Chapter 3: Top-k Query Processing and Indexing

3.1 Top-k Algorithms

3.2 Approximate Top-k Query Processing

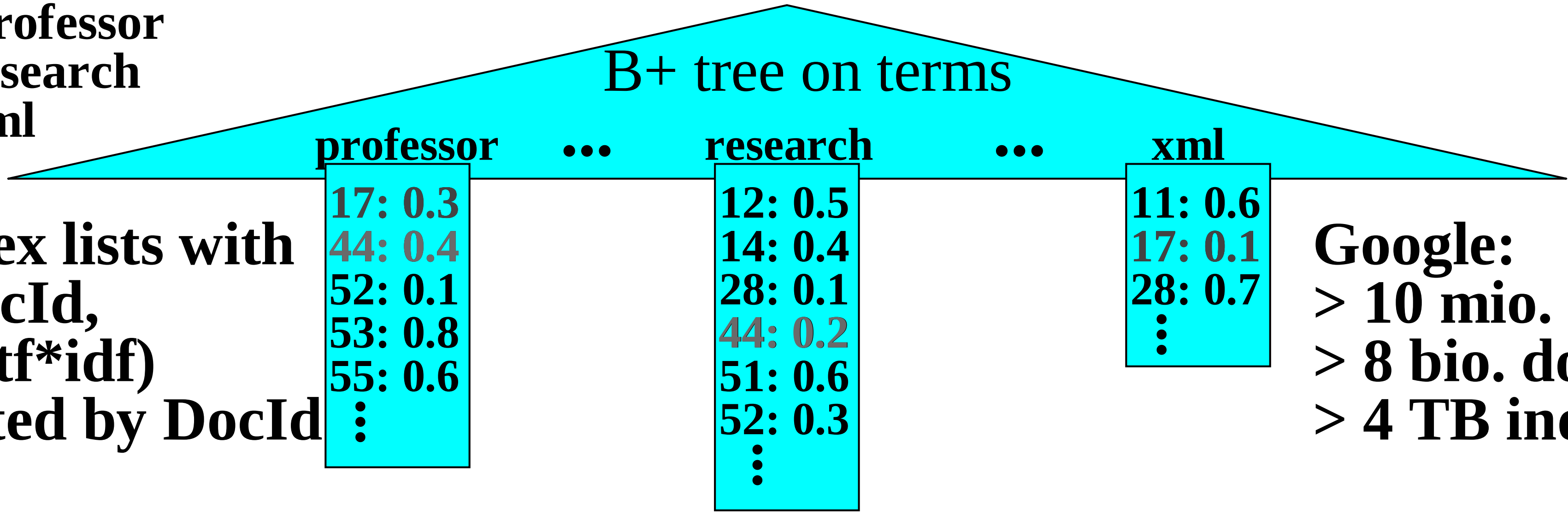
3.3 Index Access Scheduling

3.4 Index Organization and Advanced Query Types

3.1 Top-k Query Processing with Scoring

Vector space model suggests *m×n term-document matrix*,
but data is sparese and queries are even very sparse
→ better use *inverted index lists* with terms as keys for B+ tree

q: professor
research
xml



index lists with
(DocId,
s = tf*idf)
sorted by DocId

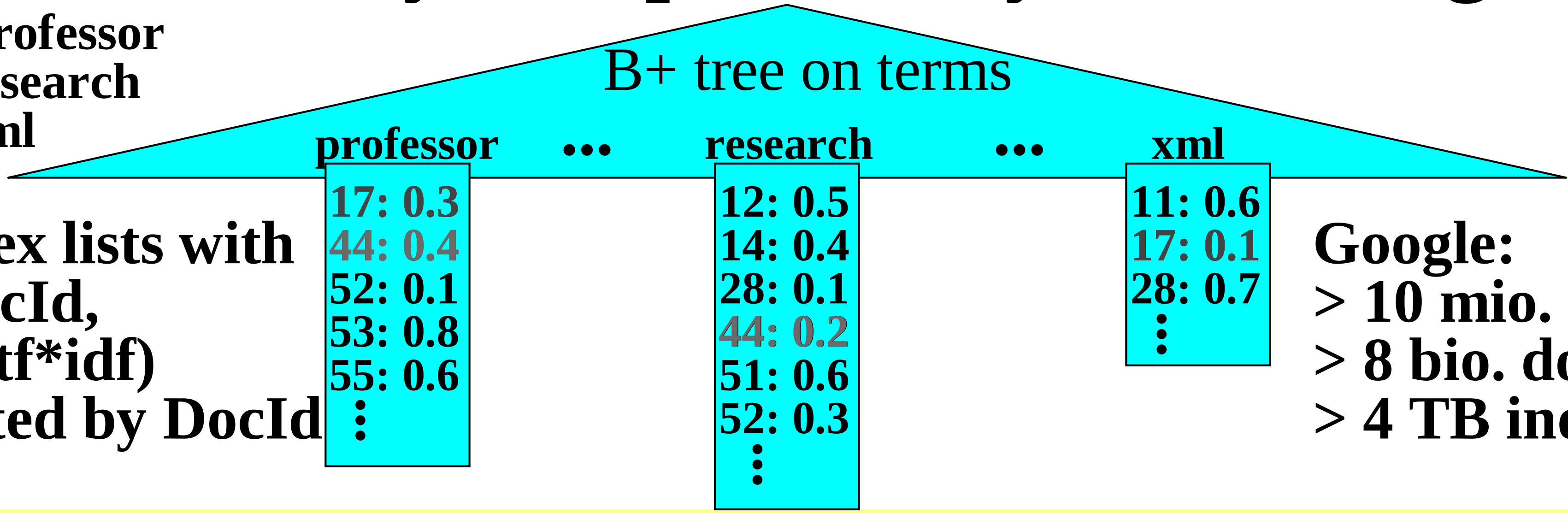
Google:
> 10 mio. terms
> 8 bio. docs
> 4 TB index

terms can be full words, word stems, word pairs,
word substrings, etc.
(whatever „dictionary terms“ we prefer for the application)

queries can be conjunctive or „andish“ (soft conjunction)

DBS-Style Top-k Query Processing

q: professor
research
xml



index lists with (DocId, s = tf*idf) sorted by DocId

Google:
> 10 mio. terms
> 8 bio. docs
> 4 TB index

<u>Given:</u> query $q = t_1\ t_2\ \ldots\ t_z$ with z (conjunctive) keywords
similarity scoring function score(q,d) for docs d∈D, e.g.: $\vec{q} \cdot \vec{d}$
with precomputed scores (index weights) $s_i(d)$ for which $q_i \neq 0$

<u>Find:</u> top k results w.r.t. score(q,d) =aggr{$s_i(d)$}(e.g.: $\Sigma_{i \in q}\ s_i(d)$))

Naive join&sort QP algorithm:

top-k (
σ[term=t_1] (index) $\bowtie_{DocId}$
σ[term=t_2] (index) $\bowtie_{DocId}$
… $\bowtie_{DocId}$
σ[term=t_z] (index)) order by s desc)

