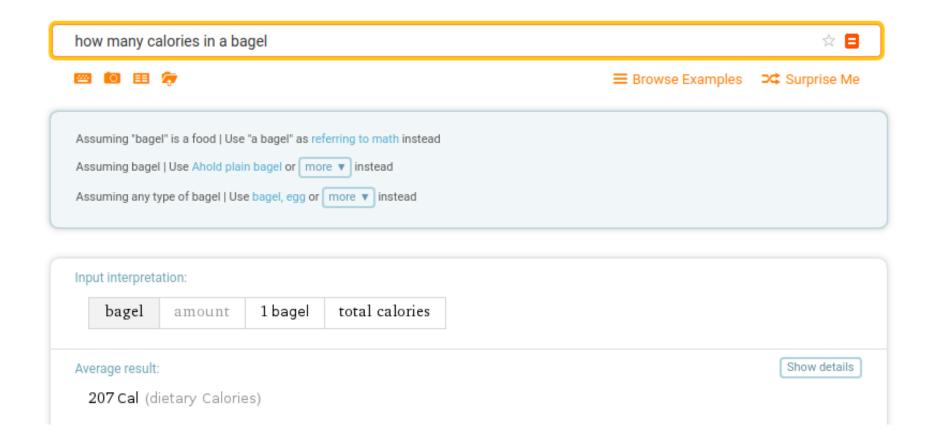
Question Answering

Natural Language Processing

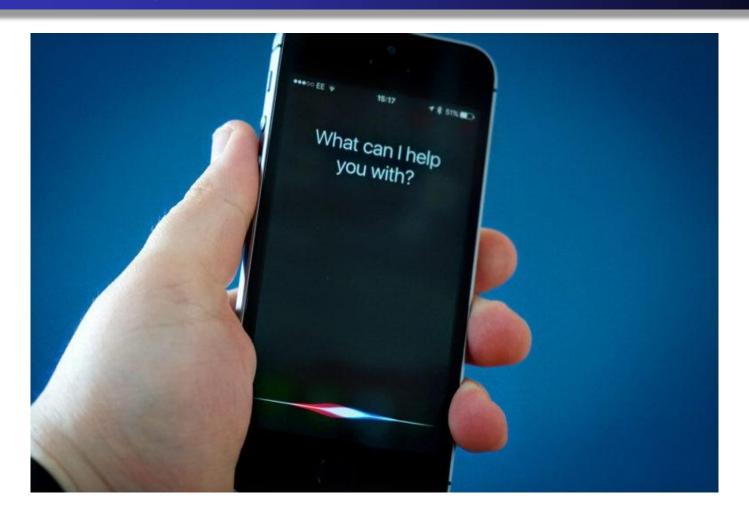
Master in Business Analytics and Big Data

acastellanos@faculty.ie.edu













What smell brings back great memories?

Go!

Passages from books

Part of the human experience is sudden recollection, spawned by new information coming in through the senses. The aroma of frying chicken take me back to summers in Alabama at my grandmother's house. Certain blossoms in Spring evoke memories of people and places from the past. 99 (view in book)



from Stranger to My Self: Inside Depersonalization : the Hidden Epidemic by Jeffrey Abugel

I worked the tissues. The smell of this old place, old people, alcohol and cigarettes from years of partying, brought back so many memories. Miss Barbara, Miss Dobbs, Miss Lang, Miss Jackson and all of them who I knew from growing up in this Big House. II (view in book)



from Granny Boop's Big House: Growing up Gay White Trash and Liking It by Frankie James

QA vs. IR

Information Retrieval

- Retrieve documents related to the query (and the snippet where the query appears)
- Boolean like
- Query Driven

Question Answering

- Answer the query
- NLP like
- Answer Driven
- IR is usually included in the QA Pipeline
 - IR to retrieve relevant documents --> QA to find the answer in the documents

