From spoken dialogue to formal summary: An utterance rewriting for dialogue summarization

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Abstract

Due to the dialogue characteristics of unstructured contexts and multi-parties with first-person perspective, many successful text summarization works have failed when dealing with dialogue summarization. In dialogue summarization task, the input dialogue is usually spoken style with ellipsis and co-references but the output summaries are more formal and complete. Therefore, the dialogue summarization model should be able to complete the ellipsis content and co-reference information and then produce a suitable summary accordingly. However, the current state-of-the-art models pay more attention on the topic or structure of summary, rather than the consistency of dialogue summarization with its input dialogue context, which may suffer from the personal and logical inconsistency problem. In this paper, we propose a new model, named ReWriteSum, to tackle this problem. Firstly, an utterance rewriter is conducted to complete the ellipsis content of dialogue content and then obtain the rewriting utterances. Then, the co-reference data augmentation mechanism is utilized to replace the referential person name with its specific name to enhance the personal information. Finally, the rewriting utterances and the co-reference replacement data are used in the standard BART model. Experimental results on both SAMSum and DialSum datasets show that our ReWriteSum significantly outperforms baseline models, in terms of both metric-based and human evaluations. Further analysis on multi-speakers also shows that ReWriteSum can obtain relatively higher improvement with more speakers, validating the correctness and property of ReWriteSum.

1 Introduction

Despite many existing text summarization works on single-speaker written documents, such as news and encyclopedia articles (Rush et al., 2015; Gehrmann et al., 2018), dialogue summarization has gain increasing attention (Zhang et al., 2021).

One reason is that it has various promising applications in real world, such as customer services and doctor-patient interaction. More importantly, the dialogue summarization process is more difficult since there are more interactive participants with first-person perspective, and unstructured context to consider (Chen and Yang, 2021), which poses great challenges for researchers in this area.

For this task, it is clear that there is a big gap between the input spoken dialogue and the output formal summaries. That is, in dialogue, users tend to use many incomplete utterances, which al-

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ways omit or refer back to entities appeared in the history, called ellipsis and co-reference. But the summary is usually formal and written, which contains rich and complete salient information. Here we give two examples, as shown in Table 1. In the first example, the incomplete utterance “I will take it” omits “laptop” which can be seen in the first sentence, while the ground-truth summary contains the complete information “Ann will take it for $250 with accessories”. We can see that the generated summary by BART confuses the accessories “bag” with the subject “laptop” and then generate a logic inconsistent summary “pick a bag”. And in the second example, many people’s names are in the contexts, which are more difficult for the summarization model to distinguish the co-reference relationship, i.e., “I’ll have to hit on her” refers to “Dave” via “I”. As a result, BART confuses “Mike” with “Dave”, and then generates a personal inconsistent summary “Mike will have to hit on her”. What’s more, such factual inconsistencies have also been observed in previous studies (Cao et al., 2018; Kryściński et al., 2019, 2020). Therefore, it is critical to complete the omission and co-reference information in dialogue utterances for dialogue summarization task.

However, the current models pay more attention on introducing intrinsic information, such as dialogue acts (Goo and Chen, 2018), key point sequence (Liu et al., 2019a) and co-reference information (Liu et al., 2021b). They demonstrate that the introduction of intrinsic information and human annotation is effective in improving the quality of summary generation. However, dialogue acts and key point sequence require a lot of human effort, so they can not be widely used in applications. The co-reference chain is integrated by GNN, which only pays attention to the referencing information of entities but not supplement and restore the referred and omitted pronouns in the dialogue utterances, resulting in the misunderstanding of omitted contents. More importantly, they all ignore the consistency between the dialogue summary and its source dialogue, which may lead to the personal and logical inconsistency problem caused by multi-speakers.

In this paper, we propose a new model, namely ReWriteSum, to tackle this problem. The core idea is to use the utterance rewriting mechanism to complete the omitted content and utilize the data augmentation strategy to enhance the co-reference information. Specifically, we first use the utterance rewriter to complete the ellipsis content in dialogue contexts, and then obtain the rewritten utterances dataset. Then, we use the co-reference data augmentation mechanism to replace the referential person name with its specific name with a certain probability to enhance the personal information. Finally, we use both the rewritten utterances and the co-reference replacement data as input, and utilize the state-of-the-art model BART to generate the corresponding summary.

