Master on Foundations of Data Science

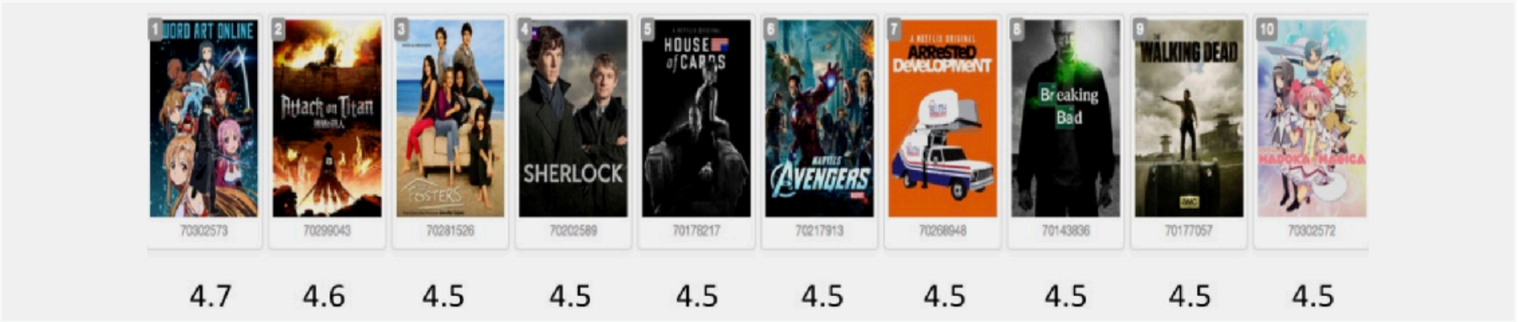
Recommender Systems

Learning to Rank

Santi Seguí | **2022-2023**

Ranking

- Most of the recommendations are **presented in a sorted list**.



- Recommendation can be understood as a ranking problem.

Optimized to achieve the best

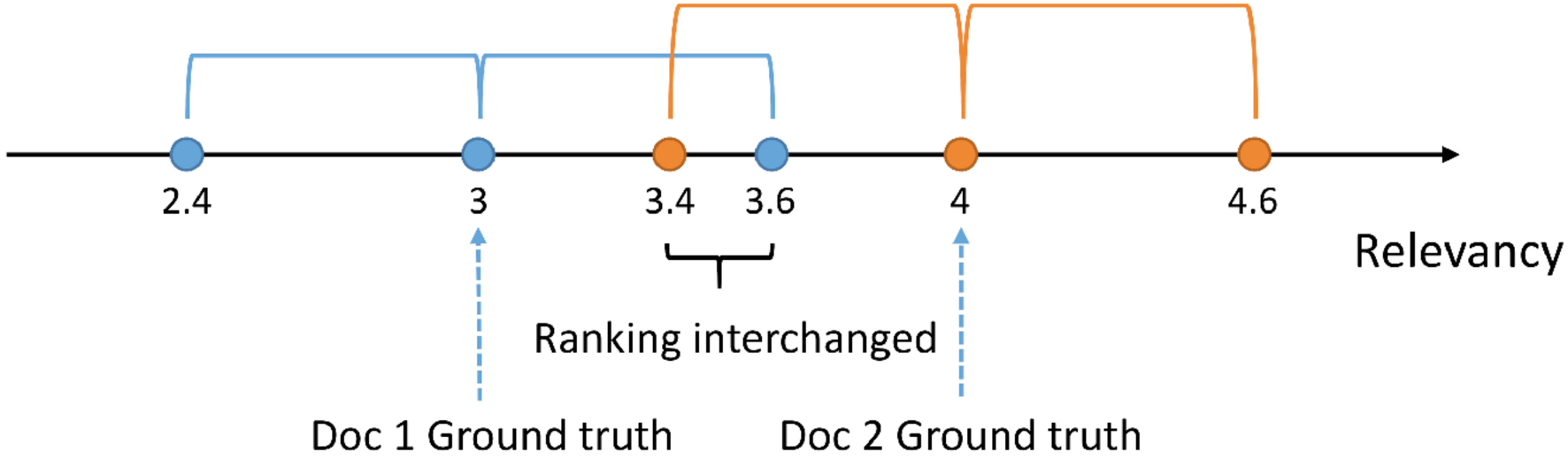
Accuracy

RMSE, MAE…

Accuracy

Any **problem** with RMSE or MAE?

Rating Prediction vs. Ranking

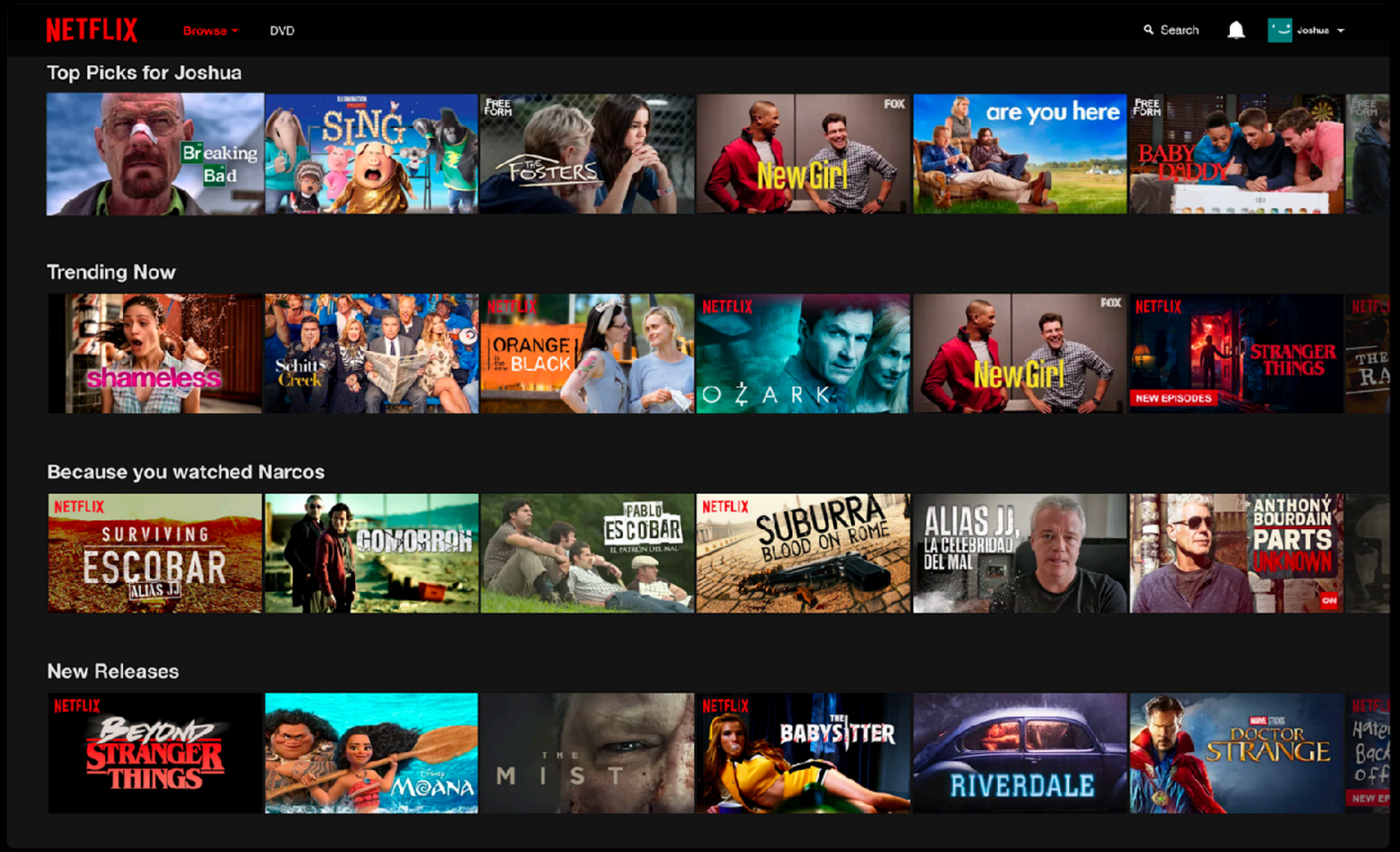


Same RMSE/MAE might lead to different rankings

Accuracy

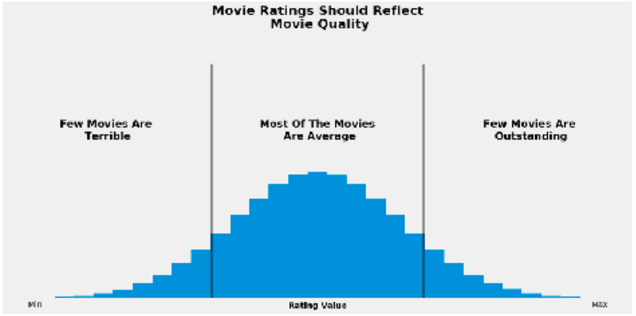
Any **problem** with RMSE or MAE?

these metrics do **not** really **measure the user experience**


NETFLIX
Browse
DVD
Search
Joshua
Top Picks for Joshua
Breaking Bad
SING
THE FOSTERS
New Girl
are you here
BABY DADDY
Trending Now
shameless
Schitt's Creek
ORANGE IS THE NEW BLACK
OZARK
New Girl
STRANGER THINGS
NEW EPISODES
Because you watched Narcos
SURVIVING ESCOBAR
ALIAS JJ
GOMORRON
PABLO ESCOBAR
EL PATRÓN DEL MAL
SUBURRA
BLOOD ON ROME
ALIAS JJ, LA CELEBRIDAD DEL MAL
ANTHONY BOURDAIN
PARTS UNKNOWN
New Releases
BEYOND STRANGER THINGS
MOANA
THE MIST
THE BABYSITTER
RIVERDALE
DOCTOR STRANGE

Top Ranking

- If we serve the recommendation as a top-ranked list **RMSE**, **MAE** and other similar metrics are not appropriate to evaluate how good is the system.



Higher **accuracy** does **not** always mean higher **satisfaction**

Solution: Consider other behaviors

Being accurate is not enough: how accuracy metrics have hurt recommender systems
SM McNee, J Riedl, JA Konstan
CHI'06 extended abstracts on Human factors in computing systems, 1097-1101

680 2006

How to evaluate the ranking?

