Banking Churn Rate – Mitigation Strategies

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Springboard Data Science Career Track

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Introduction of Problem & Objective

- Problem
  - Determining or predicting churn rate is key in increasing business effectiveness and allowing for targeted marketing and resources to increase customer retention. This is especially the case for a bank who released their user data on Kaggle for assistance on predicting churn in order to reduce it.

- Objective: The goal of this project is to provide a churn prediction model and mitigation strategies to increase overall bank revenue by 20% for the next financial quarter.

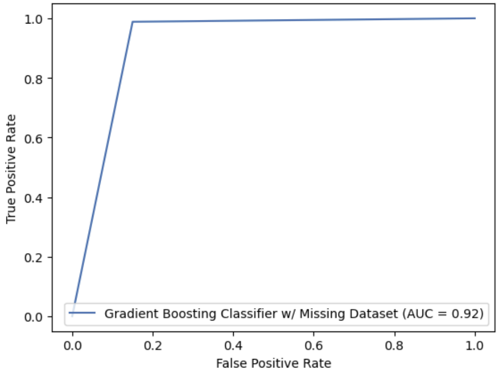
Springboard

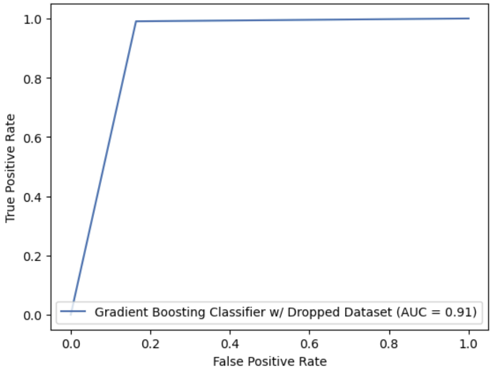
Recommendation & Key Findings

'Dropped' Correlation List 'Attrition_Flag'	
Attrition_Flag	1.000000
Total_Trans_Ct	0.364835
Total_Ct_Chng_Q4_Q1	0.281174
Total_Revolving_Bal	0.268979
Avg_Utilization_Ratio	0.185690
Total_Trans_Amt	0.170178
Total_Relationship_Count	0.149125
Total_Amt_Chng_Q4_Q1	0.133285
Gender_M	0.045186
Income_Category_$60K - $80K	0.028017
Income_Category_$40K - $60K	0.023828
Education_Level_High School	0.018403
Credit_Limit	0.017750
Marital_Status_Married	0.015278
Education_Level_College	0.012472
Education_Level_Uneducated	0.007257
Card_Category_Gold	0.003949
Card_Category_Silver	0.003173
Income_Category_$80K - $120K	0.001899
Card_Category_Blue	-0.001150
Education_Level_Graduate	-0.001751
Avg_Open_To_Buy	-0.006245
Marital_Status_Divorced	-0.006688
Dependent_count	-0.008122
Marital_Status_Single	-0.011789
Income_Category_$120K +	-0.014601
Education_Level_Post-Graduate	-0.018346
Months_on_book	-0.018599
Card_Category_Platinum	-0.022579
Customer_Age	-0.024498
Income_Category_Less than $40K	-0.033687
Education_Level_Doctorate	-0.043378
Gender_F	-0.045186
Months_Inactive_12_mon	-0.160701
Contacts_Count_12_mon	-0.203447

