Insurance Fraud Detection

The insurance industry involves the sale of insurance policies to individuals and businesses, which provide financial protection against potential losses or damages. Fraud can occur in the insurance industry in a variety of ways, including false or exaggerated claims, fake policies, and identity theft. Insurers use a variety of tools and techniques, including data analysis and machine learning, to detect and prevent fraudulent activity.


```
# Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

data = pd.read_csv('dataset.csv')
data.head()
```

```
   months_as_customer  age  policy_number policy_bind_date
policy_state  \
0                 328   48         521585       2014-10-17
OH
1                 228   42         342868       2006-06-27
```

```
IN
2                 134   29         687698       2000-09-06
OH
3                 256   41         227811       1990-05-25
IL
4                 228   44         367455       2014-06-06
IL

  policy_csl  policy_deductable  policy_annual_premium  umbrella_limit
\
0    250/500                1000                1406.91               0

1    250/500                2000                1197.22         5000000

2    100/300                2000                1413.14         5000000

3    250/500                2000                1415.74         6000000

4   500/1000                1000                1583.91         6000000


   insured_zip  ... police_report_available total_claim_amount
injury_claim  \
0       466132  ...                      YES              71610
6510
1       468176  ...                        ?               5070
780
2       430632  ...                       NO              34650
7700
3       608117  ...                       NO              63400
6340
4       610706  ...                       NO               6500
1300

  property_claim vehicle_claim  auto_make  auto_model auto_year  \
0          13020         52080       Saab         92x      2004
1            780          3510   Mercedes        E400      2007
2           3850         23100      Dodge         RAM      2007
3           6340         50720  Chevrolet       Tahoe      2014
4            650          4550     Accura         RSX      2009

  fraud_reported _c39
0              Y  NaN
1              Y  NaN
2              N  NaN
3              Y  NaN
4              N  NaN

[5 rows x 40 columns]
```

```
data.replace('?', np.nan, inplace = True)

data.describe()
```

```
       months_as_customer          age  policy_number
policy_deductable  \
count         1000.000000  1000.000000    1000.000000
1000.000000
mean           203.954000    38.948000  546238.648000
1136.000000
std            115.113174     9.140287  257063.005276
611.864673
min              0.000000    19.000000  100804.000000
500.000000
25%            115.750000    32.000000  335980.250000
500.000000
50%            199.500000    38.000000  533135.000000
1000.000000
75%            276.250000    44.000000  759099.750000
2000.000000
max            479.000000    64.000000  999435.000000
2000.000000

       policy_annual_premium  umbrella_limit    insured_zip  capital-
gains  \
count            1000.000000    1.000000e+03    1000.000000
1000.000000
mean             1256.406150    1.101000e+06  501214.488000
25126.100000
std               244.167395    2.297407e+06   71701.610941
27872.187708
min               433.330000   -1.000000e+06  430104.000000
0.000000
25%              1089.607500    0.000000e+00  448404.500000
0.000000
50%              1257.200000    0.000000e+00  466445.500000
0.000000
75%              1415.695000    0.000000e+00  603251.000000
51025.000000
max              2047.590000    1.000000e+07  620962.000000
100500.000000

        capital-loss  incident_hour_of_the_day
number_of_vehicles_involved  \
count    1000.000000               1000.000000
1000.00000
mean   -26793.700000                 11.644000
1.83900
std     28104.096686                  6.951373
1.01888
```

```
min   -111100.000000                  0.000000
1.00000
25%    -51500.000000                  6.000000
1.00000
50%    -23250.000000                 12.000000
1.00000
75%         0.000000                 17.000000
3.00000
max         0.000000                 23.000000
4.00000

       bodily_injuries    witnesses  total_claim_amount  injury_claim
\
count      1000.000000  1000.000000          1000.00000   1000.000000

mean          0.992000     1.487000         52761.94000   7433.420000

std           0.820127     1.111335         26401.53319   4880.951853

min           0.000000     0.000000           100.00000      0.000000

25%           0.000000     1.000000         41812.50000   4295.000000

50%           1.000000     1.000000         58055.00000   6775.000000

75%           2.000000     2.000000         70592.50000  11305.000000

max           2.000000     3.000000        114920.00000  21450.000000


       property_claim  vehicle_claim    auto_year  _c39
count     1000.000000    1000.000000  1000.000000   0.0
mean      7399.570000   37928.950000  2005.103000   NaN
std       4824.726179   18886.252893     6.015861   NaN
min          0.000000      70.000000  1995.000000   NaN
25%       4445.000000   30292.500000  2000.000000   NaN
50%       6750.000000   42100.000000  2005.000000   NaN
75%      10885.000000   50822.500000  2010.000000   NaN
max      23670.000000   79560.000000  2015.000000   NaN

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 40 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   months_as_customer           1000 non-null   int64
 1   age                          1000 non-null   int64
 2   policy_number                1000 non-null   int64
 3   policy_bind_date             1000 non-null   object
```

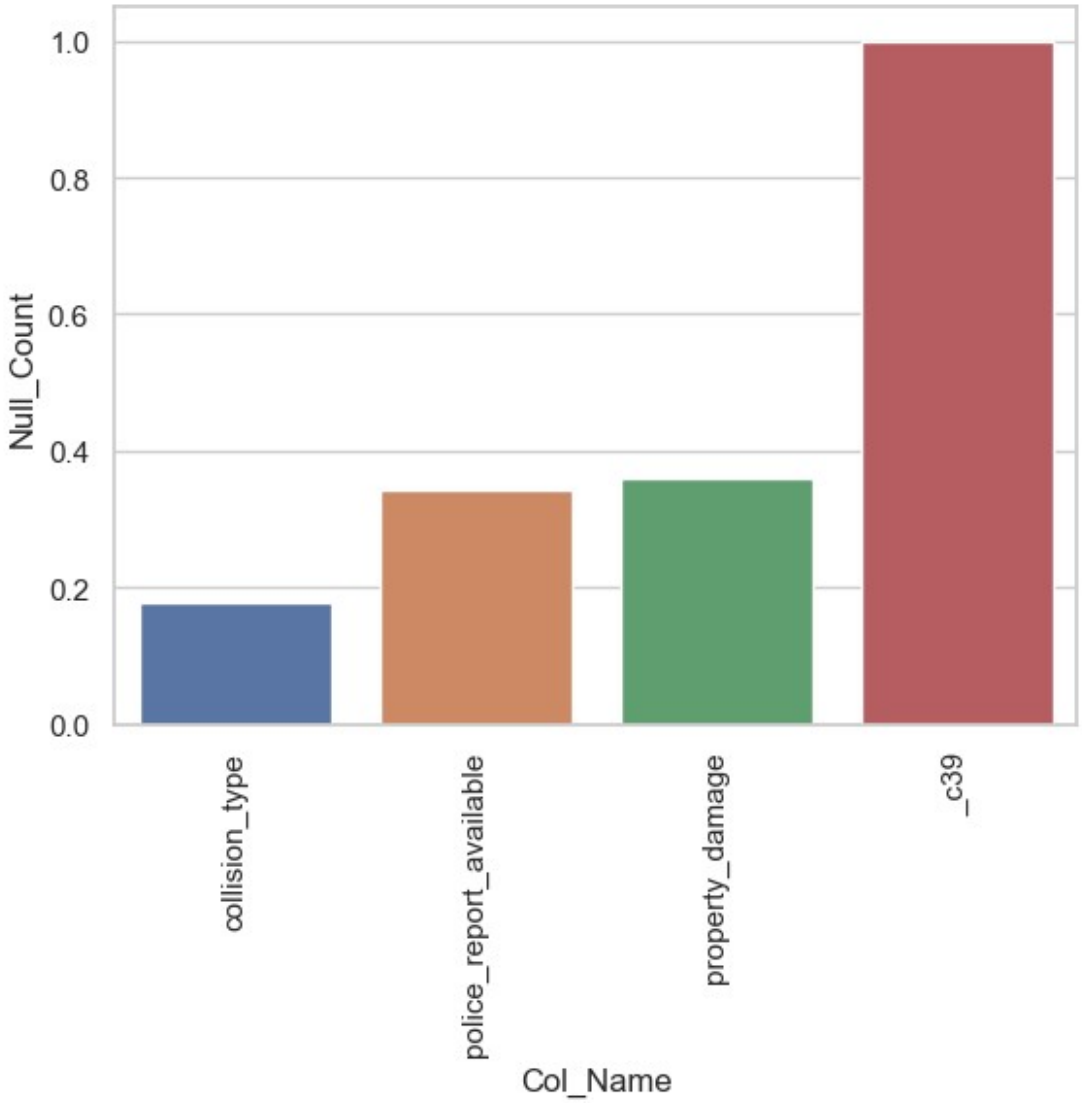
```
 4   policy_state                 1000 non-null   object
 5   policy_csl                   1000 non-null   object
 6   policy_deductable            1000 non-null   int64
 7   policy_annual_premium        1000 non-null   float64
 8   umbrella_limit               1000 non-null   int64
 9   insured_zip                  1000 non-null   int64
 10  insured_sex                  1000 non-null   object
 11  insured_education_level      1000 non-null   object
 12  insured_occupation           1000 non-null   object
 13  insured_hobbies              1000 non-null   object
 14  insured_relationship         1000 non-null   object
 15  capital-gains                1000 non-null   int64
 16  capital-loss                 1000 non-null   int64
 17  incident_date                1000 non-null   object
 18  incident_type                1000 non-null   object
 19  collision_type               822 non-null    object
 20  incident_severity            1000 non-null   object
 21  authorities_contacted        1000 non-null   object
 22  incident_state               1000 non-null   object
 23  incident_city                1000 non-null   object
 24  incident_location            1000 non-null   object
 25  incident_hour_of_the_day     1000 non-null   int64
 26  number_of_vehicles_involved  1000 non-null   int64
 27  property_damage              640 non-null    object
 28  bodily_injuries              1000 non-null   int64
 29  witnesses                    1000 non-null   int64
 30  police_report_available      657 non-null    object
 31  total_claim_amount           1000 non-null   int64
 32  injury_claim                 1000 non-null   int64
 33  property_claim               1000 non-null   int64
 34  vehicle_claim                1000 non-null   int64
 35  auto_make                    1000 non-null   object
 36  auto_model                   1000 non-null   object
 37  auto_year                    1000 non-null   int64
 38  fraud_reported               1000 non-null   object
 39  _c39                         0 non-null      float64
dtypes: float64(2), int64(17), object(21)
memory usage: 312.6+ KB
```

```
data.isna().sum()
```

