Finding Similar Items in Large Datasets

Big Data Analytics - Gandaki University MSc

Mahesh Shakya in co. with Shiva Ram Dam
Research Associate, NAAMII
Incoming PhD Student @ Hertie AI Center for Brain Health, Uni. of Tubingen, Germany

Finding Similar items in Large Datasets

Basic Solution to finding text similarity

Issues with Basic Solution

Fast Solution meaningful and fast

Problem Statement

Your company is building a plagiarism detection engine that must scan millions of student essays submitted each semester. You need to detect near-duplicates in real-time. How do you represent and compare these documents at scale?

Are these text Plagiarized off of one another?

inheritance in object oriented programming is where a new class is formed using classes which have allready been defined. These classes have have some of the behavior and attributes which where existent in the classes that it inherited from. The peropos of inheritance in object oriented programming is to minimize the reuse of existing code without modification.

Inheritance allowes classes to be categorized, similer to the way humans catagorize. It also provides a way to generalize du to the "is a" relationship between classes. For example a "cow" is a generalization of "animal" similarly so are "pigs" & cheaters". Defeining classes in this way, allows us to define attributes and behaviours which are commen to all animals in one class, so cheaters would natuarly inheart properities commen to all animals.

The advantage of inheritance is that classes which would otherwise have alot of similar code , can instead shair the same code, thus reducing the complexity of the program. Inheritance, therefore, can also be refered to as polymorphism which is where many pieces of code are controled by shared control code.

Inheritance can be accomplished by overriding methods in its ancestor, or by adding new methods.

Inheritance in object oriented programming is a way to form new classes using classes that have already been defined. The new classes, known as derived classes, inherit attributes and behaviour of the existing classes, which are referred to as base classes. With little or no modification, it is intended to help reuse existing code. It is typically accomplished either by overriding one or more methods exposed by ancestor, or by adding new methods to those exposed by an ancestor

Inheritance is also sometimes called generalization, because there is-a relationships represent a hierarchy between classes of objects. A ‘fruit’, for instance, is a generalization of "orange", "mango", "apples" and many others. One can consider fruit to be an abstraction of apple, orange, etc. Since apples are fruit (i.e., an apple is-a fruit), conversely apples may naturally inherit all the properties common to all fruit, such as being a fleshy container for the seed of a plant.

An advantage of inheritance is that modules with sufficiently similar interfaces can share a lot of code reducing the complexity of the program.

Are these text Plagiarized off of one another?

inheritance in object oriented programming is where a new class is formed using classes which have allready been defined. These classes have have some of the behavior and attributes which where existent in the classes that it inherited from. The peropos of inheritance in object oriented programming is to minimize the reuse of existing code without modification.

Inheritance allowes classes to be categorized, similer to the way humans catagorize. It also provides a way to generalize du to the "is a" relationship between classes. For example a "cow" is a generalization of "animal" similarly so are "pigs" & cheaters". Defeining classes in this way, allows us to define attributes and behaviours which are commen to all animals in one class, so cheaters would natuarly inheart properities commen to all animals.

The advantage of inheritance is that classes which would otherwise have alot of similar code , can instead shair the same code, thus reducing the complexity of the program. Inheritance, therefore, can also be refered to as polymorphism which is where many pieces of code are controled by shared control code.

Inheritance can be accomplished by overriding methods in its ancestor, or by adding new methods.

Inheritance is a basic concept of Object-Oriented Programming where the basic idea is to create new classes that add extra detail to existing classes. This is done by allowing the new classes to reuse the methods and variables of the existing classes and new methods and classes are added to specialise the new class. Inheritance models the “is-kind-of” relationship between entities (or objects), for example, postgraduates and undergraduates are both kinds of student. This kind of relationship can be visualised as a tree structure, where ‘student’ would be the more general root node and both ‘postgraduate’ and ‘undergraduate’ would be more specialised extensions of the ‘student’ node (or the child nodes). In this relationship ‘student’ would be known as the superclass or parent class whereas, ‘postgraduate’ would be known as the subclass or child class because the ‘postgraduate’ class extends the ‘student’ class.

Inheritance can occur on several layers, where if visualised would display a larger tree structure. For example, we could further extend the ‘postgraduate’ node by adding two extra extended classes to it called, ‘MSc Student’ and ‘PhD Student’ as both these types of student are kinds of postgraduate student. This would mean that both the ‘MSc Student’ and ‘PhD Student’ classes would inherit methods and variables from both the ‘postgraduate’ and ‘student classes’.

How to compare documents based on their content ?

inheritance in object oriented programming is where a new class is formed using classes which have allready been defined. These classes have have some of the behavior and attributes which where existent in the classes that it inherited from. The peropos of inheritance in object oriented programming is to minimize the reuse of existing code without modification.

Inheritance allowes classes to be categorized, similer to the way humans catagorize. It also provides a way to generalize du to the "is a" relationship between classes. For example a "cow" is a generalization of "animal" similarly so are "pigs" & cheaters". Defeining classes in this way allows us to define attributes and behaviours which are common to all animals in one class, so cheaters would natuarly inheart properities commen to all animals.

The advantage of inheritance is that classes which would otherwise have alot of similar code , can instead shair the same code, thus reducing the complexity of the program. Inheritance, therefore, can also be refered to as polymorphism which is where many pieces of code are controled by shared control code.

Inheritance can be accomplished by overriding methods in its ancestor, or by adding new methods.

Inheritance in object oriented programming is a way to form new classes using classes that have already been defined. The new classes, known as derived classes, inherit attributes and behaviour of the existing classes, which are referred to as base classes. With little or no modification, it is intended to help reuse existing code. It is typically accomplished either by overriding one or more methods exposed by ancestor, or by adding new methods to those exposed by an ancestor

Inheritance is also sometimes called generalization, because there is-a relationships represent a hierarchy between classes of objects. A ‘fruit’, for instance, is a generalization of "orange", "mango", "apples" and many others. One can consider fruit to be an abstraction of apple, orange, etc. Since apples are fruit (i.e., an apple is-a fruit), conversely apples may naturally inherit all the properties common to all fruit, such as being a fleshy container for the seed of a plant.

An advantage of inheritance is that modules with sufficiently similar interfaces can share a lot of code reducing the complexity of the program.

Highly similar

How to compare documents based on their content ?

How to compare documents based on their content ? **Basic Solution**

How to compare documents based on their content ? **Basic Solution**

- Solution 1: Count how many words are common
    - Good first solution

How to compare documents based on their content ?

