Rupali Vohra (rv5rr) CS 4710: Classifier (Homework 4) Tuesday, April 28, 2015

Summary

The implementation I chose for my classifier involved use of the Naïve Bayes method. This allowed me to easily account for both discrete and continuous variables; a simple proportion was used for discrete features, while the assumption of a Gaussian distribution for continuous variables allowed me to predict outcomes based on means and variances found from the training set.

Approach

Though a bit messy, the best way I could think of to keep track of all the various features, whether it was continuous or discrete, and what the outcome was with that given feature was to have multiple maps that kept track of that information. Since I knew I would not be deleting anything from the map, I decided that HashMaps would be the most efficient way to solve the problem.

I ended up creating 9 HashMaps. One of these (featureOptions) keeps track of each feature, and maps it to an array of all the options available for that feature. This was used to populate other HashMaps that are used to keep track of how many times each of these options appears. Two such HashMaps (frequencyMapGreater and frequencyMapLess) were used to keep track of the number of times each option occurred, depending on whether the outcome was ">50K" or "<=50K," respectively. Similarly, I created two HashMaps (valueMapGreater and valueMapLess) to keep track of the values that appeared for each continuous variable, depending on whether the outcome was ">50K" or "<=50K," respectively. The maps for discrete variables were used to calculate proportions for probabilities, and the maps for continuous variables were used to calculate the means and variances for each feature, which was then used to calculate probabilities. The probabilities calculated from the discrete variables were stored in two HashMaps (featureProbGreater and featureProbLess), which mapped probabilities for which the classification was ">50K" in the former and outcomes where the classification was "<=50K" in the latter. Similarly, probabilities for continuous variables were tracked in two HashMaps: numericValsGreater, which stored data for when the outcome was ">50K."

All of the HashMaps were populated with data from the training set. The section of the training set I actually used while testing varied (more information given below). This variation did not, obviously, affect my general approach to the problem of making predictions. I did so by following the formula: $Y \leftarrow argmax_{y_k}P(Y=y_k)\prod_i P(X_i|Y=y_k)$. In other words, I calculated the probability that each outcome of each feature in the given test case would occur if the classification were ">50K," and compared that value to the probability that that each feature's outcome would occur if the classification were "<=50K," and selected the larger probability as my classification. In the event that these two probabilities tied, I decided to return an outcome based on the decision of a random number generator.

There is a stipulation in the Naïve Bayes approach for classification that mentions the conditional independence for all features in the data set. This is, as stated in the slides, a fairly large assumption, and one that does not hold for the given training set. Specifically, the education_num field is clearly highly correlated with the education_level field, and probably derived from that field. Since I created my Classifier to work without accounting for this at first, I decided it would be interesting to see the difference such an account would make in estimations. The results of this experiment are detailed below.

During testing, I noticed that certain sections of the training set produced better results than other sections. A good way to analyze this would probably be to randomize the training set and keep running these tests over and over again. Every time a feature is in a bucket with high predictive capabilities, that feature should gain a certain number of "points." After x iterations (x can be determined by whoever runs this analysis), the best training set would consist of the individual cases with the greatest number of points. I did not run this analysis, simply because of the time that it would require to do so. I did, however, attempt to run a similar analysis with the data I already had, and tried to determine which test cases seemed most representative of the entire population thereby yielding greater accuracy from my classifier. Further interpretation and data on this approach is included below.

