Supervised Learning - Report

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Introduction

For this assignment, I picked two completely different datasets in terms of their characteristics for classification problems so that I can learn applying supervised learning algorithms on a more well-rounded way. The first dataset is somewhat a larger dataset where it consists of more than 48000 records. It is a binary classification problem and the features are categorical. The second dataset I picked is a much smaller dataset with only 304 records, and it is also a multi-class problem. For each dataset, I will explain what I did to preprocess them and then go into each of the supervised learning algorithms I applied and their corresponding performance.

For tools, I primarily used Python's scikit-learn library to perform machine learning tasks and used various libraries, including matplotlib and sklearn-evaluation to graph various performance metrics and results of the applied algorithms.

Dataset One

Preprocessing

The first dataset is from UC Irvine Machine Learning Repository, and it is called Adult data set. This is an extraction from the 1994 Census database and prediction task is to determine whether a person makes over 50K a year. Once I loaded the data with headers and the right delimiter, without any preprocessing, the dataset looks like this:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	incomeCategory
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K

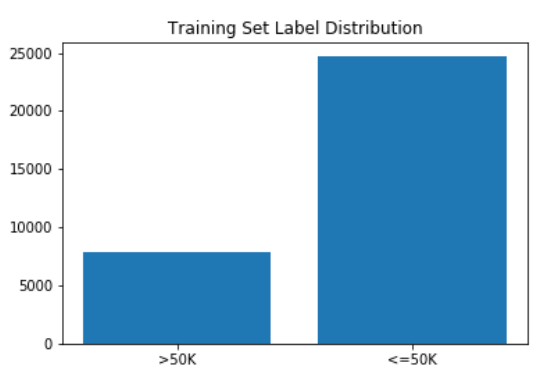
As you can seem the dataset is full of categorical features and the label (incomeCategory) is a string representation as well. Because scikit-learn's classification algorithms will not accept any string representation features, one of the first tasks is to convert them to numerical. I could enumerate the categories for each feature, for example, 0 for "Bachelors" and 1 for "HS-grad" in education, but scikit-learn will treat them as continuous data, as a result, the models could provide wrong "understanding" of these features. So the solution is one-hot-encode all of them. After encoding, it will add extra columns for each category of each of the feature. For example, row 0 will have education_Bachelors as 1, meaning it indeed has a education of Bachelors for the feature, and everything other columns for education is 0. Also, I converted the labels into 0s and 1s where 0 is "<=50K" and 1 is ">50K". Then, there were also a handful missing data, so I just set them as 0. After preprocessing, the dataset looks like this:

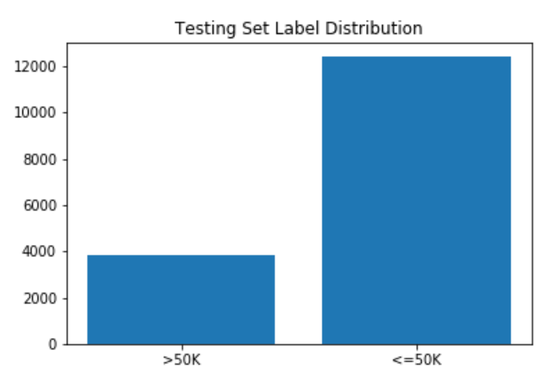
	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	workclass_?	workclass_Federal-gov	workclass_Local-gov	workclass_Never-worked	...	native-country_Puerto-Rico	nat country_Scotl
0	25	226802	7	0	0	40	0	0	0	0	...	0	
1	38	89814	9	0	0	50	0	0	0	0	...	0	
2	28	336951	12	0	0	40	0	0	1	0	...	0	
3	44	160323	10	7688	0	40	0	0	0	0	...	0	
4	18	103497	10	0	0	30	1	0	0	0	...	0	

5 rows × 108 columns

Data Investigation

After preprocessing them, I randomly divided the dataset up into thirds, 2/3 will be used for training, and 1/3 will be used to testing. Then, I wanted to check the labels to see if the distribution of classes are even. Here is the result:

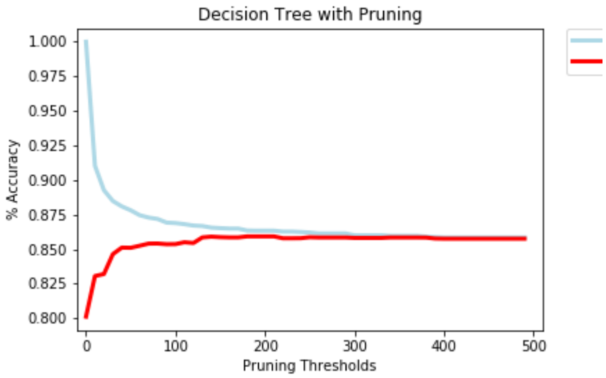




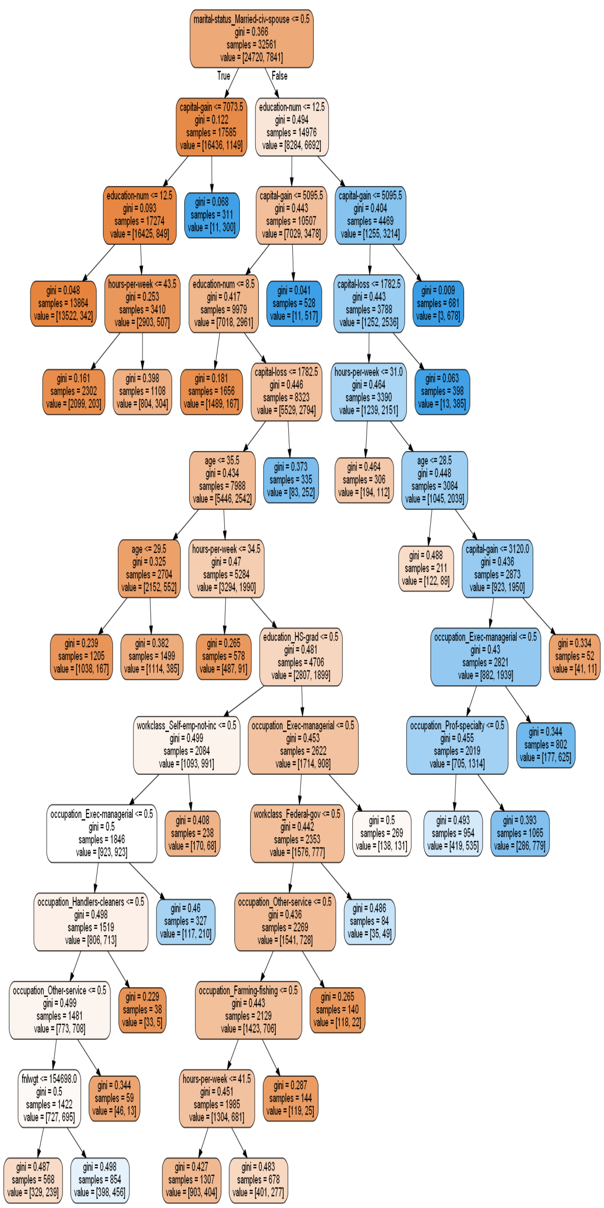
As you can see, there are far more "<=50K" labels in both the training set and testing set. So to make sure the machine learning models are performant, I should not only look at accuracy score but also f1 scores.

