# Problem Set 2: Semantic Similarity

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### Methodology

#### BUILDTERMCONTEXTMATRIX

Time complexity 
$$O(DT \log V) + O(DT \cdot W^2) + O(V^2)$$
  
Space complexity  $O(V) + O(V^2)$ 

The method buildTermContextMatrix relies on getVocab to find the number of distinct terms. The size of vocab is used as the dimensions of the  $|V| \times |V|$  term-context matrix. The method getVocab also builds an array of terms, which the program later uses to map terms to the indices of the term-context matrix. The method getVocab first uses a TreeSet to build an ordered set of V distinct terms. It takes  $O(DT \log V)$  time to add the T terms in D documents to the ordered set. After it's done reading all files, the method transfers the contents of the TreeSet to an ArrayList. It takes O(V) time to fill the ArrayList. Altogether, the method has a runtime of  $O(DT \log V + V)$ , or  $O(DT \log V)$ . It has a space complexity of O(V), because it only stores the distinct words it identifies.

The method buildTermContextMatrix first uses  $O(V^2)$  space for the term-context matrix. It also takes O(V) space to temporarily store the total frequencies for each term, which weightTerms uses to calculate PPMI. Next, buildTermContextMatrix starts to iterate across the files in the input directory. As it reads the tokens in a document, it builds a segment of size W, the window size. This task takes O(W) space total. When the segment is complete, the method passes this segment and the prior one to countTerms. The method countTerms uses two loops to find the distinct pairs of contextual terms within the two segments. The outer loop in countTerms runs from a to w, and the inner loop runs from zero to w-a. Its total runtime is

 $O(W^2)$ . Together, the two methods take  $O(DT \cdot W^2)$  time to create the term-context matrix. After the term-context matrix is complete, weightTerms takes the matrix and the aggregated frequencies in sum. It uses two loops to calculate weights for each cell in the term-context matrix. This takes  $O(V^2)$  time.

#### CALCULATESIMILARITY

Time complexity 
$$O(V)$$
  
Space complexity  $O(3)$ 

The method calculateSimularity uses a single for loop and three variables to calculate the cosine simularity for two words. This takes O(V) time.

#### **GETCONTEXT**

Time complexity 
$$O(V^2 \cdot \log V)$$
  
Space complexity  $O(V) + O(k)$ 

The method getContext uses a single for loop to iterate over the entire vocabulary V. For each term, it uses calculateSimularity to find the consine similarity between the two words. Then, it stores an object with the row number and cosine similarity in a priority queue. This action takes  $O(\log V)$  time and O(V) space. After getContext examines every word in the vocabulary, it uses a loop to store the top k words in the priority queue.

### Results

The results below demonstrate the output of the application at a window size of four, eight, and sixteen for given queries.

## CALCULATESIMULARITY

| Data, Computer |  |
|----------------|--|
| real           | $1 \text{m} 01.855 \text{s} \ 1 \text{m} 34.686 \text{s} \ 2 \text{m} 31.227 \text{s}$ |
| user           | $1 \text{m} 09.082 \text{s} \ 1 \text{m} 42.089 \text{s} \ 2 \text{m} 38.800 \text{s}$ |
| sys            | $0 \text{m} 26.240 \text{s} \ 0 \text{m} 27.483 \text{s} \ 0 \text{m} 26.011 \text{s}$ |
| 4              | 0.1173   |
| 8              | 0.1095   |
| 16             | 0.1160   |
|                |  |
| Data, Dog      |  |
| real           | $1 m02.029 s\ 1 m29.595 s\ 2 m31.415 s$  |
| user           | $1 m09.463 s\ 1 m36.940 s\ 2 m38.664 s$  |
| sys            | $0 m26.487 s\ 0 m26.451 s\ 0 m26.443 s$  |
| 4              | 0.0  |
| 8              | 0.0  |
| 16             | 0.0  |
|                |  |
| Data, Pencil   |  |
| real           | $0 m 58.257 s \ 1 m 29.073 s \ 2 m 32.061 s$   |
| user           | $1 m05.531 s\ 1 m36.252 s\ 2 m38.923 s$  |
| sys            | $0 m26.708 s \ 0 m26.621 s \ 0 m27.515 s$  |
| 4              | 0.0  |
| 8              | 0.0  |
| 16             | 0.0  |
|                |  |
| Hot, Dog       |  |
| real           | $1 m01.973 s\ 1 m29.131 s\ 2 m39.099 s$  |
| user           | $1 m09.499 s\ 1 m36.824 s\ 2 m46.906 s$  |
| sys            | $0 \text{m} 26.802 \text{s} \ 0 \text{m} 25.979 \text{s} \ 0 \text{m} 26.133 \text{s}$ |
| 4              | 0.0156   |
| 8              | 0.0113   |
|                |  |

