Credit Card Fraud Detection

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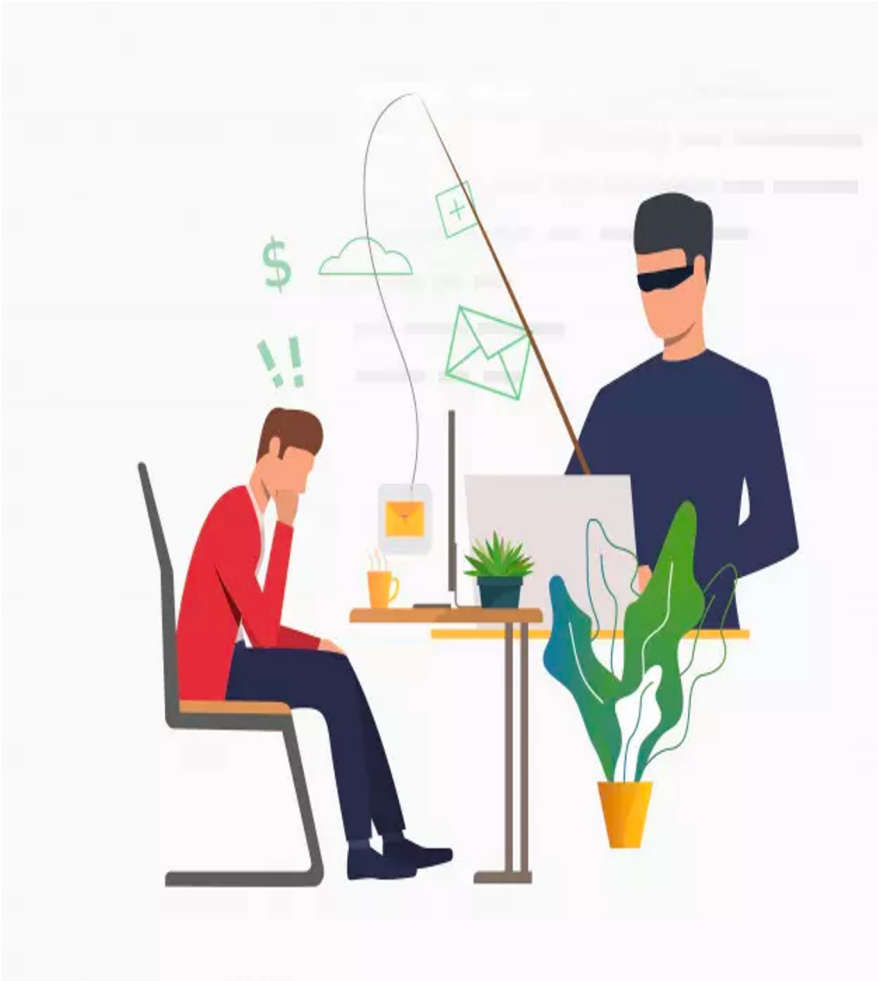

Source: Sakasegawa (2022)

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01

Understanding Credit Card Fraud

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What is Credit Card Fraud (CCF)

- Credit card fraud occurs when a person uses a stolen credit or information to make unauthorized purchases under the person's credit card name (Rafter, 2017)
- Several approaches for fraudsters to attain one's credit card information
  - Fake websites (Rafter, 2017)
  - Phishing emails (Dickey, 2021)
  - Data breaches (Rafter, 2017)

The State of Credit Card Fraud

- "Three-in-five 18-34 year olds (63%) report being a victim of at least one type of financial fraud in their lifetime" (Chartered Professional Accountants of Canada, 2023)
- 72% of participants in the study with credit cards state that they manage their finances online (Chartered Professional Accountants of Canada, 2023)
- "Costs the global economy $5.127 trillion annually" (Falco, 2023)
  - 72% of businesses globally reported an increase in fraud within 12 months

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Data Science and Credit Card Fraud

- Data science is significantly involved in collecting, summarizing, and predicting banking data to identify suspicious activities (Qualetics Team, 2019)
  - Models are created to classify credit card transactions based on features such as amount, location, merchant, month, etc.
- Machine learning plays a critical role in fraud detection (Kosourova, 2022)
  - Approached through supervised or unsupervised methods

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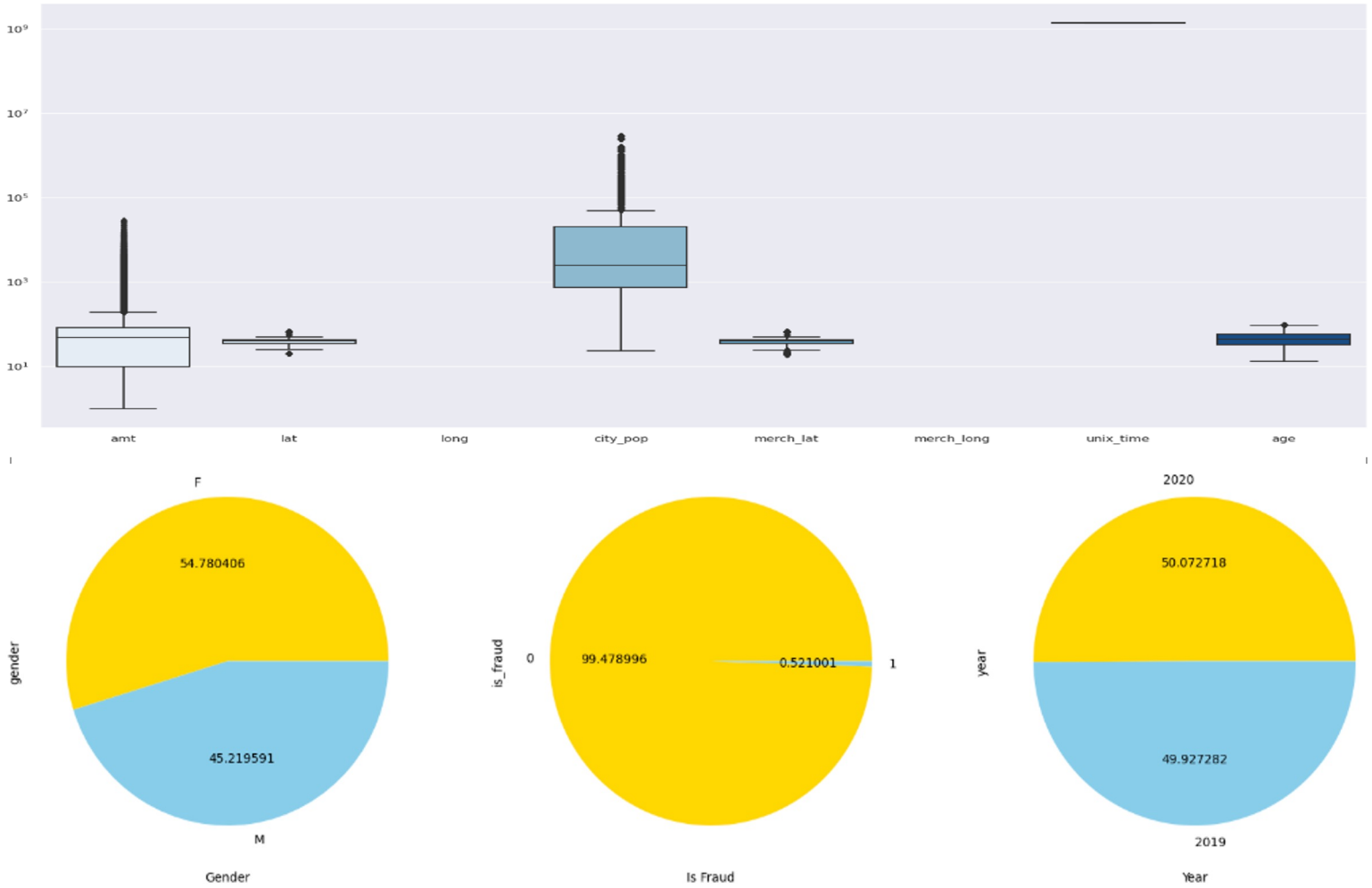
Exploring Credit Card Transaction Data



