ASK ME ANYTHING : DYNAMIC MEMORY NETWORKS

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INTRODUCTION

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- **Current Approach**

  With advancements in deep learning, most QA systems nowadays use RNNs for the same. They generate latent representations of natural language text passages rather than relying on extracted features such as part of speech tagging,parsing, named entity recognition, etc. These networks have outperformed traditional models by huge margins.

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DYNAMIC MEMORY NETWORKS

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4. While the DMN can be trained end-to-end for a variety of tasks, we trained it for question answering on the Facebook baBi Dataset.

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5. Every answer in the bAbI dataset is one word.

A PEEK INTO BABI

```
Two supporting fact example:

1 Mary got the milk there.
2 John moved to the bedroom.
3 Sandra went back to the kitchen.
4 Mary travelled to the hallway.
5 Where is the milk?   hallway   1 4
```

```
Yes/no question example:

2 John moved to the bedroom.
3 Is John in the kitchen?   no   2
```

DMN MODULES

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MODEL DESCRIPTION

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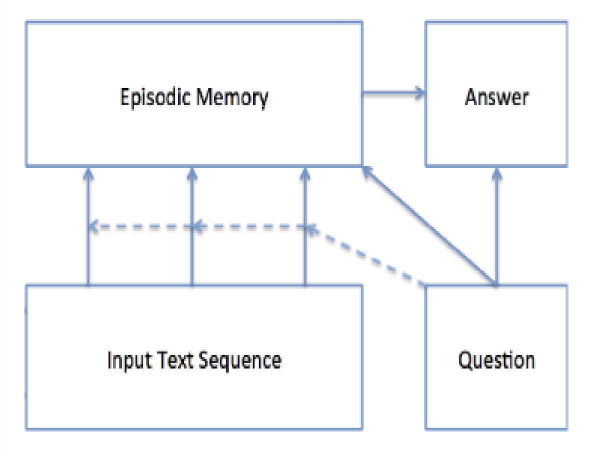
4. Answer module


Episodic Memory
Answer
Input Text Sequence
Question

1. The input module feeds word vectors through a GRU, and outputs the hidden states at the end of each sentence for the episodic memory module.

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4. The output is trained with cross entropy error classification of the correct sequence.

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3. For each sentence, the attention mechanism updates states as-

$$z_t^i = [c_t, m^{i-1}, q, c_t \circ q, c_t \circ m^{i-1}, |c_t - q|, |c_t - m^{i-1}|]$$
$$g_t^i = G(c_t, m^{i-1}, q) = \sigma(W^{(2)}\tanh(W^{(1)}z_t^i + b^{(1)}) + b^{(2)})$$
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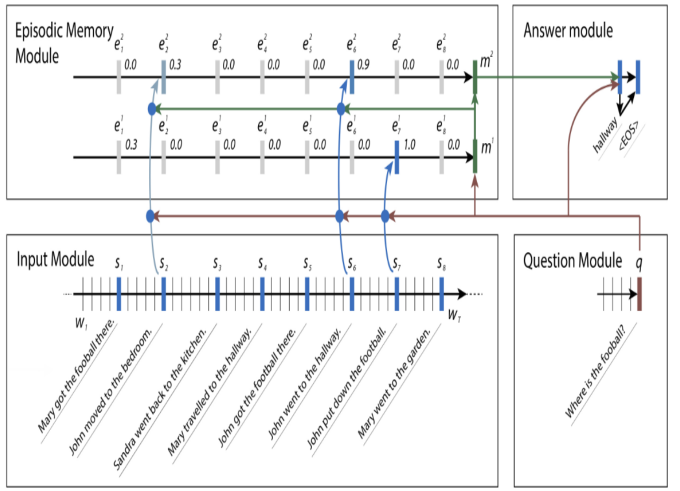
4. The memory is then updated using the current episode state and the memory state by passing through a GRU.

$$m^i = GRU(e^i, m^{i-1})$$

NEED FOR MULTIPLE EPISODES



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4. Hence, multiple passes through input sequence helps the model to make transitive inferences.

