Recommender Systems || Lecture 11

Summer 2022

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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 propsoal if you haven't yet!

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4. Anything else?!

Today

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1. Ranking loss function and metrics

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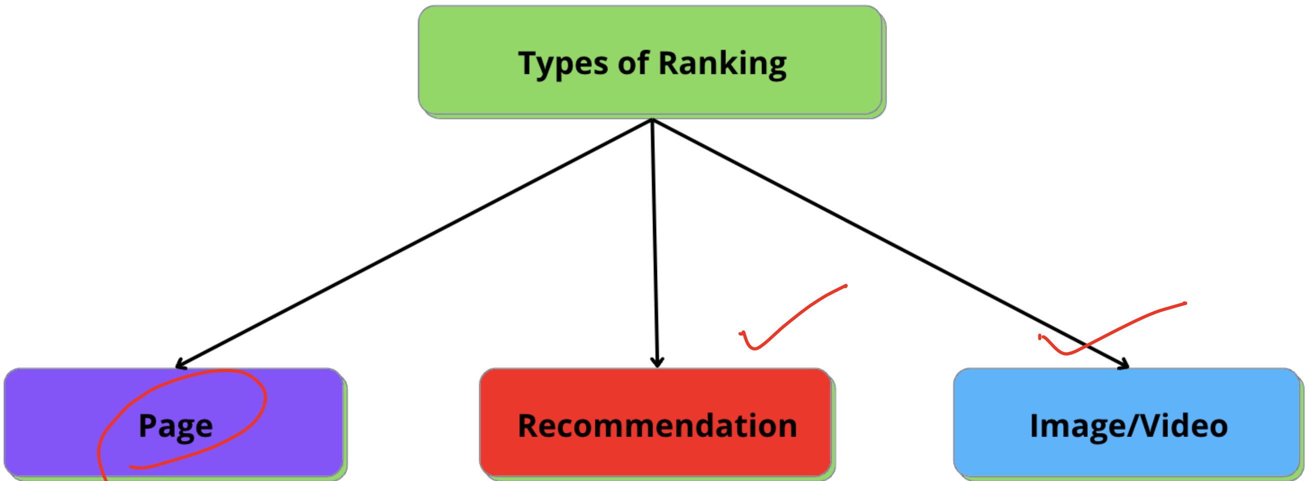
2. Page Ranking and Ranking Algorithms

Ranking Problems



Traditional Information Retrieval (IR)

IR → Traditional (Query → List of documents)

