Getting Started on LSH

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Navtalks – November 18, 2016

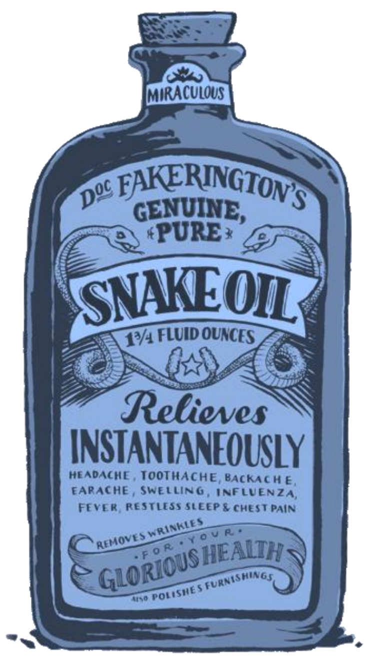
~~Gentle~~ Introduction

SPOILER ALERT!

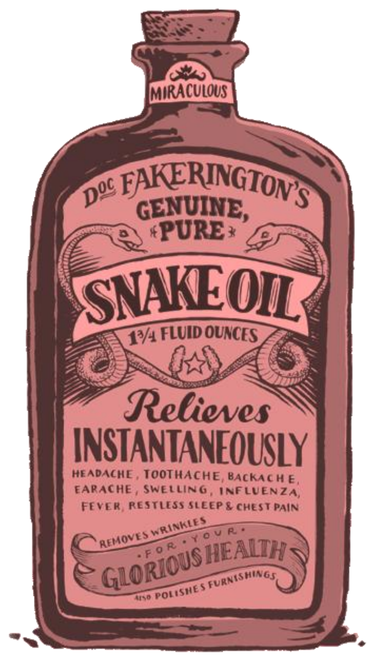
Locality Sensitive Hashing

LSH is an efficient algorithm
to **find** **<u>similar objects</u>** using **<u>hashes</u>**

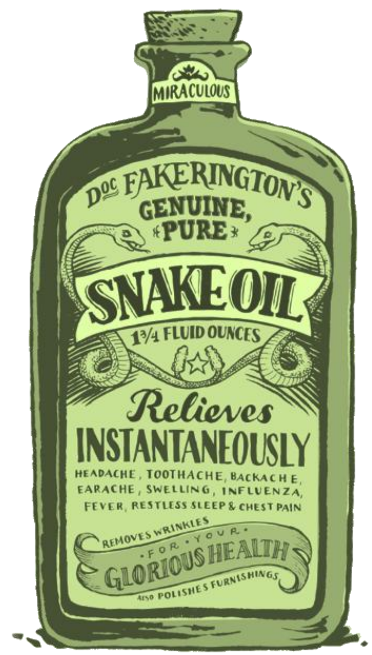
Customers who bought this object also bought . . .



★★★★★ 50€



★★★★ 35€



★★★ 20€

Recommendation Algorithms

- facebook → … **people** you may know
- tinder → … **people** you may like
- YouTube → … **videos** you may like
- NETFLIX → … **movies** you may like
- Spotify → … **music** you may like
- amazon → … **products** you may like

