# On the validity of pre-trained transformers for natural language processing in the software engineering domain

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Abstract—Transformers are the current state-of-the-art of natural language processing in many domains and are using traction within software engineering research as well. Such models are pre-trained on large amounts of data, usually from the general domain. However, we only have a limited understanding regarding the validity of transformers within the software engineering domain, i.e., how good such models are at understanding words and sentences within a software engineering context and how this improves the state-of-the-art. Within this article, we shed light on this complex, but crucial issue. We compare BERT transformer models trained with software engineering data with transformers based on general domain data in multiple dimensions: their vocabulary, their ability to understand which words are missing, and their performance in classification tasks. Our results show that for tasks that require understanding of the software engineering context, pre-training with software engineering data is valuable, while general domain models are sufficient for general language understanding, also within the software engineering domain.

Index Terms—natural language processing, transformers, software engineering

# 1 Introduction

The introduction of the transformer model [1] has permanently changed the field of Natural Language Processing (NLP) and paved the way for modern language representation models such as BERT [2], XLNet [3], and GPT-2 [4]. All of these models have in common that they use transfer learning in the form of pre-training to learn a general representation of language, which can then be fine-tuned to various downstream tasks. Pre-training is expensive and requires large text corpora. Therefore, most of the available models are pre-trained by large companies on vast amounts of general domain data such as the entire English Wikipedia or the Common Crawl News dataset [5].

While these models achieve remarkable results in a variety of NLP tasks, the learned word representations (embeddings) still reflect the general domain. This is a problem because the meaning of words varies based on context and is therefore domain dependent. Hence, there is a considerable interest in adapting language representation models to different domains, especially to the biomedical domain. Recently, Beltagy *et al.* [6] proposed SciBERT, a BERT-based model pre-trained from scratch on a scientific biomedical corpus. The authors achieved state-of-the-art results in domain-specific tasks and were able to show that the embeddings and vocabulary of SciBERT differ significantly from those of BERT. Similar models are available for different domains such as BioBERT [7] and ClinicalBERT [8].

In Software Engineering (SE) there are many technical terms that do not exist in other domains and words that

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have a different meaning within the domain. Therefore, the differences in embeddings and vocabulary should also be transferable to the SE domain. For example, the word "bug" in the general domain refers to an insect, but within the SE domain it refers to a defect. Similarly, "ant" is an insect in the general domain, but a build tool within SE. Words such as "bug" and "ant" are called polysemes, i.e., words that have different meanings depending on their context.

The notion that pre-trained language models should be adopted for the SE domain is not new and was already considered by other. Efstathiou *et al.* [9] discussed this with respect to pre-trained word2vec embeddings. In their work, they showed for a small subset of words that embeddings for polysemes within the domain differ from the original word2vec embeddings. Another approach by Tabassum *et al.* [10] pre-trained a BERT model on software engineering data and obtained good results on Named Entity Recognition (NER) tasks [10]. However, both pre-training approaches used small, homogeneous data sets and the resulting models are small in scale.

A gap within the previous research is the larger context. The work by Efstathiou *et al.* [9] only established a difference for the by now dated word2vec approach and not for transformer models. Moreover, the focus is solely on the position of a small set of terms within a vector space. This ignores the ability of transformer models to account for the context, which may be able to infer the correct meaning of polysemes. And while Tabassum *et al.* [10] successfully demonstrated that pre-training with SE data is also useful with transformer models, they used a small variant of the BERT model and did not explore why the model yielded better results. Thus, it is unclear how much better such a model is at capturing the correct meaning of words and if larger transformer models, as they are usually used within the state-of-the-art of NLP, would perform.

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Within this work, we want to close this gap through an exploratory study that aims to answer the following research questions.

**RQ1:** Are large pre-trained NLP models for SE able to capture the meaning of SE vocabulary correctly?

**RQ2:** Do large pre-trained NLP models for SE outperform models pre-trained on general domain data and smaller NLP models that do not require pretraining in SE applications?

We study these research questions using seBERT, a BERT<sub>LARGE</sub> model we pre-trained on textual data from Stack Overflow, GitHub, and Jira Issues and BERToverflow, a BERT<sub>BASE</sub> model that was pre-trained by Tabassum *et al.* [10] on data from Stack Overflow. We evaluate the capability of the models to correctly determine the meaning of terms using incomplete sentences that we ask the model to complete, a task typically referred to as Masked Language Modeling (MLM). Through this, we complement the study by Efstathiou et al. [9] to understand the ability of NLP models for SE to not only create valid embeddings, but even predict the correct words given the context. Such a prediction goes beyond similarity of single words and would be a strong indicator that NLP models for the SE domain should outperform general domain models because they are demonstrably better at capturing the correct meaning.

Moreover, we study the capability of these models to improve the performance of prediction tasks. We recently found that a shallow neural network that trains ad-hoc embeddings called fastText [11] performed best within the literature on the prediction if issues are bugs [12]. Using this as a benchmark, we evaluate how general domain and SE domain BERT models are able to conduct more accurate predictions, when only a limited amount of data for the fine-tuning is available. We compare the same algorithms for a similar task, but with very short texts, i.e., the identification of quality improving commits [13]. The comparison of the models on these two prediction tasks allows us to understand if pre-trained SE domain models are really necessary in comparison to simpler NLP approaches. Moreover, since the data for fine-tuning is limited, the BERT models cannot learn the SE context of words, but should only work if this was already achieved during the pretraining. This provides us with an additional indication if the context we capture through the pre-training with SE data really goes beyond the available information in a general domain model. Additionally, we also consider sentiment mining as fine-tuning task, a task where it was already shown that general domain transformers perform well [14]. Since sentiment mining possibly also works on SE domain data without SE domain knowledge [15], the evaluation of this tasks allows us to understand if even tasks that are not SE specific can be improved with SE domain transformers.

Through our study, we provide the following contributions to the literature.

 A benchmark corpus of sentences to evaluate the validity of NLP models for SE. We use this benchmark to show that BERT models trained with SE data are able to capture the correct meaning of SE terminology, at the cost of the correct modeling of some

- general domain concepts like geographical locations. We further show that larger models trained with more diverse data are better at capturing nuanced meanings than smaller domain specific models.
- We advance the state of issue type prediction by improving the model performance significantly with the fine-tuned seBERT model. Our data indicates that the improvement is only possibly because the model was pre-trained on SE data and also that larger NLP models outperform smaller models in the SE domain similar to the differences that can be observed between general domain models. Similarly, seBERT is also the best model we considered for the task of identifying quality improving commits.
- We found that sentiment mining was not strongly affected by domain specific pre-training and that SE domain transformers perform similar to general domain transformers for this task.
- A basic ethical evaluation of the models revealed that the SE domain models should only be used with care, because they may to have some troubling properties, especially with respect to gender bias. This warrants further research and until these aspects are better understood, such models should not be used for any tasks that may be negatively affected by gender bias, though this also warrants caution regarding other biases such as racial bias.

The remainder of this article is structured as follows. We provide some background on transformers in Section 2, followed by a discussion of related work on domain specific NLP models in Section 3. Then, we outline the creation of the SE domain model seBERT in Section 4. Based on these foundations, we introduce our method for validating transformers within the SE domain in Section 5, present the results of this validation in Section 6, and discuss these results in Section 7. Finally, we conclude in Section 8.

## 2 BACKGROUND ON TRANSFORMERS

NLP is a broad field composed of various disciplines such as computational linguistics, machine learning, artificial intelligence, computer science, and speech processing [16]. Modern NLP models have a variety of applications, including text classification, NER, machine translation, sentiment analysis, and natural language generation. In recent years, transformer models, e.g., BERT [2], BART [17], ALBERT [18], RoBERTa [19], GPT-3 [20], and Switch-C [21] established themselves at the state-of-the-art of NLP within the general domain. Since the focus of our article is on the validity of transformer models within the SE domain, we avoid an in-depth technical discussion of the underlying neural network architectures of these models and refer for this to the literature instead (e.g., [22]). Instead, we outline the concept of such models on a high level in natural language without mathematical details.

Transformers can be described in a single sentence: they are *sequence-to-sequence* networks with *self-attention*. Now we only need to understand what the highlighted aspects mean. A sequence-to-sequence network takes as input a sequence and generates a new sequence of the same length. For NLP, the input sequence is usually a tokenized text,

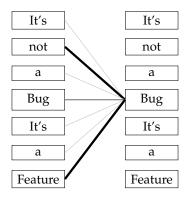


Fig. 1. Visualization of self-attention that shows how the different words in the context influence the meaning of the word bug. Artifcial example not based on actual model weights.

possibly augmented with additional tokens, e.g., to represented classes. The input sequence is then encoded, such that each input token is represented by a numeric vector, which means that we have a sequence of vectors through these embeddings. This transformation relies on the self-attention, which means that the tokens are not considered in isolation, but together. Consider this paragraph: the self-attention would consider this whole paragraph at once and, for each word, model how the *contextual meaning* depends on all other words in the paragraph. This is shown in Figure 1.

That the whole sequence is used as context for each word to understand the contextual meaning is the major difference to previously used NLP models. For example, word embeddings organize words such that words with similar meanings are close to each other [23]. However, while the context is taken into account when the embedding is calculated, each word only gets a single position. If words are polysemes, the meaning depends on the context, which cannot be accurately encoded with such a fixed embedding. Either one contextual meaning is lost, e.g., "bug" is only close to other insects, but not to words like "defect". Or different concepts become similar to each other, e.g., "bug" is close to both insects and defects, which means that insects in general are now similar to defects. Moreover, since the embedding does not take the position of a word in an actual sentence into account, the interpretation of sentences based on the grammitical relationship between words is also not possible. Recurrent Neural Networks (RNN) without selfattention, such as Long-Short-Term-Memory (LSTM) networks, can also not take the complete context accurately into account. While such models can also be sequenceto-sequence networks, the relationship between a word a specific position, and all other words, is linear. Simplified, this means that the influence on the context depends mostly on the distance to a specific word. In comparison, the self-attention learns how each word influences the context, depending on the position without a fixed influence of the distance.

