Introduction to

Information Retrieval

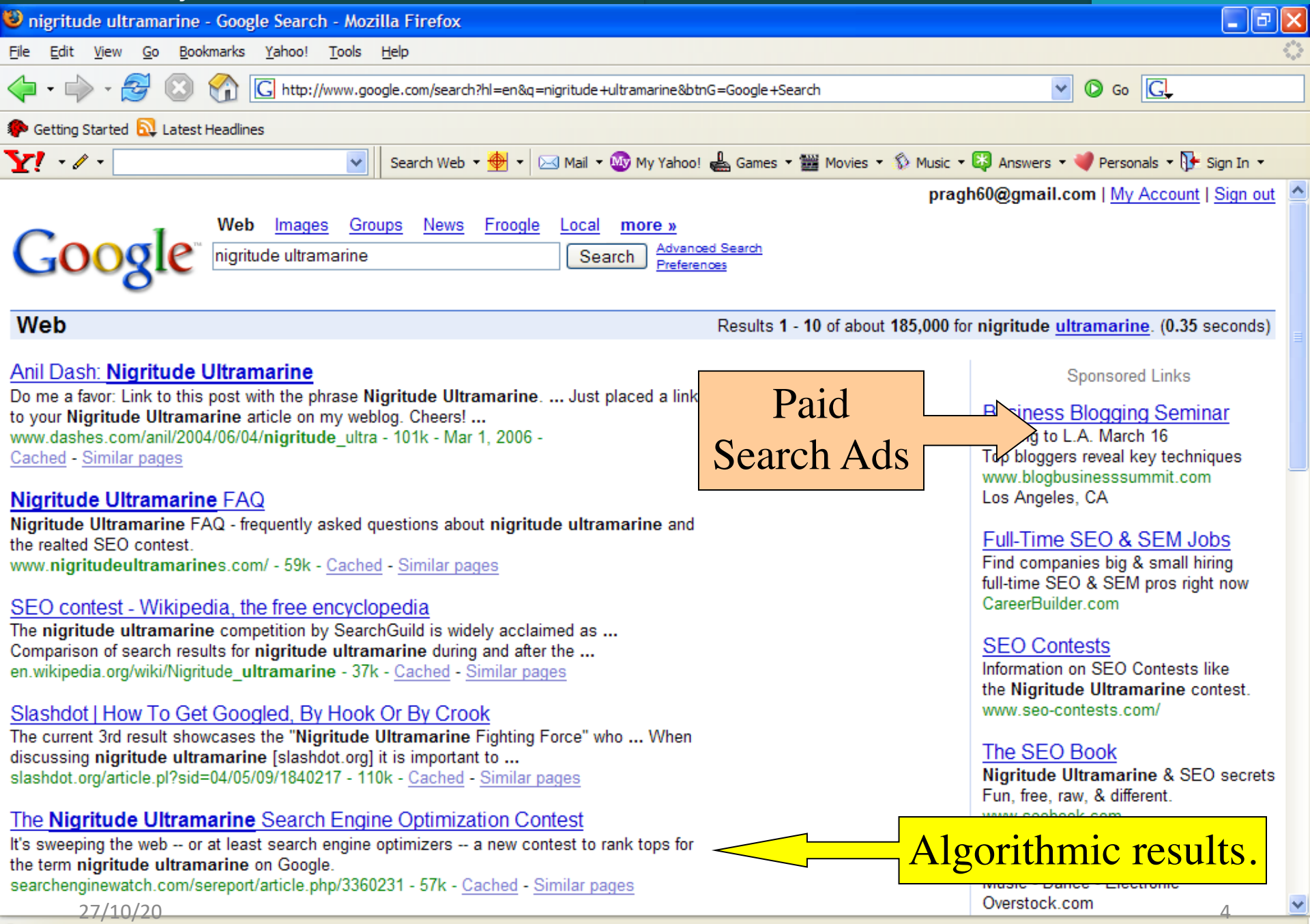
Lecture 16: Web search basics

Brief (non-technical) history

- Early keyword-based engines ca. 1995-1997
  - Altavista, Excite, Infoseek, Inktomi, Lycos
- Paid search ranking: Goto (morphed into Overture.com → Yahoo!)
  - Your search ranking depended on how much you paid
  - Auction for keywords: ***casino*** was expensive!

