```
In [10]:
           import pandas as pd
           import numpy as np
           import matplotlib.pyplot as plt
           import seaborn as sns
           import plotly.express as px
           import warnings
           warnings.filterwarnings('ignore')
           plt.style.use('ggplot')
In [11]:
           df = pd.read csv('C:/Users/ROSHAN D K/Desktop/Python Projects/insurance claims.csv')
           df.head()
             months_as_customer age policy_number policy_bind_date policy_state policy_csl policy_deductable policy_ann
Out[11]:
          0
                           328
                                 48
                                            521585
                                                         2014-10-17
                                                                           ОН
                                                                                  250/500
                                                                                                     1000
          1
                           228
                                 42
                                            342868
                                                         2006-06-27
                                                                            IN
                                                                                  250/500
                                                                                                     2000
          2
                            134
                                 29
                                            687698
                                                         2000-09-06
                                                                           ОН
                                                                                  100/300
                                                                                                     2000
          3
                            256
                                 41
                                            227811
                                                         1990-05-25
                                                                             IL
                                                                                 250/500
                                                                                                     2000
          4
                            228
                                 44
                                            367455
                                                         2014-06-06
                                                                             IL
                                                                                500/1000
                                                                                                     1000
         5 rows × 40 columns
In [12]:
           df.replace('?', np.nan, inplace = True)
In [13]:
           df.describe()
Out[13]:
                 months as customer
                                           age
                                                policy_number policy_deductable policy_annual_premium
                                                                                                      umbrella limit
                        1000.000000
                                    1000.000000
                                                   1000.000000
                                                                    1000.000000
                                                                                          1000.000000
                                                                                                       1.000000e+03
          count
                         203.954000
                                      38.948000
                                                 546238.648000
                                                                    1136.000000
                                                                                          1256.406150
                                                                                                       1.101000e+06
          mean
                         115.113174
                                       9.140287
                                                 257063.005276
                                                                     611.864673
                                                                                           244.167395
                                                                                                       2.297407e+06
            std
            min
                           0.000000
                                      19.000000
                                                 100804.000000
                                                                     500.000000
                                                                                           433.330000
                                                                                                      -1.000000e+06
           25%
                         115.750000
                                      32.000000
                                                 335980.250000
                                                                     500.000000
                                                                                          1089.607500
                                                                                                       0.000000e+00
           50%
                         199.500000
                                      38.000000
                                                 533135.000000
                                                                    1000.000000
                                                                                          1257.200000
                                                                                                       0.000000e+00
           75%
                         276.250000
                                      44.000000
                                                 759099.750000
                                                                    2000.000000
                                                                                          1415.695000
                                                                                                       0.000000e+00
                         479.000000
                                                                                                       1.000000e+07
           max
                                      64.000000
                                                 999435.000000
                                                                    2000.000000
                                                                                          2047.590000
In [14]:
           df.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 1000 entries, 0 to 999
          Data columns (total 40 columns):
           #
                                                  Non-Null Count Dtype
               Column
               _____
                                                  _____
           0
               months as customer
                                                  1000 non-null
                                                                    int64
           1
                                                  1000 non-null
                                                                    int64
                age
           2
                policy number
                                                  1000 non-null
                                                                     int64
                                                  1000 non-null
               policy bind date
                                                                     object
```

```
4policy_state1000 non-nullobject5policy_csl1000 non-nullobject6policy_deductable1000 non-nullint647policy_annual_premium1000 non-nullfloat648umbrella_limit1000 non-nullint649insured_zip1000 non-nullobject10insured_sex1000 non-nullobject11insured_education_level1000 non-nullobject12insured_occupation1000 non-nullobject13insured_hobbies1000 non-nullobject14insured_relationship1000 non-nullobject15capital-gains1000 non-nullint6416capital-loss1000 non-nullobject17incident_date1000 non-nullobject18incident_type822 non-nullobject20incident_severity1000 non-nullobject21authorities_contacted1000 non-nullobject22incident_state1000 non-nullobject23incident_location1000 non-nullobject24incident_location1000 non-nullint6425incident_hour_of_the_day1000 non-nullint6426number_of_vehicles_involved1000 non-nullint6427property_damage640 non-nullobject28bcdilw_injurios1000 non-nullint64
                        27 property_damage 640 non-null object
28 bodily injuries 1000 non-null int64
                        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
                        29 witnesses
                      dtypes: float64(2), int64(17), object(21)
                      memory usage: 312.6+ KB
In [17]:
                        # missing values
                        df.isna().sum()
                      months as customer
                                                                                                             0
Out[17]:
                                                                                                             0
                      age
                      policy number
                                                                                                            0
                      policy bind date
                                                                                                           0
                      policy state
                                                                                                            0
                      policy csl
                                                                                                         0
                      policy deductable
                                                                                                          Ω
                      policy annual premium
                      umbrella limit
                                                                                                           0
                      insured zip
                      insured sex
                                                                                                          0
                      insured education level
                      insured occupation
                                                                                                         0
                      insured hobbies
                      insured relationship
                                                                                                          0
                      capital-gains
                                                                                                           0
                      capital-loss
                                                                                                         0
                      incident date
                                                                                                         0
                                                                                                         0
                      incident type
                      collision type
                                                                                                       178
                                                                                                            0
                      incident severity
                      authorities_contacted
                                                                                                             0
                      incident state
```

```
0
        incident location
        incident_hour_of_the day
        number_of_vehicles_involved
        property_damage
                                     360
                                       0
        bodily injuries
                                       0
        witnesses
        police_report_available
                                    343
        total claim amount
                                       0
        injury_claim
                                       0
        property claim
        vehicle claim
                                       0
        auto make
        auto model
                                        0
        auto year
        fraud_reported
                                        0
                                    1000
        dtype: int64
In [18]:
        df['collision type'] = df['collision type'].fillna(df['collision type'].mode()[0])
         df['property damage'] = df['property damage'].fillna(df['property damage'].mode()[0])
         df['police report available'] = df['police report available'].fillna(df['police report available']
         df.isna().sum()
Out[18]: months_as_customer
                                        0
                                        0
        age
        policy number
        policy bind date
                                       0
        policy state
        policy csl
        policy deductable
                                       0
        policy_annual_premium
        umbrella limit
                                       0
        insured zip
        insured sex
        insured_education_level
        insured occupation
        insured hobbies
        insured relationship
                                       0
                                        0
        capital-gains
                                       0
        capital-loss
        incident date
        incident type
                                       0
        collision type
                                        0
        incident_severity
        authorities contacted
        incident state
        incident city
        incident location
        incident hour_of_the_day
        number_of_vehicles_involved
        property damage
        bodily injuries
        witnesses
        police report available
                                       0
        total claim amount
        injury claim
                                       0
        property_claim
                                        0
        vehicle claim
                                        0
                                        0
        auto make
                                        0
        auto model
        auto year
```

