# Credit Card Farud Detection Using Logistic Regression

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### Importing Necessary Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("/content/fraudTest.csv")
df.info()
       <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 50828 entries, 0 to 50827
       Data columns (total 23 columns):
                          Non-Null Count Dtype
        # Column
        0 Unnamed: 0 50828 non-null int64
        1 trans_date_trans_time 50828 non-null float64

      2
      cc_num
      50828 non-null float64

      3
      merchant
      50828 non-null object

      4
      category
      50828 non-null object

      5
      amt
      50828 non-null float64

                                         50828 non-null object
        6 first
        7 last
        8 gender
              street
        10 city
                                           50827 non-null object
        11 state
                                            50827 non-null float64
        12 zip
                                      50827 non-null float64
50827 non-null float64
50827 non-null float64
50827 non-null object
        13 lat
        14 long
        15 city_pop
        16 iob
        17 dob
                                            50827 non-null object

      18
      trans_num
      50827 non-null object

      19
      unix_time
      50827 non-null float64

      20
      merch_lat
      50827 non-null float64

        21 merch_long 50827 non-null float64
22 is fraud 50827 non-null float64
        22 is_fraud
                                              50827 non-null float64
       dtypes: float64(11), int64(1), object(11)
       memory usage: 8.9+ MB
```

### df.describe()

	Unnamed: 0	trans_date_trans_time	cc_num	amt	zip	lat	
count	50828.000000	50828.000000	5.082800e+04	50828.000000	50827.000000	50827.000000	50827
mean	25413.500000	44011.977918	4.156839e+17	69.463839	48700.820351	38.529231	-9(
std	14672.924078	5.115022	1.306796e+18	151.240739	26784.263353	5.082601	10
min	0.000000	44003.510010	6.041621e+10	1.000000	1257.000000	20.027100	-165

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt	first	last
0	0	44003.51001	2.290000e+15	fraud_Kirlin and Sons	personal_care	2.86	Jeff	Elliott
1	1	44003.51010	3.570000e+15	fraud_Sporer- Keebler	personal_care	29.84	Joanne	Williams
2	2	44003.51034	3.600000e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	Ashley	Lopez
3	3	44003.51059	3.590000e+15	fraud_Haley Group	misc_pos	60.05	Brian	Williams
4	4	44003.51061	3.530000e+15	fraud_Johnston- Casper	travel	3.19	Nathan	Massey

5 rows × 23 columns

## df.tail()

	Unnamed:	trans_date_trans_time	cc_num	merchant	category	amt	first	last
50823	50823	44020.52016	5.820000e+11	fraud_Pollich LLC	home	153.71	Larry	House
50824	50824	44020.52041	3.550000e+15	fraud_Jast and Sons	food_dining	99.68	Kayla	Obrien
50825	50825	44020.52061	2.710000e+15	fraud_Towne, Greenholt and Koepp	shopping_net	10.29	Jenna	Brooks
50826	50826	44020.52139	2.250000e+15	fraud_Berge, Kautzer and Harris	personal_care	17.76	Margaret	Gibson
50827	50827	44020.52240	4.860000e+12	fraud_Pollich LLC	home	17.98	Elizabeth	Payne

5 rows × 23 columns

	Unnamed:	trans_date_trans_time	cc_num	merchant	category	amt	first	
0	0	44003.51001	2.290000e+15	fraud_Kirlin and Sons	personal_care	2.86	Jeff	
1	1	44003.51010	3.570000e+15	fraud_Sporer- Keebler	personal_care	29.84	Joanne	W
2	2	44003.51034	3.600000e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	Ashley	
3	3	44003.51059	3.590000e+15	fraud_Haley Group	misc_pos	60.05	Brian	W
4	4	44003.51061	3.530000e+15	fraud_Johnston- Casper	travel	3.19	Nathan	Ν
50823	50823	44020.52016	5.820000e+11	fraud_Pollich LLC	home	153.71	Larry	
50824	50824	44020.52041	3.550000e+15	fraud_Jast and Sons	food_dining	99.68	Kayla	1
50825	50825	44020.52061	2.710000e+15	fraud_Towne, Greenholt and Koepp	shopping_net	10.29	Jenna	I
50826	50826	44020.52139	2.250000e+15	fraud_Berge, Kautzer and Harris	personal_care	17.76	Margaret	(
50827	50827	44020.52240	4.860000e+12	fraud_Pollich LLC	home	17.98	Elizabeth	

50828 rows × 23 columns

df.shape

(50828, 23)

 $\label{lem:checking} \mbox{\tt \#Checking for null values through function and heatmap} \\ \mbox{\tt df.isnull().any()}$ 

Unnamed: 0	False
trans_date_trans_time	False
cc_num	False
merchant	False
category	False
amt	False
first	False
last	False
gender	False
street	False
city	False
state	True
zip	True
lat	True
long	True
city_pop	True

