# Learning to Rank - Tutorial @ SEPLN 2012

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# Outline

## What is Ranking?

- For the given, request and collections of offerings we give offerings in particular relevance order.

## In case of Document retrieval

- Input: Query and collection of documents
- Output: Ranked list of documents

## Learning to Rank

- Machine Learning for Information Retrieval (IR)
- Specifically : Learning the Ranking Model

# Basic IR Concepts

## Crawling

- Crawl the necessary part of the Web and prepare a static collection of documents

## Indexing

- preprocess to convert it into raw text format (ASCII or UTF-8)
- Stop-word removal [Term Pipeline]
- Stemming [Term Pipeline] Store relevant information of terms and documents like term frequency (TF) [doc and collection] and document length in direct and inverted index.

## Query Normalisation

- Pass the query from the same pipeline

## Ranking

- The simplest yet powerful model is TF-IDF

$$Score(Q, D) = \sum_{i=1}^{n} tf(q_i, D) * idf(q_i)$$

- $tf(q_i, D) =$ Frequency of Term $q_i$ in D.
- $idf(q_i) = \log(\frac{N}{\#\ of\ docs\ containing\ q_i})$

## $tf - idf$ Example

- Doc1 = Jaume I University is in Castellón
- Doc2 = Jaume I University is in Spain
- Doc3 = UPV is in Valencia
- Q = Jaume Spain

## Ranking

- Score(Q, Doc1) = (1+0)*(0.64) = 0.64 Rank - 2
- Score(Q, Doc2) = (1+1)*(0.64) = 1.28 Rank - 1
- Score(Q, Doc3) = (0+0)*(0.64) = 0.0 Rank - 3

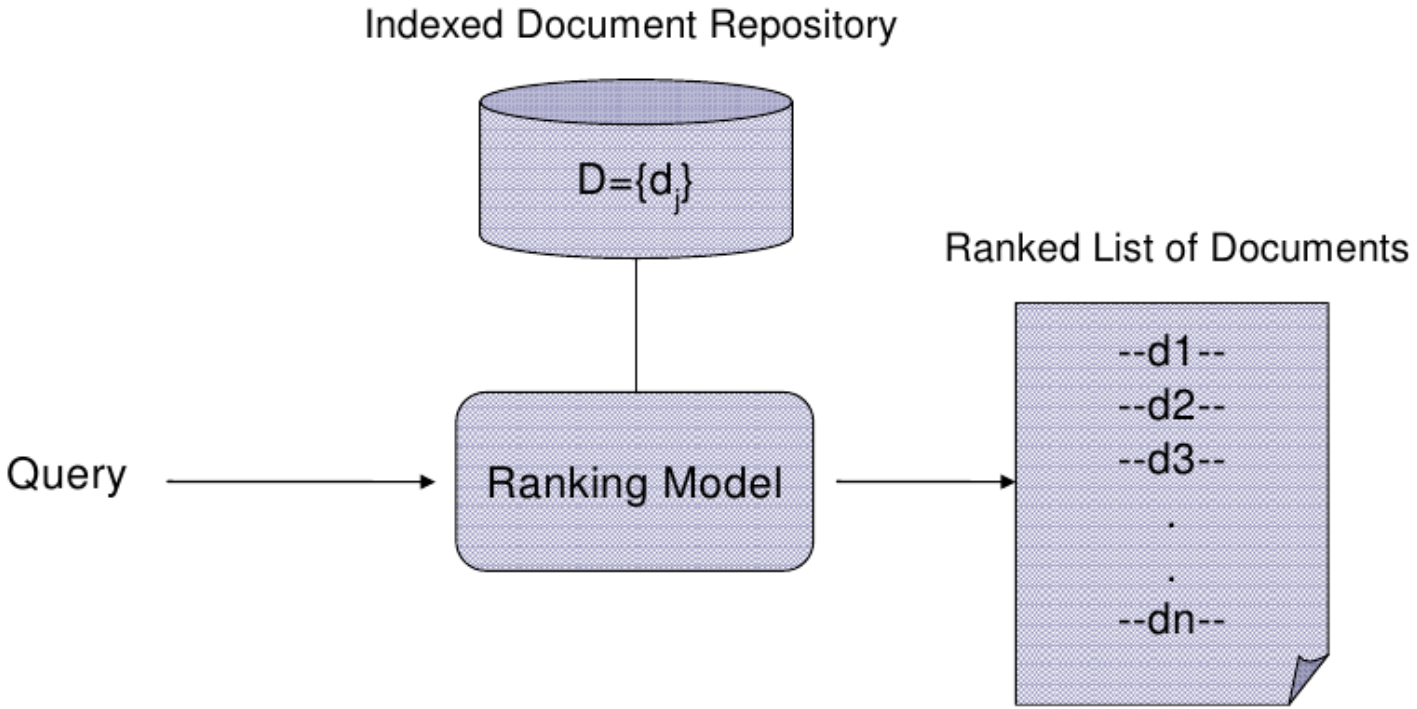
# Other Unsupervised Ranking Models

- BM25 - Probabilistic Model
- Language Model for IR

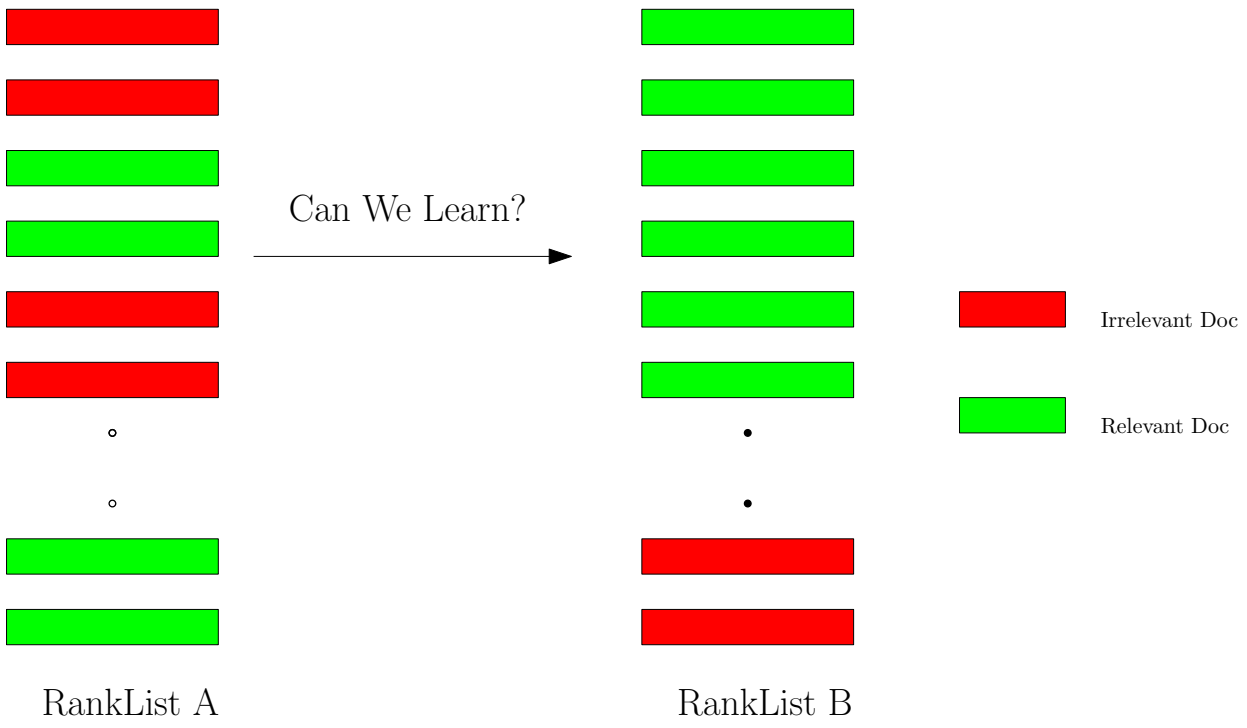
# Scope of This Tutorial

- Learning to Rank Problem Definition
- Approaches to Learning to Rank
- Applications of LTR to NLP and IR
- Research Trends with LTR
- Hands on with LTR

