

Recommender Systems || Lecture 11

Summer 2022

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UW, Seattle

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Logistics

- ① Assignment 3 due next Wednesday

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- ② Project checkpoint due next Monday
- ③ Please pick a time slot for your team to discuss project proposal if you haven't yet!

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- ④ Anything else?!

Today

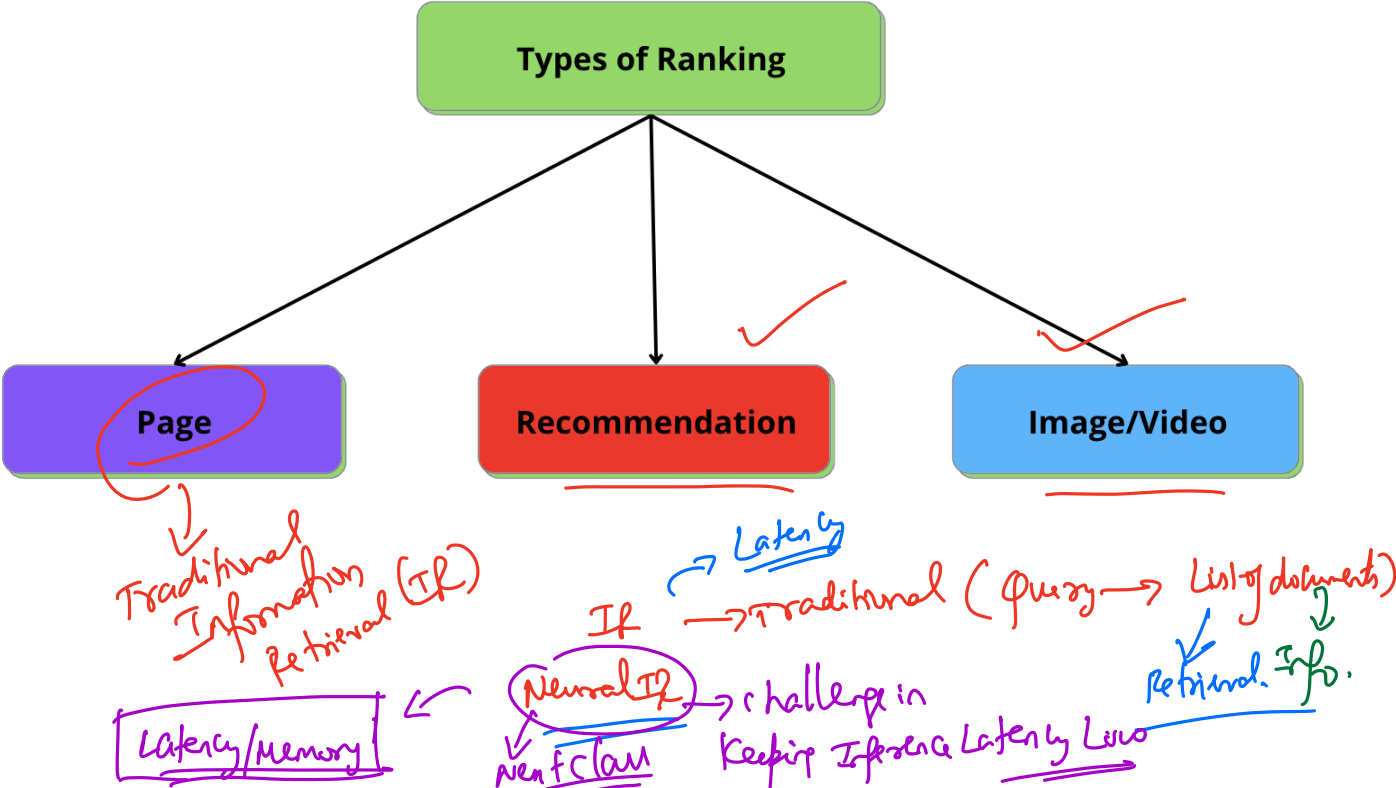
Today

- ① Ranking loss function and metrics

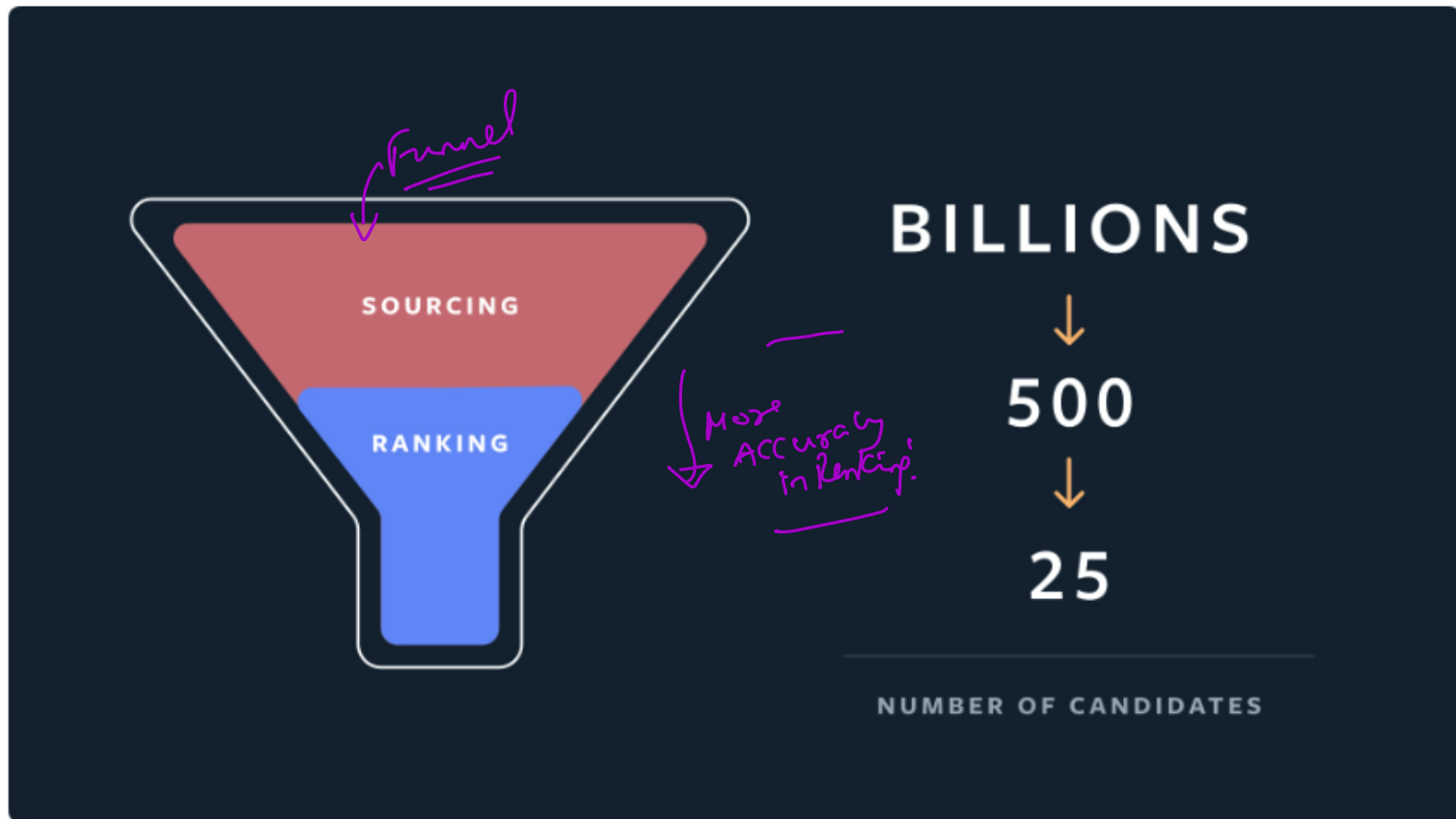
