Discovering and Exploiting Keyword and Attribute-Value Co-occurrences to Improve P2P Routing Indices

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Outline

1. Motivation
2. Minerva
3. Problem Statement
4. Our Approaches
5. Experiments
6. Conclusion

P2P Systems

Became famous through file-sharing applications, like Gnutella, KaZAA, Napster.
Applications like:

- Internet telephony (e.g. Skype)
- Filesharing
- Pub/Sub

Question:

Is there an interesting and legal P2P application?

Motivation

Why P2P Web Search?

- Benefit from intellectual input from a large user community. (Bookmarks, click-streams, ...)
- Break information monopolies
- Coverage of the web
- Exploit mostly idle resources

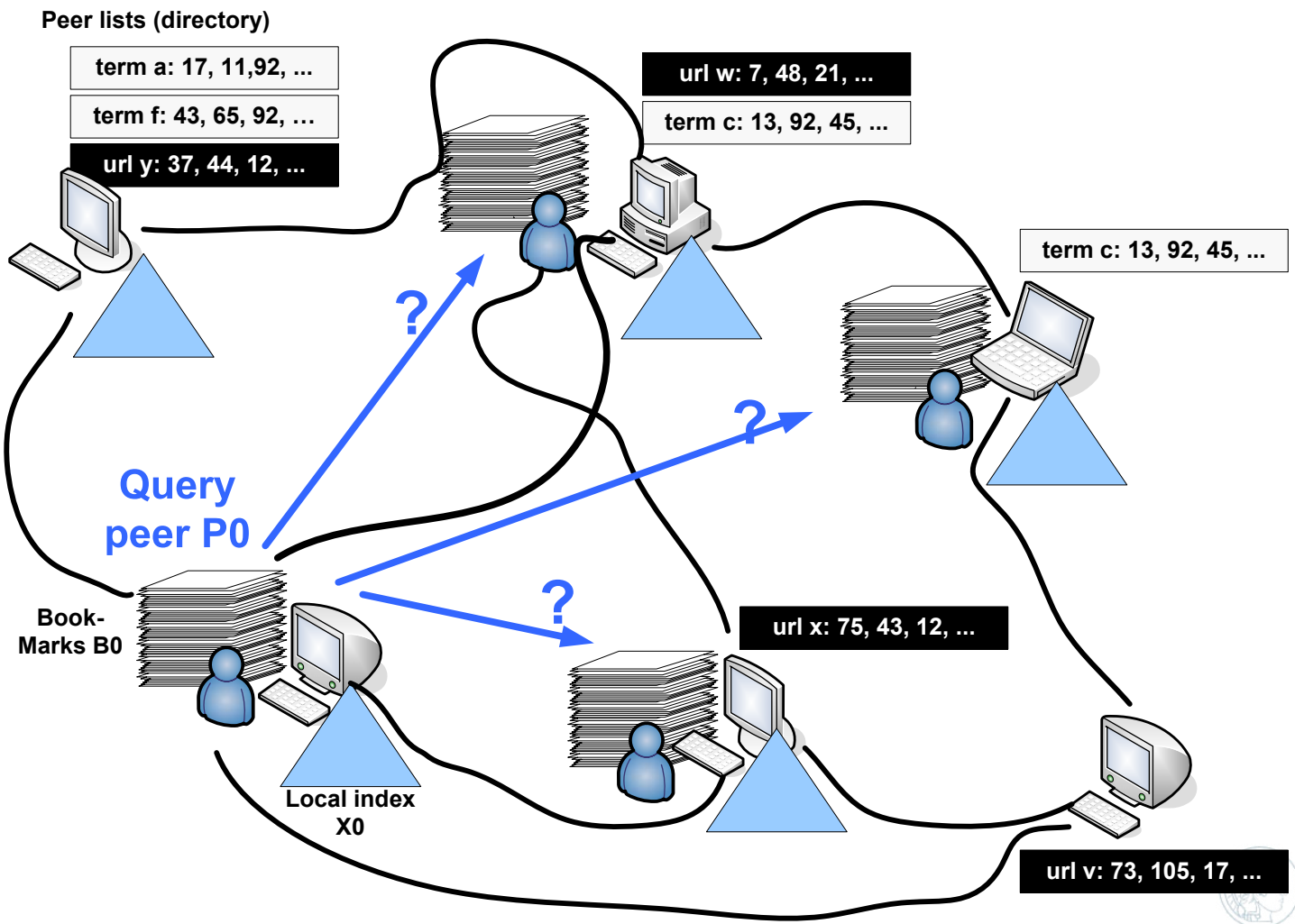
Related to distributed IR, but some additional aspects