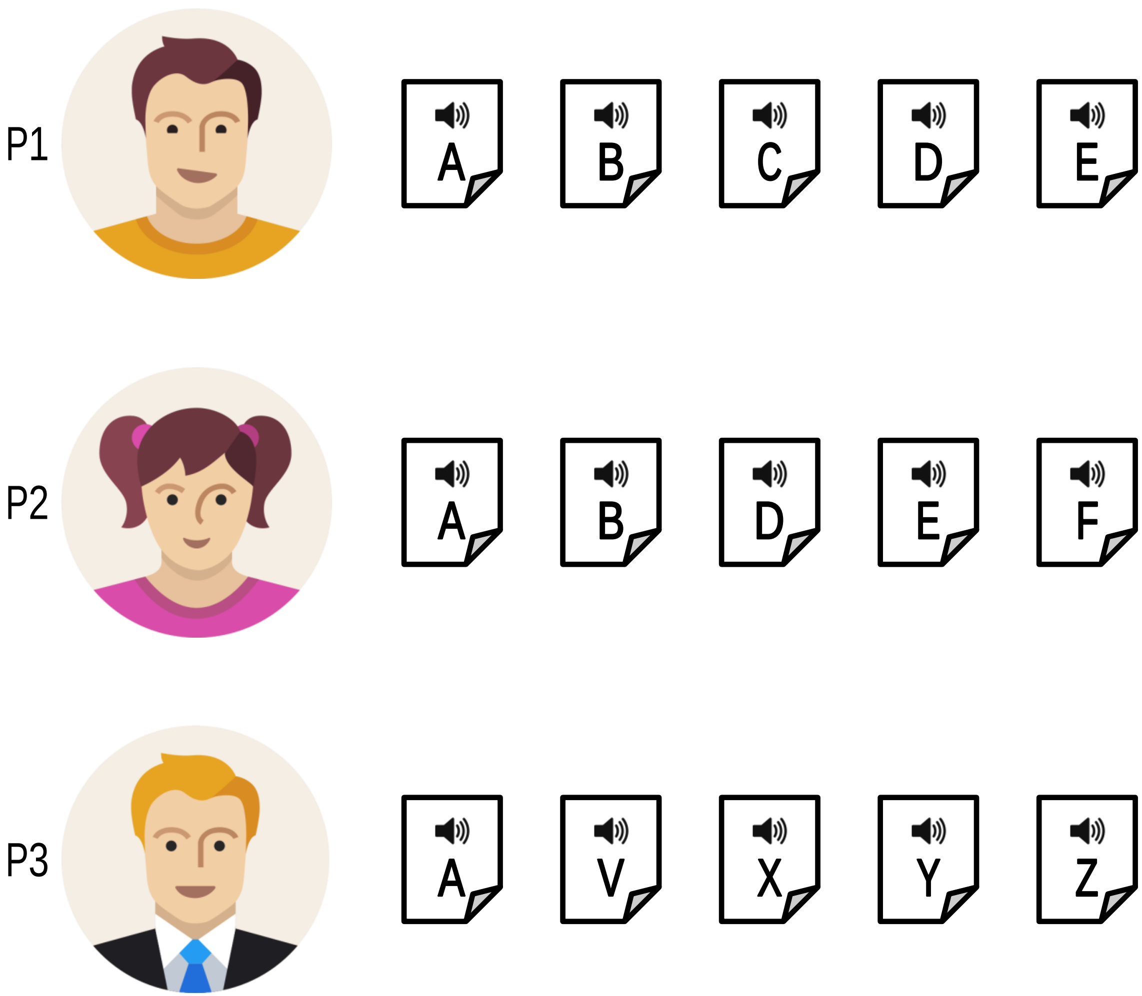
Recommendation Algorithms

Example:
Suggest something to users.

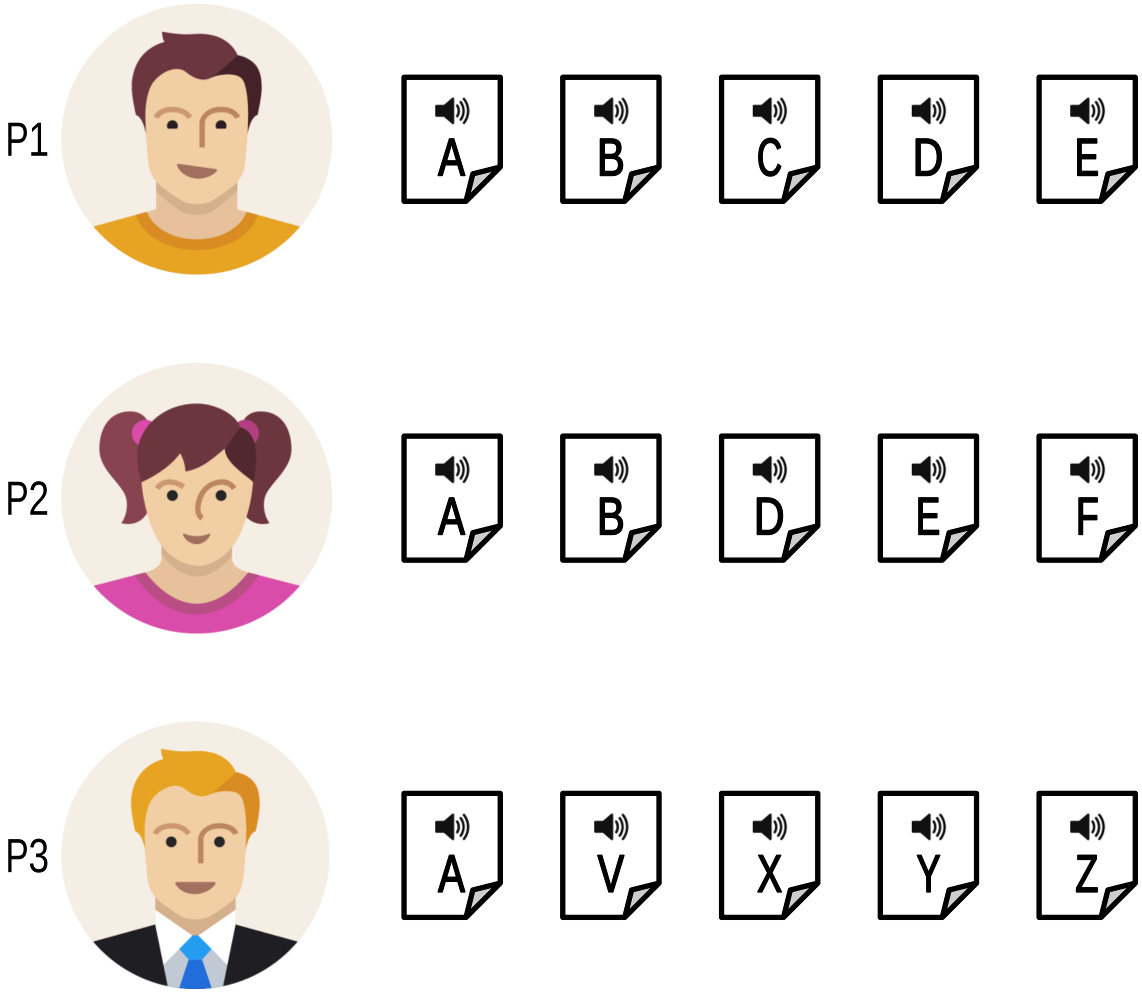
1) Find **similar users** (with similar preferences)
Comparing the list of things they like