0

incident city

```
c39
                                                                         1000
                dtype: int64
In [19]:
                  # heatmap
                 plt.figure(figsize = (18, 12))
                 corr = df.corr()
                 sns.heatmap(data = corr, annot = True, fmt = '.2g', linewidth = 1)
                 plt.show()
                 df.nunique()
                                                                   0.005
                                                                                0.018
                                                                                       0.0064
                                                                                                                        0.058
                                                                                                                                                   0.061 0.00029
                      months as customer -
                                          1
                                                0.92
                                                                                              0.02
                                                                                                                                      0.065
                                                 1
                                                      0.059
                                                             0.029
                                                                   0.014
                                                                          0.018
                                                                                 0.026
                                                                                       -0.0071
                                                                                              0.0074
                                                                                                    0.087
                                                                                                           0.022
                                                                                                                  -0.016
                                                                                                                        0.052
                                                                                                                                                   0.063
                                                                                                                                                         0.0014
                                    age
                                                                                                                                            -0.011
                           policy_number
                                         0.058
                                               0.059
                                                        1
                                                            -0.0067
                                                                   0.023
                                                                          0.009
                                                                                0.0071
                                                                                       0.0098
                                                                                              -0.0057 0.00011
                                                                                                                 -0.0046
                                                                                                                        -0.013
                                                                                                                               -0.018 -0.0088
                                                                                                                                                   -0.02
                                                                                                                                                         0.00018
                        policy_deductable -
                                                      -0.0067
                                                                                0.0045
                                                                                                                                                         0.026
                    policy_annual_premium - 0.005
                                               0.014
                                                      0.023
                                                            -0.0032
                                                                    1
                                                                          -0 0062
                                                                                0.032
                                                                                       -0.014
                                                                                              0.024
                                                                                                    -0.0016
                                                                                                           -0 046
                                                                                                                  0.027
                                                                                                                        0.0023
                                                                                                                               0.0091
                                                                                                                                     -0.018
                                                                                                                                            -0.012
                                                                                                                                                         -0.049
                                                0.018
                                                      0.009
                                                                   -0.0062
                                                                            1
                                                                                       -0.047
                                                                                                    -0.023
                                                                                                                  0.023
                                                                                                                        -0.0067
                                                                                                                                -0.04
                                                                                                                                      -0.045
                                                                                                                                            -0.024
                                                                                                                                                   -0.039
                                                                                                                                                         0.0099
                            umbrella_limit
                                                                                 1
                                                                                       0.0063
                                                                                                    0.0083
                                                                                                                                                   -0.041
                                                                                                                                                         -0.033
                                         0.018
                                               0.026
                                                      0.0071
                                                            0.0045
                                                                   0.032
                                                                                                                  0.029
                                                                                                                         0.02
                                                                                                                               -0.034
                                                                                                                                            -0.0068
                              insured_zip
                            capital-gains
                                                      0.0098
                                                                                0.0063
                                                                                        1
                                                                                                                                            0.00078
                              capital-loss
                                         0.02
                                               0.0074
                                                      -0.0057
                                                             -0.024
                                                                   0.024
                                                                          -0.024
                                                                                 0.049
                                                                                       -0.047
                                                                                               1
                                                                                                                  -0.024
                                                                                                                        -0.041
                                                                                                                                      -0.046
                                                                                                                                                         -0.057
                                                                   -0.0016
                                                                                       -0.016
                                                                                              -0.025
                                                                                                                  -0.035
                                                                                                                                            0.18
                                                                                                                                                         0.021
                   incident_hour_of_the_day
                                               0.087
                                                      0.00011
                                                             0.061
                                                                          -0.023
                                                                                0.0083
                                                                                                      1
                                                                                                                        0.0065
                number_of_vehicles_involved
                                                                   -0.046
                                                                                                            1
                                                                                                                  0.014
                                                                                                                        -0.015
                                                                                       0.056
                                                                                              -0.024
                                                                                                    -0.035
                                                                                                           0.014
                                                                                                                        -0.0056
                                                                                                                                      0.047
                                                                                                                                                   0.043
                                                                                                                                                         -0.021
                                         -0.01
                                               -0.016
                                                      -0.0046
                                                             -0.023
                                                                   0.027
                                                                          0.023
                                                                                0.029
                                                                                                                   1
                                                                                                                               0.047
                                                                                                                                             0.04
                           bodily_injuries
                                                      -0.013
                                                                   0.0023 -0.0067
                                                                                 0.02
                                                                                              -0.041
                                                                                                    0.0065
                                                                                                                  -0.0056
                                                                                                                               -0.011
                                                                                                                                     -0.025
                                                                                                                                                   -0.023
                                                                                                                                                         0.046
                                         0.062
                                                0.07
                                                      -0.018
                                                             0.023
                                                                   0.0091
                                                                          -0.04
                                                                                -0.034
                                                                                       0.016
                                                                                              -0.036
                                                                                                                  0.047
                                                                                                                        -0.011
                                                                                                                                1
                                                                                                                                      0.81
                                                                                                                                             0.81
                                                                                                                                                   0.98
                                                                                                                                                         -0.036
                       total claim amount
                             injury_claim
                                                      -0.0088
                                                                   -0.018
                                                                          -0.045
                                                                                       0.026
                                                                                              -0.046
                                                                                                                        -0.025
                                                                                                                                0.81
                                                                                                                                       1
                                                             0.065
                                                                          -0.024
                                                                                -0.0068 0.00078
                                                                                                                                0.81
                                                                                                                                             1
                           property claim
                                                                                                                                                    1
                                                                                                                                                         -0.043
                            vehicle_claim
                                         0.061
                                               0.063
                                                      -0.02
                                                            0.0053
                                                                    0.02
                                                                          -0.039
                                                                                -0.041
                                                                                       0.016
                                                                                              -0.033
                                                                                                                  0.043
                                                                                                                        -0.023
                                                                                                                                0.98
                               auto_year
                                        0.00029 0.0014
                                                      0.00018 0.026
                                                                   -0.049
                                                                         0.0099
                                   _c39
                                                                                                                                                                 650
                                                                                                            umber of vehicles involved
                                                                                                                                       injury_claim
                                                              policy_deductable
                                                                     policy annual premium
                                                                                         capital-gains
               months as customer
                                                                           391
Out[19]:
                                                                             46
                                                                         1000
                policy number
                                                                           951
                policy bind date
                                                                               3
                policy state
                policy csl
                                                                               3
                                                                               3
                policy deductable
                policy annual premium
                                                                           991
                                                                            11
                umbrella limit
                insured zip
                                                                           995
                insured sex
                                                                               2
                                                                              7
                insured education level
                insured occupation
                                                                             14
                insured hobbies
                                                                             20
                insured relationship
                                                                               6
                capital-gains
                                                                           338
```

