Lecture 16: Supervised Methods, Neural Networks and Learning to Rank

Information Retrieval

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Slides Courtesy: Learning to Rank Tutorial

Categorization/Classification

Given:

- A representation of a document d
- A fixed set of classes: $\mathrm{C} = \{\mathrm{c}_1, \mathrm{c}_2, \ldots, \mathrm{c}_\mathrm{J}\}$

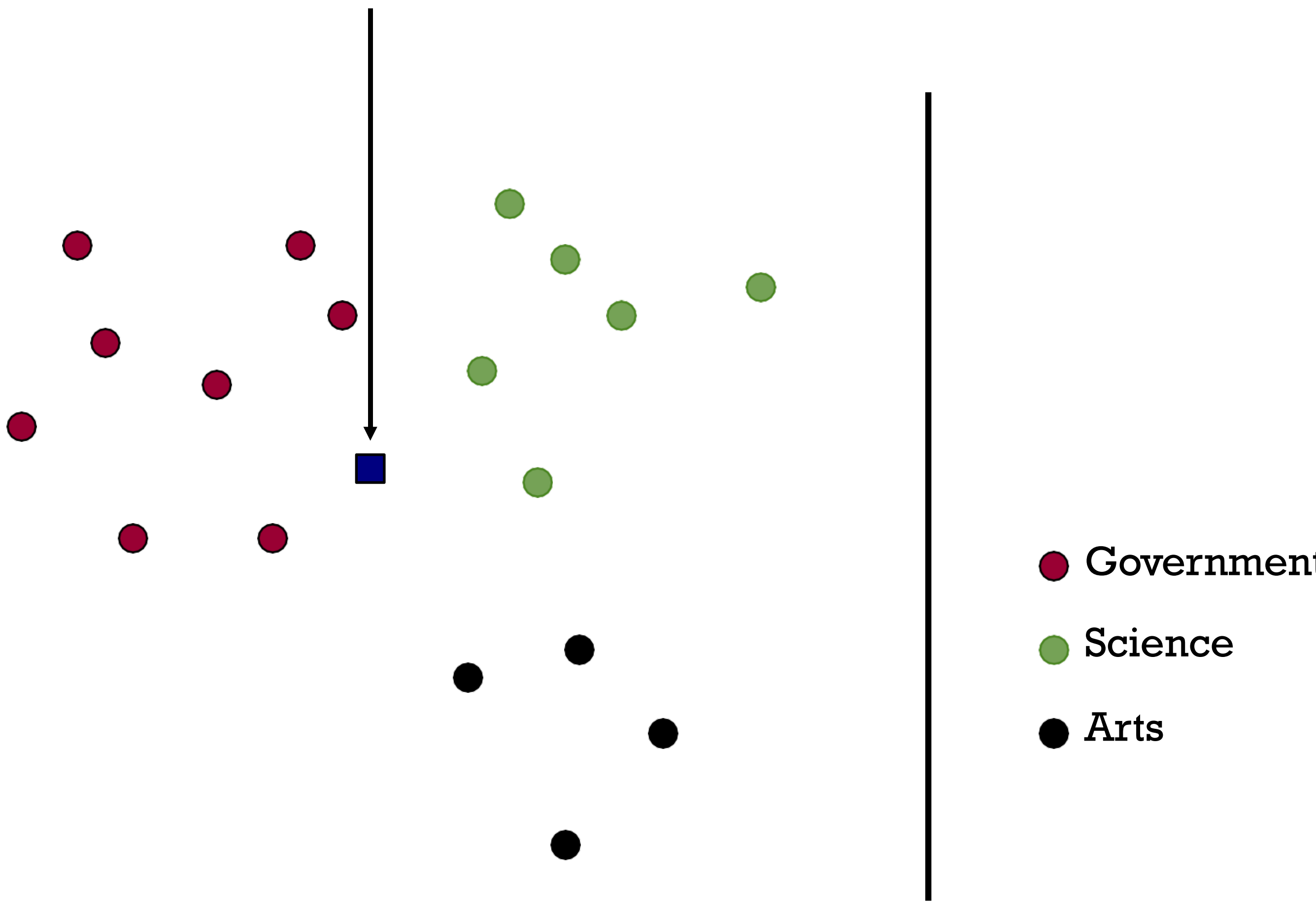
Determine:

- The category of d: $\gamma(\mathrm{d}) \in \mathrm{C}$, where $\gamma(\mathrm{d})$ is a classification function

