; Shakespeare, Romeo and Juliet; Shakespeare, Twelfth Night; Shakespeare, Measure for Measure; Shakespeare, King Lear; Shakespeare, Pericles; Shakespeare, The Tempest; Shakespeare, Much Ado About Nothing;
category4	Goethe, Reineke Fuchs; Friedrich Schiller, Die Piccolomini; Johann Wolfgang Goethe, Novelle; Goethe, Briefe aus der Schweiz; Georg Büchner, Dantons Tod; Franz Grillparzer, Die Argonauten; AEschylus, The House of Atreus; Franz Grillparzer, Der Traum ein Leben; Goethe, Iphigenie auf Tauris, Herodotus, The History of Herodotus; Hermann Hesse, Siddhartha; Theodor Mommsen, Römische Geschichte; Friedrich Hebbel, Schnock Andrew Lang, M.A., Walter Leaf, Litt.D.,, The Iliad of Homer; Friedrich Hebbel, Agnes Bernauer; William Shakespeare, Wie es euch gefällt William Shakespeare, Was ihr wollt Suetonius, The Lives Of The Caesars Michael Clarke, Story of Aeneas
category5	Nora Pembroke, Verses and Rhymes by the way; Thomas Hardy, Late Lyrics and Earlier; William Wordsworth, Lyrical Ballads, With Other Poems; Alexander Pope, Essay on Man Charles Swinburne, Two Nations; Edgar Allan Poe, The Works of Edgar Allan Poe; George Borrow, Romantic Ballads et al; Burton Stevenson, The Home Book of Verse; Emily Dickinson, Poems; William Makepeace Thackeray, Ballads; Thomas Hardy, Moments of Vision; William Morris, The Pilgrims of Hope William Morris, Poems by the Way Ella Wheeler Wilcox, Poems of Progress Hardy, Wessex Poems and Other Verses C. Patmore, The Angel in the House Esaias Tegne'r, Fridthjof's Saga Swinburne, Songs before Sunrise Jean de La Fontaine, The Fables of La Fontaine
category6	Kate Langley Bosher, Miss Gibbie Gault; Elizabeth Cleghorn Gaskell, Cousin Phillis; Robert Alexander Wason, Happy Hawkins; Anthony Trollope, Barchester Towers ; Zane Grey, The Border Legion; Kipling , Captains Courageous; D.H. Lawrence, The Trespasser; Rudyard Kipling, Kim; Joseph Conrad , A Set of Six; George MacDonald , Sir Gibbie; Louisa M. Alcott , Eight Cousins; George MacDonald, Robert Falconer Hardy, Romantic Adventures of a Milkmaid Bentley, Trent's Last Case F.W. Moorman, Yorkshire Dialect Poems George Meredith, Vittoria; Elizabeth Gaskell, Sylvia's Lovers; Charles Dickens , Hard Times Sir Walter Scott, Waverley;

Table A.2: Categories and assigned documents. "3000 test"

Appendix B

Implementation

I have made an implementation of the described methods of clusterization and categorization. To try the categorization again the categories form the "3000 test", you can use the *TextCat* demo, which is a part of the implementation. Manual, complete source cod and compiled classes are on the CD. I implemented the solution in Java. Used algorithms are not optimized. I made the implementation only for the tests. Here are the most important parts from the source code.

