MLA'08 Nanjing
Nov. 7, 2008

Machine Learning Meets Web Search

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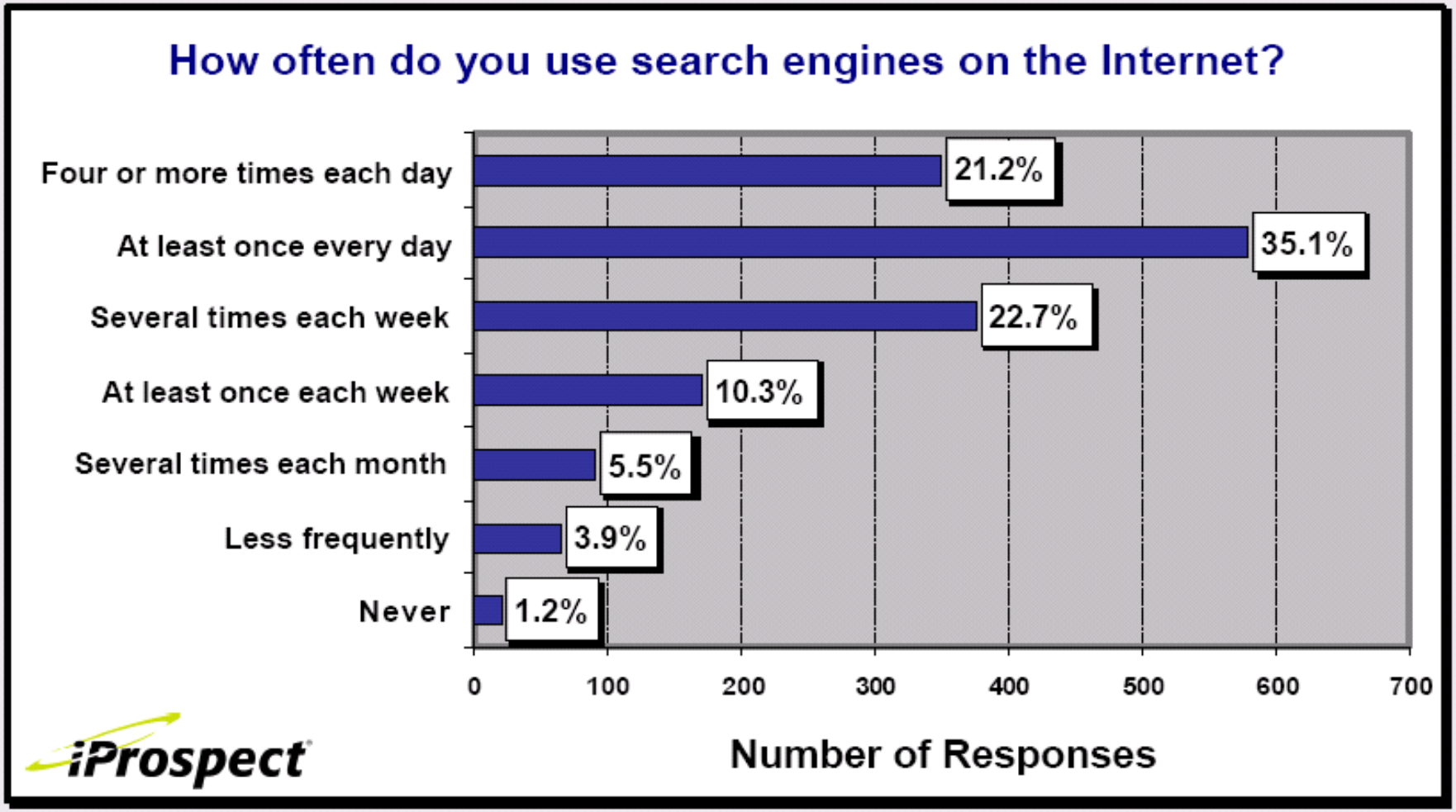
Microsoft Research Asia

Web Search is Part of Our Life

Web Users Heavily Rely on Search Engines

http://www.iprospect.com/premiumPDFs/iProspectSurveyComplete.pdf



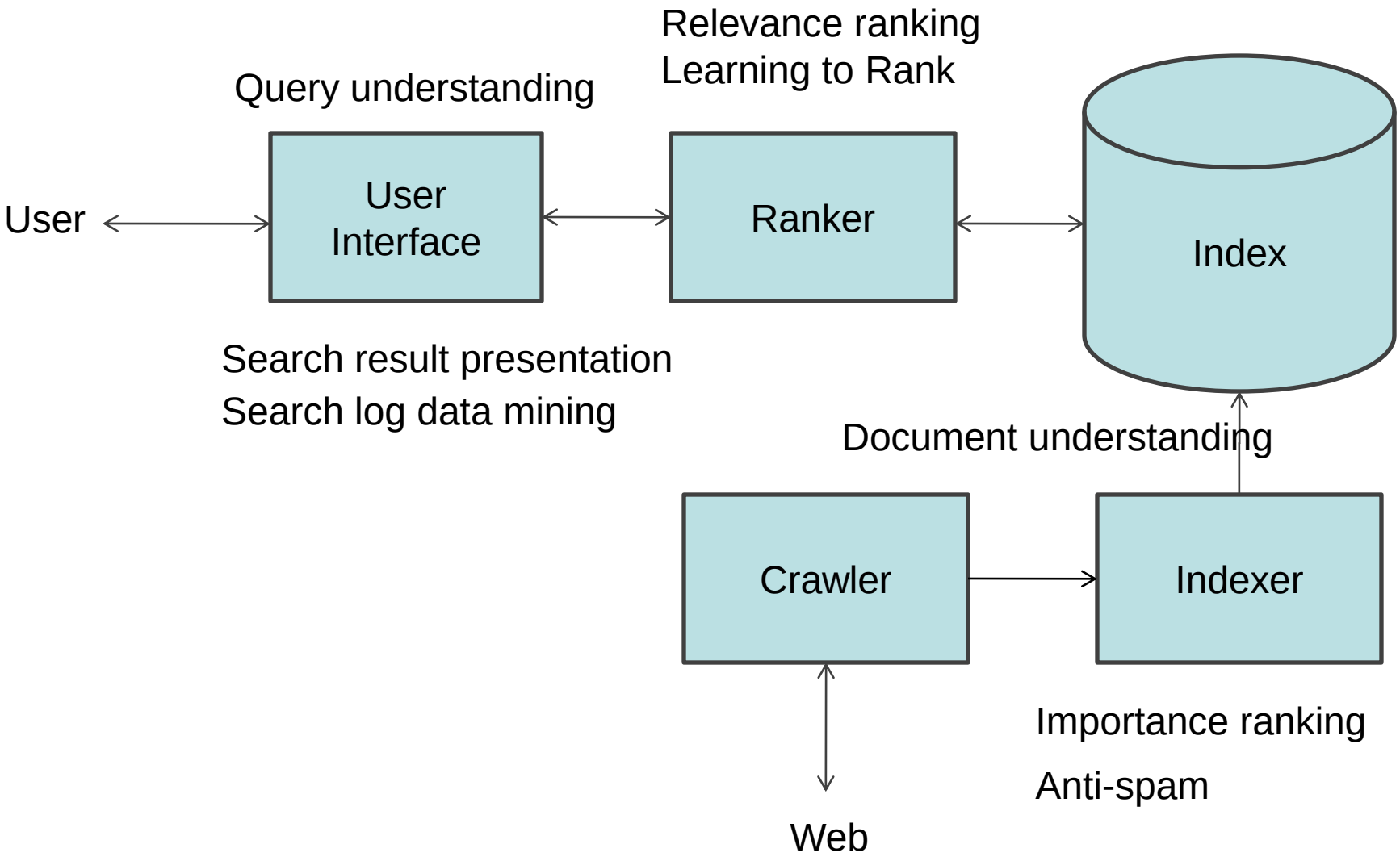
Physically Search System is Data Center

Advanced Web Search Technologies Are Used…

Statistical Learning

Large Scale Distributed Computing

Overview on Web Search System



Component Technologies for Web Search

- Relevance Ranking
- Importance Ranking
- Document Understanding
- Query Understanding
- Crawling
- Indexing
- Search Result Presentation
- Anti-Spam
- Learning to Rank
- Search Log Data Mining
- Evaluation and User Study

