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Article *in* Empirical Software Engineering · June 2018

DOI: 10.1007/s10664-017-9546-9

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Empir Software Eng
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Sentiment Polarity Detection for Software Development

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Abstract The role of sentiment analysis is increasingly emerging to study software developers' emotions by mining crowd-generated content within social software engineering tools. However, off-the-shelf sentiment analysis tools have been trained on non-technical domains and general-purpose social media, thus resulting in misclassifications of technical jargon and problem reports. Here, we present Senti4SD, a classifier specifically trained to support sentiment analysis in developers' communication channels. Senti4SD is trained and validated using a gold standard of Stack Overflow questions, answers, and comments manually annotated for sentiment polarity. It exploits a suite of both lexicon- and keyword-based features, as well as semantic features based on word embedding. With respect to a mainstream off-the-shelf tool, which we use as a baseline, Senti4SD reduces the misclassifications of neutral and positive posts as emotionally negative. To encourage replications, we release a lab package including the classifier, the word embedding space, and the gold standard with annotation guidelines.

Keywords Sentiment Analysis · Communication Channels · Stack Overflow · Word Embedding · Social Software Engineering

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Published online: 19 September 2017

1 Introduction

Sentiment analysis is the study of the subjectivity (neutral vs. emotionally loaded) and polarity (positive vs. negative) of a text (Pang and Lee 2008). It relies on sentiment lexicons, that is, large collections of words, each annotated with its own positive or negative orientation (i.e., prior polarity). The overall sentiment of a text is therefore computed upon the prior polarity of the contained words.

Recent studies suggest approaches for enhancing software development, maintenance, and evolution by applying sentiment analysis on Stack Overflow (Rahman et al. 2015), app reviews (Maalej et al. 2016), and tweets containing comments on software applications (Guzman et al. 2016). Further research on developers' emotions addresses the role of affect in social software engineering, by applying sentiment analysis to the content available in collaborative development environments such as GitHub (Guzman et al. 2014, Guzman and Bruegge 2013, Sinha et al. 2016), Jira (Mäntylä et al. 2016, Ortu et al. 2015), and Stack Overflow (Calefato et al. 2015, Novielli et al. 2015).

With a notable few exceptions (Blaz and Becker 2016, Panichella et al. 2015), empirical software engineering studies have exploited off-the-shelf sentiment analysis tools that have been trained on non-software engineering documents, such as movie reviews (Socher et al. 2013), or posts crawled from general-purpose social media, such as Twitter and YouTube (Thelwall et al. 2012). Jongeling et al. (2015) show how the choice of the sentiment analysis tool may impact the conclusion validity of empirical studies by performing a benchmarking study on seven datasets, including discussions and comments from Stack Overflow and issue trackers. By comparing the predictions of widely used off-the-shelf sentiment analysis tools, they show that not only these tools do not agree with human annotation of developers' communication channels, but they also disagree among themselves.

Another challenge to address is the negative bias of existing sentiment analysis tools, that is the misclassification of neutral technical texts as emotionally negative. It is particularly the case of bug reports or problem descriptions (Blaz and Becker 2016, Novielli et al. 2015). Novielli et al. (2015) show how sentences like "*What is the best way to kill a critical process*" or "*I am missing a parenthesis but I don't know where*" are erroneously classified as negative because both 'to kill' and 'missing' hold a negative polarity in the SentiStrength lexicon. This evidence is consistent with the *meaning-is-use* assumption that the sense of an expression is fully determined by its context of use (Wittgenstein 1965).

In this paper, we address the problem of applying sentiment analysis to the software engineering discipline. We propose a sentiment analysis classifier, named Senti4SD, which exploits a suite of lexicon-based, keyword-based, and semantic features (Basile and Novielli 2015) for appropriately dealing with the domain-dependent use of a lexicon. The approach implemented by Senti4SD successfully addresses the problem of misclassifying neutral sentences as negative. We observe a 19% improvement in precision for the negative class and a 25% improvement in recall for the neutral class with respect to the baseline, represented by SentiStrength. The emotion polarity classifier is publicly available[1] and represents the first contribution of this paper. To train and test Senti4SD, we built a gold standard of 4423 posts mined from Stack Overflow. As a second contribution of this study, we release our gold standard as well as the emotion annotation guidelines to be used in further studies on emotion

[1] The full lab package including Senti4SD, the DSM and the gold standard is available for download at: https://github.com/collab-uniba/Senti4SD

awareness in software engineering. Consistently with the *meaning-is-use* assumption, we assume that the contextual polarity of a word can be correctly inferred by its use. Thus, in order to derive our semantic features, we represent word meaning based on distributional semantics. In particular, we exploit neural-network-based approaches to distributional semantics, also known as word embedding (Levy and Goldberg 2014). Specifically, we used word2vec (Mikolov et al., 2013a) to build a Distributional Semantic Model (DSM) where words are represented as high-dimensional vectors. The DSM, which builds on a collection of over 20 million questions, answers, and comments from Stack Overflow, represents a valuable resource for software engineering researchers who intend to investigate the use of word embedding in text categorization tasks. Therefore, we release the DSM as a third contribution of this study. Finally, as a fourth contribution, we provide a better understanding of the negative bias in off-the-shelf sentiment analysis tools when applied in the software engineering domain. The contribution of lexicon-based, keyword-based, and semantic features is confirmed by our empirical evaluation leveraging different feature settings. We provide empirical evidence of better performance also in presence of a minimal set of training documents.

The paper is structured as follows. In Section 2, we present an overview of the research methods followed by the theoretical background in Section 3. Section 4 describes the annotation study for building the gold standard. In Sections 5 and 6, we describe respectively the features used by our classifier, and then, the experimental setup and evaluation. Discussion and threats to validity are presented in Sections 7 and 8, respectively. In Section 9, we position our contribution with respect to related work. Finally, in Section 10 we draw conclusions and present future work.

2 Research Methods

Our research leverages a mix of qualitative and quantitative methods, including manual coding of textual data for building a gold standard on emotion polarity in software development, natural language processing techniques for feature extraction from Stack Overflow texts, and machine learning for training our emotion polarity classifier. Figure 1 summarizes the process we followed in the current study. The complete process is organized in four sequential phases.

In Phase 1 we identified the theoretical framework of the current study and chose the emotion model to adopt in our annotation (see Section 3.1). The first output is the taxonomy of emotions and its mapping with polarity. As a second output, we defined the coding guidelines to adopt in the annotation study (see Appendix).

In Phase 2 (see Section 4), the annotation study was carried out. We built the annotation sample by leveraging questions, answers, and comments extracted from Stack Overflow (see Section 4.1). Overall, the annotation sample is composed of 4800 documents including questions, answers, and comments. User-contributed contents were preprocessed to improve their readability by discarding text elements that should not be annotated for sentiment, i.e. URLs, code snippets, and HTML tags. The annotation phase included the training of coders and a pilot annotation study before the final annotation was performed (see Sections 4.2 and 4.3).

In Phase 3 (see Section 4.3), we used the results of the annotation phase to build our gold standard for emotion polarity in software development. The interrater agreement was computed using Kappa, to assess the reliability of the annotation procedure and schema. The gold labels were assigned to documents in the annotation sample built using a majority voting criterion.

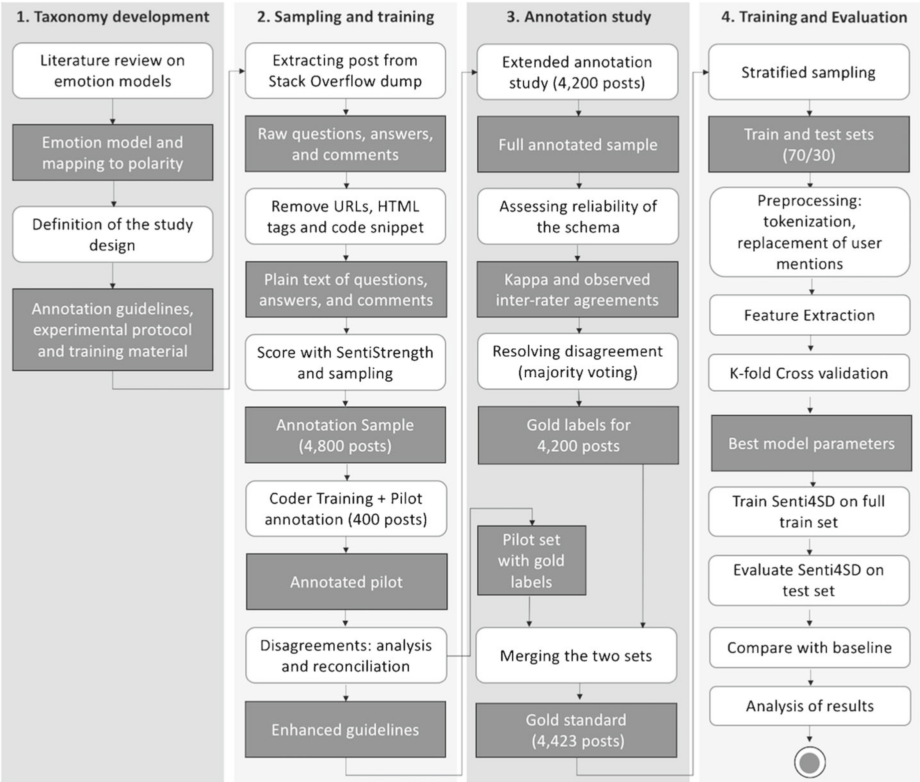

Fig. 1 Overview of the research process

In Phase 4 (see Sections 5 and 6), we used the gold standard for emotion polarity to train and evaluate our classifier, whose performance was compared with off-the-shelf tools representing the state of the art for sentiment analysis on social media.

3 Background

In order to fully comprehend the addressed problem and the proposed solution, some key concepts are needed. The main points of such supporting concepts are presented in the following sections.

3.1 Emotion Modeling

Psychologists worked at decoding emotions for decades, developing theories based on cognitive psychology and natural language communication. So far, two points of view have emerged: one considers emotions as a continuous function of one or more dimensions, while the other assumes that a limited set of basic emotions exists (Carofiglio et al. 2009).

As regards the first viewpoint (continuous function), mining affective states from text typically involves modeling them across two dimensions: (1) the affect polarity, or valence, and (2) the level of activation, also known as arousal or intensity. It is the case of the 'circumplex model' of affect, which represents emotions according to a bi-dimensional representation schema capturing the emotion valence (pleasant vs. unpleasant) and arousal (activation vs. deactivation). According to this model, each emotion can be considered a "label for a fuzzy set, defined as a class without sharp boundaries" (Russell 1980).

On the other hand, theories following the discrete viewpoint agree on the idea that a limited set of basic emotions exists, although there is no consensus about the nature and the number of these basic emotions. According to Ekman (1999), basic emotions have specific feelings, universal signals, and corresponding physiological changes. Lazarus (1991) describes nine negative (anger, fright, anxiety, guilt, shame, sadness, envy, jealousy, and disgust) and seven positive (happiness, pride, relief, love, hope, compassion, and gratitude) emotions, with their appraisal patterns: positive emotions are triggered if the situation experienced is congruent with an individual goal, otherwise negative emotions are prompted.

Shaver et al. (1987) defined a tree-structured hierarchical classification of emotions. The hierarchy organizes emotion labels in three levels of hierarchical clusters. Each level refines the granularity of the previous one, thus providing more indication on its nature. The framework includes, at the top level, six basic emotions, namely love, joy, anger, sadness, fear, and surprise. The framework is easy to understand, thanks to the intuitive nature of the emotion labels. Consistently with our goal of training a classifier for emotion polarity, we map the emotions in the model by Shaver et al. to positive, negative, and neutral polarity (see Section 4). We use this mapping as a theoretical framework to inform our annotation guidelines (see Appendix).

3.2 Polarity Detection with SentiStrength

SentiStrength (Thelwall et al. 2012) is a state-of-the-art, lexicon-based classifier that exploits a sentiment lexicon built by combining entries from different linguistic resources. In the SentiStrength lexicon, each negative word receives a sentiment score ranging from −2 to −5, which represents its prior polarity (i.e., the polarity of the term out of its contextual use). Similarly, positive words are associated with a score between +2 and +5, while neutral words receive scores equal to ±1. Positive and negative emoticons are also included in the dictionary. Based on the assumption that a sentence can convey mixed sentiment, SentiStrength outputs both positive and negative sentiment scores for any input text written in English. It determines the overall positive and negative scores to a text by considering the maximum among all the sentence scores, based on the prior polarity of their terms. Intensifiers, i.e., exclamation marks or verbs such as 'really', are treated as booster words and increase the word sentiment scores. Negations are also treated and determine the inversion of the polarity score for a given word. Therefore, the overall positive p and negative n sentiment scores issued by the tool range from ±1 (absence of positive/negative sentiment) to ±5 (extremely positive/negative). Based on their algebraic sum, SentiStrength can also report the overall trinary score, i.e. the overall positive (score = 1), negative (score = -1) and neutral (score = 0). Examples are provided in Table 1. The rationale for classification reported in the second column of the table is obtained by enabling the 'explain' option in SentiStrength.

Validated on social media, SentiStrength can deal with short informal texts that include abbreviations, intensifiers, and emoticons that typically occur in online interactions. As such, it has been widely adopted in social computing (Kucuktunc et al. 2012, Thelwall et al. 2012) and social software engineering (Guzman and Bruegge 2013, Guzman et al. 2014, Maalej et al. 2016, Novielli et al. 2015).

Table 1 Examples of Sentiment Detection in Stack Overflow using SentiStrength

Input Text	Classification Rationale based on Word and Sentence Scores	Final Sentiment Score (maximum)		Overall Score
		Negative Score	***Positive Score***	
"*I have very simple and stupid trouble*"	I have very simple and stupid [−3] trouble [−2] [sentence: 1, −3] [result: max + and – of any sentence] [overall result = −1 as pos < −neg]	−3	1 (absence of positive sentiment)	Negative (overall result = −1)
"*Thank you, that was really helpful*"	Thank [2] you, that was really helpful [2] [+1 booster word] [sentence: 3, −1] [result: max + and – of any sentence] [overall result = 1 as pos > −neg]	−1 (absence of negative sentiment)	+3	Positive (overall result = 1)
"*I want them to resize based on the length of the data they're showing.*"	I want them to resize based on the length of the data they're showing. [sentence: 1, −1] [result: max + and - of any sentence] [overall result = 0 as pos = 1 neg = −1]	−1 (absence of negative sentiment)	1 (absence of positive sentiment)	Neutral (overall result = 0)

To overcome the limitations and threats to validity derived from the use of off-the-shelf sentiment analysis tools in empirical software engineering studies (Blaz and Becker 2016, Jongeling et al., 2015, Novielli et al. 2015), we train an emotion polarity classifier in a supervised machine learning setting by leveraging a gold standard of technical texts contributed by developers in Stack Overflow.

A customized version of SentiStrength has been developed to support sentiment analysis in software engineering (Islam and Zibran 2017). The tool is called SentiStrength-SE and is built upon the SentiStrength API. It leverages a manually adjusted version of the SentiStrength lexicon and implements *ad hoc* heuristics to correct the misclassifications observed when running SentiStrength on the Ortu dataset (Ortu et al. 2016). In our evaluation, we also include the performance of SentiStrength-SE for benchmarking (see Section 6).

3.3 Distributional Semantic Models

State-of-the-art sentiment analysis tools and lexicons rely on a dictionary-based word representation (see Novielli et al. 2015 for an overview). Words are treated as atomic units and are associated to a prior polarity expressed as a sentiment score, ranging from extremely negative to extremely positive with the absence of sentiment in the middle. Since the notion of word similarity is not taken into account, the polarity of a text is only based on the prior polarity of the words it contains and cannot be adjusted based on their contextual meaning.