Decision Tree

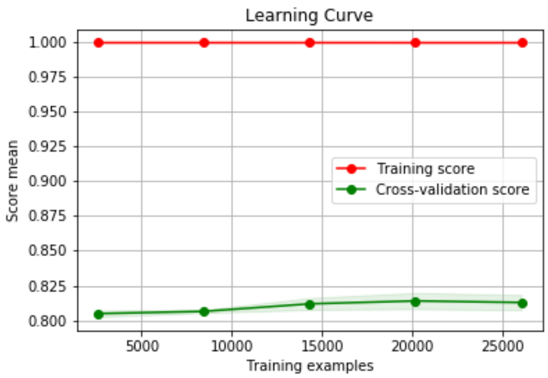
For decision tree classifier, I used scikit-learn's `DecisionTreeClassifier()` to create the model. Without pruning, the tree has more than 9000 nodes! This is very large and definitely susceptible to overfitting. So I used a custom pruning method to prune the tree after modeling. The custom pruning method takes in a threshold parameter and utilize it to check the value of each node and if the smallest value of the node is below that threshold, it will prune it and its children out. Here is a graph representing the benefit of this pruning process:



As you can see, without any pruning, the model is overfitting there it is at almost 100% accuracy when predicting training set while it is not doing so hot for testing set. As the pruning threshold increases, predictions for training set and testing set are converaging, and overfitting fades out. The final tree looks like this:

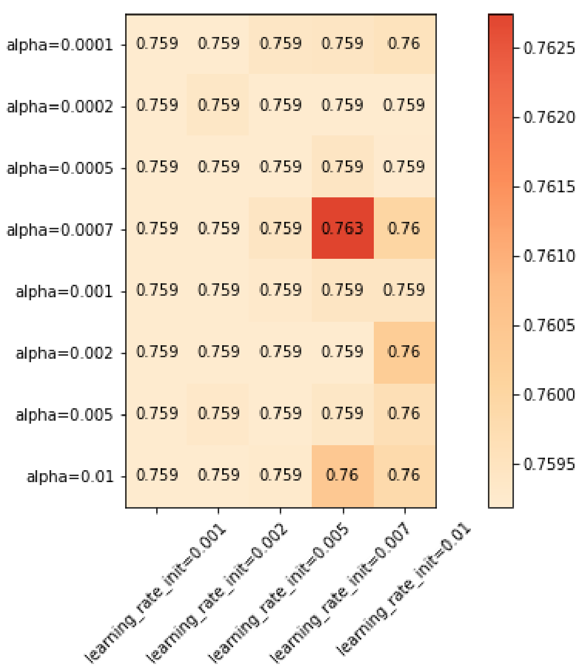


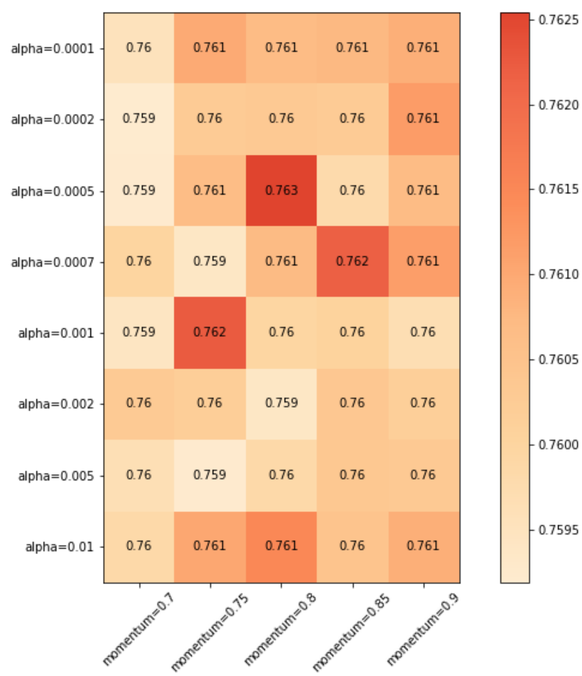
The learning curve for the best model created above is the following:



Neural Networks

For this algorithm, I used `MLPClassifier()`, and specifically, I used logistic regression in combination of stochastic gradient descent for activation because according to the lecture, calculus is better. I also incorporated k-fold cross-validation and hyperparameter tunning to try to get the best result from this algorithm. For this, I used `GridSearchCV()` provided by scikit-learn. The result is this:





As you can see that the accuracy is around 76.3% and could not get any higher as I tune the parameters. Here is the f1 score result I got from the more accurate model:

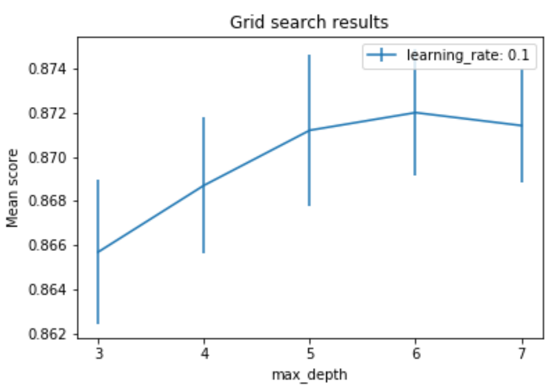
```
             precision    recall  f1-score   support

      <=50K       0.76      1.00      0.87     12435
       >50K       1.00      0.00      0.01      3846

avg / total       0.82      0.76      0.66     16281
```