Rank **Evaluation**

Top-N Recommendations

- Populars measures to evaluate the **quality of top-N rankings** are the following:
  - Precision@K
  - Mean Average Precision (MAP)
  - Normalized Discounted cumulative gain (NDCG)

Rank **Evaluation**

- Recall@K

$$recall@K = \frac{\text{number of items that the user likes among the top K}}{\text{total number of items that the user likes}}$$

Rank **Evaluation**

- Precision@K

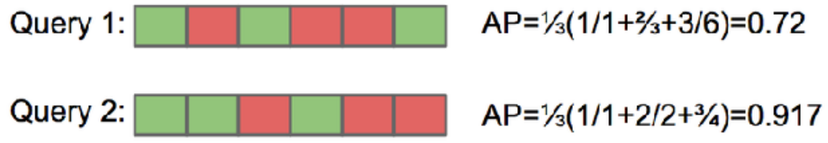
$$precision@K = \frac{\text{relevant items in the top k results}}{\text{k}}$$

Rank **Evaluation**

- **Mean Average Precision (MAP)** calculates the precision at the position of every corrected item in the ranked results list

$$AP = \frac{\sum_k P@k \cdot y_i(k)}{\text{number o frelevant documents}}$$

$$MAP = \frac{\sum_{q=1}^{Q} AP(q)}{Q}$$



MAP= (0.72+0.917)/2=0.8185

Rank **Evaluation**

Case: Kaggle Challenge Expedia

Submissions are evaluated according to the Mean Average Precision @ 5 (MAP@5):

$$MAP@5 = \frac{1}{|U|}\sum_{u=1}^{|U|}\sum_{k=1}^{min(5,n)} P(k)$$

where |U| is the number of user events, P(k) is the precision at cutoff k, n is the number of predicted hotel clusters.

Rank **Evaluation**

- **Normalized Discounted cumulative gain (NDCG).**
  - If there is items which are more relevant to others (e.g. ratings)

$$\mathrm{DCG_p} = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

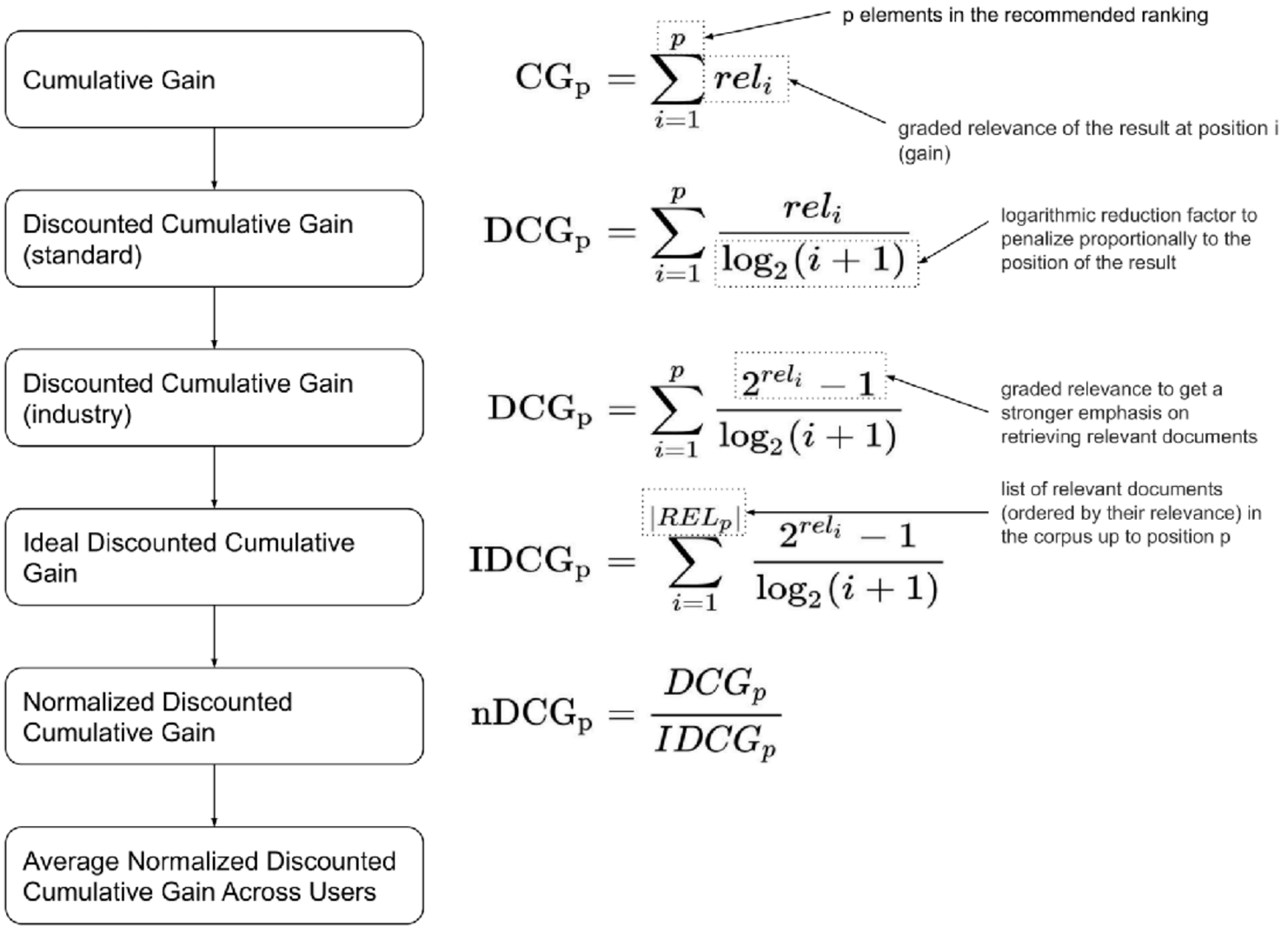
graded relevance to get a stronger emphasis on retrieving relevant documents

$$\mathrm{IDCG_p} = \sum_{i=1}^{|REL_p|} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

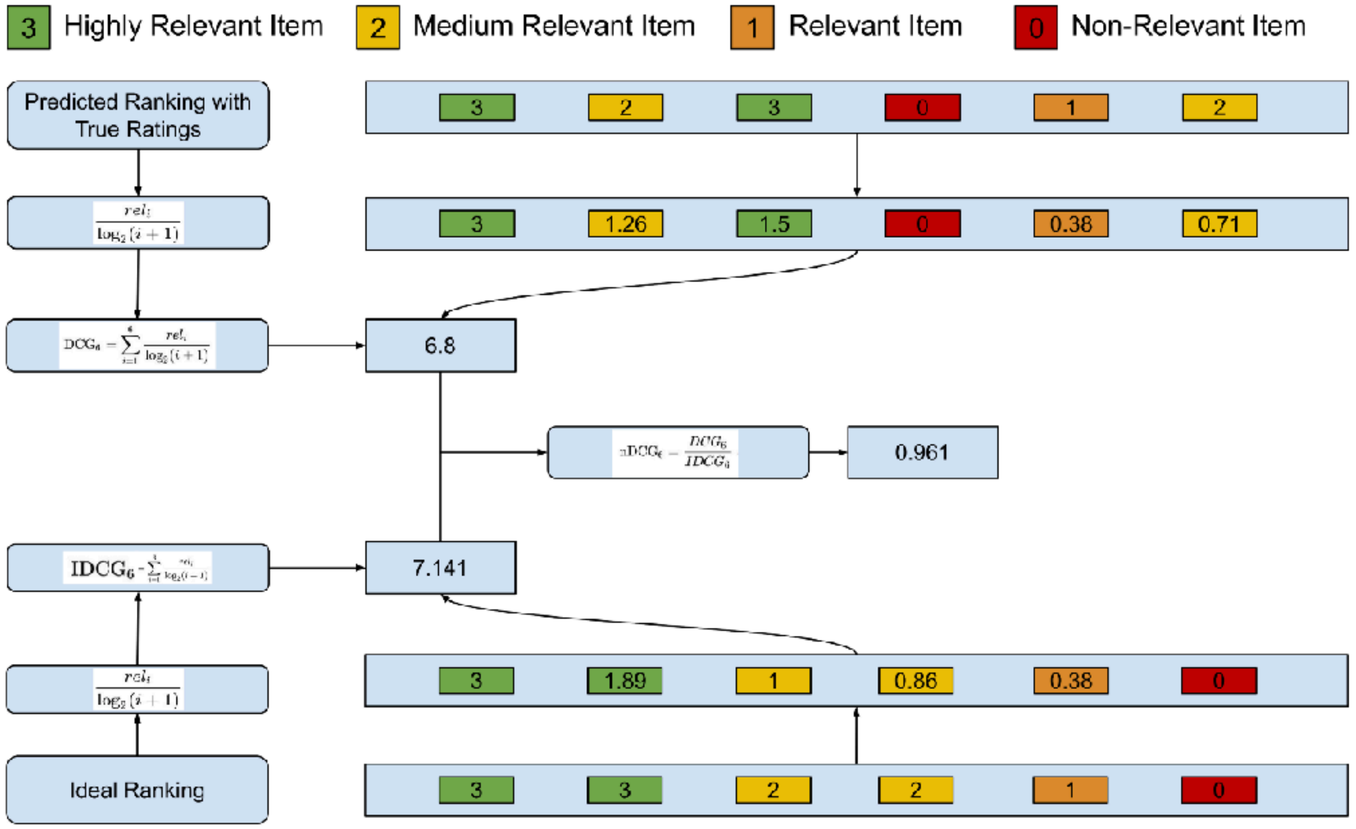
list of relevant documents (ordered by their relevance) in the corpus up to position p

