Credit Card Fraud Prediction

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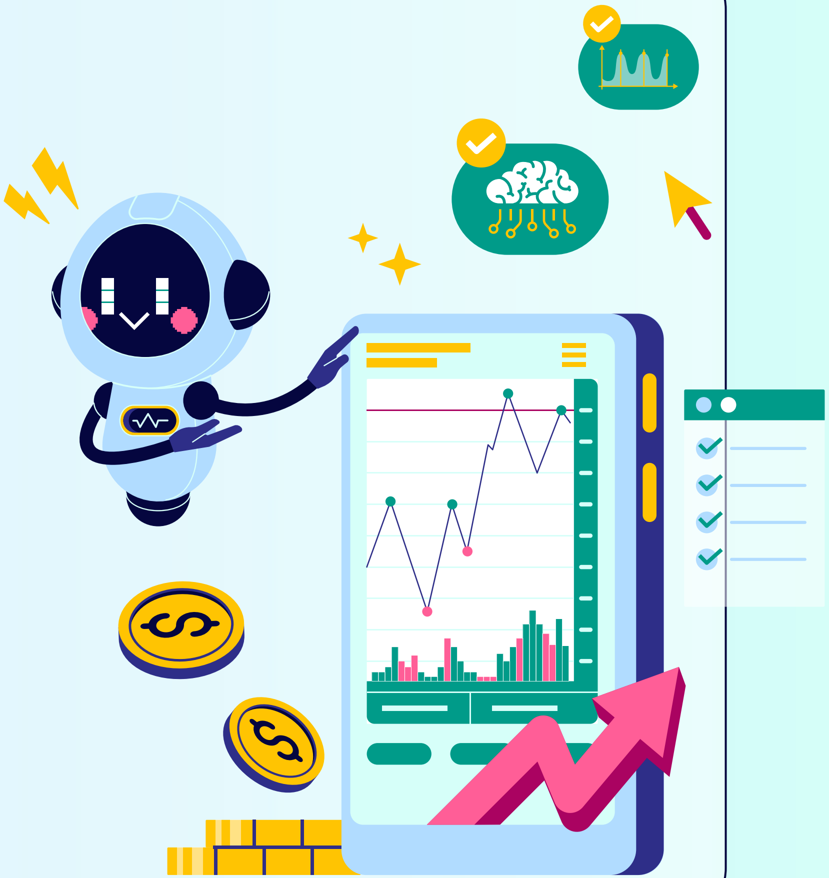
Introduction



Problem Statement

Classify the fraud (1) and non-fraud (0) credit card

```
Data columns (total 23 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   Unnamed: 0             555719 non-null  int64
 1   trans_date_trans_time  555719 non-null  object
 2   cc_num                 555719 non-null  float64
 3   merchant               555719 non-null  object
 4   category               555719 non-null  object
 5   amt                    555719 non-null  float64
 6   first                  555719 non-null  object
 7   last                   555719 non-null  object
 8   gender                 555719 non-null  object
 9   street                 555719 non-null  object
 10  city                   555719 non-null  object
 11  state                  555719 non-null  object
 12  zip                    555719 non-null  int64
 13  lat                    555719 non-null  float64
 14  long                   555719 non-null  float64
 15  city_pop               555719 non-null  int64
 16  job                    555719 non-null  object
 17  dob                    555719 non-null  object
 18  trans_num              555719 non-null  object
 19  unix_time              555719 non-null  int64
 20  merch_lat              555719 non-null  float64
 21  merch_long             555719 non-null  float64
 22  is_fraud               555719 non-null  int64
```