Distributional Semantic Models (DSMs) represent words as mathematical points in high-dimensional vector spaces. A DSM relies on the so-called *distributional hypothesis* claiming that linguistic items with similar meanings occur in the same context (Miller and Charles 1991). Based on the assumption that the meaning of a document is determined by the meaning of the words that appear in it, a text unit (e.g., a document, a sentence, a text fragment, etc.) can be represented as the vector sum of all the word vectors occurring in it. Thus, in a DSM, both words and documents are homogeneously represented as vectors and can be compared using similarity metrics that measure their closeness in the space, traditionally through cosine similarity (Mikolov et al. 2013b).

Traditional approaches to distributional semantics create word vectors by counting the occurrences of terms in a corpus and then operating a dimensionality reduction of word-by-document matrices. It is the case, for example, of Latent Semantic Analysis (Landauer and Dutnais 1997), which operates a singular value decomposition on the original term-by-document matrix to a low-dimension latent vector space. Such methods are usually referred in the literature as *context-counting* approaches (Baroni et al. 2014).

Recently, neural network-based approaches have been proposed (Bengio et al. 2003, Collobert and Weston 2008, Mikolov et al. 2013a) for learning distributed representation of words as continuous vectors. These approaches, also known as *word embedding* (Levy and Goldberg 2014), learn the vectors that maximize the probability of the contexts in which the target word appears. For this reason, they are usually referred to as *context-predicting* approaches (Baroni et al. 2014).

In our study, we leverage the approach defined by Mikolov et al. (2013a). They developed two models for implementing context-predicting approaches: (1) the Continuous Bag-of-Words (CBOW) model predicts the target word by considering the previous and following n words in a symmetrical context window; (2) the Skip-gram model predicts the surrounding words based on the target word. Both architectures are implemented in word2vec,[2] a publicly available tool for building a DSM from a large collection of documents. Both CBOW and Skip-gram models are capable of scaling up to large data sets with billions of words and are computationally more efficient for training high-dimensional spaces than context-counting approaches (Mikolov et al. 2013a). Furthermore, they outperform traditional context-counting approaches on standard lexical semantics benchmarks (Baroni et al. 2014).

4 Dataset: A Gold Standard for Emotion Polarity in Software Development

To train and evaluate our classifier for emotion polarity we built a gold standard composed of 4423 posts from Stack Overflow. The dataset is well-balanced: 35% of posts convey *positive* emotions while 27% present *negative* emotions. No emotions are observed for the remaining 38% of posts, thus they receive the *neutral* polarity label.

In the following, we describe the sampling and coding processes adopted for building the gold standard.

4.1 Creating the Annotation Sample

The annotation sample was extracted from the official Stack Overflow dump of user-contributed content from July 2008 to September 2015. To improve their readability, we pre-processed all the posts, using regular expressions, to discard all those elements that are out of the scope of the sentiment annotation task, e.g. code snippets, URLs, and HTML tags.

In a previous study (Novielli et al. 2015), we found that stronger expressions of emotions are usually detected in comments rather than in question or answers. Therefore, we consider as a unit of analysis the Stack Overflow *post*, which includes not only questions and answers, but also comments provided by community members. Hence, conceptually we are addressing 3×4 groups of posts, that is, four types of Stack Overflow posts in *{question, answer, question comment, answer comment}* with three possible emotion styles in *{positive, negative, neutral}*.

A desirable property of a training set is that its items are equally distributed across the existing classes of values (He and Garcia, 2009). Therefore, we built the dataset for the annotation by performing opportunistic sampling of posts based on both the presence of affectively-loaded lexicon and their type. To do so, we used SentiStrength to assess the presence/absence of affective lexicon in a post. We computed the positive and negative sentiment scores for the text of all the four types of posts extracted from the StackOverflow dump. Then, we randomly selected the same number of items based on the type of post and its sentiment scores. Our sample for annotation contains 4800 items overall, equally distributed with respect to the types of posts and polarity, i.e. one-third of posts scored as positive by SentiStrength, one-third as negative, and one-third as neutral.

4.2 Pilot Annotation Study

Twelve coders participated in the emotion polarity annotation task. The coders were recruited among graduate CS students at the University of Bari and trained in a joint 2-h session by the last author. She first explained the coding guidelines and then provided a sample of 25 Stack

[2] https://github.com/dav/word2vec

Overflow posts to be annotated individually in 30 min. Then, a follow-up discussion aimed at clarifying possible ambiguities in the interpretation of the coding guidelines.

Training was completed with a pilot subset of 100 items to be annotated individually at home. The twelve participants were organized into four groups of three coders each. Therefore, the pilot study was performed on 400 posts overall and each item in the dataset was assigned to three coders.

The coders were requested to indicate the emotion polarity, with a possible value in *{positive, negative, neutral, mixed}* (see Appendix for guidelines). Analogously to Murgia et al. (2014), we refer to the Shaver et al. tree-structured framework for detecting emotions in the text (see Table 12 in Appendix). The main difference with their annotation study is that we explicitly requested our coders to provide a polarity label, according to the specific emotion detected. In our study, *positive* polarity was indicated when the coders detected either joy or love. Conversely, *negative* polarity should be indicated when the coders identified anger, sadness, or fear. Regarding surprise, we asked the coders to determine the polarity based on contextual information. The *neutral* label indicates the absence of emotion. Posts conveying multiple emotions with opposite polarity (i.e., *joy* and *sadness*) were annotated as *mixed*.

The deadline was set a week after the assignment and the results of the annotation were discussed in a 2-h plenary meeting with the experimenter. During this discussion, the coders had to resolve the disagreements on the pilot sample. This session was also used to disambiguate unclear parts of the guidelines as well as to enrich them with borderline examples whose annotation was agreed upon during the meeting. After the disagreements were solved, the pilot annotation became the first building block of the gold standard.

4.3 Emotion Polarity Coding: Extended Study

Once the training was complete, we assigned a new set of 500 posts to each coder. Once again, each item was annotated by three coders. Overall, 2000 new items were annotated in this second step. Again, coders were required to perform this new annotation task individually. The deadline for returning the annotation was set in three weeks. We then assigned the final set of 600 posts to the coders. Overall, 2400 additional new items were annotated in this final step.

As an evidence of the reliability of the coding schema and procedure, we computed the weighted Cohen's *Kappa* among the pairs of raters (Cohen 1968). We are interested in distinguishing between *mild* disagreement, that is the disagreement between negative/positive and neutral annotations, and *strong* disagreement, that is the disagreement between positive and negative judgments. We assigned a weight = 2 to strong disagreement and a weight = 1 to mild disagreement. We compute the inter-coder reliability for the entire set,

Table 2 Weighted Cohen's Kappa and Observed Agreement for all the couples of coders in the Polarity annotation Study

	Weighted Cohen's Kappa for pairs of coders			*Observed Agreement for pairs of coders*		
Group	*C1 and C2*	*C1 and C3*	*C2 and C3*	*C1 and C2*	*C1 and C3*	*C2 and C3*
A	.66	.76	.68	.73	.82	.76
B	.74	.72	.74	.79	.76	.79
C	.77	.77	.77	.83	.80	.85
D	.76	.76	.76	.80	.78	.81
	Average Weighted Cohen's Kappa .74			Average Observed Agreement .79		

including the pilot set annotation. The agreement is computed for all the four groups of participants (A, B, C, D) and for all pair of coders (C1, C2, and C3) in each group (see Table 2). We note a substantial agreement with *Kappa* values ranging in [.66, .80] (average .74). This evidence is confirmed also by the values of the *observed agreement*, which is the percentage of cases on which the raters agree, ranging in [.73, .85] (average .79).

Consistently with previous research on emotion annotation (Blaz and Becker 2016, Murgia et al. 2014), we resolved the disagreements by applying a majority voting criterion. We excluded from the gold standard all the posts for which opposite polarity labels were provided, including mixed cases (3%), even in presence of majority agreement. The final gold standard resulted in 4423 posts, representing 92% of 4800 annotated items.

5 Emotion Polarity Classifier: Feature Description and System Setup

Previous research shows how combining generic and domain-specific resources improves the performance of sentiment analysis (Bollegala et al. 2013). Therefore, we exploit three different kinds of features based on: (1) generic sentiment lexicons, (2) keywords (i.e., n-grams extracted from our dataset), and (3) word representation in a distributional semantic model specifically trained on software engineering data.

5.1 Lexicon-based features

The first set of features exploits existing sentiment lexicons. The approach is totally independent of the lexicon chosen and simply requires that a sentiment score is provided for each entry of the input (Basile and Novielli, 2015). For example, in the lexicon used by SentiStrength, each negative word is associated with an *a priori* sentiment score in [−2, −5]. Similarly,

Table 3 Sentiment Lexicon-based Features

Feature	*Description*
Pos_words	The number of tokens with positive prior polarity.
Neg_words	The number of tokens with negative prior polarity.
Subj_words	The number of tokens with either negative or positive prior polarity.
Last_pos	The score of the last positive token in the post.
Last_neg	The score of the last negative token in the post.
Last_emo	The score of the last emoticon in the post.
Sum_pos	The sum of the score for the tokens with positive prior polarity.
Sum_neg	The sum of the score for the tokens with negative prior polarity.
Sum_subj	The sum of the score for the tokens with either positive or negative prior polarity.
Max_pos	The maximum score for the tokens with positive prior polarity in the post.
Max_neg	The maximum score for the tokens with negative prior polarity in the post.
Pos_emo	The number of emoticons with positive prior polarity.
Neg_emo	The number of emoticons with negative prior polarity.
Pos_Emph	Boolean, is true if the document has at least one positive token and ends with an exclamation mark, indicating emphasis.
Neg_Emph	Boolean, is true if the document has at least one negative token and ends with an exclamation mark, indicating emphasis.
End_Pos_Emph	Boolean, is true if the document ends with a positive token and an exclamation mark
End_Pos_Emph	Boolean, is true if the document ends with a negative token and an exclamation mark
End_Pos	Boolean, is true if the document ends with a positive token or emoticon.
End_Neg	Boolean, is true if the document ends with a negative token or emoticon.

positive words receive a score in [+2, +5]. A list of objective words is also provided, with scores equal to ±1.

For a given post we compute the lexicon-based features reported in Table 3. In particular, we compute the number of tokens with positive and negative prior polarity (*Pos_words* and *Neg_words*), the overall number of tokens with either positive or negative prior polarity (*Subj_words*), the score of the last emoticon (*Last_emo*), the sum of all the scores for positive (*Sum_pos*), negative (*Sum_neg*), and subjective (*Sum_subj*) tokens, and the maximum positive and negative scores observed in the post (*Max_pos* and *Max_neg*). We also capture the presence of positive/negative utterances in combination with exclamation marks, indicating emphasis (*Pos_Emph* and *Neg_Emph*). Finally, we capture the sentiment of the last token/emotion (*End_Pos*, *End_Neg*), and whether it is combined with an exclamation mark (*End_Pos_Emph*, *End_Neg_Emph*). All the lexicon-based features have been already used for the sentiment analysis of crowd-generated content (Mohammad et al. 2013). Our lexicon-based features are independent of the specific lexicon adopted. To enable fair comparison with the baseline, represented by SentiStrength, for this study, we use the SentiStrength lexicon. The choice of the SentiStrength lexicon is further supported by its ability to deal short informal text, as it includes also abbreviations, intensifiers, and emoticons that are typically used in the social web. Furthermore, it incorporates sentiment scores from other linguistic resources that were previously validated in the scope of empirical research in sentiment analysis (Stone et al., 1966) and psycholinguistics (Pennebaker and Francis, 2001).

5.2 Keywords based features

Keywords based features include word counts for n-grams appearing in a document in our case a Stack Overflow post. In our feature set we consider uni- and bi-grams. Consistently with traditional approaches to text classification (Joachims 1998) each n-gram in our corpus corresponds to a feature with the number of occurrences as its value. Other than including n-grams we designed features able to capture aspects of micro-blogging such as the use of uppercase and elongated words used as intensifiers the presence of positive and negative emoticons and the occurrence of slang expression of laughter (Basile and Novielli 2015). The total number of keyword-based features is 76,346. We report a summary in Table 4

Table 4 Keyword-Based Features

Feature	*Description*
Uni-grams	Total occurrences of uni-grams. Overall, our unigram dictionary counts 10,496 entries.
Bi-grams	Total occurrences of bi-grams. Overall, our bi-gram dictionary counts 65,844 entries.
Uppercase_words	Total occurrences of uppercase words (e.g. 'GOOD', 'BAD').
Laughter	Total occurrences of slang expressions for laughter, such as 'hahaha' or abbreviations as 'LOL' occurring in the SentiStrength list of abbreviations.
Elongated_words	Total count of tokens with repeated characters (e.g. 'scaaaaary', 'goooood').
M_repetitions	The total occurrences of strings with repeated question or exclamation marks. (e.g., '????', '!!!!', '?!?!?!?!?').
User_mentions	Total occurrences of user mentions (in the form @username).
EndWith_EXMark	Boolean, true if the document ends with an exclamation mark.

5.3 Semantic features

The semantic features capture the similarity between the vector representations of the Stack Overflow documents and *prototype vectors* representing the polarity classes in a DSM. Analogously to (Basile and Novielli 2015, Novielli and Strapparava 2013), we represent a Stack Overflow document (i.e., a question, answer, or comment) in the DSM as the vector sum of all the vectors of words occurring in the document, using the superposition operator (Smolensky 1990).

The *prototype vectors* are vector representation of the positive, negative, and neutral classes in the DSM, namely *p_pos*, *p_neg*, and *p_neu*. A prototype vector is a vector representation of the lexical profile for a given polarity class, based on a sentiment lexicon that provides prior polarity scores for words. To compute the prototype vector *p_pos* for the positive class we sum all the vectors for words with positive polarity score in the chosen sentiment lexicon. In a similar fashion, we compute *p_neg* and *p_neu* by summing up, respectively, all the negative and neutral words in the chosen sentiment lexicon. In this study, we used the list of positive, negative, and neutral words included in the SentiStrength lexicon. We further calculated the subjective prototype *p_subj* vector by summing up the positive and negative word vectors, to better capture the differences in the lexical choice of neutral sentences and affectively-loaded ones.

We used the four prototype vectors to compute the semantic features, that is the similarity scores between the document vector (i.e., a Stack Overflow post) and each prototype vector, namely *Sim_pos*, *Sim_neg*, *Sim_neu*, *Sim_subj* (see Table 5). The semantic features are computed on a DSM built on Stack Overflow data, using the CBOW architecture implemented by word2vec (Mikolov et al., 2013a), as depicted in Fig. 2. We choose a configuration with 600 vector dimensions, after having repeated the 10-fold cross-validation for parameter tuning (see Section 5.4.). We ran word2vec on a corpus extracted from the Stack Overflow official dump updated to September 2015. We extracted 3.8 million questions from the dump with the associated 5.9 million answers and 11.6 million comments. We preprocessed the posts to remove the URLs, HTML codes, and code snippets, obtaining a collection of more than 20 million posts with 912,201,785 tokens overall.

