Machine Learning Engineer Capstone Project

Project Report

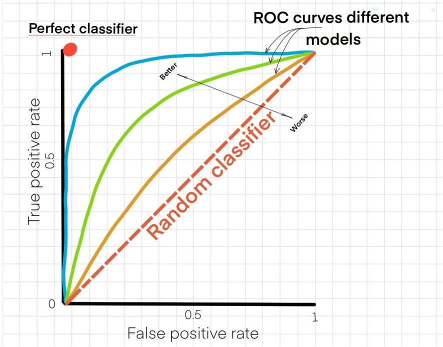
Project Overview

- Credit card fraud is a significant issue faced by credit card companies and cardholders. Recognizing fraudulent transactions promptly ensures customers aren't inaccurately charged for purchases they didn't make. This responsibility primarily falls on credit card companies and financial institutions who need to put robust measures in place to detect and prevent such fraudulent activities.
- The objective of this project is to construct a predictive model capable of analyzing transaction samples and determining whether a given credit card transaction is fraudulent or legitimate. Instead of using the traditional methods showcased during the Nanodegree Program with AWS, we will develop an endpoint utilizing Python frameworks. This alternate approach allows us to exhibit a diverse set of methods for creating operational endpoints for predictive models.

Problem Statement

- The problem is the Kaggle challenge which can be accessed via a link. Based on the credit card data, the challenge is to build a predictive model that verifies whether the credit card is a fraud or not.
- The key challenge presented by this problem is the severe class imbalance in the dataset. Traditional accuracy measures, such as confusion matrix accuracy, prove to be ineffective in this scenario, potentially leading to a high number of false negatives and subsequently undetected fraudulent transactions. Therefore, it is crucial to employ a more robust evaluation metric like the Area Under the Precision-Recall Curve (AUPRC) to effectively handle the imbalance and accurately identify instances of fraud.
- The objective is to build a robust machine learning model that can effectively predict fraudulent transactions, despite the significant class imbalance in the dataset, while maintaining high precision and recall scores. This will involve handling the skewed distribution of class labels and dealing with transformed features that maintain data confidentiality.