Today

- ① Ranking loss function and metrics
- ② Page Ranking and Ranking Algorithms

Ranking Problems



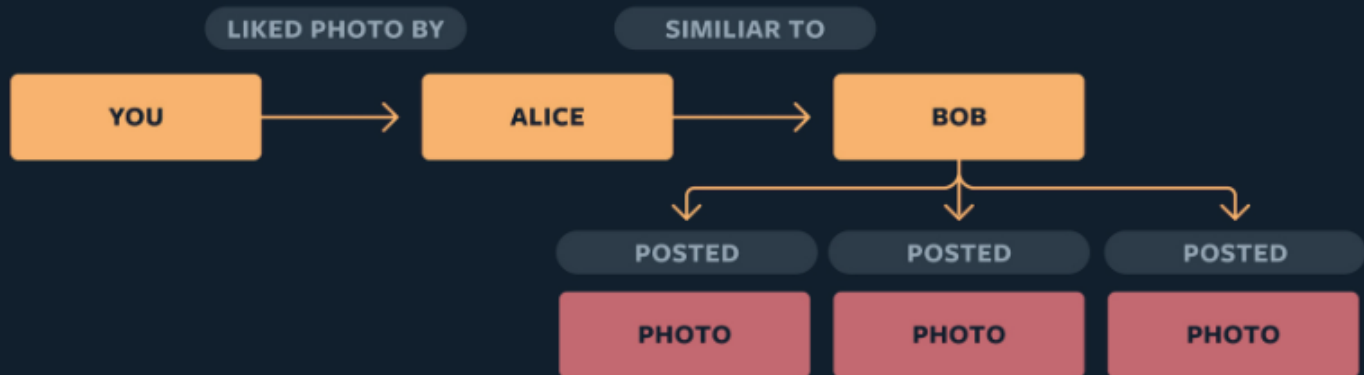
Image/Video Ranking (Instagram)



Instagram Recommendations

Image/Video Ranking (Instagram Candidate Generation)

One type of Explore source



Instagram Recommendations

Image/Video Ranking (Amazon Video)

Behavior-based Popularity Ranking on Amazon Video

With the growth in the number of video streaming services, providers have to strive hard to make relevant content available and keep customers engaged. A good experience would