Task-Oriented Dialogue

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2019-03-15

Preliminary (Task)

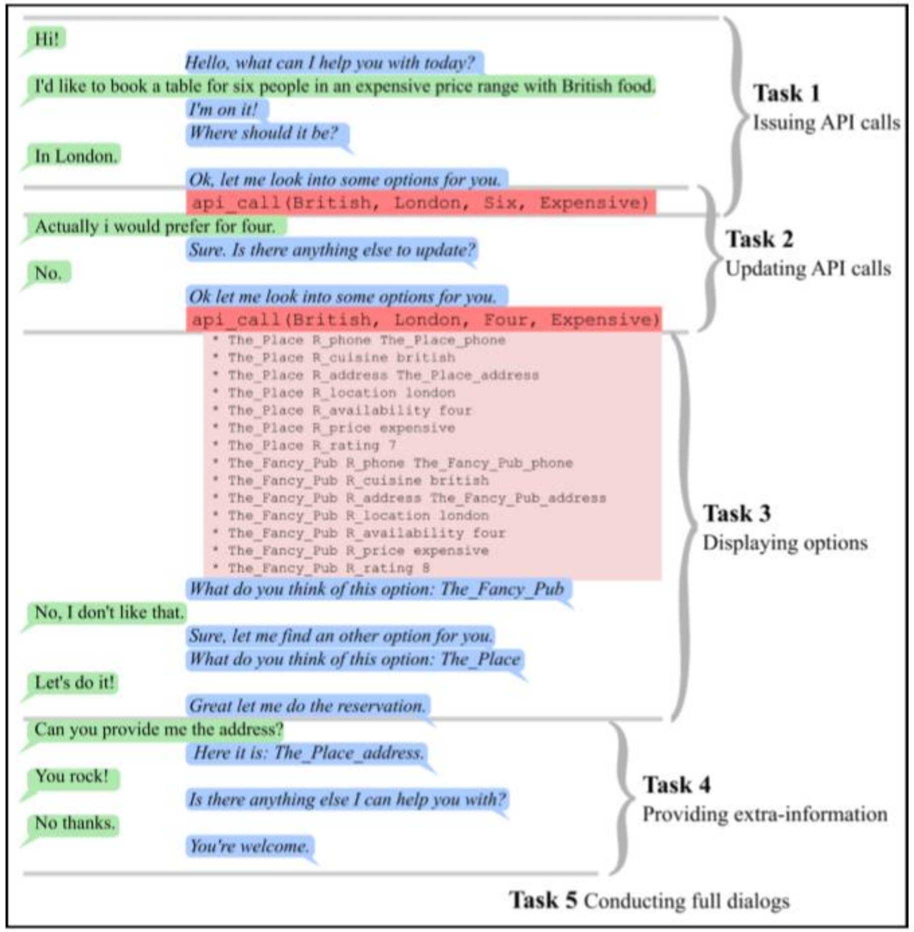

Figure 1: **Goal-oriented dialog tasks.** A user (in green) chats with a bot (in blue) to book a table at a restaurant. Models must predict bot utterances and API calls (in dark red). Task 1 tests the capacity of interpreting a request and asking the right questions to issue an API call. Task 2 checks the ability to modify an API call. Task 3 and 4 test the capacity of using outputs from an API call (in light red) to propose options (sorted by rating) and to provide extra-information. Task 5 combines everything.

Preliminary (Traditional Pipeline)

- Traditional Pipeline for Task-oriented Systems:
  - Natural Language Understanding (or a user intent classifier)
  - Dialogue State Tracking
    (or a belief tracker)
  - Dialogue Policy Learning
  - Response Generator

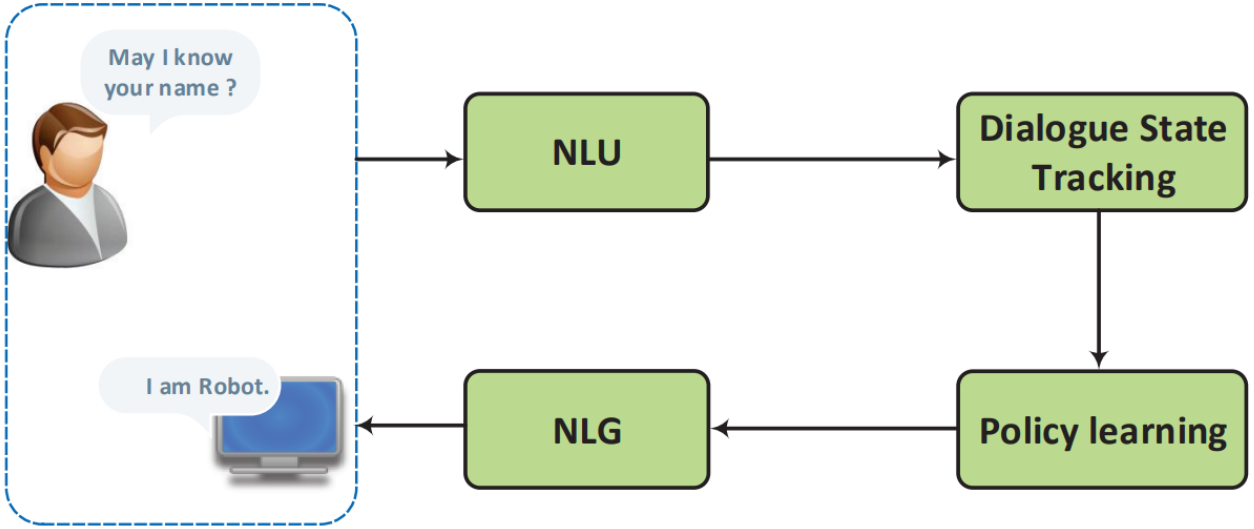

Figure 1: Traditional Pipeline for Task-oriented Systems.

Preliminary (Recent Work on DST)

- Model the task as the multiclass classification problem:
  - Neural Belief Tracker: Data-Driven Dialogue State Tracking (ACL-17)
  - A Network-based End-to-End Trainable Task-oriented Dialogue System (EACL-17)
- Multi-Task Learning for rare slots:
  - Global-Locally Self-Attentive Dialogue State Tracker (ACL-18)
  - An End-to-end Approach for Handling Unknown Slot Values in Dialogue State Tracking (ACL-18)
- ……

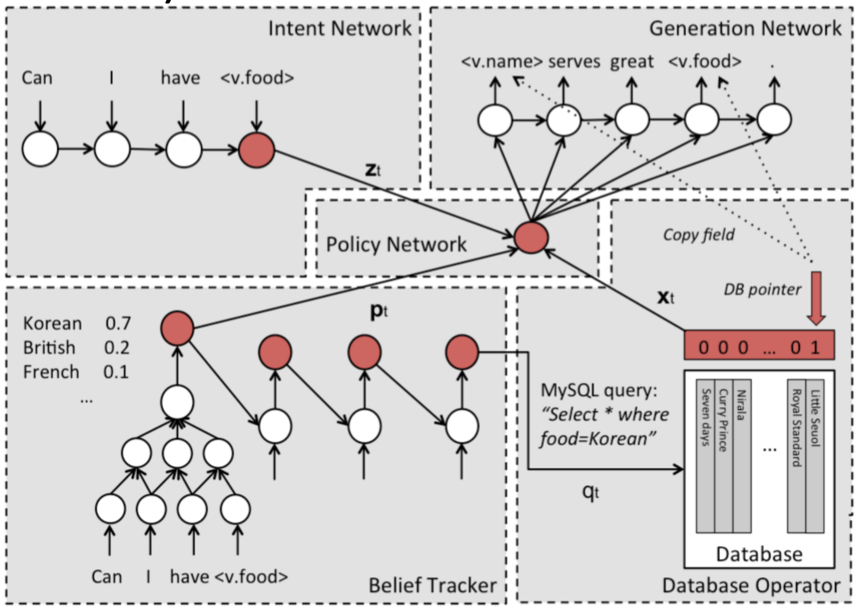

Figure 1: The proposed end-to-end trainable dialogue system framework

Preliminary (Recent Work on Dialogue Policy)

