Abstract

Currently, human-bot symbiosis dialog systems, e.g., pre- and after-sales in E-commerce, are ubiquitous, and the dialog routing component is essential to improve the overall efficiency, reduce human resource cost, and enhance user experience. Although most existing methods can fulfill this requirement, they can only model single-source dialog data and cannot effectively capture the underlying knowledge of relations among data and subtasks. In this paper, we investigate this important problem by thoroughly mining both the data-to-task and task-to-task knowledge among various kinds of dialog data. To achieve the above targets, we propose a Gated Mechanism Enhanced Multi-task Model (G3M), specifically including a novel dialog encoder and two tailored gated mechanism modules. The proposed method can play the role of hierarchical information filtering and is non-invasive to existing dialog systems. Based on two datasets collected from real world applications, extensive experimental results demonstrate the effectiveness of our method, which achieves the state-of-the-art performance by improving 8.7%/11.8% on RMSE metric and 2.2%/4.4% on F1 metric.

1 Introduction

Traditionally, a lot of human resource cost is spent on supporting the calling/online centers for customer care, such as pre-and after-sales for E-commerce and banking. With the rapid development of AI techniques for dialog systems, various bot agents have been deployed in those scenarios to reduce parts of human workload. Both the bot and human agents constitute a new and practical symbiosis dialog system which can keep a balance between service quality and human resource cost (Oraby et al., 2017).

In such a human-bot symbiosis environment, it is commonly seen that users’ needs continuously change, or sometimes they are dissatisfactory with the current servicing agents. They would request the dialog system to replace the agents with more qualified ones, because usually each bot or human agent is trained for specific domains. For example, some agents are good at handling after-sales complaints, while some others would do well in providing technical guidance. To make the whole system operate efficiently, a dialog routing component is necessary to take charge of when to transfer the conversation and which domain of agents is suitable to provide service.

To illustrate the process of dialog routing task more clearly, Figure 1 shows an example. At the beginning, the user’s query is operated by the bot agent through Flow ①, and the dialog router would continuously monitor the user’s satisfactory degree by inferring Net Promoter Score (NPS) and current dialog category. When the inferred NPS (4.8) is lower than a hand-crafted threshold (5) at the i-th dialog turn, the router chooses to switch the dialog to one of human agents skilled at the inferred category via Flow ②. Here human agent B is good at the category of ‘Completion Issue’ dialogs. From this picture, we could realize that how to implement the accurate matching between user’s needs and skilled agents is greatly correlated with the whole system’s efficiency and user experience.

Currently, most existing deployed systems are
heuristic and support to trigger the dialog routing when users actively click a button or say/type something like ‘transfer to human’. This method is less user-friendly and cannot fully leverage the ability of contemporary deep learning techniques. Recently, some learning based methods are proposed. Yu et al. well defines the dialog routing as text regression and classification problems, and proposes a learning network with CNN and RNN modules to encode dialog data (Yu et al., 2020). However, it only models the token-level utterance data and misses the information from other kinds of dialog data1; Meanwhile the model structure is shared by the two tasks (in single-task way) which cannot capture the underlying knowledge within data-to-task (intrinsic) and task-to-task (extrinsic) relations. In this paper, we investigate the dialog routing task from the multi-task learning perspective to further capture the intrinsic and extrinsic information.

Intuitively, the decision making process of dialog router could be decomposed to two subtasks, NPS prediction and dialog category classification. We adopt the same NPS prediction task as (Yu et al., 2020) since the supervised data can be obtained without any human-labeling effort. Furthermore, we observe that the data-to-task (intrinsic) and task-to-task (extrinsic) information should be leveraged to make better routing performance. On the one hand, we can argue that the more accurate NPS is predicted, the more precise the dialog category is classified, and vice versa. On the other hand, in addition to the token-level utterance data, other kinds of dialog data can also affect the final task performance. For example, if a user utterance is about the intent of ‘ask_technical_problem’, the intent information is an obvious indicator that the user should be served by the agent who is skilled at ‘Technical Issue’ category. Note that the categories of agents and dialog intents of users are often different, and usually the former is much less than the later.

