

Query Processing: Query Formulation

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NLP Systems and Applications

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Roadmap

- Motivation:
 - Retrieval gaps
- Query Formulation:
 - Question Series
 - Query reformulation:
 - AskMSR patterns
 - MULDER parse-based formulation
 - Classic query expansion
 - Semantic resources
 - Pseudo-relevance feedback

Retrieval Gaps

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 - A: The height of Everest is...
 - Q: When did the first American president take office?
 - A: George Washington was inaugurated in....

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 - Query expansion
 - Differences in structure

Query Formulation

- Convert question suitable form for IR
- Strategy depends on document collection
 - Web (or similar large collection):
 - ‘stop structure’ removal:
 - Delete function words, q-words, even low content verbs
 - Corporate sites (or similar smaller collection):
 - Query expansion
 - Can’t count on document diversity to recover word variation
 - Add morphological variants, WordNet as thesaurus
 - Reformulate as declarative: rule-based
 - Where is X located -> X is located in

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Target 27 - Jennifer Capriati	
Q27.2	Who is her coach?
Q27.3	Where does she live?

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- Least shallow approach:
 - Heuristic reference resolution

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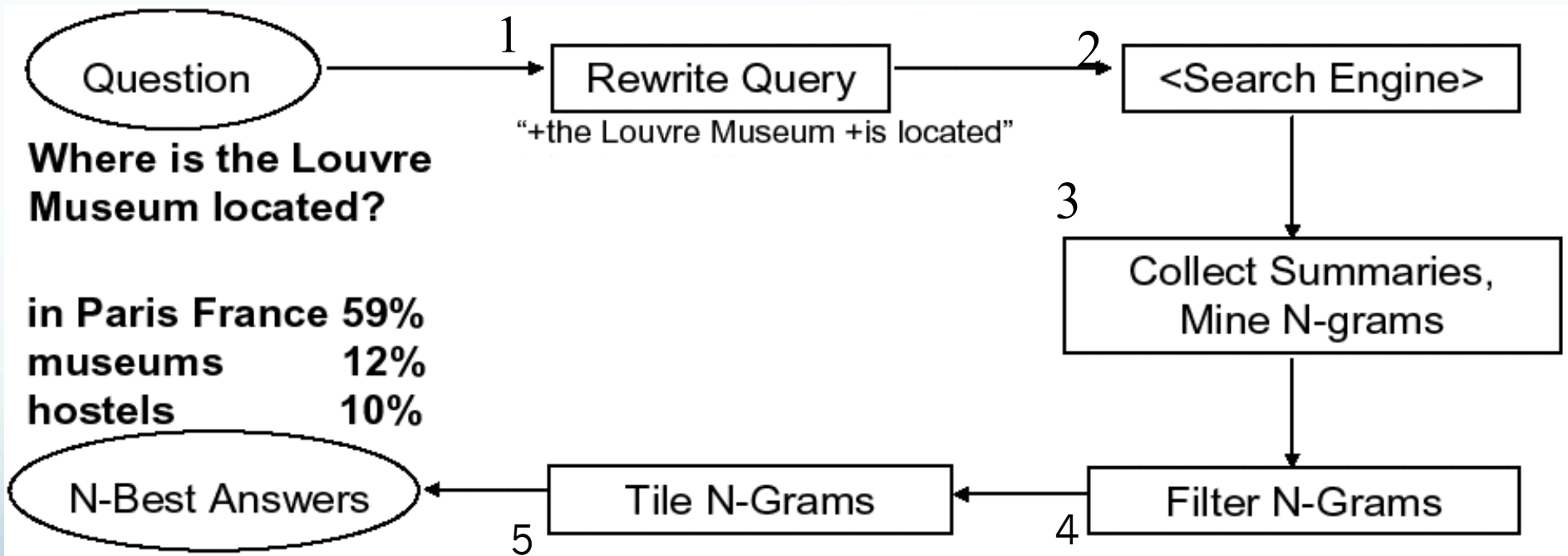
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 - When was the band formed?
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 - Most teams concatenate

AskMSR

- Shallow Processing for QA
 - (Dumais et al 2002, Lin2007)



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- Create type-specific answer type (Person, Date, Loc)

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 - Where is A? -> A is located in ?x (specific)
 - Inexact reformulation: bag-of-words

Query Reformulation

- Examples

What year did Alaska become a state?

[baseline] What year did Alaska become a state
[inexact] Alaska became a state
[exact] Alaska became a state ?x

Who was the first person to run the mile in less than four minutes?

[baseline] Who was the first person to run the mile in less than four minutes?
[inexact] the first person to run the mile in less than four minutes
[exact] the first person to run the mile in less than four minutes was ?x
[exact] ?x was the first person to run the mile in less than four minutes

Deeper Processing for Query Formulation

- MULDER (Kwok, Etzioni, & Weld)
- Converts question to multiple search queries
 - Forms which match target
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- Employs full parsing augmented with morphology

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- Question reformulation as machine translation
 - Given question logs, click-through snippets
 - Train machine learning model to transform $Q \rightarrow A$

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 - Helped, hurt, or no effect
 - With long queries & long documents, no/bad effect
- Some recent positive results on short queries
 - E.g. Fang 2008
 - Contrasts different WordNet, Thesaurus similarity
 - Add semantically similar terms to query
 - Additional weight factor based on similarity score

Similarity Measures

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- Term similarity score from Lin's thesaurus

Results

- Definition similarity yields significant improvements
 - Allows matching across POS
 - More fine-grained weighting than binary relations

Deliverable #2 Discussion

- More training data available
- Test data released
- Requirements

- Deliverable Reports