Hybrid Generative-Retrieval Transformers for Dialogue Domain Adaptation

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Abstract

Domain adaptation has recently become a key problem in dialogue systems research. Deep learning, while being the preferred technique for modeling such systems, works best given massive training data. However, in the real-world scenario, such resources aren’t available for every new domain, so the ability to train with a few dialogue examples can be considered essential. Pre-training on large data sources and adapting to the target data has become the standard method for few-shot problems within the deep learning framework. In this paper, we present the winning entry at the fast domain adaptation task of DSTC-8, a hybrid generative-retrieval model based on GPT-2 fine-tuned to the multi-domain MetaLWOz dataset. Robust and diverse in response generation, our model uses retrieval logic as a fallback, being SoTA on MetaLWOz in human evaluation (>4% improvement over the 2nd place system) and attaining competitive generalization performance in adaptation to the unseen MultiWOZ dataset.

Introduction

Goal-oriented dialogue is an area of increasingly high interest, both from academic and industrial perspectives. Data-driven approaches to developing such systems (Lemon and Pietquin 2012) proved to be more flexible and scalable to various scenarios and domains than previous techniques widely employed in industry, mostly based on expert knowledge. The benefits of methods based on machine learning (especially deep learning) can only be experienced when there are excess amounts of training data available; however, in real-world scenarios, there’s only a small amount of initial data available for a new domain. Training techniques must make the most of this small data, i.e. work in a data-efficient way, in order to enable rapid development of dialogue models for an ever-increasing number of domains and tasks. The most promising method to achieve this under the deep learning framework has become transfer learning where a large, generic model is first trained from a highly represented source of data, after which it gets adapted to the target task.

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1Code is publicly available at http://tiny.cc/grtr

In this paper, we explore this problem through the Eighth Dialogue System Technology Challenge (DSTC), Fast Domain Adaptation task. Specifically, we propose a hybrid generative/retrieval dialogue model leveraging knowledge transfer from a large-scale pre-trained general-purpose language model. Our model is able to maintain goal-oriented dialogue in a closed domain having only been exposed to a small set of in-domain dialogues as the domain description. Our hybrid model achieves state-of-the-art performance on the MetaLWOz dataset when evaluated with human judges, and attains competitive generalization level in adapting to goal-oriented MultiWOZ dataset unseen at the main training stage. Automated word overlap-based metrics demonstrate that it outperforms a series of competitive baselines—both generative-only and retrieval-only models.

Related work

Generative dialogue modeling is an actively researched area, with the sequence-to-sequence (seq2seq) model (Vinyals and Le 2015) gaining wide adoption in both chat-oriented (Serban et al. 2016) and goal-oriented dialogue (Zhao et al. 2017). Initially these architectures were based on Recurrent Neural Networks such as LSTM (Hochreiter and Schmidhuber 1997) or GRU (Chung et al. 2014) which were quite challenging to train on large amounts of conversational data, causing researchers to focus on improving response diversity (Li et al. 2015) and the overall dialogue consistency (Li and Jurafsky 2016). Quite recently, self-attention mechanisms, like those used in the Transformer (Vaswani et al. 2017), have been adopted for conversation models—together with large-scale pre-training, it resulted in a new generation of seq2seq architectures.

The data efficiency of dialogue systems has also been extensively researched in the past. Initially, when modular dialogue system architecture was the prevalent approach, dialogue managers and state trackers were the components that data-efficient methods were applied to the most. As such, the dialogue state tracker domain adaptation task was initially proposed in DSTC-3 (Henderson, Thomson, and Williams 2014) — that challenge featured approaches like Bayesian Processes (Gasic et al. 2017) and Recurrent Neural Networks (Mrksic et al. 2015). Later research was focused on...
Figure 1: Model diagram: (a) encode target the dialogue context and (b) produce the ‘generated candidate’; (c) encode support dialogue contexts in a similar way; (d) find the nearest ‘support’ neighbor and select its response as the ‘retrieved candidate’; (e) finally, rank the two candidates given the target context and produce the final result.