```
        job
        True

        dob
        True

        trans_num
        True

        unix_time
        True

        merch_lat
        True

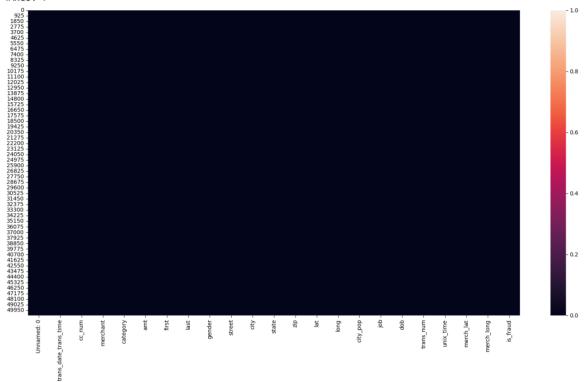
        merch_long
        True

        is_fraud
        True

        dtype:
        bool
```

plt.figure(figsize = (20,10))
sns.heatmap(df.isnull())





### df.dtypes

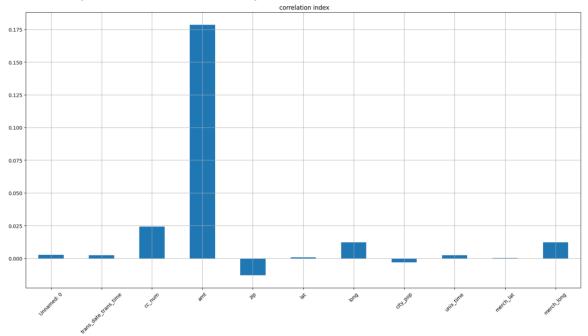
Unnamed: 0 int64
trans\_date\_trans\_time float64
cc\_num float64
merchant object
category object

amt	float64
first	object
last	object
gender	object
street	object
city	object
state	object
zip	float64
lat	float64
long	float64
city_pop	float64
job	object
dob	object
trans_num	object
unix_time	float64
merch_lat	float64
merch_long	float64
is_fraud	float64
dtype: object	

dataset\_2 = df.drop(columns = 'is\_fraud')

 ${\tt dataset\_2.corrwith(df['is\_fraud']).plot.bar(figsize = (20,10), \ title = ' \ correlation \ index', \ rot = 45, \ grid = True)}$ 

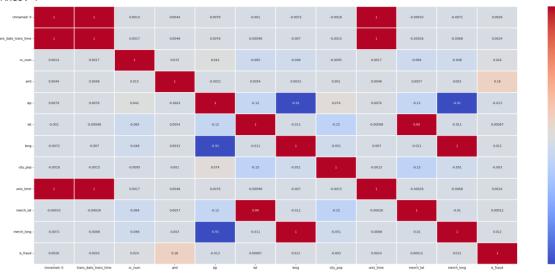
<Axes: title={'center': ' correlation index'}>



```
corr = df.corr()
plt.figure(figsize = (35,15))
sns.heatmap(corr, annot = True, cmap = 'coolwarm', linewidth = 2)
```

#### <Axes: >

Х



	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt	first	
0	0	44003.51001	2.290000e+15	fraud_Kirlin and Sons	personal_care	2.86	Jeff	
1	1	44003.51010	3.570000e+15	fraud_Sporer- Keebler	personal_care	29.84	Joanne	W
2	2	44003.51034	3.600000e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	Ashley	
3	3	44003.51059	3.590000e+15	fraud_Haley Group	misc_pos	60.05	Brian	W
4	4	44003.51061	3.530000e+15	fraud_Johnston- Casper	travel	3.19	Nathan	Ν
50823	50823	44020.52016	5.820000e+11	fraud_Pollich LLC	home	153.71	Larry	
50824	50824	44020.52041	3.550000e+15	fraud_Jast and Sons	food_dining	99.68	Kayla	1
50825	50825	44020.52061	2.710000e+15	fraud_Towne, Greenholt and Koepp	shopping_net	10.29	Jenna	ĺ
50826	50826	44020.52139	2.250000e+15	fraud_Berge, Kautzer and Harris	personal_care	17.76	Margaret	(
50827	50827	44020.52240	4.860000e+12	fraud_Pollich LLC	home	17.98	Elizabeth	

50828 rows × 22 columns

