# Information Retrieval

Metrics

#### **Useful Resources**

- 1. <a href="https://en.wikipedia.org/wiki/Evaluation-measures">https://en.wikipedia.org/wiki/Evaluation measures</a> (information retrieval)
- Alternatives to Bpref
- 3. <a href="https://hosseiniec.wordpress.com/2014/07/28/retrieval-evaluation-with-incomplete-relevance-data/">https://hosseiniec.wordpress.com/2014/07/28/retrieval-evaluation-with-incomplete-relevance-data/</a>
- 4. <a href="http://people.cs.georgetown.edu/~nazli/classes/ir-Slides/Evaluation-12.pdf">http://people.cs.georgetown.edu/~nazli/classes/ir-Slides/Evaluation-12.pdf</a>
- 5. <a href="https://link.springer.com/article/10.1007/s10791-008-9059-7">https://link.springer.com/article/10.1007/s10791-008-9059-7</a>
- 6. <a href="https://people.eng.unimelb.edu.au/jzobel/fulltext/acmtois08.pdf">https://people.eng.unimelb.edu.au/jzobel/fulltext/acmtois08.pdf</a>
- 7. <a href="https://pdfs.semanticscholar.org/6ed8/b5935be55fdc0eb2756fc376f73e098cb">https://pdfs.semanticscholar.org/6ed8/b5935be55fdc0eb2756fc376f73e098cb</a>

8.

#### **Document Retrieval**

Good Docs: D1, D2, D3, D5, D8, D13, D21, D34

Bad Docs: D4, D6, D7, D9, D10, D11, D12, D14, D15, D16, D17, D18, D19, D20

Everything else unlabelled

Example order of retrieval and ranking:

D1 D100 D6 D8 D34 D101 D302 D9 D4 D10 D105 D20 D400 D13 D500 D21 D2

#### Metrics - Familiar Metrics - Precision

- 1. How many did the system get right?
- Precision@k => |True positives till k| / k
- 3. 100% Precision? All the retrieved k documents are relevant

Good Docs: D1, D2, D3, D5, D8, D13, D21, D34

Bad Docs: D4, D6, D7, D9, D10, D11, D12, D14, D15, D16, D17, D18, D19, D20

D1 D100 D6 D8 D34 | D101 D302 D9 D4 D10 D105 D20 D400 D13 D500 D21 D2

Precision@5 - %

100% Precision possible order: D1 D13 D21 D8 D34 Precision@5 - 5/5

# Metrics - Familiar Metrics - Average Precision

$$ext{AveP} = rac{\sum_{k=1}^{n} (P(k) imes ext{rel}(k))}{ ext{number of relevant documents}}$$

Good Docs: D1, D2, D3, D5, D8, D13, D21, D34

Bad Docs: D4, D6, D7, D9, D10, D11, D12, D14, D15, D16, D17, D18, D19, D20

D1 D100 D6 D8 D34 | D101 D302 D9 D4 D10 D105 D20 D400 D13 D500 D21 D2

Average Precision - 1/1 + 2/4 + 3/5 Precision@5 - 3/5

100% Precision possible order: D1 D13 D21 D8 D34 Precision@5 - 5/5

#### Metrics - Familiar Metrics - Recall

- 1. How many right answers did the system get?
- Recall@k => |True positives till k| / |True Positives|
- 3. 100% Recall? All the relevant documents are retrieved by the position k

Good Docs: D1, D2, D3, D5, D8, D13, D21, D34 - Good Docs = 8

Bad Docs: D4, D6, D7, D9, D10, D11, D12, D14, D15, D16, D17, D18, D19, D20

D1 D100 D6 D8 D34 | D101 D302 D9 D4 D10 D105 D20 D400 D13 D500 D21 D2

Recall@5 - 3/8

100% Recall possible order\*: D1, D2, D3, D5, D8, D13, D21, D34

#### Metrics - Familiar Metrics - Recall

```
100% Recall order*: * D1, *, D2, *, D3, *, D5, *, D8, *, D13, *, D21, *, D34 *,
```

