DialDoc 2021 Shared Task:
Goal-Oriented Document-grounded Dialogue Modeling

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Abstract
We present the results of Shared Task at Workshop DialDoc 2021 that is focused on document-grounded dialogue and conversational question answering. The primary goal of this Shared Task is to build goal-oriented information-seeking conversation systems that can identify the most relevant knowledge in the associated document for generating agent responses in natural language. It includes two subtasks on predicting agent responses: the first subtask is to predict the grounding text span in the given document for next agent response; the second subtask is to generate agent response in natural language given the context. Many submissions outperform baseline significantly. For the first task, the best-performing system achieved 67.1 Exact Match and 76.3 F1. For the second subtask, the best system achieved 41.1 SacreBLEU and highest rank by human evaluation.

1 Introduction
Goal-oriented conversational systems could assist end users to query information in documents dynamically via natural language interactions. Meanwhile, there is a vast number of documents in which individuals and organizations choose to present their interests and knowledge to the world for broad applications. Thus, it attracts a lot of attentions from researchers and practitioners from different fields. There have been significant individual research threads that show promises in handling heterogeneous knowledge embedded in the documents (Talmor et al., 2021), including (1) unstructured content such as text passages (CoQA (Reddy et al., 2019), QuAC (Choi et al., 2018), ShARC (Saeidi et al., 2018), DoQA (Campos et al., 2020), Doc2Dial (Feng et al., 2020)); (2) semi-structured content such as tables or lists (SQA (Iyyer et al., 2017), HybridQA (Chen et al., 2020)); (3) multimedia such as images and videos with associated textual descriptions (RecipeQA (Yagcioglu et al., 2018), PsTuts-VQA (Colas et al., 2020), MIMOQA (Singh et al., 2021)). Despite these recent advances, the challenge remains for handling multi-turn queries of complex dialogue scenarios (Ma et al., 2020; Feng et al., 2020) and then respond based on the most relevant content in documents of various types from wide domains. As a step forward, we propose a shared task and competition to invite researchers to bring their individual perspectives and advance the field in joint effort.

We introduce DialDoc 2021 Shared Task, which focuses on building goal-oriented information-seeking dialogue that are grounded in textual content. In particular, the goal is to develop a dialogue system to comprehend multi-turn queries and identify the most relevant knowledge in the associated document for generating agent responses in natural language. It includes two subtasks for predicting agent response. The first subtask (Subtask 1) is to predict the grounding text span in the given document for next agent response; the second subtask (Subtask 2) is to generate agent response in natural language given the contexts. The dataset used for the task is a goal-oriented document-grounded dialogue dataset Doc2Dial (Feng et al., 2020). We hosted the leaderboards for Dev-Test and Test phase on eval.ai for two subtasks respectively. There are a total of 23 teams that participated Dev-Test phase. For final test phrase, 11 teams submitted to the leaderboard of Subtask 1, and 9 teams submitted to the leaderboard of Subtask 2. For the first task, the best system achieved 67.09 Exact Match and 76.34 F1. For the second subtask, the best system achieved 41.06 sacrebleu and rank the best by human evaluation.

In this work, we first describe the dataset and the two subtasks. Then, we provide a summary of the evaluation results from participating systems.
2 Dataset

We use Doc2Dial dataset \(^1\) introduced in Feng et al. (2020), which contains 4793 goal-oriented dialogues and a total of 488 associated grounding documents from four domains for social welfare: dmv, va, ssa, and studentaid. In this dataset, dialogues contain the scenarios when agent ask follow-up questions for clarification or verification based on dialogue-based and document-based context. Each turn is annotated with (1) grounding span from the associated document, (2) dialogue act, e.g., query, respond and (3) speaker role, either agent or user.

For developing models, we divide the data into training, validation and test split based on the number of dialogues. For evaluating the models, we provide a dev-test set which contains about 30% test dataset. The final test set also includes dialogue and document data from an unseen domain cdccovid that is not in the training, validation or dev-test set. The dialogues of unseen domain were collected in the same data collection process as published Doc2Dial dataset. Table 1 presents the number of dialogues (‘dials’), total turns (‘turns’) of all dialogues and total turns for prediction (‘predicts’) in each data split.

3 Task Description

This Shared Task focuses on building goal-oriented information-seeking dialogue systems. The goal is to teach a dialogue system to identify the most relevant knowledge in the associated document for generating agent responses in natural language. It includes two subtasks on predicting agent response. The agent can either provide an answer or ask follow-up question. Here we only consider the cases that use queries are answerable.

3.1 Subtask 1

This subtask is to predict the grounding span of next agent response. The input current turn, dialogue history and one associated document; the output is a text span. The evaluation is based on token-level F1 and exact match score (Rajpurkar et al., 2018).

