

ISPY: Automatic Issue-Solution Pair Extraction from Community Live Chats

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Abstract—Community live chats contain rich sets of information for potential improvement on software quality and productivity. One of the important applications is to mine knowledge on issues and their potential solutions. However, it remains a challenging problem to accurately mine such knowledge due to the noisy nature of interleaved dialogs in live chat data. In this paper, we first formulate the problem of issue-solution pair extraction from developer live chat data, and propose an automated approach, named ISPY, based on natural language processing and deep learning techniques with customized enhancements, to address the problem. Specifically, ISPY automates three tasks: 1) Disentangle live chat logs, employing a feedforward neural network to automatically disentangle a conversation history into separate dialogs; 2) Detect dialogs discussing issues, using a novel convolutional neural network (CNN), which consists of a BERT-based utterance embedding layer, a context-aware dialog embedding layer, and an output layer; 3) Extract appropriate utterances and combine them as corresponding solutions, based on the same CNN structure but with different feeding inputs. To evaluate ISPY, we compare it with six baselines, utilizing a dataset with 750 dialogs including 171 issue-solution pairs and evaluate ISPY from eight Gitter communities. The results show that, for issue-detection, our approach achieves the *F1* of 76%, and outperforms all baselines by 30%. For solution-extraction, our approach achieves the *F1* of 63%, and outperforms the baselines by 20%. Furthermore, we apply ISPY on three new communities to extensively evaluate ISPY’s practical usage. Moreover, we publish over 30K issue-solution pairs extracted from 11 communities. We believe that ISPY can facilitate community-based software development by promoting knowledge sharing and shortening the issue-resolving process.

I. INTRODUCTION

Synchronous communication via live chats allows developers to seek information and technical support, share opinions and ideas, discuss issues, and form community development [1], [2], in a more efficient way compared with asynchronous communication such as emails or forums [3]–[5]. Consequently, live chatting has become an integral component of most software development processes, not only for open source communities constituting globally distributed developers, but also for software companies to facilitate in-house team communication and coordination, esp. in accommodating remote work due to the COVID-19 pandemic [6].

Existing literature reports various motivation factors for live chatting practices. One of the frequently mentioned factors is to use live chats as a tool for issue-solving, such as installation and setup issues, bug resolution, build and compile issues [7]. In such cases, developers post questions related to some specific issues, and rely on others to provide potential solutions. Alkadhi et al. [8], [9] analyzed 8,702 chat messages of three OSS development teams, and found 24% of the messages are reporting issues, and 51% of the messages are proposing alternative issue solutions. As a result, live chat repositories usually contain rich information to shed light on knowledge regarding frequent issue-solution pairs. Fig. 1 illustrates an example slice of live chat data. In this scenario, *Tom* encountered trouble when setting up dependencies for *spark*, so he posted an issue in live chatting. *Jack* and *Mike* both provided solutions as well as suggested examples. With their help, *Tom* finally resolved that issue. From this conversation slice, we can extract the issue description, as highlighted in red, and alternative solutions colored in blue.

However, it is quite challenging to mine issue-solution pairs from live chats due to the following barriers. **(1) Entangled dialogs.** Live chat data gets big rapidly, and multiple concurrent discussions regarding different issues frequently exist in an interleaved manner. In order to perform any kind of dialog-level analysis, it is essential to have automated support for identifying and dividing sequential utterances into a set of distinct dialogs, according to the issue topics. **(2) Expensive human effort.** Chat logs are typically high-volume and contain informal dialogs covering a wide range of technical and complex topics. It is necessary to leverage manual annotation to guide the construction and training of learning-based algorithms. However, manual annotation process requires experienced analysts to spend a large amount of time so that they can understand the dialogs thoroughly. Thus, it is very expensive to classify issue-related dialogs. **(3) Noisy data.** There exists noisy utterances such as duplicate and unreadable messages in the chat log that do not provide any valuable information. The noisy data poses a difficulty to analyze and interpret the communicative dialogs.

In this paper, we propose a novel approach, named ISPY (extracting Issue-Solution Pairs from community live chats)

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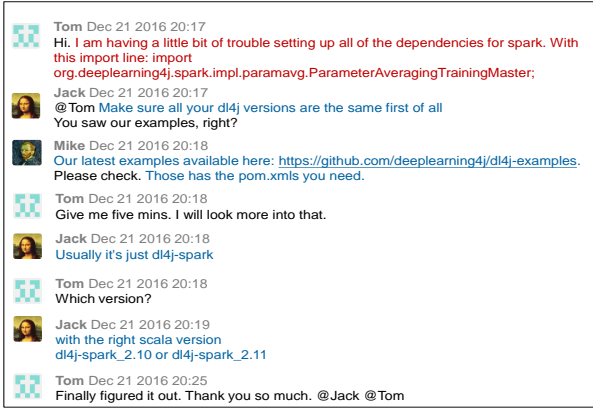


Fig. 1: An example of issue-solution pair extraction from the Deeplearning4j live chats.

to automatically extract issue-solution pairs from development community live chats. ISPY addresses the problem with three elaborated sub-tasks: 1) Disentangle live chat logs, employing a feedforward neural network to automatically disentangle a conversation history into separate dialogs; 2) Detect dialogs that are discussing issues, using a novel convolutional neural network (CNN), which consists of a BERT-based utterance embedding layer, a context-aware dialog embedding layer, and an output layer; and 3) Extract appropriate utterances and combine them as corresponding solutions, based on the same CNN structure but with different feeding inputs. To evaluate ISPY, we first collect and utilize a dataset with 750 dialogs including 171 issue-solution pairs, and evaluate ISPY from eight Gitter communities. The results show that, for issue-detection, our approach achieves the $F1$ of 76%, and outperforms baselines by 30%. For solution-extraction, our approach achieves the $F1$ of 63%, and outperforms baselines by 20%. Furthermore, we apply ISPY on three new communities to extensively evaluate its practical usage. ISPY helps provide solutions for 26 recent issues posted on Stack Overflow. Adding up the 21K pairs extracted from the former eight communities, we publish over 30K issue-solution pairs extracted from 11 communities in total. We believe that ISPY can facilitate community-based software development by promoting knowledge sharing and shortening the issue-resolving process. The major contributions of this paper are:

- We formulate the problem of issue-solution pair extraction from developer live chat data. To the best of our knowledge, this is the first study exploring this problem.
- We propose an automated approach, named ISPY, based on a convolutional neural network and introduces several customized improvements to effectively handle the characteristics of this task.

- We evaluate the ISPY by comparing with six baselines, with superior performance.
- We open-source a replication package and a large dataset with over 30K issue-solution pairs extracted by tool from 11 active communities on our website: <https://github.com/jzySaber1996/ISPY>.

In the remainder of the paper, Section II illustrates the problem definition. Section III presents the approach. Section IV sets up the experiments. Section V describes the results and analysis. Section VI illustrates the practical usage. Section VII is the discussion and threats to validity. Section VIII introduces the related work. Section IX concludes our work.

