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RecSys 2022 Tutorial

Improving Recommender Systems with Human-in-the-Loop

Dmitry Ustalov, Natalia Fedorova, Nikita Pavlichenko, Maxim Kunakov, Fedor Zhdanov

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Part II
Ranking and Its Quality

Dr. Dmitry Ustalov,
Head of Research

Tutorial Schedule

Part I Intro: 10 min
Introduction

Part II: 20 min
Ranking and Quality Metrics

Part III: 20 min
Human-in-the-Loop Essentials

Part IV: 50 min
Hands-On Practice Session

Coffee Break :
10 min

Part V: 30 min
From Human Labels to
Ground Truth

Part VI: 10 min
Conclusion

Online and Offline Metrics

How labeled data is used

1. Calculating offline metrics to evaluate how a model is performing
2. Training ML models and choosing the best model version

Offline metrics measured with data labeling

Pros

- Clear signal
- Measures designated product characteristics
- Fast results

Cons

- Not actual users (not always a representative sample)
- Can't measure business metrics

Online metrics measured with A/B tests

Pros

- Results from real users
- Measures business metrics (clicks, dwell time, leakage)

Cons

- Implicit signal
- Delayed response
- Slow results (long experiments)
- Clickbait
- Fraud

Signals

What We Need to Do

1. Evaluate every response object r with some quality measure s (create a signal)

2. Aggregate s to overall measure of quality (create a metric)

Examples

1

Search engine

- Text search
- Image search
- Ecommerce goods search

2

Recommendations

- Music feed
- Content feed
- Social media feed

3

Content Moderation

- Service quality assurance
- Social media business account behavior

Signals

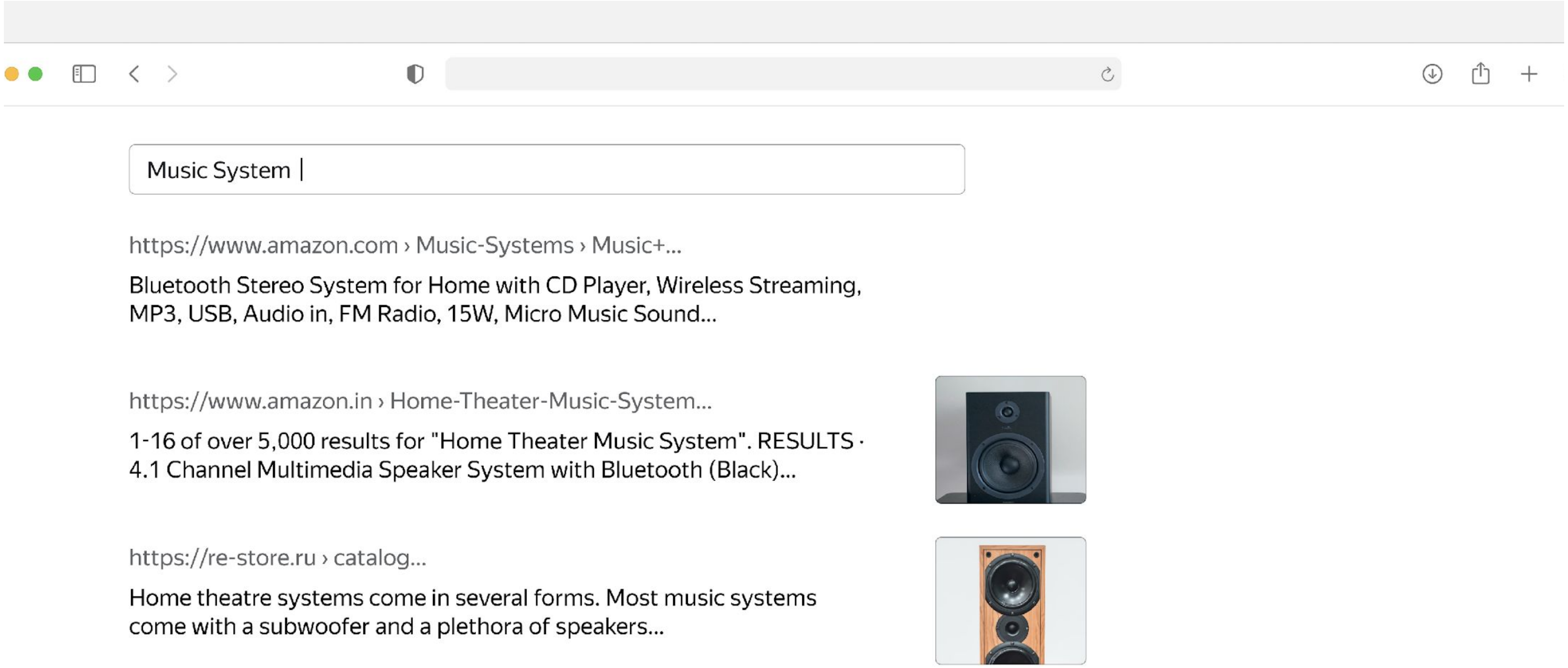
In order to calculate metric, we need to estimate response objects.

