# Outline

Morning program

- Preliminaries
- Text matching I
- Text matching II

Afternoon program

- Learning to rank
- Modeling user behavior
- Generating responses
- Outlook
- Wrap up

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- Morning program
  - Preliminaries
  - Text matching I
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- Afternoon program
  - Learning to rank
    - Overview & basics
    - Refresher of cross-entropy
    - Pointwise loss
    - Pairwise loss
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# Learning to rank (L2R)



## Definition

"... 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 user-issued query—as a numerical vector $\vec{x} \in \mathbb{R}^n$.

The ranking model $f : \vec{x} \to \mathbb{R}$ is trained to map the vector to a real-valued score such that relevant items are scored higher.

We discuss supervised (offline) L2R models first, but briefly introduce online L2R later.

# Approaches

Liu [2009] categorizes different L2R approaches based on training objectives:

- Pointwise approach: relevance label $y_{q,d}$ is a number—derived from binary or graded human judgments or implicit user feedback (e.g., CTR). Typically, a regression or classification model is trained 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. Reduces to binary classification to predict more relevant document.
- Listwise approach: directly 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 that encode IR insights

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)

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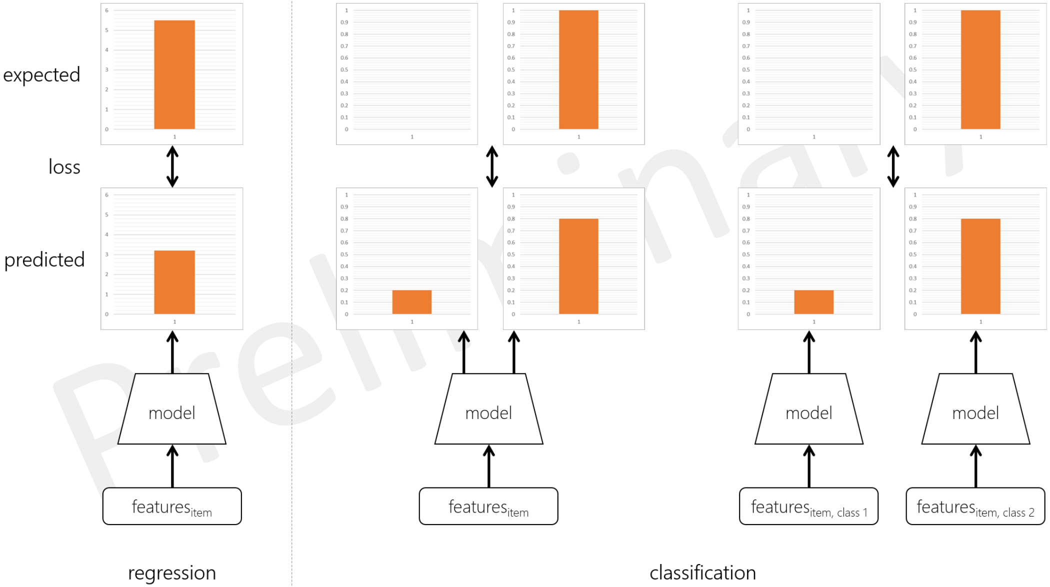
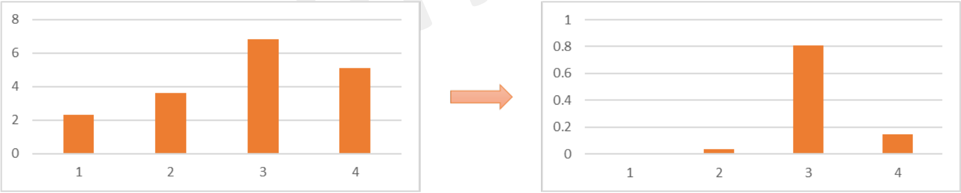
# A quick refresher - Neural models for different tasks



# A quick refresher - What is the Softmax function?

In neural classification models, the softmax function is popularly used to normalize the neural network output scores across all the classes