'Missing' Correlation List 'Attrition_Flag'	
Attrition_Flag	1.000000
Total_Trans_Ct	0.380618
Total_Ct_Chng_Q4_Q1	0.288937
Total_Revolving_Bal	0.263335
Avg_Utilization_Ratio	0.179838
Total_Trans_Amt	0.178078
Total_Relationship_Count	0.150889
Total_Amt_Chng_Q4_Q1	0.128559
Gender_M	0.047382
Income_Category_$60K - $80K	0.026338
Credit_Limit	0.024437
Education_Level_College	0.018937
Marital_Status_Married	0.017872
Income_Category_$40K - $60K	0.015050
Card_Category_Silver	0.014854
Education_Level_High School	0.009930
Education_Level_Uneducated	0.006614
Income_Category_$80K - $120K	0.005148
Education_Level_Graduate	0.004847
Avg_Open_To_Buy	0.000803
Income_Category_$120K +	-0.000831
Marital_Status_missing	-0.002723
Card_Category_Gold	-0.003397
Marital_Status_Divorced	-0.006305
Card_Category_Blue	-0.008463
Education_Level_missing	-0.009100
Education_Level_Post-Graduate	-0.013375
Marital_Status_Single	-0.013437
Income_Category_missing	-0.017580
Card_Category_Platinum	-0.020284
Dependent_count	-0.020550
Months_on_book	-0.022270
Income_Category_Less than $40K	-0.023134
Customer_Age	-0.035203
Education_Level_Doctorate	-0.039483
Gender_F	-0.047382
Months_Inactive_12_mon	-0.156552
Contacts_Count_12_mon	-0.211327

*Correlation List showcasing correlations with Target Attrition_Flag column

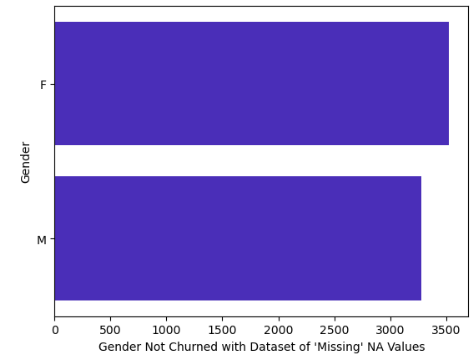


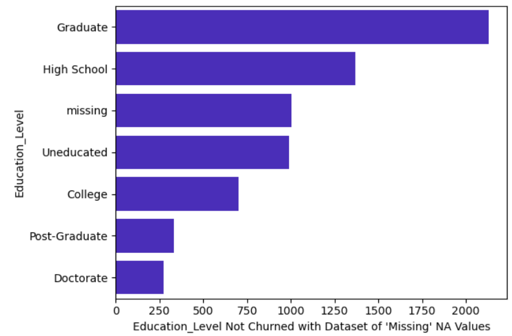


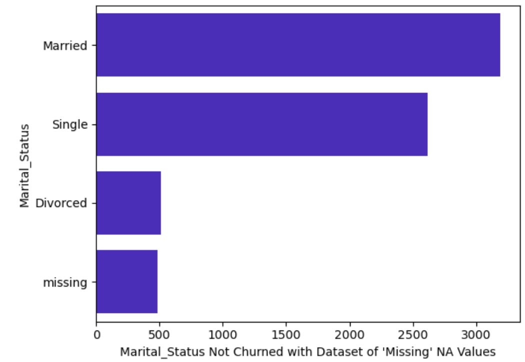
*ROC_AUC Scores from best performer and easily reproducible Gradient Boosting Model

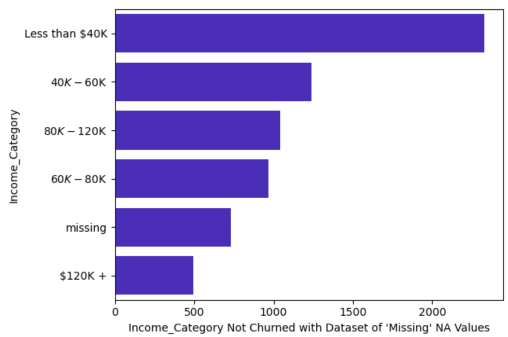
Recommended Churn Mitigation Strategies: The bank along with deploying a hyperparameterized Gradient Boosting model can focus marketing deals towards the higher to likely attrite audience of females or older demographic or maximize marketing to the not likely to churn population of younger married males with children or dependents.