5.4 System Setup and Parameter Tuning

Before extracting all features, we performed tokenization using the Stanford NLP suite (Manning et al. 2014). During the tokenization, we replaced the user mentions with the meta-token *@USER*. We did not perform any stemming nor lemmatization since an inflected form may convey important information about polarity. It is the case, for example of ‘ail’ and ‘ailing’, which holds different prior polarity in the SentiStrength lexicon. Also, we did not

Table 5 Semantic Features

Feature	*Description*
Sim_pos	The cosine similarity between the post vector and the objective prototype vector *p_pos*.
Sim_neg	The cosine similarity between the post vector and the objective prototype vector *p_neg*.
Sim_neu	The cosine similarity between the post vector and the objective prototype vector *p_neu*.
Sim_subj	The cosine similarity between the post vector and the subjective prototype vector *p_subj*.

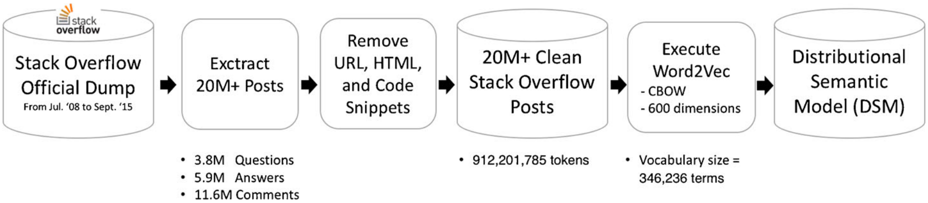

Fig. 2 Building the DSM on Stack Overflow data

remove stop words, consistently with previous research in sentiment classification tasks (Saif et al. 2014).

We trained Senti4SD using Support Vector Machines (SVM). SVM is able to learn and generalize even with a high dimensional feature space, which is a typical scenario in text classification tasks like ours (Joachims 1998). In particular, linear SVM is a state-of-the-art learning technique for such high-dimensional sparse datasets with a large number of items and a large number of features N, where each item has only $s < < N$ non-null features (Joachims 2006), as typical in presence of n-grams. One way to avoid dealing with such high dimensional input spaces would be to perform substantial feature selection. However, in supervised learning for text classification tasks, very few features are actually irrelevant, and feature selection results in a significant loss of information (Joachims 1998). Thus, we exploit the full set of features. Still, in order to assess the predictive value of our features, we analyze and rank them according to their information gain (Mitchell 1997). In Table 6, we report the top 25 features ranked by information gain.

Table 6 Top 25 features ranked by information gain

Rank	*Feature*	*Information Gain*	*Feature Group*
1	Sum_pos	0.56081	Lexicon-based
2	Max_pos	0.54642	
3	Pos_words	0.52497	
4	Last_pos	0.51273	
5	Sum_neg	0.39355	
6	Max_neg	0.39330	
7	Neg_words	0.38760	
8	Last_neg	0.38291	
9	Sum_subj	0.33765	
10	Subj_words	0.31614	
11	Sim_pos	0.26473	Semantic
12	Sim_neg	0.16507	
13	Sim_subj	0.15596	
14	Sim_obj	0.11297	
15	Last_emo	0.10775	Lexicon-based
16	Pos_emo	0.07299	
17	'great'	0.06496	Keyword-based
18	'excellent'	0.06055	
19	':)'	0.05649	
20	'thanks'	0.03856	
21	Neg_emo	0.03525	Lexicon-based
22	'hate'	0.03445	Keyword-based
23	'annoying'	0.02820	
24	Uppercase_words	0.02819	
25	':('	0.02800	

Table 7 System Setup after Parameter Optimization

	Parameter	*Value*
DSM	word2vec architecture	Continuous Bag-of-Words (CBOW)
	DSM dimensions	600
SVM	C	0.05

We ran our experiment using the R interface (Helleputte 2015) to Liblinear (Fan et al. 2008), an open source library for large-scale linear classification with SVM. For linear classification, the only parameter is the cost parameter C. Too large C values makes the cost of misclassification high, thus forcing the algorithm to better explain the training data but potentially inducing the risk of overfitting. To fine-tune the SVM parameter while still preventing overfitting, we ran the Liblinear parameter tuning utility on our training set in a 10-fold cross-validation setting. We chose the optimal value for the C parameter by maximizing the prediction accuracy. We repeated the parameter tuning with all the settings derived by combining the two available architectures in word2vec CBOW and Skip-gram, with vector space dimensions in *{200, 400, 600, 800, 1000}*. Furthermore, word2vec has two input parameters for rare-word pruning and frequent word sub-sampling: words appearing less than *min-count* times are discarded from the document collection before starting the DSM training, while frequent words (as defined by the *sample* input parameter) are down-sampled to increase the effective context window considered for vector prediction (Mikolov et al., 2013a). Consistently with previous research (Basile and Novielli 2015), we maintained the default value for the *sample* parameter while discarding the terms with less than 10 occurrences, thus obtaining a final vocabulary of 346,236 terms. The optimal configuration, used to train our final classifier over the training set, is reported in Table 7.

6 Evaluation

6.1 Creation of Training and Test Sets

We split the gold set into training (70%) and test (30%) sets, using the R (R Development Core Team 2008) package *caret* (Kuhn 2016) for stratified sampling. We used the training set to seek the optimal parameter setting for our classifier (see Section 5.4). The final model was trained on the whole training set using the optimal configuration and then evaluated on the test

Table 8 Performance of Senti4SD and comparison with SentiStrength (baseline)

	Overall			*Positive*			*Negative*			*Neutral*		
	R	***P***	***F***	***R***	***P***	***F***	***R***	***P***	***F***	***R***	***P***	***F***
Baseline (SentiStrength)	.82	.82	.82	**.92**	.89	.90	**.96**	.67	.79	.64	**.95**	.76
SentiStrength-SE	.78	.78	.78	.79	.90	.84	.79	.73	.76	.77	.73	.75
Senti4SD	**.87**	**.87**	**.87**	**.92**	**.92**	**.92**	.89	**.80**	**.84**	**.80**	.87	**.83**
Improvement over the SentiStrength baseline	*+6%*	*+6%*	*+6%*	–	*+3%*	*+2%*	*−7%*	*+19%*	*+6%*	*+25%*	*−8%*	*+9%*

set, to assess to what degree the trained model is able to generalize sentiment polarity classification on unseen new data from the held-out test set.

6.2 Results

After having trained Senti4SD, we evaluated the learned model on the Stack Overflow test set. Table 8 reports the performance obtained in terms of recall, precision, and F-measure for the single classes and overall. The overall performance is computed adopting micro-averaging as aggregated metric (Sebastiani 2002). We highlight in bold the best value for each metric.

In Table 8, we also report the performance of SentiStrength[3] on the Stack Overflow test set, which we consider as a baseline for the performance assessment of Senti4SD. We choose SentiStrength because it is the most widely employed tool in sentiment analysis studies in software engineering (Calefato et al. 2015, Guzman et al. 2016, Guzman and Bruegge 2013, Ortu et al. 2015, Sinha et al. 2016). In addition, we also report the performance of SentiStrength-SE. We mapped both SentiStrength and SentiStrength-SE scores to a categorical sentiment label in *{positive, neutral, negative}* for each entire question, answer or comment. Consistently with the approach defined by SentiStrength authors (Thelwall et al. 2012) and already adopted in previous benchmarking studies (Jongeling et al., 2015), given the positive (p) and negative (n) scores issued by the tool, we consider a text as *positive* when $p + n > 0$, *negative* when $p + n < 0$, and *neutral* if ($p = n$) and ($p < 4$). Texts with a score of p = n and $p \geq 4$ are considered having an undetermined sentiment and should be removed from the dataset. However, no such controversial cases are found in our dataset. Looking at the performance of Senti4SD, we observe a 19% improvement in precision for the negative class and a 25% improvement in recall for the neutral class with respect to the SentiStrength baseline, which in turn outperforms SentiStrength-SE.

In Table 9 we report the confusion matrix for both SentiStrength and Senti4D, showing the agreement between the manual labeling and the polarity predicted by each tool. We consider only SentiStrength because it outperforms SentiStregth-SE. We complement the evidence provided by the confusion matrix with Venn diagrams representing the posts correctly classified as negative, positive, and neutral by SentiStrength and Senti4SD (see Fig. 3). Looking at the predictions, we observe that the 24 negative cases recognized only by SentiStrength (see Fig. 3a) are classified as neutral by Senti4SD. As for positive posts (see Fig. 3b), the 10 cases missed by Senti4SD are classified mostly as neutral and only one of them is classified as negative. Conversely, the 13 recognized only by Senti4SD are misclassified by SentiStrength as positive. As for neutral, the 84 cases recognized only by Senti4SD (see Fig. 3c) are classified mainly as negative (69/84).

We complement the previous evaluation with an assessment of the advantage of including all the features defined in Senti4SD. Our goal is to assess whether the improvement of performance, with respect to SentiStrength, is a result of the adopted machine learning technique or is rather due to the additional features (full set of keyword-based, semantic features, and lexicon-based features) we propose. We start by computing the performance with a simple model including only the uni- and bi-grams. Such a model does not include consideration of any sentiment-specific feature and represents the traditional approach to text categorization based on machine learning (Joachims 1998). By doing so, we want to assess to

[3] The evaluations have been performed using the SentiStrength Java API obtained from http://sentistrength.wlv.ac.uk/ on December 2016.

Table 9 Agreement Between Manual Labeling and Prediction on the Stack Overflow Test Set

		Prediction					
		SentiStrength			*Senti4SD*		
		Negative	Positive	Neutral	Negative	Positive	Neutral
Manual	Negative	345 (95.8%)	7 (1.9%)	8 (2.2%)	321 (89.2%)	3 (0.8%)	36 (10.0%)
	Positive	30 (6.6%)	420 (91.7%)	8 (1.8%)	11 (2.4%)	423 (92.4%)	24 (5.2%)
	Neutral	140 (27.6%)	44 (8.7%)	324 (63.8%)	70 (13.8%)	32 (6.3%)	406 (79.9%)

what extent the additional features contribute to the performance by capturing sentiment-related linguistic phenomena. Then, we evaluate the performance of Senti4SD by considering incremental feature settings, in order to assess the contribution of each feature group to the classifier performance. Results are reported in Table 10 and complement the evidence provided by the information gain analysis (see Table 6) about the role of each feature group. The last column of Table 10 (*p-value* < *0.05*) indicates whether we observe a statistically significant improvement in a given setting over the previous approach. Statistical significance of the difference between settings is computed by performing the Chi-squared test with $\alpha = 0.05$.

By comparing the performance of Senti4SD leveraging different sets of features, we observe that simply training a supervised classifier based on n-grams does not yield an acceptable overall performance (F = .69). By leveraging the full set of keyboard-based features the overall performance improves to F = .79. However, such a classifier would still perform poorly if compared to the Sentistrength baseline. In particular, recall for *negative* is unsatisfying (*R* = .67). Adding the four semantic features, performance is further improved (F = .81). In particular, adding only four features (i.e., the cosine similarity of the document with the sentiment prototype vectors) we observe an improvement of the *negative* recall from .67 to .73 and of the *neutral* precision from .74 to .78. However, while the improvement is statistically significant, the recall for *negative* is still low (*R* = .73). Finally, we include consideration of lexicon-based features, which further increase the recall of *negative* up to .89 and the precision of *neutral* up to .87.

Searching for further evidence of the robustness of the approach implemented by Senti4SD, we also assess its performance by splitting our gold standard into train and test set with different percentages. Results are reported in Table 11 and compared with the SentiStrength performance on the same test set for each iteration. For each setting, we compare the behavior of the two classifiers by performing a Chi-square test on the predictions issued by Senti4SD and SentiStrength, observing a *p*-value lower than 0.05. In all the three settings, Senti4SD

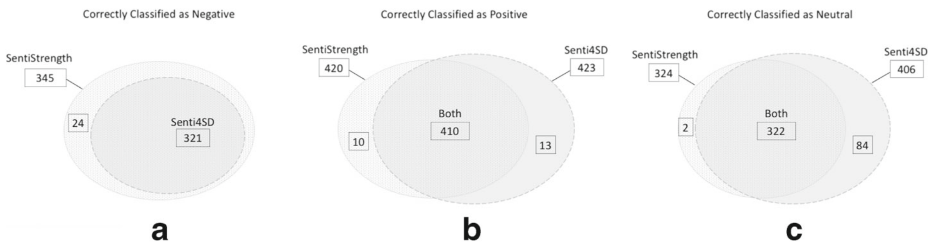

Fig. 3 Posts Correctly Classified as Negative (a), Positive (b), and Neutral (c) by Senti4SD and SentiStrength

Table 10 Performance of Senti4SD with incremental feature settings

Experimental Setting	*Overall*			*Positive*			*Negative*			*Neutral*			*p-value < 0.05*
	R	*P*	*F*	*R*	*P*	*F*	*R*	*P*	*F*	*R*	*P*	*F*	
N-grams only	.69	.69	.69	.84	.75	.79	.88	.57	.69	.42	.85	.56	
Keyword-based features	.79	.79	.79	.84	.84	.84	.67	.80	.73	.83	.74	.79	*
Keyword + Semantics	.81	.81	.81	.86	.86	.86	.73	.80	.76	.83	.78	.81	*
Keyword + Semantics + Lexicon Based (full feature set)	.87	.87	.87	.92	.92	.92	.89	.80	.84	.80	.87	.83	*

**p* < 0.05

outperforms SentiStrength, even with a reduced training set (last row of Table 11), with 30% of the gold standard used as training set. Again, we highlight in bold the best value for each metric.

7 Discussion

Comparison with the SentiStrength baseline The performance of SentiStrength on our test set (see Tables 8 and 9) confirms previous findings about its negative bias in the software engineering domain (Novielli et al. 2015). In the case of our Stack Overflow dataset, SentiStrength erroneously classifies 28% of neutral posts as negative, with a poor recall for neutral class (.64) and a low precision for the negative one (.67). Since Stack Overflow is explicitly designed to support developers looking for help, discussions are often misclassified as conveying negative polarity because they are naturally rich in the 'problem' lexicon, which does not necessarily indicate the intention to show any affective state.

Senti4SD is able to address the problem of such negative bias. Table 9 shows that the number of neutral documents misclassified as negative is reduced from 27.6% in SentiStrength to 13.8% in Senti4SD. As a consequence, the F-measure increases from .79 to .84 for the negative class and from .76 to .83 for the neutral class, thus depicting a more balanced classifier (see Table 8). In particular, our classifier improves the recall of neutral documents from .64 up to .80 (25% of improvement) and the precision of negative documents from .67 up to .80 (19% of improvement). For example, SentiStrength erroneously classifies as negative sentences that are instead neutral, as the following ones: '*This will help you to come back to the previous activity. As per your code, the application was completely killed.*', '*Or if you don't*

Table 11 Performance of Senti4SD and comparison with SentiStrength with different train/test proportions

Experimental Setting	***Classifier***	***Overall***			***Positive***			***Negative***			***Neutral***		
		R	***P***	***F***	***R***	***P***	***F***	***R***	***P***	***F***	***R***	***P***	***F***
Train = 70%	SentiStrength	.82	.82	.82	.92	.89	.90	**.96**	.67	.79	.64	**.95**	.76
Test = 30% (same as Table 8)	***Senti4SD***	***.87***	***.87***	***.87***	***.92***	***.92***	***.92***	*.89*	***.80***	***.84***	***.80***	*.87*	***.83***
Train = 50%	SentiStrength	.82	.82	.82	**.93**	.89	**.91**	**.95**	.68	.79	.64	**.94**	.77
Test = 50%	***Senti4SD***	***.85***	***.85***	***.85***	*.91*	***.89***	*.90*	*.87*	***.80***	***.83***	***.78***	*.84*	***.81***
Train = 30%	SentiStrength	.82	.82	.82	**.93**	.90	.91	**.94**	.67	.78	.64	**.93**	.76
Test = 70%	***Senti4SD***	***.84***	***.84***	***.84***	*.91*	***.91***	***.91***	*.83*	***.78***	***.80***	***.79***	*.82*	***.80***

want to worry about height calculation do this'. On the contrary, Senti4SD correctly labels the above sentences as neutral.