354

0.8

0.6

0.4

0.2

0

fraud reported

capital-loss

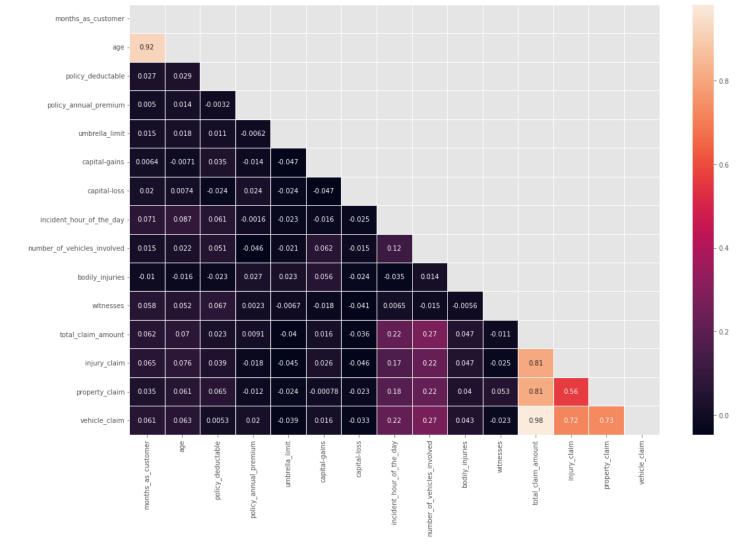
```
incident date
                                  60
                                   4
incident type
collision_type
                                   3
incident severity
                                   4
authorities contacted
                                   5
                                   7
incident state
                                   7
incident city
incident location
                                1000
incident hour of the day
                                  24
number of vehicles involved
                                   4
property damage
                                   2
bodily injuries
                                   3
witnesses
                                   4
police report available
                                   2
total claim amount
                                 763
injury claim
                                 638
property_claim
                                 626
vehicle claim
                                 726
auto make
                                  14
                                  39
auto model
auto year
                                  21
fraud_reported
                                   2
c39
                                   0
dtype: int64
```

```
In [20]:
          # dropping columns which are not necessary for prediction
         to drop = ['policy number', 'policy bind date', 'policy state', 'insured zip', 'incident locat
                     'incident state','incident city','insured hobbies','auto make','auto model','a
         df.drop(to drop, inplace = True, axis = 1)
         df.head()
```

