# Topic: Duplicate Detection and Similarity Computing 

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Some of slides are from text book [CMS] and Rajaraman/Ullman

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## Applications of Duplicate Detection and Similarity Computing

- Duplicate and near-duplicate documents occur in many situations
- Copies, versions, plagiarism, spam, mirror sites
- 30-60+\% of the web pages in a large crawl can be exact or near duplicates of pages in the other $70 \%$
- Duplicates consume significant resources during crawling, indexing, and search
- Similar query suggestions
- Advertisement: coalition and spam detection
- Product recommendation based on similar product features or user interests


## Duplicate Detection

- Exact duplicate detection is relatively easy
- Content fingerprints
- MD5, cyclic redundancy check (CRC)
- Checksum techniques
- A checksum is a value that is computed based on the content of the document
- e.g., sum of the bytes in the document file

| T | r | o | p | i | c | a | l |  | f | i | s | h | Sum |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 54 | 72 | 6 F | 70 | 69 | 63 | 61 | 6 C | 20 | 66 | 69 | 73 | 68 | 508 |

- Possible for files with different text to have same checksum


## Near-Duplicate News Articles

## sfratecom

SFGATE HOME = NEWS [NEWI - BUSINESS : SPORTS " ENTERTAINMENT - TRAVEL
SEARCH

- SFGate Web Search by YAHOO!


## Ap Associated Press

## Obama Takes on Question of Faith

By NEDRA PICKLER, Associated Press Writer
Monday, January 21, 2008

(01-21) 04:22 PST Columbia, S.C. (AP) --
Barack Obama is stepping up his effort to correct the misconception that he's a Muslim now that the presidential campaign has hit the Bible Belt.

At a rally to kick off a weeklong campaign for the South Carolina primary, Obama tried to set the record straight from an attack circulating widely on the Internet that is designed to play into prejudices against Muslims and fears of terrorism.

CLASSIFIEDS : JOBS = REAL ESTATE - CARS
Sign In | Register

MOST READ
MOST E-MAILED
TOP STORIES

1. TGI Friday's employee found slain in San Mateo restaurant
2. Girl shot to death in Oakland by boy trying to scare her, police say
3. 5 Dead As Planes Collide in SoCal
4. Rainy week ahead for Bay Area, with snow on the hills
5. Cranky Pants traded in for Gary Coleman's
6. Giants want to develop lot next to AT\&T Park
7. More men turning to implants for chests of gold


## Near-Duplicate Detection

- More challenging task
- Are web pages with same text context but different advertising or format near-duplicates?
- Near-Duplication: Approximate match
- Compute syntactic similarity with an editdistance measure
- Use similarity threshold to detect nearduplicates
-E.g., Similarity > 80\% => Documents are "near duplicates"
- Not transitive though sometimes used transitively


## Near-Duplicate Detection

- Search:
- find near-duplicates of a document $D$
- $O(N)$ comparisons required
- Discovery:
- find all pairs of near-duplicate documents in the collection
- $O\left(N^{2}\right)$ comparisons
- IR techniques are effective for search scenario
- For discovery, other techniques used to generate compact representations


## Two Techniques for Computing Similarity

1. Shingling : convert documents, emails, etc., to fingerprint sets.
2. Minhashing : convert large sets to short signatures, while preserving similarity.


## Fingerprint Generation Process for Web Documents

1. The document is parsed into words. Non-word content, such as punctuation, HTML tags, and additional whitespace, is removed.
2. The words are grouped into contiguous $n$-grams for some $n$. These are usually overlapping sequences of words, although some techniques use nonoverlapping sequences.
3. Some of the n-grams are selected to represent the document.
4. The selected n-grams are hashed to improve retrieval efficiency and further reduce the size of the representation.
5. The hash values are stored, typically in an inverted index.
6. Documents are compared using overlap of fingerprints