help customers discover new and popular videos to stream with ease. Customer streaming behavior tends to be a strong indicator of whether they found a video engaging. Aggregate customer behavior serves as a useful predictor of popularity. We discuss the use of past streaming behavior to learn patterns and predict a video's popularity using tree ensembles.

CCS Concepts: • **Information systems** → **Recommender systems**; **Content ranking**.

Additional Key Words and Phrases: video streaming; popularity; recommendations

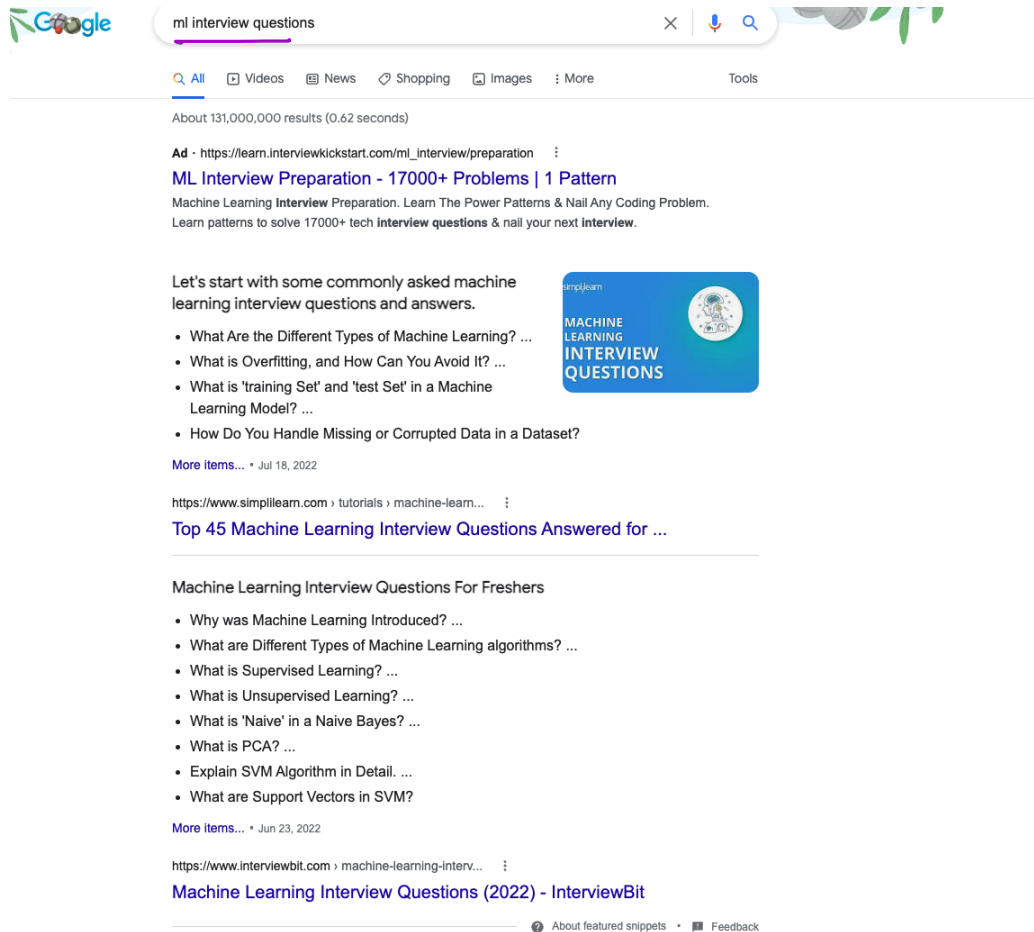
ACM Reference Format:

. 2020. Behavior-based Popularity Ranking on Amazon Video. In *Fourteenth ACM Conference on Recommender Systems (RecSys '20)*, September 22–26, 2020, Virtual Event, Brazil. ACM, New York, NY, USA, 3 pages. <https://doi.org/10.1145/3383313.3411555>

1 INTRODUCTION

On streaming platforms customers use two main approaches to find videos—search and discovery. Customers can enter a query to search for a video or browse the catalog to discover content. Streaming platforms use customer preferences,

Page/Search Ranking



The screenshot shows a Google search for "ml interview questions". The search bar is at the top with the Google logo on the left and a search icon on the right. Below the search bar, there are filters for "All", "Videos", "News", "Shopping", "Images", and "More". The search results are displayed below the filters. The first result is an advertisement for "ML Interview Preparation - 17000+ Problems | 1 Pattern" from the URL "https://learn.interviewkickstart.com/ml_interview/preparation". The ad text says "Machine Learning Interview Preparation. Learn The Power Patterns & Nail Any Coding Problem. Learn patterns to solve 17000+ tech interview questions & nail your next interview." Below the ad, there is a section titled "Let's start with some commonly asked machine learning interview questions and answers." followed by a list of five questions: "What Are the Different Types of Machine Learning? ...", "What is Overfitting, and How Can You Avoid It? ...", "What is 'training Set' and 'test Set' in a Machine Learning Model? ...", and "How Do You Handle Missing or Corrupted Data in a Dataset?". To the right of this list is a blue rectangular graphic with the text "MACHINE LEARNING INTERVIEW QUESTIONS" and a small circular icon. Below this is a link "More items..." dated "Jul 18, 2022". The next result is from "https://www.simplilearn.com" with the title "Top 45 Machine Learning Interview Questions Answered for ...". Below this is a section titled "Machine Learning Interview Questions For Freshers" with a list of seven questions: "Why was Machine Learning Introduced? ...", "What are Different Types of Machine Learning algorithms? ...", "What is Supervised Learning? ...", "What is Unsupervised Learning? ...", "What is 'Naive' in a Naive Bayes? ...", "What is PCA? ...", "Explain SVM Algorithm in Detail. ...", and "What are Support Vectors in SVM?". Below this list is another "More items..." link dated "Jun 23, 2022". The final result is from "https://www.interviewbit.com" with the title "Machine Learning Interview Questions (2022) - InterviewBit". At the bottom of the search results, there are links for "About featured snippets" and "Feedback".

Page/Search Ranking

Google ml ops

About 40,100,000 results (0.55 seconds)

Ad · <https://www.applica.ai/> :
Insights | MLOps - Real-World Application - applica.ai
Discover Applica's Deep Learning-based Automation Solution. Comprehend Even the Most Complex and Variable Business Documents. Get a Demo. Unmatched Precision. For All Complexities. All Document Types. Hyper Learning NLP.

Ad · <https://info.wallaroo.ai/mlops> :
Mlops Platform - Make Machine Learning Easy - wallaroo.ai
Learn How To Optimize Live Models Based On The Latest Data And Insights With No Downtime. Deploy, Run & Optimize Your Data For a Fraction Of The Cost. Learn How With Our eBook. Simple & Secure. Self-Service Toolkit. On-Premises. On Any Cloud.

<https://ml-ops.org> :
ML Ops: Machine Learning Operations
With Machine Learning Model Operationalization Management (MLOps), we want to provide an end-to-end machine learning development process to design, ...
[Crisp-ml\(q\)](#) · [ML Model Governance](#) · [Three Levels of ML Software](#) · [MLOps Principles](#)

People also ask :

- What are ML operations?
- What does an MLOps do?
- Is MLOps a data engineer?
- Is MLOps worth learning?

