Lecture 6: Evaluation

Information Retrieval
Computer Science Tripos Part II

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[1]Adapted from Simone Teufel's original slides

Overview

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Summary: Ranked retrieval

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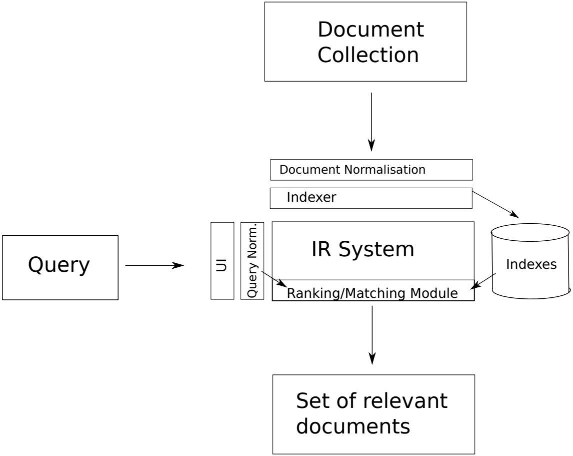
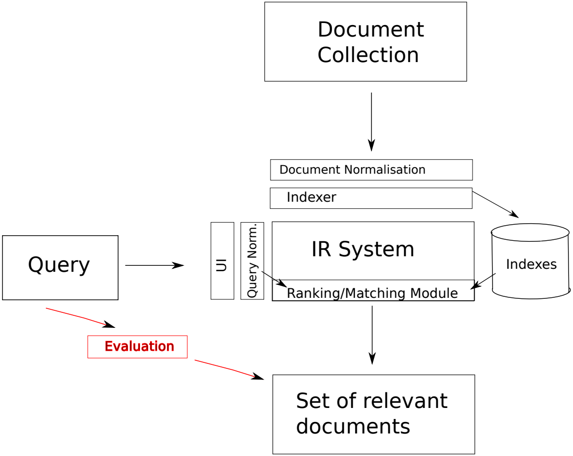
- Compute the cosine similarity between the vectors to rank
- Language models rank based on the probability of a document model generating the query

Today


Document Collection
Document Normalisation
Indexer
Query
UI
Query Norm.
IR System
Ranking/Matching Module
Indexes
Set of relevant documents



Today: how good are the returned documents?

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- Note that none of these is sufficient: blindingly fast, but useless answers won't make a user happy.

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- But how do you measure relevance?
- Standard methodology in information retrieval consists of three elements.
  - A benchmark document collection
  - A benchmark suite of queries
  - An assessment of the relevance of each query-document pair

Relevance: query vs. information need

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Information need *i*

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Query q

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At the heart of his speech was an attack on the wine industry lobby for downplaying the role of red and white wine in drunk driving.

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- So what about the following document:

Document d'

At the heart of his speech was an attack on the wine industry lobby for downplaying the role of red and white wine in drunk driving.

- d' is an excellent match for query q ...
- d' is not relevant to the information need i.

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- User happiness can only be measured by relevance to an information need, not by relevance to queries.
- Sloppy terminology here and elsewhere in the literature: we talk about query–document relevance judgments even though we mean information-need–document relevance judgments.

Overview

Precision and recall

- Precision (P) is the fraction of retrieved documents that are relevant

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	Relevant	Nonrelevant
Retrieved	true positives (TP)	false positives (FP)
Not retrieved	false negatives (FN)	true negatives (TN)

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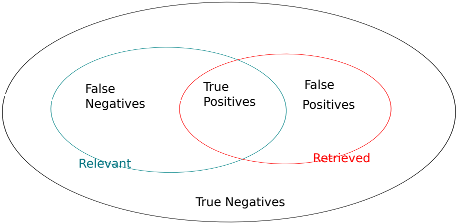

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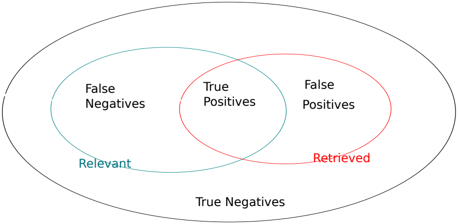

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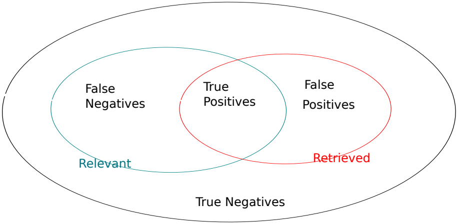

$$
\begin{aligned}
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- The converse is also true (usually): It's easy to get high precision for very low recall.