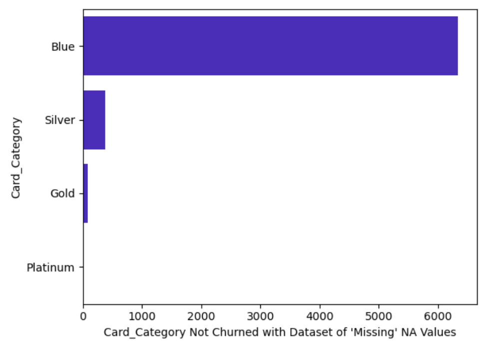
Assessing Not Churn User Base

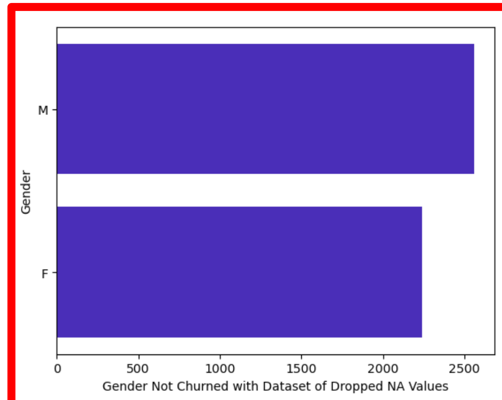








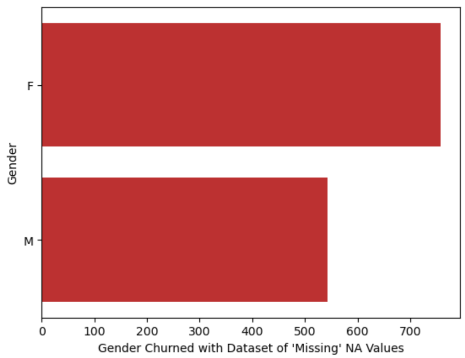


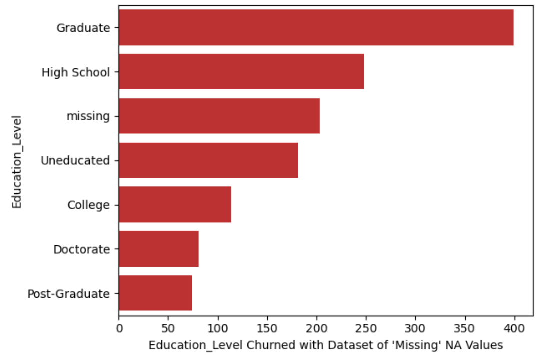


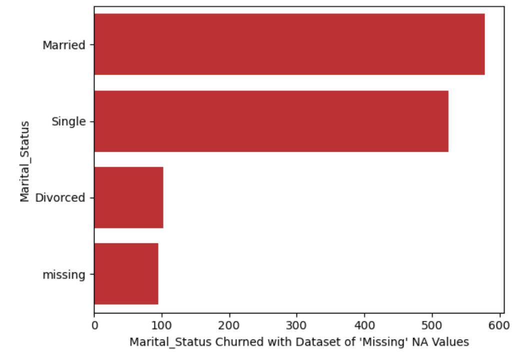
*Graphs displaying just assessment from 'Missing' Dataset values

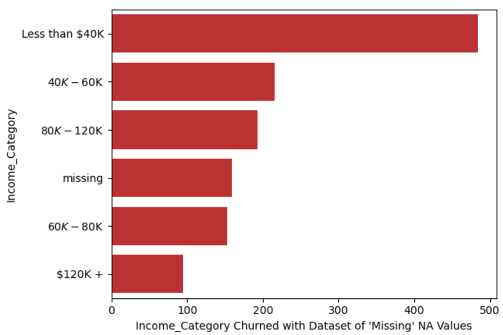
*Gender differed within 'Dropped' Dataset between Churn and Not Churned