## Computing Similarity with Shingles

- Shingles (Word $k$-Grams) [Brin95, Brod98]
"a rose is a rose is a rose" =>

$$
\begin{aligned}
& \text { a_rose_is_a } \\
& \text { rose_is_a_rose } \\
& \text { is_a_rose_is }
\end{aligned}
$$

- Similarity Measure between two docs (= sets of shingles)
- Size_of_Intersection / Size_of_Union

Jaccard measure

## Example: Jaccard Similarity

- The Jaccard similarity of two sets is the size of their intersection divided by the size of their union.
- $\operatorname{Sim}\left(\mathrm{C}_{1}, \mathrm{C}_{2}\right)=\left|\mathrm{C}_{1} \cap \mathrm{C}_{2}\right| /\left|\mathrm{C}_{1} \cup \mathrm{C}_{2}\right|$.


3 in intersection.
8 in union.
Jaccard similarity
$=3 / 8$

## Fingerprint Example for Web Documents

Tropical fish include fish found in tropical environments around the world, including both freshwater and salt water species.
(a) Original text
tropical fish include, fish include fish, include fish found, fish found in, found in tropical, in tropical environments, tropical environments around, environments around the, around the world, the world including, world including both, including both freshwater, both freshwater and, freshwater and salt, and salt water, salt water species
(b) 3-grams

93866446382249279878969143236913908694553870779
(c) Hash values

## Approximated Representation with Sketching

- Computing exact set intersection of shingles between all pairs of documents is expensive
- Approximate using a subset of shingles (called sketch vectors)
- Create a sketch vector using minhashing.
- For doc $d$, sketch $[i]$ is computed as follows:
- Let $f$ map all shingles in the universe to $0 . .2^{m}$
- Let $\pi_{\mathrm{i}}$ be a specific random permutation on $0 . .2^{m}$
- Pick MIN $\pi_{\mathrm{i}}(f(s))$ over all shingles $s$ in this document $d$
- Documents which share more than t (say 80\%) in sketch vector's elements are similar


## Example: Min-hash

## Round 1: <br> ordering $=$ [cat, dog, mouse, banana]

Document 1: \{mouse, dog\} MH-signature $=$ dog

Document 2: \{cat, mouse\} MH -signature $=$ cat

## Example: Min-hash

## Round 2: <br> ordering $=$ [banana, mouse, cat, dog]

Document 1: \{mouse, dog\}
MH -signature $=$ mouse

Document 2: \{cat, mouse\} MH-signature = mouse

## Computing Sketch[i] for Doc1

## Document 1



Start with 64 bit shingles

Permute on the number line with $\pi_{i}$

Pick the min value

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



Test for 200 random permutations: $\pi_{1}, \pi_{2}, \ldots \pi_{200}$

## Shingling with minhashing

- Given two documents d1, d2.
- Let S1 and S2 be their shingle sets
- Resemblance = |Intersection of S1 and S2| / | Union of S1 and S2|.
- Let Alpha $=\min (\pi(\mathbf{S} 1))$
- Let Beta $=\mathbf{m i n}(\pi(\mathrm{S} 2))$
- Probability (Alpha = Beta) = Resemblance
- Computing this by sampling (e.g. 200 times).


## Proof with Boolean Matrices

- Rows = elements of the universal set.
- Columns = sets.
- 1 in row $e$ and column $S$ if and only if $e$ is a member of $S$.
- Column similarity is the Jaccard similarity of the sets of their rows with 1.
- Typical matrix is sparse.

| $\mathrm{C}_{1}$ | $\mathrm{C}_{2}$ |
| :--- | :--- |
| 0 | 1 |
| 1 | 0 |
| 1 | 1 |
| 0 | 0 |
| 1 | 1 |
| 0 | 1 |

$*$
$*$
$* *$
$* *$
$*$

$$
\operatorname{sim}\left(\mathrm{C}_{\mathrm{i}}, \mathrm{C}_{\mathrm{j}}\right)=\frac{\left|\mathrm{C}_{\mathrm{i}} \cap \mathrm{C}_{\mathrm{j}}\right|}{\left|\mathrm{C}_{\mathrm{i}} \cup \mathrm{C}_{\mathrm{j}}\right|}
$$

