Hasso Plattner Institut

IT Systems Engineering | Universität Potsdam

Natural Language Processing

Question Answering

Potsdam, 21 June 2012

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Information Systems Group

Outline

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1. Introduction
2. History
3. QA Architecture

Outline

Motivation

- Finding small segments of text which answer users' questions

Motivation

Who is Warren Moon's agent? Search

Booking Warren Moon Appearances, Contact Warren Moon Agent ...
Call 1-888-246-7141 to Contact **Warren Moon Agent** for Booking **Warren Moon** for corporate appearances, **Warren Moon** speaking engagements, **Warren Moon ...**
www.athletepromotions.com/.../Warren-Moon-appearance-booking-agent.php -
Cached - Similar -

Warren Moon Speaker, Warren Moon Appearance, Warren Moon ...
Whether you are looking for a **Warren Moon** speaker event, **Warren Moon** appearance, or **Warren Moon** endorsement, TSE Speakers will help you book **Warren Moon** and **...**
athletes-celebrities.tseworld.com/sports/.../warren-moon.php - Cached - Similar -

Warren Moon Speaker Warren Moon Booking Agent Warren Moon Appearance
Call 1.800.966.1380 for **Warren Moon** speaker, **Warren Moon agent** and appearance info. Find out how to hire or book **Warren Moon** and how to contact **Warren Moon ...**
www.playingfieldpromotions.com/Warren-Moon.php - Cached - Similar -

What league did Warren Moon join? | Smart QandA: Answers and facts ...
Newspaper article from: Seattle Post-Intelligencer (Seattle, WA) ...preseason opener, **Warren Moon** was waiting to greet...Leigh Steinberg, **Moon's agent**, **...**
qanda.encyclopedia.com/.../league-did-warren-moon-join-211812.html -
Cached - Similar -

Warren Moon: Biography from Answers.com
Warren Moon football player Personal Information Born Harold **Warren Moon**, November 18, **...** situation,' **Moon's agent**, Leigh Steinberg, told the Houston Post. **...**
www.answers.com/topic/warren-moon - Cached - Similar -

Warren Moon Collectible - Find Warren Moon Collectible items for ...
After playing two seasons in the Pacific Northwest, **Moon** signed as a free **agent** with the Kansas City Chiefs in 1999. **Warren Moon** retired in the January 2001 **...**
popular.ebay.com/ns/Sports.../Warren-Moon-Collectible.html - Cached - Similar -

Seattle Seahawks Warren Moon Page
July 22, 1998 - **Warren Moon's agent** went on the offensive after another day of terse contract negotiations Tuesday, accusing the Seattle Seahawks of **...**
www.beckys-place.net/moon.html - Cached - Similar -

Press Release: A New Moon, A New Genre and a New Digital Diva ...
SAN DIEGO -- Free-**agent** quarterback **Warren Moon** will decide by no later than today whether

Motivation

Who is Warren Moon's agent? Answer

SHORT ANSWERS

Answers 1-5

- AGENT LEIGH STEINBERG
- MANNY RAMIREZ WILL CLARK STEVE
- QUARTERBACK WARREN
- CLARK STEVE YOUNG
- YOUNG WARREN

Search Engine vs. Question Answering

longer input →

keywords | **natural language questions**

documents | **short answer strings**

shorter output →

QA Types

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Closed-domain

Answering questions from a specific domain

Open-domain

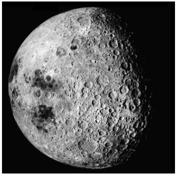
Answering any domain independent question

Outline

History

- BASEBALL [Green et al., 1963]
  - One of the earliest question answering systems
  - Developed to answer users' questions about dates, locations, and the results of baseball matches

- LUNAR [Woods, 1977]
  - Developed to answer natural language questions about the geological analysis of rocks returned by the Apollo moon missions
  - Able to answer 90% of questions in its domain posed by people not trained on the system



