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End-to-End Memory Networks: A Survey

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Abstract. Constructing a dialog system which can speak naturally with a human is considered as a major challenge of artificial intelligence. End-to-end dialog system is taken to be a primary research topic in the area of conversational systems. Since an end-to-end dialog system is structured based on learning a dialog policy from transactional dialogs in a defined extent, therefore, useful datasets are required for evaluating the learning procedures.

In this paper, different deep learning techniques are applied to the Dialog bAbI datasets [1]. On this dataset, the performance of the proposed techniques is analyzed. The performance results demonstrate that all the proposed techniques attain decent precisions on the Dialog bAbI datasets. The best performance is obtained utilizing end-to-end memory network with a unified weight tying scheme (UN2N).

Keywords: memory networks, deep learning, Dialog bAbI dataset

1 Introduction

Instructing machines that can converse like a human for real-world objectives is possibly one of the crucial challenges in artificial intelligence. In order to construct a meaningful conversation with human, the dialog system is required to be qualified in the perception of natural language, constructing intelligent decisions as well as producing proper replies [2–4]. Dialog systems, recognized as interactive conversational agents, communicate with the human through natural language in order to aid, supply information and amuse. They are utilized in an extensive applications domain from technical support services to language learning tools [5, 6].

Artificial intelligence techniques are viewed as the most efficient techniques in recent decades [7–18]. For example, Fuzzy logic systems are broadly utilized to model the systems characterizing vague and unreliable information [19–38]. In artificial intelligence area [39, 40], end-to-end dialog systems have been attained interest because of the current progress of deep neural networks. In [41] a gated

end-to-end trainable memory network is proposed which is learning in an end-to-end procedure without the utilization of any extra supervision signal. In [1] the original task is broken down into short tasks where they should be individually learned by the agent, and also built in order to perform the original task. In [42] a long short term memory (LSTM) model is suggested which learns in order to interact with APIs on behalf of the user. In [43] a dynamic memory network is introduced which contains tasks for part-of-speech classification as well as question answering, also uses two gated recurrent units in order to carry out inference. In [44] the memory network has been implemented which needed supervision in every layer of the network. In [45] a set of four tasks in order to test the capability of end-to-end dialog systems has been introduced which focuses on the domain of movies entities. In [46] a word-based method to dialog state tracking utilizing recurrent neural networks (RNNs) is proposed which needs less feature engineering. Even though neural network models include a tiny learning pipeline, they need a remarkable content of the training. Gated recurrent network (GRU) and LSTM units permit RNNs to deal with the longer texts needed for question answering. Additional advancements to be mentioned as attention mechanisms, as well as memory networks, permit the network to center around the most related facts.

In this paper, the applications of different types of memory networks are studied on data from the Dialog bAbI. The performance results demonstrate that all the proposed techniques attain decent precisions on the Dialog bAbI datasets. The best performance is obtained utilizing UN2N. The remaining of the article is organized as follows. In Section 2, different types of memory networks are demonstrated and explained in details. Experimental results are given in Section 3. Section 4 concludes the work.

2 Memory Networks

2.1 End-to-End Memory Network with Single Hop

The end-to-end Memory Network (N2N) with single hop has two stories embedding \tilde{A} , \tilde{C} , as well as a question embedding \tilde{B} , see Figure 1. Matrices dot product are utilized in order to match each word in the story with each word in the question which will cause the creation of the attention. By passing the attention through a softmax layer they will change into the probability distribution across the whole word from the story. Afterward, these probabilities are implemented to the story embedding \tilde{C} and the sum of that with the question embedding \tilde{B} passes through a dense layer and the softmax prediction layer.

2.2 End-to-End Memory Network with Stacked Hops

The N2N architecture contains two major components: supporting memories and final answer prediction [47]. Supporting memories consist of a set of input and output memory represented by memory cells. In complicated tasks with