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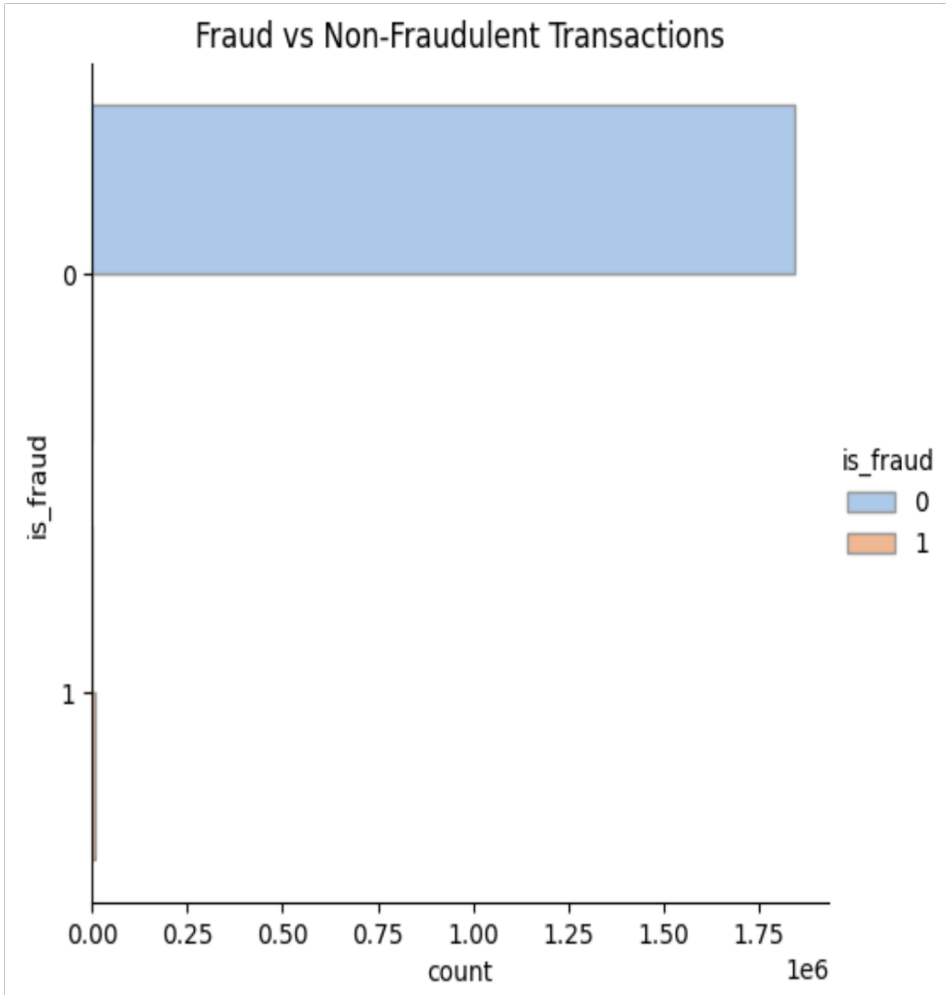
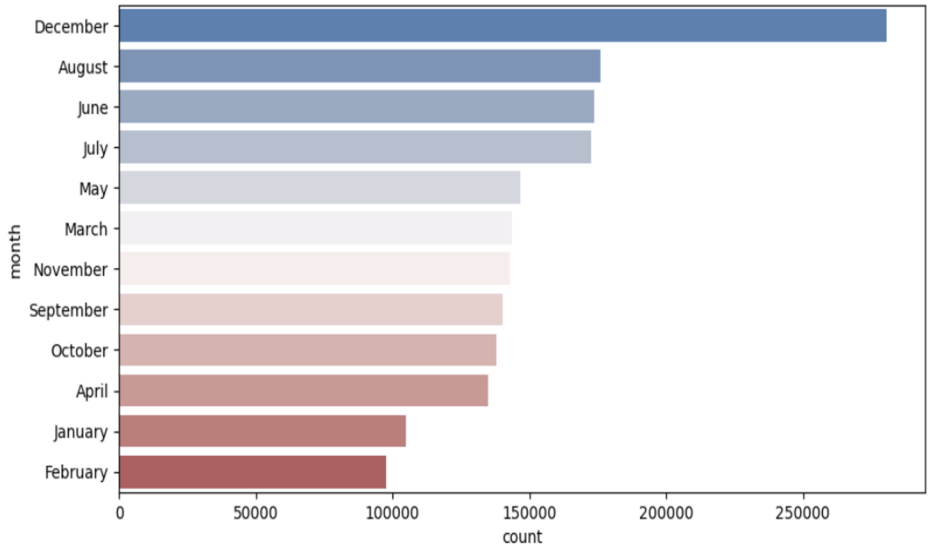
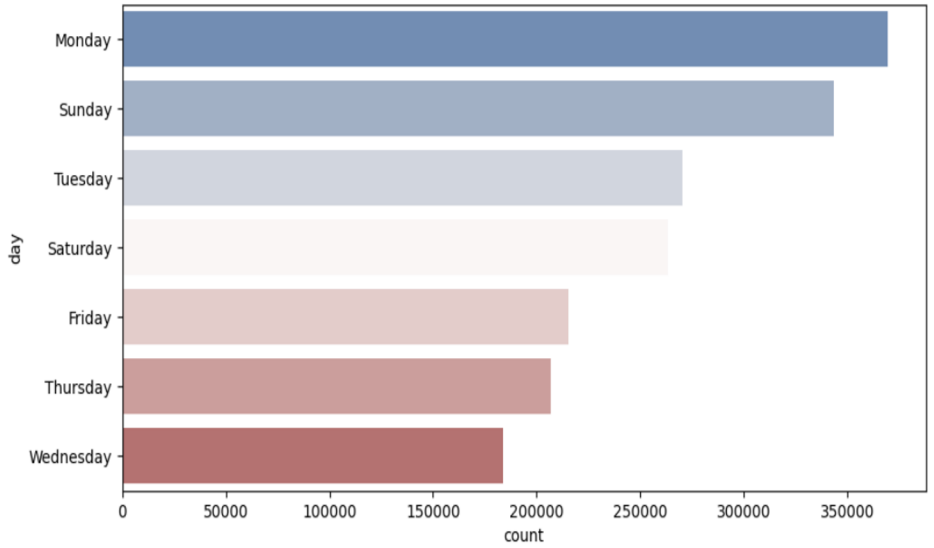
Exploring Credit Card Transaction Data







