Assignment 2 (Unit 2): Tree Based Models

MSDS 422: Machine Learning
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Pre-Phase: Preparing Data for Modeling

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

     > Ouput:
     > 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 I: Decision Trees

1. Decision Tree to Predict the Probability of Default

Evaluate the accuracy of the model on both the training and test data set:

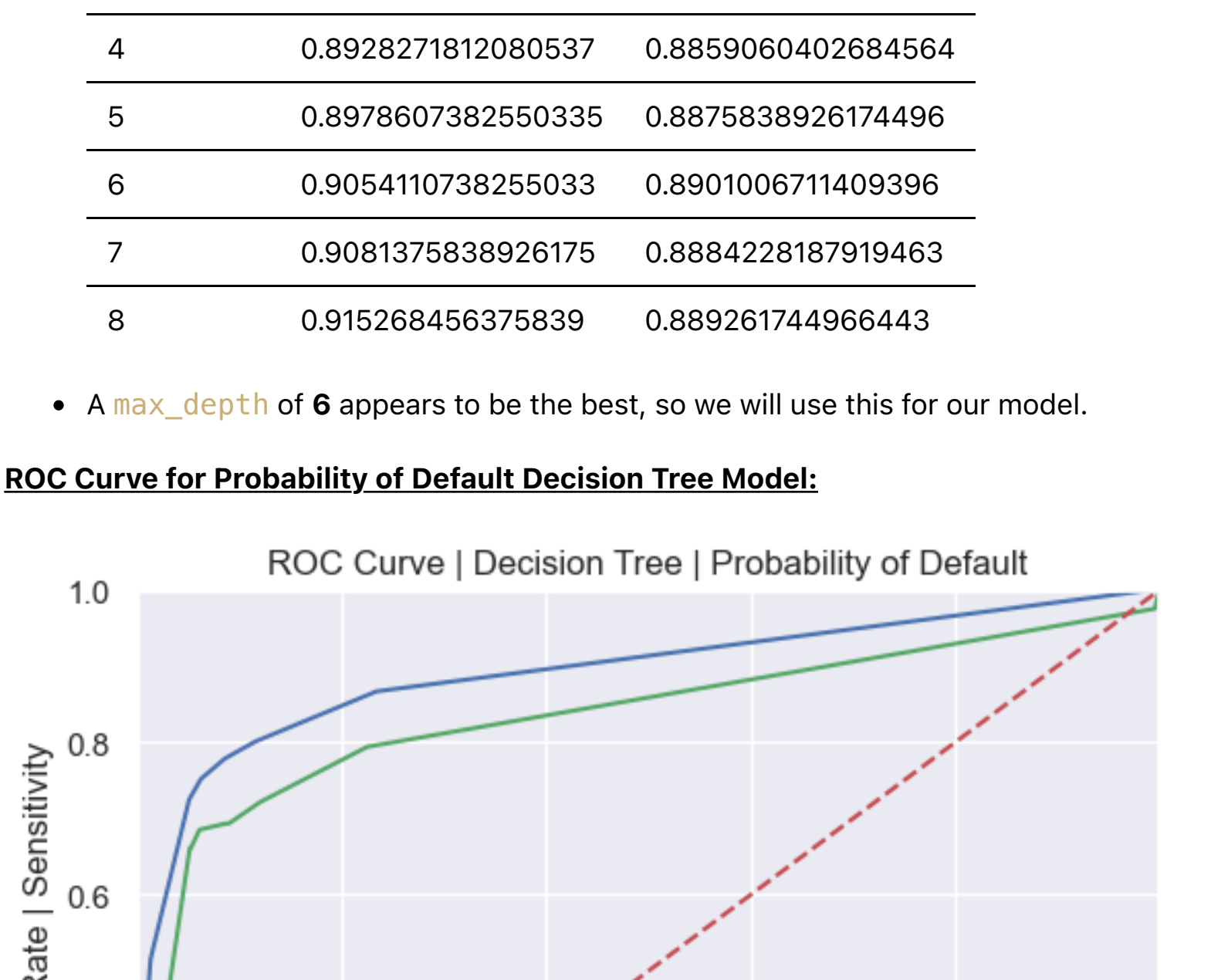
- Test a variety of `max_depth`'s to determine the best value to use.