II. PROBLEM DEFINITION

Three main concepts about community live chats are concerned in the scope of this study, including *chat log*, *utterance*, and *dialog*. Developer conversations in one chatting room are recorded in a chat log. As illustrated in Fig. 1, a typical live chat log contains a sequential set of utterances in chronological order. Each utterance consists of a timestamp, developer id, and a textual message initiating a question or responding to an earlier message. A chat log includes all the utterances sent among participants who have been chatting in the room. Typically, it contains a large number of utterances, and the utterances might be responding to different threads of conversations. We define dialog as the conversation between two or more participants toward exploration of a particular subject (e.g., resolution of a problem).

$$\begin{aligned}
 Chat_log &= \{u_1, u_2, \dots, u_n\} \\
 D &= \{u_i | S(u_i) = s, u_i \in Chat_log\} \\
 u &= \langle time, id, text \rangle
 \end{aligned} \tag{1}$$

Equation (1) provides the definitions for the three main concepts. Specifically, a chat log *Chat_log* corresponds to a sequence of n utterances in chronological order. A dialog D is a subset of *Chat_log*, containing only those utterances responding to the same subject s , which can be determined by clustering techniques [10], [11] or probability distribution estimation methods [12]–[14]. $S(u_i)$ denotes the subject of utterance u_i , and each utterance u consists of the timestamp, developer id, and textual message.

Our work targets automatically extracting issue-solution pairs from community live chats. First, we divide one dialog D into two parts: *Head* and *Body*.

$$\begin{aligned}
 Head &= u_h = u_{h1} \oplus u_{h2} \oplus \dots \oplus u_{hm} \\
 Body &= \{u_{b1}, u_{b2}, \dots, u_{bn}\} \\
 D &= \{Head, Body\}
 \end{aligned} \tag{2}$$

where *Head* (also marked as u_h) is the concatenation of all the utterances that are posted by the dialog initiator before the first reply from other developers. *Body* is the set of the remaining utterances. Dialog D is their joint set. Based on this division, we introduce a simplification assumption that the issue descriptions appear at the head utterances authored

by the dialog initiator, while solution utterances are likely to appear afterward.

Following these concepts and assumption, we formulate the problem of automatic issue-resolution pair extraction with three elaborated sub-tasks:

- 1) Dialog disentangle: Given the historical chat log $Chat_log$, disentangle it into separate dialogs $\{D_1, D_2, \dots, D_n\}$.
- 2) Issue detection: Given a separate dialog D_i , find a binary function f so that $f(Head_i)$ can determine whether the dialog head depicts issue.
- 3) Solution extraction: Given a dialog D_i involving issue discussion, find a function g so that $g(Body_i) = \{u_{s1}, u_{s2}, \dots, u_{sm}\}$, where u_{si} is the utterance within the dialog suggesting potential solutions.

Therefore, the output of our approach is a set of issue-solution pairs. Ideally, users do not need other information (e.g., the utterances between them) to understand these pairs.

III. APPROACH

The construction of ISPY consists of four main steps, as illustrated in Fig. 2. The first step includes data preprocessing and dialog disentanglement using a feedforward model. The second step is to construct utterance embedding layer, which embeds tokenized utterances into vectors with local window context. The third step is to construct dialog embedding layer, which defines and extracts three sets of features characterizing the context of potential issues or solutions. The fourth step is the output layer, which predicts two outputs, i.e., the possibility of issue description, and the possibility of solutions, for the corresponding inputs. By feeding dialog head and body into ISPY separately, we can obtain two models: issue model and solution model. Finally, ISPY apply the issue model and solution model for constructing pairs.

A. Dialog Disentanglement

1) *Data Preprocessing*: For data preprocessing, we first follow the standard pipeline of stopword removal, typo correction, lowercase conversion, and lemmatization with Spacy [15]. Additionally, due to the unique characteristics of live chat data, we employ additional data preprocessing techniques to handle special issues. Specifically, we first replace low-frequency tokens such as URL, email address, code, HTML tag, and version number with specific tokens $[URL]$, $[EMAIL]$, $[HTML]$, $[CODE]$ and $[ID]$ respectively. Second, we replace the acronym words with their full names by referring to Oxford abbreviation library [16], and normalize the emojis with specific strings to standard ASCII strings. Finally, we combine consecutive utterances that are broken from one sentence according to the perplexity scores [17] calculated by Baidu AI Cloud [18]. Following the experience from a recent study [19], we use the perplexity scores lower than 40 as the threshold value to combine broken sentences.

2) *Dialog Disentanglement Model*: Utterances from a single conversation thread is usually interleaved with other ongoing conversations. In this step, we focus on dividing chat utterances into a set of distinct conversations, leveraging on Kummerfeld et al's. technique [20]. Their model is trained from 77,563 manually annotated utterances of disentangled dialogs from online chatting. It is a feedforward neural network with 2 layers, 512-dimensional hidden vectors, and softsign non-linearities. The input of the model is a 77-dimensional vector, where each element is a numerical feature extracted from the original conversation texts, that include, time intervals from previous chat utterances posted by the current user, is there a target user in the chat content, do two chat texts contain the same words and so on. In Kummerfeld et al's study, the model is reported to achieve relatively good performance with 74.9% precision and 79.7% recall.

B. Utterance Embedding Layer

This layer aims to not only encode textual information of utterances but also capture their contextual information.

Utterance Encoding. First, for all the utterances in one dialog $D = [u_h, u_{b1}, u_{b2}, \dots, u_{bn}]$, we encode it using a pre-trained BERT model [21], as BERT has been proved to be successful in many natural language processing tasks [22], [23]. The BERT model is a bidirectional transformer using a combination of *Masked Language Model* and *Next Sentence Prediction*. It is trained from English Wikipedia with nearly 2,500M words. The BERT embedding layer outputs $\vec{u} \in \mathbb{R}^d$, which is an 800-dimensional vector for each utterance.

Local Window Context. Second, we model the contextual information of an utterance through the concept of the *local window*, and use the size of local window as a hyper-parameter. Intuitively, the consecutive reply of an issue utterance may be very different from that of non-issue ones. Therefore, we construct local window context to characterize the dynamic contextual information for extracting desired utterances in a dialog. Specifically, we use a fixed-length local window to integrate context, and define the local window of the utterance \vec{u}_i as \vec{win}_i by joining the u_i with its preceding and following k neighbor utterances. The fixed length is $2k+1$.

$$\vec{win}_i = \{u_{i-k}, \dots, u_{i-1}, \vec{u}_i, u_{i+1}, \dots, u_{i+k}\} \quad (3)$$

When the windows are out of bound, we utilize the *Zero Padding* [24] to map the fixed length. In this study, we choose $k = 1$ for the local window.

C. Dialog Embedding Layer

The goal of this layer is to encode utterance features in a multi-faced way to more comprehensively represent the live chat context. To achieve that, we define and extract features from three categories, including textual, heuristic, and contextual features.

