Assignment 3 (Unit 3): Regression-Based Modules

MSDS 422: Machine Learning
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Phase 1: Create a Training and Test Data Set

> Same as the previous assignment

1. Splitting the Data
   - We created an 80/20% split of the data into training and test data.

     > Output:
     > FLAG DATA
     > TRAINING = (4768, 32)
     > TESTING = (1192, 32)

2. Handling of Outliers For the handling of outliers for these models, we will consider outliers to be entries with a `TARGET_LOSS_AMT` value greater than $60,000.
   - Description of Test & Training Data *(Pre-Outlier-Handing):*

TRAINING	TARGET_BAD_FLAG	TARGET_LOSS_AMT	TEST	TARGET_BAD_FLAG	TARGET_LOSS_AMT
count	941.0	941.000000	count	248.0	248.000000
mean	1.0	13421.645058	mean	1.0	13387.758065
std	0.0	10662.481428	std	0.0	11508.703991
min	1.0	224.000000	min	1.0	320.000000
25%	1.0	5817.000000	25%	1.0	5214.500000
50%	1.0	10959.000000	50%	1.0	11336.500000
75%	1.0	17635.000000	75%	1.0	16734.000000
max	1.0	73946.000000	max	1.0	78987.000000

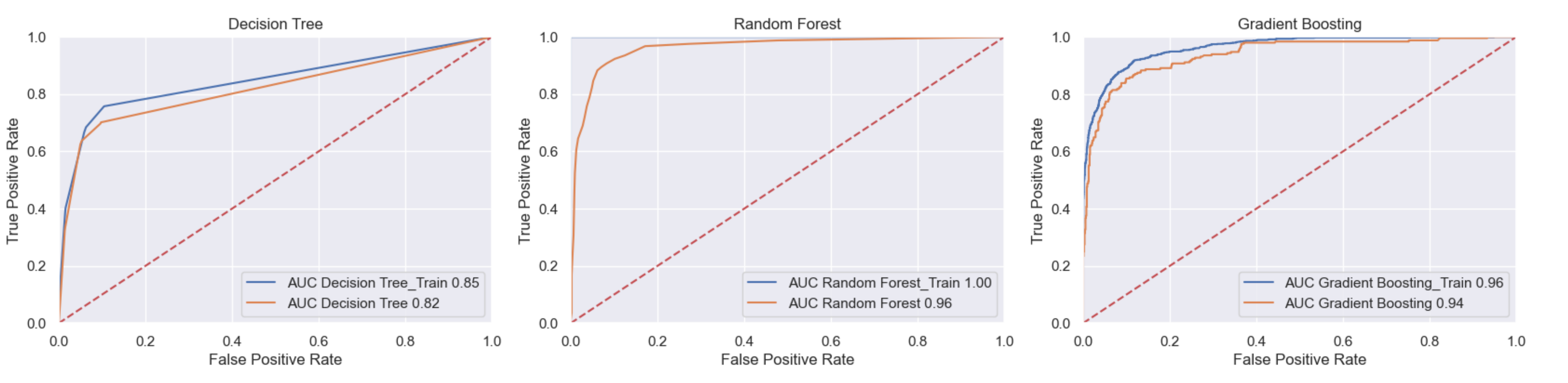
   - Description of the Test & Training Data *(Post-Outlier-Handling):*

TRAINING	TARGET_BAD_FLAG	TARGET_LOSS_AMT	TEST	TARGET_BAD_FLAG	TARGET_LOSS_AMT
count	941.0	941.000000	count	248.0	248.000000
mean	1.0	13400.475027	mean	1.0	13264.209677
std	0.0	10558.757161	std	0.0	10902.351601
min	1.0	224.000000	min	1.0	320.000000
25%	1.0	5817.000000	25%	1.0	5214.500000
50%	1.0	10959.000000	50%	1.0	11336.500000
75%	1.0	17635.000000	75%	1.0	16734.000000
max	1.0	60000.000000	max	1.0	60000.000000

Phase 2: Evaluating The Previously Created M.L. Modules from Assignment 2

> We want to evaluate the previously created M.L. modules from Assignment 2 to compare their results to the Logistic Regression and Linear Regression modules we will create in this assignment.