$$\mathrm{nDCG_p} = \frac{DCG_p}{IDCG_p}$$

Rank **Evaluation**



Rank **Evaluation**

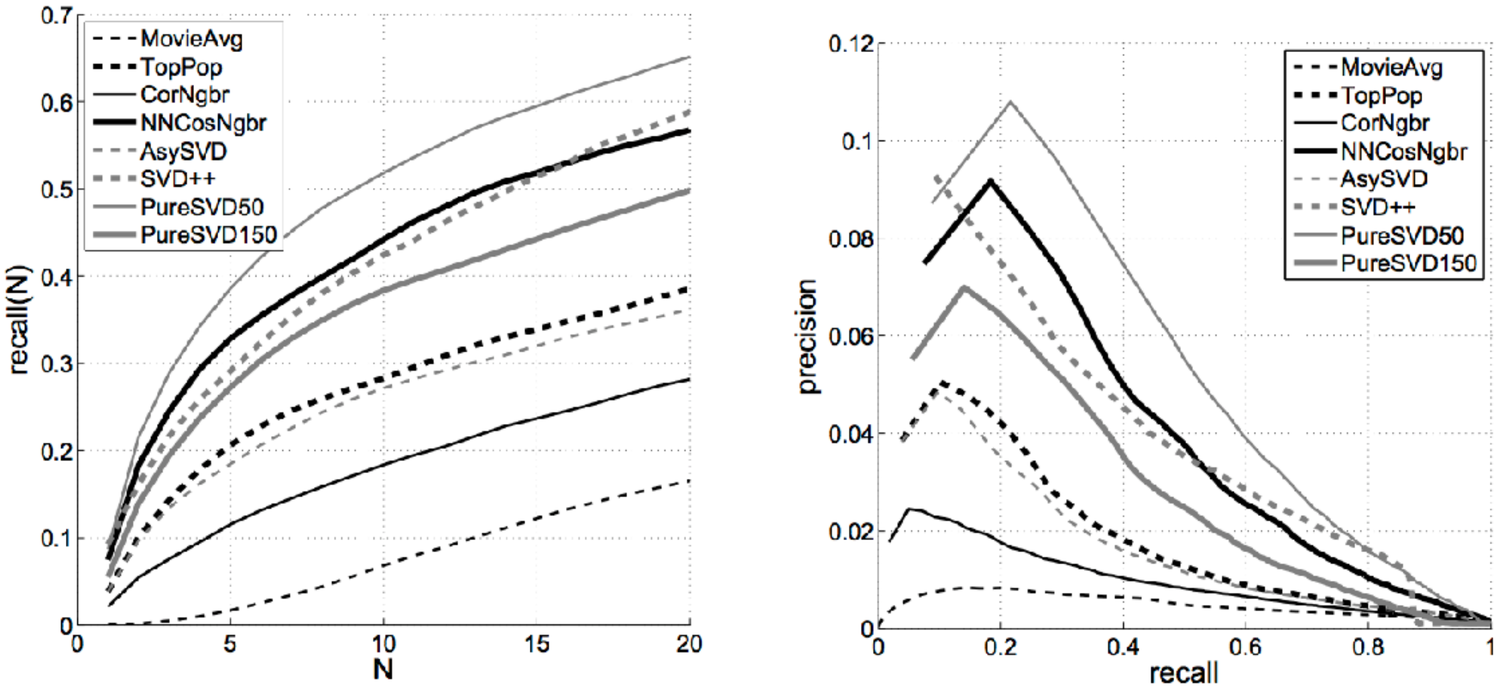


Rank **Evaluation**

- We can use the strategy followed by P. Cremonesi et.al.
- In order to measure the precision recall, first the models is trained using the training data, and then, for each item ***i*** rated with 5 stars in the test data set:
  - A set of 100 random unseen movies for the user of the item ***i*** are selected. We assume that these random movies will not be at the same interest than the 5 star movie
  - We predict the rating of the movie of item ***i*** and 100 random unseen movies.
  - We form a rank list by ordering all the 101 item according to the predicted rating. Let denote ***p*** the rank of the test item ***i*** within the list. The best results corresponds to the case the test item ***i*** precedes all the random items (i.e., p=1).
  - A top-N recommendation list by piking the **N** top ranked items from the list. If ***p≤N*** we have a hit. Otherwise we have a miss. Chances of hit increases as **N** is higher.

Performance of recommender algorithms on top-n recommendation tasks
P Cremonesi, Y Koren, R Turrin
Proceedings of the fourth ACM conference on Recommender systems, 39-46
612 2010

Rank **Evaluation**



(a) recall (b) precision vs recall

Figure 2: Movielens: (a) recall-at-N and (b) precision-versus-recall on all items.

Performance of recommender algorithms on top-n recommendation tasks
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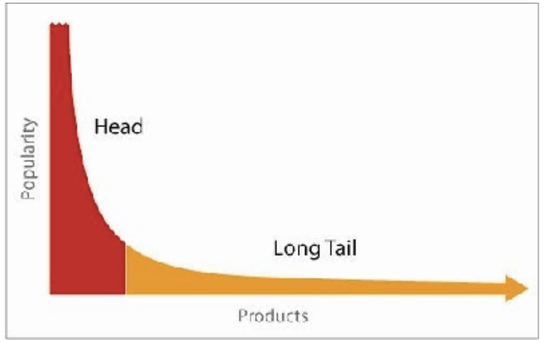
Rank **Evaluation**

- The accuracy measures are usually heavily influence by rating from populars item. Item that received very few items are practically ignored.

- However, the non-popular items are typically the ones which provides higher profit to the companies.



***Trick**: weight items according to the profit, or remove the those items which are too popular.*

How to rank?

The problem:

It is **hard to optimize** a machine learning model using the previous **measures** since they are **not differentiable**.

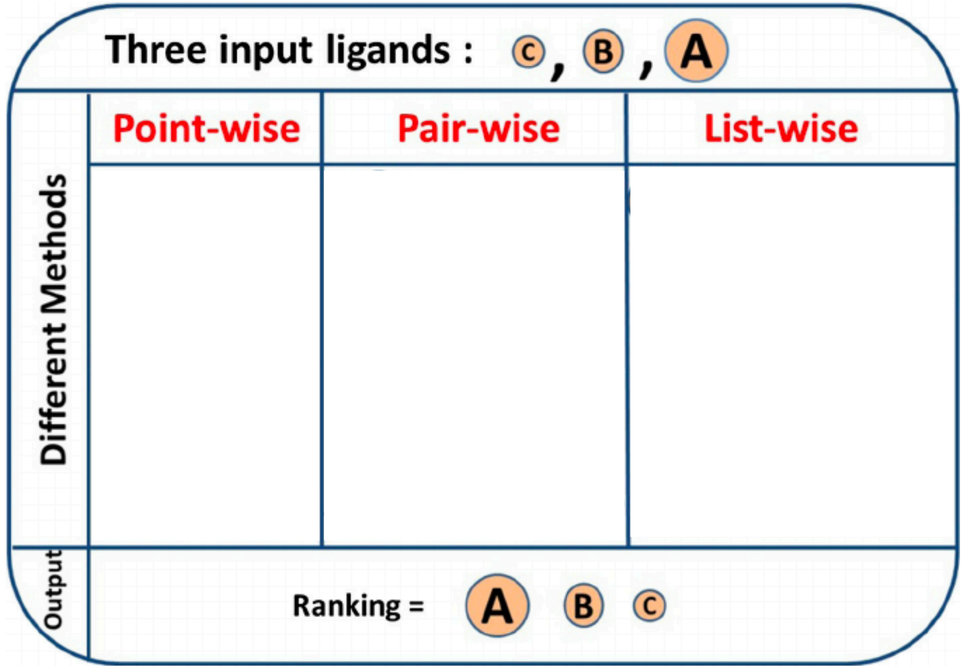
Learning to rank

- Optimization techniques that **learn rank-order directly instead of minimizing prediction error** are referred to as Learning-to-Rank (LTR).
- Three main approaches:
  - **Pointwise**:
    - Predict the absolute relevance (e.g. RMSE)
  - **Pairwise**:
    - Predict the ranking of a document pair (e.g. AUC)
  - **Listwise**:
    - Predict the ranking of a document list (e.g. cross entropy)

Learning to rank

- Using Machine Learning, the goal is to **construct a ranking model** from the training data.

- The problem can be treat as a standard classification problem



Learning to rank

- Using Machine Learning, the goal is to **construct a ranking model** from the training data.

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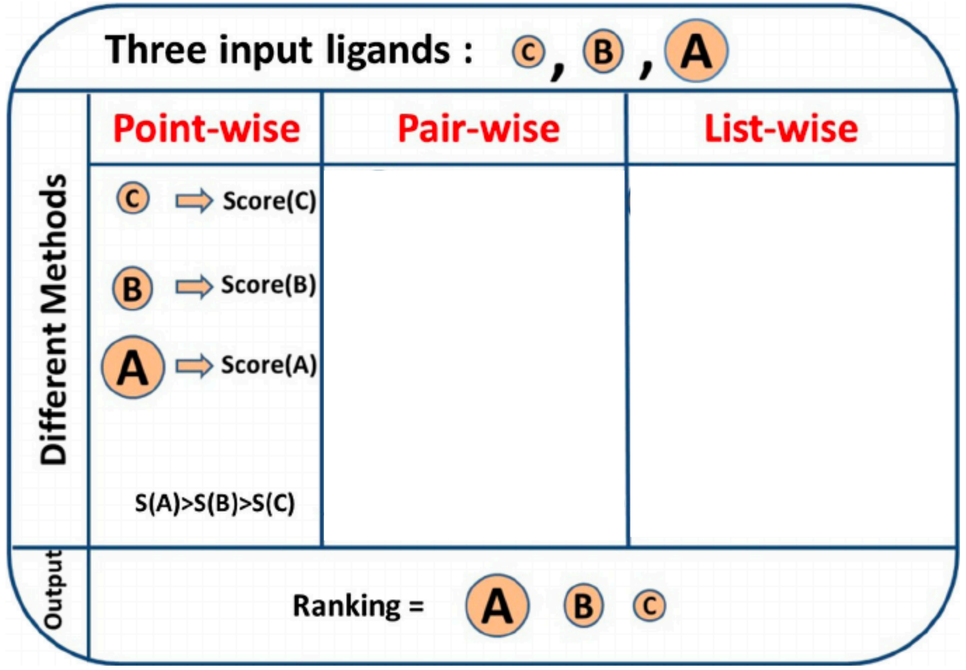
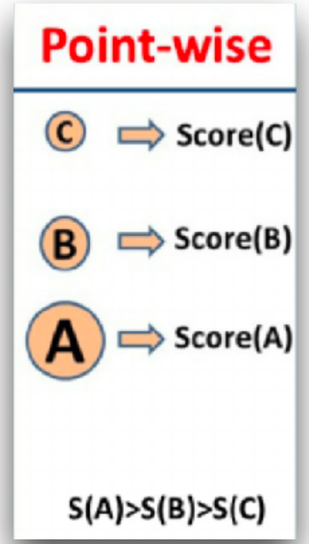
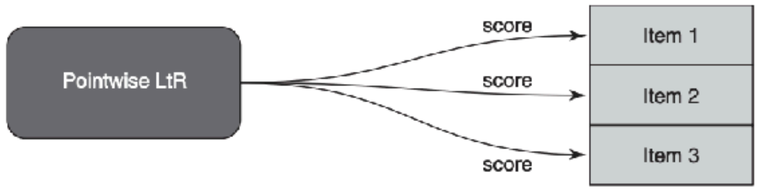