QA vs. IR



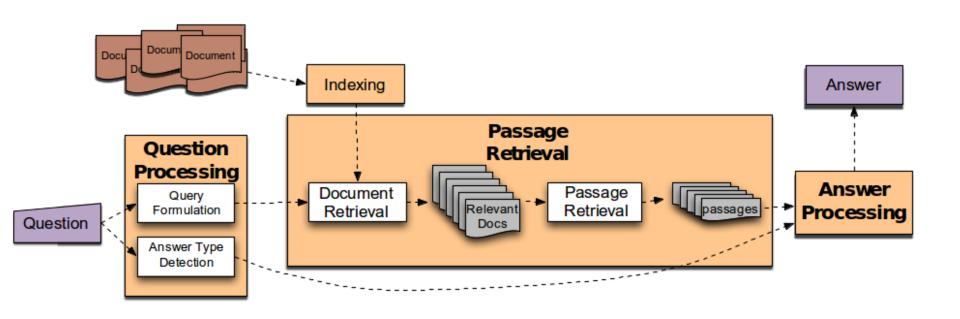
Question Answering

Information Retrieval

QA Paradigms

- IR-based approaches
 - Google

- Knowledge-based and Hybrid approaches
 - IBM Watson
 - Apple Siri
 - Wolfram Alpha



Question Answering [Dan Jurafsky, Stanford]

Question Processing

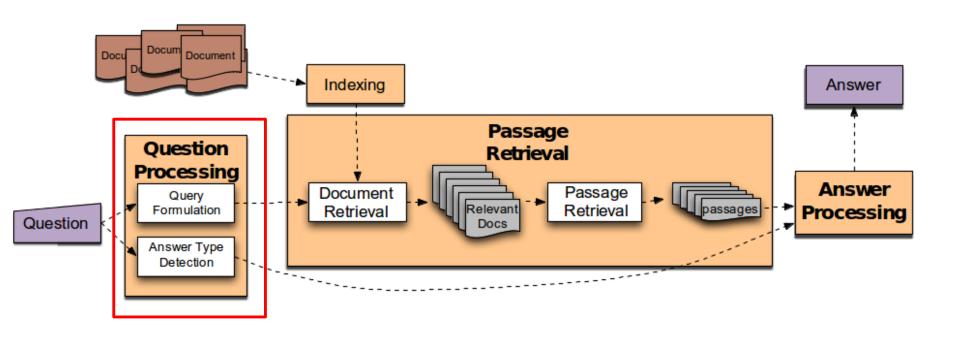
- Detect question type: (Who?, Where? How much?...)
- Formulate (i.e. construct) IR-based queries

Passage Retrieval

- Retrieve related documents
- Extract suitable passages and re-rank

Answer Processing

- Extract candidate answers
- Rank candidates
- Using evidence from the text and external sources



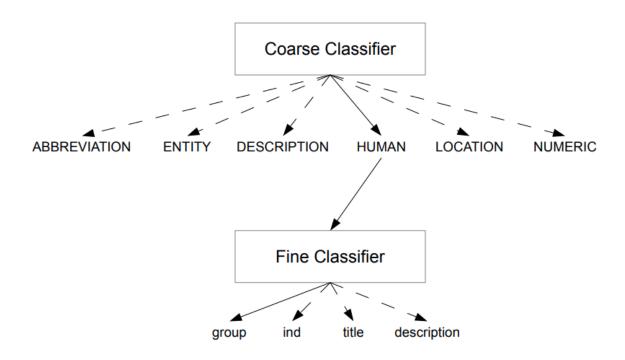
Question Answering [Dan Jurafsky, Stanford]

- Who founded Tesla?
 - PERSON

- What Spanish city has the largest population?
 - CITY

- Where is the next world cup going to be held?
 - LOCATION

- Answer Type Taxonomy
 - Xin Li, Dan Roth. 2002. Learning Question Classifiers. COLING'02



- Answer Type Taxonomy
 - Xin Li, Dan Roth. 2002. Learning Question Classifiers. COLING'02
- Answer types in Jeopardy
 - 2500 types --> 50% covered by 200 most frequent
 - Ferrucci et al. 2010. Building Watson: An Overview of the DeepQA Project. Al Magazine. Fall 2010. 59-79.

- Regular expression-based rules can get some cases:
 - In what country was X born?
 - X (PERSON) was born in Y(PLACE)
- Use question headword:
 - Headword of the first noun phrase after the wh-word
 - Which city in China has the largest number of foreign financial companies?
 - What is the state flower of California?