<https://databricks.com> › Glossaries :
MLOps - Databricks
MLOps stands for Machine Learning Operations. MLOps is a core function of Machine Learning engineering, focused on streamlining the process of taking ...
Take your ML projects from... · The Big Book of Machine... · MLOps Virtual Event

<https://en.wikipedia.org> › wiki › MLOps :
MLOps - Wikipedia

MLOps :

Mlops Book

Introducing MLOps Practical MLOps Engineering MLOps Practical MLOps

Requirements → High clicks
Retard → Diversity → Low Latency
NDCG/MAP@k

Types of Ranking

(Search)
Types of Ranking

Ranking Creation

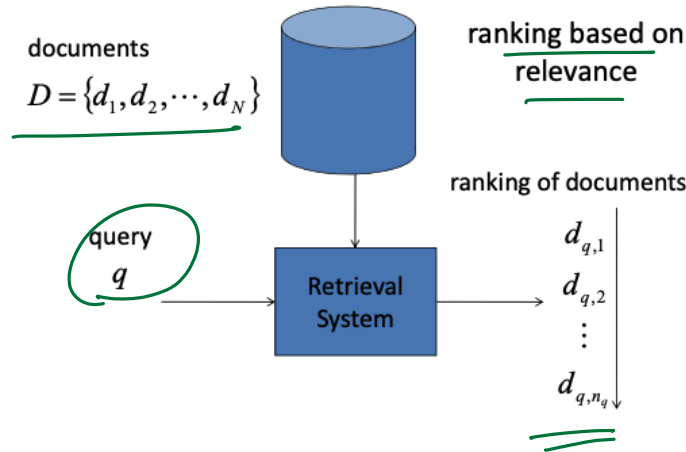
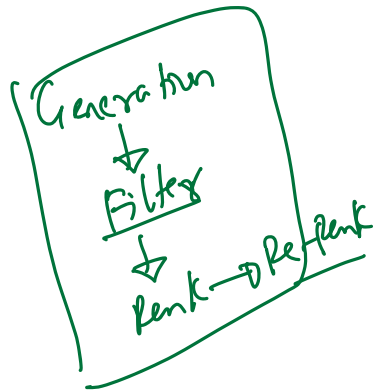
Rank a List of Documents

Ranking Aggregation

Aggregation of Ranking Lists
Example: News Aggregator

Learning to Rank Survey

Search Ranking - Document Retrieval



(diversity)
freshness / relevancy
Filter Spam /
Filter Inapp/ (context)

Learning to Rank Survey

Recommendations Ranking - Collaborative Filtering

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

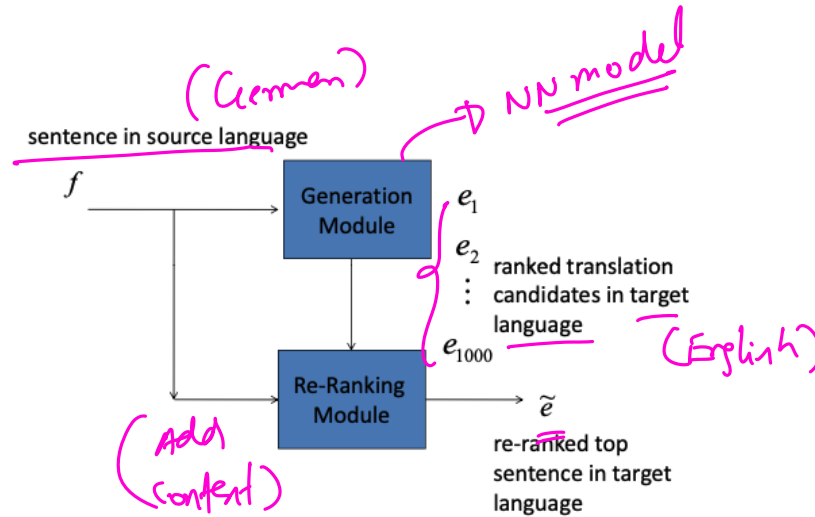
Rank Items
for each
user
user

↓

These into
(?) query like
in search!