2) Suggest what one likes and the other doesn't know yet

Example: Music Recommendation



Example: Music Recommendation



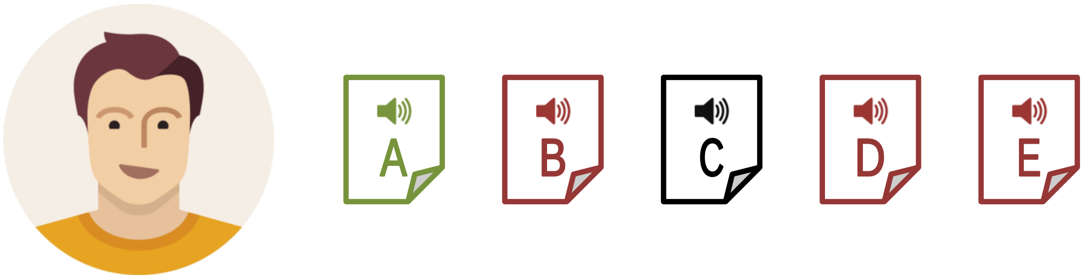
Jaccard Distance*

$$\text{Similarity} = \frac{|A \cap B|}{|A \cup B|}$$

* See extra slides for other distances

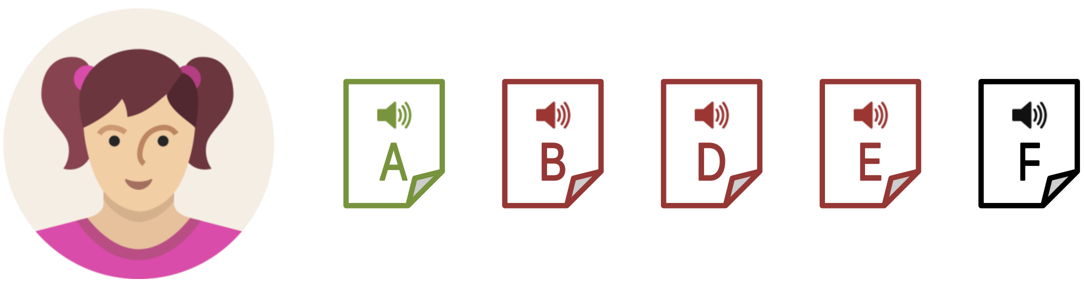
Example: Music Recommendation

P1



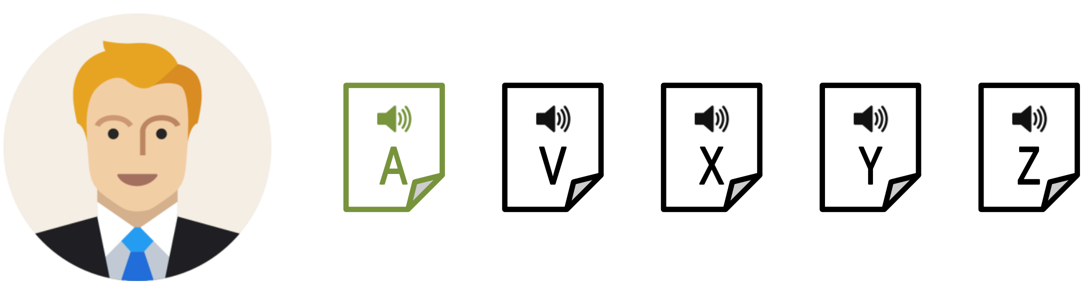
$$\frac{|P1 \cap P2|}{|P1 \cup P2|} = \frac{4}{6} = 0.667$$

P2



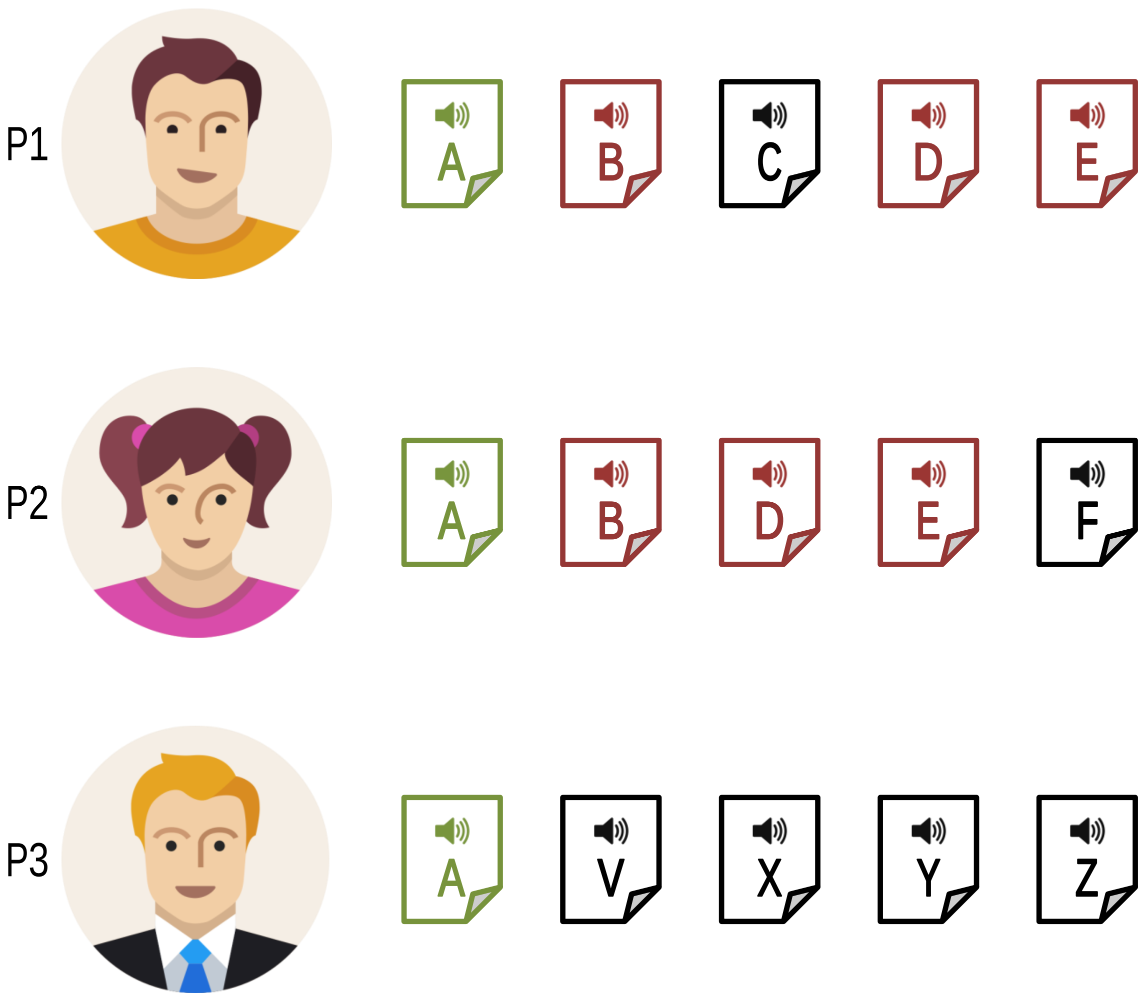
$$\frac{|P2 \cap P3|}{|P2 \cup P3|} = \frac{1}{8} = 0.125$$

