



# Deep Learning Methods for Reading Comprehension Question Answering

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## Motivation

- Reading comprehension is a fundamental and multi-faceted problem in AI applied to NLP
- Design a deep learning model for context-intelligent question answering, and examine drivers of performance for specific QA tasks

## Problem Definition

The model reads a passage of text...

...and answers questions about the contents

**Passage (Input):**  
Sandra is in the **kitchen**.  
Sandra **picked up** the **football** there. Sandra traveled to the **hallway**. Sandra **discarded** the **football** there.

**Question (Input):**  
Where is the football?

**Answer (Output):**  
Hallway

## Dataset and Context

**Dataset:** Facebook bAbI 

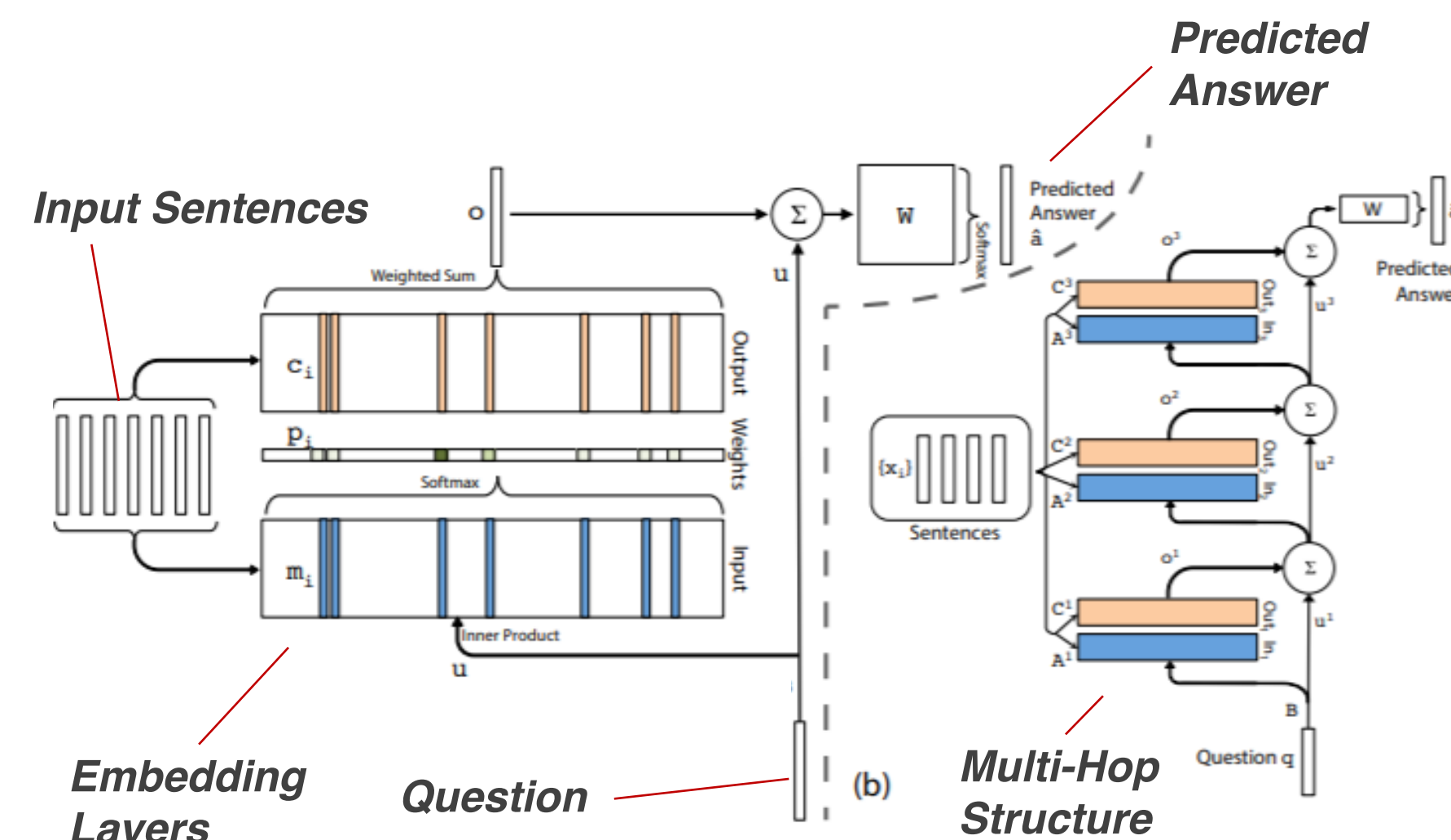
**Baseline Model:** Attention-based model with pre-trained GloVe word embeddings and bi-directional GRU for context embedding

**Evaluation Metrics:** Exact Match (EM) accuracy, cross-entropy loss function, Adam optimizer

## Methodology / Model Definition

**MemNN:** A multi-hop memory network replacing the contextual RNN embedding of our baseline with learning from an external-memory representation

