Named Entity Recognition in Query

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Outline

- Problem Definition
- Potential Applications
- Challenges
- Our Approach
- Experimental Results
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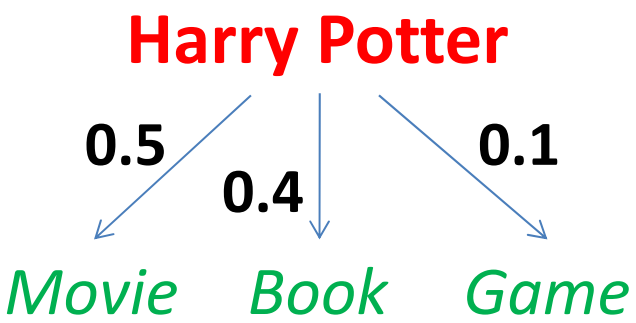
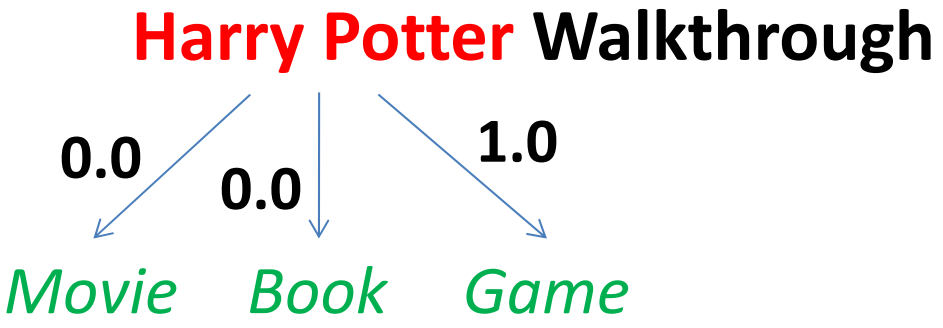
Problem Definition

Named Entity Recognition in Query (NERQ)

Identify Named Entities in Query and Assign them into Predefined Categories with Probabilities