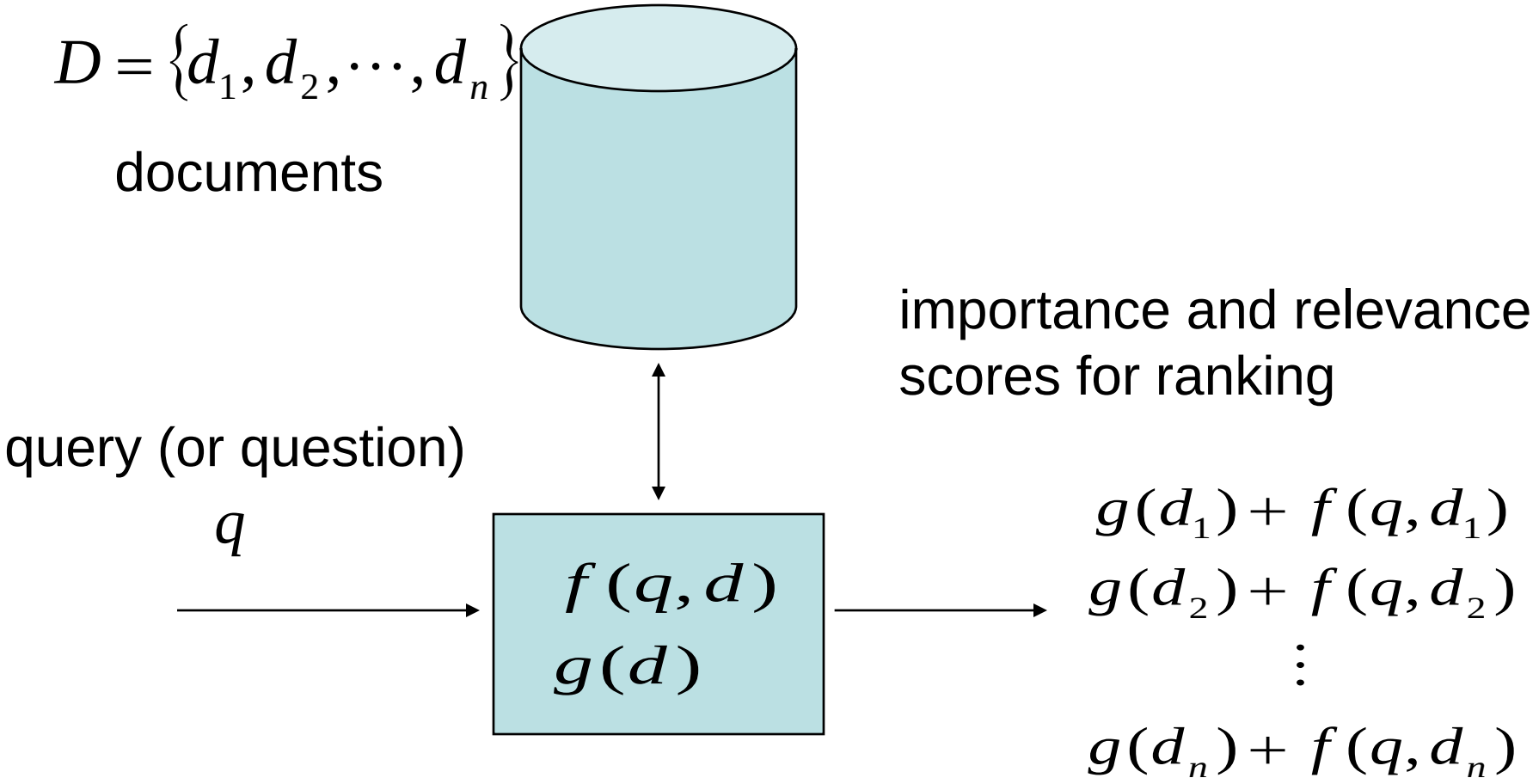
Statistical Learning Plays Key Role!

Talk Outline

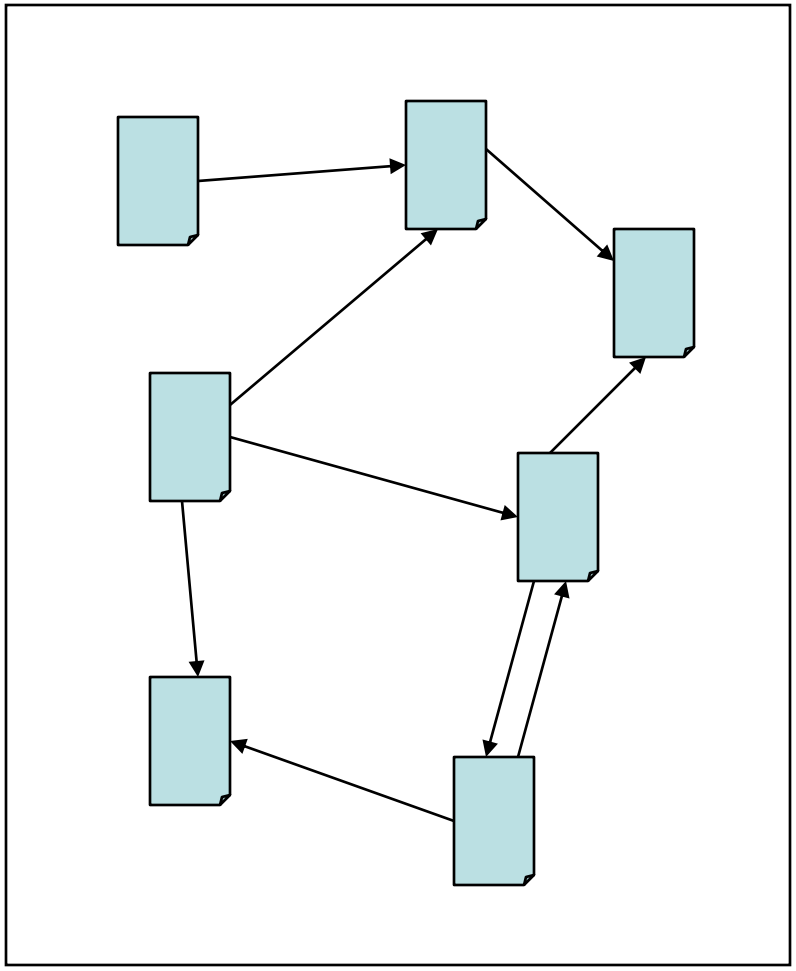
- Statistical Learning is Important for Web Search
- Statistical Learning in Web Search
  - Importance Ranking: BrowseRank
  - Anti-Spam: Temporal Classifier
  - Query Understanding: CRF for Query Reformulation
  - Web Page Understanding: HyperText Topic Model
  - Result Presentation: Context Aware Query Suggestion
  - Learning to Rank: Listwise Approach and Global Ranking

Importance Ranking: BrowseRank (SIGIR 2008 Best Student Paper)

General Model for Importance Ranking



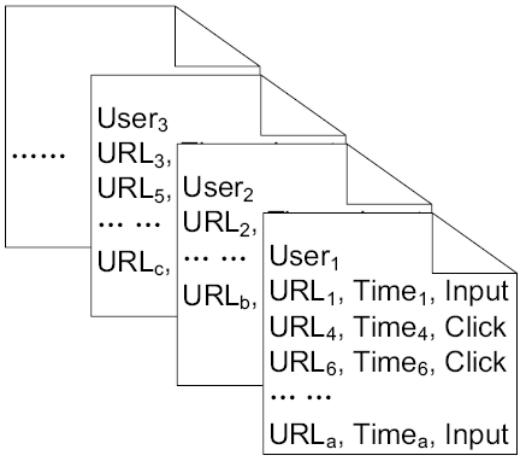
Page Rank



$$P(d_i) = \alpha \sum_{d_j \in M(d_i)} \frac{P(d_j)}{L(d_j)} + (1-\alpha)\frac{1}{n}$$

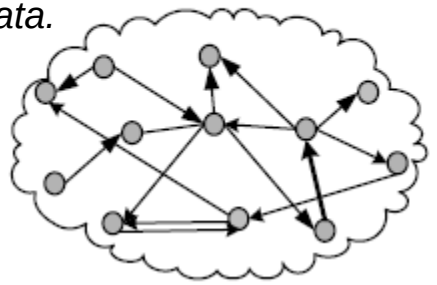
Building User Browsing Graph

User Behavior Data



User Browsing Graph

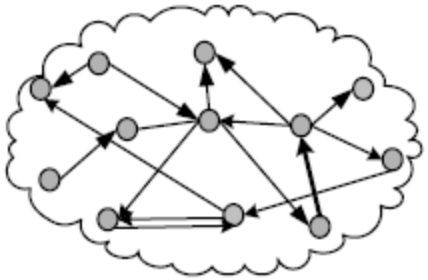
A directed graph with rich meta data.