- Any number of documents can appear in between
- 2. Order of relevant documents doesn't matter
- 3. Recall@k can be 100% iff all labelled relevant documents are retrieved at k
- 4. 100% Precision doesn't imply 100% Recall and vice versa
- 5. Optimize for P/R based on requirements of the downstream task

#### Metrics - Familiar Metrics - F Score

$$F_{eta} = rac{(1+eta^2) \cdot ( ext{precision} \cdot ext{recall})}{(eta^2 \cdot ext{precision} + ext{recall})}$$

- Balances P&R
- 2. Higher beta Recall is more imp
- 3. Common versions
  - a. F1
  - b. F2
  - c. F1.5
  - d. F0.5 Precision is more imp

#### Metrics - Familiar Metrics - Success

1. Did the system get at least one correct at k?

D1 D100 D6 D8 D34 | D101 D302 D9 D4 D10 D105 D20 D400 D13 D500 D21 D2

Success@1 is 100%

Success@5 is 100%

Success@k is 100% for any k is 100% as the first doc is a good doc

Success@3 is 0% but Success@5 is 100% D9 D4 D10 D6 D8

Success is 0 for D9 D4 D10

#### Metrics - Familiar Metrics - nDCG

$$egin{aligned} ext{DCG}_{ ext{p}} &= \sum_{i=1}^p rac{2^{rel_i} - 1}{\log_2(i+1)} \ & ext{nDCG}_{ ext{p}} &= rac{DCG_p}{IDCGp}. \end{aligned}$$

- 1. Ranking metric
- Graded Labels
- 3. Encourages to rank great results at the top
- 4. Condensed
  - a. Calculate using only labelled points
- Global Ideal DCG Use all the labelled data points
- 6. Local Ideal DCG Sorted retrieved labels

