TODSum: Task-Oriented Dialogue Summarization with State Tracking
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Abstract
Previous dialogue summarization datasets mainly focus on open-domain chitchat dialogues, while summarization datasets for the broadly used task-oriented dialogue haven’t been explored yet. Automatically summarizing such task-oriented dialogues can help a business collect and review needs to improve the service. Besides, previous datasets pay more attention to generate good summaries with higher ROUGE scores, but they hardly understand the structured information of dialogues and ignore the factuality of summaries. In this paper, we introduce a large-scale public Task-Oriented Dialogue Summarization dataset, TODSum, which aims to summarize the key points of the agent completing certain tasks with the user. Compared to existing work, TODSum suffers from severe scattered information issues and requires strict factual consistency, which makes it hard to directly apply recent dialogue summarization models. Therefore, we introduce additional dialogue state knowledge for TODSum to enhance the faithfulness of generated summaries. We hope a better understanding of conversational content helps summarization models generate concise and coherent summaries. Meanwhile, we establish a comprehensive benchmark for TODSum and propose a state-aware structured dialogue summarization model to integrate dialogue state information and dialogue history. Exhaustive experiments and qualitative analysis prove the effectiveness of dialogue structure guidance. Finally, we discuss the current issues of TODSum and potential development directions for future work.

Introduction
Text summarization is the task of automatically generating a concise, salient, coherent, and fluent summary of given long text input (Radev, Hovy, and McKeown 2002). Recent work in text summarization has made significant progress in news articles (Nallapati et al. 2016; Kedzie, McKeown, and Daumé 2018), scientific papers (Koncel-Kedziorski et al. 2019), and patents (Sharma, Li, and Wang 2019). Furthermore, the large pre-trained models, such as BERT (Devlin et al. 2019), BART (Lewis et al. 2020), and Pegasus (Zhang et al. 2020a) boost the performance. However, dialogue summarization receives significantly less attention mainly attributed to the complex context, multiple speakers, and informal language style (Chen and Yang 2020). Therefore, more valuable conversational datasets for summarization are required to facilitate the related research area.

Figure 1: An example of TODSum with dialogue states. There exists three challenges: Factual Inconsistency (factual errors in generated summaries like 3-star), Repetition and Negotiation (see hotel), and Multiple Domains.
answering, and customer-service dialogues. Open-domain chitchat, like SAMSum (Gliwa et al. 2019) and DialSumm (Chen et al. 2021), are mostly used which contains human-written online social chats. Meeting such as AMI (Carletta et al. 2005), MediaSum (Zhu et al. 2021b), and QMSum (Zhong et al. 2021) focus on the meeting scenario involving multiple people and topics. Multi-turn QA like CQA Summ (Chowdhury and Chakraborty 2019) and ConvoSumm (Fabbri et al. 2021) instead summarize user questions and system answers like Quora. Customer-service dialogues (Liu et al. 2019; Yuan and Yu 2019; Zou et al. 2021a,b) are recently proposed to address user issues about specific topics, such as the E-commerce after-sales service. But due to privacy limitations, existing customer-service dialogues are not publicly available for research.

Overall, most existing dialogue summarization datasets focus on open chitchats but overlook another kind of important dialogue type, the Task-Oriented Dialogue (TOD) (Zhang et al. 2020c) which is widely used in practical scenarios. To the best of our knowledge, there is no existing large-scale public summarization dataset for TOD. More importantly, although previous datasets make some progress, a critical question is that all of the datasets ignore the intrinsic dialogue structured information of multi-turn conversations and only focus on summarization generation, like ROUGE scores and Bleu, rather than dialogue understanding, i.e., intents and slots. Several works (Chen and Yang 2020, 2021) try to extract dialogue topics, discourse, or action graphs from raw dialogue history using handcrafted rules or unsupervised methods. However, this information can’t reveal essential characteristics of multi-turn dialogues, especially the task-oriented dialogues which contain domain-specific structured ontologies like intents and slots (He, Yan, and Xu 2020; Yan et al. 2020). Therefore, in this paper, we propose a large-scale Task-Oriented Dialogue Summarization dataset, TODSum with dialogue state knowledge to summarize the key points of the agent completing certain tasks with the user, such as the user’s target (intent), preference (cheap or expensive restaurant), and user questions. Automatically summarizing such task-oriented dialogues can help a business collect and review needs or complaints from customers to improve the service. We hope to provide a unified and high-quality structured dialogue summarization benchmark to facilitate dialogue understanding while generating summaries.