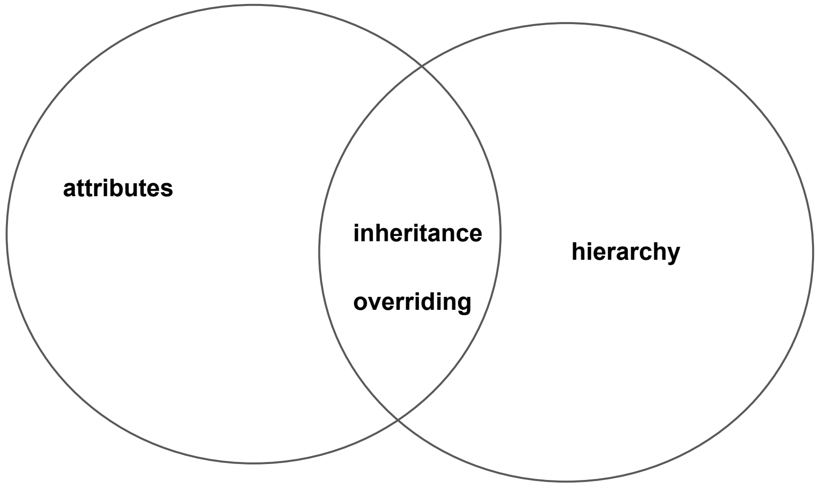
- Solution 1: Count how many words are common
  - Good first solution
  - Challenges
    - Ignores Word order and context e.g. “dog bites man” vs. “man bites dog”
    - Synonyms, paraphrase, case-sensitivity, punctuation
    - Common words such as the, in, of etc. may increase count
    - Scalable Implementation

How to compare documents based on their content ?

- Solution 1: Count how many words are common
  - Good first solution
  - Challenges
    - Ignores Word order and context e.g. “dog bites man” vs. “man bites dog”
    - Synonyms, paraphrase, case-sensitivity, punctuation
    - Common words such as the, in, of etc. may increase count
    - Scalable Implementation
  - How do we define “similar documents”?
    - Count common words: Large texts have lot more common words than short texts
    - Percentage of common words between texts?

Count common words

$C(A, B) = | A \cap B |$



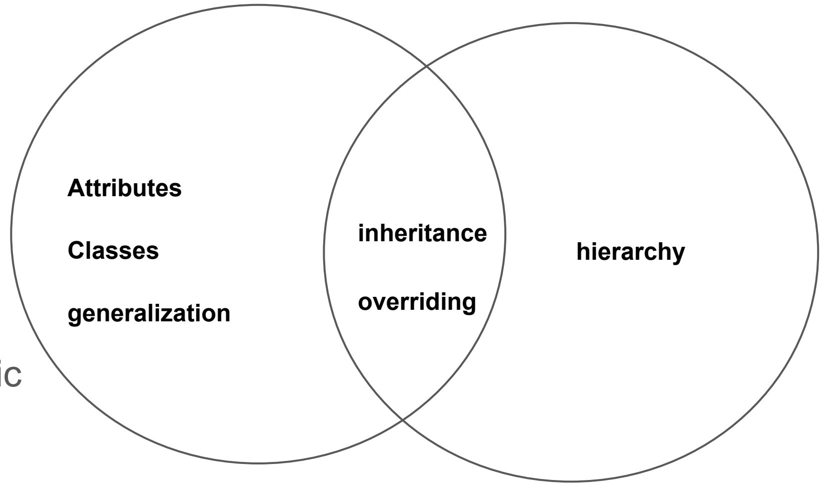
$C = |\{\text{inheritance, overriding}\}|$

How many is too many?

Percentage of common words

C_A(A , B) = | A ∩ B | / |A| = 0.4

C_B(A , B) = | A ∩ B | / |B| = 0.67



C = |{inheritance, overriding}|

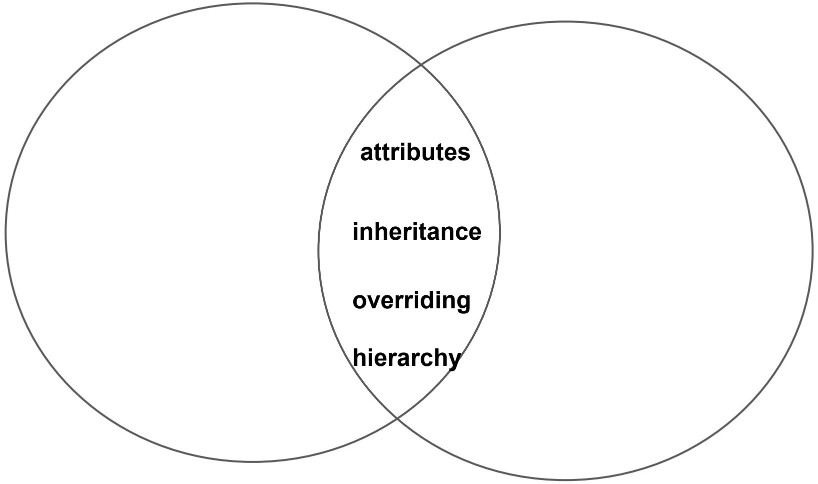
Not Symmetric

C(A,B) = 2 * |A∩B| /(|A| +|B|)
C(B,A) = 2 * |B∩A| / (|B| +|A|)

85% is too many?

How to make this **symmetric** - Jaccard Similarity

IoU, $J(A, B) = |A \cap B| / |A \cup B| = |A \cap B| / (|A| + |B| - |A \cap B|)$.
$DSC(A,B) = 2 * |A \cap B| / (|A| + |B|)$



$$J = \frac{|\{\text{inheritance, overriding}\}|}{|\{\text{attributes, inheritance, overriding, hierarchy}\}|}$$

$A = \{a, i, o, h\}$ $B = \{a,i,o,h\}$ $AUB = \{a,i,o,h,a,i,o,h\} = \{a,i,o,h\}$ $|AUB| = |A| = |B| = 4$

Set to Vector Representation - Bag of Words (BoW)

📝 Step 1: Input Documents

Document 1 (D1):

```
"ChatGPT is a helpful assistant"
```

Document 2 (D2):

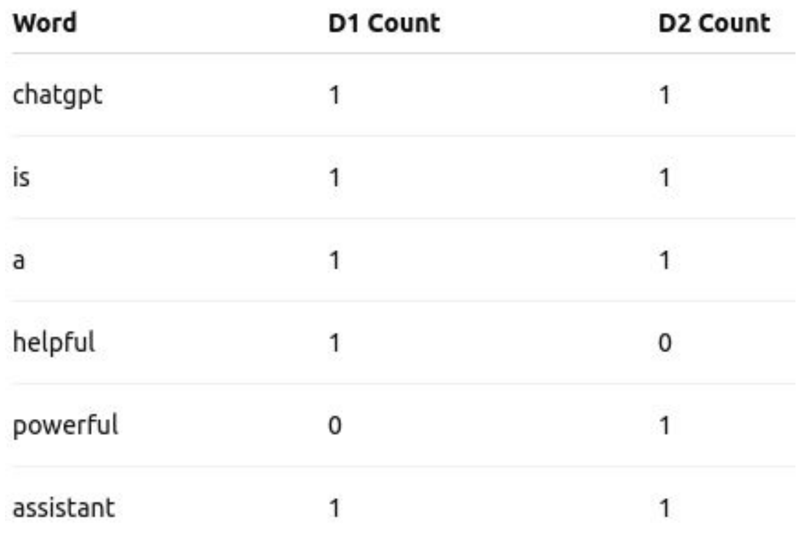
```
"ChatGPT is a powerful assistant"
```

🧾 Step 2: Create the Vocabulary

Extract all unique words (after tokenization and lowercasing):

```
Vocabulary: [chatgpt, is, a, helpful, powerful, assistant]
```

📊 Step 3: Vector Representation



Word	D1 Count	D2 Count
chatgpt	1	1
is	1	1
a	1	1
helpful	1	0
powerful	0	1
assistant	1	1

D1 → `[1, 1, 1, 1, 0, 1]`

D2 → `[1, 1, 1, 0, 1, 1]`

How to compare documents based on their content ?