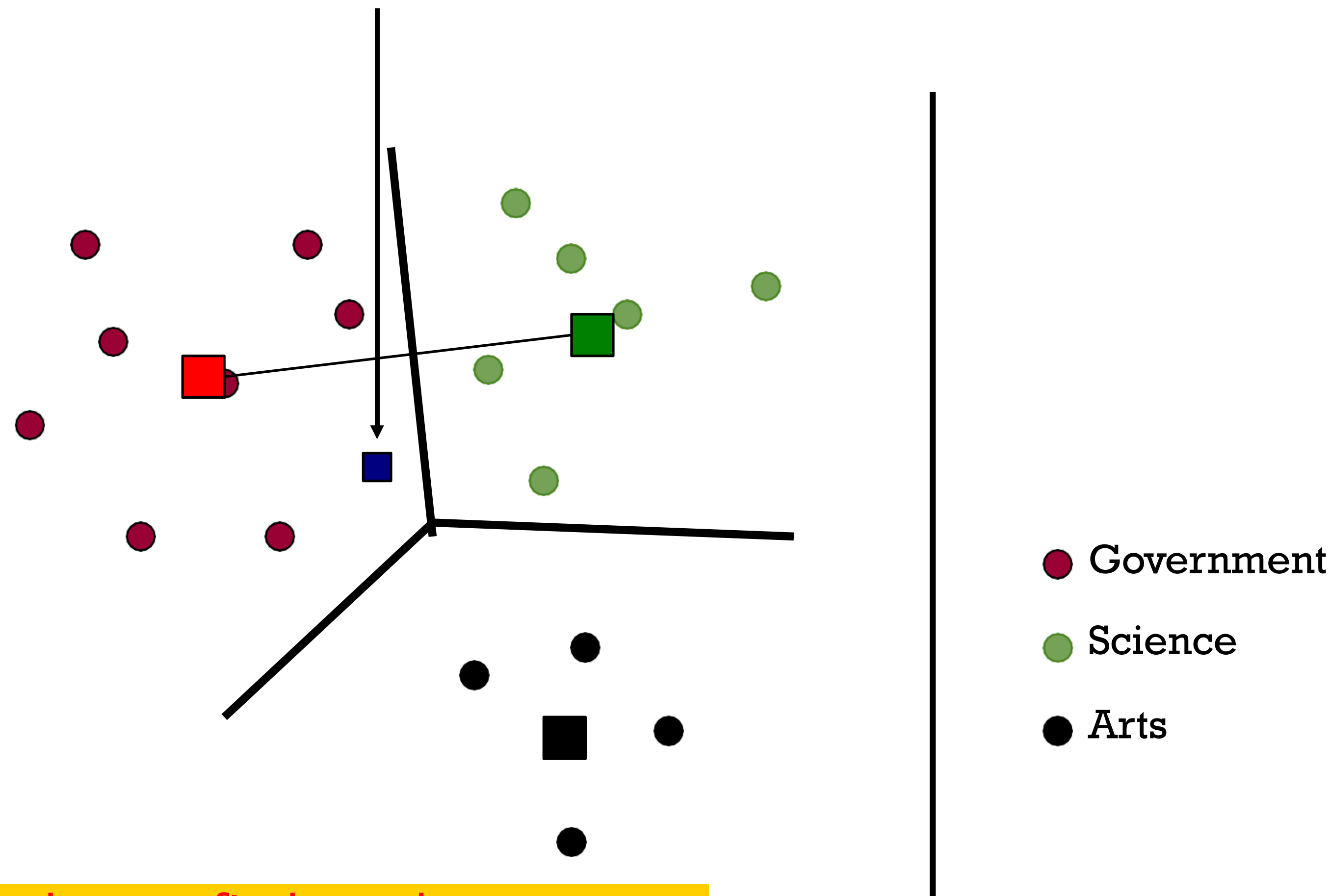
Problem:

- We want to learn classification functions ("classifiers").

Test Document of what class?



Test Document = Government



Our focus: how to find good separators

Machine learning for IR ranking?