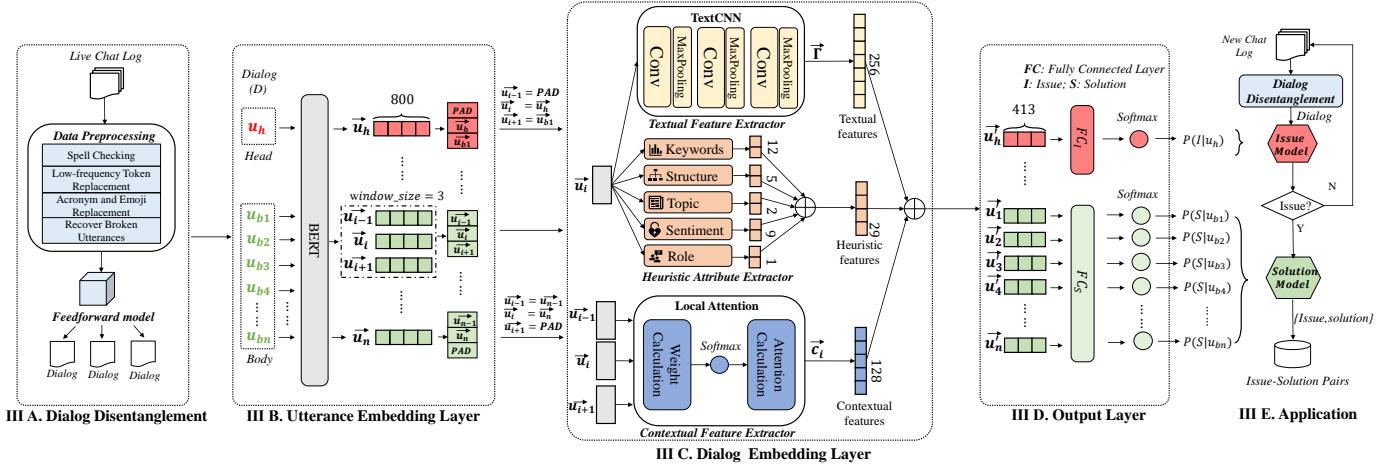


Fig. 2: The overview of ISPY.

TABLE I: Details about 15 heuristic attributes.

Type	Variable	Description	Example Value
Keyword	5W1H	Occurrence of "What", "Why", "When", "Who", "Which", and "How".	{what=1, why=0, when=0, who=0, which=0, how=0}
	Punctuation	Occurrence of "?" and "!".	{ "?"=1, "!"=0 }
	Greeting	Occurrence of greeting words: "Hello", "Good Morning", "Hi Guys", etc.	False
	Disapproval	Occurrence of disapproval words: "no", "can't work", "break down" etc.	False
	Mention	Occurrence of "simi-" and "same".	{simi=0, same=0}
Structure	NT	Number of tokens in utterance.	7
	NUT	Number of unique tokens in utterance.	7
	NST	Number of unique tokens after stemming.	6
	AP	Absolute position of utterance in dialog.	2
	RP	Relative position of utterance in dialog.	0.20
Topic	TDH	Topic deviation between the head of dialog and the entire chat.	0.33
	TDU	Topic deviation between the head of dialog and the given utterance.	0.42
Sentiment	SS	Polarity sentiment scores from NLTK [25] for positive, intermediate, and negative.	{pos.=0.25, int.=0.31, neg.=0.70}
	SW	Number of three-type polarity sentiment words (pos., int., neg.).	{pos.=1, int.=5, neg.=1}
	SE	Number of three-type polarity sentiment emojis (pos., int., neg.).	{pos.=0, int.=0, neg.=1}
Role	DI	Whether participant is the dialog initiator.	False

1) *Textual Feature Extractor*: To learn basic textual features for each utterance, we first represent utterances by using TextCNN [26]. It is a classical method for sentence modeling by using a shallow Convolution Neural Network (CNN) [27] to model sentence representation. It has an advantage over learning on insufficient labeled data, since it employs a concise network structure and a small number of parameters. TextCNN uses several convolution kernels to capture local information as the receptive field, then the global representation is produced with the local information.

Given a kernel $\vec{w} \in \mathbb{R}^h$ with kernel size h and word embedding $\vec{x} = \vec{u}_i$, one convolution feature γ_t is generated with $\vec{x}_{t:t+h-1}$:

$$\gamma_t = \text{ReLU}(\vec{w} \cdot \vec{x}_{t:t+h-1} + b) \quad (4)$$

where $b \in \mathbb{R}$ is the bias parameter, and ReLU is the activate function. We concatenate all the γ_t as a feature map:

$$\vec{\gamma} = [\gamma_1, \dots, \gamma_t, \dots, \gamma_{n-h+1}] \quad (5)$$

where the vector $\vec{\gamma} \in \mathbb{R}^{n-h+1}$. We use *Max-Pooling* strategy to calculate $\hat{\gamma} = \max(\vec{\gamma})$. We set the number of kernels as m , and input u_i into three *Convolution-Pooling* layers. The kernel number of the three layers are 1024, 512, and 256, respectively. The output of each layer is $\vec{\Gamma} \in \mathbb{R}^m$, which is a 256-dimensional textual feature vector.

$$\vec{\Gamma} = [\hat{\gamma}_1, \hat{\gamma}_2, \dots, \hat{\gamma}_m] \quad (6)$$

2) *Heuristic Attribute Extractor*: The heuristic attribute extractor aims to augment the dialog embedding results by incorporating high-level semantic attributes from five aspects: *Keyword*, *Structure*, *Sentiment*, *Topic*, and *Role*, as elaborated in Table I.

(1) *Keyword*: The occurrences of indicating words or characters about 5W1H, punctuation, etc.

(2) *Structure*: The structural characteristics of utterances in a dialog, such as the number of tokens and positions of the utterances.

(3) *Topic*: The intuition of this feature is to distinguish off-topic utterances. We first calculate *TF-IDF* [28] for each unique word in the entire chat. Then We extract the top-10 most frequent words and combine them as a 10-dimensional topic vector $T\vec{D}_c$. Similarly, we also extract top-10 most frequent words from dialog head ($T\vec{D}_h$) and the given utterance ($T\vec{D}_u$). Finally, we calculate the *Euclidean Distance* [29] between them as the topic deviation:

$$\begin{aligned} TDH &= \|T\vec{D}_c - T\vec{D}_h\|_2 \\ TDU &= \|T\vec{D}_h - T\vec{D}_u\|_2 \end{aligned} \quad (7)$$

(4) *Sentiment*: The sentiment information of the given utterance in terms of positive, intermediate, and negative.

(5) *Role*: The role of the participant who posts the utterance.

By concatenating the above heuristic attributes, this extractor output a 29-dimensional vector.

3) *Contextual Feature Extractor*: Contextual feature extractor aims to embed the contextual information for each utterance. We use *Local Attention* [30] to represent the context. The *Local Attention* mechanism mainly focuses on the impact of the neighbor utterances that locate in the same window. *Local Attention* can use low time-memory cost to highly represent semantic context. An attention function can be described as mapping a query and a set of key-value pairs to an output [31], which is a triple: $(\vec{h}_Q, \vec{h}_K, \vec{h}_V)$. The function uses the query vector \vec{h}_Q calculated by the given utterance $\vec{u}_i \in \mathbb{R}^d$ to query the attention scores with key vector \vec{h}_K . The key vector \vec{h}_K can be calculated by each utterance $\vec{u}_s \in \mathbb{R}^d$ within the local window $(i - k \leq s \leq i + k)$. The attention weight vector is calculated by multiplying value vector \vec{h}_V and sum the attention value. Therefore, we define the trainable query matrix $\mathbf{W}^Q \in \mathbb{R}^{\delta \times d}$, key matrix $\mathbf{W}^K \in \mathbb{R}^{\delta \times d}$ and value matrix $\mathbf{W}^V \in \mathbb{R}^{\delta \times d}$, and calculate the triple $(\vec{h}_Q, \vec{h}_K, \vec{h}_V)$:

$$\vec{h}_Q = \mathbf{W}^Q \vec{u}_i, \vec{h}_K = \mathbf{W}^K \vec{u}_s, \vec{h}_V = \mathbf{W}^V \vec{u}_s \quad (8)$$

where the output contextual weight vector is defined as $\vec{c}_i \in \mathbb{R}^\delta$, which can be calculated by the following equations:

$$\begin{aligned} score(\vec{h}_Q, \vec{h}_K) &= (\vec{h}_Q \cdot \vec{h}_K) \exp\left[-\frac{(s-i)^2}{2k^2}\right] \\ a_s &= softmax(\vec{h}_Q, \vec{h}_K) = \frac{score(\vec{h}_Q, \vec{h}_K)}{\sum_s score(\vec{h}_Q, \vec{h}_K)} \\ \vec{c}_i &= \sum_{i-k \leq s \leq i+k} (a_s \vec{h}_V) / \sqrt{d} \end{aligned} \quad (9)$$

