Question Answering and Chatbots

7th Practical exercise – IR-based QA

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Hochschule Anhalt

Anhalt University of Applied Sciences

Plan for today

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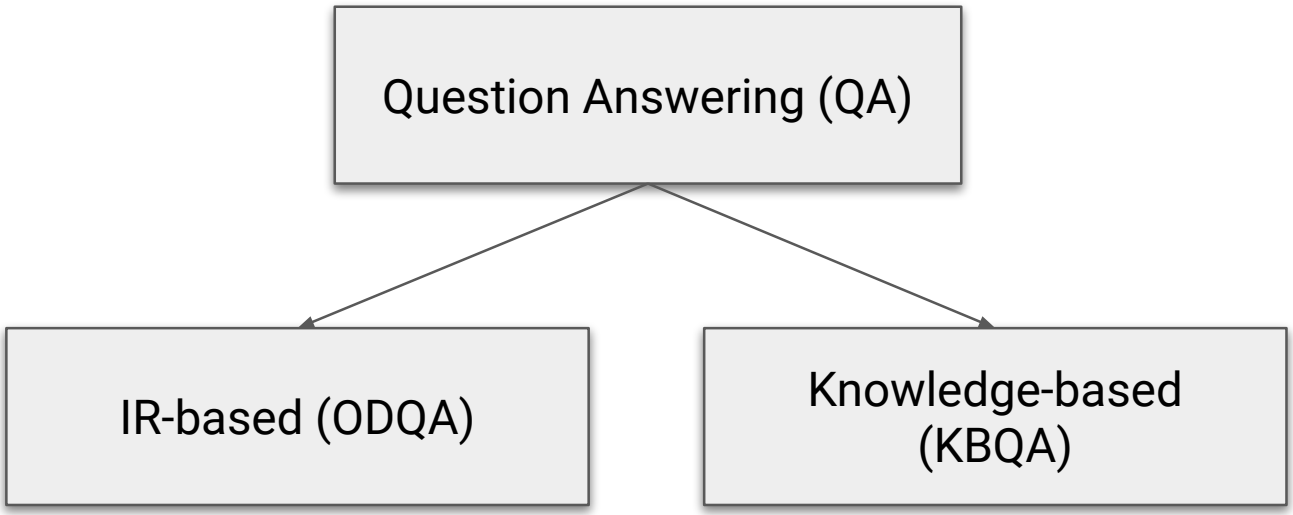
- Introduction of task 7.

Let's start the demo!

Recap: Paradigms of Question Answering



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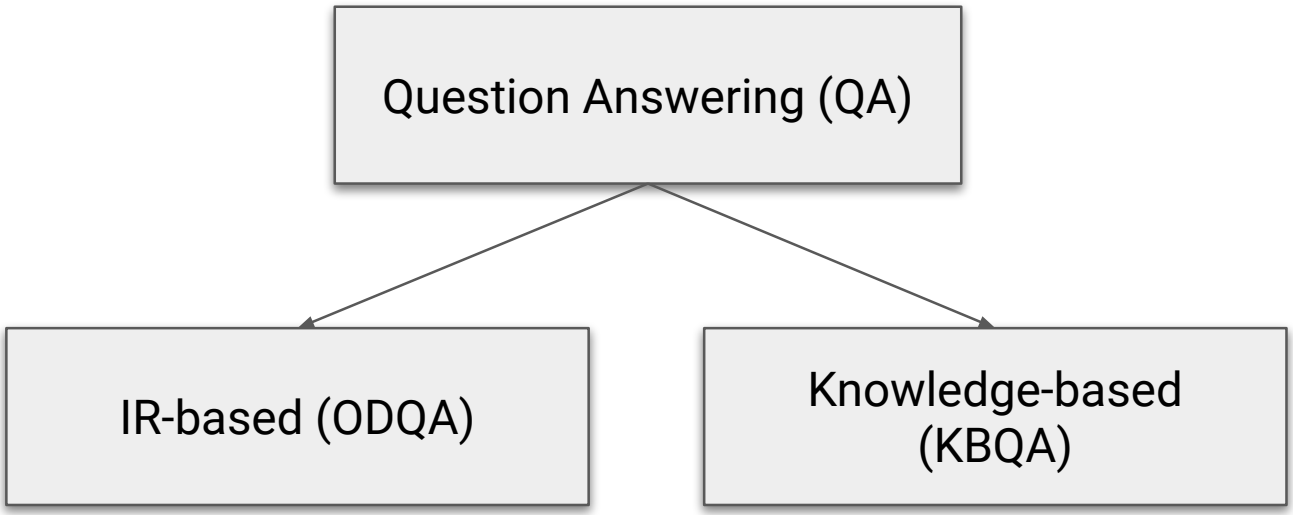

