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Prof. Dr. G. Weikum

Data Quality in Web Archiving

Marc Spaniol

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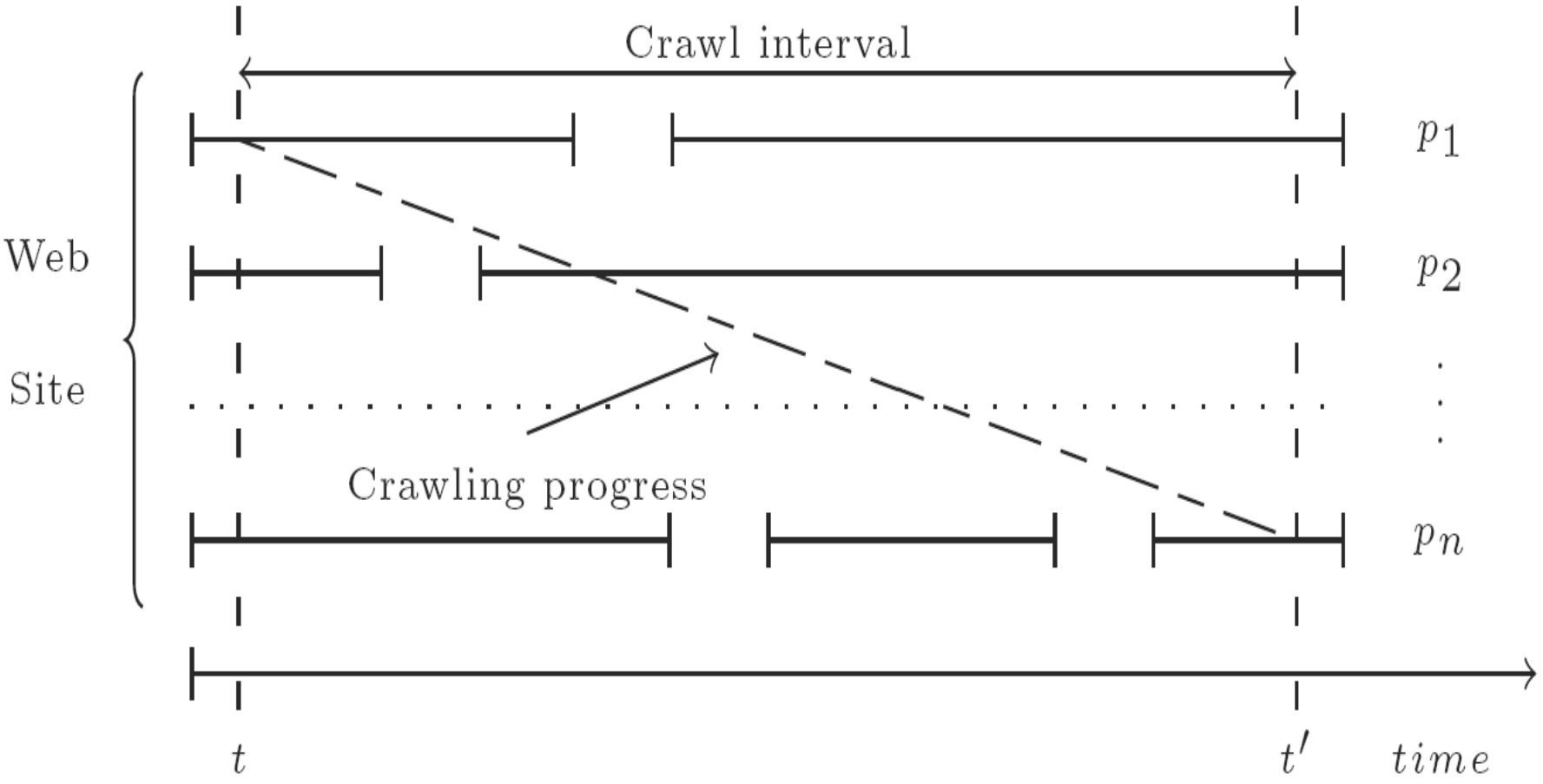
Agenda

- Motivation and problem statement
- Document similarity
  - Shingling
  - Minhashing
  - Locality-sensitive hashing
- Coherence framework
  - Coherence
  - Observable coherence
  - Measurable coherence
  - Inducible coherence
- Coherence improved capturing
  - Probability of (in-)coherence
  - Crawl scheduling
  - Experimental results
- Incoherence detection
- Summary

Motivation



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The Challenge of Archive Coherence

- Crawler operations
  - Visit (pages)
    - Extract (links from pages)
    - Compare (versions of pages)
  - Follow (links)

- Website operations
  - Modifications “inside” pages
    - Content (text)
    - Structure (links)
  - Modifications “inside” site
    - Page creation
    - Page deletion

Taking place in parallel

⇓

Potentially incoherent

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Potential Pitfalls in Web Archiving

- Crawling takes a long (!) time
  - Politeness
  - Multiple seeds per crawl
  - Spam
- Crawlers aren't "really" smart
  - Highly volatile against dynamics in CMS
  - Easy to be trapped, if not exactly configured
  - Doesn't recognize patterns of "identical" contents

  ⇒ Pre-analysis of site(s) needed
- Some examples of crawler behavior
  - Enjoy link generation from JavaScript, PHP, etc.
  - Tend to go for shopping
  - Like time travelling in calendars

⇒ Crawling is simply "unpredictable"
⇒ Crawlers need "constant" monitoring

⇒ Archive in Danger!

Smart(er) Crawling Strategies

Evaluation of Crawl Coherence

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Problem Statement

- What means coherence?
  - "The action or fact of cleaving or sticking together"
  - "Harmonious connexion of the several parts, so that the whole 'hangs together'"

Oxford English Dictionary [http://dictionary.oed.com]

- Temporal coherence in Web archiving:
  - Capturing Web sites as "authentic" as possible
  - Ensure an "as of time point x (or interval [x, y])" capture of a Web site

⇒ Periodic domain scope crawls of Web sites to obtain a best possible representation with respect to a time point / interval

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Measuring Crawl Coherence

- Online vs. offline
- Online coherence
  - "Memoryless"
  - Measures change at runtime
    - Evaluate coherence between crawl/revisit tuples
    - Evaluate coherence relative to begin of crawl
  - Identifies potential incoherence already at time of crawl
  - Covers a (minimum) interval / time-point of coherence
- Offline coherence
  - Utilizes existing domain knowledge
  - Measures change from the archive
  - Evaluates coherence between (any) captured tuples
  - May incorporate more sophisticated machine learning strategies
  - Helps to predict media specific change rates

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Incoherence Categories

- Removed contents
- Structural (changed link structure)
  - Links to new contents added
  - Links to removed contents deleted
- Content wise
  - Major changes: Text added or deleted (in “large” sections)
  - Minor changes: Text changed (in “small” sections)

$\Rightarrow$ Comparison of document similarities (syntactically not semantically)

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Document Similarity

- In general:
  - Given a body of documents, e.g., the Web
  - Find pairs of docs that have a lot of text in common
  - ⇒ Identify mirror sites, approximate mirrors, plagiarism, quotation of one document in another, “good” document with random spam, etc.

- In the case of data quality in Web archiving:
  - Characterize change (diff) between two versions of page
  - Identify relevant aspects of changes to web pages and sites
    - Content: full, – banners, – links, – photos, – style, etc.
    - Links: all, non-navigational, intra-site, etc.
  - Quantify the amount of changes
  - ⇒ Filtering of irrelevant changes

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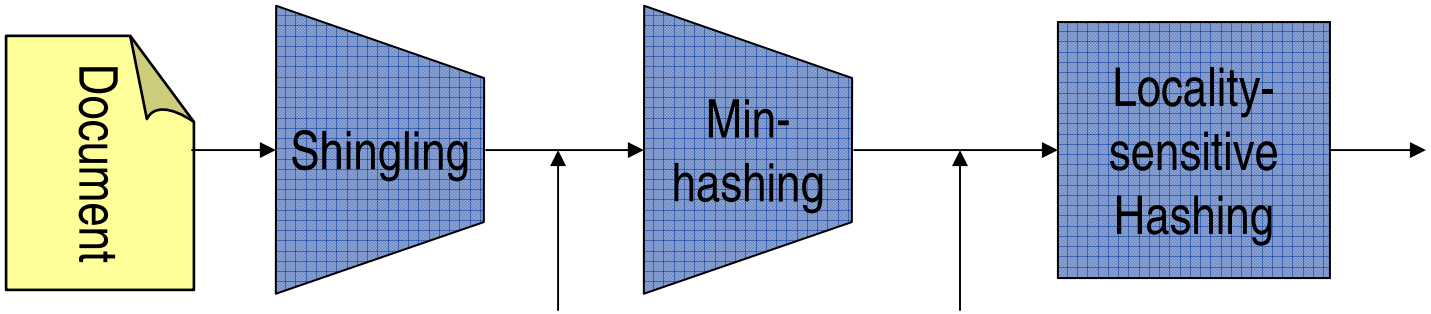
Basic Strategy



Candidate pairs: Those pairs of signatures that need to be tested for similarity

The set of strings of length *k* that appear in the document

Signatures: Short integer vectors that represent the sets, and reflect their similarity

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Shingles – k-grams

- Representation of a document by its set of shingles (or k-grams)
  - Documents that have lots of shingles in common have similar text
  - The text may even appear in different order

$\Rightarrow$ Similar documents are very likely to have many shingles in common

- Selection of k having a “useful” size is crucial:
  - If k is too small, documents might have too many shingles in common
  - If k is too large, compression is not good

- Heuristic experience:
  - k = 5 is OK for short documents
  - k = 10 is better for long documents