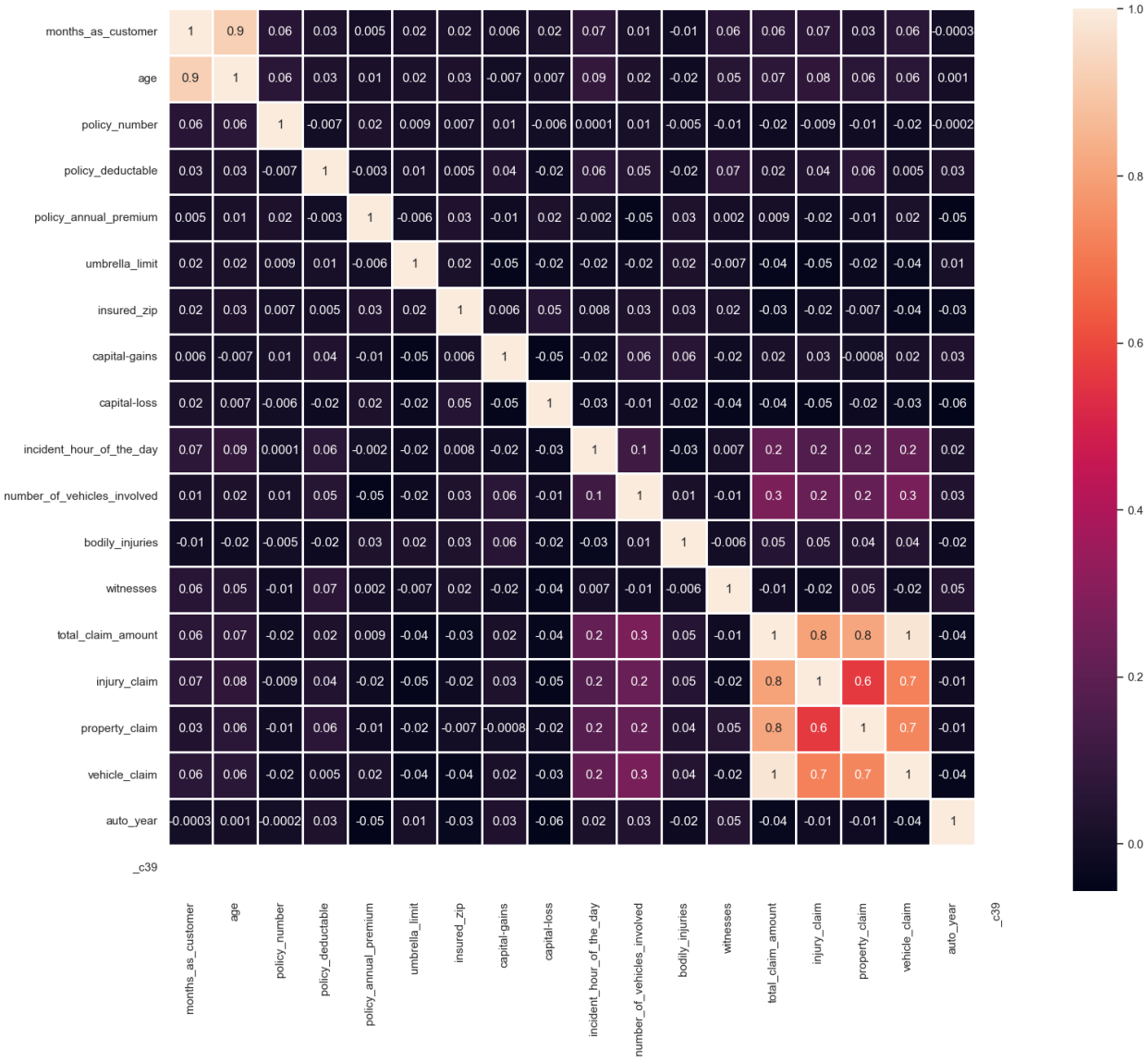
```
months_as_customer            0
age                           0
policy_number                 0
policy_bind_date              0
policy_state                  0
policy_csl                    0
policy_deductable             0
policy_annual_premium         0
umbrella_limit                0
```

```
insured_zip                      0
insured_sex                      0
insured_education_level          0
insured_occupation               0
insured_hobbies                  0
insured_relationship             0
capital-gains                    0
capital-loss                     0
incident_date                    0
incident_type                    0
collision_type                 178
incident_severity                0
authorities_contacted            0
incident_state                   0
incident_city                    0
incident_location                0
incident_hour_of_the_day         0
number_of_vehicles_involved      0
property_damage                360
bodily_injuries                  0
witnesses                        0
police_report_available        343
total_claim_amount               0
injury_claim                     0
property_claim                   0
vehicle_claim                    0
auto_make                        0
auto_model                       0
auto_year                        0
fraud_reported                   0
_c39                          1000
dtype: int64
```