In our experiments, we use two public datasets to evaluate our proposed models, i.e. SAMSum and DialSum. The results show that ReWriteSum has the ability to produce more consistent and suitable summary than traditional summarization models. Besides, we conduct an analysis on multi-speakers, and the results show that the ReWriteSum obtains relatively higher improvement with more speakers, which indicates that the incomplete utterance rewriting and co-reference data augmentation mechanism by our model are reasonable.

2 Related Work

2.1 Document Summarization

The aim of automatic document summarization is to convert a well-structured document into short text containing salient information. It has received widespread attention in recent literature, especially abstractive document summarization. For example, Rush et al. (2015) introduce an attention-based sequence-to-sequence model for abstractive document summarization. To solve out-of-vocabulary and content repeat issues, See et al. (2017) propose a pointer-generator network with copy and coverage mechanism. Chen and Bansal (2018) leverage reinforcement learning to extract salient sentences in document and then generate summary. Recent studies have focused on the pre-trained models. Liu and Lapata (2019) take use of pre-trained language model BERT (Kenton and Toutanova, 2019) in extractive summarization and abstractive summarization. Lewis et al. (2020) propose BART which combined bi-directional encoder from BERT and auto-regressive decoder from GPT (Radford et al., 2018) to obtain the results of language generation.

2.2 Dialogue Summarization

Compared with document summarization, dialogue summarization aims at generating condensed text from the dialogue contexts among multiple speakers. For instance, Shang et al. (2018) propose an
unsupervised multi-sentence compression method to generate meeting summaries. Zhao et al. (2019) employ a hierarchical encoder and a reinforced decoder based on sequence-to-sequence model to generate meeting summaries.

Some studies have focused on employing conversational analysis for dialogue summarization. Goo and Chen (2018) use sentence-gated mechanism to apply dialogue act in the generation process. Liu et al. (2019a) design a key point sequence as auxiliary information to describe the logic of the abstract. Liu et al. (2019c) and Li et al. (2019) introduce topic information for dialogue summarization. However, their methods need a large amount of human annotation. To avoid this issue, Chen and Yang (2020) use diverse conversational structures like topic segments and conversational stages to design a multi-view summarizer. Recent works often introduce intrinsic information to better model the dialogue process. Liu et al. (2021b) use the graph neural network to employ co-reference information to generate summaries. Feng et al. (2020) introduce the dialogue discourse information, and design Meeting Graph to describe them. Lei et al. (2021) introduce speaker information to improve the generation performance in the context with multi-speakers.

2.3 Incomplete Utterance Rewriting

Incomplete utterance rewriting has received extensive research attention. In question answering, Kumar and Joshi (2016) propose non-sentential utterance resolution based on sequence-to-sequence model for utterance rewriting. To resolve incomplete follow-up questions, retrieval-based sequence-to-sequence model (Elgohary et al., 2019; Quan et al., 2019) are proposed, which can generate complete questions. Liu et al. (2019b) take use of question structures to rewrite utterance in conversational semantic parsing. Pan et al. (2019) leverage BERT to select words, and use these words to generate rewritten utterance. Su et al. (2019) distinguish the weights of context utterances for utterance rewriting. Liu et al. (2020) employ edit-based text generation and semantic similarity measurement for utterance rewriting.

3 Model

In this section, we will describe our ReWriteSum model in detail, with architecture shown in Figure 1.
We adopt a neural model for abstractive dialogue summarization. In detail, given the dialogue \( D \) as input, we firstly utilize the utterance rewriting system and the co-reference resolution system to generate the new complete rewriting dialogue \( D' \). And then, we use the rewriting dialogue \( D' \) as input, instead of dialogue \( D \), to generate the dialogue summary.

### 3.2 Incomplete Utterance Rewriting

Given the whole dialogue \( D = \{u_1, \ldots, u_{|D|}\} \), we define the context as \( C = \{u_1, \ldots, u_{t-1}\} \) and the incomplete utterance as \( u_t(t \leq |D|) \). Incomplete utterance rewriting aims at rewriting \( u_t \) to \( u_t' \) through the context \( C \). After rewriting, \( u_t' \) should not only have the same meaning as \( u_t \), but also can be understood separately. Specifically, we concatenate all the contextual utterances \( C \) into a \( K \)-length word sequence \( \mathbf{c} = (c_1, \ldots, c_K) \). At the same time, the incomplete utterance is represented as \( u_t = \{x_1, \ldots, x_L\} \), where \( L \) is the length of \( u_t \). And then, the rewritten utterance \( u_t' \) can be obtained by editing the incomplete dialogue \( u_t \) using the words in \( \mathbf{c} \).