Computational Model for Top-k Queries over m-Dimensional Data Space

Assume ***local scores*** s_i for query q, data item d, and dimension i, and ***global scores s*** of the form $s(q,d) = aggr\{ s_i(q,d) \mid i = 1..m \}$

with a ***monotonic*** aggregation function $aggr : [0,1]^m \rightarrow [0,1]$

Examples: $s(q,d) = \sum_{i=1}^{m} s_i(q,d)$ $\quad s(q,d) = max\{ s_i(q,d) \mid i = 1..m \}$

Find top-k data items with regard to global scores:

- process m ***index lists*** Li with ***sorted access (SA)*** to entries (d, s_i(q,d)) in ***ascending order of doc ids*** or ***descending order of s_i(q,d)***
- maintain for each candidate d a set E(d) of evaluated dimensions and a ***partial score „accumulator"***
- for candidate d with incomplete E(d) consider looking up d in Li for all $i \in R(d)$ by ***random access (RA)***
- terminate index list scans when enough candidates have been seen
- if necessary sort final candidate list by global score

Data-intensive Applications in Need of Top-k Queries

Top-k results from ranked retrieval on

- ***multimedia data***: aggregation over features like color, shape, texture, etc
- ***product catalog data***: aggregation over similarity scores for
  cardinal properties such as year, price, rating, etc. and
  categorial properties such as
- ***text documents***: aggregation over term weights
- ***web documents***: aggregation over (text) relevance, authority, recency
- ***intranet documents***: aggregation over different feature sets such as
  text, title, anchor text, authority, recency, URL length, URL depth,
  URL type (e.g., containing „index.html“ or „~“ vs. containing „?“)
- ***metasearch engines***: aggregation over ranked results from multiple
  web search engines
- ***distributed data sources***: aggregation over properties from different sites
  e.g., restaurant rating from review site,
  restaurant prices from dining guide, driving distance from streetfinder
- ***peer-to-peer recommendation and search***

Index List Processing by Merge Join

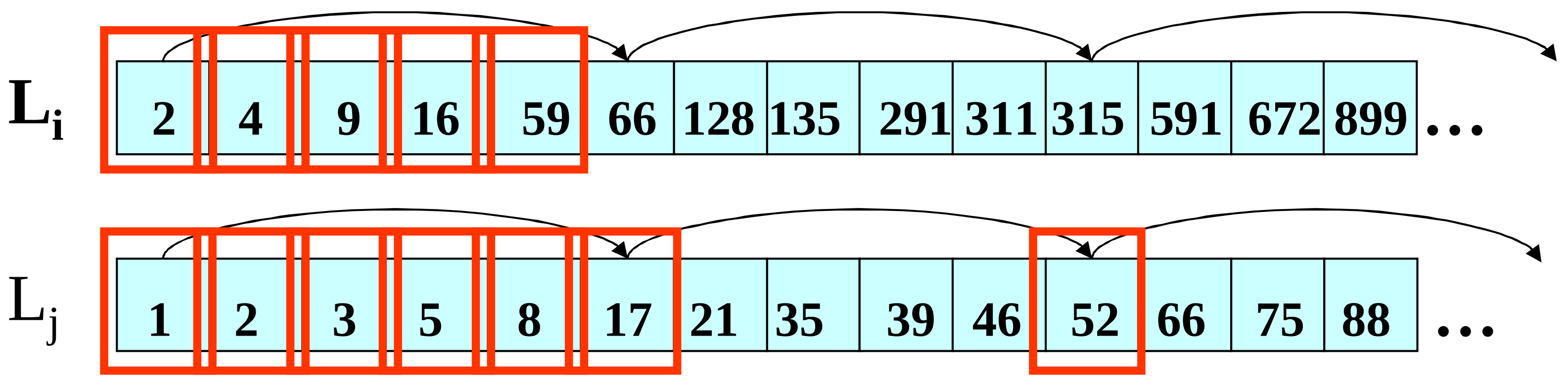
Keep L(i) in **ascending order of doc ids**

Compress L(i) by actually storing the gaps between successive doc ids
(or using some more sophisticated prefix-free code)

QP may start with those L(i) lists that are short and have high idf

Candidate results need to be looked up in other lists L(j)

To avoid having to uncompress the entire list L(j),
L(j) is encoded into groups of entries
with a skip pointer at the start of each group
→ sqrt(n) evenly spaced skip pointers for list of length n



Efficient Top-k Search

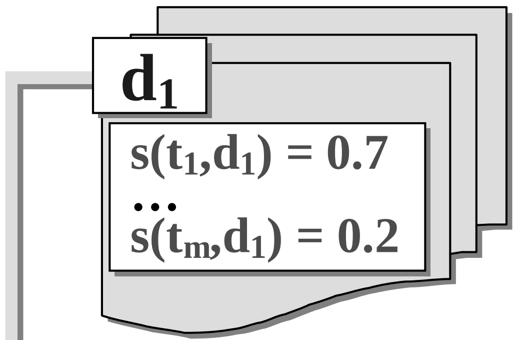
[Buckley85, Güntzer/Balke/Kießling 00, Fagin01]

threshold algorithms: efficient & principled top-k query processing with monotonic score aggr.

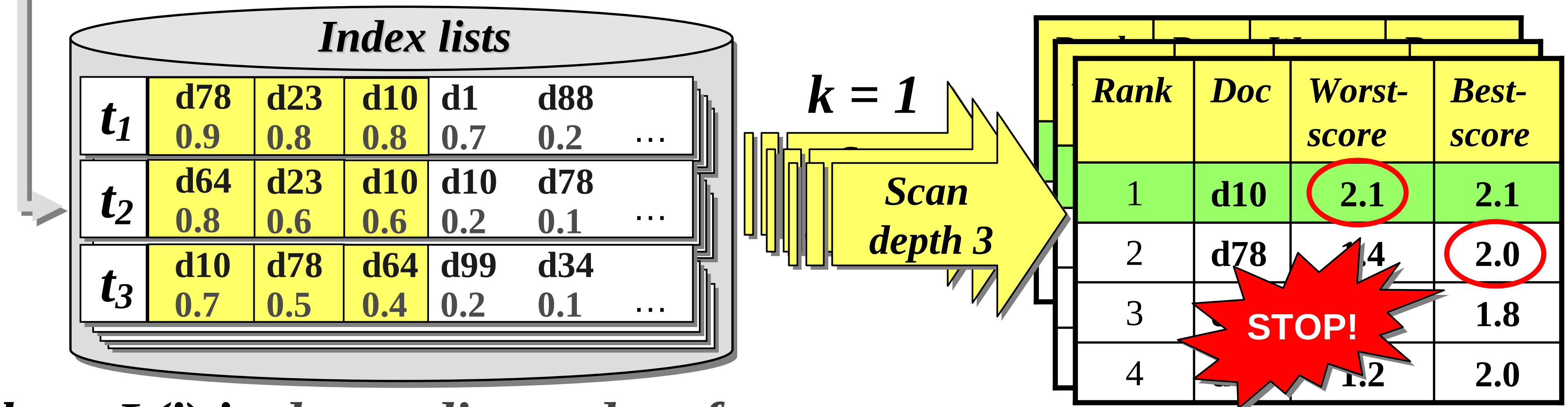
TA with sorted access only (NRA):

can index lists; consider d at pos_i in L_i;
E(d) := E(d) ∪ {i}; $high_i$:= s(t_i,d);
worstscore(d) := aggr{s(t_ν,d) | ν ∈ E(d)};
bestscore(d) := aggr{worstscore(d),
aggr{$high_\nu$ | ν ∉ E(d)}};
if worstscore(d) > min-k then add d to top-k
min-k := min{worstscore(d') | d' ∈ top-k};
else if bestscore(d) > min-k then
cand := cand ∪ {d}; s
threshold := max {bestscore(d') | d'∈ cand};
if threshold ≤ min-k then exit;