P3



$$\frac{|P1 \cap P3|}{|P1 \cup P3|} = \frac{1}{8} = 0.125$$

Example: Music Recommendation



(P1, P2) are more similar than (P1, P3) and (P2, P3)

Suggestions:
F -> P1
C -> P2

Problems

Millions of users that listen
thousands different **songs** each

Problems

Millions of users:

Users are the **objects** to **compare** – $O(n^2)$

Inserting a **new** user = compare 1 to all

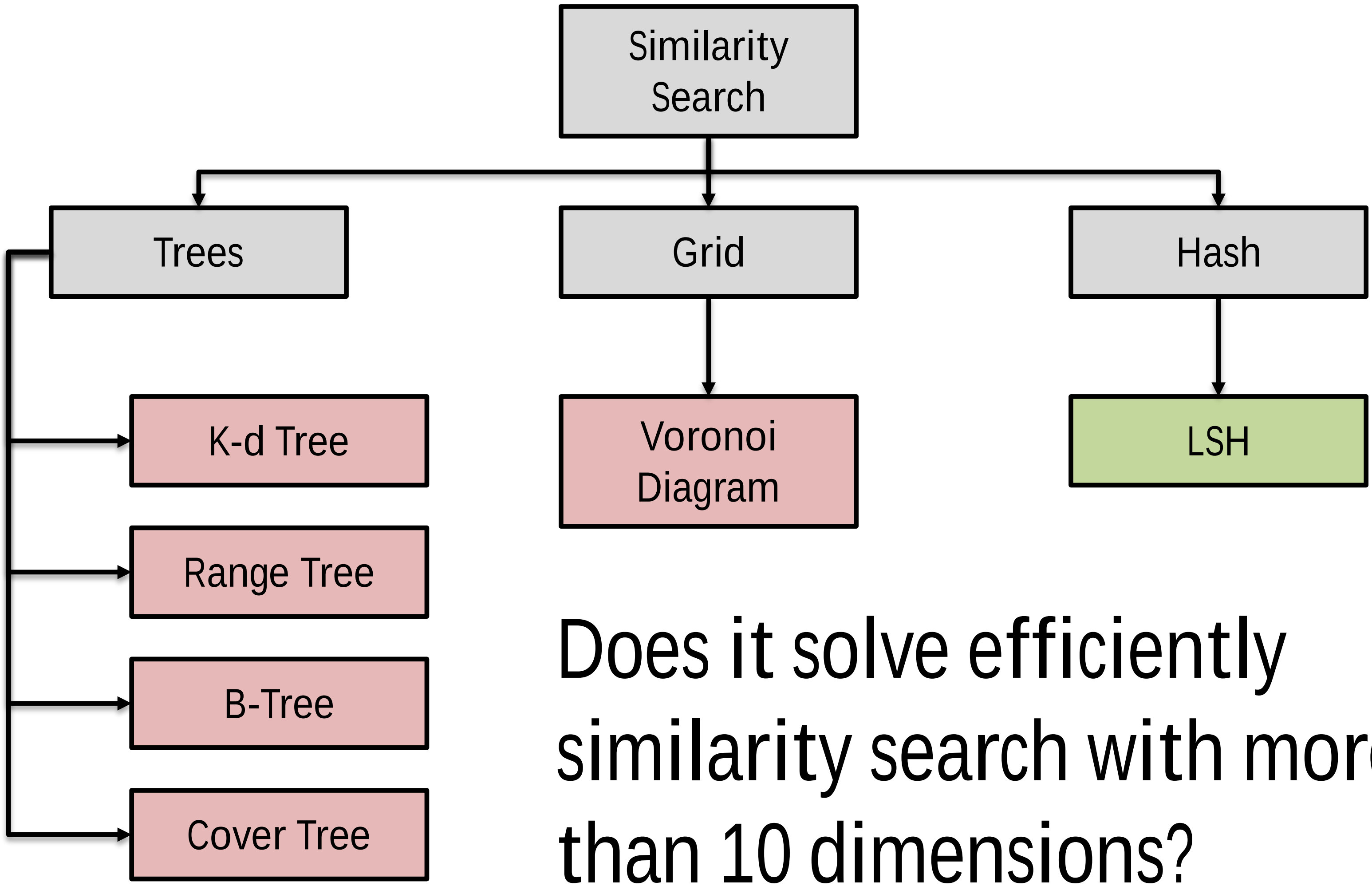
Thousands songs:

Each **song** is a **dimension*** to compare

Curse of dimension

* See extra slides for other dimension examples

Problems



Does it solve efficiently similarity search with more than 10 dimensions?