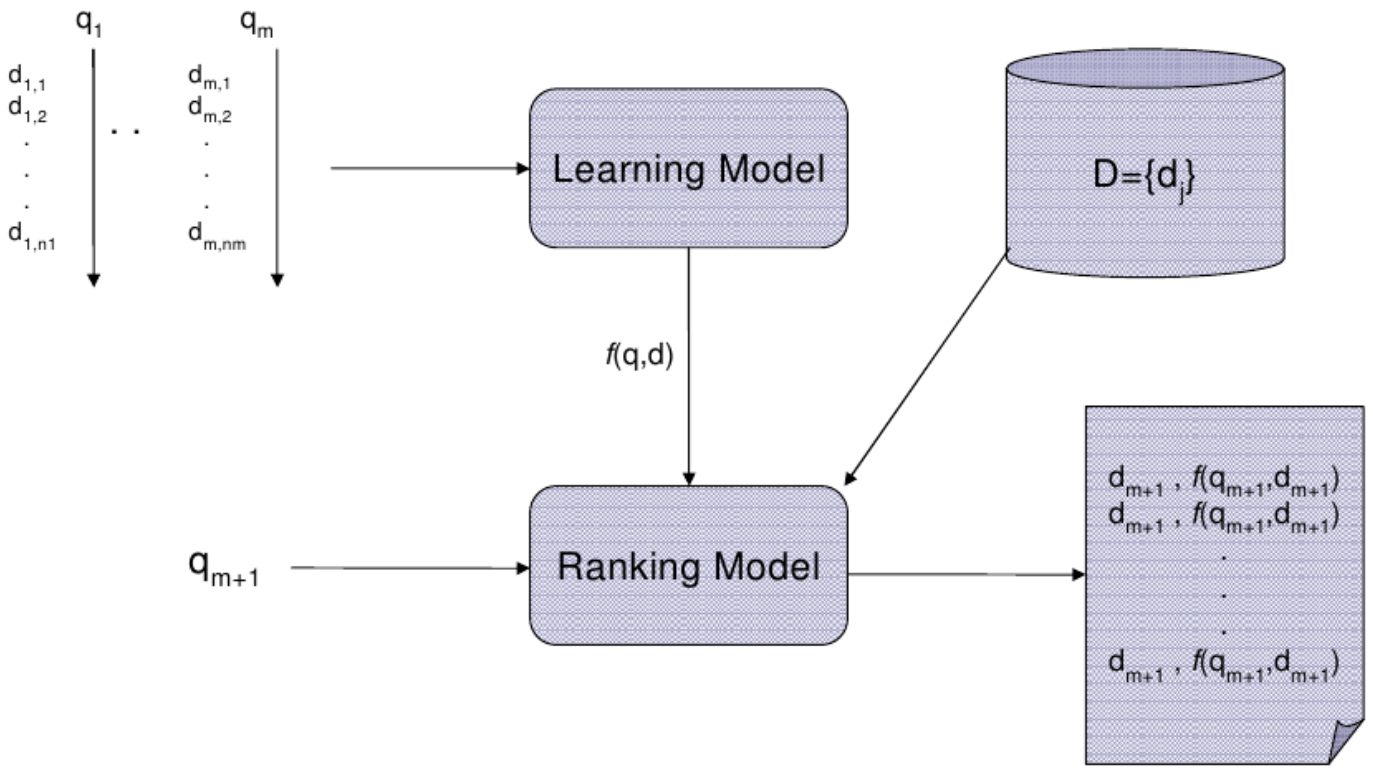
# Conventional Unsupervised Ranking Model