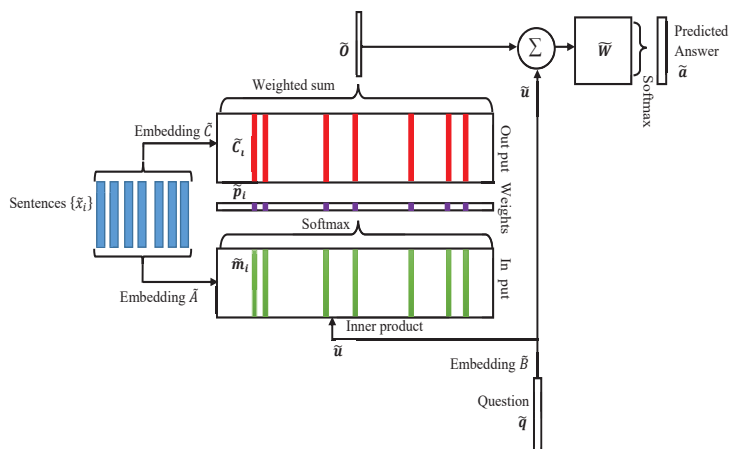


Fig. 1. End-to-end memory network with single hop

the requirement of multiple supporting memories, the model can be developed in order to contain more than one set of input-output memories by stacking a number of memory layers. Each memory layer in the model is called hop, also the input of the $(\kappa + 1)^{th}$ hop is the output of the κ^{th} hop:

$$\tilde{u}^{\kappa+1} = \tilde{\delta}^{\kappa} + \tilde{u}^{\kappa} \quad (1)$$

Each layer contains its own embedding matrices $\tilde{A}^{\kappa}, \tilde{C}^{\kappa}$, utilized in order to embed the inputs \tilde{x}_i .

The prediction of the answer to the question \tilde{q} , is carried out by

$$\tilde{a} = \text{softmax}(\tilde{W}(\tilde{\delta}^{\kappa} + \tilde{u}^{\kappa})) \quad (2)$$

where \tilde{a} is taken to be the predicted answer distribution, \tilde{W} (of size $V \times d$) is considered to be a parameter matrix for the model in order to learn, also κ is the total number of hops.

The N2N architecture with three hop operations is shown in Figure 2. The hard max operations within each layer are substituted with a continuous weighting from the softmax.

The method takes a discrete set of inputs $\tilde{x}_1, \dots, \tilde{x}_n$ which are stored in the memory, a question \tilde{q} , also outputs a reply \tilde{a} . The model can write all \tilde{x} to the memory up to a fixed buffer size, also it obtains a continuous demonstration for \tilde{x} and \tilde{q} . Afterward, the continuous demonstration is processed with multiple hops in order to generate \tilde{a} . This permits backpropagation of the error signal through multiple memory accesses back to the input while training.

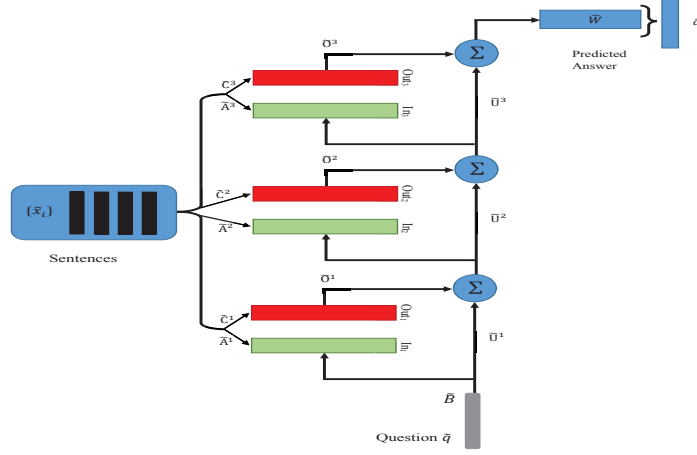


Fig. 2. A three layer end-to-end memory network

2.3 Gated End-to-End Memory Network

The gated end-to-end memory network (GN2N) is able to dynamically conditioning the memory reading operation on the controller state \tilde{u}^κ at every hop, see Figure 3. In GN2N, (1) is reformulated as below [48],

$$T^\kappa(\tilde{u}^\kappa) = \sigma(\tilde{W}_T^\kappa \tilde{u}^\kappa + \tilde{b}_T^\kappa) \quad (3)$$

$$\tilde{u}^{\kappa+1} = \tilde{\delta}^\kappa \odot T^\kappa(\tilde{u}^\kappa) + \tilde{u}^\kappa \odot (1 - T^\kappa(\tilde{u}^\kappa)) \quad (4)$$

where \tilde{W}_T^κ and \tilde{b}^κ are taken to be the hop-specific parameter matrix and bias term for the κ^{th} hop respectively. $T^\kappa(\tilde{x})$ is the transform gate for the κ^{th} hop. \odot is the Hadamard product.

