Job Title Matching

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Research Task

Compare and improve the classification of job titles of German job postings with the Taxonomy KldB 2010 by applying different vectorization techniques based on the challenges of short text classification.

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Related Work – Challenges

Domain-specific

some work for the English-speaking job market

traditional (Zhu et al 2017) vs. Deep Learning Methods (Neculoiu et al 2016)

framing as classification task (Wang et al. 2019) vs. framing as a string representation approach of similar job titles (Decorte et al. 2021)

Multiclass

decomposition into multiple binary problems vs. naturally handling

no clear answer so far

different approaches like SVM(Guo and Wang 2015) or Convolutional Neural Networks (Farooq etc. al 2017)

Short Text

Related Work – Challenges

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decomposition into multiple binary problems vs. naturally handling

no clear answer so far

different approaches like SVM(Guo and Wang 2015) or Convolutional Neural Networks (Farooq etc. al 2017)

Short Text

Related Work – Short Text Classification

- job titles have often not more than 50 characters

→sparseness

→few word co-occurrence

→missing shared context

→noisiness

→ambiguity

Related Work – Short Text Classification

- Approaches
  - criticism of “Bag of words” context
  - representation of documents as an extraction of semantic relationships
  - **dense** (Wang et al. 2017) vs. **sparse vectors** (Chen et al. 2019)
    - sparse: tf-idf and count vectorizer
    - dense: word2vec, doc2vec etc.
  - no consensus for classifiers

Research Gap

- no classification attempts for the German job market
- but would facilitate several downstream tasks:

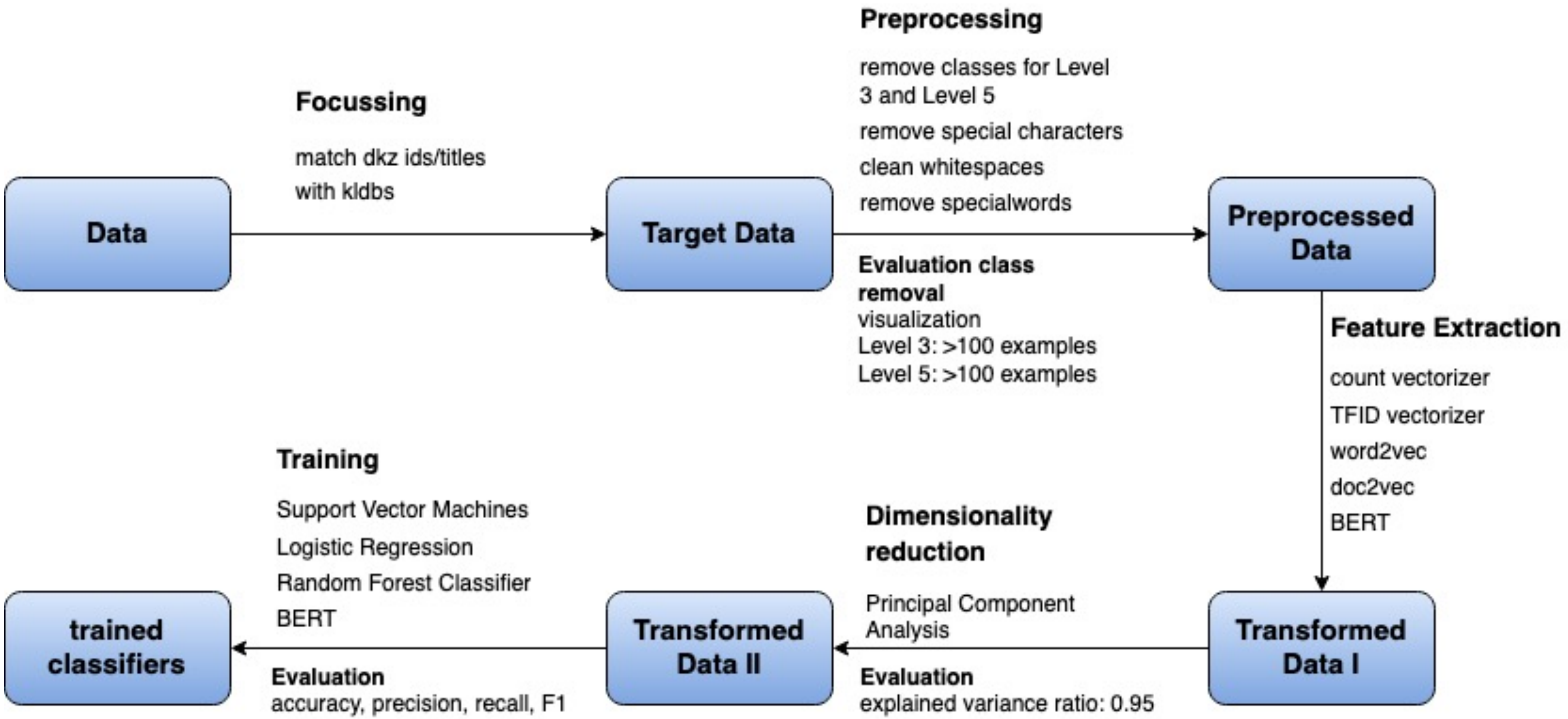
job market analyses

improvement of job search engines

improvement of job recommendation systems

- solid database

Method



Focussing
match dkz ids/titles
with kldbs
Preprocessing
remove classes for Level
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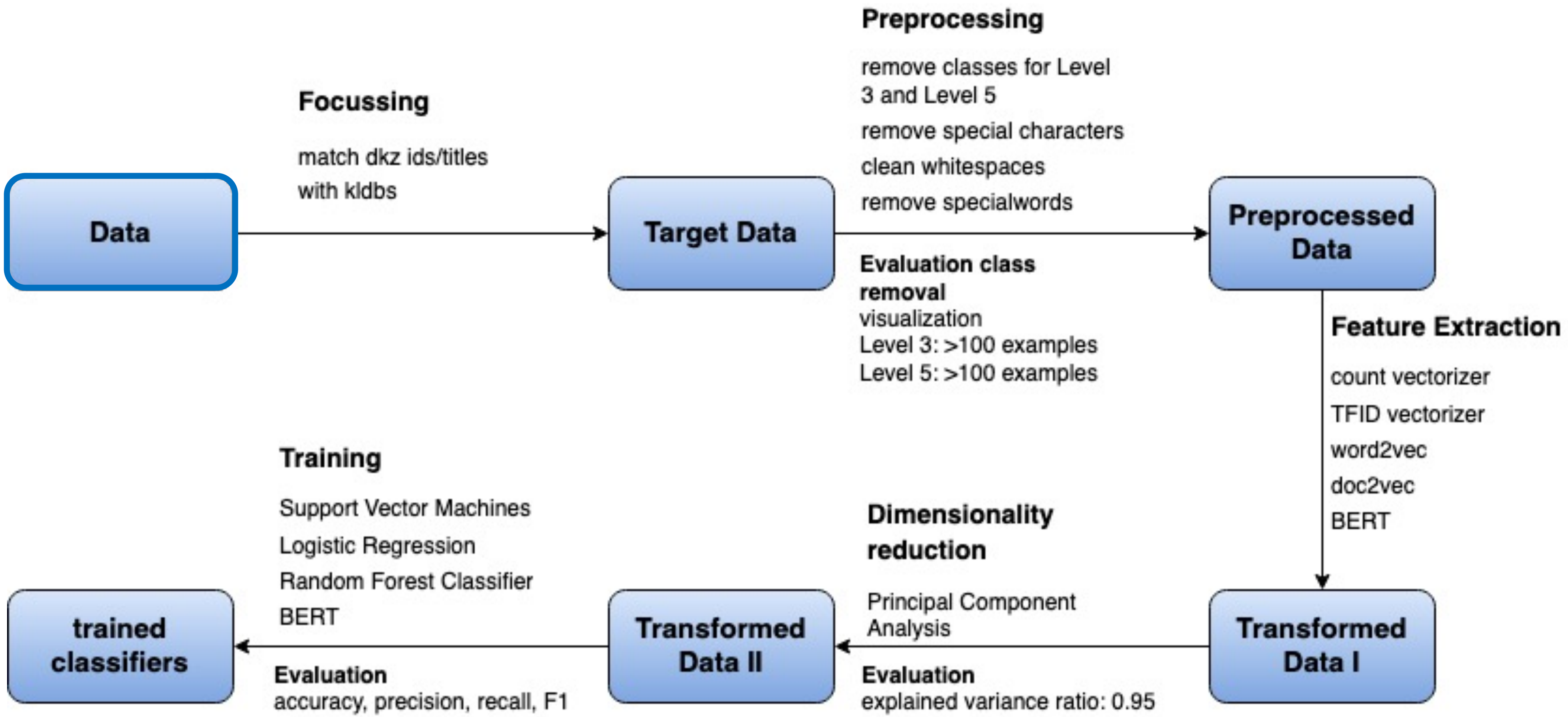
reduction
Principal Component
Analysis
trained classifiers
Transformed Data II
Transformed Data I
Evaluation
accuracy, precision, recall, F1
Evaluation
explained variance ratio: 0.95

Method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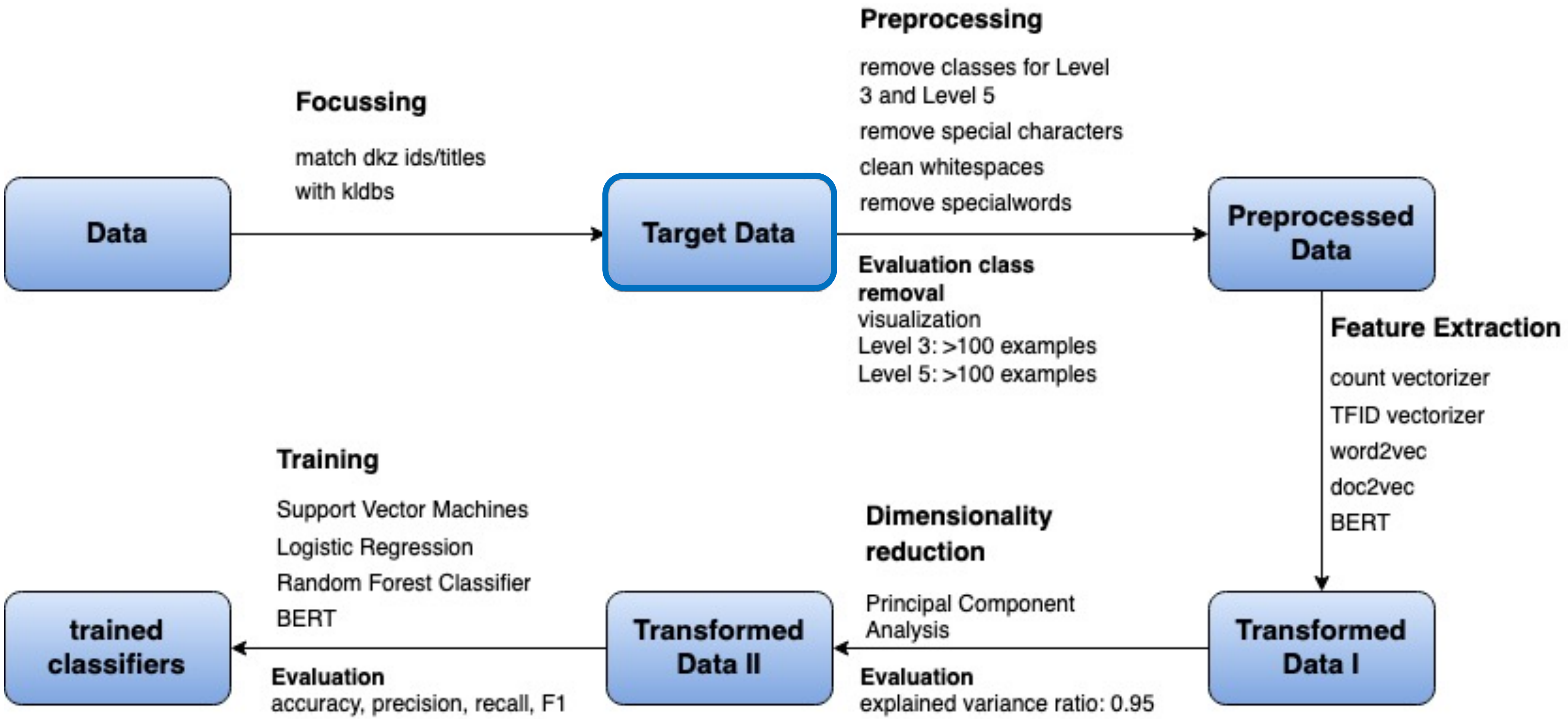
Data