Fig 1 displays an example of TODSum where a user wants to make a reservation. Compared to existing datasets, TODSum faces the following key challenges: (1) Factual Inconsistency: Multiple slot values often confuse summarization models to generate summaries with factual errors, like 3-star vs 4-star. (2) Repetition and Negotiation: The user usually negotiates some slot values with the agent many times since there is no available reservation. For example, the user changes 3-star to 4-star since there is no available hotel meeting all the constraints. (3) Multiple Domains: TODSum contains multiple domains among a single dialogue like hotel, restaurant and, taxi.

To tackle these challenges, we introduce additional dialogue state information for TODSum to enhance the faithfulness and controllability of generated summaries. We hope the better understanding of conversational content helps summarization models focus on key information and generate concise and coherent summaries. Considering that TODSum pays more attention to the factual consistency of generated summaries, we propose new state-aware factual consistency evaluation metrics based on the annotated dialogue state information for exhibiting the faithfulness of models. Then, we establish a fair benchmark and extensive strong dialogue summarization baselines for TODSum. Besides, we also propose an efficient state-aware structured dialogue summarization model to integrate the dialogue history and state information. Exhaustive experiments and analysis prove the effectiveness of dialogue structure guidance for task-oriented dialogue summarization. Finally, we perform a qualitative analysis to shed light on the current issues and future directions for TODSum. Our contributions are three-fold: (1) We introduce a task-oriented dialogue summarization dataset, TODSum along with corresponding dialogue state knowledge. (2) We establish a comprehensive benchmark and propose a general dialogue structure-aware summarization model to combine the original dialogue text and structured dialogue state. Besides, we propose new state-aware factual consistency metrics. (3) We conduct exhaustive qualitative analysis to prove the effectiveness of dialogue structure guidance and discuss current issues of TODSum and potential development directions for future work.

Related Work

Abstractive Dialogue Summarization Datasets Recently, many dialogue summarization datasets covering various scenarios have been constructed. Some research directly adopts meeting and interview transcripts as a special kind of dialogic text, such as AMI (Carletta et al. 2005), ICSI (Janin et al. 2003), and MediaSum (Zhu et al. 2021b). Since the meeting is essentially different from the dialogue in the language pattern, researchers further propose some practical conversational scenario datasets. They are either about the open-domain chitchats (Gliwa et al. 2019; Chen et al. 2021) or the multi/single turn QA scenarios (Chowdhury and Chakraborty 2019; Fabbri et al. 2021). Additionally, the studies on the customer-service dialogue summarization datasets, which is about the after-sales service or counseling, have attracted more attention and they belong to a task-oriented dialogue system. Liu et al. (2019) proposed a large-scale dataset from the logs in the DiDi customer service center and Zou et al. (2021a,b) collected a call-log dataset from the E-commerce platform. Both of them are faced with privacy issues and have higher labeling costs due to the human-written summaries. Yuan and Yu (2019) used the MultiWOZ dataset and use the self-configured instructions as the golden summaries. Because of the too-long length and the low quality of instructions, they are not suitable for choosing as the gold summaries. It is worth noting that although previous dialogue datasets have achieved some success, they ignore the most important characteristics of task-oriented dialogue, i.e., dialogue state structures. Therefore, to fill in this gap, we propose a novel TODSum dataset, which emphasizes the unique dialogue state structures of task-oriented dialogues.
Factual Consistency in Summarization

For the fact fabrication issue, some researchers are committed to designing evaluation metrics towards factual consistency, which is because that ROUGE scores correlate poorly with faithfulness. They are divided into 4 types: triple-based (Goodrich et al. 2019; Zhang et al. 2020b), textual entailment-based (Falke et al. 2019), QA-based (Wang, Cho, and Lewis 2020; Durmus, He, and Diab 2020), and pre-trained classifiers-based (Kryscinski et al. 2020). Another line of the related work focuses on enforcing factual relations in summarization models. Cao et al. (2017); Zhu et al. (2021a) proposed to encode facts in the sequential way and graph-based way, respectively. Li et al. (2018) proposed an entailment-reward augmented maximum-likelihood training objective. Dong et al. (2020); Cao et al. (2020) designed post-editing correctors to boost factual consistency in generated summaries. Considering that slots and intents are the two most important components in the task-oriented dialogue system, once there are a large number of factual errors about them appearing in the generated summaries, the summary system is completely unusable. In this paper, we try to boost the factual consistency via incorporating the dialogue state information while generating the summaries, and we also design novel state-aware factual evaluation metrics.

