Abstract

Abstractive summarization models typically generate content unfaithful to the input, thus highlighting the significance of evaluating the faithfulness of generated summaries. Most faithfulness metrics are only evaluated on news domain, can they be transferred to other summarization tasks? In this work, we first present a systematic study of faithfulness metrics for dialogue summarization. We evaluate common faithfulness metrics on dialogue datasets and observe that most metrics correlate poorly with human judgements despite performing well on news datasets. Given these findings, to improve existing metrics’ performance on dialogue summarization, we first finetune on in-domain dataset, then apply unlikely training on negative samples, and show that they can successfully improve metric performance on dialogue data. Inspired by the strong zero-shot performance of the T0 language model, we further propose T0-Score – a new metric for faithfulness evaluation, which shows consistent improvement against baseline metrics across multiple domains.

1 Introduction

Abstractive text summarization aims to condense a piece of text into a shorter version by distilling the information in the source text and rewriting it in a concise manner. Recent advancements in pretrained language models (Vaswani et al., 2017; Brown et al., 2020; Raffel et al., 2020; Lewis et al., 2020; Zhang et al., 2020) have enabled summarization systems to generate highly fluent and coherent summaries on common summarization datasets such as CNN/DailyMail (Nallapati et al., 2016), XSum (Narayan et al., 2018).

Although news domain has long been the focus of summarization research, dialogue summarization, with many practical applications has gained more research attention lately. SAMSum (Gliwa et al., 2019) is the first large-scale dataset with human annotated abstractive summaries for chat-dialogue conversations. ConvoSumm (Fabbri et al., 2021a) created the first comprehensive benchmark for conversational summarization across diverse domains of news comments, discussion forums, community question answering forums, and email threads.

Success in a summarization system’s application is crucially dependent on its faithfulness: the factual alignment between the generated summary and the source. Kryscinski et al. (2020) found that up to 30% of generated summaries are affected by factual inconsistencies. Tang et al. (2022) studied types of factual errors generated by current models on popular dialogue summarization dataset and revealed hallucination issues. Thus having metrics that can reliably identify hallucinations and source-contradicting information becomes a critical step in summarization research.

Although commonly used to evaluate summarization models, metrics based on n-gram overlaps, such as ROUGE (Lin, 2004), BLEU (Papineni et al., 2002) and METEOR (Lavie and Agarwal, 2007) are inadequate to measure a summary’s faithfulness, because of their low correlation with human judgements (Yuan et al., 2021; Deng et al., 2021; Maynez et al., 2020). Even though many newly proposed metrics specifically target faithfulness (Kryscinski et al., 2020; Wang et al., 2020; Yuan et al., 2021; Deng et al., 2021) they are only evaluated on the news domain. Because of the unique challenges inherent to dialogue data, i.e. spoken terms, special discourse structures, coreferences and ellipsis, etc. (Chen et al., 2021), we suspect they will not be as effective in evaluating dialogue summaries right out-of-the-box.

In this paper, we evaluate the faithfulness aspect of common summarization metrics in the dialogue domain and investigate various approaches to improve their reliabilities. Our contributions are:
1. We analyze faithfulness metrics for dialogue summarization and find that metrics that perform well on one domain don’t transfer directly to another domain.

2. We improve existing faithfulness evaluation metrics for dialogue summarization by fine-tuning on in-domain data and applying unlikelihood training with negative samples.

3. We propose a more general faithfulness metric, T0-Score, and show that it outperforms many metrics across multiple domains.

