Question Answering

- Following largely from Chris Manning’s slides, which includes slides originally borrowed from Sanda Harabagiu, ISI, Nicholas Kushmerick.
Question Answering from Text

- The common person’s view? [From a novel]
  - “I like the Internet. Really, I do. Any time I need a piece of shareware or I want to find out the weather in Bogota … I’m the first guy to get the modem humming. But as a source of information, it sucks. You got a billion pieces of data, struggling to be heard and seen and downloaded, and anything I want to know seems to get trampled underfoot in the crowd.”

- Question Answering:
  - Give the user a (short) answer to their question, perhaps supported by evidence.
  - An idea originating from the IR community
  - With massive collections of full-text documents, simply finding relevant documents is of limited use: we want answers from textbases

People *want* to ask questions?

- Examples of search queries
  - who invented surf music?
  - how to make stink bombs
  - where are the snowdens of yesteryear?
  - which english translation of the bible is used in official catholic liturgies?
  - how to do clayart
  - how to copy psx
  - how tall is the sears tower?
  - how can i find someone in texas
  - where can i find information on puritan religion?
  - what are the 7 wonders of the world
  - how can i eliminate stress
  - What vacuum cleaner does Consumers Guide recommend

Around 10–15% of query logs
AskJeeves (Classic)

- Probably the most hyped example of “question answering”
- It largely did pattern matching to match your question to their own knowledge base of questions
- If that works, you get the human-curated answers to that known question (which are presumably good)
- If that fails, it falls back to regular web search
- A potentially interesting middle ground, but not full QA

A Brief (Academic) History

- Question answering is not a new research area
- Question answering systems can be found in many areas of NLP research, including:
  - Natural language database systems
    - A lot of early NLP work on these
  - Spoken dialog systems
    - Currently very active and commercially relevant
- The focus on open-domain QA is new
  - MURAX (Kupiec 1993): Encyclopedia answers
  - Hirschman: Reading comprehension tests
  - TREC QA competition: 1999–
Question Answering at TREC

- Question answering competition at TREC consists of answering a set of 500 fact-based questions, e.g., “When was Mozart born?”.
- For the first three years systems were allowed to return 5 ranked answer snippets (50/250 bytes) to each question.
  - IR think
  - Mean Reciprocal Rank (MRR) scoring:
    - 1, 0.5, 0.33, 0.25, 0.2, 0 for 1, 2, 3, 4, 5, 6+ doc
  - Mainly Named Entity answers (person, place, date, …)
- From 2002 the systems are only allowed to return a single exact answer and the notion of confidence has been introduced.

The TREC Document Collection

- One recent round: news articles from:
  - AP newswire, 1998-2000
  - Xinhua News Agency newswire, 1996-2000
- In total 1,033,461 documents in the collection.
- 3GB of text
- While small in some sense, still too much text to process using advanced NLP techniques (on the fly at least)
- Systems usually have initial information retrieval followed by advanced processing.
- Many supplement this text with use of the web, and other knowledge bases
Sample TREC questions

1. Who is the author of the book, "The Iron Lady: A Biography of Margaret Thatcher"?
2. What was the monetary value of the Nobel Peace Prize in 1989?
3. What does the Peugeot company manufacture?
4. How much did Mercury spend on advertising in 1993?
5. What is the name of the managing director of Apricot Computer?
6. Why did David Koresh ask the FBI for a word processor?
7. What debts did Qintex group leave?
8. What is the name of the rare neurological disease with symptoms such as: involuntary movements (tics), swearing, and incoherent vocalizations (grunts, shouts, etc.)?

Top Performing Systems

- Currently the best performing systems at TREC can answer approximately 70% of the questions
- Approaches and successes have varied a fair deal
  - Knowledge-rich approaches, using a vast array of NLP techniques stole the show in 2000, 2001, still do well
    - Notably Harabagiu, Moldovan et al. – SMU/UTD/LCC
  - AskMSR system stressed how much could be achieved by very simple methods with enough text (and now various copycats)
  - Middle ground is to use large collection of surface matching patterns (ISI)
Webclopedia Architecture

- IR
  - Steps: create query from question (WordNet-expansion) retrieve top 1000 documents
  - Engine: MRO (Sydney) — (Lin)
  - ATIR (TREC) — (Lin)

- Segmentation
  - Steps: segment each document into topical segments
  - Engine: fixed-length (not used)
    - TextFolding (Rivest & P.) — (Lin)
  - CS99 (Chow) — (Lin)
  - MAXNET (Lin 00; not used)

- Ranking
  - Steps: score each sentence in each segment, using WordNet expansion
  - Engine: FastFinder (Sark)

- Matching
  - Steps: match general concept outlines against parse trees
  - Match desired semantic type against parse tree elements
  - Search desired words against words in sentences
  - Engine: matching (Sark)

- Ranking and answer extraction
  - Steps: rank candidate answers
  - Extract and format them
  - Engine: part of matching (Sark)

- QA prototype
  - Categorize QA types in context (Gerber)
  - Constraint patterns
  - Match desired answers in relation to other parts of the sentence (Gerber)

**TextMap Question Answering**

Please wait while Webclopedia answers to your question (potential answers will follow, within top 10 below).

