

Instituto Superior Técnico Universidade Técnica de Lisboa

## Learning to Rank Academic Experts

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## Outline

- ✓ Introduction
- ✓ Related Work
- ✓ Learning to Rank
- ✓ Features
- ✓ Algorithms
- ✓ Dataset
- ✓ Experimental Results

## Expert Finding



### Information Retrieval



## Why Expert Finding?

### Too many documents

### Information is dispersed

### Need answers quickly



## **Related Work**

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## **Candidate Centric Approach**

- 1. Gather documents associated to a candidate
- 2. Merge documents into a single profile document
- 3. Rank the profile according to the query



## **Document Centric Approach**

- 1. Gather documents containing query topics
- 2. Uncover candidates and rank them



## **Problems?**

Generative Probabilistic Models

Simple heuristics

Heuristics do not reflect expertise

Only based on textual contents



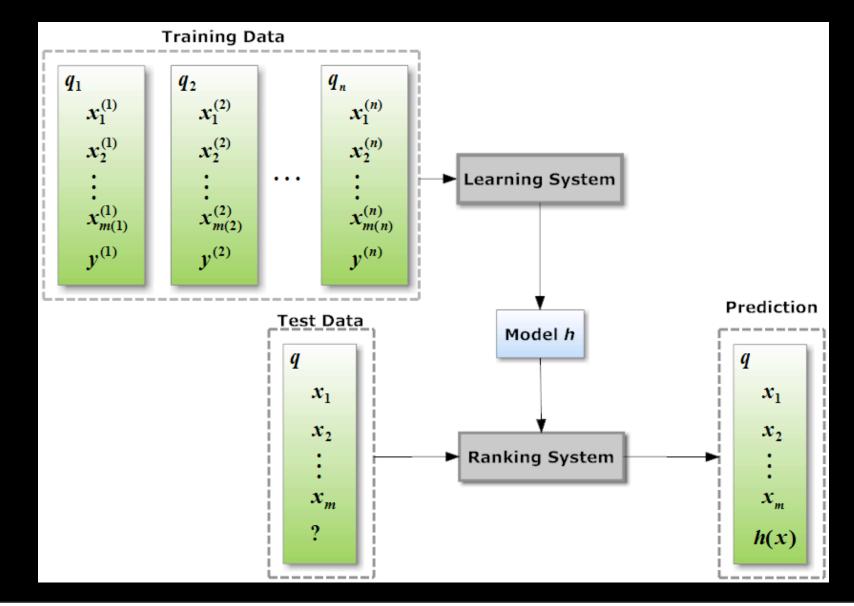
## **Our Approach**

#### A set of features to estimate expertise

#### Features combined in a **learning to rank framework**



## Learning to Rank (L2R)



## **L2R Approaches**

• Pointwise

• Pairwise

• Listwise

