Welcome to the class of

Advanced Topics in Information Retrieval !

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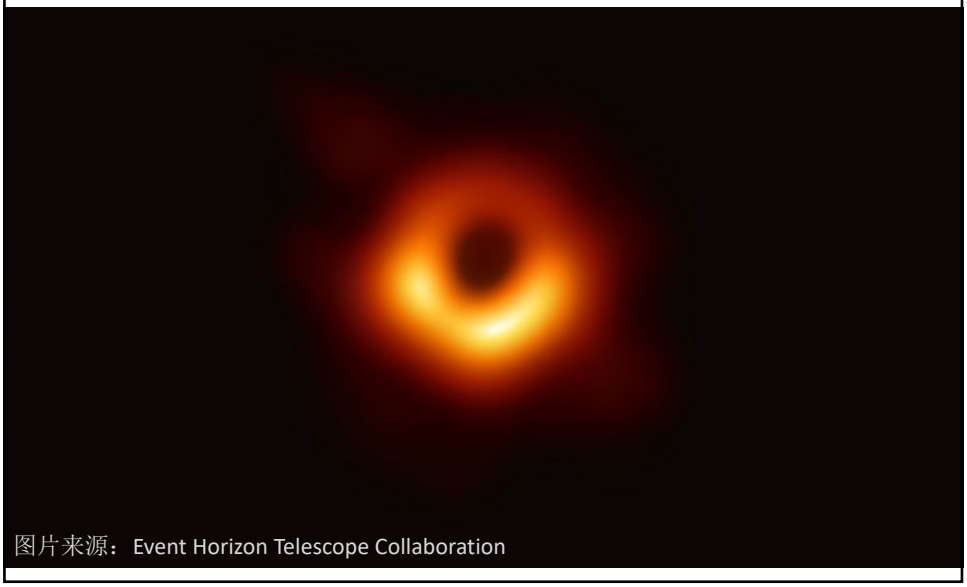
Tea Time (1): The 1st Image of Black Hole



图片来源：Event Horizon Telescope Collaboration

Tea Time （2）

检索和推荐应用中的Privacy问题

Shao Yunqiu 邵韵秋

Introduction on IR fundamental techniques (IV) – Evaluation (Cont.)

Evaluation

- Evaluation methodology
- Standard benchmarks for IR
- Annotation consistency
- Common metrics for relevance

- Precision, Recall, MAP, MRR, F
- DCG and NDCG

Discounted Cumulative Gain

- Popular measure for evaluating web search and related tasks
- Two assumptions:
  - Highly relevant documents are more useful than marginally relevant document
  - The lower the ranked position of a relevant document, the less useful it is for the user, since it is less likely to be examined

Discounted Cumulative Gain

- Uses *graded relevance* as a measure of the usefulness, or *gain,* from examining a document
  - $rel_1 + rel_2 + rel_3 + \ldots$
- Gain is accumulated starting at the top of the ranking and may be reduced, or *discounted*, at lower ranks
  - $rel_1 + \text{discounted}(rel_2) + \text{discounted}(rel_3) + \ldots$
  - Typical discount is $1/log\ (rank)$
  - With base 2, the discount at rank 4 is 1/2, and at rank 8 it is 1/3
  - $rel_1 + rel_2 / \log_2 2 + rel_3 / \log_2 3 + \ldots$

Discounted Cumulative Gain

- *DCG* is the total gain accumulated at a particular rank *p*:

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

- Alternative formulation:

$$DCG_p = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{log(1+i)}$$

  - Popularly leveraged by web search companies
  - Emphasis on retrieving highly relevant documents

DCG Example

- 10 ranked documents judged on 0-3 relevance scale:

  3, 2, 3, 0, 0, 1, 2, 2, 3, 0

- Discounted gain: $(1/\log_2 i)$

  3, 2/1, 3/1.59, 0, 0, 1/2.59, 2/2.81, 2/3, 3/3.17, 0

  = 3, 2, 1.89, 0, 0, 0.39, 0.71, 0.67, 0.95, 0

- Discounted cumulative gain (DCG@*n*):

  3, 5, 6.89, 6.89, 6.89, 7.28, 7.99, 8.66, 9.61, 9.61

Normalized DCG – NDCG

- **Doc: 3, 2, 3, 0, 0, 1, 2, 2, 3, 0**
  DCG@*n*: 3, 5, 6.89, 6.89, 6.89, 7.28, 7.99, 8.66, 9.61, 9.61
- *Normalized* by comparing the DCG at each rank with that of the *perfect ranking*
- Perfect ranking: 3, 3, 3, 2, 2, 2, 1, 0, 0, 0

Ideal DCG@n: 3, 6, 7.89, 8.89, 9.75, 10.52, 10.88, 10.88, 10.88, 10.88

- NDCG@*n* values (divide by ideal):

$$\left(\frac{3}{3}, \frac{5}{6}, \frac{6.89}{7.89}, \frac{6.89}{8.89}, \frac{6.89}{9.75}, \frac{7.28}{10.52}, \frac{7.99}{10.88}, \frac{8.66}{10.88}, \frac{9.61}{10.88}, \frac{9.61}{10.88}\right)$$

