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Stage2 - The Design Stage.

- Design Description:

  The user is given 3 different similarity measures for searching. We will begin with the first similarity measure: 1) users who select a topic and bring up a cluster of tweets related to that topic. (Search phrase and retrieve tweets with similar phrases acc to edit distance)

  ◇ **1) Tweet clustering based on semantic similarity**
  We aim to cluster tweets into different groups using Hierarchical Clustering. To do this, we require semantic similarity scores. We compute these using the 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=$\{a_1,a_2,\ldots,a_n\}$ and sentence S_2 as S_2 =$\{b_1,b_2,\ \ldots,b_m\}$. 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:

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

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

  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.

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

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

Next, we will describe searching by network similarity. Users can input either a tweet or a hashtag to find similar tweets and hashtags from the stored data. If the data does not contain those search terms, the user can choose to 'Gather New Tweets' based on the search terms.

A directed bipartite network G with two different types of nodes, tweets and hashtags, will be created. Instead of storing nodes as strings, we give a unique ID to each node. 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. As explained below, we will prune these node pairs to get an array called computed_pairs. In Algorithm 3, we apply SimRank on computed_pair to find a similarity score for every pair of nodes which are not 'far apart', a subjective measure.

SimRank is calculated using these equations: 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; we will set it as 0.8.

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 nodes is the average similarity of their neighbor. Initially, for node x, all node pairs (x,x) have score 1, while

other node pairs have score 0. Next, the similarity scores are calculated according to the equations above. This step is iterated until the updated scores do not differ much from the previous iteration. Since s(a,b) and s(b,a) are symmetric, so only need to store one of their scores. More information can be found in the original paper, the powerpoints, or by contacting this report's authors.

For memory efficiency, pairs of nodes which are far away are pruned out. Let M be the adjacency matrix of G. If entry (n,m) in M^k is nonzero, then there exists a path between n and m of length k. Let Kmax be a subjective upper bound; we will set it as 4. Consider:

$$Z = \sum_{k=1}^{Kmax} M^{2k}$$

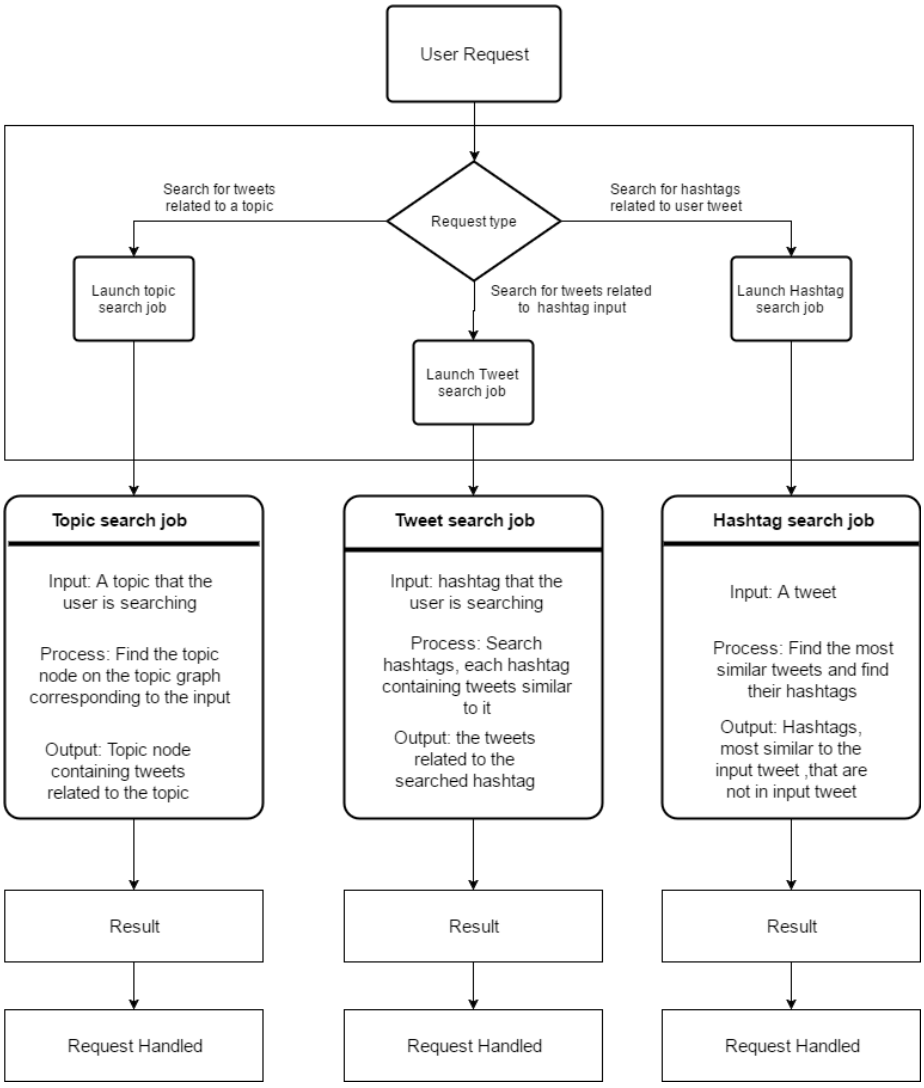
Only even powers of M are included in Z because G is bipartite. Then we will only compute similarity scores on the nonzero entries of Z, which are gathered into computed_pairs.