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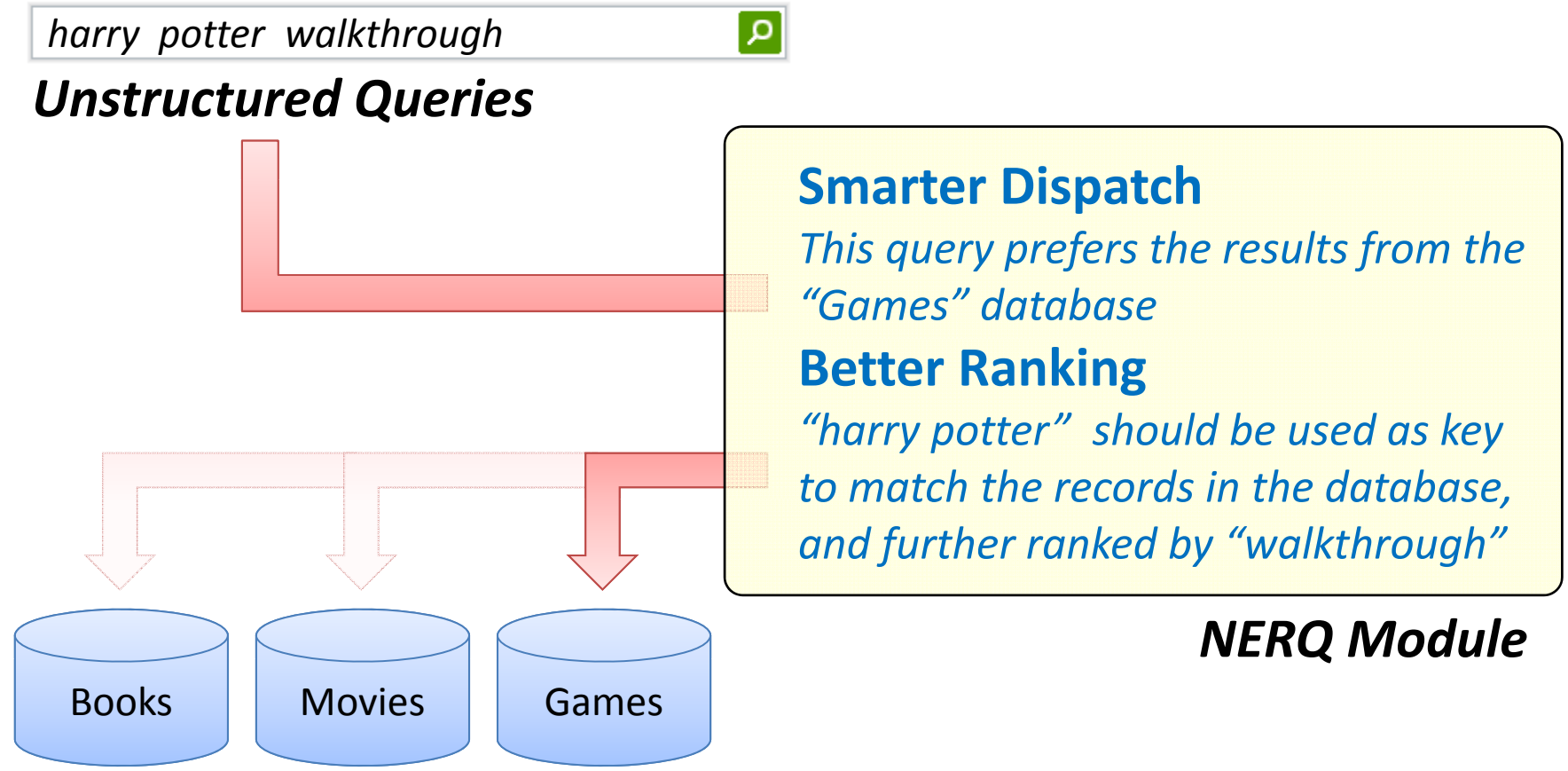
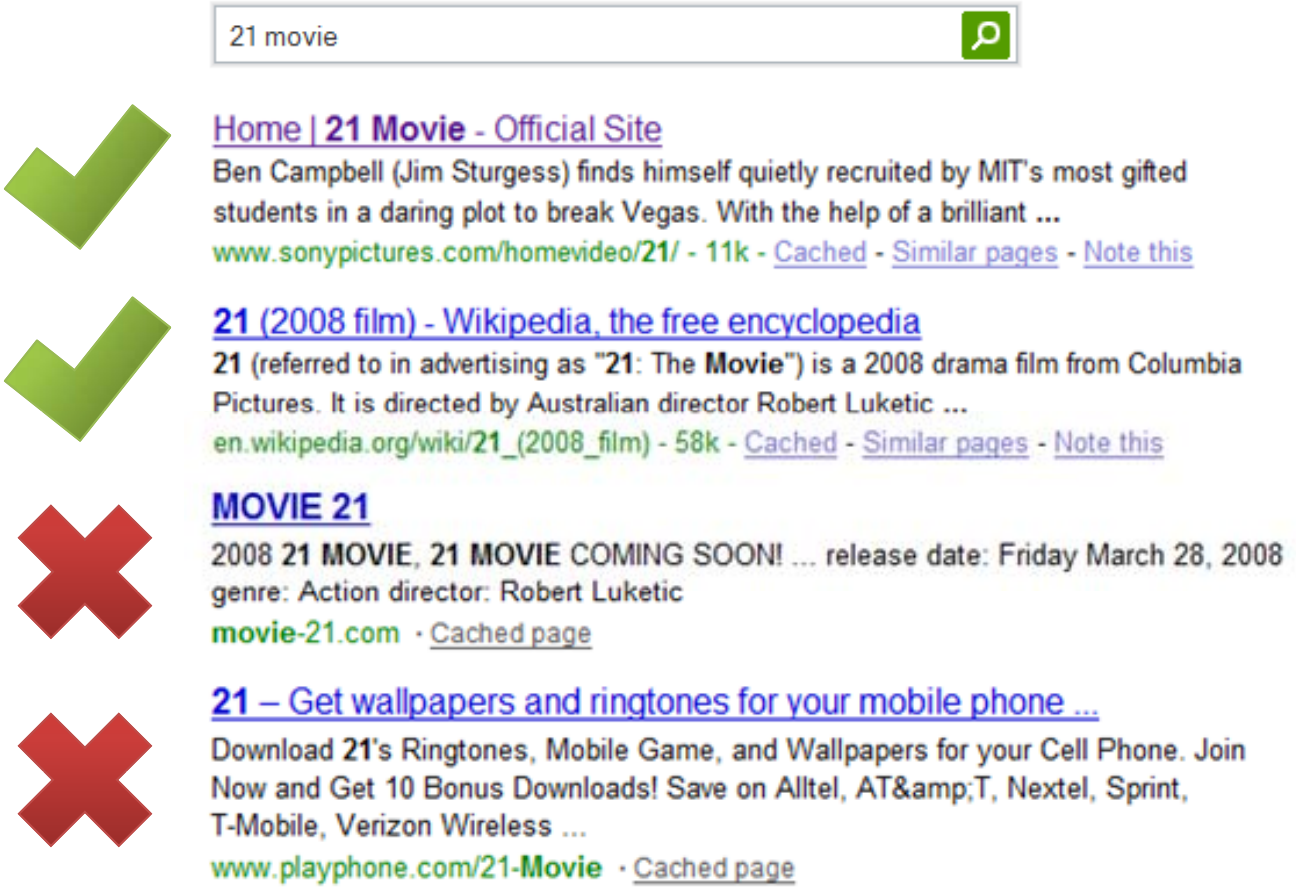
NERQ in Searching Structured Data



