Mem2Seq: Effectively Incorporating Knowledge Bases into End-to-End Task-Oriented Dialog Systems

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Abstract

End-to-end task-oriented dialog systems usually suffer from the challenge of incorporating knowledge bases. In this paper, we propose a novel yet simple end-to-end differentiable model called memory-to-sequence (Mem2Seq) to address this issue. Mem2Seq is the first neural generative model that combines the multi-hop attention over memories with the idea of pointer network. We empirically show how Mem2Seq controls each generation step, and how its multi-hop attention mechanism helps in learning correlations between memories. In addition, our model is quite general without complicated task-specific designs. As a result, we show that Mem2Seq can be trained faster and attain the state-of-the-art performance on three different task-oriented dialog datasets.

1 Introduction

Task-oriented dialog systems help users to achieve specific goals with natural language such as restaurant reservation and schedule arrangement. Traditionally, they have been built with several pipelined modules: language understanding, dialog management, knowledge query, and language generation (Williams and Young, 2007; Hori et al., 2009; Lee et al., 2009; Levin et al., 2000; Young et al., 2013). Moreover, the ability to query external Knowledge Bases (KBs) is essential in task-oriented dialog systems, since the responses are guided not only by the dialog history but also by the query results (e.g. Table 1). However, despite the stability of such pipelined systems via combining domain-specific knowledge and slot-filling techniques, modeling the dependencies between modules is complex and the KB interpretation requires human effort.

Recently, end-to-end approaches for dialog modeling, which use recurrent neural networks (RNN) encoder-decoder models, have shown promising results (Serban et al., 2016; Wen et al., 2017; Zhao et al., 2017). Since they can directly map plain text dialog history to the output responses, and the dialog states are latent, there is no need for hand-crafted state labels. Moreover, attention-based copy mechanism (Gulcehre et al., 2016; Eric and Manning, 2017) have been recently introduced to copy words directly from the input sources to the output responses. Using such mechanism, even when unknown tokens appear in the dialog history, the models are still able to produce correct and relevant entities.

However, although the above mentioned approaches were successful, they still suffer from two main problems: 1) They struggle to effectively incorporate external KB information into the RNN hidden states (Sukhbaatar et al., 2015),
since RNNs are known to be unstable over long sequences. 2) Processing long sequences is very time-consuming, especially when using attention mechanisms.

On the other hand, end-to-end memory networks (MemNNs) are recurrent attention models over a possibly large external memory (Sukhbaatar et al., 2015). They write external memories into several embedding matrices, and use query vectors to read memories repeatedly. This approach can memorize external KB information and rapidly encode long dialog history. Moreover, the multi-hop mechanism of MemNN has empirically shown to be essential in achieving high performance on reasoning tasks (Bordes and Weston, 2017). Nevertheless, MemNN simply chooses its responses from a predefined candidate pool rather than generating word-by-word. In addition, the memory queries need explicit design rather than being learned, and the copy mechanism is absent.

To address these problems, we present a novel architecture that we call Memory-to-Sequence (Mem2Seq) to learn task-oriented dialogs in an end-to-end manner. In short, our model augments the existing MemNN framework with a sequential generative architecture, using global multi-hop attention mechanisms to copy words directly from dialog history or KBs. We summarize our main contributions as such: 1) Mem2Seq is the first model to combine multi-hop attention mechanisms with the idea of pointer networks, which allows us to effectively incorporate KB information. 2) Mem2Seq learns how to generate dynamic queries to control the memory access. In addition, we visualize and interpret the model dynamics among hops for both the memory controller and the attention. 3) Mem2Seq can be trained faster and achieve state-of-the-art results in several task-oriented dialog datasets.

2 Model Description

Mem2Seq \(^1\) is composed of two components: the MemNN encoder, and the memory decoder as shown in Figure 1. The MemNN encoder creates a vector representation of the dialog history. Then the memory decoder reads and copies the memory to generate a response. We define all the words in the dialog history as a sequence of tokens \(X = \{x_1, \ldots, x_n, \$\}\), where \(\$\) is a special charter used as a sentinel, and the KB tuples as \(B = \{b_1, \ldots, b_l\}\). We further define \(U = [B; X]\) as the concatenation of the two sets \(X\) and \(B\), \(Y = \{y_1, \ldots, y_m\}\) as the set of words in the expected system response, and \(\mathcal{PTR} = \{ptr_1, \ldots, ptr_m\}\) as the pointer index set:

\[
ptr_i = \begin{cases} 
\max(z) & \text{if } \exists z \text{ s.t. } y_i = u_z \\
 n + l + 1 & \text{otherwise}
\end{cases}
\] (1)

where \(u_z \in U\) is the input sequence and \(n + l + 1\) is the sentinel position index.

2.1 Memory Encoder

Mem2Seq uses a standard MemNN with adjacent weighted tying (Sukhbaatar et al., 2015) as an encoder. The input of the encoder is word-level information in \(U\). The memories of MemNN are represented by a set of trainable embedding matrices \(C = \{C^1, \ldots, C^{K+1}\}\), where each \(C^k\) maps tokens to vectors, and a query vector \(q^k\) is used as a reading head. The model loops over \(K\) hops and

\(^1\)The code is available at https://github.com/HLTCHKUST/Mem2Seq
it computes the attention weights at hop $k$ for each memory $i$ using:

$$p^k_i = \text{Softmax}(C^k_i q^k, \text{Softmax}(C^k_i q^k T C^k_i h^k)), \quad (2)$$

where $C^k_i = C^k(x_i)$ is the memory content in position $i$, and Softmax($z_i$) = $e^{z_i}/\sum_j e^{z_j}$. Here, $p^k$ is a soft memory selector that decides the memory relevance with respect to the query vector $q^k$. Then, the model reads out the memory $o^k$ by the weighted sum over $C^{k+1}$:

$$o^k = \sum_i p^k_i C^{k+1}_i. \quad (3)$$

Then, the query vector is updated for the next hop by using $q^{k+1} = q^k + o^k$. The result from the encoding step is the memory vector $o^K$, which will become the input for the decoding step.