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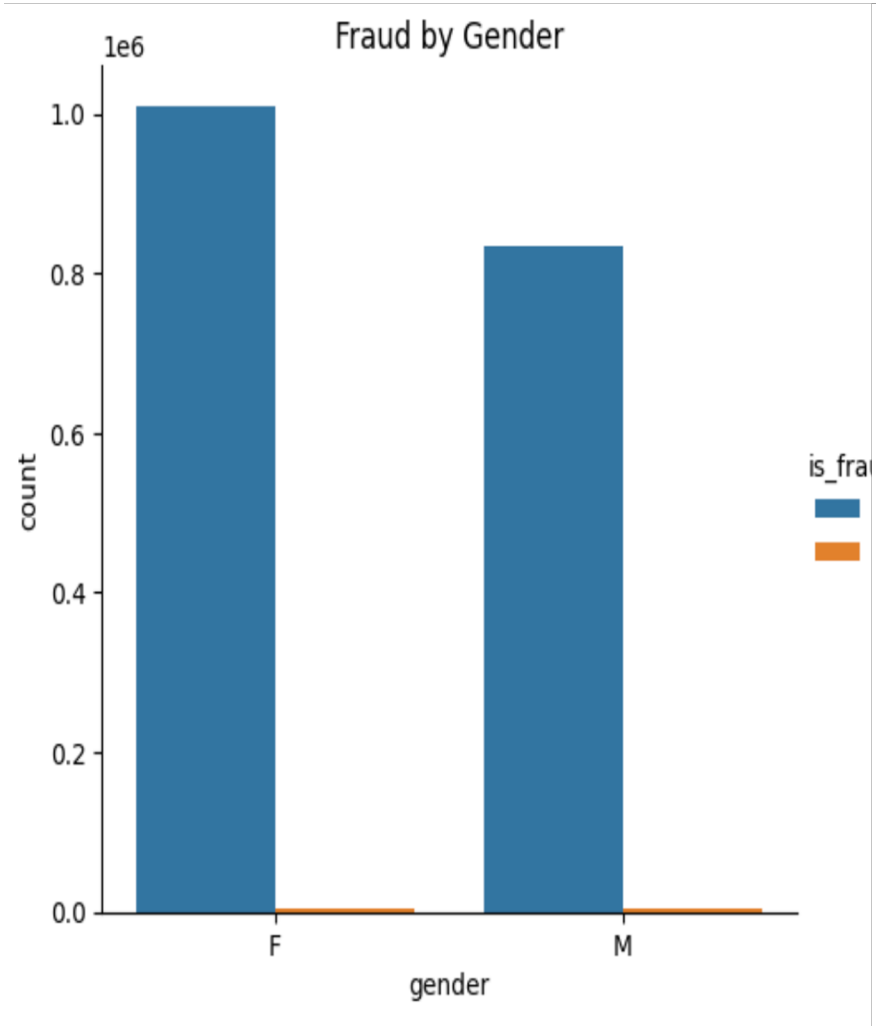
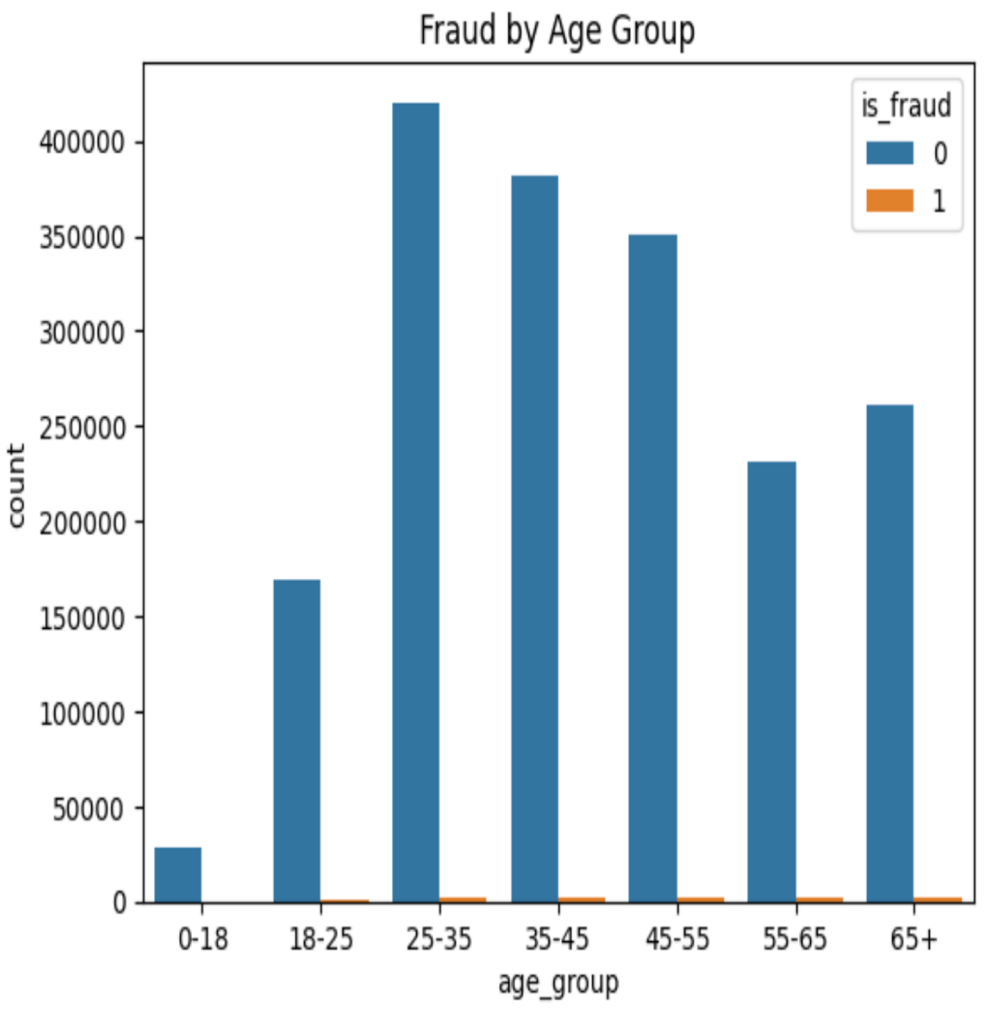
Exploring Credit Card Transaction Data





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Literature Review

- Using SMOTE to combat class imbalance, Haddab (2022) employed logistic regression, random forest, Naive Bayes, and multilayer perceptron algorithms to select the best performing classifier
  - Random forest had the best performance with an accuracy of 98.96%, precision of 97.38%, and recall of 83.63%
- Also with the goal to find the best performing classifier, Afriyie et al. (2023) used logistic regression, decision tree, and random forest along with undersampling the data
  - Random forest performed best with an AUC of 98.8%

Literature Review

- Alabrah (2023) compares five classifiers with and without the normalization of outliers to detect differences in performance
  - Machine learning models in the second experiment with outliers normalized provided more robust results
- Mustaqim et al. (2021) studied the effectiveness of feature selection and its influence on classification results by employing recursive feature elimination with cross validation (RFECV)
  - Found that applying different values of k lead to lower accuracy in decision tree model but no effect in Naive Bayes model
  - Increase in k resulted in lower number of selected features

