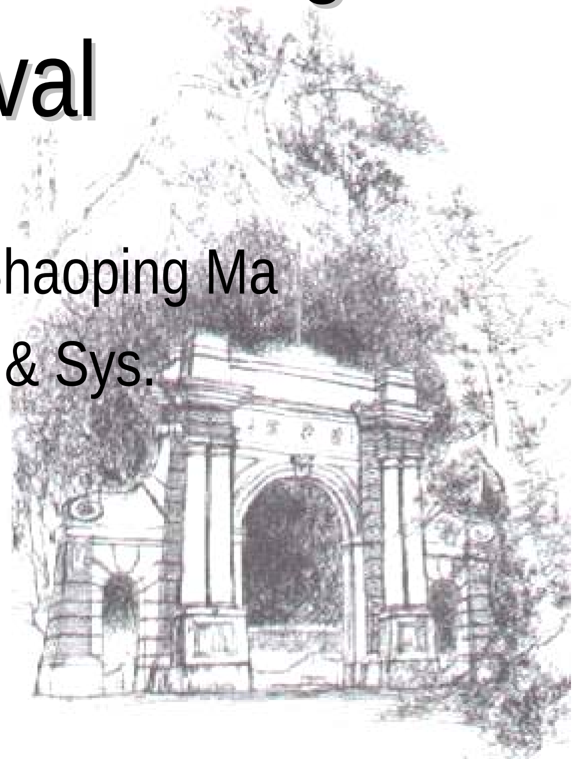
Learning-based Web Data Cleansing for Information Retrieval

Yiqun Liu, Canhui Wang, Min Zhang, Shaoping Ma
State Key Lab of Intelligent Tech. & Sys.
Tsinghua University

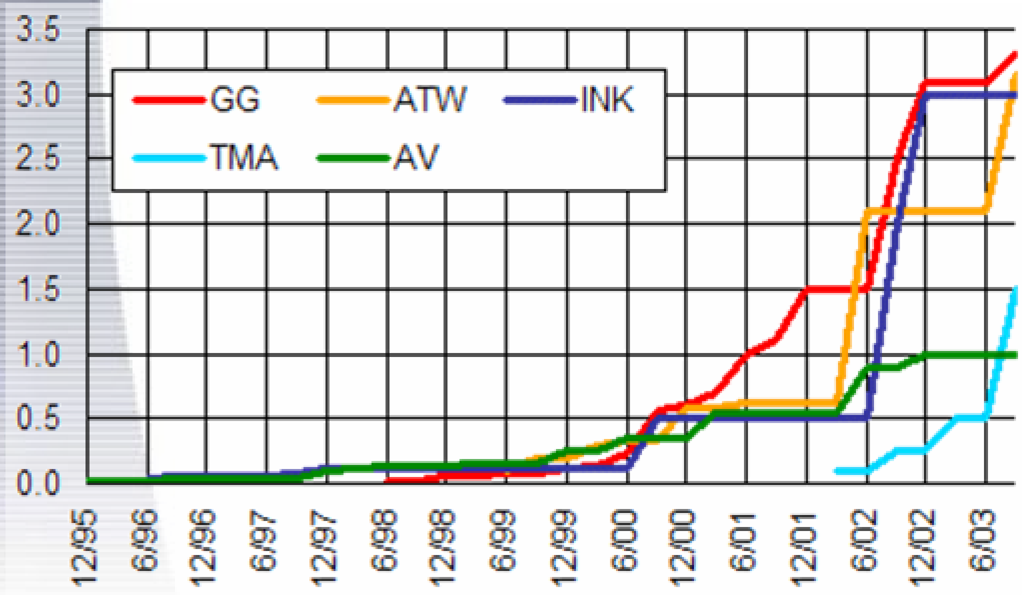


Outlines

- Data cleansing and its applications in Web IR
- Query-independent features used in data cleansing
- Algorithm and evaluation
- Conclusions and future work

Data cleansing and its applications in Web IR

- Index Size War between Search Engines
  - Billions Of Textual Documents Indexed December 1995-September 2003



From Danny Sullivan, SearchEngineWatch web site

Data cleansing and its applications in Web IR

- Index Size War between Search Engines (cont.)