Brief (non-technical) history

- 1998+: Link-based ranking pioneered by Google
  - Blew away all early engines save Inktomi
  - Great user experience in search of a business model
  - Meanwhile Goto/Overture's annual revenues were nearing $1 billion
- Result: Google added paid search "ads" to the side, independent of search results
  - Yahoo followed suit, acquiring Overture (for paid placement) and Inktomi (for search)
- 2005+: Google gains search share, dominating in Europe and very strong in North America
  - 2009: Yahoo! and Microsoft propose combined paid search offering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www.dashes.com/anil/2004/06/04/nigritude_ultra - 101k - Mar 1, 2006 -
Cached - Similar pages
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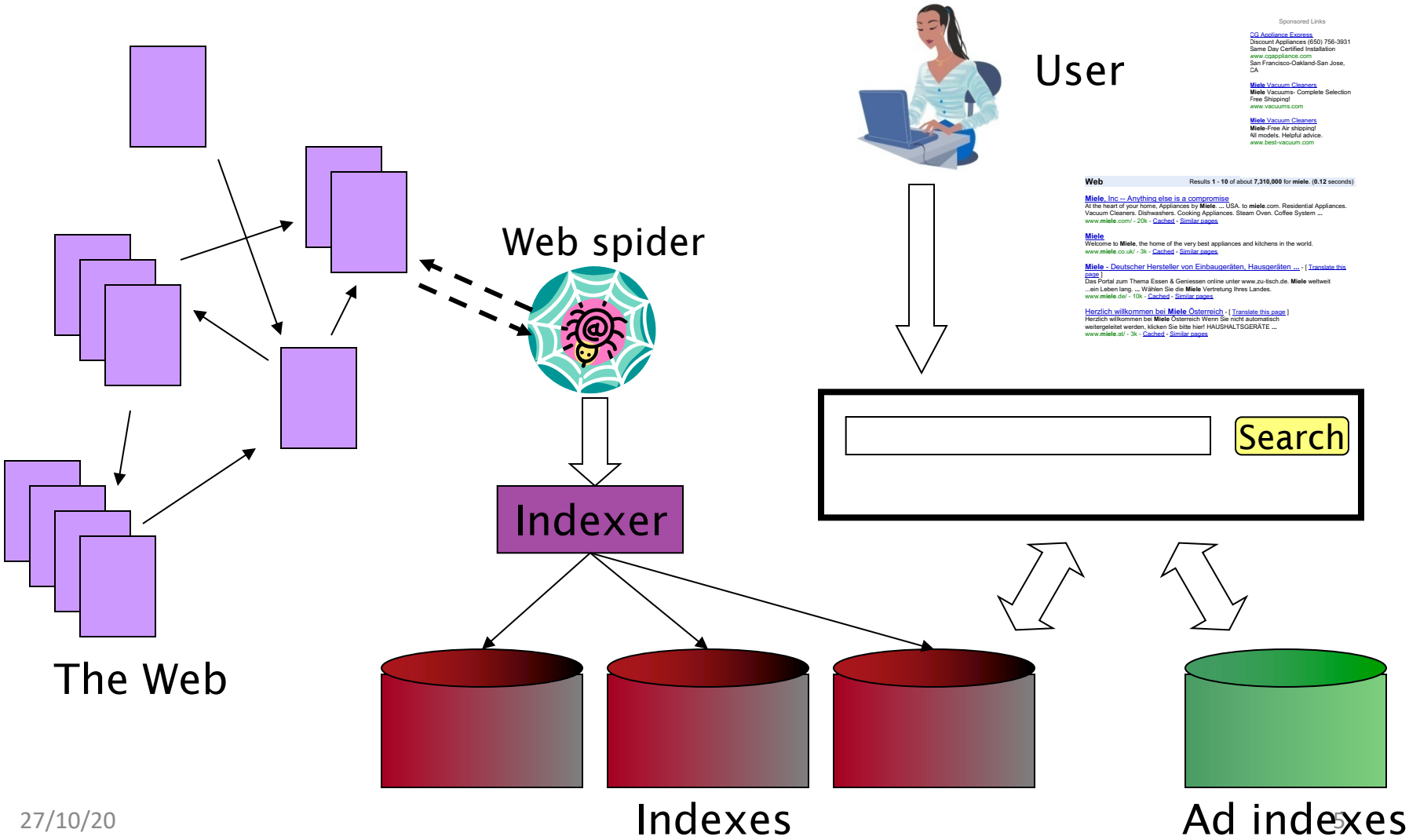
Nigritude Ultramarine FAQ - frequently asked questions about nigritude ultramarine and the realted SEO contest.
www.nigritudeultramarines.com/ - 59k - Cached - Similar pages
SEO contest - Wikipedia, the free encyclopedia
The nigritude ultramarine competition by SearchGuild is widely acclaimed as ...
Comparison of search results for nigritude ultramarine during and after the ...
en.wikipedia.org/wiki/Nigritude_ultramarine - 37k - Cached - Similar pages
Slashdot | How To Get Googled, By Hook Or By Crook
The current 3rd result showcases the "Nigritude Ultramarine Fighting Force" who ... When discussing nigritude ultramarine [slashdot.org] it is important to ...
slashdot.org/article.pl?sid=04/05/09/1840217 - 110k - Cached - Similar pages
The Nigritude Ultramarine Search Engine Optimization Contest
It's sweeping the web -- or at least search engine optimizers -- a new contest to rank tops for the term nigritude ultramarine on Google.
searchenginewatch.com/sereport/article.php/3360231 - 57k - Cached - Similar pages
Sponsored Links
Business Blogging Seminar
g to L.A. March 16
Top bloggers reveal key techniques
www.blogbusinesssummit.com
Los Angeles, CA
Full-Time SEO & SEM Jobs
Find companies big & small hiring full-time SEO & SEM pros right now
CareerBuilder.com
SEO Contests
Information on SEO Contests like the Nigritude Ultramarine contest.
www.seo-contests.com/
The SEO Book
Nigritude Ultramarine & SEO secrets
Fun, free, raw, & different.
Overstock.com
Paid Search Ads
Algorithmic results.
Done