02

Objectives and Research Questions

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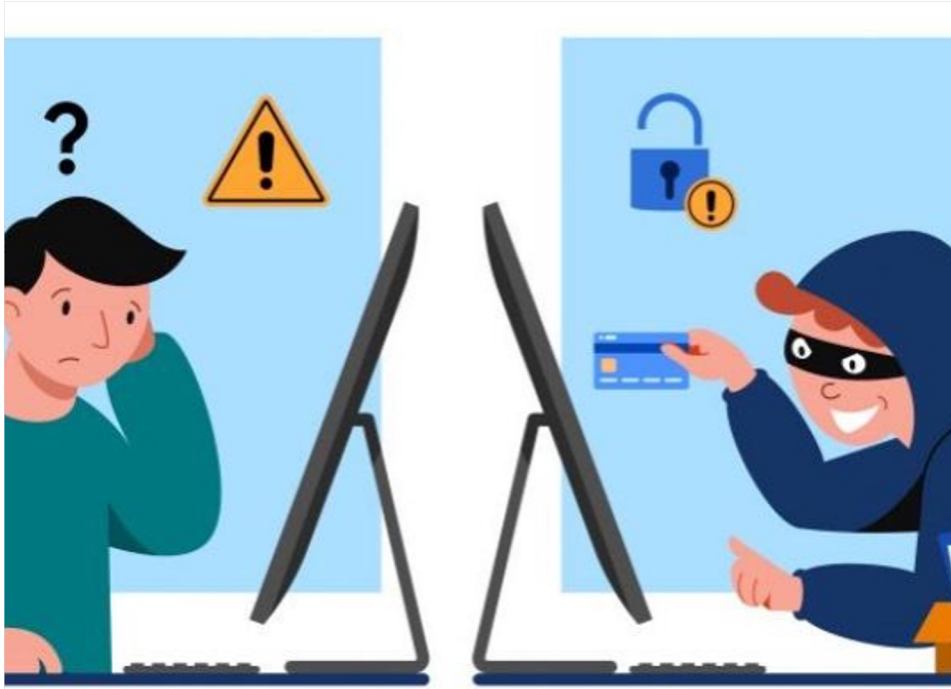
Objectives

- Compare three resampling techniques with three machine learning algorithms to identify the best performing model
- Examine differences in performance of models with and without outliers
- Observe performances of models with all and selected features



Source: Gareth (2022)

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Research Questions

1. Knowing that there exists a bias towards non-fraudulent transactions, what sampling technique will perform better for creating an accurate fraud detection model?
2. In relation to the first question, will the models perform better when outliers are present and transformed, or when no outliers exist?
3. What are the essential features that assist in determining the two classes of transactions, legitimate and fraudulent?

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03

Methodology

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Data Description

- "A simulated credit card transaction dataset containing legitimate and fraud transactions from the duration of January 1st to December 31st, 2020" (Shenoy, 2019)
  - Generated using Sparkov Data Generation tool designed by Brandon Harris
  - Contains credit cards of 1000 consumers in the United States and 800 merchants
  - 1,296,675 observations with 23 features

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Dataset

	cc_num	merchant	category	amt	first	last	gender	street	city	state
0	0 2703186189652095\n1 6304...	fraud_Rippin, Kub and Mann	misc_net	4.97	Jennifer	Banks	F	561 Perry Cove	Moravian Falls	NC
1	0 2703186189652095\n1 6304...	fraud_Heller, Gutmann and Zieme	grocery_pos	107.23	Stephanie	Gill	F	43039 Riley Greens Suite 393	Orient	WA
2	0 2703186189652095\n1 6304...	fraud_Lind-Buckridge	entertainment	220.11	Edward	Sanchez	M	594 White Dale Suite 530	Malad City	ID
3	0 2703186189652095\n1 6304...	fraud_Kutch, Hermiston and Farrell	gas_transport	45.00	Jeremy	White	M	9443 Cynthia Court Apt. 038	Boulder	MT
4	0 2703186189652095\n1 6304...	fraud_Keeling-Crist	misc_pos	41.96	Tyler	Garcia	M	408 Bradley Rest	Doe Hill	VA

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Methodology

- **Data Preparation**
  - Reading in the datasets into pandas DataFrame, data type conversions, feature engineering, dropping redundant variables
- **Exploratory Data Analysis (EDA)**
  - Univariate and bivariate analysis, data visualization (bar plots, box plots, pie charts)
  - Revisit data preparation stage
- **Data Preprocessing**
  - Create copy of dataset
  - Scaling the datasets (RobustScaler on original dataset and MinMaxScaler on copied dataset)
  - One-hot encoding of categorical features, train-test split (70% training, 30% testing), feature selection using RFECV

Methodology

- **Data Modelling**
  - Pipelines to chain resampling technique with machine learning algorithm
    - Resampling techniques: random under sampling, random over sampling, synthetic minority over sampling (SMOTE)
    - Machine learning algorithms: logistic regression, decision tree, random forest
  - Hyperparameter tuning with RandomizedSearchcv
    - Fitted with the training set
- **Performance**
  - Performance metrics: accuracy, recall, precision, Matthew's correlation (MCC), F1 score
  - Receiver operating characteristic curves (ROC) and area under the curve value (AUC)

Tools

- **Pandas**
  - Open source package for data analysis and manipulation (Pandas, 2023)
- **Scikit-learn (Sklearn)**
  - Open source package for machine learning (Pedregosa et al., 2011)
- **imblearn**
  - Open source MIT-licensed library for managing imbalanced data (The imbalance-learn developers, 2023)
- **NumPy**
  - Scientific computing package to perform operations on arrays (NumPy Developers, 2022)
- **Matplotlib**
  - Data visualization package for creating plots (The Matplotlib development team, 2023)
- **Seaborn**
  - High level interface data visualization package for graphing (Waskom, 2022)