- high dynamics
- each peer has its own collection
- peers are independently crawling the web

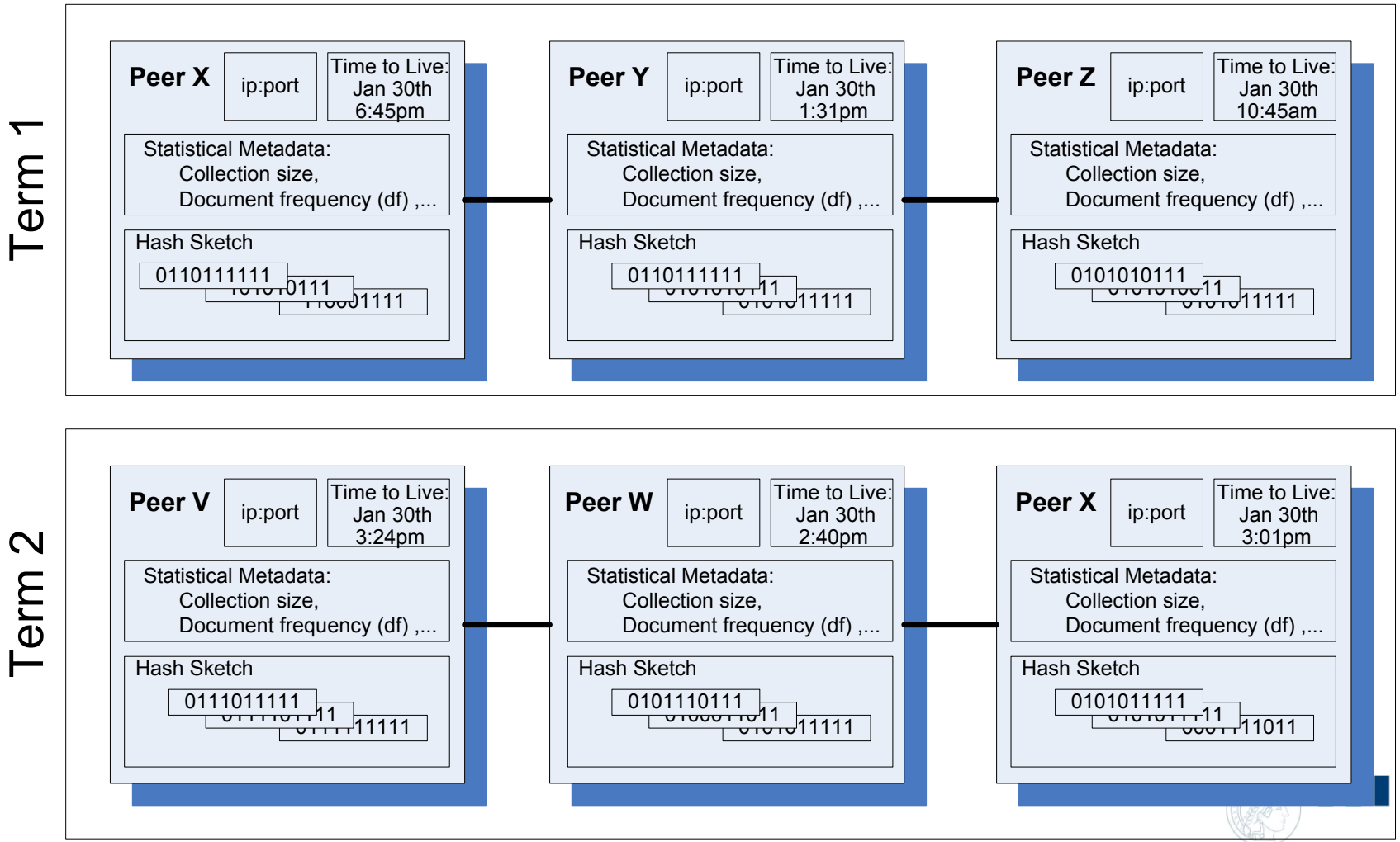
Minerva Design Fundamentals

- Peers with local collections, e.g., built by focused crawler. Tailored to the users' specific interest profiles.
- Peers share metadata about local indexes
- Form physically distributed *term* $\rightarrow$ *peer* directory
- Layered on top of DHT
- Peers use directory to discover promising peers for query

Minerva System Architecture



Inside Peerlists ...



Problem Statement

Consider (conjunctive) query a $\wedge$ b

- State-of-the-art: Identify promising peers on *per-key* statistics
  $\Rightarrow$ good peers for a, b **separately** - but how about $a \wedge b$?

Can go arbitrarily wrong:

A peer good for *American politics* and *classical music* might not have a single relevant data item about (American $\wedge$ music).
$\Rightarrow$ **Multi-key necessary for meaningful peer selection**

Contribution: Two detailed approaches:

- estimate statistics $s(a \wedge b)$ from **s**ingle-**k**ey statistics $s(a)$, $s(b)$
- provide explicit **m**ulti-**k**ey statistics $s(a \wedge b)$

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sk-STAT

Goal: estimate contribution of peer p_i from single-key statistics $s_i(a)$, $s_i(b)$

Idea:

- enrich $s_i(a)$, $s_i(b)$ with suitable statistical summaries
- use statistical summaries to estimate $s_i(a \wedge b)$

