



Conversational Agents

Chit-Chat Dialogue Systems

- No specific goal, focus on conversation flow (engagement, fluency, consistent, etc)
 and expect more conversational turns
- Work using variants of seq2seq model:
 - Seq2Seq models →
 - Seq2Seq + conversational context →
 - Knowledge-grounded Seg2Seg models

Task-Oriented Dialogue Systems

- O Personal assistant, achieve a certain task and expect less conversational turns
- Often combined rules and statistical components
 - Single domain, pipeline approaches →
 - Multi-domain, contextual, pipeline/end-to-end approaches →
 - Massively multi-domain, end-to-end approaches



Task-oriented Dialogue Systems

Description:

Achieve specific user goals within a limited dialogue turns via natural language.

Challenges:

o language understanding (LU), dialogue management (DM), knowledge base (KB) understanding, language generation (LG), etc.



Point of interest (poi)	Distance	Traffic info	Poi type	Address
The Westin	5 miles	moderate traffic	rest stop	329 El Camino Real
Round Table	4 miles	no traffic	pizza restaurant	113 Anton Ct
Mandarin Roots	5 miles	no traffic	chinese restaurant	271 Springer Street
Palo Alto Cafe	4 miles	moderate traffic	coffee or tea place	436 Alger Dr
Dominos	6 miles	heavy traffic	pizza restaurant	776 Arastradero Rd
Stanford Express Care	6 miles	no traffic	hospital	214 El Camino Real
Hotel Keen	2 miles	heavy traffic	rest stop	578 Arbol Dr



End-to-End Approaches: Advantages & Challenges

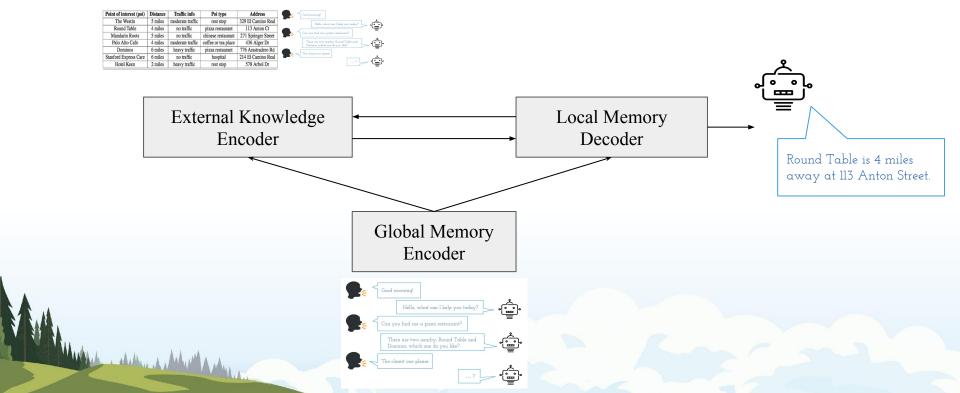
- Input:
 - Dialogue history and knowledge base
- Output:
 - System response with real slot values
- Advantages:
 - O No labels of belief states, slots, dialogue actions, intention, etc.
 - Free from learning dependency between modules
- Challenges:
 - How to incorporate large, dynamic KB into learning frameworks?
 - Entity selection, KB reasoning, etc.
 - O How to interpret dialogue systems?
 - Belief states, slot-filling, etc
 - O How to overcome rare data issue?

Good morning!
Hello, what can I help you today?
There are two nearby, Round Table and Dominos, which one do you like?
The closest one please.

