

Detection of Hidden Feature Requests from Massive Chat Messages via Deep Siamese Network

ABSTRACT

Online chatting is gaining popularity and plays an increasingly significant role in software development. Developers reveal their desired features when communicating with other developers. However, these feature requests are quickly flooded by newly incoming messages, and are likely to be buried and ignored if they are not documented. Automated mining techniques towards retrieving feature requests from massive chat messages can benefit the requirements gathering process. But it is quite challenging to perform such techniques because detecting feature requests from dialogues requires a thorough understanding of the contextual information, and it is also extremely expensive on annotating feature-request dialogues for learning. To bridge that gap, we propose a novel approach, named FRMiner, which can detect feature-request dialogues from chat messages via deep Siamese network. We design a BiLSTM-based dialog model that can learn the contextual information of a dialog in both forward direction and reverse direction. To build a performance prediction model based on a small sample of chat messages, we recast the traditional text classification task of mapping single dialog to its class into the task of determining whether two dialogues are similar or not. We incorporate two BiLSTM-based dialog models with Siamese classification network that can learn to determine similarity of two dialogues. Evaluation on the real-world projects shows that our approach significantly outperforms two sentence-wise classifiers and four traditional text classification approaches with average precision, recall and F1-score of 88.52%, 88.50% and 88.51%. The experimental results confirm that our approach could effectively detect hidden feature requests from chat messages, thus can facilitate gathering comprehensive requirements from a large number of users in an automated way.

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1 INTRODUCTION

Feature requests are requirement descriptions that express desired functionality or enhancement of stakeholders about the target system, which are largely existing in various communication channels, such as issue tracking systems, mailing lists, and online chatting. Recent studies reported that the usage of online chatting is gaining

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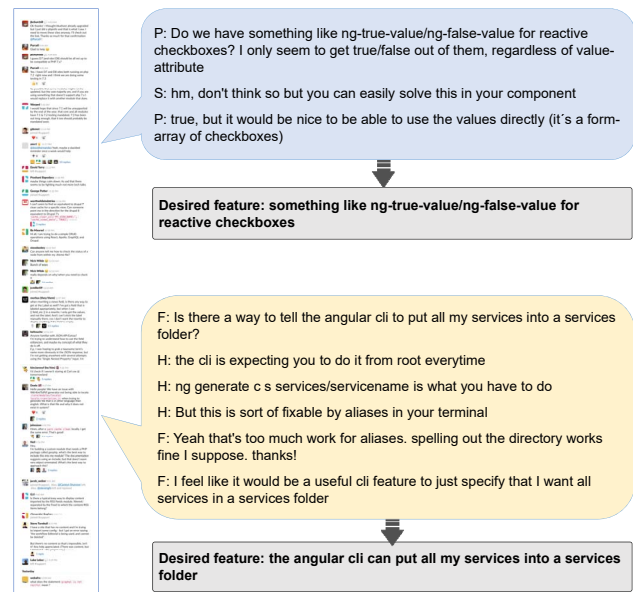


Figure 1: Example chat message from AngularJS project, where requests to desired features are buried in the massive chat history.

popularity and plays an increasingly significant role in software development, having replaced emails in some cases [31, 51, 52]. Developers are turning to public workplace chat platforms, such as Slack, IRC, HipChat, Gitter, and Freenode to share opinions and interesting insights, discuss how to resolve defects as well as what features to implement in future [8].

Although developers reveal their desired features when communicating with other software developers, the open and crowding nature of online chatting makes these feature-request dialogues get quickly flooded by newly incoming messages. Typically, the feature requests discussed in online chatting are likely to be buried and ignored if they are not documented. Taken the chat messages from AngularJS project as an example (Figure 1), developer P and F posted their questions in the online chatting. At the beginning, their intentions are asking for help from other developers to seek for feasible solutions to their problems. After discussing with other developers, they realized that existing system could not behave what they want. Their intentions shift from asking for solutions to requiring features. P requests for “something like ng-true-value/ng-false-value for reactive checkbox”, and F requests that “the angular cli can put all my services into services folder”. In practice, release team monitors a variety of communication channels to have multiple sources of information that could be relevant to a release [47, 56]. If the release team could acknowledge those hidden feature requests from chat messages, their next release planning may have

the opportunity to maximize the stakeholder satisfaction by taking more feature requests into consideration [46].

Automated mining techniques towards retrieving valuable information from massive chat messages is badly needed for gathering comprehensive feature requests from a large number of users, which contribute to requirements elicitation and release planning, and in turn promote the success of software development [6, 18, 21]. Although the chat messages could be a large volume and embedded with feature requests over time, it is quite challenging to mine massive chat messages due to the following barriers.

Dialog-wise detection. Analyzing dialogues from chat messages differs from regular text mining tasks in that it needs to consider contextual information among the dialog-wise scope when understanding one single sentence. Therefore, existing studies on sentence-wise feature requests detection [12, 21, 50] cannot be directly utilized for this task. For example, the sentence “We need add vertical Navbar option” is classified as a feature request by sentence-wise techniques. But when posted in online chat, following-up conversation pointed out the existing functionality can fulfill that request in an alternative way. Moreover, the sentence-wise detection results will be inaccurate as a large number of off-topic sentences will be identified as feature requests in the chat messages, e.g., “I really need to get my programming skills back”, “I would like to get some coffee and cookies.”

Extremely expensive annotation. The chat messages are typically large in size. Finding the feature requests dialogues among the massive chat messages is like looking for a needle in a haystack. It is extremely expensive to annotate feature requests from chat messages due to the high volume corpus and low proportion of ground-truth data. Only a few labeled chat messages are categorized into feature request types. How to make the maximum use of the few labeled data to accurately classify the unlabeled chat messages becomes a critical problem.

Entangled and noisy data. Chat messages are typically high-volume and contain informal conversations covering a wide range of topics. Two or more developers synchronously interact with each other where their utterances are largely entangled in the chat messages. Moreover, there exists noisy utterances such as duplicate and off-topic messages in chat messages that do not provide any valuable information. The entangled and noisy data pose a difficulty to analyze and interpret the communicative dialogues.