- Treat the problem as machine learning classification
 - Taxonomy of question types: Target variable
 - Annotated training data
 - Train classifiers for each question type using a rich set of features.

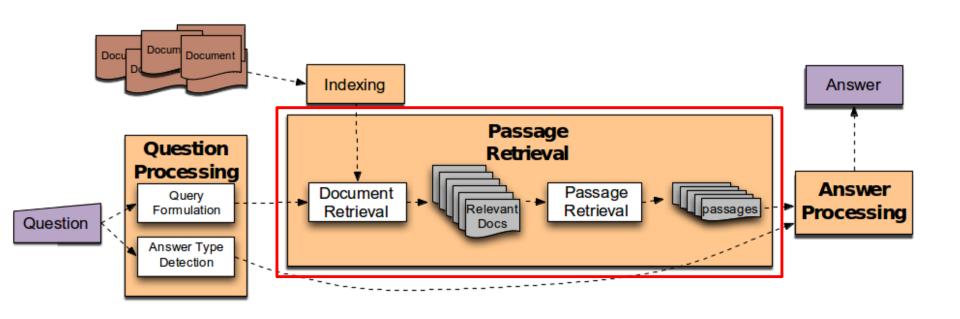
features include those hand-written rules!

- Question words and phrases
- Part-of-speech tags
- Parse features (headwords)
- Named Entities
- Semantically related words

Query Formulation

Keyword Selection

- Dan Moldovan, Sanda Harabagiu, Marius Paca, Rada Mihalcea, Richard Goodrum, Roxana Girju and Vasile Rus. 1999. Proceedings of TREC-8.
- 1. Select all non-stop words in quotations
- 2. Select all NNP words in recognized named entities
- 3. Select all complex nominals with their adjectival modifiers
- 4. Select all other complex nominals
- 5. Select all nouns with their adjectival modifiers
- 6. Select all other nouns
- 7. Select all verbs
- 8. Select all adverbs
- 9. Select the QFW word (skipped in all previous steps)
- 10. Select all other words



Question Answering [Dan Jurafsky, Stanford]

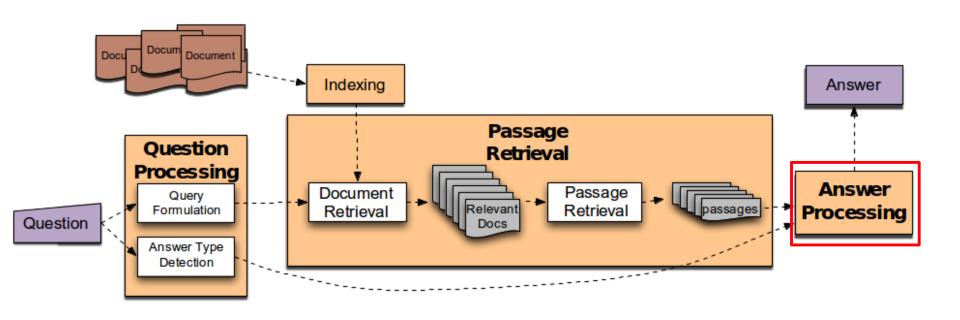
Passage Retrieval

- Step 1: IR engine retrieves documents using query terms
 - The query formulated at the previous step
- Step 2: Segment the documents into shorter units
 - Paragraph-based Tokenization
- Step 3: Passage ranking
 - Use answer type to help re-rank passages

Passage Retrieval

Features for Passage Ranking

- Number of Named Entities of the right type in passage
- Number of query words in passage
- Number of question N-grams also in passage
- Proximity of query keywords to each other in passage
- Longest sequence of question words
- Rank of the document containing passage



Answer Extraction

- Run an answer-type named-entity tagger on the passages
 - Each answer type requires a named-entity tagger that detects it
 - If answer type is CITY, tagger has to tag CITY
 - Can be full NER, simple regular expressions, or hybrid
- Return the string with the right type:
 - Who is the prime minister of India (PERSON)

Manmohan Singh, Prime Minister of India, had told left leaders that the deal would not be renegotiated.

• How tall is Mt. Everest? (LENGTH)

The official height of Mount Everest is 29035 feet

Answer Extraction

Multiple candidate answers

Q: Who was Queen Victoria's second son?