Web search basics



User Needs

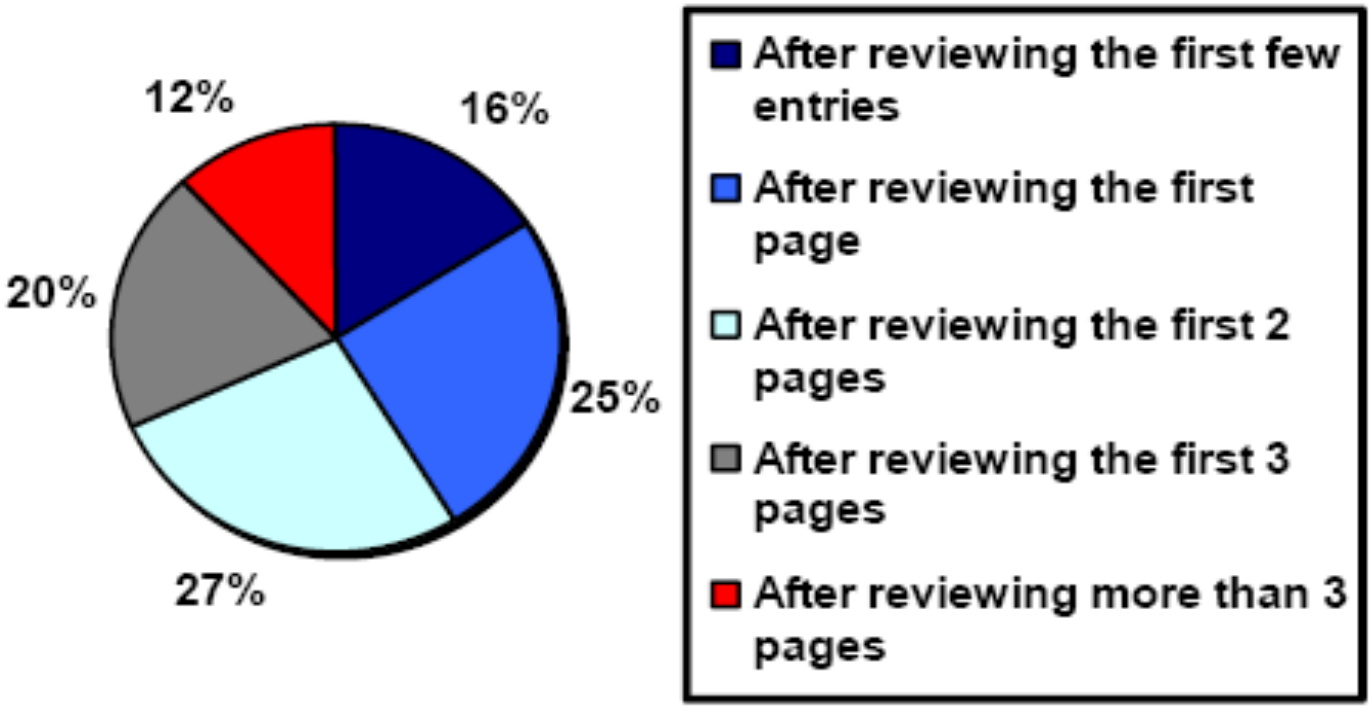
- Need [Brod02, RL04]
  - **Informational** – want to learn about something (~40% / 65%)

    `Low hemoglobin`
  - **Navigational** – want to go to that page (~25% / 15%)

    `United Airlines`
  - **Transactional** – want to do something (web-mediated) (~35% / 20%)
    - Access a service — `Seattle weather`
    - Downloads — `Mars surface images`
    - Shop — `Canon S410`
  - **Gray areas**
    - Find a good hub — `Car rental Brasil`
    - Exploratory search "see what's there"

How far do people look for results?

"When you perform a search on a search engine and don't find what you are looking for, at what point do you typically either revise your search, or move on to another search engine? (Select one)"



(Source: iprospect.com WhitePaper_2006_SearchEngineUserBehavior.pdf)

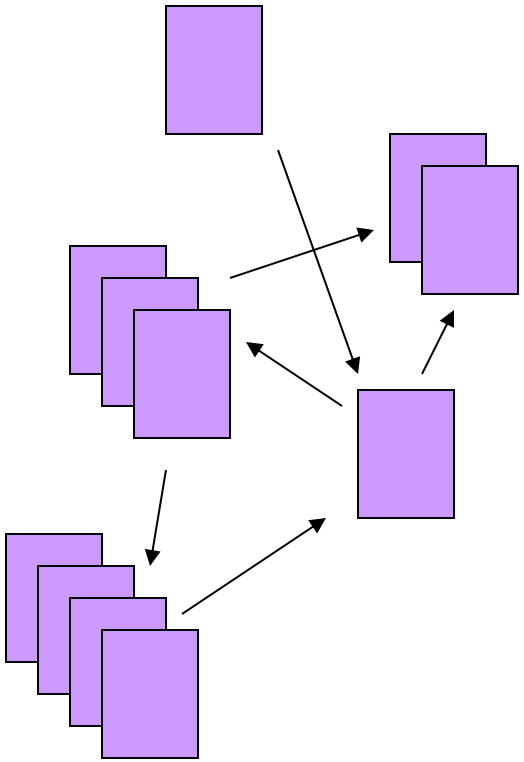
Users' empirical evaluation of results

- Quality of pages varies widely
  - Relevance is not enough
  - Other desirable qualities (non IR!!)
    - Content: Trustworthy, diverse, non-duplicated, well maintained
    - Web readability: display correctly & fast
    - No annoyances: pop-ups, etc
- Precision vs. recall
  - On the web, recall seldom matters
- What matters
  - Precision at 1? Precision above the fold?
  - Comprehensiveness – must be able to deal with obscure queries
    - Recall matters when the number of matches is very small
- User perceptions may be unscientific, but are significant over a large aggregate

Users' empirical evaluation of engines

- Relevance and validity of results
- UI – Simple, no clutter, error tolerant
- Trust – Results are objective
- Coverage of topics for polysemic queries
- Pre/Post process tools provided
  - Mitigate user errors (auto spell check, search assist,…)
  - Explicit: Search within results, more like this, refine ...
  - Anticipative: related searches
- Deal with idiosyncrasies
  - Web specific vocabulary
    - Impact on stemming, spell-check, etc
  - Web addresses typed in the search box
- "The first, the last, the best and the worst …"

The Web document collection



The Web

- No design/co-ordination
- Distributed content creation, linking, democratization of publishing
- Content includes truth, lies, obsolete information, contradictions …
- Unstructured (text, html, …), semi-structured (XML, annotated photos), structured (Databases)…
- Scale much larger than previous text collections … but corporate records are catching up
- Growth – slowed down from initial "volume doubling every few months" but still expanding
- Content can be *dynamically generated*

Spam

- (Search Engine Optimization)

Size of the web

What is the size of the web ?