In order to determine the editing operation, we define a word-level edit matrix \( \mathbf{M} \) (Liu et al., 2020), where each element \( m_{kl} \) represents the editing type between \( c_k \) and \( x_l \). There are three editing types: substitute, insert and None. The substitute operation means replacing the word \( x_l \) with the context word \( c_k \). The insert operation means inserting a word \( c_k \) before or after a certain token \( x_l \). And None means no operation. Following Liu et al. (2020), we establish a word-level edit matrix through three neural layers: a context layer, an encoding layer and a subsequent segmentation layer, as shown in Figure 2, and then generate rewritten utterance based on this word-level edit matrix.

#### 3.2.1 Context Layer

Given the contextual word sequence \( \mathbf{c} \) and the incomplete utterance \( u_t \), we firstly concatenate the \( \mathbf{c} \) and \( u_t \) as input, and employ Glove (Pennington et al., 2014) to initialize the word embedding. And then, we use BiLSTM (Schuster and Paliwal, 1997) with both the left-to-right and right-to-left text representations to obtain the contextual information:

\[
\text{BiLSTM}(\mathbf{c} ; u_t) = (g_1, \ldots, K; h_1, \ldots, L),
\]

where \( g_k \) is the hidden state of contextual word \( c_k \) in \( \mathbf{c} \) and \( h_l \) is the hidden state of the word \( x_l \) in \( u_t \).

#### 3.2.2 Encoding Layer

After obtaining the context-aware hidden states \( g \) and \( h \), we use three similarity functions to calculate the word-level relevance between context and incomplete utterance. Specifically, for each word \( c_k \) and \( x_l \), a D-dimensional vector \( \mathbf{F}(x_l, c_k) \) is set to indicate the relevance:

\[
\mathbf{F}(x_l, c_k) = |h_l \odot g_k; \cos(h_l, g_k) : h_l \mathbf{W}_{Bi} g_k|,
\]

where \( \odot \) is the element multiplication operation to obtain the element-wise similarity, \( \cos(\cdot, \cdot) \) is the cosine similarity, and \( \mathbf{W}_{Bi} \) is a learned parameter in learned bi-linear similarity. Finally, we obtain the feature map matrix \( \mathbf{F} \in \mathbb{R}^{L \times K \times D} \).

Similarity function is used to describe word-to-word relevance from various aspects, which is a necessary condition for the edit type. However, the encoder layer can only obtain local information, which is not enough for incomplete utterance rewriting. Therefore, we conduct a segmentation layer to introduce the global information.

#### 3.2.3 Segmentation Layer

Given the feature map matrix \( \mathbf{F} \in \mathbb{R}^{L \times K \times D} \) in Equation 1, we use the segmentation layer to calculate the word-level edit matrix \( \mathbf{M} \in \mathbb{R}^{L \times K} \).

The segmentation layer is inspired by U-Net (Ronneberger et al., 2015), consisting of five convolutional neural network (CNN) with skip-connection mechanism, which is used to extract the global con-
textual editing information, as shown in Figure 2:

\[ F' = \text{CNN}(F), \]
\[ F'' = \text{CNN}(\text{Pool}(F')), \]
\[ F''' = \text{DeConv}(\text{CNN}(\text{Pool}(F''))), \]
\[ F'''' = \text{DeConv}(\text{CNN}(F''', F'')), \]
\[ M = \text{FeedForward}(\text{CNN}(F''''', F')), \]

where \( \text{CNN}(.) \) is the two layers of convolutional modules, \( \text{Pool}(.) \) is the MaxPooling operation, \( \text{DeConv}(.) \) is the deconvolution neural network, and \( \text{FeedForward}(.) \) is the feedforward layer.