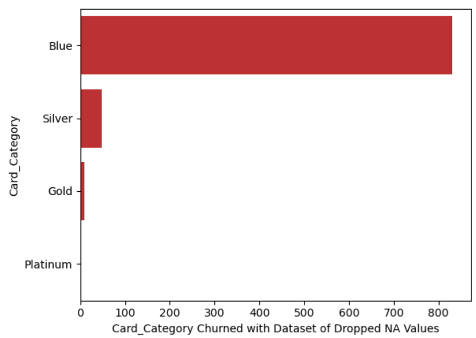
Assessing Churn User Base

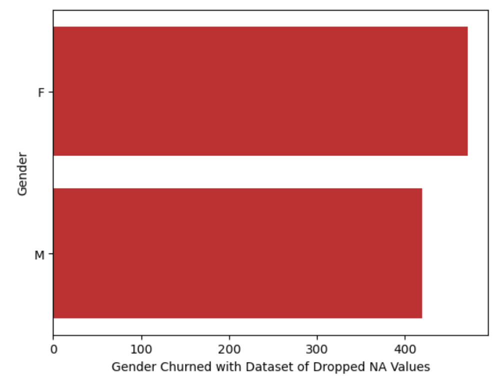












*Graphs displaying just assessment from 'Missing' Dataset values

*Gender differed within 'Dropped' Dataset between Churn and Not Churned

User Base Assessment: Most common user base are females, graduate degree holders, married individuals, those making less than 40k, and majority Blue card holders. Females less likely to disclose personal information.