2.4 End-to-End Memory Networks with Unified Weight Tying

In [47], two kinds of weight tying are proposed for N2N, namely adjacent and layer-wise. Layer-wise approach portions the input and output embedding matrices across various hops (*i.e.*, $\tilde{A}^1 = \tilde{A}^2 = \dots = \tilde{A}^\kappa$ and $\tilde{C}^1 = \tilde{C}^2 = \dots = \tilde{C}^\kappa$). Adjacent approach portions the output embedding for a given layer with the corresponding input embedding (*i.e.*, $\tilde{A}^{\kappa+1} = \tilde{C}^\kappa$). Furthermore, the matrix \tilde{W} which predicts the answer, as well as the question embedding matrix \tilde{B} , are developed as $\tilde{W}^T = \tilde{C}^\kappa$ and $\tilde{B} = \tilde{A}^1$. In [48], a dynamic mechanism is designed which permits the model to choose the proper kind of weight tying on the basis of the input. Therefore, the embedding matrices are developed dynamically for every instance which makes UN2N more efficient compared with N2N and GN2N where the same embedding matrices are implemented for each input. In UN2N

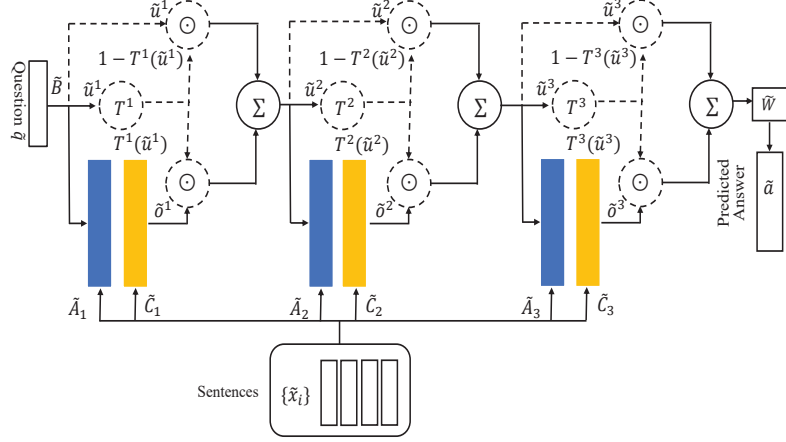


Fig. 3. Gated end-to-end memory network

a gating vector \tilde{z} , described in (8), is used in order to develop the embedding matrices, \tilde{A}^κ , \tilde{C}^κ , \tilde{B} , and \tilde{W} . The embedding matrices are influenced by the information transported by \tilde{z} related to the input question \tilde{u}^0 and the context sentences in the story \tilde{m}_t . Therefore,

$$\tilde{A}^{\kappa+1} = \tilde{A}^\kappa \odot \tilde{z} + \tilde{C}^\kappa \odot (1 - \tilde{z}) \quad (5)$$

$$\tilde{C}^{\kappa+1} = \tilde{C}^\kappa \odot \tilde{z} + \tilde{C}^{\kappa+1} \odot (1 - \tilde{z}) \quad (6)$$

where \odot is taken to be the column element-wise multiplication operation, also $\tilde{C}^{\kappa+1}$ is the unconstrained embedding matrix. In (5) and (6), the large value of \tilde{z} leads UN2N towards the layer-wise approach and the small value of \tilde{z} leads UN2N towards the adjacent approach.

In UN2N, at first, the story is encoded by reading the memory one step at a time with a gated recurrent unit (GRU) as below,

$$\tilde{h}_{t+1} = GRU(\tilde{m}_t, \tilde{h}_t) \quad (7)$$

such that t is considered to be the recurrent time step, also \tilde{m}_t is taken to be the context sentence in the story at time t . Afterward, the following relation is defined,

$$\tilde{z} = \sigma(\tilde{W}_{\tilde{z}} \begin{bmatrix} \tilde{u}^0 \\ \tilde{h}_T \end{bmatrix} + \tilde{b}_{\tilde{z}}) \quad (8)$$

where \tilde{h}_T is the last hidden state of the GRU which presents the story, $\tilde{W}_{\tilde{z}}$ is considered as a weight matrix, $\tilde{b}_{\tilde{z}}$ is bias, σ is taken to be the sigmoid function

also, $\begin{bmatrix} \tilde{u}^0 \\ \tilde{h}_T \end{bmatrix}$ is the concatenation of \tilde{u}^0 and \tilde{h}_T . A linear mapping $G \in R^{d \times d}$ is added for updating the connection between memory hops as below,

$$\tilde{u}^{\kappa+1} = \tilde{o}^\kappa + (G \odot (1 - \tilde{z}))\tilde{u}^\kappa \quad (9)$$

3 Experiments and Results

3.1 Experiment Setup

In this section, an extensive range of parameter settings along with data set configurations are utilized in order to validate the proposed techniques in this paper.

