Quality assessment

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Agenda

Metrics:

- Offline
- Online
- Other aspects

Q: what is the target metric of the service?

What is the target metric of a service?

- Money
- Traffic share (yandex vs google)
- User satisfaction
- User happiness
- Logins/Subscriptions
- …

1) Unfortunately, we cannot replay new ML models with complex human target behavior (e.g. *if we had this feature, we would attract $$*)
2) Some targets are hard to compute online (delays, is it measurable?, …)

What we can?

Create a set of easily **computable** metrics which correlate with target ones.

Satisfaction (?) vs *probability to find relevant doc*

Traffic Share (delayed) vs *MAU*

High-level evaluation techniques

Offline evaluation — result of a new model is compared with *manually [pre]processed data*

- ***On a bucket***: accuracy, precision, recall
- ***By assessors***: relevance scale
    - (assessors are humans: kappa stats, weighted, majority voting, …)

Online evaluation — a new model is *compared* with an old one by some *target metric* on a *subset of users*. Most widely used approach is A/B testing

https://dl.acm.org/doi/fullHtml/10.1145/3329188

BTW, what is *relevance*?

Information need is encoded in a **query**.

Query is used to get **results**.

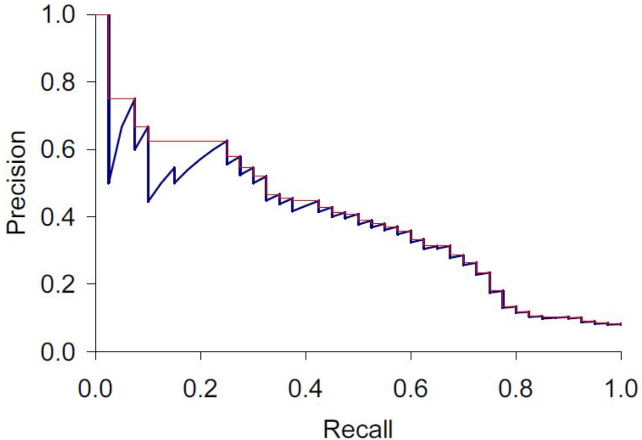
But do results **satisfy information need**?

{0, 1} or [0..1]: {IR, REL-, REL+}

Offline: accuracy, precision, recall, F_1

- **Accuracy** is not the case
- **Precision** is how many relevant out of retrieved
- **Recall** is how many relevant retrieved out of all relevant*
- **Precision-recall curve** can be used for ranked results
- $\mathbf{F_1}$ is to come up with a single number

Users are *tolerant* to irrelevant results



Mean Average Precision

Precision@K == TruePositive@K / K

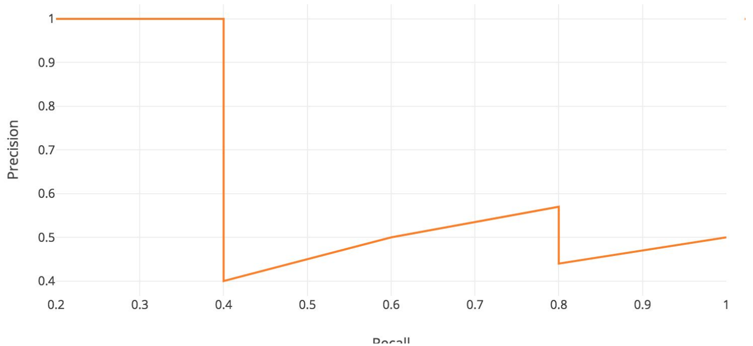
Recall@N* == TP@N / ~~AllPositive~~TP@K

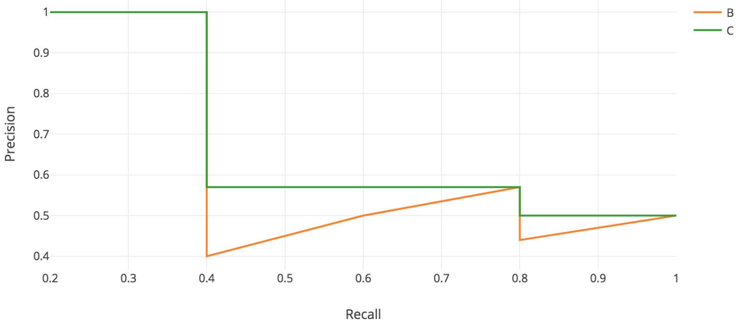
Average **P**recision: $$\mathrm{AP} = \int_0^1 p(r)dr$$