We learnt

- Methods for ranking documents in IR
  - Cosine similarity, inverse document frequency, BM25, proximity, pivoted document length normalization, Pagerank, …
- Supervised learning problems

- **RQ: Can we can use *machine learning* to rank the documents displayed in search results?**
  - Known as “machine-learned relevance” or “learning to rank”
  - Actively researched and used by Web search engines

Simple example: Using classification for ad hoc IR

Collect a training corpus of (q, d, r) triples

- Relevance r is here binary (but may be multiclass, with 3–7 values)
- Query-Document pair is represented by a feature vector
- Train a machine learning model to predict the class r of a document-query pair

- Problems With this:
  - Classification problems: Map to an unordered set of classes
  - Regression problems: Map to a real value
  - Ordinal regression (or "ranking") problems: Map to an *ordered* set of classes

"Learning to rank"

- Assume a number of categories **C** of relevance exist
  - These are totally ordered: $c_1 < c_2 < \ldots < c_J$
  - This is the ordinal regression setup

- Assume training data is available consisting of document
  - query pairs (d, q) represented as feature vectors x_i with
  - relevance ranking c_i

LEARNING TO RANK

Learning to rank (L2R)

Defnition
- "... the task to automatically construct a ranking model using training data, such that the model can *sort new objects* according to their degrees of relevance, preference, or importance." - Liu [2009]

L2R models represent
- a rankable item e.g., a document, given
- some context, e.g., a query

as a numerical vector $\vec{x} \in \mathbb{R}^n$.

The model f: $\vec{x} \rightarrow \mathbb{R}$ s.t. $f(\vec{x}_R) > f(\vec{x}_{NR})$
- **trained** to map the vector to a real-valued score such that relevant items are scored higher

Approaches

Based on training objectives [Liu 2009]:

- Pointwise approach: Relevance label $y_{q,d}$ is a number
  - Supervision: binary or graded human judgments or implicit user feedback (e.g., CTR).
  - Classification/regression to predict $y_{q,d}$, given $\vec{x}_{q,d}$.

- Pairwise approach: pairwise preference between documents for a query ($d_i \succ_q d_j$) as label.
  - Supervision: pairwise preference
  - Task: Given $\langle q, d_i, d_j \rangle$, predict 1 (if d_i is preferred) or 0 otherwise.

- Listwise approach: optimize for rank-based metric, such as NDCG
  - difficult because these metrics are often not differentiable w.r.t. model parameters.

Features

Traditional L2R models employ hand-crafted features

They can often be categorized as:

- Query-independent or static features (e.g., incoming link count and document length)

- Query-dependent or dynamic features (e.g., BM25)

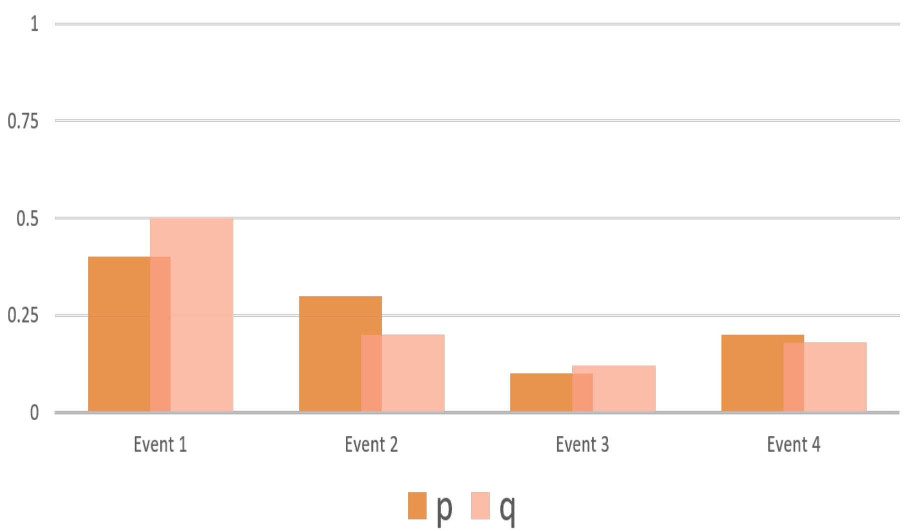
- Query-level features (e.g., query length)

Refresher: Cross-entropy

- The cross entropy between two probability distributions p and q over a discrete set of events is given by,