However, we observe that this gain in precision is obtained at the expense of the negative class recall, which decreases from .96 to .89. For example, SentiStrength correctly classifies as negative the following posts: '*Is it possible to prevent a user from editing the title of a node on the node edit screen? One of the things I really detest about Drupal is the rigidity of the title & body field in each node*' and '*Ew, that sounds a bit ugly! Is it possible for an instance of a class to be created before its unit's initialization section has run? In other words, could an instance of TMyObject try to use FLogger before it's been set in the initialization section?*'. On the contrary, the two posts are erroneously labeled as neutral by Senti4SD even in presence of the negative lexicon (i.e., '*detest*' and '*ugly*'). Such misclassifications are probably due to the prevalence of neutral lexicon in the posts. Specifically, in the first post the first sentence does not carry any sentiment while in the second post the second and third sentences are neutral. A possible way to overcome this limitation occurring with long posts is to perform finer-grained annotation at a sentence level in order to train a sentence-based version of Senti4SD.

Misclassification of positive posts as negative occurs in 6.6% of the cases when the classification is performed with SentiStrength (see Table 9). This is what we consider a strong disagreement that should be avoided. Senti4SD reduces such misclassification to 2.4% of the cases. For example, sentences like '*Is in so u need not worry! Internally the data is always stored as TEXT, so even if you create table with, SQLite is going to follow the rules of data type*' is erroneously classified by SentiStrength as negative due to the presence of negative lexicon ('worry') even if SentiStrength is supposed to correctly deal with negations (Thelwall et al. 2012) which should determine polarity inversion.

Surprisingly, SentiStrength-SE produces a lower performance than SentiStrength on our Stack Overflow gold standard albeit it outperformes SentiStrength on other technical texts (Islam and Zibran 2017). This might occur because SentiStrength-SE incorporates *ad hoc* heuristics and word polarity scores that are specifically designed to solve misclassifications observed on a small unbalanced dataset of 400 developers' comments in Jira (Ortu et al. 2016). As such, overfitting is a plausible explanation for the decay in performance of SentiStrength-SE in our study.

Implications Senti4SD was developed in the scope of our ongoing research on the role of emotions in social software engineering (Novielli et al. 2014, Mäntylä et al. 2017). More specifically, we envision the emergence of sentiment analysis tools monitoring communication between the developers as well as user-contributed technical texts (e.g., reviews in app stores), analyzing the affect expressed in this communication and translating the results into actionable insights (Gachechiladze et al. 2017). Among others, negative affective states deserve attention because of their detrimental impact on developers' productivity (Denning 2012, Ford and Parnin, 2015, Graziotin et al. 2017). When implementing a sentiment classifier, deciding whether to optimize by precision or by recall is not a trivial decision, which depends on the application scenario. Early detection of negative sentiment towards self, such as frustration, could be useful to design tools for supporting developers experiencing cognitive difficulties (i.e., learning a new language or solving tasks with high reasoning complexity) (Ford and Parnin, 2015), as well as in their daily programming tasks (Müller and Fritz 2015). In such a scenario, a monitoring tool might suggest the intervention of an expert or provide a link to further material and documentation to support the developer. However, a sentiment analysis tool with high recall and low precision for negative sentiment as SentiStrength would produce several false positives, causing undesired, erroneous interruptions that are detrimental to developers' productivity and focus. In such cases, being able to reduce the number of false positives for negative sentiment becomes crucial and Senti4SD should be preferred to SentiStrength, due to its higher precision.

Similarly, timely detection of negative sentiment towards peers, such as anger and hostility (Gachechiladze et al. 2017), might be exploited for detecting code of conduct violations (Tromp and Pechenizkiy 2015) or enhancing effective community management. For example, sentiment analysis may support GitHub users who want to be notified of heated conversation and lock them before flame wars break out.[4] In scenarios that involve human intervention to guide the contributors' behavior towards a constructive pattern, it might be desirable to optimize negative sentiment detection by recall, thus choosing to leverage SentiStrength higher sensitivity to negative emotions. Conversely, if automatic filtering of offensive comments or conversation is envisaged, it becomes important to optimize by precision by using Senti4SD, to avoid banning neutral conversations.

Finally, sentiment analysis is now regarded as a technique also useful for mining large software repositories, e.g., to understand the role of sentiment in security discussions (Pletea et al. 2014) and commits in GitHub (Guzman et al. 2014). In such scenarios, a sentiment classifier specifically trained and validated in the software engineering domain allows controlling for threats to validity due to inappropriate instrumentation, as argued by Jongeling et al. (2015).

Contribution of features Consistently with traditional approaches to supervised machine learning in text classification (Joachims 1998), we did not perform feature selection, thus including in our evaluation setting the full suite of lexicon-based, keyword-based, and semantic features described in Section 5. As a further evidence of the importance of each group of features, we performed an analysis based on information gain (see Table 6) and assessed Senti4SD performance by leveraging different feature settings (see Table 10). The top-ten predictive features belong to the group of lexicon-based, which is an expected result since they are based on sentiment lexicons specifically designed to represent the sentiment polarity association to words. They are immediately followed by the four semantic features that measure the similarity between a document and the linguistic profile of each polarity class. Among the top predicting keyword-based features, we find positive and negative emoticons (*Pos_emo* and *Neg_emo*, respectively). Expressions of gratitude (i.e., 'thanks') and appreciation (i.e., 'great', 'excellent') are also among the top uni-gram predictors, thus confirming evidence from previous research that paying gratitude for the help received as well as enthusiasm for the solution provided are the main causes for positive sentiment in the social programmer ecosystem (Calefato et al. 2015, Novielli et al. 2015, Ortu et al. 2015). Conversely, expression of anger and frustration (i.e., 'hate', 'annoying') are among the top predictors for negative sentiment. The contribution of each feature group to the classification performance is confirmed by the evaluation of Senti4SD leveraging different feature settings, as reported in Table 10. Furthermore, we provide empirical evidence that supervised training as implemented by Senti4SD produce similar performance also in presence of a minimal set of training documents (see Table 11).

[4] https://help.github.com/articles/locking-conversations

Gold standard Our manually annotated dataset is the first resource on emotion polarity to be built upon the corpus of Stack Overflow. As such, our dataset represents a valuable resource in the scope of empirical research on emotion awareness in software engineering (SEmotion 2016). Stack Overflow is an example of an online community where programmers do networking by reading and answering others' questions, thus participating in the creation and diffusion of crowdsourced documentation. Among the non-technical factors that can influence the members of online communities, the emotional style of a technical contribution does affect its probability of success (Calefato et al. 2015). Being able to identify harsh comments towards technical matters could be useful in detecting particularly challenging questions that have not been exhaustively answered (Novielli et al. 2015), which is a goal addressed by current research on effective knowledge-sharing (Anderson et al. 2012). Similarly, detecting negative attitude towards the interlocutor could allow the community moderators to guide users towards appropriate interaction patterns. This is an open problem in the Stack Overflow community, as users complain about harsh comments coming from expert contributors (Meta 2017), which may impair successful question-answering (Asaduzzaman et al. 2013).

The release of our gold standard complements the effort of Ortu et al. (2016) who recently released a dataset of 2000 issue comments and 4000 sentences written by developers, collected by mining the repositories of four open source ecosystems, namely Apache, Spring, JBoss, and CodeHaus. Their dataset is annotated using the basic emotion labels in the framework by Shaver et al. (1987) that we also adopt in the present study.

8 Threats to Validity

Our methodology could produce different results if applied outside of Stack Overflow. However, Stack Overflow is so popular among software developers (currently used by about 7 million software developers[5]) to be reasonably confident that the dataset is representative of developers' communication style. Nevertheless, we acknowledge that replications are needed to further increase the external validity to the entire software developer ecosystem.

We built our gold standard on emotion polarity through manual annotation. Emotion annotation is a subjective process since affect triggering and perception can be influenced by personality traits and personal dispositions (Scherer et al. 2004). To mitigate this threat, we provided clear guidelines (see Appendix) grounded on a theoretical framework for emotion identification based on the model by Shaver et al. (1987). Furthermore, polarity labels were assigned using majority agreement among three coders. To be more conservative, even in presence of majority agreement, we excluded from the gold standard all the posts for which opposite polarity labels were provided. The interrater agreement (average weighted Cohen's Kappa = 0.74) confirms a good reliability of the gold standard. Nevertheless, we intend to improve coding guidelines by enriching the number of examples, especially for those more controversial that lead to coding conflicts.

The sample set for the emotion annotation experiment was built using SentiStrength. We built our sample set to have one-third of posts scored by SentiStrength as positive, one-third as negative, and one-third as neutral. However, as highlighted by previous research (Blaz and Becker 2016, Jongeling et al., 2015, Novielli et al. 2015), off-the-shelf tools for sentiment

[5] Source: http://stackexchange.com/sites#questions Last accessed: June '17

analysis report limited performance when detecting sentiment in the software engineering domain. In particular, SentiStrength tends to misclassify neutral sentences as negative (see Tables 8 and 9). As a result, we ended up including in our sample set a higher proportion of neutral sentences that were originally misclassified as negative by SentiStregth and later correctly classified as neutral by our coders. Another cause of error when using SentiStrength on our data is the misclassification of positive posts as negative (see Table 9). As such, a small proportion of the posts originally included in the sample annotation set because rated as negative by SentiStrength were subsequently classified as positive by the coders. The distribution of the gold standard built through the annotation study confirms these issues and shows how the negative class is underrepresented in our dataset, i.e., the gold standard contains 35% *positive* posts, 27% *negative* posts, and 38% of neutral posts. Another consequence of using SentiStrength to create the sample set is that the sentences in our dataset contain emotion words included in the SentiStrength lexicon. Hence, we observe a very good performance of the tool on our gold standard (F = .82, Table 8), making SentiStrength a challenging baseline for our classification task.

Finally, we excluded from the gold standard all the posts for which opposite polarity labels were provided, which represent the 3% of all annotated data. Our choice is justified by the intention to not introduce noise in the data during the supervised training phase of Senti4SD. Currently, Senti4SD would classify those posts as either positive or negative. However, we acknowledge that a minority of posts might present both positive and negative emotions. In our future work, we will fine-tune Senti4SD by training separate binary classifiers for positive and negative sentiment to be able to recognize also mixed sentiment.

9 Related Work

9.1 Sentiment Analysis Resources for Software Engineering

Trying to overcome the limitations posed by using off-the-shelf sentiment analysis tools, software engineering researchers recently started to develop their own tools.

Panichella et al. (2015) applied sentiment analysis for classifying user reviews in Google Play and Apple Store. They trained their own classifier on 2000 manually-annotated reviews, using Naïve Bayes and a bag-of-word approach. However, they do not report evaluation metrics for their classifier so we are not able to make any comparison with their method. For the sake of completeness, we also experimented with Naïve Bayes, as they suggest, but we found that it is outperformed by SVM.

Mäntylä et al. (2016) investigated the potential of mining developers' emotions in issue-tracking systems to prevent loss of productivity and burnout. They measured the emotions in issue comments in terms of VAD metrics, that is, scores for the Valence (i.e., the affect polarity), Arousal (i.e., the affect intensity), and Dominance (i.e., the sensation of being in control of a situation). To estimate VAD scores, they adopted the same lexicon-based approach implemented by SentiStrength, using a VAD lexicon of over 13 K English words developed by psychology research. However, given the lack of a gold standard for VAD, they were not able to provide any evaluation of their approach to emotion mining.

Ortu et al. (2015) presented an empirical study on the correlation of emotions and issue-fixing time in the Apache issue-tracking system. They measure the emotion polarity in issue comments using SentiStrength. As for discrete emotion labels, they developed their own classifier for detecting the presence of four basic emotions framework by the Shaver et al. (1987), namely anger, joy, sadness, and love. Their approach exploits SVM using a suite of features based on the SentiStrength output, the politeness score (Danescu-Niculescu-Mizil et al. 2013), and the presence of affective words derived from WordNetAffect (Strapparava and Valitutti 2004). The classifier is evaluated on a gold standard of 4000 sentences, obtaining an F-measure score ranging from .74 for anger to .82 for sadness. At the time of writing, the classifier is not yet available for research purposes.

Blaz and Becker (2016) developed a polarity classifier for IT tickets. Their approach is based on a domain dictionary created using a semiautomatic bootstrapping approach to expanding an initial set of affectively-loaded words used as seeds. They also exploit features based on the document structure, i.e., by distinguishing between the polarity of the opening section from the polarity of the actual problem report section in the ticket. They compare different approaches with different feature settings. In the best setting, they obtain an overall performance of F = .85, that is comparable to the one achieved by Senti4SD (F = .86). However, their classifier still reports a negative bias inducing the misclassification of neutral documents as negative. Their performance on the negative class (F = .70, R = .74, P = .67) reflects such bias. Senti4SD successfully addresses this problem by obtaining a more balanced performance for both the negative (F = .84, R = .87, P = .80) and neutral (F = .83, R = .80, P = .85) classes. Furthermore, Senti4SD has been trained and evaluated on a balanced and larger dataset.

Islam and Zibran (2017) developed SentiStrength-SE, a customized version of SentiStrength for software engineering. The tool is built upon the SentiStrength API and incorporates *ad hoc* heuristics designed to solve the misclassifications of SentiStrength observed on a subset of about 400 comments from the Ortu dataset (Ortu et al. 2016). The sentiment scores of the lexicon have been manually adjusted to reflect the semantics and neutral polarity of domain words such as '*support*', '*error*', or '*default*'. The authors performed an evaluation of the tool on the remaining 5600 comments from the Ortu dataset, showing that SentiStrength-SE (F = .78, R = .85, P = .74) outperforms SentiStrength (F = .62, R = .79, P = .62) on technical texts. However, SentiStrength-SE produces a lower performance (F = .78, R = .78, P = .78) than both SentiStrength (F = .82, R = .82, P = .82) and Senti4SD (F = .87, R = .87, P = .87) when used to classify polarity of posts from our Stack Overflow gold standard (see Section 6).

9.2 Distributional Semantics in Software Engineering

To the best of our knowledge, word embedding techniques have not been applied before to sentiment analysis tasks in the software development domain. In particular, we exploit the idea of using features based on the document similarity with respect to prototype vectors modeling the lexical profile of the polarity classes. The use of prototype vectors in text classifications was successfully exploited in different domains, e.g., for unsupervised speech-act recognition in telephone conversations (Novielli and Strapparava 2013) and for sentiment analysis in micro-blogging (Basile and Novielli 2015).

However, the use of distributional semantics is not entirely new in software engineering research. Traditional, context-counting approaches to distributional semantics have already been used, including Latent Dirichlet Allocation for topic modeling in Stack Overflow (Barua et al. 2014) and Latent Semantic Analysis for recovering traceability links in software artifact (De Lucia et al. 2007). Tian et al. (2014) recently proposed the use of pointwise mutual information to represents word similarity in a high-dimensional space. They built SEWordSim, a word similarity database trained on Stack Overflow questions and answers. However, as already discussed in Section 3.3, count-based approaches suffer from the main drawback of poor scalability. In the specific case of SEWordSim, the words are represented in a high-dimensional matrix whose e_{ij} elements correspond to the pointwise mutual information between the words w_i and w_j, thus describing their semantic association. The fact that vector space dimensions equal the vocabulary size significantly limits the scalability of approaches based on such word models. Instead, word embedding overcomes the limitations of context-counting approaches – due to their poor scalability to large document collections (Mikolov et al. 2013a) – and provides more effective vector representation of words (Baroni et al. 2014, Mikolov et al. 2013b). Thus, in our study, we adopt word embedding for building our distributional semantic model.