Due to these differences, transformers quickly became the most powerful architecture for neural network based NLP. Models based on transformers are the current state of the art. The revolution was spear-headed by BERT [2], followed by similar models such as RoBERTa [19], GPT- 3 [20] that were pre-trained with more data, used larger neural networks, and/or optimized the efficiency of the self-attention mechanisms. Such models already gained traction within the SE domain: Zhang *et al.* [14], who recently established transformers as state-of-the-art for sentiment mining within the SE domain.

The drawback of transformer models is the size of the neural networks. Even a relatively small model like BERT<sub>BASE</sub> [2] already has 110 million parameters. The largest currently discussed transformer architectures like GPT-3 [20] and Switch-C [21] have more than 100 billion parameters. Thus, the training of such models requires dedicated hardware and huge amounts of data. To reduce the burden, these models are pre-trained in a self-supervised setting. This means that the neural networks are trained on a large corpus of NLP data, such that the structure of text and meaning of words is known by the network. Self-supervised means that this understanding of the language is trained in a supervised way (i.e., with labels), but that the labels are generated directly from the training data. We will show how this works for the BERT pre-training in Section 4.3. Researchers and practioners who then want to apply NLP to solve a problem, use these pre-trained models and finetune the models for a specific task on a labeled data set. This works with less data and requires only few training steps and is, therefore, usually not computationally expensive. However, this may still require dedicated hardware, due to the size of the models.

#### 3 RELATED WORK ON DOMAIN-SPECIFIC NLP

In recent years there has been considerable interest in adapting pre-trained language models such as word2vec [23], ELMo [24] and BERT to different domains. However, most of the related work concerns the biomedical or financial domain. Pyysalo et al. [25] were among the first to provide domain-specific word2vec embeddings based on biomedical corpora. Since then, recent biomedical adaptions of word2vec and BERT include Dis2Vec [26], BioBERT [7], ClinicalBERT [8] and to some extent SciBERT [6], which has been pre-trained on biomedical and computer science papers. Models such as BioBERT and SciBERT have been shown to outperform BERT in biomedical tasks and achieve stateof-the-art results [6], [7]. The same is true for FinBERT [27] which achieved state-of-the-art results in financial sentiment analysis. However, except for SciBERT, the domain-specific BERT models are not pre-trained from scratch, but use the same vocabulary as BERT or are further pre-trained using BERTs weights.

Efstathiou *et al.* [9] pre-trained a general-purpose word representation model for the software engineering domain. They trained the so\_word2vec on 15GB of textual data from Stack Overflow posts. The authors compare the so\_word2vec model with the original Google news word2vec model and show that it performs well in capturing SE specific meanings and analogies. The main difference with our work is that we consider contextual embeddings and provide a more extensive evaluation of the validity of the resulting embeddings. In addition, our seBERT model was trained using 119GB of data from multiple sources, i.e.,

we also use GitHub issues and commit messages in addition to data from Stack Overflow.

Recently, Tabassum et al. [10] proposed a similar approach to ours, in which GloVe, ELMo, and BERT models are pre-trained on 152M sentences from Stack Overflow. In addition, the authors propose a novel attention based SoftNER model designed for code and NER. Their BERT model BERTOverflow was pre-trained using a cased 64000 WordPiece vocabulary with the same configuration as original BERT<sub>BASE</sub> with 110 million parameters. The results show that BERTOverflow clearly outperforms the other models, inluding BERT<sub>BASE</sub>, on NER tasks. In contrast, we pre-train seBERT with about six times more data, including data from GitHub and Jira. Morover, seBERT uses an uncased 30522 WordPiece vocabulary and the same configuration as BERT<sub>LARGE</sub>, resulting in a much larger model with 340 million parameters. Additionally, our focus is different and not on NER tasks, but rather on the general validity of the NLP models and their usefulness for classification tasks in a pure NLP setting without considering source code.

While our focus is on pure NLP, we also want to mention similar models from the SE domain for code. Theeten et al. [28] proposed import2vec, a word2vec based approach for learning embeddings for software libraries. The embeddings are trained on import statements extracted from source code of Java, JavaScript and Python open source repositories. In their work, they show that their embeddings capture aspects of semantic similarity between libraries and that they can be clustered by specific domains or platform libraries. A more general source code based pre-training was conducted by Alon et al. [29] who proposed code2vec to represent code snippets as word embeddings. The authors show that such embeddings are a powerful tool to predict method names based on the code. Another source code based approach is CodeBERT [30], a bimodal pre-trained bidirectional transformer for natural language and programming languages. CodeBERT is pre-trained using a hybrid objective function combining the default MLM task and a Replaced Token Detection (RTD) [31] task. For the training data, the authors use both bimodal data pairs comprising a function (code) and its documentation (natural language), as well as unimodal data consisting of only of the function. The data was collected from GitHub code repositories in six different programming languages. Their results show that CodeBERT achieves state-of-the-art performance in natural language code search and code-to-document generation tasks.

#### 4 SEBERT

Within this section we describe how we trained seBERT, a large-scale transformer model for the SE domain that complements BERToverflow, because it is larger, was trained on more data diverse data with a larger volume, and is uncased (see Section 3).

## 4.1 Data

We identified four data sources for our domain-specific corpus of SE textual data:

1) **Stack Overflow posts**: With millions of questions, answers and comments, Stack Overflow posts are a

- rich source of textual data from the SE field. Same as the prior work, this is one of our main data sources. The Stack Exchange Data Dump [32] contains Stack Overflow posts from 2014 to 2020 and is hosted on the Internet Archive [33]. A Stack Overflow specific mirror is available as a public dataset on the Google Cloud Platform [34]. Using BigQuery, we extracted 62.8 Gigabyte of questions, answers and comments.
- 2) GitHub issues: GitHub is more than a code hosting environment. For many users, GitHub issues are the first place to give feedback or report software bugs and thus provide valuable insight into the communication between users and developers. GitHub issues consist of a title, a description and comments and are available through the GitHub Archive [35]. Using Google BigQuery [36] we extracted 118.5 Gigabyte of issue descriptions and comments from the years 2015 to 2019.
- 3) Jira issues: Similar to GitHub issues, Jira issues provide valuable insights into software team communication regarding bug and issue tracking. In 2015, Ortu et al. published the Jira Repository Dataset [37], which contains 700K Jira issue reports and more than 2M Jira issue comments. With 1.4 Gigabyte of unprocessed textual data, they make up the smallest part of our corpus, but provide a perspective on issues beyond GitHub.
- 4) **GitHub commit messages**: Git commit messages are used to communicate the context of changes to other developers. Commit messages consist of two parts, a subject line and a message body, the latter being optional. Similar to the GitHub issues, we extracted 21.7 Gigabyte of GitHub commit messages from the GitHub Archive using BigQuery.

In total, our data set consists of 204.4 Gigabyte of unprocessed textual data. To the best of our knowledge, this the largest and most diverse corpus of textual data in the SE domain. Prior work on pre-training focused only on data from Stack Overflow. However, this ignores important aspects of the SE domain. A key aspect of natural language communication is the description of feature requests and bugs. Such data is typically not available on Stack Overflow, with the exception of users asking how they could work around a specific issue. Through the inclusion of GitHub issues and Jira issues, we enhance the corpus with such data. Moreover, commit messages are often short and on point natural language summaries of development activities and, consequently, different from the often longer discussions within issues and on Stack Overflow.

# 4.2 Preprocessing

The textual data is mostly unstructured and needs to be preprocessed. Overall, we conducted eight different preprocessing steps.

 Basic preprocessing: We convert all documents to lowercase, remove control characters (newline, carriage return, tab) and normalize quotation marks and whitespaces.

- 2) **English**: Since we are training a model for the English language, we use the fastText<sup>1</sup> library to remove all non-English documents.
- 3) **HTML**: We remove HTML tags and extract text using the BeautifulSoup library <sup>2</sup>.
- Markdown: We use regular expressions to greedily remove Markdown formatting.
- 5) Hashes: Hashes such as SHA-1 or md5 do not provide any contextual information and should be removed. We detect hashes by checking whether alphanumeric words with a length of 7 characters or more can be cast to a hexadecimal number and replace them with [HASH] tokens.
- 6) **Code**: Source code is not natural language and should be removed. However, finding code fragments within text is a non-trivial task. We use HTML <code> tags, Markdown code blocks and other formatting to identify source code and replace it with [CODE] tokens. Code that is not within such environments is not filtered.
- User mentions: For privacy reasons, we replace usernames and mentions (@user) with [USER] tokens.
- 8) **Special formatting**: We remove special formatting and content such as Jira specific formatting, Git sign-off, or references to SVN.

The preprocessing steps differ for the data sources. For example, removal of Markdown does not make sense for Stack Overflow posts or commit messages. Table 1 shows which steps we applied to which data and Table 2 shows the amount of data from each data source after preprocessing. After preprocessing, a total of 119.7 Gigabyte of text or 20.9 billion words remain.