At the time, these were the best 10 answers found for the question:

1. 205 4:23 When John Lennon died in 1980, the tenyear flashbulb experience which took place 13 years earlier on December 8, 1966 finally made sense to me. (http://www.uncyclopedia.com/encyclopedia.php)
2. 205 4:23 When John Lennon died in 1980, the tenyear flashbulb experience which took place 13 years earlier on December 8, 1966 finally made sense to me. (http://www.uncyclopedia.com/encyclopedia.php)
3. 204 1:37 The six-year old John Lennon died in 1966 when he was shot by a fan outside his New York City home. (http://news.bbc.co.uk/hi/english/entertainment/97/9713235.stm)
9. 47 4:23 2003 after John Lennon died in New York in December 1980, Paul Onu, decided to release a limited edition of some of his
10. 47 4:23 2003 after John Lennon died in New York in December 1980, Paul Onu, decided to release a limited edition of some of his
Current top 10 (of 109) for "Who was the prime minister of Australia in 1990?" - still finding more...


Still searching for more answers... (337 not used to find 116 answers so far)
Use of Characteristic Phrases

"When was <person> born"

- Typical answers
  - "Mozart was born in 1756."
  - "Gandhi (1869-1948)..."

- Suggests phrases like
  - "<NAME> was born in <BIRTHDATE>"
  - "<NAME> ( <BIRTHDATE>-"

- as Regular Expressions can help locate correct answer

Use Pattern Learning

Example: Start with “Mozart 1756”

- Results:
  - "The great composer Mozart (1756-1791) achieved fame at a young age"
  - "Mozart (1756-1791) was a genius"
  - "The whole world would always be indebted to the great music of Mozart (1756-1791)"

- Longest matching substring for all 3 sentences is "Mozart (1756-1791)"
- Suffix tree would extract "Mozart (1756-1791)" as an output, with score of 3
- Reminiscent of IE pattern learning
Pattern Learning (cont.)

- Repeat with different examples of same question type
  - “Gandhi 1869”, “Newton 1642”, etc.
- Some patterns learned for BIRTHDATE
  - a. born in <ANSWER>, <NAME>
  - b. <NAME> was born on <ANSWER>,
  - c. <NAME> ( <ANSWER> -
  - d. <NAME> ( <ANSWER> - )

Experiments: (R+H, 2002)

- 6 different Question types
  - from Webclopedia QA Typology (Hovy et al., 2002a)
    - BIRTHDATE
    - LOCATION
    - INVENTOR
    - DISCOVERER
    - DEFINITION
    - WHY-FAMOUS
Experiments: pattern precision

- **BIRTHDATE table**:
  - 1.0 `<NAME>` ( `<ANSWER>` - )
  - 0.85 `<NAME>` was born on `<ANSWER>`,
  - 0.6 `<NAME>` was born in `<ANSWER>`
  - 0.59 `<NAME>` was born `<ANSWER>`
  - 0.53 `<ANSWER>` `<NAME>` was born
  - 0.50 - `<NAME>` ( `<ANSWER>`
  - 0.36 `<NAME>` ( `<ANSWER>` - 

- **INVENTOR**
  - 1.0 `<ANSWER>` invents `<NAME>`
  - 1.0 the `<NAME>` was invented by `<ANSWER>`
  - 1.0 `<ANSWER>` invented the `<NAME>` in

Experiments (cont.)

- **WHY-FAMOUS**
  - 1.0 `<ANSWER>` `<NAME>` called
  - 1.0 laureate `<ANSWER>` `<NAME>`
  - 0.71 `<NAME>` is the `<ANSWER>` of

- **LOCATION**
  - 1.0 `<ANSWER>``s `<NAME>`
  - 1.0 regional : `<ANSWER>` : `<NAME>`
  - 0.92 near `<NAME>` in `<ANSWER>`

- Depending on question type, get high MRR (0.6–0.9), with higher results from use of Web than TREC QA collection
Shortcomings & Extensions

- Need for POS &/or semantic types
  - "Where are the Rocky Mountains?"
  - "Denver's new airport, topped with white fiberglass cones in imitation of the Rocky Mountains in the background, continues to lie empty"
  - <NAME> in <ANSWER>

- NE tagger &/or ontology could enable system to determine "background" is not a location

Shortcomings... (cont.)