End-to-end dialogue response generation, the technique that followed modular architectures with the arrival of large conversational datasets, was also eventually approached in a data-efficient way. One such method used prior linguistic knowledge to improve zero-shot performance: Eshghi, Shalyminov, and Lemon (2017) proposed a linguistically informed model based on an incremental semantic parser (Eshghi, Purver, and Hough 2011) combined with a reinforcement learning-based agent. The parser was used for both maintaining the agent’s state and pruning the agent’s incremental, word-level generation actions to those leading to syntactically correct word sequences. While outperforming end-to-end dialogue models on bAbI Dialog Tasks (Bordes, Boureau, and Weston 2017) in the extreme zero-shot case (Shalyminov, Eshghi, and Lemon 2017), this method inherited the limitations of the dialogue grammar — specifically, it is limited to a single closed domain until a wide-coverage grammar is available.

Zhao and Eskénazi (2018) introduced zero-shot dialogue generation (ZSDG) framework under which a dialogue system was trained on dialogues from several source domains and a small amount of annotated utterances from the target domain. The key feature in their framework was the unified latent space which was used to encode user’s queries, dialogue contexts, and annotations.

Later, Shalyminov et al. (2019b, 2019a) proposed Dialogue Knowledge Transfer Networks which approached the problem in a few-shot setup with a separate out-of-domain pre-training stage on a large goal-oriented corpus (MetaWOZ, Lee et al. 2019a). In those approaches, MetaWOZ was used as source dataset for transfer, whereas we treat it as the target dataset. While the authors used full target-domain dialogues, they ended up using only a fraction of ZSDG’s data in terms of the number of utterances.

More generally, transfer learning has been widely adopted for natural language problems with the emergence of large-scale pre-trained text representation models like ELMo (Peters et al. 2018), BERT (Devlin et al. 2019), and GPT-2 (Radford et al. 2018). When applied to dialogue response generation, the most successful approaches made use of a Transformer for chat-oriented dialogue (Wolf et al. 2019) and GPT/GPT-2 for goal-oriented dialogue (Budzianowski and Vulic 2019). Our approach is based on a similar technique, though in addition to fine-tuning a pre-trained model to our task, we augment the generative model with a retrieval component in a hybrid approach.

Finally, another recent approach applied to the problem of few-shot dialogue generation is meta-learning (Qian and Yu 2019), under which the task is split into multiple sub-tasks corresponding to dialogue domains. For each of them, a specialized dialogue model was trained, with their training progress then merged into the main model. In general, the intuition behind meta-learning is training a base model which would be best suited for data-efficient fine-tuning – otherwise known as rapid adaptation – making the most efficient gradient updates from the few data points available in the target domain.

**Fast domain adaptation of a goal-oriented dialogue system**

Goal-oriented dialogue systems can be challenging to bootstrap: For a new domain, little data is available to train e.g. a natural language understanding (NLU) module or other parts...
of the pipeline. Often, a Wizard-of-Oz (WOz, [Kelley]1984,
[Rieser, Kruijff-Korbayov, and Lemon]2005) schema can be
used to obtain some initial test data, however, this requires
training human agents for the task and setting up a complex
pipeline. The value of WOz data is limited, since “users” are
mostly hired and might not conform to real users. Additionally,
any change in the chatbot interface requires collecting
more data.

In the context of the DSTC-8 domain adaptation challenge,
we aim to build a model that predicts user responses for
a goal-oriented dialogue system for which only limited in-
domain data is available. Such data could be collected from
e.g. customer service transcripts, or written by the developers
themselves. From this in-domain data, the support set, we
would like to extrapolate responses to novel dialogue contexts
(the target). However, the support set is typically too small to
train a generative dialogue model. Instead, we adapt a generic
dialogue model trained on a large corpus of conversations
over multiple source domains.

Technically, the problem setup is as follows: having trained
the base model on the source domains, the model is then fed
with one target dialogue and a support set at a time. The
model’s task is to predict the next user turn of the target dia-
logue, taking into account the support set before producing
a prediction. At prediction time, each target dialogue is pro-
cessed in isolation from other target dialogues, such that the
model cannot use knowledge or state obtained from other
target/support data.