Equation (9) shows the three processes of *Local-Attention* calculation: (1) Output attention vector with dot production as $score(\vec{h}_Q, \vec{h}_K)$ by multiplying *Gaussian Distance* between s and i ; (2) Use *Softmax* to normalize the score vector; and (3) Apply the normalized score vector to calculate the local attention. We set the parameter $d = 800$, $\delta = 128$, and obtain a 128-dimensional context vector.

Finally, we concatenate the vectors output by the three extractors into a 413-dimensional feature vector \vec{u}' .

D. Output Layer

We input the feature vector \vec{u}' into two *Full-Connected Layers* (FC), and use two *Softmax* functions to calculate the probability of issue-description utterance and the corresponding solution utterances respectively.

$$\begin{aligned} P(I|u_h) &= softmax(FC_1(\vec{u}_h')) \\ P(S|u_{bi}) &= softmax(FC_2(\vec{u}_i')) \end{aligned} \quad (10)$$

where $P(I|u_h)$ is the predicted probability of issue-description utterance, and $P(S|u_{bi})$ ($u_{bi} \in \{u_{b1}, \dots, u_{bn}\}$) is the predicted probability of solution utterance. The *Cross-Entropy Loss* are applied with the two tasks when measuring the difference

between truth and prediction. The two loss functions are defined as $Loss_I$ and $Loss_S$:

$$\begin{aligned} Loss_I &= -y_h \cdot \log P(I|u_h) \\ Loss_S &= -y_i \cdot \log P(S|u_{bi}) \end{aligned} \quad (11)$$

where y_h and y_i indicate the ground-truth labels of utterances. The issue model and solutions model are separately trained until convergence.

E. Application

When fully trained, for a given chat log, ISPY automates the three sub-tasks formulated in Section II: First, it performs dialog disentanglement; Second, for each disentangled dialog, it uses the issue model to predicts whether the dialog head is issue description; and Finally, if the issue model predicts positive, then it uses the trained solution model to predict which utterances can be selected into the solution. As a final output, it combines the predicted utterances as the corresponding solution to the issue.

IV. EXPERIMENTAL DESIGN

To evaluate the proposed ISPY approach, our evaluation specifically addresses three research questions:

RQ1: What is the performance of ISPY in detecting issue dialogs from live chat data?

RQ2: What is the performance of ISPY in extracting solutions for a given issue?

RQ3: How does each individual component in ISPY contribute to the overall performance?

A. Data Preparation

1) *Studied Communities*: Many OSS communities utilize Gitter [32] or Slack [33] as their live communication means. Considering the popular, open and free access nature, we select studied communities from Gitter¹. To identify studied communities, we select the Top-1 most participated communities from eight active domains, covering front end framework, mobile, data science, DevOps, blockchain platform, collaboration, web app, and programming language. Then, we collect the daily chat utterances from these communities. Gitter provides REST API [34] to get data about chatting rooms and post utterances. In this study, we use the REST API to acquire the chat utterances of the eight selected communities, and the retrieved dataset contains all utterances as of “2020-12”.

2) *Bootstrap Sampling*: After dialog disentanglement, the number of separate chat dialogs is large. Limited by the human resource of labeling, we randomly sample 100 dialogs from each community. Then we excluded unreadable dialogs: 1) Dialogs that are written in non-English languages; 2) Dialogs that contain too much code or stack traces; 3) Low-quality dialogs such as dialogs with many typos and grammatical errors. 4) Dialogs that involve channel robots. However, the dataset is imbalanced that the non-issue dialogs are much more than issue dialogs, as shown in Table II. Therefore, we apply

¹In Slack, communities are controlled by the team administrators, whereas in Gitter, access to the chat data is public.

TABLE II: The statistics of the eight Gitter communities.

Id	Project	Entire Population			Sample Population			
		Par.	Dial.	Utter.	Issue	Utter.	Non-issue	Utter.
P_1	Angular	22,467	79,619	695,183	17	170	80	577
P_2	Appium	3,979	4,906	29,039	27	461	60	404
P_3	DI4j	8,310	27,256	252,846	38	665	55	1,123
P_4	Docker	8,810	3,954	22,367	20	151	74	352
P_5	Ethereum	16,154	17,298	91,028	17	115	83	478
P_6	Gitter	9,260	7,452	34,147	22	315	64	575
P_7	Nodejs	18,118	13,981	81,771	14	121	81	359
P_8	Typescript	8,318	18,812	196,513	16	361	82	1,076
Total		95,416	173,278	1,402,894	171	2,359	579	4,944

an arbitrary bootstrap sampling strategy [35] for data balancing by randomly sampling issue dialogs with replacement until the number of issue dialogs and non-issue dialogs are balanced.

3) *Ground-truth Labeling*: For each sampled dialog, we first manually label whether its head discussed a certain issue. Then, for each issue-dialog, we label the utterances that should be included in the solution. The labeled results are used as the **ground-truth** dataset for performance evaluation. To guarantee the correctness of the labeling results, we built an inspection team, which consisted 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. The labeled results from the Ph.D. candidates were reviewed by others. When a labeled result received different opinions, we hosted a discussion with all team members to decide through voting. The average Cohen’s Kappa about issue-dialog is 0.85, and the average Cohen’s Kappa about solution-utterance is 0.83.

In total, we collected 173,278 dialogs from eight open-source communities, and spent 720 person-hours on annotating 750 dialogs including 171 issue-solution pairs. Table II presents the detail of our dataset. It shows the number of participants (Par.), dialog (Dial.), and utterance (Utter.) for the entire population, as well as the number of issue and non-issue dialogs with the corresponding utterances for the sample population. Moreover, to contribute to the eight communities, we apply ISPY on the 173,278 dialogs. We extract and publish 21K issue-solution pairs on our website.

B. Baselines

The first two RQs requires the comparison of ISPY with state-of-the-art baselines. Due to the slightly different focuses between RQ1 and RQ2, we employ three common baselines applicable for both, as well as three additional baselines for each RQ. This leads to a total of six baselines for each RQ.

Common Baselines applicable for RQ1 and RQ2. The three commonly used machine-learning-based baselines are utilized to comprehensively examine the classification performance, i.e., **Naive Bayesian (NB)** [36], **Random Forest (RF)** [37], and **Gradient Boosting Decision Tree (GBDT)** [38].

