Retrospective and Prospective Mixture-of-Generators for Task-oriented Dialogue Response Generation

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Abstract. Dialogue response generation (DRG) is a critical component of task-oriented dialogue systems (TDSs). Its purpose is to generate proper natural language responses given some context, e.g., historical utterances, system states, etc. State-of-the-art work focuses on how to better tackle DRG in an end-to-end way. Typically, such studies assume that each token is drawn from a single distribution over the output vocabulary, which may not always be optimal. Responses vary greatly with different intents, e.g., domains, system actions. We propose a novel mixture-of-generators network (MoGNet) for DRG, where we assume that each token of a response is drawn from a mixture of distributions. MoGNet consists of a chair generator and several expert generators. Each expert is specialized for DRG w.r.t. a particular intent. The chair coordinates multiple experts and combines the output they have generated to produce more appropriate responses. We propose two strategies to help the chair make better decisions, namely, a retrospective mixture-of-generators (RMoG) and a prospective mixture-of-generators (PMoG). The former only considers the historical expert-generated responses until the current time step while the latter also considers possible expert-generated responses in the future by encouraging exploration. In order to differentiate experts, we also devise a global-and-local (GL) learning scheme that forces each expert to be specialized towards a particular intent using a local loss and trains the chair and all experts to coordinate using a global loss. We carry out extensive experiments on the MultiWOZ benchmark dataset. MoGNet significantly outperforms state-of-the-art methods in terms of both automatic and human evaluations, demonstrating its effectiveness for DRG.

1 INTRODUCTION

Task-oriented dialogue systems (TDSs) have sparked considerable interest due to their broad applicability, e.g., for booking flight tickets or scheduling meetings [32, 34]. Existing TDS methods can be divided into two broad categories: pipeline multiple-module models [2, 5, 34] and end-to-end single-module models [11, 30]. The former decomposes the TDS task into sequentially dependent modules that are addressed by separate models while the latter proposes to use an end-to-end model to solve the entire task. In both categories, there are many factors to consider in order to achieve good performance, such as user intent understanding [31], dialogue state tracking [37], and dialogue response generation (DRG). Given a dialogue context (dialogue history, states, retrieved results from a knowledge base, etc.), the purpose of DRG is to generate a proper natural language response that leads to task-completion, i.e., successfully achieving specific goals, and that is fluent, i.e., generating natural and fluent utterances.

Recently proposed DRG methods have achieved promising results (see, e.g., LaRLAttnGRU [36]). However, when generating a response, all current models assume that each token is drawn from a single distribution over the output vocabulary. This may be unreasonable because responses vary greatly with different intents, where intent may refer to domain, system action, or other criteria for partitioning responses, e.g., the source of dialogue context [24]. To support this claim, consider the training set of the Multi-domain Wizard-of-Oz (MultiWOZ) benchmark dataset [4], where 67.4% of the dialogues span across multiple domains and all of the dialogues span across multiple types of system actions. We plot the density of the relative token frequency distributions in responses of different intents over the output vocabulary in Fig. 1. Although there is some overlap among distributions, there are also clear differences. For example, when generating the token \textit{[entrance]}, it has a high probability of being drawn from the distributions for the intent of \textit{booking an attraction}, but not from \textit{booking a taxi}. Thus, we hypothesize that a response should be drawn from a mixture of distributions for multiple intents rather than from a single distribution for a general intent.

Figure 1: Density of the relative token frequency distribution for different intents (domains in the top plot, system actions in the bottom plot). We use kernel density estimation\footnote{https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.plot.kde.html} to estimate the probability density function of a random variable from a relative token frequency distribution.
which consists of a chair generator and several expert generators. Each expert is specialized for a particular intent, e.g., one domain, or one type of action of a system, etc. The chair coordinates multiple experts and generates the final response by taking the utterances generated by the experts into consideration. Compared with previous methods, the advantages of MoGNet are at least two-fold: First, the specialization of different experts and the use of a chair for combining the outputs breaks the bottleneck of a single model [10, 19].