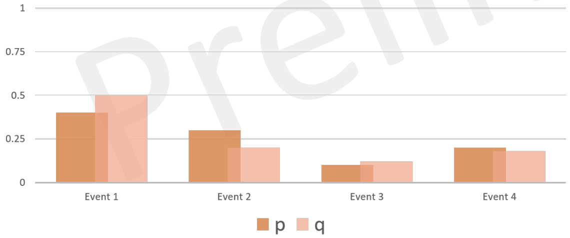
$$p(z_i) = \frac{e^{\gamma z_i}}{\sum_{z \in Z} e^{\gamma z}} \qquad (\gamma \text{ is a constant}) \tag{2}$$



# A quick refresher - What is Cross Entropy?

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

$$CE(p,q) = -\sum_i p_i \log(q_i) \tag{3}$$



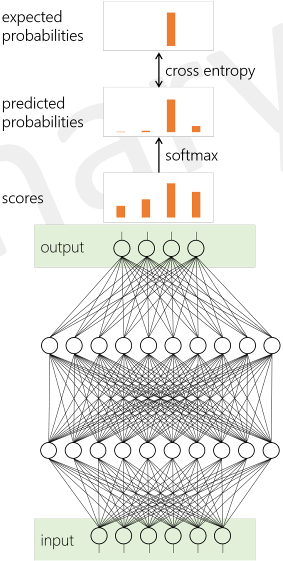

If $p_{correct} = 1$ and $p_i = 0$ for all other values of $i$ then,

$$CE(p,q) = -\log(q_{correct}) \tag{4}$$

# A quick refresher - What is the Cross Entropy with Softmax loss?

Cross entropy with softmax is a popular loss function for classification

$$\mathcal{L}_{\mathsf{CE}} = -log\left(\frac{e^{\gamma z_{correct}}}{\sum_{z \in Z} e^{\gamma z}}\right) \qquad (5)$$



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# Pointwise objectives

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,

$$\mathcal{L}_{Squared} = \|y_{q,d} - f(\vec{x}_{q,d})\|^2 \tag{6}$$

where, $y_{q,d}$ is the one-hot representation [Fuhr, 1989] or the actual value [Cossock and Zhang, 2006] of the label

# Pointwise objectives

Regression-based or classification-based approaches are popular

**Classification loss**

Given $\langle q, d \rangle$ predict the class $y_{q,d}$

E.g., Cross-Entropy with Softmax over categorical labels $Y$ [Li et al., 2008],

$$\mathcal{L}_{\mathsf{CE}}(q, d, y_{q,d}) = -log\Big(p(y_{q,d}|q, d)\Big) = -log\Big(\frac{e^{\gamma \cdot s_{y_{q,d}}}}{\sum_{y \in Y} e^{\gamma \cdot s_y}}\Big) \tag{7}$$

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

# Outline

# Pairwise objectives

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 $d_i$

Given $\langle q, d_i, d_j \rangle$, predict the more relevant document

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 $s_j = f(\vec{x}_j)$

Pairwise loss generally has the followingform [Chen et al., 2009],

$$\mathcal{L}_{pairwise} = \phi(s_i - s_j) \tag{8}$$

where, $\phi$ can be,

- Hinge function $\phi(z) = \max(0, 1 - z)$ [Herbrich et al., 2000]
- Exponential function $\phi(z) = e^{-z}$ [Freund et al., 2003]
- Logistic function $\phi(z) = \log(1 + e^{-z})$ [Burges et al., 2005]
- etc.

# RankNet

RankNet [Burges et al., 2005] is a pairwise loss function—popular choice for training neural L2R models and also an industry favourite [Burges, 2015]

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 $p$,

$$\begin{aligned} \mathcal{L}_{RankNet} &= -\bar{p}_{ij} \log(p_{ij}) - \bar{p}_{ji} \log(p_{ji}) && (9) \\ &= -\log(p_{ij}) && (10) \\ &= log(1 + e^{-\gamma(s_i - s_j)}) && (11) \end{aligned}$$

# Cross Entropy (CE) with Softmax over documents

An alternative loss function assumes a single relevant document $d^+$ and compares it against the full collection $D$

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

$$p(d^+|q) = \frac{e^{\gamma \cdot s\left(q,d^+\right)}}{\sum_{d \in D} e^{\gamma \cdot s(q,d)}} \tag{12}$$

The cross entropy loss is then given by,

$$\mathcal{L}_{\text{CE}}(q, d^+, D) = -log\Big(p(d^+|q)\Big) \tag{13}$$

$$= -log\left(\frac{e^{\gamma \cdot s\left(q,d^+\right)}}{\sum_{d \in D} e^{\gamma \cdot s(q,d)}}\right) \tag{14}$$