Suitable Synopses?

- need to describe p_i's items containing a
- need to support conceptual intersection
  - which items are contained in both $s(a)$ **and** $s(b)$?
- needs to be compact (limited bandwidth)

Hash Sketches

Estimate #distinct elements in multiset $D = \{d_1, ...d_n\}$, $|D|_{dist}$

General Idea:

- apply hash function h to every d_i
- record positions of least-significant 1-bits in a bitmap vector V

Intuition:

- $V[0]$ is set by appr. $\frac{1}{2}$ of the items, $V[1]$ by $\frac{1}{4}$, ...

$\Rightarrow$ Position of most-significant 1-bit estimates $log(|D|_{dist})$

Using Hash Sketches

Distributivity Theorem

Let $V(A)$, $V(B)$ be bitmap vectors representing sets A, B. Then $V(A \cup B) = V(A)|V(B)$ (bit-wise OR).
$\Rightarrow$ Estimator for $|A \cup B|_{dist}$

But how to estimate $|A \cap B|_{dist}$?

- No obvious way to *directly* intersect hash sketches.

Instead:

- use estimator for $|A \cup B|_{dist}$
- $|A \cap B|_{dist} = |A|_{dist} + |B|_{dist} - |A \cup B|_{dist}$

Note:

Estimates $|A \cap B|_{dist}$, but not $V(A \cap B)$

sk-STAT

Algorithm

- Enrich $s_i(a)$ with $HS_i(a)$
- For query a∧b: retrieve $s_i(a)$, $s_i(b)$, estimate p_i's contribution for $a \wedge b$
- [combine with other indicators of expected quality / novelty]

\+ readily perform estimation for *all* key sets

\+ no additional statistics required

\- high network traffic (transfer *HS* for large number of peers)

