Improving Abstractive Dialogue Summarization with Speaker-Aware Supervised Contrastive Learning

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Abstract

Pre-trained models have brought remarkable success on the text summarization task. For dialogue summarization, the subdomain of text summarization, utterances are concatenated to flat text before being processed. As a result, existing summarization systems based on pre-trained models are unable to recognize the unique format of the speaker-utterance pair well in the dialogue. To investigate this issue, we conduct probing tests and manual analysis, and find that the powerful pre-trained model can not identify different speakers well in the conversation, which leads to various factual errors. Moreover, we propose three speaker-aware supervised contrastive learning (SCL) tasks: *Token-level SCL*, *Turn-level SCL*, and *Global-level SCL*. Comprehensive experiments demonstrate that our methods achieve significant performance improvement on two mainstream dialogue summarization datasets. According to detailed human evaluations, pre-trained models equipped with SCL tasks effectively generate summaries with better factual consistency.

1 Introduction

Dialogue summarization aims to condense the essential information in the dialogue into a brief text. Compared with text summarization, the conversations are semi-structured data and contain multiple participants who shall be distinguished (Gurevych and Strube, 2004; Feng et al., 2021a). Furthermore, dialogues are characterized by informal language, coreference, and repetition (Chen and Yang, 2020). All of these bring new challenges to the existing text summarization methods.

Although pre-trained models have achieved great success in Natural Language Processing especially text summarization (Liu and Lapata, 2019; Lewis et al., 2020; Qiu et al., 2020; Lin et al., 2021), how to properly utilize them in dialogues with a special speaker-utterance structure is still an obstacle. A line of previous work utilizes pre-trained models and deals with dialogue summarization as flat text. Chen and Yang (2020) segment dialogues into blocks from multiple semantic views and process them using BART. Feng et al. (2021b) use DialoGPT (Zhang et al., 2019) as an unsupervised annotator to help models understanding conversations. However, due to the gap with the pre-training object, the pre-trained models are hard to capture speaker information. To investigate these, we conduct a manual analysis on popular datasets SAMSum (Gliwa et al., 2019) and AMI (McCowan et al., 2005). We discover that, even for the state-of-the-art model BART, **55%** of the generated summaries contain factual errors for dialogues with multiple speakers. Among them, up to **56.4%** are caused directly by speaker confusion and speaker missing

Dialogue Text
Jeff: Should we go to the village party? Lia: I'm too tired after hiking. Mico: I'd like to go, there may be some hot boys! Lia: I doubt Jim: like a real village boy? Jim: who doesn't even speak English? Mico: yes, the dummer, the better. Jim: haha, stupid fucks good, they say. Mico: I confirm! Lia: not my cup of tea. Mico: I'll go there, who wants to join? Jeff: I'll go as well. Mico: wanna drive? Jeff: so you could drink? Mico: would be nice, hahah. Jeff: not excited, but ok.
Gold Summary
Mico and Jeff will go to the village party. Jeff will drive.
Baseline Summary (by BART)
Jeff, Lia and Mico are going to the village party. Lia is too tired to go. Mico will drive.
Our Summary
Jeff and Mico are going to the village party. Lia is too tired after hiking. Jeff will drive.

Table 1: A dialogue example in the SAMSum dataset. The summary generated by BART has two factual errors: Lia is not going to the village party; it will be Jeff driving instead of Mico. Our model can generate factually correct summaries.

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Proceedings of the 29th International Conference on Computational Linguistics, pages 6540–6546
October 12–17, 2022.

(see Section 3.2). As shown in Table 1, the model's inability to identify speakers results in serious factual inconsistencies.

Another tributary of previous work (Zhao et al., 2019; Liu and Chen, 2019; Zhu et al., 2020; Lei et al., 2021) utilizes the hierarchical network instead of pre-trained models to leverage the dialogue's structural information. However, how to explicitly model the information of speakers in pre-trained sequence-to-sequence (seq2seq) models remains unsolved. Zhu et al. (2020) introduces speaker embedding to distinguish speakers for meetings with fixed participants. However, in most cases, the number and identity of the participants in the conversations are unknown. Thus the trained embedding is not a general solution.