- Most are based on Reinforcement Learning (RL):
  - Deep Dyna-Q (ACL-18)
  - BBQ-Networks (AAAI-18)
  - Switch-based Active Deep Dyna-Q (AAAI-19)
  - ……

Preliminary (Towards End-to-end)

- Advantages:
  - The dialogue states are latent without hand-crafted labels
  - Eliminate the needs to model the dependencies between modules
  - Scale up between domains
  - ……

- Main approaches:
  - Retrieval/Classification problem
  - Generative model

Preliminary (Retrieval-based model)

bAbI

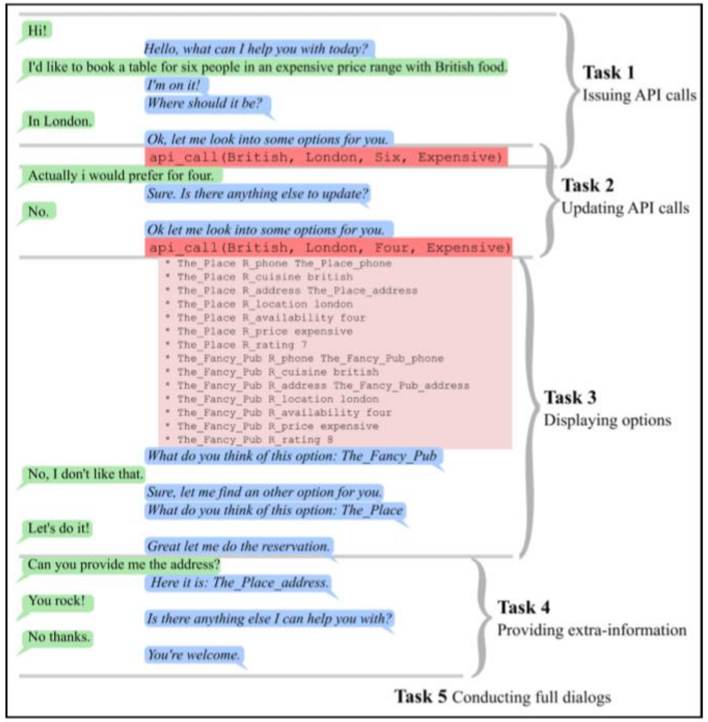

Figure 1: **Goal-oriented dialog tasks.** A user (in green) chats with a bot (in blue) to book a table at a restaurant. Models must predict bot utterances and API calls (in dark red). Task 1 tests the capacity of interpreting a request and asking the right questions to issue an API call. Task 2 checks the ability to modify an API call. Task 3 and 4 test the capacity of using outputs from an API call (in light red) to propose options (sorted by rating) and to provide extra-information. Task 5 combines everything.

	Tasks	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**Concierge**
DIALOGS *Average statistics*	Number of utterances:	12	17	43	15	55	54	8
	- user utterances	5	7	7	4	13	6	4
	- bot utterances	7	10	10	4	18	8	4
	- outputs from API calls	0	0	23	7	24	40	0
DATASETS *Tasks 1-5 share the same data source*	Vocabulary size			3,747			1,229	8,629
	Candidate set size			4,212			2,406	11,482
	Training dialogs			1,000			1,618	3,249
	Validation dialogs			1,000			500	403
	Test dialogs			1,000$^{(*)}$			1,117	402

LEARNING END-TO-END GOAL-ORIENTED DIALOG

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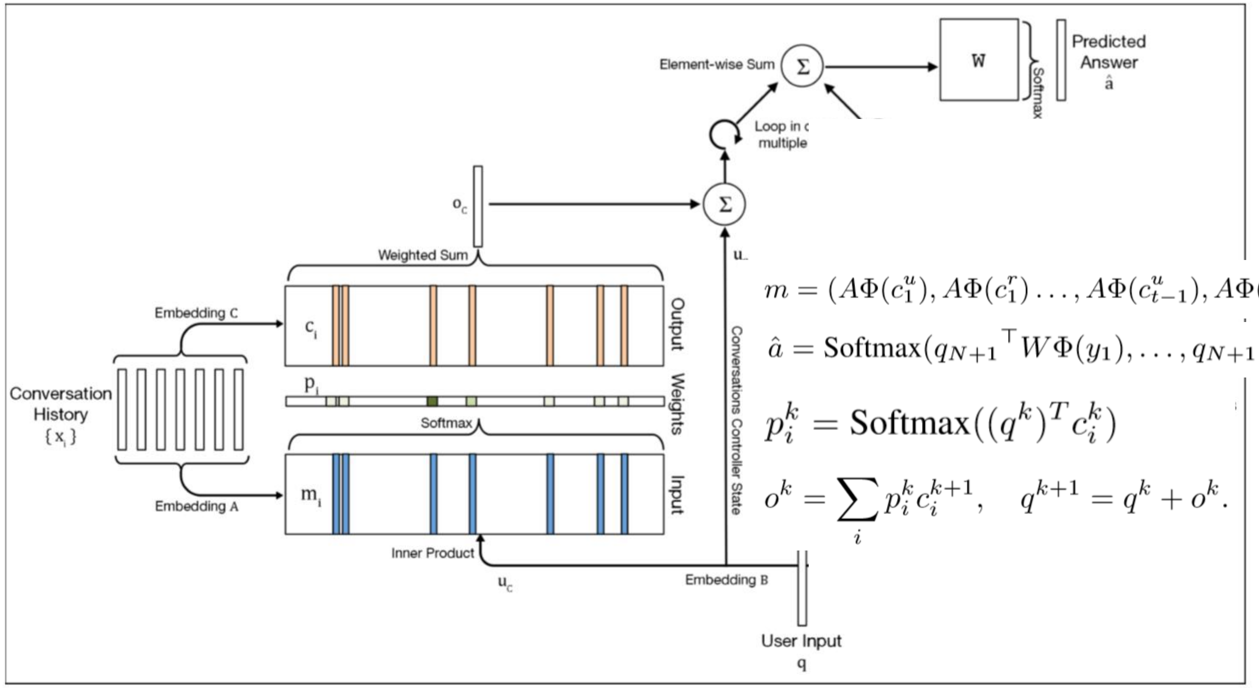
ICLR-17



$$m = (A\Phi(c_1^u), A\Phi(c_1^r) \dots, A\Phi(c_{t-1}^u), A\Phi(c_{t-1}^r))$$

$$\hat{a} = \text{Softmax}({q_{N+1}}^\top W\Phi(y_1), \dots, {q_{N+1}}^\top W\Phi(y_C))$$

$$p_i^k = \text{Softmax}((q^k)^T c_i^k)$$

$$o^k = \sum_i p_i^k c_i^{k+1}, \quad q^{k+1} = q^k + o^k.$$

Figure 2: ***Split memory*** **architecture for Memory Networks.** Profile attributes and conversation history are modeled in two separate memories. The outputs from both memories are summed to get the final response.