Data items: d_1, …, d_n



Query: $q = (t_1, t_2, t_3)$



keep L(i) in descending order of scores

Threshold Algorithm (TA, Quick-Combine, MinPro)

(Fagin'01; Güntzer/Balke/Kießling; Nepal/Ramakrishna)

scan all lists L_i (i=1..m) in parallel:
- **consider dj at position pos_i in Li;**
- **$high_i := s_i(dj)$;**
- **if dj $\notin$ top-k then {**
  - **look up $s_\nu(dj)$ in all lists L_ν with $\nu \neq i$; // random access**
  - **compute $s(dj) := aggr \{s_\nu(dj) \mid \nu=1..m\}$;**
  - **if s(dj) > min score among top-k then**
    - **add dj to top-k and remove min-score d from top-k; };**
- **threshold := aggr $\{high_\nu \mid \nu=1..m\}$;**
- **if min score among top-k $\geq$ threshold then exit;**

but random accesses are expensive !

m=3
aggr: sum
k=2

L_1	L_2	L_3
f: 0.5	a: 0.55	h: 0.35
b: 0.4	b: 0.2	d: 0.35
c: 0.35	f: 0.2	b: 0.2
a: 0.3	g: 0.2	a: 0.1
h: 0.1	c: 0.1	c: 0.05
d: 0.1		f: 0.05

top-k:

~~f: 0.75~~
a: 0.95
b: 0.8

No-Random-Access Algorithm
(NRA, Stream-Combine, TA-Sorted)

scan index lists in parallel:
- **consider dj at position pos_i in Li;**
- **E(dj) := E(dj) ∪ {i}; $high_i$:= si(q,dj);**
- **bestscore(dj) := aggr{x1, ..., xm)**
  - **with xi := si(q,dj) for i∈E(dj), $high_i$ for i ∉ E(dj);**
- **worstscore(dj) := aggr{x1, ..., xm)**
  - **with xi := si(q,dj) for i∈E(dj), 0 for i ∉ E(dj);**
- **top-k := k docs with largest worstscore;**
- **threshold := bestscore{d | d not in top-k};**
- **if min worstscore among top-k ≥ threshold then exit;**

m=3
aggr: sum
k=2

L1	L2	L3
f: 0.5	a: 0.55	h: 0.35
b: 0.4	b: 0.2	d: 0.35
c: 0.35	f: 0.2	b: 0.2
a: 0.3	g: 0.2	a: 0.1
h: 0.1	c: 0.1	c: 0.05
d: 0.1		f: 0.05

top-k:
- a: 0.95
- b: 0.8

candidates:
- ~~f: 0.7 + ? ≤ 0.7 + 0.1~~
- ~~h: 0.45 + ? ≤ 0.45 + 0.2~~
- ~~c: 0.35 + ? ≤ 0.35 + 0.3~~
- ~~d: 0.35 + ? ≤ 0.35 + 0.3~~
- ~~g: 0.2 + ? ≤ 0.2 + 0.4~~

Optimality of TA

Definition:

For a class $\mathcal{A}$ of algorithms and a class $\mathcal{D}$ of datasets,
let cost(A,D) be the execution cost of $A \in \mathcal{A}$ on $D \in \mathcal{D}$.
Algorithm B is ***instance optimal*** over $\mathcal{A}$ and $\mathcal{D}$ if
for every $A \in \mathcal{A}$ on $D \in \mathcal{D}$: cost(B,D) = O(cost(A,D)),
that is: cost(B,D) $\leq$ c*O(cost(A,D)) + c'
with optimality ratio (competitiveness) c.

Theorem:

- TA is instance optimal over all algorithms that are based on sorted and random access to (index) lists (no „wild guesses"). TA has optimality ratio $m + m(m-1)\, C_{RA}/C_{SA}$ with random-access cost C_{RA} and sorted-access cost C_{SA}
- NRA is instance-optimal over all algorithms with SA only.

if „wild guesses" are allowed,
then no deterministic algorithm is instance-optimal

Execution Cost of TA Family

Run-time cost is $O\left(n^{\frac{m-1}{m}} \cdot k^{\frac{1}{m}} \right)$ with arbitrarily high probability

(for independently distributed Li lists)

Memory cost is O(k) for TA

and $O(n^{(m-1)/m})$ for NRA (priority queue of candidates)

3.2 Approximate Top-k Query Processing

3.2.1 Heuristics for Similarity Score Aggregation

3.2.2 Heuristics for Score Aggregation with Authority Scores

3.2.3 Probabilistic Pruning

Approximate Top-k Query Processing

Approximation TA:

A ***θ-approximation*** T‘ for top-k query q with θ > 1
is a set T‘ of docs with:

- |T‘|=k and
- for each d‘∈T‘ and each d‘‘∉T‘: θ *score(q,d‘) ≥ score(q,d‘‘)

Modified TA:

...
Stop when $\boldsymbol{min_k \geq aggr(high_1, ..., high_m) / \theta}$

Pruning and Access Ordering Heuristics

General heuristics:

- disregard index lists with idf below threshold
- for index scans give priority to index lists
  that are short and have high idf

3.2.1 Pruning with Similarity Scoring (Moffat/Zobel 1996)

Focus on scoring of the form $score(q,d_j) = \sum_{i=1}^{m} s_i(t_i,d_j)$

with $s_i(t_i,d_j) = tf(t_i,d_j) \cdot idf(t_i) \cdot idl(d_j)$

Implementation based on a hash array of ***accumulators***
for summing up the partial scores of candidate results

quit heuristics
(with doc-id-ordered or tf-ordered or tf*idl-ordered index lists):

- ignore index list L(i) if idf(ti) is below threshold or
- stop scanning L(i) if idf(ti)*tf(ti,dj)*idl(dj) drops below threshold or
- stop scanning L(i) when the number of accumulators is too high

continue heuristics:

upon reaching threshold, continue scanning index lists,
but do not add any new documents to the accumulator array

Greedy QP

Assume index lists are sorted by tf(ti,dj) (or tf(ti,dj)*idl(dj)) values

Open scan cursors on all m index lists L(i)

Repeat

Find pos(g) among current cursor positions pos(i) (i=1..m)

with the largest value of idf(ti)*tf(ti,dj)

(or idf(ti)*tf(ti,dj)*idl(dj));

Update the accumulator of the corresponding doc;

Increment pos(g);

Until stopping condition

3.2.2 Pruning with Combined Authority/Similarity Scoring (Long/Suel 2003)

Focus on **score(q,dj) = r(dj) + s(q,dj)**

with normalization r(·) ≤ a, s(·) ≤ b (and often a+b=1)