Out[20]: months_as_customer age policy_csl policy_deductable policy_annual_premium umbrella_limit insured_sex insured_sex 0 0 328 48 250/500 1000 1406.91 MALE 228 1 42 250/500 2000 1197.22 5000000 MALE 2 29 2000 134 100/300 1413.14 5000000 **FEMALE** 3 256 2000 **FEMALE** 41 250/500 1415.74 6000000 228 44 500/1000 1000 1583.91 6000000 MALE

5 rows × 27 columns

```
In [21]:
         # checking for multicollinearity
         plt.figure(figsize = (18, 12))
         corr = df.corr()
         mask = np.triu(np.ones like(corr, dtype = bool))
         sns.heatmap(data = corr, mask = mask, annot = True, fmt = '.2g', linewidth = 1)
         plt.show()
```



```
In [22]:
    df.drop(columns = ['age', 'total_claim_amount'], inplace = True, axis = 1)
    df.head()
    df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 25 columns):

#	Column	Non-Null Count	Dtype
0	months_as_customer	1000 non-null	int64
1	policy csl	1000 non-null	object
2	policy_deductable	1000 non-null	int64
3	policy_annual_premium	1000 non-null	float64
4	umbrella_limit	1000 non-null	int64
5	insured_sex	1000 non-null	object
6	insured_education_level	1000 non-null	object
7	insured_occupation	1000 non-null	object
8	insured_relationship	1000 non-null	object
9	capital-gains	1000 non-null	int64
10	capital-loss	1000 non-null	int64
11	incident_type	1000 non-null	object
12	collision_type	1000 non-null	object
13	incident_severity	1000 non-null	object
14	authorities_contacted	1000 non-null	object
15	incident_hour_of_the_day	1000 non-null	int64
16	<pre>number_of_vehicles_involved</pre>	1000 non-null	int64
17	<pre>property_damage</pre>	1000 non-null	object
18	bodily_injuries	1000 non-null	int64
19	witnesses	1000 non-null	int64
20	police_report_available	1000 non-null	object

```
22 property claim
                                              1000 non-null int64
          23 vehicle claim
                                              1000 non-null int64
                                              1000 non-null object
          24 fraud reported
         dtypes: float64(1), int64(12), object(12)
         memory usage: 195.4+ KB
In [23]:
          # separating the feature and target columns
          X = df.drop('fraud reported', axis = 1)
          y = df['fraud reported']
In [24]:
          # extracting categorical columns
          cat df = X.select dtypes(include = ['object'])
          cat df.head()
Out[24]:
            policy_csl insured_sex insured_education_level insured_occupation insured_relationship incident_type collision_ty
                                                                                         Single Vehicle
         0
             250/500
                          MALE
                                                                                husband
                                                                                                     Side Collis
                                                 MD
                                                            craft-repair
                                                                                             Collision
                          MALE
                                                                                         Vehicle Theft
         1
             250/500
                                                       machine-op-inspct
                                                                            other-relative
                                                                                                     Rear Collis
                                                 MD
                                                                                         Multi-vehicle
         2
             100/300
                         FEMALE
                                                PhD
                                                                 sales
                                                                               own-child
                                                                                                     Rear Collis
                                                                                             Collision
                                                                                         Single Vehicle
         3
             250/500
                         FEMALE
                                                PhD
                                                           armed-forces
                                                                                                     Front Collis
                                                                               unmarried
                                                                                             Collision
            500/1000
                          MALE
                                                                                         Vehicle Theft
                                                                                                     Rear Collis
                                            Associate
                                                                               unmarried
                                                                 sales
In [25]:
          # printing unique values of each column
          for col in cat df.columns:
              print(f"{col}: \n{cat df[col].unique()}\n")
          cat df = pd.get dummies(cat df, drop first = True)
          cat df.head()
         policy csl:
         ['250/500' '100/300' '500/1000']
         insured sex:
         ['MALE' 'FEMALE']
         insured education level:
         ['MD' 'PhD' 'Associate' 'Masters' 'High School' 'College' 'JD']
         insured occupation:
         ['craft-repair' 'machine-op-inspct' 'sales' 'armed-forces' 'tech-support'
          'prof-specialty' 'other-service' 'priv-house-serv' 'exec-managerial'
          'protective-serv' 'transport-moving' 'handlers-cleaners' 'adm-clerical'
          'farming-fishing']
         insured relationship:
         ['husband' 'other-relative' 'own-child' 'unmarried' 'wife' 'not-in-family']
         incident type:
         ['Single Vehicle Collision' 'Vehicle Theft' 'Multi-vehicle Collision'
          'Parked Car']
         collision type:
         ['Side Collision' 'Rear Collision' 'Front Collision']
```

1000 non-null

int64

21 injury claim

```
incident_severity:
['Major Damage' 'Minor Damage' 'Total Loss' 'Trivial Damage']
authorities_contacted:
['Police' 'None' 'Fire' 'Other' 'Ambulance']
property_damage:
['YES' 'NO']
police_report_available:
['YES' 'NO']
```

Out[25]: insured_education_level policy_csl_250/500 policy_csl_500/1000 insured_sex_MALE insured_education_level_College

5 rows × 41 columns

