Job title classification - A comparision of vectorization and classification techniques for German job postings

Masterthesis

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Abbreviations

SVM Support Vector Machine 6

NB Naive Bayes 7

MLR Multinomial Logistic Regression 31

OA overall accuracy 38

KldB Klassifikation der Berufe 2010 3

ISCO International Standard Clasification of Occupations 15

BOW Bag of Words 8

TF-IDF Term Frequency - Inverse Document Frequency 8

TF Term Frequency 20

IDF Inverse Document Frequency 20

DF Document Frequency 20

CBOW continous bag of words 2

BERT Bidirectional Encoder Representations from Transformers 2

NLP Nature Language Processing 24

PCA Principal Component Analysis 29

RF Random Forest 2

CART Classification and Regression Trees 37

CNN Convolutional Neural Network 7

KNN K-nearest neighbors 7

LR Logistic Regression 2

RNN Recurrent Neural Networks 7

1 Introduction

Job titles are key information within the labor market. They are useful for job seekers to find jobs (**?**). They are an important component of job search engines (**???**) and job recommendation systems (**?**). And lastly, they serve as a valuable data source for various analyses, such as job market trend (**??**), job perception (**??**) or social science analyses (**?**). However, since job titles are not normalized, it is challenging to structure them in an appropriate way for downstream tasks. Various institutions developed job taxonomies in order to structure and generalize job titles. Established taxonomies are, for example, the "International Standard Classification of Occupation" (ISCO) for the European job market or the "Klassifikation der Berufe 2010" (KLdB) for the German job market (Uter, 2020). Matching job titles from job postings with classes from those taxonomies is inevitable in order to improve job search engines or recommendation systems as well as analyzing the labor market. In Natural Language Processing (NLP), this process of matching is known as text classification.

Text classification, a highly researched area, is the process of classifying text documents or text segments into a set of predefined classes.

2 Related work

Domain related work

As being a useful application for many downstream task, some works for the English-language job market that deal with job classification can be found. In terms of classifiers, the corresponding work can be categorized into traditional classifiers or deep learning methods. **?** for example, use a k-nearest neighbors classifier in combination with document embedding as a feature selection strategy. **?** rely on traditional methods as well, by combining a Support Vector Machine (SVM) classifier and a k-nearest neighbors 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.

While there is extensive work on job title classification for the English speaking job market, as far as I am concerned, there have not been any classification attempts for the German job market. However, an accurate classification of job titles with the German taxonomy would facilitate several downstream tasks for the German job market. With the KldB 2010, an occupational classification was created for Germany that reflects the current trends in the labor market based on empirical and theoretical foundations. Further, most of the work about job title classification suffers from solid databases. Therefore, **?**, for example, use skills to understand the meaning of job titles and to avoid manually labelling them. **?** rely on a weakly supervised approach to get enough labelled data. The advantage of classifying for the German job market is that the Federal Employment Agency of Germany provides a data set with job titles and the possibility of linking them with die KldB classes, which offers a huge and powerful training data set which in turn allows for more flexibility in which algorithms are applicable. Following **???** the task will be framed as a text classification task.

Textclassification

During the last decades, researchers 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),SVM), K-nearest neighbors (KNN), 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 labeled data is available for the classification task in this study, 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 of feature ex-

traction since they automatically extract important features. Many comparative studies on traditional and embedding techniques 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. His results reveal a better performance of CNN over the traditional methods. Hassan and Mahmood (2017) likewise shows that CNN, but also RNN outperforms traditional methods with Bag of Words (BOW) feature extraction. These results are followed by Kamath et al. (2018). Furthermore González-Carvajal and Garrido-Merchán (2020) compared the current state-of-the-art deep learning model 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 classifiers have good results overall 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 CNN and compared them to different traditional models, like BOW or "bag-of-ngrams" with TF-IDF and LR. For the smaller and moderate size news datasets, the traditional methods except for "bag-of-means" performed well, and some of them outperformed CNN. 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 traditional methods outperformed the baseline deep learning methods for specific datasets.

Comparisons of ensemble technique, traditional methods, and methods within the traditional methods indicate that not all classifications perform equally good or poor for all tasks. A comparative analysis with LR, RF and k-nearest neighbor, using TF-IDF, for news text classification indicates a good performance of LR and RF compared to k-nearest neighbors, wherby LR performed better then RF (Shah et al., 2020). A study from biomedical classfication shows best performance of SVM among RF, NB with TF-IDF (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. In terms of transparency and interpretability, algorithms like decision tree or LR are more intuitively easier to understand and interpret. In contrast, deep learning models and SVM rely on more complex computations. Especially deep learning lacks transparency (Maglogiannis, 2007). Considering BERT although it usually outperforms other machine learning algorithms for text classification, in general "there are more questions than answers about how BERT works" (Rogers et al., 2020, 853). It is, for example, 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.

Besides the classifier, 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). 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 BOW model, are high-dimensional vectors with many zeros, while word embeddings techniques have a 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 algorithms (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) conclude that they find no clear picture between BOW models and word2vec. Comparing doc2vec and word2vec Lau and Baldwin (2016) found in general good performance of doc2vec. However, the authors admit that

the qualitative differences between both techniques are 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). Nevertheless, Miaschi and Dell'Orletta (2020) reach in their study the conclusion that word2vec and BERT code similarly for sentence-related linguistic features.

Challenges of job title classification

Each text classification task has different challenges. One challenge of the presented task is the number of classes. As **?** shows in their classification of tissues, multiclass classification is more complex than binary classification problems. Partly because most classification algorithms were designed for binary problems (**?**). Approaches for multiclassification can be grouped into two types. Either binary algorithms can handle multiclassification naturally, or the problem is decomposed 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).

Another important issue is the length of input documents for classification. Job titles are 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 make it challenging to construct features that capture the meaning of the text on the one side. 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 like Twitter deliver and process 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, these attributes play little or no role in the job title classification, especially compared to the other stated issues, since job postings are usually reviewed and

controlled thoroughly before release. Due to this reason, only research concerning the first mentioned attributes is considered in the following.

A popular approach proposed by many researchers for short text classification is to add additional knowledge to the features to improve short text classification. Many studies of Twitter short texts demonstrate the power of this approach. Karimi et al. (2013), for example, use a BOW approach for disaster classification of Twitter posts. They experiment with different features enriched by additional information. While, for example, generic features like the number of hashtags improved classification, other information like incident-specific features only helped in specific settings. All in all, the use of BOW with specific features delivers quite good performance. Similarly, Sriram et al. (2010) achieved as well with thoroughly manual extracted features from the short text good performance for Twitter short text messages.

(Wang et al., 2014) criticize the BOW approach for short text classification since BOW results usually in high dimensional data. They state that this is much more harmful to short texts because they are short and sparse. They propose a "bag of concept" approach using a knowledge base. The knowledge base is used to learn concepts for each category and find a set of relevant concepts for each short text. Following this, (Wang et al., 2017a) use as well an 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. In addition, they add character-level features.

In general, in short text classification, the question arises whether to represent the features as dense or sparse vectors. In their comparison of TF-IDF and count vectorizer against the dense vectorizer word2vec and doc2vec, Wang et al. (2017b) conclude that among the classifiers NB, LR 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 outperforms state-of-art deep learning methods, like CNN, for Chinese short texts.

Sun (2012) pursues in contrast to the mentioned approaches a completely different strategy. Instead of enriching the features, he focused the features on specific keywords. In order to select the essential keywords, he used TF-IDF approaches, some with a clarity function for each word. Using LR he got pretty good results for

his classification.

Instead of feature enrichment according to Song et al. (2014), some researchers also apply feature dimensionality reduction and extraction of semantic relationship techniques 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 LR and SVM perform best, while k-nearest neighbor seems to achieve the best accuracy in Khamar (2013)'s work. Song et al. (2014) proposes to use ensemble techniques. In combination with enriched features Bouaziz et al. (2014), for example, achieve better results as for LR with ensemble techniques. Similar to job title-specific work, more recent work prefers deep learning methods, mostly CNN (Chen et al., 2019).

Implications

There are three emerging consequences from the above-discussed literature. 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 transform 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. Instead, experimenting and exploring different traditional, deep learning, and ensemble classifiers allow for identifying the best classifier based on the task and the data (Maglogiannis, 2007). Therefore I use four classifier techniques. I fall back to two traditional methods. The literature shows that SVM and LR are well compatible with other techniques, which is why I choose both of them. I also include RF as an ensemble technique. As the last method, I implement a BERT classifier since it is the state-of-Art method currently for text classification. The evaluation of different classifications built the second pillar of the comparison.