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Given the current dialogue context $x$, the utterance representation $h^U_i$, the belief state vector $h^B$, and the database vector $h^D$,

$$x = \text{tanh}(W_x h^U_i + W_b h^B + W_d h^D),$$

where $h^U_i$ is the hidden state from Eq. 1, $h^B$ is a 0-1 vector with each dimension representing a state slot-value pair; $h^D$ is also a 0-1 vector, which is built by querying the database with the current state $B$. Each dimension of $h^D$ represents a particular result from the database (e.g., whether a flight ticket is available).

### 2.3 Expert decoder

Given the current dialogue context $X$ and the current decoded tokens $Y_{0:j-1}$, the $l$-th expert outputs the probability $P(y_j^l \mid Y_{0:j-1}, X)$ over the vocabulary $V$ at the $j$-th step by:

$$P(y_j^l \mid Y_{0:j-1}, X) = \text{softmax}(U^T o_j^l + b),$$

where $U$ is the parameter matrix and $b$ is bias; $o_j^l$ is the state vector, which is initialized by the dialogue context encoder from the shared context encoder, i.e., $s_0 = x$; $y_{j-1}$ is the embedding of the generated token at time step $j - 1$; $\oplus$ is the concatenation operation; $c_j^l$ is the context vector which is calculated with a concatenation attention mechanism over the hidden representations from a shared context encoder as follows:

$$c_j^l = \sum_{i=1}^n \alpha_{ji} h_i,$$

$$\alpha_{ji} = \frac{\exp(w_{ji})}{\sum_{k=1}^n \exp(w_{kj})},$$

$$w_{ji} = v_i^T \text{tanh}(W_i^T (h_i \oplus s_{j-1}^l) + b_i),$$

where $\alpha$ is a set of attention weights; $\oplus$ is the concatenation operation. $W_i$, $b_i$, $v_i$ are learnable parameters, which are not shared by different experts in our experiments.

### 2.4 Chair decoder

Given the current dialogue context $X$ and the current decoded tokens $Y_{0:j-1}$, the chair decoder estimates the final token prediction distribution $P(y_j \mid Y_{0:j-1}, X)$ by combining the prediction probabilities from $k$ experts. Here, we consider two strategies to leverage the pre-computed data from different experts.

Specifically, the chair determines the prediction $P(y_j \mid Y_{0:j-1}, X)$ as follows:

$$P(y_j \mid Y_{0:j-1}, X) = \beta_j^C \cdot P(y_j^C \mid Y_{0:j-1}, X)$$

$$+ \sum_{l=1}^k (\beta_j^{lR} + \beta_j^{lp}) \cdot P(y_j^l \mid Y_{0:j-1}, X),$$

where $P(y_j^C \mid Y_{0:j-1}, X)$ is the prediction probability from the chair itself; $P(y_j^l \mid Y_{0:j-1}, X)$ is the prediction probability from expert $l$; $\beta_j^C, \beta_j^{lR}, \beta_j^{lp}$ are normalized coordination coefficients, which are calculated as:

$$\beta_j^C = \frac{\exp(v_j^T h_j)}{\sum_l \exp(v_j^T h_l)},$$

$$h_j = \text{MLP}(P(y_j^l \mid Y_{0:j-1}, X), h_j^R, h_j^P).$$

$\beta_j^C$, $\beta_j^{lR}$ and $\beta_j^{lp}$ are estimated w.r.t. $P(y_j^l \mid Y_{0:j-1}, X)$, $h_j^R$ and $h_j^P$, respectively. $h_j^R$ is a list of retrospective decoding outputs from all experts, which is defined as follows:

$$h_j^R = P(y_{1:j-1}^l \mid y_j, X) + \cdots + P(y_j^l \mid y_0, X) + P(y_{1:j-1}^l \mid y_0, X),$$

where $y_0$ is a special token “[BOS]” indicating the start of decoding: $P(y_{1:j-1}^l \mid y_j, X)$ is the output of expert $l$ from the 1-st to the $(j - 1)$-th step using Eq. 3; $h_j^P$ is a list of prospective decoding outputs from all experts, which is defined as follows:

$$h_j^P = P(y_{1:j+t}^l \mid y_0, X) + \cdots + P(y_{j+t}^l \mid Y_{0:j-1}, X) + P(y_{j+t}^l \mid Y_{0:j-1}, X),$$

where $P(y_{0:j+t}^l \mid Y_{0:j-1}, X)$ are the outputs of expert $l$ from the $j$-th to $(j + t)$-th step. We obtain $P(y_{j+t}^l \mid X)$ by forcing expert $l$ to generate $t$ steps using Eq. 3 based on the current generated tokens $Y_{0:j-1}$.