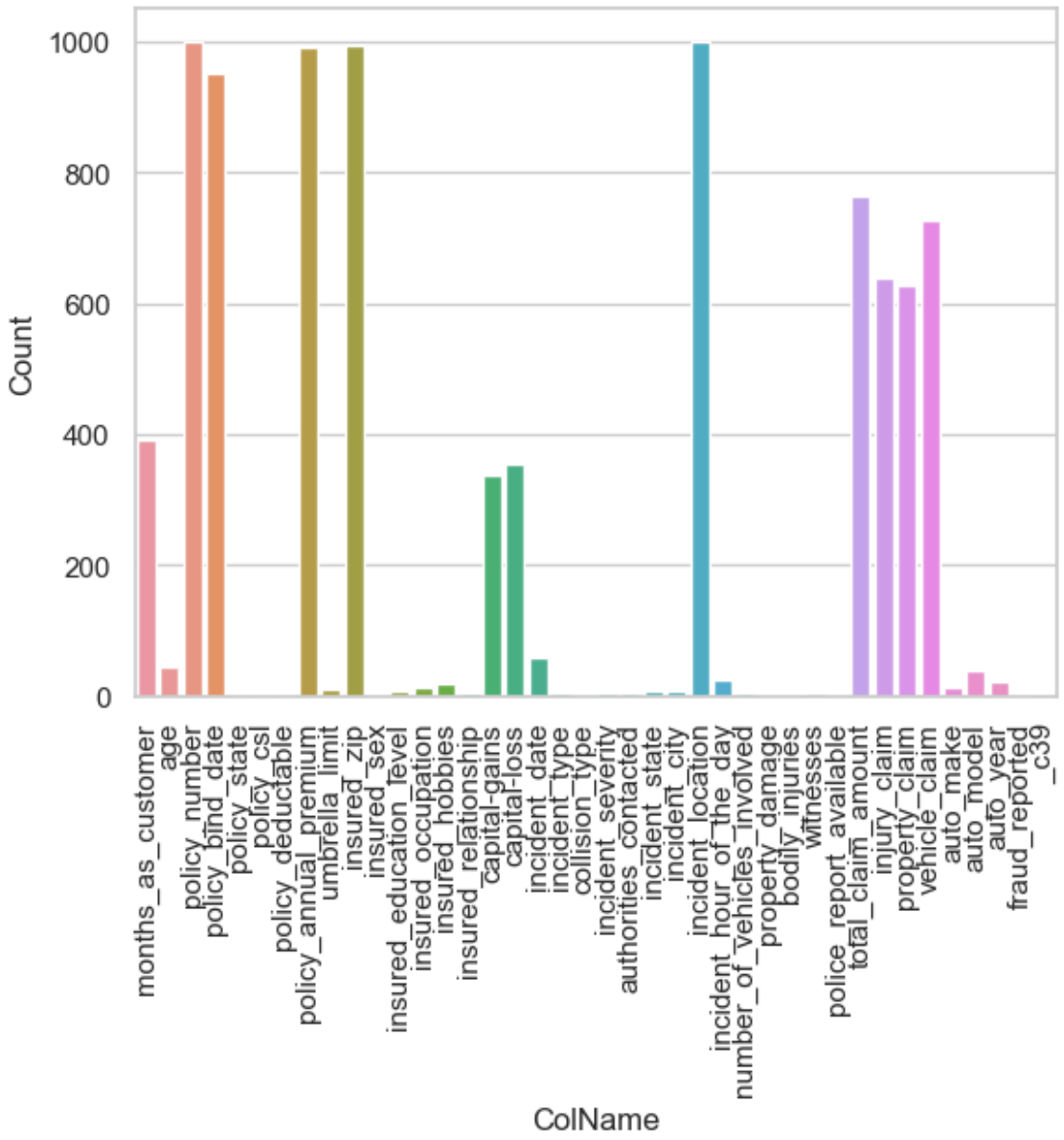
```
missing = data.isnull().sum() / len(data) # perncentage
missing = missing[missing>0]
missing.sort_values(inplace=True)
missing = missing.to_frame()
missing.columns=['Null_Count']
missing.index.names=['Col_Name']
missing = missing.reset_index()
sns.set(style='whitegrid',color_codes=True)
sns.barplot(x='Col_Name',y='Null_Count',data=missing)
plt.xticks(rotation=90)
plt.show()
```




```
data['collision_type'] =
data['collision_type'].fillna(data['collision_type'].mode()[0])
data['property_damage'] =
data['property_damage'].fillna(data['property_damage'].mode()[0])
data['police_report_available'] =
data['police_report_available'].fillna(data['police_report_available']
.mode()[0])

plt.figure(figsize = (18, 15))

corr = data.corr()

sns.heatmap(data = corr, annot = True, fmt = '.1g', linewidth = 2)
plt.show()
```




```
unique = data.nunique().to_frame()
unique.columns = ['Count']
unique.index.names = ['ColName']
unique = unique.reset_index()
sns.set(style='whitegrid',color_codes=True)
sns.barplot(x='ColName',y='Count',data=unique)
plt.xticks(rotation=90)
plt.show()
```




```
unique.sort_values(by='Count',ascending=False)
```

	ColName	Count
2	policy_number	1000
24	incident_location	1000
9	insured_zip	995
7	policy_annual_premium	991
3	policy_bind_date	951
31	total_claim_amount	763
34	vehicle_claim	726
32	injury_claim	638
33	property_claim	626
0	months_as_customer	391

```
16                  capital-loss    354
15                 capital-gains    338
17                 incident_date     60
1                            age     46
36                    auto_model     39
25     incident_hour_of_the_day     24
37                    auto_year     21
13               insured_hobbies     20
35                    auto_make     14
12            insured_occupation     14
8                 umbrella_limit     11
11      insured_education_level      7
22                incident_state      7
23                 incident_city      7
14          insured_relationship      6
21         authorities_contacted      5
29                     witnesses      4
20             incident_severity      4
26  number_of_vehicles_involved      4
18                 incident_type      4
28               bodily_injuries      3
19                collision_type      3
6              policy_deductable      3
5                     policy_csl      3
4                   policy_state      3
27               property_damage      2
30      police_report_available      2
10                   insured_sex      2
38                fraud_reported      2
39                          _c39      0
```

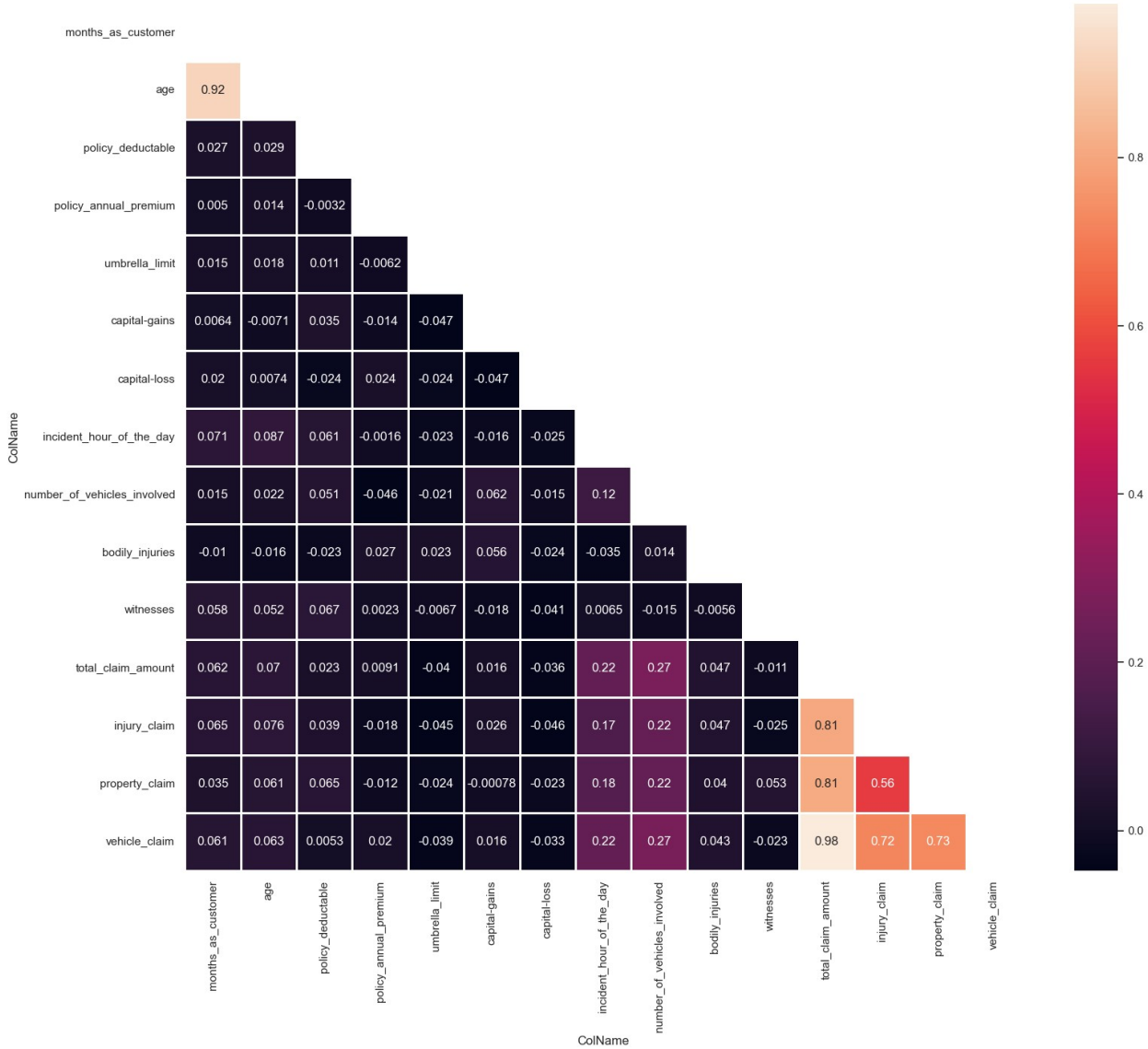
```
# Drop Columns that are not used in our project
to_drop =
['policy_number','policy_bind_date','policy_state','insured_zip','inci
dent_location','incident_date',

'incident_state','incident_city','insured_hobbies','auto_make','auto_m
odel','auto_year', '_c39']

data.drop(to_drop, inplace = True, axis = 1)

data.head()
```

```
ColName  months_as_customer  age policy_csl  policy_deductable  \
0                       328   48    250/500               1000
1                       228   42    250/500               2000
2                       134   29    100/300               2000
3                       256   41    250/500               2000
4                       228   44   500/1000               1000
```

```
ColName  policy_annual_premium  umbrella_limit insured_sex  \
0                      1406.91               0        MALE
1                      1197.22         5000000        MALE
2                      1413.14         5000000      FEMALE
3                      1415.74         6000000      FEMALE
4                      1583.91         6000000        MALE

ColName insured_education_level insured_occupation
insured_relationship  ...  \
0                            MD       craft-repair
husband  ...
1                            MD  machine-op-inspct       other-
relative  ...
2                           PhD              sales            own-
child  ...
3                           PhD       armed-forces
unmarried  ...
4                    Associate              sales
unmarried  ...

ColName  number_of_vehicles_involved  property_damage bodily_injuries
\
0                                  1             YES               1

1                                  1              NO               0

2                                  3              NO               2

3                                  1              NO               1

4                                  1              NO               0


ColName witnesses police_report_available total_claim_amount
injury_claim  \
0               2                      YES              71610
6510
1               0                       NO               5070
780
2               3                       NO              34650
7700
3               2                       NO              63400
6340
4               1                       NO               6500
1300

ColName  property_claim vehicle_claim  fraud_reported
0                13020         52080               Y
1                  780          3510               Y
2                 3850         23100               N
```