Keep index lists sorted in **descending order of „static" authority r(dj)**

Conservative authority-based pruning:

high(0) := max{r(pos(i)) | i=1..m}; high := high(0) + b;

high(i) := r(pos(i)) + b;

stop scanning i-th index list when high(i) < min score of top k

terminate algorithm when high < min score of top k

effective when total score of top-k results is dominated by r

First-k' heuristics:

scan all m index lists until k' ≥ k docs have been found

that appear in all lists;

the stopping condition is easy to check because of the sorting by r

Separating Documents with Large s_i Values

Idea (Google):
in addition to the full index lists L(i) sorted by r,
keep short ***„fancy lists"*** F(i) that contain the docs dj
with the highest values of si(ti,dj) and sort these by r

Fancy first-k' heuristics:
Compute total score for all docs in $\cap$ F(i) (i=1..m)
and keep top-k results;
Cand := $\cup_i$ F(i) $- \cap_i$ F(i);
for each dj $\in$ Cand do {compute partial score of dj};
Scan full index lists L(i) (i=1..k);
if pos(i) $\in$ Cand
{add s_i(ti,pos(i)) to partial score of pos(i)}
else {add pos(i) to Cand and set its partial score to s_i(ti,pos(i))};
Terminate the scan when k' docs
have a completely computed total score;

Authority-based Pruning with Fancy Lists

Guarantee that the top k results are complete by
extending the fancy first-k' heuristics as follows:

stop scanning the i-th index list L(i) not after k' results,
but only when we know that no imcompletely scored doc
can qualify itself for the top k results

Maintain:

r_high(i) := r(pos(i))
s_high(i) := max{si(q,dj) | dj $\in$ L(i) – F(i)}

Scan index lists L(i) and accumulate partial scores for all docs dj
Stop scanning L(i) iff

r_high(i) + Σ_i s_high(i) < min{score(d) | d $\in$ current top-k results}

Probabilistic Pruning

Idea:

Maintain statistics about the distribution of si values

For pos(i)

estimate the probability p(i) that the rest of L(i) contains a doc d for which the si score is so high that d qualifies for the top k results

Stop scanning L(i) if p(i) drops below some threshold

Simple „approximation“ by the ***last-l heuristics***:

stop scanning when the number of docs in $\cup_i F(i) - \cap_i F(i)$ with incompletely computed score drops below l (e.g., l=10 or 100)

Performance Experiments

Setup:

index lists for 120 Mio. Web pages distributed over 16 PCs
(and stored in BerkeleyDB databases)

query evaluation iterated over many sample queries
with different degrees of concurrency (multiprogramming levels)

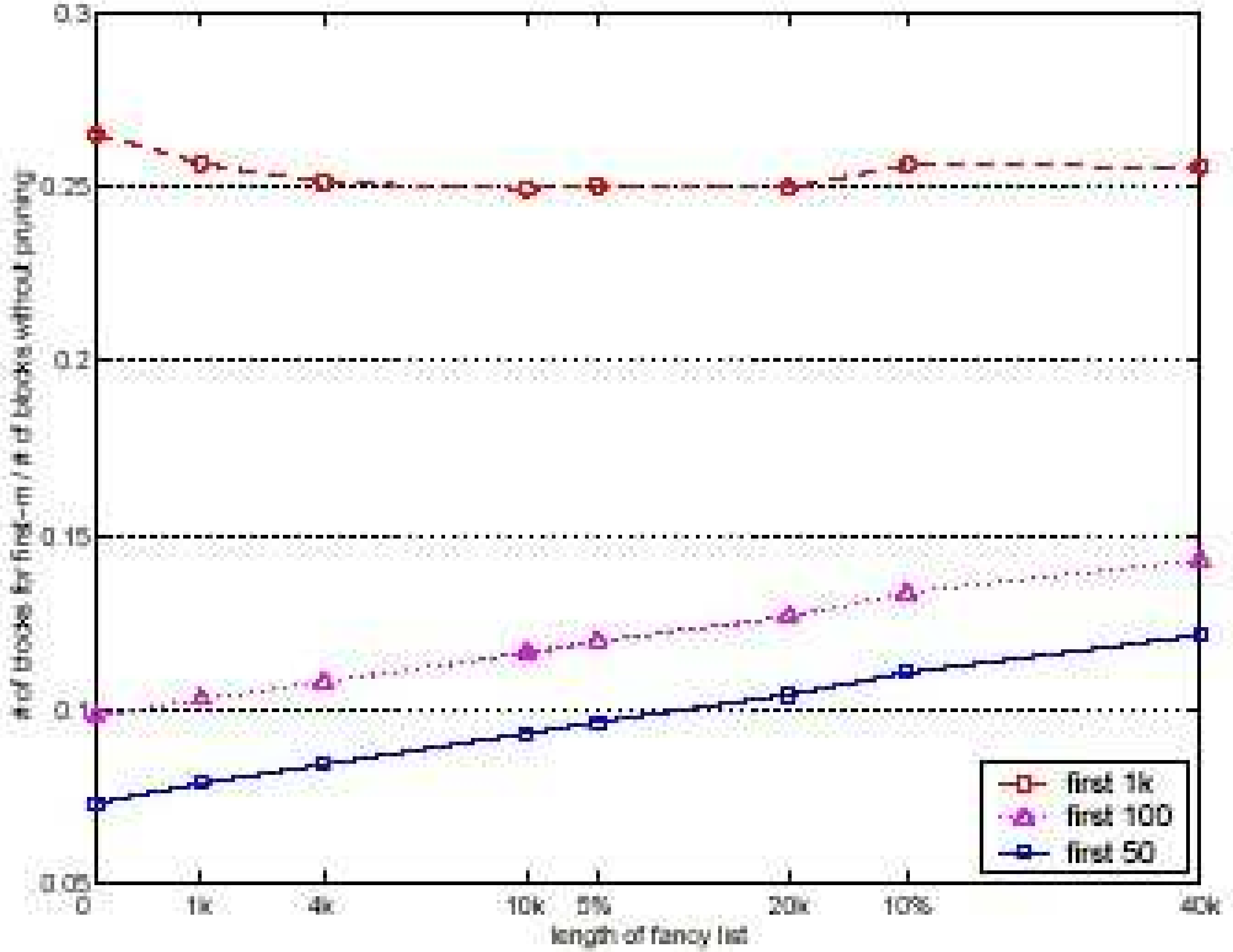
Evaluation measures:

- query throughput [queries/second]
- average query response time [seconds]
- error for pruning heuristics:

  strict-k error: fraction of queries for which the top k were not exact

  loose-k error: fraction of top k results that do not belong to true top k

Performance Experiments: Fancy First-k'



from: X. Long, T. Suel, Optimized Query Execution in Large Search Engines with Global Page Ordering, VLDB 2003

Performance Experiments: Fancy First-k’