Vertex: Web page Edge: Transition	Edge weight w_{ij}: Number of transitions	Staying time T_i: Time spend on page *i*	Vertex weight C_i: Number of visit for page *i*	Reset probability σ_i Normalized frequencies as first page of session

BrowseRank: Continuous-time Markov Model

User Browsing Graph



Hard

$P(t)$

$\pi = \pi P(t)$

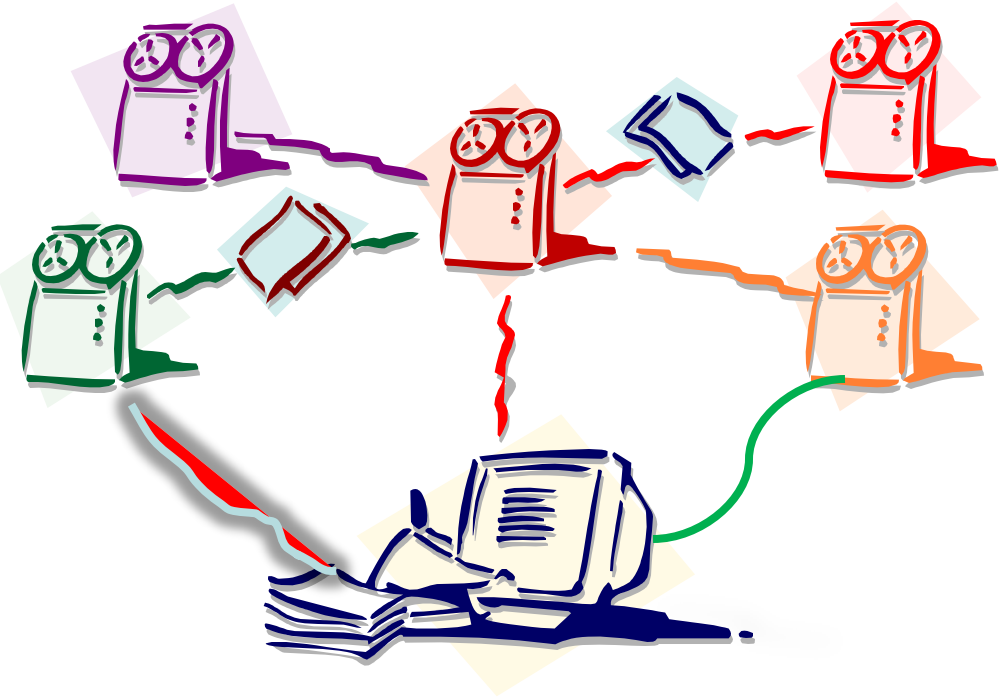
Calculating π = Estimating staying time distribution of each state + Computing the stationary distribution $\tilde{\pi}$ of a discrete-time Markov chain (*called embedded Markov chain*)

Anti-Spam: Temporal Classifier (ICDM 2006)

Anti-Spam

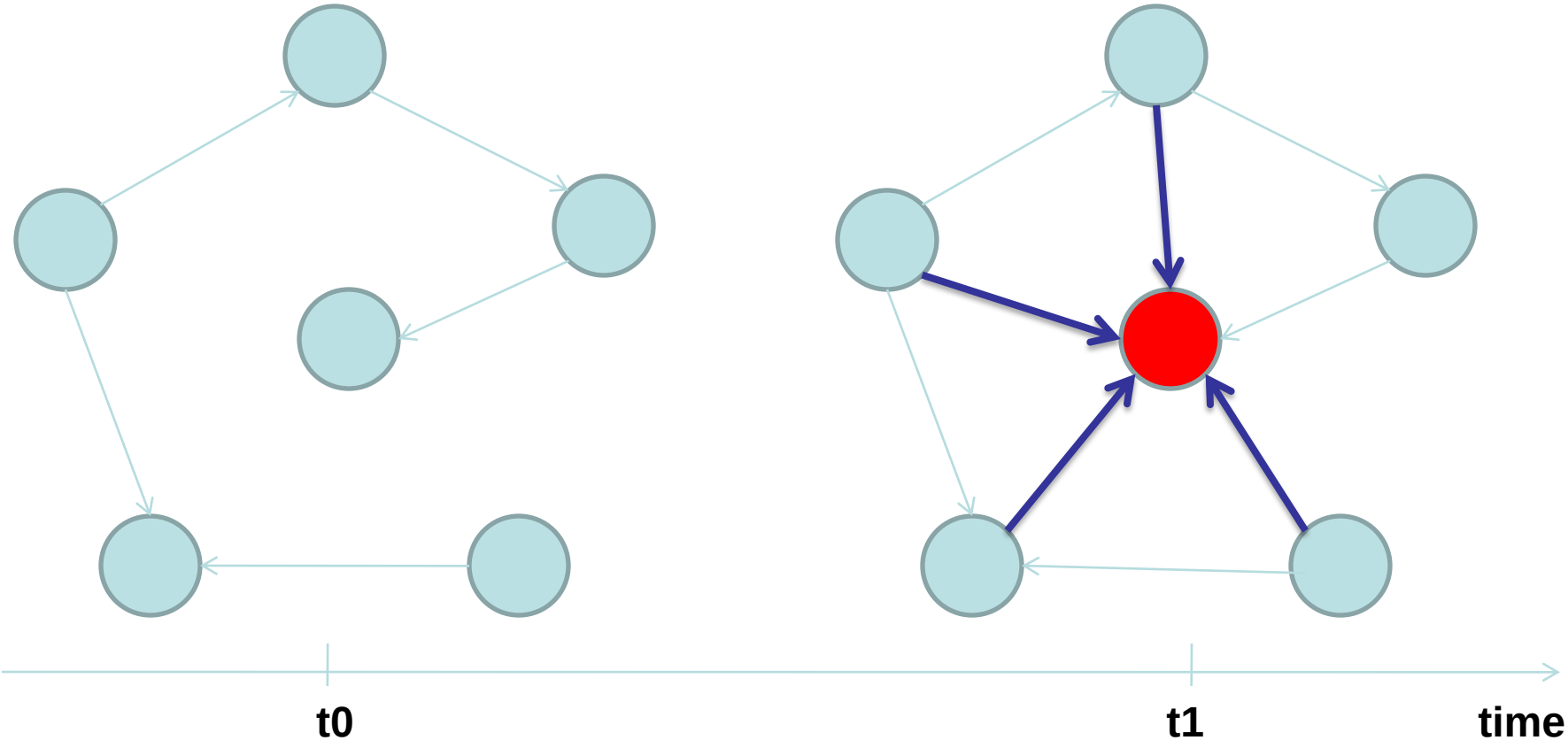
- Spam
  - Manipulate relevance and importance
  - Not ethical, if to be ranked higher beyond real value
  - “Cheating” search engines
- Spam Type
  - Content Spam
  - Link Spam
  - Cloaking

