

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_supervised.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.

2. 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

```
#!/usr/bin/env python

"""
@package css
@file css/neighbors.py
@author Edward Hunter
@author Your Name Here
@brief Nearest neighbor and nearest centroid supervised learning and evaluation methods.
"""

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# Import common modules and utilities.
from common import *

# Define method and models available.
METHOD = 'Neighbors'
MODELS = ('KNN', 'Centroid')
```

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 Template for Nearest Neighbors

First, remove the unused to-dos in `train()` and the entry point. Remove these lines from `train()`

```
#####
# Grid search and top feature output for SVMs.
#####
# TODO: SVMs only.
#####
```

and these lines from the entry point at the bottom of the file

```
#####
# Add method specific options.
#####
# TODO: SVMs only.
#####

#####
# Extract method specific options.
#####
# TODO: SVMs only.
#####
```

The required customization is very simple. Edit the remaining to-do in `train()` to create a scikit TFIDF **vectorizer** and a conditional block that is keyed by the two above methods to create the model specific classifier (**clf**) object

```
#####
# Create feature extractor, classifier.
#####
vectorizer = TfidfVectorizer(stop_words='english',sublinear_tf=True)
if model == 'KNN':
    clf = KNeighborsClassifier()
elif model == 'Centroid':
    clf = NearestCentroid()
#####
```

The 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 **KNeighborsClassifier** 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 and a common vectorizer is all that is new here as compared to lab 2. 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. Refer to the Lab 2 instructions if you need reminders for how any of the common code works.

3. 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.

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)

```
(css)$ python neighbors.py -c linear KNN 20news
. . . OUTPUT AND REPORT . . .
(css)$ python neighbors.py -c linear KNN 20news5
. . . OUTPUT AND REPORT . . .
(css)$ python neighbors.py -c linear KNN 20news4
. . . OUTPUT AND REPORT . . .
```

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

```
(css)$ ls -l reports/
total 224
drwxr-xr-x  8 edward  272 Mar  1 14:55 .
drwxr-xr-x 26 edward  884 Mar  1 14:55 ..
-rw-r--r--  1 edward 27325 Mar  1 14:55 Neighbors_KNN_20news4_confusion.png
-rw-r--r--  1 edward  699 Mar  1 14:55 Neighbors_KNN_20news4_report.txt
-rw-r--r--  1 edward 30616 Mar  1 14:55 Neighbors_KNN_20news5_confusion.png
-rw-r--r--  1 edward  756 Mar  1 14:55 Neighbors_KNN_20news5_report.txt
-rw-r--r--  1 edward 40814 Mar  1 14:55 Neighbors_KNN_20news_confusion.png
-rw-r--r--  1 edward  3326 Mar  1 14:55 Neighbors_KNN_20news_report.txt
```

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 provide a writeup of this in the report.

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

```
(css)$ python neighbors.py -c linear -d 500 linear KNN 20news
. . . OUTPUT AND REPORT . . .
(css)$ python neighbors.py -c linear -d 500 linear KNN 20news5
. . . OUTPUT AND REPORT . . .
(css)$ python neighbors.py -c linear -d 100 linear KNN 20news4
. . . OUTPUT AND REPORT . . .
```

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

```
(css)$ ls -la reports/
total 464
drwxr-xr-x 14 edward  476 Mar  1 18:02 .
drwxr-xr-x 26 edward  884 Mar  1 18:02 ..
-rw-r--r--  1 edward 29627 Mar  1 17:56 Neighbors_KNN_20news4_100_confusion.png
-rw-r--r--  1 edward  703 Mar  1 17:56 Neighbors_KNN_20news4_100_report.txt
-rw-r--r--  1 edward 27325 Mar  1 14:55 Neighbors_KNN_20news4_confusion.png
-rw-r--r--  1 edward  699 Mar  1 14:55 Neighbors_KNN_20news4_report.txt
-rw-r--r--  1 edward 29472 Mar  1 18:02 Neighbors_KNN_20news5_500_confusion.png
-rw-r--r--  1 edward  785 Mar  1 18:02 Neighbors_KNN_20news5_500_report.txt
-rw-r--r--  1 edward 30616 Mar  1 14:55 Neighbors_KNN_20news5_confusion.png
-rw-r--r--  1 edward  756 Mar  1 14:55 Neighbors_KNN_20news5_report.txt
-rw-r--r--  1 edward 41650 Mar  1 15:06 Neighbors_KNN_20news_500_confusion.png
-rw-r--r--  1 edward  3730 Mar  1 15:06 Neighbors_KNN_20news_500_report.txt
-rw-r--r--  1 edward 40814 Mar  1 14:55 Neighbors_KNN_20news_confusion.png
-rw-r--r--  1 edward  3326 Mar  1 14:55 Neighbors_KNN_20news_report.txt
```