```
In [26]: # extracting the numerical columns
    num_df = X.select_dtypes(include = ['int64'])
    num_df.head()
```

```
Out[26]:
                                                                        capital-
                                                                                capital-
               months_as_customer policy_deductable umbrella_limit
                                                                                          incident_hour_of_the_day number_of_vel
                                                                          gains
                                                                                    loss
           0
                                                                    0
                                                                                                                 5
                               328
                                                 1000
                                                                         53300
                                                                                       0
           1
                               228
                                                 2000
                                                              5000000
                                                                              0
                                                                                       0
                                                                                                                 8
           2
                               134
                                                 2000
                                                              5000000
                                                                         35100
                                                                                       0
                                                                                                                 7
           3
                               256
                                                 2000
                                                              6000000
                                                                         48900
                                                                                  -62400
                                                                                                                 5
                               228
                                                 1000
                                                              6000000
                                                                         66000
                                                                                  -46000
                                                                                                                20
```

```
In [27]: # combining the Numerical and Categorical dataframes to get the final dataset

X = pd.concat([num_df, cat_df], axis = 1)

X.head()

plt.figure(figsize = (25, 20))
plotnumber = 1

for col in X.columns:
    if plotnumber <= 24:
        ax = plt.subplot(5, 5, plotnumber)
        sns.distplot(X[col])
        plt.xlabel(col, fontsize = 15)

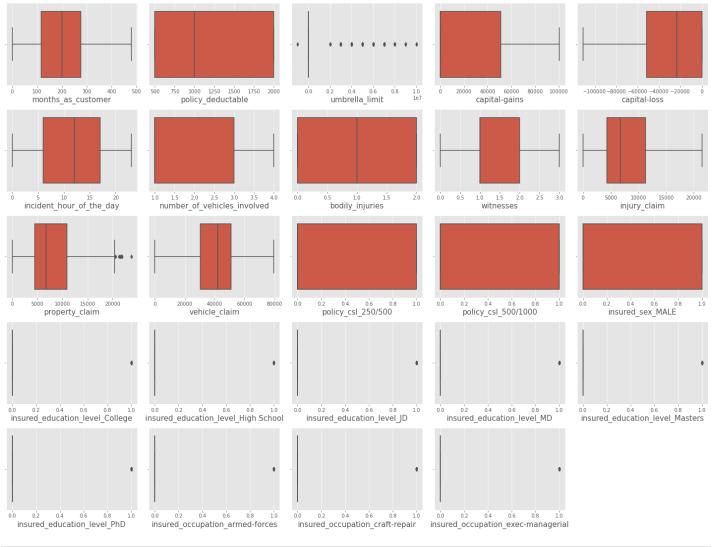
plotnumber += 1</pre>
```

```
plt.tight_layout()
plt.show()
```

plt.tight layout()

plt.show()