To achieve the above motivation, in this paper, we propose a novel Gated Mechanism enhanced Multi-task Model (G3M). Firstly, the model extends the BERT encoder to encode various kinds of dialog data in a hierarchical way. Moreover, two modules of gated mechanism are proposed to explicitly model the data-to-task and task-to-task information under multi-task learning framework. Another advantage of G3M is its good compatibility, such that it can be easily integrated into existing human-bot dialog systems in a plug-in manner. We conduct various experiments on two datasets collected from the real world. The results demonstrate our method can achieve the state-of-the-art performance on both tasks, and the ablation experiment proves our model is effective to simultaneously capture the intrinsic and extrinsic information.

In summary, this paper’s contributions include:

- We argue that both the data-to-task and task-to-task information are important to achieve better dialog routing. Hence, we propose a new multi-task learning solution, called Gated Mechanism enhanced Multi-task Model (G3M), to implement the motivation.

- We extend the BERT encoder to encode various kinds of dialog data in a hierarchical manner, and develop two modules of gated mechanism to explicitly model the data-to-task and task-to-task information.

- We conduct extensive experiments on two real world datasets. The results prove our model’s effectiveness, which can achieve the state-of-the-art performance.

2 Related Work

Compared with other dialog system tasks, there are not many related work on dialog routing study. Recently, a learning network with attention based CNN and RNN is proposed (Yu et al., 2020). It mainly models the token-level dialog data and is a single-task model, i.e., the NPS regression and dialog classification tasks share the same model structure except the last inference layer. This method cannot sufficiently leverage the underlying knowledge within subtasks and various kinds of dialog data. Another similar work is a demo system for dialog transition (Huang et al., 2021) which tries a vanilla multi-task learning method (i.e., a dialog encoder tailed with two prediction subtasks). However, it still hardly fully utilizes the knowledge among dialog data and subtasks. Different from them, we further investigate the problem by simultaneously modeling data-to-task and task-to-task information, achieving a much advanced performance.

The dialog routing task is fundamentally decomposed to two subtasks, dialog NPS regres-

1Other kinds of dialog data include speaker roles, utterance-level sequence, intent information, etc.
and dialog classification, which feature encoding various kinds of dialog data and have been separately studied by researchers from the NLP community. The representative research studies include CNN-based models (Kim, 2014), RNN-based models (Wang et al., 2018), regression-based models (Dereli and Saraçlar, 2019; Ngo-Ye and Sinha, 2014) and deep bi-directional transformers model with pre-training (Devlin et al., 2019; Cohan et al., 2019). From these works, we learn that dialog data encoder is the common key module to make sure good performance on final tasks (Dereli and Saraçlar, 2019). Those methods have not been demonstrated to be effective in the multi-task situation of dialog routing, without thoroughly mining the relations among data and subtasks.

Recently, multi-task learning on dialog data has been studied and proven successful, such as joint slot filling and intent prediction (Goo et al., 2018), dialog act sequence labeling (Kumar et al., 2018), and dialog response generation (Ide and Kawahara, 2021). These studies suggest that dialog data contains rich information and multi-task learning could dig out the underlying knowledge among data and subtasks. Moreover, among multi-task learning methods, multi-gated mechanism is widely utilized for information remembering and filtering (Chen et al., 2018; Xiao et al., 2018; Du et al., 2019), which is much suitable for tidying dialog data. Inspired by the above ideas, we propose a novel model to combine them together in our solution for further improving the performance of dialog routing task.

3 Problem Definition

We define the investigated problem formally in this section. In our task, we use the available data in a conversation session as inputs, including an utterance list $U = \{u_1, ..., u_L\}$, a speaker role list $R = \{r_1, ..., r_L\}$, and an intent list $I = \{e_1, ..., e_L\}$, where $u_i$ is an utterance, $r_i$ indicates the role of the $i$th utterance (user or agent), $e_i$ is known intent of the $i$th utterance, and $L$ is the number of utterance sequences in a conversation session. Each utterance has a token-level sequence $u_i = \{w_{i1}, ..., w_{iM}\}$, where $w_{ij}$ means the $j$th token in the $i$th utterance and $M$ is the length of the token sequence. Here we can leverage the intent information since we use an intent extraction tool\(^2\). Our model is also scalable to capture more dialog data, such as entity and dialog act information if they are available. We adopt the intent information in our solution based on the intuitive consideration of data-to-task motivation.