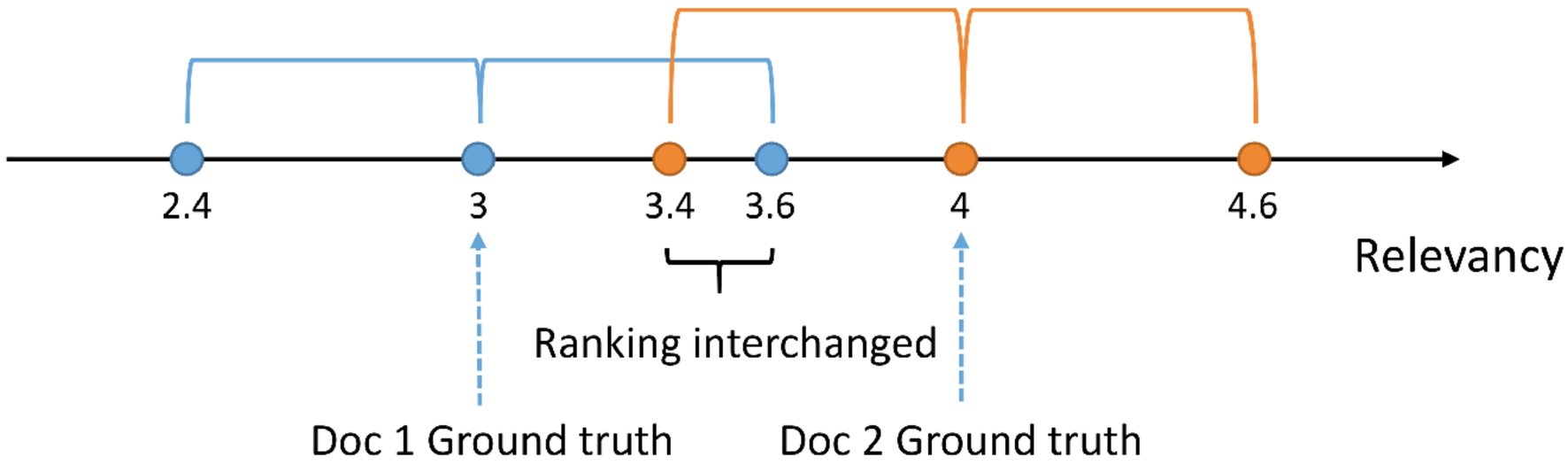
Learning to rank

- Pointwise approaches look at a **single item** at a time in the loss function. They essentially take a single item and train a classifier / regressor on it to predict how relevant it is for the current query/ user. The final ranking is achieved by simply sorting the result list by these document scores.
- For pointwise approaches, the score for each item is independent of the other items that are in the ranking list.
- All the standard regression and classification algorithms (SVM, XGBOOST, NN,…) can be directly used for pointwise learning to rank.
  - These methods tries are trained trying to minimize the error on the rating prediction… Usually RMSE, CE, or other similar loss function…
  - **Problem**: Obtained accuracy is highly biased to popular items.





Point Accuracy != Ranking Accuracy



Same square error might lead to different rankings

Learning to rank

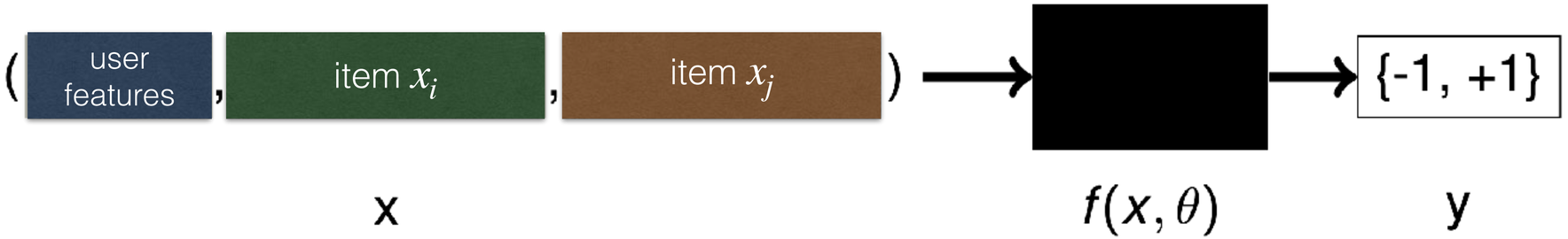
- **Pairwise/Listwise** vs. **Pointwise**
  - Train on **pair or lists of training samples** instead of individuals observations.
  - The loss functions are based on the relative ordering of items instead of the raw orders.
  - doesn’t care much about the exact score that each item gets, but cares more about the relative ordering among all the items.

Pairwise approach

Instead of focusing on recommendations as a rating prediction problem, it sometimes makes more sense to look at **how the items should be stacked -> relative preference**

Pairwise approach

- **General Criteria**: The ranking function f learns to rank pairs of items (i.e. for $\{x_i, x_j\}$, is y_i greater than y_j?).



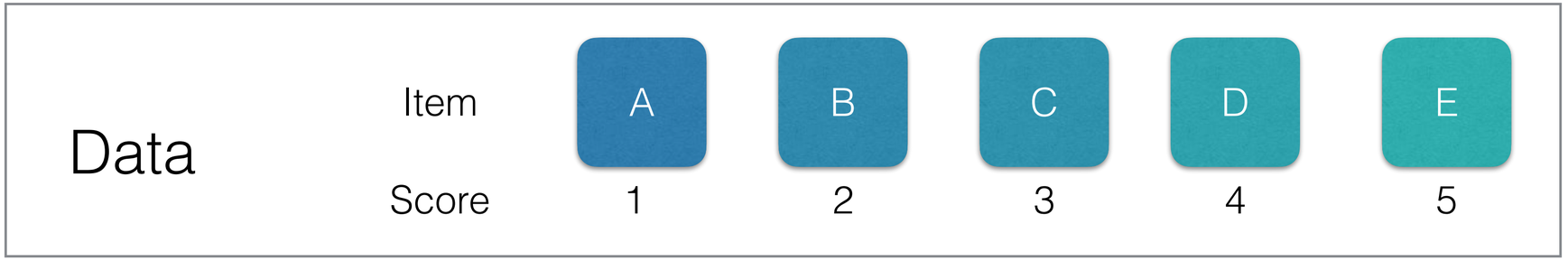
Pairwise approach

- **General Criteria**: The ranking function f learns to rank pairs of items (i.e. for $\{x_i, x_j\}$, is y_i greater than y_j?).
  - predict for every **pair of items** based on feature vector x
  - users' **relative preference** regarding the documents.
  - training determines the **parameter** θ based on a **loss function** (e.g. the number of inverted pairs)

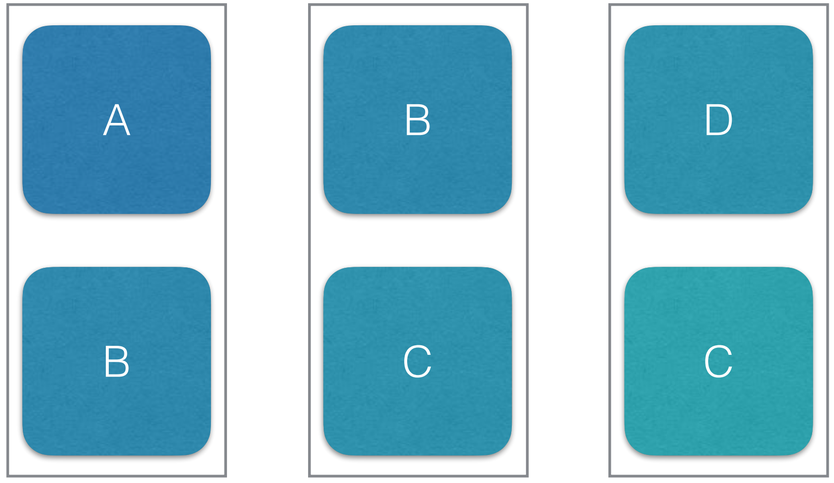
Advantage:
Models relative order

Main disadvantage:
- no distinction between excellent-bad and fair-bad
- sensitive tot noise labels.

Pairwise approach



- Training data instances are item pairs in learning



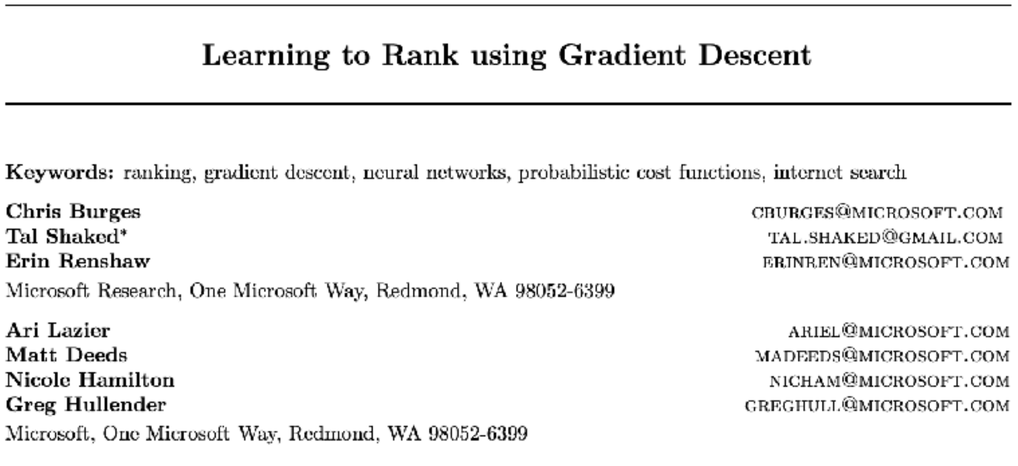
With labels:
+1 (i>j) or **-1** (j<i)

Pairwise approach

- **Several Methods**:
  - RANK SVM
  - RankBoost
  - RANK NET
  - Lambda Rank
  - Lambda Mart
  - Bayesian Personalized Ranking (BPR)

Pairwise approach
RankNet

- RankNet was originally developed using neural nets.
- **The cost function for RankNet aims to minimize the number of *inversions* in ranking**. Here an inversion means an incorrect order among a pair of results, i.e. when we rank a lower rated result above a higher rated result in a ranked list. RankNet optimizes the cost function using Stochastic Gradient Descent.



Learning to Rank using Gradient Descent

Keywords: ranking, gradient descent, neural networks, probabilistic cost functions, internet search

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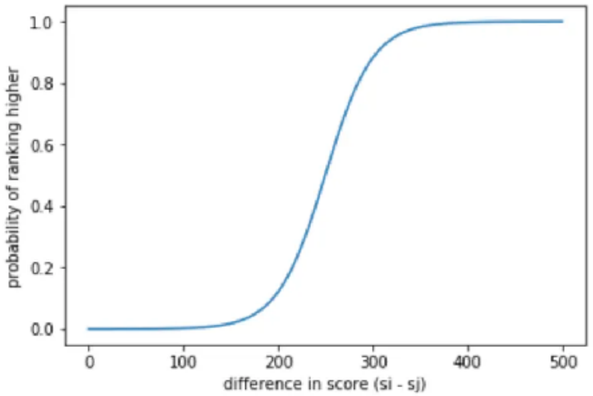
Pairwise approach
RankNet

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

- Predicted probabilities:

$$p_{i,j} = p(s_i > s_j) = \frac{1}{1 + e^{-\gamma(s_i - s_j)}}$$

$$p_{j,i} = \frac{1}{1 + e^{-\gamma(s_j - s_i)}}$$

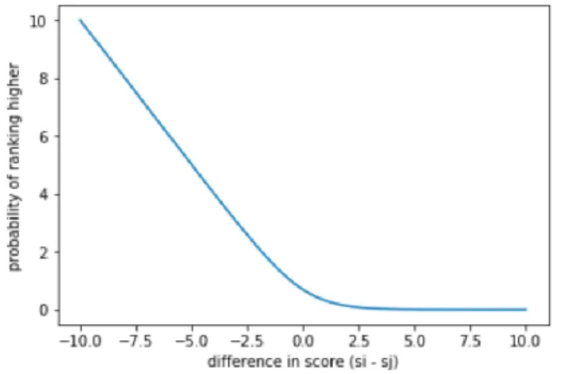


- Desired probabilities:

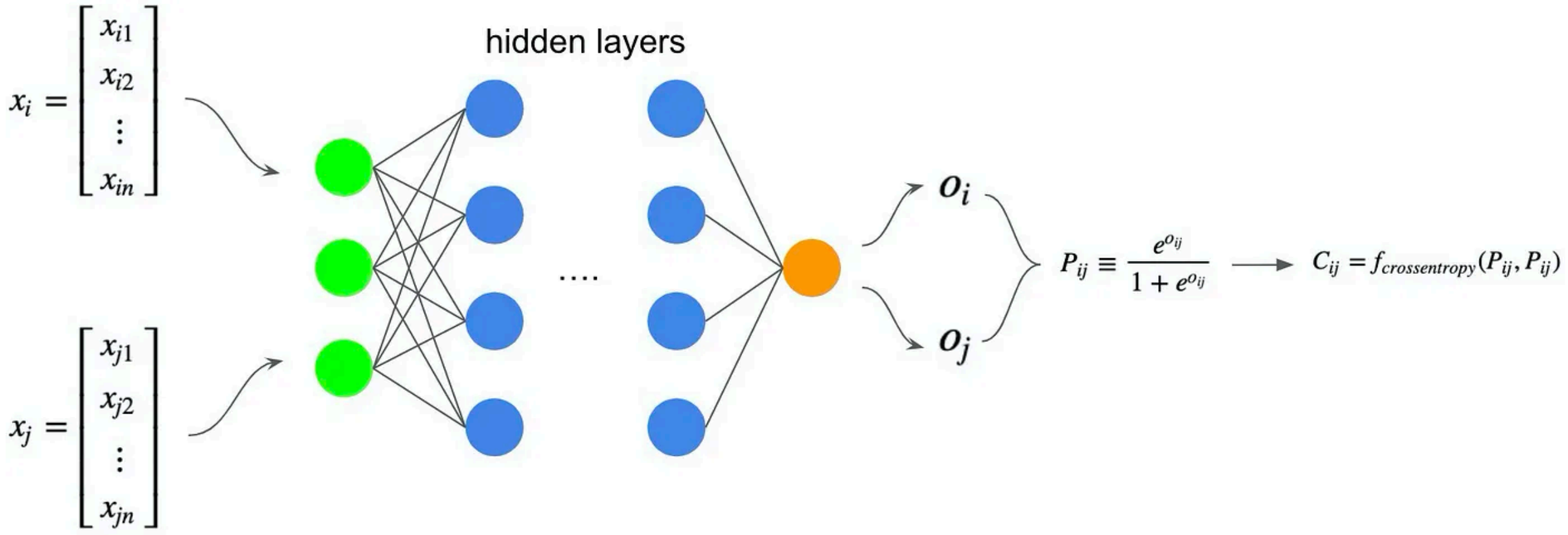
$$p_{ij} = 1 \text{ and } p_{ji} = 0$$

- Computing cross-entropy between y and p

$$L_{RankNet} = y_{ij} log(p_{ij}) - y_{ji} log(p_{ji}) = y_{ij} log(p_{ij}) - (1 - y_{ij}) log(1 - p_{ij})$$

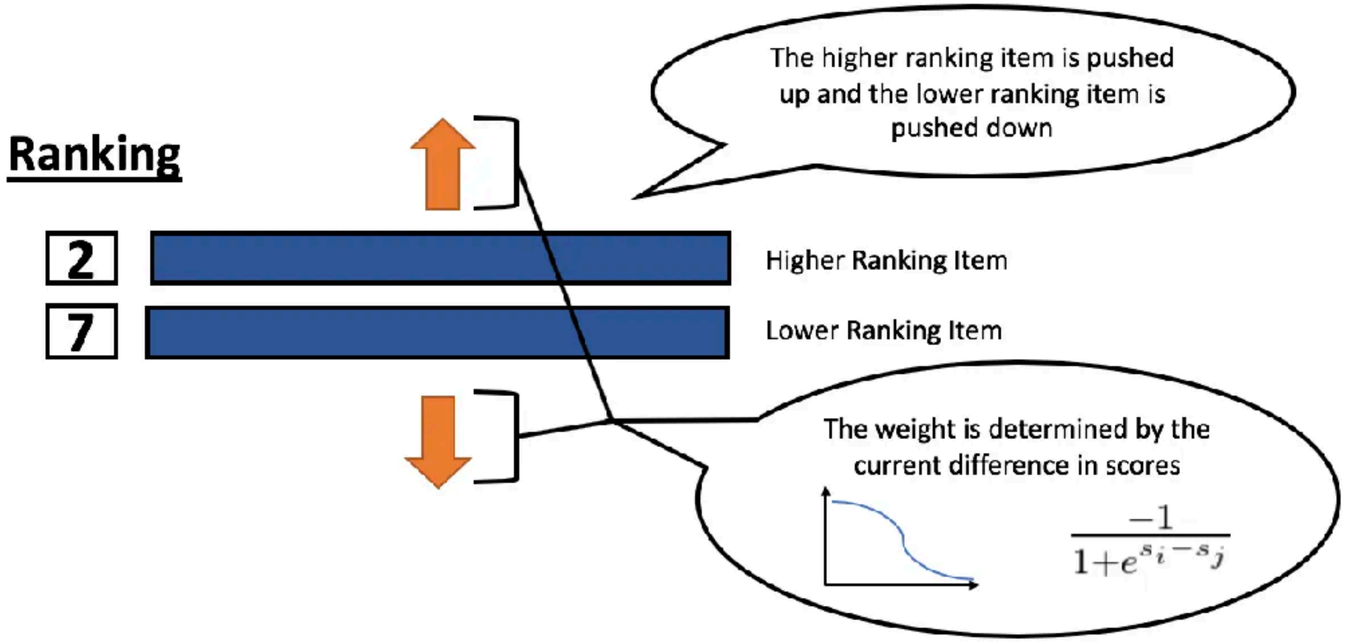


Pairwise approach
RankNet



Pairwise approach

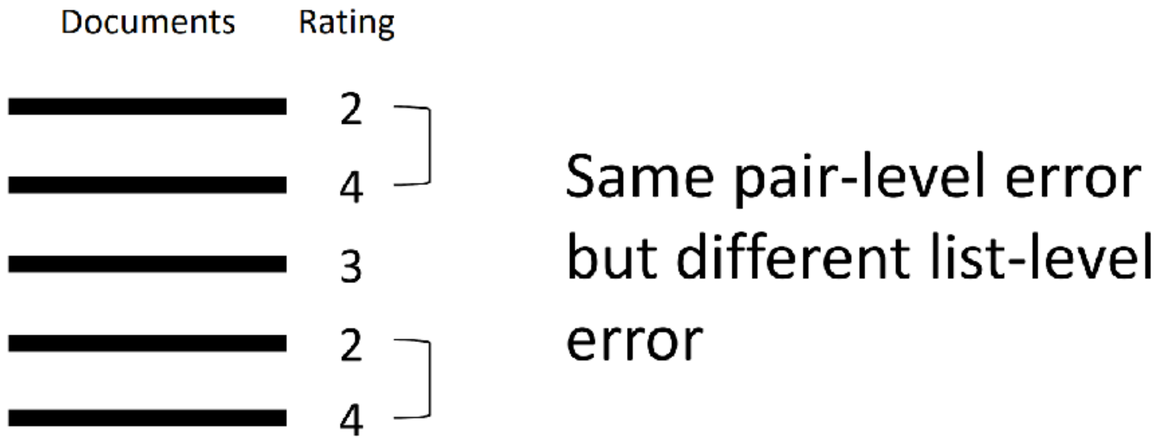
RankNet



Pairwise approach
RankNet

RankNet and is pretty good in many situations. There is one major pitfall to the RankNet approach though: the loss is agnostic to the **actual ranking** of the item.

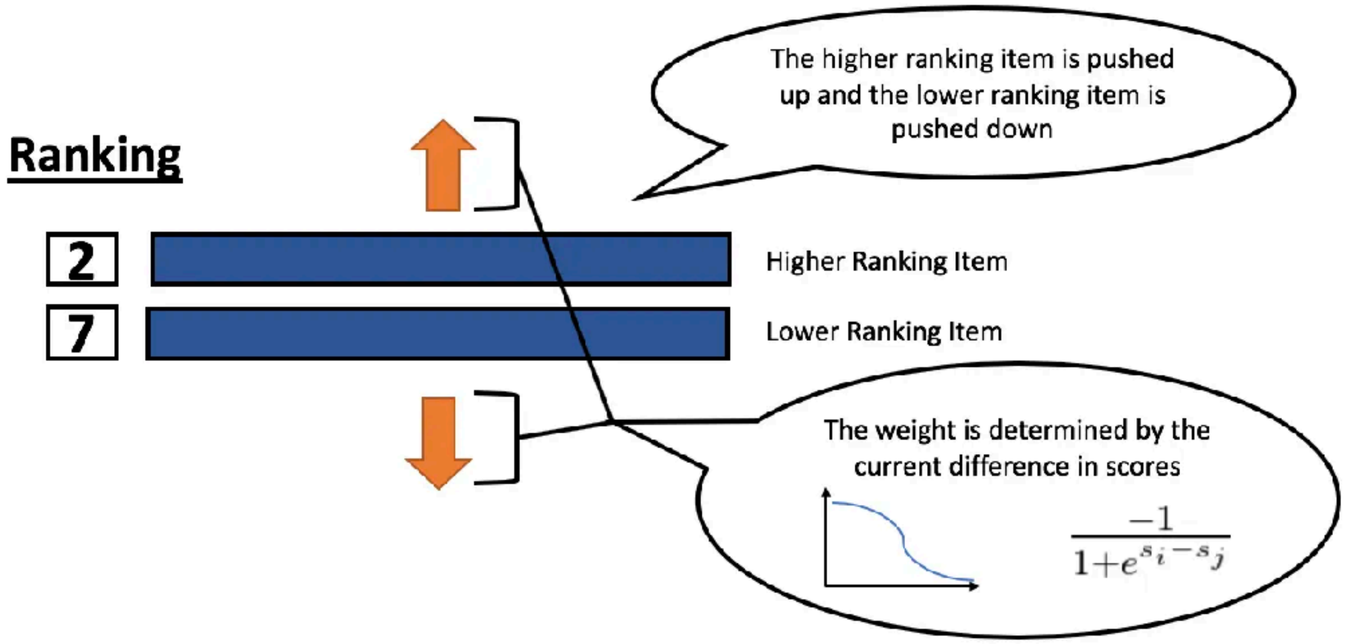
The strength of the push is determined only by the current difference in scores. So it doesn't matter if the items that rank below are 1, 2, or 500 ranks below



Pairwise approach
LambdaRank

- Burgess et. al. found that during RankNet training procedure, you don't need the costs, only need the gradients (λ) of the cost with respect to the model score. You can think of these gradients as little arrows attached to each document in the ranked list, indicating the direction we'd like those documents to move.