Additional Baselines for detecting issues (RQ1). **Casper [39]** is a method for extracting and synthesizing user reported mini stories regarding app problems from reviews. We use utterances as the extracted events, and treat its second step, i.e., classify problems, as a baseline. We use the implementation provided by the original paper [40]. **CNC_PD [41]** is the

state-of-the-art learning technique to classify sentences in comments taken from online issue reports. They proposed a CNN [42] based approach to classify sentences into seven categories of intentions: Feature Request, Solution Proposal, Problem Discovery, etc. we treat the CNN classifier that predicts utterances as the *Problem Discovery* category as a baseline for detecting issues. **DECA_PD [43]** is the state-of-the-art rule-based technique for analyzing development email content. It is used to classify the sentences of emails into problem discovery, solution proposal, information giving etc. by using linguistic rules. We use the six linguistic rules [44] for identifying “problem discovery” dialog-head as our baseline.

Additional baselines for extracting solutions (RQ2). **UIT [45]** is a context-representative classifier that uses Glove [46] to embed word, and uses TextCNN to embed the utterance. The UIT classifies utterance them into 12 categories. Specifically, we choose the “potential answer” classifier as a solution-extraction baseline. **CNC_SP** is the *Solution Proposal* classifier in [41]. **DECA_SP** is the set of 51 linguistic rules for identifying “solution proposal” sentences in [43].

C. Evaluation Metrics

We use three commonly-used metrics to evaluate the performance, i.e., *Precision*, *Recall*, *F1*. (1) *Precision*, which refers to the ratio of the number of correct predictions to the total number of predictions; (2) *Recall*, which refers to the ratio of the number of correct predictions to the total number of samples in the golden test set; and (3) *F1*, which is the harmonic mean of precision and recall. When comparing the performances, we care more about F1 since it is balanced for evaluation. Note that, since the number of utterances may largely vary across different dialogs, we calculate the performance of solution extraction in the scope of community.

D. Experiment Settings

For all experiments, we apply *Cross-Project Evaluation* on our dataset to perform the training process. We iteratively select one project as testset, and the remaining seven projects for training. The experiment environment is a Windows 10 desktop computer, NVIDIA GeForce RTX 2060 GPU, intel core i7, and 32GB RAM.

To answer RQ1, we first train the issue dataset with 8 *batch_size*. Each of convolution and dense layers use 0.6 *dropout* to avoid overfitting. The optimizer chooses *Adam*=0.001 and β_1 =0.9. We train ISPY for 100 epochs with 5 patience *Early-Stopping*. We set the threshold of predicted possibility within 0.2-0.8, and choose *threshold*=0.5 as positive-negative boundary which can reach the best performance after tuning. For baselines, NB/GDBT/RF choose the default parameter settings for training; Casper chooses *svm.SVC* as default function, with *rbf* as kernel, 3 as degree and 200 as *cache_size*; CNC_PD selects 64 as *batch_size*, 192-dimensional word embedding, four different filter sizes of [2, 3, 4, 5] with 128 filters, 50 training epochs and *dropout*=0.5. These baseline parameters are determined by a greedy strategy, and can achieve the best performance after tuning.

TABLE III: Baseline comparison across the eight communities.

Task	Methods	Angular			Appium			Docker			DL4j			Ethereum			Gitter			Nodejs			Typescript			Average		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Issue	ISPY	0.76	0.77	0.76	0.75	0.68	0.71	0.84	0.74	0.79	0.77	0.68	0.72	0.82	0.73	0.77	0.80	0.69	0.74	0.79	0.70	0.74	0.86	0.78	0.82	0.80	0.72	0.76
	NB	0.36	0.40	0.38	0.41	0.30	0.35	0.47	0.36	0.41	0.70	0.56	0.62	0.08	0.25	0.13	0.22	0.42	0.29	0.30	0.50	0.37	0.15	0.40	0.22	0.34	0.40	0.36
	RF	0.56	0.25	0.34	0.69	0.30	0.42	0.75	0.23	0.35	0.84	0.44	0.58	1.00	0.17	0.29	0.50	0.25	0.33	0.33	0.13	0.18	0.23	0.30	0.26	0.61	0.26	0.36
	GBDT	0.27	0.75	0.40	0.40	0.70	0.51	0.30	0.79	0.61	0.73	0.44	0.55	0.21	0.76	0.33	0.19	0.67	0.29	0.30	0.88	0.44	0.18	0.90	0.30	0.35	0.65	0.46
	Casper	0.39	0.35	0.37	0.08	0.03	0.05	0.59	0.26	0.36	0.46	0.40	0.43	0.19	0.42	0.26	0.14	0.17	0.15	0.05	0.06	0.06	0.15	0.40	0.22	0.26	0.26	0.26
	CNC_PD	0.20	0.55	0.29	0.33	0.50	0.32	0.23	0.36	0.38	0.12	0.32	0.17	0.24	0.42	0.30	0.12	0.42	0.19	0.10	0.50	0.17	0.05	0.40	0.10	0.16	0.43	0.24
	DECA_PD	0.33	0.50	0.40	0.28	0.37	0.31	0.33	0.36	0.34	0.64	0.28	0.39	0.42	0.42	0.42	0.44	0.67	0.53	0.32	0.50	0.39	0.04	0.10	0.06	0.35	0.40	0.37
Solution	ISPY	0.61	0.58	0.69	0.68	0.57	0.62	0.71	0.60	0.65	0.66	0.62	0.58	0.73	0.63	0.68	0.62	0.56	0.59	0.68	0.58	0.63	0.72	0.67	0.69	0.68	0.59	0.63
	NB	0.21	0.58	0.30	0.24	0.48	0.32	0.31	0.59	0.40	0.58	0.49	0.53	0.33	0.80	0.47	0.10	0.67	0.17	0.37	0.55	0.44	0.08	0.09	0.09	0.28	0.53	0.37
	RF	0.26	0.83	0.39	0.27	0.52	0.36	0.31	0.56	0.40	0.80	0.13	0.22	0.15	0.40	0.22	0.10	0.33	0.15	0.50	0.65	0.57	0.54	0.64	0.58	0.37	0.51	0.43
	GBDT	0.26	0.92	0.40	0.26	0.74	0.38	0.22	0.62	0.32	0.71	0.16	0.26	0.11	0.40	0.17	0.10	0.67	0.17	0.42	0.75	0.54	0.42	0.73	0.53	0.31	0.62	0.41
	UIT	0.29	0.17	0.21	0.21	0.13	0.17	0.30	0.12	0.17	0.24	0.07	0.12	0.37	0.16	0.22	0.27	0.11	0.17	0.19	0.15	0.18	0.31	0.18	0.23	0.27	0.14	0.18
	CNC_SP	0.18	0.17	0.17	0.26	0.28	0.27	0.21	0.31	0.25	0.46	0.20	0.28	0.30	0.14	0.19	0.46	0.54	0.50	0.41	0.28	0.33	0.38	0.25	0.30	0.33	0.27	0.30
	DECA_SP	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.09	0.12	0.25	0.02	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.20	0.30	0.33	0.09	0.14	0.17	0.05	0.08

For RQ2, we use the same parameters with RQ1 for ISPY. We only change the predicting threshold from 0.5 to 0.4 since 0.4 can reach the best performance on solution extraction after tuning. For baselines, we choose default parameter settings for NB/GBDT/RF training. For UIT, we select 32 as *batch_size* and 0.6 as *dropout*.

For RQ3, we compare ISPY with its three variants: 1) **ISPY-CNN**, which removes the textual feature extractor from ISPY, 2) **ISPY-Heu**, which removes the heuristic attribute extractor from ISPY, and 3) **ISPY-LocalAttn**, which removes the contextual feature extractor from ISPY. Three variants use the same parameters when training.