Link Spam



- Link from Blog, Forum, etc
- Link Exchange
- Link Farm

Inlink May Increase Drastically at Spam Page



Detection Using Temporal Information

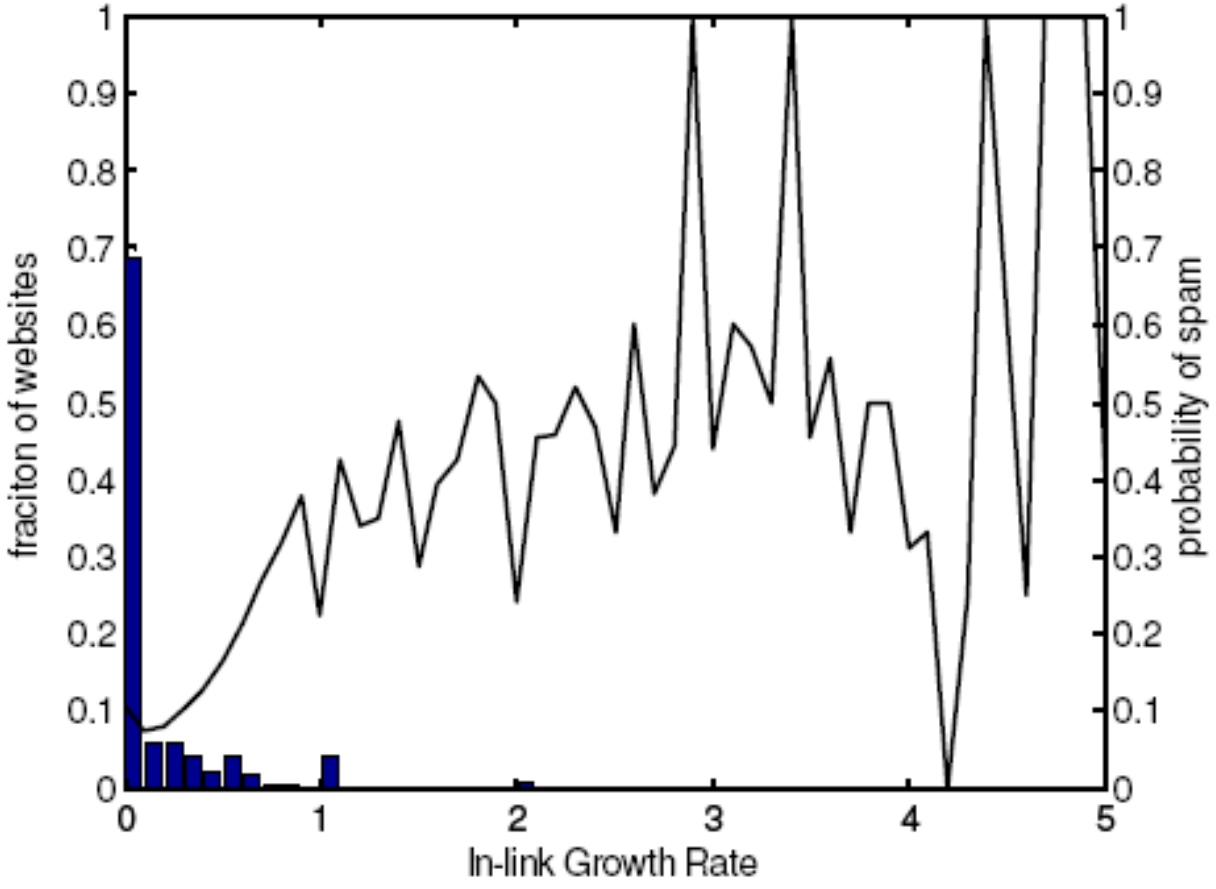


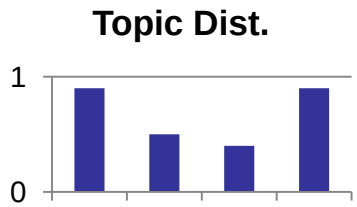
Figure 1. Probability of spam versus IGR.

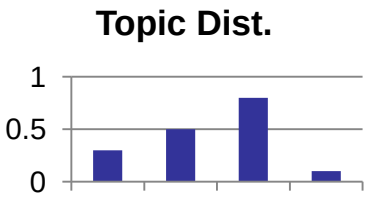
Web Page Understanding: Topic Model for Hypertext (EMNLP 2008)

Web Page Understanding

- Web Information Extraction
  - Block Analysis
  - Metadata Extraction (Title, Date, etc)
  - Text Information Extraction
  - Wrapper Generation
- Web Page Classification
  - Based on Semantics
  - Based on Type (Homepage, Spec, etc)

LDA (Latent Dirichlet Allocation)