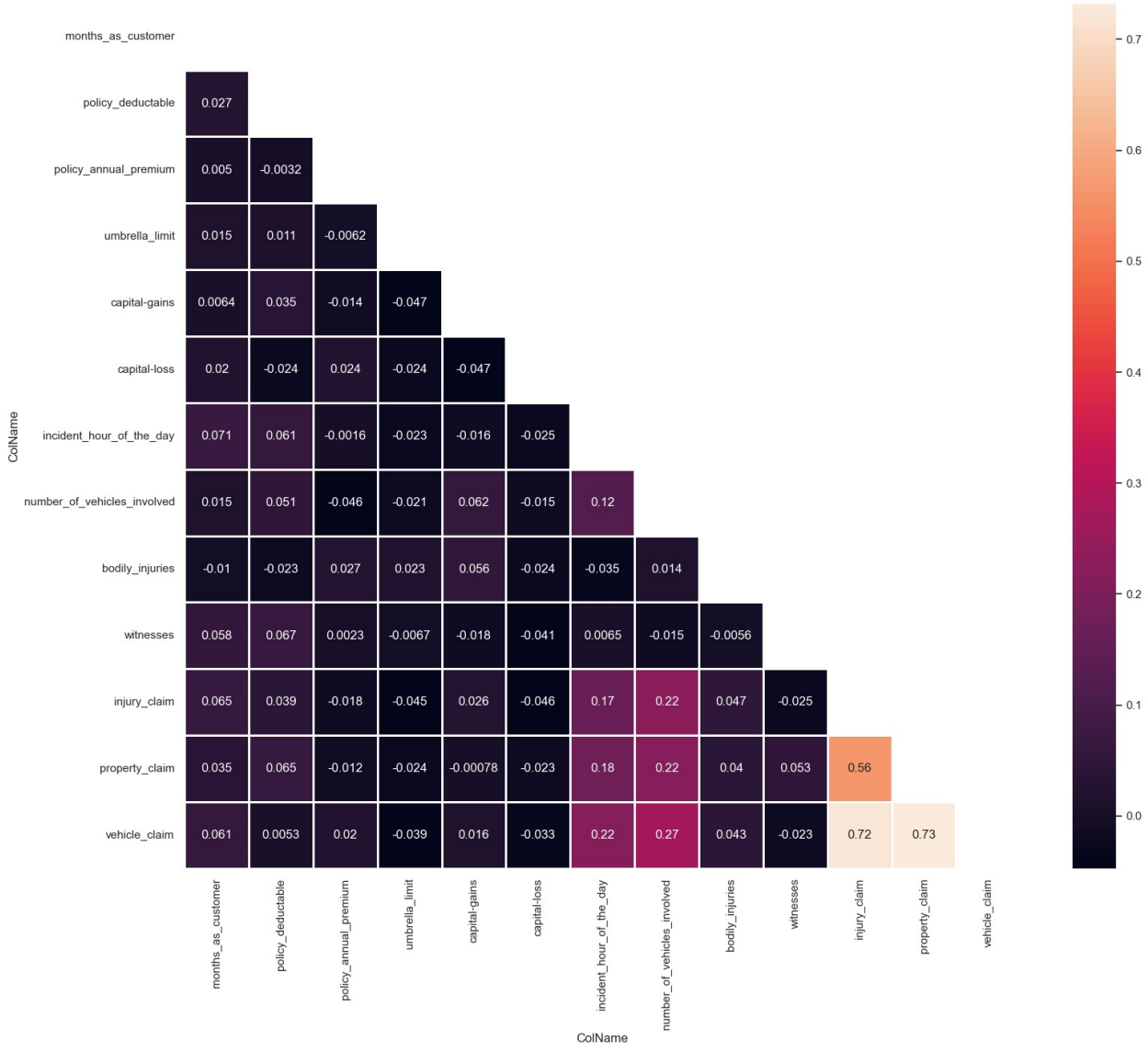
```
3                    6340          50720                 Y
4                     650           4550                 N

[5 rows x 27 columns]
```

```
plt.figure(figsize = (18, 15))

corr = data.corr()
mask = np.triu(np.ones_like(corr, dtype = bool))

sns.heatmap(data = corr, mask = mask, annot = True, fmt = '.2g',
linewidth = 1)
plt.show()
```



High Correlation in 'age' and 'month_as_customer' columns, along with columns like - 'total_claim_amount','injury_claim','property_claim', 'vehicle_claim'. So removing columns 'age' and 'total_claim_amount' to change the correction between them, Other I don't delete because we need others in our model.

```
plt.figure(figsize = (18, 15))

corr = data.corr()
mask = np.triu(np.ones_like(corr, dtype = bool))

sns.heatmap(data = corr, mask = mask, annot = True, fmt = '.2g',
linewidth = 1)
plt.show()
```



```
data.drop(columns = ['age', 'total_claim_amount'], inplace = True,
axis = 1)

data.head()
```

```
ColName  months_as_customer policy_csl  policy_deductable  \
0                        328    250/500               1000
1                        228    250/500               2000
2                        134    100/300               2000
3                        256    250/500               2000
4                        228   500/1000               1000

ColName  policy_annual_premium  umbrella_limit insured_sex  \
0                       1406.91               0        MALE
1                       1197.22         5000000        MALE
2                       1413.14         5000000      FEMALE
3                       1415.74         6000000      FEMALE
4                       1583.91         6000000        MALE

ColName insured_education_level insured_occupation
insured_relationship  \
0                            MD       craft-repair
husband
1                            MD  machine-op-inspct       other-
relative
2                           PhD              sales            own-
child
3                           PhD       armed-forces
unmarried
4                    Associate              sales
unmarried

ColName  capital-gains  ...  incident_hour_of_the_day  \
0                53300  ...                         5
1                    0  ...                         8
2                35100  ...                         7
3                48900  ...                         5
4                66000  ...                        20

ColName number_of_vehicles_involved property_damage bodily_injuries
witnesses  \
0                                  1             YES               1
2
1                                  1              NO               0
0
2                                  3              NO               2
3
3                                  1              NO               1
2
4                                  1              NO               0
```

```
1

ColName  police_report_available  injury_claim property_claim
vehicle_claim  \
0                              YES          6510          13020
52080
1                               NO           780            780
3510
2                               NO          7700           3850
23100
3                               NO          6340           6340
50720
4                               NO          1300            650
4550

ColName  fraud_reported
0                     Y
1                     Y
2                     N
3                     Y
4                     N

[5 rows x 25 columns]
```

```
# Get Target and Indpendent Features Seperated
X = data.drop('fraud_reported', axis = 1)
y = data['fraud_reported']

# Converting Label Columns into Numerical by doing One-Encoding
categorical_cols = X.select_dtypes(include = ['object'])
categorical_cols = pd.get_dummies(categorical_cols, drop_first = True)
categorical_cols.head()
```

```
   policy_csl_250/500  policy_csl_500/1000  insured_sex_MALE  \
0                   1                    0                 1
1                   1                    0                 1
2                   0                    0                 0
3                   1                    0                 0
4                   0                    1                 1

   insured_education_level_College  insured_education_level_High
School  \
0                                0
0
1                                0
0
2                                0
0
3                                0
0
```

```
4                                     0
0

   insured_education_level_JD  insured_education_level_MD  \
0                           0                           1
1                           0                           1
2                           0                           0
3                           0                           0
4                           0                           0

   insured_education_level_Masters  insured_education_level_PhD  \
0                                0                            0
1                                0                            0
2                                0                            1
3                                0                            1
4                                0                            0

   insured_occupation_armed-forces  ...  collision_type_Side Collision
\
0                                0  ...                              1

1                                0  ...                              0

2                                0  ...                              0

3                                1  ...                              0

4                                0  ...                              0


   incident_severity_Minor Damage  incident_severity_Total Loss  \
0                               0                            0
1                               1                            0
2                               1                            0
3                               0                            0
4                               1                            0

   incident_severity_Trivial Damage  authorities_contacted_Fire  \
0                                 0                           0
1                                 0                           0
2                                 0                           0
3                                 0                           0
4                                 0                           0

   authorities_contacted_None  authorities_contacted_Other  \
0                           0                            0
1                           0                            0
2                           0                            0
3                           0                            0
4                           1                            0
```

```
   authorities_contacted_Police  property_damage_YES  \
0                             1                    1
1                             1                    0
2                             1                    0
3                             1                    0
4                             0                    0

   police_report_available_YES
0                            1
1                            0
2                            0
3                            0
4                            0

[5 rows x 41 columns]
```

