Question Answering and Chatbots

2nd Practical exercise – Question Classification

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Text Classification Task

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Types of classification:

Binary	2 classes
Multi-class	$>$ 2 classes (typically)
Multi-label	a data item might have $\geq$ 1 class

Text or Question classification

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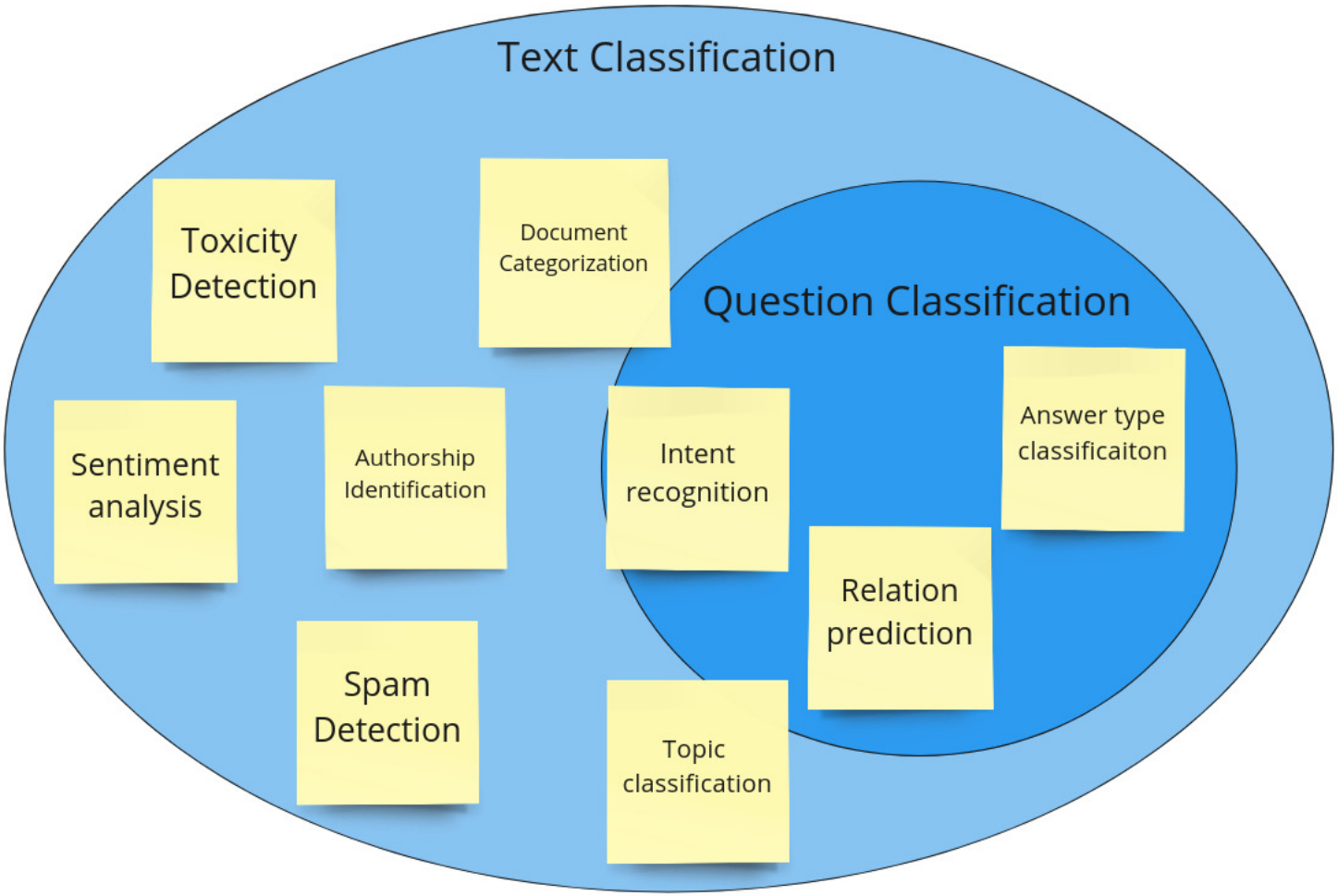