$$CE(p, q) = -\sum_i p_i \log(q_i)$$

- Single-label classification: $CE(p, q) = -\log(q_{correct})$



Refresher: CE with softmax

- Cross entropy with softmax is a popular loss function for classification

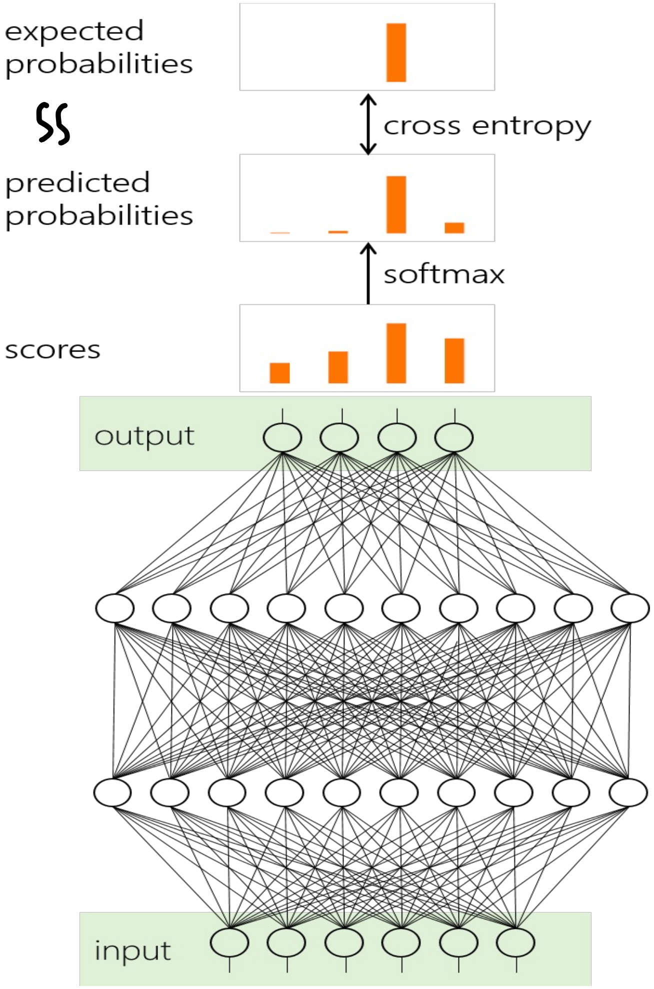
$$q(z_i) = \frac{e^{z_i}}{\sum_z e^z}$$

$$CE(p,q) = -\sum_i p_i \log(q_i)$$

- Shorthand:

$$\mathcal{L}_{CE} = -\log\left(\frac{e^{z_{correct}}}{\sum_{z \in Z} e^z}\right)$$

Where did the summation go?



L2R Loss Functions

PointWise Loss

PairWise Loss

ListWise Approaches

Pointwise Loss

Regression-based or classification-based approaches are popular

- Regression loss
  - Given $\langle q, d \rangle$ predict the value of $y_{q,d}$
  - E.g., square loss for binary or categorical labels,

$$L_{Squared} = \left\| y_{q,d} - f\left(\vec{x}_{q,d}\right) \right\|^2$$

  - where, $y_{q,d}$ is (generally) the actual value of the label

Pointwise Loss

Regression-based or classification-based approaches are popular

- Classification loss
  - Given $\langle q, d \rangle$ predict the value of $y_{q,d}$
  - E.g., Cross-Entropy with Softmax over categorical labels Y,

$$L_{CE}(q, d, y_{q,d}) = -\log\left(p(y_{q,d} | q, d)\right) = -\log\left(\frac{e^{s_{y_{q,d}}}}{\sum_{y \in Y} e^{s_y}}\right)$$

  - where, $s_{y_{q,d}}$ is model's score for label $y_{q,d}$

Pairwise Loss

Minimizes the average number of inversions in ranking

- i.e., $d_i \succ_q d_j$ but d_j is ranked higher than d_i

- For $\langle q, d_i \rangle$ and $\langle q, d_j \rangle$ Feature vectors: $\vec{x}_i$ and $\vec{x}_j$
  - Model scores: $s_i = f(\vec{x}_i)$and $s_j = f(\vec{x}_j)$
  - Say, d_i is more relevant.
    - ➔ $s_i > s_j$

- Pairwise loss generally has the following form[Chen et al., 2009],

$$L_{pairwise} = \phi(s_i - s_j)$$

where, ϕ can be,

- Hinge function $\phi(z) = \max(0;\ 1 - z)$
- Logistic function $\phi(z) = \log(1 + e^{-z})$

RankNet

RankNet [Burges et al. 2005] is a pairwise loss function
- popular choice for training Neural L2R models.