$\operatorname{Sim}\left(C_{1}, C_{2}\right)=$
$2 / 5=0.4$

## Key Observation

- For columns $\mathrm{C}_{\mathrm{i}}, \mathrm{C}_{\mathrm{j}}$, four types of rows

|  | $C_{i}$ | $C_{j}$ |
| :---: | :---: | :---: |
| A | 1 | 1 |
| B | 1 | 0 |
| C | 0 | 1 |
| D | 0 | 0 |

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

$$
\operatorname{sim} J\left(C_{i}, C_{j}\right)=\frac{A}{A+B+C}
$$

## Minhashing

- Imagine the rows permuted randomly.
- "hash" function $h(C)=$ the index of the first (in the permuted order) row with 1 in column $C$.
- Use several (e.g., 100) independent hash functions to create a signature.
- The similarity of signatures is the fraction of the hash functions in which they agree.


## Property

- The probability (over all permutations of the rows) that $h\left(\mathrm{C}_{1}\right)=\boldsymbol{h}\left(\mathrm{C}_{2}\right)$ is the same as $\operatorname{Sim}\left(\mathrm{C}_{1}\right.$, $\mathrm{C}_{2}$ ).

$$
\mathrm{P}\left\lfloor\mathrm{~h}\left(\mathrm{C}_{\mathrm{i}}\right)=\mathrm{h}\left(\mathrm{C}_{\mathrm{j}}\right)\right\rfloor=\operatorname{sim},\left(\mathrm{C}_{\mathrm{i}}, \mathrm{C}_{\mathrm{j}}\right)
$$

- Both are $A /(A+B+C)$ !
- Why?
- Look down the permuted columns $\mathrm{C}_{1}$ and $\mathrm{C}_{2}$ until we see a 1.
- If it's a type-a row, then $h\left(\mathrm{C}_{1}\right)=h\left(\mathrm{C}_{2}\right)$. If a type$b$ or type-c row, then not.


## Locality-Sensitive Hashing

## All-pair comparison is expensive

- We want to compare objects, finding those pairs that are sufficiently similar.
- comparing the signatures of all pairs of objects is quadratic in the number of objects
- Example: $10^{6}$ objects implies $5^{*} 10^{11}$ comparisons.
- At 1 microsecond/comparison: 6 days.


## The Big Picture



## Locality-Sensitive Hashing

- General idea: Use a function $f(x, y)$ that tells whether or not $x$ and $y$ is a candidate pair : a pair of elements whose similarity must be evaluated.
- Map a document to many buckets

- Make elements of the same bucket candidate pairs.
- Sample probability of collision:
$-10 \%$ similarity $\rightarrow 0.1 \%$
$-1 \%$ similarity $\rightarrow 0.0001 \%$


## Application Example of LSH with minhash

Generate $b$ LSH signatures for each url, using $r$ of the min-hash values $\quad(b=125, r=3)$

- For $i=1$... $b$
-Randomly select $r$ min-hash indices and concatenate them to form $i$ 'th LSH signature
- Generate candidate pair ( $u, v$ ) if $u$ and $v$ have an LSH signature in common in any round
- $\operatorname{Pr}(\operatorname{lsh}(\mathrm{u})=\operatorname{Ish}(\mathrm{v}))=\operatorname{Pr}(\mathrm{mh}(\mathrm{u})=\mathrm{mh}(\mathrm{v}))^{r}$
[Haveliwala, et al.]