Given the word-level edit matrix \( M \), for each word \( e_k \) in contextual utterances and \( x_l \) in incomplete utterance, the element \( M_{kl} \) determines one of three editing operations: substitute, insert and none. Specifically, when \( M_{kl} \) is close to 0, the corresponding operation is none. When close to 1, the operation is substitution, 2 is inserting before and 3 is inserting after. After that, we can rewrite each utterance \( u_l \) in \( D \) as \( u'_l \) based on \( M \).

Finally, we use all the rewritten utterances \( u'' \) to replace \( D \) as \( D' \), and obtain the rewriting dataset \( D_{rew} = \{(D'_1, S_1), (D'_2, S_2), \ldots, (D'_N, S_N)\} \).

### 3.3 Co-reference Data Augmentation

Taking into account that there are a large number of names and referential relations in the dialogue process, we propose to use the data augmentation mechanism to enhance the personal information for dialogue summarization task.

Given a dialogue content \( D \), we utilize a co-reference resolution system (Joshi et al., 2020) to obtain its corresponding co-referential chain set \( E = \{e_1, e_2, \ldots, e_{|E|}\} \), where \( e_i = \{x_{i1}, x_{i2}, \ldots, x_{ie_i}\} \) is represented as the \( i^{th} \) co-referential chain in dialogue \( D \) and \( x_{ij} \) denotes the \( j^{th} \) word in co-referential chain \( e_i \). Take the example two in Table 1 as an example, the \( E = \{\{\text{Mike}_{0}, \ldots, \_64\}, \{\text{Wendy}_{4}, \ldots, \_52\}, \{\text{Dave}_{9}, \ldots, \_79\}, \{\text{Jerry}_{80}\}\} \), where the word \( \text{id}_{dx} \) is the \( \text{id}_{dx}^{th} \) word in \( c \).

Then, we refer to all the pronouns in the whole dialogue \( D \) and replace it with its corresponding person name \( x_{\text{name}_i} \) based on a certain probability: when the length of pronouns \( |e_i^{\text{pron}}| \geq 5 \), if the output probability of co-reference system \( P(x_{ij}) \geq 0.5 \), then replace \( x_{ij} \) with \( x_{\text{name}_i} \), otherwise, no replacement; when \( 0 < |e_i^{\text{pron}}| < 5 \), if \( P(x_{ij}) \geq 0.8 \), then replace; when \( |e_i^{\text{pron}}| = 0 \), remove this example.

Finally, after the person’s name replacement, we obtain an additional dialogue dataset \( D_{aug} = \{(D'_1, S_1), \ldots, (D'_G, S_G)\} \), where \( G \) is the number of dialogue-summary pairs after removing.

### 3.4 Summary Generation

Given \( D_{rew} \) and \( D_{aug} \), we combine them to obtain our rewriting dataset \( D_{rews} \). To generate the summary, we utilize the state-of-the-art model BART (Lewis et al., 2020) to encode the dialogue content \( D \) and decode the summary \( S \) step by step.

We use maximum likelihood estimation to train our model. Given a pair of dialogue \( D \) and summary \( S = \{y_1, \ldots, y_{|S|}\} \) from \( D_{rews} \), we minimize the negative log-likelihood of the target sequence:

\[
\mathcal{L} = \sum_{D_{rews}} \sum_{t=1}^{|S|} \log P(y_t | y_1^{t-1}, D; \theta_{BART}^\text{large}).
\]

### 4 Experiments

In this section, we conduct experiments on two English dialogue summarization datasets SAMSum (Gliwa et al., 2019) and DialSum (Chen et al., 2021) to evaluate our proposed method.

#### 4.1 Experimental Settings

We first introduce some empirical settings, i.e., datasets, baselines, and evaluation measures.

##### 4.1.1 Datasets

We use two public dialogue summarization datasets. SAMSum contains everyday English message-like dialogues and annotated summary. We randomly split the SAMSum data to training, validation, and testing sets, which contains 14,732, 818 and 819 pairs, respectively. DialSum\(^1\) contains English speaking practice dialogue and annotated summary, which has been cleaned and pre-processed by publisher, including deleting non-English characters, correcting spelling errors and grammatical errors. We randomly split the DialSum data to training, validation, and testing sets, which contains 12,460, 500 and 500 pairs, respectively.

