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Intro to Data Mining – DATS 6103
12/6/2021

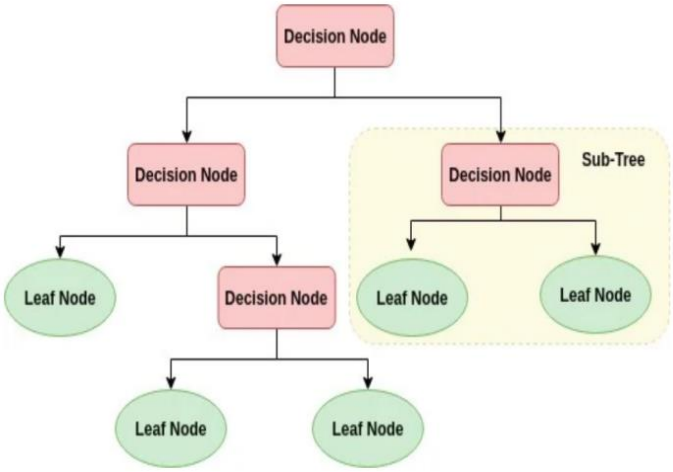
INDIVIDUAL FINAL REPORT – GROUP 4

DESCRIPTION

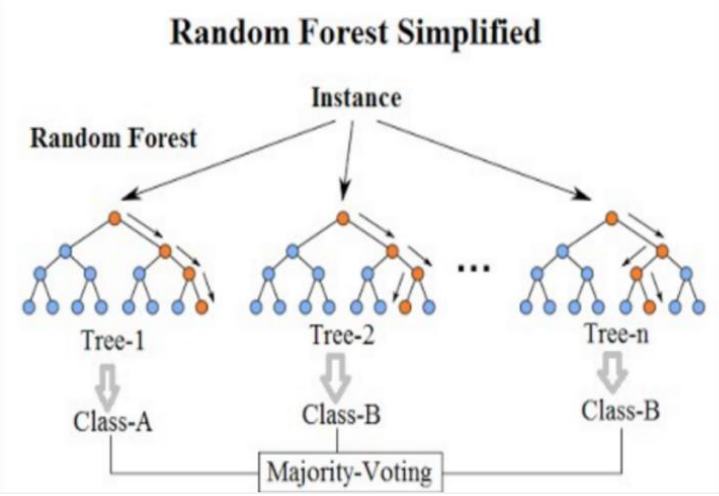
Our project examines factors that affect admission to the Masters programs in the US to see how well they predict the admission, using a dataset by UCLA graduates from Kaggle.

The workload for this project was broken into four:

- Data preprocessing
- Data visualization
- Machine learning modeling
- GUI (pyqt5)



A decision tree is a flowchart like a tree structure where a branch represents a decision rule, and the leaf node represents the outcome.



Random Forest is a ensemble of decision tree where every new data input enter each decision tree in the forest and is evaluated and classified. The most appeared classification is the result of the random forest

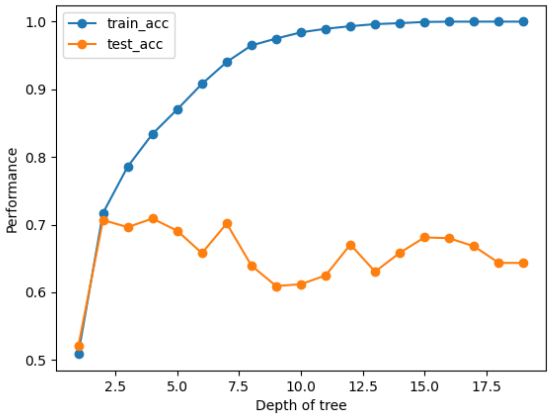
My workload for this project was broken into two:

- **Machine learning modeling**
- **GUI**

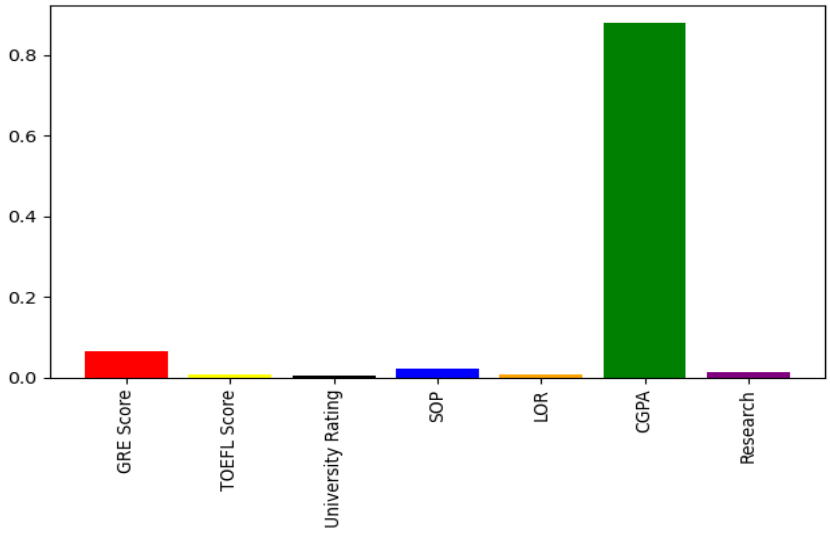
I focus on building and improving three models. Decision tree, Random Forest and Linear Regression (with the data scaled), build the model, compare model performance scores and build the feature importance's. After this I put it in PYQT5 so the user can play with the different scores and train/test size.

RESULTS:

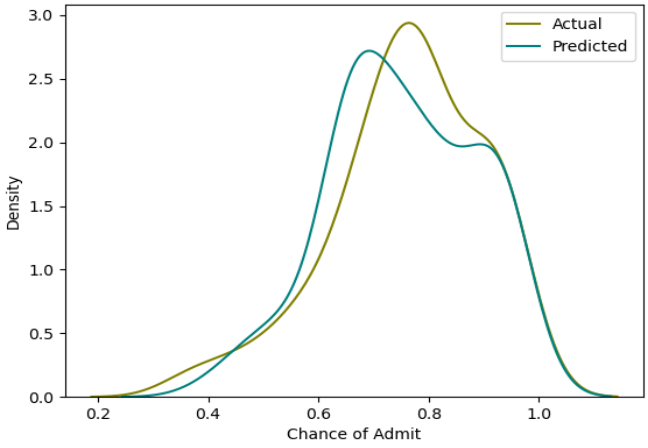
Decision Tree:
In the case of decision tree, even though our cross validation showed this was of our worst models it was the first model we learned in class and the first I built. I used this model before scaling the data. To find the max depth in our decision tree I graph the score using different max depth.



According to this graph max depth 5 was the best for our decision. This manual method wasn't efficient to find the best paraments on our model and at this point I wasn't aware of hyperparameter.



The decision tree feature importance is not helpful. It only gave important to CGPA and GRE score conflicting with our EDA and other models feature importance's.



The distribution graph of the actual y and decision tree predicted y variable shows is not similar.

Decision Tree Regressor Score: 69.8%
DT Mean Squared Error: 0.0068

Even though our decision tree mean absolute error, mean squared error and root mean squared error are great but when comparing to other models the score are higher. With that being said and the Decision tree score being 69% we decided to discard it.

Random Forest:
In the case of the random forest, since the cross validation show this was one of best models. I wanted to find the appropriate parameters to have the best model possible. There were two options GridSearchCV and RandomizedSearchCv to find the best parameters. I decided to do RandomizedSearchCv for running purposes. I really took in consideration the running time in the selection of the searchcv and the different parameters I wanted to be tried.