Metrics

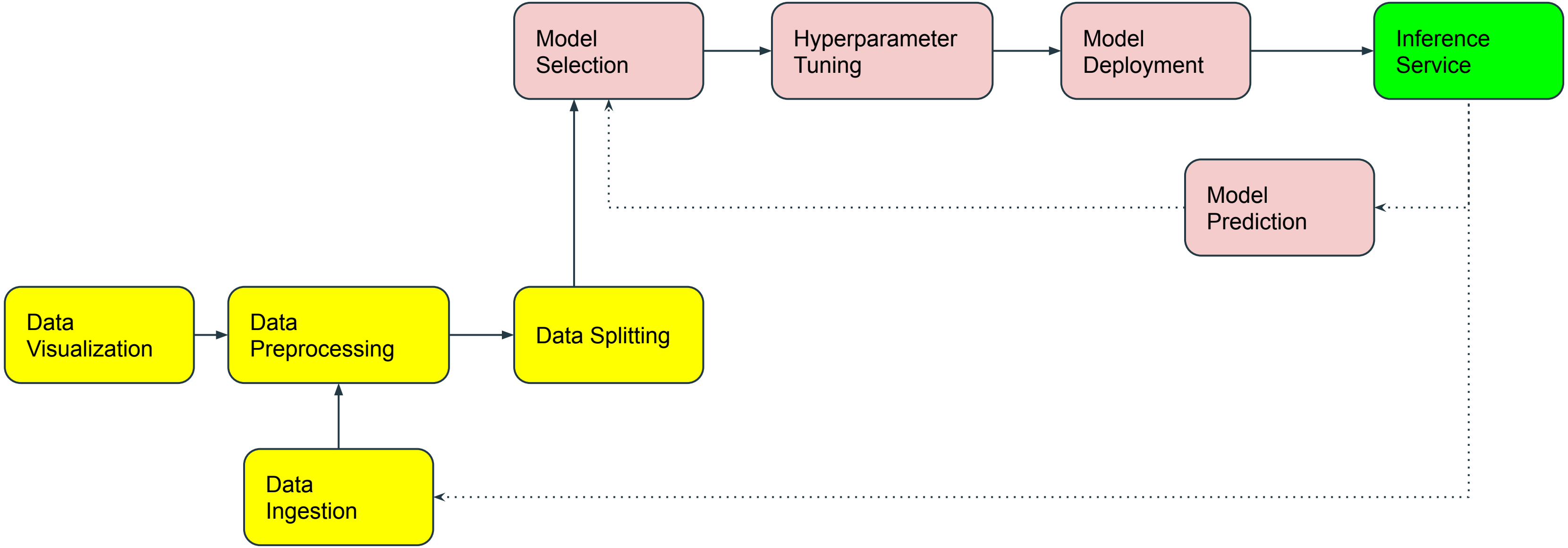


- In order to assess the performance of our model, we must rely on robust, mathematically sound metrics that correspond with our specific problem statement, and which our model can be optimized against.
- Given that our task is Classification-based, suitable metrics would include Accuracy, Recall, Precision, and F1 scores. These can be applied not only to the dataset as a whole but also to individual classes. This will enable us to discern if our model is demonstrating superior performance in specific classes, or if it exhibits a significant bias towards a certain class. We chose the Receiving Operating Characteristic score (ROC) of the classification to evaluate the performance of the trained model.

Implementation

- Download Training Data: First you will have to download the training data to local storage.
- Data exploration and processing: handle imbalanced data with SMOTE, remove outliers with Interquartile Range Method,...
- Data splitting: using cross validation with k-fold is 5.
- Train model: run that training script and train your model.
- Hyperparameter tuning: tuning some classification models and choose the best estimator.
- Model evaluation and save model to disk.
- Model deployment: serving the best trained model using Flask.

Implementation

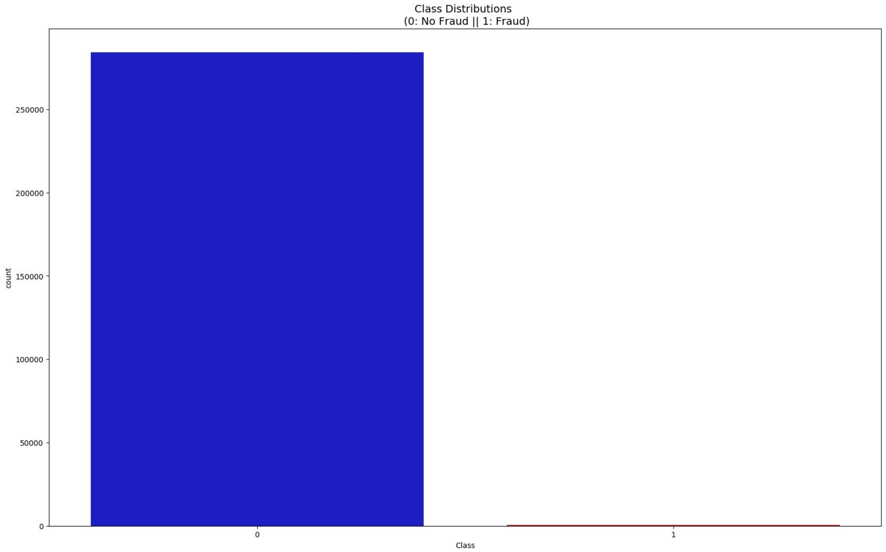


Data Exploration

- Data has not null values
- Data has 30 columns are *'Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10', 'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20','V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount','Class'.*
- Fraudulent transactions represent only 0.172% of the total transactions, which makes the task of identifying them much more complex.

