Deep Learning for QA

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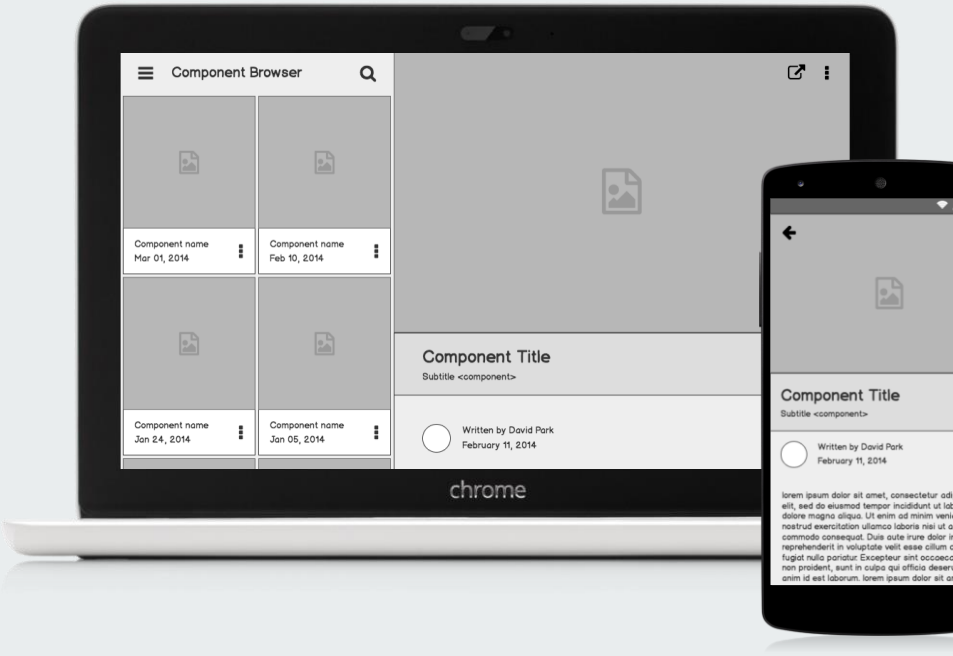


Outline

The Problem

Datasets

Literature review --Current methods

Proposed methods

The Problem

Modelling question answering (QA) using modern deep learning toolkits. This assignment will focus on using information retrieval-based (IR) systems to deduce an answer to the given question.

An Example

The first recorded travels by Europeans to China and back date from this time. The most famous traveler of the period was the Venetian Marco Polo, whose account of his trip to "Cambaluc," the capital of the Great Khan, and of life there astounded the people of Europe. The account of his travels, Il milione (or, The Million, known in English as the Travels of Marco Polo), appeared about the year 1299. Some argue over the accuracy of Marco Polo's accounts due to the lack of mentioning the Great Wall of China, tea houses, which would have been a prominent sight since Europeans had yet to adopt a tea culture, as well the practice of foot binding by the women in capital of the Great Khan. Some suggest that Marco Polo acquired much of his knowledge through contact with Persian traders since many of the places he named were in Persian.

How did some suspect that Polo learned about China instead of by actually visiting it?

Answer: through contact with Persian traders

The given question is sent for question processing to extract the query. This query is sent to an IR engine for document and passage retrieval. The answer is commonly modeled using span labeling; as in the image [1].

Key Datasets

- WebQuestions QA Benchmarking Dataset [2]. Contains training and tests data. Curated by Stanford university.
- The Stanford Question Answering Dataset SQuaD. [3]. Curated by crowd workers on Wikipedia.
- bAbl [4]. End-to-end dialog system dataset.

Review of existing approaches

Several existing approaches exist:

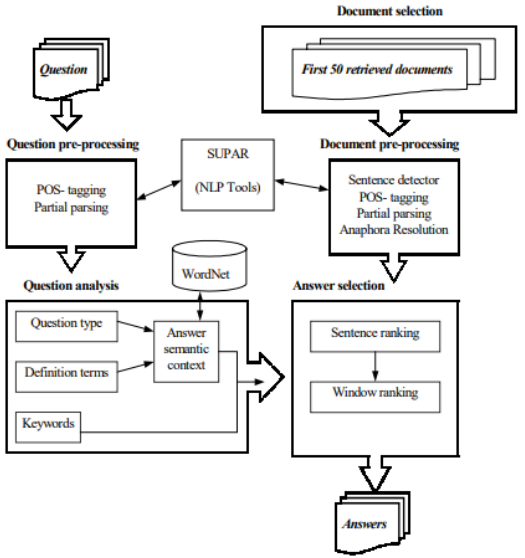
- Semantic approach; process question type and definitions in order to gain a semantic representation [5].
- Memory Networks; inference components to reason over information
- Dynamic Memory Networks; multiple passes over information

What are the current approaches for this problem

- ➔ Semantic; probabilistic and temporal inferences.
- ➔ Memory networks; mapping inputs to answers stored in memory
- ➔ Dynamic memory networks; improving on memory networks through attention mechanisms.

