Introduction to

Information Retrieval

Evaluation

How do you tell if users are happy?

- Search returns products relevant to users
  - How do you assess this at scale?
- Search results get clicked a lot
  - Misleading titles/summaries can cause users to click
- Repeat visitors/buyers
  - Do users leave soon after searching?
  - Do they come back within a week/month/… ?

Measuring relevance

- Three elements:
  1. A benchmark document collection
  2. A benchmark suite of queries
  3. An assessment of either Relevant or Nonrelevant for each query and each document

Relevance judgments

- Binary (relevant vs. non-relevant) in the simplest case
- More relevance levels also used(0, 1, 2, 3 ...)

Early public test Collections (20th C)

TABLE 4.3 Common Test Corpora

Collection	NDocs	NQrys	Size (MB)	Term/Doc	Q-D RelAss
ADI	82	35			
AIT	2109	14	2	400	>10,000
CACM	3204	64	2	24.5	
CISI	1460	112	2	46.5	
Cranfield	1400	225	2	53.1	
LISA	5872	35	3		
Medline	1033	30	1		
NPL	11,429	93	3		
OSHMED	34,8566	106	400	250	16,140
Reuters	21,578	672	28	131	
TREC	740,000	200	2000	89-3543	» 100,000

Recent datasets: 100s of million web pages (GOV, ClueWeb, …)

Now we have the basics of a benchmark

- Let's review some evaluation measures
  - *Precision*
  - *Recall*
  - DCG
  - …

Evaluating an IR system

- Note: **user need** is translated into a **query**
- Relevance is assessed relative to the **user need,** *not* the **query**
- E.g., Information need: *My swimming pool bottom is becoming black and needs to be cleaned.*
- Query: ***pool cleaner***
- Assess whether the doc addresses the underlying need, not whether it has these words

Unranked retrieval evaluation: Precision and Recall – recap from IIR 8/video

- **<u>Binary assessments</u>**

Precision: fraction of retrieved docs that are relevant = P(relevant|retrieved)

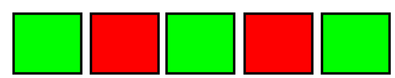
Recall: fraction of relevant docs that are retrieved = P(retrieved|relevant)

	Relevant	Nonrelevant
Retrieved	tp	fp
Not Retrieved	fn	tn

- Precision P = tp/(tp + fp)
- Recall R = tp/(tp + fn)

Precision@K

- Set a rank threshold K
- Compute % relevant in top K
- Ignores documents ranked lower than K
- Ex:
  - Prec@3 of 2/3
  - Prec@4 of 2/4
  - Prec@5 of 3/5

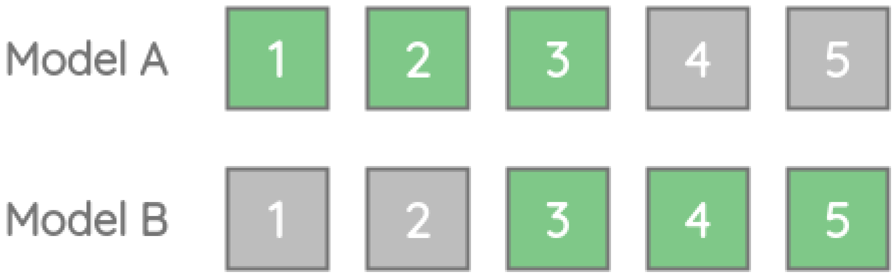


Precision@K

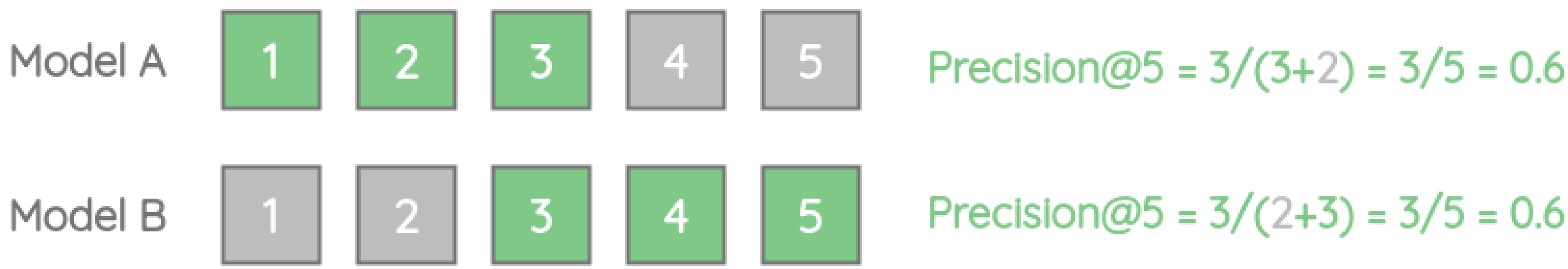
$$Precision@k = \frac{true\ positives@k}{(true\ positives@k) + (false\ positives@k)}$$