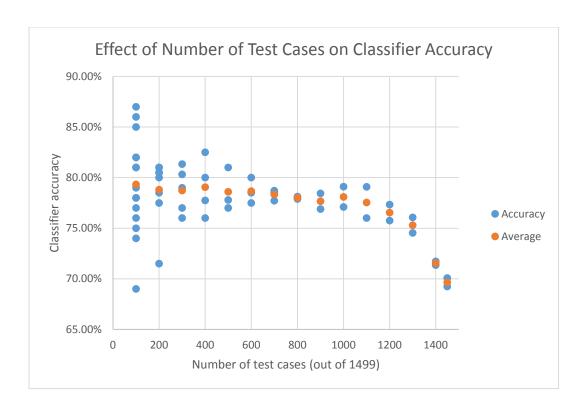
Testing and Interpretations

In order to speed up the testing process, I created a testing file called TestCaseGenerator.java. This class asks the user to provide how many of the 1499 training set cases the Classifier should use as part of the test cases, and uses the rest as the training set. Then, in order to vary the location of the test data within the training set, the code loops through various positions in the list to create buckets of test cases, and uses the rest of the training set to train the Classifier. This class then creates the test and training files from the original training set (census.train), creates a solution file from what would have been the last column in the test data, runs the classifier's prediction, and then compares the output of the classifier to that of the solution. The code prints out the success rate of the classifier.

As previously stated, I was curious to see how including features that essentially measured the same thing factored into the prediction, so I decided to keep the education-num field for my first few tests. I then adjusted my classifier to ignore education-num in its predictions, and compared the results from that version of the classifier.

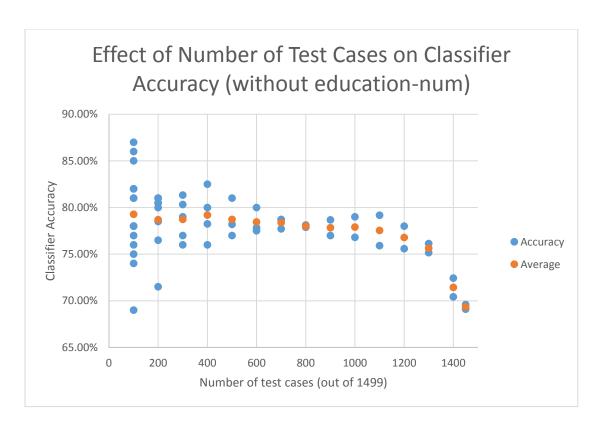
The following chart summarizes my results with the classifier that did include education-num in its predictions. There are multiple data points per training set size because I rotated where in the data my test set was located. The various data points depict the variation in results as that test set location changed. If you are curious about which specific sections led to which results, please see the appendix at the end of this write up.

¹ I have included this testing file with my source code, but since the assignment instructions specifically said not to include any other output, the testing file will not work. It relies on the Classifier saving output to a file called "mysol," the code for which has been commented out for submission.

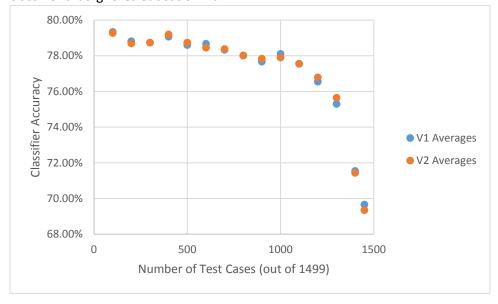


From the graph, we can tell that the number of test cases does not really matter until more than 1000 members of the training set are used as test cases, leaving only 499 cases to train on. An interesting effect is seen especially in the lower test case buckets; there is a lot of variance in the success depending on which bucket the classifier uses for the tests. This makes me wonder if there are certain portions of the training set that are more representative of the general population, and are therefore better suited to predicting outcomes. If this is true, it makes sense that there is less variance in the cases where the test set is large. Because there are only 1499 elements in all, there is a lot of overlap in the two test sets, especially at the greatest sizes of test cases.

Before exploring this possibility, I carried on with my experiment that attempted to determine whether including education-num negatively impacted the Classifier's ability to accurately classify a given test case. I adjusted my classifier to ignore the education-num values in the training set, and ran all of the same tests as before again. The results of these tests are depicted by the graph below. More in depth detail is included in the appendix.



From these two graphs, it is clear that the general trend of the classifier's accuracy is not affected whether education-num is factored in or not. The graph depicting both versions' average accuracies for each bucket size indicate that there is not much of a difference in accuracy by value, either. In this graph, V1 refers to the classifier that includes education-num, while V2 refers to the classifier that ignores education-num.