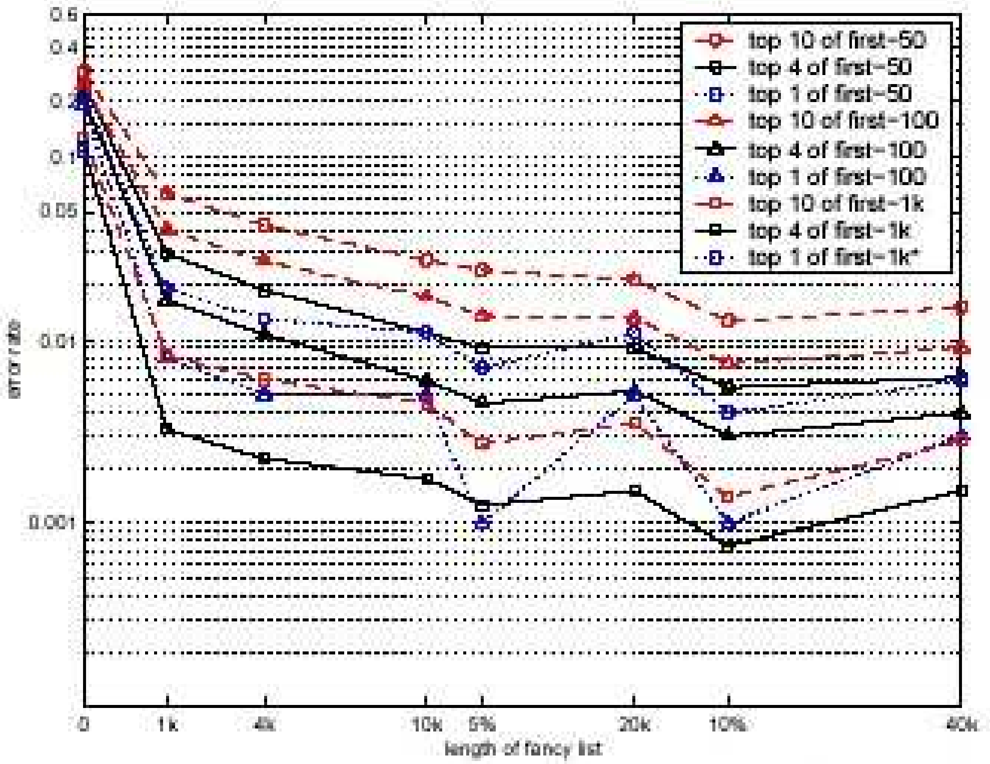


Figure 6.6: Error rate for loose-k measure, for different values of m and k, and different lengths of the fancy lists.

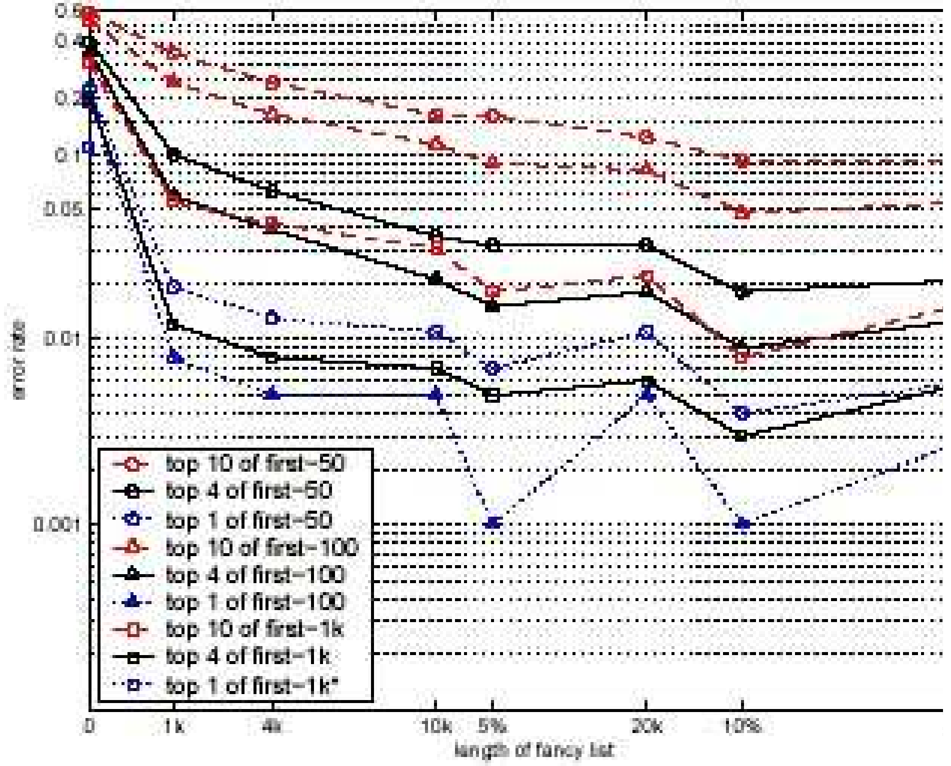


Figure 6.7: Error rate for strict-k measure, for diffe values of m and k, and different lengths of the fancy lis

from: X. Long, T. Suel, Optimized Query Execution in Large Search Engines with Global Page Ordering, VLDB 2003