2.2 Memory Decoder

The decoder uses RNN and MemNN. The MemNN is loaded with both $X$ and $B$, since we use both dialog history and KB information to generate a proper system response. A Gated Recurrent Unit (GRU) (Chung et al., 2014), is used as a dynamic query generator for the MemNN. At each decoding step $t$, the GRU gets the previously generated word and the previous query as input, and it generates the new query vector. Formally:

$$h_t = \text{GRU}(C^1(\hat{y}_{t-1}), h_{t-1}); \quad (4)$$

Then the query $h_t$ is passed to the MemNN which will produce the token, where $h_0$ is the encoder vector $o^K$. At each time step, two distribution are generated: one over all the words in the vocabulary ($P_{\text{vocab}}$), and one over the memory contents ($P_{\text{ptr}}$), which are the dialog history and KB information. The first, $P_{\text{vocab}}$, is generated by concatenating the first hop attention read out and the current query vector.

$$P_{\text{vocab}}(\hat{y}_t) = \text{Softmax}(W_1[h_t; o^1]) \quad (5)$$

where $W_1$ is a trainable parameter. On the other hand, $P_{\text{ptr}}$ is generated using the attention weights at the last MemNN hop of the decoder: $P_{\text{ptr}} = p^K_{\text{ptr}}$. Our decoder generates tokens by pointing to the input words in the memory, which is a similar mechanism to the attention used in pointer networks (Vinyals et al., 2015).

We designed our architecture in this way because we expect the attention weights in the first and the last hop to show a “looser” and “sharper” distribution, respectively. To elaborate, the first hop focuses more on retrieving memory information and the last one tends to choose the exact token leveraging the pointer supervision. Hence, during training all the parameters are jointly learned by minimizing the sum of two standard cross-entropy losses: one between $P_{\text{vocab}}(\hat{y}_t)$ and $y_t \in \mathcal{Y}$ for the vocabulary distribution, and one between $P_{\text{ptr}}(\hat{y}_t)$ and ptr$_t \in \text{PTR}$ for the memory distribution.

2.2.1 Sentinel

If the expected word is not appearing in the memories, then the $P_{\text{ptr}}$ is trained to produce the sentinel token $\$_$, as shown in Equation 1. Once the sentinel is chosen, our model generates the token from $P_{\text{vocab}}$, otherwise, it takes the memory content using the $P_{\text{ptr}}$ distribution. Basically, the sentinel token is used as a hard gate to control which distribution to use at each time step. A similar approach has been used in (Merity et al., 2017) to control a soft gate in a language modeling task. With this method, the model does not need to learn a gating function separately as in Gulcehre et al. (2016), and is not constrained by a soft gate function as in See et al. (2017).

2.3 Memory Content

We store word-level content $X$ in the memory module. Similar to Bordes and Weston (2017), we add temporal information and speaker information in each token of $X$ to capture the sequential dependencies. For example, “hello t1 $\_u$ means “hello” at time step 1 spoken by a user.

On the other hand, to store $B$, the KB information, we follow the works of Miller et al. (2016); Eric et al. (2017) that use a (subject, relation, object) representation. For example, we represent the information of The Westin in Table 1: (The Westin, Distance, 5 miles). Thus, we sum word embeddings of the subject, relation, and object to obtain each KB memory representation. During decoding stage, the object part is used as the generated word for $P_{\text{ptr}}$. For instance, when the KB tuple (The Westin, Distance, 5 miles) is pointed, our model copies “5 miles” as an output word. Notice that only a specific section of the KB, relevant to a specific dialog, is loaded into the memory.
### 3 Experimental Setup

#### 3.1 Dataset

We use three public multi-turn task-oriented dialog datasets to evaluate our model: the bAbI dialog (Bordes and Weston, 2017), DSTC2 (Henderson et al., 2014) and In-Car Assistant (Eric et al., 2017). The train/validation/test sets of these three datasets are split in advance by the providers. The dataset statistics are reported in Table 2.

The bAbI dialog includes five end-to-end dialog learning tasks in the restaurant domain, which are simulated dialog data. Task 1 to 4 are about API calls, refining API calls, recommending options, and providing additional information, respectively. Task 5 is the union of tasks 1-4. There are two test sets for each task: one follows the same distribution as the training set and the other has out-of-vocabulary (OOV) entity values that does not exist in the training set.

We also used dialogs extracted from the Dialog State Tracking Challenge 2 (DSTC2) with the refined version from Bordes and Weston (2017), which ignores the dialog state annotations. The main difference with bAbI dialog is that this dataset is extracted from real human-bot dialogs, which is noisier and harder since the bots made mistakes due to speech recognition errors or misinterpretations.

Recently, In-Car Assistant dataset has been released. which is a human-human, multi-domain dialog dataset collected from Amazon Mechanical Turk. It has three distinct domains: calendar scheduling, weather information retrieval, and point-of-interest navigation. This dataset has shorter conversation turns, but the user and system behaviors are more diverse. In addition, the system responses are variant and the KB information is much more complicated. Hence, this dataset requires stronger ability to interact with KBs, rather than dialog state tracking.

#### 3.2 Training

We trained our model end-to-end using Adam optimizer (Kingma and Ba, 2015), and chose learning rate between $[1e^{-3}, 1e^{-4}]$. The MemNNs, both encoder and decoder, have hops $K = 1, 3, 6$ to show the performance difference. We use simple greedy search and without any re-scoring techniques. The embedding size, which is also equivalent to the memory size and the RNN hidden size (i.e., including the baselines), has been selected between $[64, 512]$. The dropout rate is set between $[0.1, 0.4]$, and we also randomly mask some input words into unknown tokens to simulate OOV situation with the same dropout ratio. In all the datasets, we tuned the hyper-parameters with grid-search over the validation set, using as measure to the Per-response Accuracy for bAbI dialog and DSTC2, and BLEU score for the In-Car Assistant.