NERQ in Web Search



Search results can be better if we know that
"21 movie" indicates searcher wants the movie named 21

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Challenges

- NER (Named Entity Recognition)
  - Well formed documents (e.g. news articles)
  - Usually a supervised learning method based on a set of features
    - Context Feature: whether “Mr.” occurs before the word
    - Content Feature: whether the first letter of words is capitalized
- NERQ
  - Queries are short (2-3 words on average)
    - Less context features
  - Queries are not well-formed (typos, lower cased, …)
    - Less content features

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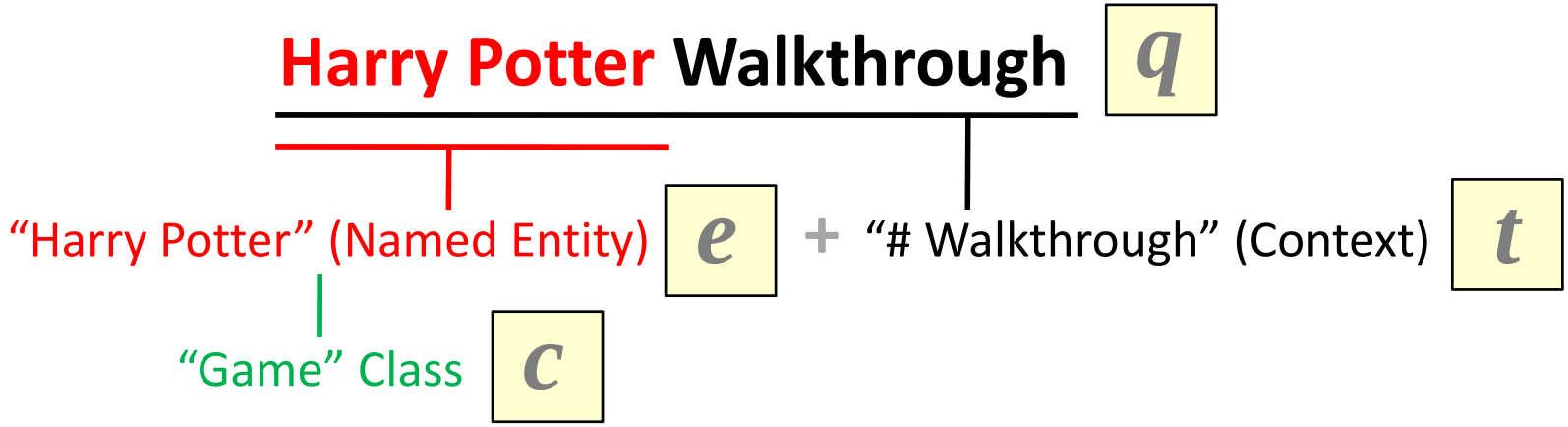
Our Approach to NERQ



