ACML 2009 Tutorial
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Nanjing

Learning to Rank

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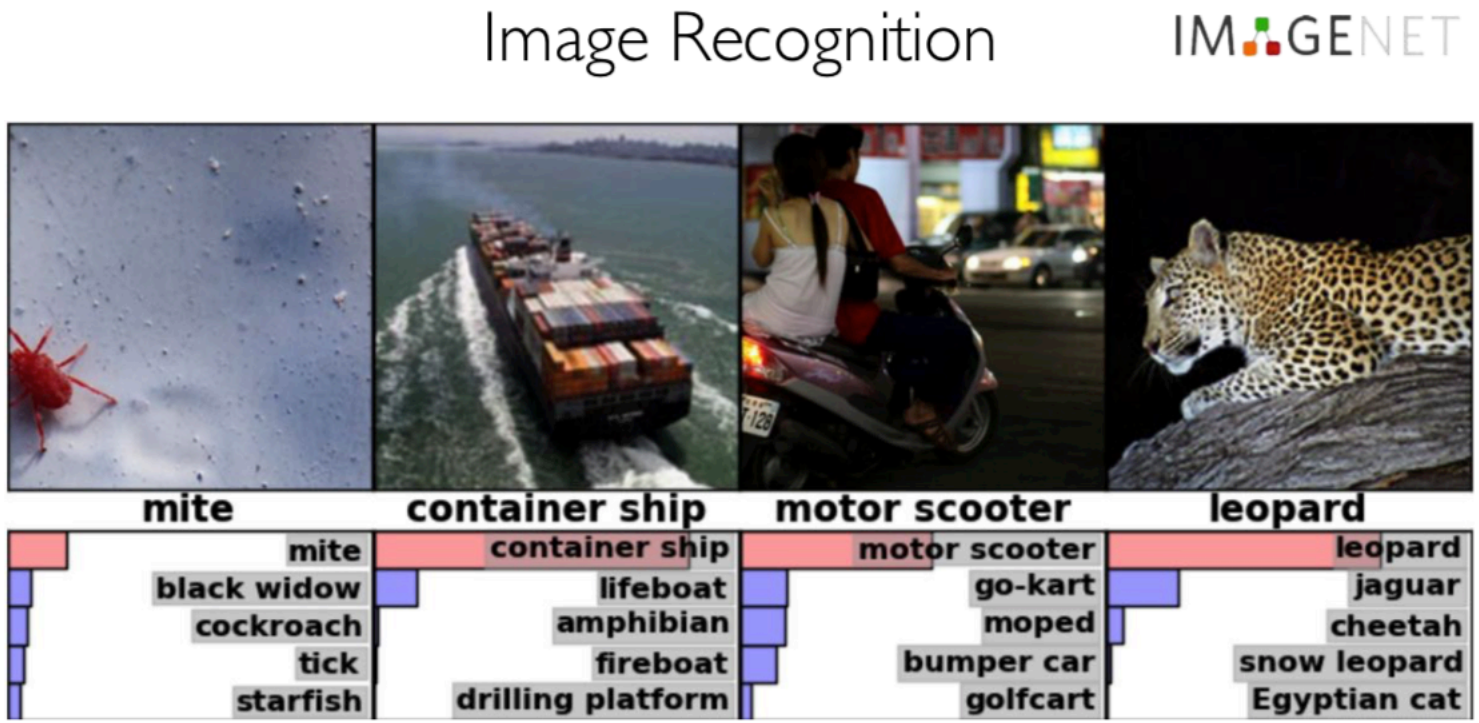
Deep Learning Success: Vision

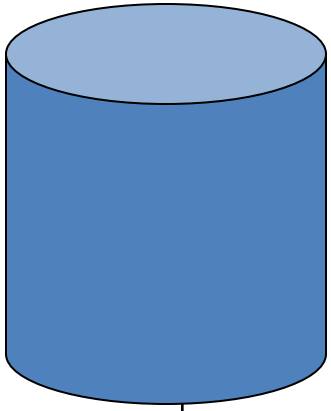


1. Introduction

Ranking Problem: Example = Document Search

documents

$D = \{d_1, d_2, \cdots, d_N\}$



ranking based on relevance, importance, preference

ranking of documents

query

q

$f(q,d)$

$d_{q,1}$

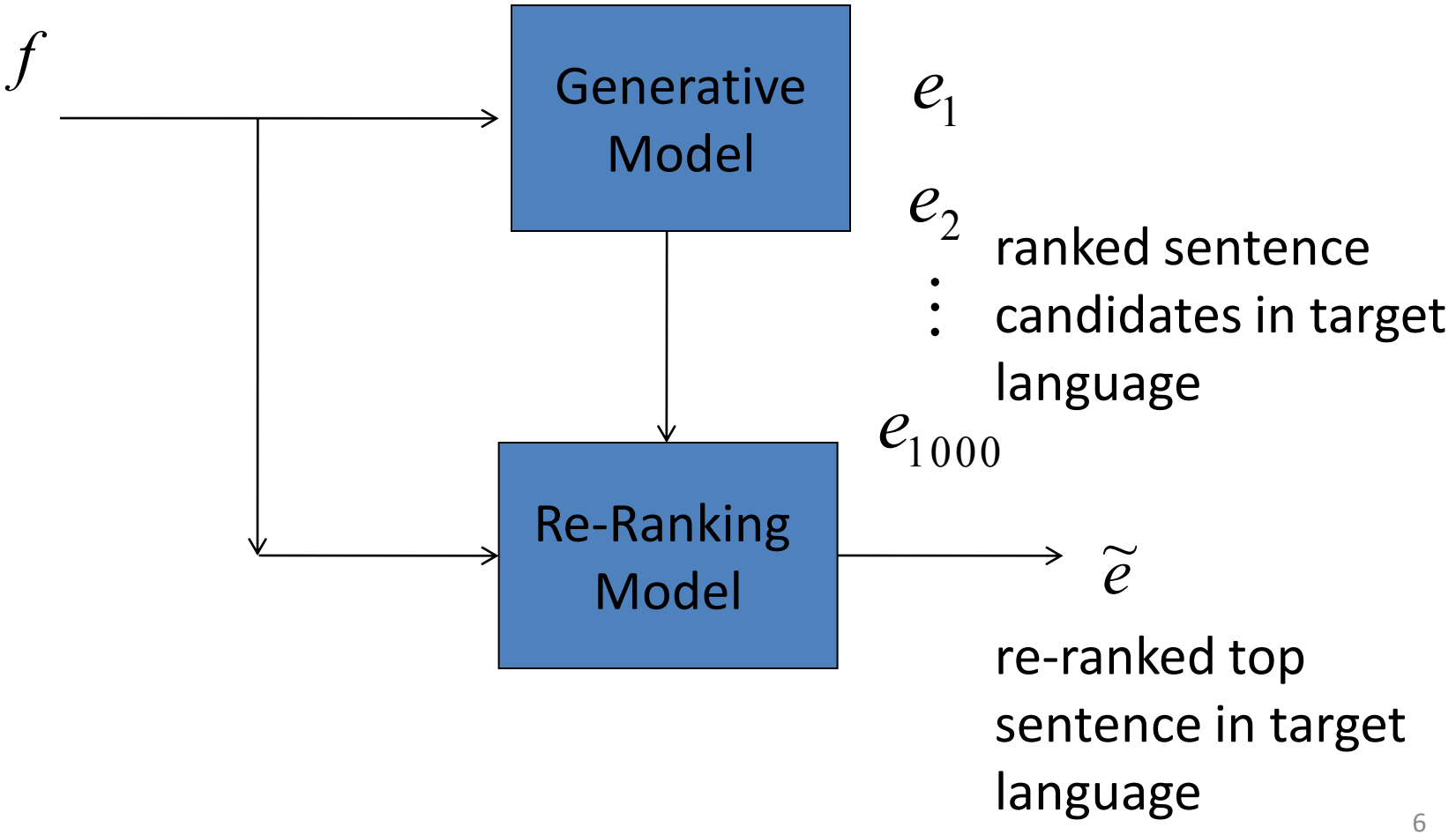
$d_{q,2}$

$\vdots$

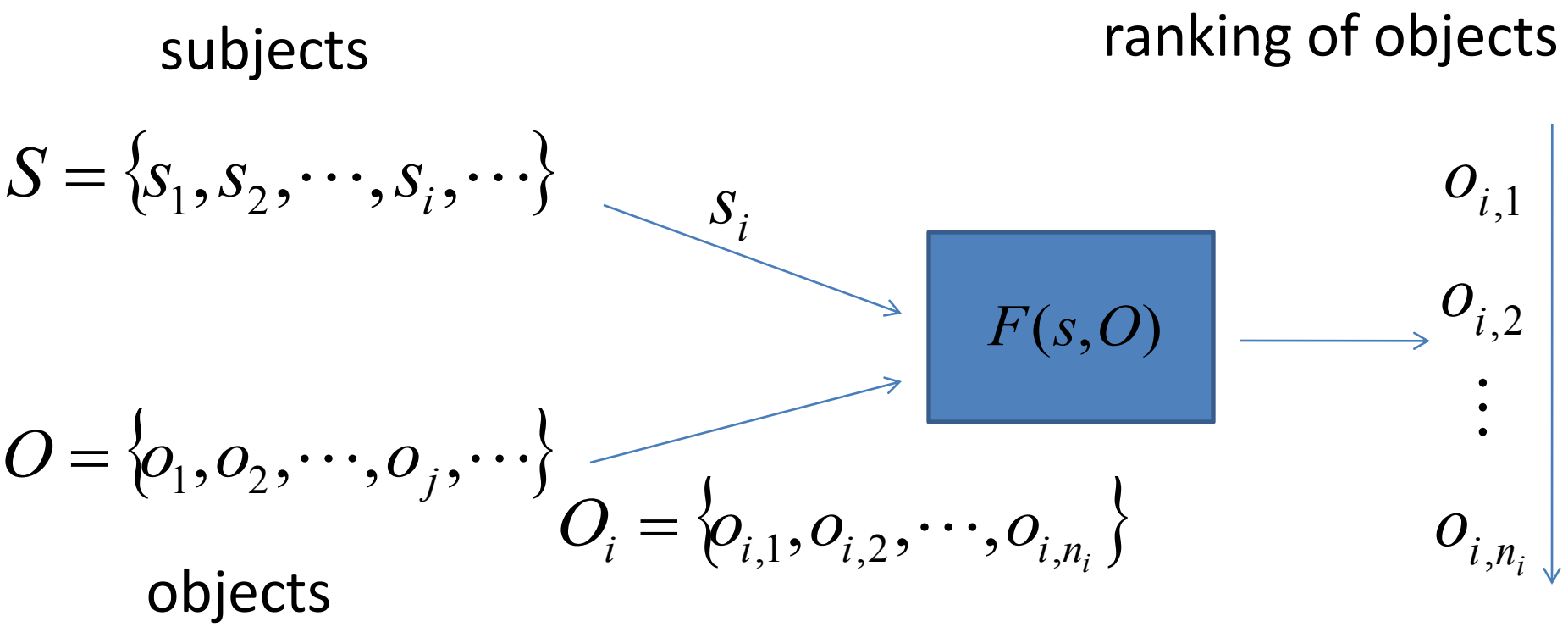
d_{q,n_q}

Ranking Problem
Example = Machine Translation

sentence source language



Ranking Problem



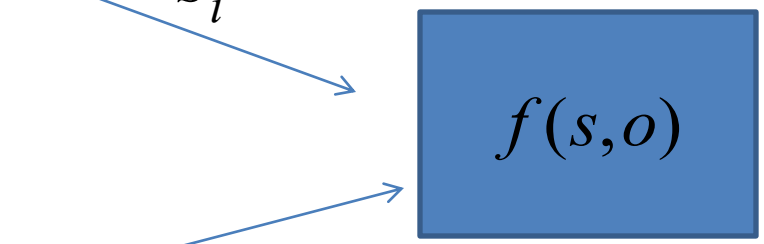
By Ranking Function

subjects

$S = \{s_1, s_2, \cdots, s_i, \cdots\}$

$O = \{o_1, o_2, \cdots, o_j, \cdots\}$

objects



$O_i = \{o_{i,1}, o_{i,2}, \cdots, o_{i,n_i}\}$

ranking of objects

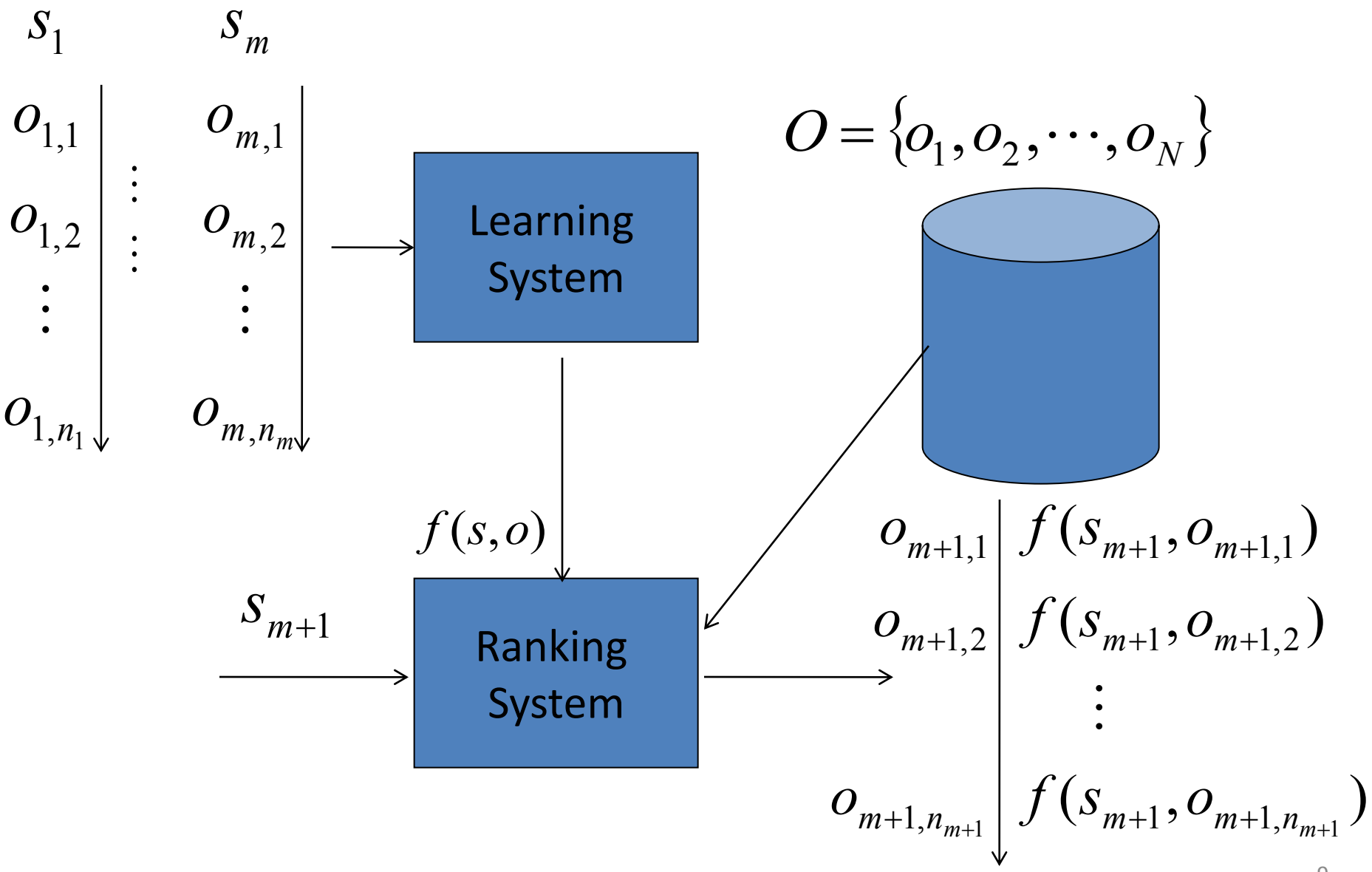
$o_{i,1} \quad f(s_i, o_{i,1})$

$o_{i,2} \quad f(s_i, o_{i,2})$

$\vdots$

$o_{i,n_i} \quad f(s_i, o_{i,n_i})$

Learning to Rank



Ranking Plays Key Role in Many Applications

Applications of Learning to Rank

- Search (Document Search, Entity Search, etc)
- Recommender System (Collaborative Filtering)
- Key Phrase Extraction
- Question Answering
- Document Summarization
- Opinion Mining
- Sentiment Analysis
- Machine Translation