1. Improve “steps”

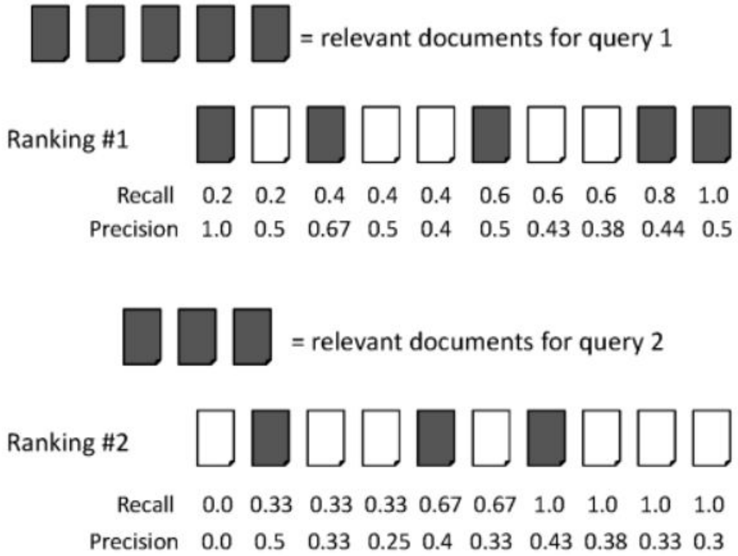
2. AP@n $$\mathrm{AveP} = \sum_{k=1}^{n} P(k)\Delta r(k)$$

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





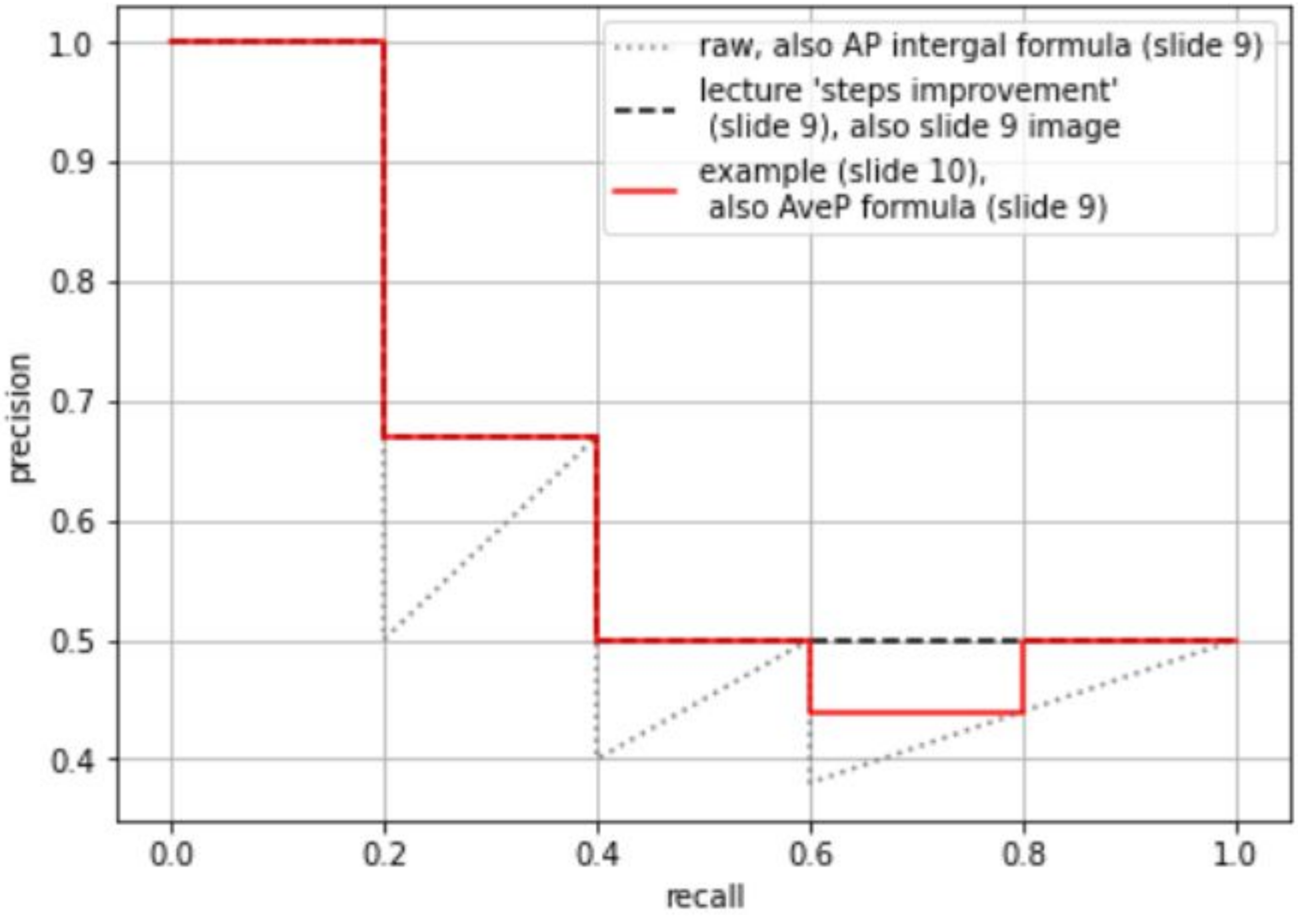
MAP



$$\textit{average precision query 1} = (1.0 + 0.67 + 0.5 + 0.44 + 0.5)/5 = 0.62$$
$$\textit{average precision query 2} = (0.5 + 0.4 + 0.43)/3 = 0.44$$