### 2.5 Learning scheme

We devise a global-and-local learning scheme to train MoGNet. Each expert $l$ is optimized by a localized expert loss defined on $S_l$, which forces each expert to specialize on one of the portions of data $S_l$. We use cross-entropy loss for each expert and the joint loss for all experts is as follows:

$$L_{\text{experts}} = \sum_{l=1}^k \sum_{(x_j, y_j) \in S_l} \sum_{j=1}^n \mu_j y_j \log P(y_j^l \mid Y_{0:j-1}, X),$$

where $P(y_j^l \mid Y_{0:j-1}, X)$ is the token prediction by expert $l$ (Eq. 3) computed on the $r$-th data sample; $y_j^l$ is a one-hot vector indicating the ground truth token at $j$.

We also design a global chair loss to differentiate the losses incurred from different experts. The chair can attribute the source of errors to the expert in charge. For each data sample in $D$, we calculate the combined taken prediction $P(y_j \mid Y_{0:j-1}, X)$ (Eq. 3). Then the global loss becomes:

$$L_{\text{chair}} = \sum_{r=1}^{|D|} \sum_{j=1}^n \mu_j y_j \log P(y_j \mid Y_{0:j-1}, X).$$

Our overall optimization follows the joint learning paradigm that is defined as a weighted combination of constituent losses:

$$L = \lambda \cdot L_{\text{experts}} + (1 - \lambda) \cdot L_{\text{chair}},$$

where $\lambda$ is a hyper-parameter to regulate the importance between the experts and the chair for optimizing the loss.
3 EXPERIMENTAL SETUP

3.1 Research questions

We seek to answer the following research questions: (RQ1) Does MoGNet outperform state-of-the-art end-to-end single-module DRG models? (RQ2) How does the choice of a particular coordination mechanism (i.e., RMoG, PMoG, or neither of the two) affect the performance of MoGNet? (RQ3) How does the GL learning scheme compare to using the general global learning as a learning scheme?

3.2 Dataset

Our experiments are conducted on the MultiWOZ \cite{budzianowski2018multiwoz} dataset. This is the latest large-scale human-to-human TDS dataset with rich semantic labels, e.g., domains and dialogue actions, and benchmark results of response generation. \cite{budzianowski2018multiwoz} MultiWOZ consists of ~10k natural conversations between a tourist and a clerk. It has 6 specific action-related domains, i.e., Attraction, Hotel, Restaurant, Taxi, Train, and Booking, and 1 universal domain, i.e., General. 67.4% of the dialogues are cross-domain which covers 2–5 domains on average. The average number of turns per dialogue is 13.68; a turn contains 13.18 tokens on average. The dataset is randomly split into 8,438/1,000/1,000 dialogues for training, validation, and testing, respectively.

3.3 Model variants and baselines

We consider a number of variants of the proposed mixture-of-generators model:

- **MoGNet**: the proposed model with RMoG and PMoG and GL learning scheme.
- **MoGNet-P**: the model without prospection ability by removing PMoG coordination mechanism from MoGNet.
- **MoGNet-P-R**: the model removing the two coordination mechanisms and remaining GL learning scheme.
- **MoGNet-GL**: the model that removes GL learning scheme from MoGNet.

See Table 1 for a summary. Without further indications, the intents used are based on identifying eight different domains: Attraction, Booking, Hotel, Restaurant, Taxi, Train, General, and UNK.

<table>
<thead>
<tr>
<th>Table 1: Model variants.</th>
</tr>
</thead>
<tbody>
<tr>
<td>β_j^C</td>
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<tr>
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</tr>
<tr>
<td>MoGNet</td>
</tr>
<tr>
<td>MoGNet-P</td>
</tr>
<tr>
<td>MoGNet-P-R</td>
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<tr>
<td>MoGNet-GL</td>
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</tbody>
</table>

\(\beta_j^C, \beta_j^L, \beta_j^P\) are from Eq. 5. “True” means we preserve it and learn it as it is. “False” means we remove it (set it to 0). \(\lambda\) is from Eq. 1 and we report two settings, 0.0 and 0.5. See footnote 1.