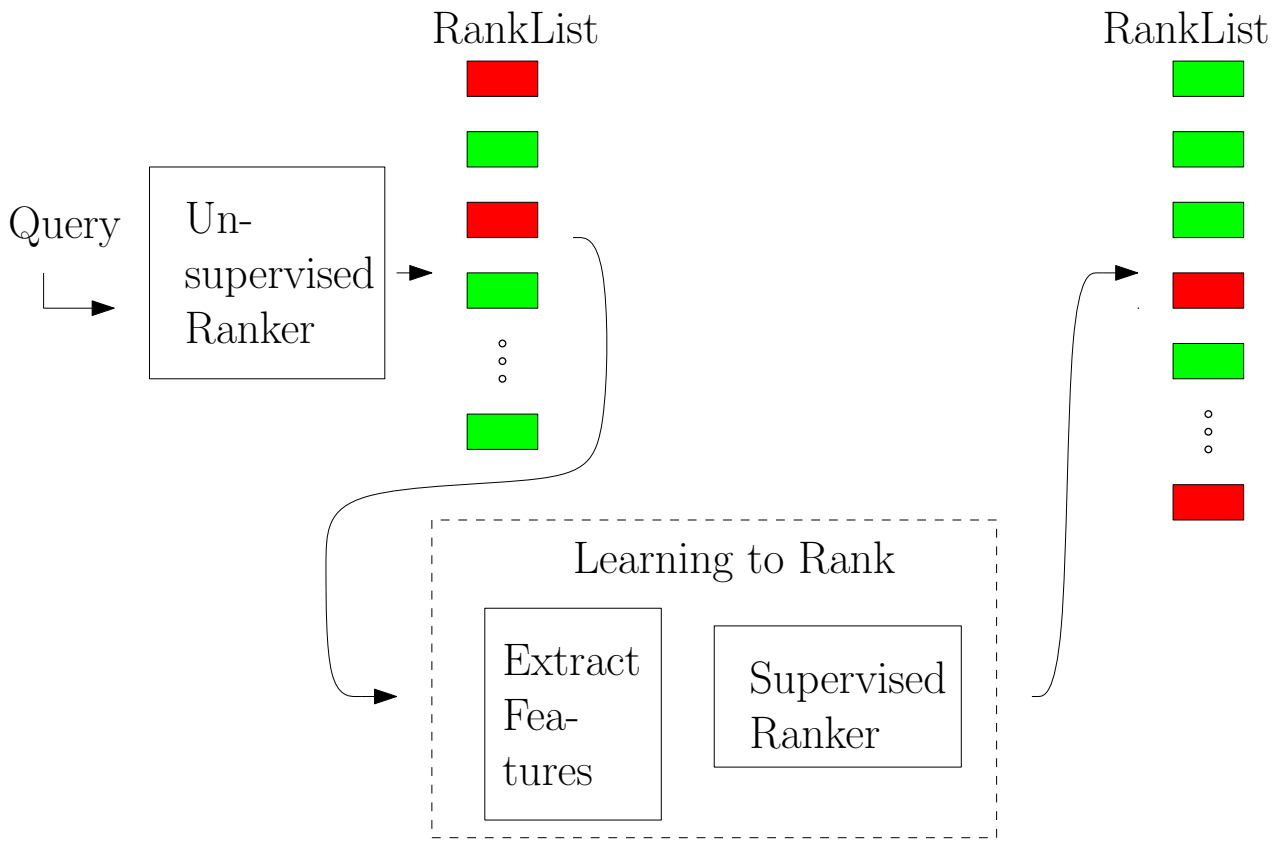
# Motivation


Can We Learn?
Irrelevant Doc
Relevant Doc
RankList A
RankList B

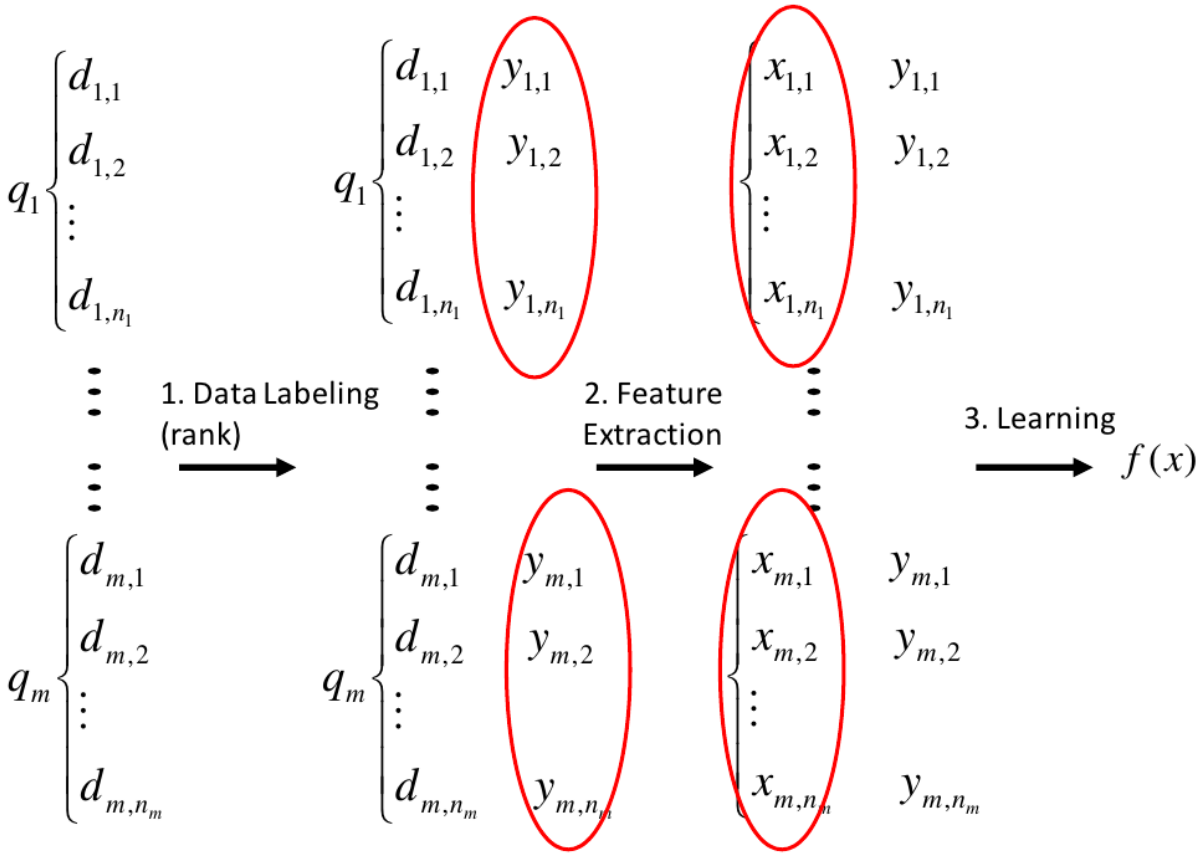
# Supervised Learning-to-Rank (LetoR) Model [Qin et al., 2010]



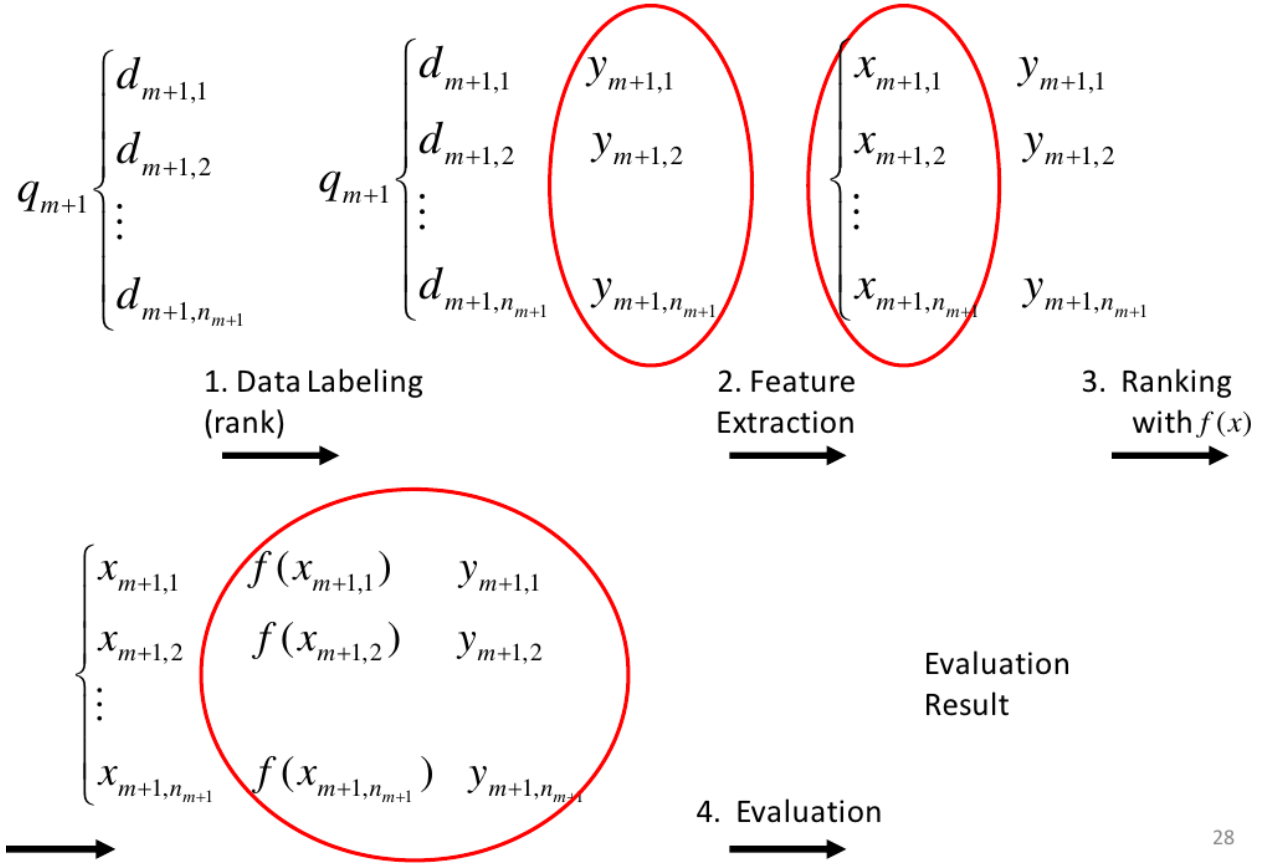
# Practical Ranking



# Training Process (*fig. taken from [Li, 2009]*)



# Testing Process (*fig. taken from [Li, 2009]*)



# Letor 4.0 Dataset [Qin et al., 2010]

- Gov2 web page collection and two query sets of Million Query (MQ) track of TREC07 and TREC08.
- Given in form of query document pairs.

```
2 qid:10032 1:0.056537 2:0.000000 ... 45:0.000000 46:0.076923 #docid = GX029-35-5894638
0 qid:10032 1:0.279152 2:0.000000 ... 45:0.250000 46:1.000000 #docid = GX030-77-6315042
1 qid:10032 1:0.593640 2:1.000000 ... 45:0.500000 46:0.000000 #docid = GX256-43-0740276
```