$$\textit{mean average precision} = (0.62 + 0.44)/2 = 0.53$$

https://web.stanford.edu/class/cs276/handouts/EvaluationNew-handout-1-per.pdf


raw, also AP intergal formula (slide 9)
lecture 'steps improvement'
(slide 9), also slide 9 image
example (slide 10),
also AveP formula (slide 9)
1.0
0.9
0.8
0.7
0.6
0.5
0.4
precision
0.0
0.2
0.4
0.6
0.8
1.0
recall

$$\text{AveP} = \sum_{k=1}^{n} P(k)\Delta r(k)$$

Whiteboard time (MAP)

Q	*“vk”*	*“Good search engine”*	*“Fanny Animal Imajes”*	*“Who let the dogs out?”*
1	**vk.com**	Good engine repair	Images of Fanny Ardant	**Baha Men - Who Let The Dogs Out (Youtube)**
2	vkusvill	*yahoo.com*	**9GAGs**	CNN: old men let the dogs out to prevent robbery
3	МЛ	**google.com**	**fishki.net**	*Who Let The Dogs Out Wikipedia*
4	Some trash	**yandex.ru**	CNN.com	Funny Dogs website
5	*facebook.com*	*altavista*	*Moscow Zoo*	**Baha Men - Who Let The Dogs Out (Lyrics)**

Offline: simple is ok

Mean reciprocal rank (MRR): $$\text{MRR} = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{\text{rank}_i}.$$

Q — bucket of queries

rank$_i$ — rank of the **first** relevant document

Whiteboard time (MRR)

$$\mathrm{MRR} = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{\mathrm{rank}_i}.$$

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Offline: discounted gain model

Cumulative gain CG@p: $\mathrm{CG_p} = \sum_{i=1}^{p} rel_i$ (***p*** — e.g. 10 items on SERP, rel_i - 0/1 or 0..1)

Discounted CG@p: $\mathrm{DCG_p} = \sum_{i=1}^{p} \frac{rel_i}{\log_2(i+1)} = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2(i+1)}$ $\mathrm{DCG_p} = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{\log_2(i+1)}$

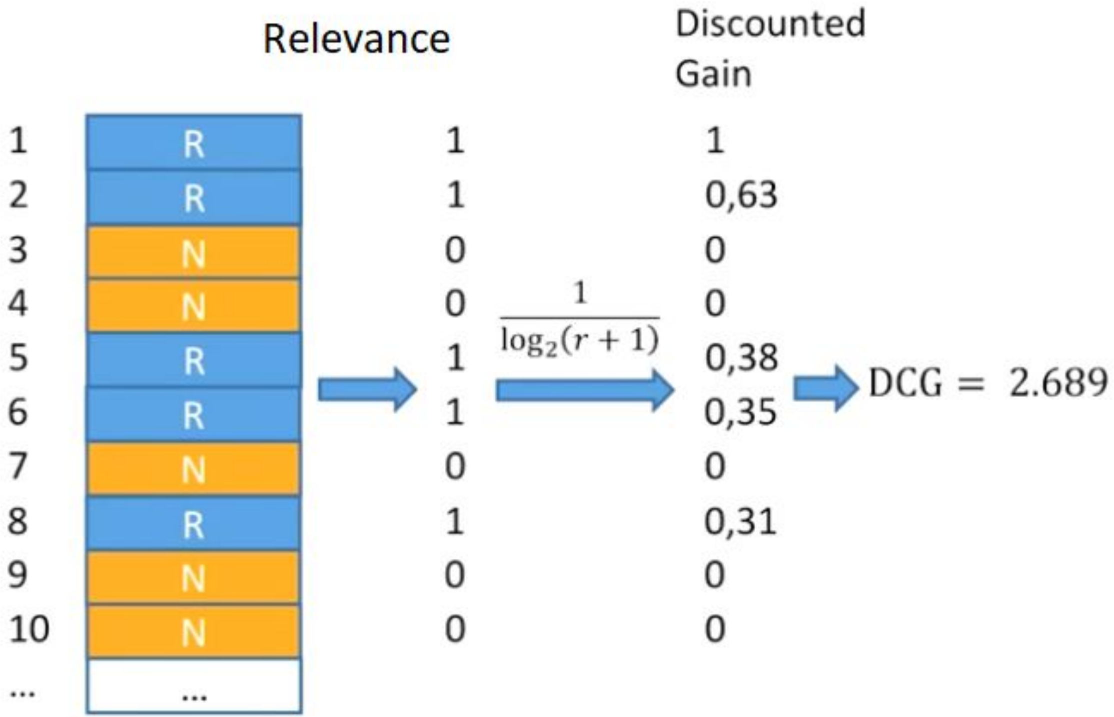
Normalized DCG: divide DCG by the best possible achievable (***I***deal) DCG:

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

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

$$\mathrm{DCG_p} = \sum_{i=1}^{p} \frac{rel_i}{\log_2(i+1)} = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2(i+1)}$$

DCG example



https://ru.coursera.org/lecture/vvedeniye-informatsionnyy-poisk/dcg-yuwSI

$$\mathrm{DCG_p} = \sum_{i=1}^{p} \frac{rel_i}{\log_2(i+1)} = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2(i+1)}$$

* Whiteboard time (DCG)

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Offline: pFound

pFound idea is similar. Estimate probability to find relevant item.

Presets:

- **max relevance is 0.4** (R)**,** otherwise is 0 (NR, maybe R);
- probability to quit with no reason ***pBreak*** - 0.15;
- User watches from top to bottom, stops if *found* relevant OR if *tired*;

$$pLook[i] = pLook[i-1] * (1 - pRel[i-1]) * (1 - pBreak)$$

$$pfound = \sum_{i=1}^{n} pLook[i] * pRel[i]$$

$$pLook[i] = pLook[i-1] * (1 - p\mathrm{Rel}[i-1]) * (1 - pBreak)$$

$$pfound = \sum_{i=1}^{n} pLook[i] * p\mathrm{Rel}[i]$$

Whiteboard time

Q	***"Fanny Animal Imajes"***
1	Images of Fanny Ardant
2	**9GAGs**
3	**fishki.net**
4	CNN.com
5	*Moscow Zoo*

pLook[1] = 1

pLook[2] =

pLook[3] =

pLook[4] =

pLook[5] =

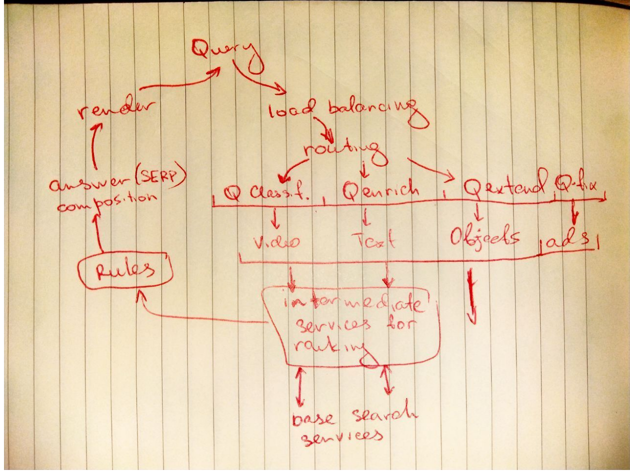
pFound =

Online: A/B testing

Online testing allows to test of a *target metric*!

1. Is *relative*. Create **alternative** model
2. Formulate **target metric** (CTR, dwell-time, total revenue, ARPU)
3. Prepare **representative subset of users** (for complex setups use multinomial experiments)
4. Run controlled experiment, **aggregate statistics** on your metric
5. Run **statistical test** (Welch, Fisher, Student, …) to see that **mean shift** for a distribution is significant*
6. Make a **decision** to accept (no always ““better” for new features)

A/B testing infrastructure



- User **identification** method (logged in, cookies, fingerprints)
- **Experiment support** in the whole infrastructure (should not be as usual traffic) with flags/parameters
- Mapping **registry** (users to experiments)
- **Statistical tools** ready before you start experiment

Use a platform: Google Analytics, Optimizely, VWO, ...

Other quality aspects

New users should get most ranked items, whereas old users should be **surprised** with quality items from “long tail” [ref]

Add **diversity** to recommendations, get out of the bubble [ref]

Novelty issue (did I see this before?) [ref]

Stay **legally** and **ethically** safe (no medical questions, no porn, no swearing)

~~Search engine~~ One company's target

User should **solve a problem** with a service: get an answer to the question, a service or an item without leaving portal. Steps to achieve:

- Keep users *logged in*
- Evaluate user intent (surfing, buying, asking, ...)
- Provide a *quality service* for each intent (first, specific search, then specific service)
- Don't be evil

DON'T BE EVIL*

***Unless It's Profitable**

Google