I now decided to try and determine an optimal training set based on the results of this experiment, specifically using the data included in the appendix. I assigned points to each case depending on the prior data's results. These point values are available in the appendix. There seemed to

be a drop in the points at around the 1000th element, so I decided to cut off the cases with the lowest 499 point values from the original census.train file, and created a new training file² with the higher-valued cases. While attempting to run similar tests with the smaller data set, I had to rearrange my testing code, ultimately causing the training set's location to be rotated instead of the test set. This caused a marked difference in the results, and the relative comparison between the two tests no longer gives any meaningful data. Because I had spent so long working on this, I decided to include the progress I had made in creating a new training set, but I am not sure how well it works.

It is interesting, however, that changing whether the testing set is rotated or the training set is rotated makes a difference. Further analysis into the specific features causing these variations in the data could be interesting to look at.

Appendix

For the following data, the first bolded line describes the test numbers relevant to the given information. This information includes the cardinality of the training set and the cardinality of the test set. The second line describes the average accuracy of the classifier for the given set sizes across all buckets. Finally, each set of two lines describes the information for a given test. The first line of each test describes the section in the training set from which the test set was taken. For example, if the test set was of size 100 and the test section is 0, the first 100 elements of the training set were taken as test cases, and the remaining 1399 elements would be assigned to be the training set. Because 1499 is not evenly divisible by the increments used for testing, the last test section overlaps some data with the test section before it. In other words, the size of the test data is always maintained in any given set of test cases.

Tests 1-2: 49 training set, 1450 test set Average classifier accuracy: 69.66%

Test 1: test section 0 Classifier accuracy: 69.24% **Test 2**: test section 1

Classifier accuracy: 70.07%

Tests 3-4: 99 training set, 1400 test set Average classifier accuracy: 71.54%

Test 3: test section 0 Classifier accuracy: 71.36% **Test 4:** test section 1

Classifier accuracy: 71.72%

Tests 5-6: 199 training set, 1300 test set Average classifier accuracy: 75.31%

Test 3: test section 0

Classifier accuracy: 74.53%

Classifier accuracy: 76.07%

Test 4: test section 1

Tests 7-8: 299 training set, 1200 test set Average classifier accuracy: 76.54%

Test 3: test section 0

Classifier accuracy: 77.33%

Test 4: test section 1 Classifier accuracy: 75.75%

Tests 9-10: 399 training set, 1100 test set

Average classifier accuracy: 77.55%

Test 9: test section 0 Classifier accuracy: 76.00% **Test 10:** test section 1 Classifier accuracy: 79.09%

² Included in submission; called modified_census.train

Tests 11-12: 499 training set, 1000 test set

Average classifier accuracy: 78.05%

Test 11: test section 0 Classifier accuracy: 77.10% **Test 12:** test section 1 Classifier accuracy: 79.10%

Tests 13-14: 599 training set, 900 test set

Average classifier accuracy: 77.67%

Test 13: test section 0 Classifier accuracy: 76.89% **Test 14:** test section 1 Classifier accuracy: 78.44%

Tests 15-16: 699 training set, 800 test set

Average classifier accuracy: 78.00%

Test 6: test section 0 Classifier accuracy: 78.13% **Test 7**: test section 1

Classifier accuracy: 77.89%

Tests 17-19: 799 training set, 700 test set

Average classifier accuracy: 78.33%

Test 17: test section 0 Classifier accuracy: 78.57% Test 18: test section 1 Classifier accuracy: 77.71% Test 19: test section 2 Classifier accuracy: 78.71%

Tests 20-22: 899 training set, 600 test set

Average classifier accuracy: 78.67%

Test 20: test section 0 Classifier accuracy: 78.50% Test 21: test section 1 Classifier accuracy: 77.50% Test 22: test section 2 Classifier accuracy: 80.00%