Search Engine	Reported Size	Page Depth
Google	**8.1 billion (Dec. 2004)**	101K
MSN	5.0 billion	150K
Yahoo	19.2 bilion (Aug. 2005)	500K
Ask Jeeves	2.5 billion	101K+
All the Web	**152 billion**	605K
All the Surface Web	**10 billion**	8K

From Danny Sullivan, SearchEngineWatch web site

Data cleansing and its applications in Web IR

- An end to the index size war?
  - In Sep. 2005, Google removes the number of indexed pages because "absolute numbers are no longer useful"
  - No search engine can cover all resources on the Web

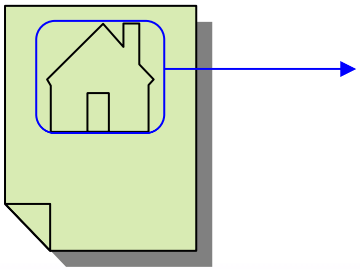
	Google	Yahoo!	MSN	Teoma
Round 1	76.30%	69.28%	62.03%	57.58%
Round 2	76.09%	69.29%	61.90%	57.69%
Round 3	76.27%	69.37%	61.87%	57.70%
Round 4	76.05%	69.30%	61.73%	57.57%
Round 5	76.11%	69.26%	61.96%	57.56%
Average	76.16%	69.32%	61.90%	57.62%

Data cleansing and its applications in Web IR

- Data quality is more important than quantity for Web IR tools
  - Spams and SEOs
  - Duplicates in Web pages
  - Unreliable, out-dated data
- Current data cleansing algorithms in Web IR
  - Local scale data cleansing
  - Global scale data cleansing

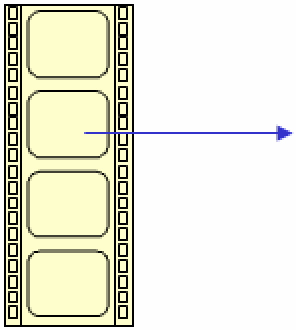
Data cleansing and its applications in Web IR

- Local scale data cleansing
  - To reduce the useless blocks / To find the important blocks inside a Web page
  - Reduce spam hyperlinks / useless hyperlinks (Kushmerick et. al.)
  - Reduce Ad. Contexts (Davison et. al.)
  - VIsion Based Page Segmentation, VIPS, MSRA
  - Site template detecting (Yossef et. al.)



Data cleansing and its applications in Web IR

- Global scale data cleansing
  - To reduce low quality pages / To locate important pages inside a given Web page corpus
  - Hyperlink structure analysis algorithms
    - PageRank, HITS
    - Hypothesis 1: Recommendation
    - Hypothesis 2: Topic locality
    - Challenged by Spam links and SEOs



