# seminer-project._1.0

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# 1 Welcome

### 1.0.1 Seminar in data sceince, project notebook

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- Fraud Detection in car insurance

# 2 Part 0 - Load packages and dataset

### 2.0.1 0.a - Packages

[ ]:
```
#imort packages
import numpy as np # linear algebra
import pandas as pd # Data frames
import seaborn as sns # plots
import matplotlib.pyplot as plt #plots
import sklearn # Data science package
from sklearn.impute import SimpleImputer # for replace NA with avarge
from sklearn.model_selection import train_test_split  # for spliting the data
from sklearn.ensemble import RandomForestClassifier # RF classifier
from sklearn.tree import plot_tree
from sklearn.inspection import permutation_importance  #feature importance
from sklearn.pipeline import make_pipeline
from sklearn.svm import SVC # SVM classifier
from sklearn.feature_selection import SelectKBest, chi2,mutual_info_classif␣
 ↪#feature selection
from sklearn.preprocessing import StandardScaler # normlize features
from sklearn.naive_bayes import BernoulliNB , ComplementNB, CategoricalNB #NB␣
 ↪classifiers
# for evaluating preformance
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score, accuracy_score, confusion_matrix,␣
 ↪ConfusionMatrixDisplay, f1_score,fbeta_score, precision_recall_curve,auc
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
```

```
##
from collections import Counter
import researchpy as rp #for crosstab
import scipy.stats as stats # chi^2 test
from scipy.stats import pearsonr #correlation
import random #  for comuting random seed
 #preprocessing
from category_encoders.ordinal import OrdinalEncoder
from category_encoders.binary import BinaryEncoder
from category_encoders.one_hot import OneHotEncoder
##
import imblearn
from imblearn.over_sampling import SMOTE #oversampling
from imblearn.metrics import geometric_mean_score #metric
from imblearn.under_sampling import NearMiss #undersampling
```

[ ]:
```
np.random.seed(2020)
```

### 2.0.2 0.b - Load Vechicle Insures Dataset

[ ]:
```
url = "https://raw.githubusercontent.com/Eladgo10/DS-Seminar-project-/main/
 ↪fraud_oracle.csv" #github link
dataset = pd.read_csv(url)
dataset
```

[ ]:
```
       Month  WeekOfMonth  DayOfWeek     Make AccidentArea DayOfWeekClaimed  \
0        Dec            5  Wednesday    Honda        Urban          Tuesday
1        Jan            3  Wednesday    Honda        Urban           Monday
2        Oct            5     Friday    Honda        Urban         Thursday
3        Jun            2   Saturday   Toyota        Rural           Friday
4        Jan            5     Monday    Honda        Urban          Tuesday
…      …          …        …      …        …              …
15415    Nov            4     Friday   Toyota        Urban          Tuesday
15416    Nov            5   Thursday  Pontiac        Urban           Friday
15417    Nov            5   Thursday   Toyota        Rural           Friday
15418    Dec            1     Monday   Toyota        Urban         Thursday
15419    Dec            2  Wednesday   Toyota        Urban         Thursday

      MonthClaimed  WeekOfMonthClaimed     Sex MaritalStatus  …  \
0              Jan                   1  Female        Single  …
1              Jan                   4    Male        Single  …
2              Nov                   2    Male       Married  …
3              Jul                   1    Male       Married  …
4              Feb                   2  Female        Single  …
…              …                  …      …           …  …
15415          Nov                   5    Male       Married  …
15416          Dec                   1    Male       Married  …
```

```
15417          Dec                   1    Male        Single  …
15418          Dec                   2  Female       Married  …
15419          Dec                   3    Male        Single  …

      AgeOfVehicle AgeOfPolicyHolder PoliceReportFiled WitnessPresent  \
0          3 years          26 to 30                No             No
1          6 years          31 to 35               Yes             No
2          7 years          41 to 50                No             No
3      more than 7          51 to 65               Yes             No
4          5 years          31 to 35                No             No
…              …               …               …             …
15415      6 years          31 to 35                No             No
15416      6 years          31 to 35                No             No
15417      5 years          26 to 30                No             No
15418      2 years          31 to 35                No             No
15419      5 years          26 to 30                No             No

      AgentType  NumberOfSuppliments  AddressChange_Claim  NumberOfCars  Year  \
0      External                 none               1 year        3 to 4  1994
1      External                 none            no change     1 vehicle  1994
2      External                 none            no change     1 vehicle  1994
3      External          more than 5            no change     1 vehicle  1994
4      External                 none            no change     1 vehicle  1994
…          …                   …                  …            …   …
15415  External                 none            no change     1 vehicle  1996
15416  External          more than 5            no change        3 to 4  1996
15417  External               1 to 2            no change     1 vehicle  1996
15418  External          more than 5            no change     1 vehicle  1996
15419  External               1 to 2            no change     1 vehicle  1996

       BasePolicy
0       Liability
1       Collision
2       Collision
3       Liability
4       Collision
…           …
15415   Collision
15416   Liability
15417   Collision
15418  All Perils
15419   Collision

[15420 rows x 33 columns]
```