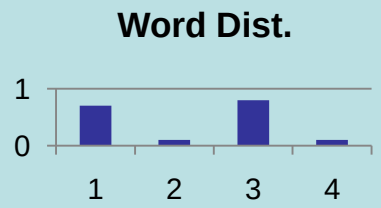


Web Page

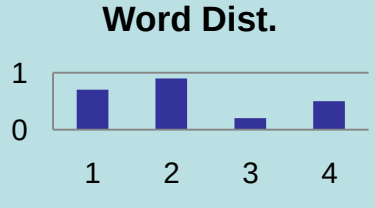
Web Page

Web Page

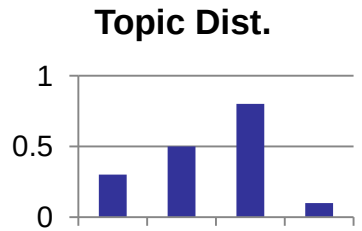
Topic1

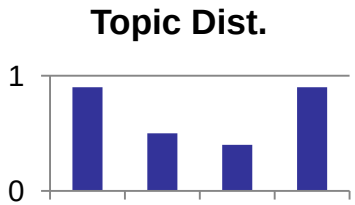


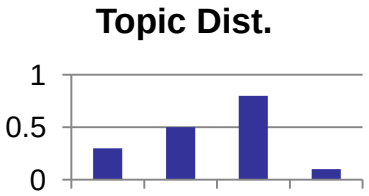
Topic2



HTM: Topic Model for Hyper Text





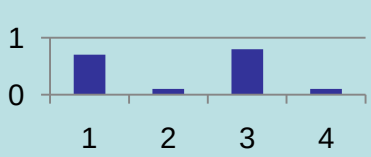


Cited Page

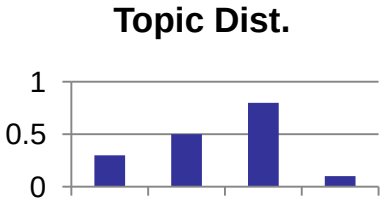
Cited Page

Cited Page

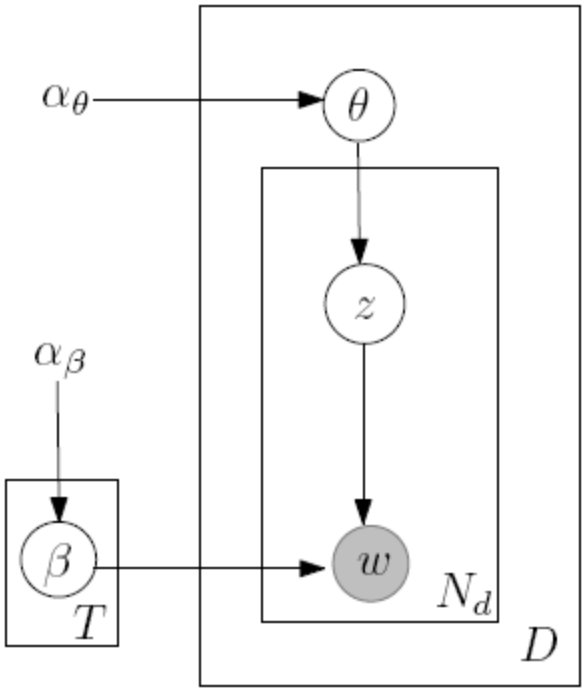
Topic



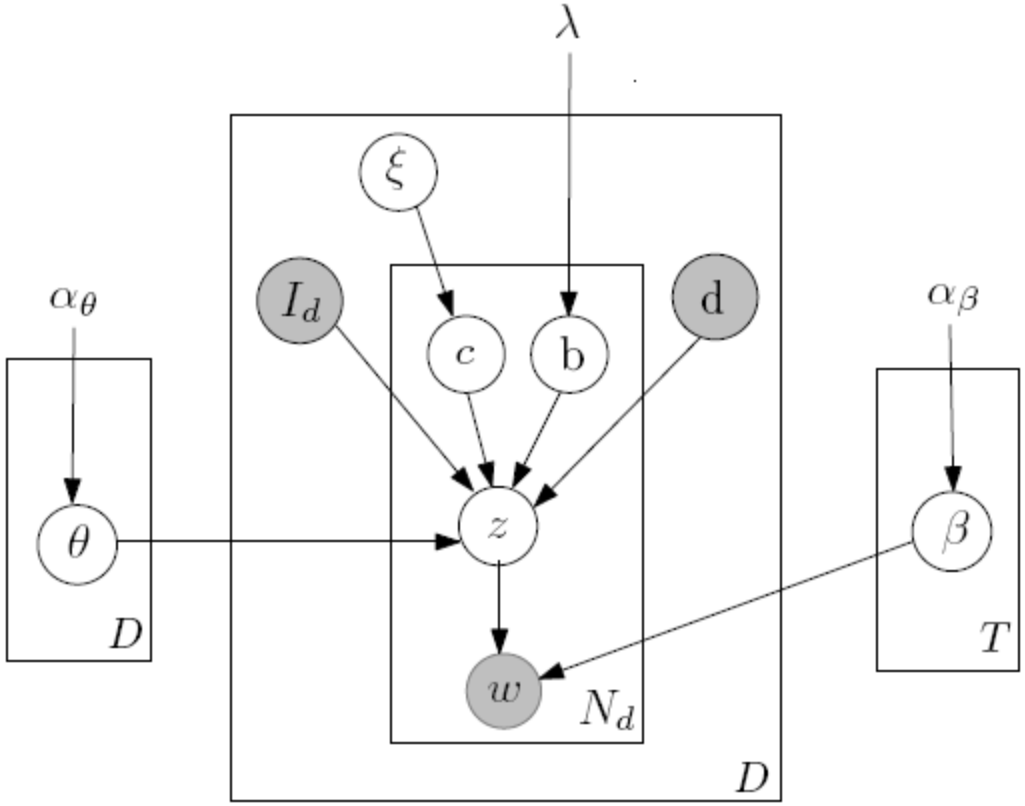
Citing Page



LDA vs HTM



(a) LDA



(b) HTM

Query Understanding: Query Refinement (SIGIR 2008)

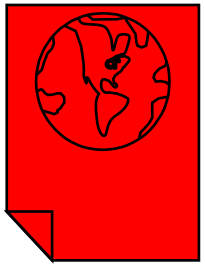
Query Understanding

- Spelling Error Correction
- Query Refinement
  - E.g., “ny times” → “new york times”
- Query Classification
  - Based on Semantics (Sport, etc)
  - Based on Type (Name Query, etc)
- Query Segmentation
  - E.g., “harry porter book” → “[harry porter] book”

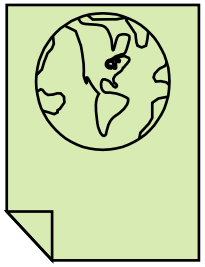
Mismatching between Query Term and Document Term

I want to search “myspace”

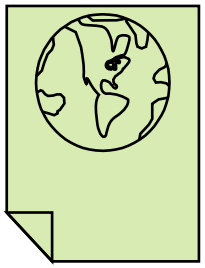
my space



myspace



space



my

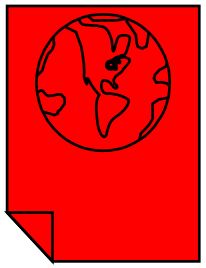
Understanding the Intent and Solving the Mismatch

I want to search “myspace”

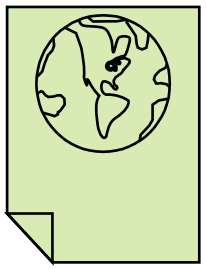
my space

Query Understanding

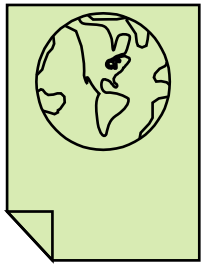
myspace



myspace

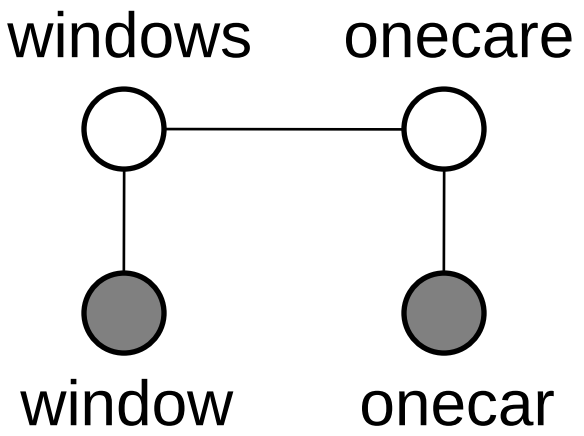


space



my

Structured Prediction Problem



"Ideal" word sequence

Observed "noisy" word sequence

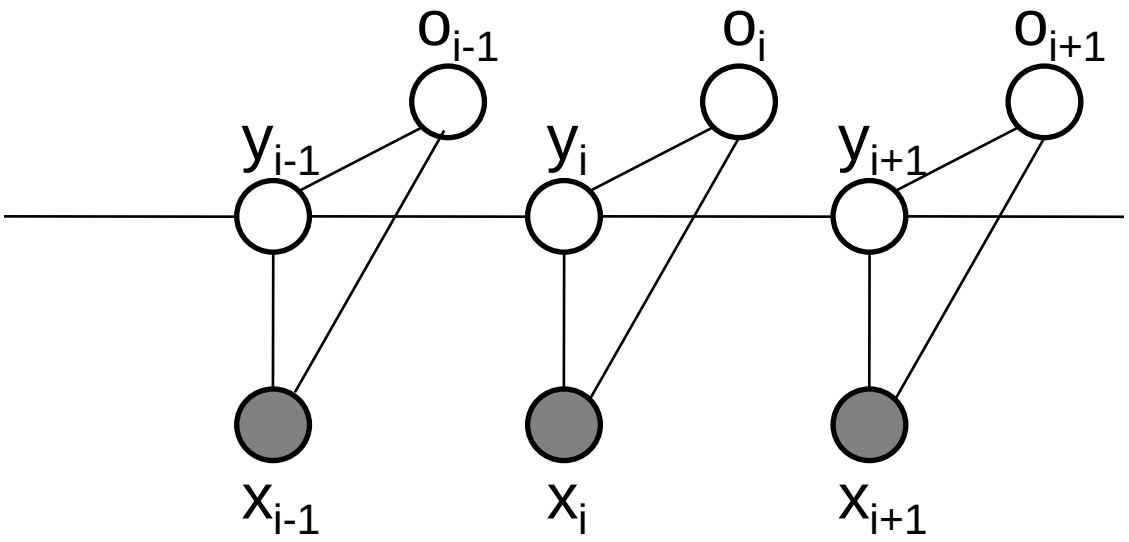
$$y^* = \arg\max_{y} \Pr(y|x)$$

"ideal" query word sequence

original query word sequence

Conditional Random Fields for Query Refinement

Introducing Refinement Operations



$$\Pr(\boldsymbol{y}, \boldsymbol{o}|\boldsymbol{x}) = \frac{1}{Z(\boldsymbol{x})} \prod_{i=1}^{n} \phi(y_{i-1}, y_i)\phi(y_i, o_i, \boldsymbol{x})$$