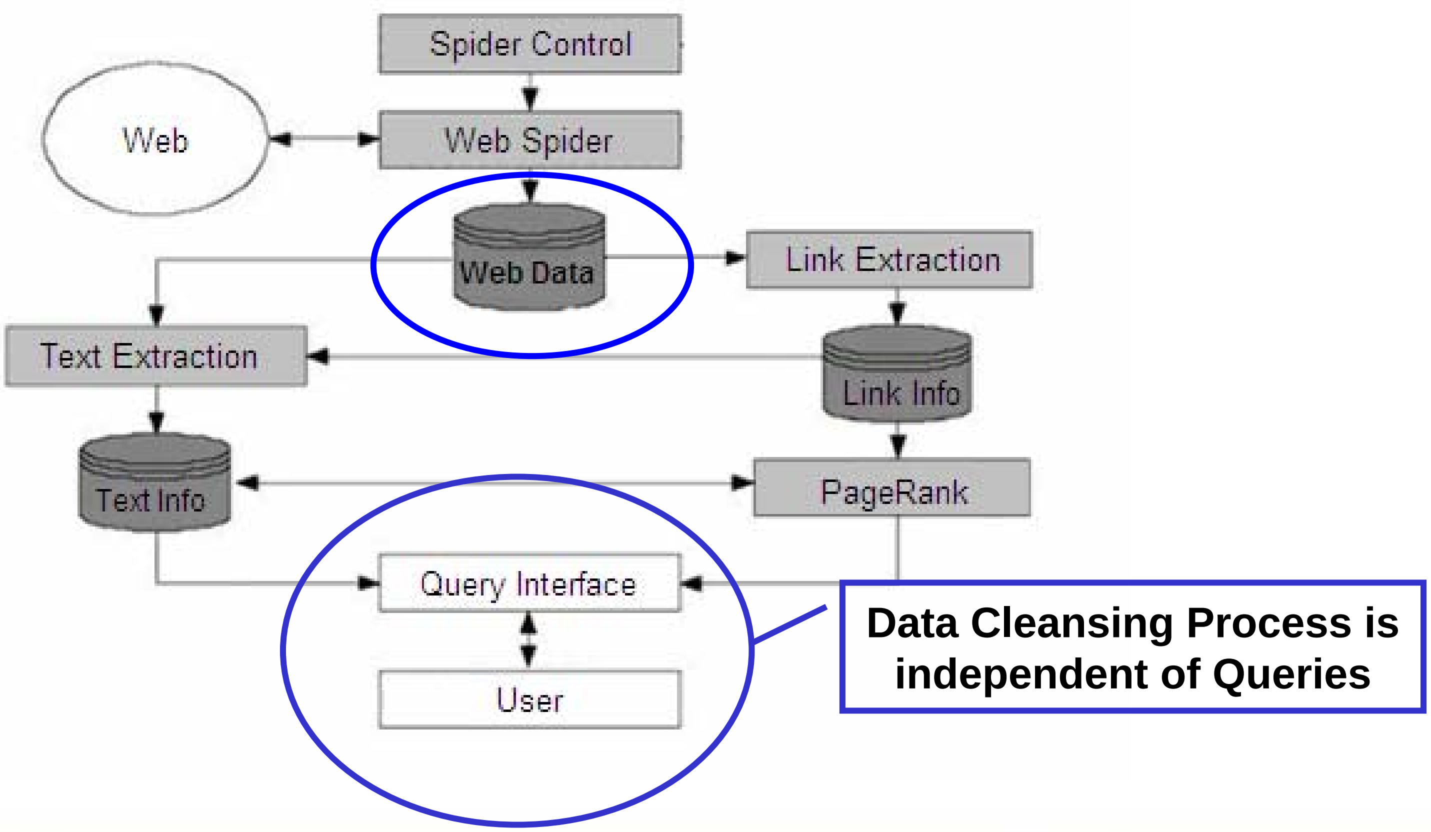
  - Monika Henzinger (Google Research Director): A better estimate of the quality of a page requires additional sources of information.

Data cleansing and its applications in Web IR

- Our data cleansing method
  - Global scale data cleansing
  - Learn from “what users need”
  - Users’ information requirement is reflected in their search target pages (pages that they want to find)
  - A better data cleansing method should judge the quality of a Web page by whether it can be a search target for a certain user query.
  - Both hyperlink structure features and other kinds of features should be considered in data cleansing

Data cleansing and its applications in Web IR

- Query-independent Data Cleansing



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Query-independent features used in data cleansing