## 4.3 Pre-training

The BERT implementation by Devlin *et al.* [2] uses Word-Piece embeddings with a 30522 token vocabulary. We train a new SE domain-specific vocabulary of the same size using all our data and the BertWordPieceTokenizer by Hugging-Face.<sup>3</sup>

An important parameter in BERT pre-training is the maximum sequence length. Training sequences shorter than the maximum sequence length are padded with [PAD] tokens, while longer sequences are truncated. Since the selfattention mechanism of BERT has a quadratic complexity with respect to the sequence length [2], the parameter significantly affects the training time and the memory requirements. Therefore, the authors recommend training 90% of the training steps with a sequence length of 128 and 10% of the steps with a sequence length of 512 to learn longer contexts [2]. We analyzed the sequence length for all our data through histograms, which are shown in Figure 2. The sequence lengths follow exponential distribution and 96.7% of all training sequences are shorter than 256 and 90.1% are shorter than 128. Therefore, since most of our data is shortsequence data, we train with a sequence length of 128 for all

- 1. https://fasttext.cc/
- $2.\ https://beautiful\text{-}soup\text{-}4.readthedocs.io/\\$
- 3. https://huggingface.co/

steps at the cost of a possible small disadvantage with very long contexts.

BERT pre-training is self-supervised based on MLM and Next Sentence Prediction (NSP) tasks. For the NSP task, we format the data using the NLTK library<sup>4</sup> so that each line contains a sentence and documents are separated by blank lines. For the NSP task, the input data is then prepared such that each subsequent pairs of sentences makes up one input sequence of the form [CLS] sentence\_1 [SEP] sentence\_2 [SEP]. We re-use code from the original BERT to prepare the data for the MLM task.<sup>5</sup> The provided script duplicates the input sequences by a dupe factor and creates training samples by randomly masking 15% of the whole words. Whole word masking was not part of the original BERT implementation and only added later by the authors as improvement of the preprocessing. With whole word masking all tokens of a word are masked at once, which means that it is not possible that words are only partially masked. Figure 3 shows this for a document with three sentences. As a result of this data preparation, we have 2.4 Terabyte of data which we can use as input for the pretraining of BERT with TensorFlow.

We pre-train seBERT using the same configuration as BERT<sub>LARGE</sub>, i.e., with 24 layers, a hidden layer size of 1024, and 16 self-attention heads, which leads to a total of 340 million parameters. Pre-training of BERT is expensive, e.g., the original BERT<sub>LARGE</sub> was pre-trained on 16 Cloud TPUs for 3 days. Since then, several optimizations have been proposed to reduce the training time of BERT. You et al. [38] proposed a Layer-wise Adaptive Moments Based (LAMB) optimizer that allows the use of larger minibatches compared to the originally used ADAMW optimizer. NVIDIA then implemented their own version NVLAMB and combined it with Automatic Mixed Precision (AMP) [39], which accelerates training time and reduces memory usage by autocasting variables to 16 bit floating point numbers upon retrieval, while storing variables with the usual 32 bit precision. We used this NVIDIA implementation of the BERT pretraining to facilitate the effective usage of the system we had available with 2x24 CPU cores, 384 GB RAM and 8x NVIDIA Tesla V100 32G GPUs. The pre-training of seBERT required about 4.5 days.

# 5 VALIDATION OF SE DOMAIN MODELS

The evaluation of pre-trained language models is usually performed with benchmarks such as the GLUE benchmark [40], its successor SuperGLUE [41] or SQuAD [42]. However, these benchmarks require fine-tuning and are designed for the general domain and therefore not suitable for the evaluation of NLP models for the SE domain. Moreover, while the evaluation on benchmark data is useful to evaluate the overall predictive capabilities of a model, they are not suitable to understand the reasoning within a model. Therefore, we propose a different approach for the evaluation of transformer models within the SE domain, that considers the validity from three different perspectives: the vocabulary, context sensitive prediction of masked words,

<sup>4.</sup> https://www.nltk.org/

<sup>5.</sup> https://github.com/google-research/bert

Processing	GitHub issues	Commit messages	Stack Overflow	Jira issues
Basic	Х	Х	X	Х
English	X	X		
HTML			X	
Markdown	X			
Hashes	X	X	X	X
Code	X		X	X
User mentions	X		X	
Special formatting		X		X
		TABLE 1		

The applied preprocessing steps for each data source.

GitHu	ıb	Stack	Overflow	Jira		
Issues Comments Commit messages	29.7 Gigabyte 39.3 Gigabyte 18.2 Gigabyte	Answers	10 Gigabyte 10.1 Gigabyte 11.3 Gigabyte	Issues Comments	502 Megabyte 613 Megabyte	

TABLE 2
The size of the data after preprocessing.

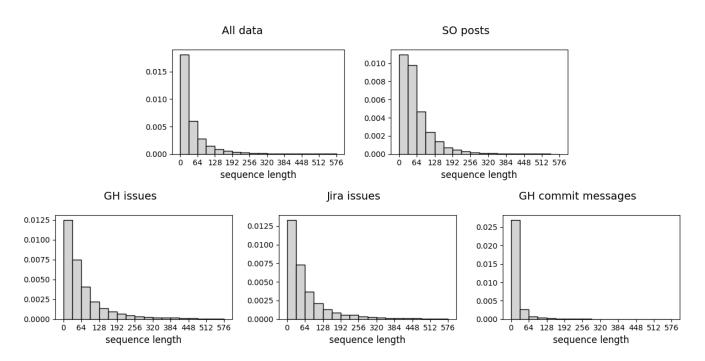


Fig. 2. Histograms of sequence length for each data source and all data combined.

and a fine-tuned benchmarks using a limited amounts of data for classification.

#### 5.1 Vocabulary

One of the main differences between a domain-specific language model and a general domain language model should be the vocabulary. We expect that the SE specific models should gain words from the SE domain, while lost words should be from other domains. Since alphanumeric words are more prevalent in the domain, a larger proportion of words should be alphanumeric.

We take pattern from Beltagy et al. [6] and perform a vocabulary analysis by computing the WordPiece overlap, i.e., the percentage of identical tokens between vocabularies. Additionally, we examine the vocabularies for differences in

structure, tokenization, and the types of words gained or lost through a manual analysis of the differences.

# 5.2 Contextual embeddings

Transformer models such as BERT go beyond word similarities and instead consider the complete context to infer the meaning. This goes beyond the context-free finding of similar words that was used by Efstathiou *et al.* [9] to determine if word embeddings from the SE domain are valid. Instead, we suggest to use MLM tasks to evaluate the validity of the embeddings, i.e., the evaluation of understanding how good the model is at predicting missing words in a text [2], [6]. We devise three categories of sentences suitable for validating language representation models for the software engineering domain with the goal to understand if seBERT and BERToverflow behave as expected due to the differences



Fig. 3. Example for preparation of data for training with BERT.

in training data from the original BERT. The three categories are the following.

- Positive examples: Prediction of masked tokens within a software engineering context. We expect domain-specific models to produce accurate predictions, while the original BERT may struggle because of the SE context.
- 2) Negative examples: Prediction of masked tokens outside a software engineering context, where the missing word or context words are polysemous. Given the polysemy of the negative examples, domain-specific models should produce domainspecific predictions, which are not suitable for the sentences from the general domain.
- 3) Neutral examples: Prediction of masked tokens outside a SE context, where the missing word can be inferred from general language understanding (e.g. idioms, opposites, antimetaboles). General language understanding should be preserved across domains, we all models to perform well.

Since sentences of these categories can only demonstrate the validity by way of example, we refer to them as "Validation Examples". Below we describe the categories and give one example per category. We defined ten examples per category. Due to space restrictions, we only list the sentences together with the predictions by the models in Section 6.2 in tables 4-6.

# 5.3 Fine-tuned Prediction Tasks

The first check regarding the validity is to analyze the pretrained model directly. However, it is unclear if the actual use of these models in fine-tuned applications would also be affected. We propose to evaluate the validity of the models by applying them to a classification task within the SE domain, for which only a limited amount of data is available. We propose to always use (at least) two types of tasks to evaluate the capabilities of the fine-tuning. The first type of task should have longer texts. This task is suitable to evaluate how good the model is at understanding longer texts and contexts. The second type of task should have shorter text, to evaluate how good the model is for short texts. The third task should be sentiment mining, as a general domain use case that is already well understood in the SE domain [15], incl. strong, already existing results that general domain transformer models are the current state-of-the-art for sentiment mining in the SE domain [14]. Since the work by Novielli *et al.* [15] suggest that SE domain models for sentiment mining may not be better than general domain models, this task allows us to evaluate if pre-trained SE domain transformer models are also better on SE domain data for use cases that do not require domain knowledge.

We propose to use the prediction if issues are bugs [12] as task with longer sequences. This task has several properties that make it a good candidate to evaluate the validity and benefits of transformer models. Issues are among the longer texts within SE data (see Figure 2), Moreover, there is an established baseline performance which shows that a simple neural network approach without pre-training based on fastText [11] performs well. Thus, we can not only compare pre-trained models to each other, but also their benefit over simpler models that can be trained in minutes without any special hardware. Second, the task is hard and often not solved correctly by humans, unless careful manual validation is used [43], [44], [45].