Even though the precision for ">50K" is at 1, the recall is at 0, causing f1 score to be very low. Comparatively, the model I was able to produce from neural networks is not as good as the decision tree model above. Let's look at the learning curve:

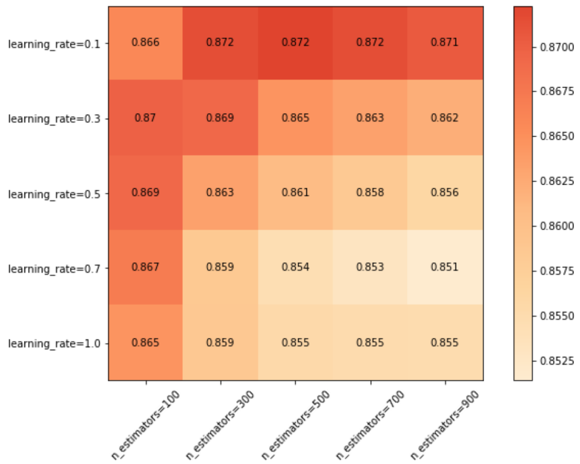
Boosting

Here I am using `GradientBoostingClassifier()` which uses gradient tree boosting, a generalization of boosting to arbitrary differentiable loss functions. There are a number of parameters that I can tune for this classifier, and I am going to focus on the number of estimators, the learning rate, and maximum depth of the gradient decision tree. The graph below shows a fixed learning rate with a variation of numbers of estimators.

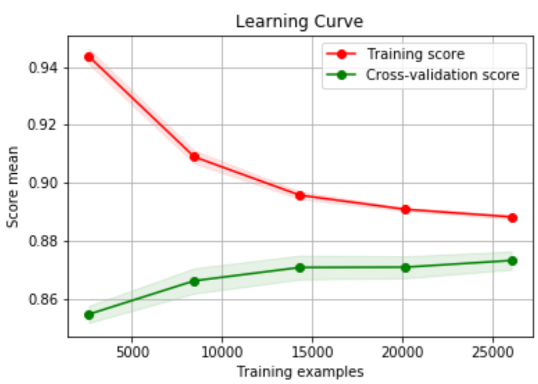
As you can see that the cross validation mean accuracies reaches a peak at 500 estimators. Let's see anothe graph oh maximum depth with fixed learning rate to see if it makes much difference in accuracy.



This shows that the cross-validation accuracy is the highest when the max depth is at 6. Now, let's do a grid search on variations of numbers of estimators and learning rate, setting max depth as 6.

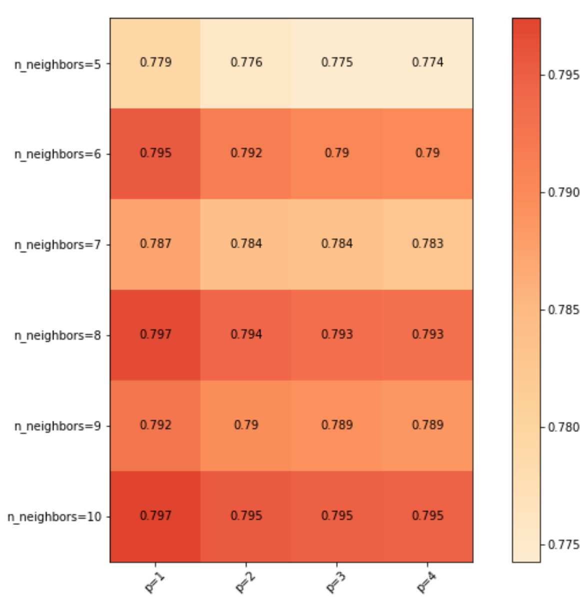


From the graph, as you can see that the best accuracy I could get is using learning rate of 0.1, number of estimators of 900, with a max depth of 6. The learning curve for these parameters is:

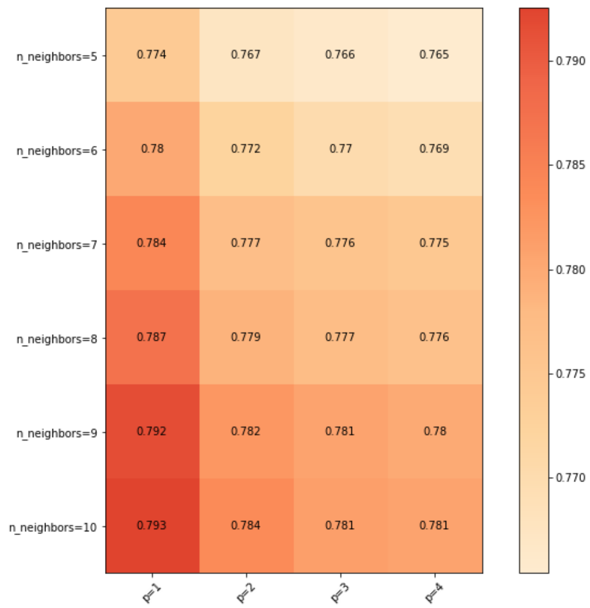


KNN

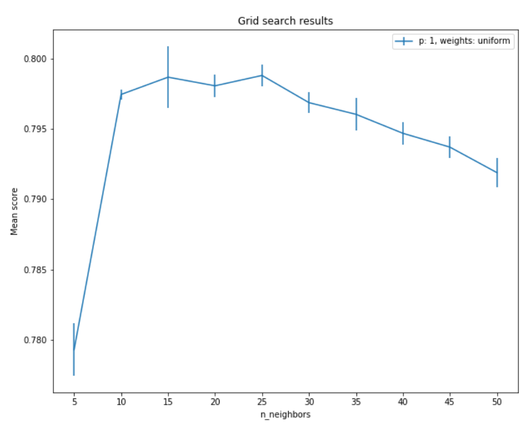
Again, I am using scikit-learn's KNN algorithm `KNeighborsClassifier()`. For this method, I am tunning number of neighbors, the weights on the neighbors, and a p value which is power parameter for the Minkowski metric. When p is 1, this is equivalent to using manhattan distance, and euclidean_distance for p is 2. For arbitrary p, minkowski distance is used. The first graph I am showing below is using uniform weights for the nearest neighbors.



