

Credit Card Fraud Detection

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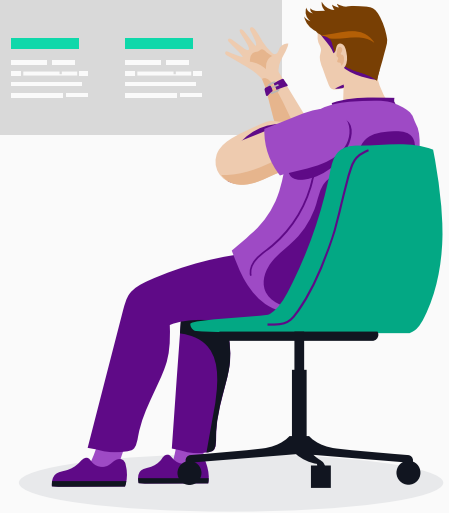
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Key Takeaways

01

Background

What is the importance and history of fraud detection?





\$28.7 Trillion

Total value of credit card transactions as of 2019



Fraud VS Transactions

As credit card use increases,
fraud increases.





**Total Losses
From Credit
Card Fraud**

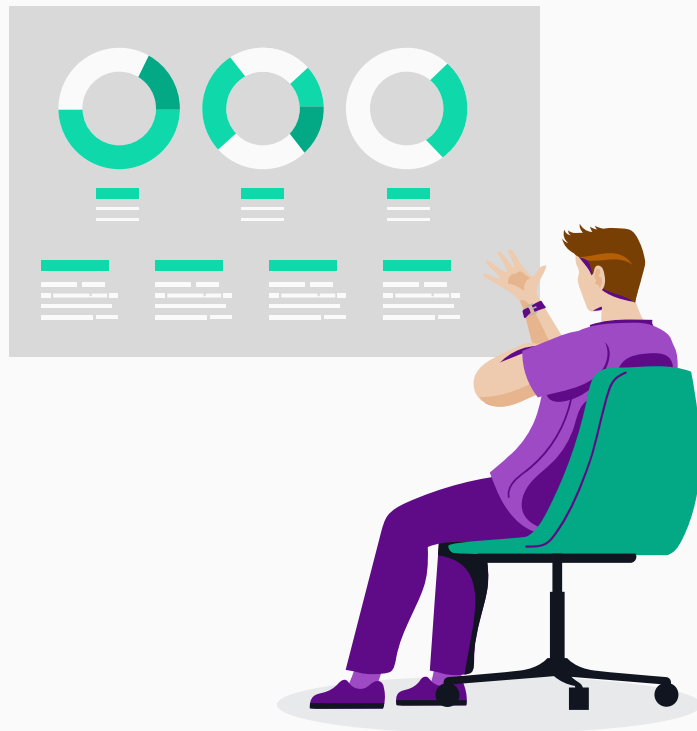
It Has Taken a Toll on **EVERYONE!**



02

Dataset

What dataset did we use?