To answer RQ1, we compare MoGNet with the following methods that have reported results on this task according to the official leaderboard:\footnote{https://dialogue.mi.eng.cam.ac.uk/index.php/corpus/}

- **S2SAttLSTM**: We follow the dominant Sequence-to-Sequence (Seq2Seq) model under an encoder-decoder architecture\footnote{The Context-to-text Generation task at https://github.com/budzianowski/multiwoz} and reproduce the benchmark baseline, i.e., single-module model named S2SAttLSTM [3, 4], based on the source code provided by the authors. See footnote 4.
- **S2SAttGRU**: A variant of S2SAttLSTM, with Gated Recurrent Units (GRUs) instead of LSTMs and other settings kept the same.
- **LaRLAttnGRU**: The state-of-the-art model [56], which uses reinforcement learning and models system actions as latent variables. LaRLAttnGRU uses ground truth system action annotations and user goals to estimate the rewards for reinforcement learning during training.

3.4 Evaluation metrics

We use the following commonly used evaluation metrics\footnote{https://github.com/budzianowski/multiwoz} [3, 55]:

- **Inform**: the fraction of responses that provide a correct entity out of all responses.
- **Success**: the fraction of responses that answer all the requested attributes out of all responses.
- **BLEU**: for comparing the overlap between a generated response to one or more reference responses.
- **Score**: defined as \(Score = (0.5 \times Inform + 0.5 \times Success + BLEU) \times 100\). This measures the overall performance in terms of both task completion and response fluency\footnote{https://github.com/Jiahuan-Pei/multiwoz-mdrg}.
- **PPL**: denotes the perplexity of the generated responses, which is defined as the exponentiation of the entropy. This measures how well a probability DRG model predicts a token in a response generation process.

We use the toolkit released by Budzianowski et al. [3] to compute the metrics. Following their settings, we also use Score as the selection criterion to choose the best model on the validation set and report the performance of the model on the test set. We use a paired t-test to measure statistical significance (\(p < 0.01\)) of relative improvements.

3.5 Implementation details

Theoretically, the training time complexity of each data sample is \(O(n \times (k + 1) + n)\), where \(n\) is the number of response tokens. To reduce the computation cost, we assign \(j + t = n\) and compute the expert prediction with Eq. 3. This means that the chair will make a final decision only after all the experts have decoded their final tokens. Thus, the time complexity decreases to \(O(n \times (k + 1) + n)\).

For a fair comparison, the vocabulary size is the same as Budzianowski et al. [4], which has 400 tokens. Out-of-vocabulary words are replaced with “[UNK]”. We set the word embedding size to 50 and all GRU hidden state sizes to 150. We use Adam\footnote{https://github.com/Jiahuan-Pei/multiwoz-mdrg} as our optimization algorithm with hyperparameters \(\alpha = 0.005, \beta_1 = 0.9, \beta_2 = 0.999\), and \(\epsilon = 10^{-8}\). We also apply gradient clipping\footnote{https://github.com/Jiahuan-Pei/multiwoz-mdrg} with range \([-5, 5]\) during training. We use f2 regularization to alleviate overfitting, the weight of which is set to \(10^{-5}\). We set the minibatch size to 64. We use greedy search to generate the responses during testing. Please note that if a data point has multiple intents, then we assign it to each corresponding expert, respectively. The code is available online.\footnote{https://github.com/budzianowski/multiwoz-mdrg}
not only improves the satisfaction of responses but also improves the quality of the language modeling process. MoGNet also achieves more than 6.70% overall improvement over the benchmark baseline S2SAttnLSTM and its variant S2SAttnGRU. This proves the effectiveness of the proposed MoGNet model.

