# **Long Dialog Summarization: An Analysis**

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## **Abstract**

Dialog summarization has become increasingly important in managing and comprehending large-scale conversations across various domains. This task presents unique challenges in capturing the key points, context, and nuances of multi-turn long conversations for summarization. It is worth noting that the summarization techniques may vary based on specific requirements such as in a shopping-chatbot scenario, the dialog summary helps to learn user preferences, whereas in the case of a customer call center, the summary may involve the problem attributes that a user specified, and the final resolution provided. This work emphasizes the significance of creating coherent and contextually rich summaries for effective communication in various applications. We explore current state-of-the-art approaches for long dialog summarization in different domains and benchmark metrics based evaluations show that one single model does not perform well across various areas for distinct summarization tasks.

#### 1 Introduction

Dialog summarization has emerged as a crucial aspect of managing and understanding large-scale conversations in various contexts such as online tutoring (Jain et al., 2023), customer service (Liu et al., 2019), patient consultations (Abacha et al., 2023; Joshi et al., 2020), and casual chatbot interactions. While the automatic summarization of text remains inherently challenging due to the complexity of determining and preserving the most relevant content, this paper aims to devise goal-oriented summarization and how current state of the art language models can be utilised effectively to achieve superior performance in the domain of large-scale dialog summarization.

Summarization will vary according to the requirements - it can be a context driven summary or an object oriented summary as in Fig 1. In the former case, in a dialogue session about techni-

cal smartphone issues, a context-driven summary would capture the sequential troubleshooting steps and relevant device details, providing a concise overview of the problem-solving process. In the object driven summary, in a travel planning conversation, an objective-driven summary would prioritize the user's goal of obtaining the best itinerary within specified criteria. The summary would highlight suitable destinations, recommended accommodations, transportation options, tailored to the user's preferences and constraints. Thus, the same summarization approach may not lead to the best summaries which will be very useful according to the user's need and leads us to achieve the goal using rubric-driven summarization with the use of custom-trained language models.

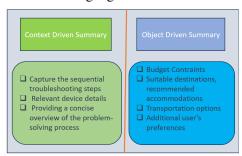


Figure 1: Different Summarization Process

The cornerstone of our approach involves specifying context-driven rubrics in a natural language format, which can guide the fine-tuning of large language models (LLMs) for better goal-oriented summarization performance. As these rubrics address the nuances of different dialog settings and user groups, the fine-tuned models are expected to generate summaries that exhibit a deeper understanding of the conversation, capturing critical information in a coherent and contextually relevant manner. In essence, this paper delves into the foundational objective of enriching the dialog summarization task and create LLM driven solutions that cater to diverse contexts and objectives. By exploring this direction, our work surpasses traditional

summarization techniques and offers a compelling groundwork for anyone seeking a deeper comprehension of the intricacies of dialog summarization and its potential applications.

Earlier researchers explore dialog summarization in different directions. Vig et al. (2022); Zhang et al. (2022); Zhu et al. (2020) provide different approaches for conversation summarization tasks. Xiong et al. (2022); Pagnoni et al. (2022) and Fact-Pegasus (Wan and Bansal, 2022) study pretraining pipeline for summarizations. Different state-of-theart models like LongFormer (Beltagy et al., 2020), BART (Lewis et al., 2019), T5 (Raffel et al., 2020), Flan T5 (Chung et al., 2022) are useful to extract summarized information from dialogs. Leuski et al. (2003) present interactive summarization with user control. There exists several benchmarked conversational datasets with summary - QmSum (Zhong et al., 2021), Multiwoz (Budzianowski et al., 2018; Eric et al., 2020), SParC (Yu et al., 2019), Sum-Screen (Tv series summary) (Chen et al., 2021), SQuALITY (Pang et al., 2021) etc. Some researchers focus on developing evaluation criteria to detect the usefulness of different summarization approaches. ROUGE (Lin, 2004), BLEU (Papineni et al., 2002), Meteor (Banerjee and Lavie, 2005), BERTScore(Zhang et al., 2019) are state of the art metrics to assess dialog summaries.

Researchers make impressive advancements on a wide range of downstream applications for summarizations. Since, one approach is not working best across different tasks and different domains, the real-world implications of such advancements are largely unexplored. In this paper, we study utilities of different summarization approaches for extracting compressed contexts from domain specific conversations. Our through extensive experiments on two benchmarked datasets show that different approaches can be useful in different contexts.