Task-Oriented Dialogue System

Compared to open-domain chitchats whose goal is to maximize user engagement (Huang, Zhu, and Gao 2020), a task-oriented dialogue (TOD) system aims to assist the user in completing certain tasks in a specific domain, such as restaurant booking, which is valuable for the real-world business (Zhang et al. 2020c). TOD systems are built on top of a structured ontology, which defines the domain knowledge of the tasks, like intents and slots. A key component of TOD is the dialogue state tracker (DST) which tracks the dialogue process in each time step by taking the entire dialog context as input (Wu et al. 2019; Wang et al. 2020).

Problem Formulation

Given a dialogue \( x = \{x_1, ..., x_m\} \) with \( m \) utterances, traditional dialogue summarization datasets aim to generate the target summary \( y = \{y_1, ..., y_k\} \) conditioned on the source dialogue \( x \) as \( \log p(y^i \mid x^i; \theta) \), where \( \theta \) are model parameters. Furthermore, TODSum feeds the dialogue state \( s \) into the model in addition to the source dialogue \( x \):

\[
\arg \max_{\theta} \sum_{(x^i, y^i, s^i) \in \langle x, y, s \rangle} \log p(y^i \mid x^i, s^i; \theta)
\]

where the dialogue state \( s \) is a set of slots and their corresponding values extracted from the conversation, such as (price, cheap) and (area, center). Note that TODSum contains multiple domains and intents thus we also add the domain and intent fields of a given pair, i.e., (slot, value), to avoid overlapping.

TODSum

In this section, we introduce our dataset selection, construction and processing, the characteristics of our proposed dataset TODSum, and new state-aware factual consistency evaluation metrics.

Data Collection

We construct the TODSum based on MultiWOZ (Budzianowski et al. 2018), which is the largest existing human conversational corpus containing 10,438 samples over 7 domains. MultiWOZ has 30 \((\text{domain}, \text{slot})\) pairs and over 4,500 possible values. Following Wu et al. (2019), we use five domains \(\text{restaurant}, \text{hotel}, \text{attraction}, \text{taxi}, \text{train}\) because the other two domains \(\text{hospital}, \text{police}\) lack enough annotations.

Dataset Construction and Processing

In this section, we will introduce our annotation method using the human-in-the-loop interaction. The overall procedure is shown in Fig 2. Firstly, we use the user goals from MultiWOZ as input and feed them into the state-of-the-art natural language generation model SC-GPT (Peng et al. 2020) to generate candidate summaries. Then we perform the human evaluation and correction on a part of generated summaries. The corrected summaries can be used to re-train SC-GPT. We iteratively repeat the above process and finally obtain a well-annotated TODSum.

Automatic Annotation

To avoid expensive human annotations, we use the SC-GPT to generate candidate summaries from user goals related to each dialogue. MultiWOZ uses a Wizard-of-Oz framework (WOZ) of human-to-human data collection, where each dialogue is set up with a corresponding user goal. The user goal can be regarded as a task template containing all necessary key information of the dialogue, such as intents and slots. We display an example in the Appendix. Then we use a strong Template2Text model SC-GPT to generate summaries. To control the quality of summaries, we also introduce human correction.

Human Evaluation and Correction

We randomly sample 100 generated template, summary for each domain and modify the generated summaries. Then we finetune the SC-GPT using human-annotated labels.

Human-in-the-loop

We perform the human-in-the-loop interaction to improve the quality of generated summaries without excessive labor-consuming annotations. We interactively perform the automatic annotation and human correction three times. Finally, we obtain the high-quality TODSum with 95% accuracy 1.

Data Post-processing

We clean the annotated data and divide training/valid/test following Wu et al. (2019). Note that we also keep the original dialogue state annotations of MultiWOZ. We hope this information can guide the summarization model to better model the dialogue context and gen-

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1We employ three annotators to independently evaluate whether the summary is suitable for the raw dialogue. We think the summary is accurate only when all the annotators say yes.
The user wants to know ...

Figure 3: Overall architecture of our model.

**State-Aware Structured Dialogue Summarization Model**

**Model Architecture**

Figure 3 provides a description of our model. Inspired by Zhu et al. (2021a) and Dou et al. (2021), we feed both the source dialogues and dialogue state information into the model. Note that it is a general framework based on the pre-trained models, i.e., BART and BERT, with the Transformer model (Vaswani et al. 2017) as the backbone structure. To encode the dialogue state structures, we design a novel dialogue state encoder to complement the dialogue encoder.

