Finding Near-Duplicates

Mining Massive Datasets

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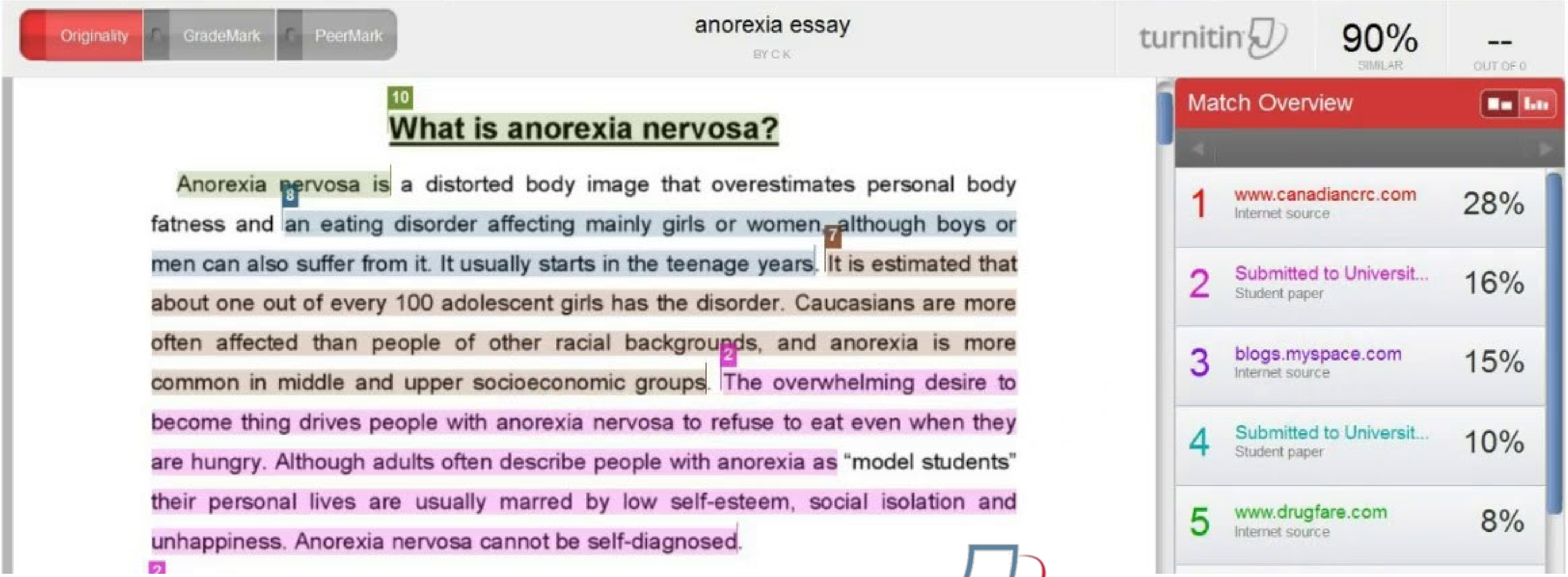
Source for this deck

- Mining of Massive Datasets 2nd edition (2014) by Leskovec et al. (Chapter 3) [slides ch3]

Fast near-neighbor applications

- For documents
  - Find “legitimate” duplicates
    - Copies of the same press release or cable
    - Mirrors of the same documents, for efficiency
  - Find “illegitimate” duplicates
    - Plagiarism
- For baskets
  - Find customers who purchase similar items

