Evaluation Metrics

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Batch Evaluation

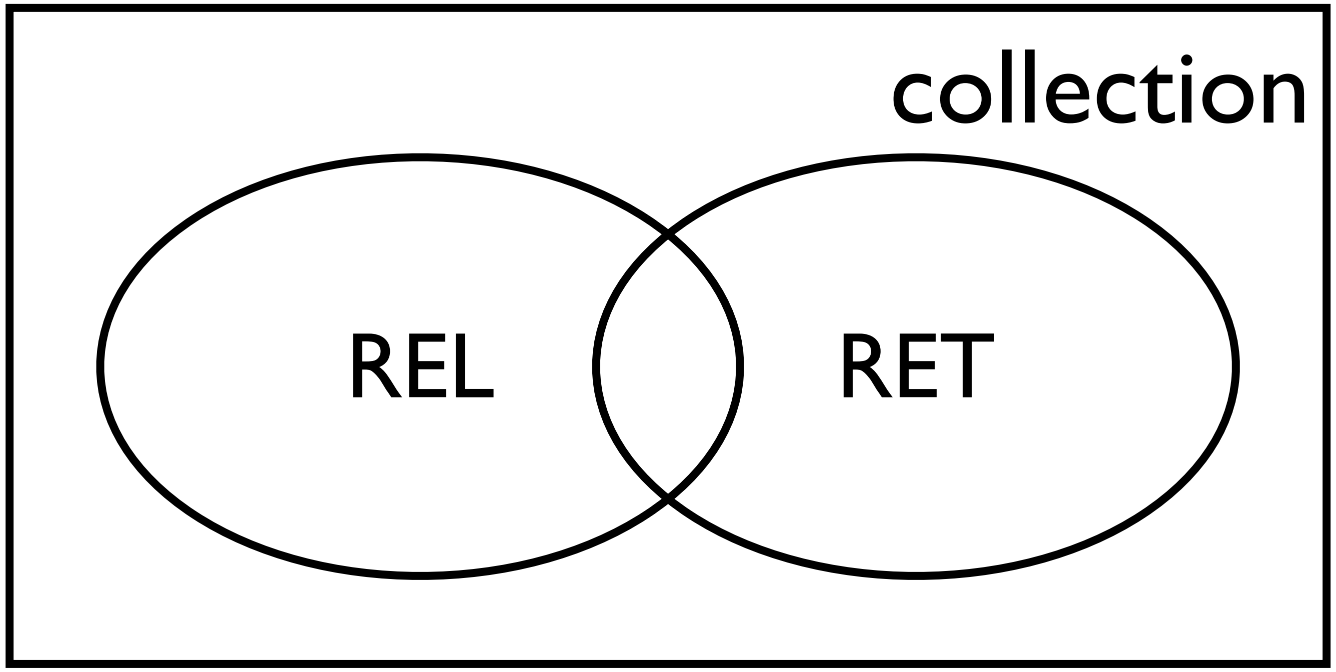
evaluation metrics

- At this point, we have a set of queries, with identified relevant and non-relevant documents
- The goal of an evaluation metric is to measure the quality of a particular ranking of known relevant/non-relevant documents

Set Retrieval

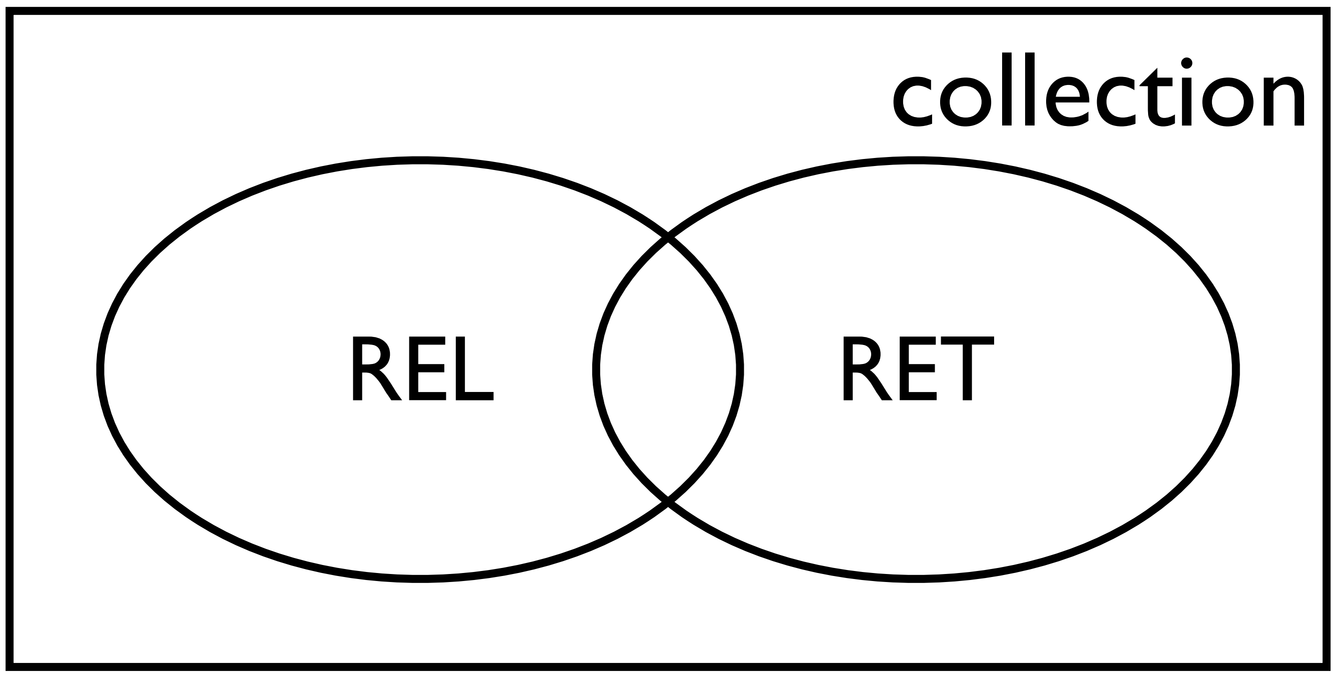
precision and recall

- So far, we've defined precision and recall assuming boolean retrieval: a set of relevant documents (REL) and a set of retrieved documents (RET)



Set Retrieval
precision and recall

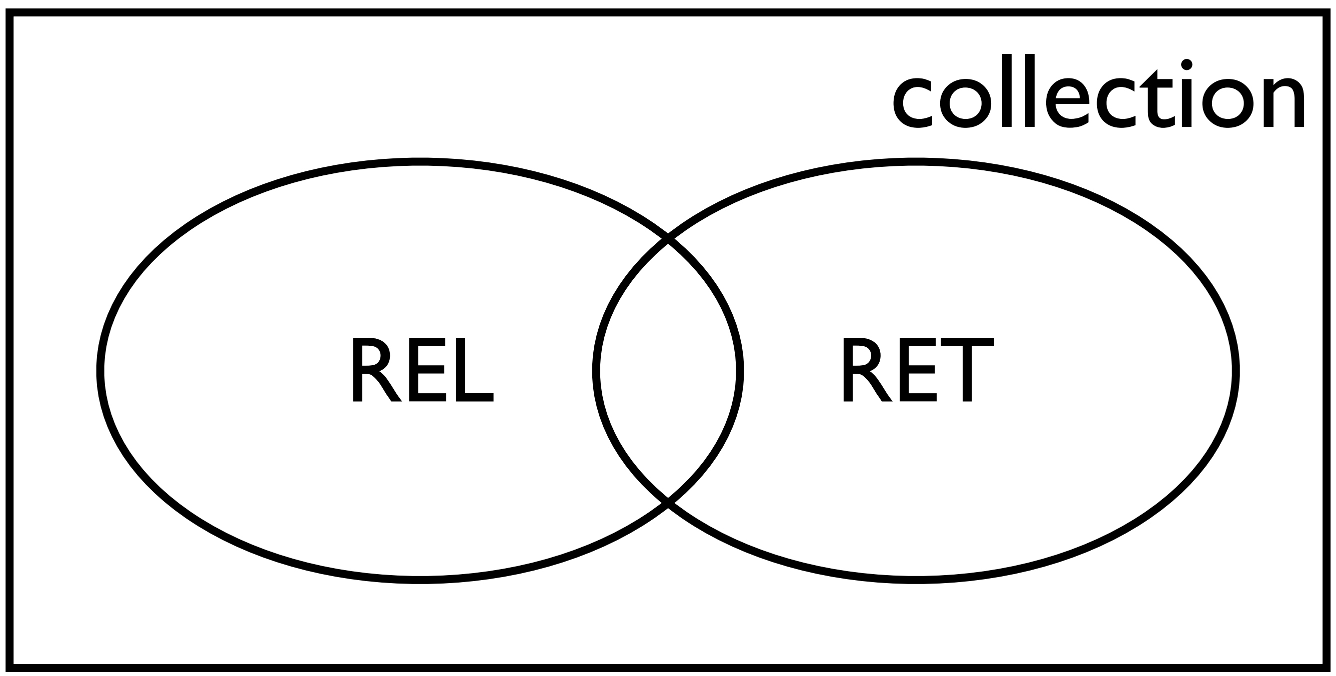
- Precision (P): the proportion of retrieved documents that are relevant



$$\mathcal{P} = \frac{|RET \cap REL|}{|RET|}$$

Set Retrieval
precision and recall

- Recall (R): the proportion of relevant documents that are retrieved



$$\mathcal{R} = \frac{|RET \cap REL|}{|REL|}$$

Set Retrieval
precision and recall

- Recall measures the system's ability to find all the relevant documents
- Precision measures the system's ability to reject any non-relevant documents in the retrieved set

Set Retrieval
precision and recall

- A system can make two types of errors:
  - a false positive error: the system retrieves a document that is non-relevant (should not have been retrieved)
  - a false negative error: the system fails to retrieve a document that is relevant (should have been retrieved)
- How do these types of errors affect precision and recall?

Set Retrieval
precision and recall

- A system can make two types of errors:
  - a false positive error: the system retrieves a document that is non-relevant (should not have been retrieved)
  - a false negative error: the system fails to retrieve a document that is relevant (should have been retrieved)
- How do these types of errors affect precision and recall?
- Precision is affected by the number of false positive errors
- Recall is affected by the number of false negative errors

Set Retrieval
combining precision and recall

- Oftentimes, we want a system that has high-precision and high-recall
- We want a metric that measures the balance between precision and recall
- One possibility would be to use the arithmetic mean:

$$\text{arithmetic mean}(\mathcal{P}, \mathcal{R}) = \frac{\mathcal{P} + \mathcal{R}}{2}$$

- What is problematic with this way of summarizing precision and recall?

Set Retrieval

combining precision and recall

- It's easy for a system to "game" the arithmetic mean of precision and recall
- Bad: a system that obtains **1.0** precision and near **0.0** recall would get a mean value of about **0.50**
- Bad: a system that obtains **1.0** recall and near **0.0** precision would get a mean value of about **0.50**
- Better: a system that obtains **0.50** precision and near **0.50** recall would get a mean value of about **0.50**

Set Retrieval

F-measure (also known as F1)

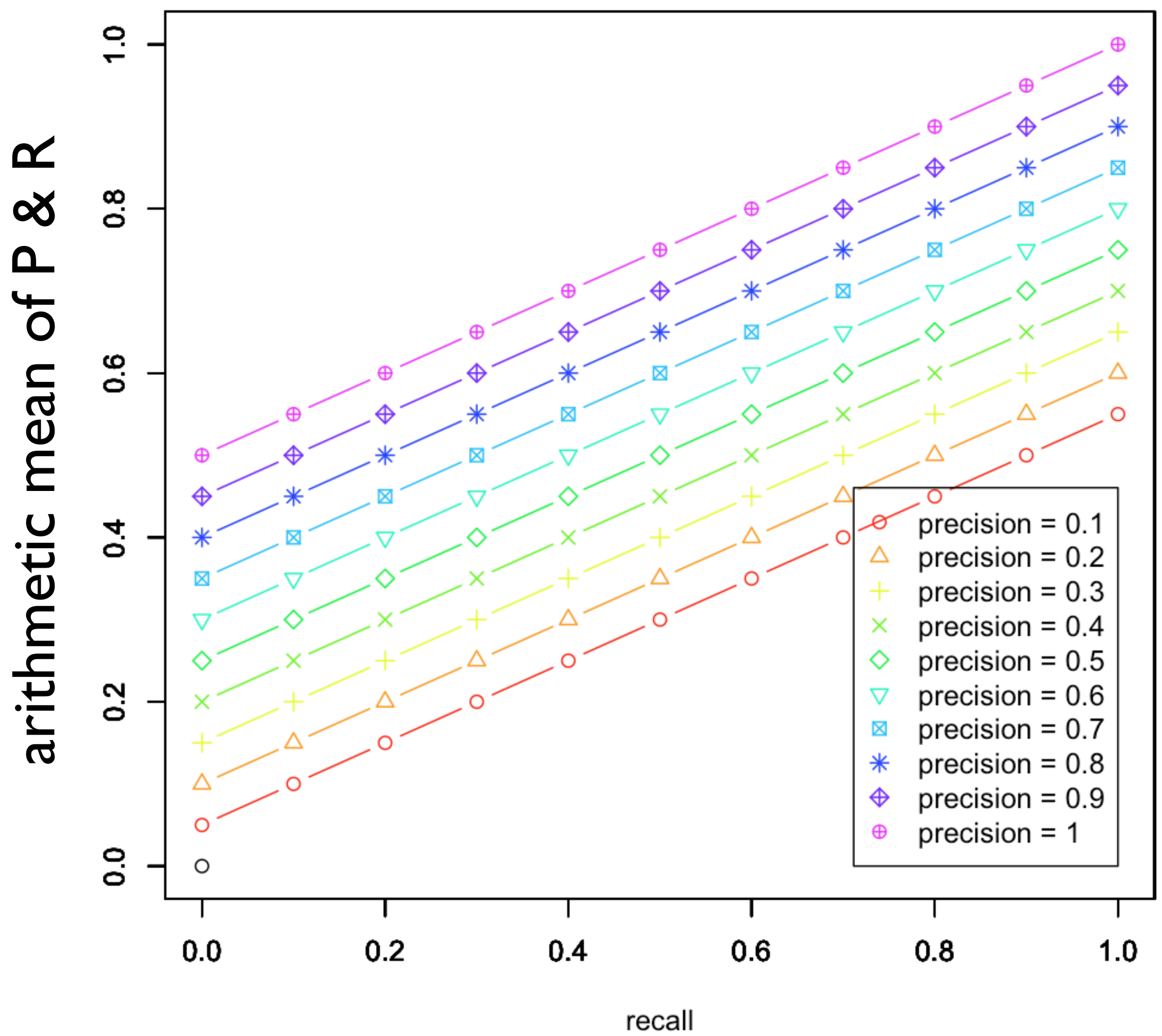
- A system that retrieves a single relevant document would get 1.0 precision and near 0.0 recall
- A system that retrieves the entire collection would get 1.0 recall and near 0.0 precision
- Solution: use the harmonic mean rather than the arithmetic mean
- F-measure:

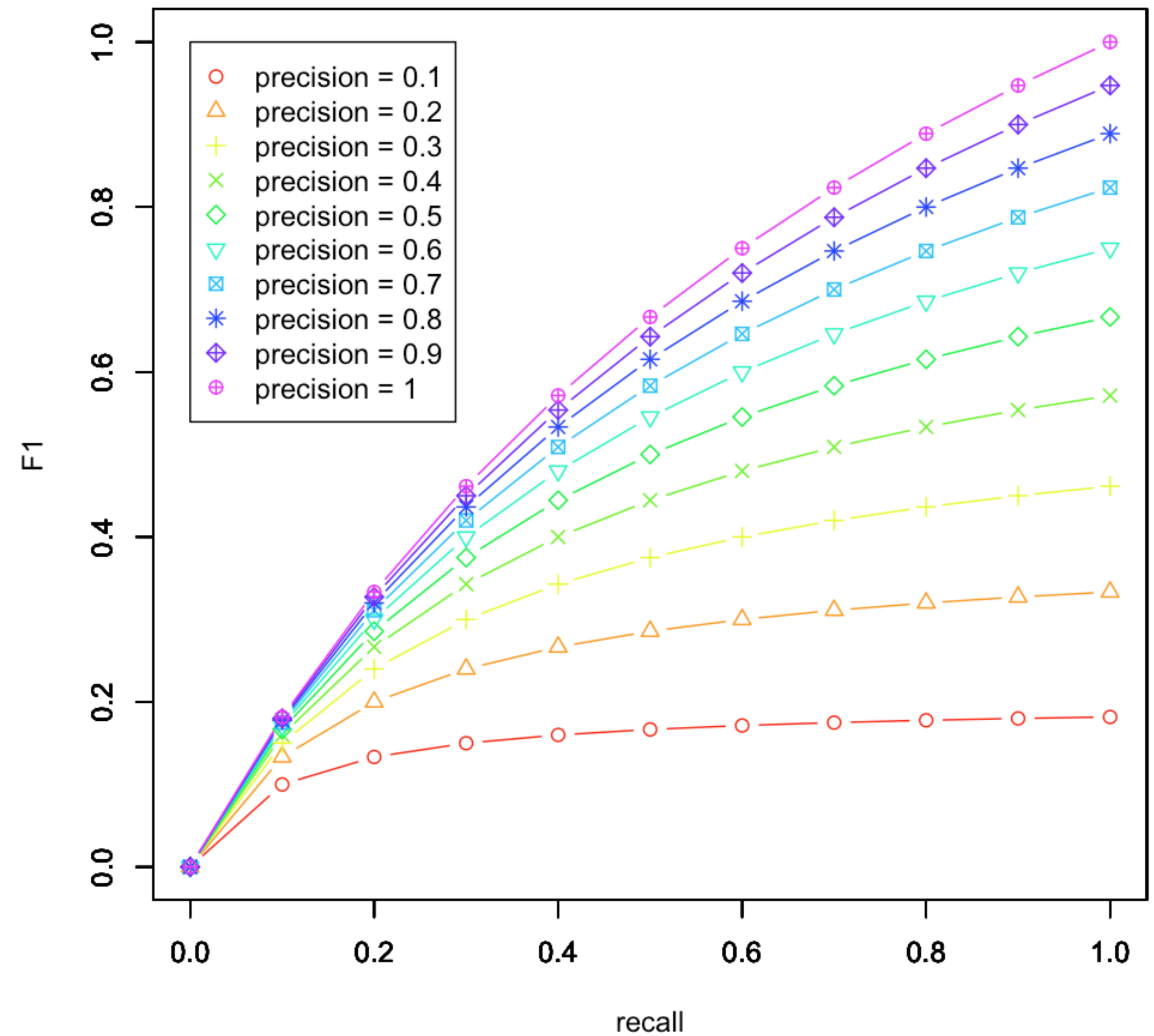
$$\mathcal{F} = \frac{1}{\frac{1}{2}\left(\frac{1}{\mathcal{P}} + \frac{1}{\mathcal{R}}\right)} = \frac{2 \times \mathcal{P} \times \mathcal{R}}{\mathcal{P} + \mathcal{R}}$$

Set Retrieval

F-measure (also known as F1)

- The harmonic mean punishes small values





(slide courtesy of Ben Carterette)

Ranked Retrieval
precision and recall

- In most situations, the system outputs a ranked list of documents rather than an unordered set
- User-behavior assumption:
  - The user examines the output ranking from top-to-bottom until he/she is satisfied or gives up
- Precision and recall can also be used to evaluate a ranking
- Precision/Recall @ rank *K*

Ranked Retrieval

precision and recall

- Precision: proportion of retrieved documents that are relevant
- Recall: proportion of relevant documents that are retrieved

Ranked Retrieval

precision and recall

- P@K: proportion of ~~retrieved~~ top-K documents that are relevant
- R@K: proportion of relevant documents that are ~~retrieved~~ in the top-K
- Assumption: the user will only examine the top-K results

Ranked Retrieval

precision and recall: exercise

- Assume 20 relevant documents

K = 1

K	P@K	R@K
1	(1/1) = 1.0	(1/20) = 0.05
2		
3		
4		
5		
6		
7		
8		
9		
10		

Ranked Retrieval

precision and recall: exercise

- Assume 20 relevant documents

K	P@K	R@K
1	(1/1) = 1.0	(1/20) = 0.05
2	(1/2) = 0.5	(1/20) = 0.05
3		
4		
5		
6		
7		
8		
9		
10		

K = 2

Ranked Retrieval

precision and recall: exercise

- Assume 20 relevant documents

K = 3

K	P@K	R@K
1	(1/1) = 1.0	(1/20) = 0.05
2	(1/2) = 0.5	(1/20) = 0.05
3	(2/3) = 0.67	(2/20) = 0.10
4		
5		
6		
7		
8		
9		
10		

Ranked Retrieval

precision and recall: exercise

- Assume 20 relevant documents

K	P@K	R@K
1	(1/1) = 1.0	(1/20) = 0.05
2	(1/2) = 0.5	(1/20) = 0.05
3	(2/3) = 0.67	(2/20) = 0.10
4	(3/4) = 0.75	(3/20) = 0.15
5		
6		
7		
8		
9		
10		

K = 4

Ranked Retrieval

precision and recall: exercise

- Assume 20 relevant documents

K = 5

K	P@K	R@K
1	(1/1) = 1.0	(1/20) = 0.05
2	(1/2) = 0.5	(1/20) = 0.05
3	(2/3) = 0.67	(2/20) = 0.10
4	(3/4) = 0.75	(3/20) = 0.15
5	(4/5) = 0.80	(4/20) = 0.20
6		
7		
8		
9		
10		

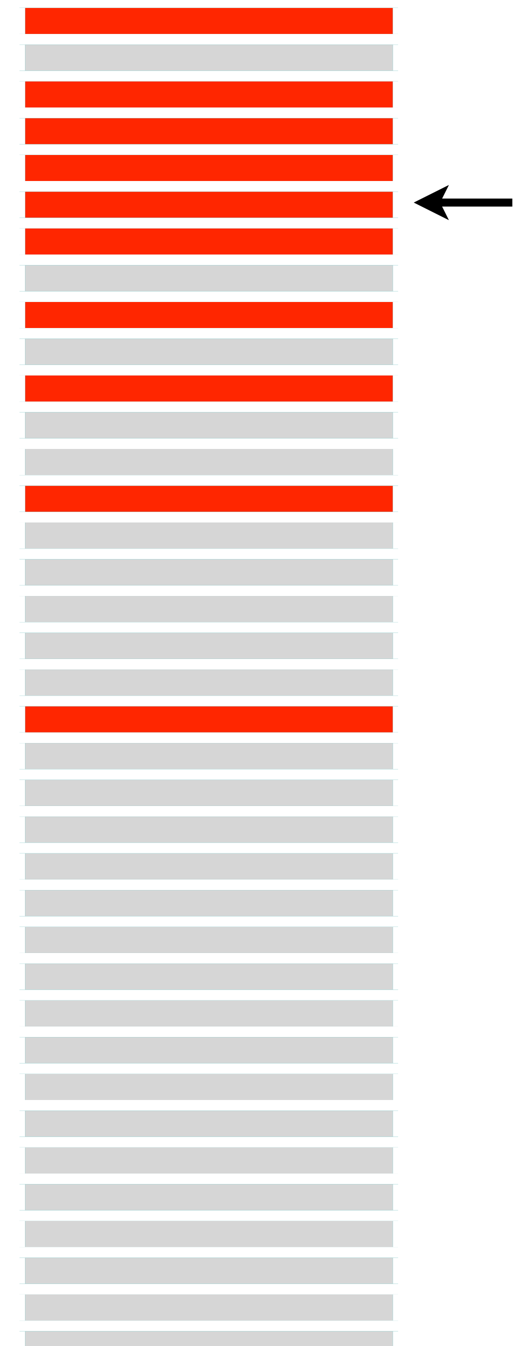
Ranked Retrieval

precision and recall: exercise

- Assume 20 relevant documents

K = 6

K	P@K	R@K
1	(1/1) = 1.0	(1/20) = 0.05
2	(1/2) = 0.5	(1/20) = 0.05
3	(2/3) = 0.67	(2/20) = 0.10
4	(3/4) = 0.75	(3/20) = 0.15
5	(4/5) = 0.80	(4/20) = 0.20
6	(5/6) = 0.83	(5/20) = 0.25
7		
8		
9		
10		

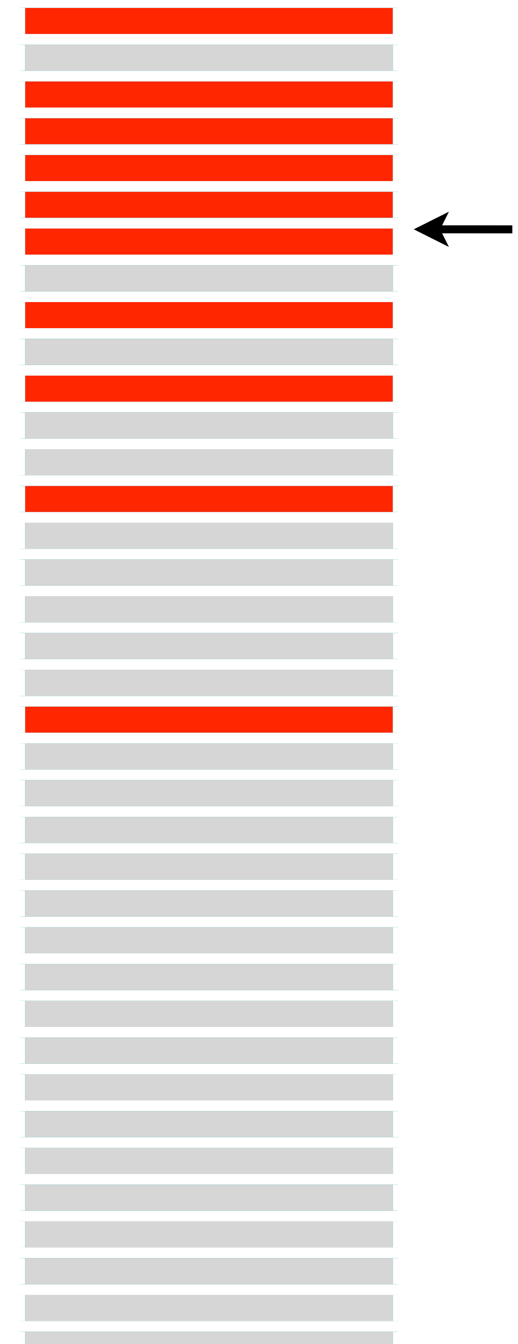


Ranked Retrieval

precision and recall: exercise

- Assume 20 relevant documents

K = 7



K	P@K	R@K
1	(1/1) = 1.0	(1/20) = 0.05
2	(1/2) = 0.5	(1/20) = 0.05
3	(2/3) = 0.67	(2/20) = 0.10
4	(3/4) = 0.75	(3/20) = 0.15
5	(4/5) = 0.80	(4/20) = 0.20
6	(5/6) = 0.83	(5/20) = 0.25
7	(6/7) = 0.86	(6/20) = 0.30
8		
9		
10		

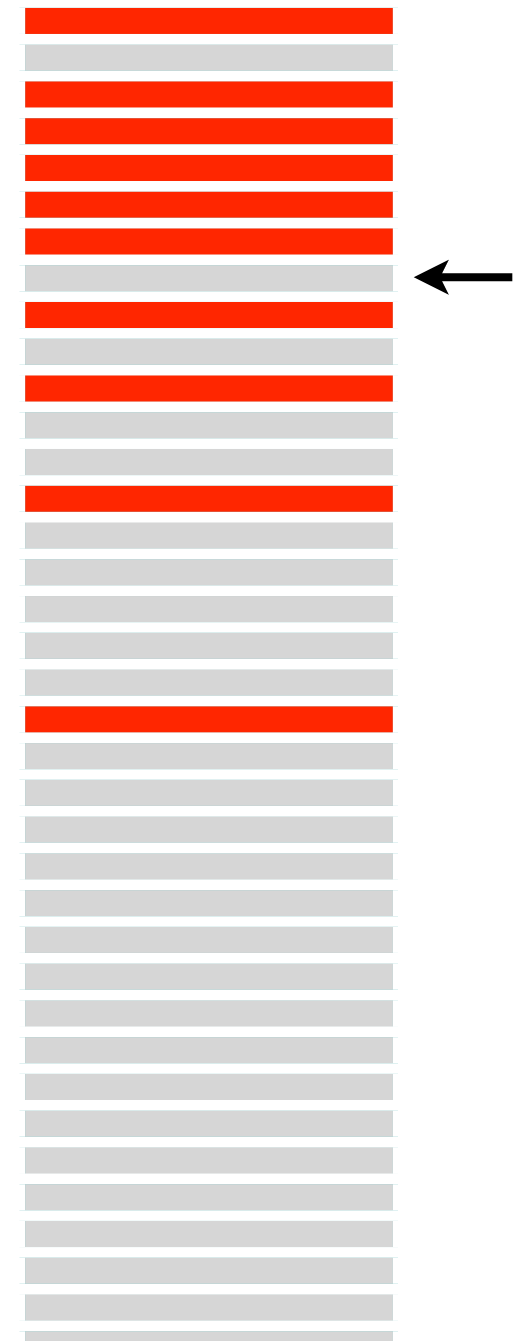
Ranked Retrieval

precision and recall: exercise

- Assume 20 relevant documents

K	P@K	R@K
1	(1/1) = 1.0	(1/20) = 0.05
2	(1/2) = 0.5	(1/20) = 0.05
3	(2/3) = 0.67	(2/20) = 0.10
4	(3/4) = 0.75	(3/20) = 0.15
5	(4/5) = 0.80	(4/20) = 0.20
6	(5/6) = 0.83	(5/20) = 0.25
7	(6/7) = 0.86	(6/20) = 0.30
8	(6/8) = 0.75	(6/20) = 0.30
9		
10		