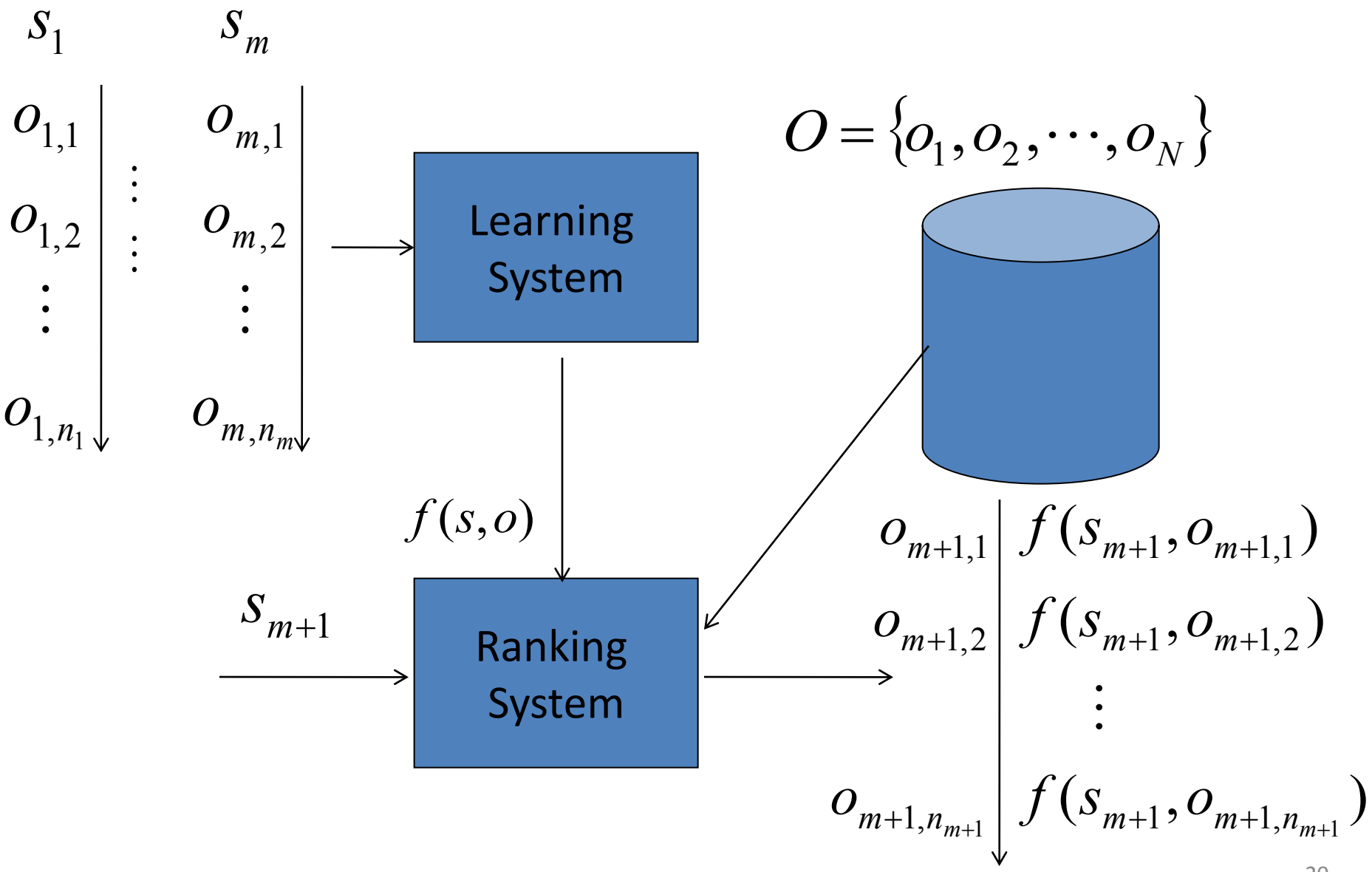
2. Learning to Rank Problem

Learning to Rank Problem

- 2.1 Problem Formulation
- 2.2 Example: Learning to Rank for Search
- 2.3 Issues in Learning to Rank
- 2.4 Relations with Other Learning Tasks

2.1 Problem Formulation

Learning to Rank

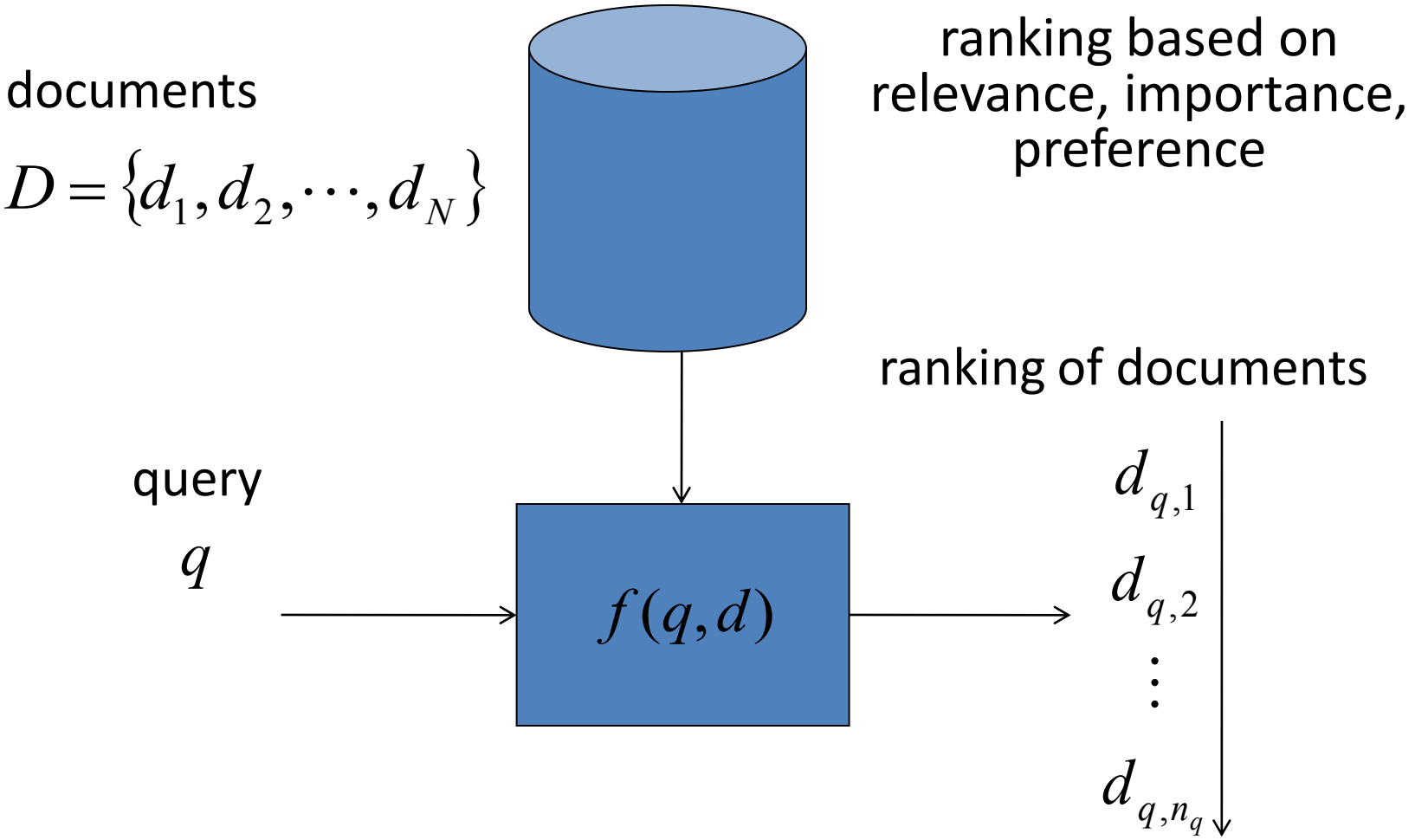


Characteristics of Learning to Rank

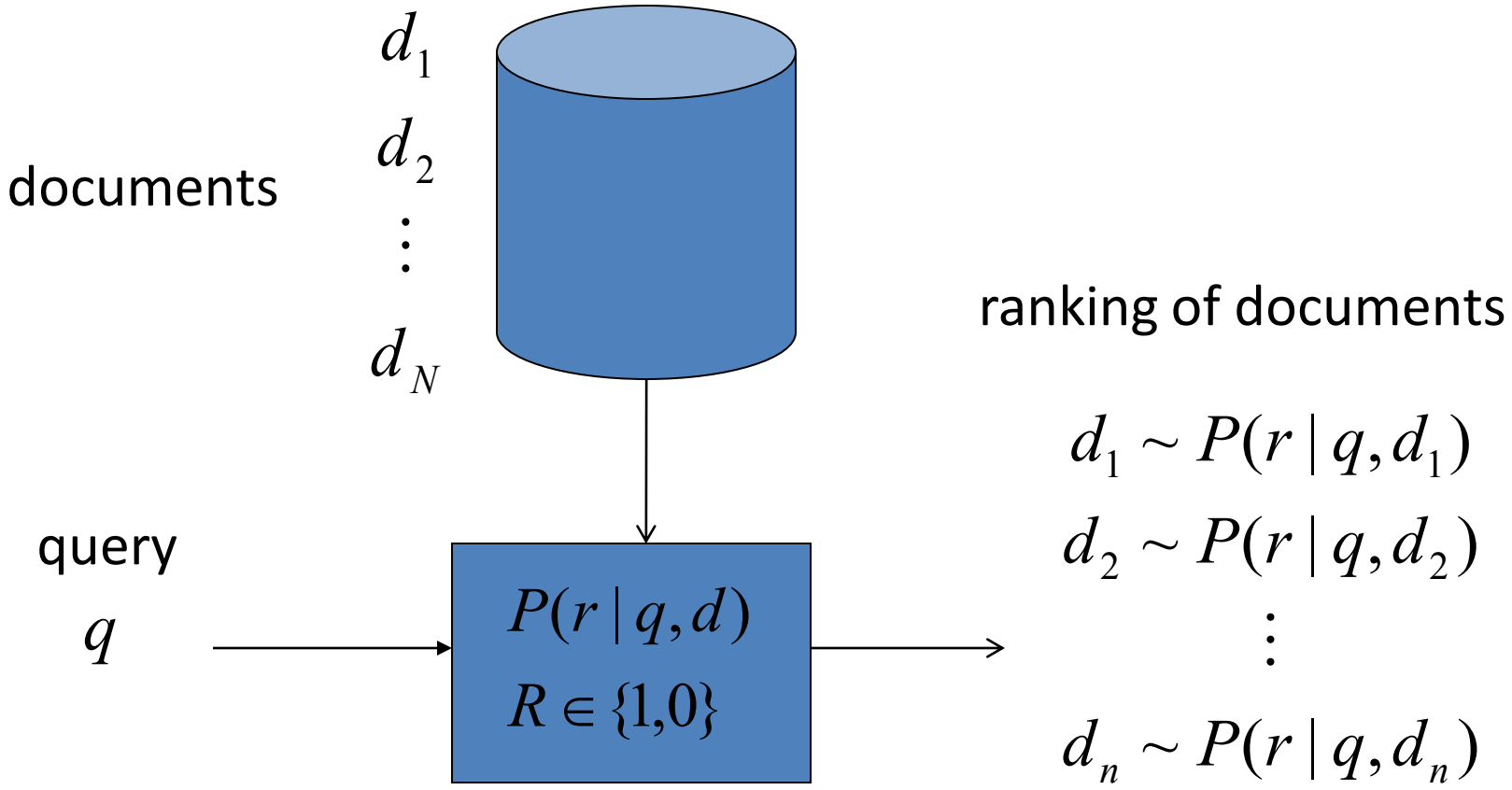
- Machine learning technologies
- Ranking of objects by subject
- Learning ranking function $f(s,o)$
- Using labeled data (supervised learning)
- Ranking function is feature based
- This tutorial mainly takes *document search* as example