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Global-to-local Memory Pointer Networks (GLMP): Block Diagram



GLMP: External Knowledge

End-to-end Memory Networks

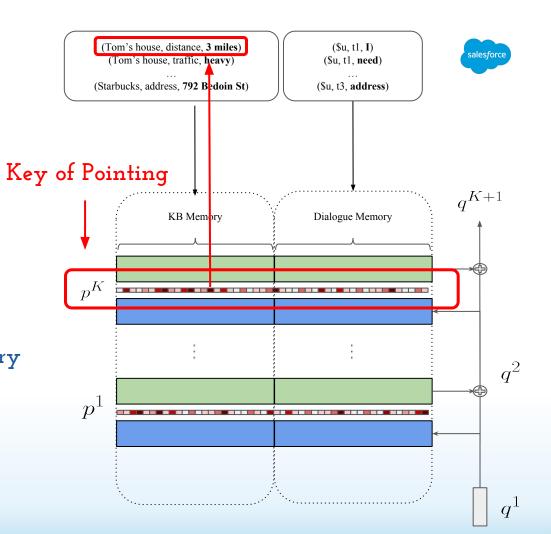
- A query vector
- A set of trainable embeddings
- Memory attention weights
- Multiple hops reasoning

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

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

• KB memory & Dialogue memory

- o (Subject, Predicate, Object)
- Copy Object word



GLMP: Global Memory Encoder

Context RNN

- Encode plain text dialogue history
- Query external knowledge

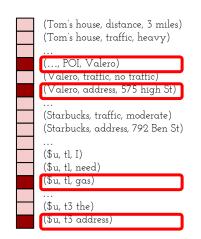
Contextual Dialogue History

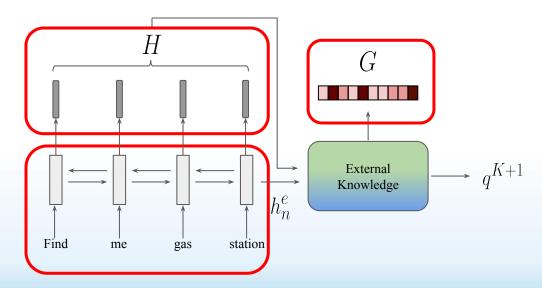
- Write hidden states into dialogue memory module
- Mitigate OOV copying problem

• Global Memory Pointer

- O Point to all the words that may appear in the system response.
- Multi-label classification

$$g_i = \text{Sigmoid}((q^K)^T c_i^K)$$





GLMP: Local Memory Decoder

Sketch RNN

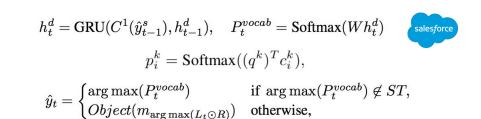
- Initialize with encoded dialogue history and KB
- Generate sketch response. Ex:@poi is @distance away.
- Query external knowledge using its hidden states

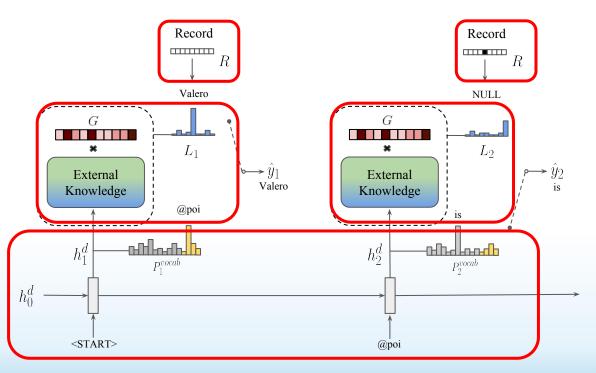
Local Memory Pointer

- Filter external knowledge using global memory pointer
- Copy one single word at each time step