Ye et al. (2016) already exploited word embedding for enhancing information retrieval in software engineering. They run word2vec on a collection of over 12 K Java SE 7 documents to represent both natural language words and source code tokens in a distributional semantic model. Their final goal is to bridge the lexical gap between code fragments and natural language description that can be found in tutorials, API documentations, and bug reports. They empirically demonstrate how exploiting word embedding improves over state-of-the-art approaches to bug localization. Furthermore, they demonstrate the benefit of exploiting word embedding for linking API documents to Java questions posted in Stack Overflow.

10 Conclusions

We presented Senti4SD, a sentiment polarity classifier for software developers' artifacts. The classifier is trained and tested on a gold standard of over 4 K posts mined from Stack Overflow and manually annotated with emotion polarity. The gold standard is publicly available for further studies on emotion awareness in software engineering. We also release the guidelines for an annotation to encourage the community to extend and further validate our dataset by replicating the annotation experiment.

The semantic features of Senti4SD are computed based on a distributional semantic model built exploiting word embedding. We built the DSM by running word2vec on a collection of over 20 million documents from Stack Overflow, thus obtaining word vectors that are representative of developers' communication style. The DSM is released, with the replication kit, for future research on word embedding for text categorization and information retrieval in software engineering.

By combining lexicon-based, keyword-based and semantic features, Senti4SD successfully addresses the problem of the negative bias in off-the-shelf sentiment analysis tools. In particular, we observe a 19% improvement in precision for the negative class and a 25% improvement in recall for the neutral class with respect to the baseline represented by SentiStrength.

As future work, we intend to explore the contribution of additional features to capture further meaningful aspects of language use, such as part-of-speech and the rhetorical structure of sentences. We also intend to fine-tune Senti4SD to recognize content with mixed sentiment. As a further assessment of our approach, we intend to evaluate Senti4SD performance on further crowd-generated content from other social software engineering tools and repositories (e.g., GitHub, issue tracking systems). Besides, we plan to provide further benchmarking with other sentiment analysis tools and lexicons. Finally, we are also working on an extended version of our gold standard that will include emotion labels (e.g., love, anger, sadness, joy), as a first step towards building a classifier to detect specific emotions.

Acknowledgements This work is partially supported by the project 'EmoQuest - Investigating the Role of Emotions in Online Question & Answer Sites', funded by the Italian Ministry of Education, University and Research (MIUR) under the program "Scientific Independence of young Researchers" (SIR). The computational work has been executed on the IT resources made available by two projects, ReCaS and PRISMA, funded by MIUR under the program "PON R&C 2007–2013". We thank Pierpaolo Basile for insightful discussions and helpful comments and the annotators involved in the gold standard building.

Appendix: Coding Guidelines

In the following, we report the task description and the guidelines used for training the coders involved in the emotion annotation study.

Task Description and Annotation Guidelines. You are invited to take part in the annotation study of developers contributed texts in Stack Overflow. We are interested in annotating the presence of emotions in technical documents authored by developers during their online interactions.

The data source is the official Stack Overflow dump released by Stack Exchange on May '15. You will be required to annotate randomly selected posts, including questions, answers, and comments. The unit of annotation is the entire post.

You will use the coding schema reported in Appendix Table 12. For each post, please indicate what emotion it conveys (if any) among the basic emotions (first column in the table), that are, *love, joy, surprise, anger, sadness,* and *fear*. Multiple Emotion labels are allowed but you should try to avoid if possible. You can use the second and third level in the schema as a reference for choosing the primary emotion, as shown in Appendix Table 13.

Once you define the emotion label, please specify the emotion polarity accordingly, choosing among *positive, negative, neutral,* and *mixed*. If the post does not contain any emotion, it should be annotated as neutral. The surprise is the only emotion that could match any of the polarity value: please, carefully evaluate each post in order to determine if it conveys positive, negative, or neutral polarity. If multiple emotion labels are indicated in a given text, you should define the polarity accordingly. A text annotated with one or more positive emotions only has a positive polarity. Conversely, a post annotated with one or more negative emotions holds a negative polarity. If both positive and negative emotions are found, you should indicate both. If you wish to indicate a polarity label you are required to specify the corresponding emotion. The absence of emotion can be annotated exclusively as neutral. The list of all possible combination allowed and not allowed by our coding schema is reported in Appendix Table 14.

Table 12 Mapping the Shaver et al. emotion framework to sentiment polarity

Emotion Polarity	*Basic Emotions*	*Second level Emotions*	*Third level Emotions*
Positive	Love	Affection	Liking, Caring, Compassion, Fondness, Affection, Love, Attraction, Tenderness, Sentimentality
		Lust	Desire, Passion, Infatuation, Arousal
		Longing	–
	Joy	Cheerfulness	Happiness, Amusement, Satisfaction, Bliss, Gaiety, Glee, Jolliness, Joviality, Joy, Delight, Enjoyment, Gladness, Jubilation, Elation, Ecstasy, Euphoria
		Zest	Enthusiasm, Excitement, Thrill, Zeal, Exhilaration
		Contentment	Pleasure
		Optimism	Hope, Eagerness
		Pride	Triumph
		Enthrallment	Rapture
Negative	Anger	Irritation	Annoyance, Agitation, Grumpiness, Aggravation, Grouchiness
		Exasperation	Frustration
		Rage	Anger, Fury, Hate, Dislike, Resentment, Outrage, Wrath, Hostility, Bitterness, Ferocity, Loathing, Scorn, Spite, Vengefulness
		Disgust	Revulsion, Contempt
		Envy	Jealousy
		Torment	–
	Sadness	Suffering	Hurt, Anguish, Agony
		Sadness	Depression, Sorrow, Despair, Gloom, Hopelessness, Glumness, Unhappiness, Grief, Woe, Misery, Melancholy
		Disappointment	Displeasure, Dismay
		Shame	Guilt, Regret, Remorse
		Neglect	Embarrassment, Insecurity, Insult, Rejection, Alienation, Isolation, Loneliness, Homesickness, Defeat, Dejection, Humiliation
		Sympathy	Pity
	Fear	Horror	Alarm, Fright, Panic, Terror, Fear, Hysteria, Shock, Mortification
		Nervousness	Anxiety, Distress, Worry, Uneasiness, Tenseness, Apprehension, Dread
Either Positive or Negative	Surprise	Surprise	Amazement, Astonishment

Table 13 Examples of Annotated Posts

Input Text	Annotation		Rationale for annotation *(second and third level emotion found)*
	Basic Emotion(s) found	***Polarity***	
"*Thanks for your input! You're, like, awesome*"	Love	Positive	Liking (third level), Affection (second level) indicating gratitude.
"*I'm happy with the approach and the code looks good*" .	Joy	Positive	Happiness, Satisfaction (third), Cheerfulness (second)
"*I still question the default, which can lead to surprisingly huge memory use*"	Surprise	Negative	Surprise (second) due to the unexpected undesirable behavior of the code.
"*I will come over to your work and slap you*"	Anger	Negative	Hostility (third), Rage (second)
"*Sorry for the delay Stephen*"	Sadness	Negative	Guilt (third), Shame (second)
"*I'm worried about some subtle differences between char and Character*"	Fear	Negative	Worry (third)

Table 14 Combinations of Values Allowed and Not allowed by Our Annotation Schema

Love	Joy	Surprise	Anger	Sadness	Fear	Polarity	Explanation
				Annotation allowed by our schema			
			x			Negative	*Negative emotion and negative polarity*
	x					Positive	*Positive emotion and positive polarity*
		x				Negative	*Surprise is intrinsically ambiguous, all polarity*
		x				Positive	*values are allowed*
		x				Neutral	
x	x					Positive	*Multiple emotion labels, positive polarity*
			x	x		Negative	*Multiple emotion labels, negative polarity*
	x		x			Mixed	*Multiple emotion labels, mixed polarity*
						Neutral	*Absence of emotion*
				Annotation NOT allowed by our schema			
						Negative	*No emotion and negative polarity*
						Positive	*No emotion and positive polarity*
						Mixed	*No emotion and mixed polarity*
x						Neutral	*Emotion label different from surprise and neutral*
				x		Neutral	*polarity*

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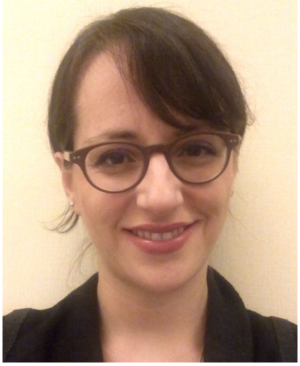

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Exploiting the Unique Expression for Improved Sentiment Analysis in Software Engineering Text

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***Abstract*— Sentiment analysis on software engineering (SE) texts has been widely used in the SE research, such as evaluating app reviews or analyzing developers' sentiments in commit messages. To better support the use of automated sentiment analysis for SE tasks, researchers built an SE-domain-specified sentiment dictionary to further improve the accuracy of the results. Unfortunately, recent work reported that current mainstream tools for sentiment analysis still cannot provide reliable results when analyzing the sentiments in SE texts. We suggest that the reason for this situation is because the way of expressing sentiments in SE texts is largely different from the way in social network or movie comments. In this paper, we propose to improve sentiment analysis in SE texts by using sentence structures, a different perspective from building a domain dictionary. Specifically, we use sentence structures to first identify whether the author is expressing her sentiment in a given clause of an SE text, and to further adjust the calculation of sentiments which are confirmed in the clause. An empirical evaluation based on four different datasets shows that our approach can outperform two dictionary-based baseline approaches, and is more generalizable compared to a learning-based baseline approach.**

Keywords—sentence structure, sentiment analysis, software engineering, nature language processing

I. Introduction

Sentiment analysis is the study of the subjectivity and polarity of a manually-written text (usually identified as positive, neutral, or negative) [1]. Modern software development process relies on a large number of manual efforts and collaborations because the scale of software is significantly larger and software development has become much more iterative [2]. Thus, the key performance indicators of software development, such as its quality, productivity, creativity, etc., will be inevitably affected by its participators' sentiments due to their indivisibility of human nature [3]. Meanwhile, the intense human collaborations of current software development are largely supported by different kinds of online tools, such as forums, communities, software repositories, and issue tracking tools. These tools then record abundant manually-written texts about the development process in the domain of software engineering (SE). These SE texts provides a valuable perspective for researchers to detect the developers' satisfaction or difficulties about the project, i.e., their positive or negative sentiments. Thus, to better support software engineering (e.g., [22]) and program comprehension (e.g., [25]) tasks, a growing body of work [19-28] applies automated sentiment analysis on SE texts from different online tools such as app stores [34-35], Stack Overflow [4, 32, 36], GitHub [29-31], and JIRA [21, 22]. These analyses are also favorable in daily SE practice because unlike the traditional approaches [5, 6, 42], they do not need direct observations or interactions on the developers, thus not likely to hinder them from their assigned development tasks.

When analyzing SE texts, the majority of the discussed work uses off-the-shelf sentiment analysis tools built on texts that are irrelevant to the SE domain, such as movie comments [7], or posts from typical social network such as Myspace [11]. To improve the performance of sentiment analysis in the SE domain, researchers further customized automated tools for SE texts by either training the particularly collected and labeled SE texts [13, 36], or building a SE-specified dictionary (e.g., mark "failure" and "exception" as neutral in SE text) [12]. Unfortunately, when analyzing the sentiments on Stack Overflow discussions to help recommend code libraries to developers, Lin et al. [36] found that no current sentiment analysis tools, even including two SE-customized tools (i.e., the domain-dictionary-based tool named SentiStrength-SE [12], and the adapted learning-based tool trained on the authors' labeled dataset from Stack Overflow), can provide reliable results of developers' sentiments in the SE texts. The reported negative results not only warn researchers about the limitations of current sentiment analysis on SE texts but also require them to further discover how developers express their sentiments in the SE texts from online collaborative tools.

In this regard, we made a close observation and found that *the expression of sentiments in SE texts are more indirect and dispersed compared to the way in the texts of common social media* (referred to as *social texts* in this paper). Specifically, we first observed that the author of an SE text often has to describe the issues that she encountered or proposed in detail before or after she expresses her sentiments, due to the overall complicacy of software tasks (such as bug fixing or comprehending code and features). Therefore, instead of assuming the entire SE text (with

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2643-7171/21/$31.00 ©2021 IEEE
DOI 10.1109/ICPC52881.2021.00023

TABLE I. THE SAMPLES TO SHOW HOW SENTISTRENGTH WORKS BASED ON ITS DICATIONARIES AND RULES WITH AN OVERALL RESULT

Sample Text	*Sent. Score*		**Overall result**	*Dictionaries or Rules in Use*	*Explanation*
	ρ	η			
It's a good feature.	2	-1	1	Sentimental Word	The sentimental score of the word *'good'* is 02; so the sentence is assigned a positive score 02.
It's a very good feature.	3	-1	1	Booster Word, Sentimental Word	As the booster word *'very'* before the sentimental word has the effect of +1, the sentence is assigned a positive score 03.
It's not good feature.	1	-2	-1	Sentimental Word Negative Word	The polarity of the sentimental word is flipped due to the use of the negation word *'not'* before sentimental word.
It's a good feature!	3	-1	1	Sentimental Word "!" Rule	"!" will strengthen the sentimental strength.
It's a gooooood feature.	3	-1	1	Sentimental Word Letter Repetition Rule	Repeated letters that appear more than twice above the letters required for correct spelling are used to enhance the emotional intensity of 1 unit.

one or more sentences) as sentimental, SE-specified sentiment analysis needs to ignore clauses that are not likely to express sentiments in all sentences. We then observed that due to the more complicated writing, the sentence structures become very helpful to better understand the sentiments in SE texts, e.g., to ignore subjunctive clauses or to distinguish polysemous words.

Based on the observations, we proposed a dictionary-based approach that uses sentence structures to improve sentiment analysis on SE texts. We build our approach based on the state-of-the-art dictionary-based tool (i.e., SentiStrength [11]) instead of retraining because: (1) we can integrate our heuristics into the dictionary-based tool naturally based on our observations, and explicitly test their effects; (2) more importantly, the dictionary-based approach tends to have better generalizability on different kinds of SE texts without requiring a large amount of labeled data for training, and thus we can use four different datasets to better evaluate our observations and proposed approach. In particular, our approach consists of three major steps: (1) it preprocesses and segments a given SE text into clauses; (2) it ignores the clauses that are not likely to express sentiments according to our proposed filter rules based on the sentence structures of the SE text; (3) when identifying sentiments on the possibly sentimental clauses, our approach further uses proposed adjust rules to enhance the results of dictionary-based sentiment analysis. We evaluated our approach with the antecedent observations on four datasets that are collected from three online collaborative tools for software development: Stack Overflow, app reviews, and JIRA. The evaluation showed that our approach can substantially outperform two dictionary-based baseline approaches [7, 12] and our filter-adjust rules have a strong complementary effect to the two baselines. This result also showed that our observations, which are the basis of our proposed filter-adjust rules, are valid because they can help SentiStrength, the state-of-the-art dictionary-based tool of sentiment analysis, to achieve better performance on SE texts without modifying its dictionary of sentimental words. The evaluation also showed that our approach has a better generalizability on all four datasets than a learning-based baseline approach [13] that is trained on one dataset only.