04

Results

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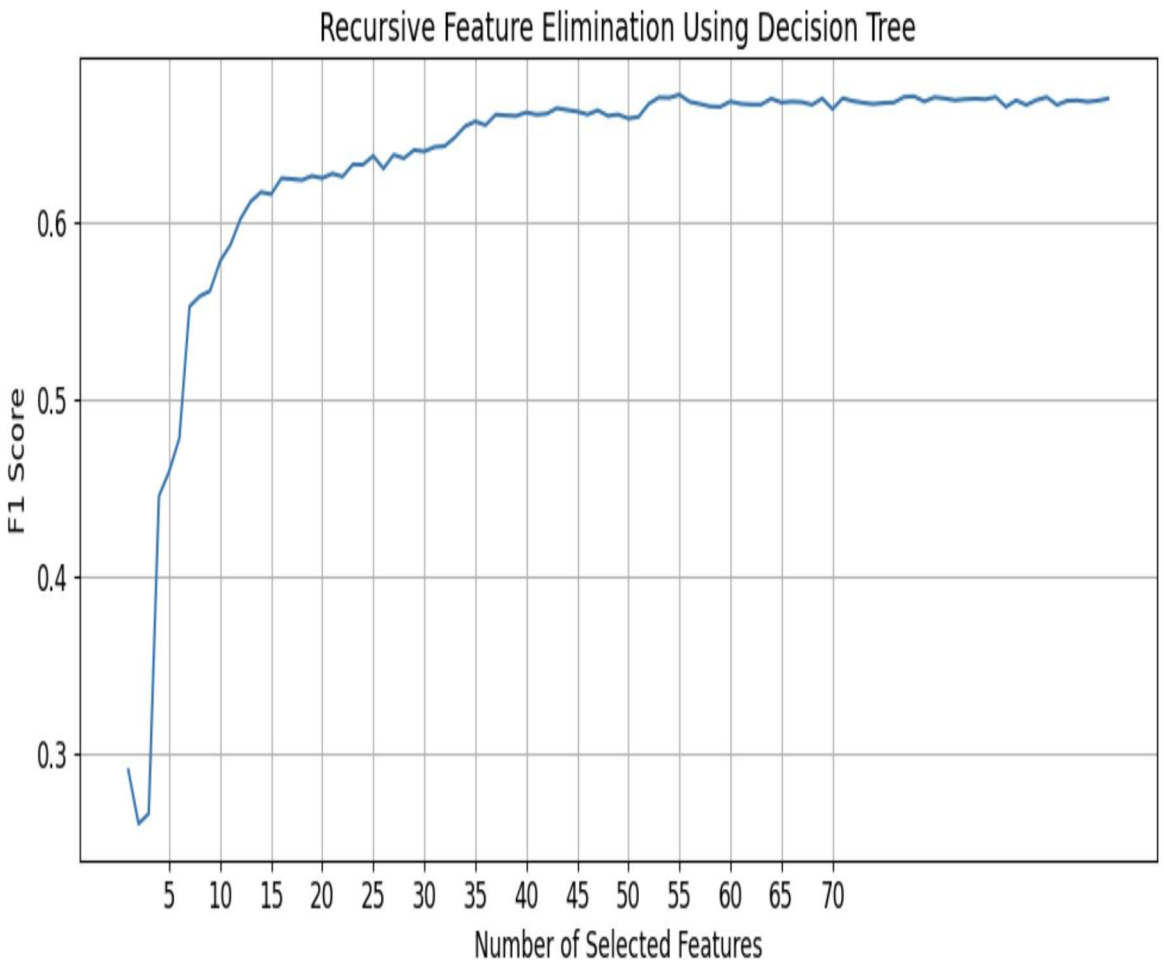
Feature Selection

- Best performing number of features was 55
- Features selected included:
  - amt (amount)
  - gender
  - lat (latitude)
  - long (longitude)
  - year
  - age



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Performance of models on original dataset using RobustScalar containing all features vs selected features

Table 1: Performance of using random under sampling on three machine learning algorithms on original dataset.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.96	0.75	0.96	0.09	0.99	0.25	0.16	0.86
Decision Tree	0.96	0.96	0.96	0.11	0.99	0.32	0.20	0.96
Random Forest	0.98	0.93	0.98	0.21	0.99	0.44	0.34	0.96

Table 2: Performance of using random over sampling on three machine learning algorithms on original dataset.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.90	0.75	0.90	0.04	0.99	0.16	0.07	0.83
Decision Tree	0.99	0.79	0.99	0.32	0.99	0.50	0.46	0.89
Random Forest	0.99	0.82	0.99	0.67	0.99	0.74	0.74	0.91

Table 3: Performance of using SMOTE on three machine learning algorithms on original dataset.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.98	0.69	0.99	0.21	0.99	0.37	0.31	0.84
Decision Tree	0.99	0.87	0.99	0.31	0.99	0.52	0.46	0.93
Random Forest	0.99	0.83	0.99	0.55	0.99	0.71	0.71	0.91

Table 7: Performance of using random under sampling on three machine learning algorithms on original dataset with selected features.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.96	0.75	0.96	0.09	0.99	0.25	0.16	0.86
Decision Tree	0.95	0.95	0.95	0.09	0.99	0.28	0.16	0.95
Random Forest	0.98	0.92	0.98	0.23	0.99	0.46	0.37	0.95

Table 8: Performance of using random over sampling on three machine learning algorithms on original dataset with selected features.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.90	0.76	0.90	0.04	0.99	0.16	0.08	0.83
Decision Tree	0.98	0.85	0.98	0.23	0.99	0.43	0.36	0.92
Random Forest	0.99	0.86	0.99	0.56	0.99	0.69	0.68	0.93

Table 9: Performance of using SMOTE on three machine learning algorithms on original dataset with selected features.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.98	0.69	0.98	0.14	0.99	0.31	0.23	0.83
Decision Tree	0.97	0.80	0.97	0.12	0.99	0.30	0.21	0.88
Random Forest	0.99	0.81	0.99	0.38	0.99	0.56	0.52	0.91

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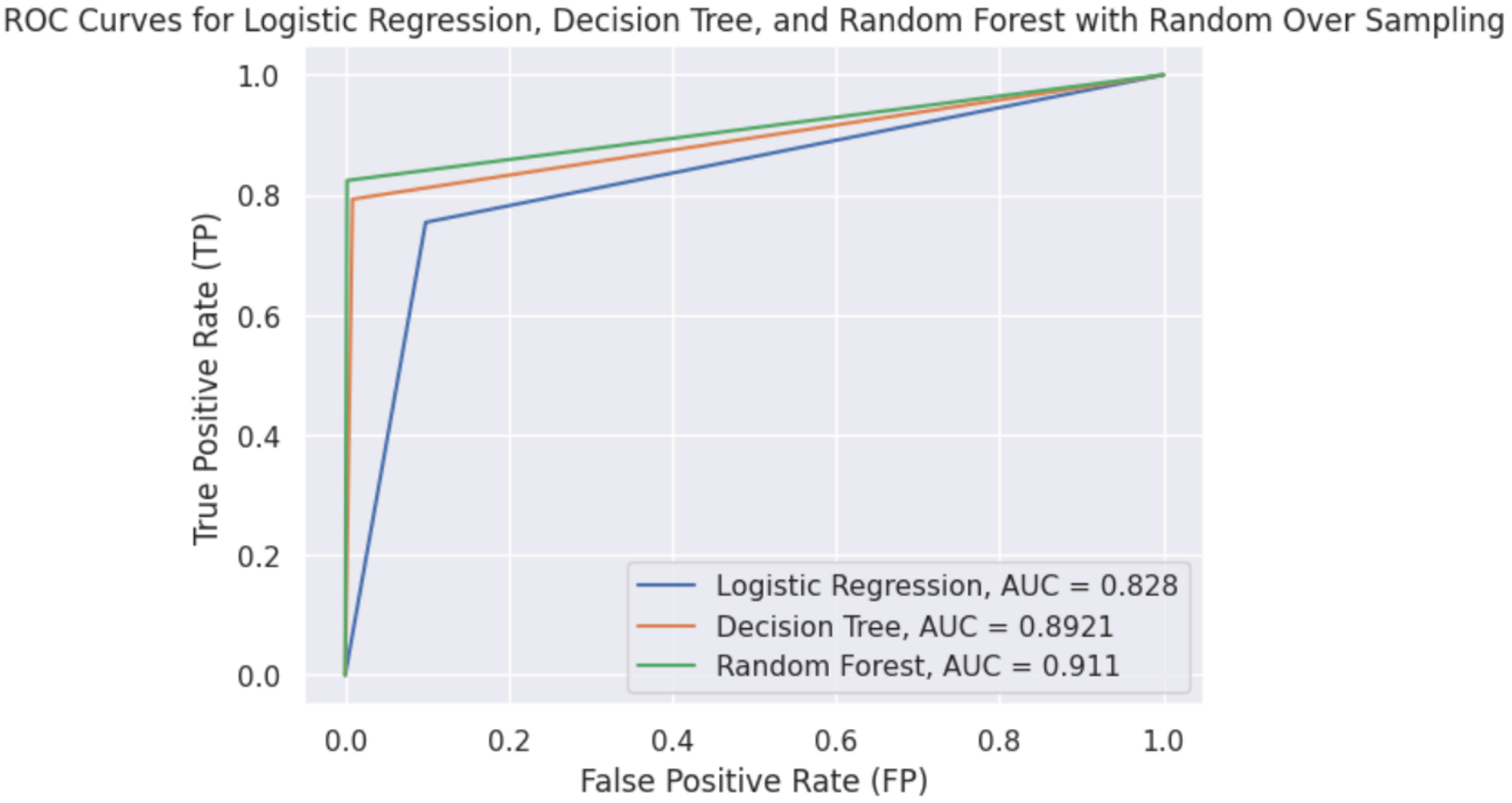
ROC Curves for Random Over Sampling