Predicted probabilities: $p_{ij} = p(s_i > s_j) \equiv \frac{e^{\gamma \cdot s_i}}{e^{\gamma \cdot s_i} + e^{\gamma \cdot s_j}} = \frac{1}{1+e^{-\gamma(s_i - s_j)}}$

and $p_{ji} \equiv \frac{1}{1+e^{-\gamma(s_j - s_i)}}$

Desired probabilities: $\bar{p}_{ij} = 1$ and $\bar{p}_{ji} = 0$

Computing cross-entropy between $\bar{p}$ and p,

$$\begin{aligned}
\mathcal{L}_{RankNet} &= -\bar{p}_{ij}\log(p_{ij}) - \bar{p}_{ji}\log(p_{ji}) \\
&= -\log(p_{ij}) \\
&= log(1 + e^{-\gamma(s_i - s_j)})
\end{aligned}$$

CE with softmax over Documents

Alternative:

- Assume a single relevant document d^+.
- Compare against full collection D

Probability of retrieving d^+ for q is given by the softmax function,

$$p(d^+|q) = \frac{e^{\gamma \cdot s\left(q, d^+\right)}}{\sum_{d \in D} e^{\gamma \cdot s(q,d)}}$$

The cross entropy loss is then given by,

$$\begin{aligned}\mathcal{L}_{\text{CE}}(q, d^+, D) &= -log\Big(p(d^+|q)\Big) \\ &= -log\Big(\frac{e^{\gamma \cdot s\left(q, d^+\right)}}{\sum_{d \in D} e^{\gamma \cdot s(q,d)}}\Big)\end{aligned}$$

Look at the summation at the bottom.

CE vs RankNet

- If we consider only a pair of relevant and non-relevant documents in the denominator, CE reduces to RankNet

- Computing the denominator is prohibitively expensive -- L2R models typically consider few negative candidates

- Large body of work in NLP to deal with similar issue that may be relevant to future L2R models
  - Importance sampling, negative sampling

ListWise

A Simple Example:

- function f: $f(A)=3, f(B)=0, f(C)=1$ ACB
- function h: $h(A)=4, h(B)=6, h(C)=3$ BAC
- ground truth g: $g(A)=6, g(B)=4, g(C)=3$ ABC

Question: which function is closer to ground truth?

- Based on pointwise similarity: $sim(f,g) < sim(g,h)$.
- Based on pairwise similarity: $sim(f,g) = sim(g,h)$
- Based on cosine similarity between score vectors?

f:<3,0,1> g:<6,4,3> h:<4,6,3>

Sim(f,g)=0.85 *Sim(g,h)=0.93*

- According to position-wise discount f should be closer to g.

Permutation Probability Distribution

Question:

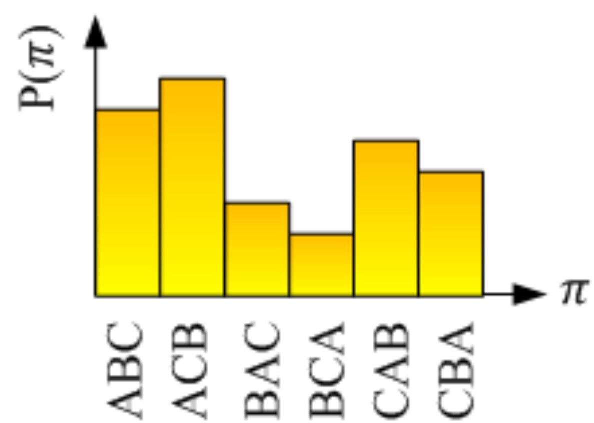
- How to represent a ranked list?

Solution

- Ranked list ←→ Permutation probability distribution
- More informative representation for ranked list: permutation and ranked list has 1-1 correspondence.

f: $f(A)=3$, $f(B)=0$, $f(C)=1$;
Ranking by f: ACB

$\leftrightarrow$



Luce Model: Defining Permutation Probability

- Probability of permutation π is defined as

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

P(ABC) > P(ACB)

- Example:

$$P_f(\text{ABC}) = \boxed{\frac{\varphi(f(\text{A}))}{\varphi(f(\text{A}))+\varphi(f(\text{B}))+\varphi(f(\text{C}))}} \cdot \boxed{\frac{\varphi(f(\text{B}))}{\varphi(f(\text{B}))+\varphi(f(\text{C}))}} \cdot \boxed{\frac{\varphi(f(\text{C}))}{\varphi(f(\text{C}))}}$$

P(A ranked No.1)

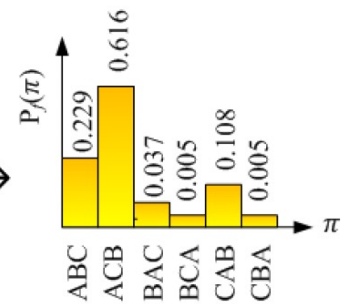
P(B ranked No.2 | A ranked No.1)
= P(B ranked No.1)/(1- P(A ranked No.1))