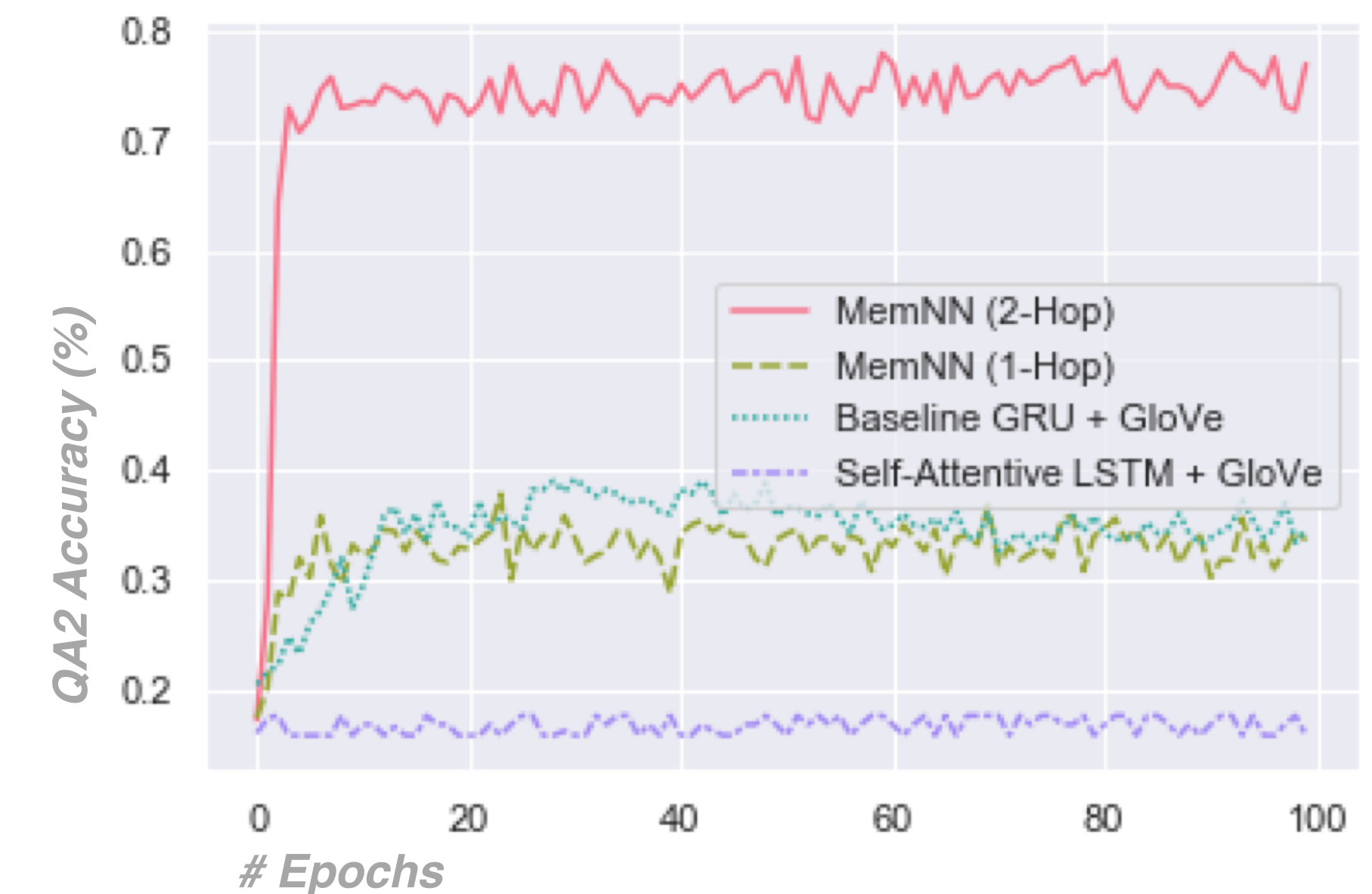
- Probability of the encoded question  $u$  across inputs  $\{m_1, m_2 \dots m_i\}$ :  
$$p_i = \text{Softmax}(u^T m_i)$$
- Output memory representation of encoded inputs  $c_i$ :  
$$o = \sum_i p_i c_i$$
- Final prediction and activation:  
$$\hat{a} = \text{Softmax}(W(o + u))$$
- K-stacking of “hops” in the memory network:  
$$u^{k+1} = u^k + o^k$$



**Self-Attention:** Based on Microsoft R-Net – “dense” attention calculation for each representation  $\{v_1 \dots v_N\}$

- Dot multiplication  
$$e_j^i = v^T \tanh(W_1 v_j + W_2 v_i)$$
- Activation  
$$\alpha_i = \text{Softmax}(e^i)$$
- Self-attention output  
$$a^i = \sum_{j=1}^N \alpha_j^i v_j$$

## Results and Analysis



QA2 accuracies of ~80% reached at convergence with MemNN-2Hop, but single-hop mostly mirrored baseline

RNN vs. external memory exhibit clear pros and cons depending on task (contextual vs. factual intelligence)

QA Challenge	Baseline	LSTM + Self-Attn	MemNN One-Hop	MemNN Two-Hop
QA1 Single Supporting Fact	42%	51%	99%	99%
QA2 Two Supporting Facts	33%	17%	36%	75%
QA4 Two Argument Relations	79%	70%	67%	68%
QA6 Yes/No Questions	74%	50%	50%	50%
QA7 Counting	76%	57%	80%	83%
QA8 Lists Sets	72%	77%	86%	89%
QA9 Simple Negation	71%	64%	90%	90%
QA10 Indefinite Knowledge	62%	44%	82%	82%