Job Title Classification Strategies for the German Labor Market

Masterthesis

submitted by

Rahkakavee Baskaran

at the

Universität Konstanz

Department of Politics and Public Administration

Center for Data and Methods

1.Gutachter: Prof. Dr. Susumu Shikano

2.Gutachter: JunProf Juhi Kulshresthra

Konstanz, January 16, 2022

Contents

Abbreviations

SVM Support Vector Machine 5

NB Naive Bayes 5

MLR Multinomial Logistic Regression 6

OA overall accuracy 37

KldB Klassifikation der Berufe 2010 11

ISCO International Standard Clasification of Occupations 13

BOW Bag of Words 7

TF-IDF Term Frequency - Inverse Document Frequency 6

TF Term Frequency 18

IDF Inverse Document Frequency 18

DF Document Frequency 18

CBOW continous bag of words 19

BERT Bidirectional Encoder Representations from Transformers 6

NLP Nature Language Processing 23

PCA Principal Component Analysis 28

RF Random Forest 5

CART Classification and Regression Trees 35

CNN Convolutional Neural Network 5

KNN K-nearest neighbors 5

LR Logistic Regression 5

RNN Recurrent Neural Networks 5

1 Introduction

2 Related work

2.1 Textclassification

Text classification, a highly researched area, is the process of classifying text documents or text segments into a set of predefined classes. During the last decades, researches developed a various number of classifiers. As Kowsari et al. (2019) summarize in their survey of classifiers, we can group the approaches mainly into three groups. The first group contains traditional methods like Naive Bayes (NB),Support Vector Machine (SVM)), K-nearest neighbors (KNN), Logistic Regression (LR) or Decision Trees (Vijayan et al., 2017; Colas and Brazdil, 2006; Kowsari et al., 2019; Sebastiani, 2001). Deep learning methods like Convolutional Neural Network (CNN) or Recurrent Neural Networks (RNN), which are currently the most advanced algorithms for NLP, form the second group. The last group consists of ensemble learning techniques like Boosting and Bagging. Each group can be further split mainly into supervised and unsupervised learning techniques. Since labelled data is available for the classificaiton task in this paper, in the following the focus will be on supervised learning techniques.

Classification algorithms can be selected on different criteria. Certainly one of the most important criteria is performance. Currently deep learning methods often outperform traditional methods and ensemble techniques. Deep Learning methods are advanced methods of traditional machine learning algorithms. In contrast to traditional methods they do not require a substantive understanding for feature extraction since they automatically extract important features. A lot of comparative studies on traditional and embedding techqniues vs. deep learning text classification tasks show the strength of deep learning. Wang and Qu (2017) compared SVM and KNN for web text classification against CNN. Additionally he trained a combined CNN with SVM approach. Despite that the latter show the best performance, his results also reveal a better performance of CNN over the traditional methods. Hassan and Mahmood (2017) also shows that CNN, but also RNN outperforms traditional methods with bag of words feature extraction. These results are followed by Kamath et al. (2018) who examines among others LR and Random Forest (RF),

a ensemble techniques. Furthmore González-Carvajal and Garrido-Merchán (2020) compared the current state-of-the art deep learning model Bidirectional Encoder Representations from Transformers (BERT) with traditional methods using Term Frequency - Inverse Document Frequency (TF-IDF) feature selection method and shows clear outperformance by BERT. Although deep learning models often outperform traditional methods in these comparative studies, not all classifier have constantly good results over all applications. In contrast to traditional methods, deep learning models also usually require millions of data to train an effective model (Chauhan and Singh, 2018). Thus deep learning methods are not necessarily always the right choice. For example, Zhang et al. (2015), conducted experiments on character-level convolutional neural networks and compared them to different traditional models, like bag-of-words or bag-of-ngrams with TF-IDF and LR. As data source they fall back on news and review datasets of different size. For the smaller and moderate size datasets the traditional methods except of Bag-of-means performed well and some of them outperformed CNN. But for bigger datasets CNN worked better. Another study from Yan et al. (2018) rely on a siamese CNN deep learning approach with few shot learning for short text classification using different Twitter benchmark data. He compared his results to some baseline deep learning methods and traditional methods, among all SVM, ensemble techniques and LR. Although the siamese CNN outperformed all the other methods clearly the results are also interesting in another way. Some of the traditional methods outperformed the baseline deep learning methods for specific datasets.

Comparisons of ensemble technique, traditional methods and methods within the traditional methods indicate as well that not all classifications perform for all tasks equally good or poor. A comparative analysis with Multinomial Logistic Regression (MLR), RF and K-nearest neighbor, using TF-IDF, for news text classification indicates a good performance of MLR and RF compared to K-nearest neighbors, wherby MLR performed better then RF (Shah et al., 2020). A study from biomedical classfication shows best performance of SVM among Random Forest, Naive Bayes with TFIDF (Danso et al., 2014).

Although performance is essential, other criteria like the transparency of the algorithm, the interpretability and efficiency in terms of the runtime are not irrelevant. Methods like NB or LR are much faster than neural networks or SVMs. Considering the transparency and the interpretability algorithms like decision tree or LR

are more intuitively, easier to understand and to interpretate, while deep learning models and SVM rely on complexer computations. Especially deep learning lacks from transperancy (Maglogiannis, 2007). Considering BERT although it outperforms usually other machine learning algorithms for text classification, in general '"there are more questions than answers about how BERT works" (Rogers et al., 2020, 853). For example it is not well-understood so far, what exactly happens during the fine-tuning process of BERT (Merchant et al., 2020). However, the main focus of this analysis is on performance.

In addition to the criteria of the classifier itself, it is also important for the performance with which inputs the classifiers are fed. Texts must be converted into a numerical representation to make them machine-readable (Singh and Shashi, 2019). Mainly the numerical vector representations of a text or document can be divided into sparse and dense vectors, also called word embeddings. Sparse vectors, relying on the Bag of Words (BOW) model, are high-dimensional vectors with a lot of zeros, while word embeddings techniques are fixed length representation (Almeida and Xexéo, 2019). Sparse vectors are for example TF-IDF or count vectorizer. Examples for word embedding techniques are word2vec, doc2vec and BERT.

Unsuitable features considerably affect the performance of the classification algorithm (Cahyani and Patasik, 2021). The correct selection of a feature extraction technique depends on many factors, like the length of the dataset or the specific domain (Arora et al., 2021). Empirically, this is reflected in the diverse and conflicting studies in the literature. Considering the sparse vectors (Wendland et al., 2021) compared for fake news data TF-IDF and count vectorization and found slightly better results with TF-IDF while the results of Wang et al. (2017b) show no difference between them. Some studies from different domains demonstrate the strength of word2vec comparing to TF-IDF (Arora et al., 2021; Rahmawati and Khodra, 2016), while others show opposite results. (Zhu et al., 2016; Cahyani and Patasik, 2021). Shao et al. (2018) conlcude that they find no clear picture between BOW models and word2vec. Comparing doc2vec and word2vec Lau and Baldwin (2016) found in general a good performance of doc2vec. Although the authors admit that the qualitative differences between both techniques is not clear. Both Shao et al. (2018) and Wang et al. (2017b) obtain the worst results for doc2vec compared to word2vec and BOW vectorization techniques. BERT shows overall a good performance (González-Carvajal and Garrido-Merchán, 2020). However, Miaschi and

Dell'Orletta (2020) reach in their study the conclusion that word2vec and BERT code similarly for sentence-related linguistic features.

2.2 Challenges of job title classification

Domain-specific and multiclass challenge

Each text classification task presents different challenges. One challenge is that domain-specific problems may arise. There is some work that deals with job classification in the English speaking job market. In terms of classifiers, the corresponding work can be categorised into traditional classifiers or deep learning methods. **?** for example, use a KNN classifier in combination with document embedding as feature selection strategy. **?** rely on traditional methods as well, by combining a SVM classifier and a KNN classifier for their job recommendation system. In contrast, the approaches of **?**, **?** and **?** are based on Deep Learning methods. From a higher perspective, there is another dividing line between the approaches. As mentioned earlier, job title normalization can be considered as a typical text classification task (**???**). **?** and **?**, however, formulate the task as a string representation approach of similar job titles.

Another challenge of text classification tasks comes with the number of classes. As **?** show in their classification of tissue, multiclass classification is more difficult than binary classification problems. Partly, because most of classification algorithms were designed for binary problems (**?**). Approaches for multiclassification can be grouped into two types. Binary algorithms can handle multiclassification naturally. This is, for example, the case for Regression, DT, SVM, KNN and NV. The second type is the decomposition of the problem into binary classification tasks (for the different subtypes see **?**). The literature so far does not have a clear answer to solve multiclassification problems. Different approaches, like Boosting (**?**) or CNN (**?**) are applied. It is noticeable, however, that many works use variations of SVM (Guo and Wang, 2015; Tomar and Agarwal, 2015; Tang et al., 2019).

2.3 Short Text classification

Besides the domain specific challenges and multiclassfication another important issue is the length of input documents for classification. Job titles are clearly short text with often not more than 50 characters. Short texts suffer from sparseness, few word

co-occurrences, missing shared context, noisiness and ambiguity. These attributes makes it on the one side difficult to construct features, which are capture the meaning of the text. On the other side traditional methods are based on word frequency, high word co-occurrence and context, which is why they often fail to achieve high accuracy for short texts (Song et al., 2014; Wang et al., 2017b, 2014; Alsmadi and Gan, 2019). Besides this short texts are also often characterized as having a lot of misspelling and informal writing. In addition applications delivers and processes short texts in real time. The last three attributes of short texts are indeed a problem, e.g. for Twitter data, which is a popular topic for short text data (Karimi et al., 2013; Sriram et al., 2010; Yan et al., 2018). However, for the job title classification they play a little or no role, especially compared to the other stated issues, since job postings are usually reviewed and controlled thoroughly before release. Due to this reason in the following only research concerning the first mentioned attributes is considered.

A popular approach researches propose for short text classification is to introduce additional knowledge im some way to the features to enhance the short texts. Many studies from the field of Twitter analysis show the power of this approach. Karimi et al. (2013), for example, use a bag of words approach for disaster classification of twitter posts. They experiment with different features enriched by additional information. While for example generic features like number of hashtags improved classifaction other information like incident specific features only helped in spefic settings. All in all they use of bag of words with specific features shows quite good performance. Similarly Sriram et al. (2010) achieved with as well with thorougly manual extracted features from the short text good performance for twitter short text messages.

(Wang et al., 2014) criticze the bag of words approach for short text classification, since it result in high dimenisonal data. Especially short text this is much more harmful, because they are short and sparse anyway. They propose a 'Bag of concept" approach by using a knowledge base. The knowledgebase is used for learning concepts for each category and find a set of relevant concepts for each short text. Following this, (Wang et al., 2017a) use as well a enriching concept for short text classification. They use a concept vector with the help of a taxonomy knowledgebase which indicates how much a text is related to the concept. Those are merged with the word embeddings and in addition they add character level features.

In general in short text classifcation the question arises whether to represent

the features as dense or sparse vectors. In their comparison between tf-idf/counter vectorizer and the dense vectorizer word2vec and doc2vec, Wang et al. (2017b) conclude that among the classifiers Naive Bayes, Logisitic Regression and SVM, the sparse vectorizers achieve the highest accuracy. Chen et al. (2019), conversely, see limitations in sparse representation as it cannot capture the context information. In their work, they integrate sparse and dense representation into a deep neural network with Knowledge powered Attention, which outperform state-of-art deep learning methods, like CNN, for Chinese short texts.

Sun (2012) pursues in contrast to the mentioned approaches a complete different strategy. Instead of enriching the features he focused the features on specific keywords. In order to select the important key words he used TF-IDF approaches, some with a clarity function for each word. Using LR he get quite good results for his classification.

Instead of feature enrichment according to Song et al. (2014) a lot of literature focuses on feature dimensionality reduction and extraction of semantic relationship methods using for example Latent Dirichlet approaches.

Concerning the classifiers, there is no consensus approach for short text classification. For traditional approaches Wang et al. (2017b)'s results indicate that logistic regression and SVM perform best, while KNN seems to achieve best accuracy in Khamar (2013)'s work. Song et al. (2014) proposes to use ensemble technqiues. In combination with enriched features Bouaziz et al. (2014), for example, achieve better results as for LR. Similar to job title specific work, more recent work prefers deep learning methods, mostly CNN (Chen et al., 2019).

2.4 Implications

From the above discussed literature three consequences are emerging. First appropriate feature selection or vectorization plays a decisive role in the performance. For that reason, I implement several feature extraction techniques covering sparse and dense vectors. For sparse vectors I vectorize the data with count vectorizer and TF-IDF vectorizer. Word2vec, Doc2vec and BERT embedding built the group of dense vectorization techniques. The discussion of the different techniques will be the first pillar of the comparison.