K = 8

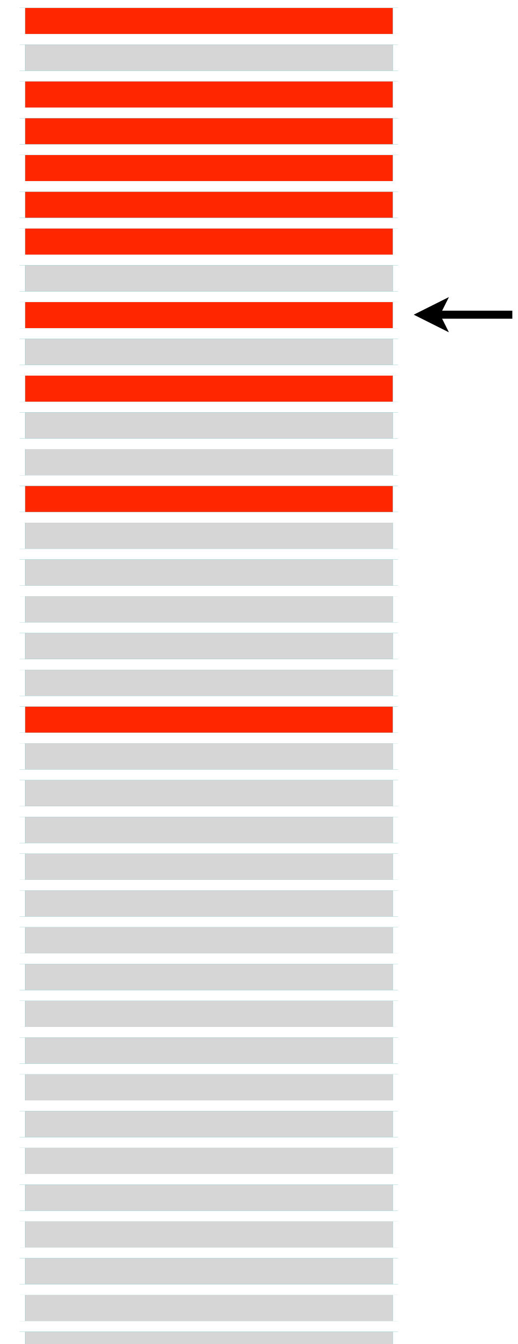


Ranked Retrieval

precision and recall: exercise

- Assume 20 relevant documents

K = 9



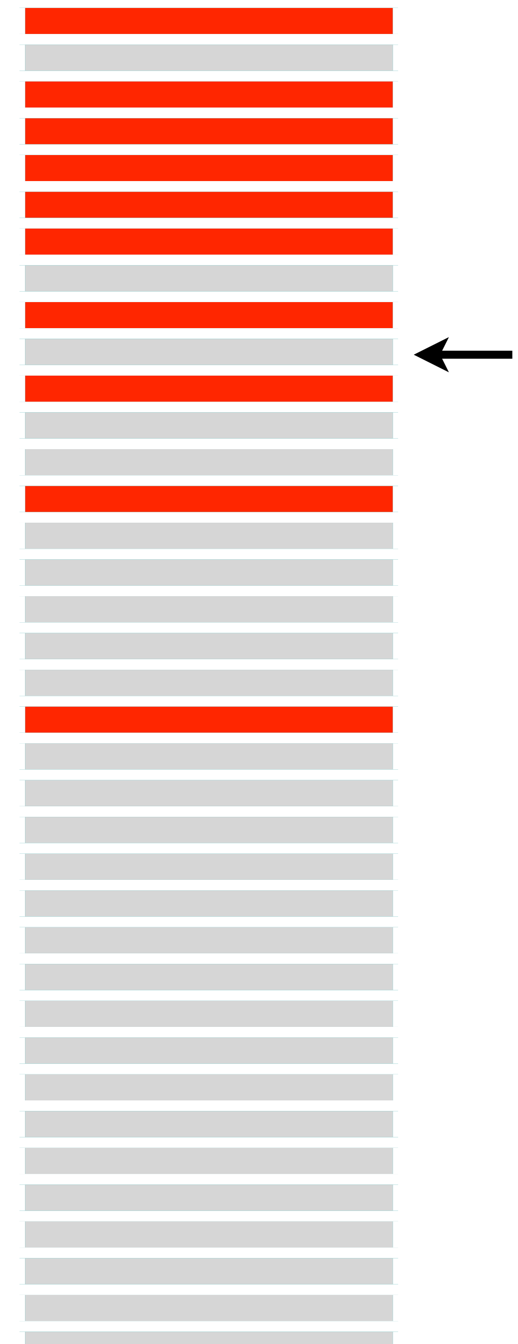
K	P@K	R@K
1	(1/1) = 1.0	(1/20) = 0.05
2	(1/2) = 0.5	(1/20) = 0.05
3	(2/3) = 0.67	(2/20) = 0.10
4	(3/4) = 0.75	(3/20) = 0.15
5	(4/5) = 0.80	(4/20) = 0.20
6	(5/6) = 0.83	(5/20) = 0.25
7	(6/7) = 0.86	(6/20) = 0.30
8	(6/8) = 0.75	(6/20) = 0.30
9	(7/9) = 0.78	(7/20) = 0.35
10		

Ranked Retrieval

precision and recall: exercise

- Assume 20 relevant documents

K = 10

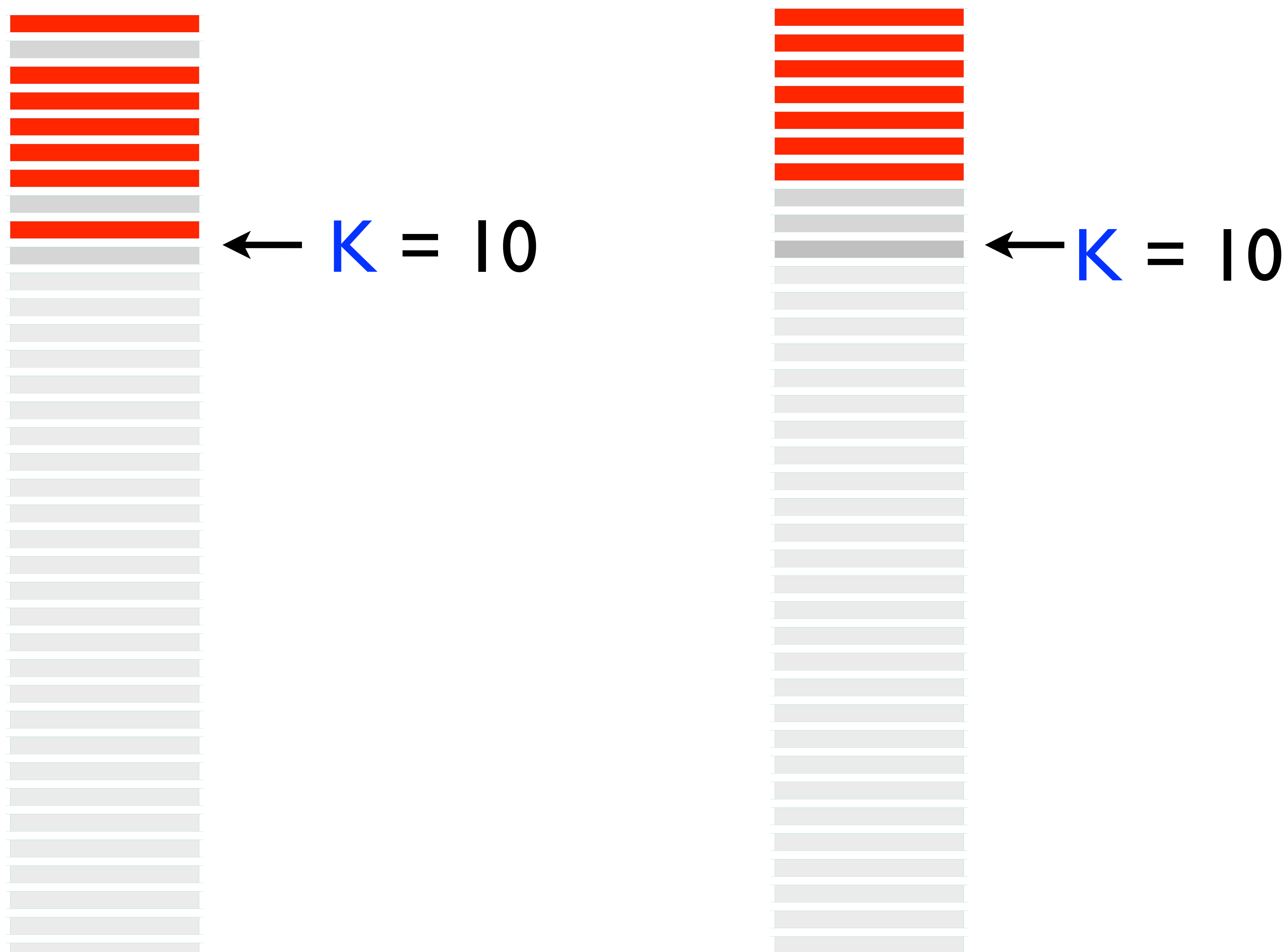


K	P@K	R@K
1	(1/1) = 1.0	(1/20) = 0.05
2	(1/2) = 0.5	(1/20) = 0.05
3	(2/3) = 0.67	(2/20) = 0.10
4	(3/4) = 0.75	(3/20) = 0.15
5	(4/5) = 0.80	(4/20) = 0.20
6	(5/6) = 0.83	(5/20) = 0.25
7	(6/7) = 0.86	(6/20) = 0.30
8	(6/8) = 0.75	(6/20) = 0.30
9	(7/9) = 0.78	(7/20) = 0.35
10	(7/10) = 0.70	(7/20) = 0.35

Ranked Retrieval

precision and recall

- Problem: what value of K should we use to evaluate?
- Which is better in terms of P@10 and R@10?



Ranked Retrieval

precision and recall

- The ranking of documents within the top K is inconsequential
- If we don't know what value of K to chose, we can compute and report several: P/R@{1,5,10,20}
- There are evaluation metrics that do not require choosing K (as we will see)
- One advantage of P/R@K, however, is that they are easy to interpret

Ranked Retrieval

what do these statements mean?

- As with <u>most</u> metrics, experimenters report average values (averaged across evaluation queries)
- System A obtains an average P@10 of 0.50
- System A obtains an average P@10 of 0.10
- System A obtains an average P@1 of 0.50
- System A obtains an average P@20 of 0.20

Ranked Retrieval

comparing systems

- Good practice: always ask yourself “Are users likely to notice?”
- System A obtains an average P@1 of 0.10
- System B obtains an average P@1 of 0.20
- This is a 100% improvement.
- Are user’s likely to notice?

Ranked Retrieval

comparing systems

- Good practice: always ask yourself "Are users likely to notice?"
- System A obtains an average P@1 of 0.05
- System B obtains an average P@1 of 0.10
- This is a 100% improvement.
- Are user's likely to notice?

Ranked Retrieval

P/R@K

- Advantages:
  - easy to compute
  - easy to interpret
- Disadvantages:
  - the value of K has a huge impact on the metric
  - the ranking above K is inconsequential
  - how do we pick K?

Ranked Retrieval

motivation: average precision

- Ideally, we want the system to achieve high precision for varying values of K
- The metric average precision accounts for precision and recall without having to set K

Ranked Retrieval

average precision

1. Go down the ranking one-rank-at-a-time
2. If the document at rank K is relevant, measure P@K
   - proportion of top-K documents that are relevant
3. Finally, take the average of all P@K values
   - the number of P@K values will equal the number of relevant documents