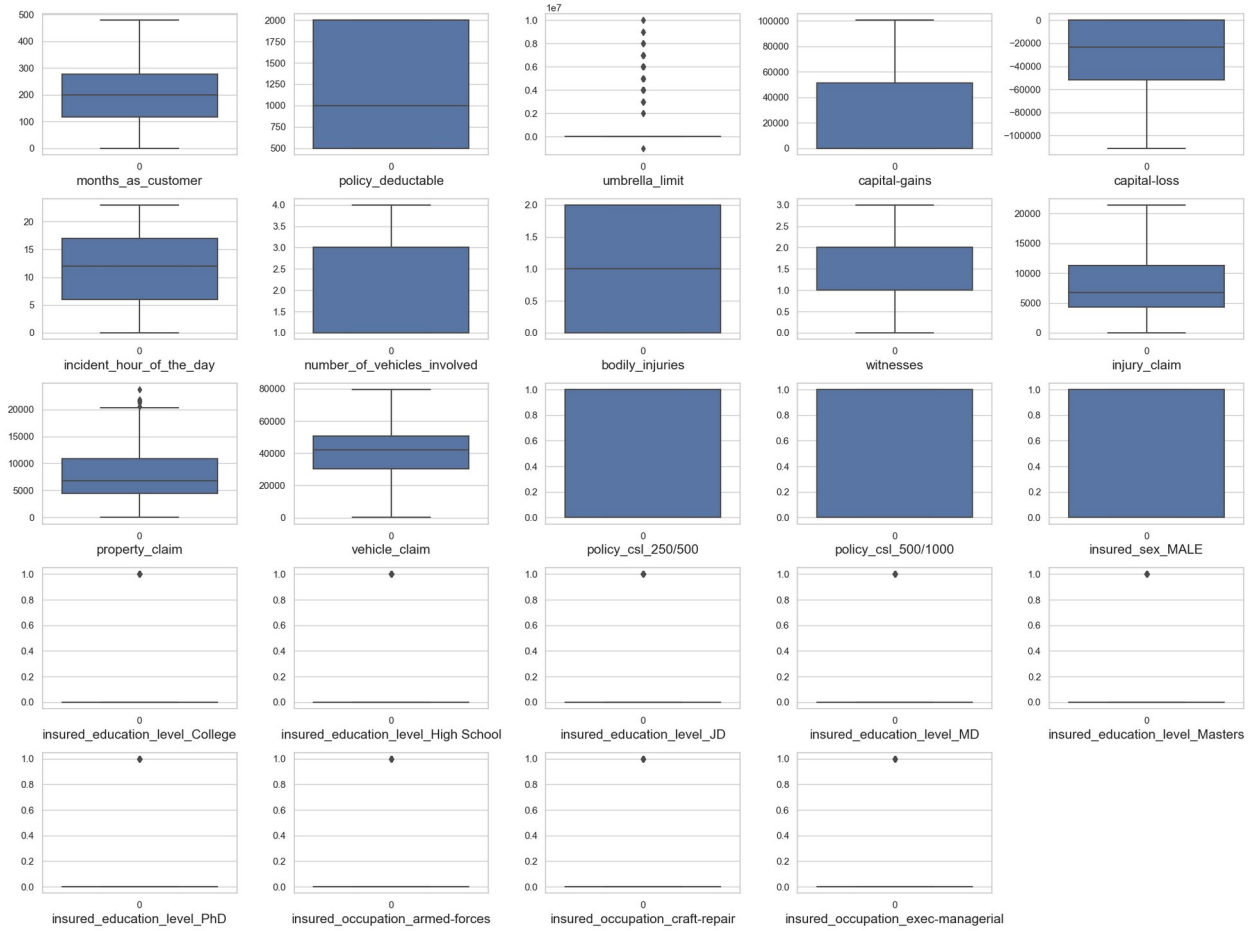
```
numerical_col = X.select_dtypes(include = ['int64'])
X = pd.concat([numerical_col, categorical_cols], axis = 1)

X.head()
```

```
   months_as_customer  policy_deductable  umbrella_limit  capital-
gains  \
0                 328               1000               0
53300
1                 228               2000         5000000
0
2                 134               2000         5000000
35100
3                 256               2000         6000000
48900
4                 228               1000         6000000
66000

   capital-loss  incident_hour_of_the_day  number_of_vehicles_involved
\
0             0                         5                            1

1             0                         8                            1

2             0                         7                            3

3        -62400                         5                            1

4        -46000                        20                            1


   bodily_injuries  witnesses  injury_claim  ...  \
0                1          2          6510  ...
1                0          0           780  ...
```

```
2                  2          3          7700  ...
3                  1          2          6340  ...
4                  0          1          1300  ...

   collision_type_Side Collision  incident_severity_Minor Damage  \
0                              1                               0
1                              0                               1
2                              0                               1
3                              0                               0
4                              0                               1

   incident_severity_Total Loss  incident_severity_Trivial Damage  \
0                             0                                 0
1                             0                                 0
2                             0                                 0
3                             0                                 0
4                             0                                 0

   authorities_contacted_Fire  authorities_contacted_None  \
0                           0                           0
1                           0                           0
2                           0                           0
3                           0                           0
4                           0                           1

   authorities_contacted_Other  authorities_contacted_Police  \
0                            0                             1
1                            0                             1
2                            0                             1
3                            0                             1
4                            0                             0

   property_damage_YES  police_report_available_YES
0                    1                            1
1                    0                            0
2                    0                            0
3                    0                            0
4                    0                            0

[5 rows x 53 columns]
```

```
# Outlier Check

plt.figure(figsize = (20, 15))
plotnumber = 1

for col in X.columns:
    if plotnumber <= 24:
        ax = plt.subplot(5, 5, plotnumber)
        sns.boxplot(X[col])
```

```
        plt.xlabel(col, fontsize = 15)

    plotnumber += 1
plt.tight_layout()
plt.show()
```



Outliers are in there, so we need to Standarise those columns using Standard Scaler

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.25)

X_train.head()
```

```
     months_as_customer  policy_deductable  umbrella_limit  capital-
gains  \
860                 230                1000               0
0
```

```
396                  409                1000         6000000
55600
800                   95                2000               0
48900
249                   94                2000               0
0
419                  138                 500         5000000
56900

     capital-loss  incident_hour_of_the_day
number_of_vehicles_involved  \
860        -45300                         13
3
396             0                         19
1
800             0                         22
1
249        -52600                         19
1
419        -56900                          6
1

     bodily_injuries  witnesses  injury_claim  ...  \
860                1          2         10700  ...
396                1          0          6110  ...
800                0          3          3480  ...
249                1          3          6410  ...
419                2          0         14740  ...

     collision_type_Side Collision  incident_severity_Minor Damage  \
860                              0                               1
396                              1                               0
800                              0                               1
249                              0                               0
419                              1                               1

     incident_severity_Total Loss  incident_severity_Trivial Damage  \
860                             0                                 0
396                             0                                 0
800                             0                                 0
249                             0                                 0
419                             0                                 0

     authorities_contacted_Fire  authorities_contacted_None  \
860                           0                           0
396                           0                           0
800                           0                           0
249                           1                           0
419                           0                           0
```

```
     authorities_contacted_Other  authorities_contacted_Police  \
860                            1                             0
396                            1                             0
800                            0                             1
249                            0                             0
419                            1                             0

     property_damage_YES  police_report_available_YES
860                    0                            1
396                    0                            0
800                    1                            0
249                    0                            1
419                    0                            0