Second, relying on one classification does not seem a reasonable option. In-

stead experimenting and exploring different traditional, deep learning and ensemble classifiers allows for identifying the best classifier based on the task and the data (Maglogiannis, 2007). Therefore I use 4 classifier techniques. I fall back to two traditional methods. The literature shows that SVM and MLR are well compatible with other technqiues, which is why I choose both of them. I also include an ensemble techqniue: RF. As a last method I implement a BERT classifier since it is the State-of-Art method currently for text classification. The evaluation of different classifications will built the second pillar of the comparision.

Third as mentioned above the focus of the presented three challenges is on short text classification. The literature on short text classification reveals two points. There are different results on whether sparse or dense techqniques are better suited. Testing different sparse and dense vectorization techniques allows to cover for that point. Second most of the solutions include additional knowledge. Therefore, I use for the training of the dense embedding techqniques additional knowledge from the Taxonomy and compare the results to the models without adding the knowledge, which will build the last pillar of the comparision.

3 Job title data and taxonomy

The training data consists of two data sets. The classes are extracted from the first data set, referred to below as the Klassifikation der Berufe 2010 (KldB) dataset. The KldB dataset contains all information of the KldB taxonomy. The second dataset, called job title dataset in the following, contains the necessary data from the job titles. In the first part of this chapter a brief explanation about the Taxonomy structure and both datasets is given. The second part contains of a descriptive analysis of the class distribution of the data.

3.1 KldB 2010 Taxonomy

The "KldB" is structured hierarchically with 5 levels. On each level there is a different number of classes. In the following these classes are also referred to as kldb. On level 1 each class has an id of length one with a number from 0 to 9. Table 1 shows the 10 classes of level 1 with their class names. On level 2, then, each of the 10 classes are divided into one or more subclasses having a class id of length 2

IDs KldB 2010	Berufsbereich (Level 1)
1	Land-, Forst- und Tierwirtschaft und Gartenbau
2	Rohstoffgewinnung, Produktion und Fertigung
3	Bau, Architektur, Vermessung und Gebäudetechnik
4	Naturwissenschaft, Geografie und Informatik
5	Verkehr, Logistik, Schutz und Sicherhe
6	Kaufmännische Dienstleistungen, Warenhandel, Vertrieb, Hotel und Tourismus
7	Unternehmensorganisation, Buchhaltung, Recht und Verwaltung
8	Gesundheit, Soziales, Lehre und Erziehung
9	Sprach-, Literatur-, Geistes-, Gesellschafts- und Wirtschaftswissenschaften, Medien, Kunst, Kultur und Gestaltung
0	Militär

Table 1: Overview of classes Level 1 - Berufsbereiche (edited after (Bundesagentur für Arbeit, 2011b))

with the first digit indicating the class of level 1 and the second digit the class of level 2. An overview of the all 5 levels with an example of classes is given in table 2. Note that the example in table 2 does not show on level 2 to level 5 all classes. Thus on level 2 there exists also, e.g. the class id 41 with "Mathematik-, Biologie-Chemie- und Physikberufe", which in turn is divided into other classes on level 3 etc.. With this procedure this ultimatley leads to class ids of length 5 on level 5. An occupation can be classified on every level in the Taxonomy. Considering the classes of the example in table 2, the job title "Java Developer" could be classified on level 5 to the class 43412. From this id, it is also derivable that the jobtitle belongs, for example, on level 3 to the class "Sofwareentwicklung" (Bundesagentur für Arbeit, 2011a,b; Paulus and Matthes, 2013)

The KldB contains of two dimension. The first dimension, the so-called "Berufsfachlichkeit" structures jobs according to their similarity in knowledge, activties and jobs. This is reflected in the first 4 levels. Considering the again the example from above and the job title "Fullstack PHP-Entwickler" it is reasonable to classify both on level 1 to "Naturwissenschaft, Geografie and Information", because both of them are related to computer science. It also make sense to classifiy them for example to 4341, because both are about sofware development. On level 5, then, a second dimension is introduced. the "Anforderungsniveau". This dimension gives information on the level of requirement for a job and 4 possible requirements. In table 3 they are summarized. From the class id of job title "Java Developer", we can see that the job has been assigned to the second requirement level, since the last digit is a 2 (Bundesagentur für Arbeit, 2011a,b; Paulus and Matthes, 2013)

With the KldB 2010, an useful and information-rich occupational classification was created for Germany that reflects the current trends in the labor market (Paulus and Matthes, 2013). One strength relies in the construction of the KldB. Instead

of just including expert knowledge into the Taxonomy the developement process is based on systematical consideration of information about occupations, as well as statistical procedures for taxonomy developement. Furthermore, the taxonomy was reviewed qualitatively several times in relation to professions and revised. Considering the expressiveness, the KldB has some more benefits. Since the taxonmy is quite recent, it reflects new job classes and market trends very adequately. Further, by including the second dimension, the taxonomy provides a powerful tool to organize job titles into simple requirement classes. In addition, the taxonomy also distinguishes between managerial, supervisory, and professional employees, which is also valuable information. Finally, the taxonomy also convinces with the possibility to switch to "International Standard Clasification of Occupations (ISCO)" through its IDS and thus to normalize jobs to a global standard (Bundesagentur für Arbeit, 2011b).

The KldB dataset contains different information related to the structure descriped above. Besides the class label, the level and the title, on level 5 for each kldb some searchwords are given. There are two types of keywords. One is the job titles that match the respective kldb. On the other hand, real search words, with the help of which the associated kldb can be inferred. Therefore, these searchwords are very helpful knowledge for training classificaiton algorithms, because they contain kldb specific words that are also often present in the job titles. The searchwords will be termed additional knowledge in the rest of the work.

3.2 Job title data

Job Titles can be scraped from the Federal Employment Agency's job board. Employers must provide additional data for each job posting, including the job title, as well as a main internal documentation code that indicates a class in the KldB taxonomy. There is an option to provide alternative documentation codes if more than one KLDB class is being considered. An example snippet of the scraped data

Name	Level	Number of classes	Example
Berufsbereiche	1	10	4: Naturwissenschaft, Geografie und Informatik
Berufshauptgruppen	2	37	43: Informatik-, Informations- und Kommunikationstechnologieberufe
Berufsgruppen	3	144	434: Sofwareentwicklung
Berufsuntergruppen	4	700	4341: Berufe in der Sofwareentwicklung
Berufsgattungen	5	1286	43412: Berufe in der Sofwareenetwicklung - fachlich ausgerichtete Tätigkeiten

Table 2: Overview of KldB (edited after (Bundesagentur für Arbeit, 2011b))

Level of requirement	Class ID	Name long	Name short
1	xxxx1	Helfer- und Anlerntätigkeit	Helfer
2	xxxx2	fachlich ausgerichtete Tätigkeiten	Fachkraft
3	xxxx3	komplexe Spezialstentätigkeiten	Spezialist
4	xxxx4	hoch komplexe Tätigkeiten	Experte

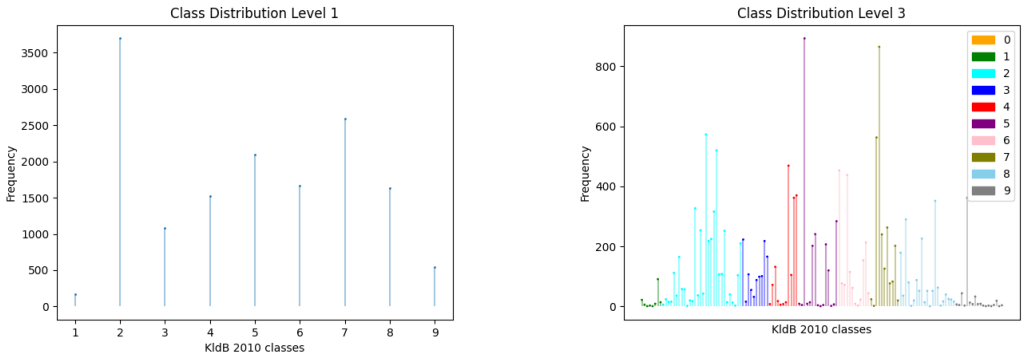
Table 3: Overview of Level of requirements on Level 5
(edited after (Bundesagentur für Arbeit, 2011b))

is provided in the Appendix [1] The documentation code is an internal number of the Federal Employment Agency, which can be uniquely assigned to a KldB, which, as already mentioned, is specified in the taxonomy data for each kldb. A snippet of the matched training data with the KLDB labels is given in the appendix.

Initially, in total, the training data set contained of 269788 examples. However, during the training phase, it became clear, that there are problems especially with SVM classifier, concerning the running time and memory. Due to limited resources, a sample with the same distribution from the long dataset had to be taken. A sample size of 15000 examples proved to be feasible. Figures 1a and 1b show the distribution of the classes in level 1 und level 3 [2]. Both figures show the absolute number of examples for each kldb in the respective levels. In figure 1b the number of examples is coloured with the belonging kldb level 1 class to give better overview of the 144 kldbs on level 3. In general from both levels it is clear that there is in fact that the data is not distributed equally. For the class distribution if level 1 on Figure 1a class 1 and class 9 have really few examples, while class 2 has considerably more examples than all other classes. Although the data is imbalanced, all classes have at least some examples in order to get meaningful performance measurements. Note that kldbs with digit 0 are missing. 0 stands for 'Militär". Jobs in this category are not normally posted frequently on the Employment Agency Job Board page. At level 3, the uneven distribution is even more apparent.Compared to level 1, the problem is that there are a lot of classes with only one example, which is problematic for obtaining interpretable measurements. This problem will be discussed in the results part. In total 8 classes do not have any examples and thus cannot be trained with the classifier.

[1] There are two version of the raw data since the Federal Employement Agency changed during the scraping phase the datastructure. Both version are given in the Appendix.

[2] The class distribution of the long dataset is given in the Appendix.



(a) Class distribution Level 1 (b) Class distribution Level 3

Figure 1: Class distribution of the training data

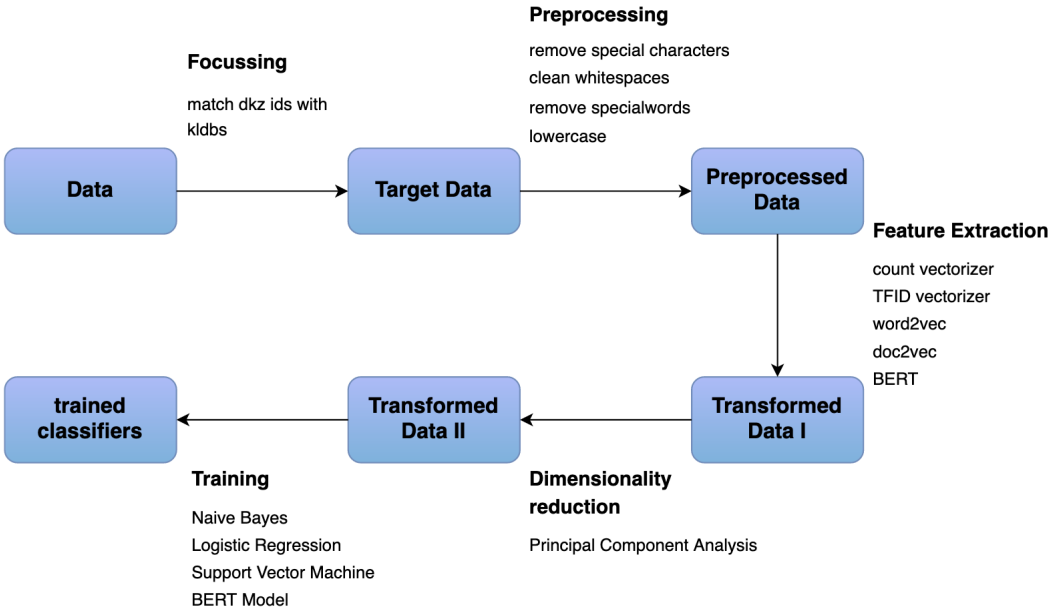


Figure 2: Training Pipeline

4 Method

4.1 Conceptual overview

The classification process is divided into several steps. Figure 2 gives an overview of the procedure. In the first step, the KldB and the job title data are focused on the necessary variables. This is done by matching the kldb ids from the KldB data set with the internal documentation id from the job title data. In the next steps, the targeted data is preprocessed. This preprocessed data is then transformed into numerical vectors. For this purpose, different vector representations are created using five vectorization techniques. The transformed data is then reduced to lower

dimensions using principal component analysis. The resulting data is the input for the classifier. In the last step, the four classifiers are trained. Note that the BERT classification algorithm follows a different pipeline, which is why the algorithm is presented separately. Here, the data is used as input to the deep learning model directly after preprocessing and the model is trained. The targeting of the data has already been described in the previous chapter. In the following, the procedure and the associated methods are explained in detail.

4.2 Preprocessing

Preprocessing is crucial step which has to be taken before vectorization. There are several standarized practices for preprocessing like tokenization, stemming, stopword removal and lowercasing (Alsmadi and Gan, 2019). Preprocessing can have an essential influence on the performance of a classifier (Uysal and Gunal, 2014; HaCohen-Kerner et al., 2020; Gonçalves and Quaresma, 2005). Therefore, the methods of preprocessing are justified below.