Ranked Retrieval

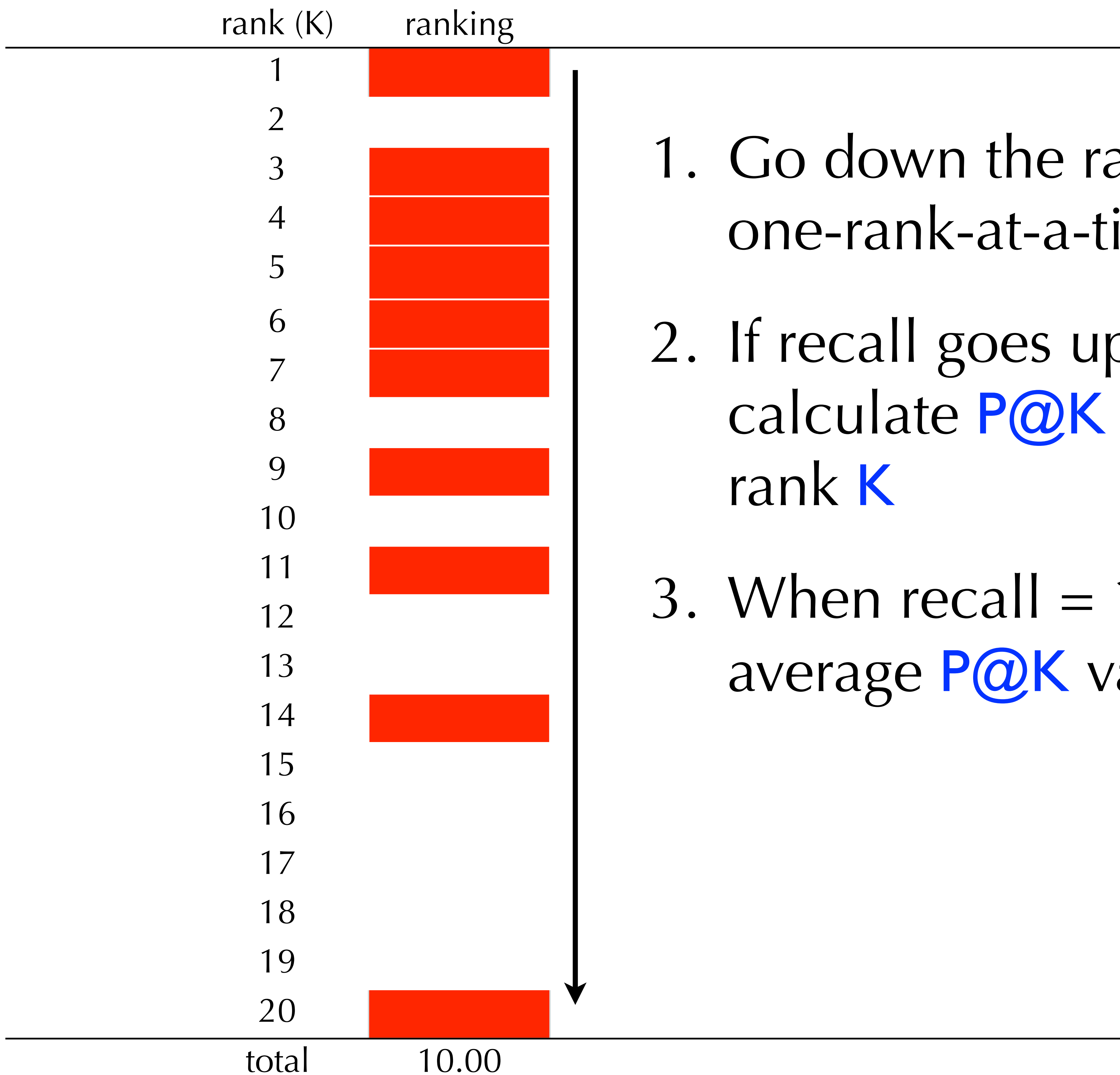
average-precision

rank (K)	ranking
1	
2	
3	
4	
5	
6	
7	
8	
9	
10	
11	
12	
13	
14	
15	
16	
17	
18	
19	
20	
total	10.00

Number of relevant documents for this query: 10

Ranked Retrieval

average-precision



1. Go down the ranking one-rank-at-a-time
2. If recall goes up, calculate P@K at that rank K
3. When recall = 1.0, average P@K values

Ranked Retrieval

average-precision

rank (K)	ranking	R@K	P@K
1		0.10	1.00
2		0.10	0.50
3		0.20	0.67
4		0.30	0.75
5		0.40	0.80
6		0.50	0.83
7		0.60	0.86
8		0.60	0.75
9		0.70	0.78
10		0.70	0.70
11		0.80	0.73
12		0.80	0.67
13		0.80	0.62
14		0.90	0.64
15		0.90	0.60
16		0.90	0.56
17		0.90	0.53
18		0.90	0.50
19		0.90	0.47
20		1.00	0.50
total	10.00	average-precision	0.76

Ranked Retrieval

average-precision

rank (K)	ranking	R@K	P@K
1		0.10	1.00
2		0.20	1.00
3		0.30	1.00
4		0.40	1.00
5		0.50	1.00
6		0.60	1.00
7		0.70	1.00
8		0.80	1.00
9		0.90	1.00
10		1.00	1.00
11		1.00	0.91
12		1.00	0.83
13		1.00	0.77
14		1.00	0.71
15		1.00	0.67
16		1.00	0.63
17		1.00	0.59
18		1.00	0.56
19		1.00	0.53
20		1.00	0.50
total	10.00	average-precision	1.00

Ranked Retrieval

average-precision

rank (K)	ranking	R@K	P@K
1		0.00	0.00
2		0.00	0.00
3		0.00	0.00
4		0.00	0.00
5		0.00	0.00
6		0.00	0.00
7		0.00	0.00
8		0.00	0.00
9		0.00	0.00
10		0.00	0.00
11		0.10	0.09
12		0.20	0.17
13		0.30	0.23
14		0.40	0.29
15		0.50	0.33
16		0.60	0.38
17		0.70	0.41
18		0.80	0.44
19		0.90	0.47
20		1.00	0.50
total	10.00	average-precision	0.33

Ranked Retrieval

average-precision

rank (K)	ranking	R@K	P@K
1		0.10	1.00
2		0.10	0.50
3		0.20	0.67
4		0.30	0.75
5		0.40	0.80
6		0.50	0.83
7		0.60	0.86
8		0.60	0.75
9		0.70	0.78
10		0.70	0.70
11		0.80	0.73
12		0.80	0.67
13		0.80	0.62
14		0.90	0.64
15		0.90	0.60
16		0.90	0.56
17		0.90	0.53
18		0.90	0.50
19		0.90	0.47
20		1.00	0.50
total	10.00	average-precision	0.76

Ranked Retrieval

average-precision

swapped ranks 2 and 3

rank (K)	ranking	R@K	P@K
1		0.10	1.00
2		0.20	1.00
3		0.20	0.67
4		0.30	0.75
5		0.40	0.80
6		0.50	0.83
7		0.60	0.86
8		0.60	0.75
9		0.70	0.78
10		0.70	0.70
11		0.80	0.73
12		0.80	0.67
13		0.80	0.62
14		0.90	0.64
15		0.90	0.60
16		0.90	0.56
17		0.90	0.53
18		0.90	0.50
19		0.90	0.47
20		1.00	0.50
total	10.00	average-precision	0.79

Ranked Retrieval

average-precision

rank (K)	ranking	R@K	P@K
1		0.10	1.00
2		0.10	0.50
3		0.20	0.67
4		0.30	0.75
5		0.40	0.80
6		0.50	0.83
7		0.60	0.86
8		0.60	0.75
9		0.70	0.78
10		0.70	0.70
11		0.80	0.73
12		0.80	0.67
13		0.80	0.62
14		0.90	0.64
15		0.90	0.60
16		0.90	0.56
17		0.90	0.53
18		0.90	0.50
19		0.90	0.47
20		1.00	0.50
total	10.00	average-precision	0.76

Ranked Retrieval

average-precision

swapped ranks 8 and 9

rank (K)	ranking	R@K	P@K
1	■	0.10	1.00
2		0.10	0.50
3	■	0.20	0.67
4	■	0.30	0.75
5	■	0.40	0.80
6	■	0.50	0.83
7	■	0.60	0.86
8	■	0.70	0.88
9		0.70	0.78
10		0.70	0.70
11	■	0.80	0.73
12		0.80	0.67
13		0.80	0.62
14	■	0.90	0.64
15		0.90	0.60
16		0.90	0.56
17		0.90	0.53
18		0.90	0.50
19		0.90	0.47
20	■	1.00	0.50
total	10.00	average-precision	0.77

Ranked Retrieval

average precision

- Advantages:
  - no need to choose K
  - accounts for both precision and recall
  - ranking mistakes at the top of the ranking are more influential
  - ranking mistakes at the bottom of the ranking are still accounted for
- Disadvantages
  - not quite as easy to interpret as P/R@K

Ranked Retrieval

MAP: mean average precision

- So far, we've talked about average precision for a <u>single</u> query
- Mean Average Precision (MAP): average precision averaged across a <u>set of queries</u>
    - yes, confusing. but, better than calling it "average average precision"!
    - one of the most common metrics in IR evaluation

Ranked Retrieval

precision-recall curves

- In some situations, we want to understand the trade-off between precision and recall
- A precision-recall (PR) curve expresses precision as a function of recall

Ranked Retrieval

precision-recall curves: general idea

- Different tasks require different levels of recall
- Sometimes, the user wants a few relevant documents
- Other times, the user wants most of them
- Suppose a user wants some level of recall **R**
- The goal for the system is to minimize the number of false negatives the user must look at in order to achieve a level of recall **R**

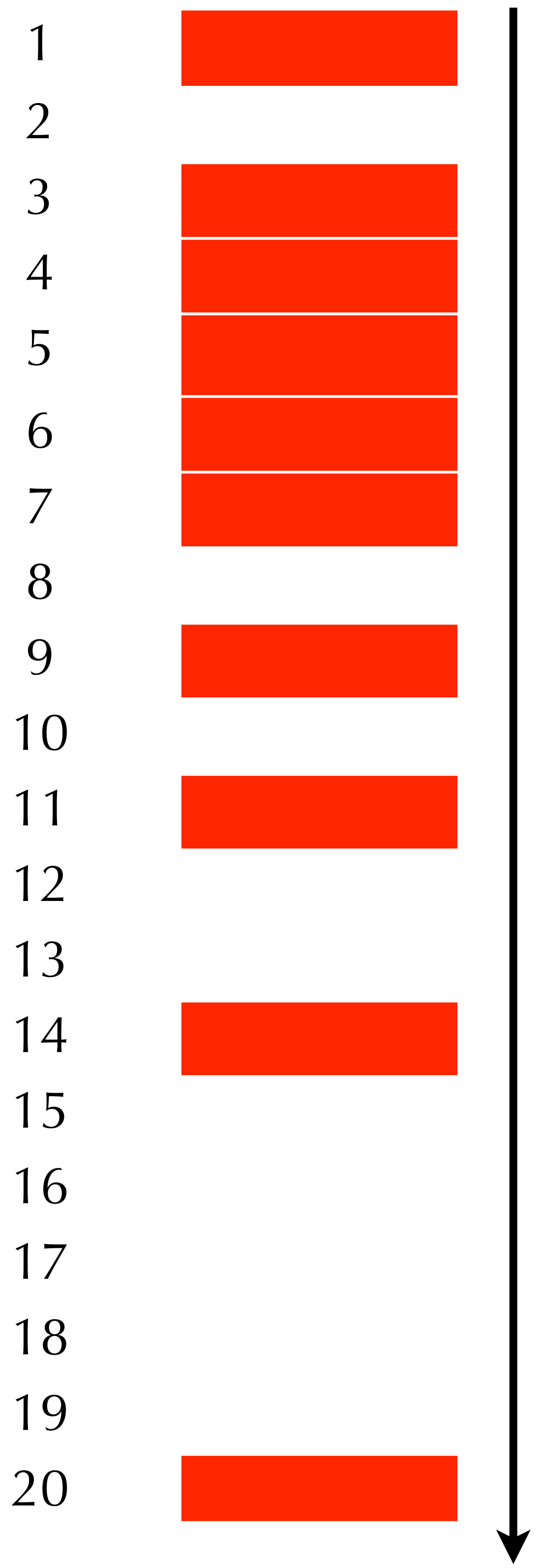
Ranked Retrieval

precision-recall curves: general idea

- False negative error: not retrieving a relevant document
  - false negative errors affects recall
- False positive errors: retrieving a non-relevant document
  - false positives errors affects precision
- If a user wants to avoid a certain level of false-negatives, what is the level of false-positives he/she must filter through?

Ranked Retrieval

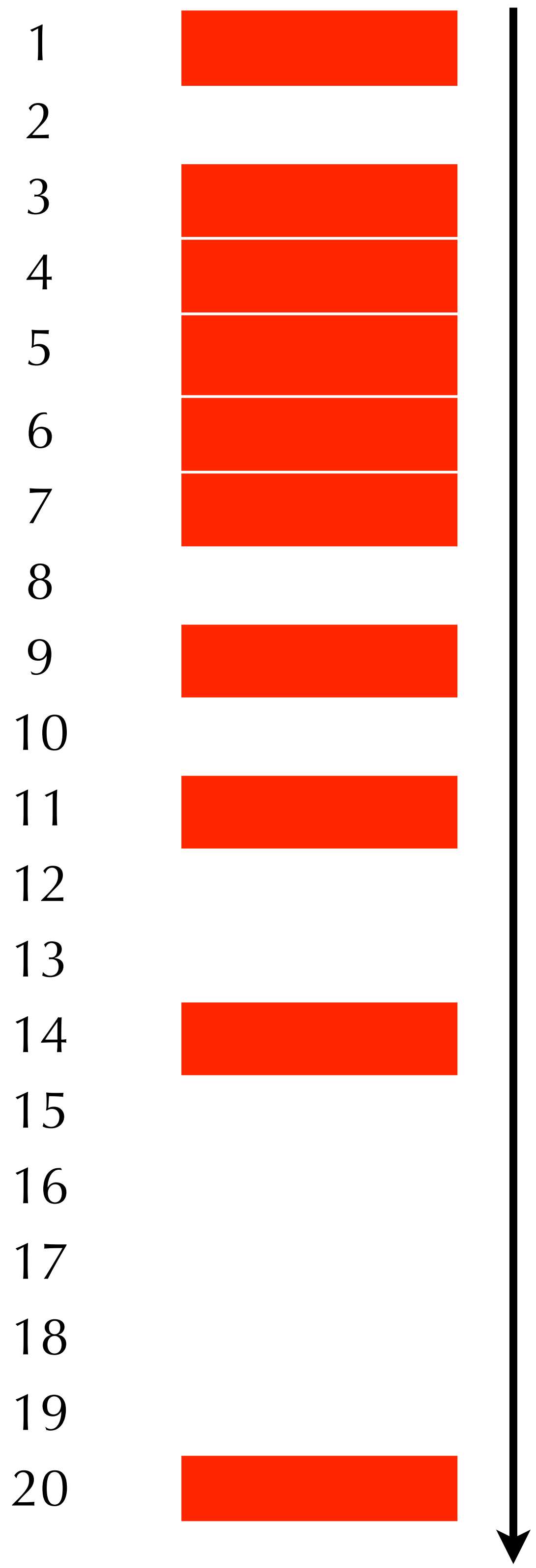
precision-recall curves



- Assume 10 relevant documents for this query
- Suppose the user wants **R = (1/10)**
- What level of precision will the user observe?