- Further they found that scaling the gradients by the change in NDCG found by swapping each pair of documents gave good results. The core idea of LambdaRank is to use this new cost function for training a RankNet. On experimental datasets, this shows both speed and accuracy improvements over the original RankNet.



$$\text{Now, } \lambda_{ij} = \frac{-\Delta(i,j)}{1+e^{(s_i-s_j)}}$$

where $\Delta(i,j)$ is a penalty corresponding to how "bad" it is to rank items i and j in the wrong order.

Multiple metrics can be used to compute Δ, but the most common is the NDCG (normalized discounted cumulative gain)

Pairwise approach
Bayesian Personalized Ranking (BPR)

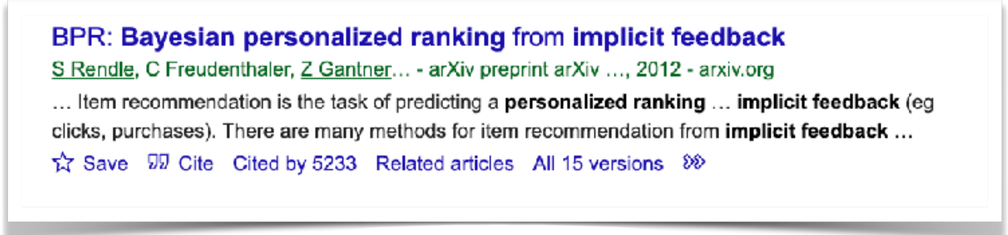
- With implicit feedback, the notion of "ratings" become less precise. As a result, matrix factorization models moved away from estimating a specific set of ratings to, instead, model the relative preferences (or orders) between different items.

- Let D_i be a set of item pairs (j, k) where user i has interacted with item j but not item k , assuming user i might be more interested in item j than item k, BPR minimizes the pairwise ranking loss

$$\min_{\mathbf{u}_*, \mathbf{v}_*} \sum_{i \in \mathcal{I}} \sum_{(j,k) \in \mathcal{D}_i} -log\ \sigma(\mathbf{u}_i^T \mathbf{v}_j - \mathbf{u}_i^T \mathbf{v}_k) + \lambda_u \|\mathbf{u}_i\|^2 + \lambda_v \|\mathbf{v}_j\|^2,$$

  - where σ is the sigmoid function.

- Problem: BPR loss does not sufficiently penalize the items that are at a lower rank



Pairwise approach

Bayesian Personalized Ranking (BPR)

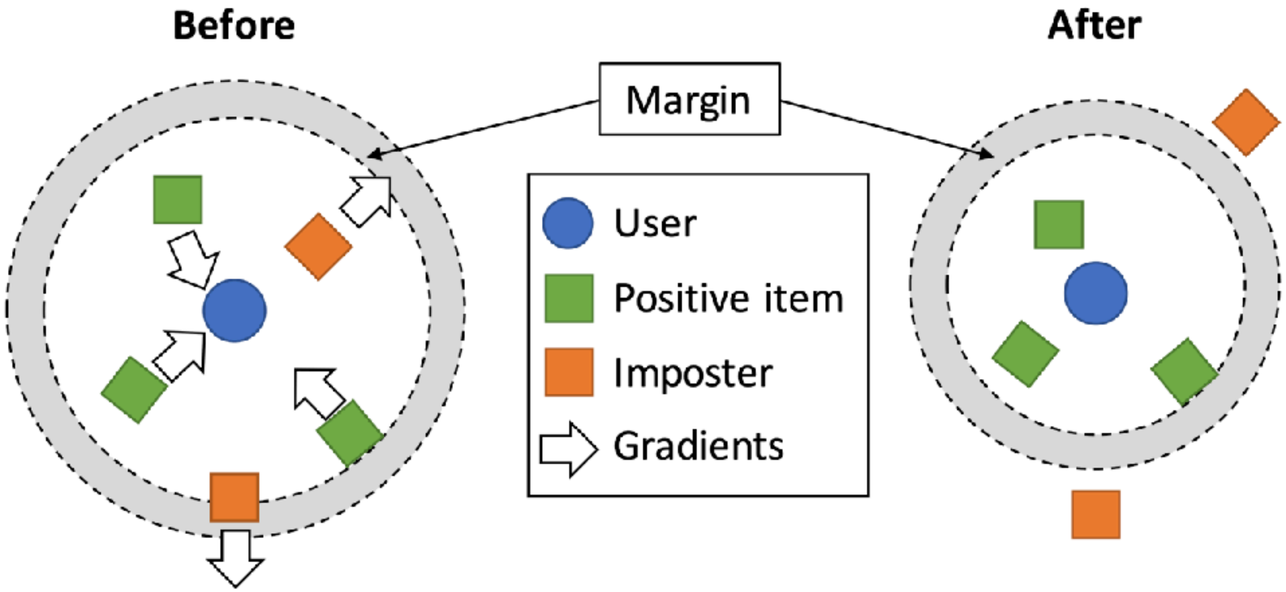
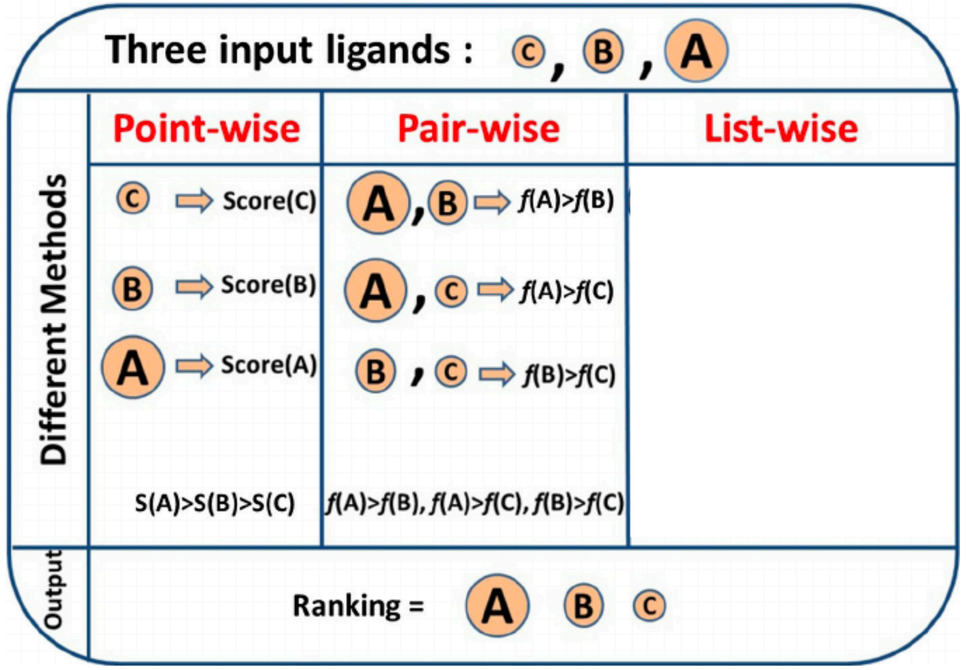


Figure 1: An illustration of collaborative metric learning. The hinge loss defined in Eq. 1 creates a gradient that *pulls* positive items closer to the user and *pushes* the intruding impostor items (i.e., items that the user did not like) away until they are beyond the safety margin.

Learning to rank

- Using Machine Learning, the goal is to **construct a ranking model** from the training data.

- The problem can be treat as a standard classification problem



Listwise approach

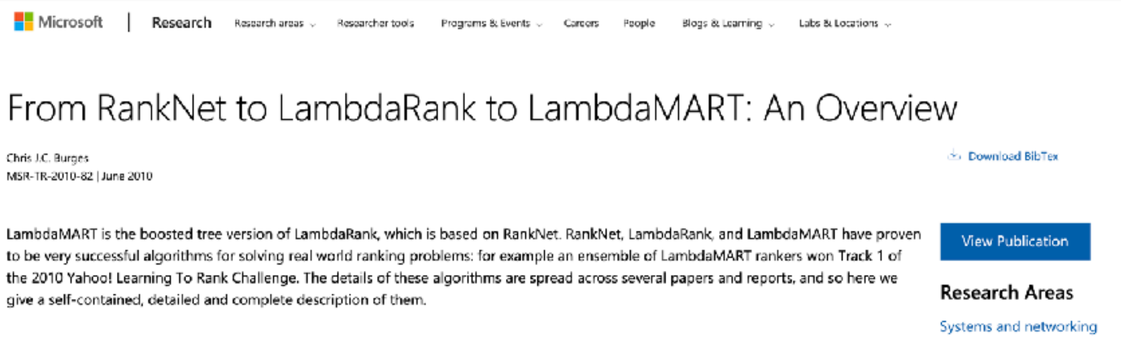
- predict for ranked list of documents based on feature vector x
- **effectiveness** of ranked list **y** (e.g., MAP or nDCG)
- training determines the **parameter** θ based on a **loss function**

Advantage:
positional infirmation visible to loss function

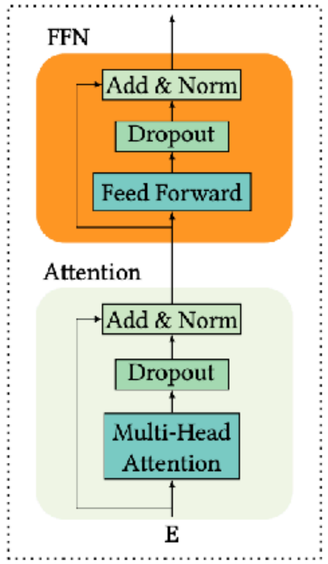
Main disadvantage:
- high training complexity

Lambda Mart

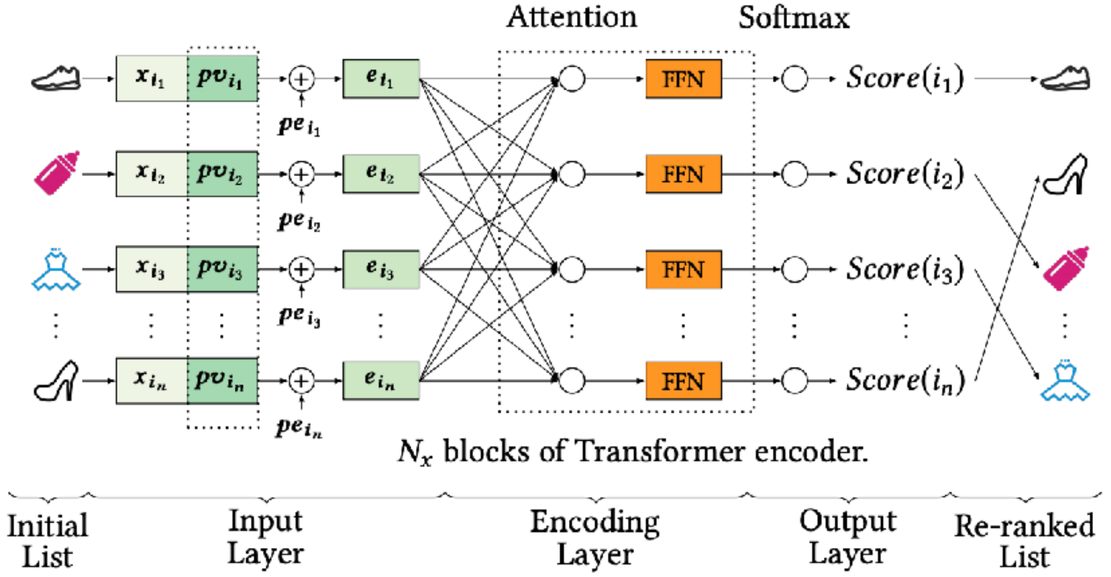
- LambdaMART combines LambdaRank and MART (Multiple Additive Regression Trees)
- MART uses gradient boosted decision trees for prediction tasks, LambdaMART uses gradient boosted decision trees using a cost function derived from LambdaRank for solving a ranking task