Tests 23-25: 999 training set, 500 test set

Average classifier accuracy: 78.60%

Test 23: test section 0 Classifier accuracy: 77.80%

Test 24: test section 1 Classifier accuracy: 77.00% **Test 25:** test section 2

Classifier accuracy: 81.00%

Tests 26-29: 1099 training set, 400 test set

Average classifier accuracy: 79.06%

Test 26: test section 0 Classifier accuracy: 77.75% Test 27: test section 1 Classifier accuracy: 80.00% Test 28: test section 2 Classifier accuracy: 76.00% Test 29: test section 3 Classifier accuracy: 82.50%

Tests 30-34: 1199 training set, 300 test set

Average classifier accuracy: 78.73%

Test 30: test section 0 Classifier accuracy: 77.00% Test 31: test section 1 Classifier accuracy: 80.33% Test 32: test section is 2 Classifier accuracy: 76.00% Test 33: test section 3 Classifier accuracy: 79.00% Test 34: test section 4

Classifier accuracy: 81.33%

Tests 35-42: 1299 training set, 200 test set

Average classifier accuracy: 78.81%

Test 35: test section 0 Classifier accuracy: 77.50% Test 36: test section 1 Classifier accuracy: 80.00% Test 37: test section 2 Classifier accuracy: 80.50% Test 38: test section 3 Classifier accuracy: 81.00% Test 39: test section 4

Classifier accuracy: 71.50% **Test 40:** test section 5

Classifier accuracy: 80.50%

Test 41: test section 6

Classifier accuracy: 78.50% **Test 42:** test section 7 Classifier accuracy: 81.00%

Tests 43-57: 1399 training set, 100 test set

Average classifier accuracy: 79.33%

Test 43: test section 0
Classifier accuracy: 79.00%
Test 44: test section 1
Classifier accuracy: 78.00%
Test 45: test section 2
Classifier accuracy: 77.00%
Test 46: test section 3
Classifier accuracy: 82.00%
Test 47: test section 4
Classifier accuracy: 81.00%
Test 48: test section 5
Classifier accuracy: 81.00%

Without education-num results:

Tests 1-2: 49 training set, 1450 test set Average classifier accuracy: 69.34%

Test 1: test section 0 Classifier accuracy: 69.10% **Test 2**: test section 1

Classifier accuracy: 69.59%

Tests 3-4: 99 training set, 1400 test set Average classifier accuracy: 71.43%

Test 3: test section 0 Classifier accuracy: 70.43% **Test 4:** test section 1

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Classifier accuracy: 72.43%

Tests 5-6: 199 training set, 1300 test set Average classifier accuracy: 75.73%

Test 3: test section 0 Classifier accuracy: 75.15%

Test 4: test section 1

Classifier accuracy: 76.31%

Tests 7-8: 299 training set, 1200 test set Average classifier accuracy: 76.79%

Test 49: test section 6
Classifier accuracy: 85.00%
Test 50: test section 7
Classifier accuracy: 78.00%
Test 51: test section 8
Classifier accuracy: 69.00%
Test 52: test section 9
Classifier accuracy: 74.00%
Test 53: test section 10
Classifier accuracy: 76.00%
Test 54: test section 11
Classifier accuracy: 86.00%
Test 55: test section 12
Classifier accuracy: 82.00%

Classifier accuracy: 82.00% **Test 56:** test section 13 Classifier accuracy: 75.00% **Test 57:** test section 14 Classifier accuracy: 87.00%

Test 3: test section 0 Classifier accuracy: 75.58%

Test 4: test section 1

Classifier accuracy: 78.00%

Tests 9-10: 399 training set, 1100 test set Average classifier accuracy: 77.55%

Test 9: test section 0 Classifier accuracy: 75.91% Test 10: test section 1 Classifier accuracy: 79.18%

Tests 11-12: 499 training set, 1000 test set

Average classifier accuracy: 77.90%

Test 11: test section 0 Classifier accuracy: 76.80% **Test 12:** test section 1 Classifier accuracy: 79.00%