For the outputs of our task, at each dialog turn $i$, our model can make predictions of NPS $y_i^{(N)}$ and dialog category $y_i^{(C)}$. In summary, given $U_i = \{u_1, ..., u_i\}$, $R_i = \{r_1, ..., r_i\}$ and $I_i = \{e_1, ..., e_i\}$, we formally state the problem as follows:

\(^2\)More information can be referred in Section Experiments.
\[ y_i^{(N)} , y_i^{(C)} = f(U_i, R_i, I_i). \] (1)

4 Proposed Method

The proposed model generally contains three parts: (1) Dialog Encoder, (2) Gated Mechanism, and (3) Multi-Task Prediction. Figure 2 shows the overview of model’s architecture, which will be introduced next.

4.1 Dialog Encoder

To encode the various kinds of dialog data, we leverage and extend the BERT encoder. As presented in Figure 2, given an utterance sequence \{u_1, ..., u_i\}, firstly all the utterances are flattened and concatenated to a long token sequence. Then we add a [CLS] token at the beginning and insert [SEP] tokens between any two utterances. Similar to BERT encoder that embeds the whole token sequence by Transformer model, we get the representation of the \(i\)th [SEP] token, \(T_i[SEP]\), and regard it as the representation of the \(i\)th utterance. The representation of head token, \(T_{CLS}\), would be used in the following Gated Mechanism part as a kind of context information which encodes all the utterances.

With the utterance representations of \(T_i[SEP]\), the role \{\(r_1, ..., r_i\)\} and intent \{\(e_i, ..., e_i\)\} information (one-hot vectors) are concatenated to their corresponding utterance representations. After a MLP operation, we can obtain the final representation of each utterance by \(T_i[SEP] = MLP(r_i ⊕ e_i ⊕ T_i[SEP])\).

Our method to encode dialog data is inspired by the Sequential Sentence Classification (SCC) model (Cohan et al., 2019) which also is based on BERT encoder and organizes the dialog data in the hierarchical manner. However, our model is different from SCC model in two aspects. Firstly, the representation of head token [CLS] is additionally utilized as context information in the following modules. Secondly, our encoder can integrate the extra role and intent information.

4.2 Gated Mechanism

Besides the basic mechanism via sharing parameters of the encoder in vanilla multi-task learning paradigm, we leverage gated mechanism and propose two modules for dialog routing to better model the task-to-task and data-to-task information.

4.2.1 IC-Gated Module

The Intent-Category-Gated (IC-Gated) module is designed to model the relation between intent, role and dialog category (data-to-task) information. The right down yellow part in Figure 2 illustrates the detailed module structure.

With the context representation \(T_{CLS}\) and utterance representations \(T_i[SEP]\), we extend a commonly used way (Goo et al., 2018) to capture the relations between intent, role and dialog context by learning a weighted feature for data-to-task (i.e., intent, role to dialog category) modeling. Thus we obtain the weighted feature from various levels of the input dialog data after max pooling operation on the utterance sequence by the following equation:

\[
g^{(I)} = V \cdot \tanh(T_{CLS}) + W \cdot \text{Pooling}(T_i[SEP], ..., T_N[SEP]),
\] (2)

where \(V\) and \(W\) denote the parameters to learn.

With the weighted feature \(g^{(I)}\) that attends intent and role information on dialog context, the context information \(T_{CLS}\) is used again to calculate the final weighted representation of dialog data with a flatten operation as the following equation:

\[
T^{(IC)} = \text{Flatten}(g^{(I)} \cdot (T_{CLS})^T). \tag{3}
\]

The IC-Gated module can learn the representation from dialog data and meanwhile consider the related information between intent, role and dialog context, which would benefit the later dialog category classification task.

4.2.2 NC-Gated Module

The NPS-Category-Gated (NC-Gated) module is designed to further model the underlying relation between subtasks (task-to-task). The right top blue part in Figure 2 shows the structure detail.

