**Lab 3: Nearest Neighbor Text Classification**

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1. **Introduction**

In this lab, we extend our work from lab 2 to experiment with Nearest Neighbor methods by following a similar method of customizing the template\_supervized.py file with scikit-learn code. We omit discussion of the common code pieces that we explained in detail there and focus on the Nearest Neighbor code customizations and experiment with training and testing runs with our 20 Newsgroup and Reuters datasets. Experiments will illuminate some aspects of using these methods in high-dimensional text spaces where training data is limited and how that can be addressed with dimension reduction and centroid models.

1. **Create the Neighbors program**

From your /soc290 project directory make a copy of the template\_supervised.py file called neighbors.py and open the copy in your editor. As before we begin by editing the prelude docstring with the new file metadata and editing the file globals to define the method and models we will support. Edit the beginning of your new file this way



The docstring prelude now carries the correct file and package name. As before add your name as an @author. We have also defined the METHOD global as the string ‘Neighbors’ and the MODELS variable as a tuple with the strings ‘KNN’ and ‘Centroid,’ for K-Nearest Neighbors and Nearest Centroid, respectively, after the Nearest Neighbor methods we described in lecture.

**Customizing the functions for Nearest Neighbors**

Again, we just need to edit our to-do sections with scikit code to customize for the above methods. In fact, the only part that is different that lab 2 is the first to-do in train(). Here we create a conditional if statement that is keyed by the choice of one of the two above methods to create scikit **vectorizer** and classifier (**clf**) objects



In this case we see that a TFIDF **vectorizer** is constructed before the if clause. That means that we use the same bag-of-words model (TFIDF) for both methods. The scikit **KNeighborsClassifer** object is created if the KNN model is specified, and the scikit **NearestCentroid** object is created if the Centroid model is specified; either way the classifier is assigned to **clf** as before.

Creating a different kind of classifier is all that is new here as compared to lab 2. The other three to-dos in train() and in the other functions and entry point are filled out exactly like before. For convenience, we repeat the sections here that have to be edited: the dimension reducer, the feature extractor and the training function look like this







In predict() we have



In eval()



You can just cut and paste these common sections from the naive\_bayes.py file to make life easy. And again we remove the to-dos from the entry point



So you notice from this that there is a lot of code reuse going on here. We only need slight modifications to make very different behavior in our programs. With slightly more sophisticated programming techniques, we could even make this reuse explicit in our programs so there would be no cut-and-paste involved. But for simplicity sake, we are just going to edit the templates this way. If you have a little more programming experience, know about object-oriented concepts or are just adventurous, see the instructor and we can outline an even better design you can try out or use for your future work.

1. **Collecting Nearest Neighbor Performance Data and Preparing Results**

Let’s run our Nearest Neighbors program on the testing data to see how they perform. We’ll do this for 20 Newsgroups and Reuters data with both models, and also with a dimension reduction option to see how that effects performance. After collecting and assembling results, we’ll pose some questions in the next section to answer in the report.

First lets gather data for the basic KNN model on the 20 Newsgroups data. The command lines for doing this on the 3 flavors of newsgroups data are as follows (output omitted)



Here we have run the full 20 Newsgroups, 20news5 and 20news4 datasets all with a KNN model and generated a linear confusion matrix along with a report file for each. The contents of /soc290/reports, assuming it is initially empty or deleted will look like this



So as before, we have report files (same as seen on the command line output) and confusion image files for each of the 20 Newsgroups datasets.

Take a moment to open and examine these files and notice what you see. Does this performance look very good to you? Think about how these cases perform on average as well as how the best and worst performing individual categories look in the performance distributions. We’ll ask some questions about this in the next section.

Now lets perform the same analysis but instruct the processing to limit the feature dimension by using the chi-squared statistic to select the top features in advance of training and classification. The command lines are



Notice we used the –d option here. The argument to –d is an integer specifying the desired feature dimension, so in 20news and 20news5 we are training and classifying with a 500-dimensional bag-of-words model, while the 20news4 using a 100-dimensional model. The new reports and confusion images are now in your reports directory



The \_500\_ and \_100\_ annotations in the file name gives the dimension size when –d is specified.

You are probably wondering at this point how we came up with the choice of dimension. These parameters are usually determined empirically in practice. In smaller scale exploratory work we can often do this just by trial and error to find an acceptable parameter. In more complicated settings, or in a production or research setting where we must find the optimal performance, we can run the tests in a loop called a **grid search**. This means we specify the range and step resolution of the unknown parameters and run the training set across all possibilities to identify the best settings. Here we’ve done a little experimentation ahead of time for you to identify some reasonable dimension parameters. Take a moment to open the dimensionally reduced output files and compare them to the full dimension KNN models. Notice a difference?

Following the same steps for the Reuters data we have the following command lines and the new reports. Notice that we ask for a log confusion matrix, and for the dimension reduction case, 200 features.



Finally, let’s collect results using the Nearest Centroid classifier on our datasets. The command line and results without dimension reduction are



The full set of reports in /soc290/reports is



As before, the results section of the lab report should have the following 9 pages, titled as below.

1. **Data 1: KNN 20news**
2. **Data 2: KNN 20news5 and 20news4**
3. **Data 3: KNN 20news, dim=500**
4. **Data 4: KNN 20news5 dim=500, 20news4 dim=100**
5. **Data 5: KNN Reuters**
6. **Data 6: KNN Reuters, dim=200**
7. **Data 7: Nearest Centroid, 20news**
8. **Data 8: Nearest Centroid, 20news5 and 20news4**
9. **Data 8: Nearest Centroid, Reuters**
10. **Analyzing the Data and Preparing the Lab Report**

In the analysis section at the beginning of the report, provide the following sections with discussion of the following questions. When done, add a cover page with your name, email and lab title. Save the document as a pdf and email to the instructor and TA.

**Analysis of Results: 20news, 20news5, 20news4 and Reuters**

1. How would you characterize the performance of overall in each of the tests? Justify your argument with specific references to the average precision and recall and their distributions across document categories in each case.
2. How does this performance compare to the Naïve Bayes TFIDF model? Based on our discussion in lecture, how can you explain this difference?
3. We learned in lecture that KNN classifiers have quite strong performance guarantees. Describe these guarantees in your own words. Do you think these performance guarantees are valid for these results? Why or why not?
4. Why and how might performance be improved in these models?

**Analysis of Results: 20news dim=500, 20news5 dim=500, 20news4 dim=100 and Reuters dim=200**

1. How would you characterize the performance of overall in each of the tests? Justify your argument with specific references to the average precision and recall and their distributions across document categories in each case.
2. Dimension reduction has the effect of markedly improving performance over full-dimensional models. Describe why reduction in feature dimension has the effect you observe. How do you think this is related to the data sample size?

**Analysis of Results: Centroid Models**

1. How do the centroid models compare to both their full and reduced dimension equivalents?
2. What does the performance of these centroid models say about how these particular data are distributed geometrically in document space? Do you think centroid models will always perform this way (i.e. with any dataset)? Under what conditions might they perform less well?