Learning to Retrieve Entity-Aware Knowledge and Generate Responses with Copy Mechanism for Task-Oriented Dialogue Systems

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Abstract

Task-oriented conversational modeling with unstructured knowledge access, as track 1 of the 9th Dialogue System Technology Challenges (DSTC 9), requests to build a system to generate response given dialogue history and knowledge access. This challenge can be separated into three subtasks, (1) knowledge-seeking turn detection, (2) knowledge selection, and (3) knowledge-grounded response generation. We use pre-trained language models, ELECTRA and RoBERTa, as our base encoder for different subtasks. For subtask 1 and 2, the coarse-grained information like domain and entity are used to enhance knowledge usage. For subtask 3, we use a latent variable to encode dialog history and selected knowledge better and generate responses combined with copy mechanism. Meanwhile, some useful post-processing strategies are performed on the model’s final output to make further knowledge usage in the generation task. As shown in released evaluation results, our proposed system ranks second under objective metrics and ranks fourth under human metrics.

1 Introduction

The traditional task-oriented dialogue systems, which focuses on providing information and performing actions by the given databases(DB) or APIs, often meet the limitation that the DB/API can not cover enough necessary cases. A good enhancement can be achieved with lots of relevant domain knowledge in the form of descriptions, FAQs and customer reviews, which we call unstructured knowledge. Track 1 of the 9th Dialogue System Technology Challenges (DSTC 9) (Gunasekara et al. 2020), Beyond Domain APIs: Task-oriented Conversational Modeling with Unstructured Knowledge Access (Kim et al. 2020), aims at generating a response based on dialogue history and unstructured knowledge access. The whole task can be divided into three subtasks, knowledge-seeking turn detection, knowledge selection and knowledge-grounded response. Test set of this track includes seen and unseen parts. The unseen test set are collected on different domains, entities, and locales, aiming to evaluate models’ generalization ability.

Knowledge-seeking turn detection, as the first subtask, needs to determine whether the related knowledge is contained in the unstructured knowledge base. In other words, this subtask can be modeled as a binary classification problem. If the model predicts that there exists related knowledge, then subtask 2 (knowledge selection) will search for the most relevant knowledge snippets and then pass them to the generation process (knowledge-grounded response generation). If the model predicts that there is no related knowledge for the specific question, the remaining two subtasks will not be performed. In this paper, we first conduct an entity matching for each question and then add the domain label from matching results to the end of dialogue history as model input.

Knowledge selection is to retrieve the most relevant knowledge snippets from the database according to the dialogue history and provide information for the subsequent response generation. The dialogue history is a conversation between the human speaker and the machine. Close to the end of the conversation, the human speaker brings up a question about a certain place (e.g., hotel, restaurant) or service (e.g., train, taxi). The given knowledge database consists of question-answer pairs involving diverse facts and is organized by different domains and entities. In this paper, we first apply retrieval techniques to narrow down the searching space and then use a neural network initialized by a pre-trained model to formulate the ranking function.

Knowledge-grounded response generation requests to give a response automatically from the model using dialogue history and unstructured knowledge as input. There are two different types of dialogue systems, retrieval-based system, and generation-based system. Retrieval-based dialogue system, giving responses from a list of candidate sentences, only has fixed answer forms in candidate sets. To deal with our problem, which needs more flexible and natural responses, the generation-based model is a better choice. Dialogue generation requires an encoder to represent the in-

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put and a decoder to generate the response. The network often needs to minimize the cross-entropy loss between the output and the ground truth. In this paper, we use a latent variable to encode dialog history and selected knowledge better and generate responses combined with copy mechanism.

As shown in released evaluation results (Gunasekara et al. 2020), our proposed system ranks second under objective metrics and ranks fourth under human metrics. In the following sections, we will explain the details of our proposed model. Experiment results will be shown next with some analysis and conclusions.

