Domain and Language Independent
Feature Extraction for Statistical Text Categorization

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Abstract
A generic system for text categorization is presented which uses a representative text corpus to adapt the processing steps: feature extraction, dimension reduction, and classification. Feature extraction automatically learns features from the corpus by reducing actual word forms using statistical information of the corpus and general linguistic knowledge. The dimension of feature vector is then reduced by linear transformation keeping the essential information. The classification principle is a minimum least square approach based on polynomials. The described system can be readily adapted to new domains or new languages. In application, the system is reliable, fast, and processes completely automatically. It is shown that the text categorizer works successfully both on text generated by document image analysis - DIA and on ground truth data.

1 Introduction
Text categorization is an important task in handling electronic text automatically and assigns a pre-defined category (message type) to a text consisting of a sequence of words. Possible applications of text categorization systems are information filtering and information retrieval. Furthermore, text categorization is necessary to reduce the complexity for subsequent natural-language processing.

The text categorizer presented is embedded in a system which handles text documents. The goal of the system (see [2]) is to extract the information from paper documents in order to support subsequent processing. The analysis starts with document image analysis - DIA (see [3]) and returns an electronic text which contains a certain amount of errors, due to segmentation and character recognition errors. Based on this electronic text, the document is assigned to a certain message type by the text categorizer.

In the following section, the system for categorization is regarded as a task of statistical pattern classification based on a training corpus. The subsequent two sections describe the features extracted from the text, the feature transformation, and the classification principles applied. Finally, categorization results are discussed for an exemplary task.

2 System Overview
In the approach presented here, text categorization is regarded as a task of statistical pattern classification task (see [2]) where each text represents one pattern and a text category represents a class. Hence, a training phase and an application phase must be distinguished. During training text samples are observed which define the feature set (text descriptors),
the rules for dimension reduction and classification; during application the text object is mapped to its class using these sources.

Since feature extraction and classification are adapted by statistical observations (training corpus), this architecture leads to a **generic categorization system** which is not designed to solve a specific task but consists of tools which are trained for each new task arising. Hence, the categorization system is **domain and language independent**.

A consequence is that an adapted categorizer is fault tolerant to high degree if the errors which occur in the text are systematic such as DIA errors. Thus, corrupted DIA output is categorized equally well as error-free text. Another consequence is that the adaptation of a new categorizer costs only computation time. Hardly any manual effort must be spent. The only prerequisite the system has is that a representative set of training texts (text corpus) along with their class membership (labels) is available.

Figure 1: All components of the generic system are adapted: dictionaries collect features which generate the eigenvector matrix; both create the classifier matrix.

The three steps of the system: **Feature Extraction, Feature Transformation, and Classification** are trained in three steps as sketched in Fig. 1. First, relevant features (descriptors) are acquired from the training corpus (see sect. 3), automatically generating a list of stop words and a dictionary of features represented as a vector of fixed length $L$. Using these lists, each text of the training corpus is converted to its feature vector. Second, these features are used to create the transformation matrix used to map the feature vectors from dimension $L$ to a lower dimensional vector space $L'$ and third, the same features and the matrix are used to adapt the coefficients of the classifier (both see sect. 4).

During application, a text is classified to its category as sketched in Fig. 2. Stop words and descriptors are used to generate the feature vector of dimension $L$, which is transformed and classified by using the two learned matrices. The classification results in vector of length $K$, where each component $k_i$ denotes the a-posteriori probability of vector $v$: $k_i = p(k_i|v)$. Currently, the decision rule, which is also used in the sect. 5, is forced recognition, meaning that class $i$ with the maximum $k_i$ is selected.
3 Feature Extraction

Feature extraction defines which linguistic parts (character strings, morphemes, word forms, phrases) are useful features for the classifying task and how these features are gained from the texts to be categorized. To be useful for the classifying task means that features are typical for the category which is assigned to the text and not specific for the text itself.

