END-TO-END DYNAMIC QUERY MEMORY NETWORK FOR ENTITY-VALUE INDEPENDENT TASK-ORIENTED DIALOG

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Introduction

- **Task-oriented dialog systems** require machines to understand the human intent and generate proper responses for an assigned task via natural language.
- Traditionally, these dialog systems have been built as a pipeline, with modules for language understanding, state tracking, action selection, and language generation. However, modeling the dependencies between modules is complex and expensive.
- Recently, end-to-end approaches using recurrent neural networks [1, 2, 3] are attractive solutions. In particular, **end-to-end memory networks** (MemNNs), which are recurrent attention models over a possibly large external memory [4], can achieve promising results.

Dialog Example

Usr:	Hi
Sys:	Hello what can i help you with today?
Usr:	Chinese cuisine in a moderate price range for four
Sys:	I'm on it
Usr:	<Silence >
Sys:	Where should it be?
Usr:	Paris please
Sys:	Ok let me look into some options for you
Usr:	<Silence >
Sys:	api_call Chinese Paris four moderate
Usr:	Instead could it be in Taiwan?
Sys:	Sure is there anything else to update?
Usr:	No
Sys:	Ok let me look into some options for you
Usr:	<Silence >
Sys:	api_call Chinese Taiwan four moderate
KB1:	DimSum, rating ..., address ..., phone ..., ...
KB2:	DinTaiFung, rating ..., address ..., phone ..., ...
...	...
KBN:	SiChuan, rating ..., address ..., phone ..., ...
Usr:	<Silence >
Sys:	What do you think of this option: DinTaiFung?
Usr:	Let's do it
Sys:	Great let me do the reservation
Usr:	Can you provide the address?
Sys:	Here it is 101_Taipei_Street
Usr:	Thank you
Sys:	You are welcome

Contribution

In this paper, we propose an end-to-end **Dynamic Query Memory Network (DQMemNN)** for task-oriented dialog systems with a **Recorded Delexicalization (RDL)** mechanism.

1. DQMemNN is designed to address one major drawback of MemNN: be insensitive to represent temporal dependencies between memories, which may influence the conversational semantics.
2. RDL is performed to reduce the learning complexity and to alleviate the out-of-vocabulary (OOV) entity problems.
3. Our framework achieves a promising average per-response accuracy of 99.7% and per-dialog accuracy of 97.8% on bAbI Dialog dataset.

Recorded Delexicalization

The intuition of RDL is to replace entities in the raw dialog history with a simplified ordered templates. Moreover, the number of system utterances can be reduced to a smaller size of action template candidates.

[Cui-1]	chinese	[Pri-1]	moderate
[Num-1]	four	[Loc-1]	Paris
[Loc-2]	Taiwan	[Res-1]	DimSum
[Addr-1]	100_hk_St	[Res-2]	DinTaiFung
[Addr-2]	101_Taipei_St	...	...

References

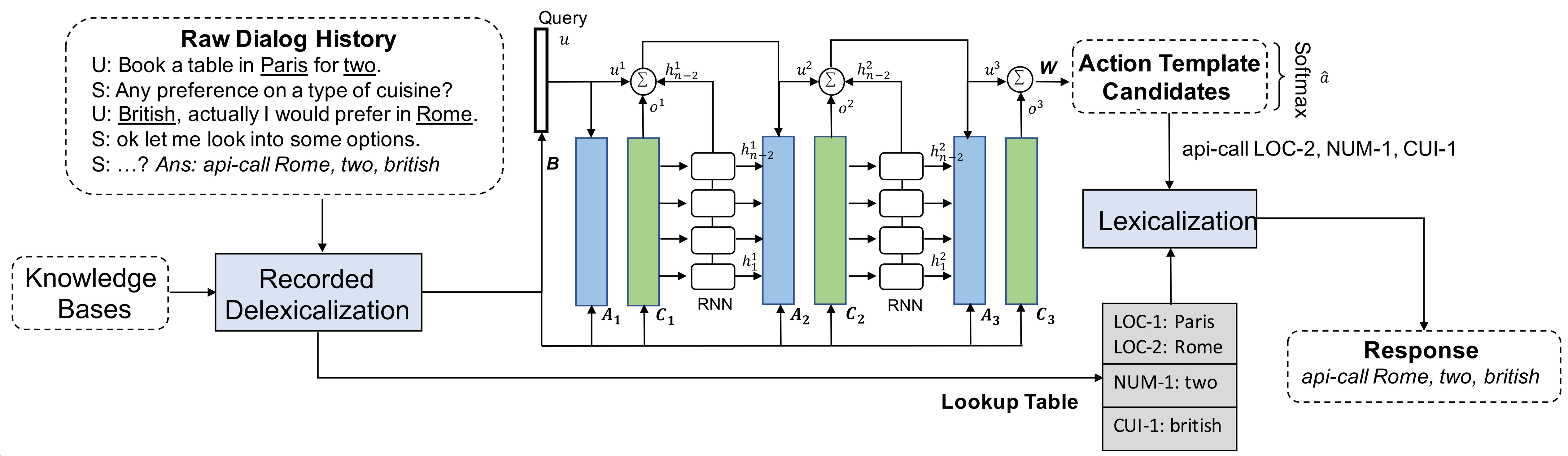
[1] Seo et al. Query-reduction networks for question answering. *ICLR*, 2017.

[2] Antoine Bordes and Jason Weston. Learning end-to-end goal-oriented dialog. *ICLR*, 2017.

[3] Williams et al. Hybrid code networks: practical and efficient end-to-end dialog control with supervised and reinforcement learning. In *ACL*, 2017.