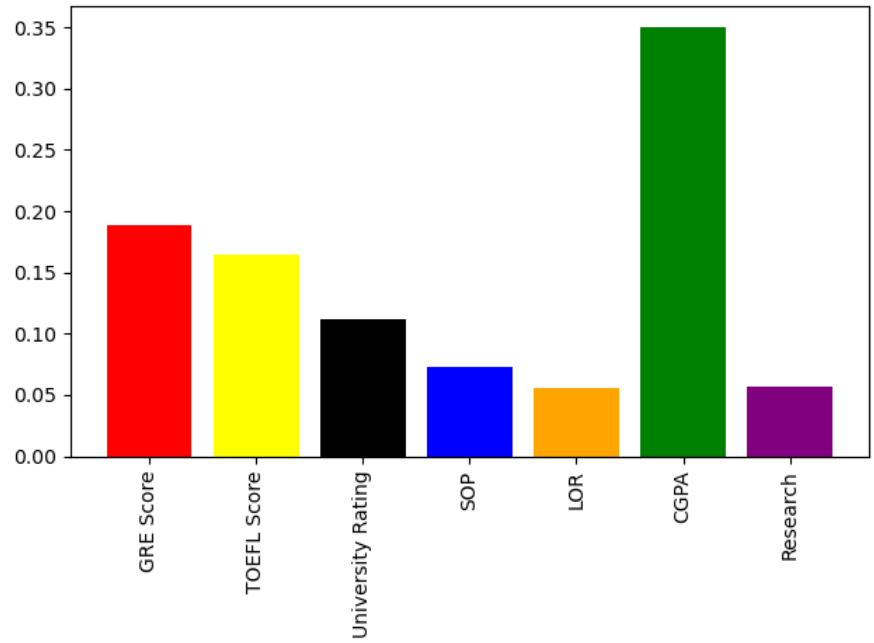
```
# Fitting Random Forest
rf = RandomForestRegressor()
# Number of trees in random forest
n_estimators = list(np.arange(10, 100, 10))
# Criteriion for the random forest
criterion = ['mse', 'mae']  ## if you put this as a parameters , takes a long time to run and performance
goes down
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = list(np.arange(4, 12))
# Minimum number of samples required to split a node
min_samples_split = [2, 5]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2]
# Method of selecting samples for training each tree
bootstrap = [True, False]
rf_param = {'n_estimators': n_estimators,
          'max_features': max_features,
          'max_depth': max_depth,
          'min_samples_split': min_samples_split,
          'min_samples_leaf': min_samples_leaf,
          'bootstrap': bootstrap}
```

This were my different parameters I wanted to try for my random forest, I choose this parameters to avoid overfitting . I decided to opt out on the different criterion since the running time increased heavily and my computer couldn't handle it.

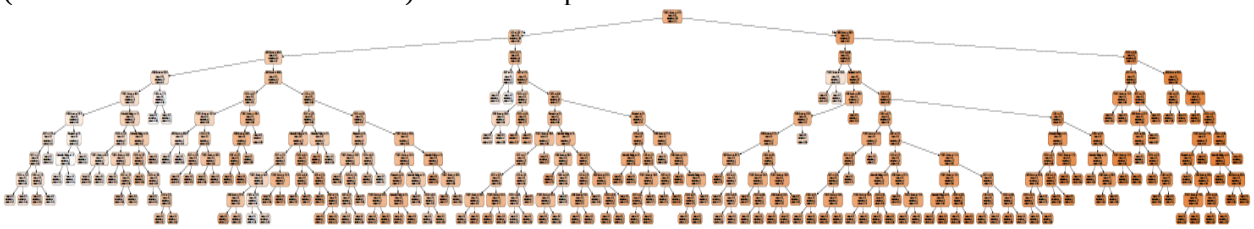
After the randomized searchcv which I iterate 100 I found the best parameters were.

```
rf = RandomForestRegressor(n_estimators=80, min_samples_split=2, min_samples_leaf=1,
max_features='sqrt', max_depth=10,
                           bootstrap=True)
```

This Random Forest gave me a score 80% with a low score MSE. This was a good and decided to good ahead with the parameters and the model and include it in my PYQT5.