For dialogue state encoder, the dialogue state information is concatenated as the input sequence:  
\[
\text{input} = \text{domain}_1 \; \text{intent}_1(\text{slot}_1 = \text{value}_1; \text{slot}_2 = \text{value}_2) \; \text{intent}_2(\text{slot}_1 = \text{value}_1; \text{slot}_2 = \text{value}_2) ...
\]

The dialogue state encoder consists of multiple layers, each of which containing a self-attention block and a feed-forward block, just like the dialogue encoder. These two encoders share the parameters of the bottom layers and the word embedding layers, and only use different parameters in the last layer. Besides, in order to deal with the dialogue state information, we improve the standard Transformer. For each decoder layer, an additional cross-attention layer is added before the cross-attention layer of the dialogue to focus on the extraction of dialogue state information. In this case, the decoder will first attend to the dialogue state information and generate the corresponding representations, and then it will attend to the entire dialogue based on the dialogue state-aware information.

**Evaluation Metrics**

Along with the widely used automatic metric ROUGE scores (Lin and Och 2004), we pay more attention to the factual consistency of generated summaries. For example, a user books a cheap hotel with 2 people but the model summarizes an expensive hotel with 3 people, which is a fatal mistake for practical applications. We use $N_t$ and $N_h$ to denote the number of (domain, intent, slot, value) tuple in the target (golden dialogue state) and hypothesis (generated summary) $^2$ respectively. $N(h \cap t)$ denotes the number of slot tuples exactly matched between generated summary and golden dialogue state. We define state-aware factual consistency metrics as follows:  
\[
\text{Precision} = \frac{N(h \cap t)}{N(h)}, \quad \text{Recall} = \frac{N(h \cap t)}{N(t)}.
\]

The former and latter respectively denote the percentage of exactly matched slot tuples in the generated summaries and golden dialogue states. We compute the overall F1 score using  
\[
F1 = 2 \cdot \text{Precision} \cdot \text{Recall} / (\text{Precision} + \text{Recall}).
\]

$^2$We extract related slot values from generated summaries based on the task ontology.

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| Dataset         | Size  | Dialog.len | Turn.num | Summ.len | Lang | Multi-domain | Public |
|-----------------|-------|------------|----------|----------|------|--------------|--------|
| AMI (Carletta et al. 2005) | 137   | 6000.7     | 535.6    | 296.6    | EN   | ×            | ✓      |
| SAMSum (Gliwa et al. 2019)  | 16,369| 83.9       | 9.9      | 20.3     | EN   | -            | ✓      |
| CQA_Sum (Chowdhury and Chakraborty 2019) | 100,001 | 781.4     | 12       | 100      | EN   | ×            | ✓      |
| E-commerce (Zou et al. 2020) | 18,860| 1285.3     | 26.1     | 54.2     | CH   | ×            | ×      |
| DialSumm (Chen et al. 2021)  | 13,640| 131        | 9.5      | 22.6     | EN   | -            | ✓      |
| QMSum (Zhong et al. 2021)   | 232   | 9069.8     | 556.8    | 69.6     | EN   | ✓            | ✓      |
| ConvoSumm (Fabbri et al. 2021) | 2,021| 1,096      | 9.8      | 72.8     | EN   | ×            | ✓      |
| TODSum(ours)         | 9,906 | 186.9      | 14.1     | 45.4     | EN   | ✓            | ✓      |

Table 1: Comparison between TODSum and existing dialogue summarization datasets. Summ.len denotes the average length of golden summaries. Multi-domain denotes whether the dataset contains multi-domain cases among a single conversation.
Table 2: ROUGE scores and factual consistency scores of different models on TODSum. Results are averaged over three random runs. † means our methods. DS(pred) and DS(oracle) denote automatic prediction and oracle extraction at test time respectively. (p < 0.05 under t-test)

| Model               | ROUGE-1 | ROUGE-2 | ROUGE-L | Factuality |
|---------------------|---------|---------|---------|------------|
|                     | F  | P   | R  | F  | P   | R  | F  | P   | R  |
| Lead-3              | 24.06| 27.99| 22.43 | 5.01| 6.29| 4.52| 20.27| 23.63| 18.85|
| BertExt             | 41.49| 42.87| 42.10 | 13.13| 14.94| 12.45| 36.11| 37.42| 36.55|
| Oracle              | 46.07| 49.04| 44.90 | 15.66| 18.41| 14.24| 39.79| 42.45| 38.69|
| BertAbs             | 71.37| 67.86| 78.11 | 54.12| 52.52| 59.26| 68.89| 65.53| 75.36|
| BertAbs w. DS(pred) | 72.00| 69.04| 78.25 | 54.65| 53.14| 59.91| 69.74| 66.87| 75.82|
| BertAbs w. DS(oracle)† | 73.71| 70.25| 80.39 | 57.11| 55.25| 62.60| 71.58| 68.23| 78.07|
| BART                | 70.90| 68.10| 76.14 | 55.65| 53.39| 60.62| 68.23| 65.57| 73.21|
| BART w. DS(pred)†   | 72.46| 79.67| 72.46 | 57.82| 54.02| 64.91| 69.71| 65.61| 76.59|
| BART w. DS(oracle)† | 73.96| 69.81| 81.12 | 60.66| 56.93| 67.87| 72.02| 68.00| 78.94|