Operations

Spelling: insertion, deletion, substitution, transposition, …

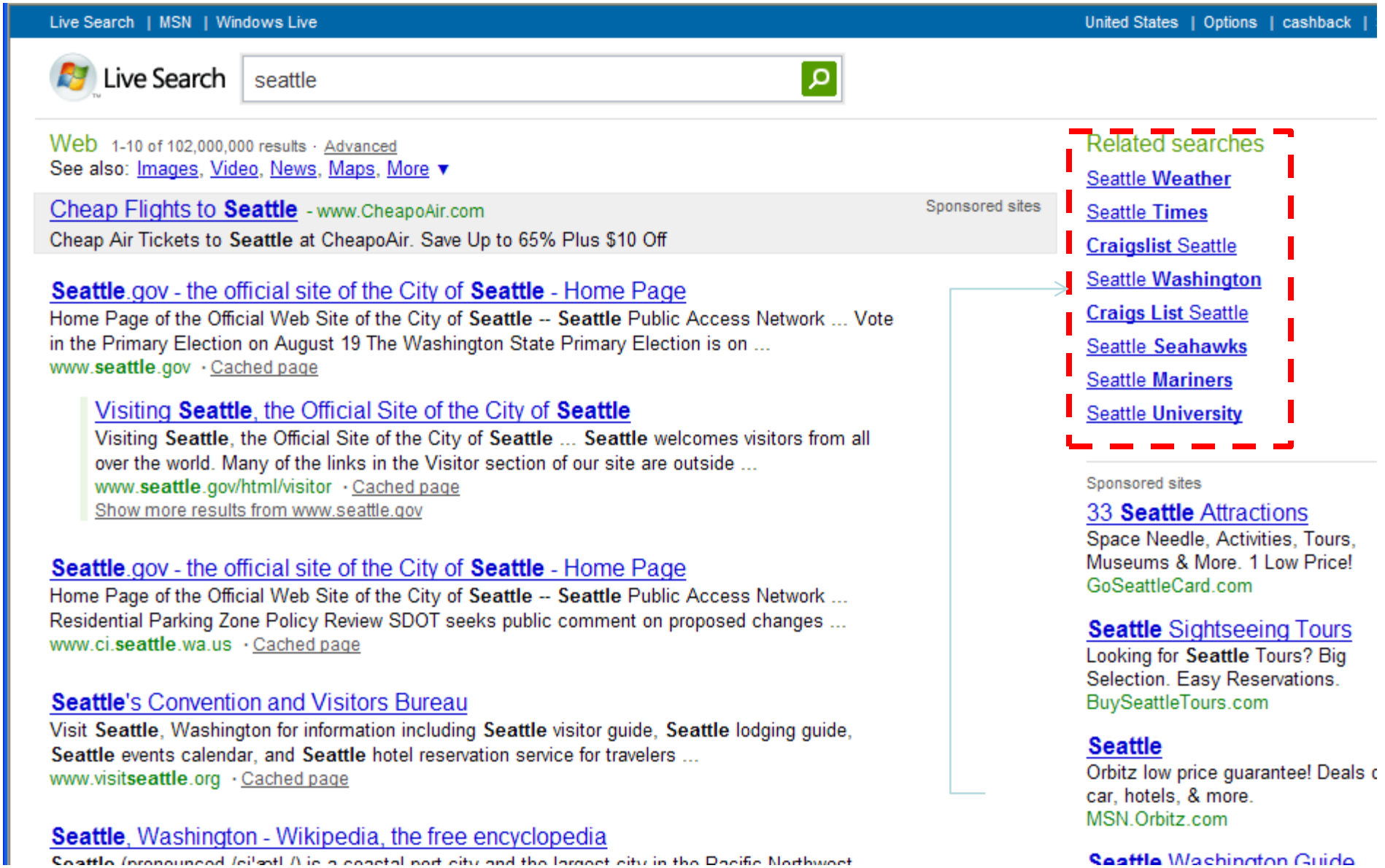
Word Stemming: +s/-s, +es/-es, +ed/-ed, +ing/-ing, …

Result Presentation:
Query Suggestion
(KDD 2008 Best Application Paper)

Result Presentation

- Snippet Generation
- Query Suggestion
- Result Clustering and Classification

Query Suggestion

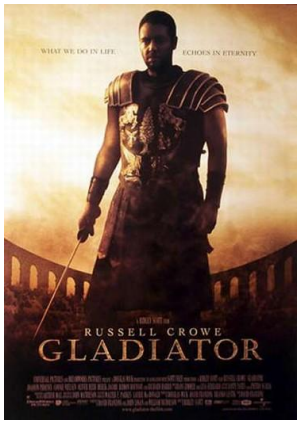


Search Intent and Context

- Suppose a user raises a query "*gladiator*"

History?

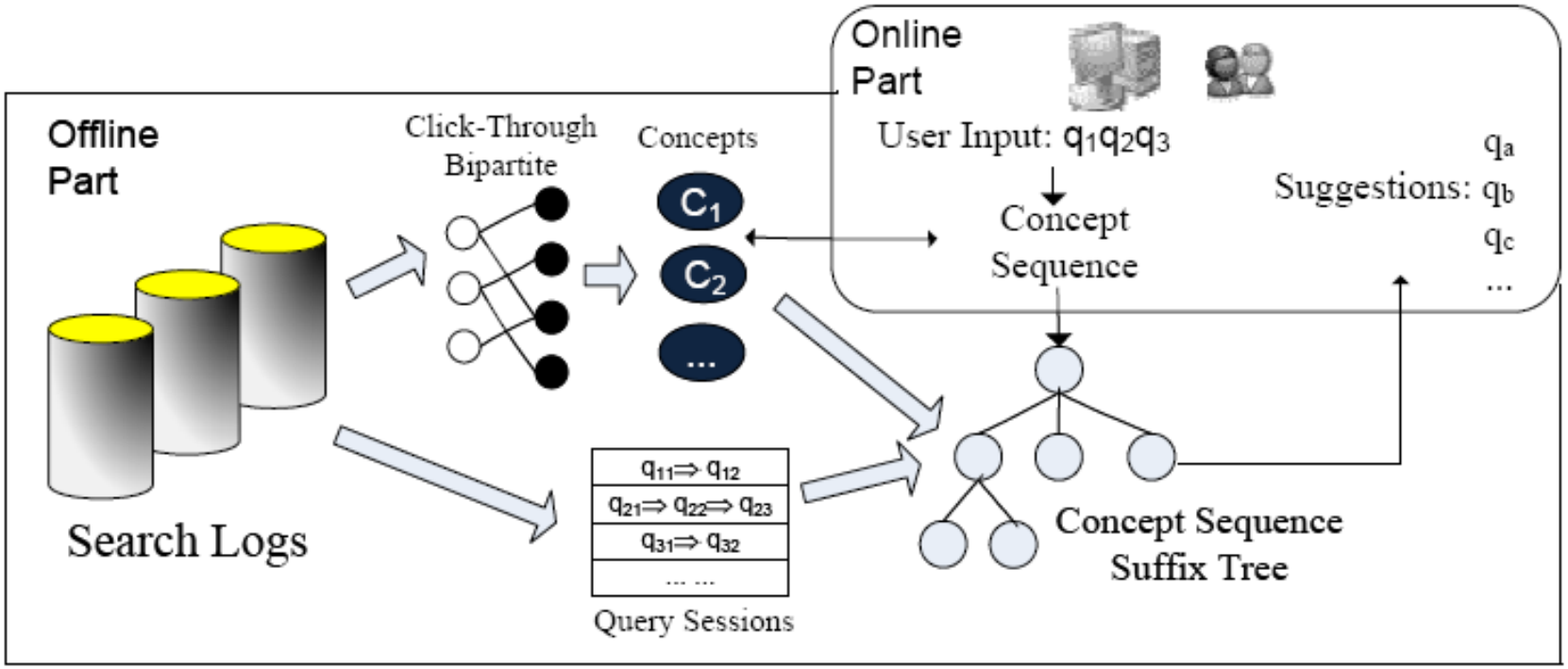
People?



Film?

- If we know the user raises query *"beautiful mind"* before *"gladiator"*
  - User is likely to be interested in the film
  - User is likely to be searching the films played by Russell Crowe.