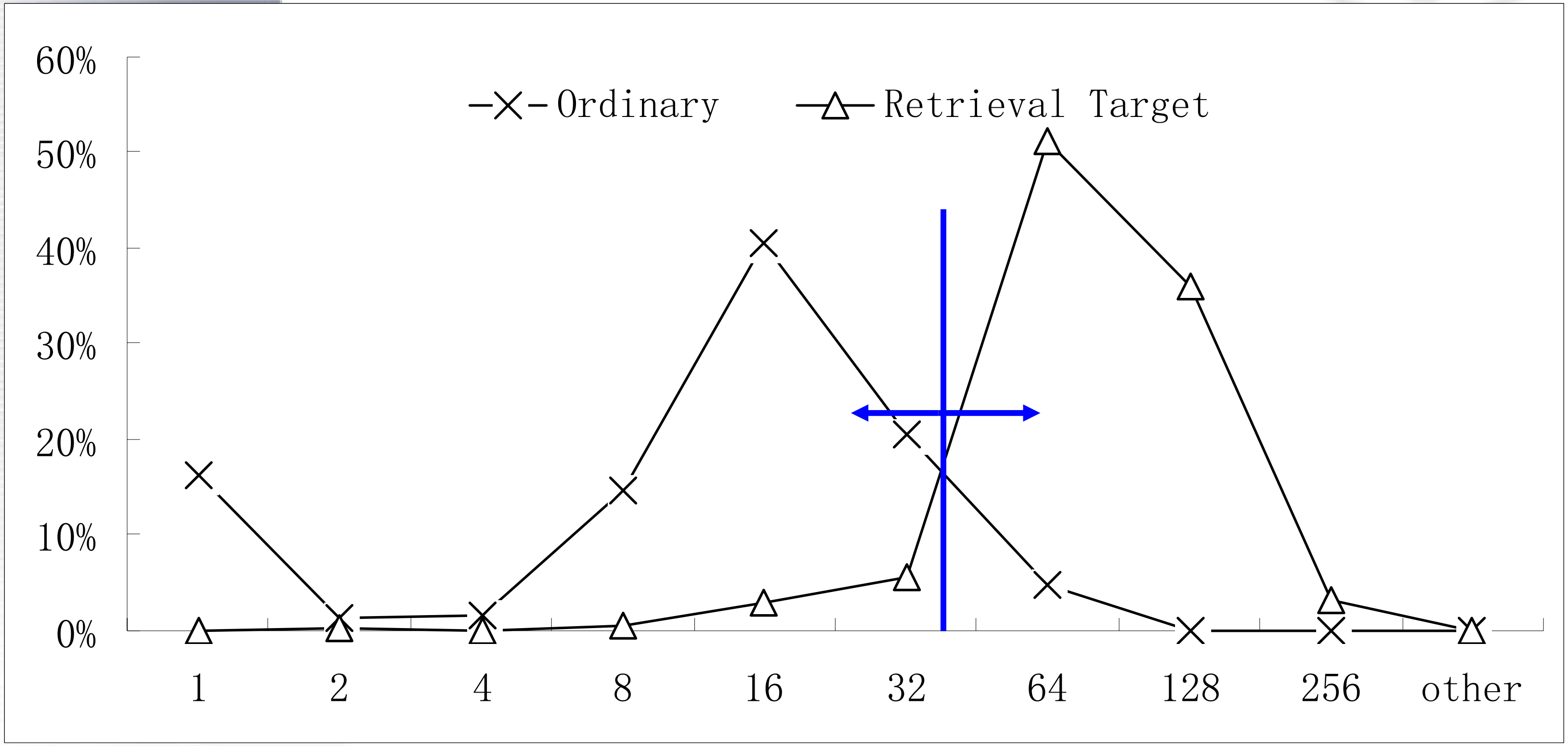
- Query-independent feature analysis of High Quality Pages
  - Corpus
    - 37M Chinese web pages collected in Nov. 2005
    - Over 0.5 Terabyte.
    - Obtained from Sogou.com
  - High Quality Page (Search Target Page)
    - Training set: 1600 pages
    - Test set: 17000 pages
    - Evaluated manually by Sogou engineers

