Learning to Rank

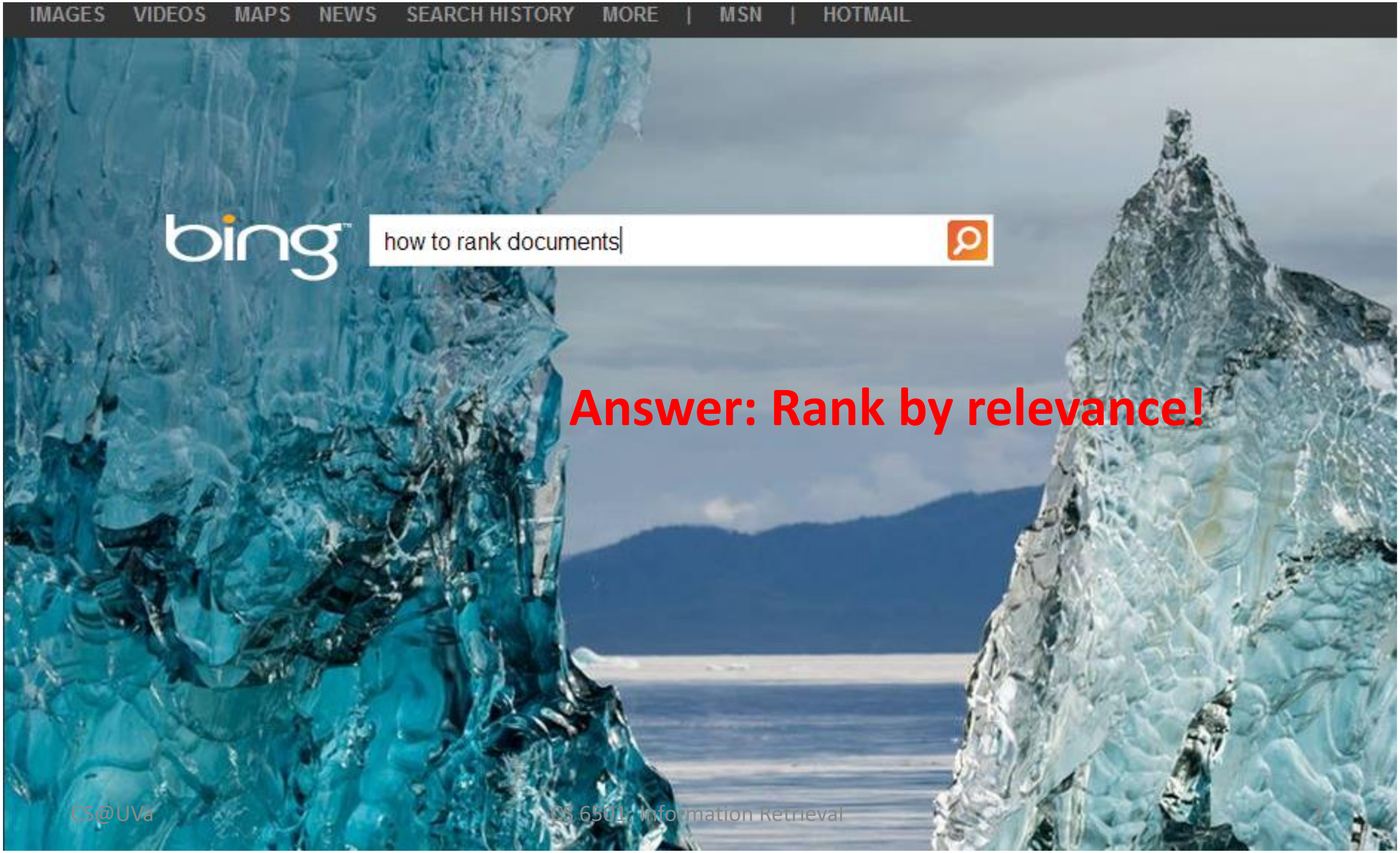
from heuristics to theoretic approaches

Hongning Wang

Congratulations

- Job Offer
  - Design the ranking module for Bing.com

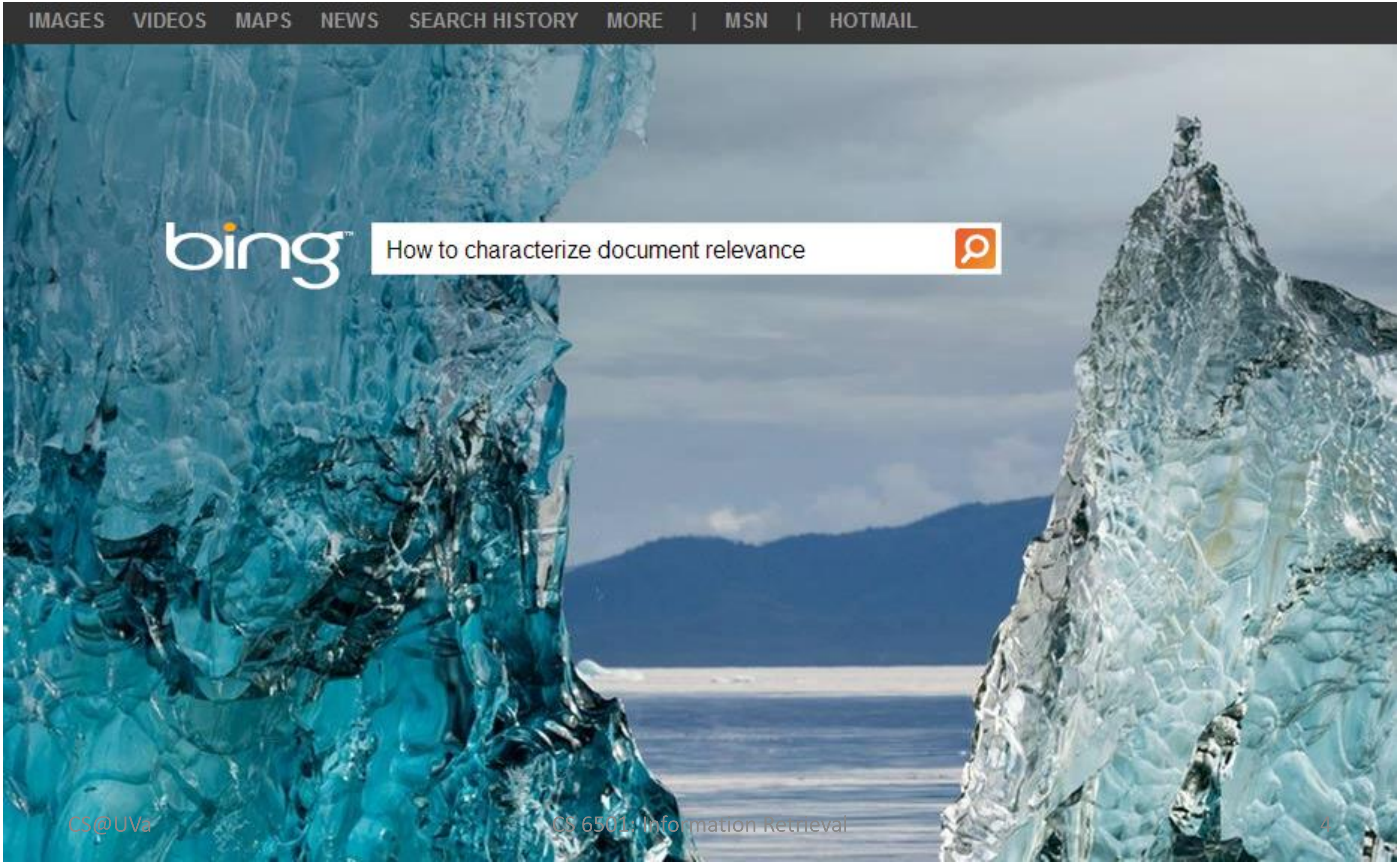
How should I rank documents?



how to rank documents

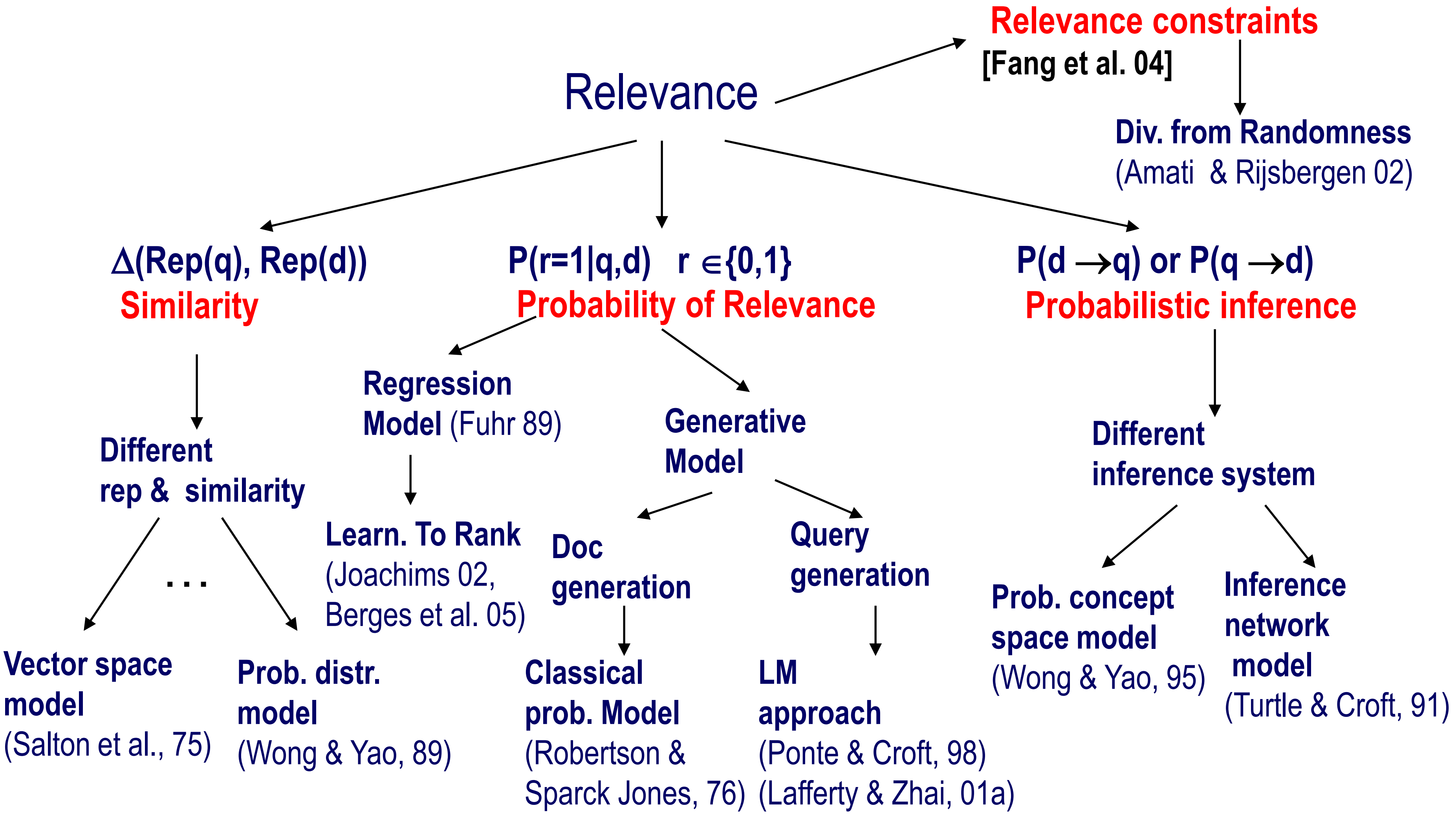
Answer: Rank by relevance!

Relevance ?!



How to characterize document relevance

The Notion of Relevance



Relevance

Relevance constraints
[Fang et al. 04]

Div. from Randomness
(Amati & Rijsbergen 02)

Δ(Rep(q), Rep(d))
Similarity

Different
rep & similarity

Vector space
model
(Salton et al., 75)

. . .

Prob. distr.
model
(Wong & Yao, 89)

P(r=1|q,d) r ∈{0,1}
Probability of Relevance

Regression
Model (Fuhr 89)

Learn. To Rank
(Joachims 02,
Berges et al. 05)

Generative
Model

Doc
generation

Classical
prob. Model
(Robertson &
Sparck Jones, 76)

Query
generation

LM
approach
(Ponte & Croft, 98)
(Lafferty & Zhai, 01a)

P(d →q) or P(q →d)
Probabilistic inference

Different
inference system

Prob. concept
space model
(Wong & Yao, 95)

Inference
network
model
(Turtle & Croft, 91)

Lecture notes from **CS598CXZ**

Relevance Estimation

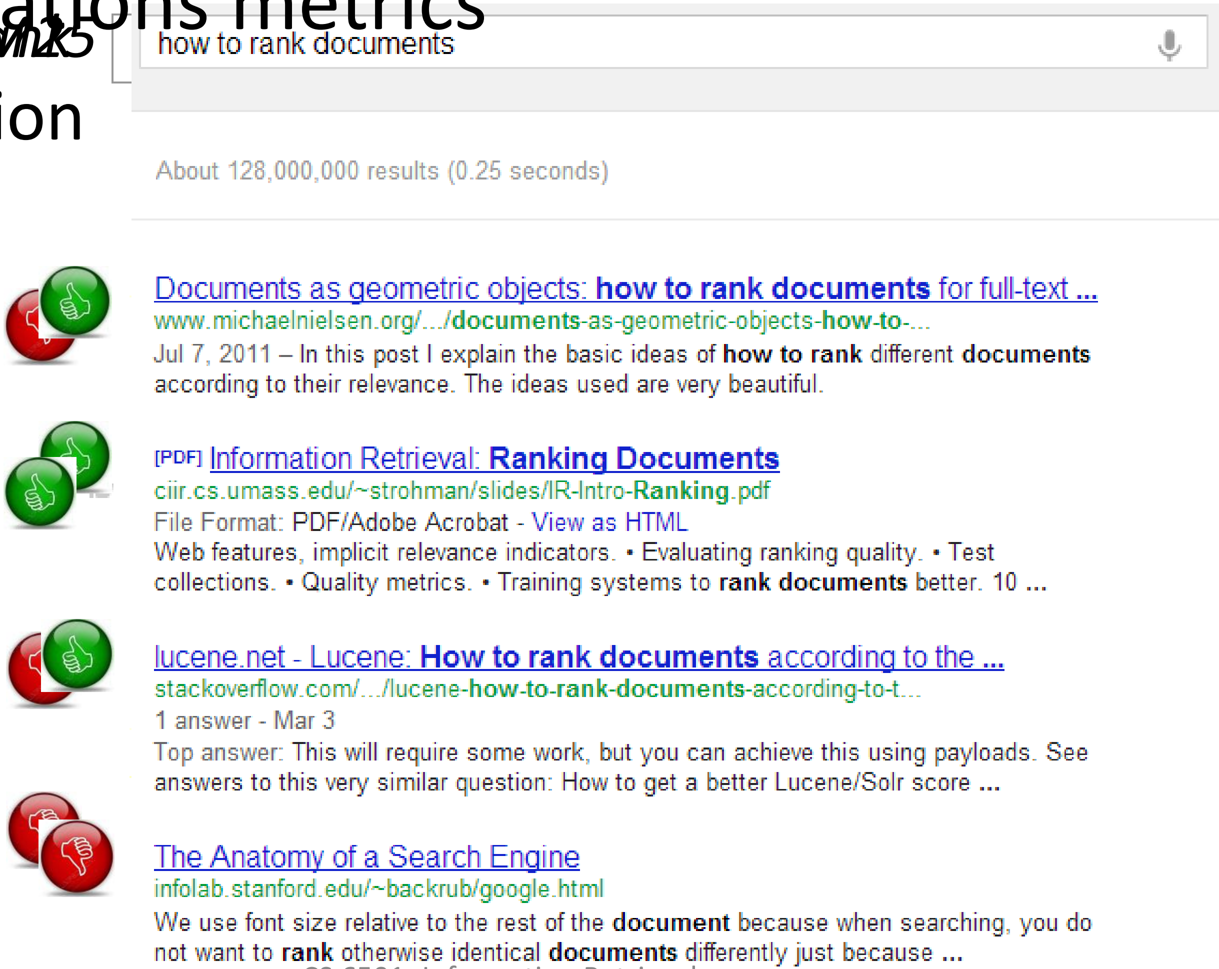
- Query matching
  - Language model
  - BM25
  - Vector space cosine similarity
- Document importance
  - PageRank
  - HITS

Did I do a good job of ranking documents?

- IR evaluations metrics

  PageRank
  BM25

  - Precision
  - MAP
  - NDCG



how to rank documents

About 128,000,000 results (0.25 seconds)

Documents as geometric objects: **how to rank documents** for full-text ...
www.michaelnielsen.org/.../**documents**-as-geometric-objects-**how-to**-...
Jul 7, 2011 – In this post I explain the basic ideas of **how to rank** different **documents** according to their relevance. The ideas used are very beautiful.

[PDF] Information Retrieval: **Ranking Documents**
ciir.cs.umass.edu/~strohman/slides/IR-Intro-**Ranking**.pdf
File Format: PDF/Adobe Acrobat - View as HTML
Web features, implicit relevance indicators. • Evaluating ranking quality. • Test collections. • Quality metrics. • Training systems to **rank documents** better. 10 ...

lucene.net - Lucene: **How to rank documents** according to the ...
stackoverflow.com/.../lucene-**how-to-rank-documents**-according-to-t...
1 answer - Mar 3
Top answer: This will require some work, but you can achieve this using payloads. See answers to this very similar question: How to get a better Lucene/Solr score ...

The Anatomy of a Search Engine
infolab.stanford.edu/~backrub/google.html
We use font size relative to the rest of the **document** because when searching, you do not want to **rank** otherwise identical **documents** differently just because ...

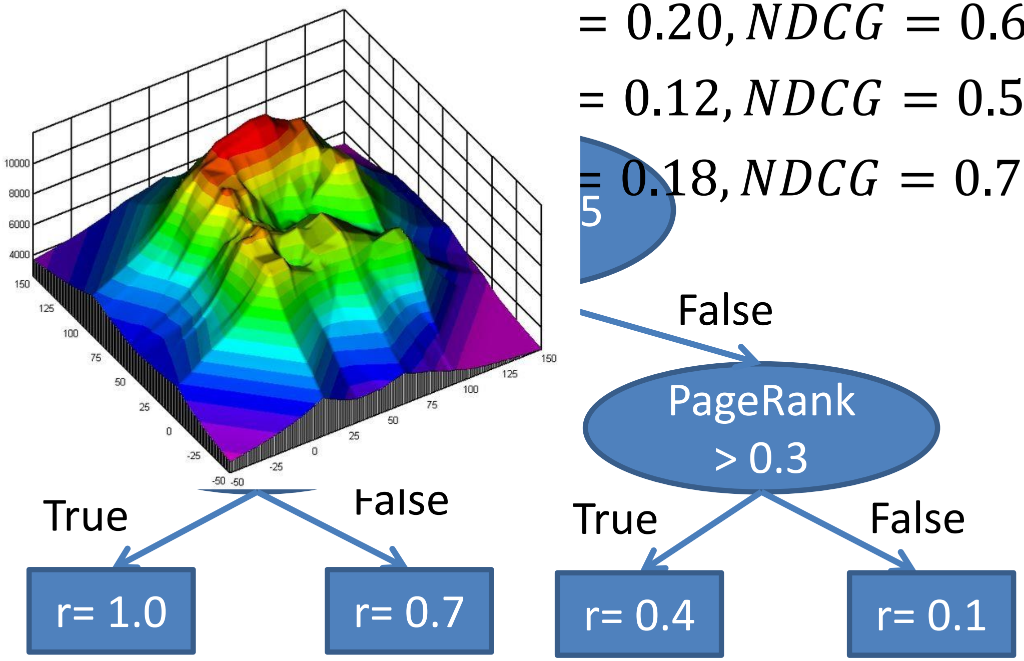
Take advantage of different relevance estimator?