Intuitively, if the representation derived from the encoder has sufficient information to identify speakers, the decoder will produce superior summaries, especially for summaries that follow a pattern of *someone does something* as shown in Table 1. In this paper, we first conduct a probing experiment to show that the representation of the dialogue obtained from BART can not distinguish speakers well. To address this issue, we use contrastive learning to improve the alignment of the representation derived from the encoder, i.e., to make the encoder output diverse hidden states based on corresponding speakers. We propose three speaker-aware supervised contrastive learning tasks: *Token-level SCL*, *Turn-level SCL*, and *Global-level SCL*. By jointly training these tasks in the fine-tuning stage, we can substantially improve the model's ability to identify different speakers and further understand the content of the whole dialogue. Comprehensive experiments and human evaluations on SAMSum and AMI (McCowan et al., 2005) reveal that our models generate summaries with higher ROUGE scores and better factual consistency. Our main contributions include (a) this is the first work to give a detailed investigation of the speaker identification problem in dialogue summarization, (b) proposing speaker-aware SCL tasks to address the problem, and evaluating our methods with the experimental and manual examination.

2 Method

2.1 Probing Test

To investigate how well pre-trained seq2seq models can distinguish speakers, we conduct a simple probing experiment on SAMSum, a widely-used dialogue summarization corpus. Concretely, we first encode the integral dialogue text with the BART (Lewis et al., 2020) encoder and randomly sample K tokens to obtain their hidden states. Then, in pairs, we aggregate and feed these hidden states into MLP to determine whether they are from the same speaker. To investigate the compatibility of the pre-trained seq2seq model with flat dialogue text, we freeze the parameters of the BART encoder and solely fine-tune the MLP classification layers during training stage. Then we evaluate the classification accuracy on the test set. Intuitively, the binary classification task is easy, but the accuracy is only **58.1%** for vanilla BART. Even after fine-tuning BART with the summarization task (parameters of BART are not frozen) on SAMSum before the probing test , the accuracy is still only **60.2%**[1]. The result indicates that pre-trained seq2seq models can not identify speakers well from flat dialogue text, and simply fine-tuning with the dialogue summarizing task is unhelpful. We need more explicit methods to help models understand flat dialogue text.

2.2 Supervised Contrastive Learning Tasks

To address the above problem, inspired by the research about contrastive learning (Mikolov et al., 2013; Saunshi et al., 2019; He et al., 2020; Velickovic et al., 2019), we introduce SCL tasks to help models identify speakers. The model is supposed to minimize the distance between representations of utterances from the same speaker and vice versa by optimizing the SCL loss during the fine-tuning stage.

Regular Paradigm for Dialogue Summarization Formally, a dialogue $D = (t_1, t_2, \cdots, t_n)$ consists of n turns, and each turn t_i contains the utterance u_i and the corresponding speaker s_i, that is, $t_i = (s_i, u_i)$. Firstly, we use Transformer-Encoder (Vaswani et al., 2017) to model the dialogue-level contextual representation of each tokens from the flat dialogue text.

$$H = \text{Transformer-Encoder}(D), \tag{1}$$

where the input sequence is the concatenation of all turns. Then, we can generate the summary $\hat{y}$ with Transformer-Decoder. The generation loss $\mathcal{L}_{gen}$ is cross-entropy loss between $\hat{y}$ and gold summary y.

[1]By jointly training the Global-level SCL task in fine-tuning stage, the accuracy reaches **77.9%**.

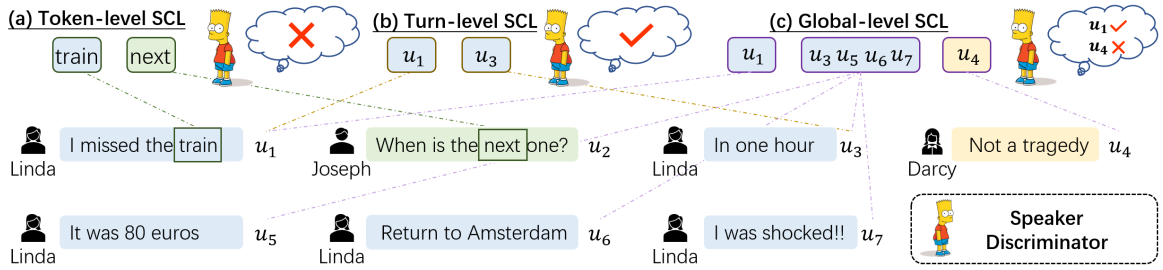

Figure 1: Overview of our speak-aware SCL tasks. *Token-level SCL* and *Turn-level SCL* mean the model needs to discriminate whether two tokens/turns are from the same speaker. *Global-level SCL* let the model choose what the speaker might say in a particular turn when given all the utterances of this speaker. The representations are obtained by inputting the whole dialogue into the encoder.