# Notes on Cross Entropy (CE) loss

- 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 [Huang et al., 2013, Mitra et al., 2017, Shen et al., 2014]
- Large body of work in NLP to deal with similar issue that may be relevant to future L2R models
  - E.g., hierarchical softmax [Goodman, 2001, Mnih and Hinton, 2009, Morin and Bengio, 2005], Importance sampling [Bengio and Senécal, 2008, Bengio et al., 2003, Jean et al., 2014, Jozefowicz et al., 2016], Noise Contrastive Estimation [Gutmann and Hyvärinen, 2010, Mnih and Teh, 2012, Vaswani et al., 2013], Negative sampling [Mikolov et al., 2013], and BlackOut [Ji et al., 2015]

# Outline

# Listwise

Blue: relevant Gray: non-relevant

NDCG and ERR higher for left but pairwise errors less for right

Due to strong position-based discounting in IR measures, errors at higer ranks are much more problematic than at lower ranks

But listwise metrics are non-continuous and non-differentiable

[Burges, 2010]

# LambdaRank

Key observations:

- To train a model we dont need the costs themselves, only the gradients (of the costs w.r.t model scores)
- It is desired that the gradient be bigger for pairs of documents that produces a bigger impact in NDCG by swapping positions

**LambdaRank** [Burges et al., 2006]
Multiply actual gradients with the change in NDCG by swapping the rank positions of the two documents

$$\lambda_{LambdaRank} = \lambda_{RankNet} \cdot |\Delta NDCG| \tag{15}$$

# ListNet and ListMLE

According to the Luce model [Luce, 2005], given four items $\{d_1, d_2, d_3, d_4\}$ the probability of observing a particular rank-order, say $[d_2, d_1, d_4, d_3]$, is given by:

$$p(\pi|s) = \frac{\phi(s_2)}{\phi(s_1) + \phi(s_2) + \phi(s_3) + \phi(s_4)} \cdot \frac{\phi(s_1)}{\phi(s_1) + \phi(s_3) + \phi(s_4)} \cdot \frac{\phi(s_4)}{\phi(s_3) + \phi(s_4)} \tag{16}$$

where, $\pi$ is a particular permutation and $\phi$ is a transformation (e.g., linear, exponential, or sigmoid) over the score $s_i$ corresponding to item $d_i$

# ListNet and 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.

# Outline

# Training under different levels of supervision

## Data requirements for training an off-line 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 off-line evaluation measures.

Graded or binary. "documents may be relevant to a different degree" [Järvelin and Kekäläinen, 2000]

Absolute or relative? Zheng et al. [2007]

# How to satisfy data-hungry models?

There are different ways to obtain query/document pairs.

Most expensive ↓ Least expensive

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

# Human judgments

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 $\Rightarrow$ 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].

# Extracting pairs from click-through data (evaluation)



Clicks can also be used to evaluate different rankers.

- Radlinski et al. [2008] discuss how absolute metrics (e.g., abandonment rate) do not reliable reflect retrieval quality. However, relative metrics gathered using interleaving methods, do reflect retrieval quality.
- Carterette and Jones [2008] propose a method to predict relevance score of unjudged documents. Allows for comparisons across time and datasets.

# Side-track: Online LTR

As mentioned earlier, we focus mostly on offline LTR. Besides an active learning set-up, where models are re-trained frequently, neural models have not yet conquered the online paradigm.

See the SIGIR'16 tutorial of Grotov and de Rijke [2016] for an overview.

# Pseudo relevance judgments

Pseudo relevance collections (discussed first on Slide 86) can also be used to train LTR systems.

Web search: Asadi et al. [2011] construct a pseudo relevance collection from anchor texts in a web corpus. LTR trained using pseudo relevance outperform non-supervised retrieval functions (e.g., BM25) on TREC collections.

Microblog search: Berendsen et al. [2013] use hashtags as a topical relevance signal. Queries are constructed by sampling terms from tweets.

Personalized product search: Ai et al. [2017] synthesize purchase behavior from Amazon user reviews. Queries and relevance are constructed according to the human-curated Amazon product categories [Van Gysel et al., 2016]. They learn vector space representations for query terms, users and products.