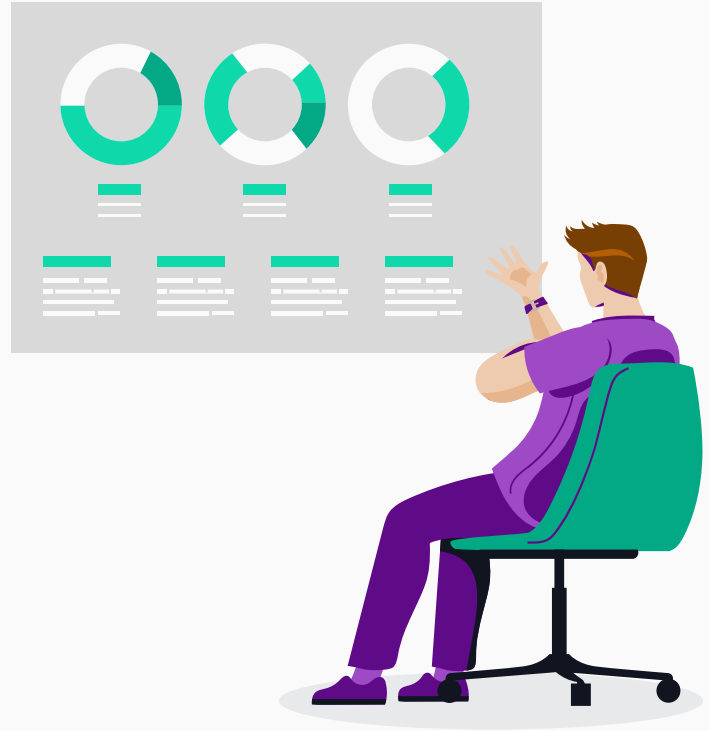
Simulated Dataset

- Dataset obtained from a [Kaggle](#) page
- Generated from the [Sparkov](#) simulator
 - ◆ Created by Brandon Harris
- The simulator is tuned to the parameters which included:
 - ◆ Date range from: January 1st 2019 to December 31st 2020
 - ◆ Around 1000 customers and cards
 - ◆ 800 different merchants for purchases
 - ◆ Included legitimate and fraudulent for testing
- Prior to starting, we also split into the test and train set

03

Attributes

What were the main variables to look at?



Δ state	# zip	Δ lat	# long	# city_pop	Δ job	📅 dob	∞ trans_num	# unix_time	# merch_lat	# merch_long
SC	29209	33.9659	-80.9355	333497	Mechanical engineer	1968-03-19	2da90c7d74bd46a 0caf3777415b3eb d3	1371816865	33.986391	-81.200714

📅 trans_date...	# cc_num	Δ merchant	Δ category	# amt	Δ first	Δ last	Δ gender	Δ street	Δ city
2020-06-21 12:14:25	229116393386724 4	fraud_Kirlin and Sons	personal_care	2.86	Jeff	Elliott	M	351 Darlene Green	Columbia

Our model utilized many attributes to decide on whether a transaction is fraudulent or not.

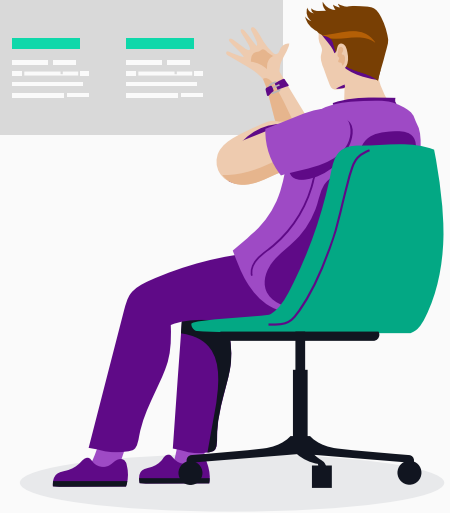
The main ones we used are:

- Merchant
- Amount
- Date

04

Methods Used & Results

What was the outcome?



Implementation

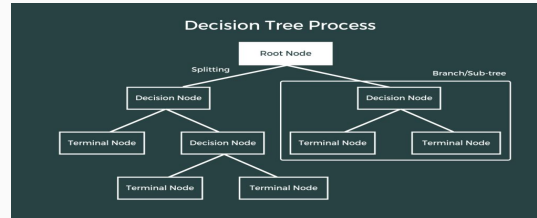
```
import pandas as pd
import numpy as np
from sklearn.tree import DecisionTreeClassifier, plot_tree, export_text
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error, mean_absolute_percentage_error
from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score, accuracy_score
from sklearn.preprocessing import StandardScaler
```

