Dialogue Disentanglement in Software Engineering: How Far are We?

Abstract

Despite the valuable information contained in software chat messages, disentangling them into distinct conversations is an essential prerequisite for any in-depth analyses that utilize this information. To provide a better understanding of the current state-of-the-art, we evaluate five popular dialog disentanglement approaches on software-related chat. We find that existing approaches do not perform well on disentangling software-related dialogues that discuss technical and complex topics. Further investigation on how well the existing disentanglement measures reflect human satisfaction shows that existing measures cannot correctly indicate the human satisfaction on disentanglement results. Therefore, in this paper, we introduce and evaluate a novel measure, named *DLD*. Using results of human satisfaction, we further summarize four most frequently appeared bad disentanglement cases on software-related chat to insight future improvements. These cases include (i) ignoring interaction patterns; (ii) ignoring contextual information; (iii) mixing up topics; and (iv) ignoring user relationships. We believe that our findings provide valuable insights on the effectiveness of existing dialog disentanglement approaches and these findings would promote a better application of dialogue disentanglement in software engineering.

1 Introduction

Online communication platforms such as Gitter[1] have been heavily used by software organizations as the collaborative team communication tools for their software development teams. Conversations on these platforms often contain a large amount of valuable information that may be used, for example, to improve development practice, to observe software development process, and to enhance software maintenance. However, these conversations oftentimes appear to be entangled. While some developers may participate in active discussions on one topic, others could address previous conversations on different topics in the same place. Without any indications of separate conversations, it is difficult to extract useful information when all messages appear together.

A number of approaches has been proposed to address such issue of dialogue entanglement. Early work uses simple classifiers with handcrafted features to analyze the coherence of message-pairs [Elsner and Charniak, 2010]. In addition, neural network is used to obtain the relationships with the development of deep learning, such as *FeedForward* (*FF*) [Kummerfeld *et al.*, 2019], *CNN* [Jiang *et al.*, 2018] and *BiLSTM* [Mehri and Carenini, 2017] *etc.*. Meanwhile, sequential encoder/decoder based models are recently introduced with pre-trained *BERT* [Li *et al.*, 2020], session-state dialogue encoders [Liu *et al.*, 2020], and pointer networks [Yu and Joty, 2020]. To evaluate their approaches, most of these studies use conversations mined from social platforms, such as Reddit and Twitter. The content of these conversations usually focuses on general topics, such as movies and news. However, the disentanglement performance on software-related chat has rarely been evaluated. [Kummerfeld *et al.*, 2019] and [Yu and Joty, 2020] evaluate their models on a set of Ubuntu IRC dataset but the generalizability of the results is limited due to the small sample size. Moreover, although the goal of dialogue disentanglement is to provide users with the ease of finding valuable information from entangled messages, none of the previous studies investigate how well existing disentanglement measures reflect human satisfaction. Thus, it remains unclear how far we are from effective dialogue disentanglement towards software-related chat that contains the majority of technical and professional conversations.

In this paper, we conduct an exploratory study on 7,226 real-world developers' dialogues mined from eight popular open-source projects hosted on Gitter. First, we compare five state-of-the-art dialogue disentanglement approaches based on two strategies: transferring the original models across domains and retraining the models on software-related dialogues. Second, we further investigate how well the existing disentanglement measures reflect human satisfaction. The results show that the existing measures are unable to accurately indicate human satisfaction on the disentanglement results. Therefore, we propose and evaluate a novel measure that measures human satisfaction on disentanglement results by incorporating Levenshtein distance, named *DLD*, to complement the existing literature. To further understand why existing approaches fail to disentangle software-related chat,

[1] www.gitter.im

we summarize four bad cases of the incorrect disentanglement. We believe that the findings we have uncovered will promote a better application of dialog disentanglement in the software engineering domain.

The major contributions of this paper are as follows:

- We conduct a comparative empirical study on evaluating the state-of-the-art disentanglement approaches on software-related chat;
- We propose a novel measure, named *DLD*, for quantitatively measuring human satisfaction on disentanglement results;
- We identify four categories of incorrect disentanglement that are useful for improving existing literature;
- We release a dataset[2] of disentangled software-related dialogues to facilitate the replication of our study and future improvements.