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

Distance between Ranked Lists

$\varphi = exp$

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

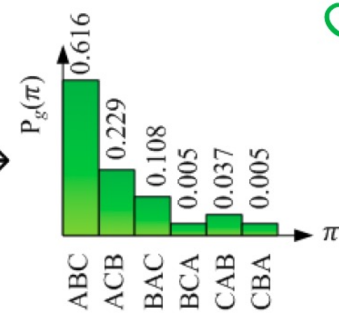


Using **KL-divergence** to measure difference between distributions

$dis(f,g) = 0.46$

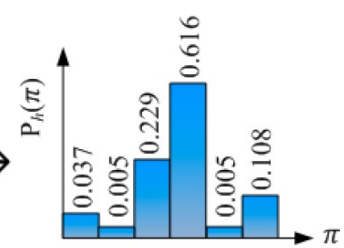
Closer!

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



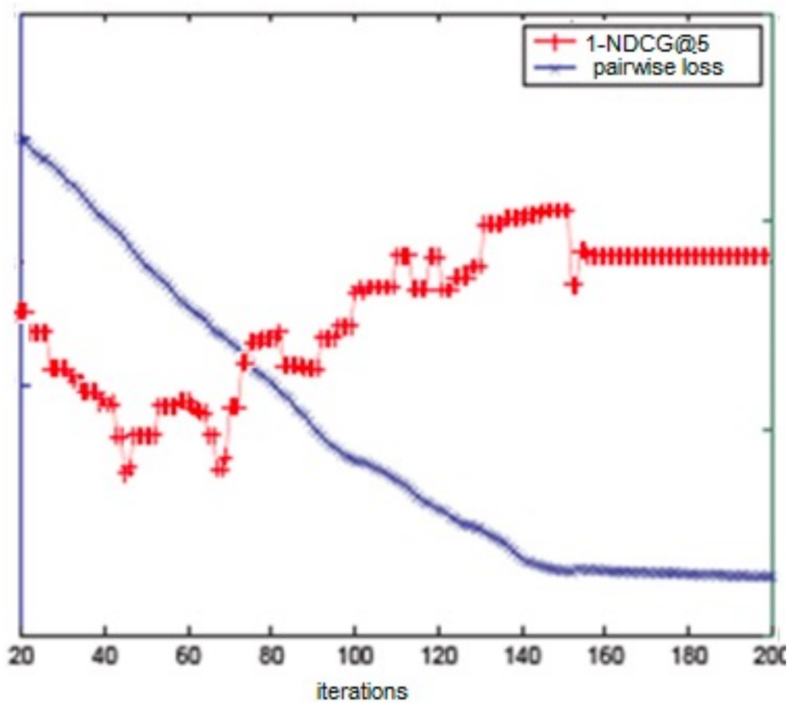
$dis(g,h) = 2.56$

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

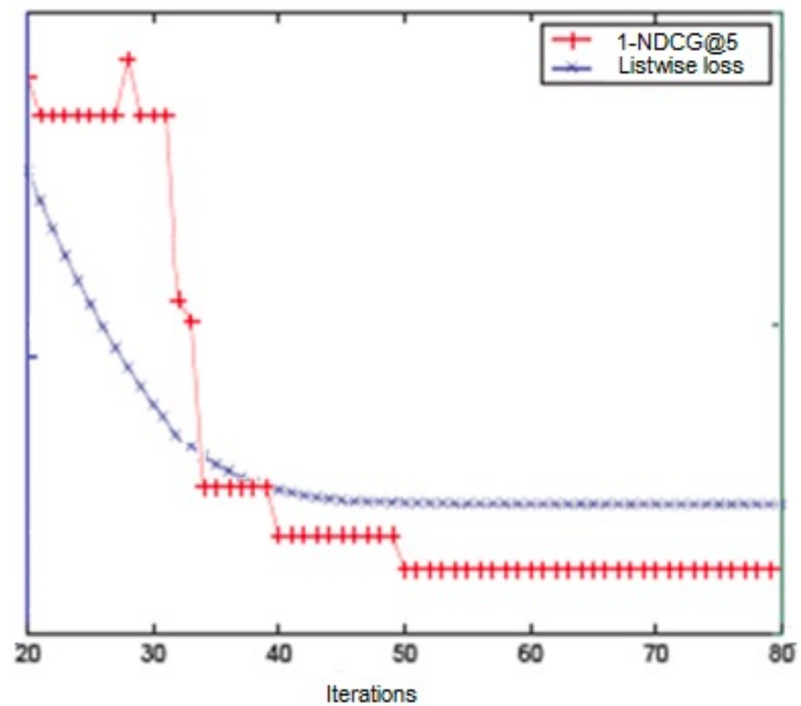


Experimental Results (ListNet)