\- limited accuracy

\- unavailability of $HS(a \wedge b)$

mk-STAT

Goal: Use explicit multi-key statistics for carefully selected key sets

Necessary Steps:

- *Discover* candidate key sets
- *Assess* degree of correlation for candidate key sets
- *Notify* peers to *generate and disseminate* explicit statistics
- *Leverage* additional statistics for peer selection process

Measure of Key Correlation

Our approach: Consider **Conditional Probability** $P(a|b)$

- $P(a|b) = \frac{df(a \wedge b)/|D|_{dist}}{df(b)/|D|_{dist}} = \frac{df(a \wedge b)}{df(b)}$

  $\Rightarrow$ Estimation without knowledge of $|D|$

- Captures existing asymmetry:

Key a	**Key** b	$P(a\|b)$	$P(b\|a)$
andy	roddick	0.5106	0.0216
anna	kournikova	0.9613	0.0655
berlin	marathon	0.0611	0.0126

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mk-STAT: Query-driven Key Set Discovery

Limit Discovery of Interesting Key Sets to Query Logs

Key set is beneficial only if it is frequently queried (*support*) and if its keys coincide in a certain fraction of occurrences (*confidence*)
$\Rightarrow$ **Highly correlated** key sets are of interest

Efficient piggybacking onto existing communication:

- include *complete query* when retrieving $s(a)$ from $p(a)$
  $\Rightarrow$ $p(a)$ sees all queries containing a
- $p(a)$ performs query log analysis to discover candidate key sets

mk-STAT: Data-driven Assessment

Assess relatedness based on data

Flawed intuition: Pick key pairs with correlation *above* threshold

- For queries with highly correlated keys, e.g., Anna Kournikova, it is sufficient to find good peers for Kournikova alone

$\Rightarrow$ **Hardly correlated** key sets benefit from extra information

Efficient assessment:

- $p(a)$ retrieves $HS(b)$ from $p(b)$ (only *one* combined HS)
- estimates $P(a|b)$ and $P(b|a)$
- identifies key sets with *both* probabilities below threshold

mk-STAT: Notification and Statistics Dissemination

Notification of Peers

Use statistics refreshments to disseminate assessed key sets:

- When p_i publishes $s_i(a)$ to $p(a)$, $p(a)$ returns key set $(a \wedge b)$
- p_i can start to produce $s(a \wedge b)$

Where to store $s(a \wedge b)$?

1^{st} thought: identify $p(a \wedge b)$, typically: $p(a \wedge b) \neq p(a) \neq p(b)$

$\Rightarrow$ Load-balancing peers - but what about communication?!?

2^{nd} thought: Use $p(a)$, $p(b)$

$\Rightarrow$ contacted anyway, piggybacking to avoid extra messages

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mk-STAT: Enhanced Peer Selection

Remember: $s(a \wedge b)$ stored at $p(a)$, $p(b)$

- makes peer selection easy
- provides simple fall-back strategy

Enhanced Peer Selection Algorithm

For query $(a \wedge b)$, query initiator p_i:

- contact $p(a)$, $p(b)$ as usual
- if available, retrieve $s(a \wedge b)$, otherwise $s(a)$, $s(b)$
  - No need for p_i to know about existence of key set $(a \wedge b)$!
- [combine with other indicators of expected quality / novelty]