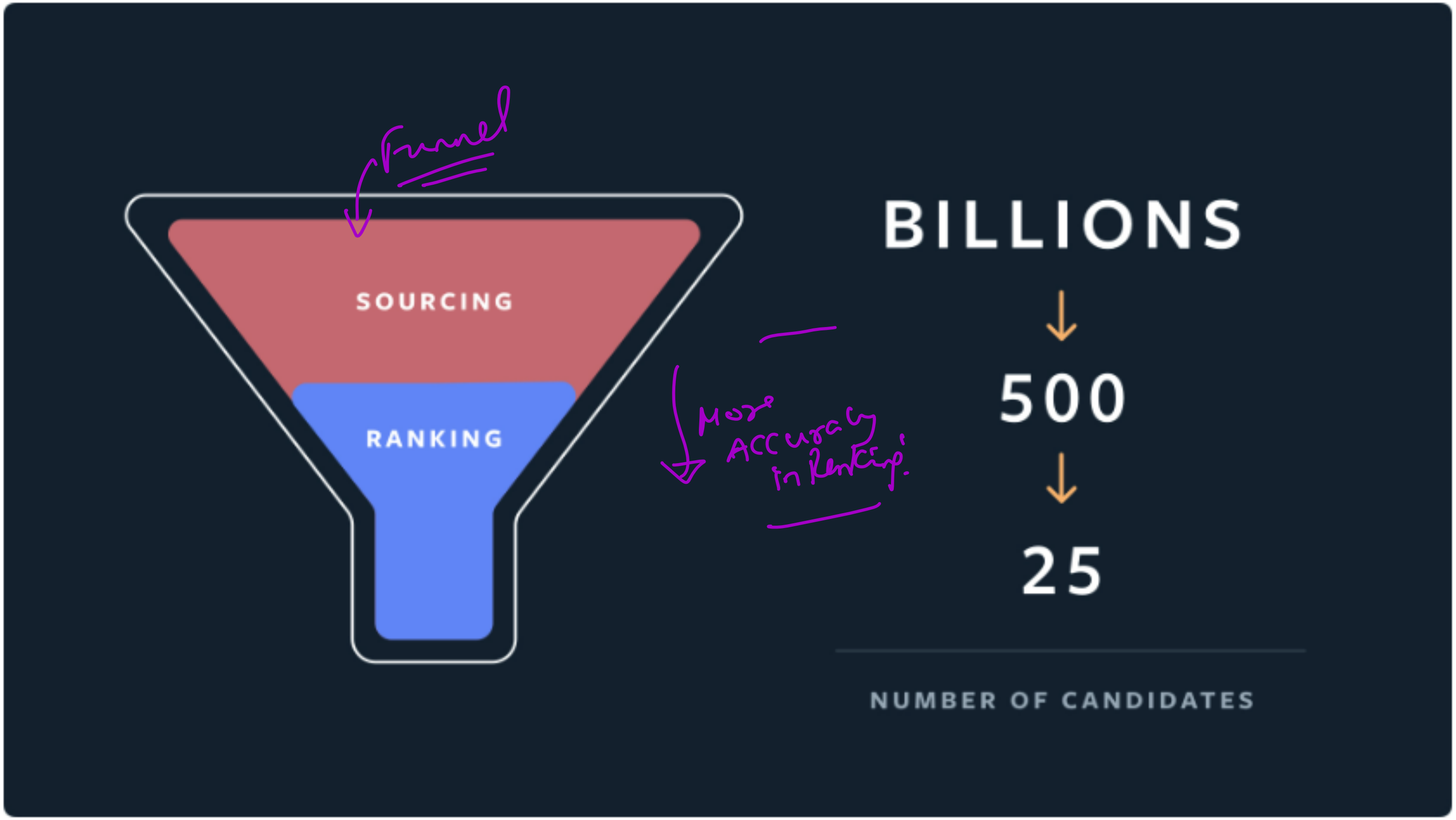
Latency

Retrieval Info.

