

Query Reformulation & Answer Extraction

Ling 573
NLP Systems and Applications
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Comparing Question Reformulations

- “Exact Phrases in Information Retrieval for Question Answering”, Stoyanchev et al, 2008
- Investigates
 - Role of ‘exact phrases’ in retrieval for QA
 - Optimal query construction through document retrieval
 - From Web or AQUAINT collection
 - Impact of query specificity on passage retrieval

Motivation

- Retrieval bottleneck in Question-Answering
 - Retrieval provides source for answer extraction
 - If retrieval fails to return answer-contained documents, downstream answer processing is guaranteed to fail
 - Focus on recall in information retrieval phase
 - Consistent relationship b/t quality of IR and of QA

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 - Consistent relationship b/t quality of IR and of QA
- Main factor in retrieval: query
 - Approaches vary from simple to complex processing or expansion with external resources

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- Evaluate query construction for sentence retrieval
 - Analyze specificity

Data Sources & Resources

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- Resources:
 - IR: Lucene; NLTK, Lingpipe: phrase, NE annotation
 - Also hand-corrected

Query Processing Approach

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 - Combined with target in all cases
- Max 20 documents: expensive downstream process
 - Sentences split, ranked

Query Components

Target Question	United Nations What was the number of member nations of the U.N. in 2000?
Named Entity	U.N., United Nations
Phrases	"member nations of the U.N."
Converted Q-phrase	"member nations of the U.N. in 2000"
Baseline Query	was the number of member nations of the U.N. in 2000 United Nations
Lucene Query with phrases and NE	was the number of member nations of the U.N. in 2000 "United Nations", "member nations of the u.n."
Cascaded web query	
query1	"member nations of the U.N. in 2000" AND (United Nations)
query2	"member nations of the u.n." AND (United Nations)
query3	(number of member nations of the U.N. in 2000) AND (United Nations)
query4	(United Nations)

Query Components in Supporting Sentences

	sent w/ answer		all sentences		precision
	num	proportion	num	proportion	
Named Entity	907	0.320	4873	0.122	.18
Phrases	350	0.123	1072	0.027	.34
Verbs	396	0.140	1399	0.035	.28
Q-Phrases	11	0.004	15	0.00038	.73
Words	2573	0.907	29576	0.745	.086
Total Sentences	2836		39688		

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Highest precision: Converted q-phrase, then phrase,..
Words likely to appear, but don't discriminate

Results

- Document and sentence retrieval
- Metrics:
 - Document retrieval:
 - Average recall
 - MRR
 - Overall document recall: % of questions w/ ≥ 1 correct doc
 - Sentence retrieval
 - Sentence MRR
 - Overall sentence recall
 - Average prec of first sentence
 - # correct in top 10, top 50

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	avg doc recall	avg doc MRR	overall doc recall	avg sent MRR	overall sent recall	avg corr sent in top 1	avg corr sent in top 10	avg corr sent in top 50
IR with Lucene on AQUAINT dataset								
baseline (words disjunction from target and question)	0.530	0.631	0.756	0.314	0.627	0.223	1.202	3.464
baseline + auto phrases	0.514	0.617	0.741	0.332	0.653	0.236	1.269	3.759
words + auto NEs & phrases	0.501	0.604	0.736	0.316	0.653	0.220	1.228	3.705
baseline + manual phrases	0.506	0.621	0.738	0.291	0.609	0.199	1.231	3.378
words + manual NEs & phrases	0.510	0.625	0.738	0.294	0.609	0.202	1.244	3.368
IR with Yahoo API on WEB								
baseline words disjunction	-	-	-	0.183	0.570	0.101	0.821	2.316
cascaded using auto phrases	-	-	-	0.220	0.604	0.140	0.956	2.725
cascaded using manual phrases	-	-	-	0.241	0.614	0.155	1.065	3.016

Discussion

- Document retrieval:
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- Sentence retrieval:
 - Lower, correct sentence ~ rank 3
- Little difference for exact phrases in AQUAINT
- Web:
 - Retrieval improved by exact phrases
 - Manual more than auto (20-30%) relative
 - Precision affected by tagging errors

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 - Answer: 310.5 million

Challenges

- ISI's answer extraction experiment:
 - Given:
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 - Given:
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- Accuracy:
 - Systems: 68.2%, 63.4%, 56.7%
 - Still missing 30%+ answers

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 - Task: Pin-point specific answer string
- Accuracy:
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 - Still missing 30%+ answers
 - Oracle (any of 3 right): 78.9% (20% miss)

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 - Semantic:
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- Combine with machine learning to select

Pattern Matching Example

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Pattern	Question	Answer
<AP> such as <QP>	What is autism?	“, <u>developmental disorders</u> such as autism”
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 - Question: When was Mozart born?
 - Answer: Mozart was born on
 - Pattern: <QP> was born on <AP>
 - Pattern: <QP> (<AP> -)

Basic Strategies

- N-gram tiling:
 - Typically as part of answer validation/verification
 - Integrated with web-based retrieval
 - Based on retrieval of search ‘snippets’
 - Identifies frequently occurring, overlapping n-grams
 - Of correct type