3.2 Subtask 2

This subtask is to generate the next agent utterance. The input is current turn, dialogue history and the

\(^1\)https://doc2dial.github.io/file/doc2dial_v1.0.1.zip

|     | train | val  | test-dev | test |
|-----|-------|------|----------|------|
| dials | 3474  | 661  | 198      | 787  |
| turns | 44149 | 8539 | 1353     | 5264 |
| predicts | 20431 | 3972 | 198      | 787  |

Table 1: Statistics of dialogue data of different data splits.

document context; the output is utterance in natural language. The evaluation is based on SacreBLEU (Post, 2018). We also perform human evaluation on the top three submissions with highest SacreBLEU for determining the final rank.

Human evaluation We ask human annotators to rank a group of three utterances from the three submissions based on relevance and fluency given document context and dialogue history. relevance is used to measure how well the generated utterance is relevant to grounding span as a response to the previous dialogue turn(s). fluency indicates whether the generated utterance is grammatically correct and generally fluent in English. We randomly select 100 generated turns where the utterances are not all the same. We collect five judgements per group.

4 Baseline

Subtask 1 The baseline model for Subtask 1 is based on BERT-QA (Devlin et al., 2019). For each token, it computes the probabilities of start and end positions by a linear projection from the last hidden layers of the BERT model. Then it multiplies the scores of the start and end positions for estimating the probability of the corresponding span. As a baseline, we fine-tune BERT-base on Doc2Dial dataset where the input is dialogue query and the associated document context. The dialogue query is the concatenation of dialogue turns in reverse order.

Subtask 2 The task is formulated as an end-to-end text generation task. The baseline approach for Subtask 2 is based on sequence-to-sequence model BART by (Lewis et al., 2020). We fine-tune the pre-trained BART model (bart-cnn-large) on Doc2Dial dataset. The source input consists of current turn, dialogue history along with document title and content that are separated by special tokens. The target output is next agent utterance.
5 Shared Task Submissions

We hosted the leaderboards \(^2\) for Dev-Test and Test phase for the two subtasks on eval.ai. The Dev-Test and Test phase lasted three months and one week respectively. There are a total of 23 teams that participated Dev-Test phase. For final Test phrase, 11 teams submitted to the leaderboard of Subtask 1, and 9 teams submitted to the leaderboard of Subtask 2. Among the best-performing systems, some teams utilize additional data for augmentation for pre-training (e.g., CAiRE (Xu et al., 2021), SCIR-DT (Li et al., 2021)), some teams employ neural retrievers for obtaining most relevant document passages (e.g., RWTH (Daheim et al., 2021) and ER). For the first task, the best system achieved 67.1 Exact Match and 76.3 F1. For the second subtask, the best system achieved 41.1 sacrebleu and rank the best by human evaluation. Next, we provide a brief summary of the work by 8 teams as listed in Table 2, who submitted their technical system papers.

5.1 ER

ER\(^3\) participates Subtask 1. It introduces a model that leverages the structure in grounding document and dialogue context. It applies a multi-passage reader model based on transformer-based encoder to encode each passage concatenated with dialogue context and document title. It optimizes both passage selection, start and end position selection with gold knowledge passage during training. The final submission is an ensemble of 12 models and achieves the best results for Subtask 1.

5.2 SCIR-DT

SCIR-DT (Li et al., 2021) participates Subtask 1. Their methods include data augmentation, model pretraining/fine-tuning, postprocessing, and ensemble. For data augmentation, they use back-translation and synonym substitution to obtain 5 times of document and dialogue data, which are then paired into 25 times data. They use the augmented data for pretraining BERT and RoBERTa with whole word masking technique and doc2dial data for fine-tuning BERT, RobBERTa and ELECTRA. The ensemble method selects the most probably rank span based on the linear combination of ranking results per model and learn the hyperpar-

\(^2\)https://eval.ai/web/challenges/challenge-page/793/overview

\(^3\)The submission is non-archival.

| Team     | Affiliation                                      |
|----------|--------------------------------------------------|
| CAiRE    | The Hong Kong University of Science and Technology |
| ER       | Anonymous                                        |
| JARS     | Carnegie Mellon University                      |
| KU_NLP   | Konkuk University & Kangwon National University  |
| RWTH     | RWTH Aachen University                          |
| SB_NITK  | National Institute of Technology Karnataka       |
| Schlussstein | Carnegie Mellon University Bosch Research Pittsburgh |
| SCIR-DT  | Harbin Institute of Technology                   |

Table 2: Participating teams and affiliations.

rameter for inference. The team ranks 2nd based on the average of normalized F1 and EM scores used for the final evaluation.