#### 3.3 Evaluation Metrics

**Per-response/dialog Accuracy**: A generative response is correct only if it is exactly the same as the gold response. A dialog is correct only if every generated responses of the dialog are correct, which can be considered as the task-completion rate. Note that Bordes and Weston (2017) tests their model by selecting the system response from predefined response candidates, that is, their system solves a multi-class classification task. Since Mem2Seq generates each token individually, evaluating with this metric is much more challenging for our model.

**BLEU**: It is a measure commonly used for machine translation systems (Papineni et al., 2002), but it has also been used in evaluating dialog systems (Eric and Manning, 2017; Zhao et al., 2017) and chat-bots (Ritter et al., 2011; Li et al., 2016). Moreover, BLEU score is a relevant measure in task-oriented dialog as there is not a large variance between the generated answers, unlike open domain generation (Liu et al., 2016). Hence, we include BLEU score in our evaluation (i.e. using Moses multi-bleu.perl script).

**Entity F1**: We micro-average over the entire set of system responses and compare the entities in plain text. The entities in each gold system response are selected by a predefined entity list. This metric evaluates the ability to generate relevant entities from the provided KBs and to capture the semantics of the dialog (Eric and Manning, 2017; Eric et al., 2017). Note that the original In-Car Assis-
Table 3: Per-response and per-dialog (in the parentheses) accuracy on bAbI dialogs. Mem2Seq achieves the highest average per-response accuracy and has the least out-of-vocabulary performance drop.

Table 4: Evaluation on DSTC2. Seq2Seq (+attn and +copy) is reported from Eric and Manning (2017).

Table 5: Evaluation on In-Car Assistant. Human, rule-based and KV Retrieval Net evaluation (with *) are reported from (Eric et al., 2017), which are not directly comparable. Mem2Seq achieves highest BLEU and entity F1 score over baselines.

4 Experimental Results

We mainly compare Mem2Seq with hop 1,3,6 with several existing models: query-reduction networks (QRN, Seo et al. (2017)), end-to-end memory networks (MemNN, Sukhbaatar et al. (2015)), and gated end-to-end memory networks (GMemNN, Liu and Perez (2017)). We also implemented the following baseline models: standard sequence-to-sequence (Seq2Seq) models with and without attention (Luong et al., 2015), and pointer to unknown (Ptr-Unk, Gulcehre et al. (2016)). Note that the results we listed in Table 3 and Table 4 for QRN are different from the original paper, because based on their released code, we discovered that the per-response accuracy was not correctly computed.

bAbI Dialog: In Table 3, we follow Bordes and Weston (2017) to compare the performance based on per-response and per-dialog accuracy. Mem2Seq with 6 hops can achieve per-response 97.9% and per-dialog 69.6% accuracy in T5, and 84.5% and 2.3% for T5-OOV, which surpass existing methods by far. One can find that in T3 especially, which is the task to recommend restaurant based on their ranks, our model can achieve promising results due to the memory pointer. In terms of per-response accuracy, this indicates that our model can generalize well with few performance loss for test OOV data, while others have around 15-20% drop. The performance gain in OOV data is also mainly attributed to the use of copy mechanism. In addition, the effectiveness of hops is demonstrated in tasks 3-5, since they require reasoning ability over the KB information. Note that QRN, MemNN and GMemNN viewed bAbI dialog tasks as classification problems. Although their tasks are easier compared to our generative methods, Mem2Seq models can still overpass the performance. Finally, one can find that Seq2Seq and Ptr-Unk models are also strong baselines, which further confirms that generative methods can also achieve good performance in task-oriented dialog systems (Eric and Manning, 2017).
DSTC2: In Table 4, the Seq2Seq models from Eric and Manning (2017) and the rule-based from Bordes and Weston (2017) are reported. Mem2Seq has the highest 75.3% entity F1 score and an high of 55.3 BLEU score. This further confirms that Mem2Seq can perform well in retrieving the correct entity, using the multiple hop mechanism without losing language modeling. Here, we do not report the results using match type (Bordes and Weston, 2017) or entity type (Eric and Manning, 2017) feature, since this meta-information are not commonly available and we want to have an evaluation on plain input output couples. One can also find out that, Mem2Seq comparable per-response accuracy (i.e. 2% margin) among other existing solution. Note that the per-response accuracy for every model is less than 50% since the dataset is quite noisy and it is hard to generate a response that is exactly the same as the gold one.

In-Car Assistant: In Table 5, our model can achieve highest 12.6 BLEU score. In addition, Mem2Seq has shown promising results in terms of Entity F1 scores (33.4%), which are, in general, much higher than those of other baselines. Note that the numbers reported from Eric et al. (2017) are not directly comparable to ours as we mention below. The other baselines such as Seq2Seq or Ptr-Unk especially have worse performances in this dataset since it is very inefficient for RNN methods to encode longer KB information, which is the advantage of Mem2Seq.

Furthermore, we observe an interesting phenomenon that humans can easily achieve a high entity F1 score with a low BLEU score. This implies that stronger reasoning ability over entities (hops) is crucial, but the results may not be similar to the golden answer. We believe humans can produce good answers even with a low BLEU score, since there could be different ways to express the same concepts. Therefore, Mem2Seq shows the potential to successfully choose the correct entities.

Note that the results of KV Retrieval Net baseline reported in Table 5 come from the original paper (Eric et al., 2017) of In-Car Assistant, where they simplified the task by mapping the expression of entities to a canonical form using named entity recognition (NER) and linking. Hence the evaluation is not directly comparable to our system. For example, their model learned to generate responses such as “You have a football game at football_time with football_party,” instead of generating a sentence such as “You have a football game at 7 pm with John.” Since there could be more than one football party or football time, their model does not learn how to access the KBs, but it rather learns the canonicalized language model.