The first preprocessing step is the removal of special characters. This is necessary because most titles contain slashes and brackets to distinguish gender forms in occupational titles. Some job titles contain emojis, such as asterisks, which need to be removed as they are not related directly to specific job titles.

Capitalized words are usually convert to lowercase in order to treat them equally for the classification. However, lowercase can be at the same time harmful for the performance, if the interpretation changes with converting. Considering the word 'US", which refers to the United States of America. Converting to lowercase it is equal to the pronoun 'us" and this can affect the performance if the differentiations plays a role for the classification (Kowsari et al., 2019). For occupational names in German, conversion makes sense, since capitalization plays a major role in German. In turn, I don't expect conversion to cause problems often, as described in the example above, since occupational titles usually have their own names and their lowercase variants do not often lead to other words or word classes. Thus in a second step titles are all converted to lowercase.

As in every text classification task stop words removal is a common praxis. I removed all stopwords, which are listed in the german stopwords list of the Nature Language Toolkit package (Bird et al., 2009). In addition to this standardized

processes, the data contained other peculiarities that justify further words removal besides stopwords. Job titles very often contain words, such as "employee" or "effective immediately", that do not contain important information and are not specific to particular job titles. These should be removed. To identify a list of such words, the frequencies of each word across all documents are calculated after the aforementioned preprocessing steps. These frequencies are then used to identify words, such as "employee", that are common but not relevant. As a final preprocessing step, the identified words are then also deleted from all job titles.

4.3 Vectorization Techniques

Count vectorizer

The count vectorizer is one of most simple techniques of converting texts to vectors. It belongs to the family of BOW models. BOW models are based on vectors, where each dimension is a word from a vocabulary or corpus. The corpus is built by all words across all documents. BOW models have two important properties. First, they do not consider the order of the words, sequences or the grammar, which is why they also called BOW. Second, each word in the corpus is represented by it's own dimension. Thus the vectors contains a lot of zeros, especially for short texts, which is why they belong to the family of sparse vectors (Ajose-Ismail et al., 2020). Assuming, for example, a corpus contains of 1000 words, meaning each text is built only with these 1000 words, the vector for each text has a length of 1000, thus, producing sparse, high-dimensional vectors (Kulkarni and Shivananda, 2021; Sarkar, 2016)

For the count vectorizer the values for the vector are generated by counting for each text the frequency of the words occuring. Considering a corpus including only the three words "java", "developer" and "python", the titles "java developer" and "python developer" would be encoded as follows:

	java	developer	python
java developer	1	1	0
python developer	0	1	1

Table 4: Encoding with count vectorizer

The table 4 results in the vectors $(1, 1, 0)$ and $(0, 1, 1)$. Note that if the title "java developer" contains, for example, two times the word "java" then the vector would

change to (2,1,0). But since this is not a likely case for short text and especially job titles, the count vectorization here is for the most titles similar to one-hot vector encoding, which only considers the occurence of the words, but not the frequency (Kulkarni and Shivananda, 2021; Sarkar, 2016)

While being one of the most simple techniques, count vectorizer has several limitations. The main downside is that it does not consider information like the semantic meaning of a text, the order, sequences or the context. In other words a lot of information of the text is losen (Sarkar, 2016). In addition, count vectorizer does not take into account the importance of words in terms of a higher weighting of rare words and a lower weighting of frequent words across all documents. (Suleymanov et al., 2019)

TFIDF vectorizer

TF-IDF belongs like the count vectorizer, to the family of BOW and is as well a sparse vector. In contrast to count vectorizer, it considers the importance of the words by using the Inverse Document Frequency (IDF). The main idea of TF-IDF is to produce high values for words which occur often in a documents, but are rare over all documents. The Term Frequency (TF) represents the frequency of a word t in a document d and is denoted by $tf(t, d)$. The Document Frequency (DF), denoted by df, quantifies the occurence of a word over all documents. By taking the inverse of DF we get the IDF. Intuitvely the IDF should quantify how distinguishable a term is. If a term is frequent over all documents it is not usful for the distinction between documents. Thus the IDF produces low values for common words and high values for rare terms and is calculated as follows (Sidorov, 2019; Kuang and Xu, 2010):

$$idf(t) = log\frac{N}{df}$$

where N is the set of documents. The log is used to attenuate high frequencies. If a term occurs in every document, so $df = N$ the IDF takes a value of 0 ($log(\frac{N}{N})$) and if a term is occuring only one time over all documents, thus distinguish perfectly the document from other documents, $idf(t) = log(\frac{N}{1}) = 1$. (Sidorov, 2019) Note that there are slight adjustments to calculate the IDF. (Robertson, 2004) The implementation of sklearn package, which is used in this work uses an adapted

calculation (Pedregosa et al., 2011):

$$idf(t) = log\frac{1+n}{1+df(t)} + 1$$

Given the $idf(t)$ and tf the TF-IDF can be obtained by multiplying both metrics. The implementation of sklearn normalize in addition the resulting TF-IDF vectors v by the Euclidean norm (Pedregosa et al., 2011):

$$v_{norm} = \frac{v}{||v||_2}$$

Although TF-IDF considers the importance of words compared to count vectorizer, as a BOW model it suffers from the same limitation as count vectorizer of not taking semantic, grammatic, sequences and context into account (Sarkar, 2016).

Word2Vec

In contrast to the sparse techniques method mentioned above, word embedding techniques are another popular approach for vectorization. Word embedding vectors are characterised by low dimensions, dense representation and a continous space. They are usually trained with neural networks (Li et al., 2015; Jin et al., 2016).

Word2Vec, introduced by Mikolov et al. (2013), is one computionally efficient word embedding implementation. The main idea of Word2Vec is based on the distributional hypothesis, which states that similar words appear often in similar context (Sahlgren, 2008). Thus, Word2Vec learns with the help of the context representations of words, which includes the semantic meaning and the context. In such a way it words which are similar are encoded similarily (Sarkar, 2016).

There exists two variants of Word2Vec. The first variant is based on BOW, the so-called continous bag of words (CBOW), which predicts a word based on surrounding words. In contrast, the second variant, Skip-Gram, predicts the context words from a word (Ajose-Ismail et al., 2020; Sarkar, 2016). Since in this work a pretrained model from Google is used, which is trained with CBOW, in the following the focus is on CBOW.

CBOW Word2vec is a 2-layer neural network with a hidden layer and a output softmax layer, which is visualized in figure 3. The goal is to predict a word, the so-called target word, by using the target word's context words. The number of context words is defined by a certain window size. If the window size is 2, the 2

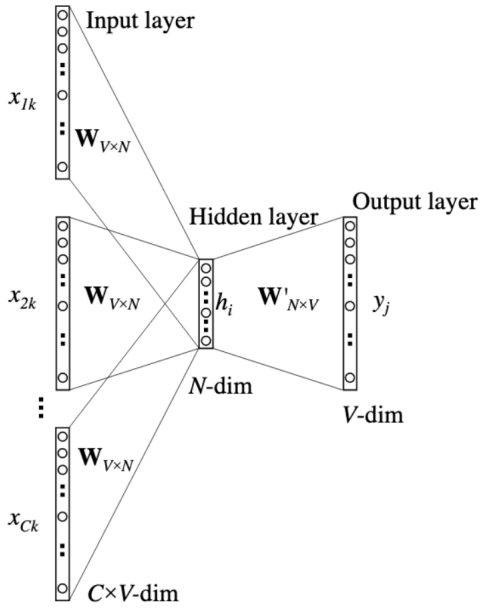


Figure 3: CBOW (Rong, 2014, 6)

words before and the 2 two words after the target word are considered. Given a vocabulary V, which is a the unqiue set of the words from the corpus, each context word c is fed into the neural network, encoded with one-hot encoding of the length of V, building vector x_c. Thus in figure 3 x_{1k}, for example, could be a one-hot encoded vector of the word before the target word.

The weights between the input layer and the hidden layer are shown in figure 3. Taking the dimension of V and N results in the $V \times N$ matrix W. Given that each row v_w in W represents the weights of the associated word from the input and C equals to the number of context words, the hidden layer h is calculated as follows (Rong, 2014):

$$h = \frac{1}{C} W^T (x_1 + x_2 + ... + x_c) = \frac{1}{C} (v_{w_1} + v_{w_2} + ... + v_{w_C})$$

Since the context words are encoded with one hot vector encoding, all except of the respective word value in the vector, which is 1, will be zero. Thus calculating h is just copying the k-th row of matrix W, thus a n-dimensional vector, which explains the second part of the equation. The hidden-layer matrix builds later the word embedding, which is why the decision of the size of the hidden layer defines the dimensions later for the word embedding vector (Rong, 2014)

From the hidden to the output layer a $N \times V$ weight matrix is used to calculate scores for each word in V. A softmax function is used to get the word representation.

Caluculating the error and using backpropagation the weights are updated respectivley resulting then in a trained neural network. In practice, due to computional efficiency, instead of the softmax function Word2Vec is trained with hierarchical softmax or negative sampling. Both methods are efficient in the sense that they reduce the amount of weight matrix updates. [3]. (Rong, 2014; Simonton and Alaghband, 2017).

Based on the given theoretical insights, I train two Word2vec models. Both models use a pretrained model from Google and are fine tuned with different data. The first model is fine tuned with the complete dataset. The second model includes the additional knowledge. The model setting is as follows: I use CBOW Word2Vec models with negative sampling technique. The hidden layer size and thus the word embedding vectors is 300, since the vectors have to have the same size as the pretrained Google vectors, which have a size of 300. The minimal count of words is set to 1. The number of times the training data set is iterated, the epoch number, is set to 10. Lastly, the window size for the context is set to 5.

As last step the resulting word embeddings need to be processd in some way to get sentence embeddings for each job title. As the name already indicates Word2Vec cannot output sentence embeddings directly. In order to get the sentence embeddings the word vector embeddings of each job title are averaged.

Doc2vec

Doc2vec, also known as paragraph vectors or Distributed Memory Model of Paragraph Vectors is an extension method of Word2Vec, which outputs directly embeddings for each document (Lau and Baldwin, 2016) It was proposed by Le and Mikolov (2014). Doc2Vec can be used for a variable length of paragraphs, thus it is applicable for bigger documents, but also for short sentences like job titles (Le and Mikolov, 2014).

The main idea is, like for Word2Vec, to predict words in a paragraph. To do so, a paragraph vector and word vectors, like in Word2Vec, for that paragraph are concatenated. The paragraph vector '"acts as memory that remembers what is missing from the current contest - or the topic of the paragraph" (Le and Mikolov,

[3]Since the focus is relying here on the word embeddings from the hidden layer and not the trained neural network itself, no further mathematical details will be given concerning the updating. For a detailed derivation see (Rong, 2014)

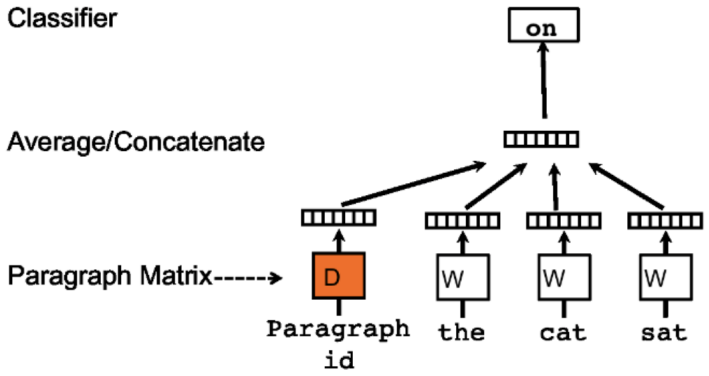


Figure 4: Doc2vec - Distributed Memory Model of Paragraph Vectors (Le and Mikolov, 2014, 3)

2014, 3). Therby the paragraph vectors are trained as well with stochastic gradient descent and backpropagation. Similar to Word2Vec practical implementation use hierarchical softmax or negative sampling to fast up training time (Lau and Baldwin, 2016).

In figure 4 the algorithm is visualized. As an input the neural networks takes word vectors and a paragraph vector. While the word vectors are shared over all paragraphs, the paragprah vectors are unique for each paragraph. Those paragraphs are represented as unique vectors in a column of a matrix D. The word vectors are respresented in the matrix W as before. In order to predict the word both vectors are combined for example by averaging or concatenating. The Doc2vec implementation described by Le and Mikolov (2014) and also used in this work here concatenate the vectors. Formally this only changes the calculation of h. (Lau and Baldwin, 2016)

Since Doc2vec is a word embedding method it has the same advantages mentioned above in the Word2Vec part. In addition Doc2Vec takes the word order into account. At least in the same way of a large n-gram (Le and Mikolov, 2014).

Besides the model explained above, Doc2Vec comes also in a second variant, the so-called Distributed Bag of Words of Paragraph model, which ignores the word order. It is not clear which model performs better, although the inventor of Doc2vec propose the first version (Lau and Baldwin, 2016)

Based on this disussion, I created two Distributed Memory Models of Paragraph Vectors. Instead of fine tuning a pretrained model, I trained two custom models, one with the training data and one including the additional knowledge. I set the vector size to 300 with a window size of 5, a minimal count of 1 and trained 10

epochs. Like Word2vec, the models are trained with negative sampling.