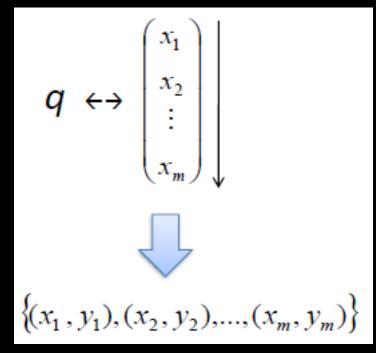


### **L2R Pointwise Approaches**

Use feature vectors for each

individual **<q, x>** 

**Goal**: directly support the application of existing algorithms of regression or classification

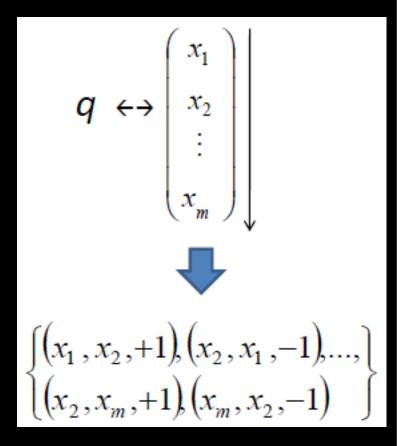


### **L2R Pairwise Approaches**

Use feature vectors for each

pair **<q, x1, x2>** 

# **Goal**: minimize number of misclassified document pairs

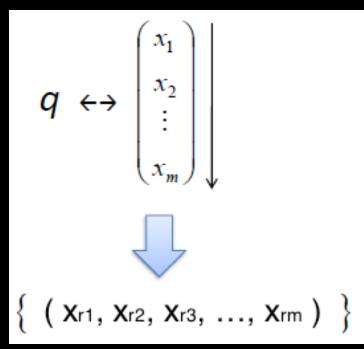


### **L2R Listwise Approaches**

Use feature vectors for the

list **<q, x1, x2, ..., xm>** 

**Goal**: optimize an Information Retrieval evaluation metric

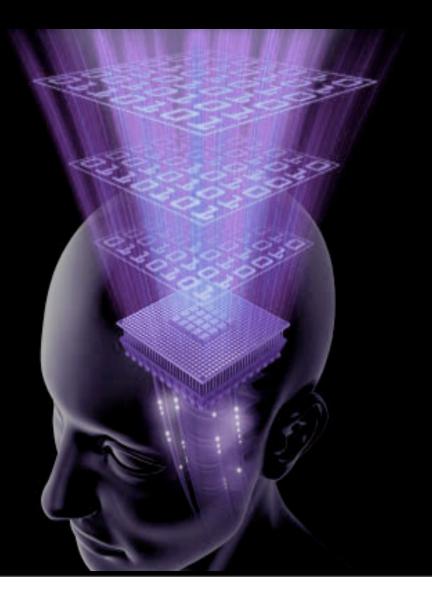


### Features

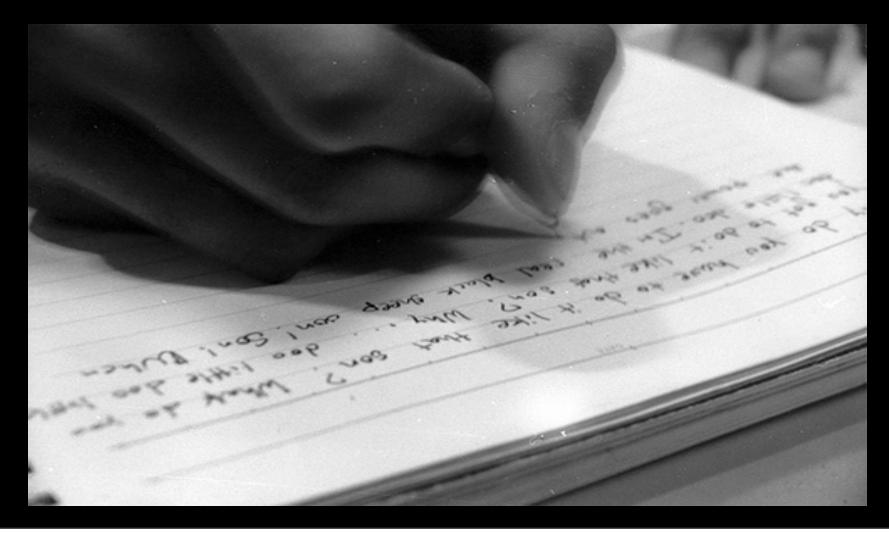
#### **Textual Similarities**

#### **Profile Information**

#### Graph Structure

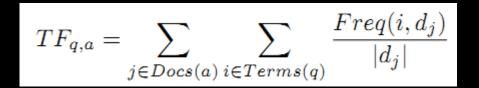


## **Textual Features**



## **Textual Features**

#### ΤF



### IDF

$$IDF_q = \sum_{i \in Terms(q)} \log \frac{|D|}{f_{i,D}}$$

#### **BM25**

$$BM25_{q,a} = \sum_{j \in Docs(a)} \sum_{i \in Terms(q)} \log\left(\frac{N - Freq(i) + 0.5}{Freq(i) + 0.5}\right) \times \frac{(k_1 + 1) \times \frac{Freq(i,d_j)}{|d_j|}}{\frac{Freq(i,d_j)}{|d_j|} + k_1 \times (1 - b + b \times \frac{|d_j|}{\mathcal{A}})}$$