Locality Sensitive Hashing

Locality
Sensitive
Hashing

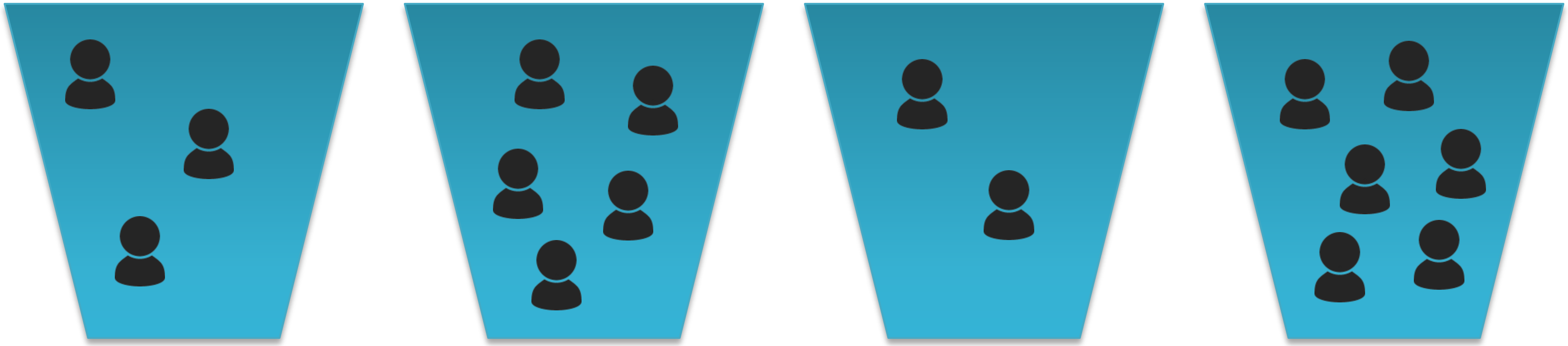
NOT A SPOILER ANYMORE!

LSH is an efficient algorithm
to **find** **<u>similar objects</u>** using **<u>hashes</u>**

Locality Sensitive Hashing

Cluster similar objects into hash buckets

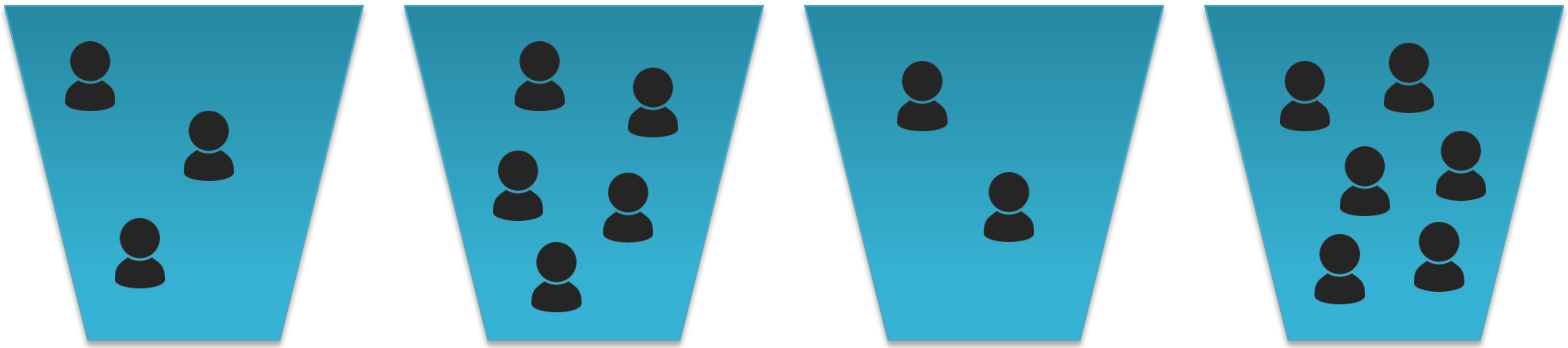
(with a similarity threshold)



Locality Sensitive Hashing

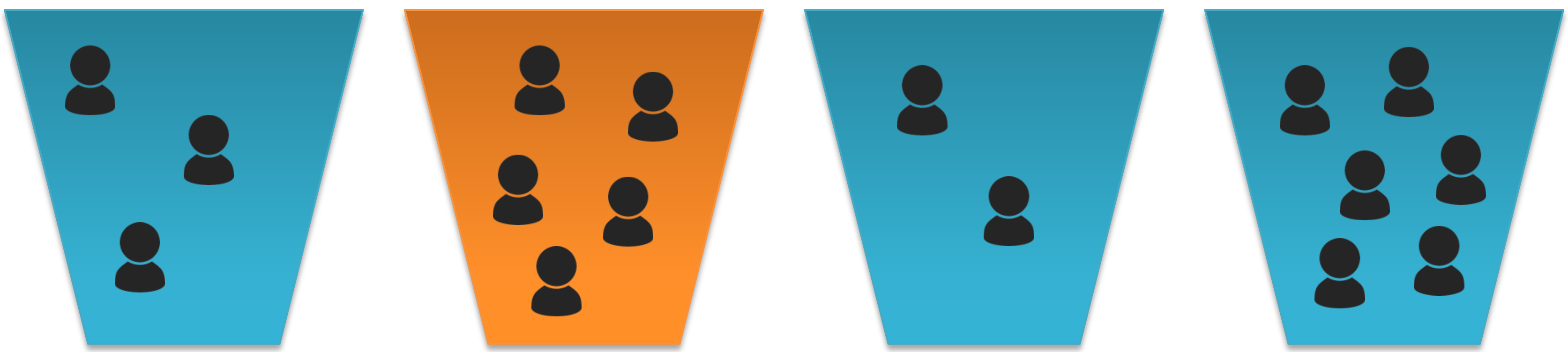
Crypto hashes:
Similar objects -> very different hashes