Neural IR → challenge in Keeping Inference Latency Low

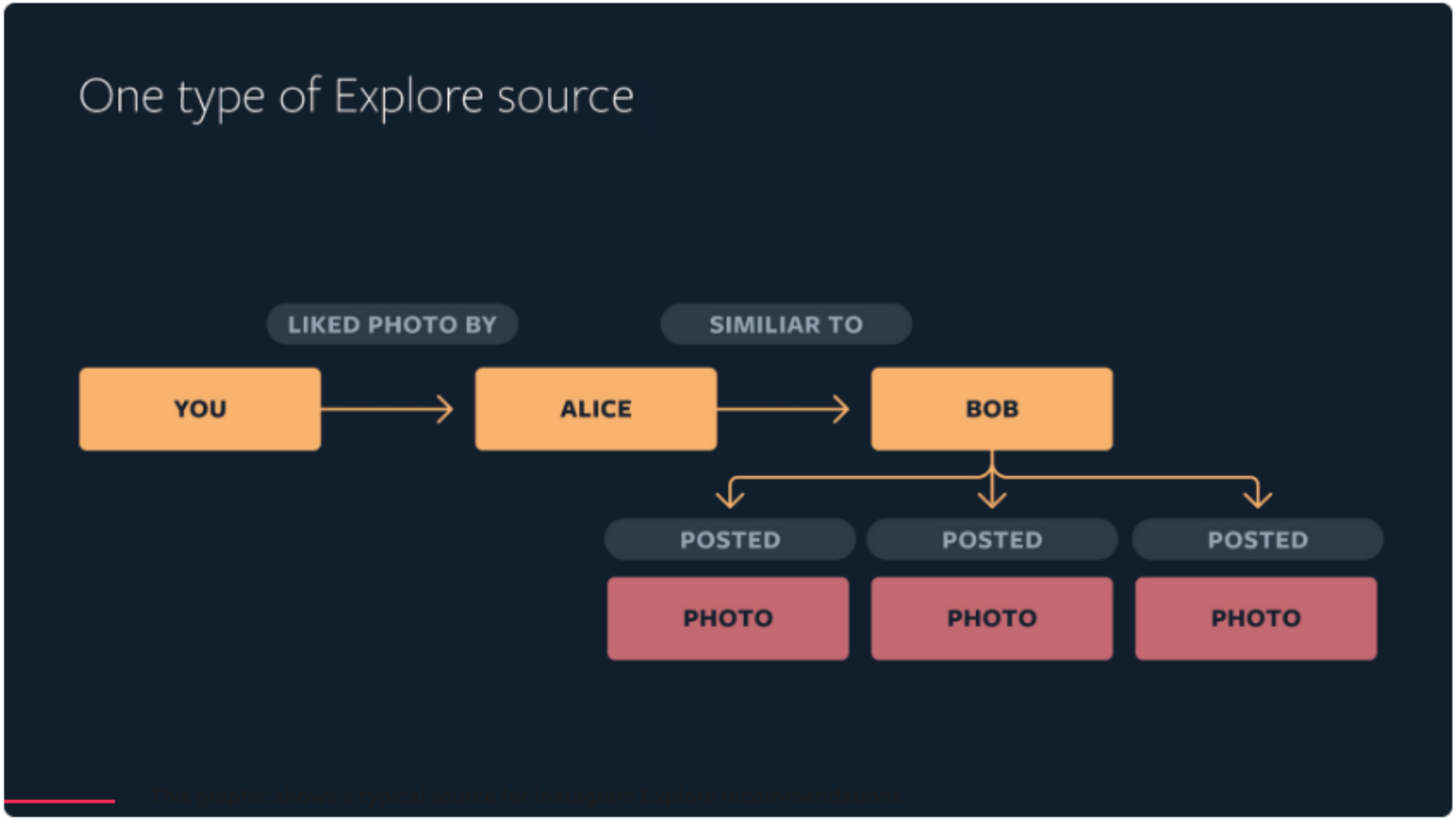
Latency/Memory

Image/Video Ranking (Instagram)



Instagram Recommendations

