SJSU CMPE 239 Data Mining

Homework 2 - Report

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Rank & Accuracy score at the time of writing the report: 6, 79.94

Steps Followed:

First I started with a general framework for the KNN classifier assuming K = 3. Later added evaluation mode to find the best K. Also added several preprocessing steps such as filterLen, stemmers, K-mer (with K=2 and K=3).

For Preprocessing the train and test files, I followed the following steps:

1. Open train.dat file in read mode and read the lines.
2. Create list variable train_labels with all the labels (+1 and -1) from train.dat file
3. Remove special characters and convert all words to lowercase
4. Use filterLen function to filter out words that have less than 4 letters except for the word “bad”
5. Remove suffixes (and in some cases prefixes) in order to find the root word or stem of a given word using Potter2 stemmer.
6. K-mer implementation with K=2 and K=3: Every document is passed through grouper function which groups 2 simultaneous and 3 simultaneous words and adds them to the original list of words.
7. Repeat the steps 1-6 (except step 2) for test.dat file.
8. Preprocessed train and test reviews are obtained in 2 different lists. Python extend function was used to combine these two lists.

For building the csr_matrix and to normalize it following steps were followed:

9. The build_matrix function was used to transform the list of lists of words obtained in Step 8 into a sparse matrix
10. csr_idf function was used to decrease the importance of popular words
11. csr_l2normalize function was then used to normalize the matrix to simplify cosine similarity calculation

After step 11, The first half of the csr_matrix had normalized train vectors and second half had normalized test vectors.

For finding cosine similarity between test vectors and each of the train vectors, initially I used numpy.dot function. This implementation took a lot of time (hours) to run and sometimes didn’t give results. I learnt that numpy is a dense linear algebra library. It converts the sparse matrix to dense matrix before computing the dot product. Hence the computation took a lot of time. Then I used cosine_similarity function from sklearn.metrics.pairwise to get pairwise cosine similarity using the sparsity of the matrix. This computation took relatively less time. (under 10 minutes)

For K nearest neighbor classifier following steps were followed:

12. Pairwise similarities are converted to list of lists with similarity of each test vector with each of the train vectors.

13. Each of the list within the list of lists was zipped with train_label information obtained from Step 2 to get each similarity and corresponding label in tuple format.
14. Then the list of lists is sorted in descending order and top k similarities are chosen. The corresponding labels are added, if the result is zero, then a random integer between (-1,2) is chosen until +1 or -1 is obtained. If a positive result is obtained, then a label '+1' is assigned, else a label '-1' is assigned.
15. The assigned labels are then written to output file.

For finding the Best k value I defined 2 modes of operation (K values in range [0,20] were considered):

Evaluation Mode: In this mode, I split the train.dat file randomly (using random.shuffle) into 2 parts. I considered first part as train data and second as test data.

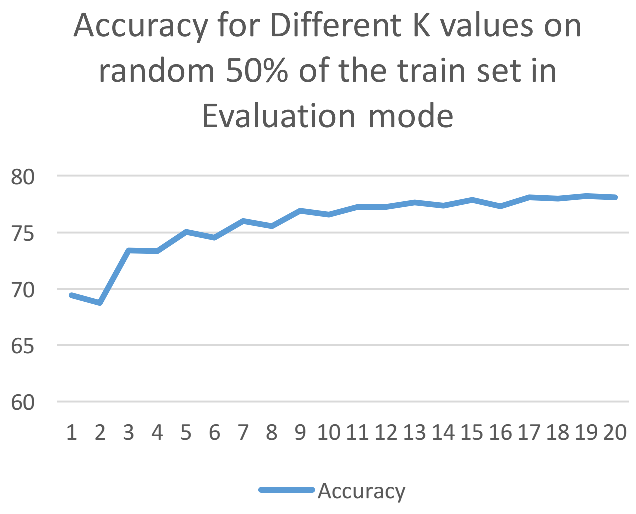
16. Removed all labels from the test data and stored in evaluation_labels list.
17. Steps 1-11 were repeated with the new train and test files
18. After obtaining the pairwise cosine similarity, for each of the K values, steps 12-14 are repeated.
19. To check accuracy with different K values, the labels assigned in step 14 are compared with evaluation_labels (using numpy.isclose) from step 16
20. The K with maximum similarity count is selected as Best K.

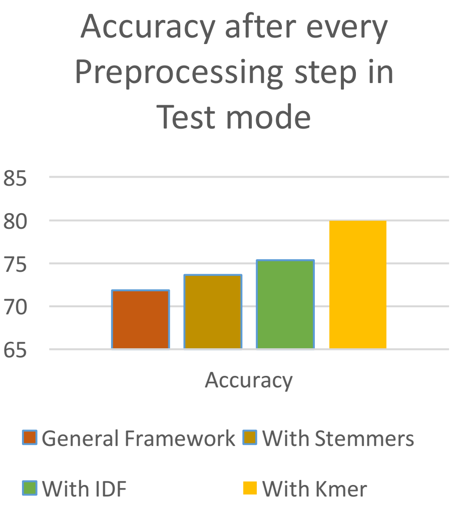
Test Mode:

21. Steps 1-15 are repeated with original test.dat and train.dat files with the Best K value obtained from Step 20.

Results obtained:

Best K value obtained for the last run was K = 19. Accuracy obtained during evaluation mode for K ranging from [1-20] is shown in the line graph below. Accuracy significantly increased from 71.85% to 79.94% when I included Stemmers and Inverse Document Frequency and K-mer steps. Different accuracies obtained after each preprocessing step is shown in the column graph below.


Accuracy for Different K values on random 50% of the train set in Evaluation mode
Accuracy


Accuracy after every Preprocessing step in Test mode
Accuracy
General Framework
With Stemmers
With IDF
With Kmer