

Exploiting the Web for Text and Language Reuse Applications

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Webis Group

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Benno Stein

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Tim Gollub

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Tsvetomira Palakarska

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Steven Burrows

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Martin Trenkmann

Marie-Theresa Hansens

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Nadin Glaser

Webis Group



Benno Stein



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Maik Anderka



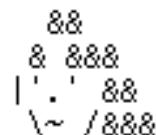
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Nedim Lipka

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Tim Gollub



Tsvetomira Palakarska

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Nadin Glaser

Marie-Theresa Hansens

Talk

- The Netspeak Word Search Engine
- Query Segmentation
- Candidate Retrieval at PAN'12

Quicklinks

- **Netspeak** [video]
- **ChatNoir**
- **PicaPica** [video]

Webis Group

- **Projects** [local]
- **Teaching** [local]
- **People** [local]

The Netspeak Word Search Engine

The Netspeak Word Search Engine

Introduction

- ❑ Writing is not so much about what to write, but how to write.
- ❑ Finding the right words is essential to ease understanding.
- ❑ Searching for words is not well supported.

The Netspeak Word Search Engine

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We got for ...

□ spelling problems	→ spell checkers
□ grammar mistakes	→ grammar checkers
□ translation questions	→ dictionaries, machine translation tools
□ word choice ambiguities	→ thesauri
□ writing style analysis	→ reading and writing measures

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With Net**speak** we address:

- finding the most common word (correctness vs. commonness)
- finding appropriate words in context

Netspeak Common Language Search

looks good ? me

i



Frequency	Phrase	Examples
56,925	83.6 % looks good to me	⊕
10,047	14.8 % looks good on me	⊕
1,123	1.6 % looks good for me	⊕
68,095	100.0 %	0.048 seconds

The Netspeak Word Search Engine

Corpus Statistics

- Net**speak** is based on the Google n-gram corpus "Web 1T 5-gram Version 1" from 2006:

Subset	n-gram number	Space	after postprocessing
1-gram	13 588 391	177.0 MB	3.75 %
2-gram	314 843 401	5.0 GB	43.26 %
3-gram	977 069 902	19.0 GB	48.65 %
4-gram	1 313 818 354	30.5 GB	49.54 %
5-gram	1 176 470 663	32.1 GB	47.16 %
Σ	3 354 253 200	77.9 GB	54.20 %

- Postprocessing includes:
 - all n-grams: conversion to lower case
 - 1-grams: deletion of words with frequency below 3 000
deletion of words with certain special characters (blacklist)
→ about 1.5 million 1-grams remain
 - 2/3/4/5-grams: filtering with respect to the 1.5 million 1-grams
- See Net**speak** load statistics online.

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Related Research

Wildcard search	[Cafarella and Etzioni, WWW 2005] [Resnik and Elkiss, ACL 2005] [Rafiei and Li, CIKM 2009] [Tsang and Chawla, CIKM 2011] [Vaele, ACL 2011]
n-Gram indexing	[Lin et al., LREC 2010] [Hawker et al., ALT 2007] [Carlson, Carnegie Mellon 2008] [Brants, EMNLP/CONLL 2007] [Guthrie and Hepple, EMNLP 2010]
Error correction	[Leacock et al., Morgan & Claypool 2010] [Brockett et al., ACL 2006]
Digital humanities	[Michel et al., Science 2010]

The Netspeak Word Search Engine

Problem Statement

Given: A set D of n-grams, $n \leq 5$, with frequencies $f : D \rightarrow \mathbf{N}$.
A query q as a sequence of words and wildcards.

query	=	{ word wildcard } ₁ ⁵
wildcard	=	"?" "*" synonyms multiset optionset
synonyms	=	"#" word
multiset	=	"{ " word { word } " }"
optionset	=	"[" word { word } "]"

Task: Retrieve all n-grams in D that match q .

The Netspeak Word Search Engine

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Task: Retrieve all n-grams in D that match q .

Straightforward solution:

1. Construct an inverted index $\mu : V \rightarrow \mathcal{P}(D)$, where V is D 's vocabulary.
2. Retrieve the n-grams $R = \bigcap_{w \in q} \mu(w)$ that contain all of q 's words $w \in V$.
3. Compile a pattern matcher from q and filter R .

The Netspeak Word Search Engine

Index Construction

Considerations and implications:

- Exploit closed retrieval setting (D is constant): perfect hashing
- Exploit small n-gram lengths: **compile filtering effort into index**
 - multiple indexes for fixed query lengths
 - uniform query representation by enfolding
 - positional subqueries as index keys

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$q = \text{hello kitty ?}$

The Netspeak Word Search Engine

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$q = \text{hello kitty ?} \rightarrow \mu(\text{hello})$
 $\rightarrow \mu(\text{kitty})$

The Netspeak Word Search Engine

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```
q = hello kitty ? →  $\mu(\text{hello})$  → hello          33 000 000
                     →  $\mu(\text{kitty})$    hello all      800 000
                           hello to all  140 000
                           say hello     1 000 000
                           posted by hello 339 000
                           say hello to  374 000
```

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$q = \text{hello kitty ?} \rightarrow \boxed{\mu(\text{hello})}$	$\rightarrow \text{hello}$	33 000 000	1-gram index
$\rightarrow \mu(\text{kitty})$	hello all	800 000	2-gram index
	hello to all	140 000	3-gram index
	say hello	1 000 000	4-gram index
	posted by hello	339 000	5-gram index
	say hello to	374 000	

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$q = \text{hello kitty ?} \rightarrow \boxed{\mu(\text{hello})}$	$\rightarrow \text{hello}$	33 000 000	1-gram index
$\rightarrow \mu(\text{kitty})$	hello all	800 000	2-gram index
	hello to all	140 000 $\leftarrow \mu_3(\text{hello})$	$\boxed{3\text{-gram index}}$
	say hello	1 000 000	4-gram index
	posted by hello	339 000 \leftarrow	5-gram index
	say hello to	374 000 \leftarrow	

The Netspeak Word Search Engine

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$q = \text{hello} * \text{kitty} *$

The Netspeak Word Search Engine

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```
q = hello * kitty * → hello kitty
                           hello ? kitty
                           hello kitty ?
                           hello ? ? kitty
                           hello ? kitty ?
                           hello kitty ? ?
                           hello ? ? ? kitty
                           hello ? ? kitty ?
                           hello ? kitty ? ?
                           hello kitty ? ? ?
```

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$q = \text{hello} * \text{kitty} * \rightarrow \text{hello kitty}$

hello ? kitty → ? ? kitty

hello kitty ? → ? kitty ?

hello ? ? kitty

hello ? kitty ?

hello kitty ? ?

hello ? ? ? kitty

hello ? ? kitty ?

hello ? kitty ? ?

hello kitty ? ? ?

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$q = \text{hello} * \text{kitty} * \rightarrow \text{hello kitty}$

hello	<table border="1"><tr><td>?</td><td>kitty</td></tr></table>	?	kitty	$\rightarrow ? ? \text{kitty} \rightarrow \mu_{3P}(\text{kitty}, 3, 2)$
?	kitty			
hello	<table border="1"><tr><td>kitty</td><td>?</td></tr></table>	kitty	?	$\rightarrow ? \text{kitty} ? \rightarrow \mu_{3P}(\text{kitty}, 3, 1)$
kitty	?			
hello	?	?	kitty	
hello	?	kitty	?	
hello	kitty	?	?	
hello	?	?	?	kitty
hello	?	?	kitty	?
hello	?	kitty	?	?
hello	kitty	?	?	?

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`q = hello kitty ?`

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 - positional subqueries as index keys
- Exploit task characteristics: trade retrieval recall for retrieval time

```
q = hello kitty ?  →  μ3P(hello, 3, 0)
                      →  μ3P(kitty, 3, 1))
```

The Netspeak Word Search Engine

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- Exploit task characteristics: trade retrieval recall for retrieval time

$q = \text{hello kitty ?} \rightarrow \mu_{3P}(\text{hello}, 3, 0)$	→ hello, my	500 000
$\rightarrow \mu_{3P}(\text{kitty}, 3, 1))$	hello and welcome	261 000
	hello world!	175 000
	hello
	hello my friend	13 000
	hello kitty princess	8 400
	hello is there	4 600
	hello and how	2 600
	hello is any	320

The Netspeak Word Search Engine

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The Netspeak Word Search Engine

Index Construction

Examples:

n-gram	Frequency	Identifier	Postlist entry	Index	Key
hello	33 000 000	1	(1, 33 000 000)	symbol table	hello
world	432 000 000	3	(3, 432 000 000)	symbol table	world
hello world	712 963	4	(4, 712 963)	symbol table	hello world
				2-gram	(hello, 2, 0)
				2-gram	(world, 2, 1)

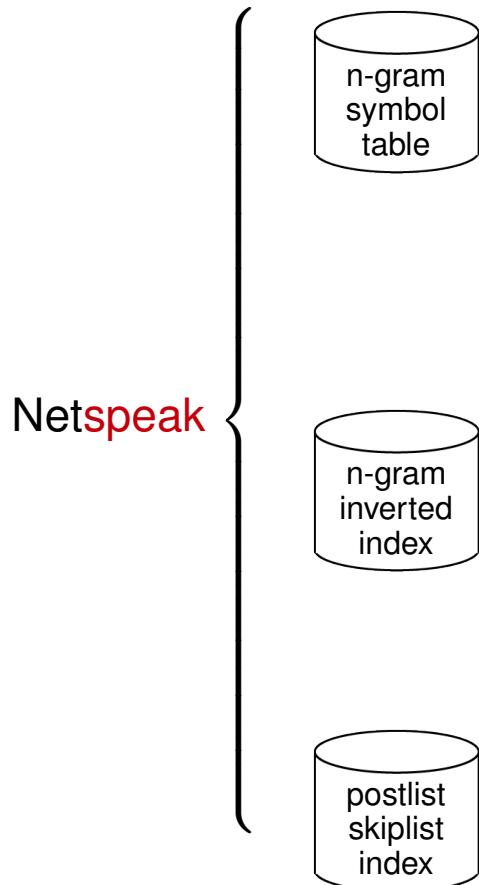
Part of the symbol table is used as 1-gram index at the same time.

Net**spe**ak index statistics:

- 2 013 781 863 keys in n-gram symbol table
- 19 346 361 keys in 2/3/4/5-gram indexes
- 7 782 365 325 postlist entries
- 134 GB index size, 1.7 GB memory footprint

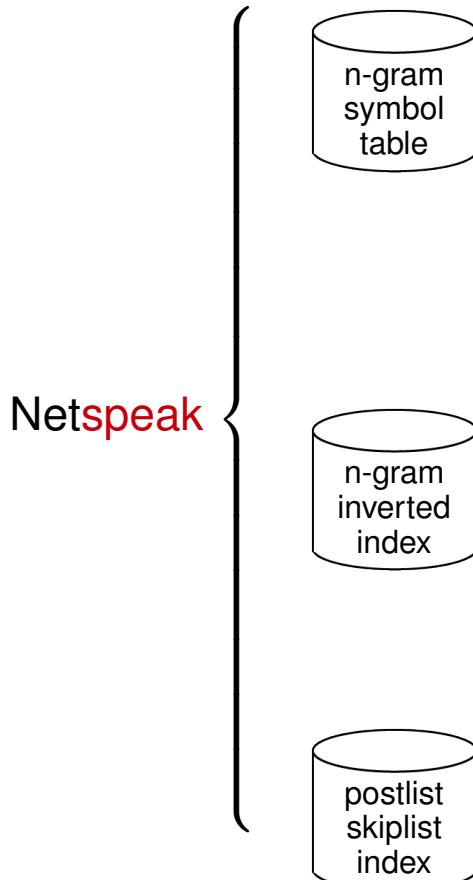
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Index Construction



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Index Construction



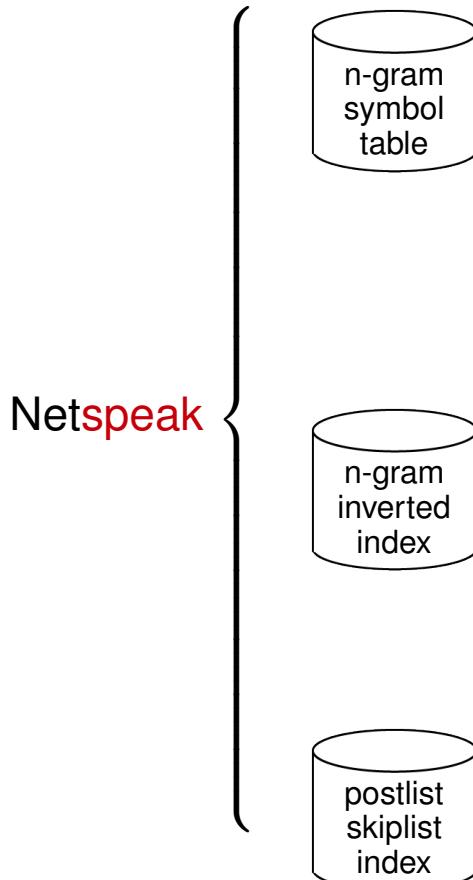
Bijective mapping between all n-grams and their postlist entries.
I.e., frequency information is symbol table payload.

Example: `hello world` \mapsto (4, 712963) // n-gram \mapsto (id, frequency)
(4, 712963) \mapsto `hello world` // (id, frequency) \mapsto n-gram

Rationale: Follow design of inverted indexes.
Lookup table for non-wild-card queries.
Database with underestimations for skip heuristics.

The Netspeak Word Search Engine

Index Construction



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Example: $\text{hello world} \mapsto (4, 712963)$ // n-gram $\mapsto (\text{id, frequency})$
 $(4, 712963) \mapsto \text{hello world}$ // (id, frequency) \mapsto n-gram

Rationale: Follow design of inverted indexes.
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Inverted index where n-grams are in the role of documents.