21 Features, 1 target (1=fraud/0=non-fraud)

Dataset Characteristics

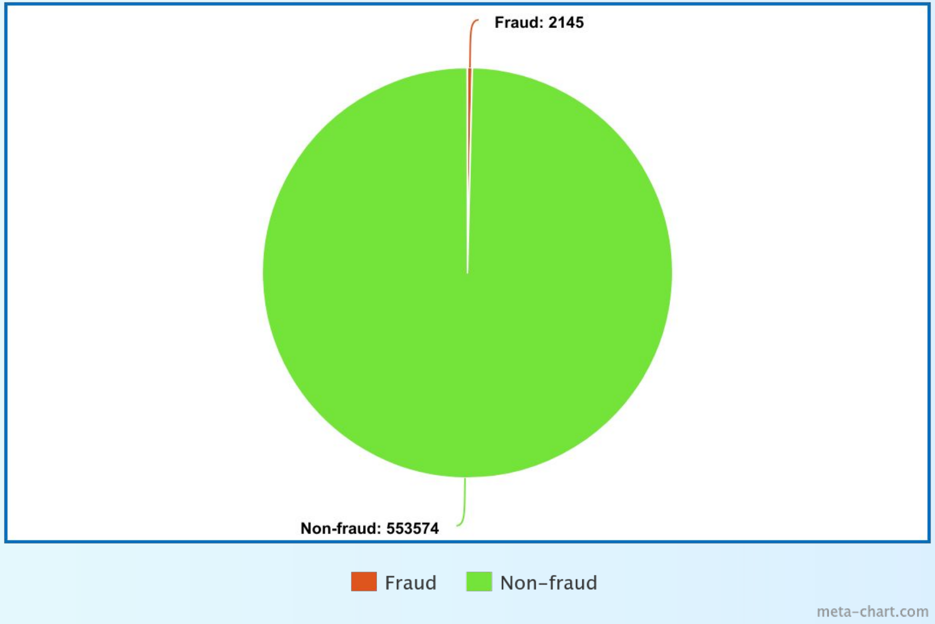
No null values 😋

```
df.isnull().sum()

Unnamed: 0               0
trans_date_trans_time    0
cc_num                   0
merchant                 0
category                 0
amt                      0
first                    0
last                     0
gender                   0
street                   0
city                     0
state                    0
zip                      0
lat                      0
long                     0
city_pop                 0
job                      0
dob                      0
trans_num                0
unix_time                0
merch_lat                0
merch_long               0
is_fraud                 0
dtype: int64
```

Extremely imbalanced data 😡

Only 0.386% of samples are fraud!



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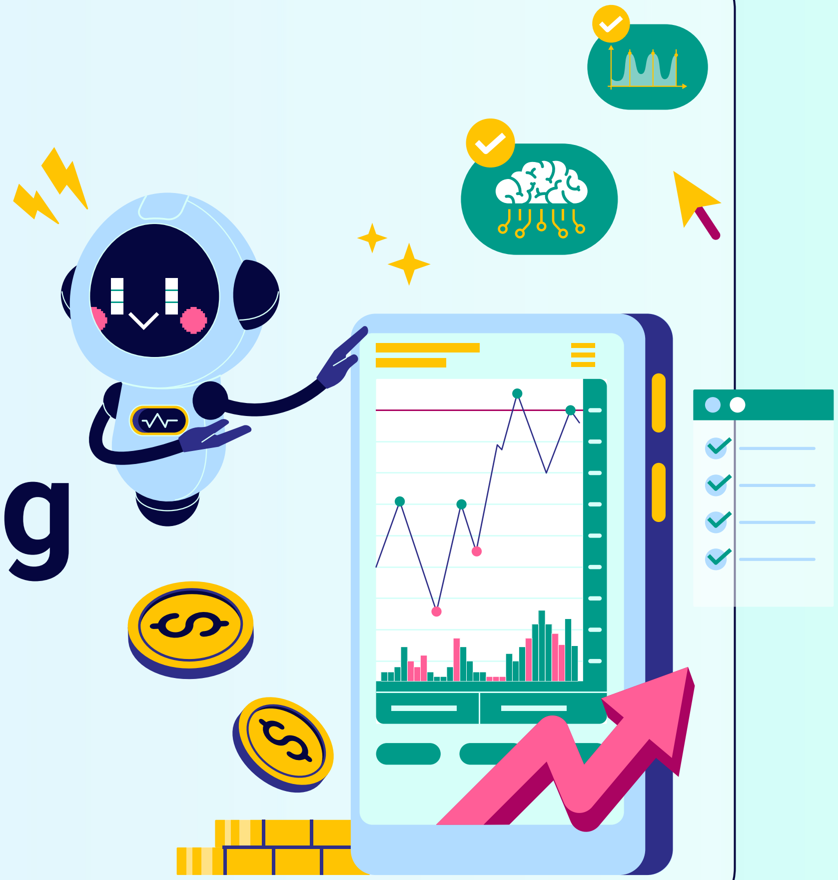
Preprocessing