1, 0.83, 0.87, 0.76, 0.71, 0.69, 0.73, 0.8, 0.88, 0.88

Notes on the "Perfect Ranking"

- It is NOT the ideal sequence of THIS SE's results, but the ideal sequence of the results by ALL SEs, if we are comparing multiple SEs.
- SE A: 0 3 2 0 2 1 0 0 0 0 (pages are: a b c d e f g h i j)
- SE B: 3 2 0 1 1 1 0 2 0 0 (pages are: b c a l m f i n k o)
- Then we have:
  a0 b3 c2 d0 e2 f1 g0 h0 i0 j0 k0 l1 m1 n2 o0
- So the ideal sequence of top 10 results should be:
  3 2 2 2 1 1 1 0 0 0

NDCG@*n*

- *Normalized* by comparing the DCG at each rank with that of the *perfect ranking*
  - Makes averaging easier for queries with different number of relevant documents
- NDCG ≤ 1 at any rank position
- Takes grade relevance and position information into consideration.
- One of the most popular used metrics in IR research and industry.

Overview: Evaluation

- **Evaluation methodology**
  - Cranfield-like evaluation
- **Annotation Consistency**
  - Kappa Coefficient
- **Common metrics for relevance**
  - Precision, Recall, MAP, MRR, F-measure
  - DCG and NDCG

Part II. Search Engine Techniques

— （I） Link-based Analysis

Web IR Techniques: Link-based IR

- Counting node degree
- PageRank
- HITS (authorities and hubs)
- TrustRank
- Spreading activation
- Anchor text

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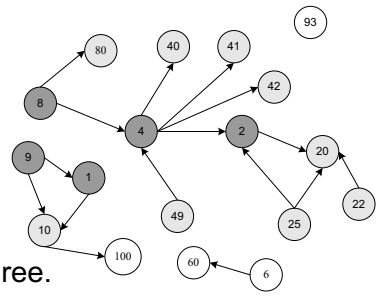
Counting node degree



- Index node:
  Whose out-degree is significantly larger than the average out-degree.
- Reference node:
  Whose in-degree is significantly larger than the average in-degree
- Propose measures of centrality
  - Based on node-to-node distances in the link structure graph
  - Rank = in-degree + out-degree
- A "counting" notion of WWW link structure

Web IR Techniques: Link-based IR

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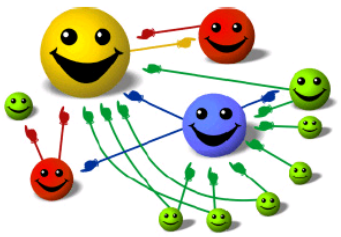
PageRank -- background

- Measure the importance of the Web pages
- Recommendation assumption:
  - If A has a link that points to B, then the author of A recommend page B.
  - The more being recommended, the better.
  - Good recommender gives better recommendations.



PageRank – basic idea

- Sergey Brin and Larry Page 1998 (Google)
  - 15925 Citations on Google Scholar
- A model of user behavior
- A "Random surfer" – random walk model:
  - Randomly given a webpage
  - Keep clicking
  - Never hitting "back"
  - Eventually get starts on another random page
- Simulate the user's navigation procedure with Markov chain
  - t→∞, the probability of each page that the user stays: PR

The anatomy of a large-scale hypertextual Web search engine, S. Brin, L. Page, www7, 1998
L. Page, S. Brin, R. Motwani, and T. Winograd. The pagerank citation ranking: Bringing order to the web. Technical report, Stanford Digital Library Technologies Project, 1998

PageRank -- computation

- Computes a document's score based on the scores of documents that link to it.

$$PR(A) = \frac{d}{N} + (1-d)\left(\frac{PR(T_1)}{L(T_1)} + \cdots\cdots + \frac{PR(T_n)}{L(T_n)}\right)$$

T_i links to A, $L(T_i)$: out-degree of page T_i N: # of pages
d: probability of re-start (i.e. not following links), (0,1) ~ generally 0.15

- A probability distribution over web pages, Sum of all PR(A) = 1
  - A simple iterative algorithm
  - Corresponding to the principal eigenvector of the normalized link matrix of the web

PageRank – computation (cont.)

- Don't forget to dealing with pages with NO out-link

Algorithm:

- Initialize $PR(T_i)$ for each page T_i, $\sum_{T_i} PR(T_i) = 1$
- In each loop:
  1. For each page *A*, $I(A) = \frac{d}{N}$
  2. For each page T_i
     - if outdegree$(T_i) > 0$,
       - *For each A that* $T_i \rightarrow$ A , $I(A) = I(A) + (1-d)\frac{PR(T_i)}{L(T_i)}$
     - else (i.e. outdegree$(T_i) = 0$)
       - *For each A,* $I(A) = I(A) + (1-d)\frac{PR(T_i)}{N}$
  3. For each page *A*, $PR(A) = I(A)$

You needn't normalize PR scores by the end of each loop. It's already been guaranteed.