## Issues in Learning to Rank

- Relevance Labels - manual judgments vs. click-through data
- Feature Extraction - (Q, D, Q+D)
- Evaluation Measure - multi-level relevance labels

# Why so popular?

- Easy to incorporate new features
  - age of the document
  - link information in web graph
  - click information
  - geographical information of the user etc.
- Easy to tune parameters of the ranking model automatically

# Evaluation Metrics

## Mean Average Precision (MAP)

$$\text{MAP} = \frac{\sum_{k=1}^{n}(P(k) * rel(k))}{\text{Number of Relevant Documents}}$$

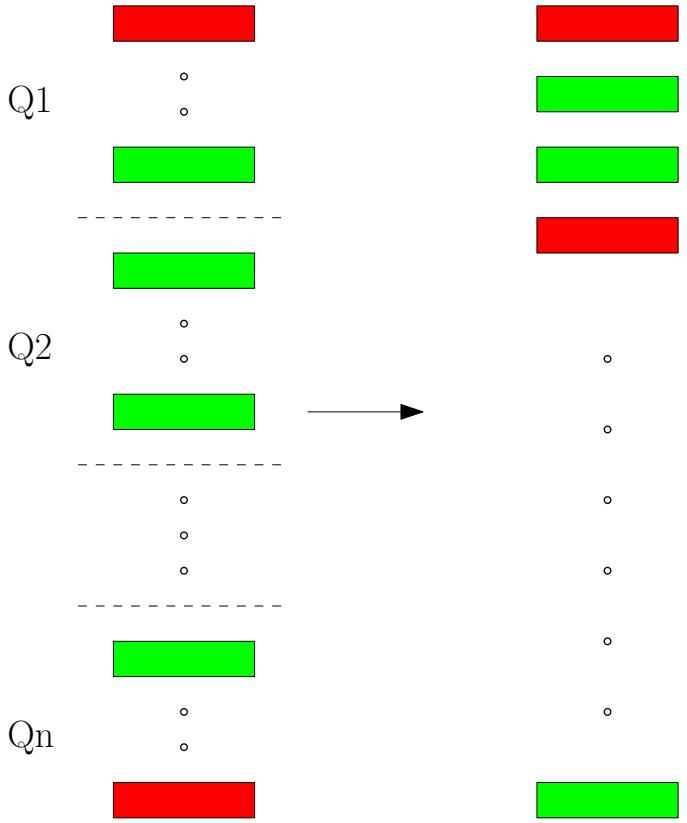
## Normalized Discounted Cumulative Gain (nDCG)

$$\text{NDCG @ n} = Z_n * \sum_{j=1}^{n}\left[\frac{2^{c(j)}-1}{\log(1+j)}\right]$$

# Approaches

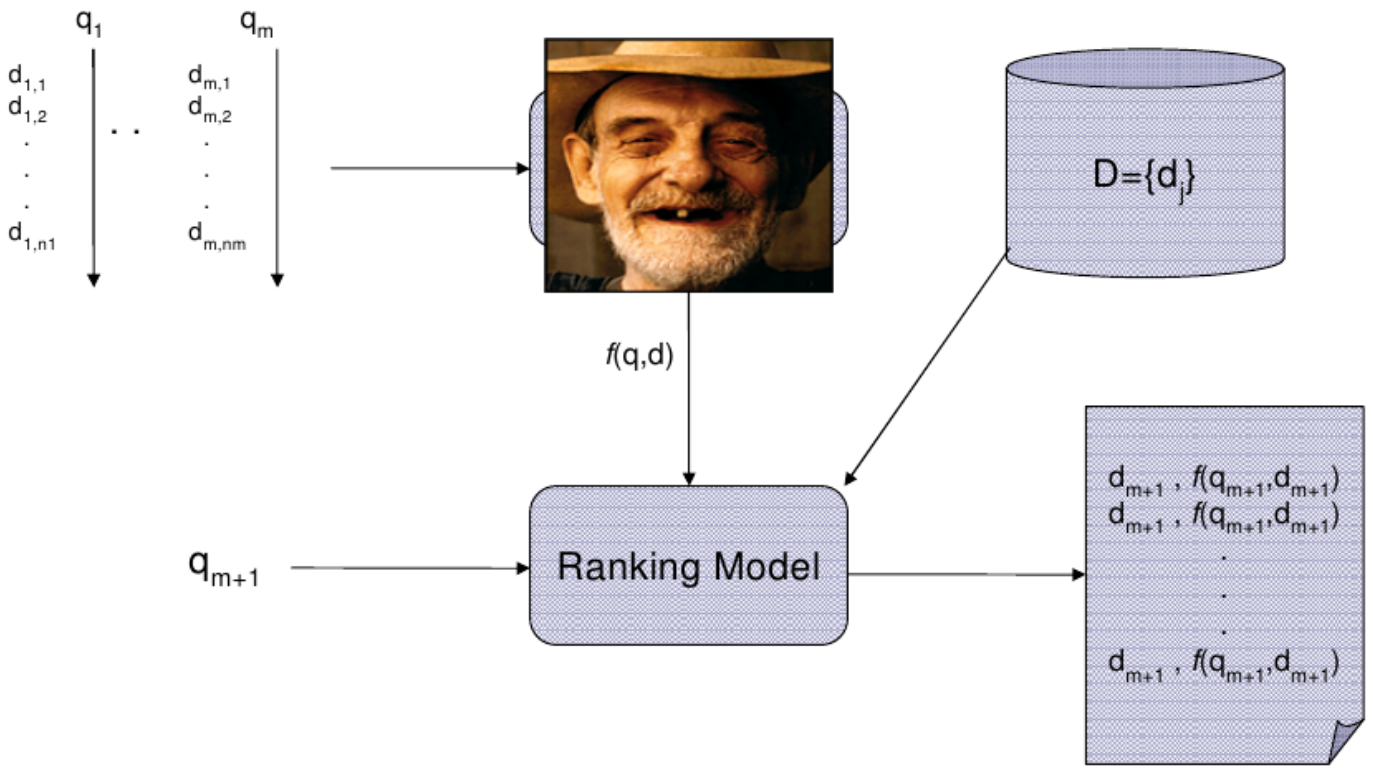
- Pointwise Approach — Individual doc is used for learning
- Pairwise Approach — Pairs of two documents for a query is used for learning
- Listwise Approach — Whole ranked list for a query is used for learning

# Pointwise Approach




- Use individual entity for learning even without query information

# Pointwise Learning-to-Rank (LetoR) Model



## Regression Approach

- Directly methods like regression or classification can be applied to solve the ranking problem.
- Consider relevance judgments as
  - Real values - in case of regression
  - Non-ordered categories - in case of classification

## Regression Approach contd.

- Least Squares Retrieval Function [Fuhr, 1989]
- Loss Function can be LSE.
- Regression model is Multiple Linear Regression.

- Basic idea is to map the feature vector the the real value.

## Regression Approach contd.

- Discriminative models [Nallapati, 2004]
- Here real score can be looked as probability of relevance given document and query.
- Here the weight vector can be estimated using gradient descent algorithm.

## Classification Approach

- BayesNetRank [Gupta, 2011], McRank [Li et al., 2007]
- Solve the Ranking Problem using Classification
- Classes : Relevance Levels [ 0 , 1 , 2 ]
- Classification Model : Bayesian Networks (BayesNetRank) and Neural Networks (McRank)
- Ranking Function on top of Classification Probabilities.

