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Stage2 - The Design Stage.

- Design Description:

  There are three types of users who will use this system. We will begin with the first user type: 1) users who select a topic and bring up a cluster of tweets related to that topic.

  ◇ 1) Tweet clustering based on semantic similarity

    ◇ 1.1) Semantic Similarity Measurement
    We aim to cluster tweets into different groups using Hierarchical Clustering. To do this, we require semantic similarity scores between two tweets (or sentences, documents. We may use these terms interchangeably.). We propose two methods for calculating the similarity between two sentences: (1) Edit distance based approach (2) TF-IDF based approach.

      ◇ 1.1a) Extended Edit Distance Algorithm
      We utilize an extended **Edit Distance** algorithm integrated **Word2Vec** embedding to compute the distance between sentences in the tweets, and by grouping by shortest distance we divide tweets into different groups.

      In details, we describe tweet sentence S_1 as S_1=$\{a_1$,a_2,...,$a_n\}$ and sentence S_2 as S_2 =$\{b_1$,b_2, ...,$b_m\}$. S_1 consists of n words and S_2 consists of m words. a_i is the i th word of S_1 and b_j is the j th word of S_2. We use Sim(S_1,S_2) to describe the similarity between S_1 and S_2, with the range of 0 (no relation) to 1 (semantic equivalence). For edit distance, we utilize Levenshtein Distance algorithm to extend to the word sets in sentences. We define the Levenshtein distance between S_1 and S_2 is L(n,m), where $0 \leq i \leq n$ and $0 \leq j \leq n$. And we have:

$$L(i,j) = max(i,j) \qquad if \quad min(i,j) = 0,$$

$$L(i,j) = min \begin{cases} L(i-1,j-1) + c(a_i,b_j) \\ L(i,j-1) + 1 \\ L(i-1,j) + 1 \end{cases} \qquad otherwise.$$

      Where the function c(a_i,b_j) is defined as

$$c(a_i,b_j) = \begin{cases} 0 & (a_i = b_j) \\ 1 & (a_i \neq b_j) \end{cases}$$

We also need to consider the circumstances that if two different words have the same or similar meaning (e.g., "cat" and "kitty"), in which case edit distance defines them as a mismatch. We address this issue by introducing Word2vec to measure semantic similarity between words. Word2vec[1] is an unsupervised deep learning algorithm that maps each word to a vector $\in \mathcal{R}^n$ such that the semantically similar words are mapped to the vectors that are close to each other in the geometry space. In our settings, given any two words, e.g., a_i and b_j in the above, we first apply word2vec to map them to two vectors, $\vec{v}_1$ and $\vec{v}_2$, and then use the euclidean distance, $\|\vec{v}_1 - \vec{v}_2\|$, to measure the cost of the replacement. We may normalize the cost into a relatively small range.

$$\begin{gathered} c(a_i, b_j) = \|\vec{v}_1 - \vec{v}_2\| \\ where \quad \vec{v}_1 = word2vec(a_i), \vec{v}_2 = word2vec(b_j) \end{gathered}$$

◇ 1.1b) TF-IDF Weighting

The other method for calculating the similarity is using the TF-IDF algorithm. Similar to the above Edit distance based algorithm, the TF-IDF based method also needs to represent the words to vectors. In addition, the TF-IDF based method also needs to represent the documents as vectors. The traditional method to represent word and document vectors is Bag of Words. The bag-of-words feature vector is the sum of all one-hot vectors of the words, and therefore has a zero value for every word that did not occur. In the weighted variation, it is a weighted sum according to term frequency or TF-IDF scores. But the problem is that the document vector constructed by this method is high dimensional and sparse(because there are thousands of words in the corpus but a tweet can at most contain 140 words, so most of the values in the document vector is 0). In order to solve this problem, we use **Word2Vec**[1] to get a dense, low-dimensional embedding vector of each words. Then, we will use two divergent algorithms to measure the similarity of documents, the first one is based on extended Edit Distance and the second one is based on TF-IDF weighting.

After getting vectors of words, we can use weighted sum of word vectors to represent document vectors, then use cosine distance of document vectors to measure the similarity between them. We first introduce the concept of TF-IDF.