V. RESULTS

A. Performance in Detecting Issues

The upper half of Table III demonstrates the comparison results between the performance of ISPY and those of the six baselines across data from eight OSS communities, for **issue detection** tasks. The columns correspond to Precision, Recall, and F1 score. The highlighted cells indicate the best performances from each column. We conduct T-test between each two methods. Overall, ISPY significantly ($p - value < 0.05$) outperforms the six baselines in terms of the average Precision, Recall, and F1 score. Specifically, when comparing with the best Precision-performer among the six baselines, i.e., RF, ISPY can improve its average precision by 19%. Similarly, ISPY improves the best Recall-performer, i.e. GBDT, by 0.07 for average recall, and improves the best F1-performer, i.e. GBDT, by 0.30 for average F1 score. At individual project level, ISPY can achieve the best performances on most of the eight communities. These results indicate that ISPY can more accurately detect whether a dialog is discussing issue, than all comparison baselines.

We believe that the performance advantage of ISPY is mainly attributed to the rich representativeness of its internal construction, from two perspectives: (1) ISPY is able to accurately capture the semantic relationship between the issue description and its first reply, by using the local window and local attention mechanism. This enables it to learn more comprehensive contextual knowledge, e.g. what kind of first issue-replies represents a dialog head containing issue descriptions. Therefore, it contributes to more accurate classification. (2) ISPY augments the textual vectors with high-level semantic information by employing 15 heuristic attributes. For example, three out of the 15 attributes are characterizing sentiment attributes, this design is based on the observation that issue

descriptions are likely to contain negative tones such as “fail”, “error” and “annoy”. By calculating three types of polarity sentiment scores as shown in Table I, the sentiment attributes can be fit into the deep learning network to help with issue-description detection.

Answering RQ1: ISPY outperforms the six baselines in detecting issue dialogs across most of the studied projects, and the average Precision, Recall, and F1 are 80%, 72%, and 76% respectively, improving the best F1-baseline GBDT by 30% on average F1 score.

B. Performance in Extracting Solutions

Similarly, the bottom part of Table III summarizes the comparison results between the performance of ISPY and those of the six baselines across data from eight OSS communities, for **solution extraction** task. We can see that, ISPY can achieve the highest performance in most of the columns. It significantly ($p = 10^{-5}$) outperforms the six baselines. On average, although ISPY are slightly below GBDT by 3% of Recall, it reaches the highest F1 score (63%), improving the best baseline RF by 20%. It also reaches the highest precision (68%), significantly higher than other baselines (i.e., ranging from 17% to 37%). These results imply that ISPY can effectively extract utterances as the corresponding solutions from development dialogs. (1) Our approach is sensitive

TABLE IV: Test example.

Dialog
(u ₁)A: I'm training a DNN+CNN model. The F1 score is around 50. But there are some warnings that some classes are never predicted. Shall I create a dataset which is balanced for five types?
(u ₁)B: What do you mean "DNN+CNN" model : ?
(u ₂)B: Beyond trained on conv yes, minibatches should always be balanced.
(u ₃)B: If minibatch it should ideally be as close to representative of your whole population as possible.
(u ₄)A: I mean danse Layer+CNN. I used wrong word, I guess....
(u ₅)B: The reason why I ask is because batchsize largely depends on data dimension.
(u ₆)B: The main thing it had going for it was the catalyst compiler for Tensorflow ops.
(u ₇)A: Nice! Thank you!
ISPY
Beyond trained on conv yes, minibatches should always be balanced. If minibatch it should ideally be as close to representative of your whole population as possible. The main thing it had going for it was the catalyst compiler for Tensorflow ops.
NB
What do you mean "DNN+CNN" model? Beyond trained on conv yes, minibatches should always be balanced.
RF
What do you mean "DNN+CNN" model? Beyond trained on conv yes, minibatches should always be balanced. I mean danse Layer+CNN. I used wrong word, I guess.
GBDT
What do you mean "DNN+CNN" model? Beyond trained on conv yes, minibatches should always be balanced. I mean danse Layer+CNN. I used wrong word, I guess. The reason why I ask is because batchsize largely depends on data dimension. The main thing it had going for it was the catalyst compiler for Tensorflow ops.
UIT
Beyond trained on conv yes, minibatches should always be balanced. The main thing it had going for it was the catalyst compiler for Tensorflow ops. Nice! Thank you!
CNC_SP
Beyond trained on conv yes, minibatches should always be balanced. If minibatch it should ideally be as close to representative of your whole population as possible.
DECA_SP
(Empty)

to identifying solutions including consecutive utterances by

employing local attention mechanism. In live chats, there are some solutions that include consecutive utterances from the same participants. For example, the utterance u_{b2} and u_{b3} in Table IV are both selected as solution utterances. Our approach can learn that knowledge by adjusting the weight of u_{b3} to be higher, in order to increase its probability according to the local attention learning. While baselines (e.g., NB, RF, GDBT, UIT, DECA_SP) separately learn the textual characteristics of each utterance, thus are more prone to predict u_{b3} as a non-solution utterance. (2) Our approach can screen negative feedbacks in consecutive utterance and reject ineffective solutions based on the heuristic attributes (i.e., disapproval keywords and negative sentiment attributes) and local attention mechanism. In live chats, there are some utterances that indeed are solutions, but are proved to be ineffective (e.g., those have follow-up utterances like “It doesn’t work”) by the dialog initiator later. In such cases, ISPY can detect whether its follow-up utterances contain negative feedback based on the heuristic attributes and local attention learning, while other methods cannot.

We also notice that, the DECA_SP baseline can hardly extract the solution utterances correctly. By investigating their 51 linguistic rules and our test dataset, we consider that it comes from two reasons. First, the DECA_SP rules are designed for extracting solution proposal from email contents, which have different expressing styles from live chats. Second, the DECA_SP rules are kind of strict for live chats. For example, the rule “[something] can be fixed by [something]” cannot deal with its similar variants such as “[something] could/should be fixed by [something]”.

Answering RQ2: ISPY outperforms the six baselines in extracting solution utterances in terms of Precision and F1. The average Precision, Recall, and F1 are 68%, 59%, and 63% respectively, improving the best F1-baseline RF by 20% on average F1 score.

C. Effects of Main Components

Fig. 3 presents the performances of ISPY and its three variants respectively. We can see that, the F1 performances of ISPY are higher than all three variants in both issue-dialog detection and solution extraction tasks.

When compared with ISPY and ISPY-LocalAttn, removing the LocalAttn component will lead to a dramatic decrease of the precision (-35%), recall (-60%), and F1 score (-57%) for the solution-utterance extraction task, as well as a decrease of the precision (-41%), recall (-46%), and F1 score (-46%) for the solution extraction task. This indicates that the local attention mechanism is an essential component to contribute to ISPY’s high performance in both detecting issues and extracting solution utterances. The top three charts in Fig. 3 compare the precision, recall, and F1-score of ISPY and its three variants, for issue-detection task. Compared to ISPY-Heu and ISPY-CNN, ISPY has moderately better precision and F1, and the recalls of all the three remain very close. It is because that, the contextual information is quite effective in retrieving all the positive-truth instances back for this task, while the

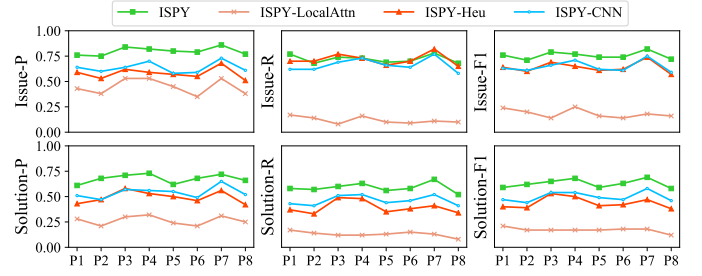


Fig. 3: The component analysis.
TABLE V: The statistics of ISPY’s contribution on answering questions for Stack Overflow.