2.1 Default Probability ROCs for the Previously Created ML Modules:



2.2 Default Probability Classification Accuracy Scores for the Previously Created ML Modules

Accuracy Scores	Decision Tree	Random Forest	Gradient Boosting
Training Score	0.8873741610738255	0.9997902684563759	0.9259647651006712
Test Score	0.8825503355704698	0.9161073825503355	0.9068791946308725

- For the previous ML models created, the **Random Forest** model performed the best at predicting the probability of default, with a 0.96 AUC and 0.916 accuracy score.

2.3 Amount Lost Assuming Default RMSE Scores for the Previously Created ML Modules

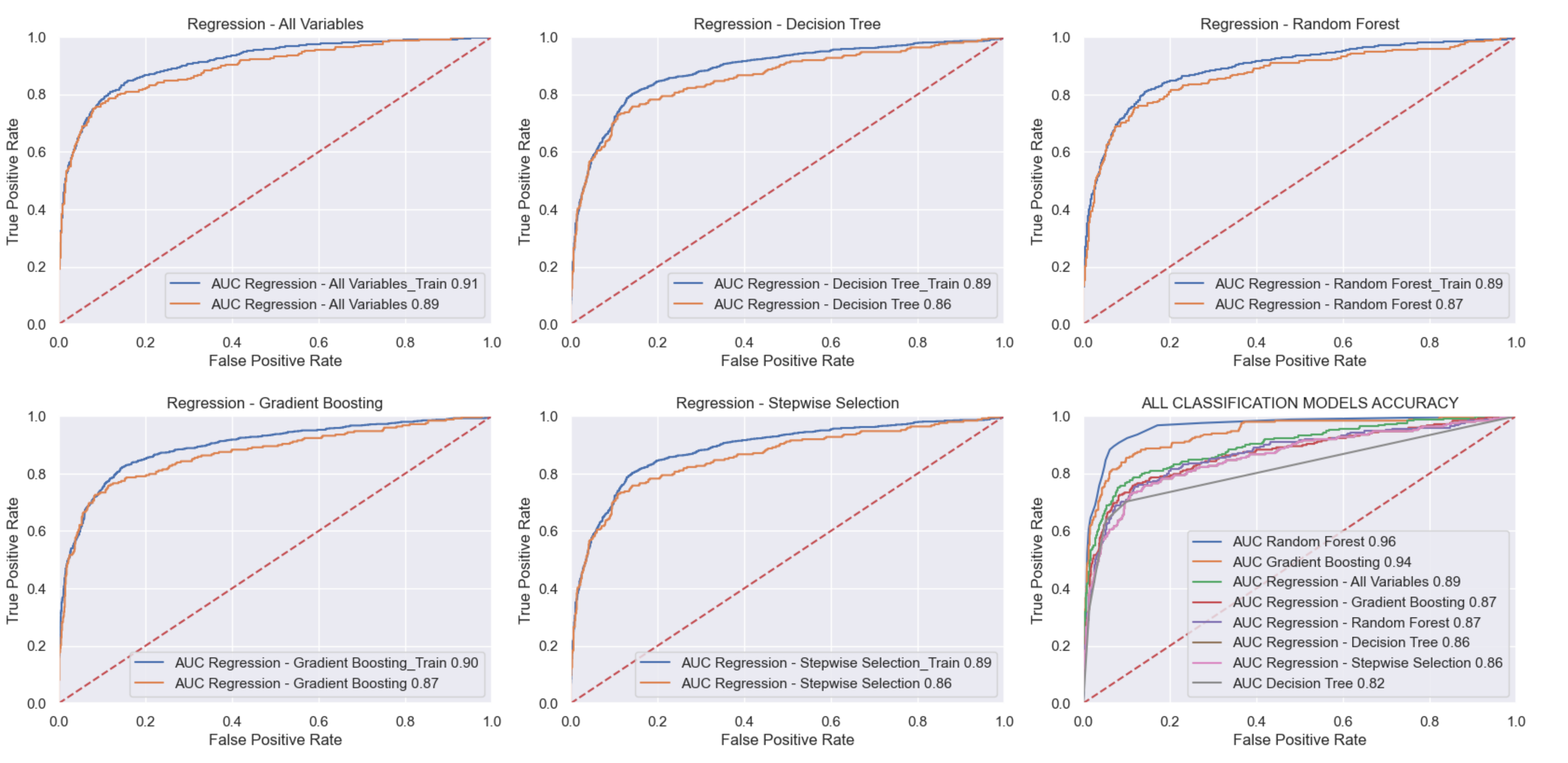
RMSE Scores	Decision Tree	Random Forest	Gradient Boosting
Training Score	4376.115301768929	1215.1036374284365	1216.8745387135345
Test Score	5300.687819418662	2725.840164535692	2272.6913845727468