Improvements on PageRank

- On speed-up of the computation
- On refinement and enrichment of the model
  - PageRank – nothing about content
    - Topic-sensitive PageRank, Query-dependent PageRank
  - Block-based PageRank, ……
- Others
  - Modifying the personalized vector
  - Introducing inter-domain and intra-domain link weights
    - HostRank, SiteRank, ……
  - TrustRank, anti-TrustRank

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HITS: Hypertext-Induced Topic Search

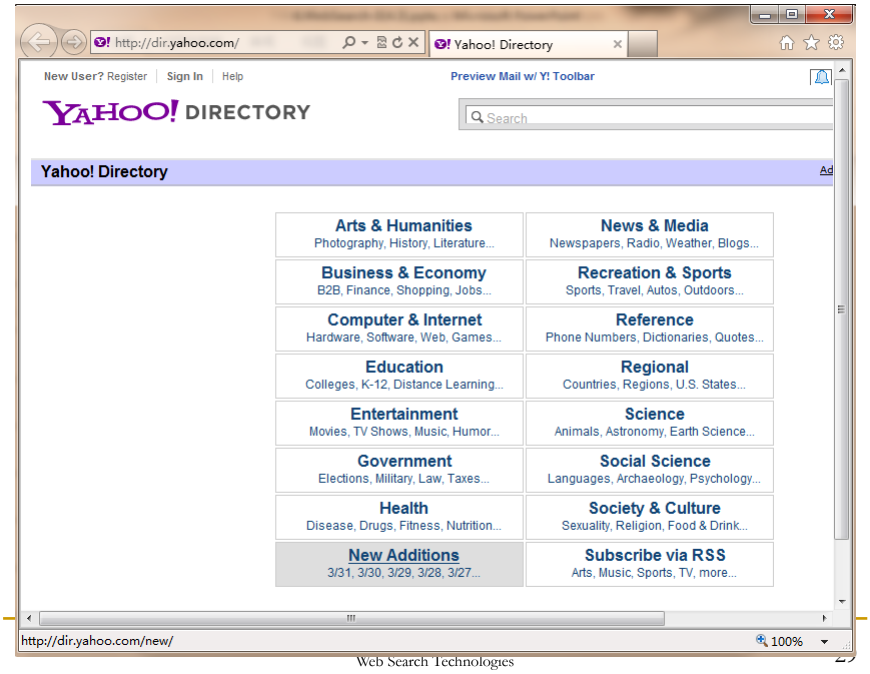
- John Kleinberg 1998 (Cornell)
  - *"Authoritative Sources in a Hyperlinked Environment"*
  - 10783 citations on Google Scholar
- ONR (*Office of Naval Research*) Young Investigator Award
- A MacArthur Foundation Fellowship
- A Packard Foundation Fellowship
- A Sloan Foundation Fellowship
- Member of the National Academy of Engineering
- And the American Academy of Arts and Sciences

HITS: Hypertext-Induced Topic Search

- 3 types of queries (examples from the original paper)
  - Specific queries
    - "Does Netscape support the JDK 1.1 code-signing API?" *far too large #relevant_docs, need authoritative or definitive one*
  - Broad-topic queries
    - "Find information about the Java programming language."
  - Similar-page queries
    - "Find pages 'similar' to java.sun.com."

HITS: Hypertext-Induced Topic Search

- Authority page
  - Good sources of **content**
  - Large **in-degree**, e.g.
  - www.amazon.com, www.wikipedia.com , zhidao.baidu.com
- Hub pages
  - good sources of **links**
  - Pull together authorities on a given topic
  - Throw out unrelated pages of large in-degree
  - E.g. **dir.yahoo.com**



HITS: Hypertext-Induced Topic Search

- Authority page
  - Good sources of **content**
  - Large **in-degree**, e.g.
  - www.amazon.com, www.wikipedia.com , zhidao.baidu.com
- Hub pages
  - good sources of **links**
  - Pull together authorities on a given topic
  - Throw out unrelated pages of large in-degree
  - E.g. **dir.yahoo.com**
- Relationship of authorities and hubs
  - **Mutually reinforcing relationship**
  - A good hub points to many good authorities
  - A good authority is pointed by many good hubs

