floky

Release 0.2

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CHAPTER

ONE

GETTING STARTED

floky exposes Python bindings to the LSH implementation of lsh-rs. An LSH implementation in Rust. floky is therefore blazingly fast.

Below shows how you can get started with floky.

```
from floky import SRP
import numpy as np

N = 10000
n = 100
dim = 10

# Generate some random data points
data_points = np.random.randn(N, dim)

# Do a one time (expensive) fit.
lsh = SRP(n_projections=19, n_hash_tables=10)
lsh.fit(data_points)

# Query approximated nearest neigbors in sub-linear time
query = np.random.randn(n, dim)
results = lsh.predict(query)
```

CHAPTER TWO

INSTALLATION

Hopefully installation is as easy as

```
$ pip install floky
```

The floky wheels are only compiled for **Linux** at the moment. Are you on Linux and do you encounter an error? Please open an issue.

If you are on **macOs or Windows**, you can compile from source. You probably need a Fortran compiler to be able to. If you have succeeded, please help me add your steps to travis.

CHAPTER THREE

LSH

Locality Sensitive Hashing can help you search through enormous data sets for approximated nearest neighbors. If you want to read more about this algorithm try the following sources:

- Introduction

The gist of the algorithm is that data points (vectors) that are close in some high dimensional space will be likely to have the same hash. The hash functions we choose to hash the vectors determine the distance function we use to define "closeness". At the moment we expose the following hashers:

Hasher	Distance/ similarity
Sign Random Projections	Cosine similarity
P-stable distributions	Euclidean

3.1 Hyperparameters

The LSH algorithm requires two hyperparameters:

- The length of the generated hash **k**. A larger value for **k** leads to less hash collisions, thus faster query times.
- The number of different hash tables **L**. There will be **L** hash tables with **L** randomly generated hash functions.

The **L** hyperparamter can be derived from the query success probability and **k**. Read my blog post on that subject to get an explanation.

3.1.1 L2

The L2 LSH has an additional hyperparameter **r**. This is the width of bucket hash values can fall in. If you normalize your data by the distance threshold R this hyperparameter should be approximately 4.

CHAPTER

FOUR

BASE LSH AND MULTI PROBE LSH EXAMPLE

Download color histograms of the flick30k dataset here.

[1]:
```
import numpy as np
from scipy.spatial.distance import cdist
from floky import L2
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.ticker import ScalarFormatter
import time
```

4.1 Data preparation

First we load the data in numpy. Next we compute the real N nearest neighbors with `scipy.spatial.distance.cdist`.

From these N distance results we compute the mean and determine the top k results. Next we scale the data by R. This makes it easier to verify if the LSH algorithm can find nearest neighbors. If we scale the data by $\frac{1}{R}$ we expect the exact Nearest Neighbor to have a distance smaller than 1. If this isn't the case, we need to choose another distance R.

[2]:
```
with open("flickr30k_histograms.csv") as f:
    a = np.loadtxt(f, delimiter=",")
```

[3]:
```
# We will do N queries and compute recall and query times.
N = 100
```

[23]:
```
# Find the exact nearest neighbors. This is needed to compute recall.
t0 = time.time_ns()
dist = cdist(a[:N], a)
# ms
exact_duration = (time.time_ns() - t0) / 1e6
exact_duration
```

[23]:
```
1808.042179
```

[5]:
```
# non trivial top 1
# we skip the first as that is the query point itself
top_k = dist.argsort(1)[:, 1:2]
mean = dist.mean()
top_k_dist = dist[np.arange(N)[:, None], top_k]
```

[6]:
```
# Scale data by distance. So scaled R will be 1.
R = mean / 2.5
a /= R
dist /= R
top_k_dist /= R
R
```

[6]:
```
12717.77025887411
```

[7]:
```
# Check if real nearest neigbors are < R = 1
print("{}% < R".format((top_k_dist < 1).sum() / (top_k_dist.shape[0] * top_k_dist.
↪shape[1]) * 100))
top_k_dist[:10]
```

```
83.0% < R
```

[7]:
```
array([[0.99372539],
       [0.45435497],
       [0.79676334],
       [1.14787659],
       [0.78890876],
       [0.63275089],
       [0.58949666],
       [0.99201873],
       [1.52371323],
       [1.61113221]])
```

4.2 Comparison Query / Preprocessing duration and Recall

Below we'll examine the impact of the query duration on the recall.

We take a look at two **k** (# of values in the hash) values: * 15 * 30

For Base LSH we increase the numebr of hash tables to increase the recall. For Multi-probe LSH we increase the number of probes we execute. We will keep the number of hash tables constant to only **5**.