#### 2 Dataset

We explore two different datasets for the evaluations: 1) **QmSum** (**Zhong et al., 2021**): It is a multi-domain query-based meeting summarization dataset consisting of 1,808 queries and 232 long meeting transcripts, with different topic of discussions such as software product, academics, and committee meetings. 2) **SumScreen** (**Chen et al., 2021**): This summarization dataset comprises 26.9K pairs of TV series transcripts ('Forever Dreaming' and 'TvMegaSite') and human an-

notated recaps. These TV shows are of different genres like drama, romance, family, etc. Due to the larger size of the datasets, we randomly sample 15% of the 'Forever Dreaming' data from train, dev and test set for our experiment purposes.

## 3 Summarization Approaches

We evaluate various state-of-the-art summarization algorithms along with different settings<sup>1</sup> corresponding to the two datasets discussed above.

## 3.1 Algorithms

LongFormer (Beltagy et al., 2020): The Longformer (LF) is a transformer-based model designed to handle long documents efficiently using an attention pattern that effectively combines local and global information, enabling to handle long inputs. T5 (Raffel et al., 2020): "Text-to-Text Transfer Transformer" (T5) model is a transfer learning technique can be used to generate summary. We use T5-base model (770 million parameters).

Flan T5 (Chung et al., 2022): Flan T5 (FT5) is a instruction fine-tuned approach that shows fine-tuning can improve performance across a range of models, prompting setups, and evaluation tasks.

BART (Lewis et al., 2019): BART is a denoising

autoencoder for pretraining sequence-to-sequence models. Pretraining which can generate summary. Chat-GPT (Aydın and Karaarslan, 2023; Wang et al., 2023): We apply ChatGPT (V3.5) to generate summary from dialogs. We apply two different versions of ChatGPT - (P1): where we feed summary and dialog together as text (P2): where we feed the summary as prompt and dialog as text. In (P2), we specify the summary explicitely.

## 3.2 Input Settings

Since, the conversations exceed the maximum token limit of the models, we follow various settings: **A) Direct:** Apply the model directly on the whole dataset. In this setting, the models automatically truncate the input to the maximum token limit. It is shown for the case of LongFormer (LF).

- **B)** Chunk and Summarize: In this technique, we tokenize the conversation with chunks of maximum token limit and feed individual segments to the models in the following two ways:
- i) Feed each conversation segment independently to generate individual summaries of each segment and finally merge the summaries to get the overall

<sup>&</sup>lt;sup>1</sup>Code/Data is available: https://shorturl.at/tyzD8

summary. In Table 1 these methods are shown as method-name with the chunk size (e.g., LF-8192).

ii) Generate the summary of the first segment and then feed the obtained summary to the models along with the next conversation segment to generate an updated summary at each step. Continuing with this approach, finally, we get the overall summary from the last conversation segment. This approach is used to preserve the context of a dialog. This is shown as "type-2" in the Table 1.

C) Extract then summarize: In this setting, initially we retrieve sentences from the dialogs (train set) so that the total token size of extracted sentences are within the maximum token limit of the models and then feed it to the summarization frameworks to generate the final summary. The sentences are extracted using the approach similar to Mukherjee et al. (2022). We apply Sentence-BERT (Reimers and Gurevych, 2019) to generate the embeddings of the sentences of dialogues and summaries and then calculate the pair-wise cosine similarity. Thereafter, we set a minimum similarity threshold to extract certain dilaog sentences of high similarity (>30%) with the summary sentences. Then, we feed the extracted dialogs to the models to generate summaries (In Table 1 these are named as Ex-model like 'Ex-T5', 'Ex-FT5' etc.).

## 4 Experimental Results

In this section, we evaluate the quality of the final summary generated for a given dialog. For this purpose, we rely on two different approaches, one based on comparing our generated summary using different methods described in Sec. 3 while the other is based on comparing the coverage of intents and entities in the original dialog with that of the generated summary.

