

IT Systems Engineering | Universität Potsdam

Question Answering Systems

An Introduction Potsdam, Germany, 14 July 2011

Saeedeh Momtazi Information Systems Group



1 Introduction



1 Introduction

2 History



1 Introduction

2 History

QA Architecture
Factoid QA
Opinion QA



Introduction

2 History

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Opinion QA





1 Introduction

2 History

QA Architecture
Factoid QA
Opinion QA

4 Summary















Who is Warren Moon's agent?



Search



Who is Warren Moon's agent?



Booking Warren Moon Appearances, Contact Warren Moon Agent ...

Call 1-388-245-7141 to Contact Warren Moon Agent for Booking Warren Moon for corporate appearances, Warren Moon speaking engagement, Swarren Moon... www.athietepromotions.com/.../Warren-Moon-appearance-booking-agent.php -Cached - Simular - C IR IX

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 - Cirk R

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.playingliedpromotions.com/Warren-Moon.php-Cachad-Similar-ORA

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 great...bigh Steinberg, Moon's agent.... canzta en yclopedia.com/../segue-stdi-warren-moon-join-211812.html -Canzted - Similar - Com R|X|

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 - <u>Cached</u> - Similar - C A X

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.ebsy.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 Seathawks of ... www.bcckys-place.net/moon.html - <u>Cached</u> - <u>Similar</u> - ⊙ | ★| | ★|

Press Release: A New Moon, A New Genre and a New Digital Diva ...



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Sports

Blogs



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Press Belease: A New Moon, A New Genre and a New Digital Diva ...

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Fontball

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Press Release: A New Moon, A New Genre and a New Digital Diva ...

Decame easy to you would also not not even is rainine. Showing great <u>resulant</u>, Moorrensed to acknowledge the heckling, and when the boos turned to <u>cheers</u> he accepted the praise without bittemess.

His tenaotiv was rewarded in 1977, when the Huskies won their conference championship and met the University of Michigan in the 1978 Rose Bowl game. The underdog Huskies won the Rose Bowl under Moors' leadership, and he was named Rose Bowl Moot Valuable Player and the Pacific 8 Player of the Year. Overall, Moon passed for 3,277 yards and 19 touchdowns in his collegiate cares.

Although Noon managed to win over Washington's fars, he failed to convince skeptical NEL source of his playing abilit, with sole sole optionmano <u>public historiandin</u>, he was a table quarterback tenth best quarterback in the 1073 draft. The stereotype was that he was a black quarterback and he was point on run and like <u>amatimar</u>, but he wouldn't be able to throw very well, former Edimotro Eskinos and Houston Olles souch Hugh Cancella told the *Loc Argues Transe*. 50, once again, Noon decided to prove hinself elsewhere, signing with the Eskinos of the Canadian Fortball League.

During Moon's six seasons in Canada, he put up some <u>stunning</u> numbers--21,228 yards passing and 1,700 yards rushing. He had back-boack 5,000-yard passing seasons. His 5,648 yards passing over 16 games in 1983 remains an all-time high for pro football. In addition, the Eskimos won five straint forev Cup trophies as champions of the CPL from 1978 to 1982.

9: 1964 Moon had nothing left to prove. When his contrast, with Edinotone napined, seven NFL teams sought to spin him as a free again. Moon initially leaved to ward the Seath Seahawis, which would allow him to return to his college town, but he eventually choes the Houston Olers, the team that had here his former Edinomoto noach, Campbell. The Olers tendered and Fer-ear, \$25 million contrast, which, at the time, made Moon the highest paid player in the NFL-before he even played in a leage game.

When Moon spined Houston, it was the sorriest franchise in the NEL, having won only three games in the previous two seasons. "One of the challenges of Houston was to be part of a opining soluabon," Moon's agent, Laigh Stanberg, Iodi Heuston? Ast. "He inwer it would take onger (to be on a championphip team), but when it came, he knew he would be an instrumental act of the buildne process."

In 1984 Moon was a rooks sensation. His six years in the CR, gare him a weath of experience, and he three for a time-Houston-record 1,338 yards on the season. Silt the Clears were 3.13. finshing last in their division. The next season, after the lob won just; five of its first 14 games, Campbell was freed and a defensive-circularde coxh, jarve; Glanwilli, took over. "Those early years (in Houston) were really hard for ne to deal with a first," Moon told the 2*L* cours *Fost*-Closesch. "There were some uncertainties about, rozer here because of the coshing change. That left

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6





longer input







QA vs. SE



natural language questions







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QA vs. SE

keywords · YAHOO! Google Search Engine Marketing documents

natural language questions



shorter output

longer input







Closed-domain

only answer questions from a specific domain.

Open-domain

answer any domain independent question.