Table 2: ROUGE scores and factual consistency scores of different models on TODSum. Results are averaged over three random runs. † means our methods. DS(pred) and DS(oracle) denote automatic prediction and oracle extraction at test time respectively. (p < 0.05 under t-test)

**Choices of Dialogue Structure**

Following Dou et al. (2021), we feed two different variants of the dialogue state into our proposed model: oracle extraction and automatic prediction, called DS(oracle) and DS(pred) in subsequent experiments respectively. As for oracle extraction, we use the golden dialogue state corresponding to the last turn of the dialogue. For automatic prediction, we use the dialogue state predicted by the dialogue state tracking model TRADE (Wu et al. 2019). It is worth noting that the introduction of these two dialogue structures does not require human participation. Subsequent experiments show that oracle extraction improves the model performance more than automatic prediction.

**Joint Dialogue Understanding and Summarization**

A simple joint model is also designed to verify the ability of our model to simultaneously generate the dialogue states and summaries. We modify the input sequence of the decoder of the above model: input decoder=dialogue state <endoftext> golden summary. During training, the entire generated sequence is regarded as a whole to be calculated to get the final loss. However, different evaluation metrics are used to evaluate the dialogue states and summaries respectively at test time.

**Experiments**

**Baselines**

We compare our methods with several baselines. The extractive baselines are included: (1) Oracle; (2) Lead-3; (3) BertExt (Liu and Lapata 2019). We also add pretrained model-based abstractive methods for comparison: (1) BertAbs (Liu and Lapata 2019); (2) BART (Lewis et al. 2020).\(^3\) We give the details in Appendix.

**Main Results**

Table 2 displays the main results of different models on TODSum. We perform experiments based on two strong baselines, BertAbs (Liu and Lapata 2019) and BART (Lewis et al. 2020). We also add several extractive summarization models for comparison.\(^4\) We find that using the struc-

\(^3\)We will release our code at ***.

\(^4\)Since key information scatters sparsely across the whole conversation, extractive models are extremely worse than abstractive

**Qualitative Analysis**

**Dialogue Structure-Based Factual Consistency**

Fig 4 displays the different types of factual errors of BART and BART w. DS(pred). We annotate the same set of 100 randomly sampled summaries and classify the errors into five types: domain error, intent error, slot missing, slot redundancy, and slot value error. We report the average number of each error type that occurs on each sample and compare the difference between the two models. Results show tuned dialogue state information consistently outperforms both baselines on ROUGE and factual metrics. Specifically, BertAbs w. DS(oracle) outperforms BertAbs by 2.34% on ROUGE-1, 2.99% on ROUGE-2, and 2.69% on ROUGE-L. BART w. DS(oracle) outperforms BART by 3.06% on ROUGE-1, 5.01% on ROUGE-2, and 3.79% on ROUGE-L. The significant improvements prove the effectiveness of explicitly modeling dialogue states. For factual consistency metric F1, BertAbs w. DS(oracle) outperforms BertAbs by 4.21% and BART w. DS(oracle) outperforms BART by 10.62%. The higher improvements than ROUGE scores demonstrate our proposed state-aware structured dialogue summarization model significantly improves the faithfulness of generated summaries. It confirms that understanding dialogue structure is essential to factual consistency. Besides, comparing DS(pred) with DS(oracle), BART-based oracle outperforms pred by 1.50% on ROUGE-1, 2.84% on ROUGE-2, 2.31% on ROUGE-L, which shows the quality of dialogue state information has an effect on the summarization performance. We leave the detailed analysis in the following section: Robustness.

**Figure 4: Analysis of different types of factual errors.**

We find that using the struc-

\[^3\]We will release our code at ***.

\[^4\]Since key information scatters sparsely across the whole conversation, extractive models are extremely worse than abstractive

ones. We only add dialogue state knowledge based on abstractive baselines.
Figure 5: Effect of different quality of dialogue states for training. The X-ray denotes the tuple-level accuracy of the noisy dialogue states.