## Constraint

- Bayesian Networks accept only discrete data -> MDL based discretization scheme is used [Fayyad and Irani, 1993]

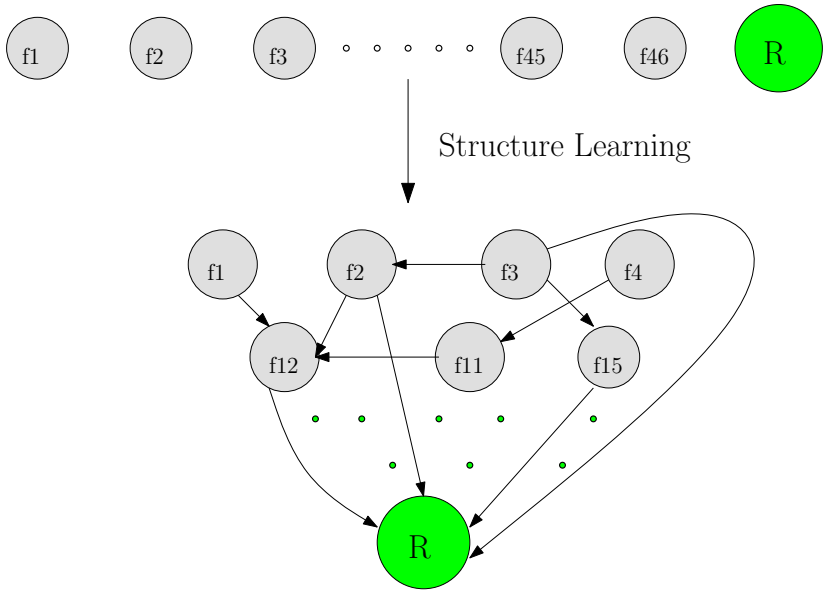
## Bayesian Networks: Structure Learning

- E= set of Edges i.e. the structure of the Network
- So we have to Estimate

$$P(E|X) = \frac{P(X|E) * P(E)}{P(X)}$$

  - Where P(E) = Prior
  - And P(x) is constant
  - $P(X|E)$ is likelihood term, Cooper Herkovitz Likelihood

$$P(X|E) = \prod_{j=1}^{d} \prod_{l=1}^{q_j} \prod_{i=1}^{k_j} \Theta_{jil}^{n_k(x_j^{(i)}|\pi_j^{(l)})}$$



## Structure Learning contd..

$$P(X|E) = \prod_{j=1}^{d} \prod_{l=1}^{q_j} \prod_{i=1}^{k_j} \Theta_{jil}^{n_k(x_j^{(i)}|\pi_j^{(l)})}$$

- $d$ is the number of variables (No of nodes)
- $k_j$ is number of possible states that the variable $X_j$ can take
- $q_j$ is the number of possible parent configurations for variable $X_j$ and

$$\Theta_{jil} = P(X_j = x_j^{(i)} | \Pi_j = \pi_j^{(l)})$$

## Structure Learning contd..

- The likelihood has to be computed for all the possible graph structure and the graph that maximizes it, is chosen.
- NP-Hard Problem: because possible number of DAGs grows super-exponentially with no. of nodes.
- e.g. for N=10, possible DAGs = 4.2 x $10^{18}$
- So there are different ways to select subset of all the DAGs for consideration
- e.g. K2, HC etc

## Bayesian Networks: Parameter Learning

- Now we know the structure and so the parent set of our Class node [Relevance in our case].
- We use the Maximum Likelihood Estimation(MLE) to give the probabilities, where Likelihood function is same [Cooper Herkovitz likelihood] as described in Structure Learning Section.

## Ranking Function

- Bayesian Network will give us, P(R=0), P(R=1) and P(R=2)
- But we want a real score for the document
- Very straightforward yet effective function 'Expected Relevance' [Li et al., 2007]

$$\text{Score}(X_i) = \sum_i i * P(R = i)$$

## Issues with Regression Approach

- Here relevance is considered as either non-ordered categories or real values, which is not true in reality.
- This approach does not take any advantage of pairwise preference or total order information in learning.

## Ordinal Regression

- Ordinal regression can be a better choice than Regression Approach.
- Because here categories are ordered while in classification the categories are non ordered.

## Ordinal Regression contd.

- $P$ranking for Ranking [Crammer and Singer, 2001]
  - Here we project the $\vec{w}^T \cdot \vec{x}$ in the ordered categories $b_1 < b_2 < \cdots < b_n$.
  - In the training phase if the predicted category is not equal to the actual category then we modify vector $\vec{w}$ and thresholds.

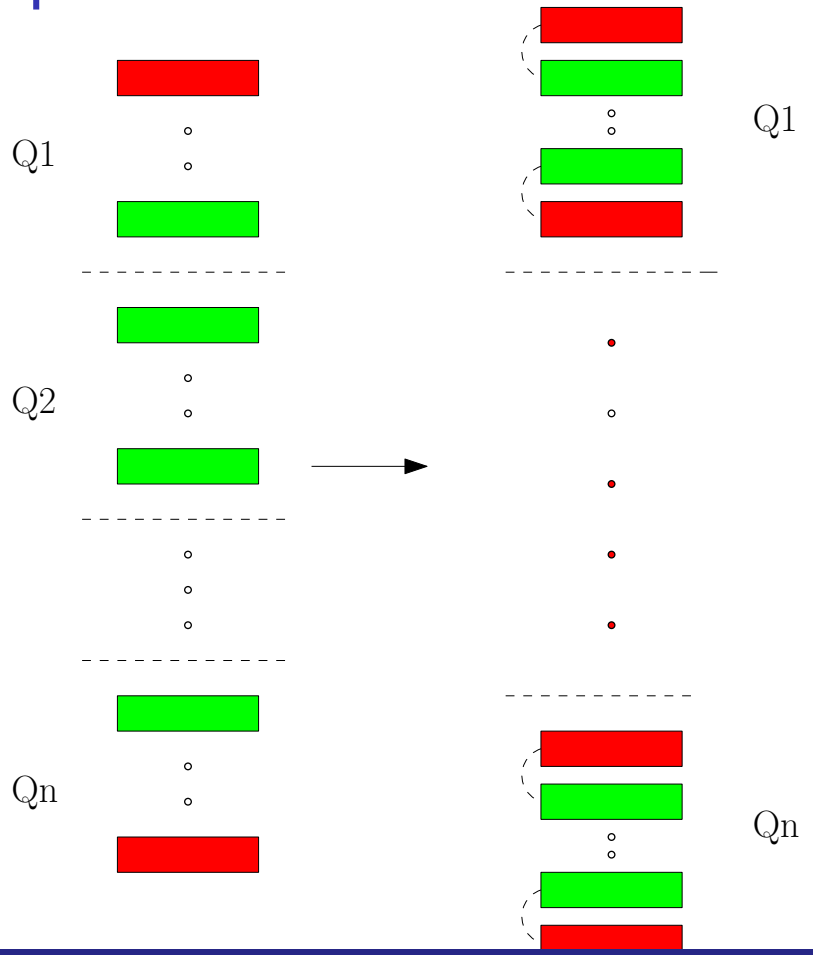
Concerns:

- Still consider the absolute relevance
- does not take information of pairwise preference or total order information in learning.