Answer Type: **Person**

The Marie biscuit is named after Marie

Alexandrovna, the daughter of Czar Alexander II of

Russia and wife of Alfred, the second son of Queen

Victoria and Prince Albert

Features for ranking candidate answers

- Answer type match: Candidate contains a phrase with the correct answer type.
- **Pattern match:** Regular expression pattern matches the candidate.
- Question keywords: # of question keywords in the candidate.
- Keyword distance: Distance in words between the candidate and query keywords
- Novelty factor: A word in the candidate is not in the query.
- Apposition features: The candidate is an appositive to question terms
- Punctuation location: The candidate is immediately followed by a comma, period, quotation marks, semicolon, or exclamation mark.
- **Sequences of question terms:** The length of the longest sequence of question terms that occurs in the candidate answer.

Answer Sentence Selection

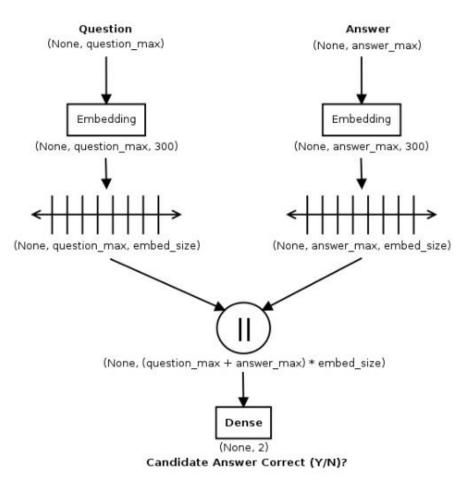
| Algorithm | Reference | MAP 🗗 | MRR 🕏 | |
|--|------------------------------|-------|-------|--------------|
| Punyakanok (2004) | Wang et al. (2007) | 0.419 | 0.494 | |
| Cui (2005) | Wang et al. (2007) | 0.427 | 0.526 | |
| Wang (2007) | Wang et al. (2007) | 0.603 | 0.685 | |
| H&S (2010) | Heilman and Smith (2010) | 0.609 | 0.692 | Dog |
| W&M (2010) | Wang and Manning (2010) | 0.595 | 0.695 | Bag |
| Yao (2013) | Yao et al. (2013) | 0.631 | 0.748 | alignn |
| S&M (2013) | Severyn and Moschitti (2013) | 0.678 | 0.736 | (/ T |
| Shnarch (2013) - Backward | Shnarch (2013) | 0.686 | 0.754 | |
| Yih (2013) - LCLR | Yih et al. (2013) | 0.709 | 0.770 |]/ |
| Yu (2014) - TRAIN-ALL bigram+count | Yu et al. (2014) | 0.711 | 0.785 | / |
| W&N (2015) - Three-Layer BLSTM+BM25 | Wang and Nyberg (2015) | 0.713 | 0.791 | \downarrow |
| Feng (2015) - Architecture-II | Tan et al. (2015) | 0.711 | 0.800 | |
| S&M (2015) | Severyn and Moschitti (2015) | 0.746 | 0.808 | Deep |
| W&I (2015) | Wang and Ittycheriah (2015) | 0.746 | 0.820 | |
| Tan (2015) - QA-LSTM/CNN+attention | Tan et al. (2015) | 0.728 | 0.832 | |
| dos Santos (2016) - Attentive Pooling CNN | dos Santos et al. (2016) | 0.753 | 0.851 | |
| Wang et al. (2016) - Lexical Decomposition and Composition | Wang et al. (2016) | 0.771 | 0.845 | |

Bag of words, Word alignment, Dependency Tree Matching

Deep Neural Networks, LSTM

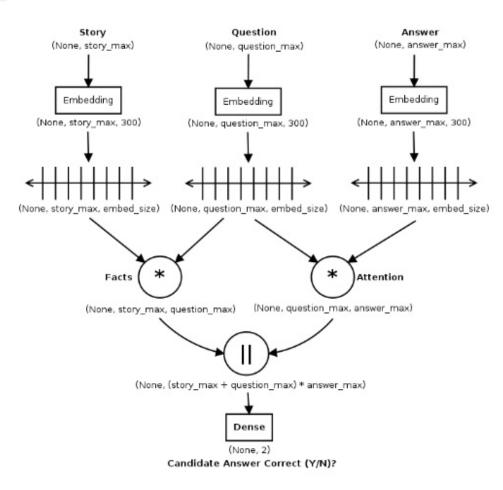
http://aclweb.org/aclwiki/index.php?title=Question_Answering_(State_of_the_art)