[5 rows x 53 columns]
```

```
numerical_data = X_train[['months_as_customer', 'policy_deductable',
'umbrella_limit',
       'capital-gains', 'capital-loss', 'incident_hour_of_the_day',
       'number_of_vehicles_involved', 'bodily_injuries', 'witnesses',
'injury_claim', 'property_claim',
       'vehicle_claim']]

# Standardization

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaled_data = scaler.fit_transform(numerical_data)

scaled_num_df = pd.DataFrame(data = scaled_data, columns =
numerical_data.columns, index = X_train.index)
scaled_num_df.head()
```

```
     months_as_customer  policy_deductable  umbrella_limit  capital-
gains  \
860            0.245144          -0.251318       -0.484594      -
0.896757
396            1.798116          -0.251318        2.093035
1.103092
800           -0.926092           1.373582       -0.484594
0.862103
249           -0.934768           1.373582       -0.484594      -
0.896757
419           -0.553032          -1.063768        1.663430
1.149851

     capital-loss  incident_hour_of_the_day
number_of_vehicles_involved  \
860     -0.637476                  0.202688
1.132368
396      0.968540                  1.068874                    -
```

```
0.824489
800      0.968540                  1.501968                    -
0.824489
249     -0.896282                  1.068874                    -
0.824489
419     -1.048729                 -0.807864                    -
0.824489

     bodily_injuries  witnesses  injury_claim  property_claim
vehicle_claim
860        -0.004924   0.493161      0.680899        0.686933      -
0.022682
396        -0.004924  -1.324385     -0.267899        1.003269
0.902574
800        -1.235854   1.401934     -0.811545       -0.091418      -
0.713195
249        -0.004924   1.401934     -0.205886       -0.205882
0.706867
419         1.226006  -1.324385      1.516007        1.527719
1.500772
```

```
X_train.drop(columns = scaled_num_df.columns, inplace = True)
```

```
X_train = pd.concat([scaled_num_df, X_train], axis = 1)
```

```
X_train.head()
```

```
     months_as_customer  policy_deductable  umbrella_limit  capital-
gains  \
860            0.245144          -0.251318       -0.484594      -
0.896757
396            1.798116          -0.251318        2.093035
1.103092
800           -0.926092           1.373582       -0.484594
0.862103
249           -0.934768           1.373582       -0.484594      -
0.896757
419           -0.553032          -1.063768        1.663430
1.149851

     capital-loss  incident_hour_of_the_day
number_of_vehicles_involved  \
860     -0.637476                  0.202688
1.132368
396      0.968540                  1.068874                    -
0.824489
800      0.968540                  1.501968                    -
0.824489
249     -0.896282                  1.068874                    -
0.824489
```

```
419    -1.048729                -0.807864                      -
0.824489

     bodily_injuries  witnesses  injury_claim  ...  \
860         -0.004924   0.493161      0.680899  ...
396         -0.004924  -1.324385     -0.267899  ...
800         -1.235854   1.401934     -0.811545  ...
249         -0.004924   1.401934     -0.205886  ...
419          1.226006  -1.324385      1.516007  ...

     collision_type_Side Collision  incident_severity_Minor Damage  \
860                              0                               1
396                              1                               0
800                              0                               1
249                              0                               0
419                              1                               1

     incident_severity_Total Loss  incident_severity_Trivial Damage  \
860                             0                                 0
396                             0                                 0
800                             0                                 0
249                             0                                 0
419                             0                                 0

     authorities_contacted_Fire  authorities_contacted_None  \
860                           0                           0
396                           0                           0
800                           0                           0
249                           1                           0
419                           0                           0

     authorities_contacted_Other  authorities_contacted_Police  \
860                            1                             0
396                            1                             0
800                            0                             1
249                            0                             0
419                            1                             0

     property_damage_YES  police_report_available_YES
860                    0                           1
396                    0                           0
800                    1                           0
249                    0                           1
419                    0                           0

[5 rows x 53 columns]
```

Modelling

Support Vector Classifier

```
from sklearn.svm import SVC

svc_model = SVC()
svc_model.fit(X_train, y_train)

y_pred = svc_model.predict(X_test)

from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report

svc_model_train_acc = accuracy_score(y_train,
svc_model.predict(X_train))
svc_model_test_acc = accuracy_score(y_test, y_pred)

print("Training Accuracy: ",svc_model_train_acc)
print("Testing Accuracy: ", svc_model_test_acc)
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Training Accuracy:  0.828
Testing Accuracy:  0.776
[[194   0]
 [ 56   0]]
              precision    recall  f1-score   support

           0       0.78      1.00      0.87       194
           1       0.00      0.00      0.00        56

    accuracy                           0.78       250
   macro avg       0.39      0.50      0.44       250
weighted avg       0.60      0.78      0.68       250
```

K-Nearest Neighborhood

```
from sklearn.neighbors import KNeighborsClassifier

knn_model = KNeighborsClassifier(n_neighbors = 30)
knn_model.fit(X_train, y_train)

y_pred = knn_model.predict(X_test)

from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report

knn_model_train_acc = accuracy_score(y_train,
```

```
knn_model.predict(X_train))
knn_model_test_acc = accuracy_score(y_test, y_pred)

print("Training Accuracy: ",knn_model_train_acc)
print("Testing Accuracy: ", knn_model_test_acc)
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Training Accuracy:  0.7466666666666667
Testing Accuracy:  0.776
[[194   0]
 [ 56   0]]
              precision    recall  f1-score   support

           0       0.78      1.00      0.87       194
           1       0.00      0.00      0.00        56

    accuracy                           0.78       250
   macro avg       0.39      0.50      0.44       250
weighted avg       0.60      0.78      0.68       250
```

Decision Tree Classifier

```
from sklearn.tree import DecisionTreeClassifier

decision_tree_model = DecisionTreeClassifier()
decision_tree_model.fit(X_train, y_train)

y_pred = decision_tree_model.predict(X_test)

from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report

decision_tree_model_train_acc = accuracy_score(y_train,
decision_tree_model.predict(X_train))
decision_tree_model_test_acc = accuracy_score(y_test, y_pred)

print("Training accuracy: ",decision_tree_model_train_acc)
print("Test accuracy: ",decision_tree_model_test_acc)

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Training accuracy:  1.0
Test accuracy:  0.3
[[ 48 146]
 [ 29  27]]
              precision    recall  f1-score   support

           0       0.62      0.25      0.35       194
```

```
           1       0.16      0.48      0.24        56

    accuracy                           0.30       250
   macro avg       0.39      0.36      0.30       250
weighted avg       0.52      0.30      0.33       250
```

```
from sklearn.model_selection import GridSearchCV

grid_params = {
    'criterion' : ['gini', 'entropy'],
    'max_depth' : [3, 5, 7, 10],
    'min_samples_split' : range(2, 10, 1),
    'min_samples_leaf' : range(2, 10, 1)
}

grid_search = GridSearchCV(decision_tree_model, grid_params, cv = 5,
n_jobs = -1, verbose = 1)
grid_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 512 candidates, totalling 2560 fits
```

```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [3, 5, 7, 10],
                         'min_samples_leaf': range(2, 10),
                         'min_samples_split': range(2, 10)},
             verbose=1)
```

```
print(grid_search.best_params_)
print(grid_search.best_score_)
```

```
{'algorithm': 'SAMME.R', 'learning_rate': 0.001, 'n_estimators': 70}
0.8013333333333333
```

```
decision_tree_model = grid_search.best_estimator_
y_pred = decision_tree_model.predict(X_test)

from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report

decision_tree_model_train_acc = accuracy_score(y_train,
decision_tree_model.predict(X_train))
decision_tree_model_test_acc = accuracy_score(y_test, y_pred)

print(f"Training accuracy of Decision Tree is :
{decision_tree_model_train_acc}")
print(f"Test accuracy of Decision Tree is :
{decision_tree_model_test_acc}")
```

```
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Training accuracy of Decision Tree is : 0.8066666666666666
Test accuracy of Decision Tree is : 0.844
[[169  25]
 [ 14  42]]
              precision    recall  f1-score   support