Question classification in QA

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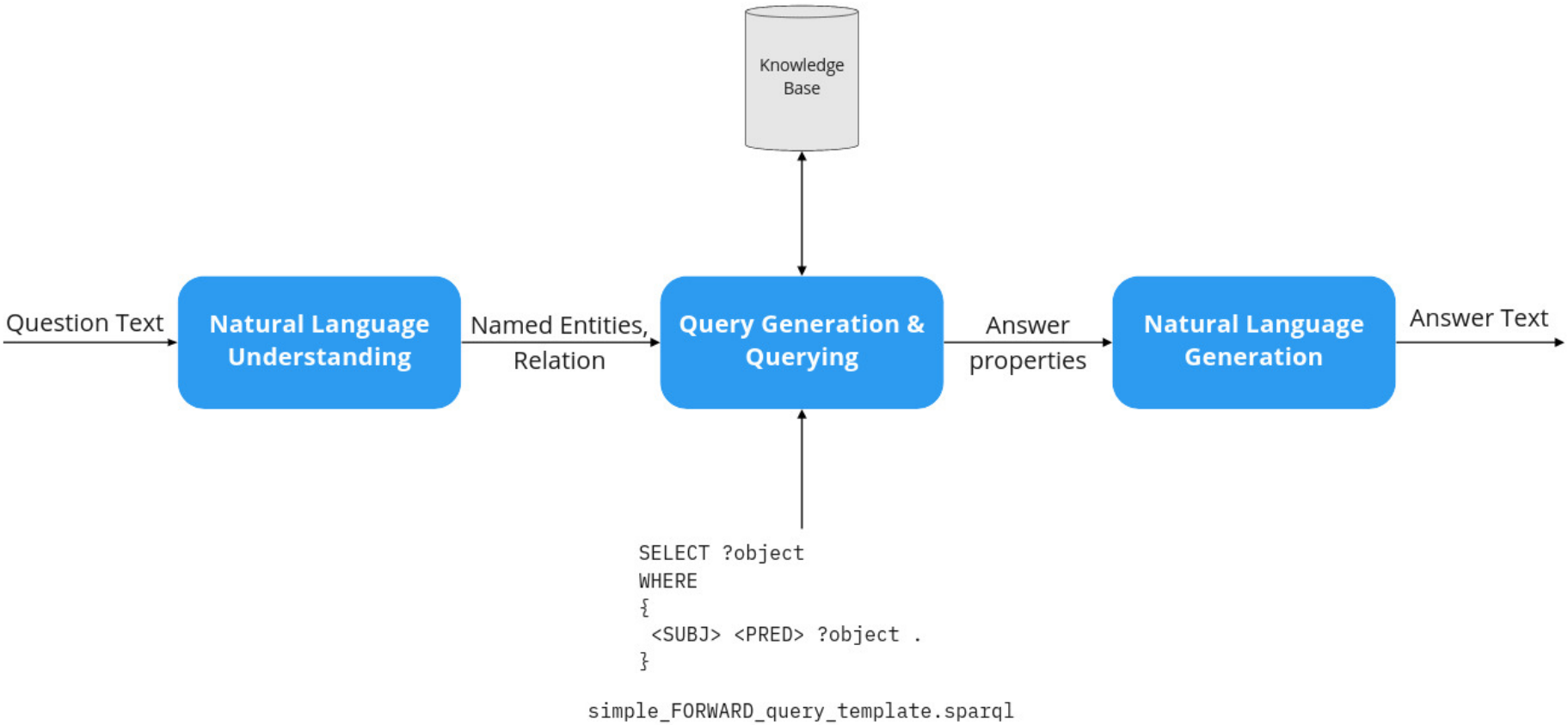

Figure: QA system architecture for "Simple Questions"