It can be done through multiple approaches

- Pointwise
- Listwise
- Pairwise

Signals are usually obtained through experts or crowdsource platforms, less commonly — from precomputed data.

Ranking and Recommender Evaluation



Pointwise

Given a query q and a single response r_i, we can judge how well does this object match to a user query

Pros	Cons
Easy to obtain	Low resolution

Pointwise

Examples

1

Binary relevance

- 1 or 0

2

Multiple grade relevance

- Relevant
- Semi-relevant
- Non-relevant
- Etc.

3

Match score from 0 to 100%

Listwise

Order all objects at once and use ranks as signal

Useful in training ML algorithms

Pros	Cons
► Provides full information	► Expensive
► Judge has all available context	► Inconsistent
	► Relative

Pairwise

Pointwise is of low resolution, listwise is inconsistent

Pairwise comparisons tackle both of this problems, they are a perfect example of task decomposition.

Pros	Cons
▶ Consistent	▶ Still quite expensive
▶ Simple	▶ Relative signal

1. Ranking: Compare, don't score https://ieeexplore.ieee.org/abstract/document/6120246

Which one?

1. In the beginning, use **pointwise** as baseline
2. When you have a working service, use **pairwise** (for incremental improvements)

We will focus on pairwise evaluation in our practice.

Metrics

Ranking metrics

1. Mean Average Precision (mAP) measures trade-off between precision and recall going down through service response
2. Normalized Discounted Cumulative Gain (nDCG) measures quality of objects with discount factor
3. Expected Reciprocal Rank (ERR) is a cascade model of user interaction with service response

mAP (mean average precision)

Let us recall some definitions from binary classifier ($s_i \in \{0, 1\}$):

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

Precision@k and Recall@k: precision and recall over top-k elements

		Predicted class	
		P	N
Actual Class	P	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

mAP (mean average precision)