2 Related Work

2.1 Summarization Metrics

Common summarization metrics ROUGE, BLEU, and METEOR (Lin, 2004; Papineni et al., 2002; Banerjee and Lavie, 2005) are based on n-gram overlaps, which were shown to not correlate well with human judgements of factual consistency (Falke et al., 2019; Kryscinski et al., 2020). Newly proposed metrics aim to solve this problems with various approaches: FactCC (Kryscinski et al., 2020) generates weakly supervised training data and treat consistency evaluation as an NLI task. QAGS and FEQA (Wang et al., 2020; Durmus et al., 2020) model consistency evaluation as question generation and answering. BERTScore (Zhang* et al., 2020) uses contextualized embeddings to compute similarities between the generated and the reference summaries. CTC (Deng et al., 2021), when evaluating consistency with its discriminative model, works by predicting the probability of each token in the hypothesis being consistent with the source. Training requires constructing negative training samples. BARTScore (Yuan et al., 2021) when used to evaluate factuality, works by conditioning on the source and predicting the probability of a hypothesis being generated with a seq2seq language model.

2.2 Meta-Evaluation of Summarization

Maynez et al. (2020) conducted a human evaluation of hallucinated content in system generated summaries on XSum data and found textual entailment scores are best correlated with summary faithfulness. Fabbri et al. (2021b) assembled SummEval, a collection of model-generated CNNDM summaries and their human judgement scores along four axes including factual consistency. They found, on system-level, metrics using higher-order n-gram overlap such as ROUGE-3 are more effective. Similarly, Pagnoni et al. (2021) composed FRANK, consists of generated summaries from CNNDM and XSum and corresponding human annotations of factuality based on a typology of factual errors. They observe all tested metrics exhibit low correlations with human judgements with the best metric FactCC achieving 0.3 Spearman correlation. Gabriel et al. (2021) proposed a meta-evaluation framework, Go Figure, which evaluates the sensitivity and validity of factual consistency metrics with only reference summaries. They found SummaQA, ROUGE-(2/3), and BERTScore perform better than ROUGE(1/L).

3 Metrics and Data

Baseline Metrics We compare 4 summarization metrics that are either widely used or shown to correlate well with human judgement in terms of faithfulness in news domain and seek further improvement of automatic metrics for faithfulness on dialogue summarization.

ROUGE (Lin, 2004) measures summarization quality by counting n-gram overlaps between the hypothesis and the human written reference summary.

BERTScore (Zhang* et al., 2020) compares the similarity between the hypothesis and the reference by measuring the cosine similarities between each of their token’s contextualized embedding.

CTC (Deng et al., 2021), when evaluating consistency with its discriminative model, works by predicting the probability of each token in the hypothesis being consistent with the source. Training requires constructing negative training samples.

BARTScore (Yuan et al., 2021) when used to evaluate factuality, works by conditioning on the source and predicting the probability of a hypothesis being generated with a seq2seq language model.

Datasets We use SAMSum (Gliwa et al., 2019) dataset to study faithfulness metrics for dialogue summarization. The SAMSum corpus is a large-scale dialogue summarization dataset that contains 16k English daily conversations with corresponding summaries written by linguists. We use the human annotation of SAMSum summaries in ConFiT (Tang et al., 2022) as our meta-evaluation dataset, where they generate summaries from six summarization models and collected faithfulness score on a scale of 1-10. We refer to this dataset as MetaSAMSum.

4 Methods

During evaluation, we found that off-the-shelf CTC and BARTScore perform poorly on MetaSAMSum.
(see "Vanilla" column of Table 1). We hypothesize that the low performance of CTC and BARTScore on the SAMSum dataset is twofold. 1. Neither of them are trained on dialogue data and their performance transfer poorly with shifted domain. 2. BARTScore has never seen negative samples, so it struggles to recognize unfaithful summaries. Thus, we design two approaches to improve them.

4.1 In-domain Training

Yuan et al. (2021) have shown when evaluating the factuality of generated text BARTScore fine-tuned on CNNDM performs the best. CTC is also trained on data constructed from CNNDM and XSum. However, since we find that they don’t transfer well to evaluating dialogue summarization, based on hypothesis 1, we experiment with adapting CTC and BARTScore to the dialogue domain by training on in-domain data.