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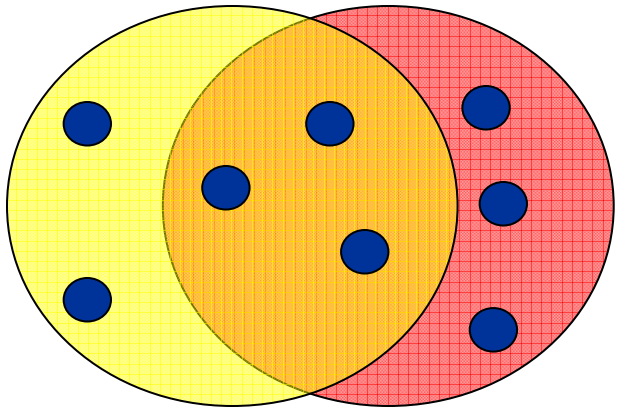
Basic Data Model: Sets

- Many similarity problems can be expressed as finding subsets of some universal set that have significant intersection
- A k-shingle (or k-gram) of a document is a sequence of k characters that appears in the document
- Documents are represented by their k-shingles
  - All possible k-shingles represent universe *U*
  - Degree of “overlap” between shingle sets represents similarity of documents
- Example:
  - Document = abcab
  - $k = 2$
  - Set of 2-shingles = {ab, bc, ca}.
- Option: Regard shingles as a bag → count “ab” twice

Jaccard Similarity of Sets

- The Jaccard similarity of two sets C_1 and C_2:
  Size of their intersection divided by the size of their union:
  $Sim(C_1, C_2) = |C_1 \cap C_2| / |C_1 \cup C_2|$



3 elements in intersection
8 elements in union

$\Rightarrow$ Jaccard similarity = 3/8

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From Sets to Boolean Matrices

- Matrix representation of data in the form of subsets of a universal set
  - Rows = elements of the universal set (shingles)
  - Columns = sets (documents)
  - 1 in row *r*, column *c* iff document *c* contains shingle *r*
  - Column similarity is the Jaccard similarity of the sets of their rows with 1

$\Rightarrow$ Typically the matrix is sparse

- Implementation
  - Might not really represent the data by a boolean matrix
  - List of places where there is a non-zero value.

$\Rightarrow$ Matrix illustration is conceptually useful

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Row Types

- Given columns C_1 and C_2, rows may be classified as:

C_1	C_2		
1	1	←	a
1	0	←	b
0	1	←	c
0	0	←	d

- a = # rows of type a , etc.
- Note: $Sim(C_1, C_2) = a / (a + b + c)$

Example

C_1	C_2		
0	1	←	
1	0	←	
1	1	←	✓
0	0		
1	1	←	✓
0	1	←	

$Sim(C_1, C_2) = 2/5 = 0.4$

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Problems

- Computational complexity
  - Creation of shingles
  - Comparison of columns (often pair wise)
- "Compression" of columns wanted, so that
  - Similar documents obtain related signatures
  - Dissimilar documents receive discriminative signatures
- ~~Idea:~~
  - ~~Pick m ($m << k$) rows at random~~
  - ~~Let the signature of column C be the m bits of C in those rows~~
  - ~~$\Rightarrow$ Matrix is sparse~~
  - ~~$\Rightarrow$ Many columns will have 00. . .0 as a signature~~
  - ~~$\Rightarrow$ "Everything" is dissimilar because their 1's are in different rows~~

Minhashing

- Key idea: "Hash" each column C_i to a small *signature* S_i
- Basic goals:
  - S_i is sufficiently small (e.g. to be processed in the main memory)
  - $Sim(C_1, C_2)$ corresponds to $Sim(S_1, S_2)$
- Basic idea:
  - Imagine the rows permuted randomly and equally distributed
  - Define hash function $h(C)$ to compute smallest number of the (in the permuted order) row in which column C has 1
  - Use several ($m << k$) independent hash functions to create a signature
  - Optional: Check that columns with similar signatures are really similar

Minhashing Example

Input matrix → Signature matrix *M*

h_1	h_2	h_3	C_1	C_2	C_3	C_4
1	4	3	1	0	1	0
3	2	4	1	0	0	1
7	1	7	0	1	0	1
6	3	6	0	1	0	1
2	6	1	0	1	0	1
5	7	2	1	0	1	0
4	5	5	1	0	1	0

S_1	S_2	S_3	S_4
2	1	2	1
2	1	4	1
1	2	1	2

Similarities:

	$C_1 C_3$	$C_2 C_4$	$C_1 C_2$	$C_3 C_4$
Col/Col	0.75	0.75	0	0
Sig/Sig	0.67	1.00	0	0

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Challenges

- In general:
  - Suppose huge documents (e.g., 1 billion rows)
  - Hard to pick a random permutation from 1…billion
  - Representing a random permutation requires 1 billion entries
  - Accessing rows in permuted order leads to thrashing

  $\Rightarrow$ A good approximation to permuting rows: Pick $m << k$ hash functions

- In the case of data quality in Web archiving:
  - Document size less problematic
  - Usually only few pair wise comparisons needed
  - Random contents or automatically generated contents in CMS ruin all efforts

  $\Rightarrow$ Data scrubbing is crucial

$\Rightarrow$ Defining “good” hash functions are an own research topic!

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Implementation

- For each column c and each hash function h_i, keep a "slot" $M(i, c)$
- $M(i, c)$ becomes the smallest value of $h_i(r)$ having 1 in column c at row r
- $h_i(r)$ gives order of rows for i th permuation

for each row r
  for each column c
    if c has *1* in row r
      for each hash function h_i **do**
        if $h_i(r)$ is a smaller value than $M(i, c)$ **then**
          $M(i, c) := h_i(r)$;

- Optimization:
  - Our case: columns = documents, rows = shingles
  - Sort matrix once so it is by row
  - Compute $h_i(r)$ only once for each row

Example

Row	C_1	C_2
1	1	0
2	1	1
3	0	1
4	1	1
5	0	1

$h(x) = x \bmod 5$

$g(x) = 2x+1 \bmod 5$

	S_1	S_2
$h(1) = 1$	1	-
$g(1) = 3$	3	-
$h(2) = 2$	1	2
$g(2) = 0$	0	0
$h(3) = 3$	1	2
$g(3) = 2$	0	0
$h(4) = 4$	1	2
$g(4) = 4$	0	0
$h(5) = 0$	1	0
$g(5) = 1$	0	0

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Challenges

- In general:
  - Data represents a large number of objects in main memory
    - Document shingles
    - Signatures after minhashing
  - Only few pairs (*candidate pairs*) are sufficiently similar to be compared
  - Comparison of signatures of all pairs of columns is very (!) expensive

  $\Rightarrow 10^6$ columns: $5*10^{11}$ column-comparisons (quadratic in the number of columns)

- In the case of data quality in Web archiving:
  - Coherence evaluation wrt to non-relevant changes
    - *Candidate pairs c*, *d* are given beforehand
    - Similarity comparison of signatures according to predefined threshold
  - Long term coherence studies are more computational intense

  $\Rightarrow$ *Candidate pair* detection more important for Web spam or duplicate detection

$\Rightarrow$ Locality-sensitive hashing

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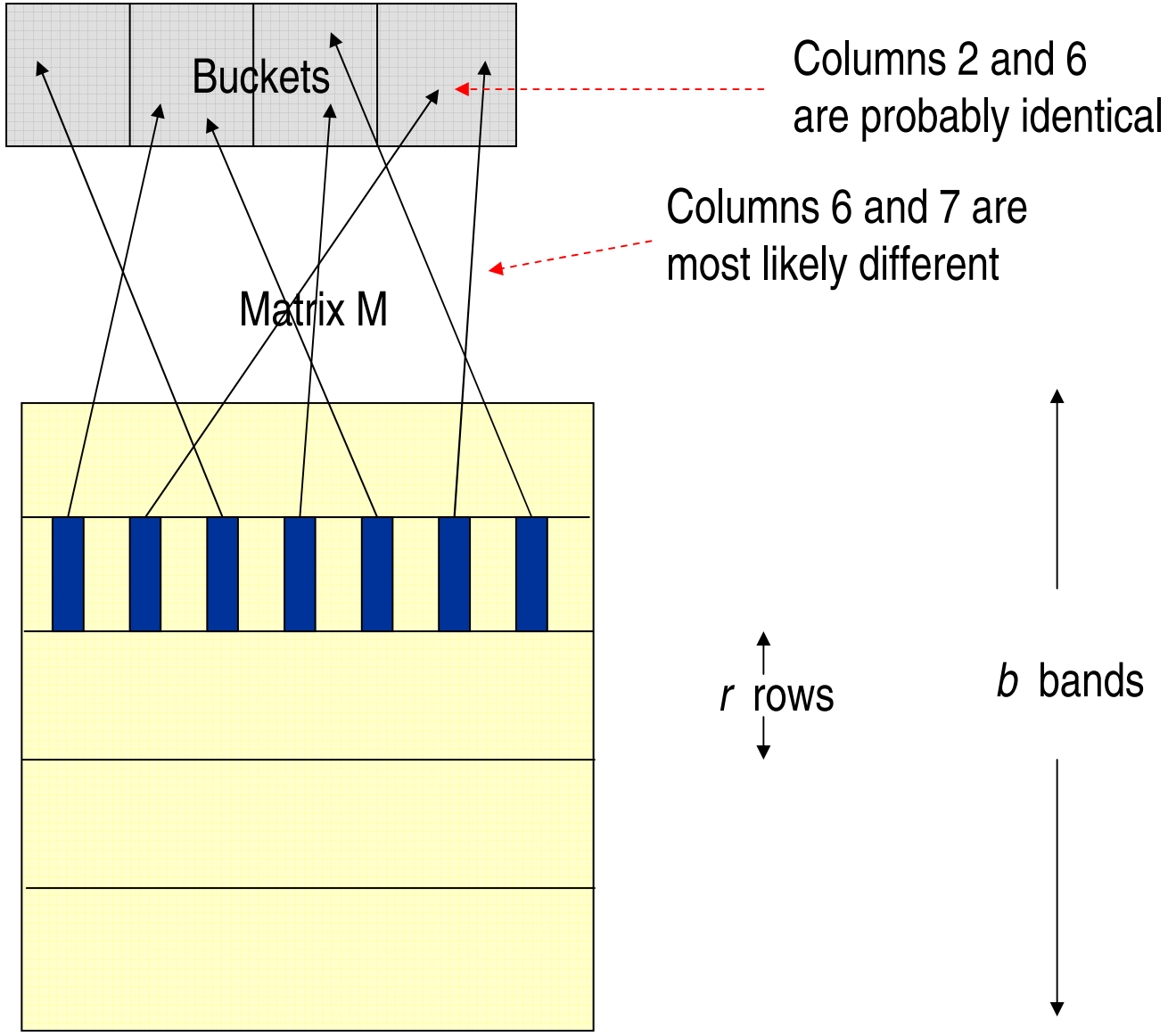
Locality-Sensitive Hashing

