



Processamento  
e Recuperação  
de Informação

Search Engine  
Ranking

Ranking  
Signals

The Ranking  
Function

Unsupervised  
Rank Fusion

Learning to  
Rank

Some Context

Learning to  
Rank (cont.)

# Processamento e Recuperação de Informação

## Learning to Rank

Departamento de Engenharia Informática  
Instituto Superior Técnico

1º Semestre  
2018/2019



# Outline

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# Bibliography

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- Ricardo Baeza-Yates, Berthier Ribeiro-Neto, Modern Information Retrieval, 2nd edition. Chapter 11.
- T.-Y. Liu, "Learning to rank for information retrieval," Foundations and Trends in Databases, vol. 3, no. 3, pp. 225-331, 2009.



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# Search Engine Ranking

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**Ranking** is the hardest and most important function of a search engine

## Main challenges:

- Evaluation
- Managing Web spam
- Identification of relevant content
- Defining the ranking function



# Evaluating the Ranking

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- Devise an adequate process of **evaluating the ranking**, in terms of **relevance** of results to the user
- Without such evaluation, it is close to impossible to fine tune the ranking function
- Without fine tuning the ranking, there is no state-of-the-art engine—this is an empirical field of science



# Dealing with Web Spam

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- Avoiding, preventing, managing Web spam
- Spammers are malicious users who try to trick search engines by artificially inflating signals used for ranking
- A consequence of the economic incentives of the current advertising model adopted by search engines



# Defining Relevant Content

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Evidence of quality can be indicated by several signals such as:

- Domain names
- Text content
- Links (e.g. PageRank)
- Web page access patterns

Additional useful signals are provided by the layout of the Web page, its title, metadata, font sizes, etc.





# The Ranking Function

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Following: from simple ranking functions to complex combinations of signals



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# Evidences for Relevance

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Three main types of signals:

- 1 Content
- 2 Structure
- 3 Usage

In total we can have hundreds of distinct signals

- Bing claims to use  $> 1000$  (see [here](#))
- Google claims to use  $> 200$  many with  $> 50$  variations



# Content Signals

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- Related to the **text** itself
- Can vary from **simple word counts** to a **full IR score**, such as TF-IDF or BM25
- Can be provided by the layout, that is, the HTML source
  - Simple **format** indicators (more weight given to titles/headings)
  - Sophisticated indicators as the **proximity** of certain tags in the page



# Structure Signals

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- Intrinsic to the **linked structure** of the Web
- Some of them are textual in nature, such as **anchor text**
- Others pertain to the links themselves, such as **in-links** and **out-links** from a page
- Link-based signals find broad usage beyond classic search engine ranking



# Web Usage Signals

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- Main one is the implicit feedback provided by the user clicks (**click-through**)
- Other usage signals include:
  - information on the user's **geographical context** (IP address, language)
  - **technological context** (operating system, browser)
  - **temporal context** (query history by the use of cookies)
  - even **site speed**



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# Simple Ranking Scheme

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- Use only **text-based ranking**
  - E.g. BM25 or cosine similarity
- Applied in early search engines

Or...

- Use a global ranking function such as **PageRank**
- Quality of a Web page in the result set is independent of the query
- The query only selects pages to be ranked





# Simple Combination of Signals

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- Use a linear combination of different ranking signals

## Example

- Consider the pages  $p$  that satisfy query  $Q$
- Rank score  $R(p, Q)$  of page  $p$  with regard to query  $Q$  can be computed as

$$R(p, Q) = \alpha BM25(p, Q) + (1 - \alpha) PR(p)$$

- $\alpha = 1$ : text-based ranking
- $\alpha = 0$ : link-based ranking, independent of the query



# A More Complex Combination

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- Current engines combine a text-based ranking with a link-based ranking, most of them a lot more complex than BM25 and PageRank
- Value of  $\alpha$  is tuned experimentally using
  - Labeled data as ground truth, or
  - Clickthrough data
- $\alpha$  might even be query dependent
  - for *navigational* queries  $\alpha$  could be made smaller than for *informational* queries



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# Principle

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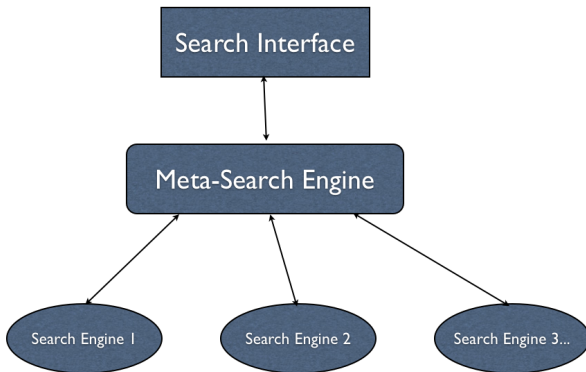
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# Combining Similarity Scores