k	1	2	3	4	5
Precision@k	$\frac{1}{1} = 1$	$\frac{1}{2} = 0.5$	$\frac{2}{3} = 0.67$	$\frac{2}{4} = 0.5$	$\frac{3}{5} = 0.6$

Calculate Precision@5



Calculate Precision@5



Model A: first three items relevant,
Model B: last three items relevant.
Precision@5 same for both of these models even though model A is better.

Doesn't consider the position of the relevant items !!

Recall@K

$$Recall@k = \frac{true\ positives@k}{(true\ positives@k) + (false\ negatives@k)}$$

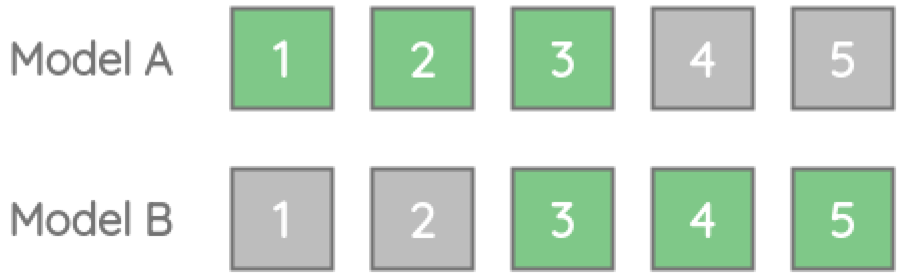
Recall@1 = 1/3 = 0.33

Recall@3 = 2/(2+1) = 2/3 = 0.67

Recall@K

k	1	2	3	4	5
Recall@k	$\frac{1}{(1+2)} = \frac{1}{3} = 0.33$	$\frac{1}{(1+2)} = \frac{1}{3} = 0.33$	$\frac{2}{(2+1)} = \frac{2}{3} = 0.67$	$\frac{2}{(2+1)} = \frac{2}{3} = 0.67$	$\frac{3}{(3+0)} = \frac{3}{3} = 1$

Calculate Recall@5



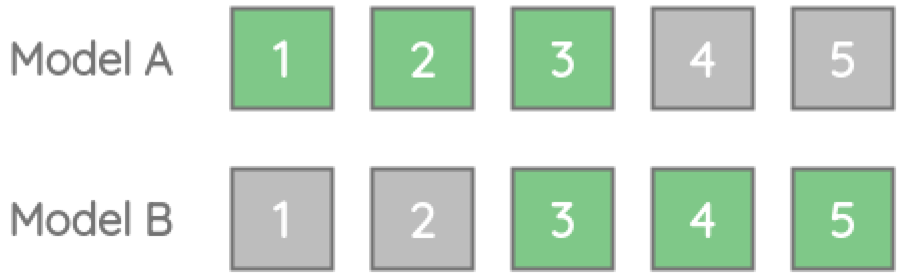
F1 Score@K

F1 Score: Harmonic mean of precision and recall

$$F1@k = \frac{2 * (Precision@k) * (Recall@k)}{(Precision@k) + (Recall@k)}$$

k	1	2	3	4	5
Precision@k	1	1/2	2/3	1/2	3/5
Recall@k	1/3	1/3	2/3	2/3	1
F1@k	$\frac{2*1*(1/3)}{(1+1/3)} = 0.5$	$\frac{2*(1/2)*(1/3)}{(1/2+1/3)} = 0.4$	$\frac{2*(2/3)*(2/3)}{(2/3+2/3)} = 0.666$	$\frac{2*(1/2)*(2/3)}{(1/2+2/3)} = 0.571$	$\frac{2*(3/5)*1}{(3/5+1)} = 0.749$

