QIC: Incorporating Context into a User Query

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Outline

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  - Concept Extraction
  - Learning to Rank and Dynamic Clustering
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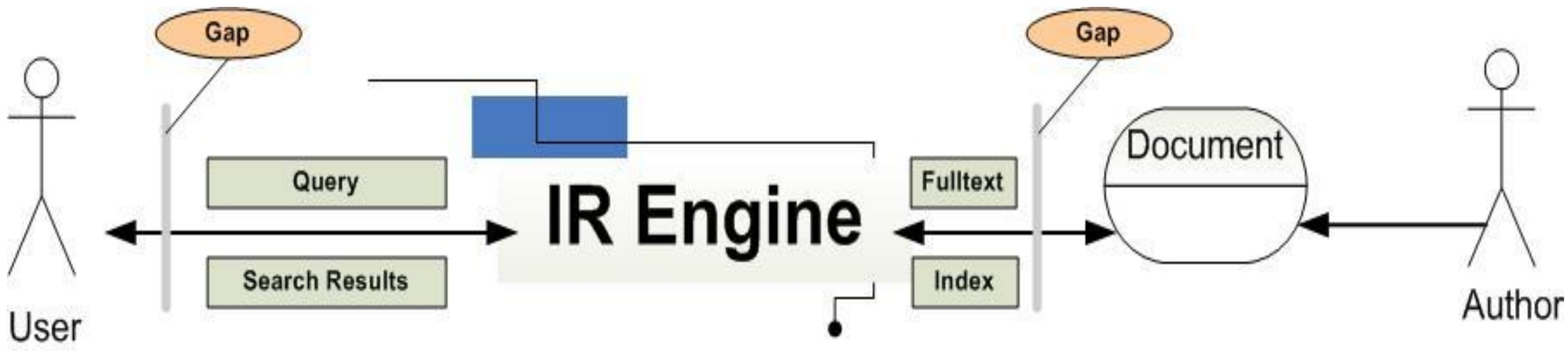
Research Problems

People want search results to reflect exactly what they **meant**, **all** that they meant, and **only** what they meant, and they want it **quickly**.



- There are gaps….
  - Gap between what the user wants (information need) and the query that the user formulates
  - Gap between what the document represents and indexes that the IR engine built

Research Goals

- The purpose of the project is three-fold:
  1. **Incorporating inference of user preferences in Query Expansion**

     Our approach: QEQIC

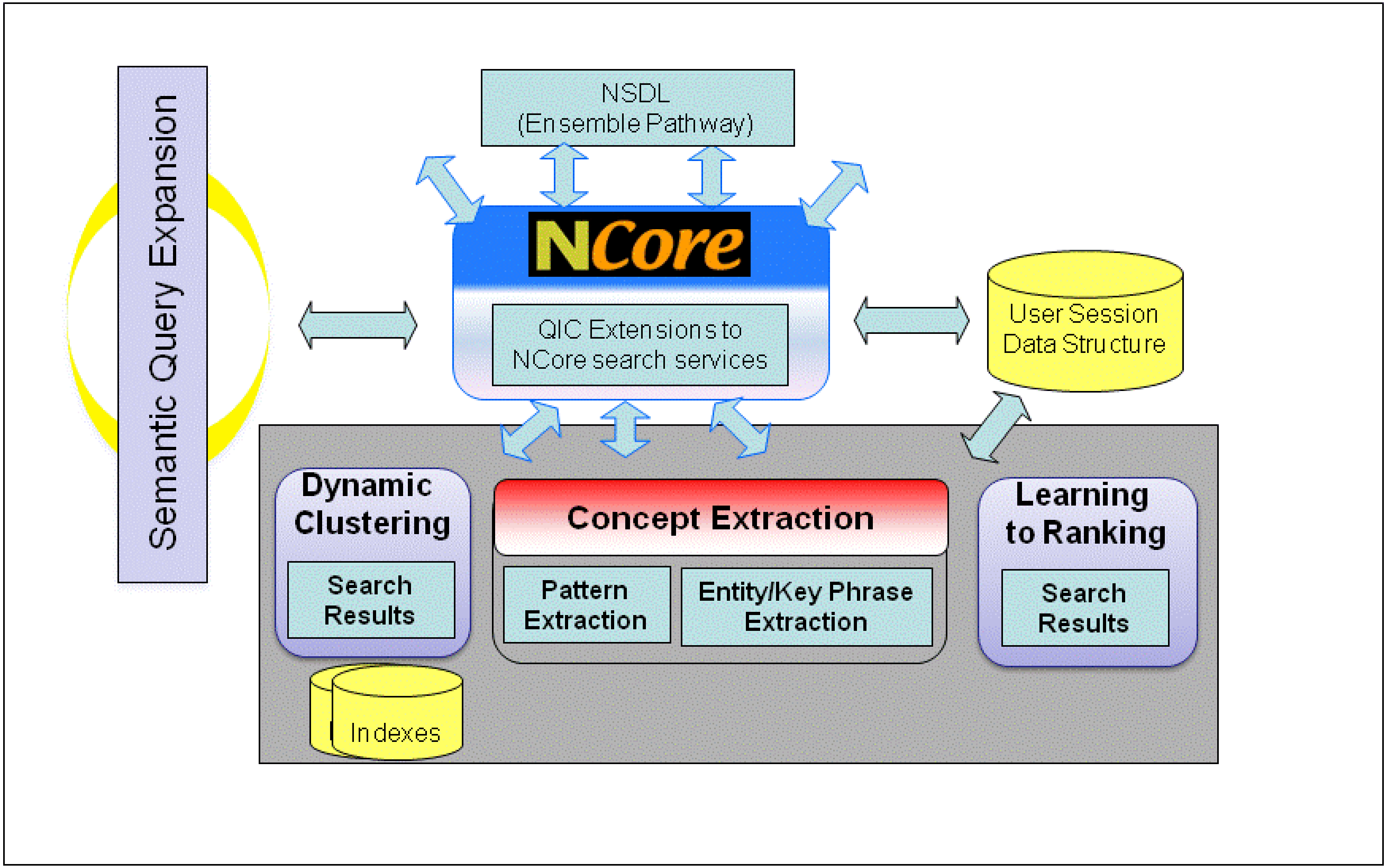
  2. **Capturing meanings** embedded in documents