- Basic idea
  - Function f(x,y) tells whether or not *x* and *y* is a *candidate pair*
  - *Candidate pairs* of elements whose similarity must be evaluated

- Process (simplified)
  - Divide matrix *M* into *b* bands of *r* rows
  - For each band, hash its portion of each column to a hash table with *k* buckets
    - Make *k* as large as possible
  - Candidate column pairs are those that hash to the same bucket for ≥ 1 band
  - Tune *b* and *r* to catch most similar pairs, but few non-similar pairs

  ⇒ Similarity comparison of signatures of candidate pairs only

Example


Buckets
Columns 2 and 6 are probably identical
Columns 6 and 7 are most likely different
Matrix M
r rows
b bands

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Coherence Framework

- Basic Assumptions
  - Web site to be crawled consists of *n* Web pages
  - Changes of Web pages occur per time unit and independent of each other
  - Change rates are assumed / given
  - Delay between downloads of pages is the same
  - Download time is neglected

- Basic Notation
  - Crawl: c
  - Web pages: $p_1,\ldots, p_n$
  - Change probability of page p_i: λ_i
  - Time of downloading page p_i: $t(p_i)$
  - Last modified value of page p_i: μ_i
  - Content hash or etag of page p_i: $\theta(p_i)$
  - Crawl interval: $[t_s,t_e]$

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Coherence

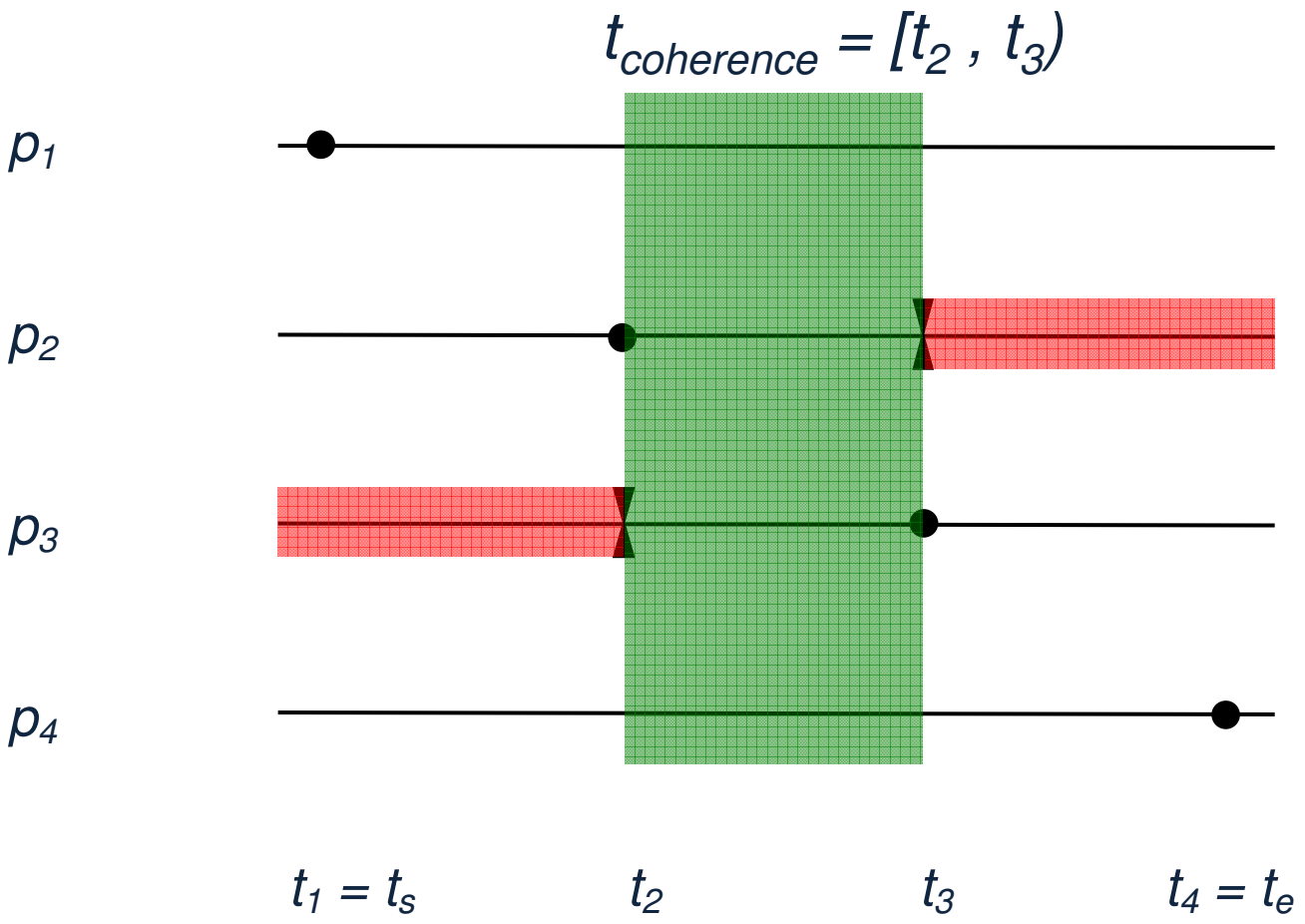
Definition:

1. A single Web page is always coherent.
2. The invariance interval $[\mu_i,\mu_i^*]$ of page p_i lies between the last modified time stamp μ_i at time $t(p_i)$ of downloading p_i ($\mu_i \leq t(p_i)$) and the next change μ_i^* following $t(p_i)$.
3. Two or more pages are coherent if

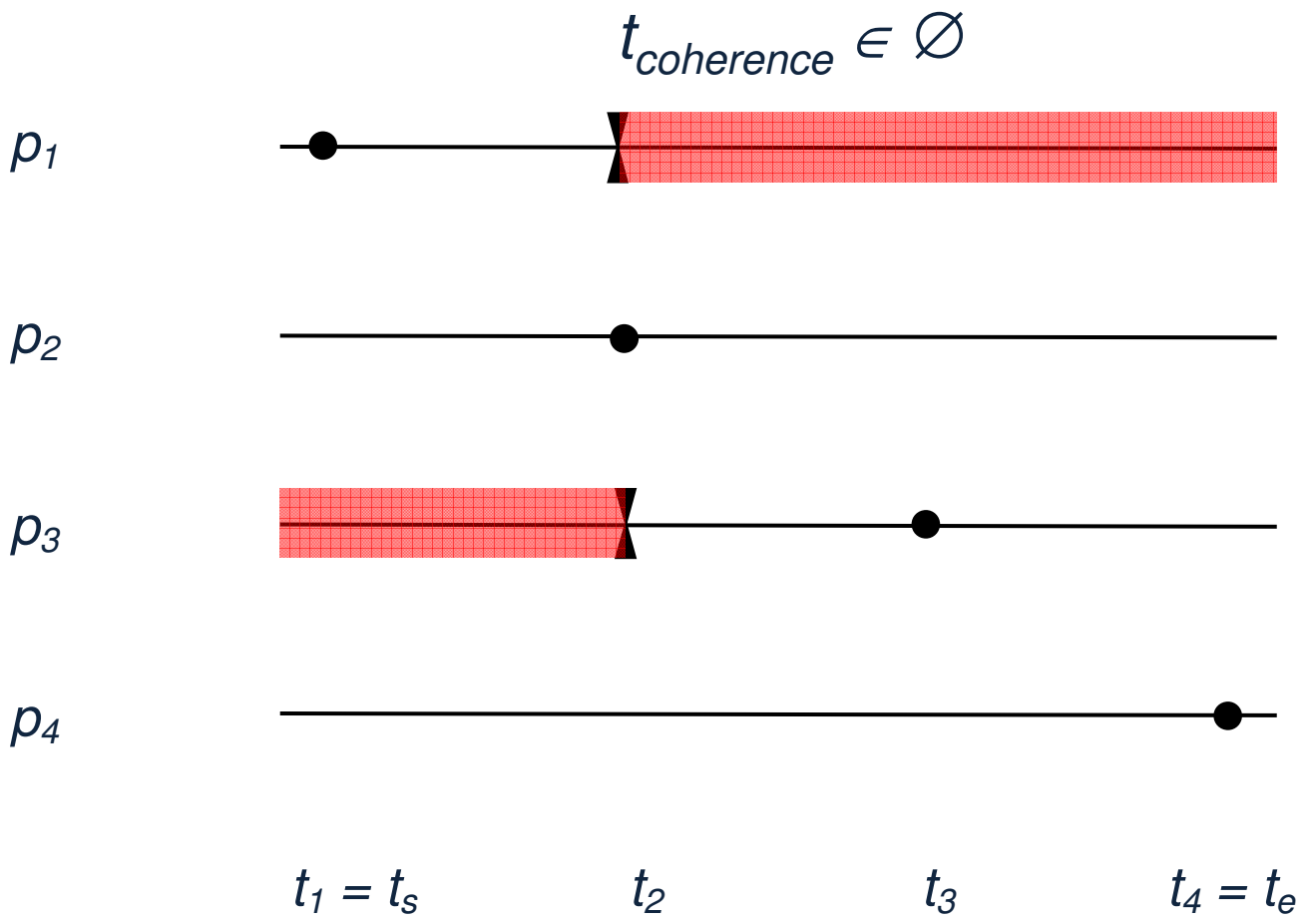
   there is a time point (or interval) $t_{coherence}$ so that a non-empty intersection among the invariance interval of all pages exists:

$$\forall p_i, \exists t_{coherence} : t_{coherence} \in \bigcap_{i=1}^{n} [\mu_i, \mu_i^*] \neq \emptyset$$