In previous works, several approaches and aspects of feature extraction have been described. [10] discusses which parts of text are suited as features and evaluates words and phrases with different frequencies in different kinds of English text. Other work, mostly for texts of morphological richer languages than English, considers smaller parts of text like morphemes (gained by linguistic lexicon-based analysis see [7]) or n-grams (gained by statistical computations see [5]). N-grams have the advantage that they can be easily computed, but it is difficult to select and weight them for classification tasks. This is even more problematic if DIA errors drastically increase their number. On the other hand, linguistically analyzed morphemes are well defined but a respective lexicon must be accommodated. A further aspect of feature extraction is whether domain-specific features are superior to general ones (discussed and supported by [1]).

According to [1], we propose the use of features which are specific for the actual categorization task. A generic procedure acquires these features using the training corpus and builds dictionaries of features and of stop words. This approach is similar to [11] (generation of a domain specific lexicon using a corpus of training texts) and [4] (reduction of complex morphemes using simpler morphemes detected in the training corpus), since a corpus of training texts is the base for the acquisition of knowledge which is necessary for a specific task. The main advantage of this approach is that characteristics of the actual categorization task like a specific vocabulary or DIA errors are automatically integrated into the categorizer.

Therefore, the basic idea of our feature extraction is that generic procedures reduce rather autonomously actual word forms of the corpus to features and result in gathering these features into a dictionary. The reduction is able to consider statistical information inherent in the corpus and restrictions of simple but appropriate general linguistic knowledge. Further knowledge bases are not necessary.

In the following, the steps needed to build and to use task-specific dictionaries are described in detail. For illustrative purpose, we refer to the exemplary categorization task of DIA‘ed abstracts of technical reports in German. This example handles a language with complex morphology and word forms with recognition and segmentation errors. The computational complexity of this learning depends on the number of different word forms ($WF$) in the corpus and is maximally $O(WF^2)$. 

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Figure 2: Text categorizer: all learned sources are used to map a text to a category.
3.1 Corpus-Based Learning of Dictionaries: from Words to Features

In order to learn task-specific dictionaries of features and of stop words, all word forms of the corpus together with their frequencies are collected into a list. Here, a word form is defined as a character string between blanks without punctuation marks. It includes also forms with recognition and segmentation errors. In the following, the steps necessary to transforms this list of word forms into a dictionary of features are described:

**Statistical determination of stop words**

| exemplary stop words |
|----------------------|
| Arbeit | Dabei | Die | Ein |
| Auch | Damit | Dio | Eine |
| Auf | Das | Diese | Einen |
| Aus | Dad | Diesem | ... |
| Bei | Dem | Dieser |
| Bericht | Den | Diskutiert |
| Beschrieben | Der | Durch |
| Bis | Des | Eigenschaften |

Figure 3: Exemplary stop words of the task abstracts of technical reports in German

Stop words are defined according to their frequency in the corpus and a given threshold which has to be set and inspected. Fig. 3 lists some stop words of our categorization task. Stop words include the typical function words of German (articles, prepositions, auxiliaries like *der, die, auf, bei*, etc.). Since all texts belong to a domain with specific vocabulary, stop words also include domain-specific terms which are equally distributed in all categories (typical words of abstracts which are independent of the specific category like *arbeit - 'work', bericht - 'report', beschreiben - 'describe'). Even words containing frequent DIA errors are considered as stop words (e.g. the wrongly recognized *dio* instead of *die*). All stop words are collected in a dictionary of stop words and eliminated from the list of word forms.

**Setting of linguistic parameters**

A small number of linguistically motivated parameters are needed to model language-specific characteristics which a categorizer has to respect. First, they define the character set of the texts, distinguished into vowels and consonants. Then, they represent orthographic conventions (e.g. German character strings like *sch* or *ck* express only one consonant and are therefore treated as one character). Both definitions are necessary to restrict the minimal form of a feature: it consists of 3 or more characters and at least one of the characters has to be a vowel. This minimal form restricts the further reduction of word forms to features because the remaining parts of every split or shortening has to agree with this definition — otherwise, the iterative procedure of splitting word forms could terminate with the alphabet.

**Statistical determination of prefixes and suffixes**

Before splitting the word forms, typical affixes of the training corpus are statistically computed according to their frequency and a given threshold which has to be manually set
and inspected. Fig. 4 shows the results for our categorization task. Domain-specific content words which are frequent parts in composite words and which are equally distributed in all categories like *verfahren* - 'procedure’ are treated as suffixes.