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    - Simple: $[c_t, m, q]$

EXPERIMENTAL RESULTS

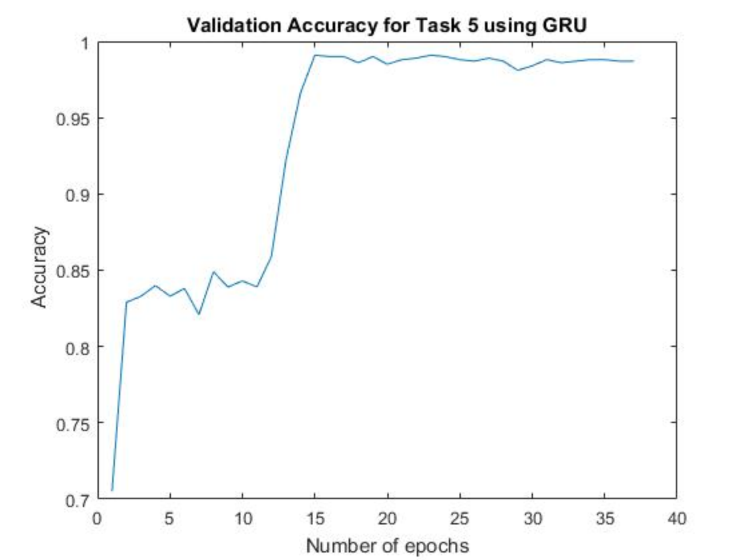
Table: Comparision of test accuracies of various architectures

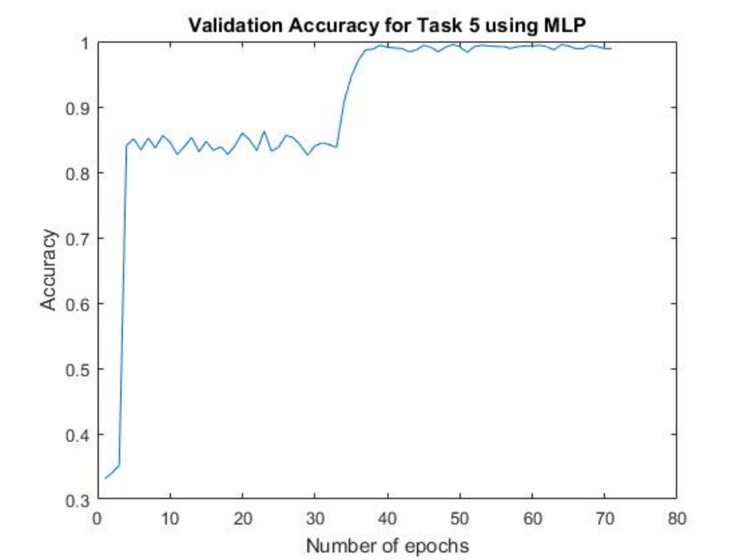
Task	DMN (GRU+custom)	DMN (FNN+custom)	DMN (GRU+simple)	DMN (FNN+simple)
1	100	100	100	100
2	78.5	87.7	88.2	89.6
3	44.8	54.9	43.7	42.2
4	100	100	100	100
5	94.6	98.9	98.3	98.8
6	50.5	49.6	49	49.7
7	97.6	97.1	96.6	95.8
8	99.4	99.2	99.5	99.3
9	99.0	90.7	100	79.8
10	88.4	51	52	50.3

Table: Comparision of test accuracies for various architectures(continued)

Task	DMN (GRU+custom)	DMN (FNN+custom)	DMN (GRU+simple)	DMN (FNN+simple)
11	94.6	93.0	100	84.8
12	100	100	100	100
13	91.5	91.7	91.8	93.7
14	64.1	32.5	18.1	47.3
15	100	98.2	99.3	100
16	44.2	44.4	44.1	45.2
17	59.1	62.8	60.4	62.2
18	91.1	91.2	90.1	90.2
19	35.1	45.8	41.2	31.2
20	99.2	100	96	90.9

ACCURACY CURVES




Validation Accuracy for Task 5 using MLP
Accuracy
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
10
20
30
40
50
60
70
80
Number of epochs

POSSIBLE EXTENSIONS

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2. A fifth module can be introduced, called Summarizing module, which reduces the number of vectors that the episodic memory has to deal with. This can be used to create a summary of the passage, similar to how humans first skim through the document to find relevant parts.

REFERENCES

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1. This project was based on:
   `https://arxiv.org/abs/1506.07285`

2. Our repository for the project:
   `https://github.com/gsaket/DMN-NLP`