This paper aims to improve sentiment analysis for software engineering by characterizing the unique way of expression in SE texts based on sentence structures. We name our approach as **SESSION** (**S**ent**E**nce-**S**tructure-based **S**ent**I**ment analysis for s**O**ftware e**N**gineering). This paper makes two contributions: (1) we observe and find the uniqueness of sentiment expression in SE texts; (2) we improve the accuracy of dictionary-based sentiment analysis on SE texts based on our heuristics elicited from antecedent observations by using sentence structures of the SE texts. Our tool is publicly available [43].

The rest of this paper is structured as follows. Section II introduces the background of dictionary-based sentiment analysis and our observations on sentiment expression in SE texts. Section III presents our approach. Section IV introduces the experiment and research questions. Section V answers the research questions based on the experiment results. Section VI discusses possible threats. Section VII discusses related work. Section VIII makes conclusions and refers to future work.

II. BACKGROUND AND OBSERVATIONS ON SENTIMENT EXPRESSION IN SE TEXTS

In this section, we first introduce SentiStrength [11] which is the basis of SESSION. We then discuss the differences between SE texts and social texts when they express sentiments.

A. How SentiStrength Works

SentiStrength is a dictionary-based sentiment classifier which is developed for common texts. It contains a series of sentiment dictionaries, including the sentimental words list, the booster word list, and the negative word list. These lists play a vital role in the computation of sentiments. The sentimental words list gives sentiment scores to the matched words. The booster word list contains words that can strengthen or weaken affected sentiment scores. The words in the negative word list are used to flip the sentimental polarity of a word right after it. For the input text, SentiStrength will assign sentiment scores to each word according to the dictionaries and use minor rules to adjust the result. We use samples in Table I to show how SentiStrength works based on its dictionaries and rules. Variables ρ and η respectively refer to the positive and negative scores for each sentence, where $+1 \leqslant \rho \leqslant +5$ and $-5 \leqslant \eta \leqslant -1$. To better detect sentiment, the default result of SentiStrength contains both two scores. Only the score of (1, -1) indicates neutrality for a text. However, it also provides a "trinary" option to output an overall sentiment that is either positive, neutral, or negative. It is worth mentioning that SentiStrength determines the sentiment scores based on the sentimental words assigned by the highest positive and negative sentiments without considering the number of clauses in the input text. This setting helps SentiStrength to focus on the most sentimental part of the input text, especially when the text size is large. We follow the same setting in our approach, but use the clauses segmented from the input text as the basis of our proposed filter-adjust rules.

B. Different Expressions between SE Texts and Social Texts

Making close observations on SE texts and social texts, we find visible differences between two types of texts in expressing sentiments. The samples for social texts we selected are 1041 MySpace comments from the SentiStrength benchmark [11]. The samples for SE texts we selected are 4423 Stack Overflow posts from the Senti4SD benchmark [13]. Next, we will introduce our observed differences in detail.

We first find that SE texts tend to express fewer sentiments by comparing the percentage of sentimental texts from two sets of samples. For the 1041 MySpace comments, there are 938 texts manually labeled as sentimental (positive or negative). The percentage of sentimental texts is 90.1%. For the 4423 Stack Overflow posts, there are 2729 texts manually labeled as sentimental. The percentage of sentimental texts is 61.7%. In addition to the fewer sentiments, when it comes to expressing emotions, SE texts are more indirect and dispersed. We use sentimental density to reflect this characteristic of SE texts. The sentimental density ρ of a text equals the number of sentimental words (according to the sentimental words list of SentiStrength) in the text n_s divided by the total number of words in the text n_w. The average ρ of the 938 MySpace sentimental texts is 0.148, while the average ρ of 2729 Stack Overflow sentimental texts is 0.092. To more intuitively depict the differences, we show two samples with their ρ values close to the average from the two sets of texts, respectively. The text representing MySpace is "*Thanks for the add Jeremy!! Gotta love those Macross toy pics. Sadly I don't have them anymore...* ", while the one representing Stack Overflow is "*The error occurs because of looking in the wrong environment (i.e., not inside the data frame). You could explicitly specify the but that would be ugly, awful code. Much better to use as Iselzer suggests.*" It can be observed that social texts directly express sentiments, while SE texts usually have to describe the issues first and then express the author's sentiments about the issues. An additional observation is that "error", a typical negative word for social texts, is neutral in the SE text to discuss a code issue.

We then observed that the structure of SE texts is more complicated due to the use of long and complicated sentences in SE texts to describe development-related issues. We thus measure the average length of texts in the two sets of texts by counting the number of characters. The average length of MySpace comments is 102, while the average length of Stack Overflow posts is 169. To show this difference, we also choose two texts with their length close to the average length from each of the two datasets. The text representing MySpace is "*HAPPY BIRTHDAY BEAUTIFIL... HOPE YOU SEE MANY MORE.. BETTER YET I KNOW YOU WILL...GOD BLESS YOU..STAY UP*". The whole text basically uses imperative sentences to express blessing. While the text representing Stack Overflow is "*I generally do it before importing anything. If you're worried that your module names might conflict with the Python stdlib names, then change your module names!*". The structure of this text, which contains a subjunctive clause, is more complicated.

Thus, we argue that these observed differences lead to the unreliable results provided by off-the-shelf sentiment analysis tools built on social texts, and greatly raise the difficulty to customize these tools for SE texts. The dispersed expression of sentiments requires SE-specified tools to identify whether the author is expressing sentiments in different parts of an SE text. Hence, the complicated sentence structures in SE texts become very important for us to set up filter rules to ignore possible neutral clauses, and adjust rules to enhance the output result. Our approach is built on SentiStrength with our proposed rules. The evaluation shows that our filter-adjust rules are able to customize SentiStrength for SE texts, even without updating its sentiment dictionary. For example, our approach will ignore the sentence containing the word "error" in the discussed SE-text sample instead of modifying it as "neutral" in the dictionary.

III. Proposed Approach

We propose a three-step approach. First, we preprocess the input SE text and use Stanford CoreNLP[37] for segmentation (Step 1). Second, we use filter rules to identify whether a sentence can trigger the follow-on analysis (Step 2). Third, we use adjust rules to enhance the original output of SentiStrength (Step 3). It is worth-while noticing that our approach makes no change to SentiStrength's dictionaries. Each step will be explained with more details in the following subsections.

A. Step 1: Preprocessing and Segmenting SE Texts

First, we adapted the preprocessing methods used by the customized tool SentiStrength-SE [12] to filter out technical words based on regular expressions and filter names containing characters such as "Dear", "Hi", "@". One difference is that we don't filter out the words fully composed by capital letters. These words are likely to express an exaggerated sentiment, rather than be just part of technical texts. We also keep exclamation marks as part of the input for Step 3. The text "*FEAR!!!!!!!!!!!* " is a good sample to illustrate the above two differences. Besides, we will also filter out the words surrounded by the following brackets "[]", "{}", "<%%>", and double quotation marks because we think that these words are more likely to be quotations, examples, or technical words and to not express sentiments. For example, in the sentence "*CREATE TABLE [[With Spiteful]]] ...*", "spiteful" is a negative word but it is part of the table's name and doesn't express sentiments. Similarly, the negative word "tommyrot" in the sentence "*It is actually spelled "tommyrot".*" does not indicate negative sentiment because it is quoted as an example. Additionally, the sentence with underline symbols, e.g., "CODE_FRAGMENT", will be filtered too because this symbol is also a feature of technical text.

Second, to deal with SE texts which have more complicated sentence structures, we introduce Stanford NLP to segment, instead of following SentiStrength to segment texts according to punctuation marks only. Our segmentation first divides the whole text (named as *paragraph*) into multiple *sentences*. It then divides each sentence into clauses based on punctuations and conjunctions such as "because", "but", and "so". Furthermore, we use Stanford POS tagger to annotate each *word* in the clauses of each sentence with its *part of speech(POS)* tagging. The preprocessed, segmented, and tagged SE texts lays the foundation of the following steps of our approach.

B. Step 2: Matching Patterns to Trigger Follow-on Analysis

To distinguish whether the author is expressing sentiments or describing issues, we propose our filter rules. Specifically, any sentence that did not fit the following three patterns will be filtered out. Only the sentence that matches at least one defined pattern will be considered as likely to express sentiments, and will go to the next step for calculating its sentiment scores. A detailed description of patterns is as follows.

1) Direct Sentiment Pattern. A given sentence fits Direct Sentiment Pattern when it matches just one of the following six situations: (1) it contains the exclamation marks; (2) it contains emoji recorded in the SentiStrength's emoji list, such as " **:)** "; (3) it contains interjection word according to the tagged POS, such as "wow"; (4) it contains the four four-letter curse words that respectively start with letters "fu", "da", "sh", and "he"; (5) at least one of its given clauses starts with a sentimental word (except "please" and "plz"); (6) it is an imperative sentence and has a sentimental density larger than 0.3.

Intuitively, the first four situations indicate that the authors strongly expressed their sentiments. Meanwhile, we propose the fifth and the sixth situations to deal with imperative sentences. The fifth situation is proposed to cover the following two sample sentences: "*Thanks for your patience.*" and "*Owen, thanks for the slides.*". We exclude "please" and "plz" in the fifth situation because they are more likely to express requests instead of their intended positive sentiments. The sixth situation is proposed to cover the following sample sentence: "*Sounds good.*" . How to calculate the sentimental density for each sentence is discussed in Section II.B.

2) Decorated Sentiment Pattern. A given sentence fits Decorated Sentiment Pattern when it contains a sentimental word that is an adverb, or it contains a sentimental word that is decorated by an adverb (implying that this sentimental word must be a verb or an adjective). We suggest that when using sentimental adverbs, or adverbs to decorate a sentimental word, the author is determined to express her sentiments in the text because adverbs are used to indicate degree or scope. For example, in the sentence "*This is very frustrating.*", the adverb "very" indicates a deeper frustration (i.e., negative sentiment). While in the sentence "*The performance degrades horrendously*", the adverb "horrendously" indicates the degree of performance degradation is too large and thus showing the author's negative sentiment as well. Furthermore, for the three adverbs "always", "even", and "still", we will find decorated sentimental words from these words to the end of the sentence because they have a wider coverage based on their semantics. Finally, we treat "how", "sort of", and "enough" (after sentimental words) as adverbs because they are also highly likely to indicate the degree or scope of potential sentiments.

3) "About Me" Pattern: A given sentence fits "About Me" Pattern when it matches the following three situations: (1) its subject is "I" and it contains a sentimental word (e.g. "*I like…*"); (2) it contains a sentimental verb followed by the object "me" (e.g. "*...confuse me*"); (3) it contains a sentimental adjective or noun that follows "me" (e.g. "*...make me confused*"); (4) it contains a sentimental word that is decorated by "my" (e.g., "*This was my bad.*"). We propose the four situations because we suggest that the author is determined to express her sentiments in the first-person view. On contrary, the third-person view is usually more likely to describe a fact, instead of expressing sentiments. For example, the sentence "*he hates p tags, clearly*" is manually labeled as neutral.

4) "Judgement" Pattern: A given sentence fits "Judgement" Pattern when it contains the following four sentence structures (1) "be verb + sentimental adjectives/nouns" (e.g., "*It's ugly and inefficient*"); (2) "pronoun + sentimental verb" (e.g., "*This sucks so much.*"); (3) "get + sentimental word" (e.g., "*The problem just gets worse.*"); (4) "sentimental nouns + be verb" (e.g., "*The biggest reason for failure is your carelessness*"); (4) "a/an/the + adjective + noun" ("*It has an excellent command line interface.*"). We argue that the author usually expresses her sentiments when she makes a judgement to other things or people, and the five proposed situations can largely cover the potential judge-and-express scenarios.

C. Step 3: Adjusting the Sentiment Analysis

We argue that sentence structures are also helpful to better understand expressed sentiments in SE texts. So we propose to adjust rules based on SentiStrength to further enhance the results.

1) Recognizing Subjunctive Mood: Subjunctive mood expresses the author's subjective wishes, suspicions, suggestions, or hypotheses, but does not express real sentiments. Therefore, we ignore the sentimental words occurred in clauses of subjunctive mood. Our approach identifies subjunctive mood by recognizing "if" and "unless" as conditional adverbials in the clauses of a given sentence. We will not identify the sentiments in these clauses. For example, in the sentence "*If you're really worried about this, Java is not the language for you.*" the negative sentimental word "worried" is in the subjunctive clause, so it reflects no facts and does not express the author's sentiments.

2) Identifying Polysemous Words by the Sentence Structure: SentiStrength assigns a sentimental score to each sentimental word. However, when sentimental words express different meanings according to the different sentence structures, a single sentimental score will lead to possibly wrong results. During our observations, we summarized several polysemous words that can easily lead to mistakes. These words are categorized into two groups. We then confirm the meaning of first-group words based on the POS tags, and the meaning of second-group words based on their collocations with other words.

The first group of polysemous words that can be confirmed by the POS tags is as follows:

Like: SentiStrength detects this word as positive. In the sentence "*I like playing with you*", the word "like" is positive and it means that the subject prefers to do something. However, in the sentence " *it looks like this.* ", its meaning is close to "similar to" and it doesn't express positive sentiments. When "like" means " similar to", its POS is a preposition. So when its POS is preposition, we do not mark this word as positive, but as neutral instead.

Pretty and Super: SentiStrength detects these words as positive. In the sentence "*She is pretty.* ", the word "pretty" is positive and it means someone is attractive. However, in the sentence " *I'm pretty sure* " its meaning is close to "very" and it doesn't express positive sentiments. When "pretty" means "very", its POS is an adverb. So when its POS is an adverb, we do not mark this word as positive but as neutral. It will also play the role of booster words that can strengthen the intensity of the following sentiment word, like "very". "Super" is similar to "pretty". When its POS is an adverb and it is used to indicate something with a high or extreme degree, we detect it as neutral and it will play the role of booster words as well.

Block and Force: SentiStrength detects these words as negative. In sentences " *Lack of training acts as a block to progress in a career.*", the word "block" is negative and it means something that makes movement or progress difficult or impossible, but in sentences similar to " *I'm sure at first the code blocks*", it means a quantity of something that is considered as a single unit and does not express any negative sentiments. When "block" means " a unit", its POS is a noun. So when its POS is noun, we do not mark it as negative but as neutral. "Force" is similar to "block". When its POS is a noun, it means physical strength and we mark it as neutral instead of negative.

The second group of polysemous words that can be confirmed by their collocations with other words is as follows:

Lying: SentiStrength detects the word as negative. In the sentence "*He was lying.*", the word "lying" is negative and it means something deviating from the truth, but in sentences similar to "*It's lying all over the internet.*", its meaning is close to "be in" and it does not express negative sentiments. When "lying" means "be in", it is often used with prepositions, except "to" (excluding the phrase "lie to"). So when we recognize this collocation, we do not mark it as negative but as neutral.

Spite and Kind: SentiStrength detects the word "spite" as negative, but in the phrase "in spite of", the whole phrase represents a turning relationship and expresses no negative sentiments. So when found in this phrase, we do not mark it as negative but as neutral. "Kind" is similar to "spite". In the phrase "kind of", the meaning of the phrase is close to " to some extent" and the phrase expresses no positive sentiments. So we do not detect it as positive but as neutral when found in this phrase.