Feature Selection & Encoding

```
h_cardinality = [var for var in obj_features if df[var].nunique() > 100 and var != 'trans_date_trans_time']
h_cardinality
```

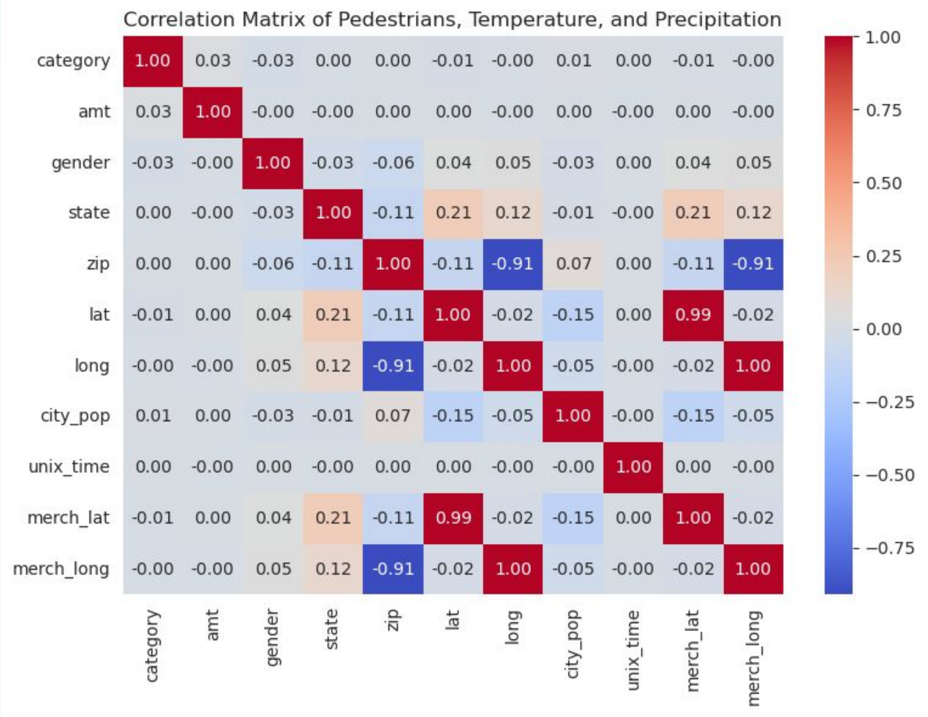
```
['merchant', 'first', 'last', 'street', 'city', 'job', 'dob', 'trans_num']
```

- Checked and removed object features with more than 100 unique values

```
X.category = X.category.astype('category').cat.codes
X.gender = X.gender.astype('category').cat.codes
X.state= X.state.astype('category').cat.codes
```

- Encoded the categorical data

Examine duplicate features



Extremely high correlation

- Zip & (merchant) longitude
- Longitude & merchant_longitude
- Latitude & merchant_latitude

Keep merchant_longitude & merchant_latitude

Data Scaling

```
scaler=StandardScaler()
scaler.fit(X)
X_train= scaler.transform(X_train)
X_test= scaler.transform(X_test)
X_val = scaler.transform(X_val)
```

Under/Oversampling

```
sampler = RandomUnderSampler(random_state=42)
X_train, y_train = sampler.fit_resample(X_train, y_train)
X_train.shape
```

```
(3090, 8)
```

```
from imblearn.over_sampling import SMOTE

sampler = SMOTE(random_state=42)
X_train, y_train = sampler.fit_resample(X_train, y_train)
```

```
(542558, 45)
```

Undersampling

- SVM (too slow using SMOTE)