Third, from the two challenges presented, the focus is on the classification of short texts. The literature on short text classification reveals two points. There are different results on whether sparse or dense techniques are better suited. Testing different sparse and dense vectorization techniques allows covering for that point.

Second, most of the solutions include additional knowledge. Therefore, I introduce a second model for each word2vec and doc2vec with additional knowledge from the taxonomy. The model comparison between these models built the last pillar of the comparison.

3 Job title data and taxonomy

The training data consists of two data sets. [1] The classes are extracted from the first data set, referred to below as the KldB dataset. The KldB dataset contains all information of the KldB taxonomy. The second dataset, called the job title dataset, 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 are given. The second part contains a descriptive analysis of the class distribution of the data.

3.1 KldB 2010 Taxonomy

The "KldB" dataset is structured hierarchically with five levels, with each level containing a different number of classes. The classifiers are trained for level 1 and level 3. In the following, these classes are also referred to as "kldbs". On level 1, each class has an id of length 1 with a number from 0 to 9. Table 1 shows the ten classes of level 1 with their class names. On level 2, each of the ten classes is divided into one or more subclasses having a class id of length 2, with the first digit indicating the class of level 1 and the second digit the class of level 2. An overview of all five 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. This procedure ultimately leads to class ids of length five 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 job title belongs, for example, on level 3 to the class "Sofwareentwicklung" (Bundesagentur für Arbeit, 2011a,b; Paulus and Matthes, 2013)

[1] Both datasets are provided for the study by cause&effect DFSG UG. They are not publicly available.

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))

The KldB contains two dimensions. The first dimension, the so-called "Berufsfachlichkeit", structures jobs according to their similarity in knowledge, activities, and jobs, reflected in the first four levels. Considering the example above and the job title "Fullstack PHP-Entwickler". It is reasonable to classify both on level 1 to "Naturwissenschaft, Geografie and Information" because they are related to computer science. It also makes sense to classify them, for example, to 4341 because both are about software 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 four 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 two (Bundesagentur für Arbeit, 2011a,b; Paulus and Matthes, 2013).

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))

With the KldB 2010, a valuable 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 upon the construction of the KldB. Instead

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))

of just including expert knowledge into the Taxonomy, the development process is based on systematical consideration of occupations and statistical procedures for taxonomy development. Furthermore, the taxonomy was reviewed qualitatively several times concerning professions. Considering the expressiveness, the KldB has some more benefits. Since the taxonomy is relatively recent, it reflects new job classes and market trends adequately.

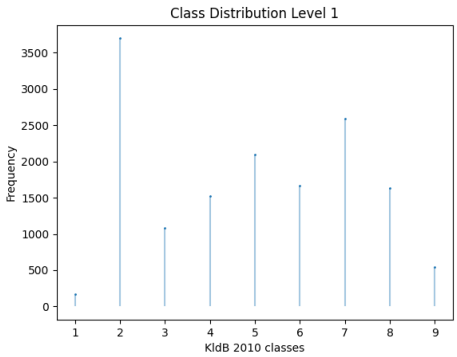
Further, the taxonomy provides a powerful tool to organize job titles into simple requirement classes by including the second dimension. In addition, the taxonomy also distinguishes between managerial, supervisory, and professional employees, which is also valuable information. Finally, the taxonomy 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 described above. Some search words are given besides the class label, the level, and the title, on level 5 for each "kldb". There are two types of keywords. First, job title search words that match the respective kldb. Second actual search words, with the help of which the associated kldb can be inferred. Therefore, these search words are beneficial knowledge for training classification algorithms because they contain "kldb" specific words that are also often present in the job titles. The search words will be termed additional knowledge in the rest of the work.

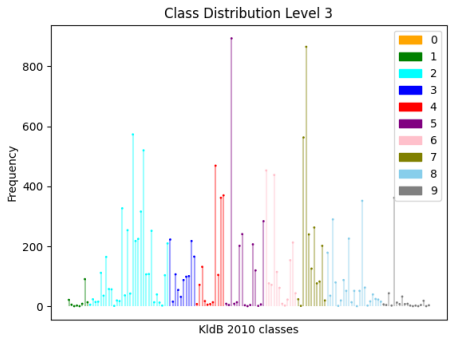
3.2 Job title data

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 an 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" is believed. An example snippet of the scraped data is provided in the appendix [2] 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 "kldbs" is given in the appendix.

[2]There are two versions of the raw data since the Federal Employment Agency changed during the scraping phase the data structure. Both versions are given in the appendix.



(a) Class distribution Level 1



(b) Class distribution Level 3

Figure 1: Class distribution of the training data

Initially, in total, the training data set contained 269788 examples. However, during the training phase, it became clear that there are problems, especially with the 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. The data is divded into training and test data, with 0.25% of the examples assigned to the test data. Figures 1a and 1b show the distribution of the classes in level 1 and level 3 [3]. Both figures show the absolute number of examples for each "kldb" in the respective levels. In figure 1b the number of examples is colored with the belonging kldb level 1 class to give a better overview of the 144 "kldbs" on level 3. In general, from both levels, it is clear that the data is not distributed equally. For the class distribution of 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 to get meaningful performance measurements. Note that "kldb" 0 is missing. 0 stands for "Militär". Jobs in this category are generally not posted frequently on the Employment Agency Job Board page, so it was not possible to get examples for this "kldb". At level 3, the uneven distribution is even more apparent. Compared to level 1, the problem is that there are many classes with only one example, which is problematic for obtaining interpretable measurements. This problem will be discussed in the results part. Eight classes do not have any examples and thus cannot be trained with the classifier.

[3]The class distribution of the long dataset is given in the appendix.

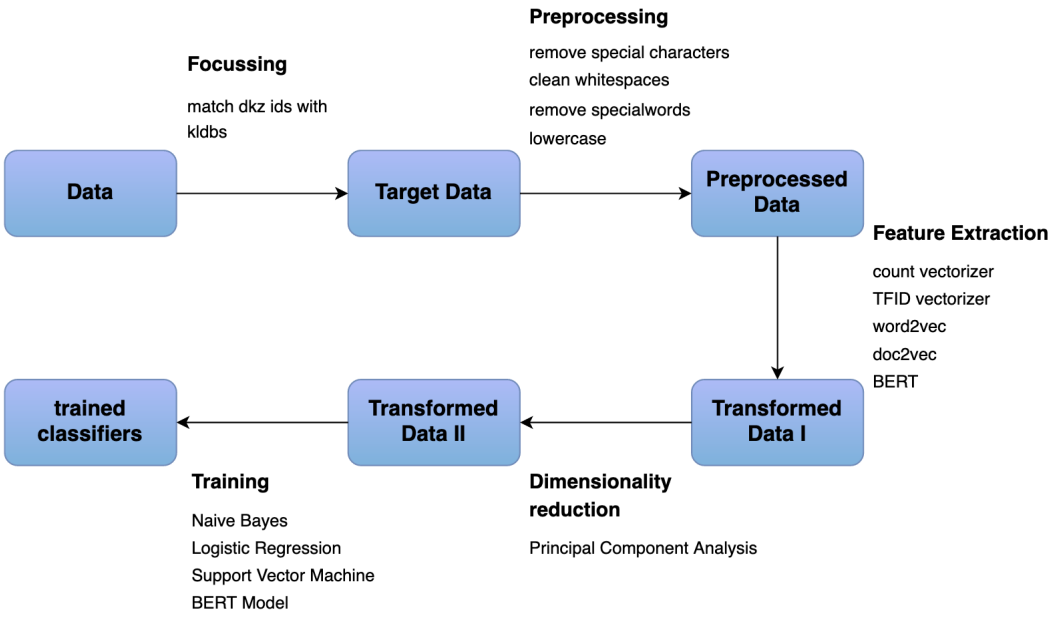


Figure 2: Training Pipeline

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 following 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 deep learning algorithm follows a different pipeline, which is why the algorithm is presented separately. Here, the data is directly input to the deep learning model after preprocessing, and the model is trained. The targeting of the data has already been described in the previous chapter. The procedure and the associated methods are explained in detail in the following.

4.2 Preprocessing

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

The first preprocessing step is removing special characters, which 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 because they are not related to specific job titles.

Capitalized words are usually converted to lowercase 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" , which can affect the performance if the differentiations play a role in the classification (Kowsari et al., 2019). Conversion makes sense for occupational names in German since capitalization plays a major role in German. In turn, I do not expect the conversion to cause problems often, as described in the example above, since occupational titles usually have specific 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, the data contained other peculiarities that justify other words removal besides stopwords. Job titles often contain words, such as "employee" or "effective immediately", that do not contain important information and are not specific to particular job titles. In order to identify such words, the frequencies of each word across all documents are calculated. 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 deleted from all job titles.