Second, LaRLAttnGRU achieves the highest performance in terms of Success, followed by MoGNet. However, it results in a 7.33% decrease in BLEU and a 2.56% decrease in Informativeness compared to MoGNet. Hence, LaRLAttnGRU is good at answering all requested attributes but not as good at providing more appropriate entities with high fluency as MoGNet. LaRLAttnGRU tends to generate more slot values to increase the probability of answering the requested attributes. Take an extreme case as an example: if we force a model to generate all tokens with slot values, then it will achieve an extremely high Success but a low BLEU.

Third, S2SAttnLSTM is the worst model in terms of overall performance (Score). But it achieves the best PPL. It tends to generate frequent tokens from the vocabulary which exhibits better language modeling characteristics. However, it fails to provide useful information (the requested attributes) to meet the user goals. By contrast, MoGNet improves the user satisfaction (i.e., Score) greatly and achieves response fluency by taking specialized generations from all experts into account.

4.2 Human evaluation

To further understand the results in Table 2, we conducted a human evaluation of the generated responses from S2SAttnGRU, LaRLAttnGRU, and MoGNet. We ask workers on Amazon Mechanical Turk (AMT) to read the dialogue context, and choose the responses that satisfy the following criteria: (i) Informativeness measures whether the response provides appropriate information that is requested by the user query. No extra inappropriate information is provided. (ii) Consistency measures whether the generated response is semantically aligned with the ground truth response. (iii) Satisfaction measures whether the response has a overall satisfactory performance promising both Informativeness and Consistency. As with existing studies, we sample one hundred context-response pairs to do human evaluation. Each sample is labeled by three workers. The workers are asked to choose either all responses that satisfy the specific criteria or the "NONE" option, which denotes none of the responses satisfy the criteria. To make sure that the annotations are of high quality, we calculate the fraction of the responses that satisfy each criterion out of all responses that passes the golden test. That is, we only consider the data from the workers who have chosen the golden response as an answer.

The results are displayed in Table 3. MoGNet performs better than S2SAttnGRU and LaRLAttnGRU on Informativeness because it frequently outputs responses that provide richer information (compared with S2SAttnGRU) and fewer extra inappropriate information (compared with LaRLAttnGRU). MoGNet obtains the best results, which means MoGNet is able to generate responses that are semantically similar to the golden responses with large overlaps. The results of LaRLAttnGRU outperforms S2SAttnGRU in all cases except for Satisfaction under the strict condition (≥ 2). This reveals that balancing between Informativeness and Consistency makes it difficult for the mturk workers to assess the overall quality measured by Satisfaction. In this case, MoGNet receives the most votes on Satisfaction under the strict condition (≥ 2) as well as the loose condition (≥ 1). This shows that the workers consider the responses from MoGNet more appropriate than the other two models with a high degree of agreement. To sum up, MoGNet is able to generate user-favored responses in addition to the improvements for automatic metrics.

4.3 Coordination mechanisms

In Table 4, we contrast the effectiveness of different coordination mechanisms. We can see that MoGNet-P loses 4.32% overall performance with a 0.62% decrease of BLEU, 5.90% decrease of Informativeness and 1.50% decrease of Success. This shows that the prospection design of the PMoG mechanism is beneficial to both task completion and response fluency. Especially, most improvements come from providing more correct entities while improving generation fluency. MoGNet-P-R reduces 2.62% Score with 1.97% lower of BLEU, 0.2% lower of Informativeness and 1.10% of Success. Thus, the MoGNet framework is effective thanks to its design with two types of roles: the chair and the experts.

4.4 Learning scheme

We use MoGNet-GL to refer to the model that removes the GL learning scheme from MoGNet and uses the general global learning instead. MoGNet-GL results in a sharp reduction of 6.95% overall performance with 6.90% of BLEU, 6.90% of Informativeness and 5.40% of Success. The main improvement is attributed to the strong task completion and response fluency. Especially, most improvements come from providing more appropriate entities with a high degree of agreement.