Learning to Rank Survey

Re-ranking in Machine Translation



MT is based on
Seq2Seq models
(SOTA)

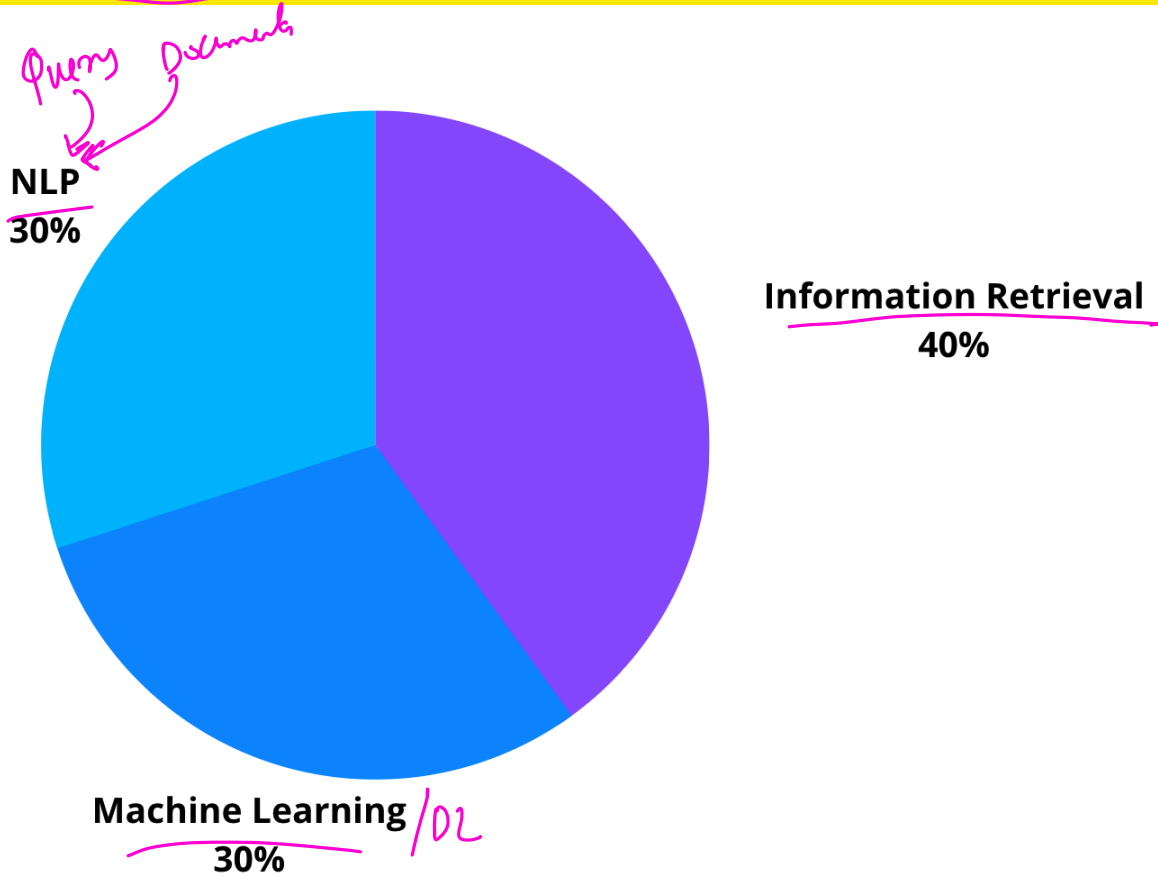
(add context)

(Style of Language, personalization, etc)