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. In Lab 4 where we study SVMs that can less intuitive parameters to tune, we will experiment with grid search. 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.

```
(css)$ python neighbors.py -c log KNN reuters21578-10
. . . OUTPUT AND REPORT . . .
(css)$ python neighbors.py -c log -d 200 KNN reuters21578-10
. . . OUTPUT AND REPORT . . .
```

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

```
(css)$ python neighbors.py -c linear Centroid 20news
... OUTPUT AND REPORT ...
(css)$ python neighbors.py -c linear Centroid 20news5
... OUTPUT AND REPORT ...
(css)$ python neighbors.py -c linear Centroid 20news4
... OUTPUT AND REPORT ...
(css)$ python neighbors.py -c log Centroid reuters21578-10
... OUTPUT AND REPORT ...
```

The full set of reports in /soc290/reports is

```
(css)$ ls -lora reports/
total 944
drwxr-xr-x 26 edward 884 Mar 1 16:45 .
drwxr-xr-x 26 edward 884 Mar 1 14:55 ..
-rw-r--r-- 1 edward 30026 Mar 1 16:45 Neighbors_Centroid_20news4_confusion.png
-rw-r--r-- 1 edward 704 Mar 1 16:45 Neighbors_Centroid_20news4_report.txt
-rw-r--r-- 1 edward 29980 Mar 1 16:44 Neighbors_Centroid_20news5_confusion.png
-rw-r--r-- 1 edward 786 Mar 1 16:44 Neighbors_Centroid_20news5_report.txt
-rw-r--r-- 1 edward 41992 Mar 1 16:44 Neighbors_Centroid_20news_confusion.png
-rw-r--r-- 1 edward 3731 Mar 1 16:44 Neighbors_Centroid_20news_report.txt
-rw-r--r-- 1 edward 34236 Mar 1 16:45 Neighbors_Centroid_reuters21578-10_confusion.png
-rw-r--r-- 1 edward 1426 Mar 1 16:45 Neighbors_Centroid_reuters21578-10_report.txt
-rw-r--r-- 1 edward 28734 Mar 1 15:07 Neighbors_KNN_20news4_100_confusion.png
-rw-r--r-- 1 edward 703 Mar 1 15:07 Neighbors_KNN_20news4_100_report.txt
-rw-r--r-- 1 edward 27325 Mar 1 14:55 Neighbors_KNN_20news4_confusion.png
-rw-r--r-- 1 edward 699 Mar 1 14:55 Neighbors_KNN_20news4_report.txt
-rw-r--r-- 1 edward 29472 Mar 1 15:07 Neighbors_KNN_20news5_500_confusion.png
-rw-r--r-- 1 edward 785 Mar 1 15:07 Neighbors_KNN_20news5_500_report.txt
-rw-r--r-- 1 edward 30616 Mar 1 14:55 Neighbors_KNN_20news5_confusion.png
-rw-r--r-- 1 edward 756 Mar 1 14:55 Neighbors_KNN_20news5_report.txt
-rw-r--r-- 1 edward 41650 Mar 1 15:06 Neighbors_KNN_20news_500_confusion.png
-rw-r--r-- 1 edward 3730 Mar 1 15:06 Neighbors_KNN_20news_500_report.txt
-rw-r--r-- 1 edward 40814 Mar 1 14:55 Neighbors_KNN_20news_confusion.png
-rw-r--r-- 1 edward 3326 Mar 1 14:55 Neighbors_KNN_20news_report.txt
-rw-r--r-- 1 edward 33714 Mar 1 15:18 Neighbors_KNN_reuters21578-10_200_confusion.png
-rw-r--r-- 1 edward 1425 Mar 1 15:18 Neighbors_KNN_reuters21578-10_200_report.txt
-rw-r--r-- 1 edward 33652 Mar 1 15:18 Neighbors_KNN_reuters21578-10_confusion.png
-rw-r--r-- 1 edward 1421 Mar 1 15:18 Neighbors_KNN_reuters21578-10_report.txt
```

4. Analyzing the Data and Preparing the Lab Report

As before, collect the results (report output and confusion images) of your analysis into a lab report Word file with the following 9 data results 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

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.

Results Analysis

Summary: For each of the datasets 20news, 20news5, 20news4 and reuters21578-10, and models KNN (full and reduced dimension cases) and Centroid:

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. 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? What option do we have to improve performance in these models?

Comparisons:

1. Describe why reduction in feature dimension has the effect you observe in KNN models. How do you think this is related to the data sample size?
1. How do the KNN and Centroid models compare? 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?

Lab reports and submission

When you have completed your report, title and export the file as soc290_lab3_your_last_name.pdf. Instructions will be given in class for how and when to submit your report.