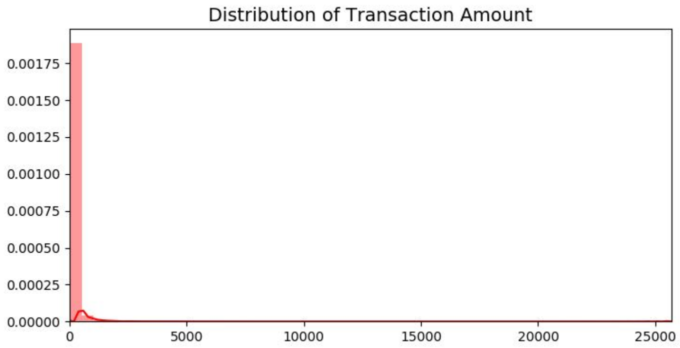
Data Exploration

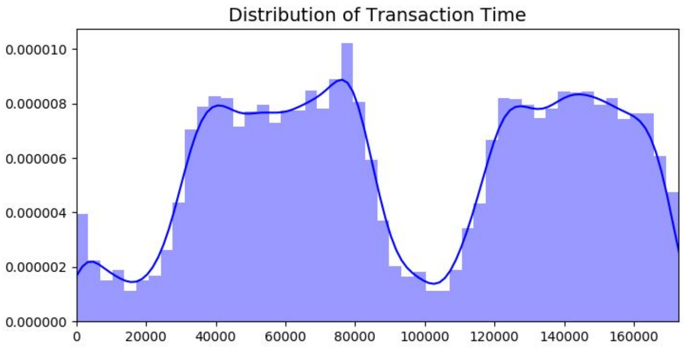
- Through analyzing the distributions, we gain insights into the skewness of these features, while also getting a glimpse into the distributions of other variables. Various techniques exist to reduce skewness in these distributions, which we will look to incorporate into this notebook in upcoming iterations.



Data Exploration

- Initially, we'll standardize the 'Time' and 'Amount' columns to align with the scaling of other columns. Concurrently, we'll generate a balanced subset of the dataframe, ensuring equal representation of Fraud and Non-Fraud cases. This balanced distribution aids our algorithms in discerning patterns that accurately differentiate between fraudulent and legitimate transactions.





Data Exploration

- It spans across two days and includes a total of 284,807 transactions, out of which 492 were fraudulent. A significant challenge with this dataset, and indeed the issue of credit card fraud detection in general, is the high imbalance between legitimate and fraudulent transactions.

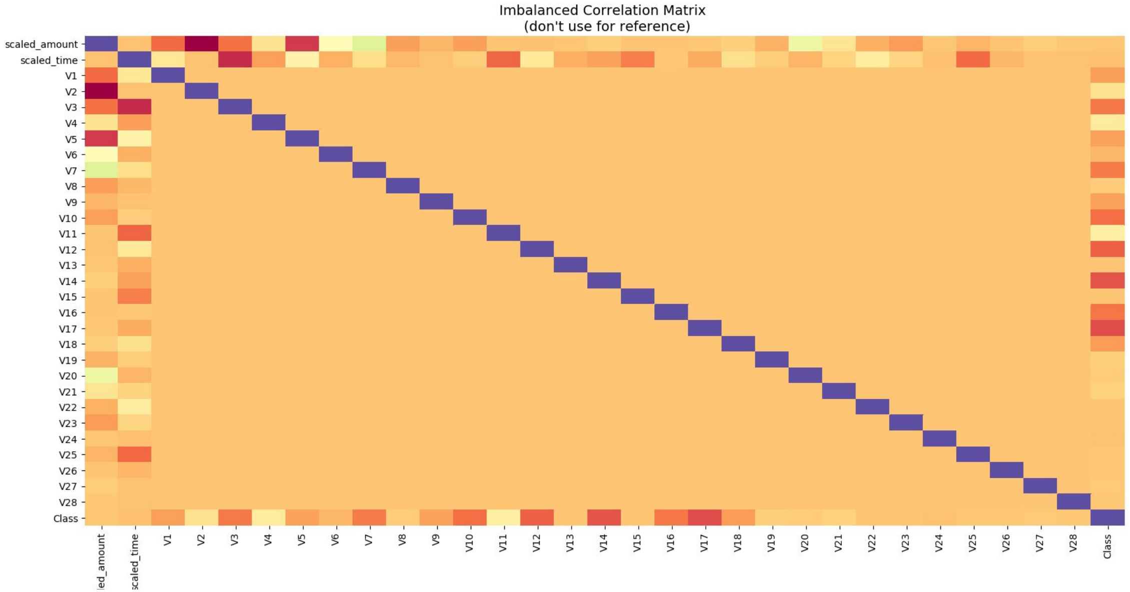
	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	...
mean	94813.859575	3.918649e-15	5.682686e-16	-8.761736e-15	2.811118e-15	-1.552103e-15	2.040130e-15	-1.698953e-15	-1.893285e-16	-3.147640e-15	...
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+00	1.332271e+00	1.237094e+00	1.194353e+00	1.098632e+00	...
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+02	-2.616051e+01	-4.355724e+01	-7.321672e+01	-1.343407e+01	...
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-01	-7.682956e-01	-5.540759e-01	-2.086297e-01	-6.430976e-01	...
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-02	-2.741871e-01	4.010308e-02	2.235804e-02	-5.142873e-02	...
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-01	3.985649e-01	5.704361e-01	3.273459e-01	5.971390e-01	...
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+01	7.330163e+01	1.205895e+02	2.000721e+01	1.559499e+01	...