In this work, we take the first step towards dialog-wise techniques by aiming to automatically detect hidden feature requests posted in chat messages. We propose a novel approach, named FRMiner, which can detect feature-request dialogues from chat messages via deep Siamese network. To better understand the contextual information in the dialog-wise scope, we first build a context-aware dialog model based on a bidirectional LSTM (BiLSTM) structure that can deeply learn the contextual information of a dialog in both forward and reverse direction. Inspired by the few-shot learning techniques that aim to build a performance prediction model by utilizing insufficient labeled resources, we recast the traditional text classification task of mapping single dialog to its class into the task of determining whether two dialogues belong to the same or different class. Hence, we combine context-aware dialog models with Siamese network to learn the similarity between a pair of dialogues rather than the patterns of a specific class. The

prediction result of a feature-request dialog can be inferred based on the similarity prediction and the observed class of its partner dialog in the pair. To evaluate the proposed approach, we annotate 1,035 dialogues taken from three popular open source projects. The experimental results show that our approach significantly outperforms two sentence-wise classifiers and four traditional text classification approaches with average precision, recall and F1-score of 88.52%, 88.50% and 88.51%. Meanwhile, we conduct cross-project validation on the three projects, the results show that FRMiner is generalizable to unfitted projects. The results confirm that our approach could effectively detect hidden feature requests from chat messages, thus can facilitate gathering comprehensive requirements from a large number of users in an automated way.

The major contributions of this paper are as follows.

- We are the first to propose to use a deep Siamese Network to detect hidden feature requests from massive chat messages that can promote comprehensive requirements gathering.
- We introduce a solution that can effectively predict feature-request dialogues based on limited labeled data by incorporating Siamese Network, which significantly relieve the burden of collecting supervised data.
- We evaluate our approach on three active open source projects, and an empirical comparison shows that the proposed approach outperforms existing studies and four text classification approaches.
- Publicly accessible dataset and source code¹ to facilitate the replication of our study and its application in other context.

The remainder of the paper is organized as follows. Section II elaborates the approach. Section III presents the experimental setup. Section IV describes the results and analysis. Section VI shows the threats to validity. Section VII introduces the related work. Section VIII concludes our work.

2 BACKGROUND

This section describes three key technologies related to this research: TextCNN, BiLSTM, and few-shot learning techniques. We include them here because our work is based on these technologies.

2.1 TextCNN

Dialogues in chat messages are the form of textual sentences recorded in the chronological order that they were discussed by a community of developers during online communications. Modeling sentence representation is the foundation of high-level dialog analysis. In this paper, we represent sentences by using TextCNN, which has an advantage over learning on insufficient labeled data as it employs concise network structure and a small quantity of parameters.

TextCNN is a classical method for sentence modeling [26] which uses a shallow Convolutional Neural Network (CNN) [28] to model sentence representation. CNN is one kind of deep learning model that is widely used in computer vision. It uses several convolutional kernels to capture local information as the receptive field, and then gathers the local information into global representation. Analogously, in Natural Language Processing (NLP), CNN can gather n-gram information to model sentence representation. TextCNN

¹<https://github.com/FRMiner/FRMiner>

takes the pre-trained or random generated word embedding as input. The dimension of its output depends on the number and the size of convolutional kernels. A n -length sentence can be represented as a matrix with a shape of $n \times d$, where d is the dimension of word embedding. Each kernel $w \in \mathbb{R}^{kd}$, where k is the convolution kernel size, is applied to a window of k words to be mapped into a new one-dimension vector. Let $X_{i:i+k}$ represent the concatenation of k -gram words in original sentence, and then a convolution operation will be performed on it. The output of the convolution layer can be computed as $o_i = f(w \cdot X_{i:i+k} + b)$ where b is a bias term and f is an activation function. Given the length l of a sentence and the convolution kernel size k , we can get the representation of sentence, whose size is $l - k + 1$. The convolution layer is followed by a max polling layer, which can capture the key information with highest value.

In order to obtain more sufficient semantic information ensemble by different scales of local information, multiple convolution kernels with different size are applied to the sentence. Hence, for a sentence, given $n \times m$ convolution kernels, where n is the number of different sizes of kernels, and m is the number of kernels of each size, we can get the sentence representation with size of $n \times m$, which encodes the different scales of local information into a global representation of the sentence.

2.2 Bidirectional LSTM

Analyzing dialogues from chat messages is a high-level text mining task as it needs to consider contextual information among the dialog-wise scope when understanding one single sentence. In this paper, we utilize Bidirectional Long Short Term Memory network (BiLSTM) to capture contextual information by encoding the dialogues through the sentences embedded by TextCNN.

BiLSTM was proposed by Graves et al. [17] to learn bidirectional information for sequence learning task. BiLSTM stacks two standard Long Short Term Memory network (LSTM) [20] layers with opposite directions to learn the one-way representation respectively. Then it combines the forward and backward representation as the bidirectional embedding.

Long Short Term Memory network (LSTM) is an optimized Recurrent Neural Network (RNN) structure based on gate mechanism that was proposed by Hochreiter et al. [20]. LSTM utilizes gate mechanism to filter key information and pass them down to the long sequence. A LSTM cell composes of input gate, forget gate, cell state and output gate. The outputs of LSTM cell gates can be specified as follows:

$$\begin{bmatrix} i_t \\ f_t \\ \tilde{c}_t \\ o_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \tanh \\ \sigma \end{bmatrix} \left(W \begin{bmatrix} x_t \\ h_{t-1} \end{bmatrix} + b \right)$$

$$c_t = \tilde{c}_t \odot i_t + c_{t-1} \odot f_t$$

$$h_t = o_t \odot \tanh(c_t)$$

where x_t is the i^{th} token in the input sequence; W is the weight matrix of LSTM cells; b is the bias term; σ denotes logistic sigmoid activation function and \tanh denotes hyperbolic tangent activation function; \odot denotes element-wise multiplication.

Hence, the final representation of BiLSTM can be formed as $h = [\vec{h} \oplus \overleftarrow{h}]$, where \vec{h} and \overleftarrow{h} denote the output of two LSTM layers respectively and \oplus is concatenate operation.

2.3 Few-shot learning

Deep learning has gained significant success both in the field of computer vision and natural language processing. But it relies on adequate volume training data heavily, and finds difficulty in performing where there is low labeled resource data available. Automated mining in chat messages also faces the low labeled resource problem. For online chatting, a large community of developers create plenty of discussions in a short time. It is a extremely time-consuming task to annotate a large number of dialog data for learning effective models since they are quite long and require domain knowledge to thoroughly understand. Few-shot learning approaches are proposed to overcome these constrains [59]. The few-shot learning approaches can be classified into three categories [9]. Model-based approaches aim at learning a projector from few labeled data to a taxonomy through model designing. Optimizer-based approaches adjust the tradition gradient descent optimizer method to fit the data. Metric-based approaches classify samples through learning a similarity metric function.