- Ensemble the cues
  - Linear?
    - $a_1 \times BM25 + \alpha_2 \times LM + \alpha_3 \times PageRank + \alpha_4 \times HITS$
  - Non-linear?
    - Decision tree-li

$\{\alpha_1 = 0.4, \alpha_2 = 0.2, \alpha_3 =$ $= 0.20, NDCG = 0.6\}$

$\{\alpha_1 = 0.2, \alpha_2 = 0.2, \alpha_3 =$ $= 0.12, NDCG = 0.5\}$

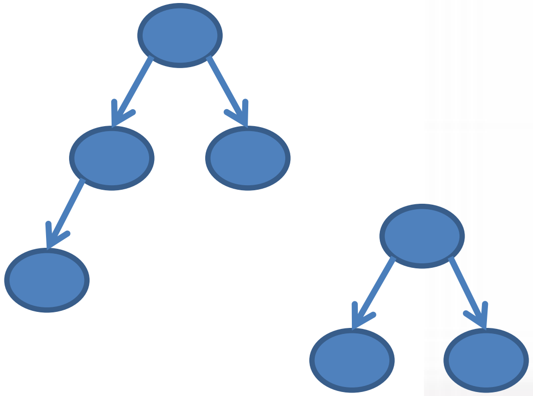
$\{\alpha_1 = 0.1, \alpha_2 = 0.1, \alpha_3 =$ $= 0.18, NDCG = 0.7\}$

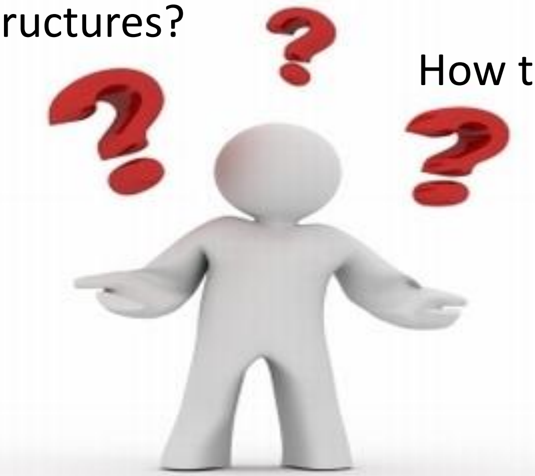


What if we have thousands of features?

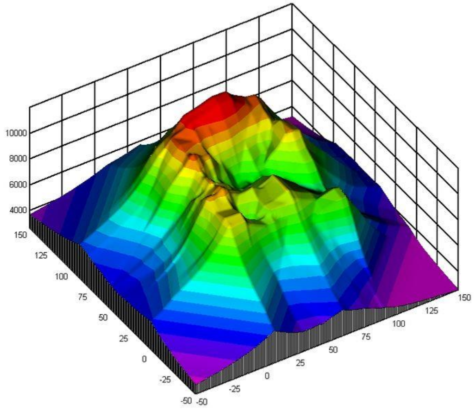
- Is there any way I can do better?
  - Optimizing the metrics automatically!

Where to find those tree structures?





How to determine those αs?



Rethink the task

- Given: (query, document) pairs represented by a set of relevance estimators, a.k.a., features

DocID	BM25	LM	PageRank	Label
0001	1.6	1.1	0.9	0
0002	2.7	1.9	0.2	1

- Needed: a way of combining the estimators
  - $f\left(q, \{d\}_{i=1}^{D}\right) \rightarrow$ ordered $\{d\}_{i=1}^{D}$
- Criterion: optimize IR metrics ⬅ **Key!**
  - P@k, MAP, NDCG, etc.

Machine Learning

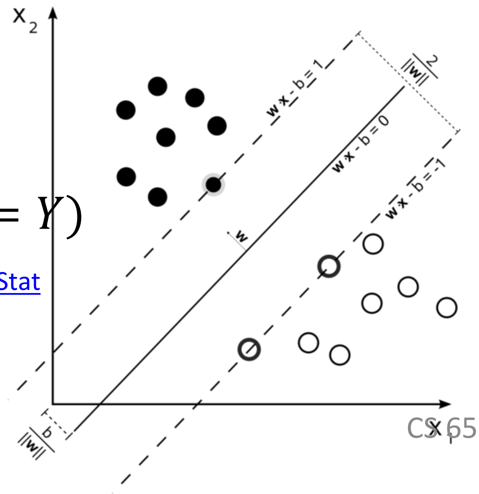
- Input: $\{(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)\}$, where $X_i \in R^N, Y_i \in R^M$
- Object function : $O(Y', Y)$
- Output: $f(X) \rightarrow Y$, such that $f = \mathrm{argmax}_{f' \subset F} O(f'(X), Y)$

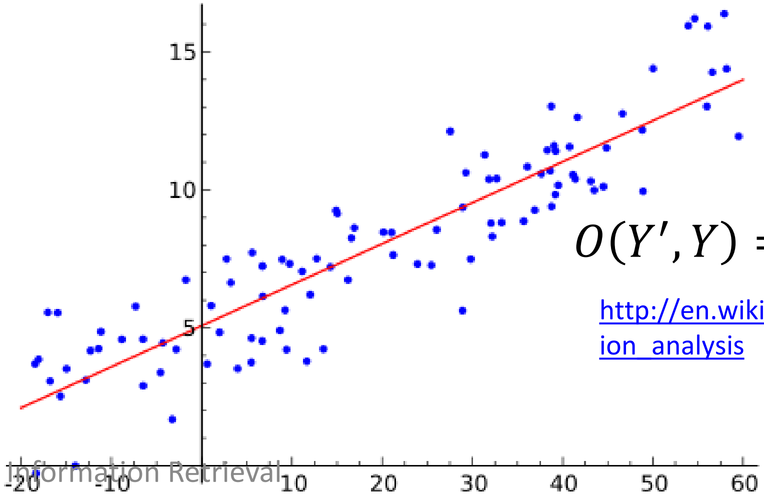
NOTE: We will only talk about supervised learning.

Classification

$$O(Y', Y) = \delta(Y' = Y)$$

http://en.wikipedia.org/wiki/Statistical_classification





Regression

$$O(Y', Y) = -||Y' - Y||$$

http://en.wikipedia.org/wiki/Regression_analysis

Learning to Rank

- General solution in optimization framework
  - Input: $\{((q_i, d_1), y_1), ((q_i, d_2), y_2), \ldots, ((q_i, d_n), y_n)\}$, where $\mathrm{d_n} \in R^N, y_i \in \{0, \ldots, L\}$
  - Object: O = {P@k, MAP, NDCG}
  - Output: $f(q, d) \to Y$, s.t., $f = \mathrm{argmax}_{f' \subset F} O(f'(q, d), Y)$

DocID	BM25	LM	PageRank	Label
0001	1.6	1.1	0.9	0
0002	2.7	1.9	0.2	1

Challenge: how to optimize?

- Evaluation metric recap
  - Average Precision
    - $\mathrm{AveP} = \frac{\sum_{k=1}^{n}(P(k) \times rel(k))}{\text{number of relevant documents}}$
  - DCG
    - $\mathrm{DCG_p} = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2 i}.$

Not continuous with respect to f(X)!

- Order is essential!
  - f → **order** → metric

Approximating the Objects!

- Pointwise
  - – Fit the relevance labels individually
- Pairwise
  - – Fit the relative orders
- Listwise
  - – Fit the whole order

Pointwise Learning to Rank

- Ideally perfect relevance prediction leads to perfect ranking
  - f → **score** → order → metric
- Reducing ranking problem to
  - Regression
    - $O(f(Q,D),Y) = -\sum_i ||f(q_i,d_i) - y_i||$
    - Subset Ranking using Regression, D.Cossock and T.Zhang, COLT 2006
  - (multi-)Classification
    - $O(f(Q,D),Y) = \sum_i \delta(f(q_i,d_i) = y_i)$
    - Ranking with Large Margin Principles, A. Shashua and A. Levin, NIPS 2002

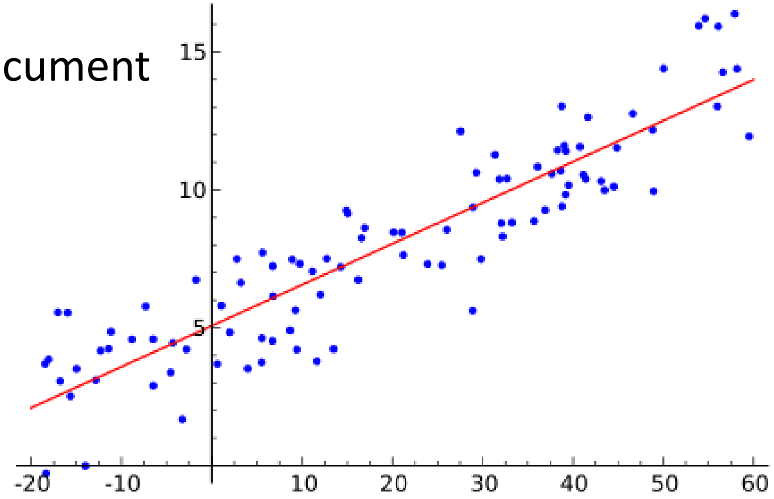
Subset Ranking using Regression

D.Cossock and T.Zhang, COLT 2006

- Fit relevance labels via regression
  - $\hat{f} = \arg\min_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^{n} \left[\underline{\sum_{j=1}^{m} (f(x_{i,j}, S_i) - y_{i,j})^2} \right]$
  - Emphasize more on relevant documents
    - $\sum_{j=1}^{m} w(x_j, S)(f(x_j, S) - y_j)^2 + u \sup_j w'(x_j, S)(f(x_j, S) - \delta(x_j, S))_+^2$

Weights on each document

Most positive document

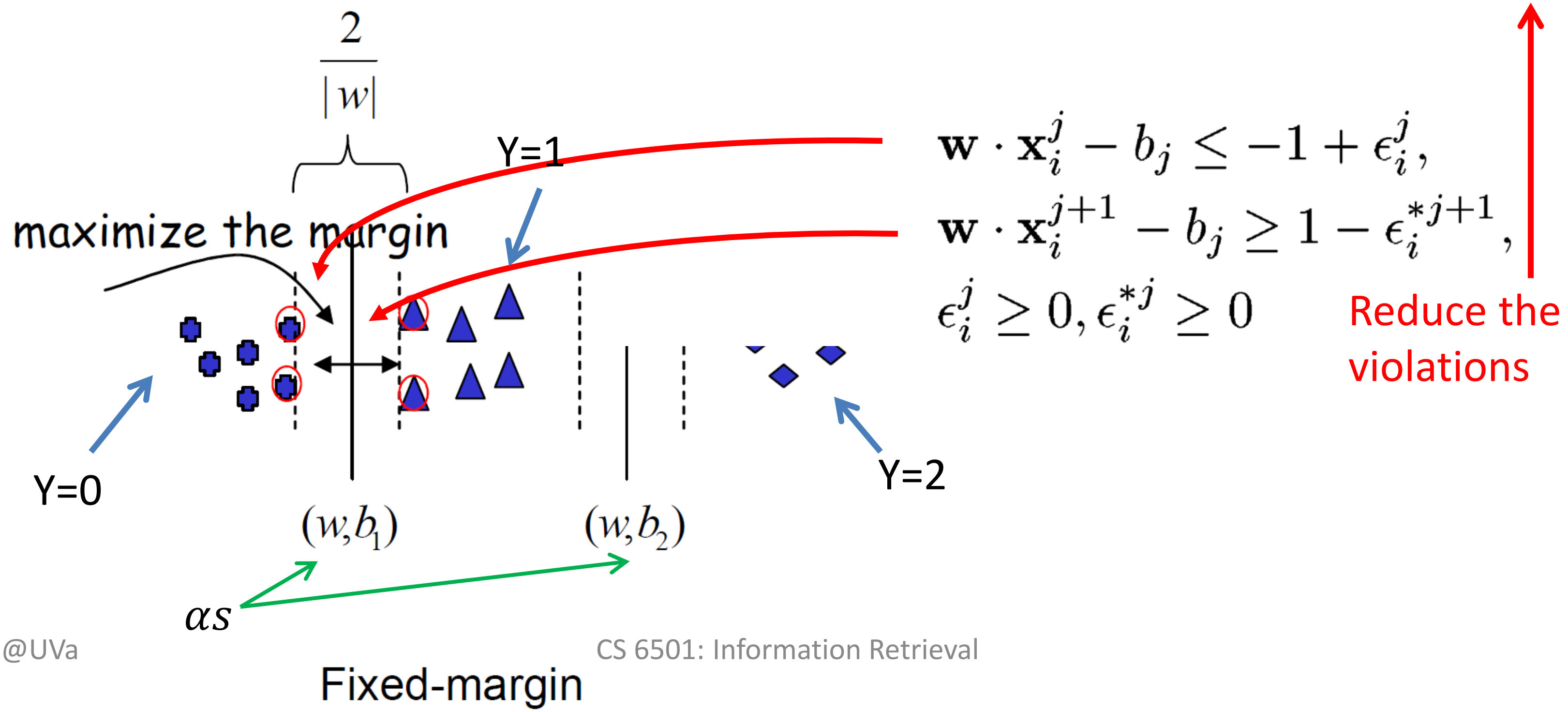


http://en.wikipedia.org/wiki/Regression_analysis

Ranking with Large Margin Principles

A. Shashua and A. Levin, NIPS 2002

- Goal: correctly placing the documents in the corresponding category and maximize the margin



$$\mathbf{w} \cdot \mathbf{x}_i^j - b_j \leq -1 + \epsilon_i^j,$$

$$\mathbf{w} \cdot \mathbf{x}_i^{j+1} - b_j \geq 1 - \epsilon_i^{*j+1},$$

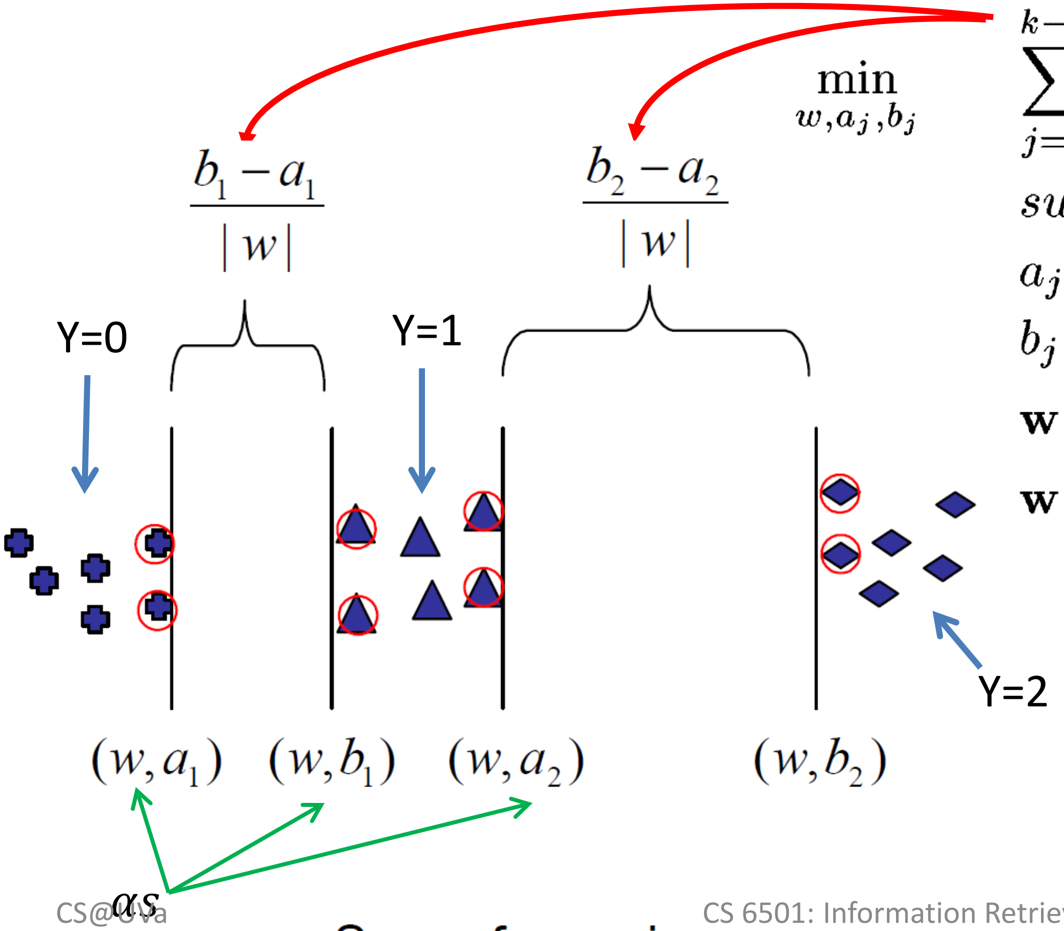
$$\epsilon_i^j \geq 0, \epsilon_i^{*j} \geq 0$$

Reduce the violations

Ranking with Large Margin Principles

A. Shashua and A. Levin, NIPS 2002

- Maximizing the sum of margins



Sum-of-margins

$$\min_{w,a_j,b_j} \sum_{j=1}^{k-1}(a_j-b_j)+C\sum_i\sum_j\left(\epsilon_i^j+\epsilon_i^{*j+1}\right)$$

subject to

$$a_j \le b_j,$$

$$b_j \le a_{j+1}, \quad j=1,...,k-2$$

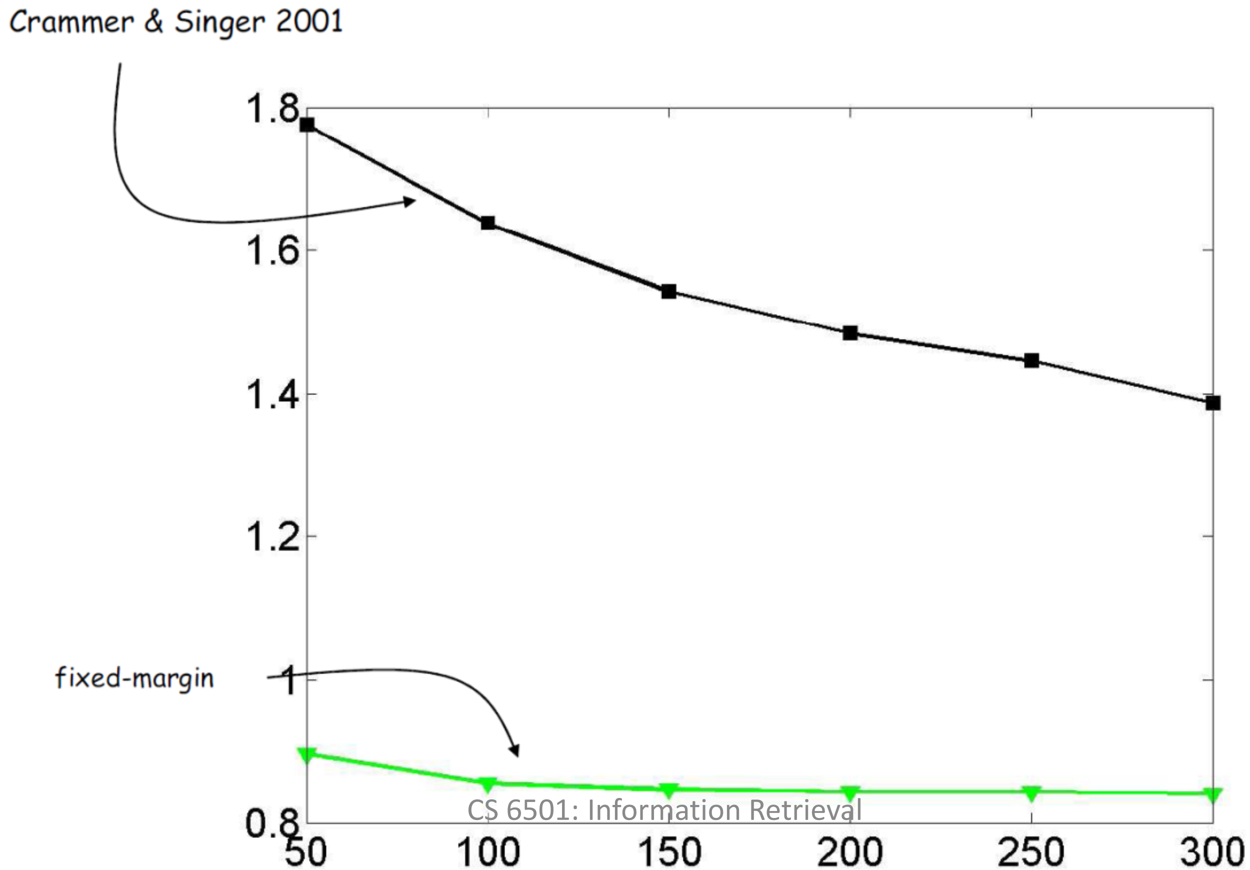
$$\mathbf{w}\cdot\mathbf{x}_i^j \le a_j+\epsilon_i^j, \;\; b_j-\epsilon_i^{*j+1} \le \mathbf{w}\cdot\mathbf{x}_i^{j+1}$$

$$\mathbf{w}\cdot\mathbf{w} \le 1, \;\; \epsilon_i^j \ge 0, \epsilon_i^{*j+1} \ge 0$$