- Goal of NERQ becomes to find the best triple $(e, t, c)^*$ for query q satisfying

$$(\mathrm{e}, \mathrm{t}, \mathrm{c})^* = \arg\max_{(e,t,c)\in G(q)} p(e,t,c)$$

$$= \arg\max_{(e,t,c)\in G(q)} p(e)p(c|e)p(t|c)$$

Training With Topic Model

- Ideal Training Data $T = \{(e_i, t_i, c_i)\}$

$$\max \prod_i p(e_i, t_i, c_i)$$

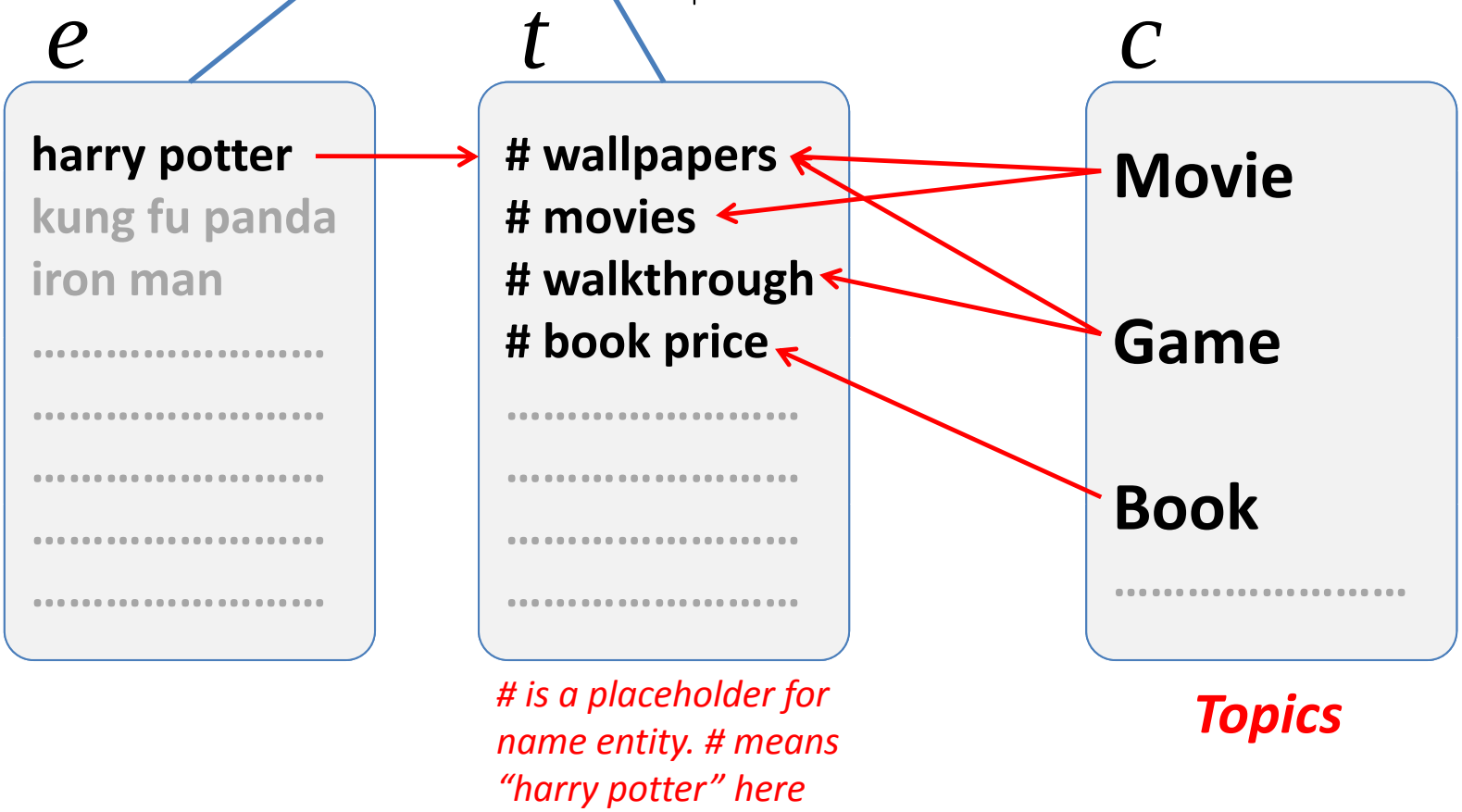
- Real Training Data $T = \{(e_i, t_i, *)\}$
  - Queries are ambiguous (**harry potter**, **harry potter** review)
  - Training data are a relatively few