##### 4.1.2 Baselines and Parameters Setting

Seven baseline models are used for comparison on SAMSum, and four baseline models on DialSum. Lead3 (See et al., 2017) model extracts

\(^1\)https://github.com/cylnlp/DialogSum
the first three leading sentences in the article as the summary. LONGEST (Gliwa et al., 2019) model selects the top N longest sentences as the summary. PTGen (See et al., 2017) model introduces copy and coverage mechanisms into the basic sequence-to-sequence model. FastAbs-RL (Chen and Bansal, 2018) model firstly selects salient sentences and then generates abstractive summaries through reinforcement learning. DynamicConv + GPT-2/News (Wu et al., 2018) model replaces the attention mechanism with a lightweight dynamic in transformer. BART (Lewis et al., 2020) is a pre-trained model, which uses the noise function to destroy text, and then reconstructs the original text, including two versions, BART(base) and BART(large). Multiview BART (Chen and Yang, 2020) extracts different views of dialogue features, and then uses a multi-view decoder to combine these features to generate summaries.

Our model uses a pre-trained model BART(large) for initialization. In detail, BART (large) has 12 layers of encoder-decoder Transformer structure. Each layer has 16 attention heads. The hidden size and feed forward filter size are 1024 and 4096, respectively. It contains a total of 400M trainable parameters. The dropout rates for all layers are set to 0.1. The optimizer uses Adam (Kingma and Ba, 2015) with 200 warmup. The learning rates of SAMSum and DialSum are both 3e-5, and the maximum tokens for a certain batch are 800 and 1000, respectively. We run our models on a Tesla V100 GPU card with Pytorch.

4.1.3 Evaluation Measures
To evaluate our models, we utilize both quantitative metrics and human evaluation in our experiment. In detail, we use ROUGE-1, ROUGE-2 and ROUGE-L as quantitative metrics, which is widely used in NLP and summary tasks (Liu et al., 2021a,b; Chen and Yang, 2020). For human evaluation, we randomly select 100 dialogue-summary pairs from the test set of SAMSum and DialSum, respectively. Five annotators(all CS majored students studying NLP) are demanded to give the comparison between our model and baseline models. They are not told which summaries are derived from the baseline model and which summaries are derived from our model. They are required to evaluate the generated summary from three aspects: whether the generation is fluent, whether it has omitted content, and whether it has factual inconsistent errors. The evaluation results are represented as win, loss and tie, respectively indicating that the quality of generated summary by ReWriteSum is better, weaker or equal to baselines.

4.2 Experimental Results
In this section, we demonstrate our experiment results on SAMSum and DialSum datasets.

4.2.1 Metric-based Evaluation
The quantitative evaluation results on SAMSum and DialSum datasets are shown in Table 2. For SAMSum dataset, we refer to (Gliwa et al., 2019) to show the results of Lead3, PTGen, DynamicConv+GPT-2/News, and FastAbs-RL. From the results, we can see that the pretrained models, such as BART and Multiview BART, outperform the traditional summarization models, showing the effectiveness of pre-training.

| Model       | Lead3 | PTGen | DynamicConv+GPT-2 | FastAbs-RL | DynamicConv+News |
|-------------|-------|-------|-------------------|------------|------------------|
| R-1         | 31.4  | 40.1  | 41.8              | 42.0       | 45.4             |
| R-2         | 8.7   | 15.3  | 16.4              | 18.1       | 20.7             |
| R-L         | 29.4  | 36.6  | 37.6              | 39.2       | 41.5             |
| BART(large) | 50.9  | 25.0  | 47.1              | 49.9       | 51.2             |

| Model       | ReWriteSum vs. Multi-view | ReWriteSum vs. BART |
|-------------|---------------------------|---------------------|
| win(%)      | 48.5                      | 52.6                |
| loss(%)     | 6.9                       | 5.1                 |
| tie(%)      | 44.6                      | 42.3                |

Table 2: Metric-based evaluations of ReWriteSum and baselines on SAMSum and DialSum. R-1, R-2, R-L denote ROUGE-1, ROUGE-2, ROUGE-L, respectively.

| Model       | Multi-view | BART |
|-------------|------------|------|
| win(%)      | 42.3       | 46.8 |
| loss(%)     | 8.1        | 7.3  |
| tie(%)      | 49.6       | 45.9 |