Incorporating Contrastive Loss To enable the utterance representation to contain more speaker information, we incorporate three levels of contrastive losses into the regular fine-tuning paradigm.

Generally, let (o_i, s_i) denote a sampled token or utterance and the associative speaker. The contrastive loss $\mathcal{L}_{ctr}$ for the SCL task is calculated as follows:

$$\mathcal{L}_+ = \sum_{i,j}^{s_i=s_j} -\log(\sigma(\mathbf{o}_i \cdot \mathbf{o}_j)), \quad (2)$$

$$\mathcal{L}_- = \sum_{i,j}^{s_i\neq s_j} -\log(1-\sigma(\mathbf{o}_i \cdot \mathbf{o}_j)), \quad (3)$$

$$\mathcal{L}_{ctr} = \mathcal{L}_+ + \mathcal{L}_-, \quad (4)$$

where σ is logistic function that measures the similarity between two representations and $\mathbf{o}_i$ is the contextual representation of o_i derived from H. The detailed sampling methods of o_i are dicussed in Section 2.2.1 $\sim$ 2.2.3.

The final loss $\mathcal{L} = \lambda\mathcal{L}_{ctr} + \mathcal{L}_{gen}$ and λ is the weight coefficient to adjust the ratio of $\mathcal{L}_{ctr}$ and $\mathcal{L}_{gen}$ in the final loss $\mathcal{L}$. The model is supposed to maximize similarity among samples of the same speaker and vice versa while being optimized for the summary generation.

Next, we introduce our proposed supervised contrastive tasks in detail.

2.2.1 Token-level SCL

The first task is the Token-level SCL which means the model distinguishes whether two tokens are from the same speaker. As illustrated in Figure 1(a), we randomly sample m token-speaker pairs $T = \{(o_1, s_1), (o_2, s_2), ..., (o_m, s_m)\}$ from D, where o_i is a token and s_i is the corresponding speaker. The hidden state of o_i obtained through the encoder is used to represent the i-th sample.

2.2.2 Turn-level SCL

Compared with Token-level SCL, we increase the granularity of the input to fuse the semantic information of the context. As shown in Figure 1(b), we randomly sample two turns from D and mask the speaker names in text, denoted as (o_i, s_i) and (o_j, s_j). Then we derive $\mathbf{o}_i$ by taking the mean pooling of the hidden states of all tokens in o_i.

2.2.3 Global-level SCL

To maximize the mutual information between utterances of the same speaker (Linsker, 1988; Kong et al., 2019), we extend the Turn-level SCL task to Global-level SCL by introducing global information. Intuitively, we can understand the speaking style of a specific person from all the words he or she has said. Therefore, we provide the model with all the utterances of a certain speaker and let it choose what this speaker might say in a particular turn (described in Figure 1(c)). Concretely, we first mask all the speaker names and randomly sample a speaker whose utterances set $\tilde{S}_i$ which has at least two elements. Among $\tilde{S}_i$, we randomly choose a utterance (o_i, s_i) as the positive sample, and randomly choose another utterance (o_j, s_j) from $D - \tilde{S}_i$ as the negative sample. Thus the global utterance sample of this speaker is $(\tilde{S}_i - o_i, s_i)$. The model is supposed to maximize the mutual information between the representation of the global sample and the positive sample, and vice versa. The representations are derived from mean pooling, the same as what we do in Turn-level SCL. In contrast to Turn-level SCL, Global-level SCL needs the model's overall comprehension of the dialogue-format context.