Ranked Retrieval

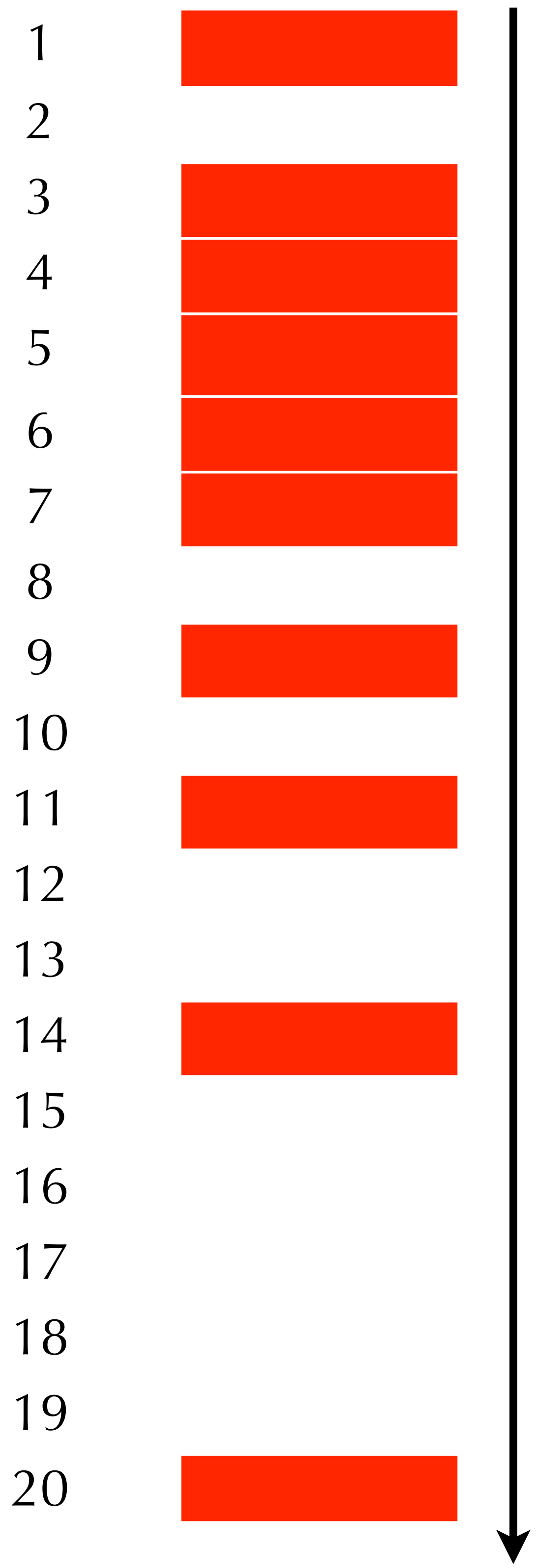
precision-recall curves



- Assume 10 relevant documents for this query
- Suppose the user wants **R = (2/10)**
- What level of precision will the user observe?

Ranked Retrieval

precision-recall curves



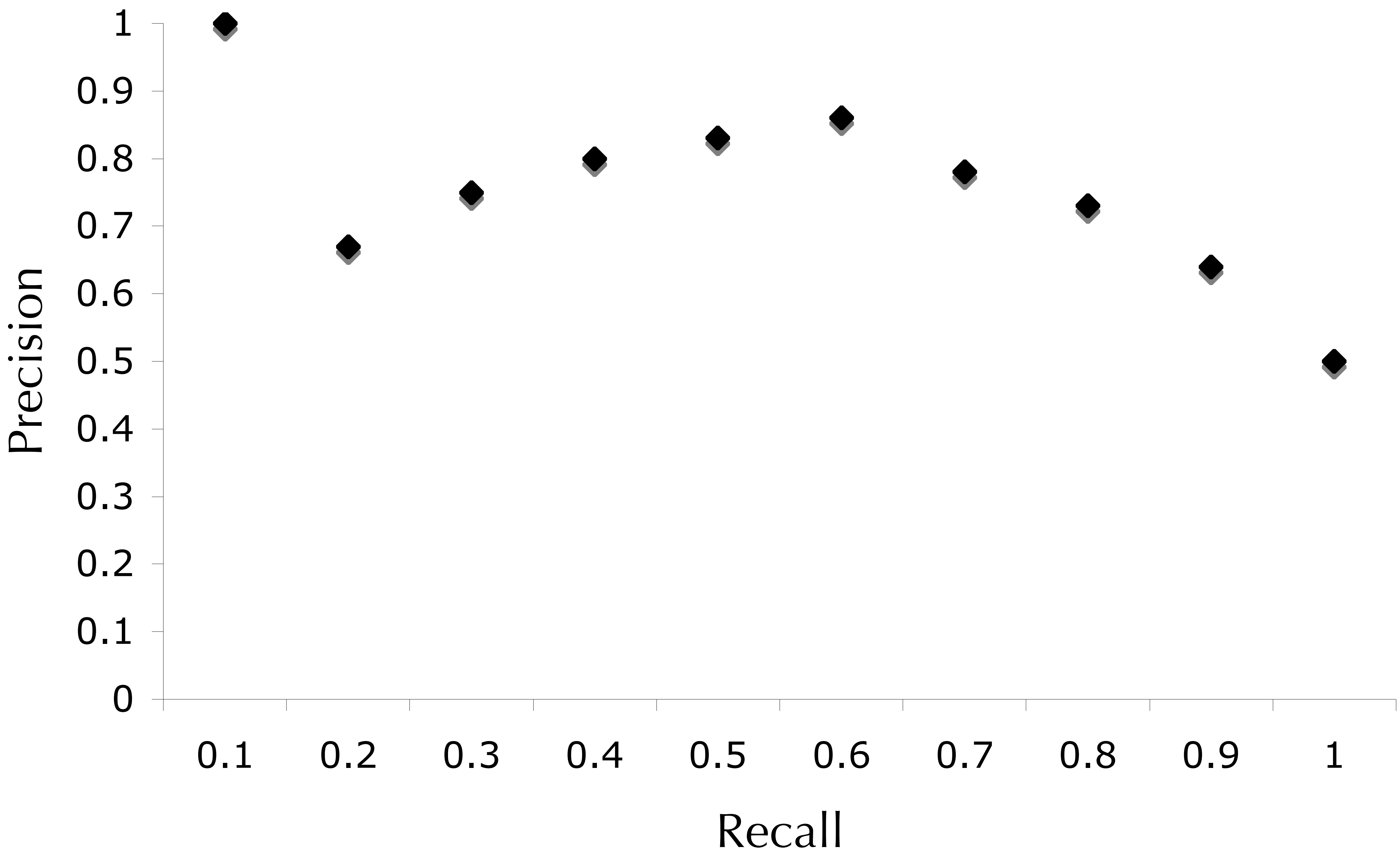
- Assume 10 relevant documents for this query
- Suppose the user wants **R = (10/10)**
- What level of precision will the user observe?

Ranked Retrieval

precision-recall curves

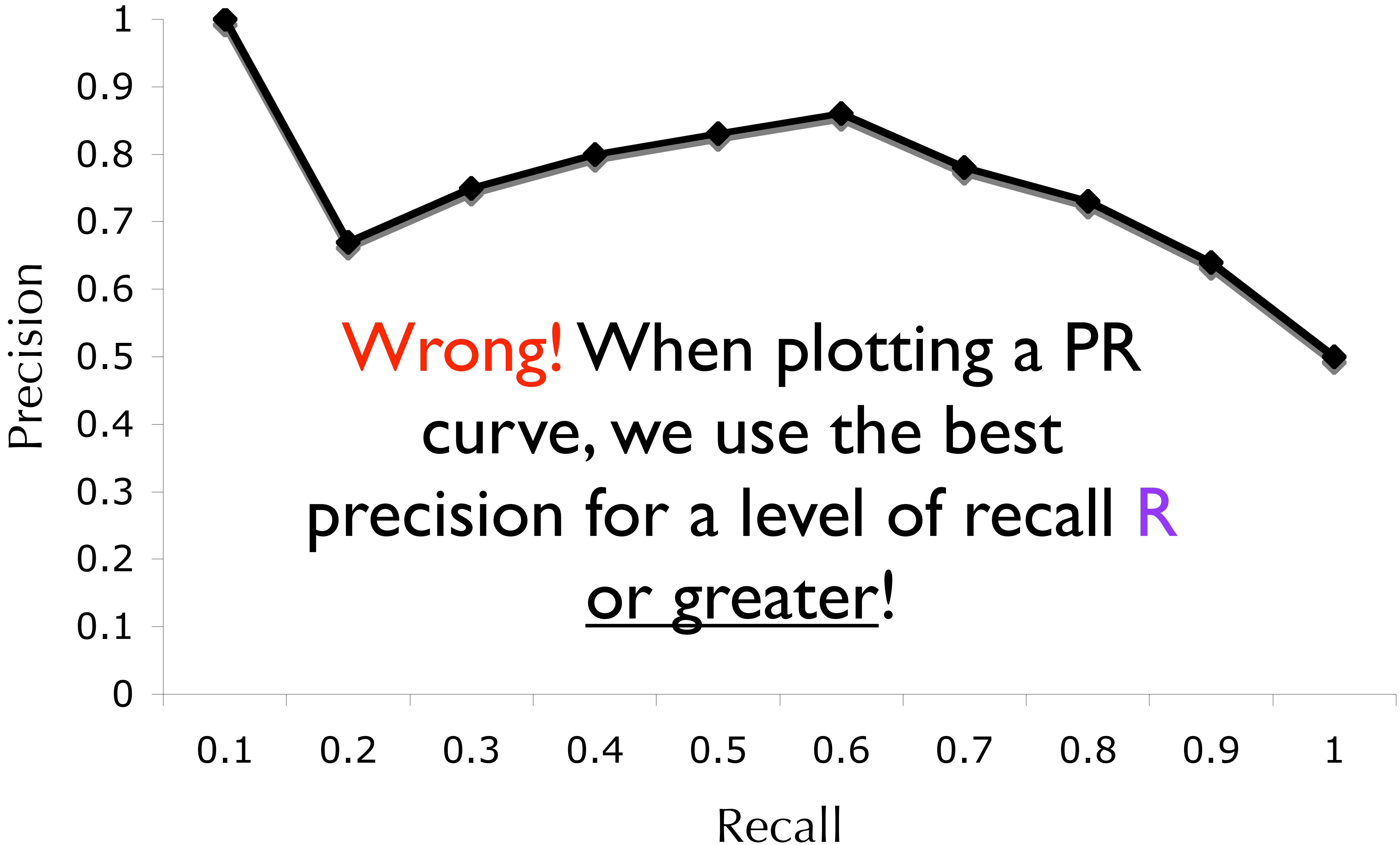
rank (K)	ranking	R@K	P@K
1		0.10	1.00
2		0.10	0.50
3		0.20	0.67
4		0.30	0.75
5		0.40	0.80
6		0.50	0.83
7		0.60	0.86
8		0.60	0.75
9		0.70	0.78
10		0.70	0.70
11		0.80	0.73
12		0.80	0.67
13		0.80	0.62
14		0.90	0.64
15		0.90	0.60
16		0.90	0.56
17		0.90	0.53
18		0.90	0.50
19		0.90	0.47
20		1.00	0.50

Ranked Retrieval
precision-recall curves



Ranked Retrieval

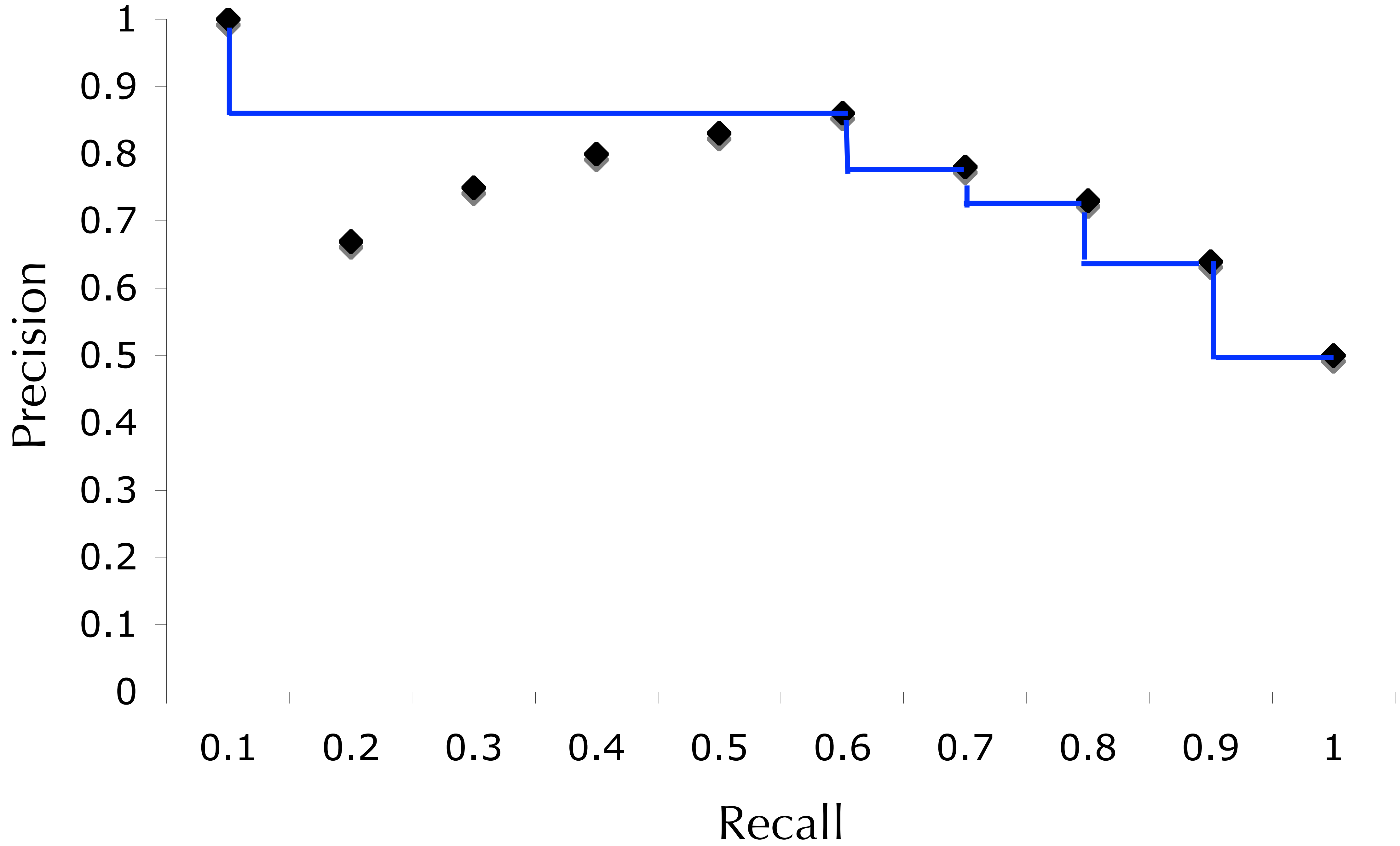
precision-recall curves



Wrong! When plotting a PR curve, we use the best precision for a level of recall R or greater!