Unnamed: 0		cc_num	merchant	category	amt	gender	zip	lat	long	merch_lat	merch_long	year	month	day	hour	minute	second
0	0	2703186189652095	514	8	4.97	0	28654	36.0788	-81.1781	36.011293	-82.048315	2019	1	1	0	0	18
1	1	630423337322	241	4	107.23	0	99160	48.8878	-118.2105	49.159047	-118.186462	2019	1	1	0	0	44
2	2	38859492057661	390	0	220.11	1	83252	42.1808	-112.2620	43.150704	-112.154481	2019	1	1	0	0	51
3	3	3534093764340240	360	2	45.00	1	59632	46.2306	-112.1138	47.034331	-112.561071	2019	1	1	0	1	16
4	4	375534208663984	297	9	41.96	1	24433	38.4207	-79.4629	38.674999	-78.632459	2019	1	1	0	3	6

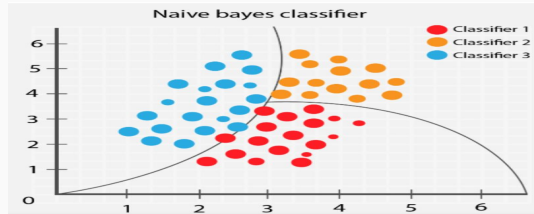
[+ Code](#)[+ Markdown](#)

Methods Used

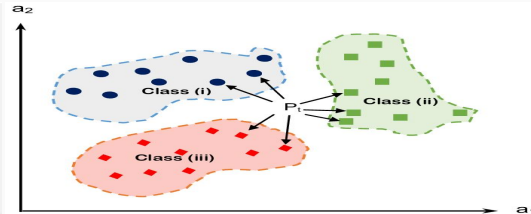
Decision Tree



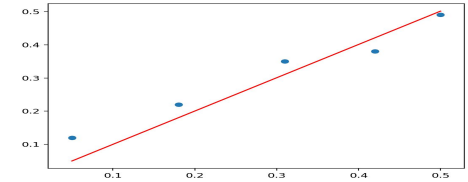
Naive Bayes



K-NN



LNR-Regression



Decision Tree

- Supervised learning method for classification or regression.
- Data set required a classification model so utilized a decision tree classifier.
- Tuned the classifier to a max depth of 9 which produced the best results.

Sample of Tree

[illegible]

Results

Accuracy

99.83%

Precision

82.17%

Recall

69.83%

F1 Score

75.5%

R2 Score

54.51%

Matrix

```
[[553249 325]  
 [ 647 1498]]
```


Other Models

LNR-Regression

1. Mean Absolute Error: 0.995%
2. Mean Squared Error: 0.385%
3. Root Mean Squared Error: 6.204%
4. R2 Score: -0.0012893538391397942

K-NN

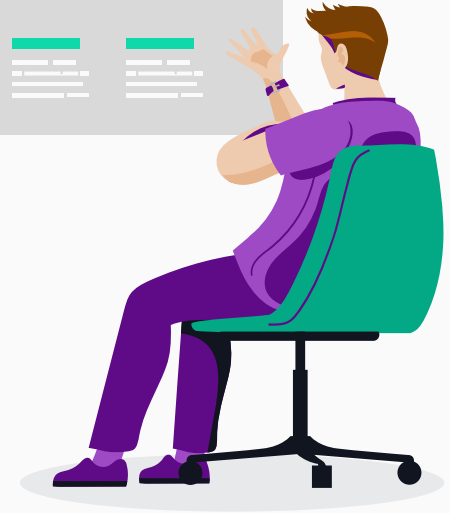
1. Accuracy: 99.54%
2. Precision: 0.2.98%
3. Recall: 0.559%
4. F1 Score: 0.942%
5. Confusion Matrix:
[[553184, 390]
[2133, 12]]

Naive Bayes

1. Accuracy: 99.61%
2. Mean Absolute Error: 0.386%
3. Mean Squared Error: 0.386%
4. Root Mean Squared Error: 6.213%
5. Confusion Matrix:
[[553574, 0]
[2145, 0]]

06 Challenges & Key Takeaways

What have we learned and what obstacles did we face?



Dataset

Very small proportion of actual fraudulent data (0.3% of transactions were fraudulent)

Model Selection

Very large data set doesn't allow for tuning of hyperparameters

Thank You!