8 rows × 31 columns

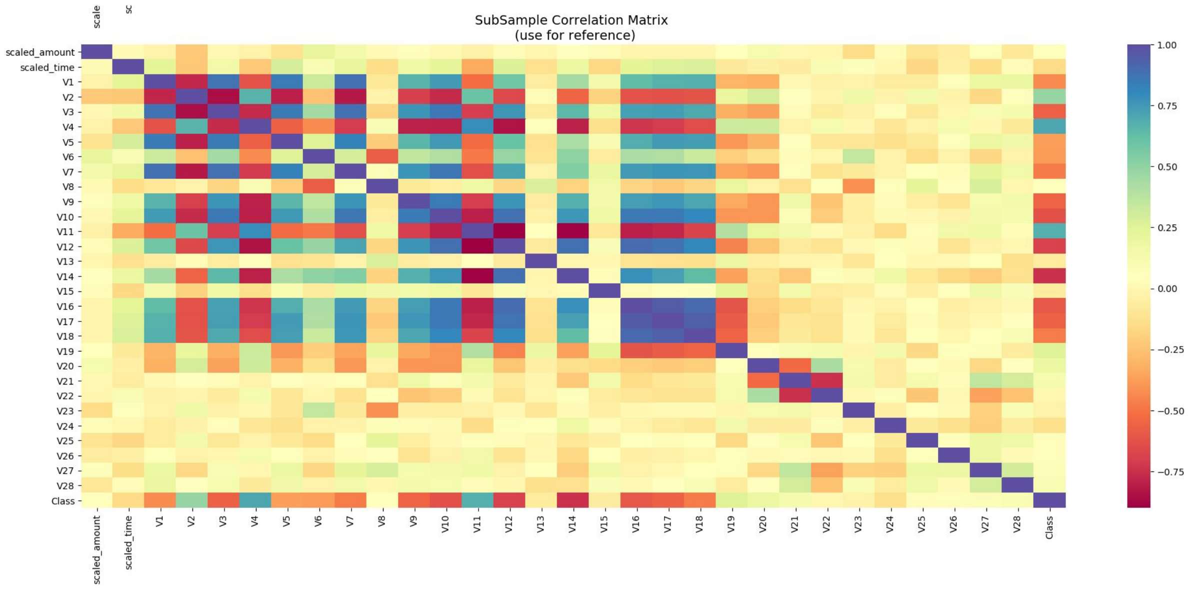
Exploratory Visualization

- Correlation matrices are integral to gaining insights into our data. They enable us to identify features that significantly sway the likelihood of a transaction being fraudulent. However, it's crucial that we utilize the appropriate dataframe (in this case, the subsample) to accurately observe which features exhibit strong positive or negative correlations in relation to fraudulent transactions.