Ranking with Large Margin Principles

A. Shashua and A. Levin, NIPS 2002

- Ranking lost is consistently decreasing with more training data



What did we learn

- Machine learning helps!
  - Derive something optimizable
  - More efficient and guided

There is always a catch

- Cannot directly optimize IR metrics
  - (0 → 1, 2 → 0) worse than (0->-2, 2->4)
- Position of documents are ignored
  - Penalty on documents at higher positions should be larger
- Favor the queries with more documents

Pairwise Learning to Rank

- Ideally perfect partial order leads to perfect ranking
  - f → **partial order** → order → metric
- Ordinal regression
  - $O(f(Q,D),Y) = \sum_{i \neq j} \delta(y_i > y_j)\delta(f(q_i,d_i) > f(q_i,d_i))$
    - Relative ordering between different documents is significant
    - E.g., (0->-2, 2->4) is better than (0 → 1, 2 → 0)
  - Large body of work

Optimizing Search Engines using Clickthrough Data

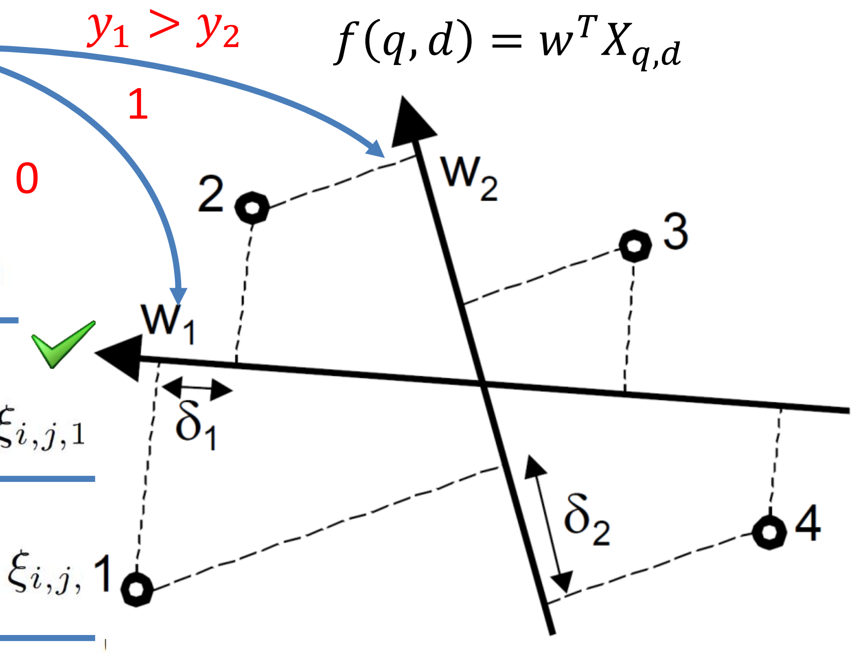
Thorsten Joachims, KDD'02

- Minimizing the number of mis-ordered pairs

linear combination of features

$$y_1 > y_2, y_2 > y_3, y_1 > y_4$$

$$f(q,d) = w^T X_{q,d}$$



minimize: $$V(\vec{w}, \vec{\xi}) = \frac{1}{2}\vec{w}\cdot\vec{w} + C\underline{\sum \xi_{i,j,k}}$$

subject to:

$$\forall (d_i, d_j) \in r_1^* : \vec{w}\Phi(q_1, d_i) \geq \vec{w}\Phi(q_1, d_j) + 1 - \underline{\xi_{i,j,1}}$$

$$\ldots$$

$$\forall (d_i, d_j) \in r_n^* : \vec{w}\Phi(q_n, d_i) \geq \vec{w}\Phi(q_n, d_j) + 1 - \underline{\xi_{i,j,}}$$

$$\forall i \forall j \forall k : \xi_{i,j,k} \geq 0$$

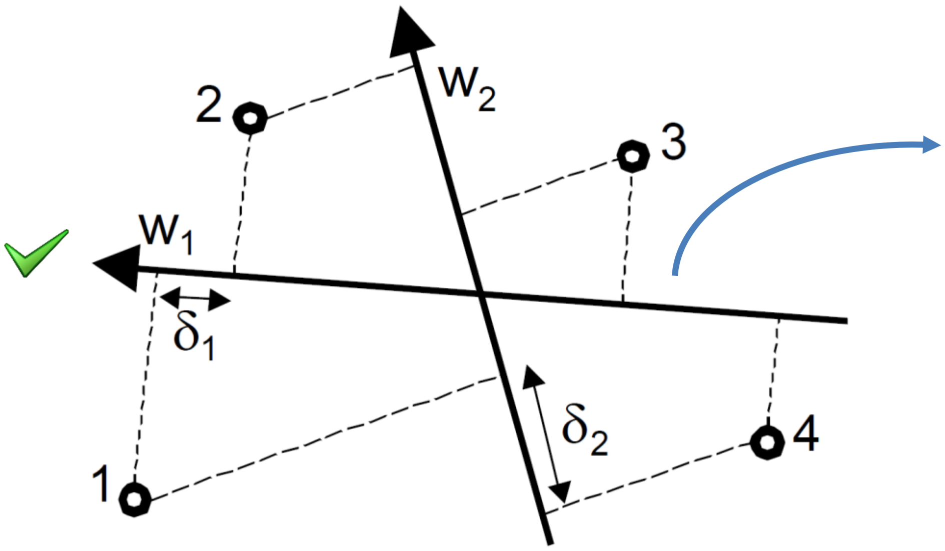
Keep the relative orders

RankingSVM

Optimizing Search Engines using Clickthrough Data

Thorsten Joachims, KDD'02

- How to use it?
  - $f \rightarrow \mathbf{score} \rightarrow$ order



$y_1 > y_2 > y_3 > y_4$

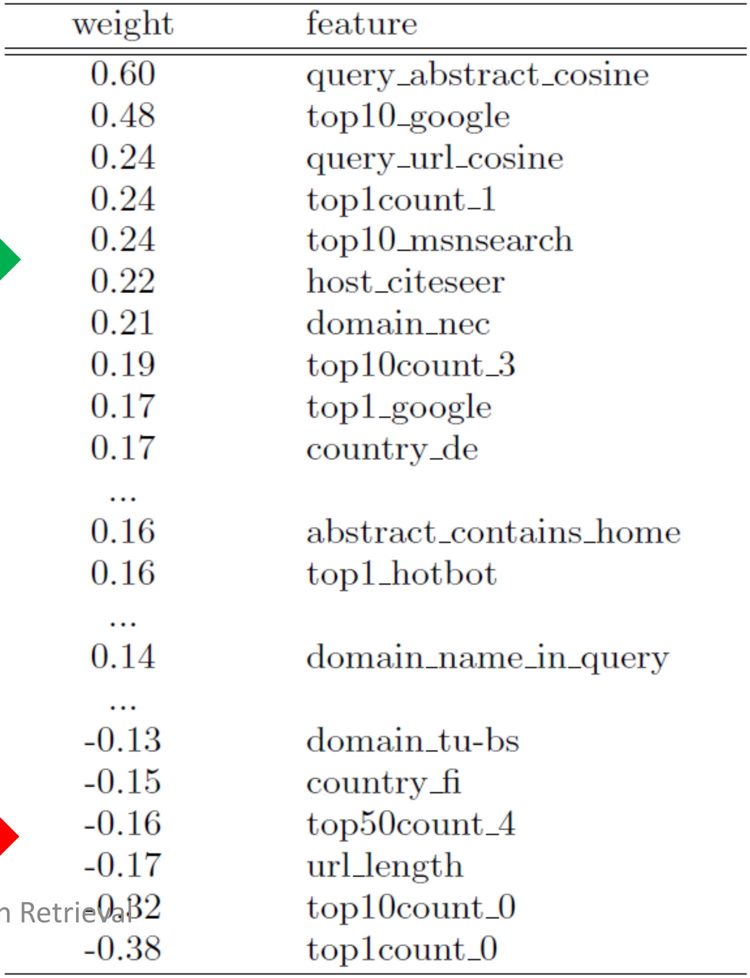
Optimizing Search Engines using Clickthrough Data

Thorsten Joachims, KDD'02

- What did it learn from the data?
  - Linear correlations

Positive correlated features

Negative correlated features

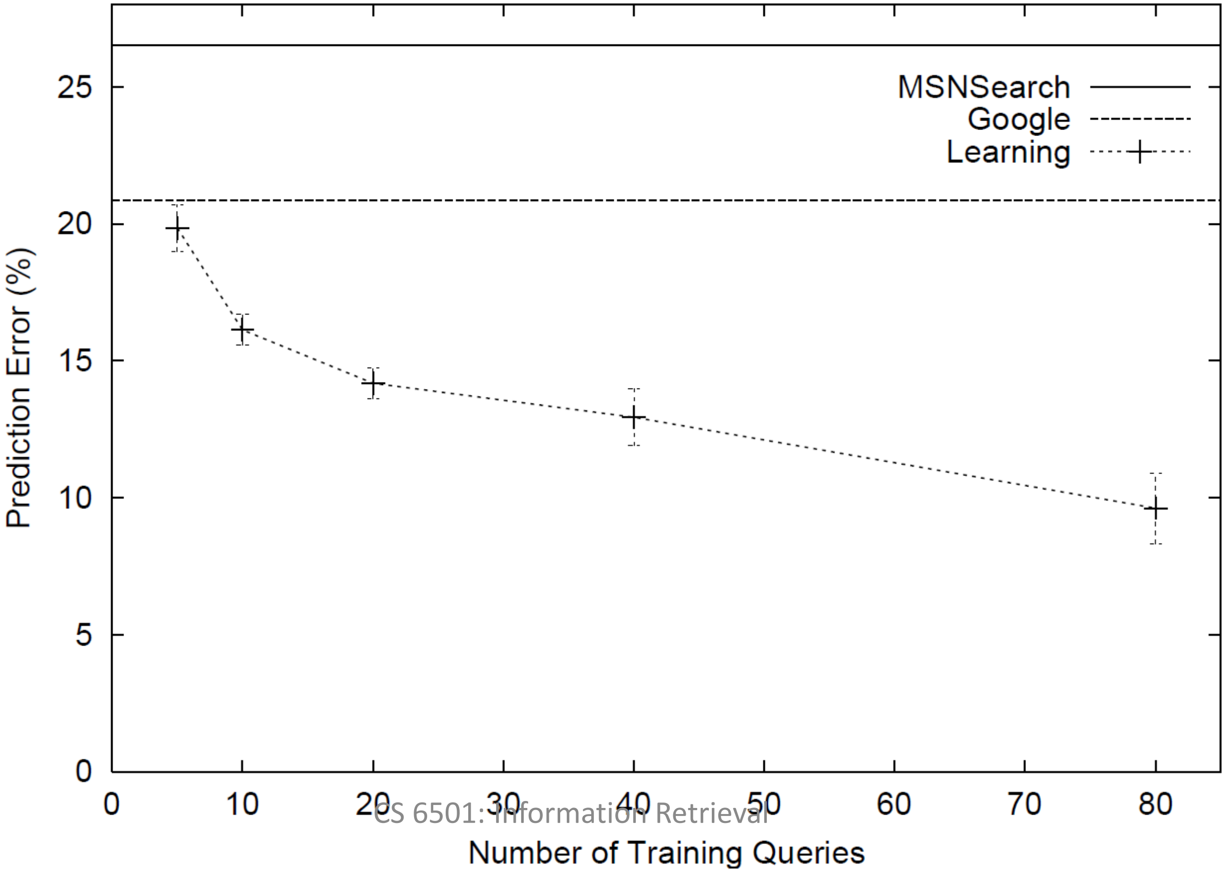


weight	feature
0.60	query_abstract_cosine
0.48	top10_google
0.24	query_url_cosine
0.24	top1count_1
0.24	top10_msnsearch
0.22	host_citeseer
0.21	domain_nec
0.19	top10count_3
0.17	top1_google
0.17	country_de
...	
0.16	abstract_contains_home
0.16	top1_hotbot
...	
0.14	domain_name_in_query
...	
-0.13	domain_tu-bs
-0.15	country_fi
-0.16	top50count_4
-0.17	url_length
-0.32	top10count_0
-0.38	top1count_0

Optimizing Search Engines using Clickthrough Data

Thorsten Joachims, KDD'02

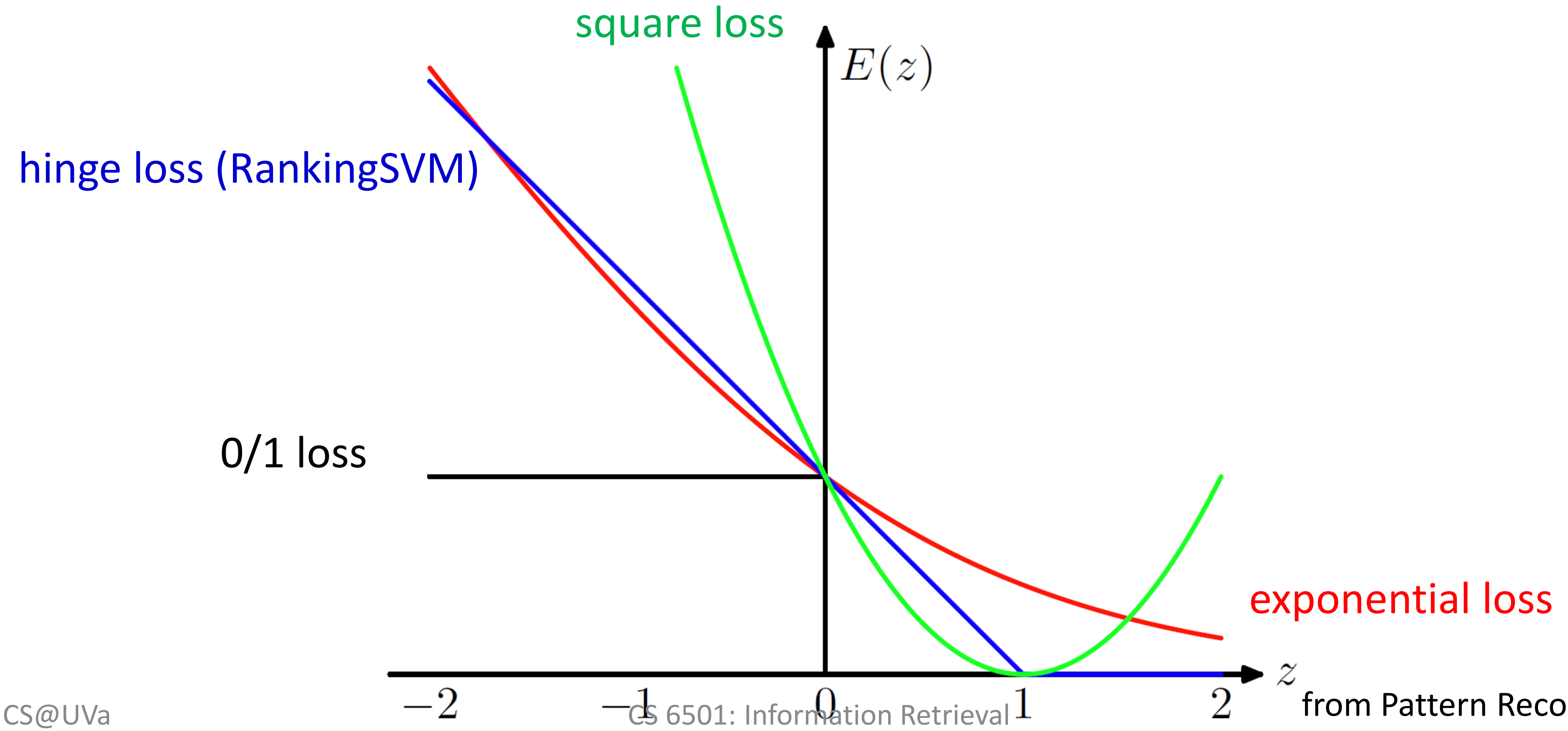
- How good is it?
  - Test on real system



An Efficient Boosting Algorithm for Combining Preferences

Y. Freund, R. Iyer, et al. JMLR 2003

- Smooth the loss on mis-ordered pairs
  - $\sum_{y_i>y_j} Pr(d_i,d_j)\underline{exp[f(q,d_j)-f(q,d_i)]}$

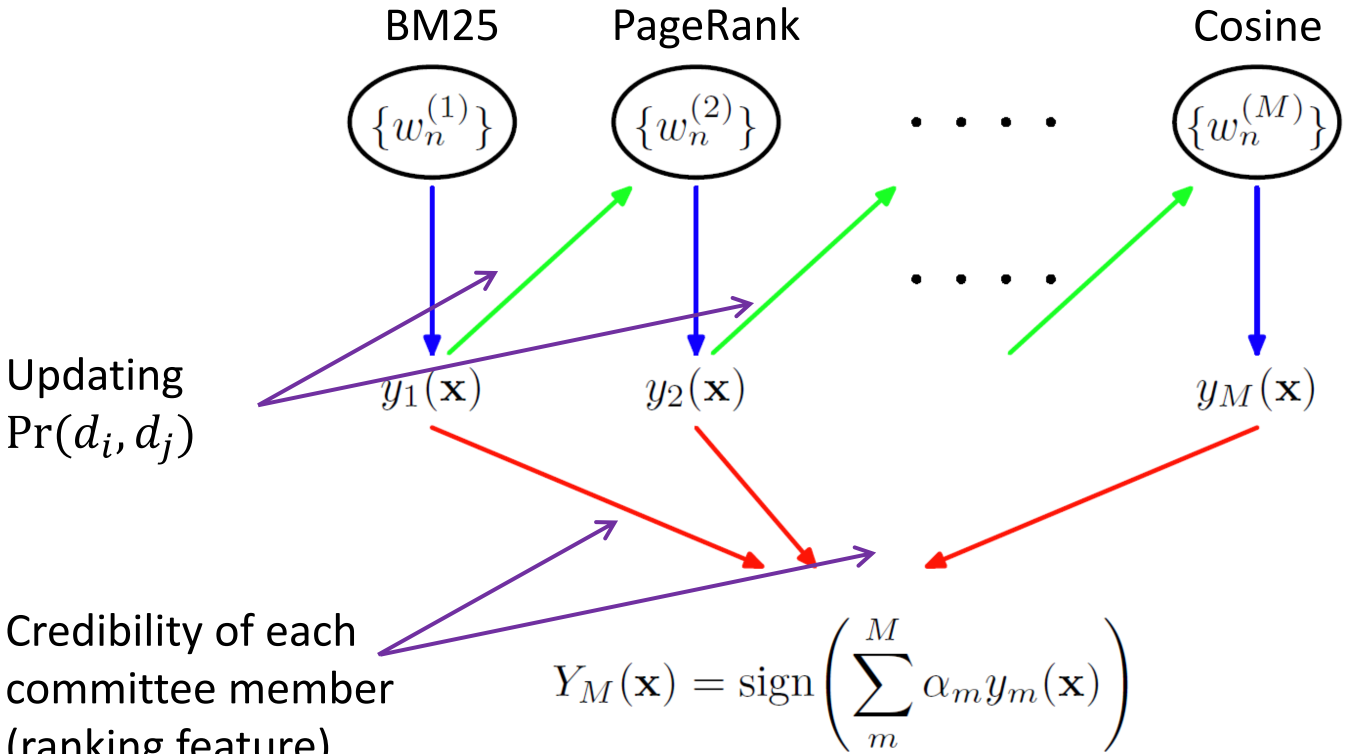


from Pattern Recognition and Machine Learning, P337

An Efficient Boosting Algorithm for Combining Preferences

Y. Freund, R. Iyer, et al. JMLR 2003

- RankBoost: optimize via boosting
  - Vote by a committee



Updating $\Pr(d_i, d_j)$

Credibility of each committee member (ranking feature)