- Issues
  - The web is really infinite
    - Dynamic content, e.g., calendar
    - Soft 404: www.yahoo.com/<anything> is a valid page
  - Static web contains syntactic duplication, mostly due to mirroring (~30%)
  - Some servers are seldom connected
- Who cares?
  - Media, and consequently the user
  - Engine design
  - Engine crawl policy. Impact on recall.

What can we attempt to measure?

- The relative sizes of search engines
  - The notion of a page being indexed is still *reasonably* well defined.
  - Already there are problems
    - Document extension: e.g. engines index pages not yet crawled, by indexing anchortext.
    - Document restriction: All engines restrict what is indexed (first *n* words, only relevant words, etc.)
- The coverage of a search engine relative to another particular crawling process.

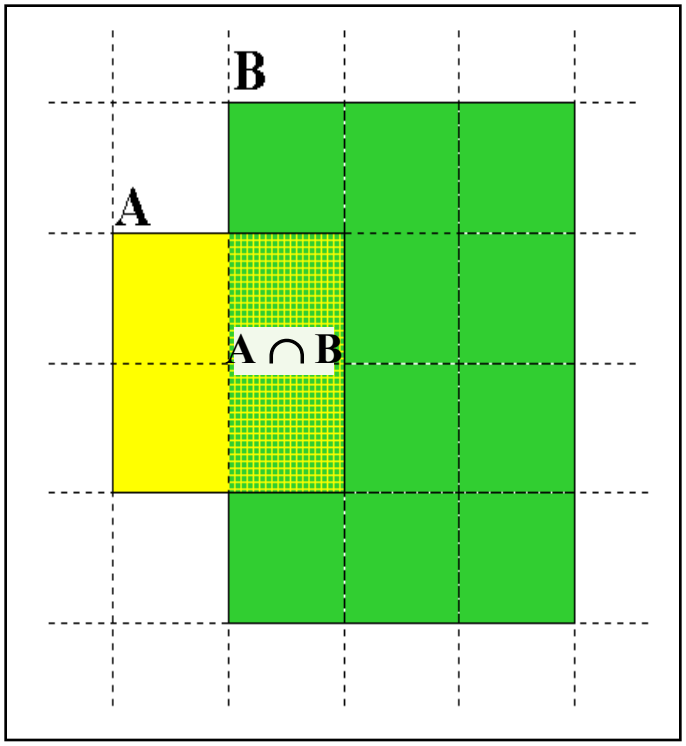
New definition?

(IQ is whatever the IQ tests measure.)

- The statically indexable web is whatever search engines index.

- Different engines have different preferences
  - max url depth, max count/host, anti-spam rules, priority rules, etc.
- Different engines index different things under the same URL:
  - frames, meta-keywords, document restrictions, document extensions, ...

Relative Size from Overlap
Given two engines A and B



Sample URLs randomly from A

Check if contained in B and vice versa

$$A \cap B = (1/2) * \text{Size } A$$

$$A \cap B = (1/6) * \text{Size } B$$

$$(1/2)*\text{Size } A = (1/6)*\text{Size } B$$

$$\therefore \text{ Size } A / \text{ Size } B = (1/6)/(1/2) = 1/3$$

Each test involves: (i) Sampling (ii) Checking

Sampling URLs

- Ideal strategy: Generate a random URL and check for containment in each index.
- Problem: Random URLs are hard to find! Enough to generate a random URL contained in a given Engine.
- Approach 1: Generate a random URL contained in a given engine
  - Suffices for the estimation of relative size
- Approach 2: Random walks / IP addresses
  - In theory: might give us a true estimate of the size of the web (as opposed to just relative sizes of indexes)

Statistical methods

- Approach 1
  - Random queries
  - Random searches
- Approach 2
  - Random IP addresses
  - Random walks

Random URLs from random queries

- Generate random query: how?
  - **Lexicon:** 400,000+ words from a web crawl
  - **Conjunctive Queries:** w_1 and w_2

    e.g., vocalists AND rsi

Not an English dictionary

- Get 100 result URLs from engine A
- Choose a random URL as the candidate to check for presence in engine B
- This distribution induces a probability weight W(p) for each page.
- Conjecture: $W(SE_A) / W(SE_B) \sim |SE_A| / |SE_B|$

Query Based Checking

- *Strong Query* to check whether an engine *B* has a document *D*:
  - Download *D*. Get list of words.
  - Use 8 low frequency words as AND query to *B*
  - Check if *D* is present in result set.
- Problems:
  - Near duplicates
  - Frames
  - Redirects
  - Engine time-outs
  - Is 8-word query good enough?

Advantages & disadvantages

- Statistically sound under the induced weight.
- Biases induced by random query
  - Query Bias: Favors content-rich pages in the language(s) of the lexicon
  - Ranking Bias: *Solution:* Use conjunctive queries & fetch all
  - Checking Bias: Duplicates, impoverished pages omitted
  - Document or query restriction bias: engine might not deal properly with 8 words conjunctive query
  - Malicious Bias: Sabotage by engine
  - Operational Problems: Time-outs, failures, engine inconsistencies, index modification.