We use conversations from Pushshift Reddit (Baumgartner et al., 2020) as unsupervised in-domain training data. Since Reddit conversations have no associated reference summaries, and results from CTC (in Table 4) have shown using extractive summaries on conversation data hurts performance, to train BARTScore, we generate fake references with T0 (Sanh et al., 2022), a multi-task seq2seq LM exhibiting strong zero-shot generalization abilities. For each conversation, we generate multiple summaries with different prompts and pick the summary with the highest ROUGE-L score comparing against the source as the fake reference to prevent it from deviating too much from the source. In addition, We also investigate training directly on SAMSum, the task data.

4.2 Unlikelihood Training with Negative Samples

BARTScore works by predicting the probability of a hypothesis being generated given a source text. In the finetuning stage, standard MLE training aims to maximize the probability of positive tokens but does not explicitly minimize those of negative tokens. Based on hypothesis 2, i.e. without explicit guidance, it is difficult for the model to discern the unfaithful content, we remedy this difficulty by leveraging unlikelihood loss (Welleck et al., 2020) to penalize negative tokens, teaching the model to assign low probabilities to unfaithful tokens.

Consider the sequence \( S = (x_1, ..., x_T) \), \( N \) is the set of indices of its negative tokens. The loss for \( S \) is given as

\[
L_S = \begin{cases} 
- \sum_{t} \log p_{\theta}(x_t | x_{<t}), & \text{if } S \text{ is pos} \\
- \alpha \sum_{t \in N} \log (1 - p_{\theta}(x_t | x_{<t})), & \text{if } S \text{ is neg}
\end{cases}
\]

Where \( p_{\theta} \) is the model parameterized by \( \theta \), \( \alpha \) is a hyperparameter representing the weight of the unlikelihood loss.

Inspired by Cao and Wang (2021), we generate three types of negative samples from SAMSum reference summaries. Swapent shuffles entities of the same type, simulating wrong reference error which is a common error type for dialogue summarization. Maskent randomly masks one entity of each type, and fill the masks with BART, simulating summaries with incorrect subjects or objects. Hallu generates SAMSum summaries using BART trained on XSum with top \( p \) sampling where \( p = 1.0 \), simulating complete hallucinations. We show examples of negative samples generated by our system in Appendix A.

5 Experiments & Analysis

We report and discuss experiment results and new findings in this section. Each model is trained on 4 A100 GPUs using the AdamW optimizer with learning rate set to 2e-5. Trained with DDP, the effective batch size is 64. All reported numbers are the average of 3 runs using different random seeds.

|           | Vanilla w. Reddit | w. SAMSUm |
|-----------|-------------------|-----------|
| BScore    | 0.1844            | 0.2667    | 0.3275    |
| CTC       | 0.1245            | 0.0552    | 0.0692    |

Table 1: Spearman correlations of BARTScore (BScore) and CTC on SAMSum data with in-domain training. "Vanilla" uses bart-large-cnn and D-XSum for BARTScore and CTC respectively.

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1 An existing dataset extracted and obtained by a third party and made available on pushshift.io
## Types of Negatives

| ref | swapent | maskent | hallu | correlations |
|-----|---------|---------|-------|--------------|
| ✔   | ✔️      | ✔️      | ✔️    | 0.3275       |
| ✔   | ✔️      | ✔️      | ✔️    | 0.3414       |
| ✔   | ✔️      | ✔️      | ✔️    | 0.3400       |
| ✔   | ✔️      | ✔️      | ✔️    | 0.3302       |
| ✔   | ✔️      | ✔️      | ✔️    | 0.3349       |
| ✔   | ✔️      | ✔️      | ✔️    | 0.3441       |

Table 2: Spearman correlations of BARTScore on SAMSum data. BART models are trained on SAMSum’s human written references and different combinations of negative examples.

| Metrics          | SAMSum  | CNN     | XSum    |
|------------------|---------|---------|---------|
| CTC              | 0.1129  | 0.4293  | 0.3149  |
| BARTScore        | 0.3441  | 0.3820  | 0.1705  |
| T0-Score (3B)    | 0.3049  | 0.4141  | 0.1829  |
| T0-Score (11B)   | 0.3780  | 0.4573  | 0.1862  |

Table 3: Spearman correlations of CTC, BARTScore, and T0-Score, on SAMSum, CNNDM, and XSum.

domain. We suspect this is due to CTC’s negative generation pipeline being not suitable for dialogues, producing low-quality negative samples.