Introduction

2 History

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History

- BASEBALL [Green et al., 1963]
 - One of the earliest question answering systems
 - Developed to answer user 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



10

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 in cities within Germany





Closed-domain systems

Extracting answers from structured data (database)

Converting natural language question to a database query



Converting natural language question to a database query

Easy to implement

Open-domain QA



Closed-domain QA \Rightarrow Open-domain QA

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

Open-domain QA



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



Covering many subjects Information constantly added and updated No manual work for building database

Open-domain QA



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Covering many subjects Information constantly added and updated No manual work for building database



Some times information is not up to date Some information is wrong More irrelevant information


Closed-domain $QA \Rightarrow$ Open-domain QA

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



Covering many subjects Information constantly added and updated No manual work for building database More complex systems are required



Some times information is not up to date Some information is wrong More irrelevant information



13

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



Ask Question Clear



START [Katz, 1997]

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13

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IBM Watson



Webpage: IBM Watson

http://www-03.ibm.com/innovation/us/watson/index.html

Video: IBM and the Jeopardy Challenge

http://www.youtube.com/watch?v=FC3IryWr4c8&feature=relmfu

http://www.youtube.com/watch?v=_1c7s7-3fXI

Video: A Brief Overview of the DeepQA Project

http://www.youtube.com/watch?v=3G2H3DZ8rNc



Outline



Introduction

2 History

3 QA Architecture Factoid QA Opinion QA

4 Summary



16







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Target Extraction

17

- Extracting the target of the question
- Using question target at the query construction step



Target Extraction

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Pattern Extraction

- 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 at the answer extraction step



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Pattern Extraction

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- Matching the pattern with a list of pre-defined question patterns
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examples:

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

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

Answer Pattern: "X was born in Y."



Target Extraction

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Pattern Extraction

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- Realizing the position of the answer in the sentence at the answer extraction step

Parsing

- Using a dependency parser to extract the syntactic relations between question terms
- Using the dependency relation path between question words to extract the correct answer at answer extraction step



- Classifying the input question into a set of question types
- Defining a map between question types and available named entity labels
- Using question type to extract strings that have the same type as the input question at the answer extraction step



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Example:

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

Type: Country



- 19
- Classification taxonomies
 - BBN
 - Pasca & Harabagiu
 - Li & Roth



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19

- Classification taxonomies
 - BBN
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 - 🗆 Li & Roth





- Using available classifiers based on the favorite model
 - SVM: SVM-light
 - Maximum Entropy: Maxent, Yasmet
 - Naive Bayes

Query Construction



Goal:

Formulating a query with a high chance of retrieving relevant documents

Task:

- Assigning a higher weight to the question target
- Using query expansion techniques to expand the query
 - Thesaurus-based query expansion
 - Relevance feedback
 - Pseudo-relevance feedback

Document Retrieval



22

Importance:

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

- Task:
 - Reducing the search space for the subsequent modules
 - 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

Document Retrieval



- Using available information retrieval models
 - Vector Space Model

23

- Probabilistic Model
- Language Model
- Using available information retrieval toolkits







Task:

24

Finding a small segment of text that contains 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



25

Language model-based sentence retrieval





- 25
- Language model-based sentence retrieval



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



Challenge:

The term mismatch problem in sentence retrieval is more critical than document retrieval



Challenge:

The term mismatch problem in sentence retrieval is more critical than document retrieval

Approaches:



Challenge:

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- Approaches:
 - Query expansion, (Pseudo-)Relevance Feedback



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The term mismatch problem in sentence retrieval is more critical than document retrieval

Approaches:

Query expansion, (Pseudo-)Relevance Feedback
Does not work at
Does not work at



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The term mismatch problem in sentence retrieval is more critical than document retrieval

Approaches:

Query expansion, (Pseudo-)Relevance Feedback
Does not work at
Does not work at

- Term relationship models
 - WordNet
 - Term clustering model
 - Translation model
 - Triggering model

Sentence Annotation



- 27
- Annotating relevant sentences using linguistic analyses:
 - Named entity recognition
 - Dependency parsing
 - Noun phrase chunking
 - Semantic role labeling

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Sentence Annotation



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- Annotating relevant sentences using linguistic analyses:
 - Named entity recognition
 - Dependency parsing
 - Noun phrase chunking
 - Semantic role labeling

Example (NER):

Sentence1: "Albert Einstein was born on 14 March 1879."

Sentence2: "Albert Einstein was born in Germany ."