2.2 Example: Learning to Rank for Search

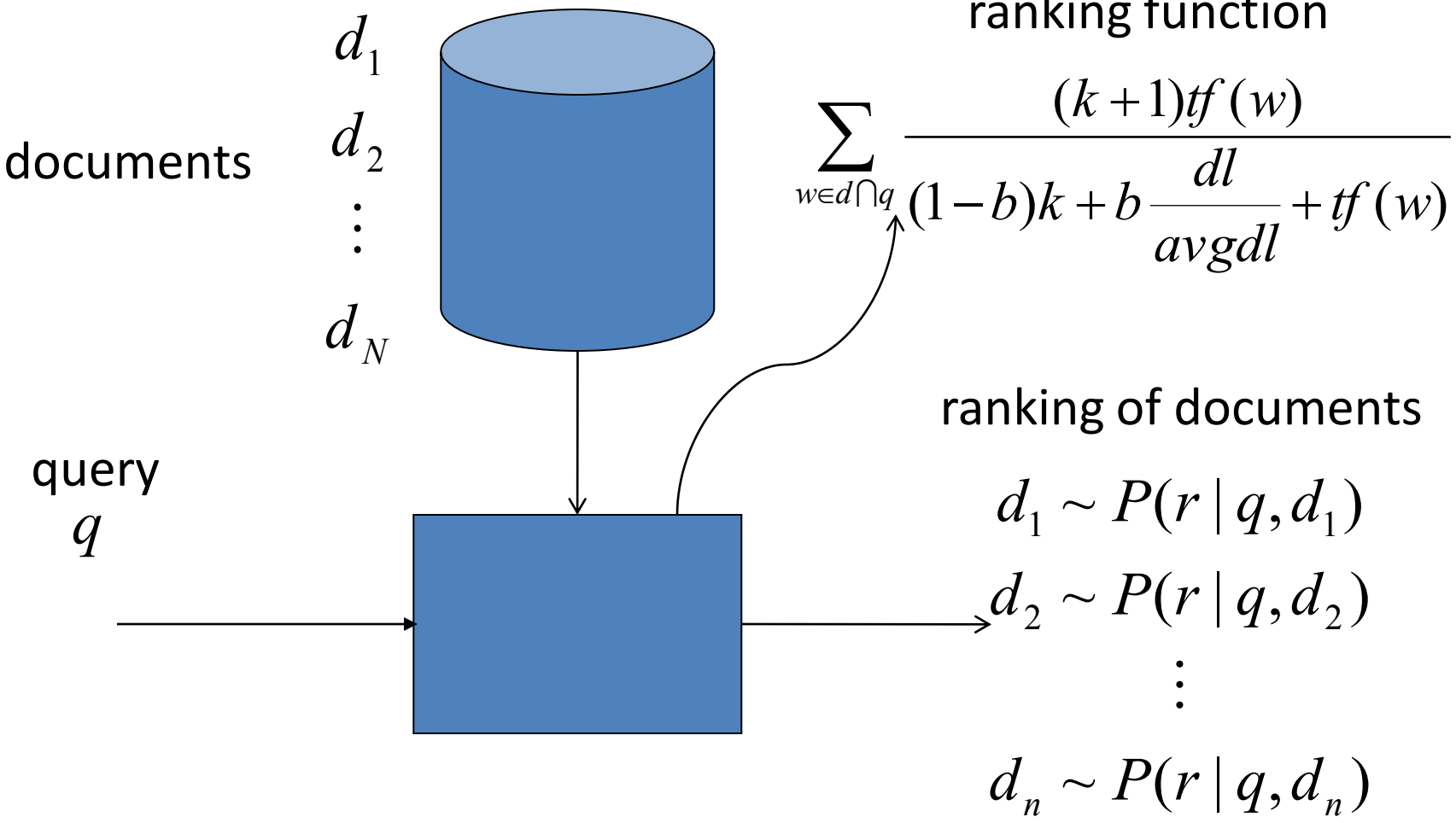
Ranking Problem: Example = Document Search



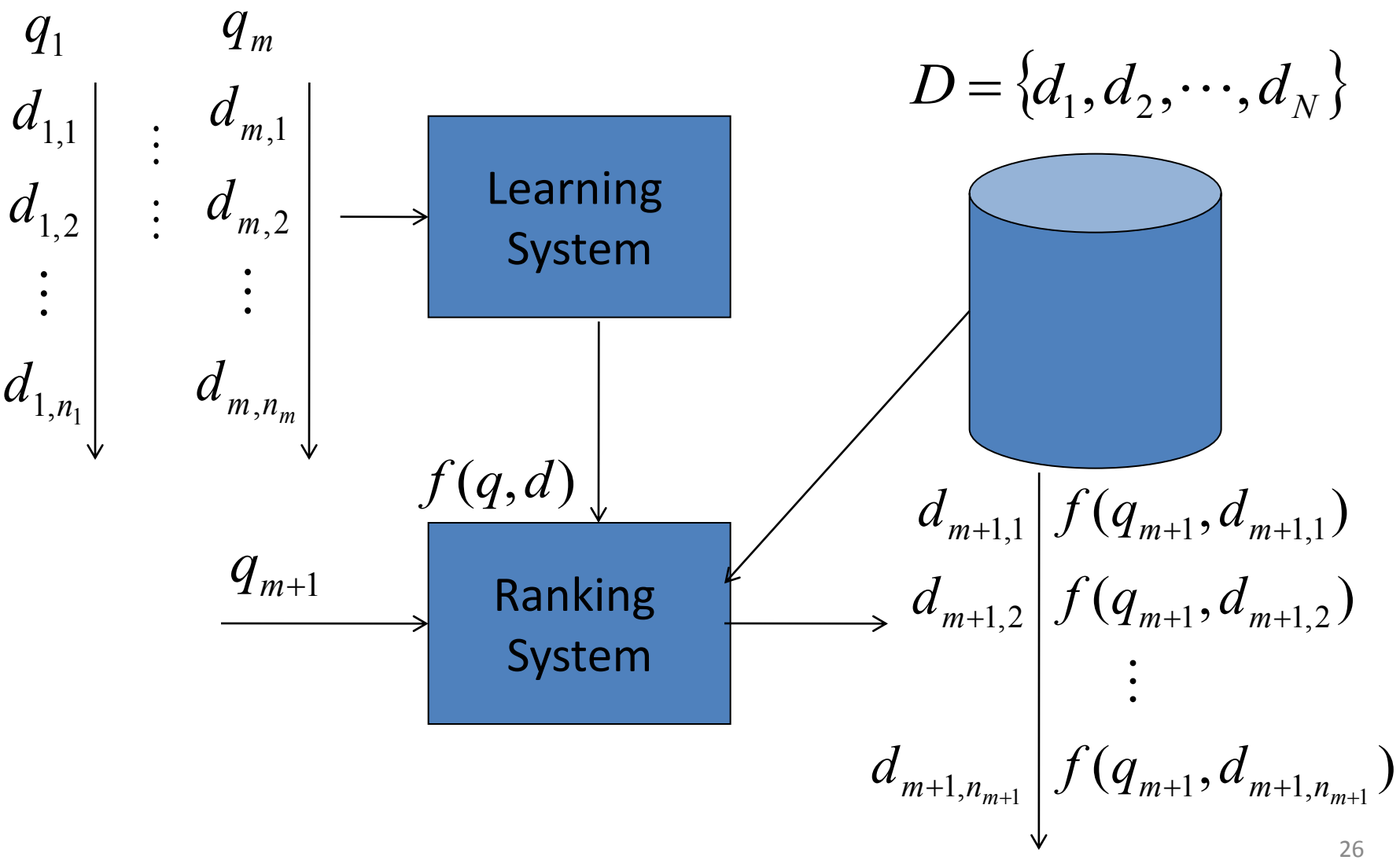
Traditional Approach = Probabilistic Model



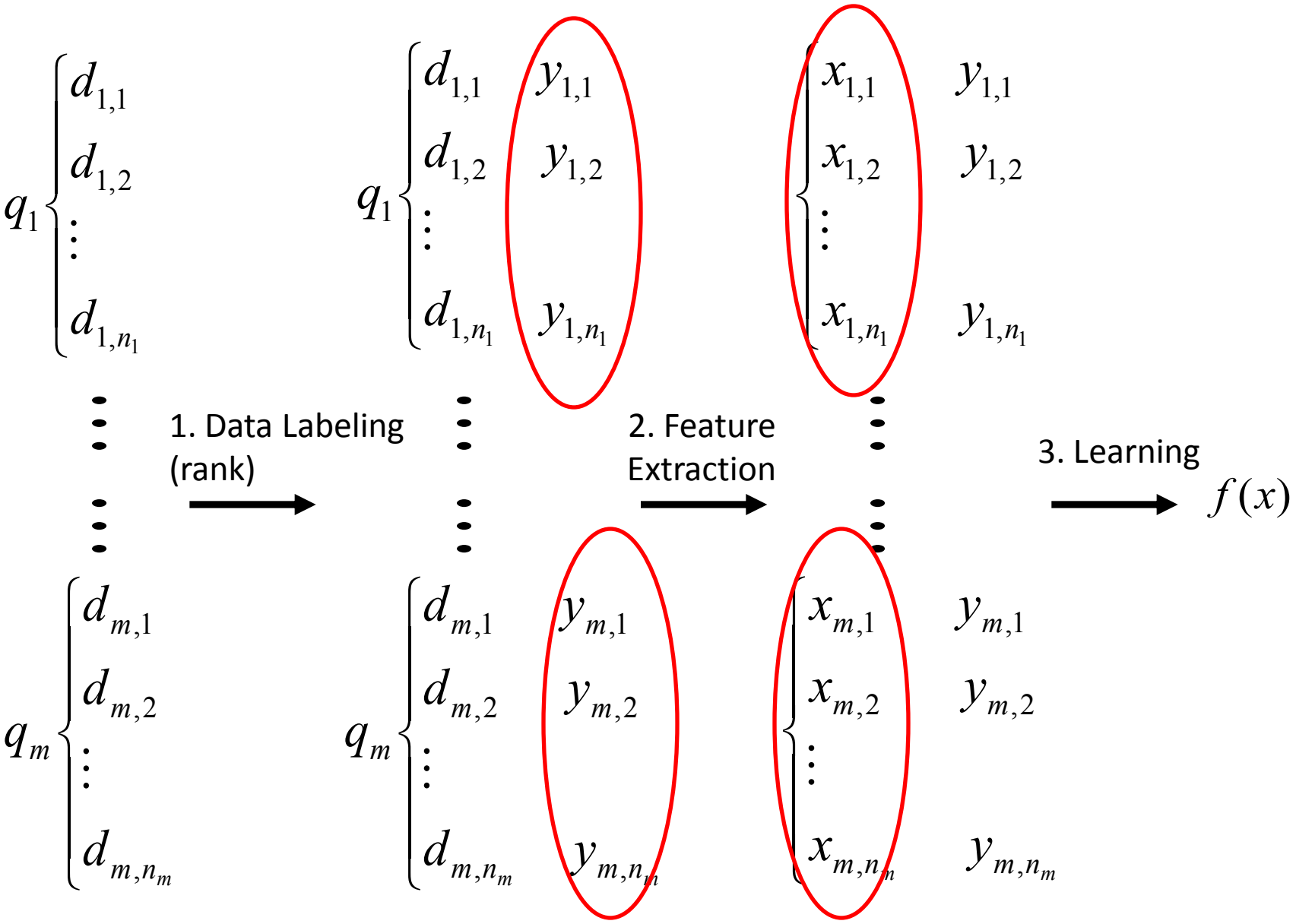
BM25


documents
d_1
d_2
$\vdots$
d_N
query
q
ranking function
$\sum_{w \in d \cap q} \frac{(k+1)tf(w)}{(1-b)k + b\frac{dl}{avgdl} + tf(w)}$
ranking of documents
$d_1 \sim P(r \mid q, d_1)$
$d_2 \sim P(r \mid q, d_2)$
$\vdots$
$d_n \sim P(r \mid q, d_n)$

New Approach = Learning to Rank



Training Process



Testing Process

$$q_{m+1}\begin{cases} d_{m+1,1} \\ d_{m+1,2} \\ \vdots \\ d_{m+1,n_{m+1}} \end{cases} \quad q_{m+1}\begin{cases} d_{m+1,1} & y_{m+1,1} \\ d_{m+1,2} & y_{m+1,2} \\ \vdots & \\ d_{m+1,n_{m+1}} & y_{m+1,n_{m+1}} \end{cases} \quad \begin{cases} x_{m+1,1} & y_{m+1,1} \\ x_{m+1,2} & y_{m+1,2} \\ \vdots & \\ x_{m+1,n_{m+1}} & y_{m+1,n_{m+1}} \end{cases}$$

1. Data Labeling (rank) →

2. Feature Extraction →

3. Ranking with $f(x)$ →

$$\begin{cases} x_{m+1,1} & f(x_{m+1,1}) & y_{m+1,1} \\ x_{m+1,2} & f(x_{m+1,2}) & y_{m+1,2} \\ \vdots & & \\ x_{m+1,n_{m+1}} & f(x_{m+1,n_{m+1}}) & y_{m+1,n_{m+1}} \end{cases}$$

→

4. Evaluation →

Evaluation Result

Notes

- Features are functions of query and document
- Query and associated documents form a group
- Groups are i.i.d. data
- Feature vectors within group are not i.i.d. data
- Ranking model is function of features
- Several data labeling methods (here labeling of rank as example)

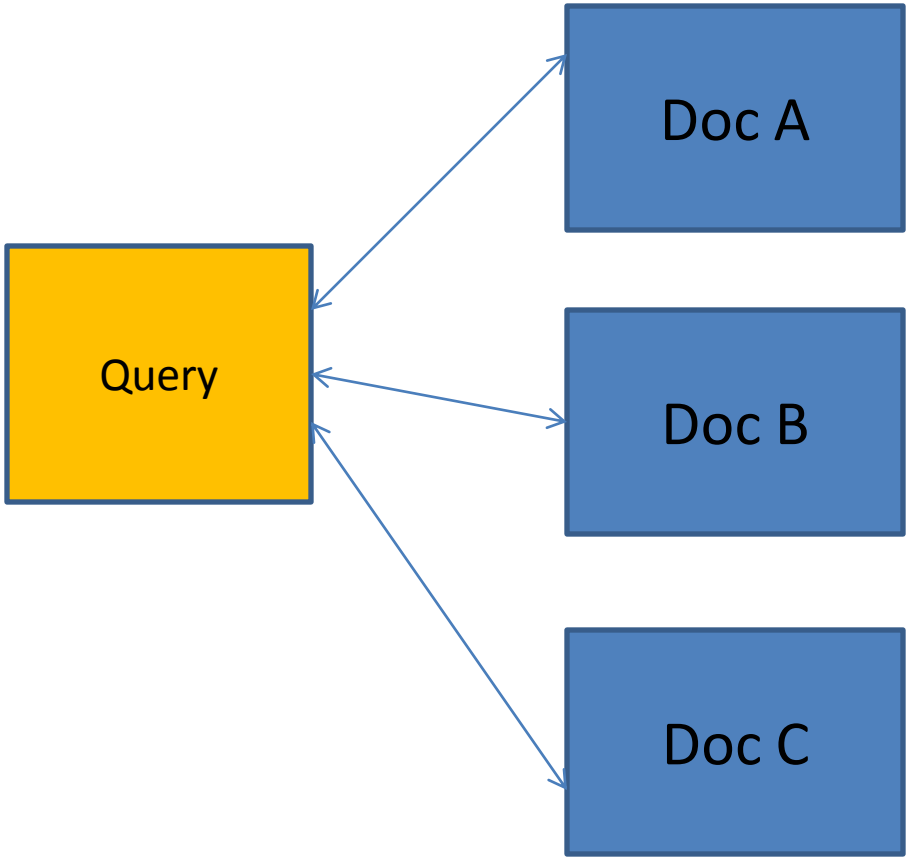
2.3 Issues in Learning to Rank

Issues in Learning to Rank

- Data Labeling
- Feature Extraction
- Evaluation Measure
- Learning Method (Model, Loss Function, Algorithm)