TF is a short-cut for term frequency, which means how frequently a term occurs in a certain document. IDF is a short cut for Inverse Document Frequency, which measures how important the term is. Let TF(i, j) be the term frequency of $word_i indocuments_j$, count(i, j) be the times that $word_i$ appears in $document_j$, C be the total number of words in all documents. N be the total number of documents, df(i, j) be the number of documents containing $word_i$. The formula of TF-IDF are shown as followes.

$$TF - IDF(i,j) = TF(i,j) * IDF(i,j)$$
$$TF(i,j) = \frac{count(i,j)}{C}$$
$$IDF(i,j) = \log \frac{N}{df(i,j)}$$

We can represent each document as a matrix with C rows, each row i of the matrix is the embedding vector of the $word_i$ if $word_i$ is in the document or a vector consisting of zero if $word_i$ is not in the document. Then, we use TF-IDF method to calculate a weighting vector, the vector contains C rows, each row of the vector is the TF-IDF value of corresponding words. The paragraph vector of a document is the dot product of document matrix and weighting vector. Then, we can use cosine similarity of two vectors measure the distances. For any two vectors a, b

$$cos(a,b) = \frac{a \cdot b}{|a| \cdot |b|}$$

◇ 1.2) Clustering Algorithm

After completing similarity measurement, we need to choose a clustering algorithm to cluster the tweets. Since we did not know the exact number of categories, so clustering algorithms based on partitions such as K-means are not suitable. Hierarchical Clustering would be a better choice. We choose agglomerative clustering algorithm.

Agglomerative clustering algorithm treats each tweet as a singleton cluster at first and repeatedly merge pair of clusters with minimum distance until the pairwise distances between all remaining clusters are lower than certain number. The function which is used to measure the distance between two different cluster C_i and C_j is usually called linkage function. There several types of linkage function: single linkage, complete linkage and average linkage. Assume distance(m, n) is the semantic distance between tweet m in cluster C_1 and tweet n in cluster

C_i. Single linkage is the minimum of the distance(m, n) for all $m \in C_i, n \in C_j$, Complete linkage is the maximum of the distance(m, n) for all $m \in C_i, n \in C_j$, Average linkage is the average of the distance(m, n) for all $m \in C_i, n \in C_j$. The formula of above three linkage functions are shown as follows:

$$single(C_i, C_j) = \min_{\forall m \in C_i, n \in C_j} distance(i, j)$$

$$complete(C_i, C_j) = \min_{\forall m \in C_i, n \in C_j} distance(i, j)$$

$$average(C_i, C_j) = \frac{\sum\limits_{\forall m \in C_i, n \in C_j} distance(i, j)}{|C_i||C_j|}$$

◇ 2a) Recommending similar tweets and hashtags based on structural similarity

Next, we will describe the other 2 user types: 2) users, searching for a hashtag H, who want to find tweets related to H, but do not contain H and 3) users who want to find hashtags similar to a tweet that does not contain those hashtags. In case 2), the Tweet Search job algorithm will be invoked. In case 3), the Hashtag Search job algorithm will be invoked.

Before any search jobs are invoked, a directed bipartite network G with two different types of nodes, tweets and hashtags, will be created. Instead of storing them as strings, we give a unique ID to each tweet and hashtag that allows for efficient identification. A tweet will have an outgoing edge to a hashtag if it contains it. The graph G^2 has as its nodes every pair of tweets and every pair of hashtags in G. In Algorithm 3, we apply SimRank on G^2 to find a similarity score for every pair of tweets. The more outgoing edges two tweets have to the same hashtags, the more similar they are. If this network does not contain the tweet or the hashtag that the user inputs, then the search algorithms will return that no results were found.

The structural similarity, based on SimRank, is evaluated using these two equations, which will be explained below: Let A and B be tweets. O(v) are the outgoing neighbors of v. The similarity s(A,B) is:

$$s(A, B) = \frac{C_1}{|O(A)||O(B)|} \sum_{i=1}^{|O(A)|} \sum_{j=1}^{|O(B)|} s(O_{\mathrm{i}}(A), O_{\mathrm{j}}(B))$$

C is a constant between 0 and 1. It is the decay factor and is the only adjustable parameter of the algorithm. The reason for using C will be explained later.