Time Per-Epoch: We also compare the training time in Figure 2. The experiments are set with batch size 16, and we report each model with the hyper-parameter that can achieved the highest performance. One can observe that the training time is not that different for short input length (bAbI dialog tasks 1-4) and the gap becomes larger as the maximal input length increases. Mem2Seq is around 5 times faster in In-Car Assistant and DSTC2 compared to Seq2Seq with attention. This difference in training efficiency is mainly attributed to the fact that Seq2Seq models have input sequential dependencies which limit any parallelization. Moreover, it is unavoidable for Seq2Seq models to encode KBs, instead Mem2Seq only encodes with dialog history.

5 Analysis and Discussion

Memory Attention: Analyzing the attention weights has been frequently used to show the memory read-out, since it is an intuitive way to understand the model dynamics. Figure 8 shows the attention vector at the last hop for each generated token. Each column represents the \( P_{ptr} \) vector at the corresponding generation step. Our model has a sharp distribution over the memory, which im-
plies that it is able to select the right token from the memory. For example, the KB information "270_altair_walk" was retrieved at the sixth step, which is an address for "civic_center_garage". On the other hand, if the sentinel is triggered, then the generated word comes from vocabulary distribution \( P_{vocab} \). For instance, the third generation step triggered the sentinel, and "is" is generated from the vocabulary as the word is not present in the dialog history.

**Multiple Hops:** Mem2Seq shows how multiple hops improve the model performance in several datasets. Task 3 in the bAbI dialog dataset serves as an example, in which the systems need to recommend restaurants to users based on restaurant ranking from highest to lowest. Users can reject the recommendation and the system has to reason over the next highest restaurant. We found out there are two common patterns between hops among different samples: 1) the first hop is usually used to score all the relevant memories and retrieve information; 2) the last hop tends to focus on a specific token and makes mistakes when the attention is not sharp. Such mistakes can be attributed to lack of hops, for some samples. For more information, we report two figures in the supplementary material.

**Query Vectors:** In Figure 4, the principal component analysis of Mem2Seq queries vectors is shown for different hops. Each dot is a query vector \( h_t \) during each decoding time step, and it has its corresponding generated word \( y_t \). The blue dots are the words generated from \( P_{vocab} \), which triggered the sentinel, and orange ones are from \( P_{ptr} \). One can find that in (a) hop 1, there is no clear separation of two different colors but each of which tends to group together. On the other hand, the separation becomes clearer in (b) hop 6 as each color clusters into several groups such as location, cuisine, and number. Our model tends to retrieve more information in the first hop, and points into the memories in the last hop.
**Examples:** Table 1 and 6 show the generated responses of different models in the two test set samples from the In-Car Assistant dataset. We report examples from this dataset since their answers are more human-like and not as structured and repetitive as others. Seq2Seq generally cannot produce related information, and sometimes fail in language modeling. Instead, using attention helps with this issue, but it still rarely produces the correct entities. For example, Seq2Seq with attention generated 5 miles in Table 1 but the correct one is 4 miles. In addition, Ptr-Unk often cannot copy the correct token from the input, as shown by “PAD” in Table 1. On the other hand, Mem2Seq is able to produce the correct responses in this two examples. In particular in the navigation domain, shown in Table 1, Mem2Seq produces a different but still correct utterance. We report further examples from all the domains in the supplementary material.

**Discussions:** Conventional task-oriented dialog systems (Williams and Young, 2007), which are still widely used in commercial systems, require a multitude of human efforts in system designing and data collection. On the other hand, although end-to-end dialog systems are not perfect yet, they require much less human interference, especially in the dataset construction, as raw conversational text and KB information can be used directly without the need of heavy preprocessing (e.g. NER, dependency parsing). To this extent, Mem2Seq is a simple generative model that is able to incorporate KB information with promising generalization ability. We also discovered that the entity F1 score may be a more comprehensive evaluation metric than per-response accuracy or BLEU score, as humans can normally choose the right entities but have very diversified responses. Indeed, we want to highlight that humans may have a low BLEU score despite their correctness because there may not be a large n-gram overlap between the given response and the expected one. However, this does not imply that there is no correlation between BLEU score and human evaluation. In fact, unlike chat-bots and open domain dialogs where BLEU score does not correlate with human evaluation (Liu et al., 2016), in task-oriented dialogs the answers are constrained to particular entities and recurrent patterns. Thus, we believe BLEU score still can be considered as a relevant measure. In future works, several methods could be applied (e.g. Reinforcement Learning (Ranzato et al., 2016), Beam Search (Wiseman and Rush, 2016)) to improve both responses relevance and entity F1 score. However, we preferred to keep our model as simple as possible in order to show that it works well even without advanced training methods.

6 **Related Works**

End-to-end task-oriented dialog systems train a single model directly on text transcripts of dialogs (Wen et al., 2017; Serban et al., 2016; Williams et al., 2017; Zhao et al., 2017; Seo et al., 2017; Serban et al., 2017). Here, RNNs play an important role due to their ability to create a latent representation, avoiding the need for artificial state labels. End-to-End Memory Networks (Bordes and Weston, 2017; Sukhbaatar et al., 2015), and its variants (Liu and Perez, 2017; Wu et al., 2017, 2018) have also shown good results in such tasks. In each of these architectures, the output is produced by generating a sequence of tokens, or by selecting a set of predefined utterances.

Sequence-to-sequence (Seq2Seq) models have also been used in task-oriented dialog systems (Zhao et al., 2017). These architectures have better language modeling ability, but they do not work well in KB retrieval. Even with sophisticated attention models (Luong et al., 2015; Bahdanau et al., 2015), Seq2Seq fails to map the correct entities to the generated input. To alleviate this problem, copy augmented Seq2Seq models Eric and Manning (2017), were used. These models outperform utterance selection methods by copying relevant information directly from the KBs. Copy mechanisms has also been used in question answering tasks (Dehghani et al., 2017; He et al., 2017), neural machine translation (Gulcehre et al., 2016; Gu et al., 2016), language modeling (Merity et al., 2017), and summarization (See et al., 2017).