(Z. Cao, T. Qin, T. Liu, et al. ICML 2007)



Pairwise (RankNet)



ListWise (ListNet)

Training Performance on TD2003 Dataset

ListNet vs ListMLE

ListNet [Cao et al., 2007]

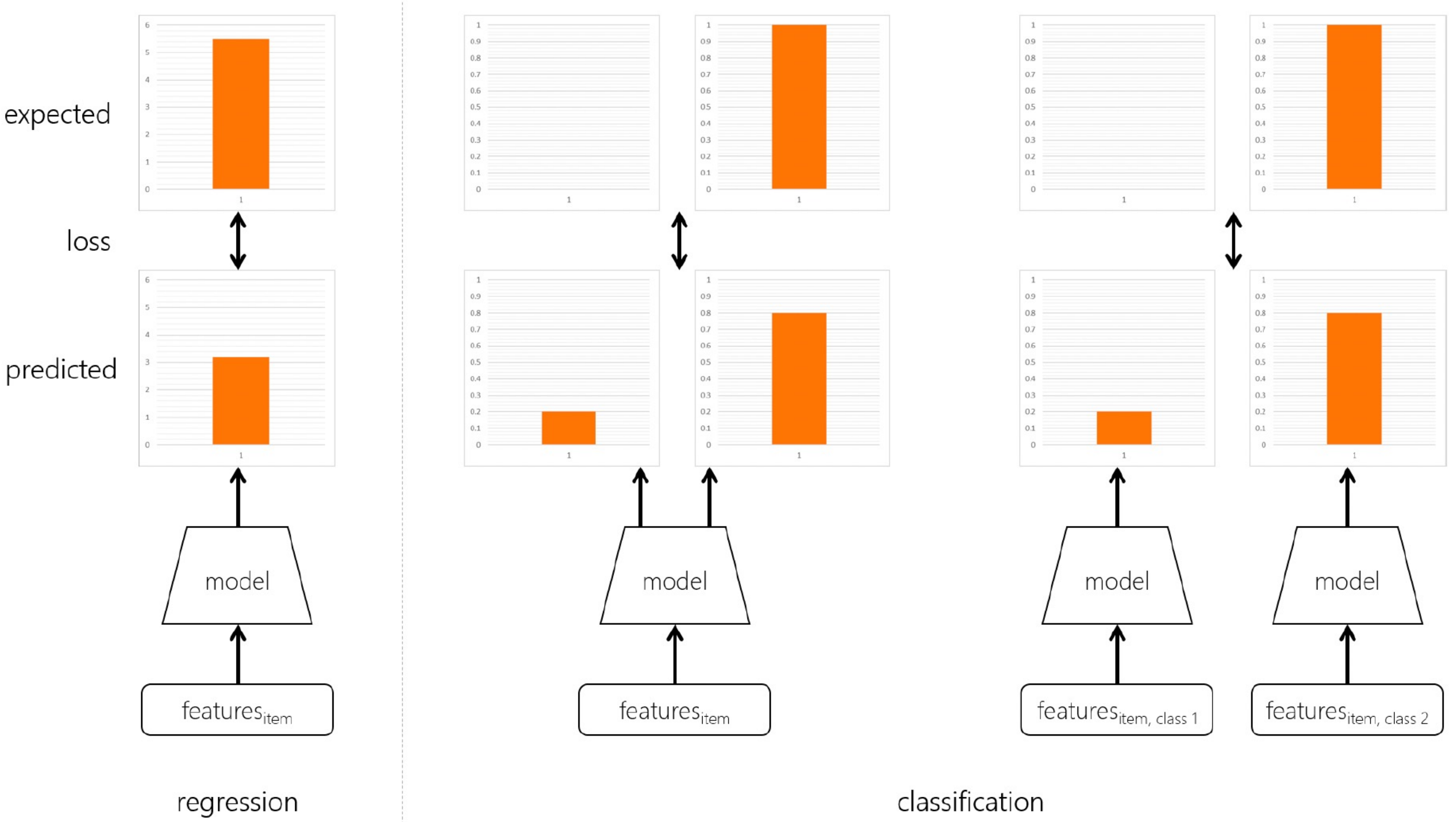
- Compute the **probability distribution over all possible permutations** based on model score and ground-truth labels. The loss is then given by the K-L divergence between these two distributions.
- This is computationally very costly, computing permutations of only the top-K items makes it slightly less prohibitive

ListMLE [Xia et al. 2008]

- Compute the probability of the ideal permutation based on the ground truth. However, with categorical labels more than one permutation is possible which makes this difficult.

