



Approximate
Nearest Neighbor
Search via Group
Testing

Authors

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

APPROXIMATE NEAREST NEIGHBOR SEARCH VIA GROUP TESTING

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CS754: ADVANCED IMAGE PROCESSING
UNDER PROF. AJIT RAJWADE

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Contents



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

- 1 Introduction
- 2 Locality Sensitive Hashing
- 3 Distance-Sensitive Bloom Filters
- 4 Algorithm
- 5 Theory
- 6 Results

Nearest Neighbor Search



Approximate
Nearest Neighbor
Search via Group
Testing

Authors

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

- Nearest neighbor search is a fundamental problem with many applications in machine learning systems.
- **Task:** Given a dataset $D = \{x_1, x_2, \dots, x_N\}$, the goal is to build a data structure that can be queried with any point q to obtain a small set of points $x_i \in D$ that have high similarity (low distance) to the query. This structure is called an index.
- Such tasks frequently arise in genomics, web-scale data mining, machine learning, and other large-scale applications.

Group Testing



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

- We are given a set D of N items, with k positives (“hits”) and $N - k$ negatives (“misses”).
- **Goal:** Identify all positive items using fewer than N group tests.
- A *group test* is positive iff at least one item in the group is positive.
- **Testing Variants:** Can be *noisy* (with false positives/negatives), *adaptive* (tests depend on previous results), or *non-adaptive* (all tests run in parallel).
- The paper uses a **doubly regular design**: Each item appears in an equal number of tests; each test has an equal number of items.

Formal Problem Statement



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

- **(R, c)-Approximate Near Neighbor:** Given a dataset D , if there exists a point within distance R of a query y , return some point within distance $c \cdot R$, with high probability.
 - R is the distance threshold (radius).
 - $c > 1$ is the approximation factor.
- Any algorithm that solves the randomized nearest neighbor problem also solves the approximate near neighbor problem with $c = 1$ and any $R \geq$ distance to the nearest neighbor.
- (Definition) **Randomized Nearest neighbor:** Given a dataset D and a distance metric $d(\cdot, \cdot)$ and a failure probability $\delta \in [0, 1]$, construct a data structure which, given a query point y reports the point $x \in D$ with the smallest distance $d(x, y)$ with probability greater than $1 - \delta$.

Locality Sensitive Hashing



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

A hash function $h(x) \rightarrow \{1, \dots, R\}$ is a function that maps an input x to an integer in the range $[1, R]$.

The two points x and y are said to collide if $h(x) = h(y)$.

$$s(x, y) = Pr_H(h(x) = h(y))$$

For now, we will assume that $s(x, y) = sim(x, y)$.

For any positive integer L , we may transform an LSH family H with collision probability $s(x, y)$ into a new family having $s(x, y)^L$ by sampling L hash functions from H and concatenating the values to obtain a new hash code $[h_1(x), h_2(x), \dots, h_L(x)]$. If the original hash family had the range $[1, R]$, the new hash family has the range $[1, R^L]$.

Locality Sensitive Hashing



Approximate
Nearest Neighbor
Search via Group
Testing

Authors

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

- **Locality Sensitive Hashing (LSH)** algorithms use an LSH function to partition the dataset into buckets.
- The hash function is selected so that the distance between points in the same bucket is likely to be small.
- To find the near neighbors of a query, we hash the query and compute the distance to every point in the corresponding bucket.
- **Count-Based LSH** identifies neighbors by simply counting how many times two points land in the same hash bucket across multiple hash functions.

Distance-Sensitive Bloom Filters



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

- (Definition) **Approximate Set Membership:** Given a set D of N points and similarity thresholds S_L and S_H , construct a data structure which, given a query point y , has:
True Positive Rate: If there is $x \in D$ with $\text{sim}(x, y) > S_H$, the structure returns true w.p. $\geq p$
False Positive Rate: If there is no $x \in D$ with $\text{sim}(x, y) > S_L$, the structure returns true w.p. $\leq q$
- The distance-sensitive Bloom filter solves this problem using LSH functions and a 2D bit array. The structure consists of m binary arrays that are each indexed by an LSH function. There are three parameters: the number of arrays m , a positive threshold $t \leq m$, and the number of concatenated hash functions L used within each array.