Less related to dialog systems, but related to our work, are the memory based decoders and the non-recurrent generative models: 1) Mem2Seq query generation phase used to access our memories can be seen as the memory controller used in Memory Augmented Neural Networks (MANN) (Graves et al., 2014, 2016). Similarly, memory encoders have been used in neural machine translation (Wang et al., 2016), and meta-learning application (Kaiser et al., 2017). However, Mem2Seq differs from these models as such: it uses multi-
hop attention in combination with copy mechanism, whereas other models use a single matrix representation. 2) non-recurrent generative models (Vaswani et al., 2017), which only rely on self-attention mechanism, are related to the multi-hop attention mechanism used in MemNN.

7 Conclusion

In this work, we present an end-to-end trainable Memory-to-Sequence model for task-oriented dialog systems. Mem2Seq combines the multi-hop attention mechanism in end-to-end memory networks with the idea of pointer networks to incorporate external information. We empirically show our model’s ability to produce relevant answers using both the external KB information and the predefined vocabulary, and visualize how the multi-hop attention mechanisms help in learning correlations between memories. Mem2Seq is fast, general, and able to achieve state-of-the-art results in three different datasets.

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References

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. International Conference on Learning Representations.

Antoine Bordes and Jason Weston. 2017. Learning end-to-end goal-oriented dialog. International Conference on Learning Representations, abs/1605.07683.

Junyoung Chung, Caglar Gulcehre, Kyunghyun Cho, and Yoshua Bengio. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. NIPS Deep Learning and Representation Learning Workshop.

Mostafa Dehghani, Sascha Rothe, Enrique Alfonseca, and Pascal Fleury. 2017. Learning to attend, copy, and generate for session-based query suggestion. In Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, CIKM ’17, pages 1747–1756, New York, NY, USA. ACM.

Mihail Eric, Lakshmi Krishnan, Francois Charette, and Christopher D. Manning. 2017. Key-value retrieval networks for task-oriented dialogue. In Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue, pages 37–49. Association for Computational Linguistics.

Mihail Eric and Christopher Manning. 2017. A copy-augmented sequence-to-sequence architecture gives good performance on task-oriented dialogue. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pages 468–473, Valencia, Spain. Association for Computational Linguistics.

Alex Graves, Greg Wayne, and Ivo Danihelka. 2014. Neural turing machines. CoRR.

Alex Graves, Greg Wayne, Malcolm Reynolds, Tim Harley, Ivo Danihelka, Agnieszka Grabska-Barwińska, Sergio Gómez Colmenarejo, Edward Grefenstette, Tiago Ramalho, John Agapiou, et al. 2016. Hybrid computing using a neural network with dynamic external memory. Nature, 538(7626):471–476.

Jiatao Gu, Zhengdong Lu, Hang Li, and Victor O.K. Li. 2016. Incorporating copying mechanism in sequence-to-sequence learning. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1631–1640, Berlin, Germany. Association for Computational Linguistics.

Caglar Gulcehre, Sungjin Ahn, Ramesh Nallapati, Bowen Zhou, and Yoshua Bengio. 2016. Pointing the unknown words. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 140–149, Berlin, Germany. Association for Computational Linguistics.

Shizhu He, Cao Liu, Kang Liu, and Jun Zhao. 2017. Generating natural answers by incorporating copying and retrieving mechanisms in sequence-to-sequence learning. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 199–208, Vancouver, Canada. Association for Computational Linguistics.

Matthew Henderson, Blaise Thomson, and Jason D Williams. 2014. The second dialog state tracking challenge. In Proceedings of the 15th Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL), pages 263–272.

Chiiori Hori, Kiyomori Ohtake, Teruhisa Misu, Hideki Kashioka, and Satoshi Nakamura. 2009. Statistical dialog management applied to wfsf-based dialog systems. In IEEE International Conference on Acoustics, Speech and Signal Processing, 2009. ICASSP 2009., pages 4793–4796. IEEE.

Łukasz Kaiser, Ofer Nachum, Aurko Roy, and Samy Bengio. 2017. Learning to remember rare events.
Cheongjae Lee, Sangkeun Jung, Seokhwan Kim, and Diederik P Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. *International Conference on Learning Representations*.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, Kishore Papineni, Salim Roukos, Todd Ward, and Wei-ning. 2015. End-to-end memory networks. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1412–1421, Lisbon, Portugal. Association for Computational Linguistics.

Chia-Wei Liu, Ryan Lowe, Julian Serban, Mike Noseworthy, Laurent Charlin, and Joelle Pineau. 2016. How not to evaluate your dialogue system: An empirical study of unsupervised evaluation metrics for dialogue response generation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2122–2132, Austin, Texas. Association for Computational Linguistics.

Fei Liu and Julien Perez. 2017. Gated end-to-end memory networks. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, pages 1–10, Valencia, Spain. Association for Computational Linguistics.

Thang Luong, Hieu Pham, and Christopher D. Manning. 2015. Effective approaches to attention-based neural machine translation. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1412–1421, Lisbon, Portugal. Association for Computational Linguistics.

Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher. 2017. Pointer sentinel mixture models. *International Conference on Learning Representations*.

Alexander Miller, Adam Fisch, Jesse Dodge, Amir-Hossein Karimi, Antoine Bordes, and Jason Weston. 2016. Key-value memory networks for directly reading documents. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1400–1409, Austin, Texas. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Marc’Aurelio Ranzato, Sumit Chopra, Michael Auli, and Wojciech Zaremba. 2016. Sequence level training with recurrent neural networks. *International Conference on Learning Representations*.

Alan Ritter, Colin Cherry, and William B. Dolan. 2011. Data-driven response generation in social media. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, pages 583–593, Edinburgh, Scotland, UK. Association for Computational Linguistics.

Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. Get to the point: Summarization with pointer-generator networks. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1073–1083, Vancouver, Canada. Association for Computational Linguistics.

