Near-duplicate detection with Locality-Sensitive Hashing and Datasketch

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Here we do a review of Locality-Sensitive Hashing for near-duplicate detection. We demonstrate the principle, and provide a quick intro to `Datasketch` which is a convenient library to run near-duplicate detection at scale.

Literature:

- "Mining massive datasets", ch. 3 – theoretical foundation of Locality-Sensitive Hashing
- A blog post on this topic
- Datasketch – a Python library implementing, among all, the `MinHashLSH` algorithm

MinHash LSH – the principle

1. When we need to deduplicate a single dataset.

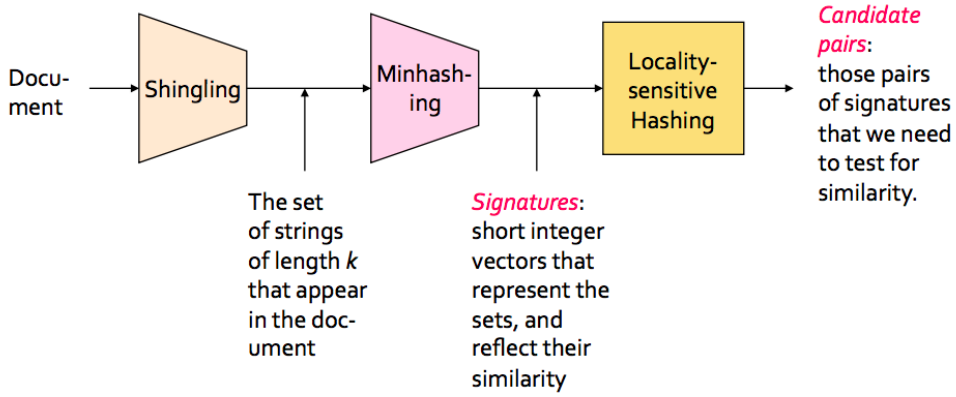


image credit

2. When we have incoming "query" data that we want to compare to a large "index" dataset

Here "historical" data can be a large dataset, e.g. 5 mln. documents.

The "query" dataset is much smaller, e.g. 10K documents that we receive daily, say via some API, and would-like to deduplicate.

We can do without LSH at all just comparing 10K fresh documents to 5 mln. historical documents. But that'd require 50 bln. comparisons each day, might be too computationally prohibitive (a dumb idea leading, above all, to a considerable carbon footprint). LSH is a technique that approximates the exact similarity function.

Historical data ("Index")

DocID	Signature
CAP-D-19-00286	[-2096899409,1723623087,-**154171432**,-1926142670,-516596911,104414951
ECM-D-19-00380	[-1591691089,1225902519,-1845977603,-1611079781,665121211,-10404492
EJC-D-19-00624	[401283074,737101595,1779223802,-1358575362,1864184254,1197664475,-
CEJ-D-19-12284	[-922202158,-**1396469601**,-771101093,-1989270244,-1028702944,-10636292

New data ("Query")

DocID	Signature
PLA-D-19-01787	[1749160491,-1652962931,-**154171432**,31352555,1230467029,-515842999,144
CHB-D-19-00266	[-853445745,-**1396469601**,1224604002,-918402261,1334788651,1395736370,1
IJPE-D-19-01691	[2147067545,318782322,-2077144847,-1028197663,-1287137942,-2075370958

Candidate pairs (near-duplicates)

DocID_1	DocID_2
PLA-D-19-01787	CAP-D-19-00286
CHB-D-19-00266	CEJ-D-19-12284

The essence of the algorithm is to create **signatures** for each piece of text that is identified here by a `DocID`. Signatures are just numeric vector of some fixed dimension, e.g. 128.

For two pieces of text to be considered as candidates for near-duplicates, it suffices for their hash signatures to match in at least one component. In the picture above, a pair highlighted in green is a candidate, and a pair highlighted in orange is another one. Bolded are those matching hash values.