We suggest to use the five projects from Herzig *et al.* [44] and the 38 projects from Herbold *et al.* [45] together and conduct a leave-one-project-out cross validation experiment. This means that one project is used for testing and the remaining 42 projects for the training of the classifier, i.e., of the a fastText model as baseline and for the fine-tuning of the BERT models. Since there are 38,219 issues in the data and the largest project has 2,399 issues, we create 43 fine-tuned models trained with at least 35,820 issue descriptions. Following Herbold *et al.* [12], we suggest to conduct a statistical comparison based on the *F1 score* which is defined as

$$egin{aligned} \mathit{recall} &= \dfrac{tp}{tp + fn} \ \mathit{precision} &= \dfrac{tp}{tp + fp} \ \mathit{F1 \, score} &= 2 \cdot \dfrac{\mathit{recall} \cdot \mathit{precision}}{\mathit{recall} + \mathit{precision}} \end{aligned}$$

where tp are true positives, i.e., bugs that are classified as bugs, tn true negatives, i.e., non bugs classified as non bugs, fp bugs not classified as bugs and fn non bugs classified as bugs. Additionally, the recall and precision should be reported to allow us to understand the nature of the errors made by the models. We suggest to use a Bayesian approach for the statistical comparison following the guidelines by Benavoli  $et\ al.\ [46]$ . The authors suggest to use a Bayesian signed rank test for a comparison of results on multiple data sets, as is the case here. The advantage of the Bayesian approach is that the number of models that are compared does not influence the results, as this directly estimates that one approach performs better, which does not require an adjustment of the significance level [46].

As second fine-tuning task with shorter sequences, we suggest the automated classification of commits based on commit messages. Commit messages are usually very short (see Figure 2). Unfortunately, we are not aware of a solid benchmark for the machine-learning based classification of commit messages. Due to the good results for issues, we assume that fastText is also a good baseline for the classification of commit messages. As data, we use manually validated data from Trautsch et al. [13], i.e., we have a sample with a total size of 2533 commit messages that has as class label whether a commit is perfective or not. We follow the approach outlined by Benavoli et al. [46] for the comparison of classifiers on a single data set: we conduct 10x10 cross-validation and obtain 100 results for each classifier. We then use the Bayesian correlated t-test to compare the results. Same as above, we use the F1 score as foundation for the statistical comparison and report the recall and precision to understand the nature of the errors made by the models.

As third fine-tuning task we propose sentiment mining [14], [15]. We use three data sets that were also used by Zhang *et al.* [14] in a prior benchmark: the SO [47] and API [48] data with 4522 resp. 1500 sentences from Stack Overflow posts and the GH data [49] with 7122 sentences from GitHub pull requests and commit messages. All three data sets have three labels, i.e., positive, neutral, and negative sentiment. For each of these data sets, we use the same experimental setting as for the second fine-tuning task, i.e., we conduct 10x10 cross-validation. Since Zhang *et al.* [14] also the *F1 score*, we follow this approach and report the macro averages of the *F1 score*, recall, and precision, same as for the other use cases.

For all fine-tuning tasks, we propose to simply re-use the classification implementation for BERT from Hugging-Face: this implementation adds a single fully connected layer which produces the classification based on the output sequence of the BERT model. We then train each model for five epochs on the issue, commit, respectively, sentiment data for the fine-tuning. We use 80% of the training data for the fine-tuning and 20% as validation data to determine when the models start to overfit.

We note that we use different fine-tuning tasks than the NER task that was used by Tabassum *et al.* [10]. Our rational for using a classification task instead is that the NER task is very specific, especially with the respect that the exploitation of casing and special characters like the underscore is a major aspect of NER within natural language models. Thus, this task does not aim to understand the meaning, but rather at the inference of a specific language construct. In comparison, our tasks require the interpretation of the meaning of natural language.

# 6 EXPERIMENTS

We conducted an experiment to evaluate the validity of the SE models seBERT and BERToverflow in comparison to the general domain BERT models. Since seBERT is based on BERT<sub>LARGE</sub> and BERT<sub>BASE</sub>, we use both of these models within our comparison. We follow the procedure outlined

 $6.\ https://hugging face.co/transformers/v4.2.2/model\_doc/bert. \\ html$ 

in Section 5. This means we first compare the vocabularies. Then, we proceed to look at the validity of the models without fine-tuning through their ability to infer the correct meaning of terms. Finally, we evaluated how the different models perform when fine-tuned with a limited amount of labeled data for a prediction task.

All results, as well as the required scripts and link to the data for pre-training seBERT are available as part of our replication kit.<sup>7</sup> Additionally, we prepared a playground, which can be used to fill in masked words using the models.<sup>8</sup>

## 6.1 Vocabulary Comparison

The vocabularies of BERT<sub>BASE</sub> and BERT<sub>LARGE</sub> are equal, and we refer to them as BERT vocabulary in the following. The WordPiece overlap between BERT and seBERT is 38.3%. A major difference between the vocabularies is the number of "##" sub-word WordPieces, with seBERT (7430) having almost twice as many as BERT (3285). Most of the words added to the seBERT vocabulary are from the SE domain (e.g. "bugzilla", "jym", "debug") or internet slang (e.g. "fanboy"). Lost words are mainly from the geographical (e.g. "madrid", "switzerland", "egypt"), religious (e.g. "jesus", "buddha") or political (e.g. "president", "minister", "clinton") domain.

For words that occur in only one of the two vocabularies, we use the tokenizer of the other model to break them down into their respective WordPieces. We have presented the results for a small subset of words in Table 3. As we can see, BERT tokenizes SE domain words inconsistently, e.g. "bugzilla" is tokenized into "bug ##zil ##la", but "debug" into "de ##bu ##g", showing that there is no WordPiece for "##bug". In addition, in-domain abbreviations such as JVM are unknown and broken down into their individual characters. In contrast, seBERT breaks down general outof-domain words into in-domain WordPieces, e.g., "drama" into dynamic random-access memory (DRAM) or "infantry" into "inf" and "ant". Since the vocabularies are frequencybased, an interesting finding is that "woman" is not in the seBERT vocabulary and is tokenized into "wo ##man". This implies that "woman" is used less frequently within the domain, highlighting the ethical issues that can arise in machine learning. The full lists of out-of-vocabulary words and their tokenizations are available as supplemental material in the seBERT replication repository.

Since the BERToverflow vocabulary is cased, a direct comparison of the overlap is not feasible. Instead, we lower case the vocabulary of BERToverflow and remove duplicates. Since the vocabulary of BERToverflow is larger than that of (se)BERT, we still cannot directly compute the overlap, because this is a ratio with respect to the vocabulary size. Instead, we calculate i) the ratio of WordPieces of the (se)BERT vocabulary within the uncased BERToverflow vocabulary and ii) the ratio of uncased BERToverflow WordPieces within the BERT vocabulary.

After lower casing, there are 58,854 unique WordPiece tokens. 24,263 of these tokens are also in the seBERT vocab-

<sup>7.</sup> https://github.com/smartshark/seBERT

<sup>8.</sup> https://smartshark2.informatik.uni-goettingen.de/sebert/index.html

Word	BERT Tokenization	Word	seBERT Tokenization	BERToverflow Tokenization
bugzilla	bug ##zil ##la	catholic	cat ##hol ##ic	cath ##olic
chromium	ch ##rom ##ium	drama	dram ##a	drama
debug	de ##bu ##g	infantry	inf ##ant ##ry	inf ##ant ##ry
jvm	j ##v ##m	palace	pal ##ace	pal ##ace
refactoring	ref ##act ##orin ##g	woman	wo ##man	woman

TABLE 3

Example words not included in the BERT or seBERT vocabulary broken down into their WordPieces using the respective tokenizer. ## indicates the start of a subword token.

ulary. This means seBERT covers about 40% of the uncased BERToverflow vocabulary and the uncased BERToverflow covers about 80% of the seBERT vocabulary. That BERToverflow has more tokens is not surprising, due to the larger vocabulary size. While the overlap of 80% of the seBERT tokens with BERToverflow is substantial, we would have expected an even larger overlap, given that BERToverflow has about twice the amount of uncased tokens. This should be sufficient to more or less cover the seBERT vocabulary, assuming that the textual data from Stack Overflow on which BERToverflow is pre-trained, is representative for the SE domain. A manual check revealed that many of the missing tokens are related to tools, e.g., "matplot", "xenial" or "hashicorp". We can only speculate regarding the reason for this. One possible explanation is that tools are less frequently discussed on Stack Overflow than, e.g., programming languages. However, while this may the case to a certain degree, questions regarding the usage of specific tools are common Stack Overflow. Another possible explanation is the casing that is used when writing tools. For example, users may write "HashiCorp", "Hashicorp", or "hashicorp". Within the uncased seBERT vocabulary, this would not make a difference and all occurrences would be counted together, possibly leading to larger importance and the inclusion in the vocabulary.

We also manually evaluated which additional terms are within the BERToverflow vocabulary, that are not within the seBERT vocabulary. In addition to more terms from the general domain (see the comparison to BERT below), we noticed two additional aspects. First, there were many Unicode tokens, such as special characters only used in non-English texts. Second, there were many terms that seem to come from code snippets, such as "strftime".

The BERT vocabulary has an overlap of 15,926 Word-Piece tokens with the uncased BERToverflow vocabulary. This means that about 50% of the BERT tokens are within the BERToverflow vocabulary, which is slightly more than the overlap of 38% between seBERT and BERT. However, this increase is plausible, given the overall larger vocabulary size of BERToverflow. This is also visible in the tokenization, e.g., the terms "women" and "drama" are within BERToverflow vocabulary, meaning that is covers more general domain concepts that seBERT.

#### 6.2 Contextual Comparison

Next, we use the capability of the models to predict masked words. Tables 4-6 show ten examples of sentences for the positive, negative, and neutral category.