Preliminary (Retrieval-based model)

Permuted-bAbI dataset

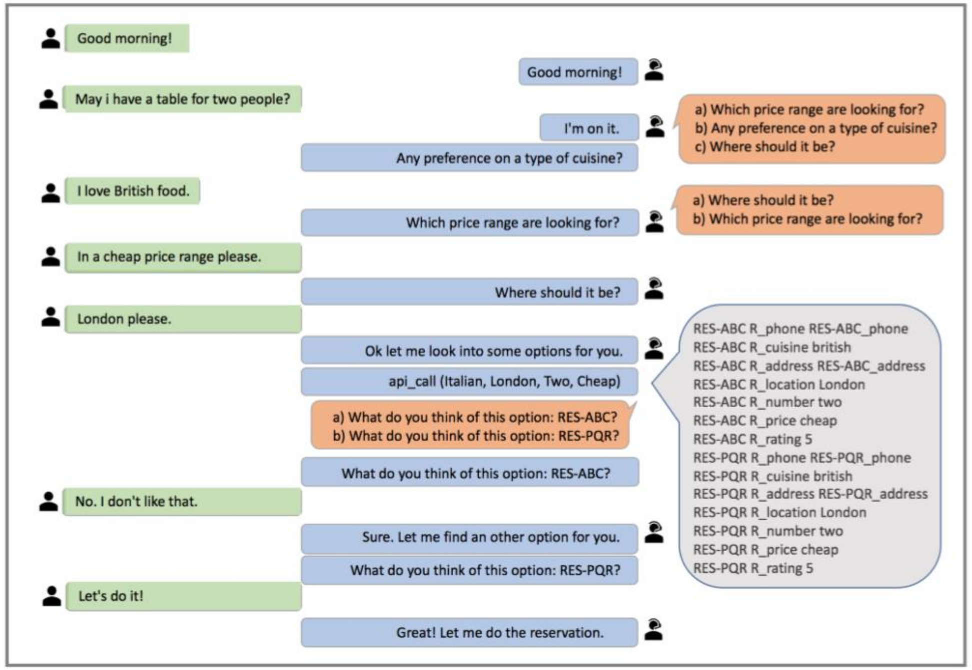


Figure 2: **Permuted-bAbI dialog tasks.** A user (in green) chats with a dialog system (in blue) to book a table at a restaurant. At a given point in the dialog, the dialog system has multiple correct next utterances (in orange). The dialog system can choose either of the multiple correct utterances as the next utterance. The list of restaurants are returned from the API_call (in grey) also contain multiple restaurants with the same rating, giving the dialog system more options to propose to the user.

There are around 11,000 dialogs in each set.

Learning End-to-End Goal-Oriented Dialog with Multiple Answers

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EMNLP-18

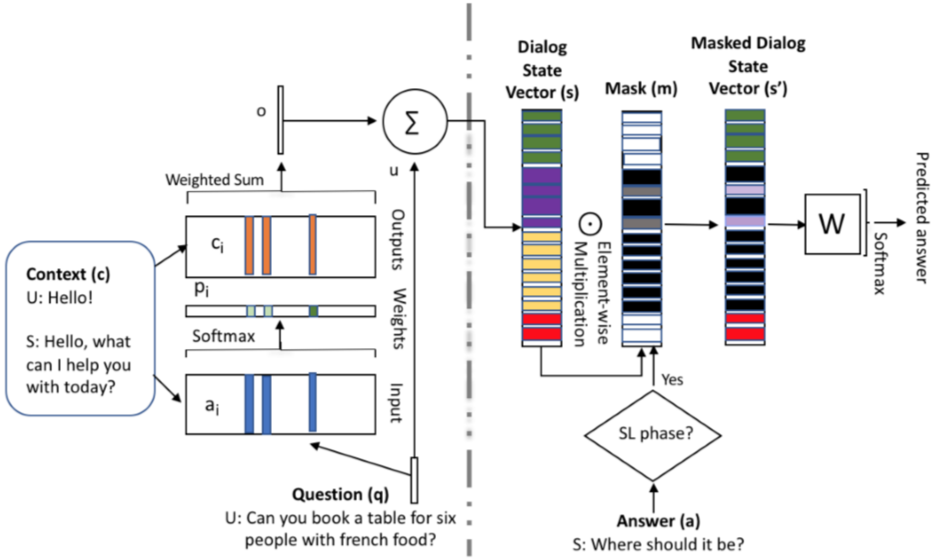

Figure 1: **Mask-memN2N** - *Left*: A single layer version of memN2N. *Right*: Masking

Preliminary (Retrieval-based model)

Personalized-bAbI

Figure 1: **Personalized Restaurant Reservation System.** The user (in green or yellow) conducts a dialog with the bot (in blue) to reserve a table at a restaurant. At each turn, a model has access to the user's profile attributes, the conversation history and the outputs from the API call (in light red) and must predict the next bot utterance or API call (in dark red). The horizontal lines between dialog groups signify the separate tasks that are described in the following sections. (Illustration adapted from Figure 1, Bordes and Weston [2016].)

Task	PT1	PT2	PT3	PT4	PT5	bAbI dialog tasks (T1-T5)
Vocabulary size			14819			3747
Candidate set size			43863			4212
Training dialogs	6000 (1000)	6000 (1000)	12000 (1000)	6000 (1000)	12000 (1000)	1000 each
Validation dialogs	6000 (1000)	6000 (1000)	12000 (1000)	6000 (1000)	12000 (1000)	1000 each
Test dialogs	6000* (1000*)	6000* (1000*)	12000* (1000*)	6000* (1000*)	12000* (1000*)	1000* each

Personalization in Goal-oriented Dialog

NIPS-17

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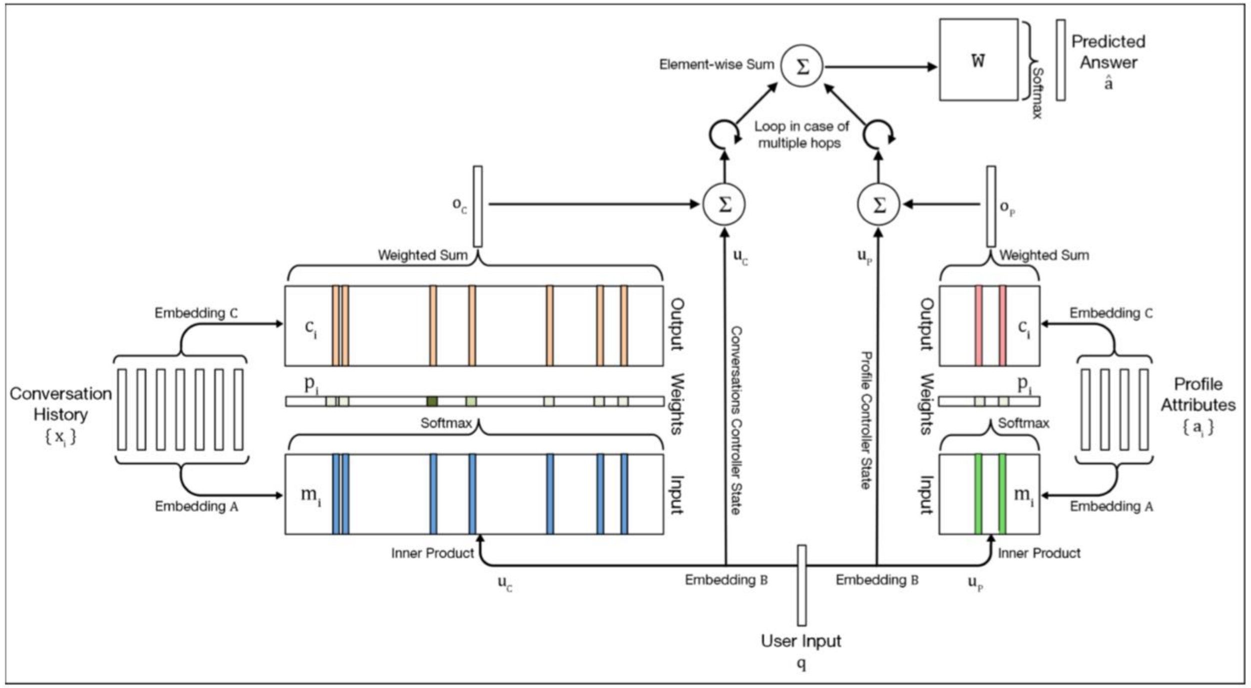

Figure 2: ***Split memory* architecture for Memory Networks.** Profile attributes and conversation history are modeled in two separate memories. The outputs from both memories are summed to get the final response.