Data Labeling Problem

- E.g., relevance of documents w.r.t. query

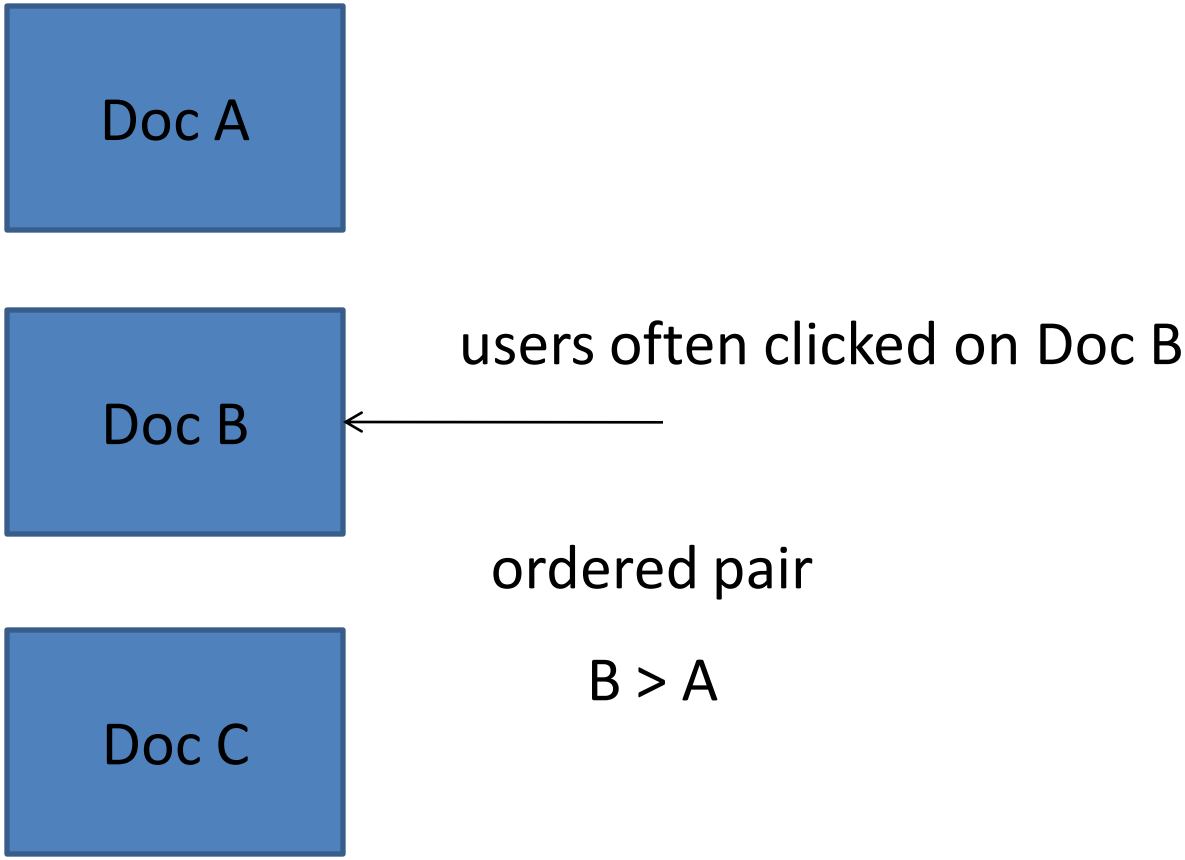


Data Labeling Methods

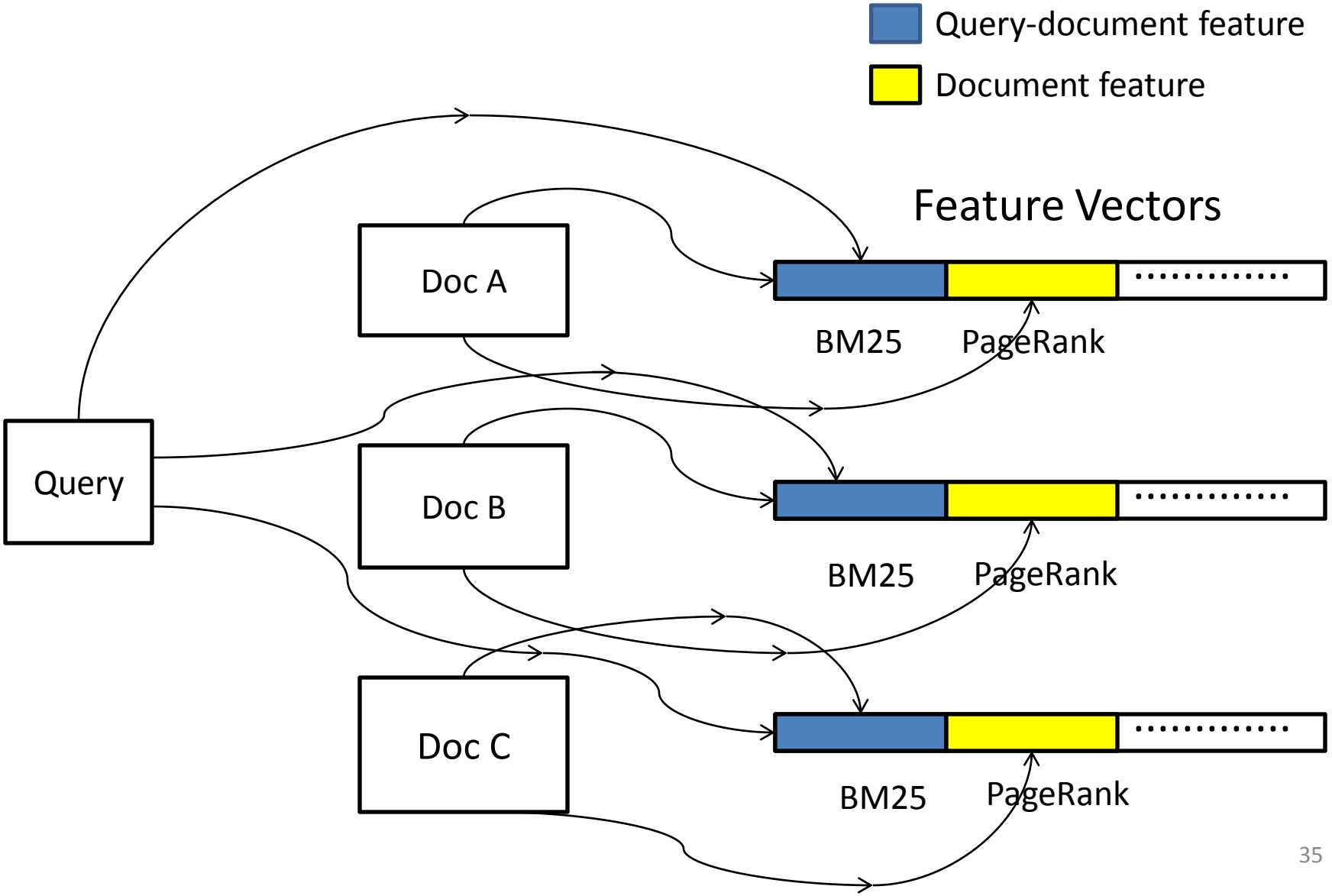
- Labeling of Ranks
  - Multiple levels (e.g., relevant, partially relevant, irrelevant)
  - Widely used in IR
- Labeling of Ordered Pairs
  - Ordered pairs between documents (e.g. A>B, B>C)
  - Implicit relevance judgment: derived from click-through data
- Creation of List
  - List (or permutation) of documents is given
  - Ideal but difficult to implement

Implicit Relevance Judgment

ranking of documents at search system



Feature Extraction



Example Features

- Relevance: BM25
- Relevance: proximity
- Relevance: query exactly occurs in document
- Importance: PageRank

Evaluation Measures

- Important to rank top results correctly
- Measures
  - NDCG (Normalized Discounted Cumulative Gain)
  - MAP (Mean Average Precision)
  - MRR (Mean Reciprocal Rank)
  - WTA (Winners Take All)
  - Kendall's Tau

NDCG

- Evaluating ranking using labeled ranks
- NDCG at position *j*

$$\frac{1}{n_j}\sum_{i=1}^{j}(2^{r(i)}-1)/\log(1+i)$$

NDCG (cont')

- Example: perfect ranking
  - (3, 3, 2, 2, 1, 1, 1) rank *r=3,2,1*
  - (7, 7, 3, 3, 1, 1, 1) gain $2^{r(j)}-1$
  - (1, 0.63, 0.5, 0.43, 0.39, 0.36, 0.33) position discount $1/\log(1+j)$
  - (7, 18.11, 24.11, …) DCG

$$\sum_{i=1}^{j}(2^{r(i)}-1)/\log(1+i)$$

  - (1/7, 1/18.11, 1/24.11, …) normalizing factor n_j
  - (1, 1,1,1,1,1,1) NDCG for perfect ranking

NDCG (cont’)

- Example: imperfect ranking
  - (2, 3, 2, 3, 1, 1, 1)
  - (3, 7, 3, 7, 1, 1, 1) Gain
  - (1, 0.63, 0.5, 0.43, 0.39, 0.36, 0.33) Position discount
  - (3, 14.11, 20.11, …) DCG
  - (0.43, 0.78, 0.83, ….) NDCG

- Imperfect ranking decreases NDCG

2.4 Relations with Other Learning Tasks

Relations with Other Learning Tasks

- No need to predict category
  - vs Classification
- No need to predict value of $f(q,d)$
  - vs Regression
- Relative ranking order is more important
  - vs Ordinal regression
- *Learning to rank can be approximated by classification, regression, ordinal regression*

Ordinal Regression (Ordinal Classification)

- Categories are ordered
  - 5, 4, 3, 2, 1
  - e.g., rating restaurants
- Prediction
  - Map to ordered categories

3. Learning to Rank Methods

Learning to Rank Methods

- 3.1 Overview of Learning to Rank Methods
- 3.2 Pairwise Classification
- 3.3 Cost-sensitive Pairwise Classification
- 3.4 Probabilistic Model for Ranking
- 3.5 Direct Optimization of Evaluation Measure
- 3.6 Approximation of Evaluation Measure
- 3.7 Evaluation Results

3.1 Overview of Learning to Rank Methods

Three Major Approaches

- Pointwise approach
- Pairwise approach
- Listwise approach

- First is suitable to ordinal regression
- Latter two are more suitable to learning to rank (e.g., ranking in search)

Pointwise Approach

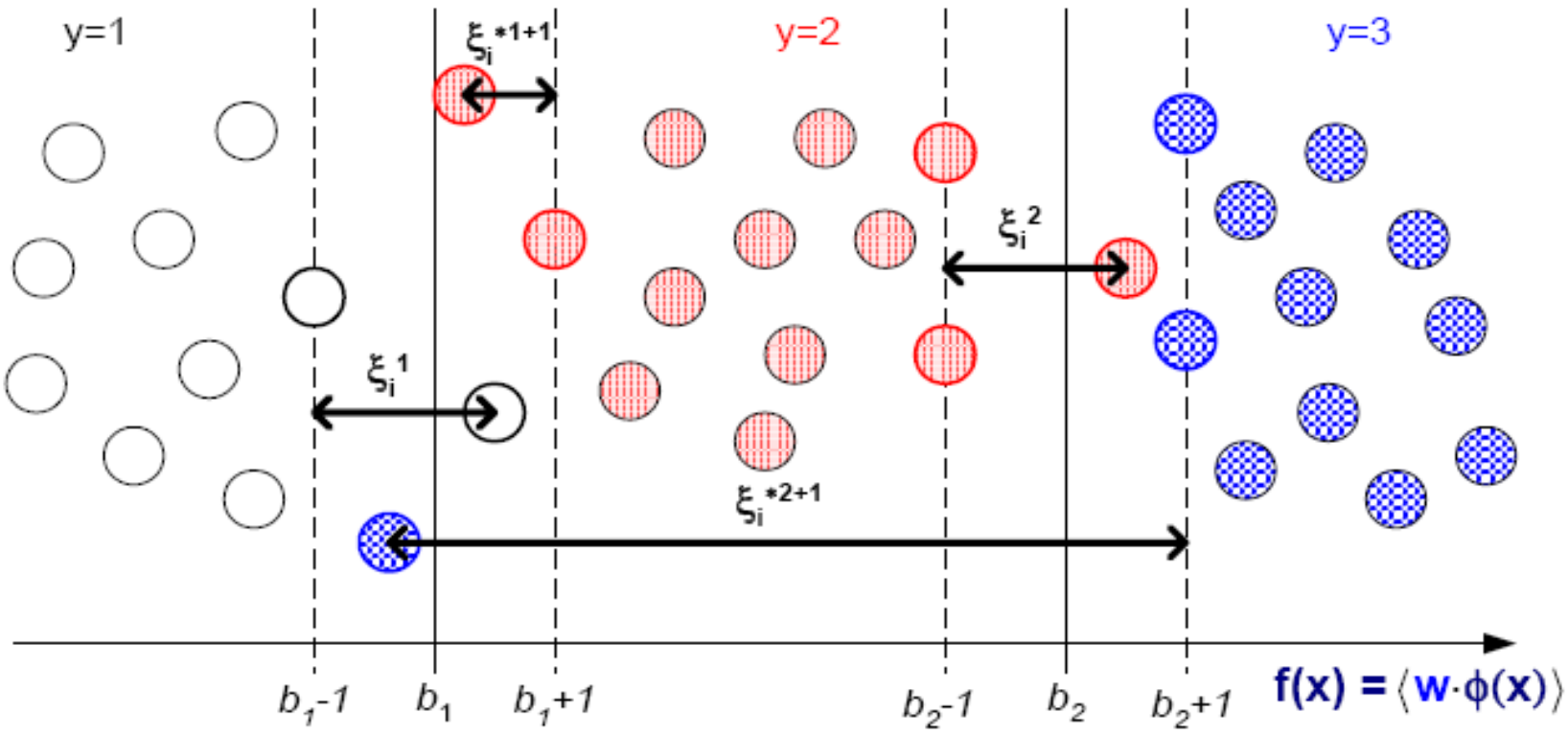
- Transforming ranking to regression, classification, or ordinal regression
- Query-document group structure is ignored

Pointwise Approach

	Learning		
	Regression	**Classification**	**Ordinal Regression**
Input	Feature vector x		
Output	Real number $y = f(x)$	Category $y = \text{classifier}(x)$	Ordered category $y = \text{thresold}(f(x))$
Model	Ranking function $f(x)$		
Loss Function	Regression loss	Classification loss	Ordinal regression loss