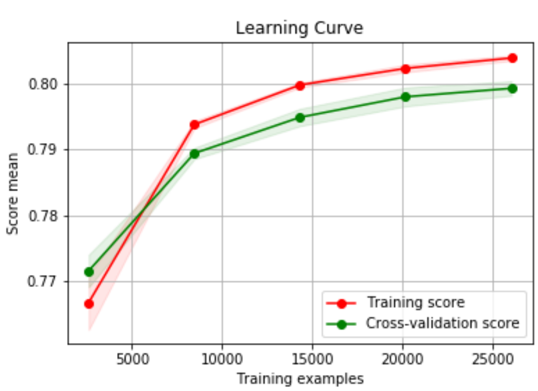
As you can see that the cross validation accuracy is higher then the number of neighbors increases. It also shows that manhattan distance creates better accuracies overall for my dataset. The next graph, I am using the "distance" weights which means the closer neighbors will have higher weights.



Again, it has similar trends as the last graph's where the accuracy increases as the number of neighbors increases. Also, manhattan distance has beeter accuray. Now, let's have a constant p value and uniform weight.



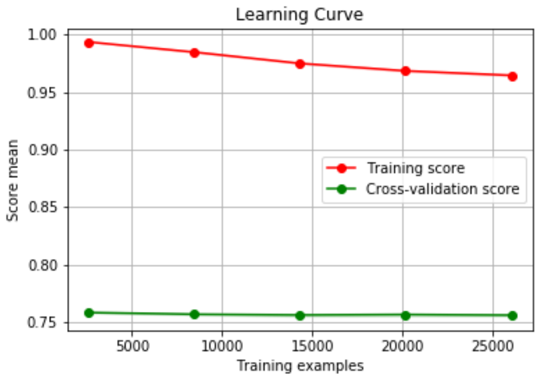
The learning curve for the best model created by KNN is the following:



Support Vector Machine

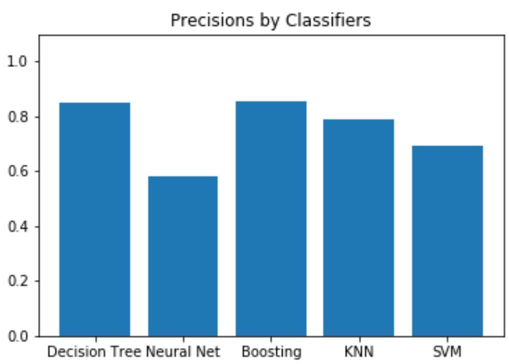
Using scikit-learn's SVM classifier, it is pretty slow to train a model running on my machine. Once I added k-fold cross validation, it doesn't finish at all. In their documentation, it says that "the fit time complexity is more than quadratic with the number of samples which makes it hard to scale to dataset with more than a couple of 10000 samples." This dataset has more than 48000 training samples, as a result, I do any k-fold cross validation and parameters tunning because of the runtime and no convergency.

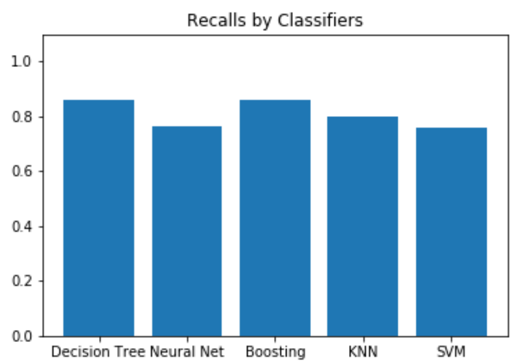
The learning curve for a basic model is the following:

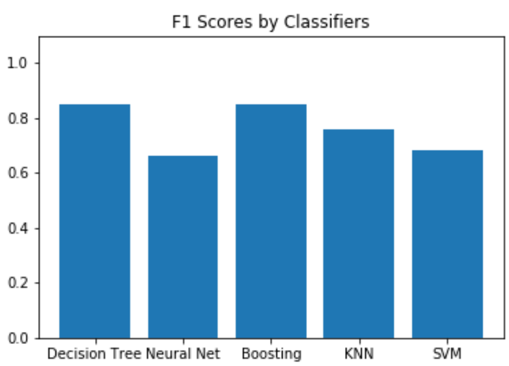


Conclusion

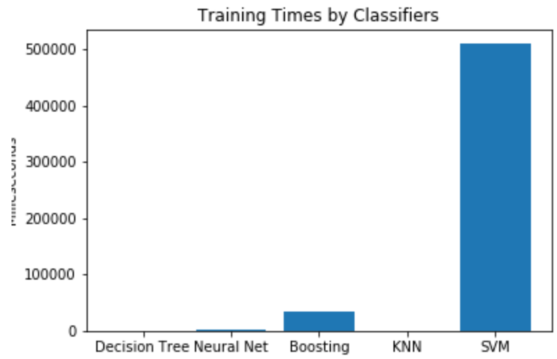
Now I am going to compare the precision, recall as well as f1 scores of the best models from each algorithm because they will provide me useful information in selecting classification algorithm for this dataset. Keep in mind that the training set label distribution is imbalanced so that f1 score is a better metric than just simply accuracy of the cross-validation.

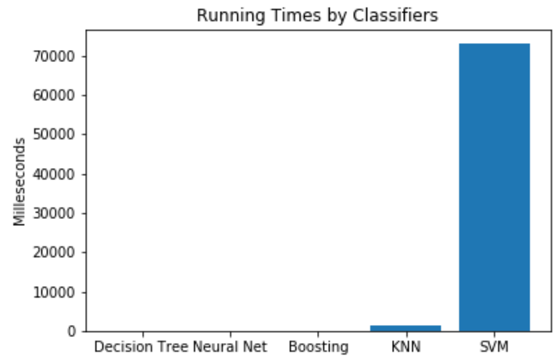






As you can see that boosting and decision tree algorithms are among the better ones. Let's look at the training and running times before making a conclusion.





From these two graphs, it shows that SVM algorithm take a significant amount of time to train compare to others. Decision tree models have better training times so decision tree is preferred over boosting algorithms for this dataset.