Text-to-vector transformation

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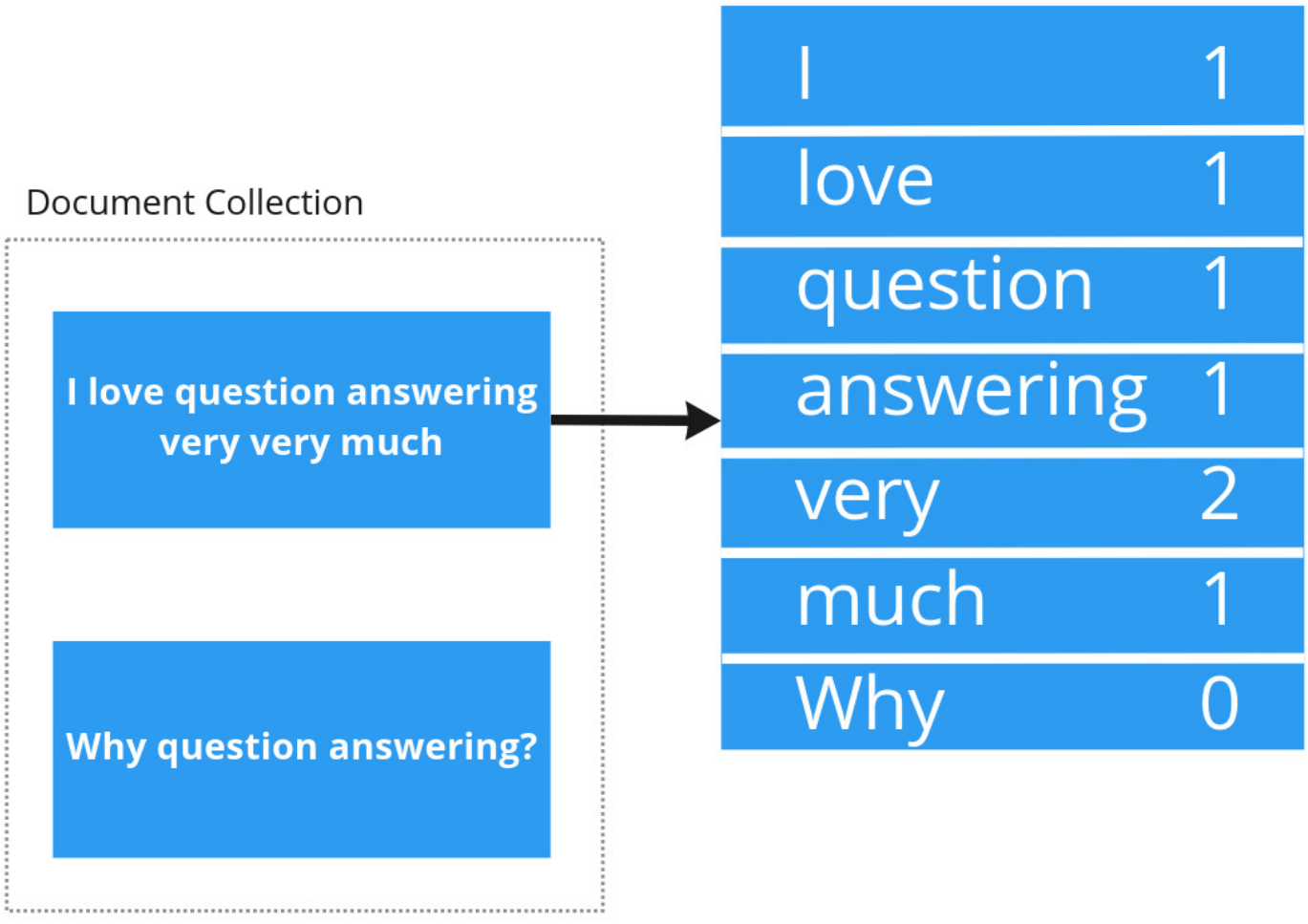
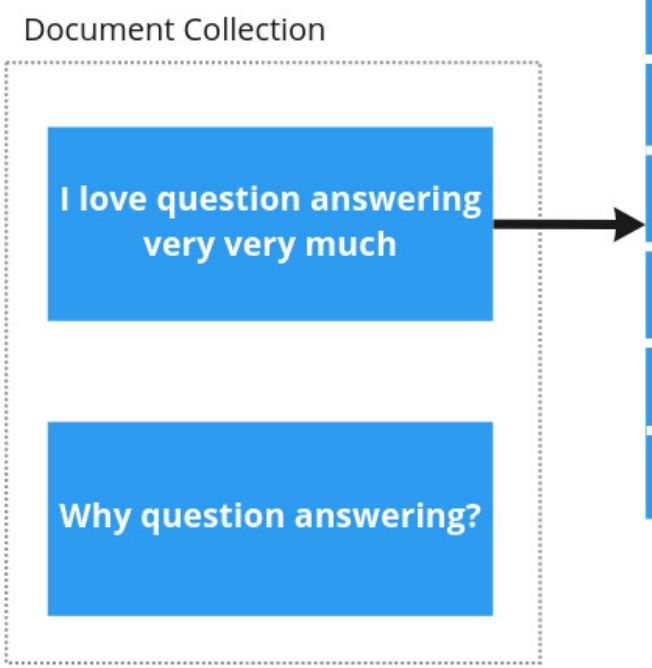
Bag of Words