**Iterative splitting of complex word forms using simpler forms**

This step is the most expensive and transforms the list of word forms into the list of possible features. By iterative pattern matching, complex word forms are split into smaller ones. Fig. 5 illustrates how the list of word forms is transformed: in the first cycle *halbleitertechnik* - 'technology of semi-conductors’, 'solid state technology’ is split into *halbleiter* and *technik* (and removed from the list) since *halbleiter* is part of the list and both *halbleiter* and *technik* are conform to the linguistic parameters. The frequency of *halbleitertechnik* is added to the frequency of *halbleiter*) and is set as the frequency of the new list item *technik*. The next cycle splits *halbleiter* since *halb* is part of the list and results in the new list item *leiter*. If no further split is possible, the procedure terminates.

This procedure exploits the morphological regularity that parts of composite words exist as simple forms. If both, the complex form and a simpler one which is part of it, are members of the list of word forms, the complex form is divided into the simple one and the remaining character string (which has to respect the linguistic parameters). According to language specific properties, several cycles of splitting complex character strings into simple ones are necessary for German word forms whereas only a few are needed for English ones.

**Subsequent elimination of suffixes and prefixes**

In order to eliminate character strings which have mostly formative and no content function, the computed suffixes and prefixes are used to shorten the forms of the list as long as the linguistic parameters are respected. Since this shortening has the effect that different forms become equal (augmenting their frequency), the list contains less forms.

A German morphological characteristic is that formative elements exist between the parts of a composite word. The most prominent example is the *Fugenelement* 's’, e.g. in *anfangswert* - 'start value’. A further rule matches two forms of the list, if they are the same except that one of them starts or ends with such a formative element.

Fig. 6 shows the final (split and shortened) forms together with their resulting frequencies. A final form of the list can be interpreted as lying between n-grams (3 or more characters) and word stems according to text quality and language. If the DIA results in oversegmented
| word forms before splitting procedure | forms after first cycle | forms after second cycle | forms after third cycle | forms after splitting procedure |
|--------------------------------------|------------------------|-------------------------|------------------------|--------------------------------|
| halbleiteroberflächen                | glasfaser-lichtleitern  | strukturierung          | strukturierung          | strukturierung                 |
| halbleiterlichtleitern               | halbleiterlichtleitern  | wellenleitern           | wellenleitern           | wellenleitern                  |
| halbleitertechnologie                | halbleiterscheinrichtung| leiterplatten           | leiterplatten           | leiterplatten                  |
| halbleitereinstellung                | laserstrahls            | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterscheibendelemente          | halbleiterstruktur      | schätzung               | schätzung               | schätzung                      |
| halbleiterstruktur                  | lichtleiter             | strahlung               | strahlung               | strahlung                      |
| halbleiterlasers                    | laserstrahls            | impulsen                | impulsen                | impulsen                       |
| halbleiterlasern                    | lichtleistung           | lichtleistung           | lichtleistung           | lichtleistung                  |
| halbleiterlichtleitern               | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterlichtleitern               | lichtleistung           | lichtleistung           | lichtleistung           | lichtleistung                  |
| halbleiterlichtleitern               | lichtleistung           | lichtleistung           | lichtleistung           | lichtleistung                  |
| halbleiterlichtleitern               | lichtleistung           | lichtleistung           | lichtleistung           | lichtleistung                  |
| halbleiterscheibendelemente          | halbleiterstruktur      | schätzung               | schätzung               | schätzung                      |
| halbleiterstruktur                  | lichtleiter             | strahlung               | strahlung               | strahlung                      |
| halbleiterlasers                    | laserstrahls            | impulsen                | impulsen                | impulsen                       |
| halbleiterlasern                    | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterlichtleitern               | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterscheibendelemente          | halbleiterstruktur      | schätzung               | schätzung               | schätzung                      |
| halbleiterstruktur                  | lichtleiter             | strahlung               | strahlung               | strahlung                      |
| halbleiterlasers                    | laserstrahls            | impulsen                | impulsen                | impulsen                       |
| halbleiterlasern                    | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterlichtleitern               | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterscheibendelemente          | halbleiterstruktur      | schätzung               | schätzung               | schätzung                      |
| halbleiterstruktur                  | lichtleiter             | strahlung               | strahlung               | strahlung                      |
| halbleiterlasers                    | laserstrahls            | impulsen                | impulsen                | impulsen                       |
| halbleiterlasern                    | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterlichtleitern               | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterscheibendelemente          | halbleiterstruktur      | schätzung               | schätzung               | schätzung                      |
| halbleiterstruktur                  | lichtleiter             | strahlung               | strahlung               | strahlung                      |
| halbleiterlasers                    | laserstrahls            | impulsen                | impulsen                | impulsen                       |
| halbleiterlasern                    | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterlichtleitern               | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterscheibendelemente          | halbleiterstruktur      | schätzung               | schätzung               | schätzung                      |
| halbleiterstruktur                  | lichtleiter             | strahlung               | strahlung               | strahlung                      |
| halbleiterlasers                    | laserstrahls            | impulsen                | impulsen                | impulsen                       |
| halbleiterlasern                    | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterlichtleitern               | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterscheibendelemente          | halbleiterstruktur      | schätzung               | schätzung               | schätzung                      |
| halbleiterstruktur                  | lichtleiter             | strahlung               | strahlung               | strahlung                      |
| halbleiterlasers                    | laserstrahls            | impulsen                | impulsen                | impulsen                       |
| halbleiterlasern                    | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterlichtleitern               | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterscheibendelemente          | halbleiterstruktur      | schätzung               | schätzung               | schätzung                      |
| halbleiterstruktur                  | lichtleiter             | strahlung               | strahlung               | strahlung                      |
| halbleiterlasers                    | laserstrahls            | impulsen                | impulsen                | impulsen                       |
| halbleiterlasern                    | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |
| halbleiterlichtleitern               | lichtleistung           | leistungsleistung       | leistungsleistung       | leistungsleistung              |