```
У
```

```
0.0
0
       0.0
       0.0
2
3
       0.0
       0.0
      0.0
50823
50824
       0.0
50825
       0.0
50826
       0.0
50827
      NaN
```

Name: is\_fraud, Length: 50828, dtype: float64

```
df.groupby('is_fraud').mean()
```

is fraud

print(x\_train.dtypes)

```
0.0
               25410.566530
                                      44011.976974 4.136740e+17 67.756165 48722.974913 38.529015 -90.1396
        1.0
               26019.857143
                                      44012.171027 9.189346e+17 495.575911 43175.931034 38.583064 -87.5121
x=df.drop('is_fraud',axis=1)
y=df['is fraud']
y.shape
     (50828,)
x.shape
     (50828, 22)
missing_values = y.isnull().sum()
if missing_values.any():
    print("There are missing values in 'y'.")
     There are missing values in 'y'.
# Option 2: Impute missing values
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="mean")
y = imputer.fit_transform(y.to_frame().values)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, stratify=y, random_state=42)
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
x_train = x_train.drop('trans_date_trans_time', axis=1)
print(x_train.head())
            Unnamed: 0
                             cc num
                                        amt
                                                 zip
                                                          lat
                                                                 long city pop \
                                      64.76 23937.0 36.9688 -78.5615
     9216
                 9216 6.010000e+15
                                                                          1970.0
     42868
                                     75.18 39769.0 33.3570 -89.0473
                 42868 2.230000e+15
                                                                          1923.0
     40853
                40853 3.590000e+15
                                       8.36 21750.0 39.6991 -78.1762
                                                                          3766.0
     22311
                22311 6.010000e+15 57.48 73754.0 36.3850 -98.0727
                                                                          1078.0
     4832
                 4832 3.030000e+13 133.29 72165.0 35.5762 -91.4539
                                                                          111.0
                dob
                                                          unix_time merch_lat \
                                            trans num
     9216
            02-09-85 205b896137189f145f86261f6b00e75d 1.372018e+09 37.300259
     42868 16-01-60 68661acb2f7b6bf0acad21f563cf4a01 1.373091e+09 33.787372
     40853
           14-02-84 bd0445c0bf554893fd3ccd1adfd530dc 1.373044e+09
                                                                    40.087332
     22311 06-07-52 81b20a651bb36ef406895e74245fa110 1.372471e+09
                                                                    36.388727
     4832 13-06-00 2ffeb77b10ee6744f85a6602a471faaf 1.371924e+09 35.665908
            merch_long
     9216
            -78.493307
     42868 -88.930328
     40853 -77.672439
     22311 -97.967321
     4832
           -90.630391
```

```
Unnamed: 0
                       int64
     cc_num
                     float64
                    float64
     amt
                     float64
     zip
     lat
                     float64
     long
                     float64
     city_pop
                     float64
                     object
     dob
     trans num
                     obiect
     unix_time
                    float64
     merch_lat
                     float64
                    float64
     merch long
     dtype: object
x train = x train.drop('trans num', axis=1)
print(x train.columns)
print(x_test.columns)
     dtype='object')
     ucype= object')
Index(['Unnamed: 0', 'trans_date_trans_time', 'cc_num', 'merchant', 'category',
    'amt', 'first', 'last', 'gender', 'street', 'city', 'state', 'zip',
    'lat', 'long', 'city_pop', 'job', 'dob', 'trans_num', 'unix_time',
    'merch_lat', 'merch_long'],

dtype_'chicst')
            dtype='object')
missing_cols = set(x_train.columns) - set(x_test.columns)
if missing cols:
    raise ValueError(f"Missing columns in x test: {missing cols}")
x test.columns
     dtype='object')
print("Columns in x_train:", x_train.columns)
print("Columns in x_test:", x_test.columns)
     Columns in x_train: Index(['Unnamed: 0', 'cc_num', 'amt', 'zip', 'lat', 'long', 'city_pop',
              'unix_time', 'merch_lat', 'merch_long'],
            dtype='object')
     Columns in x_test: Index(['Unnamed: 0', 'trans_date_trans_time', 'cc_num', 'merchant', 'category',
             'amt', 'first', 'last', 'gender', 'street', 'city', 'state', 'zip', 'lat', 'long', 'city_pop', 'job', 'dob', 'trans_num', 'unix_time',
             'merch_lat', 'merch_long'],
            dtype='object')
# Check and align columns in x_train and x_test
common_columns = set(x_train.columns) & set(x_test.columns)
x train = x train[common columns]
x \text{ test} = x \text{ test[common columns]}
# Now, fit and predict
model = LogisticRegression()
model.fit(x_train, y_train)
ypred = model.predict(x_test)
```