Miss: The word "miss" is assigned both a positive score 02 and a negative score 02 by SentiStrength because when its meaning is close to "remember fondly", it is frequently used to express sadness and loves simultaneously. However, when its meaning is close to "notice something not there", it expresses negative sentiments in SE texts. According to our observation, when it means "remember fondly", it is often followed by personal pronouns. When it means "notice something not there", it is followed by the object. Therefore, we will check the object of this word, only when its object is a personal pronoun, we will calculate its positive and negative sentiments at the same time.

3) Dealing with Negations. The original rule about negations in SentiStrength will flip the polarity of a sentimental word by multiplying a factor of -0.5 when a negation word is right in front of it. This rule overcompensates and ignores too many negation scenarios, especially for SE texts. For example, the sentiment of this text "***not** to **worry**, it was a permissions issue with the file*." will be identified as positive according to the original negation rule, but it is labeled as neutral. Instead in our approach, the words in the negation words list and the words ending with "**'t**" (e.g., "isn't") will neutralize the sentiment of the words within the following three words ("to" excluded). We also add three more words "nothing", "no", and "without" (not in the original negation list of SentiStrength) to neutralize the sentiment of the first word ("to" excluded) right behind them. The limited negation scope of the added three negation words is because their POS are nouns or prepositions, while the negation words in the original list or ending with "'t" are auxiliary verbs.

TABLE II. THE ANALYSIS (WITH TRINARY OUTPUT) OF SENTISTRENGTH

Sentence	***Senti. Score***	
	ρ	**η**
This app is *really good*[2] [+1 booster word] in *spite* [-4] of some (minor) *shortcomings*[-2] .	3	-4
Its font sizes will get bigger or smaller to fit the space for them and i *don't like*[2] [*-0.5 approx. negated multiplier] .	2	-1
If the *problem*[-2] solved, I think it will be more practical .	1	-2
Overall ,it's a *good*[2] app though .	2	-1
Overall result = -1 as Max(ρ) < Max(abs(η))		

TABLE III. THE ANALYSIS (WITH TRINARY OUTPUT) OF SESSION

Sentence	***Senti. Score***	
	ρ	**η**
[fit "Decorated sentiment Pattern"] This app is *really good*[2] [+1 booster word] in *spite* [polysemous words] of some (minor) *shortcomings*[-2] .	3	-2
[fit "'About Me' Pattern"] Its font sizes will get bigger or smaller to fit the space for them and i *don't like* [neutralized by negations] .	1	-1
[does not fit any pattern] If the problem solved, I think it will be more practical .	1	-1
[fit "'Judgement' Pattern"] Overall ,it's a *good*[2] app though .	2	-1
Overall result = 1 as Max(ρ) > Max(abs(η))		

D. Summary through a Sample SE Text

We now use the following sample SE text to show how SESSION works: " *This app is a really good in spite of some (minor) shortcomings. Its font sizes will get bigger or smaller to fit in the space allocated for them which I don't like. If you can solve the problem, I believe it will be more practical. Overall, it's a good app though.*". The sentiment of this text is manually labeled as positive. The analysis and results from original SentiStrength are shown in Table II, while the analysis and results from SESSION is shown in Table III. It can be observed that, based on our proposed filter rules and adjust rules (Step 2 and Step 3) that rely on the segmentation and POS tagging of preprocessed SE texts in Step 1, SESSION correctly identifies the positive sentiment for this text, while SentiStrength is misled by the text to wrongly identify its sentiment as negative.

IV. EXPERIMENTAL SETUP

We now introduce our experimental setup to evaluate our approach. Section IV.A introduces the four datasets of SE texts for the evaluation. Section IV.B defines metrics for evaluating the performance of the proposed approach. Section IV.C introduces our research questions and the design of experiments.

A. The Benchmark with Four Datasets

We first bring in the benchmark that Lin et al. studied and reported that no current sentiment analysis tools can provide reliable results of sentiments expressed in the SE texts [36]. It consists of three datasets that are built on 1500 Stack Overflow discussions, 341 app reviews, and 926 JIRA comments, respectively. We then introduce the fourth dataset that is built on 4423 Stack Overflow posts by Calefato et al. to propose a

TABLE V. THE PERFORMANCE OF SESSION AND THREE BASELINES ON THE FOUR DATASETS

Dataset	*Tool*	*overall accuracy*	*positive*			*neutral*			*negative*		
			P	*R*	*F*	*P*	*R*	*F*	*P*	*R*	*F*
Stack Overflow 4423	SentiStrength	81.55%	88.90%	92.34%	0.906	92.76%	63.58%	0.754	66.83%	93.18%	0.778
	SESSION	86.30%	90.15%	94.70%	0.924	90.19%	75.97%	0.825	77.87%	90.18%	0.836
	SentiStrength-SE	78.86%	90.47%	82.06%	0.861	72.74%	77.80%	0.752	74.80%	76.29%	0.755
	Senti4SD	**95.27%**	97.25%	97.45%	0.974	95.02%	93.51%	0.943	93.15%	95.01%	0.941
Stack Overflow 1500	SentiStrength	68.00%	19.28%	36.64%	0.253	86.20%	74.98%	0.802	36.74%	44.38%	0.402
	SESSION	**78.13%**	30.89%	29.01%	0.299	85.10%	89.67%	0.873	54.10%	37.08%	0.44
	SentiStrength-SE	78.00%	31.18%	22.14%	0.259	82.72%	92.86%	0.875	50.00%	19.66%	0.282
	Senti4SD	76.93%	27.59%	30.53%	0.29	83.11%	90.51%	0.867	62.07%	20.22%	0.305
App Reviews	SentiStrength	67.45%	71.81%	87.63%	0.789	4.76%	4.00%	0.043	70.97%	50.77%	0.592
	SESSION	**68.62%**	76.17%	87.63%	0.815	9.76%	16.00%	0.121	77.91%	51.54%	0.62
	SentiStrength-SE	61.58%	74.15%	81.72%	0.777	9.59%	28.00%	0.143	80.95%	39.23%	0.528
	Senti4SD	63.93%	71.24%	86.56%	0.782	9.80%	20.00%	0.132	81.25%	40.00%	0.536
JIRA Issue	SentiStrength	**81.21%**	86.03%	93.45%	0.896	——	——	——	98.16%	75.63%	0.854
	SESSION	80.56%	93.13%	93.45%	0.933	——	——	——	98.55%	74.69%	0.85
	SentiStrength-SE	77.21%	95.26%	90.00%	0.926	——	——	——	99.34%	71.38%	0.831
	Senti4SD	57.88%	81.55%	86.90%	0.841	——	——	——	99.65%	44.65%	0.617

learning-based approach of sentiment analysis on SE texts. Table IV reports the total number of texts, and the number of positive, neutral , and negative texts for each dataset.

B. Metrics

We first leverage three metrics to measure the accuracy of sentiment analysis for each of the three sentimental polarities (i.e., positivity, negativity, and neutrality). Given a set S of texts, *precision (P)*, *recall (R)*, and *F-measure (F)* for a particular sentimental polarity is calculated as follows:

$$P = \frac{|S_c \cap S_c'|}{|S_c'|} \quad R = \frac{|S_c \cap S_c'|}{|S_c|} \quad F = \frac{2 \times P \times R}{P + R} \quad (1)$$

where S_c represents the set of texts having sentimental polarity c, and S_c' represents the set of texts classified to have sentimental polarity *c* by a tool. F-measure is the weighted harmonic mean of precision and recall. A higher F-measure means both precision and recall are high, and the tool performs better. We further introduce the overall accuracy of sentimental analysis on the set S for all of the three sentimental polarities with metric *Overall Accuracy* calculated as follows:

$$Overall\ Accuracy = \frac{\sum_{c \in polarities} |S_c \cap S_c'|}{|S|} \quad (2)$$

where we accumulate the numbers of texts in S_c' which have the same sentimental polarity "c" in S_c for all three polarities, and then calculate the proportion of it in the given set S of texts.

C. Research Question

In this paper, we aim to study whether sentence structures can effectively improve the performance of sentiment analysis in SE texts. Therefore, we propose the following three research questions:

TABLE IV. DATASETS USED FOR OUR EVALUATION

Dataset	*sentences*	*positive*	*neutral*	*negative*
Stack Overflow 4423	4423	1527	1694	1202
Stack Overflow1500	1500	131	1191	178
App Reviews	341	186	25	130
JIRA issue	926	290	0	636

RQ1: Can our proposed approach outperform the baseline in analyzing sentiments for SE texts?

RQ2: How much contribution do our filter rules make?

RQ3: How much contribution do our adjust rules make?

To study *RQ1*, we introduce the following three baselines: (1) *SentiStrength* [11], the state-of-the-art dictionary-based tool and the basis of our approach; (2) *SentiStrength-SE* [12], a representative dictionary-based tool that builds a new dictionary specified for SE texts; (3) *Senti4SD* [13], a representative SE-Customized, learning-based tool that is trained on the **Stack Overflow 4423** dataset (also part of our evaluated datasets). Based on the comparison with the three baseline approaches, we expect to find out whether our approach can have a better performance, as well as whether our observations about the uniqueness of sentiment expression in SE texts are valid. To study *RQ2* and *RQ3*, We will run SentiStrength with our filter rules only (*SS + Filter*) and with our adjust rules only (*SS + Adjust*) on the four database, respectively, to further compare their performances with SentiStrength and SESSION.

V. RESULTS AND DISCUSSIONS

A. RQ1: Can our proposed approach outperform the baseline in analyzing sentiments for SE texts?

Table V shows the performances of the evaluated four approaches. First, we compare the performance of SESSION with SentiStrength. We found that the overall accuracy of SESSION in **Stack Overflow 4423**, **Stack Overflow 1500**, and **App Reviews** is better than that of SentiStrength. Its overall accuracy on **Stack Overflow 1500** can be 10% higher than that of SentiStrength. Our previous observations show that social texts are more sentimental and their expression is more direct than SE texts. This difference makes SentiStrength tend to output more positive and negative results. This tendency can be observed through the low recall of identified neutral texts achieved by SentiStrength in Table V. On the other hand, we propose filter rules and adjust rules to address the issue that the sentiments expression in SE texts is more indirect and dispersed. Our approach thus achieves 12% more recall than SentiStrength on **Stack Overflow 4423**. The proposed filter-adjust rules also

TABLE VI. SAMPLES FOR COMPARING SESSION (SN) WITH SENTISTRENGTH (SS, M STANDS FOR MANUAL LABEL)

Sentence	*M*	*SN*	*SS*
It's pretty easy to prevent aliasing by adding a conditon *a != *b.	0	0	1
If you're really worried about this, Java is not the language for you	0	0	-1
why do people hate anonymous block initializers	0	0	-1

contribute to help our approach outperform SentiStrength in the F-Measures of all three sentiment polarities on the evaluated datasets, except **JIRA Issue**. Unlike the two datasets from Stack Overflow, **JIRA Issue** has no neutral texts. Thus, it leaves little room for our filter-adjust rules to work. However, our approach still outperforms SentiStrength in the F-Measure of positive sentiments on **JIRA Issue**, while only performs slightly worse in the F-Measure of negative sentiments. Because **JIRA Issue** contains about two times more negative texts than its positive texts and no neutral texts, SESSION thus performs slightly worse in the overall accuracy (further discussions are in the end of this section). We then use sample texts (from the four datasets) shown in Table VI to demonstrate how SESSION outperforms SentiStrength. In the table, the first sentence is identified as positive by SentiStrength because of "!", while SESSION can filter out "!=" as part of technical text. The second sentence is identified as negative by SentiStrength because of "worried", while SESSION locates its subjunctive mood and identifies it as neutral. Because of "hate", the third sentence is identified as negative by SentiStrength, while this sentence cannot fit any patterns in our filter rules and SESSION identifies it as neutral.

Second, we compare their performances between SESSION and SentiStrength-SE. From Table V we can find that SESSION outperforms SentiStrength-SE in overall accuracy and almost in all the other metrics on the four datasets, except the recall and F-Measure of neutral sentiments on **Stack Overflow 1500** and **App Reviews**, and the recall of neutral sentiments on **Stack Overflow 4423** where SESSION slightly performs worse. Both approaches actually exploited the neutral tendency of SE texts. SentiStrength-SE chooses to establish a SE-domain-specified dictionary, while our approach chooses to use filter-adjust rules to enhance SentiStrength. We found that the overall accuracies for SentiStrength-SE and SESSION differ little on **Stack Overflow 1500**. However, to cope with the neutral tendency, the updated sentimental word list of SentiStrength-SE is shortened to 550 words only, while the original list in SentiStrength has more than 2,000 words. Consequently, SentiStrength-SE covers much fewer possible positive and negative sentiments than SESSION and SentiStrength. Sentences like "*I'm loving.*" will not be identified as sentimental by SentiStrength-SE because it lacks the sentimental word "loving" in its list. We then argue that our observations and proposed filter-adjust rules better

TABLE VII. SAMPLES FOR COMPARING SESSION (SN) WITH SENTISTRENGTH-SE (SE, M STANDS FOR MANUAL LABEL)

Sentence	*M*	*SN*	*SE*
Joei get it! i guess you are right	1	1	0
How to correctly print a CString to messagebox? There is nothing appear..	0	0	-1
Are you afraid of a trademark lawsuit?	0	0	-1

exploit the unique expression of sentiments in SE texts. We use sample texts shown in Table VII to demonstrate how SESSION outperforms SentiStrength-SE. In the table, the first sentence is classified as neutral by SentiStrength-SE because it will delete "!" during preprocessing. The preprocessing rule of SESSION will keep "!" so the text won't be misclassified. The second sentence is classified as negative by SentiStrength-SE because the word "messagebox" matches its wildcard "mess*" which has negative score 02 in SentiStrength-SE's sentimental word list. This word doesn't match in SESSION's sentimental word list so the text won't be misclassified. The third sentence is classified as negative by SentiStrength-SE because of "afraid", while this sentence cannot fit any patterns in our filter rules and SESSION identifies it as neutral.

Third, we compare their performances between SESSION and Senti4SD. From Table V, we found that Senti4SD significantly outperforms SESSION in its training set **Stack Overflow 4423**. We think this result is reasonable because, with the help of improved feature engineering to cover more implicit facts [13], Senti4SD can better predicate the sentiments in the SE texts, especially from **Stack Overflow 4423** where Senti4SD fine-tunes the parameters of its trained SVM model for classification. However, when applied to other datasets, the performance of Senti4SD begins to decrease. Its performance on **Stack Overflow 1500**, the dataset similar to its training set, is lower than SESSION. The same comparison can also be observed on **App Reviews**. Moreover, its overall accuracy on **JIRA Issue** is only 57.88% and its negative recall is only 44.65%. On the other hand, SESSION is able to achieve balanced recall and precision for all sentiments. The recall of negative text is about 10%-30% higher than that of Senti4SD. We argue that SESSION achieves a comprehensively better performance than Senti4SD, especially in the generalizability.

Our overall observation on the evaluation shows that tools (SentiStrength-SE, Senti4SD) developed from software engineering texts can often achieve higher precision in sentiment texts, but has to suffer the cost of a lower recall. Tools (SentiStrength) developed for social texts can often achieve higher recall in sentiment texts, but to suffer the loss of precision. In contrast, our tools, which exploit the unique expression of sentiments in SE texts based on sentence structures, can achieve a good and balanced performance in precision and recall, and a better generalizability when compared to a learning-based tool.