In this paper, we leverage a metric-based few-shot learning technique, named Siamese network [7]. Traditional classification models are trying to learn a mapping from single instance to its class, but they cannot always work well when there is low labeled resource data available. Differ from the tradition approaches, Siamese network takes pair of instances as input, aiming at learning key characteristics that determine whether the two instances belong to the same or different class. It mainly consists two identical sub-components that not only share model structure but also parameters to encode the pair of instance respectively. Intuitively, it is easier for us to determine whether two dialogues are similar rather than given the exactly class for each dialog. Since Siamese network takes pairs as inputs, the dataset is converted from element-wise to pair-wise, and can be augmented with permutations. Siamese network is currently widely used to measure the semantic similarity among texts or images [41].

3 APPROACH

Figure 2 demonstrates the overall framework of our approach. First, we construct the training dataset by a set of data preparation steps. Second, we build a hierarchical context-aware dialog model for each dialogue. The context-ware dialog model encodes dialogues by BiLSTM structure which uses TextCNN-based sentence embedding results as inputs. Third, we build a Siamese network with two identical context-aware dialog models. Finally, we infer the predictive class based on the probabilities produced by Siamese network and the actual label of another dialog in the pair instance.

3.1 Build Context-aware Dialog Model

We design a hierarchical context-ware dialog model that can capture the contextual information as well as the semantic meaning of each sentence in a dialog. As shown in Figure 3, the context-aware dialog model consists of four layers: input layer, sentence embedding layer, dialog embedding layer, and output layer.

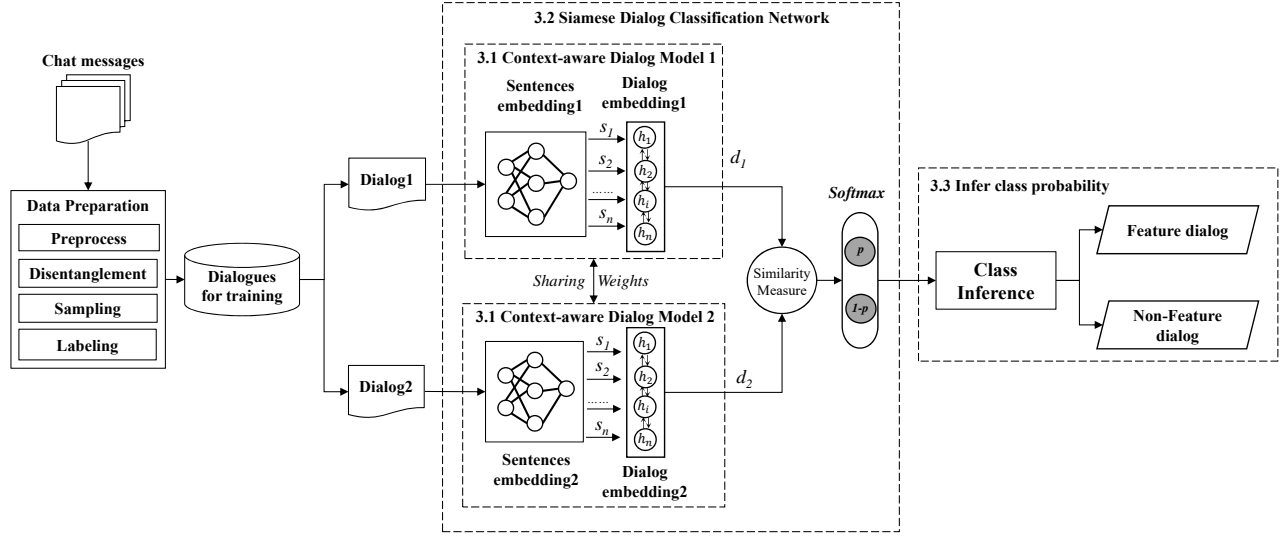


Figure 2: The Overview of FRMiner

Input layer. We first tokenize the sentences into tokens as the basic terms. To obtain a better performance, we utilize the pre-trained word embedding as the initial vector of each word. Moreover, since the part-of-speech (POS) tag can benefit semantic understanding, we add POS tag information into word representation to enhance its feature. Specifically, each type of POS tag will be embedded into a vector and optimized during training. Hence, each word can be represented as $w_i = [we_i \oplus pos_i]$, where we_i denotes the corresponding word embedding and pos_i denotes the embedding of the POS tag of the word. **Sentence embedding layer.** After transforming the original sentence into a matrix stacked with word embedding and POS tag embedding, we feed the embedding matrix into TextCNN and obtain the sentence representation. Details of representing sentences by TextCNN has been introduced in Section 2.1. **Dialog embedding layer.** In dialog embedding layer, we use a sequence of sentence embeddings to represent a dialog. Each embedded sentence acts as a token and inputs the BiLSTM encoder according to their sequence in the dialog. After the encoding of BiLSTM, a bidirectional contextual information of the dialog will be

learned. **Output layer.** In the output layer, we combine the two direction representations \vec{h} and \overleftarrow{h} encoded by BiLSTM as the output vector of the input dialog, which can be presented as $h = [\vec{h} \oplus \overleftarrow{h}]$.

3.2 Construct Siamese Dialog Classification Network

In order to alleviate the insufficient labeled data problem, we construct Siamese dialog classification network that can augment the dataset by recasting the traditional text classification task of mapping single dialog to its class into the task of determining whether two dialogues belong to the same or different class. For the purpose of clarity, we will use **feature dialog** and **non-feature dialog** in the rest of this paper to refer to the dialogues that are requesting features and dialogues that are not requesting features.

The dashed box of ‘3.2’ in Figure 2 presents the detailed architecture. The Siamese dialog classification network contains two context-aware dialog models which share structure and parameters to encode a pair of dialogues to d_1 and d_2 respectively. We use the combination forms of d_1 and d_2 , $[d_1 \oplus d_2]$, as representation of the relation between the two dialogues. Thus the representation of the relation between a pair of dialogues is projected from the dialog embedding to similarity metric.

