

# Memory Network For Question Answering

Virgile Audi  
Nicolas Drizard

TF: Sam Wiseman  
May, 3<sup>rd</sup> 2015

# Outline

- 1 Motivation
  - Questions
  - Intuition
- 2 Baseline Model
- 3 End-to-end Memory Network
  - Architecture
  - Parameters Tying
  - Implementation Details
- 4 Result
- 5 Future Steps

# Table of Contents

- 1 Motivation
  - Questions
  - Intuition
- 2 Baseline Model
- 3 End-to-end Memory Network
  - Architecture
  - Parameters Tying
  - Implementation Details
- 4 Result
- 5 Future Steps

# Supporting Facts

## Story

Mary went to the bathroom.  
John moved to the hallway.  
Mary travelled to the office.

**Q** Where is Mary? **A** office

## Story

John picked up the apple.  
John went to the office.  
John went to the kitchen.  
John dropped the apple.

**Q** Where was the apple before the kitchen? **A** office

# Reasoning

## Story

Sheep are afraid of wolves.  
Cats are afraid of dogs.  
Mice are afraid of cats.  
Gertrude is a sheep.

**Q** What is Gertrude afraid of? **A** wolves

## Story

Lily is a swan.  
Lily is white.  
Bernhard is green.  
Greg is a swan.

**Q** What color is Greg? **A** white

# Intuition

How do Humans build their answer?

- ① Type of question
- ② Occurrence of the words from the question
- ③ Associations of words (*memory*)
- ④ Meaning of words (*reasoning, interpretation*)

# Table of Contents

- 1 Motivation
  - Questions
  - Intuition
- 2 Baseline Model
- 3 End-to-end Memory Network
  - Architecture
  - Parameters Tying
  - Implementation Details
- 4 Result
- 5 Future Steps

# Count Based Model

Prediction based on two features:

$$\hat{y}(X, Q) = \operatorname{argmax}(\log(f_1(X)) + \log(f_2(Q)))$$

with

- $(X, Q)$  tuple story, question
- $f_1(X)$ : answer words counts in the story (weighted by order of appearance)
- $f_2(Q)$ : embedding of the question based on possible answers question word



# Table of Contents

- 1 Motivation
  - Questions
  - Intuition
- 2 Baseline Model
- 3 End-to-end Memory Network
  - Architecture
  - Parameters Tying
  - Implementation Details
- 4 Result
- 5 Future Steps

# Single Hop Architecture

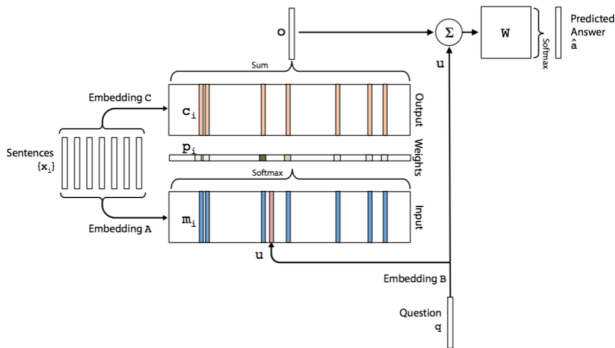


Figure: Single Hop architecture

Source: End-To-end Memory Networks

# Multiple Hops Architecture

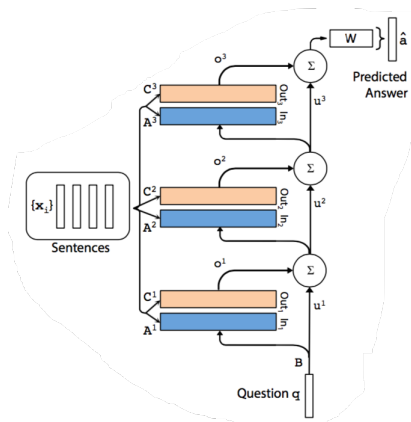


Figure: Multiple Hops architecture

Source: End-To-end Memory Networks

# Parameters Tying

Two Approaches to reduce the number of parameters:

- **Adjacent**

- $A^{k+1} = C^k$
- $B = A^1$

- **RNN-like**

- $A^1 = A^2 = \dots = A^k$
- $C^1 = C^2 = \dots = C^k$
- $u^{k+1} = Hu^k + o^k$

# Implementation Tricks

- bag-of-words representation  $x_i = \{x_{i1}, \dots, x_{is}\}$  becomes  $m_i = \sum_j A x_{ij}$
- Temporal encoding  $m_i = \sum_j A x_{ij} + T_A(i)$
- high variance, best model over several training

# Table of Contents

- 1 Motivation
  - Questions
  - Intuition
- 2 Baseline Model
- 3 End-to-end Memory Network
  - Architecture
  - Parameters Tying
  - Implementation Details
- 4 Result**
- 5 Future Steps

# Table of Contents

- 1 Motivation
  - Questions
  - Intuition
- 2 Baseline Model
- 3 End-to-end Memory Network
  - Architecture
  - Parameters Tying
  - Implementation Details
- 4 Result
- 5 Future Steps