Learning End-to-End Goal-Oriented Dialog

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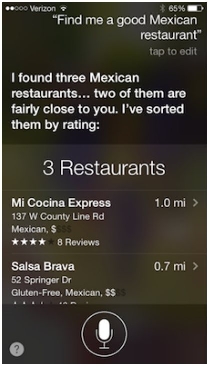
Outline

1. Goal Oriented Dialog Tasks
2. Models
   - Rule-based Systems
   - Classic IR Methods
   - Supervised Embedding Models
   - Memory Networks
3. Experiments
4. Conclusions

Goal Oriented Dialog

- **Goal oriented dialog**: understand a user request and complete a task
- **“Slot filling”**: predefine the structure of a dialog state as a set of slots to be filled
    - e.g. restaurant reservation system slots: location, price, cuisine type
    - Doesn't scale to new domains



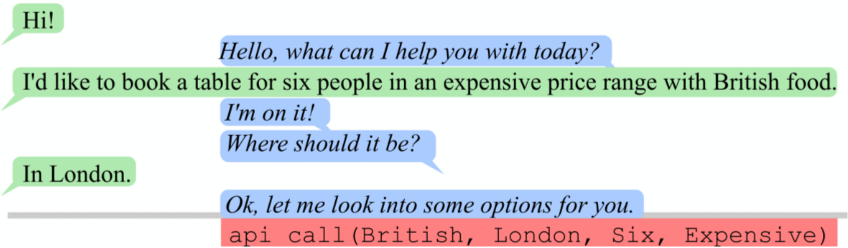
End-to-end Dialog Systems

- All components are trained on past dialog. Usually done in non-goal oriented "chit-chat" settings
- Goal oriented dialog goes beyond language modeling.
  - e.g. asking questions to clearly define user requests, querying KBs
- **This paper**: can end-to-end models be competitive with traditional slot-filling models?

Restaurant Reservation Simulation

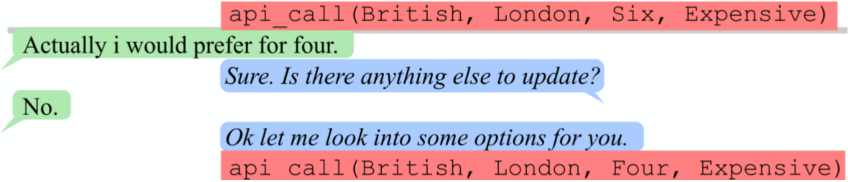
- Goal: book a table at a restaurant
- Data: simulation based on a KB whose facts contain restaurants and four types of properties:
  1. Type: 10 choices (French, Thai, ...)
  2. Location: 10 choices (London, Tokyo, ...)
  3. Price Range: 3 choices (cheap, moderate, expensive)
  4. Rating: 8 choices (1,2,...,8)
- Approach: evaluate models on 4 sub-tasks of restaurant reservation

Task 1: Issuing API Calls



- Bot must ask questions for filling the missing fields and eventually generate the correct corresponding API call.

Task 2: Updating API Calls

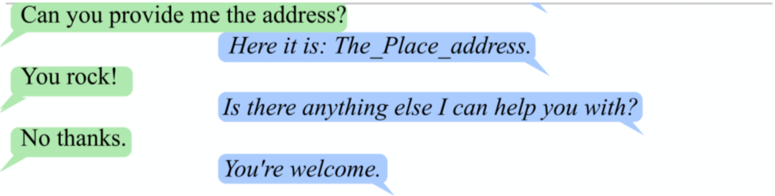


- Users ask to update their requests between 1 and 4 times (sampled uniformly). Bot must correct for changes.

Task 3: Displaying Options

- Given a user request, query the KB using API call and add the facts from the call to dialog history.
- Propose options to users by listing restaurant names sorted by rating

Task 4: Providing Extra Info



- Users ask for the phone number of the restaurant, address, or both
- Bot must learn to use the KB facts correctly to answer

Task 5: Full Dialog

Task 5 Conducting full dialogs

Datasets

	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

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- At each turn of the dialog, test if model can predict bot utterances and API calls by selecting a candidate
- Candidates are ranked from a set of all bot utterances and API calls

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Rule-based Systems

- For tasks T1-T5, it is possible to hand-code a rule based system that achieves 100%.
- Tasks T6 and Concierge are not simulated, so they require more complex rules (which is hopefully where machine learning can help).