5 ANALYSIS

In this section, we explore MoGNet in more detail. In particular, we examine (i) whether the intent partition affects the performance of MoGNet (§5.1), (ii) whether the improvements of MoGNet could simply be attributed to having a larger number of parameters (§5.2), (iii) how the hyper-parameter λ (Eq. 1) affects the performance of MoGNet among the baselines.

| Table 2: Comparison results of MoGNet and the baselines. | Table 3: Results of human evaluation. |
|---------------------|---------------------|---------------------|---------------------|---------------------|
| BLEU | Inform | Success | Score | PPL |
| S2SAttnLSTM | 18.90% | 71.33% | 60.96% | 85.05 | 3.98 |
| S2SAttnGRU | 18.21% | 81.50% | 68.80% | 93.36 | 4.12 |
| Structured Fusion | 16.34% | 82.70% | 72.10% | 93.74 | - |
| LaRLAttnGRU | 12.80% | 82.78% | 79.20% | 93.79 | 5.22 |
| MoGNet | 20.13% * | 85.30% * | 73.30% | 99.43* | 4.25 |

Bold face indicates the worst results with a statistically significant decrease in BLEU. Bold face indicates the best results. (≥ n means that at least n AMT workers regard it as a good response w.r.t. Informativeness, Consistency and Satisfaction.)

| Table 4: The impact of coordination mechanisms. |
|---------------------|---------------------|---------------------|---------------------|---------------------|
| BLEU | Inform | Success | Score | PPL |
| MoGNet | 20.13% | 85.30% | 73.30% | 99.43 | 4.25 |
| MoGNet-P | 19.51% | 79.40% | 71.80% | 95.11 | 4.19 |
| MoGNet-P-R | 18.16% | 85.10% | 72.20% | 96.81 | 4.12 |

Underlined results indicate the worst results with a statistically significant decrease compared to MoGNet (paired t-test, p < 0.01).
MoGNet consistently outperforms the baseline S2SAttnGRU for both ways of partitioning intents. Interestingly, MoGNet-domain greatly outperforms MoGNet-action. We believe there are two reasons: First, the system actions are not suitable for grouping intents because some partition subsets are hard to be distinguished from each other, e.g., OfferBook and OfferBooked. Second, some system actions only have a few data samples, simply not enough to specialize the experts. The results show that different ways of partitioning intents may greatly affect the performance of MoGNet. Therefore, more effective intent partition methods, e.g., adaptive implicit intent partitions, need to be explored in future work.

5.2 Hyper-parameter analysis

To address (ii), we compared two hyper-parameters of MoGNet. MoGNet-domain and MoGNet-action denote the intent partitions w.r.t. domains and system actions, respectively. MoGNet-domain has 8 intents (domains) and MoGNet-action has 14 intents (actions), as shown in Table 5. The results are shown in Table 7.

To address (i), we compared two ways of partitioning intents. MoGNet-domain and MoGNet-action denote the intent partitions w.r.t. domains and system actions, respectively. MoGNet-domain has 8 intents (domains) and MoGNet-action has 14 intents (actions), as shown in Table 6. The results are shown in Table 7.

Table 5: Impact of the learning scheme.

<table>
<thead>
<tr>
<th>BLEU</th>
<th>Inform</th>
<th>Success</th>
<th>Score</th>
<th>PPL</th>
</tr>
</thead>
<tbody>
<tr>
<td>MoGNet</td>
<td>20.13%</td>
<td>85.30%</td>
<td>73.30%</td>
<td>99.43</td>
</tr>
<tr>
<td>MoGNet-GL</td>
<td>19.33%</td>
<td>79.40%</td>
<td>69.70%</td>
<td>92.48</td>
</tr>
</tbody>
</table>

Table 6: Two groups of intents that are divided by domains and the type of system actions.

<table>
<thead>
<tr>
<th>Type</th>
<th>Intents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domain</td>
<td>Attraction, Booking, Hotel, Restaurant, Taxi, Train, General, UNK.</td>
</tr>
<tr>
<td>Action</td>
<td>Book, Inform, NoBook, NoOffer, OfferBook, OfferBooked, Select, Recommend, Request, Bye, Greet, Reqmore, Welcome, UNK.</td>
</tr>
</tbody>
</table>

To address (iii), we report the BLEU, Inform, Success, Score, and PPL values of MoGNet with different hyper-parameters. MoGNet consistently outperforms the baseline S2SAttnGRU for both ways of partitioning intents. Interestingly, MoGNet-domain greatly outperforms MoGNet-action. We believe there are two reasons: First, the system actions are not suitable for grouping intents because some partition subsets are hard to be distinguished from each other, e.g., OfferBook and OfferBooked. Second, some system actions only have a few data samples, simply not enough to specialize the experts. The results show that different ways of partitioning intents may greatly affect the performance of MoGNet. Therefore, more effective intent partition methods, e.g., adaptive implicit intent partitions, need to be explored in future work.