We train the Siamese Dialog Classification Network according to the following steps. (1) we divide the sample dataset into training and testing dataset. For each dialog in the training dataset ($Train_d$), we randomly select a positive partner with ‘feature’ label, and a negative partner with ‘non-feature’ label from training dataset ($Train_d$). Due to the one-positive-one-negative sampling policy, our training data can be balanced naturally. (2) we construct the training dataset ($Train_p$) for Siamese network according to whether the paired dialogues own the same label. For example, if the two dialogues are all *feature dialog* or *non-feature dialog*, we will assign the pair with label-“same”, otherwise “diff”. Besides, suppose we have m *feature dialogues* and n *non-feature dialogues* in $Train_d$, we can augment the origin data set to size of $\binom{2}{m} + \binom{2}{n} + m \times n$

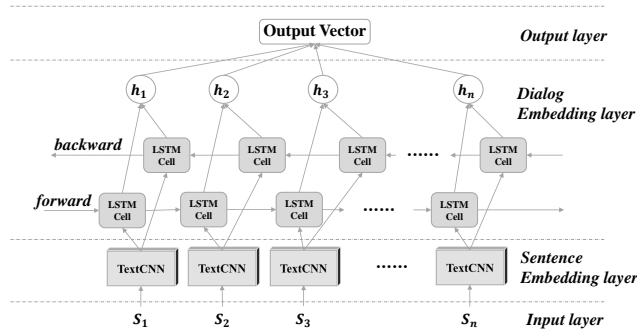


Figure 3: Hierarchical Context-aware Dialog Model

in $Train_p$. Finally, since each pair of dialogues belongs to either ‘same’ class or ‘diff’ class, the output of similarity measure is a 2-length vector $[score_1, score_2]$ that represents the scores of the two classes, where $score_i \in \mathbb{R}$. We perform softmax on the 2-length vector, which can be specified as

$$Softmax(score_i) = \frac{e^{score_i}}{\sum_{j=1}^2 e^{score_j}}$$

Then the $[score_1, score_2]$ can be normalized to probabilities $[p, 1 - p]$, where $p \in [0, 1]$.

3.3 Infer Class Probability

The output of Siamese dialog classification network is the probabilities that indicating whether two dialogues are *same* or *diff*. But what we need is the probabilities that indicating whether a dialog is a *feature dialog* or not, thus, we need infer the label of a dialog based on the probabilities and the actual label of another dialog in the pair instance. For example, we sample a pair of dialogues $\langle Dialog_1, Dialog_2 \rangle$, where $Dialog_1$ is the golden dialog with observed ‘non-feature dialog’ label, and $Dialog_2$ is the unknown dialog to be predicted. We input the pair of them into the Siamese dialog classification network, then a prediction for deciding the two dialogues are *same* or *diff* is made. Suppose the prediction is *diff*, then we can infer that the class of $Dialog_2$ is *feature dialog*. If the actual label of $Dialog_2$ is *feature dialog*, it indicates that this prediction made by our model is true positive. Otherwise, we get a false positive prediction.

3.4 Tool Implementation

We implement our proposed approach, FRMiner, using Allennlp [14] which is an open source NLP library build on PyTorch [13].

Implementation details. To convert the words to vectors, we utilize the 50 dimension Glove word embeddings [45] that are pre-trained on 6 billions words of Wikipedia and Gigaword corpus as the initial vectors of the corresponding words. The dimension of POS tag embedding is 50, the same as word embedding, and embedded in sparse way. Then, we can use $s = [w_1, w_2 \dots w_n]$ as the representation of sentences, where $w_i = [we_i \oplus pos_i]$. In order to obtain more sufficient semantic information ensembled by different scales of local information, multiple convolution kernels with different sizes are applied to the sentence. We set 4 different kernel sizes which are 2, 3, 4, 5 respectively and 25 feature maps for each kernel. The output dimension of BiLSTM is 300 (150 for each direction). We use a linear layer to project the 300 dimension vector to two values that represent the scores of two classes.

Optimization. In addition, to avoid over-fitting problem, we apply dropout [54] on the input embeddings with 0.1 drop rate, that means, 10% neuron cell will be randomly masked to reduce the parameters that need to be trained in each batch training. We also use the strategy of early stopping [48]. If the performance on the test dataset did not promote for 10 epochs, the training process will be stopped.

Application. When we apply our model on unlabeled data, for a new dialog d_n to be predicted, we randomly select one dialog d_l in labeled data as the golden instance, and combine the two dialogues as a pair $\langle d_n, d_l \rangle$. After passing the pair into FRMiner, we can

infer the label of the dialog d_n based on the prediction of FRMiner and the label of d_l .

4 EXPERIMENTAL DESIGN

In this section, we describe the experimental setup in detail, including research questions, data preparation, and experiment settings, baselines, and performance measures.

4.1 Research Questions

In this paper, our evaluation addresses the following three research questions.

RQ1: How effective is our approach for detecting hidden feature requests? To investigate the effectiveness of our approach, we conduct 3-fold cross-validation on detecting feature dialogues from chat messages of three open source projects. We also compare the performance of two sentence-wise approaches that classify sentences of online discussions into feature requests and other types. We adapt the two approaches to our task by predicting dialogues that contain feature-request sentences as feature dialogues. In addition, we examine the performances of four widely used text classification methods on the limited labeled resources to perceive the difficulties of automated feature request mining in chat messages.

RQ2: How dose the few-shot learning technique facilitate feature requests detection? RQ2 examines the performance enhancement introduced by the few-shot learning technique. We construct a context-aware dialog classifier by removing the Siamese network in FRMiner. We use p-FRMiner to denote the FRMiner without data augment. We then compare the performance of p-FRMiner that are directly trained by dialog-instances, with the FRMiner that are trained by pair-instances. Then we increasingly enlarge the size of the training pair-instances to examine the performance enhancement.

RQ3: Dose our approach work well in cross-project validation? RQ3 examines the generalizability of our approach via cross-project validation on three open source projects. We iterately use two projects for training and the reserving one for testing. We also conduct cross-project validation on baseline approaches.

4.2 Data Preparation

Our experimental data is collected from three open source projects: AngularJS [15], Bootstrap [55], and Chromium [16]. We select the three projects for the following reasons. First, they are under active developments. Second, large communities are formed around those projects. Third, developers from these projects actively use online chatting to share opinions, interesting insights, and discuss what features to implement in future. For example, In the last three years, an average of 2,823 utterances are made per week in AngularJS community. Moreover, their historical chat messages are all documented and publicly accessible [1], which provide rich resources for mining valuable information. Our data is collected from these projects, and was prepared in the following steps:

Step 1: Preprocess. We first normalize non-ascii characters like emojis to standard ascii strings. There are also some low-frequency tokens that cannot contribute the result of classification such as URL, email address, code, html tags, and some ids like version id

Table 1: The statistic of labeled dialogues

	Massive chat messages			Sample		
	Duration	#dialog	#sentence	#dialog	#sentence	#FR
AngularJS	2016.5-2019.4	38266	406553	316	9220	36
Bootstrap	2014.7-2019.5	10358	58871	379	2371	76
Chromium	2015.5-2019.7	16804	118890	340	4465	27
Total		65428	584314	1035	16056	139

referred in discussion. We replace them with specific tokens `<URL>`, `<EMAIL>`, `<HTML>`, `<CODE>`, and `<ID>` respectively. We utilize Spacy [2] to tokenize sentences into terms. In order to alleviate the influence of word morphology, we then perform lemmatization and lowercasing on terms with Spacy.