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- ① eliminate **duplicates**
- ② apply a fusion algorithm
  - using similarity scores provided by underlying SE

these techniques can be used also to combine ranking functions within a search engine



# Combination Using Similarities

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- $CombMIN(d_j) = \min(s_{1j}, s_{2j}, \dots, s_{kj})$   
(use the minimum ranking)
- $CombMAX(d_j) = \max(s_{1j}, s_{2j}, \dots, s_{kj})$
- $CombSUM(d_j) = \sum s_{ij}$   
(add the similarity scores)
- $CombMNZ(d_j) = CombSUM(d_j) \times r_j$ , where  $r_j$  is the number of systems that retrieved  $d_j$

*CombSUM* and *CombMNZ* perform better. *CombMNZ* slightly outperforms *CombSUM* in most cases.



# Combination using ranking positions

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**Borda(1770) Ranking:** each voter assigns a linear preference order of candidates,  $n$  to the first,  $n - 1$  to the second, etc. Unranked candidates divide the votes. Winner gets the most points.

**Condorcet (1787) Ranking:** do pairwise comparisons to count how many times a doc “wins”, “loses” or “ties” against other documents (as in a soccer tournament). Doc with most wins gets highest score. Ties broken on number of losses.

**Reciprocal ranking:** assign a score  $1/pos$  to each doc. Rank based on sum of scores.



# Borda Ranking

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5 underlying search engines,  
which have ranked four candidate pages  $a, b, c, d$ .

System 1:  $a, b, c, d$

System 2:  $b, a, d, c$

System 3:  $c, b, a, d$

System 4:  $c, b, d$

System 5:  $c, b$

Scores:

$$\text{Score}(a) = 4 + 3 + 2 + 1 + 1.5 = 11.5$$

$$\text{Score}(b) = 3 + 4 + 3 + 3 + 3 = 16$$

$$\text{Score}(c) = 2 + 1 + 4 + 4 + 4 = 15$$

$$\text{Score}(d) = 1 + 2 + 1 + 2 + 1.5 = 7.5$$

The final ranking is:  $b, c, a, d$





# Condorcet Ranking

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System 1: a,b,c,d

System 2: b,a,d,c

System 3: c,b,a,d

System 4: c,b,d

System 5: c,b

comparisons (win:lose:tie):

pair	a	b	c	d
a	-	1:4:0	2:3:0	3:1:1
b	4:1:0	-	2:3:0	5:0:0
c	3:2:0	3:2:0	-	4:1:0
d	1:3:1	0:5:0	1:4:0	-

The final ranking is: *b, c, a, d*



# Reciprocal Ranking

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5 underlying search engines,  
which have ranked four candidate pages  $a, b, c, d$ .

System 1:  $a, b, c, d$

System 2:  $b, a, d, c$

System 3:  $c, b, a, d$

System 4:  $c, b, d$

System 5:  $c, b$

Scores:

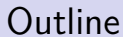
$$\text{Score}(a) = 1 + 1/2 + 1/3 + 0 + 0 = 1.83$$

$$\text{Score}(b) = 1/2 + 1 + 1/2 + 1/2 + 1/2 = 3$$

$$\text{Score}(c) = 1/3 + 1/4 + 1 + 1 + 1 = 3.55$$

$$\text{Score}(d) = 1/4 + 1/3 + 1/4 + 1/3 + 0 = 1.17$$

The final ranking is:  $c, b, a, d$



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# Why Learning to Rank?

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- Manual parameter tuning is usually difficult
  - Especially when there are many parameters and the evaluation measures are non-smooth
- Manual parameter tuning sometimes leads to **overfitting**
- It is non-trivial to combine the large number of models proposed in the literature (e.g. BM25, etc.) to obtain an even more effective model



# What is Learning to Rank?

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**L2R:** apply machine learning techniques to learn the ranking of the results

- Use a **learning algorithm** fed with **training data** that contains ranking information
- **loss function to minimize:** number of mistakes done by the learned model



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# Supervised Learning

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Input:  $\{(x_i, y_i)\}_{i=1}^N, x_i \in \mathcal{R}^M, y_i \in \mathcal{R}$

Hypothesis space:  $h^* \in H$

Loss function:  $L(h(x), y)$

Learning Algorithm:  $\hat{h} = A(\{(x_i, y_i)\}_{i=1}^N)$ , such that  
$$\hat{h} = \operatorname{argmin}_h \sum_{i=1}^N L(h(x_i), y_i)$$