Distance-Sensitive Bloom Filters



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

- To construct the filter, we insert elements $x \in D$ by setting the bit located at array index $[m, h_m(x)]$ to 1.
- To query the filter, we determine the m hash values of the query y . If at least t of the corresponding bits are set, we return true. Otherwise, we return false.
- (Theorem) Assuming the existence of an LSH family with collision probability $s(x, y) = \text{sim}(x, y)$, the distance-sensitive Bloom filter solves the approximate membership query problem with

$$p \geq 1 - \exp(-2m(-t + S_H^L)^2)$$

$$q \leq \exp(-2m(-t + NS_L^L)^2)$$



Input: Dataset D of size N , positive integers B and R , similarity threshold S

Output: A FLINNG search index consisting of membership sets $M_{r,b}$ and group tests $C_{r,b}$

- For $r = 0$ to $R - 1$:
 - Let $\pi(D)$ be a random permutation of D
 - For $b = 0$ to $B - 1$:
 - Define $M_{r,b} = \{\pi(D)_i \mid i \bmod B = b\}$
- For $r = 0$ to $R - 1$:
 - For $b = 0$ to $B - 1$:
 - Construct a classifier $C_{r,b}$ for membership set $M_{r,b}$ with true positive rate p and false positive rate q



- If we apply a similarity threshold to the dataset, we obtain a near neighbor set $K = \{x \in D | \text{sim}(x, y) \geq S\}$. We consider K to be the set of “positives” in the group testing problem.
- In order to do so, we split the dataset D into a set of groups, which we visualize as a $B \times R$ grid of cells. Each cell has a group of items $M_{r,b}$ and a corresponding group test $C_{r,b}$. To assign items to cells, we evenly distribute the N points among the B cells in each column of the grid, and we independently repeat this assignment process R times.



Input: A FLINNG index and a query y

Output: Approximate set \hat{K} of neighbors with similarity greater than the threshold S

- Initialize $\hat{K} = \{1, \dots, N\}$
- For $r = 0$ to $R - 1$:
 - Initialize $Y = \emptyset$
 - For $b = 0$ to $B - 1$:
 - If $C_{r,b}(y) = 1$ then: $Y = Y \cup M_{r,b}$
 - $\hat{K} = \hat{K} \cap Y$



- To query the index with a point y , we begin by querying each classifier. If $C_{r,b}(y) = 1$, then at least one of the points in $M_{r,b}$ has high similarity to y . We collect all of these “candidate points” by taking the union of the $M_{r,b}$ sets for which $C_{r,b}(y) = 1$.
- We repeat this process for each of the R repetitions to obtain R candidate sets, one for each column in the grid.
- With high probability, each candidate set contains the true neighbors, but it may also have some non-neighbors that were included in $M_{r,b}$ by chance. To filter out these points, we intersect the candidate sets to obtain our approximate near neighbor set \hat{K} .

Group Testing: Runtime and Accuracy



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

[Introduction](#)

[Locality Sensitive
Hashing](#)

[Distance-
Sensitive Bloom
Filters](#)

[Algorithm](#)

[Theory](#)

[Results](#)

Lemma 1: Suppose we have a dataset D of points, where a subset $K \subseteq D$ is “positive” and the rest are “negative”. Construct a $B \times R$ grid of tests, where each test has i.i.d true positive rate p and false negative rate q . Then the algorithm reports points as “positive” with probability:

$$\Pr(\text{Report } x \mid x \in K) \geq p^R$$

$$\Pr(\text{Report } x \mid x \notin K) \leq \left[q \left(\frac{eN(B-1)}{B(N-1)} \right)^{|K|} + p \left(1 - \left(\frac{N(B-1)}{eB(N-1)} \right)^{|K|} \right) \right]^R$$

Group Testing: Runtime and Accuracy



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

The cost of group testing inference includes the cost to do all $B \times R$ tests, plus the cost of intersecting the positive groups.