2 Related Work

All three subtasks use the pre-trained language model to represent sentences better and deal with the unseen test set. For subtask 1, we use ELECTRA (Clark et al. 2020) as our baseline model, while for subtask 2 and subtask 3, we use RoBERTa (Liu et al. 2019) as base encoder. ELECTRA and RoBERTa are BERT-like (Devlin et al. 2019) architecture with the bi-directional attention mechanism, while GPT (Radford et al. 2018, 2019) only has uni-directional attention.

Knowledge-seeking Turn Detection To our best knowledge, the Knowledge-seeking Turn Detection is newly proposed by this contest (Kim et al. 2020). Essentially, Knowledge-seeking Turn Detection is a general classification task that has been explored by NLP community for decades. There are some relevant research topics, such as sentiment analysis and natural language inference (NLI). Currently, the main stream pre-trained models (Devlin et al. 2019; Liu et al. 2019; Clark et al. 2020) can get state-of-the-art performance on these classification tasks. According to our experiments, ELECTRA reached the highest performance on subtask 1, so we select ELECTRA as our baseline model on this subtask.

Knowledge Selection Information retrieval (IR) techniques are widely applied to search for related candidates in retrieval-based knowledge-grounded system. Some researchers (Song et al. 2018; Dinan et al. 2018) compute the traditional tf-idf score to search the most relevant document to the user’s query, while others (Yan and Zhao 2018; Zhao et al. 2019; Gu et al. 2019; 2020) leverage the power of neural networks to learn the ranking score directly through an end-to-end learning process. Recently, due to the significant improvements on numerous natural language processing tasks, large scale pre-trained language models have also been applied to better model the semantic relevance in knowledge selection (Zhao et al. 2020).

Dialogue Generation Two architectures are often used in generation, sequence-to-sequence (Seq2Seq) (Vinyals and Le 2015; Serban et al. 2016; Vaswani et al. 2017) and language model (Radford et al. 2018, 2019). Pre-trained language models make a great progress on dialogue generation (Dong et al. 2019; Wolf et al. 2019b; Zhang et al. 2019). PLATO (Bao et al. 2020a) and PLATO-2 (Bao et al. 2020b) use uni- and bi-directional processing to further pre-train on large-scale Reddit and Twitter conversations dataset to reduce data distribution gaps. Moreover, a latent variable is used to capture one-to-many relations of post-response pairs.

Conditional Dialogue Generation Being viewed as conditional dialogue response generation, this subtask is closed to persona-chat (Zhang et al. 2018), which aims to generate responses within dialogue by given personality of speakers. (Wolf et al. 2019b) use GPT-2 as their base model by concatenating the personality and dialogue history splitting by speaker tokens. They also use an auxiliary task, binary classification, to decide whether the response is true under given condition. Baseline given by organizer (Kim et al. 2020) also using GPT-2 with concatenating the knowledge and dialogue history with speaker tokens.

Pointer Network Knowledge-based dialogue generation struggles with out-of-vocabulary (OOV) words since knowledge will be exact time or some strange proper nouns, which will not be seen by pre-trained language models. To deal with OOV problems, (See, Liu, and Manning 2017) provided a method to generate words by adding the attention distribution into standard decoder output. It is also called the copy mechanism since the probability of input words would be copied as answers.

3 Methodology

Following the task introduction, we separated our system into three subtasks, and three different models were applied respectively.

To clarify the problem, let \( S = \{s_1, s_2, \ldots, s_n\} \) denote the dialogue history, where \( s_i \) is the \( i^{th} \) utterance in the dialogue and \( n \) is the total number of the utterances. And let \( r = \{r_1, r_2, \ldots, r_l\} \) denote the response of dialogue, where \( r_i \) is the \( i^{th} \) token in the dialogue and \( l \) is the total number of the tokens. The knowledge database is a collection of knowledge snippets that are question-answer pairs to provide certain facts. Each knowledge snippet in the database contains a domain label \( dom \), which indicates the domain (e.g., hotel, restaurant, train, taxi) of the knowledge snippet, an entity label \( ent \), which indicates the name of the place (e.g., Avalon Hotel) associated with the knowledge snippet and the knowledge document \( doc \) which is a question-answer pair (e.g., Question: Are pets allowed on site? Answer: Not allowed.).