To address (iv), we select an example to illustrate the influence of RMoG, PMoG, and GL. Table 8 exhibits the responses generated by comparable baselines (i.e., S2SAttnGRU, LaRLAttnGRU) and MoGNet variants as in Table 4. In red we highlight the responses. Without PMoG, MoGNet-P and MoGNet-P-R ignore the fact that the attribute time is important for searching a train ticket (1st turn) and omit the exact departure time (value-time) of the train (2nd turn). Without GL, MoGNet-GL ignores the primary time information and does not attribute time information to the day (1st turn) and ignores the implicit need of [value_price] (4th turn). There are also some low-quality cases, e.g., MoGNet and the baselines occasionally generate redundant and lengthy responses, because none of them has addressed this issue explicitly during training.

6 RELATED WORK

Traditional models for DRG [8,33] decompose the task into sequentially dependent modules, e.g., Dialogue State Tracking (DST) [27], Policy Learning (PL) [35], and Natural Language Generation (NLG) [21]. Such models allow for targeted failure analyses, but inevitably incur upstream propagation problems [8]. Recent work views DRG as a source-to-target transduction problem, which maps a dialogue context to a response [11,17,31]. Sordoni et al. [28] show that using an RNN to generate text conditioned on dialogue history results in more natural conversations. Later improvements include the addition of attention mechanisms [16,29], modeling the hierarchical structure of dialogues [26], or jointly learning belief and state values of $\lambda$ (Eq. 11), as shown in Fig. 4. When $\lambda = 0$, no expert is trained on a particular intent. When $\lambda = 1$, the model ignores the global loss, i.e., the RMoG and PMoG mechanisms are not used and the chair is only trained as a general expert. We can see that these two settings decrease the performance greatly which further verifies the effectiveness of RMoG and PMoG as well as the MoGNet framework. We also note that the performance of MoGNet is quite stable when $\lambda \in [0.1, 0.7]$ with the best performance for $\lambda = 0.7$. Hence, MoGNet is not very sensitive to the hyper-parameter $\lambda$.

Figure 3: Score of MoGNet and S2SAttnGRU with different number of parameters.

Figure 4: Score of MoGNet with different values of $\lambda$. 

Table 7: Results of MoGNet with two intent partition ways.

<table>
<thead>
<tr>
<th>BLEU</th>
<th>Inform</th>
<th>Success</th>
<th>Score</th>
<th>PPL</th>
</tr>
</thead>
<tbody>
<tr>
<td>MoGNet-domain</td>
<td>20.13%</td>
<td>85.30%</td>
<td>73.30%</td>
<td>99.43</td>
</tr>
<tr>
<td>MoGNet-action</td>
<td>17.28%</td>
<td>79.40%</td>
<td>69.70%</td>
<td>91.83</td>
</tr>
</tbody>
</table>

Figure 4: Score of MoGNet with different values of $\lambda$. 

To address (iv), we select an example to illustrate the influence of RMoG, PMoG, and GL. Table 8 exhibits the responses generated by comparable baselines (i.e., S2SAttnGRU, LaRLAttnGRU) and MoGNet variants as in Table 4. In red we highlight the responses. Without PMoG, MoGNet-P and MoGNet-P-R ignore the fact that the attribute time is important for searching a train ticket (1st turn) and omit the exact departure time (value-time) of the train (2nd turn). Without GL, MoGNet-GL ignores the primary time information and does not attribute time information to the day (1st turn) and ignores the implicit need of [value_price] (4th turn). There are also some low-quality cases, e.g., MoGNet and the baselines occasionally generate redundant and lengthy responses, because none of them has addressed this issue explicitly during training.
Table 8: Example responses from MoGNet with the ablation settings in a 4-turn dialogue.