- For the previous ML models created, the **Gradient Boosting** model best predicted the amount lost assuming default, with an RMSE score of 2272.7.

Phase 3: Developing Logistic Regression

> We will evaluate logistic regression models using the following variable selection:
>
> - All Variable
> - Decision Tree Variables
> - Random Forest Variables
> - Gradient Boosting Variables
> - Stepwise Selection Variables

3.1 Default Probability ROCs for Logistic Regression Models:



3.2 Default Probability Accuracies for Logistic Regression Models:

Variable Selection Method	Training Accuracy Score	Test Accuracy Score
Regression - All Variables	0.8934563758389261	0.889261744966443
Regression - Decision Tree	0.8754194630872483	0.8741610738255033
Regression - Random Forest	0.8798238255033557	0.8741610738255033
Regression - Gradient Boosting	0.8812919463087249	0.8800335570469798
Regression - Stepwise Selection	0.8754194630872483	0.8741610738255033

> Amoung the Logistic Regression Model the used, the Logistic Regression using Gradient Boosting variables was the most accurate, with an accuracy score of 0.88 and an AUC of 0.87. However, the previously created Random Forest model with an accuracy score of 0.916 and AUC of 0.96 still remains the most accurate model; therefore, I recommend the **Random Forest** model for predicting whether a loan will default.

3.2.1 Variables Used in Each Logistic Regression Model:

Variable Selection Method	Variables Used
Regression - All Variables	All 33 variables were used for this model
Regression - Decision Tree	INTERCEPT, M_DEPTINC, IMP_DEBTINC, M_DEROG, IMP_DELINQ, IMP_CLAGE
Regression - Random Forest	INTERCEPT, M_DEBTINC, IMP_DEBTINC, IMP_DELINQ, IMP_CLAGE, IMP_LOAN, IMP_CALUE, IMP_CLNO, IMP_MORTDUE, IMP_YOJ, IMP_DEROG, IMP_NINQ
Regression - Gradient Boosting	INTERCEPT, M_DEBTINC, IMP_DEBTINC, IMP_DELINQ, IMP_CLAGE, M_VALUE, IMP_DEROG
Regression - Stepwise Selection	INTERCEPT, M_DEBTINC, IMP_DEBTINC, M_DEROG, IMP_DELINQ, IMP_CLAGE

3.3 Examining Coefficients for Gradient Boosting Logistic Regression Model

There were **7** total variables used for the Logistic Regression Model using the **Gradient Boosting** variables These included:

Variable	Coefficient
INTERCEPT	-5.432779
M_DEBTINC	2.753325
IMP_DEBTINC	0.099528
IMP_DELINQ	0.646958
IMP_CLAGE	-0.006143
M_VALUE	3.526238
IMP_DEROG	0.575937

All of the variables make sense for why they would predict whether a loan will default because they are likely indicators of fraud. The variables with the most significant coefficients are whether or not the person is missing a debt-to-income ratio and whether the value of the person's own is missing. These two important values being missing are very suspicious, and these large coefficients support that. It also makes sense that as a borrower's number of credit delinquencies and derogatory marks increases, so does their likelihood of default. Additionally, it is unsurprising that the age of a borrower's credit line has a negative coefficient since the longer a person has a line of credit, the more experience they have managing debt.