- data from the job portal of the ”Bundesagentur für Arbeit” (BA):
  - job title
  - “Dokumentationskennziffer” (Dkz)
- KldB Taxonomy 2010

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

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

Method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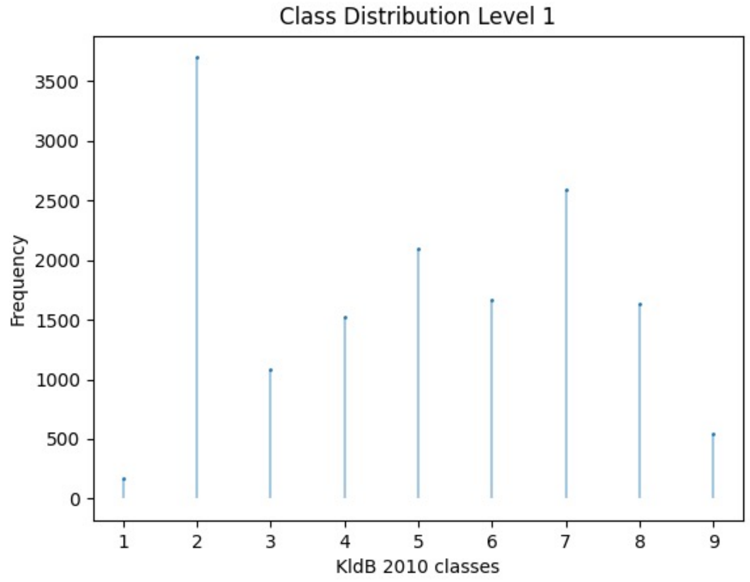
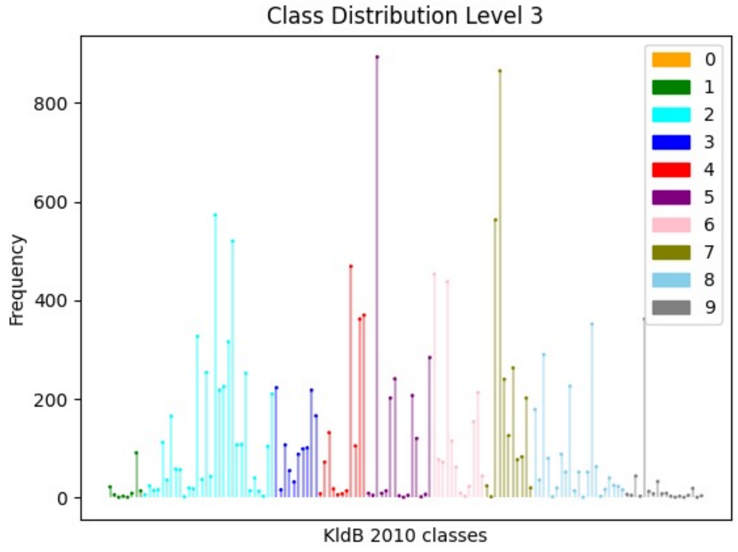
Target Data

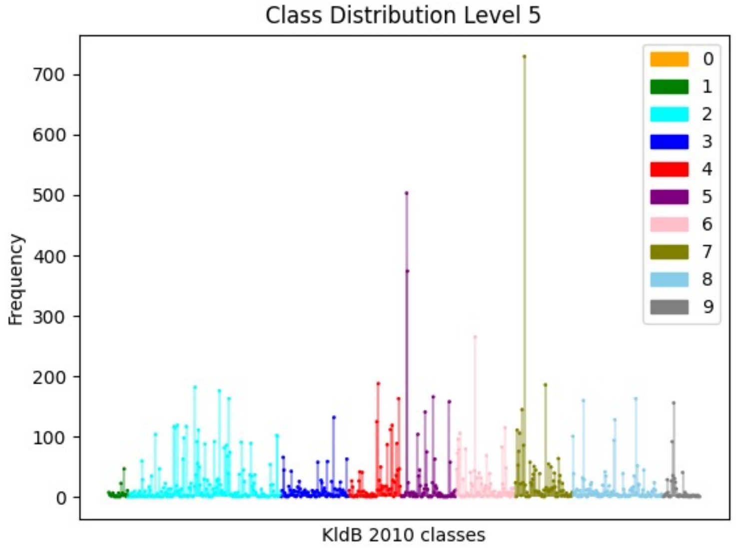
- the ”Dkz” id from the “BA” can be matched with the KldB class id
- trainings data example (Level 1)

```
[{'id': '82312', 'title': 'Friseur oder Friseurmeister (m/w/d)'},
 {'id': '81713', 'title': 'Köln - Kinder-Physiotherapeut (m/w/d) TZ'},
 {'id': '73203',
  'title': 'Sachbearbeiterin / Sachbearbeiter (m/w/d) Qualitätssicherung'}]
```