N-gram Tiling

Scores

20

Charles Dickens

15

Dickens

10

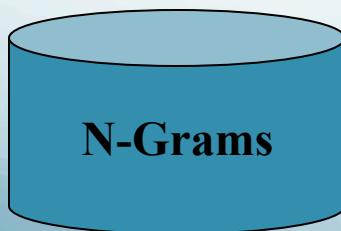
Mr Charles

merged,

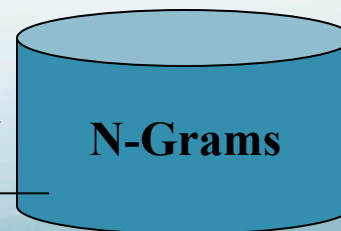
discard
old n-grams

Score 45

Mr Charles Dickens



tile highest-scoring n-gram



Repeat, until no more overlap

Automatic Pattern Learning

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 - Best TREC 2001 system:
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 - Many patterns strongly associated with answer types
 - E.g. <NAME> (<DATE>.-<DATE>)
 - Person's birth and death

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 - Have to tag training samples, need training samples
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 - Guidance from small number of seed samples
 - Can use answer data from web

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 - Select only sentences w/qterm and aterm
 - Identify all substrings and their counts
 - Implemented using suffix trees for efficiency
 - Select only phrases with qterm AND aterm
 - Replace qterm and aterm instances w/generics

Example

- Q: When was Mozart born?
- A: Mozart (1756-.....

Example

- Q: When was Mozart born?
- A: Mozart (1756 –
- Qterm: Mozart; Aterm: 1756
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- Convert to : <Name> (<ANSWER>

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- Collect more patterns:
 - E.g. for Birthdate
 - a. born in <ANSWER> , <NAME>
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- Is this enough?
 - No – some good patterns, but
 - Probably lots of junk, too; need to filter

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 - b) matches/w right aterm: C_a
 - Compute precision $P = C_a/C_o$
 - Retain if match > 5 examples

Pattern Precision Example

- Qterm: Mozart
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- Pattern: <NAME> was born in <ANSWER>
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- Match: Mozart born in 1756.
- Precisions:
 - 1.0 <NAME> (<ANSWER> -)
 - 0.6 <NAME> was born in <ANSWER>
 -

Nuances

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 - E.g. dates in different formats, full names, etc
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 - E.g. dates in different formats, full names, etc
 - Use alternate forms in pattern search
- Precision assessment:
 - Use other examples of same type to compute
 - Cross-checks patterns

Answer Selection by Pattern

- Identify question types and terms
- Filter retrieved passages, replace qterm by tag
- Try to match patterns and answer spans
- Discard duplicates and sort by pattern precision

Pattern Sets

- WHY-FAMOUS

1.0 <ANSWER> <NAME> called

1.0 laureate <ANSWER> <NAME>

1.0 by the <ANSWER> , <NAME> ,

1.0 <NAME> - the <ANSWER> of

1.0 <NAME> was the <ANSWER>

of

- BIRTHYEAR

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

Results

- Improves, though better with web data

TREC Corpus

Question type	Number of questions	MRR on TREC docs
BIRTHYEAR	8	0.48
INVENTOR	6	0.17
DISCOVERER	4	0.13
DEFINITION	102	0.34
WHY-FAMOUS	3	0.33
LOCATION	16	0.75

Web

Question type	Number of questions	MRR on the Web
BIRTHYEAR	8	0.69
INVENTOR	6	0.58
DISCOVERER	4	0.88
DEFINITION	102	0.39
WHY-FAMOUS	3	0.00
LOCATION	16	0.86

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 - Wildcards impractical
- Long-distance dependencies not practical
 - Less of an issue in Web search
 - Web highly redundant, many local dependencies
 - Many systems (LCC) use web to **validate** answers

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- Requires information about:
 - Answer length, type; logical distance (1-2 chunks)
- Also,
 - Can only handle single continuous qterms
 - Ignores case
 - Needs handle canonicalization, e.g of names/dates

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 - Integrate with machine learning
 - MAXENT!!!
 - Re-ranking approach

Answering w/Maxent

$$P(a | \{a_1, a_2, \dots, a_A\}, q) = \frac{\exp[\sum_{m=1}^M \lambda_m f_m(a, \{a_1, a_2, \dots, a_A\}, q)]}{\sum_{a'} \exp[\sum_{m=1}^M \lambda_m f_m(a', \{a_1, a_2, \dots, a_A\}, q)]}$$

$$\hat{a} = \operatorname{argmax}_a [\sum_{m=1}^M \lambda_m f_m(a, \{a_1, a_2, \dots, a_A\}, q)]$$

Feature Functions

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 - Binary feature

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 - # times answer appears in retrieval results
- Answer type match (binary)
- Question word absent (binary):
 - No question words in answer span
- Word match:
 - Sum of ITF of words matching b/t questions & sent

Training & Testing

- Trained on NIST QA questions
 - Train: TREC 8,9;
 - Cross-validation: TREC-10
- 5000 candidate answers/question
- Positive examples:
 - NIST pattern matches
- Negative examples:
 - NIST pattern doesn't match
- Test: TREC-2003: MRR: 28.6%; 35.6% exact top 5