Random searches

- Choose random searches extracted from a local log [Lawrence & Giles 97] or build "random searches" [Notess]
  - Use only queries with small result sets.
  - Count normalized URLs in result sets.
  - Use ratio statistics

Advantages & disadvantages

- Advantage
  - Might be a better reflection of the human perception of coverage
- Issues
  - Samples are correlated with source of log
  - Duplicates
  - Technical statistical problems (must have non-zero results, ratio average not statistically sound)

Random searches

- 575 & 1050 queries from the NEC RI employee logs
- 6 Engines in 1998, 11 in 1999
- Implementation:
  - Restricted to queries with < 600 results in total
  - Counted URLs from each engine after verifying query match
  - Computed size ratio & overlap for individual queries
  - Estimated index size ratio & overlap by averaging over all queries

Queries from Lawrence and Giles study

- *adaptive access control*
- *neighborhood preservation topographic*
- *hamiltonian structures*
- *right linear grammar*
- *pulse width modulation neural*
- *unbalanced prior probabilities*
- *ranked assignment method*
- *internet explorer favourites importing*
- *karvel thornber*
- *zili liu*
- *softmax activation function*
- *bose multidimensional system theory*
- *gamma mlp*
- *dvi2pdf*
- *john oliensis*
- *rieke spikes exploring neural*
- *video watermarking*
- *counterpropagation network*
- *fat shattering dimension*
- *abelson amorphous computing*

Random IP addresses

- Generate random IP addresses
- Find a web server at the given address
  - If there's one
- Collect all pages from server
  - From this, choose a page at random

Random IP addresses

- HTTP requests to random IP addresses
  - Ignored: empty or authorization required or excluded
  - [Lawr99] Estimated 2.8 million IP addresses running crawlable web servers (16 million total) from observing 2500 servers.
  - OCLC using IP sampling found 8.7 M hosts in 2001
    - Netcraft [Netc02] accessed 37.2 million hosts in July 2002
- [Lawr99] exhaustively crawled 2500 servers and extrapolated
  - Estimated size of the web to be 800 million pages
  - Estimated use of metadata descriptors:
    - Meta tags (keywords, description) in 34% of home pages, Dublin core metadata in 0.3%

Advantages & disadvantages

- Advantages
  - Clean statistics
  - Independent of crawling strategies
- Disadvantages
  - Doesn't deal with duplication
  - Many hosts might share one IP, or not accept requests
  - No guarantee all pages are linked to root page.
    - Eg: employee pages
  - Power law for # pages/hosts generates bias towards sites with few pages.
    - But bias can be accurately quantified IF underlying distribution understood
  - Potentially influenced by spamming (multiple IP's for same server to avoid IP block)

Random walks

- View the Web as a directed graph
- Build a random walk on this graph
  - Includes various "jump" rules back to visited sites
    - Does not get stuck in spider traps!
    - Can follow all links!
  - Converges to a stationary distribution
    - Must assume graph is finite and independent of the walk.
    - Conditions are not satisfied (cookie crumbs, flooding)
    - Time to convergence not really known
  - Sample from stationary distribution of walk
  - Use the "strong query" method to check coverage by SE

Advantages & disadvantages

- Advantages
  - "Statistically clean" method at least in theory!
  - Could work even for infinite web (assuming convergence) under certain metrics.
- Disadvantages
  - List of seeds is a problem.
  - Practical approximation might not be valid.
  - Non-uniform distribution
    - Subject to link spamming

Conclusions

- No sampling solution is perfect.
- Lots of new ideas ...
- ....but the problem is getting harder
- Quantitative studies are fascinating and a good research problem

Duplicate detection

Duplicate documents

- The web is full of duplicated content
- Strict duplicate detection = exact match
  - Not as common
- But many, many cases of near duplicates
  - E.g., Last modified date the only difference between two copies of a page

Duplicate/Near-Duplicate Detection

- *Duplication*: Exact match can be detected with fingerprints
- *Near-Duplication*: Approximate match
  - Overview
    - Compute syntactic similarity with an edit-distance measure
    - Use similarity threshold to detect near-duplicates
      - E.g., Similarity > 80% => Documents are “near duplicates”
      - Not transitive though sometimes used transitively

Computing Similarity

- Features:
  - Segments of a document (natural or artificial breakpoints)
  - Shingles (Word N-Grams)
  - ***a rose is a rose is a rose*** →