Figure 5: Exemplary splitting of the task *abstracts of technical reports in German*
forms after removing prefixes, suffixes and (for German) leading "s"
sorted by their frequency

|    |    |    |    |    |
|----|----|----|----|----|
| lei | 26 | fang | 2 | las | 1 |
| halb | 18 | fas | 2 | gla | 2 |
| lich | 8 | ker | 2 | ablei | 1 |
| truktu | 6 | mittel | 2 | chränk | 2 |
| chich | 5 | peich | 2 | dio | 2 |
| wel | 3 | rechne | 2 | gebenen | 1 |
| wor | 3 | stel | 2 | impul | 1 |
| chal | 3 | strah | 2 | läng | 1 |
| cod | 3 | tes | 2 | lichto | 1 |

|    |    |    |    |    |
|----|----|----|----|----|
| half | 18 | fas | 2 | ätz | 1 |
| las | 8 | gla | 2 | ablei | 1 |
| lich | 8 | ker | 2 | beschr | 1 |
| truktu | 6 | mittel | 2 | bild | 1 |
| chich | 5 | peich | 2 | chränk | 1 |
| wer | 4 | pla | 2 | dio | 1 |
| wel | 3 | rechne | 2 | gebenen | 1 |
| wor | 3 | stel | 2 | impul | 1 |
| chal | 3 | strah | 2 | läng | 1 |
| cod | 3 | tes | 2 | lichto | 1 |

Figure 6: Exemplary features of the task abstracts of technical reports in German

character strings, these faulty-segmented strings further split word forms and the features are similar to n-grams. If the text quality is good and the text contains only a few DIA errors, the features in morphological rich languages as German correspond to word stems.

Selecting features according to a given frequency threshold
Finally, the genuine features have to be selected from the list of final forms according to their frequency. Generally, all forms that occur only once or twice are irrelevant for the following classification, therefore, the threshold has to be higher than 2. For actual categorization tasks, different thresholds have been set between 3 and 19.

The selected features are then stored in a dictionary of features which together with the dictionary of stop words constitutes the knowledge base of the following step.