$$\max \prod_i \sum_c p(e_i, t_i, c) = \max \prod_i p(e_i) \sum_c p(c|e_i) p(t_i|c)$$

$$= \max \prod_e \prod_{i|e_i=e} p(e) \sum_c p(c|e) p(t_i|c)$$

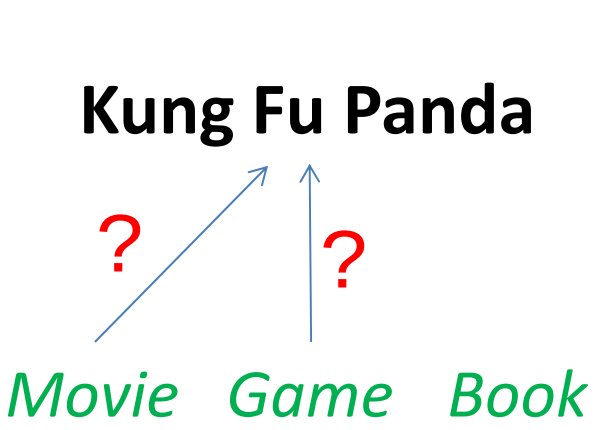
Training With Topic Model (cont.)

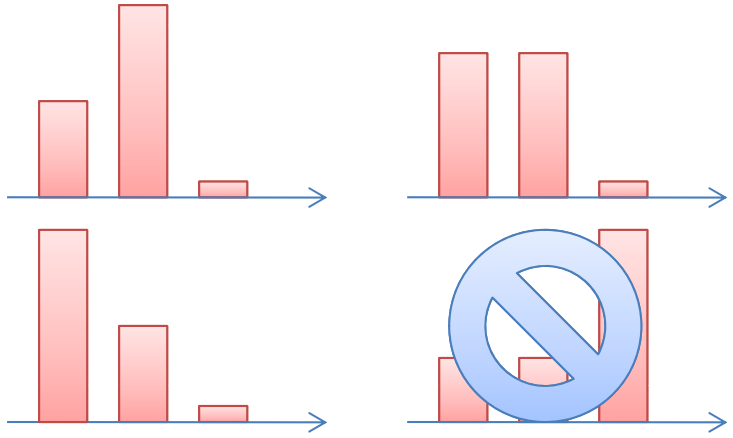
$$\max \prod_e p(e) \prod_{i|e_i=e} \sum_c p(c|e) p(t_i|c)$$



Weakly Supervised Topic Model

- Introducing Supervisions
  - Supervisions are always better
  - Alignment between ***Implicit Topics*** and ***Explicit Classes***
- Weak Supervisions
  - Label named entities rather than queries (doc. class labels)
  - Multiple class labels (Binary Indicator)





Distribution Over Classes

Weakly Supervised LDA (WS-LDA)

- LDA + Soft Constraints (w.r.t. Supervisions)