## Algorithms

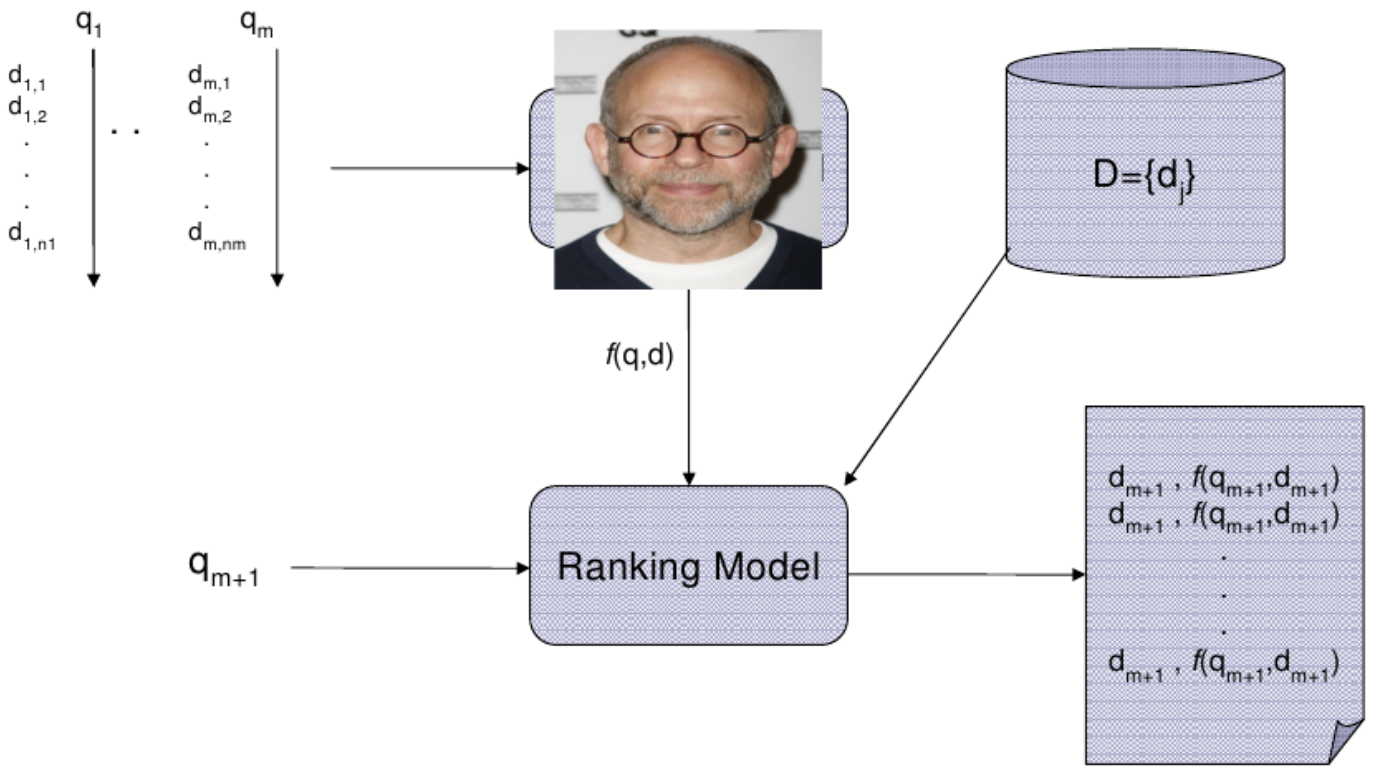
- Regression
- Classification - McRank [Li et al., 2007], BayesNetRank [Gupta, 2011]
- Ordinal Regression - PRanking [Crammer and Singer, 2001], Large margin [Shashua and Levin, 2002]

# Pairwise Approach




- Create Correct and Incorrect Ranked Pairs for each Query
- Use these pairs for Learning

# Pairwise Learning-to-Rank (LetoR) Model



## Pairwise Approach

- Take the pairs of documents
- Input: $X_i$ , $X_j \in R_t$ where $X_i > X_j$
- Output : $Y \in$ +1,-1, where '+1' denotes that $X_i > X_j$ is correct order and '-1' otherwise.
- Ex. if given data is like ($X_1$,2), ($X_2$,1), ($X_3$,0) where 0,1 and 2 are the relevance labels
- New training data will be, ($X_1$,$X_2$,+1), ($X_2$,$X_1$,-1), ($X_1$,$X_3$,+1), ($X_3$,$X_1$,-1), ($X_2$,$X_3$,+1) and ($X_3$,$X_2$,-1).

## Pairwise Approach - RankSVM [Herbrich et al., 2000]

- The SVM model is as shown below,

$$\text{minimize } \frac{1}{2} \parallel w \parallel^2 + C \sum_i \zeta_i$$

$$\text{subject to } z_i \left\langle w, x_i^1 - x_i^2 \right\rangle \geq 1 - \zeta_i, \zeta_i \geq 1, i = 1, 2, \ldots, l$$

Where,

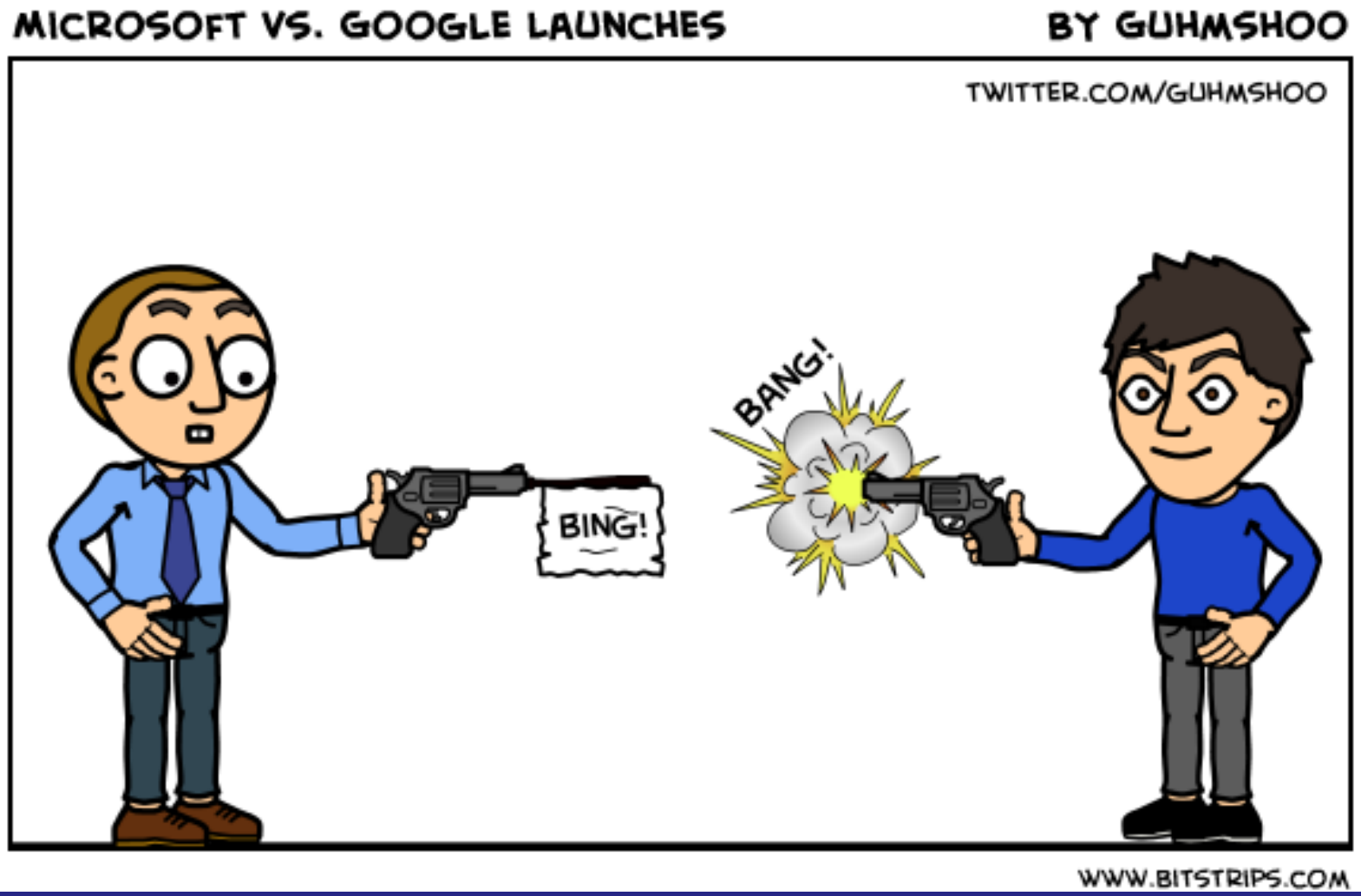
$$z_i = \begin{cases} +1 & \text{if } y_i^1 \prec y_i^2 \\ -1 & \text{if } y_i^2 \prec y_i^1 \end{cases}$$