We set a task-to-task relation matrix \(D \in \mathbb{R}^{d_N \times d_C}\) to preserve the empirical distribution of co-occurrence between NPS and dialog categories among dataset with min-max normalization (Singh et al., 2015), where \(d_N\) and \(d_C\) are the numbers of NPS intervals and dialog categories respectively. We partition the NPS ranging from 0 to 10 into ten intervals. Then with the representation from IC-Gated module \(T^{(IC)}\), the output representation of NC-Gated module is calculated by combining a MLP layer and the task-to-task relation matrix \(D\):

\[ Flatten(\cdot) \text{ function reshapes the input matrix into a one-dimension vector.} \]
where \( \odot \) is Hadamard product to measure the similarity. \( D_i \) is the \( i \)th row vector which means a representation of the \( i \)th NPS interval corresponding to every dialog category, and it depends on the predicted NPS. The reason that uses NPS to query the matrix instead of using predicted dialog category to query NPS, is that we empirically find the effect from the NPS regression task is more significant than the dialog category classification task.

Note that except for the multi-task learning paradigm that can capture the relation between tasks via parameter sharing, we use the relation matrix \( D \) as prior knowledge (or attention weights) and design the NC-Gated module for better representation learning of dialog data by further capturing the task-to-task information.

### 4.3 Multi-Task Prediction

Dialog routing has two subtasks, namely NPS regression and dialog category classification. For the former task, the enhanced representation \( T^{(IC)} \) learned by the IC-Gated module from data-to-task information and the dialog context representation \( T^{[CLS]} \) are concatenated together to make the prediction of NPS. The predicted NPS \( \hat{y}^{(N)} \) can be defined as:

\[
\hat{y}^{(N)} = W^{(N)}(T^{[CLS]} \odot T^{(IC)}) + b^{(N)}. \tag{5}
\]

\( W^{(N)} \) and \( b^{(N)} \) are parameters to learn.

The dialog classification task uses the enhanced representation \( T^{(NC)} \) as input, which is learned by the NC-Gated module from task-to-task information. The predicted dialog category \( \hat{y}^{(C)} \) is calculated by a softmax function:

\[
\hat{y}^{(C)} = \text{Softmax}(W^{(C)}T^{(NC)} + b^{(C)}). \tag{6}
\]

\( W^{(C)} \) and \( b^{(C)} \) are parameters to learn.

### 4.4 Model Training

To jointly train our model from the two tasks together under the multi-task learning paradigm, we design a loss function by combining a mean squared loss for NPS regression and a cross-entropy loss for dialog classification. To avoid over-fitting, \( L_2 \) regularization terms are adopted. The overall objective function is defined as:

\[
L = \frac{\alpha}{N} \sum_{k=1}^{N} |y_k^{(N)} - \hat{y}_k^{(N)}|^2 - \frac{\beta}{N} \sum_{k=1}^{N} \sum_{y} y_k^{(C)} \log(\hat{y}_k^{(C)}) + \frac{\gamma}{2} \left( \|W^{(N)}\|^2 + \|W^{(C)}\|^2 \right). \tag{7}
\]

where \( N \) is the number of all training samples, \( \hat{y}_k^{(N)} \) and \( \hat{y}_k^{(C)} \) are the inferred NPS and category labels, and \( y_k^{(N)} \) and \( y_k^{(C)} \) are the ground truth. \( \alpha, \beta \) and \( \gamma \) are hyper-parameters to balance the weights of terms.

### 5 Experiments

#### 5.1 Corpus

To our knowledge, there is no public corpus contains both the NPS and category labels, we collect two corpora from the real-world dialog systems to evaluate our method.

**Learning Corpus** is collected from an online education platform, where the dialog system for customer care is constituted of 7 dialog categories with all human agents: Badge Issue, Completion Issue, Finding Content, System Help, Technical Issue, Ticket Status, and Other.

**MacHelp Corpus** is collected from an after-sale technical support platform for users who have troubles with their Mac laptops, where the dialog system is constituted of 4 dialog categories for human agents: Login Problem, Apps Issue, Raise Tickets, Account Issue.

### 5.2 Corpus Preprocessing

For the two raw corpora, we preprocess them into a consistent format for model training and testing. Table 1 shows an example of the data structure of dialog session. In a dialog session, we have an utterance sequence, a role sequence to indicate the speaker role of each utterance (0 means user and 1 means agent), and an intent sequence labeled by an online tool which is separately trained from supervised information for the domain of customer care. We use the off-the-shelf extraction tool and obtain 66 and 28 types of intents on the two corpora respectively.