Text-to-vector transformation

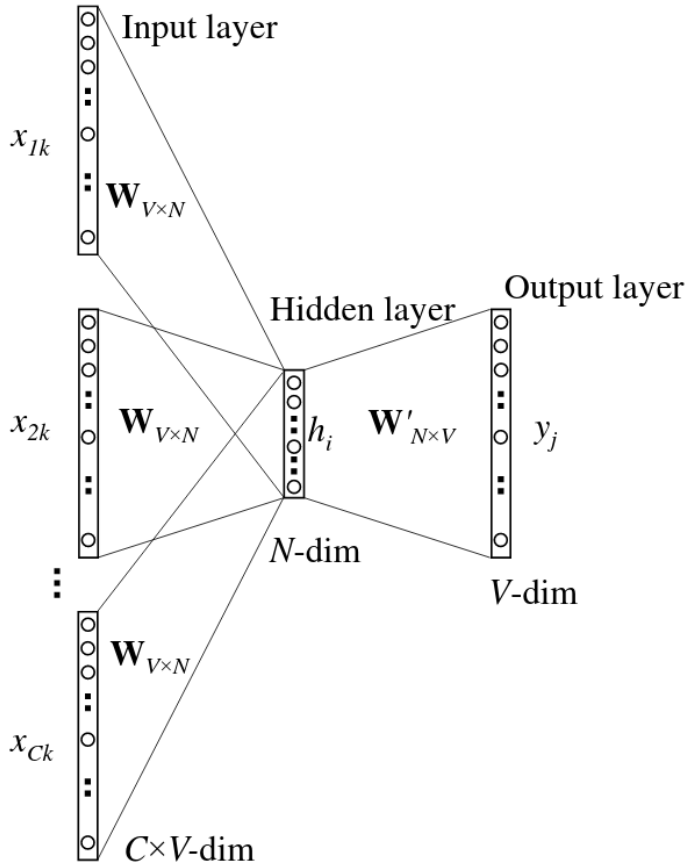
Term Frequency - Inverse Document Frequency (TF-IDF)



	TF	IDF	TFxIDF
I	1/7	log(2/1)	0.099
love	1/7	log(2/1)	0.099
question	1/7	log(2/2)	0.0
answering	1/7	log(2/2)	0.0
very	2/7	log(2/1)	0.198
much	1/7	log(2/1)	0.099
Why	0/7	log(2/1)	0.0