Point-wise learning

- Goal is to learn a threshold to separate each rank



Pointwise Approach

	Ranking
Input	$\mathbf{x} = \{x_i\}_{i=1}^{n}$
Output	Permutation on vectors $\boldsymbol{\pi} = \mathrm{sort}(\{f(x_i)\}_{i=1}^{n})$
Model	Ranking function $f(x)$
Loss Function	Ranking evaluation measure

Pairwise Approach

- Transforming ranking to pairwise classification
- Query-document group structure is ignored

Pairwise Approach

	Learning	Ranking
Input	Ordered feature vector pair $(x_i, x_j), x_i > x_j$	Feature vectors $\mathbf{x} = \{x_i\}_{i=1}^{n}$
Output	Classification on order of vector pair $y_{i,j} = \text{classifier}\,(x_i - x_j)$	Permutation on vectors $\boldsymbol{\pi} = \text{sort}(\{f(x_i)\}_{i=1}^{n})$
Model	Ranking function $f(x)$	
Loss Function	Pairwise classification loss	Ranking evaluation measure

Listwise Approach

- List as instance
- Query-document group structure is used
- Straightforwardly represents learning to rank problem

Listwise Approach

	Learning & Ranking
Input	Feature vectors $\mathbf{x} = \{x_i\}_{i=1}^{n}$
Output	Permutation on feature vectors $\boldsymbol{\pi} = \mathrm{sort}(\{f(x_i)\}_{i=1}^{n})$
Model	Ranking function $f(x)$
Loss Function	Listwise loss function (ranking evaluation measure)

Learning to Rank Methods

- Pointwise Approach
  - Subset Ranking [Cossock and Zhang, 2006]: Regression
  - SVM [Nallapati, 2004]: Binary Classification Using SVM
  - McRank [Li et al 2007]: Multi-Class Classification Using Boosting Tree
  - Prank [Crammer and Singer 2002]: Ordinal Regression Using Perceptron
  - Large Margin [Shashua & Levin 2002]: Ordinal Regression Using SVM

Learning to Rank Methods

- Pairwise Approach
  - Ranking SVM: Pairwise Classification Using SVM
  - RankBoost [Freund et al 2003]: Pairwise Classification Using Boosting
  - RankNet [Burges et al 2005]: Pairwise Classification Using Neural Net
  - Frank [Tsai et al 2007]: Pairwise Classification Using Fidelity Loss and Neural Net
  - GBRank [Zheng et al 2007]: Pairwise Regression Using Boosting Tree
  - IR SVM [Cao et al 2006]: Cost-sensitive Pairwise Classification Using SVM
  - Multiple SVMs [Qin et al 2007]: Multiple SVMs

Learning to Rank Methods

- Listwise Approach
  - ListNet [Cao et al 2007]: Probabilistic Ranking Model
  - ListMLE [Xia et al 2008]: Probabilistic Ranking Model
  - AdaRank [Xu and Li 2007]: Direct Optimization of Evaluation Measure
  - SVM Map [Yue et al 2007]: Direct Optimization of Evaluation Measure
  - PermuRank [Xu et al 2008]: Direct Optimization of Evaluation Measure
  - Soft Rank [Taylor et al 2008]: Approximation of Evaluation Measure
  - Lambda Rank [Burges et al 2007]: Using Implicit Loss Function

Learning to Rank Methods

- Other Methods
  - K-Nearest Neighbor Ranker [Geng et al 2008]
  - Semi-Supervised Learning [Jin et al 2008]

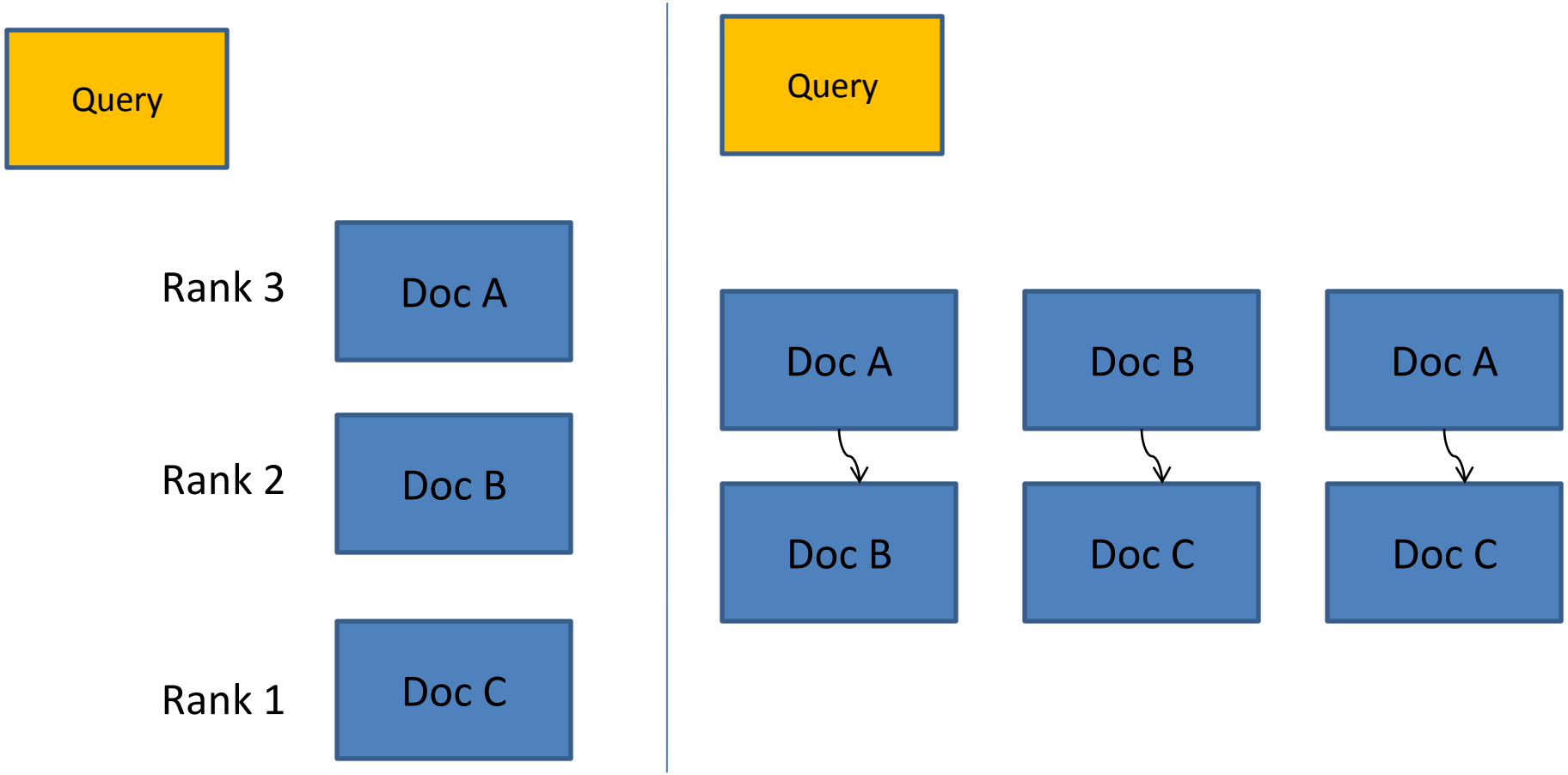
3.2 Pairwise Classification

Pairwise Classification Methods

- Ranking SVM
- RankBoost
- RankNet

Pairwise Classification

- Converting document list to document pairs



Ranking SVM

Transforming Ranking to Pairwise Classification

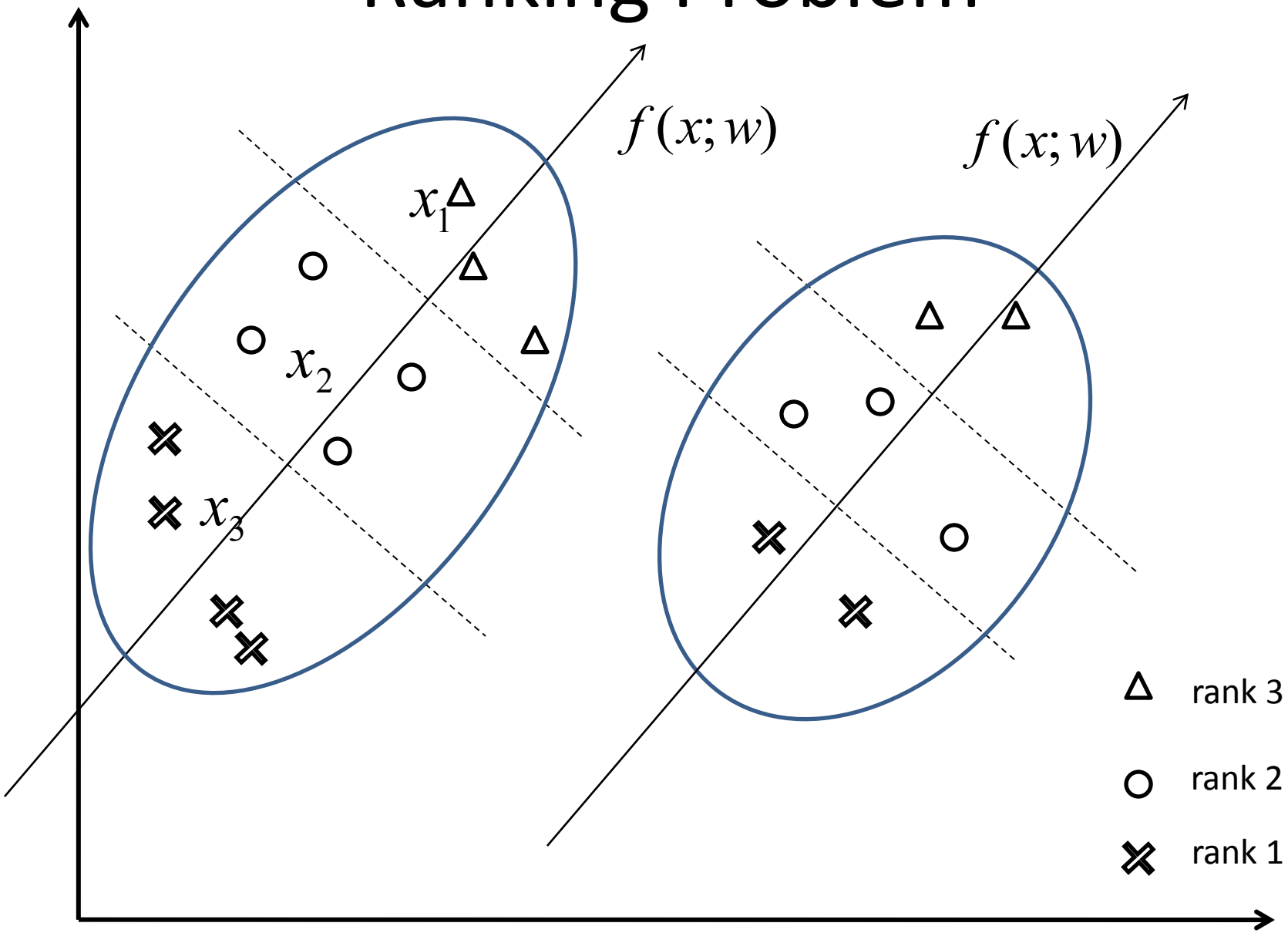
- Input space: *X*
- Ranking function $f : X \to R$
- Ranking: $x_i \succ x_j \;\Leftrightarrow\; f(x_i; w) > f(x_j; w)$
- Linear ranking function: $f(x; w) = \langle w, x \rangle$

$$\langle w, x_i - x_j \rangle > 0 \quad \Leftrightarrow \quad f(x_i; w) > f(x_j; w)$$

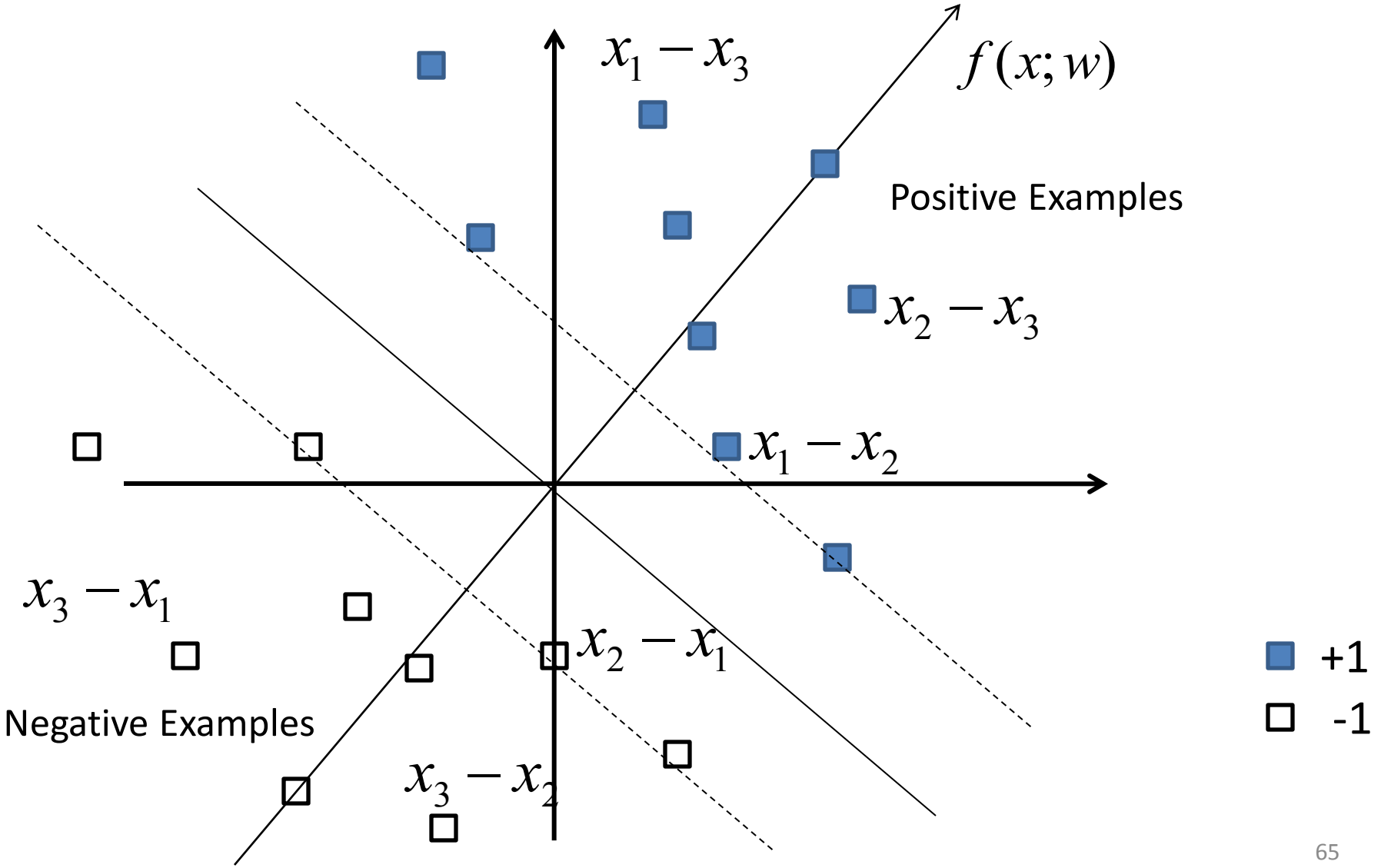
- Transforming to pairwise classification:

$$(x_i - x_j, z),\ z = \begin{cases} +1 & x_i \succ x_j \\ -1 & x_j \succ x_i \end{cases}$$

