# ESE 545 Project1

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## **Problem 1**

**Statement**: Pre-processing data to the correct format with ('reviewerID', 'reviewText')

## Approach:

- Read data using Pandas dataframe
- Discard the other unrelated columns such as 'asin', 'reviewerName', 'helpful', 'overall', 'summary', 'unixReviewTime', 'reviewTime' from the data set
- Remove stop words
- Convert punctuation to empty space
- Convert duplicate empty space to one empty space
- Drop the review with length less than shingles length (k)

Result: Name: ReviewText; Length: 157680

## **Problem 2**

**Statement**: Convert each review into a set of k-shingles

### Approach:

- Define a coo-matrix with shape=(37\*\*4, len(ReviewText))
- Create a function *find\_index\_in\_binary\_matrix*, which will take a review as input and calculate the corresponding index for each shingle
- Use Pandas.apply to apply the *find\_index\_in\_binary\_matrix* in each review in parallel
- Generate the sparse matrix using row, column and data values

**Result**: Binary Matrix; Dimensions: 1874161 \* 157680

## **Problem 3**

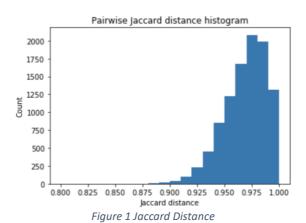
**Statement**: Pick 10,000 pairs of reviews at random and compute the average Jac-card distance and the lowest distance among all pairs.

## Approach:

- Shuffle the index of 142 documents randomly from total documents because we could make 10011 pairs out of 142 documents
- Convert the coo-matrix to numpy array
- Calculate the Jaccard distance for each pair
- Jaccard Distance = 1 intersection(Pair1, Pair2) / union(Pair1, Pair2)
- Plot the histogram for each pair

#### **Result:**

Average value of Jaccard Distance: 0.972 Minimum value of Jaccard Distance: 0.819



**Problem 4** 

**Statement**: More effective to store data to find the approximate nearest neighbor of a review **Approach**: Min Hashing and Locality Sensitive Hashing is used to reduce the time and space complicity while computing the nearest neighbour

## 1. Min Hashing:

- For each document, find the indexes where there is one and store in a numpy array as binary\_matrix\_index
- Create m (m=120) hash function; select the corresponding a and b for these m hash function in random from 0 to 2000
- Permute the indexes of each document to new index with respect to the function: permuted index =  $(a*x + b) \% (37^4)$
- Hence, we get m Hash value for each document of size [120, 157680]

### 2. Local Sensitivity Hashing:

- Create b (b=20) bands each consisting of r (r=6) rows; select the corresponding a and b for these functions from 0 to 982451653
- Permute the hash value of each document to new index with respect to the function:  $permuted\_index = (a*x + b) % p$
- Calculate the sum of each vector band, and the size of the Hash table with the size of [20, 157680]

### **Result:**

1. Original Dataset Sample (sparse matrix)

Index	Value
(455083, 0)	1.0
(1844800, 0)	1.0
	1.0
(779631, 157679)	1.0
(733950, 157679)	1.0

## 2. Hash Table Sample

```
[[ 7472 38742 4912 ... 818 412 5894]

[13935 21572 759 ... 2686 7653 840]

[ 2177 8327 24461 ... 2302 11211 4704]

...

[ 454 5149 8626 ... 3082 10588 4072]

[ 4858 11040 7411 ... 519 14642 1710]

[ 3268 16920 11002 ... 3268 7075 6706]]
```

## 3. Local Sensitivity Hashing Table

```
[[2.42815561e+09 2.61687555e+09 ... 2.94125897e+09 2.43340210e+09]
[3.15663816e+09 3.04152007e+09 ... 3.61470857e+09 3.20712201e+09]
[3.38655209e+09 3.83028871e+09 ... 1.96893080e+09 2.40676553e+09]
...
[3.12568361e+09 2.94625217e+09 ... 2.18965851e+09 4.08602568e+09]
[2.72879242e+09 3.32631730e+09 ... 1.97086841e+09 3.63960968e+09]
[2.78486404e+09 2.85245843e+09 ... 4.22640403e+09 3.16024730e+09]]
```

## Problem 5

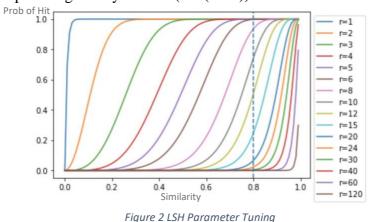
**Statement**: Effective way to detect all pairs of reviews that are close to one another

## Approach:

- Each band of the local sensitivity hashing table is checked with other documents and a document is similar if any one of the band values matches at that position.
- Similar pairs are matched to each other and they are mapped to the same bucket if they have Jaccard distance of less than 0.2
- Calculate the Jaccard distance of similar pairs are calculated using the sparse matrix

### **Parameter Justification:**

The following diagram shows the relationship between similarity and the probability of hitting. The value of Band(b1) = 20 and rows per band r = 6 give better results as we get less false negatives. The values of r1 and b give better results with probability 0.9977. The probability of finding similar pairs is given by  $P = 1 - (1 - (S ^r)) ^b$ .



## **Result:**

We found 1113 pairs when Jaccard distance < 0.2.



Figure 3 Result of Nearest Pairs

## **Problem 6**

Statement: Find the nearest neighbor of a given input review

## Approach:

- Pre-processing the review according to the required format
- Create shingle representation for this review as a binary matrix consisting 0 or 1
- Min hashing and local sensitivity hashing are applied to shingle representation of this review and the band matrix is obtained. The values of a1, b1, r, a2, b2, p used are the same as the signature matrix and the band matrix of other reviews
- The band values are checked against the document in the data set and if at least one bad match, the new user and the user in that column of the data set are similar
- If there are not band value match, return None
- If there are band value match, we determine the Jaccard distance to determine which is the nearest neighbour with minimum Jaccard distance

### **Result:**

If we input a new review as ' i. me,, great! so: |', it will return the index of the nearest neighbour as [ 133 57364 85048 112897 119030 151045], and store the review text in a csy file.

## NearestNeighbor

reviewerID	reviewText
A1K9SIFW86UAT8	great
A2SLF3KZ6O52Q3	great
A29QGJTAKBJ5J2	great
A1KEG0JF0IJ753	great
A3APM5ZLH7W9KM	great
A1KXH84YZ9SEK	great

Figure 4 Result of the Function to Nearest Neighbor

## **Problem 7**

**Statement**: Briefly discuss the complexity of your implementation and how it is better than the naive implementations.

### **Answer**:

The naïve implementation requires  $O(N_2)$  comparison, so the time complexity is  $O(n_2)$ . In the min hashing method and local sensitivity hashing, the hash function can be computed in time O(M) of the given sets, where M is the number of hash function. Specifically, for set size N documents, the min hashing method takes O(M\*N) time. Assuming N>>M such the number of documents is always large, we could get O(n) time to maintain the queue of minimum hash values.

Thus, min hashing and local sensitivity hashing requires O(n) time, while the naïve way requires O(n2) time.