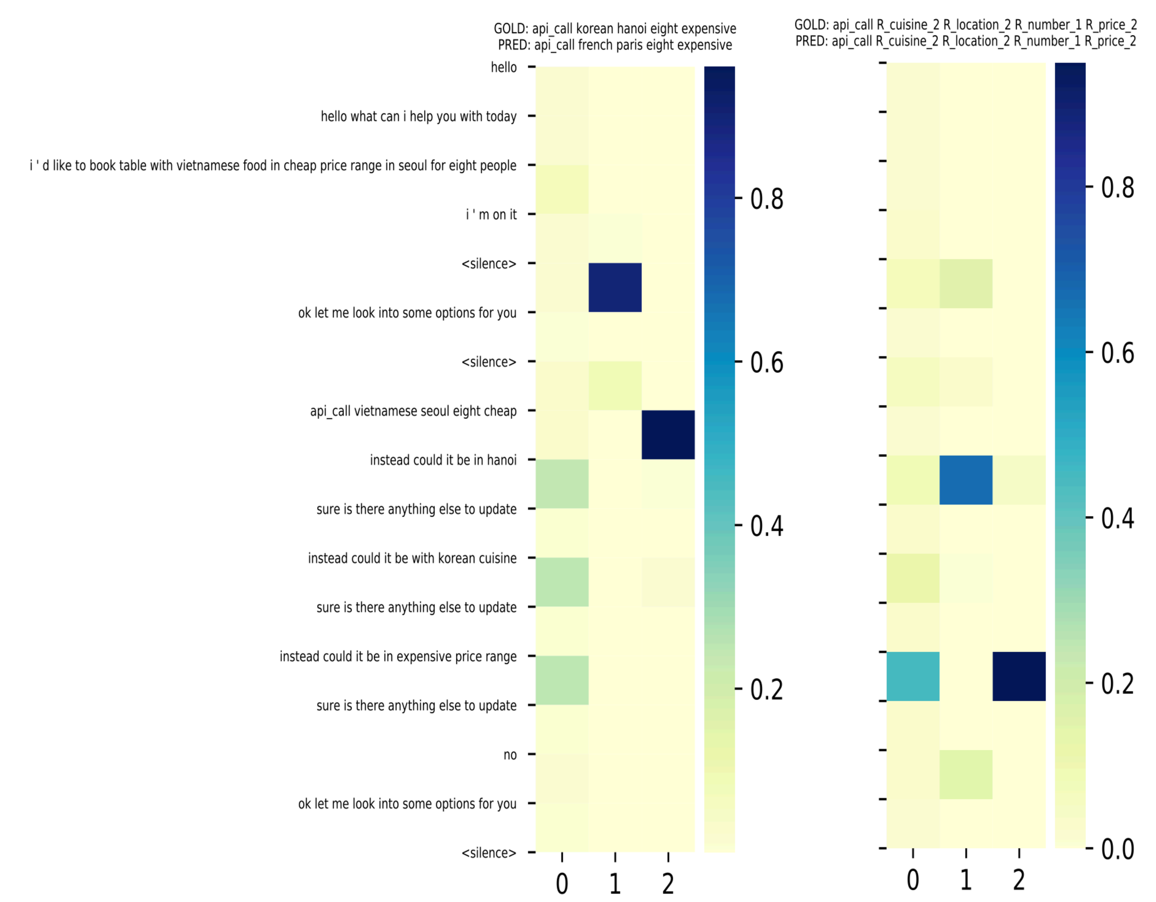
[4] Sukhbaatar et al. End-to-end memory networks. In *NIPS*, 2015.

Framework Description



Results and Visualization

- The bAbI dialog dataset [2] is used to evaluate the performance of our model.
- Task 1-5 are issuing API call, refining API call, recommending options, providing additional information, and full-dialog, respectively.
- One test set follows the same distribution as the training set, and another has OOV words from a different knowledge base.
- All experiments used a 3-hop model with the adjacent weight sharing scheme. During training, all embedding matrices are jointly learned by minimizing a standard cross-entropy loss.



Task	QRN*[1]	MemNN[2]	GMemNN	HCN[3]	DQMemNN	DQMemNN+RDL
T1	99.4 (-)	99.9 (99.6)	100 (100)	-	100 (100)	100 (100)
T2	99.5 (-)	100 (100)	100 (100)	-	100 (100)	100 (100)
T3	74.8 (-)	74.9 (2.0)	74.9 (3.0)	-	74.9 (2.0)	98.7 (90.8)
T4	57.2 (-)	59.5 (3.0)	57.2 (0)	-	57.2 (0)	100 (100)
T5	99.6 (-)	96.1 (49.4)	96.3 (52.5)	-	99.2 (88.7)	99.9 (98.3)
Test Avg.	86.1 (-)	86.1 (50.8)	85.7 (50.5)	-	86.3 (58.1)	**99.7** (**97.8**)
T1-OOV	83.1 (-)	72.3 (0)	82.4 (0)	-	82.5 (0)	100 (100)
T2-OOV	78.9 (-)	78.9 (0)	78.9 (0)	-	78.9 (0)	100 (100)
T3-OOV	75.2 (-)	74.4 (0)	75.3 (0)	-	74.9 (0)	98.7 (90.4)
T4-OOV	56.9 (-)	57.6 (0)	57.0 (0)	-	57.0 (0)	100 (100)
T5-OOV	67.8 (-)	65.5 (0)	66.7 (0)	100 (100)	72.0 (0)	99.4(91.6)
Test-OOV Avg.	72.4 (-)	69.7 (0)	72.1 (0)	-	71.8 (0)	**99.6**(**96.4**)