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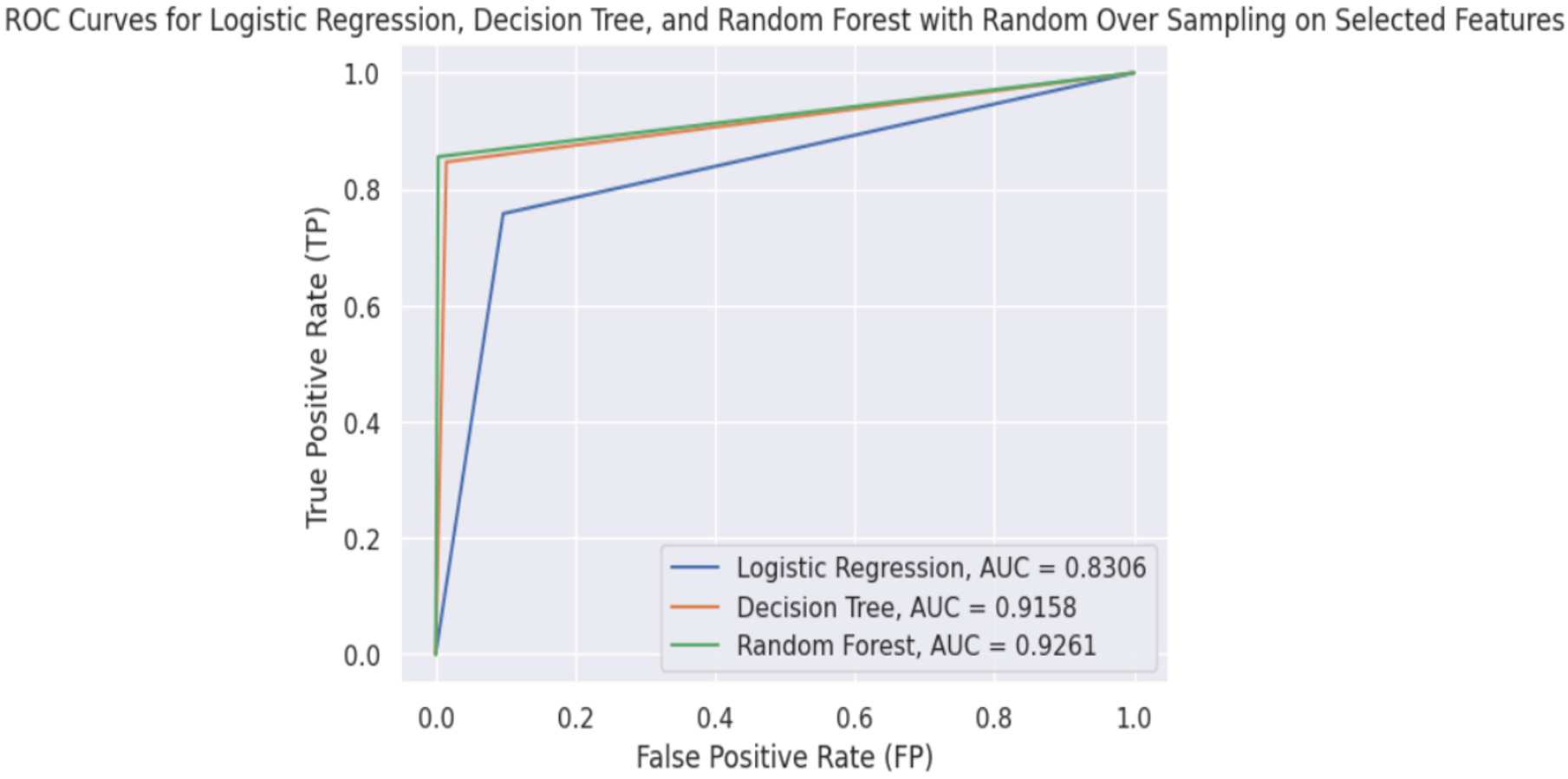
ROC Curves for Random Over Sampling (Selected Features)



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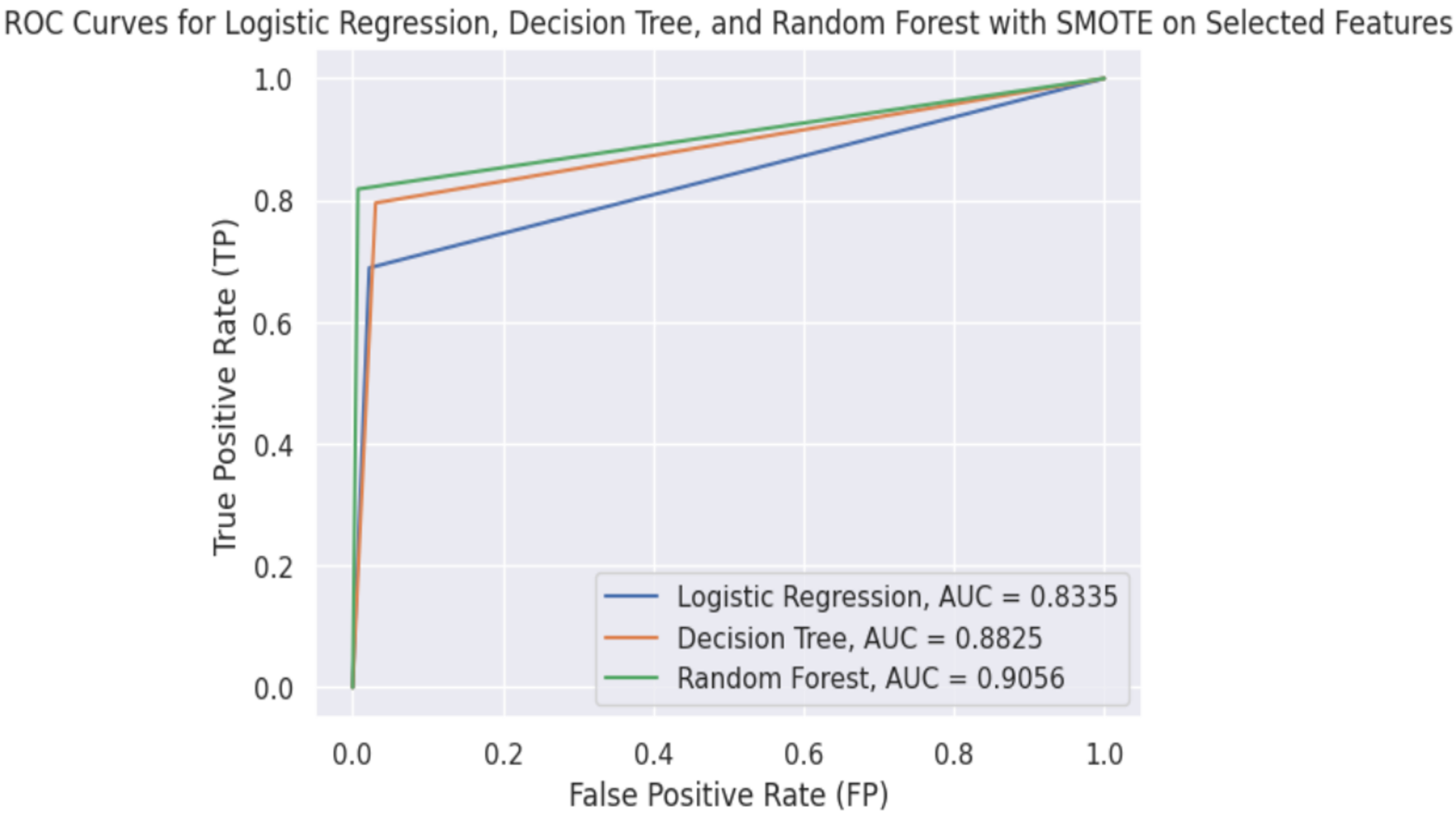
ROC Curves for SMOTE (Selected Features)