Performance Experiments: Authority-based Pruning with Fancy Lists

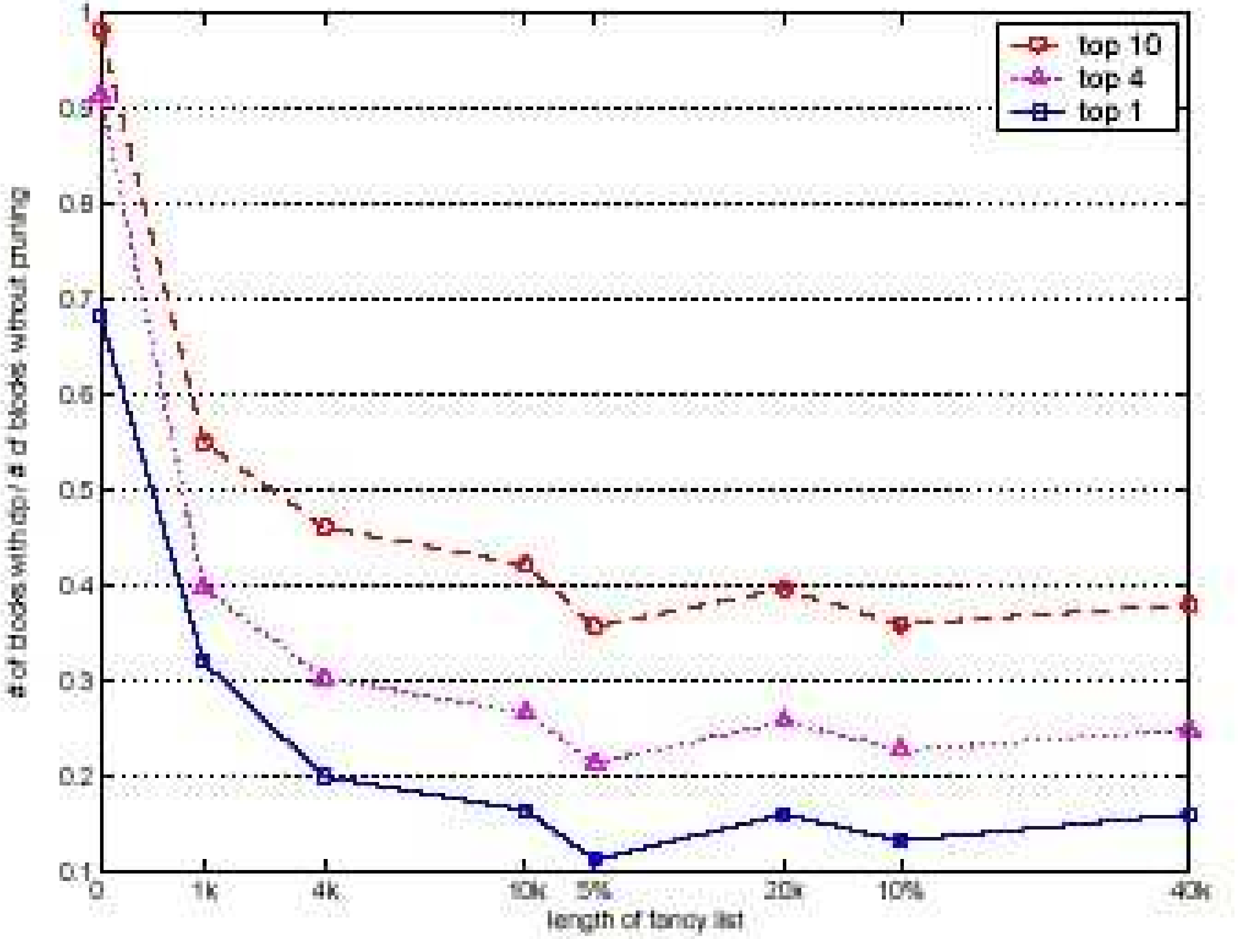


Figure 6.8: Ratio of the number of blocks accessed by reliable pruning and the baseline scheme, for different k and different lengths of the fancy lists.

from: X. Long, T. Suel, Optimized Query Execution in Large Search Engines with Global Page Ordering, VLDB 2003

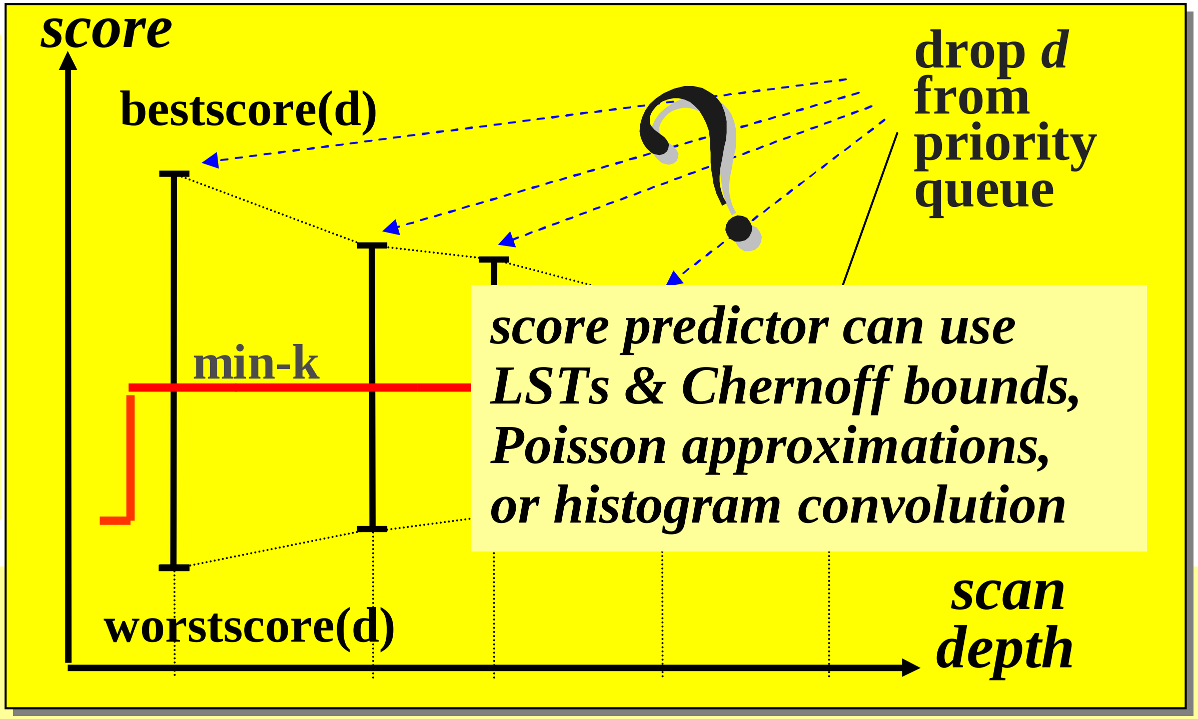
3.2.3 Approximate Top-k with Probabilistic Pruning

TA family of algorithms based on invariant (with sum as aggr):

$$\underbrace{\sum_{i \in E(d)} s_i(d)}_{\text{worstscore(d)}} \le s(d) \le \underbrace{\sum_{i \in E(d)} s_i(d) + \sum_{i \notin E(d)} high_i}_{\text{bestscore(d)}}$$

- **Add *d* to top-k result, if *worstscore(d)* > *min-k***
- **Drop *d* only if *bestscore(d)* < *min-k*, otherwise keep in PQ**

→ Often overly conservative (deep scans, high memory for PQ)



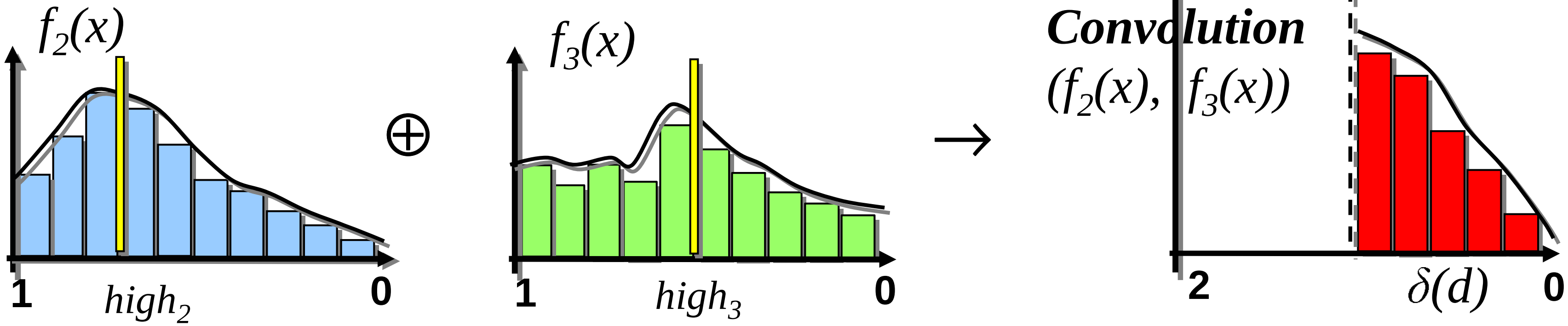
→ Approximate top-k with probabilistic guarantees:

$$p(d) := P\left[\sum_{i \in E(d)} s_i(d) + \sum_{i \notin E(d)} S_i > \delta\right]$$

discard candidates d from queue if p(d) ≤ ε ⇒ E[rel. precision@k] = 1–ε

Probabilistic Threshold Test

cand doc d
with
$2 \notin E(d)$,
$3 \notin E(d)$



- **postulating *uniform or Zipf* score distribution in [0, high$_i$]**
  - **compute convolution using LSTs**
  - **use Chernoff-Hoeffding tail bounds or generalized bounds for correlated dimensions (Siegel 1995)**
- **fitting *Poisson* distribution (or Poisson mixture)**
  - **over equidistant values:** $P[d = v_j] = e^{-\alpha_i} \frac{\alpha_i^{\,j-1}}{(j-1)!}$
  - **easy and exact convolution**
- **distribution approximated by *histograms*:**
  - **precomputed for each dimension**
  - **dynamic convolution at query-execution time**

engineering-wise histograms work best!