```
In [30]: # Scaling the numeric values in the dataset
    from sklearn.preprocessing import StandardScaler
    scaler = StandardScaler()
    scaled_data = scaler.fit_transform(num_df)
    scaled_num_df = pd.DataFrame(data = scaled_data, columns = num_df.columns, index = X_train scaled_num_df.head()
    X_train.drop(columns = scaled_num_df.columns, inplace = True)
    X_train = pd.concat([scaled_num_df, X_train], axis = 1)
    X_train.head()
```

	1 420102					4.466720
267	-1.428192	1.400591	-0.484263	0.953726	-0.747459	1.466730
455	0.506379	1.400591	-0.484263	-0.894855	0.628276	-0.388325
4	0.202254	-0.242010	2.138100	1.446917	-0.715215	1.181337
76	0.557066	-0.242010	-0.484263	-0.894855	0.227020	0.895944
254	-1.554911	-0.242010	-0.484263	-0.894855	0.932801	1.324034
5 rows × 53 colu	mns					
<pre>from sklearr</pre>	n.svm import	SVC				
<pre>svc = SVC() svc.fit(X_tr</pre>	rain, y_trair	1)				
y_pred = svc	c.predict(X_t	test)				
# accuracy_s	score, confus	sion_matri	x and classi	fication_	report	
<pre>from sklearr</pre>	n.metrics im r	ort accura	acy score, co	onfusion n	matrix, classi	lfication repor
svc_test_acc	_					
print(f"Trai print(f"Test print(confus print(classi	accuracy of sion_matrix(\subseteq fication_reparts)	Support Votest, y_test, y_test, y_test port(y_test) port Vecto Vector Cl	<pre>rector Class: pred)) c, y_pred)) r Classifier</pre>	ifier is is: 0.8 : 0.728	is: {svc_trace: {svc_trace	cc}")
print(f"Trai print(f"Test print(confus print(classi Training accu Test accuracy [[182 0] [68 0]]	sion_matrix(\structure sion_matrix(\structure sion_report support)	y_test, y_port(y_test) port(y_test) port Vecto Vector Cl	<pre>pred()) c, y_pred()) r Classifier assifier is f1-score</pre>	ifier is is: 0.8 : 0.728 support	: {svc_test_ad	cc}")
print(f"Trai print(f"Test print(confus print(classi Training accu Test accuracy [[182 0]	accuracy of sion_matrix(\strace{\symbol{\strace{\symbol{\sinq}}{\sing{\sin}}}}}}}}}}}}}}}}}}}}}}}}}}}}}}}}}}}}	Support Votest, y_test, y_test, y_test port(y_test) port Vecto Vector Cl	Vector Class: Dred)) L, y_pred)) r Classifier assifier is	ifier is is: 0.8 : 0.728	: {svc_test_ad	cc}")
print(f"Trai print(f"Test print(confus print(classi Training accu Test accuracy [[182 0] [68 0]]	sion_matrix() fication_reparacy of Support precision 0.73	y_test, y_port(y_test) port(y_test) port Vecto Vector Cl recall 1.00	Vector Class: pred)) c, y_pred)) r Classifier assifier is f1-score 0.84	ifier is is: 0.8 : 0.728 support 182	: {svc_test_ad	cc}")
print(f"Trai print(f"Test print(confus print(classi Training accu Test accuracy [[182 0] [68 0]]	sion_matrix() fication_reparacy of Support precision 0.73	y_test, y_port(y_test) port(y_test) port Vecto Vector Cl recall 1.00	Vector Class: pred)) c, y_pred)) r Classifier assifier is f1-score 0.84	ifier is is: 0.8 : 0.728 support 182	: {svc_test_ad	cc}")
print(f"Trai print(f"Test print(confus print(classi Training accu Test accuracy [[182 0] [68 0]]	sion_matrix(y sion_matrix(y fication_rep aracy of Supp y of Support precision 0.73 0.00 0.36	y_test, y_port(y_test) port(y_test) port Vecto Vector Cl recall 1.00	r Classifier assifier is f1-score 0.84 0.00	ifier is is: 0.8 : 0.728 support 182 68	: {svc_test_ad	cc}")
print(f"Train print(confus print(classing print(cla	sion_matrix(y sion_matrix(y fication_rep aracy of Supp y of Support precision 0.73 0.00 0.36	y_test, y_port(y_test) port(y_test) port Vecto Vector Cl recall 1.00 0.00 0.50 0.73	rector Class: pred)) c, y_pred)) r Classifier assifier is f1-score 0.84 0.00 0.73 0.42 0.61	ifier is is: 0.8 : 0.728 support 182 68 250 250 250	: {svc_test_ad	cc}")
print (f"Train print (confus print (classing p	sion_matrix(y sion_matrix(y fication_rep aracy of Supp y of Support precision 0.73 0.00 0.36 0.53	recall 1.00 0.50 0.73 import KNext	r Classifier assifier is f1-score 0.84 0.00 0.73 0.42 0.61	ifier is is: 0.8 : 0.728 support 182 68 250 250 250	: {svc_test_ad	cc}")
print (f"Train print (f"Test print (confus print (classing pri	sion_matrix() si	recall 1.00 0.00 0.50 0.73 import KNess Ler(n_neight)	r Classifier assifier is f1-score 0.84 0.00 0.73 0.42 0.61	ifier is is: 0.8 : 0.728 support 182 68 250 250 250	: {svc_test_ad	cc}")
print (f"Train print (confus print (classing p	sion_matrix(y_fication_reparacy of Support precision 0.73 0.00 0.36 0.53 n.neighbors into the control of	recall 1.00 0.00 0.50 0.73 import KNessest)	Vector Class: Dred)) c, y_pred)) r Classifier assifier is f1-score 0.84 0.00 0.73 0.42 0.61 ighborsClass: nbors = 30)	ifier is is: 0.8 : 0.728 support 182 68 250 250 250	: {svc_test_ad	cc}")

knn_train_acc = accuracy_score(y_train, knn.predict(X_train))

capitalloss

incident_hour_of_the_day number_

capital-

gains

months_as_customer policy_deductable umbrella_limit

Out[30]:

```
knn test acc = accuracy score(y test, y pred)
        print(f"Training accuracy of KNN is : {knn train acc}")
        print(f"Test accuracy of KNN is : {knn test acc}")
        print(confusion matrix(y test, y pred))
        print(classification report(y test, y pred))
        Training accuracy of KNN is : 0.76133333333333333
        Test accuracy of KNN is: 0.376
        [[ 29 153]
        [ 3 65]]
                     precision recall f1-score support
                        0.91 0.16 0.27
                                                       182
                         0.30
                                  0.96
                                           0.45
                                                       68
                                            0.38
                                                      250
           accuracy
          macro avg
                        0.60 0.56
                                           0.36
                                                      250
                         0.74 0.38
        weighted avg
                                           0.32
                                                      250
In [38]:
        from sklearn.tree import DecisionTreeClassifier
        dtc = DecisionTreeClassifier()
        dtc.fit(X train, y train)
        y pred = dtc.predict(X test)
         # accuracy score, confusion matrix and classification report
        from sklearn.metrics import accuracy score, confusion matrix, classification report
        dtc train acc = accuracy score(y train, dtc.predict(X train))
        dtc test acc = accuracy score(y test, y pred)
        print(f"Training accuracy of Decision Tree is : {dtc train acc}")
        print(f"Test accuracy of Decision Tree is : {dtc test acc}")
        print(confusion matrix(y test, y pred))
        print(classification report(y test, y pred))
        Training accuracy of Decision Tree is: 1.0
        Test accuracy of Decision Tree is: 0.392
        [[ 44 138]
         [ 14 54]]
                     precision recall f1-score support
                                        0.37
                  N
                         0.76 0.24
                                                      182
                         0.28
                                  0.79
                                           0.42
                                                       68
                                            0.39
                                                      250
           accuracy
                                           0.39
                        0.52 0.52
                                                       250
          macro avg
        weighted avg
                         0.63
                                  0.39
                                           0.38
                                                      250
In [39]:
         # hyper parameter tuning
        from sklearn.model selection import GridSearchCV
        grid params = {
            'criterion' : ['gini', 'entropy'],
            'max depth' : [3, 5, 7, 10],
            'min samples split' : range(2, 10, 1),
```