2 Dataset Preparation

Study Projects. Gitter is selected due to its high popularity and being openly accessible. A sample dataset is constructed from the most participated projects found in eight popular domains, including front-end framework, mobile, data science, DevOps, blockchain platform, collaboration, web app, and programming language. The total number of participants across these eight projects is 95,416, which accounts for 13% of the entire Gitter's participant population.

Data prepossessing. For each project, we collect all the utterances recorded before "2020-11-20". Data is then preprocessed by the following steps:

(1) *Formatting*. To pre-possess the textual utterances, we first normalize the non-ASCII characters (*i.e.,* emojis) to standard ASCII strings. Since low-frequency tokens such as URL, email address, code, HTML tags, and version numbers do not contribute to the classification results in chat utterances, we replace them with specific tokens *[URL], [EMAIL], [HTML], [CODE]* and *[ID]* respectively. We also utilize Spacy[3] to tokenize sentences into terms. To alleviate the influence of word morphology, we then perform lemmatization and lowercasing on terms with Spacy. (2) *Disentanglement*. We use a state-of-the-art disentanglement model to separate the dialogues. In total, we obtain 173,278 dialogues. (3) *Sampling*. We randomly sample 100 dialogues from each project for further manual analysis. (4) *Exclusion*. We then exclude unreadable dialogues, including a) dialogues that are written in non-English languages; b) dialogues that contain too many specific tokens; and c) dialogues with many typos and grammatical errors.

The final dataset contains 749 disentangled dialogues consisting of 7,226 utterances, contributed by 822 participants. Detailed statistics are shown in Table 1.

3 Model Comparison

In this section, we conduct an in-depth empirical study to evaluate the state-of-the-art dialogue disentanglement models towards software-related chat.

[2]https://github.com/disensoftware/disentanglement-for-software

[3]https://www.spacy.io/

Id	Project	Domain	Entire Population			Sample Population		
			PA	Dial.	Utter.	SP	SD	SU
P_1	Angular	Frontend Framework	22,467	79,619	695,183	125	97	778
P_2	Appium	Mobile	3,979	4,906	29,039	73	87	724
P_3	Dl4j	Data Science	8,310	27,256	252,846	93	100	1,130
P_4	Docker	DevOps	8,810	3,954	22,367	74	90	1,126
P_5	Ethereum	Blockchain Platform	16,154	17,298	91,028	116	96	516
P_6	Gitter	Collabration Platform	9,260	7,452	34,147	87	86	515
P_7	Typescript	Programming Language	8,318	18,812	196,513	110	95	1,700
P_8	Nodejs	Web-App Framework	18,118	13,981	81,771	144	98	737
Total			*95,416*	*173,278*	*1,402,894*	*822*	*749*	*7,226*

Table 1: The characteristics of selected projects. *PA* and *SP* represent the number of participants in the entire population and the representative sample dataset respectively. *Dial.* and *SD* represent the number of dialogues, *Utter.* and *SU* represent the number of utterances respectively.

3.1 Model Selection

By searching through the literature published in the representative venues (*Computational Linguistics, NAACL, ACL, IJCAI, EMNLP and SIGIR*) for the last 15 years, we choose eight approaches as the candidate models for our study. Their code accessibility, dataset accessibility, and learning technologies are summarized in Table 2. From the table, we can observe that five out of the eight models provide public assess to their source code and dataset. Moreover, these five models also utilize more advanced technologies such as deep neural network. Thus, we select *FF*, *BiLSTM*, *BERT*, *E2E* and *PtrNet* as the state-of-the-art (SOTA) models to be compared in our study. Each model is described in detail as follows.