Image/Video Ranking (Instagram Candidate Generation)



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

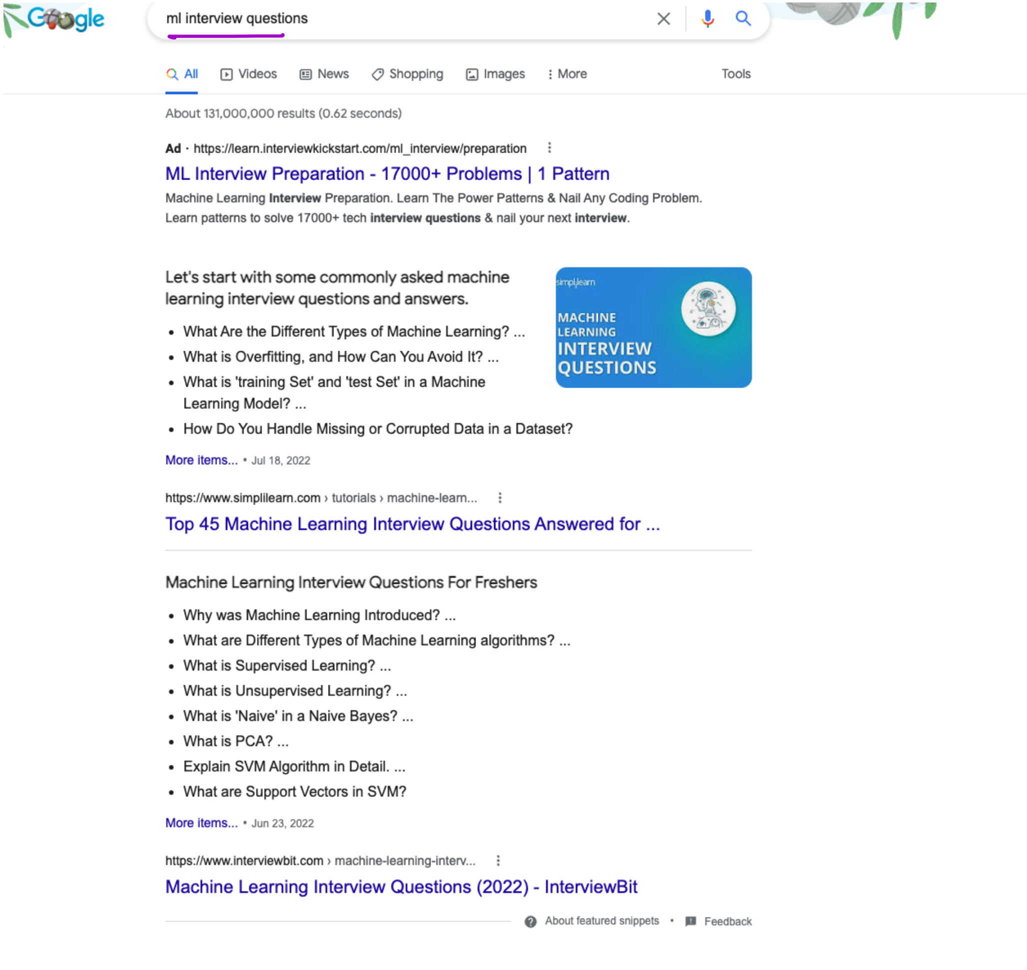
ACM Reference Format:

. 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

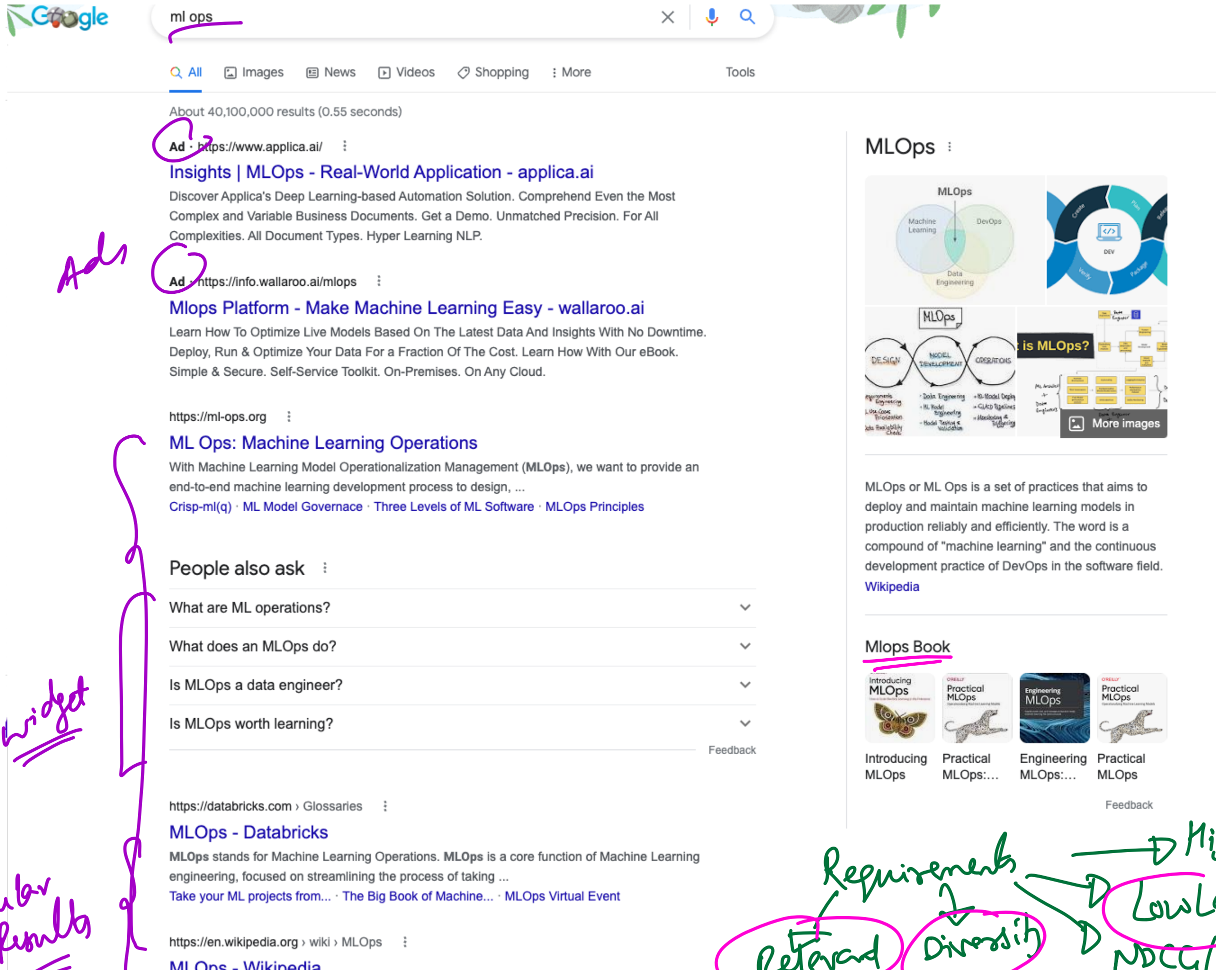
1 INTRODUCTION

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



Page/Search Ranking



Ads

widget

Regular Results

Requirements

Relevant

Diversity

→ High clicks

→ Low Latency

→ NDCG/MAP metrics

Types of Ranking

Types of Ranking (search)

Ranking Creation → Rank a List of Documents

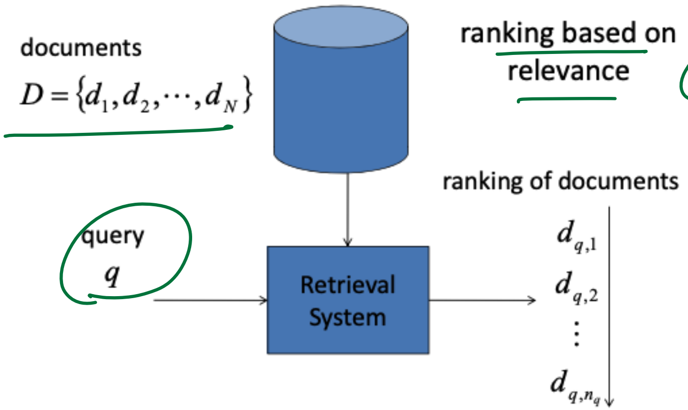
Ranking Aggregation

Aggregation of Ranking Lists → Example:- News Aggregator

Learning to Rank Survey

Search Ranking - Document Retrieval

Generation
↓
Filter
↓
Rank → ReRank



(diversity / freshness / recency / Filter Spam / Filter Inapp. Content)

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

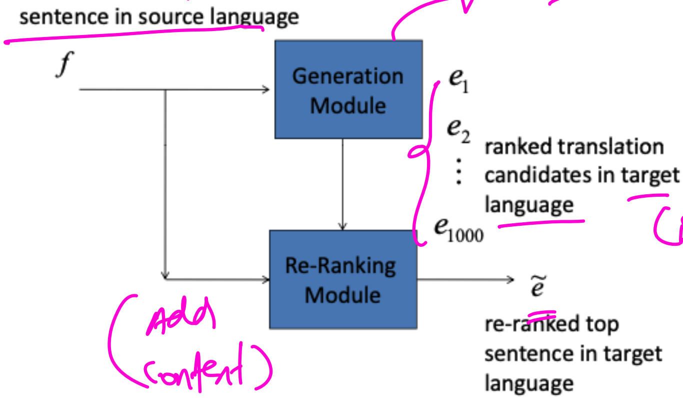
These into query like (q) in search!

Learning to Rank Survey

Re-ranking in Machine Translation

(German)

→ NN model



(English)

(Add content)