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

Sentence Annotation



- Annotating relevant sentences using linguistic analyses:
 - Named entity recognition
 - Dependency parsing
 - Noun phrase chunking
 - Semantic role labeling





- ²⁸ Ext
 - Extracting candidate answers based on various informations:
 - The extracted patterns from question analysis
 - The dependency pars of question from the question analysis
 - The question type from question classification
 - All annotated data from sentence annotation



- 28
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Example:

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



28

Extracting candidate answers based on various informations:

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Example:

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



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Example:

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

Question Type: LOCATION - COUNTRY



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Example (Pattern):

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- Using the Web as a knowledge resource
- Sending question keywords and answer candidates to a search engine
- Finding the frequency of the answer candidate within the Web data
- Selecting the most likely answers based on the frequencies



30

Query model:

- Bag-of-Word
- Noun-Phrase-Chunks
- Declarative-Form



30

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Example:

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



30

Query model:

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- Noun-Phrase-Chunks
- Declarative-Form

Example:

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

Answer Candidate: Germany



30

Query model:

- Bag-of-Word
- Noun-Phrase-Chunks
- Declarative-Form

Bag-of-Word:

Albert Einstein born Germany



30

Query model:

- Bag-of-Word
- Noun-Phrase-Chunks
- Declarative-Form

Bag-of-Word: Albert Einstein born Germany

Noun-Phrase-Chunks:

"Albert Einstein" born Germany



30

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"





Fact vs. Opinion



32

Factual questions

"Who is Warren Moon's Agent?"

"When was Mozart born?"

"In what country was Albert Einstein born?" "Who is the director of the Hermitage Museum?"

Fact vs. Opinion



Opinionated questions

"What do people like about Wikipedia?"

"What are the public opinions on human cloning?" "What organizations are against universal health care?"

"How do students feel about Microsoft products?"

Outline



34

Introduction

2 History

QA Architecture
Factoid QA
Opinion QA

4 Summary



35





35











35





35









35





35





35



Q Polarity Classification



- 36
- Running in parallel with question classification
- Task:
 - Decide whether the input question has a positive or negative polarity

Q Polarity Classification



- 36
- Running in parallel with question classification
- Task:
 - Decide whether the input question has a positive or negative polarity

examples:



"What do people like about Wikipedia?"



"Why people hate reading Wikipedia articles?"

Q Polarity Classification



- 36
- Running in parallel with question classification
- Task:
 - Decide whether the input question has a positive or negative polarity
- Approaches:
 - Using a rule-based model based on subjectivity lexicon
 - Running a classifier trained on an annotated corpus
 - Training on overall vocabulary of the dataset
 - Training on all polarity expressions from the subjectivity lexicon

S Opinion Classification



37

Importance:

- □ Sentence retrieval output is mixed (factual & opinionated)
- Opinion question answering systems are looking for opinionated sentences


37

Importance:

- Sentence retrieval output is mixed (factual & opinionated)
- Opinion question answering systems are looking for opinionated sentences
- Goal:
 - Classifying retrieved sentences as opinionated or factual.



37

Importance:

- Sentence retrieval output is mixed (factual & opinionated)
- Opinion question answering systems are looking for opinionated sentences

examples:

Question: "What do people like about Wikipedia?"



Importance:

- Sentence retrieval output is mixed (factual & opinionated)
- Opinion question answering systems are looking for opinionated sentences

examples:

S1: "I agree Wikipedia is very much in handy when your online; however, I can not use it when I am not online."

S2: "Wikipedia began as a complementary project for Nupedia, a free online English-language encyclopedia project."

S3: "Jimmy Wales and Larry Sanger co-founded Wikipedia in January 2001."

S4: "Wikipedia is a great way to access lots of information."



Importance:

- □ Sentence retrieval output is mixed (factual & opinionated)
- Opinion question answering systems are looking for opinionated sentences

Opinion

S1: "I agree Wikipedia is very much in handy when your online; however, I can not use it when I am not online."

S4: *"Wikipedia is a great way to access lots of information."*

Fact

S2: "Wikipedia began as a complementary project for Nupedia, a free online English-language encyclopedia project."

S3: "Jimmy Wales and Larry Sanger co-founded Wikipedia in January 2001."



Importance:

- Sentence retrieval output is mixed (factual & opinionated)
- Opinion question answering systems are looking for opinionated sentences
- Goal:
 - Classifying retrieved sentences as opinionated or factual.
- Approaches:
 - Running a classifier trained on an annotated corpus
 - SVM
 - Maximum Entropy
 - Naive Bayes

S Polarity Classification



38

Task:

- Distinguishing between positive and negative sentences
- Returning sentences which have the same polarity as the input question
- Approach:
 - Using a classifier to classify opinionated sentences as positive or negative
 - Using a small set of lightweight linguistic polarity features
 - Considering the distance between polarity features and the topic in the sentence
 - Using a dependency parser to consider syntactic features

Outline

Introduction

2 History

 QA Architecture Factoid QA Opinion QA







40





Next Semester



41

Master Seminar on Question Answering Systems

Next Semester



Master Seminar on Question Answering Systems