Model	Code Available	Dataset Available	Technology
Weighted-SP [Shen *et al.*, 2006]	No	No (Linux)	Weight Calculation
ME Classifier [Elsner and Charniak, 2010]	No	No (Ubuntu)	Traditional Classifier
BiLSTM [Mehri and Carenini, 2017]	Yes	Yes (Movie)	Recurrent Neural Network
CISIR [Jiang *et al.*, 2018]	No	Yes (News)	Convolutional Neural Network
FF [Kummerfeld *et al.*, 2019]	Yes	Yes (Ubuntu)	FeedForward Neural Network
BERT [Li *et al.*, 2020]	Yes	Yes (Movie)	Encoder/Decoder Network
E2E [Liu *et al.*, 2020]	Yes	Yes (Movie)	Encoder/Decoder Network
PtrNet [Yu and Joty, 2020]	Yes	Yes (Ubuntu)	Encoder/Decoder Network

Table 2: Candidate disentanglement models.

Given a graph of utterances $G\{V, E\}$, the goal of *FF model* and *BiLSTM model* is to predict whether there is an edge E between the utterance u_j and u_k, where utterances are nodes and edges indicate that one utterance is a response to another. Each connected component is a conversation.

$$\begin{aligned} G &= \{V, E\} \\ V &= \{u_1, u_2, ...u_n\} \\ E &=< u_j, u_k > \end{aligned} \tag{1}$$

(1) **FF model** is a feedforward neural network with two layers, 256 dimensional hidden vectors, and softsign nonlinearities. The input is a 77 dimensional numerical feature extracted from the utterance texts, which includes TF-IDF, user name, time interval, whether two utterances contain the

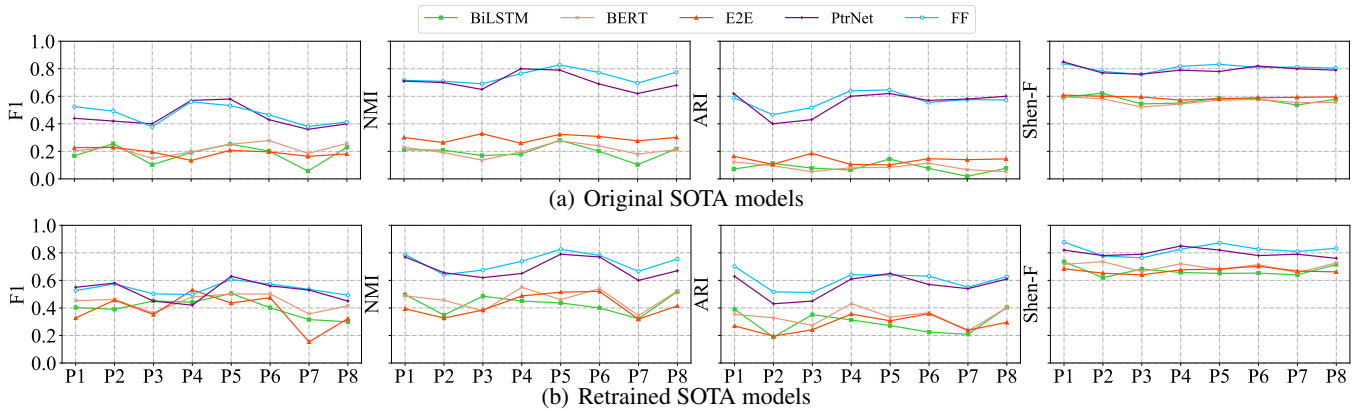


Figure 1: Performance comparison of five SOTA models.

same words and *etc.*. *FF* model is trained from 77,563 manually annotated utterances.

(2) **BiLSTM model** is a bidirectional recurrent neural network with 160 context maximum size, 200 neurons with one hidden layer. The input is a sequence of 512 dimensional word vectors. *BiLSTM* model is trained from 7.1 million utterances and 930K dialogues.

Unlike *FF* and *BiLSTM*, given a sequence of utterances $[u_1, u_2, ..., u_n]$, the goal of *BERT*, *E2E* and *PtrNet* is to learn the following probability distribution, where y_i is the action decision for the utterance u_i.

$$P(D) = \prod_{i=1}^{n} P(y_i|y_{<i}, u_{\leq i}); 1 \leq i \leq n \quad (2)$$

(3) **BERT model** uses the *Masked Language Model* and *Next Sentence Prediction* [Devlin *et al.*, 2018] to encode the input utterances, with 512 embedding size and 256 hidden units. *BERT* model is trained from 74,963 manually annotated utterances.