Step 2: Conversation Disentanglement. Chatting channels is a type of synchronous textual communication between a community of developers. Messages in chats form a stream information, with conversations often entangling such as a single conversation thread is interleaved with other conversations. Dividing chat messages into a set of distinct conversations is an essential prerequisite for any kind of high-level dialogue analysis. We leveraged the state-of-the-art technique for conversation disentanglement proposed by Kummerfeld et al. [29]. Their model is trained from 77,563 manually annotated messages of disentangled dialogues from online chatting. It is a feedforward neural network with 2 layers, 512 dimensional hidden vectors, and softsign non-linearities. The model can achieve relatively good performance with 74.9% precision and 79.7% recall.

Step 3: Dialogues Sampling. There are a large number of chat dialogues are identified after disentanglement. In order to observe the characteristics of the entire dialogues population, we randomly sample 400 dialogues from the three projects. Then we excluded unreadable dialogues: 1) Dialogues that are written in non-English languages; 2) Dialogues that contain too much code or stack traces; 3) Low quality dialogues such as dialogues with many typos and grammatical errors. 4) Dialogues that involve channel robots.

Step 4: Ground-truth Labeling. The labeled dialogues are used as the ground-truth dataset for method definition and performance evaluation. To guarantee the correctness of the labeling results, we built an inspection team, which consisted two senior researchers with four Ph.D candidates. All of them are fluent English speakers, and have done either intensive research work with software development or have been actively contributing to open source projects. We divided the team into two groups. Each group consisted a leader (senior researcher) and two members. The leaders trained members on how to label and provided consultation during the process. The labeling results from the members were reviewed by the leaders while results from the leaders were reviewed by other leaders. We only accepted and included dialogues to our dataset when the dialogues received full agreement among the groups. When an dialog received different labeling results, we hosted a discussion with all the six people to decide through voting.

In total, we collect 65,428 dialogues from three popular open source projects, and spend 720 person hours on annotating 1,035 (1.6%) dialogues. The detailed characteristics of labeled dialogues are described in Table 1. The last column denotes the number of feature dialogues.

4.3 Experiment Settings

The experimental environment is a desktop computer equipped with a NVIDIA 1060 GPU, intel core i7 CPU, 16GB RAM, running on Ubuntu OS.

We conduct 3-fold cross-validation [27] when evaluating the predictive results. With this method we randomly divide our dataset into 3 parts. We use 2 of those parts for training and reserve one part for testing. We repeat this procedure 3 times each time reserving a different part for testing.

Experiment I (RQ1) To prove the effectiveness of our approach, we select two advanced sentence-wise approaches and four text classification approaches as baselines. Detail information about baselines will be introduced in section 4.4. For the two sentence-wise approaches, we use the codes and models provided in the publications. For the four text classification approaches, we train and test them by using exactly the same dataset with our approach. We apply the random over-sampling [32] to tackle with imbalance dataset. We extracted the Term Frequency and Inverse Document Frequent (TFIDF) [23] as feature vectors for each dialog. We train and fine-tuned hyper-parameters for the four text classification approaches to achieve their best performances. In RF, we set the max depth of trees as 2. As for GBDT, we set the initial learning as 1.0 and the max depth of trees is 1. We trained 100 epochs for FT, and set the initial learning rate as 1.0, the window size of input n-gram as 2.

Experiment II (RQ2) In this experiment, we compare FRMiner with p-FRMiner and investigate how does the data augment improve performance. Note that the p-FRMiner is a classification model for a single dialog which based on the context-aware dialog model following with an additional classification layer. First, we use the same size of data to train FRMiner and p-FRMiner, and observe the performance enhancement. Then we augment the training dataset of FRMiner into 5, 10, 20, and 30 times to investigate the performance changes. Since FRMiner can tackle with imbalanced dataset issue by applying Siamese network while p-FRMiner can not, we balance the samples by applying random over-sampling [32] when training p-FRMiner. To ensure the correctness of our experiments, FRMiner and p-FRMiner are trained with the same hyper-parameters, including dimension for each layer, depth of network, and learning rate.

Experiment III (RQ3) In order to validate whether our approach is generalizable to unfitted projects, we trained the FRMiner on two projects and evaluate on third projects. We also evaluate other baselines on the cross-project dataset with the identical hyper-parameters of experiment II.

4.4 Baselines

To further demonstrate the advantages of our approach, we compare FRMiner with two advanced sentence-wise approaches as our baselines.

CNN-based Classifier (CNC) [21]. It is the state-of-the-art learning technique to classify sentences in comments taken from online issue reports. They proposed a convolution neural network (CNN) based approach to classify sentences into seven categories of intentions: Information Giving, Information Seeking, Feature Request, Solution Proposal, Problem Discovery, Aspect Evaluation,

and Meaningless. We utilize the Feature Request category to predict dialogues that contain feature requests.

Rule-based Classifier (FRA) [50]. It is the state-of-the-art rule-based technique to classify sentences in feature requests from online issue tracking systems. They proposed 81 fuzzy rules to classify sentences into 6 types. We consider the dialogues that contain the *Intent* type of sentences are predicted to be feature dialogues, and dialogues do not contain the *Intent* type of sentences are predicted to be non-feature dialogues.

In general, classifying dialogues into feature and non-feature dialogues belongs to text classification. Besides the two sentence-wise approaches, we also compare with four commonly used text classification approaches.

NB, RF, GBDT, and FT. Naive Bayesian (NB) [34] is a simple generation model for text classification based on bag-of-words assumption and bayesian rules. It conducts the joint probability of a sentence through prior probability and conditional probability learned by the model and training data. Then, given a sentence, it can deduce the probabilities of all the taxonomies. Random Forest (RF) [30] is an ensemble machine learning method that is constructed with several trees, and each tree can contribute the final classification result. Gradient Boosting Decision Tree (GBDT) [25] is another kind of ensemble method, and the difference with RF is that its trees are decided by the residual error bring by the previous trees. FastText (FT) [24] is a state-of-the-art text classification approach with a shallow neural network that is similar with the architecture of word2vec [38].

