

# LING572 Hw4 (kNN)

## Due: 11pm on Feb 2, 2021

The example files are under `dropbox/20-21/572/hw4/examples/` and `hw4/example_output/`.

**Q1 (40 points):** Write a script, **build\_kNN.sh**, that implements the kNN algorithm. It classifies a test instance  $x$  by letting the  $k$  nearest neighbors of  $x$  vote.

- The learner should treat features as real-valued.
- Use majority vote; that is, each of the  $k$  nearest neighbors has one vote.
- The format is: `build_kNN.sh training_data test_data k_val similarity_func sys_output > acc_file`
- `training_data` and `test_data` are the vector files in the text format (cf. **train.vectors.txt**).
- `k_val` is the value of  $k$ ; i.e., the number of nearest neighbors chosen for classification.
- `similarity_func` is the id of the similarity function. If the variable is 1, use Euclidean distance. If the value is 2, use Cosine function. **Notice that Euclidean distance is a dissimilarity measure; that is, the longer the distance between two instances is, the more dissimilar (i.e., the less similar) the instances are.**
- `sys_output` and `acc_file` have the same format as the one specified in Hw3, and they should include the classification results for both training and test data. When choosing  $k$  nearest neighbors for a training instance  $x$ , one of such neighbors is  $x$  itself. Notice that since other  $k-1$  neighbors could have labels different from that of  $x$ , the training accuracy could be lower than 100%.
- For each line of `sys_output`, remember to sort the  $(c_i, p_i)$  pairs by the value of  $p_i$  in **descending order**. If two class labels have the same probability, either order of two  $(c_i, p_i)$  pairs is ok.

Run `build_kNN.sh` with **train.vectors.txt** as the training data and **test.vectors.txt** as the test data. Fill out Table 1 with different values of  $k$  and similarity function.

Table 1: Test accuracy using **real-valued** features

k	Euclidean distance	Cosine function
1		
5		
10		

**Q2 (35 points):** Write a script, `rank_feat_by_chi_square.sh`, that ranks features by  $\chi^2$  scores.

- The format for command line is: `cat input_file | rank_feat_by_chi_square.sh > output_file`
- `input_file` is a feature vector file in the text format (e.g., **train.vectors.txt**).
- The `output_file` has the format “featName score docFreq”. The score is the chi-square score for the feature; docFreq is the number of documents that the feature occurs in. The lines are sorted by  $\chi^2$  scores in descending order (e.g., **feat\_list.ex**).

- For  $\chi^2$  calculation, treat each feature as binary; that is, suppose the `input_file` has  $a_i$  instances with class label  $c_i$ . Out of these  $a_i$  instances,  $b_i$  of them contain the feature  $f_k$ , then the corresponding contingency table for feature  $f_k$  is shown in Table 2.
- Run “`cat train.vectors.txt | rank_feat_by_chi_square.sh > feat_list`” and submit `feat_list`.

Table 2: A contingency table for feature  $f_k$

	$c_1$	$c_2$	$c_3$
$f_k$	$a_1 - b_1$	$a_2 - b_2$	$a_3 - b_3$
$f_k$	$b_1$	$b_2$	$b_3$

**Submission:** Submit the following to Canvas:

- Your note file *readme.(txt | pdf)* that includes Table 1 and any notes that you want the TA to read.
- `hw.tar.gz` that includes all the files specified in `dropbox/20-21/572/hw4/submit-file-list`, plus any source code (and binary code) used by the shell scripts.
- Make sure that you run **`check_hw4.sh`** before submitting your `hw.tar.gz`.