Figure 6: Effect of different quality of dialogue states for test.

that the BART baseline suffers from severe slot-related errors while our proposed BART w. DS can effectively alleviate these errors using dialogue state knowledge.

Robustness Analysis

To verify the effect of the quality of dialogue state information, we perform the robustness analysis in this section. We construct the noisy variant dataset, Noisy-TODSum. Specifically, we add random noise to the oracle dialogue states, including delete (slot, value) tuples, replace slot values, and insert new (slot, value) tuples. We respectively add noise to the training set and the test set to show how the noisy state information affects the performance of summarization.

Training Robustness Fig 5 shows the ROUGE and factual scores of our proposed BART w. DS(pred) under different noisy state information in the training set. We use the same oracle state for test. We find that, with the increase of state accuracy, BART w. DS(pred) gets better performance both on ROUGE and factual scores. Besides, the performance is similar when state accuracy is more than 70%, which indicates we don’t need to rely heavily on high-quality human annotated states and directly use existing DST models.

Test Robustness Similarly, we also show the performance comparison (Fig 6) under different noisy state information in the test set. Note that we add two special test accuracy, pred(acc=85%) and oracle(acc=100%) corresponding with BART w. DS(pred) and BART w. DS(oracle) in Table 2.

Table 3: F1 scores of ablation study. BART denotes only using original dialogue history. Instead, BART only DS takes dialogue states as the only input.

We find that higher test state accuracy results in better summarization performance. Comparing training noise with test noise, our model is more sensitive to the test noise, which proves dialogue state knowledge can effectively improve the controllability of generated summaries.

Domain Adaptation

Fig 7 shows the results of domain adaptation where we split dialogues into single domains, and choose four domains as training data, the other domain as test data, named DATODSum. We find zero-shot adaptation can’t generate reasonable summaries thus we also sample 10% target domain data for training to simulate few-shot domain adaptation. We choose each domain as the target domain and report the average scores for five runs. Results show our model with DS significantly outperforms BART, even higher than improvements of main results, which proves the effectiveness of dialogue state knowledge in the few-shot learning.

Ablation Study

We display the ablation study in Table 3 to show the importance of different input sources. Comparing dialogue history with pred state, only using pred state gets similar ROUGE scores but much higher factual scores (+5.39%), which proves dialogue state helps summarization models enhance faithfulness but get a drop in fluency. Combining both as input, our proposed state-aware structured dialogue summarization model gets the best performance for ROUGE and factual scores.

Joint Model

Table 4 shows the result of the joint model. We report the summarization metrics, ROUGE and factual scores, and dialogue state tracking metrics, Turn Acc. We find the joint model gets a worse performance than BART baseline on ROUGE and factual scores, and a lower acc than the DST model, TRADE(98.76). Although the joint model is simple and weak, more future work for joint dialogue understanding and summarization is worth being explored, like graph
Table 4: Results of joint model. Acc denotes the turn-level accuracy of dialogue state tracking.

| Model                  | R-1   | R-2   | R-L   | Factuality | Acc  |
|------------------------|-------|-------|-------|------------|------|
| BART                   | 70.90 | 55.65 | 68.23 | 55.53      | -    |
| BART w. DS(pred)       | 72.46 | 57.82 | 69.71 | 61.21      | -    |
| Joint Model            | 65.75 | 49.58 | 63.06 | 43.18      | 75.40|

Table 5: Human evaluation on Fluency (Flu.), informativeness (Inf.), Redundancy (Red.), and Factualness (Fac.)

| Model                  | Flu. | Inf. | Red. | Fac.  |
|------------------------|------|------|------|-------|
| Ground Truth           | 4.93 | 4.58 | 4.37 | 4.26  |
| BertAbs                | 4.20 | 4.13 | 3.51 | 3.19  |
| BertAbs w. DS(pred)    | 4.37 | 4.29 | 3.57 | 3.28  |
| BART                   | 4.18 | 4.22 | 3.55 | 3.57  |
| BART w. DS(pred)       | 4.41 | 4.36 | 3.63 | 4.12  |

### Human Evaluation

We conduct a manual evaluation to assess the models. 100 samples are randomly selected from the TODSum and five native speakers of English are hired to rate the ground truth and summaries generated by different models. Each annotator scores summaries from 1 (worst) to 5 (best) on fluency, informativeness, redundancy, and factualness. Each instance is rated by three annotators and the scores for each summary are averaged. The intra-class agreement score is 0.592.