4.3 Vectorization Techniques

Count vectorizer

The count vectorizer is one of the simplest methods for 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 essential properties. First, they do not consider the order of the words, sequences, or grammar, which is why they are also called BOW. Second, each word in the corpus is represented by its own dimension. Thus the vectors contain many zeros, especially for short texts, which is why they belong to the family of sparse vectors (Ajose-Ismail et al., 2020). Assuming that a corpus contains 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)

The values for the vector are generated by counting for each text the frequency of the words occurring. 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 occurrence of the words, but not the frequency (Kulkarni and Shivananda, 2021; Sarkar, 2016)

While it is one of the most simple techniques, the 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, much information of the text is lost (Sarkar, 2016). In addition, the count vectorizer does not consider 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 that often occur in 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 occurrence of a word over all documents. By taking the inverse of DF, we get the IDF. Intuitively the IDF should quantify how distinguishable a term is. If a term is frequent over all documents, it does not help distinguish 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, 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 mentioned above, word embedding techniques are another popular approach for vectorization. Word embedding vectors are characterized by low dimensions, dense representation, and continuous 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 computationally efficient word embedding implementation. The main idea of word2vec is based on the distributional hypothesis, which states that similar words often appear in similar context (Sahlgren, 2008). Thus, word2vec learns with the help of the context representations of words, which include the semantic meaning and the context. In such a way, similar words are encoded similarly (Sarkar, 2016).

There exist two variants of word2vec. The first variant is based on BOW, the so-called 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). This study uses a pre-trained model from Google, which is trained with CBOW,. Thus in the following, the focus is on CBOW.

CBOW Word2vec is a 2-layer neural network with a hidden layer and an 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. A certain window size defines the number of context words. If the window size is 2, the two words before and after the target word are considered. Given a vocabulary V, which is the unique set of the words from the corpus, each context word c is fed into the neural network, encoded with a 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):

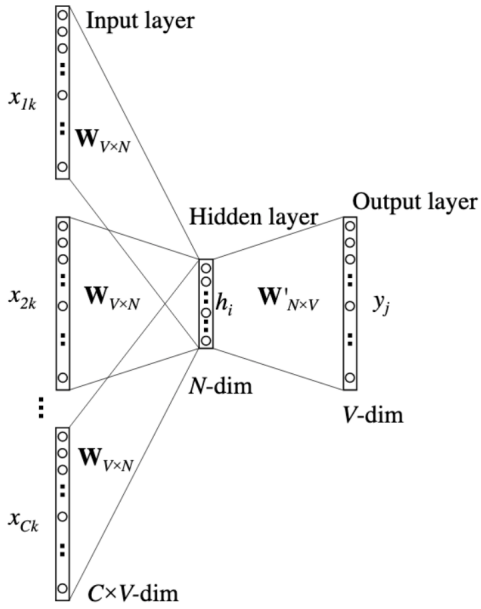


Figure 3: CBOW (Rong, 2014, 6)

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

Since the context words are encoded with one hot vector encoding, all except the respective word value in the vector, which is 1, will be 0. Thus calculating h is just copying the k-th row of matrix W, thus an 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. Calculating the error and using backpropagation, the weights are updated respectively, resulting in a trained neural network. Due to computational efficiency, word2vec is trained with hierarchical softmax or negative sampling instead of the softmax function. Both methods are efficient because they reduce the amount of weight matrix updates. [4] (Rong, 2014; Simonton and Alaghband, 2017).

Based on the given theoretical insights, I trained two word2vec models. Both models use a pre-trained model from Google and are fine-tuned with different data.

[4]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)

The first model is fine-tuned with the complete dataset. The second model includes additional knowledge. The set-up is as follows: I use CBOW Word2Vec models with a 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 pre-trained Google vectors. 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 the last step, the resulting word embeddings need to be processed in some way to get sentence embeddings for each job title. Word2vec cannot output sentence embeddings directly, which is why 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 embeddings directly 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 more extensive 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, 2014, 3). Thereby the paragraph vectors are trained 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. The neural networks take word vectors and a paragraph vector as input. While the word vectors are shared over all paragraphs, each paragraph's paragraph vectors are unique. The paragraphs are represented as unique vectors in a column of a matrix D. The word vectors are expressed 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)

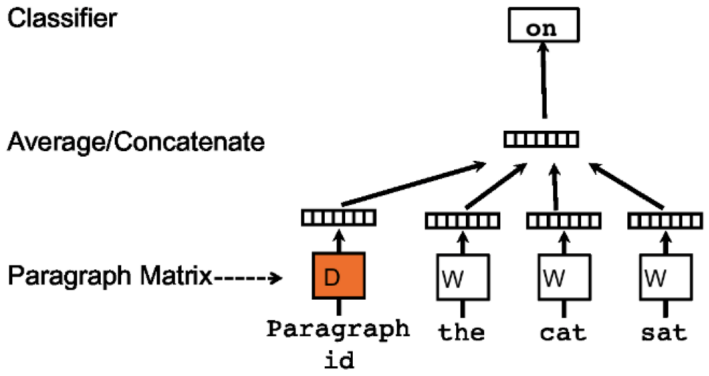


Figure 4: Doc2vec - Distributed Memory Model of Paragraph Vectors (Le and Mikolov, 2014, 3)

Since doc2vec is a word embedding method, it has the same advantages mentioned for word2vec. 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 also comes 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 discussion, I created two Distributed Memory Models of Paragraph Vectors. Instead of fine-tuning a pre-trained 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 ten 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 [5] 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 softmax function are applied in order to calculate an attention matrix Z [6]. 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”’

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

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

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).

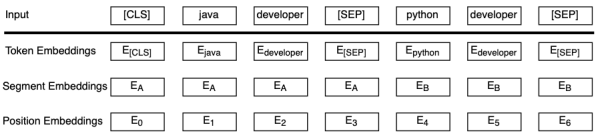


Figure 5: Input BERT (Devlin et al., 2018, 5)

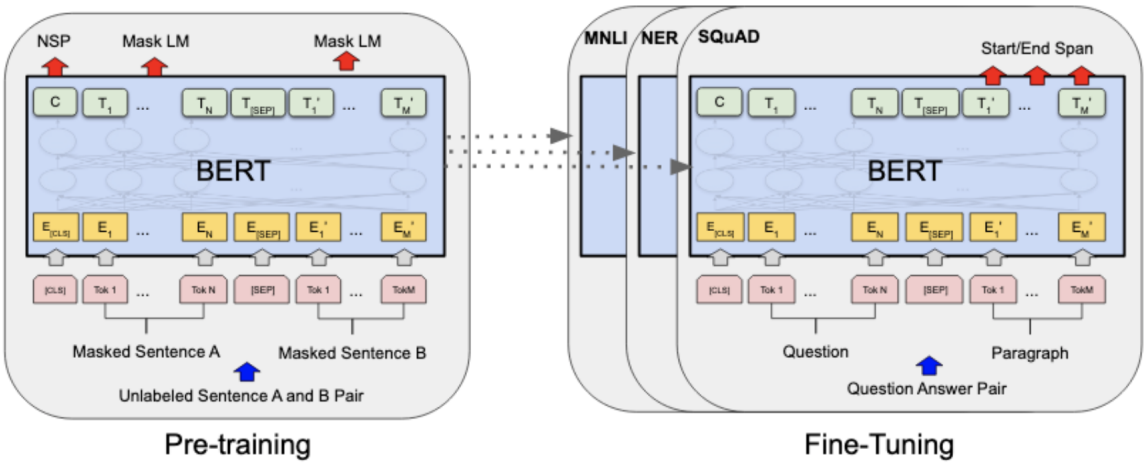


Figure 6: Overview BERT (Devlin et al., 2018, 3)

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 [7]. 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 [8]. 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 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

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

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

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 [9] (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 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

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

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. [10]. 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.

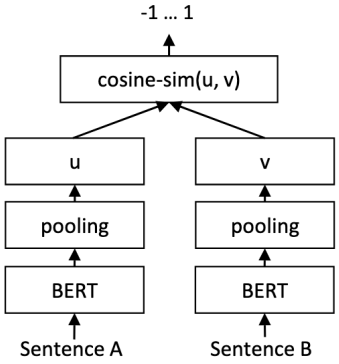


Figure 7: Sentence-BERT siamese architecture (Reimers and Gurevych, 2019, 3)

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.