Decision Tree | Probability of Default

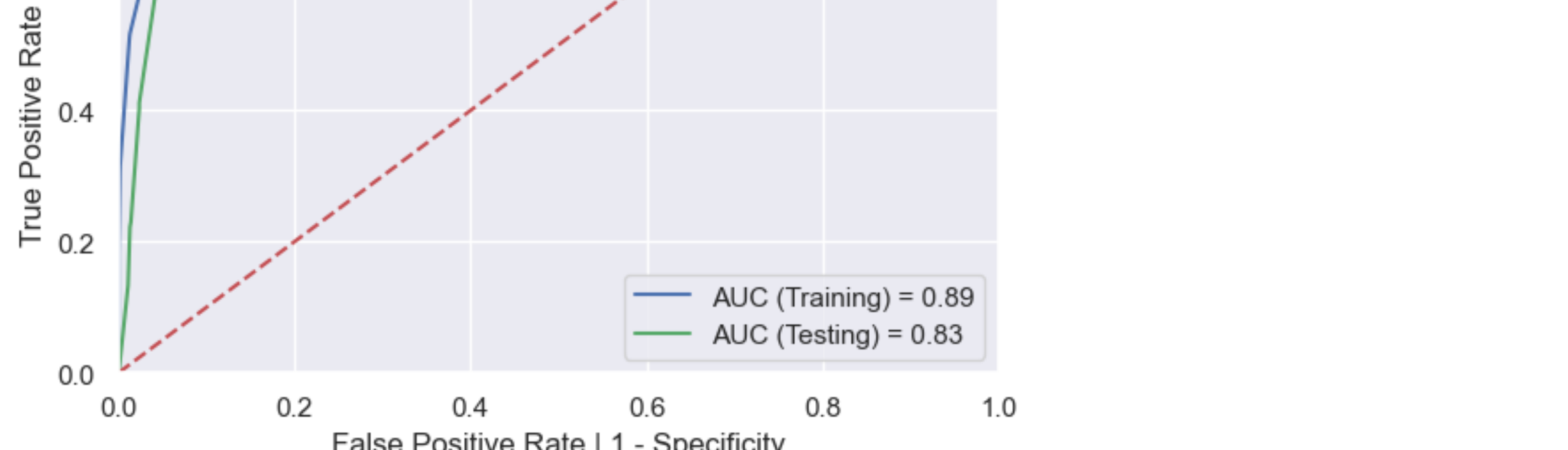
Max Depth	Accuracy (Training)	Accuracy (Testing)
3	0.8873741610738255	0.8825503355704698
4	0.8928271812080537	0.8859060402684564
5	0.8978607382550335	0.8875838926174496
6	0.9054110738255033	0.8901006711409396
7	0.9081375838926175	0.8884228187919463
8	0.915268456375839	0.889261744966443

- A `max_depth` of **6** appears to be the best, so we will use this for our model.

ROC Curve for Probability of Default Decision Tree Model:



Decision Three Visualization (using Graphviz):



Variables Included in Decision Tree to Predict Loan Default:

1. M_VALUE
2. IMP_VALUE
3. IMP_LOAN
4. M_DEBTINC
5. IMP_DEBTINC
6. IMP_MORTDUE
7. M_YOJ
8. IMP_YOJ
9. M_DEROG
10. IMP_DEROG
11. IMP_DELINQ
12. IMP_CLAGE
13. IMP_NINQ
14. IMP_CLNO
15. z_IMP_JOB_Office
16. z_IMP_JOB_Sales