Within a dialog session, we partition the data to several training and testing samples.
Table 1: Data format example of a dialog session.

\[
S_i = \{\{u_1, ..., u_i\}, \{r_1, ..., r_i\}, \{e_1, ..., e_i\}, y_i^{(N)}, y_i^{(C)}\}
\]

Ground truths are obtained by the following rules:

- The NPS of \(u_{i+1}\) is regarded as the label (i.e., \(y_i^{(N)}\)) for NPS regression task.
- The agent category of \(u_{i+1}\) is regarded as the label (i.e., \(y_i^{(C)}\)) for dialog classification task.
- If there is no feedback provided by user on the session, our task degrades to gated-mechanism single-task dialog classification.

Note that although the ground truths of NPS and category label are naturally obtained from the users’ feedback and human agent category, to guarantee the data quality, three humans are invited to review the correctness of all the labels, and we only adopt the samples agreed by all of them. As a result, we obtain about 90% valid sessions from the corpora. Table 2 shows the statistic information of the final two processed datasets.

The real NPS is from user’s feedback by clicking or typing a score, and the two corpora have different NPS ranges (one is an integer in [0,10] and the other is a decimal in [0,5]). Therefore we use zero-mean normalization (z-score) (Singh et al., 2015) method to normalize the scores with a mean of 0 and a standard deviation of 1 as the following: 
\[
z\text{-score} = \frac{x_i - \bar{x}}{\sigma}, \text{ where } x_i \text{ is NPS, } \bar{x} \text{ is the mean value and } \sigma \text{ is the standard deviation.}
\]
By our statistics, we have about 47% and 56% of dialog sessions that have valid NPS labels for Learning and MacHelp datasets respectively, which makes the dialog routing become a much more challenging task in the real world.

### 5.3 Training Settings

We implement our model based on the Transformer library\(^5\). We use the Adam (Kingma and Ba, 2014) optimizer to train models on each dataset for 5 epochs. The learning rate is set as 2e-5 and the dropout rate is set as 0.1. We use the largest batch size that can fit in the memory of GPU. \(\alpha, \beta\) and \(\gamma\) are set as 0.9, 1, 0.01 respectively by our empirical experiments. All the experiments are conducted on V100 32GB GPUs. Each dataset is randomly split into training/validating/testing sets in the proportion of 8:1:1. All the parameters are tuned on the validation set and the results follow the 5-fold cross validation in testing set.

### 5.4 Baselines

We compare our proposed model to several baselines which belong to two groups. One includes single-task models for NPS prediction and dialog category classification separately, while the other contains methods under multi-task learning paradigm. To make a fair comparison between baselines and the G3M, we concatenate the role and intent information ahead each utterance only if the baseline model can employ that information. Thus all the baseline models have the consistent input information as ours. The evaluated baselines are listed as follows:

- **fastText** (Joulin et al., 2017) is a simple and efficient model for regression or classification.
- **HAN** (Yang et al., 2016) is a document classification model based on hierarchical attention network by considering both word-level and sentence-level information.
- **textReg** (Dereli and Saraçlar, 2019) is a regression model based on convolution neural networks, which achieves the state-of-the-art performance on financial prediction.
- **CNN-BiRNN-Att** (CBA) (Yu et al., 2020) is a cascade model with CNN, bi-directional RNN and attention mechanism. We adapt the last layer to support either the regression or classification tasks.
- **BERT** (Devlin et al., 2019) is a model which can be fine-tuned by adjusting the task-specific output layers. We use the pre-trained

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\(^5\)https://github.com/huggingface/transformers
BERT-base-cased model to separately fine-tune the two tasks with default parameters.

- **XLNET** (Yang et al., 2019) is a generalized auto-regressive pre-training method which can be fine-tuned by tailing a task-specific output layers. We fine-tune the two tasks with this pre-trained model similar to BERT.

- **Joint-CNN-BiRNN-Att** (Joint-CBA) is a multi-task model by extending the last layer of CBA model to simultaneously predict NPS and dialog categories.

- **Vanilla Multi-task Model** (VMM) follows the vanilla multi-task learning paradigm and uses the standard BERT encoder to encode only the utterance data (Huang et al., 2021), without any gated-mechanism modules.

To measure the performance, we use the root mean squared error (RMSE) for the NPS regression task and micro F1 score (Micro-F1) for the dialog category classification task.