3.2 Task explanations

The tasks in the dataset are divided into 5 groups where each group focus on a special objective.

Task 1: Issuing API calls The chatbot asks questions in order to fill the missing areas, and finally produces a valid corresponding API call. The questions asked by the bot is for collecting information in order to make the prediction possible.

Task 2: Updating API calls In this part users update their requests. The chatbot asks from users if they have finished their updates, then chatbot generates updated API call.

Task 3: Demonstrating options The chatbot provides options to users utilizing the corresponding API call.

Task 4: Generating additional information User can ask for the phone number and address and the bot should use the knowledge bases facts correctly in order to reply.

Task 5: Organizing entire dialogs Tasks 1-4 are combined in order to generate entire dialogs.

For evaluating the capability of the techniques in order to deal with out-of-vocabulary (OOV) items a set of test data is used which contains entities different from the training set. Task 6 is the Dialog state tracking 2 task (DSTC-2) [49] with real dialogs, and only has one setup.

3.3 Experimental Results

Efficiency results on Dialog bAbI tasks are demonstrated in Table 1, with seven techniques which are among the most important techniques, namely rule-based systems, TF-IDF, nearest neighbor, supervised embedding, N2N, GN2N, and UN2N. As is shown in Table 1, the rule-based system has a high performance on tasks 1-5. However, its performance reduces when dealing with DSTC-2 task. TF-IDF match has poor performance compared with other methods on both the

Table 1. The accuracy results of rule-based systems, TF-IDF, nearest neighbor, supervised embedding, N2N, GN2N, and UN2N methods

Task	Rule-based Systems	TF-IDF Match		Nearest Neighbor	-match				match			
		no type	type		S-Emb	N2N	GN2N	UN2N	S-Emb	N2N	GN2N	UN2N
1. Issuing API calls	100.0	5.6	22.4	55.1	100.0	99.9	100.0	100.0	83.2	100.0	100.0	100.0
2. Updating API calls	100.0	3.4	16.4	68.3	68.4	100.0	100.0	100.0	68.4	98.3	100.0	100.0
3. Displaying options	100.0	8.0	8.0	58.8	64.9	74.9	74.9	74.9	64.9	74.9	74.9	74.9
4. Generating additional information	100.0	9.5	17.8	28.6	57.2	59.5	57.2	57.2	57.2	100.0	100.0	100.0
5. Organizing entire dialogs	100.0	4.6	8.1	57.1	75.4	96.1	96.3	99.2	76.2	93.4	98.0	99.4
Average	100.0	6.2	14.5	53.6	73.2	86.1	85.7	86.3	70.0	93.3	94.6	99.4
1. (OOV) Issuing API calls	100.0	5.8	22.4	44.1	60.0	72.3	82.4	83.0	67.2	96.5	100.0	100.0
2. (OOV) Updating API calls	100.0	3.5	16.8	68.3	68.3	78.9	78.9	78.9	68.3	94.5	94.2	94.5
3. (OOV) Displaying options	100.0	8.3	8.3	58.8	65.0	74.4	75.3	75.2	65.0	75.2	75.1	75.3
4. (OOV) Generating additional information	100.0	8.8	17.2	28.6	57.0	57.6	57.0	57.0	57.1	100.0	100.0	100.0
5. (OOV) Organizing entire dialogs	100.0	4.6	9.0	48.4	58.2	65.5	66.7	67.8	64.4	77.7	79.4	79.5
Average	100.0	6.4	14.7	49.6	61.7	69.7	72.1	72.4	64.4	88.8	89.7	89.8
6. Dialog state tracking 2	33.3	1.6	1.6	21.9	22.6	41.1	47.4	42.4	22.1	41.0	48.7	42.9

simulated tasks 1-5 and on the real data of task 6. The performance of the TF-IDF match with match type features considerably increases but is still behind the nearest neighbor technique. Supervised embedding has higher performance compared with TF-IDF match and nearest neighbor technique. In task 1, supervised embedding is fully successful but its performance reduces in task 2-5, even with match type features. GN2N and UN2N models outperform the other methods in DSTC-2 task and Dialog bAbI tasks respectively.

4 Conclusion

End-to-end learning scheme is suitable for constructing the dialog system because of its simplicity in training as well as effectiveness in model updating. In this paper, the applications of various memory networks are studied on data from the Dialog bAbI. The performance results demonstrate that all the proposed techniques attain decent precisions on the Dialog bAbI datasets. The best performance is obtained utilizing UN2N. In order to evaluate the true performance of the proposed methods, extra experimentations are required utilizing wide non-synthetic data set.

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