- Solution 1: Count how many words are common
  - Good first solution
  - Challenges
    - Ignores Word order and context e.g. “dog bites man” vs. “man bites dog”
    - Synonyms, paraphrase, case-sensitivity, punctuation
    - **Common words such as the, in, of etc. may increase count**
    - Scalable Implementation
  - How do we define “similar documents”?
    - Count common words: Large texts have lot more common words than short texts
    - Percentage of common words between texts?

How to handle common words like “a of …” ?

📝 Step 1: Input Documents

Let’s take two short documents:

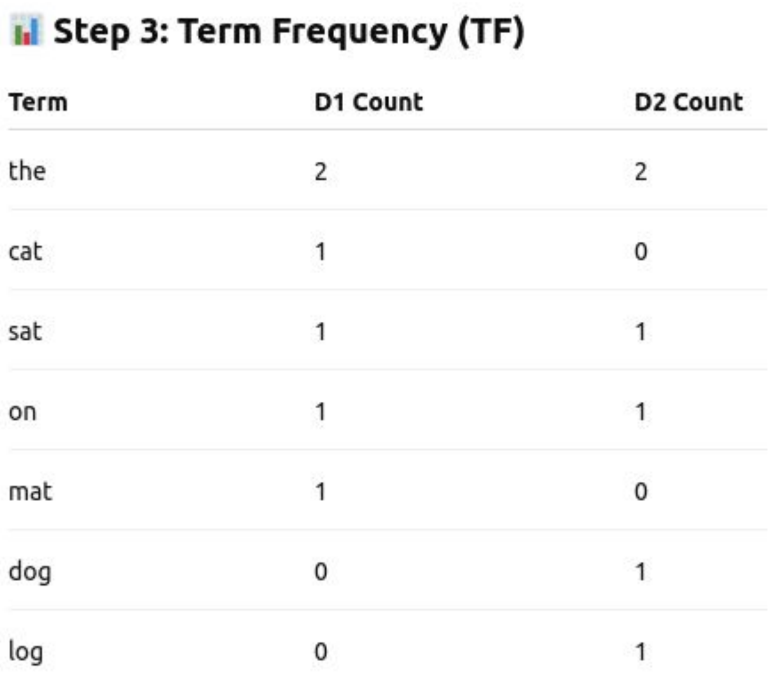
- **D1:** `"the cat sat on the mat"`
- **D2:** `"the dog sat on the log"`

🧾 Step 2: Create the Vocabulary

Vocabulary:
`[the, cat, sat, on, mat, dog, log]`

TF (raw frequency) vectors:

- **D1** → `[2, 1, 1, 1, 1, 0, 0]`
- **D2** → `[2, 0, 1, 1, 0, 1, 1]`



📊 Step 3: Term Frequency (TF)

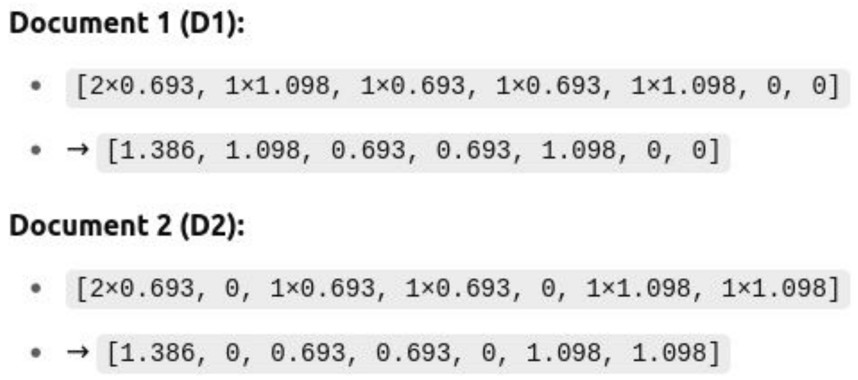
Term	D1 Count	D2 Count
the	2	2
cat	1	0
sat	1	1
on	1	1
mat	1	0
dog	0	1
log	0	1

How to handle common words like “a of …” ?

TF (raw frequency) vectors:

- **D1** → `[2, 1, 1, 1, 1, 0, 0]`
- **D2** → `[2, 0, 1, 1, 0, 1, 1]`

Vocabulary:
`[the, cat, sat, on, mat, dog, log]`

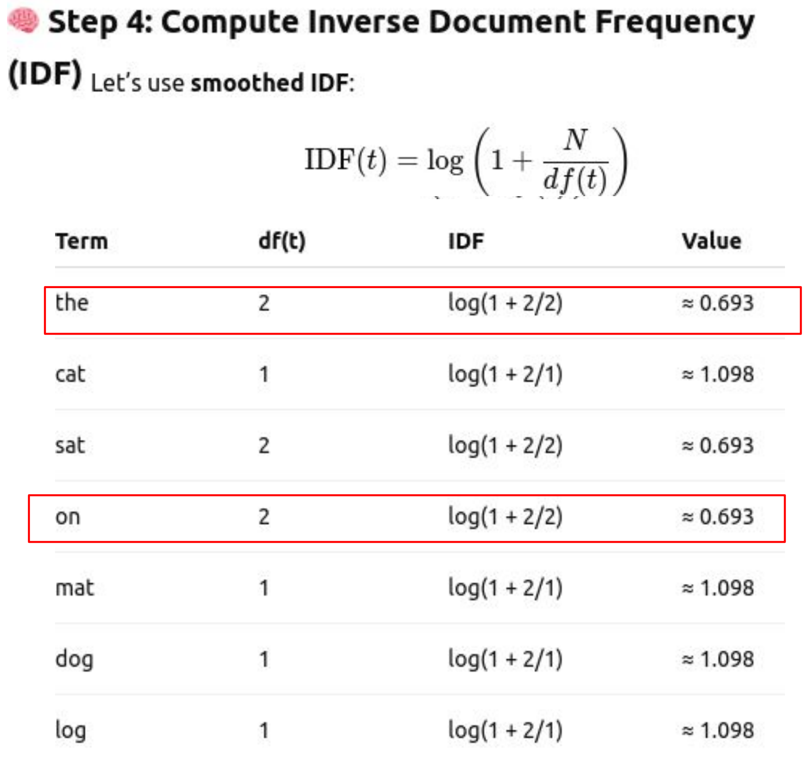


Document 1 (D1):

- `[2×0.693, 1×1.098, 1×0.693, 1×0.693, 1×1.098, 0, 0]`
- → `[1.386, 1.098, 0.693, 0.693, 1.098, 0, 0]`

Document 2 (D2):

- `[2×0.693, 0, 1×0.693, 1×0.693, 0, 1×1.098, 1×1.098]`
- → `[1.386, 0, 0.693, 0.693, 0, 1.098, 1.098]`



