Learning to Rank

Zoekmachines 2023 - IR0

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About me

- PhD student with Maarten de Rijke
- IRLab at UvA and the Mercury ML Lab at Booking.com
- **Previously:**
    - Recommender systems at Blinkist, Berlin
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- **Research interests:** Ranking with user interactions, user simulation, and evaluating IR systems offline.

Motivation

Google

attractions in Amsterdam

TripAdvisor
https://www.tripadvisor.com › Attractions-g188590-A...

THE 15 BEST Things to Do in Amsterdam

Top **Attractions in Amsterdam** · 1. Anne Frank House · 2. Van Gogh Museum · 3. Rijksmuseum · 4. Vondelpark · 5. The Jordaan · 6. Centraal Station · 7. Heineken ...

Attractions: 3,115

Attraction Photos: 309,790

Attraction Reviews: 645,083

iamsterdam.com
https://www.iamsterdam.com › see-and-do › attraction...

Attractions and sights | I amsterdam

Most popular **attractions** · Heineken Experience · ARTIS · Koninklijk Paleis (Royal Palace) · Anne Frank House · **Amsterdam** Canal Cruise - 100 highlights · Johan Cruijff ...

Free things to do in Amsterdam · Rembrandts Amsterdam... · This is holland

PlanetWare
https://www.planetware.com › amsterdam-nl-nh-amst

24 Top-Rated Tourist Attractions in Amsterdam

Signals in Web Search

Textual Signals:

- **Query content**: text
- **Document content**: title, page content

How well does the query text match the document text? [6]

- BM-25
- TF-IDF / vector space models
- Language models

Signals in Web Search

But there are many signals beyond text:

- **Query**: type, language
- **Document**: urls, images
- **User context**: location, date, device, search history
- **Metadata**: popularity, recency, page quality, spam, adult content, ...
- **External stakeholders**: advertisers, auctions, content creators, ...

Signals in Web Search

Modern search engines use a lot of features:

- **Airbnb** [10]: $>$ 195 features
- **Bing** [15]: $>$ 136 features
- **Istella** [7]: $>$ 220 features
- **Yahoo** [2]: $>$ 700 features

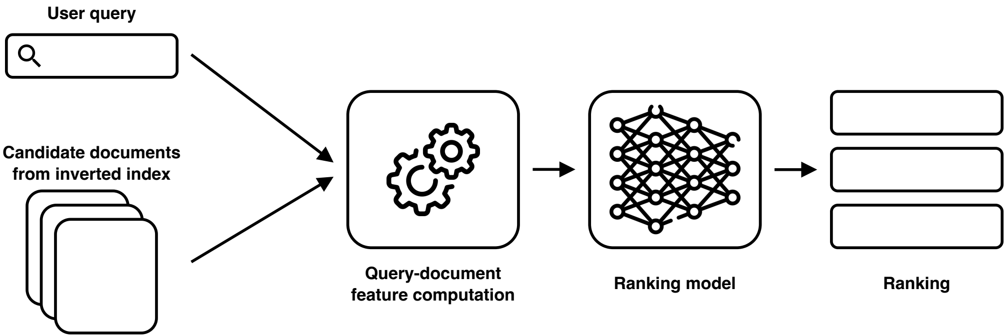
How do we combine all of these signals?

Learning to Rank

Learning to Rank (LTR) is

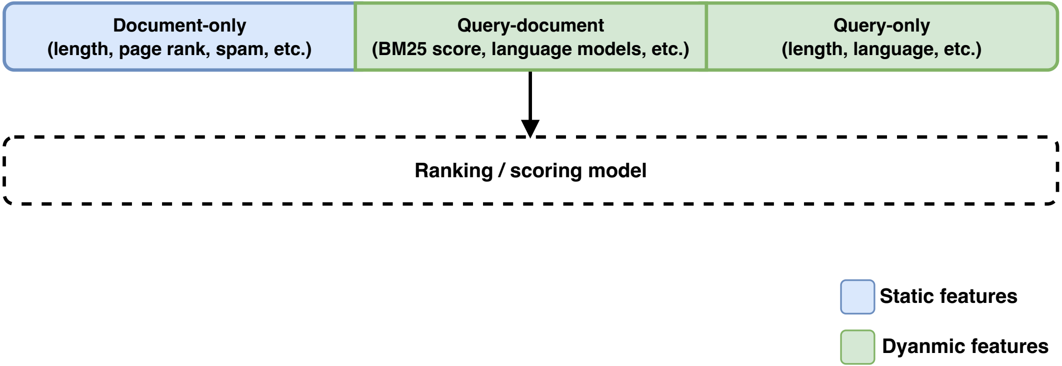
"... a task to automatically construct a ranking model using training data, such that the model can sort new objects according to their degrees of relevance, preference, or importance." – Liu [13]