Minjoon Seo, Seown Min, Ali Farhadi, and Hannaneh Hajishirzi. 2017. Query-reduction networks for question answering. *International Conference on Learning Representations*.

Iulian Vlad Serban, Alessandro Sordoni, Yoshua Bengio, Aaron C Courville, and Joelle Pineau. 2016. Building end-to-end dialogue systems using generative hierarchical neural network models. In *AAAI*, pages 3776–3784.

Iulian Vlad Serban, Alessandro Sordoni, Ryan Lowe, Laurent Charlin, Joelle Pineau, Aaron C Courville, and Yoshua Bengio. 2017. A hierarchical latent variable encoder-decoder model for generating dialogues. In *AAAI*, pages 3295–3301.

Sainbayar Sukhbaatar, Jason Weston, Rob Fergus, et al. 2015. End-to-end memory networks. In *Advances in neural information processing systems*, pages 2440–2448.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, pages 6000–6010.

Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015. Pointer networks. In C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, editors, *Advances in Neural Information Processing Systems 28*, pages 2692–2700. Curran Associates, Inc.

Mingxuan Wang, Zhengdong Lu, Hang Li, and Qun Liu. 2016. Memory-enhanced decoder for neural machine translation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 278–286, Austin, Texas. Association for Computational Linguistics.
Tsung-Hsien Wen, Milica Gasic, Nikola Mrksic, Lina Maria Rojas-Barahona, Pei hao Su, Stefan Ultes, David Vandyke, and Steve J. Young. 2017. A network-based end-to-end trainable task-oriented dialogue system. In EACL.

Jason D Williams, Kavosh Asadi, and Geoffrey Zweig. 2017. Hybrid code networks: practical and efficient end-to-end dialog control with supervised and reinforcement learning. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 665–677, Vancouver, Canada. Association for Computational Linguistics.

Jason D Williams and Steve Young. 2007. Partially observable markov decision processes for spoken dialog systems. Computer Speech & Language, 21(2):393–422.

Sam Wiseman and Alexander M. Rush. 2016. Sequence-to-sequence learning as beam-search optimization. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 1296–1306, Austin, Texas. Association for Computational Linguistics.

Chien-Sheng Wu, Andrea Madotto, Genta Winata, and Pascale Fung. 2017. End-to-end recurrent entity network for entity-value independent goal-oriented dialog learning. In Dialog System Technology Challenges Workshop, DSTC6.

Chien-Sheng Wu, Andrea Madotto, Genta Winata, and Pascale Fung. 2018. End-to-end dynamic query memory network for entity-value independent task-oriented dialog. In IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).

Steve Young, Milica Gašić, Blaise Thomson, and Jason D Williams. 2013. Pomdp-based statistical spoken dialog systems: A review. Proceedings of the IEEE, 101(5):1160–1179.

Tiancheng Zhao, Allen Lu, Kyusong Lee, and Maxine Eskenazi. 2017. Generative encoder-decoder models for task-oriented spoken dialog systems with chatting capability. In Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue, pages 27–36. Association for Computational Linguistics.
8 Tables

8.1 Time per Epoch

|                      | T1  | T2  | T3  | T4  | T5  | DSTC2 | In-Car |
|----------------------|-----|-----|-----|-----|-----|-------|--------|
| Seq2Seq              | 0.7 | 1.22| 0.85| 0.15| 1.57| 9.36  | 2.00   |
| +Attn                | 1.18| 2.38| 2.2 | 0.32| 6.04| 22.07 | 6.18   |
| Ptr-Unk              | 1.28| 2.5 | 2.21| 0.38| 6.10| 20.39 | 6.48   |
| Mem2Seq H1           | 0.73| 1.10| 0.55| 0.15| 1.05| 1.49  | 0.68   |
| Mem2Seq H3           | 0.97| 1.48| 0.77| 0.21| 1.33| 2.36  | 1.02   |
| Mem2Seq H6           | 1.23| 2.14| 1.11| 0.33| 2.20| 4.22  | 1.43   |

Table 7: Minutes per-epoch. Mem2Seq is faster compared to others especially for longer inputs.

8.2 Hyper-parameters

|                      | T1  | T2  | T3  | T4  | T5  | DSTC2 | In-Car | lr     |
|----------------------|-----|-----|-----|-----|-----|-------|--------|--------|
| Seq2Seq              | 256 (0.1)| 256 (0.1)| 128 (0.1)| 256 (0.1)| 256 (0.1)| - | 512 (0.3) | 0.0001 |
| +Attn                | 256 (0.1)| 256 (0.1)| 256 (0.1)| 256 (0.1)| 128 (0.1)| - | 512 (0.0) |
| Ptr-Unk              | 256 (0.1)| 256 (0.1)| 256 (0.1)| 256 (0.1)| 128 (0.1)| - | 512 (0.0) |
| Mem2Seq GRU L1       | 256 (0.3)| 256 (0.2)| 128 (0.2)| 256 (0.2)| 256 (0.1)| 256 (0.1)| 256 (0.2) | 0.001  |
| Mem2Seq GRU L3       | 256 (0.1)| 256 (0.3)| 128 (0.2)| 256 (0.3)| 128 (0.1)| 128 (0.2)| 256 (0.1) |
| Mem2Seq GRU L6       | 256 (0.2)| 128 (0.3)| 256 (0.1)| 128 (0.3)| 256 (0.2)| 256 (0.1)| 256 (0.2) |

Table 8: Selected hyper-parameters in each datasets for different hops. The values is the embedding dimension and the GRU hidden size, and the values between parenthesis is the dropout rate. For all the models we used learning rate equal to 0.001, with a decay rate of 0.5.
9 Visualization

9.1 Multiple Hops Attention

![3-hop memory attention visualization from bAbI dialog task 3. In the generation step 8, the attention at hop 1 is shallow and divided equally over the 5 possible choice, and becomes very sharp at hop 3.]
Figure 6: 3-hop memory attention visualization from bAbI dialog task 3. The model tends to make mistake if the attention at last hop is not sharp.
9.2 Last Hop Attention