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 consider-

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

ably 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

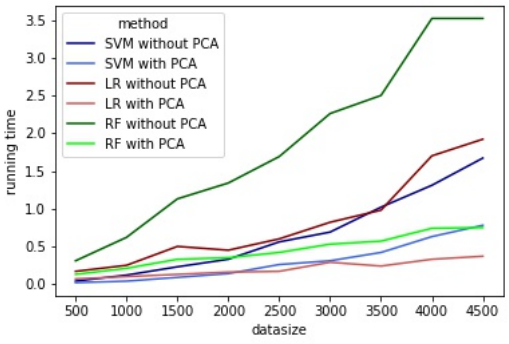


Figure 8: Running time of word2vec with different data sizes

transposed vectors (Smith, 2002).

4.5 Classifier

As pointed out in the literature review NB, Multinomial Logistic Regression (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 $\mathbf{W}$ and are the weight vectors related to a class labelled with 1 (Jurafsky and Martin, 2021).

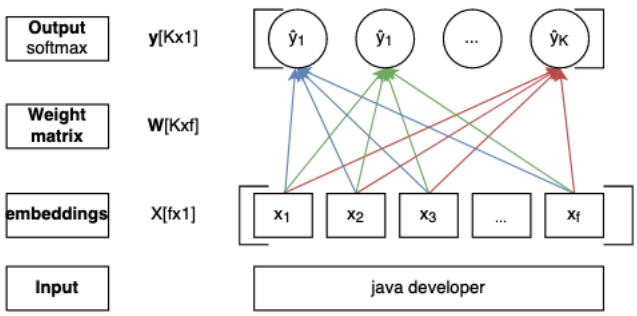


Figure 9: Multinomial Logistic Regression (edit after (Jurafsky and Martin, 2021, p.))

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). [11].

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

[11]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)

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 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 descriptive 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	0.72	0.69	0.65
TFIDF	0.72	0.69	0.65
Word2Vec_I	0.54	0.53	0.61
Word2Vec_II	0.54	0.52	0.62
Doc2Vec_I	0.48	0.46	0.56
Doc2Vec_II	0.45	0.42	0.53
BERT	0.78	0.78	0.77

Table 6: Evaluation of Level 1 classification - Accuracy

Comparing the accuracy of the vectorization techniques BERT outperforms with approx 78% accuracy clearly the other methods. A look at the macro table 7 for BERT confirms the high performance with relative similar macro scores over all classifiers. Only in combination with RF the recall and thus the f1 score is lower with BERT compared to the 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 18% 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 24% 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

	LR	**SVM**	**RF**
CountVectorizer	p: 0.76, r: 0.61, F1: 0.66	p: 0.72, r: 0.58, F1: 0.63	p: 0.66, r: 0.53, F1: 0.57
TFIDF	p: 0.77, r: 0.61, F1: 0.65	p: 0.73, r: 0.58, F1: 0.62	p: 0.67, r: 0.53, F1: 0.57
Word2Vec_I	p: 0.58, r: 0.39, F1: 0.42	p: 0.46, r: 0.40, F1: 0.41	p: 0.58, r: 0.52, F1: 0.54
Word2vec_II	p: 0.59, r: 0.41, F1: 0.45	p: 0.48, r: 0.41, F1: 0.43	p: 0.59, r: 0.53, F1: 0.55
Doc2Vec_I	p: 0.51, r: 0.33, F1: 0.35	p: 0.41, r: 0.33, F1: 0.34	p: 0.59, r: 0.40, F1: 0.43
Doc2Vec_II	p: 0.54, r: 0.30, F1: 0.32	p: 0.37, r: 0.30, F1: 0.31	p: 0.55, r: 0.38, F1: 0.40
BERT	p: 0.76, r: 0.76, F1: 0.76	p: 0.75, r: 0.77, F1: 0.76	p: 0.78, r: 0.72, F1: 0.74

Table 7: Evaluation of Level 1 classification - macro

	accuracy	precision macro	recall macro	f1 macro
BERT clf level 1	0.76	0.71	0.71	0.71
BERT clf level 3	0.44	0.20	0.18	0.17

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

compared to BERT all other vectorizer are performing lower taking the macro score as performance metric instead of accuracy. Note that doc2vec has ill-defined scores for LR and RF and word2vec for SVM since they have no predictions for the class 1. Considering the formula of macro score 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 for these vectorization techniques in combination with the respective classifiers.

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 [12]. 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, but not remarkable. The macro results for word2vec shows sligthley better performance adding knowledge for SVM and LR, but for RF this improvement is almost disappeared.

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, thus there are often zero predictions for a lot of classes over all classifiers and vectorization methods. This leads as for level 1 to ill-defined precision, recall and f1 score for macro scores. At the same time the accuracy still suffers from the mentioned problems of favoring

[12]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 the BERT deep learning model was trained differently and allows no direct comparison

classes. Nevertheless, the performance of the classifier can at least be compared, since all suffer about equally from the classes without predictions. However, not too much meaning should be given to the exact percentages of accuracy and macro scores.

	LR	**SVM**	**RF**
CountVectorizer	0.50	0.52	0.44
TFIDF	0.48	0.53	0.45
Word2Vec_I	0.30	0.15	0.36
Word2Vec_II	0.30	0.20	0.35
Doc2Vec_I	0.19	0.19	0.30
Doc2Vec_II	0.16	0.16	0.27
BERT	0.50	0.46	0.45

Table 9: Evaluation of Level 3 classification - Accuracy

	LR	**SVM**	**RF**
CountVectorizer	p: 0.41, r: 0.27, F1: 0.30	p: 0.40, r: 0.34, F1: 0.35	p: 0.36, r: 0.25, F1: 0.28
TFIDF	p: 0.40, r: 0.23, F1: 0.27	p: 0.39, r: 0.33, F1: 0.35	p: 0.39, r: 0.26, F1: 0.29
Word2Vec_I	p: 0.18, r: 0.12, F1: 0.12	p: 0.08, r: 0.06, F1: 0.05	p: 0.24, r: 0.19, F1: 0.20
Word2vec_II	p: 0.25, r: 0.14, F1: 0.17	p: 0.13, r: 0.11, F1: 0.10	p: 0.27, r: 0.20, F1: 0.22
Doc2Vec_I	p: 0.11, r: 0.05, F1: 0.05	p: 0.12, r: 0.09, F1: 0.09	p: 0.22, r: 0.13, F1: 0.14
Doc2Vec_II	p: 0.09, r: 0.04, F1: 0.04	p: 0.11, r: 0.07, F1: 0.08	p: 0.19, r: 0.11, F1: 0.12
BERT	p: 0.58, r: 0.51, F1: 0.53	p: 0.52, r: 0.48, F1: 0.48	p: 0.48, r: 0.33, F1: 0.36

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 metrices. 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 the BERT vectorization 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 reveals no noticeable improvement for LR and RF. For SVM there seems to be slight improvement. The trend of macro results across all classifiers seem to confirm the improvement, although for RF the improvement is not too high and should not be given too much attention due to the ill-defined scores. The same problem applies to Doc2vec. Roughly compared, there is no difference between Doc2vec_I and Doc2vec_II. However, a slightly poor performance of Doc2vec_II with some classification algorithms becomes apparent.

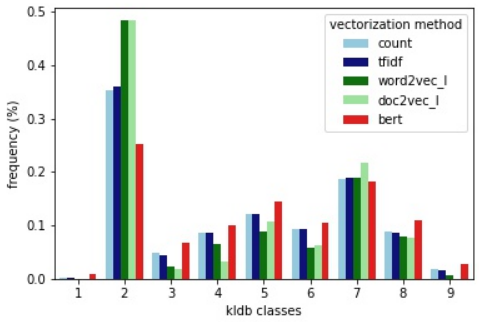
5.3 Deeper dive into the results

Looking at the results, we see some trends emerging. Comparing the vectorization techniques in both Level 1 and Level 3, BERT vectorizer has the best performance. The sparse ones perform better than the embedding techniques word2vec and do2vec for LR and SVM, while for RF there is not much difference. Doc2vec everywhere performs the worst. Concerning the classifiers RF has lower performance overall, but better performance for Word2vec and Doc2vec compared to their results for LR and RF. While the deep learning model for level 1 has comparable, but lower performance to BERT vectorization it slips down to the performance of sparse vectors at level 3. Finally, the additional knowledge seems to lead to slightly better results for word2vec except for RF for level 1. Doc2vec in contrast show often sligthley better results without adding the knowledge. One further noticebale result is that macro results are often worse than accuracy, except for BERT. All these trends require explanation. 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.

