Global-to-local Memory Pointer Networks for Task-Oriented Dialogue

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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 Seq2Seq models

- **Task-Oriented Dialogue Systems**
  - 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

Source: https://sites.google.com/view/deepdial/
Task-oriented Dialogue Systems

- **Description**: Achieve specific user goals within a limited dialogue turns via natural language.

- **Challenges**: language understanding (LU), dialogue management (DM), knowledge base (KB) understanding, language generation (LG), etc.

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Good morning!

Hello, what can I help you today?

Can you find me a pizza restaurant?

There are two nearby, Round Table and Dominos, which one do you like?

The closest one please.

...?
End-to-End Approaches: Advantages & Challenges

- **Input:**
  - Dialogue history and knowledge base

- **Output:**
  - System response with real slot values

- **Advantages:**
  - 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.
  - How to interpret dialogue systems?
    - Belief states, slot-filling, etc.
  - How to overcome rare data issue?
Global-to-local Memory Pointer Networks (GLMP): Block Diagram

External Knowledge Encoder

Local Memory Decoder

Global Memory Encoder

Round Table is 4 miles away at 113 Anton Street.
**GLMP: External Knowledge**

- **End-to-end Memory Networks**
  - A query vector
  - A set of trainable embeddings
  - Memory attention weights
  - Multiple hops reasoning
  
  \[
p_i^k = \text{Softmax}((q^k)Tc_i^k),
  \]
  \[
o^k = \sum_i p_i^k c_i^{k+1}, \quad q^{k+1} = q^k + o^k.
  \]

- **KB memory & Dialogue memory**
  - (Subject, Predicate, Object)
  - Copy Object word

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**Key of Pointing**

- (Tom’s house, distance, 3 miles)
- (Tom’s house, traffic, heavy)
- (Starbucks, address, 792 Bedford St)
- ($u, t1, I$)
- ($u, t1, need$)
- ($u, t3, address$)
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**
  - 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

Mathematical equations:

\[ h_t^d = \text{GRU}(C^1(\hat{y}_{t-1}^d), h_{t-1}^d), \quad P_t^{\text{vocab}} = \text{Softmax}(W h_t^d) \]
\[ p_i^k = \text{Softmax}((q^k)^T c_t^k), \]
\[ \hat{y}_t = \begin{cases} \arg \max(P_t^{\text{vocab}}) & \text{if } \arg \max(P_t^{\text{vocab}}) \notin ST, \\ \text{Object}(m_{\arg \max(L_t \cap R)}) & \text{otherwise}, \end{cases} \]
GLMP: Workflow

System Response: Valero is 3 miles away
Experiment Setup

- **Datasets:**
  - **bAbI dialogue:**
    - Simulated dialogues on restaurant domain.
    - Include out-of-vocabulary setting for slot values.
    - Evaluation metrics: per-response accuracy, per-dialogue accuracy
  - **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 F1, human evaluation

- **Objective functions:**
  - \( \text{Loss} = \alpha \text{Loss}_g + \beta \text{Loss}_v + \gamma \text{Loss}_l \)
  - Global memory pointer (Loss\(_g\)) : binary cross-entropy loss
  - Sketch RNN (Loss\(_v\)) : cross-entropy loss
  - Local memory pointer (Loss\(_l\)) : 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)**
  - [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**
  - [Luong et al., EMNLP 2015]
- **Pointer Network (Ptr-Unk)**
  - [Gulcehre et al., ACL 2016]
- **Memory-to-sequence (Mem2Seq)**
  - [Madotto et al., ACL 2018]
## Results: bAbI Dialogue