Experimental Setup

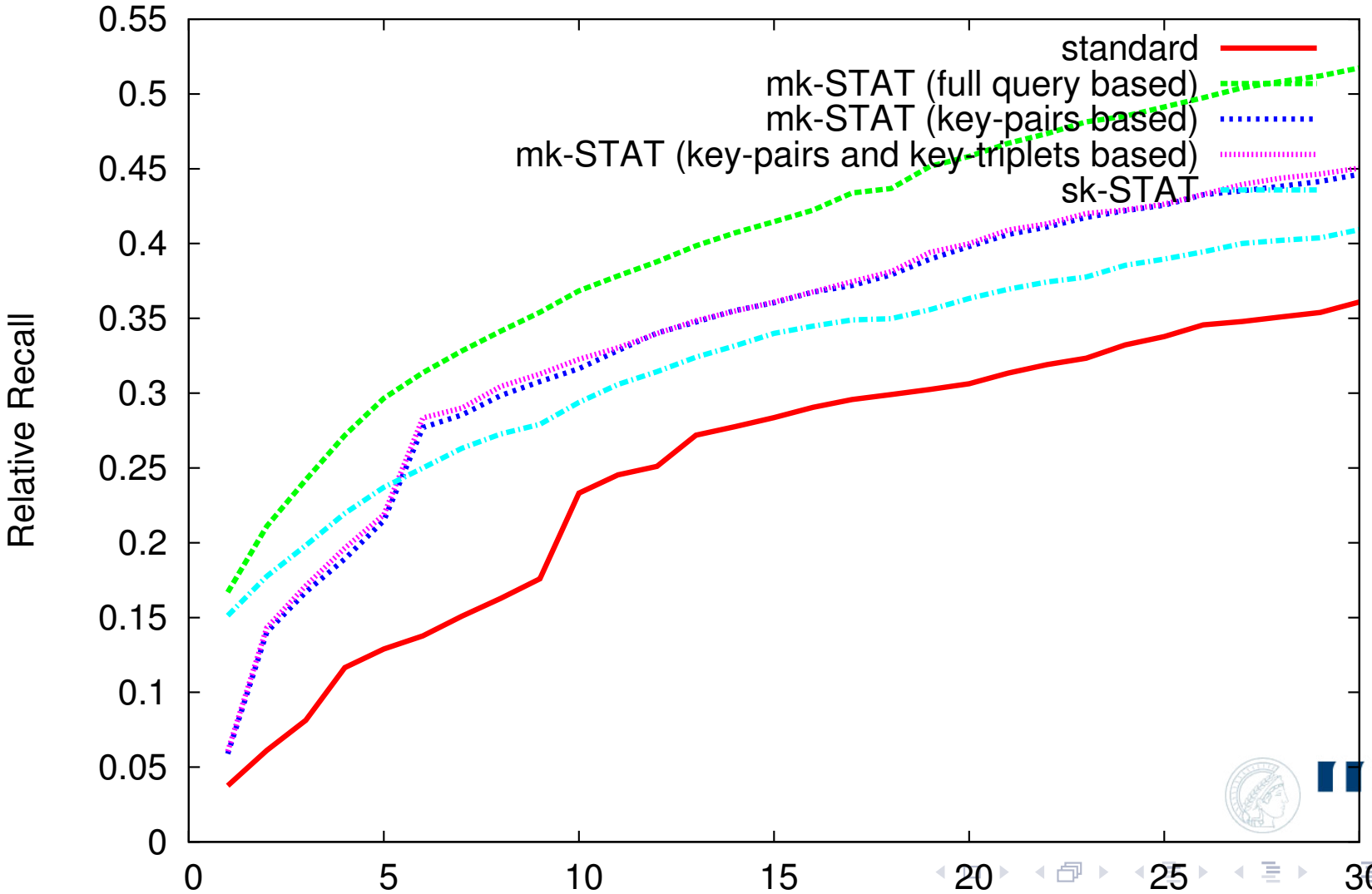
Gnutella Dataset:

- April 2003 crawl of Gnutella network
- $\sim$ 850,000 file descriptors, $\sim$ 4,000 user ids, 11,000+ queries
- Key set discovery: US top-40 single charts (April 12, 2003)
- Queries: All music-related queries from crawl
- Report *relative recall* averaged over *distinct* queries