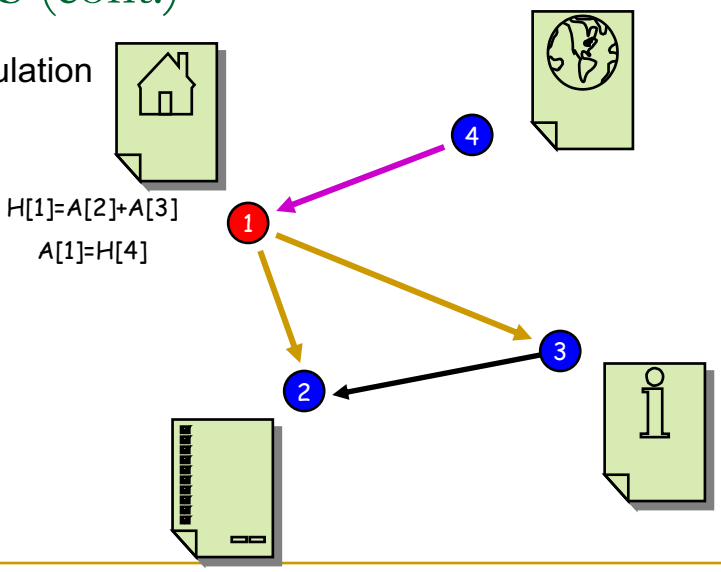
HITS

- A good *Base Set* R_σ is quite important
  - *a)* R_σ is relatively small.
  - *b)* R_σ is rich in relevant pages.
  - *c)* R_σ contains most (or many) of the strongest authorities.
- A root set
  - Collect the *t* highest-ranked pages for the query σ (e.g. t=200)
    - Good for a) and b), not enough for c)
- Expand root set to base set
  - Add all pages that the root set link to
  - Add 50 pages that link to the root set
  - Remove in-site links

Then its size is generally 1000-5000

HITS (cont.)

- Calculation



HITS (cont.)

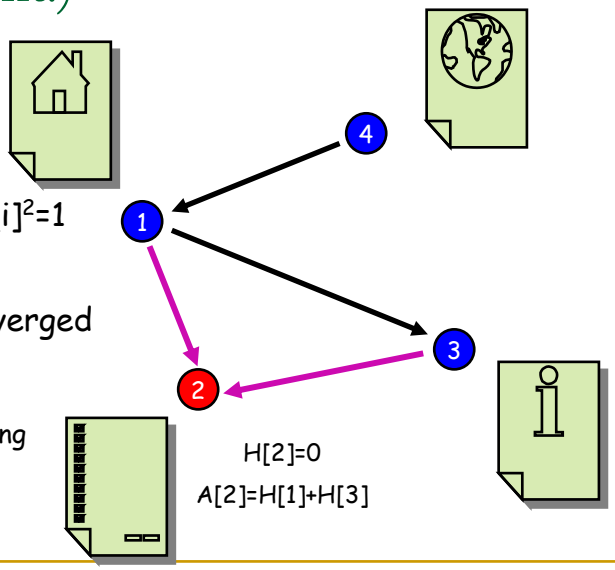
- Calculation

Normalization:

$\sum A[i]^2=1, \quad \sum H[i]^2=1$

Repeat until converged

Generally be used within the searching result documents -- topic specific / query dependent



H[2]=0

A[2]=H[1]+H[3]

Improvements on HITS

- Problems: can not work well in all cases
  - Mutually reinforcing relationships between hosts
  - Automatically generated links
  - Non-relevant nodes (topic drifting problem)

    e.g. "mango fruit" → "fruit"
- Some ideas
  - **Hosts problem** solution: A(n) → A(n)/k H(n) → H(n)/l
  - 2 basic approaches to tackle **topic drift**
    - Elimination non-relevant nodes from the graph
    - Regulating the influence of a node based on its relevance

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TrustRank – link-based spam page detection

- Trust Rank
  - Rationale: The approximate isolation of the good set
    - Good pages seldom point to bad ones.
  - Basic Idea: in-link based trust propagation
  - Select seed set
    - With high Invert PageRank (outlink-based PR)
      - To spread the trust score quickly
    - (And) high PageRank
      - To guarantee the quality of seed pages
    - Initial score t* = d
      - *d: normalize static score distribution, seed:1 others: 0*

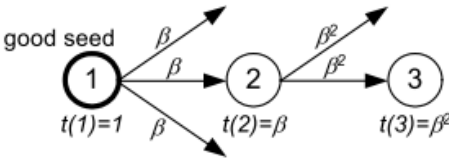
Trust Attenuation

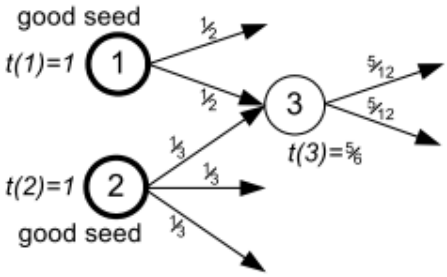
Type I:

- Trust dampening

Type II:

- Trust splitting





$0 < \beta < 1$

TrustRank Algorithm

function TrustRank
input

	$\mathbf{T}$	transition matrix
	N	number of pages
	L	limit of oracle invocations
	α_B	decay factor for biased PageRank
	M_B	number of biased PageRank iterations

output

	$\mathbf{t}^*$	TrustRank scores

α_B: generally set to ~0.85,

```
begin
        // evaluate seed-desirability of pages
(1)     s = SelectSeed(...)
        // generate corresponding ordering
(2)     σ = Rank({1,...,N}, s)
        // select good seeds
(3)     d = 0_N
        for i = 1 to L do
                if O(σ(i)) == 1 then
                        d(σ(i)) = 1
        // normalize static score distribution vector
(4)     d = d/|d|
        // compute TrustRank scores
(5)     t* = d
        for i = 1 to M_B do
                t* = α_B · T · t* + (1 − α_B) · d
        return t*
end
```