Example: plagiarism detection



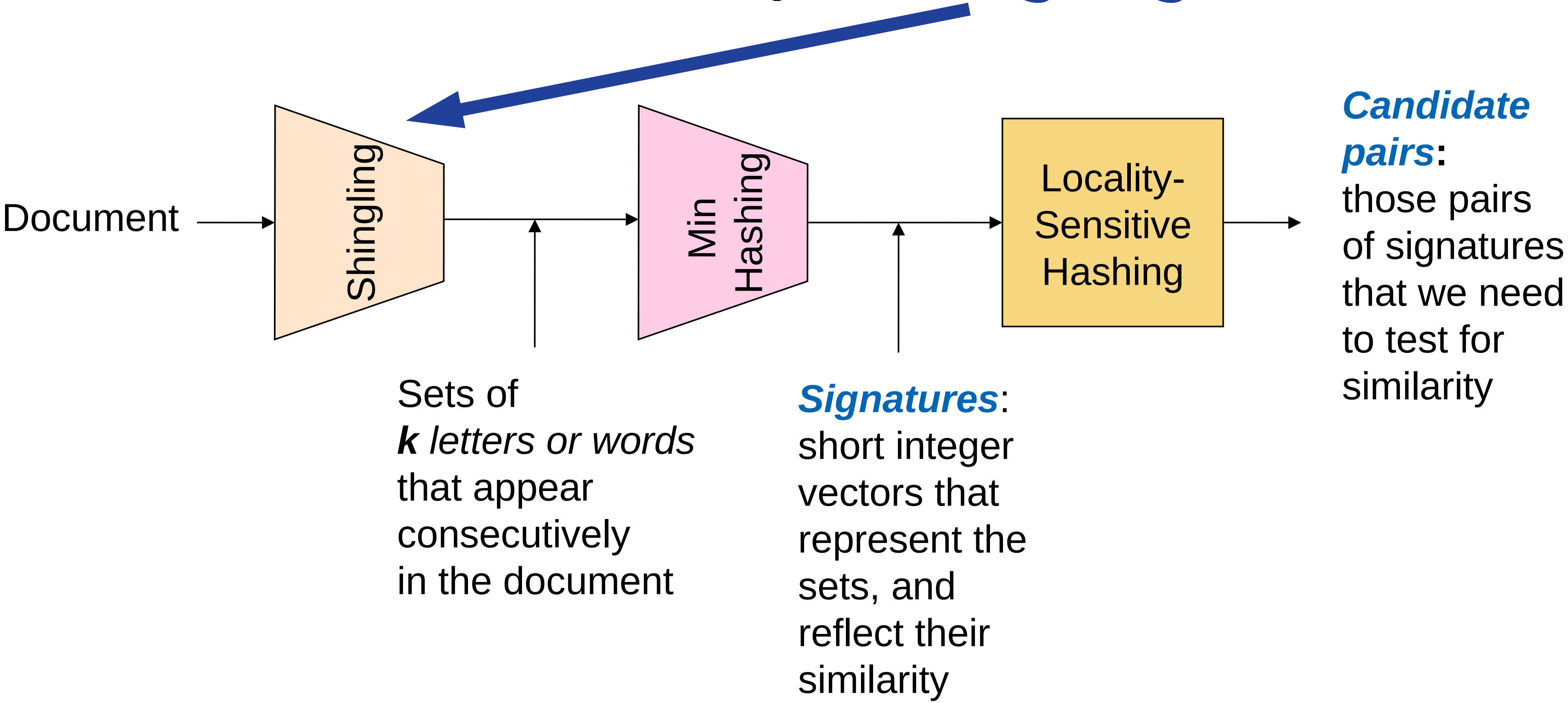
turnitin

Fast near-neighbor challenges

- Too many documents to compare all pairs
  - OK to pay linear or log cost, but not quadratic
- Documents cannot fit in main memory
  - They are too large or too many
- Many small pieces of one document can appear out of order in another

Shingling
(ngrams)

First step: shingling



Naïve solution: feature selection over bag of words

- Document = set of terms

  $\rightarrow$ Document = set of important terms

- Now, compute all pairs similarity

- Doesn't work for at least two reasons, why?