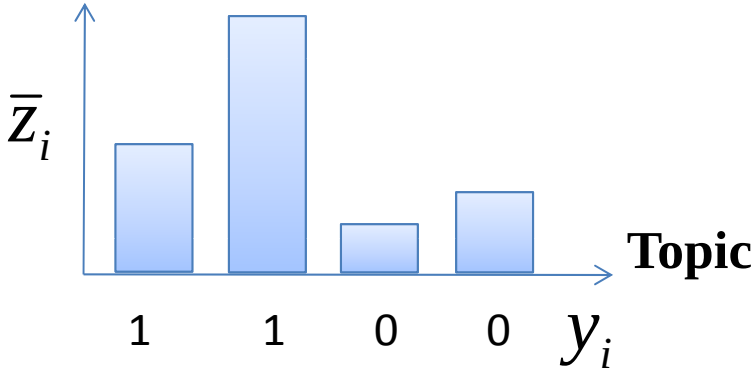
$$\mathrm{O}(w, y) = \underbrace{\log p(w|\alpha, \beta)}_{\textbf{\textit{LDA Probability}}} + \underbrace{\lambda C(y|\alpha, \beta)}_{\textbf{\textit{Soft Constraints}}}$$

- Soft Constraints

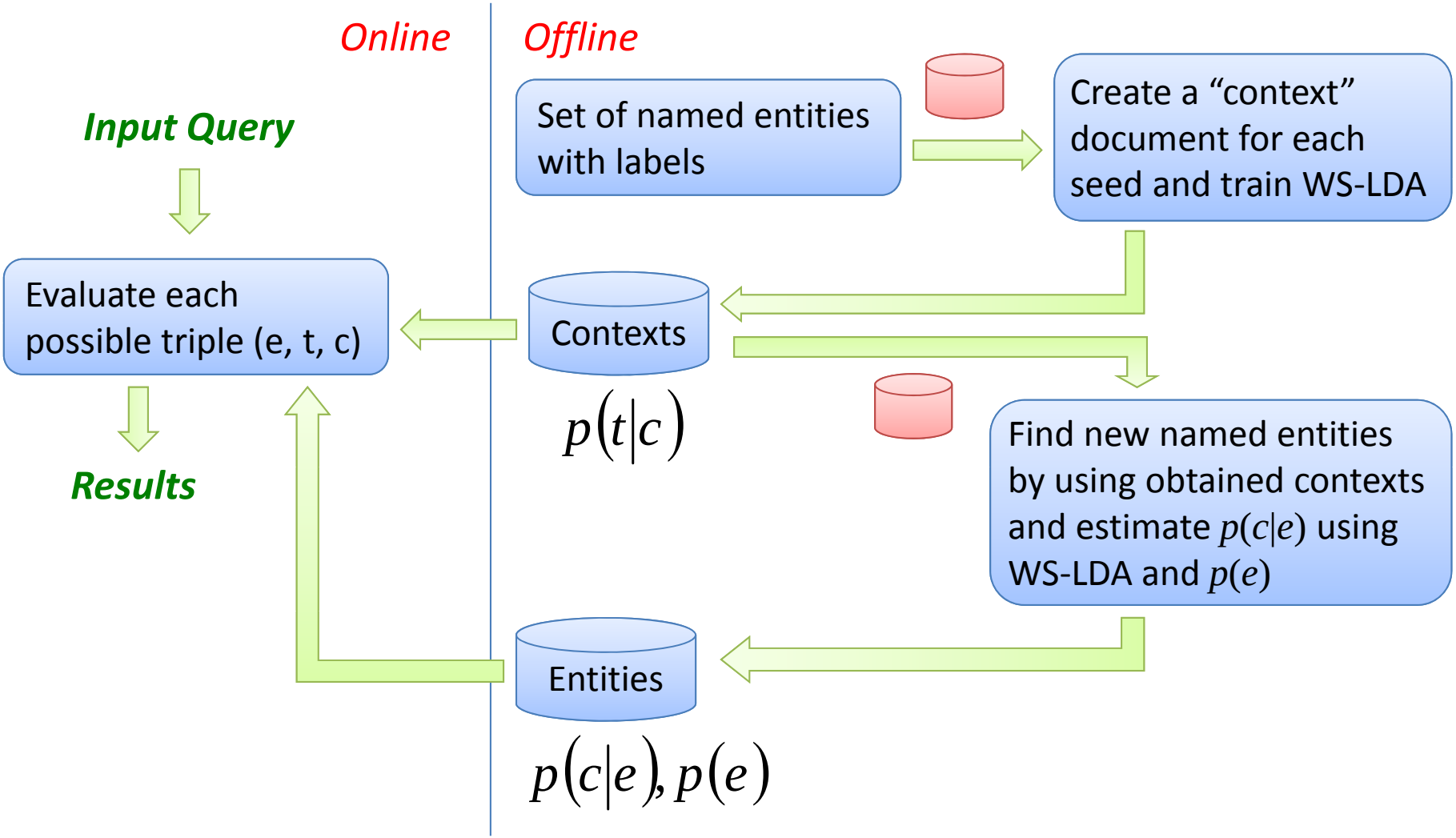
$$C(y|\alpha, \beta) = \sum_i y_i \bar{z}_i$$