(4) **E2E model** performs the dialogue Session-State encoder to predict dialogue clusters, with 512 embedding size, 256 hidden neurons and 0.05 noise ratio. *E2E* model is trained from 56,562 manually annotated utterances.

(5) **PtrNet model** utilizes the pointer network to predict links within utterances, with 512 embedding size and 256 hidden units. *PtrNet* model is trained from 52,641 manually annotated utterances.

3.2 Evaluation Measures

We investigate the evaluation measures that are adopted by existing literature, as shown in Table 3. There are four evaluation measures that are frequently used: *ARI* [Santos and Embrechts, 2009], *NMI* [Strehl and Ghosh, 2002], *Shen-F* [Shen *et al.*, 2006], *F1* [Crestani and Lalmas, 2001].

Adjusted Rand Index (ARI) is commonly used in cluster analysis to measure the degree of agreement between two data clusters. An index value that is closer to 0 represents random labeling, where a value of 1 indicates that the data clusters are identical. **Normalized Mutual information (NMI)** is a normalization of the Mutual Information (MI) score to scale the results between 0 (no mutual information) and 1 (perfect correlation). NMI evaluates the distribution consistency of predicted and true clustering, regardless of the sorting of the clustering. **F1** calculates the number of perfectly matched dialogues and is considered as the most strict measure. **Shen-F** defines a weighted sum of F1 scores over all dialogues. The F1 weights are calculated based on the number of utterances in the dialogues.

	P	R	**F1**	1-to-1	loc_3	MAP	MRR	**NMI**	**ARI**	**Shen-F**
Weighted-SP			✓							✓
ME Classifier	✓	✓								
CISIR				✓	✓					✓
BiLSTM			✓			✓		✓	✓	✓
FF	✓	✓	✓		✓		✓			✓
BERT			✓					✓	✓	✓
E2E			✓					✓	✓	✓
PtrNet	✓	✓	✓					✓	✓	

Table 3: Selection of representative measures.

3.3 Experiments

We conduct two experiments to evaluate how effective SOTA models are at disentangling software-related chat.

Experiment #1 (Original). We use the five original SOTA models as described and trained in the existing literature to disentangle software-related chat. As shown in Figure 1(a), *BiLSTM*, *Bert*, and *E2E* models can only achieve medium-level scores on Shen-F, with low performances on F1, NMI and ARI. *FF* and *PtrNet* models significantly[4] outperform the other three models. However, further analysis shows no significant difference ($p = 0.56$) between *FF* and *PtrNet* models. Since *FF* model achieves slightly higher performances than *PtrNet* model on average, we consider *FF* model performs the best at disentangling software-related dialogues in this experiment. Specifically, *FF* model can achieve high scores on clustering measures (avg(NMI)=0.74 and avg(Shen-F)=0.81), medium-level scores on perfectly matching (avg(F1)=0.47), and pairwise clustering similarity (avg(ARI)= 0.57).

Experiment #2 (Retraining). We then retrain the five SOTA models on software-related chat. For each SOTA model, we train with seven projects and evaluate with the

[4]All the p values in Significance T-test are below 0.05.

eighth project. In order to study the significance of the performance improvement contributed by retraining, we conduct five paired t-tests between each original model and its retrained model. The p values indicate that the retrained *FF* and *PtrNet* do not have significant improvement ($p_1 = 0.43$, $p_2 = 0.62$) to the original model. More specifically, the retraining strategy does not guarantee performance improvement from their original models. As shown in Figure 1, while the retrained FF model increases its F1, ARI, and Shen-F by 0.03, 0.03, and 0.01 on average respectively, the average NMI score decreases by 0.01. The retrained *PtrNet* model displays a similar trend. The F1 and ARI increase by 0.07 and 0.01 respectively on average, while the average Shen-F shows no change and the average NMI score decreases by 0.02. On the contrary, the retrained *BiLSTM*, *BERT* and *E2E* models significantly ($p_3 = 10^{-5}$, $p_4 = 10^{-6}$, $p_5 = 10^{-3}$) outperform the original ones. As shown in Figure 1, the retrained *BERT* model obtains the largest performance improvement among the three models: the average F1, NMI, ARI and Shen-F increases by 0.22, 0.25, 0.26, and 0.13 respectively. However, the retrained *FF* and *PtrNet* models still significantly outperform the other three retrained models.