Proposed model

We use a language model pre-trained on a very large and
diverse collection of textual data providing a strong language
prior and then adapt the model for our tasks in the form of
fine-tuning. Our base model is GPT-2 (Wolf et al. 2019), a
transformer-based language model. In order to adapt GPT-2
dialogue generation, we first augment the input embed-
dings for each token in the dialogue with (1) a speaker tag
embedding identifying the speaker and (2) a turn embed-
ding, identifying the turn number in the current dialogue.
These additional embedding matrices are learned solely using
the dialogue data. The input token embeddings are then obtained by
summing up these representations. We also add
two task-specific output layers (or “heads”) for our purposes:
a language modeling (LM) head and a next-sentence predic-
tion (NSP) classification head, both trained from randomly
initialized parameters.

We fine-tune GPT-2 for response generation by minimizing the
negative log-likelihood of response tokens given the
concatenation of dialogue context and the previous tokens in
the response,

\[
\mathcal{L}_{LM} = \sum_{i=1}^{\left|X\right|} \log P_L M(x_i \mid x_{i-1}, \ldots, x_1, C),
\]

(1)

where \(X\) is the response and \(C\) is the dialogue context, i.e.
the concatenation of the tokens in the previous utterances.

To predict the next sentence, we proceed as follows: given
a context/response pair \((C, X)\), the classification head is
trained to produce a binary label \(y\), which is 1 if \(X\) is the
correct response given the context \(C\), and 0 if \(X\) is a distractor
(a random utterance from the corpus). We minimize a binary
cross-entropy:

\[
\mathcal{L}_{NSP} = -y \log P_{NSP}(y \mid X, C)
- (1 - y) \log P_{NSP}(1 - y \mid X, C),
\]

(2)

\[
P_{NSP}(y \mid X, C) = \text{softmax}(f_{NSP}(h_{X, C})),
\]

(3)
does not use support set. As every test dialogue in the target domain/task is accompanied with a small support set of dialogues from the same domain/task, we make use of this data by further fine-tuning the dialogue model on the support dialogues. Crucially, we make sure not to accumulate any information between test dialogues; after each fine-tuning on the support set, we reset the weights of the model to the dialogue prior obtained by the fine-tuning stage described in the previous section.

In order to add diversity to the responses, GPT-2 uses nucleus (top-\(p\)) sampling \cite{holtzman2019curious} during generation, i.e. the model’s vocabulary \(V\) is pruned into \(V^p\), the smallest set such that

\[
\sum_{x \in V^p} p(x \mid x_{1:i-1}, C) \geq p,
\]

and the final distribution from which the words are sampled is rescaled as follows:

\[
P'(x \mid x_{1:i-1}) = \begin{cases} \frac{P(x \mid x_{1:i-1}, C)}{\sum_{x \in V^p} P(x \mid x_{1:i-1}, C)} & \text{if } x \in V^p \\ 0, & \text{otherwise} \end{cases}
\]

Hybrid generative-retrieval prediction

In our experiments, we found that retrieval baselines are quite effective in the automatic metrics considered. Combining retrieval techniques with our generative model in a hybrid approach produced a stronger model.

The retrieval component is set up as follows: when predicting the \(t\)-th turn of the test dialogue, the model embeds its context of length \(t - 1\) as well as all the support dialogue contexts of the same length \(t - 1\) using the fine-tuned dialogue encoder. The encoding for the dialogue context is the hidden state of the last layer of the Transformer model at the position corresponding to the last token in the context. Then, it selects the nearest support context to the target context and picks its \(t\)-th turn as the retrieved candidate response.

Finally, the model’s own generated response and the best retrieved candidate response are ranked using the NSP classification head, i.e. both responses are concatenated with the ground-truth context and the one with the higher \(P_{NSP}\) \cite{wu2020roberta} is selected. The model is visualized in Figure 1.