🧠 Step 4: Compute Inverse Document Frequency (IDF) Let’s use **smoothed IDF**:

$$\mathrm{IDF}(t) = \log\left(1 + \frac{N}{df(t)}\right)$$

Term	df(t)	IDF	Value
the	2	log(1 + 2/2)	≈ 0.693
cat	1	log(1 + 2/1)	≈ 1.098
sat	2	log(1 + 2/2)	≈ 0.693
on	2	log(1 + 2/2)	≈ 0.693
mat	1	log(1 + 2/1)	≈ 1.098
dog	1	log(1 + 2/1)	≈ 1.098
log	1	log(1 + 2/1)	≈ 1.098

How to count common words in vector representation - Cosine Similarity

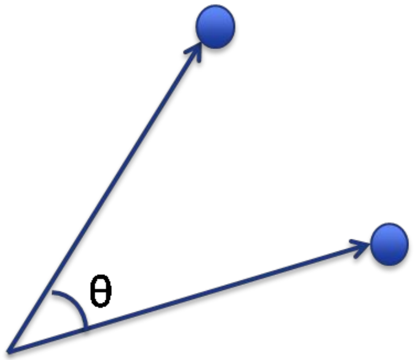
Document 1 (D1):
`"ChatGPT is a helpful assistant"`

Document 2 (D2):
`"ChatGPT is a powerful assistant"`

📐 **Step 4: Cosine Similarity Calculatio**

D1 → `[1, 1, 1, 1, 0, 1]`

D2 → `[1, 1, 1, 0, 1, 1]`



$$\cos(\theta) = \frac{\vec{D1} \cdot \vec{D2}}{||\vec{D1}|| \cdot ||\vec{D2}||}$$

1. Dot Product:

$$(1 \cdot 1) + (1 \cdot 1) + (1 \cdot 1) + (1 \cdot 0) + (0 \cdot 1) + (1 \cdot 1) = 4$$

2. Magnitudes:

$$||\vec{D1}|| = \sqrt{1^2 + 1^2 + 1^2 + 1^2 + 0^2 + 1^2} = \sqrt{5}$$

$$||\vec{D2}|| = \sqrt{1^2 + 1^2 + 1^2 + 0^2 + 1^2 + 1^2} = \sqrt{5}$$

3. Cosine Similarity:

$$\cos(\theta) = \frac{4}{\sqrt{5} \cdot \sqrt{5}} = \frac{4}{5} = 0.8$$

Similarity Metric

A Similarity metric is a function that takes A and B and returns a scalar R
F(A,B) -> R [0, +inf] , higher the better.

Properties

1. A should be similar to A

   F(A,A) = large

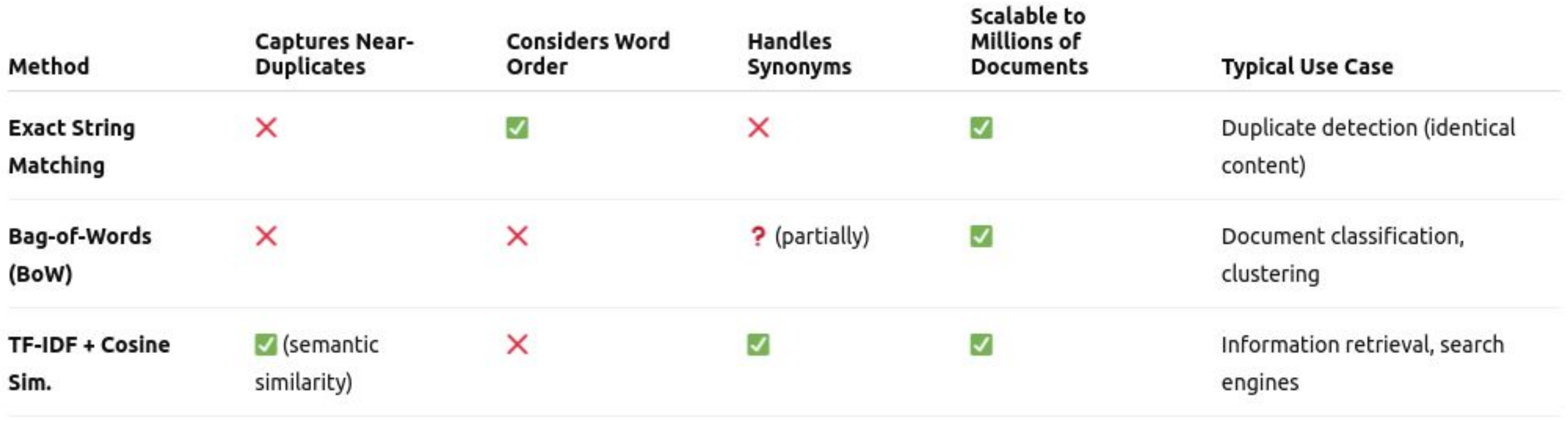
2. Symmetric

   F(A,B) = F(B,A)

3. Distance Inequality

   F(A,B) + F(B,C) <= F(A,C)

Comparison of Methods to Compare documents



Method	Captures Near-Duplicates	Considers Word Order	Handles Synonyms	Scalable to Millions of Documents	Typical Use Case
Exact String Matching	❌	✅	❌	✅	Duplicate detection (identical content)
Bag-of-Words (BoW)	❌	❌	❓ (partially)	✅	Document classification, clustering
TF-IDF + Cosine Sim.	✅ (semantic similarity)	❌	✅	✅	Information retrieval, search engines

How to compare documents based on their content ?

- Solution 1: Count how many words are common
  - Good first solution
  - Issues
    - **Ignores Word order and context e.g. “dog bites man” vs. “man bites dog” (N-gram)**
    - Synonyms, paraphrase, case-sensitivity, punctuation
    - Common words such as the, in, of etc. may increase count
    - **Scalable Implementation (N-gram hinders scalable Implementation)**
  - How do we define “similar documents”?
    - Count common words: Large texts have lot more common words than short texts
    - Percentage of common words between texts? Jaccard Similarity, Cosine Similarity

N-gram model

Dog bites man

Man bites Dog.