Model	SAMSum			AMI		
	R-1	R-2	R-L	R-1	R-2	R-L
PGNet (See et al., 2017)	40.08	15.28	36.63	42.60	14.01	22.62
UniLM (Dong et al., 2019; Zhu et al., 2021)	50.00	26.03	42.34	50.61	**19.33**	25.06
Multi-view BART (Chen and Yang, 2020)	53.42	27.98	49.97	-	-	-
BART+DialoGPT (Feng et al., 2021b)	53.70	28.79	50.81	-	-	-
PGN+DialoGPT (Feng et al., 2021b)	-	-	-	50.91	17.75	24.59
BART	53.01	28.05	49.89	50.67	17.18	24.96
BART + Token-level SCL task	53.85	29.21	50.94	51.03	17.23	25.21
BART + Turn-level SCL task	54.12	29.53	51.10	51.15	17.85	**25.45**
BART + Global-level SCL task	**54.22**	**29.87**	**51.35**	**51.40**	17.81	25.30

Table 2: Results on the test sets of SAMSum and AMI, and "R" is short for "ROUGE". Our results are significantly better than the baseline model ($p < 0.05$).

3 Experiment

In this section, we conduct experiments and human evaluations on the popular datasets SAMSum and AMI. More descriptions of the datasets and the implementation details can be found in the Appendix.

3.1 Experimental Result and Analysis

We provide several latest strong seq2seq models as baselines, including PGNet (See et al., 2017), UniLM (Dong et al., 2019) and BART+DialoGPT (Feng et al., 2021b) in the first part of Table 2. Following previous settings (Gliwa et al., 2019; Feng et al., 2021a), we use *py-rouge*[2] package for evaluation on SAMsum and use *pyrouge*[3] on AMI. Experimentally, our models obtain clear improvement on both two datasets compared to the BART baseline, and achieve the state-of-the-art result on SAMSum.

Specific to the three tasks, the improvement brought by *Token-level SCL* is relatively tiny. The reason may be that the utilization of positional information is enough for BART to optimize the contrastive loss for two tokens. For *Turn-level SCL* and *Global-level SCL*, the pooling layer reduces the impact of position embedding, thereby forcing the model to focus on the semantic information of the utterances. Therefore, the model can further capture the characteristics of the dialogue data. *Global-level SCL* performs best in both datasets, which illustrates that when the model has global perspectives for each speaker, it can enhance the model's comprehension of the whole dialogue.

[2] https://pypi.org/project/py-rouge/

[3] https://github.com/bheinzerling/pyrouge

3.2 Human Evaluation

We also conduct human evaluations to investigate if our method leads to fewer factual errors. Automatic metrics like FACTCC (Kryściński et al., 2019) are not used since the neural-model-based metrics perform poorly in dialogue data due to the significant domain gap. And most of the factual errors in the dialogue summarization are caused by misidentification of the speaker, which can not be reflected by automatic metrics. Here we use BART and BART with the Global-level SCL task for comparison.

Error Types Firstly, we divide the factual errors into three categories manually:(a) **Speaker Confusion**: Model confuses speakers participating in a specific event; (b) **Speaker Missing**: A speaker is mentioned in the gold summary, while the model hits the event but misses this speaker. (c) **Semantic Error**: Errors caused by a misunderstanding of semantics, and they are not directly related to any speakers. More cases about the error types can be found in Appendix.

Model	BART	BART + Global SCL
Speaker Confusion Rate	0.100	0.067
Speaker Missing Rate	0.267	0.167
Semantic Errors Rate	0.283	0.242

Table 3: The rate of factual errors for the baseline model and our model on SAMSum and AMI. Please note that multiple types of factual errors can occur in a single data sample.

Result We evaluate 100 dialogues from the test set of SAMsum and all 20 dialogues of the AMI test set. For the SAMSum dataset, to explore the model's ability to understand multi-person interaction, we choose all 64 dialogues with more than

three speakers and randomly choose 36 dialogues with three speakers. The result is shown in Table 3. **55%** of the summaries generated by BART contain factual errors, of which **56.4%** are related to the Speaker Confusion or Speaker Missing. In comparison, our model decreases the number of speaker-related factual errors by **36.4**%. The SCL task helps the model to better distinguish the speakers and intuitively reduce the confusion. Furthermore, the SCL task helps the model to better perceive the speakers and reduce the Speaker Missing errors.