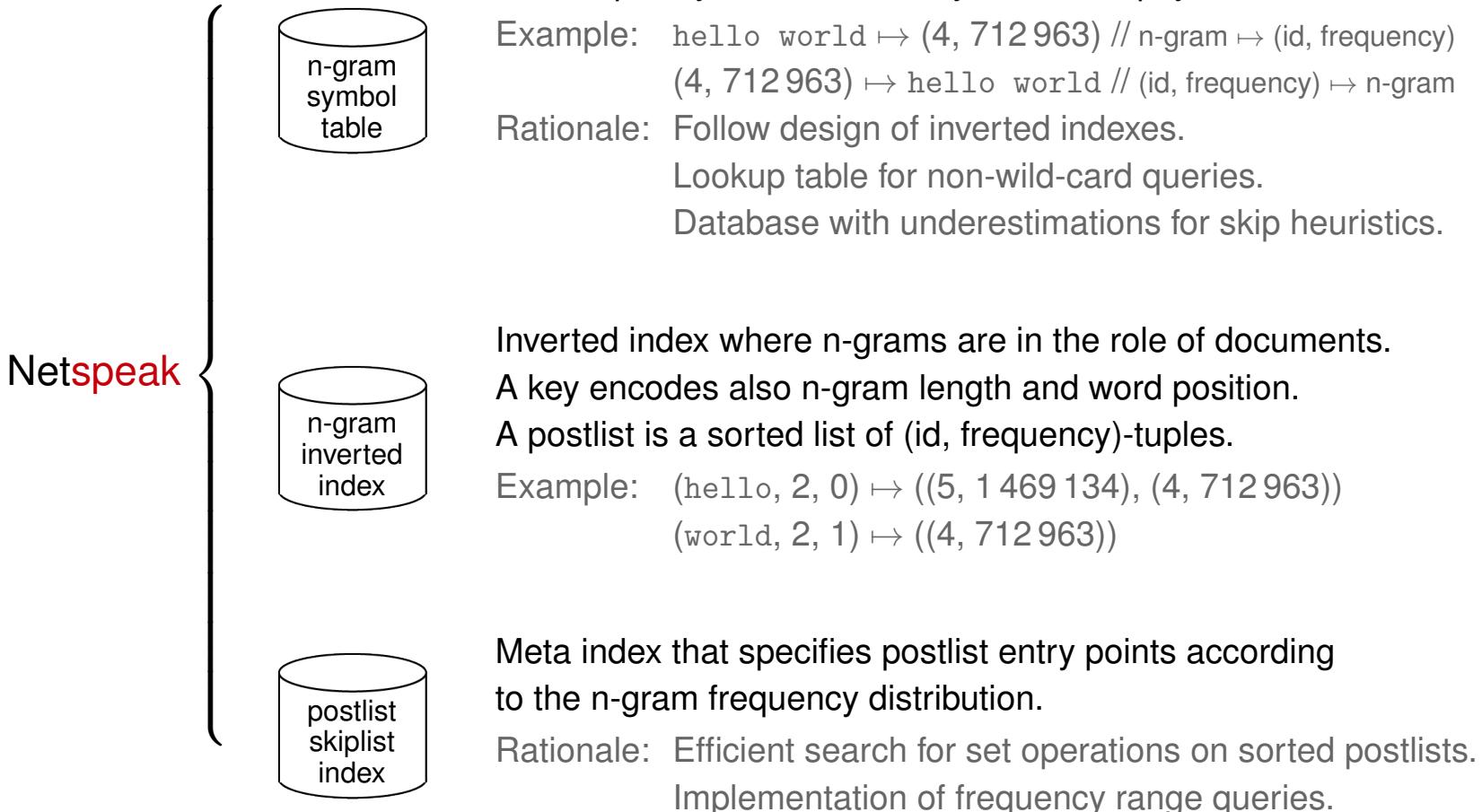
A key encodes also n-gram length and word position.

A postlist is a sorted list of (id, frequency)-tuples.

Example: $(\text{hello}, 2, 0) \mapsto ((5, 1469134), (4, 712963))$
 $(\text{world}, 2, 1) \mapsto ((4, 712963))$

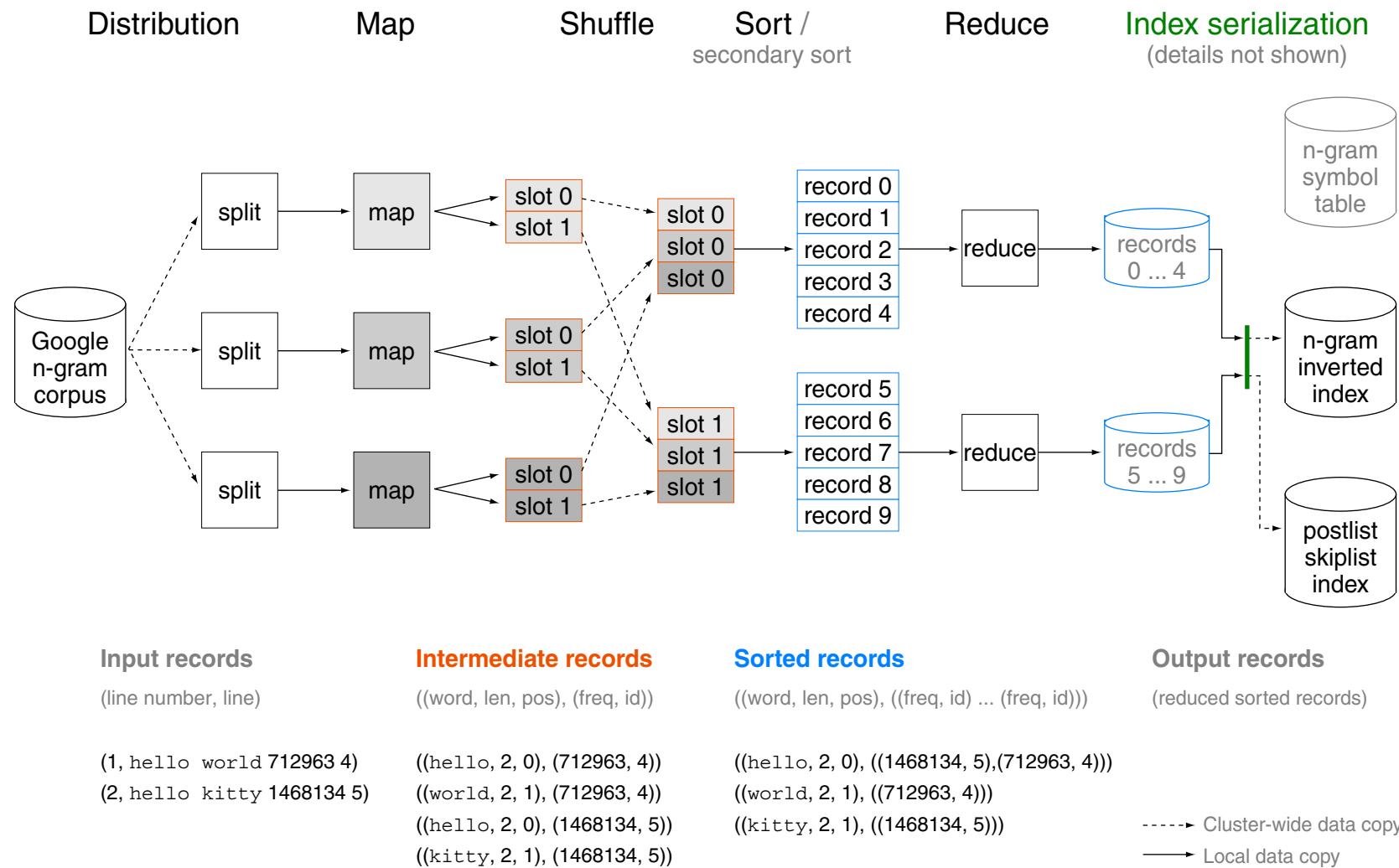
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Index Construction



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Construction Pipeline



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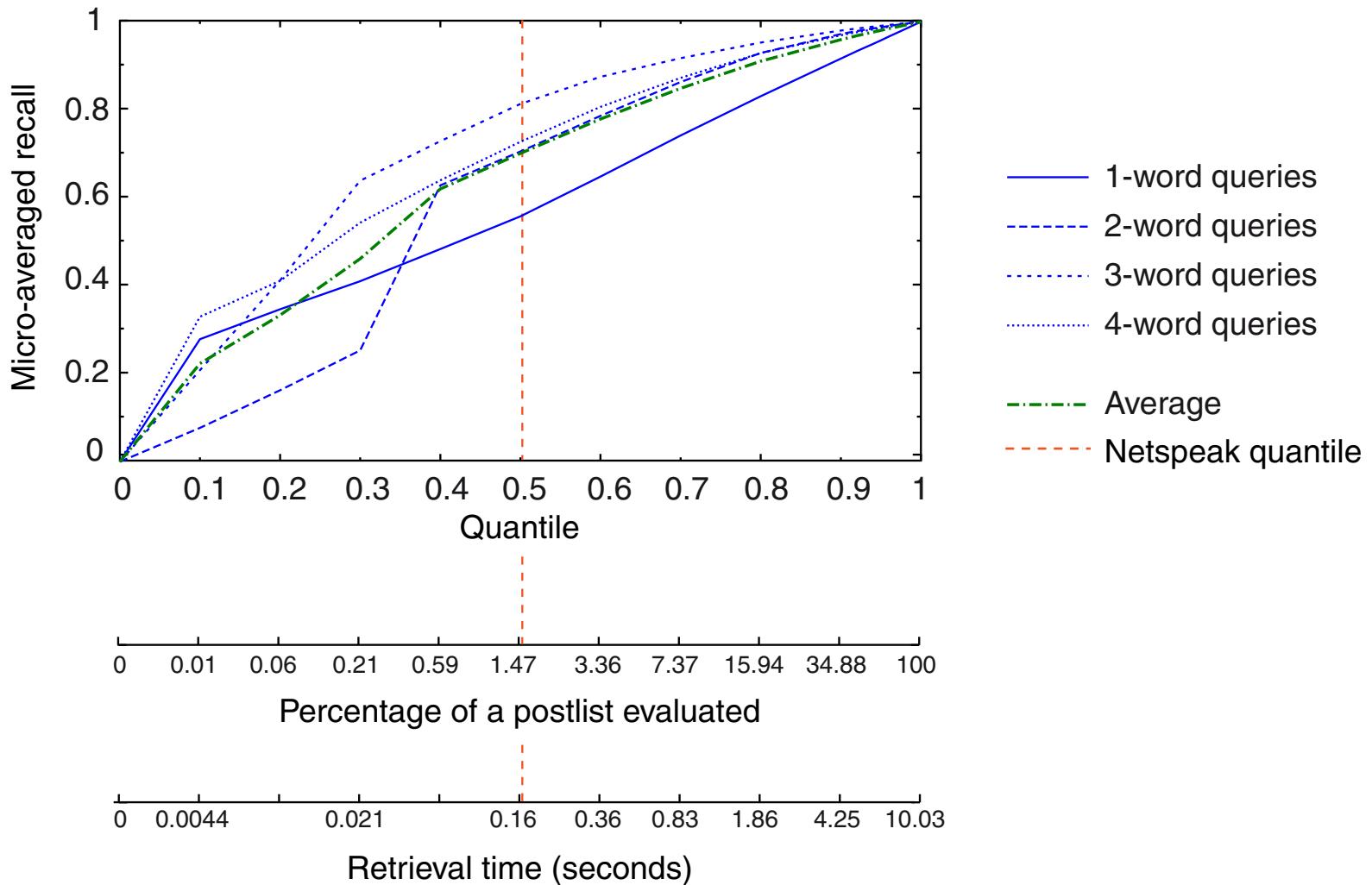
Selected Index Performance Issues

- n-gram symbol table (external)
 - n-gram \mapsto (id, frequency)
minimal perfect hash functions via BDZ algorithm [Belazzougui/Botelho/Dietzfelbinger 2009]
 - (id, frequency) \mapsto n-gram
four external arrays encoding the 2/3/4/5-grams via their 1-gram ids
- n-gram inverted index (external)
 - tailored indexing of 2/3/4/5-grams that enable positional subquery lookup
 - header tables that map positional subqueries to postlists on the harddisk
- postlist skip list index (external)
 - applies to postlists that fit not into memory ($> 10^5$ entries)
 - skip density models frequency distribution and enables task-specific pruning strategies
 - heuristic retrieval that considers the number of matches or postlist entries
 - heuristic retrieval that considers the word class. Pruning strategy for phrase ranking:

immediate response	non-stopword postlist stopword postlist	0.80 quantile 0.30 quantile
near 1-recall response	non-stopword postlist stopword postlist	0.95 quantile 0.50 quantile
- result caching

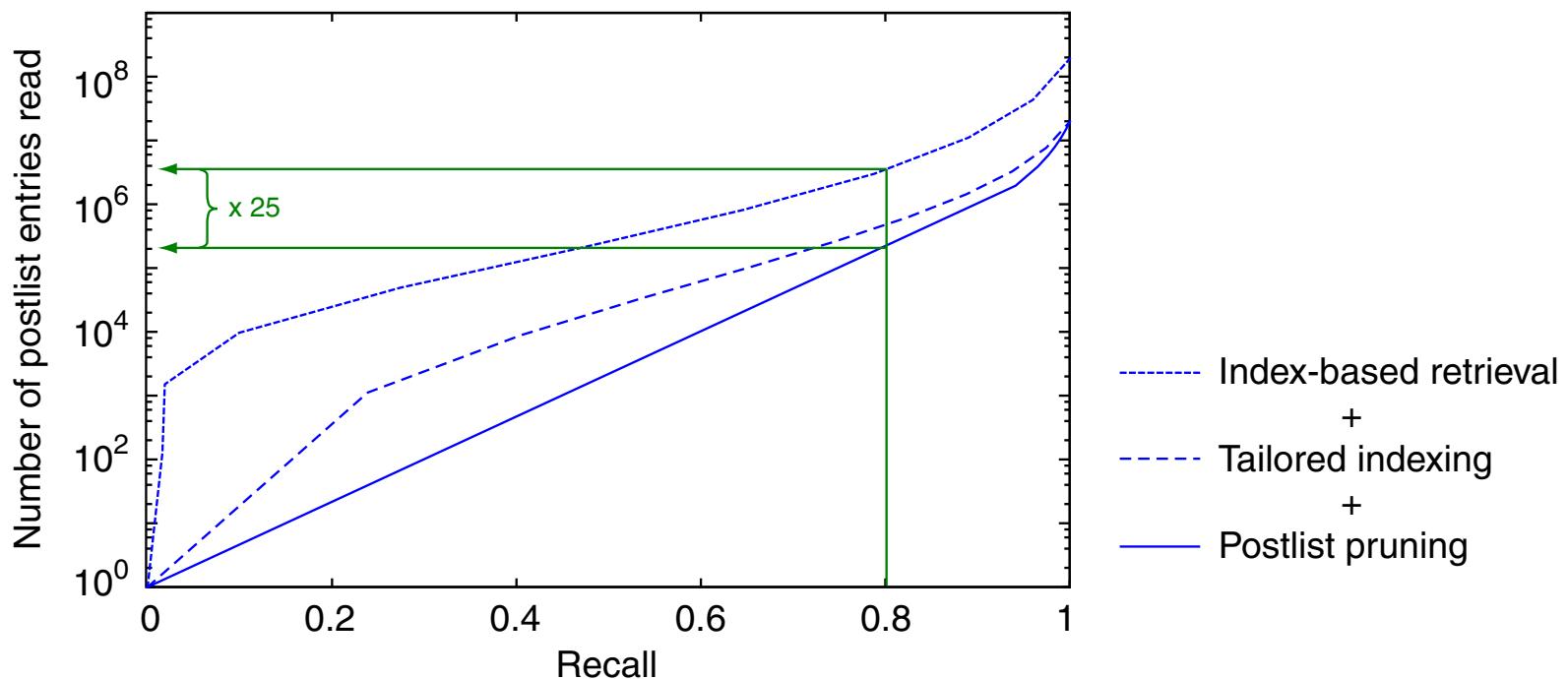
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Retrieval Performance—Data Perspective: Completeness → Recall



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Retrieval Performance—Technology Perspective: Effort → Recall



- reduction of retrieval effort by factor 25 due to indexing technology

The Netspeak Word Search Engine

Netspeak in a Nutshell

Given: A set D of n-grams, $n \leq 5$, with frequencies $f : D \rightarrow \mathbf{N}$.
A query q as a sequence of words and wildcards.