History

- STUDENT
  - Built to answer high-school students' questions about algebraic exercises

- PHLIQA
  - Developed to answer the user's questions about European computer systems

- UC (Unix Consultant)
  - Answered questions about the Unix operating system

- LILOG
  - Was able to answer questions about tourism information of cities in Germany

Closed-domain QA

- Closed-domain systems
- Extracting answers from structured data (database)

Labor intensive to build

- Converting natural language questions to database queries

Easy to implement

Open-domain QA

Closed-domain QA ⇒ Open-domain QA

Using a large collection of unstructured data (e.g., the Web) instead of databases

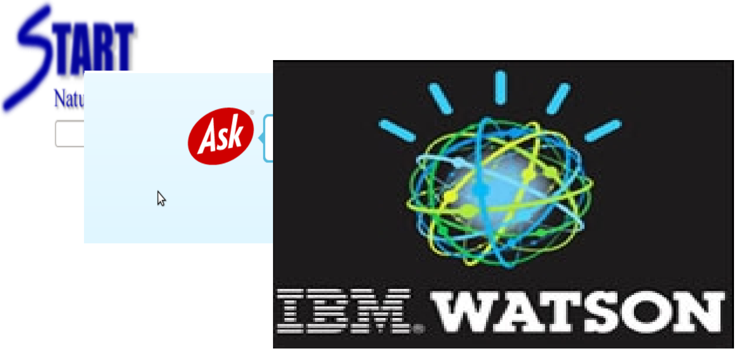
- Many subjects are covered
- Information is constantly added and updated
- No manual work is required to build databases

More complex systems are required

- Information is not always up-to-date
- Wrong information is not avoidable
- Much irrelevant information is found

Open-domain QA

- START [Katz, 1997]
  - Utilized a knowledge-base to answer the user’s questions
  - The knowledge-base was first created automatically from unstructured Internet data
  - Then it was used to answer natural language questions



IBM Watson

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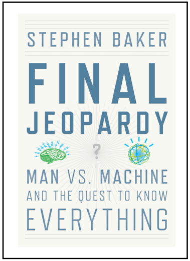
- Playing against two greatest champions of Jeopardy
- Challenges
  - Knowledge
  - Speed
  - Confidence



Building Watson: An Overview of the DeepQA Project

David Ferrucci, Eric Brown, Jennifer Chu-Carroll, James Fan, David Gondek, Aditya A. Kalyanpur, Adam Lally, J. William Murdock, Eric Nyberg, John Prager, Nico Schlaefer, and Chris Welty

AI Magazine, 2010

Outline

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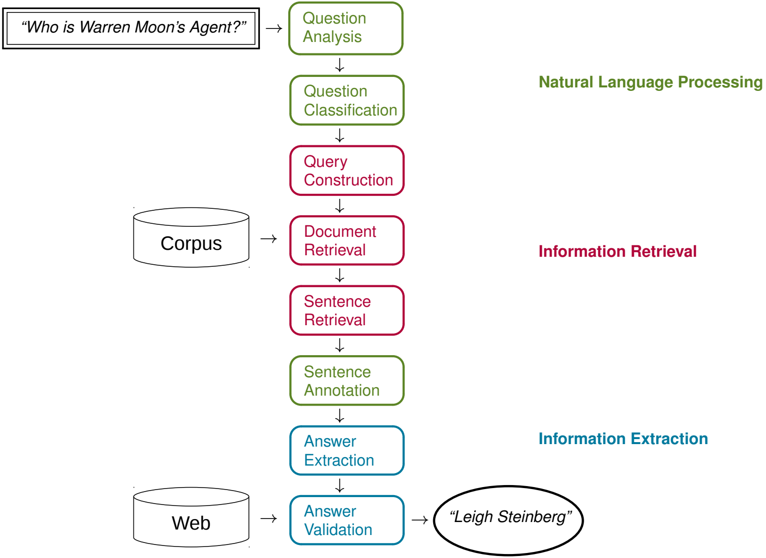
3. QA Architecture