Phase 4: Developing Linear Regression

> We will evaluate linear regression models using the same variable selection methods as for the linear regression.

4.1 Amount Lost Assuming Default RMSE Scores for Linear Regression Models:

Variable Selection Method	Training RMSE Score	Test RMSE Score
Regression - All Variables	3578.3595491074625	3213.6502698249487
Regression - Decision Tree	4448.604572853346	4329.837423823597
Regression - Random Forest	4546.38193698269	4416.2363896732695
Regression - Gradient Boosting	4546.38193698269	4416.2363896732695
Regression - Stepwise Selection	4546.38193698269	4416.2363896732695

> Among the Linear Regression models created, the Linear Regression using the Decision Tree variables was the most accurate, with an RMSE Score of 4329.8. This is not surprising given that the decision tree linear regression model utilized the largest number of variables (6 versus 3 for all the others). Using a model with 6 variables is also much more feasible than a model with all 33 variables. However, the previously created **Gradient Boosting** model is still much more accurate than the Linear Regression using Decision Tree variables, with an RMSE score of 2272.7; therefore, I would recommend using the **Gradient Boosting** model for predicting the amount lost assuming default.

4.1.1 Variables Used in Each Linear Regression Model:

Variable Selection Method	Variables Used
Regression - All Variables	All 33 variables were used for this model
Regression - Decision Tree	INTERCEPT, IMP_LOAN, M_DEBTINC, IMP_NINQ, IMP_CLNO, z_IMP_REASON_DebtCon
Regression - Random Forest	INTERCEPT, IMP_LOAN, IMP_CLNO, M_DEBTINC
Regression - Gradient Boosting	INTERCEPT, IMP_LOAN, IMP_CLNO, M_DEBTINC
Regression - Stepwise Selection	INTERCEPT, IMP_LOAN, IMP_CLNO, M_DEBTINC

4.2 Examining Coefficients for Decision Tree Linear Regression Model

There were **6** total variables used for the Linear Regression Model using the **Decision Tree** variables These included:

Variable	Coefficient
INTERCEPT	-4.889730
M_DEBTINC	2.819198
IMP_DEBTINC	0.092259
M_DEROG	-0.803461
IMP_DELINQ	0.736207
IMP_CLAGE	-0.006332

All of the variables included in the linear regression model using the Decision Tree variables make sense.

- Missing Debt-to-Income Ratio (2.82): It is suspicious if someone does not have this information, and thus, it makes sense that this has a large coefficient.
- Number of Delinquencies on Current Credit Report (0.74): It is unsurprising that someone with a large number of delinquencies would be more likely to lose a large amount upon default.
- Debt-to-Income Ratio (0.09): This makes sense; however, I'm surprised that this coefficient is not large; it would seem that someone with significantly more debt than income would have a more difficult time paying off the loan and thus would default on a large amount. We should consult with an industry expert regarding this.
- Missing Derogatory (-0.80): I would assume that if someone's number of derogatory marks is missing, that would indicate they likely don't have a history of derogatory marks, and thus this coefficient would make sense. Should consult with industry experts to confirm that this interpretation is correct.
- Credit Line Age (-0.01): I'm not surprised that this variable is included, and it makes sense that this coefficient would be negative for the reason previously stated in Section 3.3.
- NOTE: I am surprised to see that `LOAN` (The Home Equity Line of Credit Amount) is not included in the variables used to predict the amount lost upon default. It would make sense that the larger the line of credit, the larger the loss upon default. Consult an industry expert to see if the omission of this variable is appropriate.