Calculate F1 Score@5



Order aware metrics

Mean Reciprocal Rank

useful when we want system to return best relevant item and want that item to be at higher position.

$$MRR = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{rank_i}$$

$|Q|$ denotes total number of queries

$rank_i$ denotes the rank of the first relevant result

Mean Reciprocal Rank

Calculate reciprocal of rank and then average across queries

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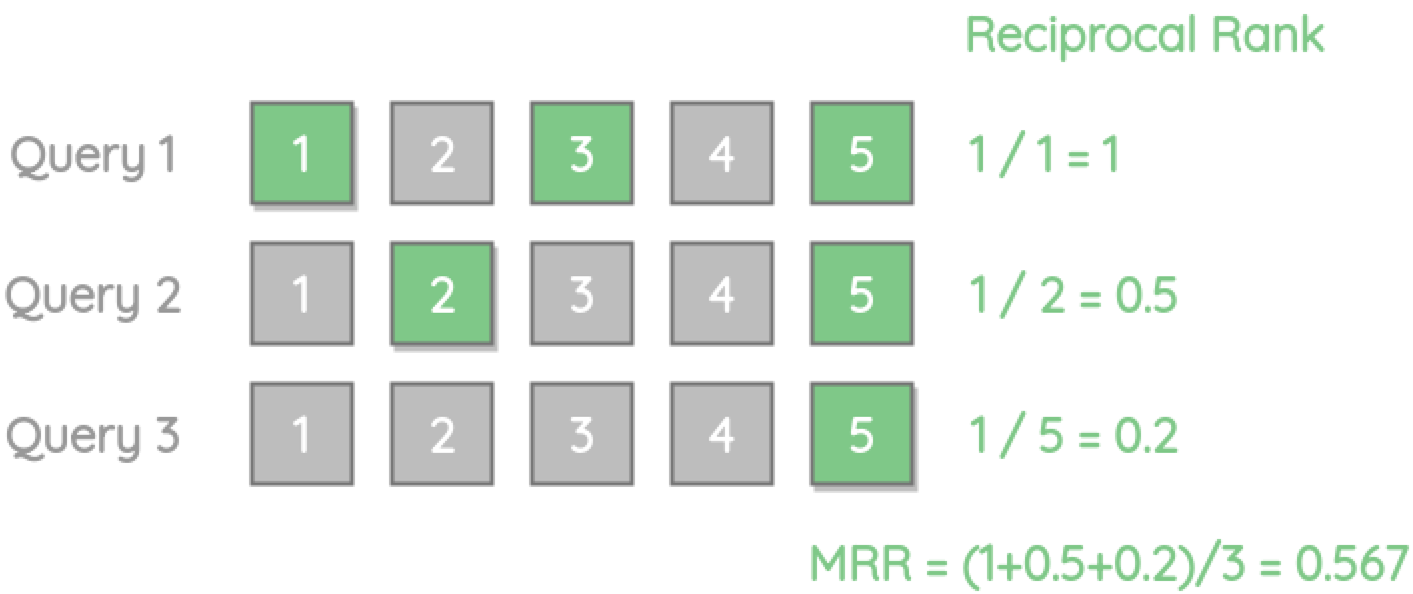
Calculate reciprocal of rank and then average across queries



MRR doesn't care about position of remaining relevant results.
If use-case requires returning multiple relevant results in the best possible way, it may not be a good metric

Average precision (AP)

Evaluates whether all of the ground-truth relevant items selected by model are ranked higher or not.

Unlike MRR, it considers all the relevant items.

$$AP = \frac{\sum_{k=1}^{n} (P(k) * rel(k))}{number\ of\ relevant\ items}$$

$rel(k)$ indicator function which is 1 when item at rank K is relevant.