BERT

The last vectorization technique, BERT, is the state-of-art language modeling technique developed by (Devlin et al., 2018) at Google. BERT stands out from other langugage models in several ways and outperforms other models for many Nature Language Processing (NLP) tasks. First, BERT uses bidirectional pretraining. Thus is does not only process from left-to-right or right-to-left, but it merge both of them. Second, it is possible to fine tune the model for specific task without heavily-engineered and computionally costly architectures. Third compared to word2vec it is a context-dependent model. Thus, while word2vec would produce only one word embedding for "'Python" BERT can give based on the context different embeddings. Here '"Python" as a snake or as a programming language.

Architecture

BERT uses a multi-layer bidirectional Transformer encoder as the architecture. This transformer architecture was introduced by Vaswani et al. (2017). It consists of encoder and a decoder and make use of self-attention. Both, encoder and decoder stack include a number of identical layer, each of them including two sub-layers: a Multi-head attention and a feedforward network layer [4] It is out of the scope to elaborate the technical details and implementation of the attention mechanism, which is why in the following a simplified explanation of the attention mechanism is given.

The self-attention mechanism improves the representation of a word, represented by a matrix X, by relating it to all other words in the sentence. In the sentence '"A dog ate the food because it was hungry"' (Ravichandiran, 2021, 10) the self-attention mechanism, for example, could identify by relating the word to all other words, that '"it" belongs to '"dog" and not to '"food". In order to compute the self attention of a word three additional matrices, the query matrix Q, the key matrix K and a value matrix V are introduced. Those matrices are created by introducing weights for each of them and multiplying those weights with X. Based on those matrices, the dot product between the Q and the K matrix, a normalization and a

[4] A simplified visualization with a two layer encoder, as well the architecture of a can be found in the Appendix.

softmax function are applied in order to calculate an attention matrix Z [5]. BERT uses a multi-head-attention, which simply means that multiple Z attention matrices instead of a single one are used.

BERT takes one sentence or a pair of sentences as input. To do so it uses WordPiece tokenizer and three special embedding layers, the token, the segement and the position embedding layer for each token, which is visualized in 5. A WordPiece tokenizes each word which exits in the vocabulary. If a word does not exists words are splitas long a subword matches the vocabulary or a individual character is reached. Subwords are indicated by hashes. For the token embeddings the sentence is tokenized first, then a [CLS] is added at the beginning of the sentence and [SEP] token at the end. For example the job title '"java developer" and '" python developer"' becomes to tokens as shown in the second row of 5. In order to distinguish between the two titles a segment embedding is added, indicating the sentences. Last the BERT model takes a position embedding layer, which indicates the order of the words. For each token those layers are summed up to get the representation for each token (Devlin et al., 2018; Ravichandiran, 2021).

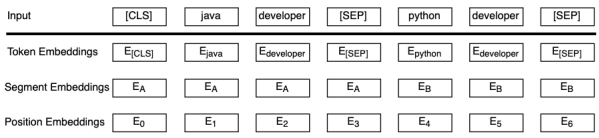


Figure 5: Input BERT (Devlin et al., 2018, 5)

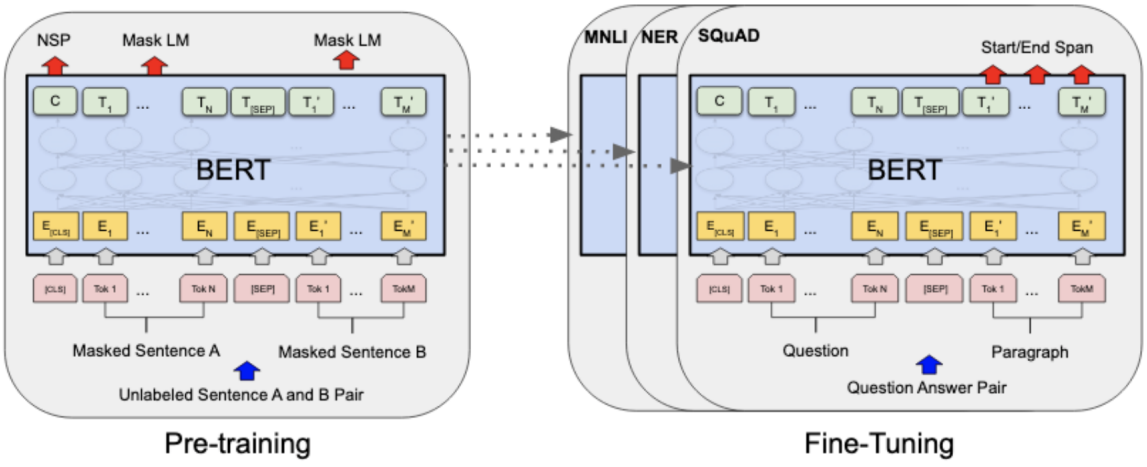


Figure 6: Overview BERT (Devlin et al., 2018, 3)

[5]For a step-by-step calculating see (Ravichandiran, 2021)

The BERT algorithm can be described in two steps. First the pretraining phase, which is illustrated on the left-hand side of the figure 6 and the fine-tuning phase, visualized on the right-hand side of figure 6. The pretraining phase consists of two jobs: Masked language modeling and next sentence prediction.

Pretraining

Masked language modeling means that a percentage of the input tokens are masked at random. For example the job title '"python developer" could be masked as follows: [[CLS] python [MASK] [SEP]]. Since in fine tuning tokens are not masked a mismatch would occur between fine tuning and pretraining, which is why not all of the masked tokens are actually matched with a [mask] token, but also with random token or the real tokens [6]. Instead of predicting the complete sentence, BERT trains to predict the masked tokens. The prediction is performed with a feed forward network and a softmax activation (Devlin et al., 2018; Ravichandiran, 2021).

The second task takes again two sentences, but predict whether the second sentence follows the first one. This helps to understand the relationship between the sentences. Each sentence pair is labelled with either isNext or NotNext. By using the [CLS] token, which has the aggregating representation of all tokens, a classification task of whether a sentence pair is isNext or NotNext can be carried out (Ravichandiran, 2021; Devlin et al., 2018)

The pretraining of BERT is in contrast to the fine tuning process computionally expensive. Therefore, Devlin et al. (2018) initially developed different sizes of BERT like BERT-base and BERT-large. Besides those two models, there are plenty of pretrained BERT models for the German case, like BERT-base-german-cased or distilbert-base-german-cased [7]. In an evaluation of German pre-trained language models, (Aßenmacher et al., 2021) conclude that the bert-base-german-dbmd-uncased algorithm works quite well. Following their results and own tests on different mode bert-base-german-dbmd-uncased seems to have the best result, which is why I use it for the fine tuning process. The model consists of 12 encoder layers, denoted by L, 12 attention heads, denoted by A and 768 hidden units, which results

[6] There are specific rules of how to mask. See Devlin et al. (2018) for detailed implementation

[7] All german BERT are open source and are accessible through the transformers library (Wolf et al., 2020)

in total in 110 million parameters. It was trained with 16GB of German texts.

Fine-Tuning

The second phase, the fine-tuning, can be performed in different ways, also depending on the task. For text classifcation there are two main strategies. Either the weights of the pretraind model are updated during the classifcation process. Or the pretrained model is first fine-tuned and then used as a feature extractor. Such it can be then in turn used for, for example, calculating similarities or as an input for classification algorithms.

I train two models with BERT. While the first model includes a classifcation layer, in the following named as BERT classifier, the second model applies BERT as a feature extraction method, in the following named BERT vectorizer.

The BERT classifier is fine tuned with the complete training data set. Practically this is done by converting the sentences of the dataset to the appropriate data format as described above and train it with the supervised dataset on some epochs, which then outputs the labels. From a theoretical point of view the last hidden state of the [CLS] token with the aggregation of the whole sentence is used for the classifcation. In order to get the labels BERT uses a softmax function [8] (Sun et al., 2019). As already state in the literature review in the literature it is not well-understood so far, what exactly happens during the fine-tuning. An analysis of Merchant et al. (2020) indicates that the fine tuning process is relatively conservative in the sense that they affect only few layers and are specific for examples of a domain. Note that this analysis focussed on other nature language processing task than text classifcation. The set-up of the training is as follows: Testing different epoch numbers indicates that lower epoch size have better results for the model, which is why I fine tune in 6 epochs. For the optimization an adam algorithm, a gradient based optimizer (Kingma and Ba, 2014), with a learning rate of $1e^{-5}$ is used.

In order to get sentence embeddings different strategies, like averaging the output layer of BERT or using the [CLS] token, are applied. Another method, developed by Reimers and Gurevych (2019) is Sentence-BERT, which is computionally efficient and practicable to implement. Thus, it faciliate to encode sentences directly into embeddings, which is why I use it for the BERT vectorizer. The model is constructed with the bert-base-german-case model and a pooling layer. The pooling layer is

[8] The explanation of the softmax function follows in the chapter of the classifiers

added to output the sentence embeddings. The fine tuning process uses a siamese network architecture to update the weights. 7 shows the architecture. The network takes pairs of sentences with a score as an input. Those scores indicate the similarity between the sentences. The network update the weights by passing the sentences through the network, calculating the cosine similarity and comparing to the similarity score (Reimers and Gurevych, 2019). I create from the job title dataset and from the kldb dataset pairs of similar and dissimilar job titles or searchwords. Similar pairs are pairs from the same kldb class. As a score I choose 0.8. Dissimilar pairs are defined as pairs which are not from the same class. The score is 0.2. Building all combinations of titles and the searchwords for each class would results in a huge dataset. For example class 1 of the training data set has 2755 job titles. Thus we would have already have $\binom{2755}{2} = 3793635$ examples. Since this is computionally too expensive I randomly choose pairs of job titles. For level 1 the following samples are drawn: From the job title data for each class I used 3250 pairs. The same also for the searchwords for each class. For unsimilar pairs I used 1750 job titles pairs which are not from the same class. Same for searchwords. This results in total number of $(3250 + 3250) \times 9 + 2 \times 1750 = 62000$ pairs for the finetuning of level 1. [9]. For level 3 the procedure is the same, only the numbers differs. I used for similar pairs for job titles and searchwords 400 for each class and for the unsimilar 6000 pairs, which gives a total number of $(400 + 400) \times (136 - 7) + 2 \times 1500 = 61200$. Classes with only one example are not considered, because building pairs is not possible.

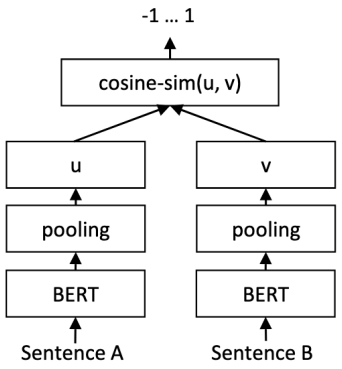


Figure 7: Sentence-BERT siamese architecture (Reimers and Gurevych, 2019, 3)

[9]The determination of the exact number of pairs is exploratory in character, and run time and performance were taken into account

4.4 Dimensionality reduction

Dimensionality reduction techniques like Principal Component Analysis (PCA) play an important role in reducing computation time and saving computing resources (Ayesha et al., 2020). Figure 8 shows the running time of all three classifiers with different data sizes and with and without PCA dimensionality reducation.

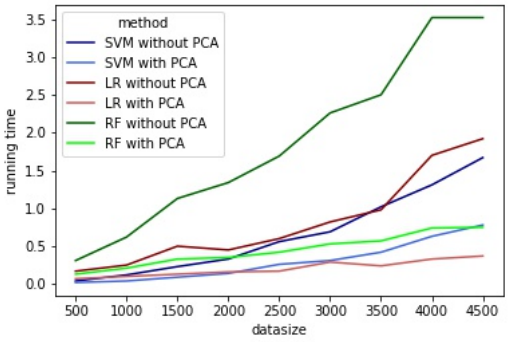


Figure 8: Running time of word2vec with different data sizes

The input of the classifiers are the word2vec word embeddings without the additional information. The bright lines show the running times without dimensionality reduction, while the dark colored lines report the running time with PCA transformation. It becomes clear that the runtime for the transformed embeddings are generally lower. While the magnitude of the differences is almost irrelevant for a data set of 500, the runtime of the non-transformed embeddings increases considerably with the size of the data set for all classifiers. This is most evident with RF. Although the runtime of the transformed embeddings also increases for all classifiers, it does so at a much slower pace. Therefore, it can be concluded that the transformation clearly contributes to keeping the runtime lower for large data sets. As already described in chapter x, the training data set is fairly large, which is why it is reasonable to reduce the dimensions.

PCA, one of the most popular technique for dimensionality reduction, aims to reduce a high-dimensional feature space to a lower subspace while capturing the most important information (Tipping and Bishop, 1999; Bisong, 2019). The main idea is to use linear combinations of the original dimensions, so called principal components, to reduce the dimensional space (Bro and Smilde, 2014; Geladi and Linderholm, 2020).