1-gram model

A = {dog, bites, man}

B = {man, bites, dog}

J(A,B) = 1 (0 completely dissimilar, 1 exactly similar/duplicates)

DSc(A,B) = 1

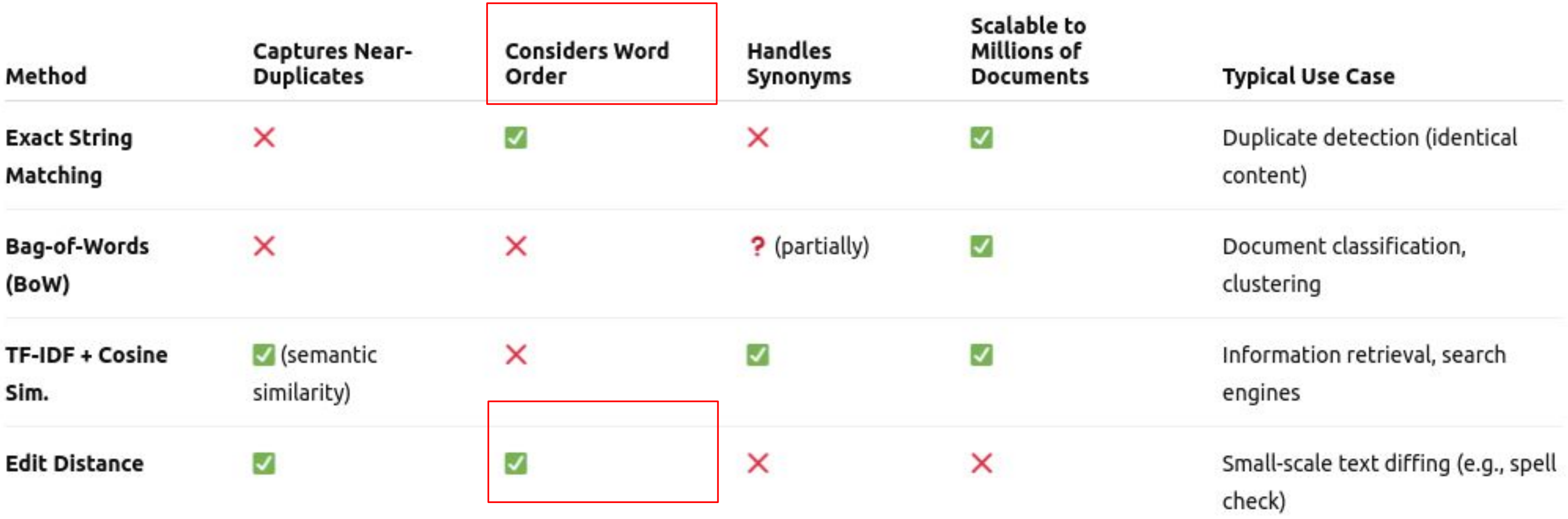
2-gram model

A = {dog, bites, man, “dog bites”, “bites man”} B = {man, bites, dog, “man bites”, “bites dog”}

J(A,B) = |A in. B| / |A U B| = 3 / 7 != 1 (not exactly similar)

DSC(A,B) = 2 * |A in. B| / (|A| +|B|) = 3 / 5 != 1

Comparison of Methods to Compare documents



Method	Captures Near-Duplicates	Considers Word Order	Handles Synonyms	Scalable to Millions of Documents	Typical Use Case
Exact String Matching	❌	✅	❌	✅	Duplicate detection (identical content)
Bag-of-Words (BoW)	❌	❌	? (partially)	✅	Document classification, clustering
TF-IDF + Cosine Sim.	✅ (semantic similarity)	❌	✅	✅	Information retrieval, search engines
Edit Distance	✅	✅	❌	❌	Small-scale text diffing (e.g., spell check)

How to compare documents based on their content ? Preserve Word Order

Doc 1: “dog bites man”
Doc 2: “man bites dog”

Bag of Words

Doc 1: [1,1,1]

Doc 2: [1,1,1]

Cosine Similarity = 1

Edit Distance = 2

Doc 1: “dog bites man”
Doc 2: “~~man~~ dog bites ~~dog~~ man”

How to compare documents based on their content ? Meaningful & **Fast!!**

📝 Step 1: Input Documents

Doc A: `"the cat sat on the mat"`

Doc B: `"the cat sat on the hat"`

🧾 Step 2: Create 3-Shingles (word-based)

Doc A shingles: `{the cat sat, cat sat on, sat on the, on the mat}`

Doc B shingles: `{the cat sat, cat sat on, sat on the, on the hat}`

Calculate Jaccard similarity:

$$\frac{|A \cap B|}{|A \cup B|} = \frac{3}{5} = 0.6$$

Local Text structure preserved!!

"dog bites man" vs. "man bites dog"

How to compare documents based on their content ? Meaningful & **Fast!!**

📝 Step 1: Input Documents

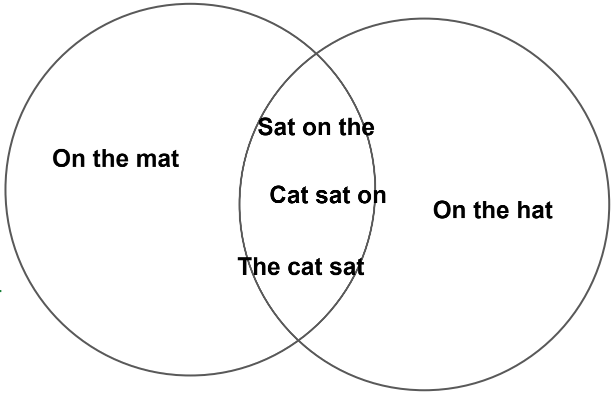
Doc A: `"the cat sat on the mat"`

Doc B: `"the cat sat on the hat"`

🧾 Step 2: Create 3-Shingles (word-based)

Doc A shingles: `{the cat sat, cat sat on, sat on the, on the mat}`

Doc B shingles: `{the cat sat, cat sat on, sat on the, on the hat}`



Calculate Jaccard similarity:

$$\frac{|A \cap B|}{|A \cup B|} = \frac{3}{5} = 0.6$$

Set size increases 😞
Cannot calculate exact similarity, too big!

How to calculate **approximate** similarity between sets? **Fast!!**

If two documents are similar, their shingle sets will have a high Jaccard similarity. But computing exact Jaccard similarity is expensive for large datasets. How can we estimate similarity efficiently?

Realtime constraint!!