## **Profile Features**

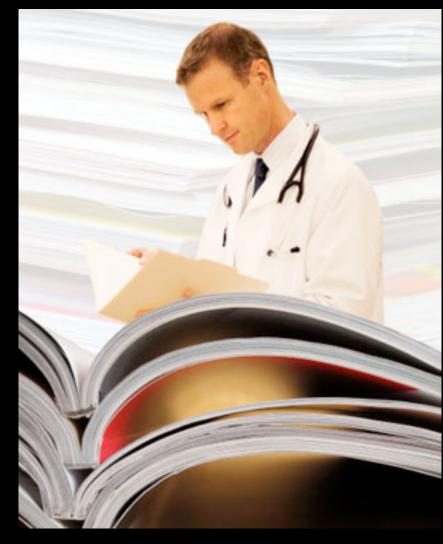


## **Profile Features**

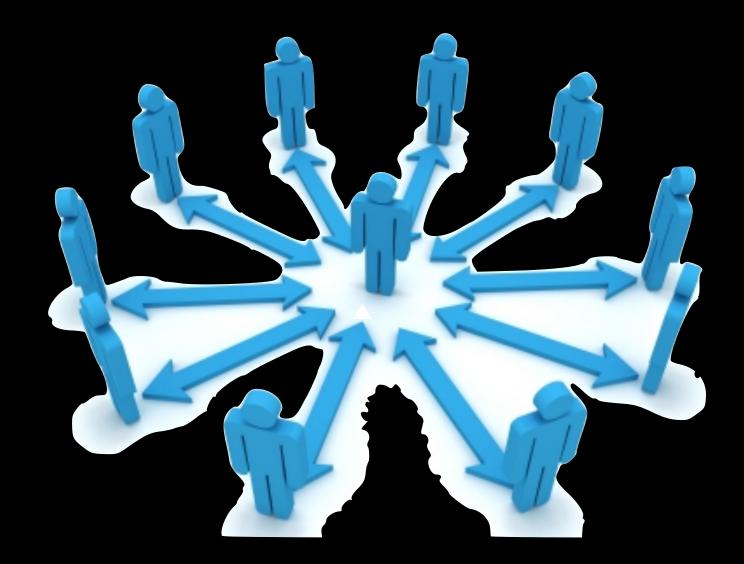
#### Number of Publications

#### Years Between Publications

#### Number of Articles



## **Graph Features**

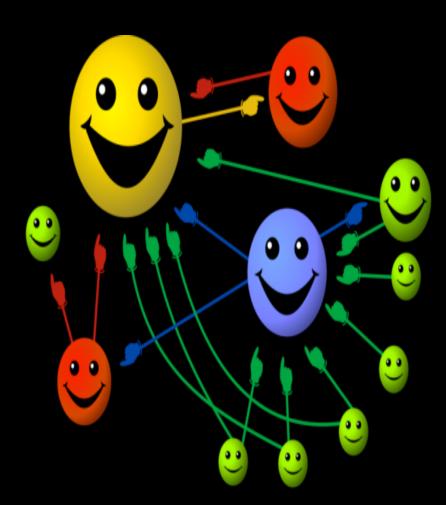


## **Graph Features**

#### **Citations Graphs**

#### Co-authorship Graphs

#### Academic