Target Data – Class Distribution







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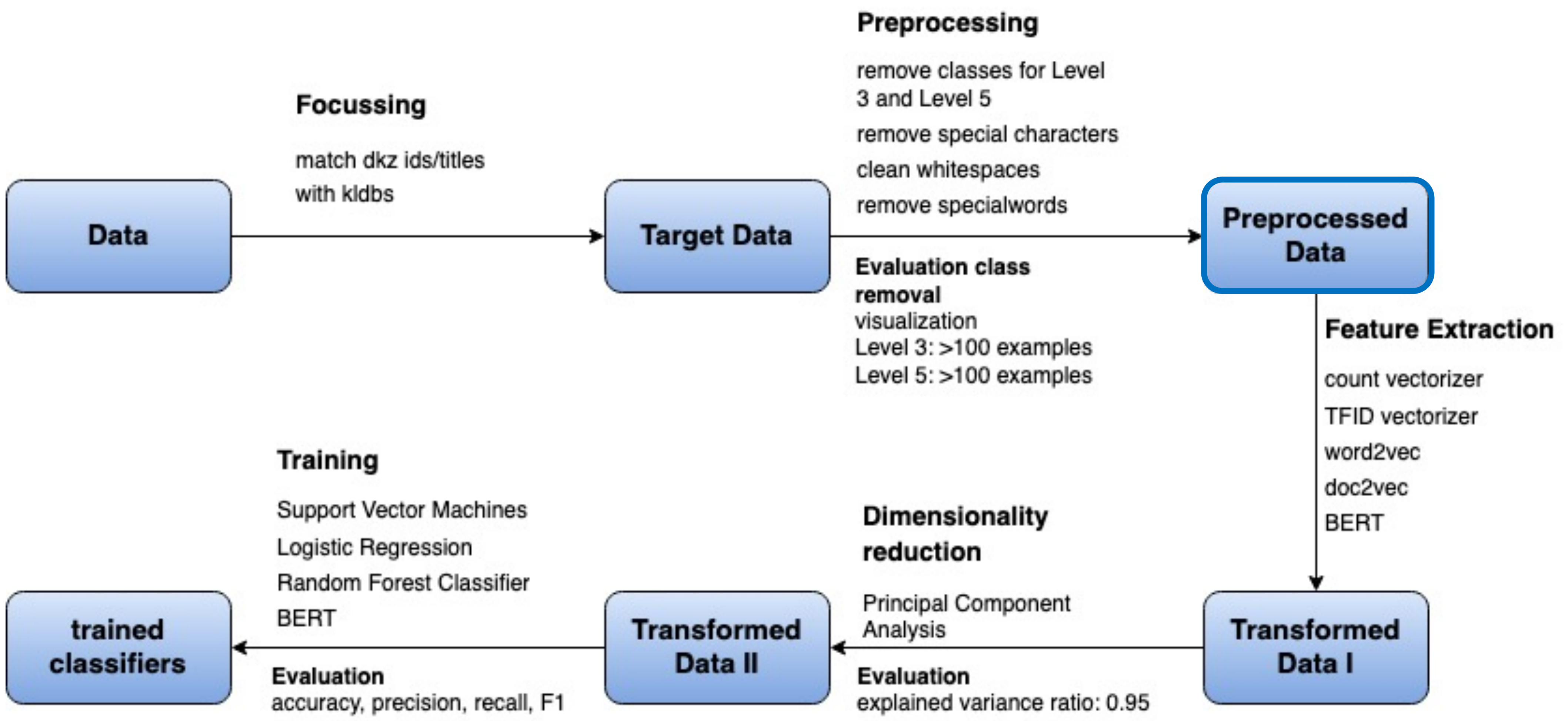
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Preprocessed Data