Things to Improve

There are a number of things I could improve on my analysis. For example, I did not do any feature selection when running these algorithms, and doing so might drastically improve the accuracy as some features might not be significant when training. Also, I could have tried up-sampling or down-sampling to make the label distribution more balanced to create a better training set for creating models. I am doing this for the next dataset though as you will see why.

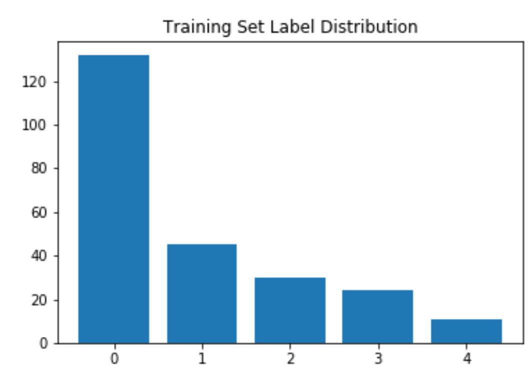
Dataset Two

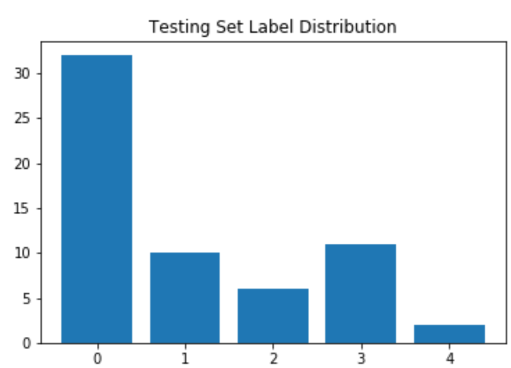
Data Preprocessing & Investigation

As I mentioned before, this dataset has 4 classes for its labels. It is from also from UCI's machine learning repository on heart disease data. It only has 303 records however, which caused some issues which I will describe in a little bit. There are 13 features from this dataset, and fortunately all of them are numeric so I don't need to do any encoding. The labels are ranging from 0 to 4 where 0 means no presence of heart disease. While range 1-4 means there are potential heart disease present where 1 means least likely and 4 means most likely. The dataset looks like this:

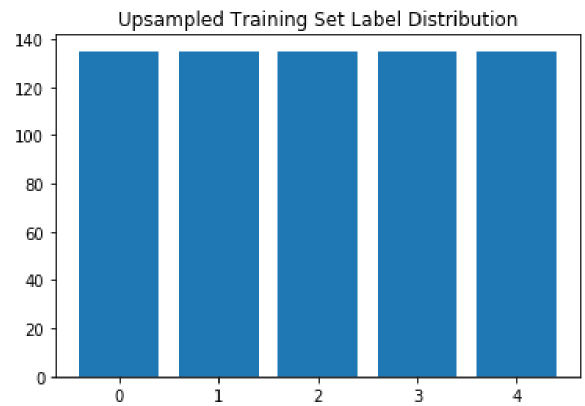
	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	cancerPresence
248	52.0	1.0	4.0	125.0	212.0	0.0	0.0	168.0	0.0	1.0	1.0	2.0	7.0	3
146	57.0	1.0	4.0	165.0	289.0	1.0	2.0	124.0	0.0	1.0	2.0	3.0	7.0	4
73	65.0	1.0	4.0	110.0	248.0	0.0	2.0	158.0	0.0	0.6	1.0	2.0	6.0	1
40	65.0	0.0	4.0	150.0	225.0	0.0	2.0	114.0	0.0	1.0	2.0	3.0	7.0	4
142	52.0	1.0	2.0	128.0	205.0	1.0	0.0	184.0	0.0	0.0	1.0	0.0	3.0	0

Then I split dataset into training and testing sets where testing set is 1/5 of the original dataset's size. The labels distributions for both training set and testing set looks like this:





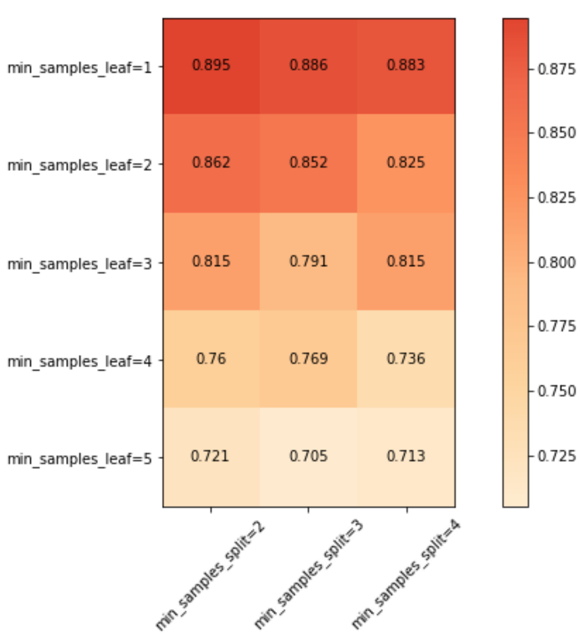
When I first saw these two graphs, I was doubting that the models created by this training set distribution might not be good because of the low number of samples for classes 1-4. However, I still went ahead and created some models to prove my doubt. Quickly after training a few models using decision tree and boosting algorithms, it shows that those models are only able to get around .59 accuracy and very low f1 scores where the recalls are close to 0 for classes 1-4. Even with lots of hyperparameters tunning, they are consistently low (below .6 accuracy scores). This indicates that I need to do something to the training set to make it evenly distributed. To do so, I used scikit-learn's `resample()` method which will resample arrays in a consistent way. Using this method, I resampled the samples having classes of 1-4 to be the same as class 0. The result label distribution is now even.