Let c and be be hashtags. I(v) are the ingoing neighbors of v. The similarity s(c,d) is:

$$s(c,d) = \frac{C_2}{|I(c)||I(d)|} \sum_{i=1}^{|I(c)|} \sum_{j=1}^{|I(d)|} s(I_{\mathrm{i}}(c), I_{\mathrm{j}}(d))$$

The similarity between two tweets is the average similarity of their hashtags, O(A) and O(B). The similarity between two hashtags is the average similarity of tweets that contain them. Let A be either a hashtag or a tweet. The starting scores for the algorithm are the nodes (A,A), which are given similarity score of 1, while all other nodes are given a similarity score of 0. In the next step, the similarity scores for hashtag nodes with an ingoing edges from tweet nodes (A,A) and tweet nodes with outgoing edges to hashtag nodes (x,x) are computed. These scores are calculated using C*s(A,A), because two nodes that share a node by 1 degree of similarity as less similar than two nodes which are the same tweet. This iteration occurs until step K, such that the scores from step K-1 are the same as the scores at step K.

Similarity scores were shown to always exist, are unique, and are symmetric for any two nodes. Since s(a,b) and s(b,a) are symmetric, so only need to store one of their scores. Algorithm 4, the tweet search job, finds node pairs, which contain the searched tweet, that are most similar to the searched tweet. Then, algorithm finds the hashtags contained in the input tweet, and stores them in a set A. It also finds the hashtags contained in these similar tweets, and stores them in a set B. Finally, it returns the relative complement B-A, the desired output. Algorithm 5, the hashtag search job, works in the same way, but switches the roles of tweets and hashtags.

Many of the hashtags that are returned will too general to characterize specific topics. For instance, many tweets may contain the hashtag #news, which may often be 2 degree of separations from #sports and #fashion. At first, this might imply that (#sports, #fashion) have high similarity because there are many (not directed) paths of length 4 connecting them, meaning they're often separated by 4 degrees. But their similarity is not only determined by the number of connections, but the score of those connected nodes. A tweet with both#sports and #news, and a tweet with both #news and #fashion, may have #news in common, but not much else. These means these tweets are often not very similar to each other, so they are weighted very lightly when determining the score of (#sports, #fashion). Thus SimRank takes these very general hashtags into account. It uses the idea of mutual reinforcement to find which hashtags can specifically characterize tweet topics.

This algorithm does not aim to find phrases which distinguish one topic from another; rather, it seeks to bridge communities by finding their similarities.

◇ 2b)Time Complexity of Algorithm 3 to 5

Assume we have constructed the graph G^2 by using graph G. Now let d = the average of $|I(a)| * |I(b)|$ over all nodes in G^2 . Let K = average number of iterations the algorithm performs. Let n be the number of nodes in G^2 . Using a 'naive' implementation of SimRank, average running time of Algorithm 3 is O(K*n*d). Its worst case mainly depends on K.

Algorithms 4 and 5 are essentially the same, but switch the roles of tweets and hashtags. P = the number of tweet (for Algorithm 5) or hashtag (for Algorithm 5) nodes of G^2 . WLOG, we will analyze Algorithm 4 and say Algorithms 4 and 5 have the same running time. First, it finds all the node pairs containing the input, which takes O(P); if the input is not in the graph, it returns "No results were found."