Findings: Both *FF* and *PtrNet* models outperform the rest in both experiments. However, we observe that the retraining strategy is unable to contribute significantly to the original models in terms of performance improvement. Since the original *FF* model can achieve slightly higher performances on average than the original *PtrNet* model, we recommend adopting the original *FF* model as the best model to disentangle software-related dialogues. Despite the original *FF* model being the best, the average F1 score is only 0.47, which indicates a relatively low perfectly matching score.

4 Human Satisfaction Measures

Since the goal of dialogue disentanglement is to make it easy for users to find information from entangling dialogues, it is essential to evaluate the quality of the disentangled results against human satisfaction. Various measures (as introduced in Section 3.2) have been proposed to calculate how close the disentangled results are from the ground-truth data. To understand how well these measures reflect human satisfaction, we conduct an experiment to compare these existing measures with manually-scored human satisfaction.

4.1 Measures Analysis

Manually Scoring Human Satisfaction

We build two teams to manually score human satisfaction of the disentangled dialogues produced by the original FF model. Each team consists of one Ph.D. candidate and one developer. 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 leverage a five-point Likert scale [Hartson and Pyla, 2019] to score human satisfaction. The rating scale goes from "strongly unsatisfied" to "strongly satisfied", with the values of 1 to 5 respectively. Each disentangled dialogue receives two scores from two team members. We host discussions for dialogues with inconsistent ratings.

Category	Error[1]		Correlation[2]	Hypothesis[3]		
Analysis	RMSE	MAE	PEA	IST	PST	ANOVA
NMI	0.38	0.34	0.08	10^{-55}	10^{-46}	10^{-55}
ARI	0.37	0.32	0.02	10^{-19}	10^{-17}	10^{-19}
Shen-F	0.41	0.36	0.17	10^{-69}	10^{-59}	10^{-69}
F1	0.19	0.14	0.85	10^{-4}	10^{-14}	10^{-4}
DLD	**0.08**	**0.07**	**0.92**	0.51	0.31	0.51

[1] Negative correlation with effectiveness.
[2] Positive correlation with effectiveness (upper bound 1).
[3] Significance test, where $p < 0.05$ indicates significant difference.

Table 4: Deviation analysis results between existing measures and human satisfaction scores.

Deviation Analysis

We then conduct a quantitative analysis to compare the differences between the existing measures and the manually-scored human satisfaction.

Since F1, ARI, NMI, and Shen-F all range from 0 to 1, while manually-scored human satisfaction scales from 1 to 5, to compare the differences, we normalize human satisfaction into $score \in [0, 1]$ with a linear function: $score = 0.25 \times (score - 1)$.

We then analyze the deviation between existing measures and manually-scored human satisfaction in the following aspects:

(1) Error analysis: We calculate *RMSE* (Root-mean-square Error) and *MAE* (Mean Absolute Error) [Botchkarev, 2019] as the error deviation between two samples.

(2) Correlation analysis: We calculate *Pearson* (PEA) correlation coefficient between two samples.

(3) Hypothesis testing: We perform *Independent Sample T-Test* (IST), *Paired Sample T-Test* (PST), and *Analysis of Variance* (ANOVA) to measure and validate the deviation between two samples.