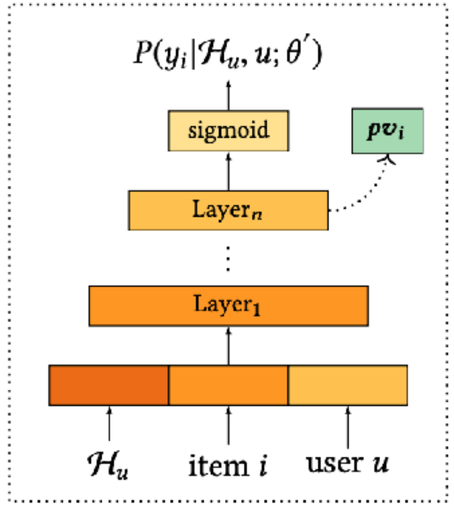
https://www.microsoft.com/en-us/research/publication/from-ranknet-to-lambdarank-to-lambdamart-an-overview/



(a) One block of Transformer encoder.



(b) Architecture of PRM.



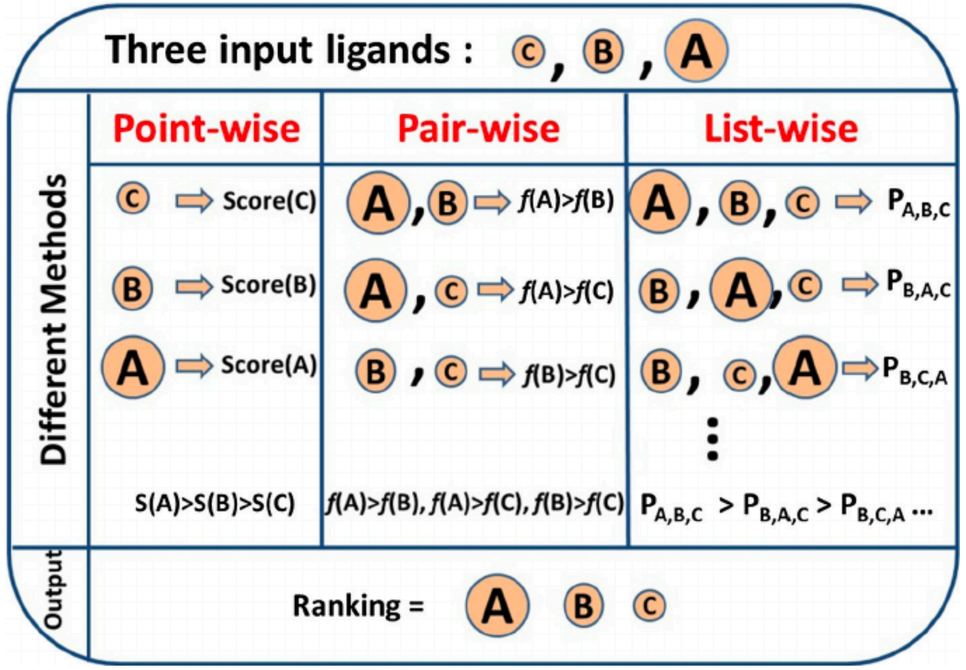
(c) The pre-trained model to generate pv_i, $i = i_1, \ldots, i_n$.

Figure 1: The detailed network structure of our PRM (Personalized Re-ranking Model) and its sub-modules.

Learning to rank

- Using Machine Learning, the goal is to **construct a ranking model** from the training data.

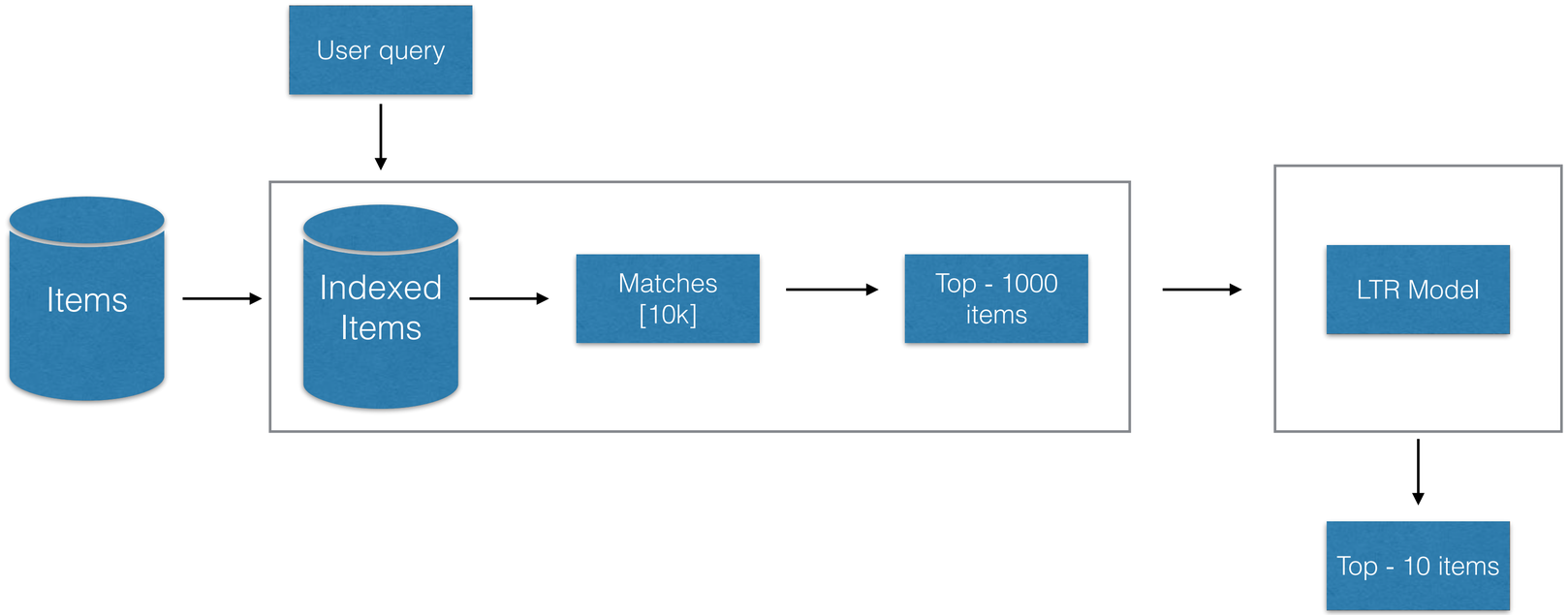
- The problem can be treat as a standard classification problem



LTR are great but
task consuming....

LTR framework

- LTR methods are computationally expensive.
- Usually used as re-rankers



If you have implicit data

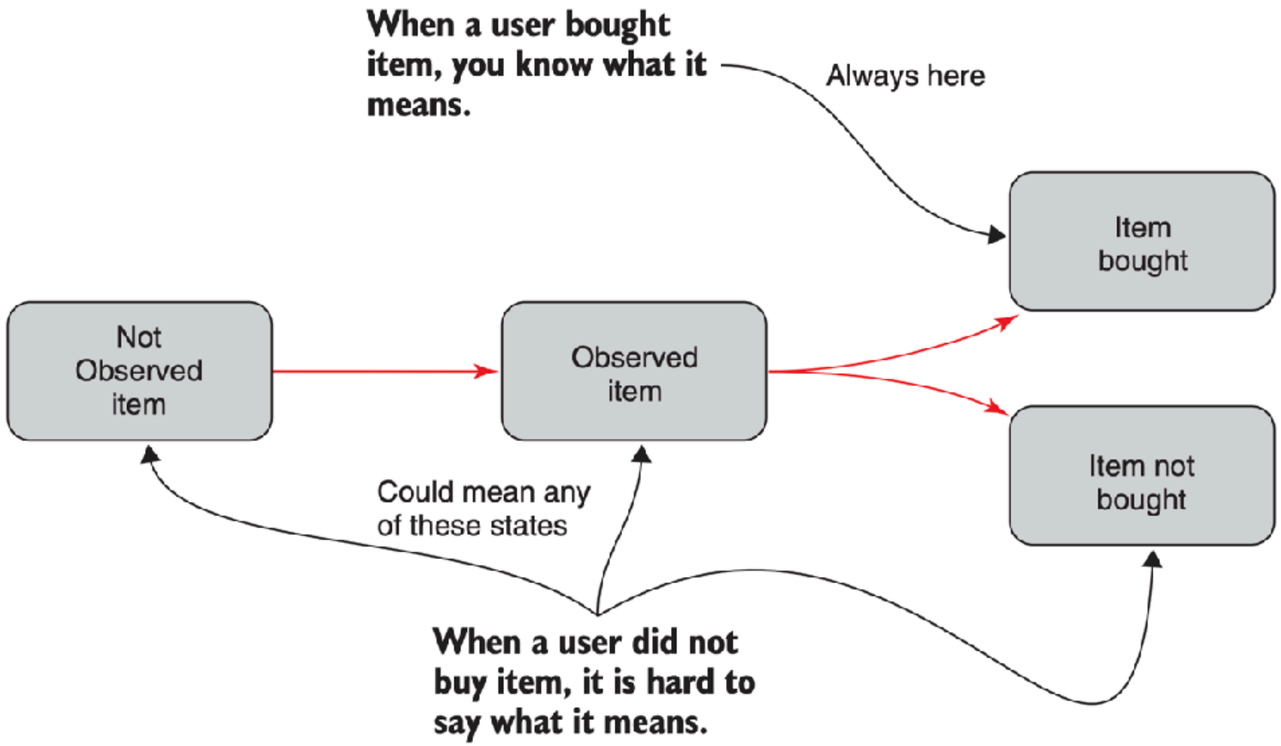


Figure 13.6 Different states of a user-item relationship. You know that when a user buys an item it's bought, but if a user doesn't buy an item, what does that mean?