Exploratory Visualization



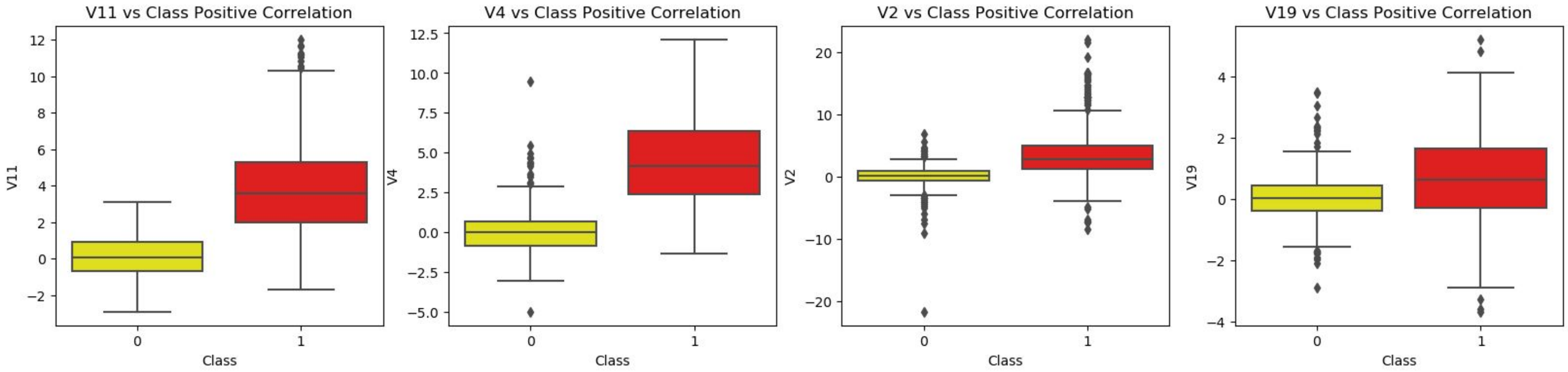
Exploratory Visualization



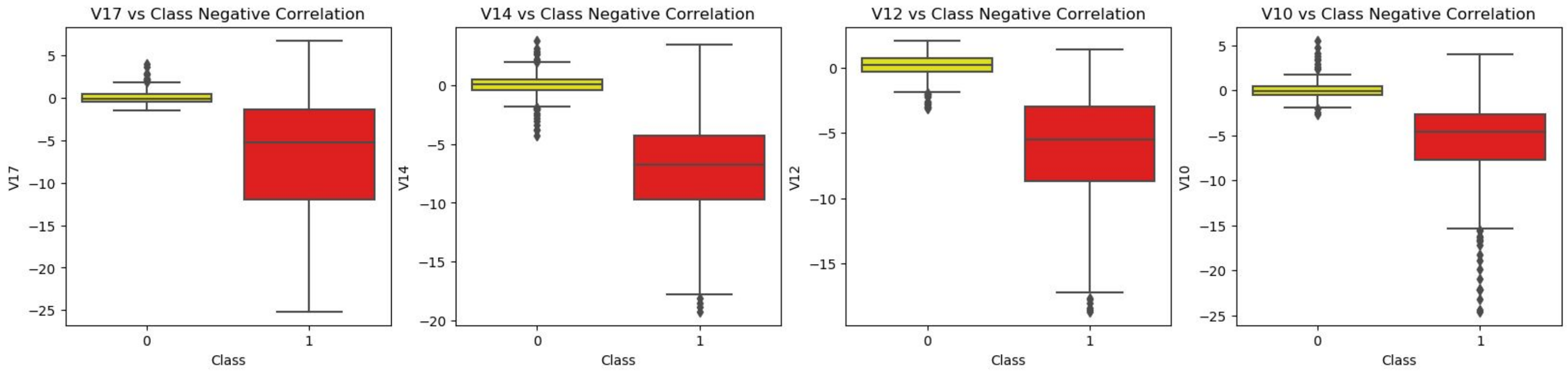
Exploratory Visualization

- Negative Correlations: V17, V14, V12 and V10 are negatively correlated. Notice how the lower these values are, the more likely the end result will be a fraud transaction.
- Positive Correlations: V2, V4, V11, and V19 are positively correlated. Notice how the higher these values are, the more likely the end result will be a fraud transaction.
- BoxPlots: We will use boxplots to have a better understanding of the distribution of these features in fradulent and non fradulent transactions.