3.2 Application of Dictionaries: from Texts to Vectors
Using the acquired task-specific dictionaries, the texts are transformed into feature texts. First, the domain specific stop words are eliminated according to the stop word dictionary. Then, the remaining word forms are replaced by features of the feature dictionary if these features are part of the word forms, otherwise the word forms are deleted. This transformation of a text (DIA’ed abstract of a technical report in German) is shown in fig. 7.

Generally, both dictionaries are rather small (the number of stop words lies between 20 and 200, the number of features between 1000 and 10000) and therefore, the completely automatic matching procedure is very fast.

Since the number of all features given by the dictionary is a-priori known, they are represented by a feature vector of fixed length $L$. In the experiments, binary feature vectors have been used. Besides binary values, frequency scores can be computed, such as inverse document frequency etc. Tests have shown that the recognition accuracy is not much affected.

Summarizing the main properties of our feature extraction:

- Task-specific dictionaries of features and stop words are acquired from corpus and applied to texts. This approach allows an easy adaptation to new domains and languages.
Es werden Versuche beschrieben, durch Mischungen eines Bleiglases mit TiO₂ in unterschiedlichen Verhältnissen sowie durch Einsatz verschiedener PbO-TiO₂-SiO₂-Al₂O₃-Systeme zu Siebdruckpasten mit auskristallisierbaren Z 2 3 dielektrischen Komponenten zu gelangen. Neben der Erprobung der eingebauten Mischungen in daraus hergestellten Testkondensatoren wurden an diesen Substanzen differentia-testmoanalytische Untersuchungen durchgeführt. Dabei konnte je nach Zusammensetzung der Mischung die Bildung von PbTiO₃, PbB₂O₃ und/oder PbAl₂O₄ beobachtet werden. An den fertigen Kondensatoren konnten E-Werte zwischen 10 und 80 gemessen werden, jedoch lagen die Anfangs-Verlustfaktoren höher als bei anderen bekannten NDk-Massen. Durch präzise Alterung konnten die Verlustfaktoren jedoch in vielen Fällen auf Werte <0,1 % gebracht werden.

Figure 7: Example of an DIA’ed text together with its corresponding feature text

- Features can be interpreted as lying between n-grams and word stems. Domain-specific content words, language-specific function words, and affixes which have only syntactic or domain overlapping meaning are ignored.

- The resulting categorizer is fault tolerant since the features are adapted to DIA input.

- The generic procedure operates only on the corpus of training texts. There is no need for expensive (lexical) resources or further knowledge bases.

4 Classification

Classification is here considered from the statistical point of view. Given a training set of objects \( o_i, i = \{1, \ldots, N\} \) along with their class label \( k \in \{1, \ldots, K\} \), a classifier is constructed. The feature vector \( v_i \in \mathbb{R}^L \) to each object \( o_i \) is calculated as described in the previous section with a dimension ranging from 1000 to 10000 in our applications. Before adapting the classifier by the set of \( v_i \), the dimension \( L \) is reduced to a reasonable small number \( L' \) of several hundreds for two reasons: First, there is a strong relationship between the dimension of the feature space \( L \) and the required number \( N \) of training samples; the higher \( L \) is, the more training examples must be provided in order to avoid overfitting to the training set. Second, such a high dimension would cause high computing effort both for the adaptation phase and for the classification.

Hence, before constructing the classifier, the dimension of the vector space is reduced by using the same training set of objects. The resulting pairs \( (v'_i, k_i) \), \( v'_i \in \mathbb{R}^{L'} \) are then the basis for constructing the classifier. Both processes are described in the following.
Dimension Reduction

One well known method to reduce the vector space \( R^L \) is the principal component analysis (PCA) which is based on the eigenvalues and eigenvectors of the covariance matrix \( C = 1/N \sum_{i=1}^{N} (v_i - \mu)(v_i - \mu)^T \), \( \mu = 1/N \sum_{i=1}^{N} v_i \). The \( L \) eigenvectors constitute an orthonormal basis \( B \) each vector \( v_i \) can be represented in: \( v'_i = B^T v_i \). The essential property of this linear transformation is the following: the PCA minimizes the Euclidean distance between \( v_i \) and \( v'_i \) (also called the reconstruction error) if \( v'_i \) is a linear combination of the \( L' \) eigenvectors belonging to the \( L' \) greatest eigenvalues, \( L' < L \).