Task: Retrieve all n-grams in D that match q .

Solution:

- Construct an inverted index $\mu : V \times \underbrace{\{1, \dots, 5\}}_{\text{n-gram length}} \times \underbrace{\{1, \dots, 5\}}_{\text{word position}} \rightarrow \mathcal{P}(D)$
- Sort $\mu(w, i, j)$ in descending order of f , where $w \in V$ and $i, j \in \{1, \dots, 5\}$.
- Let R_q denote the true retrieval result for q .
- Enfold q into $\{q_1, \dots, q_m\}$ such that $\bigcup_{i=1}^m R_{q_i} = R_q$, and each q_i matches only n-grams with a fixed length. Process sub-queries in parallel.
- Retrieve all n-grams $R_{q_i} = \bigcap_{w \in q_i} \mu(w, |q_i|, q_{i|w})$, with $q_{i|w}$ denoting w 's position in q_i .
- Process $\mu(w, i, j)$ starting at rightmost entry k , where $f(\mu(w, i, j)_k) \leq \min_{d \in \{q_1, \dots, q_m\}} (f(d))$.
- Stop processing $\mu(w, i, j)$ at entry
 - $\begin{cases} |\mu(w, i, j)| & \text{if the postlist is smaller than a page, or} \\ l_1 & \text{if a pre-specified amount of results have been retrieved, or} \\ l_2 & \text{if } \sum_{i'=0}^{l_2} f(\mu(w, i, j)_{i'}) \text{ covers } \kappa\% \text{ of the frequency distribution.} \end{cases}$

The Netspeak Word Search Engine

Netspeak Summary

Net**speak**'s targeted users want to improve their writing:

- scientists, authors, scholars, journalists, bloggers

I.e., at the beginning we were thinking of following use cases:

- scientists who speak English as a second language
- scientists who ask what is commonly written in their research field
- a Netspeak that is tailored to the genre of scientific writing
- support for corpus-linguistic research

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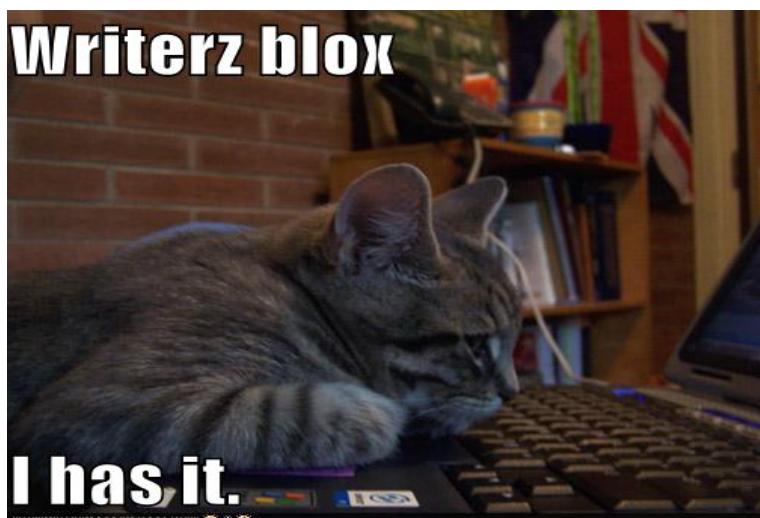
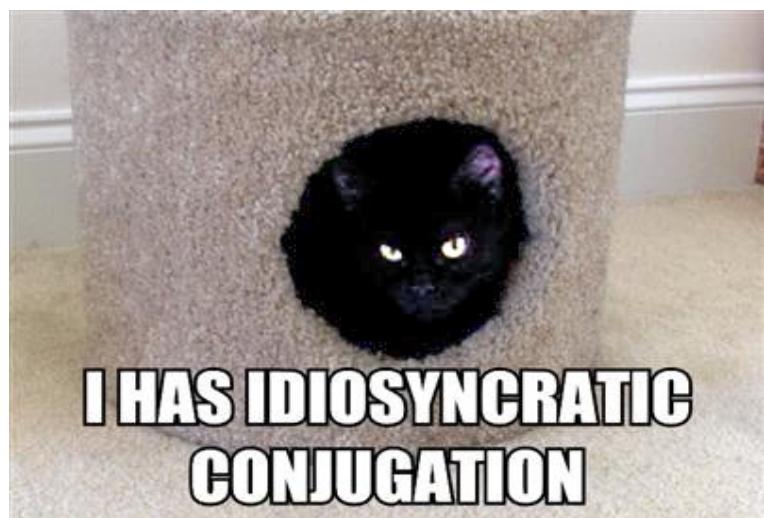
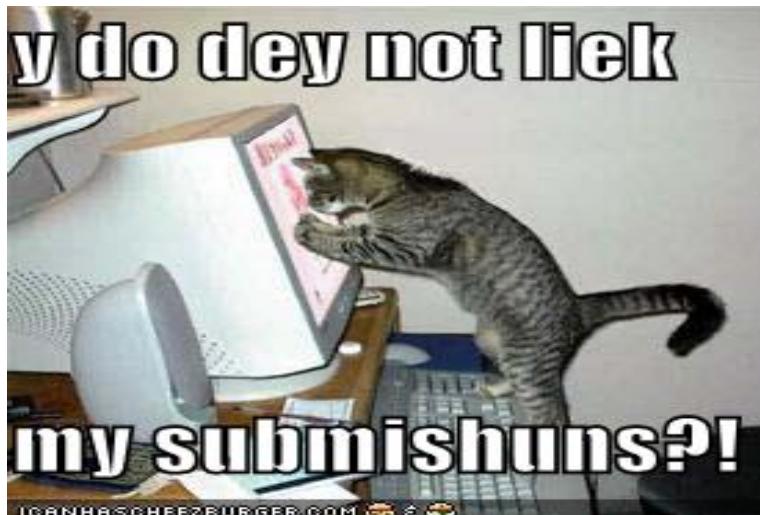
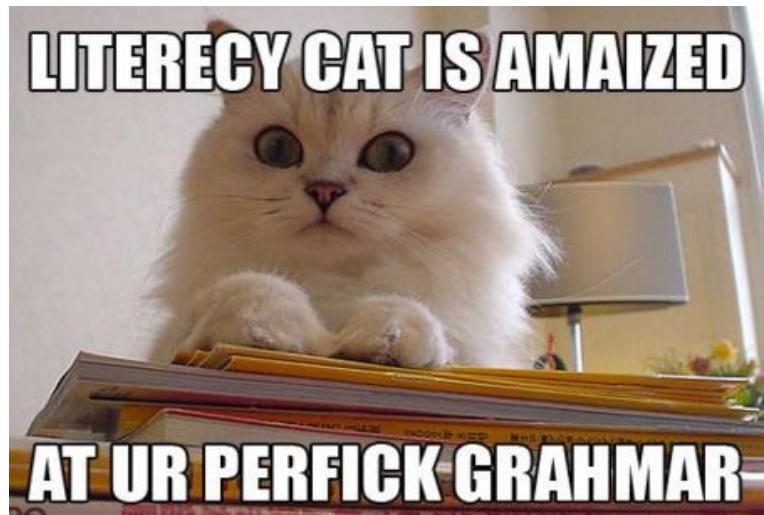
Meanwhile we are also thinking of the following (and more):

- query segmentation and query cover
- paraphrase generation and evaluation
- POS search, morphological search, partial word search

Research on subquery compilation: key space size versus filtering effort

The Netspeak Word Search Engine

What Our Users Say ;-)



Query Segmentation

Query Segmentation

What is the User Searching?

```
new york times square dance
```

Query Segmentation

What is the User Searching?

new york times square dance



All search engines face the same problem.

Query Segmentation

What is the User Searching?

new york times square dance



Image source: [<http://www.theepochtimes.com/n2/images/stories/large/2009/08/06/Bollywood1.jpg>]

Query Segmentation

What is the User Searching?

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"All the News
That's Fit to Print"

The New York Times

VOL. CLVIII . No. 54,678 © 2009 The New York Times NEW YORK, SUNDAY, MAY 17, 2009 \$5 beyond the greater New York metropolitan area. \$4.00



From a Theory To a Consensus On Emissions

Permits Gain Political Edge Over Taxation

By JOHN M. BRODER

WASHINGTON — As Congress weighs imposing a mandatory limit on climate-altering gases — an outcome still far from certain — it is likely to turn to a system that sets a government-controlled emissions cap and allows polluting industries to buy and sell permits to meet it.

That approach, known as cap and trade, has been embraced by President Obama. Democratic leaders in Congress, environmental groups and a growing number of business interests, including energy-consuming industries like autos, support it.

But not long ago, many of today's supporters dismissed the idea of tradable emissions permits as an industry-inspired Republican scheme to avoid the real cost of cutting air pollution. The right answer, they said, was strict government regulation, state-of-the-art technology and a federal tax on every ton of harmful emissions.

How did cap and trade, hatched as an academic theory in obscure economic journals half a century ago, become the policy of choice in the debate over how to slow the rise of global warming? And how did it come to eclipse the idea of simply slapping a tax on energy consumption that befalls the public square or leaves the nation hunkered to freezing nail.

Square Dance

19 U.S. States Have Designated It As Their Official State Dance

Late Edition

Today, a shower, yielding to sun, high 64. Tonight, chilly, low 45. Tomorrow, sunny and cool, high 64. Yesterday's high, 70, low, 54. Weather map and details, Page 2A.

CONSERVATIVES MAP STRATEGIES ON COURT FIGHT

MEMOS OUTLINE ATTACKS

Hoping to Re-Energize G.O.P. by Opposing Obama's Choice

By CHARLIE SAVAGE

WASHINGTON — If President Obama nominates Judge Diane P. Wood to the Supreme Court, conservatives plan to attack her as an "outspoken" supporter of abortion, including partial-birth abortion.

If he nominates Judge Sonia Sotomayor, they plan to accuse her of being too willing to expand constitutional rights beyond the text of the Constitution.

And if he nominates Kathleen M. Sullivan, a law professor at Stanford, they plan to denounce her as a "prominent supporter of homosexual marriage."

Preparing to oppose the confirmation of Mr. Obama's eventual choice to succeed Justice David H. Souter, who is retiring, conservative groups are working together to stockpile memorandums. Ten memorandums summarizing their research, obtained by The New York Times, provide a window onto how they hope to frame the confirmation hearings.

The memorandums dissect possible nominees' records, noting statements the groups find objectionable on issues like abortion, same-sex marriage, the con-

Image source: [http://blog.caseytempleton.com/wp-content/uploads/2009/05/090517_nyfroontpage1.jpg]

Image source: [http://upload.wikimedia.org/wikipedia/commons/0/03/Square_Dance_Group.jpg]

Query Segmentation

Segment Your Queries!

The benefits:

- improved precision
- potential disambiguation
- reformulation at segment level

The syntax:

- Quotes around segments: "new york" "times square" dance

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- Most web searchers are not even aware of the quotes option.

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The syntax:

- Quotes around segments: "new york" "times square" dance

The reality:

- Most web searchers are not even aware of the quotes option.

The solution:

- Automatic *pre-retrieval* query segmentation. (response time is indispensable)

Query Segmentation

Segment Your Queries!

Given: A keyword query.

Task: Find the “best” segmentation.

Boundary conditions:

- ❑ we assume correct spelling
- ❑ we do not change keywords
- ❑ we do not change word order

Examples:

Query	new york times square dance	
Valid candidates	"new york" "times square" dance	(three segments)
	"new york times" "square dance"	
No candidate	"new york" "dance times square" (a Latin dance studio in NYC)	{ (two segments each)

Query Segmentation

Related Research

Mutual information	[Risvik et al., WWW 2003] [Jones et al., WWW 2006] [Huang et al., WWW 2010]
Supervised learning	[Bergsma and Wang, EMNLP-CoNLL 2007] [Bendersky et al., SIGIR 2009]
Unsupervised learning	[Tan and Peng, WWW 2008] [Zhang et al., ACL-IJCNLP 2009]
Retrieval feedback	[Brenes et al., CERI 2010] [Bendersky et al., CIKM 2010] [Bendersky et al., ACL 2011]
Query log	[Mishra et al., WWW 2011] [Li et al., SIGIR 2011]

Query Segmentation

Our first approach [Hagen et al., SIGIR 2010]

... follows a well-known principle.



KISS—keep it simple and stupid—and use the Web as a corpus.