First is the source code of the NgramSequence class. It was used for the representation of documents and categories. It implements the addition of N-gram and the counting of ranks.

```
package org.textcat.ngram;

import java.util.ArrayList;
import java.util.Arrays;
import java.util.Comparator;
import java.util.HashMap;
import java.util.HashSet;
import java.util.Iterator;
import java.util.List;
import java.util.Map;
import java.util.Set;


/**
 * This class represents the set of pairs N-gram and value.
 * It implements adding N-grams to the sequence,
 * ordering and ranking of N-grams by the assigned values.
 * Ranks from odered list or frequencies that where assigned to N-grams
 * are here for values.
 * @author pna
 *
 */
public class NgramSequence {

    protected double lowestValue = Double.MAX_VALUE;
    private List fList;
    private Set fSet;
    protected Map map = new HashMap();


    /**
     * Returns the list of N-grams
     *
     */
    private List getList(){
        if (fList == null) fList = new ArrayList(map.keySet());
        return fList;
    }

    /**
     * Returns the set of all N-grams in the sequence
     */
    public Set getSet() {
        if (fSet == null) fSet = new HashSet(map.keySet());
        return fSet;
    }
```

```
/**
 * Order N-grams by values assigned to them.
 * Returns the final list
 */
public List orderList(){
    List list = getList();
    Object[] array = list.toArray();
    Arrays.sort(array,new Comparator(){

        public int compare(Object a, Object b) {
            double d1 = getValue(a);
            double d2 = getValue(b);
            if (d1>d2) return -1;
            if (d1<d2) return 1;
            return 0;
        }

    });
    fList = new ArrayList(Arrays.asList(array));
    return fList;
}

/**
 * Add an N-gram to the sequence. It means increase the value assigned to
 * N-gram by one
 * If there is no such N-gram insert it to sequence with the value of 1.
 *
 */
public void add(Object id) {
    add(id,1);
}


/**
 *
 * Add an N-gram to the sequence. It means increase the value assigned to N-gram by <code>value</code>
 * If there is no such N-gram insert it to sequence with the value of <code>value</code>.
 *
 */
public void add(Object id, double value) {
    Double d = (Double)map.get(id);
    if (d == null) put(id,value);
    else put(id,d.doubleValue()+value);

}

/**
 * Puts N-gram with the given value to the sequence. If there is already such N-gram,
 * it will be replaced.
 */
public void put(Object id, double value) {
    if (value<lowestValue) lowestValue = value;
    map.put(id, new Double(value));
}


/**
 * Returns the value assigned to N-gram.
 * Usually it is a frequency or a rank
 * @param id
 * @return
 */
public double getValue(Object id) {
    Double d = (Double) map.get(id);
    return (d == null)? -1 : d.doubleValue();
}


/**
 * Returns new <code>NgramSequence</code>. Ngrams in this sequence will be subset of the N-grams
 * from current sequence. Oders of N-grams is given by the <code>list<code>
 */
public NgramSequence getSubSequence(int start, int end) {
    List list = getList();
    NgramSequence res = new NgramSequence();
    int e = end;
    if (end>size())  e = size();
    for (int i = start; i < e; i++) {
        Object o = list.get(i);
        res.put(o,getValue(o));

    }
    return res;
}


/**
 * Replace the values assigned to N-grams with their rank in an ordered list.
 * The list is ordered form highest to lowest values.
 *
 */
public void countRanks(){
    lowestValue = Double.MAX_VALUE;
    List list = orderList();
    for (int i = 0; i < list.size(); i++) {
```

```
            String element  = (String)list.get(i);
            put(element,i);
        }
    }


    /**
     * Decrease values of all N-grams, by the lowest value.
     * So zerou will be the lowest value here
     *
     */
    public void normRanks(){
        double lw = lowestValue;
        for (Iterator it = map.keySet().iterator(); it.hasNext();) {
            Object element =  it.next();
            put(element,getValue(element)-lw);
        }
    }

}
```

Here is the source code of method that implements the creation of the sequence of N-grams from the plain text. During the creation, the filter of N-grams is used. It checks the value of the IDF. If it is greater than the given threshold (2.75 in this case), it will not use this N-gram.

```
    public NgramSequence buildRankedFilteredSequence(String source, int length, Filter filter){
        source=source.replaceAll("[\t\n\f\r]"," ").replaceAll(" {2,}+"," ");
        NgramSequence res = new NgramSequence();
        int i=0;
        while (i+length <= source.length()){
            String s = source.substring(i,i+length);
            if (filter.accept(s))
                res.add(s);
            i++;
        }
        res.countRanks();
        return res;
    }



/*
 * Created on 20.4.2005
 *
 */
package org.textcat.ngram;

import org.textcat.common.Filter;


/**
 * This is a filter, which accepts N-grams with the IDF value
 * higher than 2.75
 *
 * @author pna
 */
public class IDFFilter implements Filter{

    /* (non-Javadoc)
     * @see org.textcat.common.Filter#accept(java.lang.Object)
     */
    public boolean accept(Object o) {
        if (IDFTable.instance().documents/ IDFTable.instance().ns.getValue(o) >2.75)
            return true;
        return false;
    }

}
```

Here is the method, which updates the representation of a category with the new NgramSequence.

```
    /**
     * Updates the values in <code>categorie.ns</code> with the values from <code>seq</code>
     * Values are updated with the value of the rank from the end of the list.
     * So the N-grams on the first ranks will have highest values
     */
    public void join(NgramSequence seq) {
        for (Iterator it = seq.getSet().iterator(); it.hasNext();) {
            Object element = it.next();
            category.ns.add(element, seq.size()-1-seq.getValue(element));
        }
    }
```

This is the implementation of the similarity measure. The measure is described in 4.3.

```
    /**
     * Returns the "out-of-place-measure" (similarity) of
     * <code>a1</code> and <code>b1</code>.
     */
    public double compare(NgramSequence a1, NgramSequence b1){
        NgramSequence a= a1,b=b1;
        if (a.size()>b.size()) a = a.getSubSequence(0,b.size());
        if (b.size()>a.size()) b = b.getSubSequence(0,a.size());
        Set c = new HashSet(a.getSet());
        c.addAll(b.getSet());
        double res = 0;
        for (Iterator it = c.iterator(); it.hasNext();) {
            res+=distance(a,b,it.next());
        }
        return 1 - res/(c.size()*a.size());

    }

    /**
     * Returns distance between an N-gram (<code>id</code> in two sequences.
     */
    private double distance(NgramSequence a, NgramSequence b, Object id) {
        double av = a.getValue(id);
        double bv = b.getValue(id);
        if (av == -1 || bv == -1) return a.size();
        return Math.abs(av-bv);
    }

}
```