[8]:
```
def cum_mov_avg(x, avg, n):
    return (x + n * avg) / (n + 1)

def recall(k, L):
    dim = len(a[0])
    lsh = L2(k, L, dim, in_mem=True)

    t0 = time.time()
    lsh.fit(a)
    fit_duration = time.time() - t0

    t0 = time.time_ns()
    p = lsh.predict(a[:N], only_index=True, top_k=6);
    predict_duration = time.time_ns() - t0

    c = 0
    avg_collisions = 0
    for i, pi in enumerate(p):
        if pi.n_collisions == 1:
            continue
```

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```
        idx = set(pi.index[1:])
        if len(idx.intersection(top_k[i])) > 0:
            c += 1
        avg_collisions = cum_mov_avg(pi.n_collisions, avg_collisions, i)

    return c / N, avg_collisions, fit_duration, predict_duration

ks = []
Ls = []
recalls = []
avg_cs = []
duration_fit = []
duration_predict = []
for k in [15, 30]:
    for L in [5, 10, 15, 20, 50, 100]:
        ks.append(k)
        Ls.append(L)

        r, avg_collision, fit_duration, predict_duration = recall(k, L)
        duration_fit.append(fit_duration)
        duration_predict.append(predict_duration)
        recalls.append(r)
        avg_cs.append(avg_collision)
```

```
32000it [00:00, 60119.95it/s]
32000it [00:01, 30086.65it/s]
32000it [00:01, 21003.48it/s]
32000it [00:01, 16029.99it/s]
32000it [00:04, 6494.46it/s]
32000it [00:10, 2953.71it/s]
32000it [00:01, 17412.80it/s]
32000it [00:03, 9178.54it/s]
32000it [00:05, 6099.98it/s]
32000it [00:06, 5050.17it/s]
32000it [00:15, 2131.61it/s]
32000it [00:31, 1020.02it/s]
```

[9]:
```
df = pd.DataFrame({"recall": recalls,
             "avg_collisions": avg_cs,
             "L": Ls,
             "K": ks,
             "duration_fit": duration_fit,
             "duration_predict": duration_predict
             })
df
```

[9]:

	recall	avg_collisions	L	K	duration_fit	duration_predict
0	0.37	715.617084	5	15	0.559304	58695551
1	0.58	1187.012150	10	15	1.106947	79070180
2	0.76	2370.829281	15	15	1.546288	148368772
3	0.74	1914.947429	20	15	2.016144	135169832
4	0.91	4319.069349	50	15	4.948727	256704612
5	0.95	6013.273606	100	15	10.858258	407418596
6	0.14	30.292026	5	30	1.858710	12629968
7	0.26	188.690972	10	30	3.517005	31498599
8	0.30	77.511316	15	30	5.282044	21663692
9	0.37	176.957555	20	30	6.364206	26374739

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```
10    0.44      226.344361   50  30      15.053674          55477450
11    0.63      409.212477  100  30      31.411575          85154231
```

[10]:
```
def recall_multi_probe(k, budget, lsh):
    lsh.multi_probe(budget)
    t0 = time.time_ns()
    p = lsh.predict(a[:N], only_index=True, top_k=6);
    predict_duration = time.time_ns() - t0

    c = 0
    avg_collisions = 0
    for i, pi in enumerate(p):
        if pi.n_collisions == 1:
            continue
        idx = set(pi.index[1:])
        if len(idx.intersection(top_k[i])) > 0:
            c += 1
        avg_collisions = cum_mov_avg(pi.n_collisions, avg_collisions, i)

    return c / N, avg_collisions, predict_duration

ks = []
recalls = []
avg_cs = []
probes = []
duration_fit = []
duration_predict = []
for k in [15, 30]:
    dim = len(a[0])

    t0 = time.time()
    lsh = L2(k, 5, dim, in_mem=True)
    fit_duration = time.time() - t0
    lsh.fit(a)

    for probe in [10, 20, 15, 20, 50, 100]:
        ks.append(k)
        probes.append(probe)

        r, avg_collision, predict_duration = recall_multi_probe(k, probe, lsh)
        duration_predict.append(predict_duration)
        duration_fit.append(fit_duration)
        recalls.append(r)
        avg_cs.append(avg_collision)
```

```
32000it [00:00, 37000.65it/s]
32000it [00:01, 19196.08it/s]
```

[11]:
```
df_mp = pd.DataFrame({"recall": recalls,
             "avg_collisions": avg_cs,
              "probes": probes,
             "K": ks,
                                 "duration_fit": duration_fit,
             "duration_predict": duration_predict
             })
df_mp
```