Query-independent features used in data cleansing

- Hyperlink structure related features
  - PageRank
  - In-link number
  - In-link anchor text length
- Other features
  - Document length
  - Number of duplicates
  - URL length
  - Encode

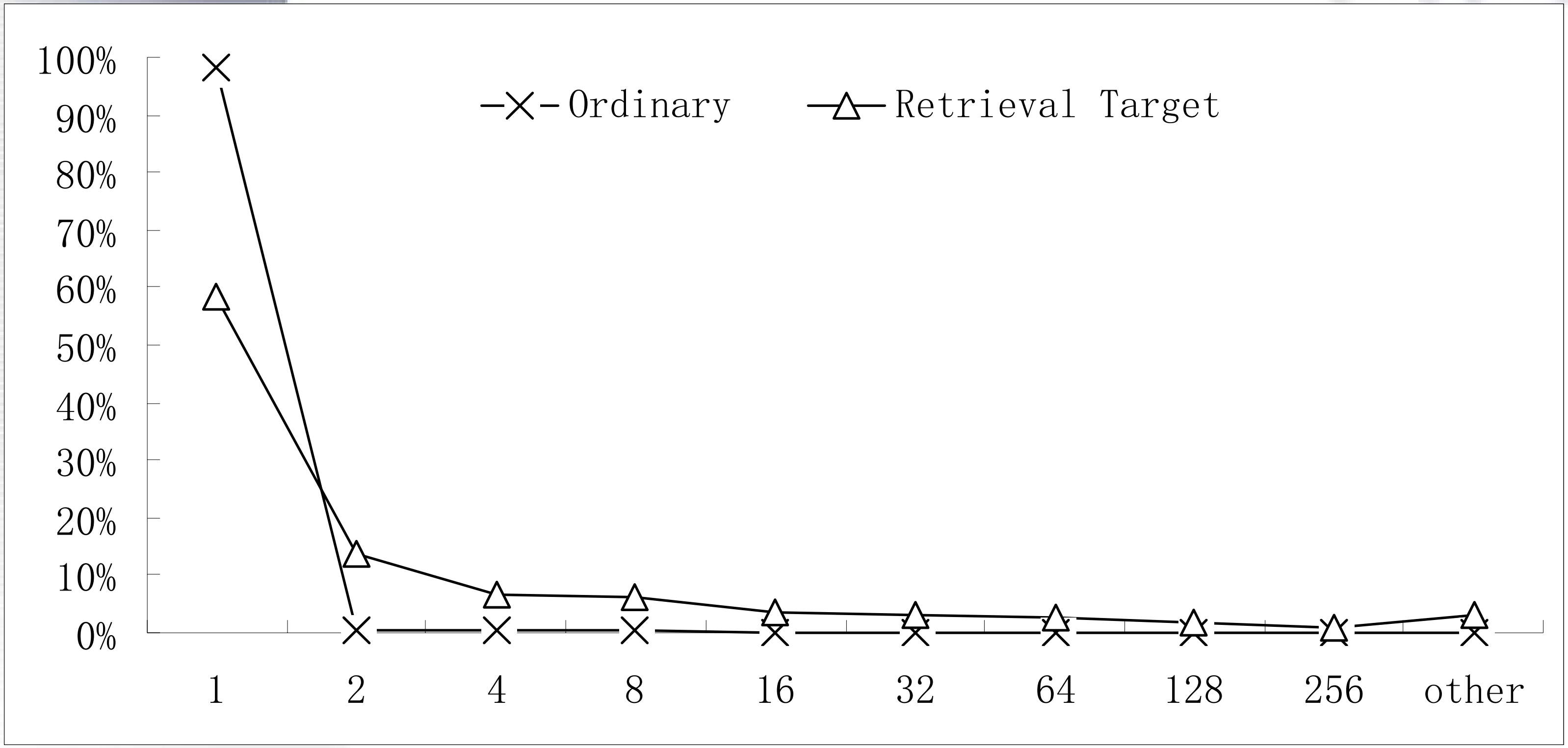
Query-independent features used in data cleansing