Record Function

Mask the copied words

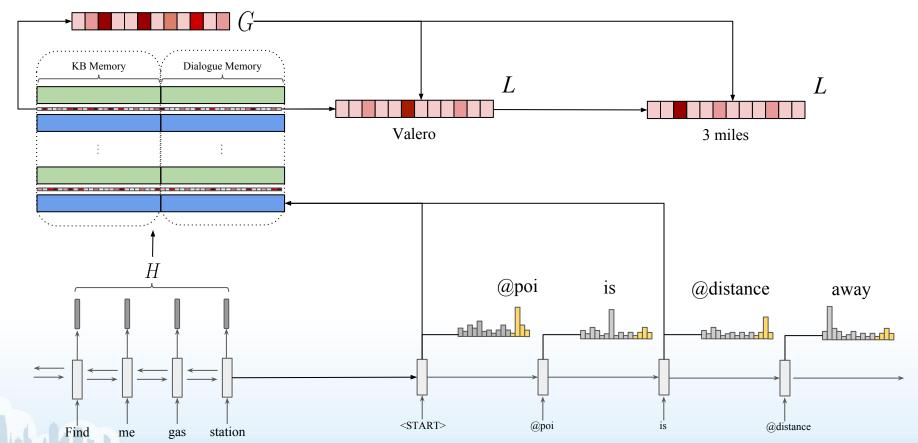




GLMP: Workflow

System Response: Valero is 3 miles away





salesforce

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

 $Loss_l = \sum_{t=1}^{m} -\log(L_t(L_t^{label})).$

Experiment Setup

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

Datasets:

- o bAbI dialogue:
 - Simulated dialogues on restaurant domain.
 - Include out-of-vocabulary setting for slot values.
 - Evaluation metrics: per-response accuracy, per-dialogue accuracy
- O Stanford multi-domain (SMD):
 - Human-human dialogue of a car assistant.
 - Three domains: calendar scheduling, weather retrieval, and point-of-interest navigation.
 - Evaluation metrics: BLEU, Entity Fl, human evaluation

Objective functions:

- $\circ \quad Loss = \alpha Loss_g + \beta Loss_v + \gamma Loss_l$
- O Global memory pointer (Loss_g): binary cross-entropy loss
- Sketch RNN (Loss_v): cross-entropy loss
- Local memory pointer (Loss_1): cross-entropy loss
- Others: Simple greedy decoding. Hyperparameter grid search over hidden size, number of hops, and dropout ratio. Adam optimizer. Without pre-trained embedding.

Baselines

- End-to-end Memory Network (MN)
 - O [Sukhbaatar et al., NIPS 2015]
- Query Reduction Network (QRN)
 - [Seo et al., ICLR 2017]
- Gated Memory Network (GMN)
 - [Liu et al., EACL 2017]
- Sequence-to-sequence (S2S) + Attention
 - o [Luong et al., EMNLP 2015]
- Pointer Network (Ptr-Unk)
 - o [Gulcehre et al., ACL 2016]
- Memory-to-sequence (Mem2Seq)
 - o [Madotto et al., ACL 2018]





Results: bAbI Dialogue

Retrieva	Generat	ion

Task	QRN	MN	GMN	82S+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)

without copy ability

with copy ability



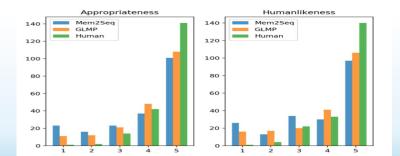
Results: Stanford Multi-Domain

Automatic Evaluation

	Rule-Based*	KVR*	S2S	S2S + Attn	Ptr-Unk	Mem2Seq	GLMP H1	GLMP H3	GLMP H6
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





Results: Ablation Study

- Ablation contextual dialogue history (w/o H)
 - The hidden states of context RNN are not written into the external knowledge
 - The performance drop is serious in bAbI OOV scenario. (-5.3% in T5)
- Ablation global memory pointer (w/o G)
 - The external knowledge is not filtered by the global memory pointer
 - The performance drop is serious in SMD human-human scenario. (-11.47%)