3.1 Knowledge-seeking Turn Detection

For knowledge-seeking turn detection, model needs to determine label \( y \in \{0, 1\} \) (1 indicates the related knowledge exists) based on the dialogue history \( S \).

Baseline Model The baseline in (Kim et al. 2020) is one-step classification. Specifically, the whole given dialogue history \( S \) will be fed into GPT-2 (Radford et al. 2019) model to get results.

Knowledge-aware ELECTRA The main drawback of GPT-2 approach is that the model fails to consider the knowledge that will be used in subsequent subtasks. This subtask’s target is to find if there is a relevant knowledge
snippet in the given knowledge base. If knowledge-seeking turn detection fails to detect the knowledge, subsequent subtasks will be missed.

To make use of knowledge, we propose a knowledge-aware ELECTRA model. The knowledge-aware ELECTRA model leverages knowledge in two steps. Firstly, we conduct an entity matching for each question. The details of entity matching will be explained in the retrieval model in Section 3.2. After entity matching, if there exists an entity in the knowledge base that also exists in the question, e.g, “Allenbell hotel”, we will concatenate the domain label dom to the end of dialogue history S. The input of subtask1 can be format as:

\[
\langle \text{bos}\rangle s_1, s_2, ..., s_{n-1} \langle \text{sep}\rangle s_n \text{ dom} \langle \text{eos}\rangle.
\]

Secondly, we add a one-bit knowledge flag to the end of the final hidden vector that corresponds to the token \(\langle \text{bos}\rangle\) obtained from the ELECTRA model, and they will be fed to the final classifier together. If the knowledge entity is found, we set the knowledge flag as 1; otherwise, the knowledge flag was set as 0. In this way, the model will also consider the existence of domain and knowledge. Specifically, there are five domain names used as dom in subtask1 i.e., taxi, train, hotel, restaurant, other. The introduction of domain sequence not only deals with out of domain cases but also makes use of the fact that different domain has different question style.

3.2 Knowledge Selection

Knowledge selection aims to select the most plausible knowledge snippets in database according to the dialogue history to facilitate subsequent dialogue completion. In this part, we only deal with the dialogues whose related knowledge history to facilitate subsequent dialogue completion. In this way, the model will also consider the existence of domain and knowledge. Specifically, there are five domain names used as dom in subtask1 i.e., taxi, train, hotel, restaurant, other. The introduction of domain sequence not only deals with out of domain cases but also makes use of the fact that different domain has different question style.

\[
\text{Algorithm 1: Retrieval Model}
\]

\[
S = \{s_1, s_2, ..., s_n\}
\]

\[
S' = \{s_{n-4}, ..., s_n\}
\]

\[
E = \text{Alias}(ent) = \{ent_1', ent_2', ..., ent_m'\}
\]

Result: \(C = \text{Retrieve Model}(E, S, \tau)\)

\[
C = [];
\]

\[
\text{for } ent' \in E \text{ do}
\]

\[
\text{for } s \in S \text{ do}
\]

\[
\text{if } \text{Exact}\_\text{Match}(ent', s) \text{ then}
\]

\[
C = C \cup \{ent\};
\]

\[
\text{end}
\]

\[
C' = \[]
\]

\[
\text{for } s \in S' \text{ do}
\]

\[
\text{if } \text{Fuzzy}\_\text{Match}(ent, s) > \tau \text{ then}
\]

\[
C' = C' \cup \{ent\};
\]

\[
\text{end}
\]

\[
C' = \text{sort}(C')
\]

\[
C = C \cup C'[:2]
\]

\[
\text{end}
\]

The baseline model is inefficient during evaluation and takes a much longer time compared with training. The model also suffers from the training-evaluation discrepancy because during training, the model has limited access to the knowledge database comparing to the evaluation. To remedy these issues, we proposed a retrieval module at the top of the ranking model to narrow down the scope of potentially useful knowledge snippets in the database, and the retrieved knowledge snippets are used for both training and evaluation.