- *Independent Sample T-Test* (IST): $H_0 : \mu_1 = \mu_2, H_1 : \mu_1 \neq \mu_2$.
- *Paired Sample T-Test* (PST): $H_0 : \mu_Z = 0, H_1 : \mu_Z \neq 0$, where $Z = X_1 - X_2$.
- *Analysis of Variance* (ANOVA): $H_0 : \sigma_1^2 = \sigma_2^2, H_1 : \sigma_1 \neq \sigma_2$

Table 4 shows the deviation analysis results. By comparing the error and correlation results of NMI, ARI, Shen-F and F1, we find that F1 is the most similar to human satisfaction scores, with the lowest Error ($RMSE = 0.19$, $MAE = 0.14$) and the highest correlation ($PEA = 0.85$). However, F1 is not statistically acceptable since the hypothesis testing shows a significant difference with human satisfaction ($p < 0.05$, *reject*). Figure 2 visualizes the value distribution of measures and human satisfaction. We can see that NMI, ARI, and Shen-F are likely to overrate the disentanglement results, while F1 slightly underrates them.

Finding: We can conclude that existing measures are unable to reflect human satisfaction accurately, thus a new measure is needed.

4.2 A Novel Measure: DLD

We leverage *Levenshtein Distance* [Christen, 2006] and *Levenshtein Ratio* [Rani and Singh, 2018] to estimate the editing

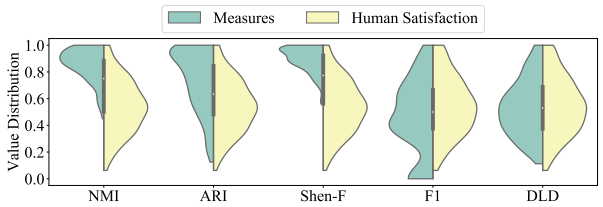


Figure 2: Value distribution of the measures and human satisfactions.

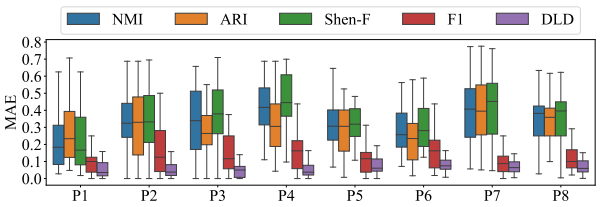


Figure 3: MAE comparison within projects.

effort of dialogue-to-dialogue transition (i.e.: *Delete*, *Insert* and *Update*).

Given the ground-truth disentanglement dialogues D_T and the predicted disentanglement dialogues D_P, we define the *Dialogue Levenshtein Revision*:

$$DLR_v = \mathbb{E}[\sigma(|D_T - D_P| + |D_P - D_T|, \eta)] \quad (3)$$

Where function $\mathbb{E}$ denotes the expectation of predicted dialogue pairs $< D_P, D_T >$ in a collection of utterances and $|D_i - D_j|$ denotes the number of utterances in D_i that are not included in D_j. We perform the Sigmod function to smooth the absolute value:

$$\sigma(x, \eta) = \frac{1}{1 + e^{x-\eta}} \quad (4)$$

Since DLR_v measures the size of absolute revisions, we further define *Dialogue Levenshtein Ratio* to measure the proportion of revisions in one dialogue:

$$DLR_t = \mathbb{E}[1 - \frac{|D_T - D_P| + |D_P - D_T|}{|D_T| + |D_P|}] \quad (5)$$

By taking both DLR_v and DLR_t into consideration, we define *Dialogue Levenshtein Distance* as a novel measure for human satisfaction:

$$DLD = \lambda DLR_t + (1 - \lambda)DLR_v, 0 \leq \lambda \leq 1 \quad (6)$$

Effectiveness of DLD

By tuning the values of η and λ, we observe that *DLD* can achieve the smallest deviation when $\eta = 5$ and $\lambda = 0.8$. The last row of Table 4 shows the error, correlation, and hypothesis testing analysis results between *DLD* and manually-scored human satisfaction. Compared with other measures, *DLD* achieves the lowest error ($RMSE = 0.08$, $MAE = 0.07$) and highest correlation ($PEA = 0.92$). Moreover, figure 3 illustrates that *DLD* can achieve the lowest error across all projects. The p values of the three hypothesis tests are all over 0.05, which indicates that *DLD* shows no significant differences when compared to manually-scored human satisfaction. Figure 2 visualizes such value distribution. *DLD* shows the most symmetric shape, which indicates that the measure is the most accurate in matching the manually-scored human satisfaction.