QA-LSTM Model



https://www.slideshare.net/sujitpal/deep-learning-models-for-question-answering

QA-LSTM Model



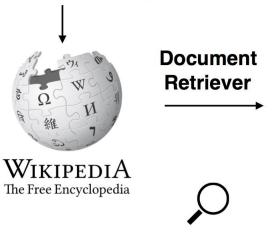
https://www.slideshare.net/sujitpal/deep-learning-models-for-question-answering

Facebook's DrQA

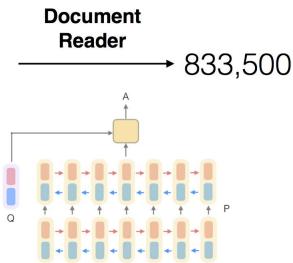
Open-domain QA

SQuAD, TREC, WebQuestions, WikiMovies

Q: How many of Warsaw's inhabitants spoke Polish in 1933?





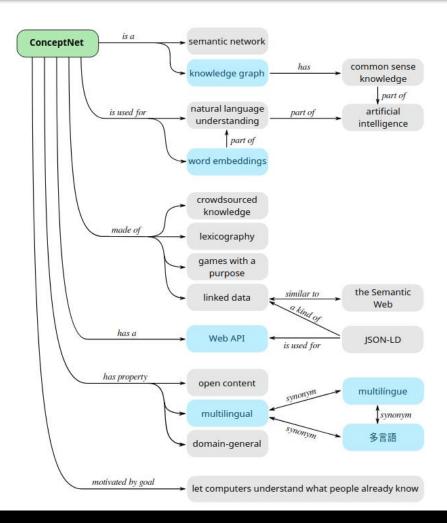


https://research.fb.com/downloads/drqa/

Knowledge-based QA

- Build a semantic representation of the query
 - Times, dates, locations, entities, numeric quantities
- Map from this semantics to query structured database
 - Geospatial databases (geonames.org, GeoQuery, OpenStreetMap)
 - Ontologies (Wikipedia infoboxes, DBPedia, WordNet, Yago, Freebase, Wikidata)
 - Review sources and reservation services (Yelp, Amazon)
 - Scientific databases

ConceptNet





Entity-centric Knowledge Databases



Build the representation

- Answers: Databases of Relations
 - Wikipedia infoboxes, DBpedia, FreeBase, etc.

```
born-in("Emma Goldman", "June 27 1869")
author-of("Cao Xue Qin", "Dream of the Red Chamber")
```

Questions: Find these relations in Questions

```
Whose granddaughter starred in E.T.? (acted-in ?x "E.T.")
(granddaughter-of ?x ?y)
```

Build the representation

Ad-hoc manual rules

- Scalability Issues
- Does not support "open-domain" questions
- Coverage

Semantic Parsing

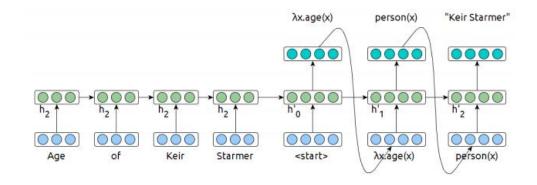
- Learn a translation function
- Language Mismatch
- Incomplete Knowledge Bases

Freebase

| Relation | Percentage unknown | | | |
|------------------|--------------------|----------|--|--|
| | All 3M | Top 100K | | |
| PROFESSION | 68% | 24% | | |
| PLACE OF BIRTH | 71% | 13% | | |
| NATIONALITY | 75% | 21% | | |
| EDUCATION | 91% | 63% | | |
| SPOUSES | 92% | 68% | | |
| PARENTS | 94% | 77% | | |
| CHILDREN | 94% | 80% | | |
| SIBLINGS | 96% | 83% | | |
| ETHNICITY | 99% | 86% | | |