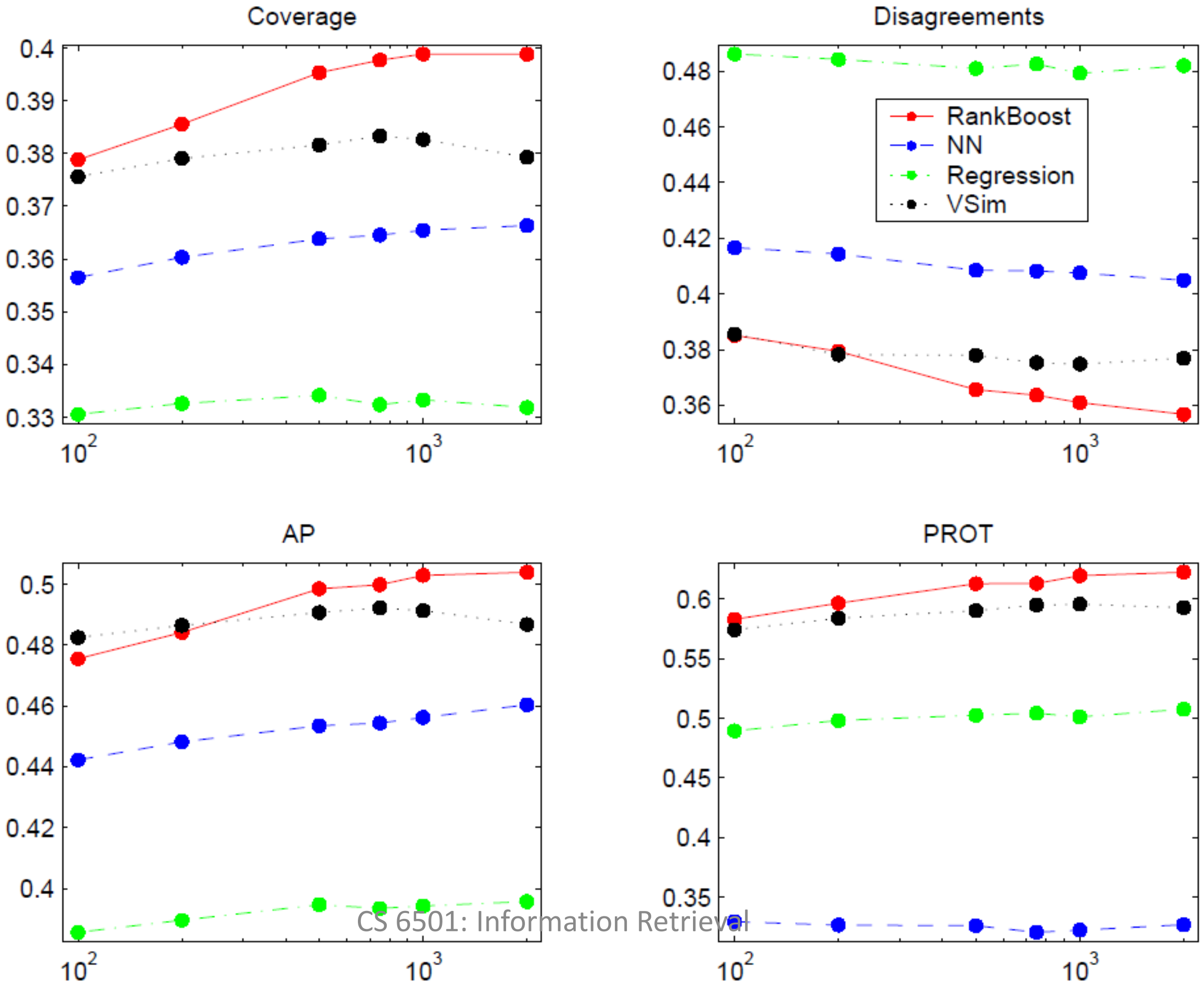
$$Y_M(\mathbf{x}) = \text{sign}\left(\sum_m^M \alpha_m y_m(\mathbf{x})\right)$$

from Pattern Recognition and Machine Learning, P658

An Efficient Boosting Algorithm for Combining Preferences

Y. Freund, R. Iyer, et al. JMLR 2003

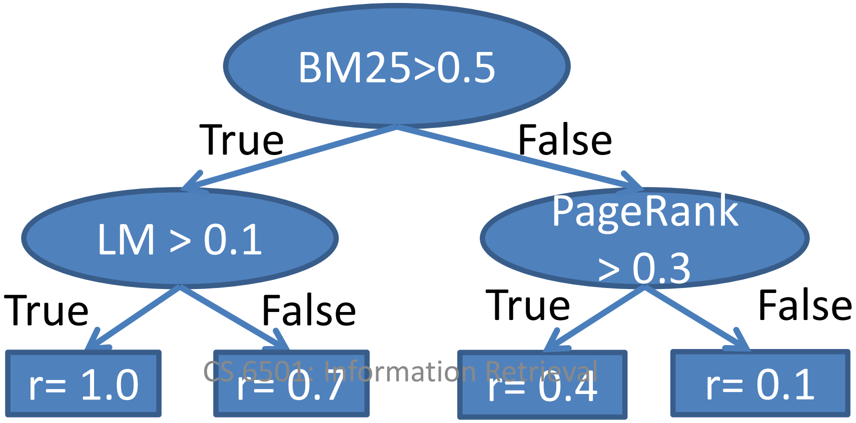
- How good is it?



A Regression Framework for Learning Ranking Functions Using Relative Relevance Judgments

Zheng et al. SIRIG'07

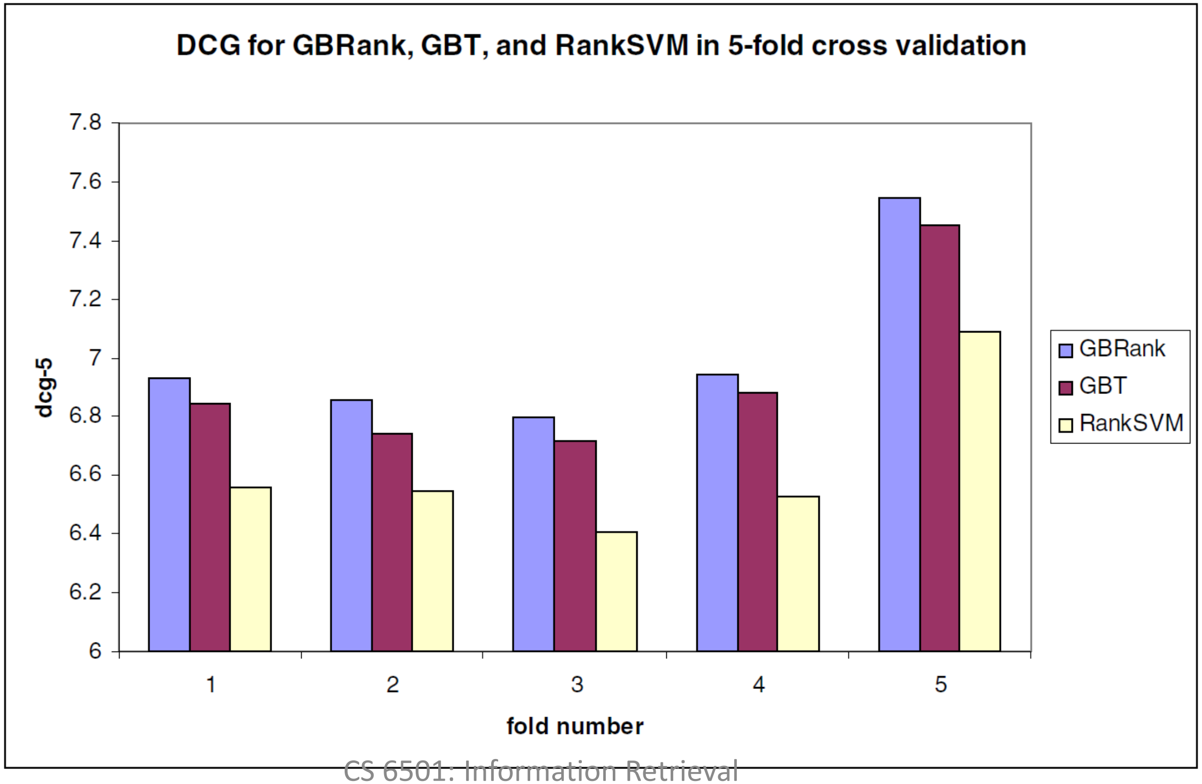
- Non-linear ensemble of features
  - Object: $\sum_{y_i>y_j}\left(\max\{0, f(q,d_j) - f(q,d_i)\}\right)^2$
  - Gradient descent boosting tree
    - Boosting tree
      - Using regression tree to minimize the residuals
      - $r^t(q,d,y) = O^t(q,d,y) - f^{(t-1)}(q,d,y)$



A Regression Framework for Learning Ranking Functions Using Relative Relevance Judgments

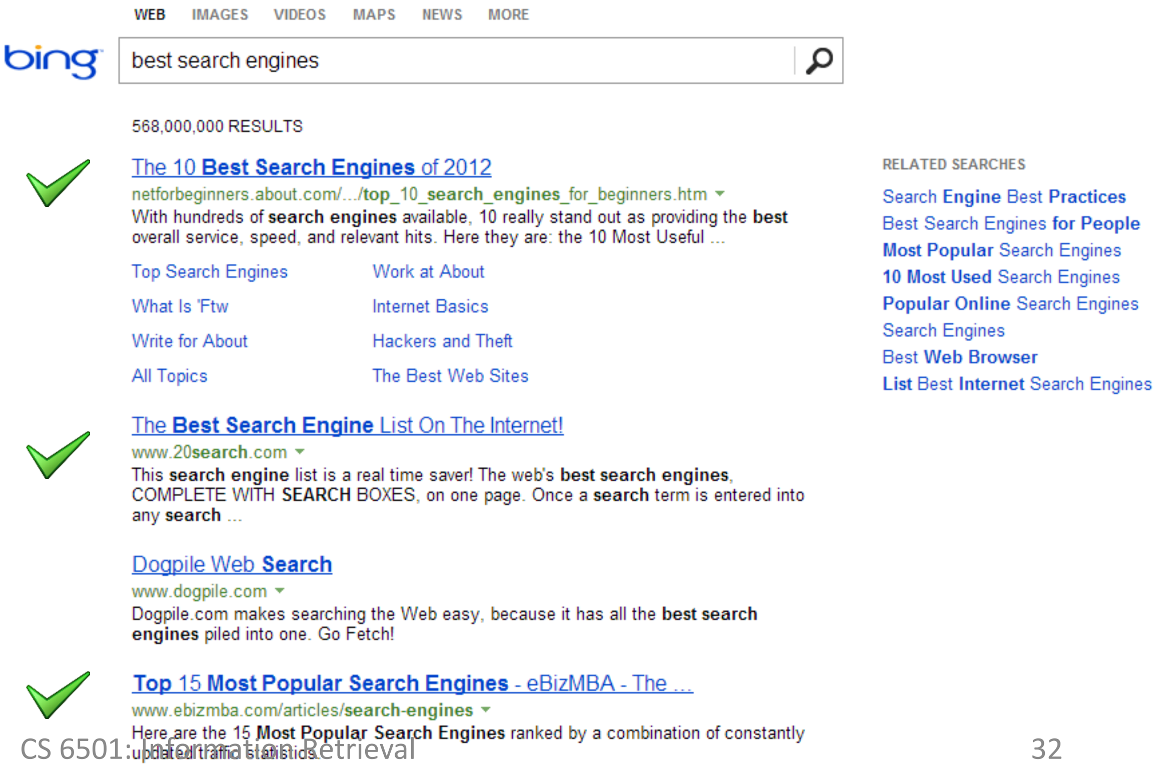
Zheng et al. SIRIG'07

- Non-linear v.s. linear
  - – Comparing with RankingSVM



Where do we get the relative orders

- Human annotations
  - Small scale, expensive to acquire
- Clickthroughs
  - Large amount, e



best search engines

568,000,000 RESULTS

✓ The 10 **Best Search Engines** of 2012
netforbeginners.about.com/.../**top_10_search_engines**_for_beginners.htm
With hundreds of **search engines** available, 10 really stand out as providing the **best** overall service, speed, and relevant hits. Here they are: the 10 Most Useful ...

Top Search Engines | Work at About
What Is 'Ftw | Internet Basics
Write for About | Hackers and Theft
All Topics | The Best Web Sites

✓ The **Best Search Engine** List On The Internet!
www.20**search**.com
This **search engine** list is a real time saver! The web's **best search engines**, COMPLETE WITH **SEARCH** BOXES, on one page. Once a **search** term is entered into any **search** ...

Dogpile Web **Search**
www.dogpile.com
Dogpile.com makes searching the Web easy, because it has all the **best search engines** piled into one. Go Fetch!

✓ **Top** 15 **Most Popular Search Engines** - eBizMBA - The ...
www.ebizmba.com/articles/**search-engines**
Here are the 15 **Most Popular Search Engines** ranked by a combination of constantly updated traffic statistics

RELATED SEARCHES
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Popular Online Search Engines
Search Engines
Best **Web Browser**
List Best **Internet** Search Engines

Accurately Interpreting Clickthrough Data as Implicit Feedback

Thorsten Joachims, et al., SIGIR'05

- Position bias

Your click is not because

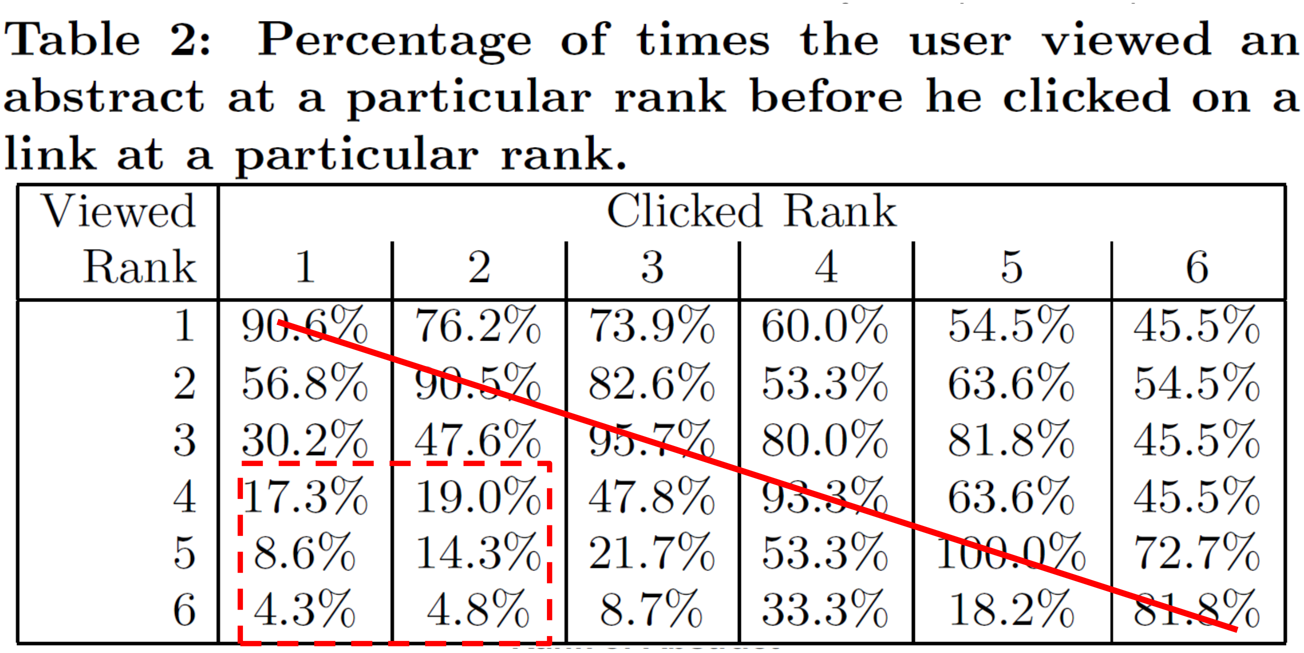


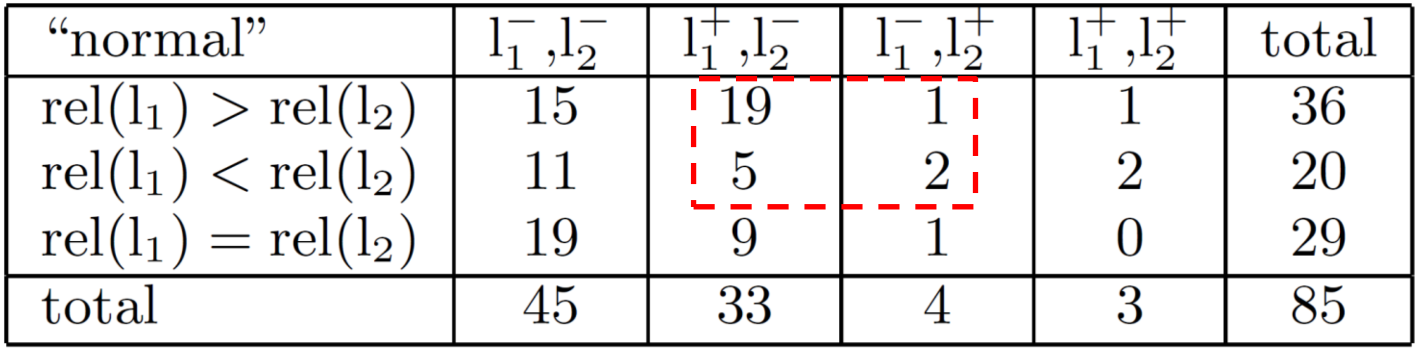
Table 2: Percentage of times the user viewed an abstract at a particular rank before he clicked on a link at a particular rank.