Ranking Problem



Transformed Pairwise Classification Problem



Ranking SVM

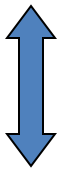
- Pairwise classification on differences of feature vectors
- Corresponding positive and negative examples
- Negative examples are redundant and can be discarded
- Hyper plane passes the origin
- Soft Margin and Kernel can be used
- *Ranking SVM* = pairwise classification SVM

Learning of Ranking SVM

$$\min_{w,\xi} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{l} \xi_i$$

$$z_i \left\langle w, x_i^{(1)} - x_i^{(2)} \right\rangle \geq 1 - \xi_i \quad i = 1, \cdots, l$$

$$\xi_i \geq 0$$



$$\min_{w} \sum_{i=1}^{l} \left[1 - z_i \left\langle w, x_i^{(1)} - x_i^{(2)} \right\rangle \right]_+ + \lambda \| w \|^2$$

$$[s]_+ = \max(0, s) \quad \lambda = \frac{1}{2C}$$

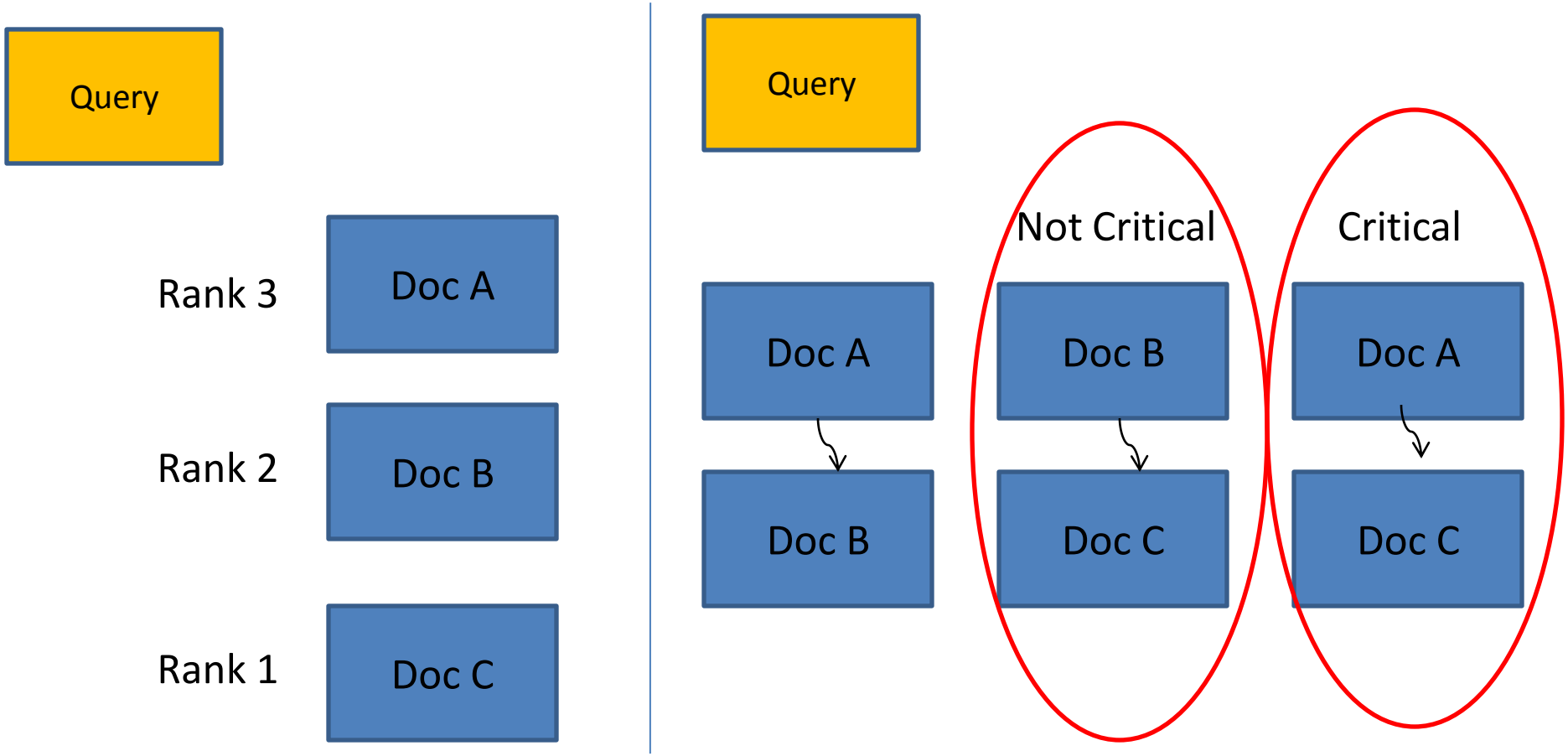
3.3 Cost-sensitive Pairwise Classification

Cost-Sensitive Pairwise Classification Methods

- IR SVM
- Multiple SVMs

Cost-sensitive Pairwise Classification

- Converting to document pairs



IR SVM

Problems with Ranking SVM

- Not sufficient emphasis on correct ranking on top

  Ranks: 3, 2, 1

  ranking 1: 2 3 2 1 1 1 1

  ranking 2: 3 2 1 2 1 1 1

  ranking 2 should be better than ranking 1

  Ranking SVM views them as the same

- Numbers of pairs vary according to queries

  q1: 3 2 2 1 1 1 1

  q2: 3 3 2 2 2 1 1 1 1 1

  number of pairs for q1 : 2*(2-2) + 4*(3-1) + 8*(2-1) = 14

  number of pairs for q2: 6*(3-2) + 10*(3-1) + 15*(2-1) = 31

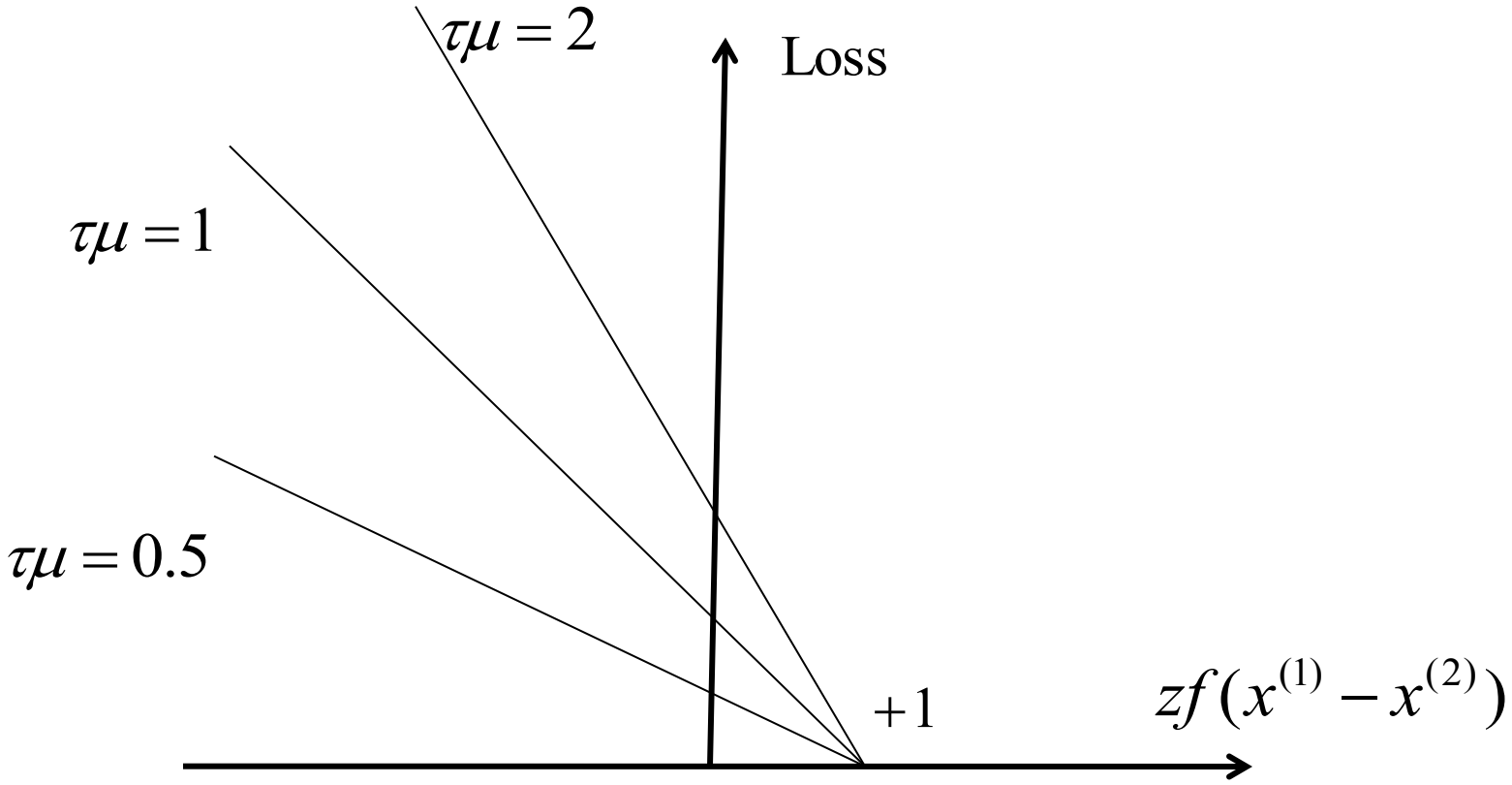
  Ranking SVM is biased toward q2

IR SVM

- Solving the two problems of Ranking SVM
- Higher weight on important rank pairs $\tau_{k(i)}$
- Normalization weight on pairs in query $\mu_{q(i)}$
- IR SVM = Ranking SVM using modified hinge loss

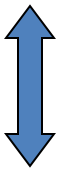
Modified Hinge Loss function

$$\min_{w} \sum_{i=1}^{l} \tau_{k(i)} \mu_{q(i)} \left[1 - z_i \left\langle w, x_i^{(1)} - x_i^{(2)} \right\rangle \right]_+ + \lambda \| w \|^2$$



Learning of IR SVM

$$\min_{w} \sum_{i=1}^{l} \tau_{k(i)} \mu_{q(i)} \left[1 - z_i \left\langle w, x_i^{(1)} - x_i^{(2)} \right\rangle \right]_+ + \lambda \| w \|^2$$



$$\min_{w,\xi} \frac{1}{2} \| w \|^2 + \sum_{i=1}^{l} C_i \xi_i$$

$$z_i \left\langle w, x_i^{(1)} - x_i^{(2)} \right\rangle \geq 1 - \xi_i \quad i = 1, \cdots, l$$

$$\xi_i \geq 0$$

$$C_i = \frac{\tau_{k(i)} \mu_{q(i)}}{2\lambda}$$

3.4 Probabilistic Model for Ranking

Methods of Using Probabilistic Models

- ListNet
- ListMLE

ListNet and ListMLE

Plackett-Luce Model (Permutation Probability)

- Probability of permutation π is defined as

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

- Example:

$$P(\mathrm{ABC}) = \frac{s_A}{s_A + s_B + s_C} \cdot \frac{s_B}{s_B + s_C} \cdot \frac{s_C}{s_C}$$

P(A ranked No.1)

P(B ranked No.2 | A ranked No.1)

P(C ranked No.3 | A ranked No.1, B ranked No.2)

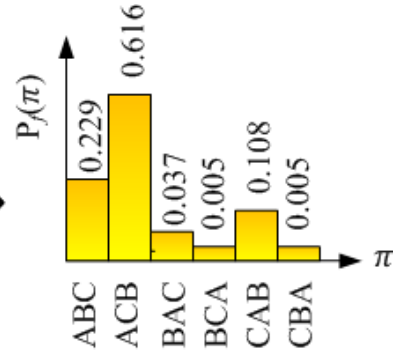
Properties of Plackett-Luce Model

- Objects: ABC
- Scores: $s_{\mathrm{A}} = 5, s_{\mathrm{B}} = 3, s_{\mathrm{C}} = 1$
- Property 1: *P*(ABC) is largest, *P*(CBA) is smallest
- Property 2: swap B and C in ABC, *P*(ABC) > *P*(ACB)

KL Divergence between Permutation Probability Distributions

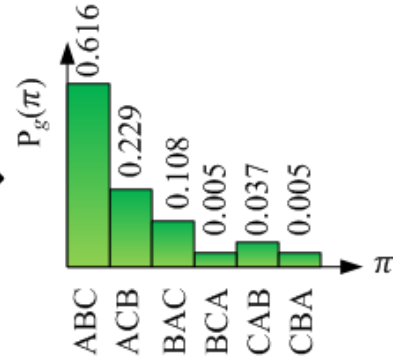
f: $f(\mathrm{A}) = 3, f(\mathrm{B})=0, f(\mathrm{C})=1;$
Ranking by f: ABC

$\leftrightarrow$



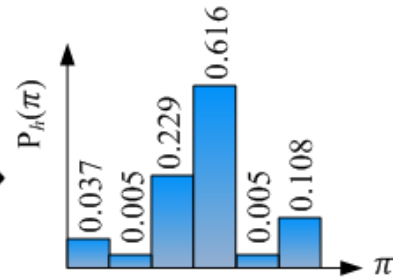
g: $g(\mathrm{A}) = 6, g(\mathrm{B})=4, g(\mathrm{C})=3;$
Ranking by g: ABC

$\leftrightarrow$



h: $h(\mathrm{A}) = 4, h(\mathrm{B})=6, h(\mathrm{C})=3;$
Ranking by h: ACB

$\leftrightarrow$



ListNet

- Parameterized Plackett-Luce Model

$$s = \exp(f(x; w))$$

$$P(G(x_1 \cdots x_k)) = \prod_{i=1}^{k} \frac{s_{x_i}}{\sum_{j=i}^{n} s_{x_j}}$$