     Our approach: Concept Extraction

  3. **Ranking search results with context-enriched features**

Our approach: Learning to Rank and Dynamic Clustering

QIC System Architecture



Data Collection

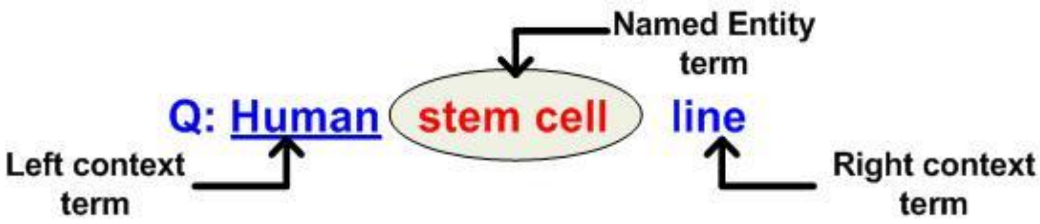
- Two different types of data:
  1. Ohsumed – biomedical data collection for proof-of-concept at the initial development phase.
  2. Ensemble Pathway – computing sciences data collections at http://www.computingportal.org/collections

jOAI, an OAI harvesting tool built in Ncore was used to crawl Ensemble.

Note: The size of data is small. This may influence the overall performance of our approach.

Query Expansion: QEQIC

- Query is initially represented as a tuple of {*context, named entities*}.



  - Named entities detected using Boosted Dictionary-based Entity Spotter (BDES).
  - A concept tuple consists of {*Computing concept, description, class*}.
    - *Computing concepts* provided by "The Free On-line Dictionary of Computing" (http://foldoc.org/).
    - *Class* assigned to a concept manually based on ACM Classification

Boosted Dictionary-based Entity Spotter

- Dictionary-based approach: tackles the problem of lack of contextual cues but:
  - too many false recognitions
  - takes too long to look up the dictionary entry.
- Our approach resolves these issues by:
  - Approximate String Distance Algorithm to retrieve candidate entries
  - Shortest-path Distance Algorithm
  - Part-Of-Speech (POS) tag
  - Syntactical properties of terms

Concept Tuple Example

- **Sentence:**

  Demonstrate the algorithm for simultaneously finding the minimum and maximum values in an array