Ranked Retrieval

precision-recall curves



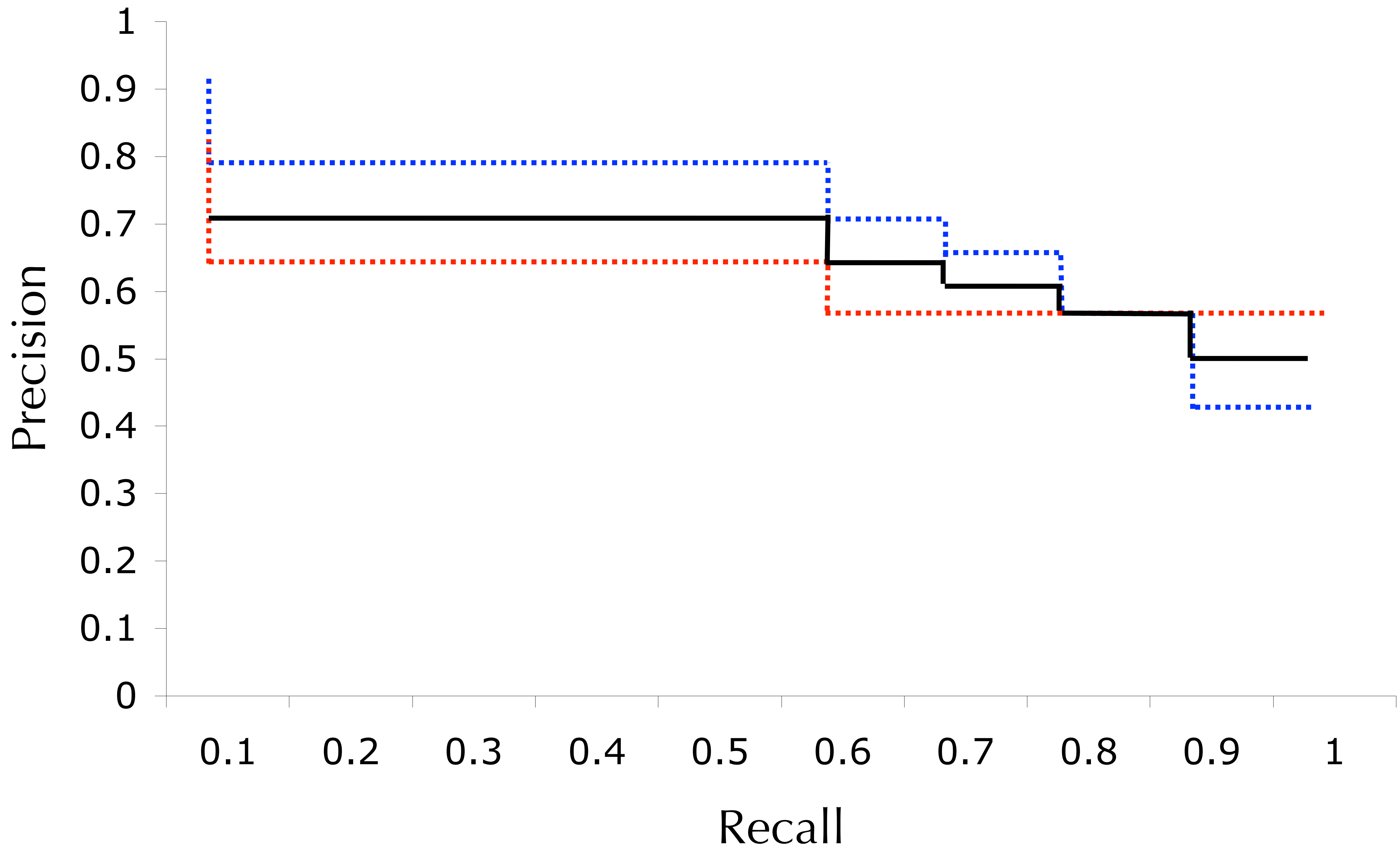
Ranked Retrieval

precision-recall curves

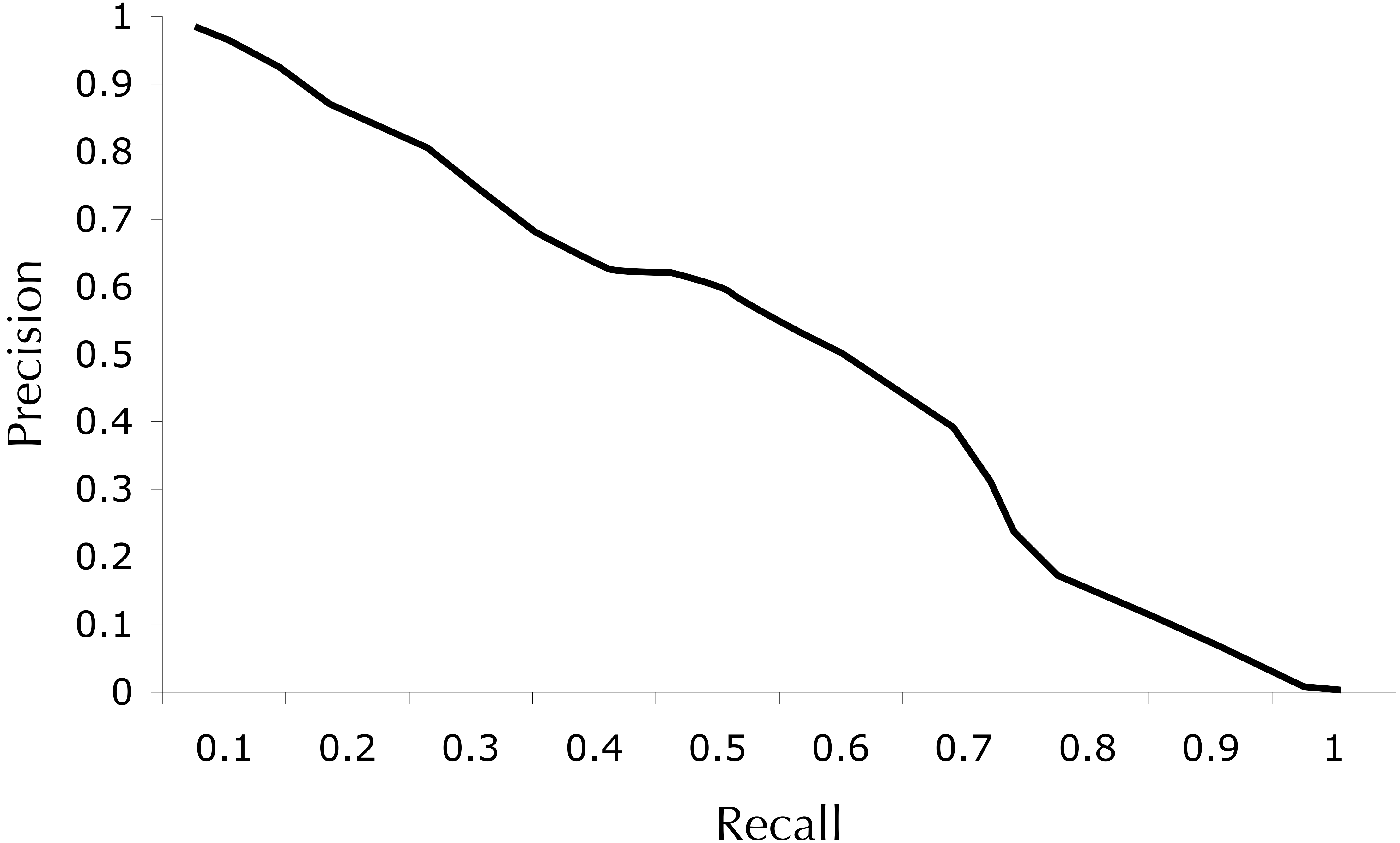
- For a single query, a PR curve looks like a step-function
- For multiple queries, we can average these curves
    - Average the precision values for different values of recall (e.g., from 0.01 to 1.0 in increments of 0.01)
- This forms a smoother function

Ranked Retrieval
precision-recall curves

- PR curves can be averaged across multiple queries

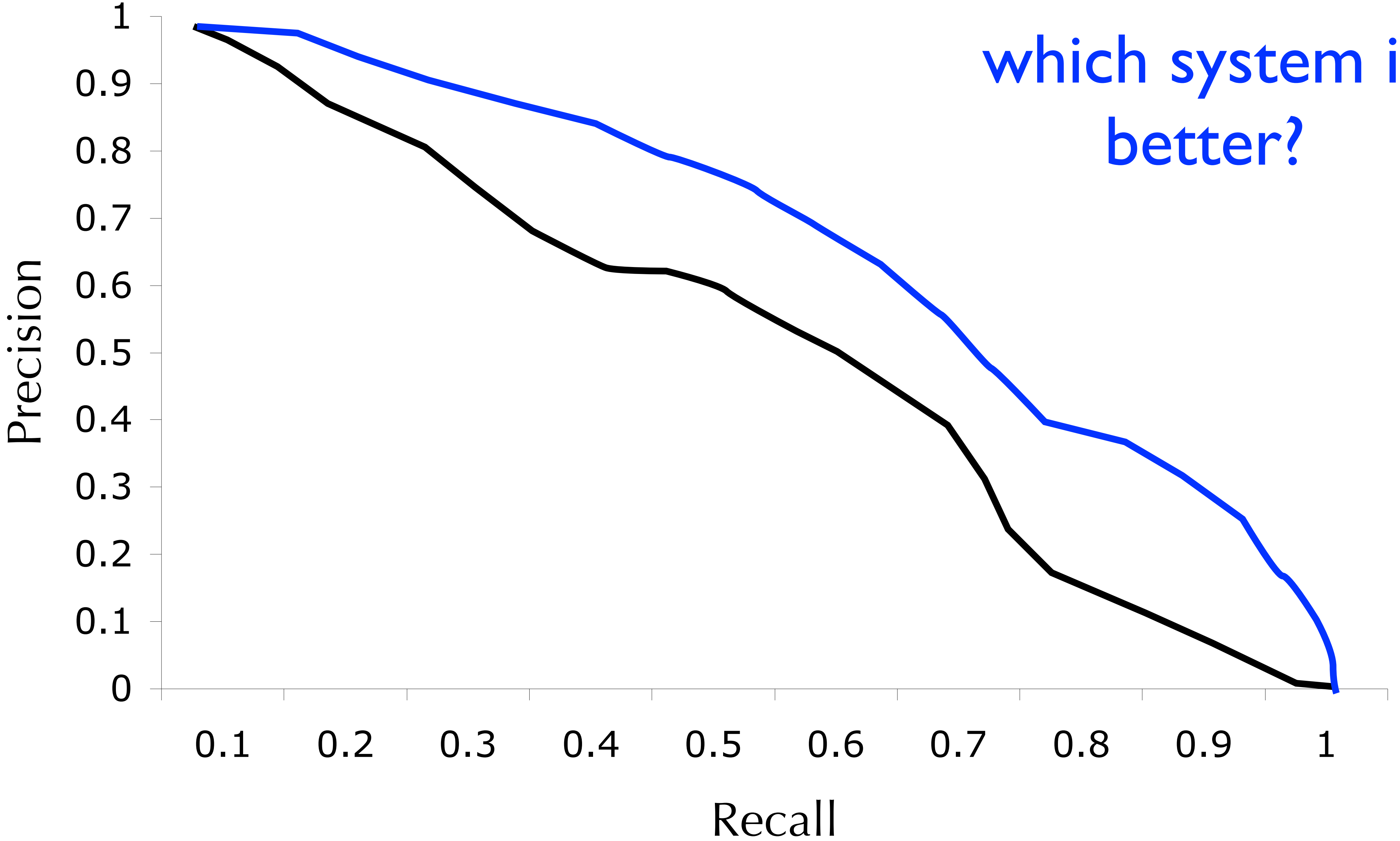


Ranked Retrieval
precision-recall curves



Ranked Retrieval

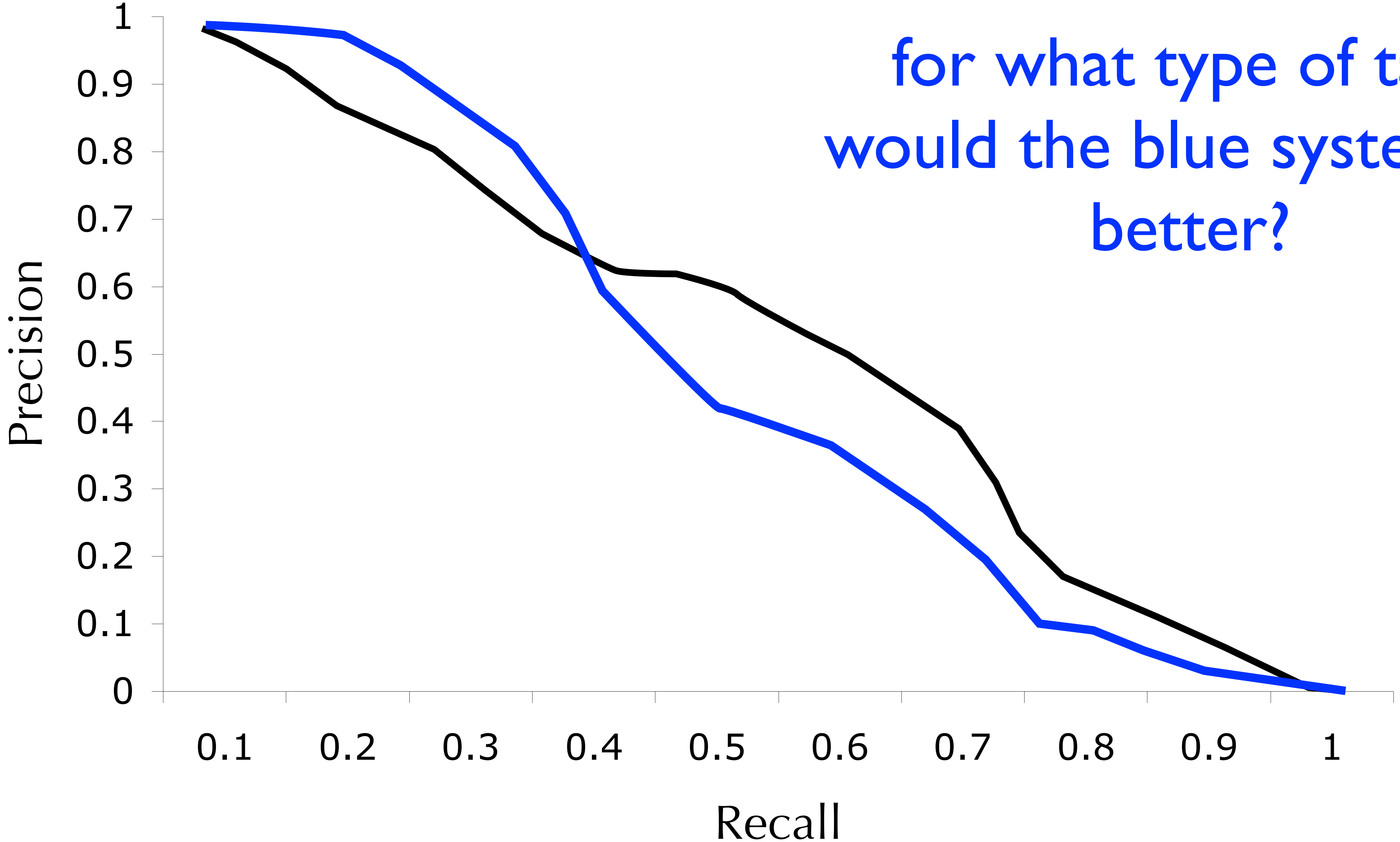
precision-recall curves



which system is better?