Tests 13-14: 599 training set, 900 test set

Average classifier accuracy: 77.83%

Test 13: test section 0 Classifier accuracy: 77.00%

Test 14: test section 1 Classifier accuracy: 78.67%

Tests 15-16: 699 training set, 800 test set Average classifier accuracy: 78.00%

Test 6: test section 0 Classifier accuracy: 78.13% **Test 7**: test section 1

Classifier accuracy: 77.88%

Tests 17-19: 799 training set, 700 test set

Average classifier accuracy: 78.38%

Test 17: test section 0 Classifier accuracy: 78.71% Test 18: test section 1 Classifier accuracy: 77.71% Test 19: test section 2 Classifier accuracy: 78.71%

Tests 20-22: 899 training set, 600 test set

Average classifier accuracy: 78.44%

Test 20: test section 0 Classifier accuracy: 77.83% Test 21: test section 1 Classifier accuracy: 77.50% Test 22: test section 2 Classifier accuracy: 80.00%

Tests 23-25: 999 training set, 500 test set

Average classifier accuracy: 78.73%

Test 23: test section 0 Classifier accuracy: 78.20% Test 24: test section 1 Classifier accuracy: 77.00% Test 25: test section 2 Classifier accuracy: 81.00%

Tests 26-29: 1099 training set, 400 test set

Average classifier accuracy: 79.19%

Test 26: test section 0
Classifier accuracy: 78.25%
Test 27: test section 1
Classifier accuracy: 80.00%
Test 28: test section 2

Classifier accuracy: 76.00% **Test 29:** test section 3 Classifier accuracy: 82.50%

Tests 30-34: 1199 training set, 300 test set

Average classifier accuracy: 78.73%

Test 30: test section 0 Classifier accuracy: 77.00% Test 31: test section 1 Classifier accuracy: 80.33% Test 32: test section is 2 Classifier accuracy: 76.00% Test 33: test section 3 Classifier accuracy: 79.00%

Test 34: test section 4 Classifier accuracy: 81.33%

Tests 35-42: 1299 training set, 200 test set

Average classifier accuracy: 78.69%

Test 35: test section 0
Classifier accuracy: 76.50%
Test 36: test section 1
Classifier accuracy: 80.00%
Test 37: test section 2
Classifier accuracy: 80.50%

Test 38: test section 3 Classifier accuracy: 81.00% Test 39: test section 4 Classifier accuracy: 71.50% Test 40: test section 5 Classifier accuracy: 80.50% Test 41: test section 6 Classifier accuracy: 78.50% Test 42: test section 7

Classifier accuracy: 81.00%

Tests 43-57: 1399 training set, 100 test set

Average classifier accuracy: 79.27%

Test 43: test section 0
Classifier accuracy: 78.00%
Test 44: test section 1
Classifier accuracy: 78.00%
Test 45: test section 2
Classifier accuracy: 77.00%

Test 46: test section 3
Classifier accuracy: 82.00%
Test 47: test section 4
Classifier accuracy: 81.00%
Test 48: test section 5
Classifier accuracy: 81.00%
Test 49: test section 6
Classifier accuracy: 85.00%
Test 50: test section 7
Classifier accuracy: 78.00%
Test 51: test section 8
Classifier accuracy: 69.00%

Test 52: test section 9
Classifier accuracy: 74.00%
Test 53: test section 10
Classifier accuracy: 76.00%
Test 54: test section 11
Classifier accuracy: 86.00%
Test 55: test section 12
Classifier accuracy: 82.00%
Test 56: test section 13
Classifier accuracy: 75.00%
Test 57: test section 14
Classifier accuracy: 87.00%

Point values for each case:

Note that the "case number" refers to the line in the original census.train file.