This is the implementation of the clusterization. Concretely it counts the components of given graph. For more details, see comments in the code. I chose only the most important parts of the

source code.

```
 * This class computes the components when the {@link org.textcat.ngram.CompareTablePart CompareTablePart}
 * is given. This table provides the acces to the similarity between two documents.
 * Only the components of relevant files are choosen. It starts at treshold of 0.1 and
 * iterates until larger as <code> maxsize</code> components are present. If the value of similarity is lower
 * than the treshold we consider it as non existing edge.
 * Arguments is the ini file. Here is an example:
*
 * table = joinedtable
 * cat = cat
 * max = 35
 * min = 10
 * step = 0.001
*
 * where table is input file containing the {@link org.textcat.ngram.CompareTablePart CompareTablePart},
 * cat is the output used for storing list of categories and create the names of categories,
 * max and min are the maximal and minimal size of created clusters and the step is a iteration value for the
 * similarity treshold.
*
 * @author pna
 */
public class SplitTable {

    CompareTablePart table;
    private List components;
    List fileNames;
    private int[] h;
    private int[] p;
    private int minsize;
    private int maxsize;
    private double step;



     /**
      * Returns the similarity of two documents
      */
    public double getDifference(String id1, String id2) {
        return table.getDifference(id1, id2);
    }


    /**
     * Counts the components. Increases the treshold until there are only smaller than relevant
     * components
     */
    public List split() {
        components = new ArrayList();

        double value = 0.01;
        if (step >= 1)
            step = 0.99;
        if (step <= 0)
            step = 0.01;
        List comp = new ArrayList();
        while (value < 1 && hasLargerComponent(comp, maxsize)) {
            comp = getComponents(fileNames, value);
            value = value + step;
            handleFinished(fileNames, comp);
            log.println(value+"   "+components.size()+"   "+comp.size() + "  " + fileNames.size() );
            log.flush();
        }
        log.close();
        return components;

    }

    /**
     * Removes the node from the small compopnents from the graph and
     * adds relevant components to ther result
     */
    private void handleFinished(List nodes, List comp) {
        for (Iterator it = comp.iterator(); it.hasNext();) {
            List element = (List) it.next();
            if (element.size() <= maxsize) {
                nodes.removeAll(element);
                if (element.size() >= minsize) {
                    components.add(element);
                }
            }
        }

    }

    /**
     * Returns true if the graph contains component larger than the <code>maxsize2<code>
     */
    private boolean hasLargerComponent(List comp, int maxsize2) {
        if (comp.size() < 1)
            return true;
        for (Iterator it = comp.iterator(); it.hasNext();) {
            List element = (List) it.next();
```

```
            if (element.size() >= maxsize2)
                return true;
        }
        return false;
    }

    /**
     * Returns components of the graph represented by <code>nodes2</code> as the vertices and
     * the similarities as edge values. Edges with lower values than <code>value</code>
     * are considered as if they do not exist.
     *
     * Finding components is impelmented with the help of <code>union</code>/<code>findSet</code> methods
     * which gives the complexity of O(m + n.log(m)) where m = n.(n-1)/2 is the number of edges and n number of nodes
     */
    protected List getComponents(List nodes2, double value) {
        p = new int[nodes2.size()];
        h = new int[nodes2.size()];
        Set c = new HashSet();
        for (int i=0;i<p.length;i++){ p[i]=i; c.add(new Integer(i));}
        for (int i= 0;i<nodes2.size()-1;i++){
            for (int j= i+1;j<nodes2.size();j++){
                if (getDifference((String)nodes2.get(i),(String)nodes2.get(j)) > value ){
                    int k1=findSet(i);
                    int k2=findSet(j);
                    if (k1 != k2){
                       int p1 = union(k1,k2);
                       c.remove((new Integer(k1)));
                       c.remove((new Integer(k2)));
                       c.add(new Integer(p1));
                    }
                }
            }
            if (c.size()<2) break;
            if (i%20==0){
                log.println(i+" "+c.size());
                log.flush();
            }
        }
        List[] comps = new List[nodes2.size()];
        for (int i = 0; i < p.length; i++) {
            int k= findSet(i);
            if (comps[k] == null) comps[k] = new ArrayList();
            comps[k].add(nodes2.get(i));
        }
        List result = new ArrayList();
        for (int i = 0; i < comps.length; i++) {
            if (comps[i]!=null) result.add(comps[i]);
        }

        return result;
    }

    /**
     * Determine the reperesentation (parent) of the component into
     *  which <code>i</code> belongs to.
     */
    private int findSet(int i){
        if (p[i]!=i) p[i]=findSet(p[i]);
        return p[i];
    }

    /**
     * Joins two components togehter
     * @param i
     * @param j
     * @return
     */
    private int union(int i, int j){
        if (h[i]<h[j]) {
            p[i]=p[j];
            h[j]=h[i]+h[j]+1;
            return p[j];
        }else {
            p[j]=p[i];
            h[i]=h[i]+h[j]+1;
            return p[i];
        }


    }

}
```