- PageRank



Query-independent features used in data cleansing

- In-link anchor text length



Query-independent features used in data cleansing

- Other features

	Ordinary	High Quality
URL contains “?”	13.06%	1.87%
Encode is not GBK	14.04%	1.39%
Hub type page	3.78%	24.77%

- The query-independent features can separate high quality pages from ordinary pages

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Algorithm and evaluation

- Difficulties in algorithms
  - Web page classification
  - Lack of negative examples (uniform sampling is difficult and sometimes not possible)
  - Learning with unlabeled data and positive examples
  - Previous work:
    - O-SVM
    - PEBL: Positive Example Based Learning
    - Not quite suitable for learning based on topic-independent features

Algorithm and evaluation

- Why is k-means used here?
  - Learn without negative examples
  - Independent of prior positive proportion knowledge
- Differences with traditional K-means
  - Fixed cluster number: true or not.
  - Initial positive example centroid is provided

Algorithm and evaluation

- Algorithm

S_{key} : key resource training set
R : estimated proportion of the positive examples

1. Choose 2 initial cluster centroids:
   - Positive centroid: $M_1 = \frac{1}{S_{key}} \sum_{X \in S_{key}} X$
   - Negative centroid: $M_2 = \frac{M(Whole\ Collection) - R \times M_1}{1-R}$
2. In the kth iterative, instance X will be assigned to the jth cluster $S_j^{(k)}$ if:

$$||X - M_j^{(k)}|| = min(||X - M_1^{(k)}||, ||X - M_2^{(k)}||) \qquad (j = 1, 2)$$

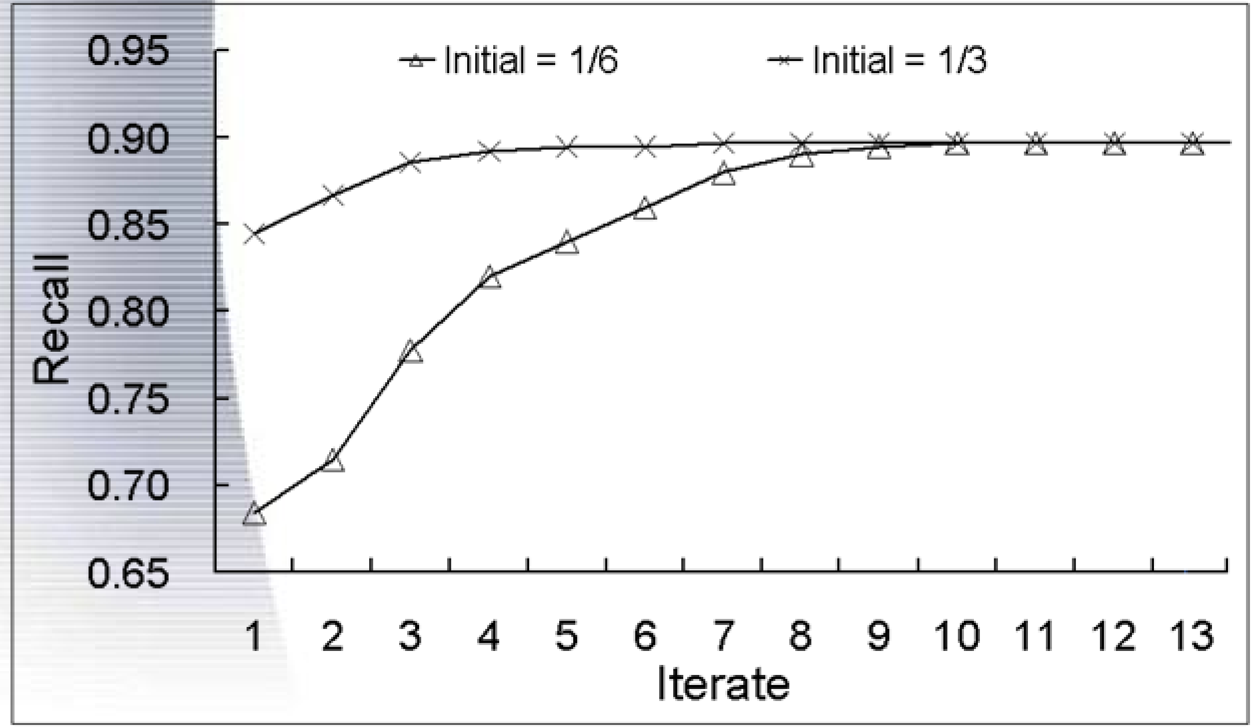
3. For $S_j^{(k)}$, caculate $M_j^{(k)}$, which is defined as:

$$M_j^{(k+1)} = \frac{1}{N_j} \sum_{X \in S_j^{(k)}} X \qquad (j = 1, 2)$$

4. If $M_1^{(k+1)} = M_1^{(k)}$, exit. Else go to 2.

Algorithm and evaluation

- Algorithm converges with different initial *R*
  - Algorithm doesn't require prior knowledge of *R*



Algorithm and evaluation

- Evaluation (Based on .GOV corpus)
  - Algorithm can cover almost all high quality pages with less than half whole collection size

	K-means Clustering
Whole Collection (.GOV) Coverage	44.30%
High Quality Page Test Set Recall	89.70%
High Quality Page Test Set Precision	67.50%
F2-measure	53.89%

  - Retrieval Experiment Settings
    - 20% navigational type queries
    - 80% informational/transactional type queries

Algorithm and evaluation

- Evaluation

	P@10 for Topic Distillation queries	MRR for Navigational query
Whole Collection	0.1025	0.7443
K-means	0.1275	0.7278
PageRank	0.1134	0.6533
Authority	0.1100	0.6700
Hub	0.1250	0.6357

  - Cleansed set gains better performance than whole collection
  - K-means based cleansing outperforms link-analysis criterion

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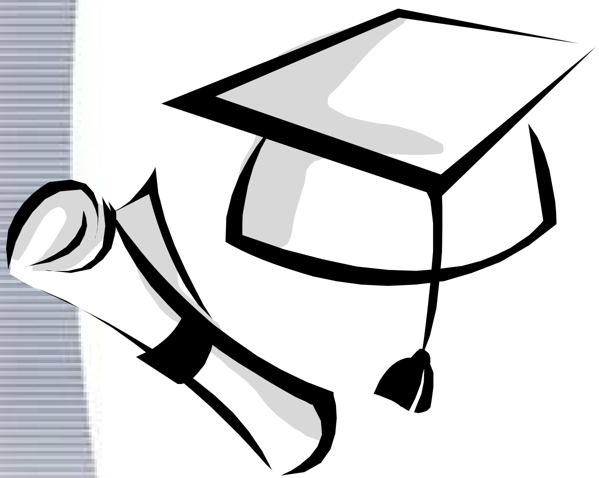
Conclusions and future work

- Conclusions:
  - Data cleansing based on K-means clustering is effective in reducing unimportant pages.
  - Cleansed set (half size of total collection) retains useful information of the Web collection.
  - Retrieval on result set gets better overall retrieval performance than the whole collection.

Conclusions and future work

- Future work
  - Algorithm Efficiency Problem
    - Naïve Bayes based learning method

      (*Data Cleansing for Web Information Retrieval using Query Independent Features*, to be appeared in JASIST, Jan, 2007)
  - Hyper link analysis in the cleansed corpus
    - The cleansed corpus retains almost all hyper link information
  - A learn-based algorithm to reduce spam pages / low quality pages
    - Similar way: learn from positive example and unlabelled data



Thank you!

Questions or comments?