  - **Concept:**

    Algorithm

  - **Class:**

    Theory of Computation

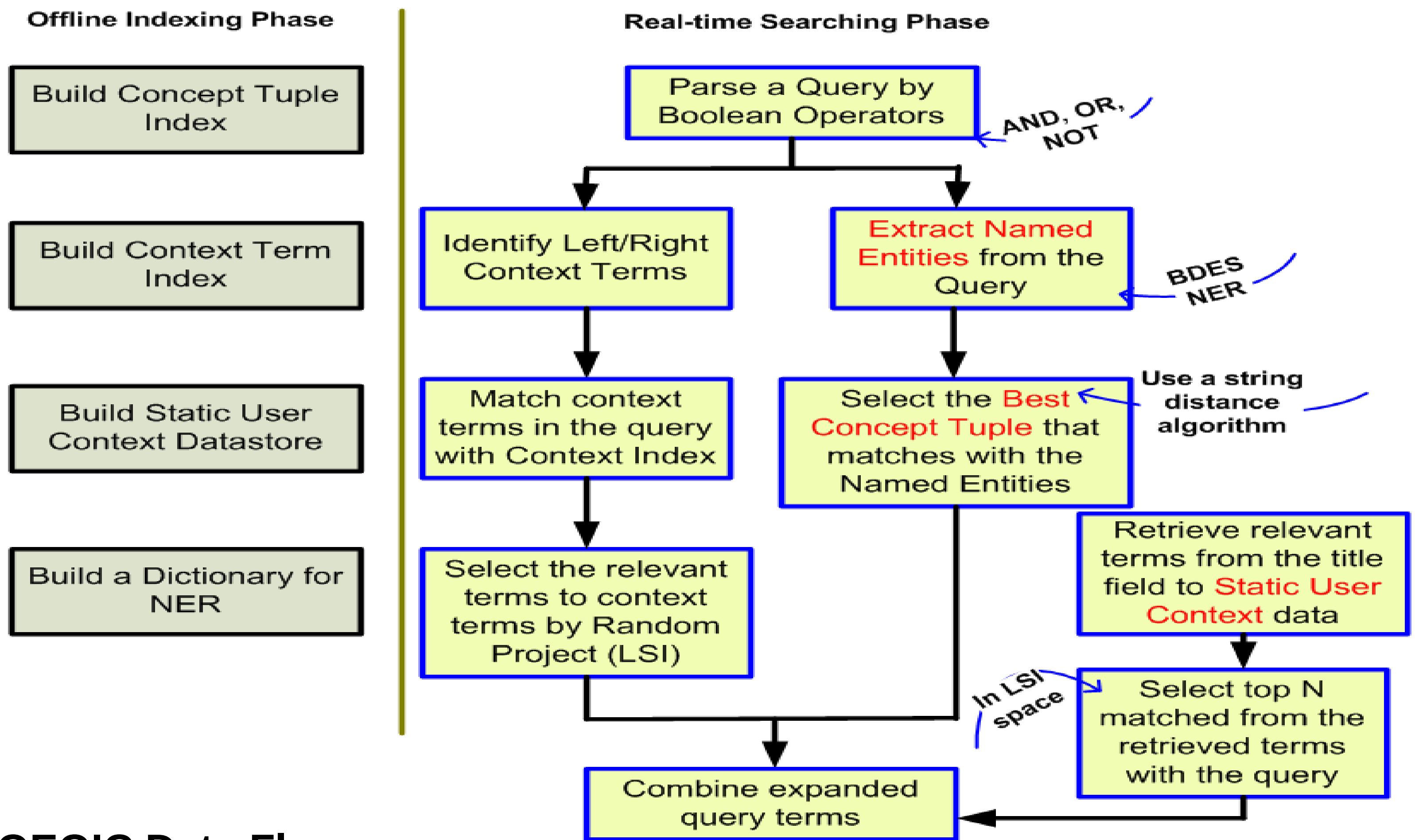
  - **Description:**

    Model of computation and algorithm

QEQIC: static user profile data

- Incorporate Static User Preference data into query expansion
  - Subject terms stored in user profile are matched with titles of data set in the Latent Semantic Index (LSI) space.
  - *N* top terms relevant to subject terms in the user profile are compared with a query.
    - If there is a good match (based on string similarity between a top term and query terms), the terms are weighted higher.

QEQIC: Semantic Query Expansion Algorithm



QEQIC Data Flow

Preliminary Results of BDES

BDES

	Genia	Geinia+MeSH	Genia+MeSH+ UMLS
Precision	0.93	0.878	0.88
Recall	0.573	0.72	0.68

BDES without POS/syntactic properties

	Genia	Geinia+MeSH	Genia+MeSH+ UMLS
Precision	0.76	0.56	0.51
Recall	0.62	0.82	0.78

Concept Extraction

- Probabilistic Combinatorial Markov Random Fields (PCMRF):
  - A supervised learning technique
  - PCMRF is a non-generative graph model.
- Training data:
  - 5000 sentences from Ensemble Pathway and other computing sciences related digital libraries.
    - These 5000 sentences are positive examples (meaning containing concepts in the sentence).
    - Combined with 5000 more sentences (negative examples), we build a concept extraction model.