Text-to-vector transformation

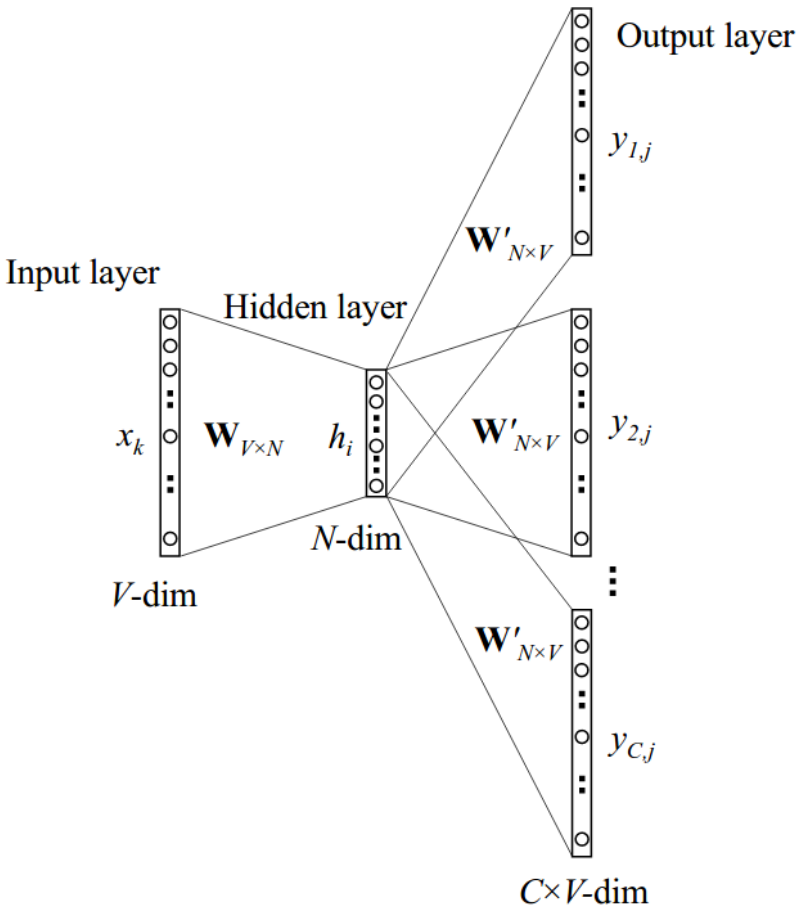
Word2Vec (2013) – Continious Bag of Words [1]



[1] `https://arxiv.org/pdf/1411.2738.pdf`

Text-to-vector transformation

Word2Vec (2013) – Skip-Gram [1]