5.3 KU_NLP

KU_NLP (Kim et al., 2021) participates both tasks. For Subtask 1, they adopt pretrained RoBERTa as backbone and predict dialogue act and span jointly. For Subtask 2, they include several tokens and embeddings based on document structure into input representation for BART. Instead of random order of the training instances, they propose to apply curriculum learning (Xu et al., 2020) based on the computed task difficulty level for each task respectively. The final submission on Subtask 2 is based on the span prediction by a single model. It achieves best SacreBLEU and human evaluation results.

5.4 RWTH

RWTH (Daheim et al., 2021) participates both tasks. For Subtask 1, it applies BERTQA with additional span-based specifics in their approach. First, they restrict start and end position only to the begin and end of sub-clauses since Doc2Dial dataset is based on preprocessed spans. In addition, they consider modeling the joint probability of a span inspired by Fajcik et al. (2020). The final submission is the ensemble of multiple models, where the probability of a span is obtained by marginalizing the joint probability of span and model over all models. For Subtask 2, they propose to cascade over all spans where they use top N (=5) spans as an approximation. The probability is computed jointly. The generation model is trained with cross-entropy using an n-best list obtained from the separately
trained selection model.

5.5 CAiRE

CAiRE (Xu et al., 2021) participates both tasks. They utilize data augmentation methods and several training techniques. For the first task, it uses QA data such as MRQA shared task dataset (Fisch et al., 2019) and conversational QA data such as CoQA (Reddy et al., 2019) for pretraining RoBERTa with multi-task learning strategy and the models are fine-tuned on Doc2Dial dataset. For the second task, they pretrain BART on Wizard-of-Wikipedia dataset (Dinan et al., 2019). Then they fine-tune the model using the knowledge prediction results from the first task. The final submission is based on the ensemble of multiple models where the best span is determined by the majority vote by models.

5.6 SB_NITK

SB_NITK (Bachina et al., 2021) participates Subtask 1. They also adapt data augmentation approaches that utilize additional Question Answering dataset such as SQuAD 2.0 (Lee et al., 2020), Natural Questions (Kwiatkowski et al., 2019) and CORD-19 (Wang et al., 2020) for pretraining several models including RoBERTa, ALBERT and ELECTRA. Then they experiment with different combinations of ensemble models. The final submission is based on the ensemble of ensemble ALBERTa and RoBERTa using all three additional datasets.

5.7 JARS

JARS (Khosla et al., 2021) participates in Subtask 1. It also uses transformer-based QA models, for which it pretrains on different Question Answering datasets such as SQuAD, different subsets of MRQA-2019 training set along with conversational QA data such as CoQA and QuAC. The experiments suggest that conversational QA datasets are more helpful comparing to QA datasets. They compare three different ensemble methods and use the highest average probability score for span prediction based on multiple models.

5.8 Schlussstein

Schlussstein (Chen et al., 2021) submit to both subtasks. For Subtask 1, they pretrain BERT on datasets such as SQuAD and CoQA before fine-tuning on Doc2Dial. To incorporate longer document content in Doc2Dial dataset, they also experiment with longer document stride and observe performance improvement. For Subtask 2, it pretrained BART model on CoQA dataset before fine-tuning it on Doc2Dial dataset.

6 Results

**Subtask 1**

We present the evaluation results on final Test phase of Subtask 1 from 7 participating teams in Table 3. The submissions are ordered based on the average of normalized F1 and EM scores. All submissions of Test Phase outperform BERT-base baseline by large margin. The scores in parentheses are by single models. All other results except the ones by KU_NLP are based on various ensemble methods, which further improve the performances significantly in most cases.

**Subtask 2**

Table 4 presents the evaluation results on final test set of Subtask 2 from 4 participating teams. We performance human evaluations on the top three submissions based on SacreBLEU scores. We use three different ways to compute majority vote to get the aggregated results: (1) we consider the rank if it is agreed among at least three annotators; (2) we consider the rank if it is agreed among at least two annotators; (3) we also use the aggregation results provided by Appen platform, which takes consideration of annotator’s historical performances.
7 Conclusion

We presented the results of 1st DialDoc 2021 Shared Task, which included two subtasks on document-grounded goal-oriented dialogue modeling. We received submissions from a total of 17 teams during entire phase for Subtask 1, and 9 teams for Subtask 2. All submissions during final Test phase outperformed baselines by a large margin for both subtasks. By organizing this shared task, we hope to invite researchers and practitioners to bring their individual perspectives on the subject, and to jointly advance the techniques toward building assistive agents to access document content for end users by conversing.

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