4.5 Performance Measures

When evaluating the effectiveness of FRMiner towards detection feature requests from chat messages, we used the following metrics: (1) Precision, which refers to the ratio of the number of correct predictions of feature dialogues to the total number of predictions of feature dialogues; (2) Recall, which refers to the ratio of the number of correct predictions of feature dialogues to the total number of feature dialogues in the golden test set; and (3) F1-Score, which is the harmonic mean of precision and recall.

5 RESULTS AND ANALYSIS

5.1 Answering RQ1

Figure 4 presents the average performances achieved by different approaches in 3-fold cross-validation, and Table 2 presents the detailed performances for each project. The best results of precision, recall, and F1-score are highlighted in bold. We can see that FRMiner achieves the best results for all the three projects, with an average of 88.52%, 88.50%, and 88.51% in precision, recall, and F1-score. We also note that p-FRMiner performs better than all the baseline approaches, which indicates that memorizing contextual information in the BiLSTM dialog model can benefit the text classification task in chat messages. We further evaluate and analyze the improvement of FRMiner over p-FRMiner in section 5.2.

For the two sentence-wise approaches, the CNN based classifier can only achieve 17.33% F1-score in average, mainly because that the CNC model is trained by sufficient data from the domain of issue comments instead of feature dialogues. However, it still achieve 48.55% recall in average, which indicates that there might

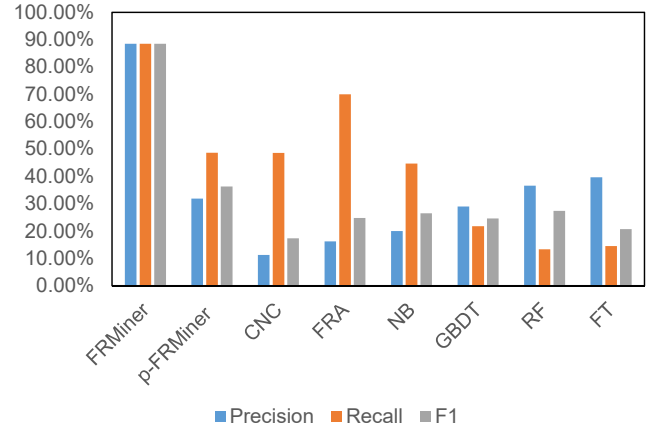


Figure 4: The average performances in 3-fold validation

be common patterns between the two domains. Transfer learning techniques might help transfer the related common knowledge from issue comments to chat messages by parameter-transfer and fine tuning [43]. Meanwhile, the rule-based classifier FRA achieves the highest recall among the six baseline approaches. The average recall is 70.00%, and it achieve 80.33% and 81% recall on AngularJS and Chromium project respectively. Although the precision is low, prediction results of FRA contain most of actual feature dialogues, which means that the feature-request sentences in chat messages also comply with FRA rules. As FRA utilizes rules instead of supervised learning, it is easier and time-saving to apply in mining massive chat messages. Meanwhile, we can take the high-recall advantage of FRA to tackle with the cold start problem where no annotated resources are provided at the beginning.

For text classification approaches, NB seems to be the best classifier among all the text classification baselines. Although RF achieves highest 27.33% F1-score in average among the four approaches, it encounters an underfitting problem on Chromium project. It can neither model the training data nor generalize to new data, mainly due to the Chromium data is not enough for RF model to learned the relevant patterns.

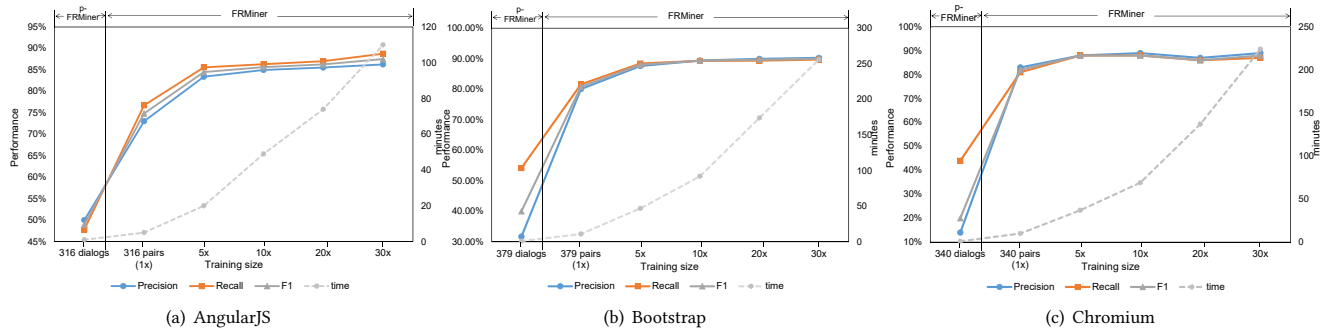
Summary: FRMiner significantly outperforms two sentence-wise baselines and four traditional text classification approaches. As the two sentence-wise baselines can be directly applied to chat messages and achieve relatively good recall, they have the natural advantages over other approaches under the cold-start situation.

5.2 Answering RQ2

Figure 5 demonstrates the performance of p-FRMiner training by single-dialogue instances and the performances of FRMiner training by different scaled sizes of pair-dialogue instances. The first value of the x axis is the size of training dataset for p-FRMiner, which is the size of 2 folds of data. The second value is the size of pair-instances generated by Siamese network. We can see that when the sizes of training dataset are the same, FRMiner can achieve much higher performances than p-FRMiner. The FRMiner improves the Precision, Recall, F1-score over the p-FRMiner by 46.79%, 31.13%, 42.90% in average.