<table>
<thead>
<tr>
<th>Turn</th>
<th>User</th>
<th>System</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>i am looking for a train departing from [value_place] that will arrive at [value_place].</td>
<td>S2SAttGru: what day would you like to travel? LaRLAttGru: there are [value_count] trains leaving [value_place] on [value_day]. what day would you like to travel? MoGNet: what day and time would you like to travel? MoGNet-P: what day will you be traveling? MoGNet-P-R: what day will you be traveling? MoGNet-GL: there are [value_count] trains ... do you have a time you would like to depart?</td>
</tr>
<tr>
<td>2</td>
<td>i would like to leave on [value_day] and arrive no later than [value_time].</td>
<td>S2SAttGru: [train_id] will arrive at [value_time]. LaRLAttGru: i have train [train_id] leaving at [value_time] and arriving at [value_time]. would you like me to book this for you?</td>
</tr>
<tr>
<td>3</td>
<td>can i please have the reference number? All: ... how many tickets do you need?</td>
<td>S2SAttGru: i have booked you [value_count] tickets on the [train_id]. your reference number is [train_reference]. is there anything else i can help you with? LaRLAttGru: i have booked [value_count] tickets on [train_id]. the reference number is [train_reference]. MoGNet: i have booked [value_count] tickets for you. the total fee is [value_price] gbp payable at the station. your reference number is [train_reference]. is there anything else i can help you with?</td>
</tr>
<tr>
<td>4</td>
<td>could you book [value_count] tickets for me and send me the reference number?</td>
<td>S2SAttGru: i have booked you [value_count] tickets on the [train_id]. your reference number is [train_reference]. is there anything else i can help you with? LaRLAttGru: i have booked [value_count] tickets on [train_id]. the reference number is [train_reference]. MoGNet: i have booked [value_count] tickets for you. the total fee is [value_price] gbp payable at the station. your reference number is [train_reference]. is there anything else i can help you with?</td>
</tr>
</tbody>
</table>

The studies listed above assume that each token of a response is sampled from a single distribution, given a complex dialogue context. In contrast, MoGNet uses multiple cooperating modules, which exploits the specialization capabilities of different experts and the generalization capability of a chair. Work most closely related to ours in terms of modeling multiple experts includes [6, 12, 13, 23]. Le et al. [13] integrate a chat model with a question answering model using an LSTM-based mixture-of-experts method. Their model is similar to MoGNet-GL-P (without PMoG and GL) except that they simply use two implicit expert generators that are not specialized on particular intents. Guo et al. [12] introduce a mixture-of-experts to use the data relationship between multiple domains for binary classification and sequence tagging. Sequence tagging generates a set of fixed labels; DRG generates diverse appropriate response sequence. The differences between MoGNet and these two approaches are threefold: First, MoGNet consists of a group of modules including a chair generator and several expert generators; this design addresses the module interdependence problem since each module is independent from the others. Second, the chair generator alleviates the error propagation problem because it is able to manage the overall errors through an effective learning scheme. Third, the models of those two approaches cannot be directly applied to task-oriented DRG. The recently published HDSA [6] slightly outperforms MoGNet on Score (+0.07), but it overly relies on BERT [9] and graph structured dialog acts. MoGNet follow the same modular TDS framework [23], but it performs substantially better due to fitting the expert generators with both retrospection and prospection abilities and adopting the GL learning scheme to conduct more effective learning.

7 CONCLUSION AND FUTURE WORK

In this paper, we propose a novel mixture-of-generators network (MoGNet) model with different coordination mechanisms, namely, RMoG and PMoG, to enhance dialogue response generation. We also devise a GL learning scheme to effectively learn MoGNet. Experiments on the MultiWOZ benchmark demonstrate that MoGNet significantly outperforms state-of-the-art methods in terms of both automatic and human evaluations. We also conduct analyses that confirm the effectiveness of MoGNet, the RMoG and PMoG mechanisms, as well as the GL learning scheme.

As to future work, we plan to devise more fine-grained expert generators and to experiment on more datasets to test MoGNet. In addition, MoGNet can be advanced in many directions: First, better mechanisms can be proposed to improve the coordination between chair and expert generators. Second, it would be interesting to study how to do intent partition automatically. Third, it is also important to investigate how to avoid redundant and lengthy responses in order to provide a better user experience.

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REFERENCES