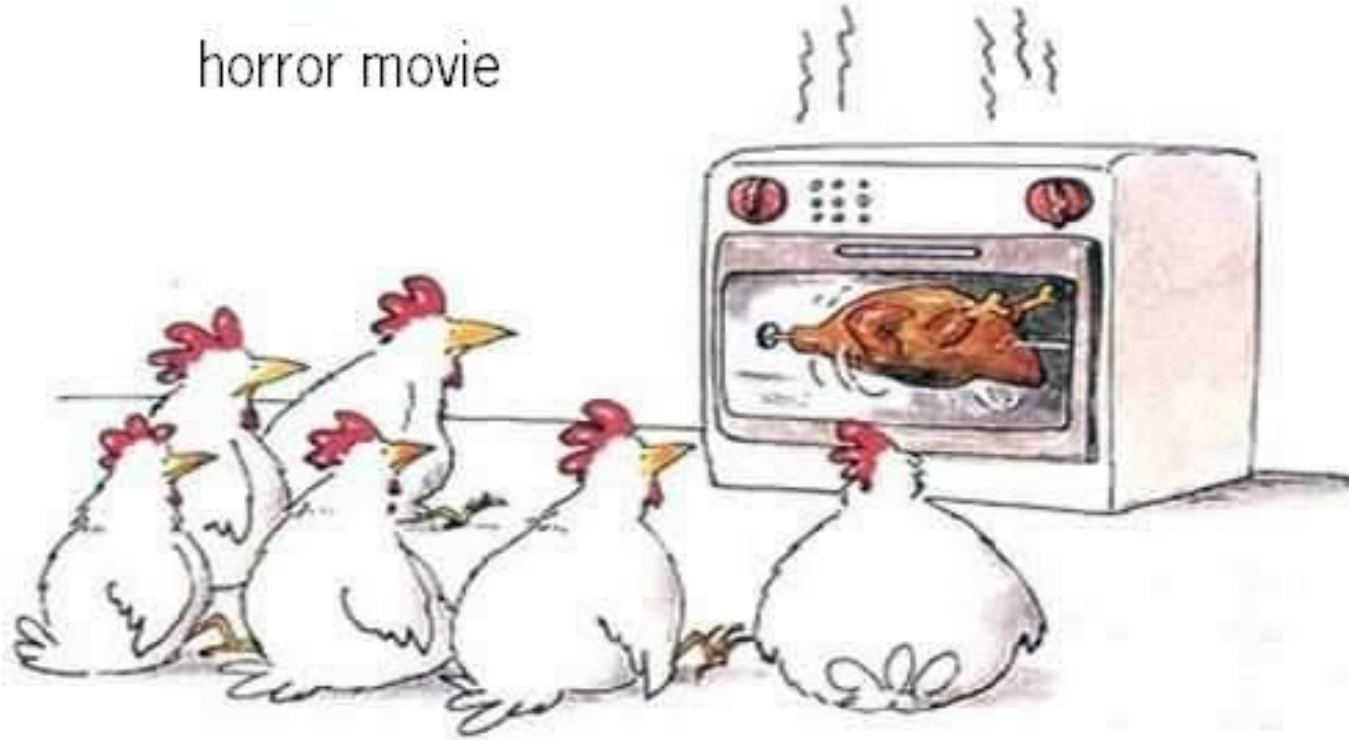
## Pairwise Approach contd.

- There are some concerns with Ranking SVM that
- It is biased towards queries with many relevant documents than those with fewer relevant documents. [Cao et al., 2006]
- It gives same weight to all the pairs.
- Also pairwise approach does not handle information of total order.

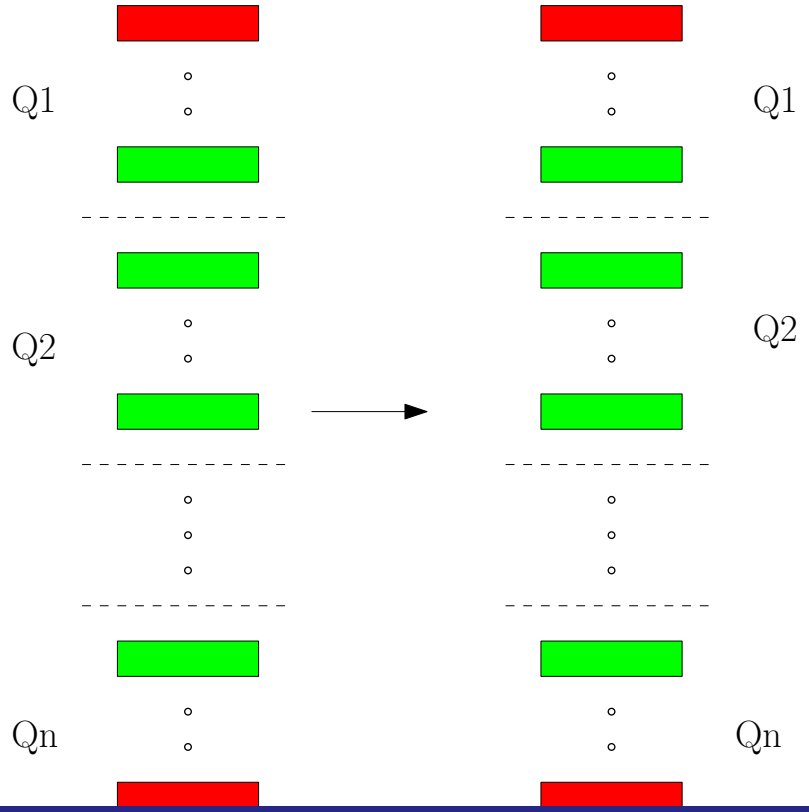
## Algorithms

- Support Vector Machines - RankSVM [Herbrich et al., 2000], IR-SVM [Cao et al., 2006]
- Neural Networks - RankNet [Burges et al., 2005]