How to calculate **approximate** similarity between sets? **Fast!!**

MinHashing = Minimum + Hash

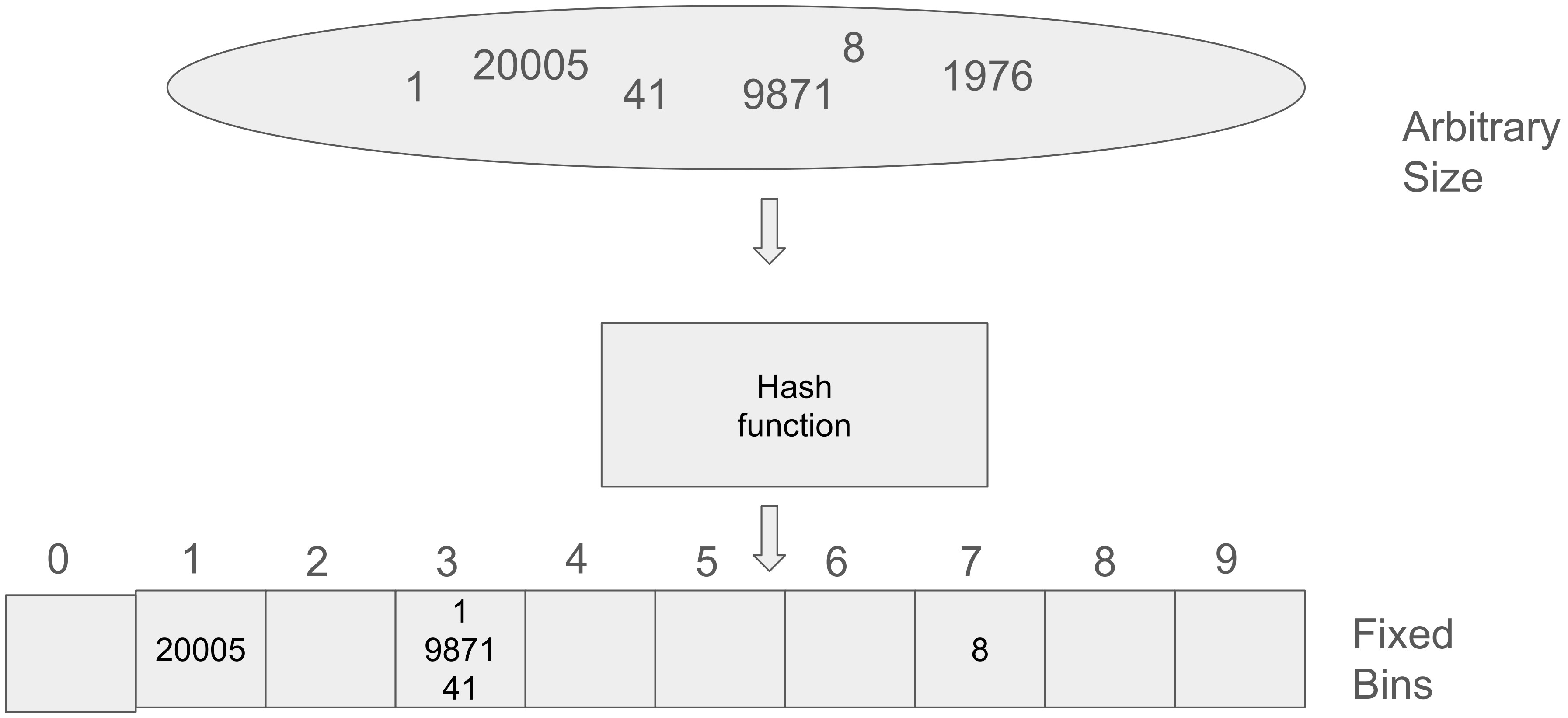
generate **compact signatures** from sets that probabilistically preserve Jaccard similarity.

A =[1,.............................0,...........1] = [1,1,0,1]

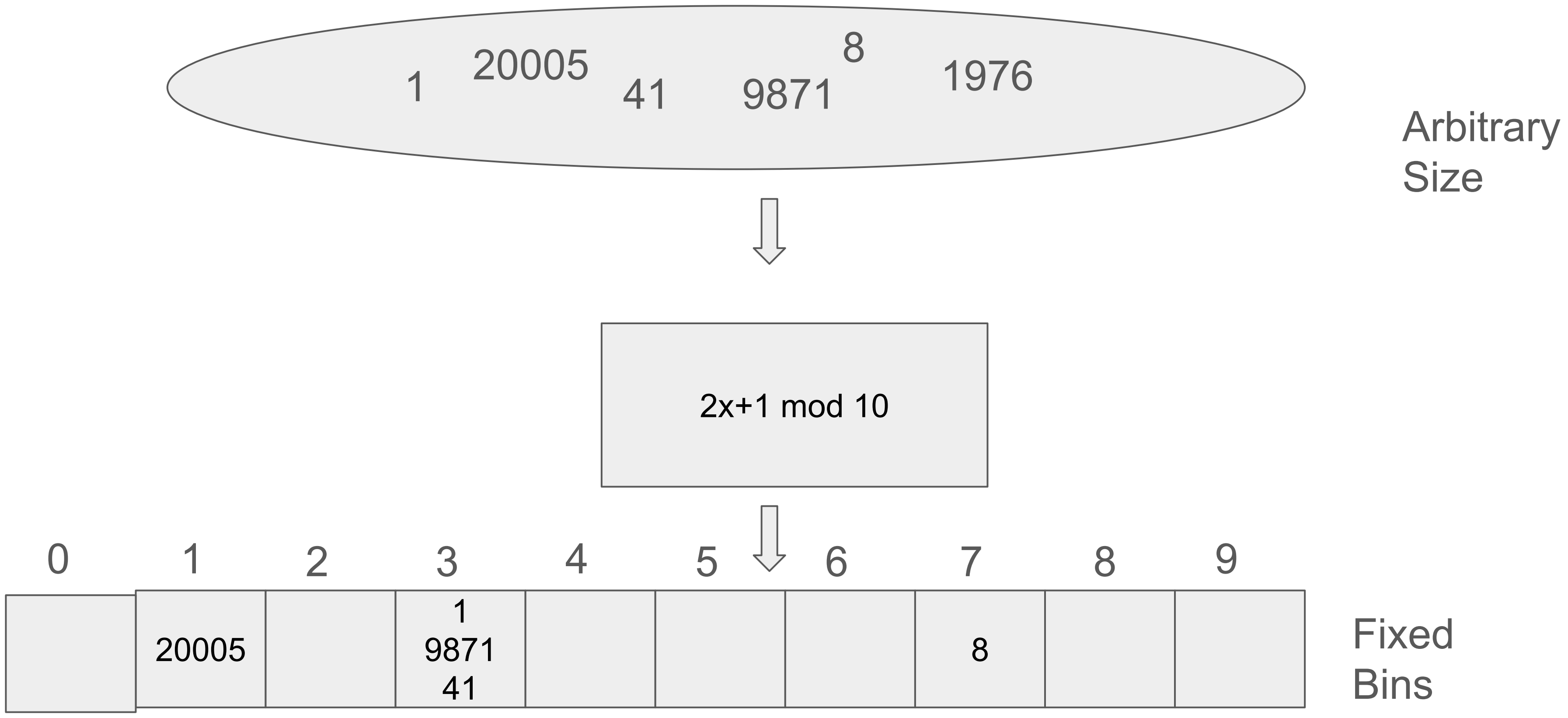
B = [0,,,,,,,,,,,,,,,,,,,,,,,,1,,,,,,,,,,,,,,,,,,,,0,,,,,,,,,1] = [0,1,0,1]

J(A’,B’) = possible to compute but is not exact but only approximate, A’:compact signature
J(A,B) = expensive to compute

Hashing / Hash Functions



Hashing



1
20005
41
9871
8
1976
Arbitrary Size
2x+1 mod 10
0
1
2
3
4
5
6
7
8
9
20005
1
9871
41
8
Fixed Bins

MinHashing

Step 1: Define two small shingle sets

Doc A shingles: `{the cat sat, cat sat on, sat on the, on the mat}`

Doc B shingles: `{cat sat on, sat of off, sat on the, on the hat}`

```
(Represent shingles as integers
for simplicity.)

Doc A shingles = {1, 3, 5, 7}

Doc B shingles = {3, 4, 5, 8}
```