Coherence by Example



Coherence by Example



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Coherence Summary

- Definition
  - Simple
  - Straightforward
- Implementation
  - Impractical
  - Crawlers are

    aware of the past (“backward-conscious”)

    but

    unaware of the future (“forward-blind”)

⇒ Only limited applicability in a real life scenario

Observable Coherence

Definition:

Two or more pages are observable coherent if

there is a single timepoint (or interval) $t_{coherence}$ so that there is a non-empty intersection of the intervals spanning the respective download time $t(p_i)$ and the corresponding last modified stamp μ_i retrieved at time of download ($\mu_i \leq t(p_i)$):

$$\forall p_i, \exists t_{coherence} : \bigcap_{i=1}^{n} [\mu_i, t(p_i)] \neq \varnothing \wedge t_{coherence} \in [\mu_i, t(p_i)]$$

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Measurable Coherence

- Specialization of observable coherence
  - Makes observable coherence measurable in a real life scenario
  - Overcomes “right-hand side blindness” of crawlers
- Ability to issue a guaranteed coherence statement
  - Valid for all contents of a Web site
  - “Regardless” of crawl duration
- Suitable coherence time point (or interval) $t_{coherence}$ needed

$\Rightarrow$ Full control is only given for $t_{coherence} = t_s$

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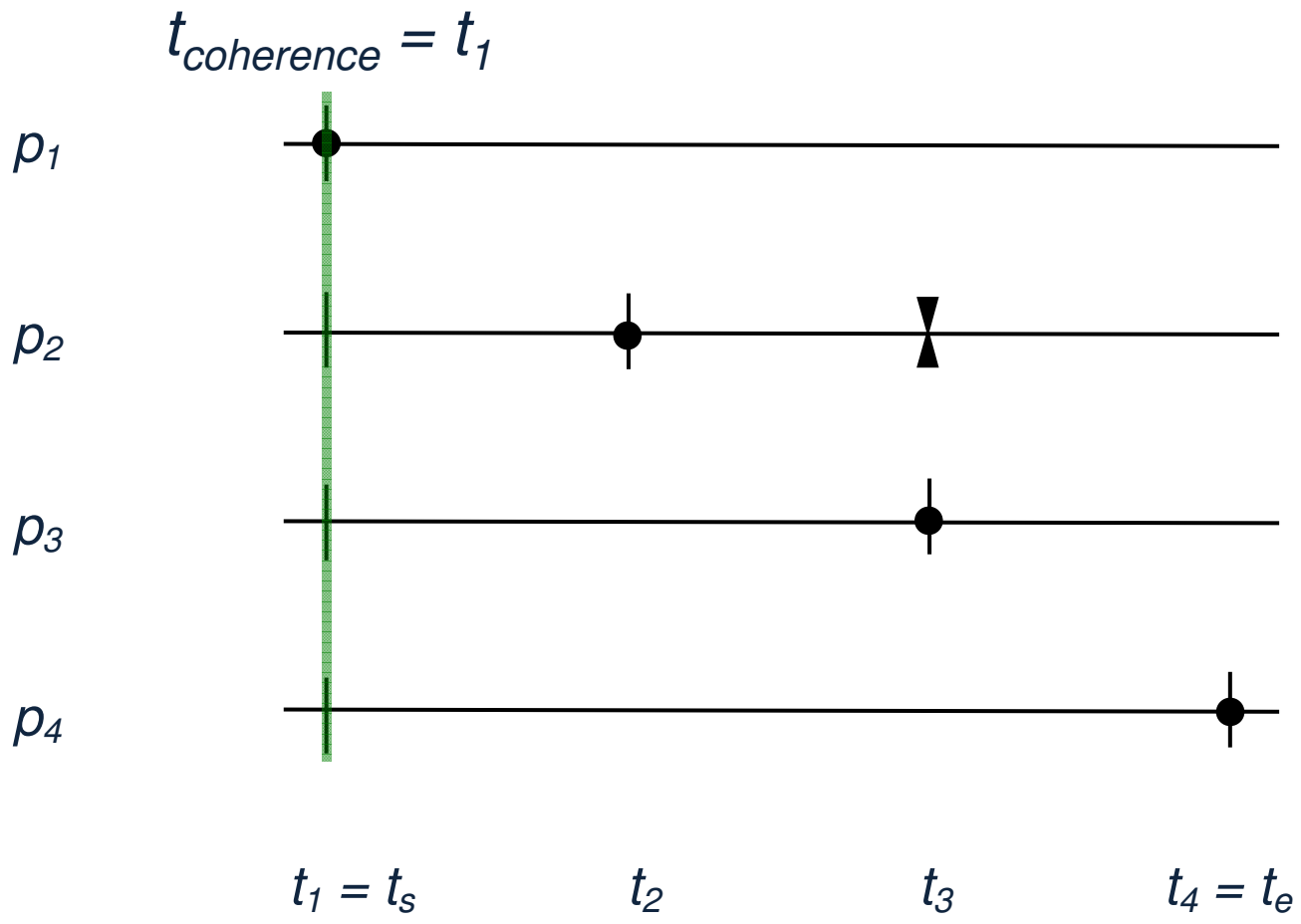
Measurable Coherence by Example



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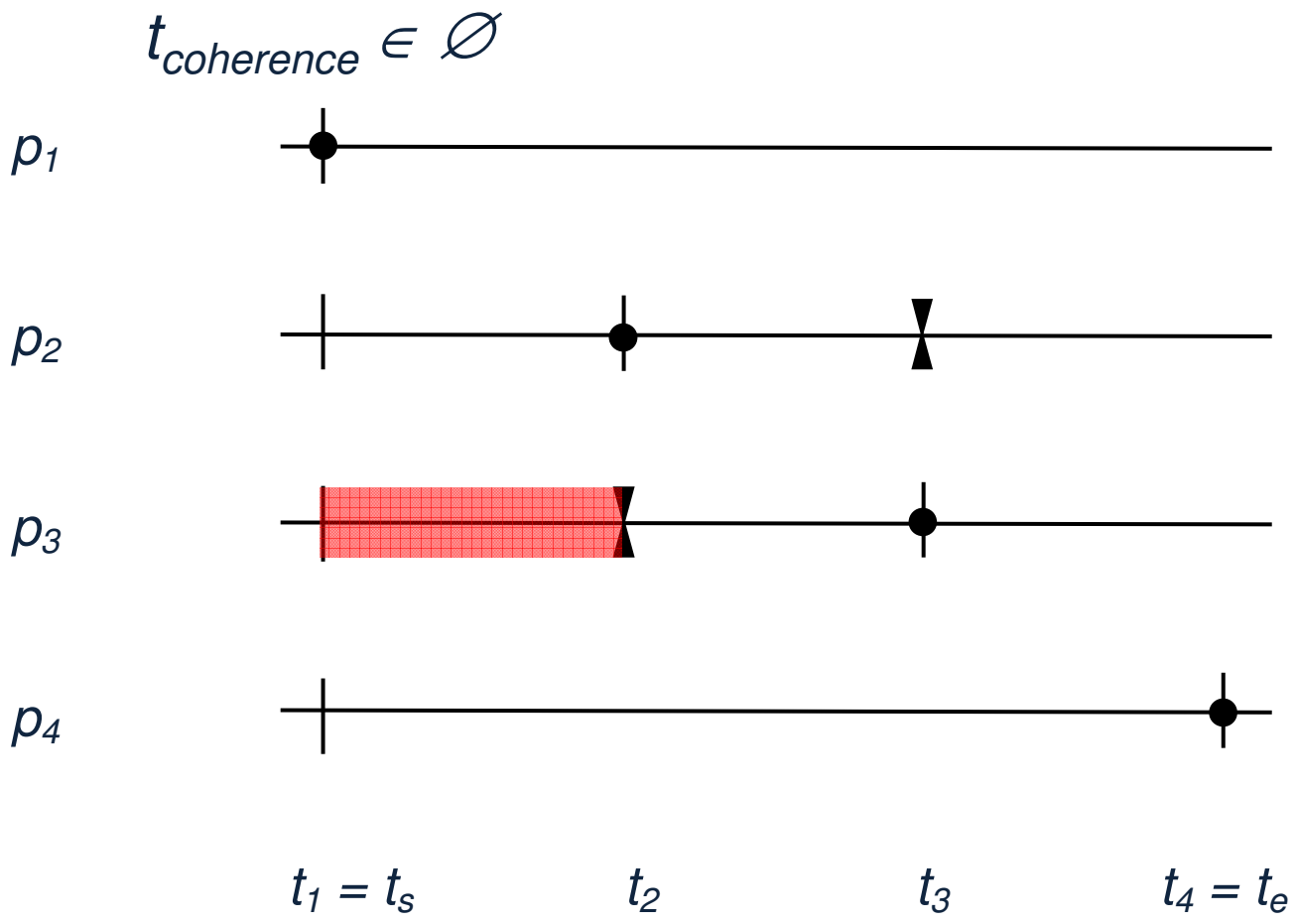
Measurable Coherence by Example



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Quantifying Measurable Coherence

Error function

$$f(p_i) = \begin{cases} 0 & \text{, if } \mu_i \leq t_s \\ 1 & \text{, else} \end{cases}$$

Coherence function

$$C(c) = 1 - \frac{\sum_{i=1}^{n} f(p_i)}{n} \quad \text{, n} \geq 1$$

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Measurable Coherence Summary

- Definition
  - Makes coherence become measurable
  - Relative to start of crawl
- Implementation
  - “Easy”
  - Ad-hoc verifiable
  - Efficient
  - Produces no extra traffic
  - Relies on accuracy of last modified stamps