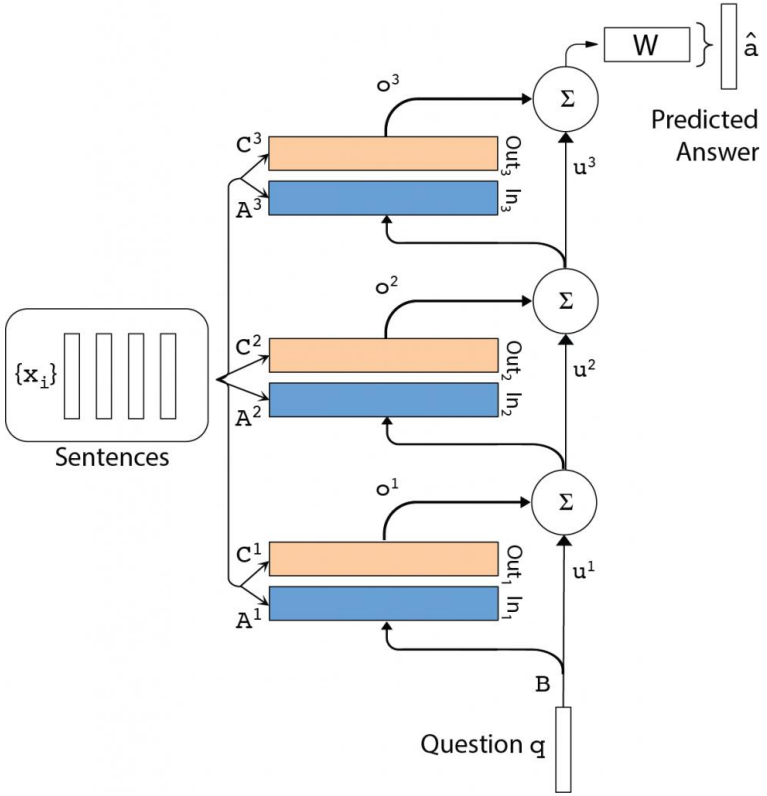
Semantic

- Keywords are selected to help potential answer sources
- Part-of-speech-tagging
- Question type detection by analysing Wh-terms mapped in to categories:
  - PERSON, GROUP, LOCATION, TIME, QUANTITY, REASON, MANNER, NONE
- Answer selection on:
  - Sentence-score = Keyword_idf_sum + (0.65 * Expanded_keyword_idf_sum)
  - Window-score = Sentence-score * (1+cos(Question_SC,Window_SC))



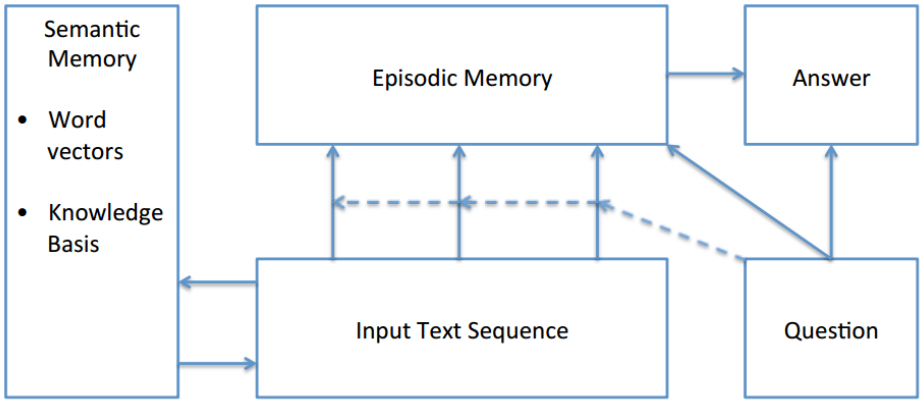
Memory Networks

- ➔ Map questions to answers stored in memory.
- ➔ Single pass in memory before providing an answer
- ➔ Provide one word answer
- ➔ Input accepts word vectors and outputs hidden states for each sentence



Dynamic Memory Networks

- ➔ Provide more efficient answers; longer
- ➔ Multiple passes of the memory before answering
- ➔ Picks relevant facts from a database by using an episodic memory module
- ➔ Parses input “story” and considers each sentences as a fact



Solution Proposal

This project will implement a dynamic memory networks and investigate avenues of improvement in both the network itself and pre-processing of the dataset

Solution description

- Use TensorFlow to implement a dynamic memory network.
- Investigate implementing a semantic memory to the network to aid in forming more relationships between words; using GloVe: Global Vectors for Word Representation [7].
- Train the network using bAbI and WebQuestions.

Why it’s better than existing solutions

Unless adequate pre-training is done on the data or if the implementation does not consider the cosine similarity between two word vectors, then low accuracy will be observed in the system. This research will investigate adding this understanding to the network.

Questions?

References

[1] P. Rajpurkar, "The Stanford Question Answering Dataset", *mlx*, 2019. [Online]. Available: https://rajpurkar.github.io/mlx/qa-and-squad/.

[2] "brmson/dataset-factoid-webquestions", *GitHub*, 2019. [Online]. Available: https://github.com/brmson/dataset-factoid-webquestions

[3] "The Stanford Question Answering Dataset", *Rajpurkar.github.io*, 2019. [Online]. Available: https://rajpurkar.github.io/SQuAD-explorer/.

[4] "bAbI - Facebook Research", *Facebook Research*, 2019. [Online]. Available: https://research.fb.com/downloads/babi/.

[5] J. Luis, *A semantic approach to Question Answering systems*. Universidad de Alicante.

References (continued)

[6] J. Pennington, "GloVe: Global Vectors for Word Representation", *Nlp.stanford.edu*, 2019. [Online]. Available: https://nlp.stanford.edu/projects/glove/.