Table 2: Automatic evaluation results on MetalWOZ

| Retrieval BERT | BLEU1 | BLEU2 | BLEU3 | CIDEr | METEOR | ROUGE-L |
|----------------|-------|-------|-------|-------|--------|---------|
| Retrieval SP+FT| 9.57  | 5.37  | 3.45  | 14.32 | 6.98   | 7.19    |
| HRED           | 8.66  | 3.86  | 2.11  | 13.73 | 6.02   | 7.57    |
| GPT-2 –sup\(^1\) | 8.20  | 3.95  | 2.22  | 16.41 | 6.10   | 8.34    |
| GPT-2 –ret\(^2\) | 11.33 | 6.45  | 4.17  | 23.38 | 8.23   | 10.74   |
| GPT-2 hybrid   | 12.73 | 7.43  | 4.88  | 28.74 | 9.23   | 11.77   |

\(^1\) does not use support set. \(^2\) fine-tuned to support set, but does not use retrieval logic

### Fine-tuning on target domains and prediction

As every test dialogue in the target domain/task is accompanied with a small support set of dialogues from the same domain/task, we make use of this data by further fine-tuning the dialogue model on the support dialogues. Crucially, we make sure not to accumulate any information between test dialogues: after each fine-tuning on the support set, we reset the weights of the model to the dialogue prior obtained by the fine-tuning stage described in the previous section.

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### Baselines

We compare our hybrid model to the retrieval baselines provided by the DSTC-8 organizers. The baselines ignore the training data and rely solely on the support sets: they embed each support dialogue’s context and find the one nearest to the target context using cosine distance as the metric. They then return the turn following the identified context as the predicted response.

There are two baselines, which differ in their encoder: (1) BERT \cite{devlin2019bert} based, taken off-the-shelf, and (2) SentencePiece/FastText-based, modeled after \cite{gu2018empirical}, \cite{serban2016building} with embeddings pre-trained on the Reddit Conversations corpus.

We also compare our model to a bidirectional LSTM-based HRED \cite{serban2016building} fine-tuned on MetalWOZ. Given the time constraints, we could only evaluate a base model without fine-tuning to support sets.

Table 3: Automatic evaluation results on MultiWOZ pure task dataset

| Retrieval BERT       | Intent F1 (%) | Intent+Slots F1 (%) |
|----------------------|---------------|--------------------|
| Retrieval SP+FT      | 48.00         | 21.95              |
| HRED                 | 51.53         | 26.58              |
| GPT-2 –sup\(^1\)     | 58.54         | 43.07              |
| GPT-2 –ret\(^2\)     | 48.00         | 37.24              |
| Team D               | 54.98         | 42.34              |
| Team C               | 61.40         | 41.87              |
| GPT-2 hybrid (Team B)| 64.50         | 48.33              |
| Team A               | 78.70         | 60.00              |
Datasets

We use MetaLWOz, the dataset for DSTC-8 Track 2 “Fast Domain Adaptation” (Lee et al. 2019a). It contains more than 37,000 human-human dialogues spanning the total of 227 tasks in 47 domains. The dialogues are collected in a Wizard-of-Oz style: human participants were assigned the role of bot or user, then given a problem domain and related specific task, and instructed to reach the user’s goal over at least 10 dialogue turns.

For evaluation purposes, we additionally use MultiWOZ (Budzianowski et al. 2018), another multi-domain, multi-task dialogue dataset. Dialogues in MultiWOZ contain NLU annotations, particularly for intent and slots, which we use in order to to evaluate the systems’ goal-oriented performance. A subset of MultiWOZ (MultiWOZ pure task), where dialogues only pertain to a single domain, was used for evaluation.

Experimental setup and evaluation

We perform training in two stages: training of the base model and fine-tuning it to the target dialogue’s support set. At the first stage, we train the model for the maximum of 5 epochs with early stopping. The second stage goes on for 1 epoch (Maystre and Grossglauser 2017) determine which responses were used to determine average ranks and assess the ranking robustness (Hall, Miller, and others 2009).