Architecture



Question Analysis

- Named Entity Recognition
- Surface Text Pattern Learning
- Syntactic Parsing
- Semantic Role Labeling

Q Analysis: Named Entity Recognition

- Recognizing the named entities in the text to extract the target of the question
- Using the question's target in the query construction step

Example:

Question: *"In what country was Albert Einstein born?"*

Target: *"Albert Einstein"*

Q Analysis: Pattern Learning

- Extracting a pattern from the question
- Matching the pattern with a list of pre-defined question patterns
- Finding the corresponding answer pattern
- Realizing the position of the answer in the sentence in the answer extraction step

Example:

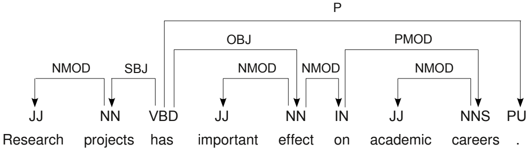
Question: *"In what country was Albert Einstein born?"*

Question Pattern: *"In what country was X born?"*

Answer Pattern: *"X was born in Y."*

Q Analysis: Syntactic Parsing

- Using a dependency parser to extract the syntactic relations between question terms
- Using the dependency relation paths between question terms to extract the correct answer in the answer extraction step



Q Analysis: Semantic Role Labeling

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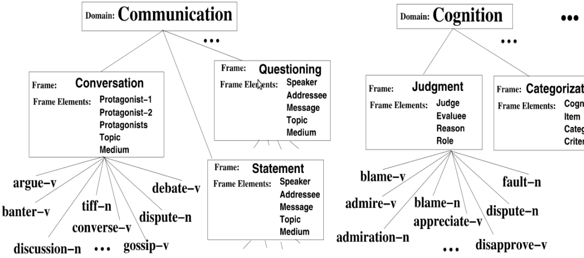
- FrameNet: a lexical database for English
- More than 170,000 manually annotated sentences
- Frame Semantics: describes the type of event, relation, or entity and the participants in it.



Q Analysis: Semantic Role Labeling

- FrameNet: a lexical database for English
- More than 170,000 manually annotated sentences
- Frame Semantics: describes the type of event, relation, or entity and the participants in it.

Example:

“$\underbrace{\textit{John}}_{\textit{Cook}}$ *grills* $\underbrace{\textit{a fish}}_{\textit{Food}}$ $\underbrace{\textit{on an open fire}}_{\textit{Heating-Instrument}}$.”

Q Analysis: Semantic Role Labeling

- Frame assignment
- Role labeling

Example:

“ $\underbrace{\textit{Jim}}_{\textbf{Driver}}$ *flew* $\underbrace{\textit{his plane}}_{\textbf{Vehicle}}$ $\underbrace{\textit{to Texas}}_{\textbf{Goal}}$.”

OPERATE–VEHICLE

Example:

“ $\underbrace{\textit{Alice}}_{\textbf{Destroyer}}$ *destroys* $\underbrace{\textit{the item}}_{\textbf{Undergoer}}$ $\underbrace{\textit{with a plane}}_{\textbf{Instrument}}$.”

DESTROYING

Q Analysis: Semantic Role Labeling

- Finding the question's head verb

Example:

" $\underbrace{\textit{Who}}_{\textit{Buyer}}$ *purchased* $\underbrace{\textit{YouTube}}_{\textit{Goods}}$ *?*"

COMMERCE–BUY

- Buyer [Subj,NP] verb Goods [Obj,NP]
- Buyer [Subj,NP] verb Goods [Obj,NP] Seller [Dep,PP-from]
- Goods [Subj,NP] verb Buyer [Dep,PP-by]
- ...