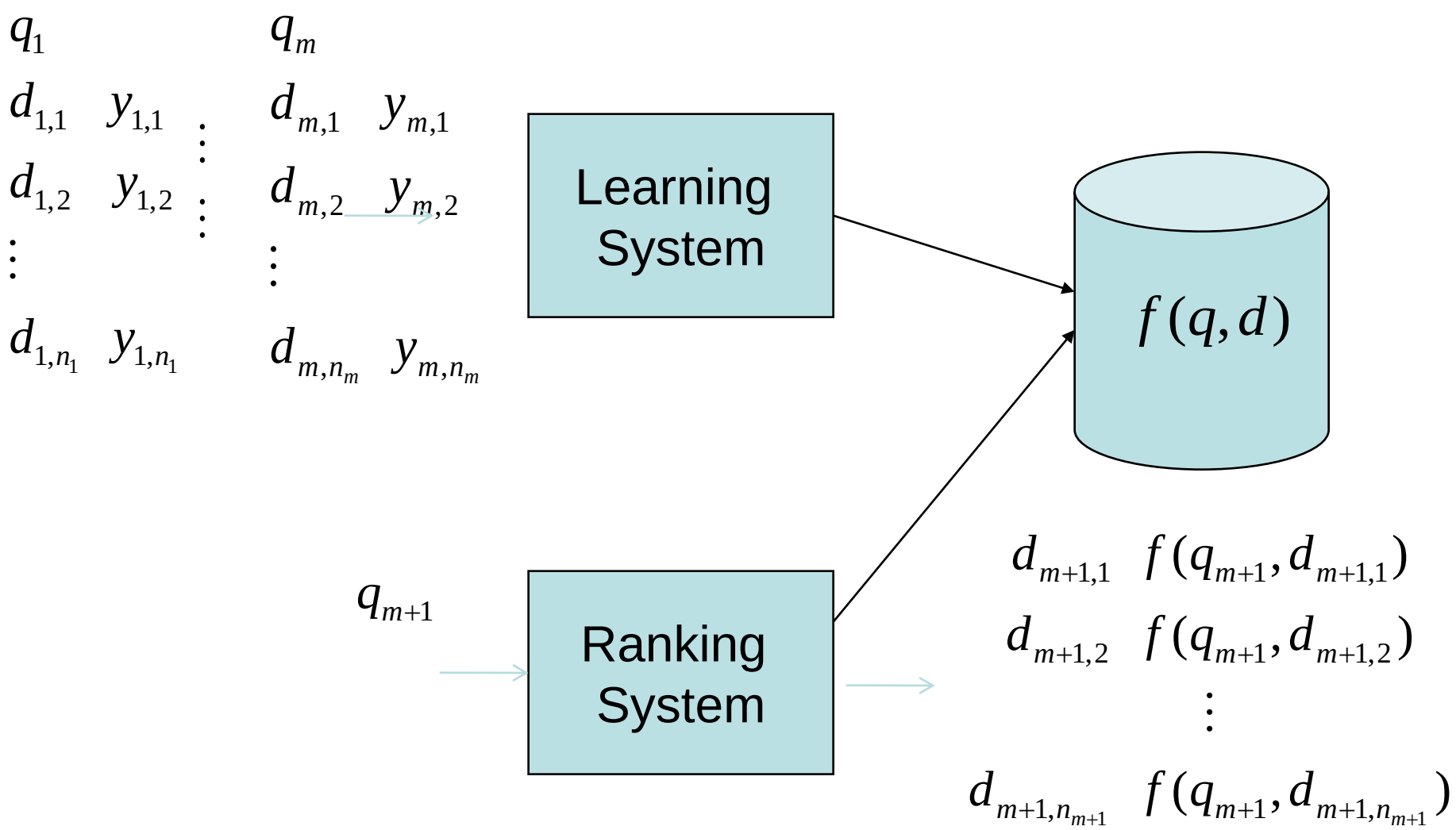
Framework



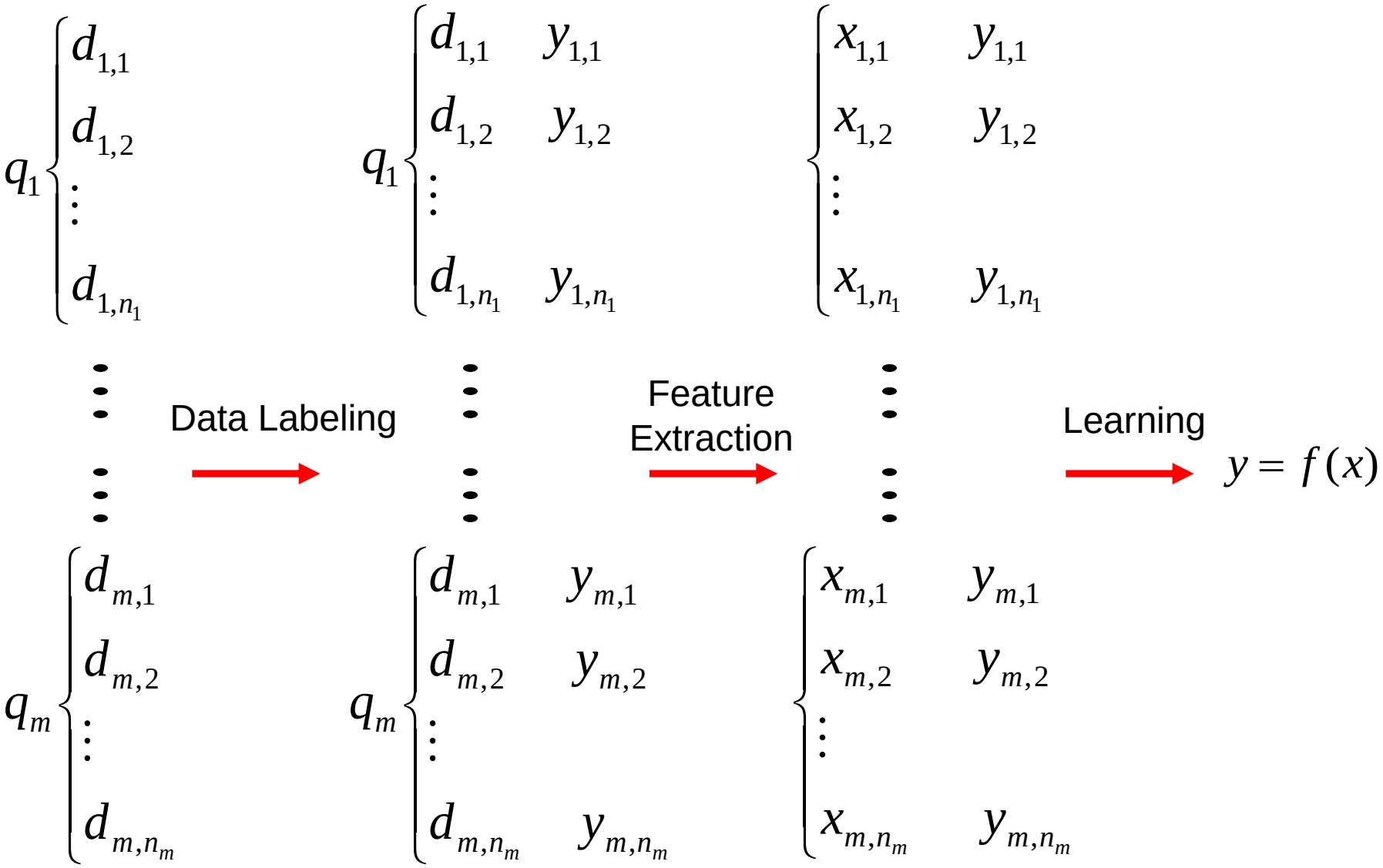
- Offline part: model learning
  - Summarizing queries into concepts by clustering click-through bipartite
  - Mining frequent patterns from session data and building a concept sequence suffix tree
- Online part: query suggestion

Learning to Rank: ListWise and Global Ranking (ICML 2008, NIPS 2008, etc)