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Performance of models with no outliers containing all features vs selected features

Table 4: Performance of using random under sampling on three machine learning algorithms on copied dataset containing no outliers.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.71	0.72	0.71	0.00	0.99	0.04	0.00	0.72
Decision Tree	0.92	0.96	0.92	0.02	0.99	0.12	0.03	0.94
Random Forest	0.89	0.97	0.89	0.01	0.99	0.10	0.03	0.93

Table 5: Performance of using random over sampling on three machine learning algorithms on copied dataset containing no outliers.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.66	0.89	0.66	0.00	0.99	0.04	0.00	0.77
Decision Tree	0.99	0.65	0.99	0.08	0.99	0.23	0.15	0.82
Random Forest	0.99	0.62	0.99	0.14	0.99	0.30	0.23	0.81

Table 6: Performance of using SMOTE on three machine learning algorithms on copied dataset containing no outliers.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.97	0.27	0.97	0.01	0.99	0.05	0.02	0.62
Decision Tree	0.99	0.62	0.99	0.07	0.99	0.20	0.12	0.80
Random Forest	0.98	0.70	0.98	0.05	0.99	0.18	0.09	0.84

Table 10: Performance of using random under sampling on three machine learning algorithms on copied dataset containing no outliers with selected features.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.73	0.69	0.73	0.00	0.99	0.04	0.00	0.71
Decision Tree	0.89	0.91	0.89	0.01	0.99	0.09	0.02	0.90
Random Forest	0.89	0.94	0.89	0.01	0.99	0.10	0.02	0.92

Table 11: Performance of using random over sampling on three machine learning algorithms on copied dataset containing no outliers with selected features.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.62	0.90	0.62	0.00	0.99	0.04	0.00	0.76
Decision Tree	0.99	0.59	0.99	0.05	0.99	0.18	0.10	0.79
Random Forest	0.99	0.60	0.99	0.11	0.99	0.26	0.19	0.80

Table 12: Performance of using SMOTE on three machine learning algorithms on copied dataset containing no outliers with selected features.

	Accuracy	Recall (+)	Recall (-)	Precision (+)	Precision (-)	MCC	F1 Score	AUC
Logistic Regression	0.81	0.59	0.81	0.00	0.99	0.04	0.00	0.70
Decision Tree	0.94	0.72	0.94	0.02	0.99	0.10	0.03	0.83
Random Forest	0.93	0.75	0.93	0.02	0.99	0.10	0.03	0.84

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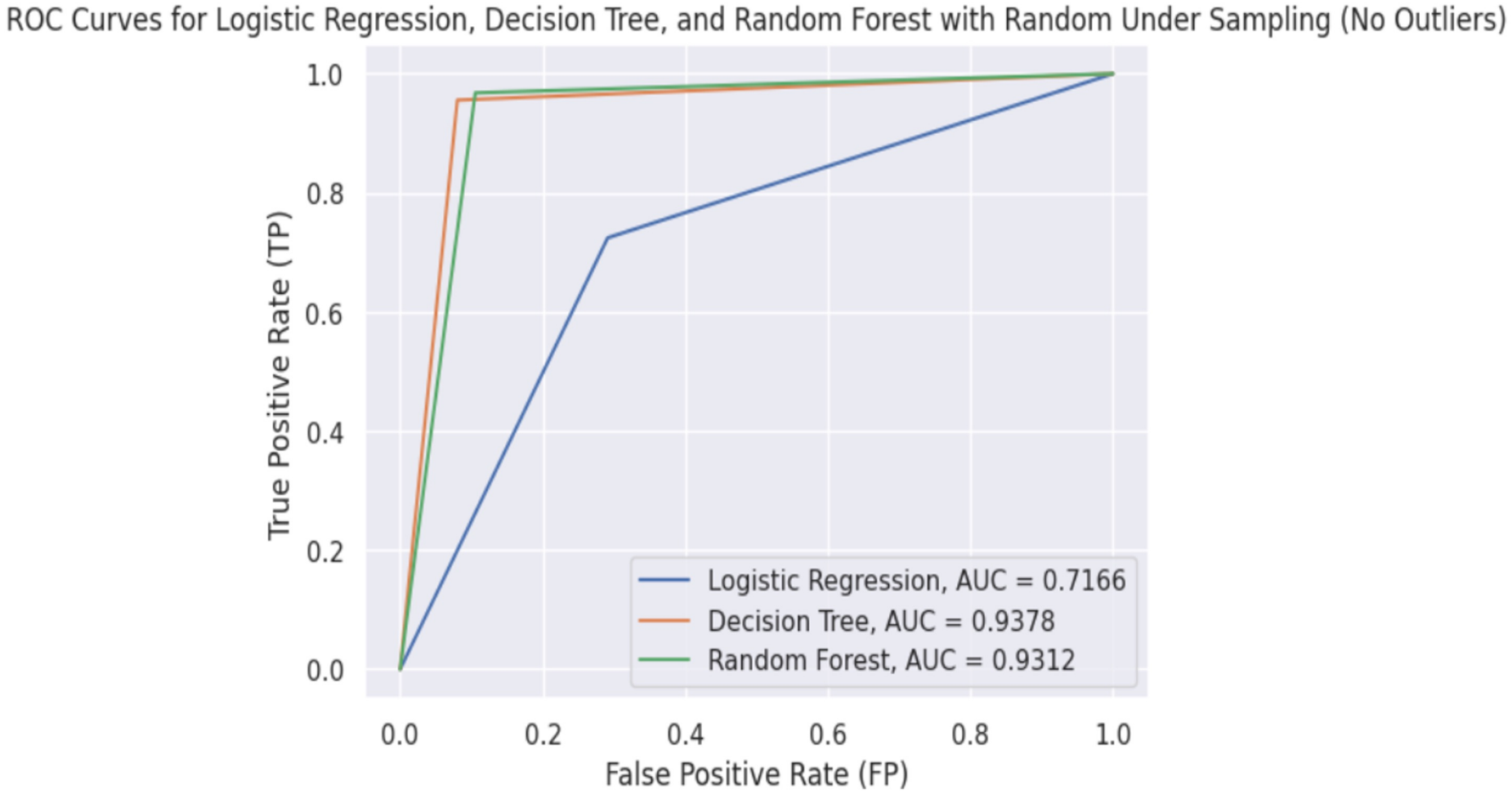
ROC Curves for Random Under sampling