### Retrieval with and without copy ability

<table>
<thead>
<tr>
<th>Task</th>
<th>QRN</th>
<th>MN</th>
<th>GMN</th>
<th>S2S+Attn</th>
<th>Ptr-Unk</th>
<th>Mem2Seq</th>
<th>GLMP K1</th>
<th>GLMP K3</th>
<th>GLMP K6</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>99.4 (-)</td>
<td>99.9 (99.6)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>100 (100)</td>
</tr>
<tr>
<td>T2</td>
<td>99.5 (-)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>96.3 (75.6)</td>
<td>96.0 (69.4)</td>
<td>96.0 (68.7)</td>
<td>100 (100)</td>
<td>100 (100)</td>
</tr>
<tr>
<td>T3</td>
<td>74.8 (-)</td>
<td>74.9 (2.0)</td>
<td>74.9 (0)</td>
<td>74.8 (0)</td>
<td>85.1 (19.0)</td>
<td>94.7 (62.1)</td>
<td>96.0 (68.7)</td>
<td>100 (100)</td>
<td>100 (100)</td>
</tr>
<tr>
<td>T4</td>
<td>57.2 (-)</td>
<td>59.5 (3.0)</td>
<td>57.2 (0)</td>
<td>57.2 (0)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>99.2 (88.5)</td>
<td>99.0 (86.5)</td>
<td>99.2 (89.7)</td>
</tr>
<tr>
<td>T5</td>
<td>99.6 (-)</td>
<td>96.1 (49.4)</td>
<td>96.3 (52.5)</td>
<td>98.4 (87.3)</td>
<td>99.4 (91.5)</td>
<td>97.9 (69.6)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>100 (100)</td>
</tr>
</tbody>
</table>

### Generation with and without copy ability

<table>
<thead>
<tr>
<th>Task</th>
<th>QRN</th>
<th>MN</th>
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<th>S2S+Attn</th>
<th>Ptr-Unk</th>
<th>Mem2Seq</th>
<th>GLMP K1</th>
<th>GLMP K3</th>
<th>GLMP K6</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>83.1 (-)</td>
<td>72.3 (0)</td>
<td>82.4 (0)</td>
<td>81.7 (0)</td>
<td>92.5 (54.7)</td>
<td>94.0 (62.2)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>99.3 (95.9)</td>
</tr>
<tr>
<td>T2</td>
<td>78.9 (-)</td>
<td>78.9 (0)</td>
<td>78.9 (0)</td>
<td>78.9 (0)</td>
<td>83.2 (0)</td>
<td>86.5 (12.4)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>99.4 (94.6)</td>
</tr>
<tr>
<td>T3</td>
<td>75.2 (-)</td>
<td>74.4 (0)</td>
<td>75.3 (0)</td>
<td>75.3 (0)</td>
<td>82.9 (13.4)</td>
<td>90.3 (38.7)</td>
<td>95.5 (65.7)</td>
<td>96.7 (72.9)</td>
<td>95.9 (67.7)</td>
</tr>
<tr>
<td>T4</td>
<td>56.9 (-)</td>
<td>57.6 (0)</td>
<td>57.0 (0)</td>
<td>57.0 (0)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>100 (100)</td>
<td>100 (100)</td>
</tr>
<tr>
<td>T5</td>
<td>67.8 (-)</td>
<td>65.5 (0)</td>
<td>66.7 (0)</td>
<td>65.7 (0)</td>
<td>73.6 (0)</td>
<td>84.5 (2.3)</td>
<td>92.0 (21.7)</td>
<td>91.0 (17.7)</td>
<td>91.8 (21.4)</td>
</tr>
</tbody>
</table>
## Results: Stanford Multi-Domain

### Automatic Evaluation

<table>
<thead>
<tr>
<th></th>
<th>Rule-Based*</th>
<th>KVR*</th>
<th>S2S</th>
<th>S2S + Attn</th>
<th>Ptr-Unk</th>
<th>Mem2Seq</th>
<th>GLMP H1</th>
<th>GLMP H3</th>
<th>GLMP H6</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLEU</td>
<td>6.6</td>
<td>13.2</td>
<td>8.4</td>
<td>9.3</td>
<td>8.3</td>
<td>12.6</td>
<td>13.83</td>
<td>14.79</td>
<td>12.37</td>
</tr>
<tr>
<td>Entity F1</td>
<td>43.8</td>
<td>48.0</td>
<td>10.3</td>
<td>19.9</td>
<td>22.7</td>
<td>33.4</td>
<td>57.25</td>
<td>59.97</td>
<td>53.54</td>
</tr>
<tr>
<td>Schedule F1</td>
<td>61.3</td>
<td>62.9</td>
<td>9.7</td>
<td>23.4</td>
<td>26.9</td>
<td>49.3</td>
<td>68.74</td>
<td>69.56</td>
<td>69.38</td>
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<tr>
<td>Weather F1</td>
<td>39.5</td>
<td>47.0</td>
<td>14.1</td>
<td>25.6</td>
<td>26.7</td>
<td>32.8</td>
<td>60.87</td>
<td>62.58</td>
<td>55.89</td>
</tr>
<tr>
<td>Navigation F1</td>
<td>40.4</td>
<td>41.3</td>
<td>7.0</td>
<td>10.8</td>
<td>14.9</td>
<td>20.0</td>
<td>48.62</td>
<td>52.98</td>
<td>43.08</td>
</tr>
</tbody>
</table>