Learning to Rank

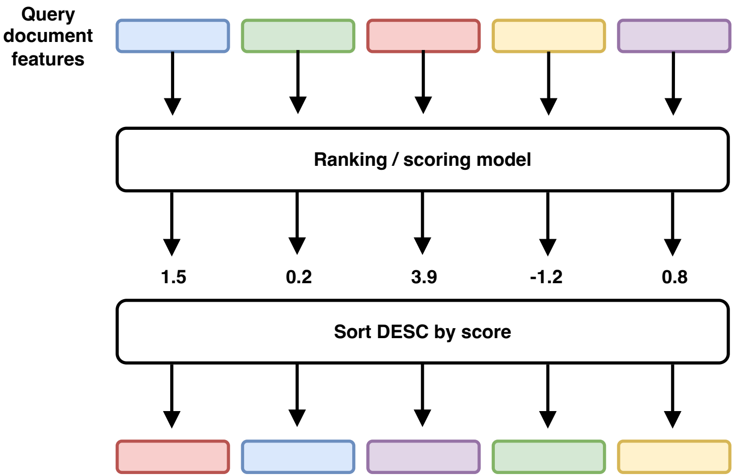


Features

Traditionally LTR used *hand-crafted* numerical features,
nowadays, we also use *deep learned* features. We can categorize features into:



Problem Formulation



The goal of learning to rank

Thus, we have:

- a **feature vector** for each query-document pair: $\vec{x}_{q,d} \in \mathbb{R}^m$
- a **relevance judgment** for each query-document pair, e.g.: $y_{q,d} \in \{0, 1, 2, 3, 4\}$

A ranking model $f : \vec{x} \rightarrow \mathbb{R}$ scores each query-document pair to optimize the order of items when sorting descendingly by $f(\vec{x}_{q,d}) = s_{q,d}$.

How can we learn a ranking model f?

Pointwise Methods

Pointwise LTR

Regression: Relevance as a real-valued score [4, 9]

For example, we can use linear regression for our ranking model:

$$f(x) = w_0 + w_1 x_1 + w_2 x_2 + \cdots + w_n x_n = s$$

We assign a **weight** w to each feature in x to minimize
the error between the predicted scores and true relevance.

Usually we quantify how far off our predictions are using the **mean squared error** loss:

$$\mathcal{L}_{mse} = \frac{1}{n} \sum_{i=1}^{n} (y_i - s_i)^2$$

Pointwise LTR - MSE

Relevance labels y	**Predicted scores** s	**Squared Error**
		$(y - s)^2$
1	**0.9**	$(1 - 0.9)^2 = 0.01$
0	**0.7**	$(0 - 0.7)^2 = 0.49$
1	**0.6**	$(1 - 0.6)^2 = 0.16$
0	**0.2**	$(0 - 0.2)^2 = 0.04$
0	**0.1**	$(0 - 0.1)^2 = 0.01$
		MSE = 0.142

Pointwise LTR

Regression: Relevance as a real-valued score [4, 9]

Classification: Relevance as *unordered* categories [3, 14]

Ordinal regression: Relevance as *ordered* categories [5, 16]

What are challenges with these approaches?

Problems of pointwise LTR

Some (solvable) challenges include:

- **Class imbalance**: We have way more irrelevant than relevant documents
- **Feature normalization**: Feature distributions can differ greatly between queries

Problems of pointwise LTR

A more fundamental problem:
Pointwise methods predict a score for each query-document independently,
but document scores are fundamentally dependent on each other in a ranking.

Meaning, minimizing a pointwise loss does not always lead to a better ranking.

Pointwise LTR: A lower loss does not imply a better ranking

Relevance labels	Predicted scores
1	0.6
0	0.5
0	0.5
0	0.5
0	0.5

What is the loss?

