

Theory of LSH

Distance Measures

LS Families of Hash Functions

S-Curves

LSH for Different Distance Measures

Mining of Massive Datasets

Leskovec, Rajaraman, and Ullman

Stanford University



Distance Measures

- Generalized LSH is based on some kind of “distance” between points.
 - Similar points are “close.”
- Jaccard similarity is not a distance; $1 - \text{Jaccard similarity}$ is.
- Two major classes of distance measure:
 1. *Euclidean*
 2. *Non-Euclidean*

Euclidean Vs. Non-Euclidean

- A *Euclidean space* has some number of real-valued dimensions and “dense” points.
 - There is a notion of “average” of two points.
 - A *Euclidean distance* is based on the locations of points in such a space.
- Any other space is *Non-Euclidean*.
 - Distance measures for non-Euclidean spaces are based on properties of points, but not their “location” in a space.

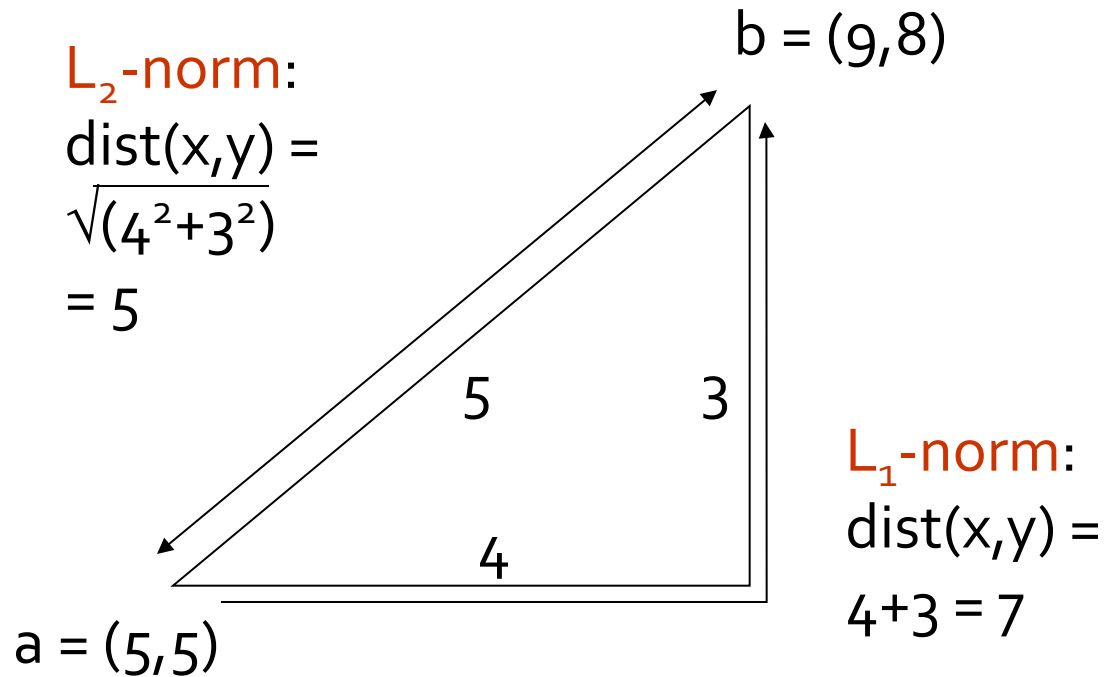
Axioms of a Distance Measure

- d is a *distance measure* if it is a function from pairs of points to real numbers such that:
 1. $d(x,y) \geq 0$.
 2. $d(x,y) = 0$ iff $x = y$.
 3. $d(x,y) = d(y,x)$.
 4. $d(x,y) \leq d(x,z) + d(z,y)$ (*triangle inequality*).

Some Euclidean Distances

- L_2 norm: $d(x,y)$ = square root of the sum of the squares of the differences between x and y in each dimension.
 - The most common notion of “distance.”
- L_1 norm: sum of the differences in each dimension.
 - *Manhattan distance* = distance if you had to travel along coordinates only.