## GETCONTEXT

| Computer                   |   |
|----------------------------|---|
| real                       | $1 \text{m} 02.276 \text{s} \ 1 \text{m} 02.276 \text{s} \ 2 \text{m} 36.153 \text{s}$  |
| user                       | $1 \text{m} 10.174 \text{s} \ 1 \text{m} 10.174 \text{s} \ 2 \text{m} 43.326 \text{s}$  |
| sys                        | $0 \text{m} 25.738 \text{s} \ 0 \text{m} 25.738 \text{s} \ 0 \text{m} 26.321 \text{s}$  |
| 4                          | lahor pakistan karachi islamaba scienc embed outsourc hadoop parallel etichet   |
| 8                          | islamaba lahor karachi pakistan scienc embed etichet parallel mooc neural   |
| 16                         | islamaba lahor karachi pakistan scienc parallel onthoud credenti embed whitepap   |
|                            |   |
| Data                       |   |
| real                       | $1 \text{m} 02.553 \text{s} \ 1 \text{m} 38.405 \text{s} \ 2 \text{m} 36.050 \text{s}$  |
| user                       | $1 \text{m} 10.140 \text{s} \ 1 \text{m} 46.046 \text{s} \ 2 \text{m} 43.234 \text{s}$  |
| sys                        | $0 \text{m} 26.243 \text{s} \ 0 \text{m} 26.559 \text{s} \ 0 \text{m} 26.772 \text{s}$  |
| 4                          | lahor pakistan karachi islamaba hadoop globalhe sentri wareh mine hatenabl  |
| 8                          | islamaba lahor karachi pakistan hadoop globalhe mine sentri analyt big  |
| 16                         | lahor islamaba karachi pakistan hadoop globalhe mine big hatenabl analyt  |
|                            |   |
| Pencil                     |   |
| real                       | $1 \text{m} 02.337 \text{s} \ 1 \text{m} 38.154 \text{s} \ 2 \text{m} 44.197 \text{s}$  |
| user                       | $1 \text{m} 10.161 \text{s} \ 1 \text{m} 45.576 \text{s} \ 2 \text{m} 52.020 \text{s}$  |
| sys                        | $0 \text{m} 25.955 \text{s} \ 0 \text{m} 27.353 \text{s} \ 0 \text{m} 25.786 \text{s}$  |
| 4                          | sharpen snail eyelin mascara lipstick crayon eras brow sketch eyeshado  |
| 8                          |   |
| 1.0                        | sharpen snail lipstick mascara eyelin brow eyeshado lip crayon eyebrow  |
| 16                         | sharpen snail lipstick mascara eyelin brow eyeshado lip crayon eyebrow<br>sharpen snail lipstick mascara eyelin eyeshado lip brow crayon bronzer                    |
| 10                         |   |
| Dog                        |   |
|                            |   |
| Dog                        | sharpen snail lipstick mascara eyelin eyeshado lip brow crayon bronzer  |
| Dog<br>real                | sharpen snail lipstick mascara eyelin eyeshado lip brow crayon bronzer $1 \bmod 2.736 \mathrm{s}\ 1 \bmod 34.042 \mathrm{s}\ 2 \bmod 46.206 \mathrm{s}$             |
| Dog<br>real<br>user        | sharpen snail lipstick mascara eyelin eyeshado lip brow crayon bronzer $1 m02.736 s\ 1 m34.042 s\ 2 m46.206 s$ $1 m10.271 s\ 1 m41.399 s\ 2 m53.791 s$              |
| Dog<br>real<br>user<br>sys | sharpen snail lipstick mascara eyelin eyeshado lip brow crayon bronzer  1m02.736s 1m34.042s 2m46.206s  1m10.271s 1m41.399s 2m53.791s  0m26.405s 0m26.754s 0m26.209s |