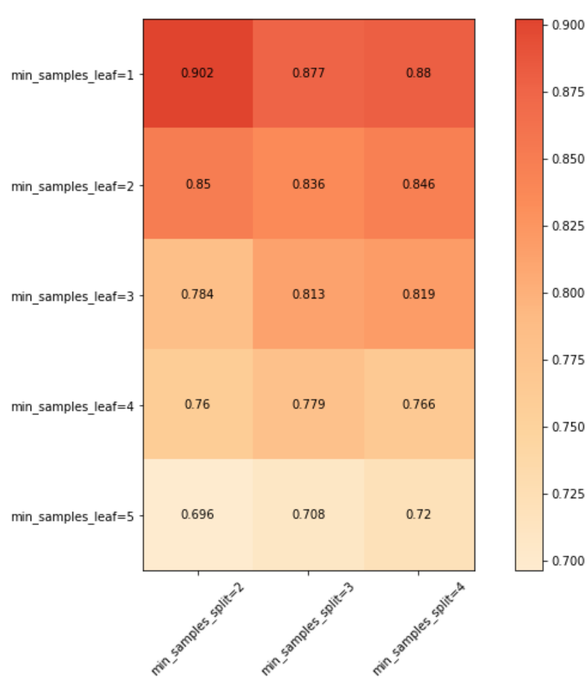


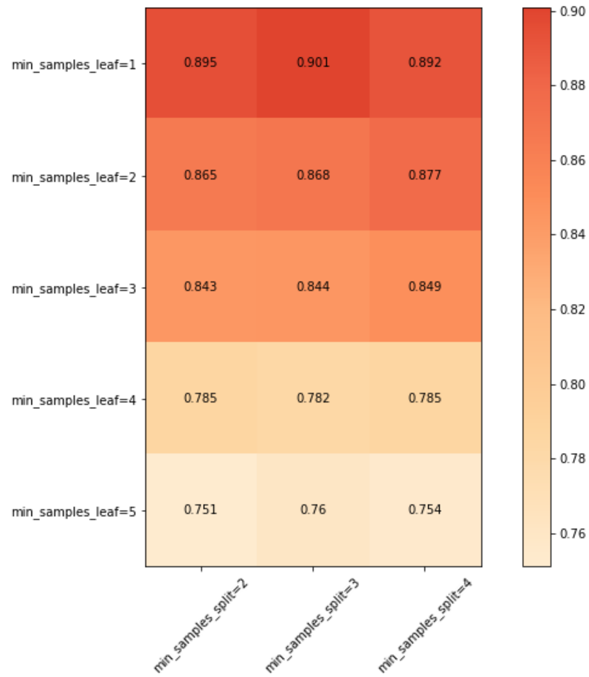
After doing so, the training set size went from around 242 to more than 500 with evenly distributed labels. Now, the dataset is finally ready for training.

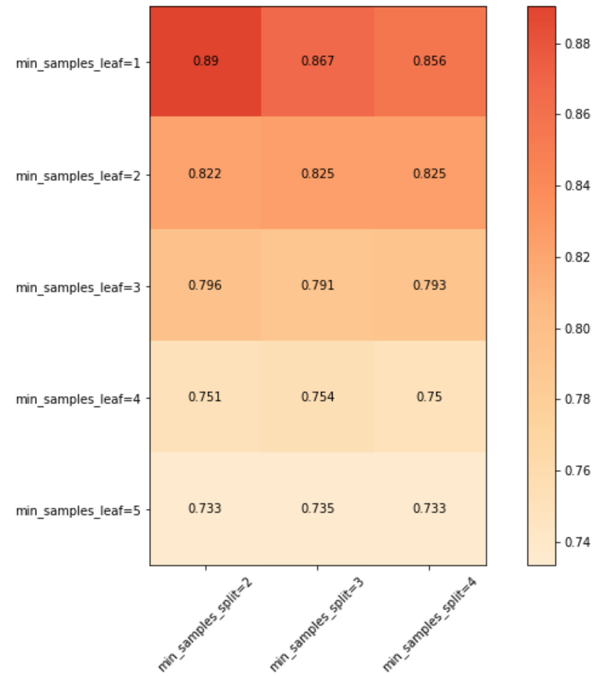
Decision Tree

Instead of using a custom pruning method, I used the built-in pruning parameters to tune the decision tree classifier for this dataset. Here I am tunning a combination of parameters, such as the minimum samples per leaf, the minimum samples per split, function to measure the quality of a split, and the strategy used to choose the split at each node.



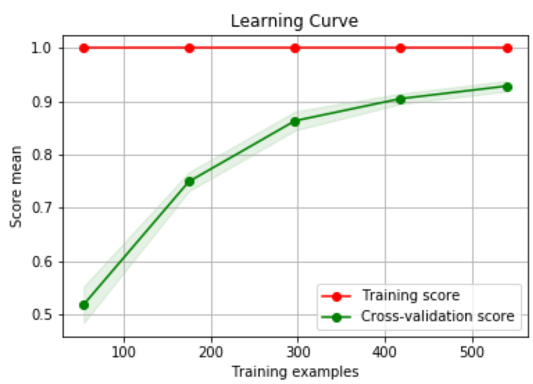






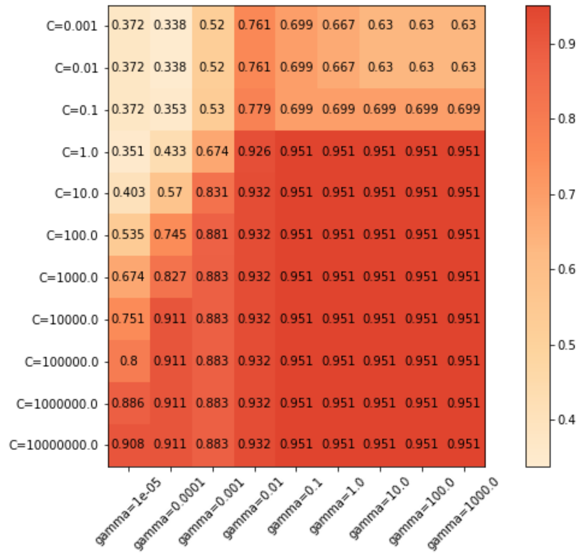
As you can see from these graphs that the best parameters are using the following: `{'criterion': 'gini', 'min_samples_leaf': 1, 'min_samples_split': 2, 'splitter': 'random'}`.