Link Based Detection

- Trust Rank Result
  - Precision and recall, PageRank vs. TrustRank

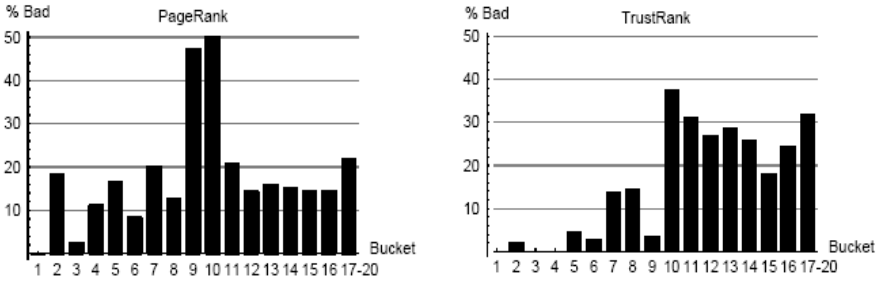


Figure 10: Bad sites in PageRank and TrustRank buckets.

Rank pages with scores. Rank 1: highest score.
Bucket setting: The sum of scores in each bucket is equal.

Z. Gyongyi, et al. Combating web spam with trustrank. In *VLDB '04, 576–587, 2004.*

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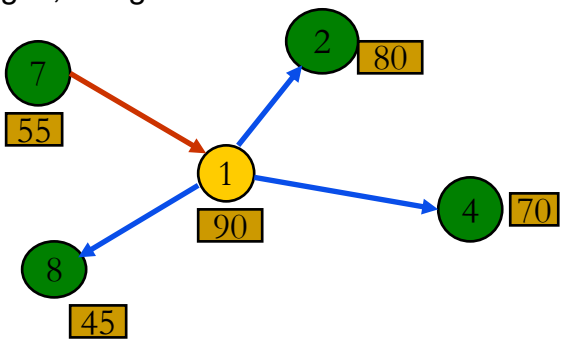
Spreading Activation

- For result re-ranking:

  When the initial relevance scores have been generated for result pages, using SA to re-rank the results.



$$RSV(D_1) = 90 + \lambda_1 * (80 + 45 + 70) + \lambda_2 * 55$$

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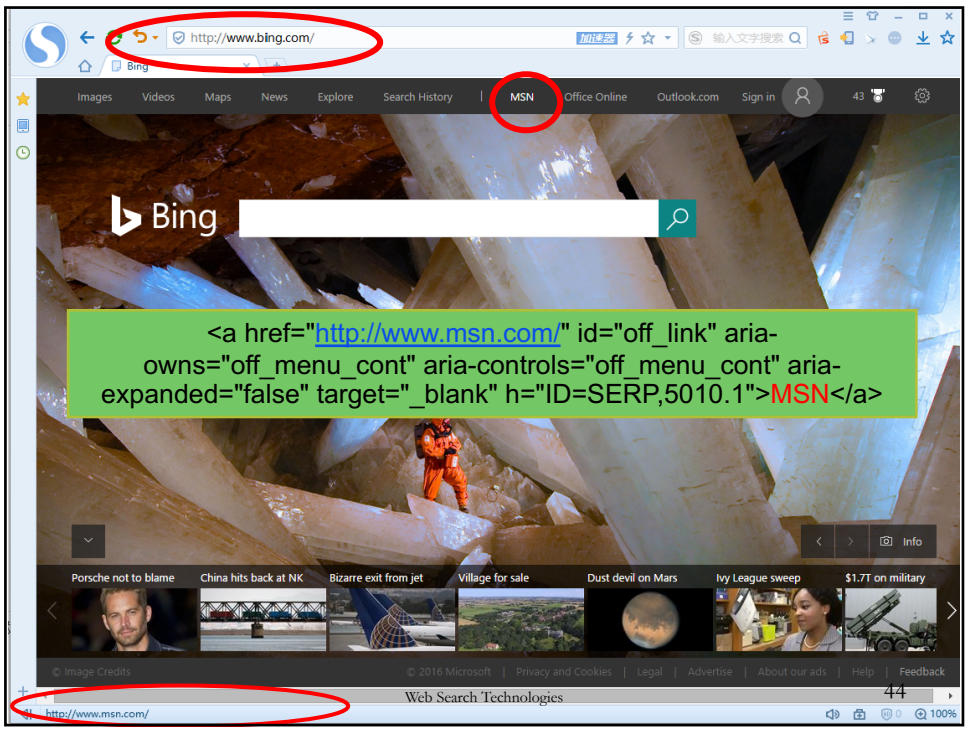