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$$F = \frac{1}{\alpha\frac{1}{P} + (1-\alpha)\frac{1}{R}} = \frac{(\beta^2+1)PR}{\beta^2 P + R} \quad \text{where} \quad \beta^2 = \frac{1-\alpha}{\alpha}$$

- $\alpha \in [0,1]$ and thus $\beta^2 \in [0,\infty]$
- Most frequently used: balanced F with $\beta = 1$ or $\alpha = 0.5$
  - This is the harmonic mean of P and R: $\frac{1}{F} = \frac{1}{2}(\frac{1}{P} + \frac{1}{R})$

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- $P = 20/(20+40) = 1/3$
- $R = 20/(20+60) = 1/4$
- $F_1 = 2\frac{1}{\frac{1}{\frac{1}{3}}+\frac{1}{\frac{1}{4}}} = 2/7$

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- Accuracy is the fraction of decisions (relevant/nonrelevant) that are correct.
- In terms of the contingency table above, accuracy $= (TP + TN)/(TP + FP + FN + TN)$.

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- Snoogle demonstrates that accuracy is not a useful measure in IR.

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- Searchers on the web (and in IR in general) want to find something and have a certain tolerance for junk.
- It's better to return some bad hits as long as you return something.
- $\rightarrow$ We use precision, recall, and F for evaluation, not accuracy.

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	Precision-critical task	Recall-critical task
Time	matters	matters less
Tolerance to cases of overlooked information	a lot	none
Information Redundancy	There may be many equally good answers	Information is typically found in only one document
Examples	web search	legal search, patent search

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- We need relevance judgments for information-need-document pairs – but they are expensive to produce.
- For alternatives to using precision/recall and having to produce relevance judgments – see end of this lecture.

Overview

1. Recap/Catchup
2. Introduction
3. Unranked evaluation
4. Ranked evaluation
5. Benchmarks
6. Other types of evaluation

Moving from unranked to ranked evaluation

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- Just compute the set measure for each "prefix": the top 1, top 2, top 3, top 4 etc results
- This is called Precision/Recall at Rank
- Rank statistics give some indication of how quickly user will find relevant documents from ranked list

Precision/Recall @ Rank

Rank	Doc
1	d_{12}
2	d_{123}
3	d_{4}
4	d_{57}
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- R@n: R@3=0.33, R@5=0.33, R@8=0.66

A precision-recall curve

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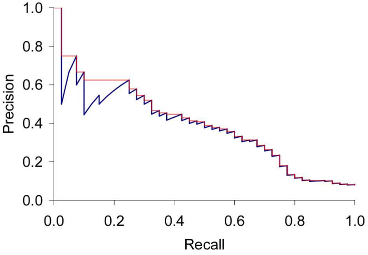

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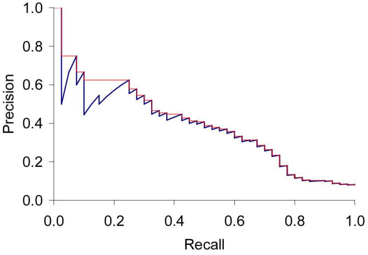

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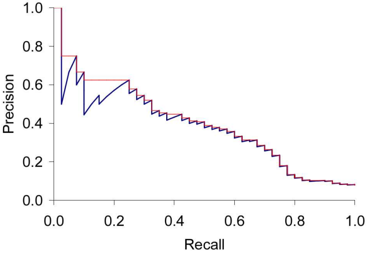

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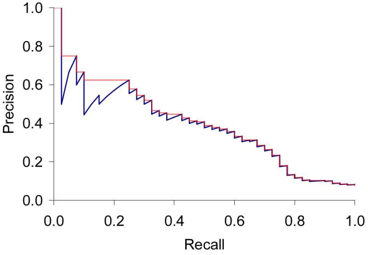

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- Interpolation (in red): Take maximum of all future points
- Rationale for interpolation: The user is willing to look at more stuff if both precision and recall get better.