### 5.5 Results and Analysis

We compare our model with various single-task and multi-task baselines on the two datasets, and the first two sections of Table 3 report the results. The performance of NPS regression task is reflected by RMSE metric, while that of dialog category classification task is embodied by Micro-F1 metric. We can learn some observations from Table 3.

Firstly, the performance of our proposed model G3M is consistent on both datasets and can outperform all the baselines. More specifically, for the NPS regression task, G3M’s RMSE is 8.72% and 11.83% lower than the best RMSE score of baseline models (VMM for Learning dataset and Joint-CBA for MacHelp dataset) on two datasets. And for the dialog category classification task, G3M upgrades the performance by achieving 2.17% and 4.40% higher Micro-F1 scores compared with the best baseline method (VMM). All the results demonstrate that our model is effective and achieves the state-of-the-art performance on both subtasks.

Secondly, comparing the single-task models with multi-task models among baselines, it is consistent that multi-task models can surpass the single-task counterparts, especially from the comparison between Joint-CBA and VMM with their single-task versions (CBA and BERT). The results suggest that the underlying relation between the two tasks is helpful and multi-task learning paradigm can well capture the knowledge.

Thirdly, comparing three multi-task models, we observe that G3M is better than the other two methods. We can conclude that both our proposed dialog encoder and gated mechanism are effective, since Joint-CBA and VMM do not contain either of the modules. Another observation is that under the same multi-task learning paradigm, BERT based dialog encoder (VMM) is better than the CNN-RNN based dialog encoder (Joint-CBA).

### 5.6 Ablation Study

To probe G3M’s effectiveness in terms of gated module level, we conduct ablation experiments and report the results in the bottom section of Table 3. We could obtain three variant models by once deducting one or two gated modules: G3M without IC-Gated module, G3M without NC-Gated module, and G3M without either module. Based on the experiments, we have some findings.

Comparing the three ablated variant models of G3M, both modules contribute positively to the two tasks. Therefore, they are effective to model the data-to-task and task-to-task information among dialog data. Specifically, it is not very clear that which module is more important than the other. However, ablating both them would damage the final performance.

Furthermore, we compare the performance between G3M without both gated modules and multi-
task baselines (Joint-CBA and VMM), we find the former model performs better than the later, which may indicate that our proposed dialog encoder is superior than the CNN-RNN based and BERT based dialog encoders.

5.7 Parameter Effect

In the IC-Gated module, there is an important parameter to be preset by humans, which is the dimension of $V$. It determines the size of weighted feature $g^{(I)}$ and therefore controls to what degree the data-to-task information can be leveraged. We investigate the effect of various dimensions of $V$ on both datasets. From the curves of RMSE and Micro-F1 scores in Figure 3, we find that the final performance is related to this parameter. Empirically, the optimal setting is 6 for Learning dataset and 4 for MacHelp dataset. We can also observe too small or too large dimensions may both play a harmful effect on extracting important knowledge from the data-to-task information. Another interesting phenomenon is that the optimal parameter values are coincidently close or equal to the numbers of dialog categories to be classified, and we would explore the potential correlation in the future.

5.8 Case Study

We conduct a case study to demonstrate how our method could work to improve the system efficiency and user experience by integrating our dialog routing component into a human-bot symbiosis dialog system. Table 4 lists the dialog utterances along with the predicted NPS and dialog category. Here the user (U) has a requirement to solve course enrollment issue. At first, the bot agent (A1) serves the user which is skilled at ‘Finding Content’ dialogs, but it wrongly understands the user that she would find some course materials. By using the dialog routing component to monitor the dialogs, the predicted NPS decreases from 5.8 to 4.8, which means the user is dissatisfactory with the A1 and the routing to other agent should be triggered\(^6\). As a result, based on the dialog category classification by dialog routing component, the dialog is transferred to a human agent (A2) who is skilled at ‘Completion Issue’ dialogs. Thanks to the right time to transfer and the correctly assigned agent, the NPS is up to 7.8 and the user is finally satisfactory with this service.

\(^6\)We can set a dissatisfaction threshold based on real situations, e.g. 5 in this case.