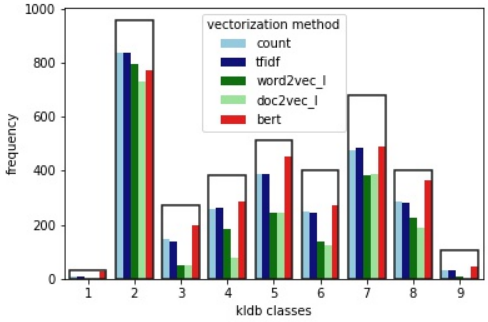
Possible explanation for Level 1 results

For this purpose, the predictions of the test data set are used. In a first step, the predictions for all methods and all classifiers are obtained. Then the distribution of the class labels is analyzed to find possible patterns. The left-hand side of figure 10 shows the share of prediction labels of LR for all vectorization techniques expect the ones with additional knowledge. The highest share of predictions falls on class two "Rohstoffgewinnung, Produktion und Fertigung" for all methods. The interesting aspect is that the share of the two embedding techniques word2vec and docv2vec is about the same, but much higher than for the other methods. Likewise, the sparse vectors form a group and have a substantially higher share than BERT. If we look at the proportions of BERT, the labels are more evenly distributed. There are two possible explanations for this. Either class 2 is indeed represented in such a high proportion in the test data set and word2vec and doc2vec have led to better recognition, or the classifiers are more or less biased towards class 2, depending on the method. Since the class distribution in Figure 1a shows that the data is imbalanced in favor of class 2 it is likely that the classifiers are biased. To shed light on this, one can additionally look at the correct predictions. The right-hand side of Figure 10 shows the correct predictions for each method for LR, as well as the number of true labels for each class. At first glance, it looks like the classifiers predicted class two very well, especially compared to BERT. However, for the other labels the two embedding techniques doc2vec and word2vec have a much worse performance compared to the other methods, which is an indices for the bias. The situation is similar for the sparse vectors compared to BERT. It is obvious that the good performance for class two is not due to the good differentiation of class two, but to the fact that simply a very high proportion of predictions lay in class two.

To evidence further the bias, it is interesting to look at the predictions of class label two in comparison to the true labels. For this purpose, the confusion matrix as explained in 5 can be considered. Figure 11 shows the confusion matrices for all methods without additional knowledge. Also TF-IDF is left out, because the sparse vectors behave relatively similar. Thus it is enough to check one of the techniques. The x-axis represents the predicted labels and the y-axis the real labels. For doc2vec and word2vec, a vertical line is visible at the predicted label 2. This line shows that both methods very often classified labels as two, although in reality they belong to

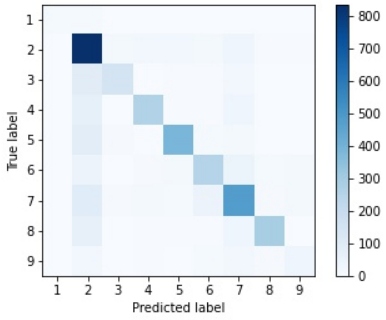


Share of predictions labels for level 1 - LR

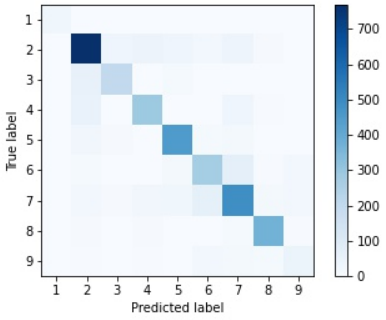


Frequency of correct predictions for each labels and frequency of true labels - LR

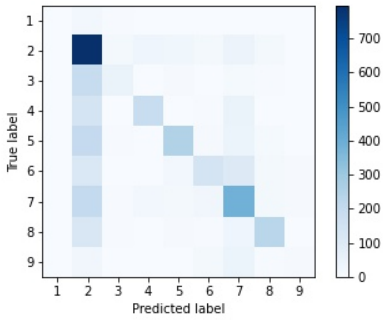
Figure 10: Confusion matrices - LR



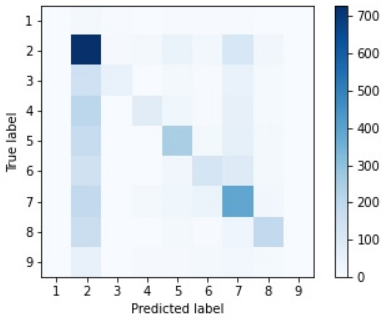
Count Vectorizer



BERT

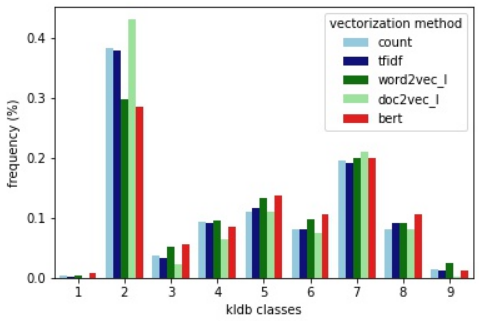


word2vec_l

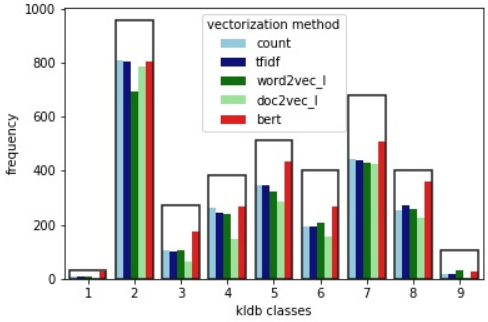


doc2vec_l

Figure 11: Confusion matrices - LR



Share of predictions labels for level 1 - RF



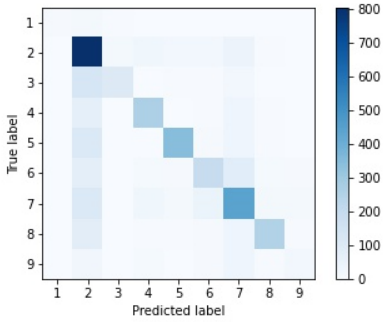
Frequency of correct predictions for each labels and frequency of true labels - RF

Figure 12: Confusion matrices Level 1- RF

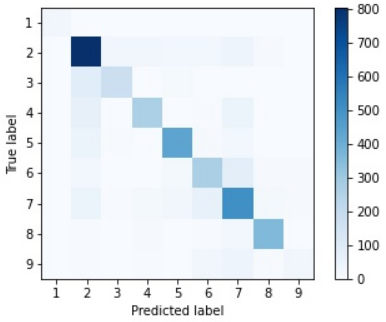
any of the other labels, which they did not do for the other labels. For doc2vec, this vertical line is even clearer. The count vectorizer also has a stronger vertical line compared to BERT, while BERT seems to have treated all labels to the same extent. Figure 11 thus again provides strong evidence for the bias.

SVM shows exactly the same picture as LR. The corresponding plots are in the appendix. In contrast RF behaves differently. Figure 12 shows the share of predictions on the left-hand side and the frequency of correct predictions on the right-hand side. While the sparse techniques almost maintain their share of label predictions, word2vec shows a significant drop in the share of predictions for 2. It is also lower for doc2vec, but not to the same extent. Looking at the right figure, we can conclude that the sparse techniques and word2vec have the same number of predictions for almost all labels and are closer to BERT. Doc2vec classifies as already for LR label 2 very well, because the share of predictions for 2 is generally higher, but underestimates the other labels. From Figure 18, no clear bias can be inferred for the sparse techniques and word2vec. However, it is clear that there seems to be no difference between the methods. The confusion matrices show that there is no difference between word2vec and count vectorizer, but there is a slight favoritism for label 2. Meanwhile, doc2vec shows a clear favoring of label 2. BERT remains unchanged.

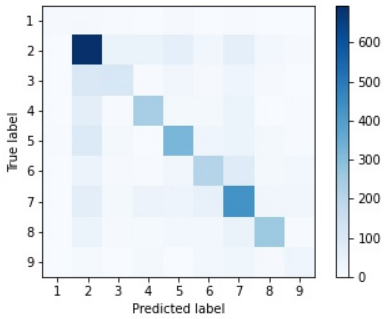
Now the question is, how does the results of this analysis is related to performance in tables 6 and 7? Considering the literature to imbalanced data in principle, it provides a possible explanation for the different performances. In their research Padurariu and Breaban (2019) compared imbalanced text data with several vector-



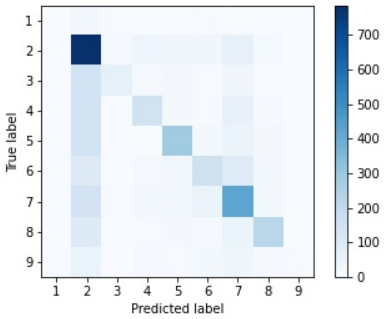
Count Vectorizer



BERT



word2vec_I



doc2vec_I

Figure 13: Confusion matrices Level 1 - RF

ization and classification techniques. They conclude for small datasets that sparse techniques are not as biased as complexer techniques, like doc2vec. Furthermore the classifiers plays as well a role. Decision trees can handle imbalanced data better than linear techniques like SVM and LR. Systematic reviews and empirical studies confirm the better handling of imbalanced data by decision trees and RF (Kaur et al., 2019; Muchlinski et al., 2016; Krawczyk, 2016).