I.e. given a set of **training data** as input, use **learning algorithm**  $A$  to discover the function  $\hat{h}$  that minimizes the **loss** (e.g. the error)



# An Example: Linear Regression

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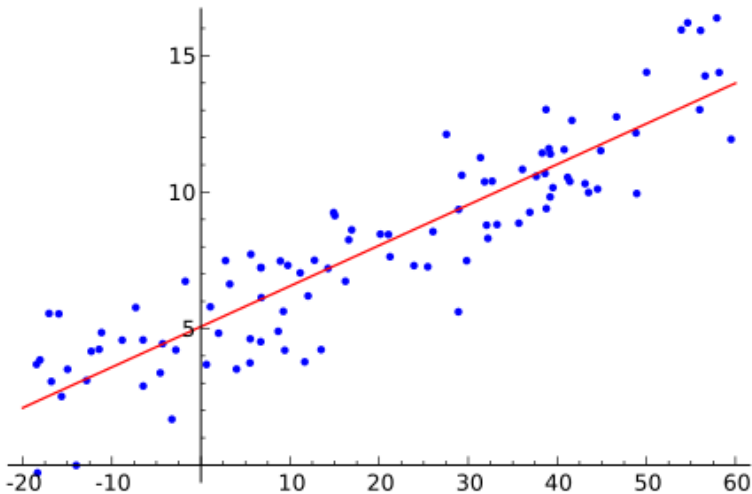
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(source: [wikipedia](#))





# Linear Regression (cont.)

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- The hypothesis space:

$$h_{\vec{w}}(x) = w_0 + w_1 x$$

where  $\vec{w} = [w_0, w_1]$

- The loss function:

$$L(h_{\vec{w}}, y) = \sum_{i=1}^N (y_i - h_{\vec{w}}(x_i))^2$$

i.e. the sum of the squared error

- We want to find

$$w^* = \underset{w}{\operatorname{argmin}} L(h_{\vec{w}}, y)$$



# Minimizing the Loss

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- In the most simple case, we can easily find one (or more) solution(s)
  - Just take the derivatives and equal to 0
- In many cases this is not possible (or we may want to enforce some constraints on the parameters)
- In practice, there are many ways to estimate  $w^*$



# An Example: Gradient Descent

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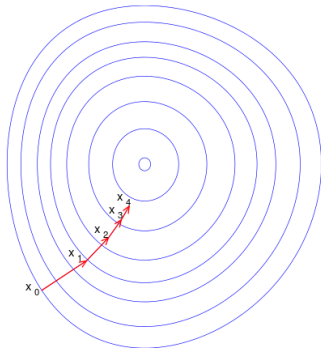
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$w \leftarrow$  any point in the  
parameter space  
**loop** until convergence **do**  
  **for each**  $w_i$  **in**  $\vec{w}$  **do**  
     $w_i \leftarrow w_i - \alpha \frac{\partial}{\partial w_i} L(h_{\vec{w}}, y)$

$\alpha =$  learning rate



(source: [wikipedia](#))



# Other Types of Supervised Learning

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(besides regression and ranking)

- Classification
  - Classify email as spam vs. ham
  - Loss: accuracy
- Structured prediction
  - Find faces in an image
  - Loss: Precision/Recall of faces



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# The L2R Framework

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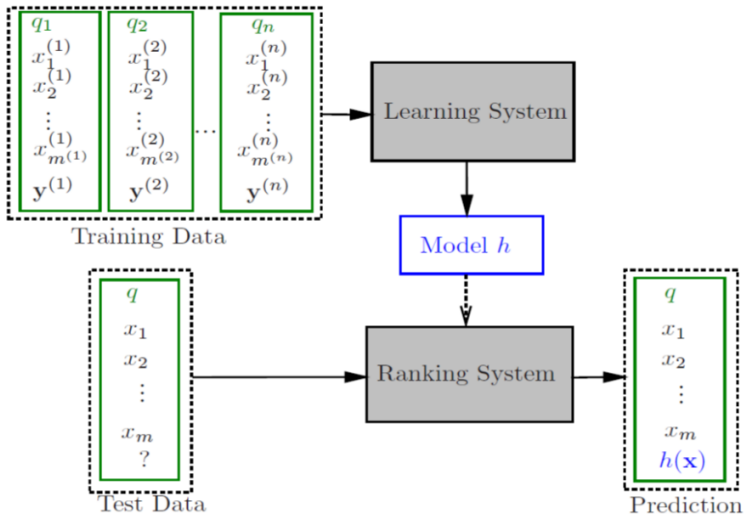
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# L2R Techniques