           0       0.92      0.87      0.90       194
           1       0.63      0.75      0.68        56

    accuracy                           0.84       250
   macro avg       0.78      0.81      0.79       250
weighted avg       0.86      0.84      0.85       250
```

Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier(criterion= 'entropy', max_depth= 15,
max_features= 'sqrt', min_samples_leaf= 1, min_samples_split= 3,
n_estimators= 140)
rf_model.fit(X_train, y_train)

y_pred = rf_model.predict(X_test)

from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report

rf_model_train_acc = accuracy_score(y_train,
rf_model.predict(X_train))
rf_model_test_acc = accuracy_score(y_test, y_pred)

print("Training accuracy: ", rf_model_train_acc)
print("Test accuracy: ", rf_model_test_acc)

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Training accuracy:  1.0
Test accuracy:  0.824
[[184  10]
 [ 34  22]]
              precision    recall  f1-score   support

           0       0.84      0.95      0.89       194
           1       0.69      0.39      0.50        56

    accuracy                           0.82       250
```

```
   macro avg       0.77      0.67      0.70       250
weighted avg       0.81      0.82      0.81       250
```

Ada Boost Classifier

```
from sklearn.ensemble import AdaBoostClassifier

ada_model = AdaBoostClassifier(base_estimator = decision_tree_model)

parameters = {
    'n_estimators' : [50, 70, 90, 120, 180, 200],
    'learning_rate' : [0.001, 0.01, 0.1, 1, 10],
    'algorithm' : ['SAMME', 'SAMME.R']
}

grid_search = GridSearchCV(ada_model, parameters, n_jobs = -1, cv = 5,
verbose = 1)
grid_search.fit(X_train, y_train)

print(grid_search.best_params_)
print(grid_search.best_score_)
```

```
{'algorithm': 'SAMME.R', 'learning_rate': 0.001, 'n_estimators': 70}
0.8013333333333333
```

```
ada_model = grid_search.best_estimator_
y_pred = ada_model.predict(X_test)

ada_train_acc = accuracy_score(y_train, ada.predict(X_train))
ada_test_acc = accuracy_score(y_test, y_pred)

print(f"Training accuracy of Ada Boost is : {ada_train_acc}")
print(f"Test accuracy of Ada Boost is : {ada_test_acc}")

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Training accuracy of Ada Boost is : 0.8066666666666666
Test accuracy of Ada Boost is : 0.844
[[169  25]
 [ 14  42]]
              precision    recall  f1-score   support

           N       0.92      0.87      0.90       194
           Y       0.63      0.75      0.68        56

    accuracy                           0.84       250
   macro avg       0.78      0.81      0.79       250
weighted avg       0.86      0.84      0.85       250
```

Gradient Boosting Classifier

```
from sklearn.ensemble import GradientBoostingClassifier

gb = GradientBoostingClassifier()
gb.fit(X_train, y_train)

# accuracy score, confusion matrix and classification report of
gradient boosting classifier

gb_acc = accuracy_score(y_test, gb.predict(X_test))

print(f"Training Accuracy of Gradient Boosting Classifier is
{accuracy_score(y_train, gb.predict(X_train))}")
print(f"Test Accuracy of Gradient Boosting Classifier is {gb_acc} \n")

print(f"Confusion Matrix :- \n{confusion_matrix(y_test,
gb.predict(X_test))}\n")
print(f"Classification Report :- \n {classification_report(y_test,
gb.predict(X_test))}")
```

```
Training Accuracy of Gradient Boosting Classifier is 0.932
Test Accuracy of Gradient Boosting Classifier is 0.284

Confusion Matrix :-
[[ 16 178]
 [  1  55]]

Classification Report :-
               precision    recall  f1-score   support

           N       0.94      0.08      0.15       194
           Y       0.24      0.98      0.38        56

    accuracy                           0.28       250
   macro avg       0.59      0.53      0.27       250
weighted avg       0.78      0.28      0.20       250
```

Stochastic Gradient Boosting

```
sgb = GradientBoostingClassifier(subsample = 0.90, max_features =
0.70)
sgb.fit(X_train, y_train)

# accuracy score, confusion matrix and classification report of
stochastic gradient boosting classifier

sgb_acc = accuracy_score(y_test, sgb.predict(X_test))

print(f"Training Accuracy of Stochastic Gradient Boosting is
```

```
{accuracy_score(y_train, sgb.predict(X_train))}")
print(f"Test Accuracy of Stochastic Gradient Boosting is {sgb_acc} \
n")

print(f"Confusion Matrix :- \n{confusion_matrix(y_test,
sgb.predict(X_test))}\n")
print(f"Classification Report :- \n {classification_report(y_test,
sgb.predict(X_test))}")
```

```
Training Accuracy of Stochastic Gradient Boosting is
0.9266666666666666
Test Accuracy of Stochastic Gradient Boosting is 0.276

Confusion Matrix :-
[[ 14 180]
 [  1  55]]

Classification Report :-
               precision    recall  f1-score   support

           N       0.93      0.07      0.13       194
           Y       0.23      0.98      0.38        56

    accuracy                           0.28       250
   macro avg       0.58      0.53      0.26       250
weighted avg       0.78      0.28      0.19       250
```

XgBoost Classifier

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
y_train = le.fit_transform(y_train)

y_test = le.fit_transform(y_test)

from xgboost import XGBClassifier

xgb = XGBClassifier()
xgb.fit(X_train, y_train)

y_pred = xgb.predict(X_test)

xgb_train_acc = accuracy_score(y_train, xgb.predict(X_train))
xgb_test_acc = accuracy_score(y_test, y_pred)

print(f"Training accuracy of XgBoost is : {xgb_train_acc}")
print(f"Test accuracy of XgBoost is : {xgb_test_acc}")

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Training accuracy of XgBoost is : 1.0
Test accuracy of XgBoost is : 0.736
[[154  40]
 [ 26  30]]
              precision    recall  f1-score   support

           0       0.86      0.79      0.82       194
           1       0.43      0.54      0.48        56

    accuracy                           0.74       250
   macro avg       0.64      0.66      0.65       250
weighted avg       0.76      0.74      0.75       250
```

```
param_grid = {"n_estimators": [10, 50, 100, 130], "criterion":
['gini', 'entropy'],
                              "max_depth": range(2, 10, 1)}

grid = GridSearchCV(estimator=xgb, param_grid=param_grid, cv=5,
verbose=3,n_jobs=-1)
grid_search.fit(X_train, y_train)

xgb = grid_search.best_estimator_

y_pred = xgb.predict(X_test)

xgb_train_acc = accuracy_score(y_train, xgb.predict(X_train))
xgb_test_acc = accuracy_score(y_test, y_pred)

print(f"Training accuracy of XgBoost is : {xgb_train_acc}")
print(f"Test accuracy of XgBoost is : {xgb_test_acc}")

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Training accuracy of XgBoost is : 0.8066666666666666
Test accuracy of XgBoost is : 0.844
[[169  25]
 [ 14  42]]
              precision    recall  f1-score   support

           0       0.92      0.87      0.90       194
           1       0.63      0.75      0.68        56

    accuracy                           0.84       250
   macro avg       0.78      0.81      0.79       250
weighted avg       0.86      0.84      0.85       250
```

Cat Boost Classifier

```
from catboost import CatBoostClassifier

cat = CatBoostClassifier(iterations=10)
cat.fit(X_train, y_train)
```

```
Learning rate set to 0.5
0:    learn: 0.5730282 total: 59.7ms    remaining: 537ms
1:    learn: 0.4637104 total: 61.5ms    remaining: 246ms
2:    learn: 0.4434368 total: 63.1ms    remaining: 147ms
3:    learn: 0.4211538 total: 64.7ms    remaining: 97ms
4:    learn: 0.3936747 total: 66.2ms    remaining: 66.2ms
5:    learn: 0.3645963 total: 68ms      remaining: 45.4ms
6:    learn: 0.3411517 total: 69.8ms    remaining: 29.9ms
7:    learn: 0.3265072 total: 71.3ms    remaining: 17.8ms
8:    learn: 0.3157283 total: 73.1ms    remaining: 8.12ms
9:    learn: 0.2972717 total: 74.7ms    remaining: 0us

<catboost.core.CatBoostClassifier at 0x7fb399ca8940>
```

```
cat_acc = accuracy_score(y_test, cat.predict(X_test))

print(f"Training Accuracy of Cat Boost Classifier is
{accuracy_score(y_train, cat.predict(X_train))}")
print(f"Test Accuracy of Cat Boost Classifier is {cat_acc} \n")

print(f"Confusion Matrix :- \n{confusion_matrix(y_test,
cat.predict(X_test))}\n")
print(f"Classification Report :- \n {classification_report(y_test,
cat.predict(X_test))}")
```

```
Training Accuracy of Cat Boost Classifier is 0.9
Test Accuracy of Cat Boost Classifier is 0.696

Confusion Matrix :-
[[140  54]
 [ 22  34]]

Classification Report :-
              precision    recall  f1-score   support

           0       0.86      0.72      0.79       194
           1       0.39      0.61      0.47        56

    accuracy                           0.70       250
   macro avg       0.63      0.66      0.63       250
weighted avg       0.76      0.70      0.72       250
```

Extra Trees Classifier