Using this set of parameters, the learning curve from it is the following:

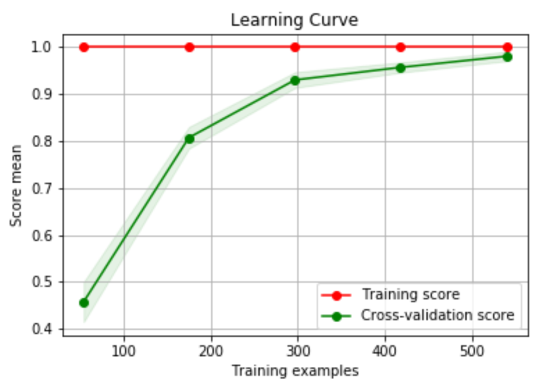


Support Vector Machine

Because of the dataset size, I am able to run more hypterparameters tunning because it is much faster per model training. Here I am tunning a penalty parameter C and gamma which is a kernel coefficient. Here is a graph of that:

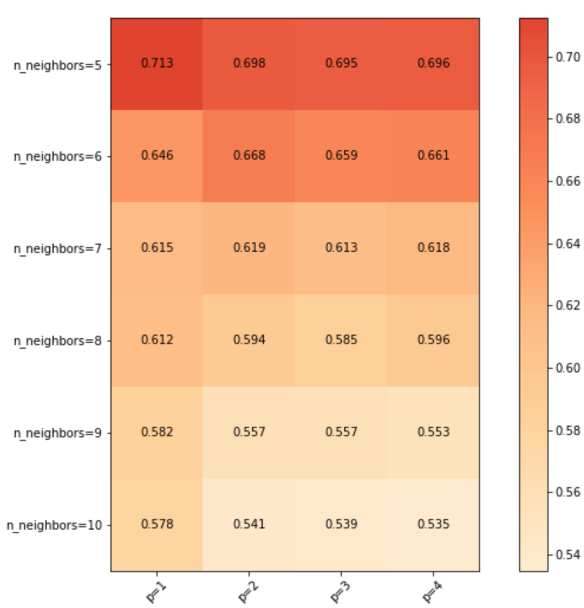


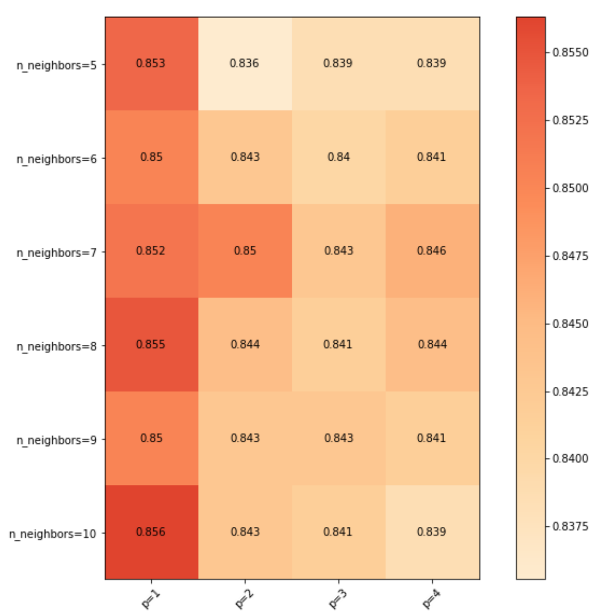
As you can see that there is a clear trend towards lower right of the graph. It is able to reach 0.951 cross-validation accuracy at `{'C': 1.0, 'gamma': 0.1}`. The learning curve for it is thw following:



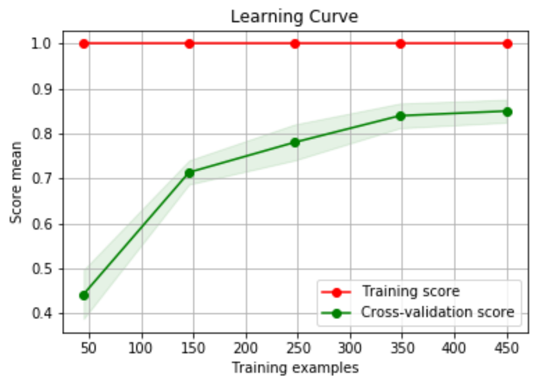
KNN

Here I am tunning the number of neighbors, weights, and a value p which I have described in previous example. The result is this where the first graph is using uniform weights while the second graph uses weights based on distance:



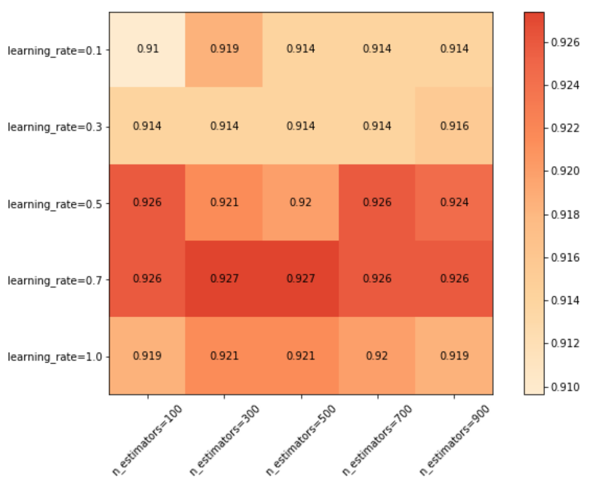


The best model created is using this set of parameters: `{'n_neighbors': 10, 'p': 1, 'weights': 'distance'}`. The learning curve using this is the following:

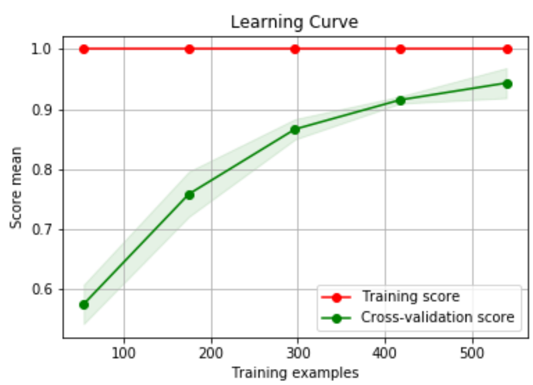


Boosting

Using the same scikit-learn gradient tree boosting method, I am tunning learning rate and number of estimators.