## 4.1 Ground truth comparison

Here we compare the ground truth summary (reference summary) with the generated summary obtained from a given model in terms of how closely the generated summary string matches the ground truth summary string. We measure the extent of similarity between the two summaries with the help of the following standard evaluation metrics: 1) **BLEU score:** BLEU (Bilingual Evaluation Understudy) metric (Papineni et al., 2002) measures the precision of n-gram overlap between the generated summary and the reference summary. 2) **ROUGE-Score**): ROUGE (Recall-Oriented Understudy for

Gisting Evaluation) is a set of evaluation metrics widely used in summarization tasks (Lin, 2004). We use ROUGE-1 (focuses on the unigram or single-word overlap), ROUGE-2 measures the bigram (two-word sequence) and ROUGE-L (considering the longest common subsequence (LCS)). 3) **METEOR:** METEOR (Metric for Evaluation of Translation with Explicit ORdering) (Banerjee and Lavie, 2005) evaluates the generated summaries that takes into account the harmonic mean of unigram precision and recall, along with a synonymy matching and sentence structure similarity component. 4) BERTScore (Zhang et al., 2019): It is a robust technique which computes token similarity using contextual embeddings. It is an useful metric to evaluate summarization models. 5) Intent-Entity coverage (IEC): To further evaluate the quality of generated summaries in capturing the key information from the original dialog conversation, we propose measuring Intent based entity overlap. These metrics enable a better understanding of how well the generated summaries preserve the primary objectives and capture salient aspects from the conversations. We use ChatGPT (Aydın and Karaarslan, 2023; Wang et al., 2023) in order to extract the set of entities from a given text (dialog conversation or summary), by providing suitable prompts to ChatGPT. The overlap in entities is computed as follows: To compute the entity Overlap based on *ChatGPT*, we extract the set of entities from both the original dialog conversation and the generated summary using prompts provided to ChatGPT. We then compute the overlap between the two entity sets using Jaccard similarity which measures the proportion of common intents in both sets to the combined unique intents.

#### 4.2 Results and Discussion

We present our experimental results in terms of the metrics defined above in Tables 1. From Table 1, we observe a diverse range of metric values across the different summary generation models, indicating the varying performance achieved by Longformer, T5, Flan-T5, BART, and ChatGPT in the challenging task of summarizing long dialog conversation. We apply segmentation in the diloags to be fed to the models with different token length as input according to token limits. Different token input lengths are - 8192 for LongFormer (LF); 4096 for for LongFormer (LF) and T5; 2048 for T5, Flan-T5 (FT-5) and BART. Although metric-

Method	QmSum							SumScreen (FD)						
	Bl	R-1	R-2	R-L	Mt	BS	IEC	Bl	R-1	R-2	R-L	Mt	BS	IEC
LF	6.09	26.81	7.11	24.40	24.76	58.96	30.81	0.32	15.39	1.42	12.52	3.63	47.20	26.38
LF-8192	3.58	23.13	5.72	21.14	18.29	56.57	29.71	0.27	14.88	1.83	11.74	3.33	43.95	11.94
LF-4096	1.74	22.85	6.01	20.88	15.45	55.93	26.15	0.20	12.73	1.50	12.74	3.55	43.82	13.71
LF-type2	0.50	10.87	1.50	7.01	2.4	25.95	23.83	0.18	14.69	1.05	13.06	3.84	42.91	12.05
Ex-LF	2.49	20.84	3.75	18.37	19.08	50.34	27.15	0.06	17.14	1.45	15.62	3.16	44.79	23.65
T5-4096	2.36	25.00	7.13	23.27	11.55	59.85	32.05	0.35	18.57	1.48	17.62	3.82	44.99	31.87
T5-2048	2.18	24.80	6.27	22.99	11.61	55.42	29.78	0.50	19.14	1.61	18.01	5.76	47.46	29.36
T5-type2	2.62	21.20	3.88	19.80	19.35	55.67	27.42	1.15	16.84	1.22	15.19	5.07	47.33	25.86
Ex-T5	7.40	24.11	7.24	22.15	22.65	54.55	23.71	0.99	17.25	1.41	15.88	13.29	45.41	21.67
FT5-2048	1.76	24.00	5.62	22.55	9.04	55.36	18.35	0.47	16.86	1.41	15.54	5.51	46.61	10.24
FT5-type2	2.62	21.20	3.88	19.80	19.35	57.02	21.12	0.62	16.05	1.47	14.22	4.56	47.33	17.20
Ex-FT5	6.84	23.88	7.29	22.41	22.23	54.51	28.13	0.39	14.66	1.36	13.54	5.24	45.51	27.98
BART-2048	0.90	24.71	5.48	21.06	13.30	47.45	25.74	0.10	19.35	2.02	17.28	8.68	43.88	23.63
BART-type2	1.94	20.49	5.03	19.42	18.31	38.20	17.32	0.39	17.03	1.37	15.54	4.29	44.92	13.84
Ex-BART	3.10	17.29	3.54	15.94	17.36	47.97	21.35	0.44	22.86	1.64	22.86	12.64	45.65	18.75
ChatGPT	0.63	15.74	2.51	13.89	9.61	54.62	25.78	0.40	25.04	4.34	18.71	18.72	57.88	28.65
ChatGPT P1	1.11	17.72	1.67	15.48	20.78	49.69	27.91	0.35	24.82	2.77	21.83	18.74	57.10	30.34
ChatGPT P2	1.00	17.31	2.40	16.97	22.01	50.98	29.12	2.19	22.97	3.11	20.17	20.32	57.33	31.67