Preliminary (Retrieval-based model)

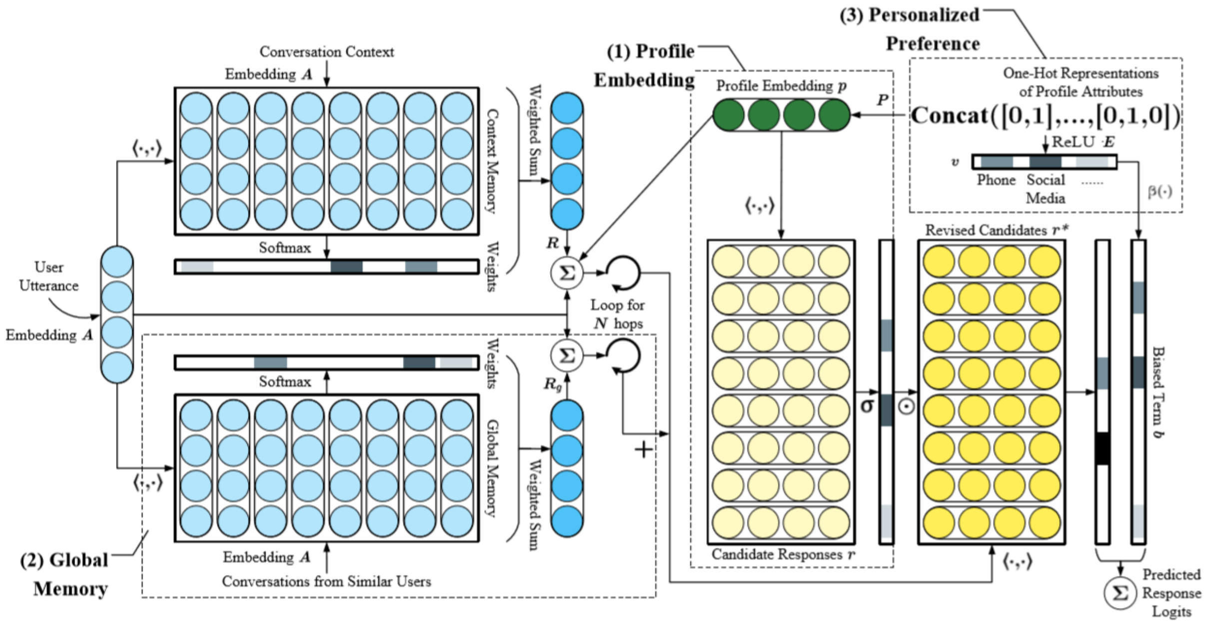

Figure 2: PERSONALIZED MEMN2N architecture. The incoming user utterance is embedded into a query vector. The model first reads the memory (at top-left) to find relevant history and produce attention weights. Then it generates an output vector by taking the weighted sum followed by a linear transformation. Part (1) is **Profile Embedding**: the profile vector $\boldsymbol{p}$ is added to the query at each iteration, and is also used to revise the candidate responses $\boldsymbol{r}$. Part (2) is **Global Memory**: this component (at bottom-left) has an identical structure as the original MEMN2N, but it contains history utterances from other similar users. Part (3) is **Personalized Preference**: the bias term is obtained based on the user preference and added to the prediction logits.

AAAI-19

Learning Personalized End-to-End Goal-Oriented Dialog

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Models	T1: Issuing API Calls	T2: Updating API Calls	T3: Displaying Options	T4: Providing Information	T5: Full Dialog
1. Supervised Embeddings	84.37	12.07	9.21	4.76	51.60
2. MemN2N	99.83 (98.87)	**99.99** (99.93)	58.94 (58.71)	57.17 (57.17)	85.10 (77.74)
3. Split MemN2N	85.66 (82.44)	93.42 (91.27)	68.60 (68.56)	57.17 (57.11)	87.28 (78.10)
4. Profile Embedding	**99.96 (99.98)**	99.96 (99.94)	71.00 (70.95)	57.18 (57.18)	93.83 (81.32)
5. Global Memory	99.76 (98.96)	99.93 (99.74)	71.01 (71.11)	57.18 (57.18)	91.70 (81.43)
6. Profile Model	99.93 (99.96)	99.94 (99.94)	71.12 (70.78)	57.18 (57.18)	93.91 (82.57)
7. Preference Model	99.80 (99.95)	99.97 (**99.97**)	68.90 (68.34)	81.38 (80.30)	94.97 (86.56)
8. Personalized MemN2N	99.91 (99.93)	99.94 (99.95)	**71.43 (71.52)**	**81.56 (80.79)**	**95.33 (88.07)**

Table 1: Evaluation results of the PRESONALIZED MEMN2N on the personalized bAbI dialog dataset. Rows 1 to 3 are baseline models. Rows 4 to 6 are the PROFILE MODEL with profile embedding, global memory and both of them, respectively. In each cell, the first number represents the per-response accuracy on the full set, and the number in parenthesis represents the accuracy on a smaller set with 1000 dialogs.

Preliminary (Generative Model)

- Vanilla Seq2seq with attention and copy mechanism
  - Relevant entities: from context
  - Doesn’t Incorporate knowledge base (KB)

A Copy-Augmented Sequence-to-Sequence Architecture Gives Good Performance on Task-Oriented Dialogue

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SIGDIAL-17

Data	Model	Per-Resp.	Per Dial.	BLEU	Ent. F_1
Test set	*MemNN*	41.1	0.0	–	–
	GMemNN	48.7	1.4	–	–
	QRN	50.7	–	–	–
	Seq2Seq (1)	46.4	1.5	55.0	69.7
	Seq2Seq (2)	43.5	1.3	54.2	67.3
	Seq2Seq (3)	44.2	**1.7**	55.4	65.9
	+ Attn.	46.0	1.4	**56.6**	67.1
	+ Copy	47.3	1.3	55.4	71.6
	+ EntType	**48.0**	1.5	56.0	**72.9**
Dev set	Seq2Seq (1)	57.0	3.6	72.1	68.7
	Seq2Seq (2)	54.1	3.0	71.3	66.3
	Seq2Seq (3)	54.0	3.2	71.5	64.3
	+ Attn.	55.2	3.4	71.9	66.1
	+ Copy	58.9	3.6	73.1	72.5
	+ EntType	59.2	3.4	72.7	72.3

Table 2: Evaluation on DSTC2 test (top) and dev (bottom) data. Bold values indicate our best performance. A dash indicates unavailable values.