Build the representation

A Deep Learning Approach



- Like in MT, using attention can be helpful
 Dong and Lapata (2016): Language to Logical Form with Neural Attention
- Exploit the highly rigid structure in the target side to constrain generation
 Ling et al. (2016): Latent predictor networks for code generation
- Make use of semi-supervised training to counter sparsity
 Kocisky et al. (2016): Semantic Parsing with Semi-Supervised Sequential Autoencoders

Relationship Reasoning

Temporal Reasoning

```
"In 1594 he took a job as a tax collector in Andalusia"
```

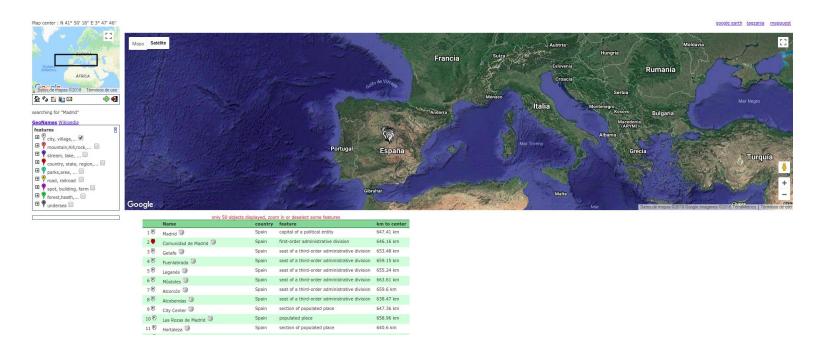
Thoreau is a bad answer (born in 1817)

Cervantes is possible (was alive in 1594)

Relationship Reasoning

Geospatial Reasoning

- Beijing is a good answer for "Asian city"
- California is "southwest of Montana"



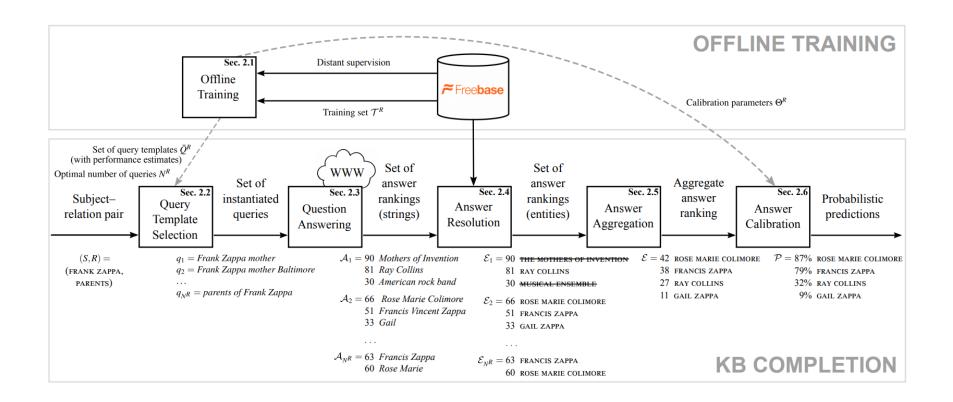
Hybrid-based QA

Build a shallow semantic representation of the query

- Generate answer candidates using IR methods
 - Augmented with ontologies and semi-structured data

- Score each candidate using richer knowledge sources
 - Geospatial databases
 - Temporal reasoning
 - Taxonomical classification

Hybrid-based QA



Knowledge Base Completion via Search-Based Question Answering [Robert West, et al., WWW 2014]

IBM Watson Architecture

Multiple interpretations

Hundreds of answer sources

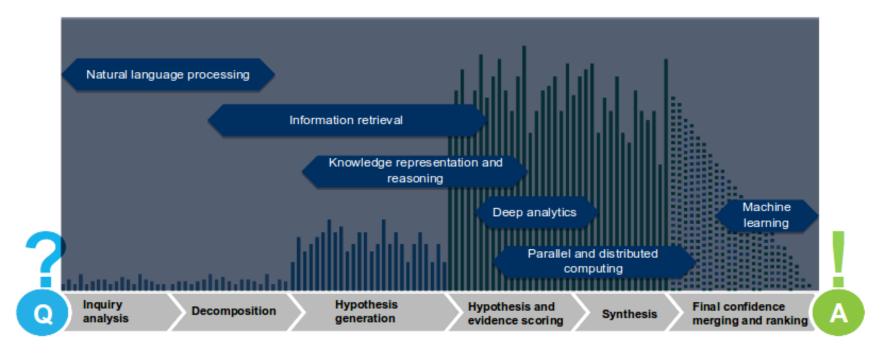
- Primary search
- Candidate answer generation