Table 1: Results (in %) in terms of BLEU (BI), Rouge (R-1, R-2 and R-L), Meteor (Mt), BERTScore (BS) and Intent-Entity Coverage (IEC) on QmSum and SumScreen ('Forever Dreaming') datasets

wise performance varies, some trends are noticeable. For instance, BART demonstrates the lowest BLEU score of 0.90, whereas Longformer attains the highest BLEU score (6.09), ROUGE-1 (26.81) and ROUGE-L (24.40) values. Conversely, T5 registers the lowest values for ROUGE-1 (21.20) and ROUGE-L (19.80) but displays the highest ROUGE-2 score, along with Longformer, at 7.13 and 7.11, respectively. Flan-T5, on the other hand, achieves the lowest ROUGE-2 score of 3.88. In terms of the METEOR metric, Longformer holds the highest score at 24.26, while Flan-T5 records the lowest score of 9.04. For a single approach results also varies for two different datasets. For QmSum, the important conversational sentences which form the summary are mostly located in first and middle segment (77.39% dialog sentences) of the conversations where as for SumScreen-FD data, 70.1% of the important conversational sentences which form the summary are from first and middle segment of the dialog. That may explain why LongFormer (LF) without token limit, works well for QmSum but not for SumScreen-FD. ChatGPT often takes into account the last segment of the dataset, which may explain why chatGPT produces better outcomes for SumScreen-FD than QmSum.

These contrasting results suggest that each model exhibits specific strengths and weaknesses depending on the aspects of summarization being evaluated. The overall low values for these metrics illustrate the inherent complexity and difficulty of the long dialog summarization task. A possible intuition for such observations is that the ability of the Longformer model to handle long-range contextual information helps it better capture essential content and overall structure. In contrast, the ca-

pability of T5 in maintaining local coherence and structure might contribute to its higher ROUGE-2 score, although its lower ROUGE-1 and ROUGE-L scores indicate room for improvement in content coverage. The lower scores of Flan-T5 may be attributed to limitations in its architecture or training data used for the task, indicating a need for further refinement. The varied performance of these models highlights the importance of choosing the most suitable architecture or ensemble strategy based on the desired outcome and evaluation metric for dialog summarization tasks.

Compared to models like Longformer, T5, Flan-T5, and BART, ChatGPT may perform better in maintaining contextual relevance and coherence in dialog summarization due to its conversational AI focus. In fact, when we explicitly provide the summary as a promot (P2), ChatGPT performs better in most of the cases. However, it may struggle to capture complete content from long dialogues, as it tends to emphasize recent information. This tendency, caused by limited context window and recency bias, results in summaries focusing on the latter parts of conversations, potentially missing crucial ideas from earlier sections.

## 5 Conclusion

In this paper, we explore how different approaches perform across various long dialog datasets for summarization task. In conclusion, the need for context and objective-driven summarization is evident, as relying on a single approach may not yield the best results. This highlights the significance of rubric-driven summarization techniques and the utilization of custom-trained language models.

#### Limitations

Our datasets are not multilingual and multimodal. So, we need to explore how state of the art approaches can be utilized in multilingual and multimodal scenarios - which we aim to do as a part of future work.

## **Ethics Statement**

Our work does not reveal any personal sensitive information and we use publicly available benchmarked datasets and models in different contexts.

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