Example:

" *In 2006,* $\underbrace{\textit{YouTube}}_{\textit{Goods}}$ *was purchased* $\underbrace{\textit{by Google}}_{\textit{Buyer}}$ *for \$1.65 billion.*"

Question Classification

- Classifying the input question into a set of question types
- Mapping question types to the available named entity labels
- Finding strings that have the same type as the input question in the answer extraction step

Example:

Question: *"In what country was Albert Einstein born?"*

Type: LOCATION - Country

Question Classification

- Classifying the input question into a set of question types
- Mapping question types to the available named entity labels
- Finding strings that have the same type as the input question in the answer extraction step

Example (NER):

S1: “ $\underbrace{\textit{Albert Einstein}}_{\textbf{Person}}$ *was born in* $\underbrace{\textit{14 March 1879}}_{\textbf{Date}}$.”

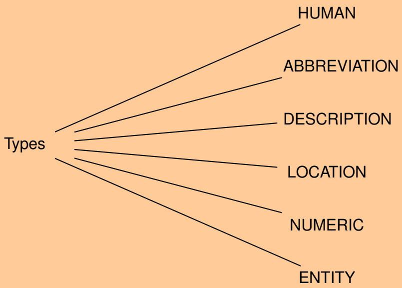
S2: “ $\underbrace{\textit{Albert Einstein}}_{\textbf{Person}}$ *was born in* $\underbrace{\textit{Germany}}_{\textbf{Country}}$.”

S3: “ $\underbrace{\textit{Albert Einstein}}_{\textbf{Person}}$ *was born in a* $\underbrace{\textit{Jewish}}_{\textbf{Religion}}$ *family.*”

Question Classification

- Classification taxonomies
  - BBN
  - Pasca & Harabagiu
  - Li & Roth

6 coarse- and 50 fine-grained classes



Question Classification

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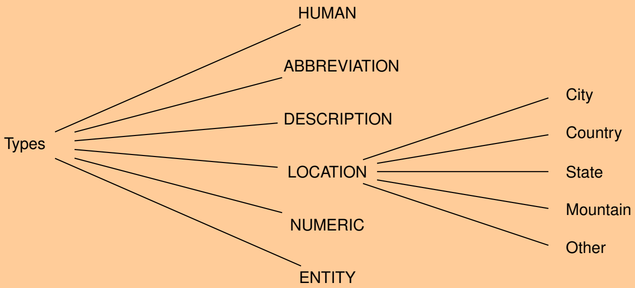

Question Classification

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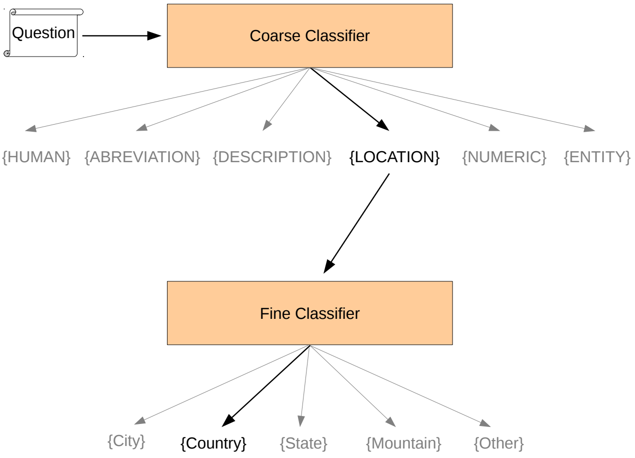
Question	Type	Sub-type
“Who killed Gandhi?”	HUMAN	Individual
“Who has won the most Super Bowls?”	HUMAN	Group
“What city did Duke Ellington live in?”	LOCATION	City
“Where is the highest point in Japan?”	LOCATION	Mountain
“What do sailors use to measure time?”	ENTITY	Technique
“Who is Desmond Tutu?”	DESCRIPTION	human