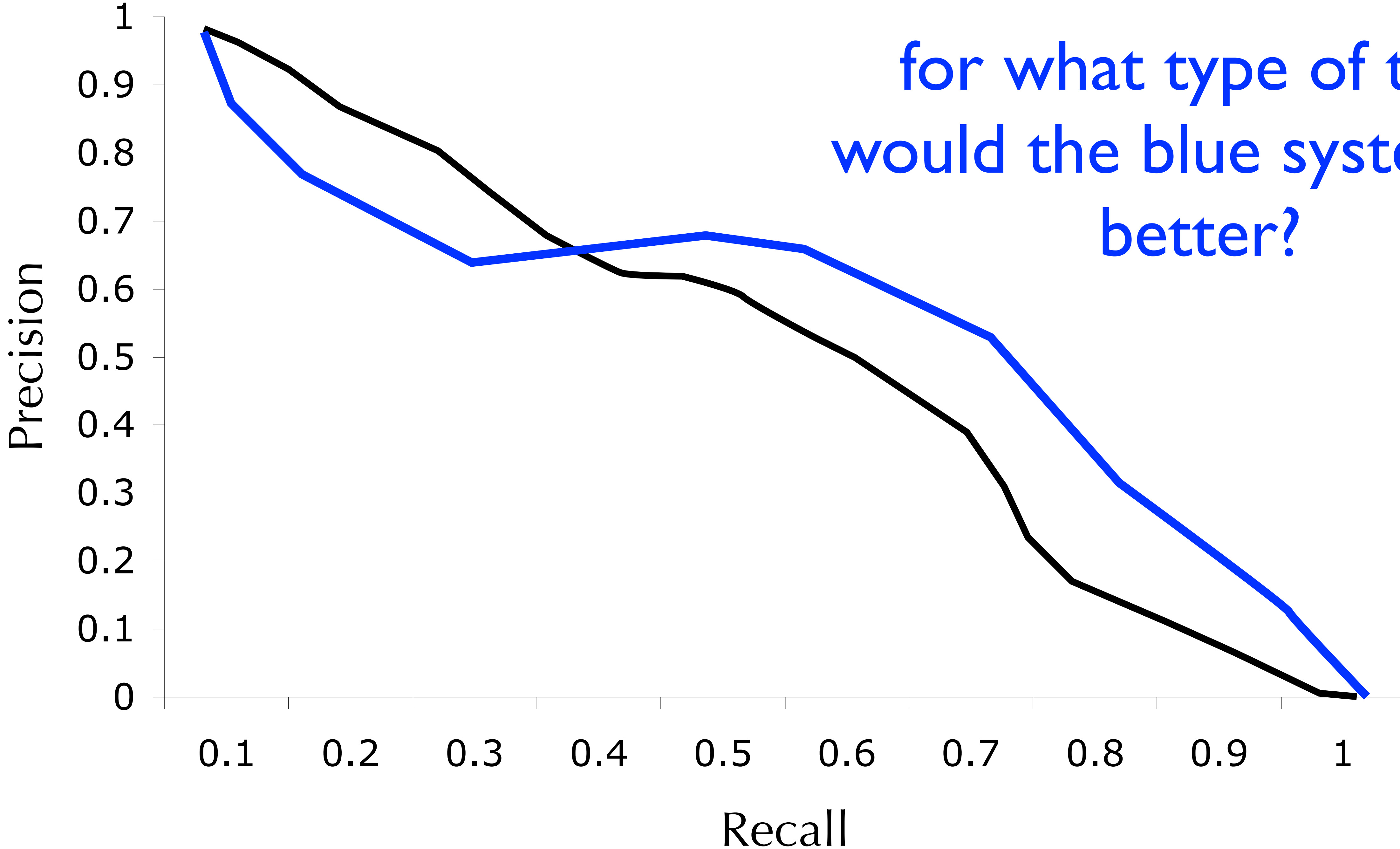
Ranked Retrieval

precision-recall curves



for what type of task would the blue system be better?

Ranked Retrieval
precision-recall curves



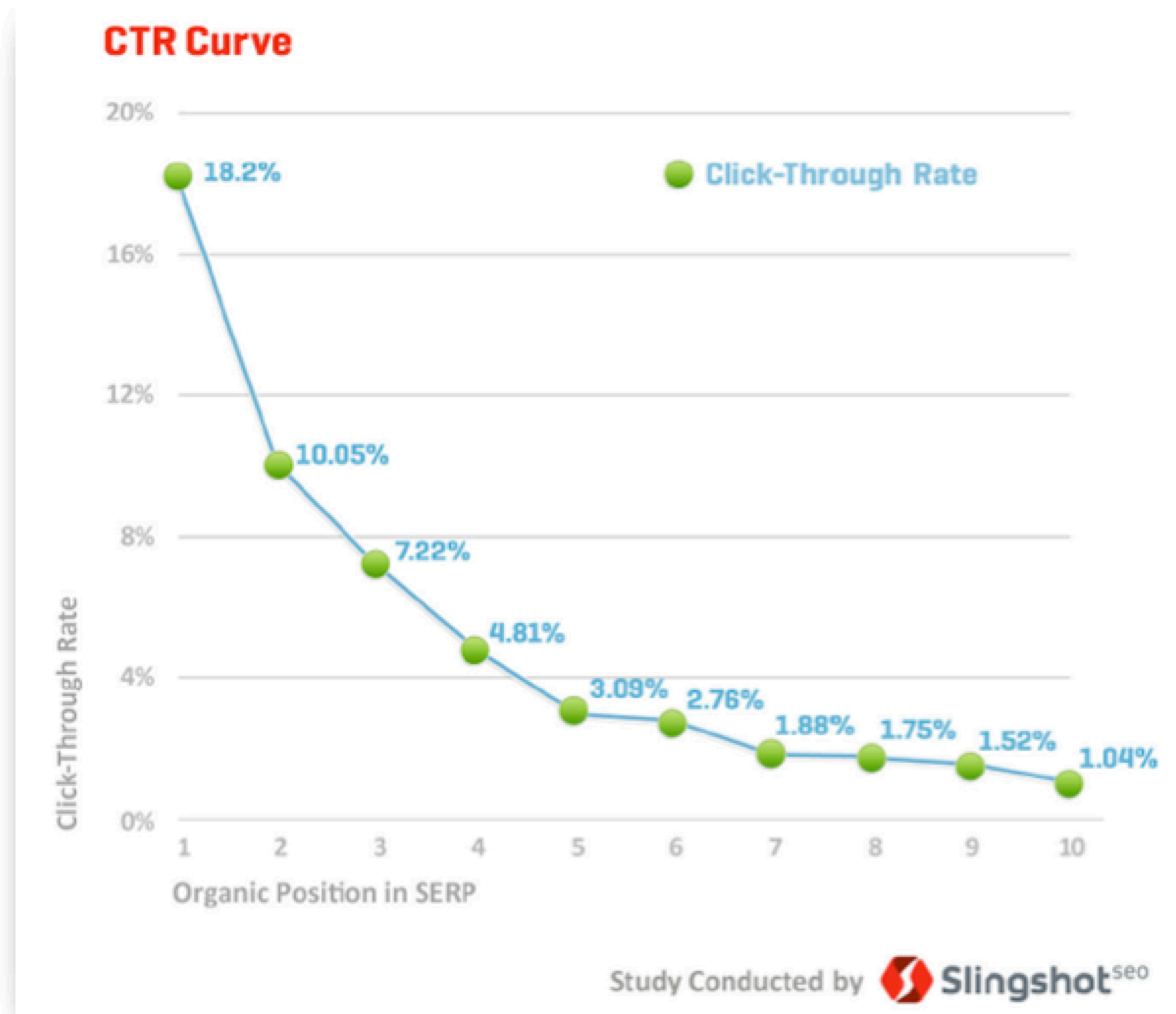
for what type of task would the blue system be better?

Ranked Retrieval

discounted-cumulative gain

- In some retrieval tasks, we really want to focus on precision at the top of the ranking
- A classic example is web-search!
  - users rarely care about recall
  - users rarely navigate beyond the first page of results
  - users may not even look at results below the "fold"
- Are any of the metrics we've seen so far appropriate for web-search?

Ranked Retrieval
discounted-cumulative gain



Ranked Retrieval

discounted-cumulative gain

- We could potentially evaluate using P@K with several <u>small</u> values of K
- But, this has some limitations
- What are they?

Ranked Retrieval

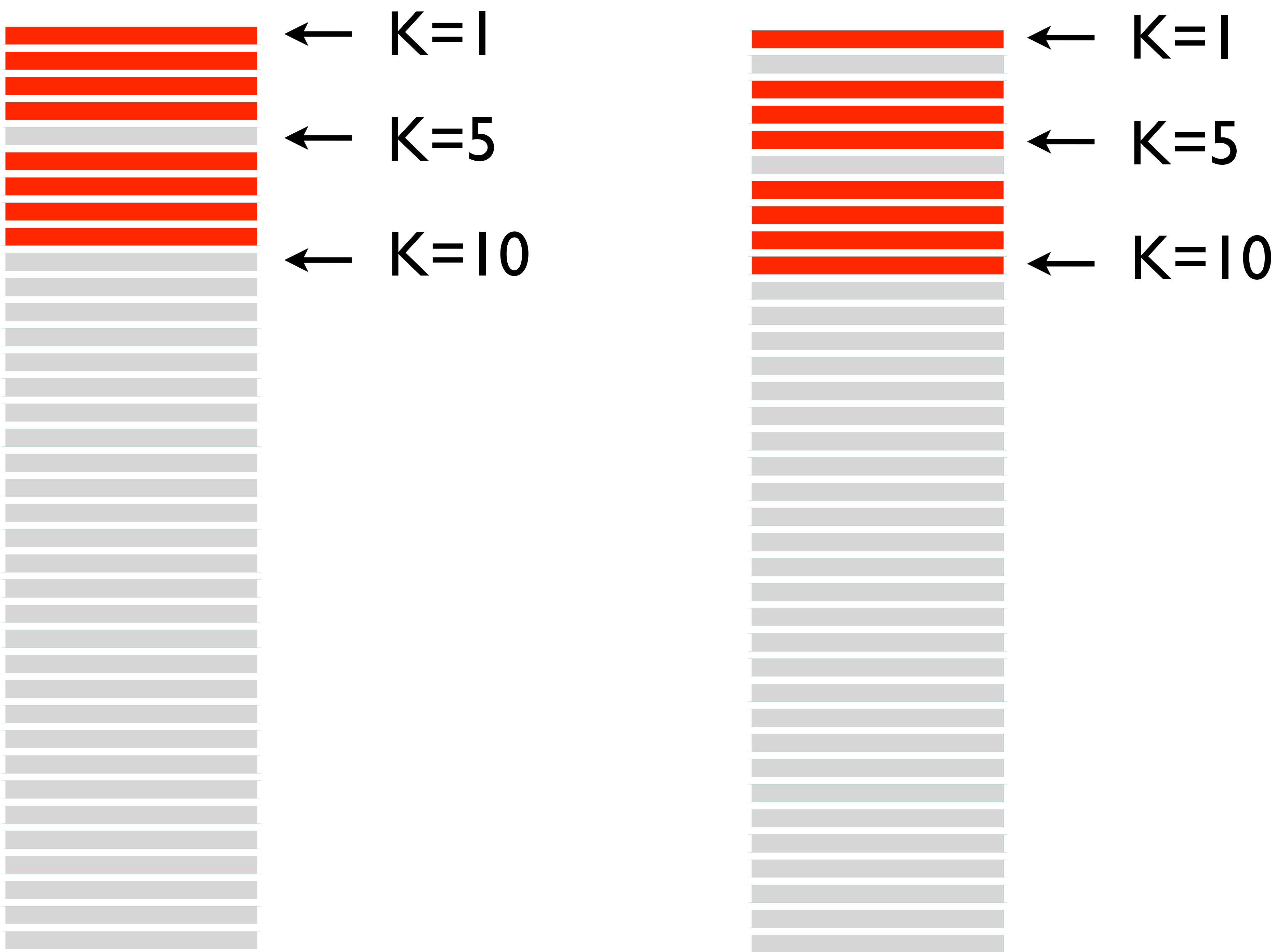
discounted-cumulative gain

- Which retrieval is better?