Locality Sensitive Hashing:
Similar objects -> similar hashes



Locality Sensitive Hashing

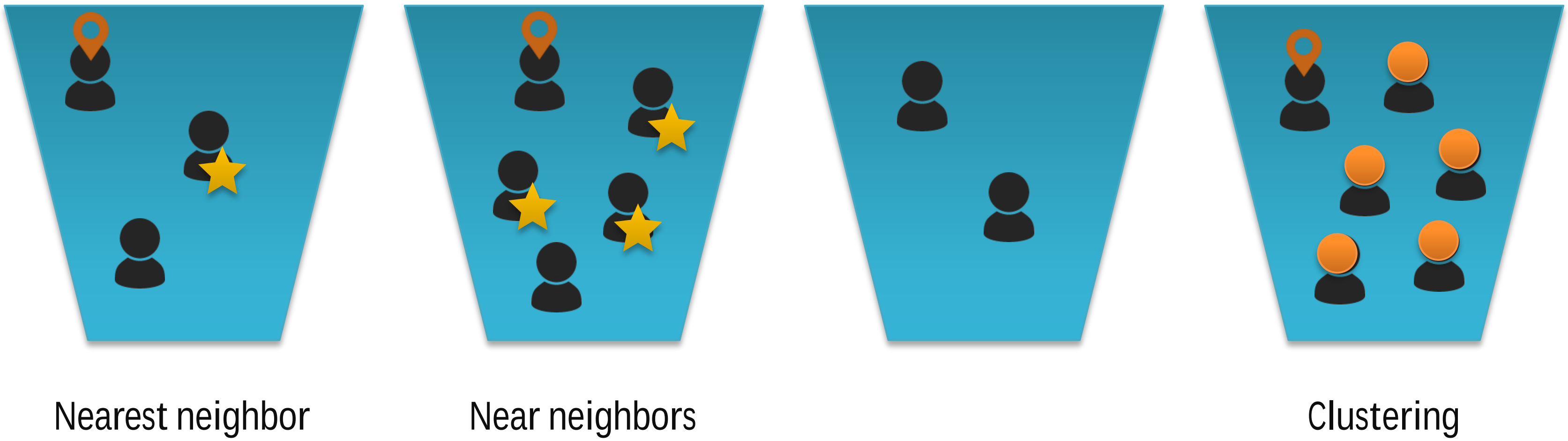
Calculate the distance between objects within the same bucket only



Locality Sensitive Hashing

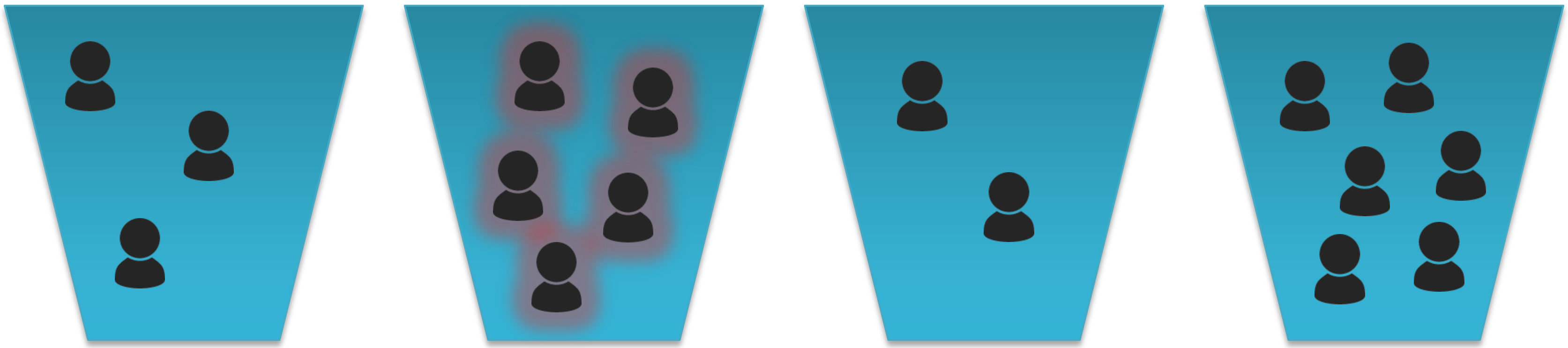
Queries (search similarity):

- Nearest neighbor ★
- Near neighbors ★★★
- Clustering



Locality Sensitive Hashing

We need to calculate the distance within a bucket to validate the distances



Locality Sensitive Hashing

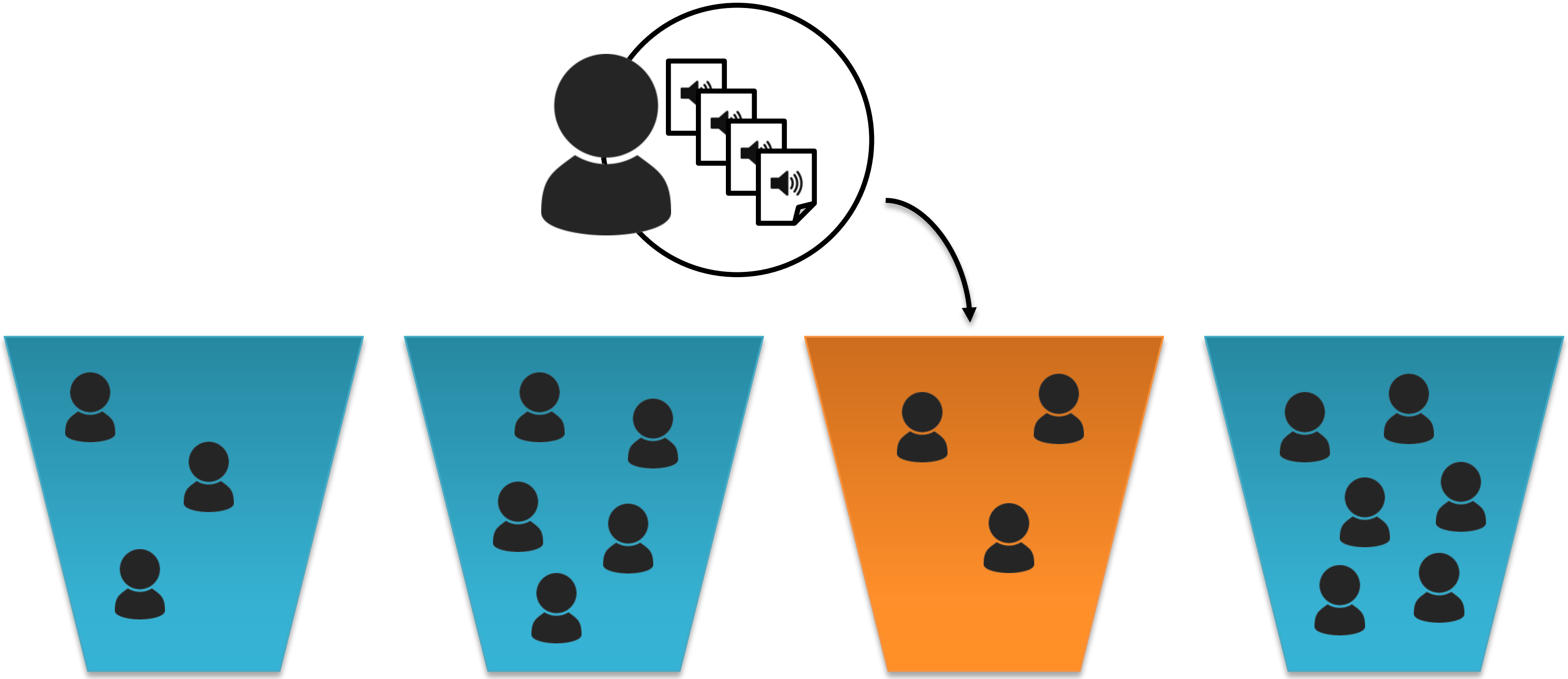
False positives and false negatives may happen (configurable)