Nonetheless, training directly on task data i.e. SAMSum with human written references yields better performance, despite SAMSum being 10 times smaller than unsupervised Reddit data.

### 5.2 BARTScore with Negatives Ablation Results

We report ablation results of BARTScore with additional unlikelihood training on negative samples in Table 2, in which the weight of unlikelihood loss $\alpha = 0.1$ and all models start from bart-large-cnn. All models trained with unlikelihood loss on negative samples in addition to MLE show performance improvements. When training with one type of negative, swapent contributes the most improvement among the three types of negative samples, and hallu contributes the least. Using all three types of negatives yields the best performance.

### 5.3 T0-Score

From previous ablations, we found that bart-large-cnn performs better than bart-large when finetuned on SAMSum for evaluation, which suggests that a more generalized model could do better as an evaluator. Because T0 is known for its strong zero-shot generalization abilities, we experiment with using its generation probability of summary conditioned on source as the faithfulness metric, which we call T0-Score.

Table 3 shows results of 2 versions of T0-Score on meta evaluation datasets from multiple domains compared to other metrics. T0-Score shows performance gains even over the best performing BARTScore on SAMSum. It also outperforms CTC on CNNDM, setting state-of-the-art performance. However, it falls short on XSum compared to CTC.

### 5.4 Discussion

Table 4 summarizes results from all metrics together with our improvements. We see that most existing summarization faithfulness metrics perform poorly on dialogue data out-of-the-box (with BERTScore being an exception). BARTScore can be significantly improved when finetuned on in-domain or task data, and additional unlikelihood training with negative samples can further boost its performance. Since a metric’s performance can be highly dependent on the domain that it is applied to, e.g. CTC is competitive on news but falls short on dialogues, we call for researchers to evaluate on multiple domains when proposing general automatic metrics for summarization evaluation.

### 6 Conclusion

We evaluate common faithfulness metrics on dialogue summarization and find that most of them
exhibit low correlations with human judgements. We experiment with ways to improve them by training on in-domain data with unlikelihood loss on negative samples, and we show both of them can bring significant improvements. We call for more domain-aware use of evaluation metrics and more comprehensive evaluation over multiple domains when proposing new metrics.

7 Limitations

The negative samples we generate from handcrafted rules are limited to three types of common errors in auto-generated summaries. To obtain more accurate faithfulness evaluations, more error types have to be proposed. Or as an alternative, obtaining token-level human annotations is another expensive but viable option.

This study is conducted using SAMSum as a proxy to dialogue data. While our approaches are shown to perform well on SAMSum as a more casual chit-chat dialogue dataset, because of the lack of annotated data, we have not tested our approaches on datasets with formal and longer conversations. When more annotated data is available, evaluating on a more diverse set of dialogue datasets could make our arguments stronger.

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A Generated Negative Samples

Table 5 shows examples of negative samples generated by our system.

| Dialogue | Amanda: I baked cookies. Do you want some? Jerry: Sure! Amanda: I’ll bring you tomorrow :-) |
|----------|------------------------------------------------------------------------------------------------|
| Reference| Amanda baked cookies and will bring Jerry some tomorrow.                                      |
| Swapent  | Jerry baked cookies and will bring Amanda some tomorrow.                                      |
| Maskent  | I have baked cookies and will bring Jerry some tomorrow.                                       |
| Hallu    | Amanda: I baked cookies, and I want to bring them to your house so you can eat them!             |

Table 5: An example SAMSum dialogue and its three types of negative summaries. Highlighted parts are negative tokens.