```
grid search = GridSearchCV(dtc, grid params, cv = 5, n jobs = -1, verbose = 1)
         grid search.fit(X train, y train)
         # best parameters and best score
         print(grid search.best params )
         print(grid search.best score )
         # best estimator
         dtc = grid search.best estimator
         y pred = dtc.predict(X test)
        Fitting 5 folds for each of 512 candidates, totalling 2560 fits
        {'criterion': 'gini', 'max_depth': 3, 'min_samples_leaf': 5, 'min samples split': 8}
        0.813333333333333
In [40]:
         # accuracy score, confusion matrix and classification report
         from sklearn.metrics import accuracy score, confusion matrix, classification report
         dtc train acc = accuracy score(y train, dtc.predict(X train))
         dtc test acc = accuracy score(y test, y pred)
         print(f"Training accuracy of Decision Tree is : {dtc train acc}")
         print(f"Test accuracy of Decision Tree is : {dtc test acc}")
         print(confusion matrix(y test, y pred))
         print(classification report(y test, y pred))
        Training accuracy of Decision Tree is: 0.816
        Test accuracy of Decision Tree is: 0.72
        [[135 47]
         [ 23 45]]
                     precision recall f1-score support
                   N
                         0.85 0.74 0.79
                                                       182
                         0.49
                                   0.66
                                            0.56
                                                        68
                                             0.72
                                                       250
            accuracy
                         0.67 0.70
           macro avq
                                            0.68
                                                       250
                         0.76 0.72 0.73
        weighted avg
                                                        250
In [44]:
        from sklearn.ensemble import RandomForestClassifier
         rand clf = RandomForestClassifier(criterion= 'entropy', max depth= 10, max features= 'sqrt
         rand clf.fit(X train, y train)
         y pred = rand clf.predict(X test)
         # accuracy score, confusion matrix and classification report
         from sklearn.metrics import accuracy score, confusion matrix, classification report
         rand clf train acc = accuracy score(y train, rand clf.predict(X train))
         rand clf test acc = accuracy score(y test, y pred)
         print(f"Training accuracy of Random Forest is : {rand clf train acc}")
         print(f"Test accuracy of Random Forest is : {rand clf test acc}")
```

'min samples leaf' : range(2, 10, 1)

```
Training accuracy of Random Forest is: 0.9666666666666667
         Test accuracy of Random Forest is: 0.728
         [[147 35]
          [ 33 35]]
                       precision recall f1-score support
                    N 0.82 0.81 0.81
Y 0.50 0.51 0.51
                                                          182
                                                            68
                                                        250
                                               0.73
            accuracy

      0.66
      0.66
      0.66

      0.73
      0.73
      0.73

           macro avg
                                                           250
         weighted avg
                                                           250
In [45]:
         # from sklearn.ensemble import AdaBoostClassifier
          # ada = AdaBoostClassifier(base estimator = dtc)
         # 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, parameters, n jobs = -1, cv = 5, verbose = 1)
          # grid search.fit(X train, y train)
          # # best parameter and best score
          # print(grid search.best params )
          # print(grid search.best score )
          # # accuracy score, confusion matrix and classification report
          # 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))
         Fitting 5 folds for each of 60 candidates, totalling 300 fits
         {'algorithm': 'SAMME', 'learning rate': 0.001, 'n estimators': 180}
         0.812
         NotFittedError
                                                    Traceback (most recent call last)
         C:\Users\ROSHAN~1\AppData\Local\Temp/ipykernel_17276/1768374190.py in <module>
              19 # accuracy_score, confusion_matrix and classification_report
              2.0
         ---> 21 ada train acc = accuracy score(y train, ada.predict(X train))
              22 ada test acc = accuracy score(y test, y pred)
         ~\anaconda3\lib\site-packages\sklearn\ensemble\ weight boosting.py in predict(self, X)
                             The predicted classes.
             699
         --> 700
                        pred = self.decision function(X)
             701
```

print(confusion_matrix(y_test, y_pred))
print(classification report(y test, y pred))

702

if self.n classes == 2:

```
1f, X)
                            class in ``classes ``, respectively.
            758
            759
        --> 760
                        check is fitted(self)
                        X = self. check X(X)
            761
            762
        ~\anaconda3\lib\site-packages\sklearn\utils\validation.py in check is fitted(estimator, at
        tributes, msg, all_or_any)
           1388
           1389
                   if not fitted:
        -> 1390
                        raise NotFittedError(msg % {"name": type(estimator). name })
           1391
           1392
        NotFittedError: This AdaBoostClassifier instance is not fitted yet. Call 'fit' with approp
        riate arguments before using this estimator.
In [46]:
         from sklearn.ensemble import GradientBoostingClassifier
         gb = GradientBoostingClassifier()
         gb.fit(X train, y train)
         # accuracy score, confusion matrix and classification report of gradient boosting classifi
         gb acc = accuracy score(y test, gb.predict(X test))
         print(f"Training Accuracy of Gradient Boosting Classifier is {accuracy score(y train, gb.r
         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 0.93866666666666666
        Test Accuracy of Gradient Boosting Classifier is 0.288
        Confusion Matrix :-
        [[ 6 176]
         [ 2 66]]
        Classification Report :-
                       precision recall f1-score support
                   M
                           0.75
                                   0.03
                                              0.06
                                                          182
                           0.27
                                     0.97
                                               0.43
                                                          68
                                               0.29
                                                         250
            accuracy
           macro avq
                          0.51 0.50
                                              0.24
                                                          250
                          0.62
                                    0.29
                                              0.16
                                                          250
        weighted avg
In [47]:
         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 boost
         sgb acc = accuracy score(y test, sgb.predict(X test))
         print(f"Training Accuracy of Stochastic Gradient Boosting is {accuracy score(y train, sgb
         print(f"Test Accuracy of Stochastic Gradient Boosting is {sgb acc} \n")
```

~\anaconda3\lib\site-packages\sklearn\ensemble_weight_boosting.py in decision function(se

```
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))}")
        Test Accuracy of Stochastic Gradient Boosting is 0.3
        Confusion Matrix :-
        [[ 8 174]
         [ 1 67]]
        Classification Report :-
                     precision recall f1-score support
                       0.89 0.04 0.08
0.28 0.99 0.43
                                                      182
                                                       68
                                            0.30
                                                      250
           accuracy
                       0.58 0.51 0.26
0.72 0.30 0.18
          macro avg
                                                      250
        weighted avg
                                                      250
In [52]:
        from xgboost import XGBClassifier
        from sklearn.preprocessing import LabelEncoder
        le = LabelEncoder()
        y train = le.fit transform(y train)
        y test = le.fit transform(y test)
        xgb = XGBClassifier()
        xgb.fit(X train, y train)
        y pred = xgb.predict(X test)
         # accuracy score, confusion matrix and classification report
        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))
        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)
         # best estimator
        xgb = grid search.best estimator
        y pred = xgb.predict(X test)
         # accuracy score, confusion matrix and classification report
         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))
```

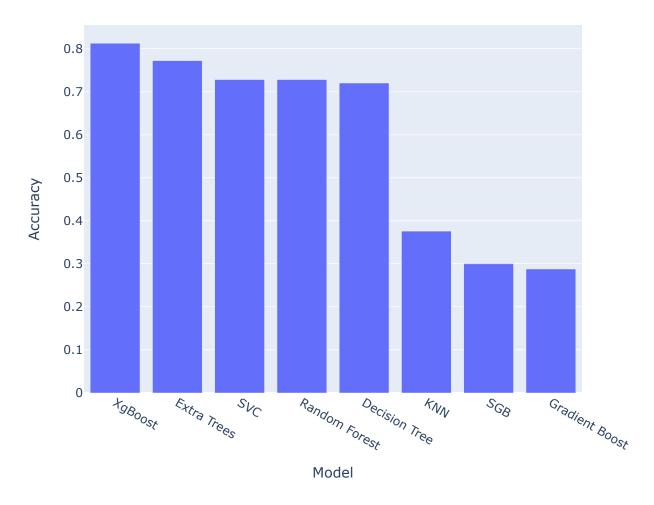
```
Test accuracy of XgBoost is: 0.728
        [[150 32]
         [ 36 32]]
                    precision recall f1-score support
                        0.81 0.82 0.82
0.50 0.47 0.48
                                                    182
                                                     68
           accuracy
                                           0.73
                                                    250
                        0.65 0.65
                                          0.65
                                                     250
          macro avg
        weighted avg
                         0.72
                                 0.73
                                           0.73
                                                     250
        Fitting 5 folds for each of 60 candidates, totalling 300 fits
        Training accuracy of XgBoost is: 0.816
        Test accuracy of XgBoost is: 0.812
        [[159 23]
        [ 24 44]]
                    precision recall f1-score support
                  0
                        0.87
                                0.87 0.87
                                                    182
                        0.66
                                 0.65
                                          0.65
                                                     68
                                                   250
                                           0.81
           accuracy
                        0.76 0.76
                                          0.76
                                                    250
          macro avq
                        0.81
                                 0.81
                                                    250
        weighted avg
                                          0.81
In [49]:
        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.predic
        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 0.772
        Confusion Matrix :-
        [[167 15]
        [ 42 26]]
       Classification Report :-
                    precision recall f1-score support
                        0.80 0.92
                                          0.85
                                                    182
                        0.63
                                 0.38
                                          0.48
                                                     68
           accuracy
                                           0.77
                                                     250
          macro avg
                        0.72 0.65
                                          0.67
                                                     250
                        0.75
        weighted avg
                                 0.77
                                          0.75
                                                     250
In [54]:
        models = pd.DataFrame({
            'Model' : ['SVC', 'KNN', 'Decision Tree', 'Random Forest', 'Gradient Boost', 'SGB', 'E
```

'Accuracy' : [svc test acc, knn test acc, dtc test acc, rand clf test acc, gb acc, sgk

Training accuracy of XgBoost is: 1.0

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

px.bar(data_frame = models, x = 'Model', y = 'Accuracy')
```



```
In [ ]:
```