Dialogue Disentanglement in Software Engineering: How Far are We?

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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 dialogs 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 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 dialog disentanglement in software engineering.

1 Introduction

Online communication platforms such as Gitter[1] have been heavily used by software organizations as 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 dialog 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 dialog 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.

Unlike general conversations, software engineering (SE) dialogs have different and distinct characteristics: (1) SE dialogs heavily focus on resolving issues, thus they are mostly in the form of question and answer. In our observation, nearly 90% of the SE dialogs are in this Q&A style. However, in the general dialogs (i.e. the news or movie dialogs), the proportion of such Q&A dialogs is much less. Existing approaches that do not consider this Q&A aspect may result in disentanglement errors (elaborated in Section 5). (2) SE dialogs are domain-specific and each domain has its own technical terms and concepts. Existing approaches that leverage general dialogs without incorporating any domain-specific terminology cannot understand jargon accurately. (3) SE dialogs usually involve more complex problems, which require developers to discuss various topics within one dialog. Thus, SE dialogs are more likely to show a higher degree of entanglement.

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 dialog 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 dialog disentanglement towards software-related chat that contains

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the majority of technical and professional conversations.

In this paper, we conduct an exploratory study on 7,226 real-world developers' dialogs mined from eight popular open-source projects hosted on Gitter. First, we compare five state-of-the-art dialog disentanglement approaches based on two strategies: transferring the original models across domains and retraining the models on software-related dialogs. 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, we summarize four bad cases of 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 summarized 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, *DLD*, for quantitatively measuring human satisfaction on disentangled results;
- We release a dataset[2] of disentangled software-related dialogs to facilitate the replication of our study and future improvements of disentanglement models.

2 Dataset Preparation

Project Studying. We select Gitter due to its high popularity and openly accessible. A sample dataset is constructed from the most participated projects found in eight popular domains, which include "Frontend", "Mobile", "Data Science", "DevOps", "Blockchain", "Collaboration", "Language", and "Web App". The total number of participants across these eight projects is 95,416, which accounts for 13% of the entire Gitter's participant population.

Data Preprocessing. We collect all the 1,402,894 utterances recorded before "2020-11-20" in each project. Data is then preprocessed by the following steps: 1) *Formatting*. To preprocess 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 to tokenize sentences into terms, and perform lemmatization and lowercasing on terms. 2) *Experiment Dataset Creation*. We employ a 3-step manual process to generate the dialog dataset for our experiments. First, we randomly sample 100 utterances from each community's live chat log, intending to trace corresponding dialogs associated with each utterance.

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

Id	Project	Domain	Entire Population		Sample Population		
			PA	UT	PA	DL	UT
P1	Angular	Frontend	22,467	695,183	125	97	778
P2	Appium	Mobile	3,979	29,039	73	87	724
P3	Dl4j	Data Science	8,310	252,846	93	100	1,130
P4	Docker	DevOps	8,810	22,367	74	90	1,126
P5	Ethereum	Blockchain	16,154	91,028	116	96	516
P6	Gitter	Collaboration	9,260	34,147	87	86	515
P7	Typescript	Language	8,318	196,513	110	95	1,700
P8	Nodejs	Web App	18,118	81,771	144	98	737
Total			*95,416*	*1,402,894*	*822*	*749*	*7,226*

Table 1: The characteristics of selected projects. *PA* refers to the #participants, *DL* refers to the #dialogs, *UT* refers to the #utterances.

This step leads to a total of 800 utterances sampled from eight projects. Next, using each utterance as a seed, we identify its preceding and succeeding utterances iteratively and grouped the related utterances into the same dialog. We use these manually disentangled dialogs as the *Ground-Truth* Data. Finally, we add the intervened utterances that are posted among those labeled dialogs back into the dataset. 3) *Exclusion*. We exclude unreadable dialogs: a) dialogs that are written in non-English languages; b) dialogs that contain too many specific tokens; and c) dialogs with typos and grammatical errors.

The final dataset contains 749 disentangled dialogs consisting of 7,226 utterances, contributed by 822 participants. Table 1 shows the detailed statistics.