Table 3: Human evaluations on SAMSum and DialSum.
| Dialogue Example 1                                    | Dialogue Example 2                                                                 |
|------------------------------------------------------|-------------------------------------------------------------------------------------|
| Mia: could anybody help me to buy a flight ticket? ... | Maria: Who’s gonna be at imf lecture tomorrow? ...                                  |
| Mia: I don’t have a credit card at the moment. ...    | Alexander: On Saturday Alexander already meet for another.                           |
| Tom: You can use mine help Mia to buy a flight ticket!| So my option is Friday afternoon or tomorrow.                                        |
| Mia: Should I send you the link to buy a flight ticket?| Sarah: Tomorrow and on Friday Sarah available ...                                   |
| Tom: Just send me the flight, company and your personal data that I may need to buy a flight ticket. | Sarah: So can we meet tomorrow evening? 17:15?                                    |
| Mia: Great, so nice of you, thanks Tom.               | Alexander: It is fine by me.                                                        |

| ReWriteSum Prediction: | BART Prediction: |
|------------------------|------------------|
| Mia doesn’t have a credit card at the moment. Tom will use his card to buy a flight ticket for himself. Tom needs the flight, company and personal data. | Alexander, Martha, Sarah, Lawrence and Sarah will meet tomorrow evening at 17:15 to discuss the imf lecture. Lawrence will be late. |

Table 4: Generated summaries from different models on SAMSum. Red words show the inconsistent content. Green words show the factual content. Blue words show the supplemented part by our model. Orange words show the name replacement by our model.

language model for dialogue summarization task. Our ReWriteSum model performs the best. Take the ROUGE-1 and ROUGE-L score for example, our ReWriteSum model obtains 54.2 and 50.1, respectively, which obviously outperforms Multiview BART model, i.e., 52.2 and 49.9.

From the results on DialSum in Table 2, we can see that our model also obtains the best performance. Take the ROUGE-1 and ROUGE-L score for example, our ReWriteSum obtains 35.1 and 32.1, respectively, which obviously outperforms BART(large), i.e., 34.1 and 31.2. However, the performance increment on DialSum is not significant as comparison on SAMSum. The reason is that utterances in DialSum are relatively more complete and the interactive speakers are fewer than SAMSum. According to statistics, there are only 13 sentences with more than 4 speakers in DialSum, which leads to relatively few errors caused by multi-speakers. We have conducted the significant test, and the result shows that the improvements of our model are significant on both datasets, i.e., p-value < 0.01.

In conclusion, our ReWriteSum model has the ability to generate a more complete and accurate summary than baselines.

### 4.2.2 Human Evaluation

Human evaluation results are shown in Table 3. The percentages of win, loss and tie, as compared with the baselines, are given to evaluate the fluency, completeness and consistency of generated summary by ReWriteSum. From the results, we can see that the proportion of evaluators who think our model better is the largest, surpassing other models. Take SAMSum dataset for example, ReWriteSum model obtains preference gains (win subtract loss) 41.6%, 47.5%, respectively.

### 4.2.3 Case Study

To further understand our proposed model, we give some generated cases in Table 4. According to the result, we can notice that ReWriteSum model performs better than baseline models. Take example1 in Table 4 as an example, BART model generates that “Tom will buy a flight ticket for himself”, but in the dialogue content, the dialogue fact is ‘Tom will buy a flight ticket for Mia’. The reason is that the dialogue content tends to be omitted in daily dialogues. From example1, we can see that, in the entire dialogue, only Mia mentions "help me to buy a flight ticket" at the beginning, and this sentence is omitted in the subsequent utterances, which makes BART unable to correctly understand who the "ticket" will be bought for. When we rewrite the incomplete dialogue (in blue font), "help Mia to buy a flight ticket" is added to the end of some utterances, so that our model can generate a more accurate and logical consistent summary.

From example2, due to the complex references in this dialogue, BART misunderstood "Lawrence will be late" as "Lawrence will meet tomorrow evening at 17:15". When co-reference data augmentation is carried out, it strengthens the connection between "you" and "Alexander, Martha, Sarah" in the sentence "Lawrence: I will be late, but you can start without me", so as to avoid this personal inconsistency error.