<table>
<thead>
<tr>
<th>Role</th>
<th>Utterances</th>
</tr>
</thead>
<tbody>
<tr>
<td>U</td>
<td>Hi</td>
</tr>
<tr>
<td>A1</td>
<td>Hello, how may I assist you?</td>
</tr>
<tr>
<td>U</td>
<td>I have enrolled in Deep Learning Course but today I can’t see this enrollment</td>
</tr>
<tr>
<td>U</td>
<td>I have completed more than 80%</td>
</tr>
<tr>
<td>U</td>
<td>Can you please help me to find / resume the course</td>
</tr>
<tr>
<td>A1</td>
<td>I’m sorry that we are not able to do that</td>
</tr>
<tr>
<td>U</td>
<td>Why so</td>
</tr>
<tr>
<td>U</td>
<td>and what help you can do?</td>
</tr>
<tr>
<td>A1</td>
<td>You could get more information in the completion dashboard in the system</td>
</tr>
<tr>
<td>U</td>
<td>You did not answer my question, I can’t find the course and I want to resume it</td>
</tr>
<tr>
<td>U</td>
<td>Can you please help me to find / resume the course</td>
</tr>
<tr>
<td>Current NPS: 5.8</td>
<td></td>
</tr>
<tr>
<td>Current dialog category: Finding Content</td>
<td></td>
</tr>
<tr>
<td>A1</td>
<td>You could get more information in the completion dashboard in the system</td>
</tr>
<tr>
<td>U</td>
<td>You did not answer my question, I can’t find the course and I want to resume it</td>
</tr>
<tr>
<td>U</td>
<td>Can you please help me to find / resume the course</td>
</tr>
<tr>
<td>Current NPS: 4.8 (under the threshold and trigger routing)</td>
<td></td>
</tr>
<tr>
<td>Current dialog category: Completion Issue</td>
<td></td>
</tr>
<tr>
<td>A2</td>
<td>Sorry for not being very helpful.</td>
</tr>
<tr>
<td>A2</td>
<td>You can’t find the course in your learning queue and the progress are all gone, correct?</td>
</tr>
<tr>
<td>U</td>
<td>Exactly</td>
</tr>
<tr>
<td>Current NPS: 6.7</td>
<td></td>
</tr>
<tr>
<td>Current dialog category: Completion Issue</td>
<td></td>
</tr>
<tr>
<td>A2</td>
<td>Is it an internal course in the Learning system, right?</td>
</tr>
<tr>
<td>U</td>
<td>Yes</td>
</tr>
<tr>
<td>Current NPS: 6.9</td>
<td></td>
</tr>
<tr>
<td>Current dialog category: Completion Issue</td>
<td></td>
</tr>
<tr>
<td>A2</td>
<td>Sorry for your confusion, sometimes it may be caused by technical issues.</td>
</tr>
<tr>
<td>A2</td>
<td>A ticket has been created for you so that it will be reflected correctly.</td>
</tr>
<tr>
<td>A2</td>
<td>Normally the technical team will get back to you in 24 hours</td>
</tr>
<tr>
<td>U</td>
<td>Thanks, bye</td>
</tr>
<tr>
<td>A2</td>
<td>Bye</td>
</tr>
<tr>
<td>Current NPS: 7.8</td>
<td></td>
</tr>
<tr>
<td>Current dialog category: Completion Issue</td>
<td></td>
</tr>
</tbody>
</table>

Table 4: A dialog session along with the predicted NPS and dialog category by equipping a dialog routing component with our method.

This case could also reveal that our method would not affect the existing dialog systems and the dialog routing system can be deployed in a plug-in manner, which has a good compatibility and is convenient for both dialog routing system and dialog system to upgrade their ability.

6 Conclusion

In current ubiquitous human-bot symbiosis dialog systems for customer care, the dialog routing component is necessary to improve the overall system efficiency, reduce human resource cost, and enhance user experience. In this paper, we argue that the data-to-task and task-to-task information among various kinds of dialog data and subtasks should be jointly leveraged to perform better dialog routing ability. We propose a Gated Mechanism
enhanced Multi-task Model (G3M) to implement that motivation. Specifically, we design a new dialog encoder to learn various kinds of dialog data by extending the BERT encoder, and two gated mechanism modules are proposed to capture data-to-task and task-to-task information. Extensive experiments on two real-world datasets demonstrate the effectiveness of our proposed model, which can achieve the state-of-the-art performance.

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References