False positives
Computing overhead

False negative
Reduces recall

Locality Sensitive Hashing

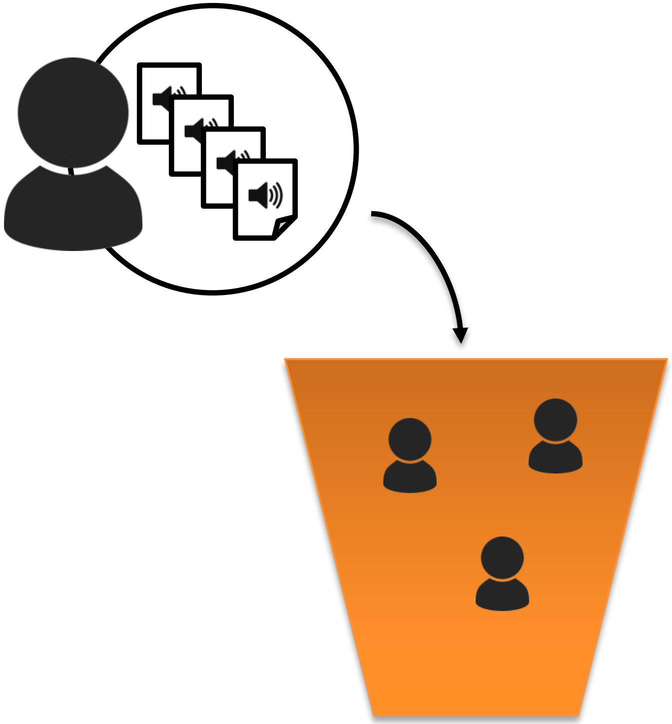
Insert: hash dimensions of new object + compare within bucket



Locality Sensitive Hashing

LSH = MinHash + MultiMap[ ]

MinHash



Hashing is crucial!

For each distance
there is a different hash family*

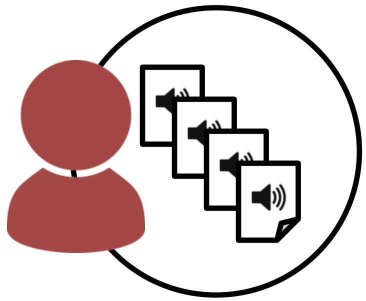
Jaccard Distance -> MinHash*

* See extra slides for other hash families

MinHash

- An array with the minimal hashes from all dimensions for each hash function

P1



minHash(P1)

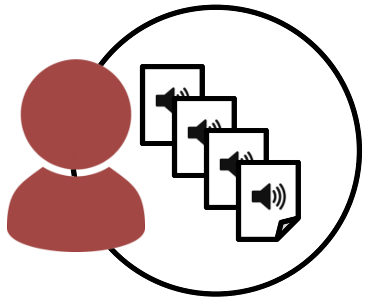
23	12	5	45	7	34	12	76	87	...

```
minHash(Object o):
    num_hashes <- 200 //defined based on a similarity threshold
    hashes <- new hash[num_hashes] //200 different hash functions
    minHash <- new int[num_hashes] //MinHash of the object
    for i in 0..hashes: // for each hash function
        for d in object.dimensions: //for each dimension (music)
                hi <- hashes[i](d) //calculate the hash of d
                minHash[i] <- min(minHash[i], hi) // store the min
```

- Converts **variable** number of dimensions **to** a **fixed** configurable number
- Using the **same order** of hash functions is important **to find similar** objects

Locality Sensitive Hashing

P1



`minHash(P1)`

23	12	5	45	7	34	12	76	87	…

break it into b bands and r rows (based also on the desired similarity threshold)

23	12	5

45	7	34

12	76	87

…

Each band of r rows is the key for a different hashtable

hashTable[0]

23	12	5	[P1]

hashTable[1]

45	7	34	[P1]

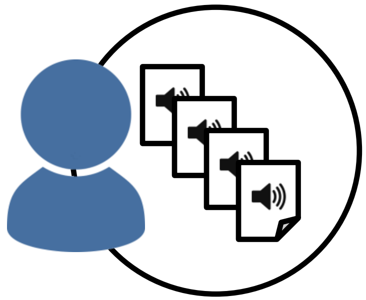
hashTable[2]

12	76	87	[P1]

LSH Index

Locality Sensitive Hashing

P2



minHash(P2)

23	12	5	73	22	15	3	28	56	…

break it into b bands and r rows (based also on the desired similarity threshold)

23	12	5

73	22	15

3	28	56

…

Each band of r rows is the key for a different hashtable

hashTable[0]

23	12	5	[P1, P2]

hashTable[1]

45	7	34	[P1]
73	22	15	[P2]

hashTable[2]

12	76	87	[P1]
3	28	56	[P2]