Another idea: Precision at Recall r

Rank	S1	S2
1	X	
2		X
3	X	
4		
5		X
6	X	X
7		X
8		X
9	X	
10	X	

$\rightarrow$

	S1	S2
p @ r 0.2	1.0	0.5
p @ r 0.4	0.67	0.4
p @ r 0.6	0.5	0.5
p @ r 0.8	0.44	0.57
p @ r 1.0	0.5	0.63

Averaged 11-point precision/recall graph

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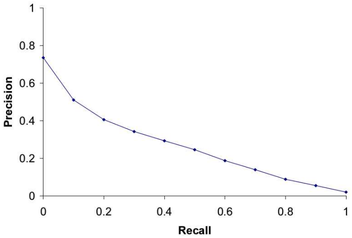

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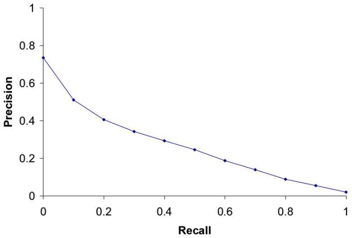

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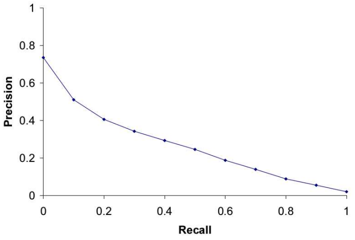

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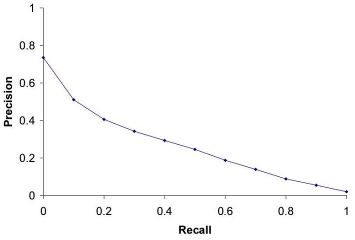

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- The curve is typical of performance levels at TREC (more later).

Averaged 11-point precision more formally

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- Worked avg-11-pt prec example for supervisions at end of slides.

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$$MAP = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{Q_j}\sum_{i=1}^{Q_j}P(doc_i)$$

with:

Q_j	number of relevant documents for query j
N	number of queries
$P(doc_i)$	precision at ith relevant document

Mean Average Precision: example $(MAP = \frac{0.564+0.623}{2} = 0.594)$

Query 1		
Rank		$P(doc_i)$
1	X	1.00
2		
3	X	0.67
4		
5		
6	X	0.50
7		
8		
9		
10	X	0.40
11		
12		
13		
14		
15		
16		
17		
18		
19		
20	X	0.25
AVG:		0.564

Query 2		
Rank		$P(doc_i)$
1	X	1.00
2		
3	X	0.67
4		
5		
6		
7		
8		
9		
10		
11		
12		
13		
14		
15	X	0.2
AVG:		0.623

ROC curve (Receiver Operating Characteristic)

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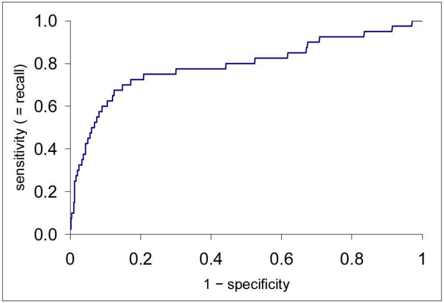

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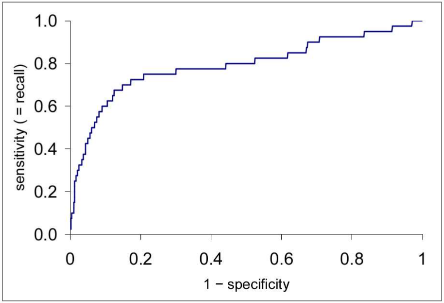

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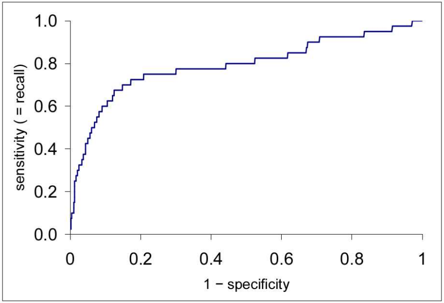