Theorem: Under the assumptions in the previous lemma, let us suppose that each test runs in $\mathcal{O}(T)$. Then with probability $1 - \delta$:

$$t_{\text{query}} = \mathcal{O} \left(BRT + \frac{RN}{B} (p|K| + qB) \log\left(\frac{1}{\delta}\right) \log N \right)$$

Bounding the Test Cost



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

[Introduction](#)

[Locality Sensitive
Hashing](#)

[Distance-
Sensitive Bloom
Filters](#)

[Algorithm](#)

[Theory](#)

[Results](#)

To distinguish between the $|K|$ nearest neighbors and the rest of the dataset:

$$S_H = \text{sim}(x_{|K|}, y) = s_{|K|}$$

$$S_L = \text{sim}(x_{|K|+1}, y) = s_{|K|+1}$$

(Definition) **γ -Stable query:** We say that the query is γ -stable if

$$\frac{\log(s_{|K|})}{\log(s_{|K|}) - \log(s_{|K|+1})} \leq \gamma$$

Theorem: Given a true positive rate p , false negative rate q and stability parameter γ , it is possible to choose m , L and t so that the resulting distance-sensitive Bloom filter has true positive rate p and false negative rate q for all γ -stable queries. The query time is

$$\mathcal{O}(mL) = \mathcal{O}(-\log(\min(q, 1 - p))N\gamma\log(N))$$

Query Time Analysis



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

[Introduction](#)

[Locality Sensitive
Hashing](#)

[Distance-
Sensitive Bloom
Filters](#)

[Algorithm](#)

[Theory](#)

[Results](#)

We will consider the query time of a $2\sqrt{N} \times R$ grid of Bloom filter classifiers and $T = mL$.

Lemma 2: Under the assumptions of Lemma 1, we can use distance-sensitive Bloom filters as tests to achieve the following query time t_{query} of our Algorithm with probability $1 - \delta$

$$t_{\text{query}} = \mathcal{O}(RN^{\frac{1}{2}+\gamma}\log(N)\max(-\log(q), -\log(1-p)) + RN^{\frac{1}{2}}\log^2(N)(|K| + qN^{\frac{1}{2}}\log(\frac{1}{\delta})))$$

Lemma 3: Under the assumptions of Lemma 1, we can build a data structure that solves the randomized nearest neighbor problem for sufficiently large N and small δ , where

$$p = 1 - \frac{\delta}{2R}, \quad q = N^{-\frac{1}{2}}, \quad R = \frac{\log(\frac{1}{\delta})}{\log(4.80N^{\frac{1}{2}}) - \log(2e^2 + 3.44N^{\frac{1}{2}})}$$

Query Time Analysis



Approximate
Nearest Neighbor
Search via Group
Testing

Authors

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

Theorem: Under the assumptions of the previous Lemma, we solve the randomized nearest problem for γ -stable queries in time t_{query} :

$$t_{\text{query}} = \mathcal{O}(N^{\frac{1}{2}+\gamma} \log^4(N) \log^3(\frac{1}{\delta}))$$

- ## Approximate Nearest Neighbor Search via Group Testing

Results

Default Choice of Parameters



Approximate
Nearest Neighbor
Search via Group
Testing

Authors

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

- **Dataset Size:** 10,000 points
- **Query Size:** 100 queries
- **Dataset Standard Deviation:** 1
- **Query Standard Deviation:** 0.5
- **Hashes per Table:** 16
- **Number of Hash Tables:** 20
- **k (Nearest Neighbors):** 1