$$\mathcal{L}_{mse} = \frac{1}{n} \sum_{i=1}^{n} (y_i - s_i)^2$$

Pointwise LTR: A lower loss does not imply a better ranking

Relevance labels	Predicted scores
1	0.6
0	0.5
0	0.5
0	0.5
0	0.5

Loss $\mathcal{L}_{mse} = 1.16$

MRR $= 1$, nDCG $= 1$

Pointwise LTR: A lower loss does not imply a better ranking

Relevance labels	Predicted scores
1	0.2
0	0.2
0	0.2
0	0.2
0	0.1

$$\text{Loss } \mathcal{L}_{mse} = 0.97$$

$$\text{MRR} = 0.2, \ \text{nDCG} = 0.39$$

Pairwise Methods

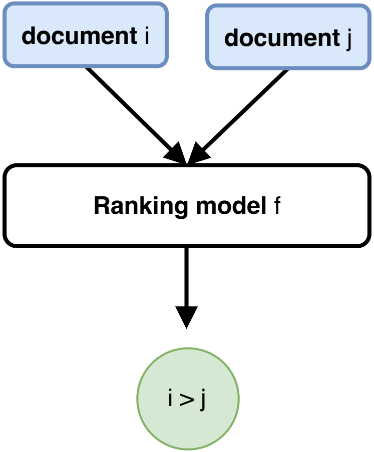
Pairwise LTR

Observation: For a good ranking, we only require relative relevance levels:

$$y_i > y_j \rightarrow s_i > s_j$$

How can we optimize a model with pairs of items?

Naive Pairwise Model



$$P(i > j) = f(x_i, x_j)$$

Naive Pairwise Model

Let's (naively) change the ranking model to take **document pairs as input**:

$$P(i > j) = f(x_i, x_j)$$

But pairwise document inputs are not a good idea:

- This method has quadratic complexity $O(N^2)$ during **training** and **inference** and thus does not scale to many documents.
- Pair-wise preferences have to be aggregated and can lead to paradoxical situations:

$$s_1 > s_2$$

$$s_2 > s_3$$

$$s_3 > s_1$$

Pairwise LTR

A better idea: Let's keep the ranking model **unchanged**:

$$f(\vec{x}_i) = s_i$$

But the **loss function** is based on pairs of documents:

$$\mathcal{L}_{pairwise}(s, y) = \sum_{y_i > y_j} \phi(s_i - s_j)$$

We still score one document at-a-time and can sort according to scores, but the model is optimized over item pairs.

Pairwise LTR

Pairwise loss functions minimize the number of incorrectly ranked pairs:

where $y_i > y_j$, but our model falsely predicts $s_i < s_j$.

Pairwise loss functions generally have the following form:

$$\mathcal{L}_{pairwise}(s, y) = \sum_{y_i > y_j} \phi(s_i - s_j)$$

where ϕ can be the:

- **Hinge** function in RankingSVM [11, 12]: $\phi(z) = \max(0, 1 - z)$
- **Exponential** function in RankBoost [8]: $\phi(z) = e^{-z}$
- **Logistic / Sigmoid** function in RankNet [1]: $\phi(z) = \log(1 + e^{-z})$

RankNet

RankNet

Introduced by Burges et al. [1] in 2005 to train neural ranking models.
Popular in industry applications and won the ICML 2015 test of time award.[1]

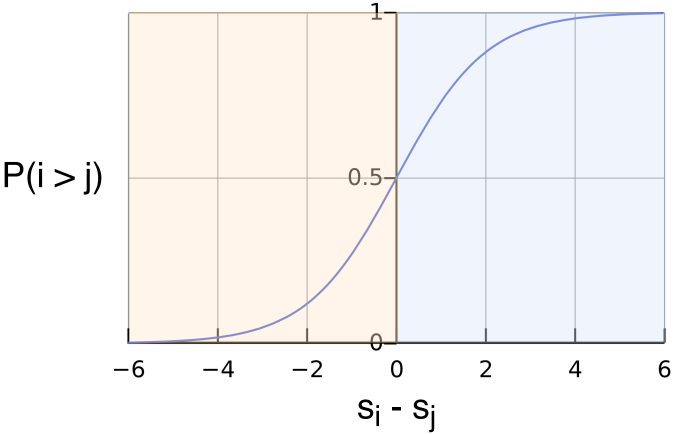
RankNet defines the probability that document i should be ranked over document j as:

$$P(i > j) = \text{sigmoid}(s_i - s_j)$$

RankNet then uses the log loss between the predicted probabilities for each pair and their true/target probability: $\bar{P}(i > j)$.

[1] https://icml.cc/2015/index.html%3Fp=51.html

RankNet



Mapping the difference in scores between to items to the **predicted probability** $P(i > j)$ using the sigmoid function.

RankNet

Now that we have a model prediction for each item pair,
where do we get the **target probability** of $\bar{P}(i > j)$ from?

1. Ask annotators to judge pairs of items (infeasible, it requires $O(N^2)$ annotations).
2. We make up probabilities based on relevance judgments:
    - If $y_i > y_j$, set $\bar{P}(i > j) = 1$
    - If $y_i = y_j$, set $\bar{P}(i > j) = 0.5$
    - If $y_i < y_j$, set $\bar{P}(i > j) = 0$

These *made-up/virtual* target probabilities were chosen mainly for convenience as they simplify the final loss to:

$$\mathcal{L}_{RankNet}(s, y) = \sum_{y_i > y_j} \log(1 + e^{-(s_i - s_j)})$$

Pairwise LTR

What are problems of pairwise methods?