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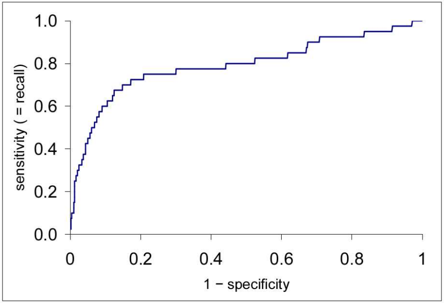

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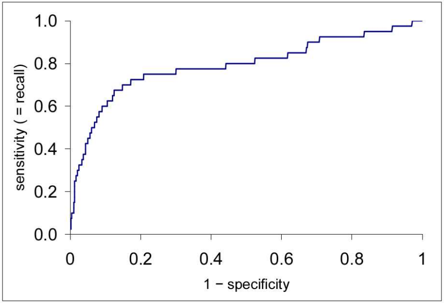

- x-axis: FPR (false positive rate): FP/total actual negatives;
- y-axis: TPR (true positive rate): TP/total actual positives, (also called sensitivity) $\equiv$ recall
- FPR = fall-out = 1 - specificity (TNR; true negative rate)
- But we are only interested in the small area in the lower left corner (blown up by prec-recall graph)

Variance of measures like precision/recall

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- For a test collection, it is usual that a system does badly on some information needs (e.g., $P = 0.2$ at $R = 0.1$) and really well on others (e.g., $P = 0.95$ at $R = 0.1$).

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- Indeed, it is usually the case that the variance of the same system across queries is much greater than the variance of different systems on the same query.
- That is, there are easy information needs and hard ones.

Overview

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- Too small, too untypical for serious IR evaluation today

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- No exhaustive relevance judgments – too expensive
- Rather, NIST assessors' relevance judgments are available only for the documents that were among the top k returned for some system which was entered in the TREC evaluation for which the information need was developed.

Sample TREC Query

<num> Number: 508

<title> hair loss is a symptom of what diseases

<desc> Description:

Find diseases for which hair loss is a symptom.

<narr> Narrative:

A document is relevant if it positively connects the loss of head hair in humans with a specific disease. In this context, “thinning hair” and “hair loss” are synonymous. Loss of body and/or facial hair is irrelevant, as is hair loss caused by drug therapy.

TREC Relevance Judgements

Humans decide which document–query pairs are relevant.

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information need	number of docs judged	disagreements
51	211	6
62	400	157
67	400	68
95	400	110
127	400	106

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- Probably the evaluation methodology that large search engines trust most

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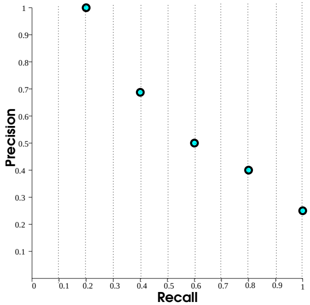
  - is the result robust across different document sets?
  - slowly becoming more common
  - underlying population distributions unknown, so apply non-parametric tests such as the sign test

Reading

- MRS, Chapter 8

Worked Example avg-11-pt prec: Query 1, measured data points



- Blue for Query 1
- Bold Circles measured

Query 1			
Rank		R	P
1	X	0.2	1.00
2			
3	X	0.4	0.67
4			
5			
6	X	0.6	0.50
7			
8			
9			
10	X	0.8	0.40
11			
12			
13			
14			
15			
16			
17			
18			
19			
20	X	1.0	0.25

$\tilde{P}_1(r_2) = 1.00$

$\tilde{P}_1(r_4) = 0.67$

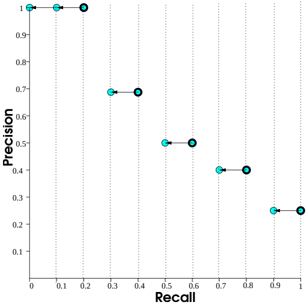
$\tilde{P}_1(r_6) = 0.50$

$\tilde{P}_1(r_8) = 0.40$

$\tilde{P}_1(r_{10}) = 0.25$

- Five r_js $(r_2, r_4, r_6, r_8, r_{10})$ coincide directly with datapoint

Worked Example avg-11-pt prec: Query 1, interpolation



- Bold circles measured
- **thin circles interpolated**

Query 1			
Rank		R	P
1	X	.20	1.00
2			
3	X	.40	.67
4			
5			
6	X	.60	.50
7			
8			
9			
10	X	.80	.40
11			
12			
13			
14			
15			
16			
17			
18			
19			
20	X	1.00	.25