Concept Extraction

- RESTful Web Services for Concept Extraction

http://localhost:8080/qic/Tagger?tag="Testing internet tagging service"


```
<tagging>
        <token>
                <name>Testing</name>
                <class>O</class>
        </token>
        <token>
                <name>internet</name>
                <class>Web</class>
        </token>
        <token>
                <name>tagging</name>
                <class>O</class>
        </token>
        <token>
                <name>service</name>
                <class>O</class>
        </token>
</tagging>
```

Dynamic Clustering of Search Results

- Clustering approach:
  - Based on a supervised learning technique - Probabilistic Combinatorial Markov Random Fields (PCMRF) technique
    - Same as our concept extraction technique
  - Requires a small set of initial training examples.
  - For performance reasons, input for clustering is a set of concepts extracted from Ensemble and stored in a database.

Rank search results with context features

- **Learning to rank** – apply supervised learning techniques to rank search results.
- Proposed technique: Mixture Support Vector Machines
  - Combines multiple models
    - Models are built with a set of features (attributes) such as TF-IDF, no. of clicks, the user's research interest, etc.
    - There are several different ways to select features:
      1) Document-driven model [11,15],
      2) Meta data-driven model [14],
      3) User static context-driven model, and
      4) User search behavior-driven model [13]

Note: The current model is based on document-related features.

Document-driven Model

- The most popular approach in learning to rank.
  - Training data is part of the LETOR package [11]
    http://research.microsoft.com/en-us/um/beijing/projects/letor/default.aspx
  - 25 features were extracted
    - 10 from title, 10 from abstract, and 5 from 'title + abstract'
    - TF, TF*IDF, BM25, Language Model ranking scores, IDF, etc

```
2 qid:1 1:3.00000000 2:2.07944154 3:0.27272727 …
25:-3.87512000 #docid = 40626
```

  - For query id "1" and document id "40626", the label is "2" (definitely relevant).

Search Behavior-driven Model

- Incorporate users' search behavior into ranking the results [13].
  - 1 - category; 2 - qid; 3 - search; 4 - abstract_text; 5 - full_text; 6 - no_visits; 7 - no_returned_citation; 8 - pos_clicked_citation; 9 - search_duration

```
0 qid:1 1:0.0 2:1.0 3:0.0 4:1 5:0 6:0 7:0.016944444
0 qid:1 1:0.0 2:2.0 3:0.0 4:2 5:0 6:1 7:4.2805557
1 qid:1 1:1.0 2:4.0 3:0.0 4:5 5:11583 6:10 7:106.29944
2 qid:1 1:8.0 2:8.0 3:11.0 4:27 5:2194 6:33 7:314.75027
0 qid:1 1:0.0 2:1.0 3:0.0 4:1 5:0 6:0 7:17.611666
0 qid:1 1:0.0 2:1.0 3:0.0 4:1 5:0 6:0 7:13.123055
1 qid:1 1:2.0 2:0.0 3:0.0 4:2 5:0 6:0 7:20.195278
```

Sample training data based on search behavior

Evaluation

- Preliminary Results with Ohsumed Data for Query Expansion
  - A set of 348,566 references from MEDLINE consisting of titles and/or abstracts from 270 medical journals over a five-year period (1987-1991).
  - Popular data set to apply supervised learning techniques to IR
  - Contains the 106 queries in test set, with patient and topic information, in the format:
    - .I Sequential identifier
    - .B Patient information
    - .W Information request
  - For the preliminary test, we used 12 out of 106 queries.

Evaluation

- The Approach
  - Use Recall and Interpolated Average Precision to measure the performance.
  - Investigate whether QEQIC performs better than the baseline Language Model technique.
  - Investigate whether adding concepts, semantic types, and context terms to QE improves the performance.

Preliminary Results

	QEQIC (title only)	baseline LM (title only)	QEQIC (title+abstract)	baseline LM (title+abstract)
Inter. Avg. Precision	0.135	0.108	0.172	0.139
Avg. Recall	0.359	0.256	0.407	0.323

Measure by Recall and Interpolated Average Precision

Preliminary Results

- Impact with different feature sets

	QEQIC+CON	QEQIC+CON+SEM	QEQIC+CON+SEM+ CXT
Avg. Precision	0.137	0.107	0.107
Avg. Recall	0.359	0.321	0.321

CON: Concept
SEM: Semantic Type
CXT: Context Term

Measure by Recall and Interpolated Average Precision

Conclusions and Future Work

- Conclusions
  - We developed a semantic query expansion technique, and tested it on a biomedical data collections.
  - We developed a new ranking technique for the search results with the “Learning to Rank” approach.
  - We developed a concept extraction technique and a dynamic clustering technique with Probabilistic Combinatorial Markov Random Fields.
  - We developed RESTful APIs for our techniques.
- Future Work
  - We plan to conduct a pilot study and the main experiment on Ensemble Pathway data

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Questions?

Thanks!