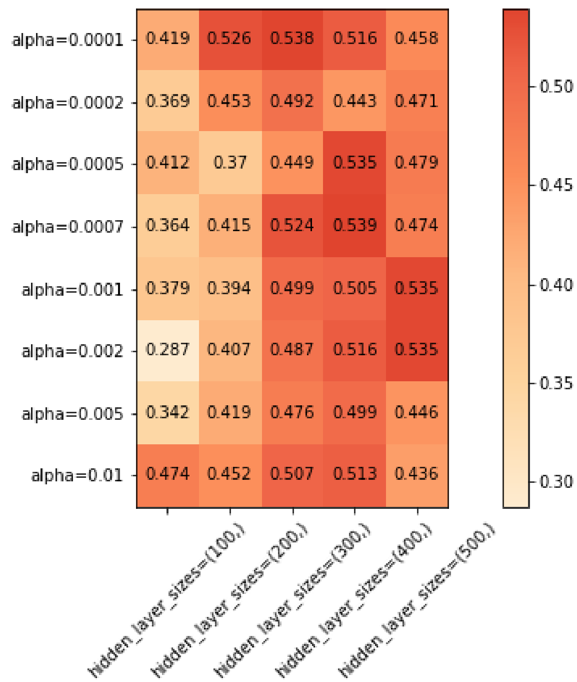


As you can see that the best model created while tunning parameters is using `{'learning_rate': 0.7, 'n_estimators': 300}`. The learning curve for this model is the following:

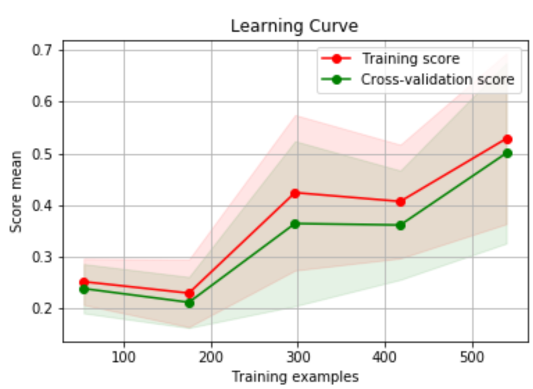


Neural Networks

For this dataset, I am tunning alphas, learning rates, and hidden layer sizes for the `MLPClassifier()`. Here is a graph showing the cross validation hyperparameters tunning result:



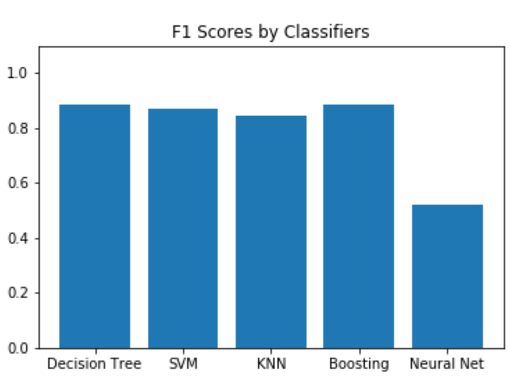
As you can see that the accuracy is low in general with the best model only having 0.538 accuracy. Here is a graph showing the learning curve:

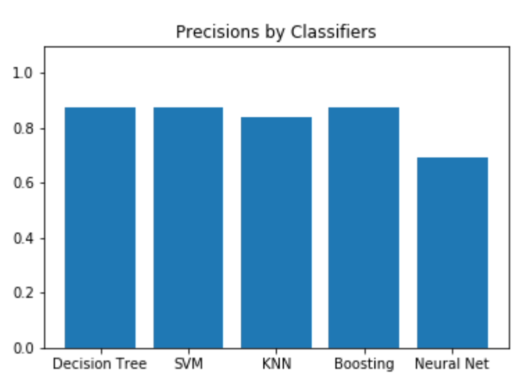


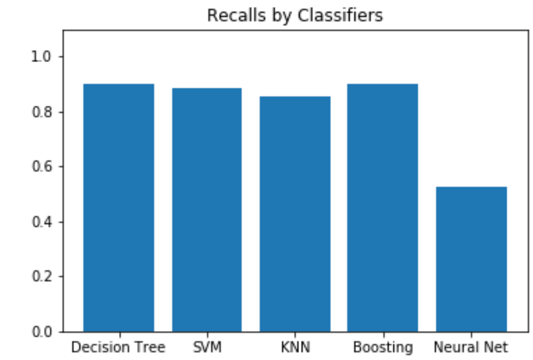
This shows somewhat a reason why I am getting low accuracy scores for MLPClassifer which is the number of training samples is low. As the training sample sizes increase, the scores tend to be better.

Conclusion

Now I am going to compare the precision, recall as well as f1 scores of the best models from each algorithm because they will provide me useful information in selecting classification algorithm for this dataset.

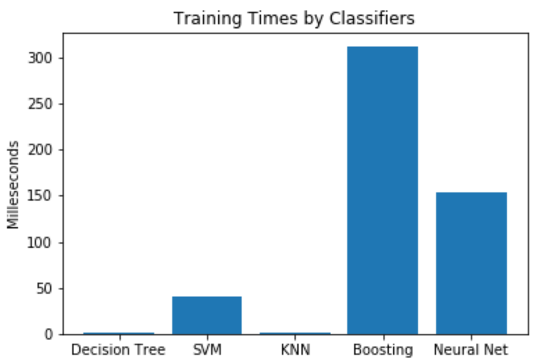


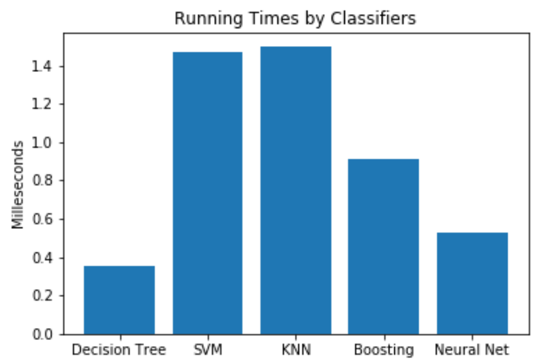




The result shows that the decision tree model has the highest f1 score of 0.9, precision of 0.88 and recall of 0.9. From this experiment, decision tree classifier after tunning can create the best result.

Now, let's compare training and running times between these classifiers.





Based on the graphs above, decision tree and KNN algorithms have the best training times for the best models. An average of 1.52 ms for decision tree and 1.23 for KNN. However, the running time of decision tree model clearly outpace the other algorithms'. Based on this and the previous analysis, decision tree is the better algorithm for this dataset.

Things to Improve

Again, I did not look at feature significance when training models. There are also issues with neural network model that I could have spent more time trying to improve such as upsampling all classes to create more training samples.