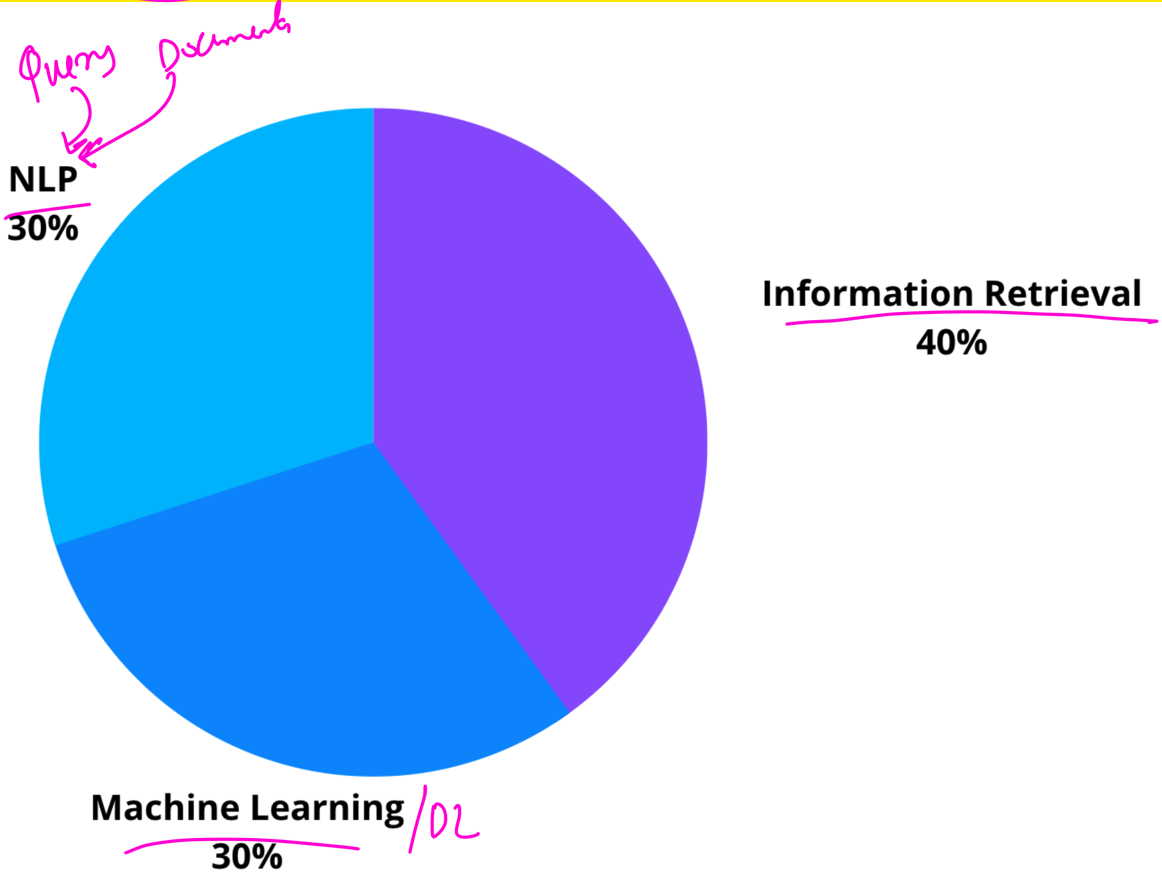
→ (Style of Language, personalization, etc)

MT is based on Seq2Seq models (SOTA)