Figure 7: Last hop memory attention visualization from the bAbI dataset. COR and GEN on the top are the correct response and our generated one.
COR: the closest parking garage is civic_center_garage located 4 miles away at 270_altaire_walk
GEN: the closest parking garage is civic_center_garage at 270_altaire_walk 4 miles away through the directions

Figure 8: Last hop memory attention visualization from the In-Car dataset. COR and GEN on the top are the correct response and our generated one.
Table 9: Example of generated responses for the In-Car Assistant on the weather domain.

| location       | monday                      | tuesday                      | wednesday                   |
|----------------|-----------------------------|------------------------------|-----------------------------|
| grand rapids   | hot, low of 50F, high of 70F | raining, low of 60F, high of 80F | rain, low of 20F, high of 50F |
| new york       | misty, low of 30F, high of 50F | snow, low of 70F, high of 80F | cloudy, low of 20F, high of 50F |
| boston         | hail, low of 90F, high of 100F | overcast, low of 60F, high of 70F | rain, low of 50F, high of 80F |
| durham         | hot, low of 90F, high of 100F | dry, low of 60F, high of 80F | misty, low of 60F, high of 80F |
| san francisco  | rain, low of 60F, high of 70F | cloudy, low of 30F, high of 60F | overcast, low of 90F, high of 100F |
| carson         | raining, low of 70F, high of 80F | humid, low of 90F, high of 100F | frost, low of 40F, high of 60F |
| san jose       | blizzard, low of 40F, high of 50F | snow, low of 90F, high of 100F | overcast, low of 60F, high of 80F |

DRIVER: Is it gonna snow in Durham during the week?

- **Seq2seq**: there is no snow in the forecast for this week
- **+Att**: there is no snow in the forecast for durham for durham
- **Ptr-Unk**: yes there is no snow in durham on week
- **Mem2Seq**: no snow, the forecast does not predict any snow on Durham
- **GOLD**: Durham does not have any snow predicted this week

Table 10: Example of generated answers for the In-Car dataset on the Weather Domain.

| monday                      | tuesday                      | friday                      | wednesday                   |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| windy, low of 40F, high of 50F | snow, low of 40F, high of 50F | frost, low of 30F, high of 40F | hail, low of 70F, high of 80F |
| rain, low of 30F, high of 40F | foggy, low of 60F, high of 70F | stormy, low of 50F, high of 60F | snow, low of 80F, high of 90F |
| cloudy, low of 20F, high of 40F | clear skies, low of 70F, high of 90F | cloudy, low of 60F, high of 80F | dry, low of 40F, high of 60F |
| warm, low of 90F, high of 100F | cloudy, low of 50F, high of 60F | clear skies, low of 90F, high of 100F | foggy, low of 30F, high of 50F |
| snow, low of 60F, high of 80F | clear skies, low of 30F, high of 50F | clear skies, low of 30F, high of 40F | dry, low of 30F, high of 50F |
| windy, low of 50F, high of 60F | drizzle, low of 40F, high of 100F | rainy, low of 80F, high of 100F | clear skies, low of 50F, high of 70F |
| clear skies, low of 60F, high of 70F | rain, low of 90F, high of 100F | foggy, low of 20F, high of 40F | hail, low of 20F, high of 30F |
| rainy, low of 80F, high of 90F | foggy, low of 40F, high of 50F | sunny, low of 40F, high of 50F | snow, low of 40F, high of 50F |
| drizzle, low of 50F, high of 60F | clear skies, low of 90F, high of 100F | manhatten | dry, low of 70F, high of 90F |
| cloudy, low of 40F, high of 40F | rain, low of 90F, high of 100F | manhattan | dry, low of 40F, high of 40F |
| overcast, low of 80F, high of 90F | blizzard, low of 20F, high of 40F | oakland | cloudy, low of 20F, high of 40F |
| raining, low of 50F, high of 60F | windy, low of 30F, high of 50F | exeter | overcast, low of 60F, high of 70F |
| dry, low of 20F, high of 30F | cloudy, low of 20F, high of 50F | mendo park | foggy, low of 50F, high of 50F |

DRIVER: Is it going to snow today?
- **CAR**: What city do you wanna know if it will snow today?

DRIVER: Please check for Oakland
- **GOLD**: Today is gonna be warm in Oakland

- **Seq2seq**: It is not snow in today in
- **+att**: No there will be snow in Oakland today
- **Ptr-Unk**: Today is gonna be PAD in
- **Mem2Seq**: it will not snow in oakland today
Table 11: Example of generated responses for the In-Car Assistant on the navigation domain.

| poi                     | distance | traffic_info | poi_type         | address               |
|-------------------------|----------|--------------|------------------|-----------------------|
| Stanford Express Care   | 3 miles  | no traffic   | hospital         | 214 El Camino Real    |
| home                    | 4 miles  | heavy traffic| home             | 5671 barringer street |
| Whole Foods             | 2 miles  | heavy traffic| grocery store    | 819 Alma St           |
| P.F. Changs             | 6 miles  | moderate traffic| chinese restaurant | 669 El Camino Real |
| Jing Jing               | 5 miles  | heavy traffic| chinese restaurant| 113 Arbol Dr         |
| Pizza My Heart          | 6 miles  | moderate traffic| pizza restaurant | 528 Anton Ct         |
| Cafe Venetia            | 4 miles  | no traffic   | coffee or tea place | 269 Alger Dr        |

**DRIVER** Find me a tea house

**Seq2seq** We’re 2 miles away from Cafe Venetia and there is a road block nearby

**+att** We’re 4 miles away from Cafe Venetia and it’s at 269 Alger drive

**PTRUNK** We’re 6 miles away from whole foods and you like the address on screen

**Mem2Seg** We’re 4 miles away from Cafe Venetia and there is no traffic

**GOLD** There is Cafe Venetia that’s 4 miles away at 269 Alger dr

Table 12: Example of generated responses for the In-Car Assistant on the navigation domain.