#### Metrics - Familiar Metrics - nDCG

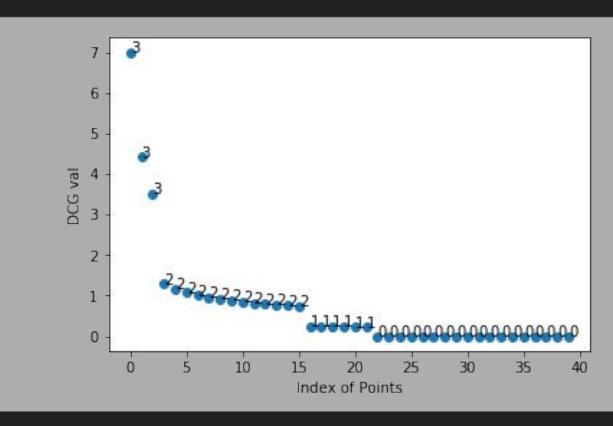
nDCG global 0.4274189765288345

nDCG global condensed 0.5244899222593769

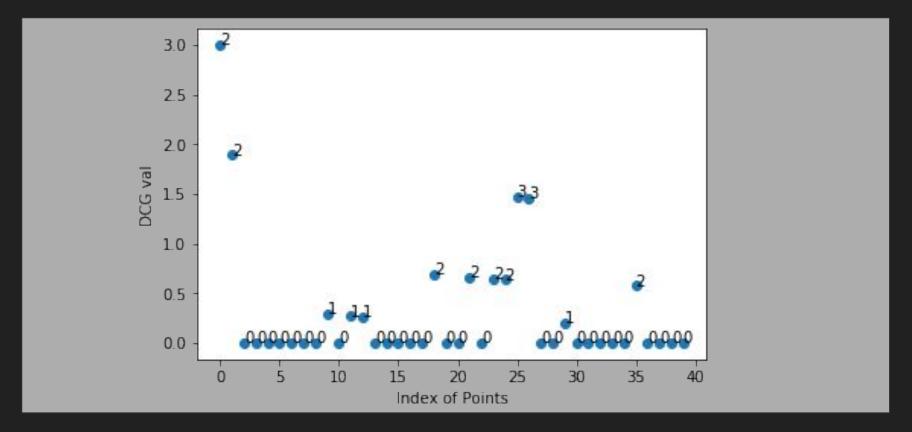
nDCG local 0.5916351066479533

nDCG local condensed 0.7260011092904043

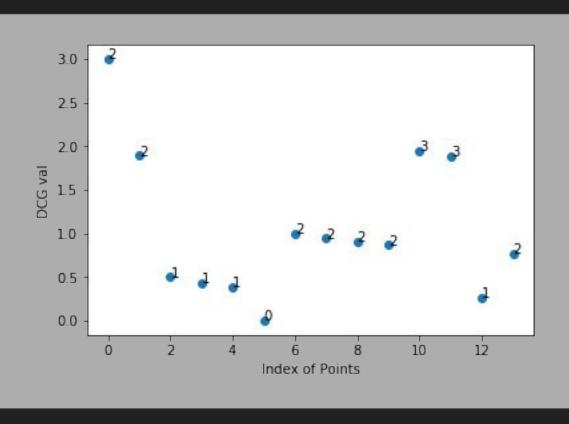
# Metrics - Familiar Metrics - nDCG - Ideal BB



## Metrics - Familiar Metrics - nDCG - Random Datum



#### Metrics - Familiar Metrics - nDCG - Random Datum - Condensed



# Metrics - New Metrics - bpref

$$bpref = \frac{1}{R} \sum_{r} 1 - \frac{|n \text{ ranked higher than } r|}{R}$$

bpref-10 = 
$$\frac{1}{R} \sum_{r} 1 - \frac{|n \text{ ranked higher than } r|}{10 + R}$$

- Consider only judged documents
- Approximately the % of wrongly ordered pairs
- If no labelled irrelevant documents are retrieved
  - a. bpref = Recall
- If no labelled relevant documents are retrieved
  - a. bpref = 0
- 5. If all labelled relevant > all labelled irrelevant
  - a. bpref = Recall
- 6. Binary Labels

# Metrics - New Metrics - bpref

Good Docs: D1, D2, D3, D5, D8, D13, D21, D34 - |Good Docs| = R = 8

Bad Docs: D4, D6, D7, D9, D10, D11, D12, D14, D15, D16, D17, D18, D19, D20

D1 D100 D6 D8 D34 | D101 D302 D9 D4 D10 D105 D20 D400 D13 D500 D21 D2

bpref@5 - 1/8 [(1 - 0/8) + (1-1/8) + (1-1/8)]

D6 D1 D100 D302 D8 D9 D34 D105 D4 D13

bpref@10 - 1/8 [(1-1/8) + (1-1/8) + (1-2/8) + (1-3/8)]

# Metrics - New Metrics - bpref

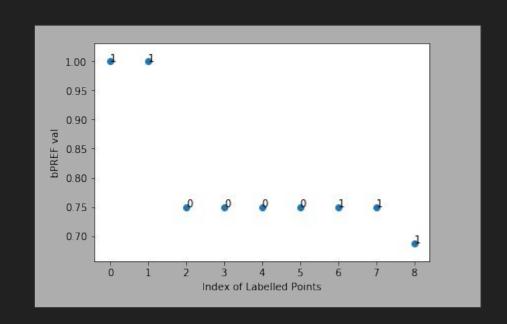
Condensed Labels

[1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1]