Viewed Rank	Clicked Rank					
	1	2	3	4	5	6
1	90.6%	76.2%	73.9%	60.0%	54.5%	45.5%
2	56.8%	90.5%	82.6%	53.3%	63.6%	54.5%
3	30.2%	47.6%	95.7%	80.0%	81.8%	45.5%
4	17.3%	19.0%	47.8%	93.3%	63.6%	45.5%
5	8.6%	14.3%	21.7%	53.3%	100.0%	72.7%
6	4.3%	4.8%	8.7%	33.3%	18.2%	81.8%

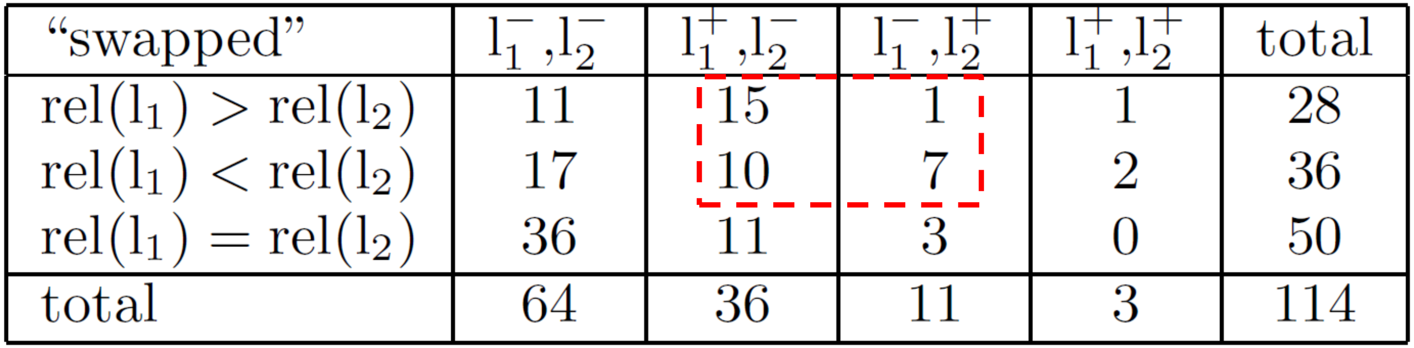
Accurately Interpreting Clickthrough Data as Implicit Feedback

Thorsten Joachims, et al., SIGIR'05

- Controlled experiment
  - Over trust of the top ranked positions



"normal"	l_1^-, l_2^-	l_1^+, l_2^-	l_1^-, l_2^+	l_1^+, l_2^+	total
$rel(l_1) > rel(l_2)$	15	19	1	1	36
$rel(l_1) < rel(l_2)$	11	5	2	2	20
$rel(l_1) = rel(l_2)$	19	9	1	0	29
total	45	33	4	3	85

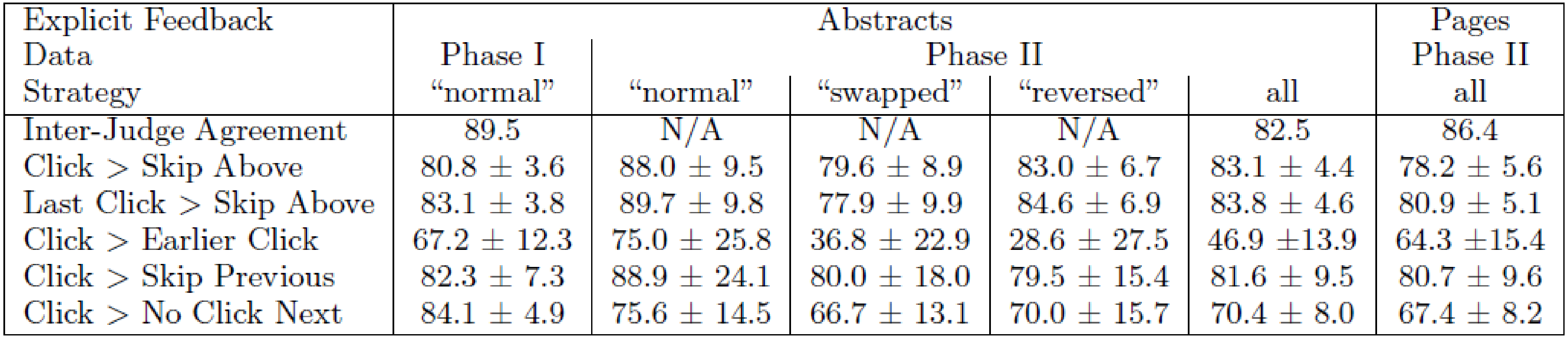


"swapped"	l_1^-, l_2^-	l_1^+, l_2^-	l_1^-, l_2^+	l_1^+, l_2^+	total
$rel(l_1) > rel(l_2)$	11	15	1	1	28
$rel(l_1) < rel(l_2)$	17	10	7	2	36
$rel(l_1) = rel(l_2)$	36	11	3	0	50
total	64	36	11	3	114

Accurately Interpreting Clickthrough Data as Implicit Feedback

Thorsten Joachims, et al., SIGIR’05

- Pairwise preference matters
  - Click: examined and clicked document
  - Skip: examined but non-clicked document



Explicit Feedback	Abstracts					Pages
Data	Phase I	Phase II				Phase II
Strategy	“normal”	“normal”	“swapped”	“reversed”	all	all
Inter-Judge Agreement	89.5	N/A	N/A	N/A	82.5	86.4
Click > Skip Above	80.8 ± 3.6	88.0 ± 9.5	79.6 ± 8.9	83.0 ± 6.7	83.1 ± 4.4	78.2 ± 5.6
Last Click > Skip Above	83.1 ± 3.8	89.7 ± 9.8	77.9 ± 9.9	84.6 ± 6.9	83.8 ± 4.6	80.9 ± 5.1
Click > Earlier Click	67.2 ± 12.3	75.0 ± 25.8	36.8 ± 22.9	28.6 ± 27.5	46.9 ±13.9	64.3 ±15.4
Click > Skip Previous	82.3 ± 7.3	88.9 ± 24.1	80.0 ± 18.0	79.5 ± 15.4	81.6 ± 9.5	80.7 ± 9.6
Click > No Click Next	84.1 ± 4.9	75.6 ± 14.5	66.7 ± 13.1	70.0 ± 15.7	70.4 ± 8.0	67.4 ± 8.2

Click > Skip

What did we learn

- Predicting relative order
  - Getting closer to the nature of ranking
- Promising performance in practice
  - Pairwise preferences from click-throughs

Listwise Learning to Rank

- Can we directly optimize the ranking?
  - f → **order** → metric
- Tackle the challenge
  - Optimization without gradient

From RankNet to LambdaRank to LambdaMART: An Overview

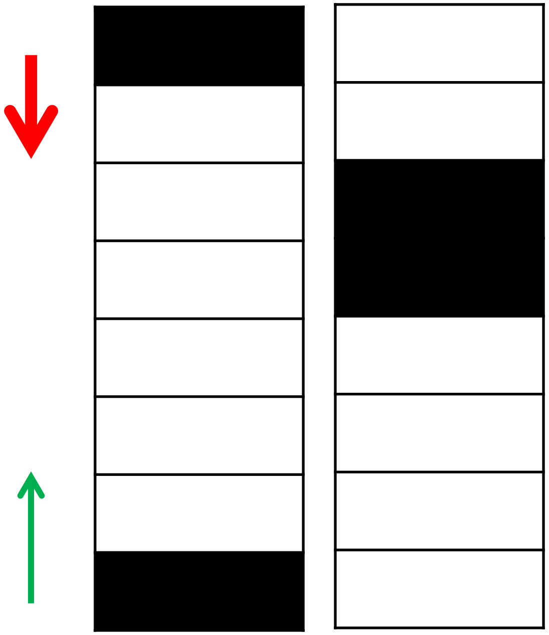
Christopher J.C. Burges, 2010

- Minimizing mis-ordered pair => maximizing IR metrics?

Mis-ordered pairs: 6

AP: $\frac{5}{8}$

DCG: 1.333



Mis-ordered pairs: 4

AP: $\frac{5}{12}$

DCG: 0.931

Position is crucial!

From RankNet to LambdaRank to LambdaMART: An Overview

Christopher J.C. Burges, 2010

- Weight the mis-ordered pairs?

  – Sc n the ri

  cument i, j

  – In

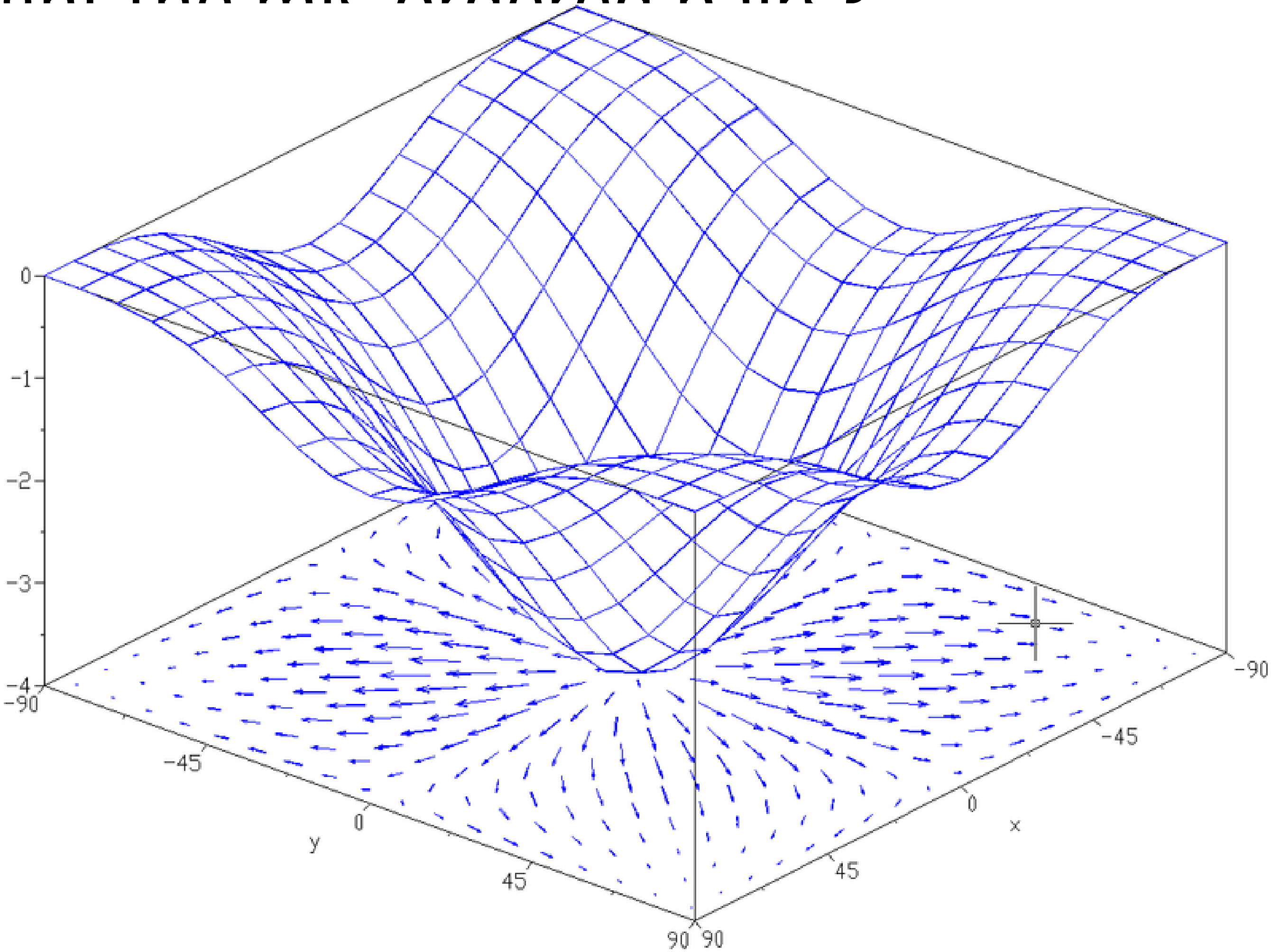
  •

  – In

  CG, if

  eaving

  •



Gradient w
i.e., expor

From RankNet to LambdaRank to LambdaMART: An Overview

Christopher J.C. Burges, 2010

- Lambda functions
  - Gradient?
    - Yes, it meets the sufficient and necessary condition of being partial derivative
  - Lead to optimal solution of original problem?
    - Empirically

From RankNet to LambdaRank to LambdaMART: An Overview

Christopher J.C. Burges, 2010

- Evolution

	RankNet
Object	Cross entropy over the pairs
Gradient (λ function)	Gradient of cross entropy
Optimization method	neural network

As we discussed in RankBoost

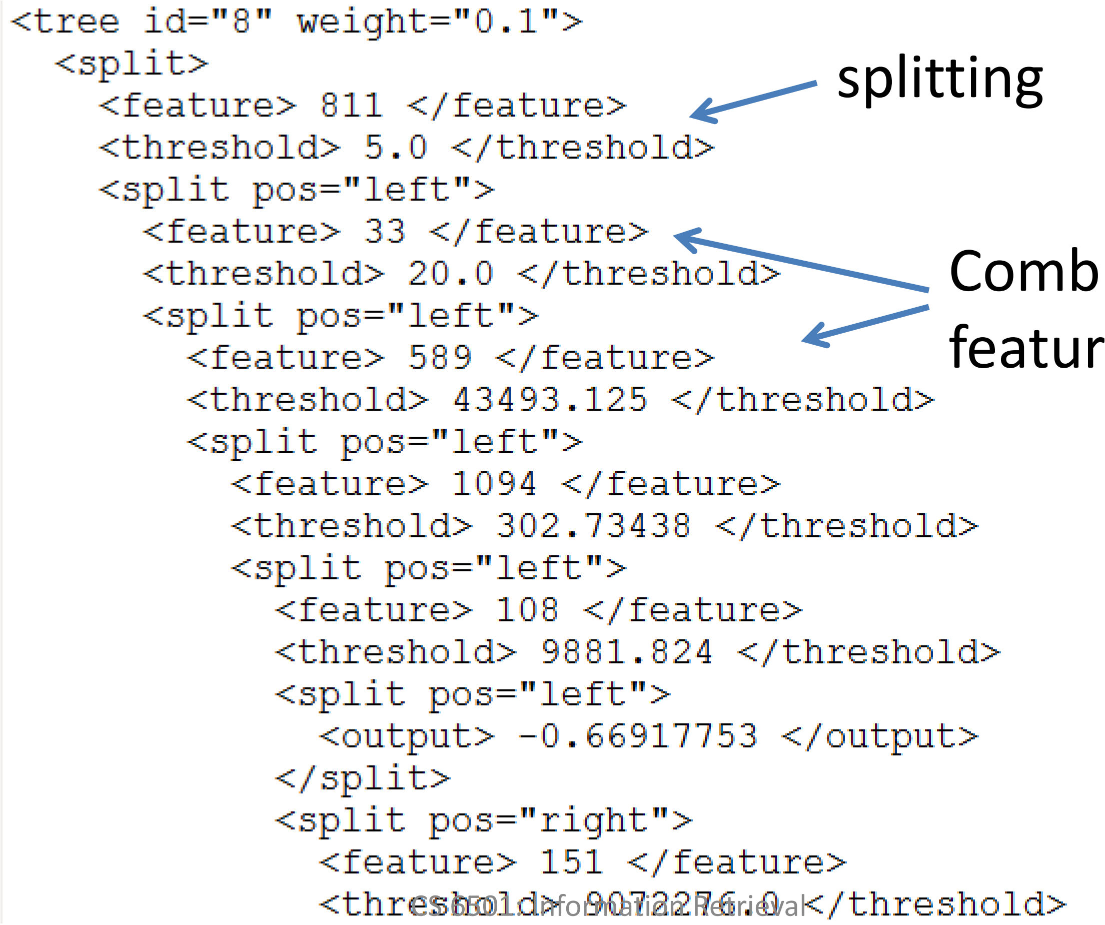
Optimize solely by gradient

Non-linear combination

From RankNet to LambdaRank to LambdaMART: An Overview

Christopher J.C. Burges, 2010

- A Lambda tree



```
<tree id="8" weight="0.1">
  <split>
    <feature> 811 </feature>
    <threshold> 5.0 </threshold>
    <split pos="left">
      <feature> 33 </feature>
      <threshold> 20.0 </threshold>
      <split pos="left">
        <feature> 589 </feature>
        <threshold> 43493.125 </threshold>
        <split pos="left">
          <feature> 1094 </feature>
          <threshold> 302.73438 </threshold>
          <split pos="left">
            <feature> 108 </feature>
            <threshold> 9881.824 </threshold>
            <split pos="left">
              <output> -0.66917753 </output>
            </split>
            <split pos="right">
              <feature> 151 </feature>
              <threshold> 9072276.0 </threshold>
```

splitting

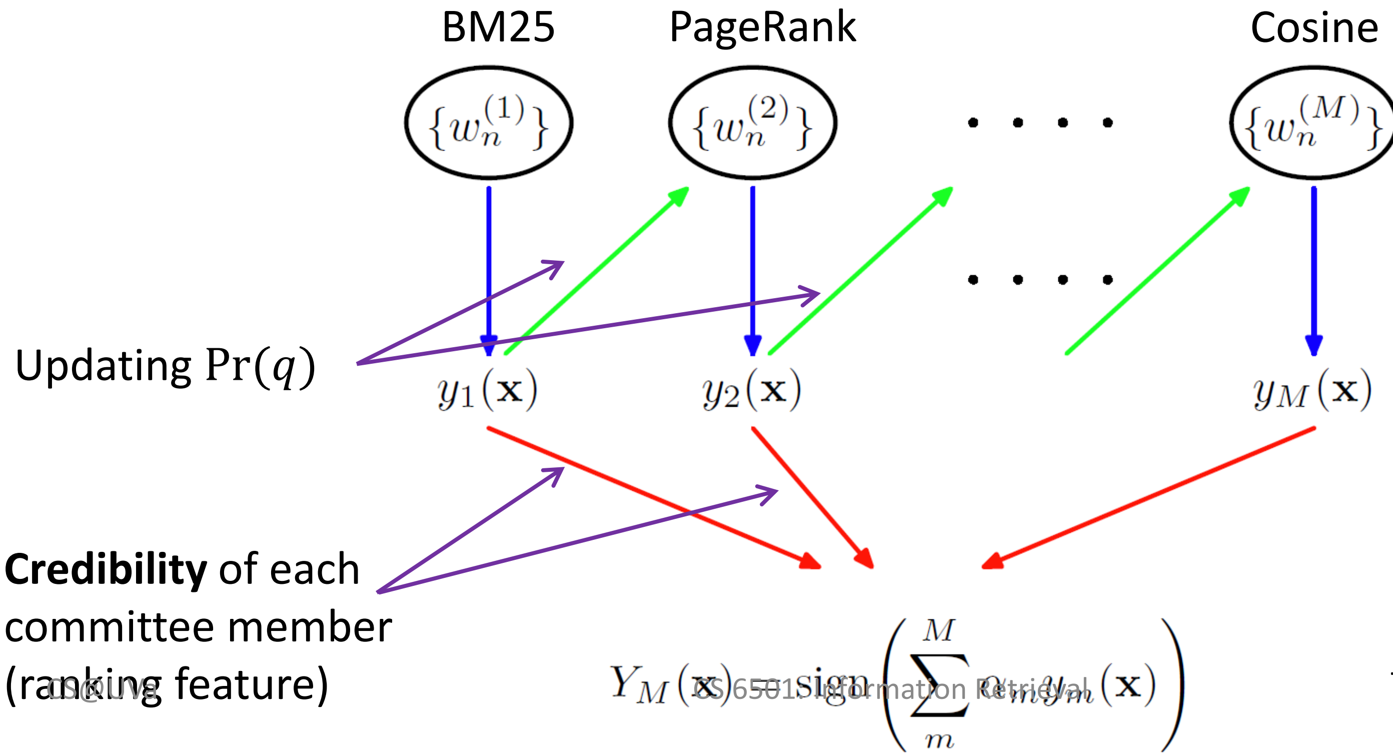
Combination of features

AdaRank: a boosting algorithm for information retrieval

Jun Xu & Hang Li, SIGIR'07

- Loss defined by IR metrics
  - $\sum_{q \in Q} Pr(q) exp[-O(q)]$
  - Optimizing by boosting

Target metrics: MAP, NDCG, MRR



$$Y_M(\mathbf{x}) = \mathrm{sign}\left(\sum_m^M \alpha_m y_m(\mathbf{x})\right)$$

from Pattern Recognition and Machine Learning, P658

A Support Vector Machine for Optimizing Average Precision

Yisong Yue, et al., SIGIR’07

RankingSVM

- Minimizing the pairwise loss

$$\textit{minimize:} \quad V(\vec{w},\vec{\xi}) = \frac{1}{2}\vec{w}\cdot\vec{w} + C\sum \xi_{i,j,k}$$

$$\textit{subject to:}$$

$$\underline{\forall (d_i, d_j) \in r_1^*} : \vec{w}\Phi(q_1, d_i) \geq \vec{w}\Phi(q_1, d_j) + 1 - \xi_{i,j,1}$$

$$\ldots$$

$$\forall (d_i, d_j) \in r_n^* : \vec{w}\Phi(q_n, d_i) \geq \vec{w}\Phi(q_n, d_j) + 1 - \xi_{i,j,n}$$

$$\forall i \forall j \forall k : \xi_{i,j,k} \geq 0$$

Loss defined on the number of mis-ordered document pairs

SVM-MAP

- Minimizing the structural loss

$$\min_{\mathbf{w},\xi\geq 0} \frac{1}{2}\|\mathbf{w}\|^2 + \frac{C}{n}\sum_{i=1}^{n}\xi_i$$

$$s.t.\ \forall i, \underline{\forall \mathbf{y} \in \mathcal{Y} \setminus \mathbf{y}_i} :$$

$$\mathbf{w}^T\Psi(\mathbf{x}_i,\mathbf{y}_i) \geq \mathbf{w}^T\Psi(\mathbf{x}_i,\mathbf{y}) + \Delta(\mathbf{y}_i,\mathbf{y}) - \xi_i$$