| distance | traffic_info   | poi_type    | address                  | poi                              |
|----------|----------------|-------------|--------------------------|----------------------------------|
| 4 miles  | heavy traffic  | rest stop   | 578 Arbol Dr             | Hotel Keen                       |
| 1 miles  | moderate traffic| hospital    | 899 Ames Ct              | Stanford Childrens Health        |
| 2 miles  | no traffic     | grocery store| 452 Arcadia Pl           | Safeway                          |
| 1 miles  | moderate traffic| coffee or tea place | 436 Alger Dr     | Palo Alto Cafe                   |
| 1 miles  | heavy traffic  | grocery store| 819 Alma St              | Whole Foods                      |
| 6 miles  | moderate traffic| coffee or tea place | 394 Van Ness Ave | Coupa                            |
| 6 miles  | heavy traffic  | coffee or tea place | 145 Amherst St         | Teavana                          |

**DRIVER** Take me to a place where i can get some hot tea

**Seq2seq** There is a way

**+att** There is a Pizza Chicago and Teavana

**PTRUNK** I have a PAD away away

**Mem2Seg** We’re 6 miles away from Palo Alto Cafe and 6 miles away from Coupa, which one do you prefer?

**GOLD** Coupa is nearby and serves tea
Table 13: Example of generated responses for the In-Car Assistant on the navigation domain.

| distance | traffic_info     | poi_type             | address             | poi          |
|----------|------------------|----------------------|---------------------|--------------|
| 3 miles  | no traffic       | chinese restaurant   | 593 Arrowhead Way   | Chef Chu’s   |
| 1 miles  | no traffic       | chinese restaurant   | 669 El Camino Real  | P.F. Changs  |
| 5 miles  | road block nearby| gas station          | 200 Alester Ave     | Valero       |
| 3 miles  | no traffic       | pizza restaurant     | 528 Anton Ct        | Pizza My Heart|
| 4 miles  | heavy traffic    | rest stop            | 753 University Ave  | Comfort Inn  |
| 5 miles  | heavy traffic    | chinese restaurant   | 842 Arrowhead Way   | Panda Express|
| 2 miles  | heavy traffic    | pizza restaurant     | 704 El Camino Real  | Pizza Hut    |
| 6 miles  | no traffic       | friends house         | 864 Almanor Ln      | jacks house  |

 DRIVER Find me the nearest gas station.

 Seq2seq the nearest parking garage is from at away
 +att The is one is away away
 PTRUNK PAD nearest gas station is is is
 Mem2Seq The nearest gas station is gas station which is you you
 GOLD The nearest gas station is located 5 miles away. Need more info?

Table 14: Example of generated responses for the In-Car Assistant on the navigation domain.

| Poi                      | Distance | Traffic_info     | Poi_type             | Address             |
|--------------------------|----------|------------------|----------------------|---------------------|
| The Westin               | 4 miles  | no traffic       | rest stop            | 329 El Camino Real  |
| Palo Alto Garage R       | 2 miles  | moderate traffic | parking garage       | 481 Amaranta Ave    |
| Mandarin Roots           | 4 miles  | moderate traffic | chinese restaurant   | 271 Springer Street |
| Sigona Farmers Market    | 4 miles  | no traffic       | grocery store        | 638 Amherst St      |
| Whole Foods              | 2 miles  | heavy traffic    | grocery store        | 819 Alma St        |
| Stanford Shopping Center | 2 miles  | moderate traffic | shopping center      | 773 Alger Dr        |
| toms house               | 1 miles  | no traffic       | friends house         | 580 Van Ness Ave    |

 DRIVER Give me directions to the closest grocery store

 CAR There are Whole Foods 2 miles away and Sigona Farmers Market 4 miles away. Where do we go?

 DRIVER I need the one that avoids all heavy traffic

 Seq2seq he is is is away at
 +Att Chef Chu’s is located at 593 Arrowhead way
 PTR-Unk PAD is the is PAD the to
 Mem2Seq Sigona Farmers Market is the only option i is 4 miles away with no traffic, setting navigation now
 GOLD Sigona Farmers Market is located 4 miles away with no traffic. It’s located at 638 Amherst St.
Table 15: Example of generated responses for the In-Car Assistant on the scheduling domain.

| DRIVER | Set me a reminder for football activity at 1pm this month on the 11th with marie |
|--------|-------------------------------------------------------------------|
| Seq2seq | Okay I am scheduling a reminder with your for at on with at |
| PTRUNK | Okay I am scheduling a football activity with on the 15th at 1pm this month on the 15th |
| Mem2Seq | Setting a reminder for football activity with marie on the 11th at 1pm |
| GOLD  | Reminder for football on the 11th of this month at 1pm with marie is set |

Table 16: Example of generated responses for the In-Car Assistant on the scheduling domain.

| room               | agenda             | time | date    | party          | event       |
|--------------------|--------------------|------|---------|----------------|-------------|
| conference room 50 | discuss the merger | 1pm  | Wednesday | infrastructure team | conference  |
| -                  | -                  | 2pm  | Wednesday | -              | yoga activity |
| conference room 50 | go over budget     | 7pm  | Monday   | infrastructure team | meeting     |
| -                  | -                  | 5pm  | Monday   | -              | dinner      |
| conference room 50 |                    | 10am | Thursday | -              | medicine    |

| DRIVER | Tell me when is my next meeting and who are invited in the meeting and what are the agenda of the next meeting |
|--------|-------------------------------------------------------------------|
| Seq2seq + att | The meeting is the meeting in conference room 100 at 1pm |
| PTRUNK | your PAD meeting PAD the in the to the the the the |
| Mem2Seq | Your next meeting is on Monday at 7pm | hr is to hr in attendance to go over the budget |
| GOLD  | Your next meeting is on Monday at 7 pm with the infrastructure team to go over budget |