Examples of Euclidean Distances



More Euclidean Distances

- L_∞ norm: $d(x,y)$ = the maximum of the differences between x and y in any dimension.
- **Note**: the maximum is the limit as r goes to ∞ of the L_r norm: what you get by taking the r^{th} power of the differences, summing and taking the r^{th} root.

Non-Euclidean Distances

- *Jaccard distance* for sets = 1 minus Jaccard similarity.
- *Cosine distance* for vectors = angle between the vectors.
- *Edit distance* for strings = number of inserts and deletes to change one string into another.
- *Hamming Distance* for bit vectors = the number of positions in which they differ.

Example: Jaccard Distance

- Consider $x = \{1,2,3,4\}$ and $y = \{1,3,5\}$
- Size of intersection = 2; size of union = 5, Jaccard similarity (not distance) = $2/5$.
- $d(x,y) = 1 - (\text{Jaccard similarity}) = 3/5$.

Why J.D. Is a Distance Measure

- $d(x,y) \geq 0$ because $|x \cap y| \leq |x \cup y|$.
- $d(x,x) = 0$ because $x \cap x = x \cup x$.
 - And if $x \neq y$, then the size of $x \cap y$ is strictly less than the size of $x \cup y$.
- $d(x,y) = d(y,x)$ because union and intersection are symmetric.
- $d(x,y) \leq d(x,z) + d(z,y)$ trickier – next slide.

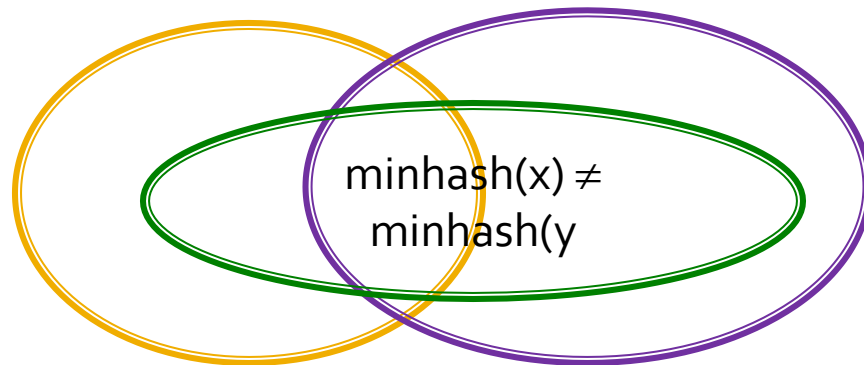
Triangle Inequality for J.D.

$$1 - \frac{|x \cap z|}{|x \cup z|} + 1 - \frac{|y \cap z|}{|y \cup z|} \geq 1 - \frac{|x \cap y|}{|x \cup y|}$$

- **Remember:** $|a \cap b|/|a \cup b|$ = probability that $\text{minhash}(a) = \text{minhash}(b)$.
- Thus, $1 - |a \cap b|/|a \cup b|$ = probability that $\text{minhash}(a) \neq \text{minhash}(b)$.

Triangle Inequality – (2)

- **Claim:** $\text{prob}[\text{minhash}(x) \neq \text{minhash}(y)] \leq \text{prob}[\text{minhash}(x) \neq \text{minhash}(z)] + \text{prob}[\text{minhash}(z) \neq \text{minhash}(y)]$
- **Proof:** whenever $\text{minhash}(x) \neq \text{minhash}(y)$, at least one of $\text{minhash}(x) \neq \text{minhash}(z)$ and $\text{minhash}(z) \neq \text{minhash}(y)$ must be true.