Preliminary (Generative Model)

SIGDIAL-17

Key-Value Retrieval Networks for Task-Oriented Dialogue

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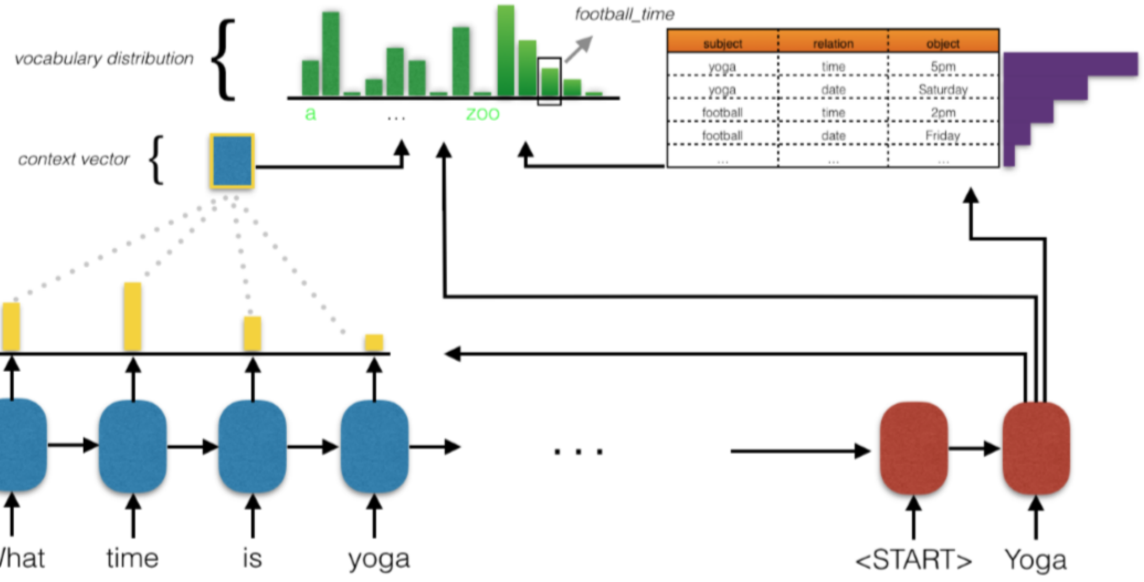

Figure 2: Key-value retrieval network. For each time-step of decoding, the cell state is used to compute an attention over the encoder states and a separate attention over the key of each entry in the KB. The attentions over the encoder are used to generate a context vector which is combined with the cell state to get a distribution over the normal vocabulary. The attentions over the keys of the KB become the logits for their associated values and are separate entries in a now augmented vocabulary that we argmax over.

Stanford Multi-domain Dialogue Datasets (In-Car Assistant)

Training Dialogues	2,425
Validation Dialogues	302
Test Dialogues	304
Calendar Scheduling Dialogues	1034
Navigation Dialogues	1000
Weather Dialogues	997
Avg. # of Utterances Per Dialogue	5.25
Avg. # of Tokens Per Utterance	9
Vocabulary Size	1,601
# of Distinct Entities	284
# of Entity (or Slot) Types	15

Table 2: Statistics of Dataset.

$$u_j^t = r^T \tanh(W_2' \tanh(W_1'[k_j, \tilde{h}_t])) \quad (7)$$

$$o_t = U[\tilde{h}_t, \tilde{h}_t'] + \tilde{v}^t \quad (8)$$

$$y_t = \mathrm{Softmax}(o_t) \quad (9)$$

Model	BLEU	Ent. F_1	Scheduling Ent. F_1	Weather Ent. F_1	Navigation Ent. F_1
Rule-Based	6.6	43.8	61.3	39.5	40.4
Copy Net	11.0	37.0	28.1	**50.1**	28.4
Attn. Seq2Seq	10.2	30.0	30.0	42.4	17.9
KV Retrieval Net (no enc. attn.)	10.8	40.9	59.5	35.6	36.6
KV Retrieval Net	**13.2**	**48.0**	**62.9**	47.0	**41.3**
Human Performance	13.5	60.7	64.3	61.6	55.2

Table 3: Evaluation on our test data. Bold values indicate best model performance. We provide both an aggregated F_1 score as well as domain-specific F_1 scores. Attn. Seq2Seq refers to a sequence-to-sequence model with encoder attention. KV Retrieval Net (no enc. attn.) refers to our new model with no encoder attention context vector computed during decoding.

ACL-18

Sequicity: Simplifying Task-oriented Dialogue Systems with Single Sequence-to-Sequence Architectures

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Sequicity (ACL-18)

- Sequicity: handle both task completion and response generation in a single seq2seq model.

$$B_t = \mathbf{seq2seq}(B_{t-1}R_{t-1}U_t|0,0)$$
$$R_t = \mathbf{seq2seq}(B_{t-1}R_{t-1}U_t|B_t,\mathbf{k}_t)$$

- Belief Tracking:
  - Two type slots: informative or requestable
  - Copy on X ([B, R]) or generate from vocab
- Response Generation:
  - Copy on B
  - From $U_1R_1 \ldots U_tR_t$ to $B_{t-1}R_{t-1}U_t$:
    - $O(T^2)$ to $O(T)$.
- Training:
  - Standard cross entropy
  - Policy gradient:

$$\frac{1}{m-m'}\sum_{j=m'+1}^{m} r^{(j)}\frac{\partial log\pi_\Theta(y_j)}{\partial\Theta} \quad (11)$$

where $r^{(j)} = r^{(j)} + \lambda r^{(j+1)} + \lambda^2 r^{(j+2)} + \ldots + \lambda^{m-j+1} r^{(m)}$. To encourage our generated re-

Turn	Dialogue
$User_1$	Can I have some Italian food please?
$Machine_1$	<Inf> Italian </Inf><Req> </Req> What price range are you looking for?
$User_2$	I want cheap ones.
$Machine_2$	<Inf> Italian ; cheap </Inf> <Req></Req> NAME_SLOT is a cheap restaurant serving western food
$User_3$	Tell me the address and the phone number please .
$Machine_3$	<Inf> Italian ; cheap </Inf> <Req>address ; phone</Req> The address is ADDRESS_SLOT and the phone number is PHONE_SLOT

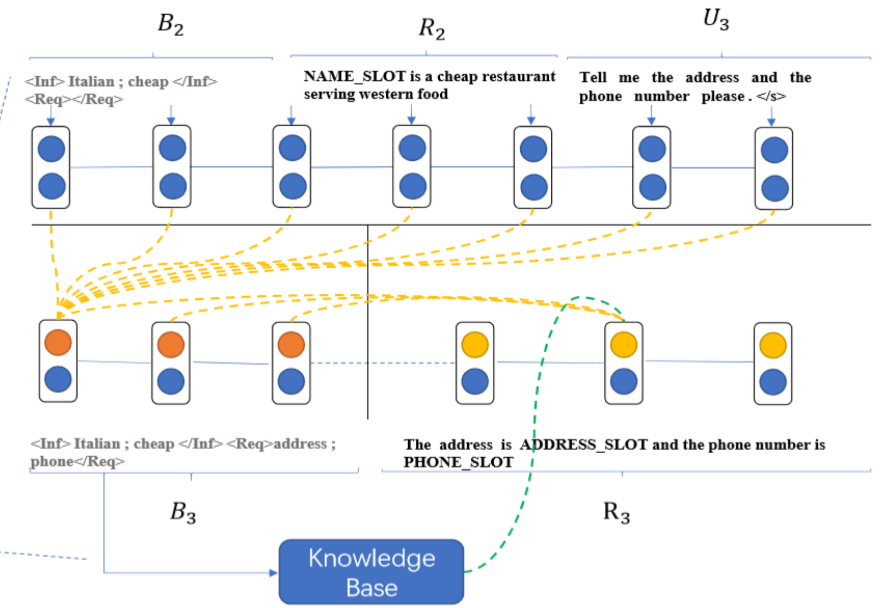

Figure 1: Sequicity overview. The left shows a sample dialogue; the right illustrates the Sequicity. B_t is employed only by the model, and not visible to users. During training, we substitute slot values with placeholders bearing the slot names for machine response. During testing, this is inverted: the placeholders are replaced by actual slot values, according to the item selected from the knowledge base.