Query Segmentation

Exploiting Web Phrase Frequencies [Google n-grams, Brants and Franz, LDC 2006]

Rationale:

- (a) web phrases = reasonable segments
- (b) more frequent = better segments

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Summing up raw frequencies won't yield a sensible ranking:

"new york" times = 165.4 million

"new york times" = 17.5 million

(short segments always win)

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From the data we derived the following segment frequency normalization:

$$|s|^{|s|} \cdot freq(s) \quad (s \text{ denotes a segment})$$

Query Segmentation

Exploiting Web Phrase Frequencies

Examples:

segment s	$freq(s)$
new york	165.4 million
new york times	17.5 million
new york times square	20 476
new york times square dance	0
york times	17.6 million
york times square	20 561
york times square dance	0
times square	1.3 million
times square dance	104
square dance	210 440

Query Segmentation

Exploiting Web Phrase Frequencies

Examples:

segment s	$freq(s)$	$ s ^{ s } \cdot freq(s)$
new york	165.4 million	661.6 million
new york times	17.5 million	472.5 million
new york times square	20 476	5.2 million
new york times square dance	0	0
york times	17.6 million	70.4 million
york times square	20 561	0.5 million
york times square dance	0	0
times square	1.3 million	5.2 million
times square dance	104	2 808
square dance	210 440	0.8 million

Query Segmentation

Exploiting Web Phrase Frequencies

The normalized segment frequencies sum up to the *score* of a query S :

$$score(S) = \begin{cases} \sum_{s \in S, |s| \geq 2} |s|^{|s|} \cdot freq(s) \\ -1 \quad \text{if } |s| \geq 2 \wedge freq(s) = 0 \text{ for some } s \in S \end{cases}$$

Ranking:

rank	segmentation S	score(S)
1	"new york" "times square" dance	666.8 million
2	"new york" times "square dance"	662.4 million
:	:	:
5	"new york times" "square dance"	473.3 million
:	:	:
13	new york "times square dance"	2808
14	new york times square dance	0
15	"new york times square dance"	-1
16	new "york times square dance"	-1

Query Segmentation

Our second approach [Hagen et al., WWW 2011]

... introduces a semantic-based frequency normalization.



Titles of articles are highly expressive—and can be found on the Web.

Query Segmentation

Exploiting Web Phrase Frequencies + Wikipedia Titles

Wikipedia article on “Time Square”:

Article [Discussion](#) [Read](#)

Times Square

From Wikipedia, the free encyclopedia
(Redirected from [Times square](#))

For the subway station, see [Times Square - 42nd Street \(New York City Subway\)](#). For other uses, see [Times Square \(disambiguation\)](#).

Times Square is a major commercial intersection in the [borough of Manhattan](#) in [New York City](#), at the junction of [Broadway](#) and [Seventh Avenue](#) and stretching from [West 42nd](#) to [West 47th Streets](#). The extended Times Square area, also called the [Theatre District](#), consists of the blocks between [Sixth](#) and [Eighth Avenues](#) from east to west, and [West 40th](#) and [West 53rd Streets](#) from south to north, making up the western part of the commercial area of [Midtown Manhattan](#).



Query Segmentation

Exploiting Web Phrase Frequencies + Wikipedia Titles

Wikipedia article on “Toilet paper orientation”:

The screenshot shows a Wikipedia article page for "Toilet paper orientation". The page has a standard header with tabs for "Article" and "Discussion", and buttons for "Read", "View source", and "View history". The main content starts with a heading "Toilet paper orientation" and a subtext "From Wikipedia, the free encyclopedia". Below this, a text block states: "There are two choices of **toilet paper orientation** when using a **toilet roll holder** with a horizontal **axle parallel** to the wall:". Two photographs are shown side-by-side. The left photograph shows a roll of toilet paper mounted on a holder, with the text "The over orientation" below it. The right photograph shows a roll of toilet paper mounted on a holder, with the text "The under orientation" below it. The left photograph shows the roll oriented such that the top edge is parallel to the wall. The right photograph shows the roll oriented such that the bottom edge is parallel to the wall.

Pure regression-based approaches will fail in cases like this.

Query Segmentation

Exploiting Web Phrase Frequencies + Wikipedia Titles

Examples:

segment s	$freq(s)$
new york	165.4 million
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times square	1.3 million
times square dance	104
square dance	210440

Query Segmentation

Exploiting Web Phrase Frequencies + Wikipedia Titles

Examples:

segment s	$freq(s)$	$wikiTitle(s)$
new york	165.4 million	✓
new york times	17.5 million	✓
new york times square	20476	-
new york times square dance	0	-
york times	17.6 million	-
york times square	20561	-
york times square dance	0	-
times square	1.3 million	✓
times square dance	104	-
square dance	210440	✓

Query Segmentation

Exploiting Web Phrase Frequencies + Wikipedia Titles

Examples:

segment s	$freq(s)$	$wikiTitle(s)$	$wikiFreq(s)$
new york	165.4 million	✓	165.4 million
new york times	17.5 million	✓	165.4 million
new york times square	20476	-	20476
new york times square dance	0	-	0
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york times square dance	0	-	0
times square	1.3 million	✓	1.3 million
times square dance	104	-	104
square dance	210440	✓	210440

Query Segmentation

Exploiting Web Phrase Frequencies + Wikipedia Titles

Examples:

$$\text{wikiFreq}(s) = \text{freq}(s') \quad \leftrightarrow \quad s' \sqsubset s \wedge \text{wikiTitle}(s)$$

with \sqsubset as subsequence operator

Query Segmentation

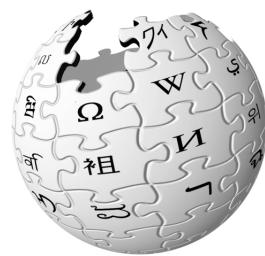
Exploiting Web Phrase Frequencies + Wikipedia Titles

The normalized segment frequencies sum up to the *score* of a query S :

Ranking:

rank	trend	segmentation S	score(S)
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2	↑↑	"new york times" square dance	496.2 million
3	↓	"new york" "times square" dance	333.4 million
:	:	:	:
13	-	new york "times square dance"	312
14	-	new york times square dance	0
15	-	"new york times square dance"	-1
16	-	new "york times square dance"	-1

Query Segmentation



...

How do our approaches perform?

Query Segmentation

About Effectiveness

The standard corpus: [Bergsma and Wang, EMNLP-CoNLL 2007]

- 500 queries from the AOL log
- each segmented by three human annotators
- often used for evaluation

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How effectiveness is measured:

Reference: "new york" "times square" dance (three segments)

Computed: "new york" times square dance (four segments)

→ Query: 0 (computed \neq reference)

→ Precision: $\frac{1}{2}$ (2 out of 4 computed segments correct)

→ Recall: $\frac{2}{3}$ (2 out of 3 reference segments found)

→ Break: $\frac{3}{4}$ (3 out of 4 between-words decisions correct)

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- 500 queries from the AOL log
- each segmented by three human annotators
- often used for evaluation

How effective we are:

	Mutual information	Bergsma/Wang	$ s ^{ s } \cdot freq(s)$	$ s \cdot wikiFreq(s)$
Query	0.583	0.702	0.700	0.726
Precision	0.693	0.812	0.800	0.820
Recall	0.697	0.831	0.796	0.807
Break	0.849	0.899	0.889	0.900

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Shortcomings of the Bergsma/Wang-corpus:

- not representative (small, just noun-phrases)
- only three annotators (40% without majority)
- duplicates, typos, encoding errors

Query Segmentation

About Effectiveness

A new evaluation corpus: [Hagen et al., WWW 2011]

- 50 000 queries (3-10 keywords) from “filtered” AOL log
- sampling considers frequency and length distribution
- semi-automatic spell checking (14% corrected)
- 10 annotators per query via Amazon Mechanical Turk

How effective we are:

	Mutual information	$ s ^{ \mathcal{S} } \cdot freq(s)$	$ s \cdot wikiFreq(s)$
Query	0.598	0.599	0.616
Precision	0.727	0.736	0.744
Recall	0.738	0.733	0.739
Break	0.844	0.842	0.850

Query Segmentation

About Efficiency

System and implementation details:

- standard quad-core PC running Ubuntu 10.04
- hash table (MPHF) for about 2 billion normalized frequencies
- 12 GB memory footprint

Throughput:

- > 3 000 queries per second
- Remark: 1 billion queries per day means 12 000 queries per second

Query Segmentation

Query Segmentation Summary

What we have done:

- exploitation of the Google n-gram corpus
- regression-based $|s|^{|s|}$ -normalization strategy
- Wikipedia-based normalization strategy
- as effective as state of the art, but more robust and faster
- new evaluation corpus (about two orders of magnitude larger than previous STA)

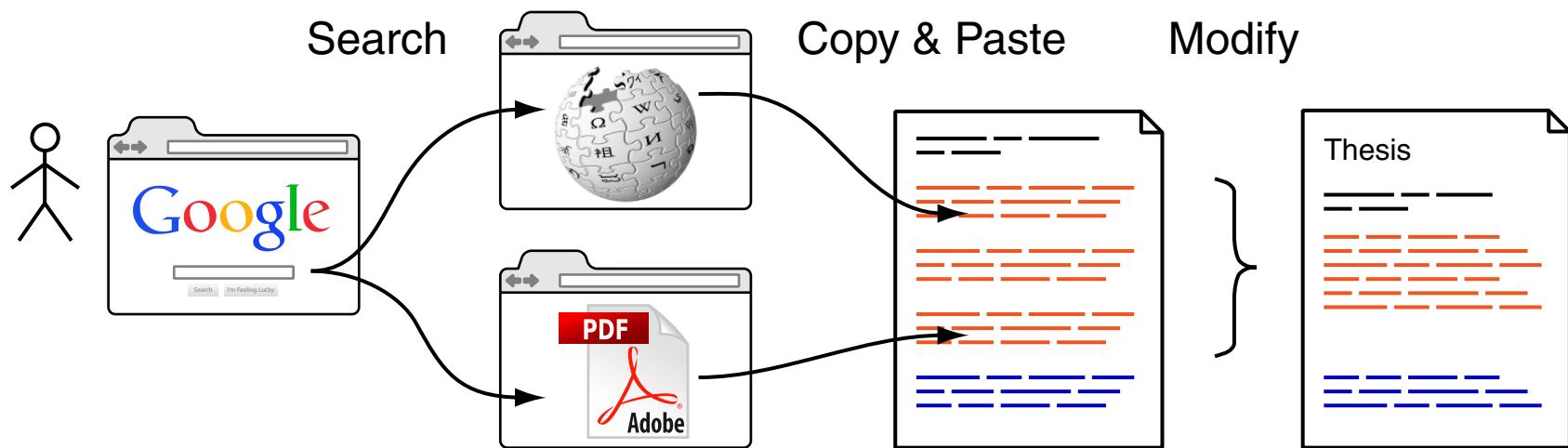
What we plan to do:

- *ranking-aware* effectiveness
- *retrieval-aware* effectiveness

Candidate Retrieval at PAN'12

Candidate Retrieval at PAN'12

How Humans Plagiarize



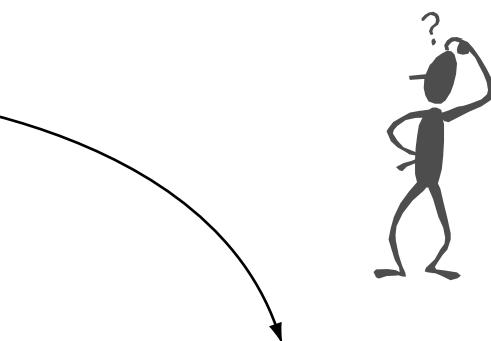
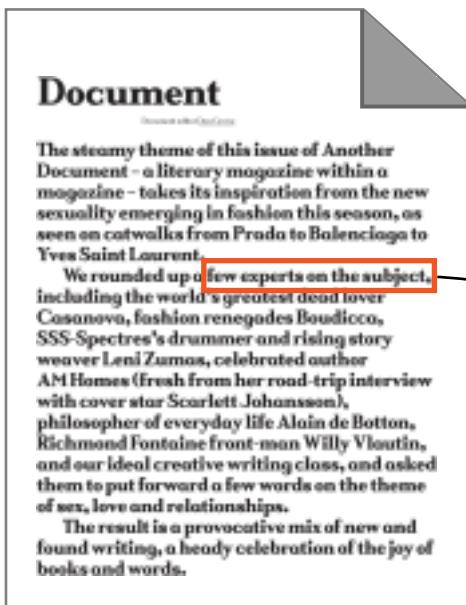
Candidate Retrieval at PAN'12

How Humans Spot Plagiarism



Candidate Retrieval at PAN'12

How Humans Spot Plagiarism



Google

where is it

About 2,210,000,000 results (0.20 seconds)

Advanced search

Everything

News

More

Any time

Latest

Past 2 days

More search tools

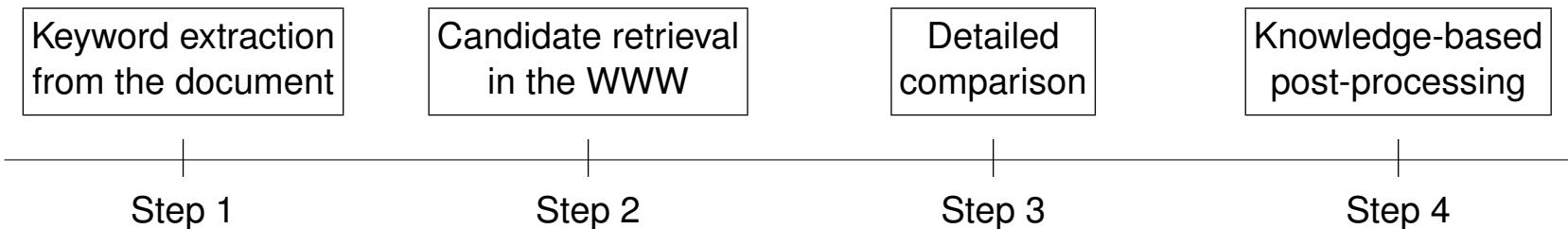
[Where Is It? 2010 - Catalog and organize your disks collection](#)
WhereIsIt is a Windows application, designed to organize and maintain a catalog of y computer media collection, including CD-ROMs, audio CDs, MP3s, ...
[www.whereisit-soft.com/](#) - Cached - Similar

[Downloads - Where Is It? 2010 - Catalog and organize your disks ...](#)
The entry page, Welcome to **WhereIsIt**; Product information on **WhereIsIt** and **WhereIsIt Lite**; The latest news bulletins about **WhereIsIt** and its development ...
[www.whereisit-soft.com/download.html](#) - Cached - Similar

Show more results from [www.whereisit-soft.com](#)

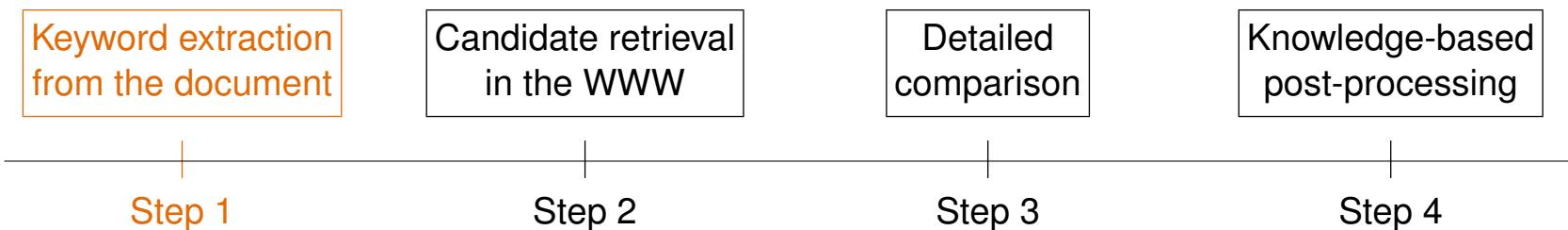
Candidate Retrieval at PAN'12

Algorithmic Plagiarism Detection



Candidate Retrieval at PAN'12

Algorithmic Plagiarism Detection



Where are the crucial keywords?