As shown in Table 5, BertAbs w. DS(pred) and BART w. DS(pred) achieve great progress in the four metrics than BertAbs and BART respectively, especially in terms of factualness. This suggests the dialogue state information enhances the ability of models to identify the key information, such as slots and intents. However, for two pre-trained models, BertAbs w. DS(pred) performs worse than BART w. DS(pred) in factualness, which demonstrates the randomly initialized decoder in BertAbs can not pay attention to the structured information in the dialogues. In addition, all models perform poorly in redundancy. This is because the model emphasizes informativeness to the greatest extent, and there is no adequate balance between it and redundancy.

### Case Study

Fig 2 in Appendix shows two examples from the TODSum dataset. For Example one, BART incorrectly generated the intent of the user about train domain, that is, the id and arrival time of the train are incorrectly recognized as the number of people. Besides, the departure and destination of the train are reversed, which belongs to wrong generation of slot values. The most serious is that BART misunderstands the intent of the user about restaurants as the attention to the attraction, which leads to the incorrect subsequent field information. For Example two, the summary generated by BART loses some slots and corresponding values, such as the name of hotel. Additionally, all information for the taxi domain is missing, such as the type of the car, the driver’s phone number, and the leaving time of the taxi. According to observations, our model avoids these errors to some extent. By designing a novel dialogue state encoder, the dialogue state features are well represented, and a dialogue state-based cross-attention layer guides our model to focus on dialogue structures, which makes generated summaries identify more key information and contain more faithful facts. However, there are some deficiencies in redundancy for our models, such as hotels with parking and internet.

### Discussion

To further understand the current issues of TODSum, we perform error analysis on generated summaries. Then we provide several potential directions to handle these issues for future work.

#### Error Analysis

Compared to the golden summaries, we observe the generated summaries by existing models and summarize the following three error types:

1. **Information Missing**: The salient elements mentioned in golden summaries, i.e., slot and intent, are missing in generated summaries.
2. **Lack of Reasoning**: Current models lack context reasoning capability while facing multi-turn negotiation. They just memorize the surface words or phrases but disregard the logical relationships between conversations, leading to the wrong selection and combination of salient elements.
3. **Redundancy**: The golden summaries do not mention what appears in the generated summaries, especially the domains and intents.

#### Future Directions

Here we discuss several potential future directions worth being explored.

- **Graph Neural Network**: Recent work (Chen and Yang 2020, 2021) have been exploring graph-based summarization methods but are limited by noisy unsupervised signals like topic modeling, discourse graphs. These signals are coarse-grained and not intended for dialogues. Based on the dialogue state, we can better understand the dialogue context for summarization generation.
- **Multi-Task Learning**: Although the current joint dialogue understanding and summarization model doesn’t achieve a good performance. We still believe understanding and summarization are both important for each other. Even, the design of a task-oriented dialogue system can be combined with a summarization module.
- **Factual Consistency**: The dialogue state provides a uniform and simple evaluation tool to compute factual consistency, which may help the progress of related work.

### Conclusion

In this paper, we introduce a task-oriented dialogue summarization dataset, TODSum. We hope to utilize the task-oriented dialogue structure to enhance the faithfulness and controllability of generated summaries. Thus we propose a general dialogue state-aware summarization model to combine original dialogue text and structured dialogue state.
conduct exhaustive qualitative analysis to show the effectiveness of dialogue structure guidance and discuss current challenges of TODSum and potential development directions for future work.

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Appendix of TODSum: Task-Oriented Dialogue Summarization with State Tracking

Baseline Description

In this section, we describe baselines in detail.

**Oracle**: This model is used to obtain an oracle with a greedy algorithm similar to ?, which treats the utterances that maximize the ROUGE-2 as a summary.

**Lead-3**: This model is commonly used in the news summarization task, which treats the first three utterances of the document as a summary.

**BertExt**: This model is proposed by ?, which is an extractive model whose parameters are initialized with BERT.

**BertAbs**: This model is proposed by ?, which is an abstractive model with encoder initialized with BERT and trained with a different optimizer than its decoder.

**BART**: This model is proposed by ?, which is a state-of-the-art abstractive summarization model pre-trained with a denoising autoencoding objective.

Implementation Details

Our methods are implemented with PyTorch (?) and are based on both BertAbs (?) and BART (?). For parameters in the original pre-trained models, we followed the default hyperparameter settings to train our summarizers. For our model built on BertAbs, there are 13 encoding layers, with the top layer randomly initialized and separately trained between the two encoders. For our model built on BART, there are 24 encoding layers, with the top layer initialized with pre-trained parameters yet separately trained between the two encoders. The first cross-attention block of the decoder is randomly initialized whereas the second cross-attention block is initialized with pre-trained parameters. Besides, The TRADE (?) is used to predict dialogue state information during test time. Unless otherwise stated, we use oracle extractions at training time.