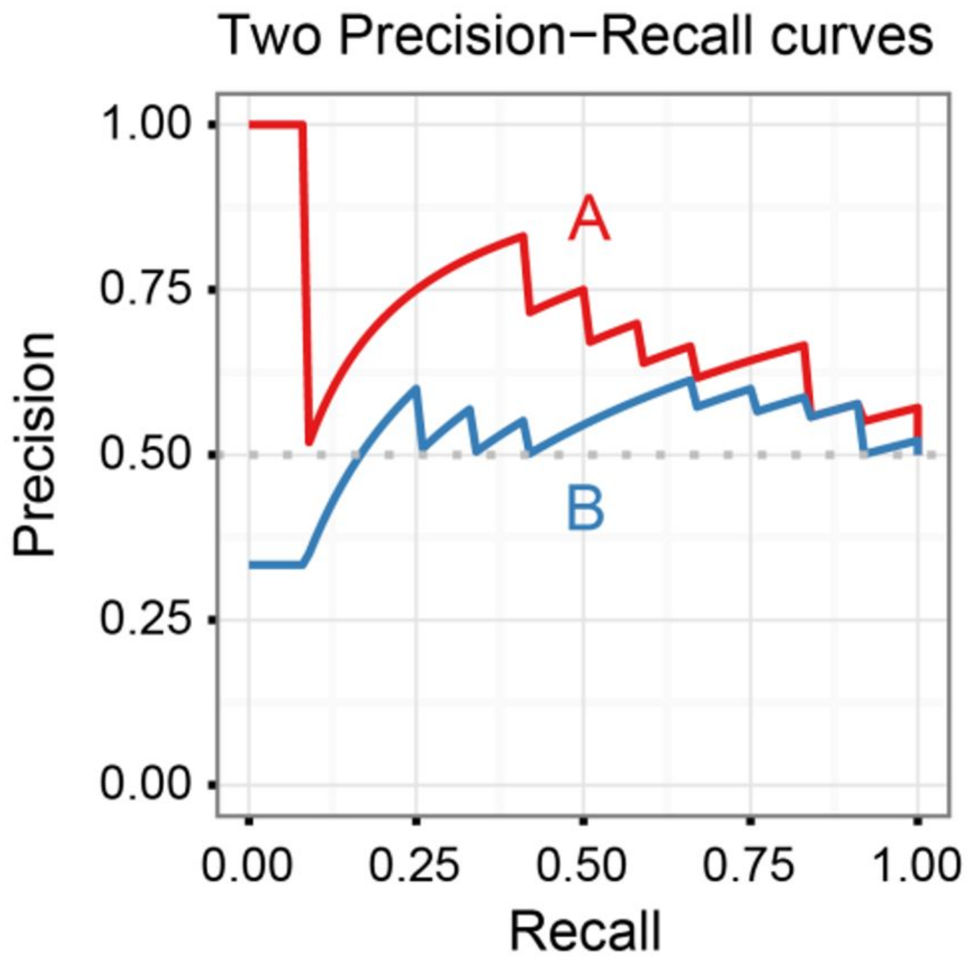
How precision and recall changes going down the list?

1. Recall increases (non-decreasing function)
2. Precision can be arbitrary

Area under precision-recall curve is:

1. Maximum for perfect order
   (positive objects on top, negative on bottom)
2. Minimum for the worst order

We can define precision as function of recall $p(r)$



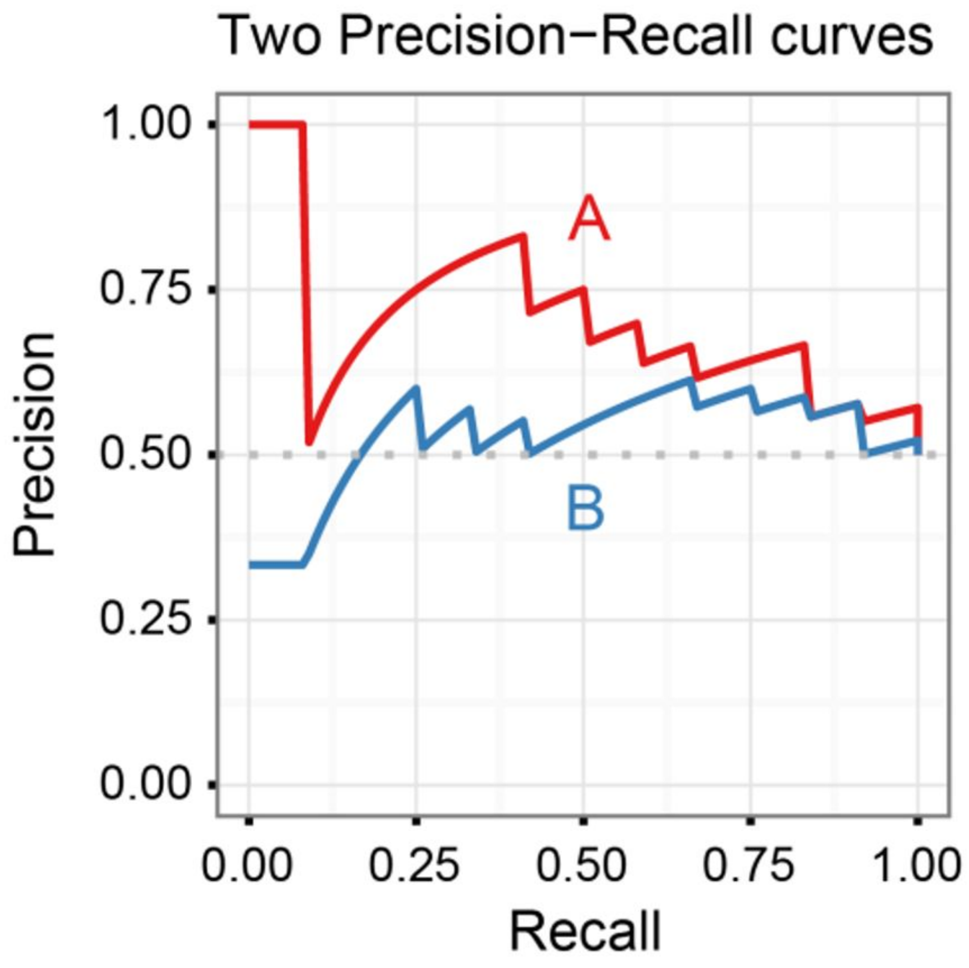
mAP (mean average precision)