4 Conclusion

In this paper, we focus on the speaker identification problem in the dialogue summarization task. Through the probing test and manual analysis, we find that the existing pre-trained model can not identify different speakers well in the conversation, leading to factual errors. Therefore, we propose three speaker-aware SCL tasks to address this problem. Experimental results and human evaluations illustrate the effectiveness of our methods.

5 Ethical Considerations

For human evaluation in section 3.2, we recruited two annotators to see if there are any factual inconsistencies in generated summaries. The generators of all summaries are hidden from the annotators to avoid any subjective bias. For the SAMsum dataset, we give more priority to dialogues with more speakers and adopt a random strategy when the numbers of speakers are same.

Acknowledgements

This work was supported by the National Key Research and Development Program of China (No. 2020AAA0108702) and National Natural Science Foundation of China (No. 62022027).

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A Datasets

We apply our methods on the large version of BART and evaluate our model on SAMSum and AMI datasets using ROUGE score (Lin and Och, 2004). SAMSum consists of 16,369 samples with an average of 2.4 participants and 83.9 words. AMI consists of 137 meeting records of four fixed speakers, which have 4,757 words on average. Due to the limitation of our computing resources, all our inputs are truncated to 1,024 tokens. We use the same split as Gliwa et al. (2019) and Zhu et al. (2020) for SAMSum and AMI, respectively.

B Implementation Details

Hyperparameters	SAMSum	AMI
Batch Size	8	24
Total Steps	10,000	600
Eval Steps	1,000	20
Learning Rate	[2e-5,3e-5]	[2e-5,3e-5]
Label Smoothing Factor	0.1	0
Warm-up Type	linear	linear
Warm-up Steps	0	100
Max Target Length	128	300

Table 4: Hyperparameters we used for fine-tuning BART on SAMSum and AMI.

Some of our hyperparameters are listed in Table 4. Other hyperparameters are the same as the default of *facebook/bart-large* of transformers[4].

[4] https://github.com/huggingface/transformers

The weight coefficient factor λ is searched from $\{0.01, 0.001\}$. It takes up to 2 hours for one run on SAMSum or AMI using one GeForce RTX 3090.

We use the validation set to select the best checkpoint, and evaluate the checkpoint on the test set.

C Case Study

In order to better illustrate the three types of errors mentioned in Section 3.2, we provide more cases here. An example of confusing speakers is shown in Table 1 of the main paper. Examples of missing speakers and semantic errors are shown in Table 5.

Dialogue Text 1
Ann: Congratulations!! Ann: You did great, both of you! Sue: Thanks, Ann Julie: I'm glad it's over! Julie: That's co cute of you, girl! Ann: Let's have a little celebration tonight! Sue: I'm in Julie: me too!!! aww
Gold Summary 1
Ann, Sue and Julie did a great job and they will have a little celebration tonight.
Baseline Summary 1 by BART
Sue and Julie are going to celebrate their success tonight.
Our Summary 1
Ann, Sue and Julie are celebrating their wins.
Dialogue Text 2
Sarah: omg Laura! sorry you didn't get any replies!!! Did you manage? Laura: hahaha! Awkssssss... no worries, I solved it Sarah: awkward silence <crickets> Laura: hahaha no it's all good really!! Raf: Laura, I'm so sorry!!! been so swamped, totally forgot to text you back! where are you?? Sarah: Exotic little island called Linate :D Laura: Sarah which hotel are you at??? I'm here too!!!
Gold Summary 2
Neither Raf nor Sarah remembered to reply to Laura but she managed anyway. Both Sarah and Laura are in Linate.
Baseline Summary 2 by BART
Laura didn't get any replies to Sarah's messages.Laura is on an island called Linate. Laura and Sarah are staying at the same hotel.
Our Summary 2
Laura didn't get any replies from Sarah and Raf. Sarah and Laura are on an exotic little island called Linate.

Table 5: Sample 1 is an example about the speaker missing error. The summary generated by BART misses Ann. The dialogue sample is from the SAMSum dataset. Sample 2 is an example about the semantic error and the speaker missing error. The summary generated by BART misses Raf (Speaker Missing Error), and makes it out of thin air that Sarah and Laura are staying at the same hotel (Semantic Error). All samples are from the SAMsum dataset.