Heatmap for Query Time



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

Introduction

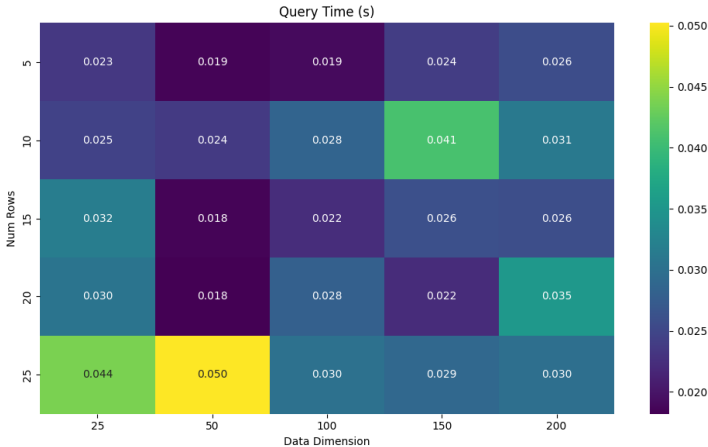
Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results



Heatmap for Average Precision



Approximate
Nearest Neighbor
Search via Group
Testing

[Authors](#)

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results



Heatmap for Average Recall



Approximate
Nearest Neighbor
Search via Group
Testing

Authors

Introduction

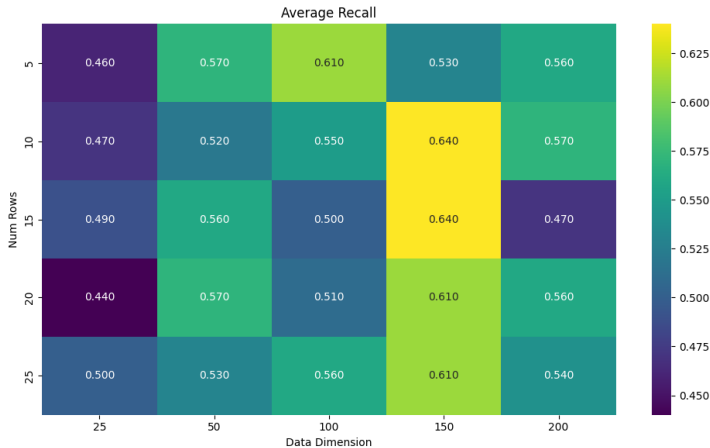
Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results



Heatmap for Average F1 Score



Approximate
Nearest Neighbor
Search via Group
Testing

Authors

Introduction

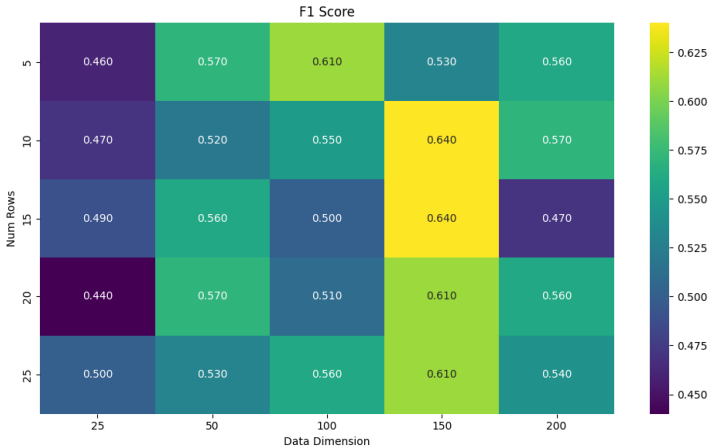
Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results



Individual Contributions



Approximate
Nearest Neighbor
Search via Group
Testing

Authors

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

- **Saksham Rathi**: Read through the paper, described the initial problem statement and the algorithms used in the paper in the report, code debugging, collection of results and adding them to the report.
- **Kshitij Vaidya**: Read through the paper, wrote the LSH, DSBF and FLINNG classes in Python and tested them for correct functionality, code debugging.
- **Ekansh Ravi Shankar**: Read through the paper, code debugging, wrote threshold relaxation algorithm.

Code and Report



Approximate
Nearest Neighbor
Search via Group
Testing

Authors

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

The code and the report can be found at the following link:

<https://github.com/sakshamrathi21/CS754-Project>



Approximate
Nearest Neighbor
Search via Group
Testing

Authors

Introduction

Locality Sensitive
Hashing

Distance-
Sensitive Bloom
Filters

Algorithm

Theory

Results

Thank You