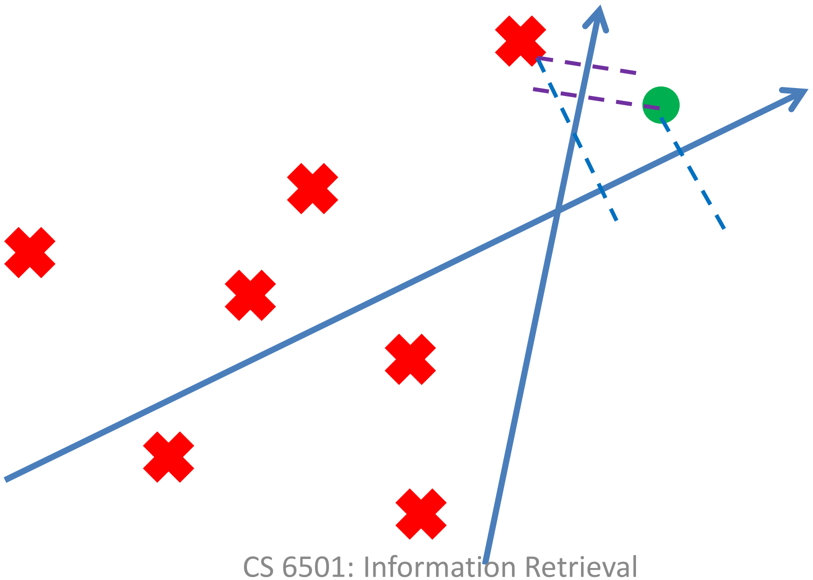
MAP difference

Loss defined on the quality of the whole list of ordered documents

A Support Vector Machine for Optimizing Average Precision

Yisong Yue, et al., SIGIR'07

- Max margin principle
  - Push the ground-truth far away from any mistakes you might make
  - Finding the most violated constraints



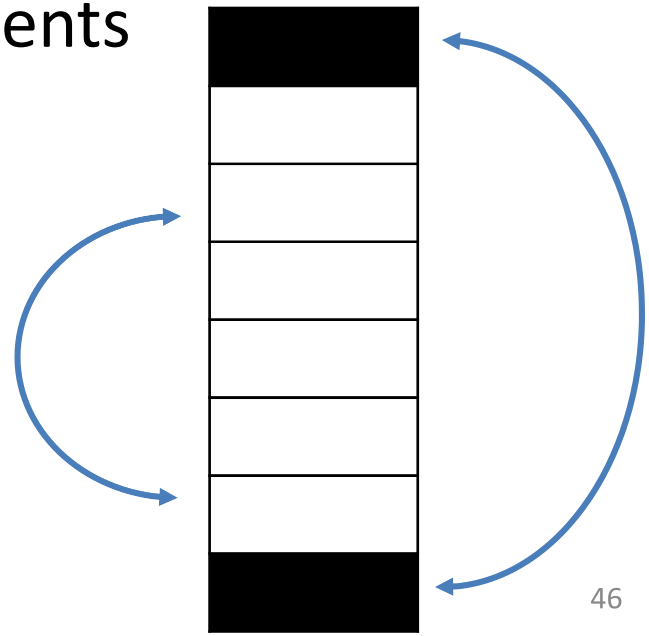
A Support Vector Machine for Optimizing Average Precision

Yisong Yue, et al., SIGIR'07

- Finding the most violated constraints
  - MAP is invariant to permutation of (ir)relevant documents
  - Maximize MAP over a series of swaps between relevant and irrelevant documents
    - $\operatorname*{argmax}_{\mathbf{y} \in \mathcal{Y}} \Delta(\mathbf{y}_i, \mathbf{y}) + \mathbf{w}^T \Psi(\mathbf{x}_i, \mathbf{y})$

Right-hand side of constraints

Start from the reverse order of ideal ranking

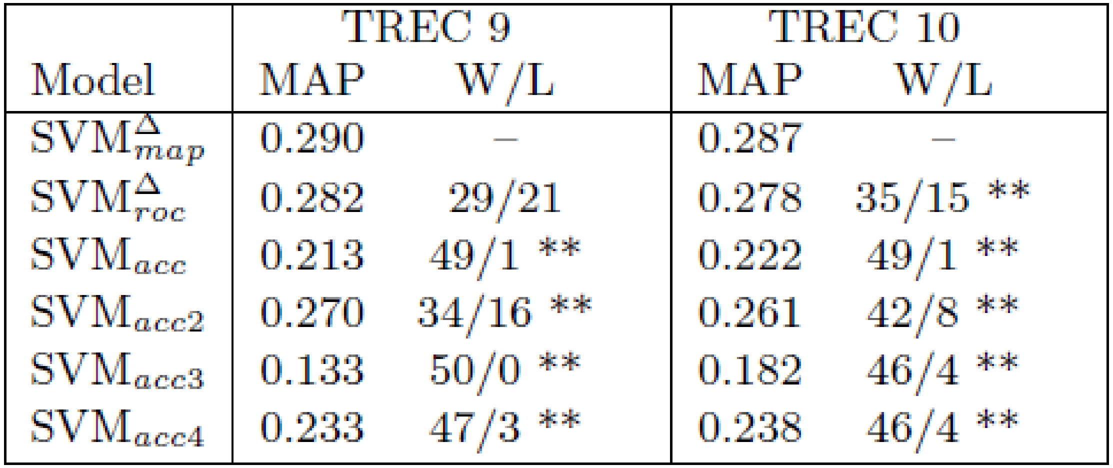


Greedy solution

A Support Vector Machine for Optimizing Average Precision

Yisong Yue, et al., SIGIR'07

- Experiment results



	TREC 9		TREC 10	
Model	MAP	W/L	MAP	W/L
$\text{SVM}^{\Delta}_{map}$	0.290	–	0.287	–
$\text{SVM}^{\Delta}_{roc}$	0.282	29/21	0.278	35/15 **
SVM_{acc}	0.213	49/1 **	0.222	49/1 **
SVM_{acc2}	0.270	34/16 **	0.261	42/8 **
SVM_{acc3}	0.133	50/0 **	0.182	46/4 **
SVM_{acc4}	0.233	47/3 **	0.238	46/4 **

Other listwise solutions

- Soften the metrics to make them differentiable
  - Michael Taylor et al., SoftRank: optimizing non-smooth rank metrics, WSDM'08
- Minimize a loss function defined on permutations
  - Zhe Cao et al., Learning to rank: from pairwise approach to listwise approach, ICML'07

What did we learn

- Taking a list of documents as a whole
  - Positions are visible for the learning algorithm
  - Directly optimizing the target metric
- Limitation
  - The search space is huge!

Summary

- Learning to rank
  - Automatic combination of ranking features for optimizing IR evaluation metrics
- Approaches
  - Pointwise
    - Fit the relevance labels individually
  - Pairwise
    - Fit the relative orders
  - Listwise
    - Fit the whole order

Experimental Comparisons

- Ranking performance

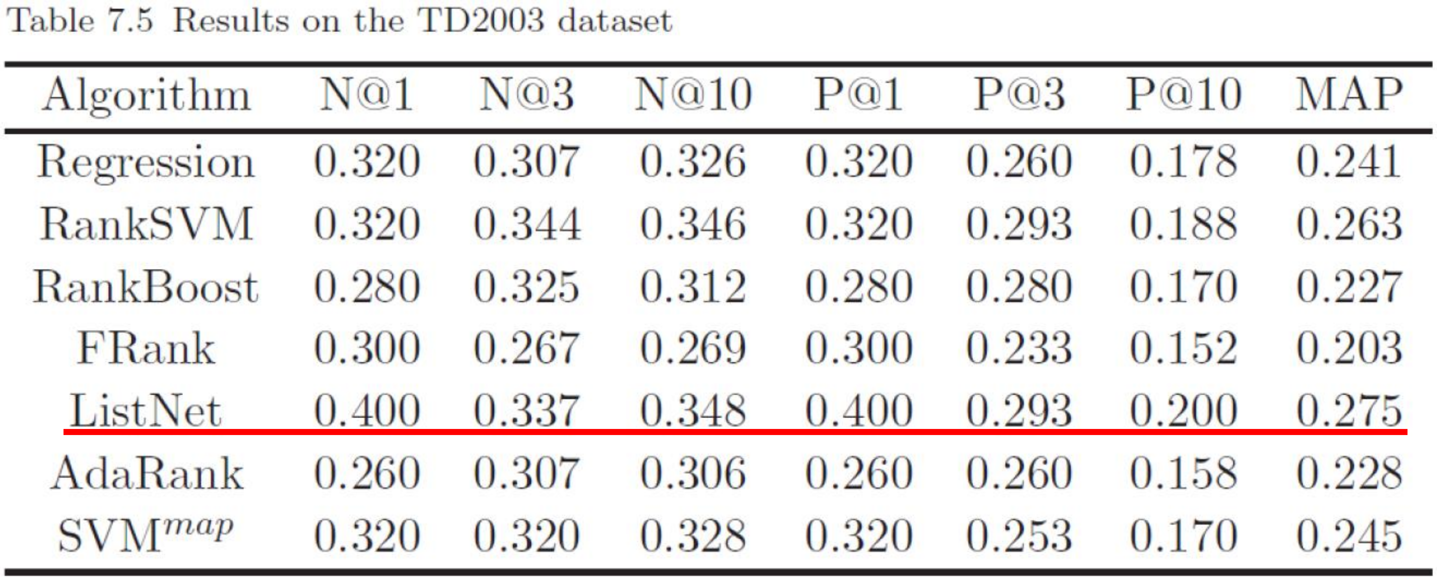


Table 7.5 Results on the TD2003 dataset

Algorithm	N@1	N@3	N@10	P@1	P@3	P@10	MAP
Regression	0.320	0.307	0.326	0.320	0.260	0.178	0.241
RankSVM	0.320	0.344	0.346	0.320	0.293	0.188	0.263
RankBoost	0.280	0.325	0.312	0.280	0.280	0.170	0.227
FRank	0.300	0.267	0.269	0.300	0.233	0.152	0.203
ListNet	0.400	0.337	0.348	0.400	0.293	0.200	0.275
AdaRank	0.260	0.307	0.306	0.260	0.260	0.158	0.228
SVM^{map}	0.320	0.320	0.328	0.320	0.253	0.170	0.245

Experimental Comparisons

- Winning count
  - Over seven different data sets

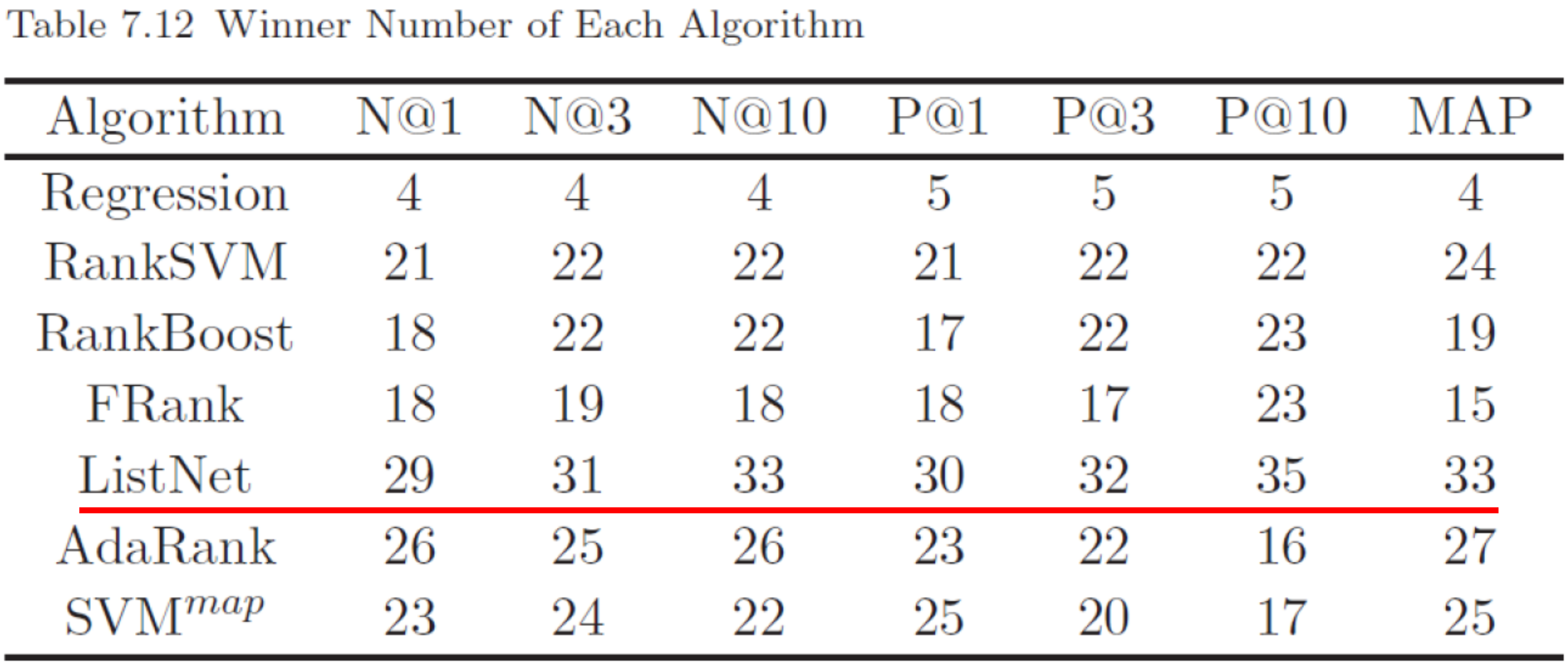


Table 7.12 Winner Number of Each Algorithm

Algorithm	N@1	N@3	N@10	P@1	P@3	P@10	MAP
Regression	4	4	4	5	5	5	4
RankSVM	21	22	22	21	22	22	24
RankBoost	18	22	22	17	22	23	19
FRank	18	19	18	18	17	23	15
ListNet	29	31	33	30	32	35	33
AdaRank	26	25	26	23	22	16	27
SVM^{map}	23	24	22	25	20	17	25

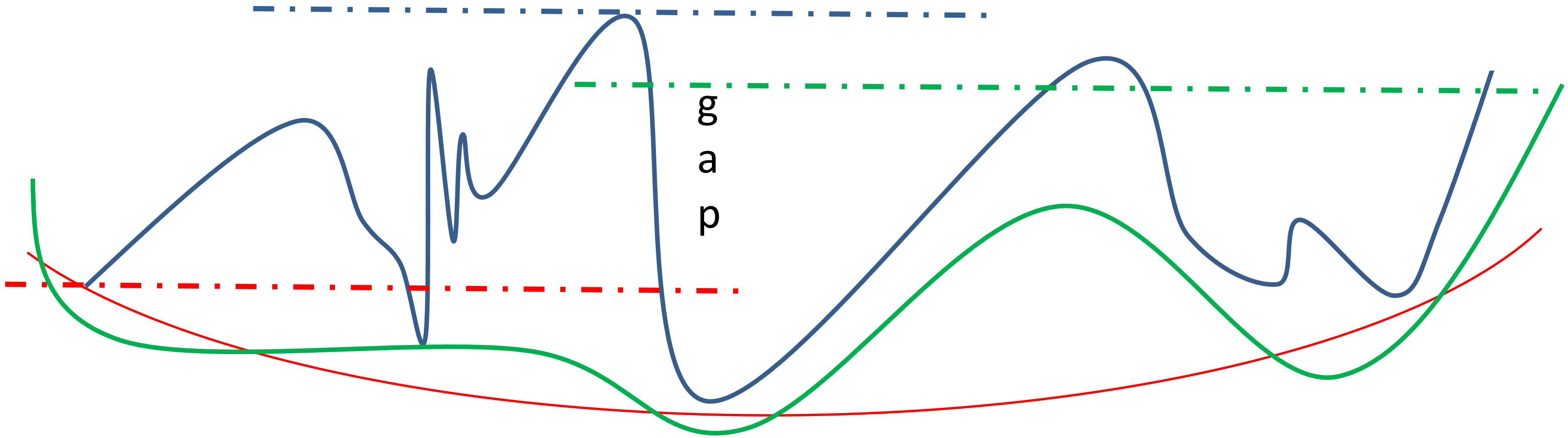
Experimental Comparisons

- My experiments
  - 1.2k queries, 45.5K documents with 1890 features
  - 800 queries for training, 400 queries for testing

	MAP	P@1	ERR	MRR	NDCG@5
ListNET	*0.2863*	*0.2074*	*0.1661*	*0.3714*	*0.2949*
LambdaMART	**0.4644**	**0.4630**	**0.2654**	**0.6105**	**0.5236**
RankNET	0.3005	0.2222	0.1873	0.3816	0.3386
RankBoost	0.4548	0.4370	0.2463	0.5829	0.4866
RankingSVM	0.3507	0.2370	0.1895	0.4154	0.3585
AdaRank	0.4321	0.4111	0.2307	0.5482	0.4421
pLogistic	0.4519	0.3926	0.2489	0.5535	0.4945
Logistic	0.4348	0.3778	0.2410	0.5526	0.4762

Analysis of the Approaches

- What are they really optimizing?
  - Relation with IR metrics



Pointwise Approaches

- Regression based

$$1 - NDCG(f) \le \frac{1}{Z_m}\left(2\sum_{j=1}^{m}\eta_j^{\varepsilon}\right)^{1/\alpha}\left(\sum_{j=1}^{m}\left(f(x_j) - y_j\right)^{\beta}\right)^{1/\beta}$$