We can define Average Precision as the following:

$$AP = \int_0^1 p(r)dr\,.$$

r is recall
$p(r)$ is precision

AP is the area under precision-recall curve (**precision-recall AUC**)



mAP (mean average precision)

In a simple discrete case, previous equation can be transformed into:

$$AP = \sum_{i=1}^{n} Precision@i \cdot \Delta Recall@i\,,$$

where $\Delta Recall@i$=Recall@i−Recall@(i−1)

mAP (mean average precision)

Since $\Delta Recall@i$ is positive iff included object is true positive, we can simplify AP to

$$AP = \frac{1}{n}\sum_{i=1}^{n} Precision@i[s_i = 1].$$

Mean average precision is defined as mean AP over set of queries:

$$mAP = \frac{1}{Q}\sum_{q} AP(q).$$

nDCG (normalized discounted cumulative gain)

- Good ranking puts the best objects on top
- Idea: sum signal values of ordered response with some discounter
- The lower the object, the lower its impact on metric is

nDCG (normalized discounted cumulative gain)

We can define discounted cumulative gain (DCG[3]) as following:

$$DCG@k = \sum_{i=1}^{k} \frac{s_i}{d(i)},$$

where $d(i)$ is a discounting factor

3. Cumulated gain-based evaluation of IR techniques https://doi.org/10.1145/582415.582418

nDCG (normalized discounted cumulative gain)

Example of discounters:

Linear: i

Logarithmic: $\log_2(i+1)$

Exponential: 2^i

nDCG (normalized discounted cumulative gain)

Raw DCG cannot be compared between queries, normalization is required

To align values of DCG we can normalized it by ideal DCG:

$$IDCG@k = \sum_{i=1}^{k} \frac{s_{(i)}}{d(i)},$$

where $s_{(i)}$ is i-th object with largest signal available

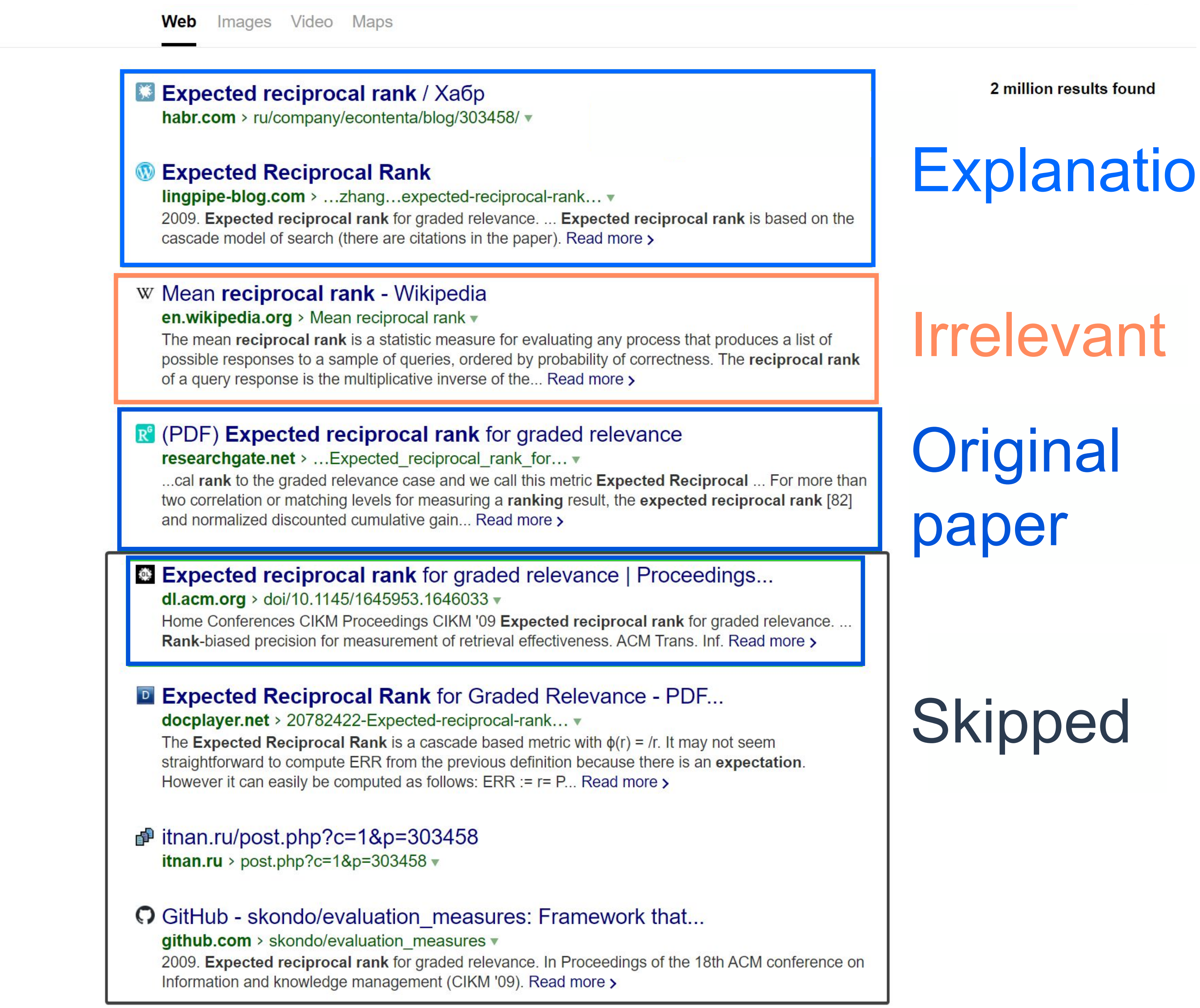
nDCG (normalized discounted cumulative gain)

Thus, nDCG is defined as following:

$$nDCG@k = \frac{DCG@k}{IDCG@k}$$

Now values are between 0 and 1 and thus cross-query comparable

Expected Reciprocal Rank (ERR)



Explanations

Irrelevant

Original paper

Skipped

Expected Reciprocal Rank (ERR)

Suppose we have signal values s_i

1. Map s_i to probability of finding answer R_i
2. Use it to model termination rank
   (on which position the user will stop)

Expected Reciprocal Rank (ERR)

Probability of user terminating their session on rank k equals to

$$P(k) = R_k \prod_{i=1}^{k-1} (1 - R_i),$$

where R_i — probability of user to find answer on rank i.