The positive examples in Table 4 show that while the general domain BERT models are not as accurate with the identification of words from the within-domain context as the in-domain models BERToverflow and seBERT. This does not mean that BERT outright fails, but rather that the inferred are not completely unrelated, but also not directly on point. In comparison, BERToverflow and seBERT both almost always suggest reasonable completions. However, we also observe that either the larger set of training data or the larger model also allows seBERT to be more accurate in some cases. The last example gives the strongest indication for this: since BERToverflow was not trained on issue data, but only on Q&A data from stack overflow, seBERT performs better in this context. For this sentence, the general domain results from BERT are actually better than BERToverflow. Our interpretation of this is that this is caused by the context of the BERToverflow data: the criticality of issues is usually not discussed on Stack Overflow. Instead, users may ask regarding a certain problem, with other users responding that the bug is known. Thus, the association of "This is a [MASK] bug" with "known" makes sense. However, the second part of the sentence further clarifies this context as "please address this asap". Such a direct request to the developers does not make sense within the Q&A context and could, therefore, not be considered by BERToverflow. In comparison, the seBERT data is aware of such direct communication with a development team and correctly infers that the missing word is likely the criticality of the issue, because it should be addressed as soon as possible.

The negative examples in Table 5 highlight that models trained with SE data fail, when it comes to understanding pure general domain context. All words are interpreted within the SE context, even if this does not make sense. In comparison, the general domain models were a lot closer to the performance of the SE domain models for the positive examples. When we consider the training corpus, this makes sense: topics like dentists, actual snakes, or the wether are extremely unlikely in our SE corpus, so it is plausible that this does not work at all. On the other hand, Wikipedia also covers software engineering topics. Thus, while this is not the focus of the general domain corpus, it also contains some software engineering data.

The neutral examples in Table 6 reveal some nuanced differences between all four models. This is the first time that we clearly observe that the BERT<sub>LARGE</sub> model is better a capturing the context than the BERT<sub>BASE</sub> model. In Sentence 28, the smaller models fail to correctly understand the context, while all other models understand this perfectly.

Sentence	Expectation	$BERT_{BA}$ Prediction	SE Prob.	$\begin{array}{c} \text{BERT}_{\text{LAI}} \\ \text{Prediction} \end{array}$	RGE <b>Prob.</b>	BERTove: Prediction	rflow Prob.	seBER Prediction	T Prob.
1) The [MASK] is thrown when an application attempts to use null in a case where an object is required.	NullPointer- Exception	rule exception coin flag penalty	0.2407 0.0742 0.0659 0.0245 0.0216	value exception coin ball flag	0.2356 0.0804 0.0342 0.0318 0.0312	exception error Null- Pointer- Exception NPE Illegal- Argument- Exception	0.4718 0.1229 0.1161 0.0995 0.0403	exception error null- pointer- exception npe illegal- argument- exception	0.5473 0.2188 0.1158 0.0291 0.0144
2) [MASK] is a proprietary issue tracking product developed by Atlassian that allows bug tracking and agile project management.	Jira	it agile eclipse flex snap	0.0382 0.0104 0.0041 0.0035 0.0031	it bug eclipse echo spark	0.0148 0.0074 0.0052 0.0046 0.0035	Jira Redmine JIRA It There	0.4914 0.1834 0.099 0.0398 0.0281	jira there zenhub it bugzilla	0.4954 0.0837 0.0763 0.0488 0.0463
3) [MASK] is a software tool for automating software build processes.	build automation tools	it agile this build gem	0.1437 0.0071 0.0062 0.0055 0.0055	it build eclipse builder agile	0.0396 0.0294 0.0107 0.0075 0.0067	CMake make Make Ant Maven	0.1541 0.0898 0.0644 0.0595 0.0558	jenkins make ninja it ant	0.1907 0.0891 0.0676 0.058 0.0536
4) Pathlib is a python library used for handeling [MASK].	paths	applications systems programs software data	0.0699 0.0431 0.0359 0.0351 0.0296	applications software programs languages systems	0.1509 0.1505 0.078 0.0631 0.052	paths files urls URLs pathnames	0.429 0.0789 0.0664 0.0391 0.0384	paths path directories filenames strings	0.8727 0.0338 0.0237 0.0168 0.0088
5) The solution posted by [USER] is [MASK] helpful. :)	positive adverb	very extremely quite always more	0.5632 0.0656 0.0424 0.0313 0.0273	very not always also most	0.3407 0.1755 0.0624 0.0593 0.0429	very really also more quite	0.5488 0.1374 0.0734 0.027 0.0237	very really quite also super	0.5719 0.1533 0.0729 0.0458 0.0166
6) The solution posted by [USER] is [MASK] helpful. :(	negative adverb	very extremely quite also always	0.5254 0.0659 0.0418 0.0349 0.0338	very not also always most	0.2764 0.1767 0.0829 0.0782 0.0455	not very really never also	0.9182 0.0331 0.0087 0.0031 0.0031	not no very really never	0.9761 0.0075 0.0038 0.0011 0.0009
7) [MASK], is a provider of Internet hosting for software development and version control using Git.	github, git- lab	microsoft net oracle org apache	0.0158 0.0136 0.0134 0.0127 0.0122	net apache parallels foundry radius	0.0127 0.011 0.0097 0.0073 0.0061	Github GitHub Bitbucket BitBucket Assembla	0.222 0.2186 0.0568 0.0509 0.0413	github gitlab git sourceforge bitbucket	0.3096 0.0397 0.0382 0.0309 0.0302
8) In object-oriented programming, a [MASK] is an extensible program-code-template for creating objects.	class	template class object model gui	0.1027 0.0391 0.0356 0.0219 0.0145	template prototype module class construct	0.6763 0.0533 0.0258 0.0136 0.0106	constructor class factory prototype Factory	0.3849 0.2664 0.1435 0.038 0.0182	class constructor factory metaclass template	0.4991 0.221 0.0669 0.0487 0.0316
9) I have to discuss this with the other [MASK].	developers	elders girls men officers council	0.0703 0.0677 0.0622 0.0526 0.0453	men members elders officers people	0.0913 0.0407 0.0399 0.0265 0.024	guys people developers person users	0.1364 0.1074 0.0918 0.0533 0.0497	developers team maintainers people devs	0.1159 0.1114 0.0797 0.0796 0.0744
10) This is a [MASK] bug, please address it asap.	critical, major	serious new major persistent big	0.286 0.1166 0.0699 0.0473 0.031	security serious minor major nasty	0.0956 0.0807 0.0458 0.0397 0.0298	known know chrome browser common	0.5999 0.029 0.02 0.014 0.0118	critical serious big major real	0.4529 0.3002 0.0607 0.0425 0.0301

TABLE 4
Prediction of words for [MASK] tokens. Results for the *positive* category, i.e., sentences where we expect that BERToverflow and seBERT perform better than BERT.

Sentence	Expectation	${ m BERT_B}$	ASE <b>Prob.</b>	${f BERT_{LA}}$	RGE Prob.	BERTOver Prediction	flow Prob.	seBERT Prediction	Prob.
11) A [MASK] crawled across her leg, and she swiped it away.	bug	spider tear hand bug mosquito	0.1417 0.1277 0.0841 0.0834 0.0534	bug spider tear flea fly	0.2087 0.1676 0.1463 0.048 0.0447	person car dog bird fox	0.1068 0.0561 0.0559 0.0405 0.0397	man person friend girl monkey	0.1042 0.0518 0.0472 0.0299 0.0248
12) Can you open the [MASK], please? It's hot in here.	window, door	door window windows blinds curtains	0.7435 0.1227 0.0349 0.0171 0.0113	door window fridge doors gate	0.8776 0.0619 0.0058 0.0057 0.0055	link file site page url	0.3264 0.0699 0.0411 0.0395 0.0307	pr issue door file link	0.2829 0.1386 0.0576 0.0466 0.0352
13) The reticulated python is among the few [MASK] that prey on humans.	snakes	snakes species reptiles animals lizards	0.6433 0.1645 0.1055 0.0278 0.0269	snakes reptiles animals species mammals	0.803 0.0779 0.0696 0.0223 0.0075	languages things tools people programmers	0.7376 0.0836 0.0087 0.0084 0.0073	things languages tools packages programs	0.5227 0.1625 0.0632 0.0348 0.0255
14) "I have a [MASK] request for you." He said to the waiter.	special	special business personal new specific	0.4258 0.0859 0.0809 0.0318 0.0225	special specific new small simple	0.8448 0.0198 0.017 0.0166 0.0128	new special test friend support	0.115 0.0361 0.0257 0.0224 0.0213	pull feature change similar merge	0.7016 0.0432 0.0171 0.0146 0.0139
15) He was admitting to a [MASK] he didn't commit, knowing it was somebody else who did it.	crime	crime murder sin lie suicide	0.7861 0.1162 0.0484 0.0084 0.0056	crime murder sin felony lie	0.9565 0.0358 0.005 0.0008 0.0005	commit change mistake fact file	0.1497 0.1223 0.0844 0.0629 0.044	change commit fix file code	0.2475 0.0974 0.0833 0.0464 0.0372
16) It's an incurable, terminal [MASK].	disease	disease condition illness death cancer	0.4208 0.3208 0.125 0.0201 0.0193	disease illness condition cancer disorder	0.8134 0.0879 0.0579 0.0203 0.0049	error operation command problem )	0.0777 0.0639 0.0517 0.0336 0.0288	issue problem bug character effect	0.0605 0.0523 0.0443 0.0377 0.0273
17) The dentist said I need to have a root [MASK].	canal	canal beer problem out cellar	0.8847 0.0307 0.0167 0.005 0.003	canal beer stop break problem	0.9827 0.01 0.0009 0.0005 0.0005	account certificate user node access	0.1919 0.0959 0.0825 0.0588 0.0474	password user account access certificate	0.1476 0.1431 0.089 0.0522 0.0475
18) Everything was covered with a fine layer of [MASK].	dust, snow	dust dirt snow paint powder	0.4895 0.1035 0.0625 0.0432 0.01	dust snow dirt ice sand	0.7656 0.0813 0.0283 0.0199 0.0122	transparency abstraction code complexity confidence	0.0518 0.0417 0.0408 0.0323 0.032	abstraction coverage testing detail documentation	0.1231 0.095 0.0894 0.0671 0.0636
19) There was not a single cloud in the [MASK].	sky	sky air distance skies room	0.9009 0.0748 0.003 0.0021 0.0017 0.0032	sky heavens distance air east	0.9425 0.0104 0.0076 0.0041 0.0032	list cloud world center database	0.0797 0.0361 0.0333 0.027 0.0263	database list dataset file cloud	0.0686 0.0663 0.0391 0.0358 0.0357
20) What does it say in your [MASK] cookie?	fortune	fortune chocolate little next sugar	0.4846 0.0534 0.0289 0.0207 0.0206	fortune favorite next chocolate sugar	0.295 0.2597 0.0484 0.0284 0.0261	browser session firebug firefox debug	0.1262 0.083 0.07 0.0508 0.032	session browser auth cookie login	0.4255 0.0994 0.0572 0.0318 0.0195