Conceptually in the first step the covariance matrix for the word embeddings, is

obtained. The covariance matrix, denoted by $\mathbf{X}$, captures the linear relationships between the features of the word embeddings. In a next step the eigenvectors of $\mathbf{X}$ are calculated. The eigenvector of X defined as (Bro and Smilde, 2014):

$$\mathbf{X}z = \lambda z$$

where z is the eigenvector and λ the eigenvalue. In order decompose $\mathbf{X}$ to get the eigenvalue Singular Value Decomposition is applied. The eigenvalues are then sorted from highest to lowest and the most significant components n are kept. To transform the data a feature vector in generated. This vector contains of the most n significant eigenvalues. After transposing the mean-adjusted the word embedding and the feature vector, the embeddings can be transformed by multiplying both transposed vectors (Smith, 2002).

4.5 Classifier

As pointed out in the literature review NB, MLR and SVM have several advantages for text classifcation tasks. In the following based on a theoretical discussion of each classifier, the exact modeling of the classifiers is justified. The focus and the depth of the explanations of the classifier's characteristics like optimization and decision function, loss or regularization depends on the complexity and the need of explanation in order to understand the basic principle of the classifiers and thus are not all equally structured.

4.5.1 Logistic Regression

MLR, a generalized linear model, is one of the most used analytical tools in social and natural science for exploring the relationships between features and categorical outcomes. For solving classification problems it learns weights and a bias(intercept) from the input vector. Figure 9 illustrate the idea of the calculation of MLR. To classify examples first the weighted sum of the input vector is calculated. For multiclassfication the weighted sum has to be calculated for each class. Thus given a $f \times 1]$ feature vector x with $[x_1, x_2, ..., x_f]$, a weight vector w_k with k indicating the class k of set of classes K, a bias vector b_k the weighted sum the dot product of w_k and $\mathbf{x}$ plus the b_k defines the weighted sum. Representing the weight vectors of each class in a $[K \times f]$ matrix $\mathbf{W}$, formally the weighted sum is $\mathbf{W}x + b$. In Figure 9 the

blue lines for example are a row in **W** and are the weight vectors related to a class labelled with 1 (Jurafsky and Martin, 2021).

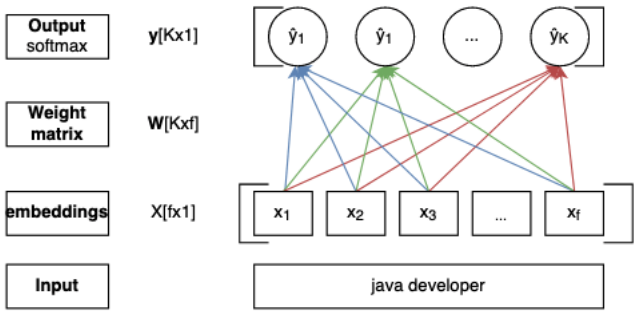


Figure 9: Multinomial Logistic Regression (edit after (Jurafsky and Martin, 2021, p.))

In a second step the weighted sums are mapped to a value range of $[0, 1]$ in order to actually classify the input. While binary logistic regression uses a sigmoid function to do so, for MLR needs a generalized sigmoid function. This generalization is called the softmax function which outputs probabilities for each of the classes, which is why MLR is also often called softmax regression in the literature. These probabilties models for each class $p(y_k = 1|x)$.

Similar to sigmoid function, but for multiple values the softmax function maps each value of an input vector z with $[z_1, z_2, ..., z_K]$ to a value of the range of $[0, 1]$. Thus outputting a vector of length z. All values together summing up to 1. Formally it is defined as:

$$softmax(z_i) = \frac{exp(z_i)}{\sum_{j=1}^{K} exp(z_j)} \; 1 \leq i \leq K$$

Then the output vector y can be calculated by

$$\hat{y} = softmax(\mathbf{W}x + b)$$

Considering the training of the weights and the bias the goal is to '"maximize the log probability of the true y labels" of the input data. This is commonly done by minimizing a generalized cross-entropy-loss function for MLR. There exists different methods for solving the optimization problem, like stochastic gradient descent or limited-memory Broyden-Fletcher-Goldfarb Shannon solver. The latter converges rapidly and is characterized by a moderate memory, which is why it can converges faster for high-dimensional data (Fei et al., 2014; Pedregosa et al., 2011).

For MLR it is common to add regularization parameter. This avoids overfitting and ensures that the model is more generalizable to unseen data. The idea is to penalize weights which have a good classifaction, but use a lot of high weights, more than weights with good classification but smaller weights. There are two popular penality term, the L1 and the L2 penalty. While for L1 the absolute values of the weights are summed and used as the penality term, L2 regualizes with a quadractic function of the weights. With the regularization a parameter C is introduced to control the strength of the regularization, with C being a positive value and smaller C regulizing stronger.

The following setting will be used for the MLR: A MLR with L2 penality with a C value of 1 is used. Since the input vectors, especially for count vectorizer and for TF-IDF are high-dimensional the limited-memory Broyden-Fletcher-Goldfarb-Shannon solver is set for solving. For some trainings converge problems appeared, which is why the maximal iteration of the classifier is set to 10000.

4.5.2 Support Vector Machines

However, SVM also performed well for text classification. Especially for multiclass tasks, as mentioned in the literature review, often different versions of the algorithm are used and showed good performance (Aiolli and Sperduti, 2005; Angulo et al., 2003; Benabdeslem and Bennani, 2006; Guo and Wang, 2015; Mayoraz and Alpaydm, 1999; Tang et al., 2019; Tomar and Agarwal, 2015). In general SVM has several advantages for text classifcation. First, text classifcation usually has a high dimensional input space. SVM can handle these large features since they are able to learn independently of the dimensionality of the feature space. In addition SVMs are known to perform well for dense and sparse vectors, which is usually the case for text classification (Joachims, 1998). Empirical results, for example Joachims (1998) or Liu et al. (2010) confirm the theoretical expectations. It is, therefore, a reasonable option to use a basic version of the SVM algorithm as a baseline.

The general idea of a SVM is to map "the input vectors x into a high-dimensional feature space Z through some nonlinear mapping chosen a priori [...], where an optimal separating hyperplane is constructed" (Vapnik, 2000, 138). In SVM this optimal hyperplane maximizes the margin, which is simply put the distance from the hyperplane to the closest points, so called Support Vectors, across both classes (Han et al., 2012). Formally, given a training data set with n training vectors

$x_i \in R^n, i = 1, ..., n$ and the target classes $y_1, ...y_i$ with $y_i \in \{-1, 1\}$, the following quadratic programming problem (primal) has to be solved in order to find the optimal hyperplane:

$$\min_{w,b} \frac{1}{2} w^T w$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1$$

where $\phi(x_i)$ transforms x_i into a higher dimensional space, w corresponds to the weight and b is the bias (Chang and Lin, 2001; Jordan et al., 2006) The given optimzation function assumes that the data can be separated without errors. This is not always possible, which is why Cortes et al. (1995) introduce a soft margin SVM, which allows for missclassfication (Vapnik, 2000). By adding a regularization parameter C with $C > 0$ and the corresponding slack-variable ξ the optimization problem changes to (Chang and Lin, 2001; Han et al., 2012):

$$\min_{w,b} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i,$$

$$\xi_i \geq, i = 1, ..., n$$

Introducing Lagrange multipliers α_i and converting the above optimization problem into a dual problem the optimal w meets (Chang and Lin, 2001; Jordan et al., 2006):

$$w = \sum_{I=1}^{n} y_i \alpha_i \phi(x_i)$$

with the decision function (Chang and Lin, 2001):

$$\text{sgn } (w^T \phi(x) + b) = sgn(\sum_{i=1}^{n} y_i \alpha K(x_i, x) + b)$$

$K(x_i, x)$ corresponds to a Kernel function, which allows to calculate the dot product in the original input space without knowing the exact mapping into the higher space (Han et al., 2012; Jordan et al., 2006).

In order to apply SVM to multiclass problems several approaches have been proposed. One stratetgy is to divide the multi-classifcation problem into several binary problems. A common approach here is the one-against-all method. In this

method as many SVM classifiers are constructed as there are classes k. The k-th classifier assumes that the examples with the k label are positive labels, while all the other examples treated as negative. Another popular approach is the one-against-one method. In this approach $k(k-1)/2$ classifiers are constructed allowing to train in each classifier the data of two classes (Hsu and Lin, 2002). Besides dividing the multiclass problem into several binary problems, some researches propose approaches to solve the task in one single optimization problem, like Crammer and Singer (2001). [10].

In order to find a strong classifier I checked SVM's with different parameters for the SVM, as well as different multiclass approaches. It appears that a SVM using a soft margin with a $C = 1$ and a one-vs-rest approach has the best results. I also test different kernels, like RBF Kernel or linear kernel. The linear kernel, formally $k(x, x') = x^T x'$, achieved the best results, which is why I choose it for the classifier.

4.5.3 Random Forest Classifier

In contrast to the previous two classifiers RF is a ensemble learning technique. The main idea of ensemble learning techniques is to create a number of learners, classifiers, and combine them. Those learners are for example descision tree or neural networks and are usually homogeneous, which means that each individual learner is based on the same machine learning algorithm. The different ensemble techniques are built on three pillars: the data sampling technique, the strategy of the training and the combination method Polikar (2012); Zhou (2009).

The first pillar, the data sampling is important in sense of that it is not desirable to have same outputs for all classifiers. Thus ensemble techniques need diversity in the output, which means the outputs should be optimally independent and negatively correlated. There are well-established methods for achieving diversity. For example bagging techniques RF falls back to boostrap (Polikar, 2012). The second pillar rises the question of which techniques should be applied to train the learners of the method. The most popular strategies for the training are bagging and boosting (Polikar, 2012). The last pillar is about the combining method. Each classifier of the method will output an individual classifcation result and those results have to be combined in some way to achieve an overall result. There are plenty of methods

[10]For a detailed overview of all different methods and the method of Crammer and Singer (2001) see Hsu and Lin (2002); Crammer and Singer (2001)

like majority voting or borda count (Polikar, 2012).

RF uses as individual classfier decision trees. Before discussing RF in more detail within the three pillars described above, a brief discussion of decision tree is given, in order to understand the mechanism and training procedure of the classifiers.

The main idea of the decision tree algorithm is to '"break up a complex decision into a union of several simple decisions" (Safavian and Landgrebe, 1991, 660) by using trees, with a root node on the top, intermediate nodes and leaf nodes on the bottom. For the root node and each of the intermediate nodes all possible splittings are checked and then are split according to the best feature. Each leaf nodes leads to one of the classification labels. Examples are then classified by traversing the tree from the top to the bottom and choosing at each intermediate node the branch which satisfy the attribute value for the example. The construction of a Decision tree is a recursive procedure (Berthold et al., 2020; Xia et al., 2008; Cutler et al., 2012). The algorithm stops for a specific node if all examples of the training set belong to the same class, or if there are no features left for splitting. This might end in tree with a high depth, which is why often pruning is applied to avoid overfitting of the tree Berthold et al. (2020).

There are two important points to discuss in constructing. First the types of splitting and second splitting criterion. There are mainly three types of splits: Boolean splits, nominal splits and continous splits. The latter chooses a particular value from the continous feature as the splitting value (Cutler et al., 2012; Berthold et al., 2020). For example considering a word embedding x with 300 dimension and a node t of a decision tree, which is split into a nodes t_{left} and t_{right}. The node t could have the split $x[209] <= 0.336$. Examples with a value smaller than or equal 0.336 at the dimension index 209 of the embedding vector are follow the branch to t_{left}, while all other examples follow the branch to t_{right}.

The splitting criterion is important to identify the best feature for splitting. Intiutively, the criterions should split the data in such a way that leaf nodes are created fast (Berthold et al., 2020). There are several measurements, so-called impurity measures to obtain the best split for each node, like gini impurity or information gain. Since RF uses gini impurity, only this criterion will be discussed in detail.

The gini value indicates the purity of a dataset D with n classes. It is defined as follows (Yuan et al., 2021, 3156):

$$Gini(D) = 1 - \sum_{i=1}^{n} p_i^2$$

p_i is th probability that a class n occurs in D. The more pure D is the lower the value of the gini value. To determine the best feature k, the dataset is partitioned based on the feature k. For continous features, as in word embeddings, this is done by continous split. Defining V as the total number of subsets and D^v as one of the subsets, the gini impurity for a feature k can be calculated as follows Yuan et al. (2021):

$$\text{Gini index}(D, k) = \sum_{v=1}^{V} \frac{|D^v|}{|D|} Gini(D^v)$$

Conceptually the Gini index is the weighted average of the gini value for each subset of D based on a feature k. Thus subsets with more samples are weighted more in the gini index. The optimal feature k^* is then determined by minimizing the Gini impurity over all features K (Yuan et al., 2021, 3156):

$$k^* = arg \min_{k \in K} \text{Gini index}(D, k)$$

.