- Long distance dependencies
  - "Where is London?"
  - "London, which has one of the busiest airports in the world, lies on the banks of the river Thames"
  - would require pattern like:
    <QUESTION>, (<any_word>)*, lies on <ANSWER>

- But: abundance & variety of Web data helps system to find an instance of patterns w/o losing answers to long distance dependencies
Shortcomings... (cont.)

- Their system uses only one anchor word
  - Doesn't work for Q types requiring multiple words from question to be in answer
    - "In which county does the city of Long Beach lie?"
    - "Long Beach is situated in Los Angeles County"
  - required pattern:
    - <Q_TERM_1> is situated in <ANSWER> <Q_TERM_2>

- Does not use case
  - "What is a micron?"
  - "...a spokesman for Micron, a maker of semiconductors, said SIMMs are..."

AskMSR

- Web Question Answering: Is More Always Better?
  - Dumais, Banko, Brill, Lin, Ng (Microsoft, MIT, Berkeley)

- Q: “Where is the Louvre located?”
  - Want “Paris” or “France” or “75058 Paris Cedex 01” or a map
  - Don’t just want URLs
AskMSR: Shallow approach

- In what year did Abraham Lincoln die?
- Ignore hard documents and find easy ones

AskMSR: Details

1. Rewrite Query
2. <Search Engine>
3. Collect Summaries, Mine N-grams
4. Filter N-grams
5. Tile N-grams

Where is the Louvre Museum located?

- in Paris France 59%
- museums 12%
- hostels 10%

N-Best Answers
Step 1: Rewrite queries

- Intuition: The user’s question is often syntactically quite close to sentences that contain the answer
  - Where is the Louvre Museum located?
  - The Louvre Museum is located in Paris
  - Who created the character of Scrooge?
  - Charles Dickens created the character of Scrooge.

Query Rewriting: Variations

- Classify question into seven categories
  - Who is/was/are/were...
  - When is/did/will/are/were ...
  - Where is/are/were ...
  a. Category-specific transformation rules
     - eg “For Where questions, move ‘is’ to all possible locations”
       - “Where is the Louvre Museum located”
       - “is the Louvre Museum located”
       - “the is Louvre Museum located”
       - “the Louvre is Museum located”
       - “the Louvre Museum is located”
       - “the Louvre Museum located is”
  b. Expected answer “Datatype” (eg, Date, Person, Location, …)
     - When was the French Revolution? → DATE

- Hand-crafted classification/rewrite/datatype rules
  (Could they be automatically learned?)
Query Rewriting: Weights

- One wrinkle: Some query rewrites are more reliable than others

Where is the Louvre Museum located?

*Weight 1*
Lots of non-answers could come back too

+Louvre +Museum +located

*Weight 5*
if we get a match, it’s probably right
+“the Louvre Museum is located”

Step 2: Query search engine

- Send all rewrites to a search engine
- Retrieve top N answers (100?)
- For speed, rely just on search engine’s “snippets”, not the full text of the actual document
Step 3: Mining N-Grams

- Simple: Enumerate all N-grams (N=1,2,3 say) in all retrieved snippets
- Weight of an n-gram: occurrence count, each weighted by “reliability” (weight) of rewrite that fetched the document
- Example: “Who created the character of Scrooge?”
  - Dickens - 117
  - Christmas Carol - 78
  - Charles Dickens - 75
  - Disney - 72
  - Carl Banks - 54
  - A Christmas - 41
  - Christmas Carol - 45
  - Uncle - 31

Step 4: Filtering N-Grams

- Each question type is associated with one or more “data-type filters” = regular expression
- When...
- Where...
- What ...
- Who ...

- Boost score of n-grams that do match regexp
- Lower score of n-grams that don’t match regexp
- Details omitted from paper...
Step 5: Tiling the Answers

Scores

<table>
<thead>
<tr>
<th></th>
<th>Charles Dickens</th>
<th>Dickens</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Mr Charles</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

merged, discard old n-grams

Score 45

Mr Charles Dickens

N-Grams

tile highest-scoring n-gram

Repeat, until no more overlap

Results

- Standard TREC contest test-bed: 
  ~1M documents; 900 questions

- Technique doesn’t do too well (though would have placed in top 9 of ~30 participants!)
  - MRR = 0.262 (ie, right answered ranked about #4-#5 on average)
  - Why? Because it relies on the redundancy of the Web

- Using the Web as a whole, not just TREC’s 1M documents… MRR = 0.42 (ie, on average, right answer is ranked about #2-#3)
Issues

- In many scenarios (e.g., monitoring an individual's email...) we only have a small set of documents
- Works best/only for "Trivial Pursuit"-style fact-based questions
- Limited/brittle repertoire of
  - question categories
  - answer data types/filters
  - query rewriting rules