Use $1/s$ to have a metric with semantic “higher is better”:

$$ERR^4 = \sum_{k=1}^{n} \frac{1}{k} R_k \prod_{i=1}^{k-1} (1 - R_i).$$

4. Expected reciprocal rank for graded relevance https://dl.acm.org/doi/10.1145/1645953.1646033

How to Sample Queries?

How to Sample Queries?

1

Most popular?

- Beak, simple queries
- Easy to process
- Affect lots of users

2

Unique queries?

- Tail, usually hard or ambiguous
- Huge amount (30%–70% depending on the service)

3

Something in the middle?

How to Sample Queries?

Simple idea: take a random sample

1. **Flip a coin with a probability p on every object**

- Heads: use the query
- Tails: skip
- On average, $p \cdot N$ queries will be sampled

2. **More sophisticated — reservoir sampling[6]:**

- Every object is considered
- Exactly k objects will be sampled

No guarantee that popular queries will be presented in sample!

6. Random Sampling with a Reservoir http://www.cs.umd.edu/~samir/498/vitter.pdf

How to Sample Queries?

Stratified sampling:

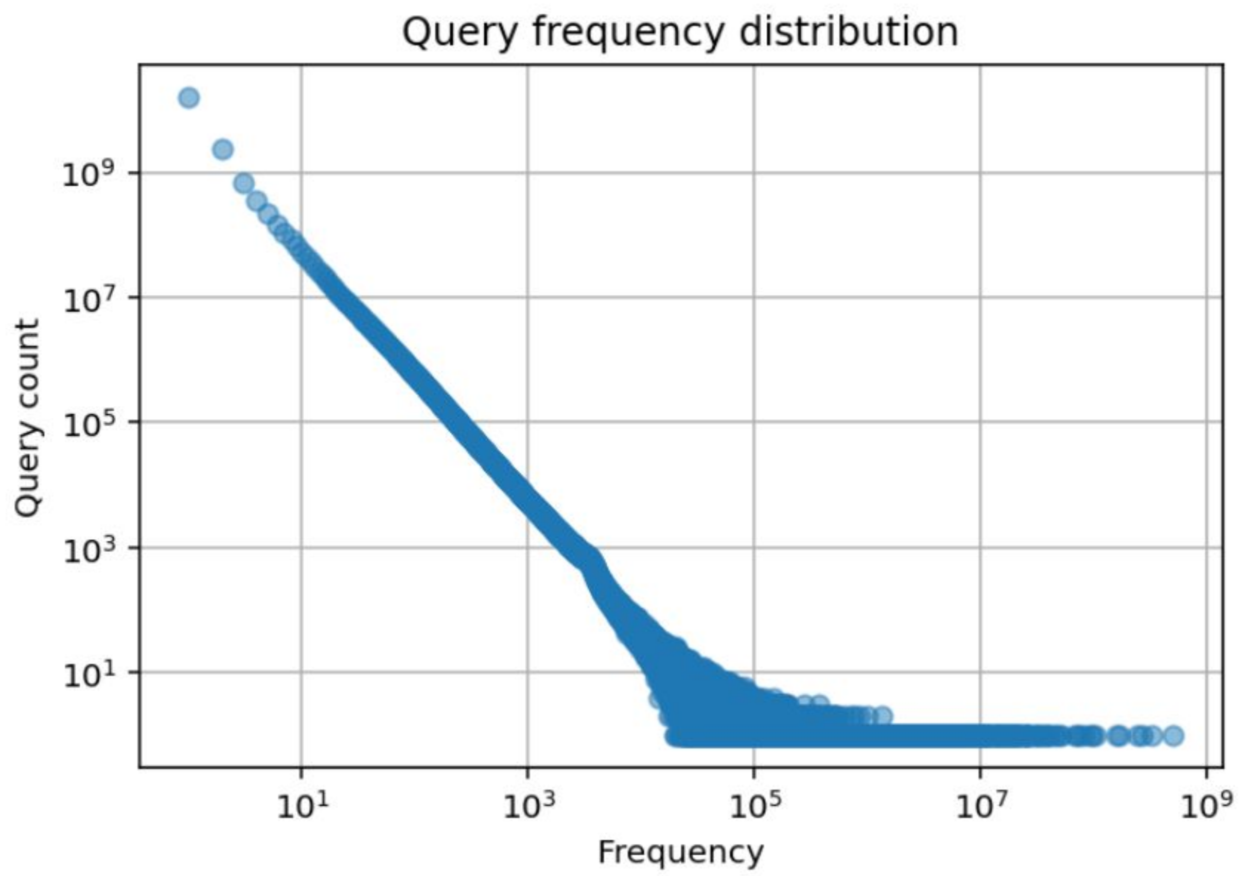
- Each query q_i has frequency f_i
- Order queries by f_i and split them in k buckets Q_k s.t.