Finding: While the existing measures evaluate the similarity between the predicted and true disentanglement results based on perfectly matching or clustering distribution, *DLD* incorporates the Levenshtein distance to quantitatively measures such similarity. When compared to the existing measures, *DLD* is able to more accurately measure human satisfaction.

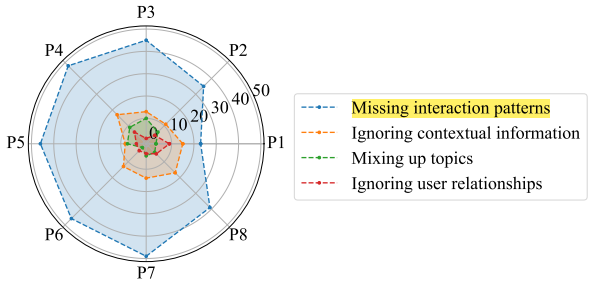


Figure 4: The distributions of four bad cases per project.

5 Bad Cases Analysis

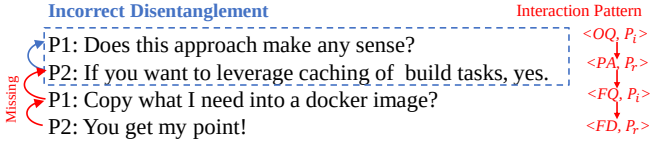
We perform an in-depth analysis on the "bad case" disentangled dialogues that received human satisfaction $score \leq 3$ to further investigate why the disentangled dialogues are unsatisfying. We classify these disentangled dialogues by using open card sorting [Rugg and Mcgeorge, 1997]. Similar to the process of scoring human satisfaction, we group participants into two teams to cross-inspect the classifications of bad cases. Discussions are hosted for inconsistent classifications.

As the result, we identify four categories: *Ignoring User Relationships, Mixing up Topics, Ignoring Contextual Information,* and *Ignoring Interaction Patterns*. As shown in Figure 4, all four bad cases occur in every sampled project. The most commonly occurred bad case (64%) is *Ignoring Interaction Patterns*. To better understand each bad case, we further elaborate on the definitions with examples.

5.1 Ignoring Interaction Patterns (64%)

Definition: The utterances in disentangled dialogues are incorrect due to missing the utterances that comply with the interaction patterns.

Example 1.



Three interaction patterns have been observed when analyzing the content of these unsatisfying disentangled dialogues. We leverage the user intents proposed by Bayer *et al.* [2020] and Qu *et al.* [2019]. These user intents represent the utterance intention, which indicates what the participants want to convey when posting messages. Each pattern is a sequence of <Intent, Role>, where Intent={OQ (Origin Question), PA (Potential Answer), FQ (Follow-up

Question), FD (Further Detail), CQ (Clarify Question)}, and Role={P_i(Dialogue Initiator), P_r (Respondent)}. The patterns can be described as follows:

(1) *Direct Answer* (<OQ, P_i >, <PA, P_r >): P_i initiates the dialogue with OQ, P_r then directly answers with PA.

(2) *Clarifying Answer* (<OQ, P_i >, <PA, P_r >, <FQ, P_i >, <FD, P_r >): P_i initiates the dialogue with OQ, a potential answer PA is posted by P_r. Then a sequence of follow-up questions is posted by dialogue initiator P_i to clarify until the answer is fully understood and accepted by P_i.

(3) *Clarifying Question* (<OQ, P_i >, <CQ, P_r >, <FD, P_i >, <PA, P_r >): P_i initiates the dialogue with OQ, a set of clarifying questions CQ is posted by P_r to clarify the original question until the original question is fully understood by P_r. Then a potential answer PA is posted by P_r.