MinHashing

Step 1: Define two small shingle sets

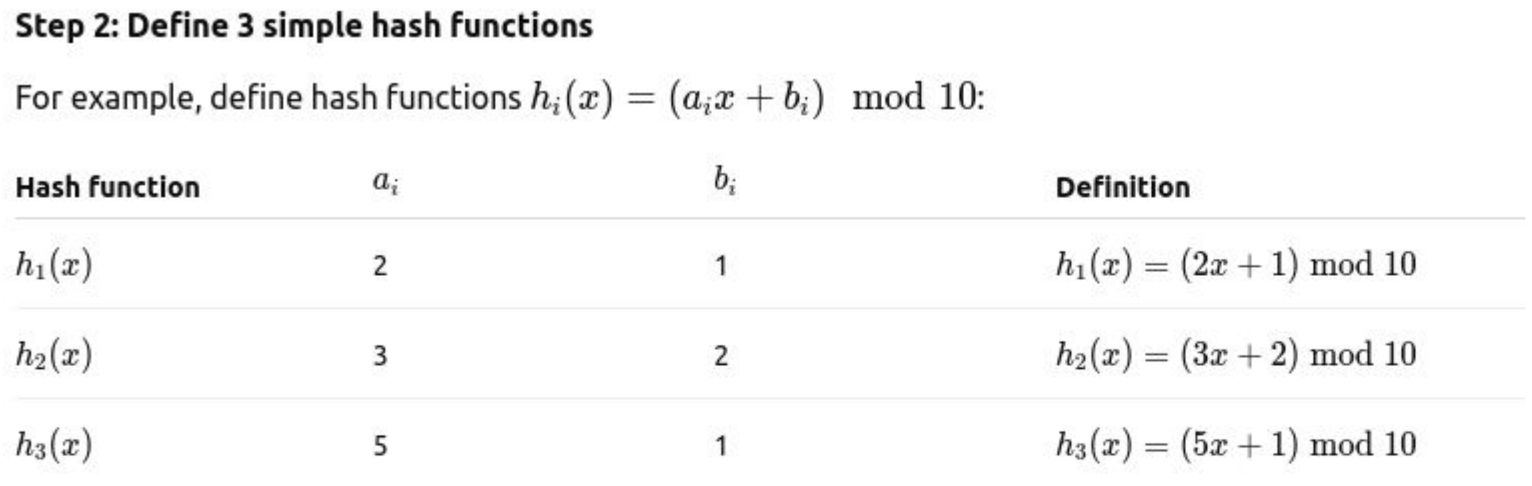
Doc A shingles: `{the cat sat, cat sat on, sat on the, on the mat}`

Doc B shingles: `{cat sat on, sat of off, sat on the, on the hat}`

```
(Represent shingles as integers
for simplicity.)

Doc A shingles = {1, 3, 5, 7}

Doc B shingles = {3, 4, 5, 8}
```



Step 2: Define 3 simple hash functions

For example, define hash functions $h_i(x) = (a_i x + b_i) \mod 10$:

Hash function	a_i	b_i	Definition
$h_1(x)$	2	1	$h_1(x) = (2x + 1) \bmod 10$
$h_2(x)$	3	2	$h_2(x) = (3x + 2) \bmod 10$
$h_3(x)$	5	1	$h_3(x) = (5x + 1) \bmod 10$

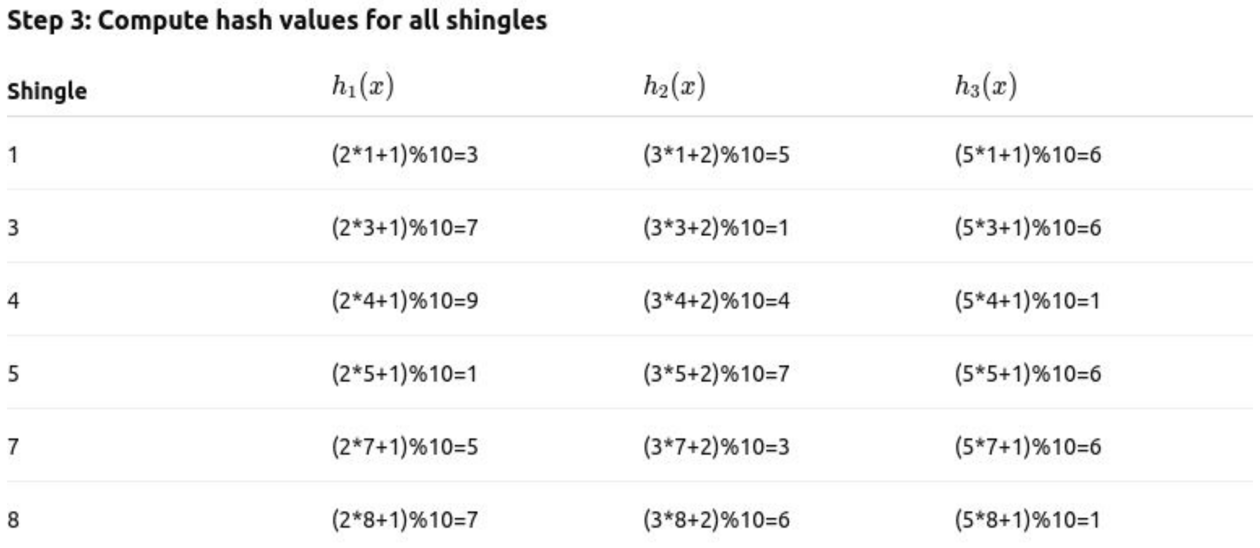
MinHashing

Step 1: Define two small shingle sets
Step 2: Define 3 hash functions

(Represent shingles as integers for **simplicity**.)

Doc A shingles = {1, 3, 5, 7}

Doc B shingles = {3, 4, 5, 8}



Step 3: Compute hash values for all shingles

Shingle	$h_1(x)$	$h_2(x)$	$h_3(x)$
1	(2*1+1)%10=3	(3*1+2)%10=5	(5*1+1)%10=6
3	(2*3+1)%10=7	(3*3+2)%10=1	(5*3+1)%10=6
4	(2*4+1)%10=9	(3*4+2)%10=4	(5*4+1)%10=1
5	(2*5+1)%10=1	(3*5+2)%10=7	(5*5+1)%10=6
7	(2*7+1)%10=5	(3*7+2)%10=3	(5*7+1)%10=6
8	(2*8+1)%10=7	(3*8+2)%10=6	(5*8+1)%10=1