    a_rose_is_a

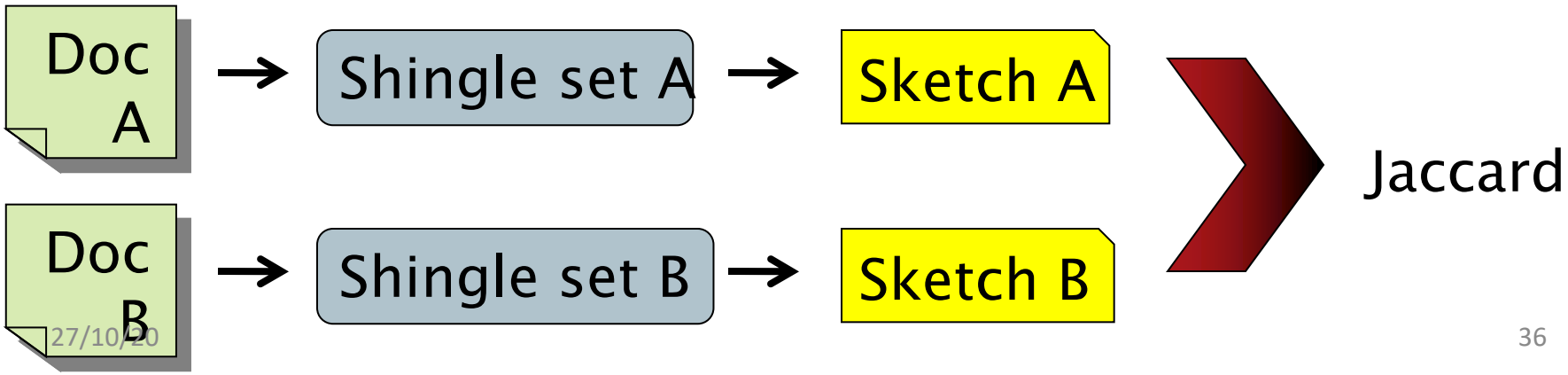
    rose_is_a_rose

    is_a_rose_is

    a_rose_is_a
- Similarity Measure between two docs (= sets of shingles)
  - Set intersection
  - Specifically (Size_of_Intersection / Size_of_Union)

Shingles + Set Intersection

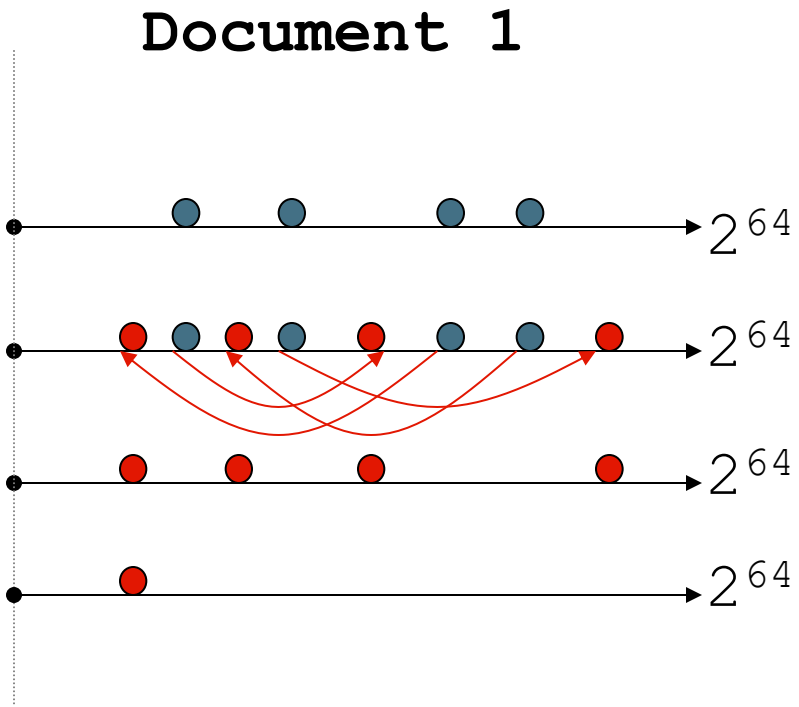
- Computing exact set intersection of shingles between all pairs of documents is expensive/intractable
  - Approximate using a cleverly chosen subset of shingles from each (a *sketch*)
- Estimate (size_of_intersection / size_of_union) based on a short sketch



Sketch of a document

- Create a "sketch vector" (of size ~200) for each document
  - Documents that share ≥ *t* (say 80%) corresponding vector elements are near duplicates
  - For doc *D*, sketch$_D$[*i*] is as follows:
    - Let f map all shingles in the universe to [0, 2^m-1] (e.g., f = fingerprinting)
    - Let π_i be a *random permutation* on [0, 2^m-1]
    - Pick MIN {π_i(f(s))} over all shingles *s* in *D*