Case	Total
number	points
1399	63.5
1199	62.5
1400	60.5
1200	59.5
1300	58
1101	57.5
1102	57.5
1103	57.5
1104	57.5
1105	57.5
1106	57.5
1107	57.5
1108	57.5
1109	57.5
1110	57.5
1111	57.5
1112	57.5
1113	57.5
1114	57.5
1115	57.5
1116	57.5
1117	57.5
1118	57.5
1119	57.5
1120	57.5
1121	57.5

1122	57.5
1123	57.5
1124	57.5
1125	57.5
1126	57.5
1127	57.5
1128	57.5
1129	57.5
1130	57.5
1131	57.5
1132	57.5
1133	57.5
1134	57.5
1135	57.5
1136	57.5
1137	57.5
1138	57.5
1139	57.5
1140	57.5
1141	57.5
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1167	57.5
1168	57.5
1169	57.5
1170	57.5
1171	57.5
1172	57.5
1173	57.5
1174	57.5
1175	57.5
1176	57.5
1177	57.5

1178	57.5
1179	57.5
1180	57.5
1181	57.5
1182	57.5
1183	57.5
1184	57.5
1185	57.5
1186	57.5
1187	57.5
1188	57.5
1189	57.5
1190	57.5
1191	57.5
1192	57.5
1193	57.5
1194	57.5
1195	57.5
1196	57.5
1197	57.5
1198	57.5
1401	55.5
1402	55.5
1403	55.5
1404	55.5
1405	55.5
1406	55.5
1407	55.5
1408	55.5
1409	55.5
1410	55.5
1411	55.5
1412	55.5
1413	55.5
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1470	54.5
1471	54.5
1472	54.5
1473	54.5
1474	54.5
1475	54.5
1476	54.5
1477	54.5
1478	54.5
1479	54.5
1480	54.5
1481	54.5
1482	54.5
1483	54.5
1484	54.5
1485	54.5
1486	54.5
1487	54.5
1488	54.5
1489	54.5
1490	54.5
1491	54.5
1492	54.5
1493	54.5
1494	54.5
1495	54.5
1496	54.5
1497	54.5
1498	54.5
1499	54.5
700	52.5
601	51.5
602	51.5
603	51.5
604	51.5
605	51.5
606	51.5
607	51.5
608	51.5
300	

609	51.5
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616	51.5
617	51.5
618	51.5
619	51.5
620	51.5
621	51.5
622	51.5
623	51.5
624	51.5
625	51.5
626	51.5
627	51.5
628	51.5
629	51.5
630	51.5
631	51.5
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691	51.5
692	51.5
693	51.5
694	51.5

695	51.5
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697	51.5
698	51.5
699	51.5
1201	50.5
1202	50.5
1203	50.5
1204	50.5
1205	50.5
1206	50.5
1207	50.5
1208	50.5
1209	50.5
1210	50.5
1211	50.5
1212	50.5
1213	50.5
1214	50.5
1215	50.5
1216	50.5
1217	50.5
1218	50.5
1219	50.5
1220	50.5
1221	50.5
1222	50.5
1223	50.5
1224	50.5
1225	50.5
1226	50.5
1227	50.5
1228	50.5
1229	50.5
1230	50.5
1231	50.5
1232	50.5
1233	50.5
1234	50.5
1235	50.5
1236	50.5
1237	50.5
1238	50.5
1230	30.3

1239	50.5
1240	50.5
1241	50.5
1242	50.5
1243	50.5
1244	50.5
1245	50.5
1246	50.5
1247	50.5
1248	50.5
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1250	50.5
1251	50.5
1252	50.5
1253	50.5
1254	50.5
1255	50.5
1256	50.5
1257	50.5
1258	50.5
1259	50.5
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1261	50.5
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1268	50.5
1269	50.5
1270	50.5
1271	50.5
1272	50.5
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1274	50.5
1275	50.5
1276	50.5
1277	50.5
1278	50.5
1279	50.5
1280	50.5
1281	50.5

1282	50.5
1283	50.5
1284	50.5
1285	50.5
1286	50.5
1287	50.5
1288	50.5
1289	50.5
1290	50.5
1291	50.5
1292	50.5
1293	50.5
1294	50.5
1295	50.5
1296	50.5
1297	50.5
1298	50.5
1299	50.5
600	50.5
500	49
1100	48.5
1301	48.5
1301	48.5
1303	48.5
1304	48.5
1305	48.5
1306	48.5
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