The retrieval model collects all knowledge snippets whose entity label ent is relevant to the dialogue history S. It operates on the entity level, so all knowledge snippets about the same place or service will be not be collected by the retrieval model at the same time. We show the retrieve algorithm in Algorithm [1]. For each entity label ent in the knowledge base, we check whether it is relevant to the current dialogue. Given an entity name ent, we first handle special tokens in the name and generate multiple aliases \(\{ent_1', ent_2', ..., ent_m'\}\). For example, we generate alias ‘A’ and ‘B’ for the name ‘A & B’. We then check whether one of the aliases appear in the complete dialogue S using exact match. We say ent matches the dialogue history if at least one alias appears in the history.

We also perform fuzzy match and check whether alias ent’ appears in the last 5 utterances S’ = \{s_{n-4}, ..., s_n\}. Specifically, we tokenize the ent’ with spaCy [Honnibal et al. 2020] and count the number of tokens with a fuzzy ratio above the threshold \(\tau = 0.8\) against the utterance. We define the fuzzy match score as the percentage of the tokens that counts. To prevent the case where the fuzzy match method returns too many matched entities, we sort the entity names by the maximum fuzzy match score over all aliases and only include the top 2 entity names.

Once an entity name ent matches the dialogue history, we
include all knowledge snippets in the database with the same entity name as our candidate knowledge snippets.

**Ranking Model**  The ranking model selects the most appropriate knowledge snippet from the candidates produced by the retrieval model. Following [Kim et al. (2020)](https://www.example.com), we build the ranking model by fine-tuning the pre-trained RoBERTa-large model ([Liu et al. 2019](https://www.example.com)). We concatenate the dialogue history $S$ and the knowledge snippet as the input:

$$X = \langle \text{bos} \rangle S \langle \text{sep} \rangle \text{dom} \langle \text{sep} \rangle \text{ent} \langle \text{sep} \rangle \text{doc} \langle \text{eos} \rangle.$$  

Here $\langle \text{bos} \rangle$, $\langle \text{sep} \rangle$, $\langle \text{eos} \rangle$ are special separating tokens predefined in RoBERTa. Based on the final layer hidden vector that corresponds to the token $\langle \text{bos} \rangle$, the ranking model outputs a ranking score $p$.

$$l_{\langle \text{bos} \rangle} = \text{Roberta}(X)$$  

$$p = f(l_{\langle \text{bos} \rangle})$$

where $f$ is a one-layer classifier. We pick the one with the highest ranking score as our final prediction for knowledge selection.

**Three-step Model**  Three-step model is similar to the ranking model, but it is applied to domain level, entity level and document level respectively in a pipeline rather than to the document level directly. The input format of the document submodule is the same as Equation (2), and the input format of domain and entity submodules are:

- **domain**: $\langle \text{bos} \rangle S \langle \text{sep} \rangle \text{dom} \langle \text{sep} \rangle$,  
- **entity**: $\langle \text{bos} \rangle S \langle \text{sep} \rangle \text{ent} \langle \text{sep} \rangle$,  
- **history**: $\langle \text{bos} \rangle S \langle \text{sep} \rangle \langle \text{ent} \rangle$,  
- **response**: $\langle \text{ros} \rangle \langle \text{sep} \rangle \langle \text{ent} \rangle$.

The candidates of entity submodule are only from the most plausible domain and the candidates of document submodule are only from the most plausible entity. Three-step model is built beyond RoBERTa-base model ([Liu et al. 2019](https://www.example.com)).

**Fine-tuned with Data Augmentation**  We generate more dialogues using the question-answer pair in the knowledge database to enhance the training data, and fine-tune the domain and entity submodules in the Three-step model with the combination of original training data and generated dialogues. Specifically, for each entity, we first sample the dialogue length according to the number of question-answer pairs under this entity and then we randomly sample the question-answer pairs and concatenate them together as a new dialogue. To mimic the situation of topic shift in the real scenario, we generate another part of dialogue under another entity and concatenate them to make eighty percent of the time.

**Ensemble Model**  We ensemble the Retrieve & Rank model with Three-step model together. The ensemble model is also divided into three submodules. In each submodule, we take the prediction with higher probability as results.