◇ 2b)Time and Space Complexity of Algorithm 3

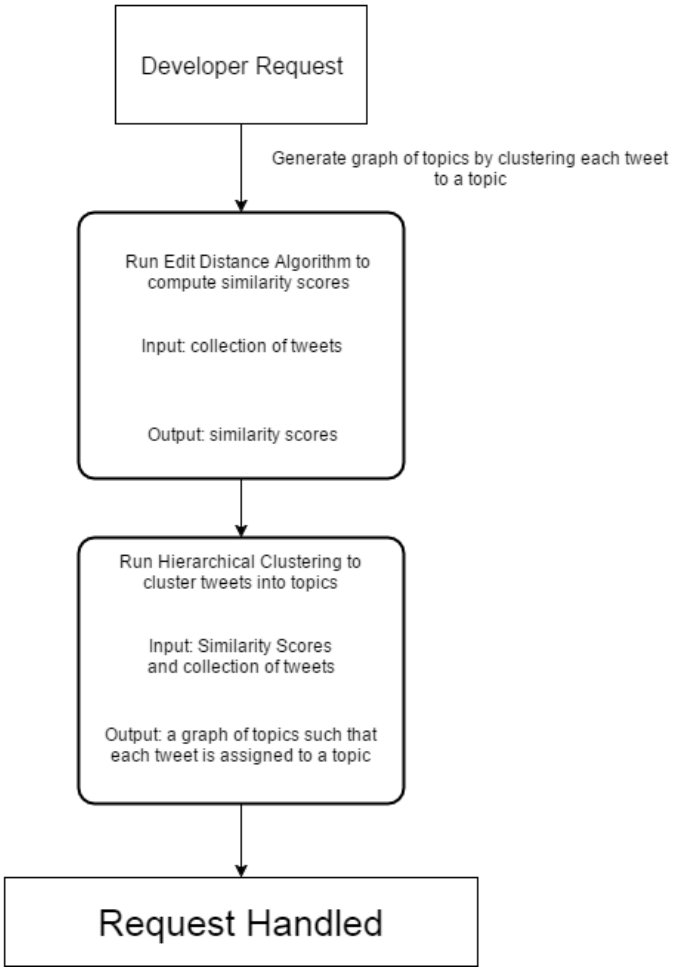
The bulk of the running time depends on the matrix multiplication used to obtain computed_pairs; this takes $\Theta(n^3)$. The second pruning approach, computing the shortest path for all pairs, takes $O(n \log n)$ for each pair, and since there are n^2 pairs, its total running time would be $O(n^3 \log n)$. Thus, the adjacency matrix multiplication approach is preferred.

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 w be the number of pairs in computed_pairs . Using a 'naive' implementation of SimRank, average running time of Algorithm 3 is O(K*w*d). Its worst case mainly depends on K. We store node_scores in a hash table, so its space complexity is O(n).

Flow Diagram For User Requests



Flow Diagram For Clustering Tweets



- **High Level Pseudo Code**

Algorithm 1: Edit Distance

input : A sentence S_1 with n words as S_1=$\{a_1,a_2,\ldots,a_n\}$ and a sentence S_2 with m words S_2 =$\{b_1,b_2,\ldots,b_m\}$

output: The edit distance between S_1 and S_2 L(n,m)

```
for i = 0 to n do
    L(i, 0) = i
end
for j = 0 to m do
    L(0, j) = j
end
for i = 1 to n do
    for j = 1to m do
        L(i, j) = min {L(i − 1, j) +1, L(i, j − 1) +1, L(i − 1, j − 1) +
          c(a_i, b_j)}
    end
end
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 + 1to 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 ≥ 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 ≠ entry.cluster1andclusterMatrix[i].size ≠ 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 : An array of node pairs called computed_pairs
output: A hash table of similarity scores for every node pair in computed_pairs

```
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 := off;
while stop_signal == off 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) :=
                        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)| > 0.05 then
            stop_signal := off
        end
        node_scores[(a,b)] := R_k(a,b)
    end
end
Return node_scores
```

- **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 $\mathcal{O}(n^2 logn)$. In Algorithm 3, the nodes with their IDs are stored in hash tables. The graphs, represented as adjacency lists, are also stored in hash tables. The node pairs and their scores are stored in hash tables. Similar tweets and hashtags are stored in arrays.

References

[1] T. Mikolov, I. Sutskever, K. Chen, G. Corrado, and J. Dean. Distributed representations of words and phrases and their compositionality. In Proceedings of the 26th International Conference on Neural Information Processing Systems, NIPS'13, pages 3111-3119, USA, 2013. Curran Associates Inc.

[2] Jeh, Glen, and Jennifer Widom. "SimRank: a measure of structural-context similarity." In Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 538-543. ACM, 2002.