On the use of anchor text

- Three ways to use anchor text – I
  - Use anchor text as the complementary document information
    - $Document_i' = Document_i \cup Anchor_i$

Where $Anchor_i = \{anchor\_text_{ij} \mid$ where doc j has link to doc $i\}$

- $Final\_score_i$ = ranking score on $Document_i'$

On the use of anchor text

- Three ways to use anchor text – II
  - Use anchor text search result to re-rank
    - $Final\_score = f(Doc\_search\_score, Anchor\_search\_score)$
    - Selection of $f()$ is quite heuristics, by experiential parameters
    - E.g. Linear combination:
      - $Final\_score = \alpha * Doc\_search\_score + (1- \alpha)\ Anchor\_search\_score$

On the use of anchor text

- Three ways to use anchor text – III
  - Only use anchor text

    $Final\_score = Anchor\_search\_score$
- An observation
  - Only use anchor text is significantly better than use the original webpage on site finding tasks

    -- by Nick Craswell, David Hawking and Stephen Robertson, SIGIR'01

Improvements on the use of anchor text

- Filtering anchor text noise
- Use anchor text for finding web synonyms
- For query expansion
- For abbreviations
- Anchor text weighting with click information (clicked anchor)
- ……

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References

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- F. McSherry. A uniform approach to accelerated pagerank computation. In *WWW '05, pages 575–582,* USA, 2005.

FINAL PROJECT PROPOSAL

- Please add a post on *learn.tsinghua.edu.cn* "*course discussion*" （课程讨论） section, with:
  - The title (including 4 parts):
    - [Name1] [Student ID1] [Name2] [Student ID2] [Proj. Name]
  - The content
    - Short description on what you will do in the project (100~200 words).

Submission deadline: by April 17th 11:59pm (Wed.)

EXTENDED READING

Precision, Recall, MAP, MRR, F

DCG and NDCG

ROC curve and AUC

Accuracy: not good enough for classifiers with rank

- Two classifiers

Rank list 1	+	+	+	+	–	+	–	–	–	–
Rank list 2	–	+	+	+	+	–	–	–	–	+

+: relevant, –: non-relevant

Accuracy of Classifier1: 4/5

Accuracy of Classifier2: 4/5

But in application and intuition, Classifier 1 is better!

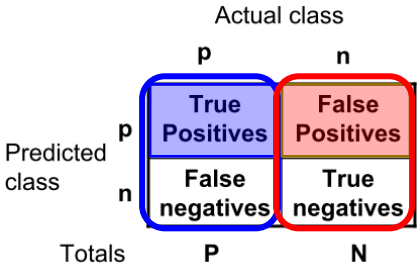
Accuracy vs ranking

- Accuracy-based: making two assumptions:
  - Balanced class distribution, and
  - Equal costs for misclassification
- Ranking: step aside these assumptions
  - Problem: Training examples are labeled, not ranked
- How to evaluate ranking?

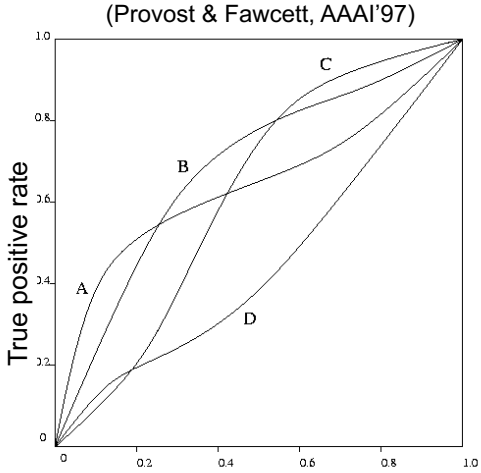
ROC curves

- *ROC* = *Receiver Operating Characteristic*
- Started in electronic signal detection theory (1940s - 1950s)
- Has become very popular in biomedical applications, particularly radiology and imaging
- Also used in machine learning applications to assess classifiers
- Can be used to compare tests/procedures

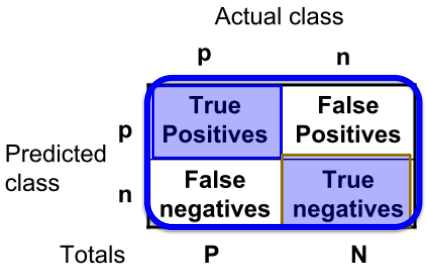
ROC curves



(Provost & Fawcett, AAAI'97)