Contribution Type	#	QID (#ans)
Accepted Answer	6	67201337(1), 67086241(1), 67101118(1), 67047528(1), 66899397(1), 67150784(2)
Potential Answer	19	61529948(1), 65619783(1), 63620416(1), 66383230(1), 57543742(1), 49303635(1), 51042100(1), 39653049(1), 65877801(1), 64455428(1), 59282213(2), 59073683(2), 63190114(2), 50233325(2), 56158365(2), 60062706(3), 42130187(3), 38848742(4), 47974757(5)
Comment	1	66378139(2)
Total		26

other two components mainly contribute to filter the negative-truth instances out thus can further improve precision. The bottom three charts in Fig. 3 compare the precision, recall, and F1-score of ISPY and its three variants, for solution-extraction task. Compared to ISPY-Heu and ISPY-CNN, ISPY has moderately better precision, recall, and F1.

Answering RQ3: The textual feature extractor, heuristic attribute extractor, and content feature extractor adopted by ISPY are helpful for extracting issue-solution pairs, while the contextual feature extractor provides a more significant contribution to the effectiveness of ISPY than others.

VI. AN APPLICATION STUDY OF ISPY

Experiments in Section V have shown the performances of our approach. In this section, we conduct an application study to further demonstrate the usefulness of our approach.

Procedure. We apply ISPY on live chat data from three new communities: Materialize, Springboot, and WebPack (note that these are different from our studied communities). According to the issue-solution pairs extracted from the three communities, we manually inspect their recently unanswered questions on Stack Overflow, and provide potential solutions correspondingly. First, we crawl the recent (January 2018 to April 2021) live chats of three new communities. Second, we apply ISPY to disentangle the live chats into about 21K dialogs, and generate a dataset with over 9K issue-solution pairs. Because all live chats are historical data, we cannot directly evaluate the usefulness of ISPY with the original developers who inquired about the issue. As an alternative, we investigate the usefulness of ISPY by sharing the discovered solutions to developers facing similar issue on Stack Overflow. Specifically, we employ four Ph.D. students to inspect the recent, unanswered questions in these three communities on Stack Overflow. When finding unanswered issues that have been discussed in live chats, we post the corresponding solutions as potential answers.

Results. Table V summarizes the results from this application study (More details can be found in our website). The “Contribution Type” column shows how ISPY’s solutions contribute to the Stack Overflow. There are three types of contribution: “*Accepted Answer*” means that ISPY’s solution has been adopted as the best answer. “*Potential Answer*” means that ISPY’s solution is listed as a potential answer, but there is no feedback from the question asker yet. “*Comment*” means that ISPY’s solution contributes as a comment while other’s answer got accepted. “QID” refers to question ID on Stack Overflow, and “#ans” refers to the total number of posted answers for the question. Overall, ISPY helps with 26 unanswered issues, and there are 6 solutions that have been accepted as the best answers. Fig. 4 presents an example of resolved issue posted on Stack Overflow. We can see that, ISPY can expedite the resolving process of “BuildProperties” issue by providing a workable solution. Specifically, ISPY can provide the unanswered issues with brief root causes (e.g., 57543742), reference documentation (e.g., 59282213), detailed guidelines (e.g., 66868053), etc. ISPY can also provide timely responses to answer-hungry issues. For example, there are 15/26 questions that have no answer at first, and ISPY’s solutions serve as their only answers (see red questions with #ans=1 in Table V).

Summing up, ISPY helps with unanswered issues on Stack Overflow, and there are 6/26 solutions that have been accepted as best answers. The results explicitly show that ISPY can promote knowledge sharing and expedite issue-resolving process.

VII. DISCUSSION AND FUTURE WORK

A. Usage Scenario

Serving potential answers. Despite the success of technical Q&A sites such as Stack Overflow, the answer-hungry problem remains a challenging issue for these forums [47]. The mined issue-solution pairs could serve as knowledge base which can be potentially integrated with, and provide queried information to these Q&A forums. When users ask issues which are similar to what people have discussed on community chats, the corresponding solutions could be automatically retrieved and recommended as potential answers, relieving the answer-

hungry problem to a large extent. On the other hand, the extracted issue-solution pairs are also useful for boosting the automation Q&A in community live chats by recommending similar questions and their corresponding discussions.

Boosting developers’ profiles. Developers who often provide solutions in community chats may have certain expert knowledge in particular areas. The issue-solution pairs extracted can be further used to recommend or assign appropriate respondents to answer questions, according to their historical answers in live chats. Researchers could also find out which modules or functionalities that the developers are familiar with by analyzing the issue topics that developers have been addressed. Thus, researchers could utilize that information to enhance crowd-sourcing tasks, such as code reviewer recommendation [48], [49] and issue triage [50], [51].

Highlighting unresolved issues. Our approach can effectively find issue-solution pairs from live chats. It can also find issues where their solutions are empty. Such issues are likely to be the unresolved issues spotted in live chats but are not reported to the project repositories (such as Github). It is valuable to make the community notice them, e.g., directly push the unresolved issues to the code repository. Otherwise, they are likely to be buried in the massive live chats, and the team might miss the opportunity to fix them in time. Therefore, a side effect of our approach is to help highlight unresolved issues that are buried in community live chats.

Augmenting Organization Knowledge Base. ISPY can augment organization knowledge base by including discovered issue-solution pairs from group live chats in an automatic and just-in-time way. Moreover, existing technologies such as ontology [52] and semantic web [53] can more be effective to support information inquiring and sharing across platforms.

B. Where Does ISPY Perform Unsatisfactorily

Case 1: Handling dialogs with an issue description utterance lagging behind. ISPY use the dialog head (all the utterances posted by the dialog initiator before any reply) as the input of our issue model, with the assumption that the dialog initiators are likely to express the issues at the beginning. However, we find that dialog initiators occasionally lag their issue description behind. Here is an example, we can see that, the issue description appears in the u_{b2} utterance, beyond the scope of dialog head. In such cases, ISPY cannot accurately detect issues. In future, we plan to dynamically extend the scope of dialog head, so that the lagging issue descriptions can be included.

```
(uh) <A> Good Morning, trying to figure out how to create the DataProvider<DataSetIterator>. [Dialog Head]
(ub1) <B> Go ahead, no need for greeting!
(ub2) <A> [CODE] incorrect. How to create a DataProvider from a RecordReaderDataSetIterator? [Issue description]
```

Case 2: Representing different confidence levels on extracted solutions. When discussing issues in community live chats, developers who post the issues often give feedbacks about the solutions provided by their peers at the end. For example, we find that some typical feedbacks are: “It works.”,

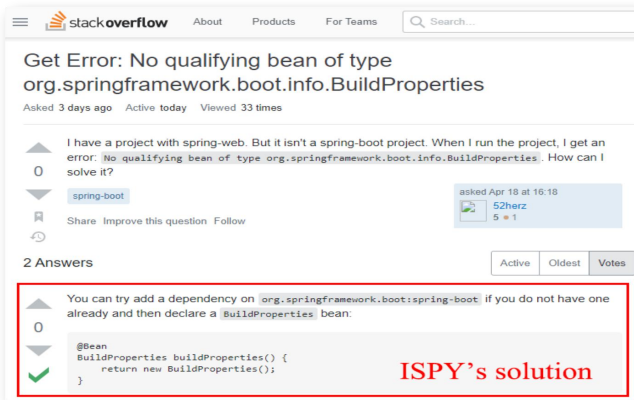


Fig. 4: An example of “BuildProperties” issue resolved by ISPY’s solution on Stack Overflow

“The issue is fixed.”, “Figured it out.”, etc. These feedbacks can indicate different confidence levels of the corresponding solution: *Confirmed* and *Candidate*. “Confirmed” refers to the solution that has been proved to work by the initiator, and “Candidate” refers to the solution that has the potential in resolving the issue. In future, we plan to refine the extracted solutions by providing different confidence levels as well.