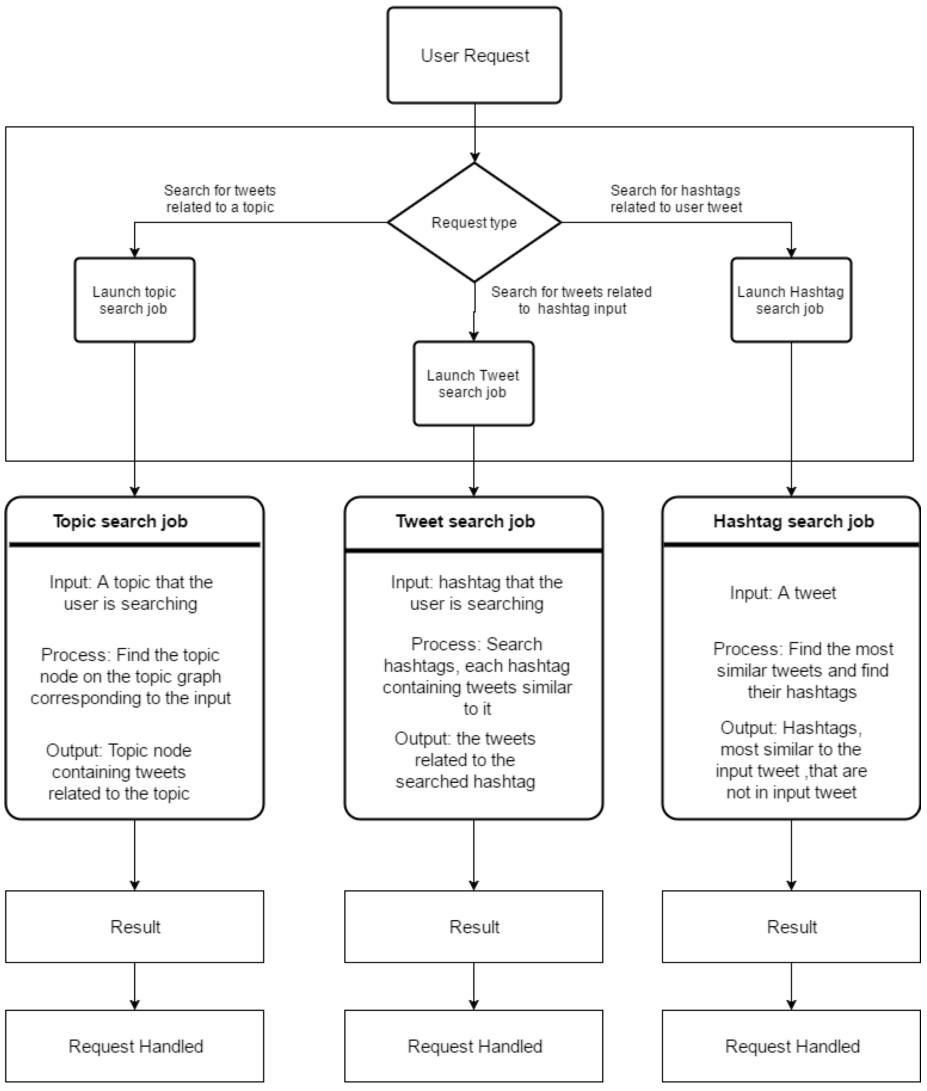
Let R be the length of the node scores hash table. The algorithm sorts the scores, and Mergesort has an average run time of O(R*log(R)). Next, it finds all the neighbors of the input. We do not have an average case, so we look at the worst case, which is O(n-P).

Most of the running time is due to computing the relative complement. Assuming the set contains no duplicate elements, this step compares two sets, so it takes O(P*(P-1)) * (the comparison cost); the comparison cost is constant because we are not comparing lengthy strings, but IDs. The total running time is: O(P + R*log(R) + (n-P) + P*(P-1)) = O(P*(P-1)), which is polynomial.

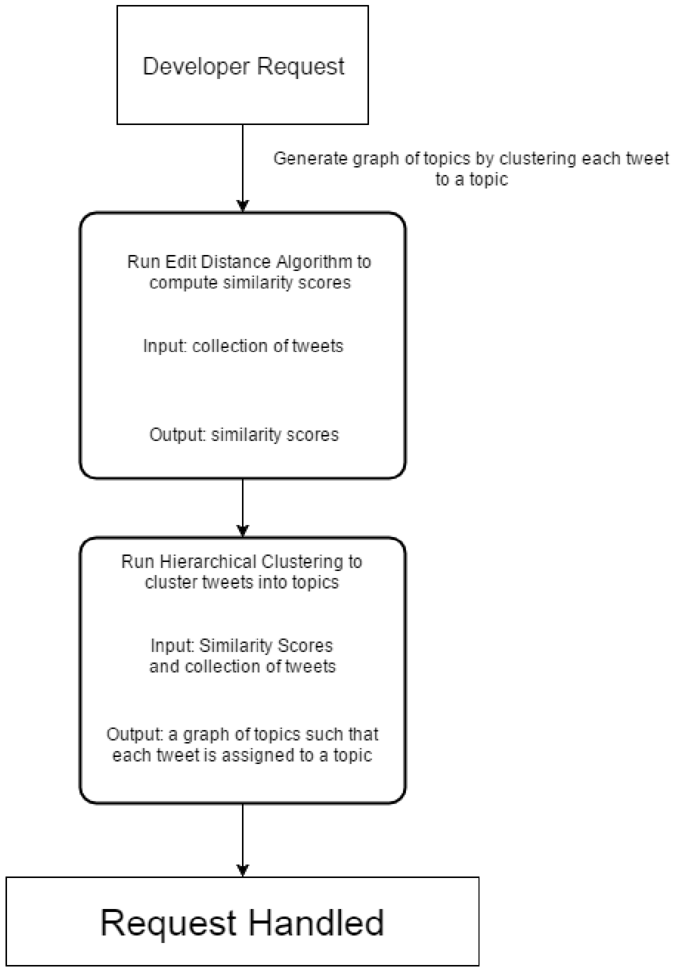
◇ 2c)Space Complexity of Algorithm 3 to 5