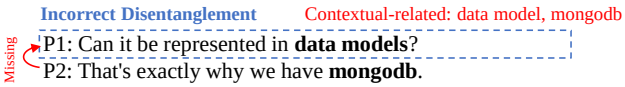
The dialogue in Example 1 illustrates the *Clarifying Answer* pattern. After P_2 provides a potential answer, P_1 asks a follow-up question to clarify the answer. Then P_2 answers the follow-up question. In this case, the existing disentanglement models fail to predict that the four utterances should be in the same dialogue. Instead, only the first two utterances are considered as one dialogue.

Thus, we recommend that disentanglement models can be optimized by identifying utterances that display the above interaction patterns.

5.2 Ignoring Contextual Information (21%)

Definition: The utterances in disentangled dialogues are incomplete due to the missing of contextual-related utterances.

Example 2.

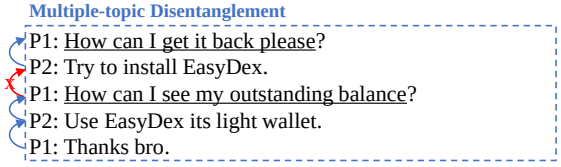


Example 2 shows an incorrect disentanglement that misses respondent utterance. P_1 asks about the usage of data models and P_2 replies with MongoDB with no further clarifications. Although we know that MongoDB is a data model and these two utterances are highly related, since the existing disentanglement models often use textual similarity, these two utterances appear to be as less related. Thus, lacking such contextual information will often lead to incorrect disentanglement. Therefore, we recommend disentanglement models to incorporate contextual similarity, such as pre-trained word vectors GloVe [Pennington *et al.*, 2014; Lowe *et al.*, 2015; Elsner and Charniak, 2008].

5.3 Mixing up Topics (9%)

Definition: The disentangled dialogues contain multiple topics that are discussed by the same group of participants.

Example 3.

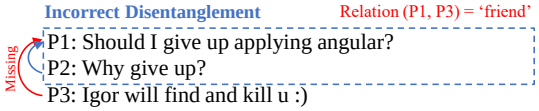


Example 3 shows an incorrect disentangled dialogue with mixed up topics in one conversation. P_1 asks two questions that belong to different topics while P_2 provides separate answers to each question. The first two utterances talk about the installation of EasyDex, while the following two utterances talk about the usage of EasyDex. Such disentangled dialogue violates the single-topic principle of dialogue disentanglement [Di *et al.*, 2020]. Therefore, we recommend integrating topic extraction algorithms, such as *LDA* [Blei *et al.*, 2013] into disentanglement models to separate topics.

5.4 Ignoring User Relationships (6%)

Definition: The utterances in disentangled dialogues are incorrect due to the lack of understanding on the relationships among the participants.

Example 4.



Example 4 shows an incorrect disentanglement when the relationship between participants is ignored. There are three utterances in this dialogue: P_1 posts a question, P_2 and P_3 reply with two distinct answers. The existing disentanglement models only predict P_1 and P_2 as one dialogue, while excluding P_3. Without understanding the relationship between P_1 and P_3, the answer posted by P_3 seems to be irrelevant. However, by analyzing their post histories, we find that 76% of the utterances posted by P_1 are associated with the utterances posted P_3. With such frequent interaction, we consider that P_1 and P_3 have a close relationship. Thus, P_3 is very likely to be in the same dialogue as P_1 and P_2. Therefore, we recommend that disentanglement models can utilize the relationship and collaboration history among participants to improve performance.

6 Conclusion

In this paper, we evaluate five state-of-the-art dialogue disentanglement models on software-related dialogues to investigate how these models can be used in the context of software engineering. To acquire the best performing model, we conduct two experiments with the original and the retrained models respectively. Considering the trade-offs between training effort and performances, the results show that the original FF model is the best model on disentangling software-related dialogues. Although the original FF model has the best performance, the evaluation measures do not accurately reflect human satisfaction. Thus, we introduce a novel measure *DLD*. Compared to other measures, *DLD* is able to more accurately measure human satisfaction. Finally, we further investigate the reasons why some disentangled dialogues are unsatisfying. By classifying these disentangled dialogues, we identify four common bad cases. We believe that our study can provide a clear direction on how existing disentanglement models can be optimized.

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