Naïve solution: feature selection over bag of words

- Document = set of terms

  $\rightarrow$ Document = set of important terms

- Now, compute all pairs similarity
- Doesn't work for at least two reasons, why?
  - Doesn't preserve the ordering
  - Unimportant terms are also relevant (stylistic)

Shingles

- An ***ngram*** in a document is a sequence of n tokens that appears in the doc
- **Shingles** are either ngrams (word-level) or sequences of characters, depending on the application
- **Character-level example:** **k=2**; document $\mathbf{D_1}$ = abcab

  Set of 2-shingles: $\mathbf{S(D_1)}$ = {ab, bc, ca}

  - **Option:** Shingles as a bag (multiset), count ab twice: $\mathbf{S'(D_1)}$ = {ab, bc, ca, ab}

Example: 4-grams (shingle = 4 consecutive words)

E.g., 4-shingles of
"`My name is Inigo Montoya. You killed my father. Prepare to die`":

{

- my name is inigo
- name is inigo montoya
- is inigo montoya you
- inigo montoya you killed
- montoya you killed my
- you killed my father
- killed my father prepare
- my father prepare to
- father prepare to die

}

Compressed representation of shingles

- To **compress long shingles**, we can **hash** them to (say) 4 bytes
- **Represent a document by the set of hash values of its *k*-shingles**
- **Idea:** Two documents could (rarely) appear to have shingles in common, when in fact only the hash-values were shared

- **Example:** **k=2**; document $\mathbf{D_1}$= abcab
  Set of 2-shingles: $\mathbf{S(D_1)}$ = {ab, bc, ca}
  Hash the singles: $\mathbf{h(D_1)}$ = {1, 5, 7}

Documents as sets of shingles

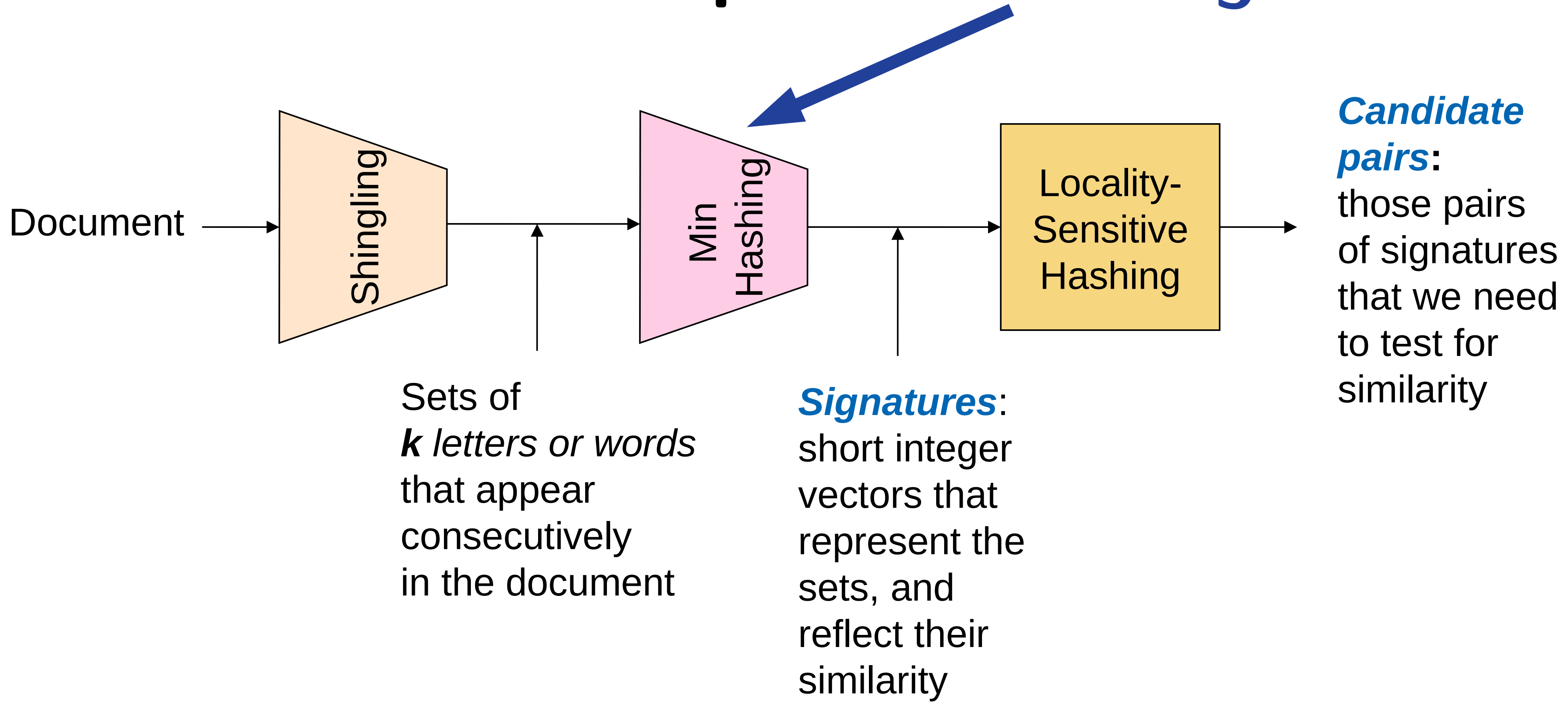
- A document is now a set of shingles
  - Dimensionality reduced from “words in a dictionary” to “number of distinct shingles”
  - Higher dimensionality but more sparse
- Working assumption
  - Documents that have lots of shingles in common have similar text, even if the text appears in different order
- Caveat: You must pick k large enough, or most documents will have most shingles
  - $k = 5$ is OK for short documents
  - $k = 10$ is better for long documents