An Example of User Goal in MultiWOZ

As we mention in the main paper, MultiWOZ uses a Wizard-of-Oz framework (WOZ) of human-to-human data collection. The Wizard-of-Oz framework (WOZ) is firstly proposed as an iterative approach to improve user experiences when designing a conversational system. The goal of WOZ data collection is to log down the conversation for future system development. To overcome the need of relying on the data collection to a small set of trusted workers, the collection set-up of MultiWOZ is designed to provide an easy-to-operate system interface for the Wizards and easy-to-follow goals for the users. This results in a bigger diversity and semantical richness of the collected data. The domain of a task-oriented dialogue system is often defined by an ontology, a structured representation of the back-end database. The ontology defines all entity attributes called slots and all possible values for each slot. In general, the slots may be divided into informable slots and requestable slots. Informable slots are attributes that allow the user to constrain the search (e.g., area or price range). Requestable slots represent additional information the users can request about a given entity (e.g., phone number). Based on a given ontology spanning several domains, a task template is created for each task through random sampling. This results in single and multi-domain dialogue scenarios and domain-specific constraints were generated. We display an example of a user goal and its explanation corresponding with the real dialogue in Figure 1.

Case Study

In this section, we show Figure 2 for case study. The detailed introduction is in the main paper.
User goal

train
  
Dialogue

Instruction

attraction 
  
Inform

book

Reference number is: 9YW0JV6V.

Figure 1: An example of a user goal and its explanation corresponding with the real dialogue.
### Example one:

**User**: I need a train on Thursday. Find me one that leaves after 14:00.

**Agent**

A: Where are you going to?

**User**: To Cambridge.

A: Alright, the booking was successful, the total fare is 10.1 GBP payable at the station. Your reference number is: PR07IP3C. Anything else I can get you?

**User**: I'm looking for information about pizza express Fen Ditton.

A: Yes they are a moderately priced Italian place in the centre of town, would you care for more information or a booking?

**User**: Could I get more information, including the address, postcode, and area?

A: The address is Jesus Lane Fen Ditton. Postal code CB51BA. And it is located in the centre of town.

**User**: Can you reserve it for me?

A: I can. Can you tell me the day, time, and number of people?

**User**: That will be all for now. Thanks for all your help! Goodbye.

A: Thank you! Please contact us if you need any assistance. **domain1: train**

**Dialogue State**

- **train book** (people=1)
- **train inform** (leave=14:00; destination=Bishops Stortford; day=thursday; departure=Cambridge)
- **restaurant inform** (name=pizza express Fen Ditton)

**Ground Truth**

- **correct domain**
- **wrong domain**
- **correct intent**
- **wrong intent**

---

### Example two:

**User**: I am staying in Cambridge soon and would like to stay at a and b guest house.

**Agent**

A: Sure, how many days and how many people?

**User**: We are staying 6 people for 4 nights starting from Tuesday.

A: Your booking is successful! Your reference number is IGRA0MI. Do you need anything else?

**User**: Yes, what to recommend if I want to see good architecture in the west part of town?

A: Unfortunately there is no good architecture on the west end but I can look in other parts of town if you want.

**User**: What about a museum?

A: There are actually seven in the west.

**User**: Great, can I get the postcode, entrance fee and address of one of them?

A: Cafe jello gallery has a free entrance fee. The address is cafe jello gallery, 13 magdalene street and the post code is CB30AL. Can I help you with anything else?

**User**: Yes please. I need a taxi to commute.

A: When would you like to leave and arrive?

**User**: I'd like to get to the Gallery by 13:45, please.

A: S... I'm sorry, can you please let me in the details of the taxi.

**User**: Yes, what to recommend if I want to see good architecture in the west part of town?

A: That's all for now. Thank you so much.

**User**: You are very welcome! Don't hesitate to check back if anything else comes up that you'd like assistance with. Goodbye!

**Agent**

A: Anything else I can get you? **domain1: hotel**

**Dialogue State**

- **hotel book** (people=6; day=tuesday; stay=4)
- **hotel inform** (name=a and b guest house)
- **attraction inform** (type=museum; area=west)
- **taxi inform** (destination=cafe jello gallery; departure=a and b guest house; arrive by=13:45)

**Ground Truth**

- **complete domain**
- **missing domain**
- **complete slot**
- **missing slot**

---

**Figure 2**: A case study for two examples from the TODSum dataset.