Discount coefficients in DCG

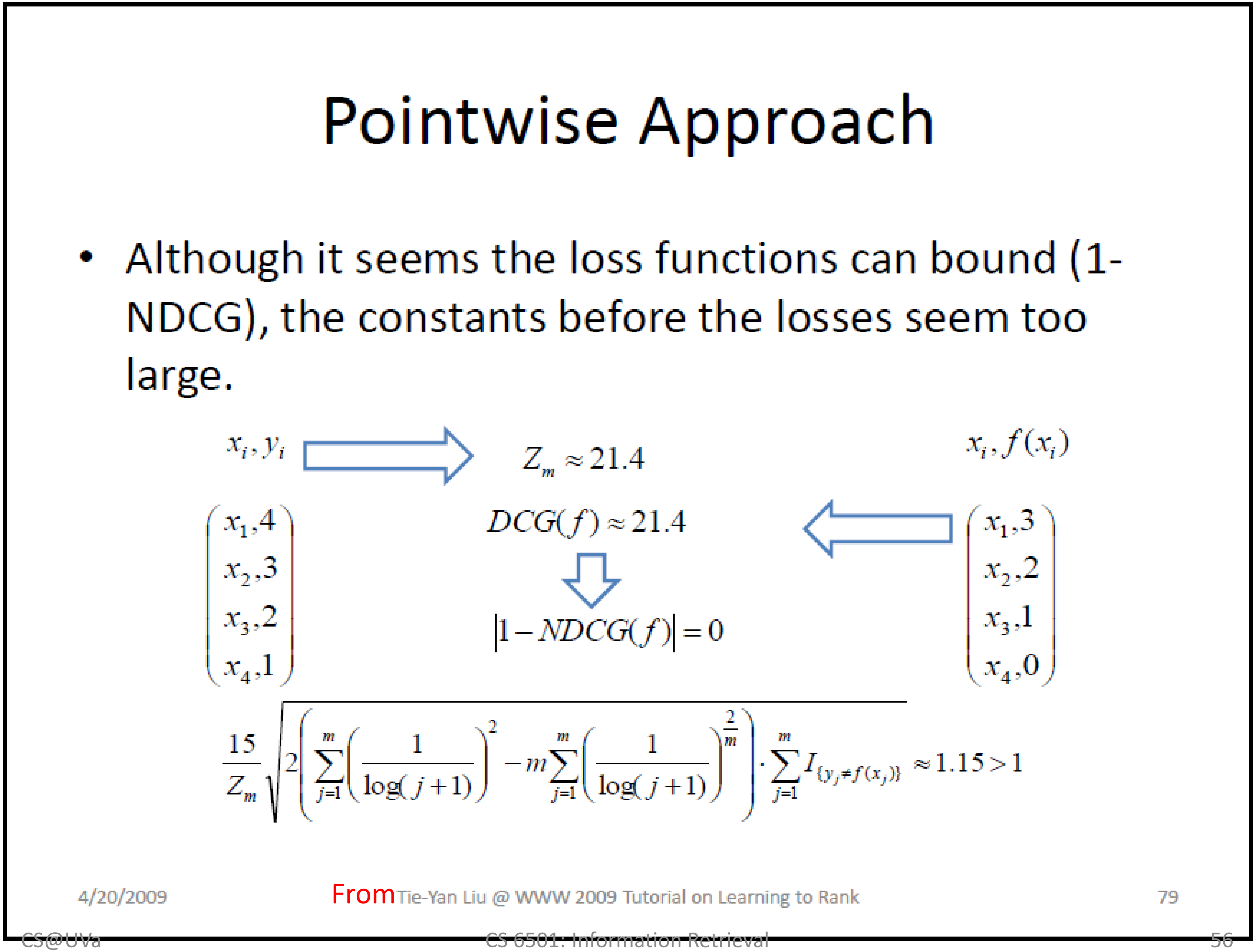
Regression loss

- Classification based

$$1 - NDCG(f) \le \frac{15}{Z_m}\sqrt{2\left(\sum_{j=1}^{m}\eta_j^{2} - m\prod_{j=1}^{m}\eta_j^{\frac{2}{m}}\right)\cdot\sum_{j=1}^{m} I_{\{y_j \neq f(x_j)\}}}$$

Discount coefficients in DCG

Classification loss



Pointwise Approach

- Although it seems the loss functions can bound (1-NDCG), the constants before the losses seem too large.

x_i, y_i $\Rightarrow$ $Z_m \approx 21.4$

$x_i, f(x_i)$

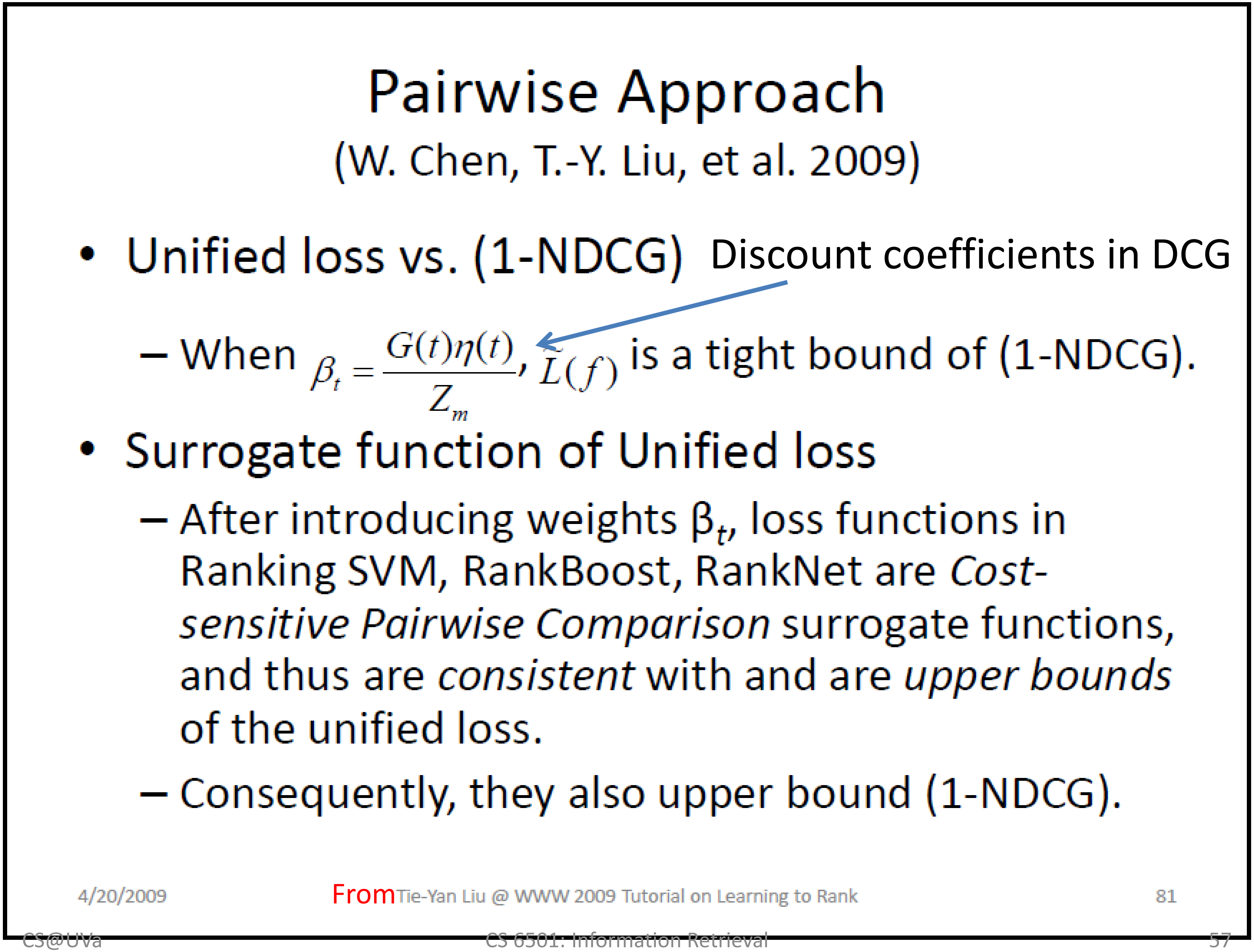
$$\begin{pmatrix} x_1,4 \\ x_2,3 \\ x_3,2 \\ x_4,1 \end{pmatrix} \qquad DCG(f) \approx 21.4 \Leftarrow \begin{pmatrix} x_1,3 \\ x_2,2 \\ x_3,1 \\ x_4,0 \end{pmatrix}$$

$$\Downarrow$$

$$\left|1 - NDCG(f)\right| = 0$$

$$\frac{15}{Z_m}\sqrt{2\left(\sum_{j=1}^{m}\left(\frac{1}{\log(j+1)}\right)^{2} - m\sum_{j=1}^{m}\left(\frac{1}{\log(j+1)}\right)^{\frac{2}{m}}\right)\cdot\sum_{j=1}^{m} I_{\{y_j \neq f(x_j)\}}} \approx 1.15 > 1$$

4/20/2009 From Tie-Yan Liu @ WWW 2009 Tutorial on Learning to Rank 79



Pairwise Approach

(W. Chen, T.-Y. Liu, et al. 2009)

- Unified loss vs. (1-NDCG)
  - When $\beta_t = \frac{G(t)\eta(t)}{Z_m}$, $\tilde{L}(f)$ is a tight bound of (1-NDCG).

Discount coefficients in DCG

- Surrogate function of Unified loss
  - After introducing weights β_t, loss functions in Ranking SVM, RankBoost, RankNet are *Cost-sensitive Pairwise Comparison* surrogate functions, and thus are *consistent* with and are *upper bounds* of the unified loss.
  - Consequently, they also upper bound (1-NDCG).

4/20/2009 From Tie-Yan Liu @ WWW 2009 Tutorial on Learning to Rank 81

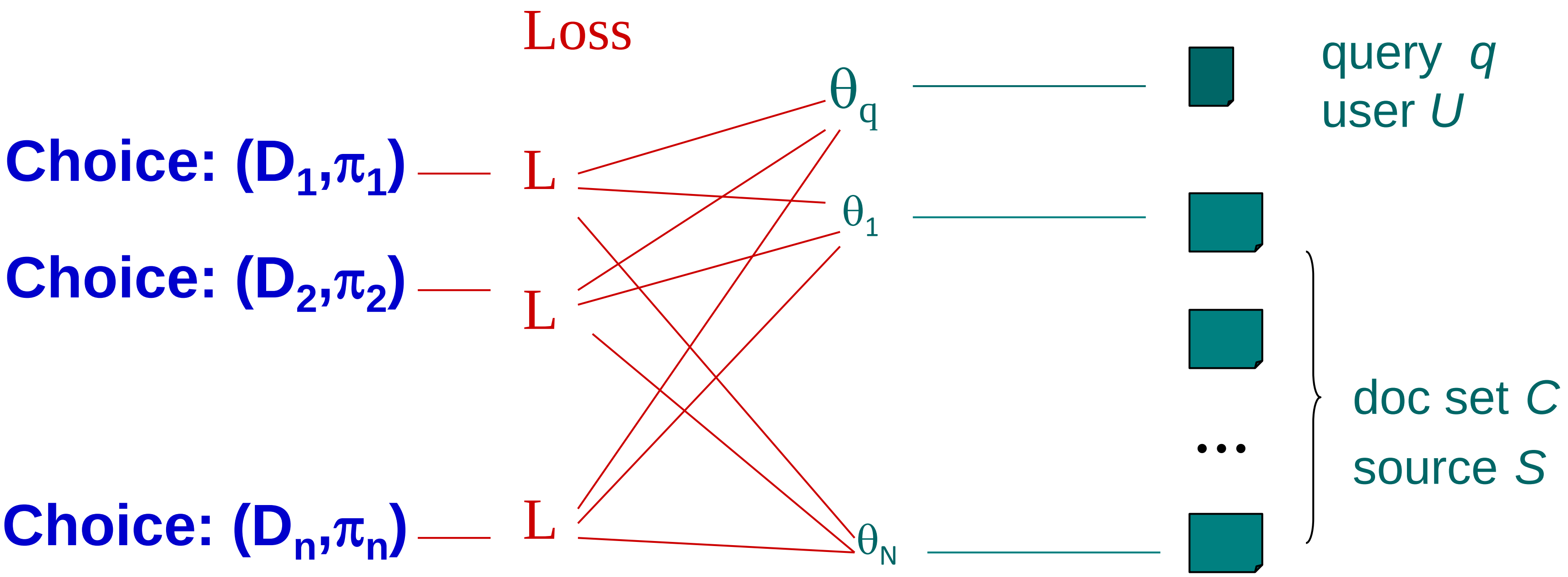
Listwise Approaches

- No general analysis
  - Method dependent
  - Directness and consistency

Connection with Traditional IR

- People have foreseen this topic long time ago
  – Nicely fit in the risk minimization framework

Applying Bayesian Decision Theory



Loss

Choice: (D_1,π_1) — L

Choice: (D_2,π_2) — L

Choice: (D_n,π_n) — L

θ_q

θ_1

θ_N

query *q*
user *U*

...

doc set *C*
source *S*

Metric to be optimized

Available ranking features

$$(D^*,\pi^*) = \arg\min_{D,\pi} \underbrace{\int_{\Theta} \underbrace{L(D,\pi,\theta)}_{\text{loss}}\, \underbrace{p(\theta}_{\text{hidden}} \mid \underbrace{q,U,C,S)}_{\text{observed}}\, d\theta}_{\text{Bayes risk for choice }(D,\,\pi)}$$

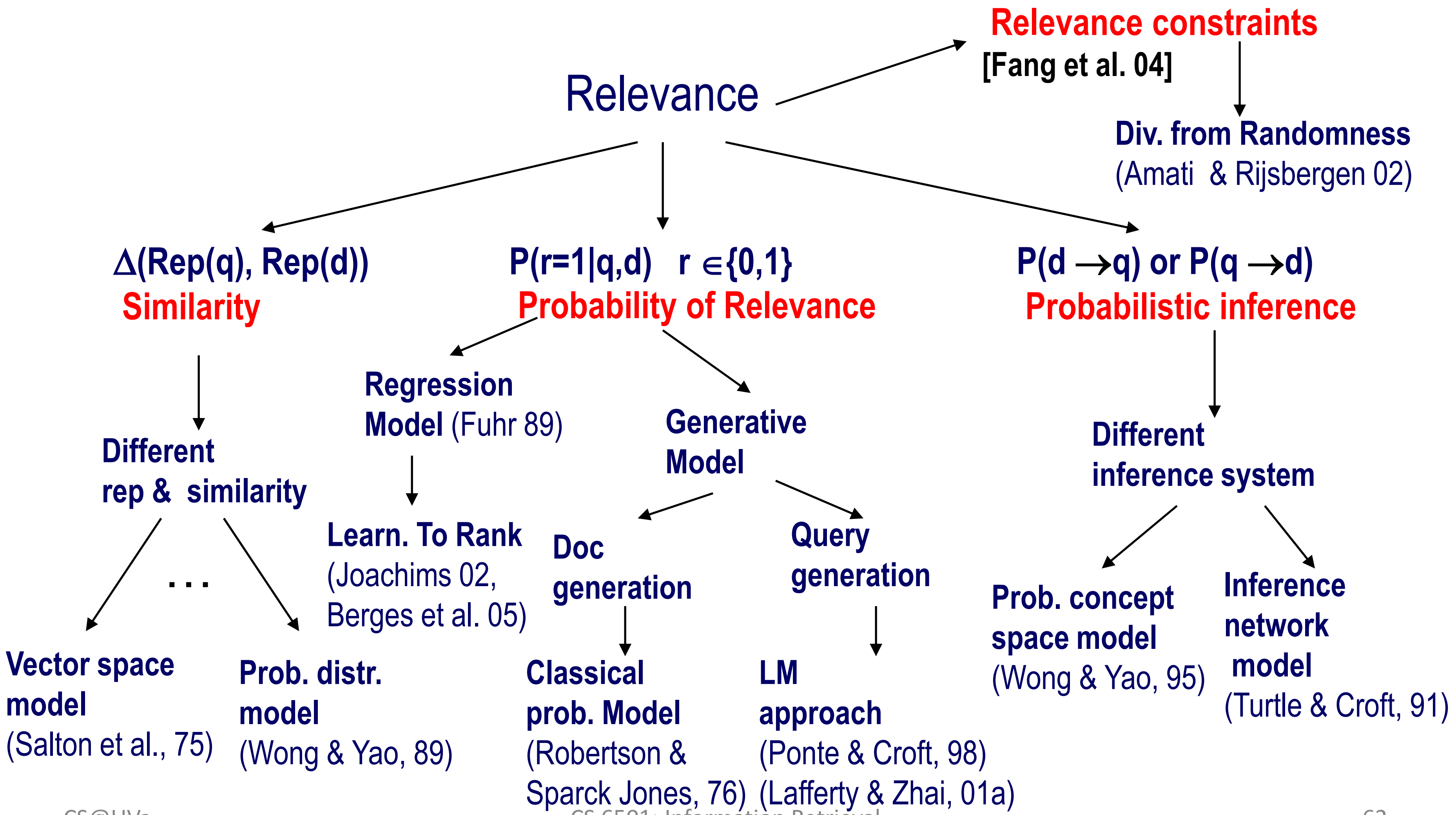
RISK MINIMIZATION

Traditional Solution

- Set-based models (choose D) → **Boolean model**
- Ranking models (choose π)
  - Independent loss ← **Pointwise**
    - Relevance-based loss → **Probabilistic relevance model** / **Generative Relevance Theory**
    - Distance-based loss → **Vector-space Model** / **Two-stage LM** / **KL-divergence model**
  - Dependent loss ← **Pairwise/Listwise**
    - MMR loss → **Subtopic retrieval model**
    - MDR loss

Unsupervised!

Traditional Notion of Relevance



Relevance

Relevance constraints
[Fang et al. 04]

Div. from Randomness
(Amati & Rijsbergen 02)

Δ(Rep(q), Rep(d))
Similarity

P(r=1|q,d) r $\in$ {0,1}
Probability of Relevance

P(d $\rightarrow$ q) or P(q $\rightarrow$ d)
Probabilistic inference

Different rep & similarity

. . .

Vector space model
(Salton et al., 75)

Prob. distr. model
(Wong & Yao, 89)

Regression Model (Fuhr 89)

Learn. To Rank
(Joachims 02, Berges et al. 05)

Generative Model

Doc generation

Classical prob. Model
(Robertson & Sparck Jones, 76)

Query generation

LM approach
(Ponte & Croft, 98)
(Lafferty & Zhai, 01a)

Different inference system

Prob. concept space model
(Wong & Yao, 95)

Inference network model
(Turtle & Croft, 91)

Broader Notion of Relevance

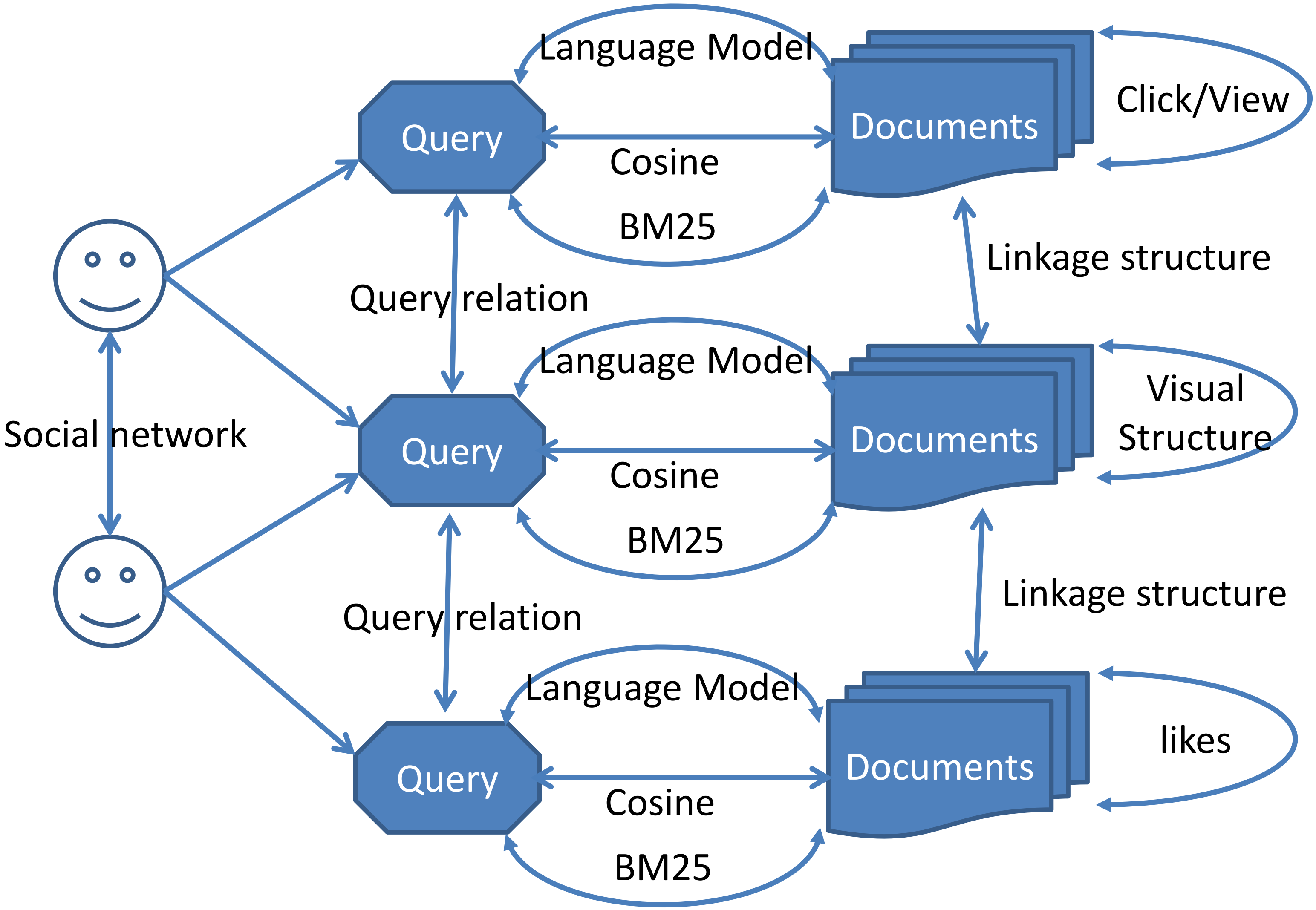
- Traditional view
  - Content-driven
    - Vector space model
    - Probability relevance model
    - Language model

Query-Document specific
Unsupervised

- Modern view
  - Anything related to the quality of the document
    - Clicks/views
    - Link structure
    - Visual structure
    - Social network
    - ….