$\Rightarrow$ Only limited applicability in a real life scenario

Inducible Coherence

Definition:

Two or more pages are inducible coherent if

there is a time point $t_{coherence}$ between the visit of pages $t(p_i)$ and the subsequent revisit $t(\tilde{p}_i)$ where the etag or content hash θ of corresponding pages ($\theta(m)$ having $m \in \{p_i, \tilde{p}_i\}$) has not changed:

$$\forall p_i, \exists t_{coherence} : \theta(p_i) = \theta(\tilde{p}_i) \wedge t_{coherence} \in \bigcap_{i=1}^{n} [t(p_i), t(\tilde{p}_i)]$$

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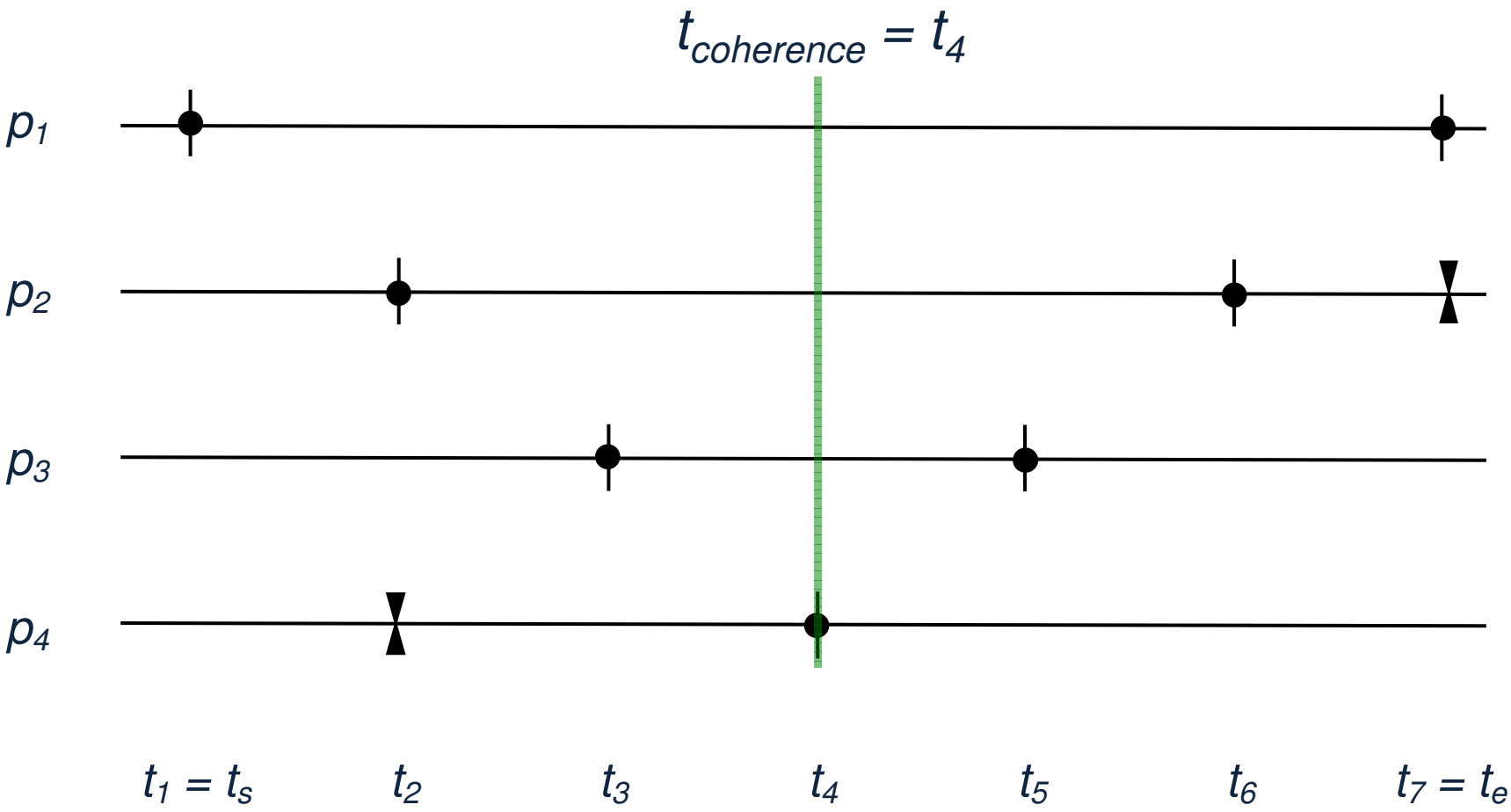
Inducible Coherence by Example



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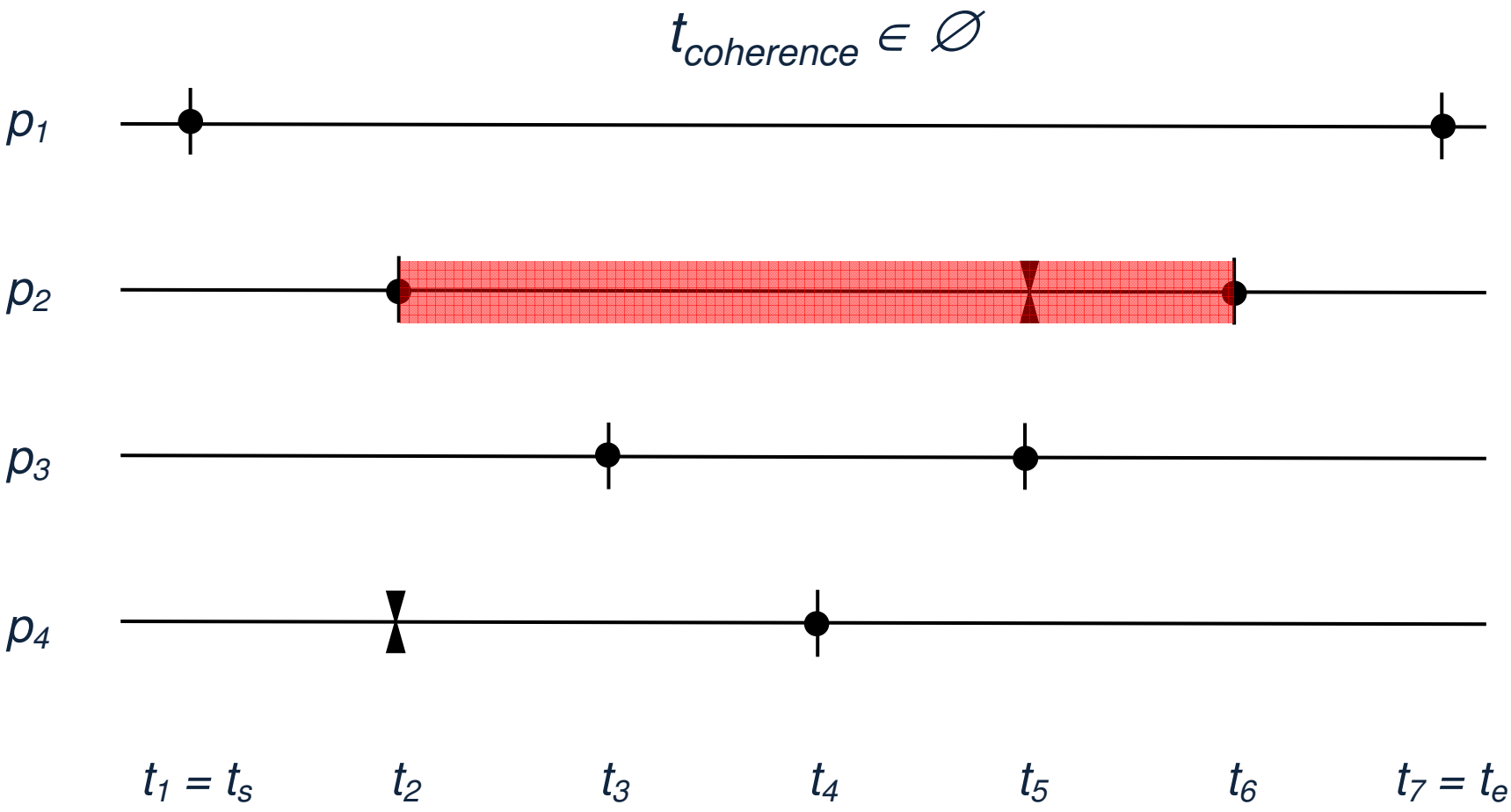
Inducible Coherence by Example



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Quantifying Inducible Coherence

Error function

$$f(p_i, \tilde{p}_i) = \begin{cases} 0 & \text{, if } \theta(p_i) = \theta(\tilde{p}_i) \\ 1 & \text{, else} \end{cases}$$

Coherence function

$$C(c) = 1 - \frac{\sum_{i=1}^{n} f(p_i, \tilde{p}_i)}{n} \quad , n \geq 1$$

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Inducible Coherence Summary

- Definition
  - Makes coherence of improper dated contents become measurable
  - Relative to end of crawl / start of revisit
- Implementation
  - More complex
  - Still efficient
    - Associated database
    - Politeness delays are the bottleneck
  - Produces extra traffic
    - Mostly conditional gets
    - Few “full” downloads
  - Full check on proper dating of contents