## Example: LSH with minhash

## Document 1: <br> \{mouse, dog, horse, ant\} <br> $\mathrm{MH}_{1}=$ horse <br> $\mathrm{MH}_{2}=$ mouse <br> $\mathrm{MH}_{3}=\mathrm{ant}$ <br> $\mathrm{MH}_{4}=\operatorname{dog}$

$\mathrm{LSH}_{134}=$ horse-ant-dog
$\mathrm{LSH}_{234}=$ mouse-ant-dog

Document 2:
\{cat, ice, shoe, mouse\}
$\mathrm{MH}_{1}=$ cat
$\mathrm{MH}_{2}=$ mouse
$\mathrm{MH}_{3}=$ ice
$\mathrm{MH}_{4}=$ shoe
$\mathrm{LSH}_{134}=$ cat-ice-shoe $\mathrm{LSH}_{234}=$ mouse-ice-shoe

## Example of LSH mapping in web site clustering

Round 1
\(\left.$$
\begin{array}{|l|l|l|l|l|}\hline \begin{array}{l}\text { sports.com } \\
\text { golf.com } \\
\text { party.com }\end{array}
$$ \& ··· . \& \begin{array}{l}music.com <br>

opera.com\end{array} \& ··· \& sing.com\end{array}\right]\)| sing- |
| :--- |
| sport- <br> team- <br> win |

Round 2

| sports.com <br> golf.com | $\ldots$. | music.com <br> sing.com | $\ldots$ | opera.com |
| :--- | :--- | :--- | :--- | :--- |

## Another view of LSH: Produce signature with bands



## Signature agreement of each pair at each band <br> Agreement? Mapped




## Signature generation and bucket comparison

- Create b bands for each document
- Signature of doc $X$ and $Y$ in the same band agrees $\rightarrow$ a candidate pair
- Use $r$ minhash values (r rows) for each band
- Tune band r to catch most similar pairs, but few nonsimilar pairs.


## Analysis of LSH

- Probability the minhash signatures of $\mathrm{C}_{1}, \mathrm{C}_{2}$ agree in one row: s
- Threshold of two similar documents
- Probability $\mathrm{C}_{1}, \mathrm{C}_{2}$ identical in one band: $\mathrm{s}^{r}$
- Probability $\mathrm{C}_{1}, \mathrm{C}_{2}$ do not agree at least one row of a band: 1-sr
- Probability $\mathrm{C}_{1}, \mathrm{C}_{2}$ do not agree in all bands: $\left(1-\mathrm{s}^{\mathrm{r}}\right)^{\mathrm{b}}$
- False negative probability
- Probability $\mathrm{C}_{1}, \mathrm{C}_{2}$ agree one of these bands: $1-\left(1-\mathrm{s}^{r}\right)^{b}$
- Probability that we find such a pair.


## Example

- Suppose $\mathrm{C}_{1}, \mathrm{C}_{2}$ are $80 \%$ Similar
- Choose 20 bands of 5 integers/band.
- Probability $\mathrm{C}_{1}, \mathrm{C}_{2}$ identical in one particular band: $(0.8)^{5}=0.328$.
- Probability $\mathrm{C}_{1}, \mathrm{C}_{2}$ are not similar in any of the 20 bands: $(1-0.328)^{20}=.00035$.
- i.e., about 1/3000th of the $80 \%$-similar column pairs are false negatives.



## Analysis of LSH - What We Want



Similarity $s$ of two docs

Probability of a similar pair to share a bucket

| $\boldsymbol{s}$ | $\mathbf{1 - ( 1 - s}^{\mathbf{r}} \mathbf{)}^{\mathbf{b}}$ |
| :---: | :---: |
| .2 | .006 |
| .3 | .047 |
| .4 | .186 |
| .5 | .470 |
| .6 | .802 |
| .7 | .975 |
| .8 | .9996 |

## LSH Summary

- Get almost all pairs with similar signatures, but eliminate most pairs that do not have similar signatures.
- Check that candidate pairs really do have similar signatures.
- LSH involves tradeoff
- Pick the number of minhashes, the number of bands, and the number of rows per band to balance false positives/negatives.
- Example: if we had only 15 bands of 5 rows, the number of false positives would go down, but the number of false negatives would go up.