Case 3: Differentiating solutions involving version numbers. From the usefulness evaluation results (Table V), we notice that the question “66378139” did not select ISPY’s solution as its best answer. This is because that the ISPY’s solution is extracted from the dialog discussing the similar issue in Spring Boot 3.0.0 while the posted issue is related to Spring Boot 2.4.3. Thus, the solution might not be completely suitable. In future, we plan to address this issue by linking each issue-solution pair to its corresponding version for better application.

Case 4: Enhancing smoothness when combining solution. We directly combine the predicted solution utterances according to their chronological orders as the solution. For the predicted utterances that are not consecutive in the original dialog, it might exist logical gaps between them. Thus, it may reduce the readability of ISPY’s solutions. In the future, we would like to improve the readability of the extracted solutions by leveraging language models [54].

C. Threats to Validity

The first threat is the generalizability of the proposed approach. It is only evaluated on eight open-source projects, which might not be representative in closed-source projects or other open-source projects. The results may be different if model is applied on other projects. However, our dataset comes from eight different fields. The variety of projects relatively reduce this threat.

The second threat may come from results of dialog disentanglement. The accuracy of disentangled dialog has impact on our results. To reduce the threat, we employed the state-of-the-art technique proposed by Kummerfeld et al. [20], which outperforms previous studies by achieving 74.9% precision and 79.7% recall. Therefore, we believe this can serve as a good foundation for our study on mining issue-solution pairs.

The third threat relates to the construct of our approach. First, we use the hypothesis that issue description is likely to appear in dialog head, which occasionally incorrect in certain cases. Second, we do not add version information to issue-solution pairs which may result in recommending inappropriate solutions. To alleviate the threat, we thoroughly analyzed where our approach perform unsatisfactorily in section VII, and planned future work for improvement.

The forth threat relates to the suitability of evaluation metrics. We utilize precision, recall, and F1 to evaluate the performance, in which we use the dialog labels and utterance labels that are manually labeled as ground truth when calculating the performance metrics. The threats can be largely relieved as all the instances are reviewed with a concluding

discussion session to resolve disagreement in labels based on majority voting.

VIII. RELATED WORK

Knowledge Extraction from Developer Conversations. Recently, more and more work has realized that community chat plays an increasingly significant role in software development, and chat messages are a rich and untapped source for valuable information about the software system [1], [3], [55]. There are several studies focusing on extracting knowledge from developer conversations. Di Sorbo et al. [43] proposed a taxonomy of intentions to classify sentences in developer mailing lists. Huang et al. [41] addressed the deficiencies of Di Sorbo et al’s taxonomy by proposing a convolution neural network (CNN)-based approach. Qu et al. [24] utilized classic machine learning methods to perform user intent prediction with an average F1 of 0.67. Shi et al. [56] proposed an approach to detect feature-request dialogues from developer chat messages via deep siamese network. Rodeghero et al. [57] presented a technique for automatically extracting information relevant to user stories from recorded conversations. Chowdhury and Hindle [58] filtered out off-topic discussions in programming IRC channels by engaging Stack Overflow discussions as positive examples and YouTube video comments. The findings of previous work motivate the work presented in this paper. Our study is different from the previous work as we focus on extracting issue-solution pairs from massive chat messages that would be important and valuable information for OSS developers to check and fix issues. In addition, our work complements to the existing studies on knowledge extraction from developer conversations.

Emerging Issue Detection. Detecting emerging issues from user feedback timely and precisely is vital for developers to update their applications. Most current work focuses on detecting the emerging issues from short-text social media (e.g., Twitter and Google Play), and determining the emerging issues based on traditional anomaly detection methods. For example, Guo et al. [39] proposed a method for extracting and synthesizing user reported mini stories regarding app problems from reviews. Vu et al. [59] detected emerging issues and trends by counting negative keywords based on Google Play. Since the single words might be ambiguous without contexts, their follow-up work [60] proposed a phrase-based clustering approach that relied on manual validation of part-of-speech (PoS) sequences. Gao et al. [61] presented a topic labeling approach, named IDEA, to automatically detect emerging issues of current versions based on statistics of previous versions. Due to the inborn limitations of topic modeling, such as the predefined topic numbers, their follow-up work [62] introduced DIVER which incorporated depth-first pattern mining with version and time-based comparisons. Most of these methods focus on detecting emerging issues embedding in short-text social media, while our approach targets to automatically extract issues with their potential solutions (if exists) from community chats, complementing the existing studies on a novel source. In addition, our approach

cannot only detect emerging issues in community chat, but also extract relevant solutions with resolved issues for reuse purposes, aiming to expedite the issue resolving process.

Community-based question and answer extraction. Generating large-scale technical question-answer pairs is critical for contributing knowledge that can facilitate software development activities. Existing studies are designed to find questions and corresponding answers from synchronous conversations, i.e., mailing lists and forums. Shrestha et al. [63] first trained a set of if-then rules to predict questions in email messages, and an another set of if-then rules to predict corresponding answers based on features of texts. Huang et al. [64] presented an approach for extracting high-quality <thread-title, reply> pairs from online forums based on SVM classifier and content-quality ranking. Cong et al. [65] proposed a sequential pattern-based classification method to detect questions in a forum thread, and a graph-based propagation method to detect answers for questions in the same thread. Since previous studies extracted only questions in interrogative forms, Kwong et al. [66] extended the scope of questions and answer detection, and pairing to encompass also questioned in imperative and declarative forms. Henß et al. [67] presented an approach to automatically extract FAQs from sources of software development mailing lists. These approaches utilize the characteristics of their corpora and are best fit for their specific tasks, but they limit each of their corpora and tasks, so they cannot directly transform their methods to the task of extracting issue-solution pairs from community chats.

IX. CONCLUSION

In this paper, we propose an approach, named ISPY, to automatically extract issue-solution pairs from development community live chats. ISPY leverages a novel convolutional neural network by incorporating a basic CNN network with 15 heuristic attributes and *Local-Attention* mechanism to handle the characteristics of this task. We build a dataset with 750 dialogs including 171 issue-solution pairs and evaluate ISPY on it. The evaluation results show that our approach outperforms both issue-detection baselines and solution-extraction baselines by substantial margins. By applying ISPY, we also automatically generate a dataset with over 30K issue-solution pairs extracted from 11 community live chats, and we utilize the dataset to provide solutions for 26 recent issues posted on Stack Overflow.

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