3 Model Comparison

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

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 networks. Thus, we select *FF*, *BiLSTM*, *BERT*, *E2E* and *Ptr-Net* as the state-of-the-art (SOTA) models to be compared in our study. Each model is described in detail as follows.

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.

$$G = \{V, E\}, V = \{u_1, u_2, ...u_n\}, E =< u_j, u_k > \quad (1)$$

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

Model	Code	Dataset	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 NN
CISIR [Jiang *et al.*, 2018]	No	Yes (News)	Convolutional NN
FF [Kummerfeld *et al.*, 2019]	Yes	Yes (Ubuntu)	FeedForward NN
BERT [Li *et al.*, 2020]	Yes	Yes (Movie)	Encoder/Decoder NN
E2E [Liu *et al.*, 2020]	Yes	Yes (Movie)	Encoder/Decoder NN
PtrNet [Yu and Joty, 2020]	Yes	Yes (Ubuntu)	Encoder/Decoder NN

Table 2: Candidate disentanglement models.

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

Table 3: Selection of representative measures.

BiLSTM. *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 dialogs.

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.

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

BERT. *BERT* model uses the *Masked Language Model* and *Next Sentence Prediction* [Devlin *et al.*, 2019] to encode the input utterances, with 512 embedding size and 256 hidden units. *BERT* model is trained from 74,963 manually annotated utterances.

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

PtrNet. *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, 2000].

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 the 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 dialogs, which is considered as the most strict measure. Shen-F defines a weighted sum of F1 scores overall dialogs. The F1 weights are all calculated based on the number of utterances in our dialogs.

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, *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 outperform the other three models. However, further analysis shows no significant[3] 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 dialogs 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. We use "retrain" to refer to the fine-tuning as well as the training on the new data. Specifically, the original *Bert*, *E2E*, *PtrNet*, and *BiLSTM* utilize pre-training for contextual embedding, so we fine-tune the four SOTA models on the new data. Since *FF* is a feedforward network, we train it on the new data directly. For each SOTA model, we retrain with seven projects and evaluate with the 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

[3]Significance T-test follows $p < 0.05$.

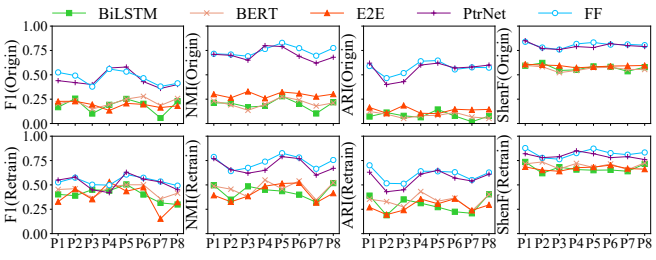


Figure 1: Performance comparison of five SOTA models.

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.

Finding. 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 SOTA models are built with general dialogs, retraining still cannot effectively address the challenges that SOTA models face in disentangling SE dialogs, such as the lack of understanding of domain-specific terminology and the inefficiency in disentangling complex dialogs with mixing up topics. Moreover, after combining dropout with early stopping to avoid risks of overfitting, we observe that convergences are already achieved at epoch 10-15, thus we believe that the retraining performance could not be better even given more data.

In this study, we recommend adopting the original *FF* model as the best model to disentangle software-related dialogs, as the original *FF* model can achieve slightly higher performances on average than the original *PtrNet* model. 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 dialog disentanglement is to make it easy for users to find information from entangling dialogs, it is essential to evaluate the quality of the disentangled results against human satisfaction. Various measures (see 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 dialogs 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 varies from "strongly unsatisfied" to "strongly satisfied", with the values of 1 to 5 respectively. Each disentangled dialog receives two scores from two team members, and we host discussions for dialogs with inconsistent ratings. The average Cohen's Kappa score [Cohen, 1960] of our study is 0.82, indicating that the participants highly agree with each other.

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

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:

Error Analysis. We calculate *Root-Mean-Square Error* (RMSE) and *Mean Absolute Error* (MAE) [Botchkarev, 2019] as the error deviation between two samples.

Correlation Analysis. We calculate *Pearson* (PEA) correlation coefficient between two samples.