Exploratory Visualization



Exploratory Visualization



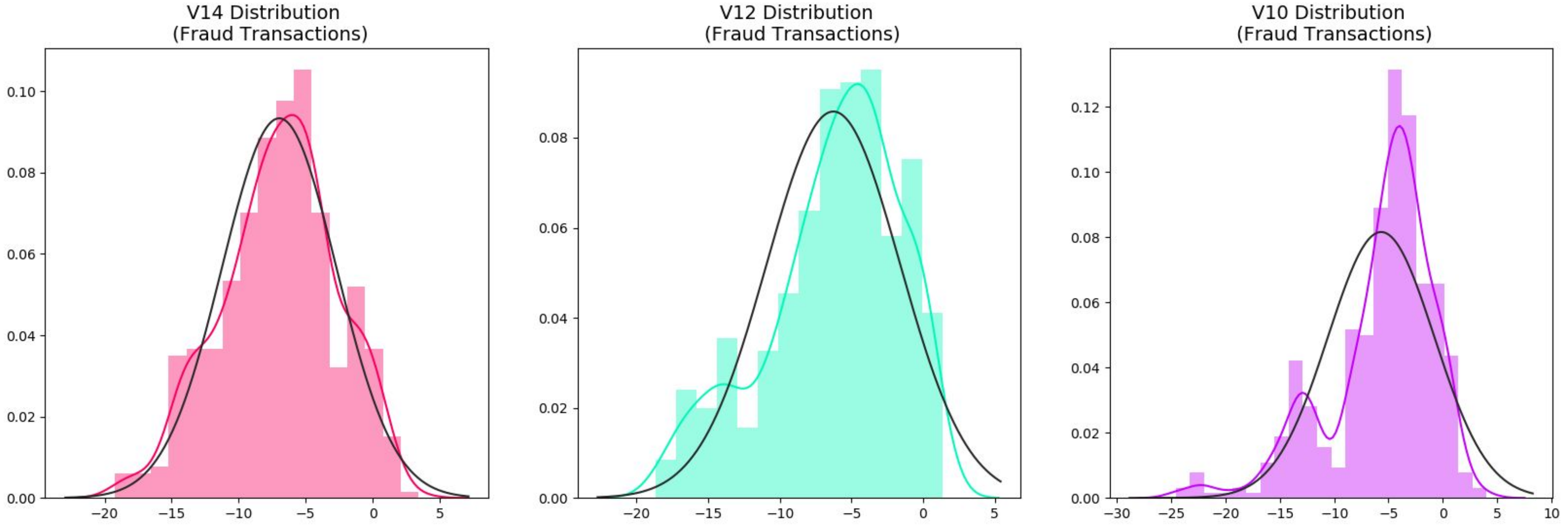
Data Processing

- The primary goal in this segment is to eliminate "extreme outliers" from features exhibiting a strong correlation with our classes. This action will contribute beneficially to enhancing the precision of our models.
- Interquartile Range Method:
    - Interquartile Range (IQR): Our approach involves calculating the interquartile range, which is the difference between the 75th and 25th percentiles. Our objective is to establish a threshold that goes beyond these percentiles, such that if any instance crosses this boundary, it gets eliminated.
    - Boxplots: Besides readily identifying the 25th and 75th percentiles, represented by the ends of the boxes, it's also straightforward to spot extreme outliers, which are the points falling beyond the upper and lower extremes.