Document Probability on the *i*-th Class

Document Binary Label on the *i*-th Class



System Flow Chat



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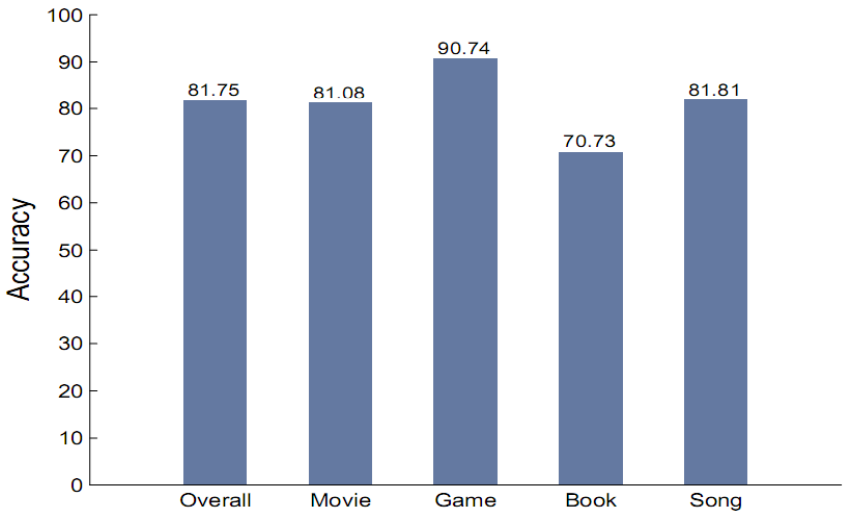
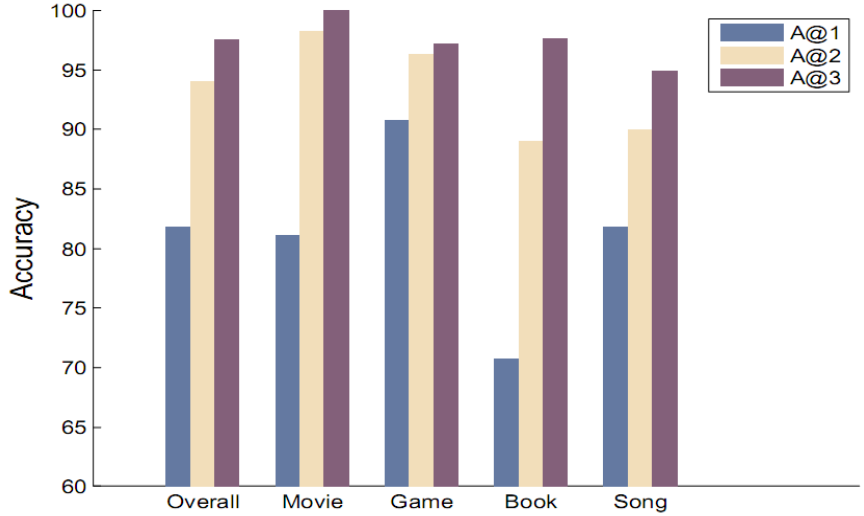
Experimental Results

- Data Set
  - Query log data
    - Over 6 billion queries and 930 million unique queries
    - About 12 million unique queries
  - Seed named entities
    - 180 named entities labeled with four classes
    - 120 named entities are for training and 60 for testing

Experimental Results (cont.)