Presentations

TASK 2

Paper presentations. 8 -10 minutes

Team	Date	Students	Paper
1	March 16th		
2	March 16th		
3	March 16th		
4	March 16th		
5	March 26th		
6	March 26th		
7	March 26th		
8	March 26th		

Paper Suggestions I

Local Item-Item Models for Top-N Recommendation

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ABSTRACT

Item-based approaches based on SLIM (Sparse LInear Methods) have demonstrated very good performance for top-N recommendation; however they only estimate a single model for all the users. This work is based on the intuition that not all users behave in the same way – instead there exist subsets of like-minded users. By using different item-item models for these user subsets, we can capture differences in their preference-based methods, which include item k-NN [8] and Sparse LInear Methods (SLIM) [16] have been shown to outperform the user-based schemes for the top-N recommendation task.

However, item-based methods have the drawback of estimating only a single model for all users. In many cases, there are differences in users' behavior, which cannot be captured by a single model. For example, there could be a pair of items that are extremely similar for a specific user subset, while they have low similarity for another user subset. By

Paper Suggestions I

Paper Suggestions I

Restricted Boltzmann Machines for Collaborative Filtering

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Abstract

Most of the existing approaches to collaborative filtering cannot handle very large data sets. In this paper we show how a class of two-layer undirected graphical models, called Restricted Boltzmann Machines (RBM's), can be used to model tabular data, such as user's ratings of movies. We present efficient learning and inference procedures for this class of models and demonstrate that RBM's can be successfully applied to the Netflix data set, containing over 100 million user/movie ratings. We also show that RBM's slightly outperform carefully-tuned SVD models. When the predictions of multiple RBM models and multiple SVD models are linearly combined, we achieve an error rate that is well over 6% better than the score of Netflix's own system.

Low-rank approximations based on minimizing the sum-squared distance can be found using Singular Value Decomposition (SVD). In the collaborative filtering domain, however, most of the data sets are sparse, and as shown by Srebro and Jaakkola (2003), this creates a difficult non-convex problem, so a naive solution is not going work.[1]

In this paper we describe a class of two-layer undirected graphical models that generalize Restricted Boltzmann Machines to modeling tabular or count data (Welling et al., 2005). Maximum likelihood learning is intractable in these models, but we show that learning can be performed efficiently by following an approximation to the gradient of a different objective function called "Contrastive Divergence" (Hinton, 2002).

2. Restricted Boltzmann Machines (RBM's)

Paper Suggestions I

Restricted Boltzmann Machines for Collaborative Filtering

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Andriy Mnih AMNIH@CS.TORONTO.EDU
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University of Toronto, 6 King's College Rd., Toronto, Ontario M5S 3G4, Canada

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2. Restricted Boltzmann Machines (RBM's)

Paper Suggestions II

This summer, I'm interning at Spotify in New York City, where I'm working on content-based music recommendation using convolutional neural networks. In this post, I'll explain my approach and show some preliminary results.

Overview

This is going to be a long post, so here's an overview of the different sections. If you want to skip ahead, just click the section title to go there.

http://benanne.github.io/2014/08/05/spotify-cnns.html

Paper Suggestions III

Deep content-based music recommendation

Aäron van den Oord, Sander Dieleman, Benjamin Schrauwen
Electronics and Information Systems department (ELIS), Ghent University
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Abstract

Automatic music recommendation has become an increasingly relevant problem in recent years, since a lot of music is now sold and consumed digitally. Most recommender systems rely on collaborative filtering. However, this approach suffers from the cold start problem: it fails when no usage data is available, so it is not effective for recommending new and unpopular songs. In this paper, we propose to use a latent factor model for recommendation, and predict the latent factors from music audio when they cannot be obtained from usage data. We compare a traditional approach using a bag-of-words representation of the audio signals with deep convolutional neural networks, and evaluate the predictions quantitatively and qualitatively on the Million Song Dataset. We show that using predicted latent factors produces sensible recommendations, despite the fact that there is a large semantic gap between the characteristics of a song that affect user preference and the corresponding audio signal. We also show that recent advances in deep learning translate very well to the music recommendation setting, with deep convolutional neural networks significantly outperforming the traditional approach.

Paper Suggestions IV

Deep Neural Networks for YouTube Recommendations

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ABSTRACT

YouTube represents one of the largest scale and most sophisticated industrial recommendation systems in existence. In this paper, we describe the system at a high level and focus on the dramatic performance improvements brought by deep learning. The paper is split according to the classic two-stage information retrieval dichotomy: first, we detail a deep candidate generation model and then describe a separate deep ranking model. We also provide practical lessons and insights derived from designing, iterating and maintaining a massive recommendation system with enormous user-facing impact.

Keywords

recommender system; deep learning; scalability

1. INTRODUCTION

YouTube is the world's largest platform for creating, sharing and discovering video content. YouTube recommendations are responsible for helping more than a billion users discover personalized content from an ever-growing corpus of videos. In this paper we will focus on the immense impact deep learning has recently had on the YouTube video recommendations system. Figure 1 illustrates the recommendations on the YouTube mobile app home.

Recommending YouTube videos is extremely challenging

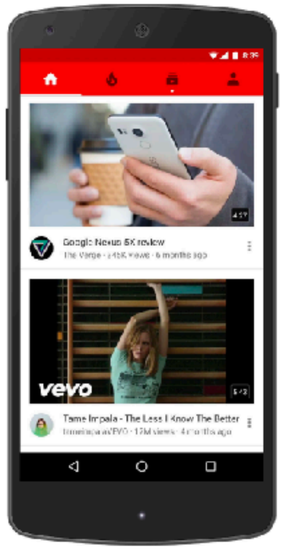

Figure 1: Recommendations displayed on YouTube mobile app home.

with well-established videos can be understood from an exploration/exploitation perspective.

Paper Suggestions V

Wide & Deep Learning for Recommender Systems

Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, Rohan Anil, Zakaria Haque, Lichan Hong, Vihan Jain, Xiaobing Liu, Hemal Shah
Google Inc.*

Paper Suggestions VI

Collaborative Knowledge Base Embedding for Recommender Systems

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ABSTRACT

Among different recommendation techniques, collaborative filtering usually suffer from limited performance due to the sparsity of user-item interactions. To address the issues, auxiliary information is usually used to boost the performance. Due to the rapid collection of information on the web, the knowledge base provides heterogeneous information including both structured and unstructured data with different semantics, which can be consumed by various applications. In this paper, we investigate how to leverage the heterogeneous information in a knowledge base to improve the quality of recommender systems. First, by exploiting the knowledge base, we design three components to extract items' semantic representations from structural content, textual content and visual content, respectively. To be specific, we adopt a heterogeneous network embedding method, termed as TransR, to extract items' structural representations by considering the heterogeneity of both nodes and relationships. We apply stacked denoising auto-encoders and stacked convolutional auto-encoders, which are two types of deep learning based embedding techniques, to extract items' textual representations and visual representations, respectively. Finally, we propose our final integrated framework, which is termed as Collaborative Knowledge Base Embedding (CKE), to jointly learn the latent representations in collaborative filtering as well as items' semantic representations from the knowledge base. To evaluate the performance of each embedding component as well as the whole system, we conduct extensive experiments with two real-

filtering (CF) based methods, which make use of historical interactions or preferences, have made significant success [23]. However, CF methods usually suffer from limited performance when user-item interactions are very sparse, which is very common for scenarios such as online shopping where the item set is extremely large. In addition, CF methods can not recommend new items since these items have never received any feedbacks from users in the past. To tackle these problems, hybrid recommender systems, which combine collaborative filtering and auxiliary information such as item content, can usually achieve better recommendation results and have gained increasing popularity in recent years [2].

Over the past years, more and more semantic data are published following the Linked Data principles[1], by connecting various information from different topic domains such as people, books, musics, movies and geographical locations in a unified global data space. These heterogeneous data, interlinked with each other, forms a huge information resource repository called knowledge base. Several typical knowledge bases have been constructed, including academic projects such as YAGO[2], NELL[3], DBpedia[4], and DeepDive[5], as well as commercial projects, such as Microsoft's Satori[6] and Google's Knowledge Graph[7]. Using the heterogeneous connected information from the knowledge base can help to develop insights on problems which are difficult to uncover with data from a single domain [6]. To date, information retrieval [9], community detection [25], sentiment analysis [4] - to name a few - are the noteworthy applications that successfully leverage the knowledge base.

Paper Suggestions VII

SESSION-BASED RECOMMENDATIONS WITH RECURRENT NEURAL NETWORKS

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ABSTRACT

We apply recurrent neural networks (RNN) on a new domain, namely recommender systems. Real-life recommender systems often face the problem of having to base recommendations only on short session-based data (e.g. a small sportsware website) instead of long user histories (as in the case of Netflix). In this situation the frequently praised matrix factorization approaches are not accurate. This problem is usually overcome in practice by resorting to item-to-item recommendations, i.e. recommending similar items. We argue that by modeling the whole session, more accurate recommendations can be provided. We therefore propose an RNN-based approach for session-based recommendations. Our approach also considers practical aspects of the task and introduces several modifications to classic RNNs such as a ranking loss function that make it more viable for this specific problem. Experimental results on two data-sets show marked improvements over widely used approaches.

https://arxiv.org/abs/1511.06939

Paper Suggestions VIII

Graph Convolutional Matrix Completion

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University of Amsterdam

Thomas N. Kipf
University of Amsterdam

Max Welling
University of Amsterdam, CIFAR[1]

Abstract

We consider matrix completion for recommender systems from the point of view of link prediction on graphs. Interaction data such as movie ratings can be represented by a bipartite user-item graph with labeled edges denoting observed ratings. Building on recent progress in deep learning on graph-structured data, we propose a graph auto-encoder framework based on differentiable message passing on the bipartite interaction graph. Our model shows competitive performance on standard

in the form of node features. Predicting ratings then reduces to predicting labeled links in the bipartite user-item graph.

We propose graph convolutional matrix completion (GC-MC): a graph-based auto-encoder framework for matrix completion, which builds on recent progress in deep learning on graphs [2, 6, 19, 5, 15, 30, 14]. The auto-encoder produces latent features of user and item nodes through a form of message passing on the bipartite interaction graph. These latent user and item representations are used to reconstruct the rating links through a bilinear decoder.

Paper Suggestions IX

Deep Models of Interactions Across Sets

Jason Hartford [*1] **Devon R Graham** [*1] **Kevin Leyton-Brown** [1] **Siamak Ravanbakhsh** [1]

Abstract

We use deep learning to model interactions across two or more sets of objects, such as user–movie ratings or protein–drug bindings. The canonical representation of such interactions is a matrix (or tensor) with an exchangeability property: the encoding's meaning is not changed by permuting rows or columns. We argue that

$\langle n, m, x \rangle \in \mathbb{X}$. Learning our function corresponds to *matrix completion*: using patterns in $\mathbb{X}$ to predict values for the remaining elements of X.

X is what we will call an *exchangeable matrix*: any row- and column-wise permutation of X represents the same set of ratings and hence the same matrix completion problem. Exchangeability has a long history in machine learning and statistics. For example, the common iid assumption implies

huge list here:

https://github.com/hongleizhang/RSPapers