Ranked Retrieval

discounted-cumulative gain

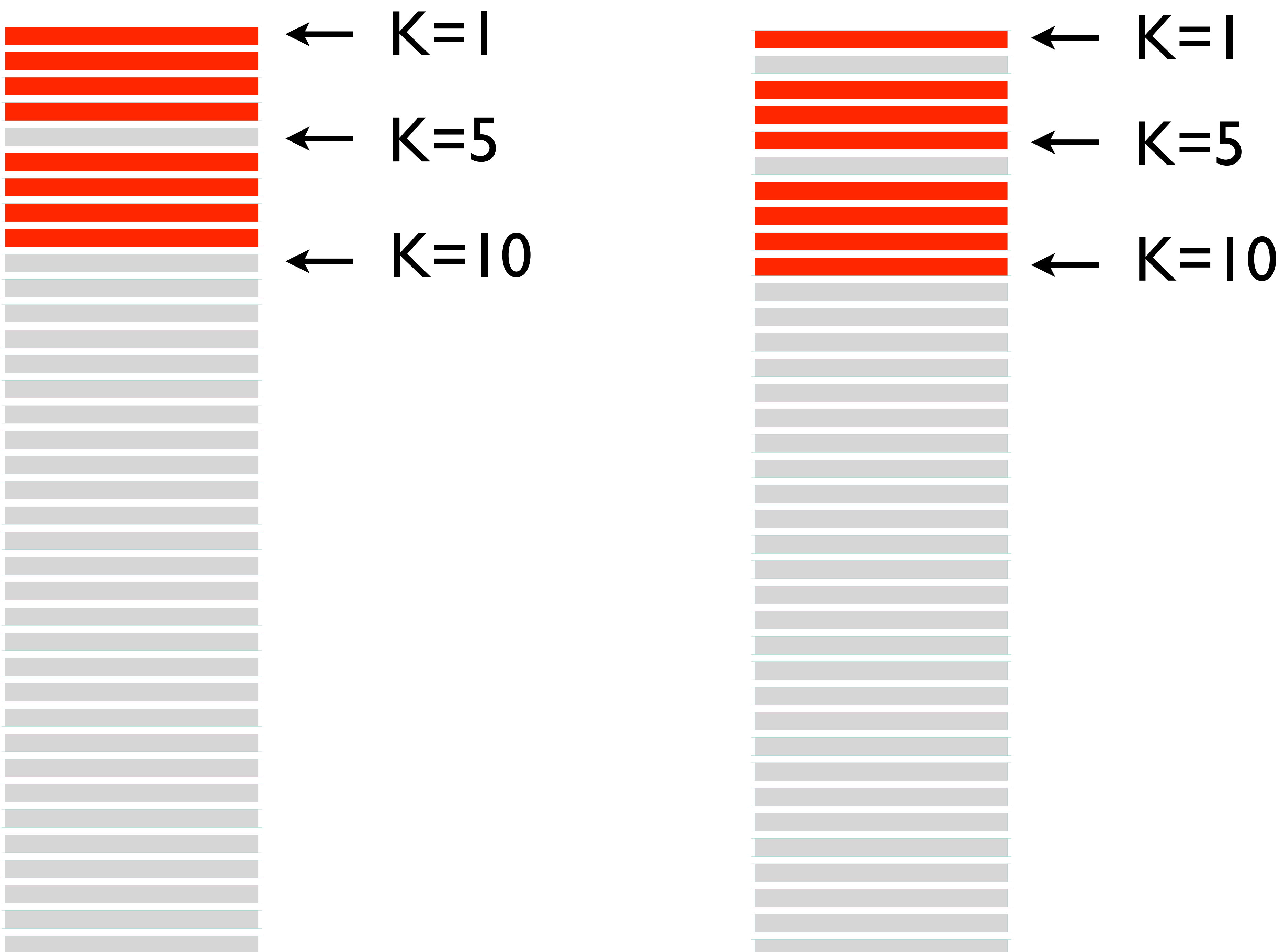
- Evaluation based on P@K can be too coarse



Ranked Retrieval

discounted-cumulative gain

- P@K (and all the metrics we've seen so far) assume binary relevance



Ranked Retrieval
discounted-cumulative gain

- DCG: discounted cumulative gain
- Assumptions:
    - There are more than two levels of relevance (e.g., perfect, excellent, good, fair, bad)
    - A relevant document's usefulness to a user decreases rapidly with rank (more rapidly than linearly)

Ranked Retrieval

discounted-cumulative gain

- Let REL_i be the relevance associated with the document at rank i
  - perfect ➔ 4
  - excellent ➔ 3
  - good ➔ 2
  - fair ➔ 1
  - bad ➔ 0

Ranked Retrieval
discounted-cumulative gain

- DCG: discounted cumulative gain

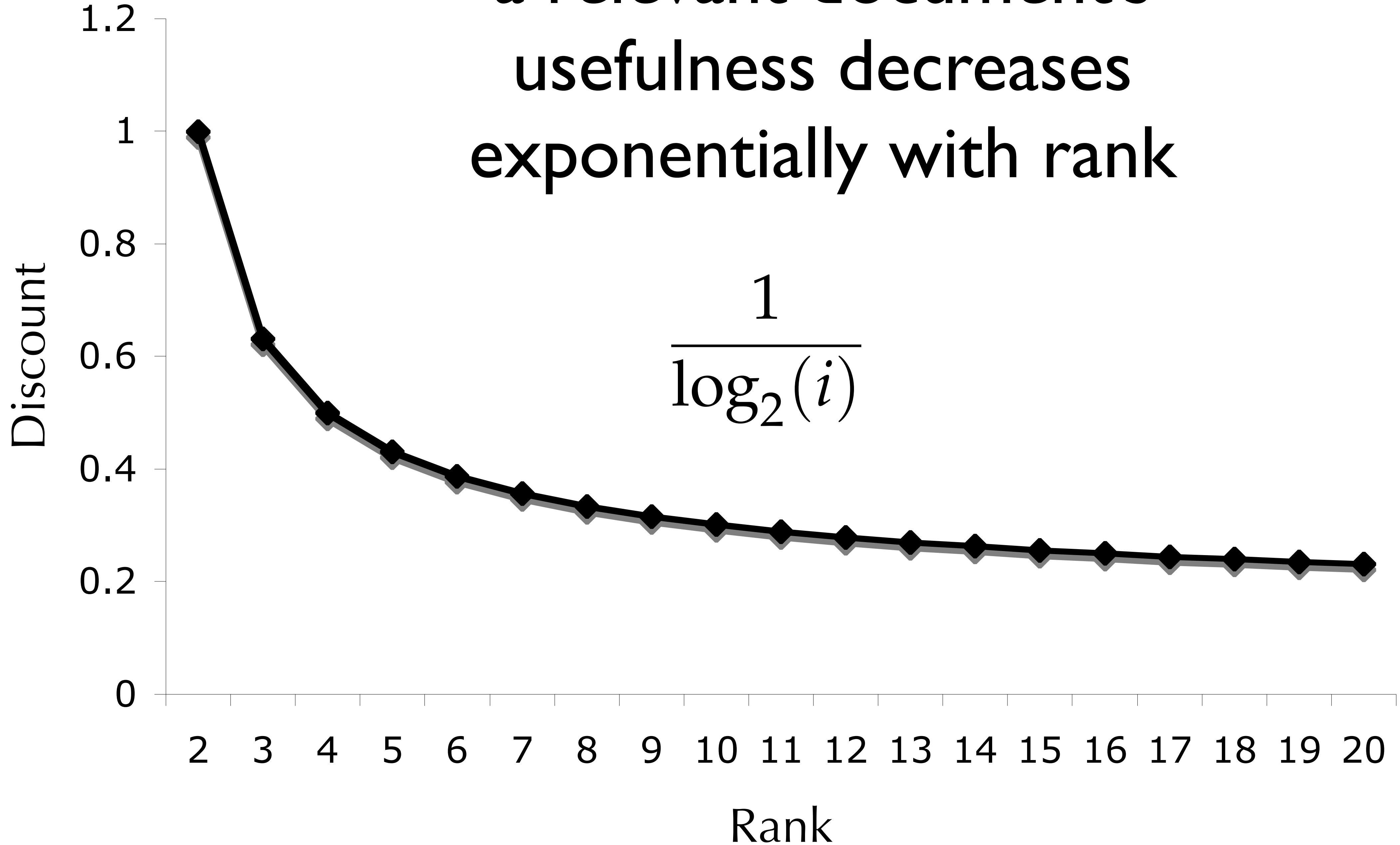
$$DCG@K = \sum_{i=1}^{K} \frac{REL_i}{\log_2(\max(i,2))}$$

Ranked Retrieval

discounted-cumulative gain

a relevant document's usefulness decreases exponentially with rank

$$\frac{1}{\log_2(i)}$$



Ranked Retrieval

discounted-cumulative gain

$$DCG@K = \sum_{i=1}^{K} \frac{REL_i}{\log_2(\max(i,2))}$$

rank (i)	REL_i
1	4
2	3
3	4
4	2
5	0
6	0
7	0
8	1
9	1
10	0

This is given!

the result at rank 1 is perfect
the result at rank 2 is excellent
the result at rank 3 is perfect

...

the result at rank 10 is bad

Ranked Retrieval

discounted-cumulative gain

$$DCG@K = \sum_{i=1}^{K} \frac{REL_i}{\log_2(\max(i,2))}$$

rank (i)	REL_i	discount factor
1	4	1.00
2	3	1.00
3	4	0.63
4	2	0.50
5	0	0.43
6	0	0.39
7	0	0.36
8	1	0.33
9	1	0.32
10	0	0.30

Each rank is associated with a discount factor

$$\frac{1}{\log_2(\max(i,2))}$$

rank 1 is a special case!

Ranked Retrieval

discounted-cumulative gain

$$DCG@K = \sum_{i=1}^{K} \frac{REL_i}{\log_2(\max(i, 2))}$$

rank (i)	REL_i	discount factor	gain
1	4	1.00	4.00
2	3	1.00	3.00
3	4	0.63	2.52
4	2	0.50	1.00
5	0	0.43	0.00
6	0	0.39	0.00
7	0	0.36	0.00
8	1	0.33	0.33
9	1	0.32	0.32
10	0	0.30	0.00

multiply REL_i by the discount factor associated with the rank!

Ranked Retrieval

discounted-cumulative gain

$$DCG@K = \sum_{i=1}^{K} \frac{REL_i}{\log_2(\max(i,2))}$$

rank (i)	REL_i	discount factor	gain	DCG_i
1	4	1.00	4.00	4.00
2	3	1.00	3.00	7.00
3	4	0.63	2.52	9.52
4	2	0.50	1.00	10.52
5	0	0.43	0.00	10.52
6	0	0.39	0.00	10.52
7	0	0.36	0.00	10.52
8	1	0.33	0.33	10.86
9	1	0.32	0.32	11.17
10	0	0.30	0.00	11.17

Ranked Retrieval

discounted-cumulative gain

$$DCG_{10} = 11.17$$

rank (i)	REL_i	discount factor	gain	DCG_i
1	4	1.00	4.00	4.00
2	3	1.00	3.00	7.00
3	4	0.63	2.52	9.52
4	2	0.50	1.00	10.52
5	0	0.43	0.00	10.52
6	0	0.39	0.00	10.52
7	0	0.36	0.00	10.52
8	1	0.33	0.33	10.86
9	1	0.32	0.32	11.17
10	0	0.30	0.00	11.17

Ranked Retrieval

discounted-cumulative gain

$$DCG_{10} = 11.17$$

rank (i)	REL_i	discount factor	gain	DCG_i
1	3	1.00	3.00	3.00
2	3	1.00	3.00	6.00
3	4	0.63	2.52	8.52
4	2	0.50	1.00	9.52
5	0	0.43	0.00	9.52
6	0	0.39	0.00	9.52
7	0	0.36	0.00	9.52
8	1	0.33	0.33	9.86
9	1	0.32	0.32	10.17
10	0	0.30	0.00	10.17

changed top result from perfect instead of excellent

Ranked Retrieval

discounted-cumulative gain

$$DCG_{10} = 11.17$$

rank (i)	REL_i	discount factor	gain	DCG_i
1	4	1.00	4.00	4.00
2	3	1.00	3.00	7.00
3	4	0.63	2.52	9.52
4	2	0.50	1.00	10.52
5	0	0.43	0.00	10.52
6	0	0.39	0.00	10.52
7	0	0.36	0.00	10.52
8	1	0.33	0.33	10.86
9	1	0.32	0.32	11.17
10	3	0.30	0.90	12.08

changed 10th result from bad to excellent

Ranked Retrieval
normalized discounted-cumulative gain

- DCG is <u>not</u> ‘bounded’
- In other words, it ranges from zero to .....
- Makes it problematic to average across queries
- NDCG: <u>normalized</u> discounted-cumulative gain
- “Normalized” is a fancy way of saying, we change it so that it ranges from 0 to 1

Ranked Retrieval

normalized discounted-cumulative gain

- $NDCG_i$: <u>normalized</u> discounted-cumulative gain
- For a given query, measure DCG_i
- Then, divide this DCG_i value by the best possible DCG_i for that query
- Measure DCG_i for the best possible ranking for a given value i

Ranked Retrieval

normalized discounted-cumulative gain

- Given: a query has two 4's, one 3, and the rest are 0's
- Question: What is the best possible ranking for i = 1
- All these are equally good:
  - 4, 4, 3, ...
  - 4, 3, 4, ...
  - 4, 0, 0, ...
  - ... anything with a 4 as the top-ranked result

Ranked Retrieval

normalized discounted-cumulative gain

- Given: the query has two 4's, one 3, and the rest are 0's
- Question: What is the best possible ranking for i = 2
- All these are equally good:
  - 4, 4, 3, ...
  - 4, 4, 0, ...

Ranked Retrieval
normalized discounted-cumulative gain

- Given: the query has two 4's, one 3, and the rest are 0's
- Question: What is the best possible ranking for i = 3
- All these are equally good:
  - 4, 4, 3, ...

Ranked Retrieval

normalized discounted-cumulative gain

- $NDCG_i$: <u>normalized</u> discounted-cumulative gain
- For a given query, measure DCG_i
- Then, divide this DCG_i value by the best possible DCG_i for that query
- Measure DCG_i for the best possible ranking for a given value i

Metric Review

- set-retrieval evaluation: we want to evaluate the set of documents retrieved by the system, without considering the ranking
- ranked-retrieval evaluation: we want to evaluate the ranking of documents returned by the system

Metric Review

set-retrieval evaluation

- precision: the proportion of retrieved documents that are relevant
- recall: the proportion of relevant documents that are retrieved
- f-measure: harmonic-mean of precision and recall
    - a difficult metric to “cheat” by getting very high precision and abysmal recall (and vice-versa)

Metric Review

ranked-retrieval evaluation

- P@K: precision under the assumption that the top-K results is the 'set' retrieved
- R@K: recall under the assumption that the top-K results is the 'set' retrieved
- average-precision: considers precision and recall and focuses mostly on the top results
- DCG: ignores recall, considers multiple levels of relevance, and focuses very must on the top ranks
- NDCG: trick to make DCG range between 0 and 1

Which Metric Would You Use?

Wikipedia W Ω И 維

bing

twitter

f

okcupid

e Harmony

PANDORA

Google

Y!

match.com

mapquest

ICON FINDER

YAHOO! ANSWERS

flickr

Picasa

acm

LinkedIn

Westlaw

The New York Times

JSTOR

yelp

YouTube Broadcast Yourself™

LexisNexis