In line with this literature, the above analysis also shows that the sparse vectors are not as affected by the bias as word2vec and doc2vec for the linear classifiers. This is reflected in the scores of LR and of SVM in Table 6 and 7 and would explain the better performance compared to word2vec and doc2vec. BERT, which is not affected by the bias, accordingly performs better. Furthermore, although the bias in RF is present, all methods are affected by it to a similar extent except doc2vec. This explains the disappearance of the differences in scores between the sparse techniques and Word2vec and the persistent poor performance of Doc2vec. At the same time, it also explains that Word2vec and Doc2vec perform better overall with RF because RF can handle imbalanced data better and since the two methods

are more affected by bias overall, this has had a positive effect on their performance. Although there seem to be a little difference in the confusion matrix of BERT the outstanding performance of BERT with RF cannot be explained completley by the analysis above.

Besides this, the analysis does not explain the generally better performance of LR and SVM compared to RF. In fact, based on the imbalanced data, one would expect RF to perform overall better. In the end, the following applies here: There is no free lunch. Some classifiers simply work better on certain data. Considering the deep learning BERT confusion matrix in figure 14, there seems to be no bias problem, which leaves the question why does BERT vectorizer with LR works better? One explanation is the difference in the size of the data. The BERT was trained with much more data. The deep learning model probably perform better with the long dataset. But on the on the other side, the interpretability and transperancy is lower compared to the BERT vectorizer. As explained for the vectorizer I controlled which pairs with which similarity are given as input to train, which makes is much more intuitvely than the deep learning model, which extract automatically the features.

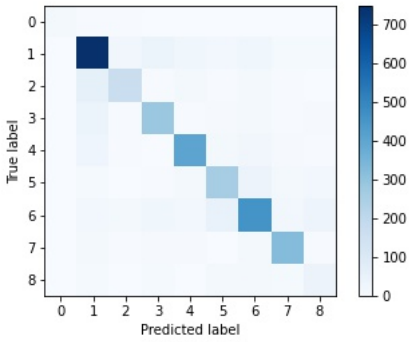
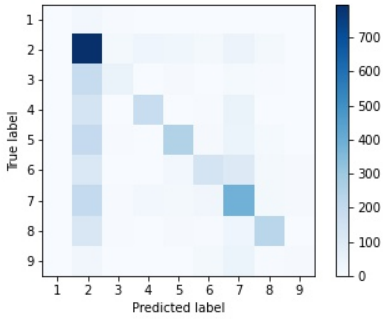
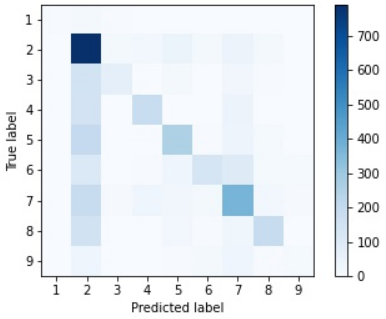


Figure 14: Covariance Matrix of BERT - Level 1)

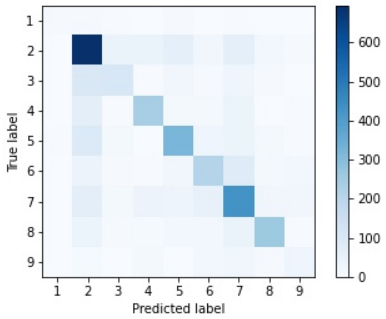
Considering the last comparison perspective still it is unexplained why doc2vec_II performed lower and word2vec_II performed slightly better. 15 and 16 report the corresponding confusion matrices for LR and RF respectivley. The share of predictions and the correct predictions are reported in the appendix. Considering word2vec there are no considerable differences. Both models seem to be biased in the same extent for LR. Same for RF. Thus the light variation between the both models might be due to the additional knowledge. In contrast the doc2vec_II has more predictions with label 2 acutally belonging to other labels. Therefore, the additional knowledge in the doc2vec model might be somewhat more biased or adding the



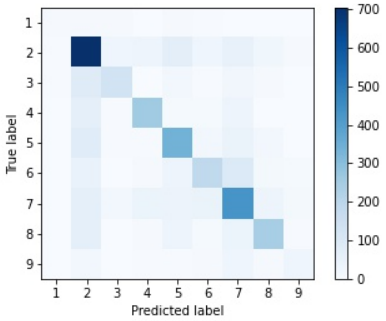
word2vec_I LR



word2vec_II LR



word2vec_I RF



word2vec_II RF

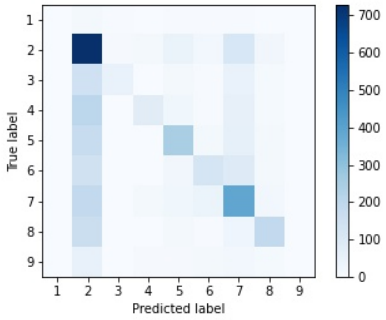
Figure 15: Confusion matrices word2vec with and without additional knowldege Level 1

additional knowledge is harmful for the doc2vec vectorizer.

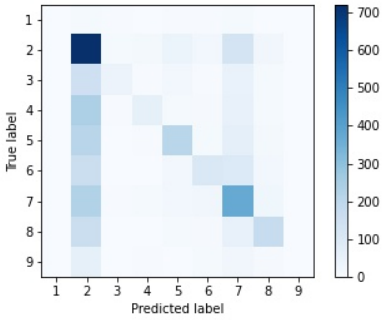
Possible explanations for Level 3 results

Considering figure 1a and the fact that level 3 reveals quite the same trends for the classifiers and methods as level 1, it is suggestible that the classifiers of level 3 suffer from the same problem. However, the considerable higher number of classes makes it challenging to examine the bias visually as was done for level 1 for the first two analyses. Instead only the confusion matrices are investigated.

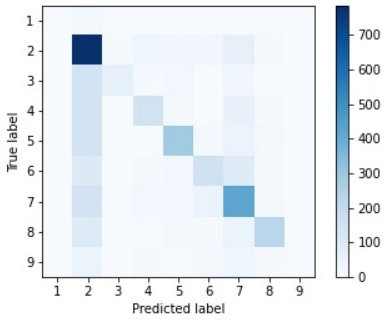
According to the trends and results for level 1, it is expected that the classifiers LR and SVM in combination with the sparse techniques as well as word2vec and doc2vec show a tendency towards imbalanced labels. This bias should be more apparent with doc2vec and word2vec. BERT, in comparison, should be less biased or not biased at all. Figure 17 shows the respective confusion matrices. For readability the class labels are removed. The predicted labels for word2vec and doc2vec indeed show clearly two vertical lines, which indicates a bias. While for count vectorizer for one label the predictions seems as well biased, BERT again does not suffer from



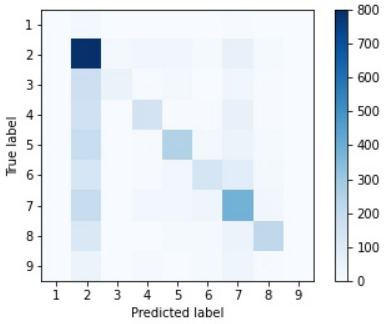
doc2vec_I LR



doc2vec_II LR

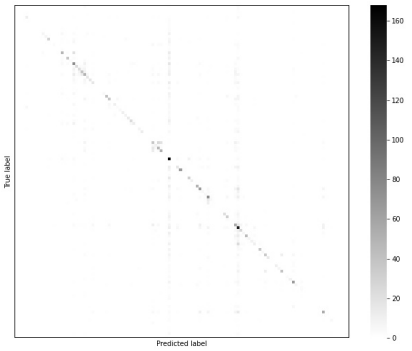


doc2vec_I RF

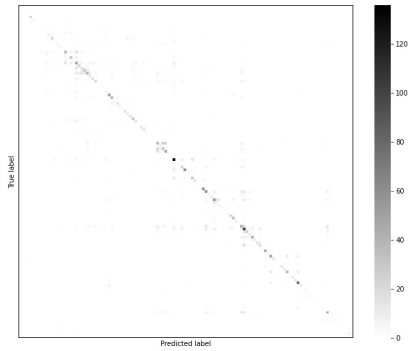


doc2vec_II RF

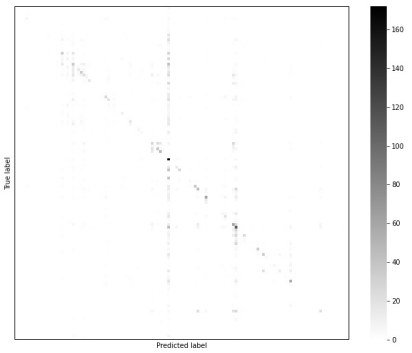
Figure 16: Confusion matrices doc2vec with and without additional knowldege Level 1