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Classic IR Methods

- **TF-IDF Match**
  - Rank candidate responses by matching score between the input and the response
- **Nearest Neighbor**
  - Using the input, find the most similar conversation in training set, and output the response from that conversation

Outline

Supervised Embedding Models

- Candidate reponse y scored against input x: $f(x, y) = (Ax)^T By$
  - A and B are $d \times V$ word embedding matrices
- Embeddings trained with margin ranking loss: $f(x, y) > m + f(x, \bar{y})$

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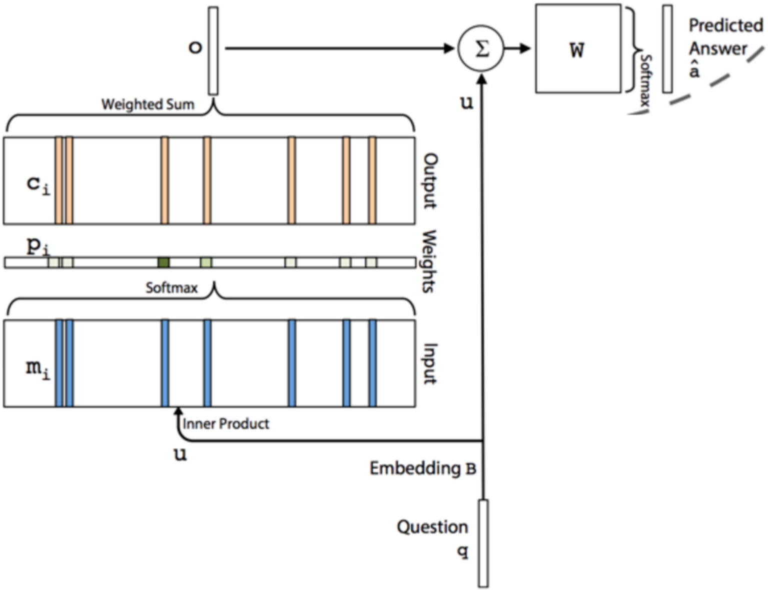
Memory Networks



Match Type Features

- Augment the vocab with 7 special words, one for each of the KB entity types (cuisine type, location, price range, party size, rating, phone number and address).

Results

Task	Rule-based Systems	TF-IDF Match no type	TF-IDF Match + type	Nearest Neighbor	Supervised Embeddings	Memory Networks no match type	Memory Networks + match type
T1: Issuing API calls	*100 (100)*	5.6 (0)	22.4 (0)	55.1 (0)	**100** (100)	**99.9** (99.6)	**100** (100)
T2: Updating API calls	*100 (100)*	3.4 (0)	16.4 (0)	68.3 (0)	68.4 (0)	**100** (100)	98.3 (83.9)
T3: Displaying options	*100 (100)*	8.0 (0)	8.0 (0)	58.8 (0)	64.9 (0)	**74.9** (2.0)	**74.9** (0)
T4: Providing information	*100 (100)*	9.5 (0)	17.8 (0)	28.6 (0)	57.2 (0)	59.5 (3.0)	**100** (100)
T5: Full dialogs	*100 (100)*	4.6 (0)	8.1 (0)	57.1 (0)	75.4 (0)	**96.1** (49.4)	93.4 (19.7)
T1(OOV): Issuing API calls	*100 (100)*	5.8 (0)	22.4 (0)	44.1 (0)	60.0 (0)	72.3 (0)	**96.5** (82.7)
T2(OOV): Updating API calls	*100 (100)*	3.5 (0)	16.8 (0)	68.3 (0)	68.3 (0)	78.9 (0)	**94.5** (48.4)
T3(OOV): Displaying options	*100 (100)*	8.3 (0)	8.3 (0)	58.8 (0)	65.0 (0)	74.4 (0)	**75.2** (0)
T4(OOV): Providing inform.	*100 (100)*	9.8 (0)	17.2 (0)	28.6 (0)	57.0 (0)	57.6 (0)	**100** (100)
T5(OOV): Full dialogs	*100 (100)*	4.6 (0)	9.0 (0)	48.4 (0)	58.2 (0)	65.5 (0)	**77.7** (0)
T6: Dialog state tracking 2	33.3 (0)	1.6 (0)	1.6 (0)	21.9 (0)	22.6 (0)	**41.1** (0)	**41.0** (0)
Concierge(*)	n/a	1.1 (0.2)	n/a	13.4 (0.5)	14.6 (0.5)	**16.7** (1.2)	n/a(†)

- Metrics: Per-response accuracy and (Per-dialog accuracy)

Conclusions

- Open dataset and task set for evaluating end-to-end goal-oriented dialog learning methods in a systematic and controlled way.
- The breakdown in tasks will help focus research and development to improve the learning methods
- Illustrated how to use the testbed using Memory Networks, which prove an effective model on these tasks relative to other baselines, but are still lacking in some key areas.