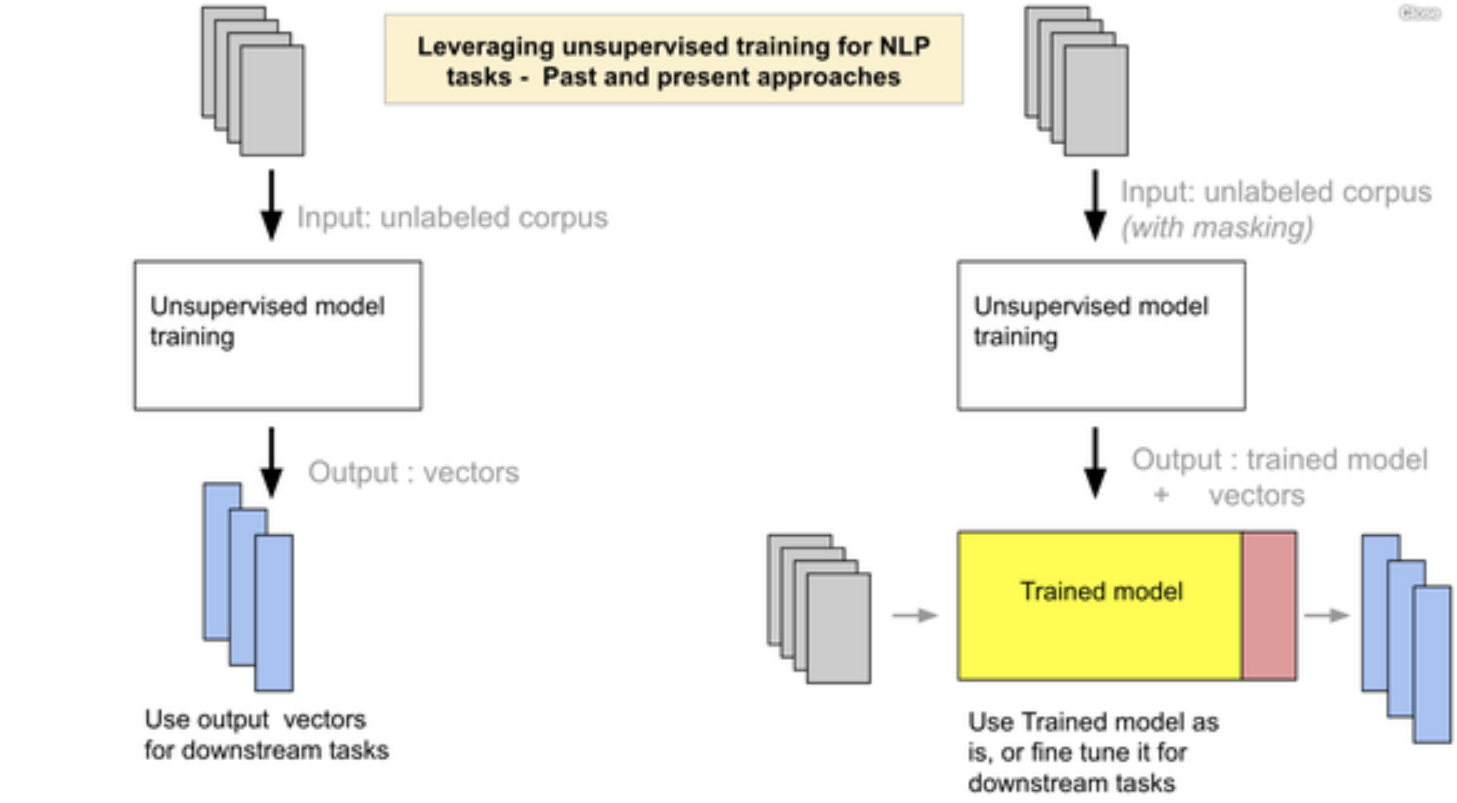
[1] https://arxiv.org/pdf/1411.2738.pdf

Text-to-vector transformation

fastText (2016) – Same as Word2Vec, but instead of words character n-grams are considered as an input.

For example the word vector “apple” is a sum of the vectors of the n-grams “ap”, “app”, ”appl”, ”apple”, ”apple”, “ppl”, “pple”, ”pple”, “ple”, ”ple”, ”le” (assuming hyperparameters for smallest ngram is 3 and largest ngram is 6).

Modern approaches



[2] https://www.quora.com/What-were-the-most-significant-Natural-Language-Processing-advances-in-2018

Let's do the exercise. Ask me if you have a question.

Exercise 2 – Context

Text classification has many applications in Natural Language Processing. Specifically, in Question Answering & Chatbots, it can be used as a **Relation (Predicate) Prediction** component.

Exercise 2 – Context

Relation (or Predicate) in terms of knowledge graphs is an **edge that is connecting two nodes (or entities)**. For example, having a triple: <Mona_Lisa> <?> <Leonardo_da_Vinci> the relation <?> is <Author> (or e.g. <Was_Created_By>).

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In this regard, Relation Prediction is the task of **recognizing a relation, based on a textual question**. In this case, question: "Who is the author of Mona Lisa?" has relation "Author" (or e.g. "Was created by").