![Figure 1: The architecture of subtask-3 model.](https://www.example.com)

### 3.3 Knowledge-grounded Response Generation

**Basic Architecture**  Inspired by PLATO model ([Bao et al. 2020](https://www.example.com)), we notice that the latent variable may be useful for getting the relations among dialogue history $S$, answer part of knowledge $k_a$, and response $r$. We first concatenate them together with some special tokens:

$$\langle \text{bos} \rangle k_a \langle \text{sp} \rangle s_1 \langle \text{sp} \rangle s_2 \cdots \langle \text{sp} \rangle r \langle \text{eos} \rangle.$$  

where $\langle \text{sp} \rangle$ represents the first speaker, $\langle \text{sp} \rangle$ represents the second speaker in our two speakers’ dialogue. Following the setting in PLATO, we assume that the latent variable $z$ is one K-way categorical variable. We want to encode response information into the $Z$ matrix, and each row of the matrix represents a special $z$ corresponding to given examples. We estimate posterior probability $q_φ(z|S, k_a, r)$ which are used to select $z$ from matrix $Z$.

However, $z$ cannot be calculated using the posterior probability at test time without accessing responses. Thus we use prior probability $p_θ(z|S, k_a)$ to approach the posterior probability. Inspired by VAE ([Kingma and Welling 2014](https://www.example.com)), we reduce the KL-divergence (KLD) loss

$$l_{\text{KLD}} = D_{\text{KL}}(q_φ(z|S, k_a, r)||p_θ(z|S, k_a))$$  

(8) to minimize the gap between posterior and prior probability. Thus we split our model into three components, as shown in ![Figure 1](https://www.example.com). We use the trapezoidal mask to prevent response information leakage from our bi-directional encoder. The first component calculates the posterior probability $q_φ(z|S, k_a, r)$ with responses as input. At the same time, the matrix $Z$ also will be updated to get the information of response. The second component is to calculate the prior probability $p_θ(z|S, k_a)$ without response. After obtaining the posterior and prior probability of $z$, we calculate KLD loss.
With dialogue history, knowledge and z, the third component generates responses with reducing negative log-likelihood (NLL) loss,

$$l_{NLL} = -E_{z \sim q_0(z|S,k_a,r)} \log p(r|S,k_a,z)$$

$$= -E_{z \sim q_0(z|S,k_a,r)} \sum_{t=1}^{T} \log p(r_t|S,k_a,z,r_{<t})$$  \hspace{1cm} (9)

The bag-of-words (BOW) loss (Zhao, Zhao, and Eskenazi 2017) is also employed to facilitate the training process of latent discrete variables,

$$l_{BOW} = -E_{z \sim q_0(z|S,k_a,r)} \sum_{t=1}^{T} \log p(r_t|S,k_a,z)$$

$$= -E_{z \sim q_0(z|S,k_a,r)} \sum_{t=1}^{T} \log \frac{e^{f(r_t)}}{\sum_{v \in V} e^{f(v)}},$$

where \(V\) refers to the whole vocabulary, and \(f\) is a linear layer with softmax on the hidden output of \(z\), \(h_z\), which tries to predict the words of response without position information,

$$f = \text{softmax}(W_1 h_z + b_1)$$  \hspace{1cm} (11)

We only pass through component 2 and 3 at test time.

**Knowledge Copy** Without the ability to utilize knowledge directly, the pure dialogue generation model will only focus on grammatical/semantical correctness, naturalness, and appropriateness. However, another main target of this task, relevance to the given knowledge, has not been taken into account. Motivated by pointer-generator network (See, et al. 2016) may generate lots of useless sentences, we propose the first-word-fixed beam search (FFBS) for our generation. Since beam search may yield similar sentences and diversity beam search (Vijayakumar et al. 2016) may generate lots of useless sentences, we propose the first-word-fixed beam search (FFBS) for our generation. Concretely, the first words of the generated response would be generated if it appears at knowledge part, which means \(p_{gen}(t)\) is decided by knowledge and hidden outputs of the encoder,

$$p_{gen}(t) = \sigma(W_p[k_m \circ h_t, k_m, h_t] + b_p)$$  \hspace{1cm} (13)

And knowledge representation \(k_m\) can be calculated by

$$k_m = \frac{1}{N_k} \sum_{i=1}^{N_k} h_{k_i}$$  \hspace{1cm} (14)

where \(N_k\) is the token numbers of knowledge in one example, and \(h_{k_i}\) is the top hidden outputs in knowledge part.