Num Labelled Docs = R = 16

B-pref - 0.45

Compared to Precision, a good document at a better rank is better



## Metrics - New Metrics - Q-Measure

$$Q\text{-}measure = \frac{1}{R} \sum_{1 \leq r \leq L} isrel(r) \frac{\beta cg(r) + count(r)}{\beta cig(r) + r}$$

r - rank R - num of relevant documents

isrel(r) - Indicator flag 1 if labelled relevant, 0 for everything else

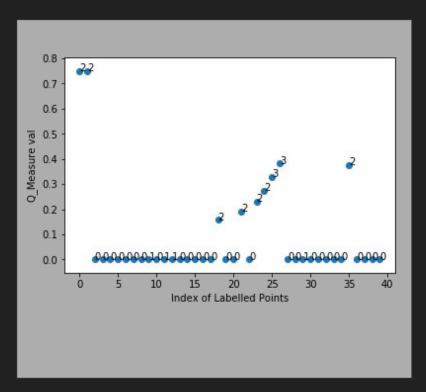
Gain - Quality of relevance - 3, 2, 1, 0

Cumulative Gain (cg) - gain(r) + cg(r-1)

Cumulative Ideal Gain (cig) - Sum of ideal order of labelled relevant qualities

count(r) - num of relevant docs till r

## Metrics - New Metrics - Q Measure

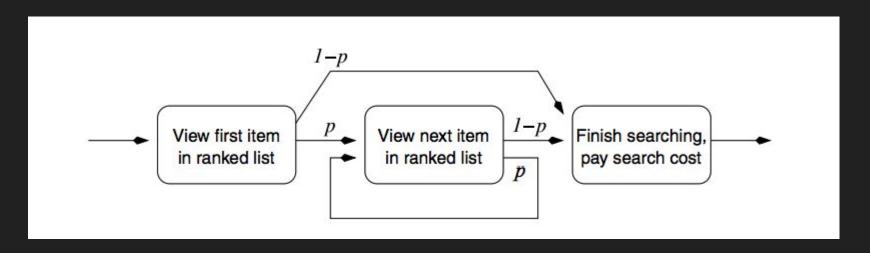


Labels - [2, 2, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 2, 0, 2, 2, 3, 3, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0]

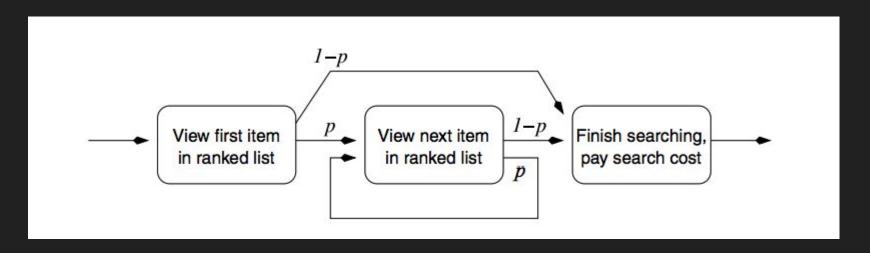
Gain from a relevant document at a better rank is higher

Continuous/Multiple relevant labels increase the count in the numerator increases the value

- 1. User oriented metric
- 2. p persistence/probability that they will look at the next doc



- 1. User oriented metric
- 2. p persistence/probability that they will look at the next doc



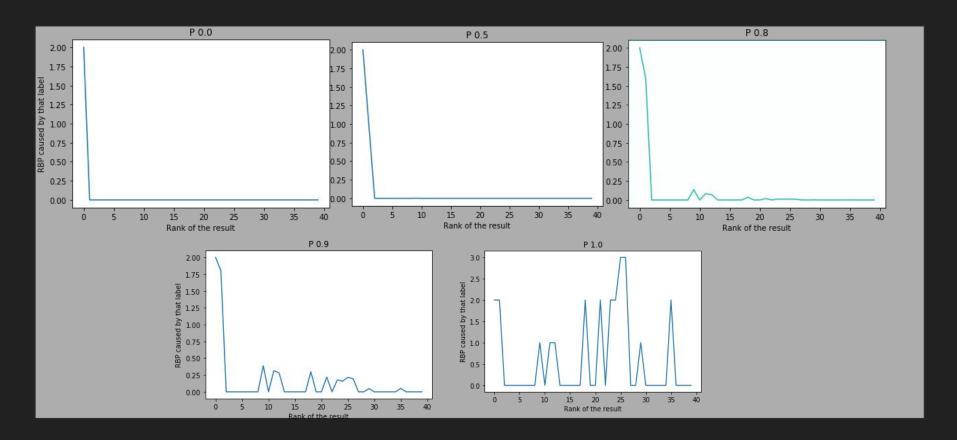
$$\text{RBP} = (1-p) \cdot \sum_{i=1}^{d} r_i \cdot p^{i-1}.$$