[11]:

	recall	avg_collisions	probes	K	duration_fit	duration_predict
0	0.84	3568.653046	10	15	0.000322	218376250
1	0.88	4608.842829	20	15	0.000322	295503006
2	0.85	4171.139471	15	15	0.000322	261069746
3	0.88	4608.842829	20	15	0.000322	297343177
4	0.91	6259.458000	50	15	0.000322	720279473
5	0.93	7812.191200	100	15	0.000322	1141625211
6	0.36	263.895373	10	30	0.006047	27857108
7	0.46	359.867660	20	30	0.006047	31135252
8	0.43	311.102990	15	30	0.006047	28399008
9	0.46	359.867660	20	30	0.006047	32754926
10	0.60	554.988570	50	30	0.006047	69406715
11	0.65	785.715304	100	30	0.006047	128893417

[38]:

```
fig, ax = plt.subplots(figsize=(20, 6), nrows=2, ncols=3)

for i, (k, df_) in enumerate(df.groupby("K")):
    color = f"C{i}"
    marker = "^"
    ax[0, 0].plot(df_.L, df_.recall, c=color, marker=marker, label=f"k = {k}")
    ax[0, 1].plot(df_.L, df_.duration_predict / 1e6, c=color, marker=marker)
    ax[0, 2].plot(df_.L, df_.duration_fit, c=color, marker=marker)

for i, (k, df_) in enumerate(df_mp.groupby("K")):
    color = f"C{i}"
    ax[1, 0].plot(df_.probes, df_.recall, c=color, marker=marker, label=f"k = {k}")
    ax[1, 1].plot(df_.probes, df_.duration_predict / 1e6, c=color, marker=marker)
    ax[1, 2].plot(df_.probes, df_.duration_fit, c=color, marker=marker)

ax[0, 0].legend()
ax[1, 0].legend()

ax[0, 1].axhline(exact_duration, c="black", label="exact search")
ax[1, 1].axhline(exact_duration, c="black", label="exact search")
ax[0, 1].legend()
ax[1, 1].legend()


plt.xlabel("L")
ax[0, 0].set_ylabel("recall")
ax[0, 0].set_ylim(0, 1)
ax[0, 0].set_xlabel("L hashtables")
ax[0, 1].set_xlabel("L hashtables")
ax[0, 1].set_ylabel("query duration [ms]")
ax[0, 1].set_ylim(0, exact_duration * 1.05)
ax[0, 2].set_ylabel("fit duration [s]")
ax[0, 2].set_xlabel("L hashtables")

ax[1, 0].set_ylabel("recall")
ax[1, 0].set_xlabel("# probes")
ax[1, 0].set_ylim(0, 1)
ax[1, 0].set_xscale("log")
ax[1, 0].xaxis.set_major_formatter(ScalarFormatter())
ax[1, 1].set_xlabel("# probes")
ax[1, 1].set_ylabel("query duration [ms]")
ax[1, 1].xaxis.set_major_formatter(ScalarFormatter())
ax[1, 1].yaxis.set_major_formatter(ScalarFormatter())
```

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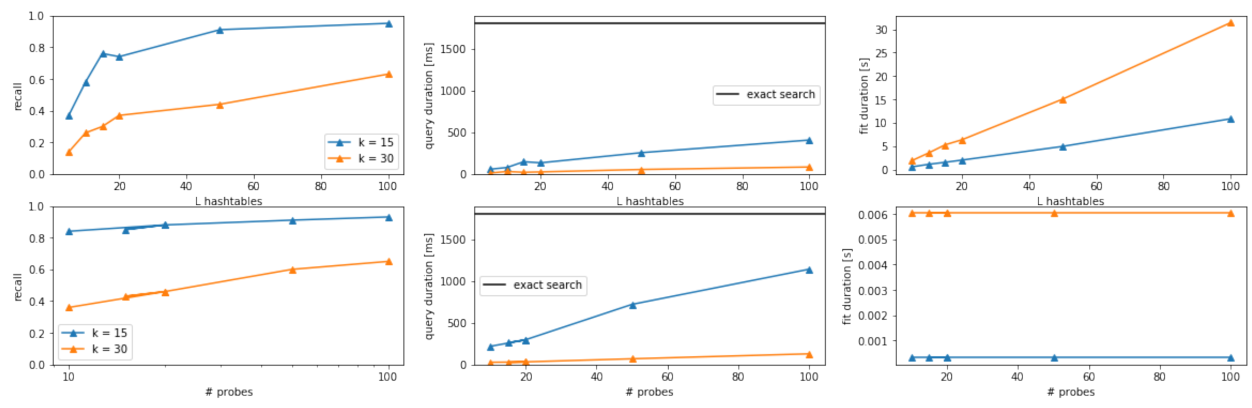
```
ax[1, 1].set_ylim(0, exact_duration * 1.05)

ax[1, 2].set_ylabel("fit duration [s]")
ax[1, 2].set_xlabel("# probes")

plt.show()
```



CHAPTER

FIVE

REFERENCE

5.1 SRP

5.2 L2

CHAPTER

SIX

INDICES AND TABLES

- genindex
- modindex
- search