MICROSOFT VS. GOOGLE LAUNCHES
BY GUHMSHOO
TWITTER.COM/GUHMSHOO
BING!
BANG!
WWW.BITSTRIPS.COM

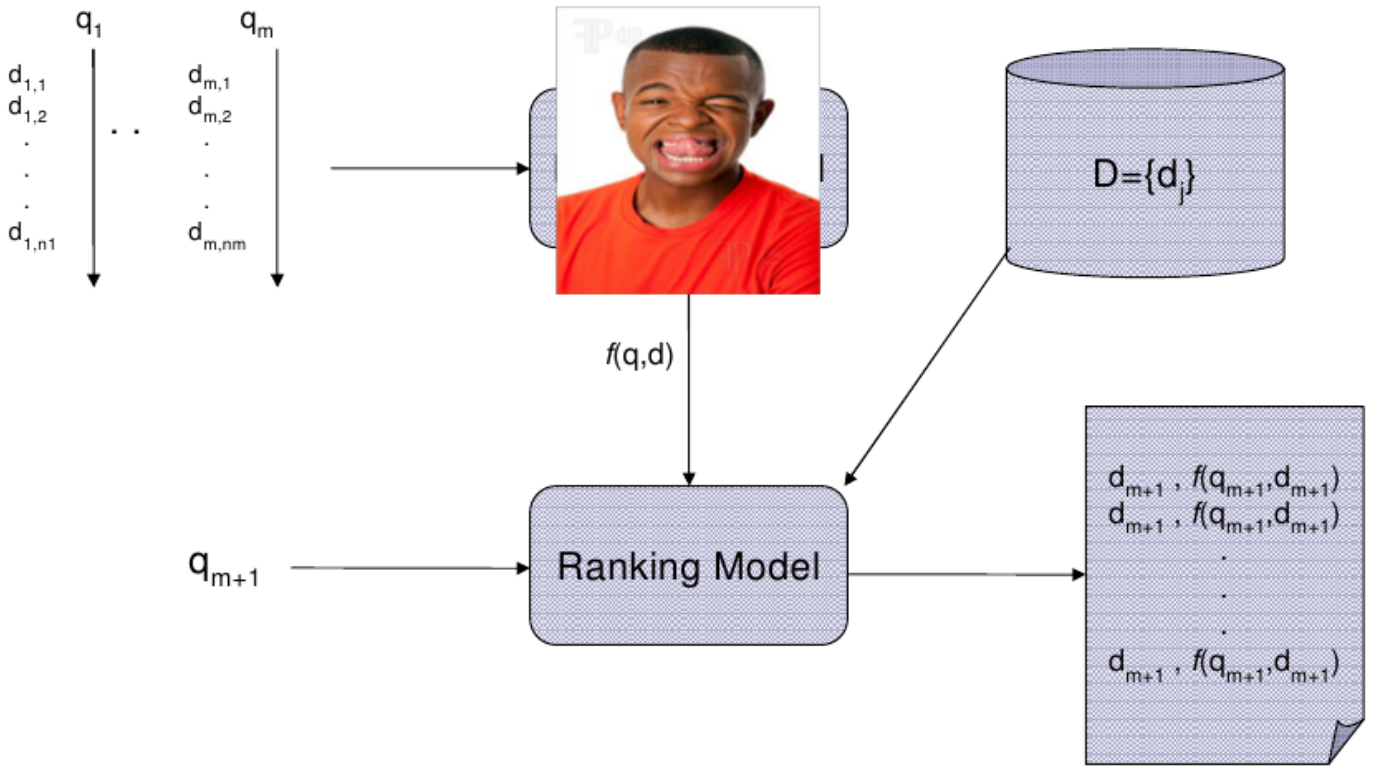

horror movie

# Listwise Approach




- Use whole ranked list for Learning

# Listwise Learning-to-Rank (LetoR) Model



## ListNet [Cao et al., 2007]

- Listwise Loss Function

$$\sum_{i=1}^{N} L(y_i, z_i)$$

  - $L$ is cross entropy $(p \log p)$
  - $z_i$ is the generated rank-list for query $i$
  - $y_i$ is the ground truth rank-list for query $i$

- Permutation Probability

$$P_s(\pi) = \prod_{j=1}^{n} \frac{s_{\pi(j)}}{\sum_{k=j}^{n} s_{\pi(k)}}$$

## ListNet contd.

- Top k Permutation Probability

$$P_s(\varsigma(j_1, j_2, ..., j_k)) = \prod_{t=1}^{k} \frac{s_{j_t}}{\sum_{l=t}^{n} s_{j_t}}$$

- Time complexity of computation : from $O(n!)$ to $O(\frac{n!}{(n-k)!})$
- Ranking model $s(.,.)$ is Neural Network
- Example, if $s(A)$=5, $s(B)$=4, $s(C)$=2 then P(ABC) is maximum and P(CBA) is minimum

## Algorithms

- Neural Networks - ListNet [Cao et al., 2007]

# Applications

- Search
- Collaborative Filtering [Freund et al., 2003]
- Key-Phrase Extraction [Jiang et al., 2009]
- Question Answering (*why* questions) [Verberne et al., 2011]

## Collaborative Filtering

- Problem formulation
  - Input: users ratings on some items
  - Output: users ratings on other items
  - Assumption: users sharing same ratings on input items tend to agree on new items
- Solution
  - Classification
  - Ordinal Regression
  - Learning-to-Rank

## Key Phrase Extraction

- Problem formulation
  - Input: document
  - Output: keyphrases of document
  - Two steps: phrase extraction and keyphrase identification
- Traditional approach
  - Classification: keyphrase vs non-keyphrase

## Key Phrase Extraction contd.

- Ranking of Phrases
- Pairwise approach

## *why* Question Answering

- Problem Formulations
  - Input: Question and Potential Answers
  - Output: Improved ranking of Answers (re-ranking)
- Traditional Approach
  - TF-IDF scoring

## Question Answering contd.

- The data is highly imbalanced
- Pairwise approaches seem to work well

# Statistics of public LTR datasets

| | Queries | Doc. | Rel. | Feat. | Year |
|---|---|---|---|---|---|
| Letor 3.0 - Gov | 575 | 568 k | 2 | 64 | 2008 |
| Letor 3.0 - Ohsumed | 106 | 16 k | 3 | 45 | 2008 |
| Letor 4.0 | 2,476 | 85 k | 3 | 46 | 2009 |
| Yandex | 20,267 | 213 k | 5 | 245 | 2009 |
| Yahoo! | 36,251 | 883 k | 5 | 700 | 2010 |
| Microsoft | 31,531 | 3,771 k | 5 | 136 | 2010 |

# Research Trends in Learning to Rank

- Feature Extraction - *What can be useful?*
- Feature Selection - *All of them are useful?*
- Data Labeling - *Do I have to judge all of them?*
- Ranking Models - *How to Rank?*
- Dimensionality Reduction - *Can feature vector be compacted?*
- Suitability of Evaluation Metric - *Does one fit all?*

## Xapian

- Xapian[1] is an Open-source search engine project
- Letor API is developed under Google's initiative to promote open-source, well known as, Google Summer of Codes (GSoC)
- Detailed description along with code of Letor API can be accessed through, wiki-page: `http://trac.xapian.org/wiki/GSoC2011/LTR`

## Motivation

- To make an end-to-end i.e. natural language query to document ranked list type infrastructure for Learning to Rank

[1] http://xapian.org/

# API

```
Xapian::Letor ltr;
...
ltr.set_database(db);
ltr.set_query(query);
...
// prepare training file
ltr.prepare_training_file("topics.txt",
  "inex2010-article.qrels",
  100);
....
// learn the model with svm parameters
ltr.letor_learn_model(4,0);

// get the new ranked list with Letor!
map<Xapian::docid,double> letor_mset = ltr.letor_score(mset);
```

## Summary

- We learnt the basic framework of Learning-to-Rank
- We explored the approaches to it
- We saw application of LTR to IR and NLP tasks
- Overview of Datasets and Xapian Letor API

Thank You! ☺

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