Computing Sketch[i] for Doc1

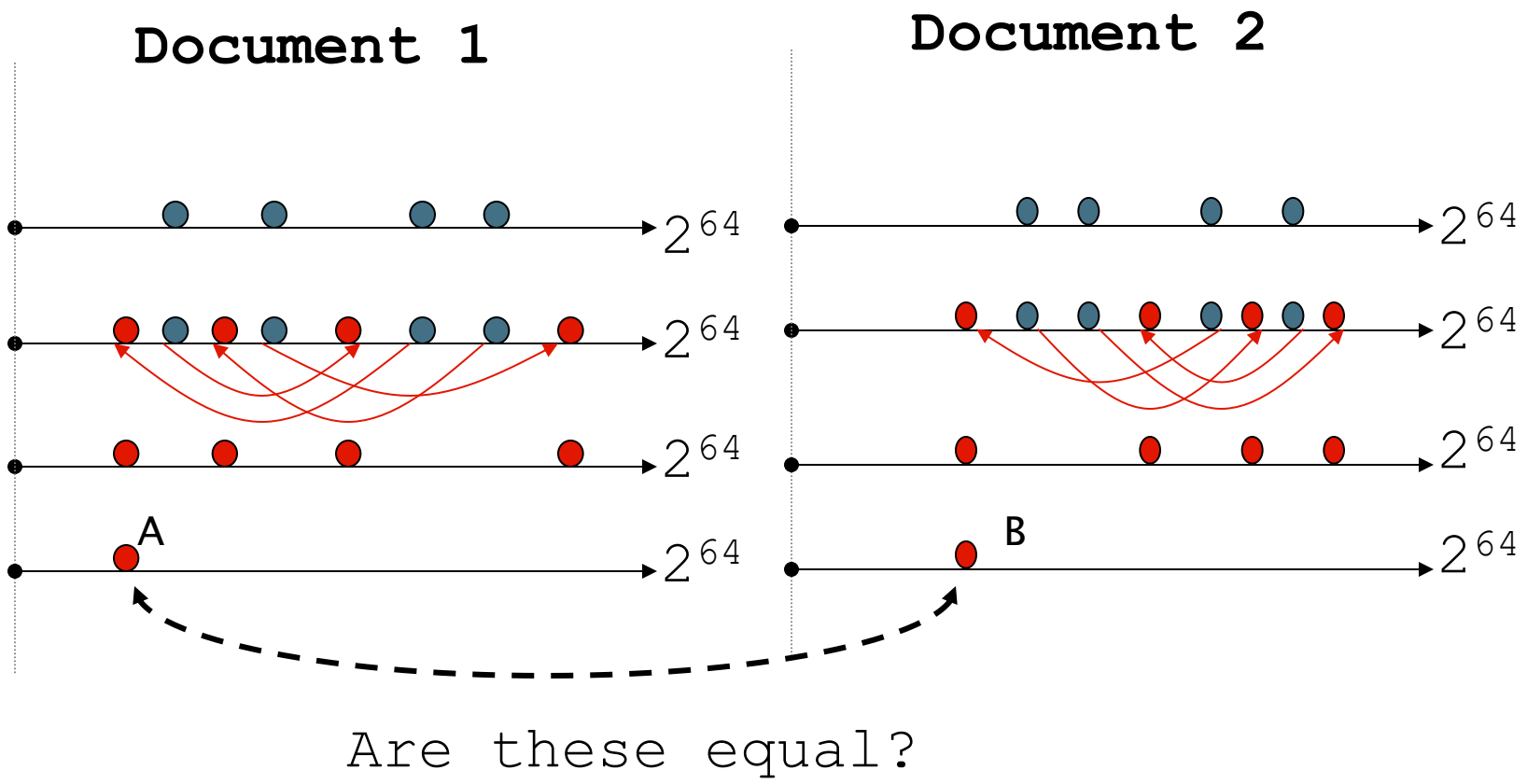


Start with 64-bit *f*(shingles)

Permute on the number line with π_i

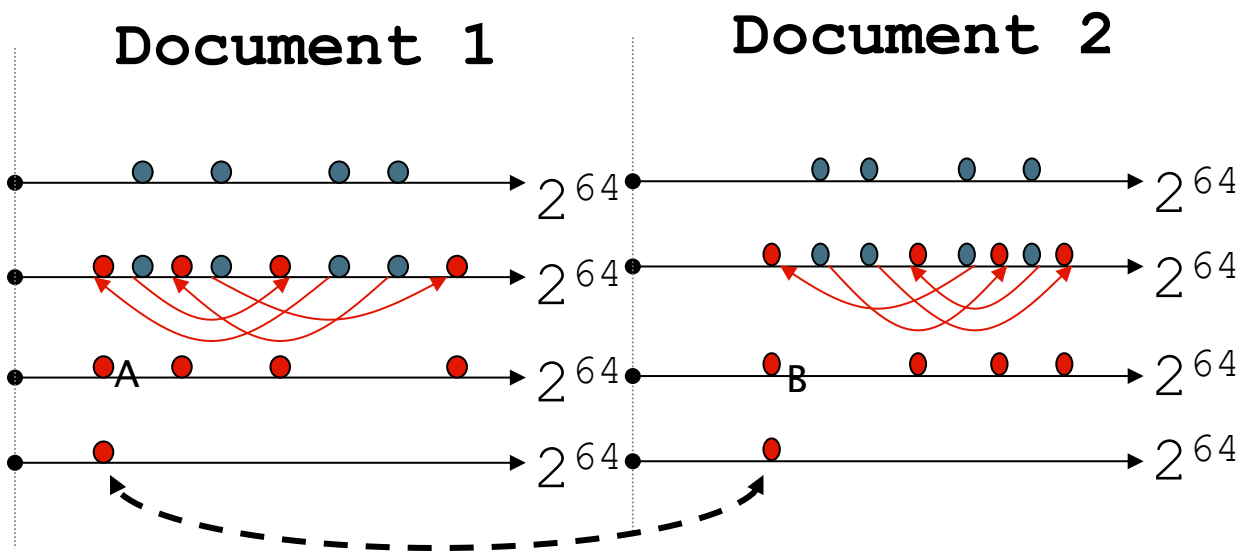
Pick the min value

Test if Doc1.Sketch[i] = Doc2.Sketch[i]



Test for 200 random permutations: $\pi_1, \pi_2, \ldots \pi_{200}$

However…



A = B iff the shingle with the MIN value in the union of Doc1 and Doc2 is common to both (i.e., lies in the intersection)

Claim: This happens with probability

Size_of_intersection / Size_of_union

Why?

Set Similarity of sets C_i , C_j

$$\text{Jaccard}(C_i, C_j) = \frac{|C_i \cap C_j|}{|C_i \cup C_j|}$$

- View sets as columns of a matrix A; one row for each element in the universe. a_{ij} = 1 indicates presence of item i in set j
- Example

C_1	C_2
0	1
1	0
1	1
0	0
1	1
0	1

Jaccard(C_1,C_2) = 2/5 = 0.4

Key Observation

- For columns C_i, C_j, four types of rows

	C_i	C_j
type A	1	1
type B	1	0
type C	0	1
type D	0	0

- Overload notation: A = # of rows of type A
- **Claim**

$$\text{Jaccard}(C_i, C_j) = \frac{A}{A + B + C}$$

"Min" Hashing

- Randomly permute rows
- Hash $h(C_i)$ = index of first row with 1 in column C_i
- Surprising Property

$$\Pr\left[\, h(C_i) = h(C_j) \,\right] = \text{Jaccard}\left(C_i, C_j\right)$$

- Why?
  - Both are A/(A+B+C)
  - Look down columns C_i, C_j until first non-Type-D row
  - $h(C_i) = h(C_j)$ ←→ type A row