TABLE 5

Prediction of words for [MASK] tokens. Results for the *negative* category, i.e., sentences where we expect that BERToverflow and seBERT perform worse than BERT.

Cantana	Et-t	BERT <sub>BASE</sub>		BERTLARGE		BERTOV		seBERT	
Sentence	Expectation	Prediction	Prob.	Prediction	Prob.	Prediction	Prob.	Prediction	Prob.
21) We can [MASK] in person if you have any specific questions.	meet	talk speak meet chat visit	0.4357 0.207 0.0971 0.0746 0.0266	meet speak talk discuss communicate	0.695 0.1173 0.1026 0.0208 0.0057	help be edit assist answer	0.2649 0.066 0.0566 0.0553 0.0477	chat talk discuss meet speak	0.5492 0.1941 0.1025 0.0913 0.0064
22) [MASK] its name, vitamin D is not a vitamin. Instead, it is a hormone that promotes the absorption of calcium in the body.	despite	despite whatever unlike in notwith- standing	0.999 0.0002 0.0002 0.0001 0.0001	despite unlike notwithstanding like whatever	0.998 0.0016 0.0002 0.0001 0.0	Despite despite by By In	0.7482 0.1184 0.0387 0.0212 0.01	despite in from unlike by	0.9396 0.0169 0.0099 0.0095 0.0068
23) Would all those in favour please raise their [MASK]?	hands	hands hand voices arms fists	0.5325 0.122 0.1177 0.031 0.0124	hands hand voices voice arms	0.537 0.1543 0.128 0.11 0.0121	opinion opinions concerns points views	0.2422 0.1803 0.0982 0.0704 0.0444	opinion concerns priority opinions interest	0.1235 0.0798 0.057 0.0531 0.043
24) She surprised him with a [MASK].	something positive	smile look laugh kiss grin	0.4748 0.1623 0.0604 0.0588 0.0502	smile laugh kiss question grin	0.4086 0.2211 0.105 0.0673 0.0369	surprise mistake message bug warning	0.1815 0.0606 0.0551 0.034 0.0322	bug question comment problem joke	0.0604 0.0485 0.0197 0.0191 0.019
25) Whoever is happy will make others [MASK] too.	happy	happy happier , smile sad	0.989 0.0025 0.0012 0.0012 0.0007	happy unhappy happier , smile	0.9716 0.0104 0.0053 0.0042 0.002	happy unhappy , pleased sad	0.9968 0.0003 0.0003 0.0002 0.0002	happy , complain sad comfortable	0.9866 0.0027 0.0007 0.0005 0.0003
26) If there are night owls, are there [MASK] owls too?	day	night day other morning bird	0.3312 0.2063 0.0275 0.0175 0.0158	day night morning other evening	0.5414 0.2378 0.0671 0.0143 0.0085	day night power weather evening	0.1331 0.0527 0.0352 0.0178 0.0149	day evening afternoon morning night	0.6346 0.1119 0.0899 0.0484 0.0302
27) Never forget, always remember. Always forget, never [MASK].	remember	forget remember forgot forgotten know	0.979 0.007 0.0018 0.0015 0.0015	forget remember forgive know forgot	0.9271 0.0666 0.0007 0.0005 0.0004	remember forget trust know read	0.4836 0.3044 0.0355 0.0102 0.0077	remember forget recall bother guess	0.881 0.0997 0.0113 0.0009 0.0006
28) If you are counting things, start from [MASK].	1, one	scratch there bottom one here	0.5561 0.0836 0.0511 0.0425 0.0286	one here zero three ten	0.1389 0.1222 0.0731 0.064 0.0497	0 1 zero 2 there	0.3938 0.293 0.164 0.0156 0.0102	zero 0 1 there 2	0.34 0.2834 0.2587 0.021 0.0132
29) Soccer has really simple rules. It's not [MASK] science.	rocket	a rocket really just pure	0.7412 0.0334 0.0227 0.0225 0.0147	rocket about a even like	0.9125 0.0356 0.032 0.0021 0.0015	rocket computer a exact perfect	0.8597 0.0513 0.0317 0.0071 0.0049	computer rocket a game about	0.4413 0.3927 0.0483 0.0146 0.0132
30) He ran out of [MASK], so he had to stop playing poker.	money, time	money time food funds cash	0.8096 0.0285 0.0126 0.0113 0.0094	money cash cards time patience	0.7833 0.0579 0.0213 0.0187 0.0074	cards players hands money memory	0.4876 0.0369 0.0309 0.0294 0.0221	pokemon memory ram money mana	0.1655 0.0767 0.0649 0.0618 0.0455

TABLE 6

Prediction of words for [MASK] tokens. Results for the *neutral* category, i.e., sentences where we expect that BERToverflow and seBERT perform worse than BERT.

The same sentence also reveals a nuanced difference: since we often start to count from zero in computer science, this is also proposed by BERToverflow and seBERT, while BERT<sub>LARGE</sub> says to start at one. We also note that the SE domain models sometimes misjudge these neutral concepts, e.g., with sentence 23. While the sentence clearly indicates that the context is voting, the term "raise" is so strongly associated with opinions within the SE domain, that hands are not suggested. This set of sentences also contains the strangest association within our data in Sentence 30: we have no idea why seBERT believes that running out of pokemon is likely. The only explanation we can think of is the tokenization by seBERT of "poker" as "poke##r". It is possible that the subword "poke" has a strong association with "pokemon", which leads to this mistake.

## 6.3 Prediction Task Comparison

Table 7, and figures 4-8 summarize the results of the prediction task comparison. The results show that seBERT and BERToverflow achieve the best performance for the issue type prediction and commit intent prediction tasks, outperforming both fastText and the general-domain BERT models. The improvement over fastText is very large with an about 11% higher F1 score for the issue type prediction and about 9% higher F1 score for the commit intent prediction. The boxplots in Figure 4 and Figure 5 indicate that the performance improvement in F1 score is due to an improvement of both recall and precision, which means the models reduced both false positives and false negatives in comparison to fastText. The Bayesian signed rank test determined that this improvement of the SE domain models over the other models is significant. The difference between seBERT and BERToverflow is not significant for the issue type prediction task. For the commit intent classification, seBERT is significantly better than BERToverflow with an absolute difference of about 3% in the F1 score. The comparison between fastText and BERT<sub>BASE</sub> shows that the generaldomain models may be better than smaller text processing models without pre-training on the issue type prediction and commit intent prediction tasks. BERT<sub>BASE</sub> significantly outperforms fastText on the issue type prediction past, on the commit intent task we do not observe a difference between fastText and BERT<sub>BASE</sub>. The BERT<sub>LARGE</sub> model from the general domain has severe problems with both use cases, i.e., several cases where the models completely failed. This happened with none of the other models and may be an indication that the amount of data is too small to fine-tune such a large model from the general domain on a domainspecific corpus.

The results for the sentiment mining show that there are only small differences between the SE domain and general domain BERT models on all three data sets. The absolute performance on the API and GH data is almost equal. The difference on the SO data is slightly larger, where BERToverflow and seBERT outperform the BERT<sub>BASE</sub> and BERT<sub>LARGE</sub> by about 3%, with a statistically significant difference. We observe that, same as before, the BERT<sub>LARGE</sub> model is sometimes unstable, likely for the same reasons as above. The difference between the transformer models and fastText is huge for this task, i.e., at least 20% in *F1 score* on all data sets.

# 7 DISCUSSION

We now discuss our results with respect to our research questions, consider the ethical implications of our work, discuss the limitations and open issues, as well as the threats to the validity.

# 7.1 Interpretation of SE Terminology

Our results indicate that SE domain models are better at modeling natural language within the SE domain than general domain models. The vocubalaries contain more tokens from the SE domain. Especially the focus of the vocabulary is interesting. Both seBERT and BERToverflow have the names of many tools such as programming languages, libraries, build tools, and operating systems. Such words are mostly missing in the BERT vocabulary.