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Three main approaches:

**Pointwise:** focuses on individual pages

**Pairwise:** focuses on comparing pairs of pages

**Listwise:** focuses on the ranked list of pages



# The Pointwise Approach

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	The Pointwise Approach		
	Regression	Classification	Ordinal Regression
Input Space	Single documents $y_j$		
Output Space	Real values	Non-ordered Categories	Ordinal categories
Hypothesis Space	Scoring function $f(x)$		
Loss Function	Regression loss	Classification loss	Ordinal regression loss
	$L(f; x_j, y_j)$		





# An Example: Ranking Perceptron

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Koby Crammer and Yoram Singer, "Pranking with ranking," In Proceedings of the 14th International Conference on Neural Information Processing Systems (NIPS'01), 2001.

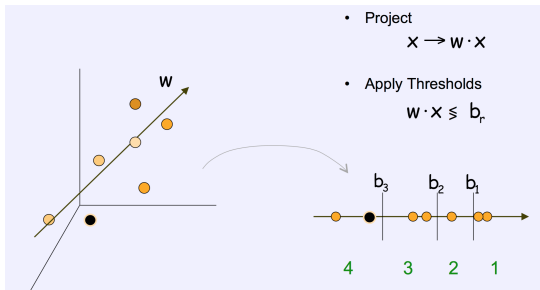
Adaptation of the *Perceptron algorithm*:

Input space:  $\mathbf{x} = \{x_j\}_{j=1}^m$

Output space:  $y_j \in \{1, 2, 3, \dots\}$

Hypothesis Space:  $f(\mathbf{x}) = \mathbf{w} \cdot \mathbf{x}$

Loss function:  $L(f, x_j, y_j) = \sum_{j=1}^T |y_j - f(x_j)|$





# The Ranking Perceptron Algorithm

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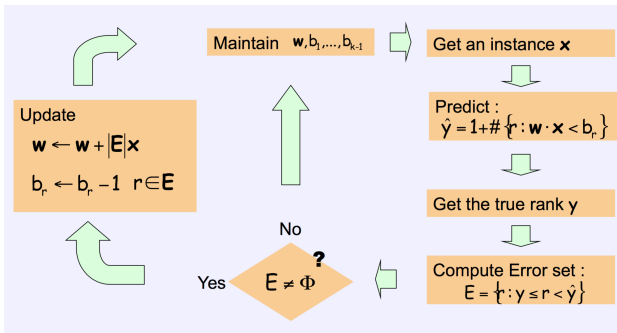
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Koby Crammer and Yoram Singer, "Pranking with ranking," In Proceedings of the 14th International Conference on Neural Information Processing Systems (NIPS'01), 2001.

Adaptation of the *Perceptron algorithm*:





# Problem with the Pointwise Approach

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- The position of documents in the ranked list is invisible to the loss functions
- The overall loss function will be dominated by queries with a large number of documents



# The Pairwise Approach

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	The Pairwise Approach
Input Space	Document pairs $(x_u, x_v)$
Output Space	Preference $y_{u,v} \in \{+1, -1\}$
Hypothesis Space	Preference function $h(x_u, x_v) = 2 \cdot I_{\{f(x_u) > f(x_v)\}} - 1$
Loss Function	Pairwise classification loss $L(h; x_u, x_v, y_{u,v})$



# An Example: RankBoost

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Y. Freund, R. Iyer, R. E. Schapire, and Y. Singer, "An efficient boosting algorithm for combining preferences," Journal of Machine Learning Research, vol. 4, pp. 933–969, 2003.

**Input space:** Document pairs  $(x_u, x_v)$

**Output space:** Relative order  $y_{u,v} \in \{-1, +1\}$

**Hypothesis Space:**  $f(x) = \sum_t \alpha_t f_t(x)$

**Loss function:**  $L(f; x_u; x_v; y_{u,v}) = e^{-y_{u,v}(f(x_u) - f(x_v))}$

---

## Algorithm 1 Learning Algorithm for RankBoost

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**Input:** document pairs

**Given:** initial distribution  $\mathcal{D}_1$  on input document pairs.

**For**  $t = 1, \dots, T$

    Train weak ranker  $f_t$  based on distribution  $\mathcal{D}_t$ .

    Choose  $\alpha_t$

    Update  $\mathcal{D}_{t+1}(x_u^{(i)}, x_v^{(i)}) = \frac{1}{Z_t} \mathcal{D}_t(x_u^{(i)}, x_v^{(i)}) \exp(\alpha_t(f_t(x_u^{(i)}) - f_t(x_v^{(i)})))$

    where  $Z_t = \sum_{i=1}^n \sum_{u,v: y_{u,v}=1} \mathcal{D}_t(x_u^{(i)}, x_v^{(i)}) \exp(\alpha_t(f_t(x_u^{(i)}) - f_t(x_v^{(i)})))$ .