- remove stopwords, special characters, lowercase
- Zipf's law: most frequent words → get a list of special words → remove from title
- remove classes for Level 3 and Level 5
- Input data example

```
[{'id': '82312', 'title': 'friseur friseurmeister'},
 {'id': '81713', 'title': 'köln kinder physiotherapeut tz'},
 {'id': '73203',
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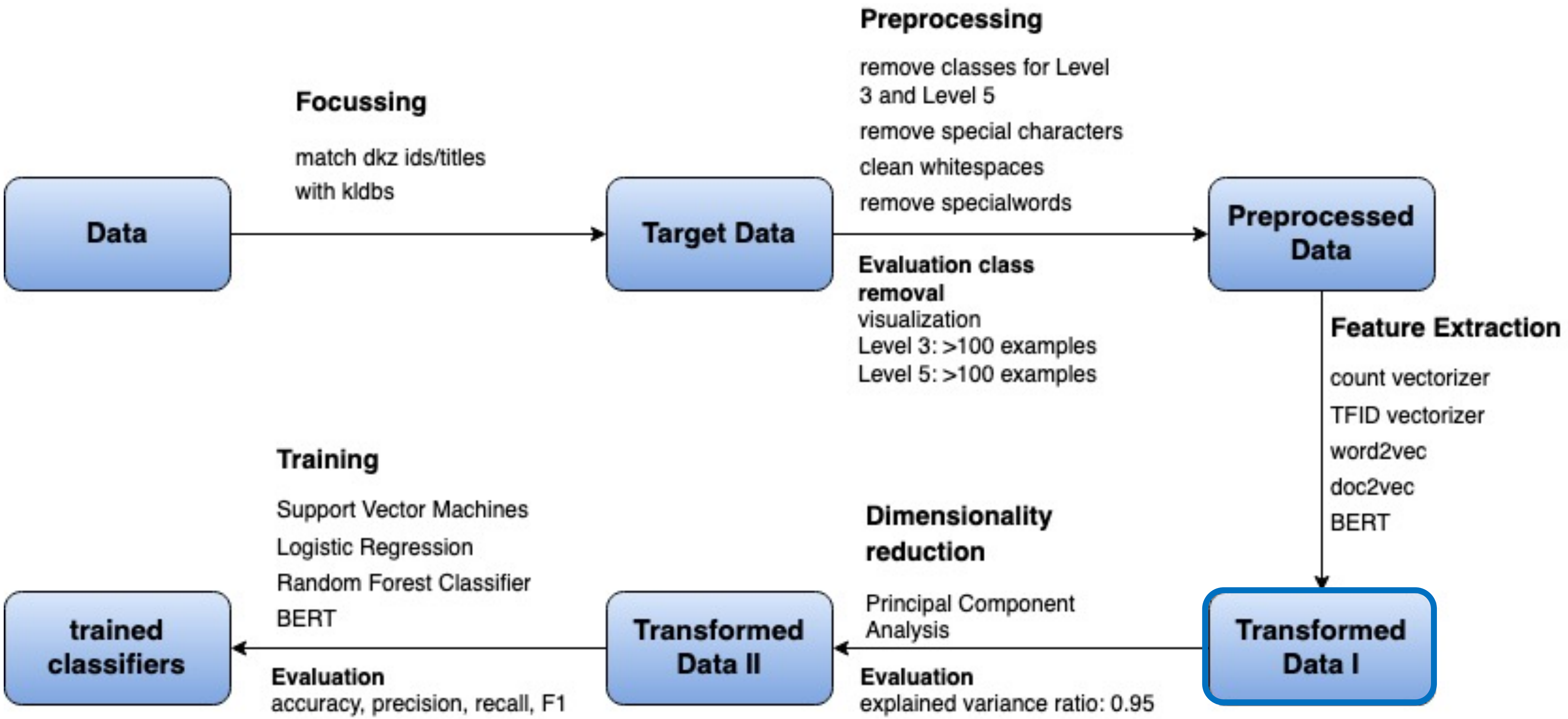
Method



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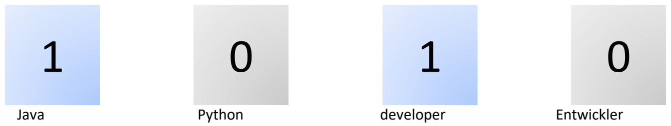
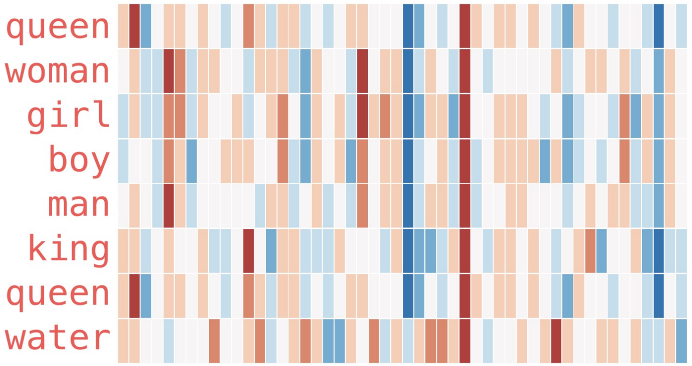
Transformed Data I

- baselines: count vectorizer and tf-idf vectorizer.
- approaches for improvement:
  - word2vec:
    - pretrained model from google with fine tuning
    - with and without additional information
  - doc2vec
    - with and without additional information (epochs=10, vector size=300, window=5)
  - BERT pretrained model
  - BERT with fine tuning and one classification layer

Example 1: „Java developer“





Source: Alammar, J. The illustrated Word2vec. 2019 <https://jalammar.github.io/illustrated-word2vec/> accessed: 09.12.2021

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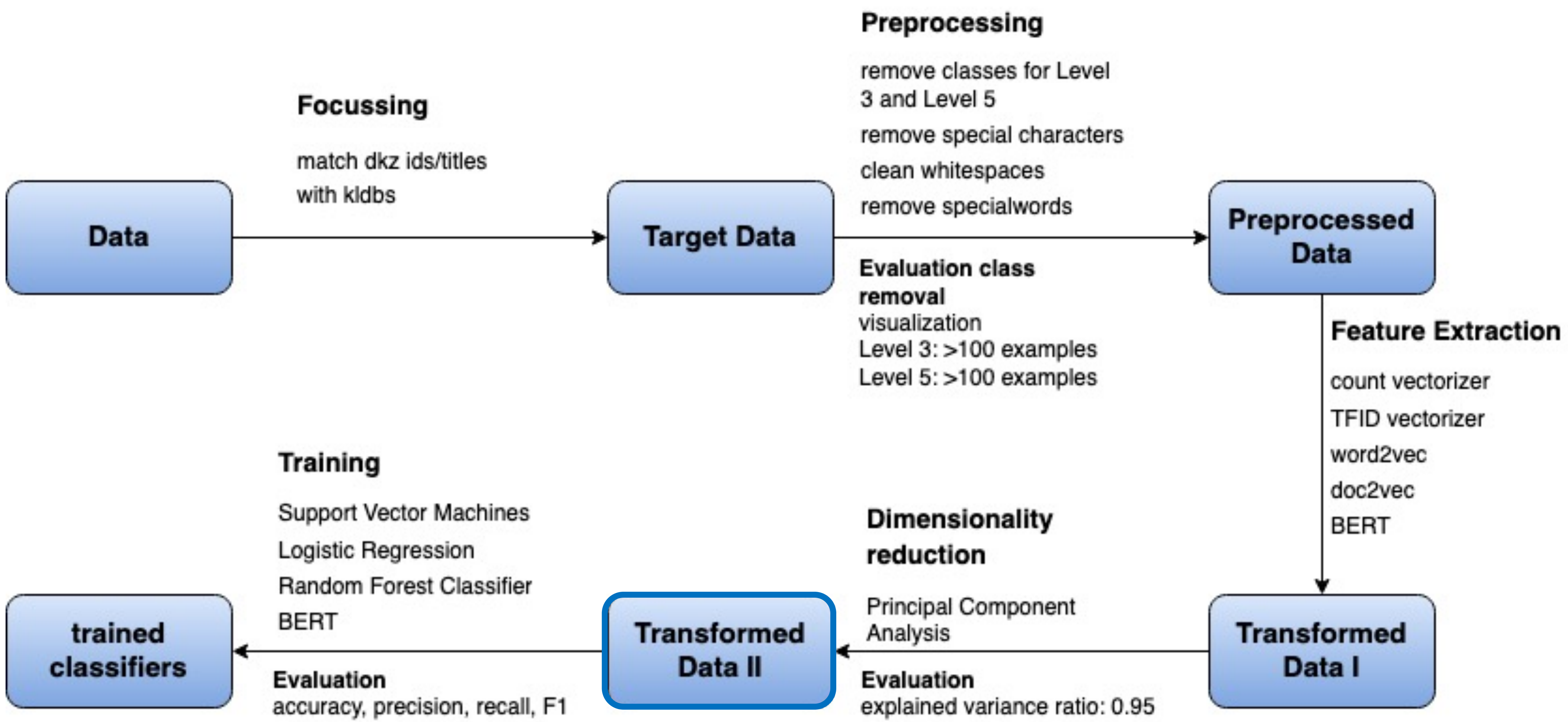
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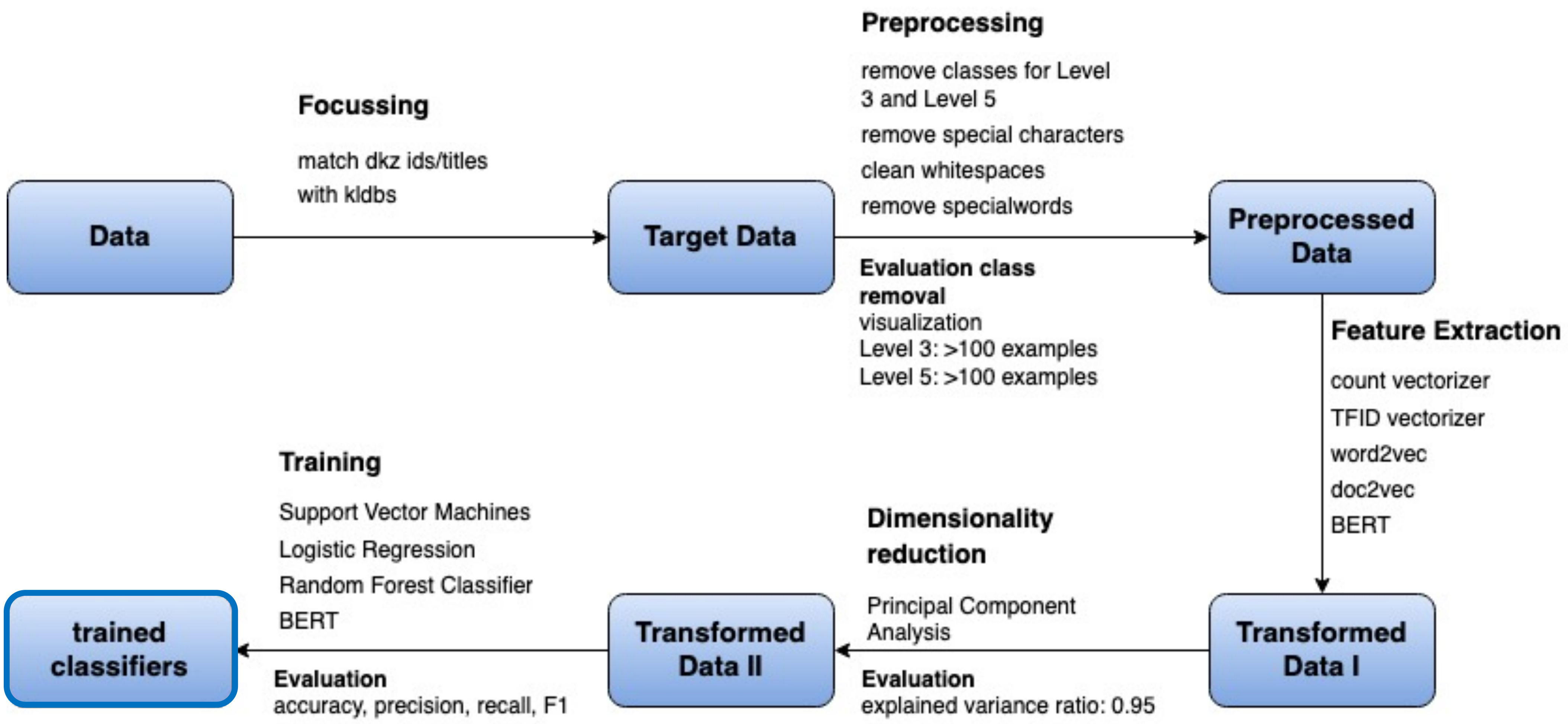
Transformed Data II

Principal component Analysis (PCA)

- reduces features to n_components to speed up the classifiers
- choose n_components such that the explained variance ratio is approx. 0.95

Results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First Results

- Evaluation measurements

Accuracy: How well does the classifier classifies across all classes?