- Ranking Model: $f(x; w)$ = Neural Net

ListNet (cont')

- Loss function = KL-divergence between two Top-k probability distributions from ground truth and ranking model

$$L(w) = -\sum_{q \in Q} \sum_{\pi \in \Omega^k} \left(\prod_{i=1}^{k} \frac{\exp(y_i))}{\sum_{j=i}^{n} \exp(y_j)} \right) \log \left(\prod_{i=1}^{k} \frac{\exp(f(x_i; w))}{\sum_{j=i}^{n} \exp(f(x_j; w))} \right)$$

- Algorithm = Gradient Descent

ListMLE

- Parameterized Plackett-Luce Model

$$s = \exp(f(x; w))$$

$$P(G(x_1 \cdots x_k)) = \prod_{i=1}^{k} \frac{s_{x_i}}{\sum_{j=i}^{n} s_{x_j}}$$

- Maximum Likelihood Estimation

$$L(w) = -\sum_{q \in Q} \log \left(\prod_{i=1}^{k} \frac{\exp(f(x_i; w))}{\sum_{j=i}^{n} \exp(f(x_j; w))} \right)$$

Plackett-Luce Model (Top-k Probability)

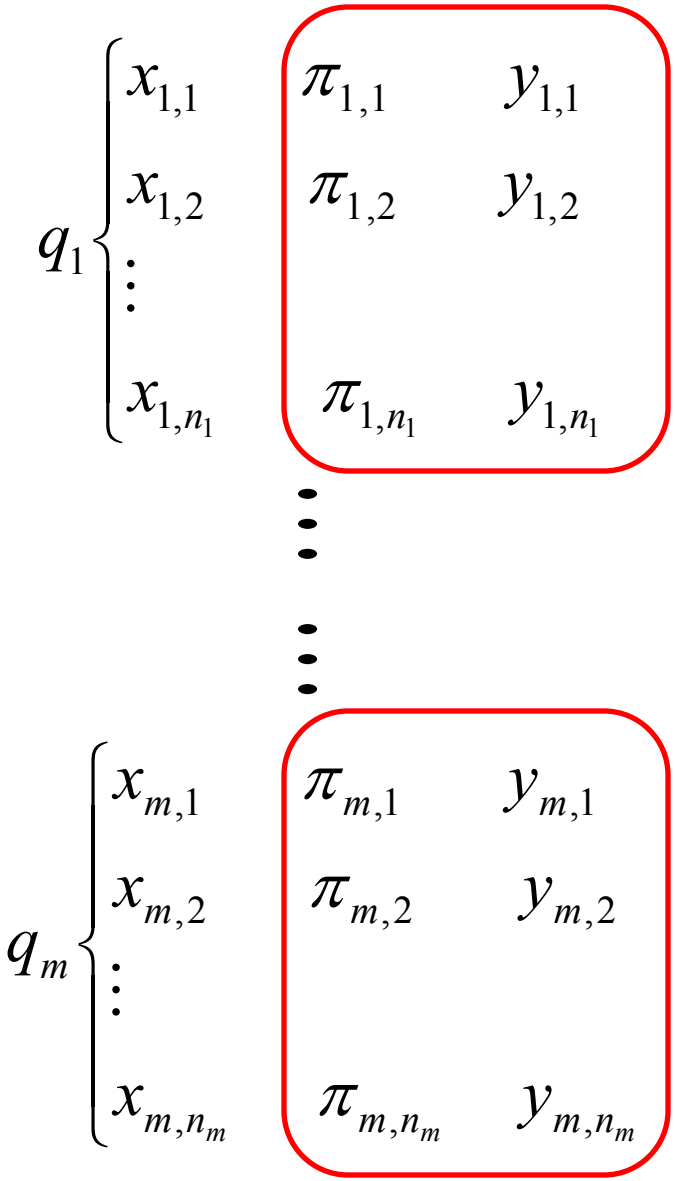
- Computation of permutation probabilities is intractable
- Top-k probability
  - Defining Top-k subgroup $G(o_1 \ldots o_k)$ containing all permutations whose top-k objects are $o_1, \ldots, o_k$
  - $P\big(G\big(o_1 \cdots o_k\big)\big) = \prod_{i=1}^{k} \frac{s_{o_i}}{\sum_{j=i}^{n} s_{o_j}}$
  - Time complexity of computation : from $n!$ to $n!/(n-k)!$
- Example: $P\big(G(\mathrm{A})\big) = \frac{s_A}{s_A + s_B + s_C}$

3.5 Direct Optimization of Evaluation Measures

Direction Optimization Methods

- AdaRank
- PermuRank
- SVM MAP

Listwise Loss



$$\max_{f \in \mathcal{F}} \sum_{i=1}^{m} E(\pi(q_i, \mathbf{d}_i, f), \mathbf{y}_i)$$

$$\min_{f \in \mathcal{F}} \sum_{i=1}^{m} (1 - E(\pi(q_i, \mathbf{d}_i, f), \mathbf{y}_i))$$

AdaRank, SVM-MAP, PermuRank

- Optimizing different upper bounds (surrogate loss functions)

$$\sum_{i=1}^{m} (1 - E(\pi(q_i, \mathbf{d}_i, f), \mathbf{y}_i))$$

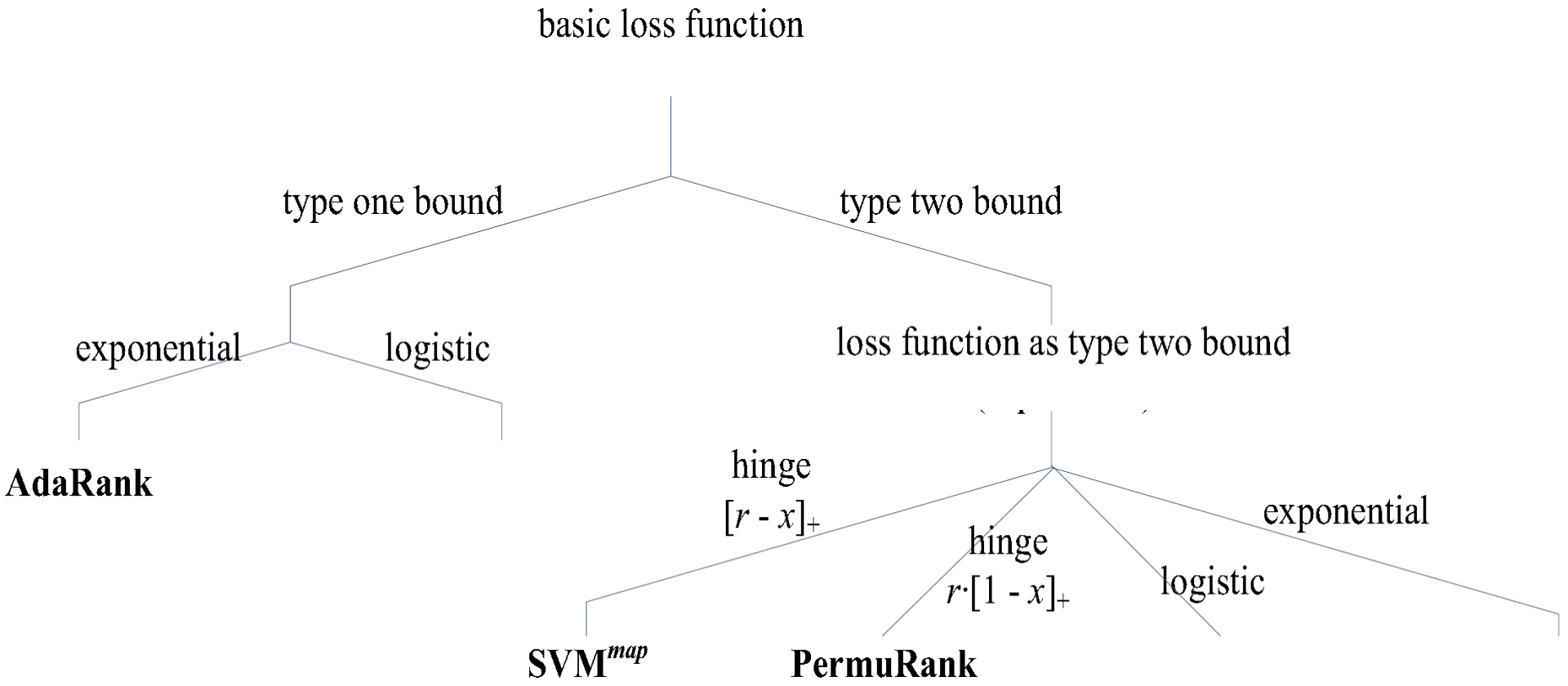
- Type One Upper Bound

$$\sum_{i=1}^{m} \exp\{-E(\pi_i, \mathbf{y}_i)\} \qquad \sum_{i=1}^{m} \log_2 \left(1 + e^{-E(\pi_i, \mathbf{y}_i)}\right)$$

- Type Two Upper Bound

$$\sum_{i=1}^{m} \max_{\pi_i^* \in \Pi_i^*; \pi_i \in \Pi_i \setminus \Pi_i^*} ((E(\pi_i^*, \mathbf{y}_i) - E(\pi_i, \mathbf{y}_i)) \cdot [\![(F(q_i, \mathbf{d}_i, \pi_i^*) \leq F(q_i, \mathbf{d}_i, \pi_i))]\!])$$

Relations between Upper Bounds



AdaRank

AdaRank

- Optimizing exponential loss function
- Algorithm: AdaBoost-like algorithm for ranking

Loss Function of AdaRank

$$\max_{f \in \mathcal{F}} \sum_{i=1}^{m} E(\pi(q_i, \mathbf{d}_i, f), \mathbf{y}_i)$$

Any evaluation measure taking value between [-1,+1]

$$\min_{f \in \mathcal{F}} \sum_{i=1}^{m} (1 - E(\pi(q_i, \mathbf{d}_i, f), \mathbf{y}_i))$$

$$e^{-x} \geq 1 - x$$

$$\min_{f \in \mathcal{F}} \sum_{i=1}^{m} \exp\{-E(\pi(q_i, \mathbf{d}_i, f), \mathbf{y}_i)\}$$

$$f(\vec{x}) = \sum_{t=1}^{T} \alpha_t h_t(\vec{x})$$

$$\min_{h_t \in \mathcal{H}, \alpha_t \in \Re^+} L(h_t, \alpha_t) = \sum_{i=1}^{m} \exp\{-E(\pi(q_i, \mathbf{d}_i, f_{t-1} + \alpha_t h_t), \mathbf{y}_i)\}$$

AdaRank Algorithm

Input: $S = \{(q_i, \mathbf{d}_i, \mathbf{y}_i)\}_{i=1}^{m}$, and parameters E and T
Initialize $P_1(i) = 1/m$.
For $t = 1, \cdots, T$

- Create weak ranker h_t with weighted distribution $\boldsymbol{P}_t$ on training data S.
- Choose α_t

$$\alpha_t = \frac{1}{2} \cdot \ln \frac{\sum_{i=1}^{m} P_t(i)\{1 + E(\pi(q_i, \mathbf{d}_i, h_t), \mathbf{y}_i)\}}{\sum_{i=1}^{m} P_t(i)\{1 - E(\pi(q_i, \mathbf{d}_i, h_t), \mathbf{y}_i)\}}.$$

- Create f_t

$$f_t(\vec{x}) = \sum_{k=1}^{t} \alpha_k h_k(\vec{x}).$$

- Update $\boldsymbol{P}_{t+1}$

$$P_{t+1}(i) = \frac{\exp\{-E(\pi(q_i, \mathbf{d}_i, f_t), \mathbf{y}_i)\}}{\sum_{j=1}^{m} \exp\{-E(\pi(q_j, \mathbf{d}_j, f_t), \mathbf{y}_j)\}}.$$

End For
Output ranking model: $f(\vec{x}) = f_T(\vec{x})$.

Theoretical Results on AdaRank

- Training error will be continuously reduced during learning phase.

THEOREM 1. *The following bound holds on the ranking accuracy of the AdaRank algorithm on training data:*

$$\frac{1}{m}\sum_{i=1}^{m} E(\pi(q_i, \mathbf{d}_i, f_T), \mathbf{y}_i) \geq 1 - \prod_{t=1}^{T} e^{-\delta^t_{min}} \sqrt{1-\varphi(t)^2},$$

where $\varphi(t) = \sum_{i=1}^{m} P_t(i) E(\pi(q_i, \mathbf{d}_i, h_t), \mathbf{y}_i)$, $\delta^t_{min} = \min_{i=1,\cdots,m} \delta^t_i$, *and*

$$\delta^t_i = E(\pi(q_i, \mathbf{d}_i, f_{t-1} + \alpha_t h_t), \mathbf{y}_i) - E(\pi(q_i, \mathbf{d}_i, f_{t-1}), \mathbf{y}_i) - \alpha_t E(\pi(q_i, \mathbf{d}_i, h_t), \mathbf{y}_i),$$

for all $i = 1, 2, \cdots, m$ *and* $t = 1, 2, \cdots, T$.