Indexes



### Academic Indexes Measure Scientific Impact!

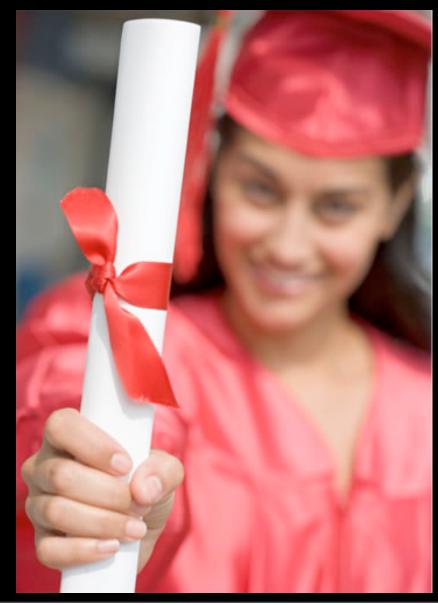


## **Academic Indexes**

#### H-Index

#### **G-Index**

#### A-Index

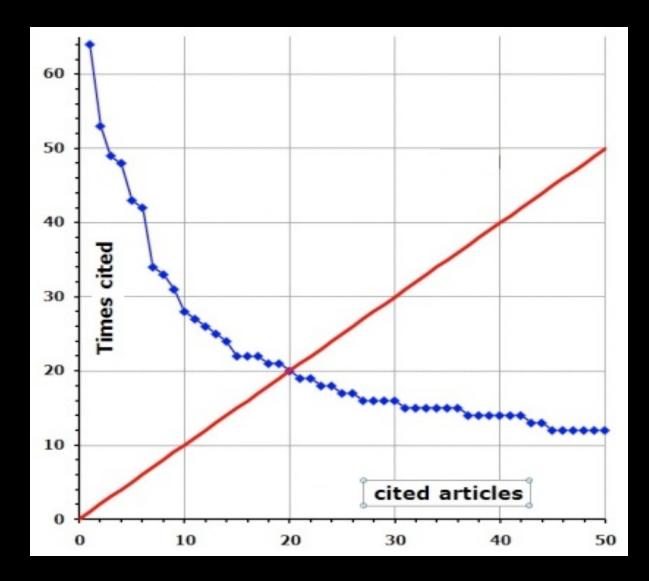




#### A given author has a Hirsch Index of *h*, if *h*

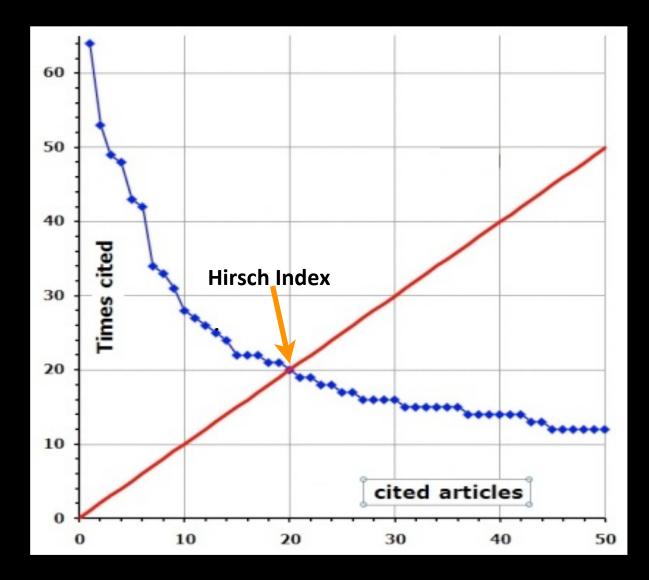
#### of his N papers have at least h citations each