Based on above theoretical explanations of the foundations of decision tree, researchers have developed several algorithms to train decision trees, like Iterative Dichotomiser 3, C4.5. or Classification and Regression Trees (CART), which is used in RF. CART produces depending on the target variable classification (for categorical variables) or regression trees (for numerical variables). It constructs only binary trees, thus each split is into two nodes. The algorithm uses as impurity measurement gini index and it can handle numerical and categorical input (Brijain et al., 2014).

RF belongs to the family of bagging ensemble techniques. Bagging selects a single algorithm and train a number of independent classifiers. The sampling technique is sampling with replacement (bootstrapping). Bagging combines the individual models by using either majority voting or averaging. RF differentiates from the classic bagging method in the way that it also allows to choose a subset of features for each classifier from which the classifiers can select instead of allowing them to select from the complete range of features (Polikar, 2012; Zhou, 2009; Berthold et al., 2020).

Formally Breiman (2001), who introduced mainly the RF algorithm defines the classifier as follows:

> '"A random forest is a classifier consisting of a collection of tree-structured classifiers $\{h(\mathbf{x}, \Theta_k), k = 1, ...\}$ where the Θ_k are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at the input $\mathbf{x}$." (Breiman, 2001, 6).

Θ_k is a random vector which is created for each k-th tree. It is important, that Θ_k is independent of the vectors $\Theta_1 ... \Theta_{k-1}$, thus from all random vectors of the previous classifiers. Although the distribution of the random vectors remain. Combined with the training set, with $\mathbf{x}$ as the input vector a classifier $h(\mathbf{x}, \Theta_k)$ is constructed (Breiman, 2001). In practical implementation the random component Θ_k is not explicitly used. Instead it is rather used implicitly to generate two random strategies (Cutler et al., 2012). The first strategy is the bootstrapping. Thus drawing sample with replacement from the training data set. In order to estimating generalization error, correlation and variable importance Breiman (2001) applied out-of-bag estimation. Out-of-bag estimation leave out some portion of the training data in each bootstrap. The second strategy is to choose random feature for the splitting. Thus at each node from the set of features only a subset is used to split. While decision trees are often pruned to avoid overfitting, RF does without. The trees grow by applying CART-algorithm. RF uses as combination method for classifcation unweighted voting (Cutler et al., 2012).

Based on the above explanations the implemented RF has the following setting: The numbers of learners is 100. Gini is used as the splitting criterion. The maximal number of features is $\sqrt{\text{number of features}}$. Note that sklearn, which is used to implement RF here, uses an optimised algorithm of CART. (Pedregosa et al., 2011).

5 Result

5.1 Evaluation metrics

There exists several metrics for the evaluation of classification approaches in the literature (Fatourechi et al., 2008). The choice of appropriate measurements is a crucial step for obtaining a qualitative comparison in the performance between

the baseline algorithms and the new approaches. Often researchers rely on popular metrics like overall accuracy (OA). However, especially for multiclass and inbalanced dataset tasks it is difficult to rely only on one measure like OA In order to select appropriate metrics for comparison in the following the most important metrics will be discussed focussing on multiclass classification and imbalanced data sets.

Most metrics rely on a confusion matrix. For the multiclass case this confusion matrix is defined as follows (Kautz et al., 2017):

	positive examples			
positive prediction	$c_{1,1}$	$c_{1,2}$	$\dots$	$c_{1,n}$
	$c_{2,1}$	$c_{i,j}$		
	$\vdots$		$\ddots$	$\vdots$
	$c_{n,1}$		$\dots$	$c_{n,n}$

Table 5: Confusion Matrix (edited after (Kautz et al., 2017, 113)

From the confusion matrix follows that $c_{i,j}$ defines examples which belong to class j and are predicted as class i. Based on the confusion matrix the true positives of a current class m can be defined $tp_m = c_{m,m}$, thus examples which are correctly predicted as the current class m. The false negatives are defined as those examples which not belonging to the current class m, but are predicted as k. Formally $fn_m = \sum_{i=1,i\neq m}^{n} c_{i,m}$. Next, the true negatives are examples belonging to the current class m, but are not predicted as m. Formally $tn_m = \sum_{i=1,i\neq m}^{n} \sum_{j=1,j\neq m}^{n} c_{i,j}$. Last, false positives are defined as examples not belonging to class m, but are predicted as such. Formally this can be expressed as: $fp_m = \sum_{i=1,i\neq m}^{n} c_{m,i}$ (Kautz et al., 2017)

As mentioned the OA is one of most common metric for performance evaluation. It represents how well the classifier classifies across all classes correctly. Given that N is the number of examples, formally the OA can be expressed as:

$$OA = \frac{\sum_{i=1}^{m} tp_i}{N}$$

Following the formula an accuracy of 1 means that all examples are correctly classified, while a 0 mean that each example is classified with the wrong class. (Berthold et al., 2020) Although OA is a widley used metric it is critized for favouring the majority classes, thus not reflecting minority classes appropriatly in unbalanced datasets (Berthold et al., 2020; Fatourechi et al., 2008)

Two more popular metrics are precision and recall. Precision respresents how

well the classifier detects actual positive examples among the positive predicted examples. Recall, also called sensitivity, in contrast, represents how many examples are labelled as positive among the actual positive examples (Berthold et al., 2020). For the multiclass scenario, two different calculation approaches for each of the metrics are proposed: micro and macro average (Branco et al., 2017). In the macro approach first the metric is calculated for each class m against all other classes. The average of all of them is built. Formally, given that K is the total number of classes:

$$precision_{macro} = \frac{1}{M} \sum_{i=1}^{m} \frac{tp_i}{tp_i + fp_i}$$

$$recall_{macro} = \frac{1}{M} \sum_{i=1}^{m} \frac{tp_i}{tp_i + fn_i}$$

In contrast the micro approach aggregates the values, which can be formally expressed as follows:

$$precision_{micro} = \frac{\sum_{i=1}^{m} tp_i}{\sum_{i=1}^{m} tp_i + fp_i}$$

$$recall_{micro} = \frac{\sum_{i=1}^{m} tp_i}{\sum_{i=1}^{m} tp_i + fn_i}$$

There is a trade-off between precision and recall (Buckland and Gey, 1994). The F-measure capture both precision and recall by taking the harmonic mean between both. It is calculated as follows (Branco et al., 2017; Pan et al., 2016):

$$F_{micro} = 2 \cdot \frac{precision_{micro} \cdot recall_{micro}}{precision_{micro} + recall_{micro}}$$

$$F_{macro} = 2 \cdot \frac{precision_{macro} \cdot recall_{macro}}{precision_{macro} + recall_{macro}}$$

A closer look at the formula of the micro scores shows that acutally the micro precision score and the recall score are exactly the same, since aggregating the false negatives and aggregating the false positive results in the same number. If the precision and recall are the same, it follows from the F-meausre calculation that it has to be as well similar. And even further the micro score is actually reducing to the accuracy, thus suffering from the same problem as accuracy (Grandini et al., 2020)

Since the job title classification involves multiclass classification and the descrip-

tive analysis show that the data is clearly unbalanced, at least for some classes in level 5, it is not reasonable to base the evaluation solely on the OA. Showing that micro score of precision, recall and f1 reducing to accuracy, it is important to take the macro precision, recall and their harmonic mean besides the accuarcy into account in order to capture the performance of the minority classes as well.

5.2 Experimental results

As explained at the top of this work, the results are compared on three perspectives: Vectorization techniques, classification algorithms and enrichment with additional knowledge. Table 6 and 7 show the results of level 1 for all vectorization methods. Each row denotes a vectorization technique. Each column represents a classifier. Table 6 reports the accuracy while table 7 report the macro precision(p), recall(r) and f1(F1) scores. The word2vec and doc2vec without additional knowledge training are the marked with I, the ones with additional knowledge by II. The results of the BERT deep learning model are reported separately in table 8.

	LR	**SVM**	**RF**
CountVectorizer	0.71	0.67	0.63
TFIDF	0.70	0.67	0.62
Word2Vec_I	0.52	0.51	0.60
Word2Vec_II	0.52	0.50	0.60
Doc2Vec_I	0.46	0.43	0.53
Doc2Vec_II	0.44	0.41	0.51
BERT	0.76	0.77	0.76

Table 6: Evaluation of Level 1 classification - Accuracy

Comparing the accuracy of the vectorization techniques BERT outperforms with 76% accuracy clearly the other methods. A look at the macro table 7 for BERT confirm the high performance with relative similar macro scores over all classifiers. Only in combination with RF the recall is approx. 3% lower with BERT compared to the

	LR	**SVM**	**RF**
CountVectorizer	p: 0.76, r: 0.63, F1: 0.68	p: 0.74, r: 0.58, F1: 0.63	p: 0.68, r: 0.54, F1: 0.57
TFIDF	p: 0.77, r: 0.61, F1: 0.66	p: 0.74, r: 0.57, F1: 0.62	p: 0.68, r: 0.52, F1: 0.55
Word2Vec_I	p: 0.60, r: 0.39, F1: 0.42	p: 0.51, r: 0.40, F1: 0.41	p: 0.62, r: 0.53, F1: 0.56
Word2vec_II	p: 0.61, r: 0.41, F1: 0.44	p: 0.50, r: 0.41, F1: 0.43	p: 0.60, r: 0.51, F1: 0.54
Doc2Vec_I	p: 0.43, r: 0.33, F1: 0.34	p: 0.40, r: 0.31, F1: 0.32	p: 0.69, r: 0.40, F1: 0.41
Doc2Vec_II	p: 0.43, r: 0.30, F1: 0.31	p: 0.37, r: 0.30, F1: 0.30	p: 0.49, r: 0.37, F1: 0.38
BERT	p: 0.75, r: 0.76, F1: 0.75	p: 0.76, r: 0.76, F1: 0.76	p: 0.79, r: 0.73, F1: 0.74

Table 7: Evaluation of Level 1 classification - macro

	accuracy	precision macro	recall macro	f1 macro
BERT clf level 1	0.76	0.73	0.70	0.71
BERT clf level 3	0.43	0.20	0.16	0.15

Table 8: Evaluation of Level 1 and 3 BERT deep learning model

other classifiers. Further both sparse techniques count vectorizer and TF-IDF performend quite well, especially compared to the word embedding techniques word2vec and doc2vec regardless of having additional knowldege or not for LR and SVM. Related to LR and SVM the worst performance is achieved by Doc2vec. However, word2vec also performs considerably below the sparse vectors and BERT. For example, Word2vec_I has 19% less accuracy than count vectorizer for LR. This picture is confirmed when looking at the macro table. Here the difference between Word2vec and Doc2vec compared to the sparse vectors and BERT shows up more strongly. Again for LR, in comparison with Word2vec_I, the count vectorizer performed 26% better, measured by the f1 score. A different picture is given for RF. The differences between the sparse methods and the word2vec techniques is almost vanished, while doc2vec performs again considerably lower. Finally compared to BERT all other vectorizer are performing lower taking the macro score as performance metric instead of accuracy.

The analysis of the classification algorithms confirms the ambiguous impression in the literature. While for the dense vectorization techniques LR and SVM have a really good performance, RF shows the best performance for the two word embedding techniques word2vec and doc2vec. For BERT, on the other hand, all classification algorithms turn out to be strong. The BERT deep learning model matches the performance of BERT vectorizer in combination with the traditional classification algorithms, thus shows no differences.

Concerning the last analysis dimension the focus relies on Word2vec_II and Doc2vec_II which are contain additional knowledge for the embeddings [11]. Analysing the accuracy table 7 the results of Word2vec_II are show no improvement by adding knowledge. For the doc2vec, the results are even slightly worse, which is reflected also in the macro results. The macro results for word2vec in contrast leave uncertainties. While for LR and SVM the f1 score of Word2vec_II is 2% higher than for

[11]The BERT model contains as well additional knowledge since searchwords pairs also were used for the fine tuning, but a model comparision is difficult, since BERT outperforms in general the other methods and there is no direct comparable method, which is why the focus will rely on the other two

Word2vec_I, it is the opposite for RF.

Table 9 and 10 contain the results of Level 3. Again thr results of the BERT deep learning model are reported separatly in 8. Bearing the class distribution of level 3 in mind, the problem is that a lot of classes only have one example. This leads to ill-defined precision, recall and f1 score for macro scores. Considering the formula above, if a class has zero examples, this class is set to zero, but is included in the average. In other words the macro scores have to be interpretated with caution. At the same time the accuracy still suffers from the mentioned problems of favoring classes. Nevertheless, the performance of the classifier can at least be compared, since all suffer about equally from the classes without prediction. However, not too much meaning should be given to the exact percentages of accuracy and macro scores.

