

### **Disclaimer**

I wrote this to my best knowledge, however, no guarantees are given whatsoever.

### **Sources**

If not noted differently, the source is the lecture slides and/or the accompanying book.

## 1 Approximate Retrieval

**Nearest-Neighbor** Find  $x^* = \operatorname{argmin}_{x \in X} d(x, y)$  given  $S, y \in S, X \subseteq S$ .

**Near-Duplicate detection** Find all  $x, x' \in X$  with  $d(x, x') \leq \epsilon$ .

### 1.1 $k$ -Shingling

Represent documents (or videos) as set of  $k$ -shingles (a. k. a.  $k$ -grams).  $k$ -shingle is a consecutive appearance of  $k$  characters/words.

Let there be  $N$  documents and  $C$   $k$ -shingles.

Binary shingle matrix  $M \in \{0, 1\}^{C \times N}$  where  $M_{i,j} = 1$  iff document  $j$  contains shingle  $i$ .

### 1.2 Distance functions

**General**  $d : S \times S \rightarrow \mathbb{R}$  is a *distance function* iff  $\forall x, x', x'' \in S$  it's positive definite except for  $x = x'$  ( $d(x, x') > 0 \iff x \neq x'$  and  $d(x, x) = 0$ ), symmetric ( $d(x, x') = d(x', x)$ ) and satisfies the Cauchy-Schwartz triangle inequality ( $d(x, x'') \leq d(x, x') + d(x', x'')$ ).

**$L_r$ -norm**  $d_r(x, y) = (\sum_i |x_i - y_i|^r)^{1/r}$ .  $L_2$ -norm also called *Euclidean*.

**Cosine similarity**  $\operatorname{Sim}_c(A, B) = \frac{A \cdot B}{|A| \cdot |B|}$ .

**Cosine distance**  $d_c(A, B) = \frac{\arccos(\operatorname{Sim}_c(A, B))}{\pi}$ .

**Jaccard similarity**  $\operatorname{Sim}_J(A, B) = \frac{|A \cap B|}{|A \cup B|}$ .

**Jaccard distance**  $d_J(A, B) = 1 - \operatorname{Sim}_J(A, B) = 1 - \frac{|A \cap B|}{|A \cup B|}$ .

### 1.3 LSH – local sensitive hashing

*Key Idea:* Similiar documents have similiar hash.

*Note:* Trivial for exact duplicates (hash-collisions  $\rightarrow$  candidate pair).

**Min-hash**  $h_\pi(C)$  Hash is the *minimum* (i. e. *first*) row index with a one after permutation:  $h_\pi(C) = \min_{i, C(i)=1} \pi(i)$ , given binary vector  $C$  and (random) permutation  $\pi$ .

*Note:*  $\Pr_\pi[h_\pi(C_1) = h_\pi(C_2)] = \operatorname{Sim}_J(C_1, C_2)$  if  $\pi \in_{\text{u.a.r.}} S_{|C|}$ .

**Min-hash signature matrix**  $M_S \in [N]^{n \times C}$  with  $M_S(i, c) = h_i(C_c)$  given  $n$  hash-fns  $h_i$  drawn randomly from a universal hash family.

**Pseudo permutation**  $h_\pi$  with  $\pi(i) = (a \cdot i + b) \bmod p \bmod N$ ,  $N$  number of shingles,  $p \geq N$  prime and  $a, b \in_{\text{u.a.r.}} [p]$  with  $a \neq 0$ .

Instead of real permutations (slow, inefficient, large storage) use pseudo permutations as hash family. Pseudo permutations only need to store  $a$  and  $b$ .

**Compute Min-hash signature matrix**  $M_S$  For all columns  $c \in [C]$  and rows  $r \in [N]$  with  $C_c(r) = 1$ , set  $M_S(i, c) = \min\{h_i(C_c), M_S(i, c)\}$  for all hash functions  $h_i$ .

**Banding as boosting** Reduce FP/FN by AND/OR-boosting, respectively.

This is done by grouping the signature matrix into  $b$  bands of  $r$  rows each. A candidate pair matches in at least one band completely. This corresponds to a  $b$ -way OR after a  $r$ -way AND boosting.

## 2 More stuff to come