⇒ LiWA temporal coherence processor V1.0 in Heritrix

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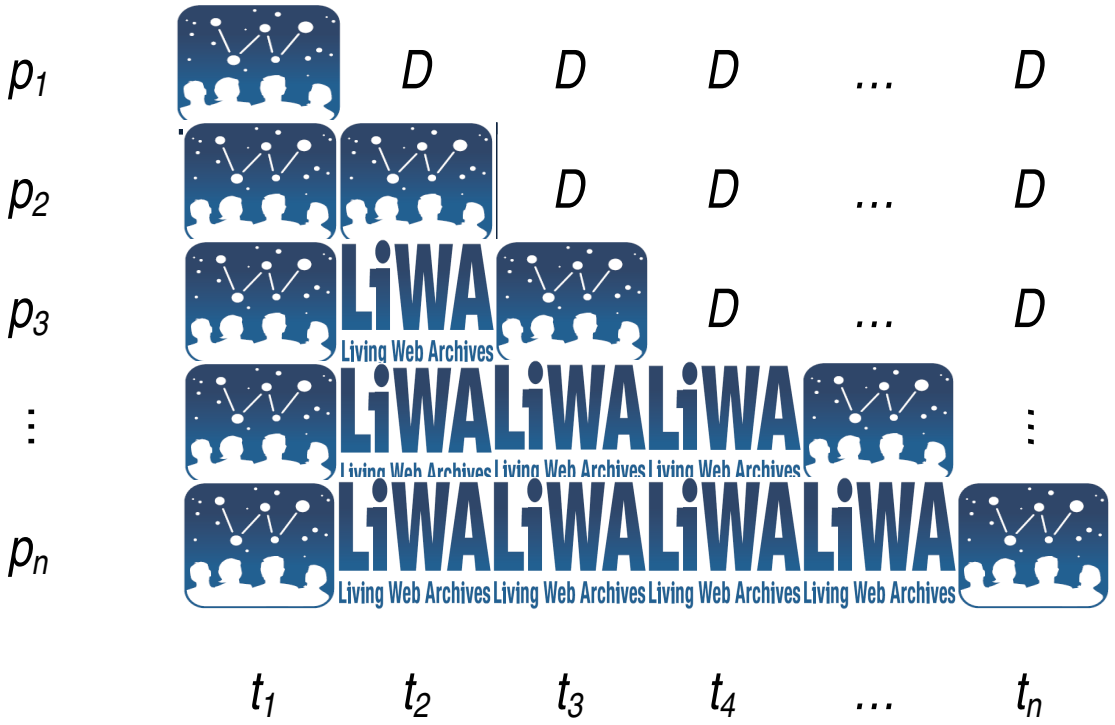
Crawl Improvement: Measurable Coherence

- Conflict probability: $\kappa(p_i) = 1 - (1 - \lambda_i)^{t(p_i) - t_s}$
- Crawling so that conflicts are "tolerable": $\kappa(p_i) < \eta$



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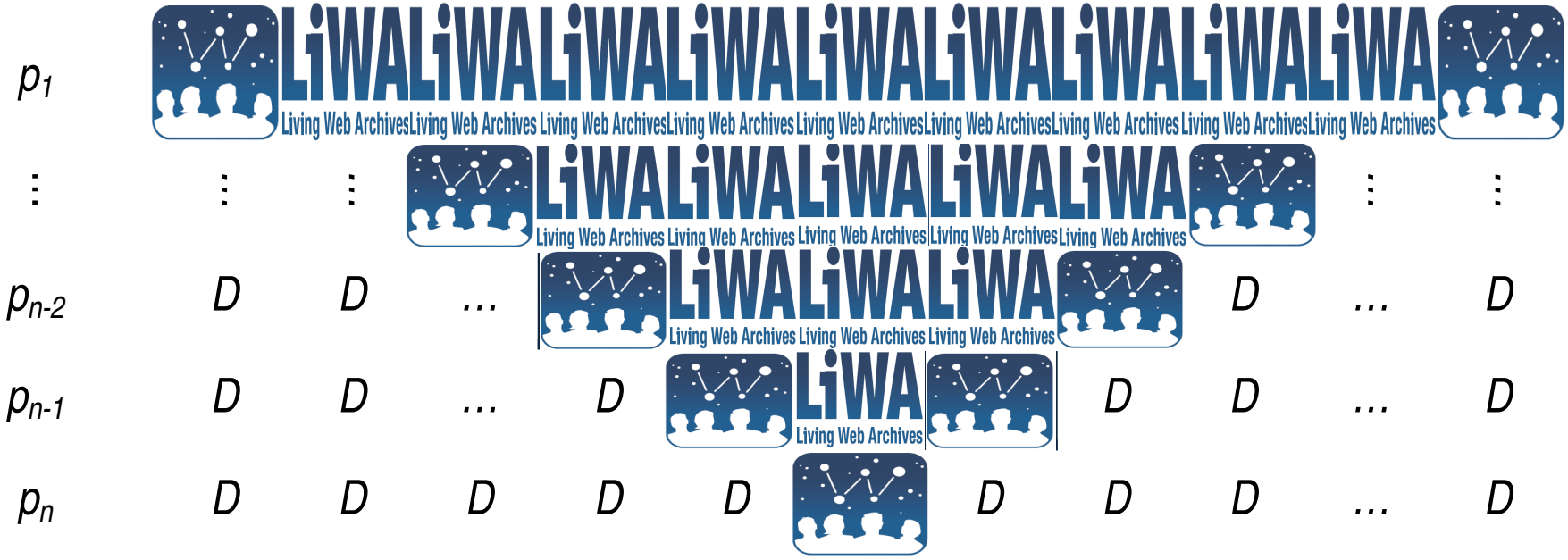
Improved Measurable Coherence Crawl Scheduling

input: $p_1,\ldots,p_n$ - list of pages in descending order of λ_i,
η - readiness to assume risk threshold

begin
Start with: *slot = 1*
while *slot* $\leq$ *n*
do
if $\kappa(p_{slot}) < \eta$ **then** /* **no conflict expected** */
Download page p_{slot}
end
Continue with next iteration: *slot ++*
end
Download skipped pages in reversed order of their index
end

Crawl Improvement: Inducible Coherence

- Conflict probability: $\kappa(p_i) = 1 - (1 - \lambda_i)^{t(\tilde{p}_i) - t(p_i)}$
- Crawling so that conflicts are "tolerable": $\kappa(p_i) < \eta$



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Improved Inducible Coherence Crawl Scheduling

input: $p_1,\ldots,p_n$ - list of pages in descending order of λ_i,
η - readiness to assume risk threshold

begin
Start with: *slot = 1*, *lastpromising = n*
while *slot* $\leq$ *lastpromising*
do
if $\kappa(p_{slot}) \geq \eta$ **then** /* **conflict expected!** */
Move p_{slot} to position *lastpromising*
Decrease promising boundary: *lastpromising* −−
end
else
Increase promising boundary: *promising* ++
end
end
slot = n **while** *slot* ≥ 1
do /* **visit from hopeless to promising** */
Download page p_{slot}
Decrease slot counter: *slot* −−
end
slot = 2 **while** *slot* $\leq n$
do /* **revisit from promising to hopeless** */
Revisit page p_{slot}
Increase slot counter: *slot* ++
end
end

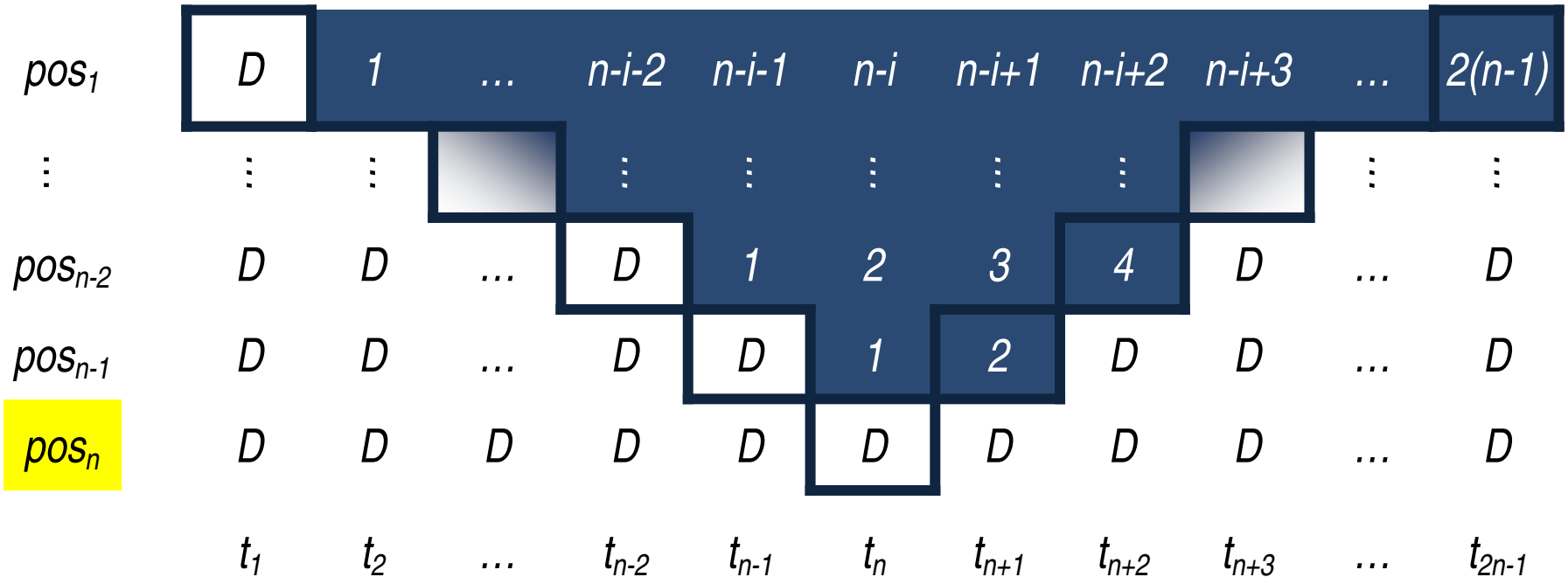
Inducible Coherence Scheduling: pos_n

Position: pos_n
Remaining λ_i : $\lambda_{n-1} >> \lambda_{n-n-2} >> \lambda_{n-2} >> \lambda_1 > \lambda_1$

Test: $1 - (1 - \lambda_n)^0 > \theta$?
$\Rightarrow$ *No!*

Promising: λ_n

Hopeless:



Inducible Coherence Scheduling: pos_{n-1}

Position: pos_{n-1}
Remaining λ_i : $\lambda_{n-3} > \lambda_{n-2} > \lambda_{n-1} > \ldots > \lambda_1$

Test: $1 - (1 - \lambda_{n-3})^2 > \theta$?
e.g. Yes!