- check for noun phrases
- find orthographic mistakes
- consider word frequency classes
- but—don't look in titles, captions, or headings

Candidate Retrieval at PAN'12

Algorithmic Plagiarism Detection



Keywords: “information retrieval”, “query formulation”, “search session”, “user support”

Google

"information retrieval" "query formulation" Advanced search

About 22,800 results (0.22 seconds)

[Scholarly articles for "information retrieval" "query formulation"](#)

[Modern information retrieval](#) - Baeza-Yates - Cited by 7825

[Extended Boolean information retrieval](#) - Salton - Cited by 670

[Information filtering and information retrieval: two sides ...](#) - Belkin - Cited by 1079

[\[PDF\] Query Formulation as an Information Retrieval Problem](#)
File Format: PDF/Adobe Acrobat - [Quick View](#)
by AHM Hofstede - 1996 - [Cited by 33](#) - [Related articles](#)

Query Formulation as an Information Retrieval Problem, 257 sentences
verbalize this domain in terms used by the domain experts; i.e. the people who will be

Candidate Retrieval at PAN'12

Algorithmic Plagiarism Detection

Keyword extraction
from the document

Candidate retrieval
in the WWW

Detailed
comparison

Knowledge-based
post-processing

Step 1

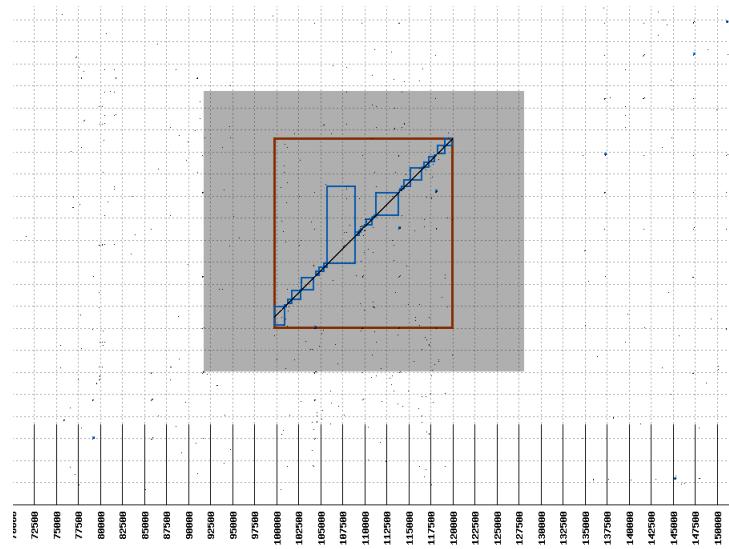
Step 2

Step 3

Step 4

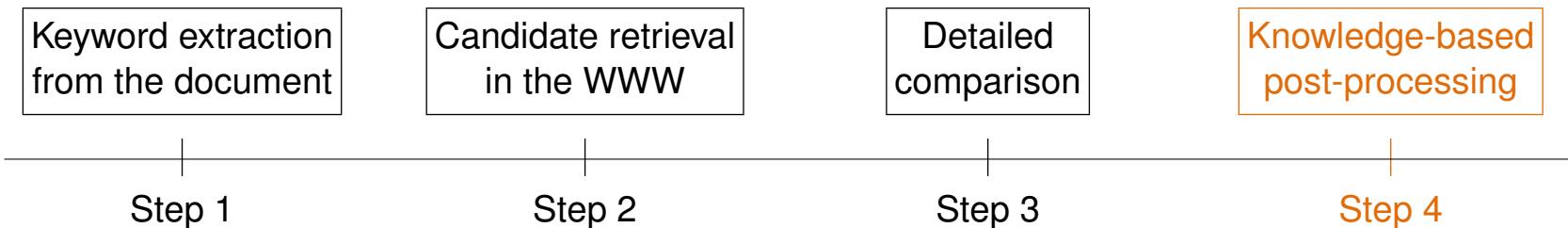


→ ... →



Candidate Retrieval at PAN'12

Algorithmic Plagiarism Detection

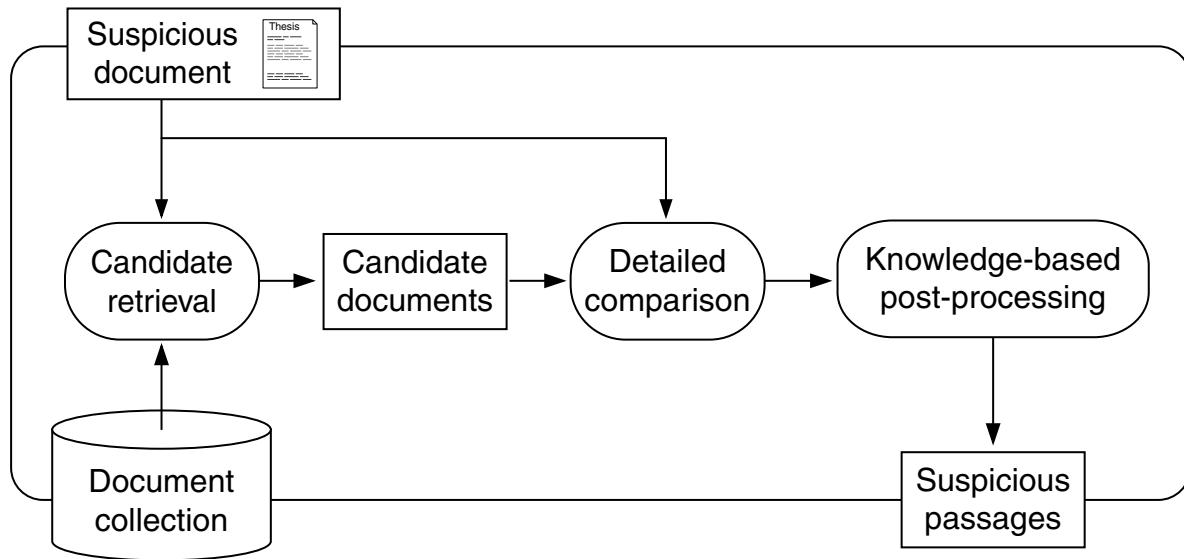


Check for problematic decisions:

- citation analysis
(difficult: consider “excuse citations” in footnotes along with a completely reused text)
- comparison of authors and co-authors
- visualization

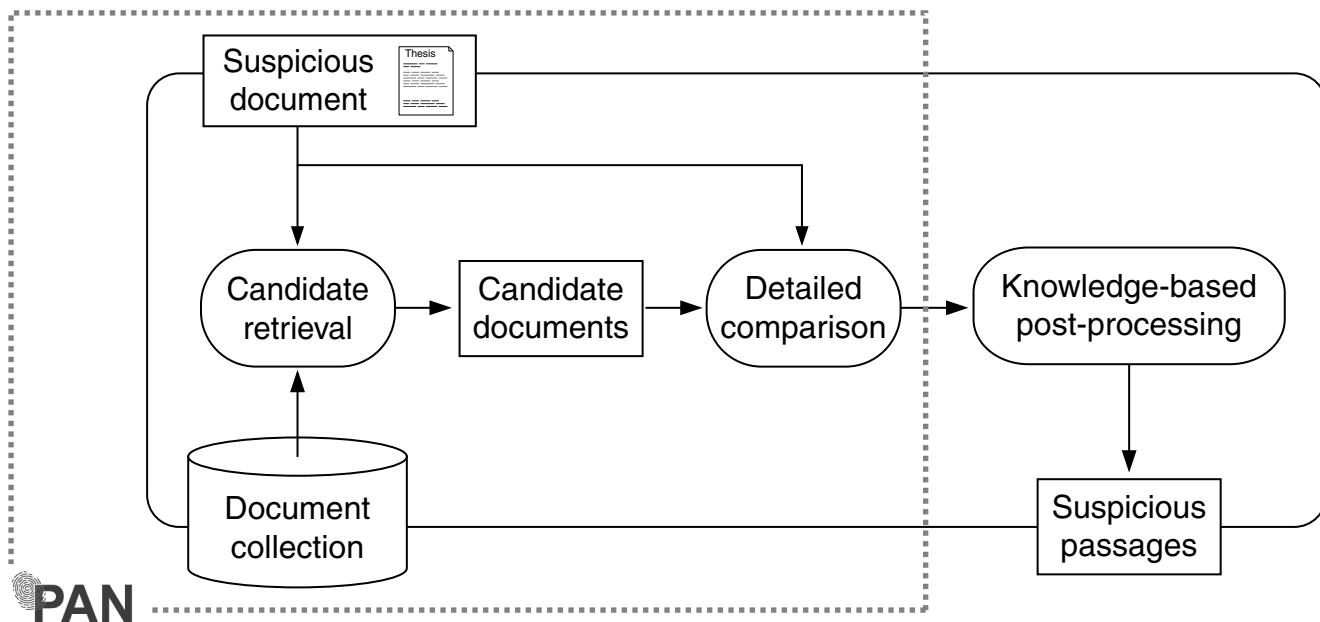
Candidate Retrieval at PAN'12

Algorithmic Plagiarism Detection



Candidate Retrieval at PAN'12

PAN Campaign [pan.webis.de]

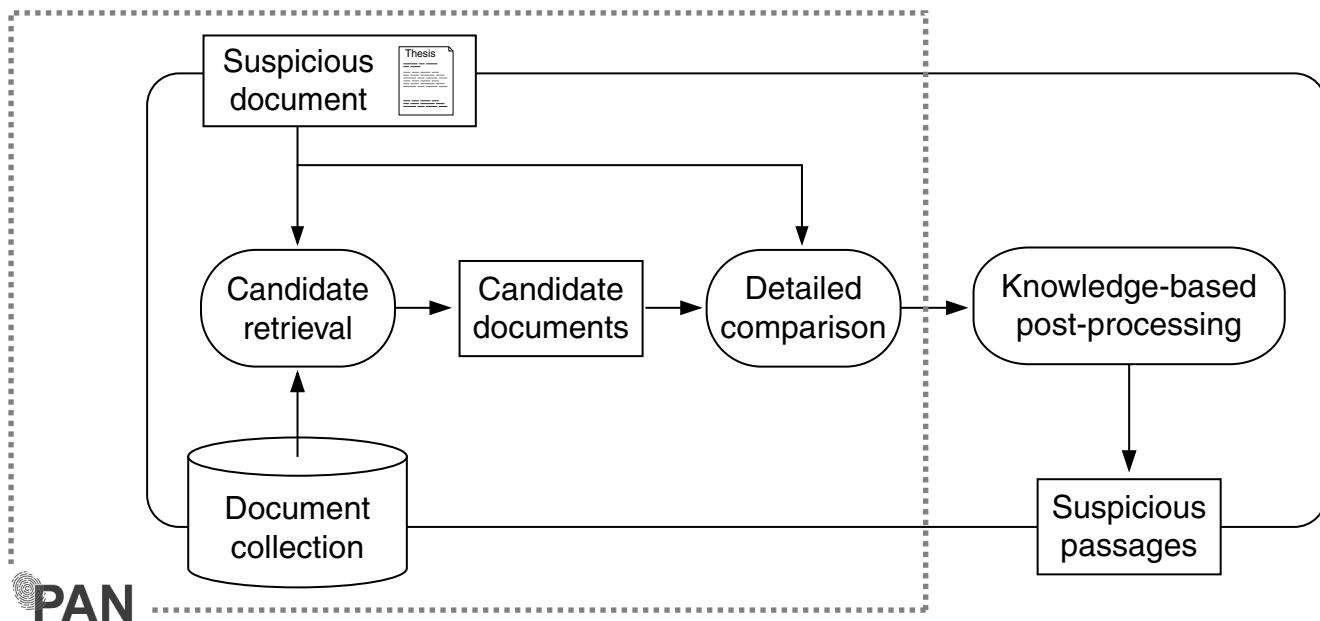


Uncovering plagiarism, authorship, and social software misuse:

- initiated in 2007
- competitions since 2009 (detection of authorship, vandalism, plagiarism, etc.)
- hosted at SIGIR, ECAI, SEPLN, and CLEF (since 2010)
- regularly >10 groups who participate in the plagiarism detection task