- 1. Higher P User will scroll/load more Patient
  - Exhaustive search habits
- 2. Lower P Impatient Top 1 Feeling Lucky
- 3. Many relevant docs at the top
  - a. Similar gains Doesn't matter if the user keeps going
- 4. Some relevant docs at the top Many at the bottom
  - a. Patient users find more documents
- 5. Bad results
  - a. No one find anything

$$\text{RBP} = (1-p) \cdot \sum_{i=1}^{d} r_i \cdot p^{i-1}.$$

- 7. 1-p normalizes the effort, and metric reflects rate of finding results
- 8. Higher RBP implies higher net satisfaction
- 9. Choosing p Reverse engineer to gather impact from the kth result of choice.
- 10. # documents the user is likely to see
- k=30 Top 3 pages based on our user behavior

## Metrics - New Metrics - RBP



# Metrics - New Metrics - r-pref

$$rpref\_N = \frac{1}{R'} \sum_{D_k \in J, \ \phi_k > 0} \phi_k \left(1 - \frac{penalty_k}{N'}\right)$$
 (2)

where

$$R' = \sum_{D_k \in J} \phi_k \tag{3}$$

$$N' = \sum_{D_k \in J} (1 - \phi_k) \tag{4}$$

and

$$penalty_k = \sum_{D_l \in J, \ r_l < r_k, \ \phi_l < \phi_k} \frac{\phi_k - \phi_l}{\phi_k} \ . \tag{5}$$

 $\phi_{k}$  = [0, 1] - Normalized grades (TODO - Need to check)

Penalty - For a retrieved relevant document, compute penalty for every judged **less** relevant docs ranked above it

Normalized by  $\phi_k$  implies that the penalties incurred by improper ranking of a great document is more than that of a good document

Directly equate to Recall if perfect ranking is

# Metrics - What does everything mean?

- High Precision User is seeing relevant results But can't decide if the results are exhaustive
- High Recall User is seeing relevant results interleaved with possibly irrelevant results
- High Precision & Recall doesn't imply perfect ranking, as they are rank agnostic
- High Local nDCG Great relevant results appear near the top User is seeing relevant results - But can't decide if the results are exhaustive
- Really High Global nDCG Great relevant results appear near the top User is seeing relevant results - More confidence that the majority of labelled relevant documents are retrieved

# Metrics - What does everything mean?

- High b-pref
  - High Recall Almost agnostic to retrieval of judged irrelevant documents
  - o Good relative ranking If there were multiple judged irrelevant documents
- Low b-pref
  - Low Recall Low relevant labelled documents are seen.
  - Lower Bad Ranking
- High q-measure
  - High frequency of relevant labelled documents at higher ranks
- Low q-measure
  - Highly relevant labelled documents are found at lower ranks
  - Proportion of relevant labelled documents is lower Not enough recall

# Metrics - What does everything mean?

- High RBP User finds a relevant result quickly based on their browsing habits
- Low RBP
  - Not enough relevant documents shown
  - Relevant documents are surfaced in later pages
  - Can take forever to find the relevant documents
  - User might end the search without seeing any relevant results

#### High R-Pref

- Highly relevant grades documents are ranked above judged lower graded documents
- Lower irrelevant document recall if ranking is perfect

#### Low R-Pref

- Ranking mistakes
- Only Low quality result recall