LCC: Harabagiu, Moldovan et al.
Value from Sophisticated NLP
Pasca and Harabagiu (2001)

- Good IR is needed: SMART paragraph retrieval
- Large taxonomy of question types and expected answer types is crucial
- Statistical parser used to parse questions and relevant text for answers, and to build KB
- Query expansion loops (morphological, lexical synonyms, and semantic relations) important
- Answer ranking by simple ML method

Abductive inference

- System attempts inference to justify an answer (often following lexical chains)
- Their inference is a kind of funny middle ground between logic and pattern matching
- But quite effective: 30% improvement
- Q: When was the internal combustion engine invented?
- A: The first internal-combustion engine was built in 1867.
- invent -> create_mentally -> create -> build
Question Answering Example

- How hot does the inside of an active volcano get?
- `get(TEMPERATURE, inside(volcano(active)))`
- “lava fragments belched out of the mountain were as hot as 300 degrees Fahrenheit”
- `fragments(lava, TEMPERATURE(degrees(300)), belched(out, mountain))`
  - volcano ISA mountain
  - lava ISPARTOF volcano  ■ lava inside volcano
  - fragments of lava HAVEPROPERTIESOF lava
- The needed semantic information is in WordNet definitions, and was successfully translated into a form that was used for rough ‘proofs’

Answer types in SOA QA systems

- Labels questions with answer type based on a taxonomy
- Classifies questions (e.g. by using a maximum entropy model)
QA Typology (from ISI USC)

- Typology of typical Q forms—94 nodes (47 leaf nodes)
- Analyzed 17,384 questions (from answers.com)

Named Entity Recognition for QA

The results of the past 5 TREC evaluations of QA systems indicate that current state-of-the-art QA is determined by the recognition of Named Entities:

- Precision of recognition
- Coverage of name classes
- Mapping into concept hierarchies
- Participation into semantic relations (e.g. predicate-argument structures or frame semantics)
Syntax to Logical Forms

- Syntactic analysis plus semantic => logical form
- Mapping of question and potential answer LFs to find the best match

The Architecture of LCC’s QA System around 2003
Answering definition questions

- Most QA systems use between 30-60 patterns
- The most popular patterns:

<table>
<thead>
<tr>
<th>Id</th>
<th>Pattern</th>
<th>Freq.</th>
<th>Usage</th>
<th>Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>person-hyponym QP</td>
<td>0.43%</td>
<td>The doctors also consult with former Italian Olympic skier Alberto Tomba, along with other Italian athletes</td>
<td>1907: Who is Alberto Tomba?</td>
</tr>
<tr>
<td>9</td>
<td>QP, the AP</td>
<td>0.28%</td>
<td>Bausch Lomb, the company that sells contact lenses, among hundreds of other optical products, has come up with a new twist on the computer screen magnifier</td>
<td>1917: What is Bausch &amp; Lomb?</td>
</tr>
<tr>
<td>11</td>
<td>QP, a AP</td>
<td>0.11%</td>
<td>ETA, a Basque language acronym for Basque Homeland and Freedom, has killed nearly 800 people since taking up arms in 1968</td>
<td>1987: What is ETA in Spain?</td>
</tr>
<tr>
<td>13</td>
<td>QA, an AP</td>
<td>0.02%</td>
<td>The kidnappers claimed they are members of the Abu Sayaf, an extremist Muslim group, but a leader of the group denied that</td>
<td>2042: Who is Abu Sayaf?</td>
</tr>
<tr>
<td>21</td>
<td>AP such as QP</td>
<td>0.02%</td>
<td>For the hundreds of Albanian refugees undergoing medical tests and treatments at Fort Dix, the news is mostly good: Most are in reasonable good health, with little evidence of infectious diseases such as TB</td>
<td>2095: What is TB?</td>
</tr>
</tbody>
</table>

Example of Complex Question

How have thefts impacted on the safety of Russia’s nuclear navy, and has the theft problem been increased or reduced over time?

Need of domain knowledge

To what degree do different thefts put nuclear or radioactive materials at risk?

Question decomposition

**Definition questions:**
- What is meant by nuclear navy?
- What does ‘impact’ mean?
- How does one define the increase or decrease of a problem?

**Factoid questions:**
- What is the number of thefts that are likely to be reported?
- What sort of items have been stolen?

**Alternative questions:**
- What is meant by Russia? Only Russia, or also former Soviet facilities in non-Russian republics?
Complex questions

- Characterized by the need of domain knowledge
- There is no single answer type that can be identified, but rather an answer structure needs to be recognized
- Answer selection becomes more complicated, since inference based on the semantics of the answer type needs to be activated
- Complex questions need to be decomposed into a set of simpler questions