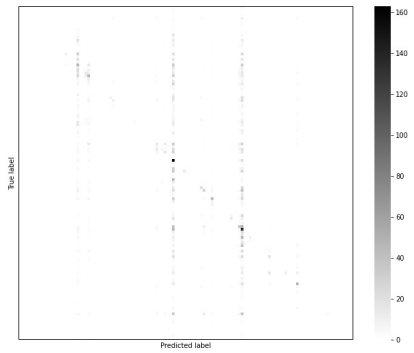
Count Vectorizer



BERT



word2vec_I

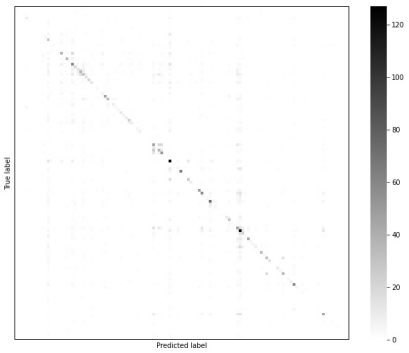


doc2vec_I

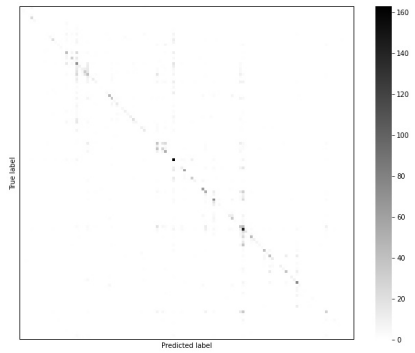
Figure 17: Confusion matrices Level 3- LR

the imbalancement of the training data. Further comparing the confusions matrices of level 1 over all classifiers to level 3 LR matrices, the diagonal line, except of for BERT is not clearly visible and for doc2vec not recognizable. This shows again the poor performance of the sparse techniques, word2vec and doc2vec for level 3 and in comparison the outstanding performance of BERT.

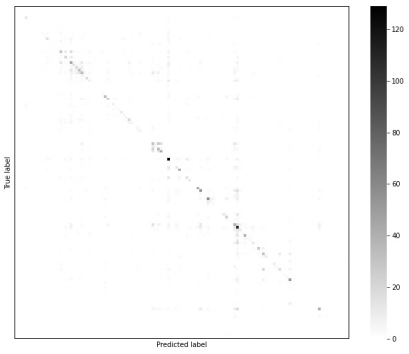
Similar to level 1 the performance for RF is, due to the better handling of imbalancement, better for word2vec and doc2vec, which is reflected in their confusion matrices in figure 18. While the performance of word2vec and doc2vec are closer to the sparse techniques for RF than for the linear techniques, the confusions matrices not clearly show differences. In addition it is interesting that BERT has a considerably better performance with RF, while the confusions matrices does not have substantial differences in terms of the bias. Thus, the differences between the results for RF remain unexplained by the analysis.



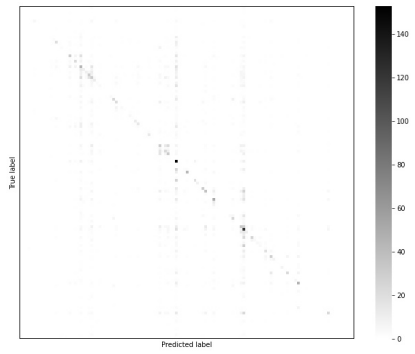
Count Vectorizer



BERT



word2vec_I



doc2vec_I

Figure 18: Confusion matrices Level 3- RF

As for level 1 the generally lower performance for RF for BERT cannot be explained by the analysis and is probably due to fact that RF is not as suitable for the application as LR and SVM. More interestingly is the low performance of the deep learning model. Figrue 19, however, shows no differences. As mentioned above for level 1 the fact that the deep learning model was trained with much lower data might have an greater impact for a classification problem with much more labels. The pairs for the vectorization are also choosed tailored specifically for level 3. Following the literature, this might be a better strategy than using a deep learning model with automatic feature selection for a small dataset.

The additional knowledge models behave similar as for level 1. The confusion matrices do not provide any remarkable differences. The additional knowldege seems to help word2vec perform slightley better, while for doc2vec this seems harmful.

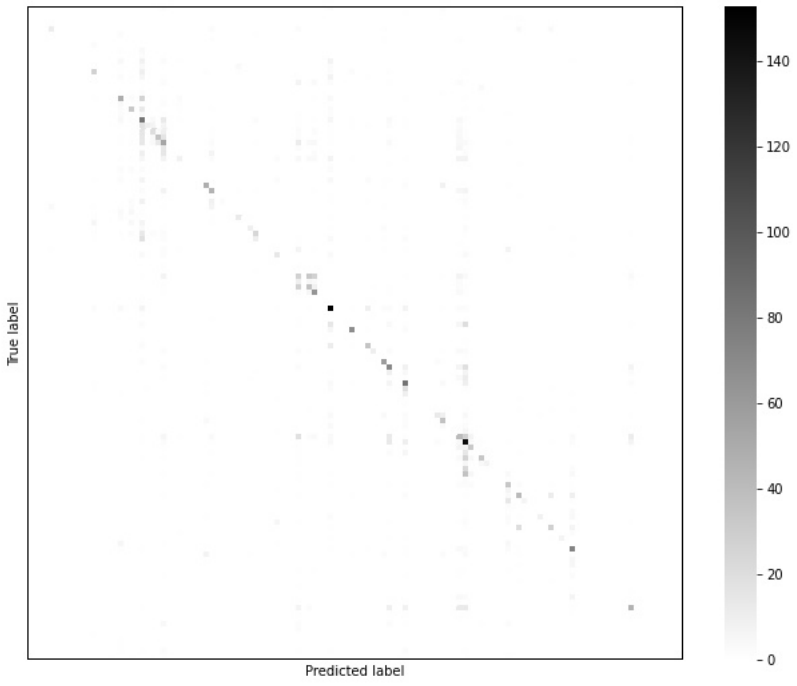


Figure 19: Confusion matrix BERT deep learning model - Level 3

6 Conclusion and Limitations

The starting point of this work was to examine the classification of job titles of German job postings with the taxonomy KldB 2010. Based on the literature on text classification and the challenges of short text classification, the analysis was guided by three pillars: Application of different vectorization techniques, training of different classification algorithms, and treatment of short job titles by adding additional knowledge.

The results revealed some interesting trends. BERT vectorization techqniue in combination with LR has the best performance. Due to imbalanced data, the other classification algorithms have developed a label bias in different settings, both for level 1 and level 3. Random Forest can reduce this bias for Doc2vec and Word2vec, but not to the extent that it overpowers the results of the sparse vectors or of BERT, especially in combination with the linear classification algorithms. The deep learning model of BERT performs overall and especially for level 3 considerably worse than BERT vectorizer in combination with LR. Adding additional knowledge does not give clear improvement. The word2vec performance seems to improve slightly, while that of doc2vec deteriorates slightly.

It can be concluded from this study that due to the stability of the BERT algorithm against the imbalanced data, as well as over all classification algorithms, the BERT vectorizer in combination with LR is promising method for the classification of job titles into the kldb classes. The possibiltiy of controlling which pairs are used as input for the fine tuning gives the BERT vectorizer in addition the advantage of being interpretable and transparent. Furthermore there is much space for improvements with this vectorizer method. Future research might combine pairs in other ways, like including the label names of the kldbs or combine searchwords for different levels with different probabilities. This produces huge datasets with millions of pairs for the fine tuning process.

There are three major limitation in this study. The first limitation concerns the dataset. As detailed in the discussion of the results, the imbalancement of the data has been problematic for most methods. Especially for level 3, where many classes have few to no examples, this was reflected in the performance. Due this fact, it was also not possible to train all classes of the taxonomy. In total, only 8 out of the 144 classes on level 3 were not trained. For level 1 class 0 could not be trained.