In Algorithm 3, we store node_scores in a hash table, so its space complexity is O(n). In Algorithm 4, we have two hash tables of hashtags, which each cost O(n-P) to store. We have one hash table of tweets, which costs O(P) to store. So the total space complexity of Algorithm 4 is O(n-P + P) = O(n). WLOG, the total space complexity of Algorithm 5 is O(n).

Flow Diagram For User Requests


User Request
Request type
Search for tweets related to a topic
Search for hashtags related to user tweet
Search for tweets related to hashtag input
Launch topic search job
Launch Tweet search job
Launch Hashtag search job
Topic search job
Input: A topic that the user is searching
Process: Find the topic node on the topic graph corresponding to the input
Output: Topic node containing tweets related to the topic
Tweet search job
Input: hashtag that the user is searching
Process: Search hashtags, each hashtag containing tweets similar to it
Output: the tweets related to the searched hashtag
Hashtag search job
Input: A tweet
Process: Find the most similar tweets and find their hashtags
Output: Hashtags, most similar to the input tweet ,that are not in input tweet
Result
Result
Result
Request Handled
Request Handled
Request Handled

Flow Diagram For Clustering Tweets


Developer Request
Generate graph of topics by clustering each tweet to a topic
Run Edit Distance Algorithm to compute similarity scores
Input: collection of tweets
Output: similarity scores
Run Hierarchical Clustering to cluster tweets into topics
Input: Similarity Scores and collection of tweets
Output: a graph of topics such that each tweet is assigned to a topic
Request Handled

- High Level Pseudo Code: refer to Algorithms 1 to 5

Algorithm 1: Edit Distance

```
input  : A sentence $S_1$ with n words as $S_1$={$a_1$,$a_2$,...,$a_n$} and a
         sentence $S_2$ with m words $S_2$ ={$b_1$,$b_2$, ...,$b_m$}
output: The edit distance between $S_1$ and $S_2$ L(n,m)
1  for $i = 0$ to $n$ do
2      L$(i, 0) = i$
3  end
4  for $j = 0$ to $m$ do
5      L$(0, j) = j$
6  end
7  for $i = 1$ to $n$ do
8      for $j = 1$to $m$ do
9          L$(i, j)$ = min {L$(i - 1, j)$ +1, L$(i, j - 1)$ +1, L$(i - 1, j - 1)$ +
             c$(a_i, b_j)$}
10     end
11 end
12 return L(m, n)
```

Algorithm 2: Hierarchical Clustering Algorithm

```
input  : An integer n represents the number of initial clusters, a
         clusterMatrix stores the sentence vector of every cluster, an
         array, a queue(implemented by binary heap) stores indices and
         distances between two cluster
output: clustered nodes
1  for $i = 1$ to $n$ do
2      initiaDistance($i, i$) = 0;
3      for $j = i + 1$to $n$ do
4          initiaDistance($i, j$) = distance($i, j$) queue add
             entry(initiaDistance($i, j$), i, j, 1, 1)
5      end
6  end
7  while $n \geq miniumClusters$ do
8      entry = queue.pop();
9      merge(entry.cluster1, entry.cluster2, entry.distance, entry.distance,
         clusterMatrix);
10     for $i$ = 1 to $n$ do
11         if $i \neq entry.cluster1andclusterMatrix[i].size \neq 0$ then
12             $first = min(entry.cluster1, i)$;
13             $second = min(entry.cluster2, i)$;
14             newDistance = getDistance(initialDistance,
                 clusterMatrix(first), clusterMatrix(second));
15             queue add entry(newDistance, first, second,
                 clusterMatrix(first).size, clusterMatrix(second).size)
16         end
17     end
18     n = n -1;
19 end
20
```