Learning to Rank Survey

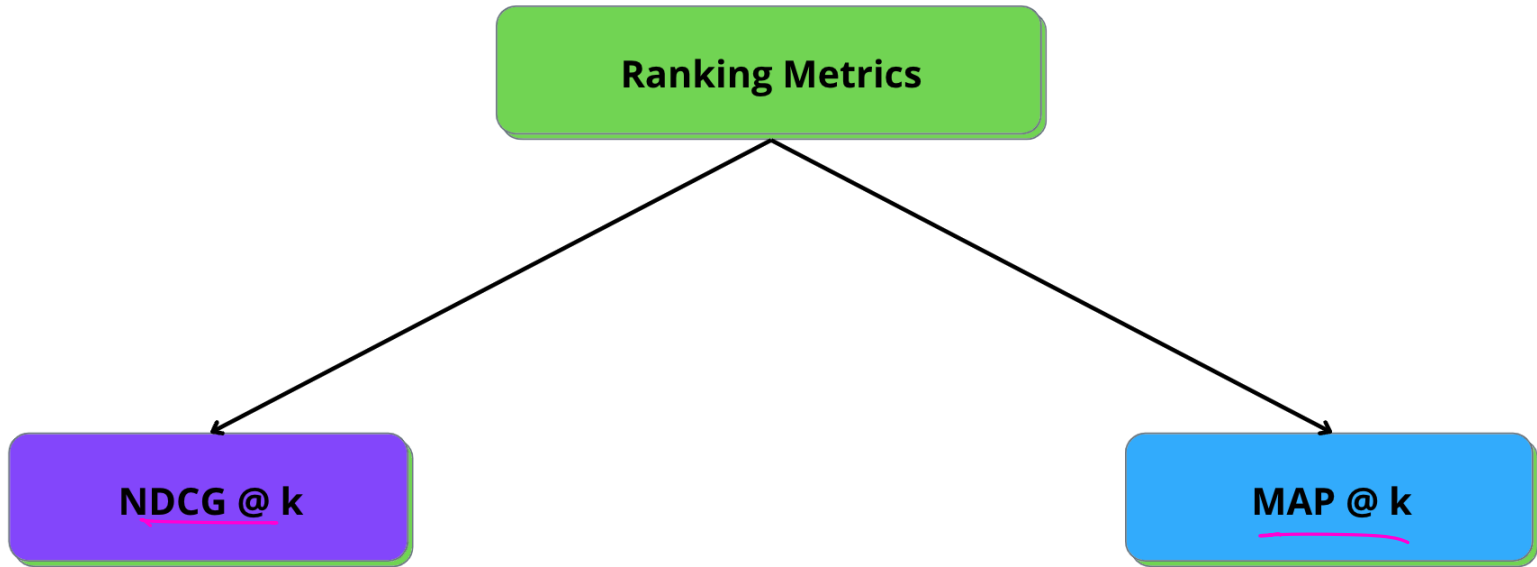
(Traditional IR)
Concepts

Learning to Rank



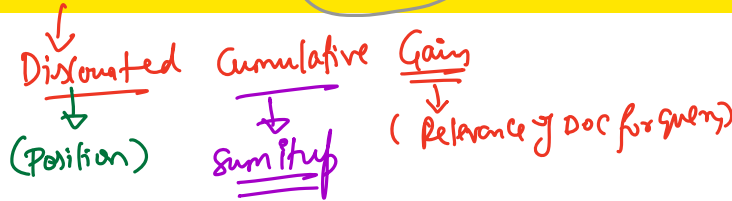
Ranking Metrics

search
Top Interview Questions on Ranking → Ranking flows
→ Ranking metrics



Learning to Rank Survey

Ranking Metric - DCG & NDCG



(Input) Queries $q_1, q_2, q_3, \dots, q_{100}$
 (Output) Documents $d_{1,1}, d_{1,2}, \dots, d_{1,10}$
 → First doc for query 3
 $d_{3,1}, d_{3,2}, \dots, d_{3,k}$
 $DCG@k$

Table 2.4: Example of NDCG

Perfect ranking	Formula	Explanation
(3, 3, 2, 2, 1, 1, 1)	Grade to Gain	grades: 3,2,1
(7, 7, 3, 3, 1, 1, 1)	$2^{y_i, j} - 1$	gains
(1, 0.63, 0.5, ...)	$1 / \log(\pi_i(j) + 1)$	position discounts
(7, 11.41, 12.91, ...)	$\sum_{j: \pi_i(j) \leq k} \frac{2^{y_i, j} - 1}{\log(\pi_i(j) + 1)}$	DCG scores
(1/7, 1/11.41, 1/12.91, ...)	$DCG_{max}^{-1}(k)$	normalizing factors
(1, 1, 1, ...)	$NDCG(k)$	NDCG scores

Imperfect ranking	Formula	Explanation
(2, 3, 2, 3, 1, 1, 1)		grades: 3,2,1
(3, 7, 3, 7, 1, 1, 1)	$2^{y_i, j} - 1$	gains
(1, 0.63, 0.5, ...)	$1 / \log(\pi_i(j) + 1)$	position discounts
(3, 7.41, 8.91, ...)	$\sum_{j: \pi_i(j) \leq k} \frac{2^{y_i, j} - 1}{\log(\pi_i(j) + 1)}$	DCG scores
(1/7, 1/11.41, 1/12.91, ...)	$DCG_{max}^{-1}(k)$	normalizing factors
(0.43, 0.65, 0.69, ...)	$NDCG(k)$	NDCG scores