→ Problem: favours majority classes

in addition

Precision: ability of model to return only relevant cases

Recall: ability of model identify all relevant instances

F-Score: harmonic mean between precision and recall

First Results – Level 1

Accuracy

	LR	SVM	RF
CountVectorizer	0.71	0.68	0.64
TFIDF	0.71	0.69	0.64
Word2Vec	0.55	0.53	0.62
Doc2Vec	0.48	0.46	0.56
BERT	0.65	0.65	0.58

Precision (p), Recall (r), F1 - Macro

	LR	SVM	RF
CountVectorizer	p: 0.74, r: 0.60, F1: 0.64	p: 0.73, r: 0.56, F1: 0.60	p: 0.67, r: 0.54, F1: 0.57
TFIDF	p: 0.75, r: 0.60, F1: 0.63	p: 0.74, r: 0.57, F1: 0.62	p: 0.65, r: 0.53, F1: 0.55
Word2Vec	p: 0.52, r: 0.40, F1: 0.42	p: 0.46, r: 0.41, F1: 0.41	p: 0.62, r: 0.54, F1: 0.56
Doc2Vec	p: 0.43, r: 0.34, F1: 0.35	p: 0.39, r: 0.33, F1: 0.33	p: 0.60, r: 0.41, F1: 0.43
BERT	p: 0.67, r: 0.57, F1: 0.60	p: 0.63, r: 0.56, F1: 0.58	p: 0.70, r: 0.46, F1: 0.50

	Accuracy	Precision	Recall	F1
BERT CLF Level 1	0.76	0.73	0.70	0.71
BERT CLF Level 3	0.53	0.56	0.46	0.46
BERT CLF Level 5	0.60	0.59	0.54	0.53

good performance

- differences depends on classifier
- for example, besides Doc2vec, all vectorizations performs quite similar for RF

- Word2vec and Doc2vec dense techniques have poor performance for LR and SVM poor

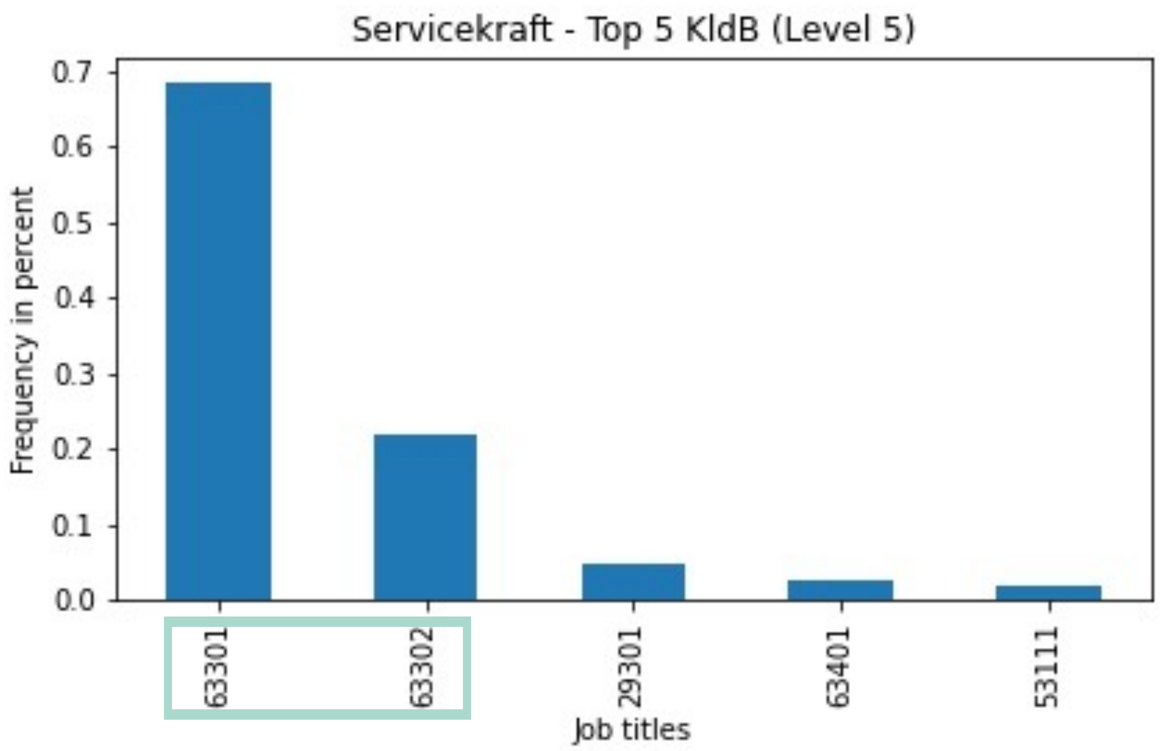
Notes: Short training data set with 15000 examples (for Level 3 and 5 results see Appendix A)

Discussion/Limitation

Occupation: „Servicekraft“

Ambiguity between level of requirement

- 6330**1**: „Berufe im Gastronomieservice (ohne Spezialisierung) – **Helfer/Anlerntätigkeiten“**