Limitations

- The method only takes care of the **lexical similarity** not semantical. Thus, with LSH, we won't identify near-duplicates that differ due to parapharasing, synonym replacement, etc.
- The method is probabilistic, i.e. some errors are allowed. Not all candidates would actually be near-duplicates. One can check this by calculating Jaccard similarity of the candidates. Thus, the algorithm is characterized by **precision** (out of all pairs of candidates found by the algorithm, what's the proportion of real near-duplicates, i.e. with their Jaccard similarity exceeding the predefined threshold) and **recall** (out of all near-duplicate pairs, what's the proportion of those found by the algorithm).
- In practice, for a large enough dataset and long pieces of text (e.g. full documents not just titles), LSH tends to work worse in terms of precision while recall can not be known

without a crazy carbon footprint. FInding true near-duplicate pairs in a relatively small collection of 50K texts requires >1.2B calls to a Jaccard similarity subroutine.

```
# imports
import json
import pickle
import re
from pathlib import Path

import numpy as np
import pandas as pd
from datasketch import MinHash, MinHashLSH
from matplotlib import pyplot as plt
from num2words import num2words
from tqdm import tqdm
```

Preprocessing and hashing

Essentially, MinHashLSH operates with shingle sets where shingles are overlapping substrings of a fixed size. The following 4 code cells show how MinHashLSH builds hash vectors (a.k.a. Signatures) for entry texts.

Further, as described in the picture above, for two pieces of text to be considered as candidates for near-duplicates, it suffices for their hash signatures to match in at least one component

```
s = "this is a piece of text"
```

```
shingle_size = 4

shingle_set = {s[i : i + shingle_size]
               for i in range(len(s) - shingle_size + 1)}
shingle_set
```

```
{' a p',
 ' is ',
 ' of ',
 ' pie',
 ' tex',
 'a pi',
 'ce o',
 'e of',
 'ece ',
 'f te',
 'his ',
 'iece',
 'is a',
 'is i',
 'of t',
 'piec',
 's a ',
 's is',
 'text',
 'this'}
```

```
def hash_func(a_string, salt: int = 1):
    return hash(a_string + str(salt))
```

These are the 5 components of a toy 5-dimensional hash signature. Each one of them is created by hashing all shingles and taking a min. value of the hashes.

```
for i, salt in enumerate(range(5)):
    print(i, min([hash_func(el, salt=salt) for el in shingle_set]))
```

```
0 -7220920153181112185
1 -9127360350460247126
2 -8803612098918371157
3 -8027849914885749588
4 -9069105076530742277
```

Datasketch LSH – a toy example

```
from datasketch import MinHash, MinHashLSH
```

```
SIMILARITY_THRESHOLD = 0.6
NUM_PERMS = 96
SHINGLE_SIZE = 4
```

Three similar strings. We'll index first two, and then look for near-duplicates for the 3rd one.

```
s1 = "This is a piece of text"
s2 = "This is a similar piece of text"
s3 = "This is also a similar piece of text"
```

Inserting strings split by whitespaces into `MinHash` objects.

```
minhash1 = MinHash(num_perm=NUM_PERMS)
minhash2 = MinHash(num_perm=NUM_PERMS)
minhash3 = MinHash(num_perm=NUM_PERMS)

for d in set(s1.split()):
    minhash1.update(d.encode("utf8"))
for d in set(s2.split()):
    minhash2.update(d.encode("utf8"))
for d in set(s3.split()):
    minhash3.update(d.encode("utf8"))
```

Create LSH index and insert first 2 `MinHash` objects in it.

```
lsh = MinHashLSH(threshold=SIMILARITY_THRESHOLD, num_perm=NUM_PERMS)
lsh.insert("text1", minhash1)
lsh.insert("text2", minhash2)
```

Querying near-duplicates for the 3rd piece of text.

```
lsh.query(minhash3)
```

```
['text2']
```

Same with Redis storage as a backend, not Python dictionaries

See MinHashLSH docs to configure the algo to run with Redis backend. The idea is that to query LSH for near-duplicates, we only need to make lookups to get signatures. Redis is an

in-memory database which allows for very fast lookups, also, it scales much better than Python dictionaries.

```
lsh_redis = MinHashLSH(
    threshold=SIMILARITY_THRESHOLD,
    num_perm=NUM_PERMS,
    storage_config={"type": "redis",
                    "redis": {"host": "localhost",
                              "port": 6379}},
)
lsh_redis.insert("text1", minhash1)
lsh_redis.insert("text2", minhash2)
```

```
lsh_redis.query(minhash3)
```

```
['text2']
```

Running LSH near-duplicate detection with a realistic dataset

Further, we run the algorithm with some realistic dataset – news about cryptocurrencies, Kaggle dataset

```
SIMILARITY_THRESHOLD = 0.8
NUM_PERMS = 128
SHINGLE_SIZE = 4
```

```
lsh = MinHashLSH(threshold=SIMILARITY_THRESHOLD, num_perm=NUM_PERMS)
```