Promising: λ_{n-3}, λ_n

Hopeless: λ_{n-1} λ_{n-2}

pos_1	D	1	…	n-i-2	n-i-1	n-i	n-i+1	n-i+2	n-i+3	…	2(n-1)
⋮	⋮	⋮		⋮	⋮	⋮	⋮	⋮		⋮	⋮
pos_{n-2}	D	D	…	D	1	2	3	4	D	…	D
pos_{n-1}	D	D	…	D	D	1	2	D	D	…	D
pos_n	D	D	D	D	D	D	D	D	D	…	D
	t_1	t_2	…	t_{n-2}	t_{n-1}	t_n	t_{n+1}	t_{n+2}	t_{n+3}	…	t_{2n-1}

Inducible Coherence Scheduling: pos_{n-2}

Position: pos_{n-2}
Remaining λ_i : $\lambda_{n-3} > \ldots > \lambda_1$

Test: $1 - (1 - \lambda_{n-3})^4 > \theta$?
e.g. Yes!

Promising: λ_{n-3}, λ_{n-2}, λ_n

Hopeless: λ_{n-1}, λ_{n-2}, λ_{n-4}

pos_1	D	1	…	n-i-2	n-i-1	n-i	n-i+1	n-i+2	n-i+3	…	2(n-1)
⋮	⋮	⋮		⋮	⋮	⋮	⋮	⋮		⋮	⋮
pos_{n-2}	D	D	…	D	1	2	3	4	D	…	D
pos_{n-1}	D	D	…	D	D	1	2	D	D	…	D
pos_n	D	D	D	D	D	D	D	D	D	…	D
	t_1	t_2	…	t_{n-2}	t_{n-1}	t_n	t_{n+1}	t_{n+2}	t_{n+3}	…	t_{2n-1}

Inducible Coherence Scheduling: pos_{n-k}

Position: pos_k
Remaining λ_i : $\lambda_i > \lambda_1$

Test: $1 - (1 - \lambda_2)^{2(k-1)} > \theta$?
e.g. Mo's!

Promising: $\lambda_4, \ldots, \lambda_{n-7}, \lambda_{n-6}, \lambda_{n-5}, \lambda_{n-3}, \lambda_n \; \lambda_n$

Hopeless: $\lambda_{n-1}, \lambda_{n-2}, \lambda_{n-4}, \lambda_{n-8}, \lambda_{n-12}, \ldots, \lambda_3 \; \lambda_2$

pos_1	D	1	…	n-i-2	n-i-1	n-i	n-i+1	n-i+2	n-i+3	…	2(n-1)
⋮	⋮	⋮		⋮	⋮	⋮	⋮	⋮		⋮	⋮
pos_{n-2}	D	D	…	D	1	2	3	4	D	…	D
pos_{n-1}	D	D	…	D	D	1	2	D	D	…	D
pos_n	D	D	D	D	D	D	D	D	D	…	D
	t_1	t_2	…	t_{n-2}	t_{n-1}	t_n	t_{n+1}	t_{n+2}	t_{n+3}	…	t_{2n-1}

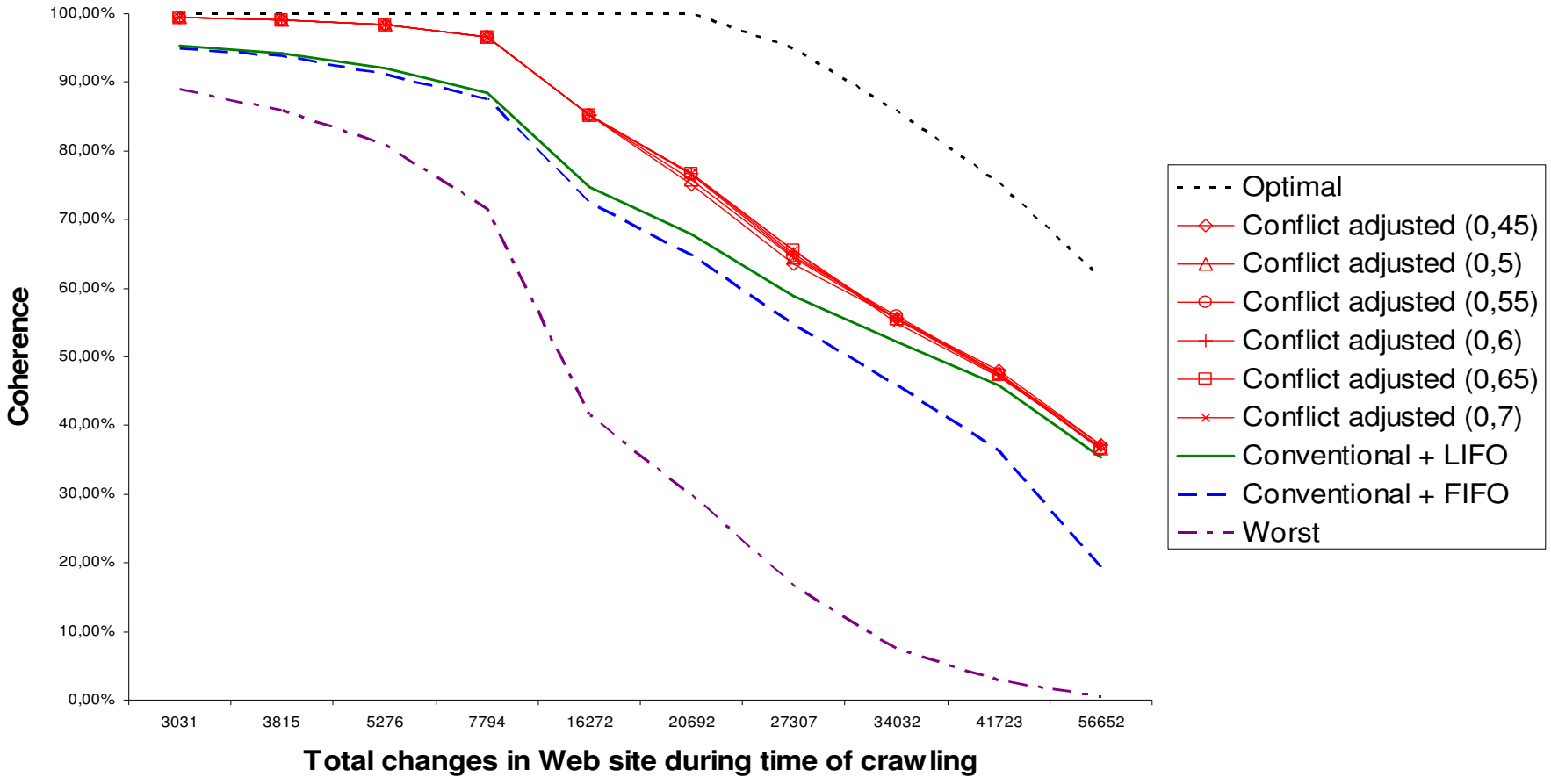
Final Crawl Sequence

Visit: $\lambda_{n-1}, \lambda_{n-2}, \lambda_{n-4}, \lambda_{n-8}, \lambda_{n-12}, \ldots, \lambda_3, \lambda_2, \lambda_1, \lambda_4, \ldots, \lambda_{n-7}, \lambda_{n-6}, \lambda_{n-5}, \lambda_{n-3}, \lambda_n$

Revisit: $\lambda_{n-3}, \lambda_{n-5}, \lambda_{n-6}, \lambda_{n-7}, \ldots, \lambda_4, \lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_{n-12}, \lambda_{n-6}, \lambda_{n-5}, \lambda_{n-3}, \lambda_{n-1}$

pos_1	D	1	…	n-i-2	n-i-1	n-i	n-i+1	n-i+2	n-i+3	…	2(n-1)
⋮	⋮	⋮		⋮	⋮	⋮	⋮	⋮		⋮	⋮
pos_{n-2}	D	D	…	D	1	2	3	4	D	…	D
pos_{n-1}	D	D	…	D	D	1	2	D	D	…	D
pos_n	D	D	D	D	D	D	D	D	D	…	D
	t_1	t_2	…	t_{n-2}	t_{n-1}	t_n	t_{n+1}	t_{n+2}	t_{n+3}	…	t_{2n-1}

Improved Inducible Coherence Crawling: Simulation of a Website 10.000 contents



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Incoherence Detection

- "Easy" for offline coherence analysis
  - Data is stored in the archive
  - Efficiency "unproblematic"
- "Difficult" for online coherence analysis
  - Data needs to be "tapped" from the crawler
  - Efficiency is a key issue
- Proper dating of content versions required
- Multistage change measurement procedure
  1) *Conditional GET (etag comparison)*
  2) *Check content timestamp (last modified comparison)*
  3) *Compare a hash of the page with a stored hash*
  4) *Non-significant differences (ads, fortunes, request timestamp)*
     - *only hash text content, or "useful" text content*
     - *compare distribution of n-grams (shingling)*
     - *compute edit distance with previous version*