- 6330**2**: „Berufe im Gastronomieservice (ohne Spezialisierung) - **fachlich ausgerichtete Tätigkeiten“**



Notes: Further example Appendix B

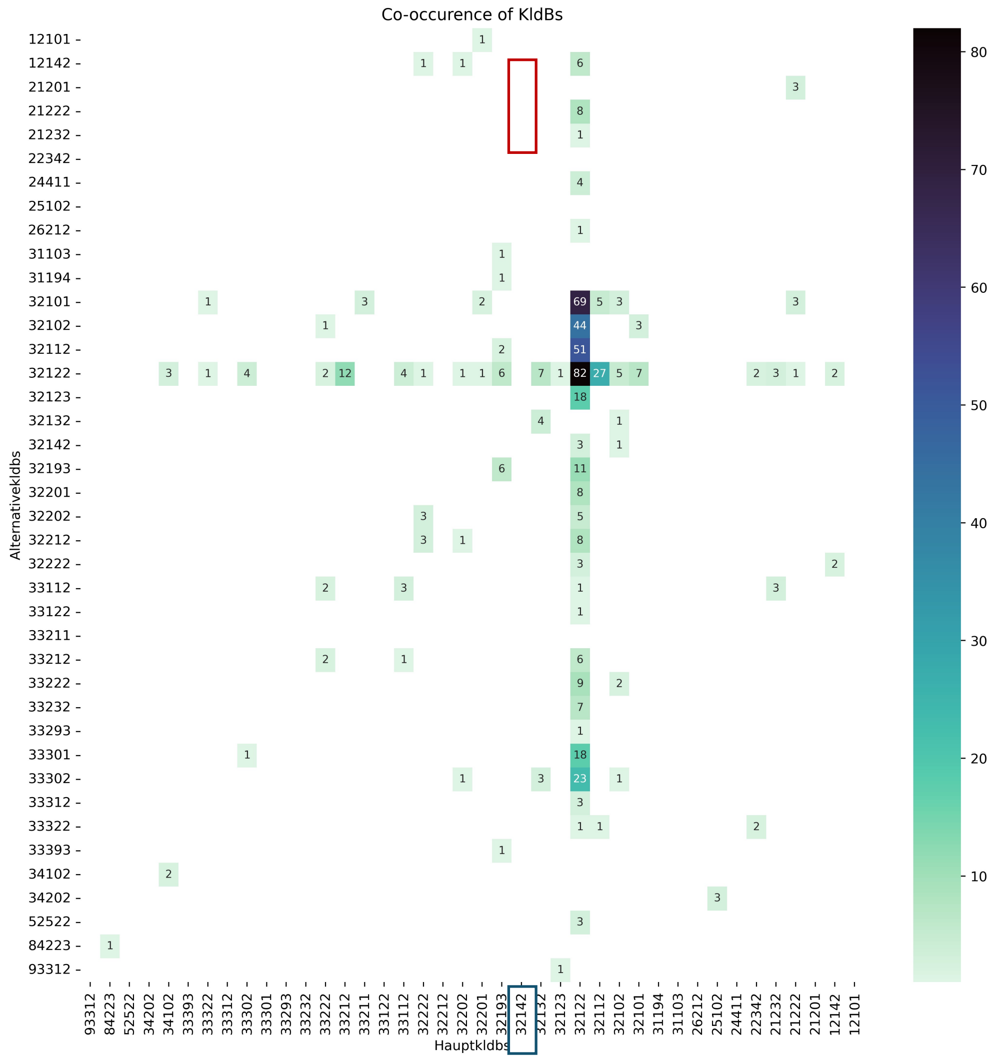
Discussion/Limitation

Occupation: „Maurer“

32122 has many alternatives
→ Differentiation is difficult

32122 often as an alternative

„Berufsuntergruppen“ (4th digit) difficult to differentiate (321**2**2, 321**1**2, 321**0**2, 321**0**1)



Discussion/Limitation

I. Pre-processing

How reasonable is it to exclude classes of level 3 and 5?

- Advantage
    - efficient in terms of time complexity
    - evaluation metrics more meaningful
- Disadvantage:
    - level 3: 46 classes remain
    - level 5: 38 classes remain

II. Evaluation

Should I add additional evaluation metrics to the existing ones, such as k-fold cross-validation?

Appendix

A. Results

A. First Results – Level 3 – classes not removed

	LR	SVM	RF
CountVectorizer	0.48	0.50	0.43
TFIDF	0.47	0.51	0.43
Word2Vec	0.28	0.14	0.35
Doc2Vec	0.19	0.20	0.31

best performance

- differences depends on classifier
- for example, besides Doc2vec, all vectorizations performs quite similar for RF

- Word2vec and Doc2vec dense techniques have poor performance for LR and SVM poor

	LR	SVM	RF
CountVectorizer	p: 0.42, r: 0.27, F1: 0.3	p: 0.41, r: 0.35, F1: 0.36	p: 0.37, r: 0.25, F1: 0.28
TFIDF	p: 0.38, r: 0.23, F1: 0.26	p: 0.41, r: 0.35, F1: 0.36	p: 0.36, r: 0.25, F1: 0.27
Word2Vec	p: 0.15, r: 0.11, F1: 0.12	p: 0.07, r: 0.05, F1: 0.04	p: 0.23, r: 0.18, F1: 0.19
Doc2Vec	p: 0.1, r: 0.05, F1: 0.05	p: 0.13, r: 0.08, F1: 0.09	p: 0.23, r: 0.13, F1: 0.14

First Results – Level 3 – classes removed

Accuracy

	LR	SVM	RF
CountVectorizer	0.54	0.52	0.47