Automatic evaluation

In addition to human evaluation, we also assess model performance using automatic metrics. The models were evaluated on MetaLWOz against word-overlap metrics such as BLEU-1–3, CIDEr, METEOR, ROUGE-L using the NLGEval package (Sharma et al. 2017). Although not ideal for the specifics of dialogue and spoken language in general (Lowe et al. 2017; Dziri et al. 2019), such metrics approximate the overall quality of a generative model and are especially useful for intermediate evaluation. We evaluate models in two modes on MetaLWOz: in pure task, support dialogues are drawn from the same domain and task as target dialogue; in cross-task, support and target dialogues are from the same domain, but different tasks.

We also perform additional evaluation of Entity/Intent F1 of the MultiWOZ dataset in pure task mode with pre-trained NLU taggers from the ConvLab package (Lee et al. 2019b). There is no MultiWOZ data available at the first stage (base model training), so all the exposure our model has to this dataset is via support dialogues. Complementary to MetaLWOz evaluation, this stage is designed for assessing the models’ goal-oriented performance.

Results and discussion

Human evaluation

Results of pairwise comparisons are shown in Table[1]. Our GPT-2 hybrid system’s responses (Team B) were preferred by the judges in 56% of direct comparisons. This surpasses the next best system (Team C) performance by more than 4%, with only the gold human responses being chosen more frequently.

Furthermore, from the bootstrap ranking distribution (Figure[2], we see that, apart from the gold human responses, our model’s outputs are consistently preferred over other submissions by the judges. Of all metrics used, the most notable are ‘appropriateness’ and ‘usefulness’. On the former, GPT-2 hybrid’s responses have the second visible peak at rank 1 competing with gold responses. On usefulness however, rank 1 is held by the gold responses with no variation, and our model has the second visible peak at rank 3, thus almost tying with Team C.

Automatic evaluation

Results on MetaLWOz and MultiWOZ against automatic evaluation metrics are shown in Tables[2] and [3] respectively. We observe that retrieval baselines attain very competitive performance on both datasets, with FastText embeddings from Reddit leading to overall better results than off-the-shelf BERT, especially in the pure task setting.

With GPT-2, we performed an ablation study to have a closer look into its performance. We evaluated three versions: ‘hybrid’ which we presented in this paper, ‘–ret’ with retrieval logic turned off, and ‘–sup’ with no retrieval logic and no fine-tuning to the support set. As seen in the Table[2], there is strong dependence on support dialogues (‘–sup’ vs. ‘–ret’) as the base model mostly struggles to compete with the baselines. Adding retrieval logic (‘hybrid’ vs. ‘–ret’) results in further performance gains. HRED and GPT-2–sup, the two
Table 4: GPT-2 Hybrid example responses

| Context | Wiz | Gold response | Predicted response |
|---------|-----|---------------|-------------------|
| Usr | I need some advice about Rome. | Wiz | What do you want to know? | Usr | I like history, where should I go? | Wiz | Who was the founder of Rome? |

| Context | Wiz | Gold response | Predicted response |
|---------|-----|---------------|-------------------|
| Usr | I'm looking for a train to broxbourne. | Wiz | Where would you like to leave from, and what day and time would you like to travel? | Usr | I'm going to be leaving from Cambridge. I need to leave on Tuesday by 13:00. | Wiz | Is there a time you would like to get there by? |

| Context | Wiz | Gold response | Predicted response |
|---------|-----|---------------|-------------------|
| Usr | How am I supposed to book a flight to Greece? Me and my kawaii girlfriend were wondering. | Wiz | I can book a flight for two if you want, There will be an evening flight | Usr | Hmm, wait, I don’t really wanna book a flight. We were just curious! She says “Hey! No bookies! :t” | Wiz | Oh, I was confused by that. Can I have your email address so I could send several flight options for you |

| Context | Wiz | Gold response | Predicted response |
|---------|-----|---------------|-------------------|
| Usr | Sure thing! My email address is “weeabooking@otaku.corn”. She says “I wanna watch my anime now! ;();” | Wiz | Hello how may I help you? | Usr | Hello, how may I help you? | Wiz | I’m looking for a train to broxbourne. |