## H Index - Example



Tuesday, October 11, 11

## H Index - Example



## **G** Index

#### Is the largest number such that the top *g* papers

#### received on average at least g citations each



### Measures the magnitude of the most influential

papers of a given author

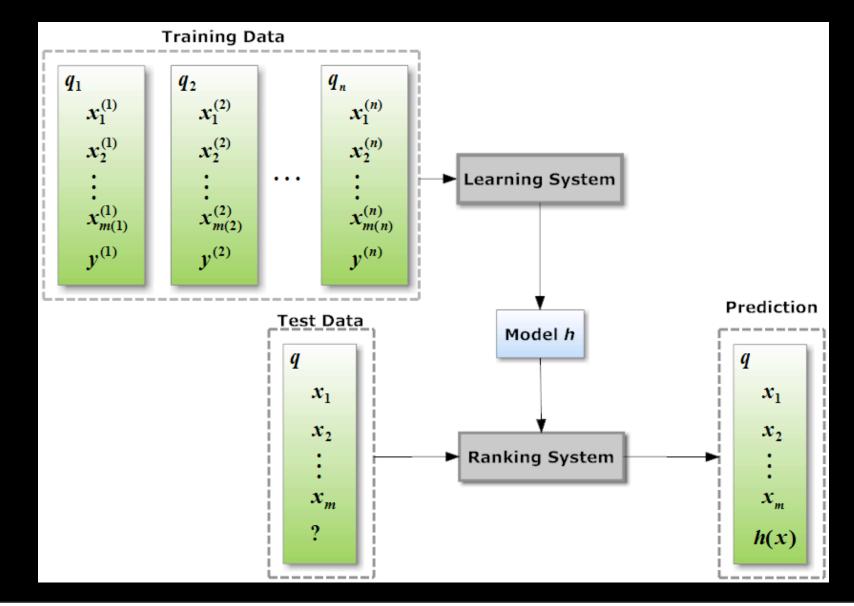
$$a = N_{c,tot}/h^2$$

### First work using academic indexes



### to estimate Expertise!

## Learning to Rank (L2R)



## **L2R Algorithms Tested**

Based on the formalisms of Support Vector Machines:

• **SVMmap** (Y. Yue and T. Finley)

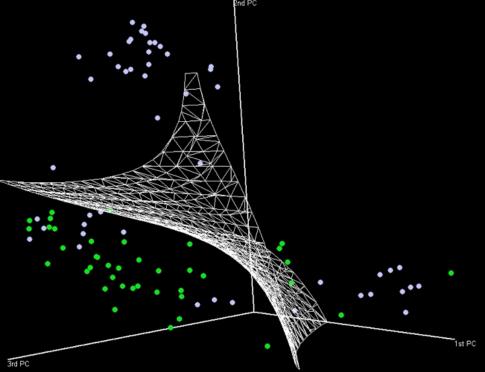
• SVMrank (T. Joachims)



## **Support Vector Machines**

### **Basic idea:**

Construct an N-dimensional hyperplane to separate data points.



## **SVMmap**

Optimizes MAP by minimizing a loss function which measures the difference between a perfect ranking and the performance of an incorrect ranking

$$\min \frac{1}{2}||w||^2 + \frac{C}{m}\sum_{i=1}^m \xi^{(i)}$$

s.t. 
$$\forall y^{c(i)} \neq y^{(i)}, w^T \Psi(y^{(i)}, x^{(i)}) \ge w^T \Psi(y^{c(i)}, x^{(i)}) + 1 - AP(y^{c(i)}) - \xi^{(i)}$$

## **SVMrank**

#### Constrains the default SVM optimization problem to perform to minimization of misclassified **pairs** of experts

$$\min \frac{1}{2} ||w||^2 + C \sum_{i=1}^n \sum_{u,v:y_{u,v}^{(i)}} \xi_{u,v}^{(i)}$$