In the experiments described below, \( L \) has been in the range of 2500 and \( L' \) has been selected from the set 50, 100, 200, 500. Fig. 8 displays the loss of information, i.e. the reconstruction error for different \( L' \) (numbers of eigenvalues selected), and motivates the selection of these 4 values. For example, using the first 50 eigenvectors (\( L' = 50 \)), approx. 70% of the information is lost; it does not seem reasonable to reduce the number further since the transformed vectors \( v'_i \) tend to become meaningless. Using the first 500 eigenvectors, 90% of the information is preserved. Selecting more than 500 coefficients does not seem to yield additional benefits since most of the information is already available.

![Figure 8: Reconstruction error in percent for different number of eigenvectors.](image)

An alternative approach, the SVD (singular value decomposition) is also applied to reduce the dimensionality of feature vectors. The SVD is not based on the covariance matrix \( C \) but on the matrix \( A \) of dimension \( N \times L \) represented by the feature vectors \( v_i \). It also minimizes the reconstruction error between \( v_i \) and \( v'_i \) if only a subset of the orthonormal vectors of the decomposed matrix are used. Hence, PCA and SVD are closely related, but not identical. Usually, such techniques are used for Latent semantic indexing (see [6]) since each component of the \( v'_i \) in the system of the eigenvectors can be interpreted as a (linear) combination of vector elements in the original feature space.

Note that the principal component analysis is class independent since each \( v_i \) regardless of its class is transformed by the same matrix \( B \). A different linear transformation for the

\footnote{we used our own software implementations for eigenvector analysis and linear regression.}
same purpose of reducing \( L \) significantly is the linear discriminant analysis which is class specific and has been used by [3].

**Classification** The final step in text categorization is the mapping of an \( L' \)-dimensional feature vector (measurement space) into one of \( K \) classes (decision space). The classification principle employed here is functional approximation based on polynomials. The \( L' \) elements of \( v_i \in R^{L'} \) are combined by a polynomial function \( x : v \rightarrow x(v) \), resulting in multiplicative combination of the elements. For example, a second order polynomial function \( x \) generates the \( L'^2 \) quadratic and \( L' \) linear polynomials of each element \( v_i^2 \) of \( v_i \). Mathematically, the polynomial classifier is defined as \( d(v) = A^T \times x(v) \), where \( A \in R^{K \times X} \) is the coefficient matrix to be adapted and \( X \) the dimension of the range of the function \( x \). The coefficients are calculated by minimizing the mean-square error between the estimation \( d(v) \) and the true value \( y \) describing the class membership of \( v \):

\[
E\{|A \times x(v) - y|^2\} = \text{Minimum}.
\]

\( E\{\ldots\} \) denotes the mathematical expectation and \( y \) the desired target vector which is a unity vector having the ‘1’ at the k-th position if \( v \) belongs to class \( k \). In the optimization problem above \( A \) is computed by linear regression assessing a training sample of size \( N \) of pairs \((v_i, y_i)\). It can be shown that the k-th element of \( d(v) \) estimates the a-posteriori probability \( p(k|v) \). For a detailed description of the polynomial classifier design see [3].

Depending on the dimension \( L' \) and on the training set size \( N \), a linear or higher order classifier can be constructed. The construction of a higher order polynomial classifier – which in general gains a higher recognition accuracy than a linear one – is only reasonable when the dimension \( L' \) is small with respect to \( N \) since the number of parameters to be adapted by the training samples grows with \( \binom{L'}{p} \), \( p \) being the order of the polynomial. Hence, a higher order (second) polynomial classifier is only appropriate if \( L' < 100 \) and the number of samples \( N_k > 1000 \) of each class \( k \).