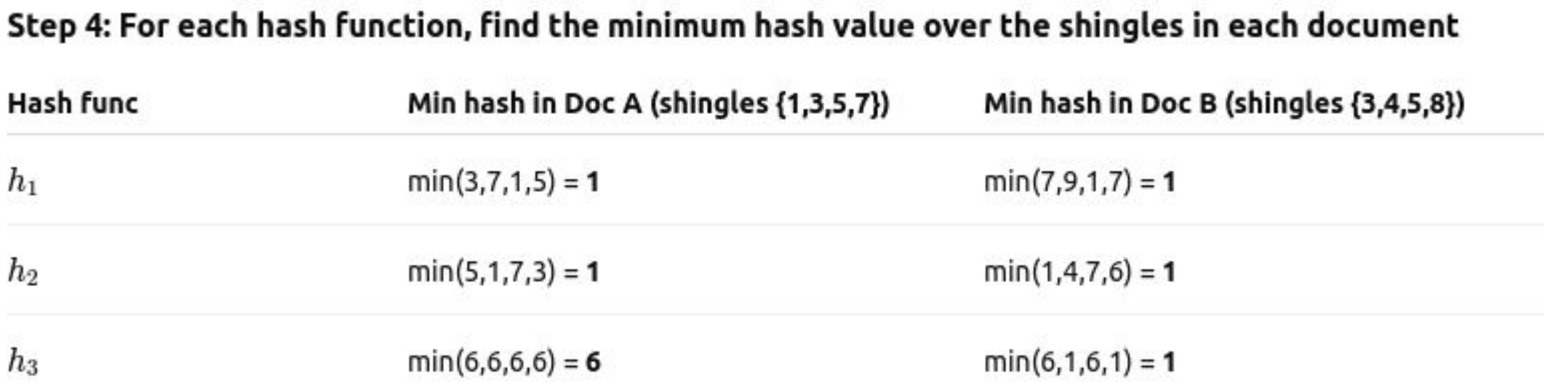
MinHashing

Step 1: Define two small shingle sets
Step 2: Define 3 hash functions
Step 3: Compute hash values for all shingles

```
(Represent shingles as integers
for simplicity.)

Doc A shingles = {1, 3, 5, 7}

Doc B shingles = {3, 4, 5, 8}
```



Step 4: For each hash function, find the minimum hash value over the shingles in each document

Hash func	Min hash in Doc A (shingles {1,3,5,7})	Min hash in Doc B (shingles {3,4,5,8})
h_1	min(3,7,1,5) = **1**	min(7,9,1,7) = **1**
h_2	min(5,1,7,3) = **1**	min(1,4,7,6) = **1**
h_3	min(6,6,6,6) = **6**	min(6,1,6,1) = **1**

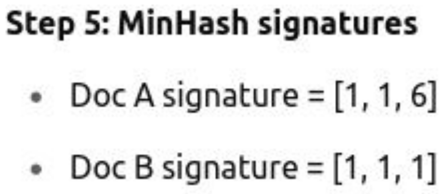
MinHashing

Step 1: Define two small shingle sets
Step 2: Define 3 hash functions
Step 3: Compute hash values for all shingles
Step 4: For each hash function, find the minimum hash values

```
(Represent shingles as integers
for simplicity.)

Doc A shingles = {1, 3, 5, 7}

Doc B shingles = {3, 4, 5, 8}
```



Step 5: MinHash signatures

- Doc A signature = [1, 1, 6]
- Doc B signature = [1, 1, 1]

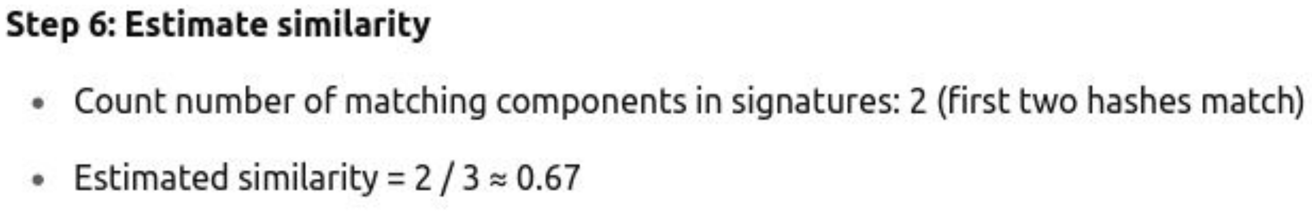
MinHashing

Step 1: Define two small shingle sets
Step 2: Define 3 hash functions
Step 3: Compute hash values for all shingles
Step 4: For each hash function, find the minimum hash values
Step 5: MinHash Signatures

(Represent shingles as integers for **simplicity**.)

Doc A shingles = {1, 3, 5, 7}

Doc B shingles = {3, 4, 5, 8}



Step 6: Estimate similarity

- Count number of matching components in signatures: 2 (first two hashes match)
- Estimated similarity = 2 / 3 ≈ 0.67

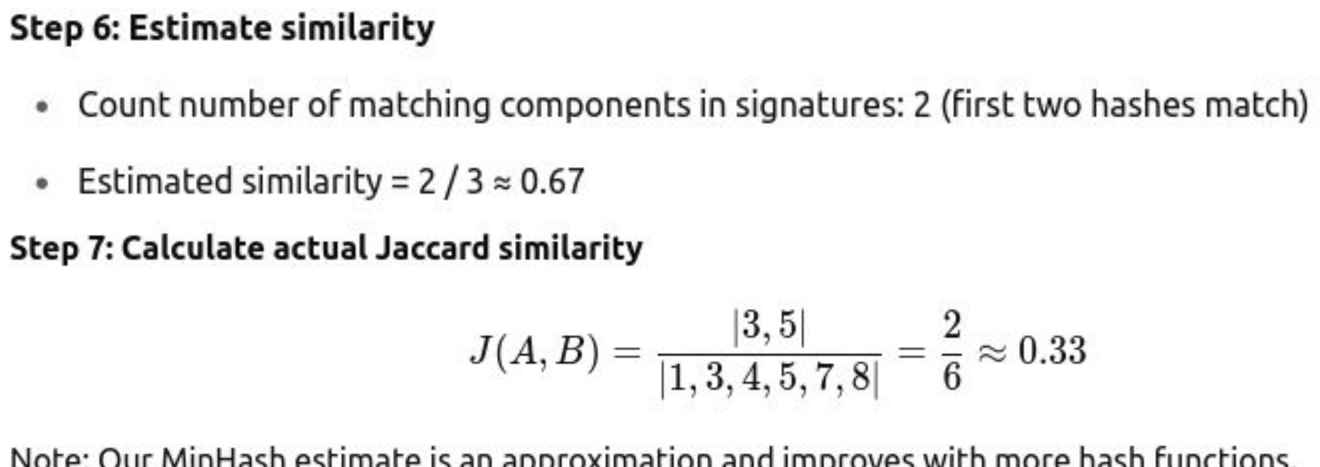
MinHashing

Step 1: Define two small shingle sets
Step 2: Define 3 hash functions
Step 3: Compute hash values for all shingles
Step 4: For each hash function, find the minimum hash values
Step 5: MinHash Signatures

```
(Represent shingles as integers
for simplicity.)

Doc A shingles = {1, 3, 5, 7}

Doc B shingles = {3, 4, 5, 8}
```



Step 6: Estimate similarity

- Count number of matching components in signatures: 2 (first two hashes match)
- Estimated similarity = 2 / 3 ≈ 0.67

Step 7: Calculate actual Jaccard similarity

$$J(A,B) = \frac{|3,5|}{|1,3,4,5,7,8|} = \frac{2}{6} \approx 0.33$$

Note: Our MinHash estimate is an approximation and improves with more hash functions.

Summary

Finding similar Items - e.g. Plagiarism Detection

Simple Solution : Count common words

Bag of Words

How to measure similarity between sets/vectors

Cosine Similarity, Jaccard Similarity

+ Preserve word order: k-Shingling (n-gram model)
+ Fast on large datasets: MinHashing (hash function, minimum, compact signature, approximate, closer to actual as we increase the number of hash function)