$P(k)$ Precision@k metric

Average precision (AP)

	1	2	3	4	5
Precision@K	1	1/2	2/3	2/4	3/5

$$AP = \frac{(1 + 2/3 + 3/5)}{3} = 0.7555$$

Calculate Average precision (AP)

	1	2	3	4	5
Precision@K	1	1	1	3/4	3/5

Calculate Average precision (AP)

	1	2	3	4	5
Precision@K	1	1	1	3/4	3/5

$$AP = \frac{(1+1+1)}{3} = 1$$

Mean Average precision (MAP)

Evaluate average precision across multiple queries

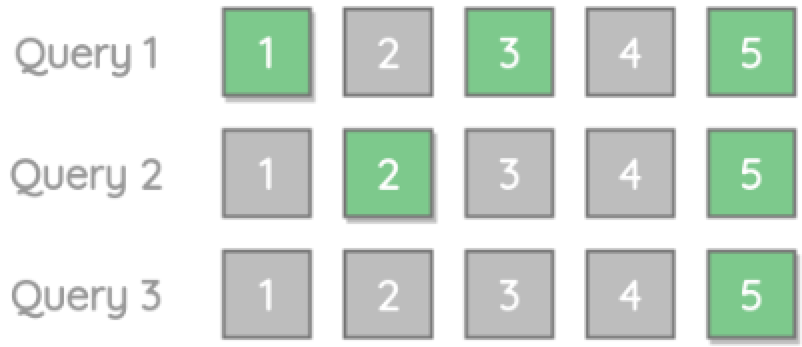
Given by: mean of average precision of different queries

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

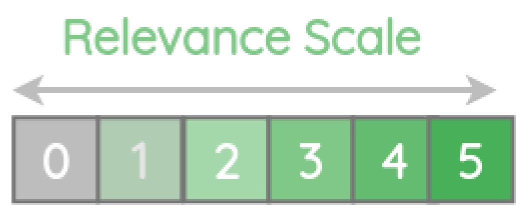
Q total number of queries

$AP(q)$ average precision for query q

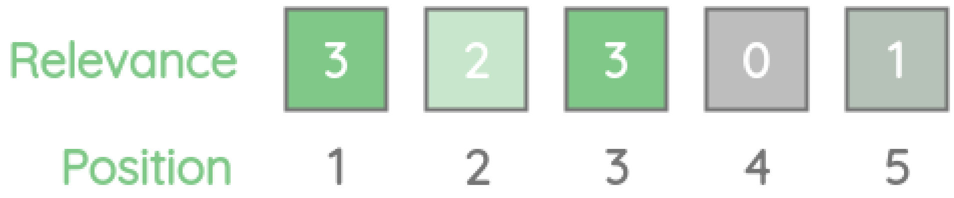
Calculate MAP



Relevance Grading



0 denotes least relevant and 5 denotes the most relevant



Cumulative Gain (CG@k)

Sum up relevance scores for top-K items

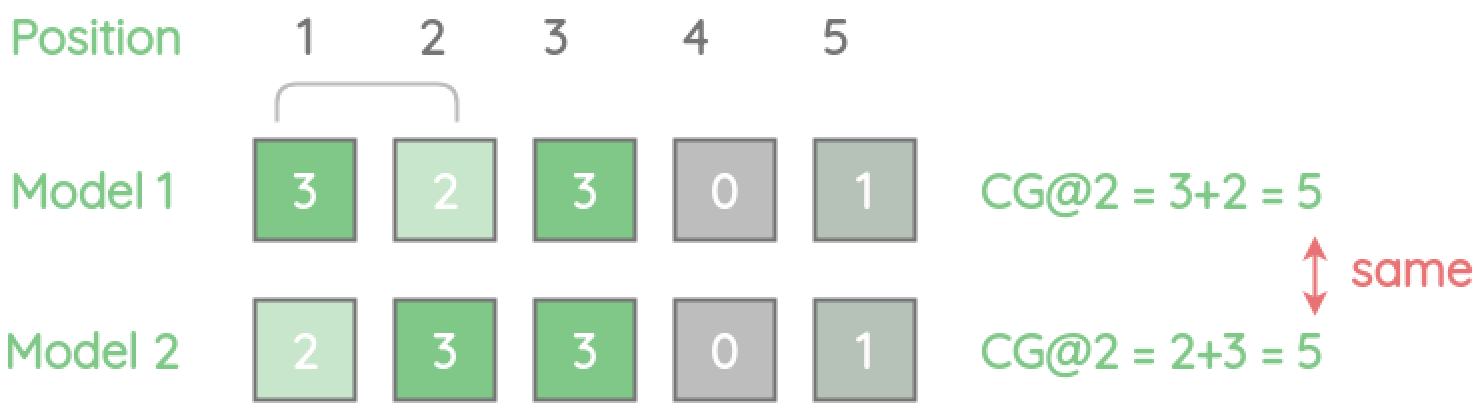
$$CG@k = \sum_{1}^{k} rel_i$$

CG@2:

Calculate Cumulative Gain (CG@k)

Position(k)	1	2	3	4	5
Cumulative Gain@k	3	3+2=5	3+2+3=8	3+2+3+0=8	3+2+3+0+1=9

Cumulative Gain (CG@k)



Item with relevance score of 3 at position 1 is better than same item relevance score 3 at position 2 !