Coping with Convolutions

via moment-generation function for arbitray independent RV's, including heterogeneous combinations of distributions

$$F_{X+Y}(z) = \int_0^z f_X(x) F_Y(z-x)\,dx \qquad M_{X+Y}(s) = M_X(s) M_Y(s)$$

$$M_X(s) = \int_0^\infty e^{sx} f_X(x)\,dx = E[e^{sX}]$$

Chernoff-Hoeffding bound: $P[X \geq t] \leq \inf\left\{ e^{-\theta t} M_X(\theta) \mid \theta \geq 0 \right\}$

for dependent RV's

generalized Chernoff-Hoeffding bounds *(Alan Siegel 1995):*

consider X = X1 + ... + Xm with dependent RV's Xi
consider Y = Y1 + ... + Ym with independent RV's Yi such that Yi has the same distribution as (the marginal distr. of) Xi

if Bi is a Chernoff bound for Yi, i.e., $P[\,Yi \geq \delta_i\,] \leq B_i$ then

$$P[X \geq \delta] \leq \inf\left\{ \max\{B_1, \ldots, B_m\} \mid \delta_1 + \ldots + \delta_m = \delta \right\}$$

(e.g., with the δ_i values chosen proportional to the high_i values)

Prob-sorted Algorithm (Conservative Variant)

Prob-sorted (RebuildPeriod r, QueueBound b):

...

scan all lists Li (i=1..m) in pa

…same code as TA-sorted…

Probabilistic Guarantees:

E[relative precision @ k] = 1-ε

E[relative recall @ k] = 1-ε

```
// queue management (one queue for each possible set E(d))
  for all priority queues q for which d is relevant do
      insert d into q with priority bestscore(d);
  // periodic clean-up
  if step-number mod r = 0 then
      // rebuild; multiple queues
      if strategy = Conservative then
          for all queue elements e in q do
              update bestscore(e) with current high_i values;
          rebuild bounded queue with best b elements;
          if prob[top(q) can qualify for top-k] < ε
          then drop all candidates from this queue q;
  if all queues are empty then exit;
```

Prob-sorted Algorithm (Smart Variant)

```
Prob-sorted (RebuildPeriod r, QueueBound b):
...
scan all lists Li (i=1..m) in parallel:
   …same code as TA-sorted…

 // queue management (one global queue)
   for all priority queues q for which d is relevant do
        insert d into q with priority bestscore(d);
   // periodic clean-up
   if step-number mod r = 0 then
        // rebuild; single bounded queue
        if strategy = Smart then
            for all queue elements e in q do
               update bestscore(e) with current high_i values;
            rebuild bounded queue with best b elements;
            if prob[top(q) can qualify for top-k] < ε then exit;
   if all queues are empty then exit;
```

Performance Results for .Gov Queries

on .GOV corpus from TREC-12 Web track:
1.25 Mio. docs (html, pdf, etc.)

50 keyword queries, e.g.:

- ***„Lewis Clark expedition“,***
- ***„juvenile delinquency“,***
- ***„legalization Marihuana“,***
- ***„air bag safety reducing injuries death facts“***

speedup by factor 10 at high precision/recall (relative to TA-sorted);

aggressive queue mgt. even yields factor 100 at 30-50 % prec./recall

	TA-sorted	Prob-sorted (smart)
#sorted accesses	2,263,652	527,980
elapsed time [s]	148.7	15.9
max queue size	10849	400
relative recall	1	0.69
rank distance	0	39.5
score error	0	0.031

Performance Results for .Gov Expanded Queries

on .GOV corpus with query expansion based on WordNet synonyms:

50 keyword queries, e.g.:

- **„juvenile delinquency *youth minor crime law jurisdiction offense prevention*“,**
- **„legalization marijuana *cannabis drug soft leaves plant smoked chewed euphoric abuse substance possession control pot grass dope weed smoke*“**

	TA-sorted	Prob-sorted (smart)
#sorted accesses	22,403,490	18,287,636
elapsed time [s]	7908	1066
max queue size	70896	400
relative recall	1	0.88
rank distance	0	14.5
score error	0	0.035

Performance Results for IMDB Queries

on IMDB corpus (Web site: Internet Movie Database):

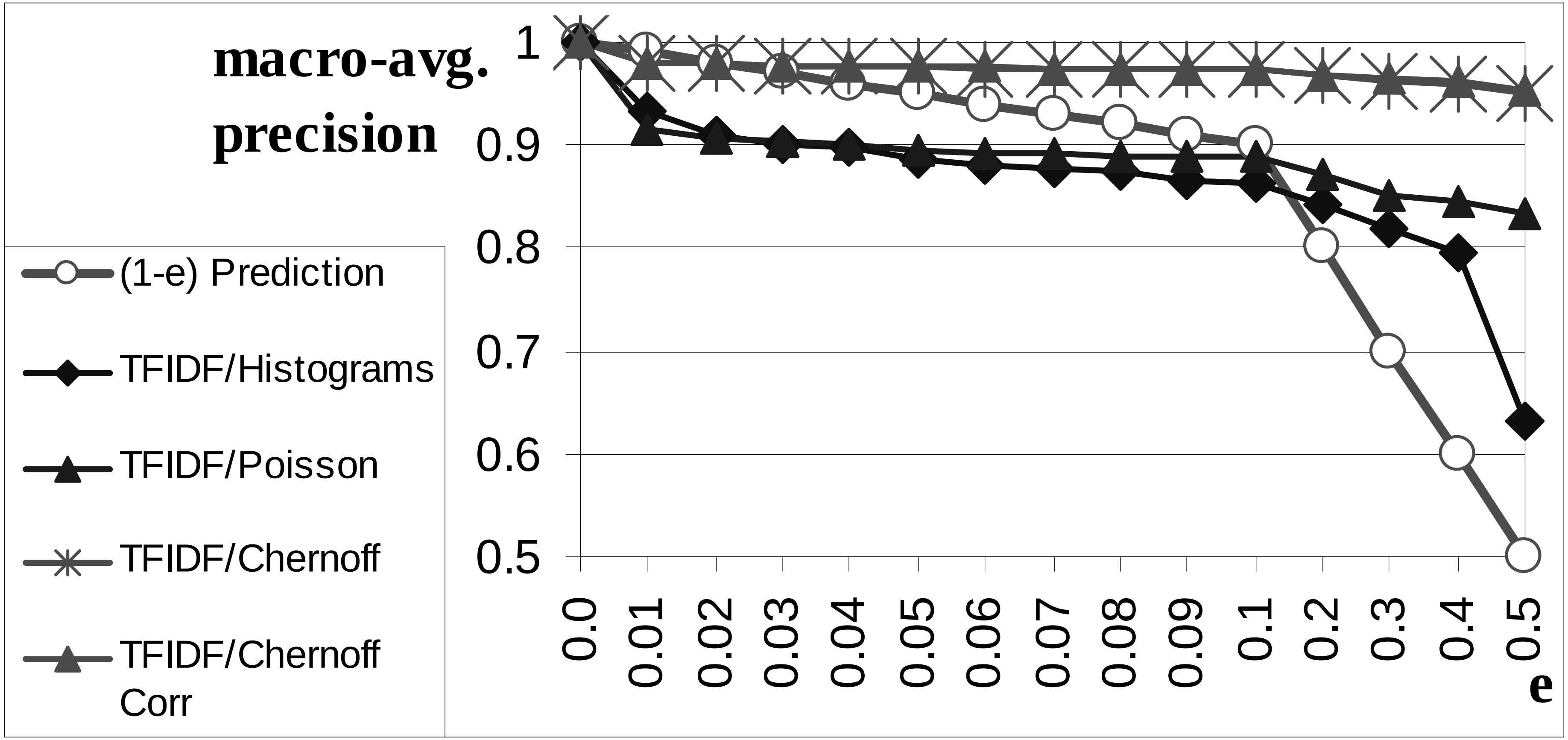
375 000 movies, 1.2 Mio. persons (html/xml)