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:

- *IST*: $H_0 : \mu_1 = \mu_2, H_1 : \mu_1 \neq \mu_2$.
- *PST*: $H_0 : \mu_Z = 0, H_1 : \mu_Z \neq 0$, where $Z = X_1 - X_2$.
- *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. 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

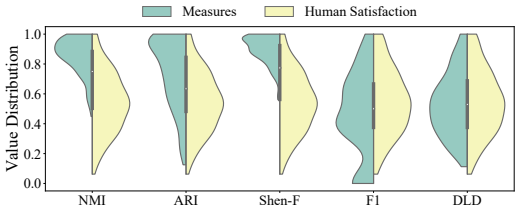


Figure 2: Value distribution of the five different measures and human satisfactions.

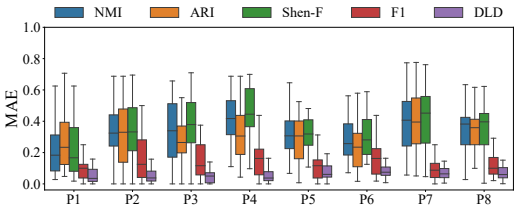


Figure 3: MAE comparison within projects.

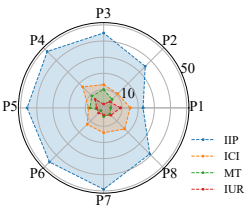


Figure 4: Distributions of bad cases in projects.

effort of dialog-to-dialog transition (i.e.: *Delete*, *Insert* and *Update*). Given the ground-truth disentanglement dialogs D_T and the predicted disentanglement dialogs D_P, we first calculate the differences between D_P and D_T:

$$\Delta(D_T, D_P) = |D_T - D_P| + |D_P - D_T|, \quad (3)$$

where $|D_i - D_j|$ denotes the number of utterances in D_i that are not included in D_j. We then perform the Sigmod function σ to normalize the absolute value into $(0, 1)$:

$$\sigma(\Delta(D_T, D_P), \eta) = 1/(1 + e^{\Delta(D_T, D_P) - \eta}), \quad (4)$$

where η is the threshold number of utterances that indicates good disentanglement or not. We define *Dialog Levenshtein Revision* as follows:

$$DLR_v = \mathbb{E}[\sigma(\Delta(D_T, D_P), \eta)], \quad (5)$$

where $\mathbb{E}$ denotes the expectation of a collection of dialog pairs $< D_P, D_T >$. Since DLR_v measures the size of absolute revisions, we further define *Dialog Levenshtein Ratio* to measure the proportion of revisions in one dialog:

$$DLR_t = \mathbb{E}[1 - \Delta(D_T, D_P)/(|D_T| + |D_P|)]. \quad (6)$$

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

$$DLD = \lambda DLR_t + (1 - \lambda)DLR_v, 0 \leq \lambda \leq 1. \quad (7)$$

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. The *DLD* shows the most symmetric shape, which indicates that our 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* can more accurately measure human satisfaction. We consider the reason is that edit distance could reflect the completeness of information in relation to the dialog structure whereas the existing measures do not. Moreover, the *DLD* can also be extensively used for general dialog disentanglement since it does not involve any SE-specific knowledge.

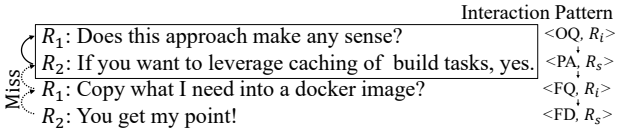
5 Bad Cases Analysis

We perform an in-depth analysis on the "bad case" disentangled dialogs that received human satisfaction $score \leq 3$ to further investigate why the disentangled dialogs are unsatisfying. We classify these disentangled dialogs 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 Interaction Patterns*, *Ignoring Contextual Information*, *Mixing up Topics*, and *Ignoring User Relationships*. 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*. These bad cases might also occur in general dialogs with different distributions. To better understand each bad case, we further elaborate definitions with examples.