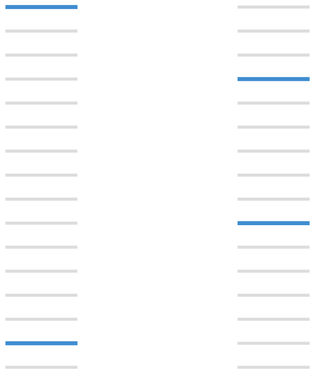
The made-up target probabilities $\bar{P} \in \{0, 0.5, 1\}$ are quite crude, since any difference in relevance labels is treated equally. For example:

$$P(4 > 1) = 1.0$$
$$P(4 > 3) = 1.0$$

Not very elegant, but works well in practice...

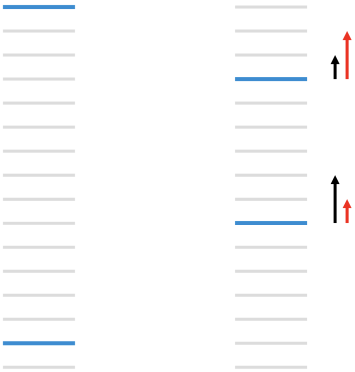
A more important limitation: We treat all item pairs as equally important, but are they?

Pairwise LTR: Minimizing pairwise errors



Reducing pairwise errors from 13 (left) to 11 (right),
while top-heavy measures like MRR and nDCG degrade [1, Figure 1].

Pairwise LTR: Minimizing pairwise errors



The **black** arrows denote the RankNet gradients,
while what we'd arguably want are the **red** arrows [1, Figure 1].

Listwise Methods

LambdaRank

Motivation: Can we directly optimize IR metrics such as nDCG, Precision, and MRR?

Reciprocal Rank: Reciprocal of the rank of the first relevant item after sorting by our scores s:

$$\mathrm{RR} = \frac{1}{\mathrm{rank}_i}$$

Discounted Cumulative Gain:

$$\mathrm{DCG} = \frac{1}{n} \sum_{i=1}^{n} \frac{2^{y_i} - 1}{\log(i+1)}$$

Non-smooth and discontinuous

- Ranking metrics typically only **depend on the rank of an item, not on its score**
- Model **scores change smoothly**, the **ranks of documents change abruptly**

Listwise LTR

Non-differentiable

Ranking metrics rely on a sorting operation that is non-smooth and discontinuous w.r.t. to model parameters θ:

$$\frac{\partial \mathrm{RR}}{\partial \theta} = ???$$

$$\frac{\partial \mathrm{DCG}}{\partial \theta} = ???$$

Thus, ranking metrics are either **flat** (with zero gradient) or **discontinuous**

Holy grail of LTR: Finding methods that (indirectly) optimize listwise IR metrics

LambdaRank

LambdaRank

Observations:

I. To train a model, we don't need the costs just the gradients (of the costs w.r.t model scores)

II. Gradients should be larger for pairs that have a greater impact on our metric

LambdaRank

Idea: Scale the RankNet gradients for each document pair based on the change in nDCG we would observe after swapping the two items:

$$\mathcal{L}_{LambdaRank}(s, y) = \sum_{y_i > y_j} \Delta\text{NDCG}(i, j) \log\left(\text{sigmoid}(s_i - s_j)\right)$$

When implementing LambdaRank using multiple additive regression trees (MART), it's called **LambdaMART** and is a very strong baseline methods for learning to rank.

Conclusion

Summary

To recap:

- Today's search and recommender systems use many signals for ranking.
- These signals can be computed beforehand (static features) or have to be computed when the user submits their query (dynamic features).
- Learning to rank is a method to learn models that automatically combine these query and document features into a single ranking.

Summary

Pointwise

- Predict **relevance independently of other items**
- Ignores that the predicted scores are used to sort items

Pairwise

- **Loss** is based on **item pairs** and minimizes the number of incorrectly ranked pairs
- Ignores that **not all document pairs have the same impact** on ranking metrics

Listwise

- Optimize a list of items based on **non-differentiable ranking metrics**
- **Approximations** by heuristics, bounding, or probabilistic ranking methods
- Typically considered the strongest method out of the three

Summary

In this lecture, we discussed:

- the motivation behind **learning to rank**
- the **pointwise, pairwise, and listwise approaches** to LTR, their pros and cons
- the intuition behind the **most important algorithms**: RankNet and LambdaRank

And with that, thanks for listening. Are there any remaining questions?

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