Oversampling

- Logistic Regression
- Neural Network

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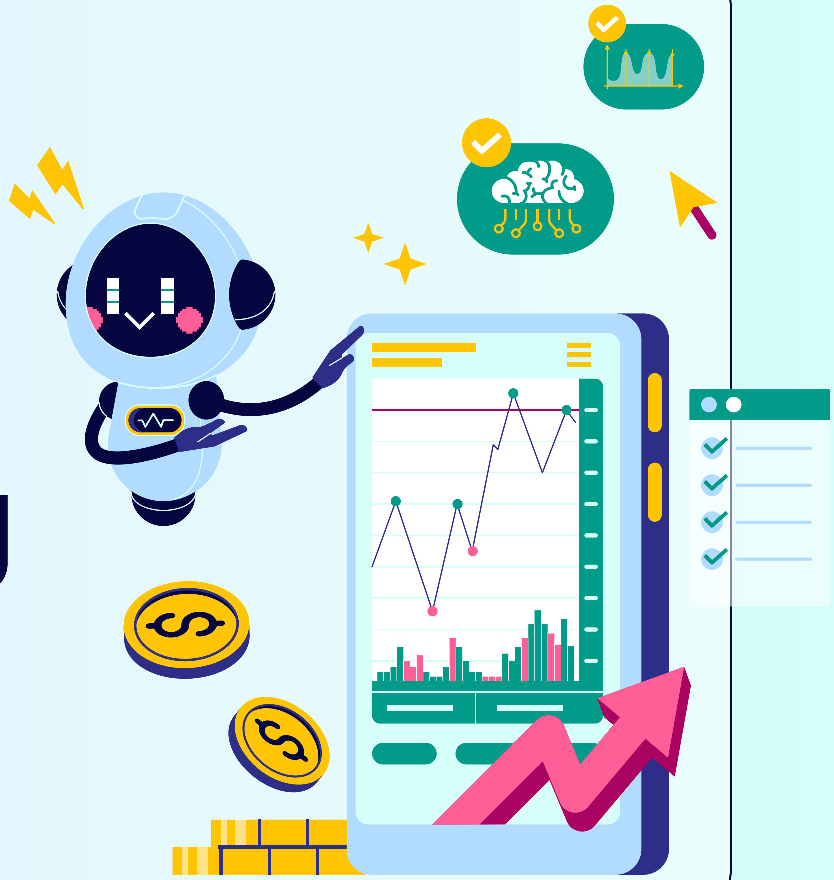
Model Training



Logistic Regression

```
from sklearn.metrics import *
from sklearn.linear_model import LogisticRegression

logReg = LogisticRegression(penalty="l1", solver='saga', C=.1)
logReg.fit(X_train, y_train)
```

13 Different Configurations

- C value
- transformation
- regularization

Trail #	C (lambda)	transformation	regularization
1	0.1	non	l2
2	1	non	l2
3	0.5	non	l2
4	1.5	non	l2
5	2	non	l2
6	0.1	non	l1
7	1	non	l1
8	0	non	non
9	0.1	poly, power=2	l2
10	1	poly, power=2	l2
11	0.1	poly, power=2	l1
12	1	poly, power=2	l1
13	0	poly, power=2	non

SVM

12 Different Configurations

- C value
- Kernel (transformation)

```
from sklearn.metrics import *
from sklearn.svm import SVC

svm = SVC(kernel='poly', C=.1 , random_state=42)
svm.fit(X_train, y_train)
```

Trail #	C (lambda)	kernel (trans)
1	1	rbf
2	10	rbf
3	0.1	rbf
4	1	linear
5	10	linear
6	0.1	linear
7	1	poly
8	10	poly
9	0.1	poly
10	0.5	poly
11	5	poly
12	50	poly

Neural Network

12 Different Configurations

- C value
- transformation
- regularization

```
from tensorflow.keras import regularizers
import tensorflow as tf
from tensorflow.keras import layers, models

model = models.Sequential([
    layers.Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    layers.Dense(32, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])
```