```
from sklearn.ensemble import ExtraTreesClassifier

etc = ExtraTreesClassifier()
etc.fit(X_train, y_train)

# accuracy score, confusion matrix and classification report of extra
trees classifier

etc_acc = accuracy_score(y_test, etc.predict(X_test))

print(f"Training Accuracy of Extra Trees Classifier is
{accuracy_score(y_train, etc.predict(X_train))}")
print(f"Test Accuracy of Extra Trees Classifier is {etc_acc} \n")

print(f"Confusion Matrix :- \n{confusion_matrix(y_test,
etc.predict(X_test))}\n")
print(f"Classification Report :- \n {classification_report(y_test,
etc.predict(X_test))}")
```

```
Training Accuracy of Extra Trees Classifier is 1.0
Test Accuracy of Extra Trees Classifier is 0.832

Confusion Matrix :-
[[180  14]
 [ 28  28]]

Classification Report :-
              precision    recall  f1-score   support

           0       0.87      0.93      0.90       194
           1       0.67      0.50      0.57        56

    accuracy                           0.83       250
   macro avg       0.77      0.71      0.73       250
weighted avg       0.82      0.83      0.82       250
```

Voting Classifier

```
from sklearn.ensemble import VotingClassifier

classifiers = [('Support Vector Classifier', svc_model), ('knn_model',
knn_model),  ('Decision Tree', decision_tree_model), ('Random Forest',
rf_model),
               ('Ada Boost', ada), ('XGboost', xgb), ('Gradient
Boosting Classifier', gb), ('SGB', sgb),
               ('Cat Boost', cat), ('Extra Trees Classifier', etc)]

vc = VotingClassifier(estimators = classifiers)
```

```
vc.fit(X_train, y_train)

y_pred = vc.predict(X_test)
```

```
Learning rate set to 0.5
0:    learn: 0.5730282 total: 2.81ms    remaining: 25.3ms
1:    learn: 0.4637104 total: 4.65ms    remaining: 18.6ms
2:    learn: 0.4434368 total: 6.5ms     remaining: 15.2ms
3:    learn: 0.4211538 total: 8.15ms    remaining: 12.2ms
4:    learn: 0.3936747 total: 9.75ms    remaining: 9.75ms
5:    learn: 0.3645963 total: 11.8ms    remaining: 7.89ms
6:    learn: 0.3411517 total: 13.6ms    remaining: 5.84ms
7:    learn: 0.3265072 total: 15.5ms    remaining: 3.88ms
8:    learn: 0.3157283 total: 17.4ms    remaining: 1.94ms
9:    learn: 0.2972717 total: 19.2ms    remaining: 0us
```

```
# accuracy_score, confusion_matrix and classification_report

vc_train_acc = accuracy_score(y_train, vc.predict(X_train))
vc_test_acc = accuracy_score(y_test, y_pred)

print(f"Training accuracy of Voting Classifier is : {vc_train_acc}")
print(f"Test accuracy of Voting Classifier is : {vc_test_acc}")

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Training accuracy of Voting Classifier is : 0.9213333333333333
Test accuracy of Voting Classifier is : 0.848
[[170  24]
 [ 14  42]]
              precision    recall  f1-score   support

           0       0.92      0.88      0.90       194
           1       0.64      0.75      0.69        56

    accuracy                           0.85       250
   macro avg       0.78      0.81      0.79       250
weighted avg       0.86      0.85      0.85       250
```

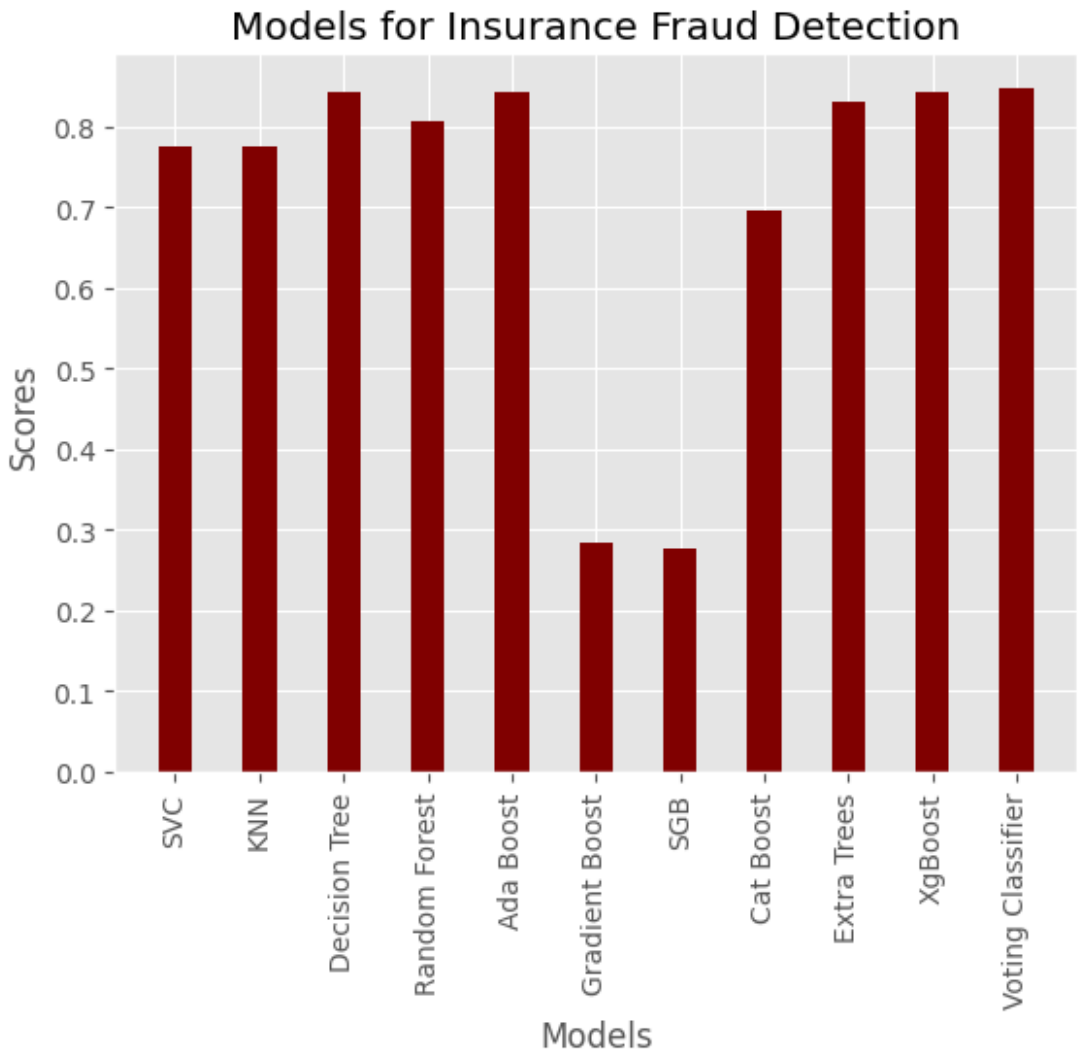
Models Comparison

```
models = pd.DataFrame({
    'Model' : ['svc_model', 'knn_model', 'Decision Tree', 'Random
Forest','Ada Boost', 'Gradient Boost', 'SGB', 'Cat Boost', 'Extra
Trees', 'XgBoost', 'Voting Classifier'],
    'Score' : [svc_model_test_acc, knn_model_test_acc,
decision_tree_model_test_acc, rf_model_test_acc, ada_test_acc, gb_acc,
sgb_acc, cat_acc, etc_acc, xgb_test_acc, vc_test_acc]
```

```
})


models.sort_values(by = 'Score', ascending = False)
```

	Model	Score
10	Voting Classifier	0.848
2	Decision Tree	0.844
4	Ada Boost	0.844
9	XgBoost	0.844
8	Extra Trees	0.832
3	Random Forest	0.808
0	SVC	0.776
1	KNN	0.776
7	Cat Boost	0.696
5	Gradient Boost	0.284
6	SGB	0.276

```
plt.bar(models['Model'],models['Score'], width=0.4, color='maroon')
plt.xlabel("Models")
plt.xticks(rotation=90)
plt.ylabel("Scores")
plt.title("Models for Insurance Fraud Detection")
plt.show()
```


Models for Insurance Fraud Detection
Scores
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
SVC
KNN
Decision Tree
Random Forest
Ada Boost
Gradient Boost
SGB
Cat Boost
Extra Trees
XgBoost
Voting Classifier
Models