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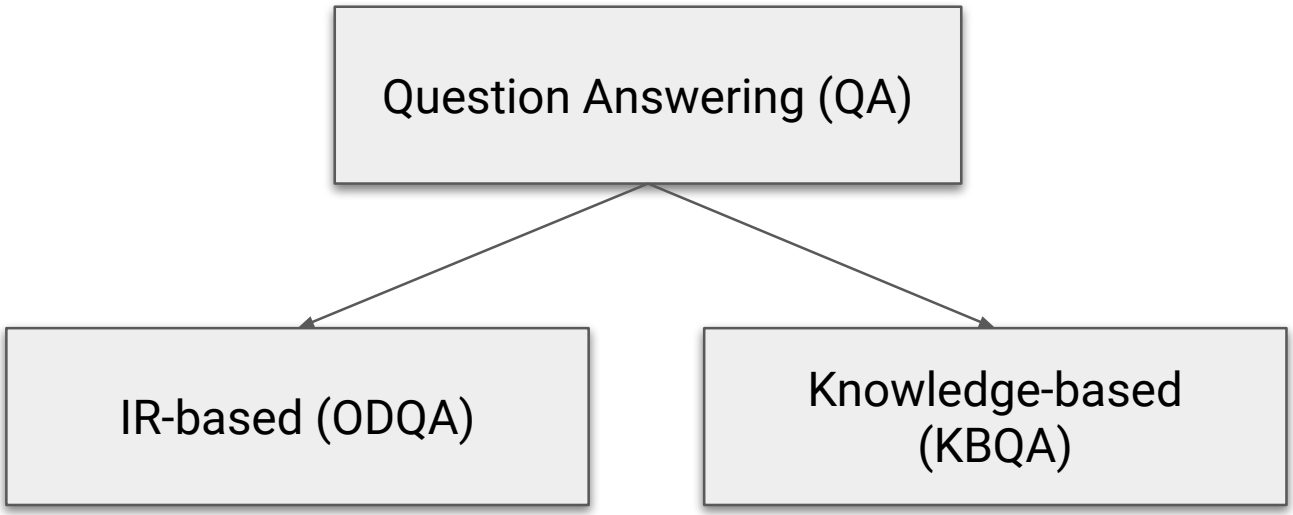

- **IR-based QA (ODQA)** – works with unstructured data;
- **Knowledge-based QA** – works with structured data.

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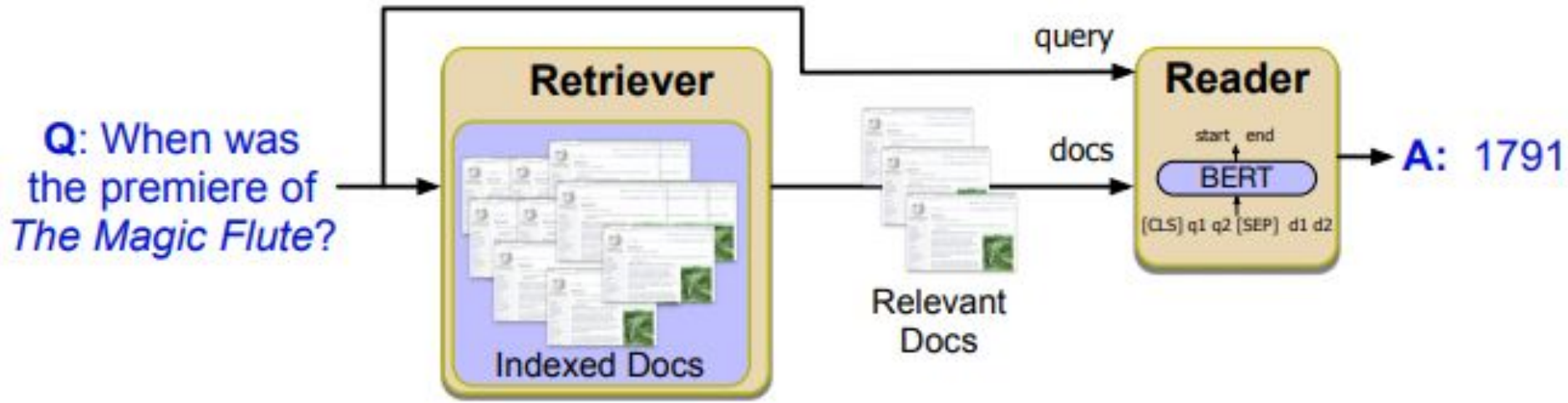
1. Retrieve the most relevant document ("passage") among the others (*retriever step*);
2. Find the answer in the retrieved document by *extracting a textual span from it* (*reader step/reading comprehension*).