In the current applications, linear classifiers have been adapted for the different sizes of \( L' \). The current linear classifier is identical to the LLSF (linear least square fit) classifier described by Yang [12] and [13]. However, the mathematical principle is different in general if higher order polynomials are used. In this case, a non-linear function (e.g. quadratic polynomial) maps the feature space to the decision space yielding better separation of classes in the decision space.

**5 Results**

One exemplary domain in which the text categorizer has been applied are abstracts of technical reports. Every technical report (total number: 1144) belongs to one of six classes: solid state physics, telecommunications, material science, information processing, opto-electronics, and pattern recognition. The cardinalities of the classes are approximately equal. It is a rather hard categorization task since some classes are closely related, e.g. information processing and pattern recognition, and some texts contain mixed subjects - even persons who labelled the abstracts had difficulties. The reports were transformed by DIA into ASCII resulting in a word accuracy of 83.6% (details about the algorithms can be found in [3]). Then, all texts were manually corrected resulting in a second input set, the ground truth data. With our experiments, we have examined the following variations:
Feature extraction  In order to evaluate the approach presented here (learned features), we also extracted feature sets by the method of tri-grams (see [3]) and for the corrected texts by morphological analysis with a complete lexicon (see [4]). All feature sets have approximately the same size of 2500 features.

Feature transformation  Since the vector length also influences the categorization result, the principal component analysis results in vector lengths of 50, 100, 200, and 500.

In the following two tables, the error rates of the categorizer under the condition of forced recognition (i.e. the categorizer always assigns one category to one text without the possibility to reject texts or to assign several categories) are shown. The first table contains results for texts generated by DIA, whereas the last table shows the results of the ground truth data.

The first categorizer in table 1 is based on 950 training texts and 140 test texts. The lowest error rate is gained with a dimension space of 500 features. The comparison of the tri-grams and the learned features shows that the tri-gram approach needs only 200 dimensions in order to have its best result whereas our approach needs 500 dimensions and is better than the best categorization result of the tri-grams.

| vector length | tri-gram features | learned features |
|---------------|-------------------|-----------------|
| 50            | 28.8%             | 25.2%           |
| 100           | 27.3%             | 20.9%           |
| 200           | 22.3%             | 20.1%           |
| 500           | 26.6%             | 17.3%           |

Table 1: Results on test texts for two different feature sets resulting from DIA input

The second categorizer in table 2 is adapted in order to compare our learned features with morphological features. In order to apply the morphology system, the texts were transformed into ground truth data and a complete dictionary for these texts was developed. Here, the number of training texts is 1004, the number of test texts 140. Again, the 500-dimensional vector space in combination with the learned features has the lowest error rate. An explanation for the surprisingly high error rate of morphemes could be that a statistical classifier is not appropriate for this kind of features.

| vector length | morphological features | tri-gram features | learned features |
|---------------|------------------------|-------------------|-----------------|
| 50            | 48.3%                  | 27.9%             | 30.7%           |
| 100           | 44.6%                  | 26.4%             | 28.6%           |
| 200           | 41.5%                  | 23.6%             | 23.6%           |
| 500           | 38.2%                  | 22.9%             | 21.4%           |

Table 2: Results on test texts for different feature sets resulting from ground truth data

It has to be pointed out that in every categorization task, the learned features extracted by our statistical approach result in the best recognition rates. Interestingly, the best error
rate on the DIA input is slightly better than the best on the ground truth data. This example indicates that errors does not deteriorate the recognition performance.

Finally, the major property of the text categorizer presented here should be stressed again, which is the minimal manual effort to adapt the complete system to new categorization tasks.

6 Future Work

Currently, a drawback of the classifier is that text objects must correspond to exactly one text category; mathematically, the target vector is a unit vector with the '1' at the class index. However, often a text can be assigned to more than one class. In the near future, the range of the target vectors is extended to the range of real values, more precisely between [0; 1]. Each non-zero value denotes then to what degree a text can be assigned to this class. The mapping can then be approximated more precisely, yielding higher recognition scores.

A second future topic is to reduce the manual effort to a minimum. Currently, several parameters during generation of the dictionaries are set by inspection of intermediate results, e.g. the thresholds for stop words and for the decision what descriptors are selected as features. These thresholds shall be replaced by statistical observations.

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