SVM MAP

Global Ranking Function

$$\sigma_i = \arg\max_{\sigma \in \Pi_i} F(q_i, \mathbf{d}_i, \sigma).$$

$$F(q_i, \mathbf{d}_i, \pi_i) = w^\top \Phi(q_i, \mathbf{d}_i, \pi_i),$$

$$\Phi(q_i, \mathbf{d}_i, \pi_i) = \frac{1}{n(q_i) \cdot (n(q_i) - 1)} \sum_{k,l:k<l} [z_{kl}(\phi(q_i, d_{ik}) - \phi(q_i, d_{il}))],$$

Equivalent to ranking with local ranking function (plus sorting)

$$f(q_i, d_{ij}) = w^T \phi(q_i, d_{ij})$$

Ranking with Global Function

$$f_A = w^T \phi_A, \quad f_B = w^T \phi_B, \quad f_C = w^T \phi_C$$

$$f_A > f_B > f_C$$

- ABC $F_{ABC} = \frac{1}{6}\left((f_A - f_B) + (f_B - f_C) + (f_A - f_C)\right)$
- ACB $F_{ACB} = \frac{1}{6}\left((f_A - f_C) + (f_C - f_B) + (f_A - f_B)\right)$

$$F_{ABC} > F_{ACB}$$

Type Two Bound

$$R(F) = \sum_{i=1}^{m} (E(\pi_i^*, \mathbf{y}_i) - E(\pi_i, \mathbf{y}_i)) = \sum_{i=1}^{m} (1 - E(\pi_i, \mathbf{y}_i)),$$

$$\sum_{i=1}^{m} \max_{\pi_i^* \in \Pi_i^*; \pi_i \in \Pi_i \setminus \Pi_i^*} ((E(\pi_i^*, \mathbf{y}_i) - E(\pi_i, \mathbf{y}_i)) \cdot [\![(F(q_i, \mathbf{d}_i, \pi_i^*) \leq F(q_i, \mathbf{d}_i, \pi_i))]\!]),$$

SVM MAP

$$\sum_{i=1}^{m} \left[\max_{\pi_i^* \in \Pi_i^*; \pi_i \in \Pi_i \setminus \Pi_i^*} ((E(\pi_i^*, \mathbf{y}_i) - E(\pi_i, \mathbf{y}_i)) \right.$$

$$\left. - (F(q_i, \mathbf{d}_i, \pi_i^*) - F(q_i, \mathbf{d}_i, \pi_i)))\right]_+ + \lambda \parallel \vec{w} \parallel^2 .$$

$$\min_{\vec{w}; \xi \geq 0} \frac{1}{2}\|\vec{w}\|^2 + \frac{C}{m}\sum_{i=1}^{m} \xi_i$$

$$s.t. \quad \forall i, \forall \pi_i^* \in \Pi_i^*, \forall \pi_i \in \Pi_i \setminus \Pi_i^* :$$

$$F(q_i, \mathbf{d}_i, \pi_i^*) - F(q_i, \mathbf{d}_i, \pi_i) \geq E(\pi_i^*, \mathbf{y}_i) - E(\pi_i, \mathbf{y}_i) - \xi_i,$$

3.6 Approximation of Evaluation Measures

Method based on Approximation of Evaluation Measure

- SoftRank
- LambdaRank

SoftRank

SoftRank

- Evaluation measures are not smooth, due to use of sorting
- Probabilistically approximate evaluation measures (Soft NDCG)
- Model: Neural Net
- Algorithm: Gradient Descent

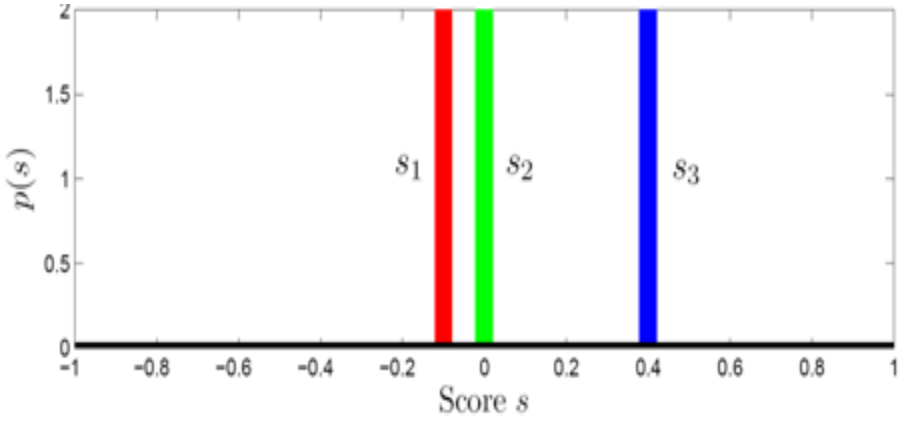
SoftRank Algorithm

- Calculate score distributions of documents
- Calculate position distributions of documents
- Compute SoftNDCG
- Optimize SoftNDCG by Gradient Descent

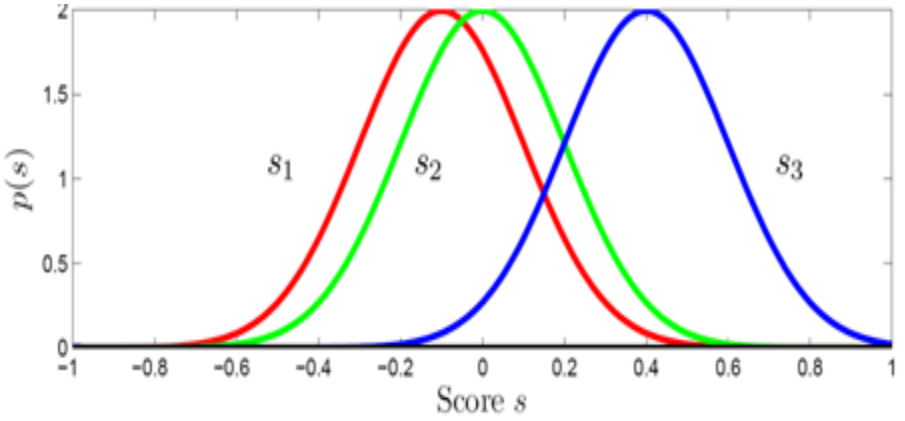
Score Distribution of Document

- Assuming that score of document s_j follows Gaussian distribution

$$p(s_j) = N(s_j \mid f(x_j), \sigma_s^2)$$



Deterministic Score



Probabilistic Score

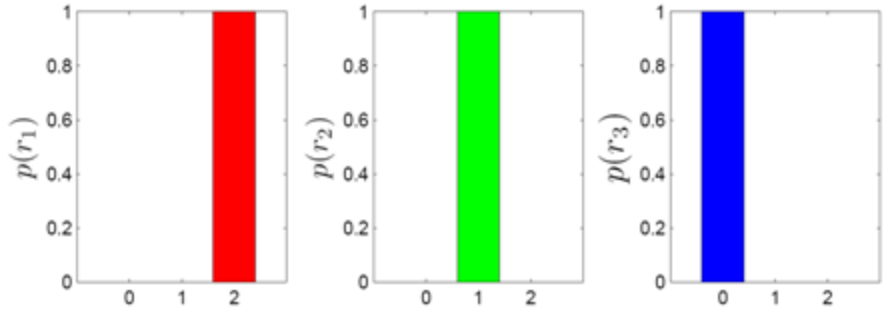
Position Distribution of Document

- Probability of document *i* being ranked before document *j*

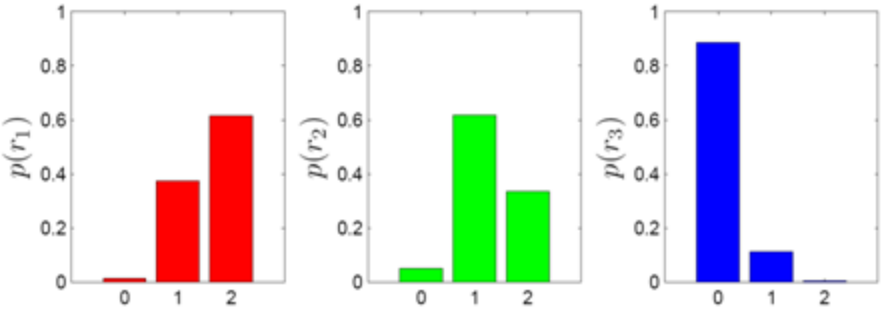
$$\pi_{ij} = \int_0^{\infty} N(s \mid f(x_i) - f(x_j), 2\sigma^2) ds$$

- Position distribution of document (recursive definition)

$$p_j^{(i)}(r) = p_j^{(i-1)}(r-1)\pi_{ij} + p_j^{(i-1)}(r)(1-\pi_{ij})$$



Deterministic Position Distribution



Probabilistic Position Distribution

Soft NDCG

- Re-writing NDCG as document (feature vector) indexed

$$G = G_{max}^{-1} \sum_{j=1}^{N} g(j) D(r_j).$$

- Only position discount is affected by ranking model
- Assume that positions of document are probabilistically determined by ranking model, rather than deterministically

Soft NDCG (cont')

- Soft NDCG

$$\mathcal{G} = G_{max}^{-1} \sum_{j=1}^{N} g(j) E[D(r_j)].$$

$$\mathcal{G} = G_{max}^{-1} \sum_{j=1}^{N} g(j) \sum_{r=0}^{N-1} D(r) p_j(r)$$

- Only need to calculate probabilities of positions of document $p_j(r)$

3.7 Evaluation Results

LETOR Data Set

- Available at
  - http://research.microsoft.com/~letor/
- Data Corpora: TREC, OHSUMED
- Training/Validation/Test split
- Standard IR Features

Evaluation Results

- Pairwise approach and listwise approach perform better than pointwise approach
- Listwise approach performs better than pairwise approach in most cases
- Listwise approach
  - ListMLE, ListNet, AdaRank, PermuRank, SVM-MAP
- Pairwise approach
  - Ranking SVM, RankNet, RankBoost
- Pointwise approach
  - Linear Regression

4. Learning to Rank Theory

Learning to Rank Theory

- 4.1 Generalization Analysis of Pairwise Methods
- 4.2 Generalization Analysis of Listwise Methods

Learning to Rank Theory

- Pairwise Approach
  - Generalization Analysis [Lan et al 2008]
- Listwise Approach
  - Generalization Analysis [Lan et al 2009]
  - Consistency Analysis [Xia et al 2008]

4.1 Generalization Analysis of Pairwise Methods

Pairwise Learning Framework (Query Level)

- Data is represented as $(z^{(q)}, y^{(q)})$, where $z^{(q)}$ is pair of feature vectors $(x_1^{(q)}, x_2^{(q)})$ and $y^{(q)}$ is ground-truth on their order, w.r.t. query *q*
- (z, y) are random variables according to distribution $P(\cdot,\cdot)$
- Training Data: $S = (q_1, S_1) \cdots (q_m, S_m)$

$$S_i = \left\{(z_1^{(i)}, y_1^{(i)}), \cdots, (z_{n_i}^{(i)}, y_{n_i}^{(i)})\right\}, i = 1, \cdots m$$

- Expected Risk:

$$R_l(f) = \int_Q L(f, q) P_Q(dq) \quad L(f, q) = \int_{X^2 \times Y} l(f; z^{(q)}, y^{(q)}) D_q(dz^{(q)}, dy^{(q)})$$

- Empirical Risk:

$$\hat{R}_l(f; S) = \frac{1}{m} \sum_{i=1}^{m} \hat{L}(f; q_i) \qquad \hat{L}(f; q_i) = \frac{1}{n_i} \sum_{j=1}^{n_i} l(f; z_j^{(i)}, y_j^{(i)})$$

Generalization Analysis

- Goal = to minimize expected risk $R_l(f)$
- Distribution is unknown we instead minimize empirical risk $\hat{R}_l(f;S)$
- Generalization analysis is concerned with upper bound of difference between expected and empirical risks

Generalization Analysis Using Stability

- With probability at least $1-\delta$

$$R_l(f) \le \hat{R}_l(f;S) + 2\tau(m) + \left(4m\tau(m) + B\right)\sqrt{\frac{\ln 1/\delta}{2m}}$$

- The bound is related to number of training queries *m*, and stability of algorithm
- If $\tau(m)$ goes to 0 very fast when *m* approaches infinity, then the bound will be tight.

Stability of Ranking SVM and IRSVM

- Ranking SVM

$$\tau(m) = \frac{4\kappa^2}{\lambda m} \frac{1 + \frac{\sigma}{\mu\sqrt{\delta/m}}}{1 - \frac{\varepsilon}{\mu}} = O\left(\frac{1}{\sqrt{m}}\right)$$

- IR SVM

$$\tau(m) = \frac{4\kappa^2}{\lambda m} = O\left(\frac{1}{m}\right)$$

- IR SVM > Ranking SVM

4.2 Generalization Analysis of Listwise Methods

Listwise Learning Framework

- Data is represented as (z, y), where z is feature vector set $z = (x_1, \cdots, x_n)$ and y is ground-truth permutation
- (z, y) are random variables according to distribution $P(\cdot,\cdot)$
- Training Data: $(z_1, y_1), \cdots, (z_m, y_m)$
- Expected Risk:

$$R_l(f) = \int_{Z \times Y} l(f; z, y) P(dz, dy)$$

- Empirical Risk:

$$R_l(f; S) = \frac{1}{m} \sum_{i=1}^{m} l(f; z_i, y_i)$$

Generalization Analysis

- Goal = to minimize expected risk $R_{l_A}(f)$
- Distribution is unknown we instead minimize empirical risk $\hat{R}_{l_A}(f;S)$
- Generalization analysis is concerned with upper bound of difference between expected and empirical risks

$$\sup(R_{l_A}(f) - \hat{R}_{l_A}(f;S))$$

Generalization Analysis Using Rademacher Complexity

- With probability at least $1-\delta$

$$\sup(R_{l_A}(f) - \hat{R}_{l_A}(f;S)) \leq \frac{4BM}{\sqrt{m}} C_A(\phi) N(\phi) + \sqrt{\frac{2\ln 2/\delta}{m}}$$

- The bound is related to:
  - $C_A(\phi)$, algorithm-dependent factor, determined by loss function and transformation function ϕ
  - $N(\phi)$, algorithm-independent factor, only determined by transformation function ϕ
  - when n approaches infinity, generalization bound vanishes at rate of $O(\frac{1}{\sqrt{m}})$.

Generalization Analysis Using Rademacher Complexity (cont')

- ListMLE

$$C_{ListMLE}(\phi) = \frac{2}{\phi(-BM)(\log n + \log \frac{\phi(BM)}{\phi(-BM)}}$$

- ListNet

$$C_{ListNet}(\phi) = \frac{2n!}{\phi(-BM)(\log n + \log \frac{\phi(BM)}{\phi(-BM)}}$$

- ListMLE > ListNet

5. Learning to Rank Applications

Learning to Rank Applications

- Search [Burges et al 2005]
- Recommender System [Freund et al 2003]
- Key Phrase Extraction [Jiang et al 2009]

Recommender System (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
- Solutions
  - Classification
  - Ordinal Regression
  - Learning to Rank

Recommender System

	Item1	**Item2**	**Item3**	**...**	
User1	5	4			
User2	1		2		2
...		?	?	?	
UserM	4	3			

Recommender System Using RankBoost

- Ranking items according to users
- Justification: users tend to rate on different scales
- Method: RankBoost
- Result: RankBoost > Nearest Neighbor

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 Using Ranking SVM

- Ranking of phrases as keyphrases
- Justification: keyphrase or non-keyphrase is relative
- Method: Ranking SVM
- Result: Ranking SVM > SVM

6. Future Directions of Learning to Rank Research

New Issues to be Further Studied

- Learning from implicit data
  - Automatically generate labeled data from implicit feedback
- Model (feature) learning
  - Automatically learn features such as BM25
- Global ranking
  - Using features of current document as well as relations with other documents

New Issues to be Further Studied (cont')

- Query-dependent ranking
  - Creating different ranking models for different queries (in search)
- New applications
  - Machine Translation, etc

7. Summary

Content of Tutorial

- Introduction
- Learning to Rank Problem
- Learning to Rank Methods
- Learning to Rank Theory
- Learning to Rank Applications
- Future Directions of Learning to Rank Research

Takeaway Message

- Learning to Rank = branch of Machine Learning
- Learning to Rank = learning for ranking objects given subject
- Learning to Rank is different from ordinal regression
- Learning to Rank has been successfully applied to search
- Existing approaches: pointwise, pairwise, listwise

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