Trail #	C (lambda)	transformation	regularization
1	0	non	non
2	0.001	non	l2
3	0.1	non	l2
4	0.005		l2
5	0.5		l2
6	0.001	non	l1
7	0.01 (0.1 caused err)	non	l1
8	0	poly, 2 dgr	non
9	0.001	poly, 2 dgr	l2
10	0.1	poly, 2 dgr	l2
11	0.001	poly, 2 dgr	l1
12	0.01 (0.1 caused err)	poly, 2 dgr	l1

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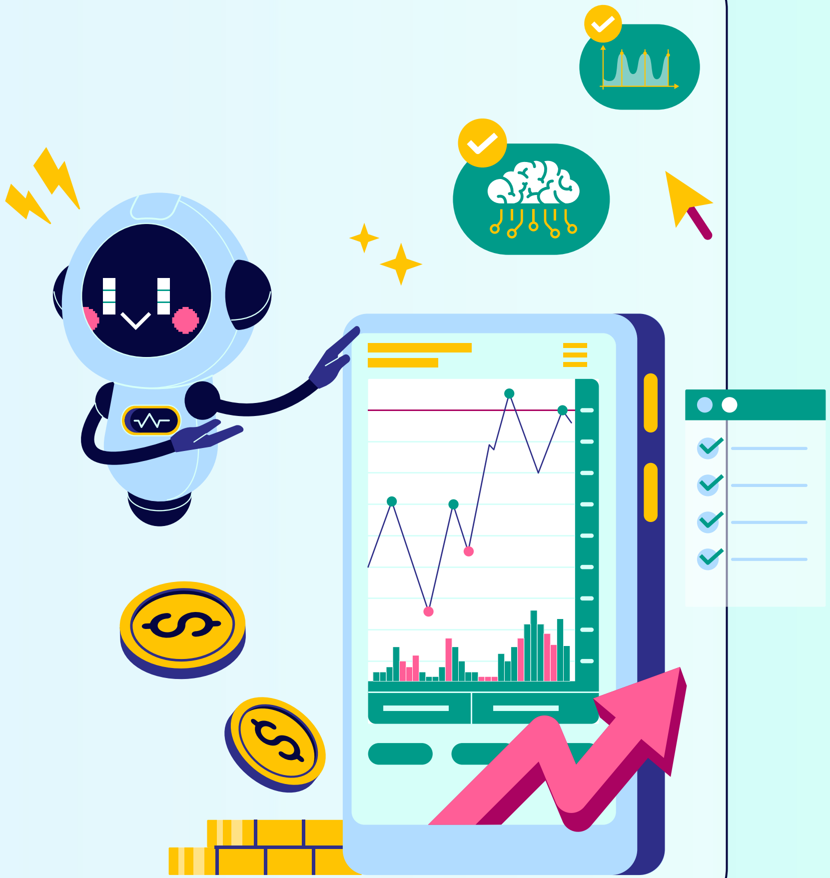
Result



Logistic Regression

	Best Accuracy
	Best Recall

Trail #	C (lambda)	transformation	regularization	train accuracy	train precision	train recall	train loss	val accuracy	val precision	val recall	val loss
1	0.1	non	l2	0.846	0.921	0.758	5.536	0.935	0.045	0.778	2.333
2	1	non	l2	0.846	0.921	0.758	5.536	0.935	0.045	0.778	2.334
3	0.5	non	l2	0.846	0.921	0.758	5.536	0.935	0.045	0.778	2.334
4	1.5	non	l2	0.846	0.921	0.758	5.536	0.935	0.045	0.778	2.334
5	2	non	l2	0.846	0.921	0.758	5.536	0.935	0.045	0.778	2.334
6	0.1	non	l1	0.846	0.921	0.758	5.535	0.935	0.045	0.778	2.331
7	1	non	l1	0.846	0.921	0.758	5.536	0.935	0.045	0.778	2.334
8	0	non	non	0.846	0.921	0.758	5.536	0.935	0.045	0.778	2.334
9	0.1	poly, power=2	l2	0.852	0.963	0.732	5.338	0.971	0.096	0.763	1.043
10	1	poly, power=2	l2	0.852	0.963	0.732	5.339	0.971	0.096	0.763	1.043
11	0.1	poly, power=2	l1	0.852	0.963	0.732	5.338	0.971	0.096	0.763	1.043
12	1	poly, power=2	l1	0.852	0.963	0.732	5.339	0.971	0.096	0.763	1.043
13	0	poly, power=2	non	0.852	0.963	0.732	5.339	0.971	0.096	0.763	1.043