Reading data

```
# you can download the dataset and customize this path
PATH_TO_DATA = Path("/Users/kashnitskiyy/Documents/data/crypto_news")
```

The following two parts of the dataset would imitate the historical part (`index_df`) and the query part (`query_df`). For each title in the qury part, we'd like to find near-duplicate titles in the historical part.

```
index_df = pd.read_csv(PATH_TO_DATA /
                       "crypto_news_parsed_2013-2017_train.csv")
query_df = pd.read_csv(PATH_TO_DATA /
                       "crypto_news_parsed_2018_validation.csv")
```

We'll identify each title by some id, so reindexing. Also, there are quire a few fields in the dataset, we'll take care only of the `title` field.

```
index_df.index = [f'train_{i}' for i in range(len(index_df))]
query_df.index = [f'val_{i}' for i in range(len(query_df))]
```

```
index_df[['title']].head(2)
```

	title
train_0	Bitcoin Price Update: Will China Lead us Down?
train_1	Key Bitcoin Price Levels for Week 51 (15 – 22 ...

```
query_df[['title']].head(2)
```

	title
val_0	Paris Hilton’s Hotel Mogul Father to Sell $38 ...
val_1	Playboy Sues Cryptocurrency Company for Breach...

```
def preprocess(string, maxlen=500):
    tmp_string = string[:maxlen]
    tmp_string = re.sub(r"(\d+)",
                        lambda x: num2words(int(x.group(0))),
                        tmp_string)
    res = re.sub(r"[\W]+", "", tmp_string).lower()
    return res


def _shingle(string, shingle_size=4):
    shings = {
        string[i : i + shingle_size]
        for i in range(len(string) - shingle_size + 1)
    }
    return set(shings)
```

LSH from Datasketch

```
lsh = MinHashLSH(threshold=SIMILARITY_THRESHOLD, num_perm=NUM_PERMS)
```

Populating the index

```
%%time

for id_, title in tqdm(index_df['title'].iteritems()):

    title_shingles = _shingle(preprocess(title),
                              shingle_size=SHINGLE_SIZE)

    title_minhash = MinHash(num_perm=NUM_PERMS)

    for shing in title_shingles:
        title_minhash.update(shing.encode("utf8"))

    lsh.insert(id_, title_minhash, check_duplication=False)
```

```
CPU times: user 46.7 s, sys: 898 ms, total: 47.6 s
Wall time: 47.2 s
```

We've indexed that many titles:

```
len(lsh.get_counts()[0])
```

```
27462
```

If needed, we can serialize the LSH object

```
with open("lsh.pkl", "wb") as f:
    pickle.dump(lsh, f)
```

```
!du -hc lsh.pkl
```

```
 35M    lsh.pkl
 35M    total
```

Get near-duplicates for the query data

```
%%time

dup_dict = {}

for id_, title in tqdm(query_df['title'].iteritems()):

    title_shingles = _shingle(preprocess(title),
                              shingle_size=SHINGLE_SIZE)

    title_minhash = MinHash(num_perm=NUM_PERMS)

    for shing in title_shingles:
        title_minhash.update(shing.encode("utf8"))

    dups = lsh.query(title_minhash)
    dup_dict[id_] = dups
```

```
CPU times: user 17.1 s, sys: 273 ms, total: 17.4 s
Wall time: 17.2 s
```

```
len(dup_dict)
```

```
11239
```

(Optional step) Analyze true Jaccard similarity

```
def jaccard_similarity(list1, list2):
    s1 = set(list1)
    s2 = set(list2)
    return len(s1.intersection(s2)) / len(s1.union(s2))
```

To access precision, we calculate the actual Jaccard similarity for the candidates identified by LSH.