Learning to Rank Survey

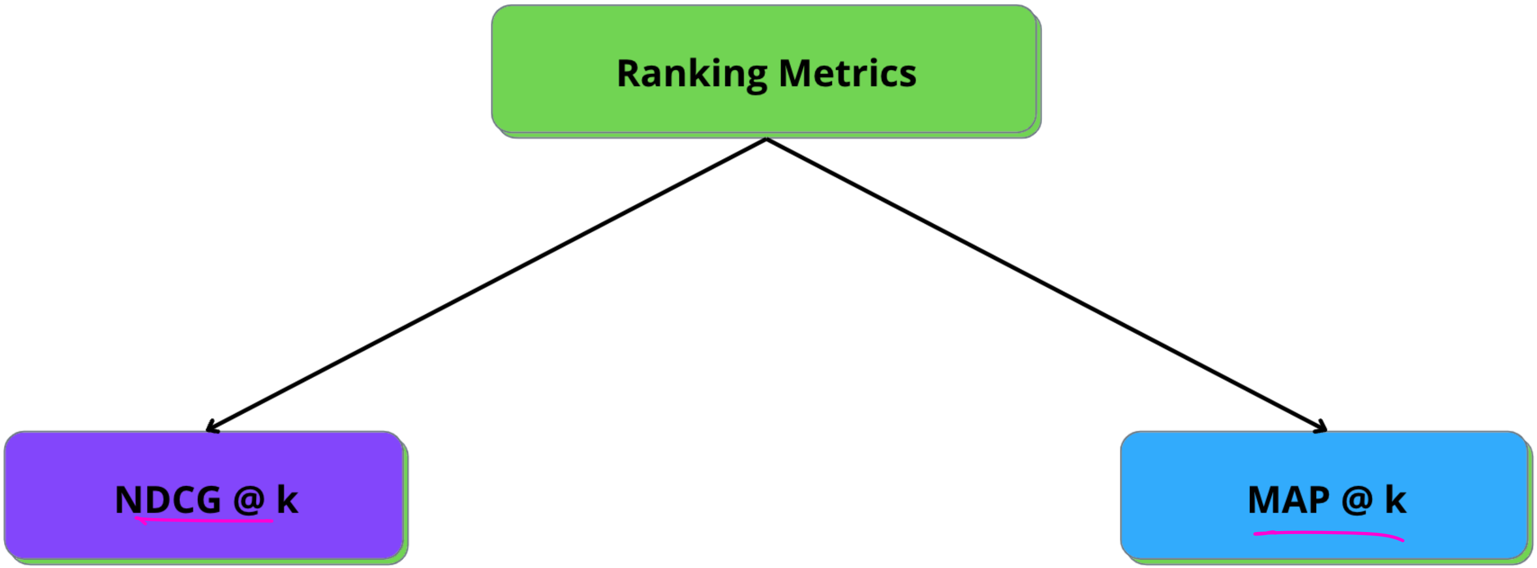
(Traditional IR) Concepts

Learning to Rank



Ranking Metrics

Top Interview Questions in search Ranking
→ Ranking loss
→ Ranking metrics



Learning to Rank Survey

Ranking Metric - DCG & NDCG

normalizing

Discounted Cumulative Gain

(Position) sum it up (Relevance of doc for query)

(Input) (Output)

Queries Documents

q_1 $d_{1,1}\ d_{1,2}, \dots d_{1,10}$

q_2

q_3 → First doc for query 3: $d_{3,1}\ d_{3,2} \dots d$

$\vdots$

q_{100}

DCG@K

Table 2.4: Example of NDCG

Perfect ranking	Formula	Explanation
(3, 3, 2, 2, 1, 1, 1)		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, ···)	$\sum_{j:\pi_i(j)\le k} \frac{2^{y_{i,j}}-1}{\log(\pi_i(j)+1)}$	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, ···)	$\sum_{j:\pi_i(j)\le k} \frac{2^{y_{i,j}}-1}{\log(\pi_i(j)+1)}$	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

Grade to Gain

Ground Truth data

$y_{i,j}$ → Grade of document j for query i

i – Query

j – document

$$DCG@4 = \sum_{j=1}^{4} \frac{Gain(j)}{Discount(j)}$$

Max value for NDCG(K) = 1

Min value for NDCG(K) = 0

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

Grades → Higher the grade – More relevant the document

Relevance of a Document

↳ human annotated

3 grades (not relevant, relevant, highly relevant)

Gains ← Function of Grade (exponentiation)

ICE #1

DCG computation

For a query, "show me top 10 thriller movies of this century" - a search engine returns 10 results: $d_1, d_2, \ldots, d_{10}$, 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

$$DCG@K = \frac{Gain(1)}{\log(1+1)} + \frac{Gain(2)}{\log(2+1)} + \cdots + \frac{Gain(K)}{\log(K+1)}$$

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

$$Gain(K) = 2^{grade(K)} - 1$$

ICE #2

NDCG computation

For a query, "show me top 10 thriller movies of this century" - a search engine returns 10 results: $d_1, d_2, \ldots, d_{10}$, 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

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

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

Ranking Metric - Mean Average Precision (MAP)

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

Precision@1 = 1/1   P@4 = 3/4

Precision@2 = 1/2

Precision@3 = 2/3

Similar to Precision@K!!

MAP = AP for all queries averaged/mean

Table 2.5: Example of MAP

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 or 1

AP@3 = ICE#3

MAP ← Improved precision metric that incorporates ranking!!

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

ICE #3

AP (Average Precision) computation

For a query, "show me top 10 thriller movies of this century" - a search engine returns 10 results: $d_1, d_2, \ldots, d_{10}$, 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

Precision $= 3/7 = 0.42$

P@3 P@6 P@1 P@2

$1/3$ $2/6$ 1 $2/2 = 1$

1 0 0 1 0 0 1 1 2 1 1 0 0 0 0 1

$AP@7 = \frac{1/3 + 2/6 + 3/7}{3} = 0.36$ $AP = \frac{1 + 1 + 3/7}{3} = 0.809$

Next Class

NDCG and approx. NDCG

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