5.1 Ignoring Interaction Patterns (IIP: 64%)

Definition. Utterances in the disentangled dialog are incorrect due to missing the utterances that comply with the interaction patterns. For example:



Three interaction patterns have been observed when analyzing the content of these unsatisfying disentangled dialogs. 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

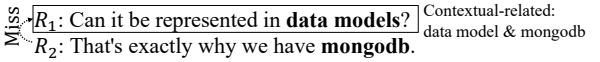
Detail), CQ (Clarify Question)}, and Role={R_i(Dialog Initiator), R_s (Respondent)}. The interaction patterns can be described as follows:

1. *Direct Answer* (<OQ, R_i >, <PA, R_s >): R_i initiates the dialog with OQ, R_s then directly answers with PA.
2. *Clarifying Answer* (<OQ, R_i >, <PA, R_s >, <FQ, R_i >, <FD, R_s >): R_i initiates the dialog with OQ, a potential answer PA is posted by R_s. Then follow-up questions are posted by dialog initiator R_i to clarify until the answer is fully understood and accepted by R_i.
3. *Clarifying Question* (<OQ, R_i >, <CQ, R_s >, <FD, R_i >, <PA, R_s >): R_i initiates the dialog with OQ, CQ are posted by R_s to clarify the original question until the original question is fully understood by R_s. Then a potential answer PA is posted by R_s.

The dialog in Example 1 illustrates the *Clarifying Answer* pattern. After R_2 provides a potential answer, R_1 asks a follow-up question to clarify the answer. Then R_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 dialog. Instead, only the first two utterances are considered as one dialog. Thus, we recommend that disentanglement models can be optimized by identifying utterances that display the above interaction patterns.

5.2 Ignoring Contextual Information (ICI: 21%)

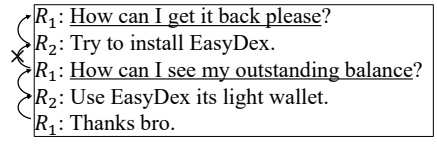
Definition. Utterances in the disentangled dialog are incomplete due to the missing of domain-specific contextual-related utterances. For example:



The example shows an incorrect disentanglement that misses respondent utterance. R_1 asks about the usage of data models and R_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 (MT: 9%)

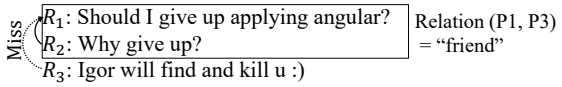
Definition. The dialog contains multiple topics that are discussed by the same group of participants. For example:



The example shows an incorrect disentangled dialog with mixed-up topics in one conversation. R_1 asks two questions that belong to different topics while R_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 dialog violates the single-topic principle of dialog disentanglement [Di *et al.*, 2020]. Therefore, we recommend integrating topic extraction algorithms, such as *LDA* [Blei *et al.*, 2003] into disentanglement models to separate topics.

5.4 Ignoring User Relationships (IUR: 6%)

Definition. Utterances in the disentangled dialog are incorrect due to the lack of understanding of the relationships among the participants. For example:



The example shows an incorrect disentanglement when the relationship between participants is ignored. There are three utterances in this dialog: R_1 posts a question, R_2 and R_3 reply with two distinct answers. The existing disentanglement models only predict R_1 and R_2 as one dialog, while excluding R_3. Without understanding the relationship between R_1 and R_3, the answer posted by R_3 seems to be irrelevant. However, by analyzing their post histories, we find that 76% of the utterances posted by R_1 are associated with the utterances posted R_3. With such frequent interaction, we consider that R_1 and R_3 have a close relationship. Thus, R_3 is very likely to be in the same dialog as R_1 and R_2. We recommend that disentanglement models can use the participants' relationship and collaboration history to improve performance.

6 Conclusion

In this paper, we evaluate five SOTA dialog disentanglement models on SE dialogs to investigate how these models can be used in the context of SE. 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 one for disentangling SE dialogs. 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* can more accurately measure human satisfaction. Finally, we investigate the reasons why some disentangled dialogs are unsatisfying. By classifying these disentangled dialogs, we identify four common bad cases. We believe that our study can provide clear directions on how to optimize existing disentanglement models.

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