Discounted Cumulative Gain (DCG@k)

Penalize scores by their position.

Introduces log-based penalty function to reduce relevance score at each position.

i	$log_2(i+1)$
1	$log_2(1+1) = log_2(2) = 1$
2	$log_2(2+1) = log_2(3) = 1.5849625007211563$
3	$log_2(3+1) = log_2(4) = 2$
4	$log_2(4+1) = log_2(5) = 2.321928094887362$
5	$log_2(5+1) = log_2(6) = 2.584962500721156$

Discounted Cumulative Gain (DCG@k)

i	$log_2(i+1)$
1	$log_2(1+1) = log_2(2) = 1$
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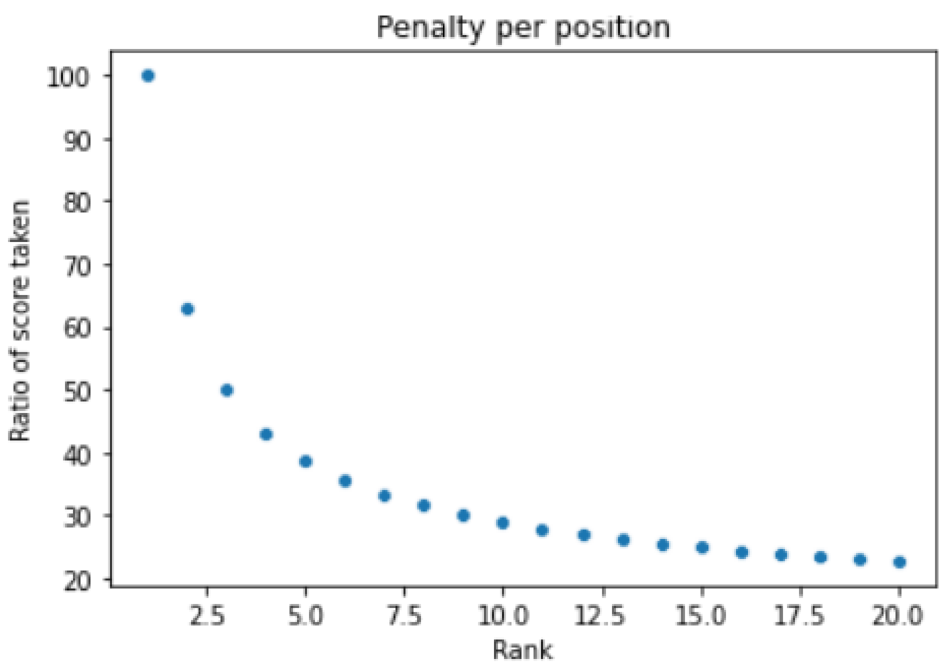


Discounted Cumulative Gain (DCG@k)

$$DCG@k = \sum_{i=1}^{k} \frac{rel_i}{log_2(i+1)}$$

$Position(i)$	$Relevance(rel_i)$	$log_2(i+1)$	$\frac{rel_i}{log_2(i+1)}$
1	3	$log_2(1+1) = log_2(2) = 1$	3 / 1 = 3
2	2	$log_2(2+1) = log_2(3) = 1.5849625007211563$	2 / 1.5849 = 1.2618
3	3	$log_2(3+1) = log_2(4) = 2$	3 / 2 = 1.5
4	0	$log_2(4+1) = log_2(5) = 2.321928094887362$	0 / 2.3219 = 0
5	1	$log_2(5+1) = log_2(6) = 2.584962500721156$	1 / 2.5849 = 0.3868