The total probability used to generate our response is the sum of two distributions with \(p_{gen}(t)\) as weight,

$$P(V, t) = p_{gen}(t)P_{lang}(V, t) + (1 - p_{gen}(t))P_{att}(V', t)$$  \hspace{1cm} (15)

where \(P(V, t)\) can be viewed as \(p(r_t|S,k_a,z,r_{<t})\) to calculate \(l_{NLL}\). If \(w \notin V\) is an out-of-vocabulary (OOV) word with \(P_{lang}(w, t)\) equaling or approaching to zero, it still can be generated if it appears at knowledge part, which means \(P_{att}(w, t)\) is not zero. This architecture is shown as generate with copy part in figure 1.

The knowledge-copy mechanism provides an efficient way to generate sentences under the given knowledge, reducing the pressure added on the decoder. It makes the model learn how to directly use knowledge, which is easier to generalize to unseen knowledge. More analysis will be done in later sections. Due to the benefits of knowledge-copy mechanism, we want to use it as much as possible, that is, to make \(p_{gen}(t)\) smaller. So a normalization loss will be added to the final loss, which is

$$l_{norm} = \sum_{t=1}^{T} p_{gen}^2(t)$$  \hspace{1cm} (16)

where \(T\) means the maximum time step of response generation.

In summary, the total integrated loss of our generation model is

$$l_{total} = \lambda_1 l_{NLL} + \lambda_2 l_{BOW} + \lambda_3 l_{KLD} + \lambda_4 l_{norm}$$  \hspace{1cm} (17)

**Segmented Response Generation** In this subtask, one response can be viewed as two parts. One is knowledge-response which needs lots of information from the knowledge candidate, and the other is greeting-response, which is less-information and does not request so much knowledge background. With given dialogue history, knowledge and latent variable \(z\), these two parts can be generated by different model respectively due to a reasonable assumption of conditional independence. We use this segmented response generation (SRG) method in our experiments and show its power in the analysis part. Note that the knowledge-copy mechanism is not applied for greeting-response generation.

**Modified Beam Search** Since beam search may yield similar sentences and diversity beam search (Vijayakumar et al. 2016) may generate lots of useless sentences, we propose the first-word-fixed beam search (FFBS) for our generation. Concretely, the first words of the generated responses are selected by top-k probability and fixed as different groups, and regular beam search will be done separately in each group. We fix the first words because they almost control the whole sentence development in auto-regressive generation models.
Post-processing Strategies Response with more knowledge is better in most cases. Inspired by this, post-processing (PP) is performed in generation using similarity between response and knowledge to re-rank our candidate responses generated by FFBS. BERTScore (Zhang et al. 2020) is applied to calculate the semantic similarity between knowledge-response and the knowledge candidate. However, it may score extremely high when the two sentences are the same. To ensure the flexibility of responses, we also calculate the Jaro–Winkler distance (JWD) (Jaro 1989; Winkler 1990), a kind of edit distance to evaluate the sentence similarity. To sum up, the score we use to re-rank response the candidate is

\[ S_{\text{total}} = \mu_1 S_{\text{NLL}} + \mu_2 S_{\text{BERT}} - \mu_3 S_{\text{JWD}} \]  

where \( S_{\text{NLL}} \) equals to log probability of each beam output from the generator, which will also be normalized in \([0,1]\). The sentences with the highest \( S_{\text{total}} \) through candidates will be selected as our final responses.

4.2 Experiment Details

Firstly, we initialized our models with pre-trained models’ weights obtained from HuggingFace’s model hub (Wolf et al. 2019a). And then, our models were fine-tuned on the dataset provided for our special task, respectively.