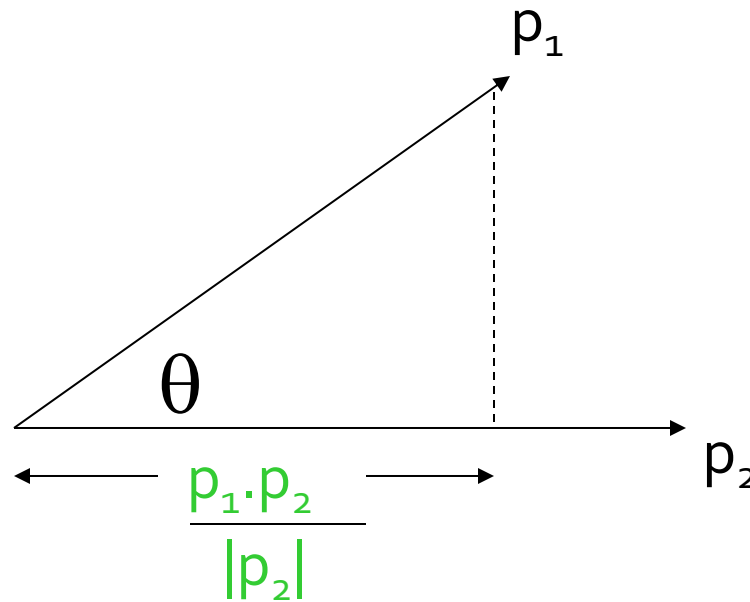
$\text{minhash}(x) \neq \text{minhash}(z)$

$\text{minhash}(z) \neq \text{minhash}(y)$

Cosine Distance

- Think of a point as a vector from the origin $(0,0,\dots,0)$ to its location.
- Two points' vectors make an angle, whose cosine is the normalized dot-product of the vectors: $p_1 \cdot p_2 / |p_2| |p_1|$.
 - **Example:** $p_1 = 00111$; $p_2 = 10011$.
 - $p_1 \cdot p_2 = 2$; $|p_1| = |p_2| = \sqrt{3}$.
 - $\cos(\theta) = 2/3$; θ is about 48 degrees.

Cosine-Measure Diagram



$$d(p_1, p_2) = \theta = \arccos\left(\frac{p_1 \cdot p_2}{|p_2| |p_1|}\right)$$

Why C.D. Is a Distance Measure

- $d(x,x) = 0$ because $\arccos(1) = 0$.
- $d(x,y) \geq 0$ because any two intersecting vectors make an angle in the range 0 to 180 degrees.
- $d(x,y) = d(y,x)$ by symmetry.
- **Triangle inequality**: physical reasoning. If I rotate an angle from x to z and then from z to y , I can't rotate less than from x to y .

Edit Distance

- The *edit distance* of two strings is the number of inserts and deletes of characters needed to turn one into the other.
- An equivalent definition: $d(x,y) = |x| + |y| - 2|LCS(x,y)|$.
 - LCS = *longest common subsequence* = any longest string obtained both by deleting from x and deleting from y .

Example

- $x = abcde$; $y = bcduve$.
- Turn x into y by deleting a , then inserting u and v after d .
 - Edit distance = 3.
- Or, $LCS(x,y) = bcde$.
- **Note:** $|x| + |y| - 2|LCS(x,y)| = 5 + 6 - 2*4 = 3$
= edit distance.

Why Edit Distance Is a Distance Measure

- $d(x,x) = 0$ because 0 edits suffice.
- $d(x,y) \geq 0$: no notion of negative edits.
- $d(x,y) = d(y,x)$ because insert/delete are inverses of each other.
- **Triangle inequality**: changing x to z and then to y is one way to change x to y .

Hamming Distance

- *Hamming distance* is the number of positions in which bit-vectors differ.
- **Example:** $p_1 = 10101$; $p_2 = 10011$.
- $d(p_1, p_2) = 2$ because the bit-vectors differ in the 3rd and 4th positions.

Why Hamming Distance Is a Distance Measure

- $d(x,x) = 0$ since no positions differ.
- $d(x,y) \geq 0$ since strings cannot differ in a negative number of positions.
- $d(x,y) = d(y,x)$ by symmetry of “different from.”
- **Triangle inequality**: changing x to z and then to y is one way to change x to y .