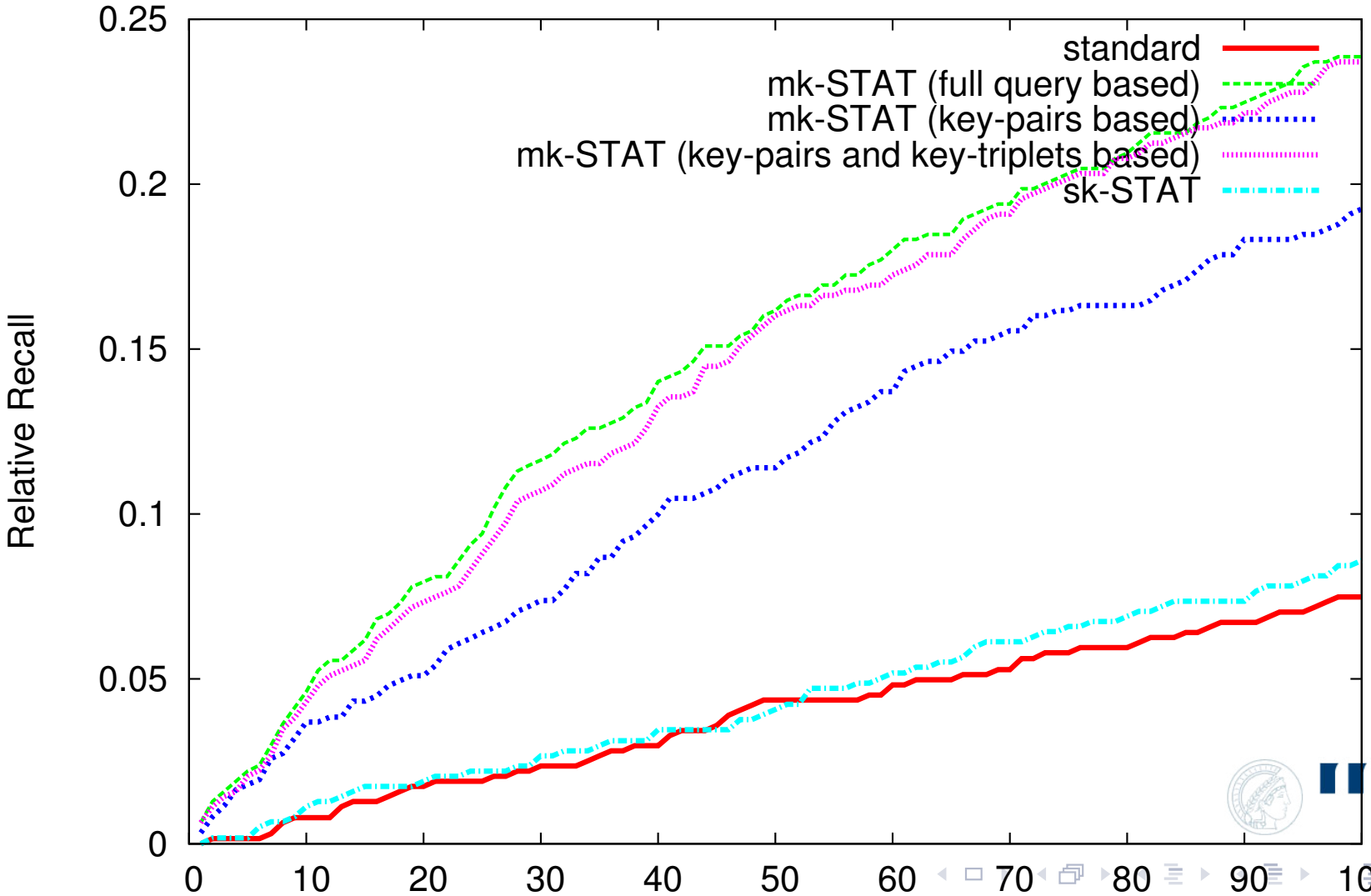
Web Dataset:

- .GOV collection (TREC benchmark), $\sim$ 1.2m documents
- randomly assign documents to 750 peers (*stress test!*)
- Queries: multi-term queries of TREC 2003 distillation track
- Report *relative recall*