Query, Document, Query-Document specific
Supervised

Broader Notion of Relevance



Future

- Tigh
- Fast
- Larg
- Wid

Resources

- Books
  - Liu, Tie-Yan. *Learning to rank for information retrieval*. Vol. 13. Springer, 2011.
  - Li, Hang. "Learning to rank for information retrieval and natural language processing." *Synthesis Lectures on Human Language Technologies* 4.1 (2011): 1-113.
- Helpful pages
  - http://en.wikipedia.org/wiki/Learning_to_rank
- Packages
  - RankingSVM: http://svmlight.joachims.org/
  - RankLib: http://people.cs.umass.edu/~vdang/ranklib.html
- Data sets
  - LETOR http://research.microsoft.com/en-us/um/beijing/projects/letor//
  - Yahoo! Learning to rank challenge http://learningtorankchallenge.yahoo.com/

References

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Thank you!

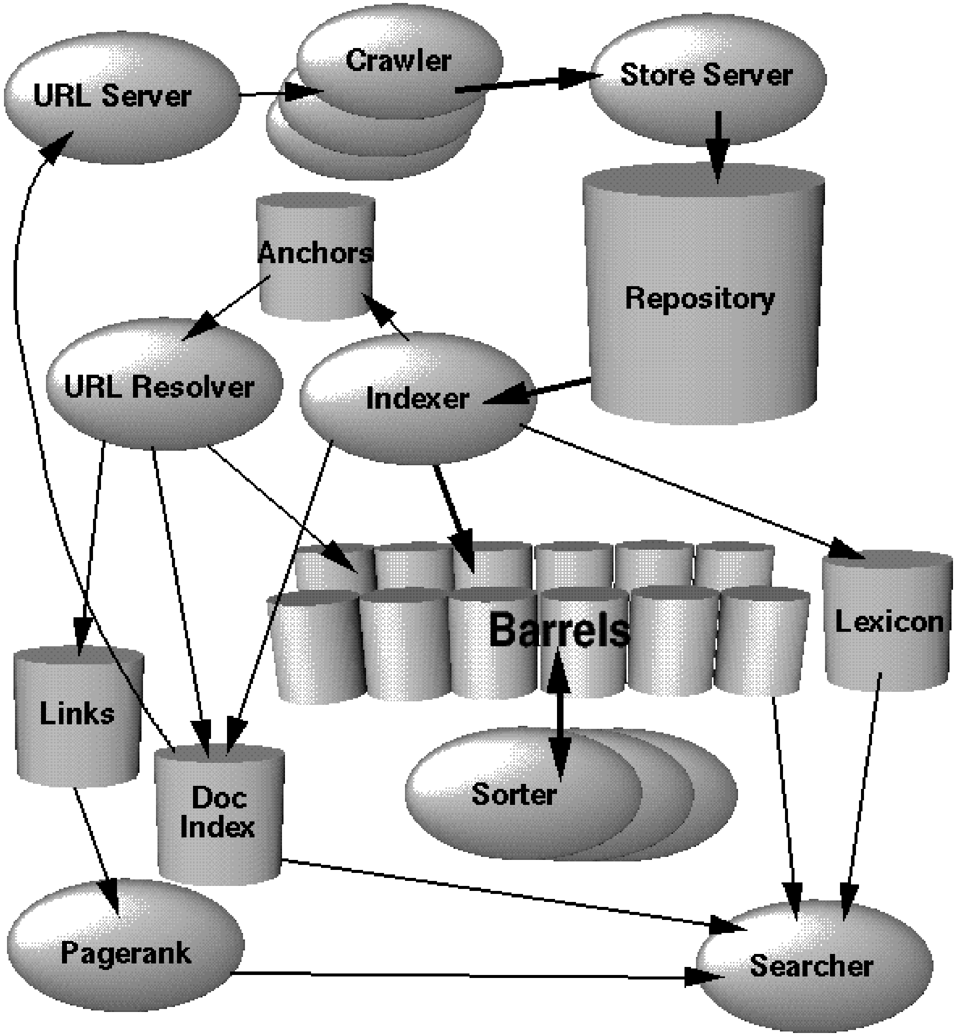
- Q&A

Recap of last lecture

- Goal
  - Design the ranking module for Bing.com

Basic Search Engine Architecture

- The ana extual
  Web sea
  - Sergey uter
    netwo): 107-117.



Your Job

Learning to Rank

- Given: (query, document) pairs represented by a set of relevance estimators, a.k.a., features

QueryID	DocID	BM25	LM	PageRank	Label
0001	0001	1.6	1.1	0.9	0
0001	0002	2.7	1.9	0.2	1

- Needed: a way of combining the estimators
  - $f\left(q, \{d\}_{i=1}^{D}\right) \rightarrow$ ordered $\{d\}_{i=1}^{D}$
- Criterion: optimize IR metrics ⬅ **Key!**
  - P@k, MAP, NDCG, etc.

Challenge: how to optimize?

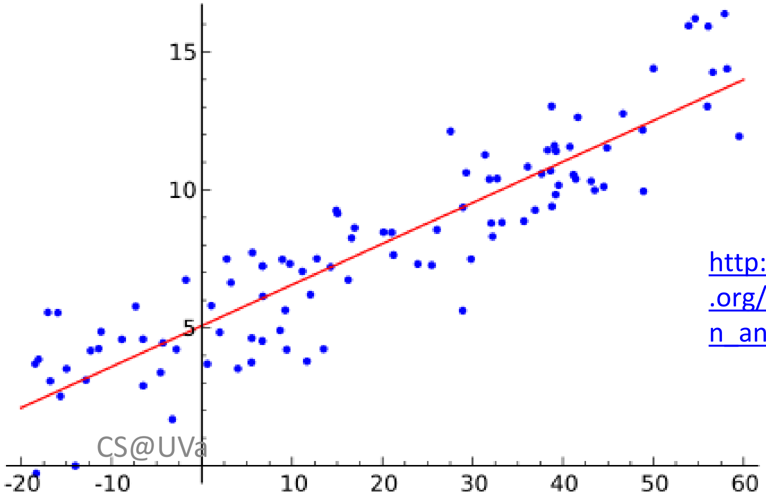
- Order is essential!
  - f → **order** → metric
- Evaluation metrics are not continuous and not differentiable

Approximating the Objects!

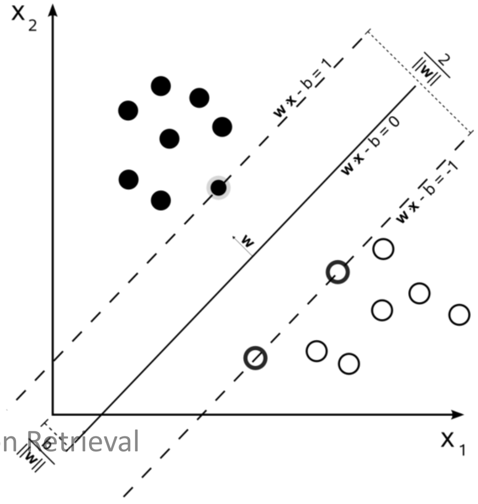
- Pointwise
  - Fit the relevance labels individually
- Pairwise
  - Fit the relative orders
- Listwise
  - Fit the whole order

Pointwise Learning to Rank

- Ideally perfect relevance prediction leads to perfect ranking
  - f → **score** → order → metric
- Reduce ranking problem to
  - Regression
  - Classification



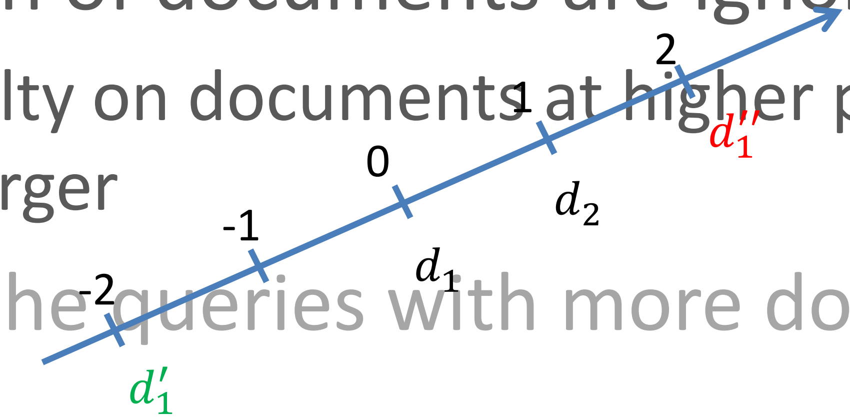
http://en.wikipedia.org/wiki/Regression_analysis



http://en.wikipedia.org/wiki/Statistical_classification

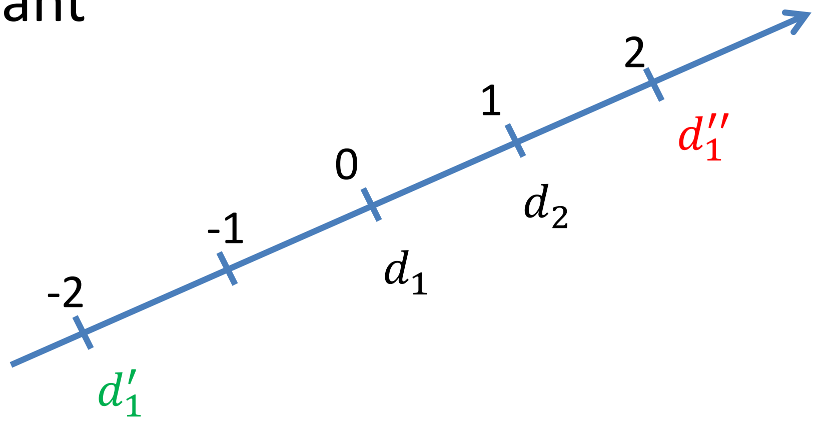
Deficiency

- Cannot directly optimize IR metrics
  - (0 → 1, 2 → 0) worse than (0->-2, 2->4)
- Position of documents are ignored
  - Penalty on documents at higher positions should be larger
- Favor the queries with more documents



Pairwise Learning to Rank

- Ideally perfect partial order leads to perfect ranking
  - f → **partial order** → order → metric
- Ordinal regression
  - $O(f(Q,D),Y) = \sum_{i\neq j} \delta(y_i > y_j)\delta(f(q_i,d_i) < f(q_i,d_i))$
    - Relative ordering between different documents is significant



RankingSVM

Thorsten Joachims, KDD'02

- Minimizing the number of mis-ordered pairs

$y_1 > y_2, y_2 > y_3 , y_1 > y_4$

linear combination of features

$f(q,d) = w^T X_{q,d}$

$y_1 > y_2$

1

0

minimize: $V(\vec{w}, \vec{\xi}) = \frac{1}{2}\, \vec{w} \cdot \vec{w} + C \sum \xi_{i,j,k}$

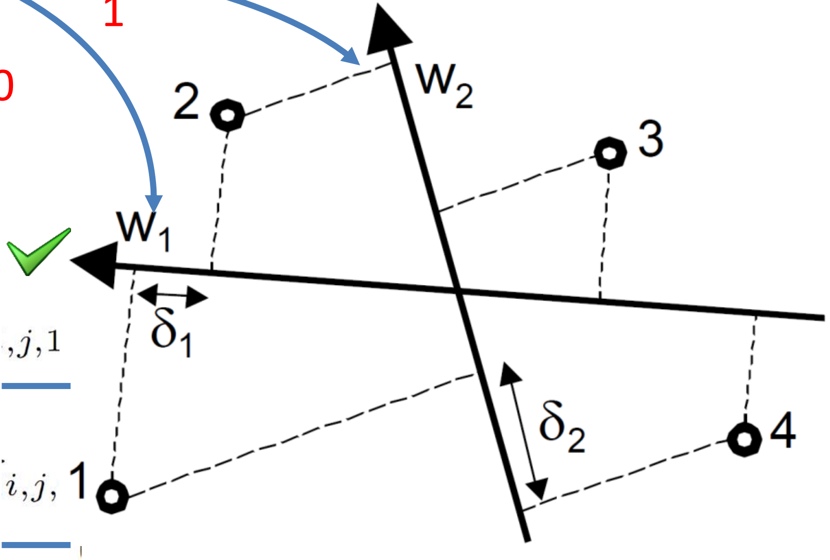
subject to:

$\forall($ … $_{,j,1}$

$\forall($ … $_{i,j,}$ 1

$\forall i \backslash$

QueryID	DocID	BM25	PageRank	Label
0001	0001	1.6	0.9	4
0001	0002	2.7	0.2	2
0001	0003	1.3	0.2	1
0001	0004	1.2	0.7	0



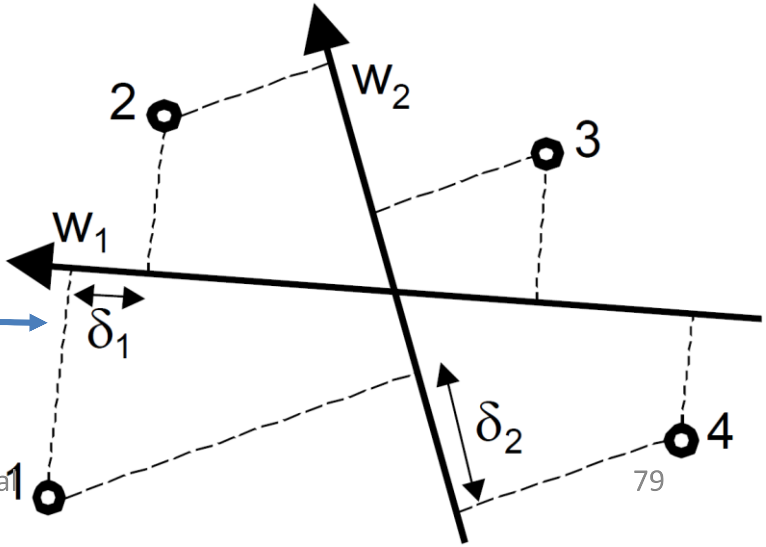
RankingSVM

Thorsten Joachims, KDD’02

- Minimizing the number of mis-ordered pairs

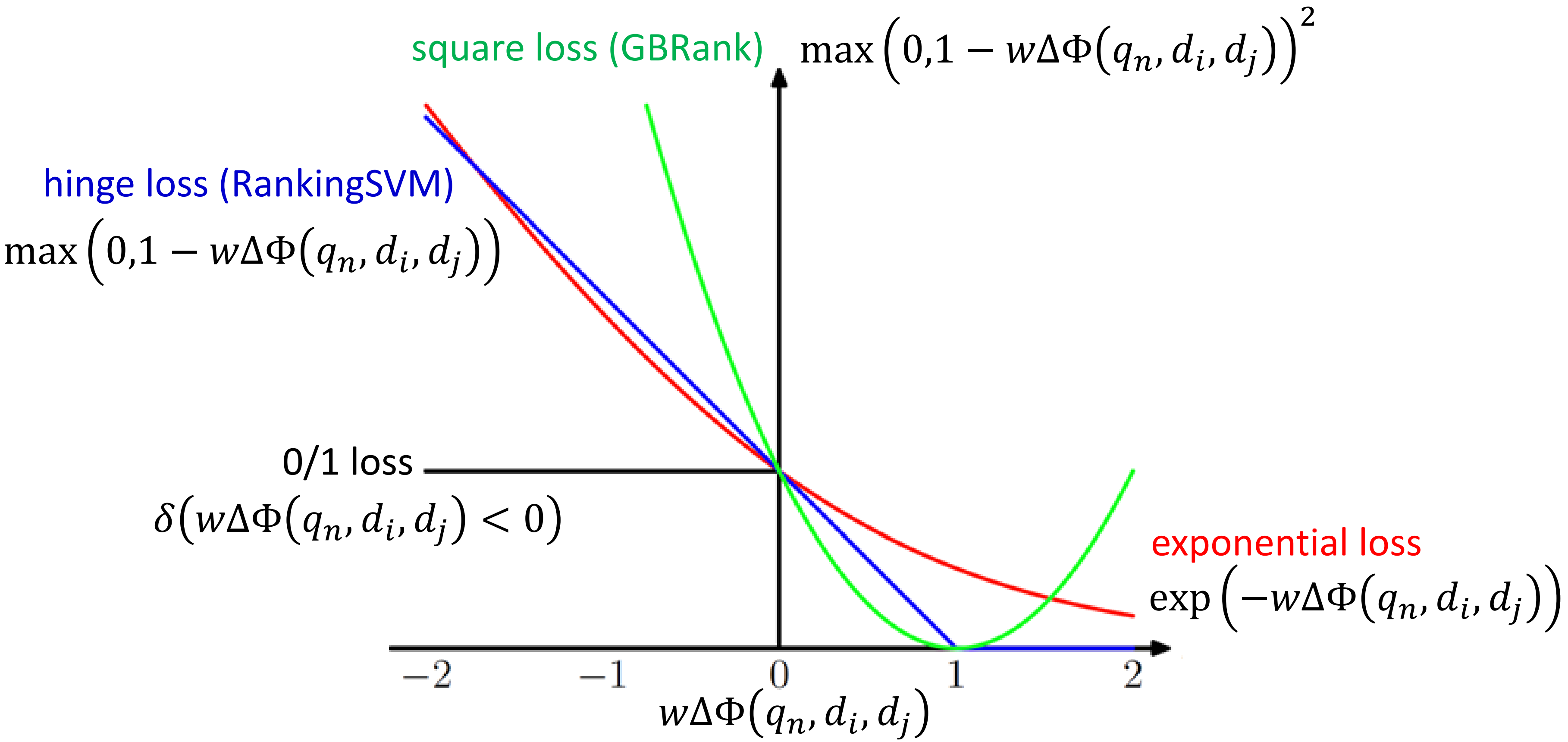
$$\begin{array}{ll} \textit{minimize:} & V(\vec{w},\vec{\xi}) = \frac{1}{2}\,\vec{w}\cdot\vec{w} + C\sum \xi_{i,j,k} \\ \textit{subject to:} & \\ \multicolumn{2}{l}{\forall (d_i,d_j) \in r_1^* : \vec{w}\Phi(q_1,d_i) \geq \vec{w}\Phi(q_1,d_j) + 1 - \xi_{i,j,1}} \\ & \ldots \\ \multicolumn{2}{l}{\forall (d_i,d_j) \in r_n^* : \vec{w}\Phi(q_n,d_i) \geq \vec{w}\Phi(q_n,d_j) + 1 - \xi_{i,j,n}} \\ \multicolumn{2}{l}{\forall i \forall j \forall k : \xi_{i,j,k} \geq 0} \end{array}$$

$$w\Delta\Phi(q_n,d_i,d_j) \geq 1 - \xi_{i,j,n}$$



General Idea of Pairwise Learning to Rank

- For any pair of $y_i > y_j$


square loss (GBRank)
$\max\left(0,1 - w\Delta\Phi(q_n, d_i, d_j)\right)^2$
hinge loss (RankingSVM)
$\max\left(0,1 - w\Delta\Phi(q_n, d_i, d_j)\right)$
0/1 loss
$\delta\left(w\Delta\Phi(q_n, d_i, d_j) < 0\right)$
exponential loss
$\exp\left(-w\Delta\Phi(q_n, d_i, d_j)\right)$
-2
-1
0
1
2
$w\Delta\Phi(q_n, d_i, d_j)$