	LR	**SVM**	**RF**
CountVectorizer	0.48	0.49	0.42
TFIDF	0.47	0.50	0.45
Word2Vec_I	0.29	0.17	0.35
Word2Vec_II	0.30	0.18	0.34
Doc2Vec_I	0.20	0.21	0.31
Doc2Vec_II	0.18	0.17	0.27
BERT	0.50	0.47	0.45

Table 9: Evaluation of Level 3 classification - Accuracy

	LR	**SVM**	**RF**
CountVectorizer	p: 0.41, r: 0.27, F1: 0.30	p: 0.38, r: 0.33, F1: 0.34	p: 0.36, r: 0.25, F1: 0.27
TFIDF	p: 0.36, r: 0.22, F1: 0.25	p: 0.39, r: 0.33, F1: 0.34	p: 0.39, r: 0.25, F1: 0.28
Word2Vec_I	p: 0.18, r: 0.11, F1: 0.12	p: 0.10, r: 0.06, F1: 0.06	p: 0.22, r: 0.18, F1: 0.19
Word2vec_II	p: 0.24, r: 0.14, F1: 0.17	p: 0.14, r: 0.10, F1: 0.10	p: 0.26, r: 0.19, F1: 0.21
Doc2Vec_I	p: 0.10, r: 0.05, F1: 0.05	p: 0.10, r: 0.09, F1: 0.08	p: 0.26, r: 0.14, F1: 0.15
Doc2Vec_II	p: 0.08, r: 0.04, F1: 0.04	p: 0.11, r: 0.07, F1: 0.08	p: 0.21, r: 0.11, F1: 0.12
BERT	p: 0.58, r: 0.55, F1: 0.55	p: 0.52, r: 0.50, F1: 0.50	p: 0.48, r: 0.35, F1: 0.38

Table 10: Evaluation of Level 3 classification - macro

In general the performance of level 3 is lower than of level 1, which is due to the higher number of classes and lower number of examples in the classes. In contrast to level 1 there is no noticeable difference for accuracy between BERT and the sparse vectors. But looking at the macro scores BERT has a much higher recall, and thus a higher f1 score than the other techniques. In general, while the macro results reveal for all other techniques much worse performance compared to the accuracy score, BERT is stable over all metrics. Thus, again it can be concluded

that BERT outperforms the other classifiers. Both sparse vectors performed relative equally. Comparing the sparse vectors against the word embeddings Word2vec and Doc2vec, the latters are the underdogs. Same as for level 1 Doc2vec has the worst performance.

Comparing the classifiers for level 3 shows exactly the same picture for sparse vectors and word embeddings. Sparse vectors perform better with LR and SVM, while the word embeddings have the best result with RF. In contrast to level 1, for BERT the best performance is achieved by LR on level 3 checking the metrics. Especially compared to the deep learning model, which performed much lower than BERT classifier and looking at the macro results even much worse than the sparse techniques. However, with respect to the results of BERT of LR and SVM, a peculiarity should be noted. During training, there was no convergence of SVM with BERT in a real running time. Therefore a maximal iteration of 10000 was set. But this might affected the performance of SVM. Thus one should be careful to rank LR as considerably better from a comparison between LR and SVM.

Including additional knowledge to word2vec might had a slightly effect on the performance. While the accuarcies do not differ considerably, comparing the macro results for Word2vec_II against Word2vec_I results in better f1 scores for Word2vec_II. Doc2vec_II on contrast has no differences checking the macro results and even performed worse than Doc2Vec_I taking the accuracy as the performance metric.

5.3 Deeper insight into the results

While the outstanding performance of BERT is intuitive and confirm the results of the literature, some of the results are suprising. In order to get better insights and to open the blackbox of the classifiers and the vectorization techniques at least a little bit, it is useful to look at the actual predictions of the classifiers and at the encoding of the individual classifiers.

6 Conclusion and Limitations

The problem just highlighted raises the question of whether the limitation is purely a data set quality issue. This can be clarified by an analysis including the alternative kldb ids that employers can provide in case of uncertainty.

References

Aiolli, F. and Sperduti, A. (2005). Multiclass classification with multi-prototype support vector machines. *Journal of Machine Learning Research*, 6:817–850.

Ajose-Ismail, B., Abimbola, O. V., and Oloruntoba, S. (2020). Performance analysis of different word embedding models for text classification. *International Journal of Scientific Research and Engineering Development*, 3(6):1016–1020.

Almeida, F. and Xexéo, G. (2019). Word embeddings: A survey. *arXiv preprint arXiv:1901.09069*.

Alsmadi, I. and Gan, K. H. (2019). Review of short-text classification. *International Journal of Web Information Systems*.

Angulo, C., Parra, X., and Català, A. (2003). K-svcr. a support vector machine for multi-class classification. *Neurocomputing*, 55:57–77.

Arora, M., Mittal, V., and Aggarwal, P. (2021). Enactment of tf-idf and word2vec on text categorization. In *Proceedings of 3rd International Conference on Computing Informatics and Networks: ICCIN 2020*, pages 199–209. Springer Singapore.

Aßenmacher, M., Corvonato, A., and Heumann, C. (2021). Re-evaluating germeval17 using german pre-trained language models. *arXiv preprint arXiv:2102.12330*.

Ayesha, S., Hanif, M. K., and Talib, R. (2020). Overview and comparative study of dimensionality reduction techniques for high dimensional data. *Information Fusion*, 59:44–58.

Benabdeslem, K. and Bennani, Y. (2006). Dendogram based svm for multi-class classification. *Proceedings of the International Conference on Information Technology Interfaces, ITI*, pages 173–178.

Berthold, M. R., Borgelt, C., Höppner, F., Klawonn, F., and Silipo, R. (2020). *Guide to Intelligent Data Science*. Springer, 2 edition.

Bird, S., Klein, E., and Loper, E. (2009). *Natural language processing with Python: analyzing text with the natural language toolkit*. " O'Reilly Media, Inc.".

Bisong, E. (2019). *Building machine learning and deep learning models on Google Cloud Platform*. Springer.

Bouaziz, A., Dartigues-Pallez, C., da Costa Pereira, C., Precioso, F., and Lloret, P. (2014). Short text classification using semantic random forest. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 8646 LNCS:288–299.

Branco, P., Torgo, L., and Ribeiro, R. P. (2017). Relevance-based evaluation metrics for multi-class imbalanced domains. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 10234:698–710.

Breiman, L. (2001). Random forests. *Machine learning*, 45(1):5–32.

Brijain, M., Patel, R., Kushik, M., and Rana, K. (2014). A survey on decision tree algorithm for classification.

Bro, R. and Smilde, A. K. (2014). Principal component analysis. *Analytical methods*, 6(9):2812–2831.

Buckland, M. and Gey, F. (1994). The relationship between recall and precision. *Journal of the American society for information science*, 45.

Bundesagentur für Arbeit, B., editor (2011a). *Klassifikation der Berufe 2010 Band 1: Systematischer und alphabetischer Teil mit Erläuterungen*.

Bundesagentur für Arbeit, B. (2011b). Klassifikation der berufe 2010 (kldb 2010) – aufbau und anwenderbezogene hinweise. Technical report.

Cahyani, D. E. and Patasik, I. (2021). Performance comparison of tf-idf and word2vec models for emotion text classification. *Bulletin of Electrical Engineering and Informatics*, 10(5):2780–2788.

Chang, C.-C. and Lin, C.-J. (2001). Libsvm: A library for support vector machines. *ACM transactions on intelligent systems and technology (TIST)*, 2.3:1–27.

Chauhan, N. K. and Singh, K. (2018). A review on conventional machine learning vs deep learning. In *2018 International Conference on Computing, Power and Communication Technologies (GUCON)*, pages 347–352. IEEE.

Chen, J., Hu, Y., Liu, J., Xiao, Y., and Jiang, H. (2019). Deep short text classification with knowledge powered attention. *33rd AAAI Conference on Artificial Intelligence, AAAI 2019*, pages 6252–6259.

Colas, F. and Brazdil, P. (2006). Comparison of svm and some older classification algorithms in text classification tasks. *IFIP International Federation for Information Processing*, 217:169–178.

Cortes, C., Vapnik, V., and Saitta, L. (1995). Support-vector networks editor. *Machine Leaming*, 20:273–297.

Crammer, K. and Singer, Y. (2001). On the algorithmic implementation of multiclass kernel-based vector machines. *Journal of Machine Learning Research*, 2:265–292.

Cutler, A., Cutler, D. R., and Stevens, J. R. (2012). Random forests. In *Ensemble machine learning*, pages 157–175. Springer.

Danso, S., Atwell, E., and Johnson, O. (2014). A comparative study of machine learning methods for verbal autopsy text classification. *arXiv preprint arXiv:1402.4380*.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Fatourechi, M., Ward, R. K., Mason, S. G., Huggins, J., Schlögl, A., and Birch, G. E. (2008). Comparison of evaluation metrics in classification applications with imbalanced datasets. *Proceedings - 7th International Conference on Machine Learning and Applications, ICMLA 2008*, pages 777–782.

Fei, Y., Rong, G., Wang, B., and Wang, W. (2014). Parallel l-bfgs-b algorithm on gpu. *Computers & graphics*, 40:1–9.

Geladi, P. and Linderholm, J. (2020). 2.03 - principal component analysis. In Brown, S., Tauler, R., and Walczak, B., editors, *Comprehensive Chemometrics (Second Edition)*, pages 17–37. Elsevier, Oxford.

Gonçalves, T. and Quaresma, P. (2005). Evaluating preprocessing techniques in a text classification problem. *São Leopoldo, RS, Brasil: SBC-Sociedade Brasileira de Computação*.

González-Carvajal, S. and Garrido-Merchán, E. C. (2020). Comparing bert against traditional machine learning text classification. *arXiv preprint arXiv:2005.13012*.

Grandini, M., Bagli, E., and Visani, G. (2020). Metrics for multi-class classification: an overview. *arXiv preprint arXiv:2008.05756*.

Guo, H. and Wang, W. (2015). An active learning-based svm multi-class classification model. *Pattern Recognition*, 48:1577–1597.

HaCohen-Kerner, Y., Miller, D., and Yigal, Y. (2020). The influence of preprocessing on text classification using a bag-of-words representation. *PloS one*, 15(5):e0232525.

Han, J., Kamber, M., and Pei, J. (2012). *Data Mining: Concepts and Techniques*. Elsevier Inc., 3 edition.

Hassan, A. and Mahmood, A. (2017). Efficient deep learning model for text classification based on recurrent and convolutional layers. In *2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pages 1108–1113. IEEE.

Hsu, C. W. and Lin, C. J. (2002). A comparison of methods for multiclass support vector machines. *IEEE Transactions on Neural Networks*, 13:415–425.

Jin, P., Zhang, Y., Chen, X., and Xia, Y. (2016). Bag-of-embeddings for text classification. In *IJCAI*, volume 16, pages 2824–2830.

Joachims, T. (1998). Text categorization with support vector machines: Learning with many relevant features. *European Conference on Machine Learning*, pages 137–142.

Jordan, M., Kleinberg, J., and Schölkopf, B. (2006). *Pattern Recognition and Machine Learning*. Springer.

Jurafsky, D. and Martin, J. H. (2021). Speech and language processing - an introduction to natural language processing, computational linguistics, and speech recognition. "`https://web.stanford.edu/~jurafsky/slp3/old_dec20/ed3book_dec302020.pdf`",.

Kamath, C. N., Bukhari, S. S., and Dengel, A. (2018). Comparative study between traditional machine learning and deep learning approaches for text classification. In *Proceedings of the ACM Symposium on Document Engineering 2018*, pages 1–11.

Karimi, S., Yin, J., and Paris, C. (2013). Classifying microblogs for disasters. In *Proceedings of the 18th Australasian Document Computing Symposium*, pages 26–33.

Kautz, T., Eskofier, B. M., and Pasluosta, C. F. (2017). Generic performance measure for multiclass-classifiers. *Pattern Recognition*, 68:111–125.

Khamar, K. (2013). Short text classification using knn based on distance function. *International Journal of Advanced Research in Computer and Communication Engineering*, 2:1916–1919.

Kingma, D. P. and Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Kowsari, K., Jafari Meimandi, K., Heidarysafa, M., Mendu, S., Barnes, L., and Brown, D. (2019). Text classification algorithms: A survey. *Information*, 10(4):150.

Kuang, Q. and Xu, X. (2010). Improvement and application of tf• idf method based on text classification. In *2010 International Conference on Internet Technology and Applications*, pages 1–4. IEEE.

Kulkarni, A. and Shivananda, A. (2021). *Natural language processing recipes*. Springer.

Lau, J. H. and Baldwin, T. (2016). An empirical evaluation of doc2vec with practical insights into document embedding generation. *arXiv preprint arXiv:1607.05368*.

Le, Q. and Mikolov, T. (2014). Distributed representations of sentences and documents. In *International conference on machine learning*, pages 1188–1196. PMLR.

Li, Y., Xu, L., Tian, F., Jiang, L., Zhong, X., and Chen, E. (2015). Word embedding revisited: A new representation learning and explicit matrix factorization perspective. In *Twenty-Fourth International Joint Conference on Artificial Intelligence*.

Liu, Z., Lv, X., Liu, K., and Shi, S. (2010). Study on svm compared with the other text classification methods. *2nd International Workshop on Education Technology and Computer Science, ETCS 2010*, 1:219–222.

Maglogiannis, I. G. (2007). *Emerging artificial intelligence applications in computer engineering: real word ai systems with applications in ehealth, hci, information retrieval and pervasive technologies*, volume 160. Ios Press.