That domain specific words replace terms from other domains is not surprising. However, the magnitude of the difference between the vocabularies is larger than we would have expected: only half of the words from BERT are within the BERToverflow vocabulary, for the smaller seBERT vocabulary this drops further to 38%. Thus, less then half of the commonly used terminology from the general domain is among the commonly used terminology within the SE domain. In comparison, the lexical similarity between English and German is about 60% [50]. While this comparison is a bit unfair and likely an overstatement, because the vocabularies require exact matches of word pieces, while the lexical similarity requires only a "similarity in both form and meaning" [51], this highlights how different texts from the SE domain are from the general domain. This also demonstrates that NLP models with a fixed vocabulary should always be retrained from scratch for the SE domain to maximize the performance, instead of basing them on general domain models with additional pre-training steps, as is, e.g., done for BioBERT [7] and ClinicalBERT [8].

The MLM task demonstrates that the better representation of the SE context goes beyond the vocabulary. With SE domain statements, the general domain models often understand that they should suggest a word from the SE domain, but often do not really understand the exact meaning, which leads to unsuitable suggestions. The SE domain models are much better at understanding the complete context of the missing word and provide suitable suggestion. However, the examples also show that for a SE domain NLP model, data from Stack Overflow alone is not sufficient, as this only represents the domain within a Q&A context. Other aspects of the NLP aspects of SE domain are not sufficiently captured by the BERToverflow model. This demonstrates that a larger amount of training data is beneficial and that data should be selected from a diverse range of sources. This also shows that we should be careful, when we use NLP models for tasks, where the text may be different from the pre-training texts. The additional MLM examples confirm what we expected about the SE domain models: their general language understanding is okay, but they are clearly inferior to general domain models for anything beyond the SE domain.

**Answer to RQ1:** Transformer models trained with general domain data have trouble understanding SE

Model	Issue Type	Commit Intent	Sentiment (SO)	Sentiment (API)	Sentiment (GH)
fastText	0.69	0.75	0.44	0.37	0.47
$BERT_{BASE}$	0.77	0.75	0.73	0.57	0.91
$BERT_{LARGE}$	0.62	0.71	0.73	0.55	0.91
BERToverflow	0.81	0.81	0.77	0.58	0.92
seBERT	0.80	0.84	0.76	0.57	0.92

TABLE 7

Median F1 score of the models for the fine-tuning tasks. Macro-average over the three classes for the sentiment mining.

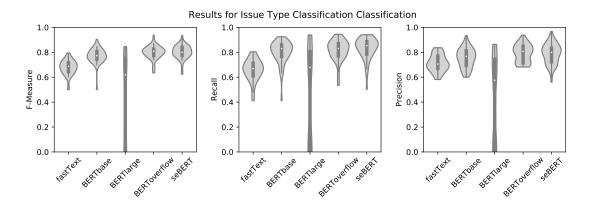


Fig. 4. Results of the prediction of bug issues.

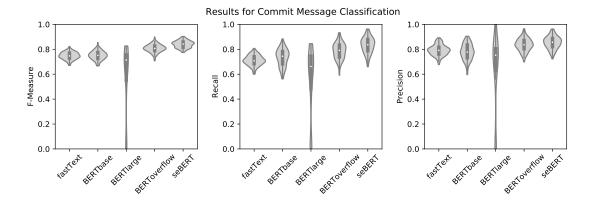


Fig. 5. Results of the prediction of quality improving commits.

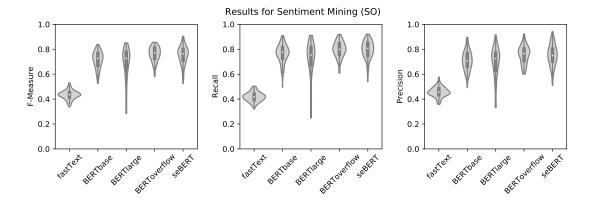


Fig. 6. Results of the sentiment mining on the SO data..

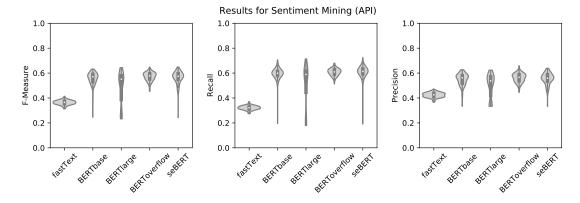


Fig. 7. Results of the sentiment mining on the API data.

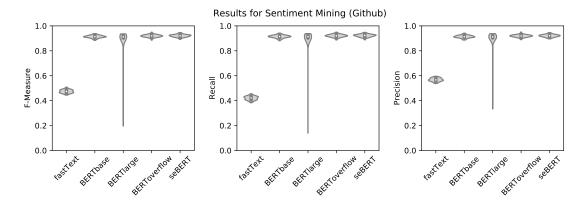


Fig. 8. Results of the sentiment mining on the GH data.

domain terminology. SE specific models are very good at understanding sentences within the SE context and in general language understanding, but do not perform well in contexts beyond the SE domain.

## 7.2 Impact on Applications

The results of the fine-tuned predictions show that SE domain transformer models easily are state-of-the-art for the two domain specific NLP tasks we considered, i.e., the issue type prediction and the commit intent prediction. In both task, seBERT and BERToverflow clearly outperform the competition and the absolute improvement is huge. Even more importantly, these models are decreasing both false negatives and false positives, i.e., they do not achieve this performance improvement through a trade-off between the errors, which indicates that this is really due to a better understanding of the language. Thus, the high validity of the domain understanding we found through the manual inspection of the vocabularies and the MLM task also translates into a better performance in relevant NLP use cases. This improvement is not explainable by the model size alone. This is demonstrated by the lower performance of the general domain BERT models. These models have the same size as our in domain-models<sup>9</sup>, but do not show the same improvement over the smaller fastText model. Moreover, our results show that the SE domain transformers are not always better when SE data is used: we could not find notable differences between the general domain BERT models and the SE domain models for the sentiment mining tasks. Thus, SE specific pre-training only seems valuable, if the use case is specific to the SE domain and requires the interpretation of text with an SE background.

The impact of our choice to use a sequence length of only 128, in comparison to the sequence lengths of 512 from the other models is also visible in the fine-tuning. For the short commit messages of the commit intent prediction task, the seBERT model outperforms all other models, including BERToverflow. This is reasonable, because of the seBERT is the overall larger model and commit messages were used for the pre-training. We do not observe such a difference in performance for the issue type prediction task. Here, seBERT and BERToverflow are very similar to each other. This could mean, that the *F1 score* of 0.8 is the performance ceiling and a better result is not possible without additional data, e.g., more training data or additional information about the issues. Alternatively, seBERT is penalized by the short sequence length of 128, which gives BERToverflow an advantage for longer issues. This could compensate the difference in model size and data for pre-training. Without extending seBERT to a sequence length of 512, we cannot answer which is the case. However, such an extension is, at this time, from our perspective not warranted due the required energy consumption (see Section 7.3) and we

<sup>9.</sup> Reminder: BERToverflow is a  $\text{BERT}_{\text{BASE}}$  model and seBERT is a  $\text{BERT}_{\text{LARGE}}$  model.

believe that the computational effort for this should only be spent if there is a clear expected advantage of considering longer sequences.

The difference between the BERT<sub>BASE</sub> and BERT<sub>LARGE</sub> model further shows that general-domain models - especially large general domain models - should be used with caution: often, this model converged to a trivial result where all instances were classified as negative. The logs of the training showed, that this happened when the finetuned model was still very bad after the first epoch. In the subsequent epochs, the optimization found that a trivial model was actually better in terms of accuracy and crossentropy than the first attempts. Unfortunately, we cannot determine the exact reason for this. However, we believe that this may be due to the combination of a small data set for fine-tuning and a lack of SE domain understanding of the general model. As a result, the training did not converge towards a reasonable solution within one epoch. Subsequently, the optimizer got stuck in the local optimum of the trivial model.<sup>10</sup> That this did not happen with the equally large seBERT provides another indication that the SE specific pre-training, in fact, the opposite happened: since the pre-training already captured the domain very well, seBERT usually achieved the optimal result within one, at most two epochs, regardless of the model size.

Together with the results from Tabassum *et al.* [10] for the NER task, that showed that the BERToverflow model was also better than a BERT $_{\rm BASE}$  model, we have a clear answer for RQ2.

Answer to RQ2: Transformer models pre-trained with SE domain data consistently outperform other models on SE use cases and should be considered as the state-of-the-art. Pre-trained models from the general domain should be used with care, especially if only a small amount of data is available for the fine-tuning. However, we also found that SE domain models perform similar to general domain models for sentiment mining on SE data, i.e., a use case that does not require SE specific knowledge.

# 7.3 Ethical Considerations

Large deep learning models for NLP, like the transformer models we consider within this work, are associated with several ethical challenges, as is, e.g., highlighted in the famous stochastic parrots paper by Bender *et al.* [52]. Due to impact of Bender *et al.* [52] and the direct relation to BERT models, we structure our consideration of ethical aspects following the four major ethical concerns highlighted in their work.

The first aspect highlighted by Bender *et al.* [52] is the energy consumption that large transformer models require. We actively considered methods to reduce the training time, e.g., by using a version of the BERT pre-training that was optimized for the hardware we were using and by restricting the sequence length to 128 tokens. Based on the

10. We cannot rule out, that other training parameters (e.g., batch size, learning rate), would yield better results with  $BERT_{LARGE}$  or any other of our models. However, this does not affect our conclusions, as we discuss in the threats to validity (see Section 7.5).

energy consumption of the system we used for training, that requires between 2.5 kW and 3.5 kW when utilized fully, we estimate that we required between 270 kWh and 378 kWh for the 4.5 days of pre-training. Under load the cooling of the data center, where the compute nodes are located, has a Power Usage Effectiveness (PUE) of about 1.23. Additional overhead regarding storage and network has also to be taken into account, so we are calculating with an overhead of approximately 30%. Hence, we estimate that we consumed at most  $378 \text{ kWh} \cdot 1.30 = 491.4 \text{ kWh}$ . Based on the 366 g CO<sub>2</sub> that is generated per kWh in 2020 in Germany [53], this means the pre-training produced up to 180 kg of CO<sub>2</sub>. This is roughly the amount of the CO<sub>2</sub> for one tank filling of an average family car, which we believe is not unreasonable from an ecological perspective for a onetime effort. In comparison, Strubell et al. [54] estimate that they required about 1507 kWh for the training of a BERT<sub>BASE</sub> model. This means that we could train the seBERT model with only one third of the environmental impact than a normal BERT<sub>BASE</sub> model, even though we use a BERT<sub>LARGE</sub> architecture and 119.7 Gigabyte instead of 16 Gigabyte of textual data for training.