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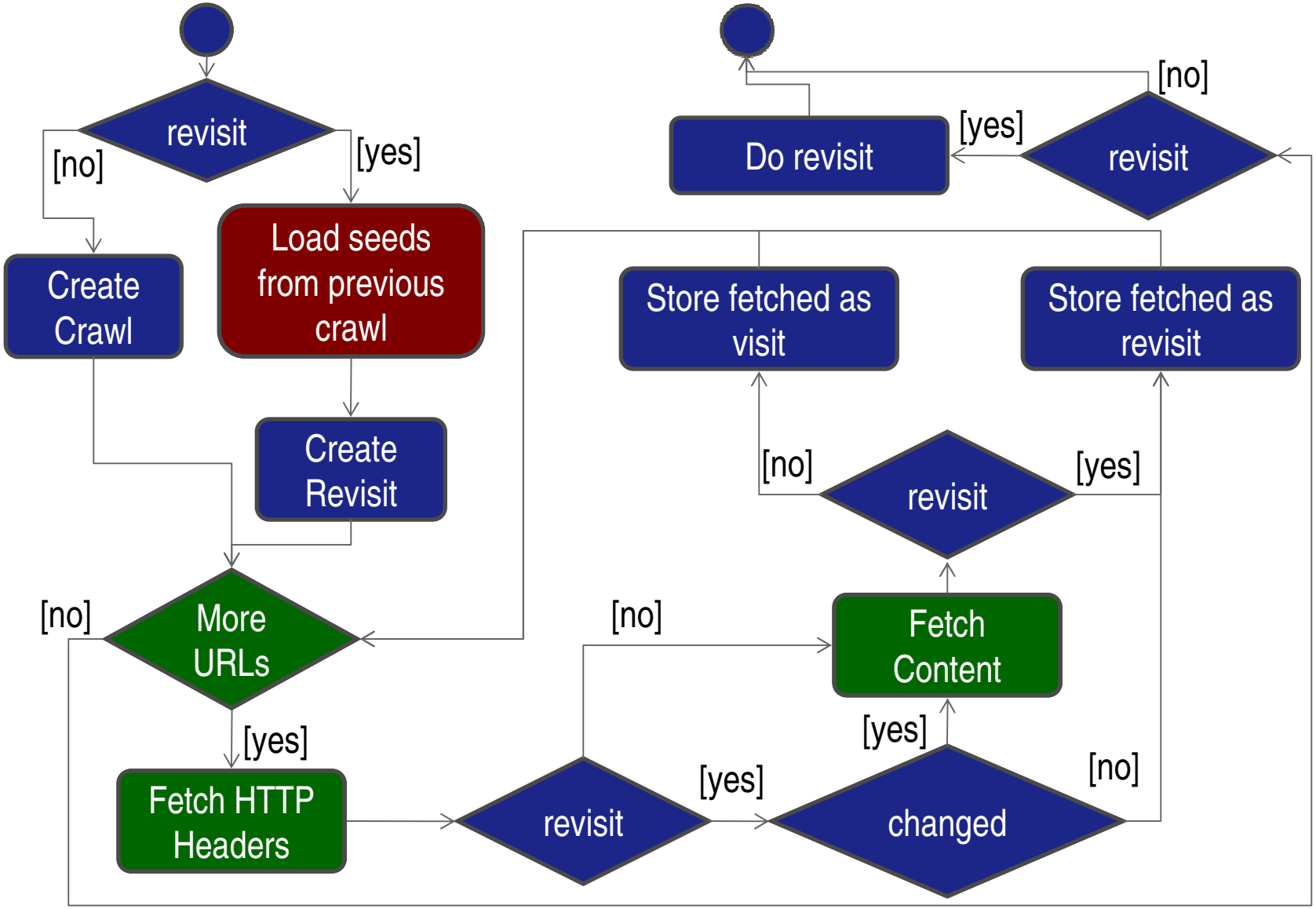
Online Coherence Analysis



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Experimental Results

- Crawling with Heritrix crawler (LiWA coherence analysis processor integrated)
  - (Meta-)Data extraction embedded
  - Revisiting strategy integrated
- Experimental crawls on the mpi-inf.mpg.de domain
  - ~ 65.000 contents
  - > 25 GB
  - ~ 4,5 hours
  - ~ 6 documents per second
- Coherence defect analysis
  - Incoherence < 3 ‰
    - ~ 1 ‰ dynamics in dns look-ups
    - ~ 1 ‰ dynamically created wiki pages
    - ~ 1 ‰ dynamically created pages by bioinf.mpi-inf.mpg.de CMS
    - < 5 pages with relevant changes
  - Largest coherent sub graph: ~20.000 contents

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Post Processing via GraphML

- File format for graphs
  - Core for the description of structural properties
  - Extension mechanisms for application-specific data
- Main features include
  - Directed, undirected, and mixed graphs
  - Hypergraphs
  - Hierarchical graphs
  - Graphical representations
  - References to external data
  - Application-specific attribute data
  - Light-weight parsers
- Based on XML
- Applied in many graph related software applications

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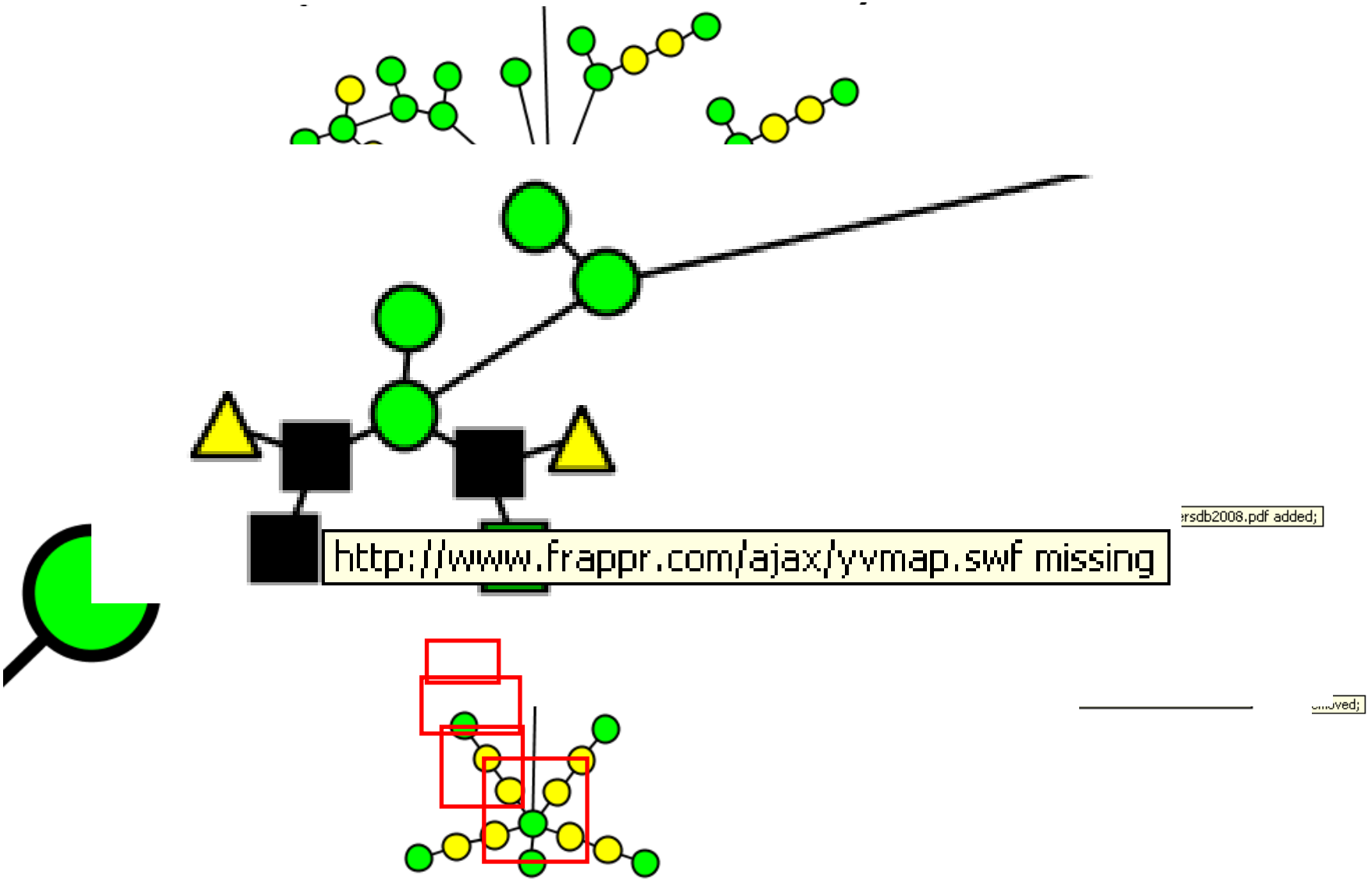
GraphML Excerpt

```
<?xml version="1.0" encoding="UTF-8" standalone="no"?>
<graphml xmlns="http://graphml.graphdrawing.org/xmlns/graphml"
    xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance" xmlns:y="http://www.yworks.com/xml/graphml"
    xsi:schemaLocation="http://graphml.graphdrawing.org/xmlns/graphml
    http://www.yworks.com/xml/schema/graphml/1.0/ygraphml.xsd">
    …
    <graph edgedefault="directed" id="G229">
        <node id="http://www.mpi-inf.mpg.de/index.html">
            <data key="d0">
                <y:ShapeNode>
                    <y:Geometry width="10.003" height="10.003"/>
                    <y:Fill color="#00FF00" transparent="false"/>
                    <y:Shape type="ellipse"/>
                </y:ShapeNode>
            </data>
            <data key="d1">http://www.mpi-inf.mpg.de/index.html OK</data>
        </node>
        …
        <edge source="http://www.mpi-inf.mpg.de/index.html" target="dns:www.mpi-inf.mpg.de"/>
        …
    </graph>
</graphml>
```

Online Coherence Visualization: mpi-inf.mpg.de



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Summary

- Measuring data quality in Web archives requires
  - Identification of relevant coherence defects
  - Data scrubbing in order to compare relevant document (sub-)sections
  - Efficient computations
    - Shingling
    - Minhashing
    - (Local sensitive hashing)
- Identification of coherence
  - HTTP time stamps → Measurable coherence
  - "Virtual" time stamps → Inducible coherence
- Data quality in Web archiving
  - Quantifiable even with improper dated contents
  - Improvable by around 10% given non-pathological Web sites (scheduling only!)
  - Can be further improved by more sophisticated search strategies
    - Partial captures
    - Identification of media- and/or URL-specific change behavior

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