Experimental Results: Gnutella Data



Experimental Results: Web Data



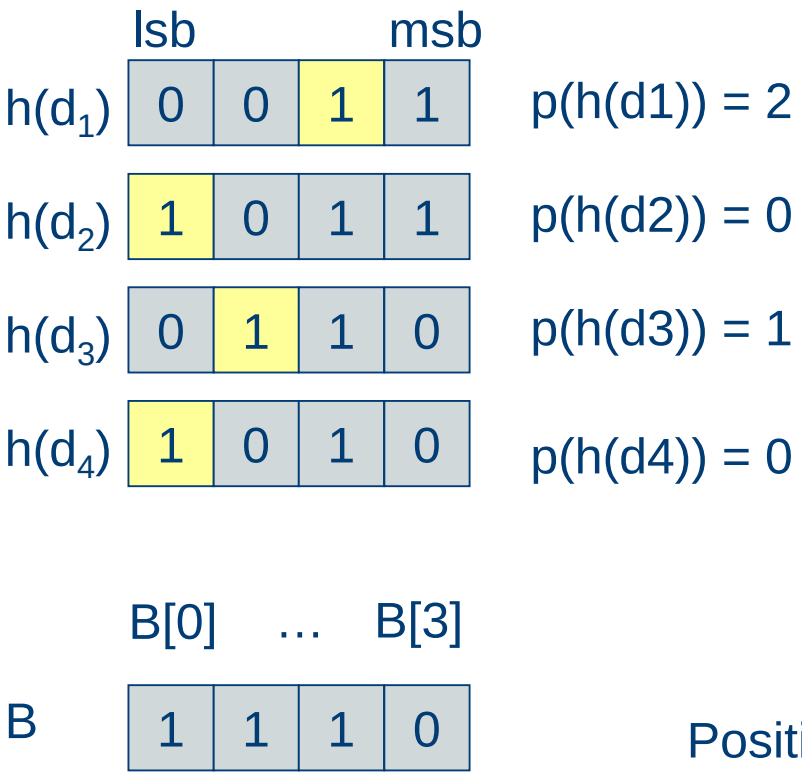
Conclusion

- Key co-occurrences benefical to peer selection
  - P2P Web Search
  - any other kind of attribute-value-style data
- sk-STAT: using existing single-key statistics
  - simple
  - versatile
  - limited accuracy
- mk-STAT: using explicit multi-key statistics
  - manageable extra effort
  - pays off

Thank You

Thank you for your attention.