Candidate Retrieval at PAN'12

PAN Campaign

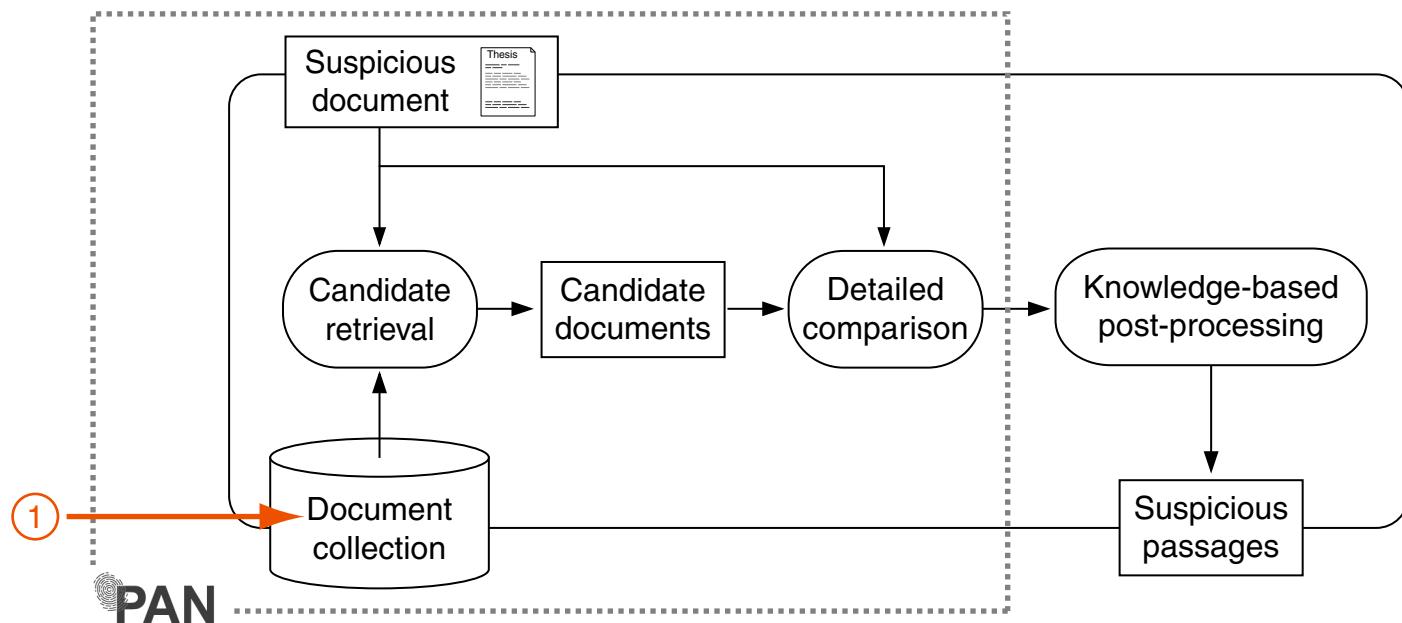


Observations, problems:

1. PAN-PC-10 corpus based on 27 073 documents, contains 68 558 plagiarism cases, addresses a broad range (by varying length, paraphrasing, topic alignment, etc.).
2. But—the corpus is too small to enforce a true candidate retrieval situation: most participants did a complete detailed comparison on all $O(n^2)$ document pairs.
3. Corpora quality issues: plagiarized passages consider not the surrounding document, paraphrasing mostly done by machines, the Web is not used as source.

Candidate Retrieval at PAN'12

PAN Campaign

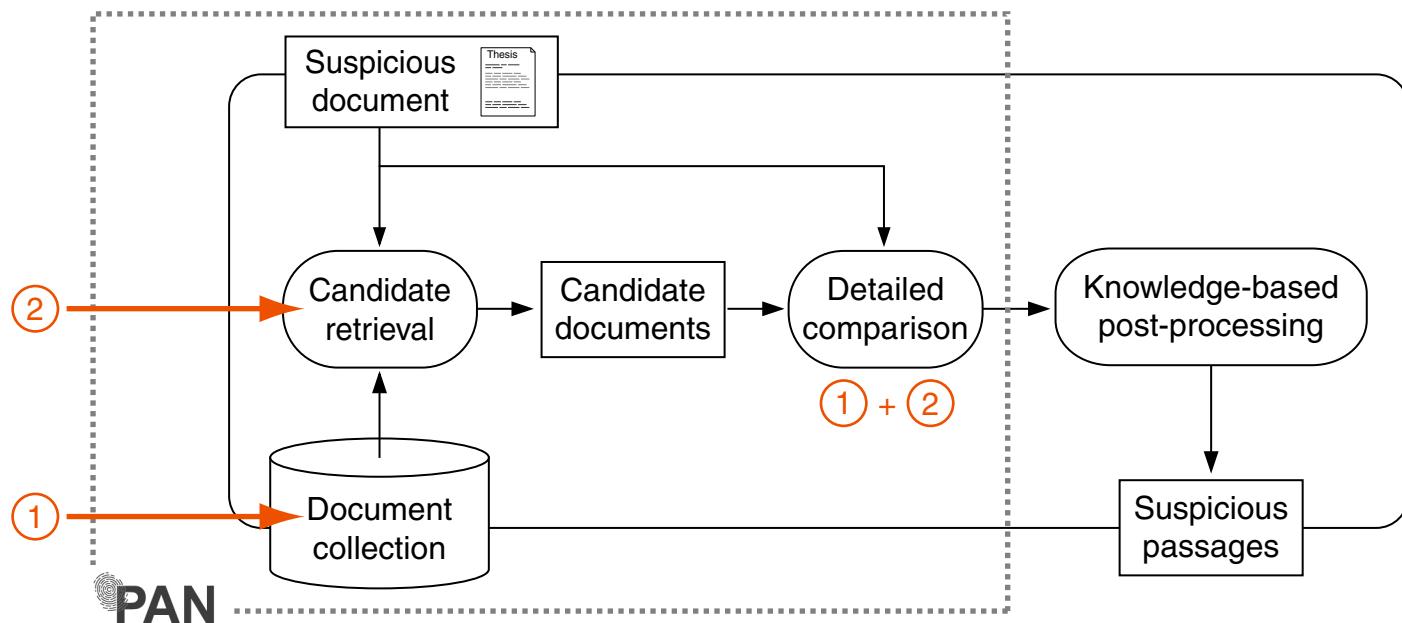


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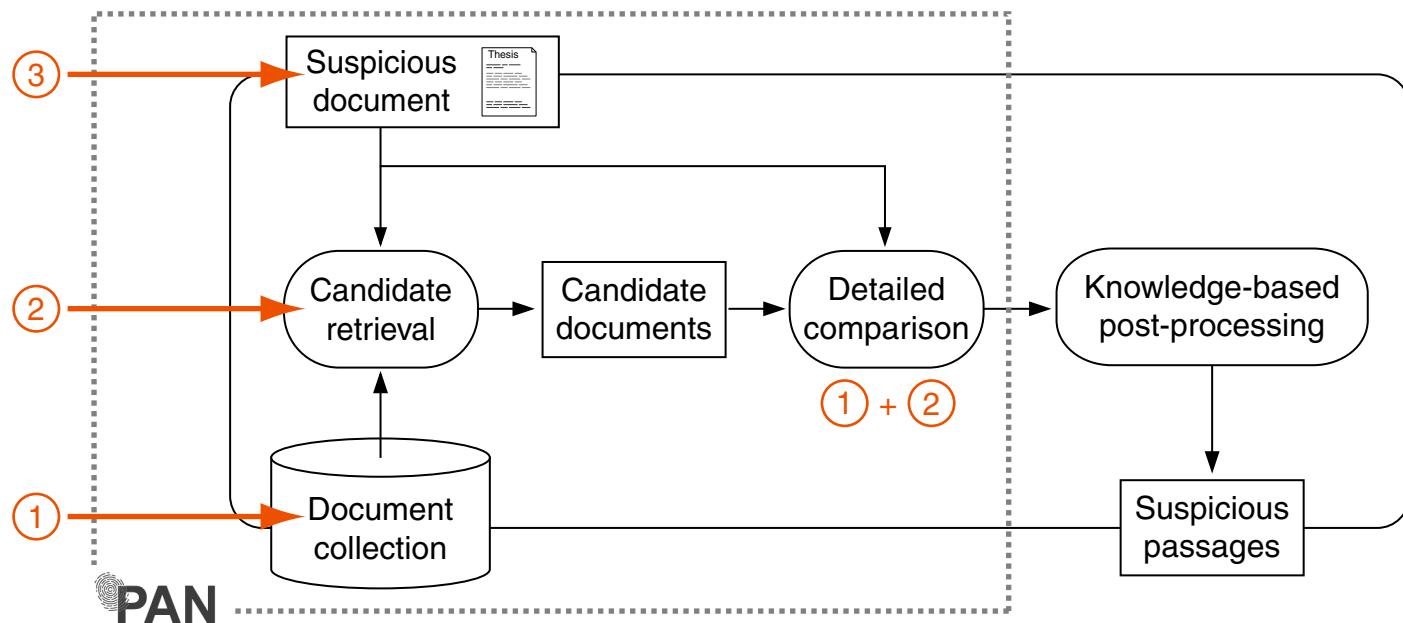


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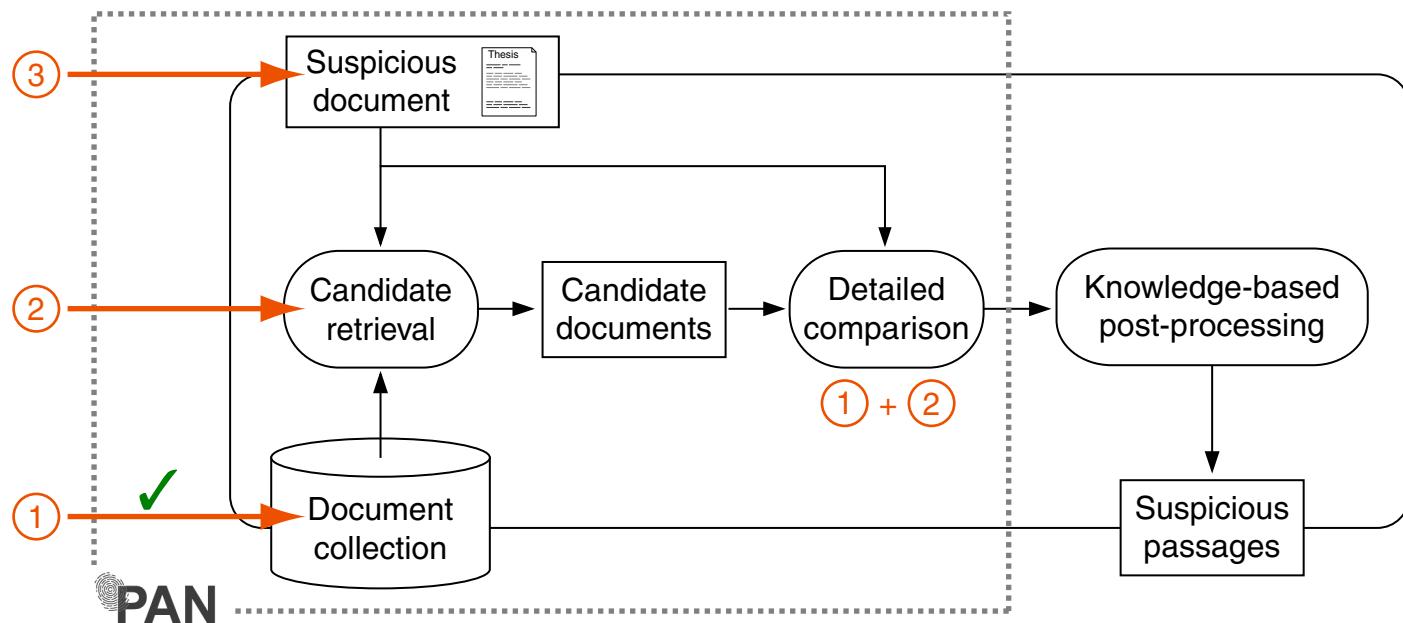


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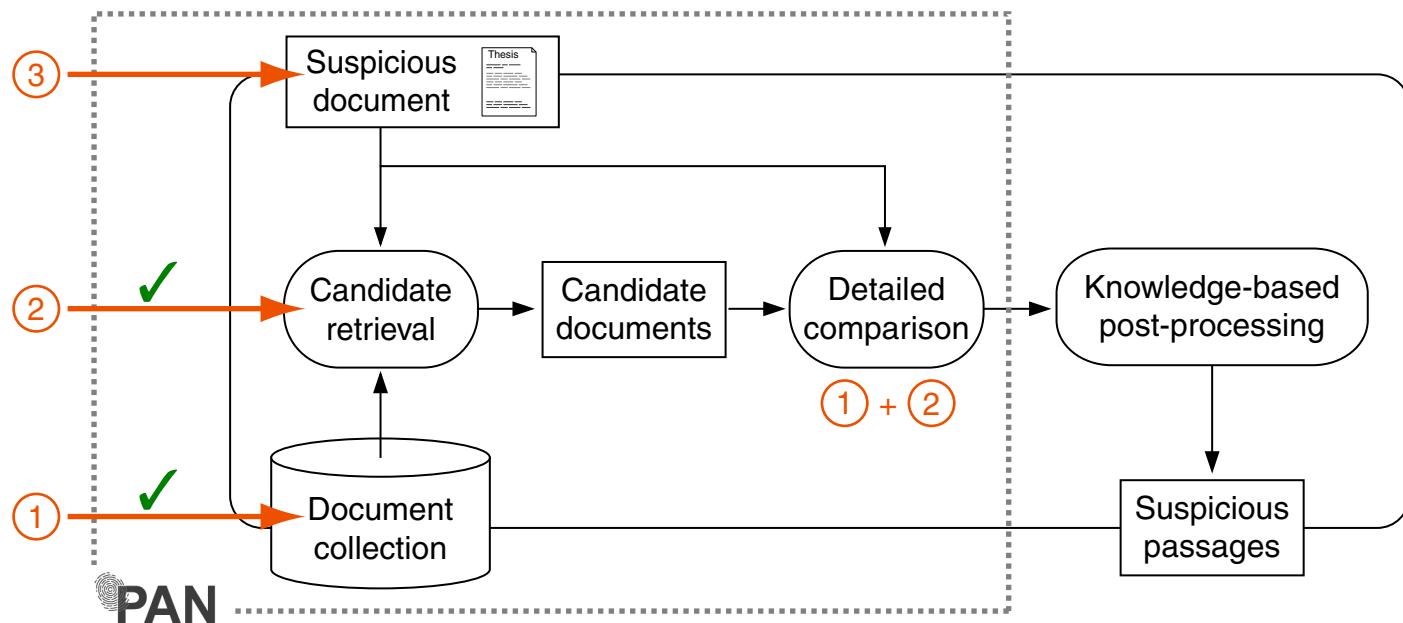


Considerations:

1. PAN'12 will use the English part of the ClueWeb09 corpus (used in TREC 2009-2011 for several tracks) as a static Web snapshot. Size: 500 million web pages, 12.5TB
2. Participants get efficient corpus access via the API of the ChatNoir search engine. ClueWeb and ChatNoir will ensure experiment reproducibility and controllability.
3. The new corpus: manually written digestible texts, typically matching plagiarism cases, Web as source (for document synthesis and plagiarism detection).