For subtask 1, we used ELECTRA-base to initialize our model. Learning rate was set to \(6.25e-5\), and batch size was set to 16.

For subtask 2, RoBERTa-large was used to initialize the Retrieve & Rank model. Learning rate was \(1e-5\) and the batch size was 72. We first retrieve entities to narrow down the candidate searching scope and then take their corresponding snippets for training and evaluation. Specifically, during training, we randomly sample five negative snippets from the retrieval results. During evaluation, we rank all retrieved snippets to get final predictions. For Three-step model and the ensemble model, we initialized them with RoBERTa-base. Learning rate was \(6.25e-5\), batch size was 4 and the candidate number in each sample was 6. For data augmentation, we generated 100 dialogues for each entity in the training/validation knowledge database.

For subtask 3, we used RoBERTa-base to initialize our model, and these hyperparameters were kept the same as the baseline provided by the organizer. Learning rate was set to \(6.25e-5\), and batch size was set to 4, with 32 gradient accumulation steps. The number of hidden variable \(z\) was set to 5. To make the knowledge-copy mechanism not merely copy the whole sentence, we masked punctuates of knowledge while getting knowledge-attention distribution. The hyperparameter \(\lambda_{1-4}\) and \(\mu_{1-3}\) were set to 1 for convenience. We trained our model in 10 epochs. At the generation stage, we used FFBS to get responses, with 4 groups and 2 beams and thus we had \(8 (4 \times 2)\) responses for one input in total.

All code is published to help replicate our results.3

4.3 Metrics

Some specific objective metrics are evaluated in each task, including precision, recall, f1-score in subtask 1, mrr@5, recall@1, recall@5 in subtask 2, BLEU-1/2/3/4, meteor, rouge-1/2/L in subtask 3. Human evaluation is also performed in subtask 3, including two aspects, appropriateness and accuracy. Appropriateness metric means how well the response is naturally connected to the conversation, ranging from 1 to 5, and the larger, the better. Accuracy means, with a given reference knowledge, how accurate each system’s response is on a scale of 1 to 5, and also the larger, the better.

4.4 Evaluation Results

Table 3 and 5 present the evaluation results on test dataset of our all three subtasks. Compared with the baseline in Kim et al. (2020), our model achieves huge improvement in all three subtasks. In addition, human metrics show that the performance of our model is close to human compared with

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3https://github.com/lxchtan/DSTC9-Track1
Table 3: Objective metrics on test set.

| Subtask-2 Model | MRR@5 | Recall@1 | Recall@5 | Domain | Error Number@1 |
|-----------------|-------|----------|----------|--------|----------------|
| Roberta (baseline) | 0.8691 | 0.8058 | 0.9428 | 215 | 72 |
| Retrieve & Rank | **0.9747** | 0.9622 | **0.9880** | 16 | 41 |
| Three-step w/ data aug. | 0.9739 | 0.9660 | 0.9828 | 7 | **37** |
| Three-step w/o data aug. | 0.9692 | 0.9607 | 0.9783 | 11 | 43 |
| Our Ensemble Model | 0.9743 | **0.9678** | 0.9813 | 9 | 38 |

Table 4: The performance of models on validation set (subtask 2).

| Subtask-3 Model | BLEU-4 | METEOR | ROUGE-L |
|-----------------|--------|--------|---------|
| Ours (w/ PP) | **0.1450** | 0.4526 | **0.4256** |
| –SRG | 0.1366 | 0.4400 | 0.4155 |
| Ours (w/o PP) | **0.1512** | 0.4534 | 0.4317 |
| –FFBS | 0.1490 | **0.4536** | **0.4342** |
| –SRG | 0.1473 | 0.4485 | 0.4311 |
| –Copy | 0.1424 | 0.4322 | 0.4194 |
| –Z | 0.1327 | 0.4210 | 0.4096 |

Table 5: Human metrics on test set.

| Subtask-1 Model | Precision | Recall | F1-score |
|-----------------|-----------|--------|----------|
| Baseline (GPT2) | 0.957 | 0.966 | 0.961 |
| Xlnet | 0.944 | 0.983 | 0.963 |
| Roberta | 0.947 | 0.993 | 0.970 |
| ELECTRA | 0.950 | 0.994 | 0.972 |
| Our | **0.996** | **0.999** | **0.998** |

Table 6: Models performance on validation set (subtask 1).

the ground-truth. The results provided by the organizer (Gunnasekara et al. 2020) show that we rank second under objective metrics and rank fourth under human metrics.