LSH Index

Interfaces

```
distance(Object o1, Object o2)

insert(Object o)

query(Object o)
    nearestNeighbor(Object o)

    nearNeighbors(Object o, int maxNeighbors)

    clustering(Object o)
```

Challenges: Implementing

- Generic to any **object**
- Providing multiple hash function families
  (generic to all **distances**)
- Being **efficient** (space and time)
- **Durability**

Challenges: Scaling up

- **MultiMaps** (1:n)
- **Off-heap** implementation (avoid garbage collection)
- **Bigger** than memory (e.g., using RAM + SSD disk space)
- **Multi-threaded** (fine-grain locks or non-blocking)
- Using **primitives** (avoid space overhead)

Challenges: Scaling out

- Distributing hash tables in several machines

  hashTable[0] -> s1
  hashTable[1] -> s2
  hashTable[2] -> s3
  hashTable[3] -> s4
  hashTable[4] -> s5

- Partitioning keys (require to inform hashTable number)

  Keys [0 – 1,000,000] -> s1 (hashTable[0-4])
  Keys [1,000,000–2,000,000] -> s2 (hashTable[0-4])
  Keys [2,000,000–3,000,000] -> s3 (hashTable[0-4])
  Keys [3,000,000–4,000,000] -> s4 (hashTable[0-4])

Available LSH implementations

- OpenLSH (https://github.com/singhj/locality-sensitive-hashing)
- Datasketch (https://github.com/ekzhu/datasketch)
- TarsosLSH (https://github.com/JorenSix/TarsosLSH)
- E2LSH (https://github.com/JorenSix/TarsosLSH)
- Many others

Some LSH papers

- Similarity Search in High Dimensions via Hashing
- Locality-Preserving Hashing in Multidimensional Spaces
- Approximate Nearest Neighbors: Towards Removing the Curse of dimensionality
- Near-Optimal Hashing Algorithms for Approximate Nearest Neighbor in High Dimensions
- Fast Search in Hamming Space with Multi-Index Hashing
- b-Bit Minwise Hashing
- LSH forest: self-tuning indexes for similarity search

Who uses LSH for what?

Google

Detect near-duplicate web pages

Detecting Near-Duplicates for Web Crawling

Google News recommendations

Google News Personalization: Scalable Online Collaborative Filtering

UBER

Detect very similar routes

https://spark-summit.org/2016/events/locality-sensitive-hashing-by-spark/

Eventbrite

Detect spam and malicious messages for event organizers

https://www.eventbrite.com/engineering/multi-index-locality-sensitive-hashing-for-fun-and-profit/

facebook

Clustering People

http://www.freepatentsonline.com/y2015/0213112.html

Spotify

Spotify recommender system

LSH forest - ANNOY

And others

Take outs

- LSH solves **similarity search**
- LSH is very **useful** for several applications
- **Similarity search** is usually **a step** to something bigger
- Think **what do with** the similarity **knowledge**

Take outs

- **Implementing** basic specific cases is **simple**
- **Being generic** is **not**
- **Scaling** requires **good engineering** and optimizations
- Take time to **experiment the best parameters** to your case

Thank you!

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Other Objects and Dimensions

1 Dimension

Binary values: 0 or 1
Numbers: age, height, weight, etc.

2 Dimensions

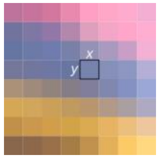
Cartesian coordinates: (x, y)
Tuples: (k, v)

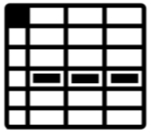
3 Dimensions

3D coordinates: (x, y, z)
Animation: (time, x, y)

N Dimensions

Characters in a string: “abcdefgh”
Substrings of a string: “abc”, “bcd”, “cde”…
Bits in a Byte array: 0011 1101
Words in a sentence: “Foo bar bar foo”
Sentences in a document
Pixels in an image
Notes in a music
Properties in an object
Columns in a DB row
Minutiae of fingerprints





Distances and LSH families

Distance	Description	LSH family
Euclidean	Distance between two vectors	Random projections
Jaccard	len(intersection)/len(union)	MinHash
Cosine	Angular distance between vectors	SimHash
Hamming	Number of Substitutions	BitSampling
Levenshtein	Minimal number of substitutions, insertions and deletions	

Links to used resources

- **Presentations:**

http://www.slideshare.net/j_singh/mining-of-massive-datasets-using-locality-sensitive-hashing-lsh
http://www.slideshare.net/j_singh/open-lsh-a-framework-for-locality-sensitive-hashing-45912645
http://www.slideshare.net/SameeraHorawalavithana/locality-sensitive-hashing (Tree on taxonomy)
http://www.slideshare.net/DmitriySelivanov/finding-similar-items-in-high-dimensional-spaces-locality-sensitive-hashing
http://www.slideshare.net/jsuchal/minhashing-fast-similarity-search
http://www.slideshare.net/SparkSummit/locality-sensitive-hashing-by-spark (Uber on similar routes)
http://www.slideshare.net/InfoQ/approximate-methods-for-scalable-data-mining-25589794
https://speakerdeck.com/polyfractal/going-organic-genomic-sequencing-in-elasticsearch
http://www.slideshare.net/huitseeker/a-gentle-introduction-to-locality-sensitive-hashing-with-apache-spark

- **Blog posts:**

https://www.eventbrite.com/engineering/multi-index-locality-sensitive-hashing-for-fun-and-profit/

- **Videos:**

https://www.youtube.com/watch?v=dgH0NP8Qxa8
https://www.youtube.com/watch?v=bQAYY8INBxg
https://www.youtube.com/watch?v=Arni-zkqMBA
https://www.youtube.com/watch?v=t_8SpFV0I7A
https://www.youtube.com/watch?v=LqcwaW2YE_c
https://www.youtube.com/watch?v=Ha7_Vf2eZvQ
https://www.youtube.com/watch?v=Dkomk2wPaoc