SVM

	Best Accuracy
	Best Recall

Trail #	C (lambda)	kernel (trans)	train accuracy	train precision	train recall	train loss	val accuracy	val precision	val recall	val loss
1	1	rbf	0.865	0.973	0.750	4.876	0.979	0.119	0.708	0.760
2	10	rbf	0.877	0.983	0.877	4.421	0.970	0.086	0.721	1.081
3	0.1	rbf	0.857	0.955	0.750	5.144	0.968	0.080	0.705	1.145
4	1	linear	0.850	0.932	0.756	5.389	0.950	0.053	0.721	1.789
5	10	linear	0.851	0.932	0.757	5.377	0.950	0.053	0.721	1.789
6	0.1	linear	0.850	0.932	0.756	5.389	0.951	0.054	0.721	1.775
7	1	poly	0.850	0.952	0.737	5.424	0.958	0.062	0.705	1.503
8	10	poly	0.864	0.951	0.768	4.899	0.948	0.051	0.726	1.890
9	0.1	poly	0.753	0.967	0.525	8.888	0.983	0.118	0.521	0.597
10	0.5	poly	0.830	0.953	0.694	6.124	0.966	0.071	0.666	1.234
11	5	poly	0.864	0.953	0.766	4.899	0.949	0.052	0.721	1.839
12	50	poly	0.864	0.951	0.767	4.911	0.946	0.050	0.737	1.948

Neural Network

	Best Accuracy
	Best Recall

Trail #	C (lambda)	transformation	regularization	train accuracy	train precision	train recall	train loss	val accuracy	val precision	val recall	val loss
1	0	non	non	0.978	0.987	0.970	0.055	0.986	0.193	0.826	0.045
2	0.001	non	l2	0.970	0.966	0.973	0.116	0.964	0.090	0.901	0.129
3	0.1	non	l2	0.855	0.953	0.747	0.373	0.963	0.076	0.763	0.273
4	0.005		l2	0.947	0.962	0.931	0.178	0.963	0.087	0.895	0.169
5	0.5		l2	0.837	0.898	0.761	0.437	0.914	0.035	0.785	0.432
6	0.001	non	l1	0.941	0.937	0.946	0.188	0.935	0.054	0.956	0.219
7	0.01 (0.1 caused err)	non	l1	0.854	0.941	0.756	0.391	0.952	0.060	0.769	0.370
8	0	poly, 2 dgr	non	0.993	0.989	0.996	0.024	0.987	0.200	0.774	0.052
9	0.001	poly, 2 dgr	l2	0.977	0.967	0.986	0.097	0.966	0.091	0.870	0.122
10	0.1	poly, 2 dgr	l2	0.888	0.939	0.831	0.303	0.946	0.056	0.809	0.258
11	0.001	poly, 2 dgr	l1	0.961	0.968	0.955	0.156	0.967	0.095	0.870	0.144
12	0.01 (0.1 caused err)	poly, 2 dgr	l1	0.857	0.856	0.859	0.329	0.856	0.023	0.846	0.360