Tens of thousands of evidence sources and scores

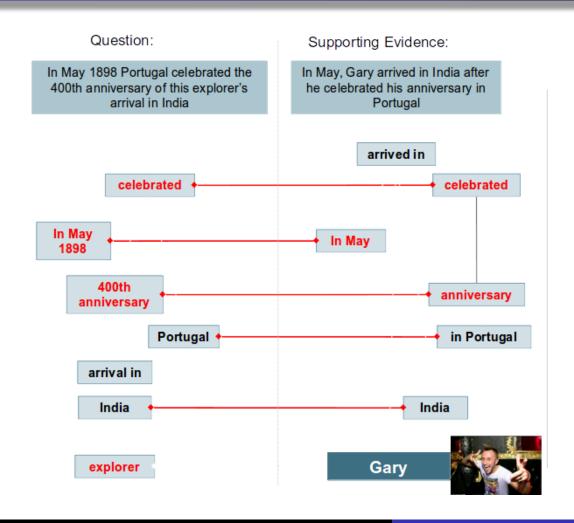
- · Answer scoring
- · Evidence retrieval
- . Deep evidence scoring

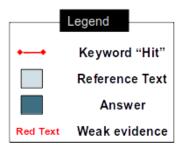
Learned models

· Combine and weigh evidence



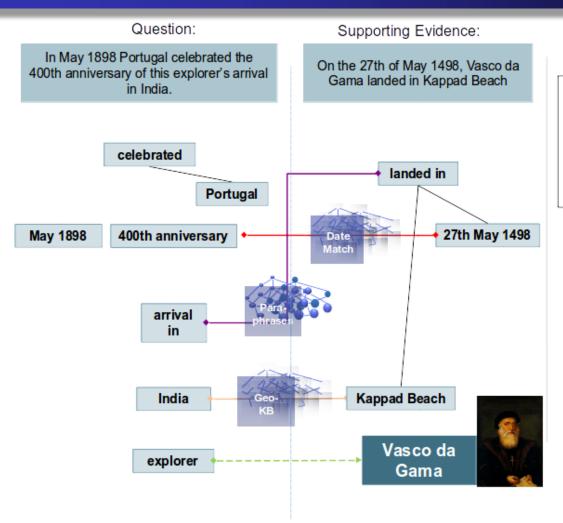
IBM Watson Architecture

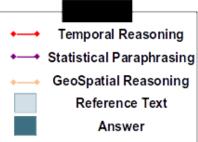




This evidence suggests
"Gary" is the answer
BUT the system must
learn that keyword
matching may be weak
relative to other types of
evidence

IBM Watson Architecture





Stronger evidence can be much harder to find and score...

Search far and wide Explore many hypotheses Find judge evidence Many inference algorithms

Resources

- A survey on question answering systems with classification https://www.sciencedirect.com/science/article/pii/S1319157815000890
- How does the [current] best question answering model work?
 https://towardsdatascience.com/how-the-current-best-question-answering-model-works-8bbacf375e2a
- QA State of the Art
 https://aclweb.org/aclwiki/Question_Answering (State of the art)
- Strategies for Advanced Question Answering
 https://pdfs.semanticscholar.org/e10b/08e1c7c5fd37b19eaf24a9addc503b4
 13c65.pdf
- Facebook DrQA
 https://github.com/facebookresearch/DrQA

Resources

Datasets

- Nguyen et al. (2016), MS MARCO: A Human Generated Machine Reading Comprehension
- Dataset Haas and Riezler (2016), A Corpus and Semantic Parser for Multilingual Natural Language Querying of OpenStreetMap
- Deep Language Modeling for Question Answering using Keras
 - https://codekansas.github.io/blog/2016/language.html