(Reward is 1 once requested slot is decoded; otherwise -0.1)

Sequicity (ACL-18)

	CamRes676					KVRET				
	Mat.	BLEU	Succ. F_1	$Time_{full}$	$Time_{N.B.}$	Mat.	BLEU	Succ. F_1	$Time_{full}$	$Time_{N.B.}$
(1) NDM	0.904	0.212	0.832	91.9 min	8.6 min	0.724	0.186	0.741	285.5 min	29.3 min
(2) NDM + Att + SS	0.904	0.240	0.836	93.7 min	10.4 min	0.724	0.188	0.745	289.7 min	33.5 min
(3) LIDM	0.912	0.246	0.840	97.7 min	14.4 min	0.721	0.173	0.762	312.8 min	56.6 min
(4) KVRN	N/A	0.134	N/A	21.4 min	–	0.459	0.184	0.540	46.9 min	–
(5) TSCP	**0.927**	**0.253**	**0.854**	7.3 min	–	**0.845**	**0.219**	**0.811**	25.5 min	–
(6) Att-RNN	0.851	0.248	0.774	7.2 min	–	0.805	0.208	0.801	23.0 min	–
(7) TSCP$\backslash k_t$	**0.927**	0.232	0.835	7.2 min	–	**0.845**	0.168	0.759	25.3 min	–
(8) TSCP\RL	**0.927**	0.234	0.834	**4.1** min	–	**0.845**	0.191	0.774	**17.5** min	–
(9) TSCP$\backslash B_t$	0.888	0.197	0.809	22.9 min	–	0.628	0.182	0.755	42.7 min	–

Table 2: Model performance on CamRes676 and KVRET. This table is split into two parts: competitors on the upper side and our ablation study on the bottom side. **Mat.** and **Succ. F1** are for match rate and success F1 respectively. $\mathbf{Time_{full}}$ column reports training time till converge. For NDM, NDM+Att+SS and LIDM, we also calculate the training time for the rest parts except for the belief tracker ($\mathbf{Time_{N.B.}}$).

ACL-18

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

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Mem2Seq (ACL-18)

- Mem2seq: to incorporate knowledge bases.
- Encoder: a standard MemNN
  - Memory representation: sum of triplet word embeddings.
  - Read: $p_i^k = \text{Softmax}((q^k)^T c_i^k)$

$$o^k = \sum_i p_i^k c_i^{k+1}, \quad q^{k+1} = q^k + o^k.$$

- Decoder: RNN and MemNN
  - Copy mechanism:
    - Vocab: $P_{vocab}(\hat{y}_t) = \text{Softmax}(W_1[h_t; o^1])$
    - Copy: $P_{ptr} = p_t^K$
- Training: Two standard cross-entropy (vocab & copy) copy
  - Label for memory copy:

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

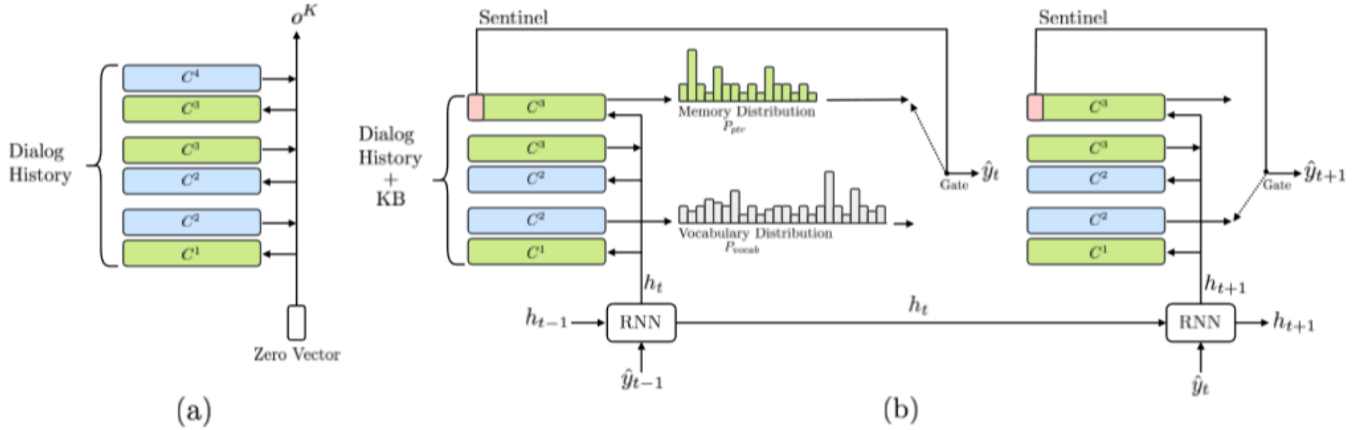

Figure 1: The proposed Mem2Seq architecture for task-oriented dialog systems. (a) Memory encoder with 3 hops; (b) Memory decoder over 2 step generation.

Mem2Seq (ACL-18)

Task	QRN	MemNN	GMemNN	Seq2Seq	Seq2Seq+Attn	Ptr-Unk	**Mem2Seq H1**	**Mem2Seq H3**	**Mem2Seq H6**
T1	99.4 (-)	99.9 (99.6)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)
T2	99.5 (-)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)
T3	74.8 (-)	74.9 (2.0)	74.9 (0)	74.8 (0)	74.8 (0)	85.1 (19.0)	87.0 (25.2)	94.5 (59.6)	**94.7 (62.1)**
T4	57.2 (-)	59.5 (3.0)	57.2 (0)	57.2 (0)	57.2 (0)	100 (100)	97.6 (91.7)	100 (100)	**100 (100)**
T5	**99.6** (-)	96.1 (49.4)	96.3 (52.5)	98.8 (81.5)	98.4 (87.3)	99.4 (91.5)	96.1 (45.3)	98.2 (72.9)	97.9 (69.6)
T1-OOV	83.1 (-)	72.3 (0)	82.4 (0)	79.9 (0)	81.7 (0)	92.5 (54.7)	93.4 (60.4)	91.3 (52.0)	**94.0 (62.2)**
T2-OOV	78.9 (-)	78.9 (0)	78.9 (0)	78.9 (0)	78.9 (0)	83.2 (0)	81.7 (1.2)	84.7 (7.3)	**86.5 (12.4)**
T3-OOV	75.2 (-)	74.4 (0)	75.3 (0)	74.3 (0)	75.3 (0)	82.9 (13.4)	86.6 (26.2)	**93.2 (53.3)**	90.3 (38.7)
T4-OOV	56.9 (-)	57.6 (0)	57.0 (0)	57.0 (0)	57.0 (0)	100 (100)	97.3 (90.6)	100 (100)	**100 (100)**
T5-OOV	67.8 (-)	65.5 (0)	66.7 (0)	67.4 (0)	65.7 (0)	73.6 (0)	67.6 (0)	78.1 (0.4)	**84.5 (2.3)**

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.