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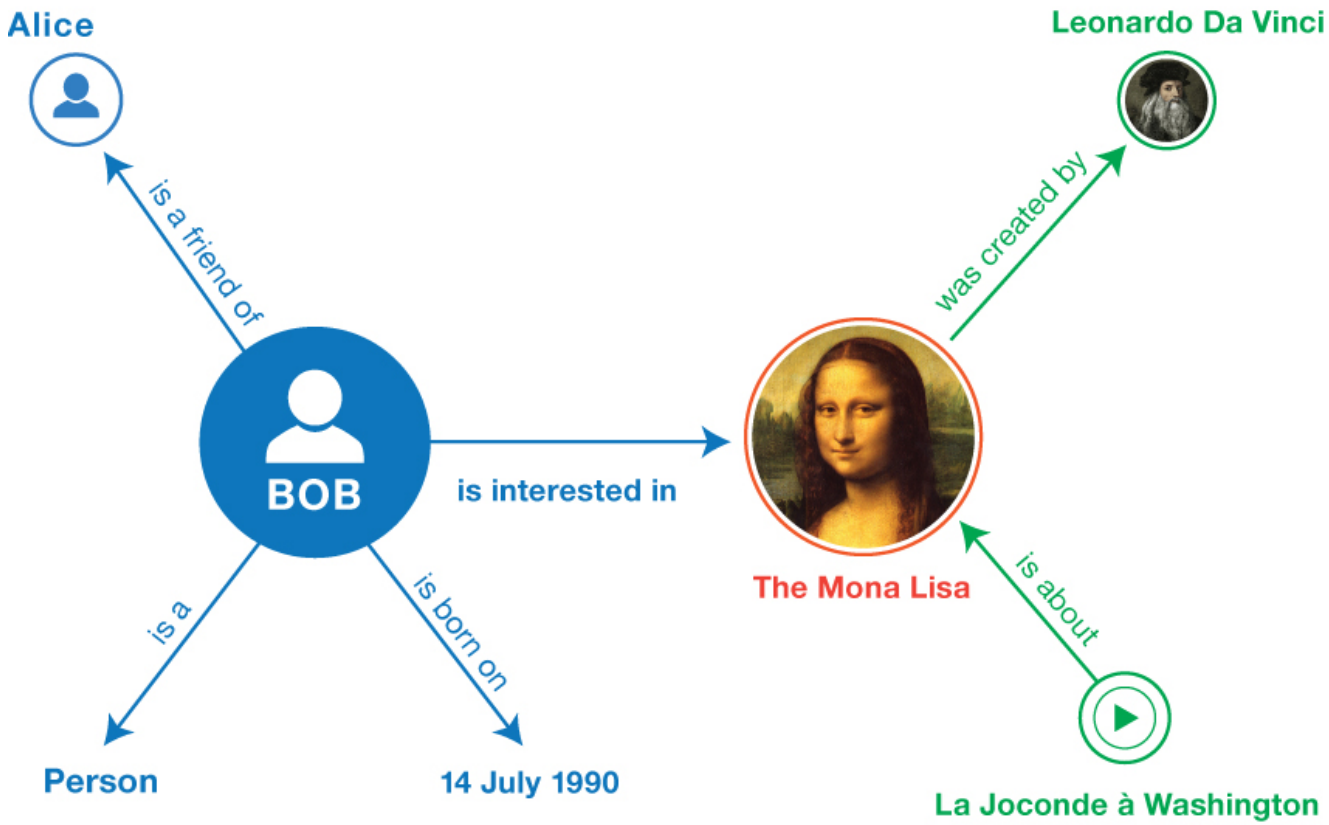

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Implement a question classification algorithm based on provided training data (see variant). You can use a Rule-Based approach (e.g., keyword classifier) or a Machine Learning approach (e.g., Bag of Words + Logistic Regression).

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Implement a question classification algorithm based on provided training data (see variant). You can use a Rule-Based approach (e.g., keyword classifier) or a Machine Learning approach (e.g., Bag of Words + Logistic Regression).
For evaluation use the following metrics: Precision, Recall, F1 Score.
See details in Moodle/Github.

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- Request path name: /predict;
- Request type: POST;
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After you establish a Web service, run all your questions through the /predict method and write the predictions into a structured JSON file.

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- Learn syntax;
- Given a set of questions – write SPARQL for DBpedia;
- Given a set of questions – write SPARQL for Wikidata;
- Create a script for executing the queries and writing the output.

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 Simple ODQA system?;
7 Evaluation of QA systems.