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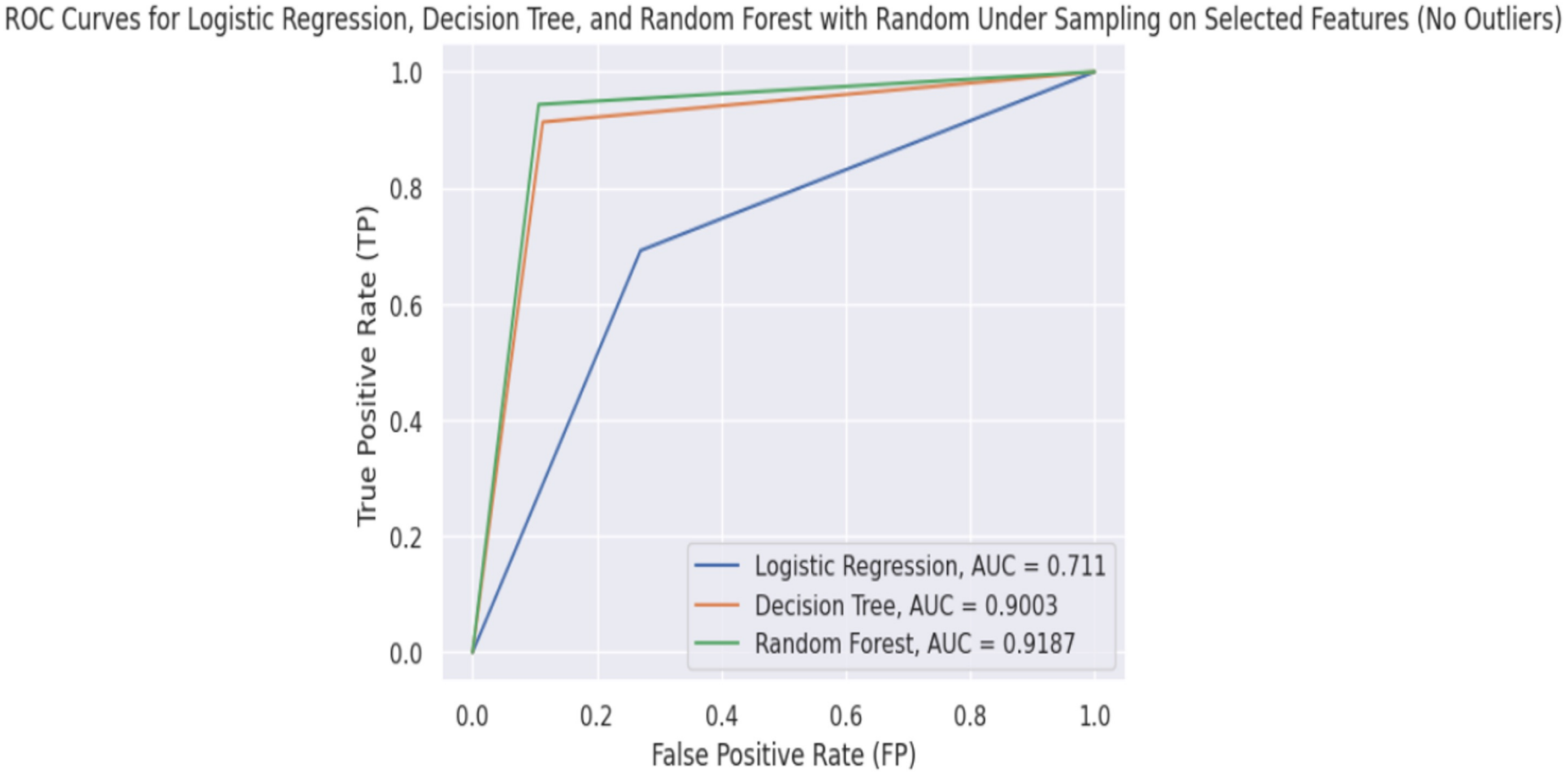
ROC Curves for Random Under sampling (Selected Features)



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Comparing Results with Previous Studies

- In this study, models created with original dataset that underwent under sampling and containing all features (Table 1) achieved somewhat better performance than Afriyie et al. (2023)
  - Logistic regression and decision tree model had an accuracy of approximately 96% in comparison to 92% in their study
  - F1 score of models in both studies were however relatively weak
  - Recall of the positive class were relatively similar

Table 11
Comparing the models' performances.

Model name	Accuracy	F1-Score	Recall	Precision	Specificity
Decision tree	0.92	0.09	0.93	0.05	0.92
Random forest	0.96	0.17	0.97	0.09	0.96
Logistics regression	0.92	0.08	0.76	0.04	0.92

Source: Afriye et al. (2023)

Comparing Results with Previous Studies

- Similar to what was observed in Alabrah's (2023) study, models created with the original dataset using RobustScalar had higher performance in comparison to models containing no outliers in terms of precision, MCC, and F1 score
- Almost in line with the findings of Afriyie et al. (2023) and Haddab (2022), random forest with random over sampling was the best performing classifier
  - With criterion set to entropy and a maximum depth of 25

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Limitations and Recommendations

- Selection of hyperparameter tuning algorithm
  - Only values selected by the user enter the grid space, leaving out other potential values that offer a more optimal set
  - Adopt Bayesian optimization as a potential alternative (Gupta, 2020)
- Utilizing ROC AUC as a performance metric
  - Provided overly optimistic results, biased towards the negative class, which is legitimate transactions
  - Employ instead precision-recall curves since more emphasis is given to the minority class (Brownlee, 2020)
- Examined limited machine learning algorithms
  - Other supervised machine learning algorithms may be better classifiers for distinguishing the two types of transactions
  - Consider Support Vector Machine (SVM), Naive Bayes, and among others

Conclusion

- Creating a fraud detection model is a continuous process
- Explored three resampling techniques with three machine learning algorithms, examined performance of models with and without outliers and with selected features
  - Three resampling techniques employed were random under sampling, random over sampling, and SMOTE
  - Three machine learning algorithms were logistic regression, decision tree, and random forest
  - Applied Sklearn RobustScalar on original dataset and MinMaxScalar for copied dataset
  - RFECV for feature selection

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Conclusion

- Models that were created using the original dataset with RobustScalar and with all features overall achieved better performance across all metrics in comparison to the copied dataset with no outliers
- Specifically, over sampling the data and using random forest on the original dataset achieved the highest performance

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