B. RQ2: How much contribution do our filter rules make?

The results of SS + Filter are shown in Table VIII. Comparing the data of SS + Filter with SentiStrength, we can find that in two Stack Overflow datasets, the overall accuracy of SS + Filter is better than that of the original tool. In **Stack Overflow 4423**, the overall accuracy of SS + Filter is 2.13% higher, and In **Stack Overflow 1500**, the overall accuracy of SS + Filter is 6.93% higher. These rules can effectively improve the precision of sentimental texts and the recall of neutral texts and especially better at neutral texts. The neutral F-measure of the tool with filter rules is all higher than that of the original tool and that of the tool with filter rules. In the other two datasets, the improvement of the overall accuracy that filter rules can bring is not high. Because there are few neutral texts on these two datasets, filter rules, which are better at neutral texts, are difficult

TABLE VIII. ANALYZING PERFORMANCES OF RULE-FILTER AND RULE-ADJUST RESPECTIVELY

Dataset	*tool*	*overall accuracy*	*positive*			*neutral*			*negative*		
			P	*R*	*F*	*P*	*R*	*F*	*P*	*R*	*F*
Stack Overflow 4423	SentiStrength	81.55%	88.90%	92.34%	0.906	92.76%	63.58%	0.754	66.83%	93.18%	0.778
	SS + Filter	83.68%	90.06%	91.94%	0.91	90.56%	70.78%	0.795	71.30%	91.35%	0.801
	SS + Adjust	84.08%	89.00%	94.89%	0.919	92.06%	68.42%	0.785	72.33%	92.43%	0.812
	SESSION	**86.30%**	90.15%	94.70%	0.924	90.19%	75.97%	0.825	77.87%	90.18%	0.836
Stack Overflow 1500	SentiStrength	68.00%	19.28%	36.64%	0.253	86.20%	74.98%	0.802	36.74%	44.38%	0.402
	SS + Filter	74.93%	23.31%	29.01%	0.259	85.12%	85.47%	0.853	48.23%	38.20%	0.426
	SS + Adjust	73.87%	27.43%	36.64%	0.314	86.23%	82.54%	0.843	41.62%	43.26%	0.424
	SESSION	**78.13%**	30.89%	29.01%	0.299	85.10%	89.67%	0.873	54.10%	37.08%	0.44
App Reviews	SentiStrength	67.45%	71.81%	87.63%	0.789	4.76%	4.00%	0.043	70.97%	50.77%	0.592
	SS + Filter	67.45%	75.36%	85.48%	0.801	10.00%	16.00%	0.123	74.44%	51.54%	0.609
	SS + Adjust	**69.21%**	73.45%	89.25%	0.806	8.33%	8.00%	0.082	74.73%	52.31%	0.615
	SESSION	68.62%	76.17%	87.63%	0.815	9.76%	16.00%	0.121	77.91%	51.54%	0.62
JIRA Issue	SentiStrength	81.21%	86.03%	93.45%	0.896	——	——	——	98.16%	75.63%	0.854
	SS + Filter	80.35%	87.91%	92.76%	0.903	——	——	——	97.94%	74.69%	0.847
	SS + Adjust	**82.18%**	91.28%	93.79%	0.925	——	——	——	98.19%	76.89%	0.862
	SESSION	80.56%	93.13%	93.45%	0.933	——	——	——	98.55%	74.69%	0.85

to bring improve. In summary, because the F-measures of SS + Filter are almost all better than SentiStrength, we can say that filter rules can actually bring improvements. However, its improvement will be a little unstable when analyzes datasets with too many sentimental texts.

C. *RQ3: How much contribution do our adjust rules make?*

The data of SS + Adjust is shown in Table VIII. We can find that the overall accuracy of SS + Adjust in four datasets is all better than SentiStrength. It can also effectively improve the precision of sentimental texts and the recall of neutral texts. The F-measures of SS + Adjust are all better than SentiStrength, so we can say that adjust rules can actually bring improvements. Compared to filter rules, they are better at sentimental texts. The positive F-measures and negative F-measures of the tool with adjust rules are almost all higher than the original tool and the tool with filter rules. For sentimental texts, adjust rules can improve the precision without losing too much recall. In **Stack Overflow 4423**, the positive precision (89.00%) of SS + Adjust and that (90.06%) of SS + Filter are similar. But the positive recall (94.89%) of SS + Adjust is higher than that (91.94%) of SS + Filter. In addition, we also find that the improvement brought by filter rules will be a little less when analyses datasets with too many sentimental texts. In two Stack Overflow datasets which have more neutral texts, the overall accuracies of SS + Adjust are 2.53% and 5.87% higher than the original tool respectively. In the other two datasets with more sentimental texts, the overall accuracies of SS + Adjust are 1.76% and 0.97% higher than the original tool, respectively.

In summary, the two sets of rules for our approach can both bring improvements because they can effectively improve the precision of sentimental texts and the recall of neutral texts. Because our rules are based on the observation that SE texts are more indirect and complicated than social texts, they will be more helpful when analyses datasets with more neutral texts. To be more specific, Table VIII shows that SESSION (with both filter rules and adjust rules) performs best on both **Stack Overflow 4423** and **Stack Overflow 1500**, while SS + Adjust performs best on both **App Reviews** and **JIRA Issue**. This observation shows that although our filter rules are better at handling neutral texts, they may also conduct a loss of the sentiment context when filtering out sentences that cannot match any patterns, especially compared to the adjust rules which performs more stably on all SE texts. However, when applied on **App Reviews** and **JIRA Issue**, our filter rules only decrease the overall accuracy by 0.59% and 1.62%, respectively. Because these two data sets only respectively contains 7% and 0% neutral texts, indicating that our filter rules have little room to work, we suggest that the possible loss of sentiment context caused by our filter rules are not significant. We then suggest that due to the more indirect and dispersed nature of sentiment expression in SE texts, both our filter rules and adjust rules are helpful for sentiment analysis on SE texts generated by the online tools for SE in practice, where neutral texts are likely to take a big part.

Additionally, we made three more observations on the experiment results. First, our experiment results for SentiStrength on the three datasets that Lin et al. also studied are a little different from the results in their paper [36]. We found that it is because Lin et al. uses the sign of the sum of positive and negative scores from SentiStrength to get the overall polarity, while our approach uses the in-built "trinary" option of SentiStrength to output the overall polarity. By comparison, we found that our results for SentiStrength are slightly better, and thus we make no bias when comparing with SentiStrength. Second, the improvement of our approach, though is balanced and stable on all datasets, is still not high. We think this situation is caused by our conservative choice of using sentence-structure-based rules to collaborate with SentiStrength. In future work, we plan to carry out a deeper study on how developers express their sentiments in SE texts and to carefully establish SE-specified dictionaries by consulting existing work [45]. Third, we found that the standards of manual labeled sentiments can vary in different datasets. During our research, we had a candidate polysemous word "work". When "work" is an intransitive verb, it means "to effect something" and can be viewed as a positive sentimental word. However, **Stack Overflow 4423** favors this candidate word, while **Stack Overflow 1500** tends to be the opposite, and thus we finally exclude this word from the adjust rules of SESSION. Our further investigation shows that although the two datasets are both created from Stack Overflow, the participants who label sentiments for **Stack Overflow 1500** tend to favor the neutral texts instead of either positive texts or negative texts. For example, in this dataset the typical positive texts such as "I appreciate your help", and the typical negative texts such as "I suspect why the decision is made", are both labeled as neutral. A possible explanation is that, in the participants' opinions, the sentiments of these texts, either identified as positive or negative, are not convincing enough to indicate the real status of the potentially related SE tasks to other developers. The similar situation also occurs in **App Reviews** where 25 texts are manually labeled as neutral, while they contain considerable number of sentimental words. These results of our investigation is able to explain why SESSION and all baseline approaches do not perform well on the positive and negative texts of **Stack Overflow 1500**, and the neutral texts of **App Reviews**. We thus suggest that it would be favorable if the SE community could agree on a unified standard for manually labeling sentiments on SE texts to help researchers (including us) establish more consistent datasets that aim to enhance the research of sentiment analysis in the SE domain.

VI. Threats to Validity

Internal Threats. A possible threat to the validity of the results of our experiments is that we cannot guarantee 100% accuracy in segmenting SE texts and recognizing POS taggers based on Stanford CoreNLP. However, existing work has reported that the accuracy of off-the-shelf NLP tools is acceptable when analyzing texts with the context of proper sentences and grammatical structures, instead of analyzing fragmented source code [44]. With additional preprocessing, we think the quality of our analyzed SE texts is able to hold usable sentence structures for our approach. During our observations, we found no obvious errors from the output of Stanford CoreNLP either. Another possible threat is that our observations are not thorough and complete enough to fully exploit how developers express their sentiments on SE texts, and thus our defined rules cannot cover all misjudged sentiments found by our observations on the evaluated datasets. Still, we think these rules defined in this paper make a good start because with their help, our approach is able to achieve an overall better performance compared to the baseline approaches. We plan to make a deeper and more comprehensive study guided by psychology and sociology theories by consulting existing work (e.g., mental workload assessment [34]) in future.

External Threats. Our work is based on four datasets containing 7,190 SE texts in total with manually labeled sentiments. The size of our experiment is not large, but we still consider our findings relevant because the four datasets come from two existing work [13, 36] and are generated from three different online tools for software development (Stack Overflow, App Reviews, and JIRA). The two datasets from Stack Overflow are able to represent developers' typical interactions through SE texts due to the wide popularity of Stack Overflow. The other two datasets, unlike the previous two, contain SE texts that are almost labeled as either positive or negative sentiments. Thus, these two datasets are very helpful to verify whether SESSION overemphasizes the neutral sentiments (the majority sentiments in the two Stack Overflow datasets) in SE texts. Our evaluation shows that the performance of SESSION hardly decreases on the App Reviews and JIRA datasets, where SentiStrength-SE and Senti4SD (the two SE-customized baseline approaches) suffer a visible loss in their performance.

VII. Related Work

In this section, we focus our discussion of related research on sentiment analysis in the software engineering domain.

A. *Sentiment Analysis Tools Applied to SE*

A comprehensive set of out-of-the-box sentiment analysis tools developed and used to detect sentiments can be found elsewhere [8, 9, 10]. Among these tools, SentiStrength [11], NLTK [39] and StanfordNLP [37] are common-used in SE domain. However, these tools do not perform well when applied to SE texts [12, 36, 40, 41] largely due to being trained on non-technical texts. Hence, some studies were conducted to improve the situation by utilizing SE texts, such as SentiCR [15], SentiStrenght-SE [12], and Senti4SD [13]. SentiCR is a supervised tool trained using Gradient Boosting Tree (GBT) [17] that is especially designed for code review comments. It generates feature vectors by computing TF-IDF [16] (Term Frequency - Inverse Document Frequency) of bag-of-words extracted from the input text. SentiStrenght-SE is a dictionary-based tool developed from SentiStrength by extending inherent dictionary with SE terms, which is the first SE-specific sentiment analysis. Senti4SD [13] is trained on a gold standard of about 4K questions, answers, and comments from Stack Overflow. It leverages three kinds of features when conducting sentiment classification tasks, including dictionary -based features (i.e., the dictionary used by SentiStrength), keyword-based features (i.e., uni-grams and bi-grams extracted from large scale Stack Overflow posts), and semantic features (based on the word embeddings trained on Stack Overflow posts). Unlike Senti4SD leveraging keyword-based features in the corpus, we paid more attention to analyze characteristics of SE texts and created a set of heuristics leveraging sentence structure information (e.g., identifying subjunctive clauses or distinguishing the meaning of polysemous words) based on our close observations. Furthermore, our approach is dictionary-based which can be more generalized to various SE texts, while learning-based methods need a large scale of labeled data to train their classifiers [15, 25, 36].

Apart from the discussed sentiment analysis tools designed to detect sentiment polarities (i.e., positivity, negativity, and neutrality) of a given text, Islam et al. [14] proposed a dictionary-based tool that can detect excitement, stress, depression, and relaxation expressed in software engineering text. To better assess the sentiment scores, their approach also integrated with a set of heuristics for sensing arousal, but it does not explicitly take advantage of the sentence structures from SE texts, while in this paper we use these sentence structures as the basis of our filter-adjust rules for our approach.

B. *Sentiment Analysis Application in SE*

In recent years, sentiment analysis is receiving increasing attention as part of human factors of SE [18] and has been widely applied in SE tasks [19-28]. A number of studies applied sentiment analysis in the collaborative online environment (e.g., GitHub, JIRA, Stack Overflow, and App store) presented as follows: Pletea et al. [29] mined emotions from security-related discussions around commits and pull request on GitHub, and found that more negative emotions are expressed in security-related discussions than in other discussions. Guzman et al. [30] used dictionary-based sentiment analysis to detect sentiment expressed in commit comments of six OSS projects in GitHub and showed that the projects with more distributed teams tend to have a higher positive polarity in their emotional content. Mantyla et al. [21] analyzed 700,000 JIRA issues containing 2,000,000 comments with VAD (Valence, Arousal, and Dominance) metrics. The result indicated that different type issues reports (e.g., Feature Request, Improvement, and Bug Report) have a fair variation of Valence, while an increase in issue priority (e.g., from Minor to Critical) typically increases Arousal. Ortu et al. [22] analyzed the relation between sentiments, emotions and politeness of developers in more than 560K JIRA comments with the time to fix a JIRA issue. They found that the happier developers (expressing emotions such as JOY and LOVE in their comments) tend to fix an issue in a shorter time. Calefato et al. [32] quantitatively analyze emotions of a set of over 87K questions from the Stack Overflow finding that successful questions usually adopt a neutral emotional style. Canfora et al. [34] showed that users feedback contains usage scenarios, bug reports, and feature requests, that can help app developers to accomplish software maintenance and evolution tasks.

However, we also need to point out that the precision and reliability of the current sentiment analysis tools in SE domain are still less than satisfaction [20, 36]. One possible reason is that many prior works leverage off-the-shelf sentiment analysis tools (such as SentiStrength [11]) built on texts that are irrelevant to the SE domain, while proposing an SE-specified sentiment analysis is challenging [36]. Therefore, in this paper we choose to first exploit the uniqueness of sentiment expressions in the SE text, and then propose our approach by integrating our filter-adjust rules into SentiStrength.

VIII. CONCLUSIONS AND FUTURE WORK

A growing body of work applies sentiment analysis on SE texts to enhance software development and program comprehension. However, current automated sentiment analysis, even including two SE-customized approaches, cannot provide reliable results on SE texts. Thus, we first observed and found that the expression of sentiments in SE texts are more indirect and dispersed compared to texts from common social network. We then proposed a set of filter and adjust rules based on sentence structures inside SE texts, and combine these heuristics with the mainstream dictionary-based approach called SentiStrength. Our evaluation based on four different datasets showed that our approach has the overall better performance and generalizability than three baseline approaches. Our tool is now publicly available [43].

The possible directions of our future work are as follows: (1) we plan to further explore how and why developers express their sentiments in SE texts under the guidance of related psychology and sociology theories so that we can fine-tune and enrich our filter-adjust rules accordingly; (2) we plan to further improve sentiment analysis on SE texts by proposing an SE-Specified dictionary by consulting existing work (e.g., [45]); (3) we plan to further explore whether the expressed sentiments on SE texts, if correctly identified, explicitly correlate to the status of ongoing software development from multiple perspectives.

ACKNOWLEDGMENT

This work is jointly supported by the National Key Research and Development Program of China (No. 2019YFE0105500) and the Research Council of Norway (No. 309494), as well as the National Natural Science Foundation of China (Grants No.62072227, 61802173, and 61690204), Intergovernmental Bilateral Innovation Project of Jiangsu Province (BZ2020017), and the Collaborative Innovation Center of Novel Software Technology and Industrialization.

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