5 Analysis

Ablation experiments were conducted to demonstrate the importance of each component in our proposed model, and the results were reported on validation set on each subtask.

Subtask 1 As shown in Table 6 in addition to our model, we report the results of Xlnet, RoBERTa, ELECTRA and GPT-2 on the validation set of subtask 1 as well. The performance of our knowledge-aware ELECTRA outperforms all of these models with a substantial margin. Compared with the original ELECTRA, the F1-score of our model has 2.6% improvement, which indicates knowledge does help ELECTRA perform better.

Subtask 2 We changed the language model from GPT2 to Roberta-base in the model proposed in (Kim et al. 2020) and used it as our baseline. The evaluation results of our ensemble model on the test dataset in subtask 2 are shown in Table 3 and it outperforms the baseline by a large margin.

To have a better idea of the performance of the base models, we present the results of our ensemble model and the two base models (i.e., Retrieve & Rank model and Three-step model) in Table 4. We also show statistics about the number of errors that occur at the domain, entity, and document level. Results on the validation set are based on the ground-truth labels of subtask 1. We can find that Retrieve & Rank model has a better recall@5 while Three-step model with data augmentation provides better recall@1, especially better in domain and entity prediction. The ablation test on data augmentation also shows that the data augmentation technique is helpful at the domain and entity level. Since the test set involves out-of-domain data, there is a gap between performance on the validation and test set. Further study is required to improve the transferability and generalization of our models.

Subtask 3 We used ground-truth labels of subtask 1 and 2 in order to study the components of subtask 3 independently. The result is shown in Table 7. At the part without post-processing, we can easily find that the latent $z$ contributes about 1% to on each metrics, while knowledge-copy mechanism wins about 0.5% on BLEU-4, about 1.6% on METEOR, about 1.2% in ROUGE-L. SRG and FFBS also im-
Can I get a written confirmation for the taxi booking?

Booking confirmations will be sent via text messages shortly.

You will be sent a confirmation text very shortly. Is there anything else I can help you with?

Confirmations will be sent via text messages shortly. Can I help you with anything else?

By the way, what hours is the station opens?

The station opens at 5:00 am Monday-Saturday and 7:00 on Sundays. Anything else I can do for you?

The hours of operation are Monday-Saturday 05:00 - 23:00, and on Sundays 07:00 - 22:55.

Monday through Saturday 5 AM to 11:00 PM, Sundays 7 AM to 11:55 PM. Can I help you with any more information?

The station opens at 5:00 am Monday-Saturday and 7:00 on Sundays. Anything else I can do for you?

Table 8: Generation examples on validation set (subtask 3).

prove our model under objective metrics. Note that the use of post-processing could increase human evaluation scores, while the objective scores may reduce. However, after using SRG, objective scores could rise without post-processing, as shown in the row Ours (w/ PP) and Ours (w/ PP) –SRG. Since objective metrics are not good enough to reflect the accuracy of used knowledge, we select some examples to explore in Table 8. We can find that post-processing and knowledge-copy mechanism have a stronger ability to capture information of knowledge.

6 Conclusion

This paper describes our overall system that is evaluated in Track 1 of DSTC 9. Pre-trained language models, ELECTRA and RoBERTa, are used as our base encoder, and task-specific components are applied to improve performance. In the released evaluation results, we rank second under objective metrics and rank fourth under human metrics. Considering the gap between validation and test set, it is worthwhile for us to further study how to generalize our model in a better way, that is, transferring our in-domain system to the out-of-domain scenario.

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