Candidate Retrieval at PAN'12

PAN Campaign

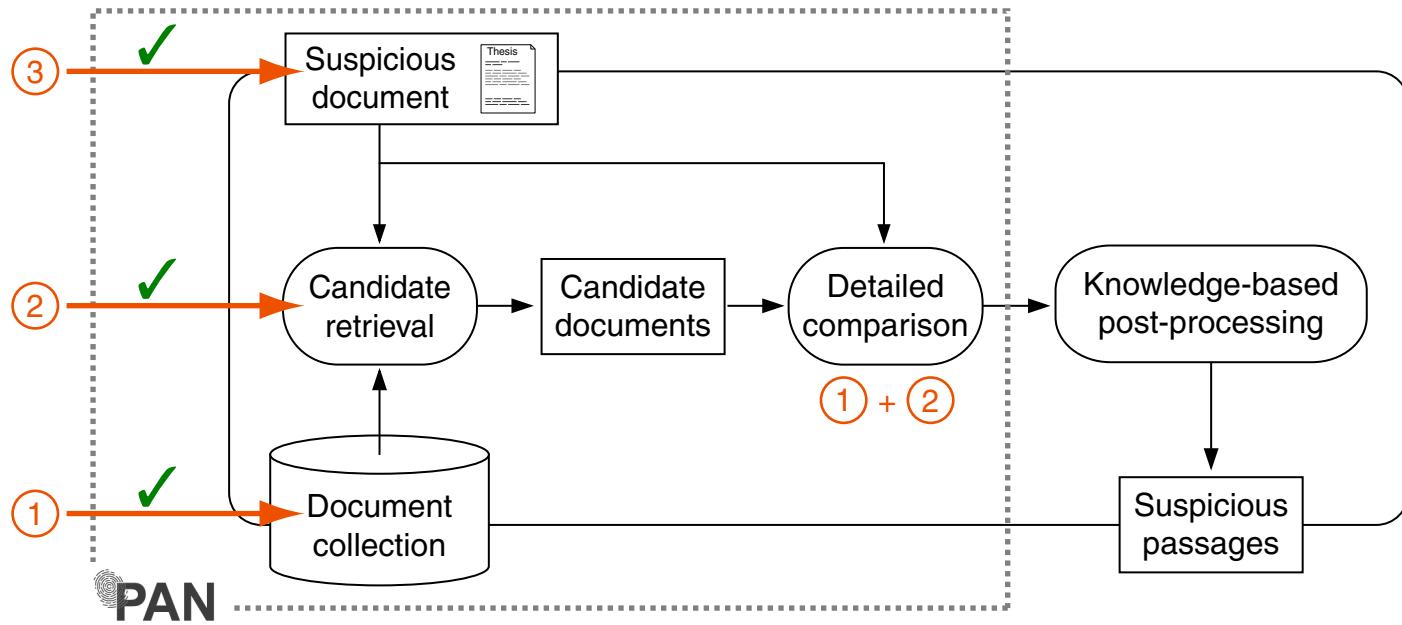


Considerations:

1. PAN'12 will use the English part of the ClueWeb09 corpus (used in TREC 2009-2011 for several tracks) as a static Web snapshot. Size: 500 million web pages, 12.5TB
2. Participants get efficient corpus access via the API of the ChatNoir search engine. ClueWeb and ChatNoir will ensure experiment reproducibility and controllability.
3. The new corpus: manually written digestible texts, typically matching plagiarism cases, Web as source (for document synthesis and plagiarism detection).

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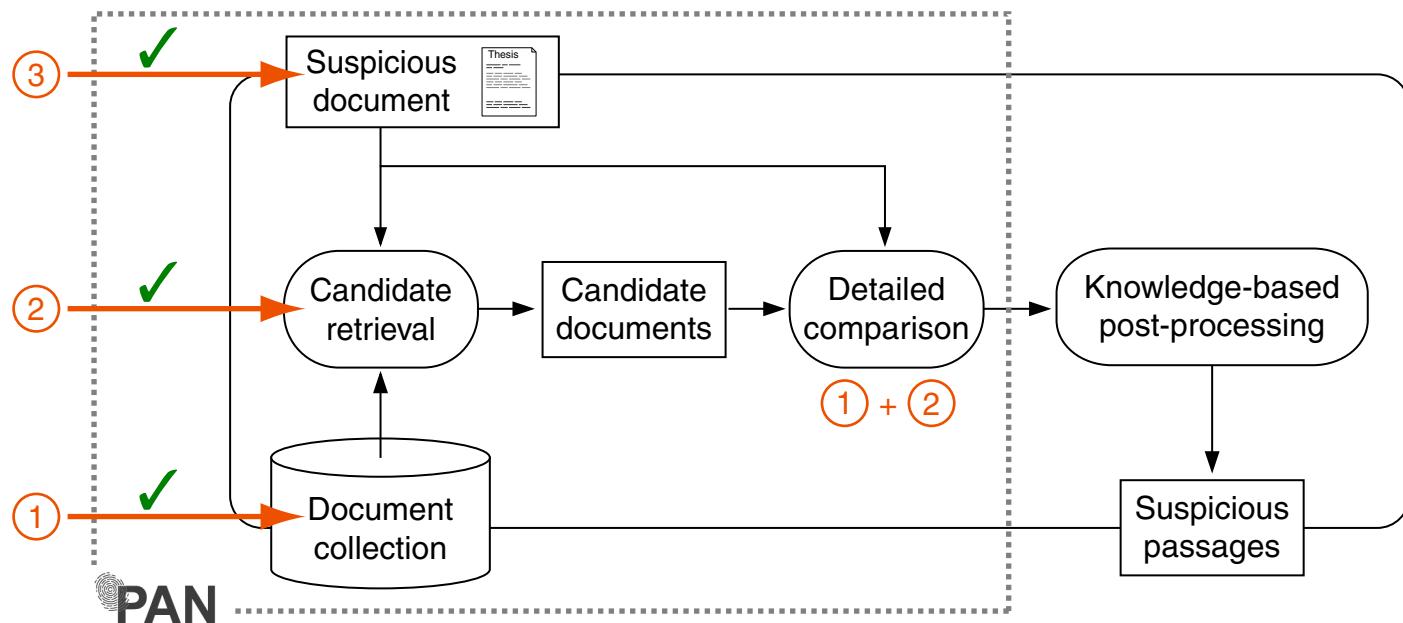


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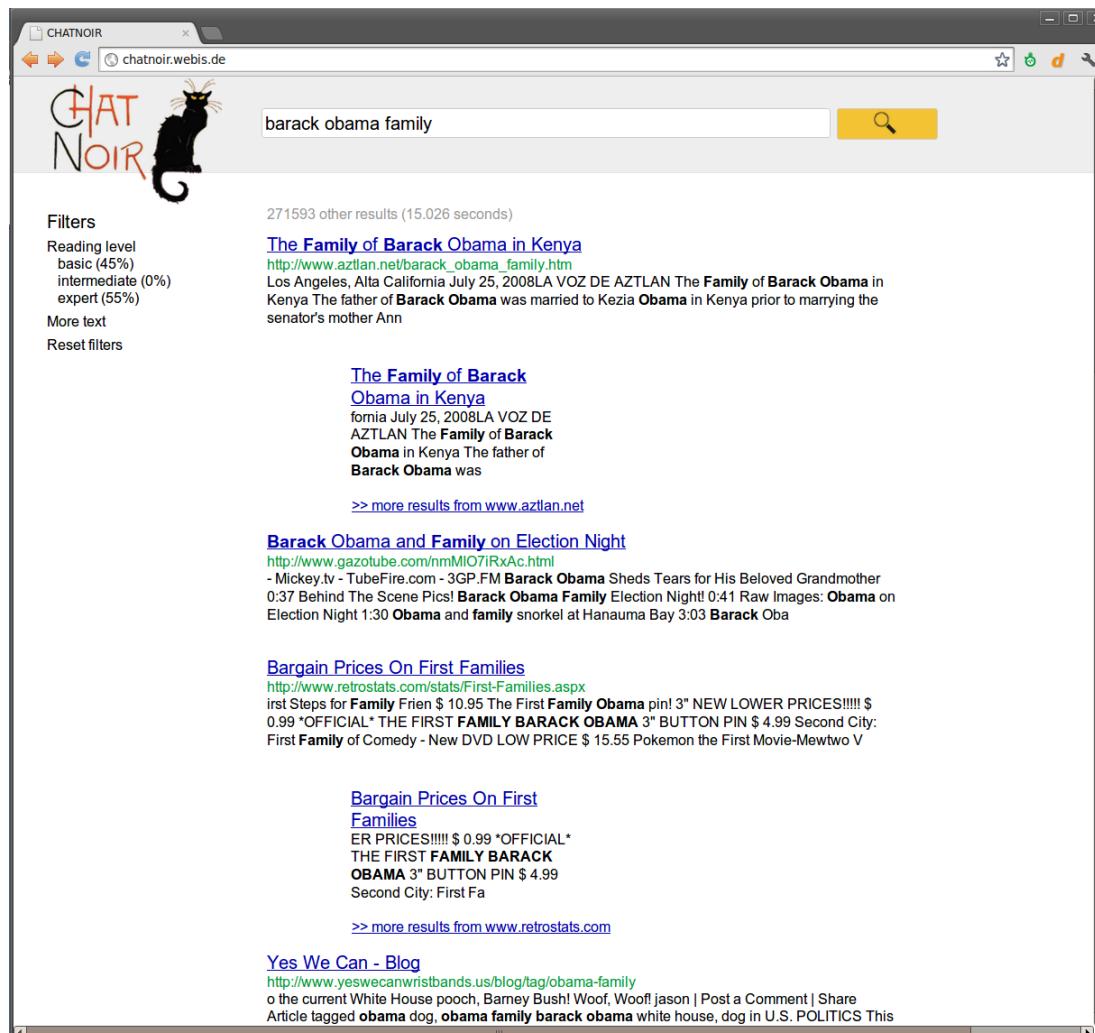


PAN competition 2012: [pan.webis.de]

- ❑ Key intention corpus: humans write essays on given topics, plagiarizing from the ClueWeb, using the ChatNoir search engine.
- ❑ Key intention competition: detectors use ChatNoir to retrieve candidate documents from the ClueWeb, using the ChatNoir search engine.
- ❑ Constraint: detectors get a budget of queries to model the cost scheme of commercial search engine APIs wrt. posed queries and downloaded documents.

Candidate Retrieval at PAN'12

About ChatNoir [chatnoir.webis.de]



CHATNOIR chatnoir.webis.de

barack obama family

271593 other results (15.026 seconds)

The Family of Barack Obama in Kenya
http://www.aztlan.net/barack_obama_family.htm
Los Angeles, Alta California July 25, 2008LA VOZ DE AZTLAN The Family of Barack Obama in Kenya The father of **Barack Obama** was married to Kezia **Obama** in Kenya prior to marrying the senator's mother Ann

The Family of Barack Obama in Kenya
fomia July 25, 2008LA VOZ DE AZTLAN The Family of Barack Obama in Kenya The father of **Barack Obama** was married to Kezia **Obama** in Kenya prior to marrying the senator's mother Ann

[>> more results from www.aztlan.net](#)

Barack Obama and Family on Election Night
<http://www.gazotube.com/nmIO7IRxAc.html>
- Mickey.tv - TubeFire.com - 3GP.FM **Barack Obama** Sheds Tears for His Beloved Grandmother 0:37 Behind The Scene Pics! **Barack Obama Family** Election Night! 0:41 Raw Images: **Obama** on Election Night 1:30 **Obama** and **family** snorkel at Hanauma Bay 3:03 **Barack Oba**

Bargain Prices On First Families
<http://www.retrostats.com/stats/First-Families.aspx>
irst Steps for **Family** Frien \$ 10.95 The First **Family Obama** pin! 3" NEW LOWER PRICES!!!! \$ 0.99 *OFFICIAL* THE FIRST **FAMILY BARACK OBAMA** 3" BUTTON PIN \$ 4.99 Second City: First **Family** of Comedy - New DVD LOW PRICE \$ 15.55 Pokemon the First Movie-Mewtwo V

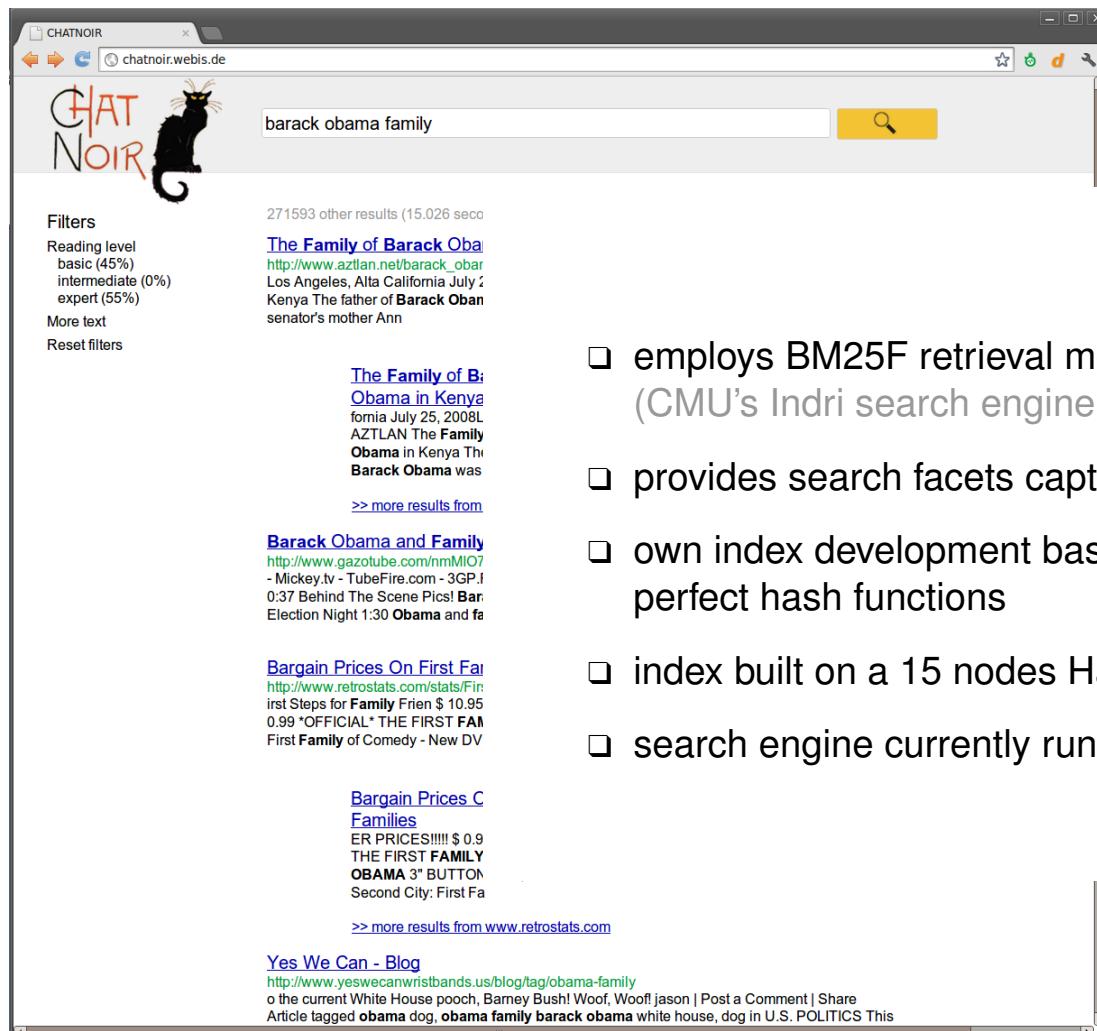
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THE FIRST **FAMILY BARACK OBAMA** 3" BUTTON PIN \$ 4.99
Second City: First Fa