Using shingles directly

- **Suppose we need to find near-duplicate documents among million documents**
- Naïvely, we would have to compute **all pairwise Jaccard similarities** ≈ **$5*10^{11}$** comparisons
- At 10^5 secs/day and 10^6 comparisons/sec, it would take **5 days**
- For 10 million, it takes more than a year…

Min hashing

Next step: min hashing



Sets can be bit vectors

- Many similarity problems involve
  finding subsets with substantial intersection

- **Remember we can encode sets using bit vectors**
  - set intersection = bitwise **AND**
  - set union = bitwise **OR**

$$J(C_1, C_2) = \frac{|C_1 \cap C_2|}{|C_1 \cup C_2|}$$

- **Example:** $\mathbf{C_1}$ = 10111; $\mathbf{C_2}$ = 10011
  - Size of intersection **= 3**; size of union **= 4**,
  - **Jaccard similarity** (not distance) **= 3/4**
  - **Distance: d(C_1,C_2) = 1 – (Jaccard similarity) = 1/4**

From sets to boolean matrices

- **Rows = items** (shingles)
- **Columns = sets** (documents)
  - 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 corresponding sets (rows with value 1)
- Typical matrix is very sparse!

Documents

Shingles				
	1	1	1	0
	1	1	0	1
	0	1	0	1
	0	0	0	1
	1	0	0	1
	1	1	1	0
	1	0	1	0

Hashing set representations

- We don't want to compare c_1, c_2, they might be too large, slowing down the computation
- Instead, we compute signatures $h(c_1)$, $h(c_2)$ that are smaller in size than c_1 and c_2
- **Desired properties**:
  $c_1 = c_2 \Rightarrow \text{Prob.}(h(c_1) = h(c_2))$ is large
  $c_1 \neq c_2 \Rightarrow \text{Prob.}(h(c_1) \neq h(c_2))$ is large

Hashing set representations (cont.)

- Naïve approach (non-LSH-based):
  - 1) Compute signatures of columns: small summaries of columns
  - 2) Examine all pairs of signatures to find similar columns
    - Essential: Similarities of signatures and columns are related
  - 3) Optional: verify that columns with similar signatures are really similar
- Warnings:
  - Comparing all pairs may take too much time: Job for LSH
  - These methods can produce false negatives, and even false positives (if the optional check is not made)

Hash function for Jaccard metric: min hashing

- Imagine the rows of the boolean matrix permuted under **random but fixed permutation** π
- Define a **"hash" function** $h_\pi(C)$ = the index of the **first** (in the permuted order π) row in which column **C** has value **1**
- Use several (e.g., 100) independent hash functions (that is, permutations) to create a signature of a column