20 structured/text queries with Dice-coefficient-based similarities of categorical attributes Genre and Actor, e.g.:

- ***Genre*** $\supseteq$ ***{Western}*** $\wedge$ ***Actor*** $\supseteq$ ***{John Wayne, Katherine Hepburn}***
  $\wedge$ ***Description*** $\supseteq$ ***{sheriff, marshall},***
- ***Genre*** $\supseteq$ ***{Thriller}*** $\wedge$ ***Actor*** $\supseteq$ ***{Arnold Schwarzenegger}***
  $\wedge$ ***Description*** $\supseteq$ ***{robot}***

	TA-sorted	Prob-sorted (smart)
#sorted accesses	1,003,650	403,981
elapsed time [s]	201.9	12.7
max queue size	12628	400
relative recall	1	0.75
rank distance	0	126.7
score error	0	0.25

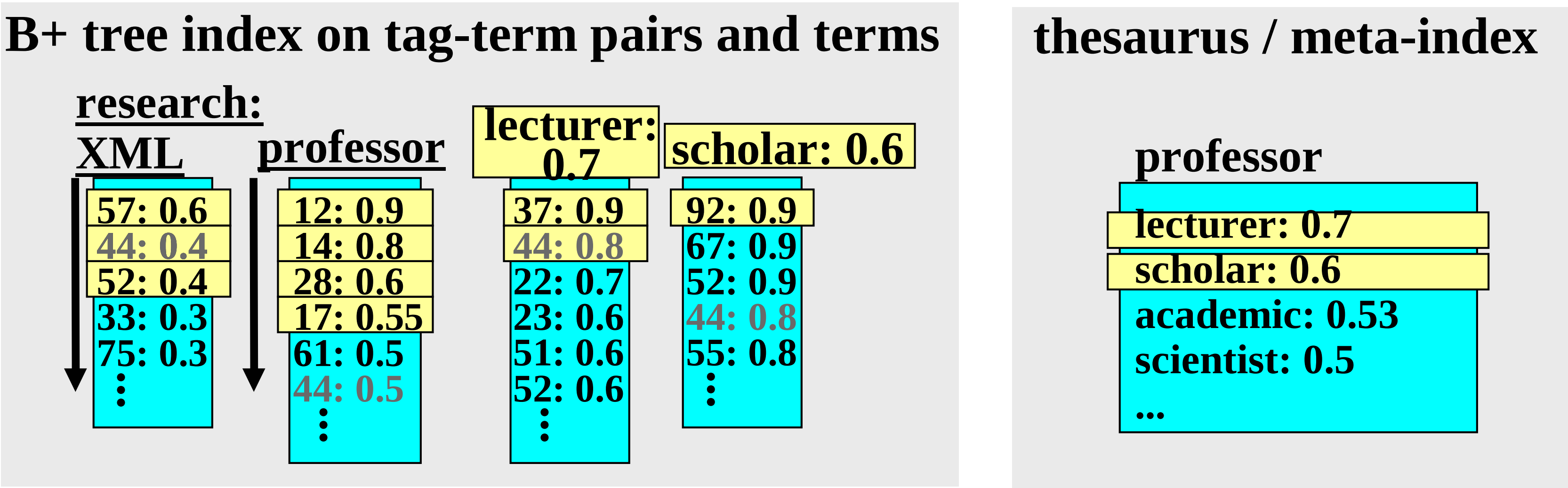
Comparison of Probabilistic Predictors



Top-k Queries with Query Expansion

consider expandable query „*~professor and research = XML*“
with score $\Sigma_{i \in q} \{\max_{j \in exp(i)} \{ sim(i,j)*s_j(d) \}\}$

dynamic query expansion with
incremental on-demand merging of additional index lists



+ much more efficient than threshold-based expansion
+ no threshold tuning
+ no topic drift

Experiments with TREC-13 Robust Track

on Acquaint corpus (news articles):
528 000 docs, 2 GB raw data, 8 GB for all indexes

50 most difficult queries, e.g.:
„transportation tunnel disasters"
„Hubble telescope achievements"
potentially expanded into:
„earthquake, flood, wind, seismology, accident, car, auto, train, ..."
„astronomical, electromagnetic radiation, cosmic source, nebulae, ..."

speedup by factor 4 at high precision/recall;
no topic drift, no need for threshold tuning;
also handles TREC-13 Terabyte benchmark

	no exp. (ε=0.1)	static exp. (θ=0.3, ε=0.0)	static exp. (θ=0.3, ε=0.1)	incr. merge (ε=0.1)
#sorted acc.	1,333,756	10,586,175	3,622,686	5,671,493
#random acc.	0	555,176	49,783	34,895
elapsed time [s]	9.3	156.6	79.6	43.8
max #terms	4	59	59	59
relative recall	0.934	1.0	0.541	0.786
precision@10	0.248	0.286	0.238	0.298
MAP@1000	0.091	0.111	0.086	0.110

with Okapi BM25 scoring model

Additional Literature for Chapter 3

Top-k Query Processing:

- Grossman/Frieder Chapter 5
- Witten/Moffat/Bell, Chapters 3-4
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- S. Nepal, M.V. Ramakrishna: Query Processing Issues in Image (Multimedia) Databases, ICDE 1999
- U. Guentzer, W.-T. Balke, W. Kiessling: Optimizing Multi-FeatureQueries in Image Databases, VLDB 2000
- C. Buckley, A.F. Lewit: Optimization of Inverted Vector Searches, SIGIR 1985
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- M. Theobald, R. Schenkel, G. Weikum: Efficient and Self-Tuning Incremental Query Expansion for Top-k Query Processing, SIGIR 2005
- X. Long, T. Suel: Optimized Query Execution in Large Search Engines with Global Page Ordering, VLDB 2003
- A. Marian, N. Bruno, L. Gravano: Evaluating Top-k Queries over Web-Accessible Databases, TODS 29(2), 2004