**Output:**  $f(x) = \sum_t \alpha_t f_t(x)$ .

---



# Improvement of Pairwise Approach

Processamento  
e Recuperação  
de Informação

Search Engine  
Ranking

Ranking  
Signals

The Ranking  
Function

Unsupervised  
Rank Fusion

Learning to  
Rank

Some Context

Learning to  
Rank (cont.)

## Advantage

Predicting relative order is closer to the nature of ranking than predicting class label or relevance score

## Problems

- Relative order of two documents still does not predict their final position
- The distribution of document pair number is more skewed than the distribution of document rank, with respect to different queries



# Document Pair Distribution

Processamento  
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de Informação

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Ranking

Ranking  
Signals

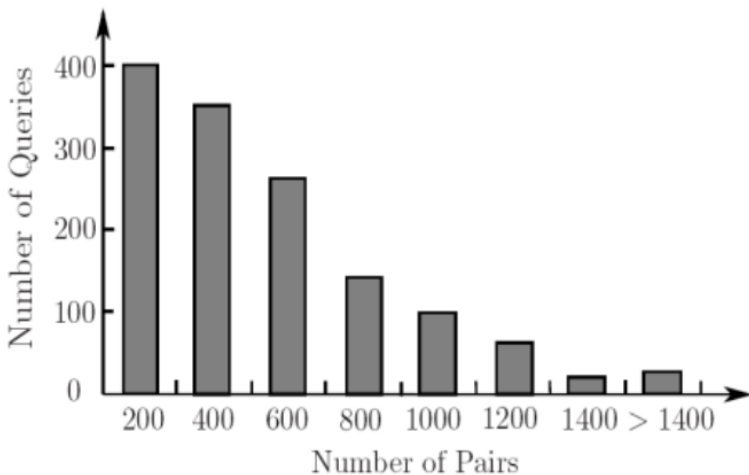
The Ranking  
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Rank (cont.)





# The Listwise Approach

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Rank (cont.)

	The Listwise Approach	
	Listwise Loss Minimization	Direct Optimization of IR Measure
Input Space	Document set $\mathbf{x} = \{x_j\}_{j=1}^m$	
Output Space	Permutation $\pi_y$	Ordered categories $\mathbf{y} = \{y_j\}_{j=1}^m$
Hypothesis Space	$h(\mathbf{x}) = \text{sort}_\circ f(\mathbf{x})$	$h(\mathbf{x}) = f(\mathbf{x})$
Loss Function	Listwise loss $L(h; \mathbf{x}, \pi_y)$	1-surrogate measure $L(h; \mathbf{x}, \mathbf{y})$





# Direct Optimization of IR Measures

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Rank (cont.)

- It is natural to directly optimize what is used to evaluate the ranking results
- However, it is non-trivial
- Evaluation measures such as NDCG are **non-continuous** and **non-differentiable** since they depend on the rank positions
- It is challenging to optimize such objective functions, since most optimization techniques in the literature were developed to handle continuous and differentiable cases



# Solutions

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Rank (cont.)

- Approximate the objective
  - Soften (approximate) the evaluation measure so as to make it smooth and differentiable
- Bound the objective
  - Optimize a smooth and differentiable upper bound of the evaluation measure
- Optimize the non-smooth objective directly
  - Use IR measure to update the distribution in Boosting
  - Use genetic programming



# An Example: RankGP

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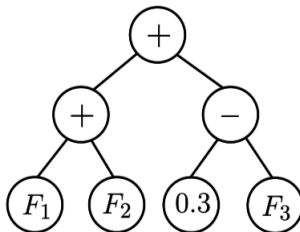
J.-Y. Yeh et al, "Learning to rank for information retrieval using genetic programming," in SIGIR 2007 Workshop in Learning to Rank for Information Retrieval, 2007.

Input space:  $\mathbf{x} = \{x_j\}_{j=1}^m$

Output space: Relative order  $\mathbf{y} = \{y_j\}_{j=1}^m$

Hypothesis Space:  $f(x)$

Loss function: IR evaluation measure





# Improvement of Listwise Approach

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Rank (cont.)

## Advantages

- Take all the documents associated with the same query as the learning instance
- Rank position is visible to the loss function

## Problems

- Complexity



- Processamento e Recuperação de Informação
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- Unsupervised Rank Fusion
- Learning to Rank
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- Learning to Rank (cont.)

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