- NERQ Precision





Experimental Results (cont.)

- Named Entity Retrieval and Ranking
  - class distribution
    - Aggregation of seed context distributions (Pasca, WWW07)
    - $p(t|c)$ from WS-LDA model
  - $q(t|e)$ as entity distribution
  - Jensen-Shannon similarity between $p(t|c)$ and $q(t|e)$

Table 6: Comparisons on Ranked Candidate Named Entities of each Class (P@N)

	Movie		Game		Book		Music		Average-Class	
	Determ	WS-LDA	Determ	WS-LDA	Determ	WS-LDA	Determ	WS-LDA	Determ	WS-LDA
P@25	0.92	1	0.98	1	0.84	1	0.96	1	0.92	1
P@50	0.9	1	0.96	1	0.82	1	0.92	1	0.905	1
P@100	0.85	1	0.93	0.98	0.79	0.98	0.89	1	0.865	0.99
P@150	0.82	1	0.92	0.953	0.767	0.98	0.833	1	0.835	0.983
P@250	0.724	0.988	0.896	0.928	0.732	0.968	0.76	0.984	0.778	0.967

Experimental Results (cont.)

- Comparison with LDA
  - Class Likelihood of e: $\sum_{i=1}^{K} y_i \, p(c_i | e)$

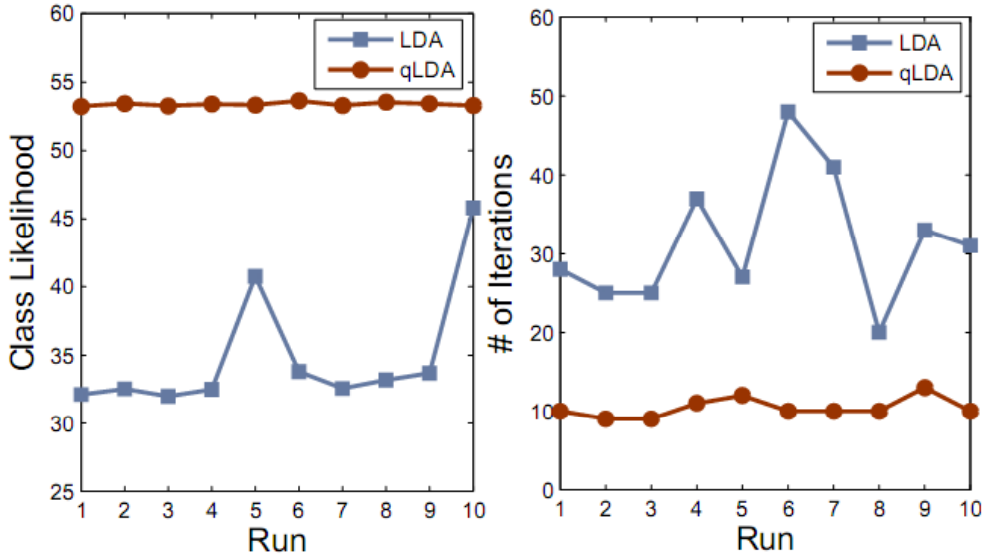


Figure 4: Comparisons between the WS-LDA and LDA approach on (a) Overall Class Likelihood on Testing Set, (b) Convergence Speed on Training Set

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Summary

- We first proposed the problem of named entity recognition in query.
- We formulized the problem into a probabilistic problem that can be solved by topic model.
- We devised weakly supervised LDA to incorporate human supervisions into training.
- The experimental results indicate that the proposed approach can accurately perform NERQ, and outperforms other baseline methods.

THANKS!