2. Decision Tree to Predict the Loss Amount Assuming that the Loan Defaults

Evaluate RMSE for Training and Test Data Sets

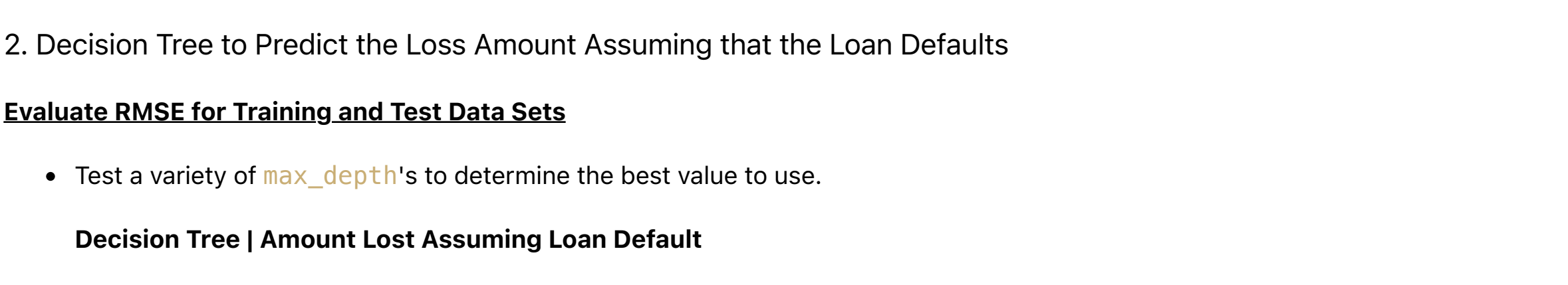
- Test a variety of `max_depth`'s to determine the best value to use.

Decision Tree | Amount Lost Assuming Loan Default

Max Depth	TREE RMSE Train	TREE RMSE Test	RMSE Ratio
3	5400.190276378008	6530.612338895066	1.2093300429545697
4	4376.115301768929	5300.687819418662	1.2112770011512262
5	3526.247152892591	4445.532172751522	1.2606978410758414
6	2635.7179394222653	4212.97475780228	1.598416391522433
7	2024.466140124873	4336.092613302751	2.141844967105892

- A `max_depth` of **6** appears to be the best, so we will use this for our model.

Decision Three Visualization (using Graphviz):



Variables Included in Decision Tree to Predict Loss Amount Assuming Default:

1. IMP_VALUE
2. IMP_LOAN
3. M_DEBTINC
4. IMP_DEBTINC
5. IMP_MORTDUE
6. IMP_YOJ
7. IMP_DEROG
8. IMP_DELINQ
9. IMP_CLAGE
10. IMP_NINQ
11. IMP_CLNO
12. z_IMP_REASON_DebtCon
13. z_IMP_JOB_Other