		SMD						
		Per-response Accuracy						
	T1	T2	Т3	T4	T5	All		
GLMP	100 (-)	100 (-)	95.5 (-)	100 (-)	92.0 (-)	57.25 (-)		
GLMP w/o H	90.4 (-9.6)	85.6 (-14.4)	95.4 (-0.1)	100 (-0)	86.2 (-5.3)	47.96 (-9.29)		
GLMP w/o G	100 (-0)	91.7 (-8.3)	95.5 (-0)	100 (-0)	92.4 (+0.4)	45.78 (-11.47)		





Results: Qualitative Study (1/2)

items	address	poi_type	traffic_info	distance
76	91_el_camino_real	gas_station	car_collision_nearby	5_miles
coupa	394_van_ness_ave	coffee_or_tea_place	road_block_nearby	6_miles
jing_jing	113_arbol_dr	chinese_restaurant	car_collision_nearby	3_miles
palo_alto_garage_r	481_amaranta_ave	parking_garage	no_traffic	5_miles
panda_express	842_arrowhead_way	chinese_restaurant	moderate_traffic	5_miles
peets_coffee	9981_archuleta_ave	coffee_or_tea_place	moderate_traffic	4_miles
stanford_childrens_health	899_ames_ct	hospital	moderate_traffic	5_miles
willows_market	409_bollard_st	grocery_store	car_collision_nearby	3_miles

Driver: Give me the directions to the closest grocery store

GLMP: The nearest grocery_store is willows_market, 3_miles away at 409_bollard_st

Driver: What is the next closest location?

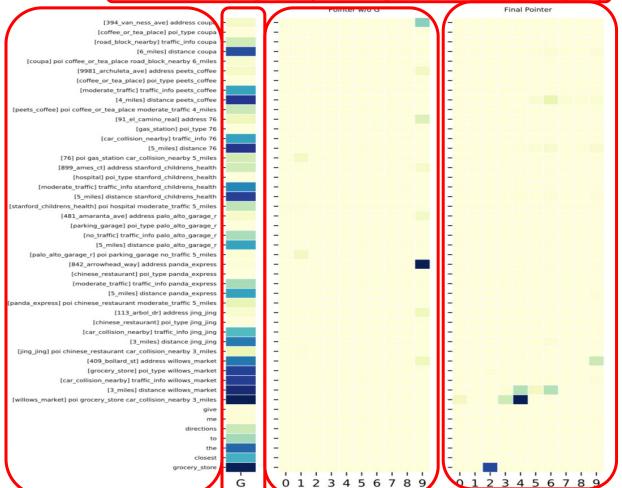
GLMP: 409_bollard_st is the only 3_miles away

Driver: Ok then make a route to willows_market, avoid all traffic

GLMP: I sent the info on your screen, drive carefully .

Results: Qualitative Study

Delexicalized Generation: the nearest @poi_type is @poi , @distance away at @address Final Generation: the nearest grocery_store is willows_market , 3_milles away at 409_bollard_st Gold: we are 3 miles away from willows market but there is a car collision nearby





Results: Error Analysis

- bAbI dialogue
 - Recommend restaurants (Task 3)
 - Keep recommending some with higher scores but rejected by users
- SMD dataset
 - KB understanding problem
 - When several options matched are found in KB, model can barely recognize
 - Ex: Are you talking about the doctor appointment on Wednesday or Friday?
 - When the response requires checking multiple nodes
 - Ex: No, it will not rain for the next week in Palo Alto
 - Copy mismatch
 - Sketch tags mismatch with entity values
 - Ex: @address tag but copy "4 miles" out.
 - Generated sketch response includes missing slot values
 - Ex: Your @event is on @day with @party

Delexicalized Generation: your @event is on @date at @time with @party Final Generation: your doctor is on the_5th at 6pm with alex Gold: are you talking about the doctor_appointment on wednesday or the one on the_5th?



Delexicalized Generation: the nearest @poi_type is @poi , @distance away at @address Final Generation: the nearest parking_garage is civic_center_garage , 4_miles away at 5_miles Gold: the closest parking_garage is civic_center_garage , located 4_miles away at 270_altaire_walk