The second aspect highlighted by Bender et al. [52] is the quality of the training data. The authors highlight that the size of the training data does not guarantee diversity, data collected from the past can, by definition, capture how language evolves, and that there is a risk that models, therefore, capture and enforce existing biases. We did not systematically evaluate BERToverflow and seBERT for such biases. One aspect we found regardless is that "women" was not in the dictionary of seBERT. Thus, we can be quite sure, even without an in depth consideration, that there is at least a severe gender bias within the data, and, consequently, within seBERT. Since BERToverflow was trained on less, but similar data, we believe that there should be a similar gender bias. We cannot comment on other biases, e.g., racial bias or similar. Tasks like NER or classification of bugs should not be affected by such biases and can safely be used. Tasks where bias is be relevant, e.g., sentiment mining of developers, the development of chat bots or automated answering of SE questions should only be conducted after a detailed consideration of such ethical considerations. For tasks where the impact of bias is unclear, e.g., the summarizing existing texts within the SE domain, could possibly be used but we still recommend to at least conduct a basic check for such biases.

The third aspect that Bender *et al.* [52] consider is that time may be better spent than on the exploration of ever larger language models. When we transfer this to our work, this means that SE researchers should not invest too much effort into the development of NLP models for the SE domain, but rather focus on the SE data and use cases. For us, this means that we should only provide SE domain models, when machine-learning driven NLP research has major advances, instead of, e.g., trying to directly find new transformer architectures for SE benchmarks with SE data. Currently, it seems like the SE community is already using such an approach, as there are only few domain specific models and they are all re-using architectures that were developed by researchers for the general domain (see Section 3).

The fourth issue raised by Bender et al. [52] is that, in the end, such large NLP models are nothing more than stochastic parrots, i.e., models that repeat what they have seen in the data, with some random component. This is due to our lack of understanding about the internal structure and reasoning within models with millions of parameters. This is also a property of SE domain models that should be respected for any later use of these models in an ethical way. For example, we found that the SE domain models are very good at suggesting technologies. When we use the sentence "You can use [MASK] for code coverage in java.", seBERT and BERToverflow predict tools like Cobertura, gcov, Emma, or Jacoco. We found that this works with different languages and different kinds of tools. However, using the models within a chat bot or Q&A system to recommend suitable tools means that the past is encoded and developers of new tools would not have a chance, unless the model is retrained. In comparison, humans learn continuously about new tools, i.e., there would not be such an ethical problem. The consequence of this issue is similar to the impact of potential biases: we recommend to be careful when using the NLP models to generate responses to actual queries, unless it was determined that the possible responses are carefully validated for the given use case.

# 7.4 Limitations and Open Issues

Our work demonstrates that NLP models pre-trained with SE domain data are useful. However, there are also limitations to the understanding of transformers that we established. The first is an issue with the external validity of our work. Since we used BERT both as general domain reference model, as well as the architecture for our models, it is unclear how the results generalize to other transformer models. While the difference to models that have a similar size like RoBERTa [19] should be relatively small, it is unclear if extremely large models like GPT-3 [20] may be able to correctly understand the meaning of texts both in the SE and general domain, same as human experts. While there is no reason that this should be the case, there is also no strong argument against this. However, currently the scale of these models is beyond almost anyone, except the largest labs and companies of the globe. Therefore, even if this were the case, such improvements could currently only be harnessed by a small elite. Thus, we believe that for the majority of SE researchers and vendors who may consider building NLP capabilities into their tools, models like BERT are a more realistic, current alternative.

A related limitation is the impact of the context length on the results. Within this work, we work with a maximum context length of 512 tokens (BERT, BERToverflow) and 128 tokens (seBERT). While we argue that most SE texts in our data are shorter anyways, this is also due to the type of text we consider. If we were to, e.g., consider README files instead, we would likely have many examples of longer texts. Thus, while our results show that even the relatively short context of 128 tokens is sufficient and actually leads to the best results in both domain-dependent fine-tuning examples we consider, this may not generalize to NLP tasks on longer inputs. Especially generative tasks, like summarizing long documents, may benefit from a longer context that is

sufficient to capture the meaning of the whole text at once. In case studies find that models with shorter contexts, like BERT, do not generate suitable results for longer documents, other transformer models, like Big Bird [55], which achieves a sequence length of 4096 tokens, could be used.

Another limitation is a corollary from our statement regarding longer documents: while our corpus is already relatively diverse, with Stack Overflow, issues, and commit messages, this still does not capture the whole SE domain and, most notably, lacks examples with longer texts. Thus, even if we wanted to train a model with a longer sequence length, this could only make a difference on a small fraction of this type of SE data and the available data would likely not be sufficient to correctly model longer contextual relationships. Unfortunately, there is neither a suitable data set that could be exploited for pre-training, nor is there a benchmark task for NLP within the SE domain that requires longer texts. Thus, to advance NLP for the SE domain for tasks with long sequences, our community would first need to solve the associated data challenge, both with respect to data for pre-training, as well as through a curated data set that is suitable for the benchmarking of a fine-tuned application.

Finally, we already highlighted the lack of an evaluation of the SE models from an ethics perspective. While this was not within the scope of our work, future work must deal with potential biases in SE domain models, unless their usage is restricted to few and possibly uncritical use cases, as is, e.g., the case in our fine-tuned examples. We note that this does not only affect seBERT and BERToverflow, but also models like CodeBERT [56], in case this is used to generate texts, e.g., automated documentation generation. From our perspective, this is a precursor of any type of generative NLP application, i.e. NLP models that actively generate texts, e.g., to answer questions like "what does this code do" or "summarize this README file", but also for any application like sentiment mining, which is known to encode biases [57].

#### 7.5 Threats to Validity

We report the threats to the validity of our work following the classification by [58] suggested for software engineering by [59]. Additionally, we discuss the reliability as suggested by [60].

# 7.5.1 Construct Validity

The construct of our validation of NLP models may be unsuitable. The direct comparison of WordPiece vocabularies neglects to account for the internal structure of the models. For example, the internal structure could achieve that the combination of tokens "wo##men" is the same as having the token "women" directly in the vocabulary. We address this issue by not only considering the overlap and tokenization, but also through a qualitative analysis of the non-overlapping words. Our data indicates that these are mostly domain specific terms, which makes sense given the training data and also means that an effect where these words are known by the model, regardless of them missing in the vocabulary. Similarly, our study of the contextual interpretation of sentences and words through the MLM task

may be unsuitable. Our lack of consideration of different parameters for training (batch sizes, learning rates, etc.) may lead to sub-optimal models after fine-tuning, which could affect our conclusions.

## 7.5.2 Internal Validity

While we have good reason to believe that the differences between the models we observe are due to the difference in the data used for pre-training the models, we cannot rule out that there may be other reasons for these differences, due to the black box nature of the models. Most threats to the internal validity should be mitigated by our construct: a pure analysis of the vocabulary may show artificial differences, but this would not explain the differences we observe with the MLM and fine-tuning tasks. And while few random differences for the MLM and fine-tuning may be explainable by alternative hypotheses, we observe clear patterns that match our expectations, including the lack of big differences between the models when general language understanding is required. Consequently, we believe that we mitigated all notable threats to the internal validity, other than the limitations of our study we acknowledge in Section 7.4.

## 7.5.3 Conclusion Validity

The statistical tests we used for the comparison of the finetuned models were suitable for the data and there is no threat to the conclusion validity of our study.

## 7.5.4 External Validity

Since our consideration of fine-tuning only considers five classification tasks, we cannot with certainty conclude that the SE domain models are also better than the general domain models for other SE tasks, e.g., summarizing content. However, since our results indicate that SE domain models are better at capturing SE specific aspects and because prior work also found a similar results regarding the NER task [10], we believe that this is unlikely. Moreover, as already discussed in Section 7.4, our results may not generalize to extremely large models, as they may be able to capture multiple domains correctly, due to their size.

# 7.5.5 Reliability

There are no threats to the reliability of this work, because no manual labeling, interviews, or a similar activity were conducted as part of this study.

# 8 Conclusion

Within our work, we find that NLP for SE can benefit from transformer models pre-trained with SE data. While this was already known for applications that include source code, there was only little evidence for other natural language tasks. Through our work we not only explored the differences in the expected performance of applications, but also the tried to understand if the models really have a better understanding of the SE domain. For this, we manually compared the vocabularies of general domain and SE domain BERT models and compared how these models completed sentences with masked words. This analysis showed that while general domain models have a rough but

imprecise understanding of the SE domain, the SE models are more precise. This improved understanding also led to significantly better results in fine-tuned within the SE domain, but not in a general task like sentiment mining applied to SE data. In conclusion, we recommend to ensure that a large amount of SE data was used for pre-training large NLP models, when these models are used for SE tasks.

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