Mayoraz, E. and Alpaydm, E. (1999). Support vector machines for multi-class classification. *Lecture Notes in Computer Science*, 1607:833–842.

Merchant, A., Rahimtoroghi, E., Pavlick, E., and Tenney, I. (2020). What happens to bert embeddings during fine-tuning? *arXiv preprint arXiv:2004.14448*.

Miaschi, A. and Dell'Orletta, F. (2020). Contextual and non-contextual word embeddings: an in-depth linguistic investigation. In *Proceedings of the 5th Workshop on Representation Learning for NLP*, pages 110–119.

Mikolov, T., Chen, K., Corrado, G., and Dean, J. (2013). Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

Pan, W., Narasimhan, H., Protopapas, P., Kar, P., and Ramaswamy, H. G. (2016). Optimizing the multiclass f-measure via biconcave programming. *IEEE 16th International Conference on Data Mining (ICDM)*, pages 1101–1106.

Paulus, W. and Matthes, B. (2013). Klassifikation der berufe : Struktur, codierung und umsteigeschlüssel. *FDZ Methodenreport*.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830.

Polikar, R. (2012). Ensemble learning. In *Ensemble machine learning*, pages 1–34. Springer.

Rahmawati, D. and Khodra, M. L. (2016). Word2vec semantic representation in multilabel classification for indonesian news article. In *2016 International Conference*

On Advanced Informatics: Concepts, Theory And Application (ICAICTA), pages 1–6. IEEE.

Ravichandiran, S. (2021). *Getting Started with Google BERT: Build and train state-of-the-art natural language processing models using BERT*. Packt Publishing.

Reimers, N. and Gurevych, I. (2019). Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084*.

Robertson, S. (2004). Understanding inverse document frequency: on theoretical arguments for idf. *Journal of documentation*.

Rogers, A., Kovaleva, O., and Rumshisky, A. (2020). A primer in bertology: What we know about how bert works. *Transactions of the Association for Computational Linguistics*, 8:842–866.

Rong, X. (2014). word2vec parameter learning explained. *arXiv preprint arXiv:1411.2738*.

Safavian, S. R. and Landgrebe, D. (1991). A survey of decision tree classifier methodology. *IEEE transactions on systems, man, and cybernetics*, 21(3):660–674.

Sahlgren, M. (2008). The distributional hypothesis. *Italian Journal of Disability Studies*, 20:33–53.

Sarkar, D. (2016). *Text Analytics with python*. Springer.

Sebastiani, F. (2001). Machine learning in automated text categorization. *ACM Computing Surveys*, 34:1–47.

Shah, K., Patel, H., Sanghvi, D., and Shah, M. (2020). A comparative analysis of logistic regression, random forest and knn models for the text classification. *Augmented Human Research*, 5(1):1–16.

Shao, Y., Taylor, S., Marshall, N., Morioka, C., and Zeng-Treitler, Q. (2018). Clinical text classification with word embedding features vs. bag-of-words features. In *2018 IEEE International Conference on Big Data (Big Data)*, pages 2874–2878. IEEE.

Sidorov, G. (2019). *Syntactic n-grams in computational linguistics*. Springer.

Simonton, T. M. and Alaghband, G. (2017). Efficient and accurate word2vec implementations in gpu and shared-memory multicore architectures. In *2017 IEEE High Performance Extreme Computing Conference (HPEC)*, pages 1–7. IEEE.

Singh, A. K. and Shashi, M. (2019). Vectorization of text documents for identifying unifiable news articles. *Int. J. Adv. Comput. Sci. Appl*, 10.

Smith, L. I. (2002). A tutorial on principal components analysis.

Song, G., Ye, Y., Du, X., Huang, X., and Bie, S. (2014). Short text classification: A survey. *Journal of Multimedia*, 9:635–643.

Sriram, B., Fuhry, D., Demir, E., Ferhatosmanoglu, H., and Demirbas, M. (2010). Short text classification in twitter to improve information filtering. In *Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval*, pages 841–842.

Suleymanov, U., Kalejahi, B. K., Amrahov, E., and Badirkhanli, R. (2019). Text classification for azerbaijani language using machine learning and embedding.

Sun, A. (2012). Short text classification using very few words. In *Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval*, pages 1145–1146.

Sun, C., Qiu, X., Xu, Y., and Huang, X. (2019). How to fine-tune bert for text classification? In *China National Conference on Chinese Computational Linguistics*, pages 194–206. Springer.

Tang, L., Tian, Y., and Pardalos, P. M. (2019). A novel perspective on multiclass classification: Regular simplex support vector machine. *Information Sciences*, 480:324–338.

Tipping, M. E. and Bishop, C. M. (1999). Mixtures of probabilistic principal component analyzers. *Neural computation*, 11(2):443–482.

Tomar, D. and Agarwal, S. (2015). A comparison on multi-class classification methods based on least squares twin support vector machine. *Knowledge-Based Systems*, 81:131–147.

Uysal, A. K. and Gunal, S. (2014). The impact of preprocessing on text classification. *Information processing & management*, 50(1):104–112.

Vapnik, V. N. (2000). *The nature of statistical learning theory*. Springer.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.

Vijayan, V. K., Bindu, K. R., and Parameswaran, L. (2017). A comprehensive study of text classification algorithms. pages 1109–1113. Institute of Electrical and Electronics Engineers Inc.

Wang, F., Wang, Z., Li, Z., and Wen, J. R. (2014). Concept-based short text classification and ranking. *CIKM 2014 - Proceedings of the 2014 ACM International Conference on Information and Knowledge Management*, pages 1069–1078.

Wang, J., Wang, Z., Zhang, D., and Yan, J. (2017a). Combining knowledge with deep convolutional neural networks for short text classification. In *IJCAI*, volume 350.

Wang, Y., Zhou, Z., Jin, S., Liu, D., and Lu, M. (2017b). Comparisons and selections of features and classifiers for short text classification. *IOP Conference Series: Materials Science and Engineering*, 261:1–8.

Wang, Z. and Qu, Z. (2017). Research on web text classification algorithm based on improved cnn and svm. In *2017 IEEE 17th International Conference on Communication Technology (ICCT)*, pages 1958–1961. IEEE.

Wendland, A., Zenere, M., and Niemann, J. (2021). Introduction to text classification: Impact of stemming and comparing tf-idf and count vectorization as feature extraction technique. In *European Conference on Software Process Improvement*, pages 289–300. Springer.

Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., Davison, J., Shleifer, S., von Platen, P., Ma, C., Jernite, Y., Plu, J., Xu, C., Scao, T. L., Gugger, S., Drame, M., Lhoest, Q., and Rush, A. M. (2020). Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural*

Language Processing: System Demonstrations, pages 38–45, Online. Association for Computational Linguistics.

Xia, F., Zhang, W., Li, F., and Yang, Y. (2008). Ranking with decision tree. *Knowledge and information systems*, 17(3):381–395.

Yan, L., Zheng, Y., and Cao, J. (2018). Few-shot learning for short text classification. *Multimedia Tools and Applications*, 77(22):29799–29810.

Yuan, Y., Wu, L., and Zhang, X. (2021). Gini-impurity index analysis. *IEEE Transactions on Information Forensics and Security*, 16:3154–3169.

Zhang, X., Zhao, J., and LeCun, Y. (2015). Character-level convolutional networks for text classification. *Advances in neural information processing systems*, 28:649–657.

Zhou, Z.-H. (2009). Ensemble learning. *Encyclopedia of biometrics*, 1:270–273.

Zhu, W., Zhang, W., Li, G.-Z., He, C., and Zhang, L. (2016). A study of damp-heat syndrome classification using word2vec and tf-idf. In *2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pages 1415–1420. IEEE.

A Data

A.1 Data snippet raw data


```
{
  "hashId": "-IgNS05-jeri5aZhe0_VK35Y0-6xQAoADg3b0
    MyraTI=",
  "hauptberuf": "Telefonist/in",
  "freieBezeichnung": "Telefonist / Telefonistin m/w/d"
    ,
  "referenznummer": "14469-20210617140207-S",
  "mehrereArbeitsorteVorhanden": false,
  "arbeitgeber": "aventa Personalmanagement GmbH",
  "arbeitgeberHashId": "MYRG2meMKxCjrQ9Cpl8JwgEDPbM133Z
    9iRCkolaOONo=",
  "aktuelleVeroeffentlichungsdatum": "2021-06-29",
  "eintrittsdatum": "2021-06-29",
  "logoHashId": "wMN78p7yNK_C0aJDJ77l63RVH3DCEzwJGxZk1
    ZzsUrY=",
  "angebotsart": "ARBEIT",
  "hauptDkz": "7389",
  "alternativDkzs": [
    "35082"
  ],
  "angebotsartGruppe": "ARBEIT",
  "anzeigeAnonym": false,
  "arbeitsort": {
    "plz": "10407",
    "ort": "Berlin",
    "region": "Berlin",
    "land": "Deutschland",
    "koordinaten": {
      "lat": 52.5335379,
      "lon": 13.4462856
```

```
      }
    },
    "_links": {
      "details": {
        "href": "http://jobboerse.arbeitsagentur.de/vamJB
          /stellenangebotAnzeigen.html?bencs=xZ8NQKDByg2
          g6avJgLLIrGwqlXZQi1GKNAI%2BzAoCWJ5RD6
          egZDnwqMFj%2B4AnUX6XN5nyEJ7NKSdBBr1EvlmnVw%3D%
          3D"
      },
      "arbeitgeberlogo": {
        "href": "https://api-con.arbeitsagentur.de/prod/
          jobboerse/jobsuche-service/ed/v1/
          arbeitgeberlogo/wMN78p7yNK_C0aJDJ77l63RVH3
          DCEzwJGxZk1ZzsUrY="
      },
      "jobdetails": {
        "href": "https://api-con.arbeitsagentur.de/prod/
          jobboerse/jobsuche-service/pc/v1/jobdetails/-
          IgNS05-jeri5aZhe0_VK35Y0-6xQAoADg3b0MyraTI="
      }
    }
  },
```


A.2 Trainingsdata snippet (without preprocessing) - Level 1

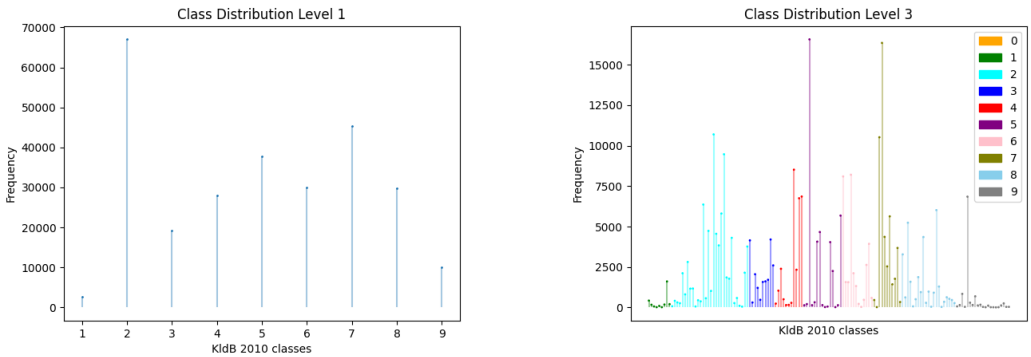

```
{'id': '2', 'title': 'Maschinenbediener (m/w/d)'}
{'id': '7', 'title': 'Controlling'}
{'id': '5', 'title': 'Lagermitarbeiter (m/w/d)'}
{'id': '2', 'title': 'Reifenmonteur (m/w/d) Facharbeiter'
  }
{'id': '5', 'title': 'Kommissionierer (m /w /d)'}
```

```
{'id': '7', 'title': 'Sachbearbeiter (m/w/d) im Einkauf Weimar'}
{'id': '5', 'title': 'Schubmaststapler Fahrer (m/w/d)'}
{'id': '3', 'title': 'Bauhelfer Elektroinstallation (m/w/d)'}
{'id': '7', 'title': 'Telefonist / Telefonistin m/w/d'}
{'id': '9', 'title': 'Telefonische Kundenbetreuung (m/w/d)'}
```

A.3 Trainingdata snippted (preprocessed) - Level 1

```
[{'id': '2', 'title': 'maschinenbediener'},
 {'id': '7', 'title': 'controlling'},
 {'id': '5', 'title': 'lagermitarbeiter'},
 {'id': '2', 'title': 'reifenmonteur facharbeiter'},
 {'id': '5', 'title': 'kommissionierer'},
 {'id': '7', 'title': 'sachbearbeiter einkauf weimar'},
 {'id': '5', 'title': 'schubmaststapler fahrer'},
 {'id': '3', 'title': 'bauhelfer elektroinstallation'},
 {'id': '7', 'title': 'telefonist telefonistin'},
 {'id': '9', 'title': 'telefonische kundenbetreuung'}]
```

A.4 Class distribution of level 1 und level 3



(a) Class distribution Level 1 (b) Class distribution Level 3

Figure 10: Class distribution of training data

B Results