TFIDF	0.53	0.54	0.49
Word2Vec	0.34	0.28	0.39
Doc2Vec	0.24	0.28	0.36
BERT	0.51	0.49	0.45

Precision (p), Recall (r), F1 - Macro

	LR	SVM	RF
CountVectorizer	p: 0.63, r: 0.49, F1: 0.53	p: 0.57, r: 0.48, F1: 0.51	p: 0.55, r: 0.42, F1: 0.46
TFIDF	p: 0.66, r: 0.47, F1: 0.52	p: 0.59, r: 0.49, F1: 0.51	p: 0.58, r: 0.44, F1: 0.48
Word2Vec	p: 0.38, r: 0.26, F1: 0.28	p: 0.31, r: 0.23, F1: 0.24	p: 0.39, r: 0.34, F1: 0.35
Doc2Vec	p: 0.36, r: 0.14, F1: 0.15	p: 0.33, r: 0.23, F1: 0.25	p: 0.42, r: 0.29, F1: 0.31
BERT	p: 0.53, r: 0.44, F1: 0.46	p: 0.44, r: 0.45, F1: 0.44	p: 0.56, r: 0.38, F1: 0.42

First Results – Level 5 – classes removed

Accuracy

	LR	SVM	RF
CountVectorizer	0.63	0.65	0.57
TFIDF	0.61	0.65	0.59
Word2Vec	0.44	0.38	0.49
Doc2Vec	0.27	0.35	0.45
BERT	0.62	0.63	0.55

Precision (p), Recall (r), F1 - Macro

	LR	SVM	RF
CountVectorizer	p: 0.71, r: 0.59, F1: 0.63	p: 0.67, r: 0.62, F1: 0.63	p: 0.63, r: 0.55, F1: 0.57
TFIDF	p: 0.72, r: 0.57, F1: 0.61	p: 0.67, r: 0.63, F1: 0.63	p: 0.63, r: 0.56, F1: 0.58
Word2Vec	p: 0.53, r: 0.38, F1: 0.42	p: 0.38, r: 0.32, F1: 0.31	p: 0.49, r: 0.46, F1: 0.46
Doc2Vec	p: 0.41, r: 0.15, F1: 0.17	p: 0.36, r: 0.3, F1: 0.31	p: 0.53, r: 0.37, F1: 0.41
BERT	p: 0.66, r: 0.58, F1: 0.60	p: 0.61, r: 0.62, F1: 0.60	p: 0.64, r: 0.49, F1: 0.53

B. Limitations

Discussion/Limitation

Occupation: „Softwareentwickler“

Ambiguity between Berufsbereichen
- 43414: **Naturwissenschaft, Geografie und Informatik**
- 26304: **Rohstoffgewinnung, Produktion und Fertigung**

Ambiguity within Berufsbereichs/ Berufshauptgruppe
- **43**323
- **43**104
- **43**414

Informatik- Informations- und Kommunikationstechnologieberufe