Extra Slides

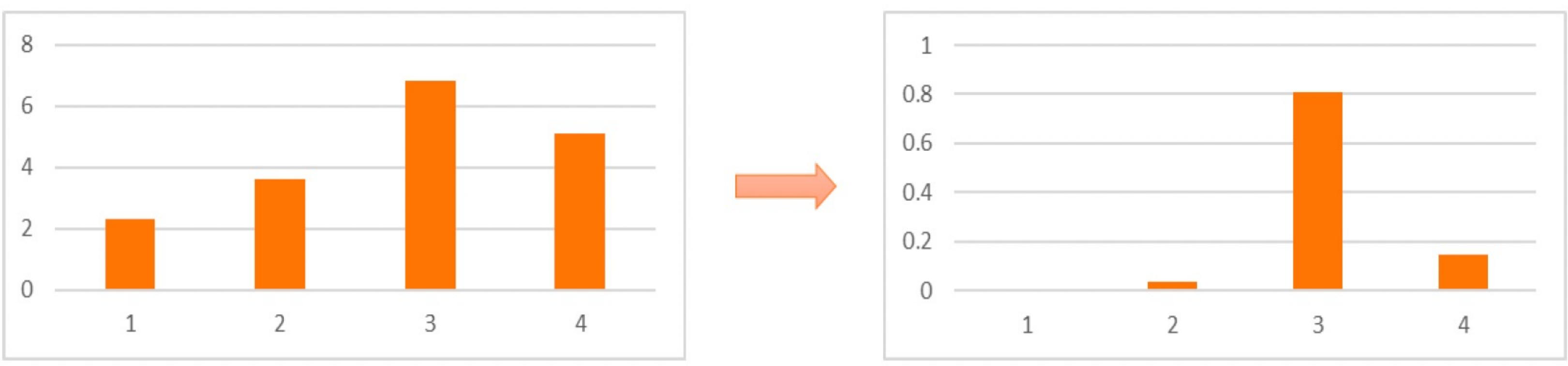
Short Intro: Cross Entropy + NN



Short Intro : What is softmax

- The softmax function is popularly used to normalize the neural network output scores across all the classes

$$p(z_i) = \frac{e^{z_i}}{\sum_z e^z}$$



Supervision/Annotations

Different Levels of Supervision

Data requirements for training an offline L2R system

- Query/document pairs that encode an ideal ranking given a particular query.
- Ideal ranking? Relevance, preference, importance [Liu, 2009], novelty & diversity [Clarke et al., 2008].
- What about personalization? Triples of user, query and document.
- Related to evaluation. Pairs also used to compute popular offline evaluation measures.
- Graded or binary. "documents may be relevant to a different degree"
- Absolute or relative? Zheng et al. [2007]

Satisfying Data-Hungry Models

There are different ways to obtain query/document pairs.

Most expensive

1. Human judgments
2. Explicit user feedback
3. Implicit user feedback
4. Pseudo relevance

Least expensive

Human Judgements

Human judges determine the relevance of a document for a given query.

How to determine candidate query/document pairs?

- Obtaining human judgments is expensive.
- List of queries: sample of incoming traffic or manually curated.
- Use an existing rankers to obtain rankings and pool the outputs [Sparck Jones and van Rijsbergen, 1976].
- Trade-off between number of queries (shallow) and judgments (deep) [Yilmaz and Robertson, 2009].

Explicit User Feedback

- When presenting results to the user, ask the user to explicitly judge the documents.
- Unfortunately, users are only rarely willing to give explicit feedback [Joachims et al., 1997].

Extracting pairs from click-through data (training)

Extract implicit judgments from search engine interactions by users.

- Assumption: user clicks $\Longrightarrow$ relevance (or, preference).
- Virtually unlimited data at very low cost, but interpretation is more difficult.
- Presentation bias: users are more likely to click higher-ranked links.
  - How to deal with presentation bias? Joachims [2003] suggest to interleave different rankers and record preference.
- Chains of queries (i.e., search sessions) can be identified within logs and more fine-grained user preference can be extracted [Radlinski and Joachims, 2005].