	Ent. F1	**BLEU**	**Per-Resp.**	**Per-Dial.**
Rule-Based	-	-	33.3	-
QRN	-	-	43.8	-
MemNN	-	-	41.1	0.0
GMemNN	-	-	**47.4**	1.4
Seq2Seq	69.7	55.0	46.4	**1.5**
+Attn	67.1	**56.6**	46.0	1.4
+Copy	71.6	55.4	47.3	1.3
Mem2Seq H1	72.9	53.7	41.7	0.0
Mem2Seq H3	**75.3**	55.3	45.0	0.5
Mem2Seq H6	72.8	53.6	42.8	0.7

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

	BLEU	**Ent. F1**	**Sch. F1**	**Wea. F1**	**Nav. F1**
*Human**	13.5	60.7	64.3	61.6	55.2
*Rule-Based**	6.6	43.8	61.3	39.5	40.4
*KV Retrieval Net**	13.2	48.0	62.9	47.0	41.3
Seq2Seq	8.4	10.3	09.7	14.1	07.0
+Attn	9.3	19.9	23.4	25.6	10.8
Ptr-Unk	8.3	22.7	26.9	26.7	14.9
Mem2Seq H1	11.6	32.4	39.8	**33.6**	**24.6**
Mem2Seq H3	**12.6**	**33.4**	**49.3**	32.8	20.0
Mem2Seq H6	9.9	23.6	34.3	33.0	4.4

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.

ICLR-19

GLOBAL-TO-LOCAL MEMORY POINTER NETWORKS FOR TASK-ORIENTED DIALOGUE

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GLMP (ICLR-19)

- Aim to incorporate knowledge bases into a learning framework.
- Formulation:
  - Input: Dialogue history X = $(x_1, \dots, x_n)$, and KB information B = $(b_1, \dots, b_l)$
  - Output: Expected response Y = $(y_1, \dots, y_m)$.
- Method:
  - Global memory encoder
    - encode dialogue history and write into external knowledge
    - Read external knowledge and generate global memory pointer
  - Local memory decoder
    - First generate sketch responses by a sketch RNN
    - Use global pointer as a filter and sketch response as a query to obtain the final response

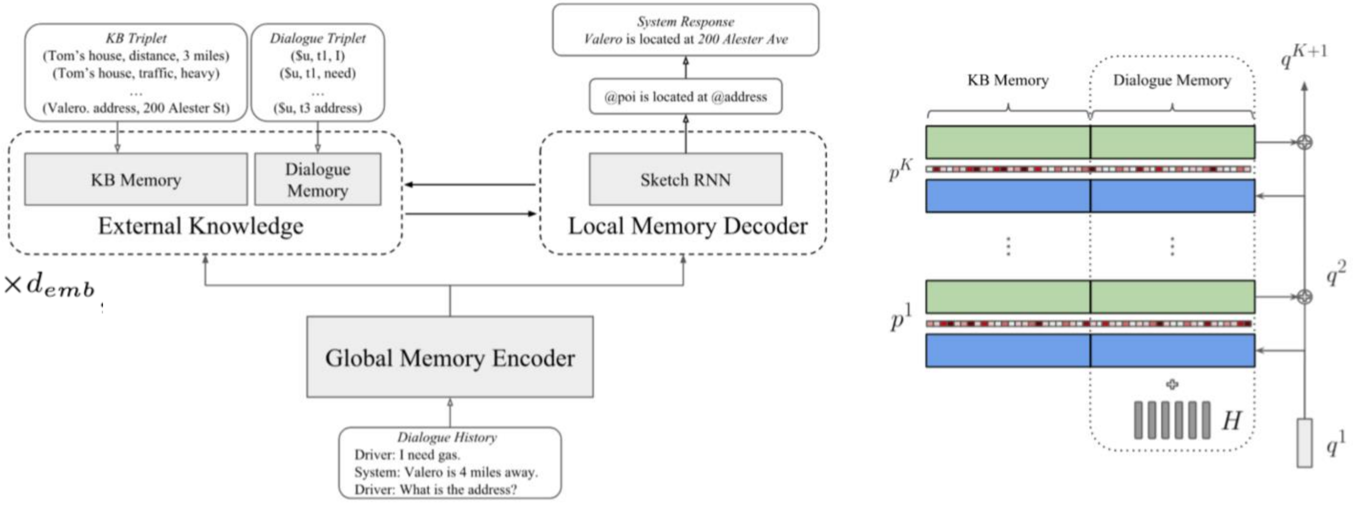
GLMP (ICLR-19)

- Contextual representation:
  - In triplet format
    - KB: (Subject, Relation, Object)
    - Context: {($user, turn1, I), ($user, turn1, need), ($user, turn1, gas)}
  - Stored with MemNN:
    - Embedding:

$$C = (C^1, \dots, C^{K+1}), \text{ where } C^k \in \mathbb{R}^{|V| \times d_{emb}}$$

    - Read: $p_i^k = \text{Softmax}((q^k)^T c_i^k)$

$$o^k = \sum_i p_i^k c_i^{k+1}, \quad q^{k+1} = q^k + o^k.$$



(a) Block diagram

(b) External knowledge

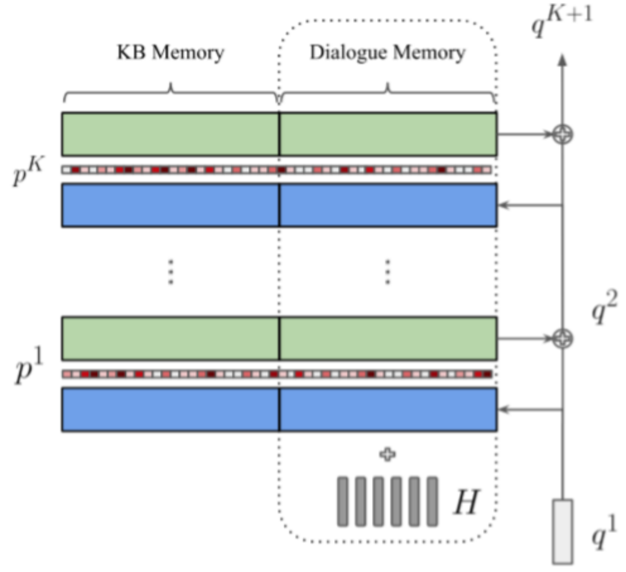
Figure 1: The proposed (a) global-to-local memory pointer networks for task-oriented dialogue systems and the (b) external knowledge architecture.

GLMP (ICLR-19)

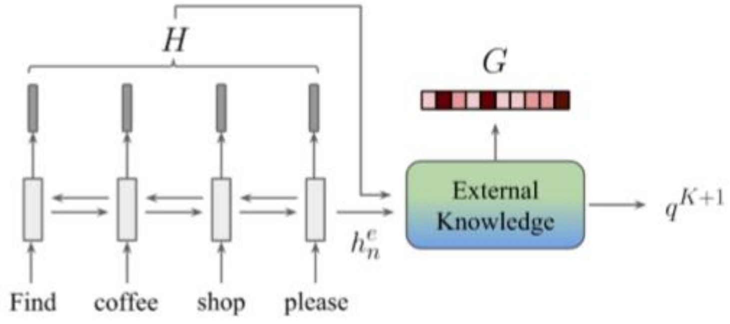
- Global Memory Encoder:
  - Context RNN to encode the history, obtaining hidden states $H = (h_1^e, \dots, h_1^e)$,
    - Last hidden state as the query
    - Update the memory with hidden states: $c_i^k = c_i^k + h_{m_i}^e$
  - Global Memory Pointer:
    - Multi-label classification task (use Sigmoid instead of Softmax!)
    - An auxiliary loss for supervision

$$g_i = \text{Sigmoid}((q^K)^T c_i^K), \quad g_i^l = \begin{cases} 1 & \text{if } Object(m_i) \in Y \\ 0 & \text{otherwise} \end{cases},$$

$$Loss_g = -\sum_{i=1}^{n+l} [g_i^l \times \log g_i + (1 - g_i^l) \times \log(1 - g_i)].$$



(b) External knowledge



(a) Global memory encoder

GLMP (ICLR-19)