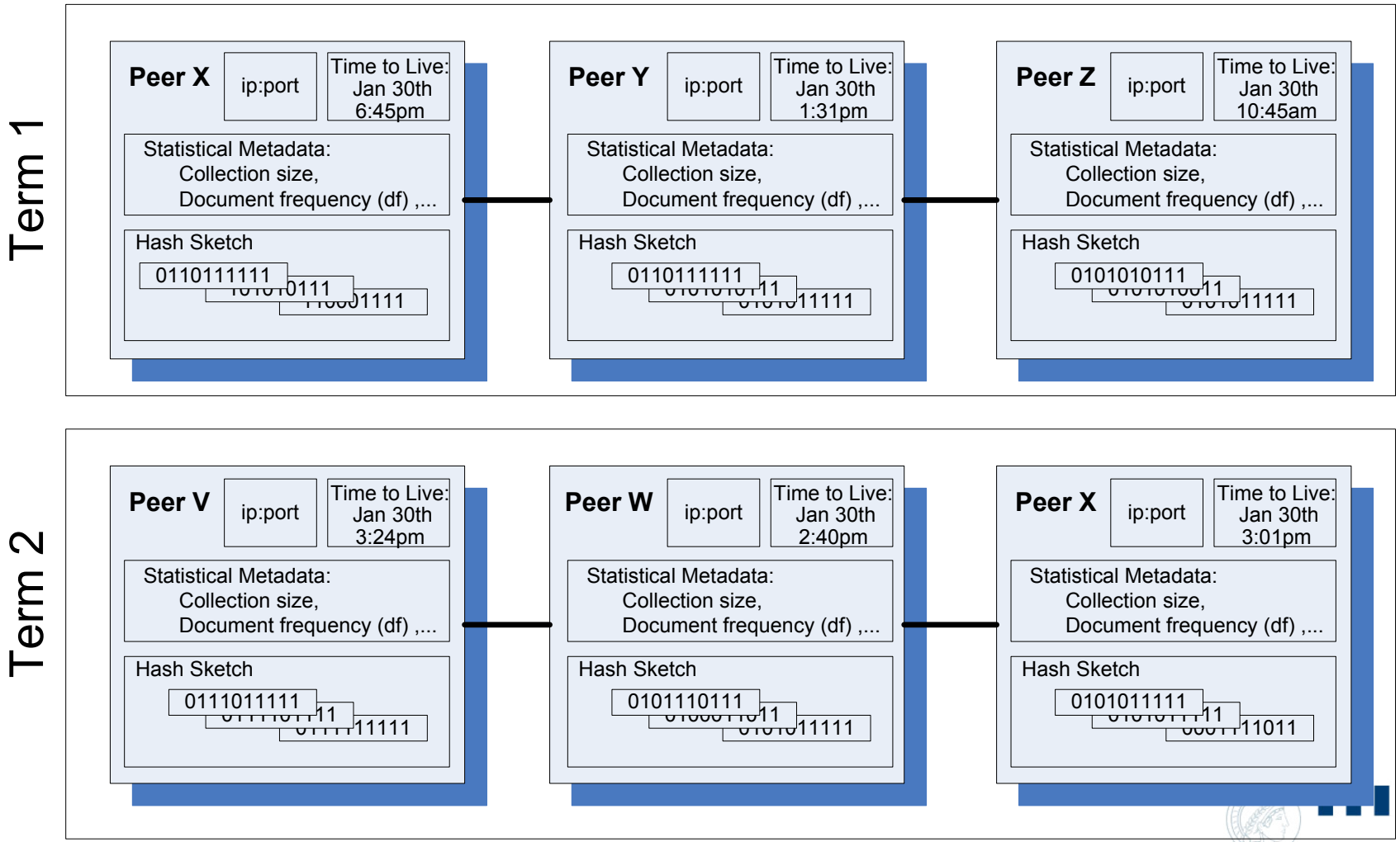
Hash Sketches Illustrated



Position of most-significant 1-bit of B: B[2]

Estimation for n: log(n) ~ 2 → n ~ 2^2 = 4

PeerLists


Term 1
Peer X
ip:port
Time to Live: Jan 30th 6:45pm
Statistical Metadata: Collection size, Document frequency (df) ,...
Hash Sketch
0110111111
Peer Y
ip:port
Time to Live: Jan 30th 1:31pm
Statistical Metadata: Collection size, Document frequency (df) ,...
Hash Sketch
0110111111
Peer Z
ip:port
Time to Live: Jan 30th 10:45am
Statistical Metadata: Collection size, Document frequency (df) ,...
Hash Sketch
0101010111
Term 2
Peer V
ip:port
Time to Live: Jan 30th 3:24pm
Statistical Metadata: Collection size, Document frequency (df) ,...
Hash Sketch
0111011111
Peer W
ip:port
Time to Live: Jan 30th 2:40pm
Statistical Metadata: Collection size, Document frequency (df) ,...
Hash Sketch
0101110111
Peer X
ip:port
Time to Live: Jan 30th 3:01pm
Statistical Metadata: Collection size, Document frequency (df) ,...
Hash Sketch
0101011111

Distributed Hash Tables

Example: Chord

- Structured P2P overlay
- Map peers and keys to the same cyclic id space
- *lookup* method to find peer currently responsible for a key
- Naive Routing: Traverse successor links linearly
- Enhanced Routing: *Finger Tables* pointing to distant peers