Question Classification

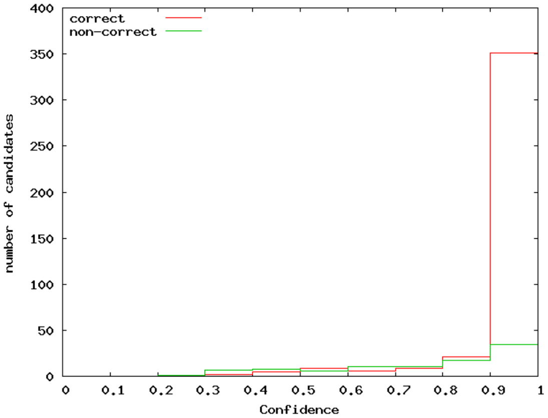


Question Classification

- Using any kinds of supervised classifiers
  - *K* Nearest Neighbor
  - Support Vector Machines
  - Naïve Bayes
  - Maximum Entropy
  - Logistic Regression
  - ...
- Benefiting from available toolkits
  - Support Vector Machine: SVM-light
  - Maximum Entropy: Maxent, Yasmet

Question Classification

- Considering the confidence measure of the classification to filter the result



Query Construction

- Goal:
  - Formulating a query with a high chance of retrieving relevant documents
- Task:
  - Assigning a higher weight to the question's target
  - Using query expansion techniques to expand the query

Document Retrieval

- Importance:
  - QA components use computationally intensive algorithms
  - Time complexity of the system strongly depends on the size of the to be processed corpus

- Task:
  - Reducing the search space for the subsequent components
  - Retrieving relevant documents from a large corpus
  - Selecting top *n* retrieved document for the next steps

Document Retrieval

- Using available information retrieval models
  - Vector Space Model
  - Probabilistic Model
  - Language Model

- Using available information retrieval toolkits

Sentence Retrieval

- Task:
  - Finding small segments of text that contain the answer

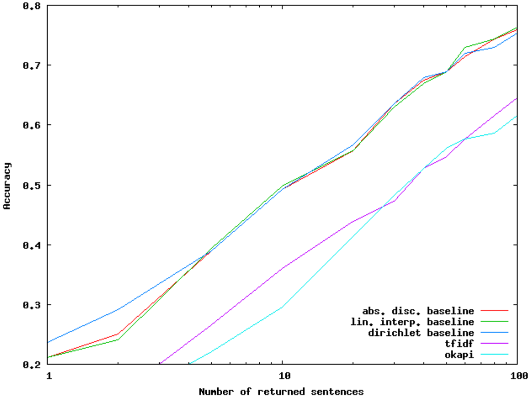
- Benefits beyond document retrieval:
  - Documents are very large
  - Documents span different subject areas
  - The relevant information is expressed locally
  - Retrieving sentences simplifies the answer extraction step

Sentence Retrieval

- Information retrieval models for sentence retrieval
  - Vector Space Model
  - Probabilistic Model
  - Language Model
    - Jelinek-Mercer Linear Interpolation
    - Bayesian Smoothing with Dirichlet Prior
    - Absolute Discounting

Sentence Retrieval

- Comparing language modeling with traditional methods



Sentence Retrieval

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- Comparison of the effects of text length on information retrieval

	MAP	P @ 10	P @ 20
Documents	0.191	0.232	0.200
750 bytes	0.064	0.186	0.149
500 bytes	0.055	0.166	0.142
250 bytes	0.036	0.136	0.117
Sentences	0.030	0.098	0.081

based on work by Vanessa Murdock

- Main problem of sentence retrieval: sentence brevity

Sentence Retrieval

- Approaches to overcome the sentence brevity problem:
  - Term relationship models
    - Translation model
    - Term clustering model

Sentence Retrieval

- Translation Model
  - Considering the relationship between sentence and query words
  - Estimating the probability of generating a query as a translation of a sentence

Word model:

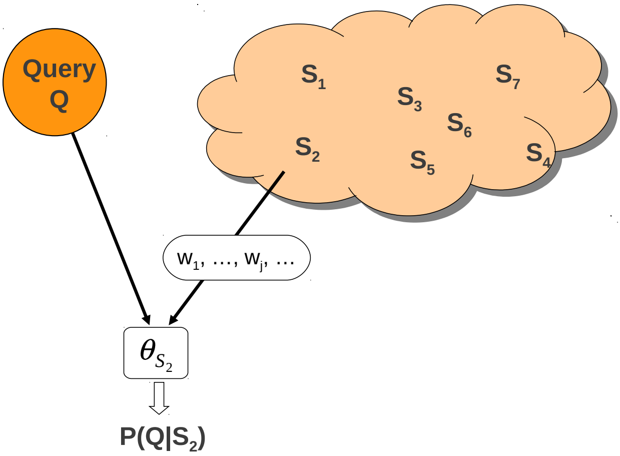
$$P(Q|S) = \prod_{i=1}^{M} P(q_i|S)$$

Translation model:

$$P(Q|S) = \prod_{i=1}^{M} \sum_{t \in S} P(q_i|t) \cdot P(t|S)$$

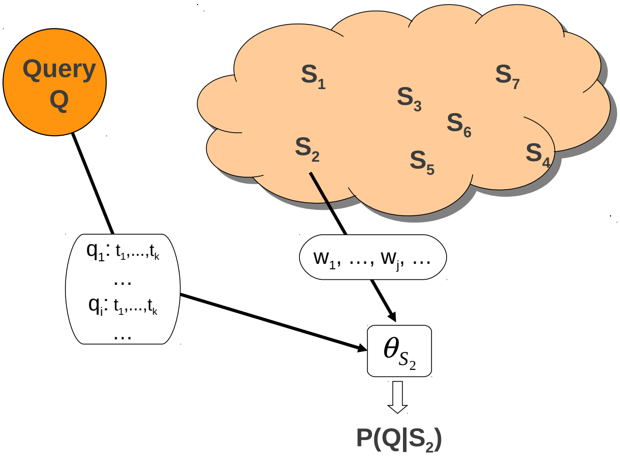
Sentence Retrieval

- Word Model



Sentence Retrieval

- Translation Model



Sentence Retrieval

- Class Model
  - Using a word clustering algorithm to cluster lexical items
  - Assigning similar words to the same cluster
  - Estimating the probability of a query term given a sentence based on the cluster which the query term belongs to

Word model:

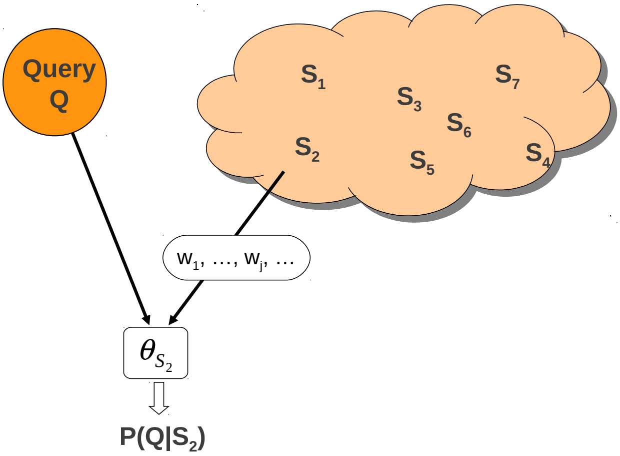
$$P(Q|S) = \prod_{i=1}^{M} P(q_i|S)$$

Class model:

$$P(Q|S) = \prod_{i=1}^{M} P(q_i|C_{q_i}, S) \cdot P(C_{q_i}|S)$$

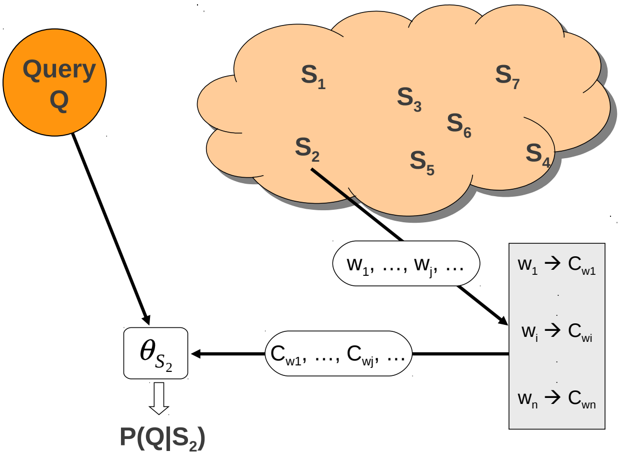
Sentence Retrieval

- Word Model



Sentence Retrieval

- Class Model



Sentence Annotation

- Annotating relevant sentences using linguistic analyses
  - Named entity recognition
  - Syntactic parsing
  - Semantic role labeling

Similar to Question Analysis

Example:

Question: *"In what country was Albert Einstein born?"*

Sentence Annotation

- Annotating relevant sentences using linguistic analyses
  - Named entity recognition
  - Syntactic parsing
  - Semantic role labeling

Similar to Question Analysis

Example (NER):

Sentence1: " $\underbrace{\textit{Albert Einstein}}_{\textbf{Person}}$ *was born in* $\underbrace{\textit{14 March 1879}}_{\textbf{Date}}$."

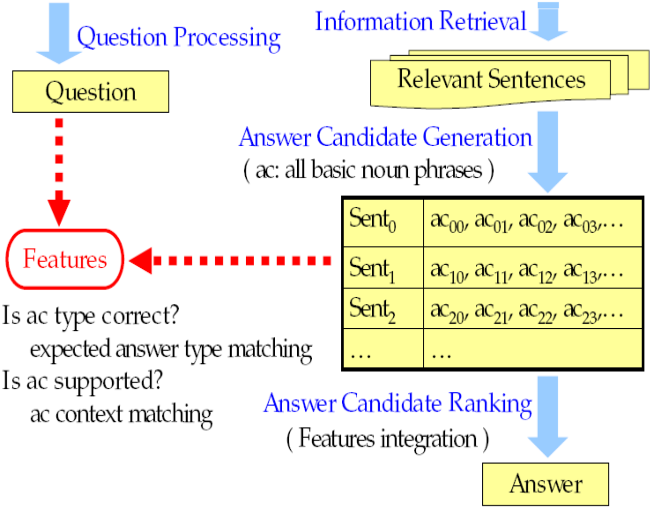
Sentence2: " $\underbrace{\textit{Albert Einstein}}_{\textbf{Person}}$ *was born in* $\underbrace{\textit{Germany}}_{\textbf{Country}}$."

Sentence3: " $\underbrace{\textit{Albert Einstein}}_{\textbf{Person}}$ *was born in a* $\underbrace{\textit{Jewish}}_{\textbf{Religion}}$ *family.*"

Answer Extraction

- Extracting candidate answers based on various information
  - Question
    - Question Analysis: patterns
    - Question Analysis: syntactic parse
    - Question Analysis: semantic roles
    - Question Classification: question type
  - Sentence
    - Sentence Annotation: all annotated data

Answer Extraction



Answer Extraction

- Using extracted patterns

Example:

Question: *"In what country was Albert Einstein born?"*

Question Pattern: In what country was X born?
Answer Pattern: X was born in Y.

Answer Extraction

- Using extracted patterns

Example (Pattern):

Sentence1: *"Albert Einstein was born in 14 March 1879."*

Sentence2: *"Albert Einstein was born in Germany."*

Sentence3: *"Albert Einstein was born in a Jewish family."*

Answer Extraction

- Using question type and entity type

Example:

Question: *"In what country was Albert Einstein born?"*

Question Type: LOCATION - Country

Answer Extraction

- Using question type and entity type

Example (NER):

Sentence1: "$\underbrace{\textit{Albert Einstein}}_{\textit{Person Name}}$ *was born in* $\underbrace{\textit{14 March 1879}}_{\textit{Date}}$*.*"