Table 2: The performance achieved by different approaches for each project in 3-fold cross-validation

Performance		AngularJS			Bootstrap			Chromium		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Our approach	FRMiner	90.28%	89.73%	90.00%	86.28%	88.78%	87.52%	89.00%	87.00%	88.00%
	p-FRMiner	31.71%	54.17%	40.00%	50.00%	47.80%	48.98%	14.00%	44.00%	20.00%
Existing studies	CNC	7.70%	44.44%	13.13%	16.38%	34.21%	22.13%	9.56%	67.00%	16.73%
	FRA	13.67%	80.33%	23.35%	23.00%	48.67%	31.00%	12.00%	81.00%	20.00%
Text classification	NB	20.00%	27.67%	22.33%	25.67%	62.00%	36.00%	14.33%	44.33%	21.00%
	GBDT	36.00%	22.33%	27.33%	41.67%	35.67%	38.33%	9.33%	7.33%	8.00%
	RF	52.67%	11.00%	16.33%	57.00%	29.00%	38.33%	0.00%	0.00%	NA
	FT	23.33%	5.33%	8.67%	57.67%	29.00%	38.33%	38.00%	9.10%	15.00%

**Figure 5: The performances under different sizes of training set****Table 3: The performance achieved by different approaches for each project in cross-project validation**

Performance		AngularJS			Bootstrap			Chromium		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Our approach	FRMiner	85.23%	86.56%	85.89%	86.84%	85.89%	86.37%	85.87%	86.81%	86.34%
	p-FRMiner	31.03%	50.00%	38.30%	27.56%	69.08%	39.40%	16.00%	50.00%	24.24%
Existing studies	CNC	7.70%	44.44%	13.13%	16.38%	34.21%	22.13%	9.56%	67.00%	16.73%
	FRA	13.67%	80.33%	23.35%	23.00%	48.67%	31.00%	12.00%	81.00%	20.00%
Text classification	NB	16.00%	75.00%	26.00%	27.00%	36.00%	31.00%	7.00%	26.00%	12.00%
	GBDT	18.00%	14.00%	16.00%	30.00%	11.00%	16.00%	20.00%	19.00%	19.00%
	RF	28.00%	14.00%	19.00%	37.00%	9.00%	15.00%	12.00%	26.00%	16.00%
	FT	32.00%	19.00%	24.00%	43.00%	13.00%	20.00%	19.00%	11.00%	14.00%

Figure 5 also illustrates the relationship between performance enhancement and rising training pair-instances quantity, along with the time cost on training phase. We can see that enlarging the size of training pair-instances can moderately increase the model performances. When enlarging the size of the training pair-instances from 1 to 30 times, the precision, recall, and F1-score increase 9.82%, 8.72%, and 9% in average. We observe that the performance sharply increases when enlarging the training dataset 5 times, and slowly increases from 5 times to 30 times on all the projects. While the time cost on training phase is linearly increased all the time. Therefore, we consider that enlarging the training dataset 5 times might be a trade-off choice between effectiveness and efficiency.

Summary: FRMiner can better resolve the classification task than p-FRMiner by significantly improving the Precision, Recall, F1-score by 46.79%, 31.13%, 42.90% in average. The results confirm that

it is easier for the model to recognize whether this two dialogues belong to the same class rather than classifying the exact class directly when labeled dialogues are few. We consider 5 times to be a trade-off choice between effectiveness and efficiency because after enlarging training dataset for 5 times, the performances slowly increase but the time cost rises largely.

5.3 Answering RQ3

Figure 6 presents the average performances achieved by different approaches in the setting of cross-project validation, and Table 3 presents the detailed performances for each project. The best results of precision, recall, and F1-score are highlighted in bold. Note that the performances of CNC and FRA are the same with 3-fold cross-validation due to the two approaches are not trained by feature dialogues. We repeat their results in Table 2 for comparison and analysis purpose.

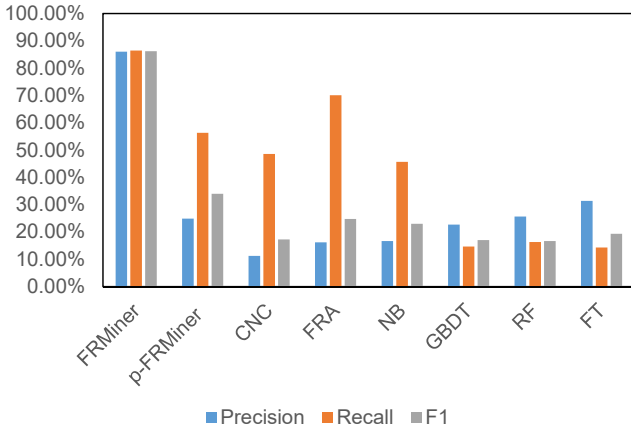


Figure 6: Average performances in cross-project validation

We can see that FRMiner can also performs well in the cross-project settings. Performance only slightly declines by 2.27% over average F1-scores compared with the result in 3-fold within-project validation. The results show that FRMiner can learn common patterns and be generalizable to other projects. It also indicates that developers express feature requests in a similar way even in different communities and projects, and the feature dialogues of different projects share similar patterns. We note that p-FRMiner does not perform as good as within-project validation. The average F1-score declines 10.51%.

For text classification approaches, NB achieves the highest F1-score of 23%, and it only slightly declines 3.44% in average compared with within-project validation. None of the text classification approaches encounter underfitting problem because the size of training dataset for cross-project validation is larger.

Summary: FRMiner can also achieve high performance on unfitted projects, which indicates that FRMiner is generalizable to other projects. We also observe that NB seems to be the best classifier among all the text classification baselines towards mining chat messages.

6 THREATS TO VALIDITY

External Validity. The external threats relate to the generalizability of the proposed approach. All the systems examined in this work were open source projects, which might not be representative of closed source projects. It is also possible that we accidentally chose systems that have better or worse than average cross-project feature requests detection performance. However, the cross-project evaluation results show that our approach is generalizable on the three studied projects, which largely alleviates the threat.

Internal Validity. The internal threats relate to the experimental errors and biases. Threats to internal validity may come from the results of conversation disentanglement. The accuracy of disentangled conversations have impacts on our results. To reduce the threat, when separating single conversations in a stream of chat messages, we employed the state-of-the-art technique proposed

by Kummerfeld et al. [29], which outperforms previous studies by achieving 73.5% F1-score and 91.5 VI².

Construct Validity. The construct threats relate to suitability of evaluation metrics. We utilize precision and recall to evaluate the performance, in which we use the manually labeled dialogues as ground-truth when calculating the performance metrics. The threats might come from the process of manual inspection and tagging. We understand that such a process is subject to mistakes. To reduce that threat, we build two inspection teams to reach agreements on different options.

7 RELATED WORK

Our work is closely related to previous studies that focused on (1) detection of feature requests; and (2) mining development communication artifacts. We briefly review the recent works in each category.

7.1 Detection of Feature Requests

The amount of research on gathering and analyzing information from a crowd to derive validated user requirements/feature requests has increased significantly in the last years.

Di Sorbo et al. [53] proposed a taxonomy of intentions to classify sentences in developer mailing lists into six categories: feature request, opinion asking, problem discovery, solution proposal, information seeking, and information giving. Although the taxonomy has been shown to be effective in analyzing development emails and user feedback from app reviews [44], Huang et al. [21] found that it cannot be generalized to discussions in issue tracking systems, and they addressed the deficiencies of Di Sorbo et al's taxonomy by proposing a convolution neural network (CNN)-based approach.