s.t. 
$$w^T (x_u^{(i)} - x_v^{(i)}) >= 1 - \xi_{u,v}^{(i)}$$
,

if 
$$y_{u,v}^{(i)} = 1$$
,  $\xi_{u,v}^{(i)} >= 0$ ,  $i = 1, \dots, n$ 

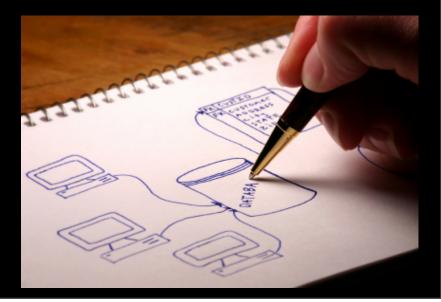
### Dataset

DBLP Computer Science Bibliography

Covers journal and conference publications

Contains publication's abstracts

Contains citation links



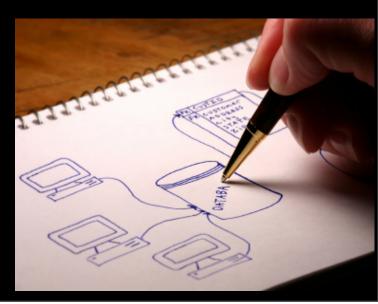
## **Dataset for Validation**

Arnetminer

Contains a set of people considered experts

Contains 13 different query topics

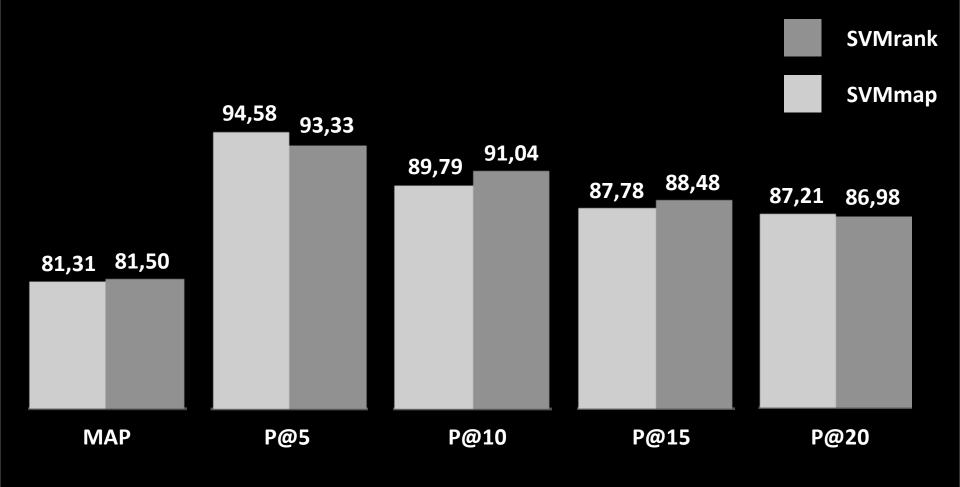
Based on people from Program Committees of important conferences



## **Experimental Results**



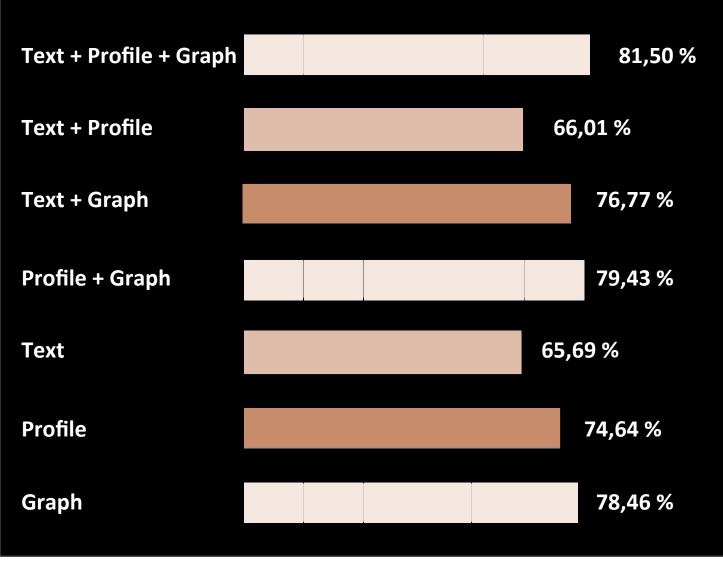
## SVMmap vs SVMrank (%)



## **Impact of the Features?**



## **Impact of the Features?**



# SVMrank Impact in the State of the Art?



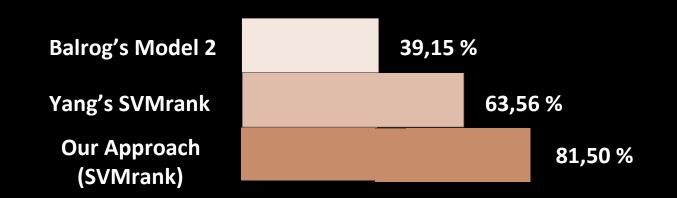
### SVMrank vs State of the Art (MAP)



### SVMrank vs State of the Art (MAP)



### SVMrank vs State of the Art (MAP)



## **Thank You!**