$\tilde{P}_1(r_0) = 1.00$

$\tilde{P}_1(r_1) = 1.00$

$\tilde{P}_1(r_2) = 1.00$

$\tilde{P}_1(r_3) = .67$

$\tilde{P}_1(r_4) = .67$

$\tilde{P}_1(r_5) = .50$

$\tilde{P}_1(r_6) = .50$

$\tilde{P}_1(r_7) = .40$

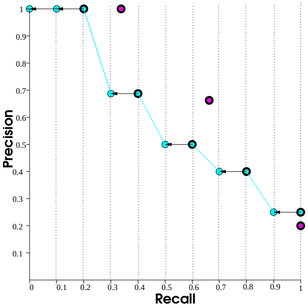
$\tilde{P}_1(r_8) = .40$

$\tilde{P}_1(r_9) = .25$

$\tilde{P}_1(r_{10}) = .25$

- The six other r_js (r_0, r_1, r_3, r_5, r_7, r_9) are interpolated.

Worked Example avg-11-pt prec: Query 2, measured data points



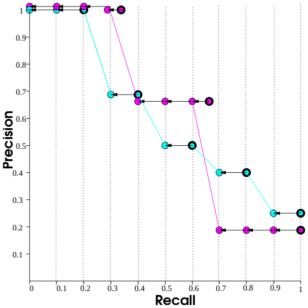
- Blue: Query 1; **Red: Query 2**
- **Bold circles measured**; thin circles interpol.

Query 2			
Rank	Relev.	R	P
1	X	.33	1.00
2			
3	X	.67	.67
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			
15	X	1.0	.2

$\tilde{P}_2(r_{10}) = .20$

- Only r_{10} coincides with a measured data point

Worked Example avg-11-pt prec: Query 2, interpolation



- Blue: Query 1; **Red: Query 2**
- Bold circles measured; **thin circles interpol.**

Query 2			
Rank	Relev.	R	P
1	X	.33	1.00
2			
3	X	.67	.67
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			
15	X	1.0	.2

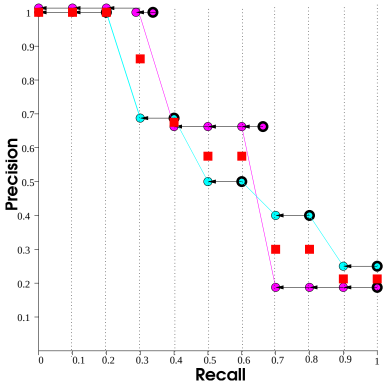
$\tilde{P}_2(r_0) = 1.00$
$\tilde{P}_2(r_1) = 1.00$
$\tilde{P}_2(r_2) = 1.00$
$\tilde{P}_2(r_3) = 1.00$

$\tilde{P}_2(r_4) = .67$
$\tilde{P}_2(r_5) = .67$
$\tilde{P}_2(r_6) = .67$

$\tilde{P}_2(r_7) = .20$
$\tilde{P}_2(r_8) = .20$
$\tilde{P}_2(r_9) = .20$
$\tilde{P}_2(r_{10}) = .20$

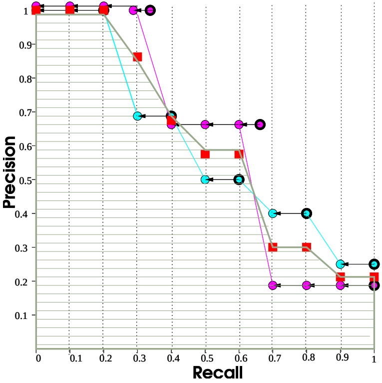
- 10 of the r_js are interpolated

Worked Example avg-11-pt prec: averaging



- Now average at each p_j
- over N (number of queries)
- $\rightarrow$ 11 averages

Worked Example avg-11-pt prec: area/result



- End result:
- 11 point average precision
- Approximation of area under prec. recall curve