### Human Evaluation

<table>
<thead>
<tr>
<th></th>
<th>Mem2Seq</th>
<th>GLMP</th>
<th>Human</th>
</tr>
</thead>
<tbody>
<tr>
<td>Appropriate</td>
<td>3.89</td>
<td>4.15</td>
<td>4.6</td>
</tr>
<tr>
<td>Humanlike</td>
<td>3.80</td>
<td>4.02</td>
<td>4.54</td>
</tr>
</tbody>
</table>
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%)

<table>
<thead>
<tr>
<th></th>
<th>bAbI Dialogue OOV</th>
<th></th>
<th>SMD</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Per-response Accuracy</td>
<td></td>
<td>Entity F1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>T1</td>
<td>T2</td>
<td>T3</td>
<td>T4</td>
<td>T5</td>
</tr>
<tr>
<td>GLMP</td>
<td>100 (-)</td>
<td>100 (-)</td>
<td>95.5 (-)</td>
<td>100 (-)</td>
<td>92.0 (-)</td>
</tr>
<tr>
<td>GLMP w/o H</td>
<td>90.4 (-9.6)</td>
<td>85.6 (-14.4)</td>
<td>95.4 (-0.1)</td>
<td>100 (-0)</td>
<td>86.2 (-5.3)</td>
</tr>
<tr>
<td>GLMP w/o G</td>
<td>100 (-0)</td>
<td>91.7 (-8.3)</td>
<td>95.5 (-0)</td>
<td>100 (-0)</td>
<td>92.4 (+0.4)</td>
</tr>
</tbody>
</table>
Results: Qualitative Study (1/2)

<table>
<thead>
<tr>
<th>items</th>
<th>address</th>
<th>poi_type</th>
<th>traffic_info</th>
<th>distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>76</td>
<td>91_el_camino_real</td>
<td>gas_station</td>
<td>car_collision_nearby</td>
<td>5_miles</td>
</tr>
<tr>
<td>coupa</td>
<td>394_van_ness_ave</td>
<td>coffee_or_tea_place</td>
<td>road_block_nearby</td>
<td>6_miles</td>
</tr>
<tr>
<td>jing_jing</td>
<td>113_arbol_dr</td>
<td>chinese_restaurant</td>
<td>car_collision_nearby</td>
<td>3_miles</td>
</tr>
<tr>
<td>palo_alto_garage_r</td>
<td>481_amaranta_ave</td>
<td>parking_garage</td>
<td>no_traffic</td>
<td>5_miles</td>
</tr>
<tr>
<td>panda_express</td>
<td>842_arrowhead_wy</td>
<td>chinese_restaurant</td>
<td>moderate_traffic</td>
<td>5_miles</td>
</tr>
<tr>
<td>peets_coffee</td>
<td>9981_archuleta_ave</td>
<td>coffee_or_tea_place</td>
<td>moderate_traffic</td>
<td>5_miles</td>
</tr>
<tr>
<td>stanford_childrens_health</td>
<td>899_ames_ct</td>
<td>hospital</td>
<td>moderate_traffic</td>
<td>5_miles</td>
</tr>
<tr>
<td>willows_market</td>
<td>409_bollard_st</td>
<td>grocery_store</td>
<td>car_collision_nearby</td>
<td>3_miles</td>
</tr>
</tbody>
</table>

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
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
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
Gold: the closest parking garage is civic_center garage, 4 miles away at 5 miles

Final Generation: your doctor is on the 5th at 6pm with alex

Final Generation: the nearest parking garage is civic_center garage, located 4 miles away at 270_altaire_walk
thank you

Q/A