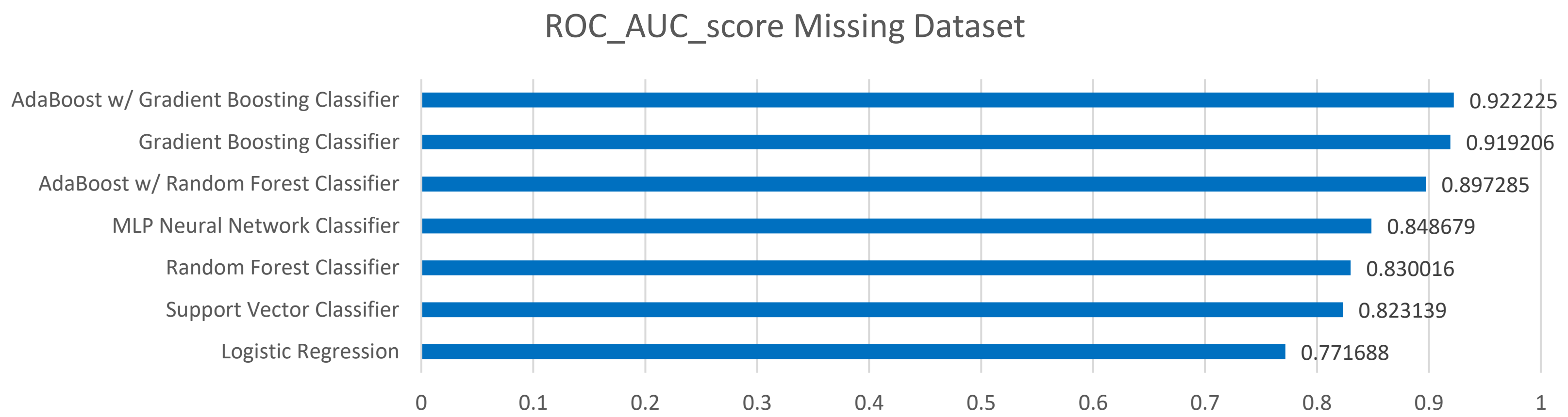
Establishing a Predictive Model

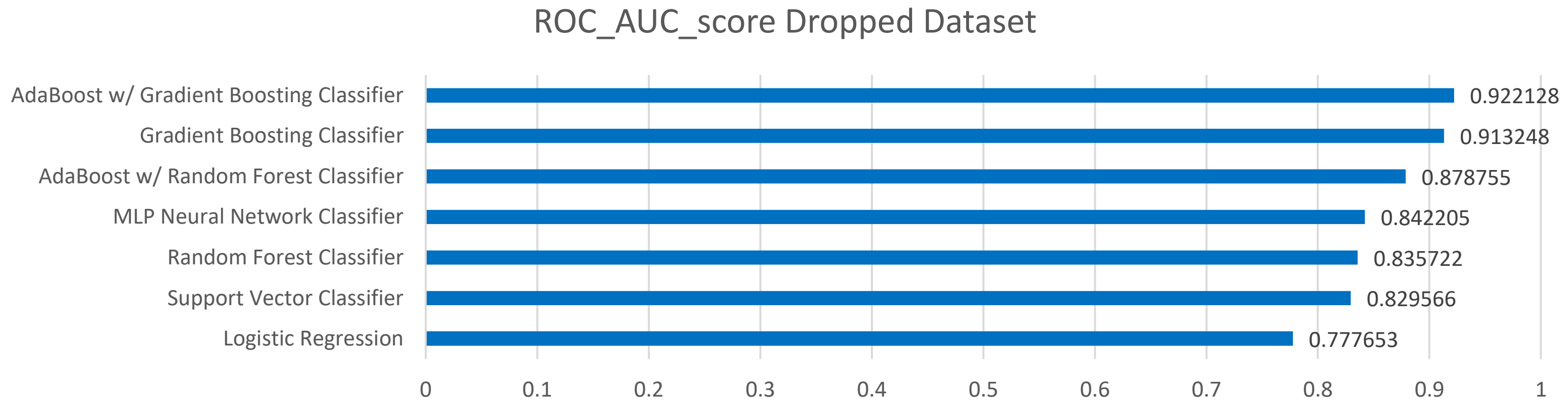
- Two Datasets (Missing and Dropped) constructed to deal with ‘Missingness’ of values.
- Each categorical feature given associated k-1 dummy variable
- Predictive models trained with 70/30 split and 5-fold Cross Validated for optimal hyperparameters
- Model performance assessed based on Accuracy, Precision, Recall, f1 score, **ROC_AUC score**, and Training Time (Sec)

Model Name	Accuracy_score	Precision_Score	Recall_score	f1_Score	ROC_AUC_score	Training Time (Sec)
Gradient Boosting Classifier w/ Missing Dataset	0.967914	0.927273	0.850000	0.886957	0.919206	846.87
Gradient Boosting Classifier w/ Dropped Dataset	0.968366	0.935780	0.836066	0.883117	0.913248	603.65

*Table Displaying Best and Easily Reproducible Gradient Boosting Model Metrics

‘Missing’ & ‘Dropped’ Dataset Model Comparison





*Bar graphs displaying Prediction model ROC_AUC scores for Missing and Dropped Datasets

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‘Missing’ vs. ‘Dropped’ & Modeling Insights

- **Logistic Regression** is the **worst performer** for both the missing and dropped datasets per predicting churn.
- Gradient Boosting Classifier is the best performer overall when applied with an AdaBoost Classifier model.
- However, the **individual Gradient Boosting Classifier** seems **sufficient** with a limitation of training time for reproducibility and scale.
- Imputing the original ‘Unknown’ values with ‘missing’ slightly improved the stronger performing Gradient Boosting and AdaBoost Classifier models.
- Future work to reduce Gradient Boosting Classifier training time and uncover feature importances and discover methods to improve MLP Neural Network Classifier.

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Summary

- Gradient Boosting Model is the best performer with an intuitive sense of reproducibility to deploy to production.

- Suggested Mitigation Strategies include:

    - Focus marketing deals towards the higher to likely attrite audience of females and older demographic.

    - Or maximize marketing to the not likely to churn population of younger married males with children or dependents.

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Thank You! Questions?

https://github.com/tpoozhikala/Bank-Churnrate/tree/main