.At first our EDA was confusing regarding the Research feature, in the heatmap it showed no correlation but the scatterplot it shows a very slight relationship with chance of admission. In our random forest model, it showed it was important in our prediction. This shows that schools value academic criteria (standardized test scores and GPA) are more important.



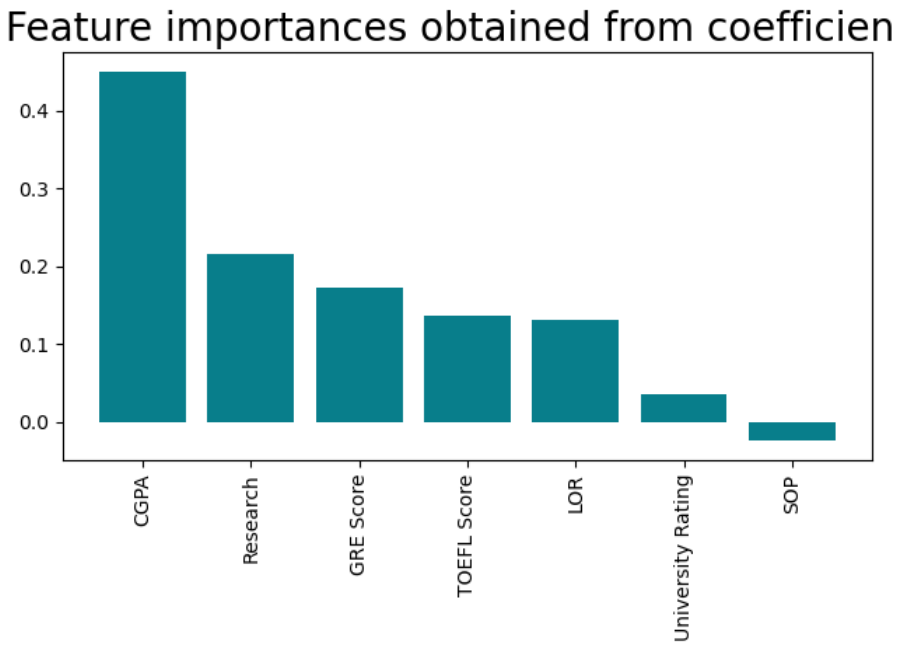
This a picture of one of our random forests, even though its width it showed no overfitting on the basis of the depth of tree and the scores it gave for test and train.

Random Forest Score RSquare: 80%
RF Mean Squared Error: 0.0044

The RF MSE is lower that the decision tree MSE and the performance score of the model is 80% which also higher that our decision tree. This is

Linear Regression Scaling:

In the case of linear regression, I had to scale our data to do the linear regression. I tried MinMaxScaler and Standard Scaler, both gave me similar result, so I decided to do Standard Scaler since our data distribution is normal.



This feature importance based on the coefficients showed research have a positive influence to predicting the chance of admission which is interesting because the results of the EDA heatmap gave research the less correlation to Change of Admission.

Linear Regression Scaling RSquare: 80%
LR Mean Squared Error: 0.19

The linear regression with scaling the feature has the same score as random forest but MSE is higher with 0.19 compared to the random forest with 0.0039

CONCLUSION:

The best model from my three models is random forest which has the highest R square and lowest MSE, even though linear regression has a similar R square , the MSE score is higher compare to DT and RF. One improvement I could do is try different ensemble techniques to find a best model. Another improvement can be to find different admission graduate dataset in USA, put it together in one big dataset and then all the preprocessing and models. I suspect there is a way to use feature creation in this dataset but all the different trials we did failed, but I still have a feeling there is feature hiding somewhere.