Min-Hash sketches

- Pick *P* random row permutations
- MinHash sketch

sketch(C) = list of *k* indexes of first rows with 1 in column C

this is a random variable

- Similarity of signatures
  - Let sim[sketch(C_i),sketch(C_j)] = fraction of permutations where MinHash values agree
  - Observe **E**[sim(sig(C_i),sig(C_j))] = Jaccard(C_i,C_j)

Practical Implementation

- Random permutation is hard to obtain; simulate them using universal hashing instead
  - h: {0, 1, 2, …, U} → {0, 1, 2, …, M}
  - h(x) = ((a*x + b) mod P) mod M
  - where
    - P >> U and is a prime number
    - a, b are two randomly chosen integers modulo P and a != 0
  - sketch(C) = { $\text{argmin}_{e \in C}$ { $h_i(e)$ } | $1 \le i \le k$}

Example

	C_1	C_2	C_3
R_1	1	0	1
R_2	0	1	1
R_3	1	0	0
R_4	1	0	1
R_5	0	1	0

Signatures

	S_1	S_2	S_3
Perm 1 = (12345)	1	2	1
Perm 2 = (54321)	4	5	4
Perm 3 = (34512)	3	5	4

Similarities

	1-2	1-3	2-3
Col-Col	0.00	0.50	0.25
Sig-Sig	0.00	0.67	0.00

Example Using the Universal Hashing

$h(x) = (7x+1 \bmod 31) \bmod 9$
$g(x) = (17x+8 \bmod 31) \bmod 9$

	C_1	C_2	C_3
R_1	1	0	1
R_2	0	1	1
R_3	1	0	0
R_4	1	0	1
R_5	0	1	0

$S_1 = \{R_1, R_3, R_4\}$
$h(e) = \{8, 4, 2\}$ ➔ min_elem = R_4
$g(e) = \{7, 1, 5\}$ ➔ min_elem = R_3
sketch(S1) = $\{R_4, R_3\}$

$S_2 = \{R_2, R_5\}$
$h(e) = \{6, 5\}$ ➔ min_elem = R_5
$g(e) = \{2, 0\}$ ➔ min_elem = R_5
sketch(S1) = $\{R_5, R_5\}$

Note: this example results in different sketches from the previous slide

Therefore, estimated similarity between S_1 and S_2 is 0/2 = 0.0

All signature pairs

- Now we have an extremely efficient method for estimating a Jaccard coefficient for a single pair of documents.
- But we still have to estimate N^2 coefficients where N is the number of web pages.
  - Still slow
- One solution: locality sensitive hashing (LSH)
- Another solution: Sorting (Henzinger 2006)

SimHash

- Generalization of LSH to other similarity measures
  [Charikar, STOC 02]
  - $\theta(\mathbf{x}, \mathbf{y})$: related to cosine
  - $h_{\mathbf{u}}(\mathbf{x}) = sign(\mathbf{u} \cdot \mathbf{x})$, where **u** is a random unit vector
  - then $\Pr[h_{\mathbf{u}}(\mathbf{x}) = h_{\mathbf{u}}(\mathbf{y})] = 1 - \theta(\mathbf{x}, \mathbf{y}) / \pi$

Note: This is a fast, but approximate implementation of SimHash (from Google)

Practical Implementation

- Near duplicate Web page detection from google [Henzinger, SIGIR06] [Manku et al, WWW07]
  - Document D ➔ set of tokens with idf weighting ➔ form a set of "features" v(D)
  - Each feature is randomly projected to *f*-dimensional binary vector of [-1,1]
  - Sum up the weighted projections of all features in v(D) ➔ **r**(D)
  - a *f*-bit signature sig(D) ➔ sign(**r**(D))
- Results (in comparison with Shingling)
  - Fairly accurate and stable
  - Does not capture order among tokens

Note: This is a fast, but approximate implementation of SimHash (from Google)

Simhash

1. Process the document into a set of features with associated weights. We will assume the simple case where the features are words weighted by their frequency.

2. Generate a hash value with b bits (the desired size of the fingerprint) for each word. The hash value should be unique for each word.

3. In b-dimensional vector V, update the components of the vector by adding the weight for a word to every component for which the corresponding bit in the word's hash value is 1, and subtracting the weight if the value is 0.

4. After all words have been processed, generate a b-bit fingerprint by setting the ith bit to 1 if the ith component of V is positive, or 0 otherwise.

Simhash Example

Tropical fish include fish found in tropical environments around the world, including both freshwater and salt water species.

(a) Original text

tropical 2 fish 2 include 1 found 1 environments 1 around 1 world 1
including 1 both 1 freshwater 1 salt 1 water 1 species 1

(b) Words with weights

tropical	01100001	fish	10101011	include	11100110
found	00011110	environments	00101101	around	10001011
world	00101010	including	11000000	both	10101110
freshwater	00111111	salt	10110101	water	00100101
species	11101110				

(c) 8 bit hash values

2 - 2 + 1
- 1 - 1 +
1 - 1 + 1
+ 1 - 1 +
1 -1 + 1
= 1

1 -5 9 -9 3 1 3 3

(d) Vector V formed by summing weights

1 0 1 0 1 1 1 1

(e) 8-bit fingerprint formed from V

count-min sketch, approximately preserves the inner product of the raw feature vectors

More resources

- IIR Chapter 19