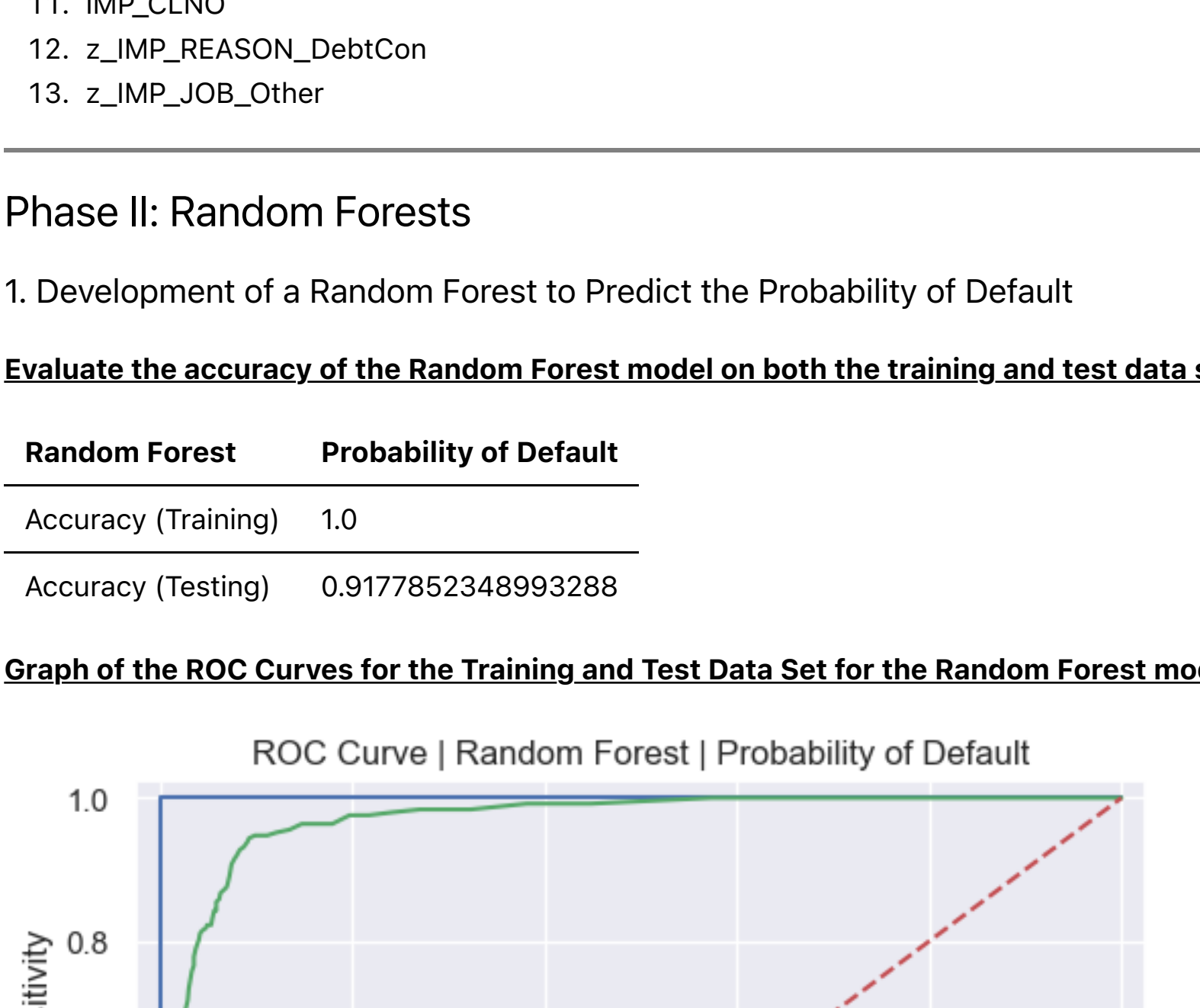
Phase II: Random Forests

1. Development of a Random Forest to Predict the Probability of Default

Evaluate the accuracy of the Random Forest model on both the training and test data set:

Random Forest	Probability of Default
Accuracy (Training)	1.0
Accuracy (Testing)	0.9177852348993288

Graph of the ROC Curves for the Training and Test Data Set for the Random Forest model:



List of Important Variables Included in the Random Forest Model to Predict Loan Default:

Variable	Importance Score
M_DEBTINC	100
IMP_DEBTINC	61
IMP_CLAGE	42
IMP_DELINQ	41
IMP_LOAN	37
IMP_VALUE	36
IMP_MORTDUE	33
IMP_CLNO	32
IMP_YOJ	28
IMP_DEROG	24
IMP_NINQ	20
M_VALUE	17

2. Development of a Random Forest to Predict the Loss Amount Assuming Loan Default

Evaluate the RMSE for both the training data set and the test data set:

Random Forest	Loss Amount
RMSE (Training)	1215.1036374284365
RMSE (Testing)	2725.840164535692

Important Variables Included in the Random Forest Model to Predict Loss Amount:

Variable	Importance Score
IMP_LOAN	100
IMP_CLNO	13
M_DEBTINC	5

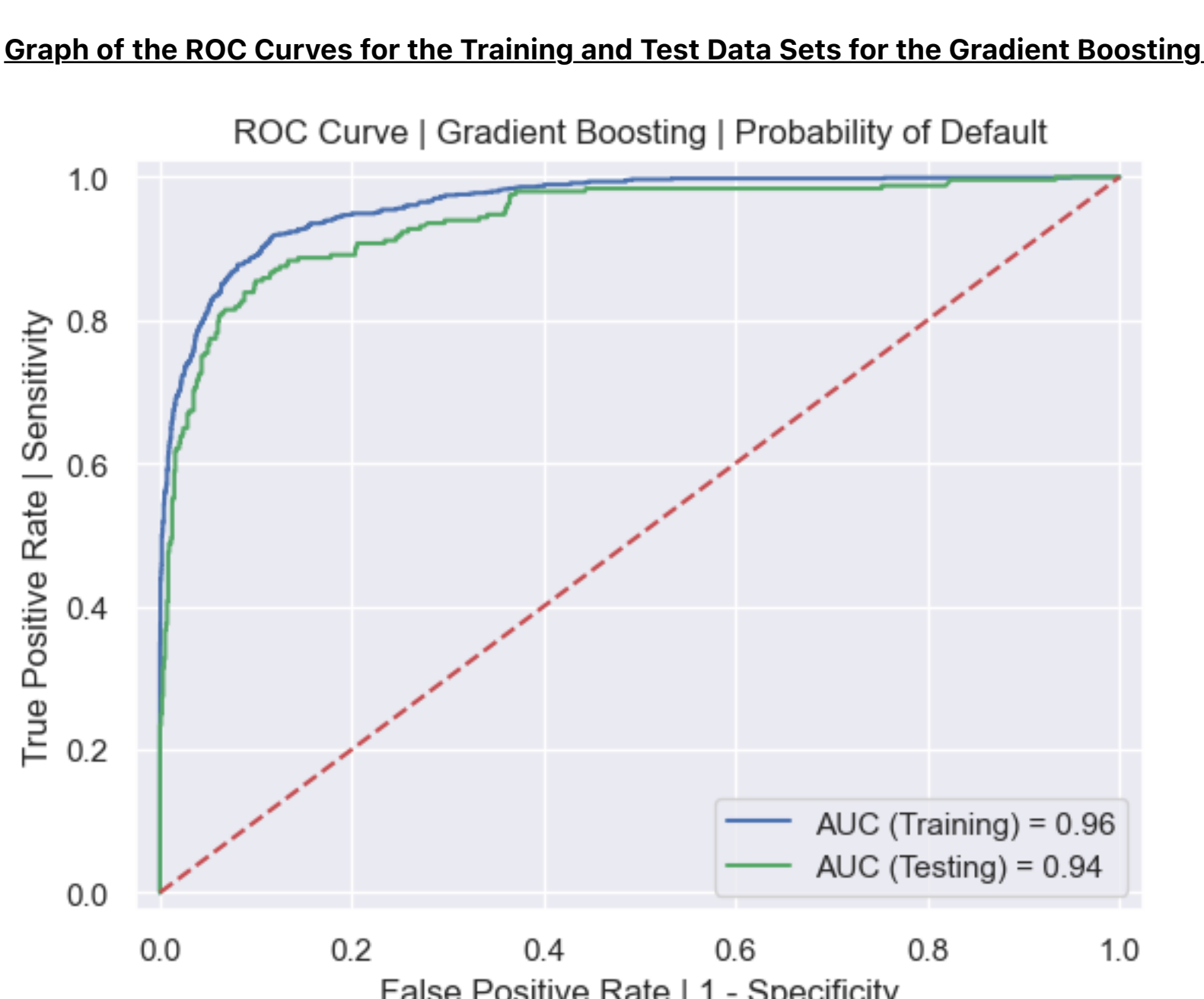
Phase III: Gradient Boosting

1. Development of a Gradient Boosting Model to Predict the Probability of Default

Evaluate the Accuracy of the Model on Both Training and Test Data Sets:

Gradient Boosting	Probability of Default
Accuracy (Training)	0.9259647651006712
Accuracy (Testing)	0.9068791946308725

Graph of the ROC Curves for the Training and Test Data Sets for the Gradient Boosting Model:



Important Variables Included in the Gradient Boosting Model to Predict Loan Default:

Variable	Importance Score
M_DEBTINC	100
IMP_DEBTINC	30
IMP_DELINQ	19
IMP_CLAGE	13
M_VALUE	7
IMP_DEROG	7

2. Development of a Gradient Boosting Model to Predict the Loss Amount Assuming the Loan Defaults

Evaluate the RMSE for Both the Training and Test Data Sets:

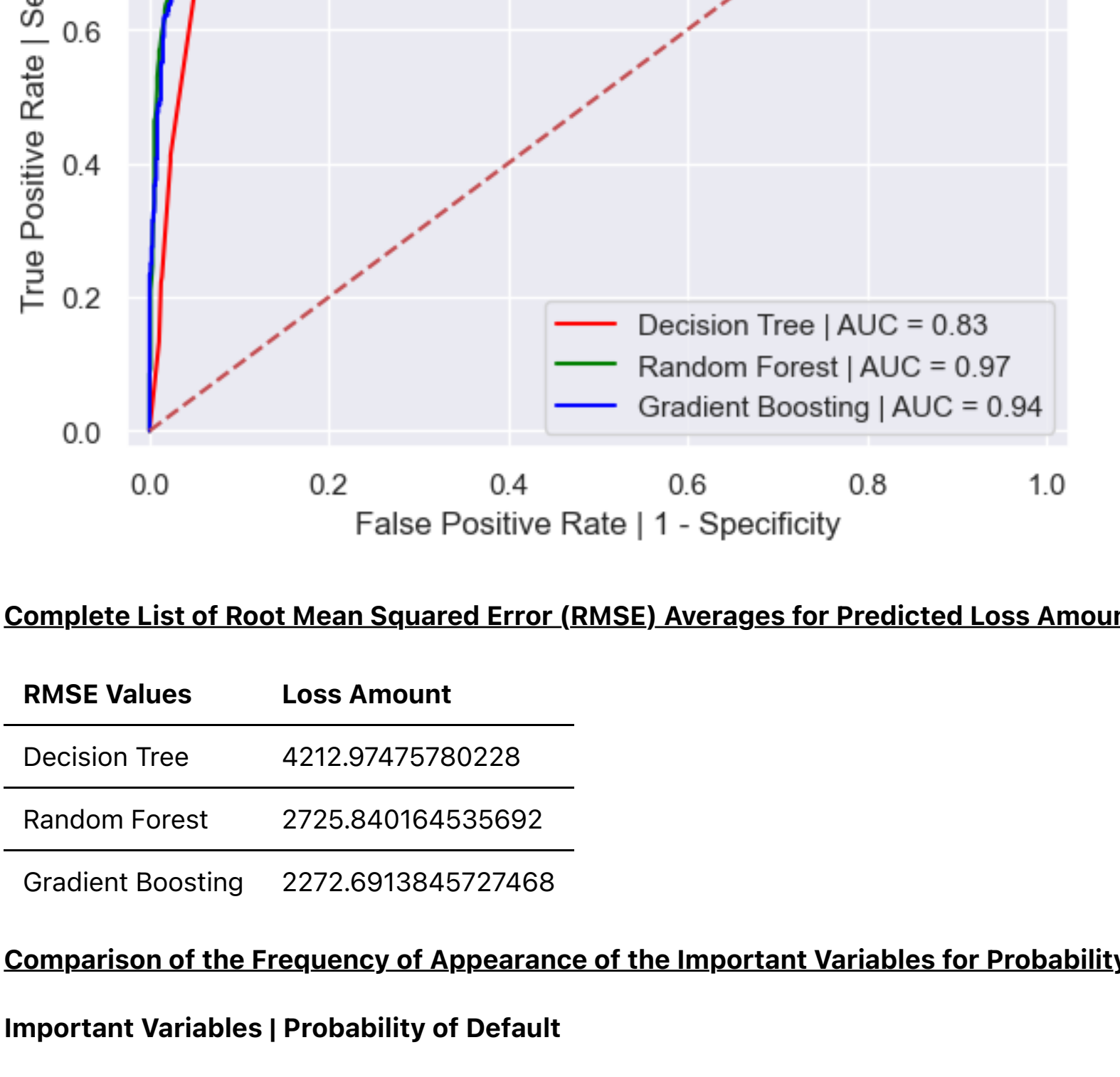
Gradient Boosting	Loss Amount
RMSE (Training)	1216.8745387135345
RMSE (Testing)	2272.6913845727468

Important Variables Included in the Gradient Boosting Model to Predict Loss Amount:

Variable	Importance Score
IMP_LOAN	100
IMP_CLNO	15
M_DEBTINC	6

Phase IV: ROC Curves Analysis

Complete ROC Curve for the Decision Tree, Random Forest, and Gradient Boosting Models Using the Test Data Set:



Complete List of Root Mean Squared Error (RMSE) Averages for Predicted Loss Amount Assuming Default:

RMSE Values	Loss Amount
Decision Tree	4212.97475780228
Random Forest	2725.840164535692
Gradient Boosting	2272.6913845727468