Learning to Rank



Learning Process



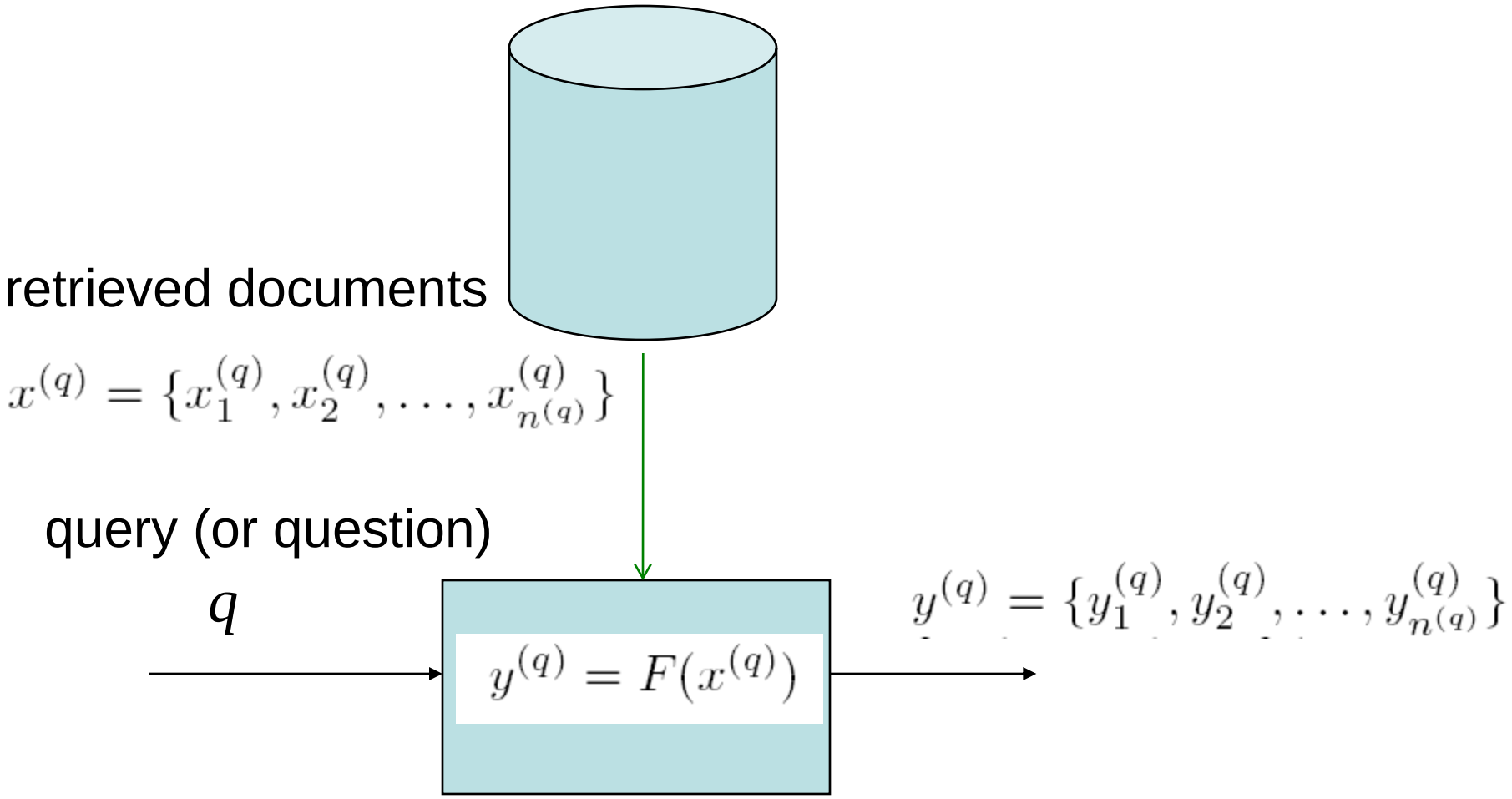
Previous Approach: Pairwise Approach

- Transforming ranking to classification
  - Ranking SVM (Herbrich et al, 2000)
  - RankBoost (Freund et al, 2003)
  - *Ranknet* (Burges et al, 2005)
  - IR-SVM (Cao et al, 2005)
  - Frank (Tsai et al, 2006)

Our Proposal = Listwise Approach

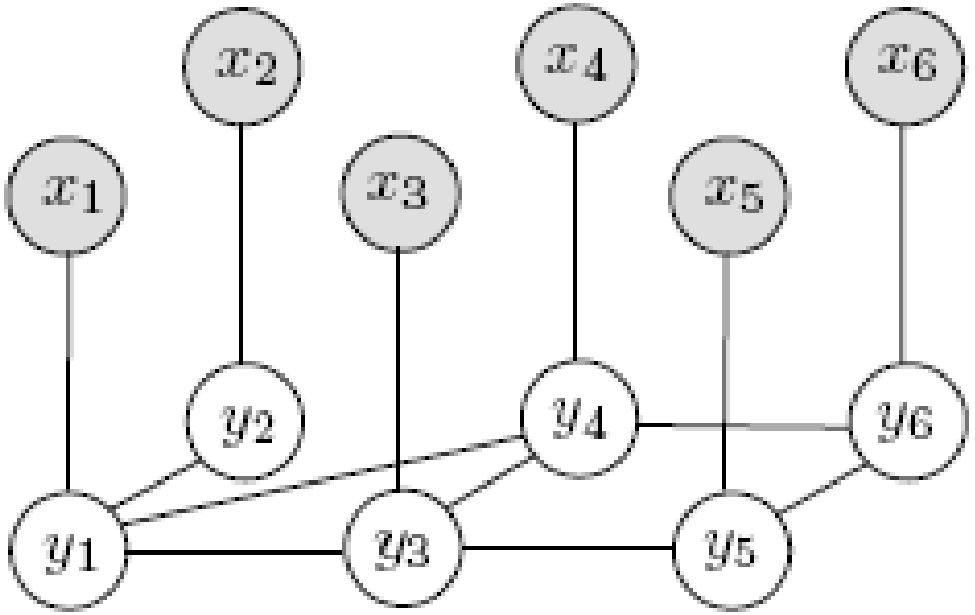
- Probabilistic Model
  - ListNet (Cao, et al 2007)
  - ListMLE (Xia, et al 2008)
- Optimizing Upper Bounds of IR Measures
  - AdaRank (Xu & Li, 2007)
  - SVM-MAP (Yue, et al, 2007)
  - PermuRank (Xu, et al 2008)
- Approximation of IR Measures
  - SoftRank (Taylor 2007)
  - ApproxRank (Qin, et al, to appear)

Global Ranking Problem



Global Ranking Using Continuous CRF

$$\Pr(y^{(q)}|x^{(q)}) = \frac{1}{Z(x^{(q)})} \exp\left\{ \sum_i \sum_{k=1}^{K_1} \alpha_k h_k(y_i^{(q)}, x^{(q)}) + \sum_{i,j} \sum_{k=1}^{K_2} \beta_k g_k(y_i^{(q)}, y_j^{(q)}, x^{(q)}) \right\}$$



Summary

- Statistical Learning is Important for Web Search
- Statistical Learning in Web Search
  - Importance Ranking: BrowseRank
  - Anti-Spam: Temporal Classifier
  - Query Understanding: CRF for Query Reformulation
  - Web Page Understanding: HyperText Topic Model
  - Result Presentation: Context Aware Query Suggestion
  - Learning to Rank: Listwise Approach and Global Ranking

References

- Yuting Liu, Bin Gao, Tie-Yan Liu, Ying Zhang, Zhiming Ma, Shuyuan He, Hang Li, BrowseRank: Letting Users Vote for Page Importance, Proc. of SIGIR 2008, 451-458. *SIGIR’08 Best Student Paper Award*.
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- Tao Qin, Tie-Yan Liu, Xu-Dong Zhang, De-Sheng Wang, Hang Li, Global Ranking Using Continuous Conditional Random Fields, Proc. of NIPS 2008, to appear.

Pao-Lu Hsu Lecture on Statistical Machine Learning and Applications

Speaker: Prof. Trevor Hastie

Talk: Regularization Paths

Time: 10:00am-12:00am, December 3, 2008

Place: Peking University Hall (北大百年讲堂会议厅)

Web Site: http://iria.pku.edu.cn/PMSIT/

Contact: Pao-Lu-Hsu@163.com

Thank You!

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