Algorithm 3: Node pair similarity scores pseudocode

```
input  : A bipartite graph G_2 of node pairs
output: A hash table of similarity scores for every node pair in G_2
Create hash table node_scores;
for (a,b) in nodes(G_2): do
    if a==b then
        Node_scores[(a,b)] := 1
    else
        Node_scores[(a,b)] := 0
    end
end
stop_signal := on;
while stop_signal == on do
    stop_signal := on;
    for (a,b) in nodes(G_2) do
        if a != b then
            {COMMENT: Let N(v) denote the neighbors of node v }
            $R_k$(a,b) :=
                $$\frac{C_1}{|N(a)||N(b)|}\sum_{i=1}^{|N(a)|}\sum_{j=1}^{|N(b)|} R_{k-1}(N_i(a), N_j(b))$$
        end
        if $R_k(a,b)$ != $R_{k-1}(a,b)$ then
            stop_signal := off
        end
        node_scores[(a,b)] := R_k(a,b)
    end
end
Return node_scores
```

Algorithm 4: Tweet Search job pseudocode

```
input  : A hashtag H that the user searches for, bipartite graph G_2,
         hash table node_scores
output: Tweets, without hashtag H, which are similar to tweets with
         hashtag H

1  Create hash table related_hashtags;
2  stop_signal := on;
3  for (a,b) in hashtag_nodes(G_2) do
4      if a == H then
5          stop_signal := off;
6          related_hashtags[b] := R_k(a,b)
7      end
8  end
9  if stop_signal == on then
10     Return "No results were found."
11 end
12 mergesort on related_hashtags by decreasing value;
13 Similar_hashtags := 100 elements of related_hashtags with highest value;
14 Create array H_tweets;
15 for (x,y) in neighbors(H) do
16     if x == y and x not in H_tweets then
17         Add x to H_tweets
18     end
19 end
20 Create array H_similar_tweets;
21 for hashtag in H_similar_hashtag do
22     for (x,y) in neighbors(hashtag) do
23         if x == y and x not in H_tweets and x not in similar_tweets then
24             Add x to H_similar_tweets
25         end
26     end
27 end
28 Return H_similar_tweets
```

Algorithm 5: Hashtag Search job pseudocode

```
input  : Hash table node_scores, input_tweet, bipartite graph G_2
output: Hashtags that not in input_tweet but are in tweets similar to
        input_tweet
1  Create hash table related_tweets;
2  stop_signal := on;
3  for (a,b) in tweet_nodes(G_2) do
4      if a == input_tweet then
5          stop_signal := off;
6          related_tweets[b] := R_k(a,b)
7      end
8  end
9  if stop_signal == on then
10     Return "No results were found."
11 end
12 mergesort on related_tweets by decreasing value;
13 Similar_tweets := 100 elements of related_tweets with highest value;
14 Create array input_tweet_hashtags;
15 for (x,y) in neighbors(input_tweet) do
16     if x == y and x not in input_tweet_hashtags then
17         Add x to input_tweet_hashtags
18     end
19 end
20 Create array similar_hashtags;
21 for tweet in similar_tweets do
22     for (x,y) in neighbors(tweet) do
23         if x == y and x not in input_tweet_hashtags and x not in
             similar_hashtags then
24             Add x to H_similar_hashtags
25         end
26     end
27 end
28 Return similar_hashtags
```

- Algorithms and Data Structures: In Algorithm 1, the major algorithm is Edit Distance in Dynamic Programming. The data structure is two-dimensional array, and the time complexity is $\mathcal{O}(mn)$. In Algorithm 2, we use Agglomerative Hierarchical Clustering Algorithm to cluster the documents. The time complexity of this algorithm is $\mathcal{O}(n^2 logn)$

The core of Algorithm 3 is the SimRank algorithm. The core of Algorithms 4 and 5 is Mergesort. Before computing the graphs, each tweet is stored as a pair of a unique identifier and an array of its hashtags. This pair will be stored as a hash table. The graphs are represented as adjacency lists (array of arrays). Each node is a pair, so it will be stored as a hash table Collections of hashtags and arrays, linked to their similarity scores, are stored in hash tables. Similar tweets and hashtags are stored in sets, a type of array.

References

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