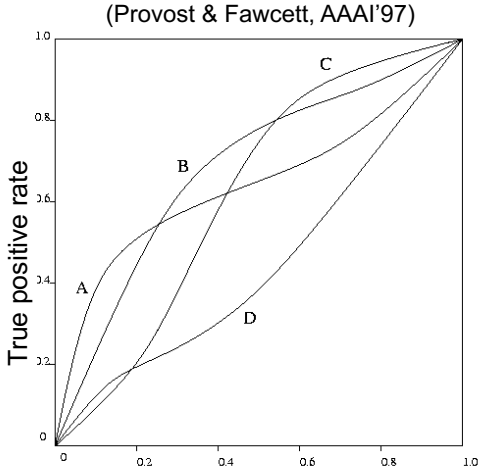
ROC curves and Accuracy



TP rate = TP / P recall (hit rate)

FP rate = FP / N (false alarm rate)

(Provost & Fawcett, AAAI'97)



ROC curves, Accuracy and Precision

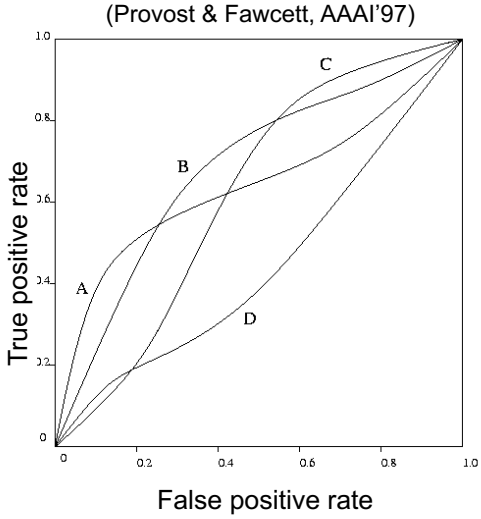
(Provost & Fawcett, AAAI'97)

		Actual class: p	Actual class: n
Predicted class	p	True Positives	False Positives
	n	False negatives	True negatives
Totals		P	N

TP rate = TP / P recall (hit rate)

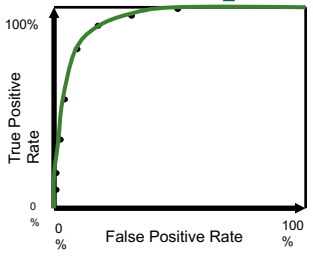
FP rate = FP / N (false alarm rate)

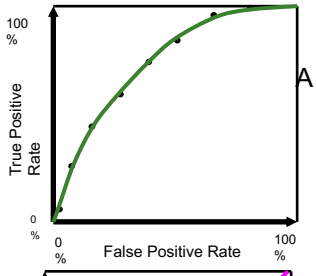
Accuracy = (TP + TN) / (P + N)



ROC curve comparison

A good test

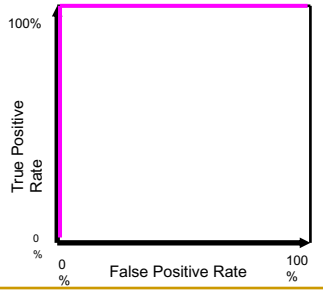


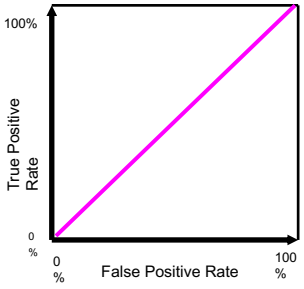


A poor test

Best Test

The distributions don't overlap at all





Worst test

The distributions overlap completely

ROC curve example

- T: threshold

Actual class	score
1	0.98
0	0.80
1	0.67
1	0.65
0	0.54
0	0.32

T=0.5

Actual class	score	class
1	0.98	1
0	0.80	1
1	0.67	1
1	0.65	1
0	0.54	1
0	0.32	0

predicted \ actual	0	1
0	1	0
1	2	3

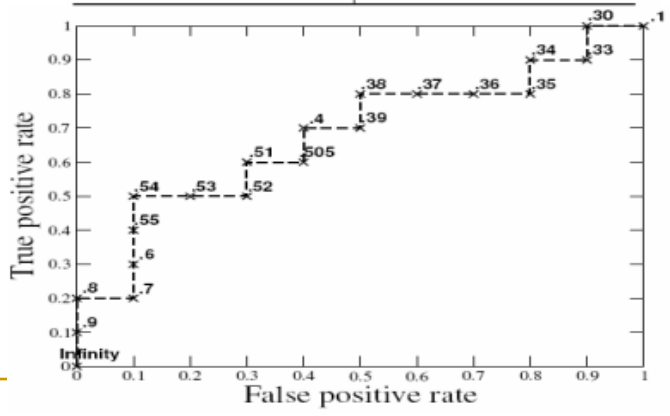
T=0.7

Actual class	score	class
1	0.98	1
0	0.80	1
1	0.67	0
1	0.65	0
0	0.54	0
0	0.32	0

predicted \ actual	0	1
0	2	2
1	1	1

For a model f, each threshold value T gives a point in ROC space

Inst#	Class	Score	Inst#	Class	Score
1	p	.9	11	p	.4
2	p	.8	12	n	.39
3	n	.7	13	p	.38
4	p	.6	14	n	.37
5	p	.55	15	n	.36
6	p	.54	16	n	.35
7	n	.53	17	p	.34
8	n	.52	18	n	.33
9	p	.51	19	p	.30
10	n	.505	20	n	.1



1. T = min-score
2. TP=0, FP=0
3. For each obs. i
   if score-i > T
      increment TP
   else
      increment FP
4. Add point (FP/N, TP/P)
   to ROC graph

-Increment T from min-score to max-score (by smallest difference between two scores)

- Repeat 1. to 4. above to add a point to the graph.