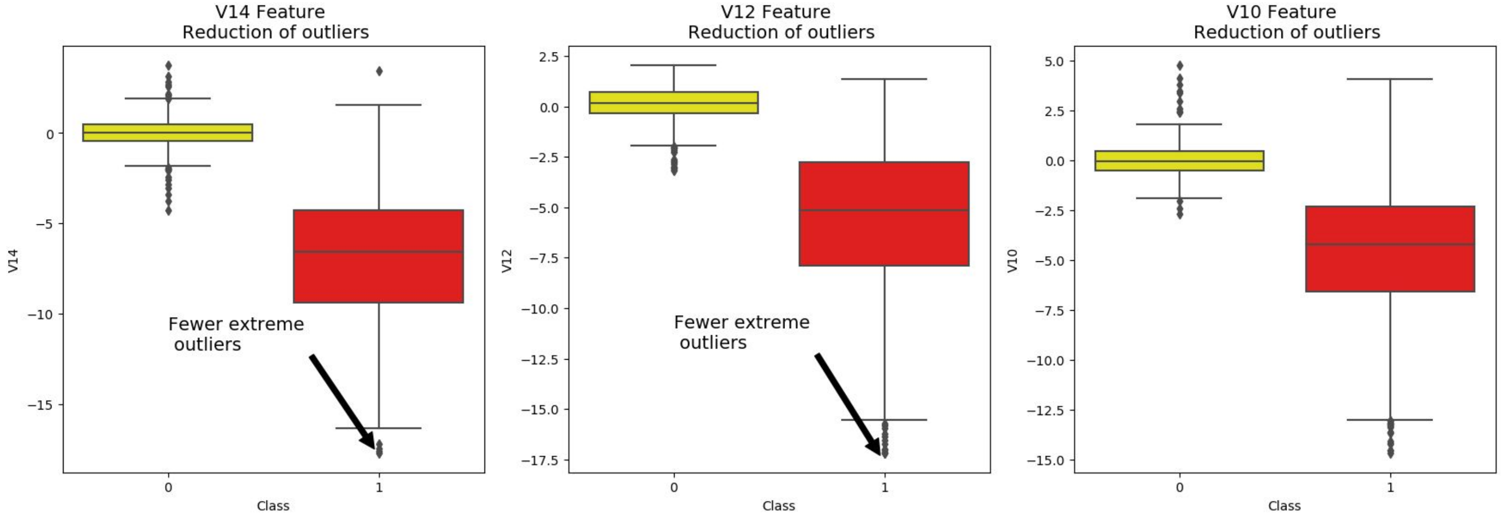
Data Processing

- Visualize Distributions: We first start by visualizing the distribution of the feature we are going to use to eliminate some of the outliers. V14 is the only feature that has a Gaussian distribution compared to features V12 and V10.
- Determining the threshold: After we decide which number we will use to multiply with the iqr (the lower more outliers removed), we will proceed in determining the upper and lower thresholds by substrating q25 - threshold (lower extreme threshold) and adding q75 + threshold (upper extreme threshold).
- \- Boxplot Representation: Visualize through the boxplot that the number of "extreme outliers" have been reduced to a considerable amount.