Retriever-Reader Architecture



https://web.stanford.edu/~jurafsky/slp3/23.pdf

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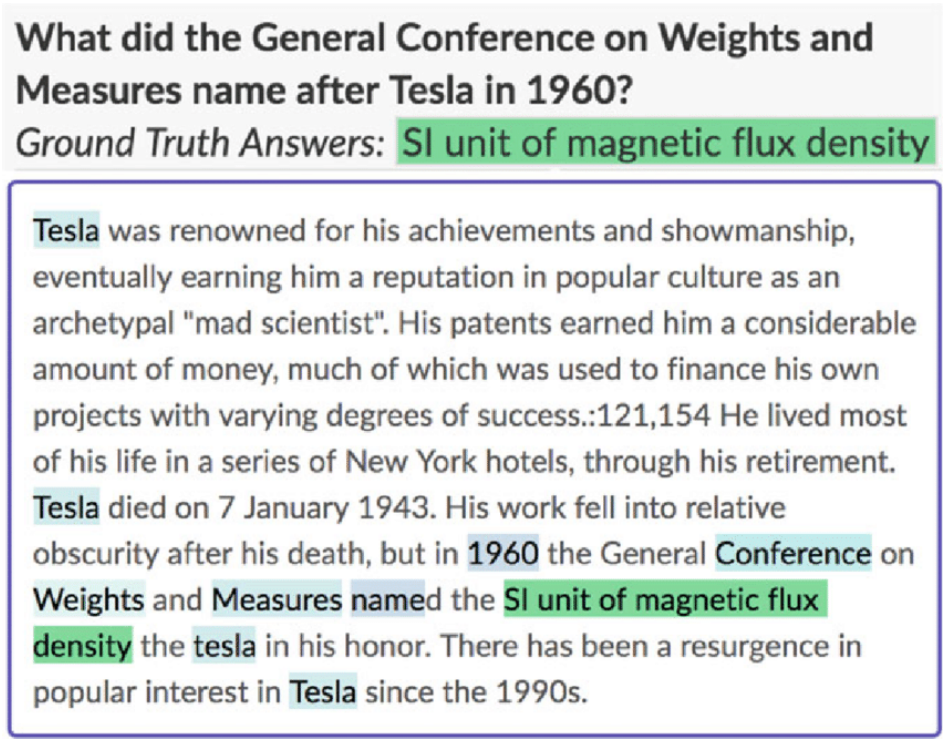
- Keyword-based search (word count);
- (1) Index the documents, (2) encode a question, (3) score the documents;
- But, we can try something else e.g., look for abstracts of named entities in a knowledge graph.

Approaches for the Reader step

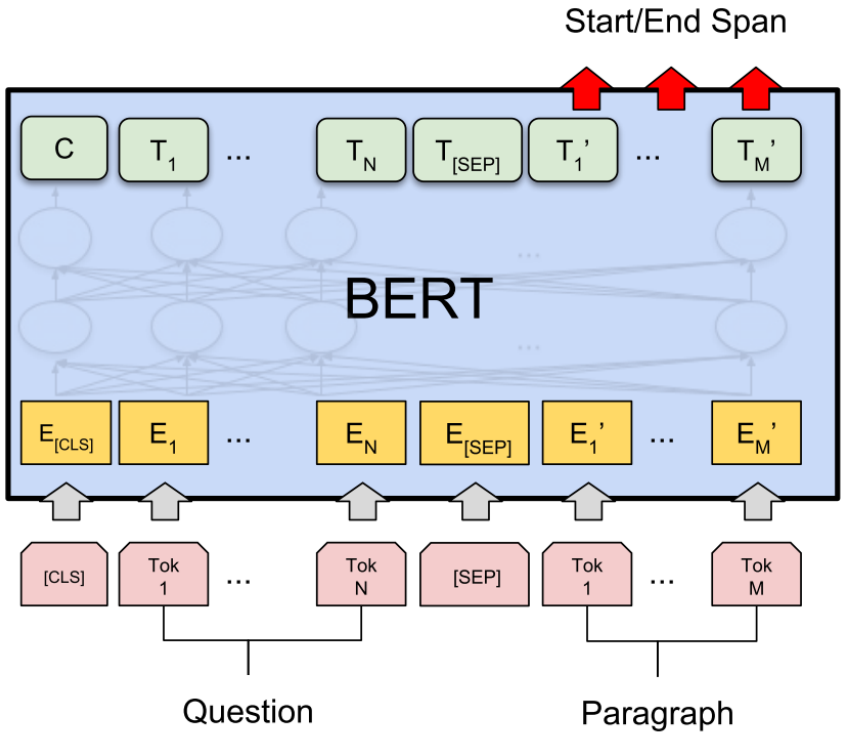
The most common approach is the *machine reading comprehension* (MRC) model



Liu, Zhiyuan. Lin, Yankai. Sun, Maosong. (2020). Document Representation.

Approaches for the Reader step

One of the examples: BERT for question-answering



Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding."

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- Work with your project team members on a first sketch of the system that should fulfill your project.
- Collect 10+ questions and the corresponding answers that should be answered in German and English.
- Create a sketch of the QA components (processing steps).

Any questions?

Let's start the work.

0 Introduction;
1 NER & NEL;
2 Question classification & Web service/API;
3 SPARQL queries over Knowledge Graphs;
4 Simple KGQA system – based on exercises 0, 1, 2, 3;
5 Qanary Framework – component oriented approach;
6 Evaluation of QA systems;
7 **Simple IR-based/ODQA system**.