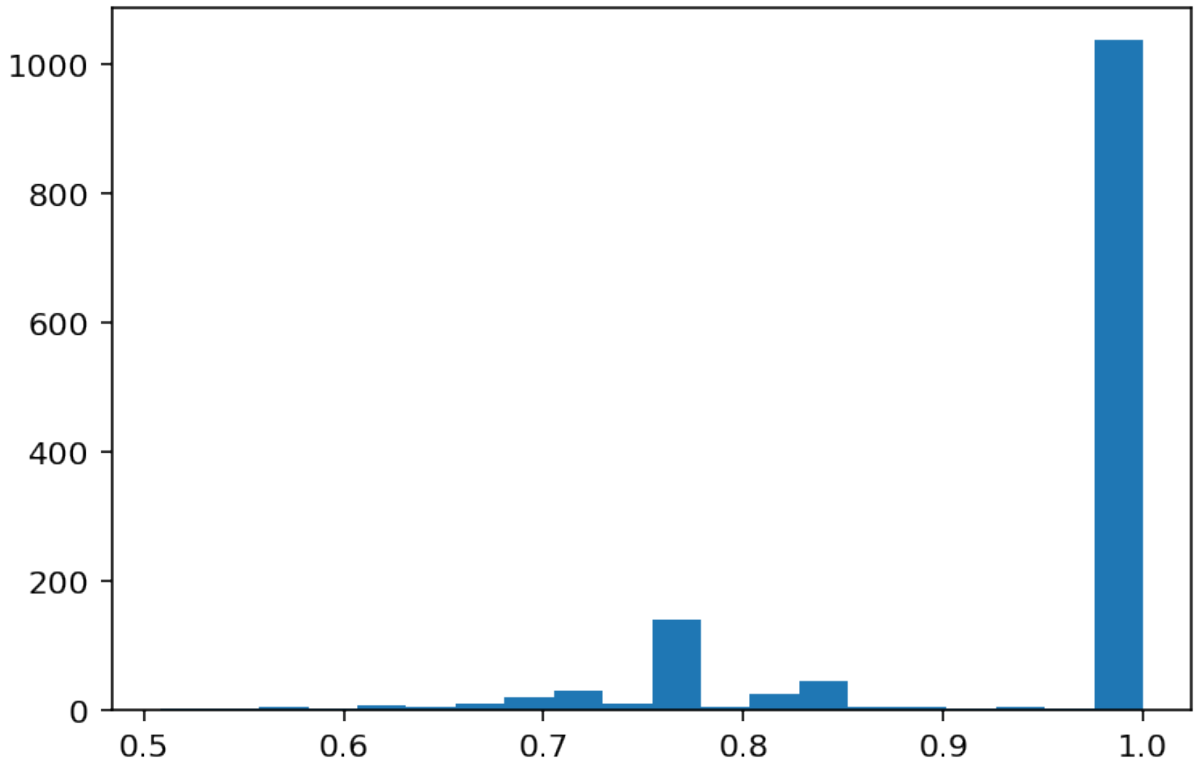
```
jaccard_sims = []

for id_, dups in tqdm(dup_dict.items()):
    if dups:
        shingle_query_title = _shingle(
                              preprocess(
                              query_df.loc[id_, "title"]))
        for dup_id in dups:
            shingle_indexed_title = _shingle(
                                    preprocess(
                                    index_df.loc[dup_id, "title"]))
            sim = jaccard_similarity(shingle_query_title,
                                     shingle_indexed_title)
            jaccard_sims.append(sim)
```

```
len(jaccard_sims)
```

```
1343
```

```
plt.hist(jaccard_sims, bins=20);
```



The distribution is nice, mostly, LSH indeed captures similar pairs.

Precision

```
(pd.Series(jaccard_sims) >= SIMILARITY_THRESHOLD).sum() / len(jaccard_s
```

```
0.8339538346984363
```

Note: That's the precision of the LSH algorithm. In practice, it's very easy to have 100% precision with an additional effort of calculating the actual Jaccard similarity for the candidate pairs (as done above) and filtering out false postives, i.e. the canidates pairs with similarity below the predefined threshold.

Recall

Skipping this computationally intensive step in this short demo. What we can do is we can calculate all pairwise Jaccard similarities between 11k query titles and 27k indexed titles, and see how many true near-duplicates the LSH algo missed.

Some notes on the productionization of this solution

At the time this tutorial is written (end of April 2021), I'm working with engineers on the productionation of the LSH-based near-duplicate detection service. First, I sketched a prototype API (Datasketch + Redis + Flask API + Streamlit GUI) which scaled fine and supported ~600 RPS (requests per second). `Datasketch` is a pretty mature, well-documented library with easy to read code, and we haven't yet experienced problems on the `Datasketch` side. The only concern is that storing LSH signatures in memory with Redis might be expensive with an ever growing index. While Cassandra did not satisfy the needs of our engineers for reasons unknown to me.