In addition, this problem led in part to ill-defined metrices, which allowed partly only a cautious interpretation of the performance. Regarding the dataset, also in this work only a small version of the dataset could be used due to computational resources. It is expected especially for the deep learning model that a larger dataset could improve the results. It will be important that future research investigate how to cope with the imbalancement of the data in order to recompare the vectorization methods without the bias problem. Another strategy would be to enrich the data manually by examples for minority classes. This would be also important to ensure the training of all classes.

The second limitation addresses the question of generalization. Often the problem is that the classifiers are overfitted to the training data. To ensure that the performance is measured on unseen data, the data was divided into a training and test data. However, since not all classes are trained, the classifiers are not able to classify titles belonging to those missing classes, restricting the generalization of the algorithm. In addition the classifiers are not multilingual and thus not generalizable to job postings than German.

Lastley concerning the additional knowledge there is more way for improvement. As shown in the literature there are several techniques for dealing with short texts except of including additional knowldege in the way it was done in this study. As BERT being a promising technique, one could combine and compare different BERT algorithms with additional knowledge. For example, Ostendorff et al. (2019) use an approache of enriching BERT with knowledge graph embeddings. This is an interesting topic for future work.

One last point regarding kldbs should be stated. Considering the occupation sofware developer, figure 20 shows the kldbs that are assigned to the title with the terms 'softwareentwickler' or 'softwareentwicklerin" in the training dataset. Most of the titles belong to '434", but approx 30% are assigned to other kldbs. Comparing the titles in the different kldbs besides the word 'softwareentwickler" most of the titles do not contain other keywords which would differentiate between the kldbs, are the same, or just are consist of the word 'softwareentwickler". Thus, the data is ambigious for some occupations and some kldbs making it impossible for a classifier to differentiate between the kldbs. This reveals the complexity of the problem and also the limitations of improvements in the performance.

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. The heatmap in 21 shows on the horizontal line the kldbs which were used for the training and on the vertical line the the alternative kldbs. Considering again the main kldb 431, the vertical line which emanates from the kldb indicates that in the real world it is not clear at all to what kldb a title might belong. [13] This raises the question whether it is adequate to develop a classifier with only one class as an output. At the same time, one should elaborate whether a multilabel classification algorithm is usful anymore for downstream tasks of this domain. In addition there are concerns about appropriate evalution measurements. This may constitute the object of future studies.

[13]Note that this analysis is on the long data set, not on the short one. This due to illustration purposes to highlight the problem. However, since a sample with the same distribution was drawn the logic is the same.

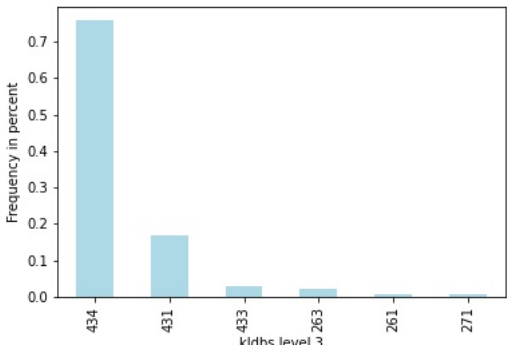


Figure 20: Share of kldbs for the occupation ‘softwareentwickler”

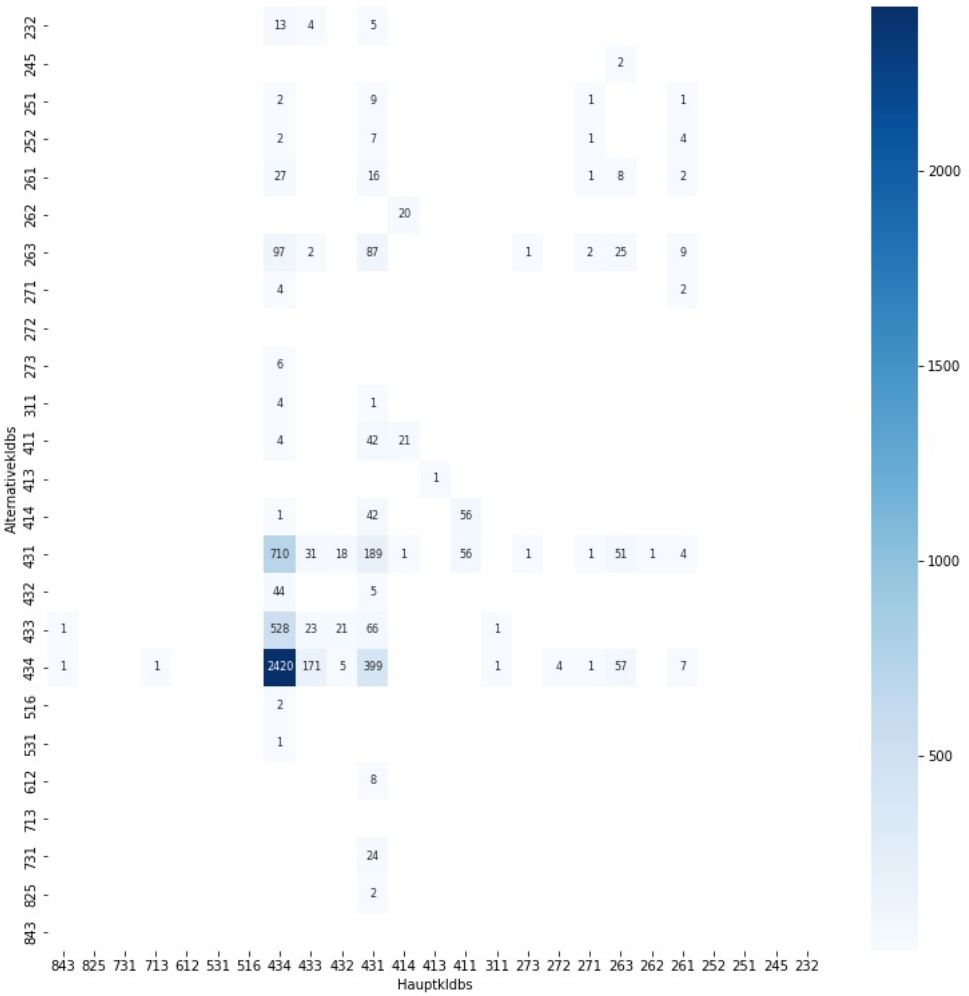


Figure 21: Co-occurence matrix for the occupation ‘softwareentwickler”

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A Data

A.1 Data snippet raw data


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  "freieBezeichnung": "Telefonist / Telefonistin m/w/d"
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  "eintrittsdatum": "2021-06-29",
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  "hauptDkz": "7389",
  "alternativDkzs": [
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    "ort": "Berlin",
    "region": "Berlin",
    "land": "Deutschland",
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      "lon": 13.4462856
```

```
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    },
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          3D"
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      },
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          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

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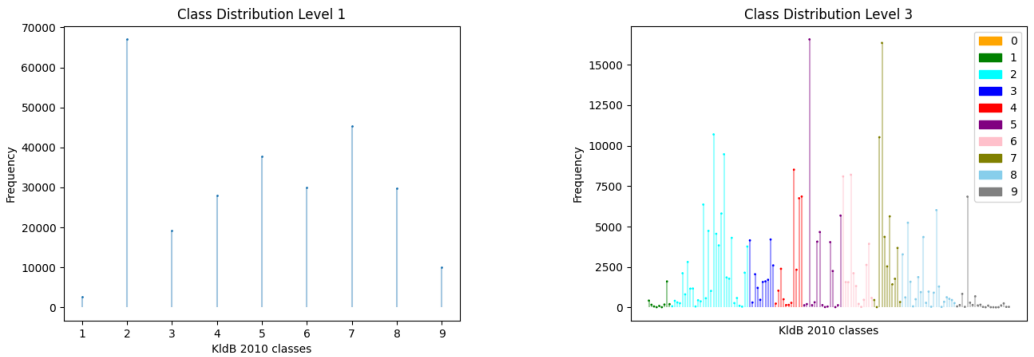
 {'id': '7', 'title': 'sachbearbeiter einkauf weimar'},
 {'id': '5', 'title': 'schubmaststapler fahrer'},
 {'id': '3', 'title': 'bauhelfer elektroinstallation'},
 {'id': '7', 'title': 'telefonist telefonistin'},
 {'id': '9', 'title': 'telefonische kundenbetreuung'}]
```

A.4 Class distribution of level 1 und level 3



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

Figure 22: Class distribution of training data

B Results