Arya et al. [6] identified 16 information types including potential new feature requests through quantitative content analysis of 15 issue discussion threads. They also provided a supervised classification solution by using Random Forest with 14 conversational features that can classify sentences expressing new feature requests with 0.66 F1-score. Morales-Ramirez et al. [39, 40] identified requirement-related information in OSS issue discussion using 20 speech-act rules supported by NLP and linguistic parsing techniques. Merten et al. [36] investigated natural language processing and machine learning features to detect software feature requests in issue tracking systems. Their results showed that software feature requests detection can be approached on the level of issues and data fields with satisfactory results. Merten et al. [37] also investigated how requirements communicated in issue tracking systems by manually reviewing 200 issues. They categorized the text and reported on the distribution of issue types and information types. Their results showed that information with respect to prioritization and scheduling can be found in natural language data. Herzig et al. [19] manually examined more than 7,000 issue reports, and discussed the impact of misclassification of bugs in the bug databases of five open source projects. Their results showed that 39% of files marked as defective actually new features, updates to documentation, or internal refactoring. The authors suggested that human should always be involved when dealing with the posted issues.

²Variation of Information (VI) is a measure of information gained or lost when going from one clustering to another

Antoniol *et al.* [5] investigated whether the text of the issues posted in bug tracking systems is enough to classify them into corrective maintenance and other kinds of activities. They alternated among various machine learning approaches such as decision trees, naive Bayes classifiers, and logistic regression to distinguish enhancement apart from other issues posted in the system. Shi *et al.* [50] proposed 81 fuzzy rules that can classify sentences in issues into six categories: intent, benefit, drawback, example, explanation, and trivia. Their work designed to help understanding and analyzing real intents of feature requests, which can also benefit the detection of feature requests.

Rodeghero *et al.* [35] presented an automated technique that extracted useful information from the transcripts of developer-client spoken conversations to construct user stories. They used machine learning classifiers to determine whether a conversation contains user story information or not. Maalej and Nabil [33] leveraged probabilistic techniques as well as text classification, natural language processing, and sentiment analysis techniques to classify app reviews into bug reports, feature requests, user experiences, and ratings. Their results showed that the classification can reach the precision between 70-95% and recall 80-90% actual results. Other studies have been found to also capture user needs from app reviews automatically [12, 22, 42, 57]. Vlas and Robinson [58] proposed a grammar-based design of software automation for the discovery and classification of natural language requirements found in open source projects repositories. Cledland-Huang *et al.* [11] designed an automated forum management (AFM) system, which was used to automated detect duplicated feature requests that have been already posted in the issue tracking systems. Shi *et al.* [49] proposed an initial approach to automated identify feature requests that ask for features that have been already implemented by applying feature tree model.

Summing up, previous approaches differ from our work as it: identified feature requests from development emails [21, 53]; identified feature requests from issue tracking systems [5, 6, 19, 36, 37, 39, 40, 50]; identified user stories from spoken conversations [35]; identified feature requests from app reviews [12, 33, 42, 44, 57]; identified feature requests from project repositories [58] detected duplicated feature requests [11] [49].

Our work differs from existing researches in that we focus on detecting hidden feature requests from chat messages which post different challenges as chat messages are informal, unstructured, noisy and typically have insufficient labeled data than the previously analyzed documents. In addition, our work complements to the existing studies on automated feature requests detection.

7.2 Mining Development Communication Artifacts

Previous researches on development communication artifacts reported that the usage of online chatting play an increasingly significant role in software development, and chat messages are a rich source for valuable information about the software system.

Lin *et al.* [31] conducted an exploratory study on how developers use Slack, which is a popular workplace chat app, and how they benefit from it. Their research revealed that developers use Slack for personal, team-wide, and community-wide purposes, and Slack

plays an increasingly significant role in software development, replacing email in some cases. Shihab *et al.* [51, 52] analyzed the usage of developer IRC meeting channels of two large open source projects from several dimensions: meeting content, meeting participates, their contribution, and meeting styles. Their results showed that IRC meetings are gaining popularity among open source developers, and highlighted the wealth of information that can be obtained from developer chat messages. Yu *et al.* [61] analyzed the usage of two communication mechanisms in global software development projects, which are synchronous (IRC) and asynchronous (mailing list). Their results showed that developers actively use both communication mechanisms in a complementary way.

Chatterjee *et al.* [8] conducted an exploratory study to investigate the usefulness and challenges of mining developer conversations for supporting software maintenance and evolution. They observed that developers are likely to share opinions and interesting insights on tool usage, best practices, and various technologies via instant conversations. They also reported that it is feasible to achieve high accuracy in disentangling conversations by adapting the techniques and training sets. Alkadhi *et al.* [3, 4] identified five rationale elements which are issue, alternative, pro-argument, con-argument, and decision from chat messages that collected from three student projects. They developed two supervised classifiers to automated detect rationale elements on the manually labeled data. Wood *et al.* [60] discovered 26 speech act types in the chat conversations during bug repair, and trained a supervised classifier to automatically detect these speech acts. Chowdhury and Hindle [10] implemented machine learning techniques to filter out off-topic discussions in programming IRC channels by engaging StackOverflow discussions as positive examples and YouTube video comments as off-topic discussion examples.

The findings of previous work motivates the work presented in this paper. Our study is different from the previous work as we focus on detecting feature requests hidden in massive chat messages that would be important and valuable information for OSS developers to enhance their software.

8 CONCLUSION AND FUTURE WORK

In this paper, we proposed a novel approach, named FRMiner, which can detect feature dialogues from chat messages via deep Siamese network. In FRMiner, we incorporated two BiLSTM-based dialog models with Siamese network to learn the similarity between a pair of dialogues rather than the class of a specific dialog. We evaluated FRMiner on a small sample of 1,035 dialogues taken from the high-volume chat messages of three popular open source projects. The experimental results showed that our approach significantly outperformed two sentence-wise classifiers and four traditional text classification approaches with average precision, recall and F1-score of 88.52%, 88.50% and 88.51%. FRMiner can also achieve high performance on unfitted projects, which indicated that FRMiner is generalizable to other projects. The experimental results confirmed that our approach could effectively detect hidden feature requests from chat messages. We also observed that NB seems to be the best classifier for chat messages among the four text classification baselines. In the future, we plan to employ NLP summarization technologies with our approach to extract brief summary for developers, which can reduce the effort on reading feature dialogues.

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