### 4.3 Analysis

In order to confirm whether the improvement is related to incomplete utterance rewriting(IUR) and co-reference data augmentation(CDA), a further analysis is conducted, containing ablation study, the impact of participants, and the error analysis.
Table 5: Ablation experiment results on SAMSum.

| Model      | R-1 | R-2 | R-L |
|------------|-----|-----|-----|
| ReWriteSum | 54.2| 27.1| 50.1|
| - w/o CDA  | 51.1| 25.1| 47.5|
| - w/o IUR  | 52.3| 25.1| 48.1|

Table 6: Percentage of typical errors in summaries generated by BART(large) and our ReWriteSum model.

| Model       | Missing Information | Wrong Reference | Incorrect Reasoning |
|-------------|---------------------|-----------------|---------------------|
| BART(large) | 36                  | 24              | 19                  |
| ReWriteSum  | 14                  | 6               | 8                   |
| - w/o CDA   | 17                  | 19              | 9                   |
| - w/o IUR   | 29                  | 7               | 11                  |

Figure 3: Rouge-L scores of ReWriteSum and BART with different number of speakers.

### 4.3.1 Ablation Study

To confirm the effectiveness of our IUR and CDA module, we conduct ablation experiments on SAMSum dataset. The results are shown in Table 6. ReWriteSum w/o IUR means that ReWriteSum model removes IUR module and only with CDA to generate summaries. From the results, we can see that when only CDA is applied, the ROUGE score is still larger than the baseline, but smaller than the ReWriteSum model. ReWriteSum w/o CDA means that our ReWriteSum model removes the CDA module and only with IUR to generate summaries. We can see that the ROUGE has decreased as compared with our ReWriteSum model, but it is still higher than baseline models. Therefore, we think that both incomplete utterance rewriting and co-reference data augmentation have positive effects for dialogue summarization.

Not only that, we also notice that the ROUGE score using IUR alone is higher than using CDA alone, indicating that IUR contributes more to the dialogue summarization task.

### 4.3.2 Impact of Participants

We conduct an experimental analysis with different number of participants, by calculating the ROUGE score for baselines and our ReWriteSum model on SAMSum. From the Figure 3, we can see that with the increase of participants, the rouge score of our model decreases more slowly, because: (1) with the increase of participants, the omitted information will also increase, but our incomplete utterance rewriting module has the ability to reduce the impact of too much omitted information in the summary; (2) our co-reference data augmentation module can reduce the impact of complex referencing caused by too many participants.

### 4.3.3 Error Analysis

To further study the impact of IUR and CDA on the quality of generated summaries, we count the following 3 kinds of errors that appear in the summaries generated by the baseline model and our model: **Missing Information**: content information that appears in gold summaries is missing from generated summaries. **Wrong Reference**: content in the generated summaries, such as the person’s actions or name, does not match what is described in the source dialogue. **Incorrect reasoning**: the conclusions drawn by the generated summaries are inconsistent with the facts in the source dialogue.

We randomly select 100 dialogues and their generations from SAMSum and count the error categories, as shown in Table 5. In terms of missing information, our model outperforms the baseline model because IUR can effectively prevent the model from missing information. According to the wrong reference numbers, our model performs better than the baselines because CDA can enhance the model’s understanding of referential information. Errors occur in incorrect reasoning are also reduced as our model complements default information and enhances understanding of referential information.

### 5 Conclusion

In this work, we propose a new dialogue summarization model, namely ReWriteSum, which leverages incomplete utterance rewriting and co-reference data augmentation mechanism to generate summaries for dialogue. Our motivation comes from the fact that there are a lot of ellipsis and demonstrative pronouns in the dialogue, which seriously affects the quality of dialogue summary generation. Our core idea is to utilize the incomplete utterance rewriting module to complete the ellipsis information in the dialogue content and enhance the personal entities with the co-reference data augmentation mechanism. We conduct exper-
iments on both SAMSum and DialSum datasets, and the results on both quantitative and qualitative analysis verify the effectiveness of our proposed model. Therefore, we obtain the conclusion that the incomplete utterance rewriting and co-reference data augmentation are effective for improving the quality of generation for dialogue summarization.

6 Ethical Considerations

The abstractive summarization dialogue system proposed in this work can be applied to dialogue scenarios. It can quickly process a lengthy dialogue into a short content containing the core idea of the dialogue. Such features can be applied to meetings, customer service, and medical scenarios to facilitate people’s life. The datasets SAMSum and DialSum used in this work are publishable and for research purposes only. There may be some biased content in the datasets, which should be viewed carefully.

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