Comparison of the Frequency of Appearance of the Important Variables for Probability of Default:

Important Variables | Probability of Default

Model	Important Variables
Vars_TREE	['M_VALUE', 'IMP_VALUE', 'IMP_LOAN', 'M_DEBTINC', 'IMP_DEBTINC', 'IMP_MORTDUE', 'M_YOJ', 'IMP_YOJ', 'M_DEROG', 'IMP_DEROG', 'IMP_DELINQ', 'M_CLAGE', 'IMP_CLAGE', 'IMP_CLNO', 'z_IMP_JOB_Sales']
Vars_RF	['M_DEBTINC', 'IMP_DEBTINC', 'IMP_CLAGE', 'IMP_DELINQ', 'IMP_LOAN', 'IMP_VALUE', 'IMP_MORTDUE', 'IMP_CLNO', 'IMP_YOJ', 'IMP_DEROG', 'IMP_NINQ', 'M_VALUE']
Vars_GB_flag	[('M_DEBTINC', 100), ('IMP_DEBTINC', 30), ('IMP_DELINQ', 19), ('IMP_CLAGE', 13), ('M_VALUE', 7), ('IMP_DEROG', 7)]

Variable	Appearance Count
M_VALUE	3
M_DEBTINC	3
IMP_DEBTINC	3
IMP_DEROG	3
IMP_DELINQ	3
IMP_CLAGE	3
IMP_VALUE	2
IMP_LOAN	2
IMP_MORTDUE	2
IMP_YOJ	2
IMP_CLNO	2
M_YOJ	1
M_DEROG	1
z_IMP_JOB_Office	1
z_IMP_JOB_Sales	1
IMP_NINQ	1

Comparison of the Frequency of Appearance of the Important Variables for Predicted Amount Lost Assuming Default:

Model	Important Variables
Vars_TREE_AMT	['IMP_VALUE', 'IMP_LOAN', 'M_DEBTINC', 'IMP_DEBTINC', 'IMP_MORTDUE', 'IMP_YOJ', 'IMP_DEROG', 'IMP_DELINQ', 'IMP_CLAGE', 'IMP_NINQ', 'IMP_CLNO', 'z_IMP_REASON_DebtCon', 'z_IMP_JOB_Other']
Vars_RF_AMT	[('IMP_LOAN', 100), ('IMP_CLNO', 13), ('M_DEBTINC', 5)]
Vars_GB_AMT	[('IMP_LOAN', 100), ('IMP_CLNO', 15), ('M_DEBTINC', 6)]

Important Variables | Loss Amount

Variable	Appearance Count
IMP_LOAN	3
M_DEBTINC	3
IMP_CLNO	3
IMP_VALUE	1
IMP_DEBTINC	1
IMP_MORTDUE	1
IMP_YOJ	1
IMP_DEROG	1
IMP_DELINQ	1
IMP_CLAGE	1
IMP_NINQ	1
z_IMP_REASON_DebtCon	1
z_IMP_JOB_Other	1

Final Observations/Conclusions About Comparative Tree-Based Models Results

- The Random Forest model for predicting the probability of default had the highest AUC value (0.97) compared to the Decision Tree (0.83) and the Gradient Boosting model (0.94). This indicates that the Random Forest model is the best model for predicting the probability of default.
- The Gradient Boosting model for predicting the loss amount had the lowest RMSE value (2,272) compared to the Decision Tree (4,212) and the Random Forest model (2,725). This indicates that the Gradient Boosting model is the best model for predicting the loss amount.
- The important variables for the probability of default varied between the models. However, the following variables appeared in the important variable lists for all three models: `M_VALUE`, `M_DEBTINC`, `IMP_DEBTINC`, `IMP_DEROG`, `IMP_DELINQ`, `IMP_CLAGE`. Based on the importance scores for the Gradient Boosting model, the most important variable appears to be `M_DEBTINC`.
- Similarly, the important variables for the loss amount varied between the models. However, the following variables appeared in the important variable lists for all three models: `IMP_LOAN`, `M_DEBTINC`, and `IMP_CLNO`. Based on the importance score for both the Random Forest and Gradient Boosting models, the most important of these variables appears to be `IMP_LOAN`.