- Local Memory Decoder:
  - Sketch RNN
    - A sketch response that excludes slot values but includes tags.
    - Trained with cross-entropy loss

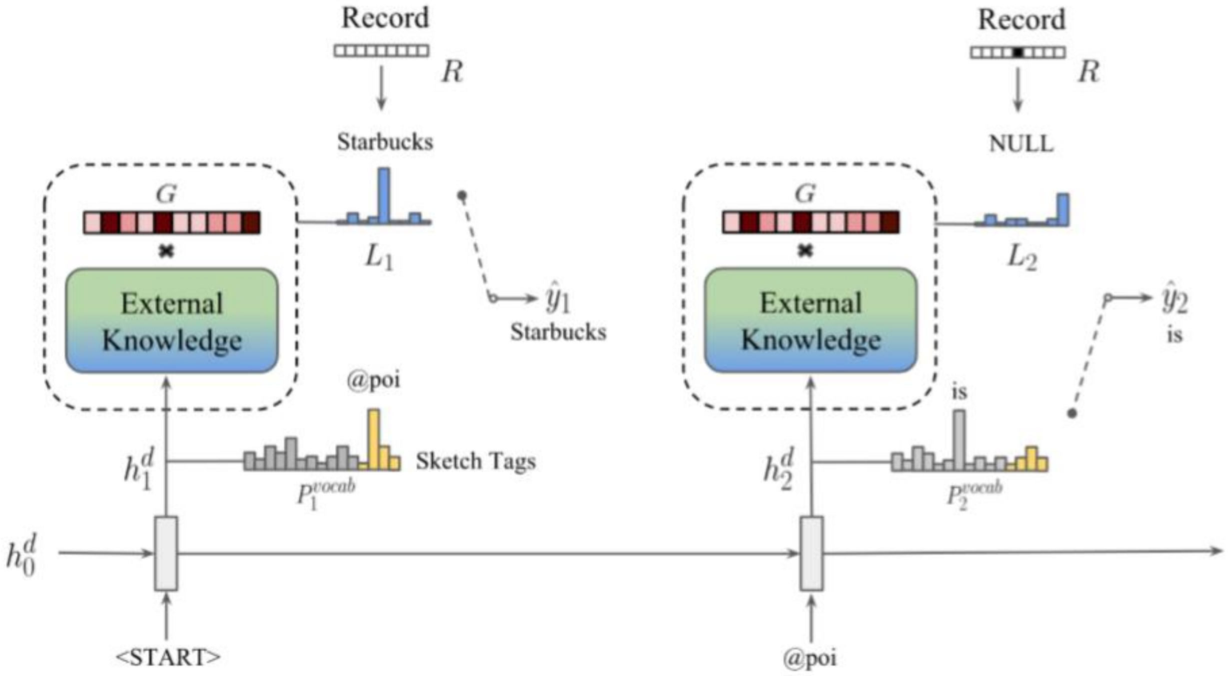
$$h_t^d = \mathrm{GRU}(C^1(\hat{y}_{t-1}^s), h_{t-1}^d), \quad P_t^{vocab} = \mathrm{Softmax}(W h_t^d)$$

$$Loss_v = \sum_{t=1}^{m} -\log(P_t^{vocab}(y_t^s)).$$

  - Local memory pointer
    - Modify memory with global pointer

$$c_i^k = c_i^k \times g_i,$$

    - Local pointer to fill the tags: $\hat{y}_t = \begin{cases} \arg\max(P_t^{vocab}) & \text{if } \arg\max(P_t^{vocab}) \notin ST, \\ Object(m_{\arg\max(L_t \odot R)}) & \text{otherwise,} \end{cases}$
    - Train with position label: $L_t^{label} = \begin{cases} max(z) & \text{if } \exists z \text{ s.t. } y_t = Object(m_z), \\ n+l+1 & \text{otherwise.} \end{cases}$ $Loss_l = \sum_{t=1}^{m} -\log(L_t(L_t^{label})).$



(b) Local memory decoder

GLMP (ICLR-19)

Table 2: Per-response accuracy and completion rate (in the parentheses) on bAbI dialogues. GLMP achieves the least out-of-vocabulary performance drop. Baselines are reported from Query Reduction Network (Seo et al., 2017), End-to-end Memory Network (Bordes & Weston, 2017), Gated Memory Network (Liu & Perez, 2017), Point to Unknown Word (Gulcehre et al., 2016), and Memory-to-Sequence (Madotto et al., 2018).

Task	QRN	MN	GMN	S2S+Attn	Ptr-Unk	Mem2Seq	GLMP K1	GLMP K3	GLMP K6
T1	99.4 (-)	99.9 (99.6)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)
T2	99.5 (-)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)
T3	74.8 (-)	74.9 (2.0)	74.9 (0)	74.8 (0)	85.1 (19.0)	94.7 (62.1)	**96.3 (75.6)**	96.0 (69.4)	96.0 (68.7)
T4	57.2 (-)	59.5 (3.0)	57.2 (0)	57.2 (0)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)
T5	**99.6 (-)**	96.1 (49.4)	96.3 (52.5)	98.4 (87.3)	99.4 (91.5)	97.9 (69.6)	99.2 (88.5)	99.0 (86.5)	99.2 (89.7)
T1 oov	83.1 (-)	72.3 (0)	82.4 (0)	81.7 (0)	92.5 (54.7)	94.0 (62.2)	**100 (100)**	**100 (100)**	99.3 (95.9)
T2 oov	78.9 (-)	78.9 (0)	78.9 (0)	78.9 (0)	83.2 (0)	86.5 (12.4)	**100 (100)**	**100 (100)**	99.4 (94.6)
T3 oov	75.2 (-)	74.4 (0)	75.3 (0)	75.3 (0)	82.9 (13.4)	90.3 (38.7)	95.5 (65.7)	**96.7 (72.9)**	95.9 (67.7)
T4 oov	56.9 (-)	57.6 (0)	57.0 (0)	57.0 (0)	100 (100)	100 (100)	100 (100)	100 (100)	100 (100)
T5 oov	67.8 (-)	65.5 (0)	66.7 (0)	65.7 (0)	73.6 (0)	84.5 (2.3)	**92.0 (21.7)**	91.0 (17.7)	91.8 (21.4)

Table 3: In SMD dataset, our model achieves highest BLEU score and entity F1 score over baselines, including previous state-of-the-art result from Madotto et al. (2018). (Models with * are reported from Eric et al. (2017), where the problem is simplified to the canonicalized forms.)

Automatic Evaluation

	Rule-Based*	KVR*	S2S	S2S + Attn	Ptr-Unk	Mem2Seq	GLMP K1	GLMP K3	GLMP K6
BLEU	6.6	13.2	8.4	9.3	8.3	12.6	13.83	**14.79**	12.37
Entity F1	43.8	48.0	10.3	19.9	22.7	33.4	57.25	**59.97**	53.54
Schedule F1	61.3	62.9	9.7	23.4	26.9	49.3	68.74	**69.56**	69.38
Weather F1	39.5	47.0	14.1	25.6	26.7	32.8	60.87	**62.58**	55.89
Navigation F1	40.4	41.3	7.0	10.8	14.9	20.0	48.62	**52.98**	43.08

Human Evaluation

	Mem2Seq	GLMP	Human
Appropriate	3.89	4.15	4.6
Humanlike	3.80	4.02	4.54

NAACL-19

Multi-Level Memory for Task Oriented Dialogs

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Paper List

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<ICLR-17> Learning End-to-end Goal-Oriented Dialog
<NIPS-15> End-To-End Memory Networks
<AAAI-19> Learning Personalized End-to-End Goal-Oriented Dialog
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Thank you!