Ground Truth Data
 y_{ij} → Grade of document j for query i
 i - query
 j - document

Max value for $NDCG@k = 1$
 Min value for $NDCG@k = 0$

$$DCG@k = \sum_{j=1}^k \frac{Gain(j)}{Discount(j)}$$

Grades → Higher the grade - More relevant the document

Relevance of a Document

↳ human annotated

3 grades (not relevant, relevant, highly relevant)

Gain → Function of grade (exponentiation)

$$NDCG(k) = \frac{DCG(k)}{DCG_{max}(k)}$$

ICE #1

DCG computation

For a query, "show me top 10 thriller movies of this century" - a search engine returns 10 results: d_1, d_2, \dots, d_{10} , where d_j represents document/page j . Let the grade of the documents be given as follows: $\{3, 2, 1, 5, 2, 4, 5, 6, 7, 4\}$. The $DCG@3$ for the results of the search is closest to:

- ① 11
- ② 21
- ③ 31
- ④ 41

$$DCG@k = \frac{Gain(1)}{\log(1+1)} + \frac{Gain(2)}{\log(2+1)} + \dots + \frac{Gain(k)}{\log(k+1)}$$

$$\frac{3-1}{\log(2)} + \frac{2-1}{\log(3)} + \frac{1-1}{\log(4)} \approx 31$$

$$Gain(k) = 2^{\text{grade}(k)} - 1$$

ICE #2

NDCG computation

For a query, "show me top 10 thriller movies of this century" - a search engine returns 10 results: d_1, d_2, \dots, d_{10} , where d_j represents document/page j . Let the grade of the documents be given as follows: $\{3, 2, 1, 5, 2, 4, 5, 6, 7, 4\}$. The $NDCG@1$ for the results of the search is closest to:

- ① 0.05
- ② 0.1
- ③ 0.15
- ④ 0.2

$$NDCG@k = \frac{DCG@k}{DCG_{max}@k} = \frac{2^3 - 1}{2^7 - 1} = \frac{7}{127} = 0.05$$

$$DCG@1 \propto 2^3 - 1 \quad DCG_{max}@1 \propto 2^7 - 1 = 127$$

Ranking Metric - Mean Average Precision (MAP)

$(1, 0, 1, 1, 0, 0, 0)$

Precision@1 = $\frac{1}{1}$

$P@4 = \frac{3}{4}$

Precision@2 = $\frac{1}{2}$

Precision@3 = $\frac{2}{3}$

Similar to Precision@k!

MAP = AP for all queries averaged/mean

Perfect ranking	Formula	Explanation
(1, 0, 1, 1, 0, 0, 0)		Ranks: 1, 0
(1, -, 0.67, 0.75, -, -, -)	$P(j)$	Precision at position j with label 1
0.81	AP	Average Precision

Grades are 0.051

$AP@3 = ICE\#3$

MAP \leftarrow Improved precision metric that incorporates Ranking!

$AP@4 = \frac{1 + 0.67 + 0.75}{4} = \underline{\underline{0.81!}}$

ICE #3

AP (Average Precision) computation

For a query, "show me top 10 thriller movies of this century" - a search engine returns 10 results: d_1, d_2, \dots, d_{10} , where d_j represents document/page j . Let the normalized grade of the documents be given as follows: $\{1, 0, 1, 1, 0, 0, 1, 0, 1, 0\}$. The $AP@3$ for the results of the search is closest to:

- ① 0.35
- ② 0.45
- ③ 0.55
- ④ 0.65

Different Example

$p@3$

$p@6$

$p@1$ $p@2$

Precision
 $= 3/7$
 $= 0.42$

$\rightarrow 1/3$

$\rightarrow 2/6$

$\rightarrow 1$ $\rightarrow 2/2 = 1$

[①

00 1 0 0 1 1

② 1 1 0 0 0 0 1

$AP@3 = \frac{1/3 + 2/6 + 3/7}{3} = 0.36$

$AP = \frac{1 + 1 + 3/7}{3} = 0.809$

Next Class

NDCG and approx. NDCG

- ① Ranking Loss functions
- ② Neural models for Search Ranking and Re-ranking