Inst#	Class	Score	Inst#	Class	Score
1	p	.9	11	p	.4
2	p	.8	12	n	.39
3	n	.7	13	p	.38
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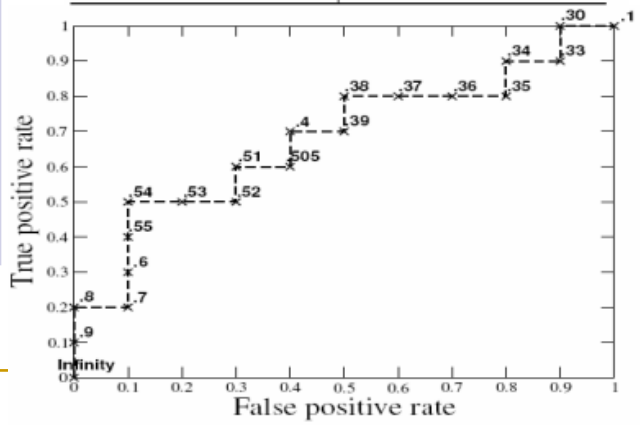
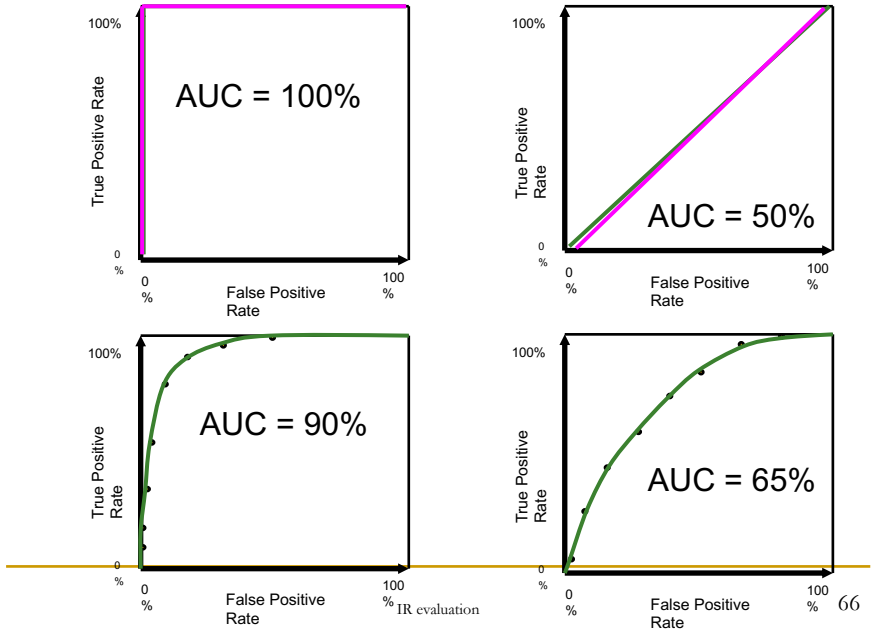


AUC: Area under ROC curve

- *Overall measure* of test performance
- *Comparisons* between two tests based on differences between (estimated) AUC
  - One ROC curve dominates the other, its AUC must be larger.
  - Intuitively, the larger the AUC of a ROC, the better.
- For continuous data, AUC equivalent to *Mann-Whitney U-statistic* (nonparametric test of difference in location between two populations)
- It represents the possibility to put positive examples before negative ones.

AUC for ROC curves



How to calculate AUC

- Rank test examples in an increasing order $\{g_1, \ldots, g_{n1}, f_1, \ldots, f_{n0}\}$. g_i: positive; f_i: negative
  - n_1: total number of positive examples
  - n_0: total number of negatives examples
  - Let r_i be the rank of ith negative example
  - $S_0 = \sum r_i$
- AUC: $\hat{A} = \dfrac{S_0 - n_0(n_0+1)/2}{n_0 n_1}$

	+ + – + – + – +
i	1 2 3
r_i	3 5 7

- (Hand & Till, 2001, MLJ)

AUC examples

- Two classifiers (ranklist):

Ranklist 1	+	+	+	+	–	+	–	–	–	–
Ranklist 2	–	+	+	+	+	–	–	–	–	+

The AUC of ranklist 1: $\frac{(5+7+8+9+10)-5\times 6/2}{5\times 5}=\frac{24}{25}$

The AUC of ranklist 2: $\frac{(1+6+7+8+9)-5\times 6/2}{5\times 5}=\frac{16}{25}$

Ranklist 1 is better than 2!