[>> more results from www.retrostats.com](#)

Yes We Can - Blog
<http://www.yeswecanwristbands.us/blog/tag/obama-family>
o the current White House pooch, Barney Bush! Woof, Woof! Jason | Post a Comment | Share Article tagged **obama dog**, **obama family** **barack obama** white house, dog in U.S. POLITICS This

Candidate Retrieval at PAN'12

About ChatNoir [chatnoir.webis.de]



The screenshot shows a web browser window for the ChatNoir search engine. The search bar contains the query "barack obama family". The results page displays 271593 other results (15.026 sec). The results are listed in a table with columns for title, URL, and snippet. The first result is "The Family of Barack Obama" with a snippet mentioning Kenya and the senator's mother Ann. The second result is "Barack Obama and Family" with a snippet mentioning the election night. The third result is "Bargain Prices On First Family" with a snippet mentioning the first family. The fourth result is "Yes We Can - Blog" with a snippet mentioning the current White House. The interface includes a sidebar with filters for reading level (basic, intermediate, expert) and a "More text" link.

Result	Title	URL	Snippet
1	The Family of Barack Obama	http://www.aztlan.net/barack_obar	Kenya The father of Barack Obama senator's mother Ann
2	Barack Obama and Family	http://www.gaztube.com/nrmIO7	Election Night 1:30 Obama and fa
3	Bargain Prices On First Family	http://www.retrostats.com/stats/First Steps for Family	Frien \$ 10.95 0.99 *OFFICIAL* THE FIRST FAM
4	Yes We Can - Blog	http://www.yeswecanwristbands.us/blog/tag/obama-family	the current White House

- employs BM25F retrieval model
(CMU's Indri search engine is language-model-based)
- provides search facets capturing readability issues
- own index development based on externalized minimum perfect hash functions
- index built on a 15 nodes Hadoop cluster
- search engine currently running on 11 machines

Candidate Retrieval at PAN'12

About Corpus Construction

The screenshot shows a web-based plagiarism editor interface. On the left, a text editor displays a document titled "Barack Obama's Family" by "plagiarized by John Doe". The document content is as follows:

Barack Obama's Family
plagiarized by John Doe

The Family of Barack Obama is an extended clan of African American, English, Indonesian, and Kenyan heritage. They are best known through the writings and political career of Barack Obama, the current President of the United States of America. His immediate family is the First Family of the United States. The Obamas are the first First Family of African American descent in the United States and the youngest to enter the White House since the Kennedys. Obama's young, energetic family harks back to days of Camelot.

<http://webis15.medien.uni-weimar.de/chatnoir/clueweb?id=100011709993&token=wt0911001-qrel>

In what follows, we give a detailed overview of Barack Obama's Family. We shed light on himself, his immediate and extended family, including maternal and paternal relations. Moreover, we give insights into the relations of Michelle Obama, Barack Obama's wife, as well as some distant relations of both.

Barack Obama

Barack Hussein Obama II is the 44th and current President of the United States. He is the first African American to hold the office. Obama was the junior United States Senator from Illinois from 2005 until he resigned following his election to the presidency. Obama is a graduate of Columbia University and Harvard Law School. He worked as a community organizer in Chicago prior to earning his law degree, and practiced as a civil rights attorney in Chicago before serving three terms in the Illinois Senate from 1997 to 2004. He also taught Constitutional Law at the University of Chicago Law School from 1992 to 2004. Following an unsuccessful bid for a seat in the U.S. House of Representatives in 2000, Obama was elected to the Senate in November 2004.

Barack Obama was born on 4 August 1961 at the Kapi'olani Medical Center for Women & Children in Honolulu, Hawaii, to Ann Dunham of Wichita, Kansas and Barack Hussein Obama, Sr. of Nyangoma-Kogelo, Nyanza Province, Kenya. His parents met while both were attending the East-West Center of the University of Hawaii at Manoa, where his father was enrolled as a foreign student. The couple married only 6 months earlier on February 2, 1961.

Childhood and Youth

When Barack Obama was two years old, his parents divorced and his father moved to Connecticut to continue his education before returning to Kenya. He saw his son only once more before dying in an automobile accident in 1982.

When Obama was six, his mother married Lolo Soetoro, an Indonesian oil manager. In 1967, when Soetoro's student visa was revoked because of political unrest in Indonesia, Dunham and Barack, then in first grade, accompanied him to Jakarta.

Instructions

Write a text about the topic specified below. The text shall contain passages which are plagiarized from different web pages.

1. Search for sources matching the topic using the [ChatNoir search engine](#). Do not use any other search engine!
2. Once you found a passage of text to plagiarize, copy it into your text.
3. Change the background color of the copied passage. Also, add a link to the source web page with the same background color. This is so we can follow up on your work.
4. Modify the plagiarized passage so that an automatic plagiarism detector (like Turnitin) won't be able to detect it.
5. Repeat these steps until your text is complete.

Remarks:

- The text shall be at least 5000 words long.
- It shall contain a couple of plagiarized passages.
- You shall also write some passages yourself.
- You may choose the text genre: an essay, a news article, a press release, a blog post, an advertisement etc.
- You may follow links on web pages found via the search engine.
- While modifying and rewriting a plagiarized passage, you may mix it with others, delete things, or add sentences.

Use the editor on the left to write your text. Do not use any other editor. Your text will be frequently saved on our servers. In case of errors, you will be notified in the status message below. Report errors back to us before you continue writing.

Topic

Obama's family tree. Write about President Barack Obama's family history, including genealogy, national origins, places and dates of birth, etc. For instance: where did Barack Obama's parents and grandparents come from; what did his mother work; etc.

Links	Contact
ChatNoir Search	pan@webis.de

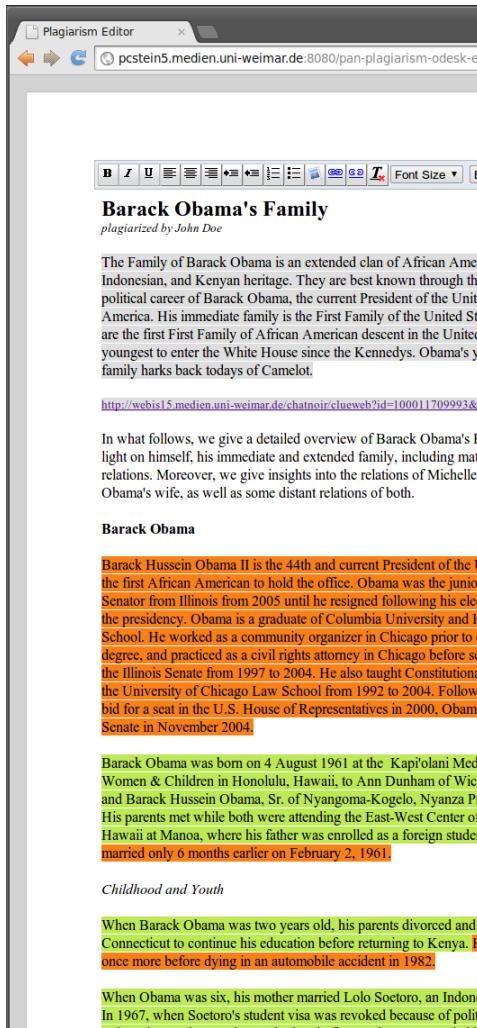
Status	Word Count
Document saved	7955

Color Key

4: [clueweb?id=100011709993&token=wt0911001-qrel](#)
5: [clueweb?id=100001018508&token=wt0911001-qrel](#)
6: [clueweb?id=002589069948&token=wt0911001-qrel](#)
8: [clueweb?id=1000178050208&token=wt0911001-qrel](#)
9: [clueweb?id=100007704609&token=wt0911001-qrel](#)
10: [clueweb?id=1000122058628&token=wt0911001-qrel](#)
16: [clueweb?id=1000136171618&token=wt0911001-qrel](#)
17: [clueweb?id=00968616391&token=wt0911001-qrel](#)
20: [clueweb?id=00010221241&token=wt0911001-qrel](#)
24: [clueweb?id=10000300500183&token=wt0911001-qrel](#)

Candidate Retrieval at PAN'12

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<http://webis15.medien.uni-weimar.de/chatnoir/clueweb?id=100011709993&...>

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When Obama was six, his mother married Lolo Soetoro, an Indonesian. In 1967, when Soetoro's student visa was revoked because of political differences, the family moved to Jakarta, Indonesia. Dunham and Barack then in first grade accompanied him to Indonesia.

- an essay has approx. 5000 words which means 8-10 pages
- corpus will be freely available after the competition
- own web editor was developed for essay writing
- the writing is crowdsourced via oDesk
- full control over:
 - plagiarized document
 - anonymized author identifier
 - set of used source documents
 - annotations of paraphrased passages
 - query log of the writer while writing the text
 - search results for each query
 - click-through data for each query
 - browsing data of links clicked within ClueWeb
 - key log of the document covering all keystrokes
 - work diary and screenshots as recorded by oDesk
- insights on how humans work when reusing text

Candidate Retrieval at PAN'12

TIRA: Experiments as a Service [tira.webis.de]



Retrieve research results along with their experiments.

Candidate Retrieval at PAN'12

TIRA: Experiments as a Service

TIRA takes a locally executable program and turns it into a web service. The TIRA approach features:

- Local execution
- Platform independence
- Result / experiment retrieval
- Web dissemination
- Peer-to-peer collaboration

Candidate Retrieval at PAN'12

TIRA: Experiments as a Service

TIRA takes a locally executable program and turns it into a web service. The TIRA approach features:

- Local execution

Data is kept confidential; the framework can reside with the data.

- Platform independence

A programs can be deployed as a web service without modifications.

- Result / experiment retrieval

Result management and online retrieval of matching experiments.

- Web dissemination

Experiments can be cited through their unique URL in publications.

- Peer-to-peer collaboration

TIRA instances can be connected to a network of experimentation nodes.

Candidate Retrieval at PAN'12

TIRA: Experiments as a Service

PAN'12 comes with a TIRA experimentation service for evaluating and communicating the participants' training results.



PAN12 -- Evaluation Service: Training Phase

Welcome to the [PAN12](#) evaluation service. In the form below, you can upload your detection results for the six datasets in the training corpus. The service expects the detection XML files you created for each pair of suspicious and source document as a zip file. Use a constant team name for your submissions to make your results easily retrievable with the Search button. When every field is filled in, press Execute and find your performance results in the result table below.

- Team Name

- Training Dataset

- Detection Zip

Team Name	Training Dataset	Detection Zip	PlagDet	Precision	Recall	Granul.	Result	Status
baseline	All datasets together	\$UPLOAD/9	0.125	0.978	0.125	2.446	scores	DONE
baseline	01_no_plagiarism	\$UPLOAD/10	1.0	1.0	1.0	1.0	scores	DONE
baseline	02_no_obfuscation	\$UPLOAD/11	0.860	0.861	0.860	1.001	scores	DONE
baseline	03_artificial_low	\$UPLOAD/12	0.100	0.997	0.111	2.997	scores	DONE
baseline	04_artificial_high	\$UPLOAD/13	0.005	0.999	0.002	1.077	scores	DONE
baseline	05_translation	\$UPLOAD/14	0.000	1.0	0.000	1.214	scores	DONE
baseline	06_simulated_paraphrase	\$UPLOAD/15	0.056	0.998	0.072	4.307	scores	DONE

Candidate Retrieval at PAN'12

TIRA: Experiments as a Service

All you need to create the shown web page:

1. The generic command to run the PAN evaluation measure:

```
python perfmeasure.py -t $team -p $truth -d $det > scores.txt
```

2. The parameter definitions:

\$team → [a-zA-Z0-9]+

\$det → [a-zA-Z0-9]+\zip

\$truth → 01_no_plagiarism | 02_no_obfuscation |
03_artificial_low | 04_artificial_high |
05_translation | 06_simulated_paraphrase

3. A program description and descriptive labels for the parameters (optional).

Candidate Retrieval at PAN'12

Candidate Retrieval Summary

Key elements of the PAN'12 plagiarism competition:

- high-quality corpus in the form of short essays created by humans
- ClueWeb corpus to create as well as to hide plagiarized texts
- ChatNoir search engine as efficient and open API for retrieval
- TIRA platform for technology comparison and result dissemination

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We are hoping to benefit in the following ways:

- realistic candidate retrieval situation from a
 - (a) plagiarism creation perspective
 - (b) plagiarism detection perspective
 - (c) computation resource perspective
- new search strategies for known-item-finding in the Web
- open and publicly available benchmarks

Almost the End

Almost the End

What We have Seen

- The Netspeak Word Search Engine
- Query Segmentation using the WAC
- Candidate Retrieval at PAN'12

Thank you for listening!