Sentence2: "$\underbrace{\textit{Albert Einstein}}_{\textit{Person Name}}$ *was born in* $\underbrace{\textit{Germany}}_{\textit{Country}}$*.*"

Sentence3: "$\underbrace{\textit{Albert Einstein}}_{\textit{Person Name}}$ *was born in a* $\underbrace{\textit{Jewish}}_{\textit{Religion}}$ *family.*"

Answer Extraction

- Using syntactic parsing
  - Different wordings possible, but similar syntactic structure

Q: Who founded the Black Panthers organization ?

subj obj

S1: Bobby Seale, a student at Merritt College, founded the Black Panther Party for self-defense .

subj obj

S2: The Black Panther Party, co-founded by Seale and Newton, flourished...

obj subj

based on work by Dan Shen

Answer Extraction

- Using syntactic parsing
  - Many syntactic variations → need robust matching approach

Q: Who founded the Black Panthers organization ?

subj obj

S1: Bobby Seale, a student at Merritt College, founded the Black Panther Party for self-defense .

subj obj

S2: The Black Panther Party, co-founded by Seale and Newton, flourished...

obj subj

S3: Hilliard introduced Bobby Seale, who co-founded the Black Panther Party here .

rel, i obj

S4: Black Panthers Co-founder Bobby Seale visits UMM.

nn appo

Answer Extraction

- Using semantic roles

Example:

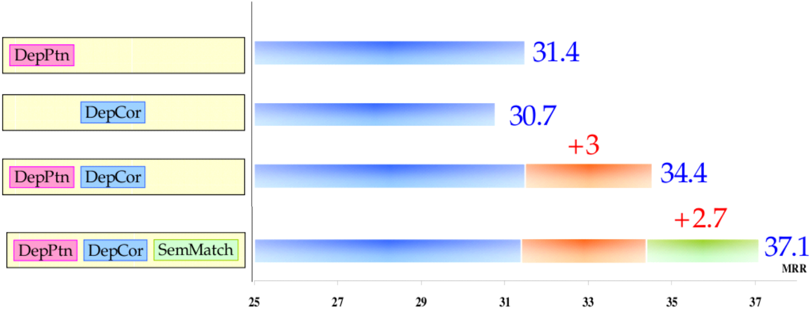
"$\underbrace{\textit{Who}}_{\textbf{Buyer}}$ *purchased* $\underbrace{\textit{YouTube}}_{\textbf{Goods}}$?"

Example:

" In 2006, $\underbrace{\textit{YouTube}}_{\textbf{Goods}}$ was *purchased* $\underbrace{\textit{by Google}}_{\textbf{Buyer}}$ for \$1.65 billion."

Answer Extraction

- Comparing answer extraction features



Answer Validation

- Using Web as a knowledge resource for validating answers

- Required steps
  - Query creation
  - Answer rating

Answer Validation

- Query creation
  - Combining the answer with a subset of the question keywords
  - Using sequences of keywords, if available
  - Choosing different combinations of subsets
    - Bag-of-Word
    - Noun-Phrase-Chunks
    - Declarative-Form

Answer Validation

- Query model:
  - Bag-of-Word
  - Noun-Phrase-Chunks
  - Declarative-Form

Example:

Question: *"In what country was Albert Einstein born?"*

Answer Candidate: *Germany*

Answer Validation

- Query model:
  - Bag-of-Word
  - Noun-Phrase-Chunks
  - Declarative-Form

Bag-of-Word:

Albert Einstein born Germany

Noun-Phrase-Chunks:

“Albert Einstein” born Germany

Declarative-Form:

“Albert Einstein born Germany”

Answer Validation

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- Answer rating
  - Passing the query to a search engine
  - Analyzing the result of the search engine
    - Counting the results
    - Parsing the result snippets
  - Other possibilities:
    - Using knowledge bases to find relations between the question keywords and the answer

Architecture