Data Processing
Dist Plot



Data Processing
Boxplot

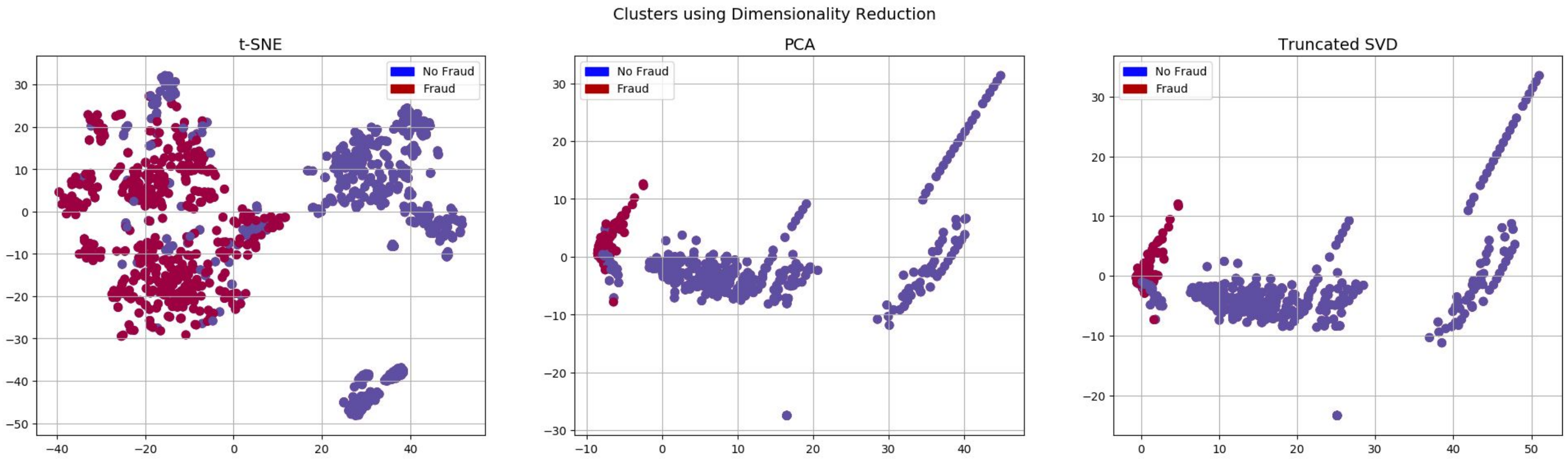


Data Processing

Dimensionality Reduction and Clustering:

- t-SNE algorithm can pretty accurately cluster the cases that were fraud and non-fraud in our dataset.
- Although the subsample is pretty small, the t-SNE algorithm is able to detect clusters pretty accurately in every scenario (I shuffle the dataset before running t-SNE)
- This gives us an indication that further predictive models will perform pretty well in separating fraud cases from non-fraud cases.

Data Processing
Dimensionality Reduction and Clustering



Algorithms and Techniques

UnderSampling

- Logistic Regression classifier is more accurate than the other three classifiers in most cases. (We will further analyze Logistic Regression)
- GridSearchCV is used to determine the parameters that gives the best predictive score for the classifiers.

Refinement

SMOTE Technique (Over-Sampling)

- Solving the Class Imbalance: SMOTE creates synthetic points from the minority class in order to reach an equal balance between the minority and majority class.
- Location of the synthetic points: SMOTE picks the distance between the closest neighbors of the minority class, in between these distances it creates synthetic points.
- Final Effect: More information is retained since we didn't have to delete any rows unlike in random undersampling.
- Accuracy || Time Tradeoff: Although it is likely that SMOTE will be more accurate than random under sampling, it will take more time to train since no rows are eliminated as previously stated.

Benchmark

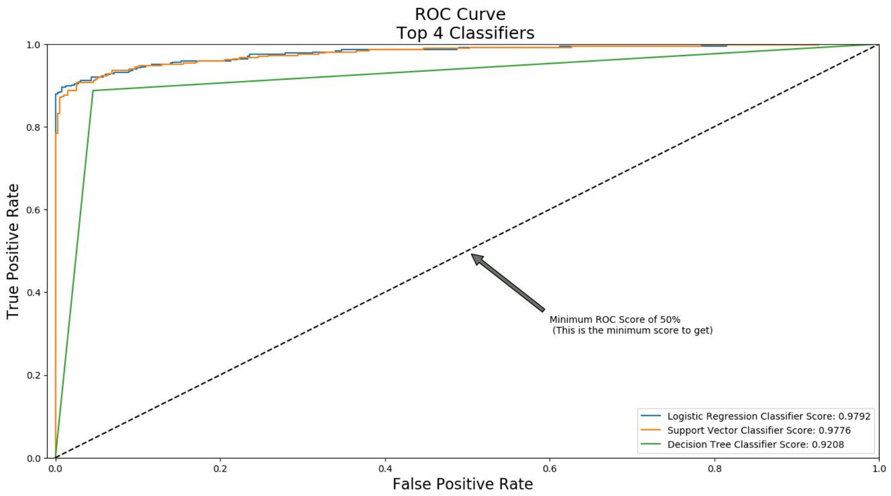
	Score (Baseline)	Score (GridSearchCV)
Logistic Regression	**0.94**	**0.9791**
SVM	0.93	0.9776
Decision Tree Classifier	0.91	0.9208

Benchmark
Logistic regression + SMOTE

	Technique	Score
0	Random UnderSampling	0.9210
1	Oversampling (SMOTE)	**0.9878**

Justification

- Logistic Regression has the best Receiving Operating Characteristic score (ROC), meaning that Logistic Regression pretty accurately separates fraud and non-fraud transactions.
- The Logistic Regression score is **0.9791**



Justification

Best score

- Logistic Regression combine with SMOTE is the best solution that has Receiving Operating Characteristic score (ROC)
- The Logistic Regression score is **0.9878**