Minhash example

Permutations

2	4	3
3	2	4
7	1	7
6	3	2
1	6	6
5	7	1
4	5	5

Rows=Shingles, Columns=Documents

D1	D2	D3	D4
1	0	1	0
1	0	0	1
0	1	0	1
0	1	0	1
0	1	0	1
1	0	1	0
1	0	1	0

Signature matrix *M*

D1	D2	D3	D4
2	1	2	1
2	1	4	1
1	2	1	2

4th element of the permutation is the first to map to a 1

Exercise: shingling

Rows=Shingles, Columns=Documents

Permutation	D1	D2	D3	D4
3	1	0	1	0
2	1	0	0	1
1	0	1	0	1
4	0	1	0	1
7	0	1	0	1
5	1	0	1	0
6	1	0	1	0

Signature matrix M

D1	D2	D3	D4

Index of the bit vector position where the first 1 occurs according to the ordering of the permutation

Minhash approximates Jaccard

- Let π be a random permutation
- Let $h_\pi(S)$ be the first element of S under the permutation π
- If $h_\pi(A) = h_\pi(B)$ and there are no collisions, then:
  - Among all elements in A ∪ B ...
  - ... the chosen element is in A ∩ B
- This happens with probability $|A \cap B|/|A \cup B| = \text{Jaccard}(A, B)$
- Hence $\mathbf{Pr}[h_{\boldsymbol{\pi}}(A) = h_{\boldsymbol{\pi}}(B)] = \textbf{Jaccard}(A, B)$

We will use multiple permutations

- Jaccard(A, B) $= \mathrm{E}[h_\pi(\mathrm{A}) = h_\pi(\mathrm{B})]$

  $=$ number of matches / number of permutations

- We will use many permutations, e.g., 100

Example: three permutations

Permutations

Rows=Shingles, Columns=Documents

			D1	D2	D3	D4
2	4	3	1	0	1	0
3	2	4	1	0	0	1
7	1	7	0	1	0	1
6	3	2	0	1	0	1
1	6	6	0	1	0	1
5	7	1	1	0	1	0
4	5	5	1	0	1	0

Signature matrix *M*

D1	D2	D3	D4
2	1	2	1
2	1	4	1
1	2	1	2

Similarities	1-3	2-4	1-2	3-4
Complete	0.75	0.75	0	0
Signatures	0.67	1.00	0	0

Minhash signatures

- **Pick $\pi_1 \ldots \pi_{100}$ random permutations of the rows (K=100)**
- Think of ***sig*(C)** as a column vector
  - ***sig*(C)[i] =** according to the *i*-th permutation, the index of the first row that has a 1 in column C
  - $\boldsymbol{sig(C)[i] = \min(\pi_i(C))}$
- The signature or “sketch” of document C has fixed size!
  - We achieved our goal: we “compressed” long bit vectors into short signatures

Implementation

- **Permuting rows even once is prohibitive**
- Instead, we create π_1 **…** π_{100} by using $\mathbf{K = 100}$ hash actual functions H_i … which map to integer numbers

  Ordering of $\{1,2,\ldots,n\}$ under H_i

  … i.e., computing h(1), h(2), …, h(n) and sorting

  … is a random permutation!

Summary

Things to remember

- **Shingling**: Convert documents to sets
  - We used hashing to assign each shingle an ID
- **Min-Hashing**: Convert large sets to short signatures, while preserving similarity
  - We used **similarity preserving hashing** to generate signatures with property $\mathbf{Pr}[h_\pi(C_1) = h_\pi(C_2)] = \mathit{sim}(C_1, C_2)$
  - We used hashing to get around generating random permutations

Exercises for TT08-TT09

- Mining of Massive Datasets 2nd edition (2014) by Leskovec et al.
  - Exercises 3.1.4 (Jaccard similarity)
  - Exercises 3.2.5 (Shingling)
  - Exercises 3.3.6 (Min hashing)
  - Exercises 3.4.4 (Locality-sensitive hashing)