Table 5: GPT-2-hybrid generate/retrieve response ratio

| Dataset / domain | Generated (%) | Retrieved (%) |
|------------------|---------------|---------------|
| **MetaLWOZ pure task** | | |
| booking flight | 64.10 | 35.90 |
| hotel reserve | 63.80 | 36.20 |
| tourism | 57.40 | 42.60 |
| vacation ideas | 61.70 | 38.30 |
| **MetaLWOZ cross task** | | |
| booking flight | 68.20 | 31.80 |
| hotel reserve | 74.80 | 25.20 |
| tourism | 73.90 | 26.10 |
| vacation ideas | 74.70 | 25.30 |
| **MultiLWOZ** | | |
| attraction | 55.60 | 44.40 |
| hospital | 60.00 | 40.00 |
| hotel | 63.00 | 37.00 |
| police | 52.10 | 47.90 |
| restaurant | 61.30 | 38.70 |
| taxi | 64.30 | 35.70 |
| train | 61.00 | 39.00 |

In goal-oriented metrics on MultiLWOZ (see Table 5), the same performance pattern is observed with retrieval models, but GPT-2 in the generative-only version performs surprisingly better when not fine-tuned to support set (‘–sup’). On the other hand, the hybrid model experiences even more performance gain than on MetaLWOZ. Presumably, generating responses for this dataset is harder due to the fact that it is not represented at the main training stage, and there is not much utterance overlap with MetaLWOZ, so little knowledge transfer takes place in this experiment. Compared to other submissions, we observe that GPT-2 hybrid still outperforms most of the competitors and only gives way to Team A’s system. We hypothesize here the best MultiLWOZ model (Team A) was fitted to the automatic evaluation metrics too tightly, with the negative side effect observable in human evaluation results of Table 1 and Figure 2, where this system was prevalently ranked 4th and 5th.

**Retrieval and Generation Frequency** In Table 5 we show per-domain ratios of retrieved/generated responses from the hybrid model. We find that the majority of the responses are generated, and the retrieval logic works as the fallback option. On MetaLWOz, which the model had more exposure to during the training, generated responses ratio is generally slightly higher than that on MultiLWOZ which was only seen by the model via support dialogues. Consequently, the model’s overall confidence on this dataset is lower, which results in more frequent fallbacks.

Overall, we observe in Table 4 that there are many cases in the data where the gold response cannot possibly be inferred from the dialogue context. Specifically, the task was posed in the way that no extra data, such as a knowledge base or task description, was provided to the system — therefore, the main goal intended for the hypothetical ideal system is to naturally model human responses in a co-operative goal-oriented dialogue, and to do that in a data-efficient way. This is reflected in the way human judges are asked about response quality.

**Conclusion and future work**

We presented a hybrid generative/retrieval approach to goal-oriented dialogue with fast domain adaptation via transfer learning. It attains robust and diverse language generation performance across domains, and uses retrieval logic as a
fallback mechanism in cases of low confidence. Our method is the winning entry at the DSTC-8 Fast Domain Adaptation task achieving state-of-the-art performance as evaluated with human judges. In additional automatic evaluation, it attains competitive generalization performance in adaptation to the goal-oriented MultiWOZ dataset without any exposure to that data during the main training stage.

Overall, we observe that transfer learning, while being in the core of state-of-the-art methods for dialogue domain adaptation and few-shot learning (Shalyminov et al. 2019a [Shalyminov et al. 2019b]), still does not attain the performance level sufficient for direct adoption in industry. It’s evident that the problem of data-efficient dialogue response generation needs further research, and one promising direction that we are going to explore in our own future work is the meta-learning framework (Qian and Yu 2019), or ‘learning to fine-tune’. Based on splitting the task into multiple subtasks and solving them with separate versions of the model with further merging of each individual learner’s progress, meta-learning approach will naturally fit our multi-domain setup as well as lead to potentially better fine-tuning performance.

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