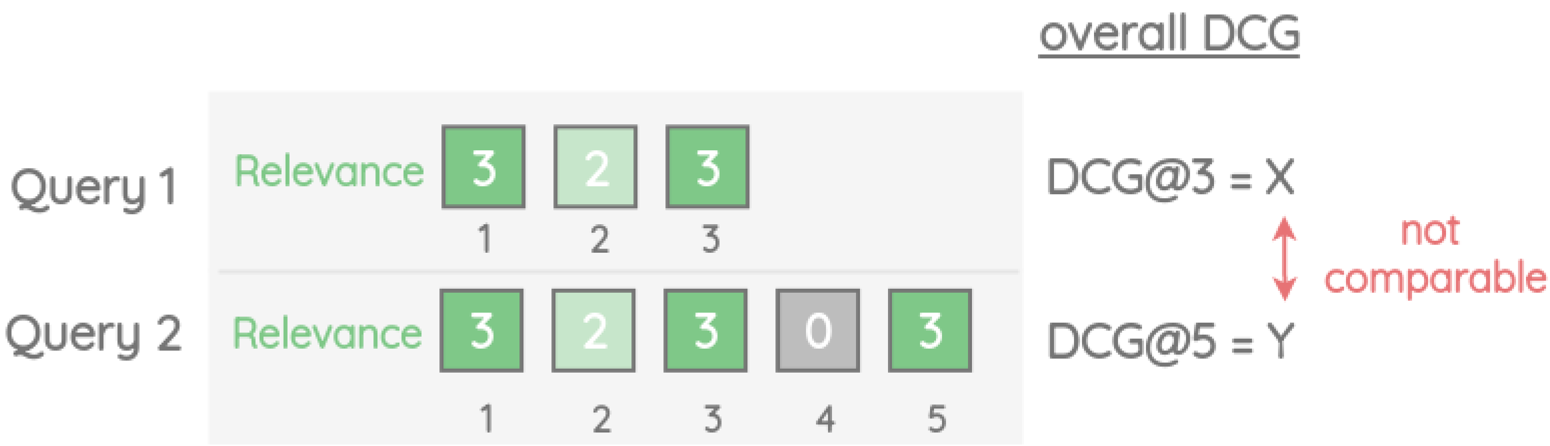
Discounted Cumulative Gain (DCG@k)

$$DCG@k = \sum_{i=1}^{k} \frac{rel_i}{log_2(i+1)}$$

k	DCG@k
DCG@1	3
DCG@2	$3 + 1.2618 = 4.2618$
DCG@3	$3 + 1.2618 + 1.5 = 5.7618$
DCG@4	$3 + 1.2618 + 1.5 + 0 = 5.7618$
DCG@5	$3 + 1.2618 + 1.5 + 0 + 0.3868 = 6.1486$

Discounted Cumulative Gain (DCG@k)

Different size queries



Normalized Discounted Cumulative Gain (NDCG@k)

Normalize DCG values using ideal order of the relevant items to allow comparison across queries

Normalized Discounted Cumulative Gain (NDCG@k)

Ideal Order of Items

Relevance	3	3	2	1	0
Position	1	2	3	4	5

$Position(i)$	$Relevance(rel_i)$	$log_2(i+1)$	$\frac{rel_i}{log_2(i+1)}$	IDCG@k
1	3	$log_2(2) = 1$	3 / 1 = 3	3
2	3	$log_2(3) = 1.5849$	3 / 1.5849 = 1.8927	3+1.8927=4.8927
3	2	$log_2(4) = 2$	2 / 2 = 1	3+1.8927+1=5.8927
4	1	$log_2(5) = 2.3219$	1 / 2.3219 = 0.4306	3+1.8927+1+0.4306=6.3233
5	0	$log_2(6) = 2.5849$	0 / 2.5849 = 0	3+1.8927+1+0.4306+0=6.3233

Normalized Discounted Cumulative Gain (NDCG@k)

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

k	DCG@k	IDCG@k	NDCG@k
1	3	3	3 / 3 = 1
2	4.2618	4.8927	4.2618 / 4.8927 = 0.8710
3	5.7618	5.8927	5.7618 / 5.8927 = 0.9777
4	5.7618	6.3233	5.7618 / 6.3233 = 0.9112
5	6.1486	6.3233	6.1486 / 6.3233 = 0.9723

Scores range between 0 and 1.
A perfect ranking would get a score of 1.
Can also compare NDCG@k scores of different queries since it's a normalized score