$$\sum_{m \in Q_i} f_m \approx \sum_{k \in Q_j} f_k \ \forall i, j,$$

$$\forall i < j \Rightarrow f_m < f_k \ \forall m \in Q_i, k \in Q_j.$$

- After that, sample the necessary amount from every bucket

Guarantees that queries of all frequencies will be presented in a sample



How to Sample Pairs?

How to Sample Pairs?

What is the right number of pairs for evaluation?

1

Lower bound

- Traditional sorting algorithms like MergeSort run $n \log n$ comparisons

2

Upper bound

- The number of all possible pairs is bound by n^2

3

Reasonable bound

- Select $kn \log n$ pairs (sort objects multiple times)
- k is a hyper-

What to Compare?

- $n \log n$ is enough when compares are transitive:

$$i > j, j > k \Rightarrow i > k$$

- Human judgements do not always provide transitivity
- But we can rely on Bradley-Terry's *linear order*

$$\frac{P(i > k)}{P(i < k)} = \frac{P(i > j)}{P(i < j)} \frac{P(j > k)}{P(j < k)}$$

Using latent scores s_i, s_j, s_k from Bradley-Terry model, we have

$$s_i - s_k = s_i - s_j + s_j - s_k$$

Applications and Problems

Metric purpose

1. Service quality monitoring (KPI metric): when you need to track what is going on with your service
2. Target for supervised learning: for training machine learning algorithms
3. Acceptance metric: final validation before the release of new features

What can go wrong

Nothing is perfectly reliable!

Basic checks: input and output, presence of judgements, service availability

Advanced checks: A/A testing, comparison with previously known verdicts, re-evaluations, DSAT

Why Crowdsourcing?

Why Crowdsourcing?

Initially: in-house experts (assessors)

Pros	Cons
▶ Trusted ▶ Can perform sensitive tasks (signed NDA) ▶ Easy to train/ control/interact	▶ Expensive ▶ Hard to scale

Why Crowdsourcing?

What is crowdsource?

- Lots of annotators
- Easy to scale
- Easy to add and remove annotators

Cons:

- Need to control quality
- Open market, compete for annotators

Why Crowdsourcing?

It is possible to replicate in-house annotation processes with crowdsourcing!

1. Same quality
2. Cheaper
3. More scalable, higher performance
4. Quality control via in-house pipeline
5. Relevance assessment in pairwise setting

References

Where to read more

1. [A Short Survey on Online and Offline Methods for Search Quality Evaluation]
2. Pairwise comparisons: https://ieeexplore.ieee.org/abstract/document/6120246
3. Just sort it: https://arxiv.org/abs/1502.05556
4. Cumulated gain-based evaluation of IR techniques: https://doi.org/10.1145/582415.582418
5. ERR: https://doi.org/10.1145/1645953.1646033
6. Reservoir sampling: http://www.cs.umd.edu/~samir/498/vitter.pdf
7. RankEval: https://github.com/hpclab/rankeval

Datasets

1. Text REtrieval Conference Data —
   https://trec.nist.gov/data.html

2. Toloka Relevance 2 & Relevance 5
   https://toloka.ai/datasets

Join our Slack:
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Dr. Dmitry Ustalov

Head of Research

dustalov@toloka.ai

https://toloka.ai/events/recsys-2022/

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