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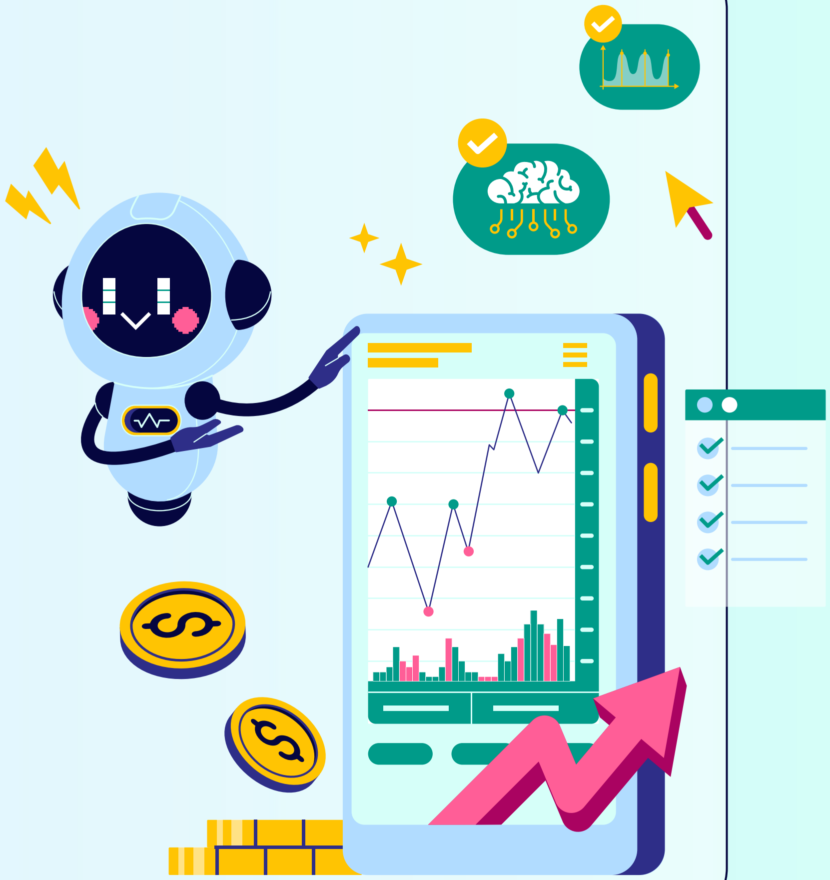
Conclusion



Analysis

- SVM generally has high accuracy but low validation recall
- Logistic regression has higher recall
- Trail 4 and Trail 6 of neural network has the highest validation recall (0.956) and validation accuracy (0.987) overall, respectively.

In reality, we care more about recall than accuracy

Recall = # all correctly predicted fraud/ # all actual fraud
(False alarm doesn't matter!)

Future Work

As trainers:

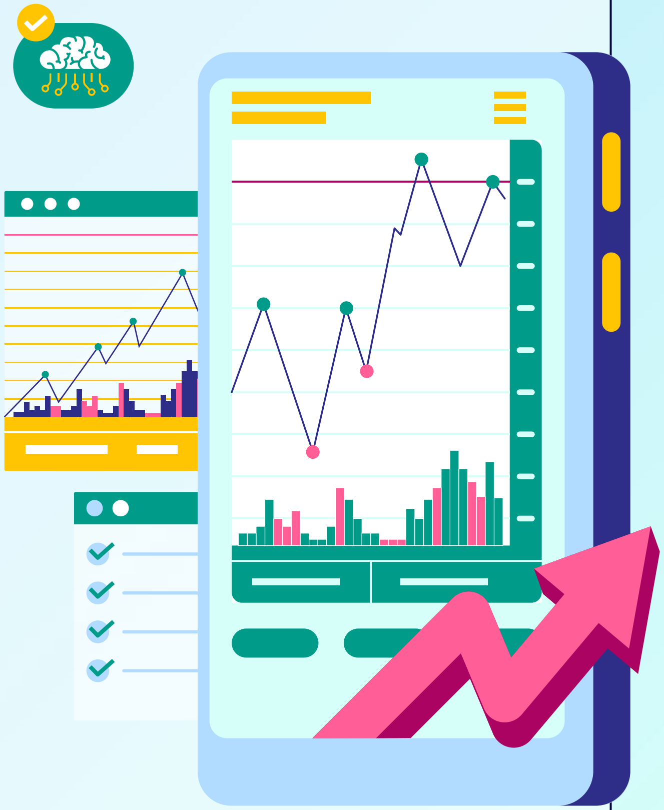
- Try more different combinations of regularization, transformation, layers (nn) and so on
- Try to use different models (random forests, decision trees, etc.)
- Use a better computer 🤣

As dataset makers:

- Try the best to make sure no null values
- Try the best to balance the data!

Thanks!

Do you have any questions?



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