[ ]:
```
dataset.columns
```

```
[ ]: Index(['Month', 'WeekOfMonth', 'DayOfWeek', 'Make', 'AccidentArea',
       'DayOfWeekClaimed', 'MonthClaimed', 'WeekOfMonthClaimed', 'Sex',
       'MaritalStatus', 'Age', 'Fault', 'PolicyType', 'VehicleCategory',
       'VehiclePrice', 'FraudFound_P', 'PolicyNumber', 'RepNumber',
       'Deductible', 'DriverRating', 'Days_Policy_Accident',
       'Days_Policy_Claim', 'PastNumberOfClaims', 'AgeOfVehicle',
       'AgeOfPolicyHolder', 'PoliceReportFiled', 'WitnessPresent', 'AgentType',
       'NumberOfSuppliments', 'AddressChange_Claim', 'NumberOfCars', 'Year',
       'BasePolicy'],
      dtype='object')
```

# 3 Part 1 - Desprective Statistics

### 3.0.1 1.a Describe numeric variables

```
[ ]: dataset.describe()
```

[ ]:

| | WeekOfMonth | WeekOfMonthClaimed | Age | FraudFound_P |
|---|---|---|---|---|
| count | 15420.000000 | 15420.000000 | 15420.000000 | 15420.000000 |
| mean | 2.788586 | 2.693969 | 39.855707 | 0.059857 |
| std | 1.287585 | 1.259115 | 13.492377 | 0.237230 |
| min | 1.000000 | 1.000000 | 0.000000 | 0.000000 |
| 25% | 2.000000 | 2.000000 | 31.000000 | 0.000000 |
| 50% | 3.000000 | 3.000000 | 38.000000 | 0.000000 |
| 75% | 4.000000 | 4.000000 | 48.000000 | 0.000000 |
| max | 5.000000 | 5.000000 | 80.000000 | 1.000000 |

| | PolicyNumber | RepNumber | Deductible | DriverRating | Year |
|---|---|---|---|---|---|
| count | 15420.000000 | 15420.000000 | 15420.000000 | 15420.000000 | 15420.000000 |
| mean | 7710.500000 | 8.483268 | 407.704280 | 2.487808 | 1994.866472 |
| std | 4451.514911 | 4.599948 | 43.950998 | 1.119453 | 0.803313 |
| min | 1.000000 | 1.000000 | 300.000000 | 1.000000 | 1994.000000 |
| 25% | 3855.750000 | 5.000000 | 400.000000 | 1.000000 | 1994.000000 |
| 50% | 7710.500000 | 8.000000 | 400.000000 | 2.000000 | 1995.000000 |
| 75% | 11565.250000 | 12.000000 | 400.000000 | 3.000000 | 1996.000000 |
| max | 15420.000000 | 16.000000 | 700.000000 | 4.000000 | 1996.000000 |

### 3.0.2 1.b Describe qualtive features

```
[ ]: dataset.describe(include=['object'])
```

[ ]:

| | Month | DayOfWeek | Make | AccidentArea | DayOfWeekClaimed | MonthClaimed | \ |
|---|---|---|---|---|---|---|---|
| count | 15420 | 15420 | 15420 | 15420 | 15420 | 15420 | |
| unique | 12 | 7 | 19 | 2 | 8 | 13 | |
| top | Jan | Monday | Pontiac | Urban | Monday | Jan | |
| freq | 1411 | 2616 | 3837 | 13822 | 3757 | 1446 | |

```
          Sex MaritalStatus         Fault         PolicyType  …  \
count   15420         15420         15420              15420  …
unique      2             4             2                  9  …
top      Male       Married  Policy Holder  Sedan - Collision  …
freq    13000         10625         11230               5584  …

       PastNumberOfClaims AgeOfVehicle AgeOfPolicyHolder PoliceReportFiled  \
count               15420        15420             15420             15420
unique                  4            8                 9                 2
top                2 to 4      7 years          31 to 35                No
freq                 5485         5807              5593             14992

       WitnessPresent AgentType NumberOfSuppliments AddressChange_Claim  \
count           15420     15420               15420               15420
unique              2         2                   4                   5
top                No  External                none           no change
freq            15333     15179                7047               14324

       NumberOfCars BasePolicy
count         15420      15420
unique            5          3
top       1 vehicle  Collision
freq          14316       5962

[4 rows x 24 columns]
```

### 3.0.3 1.c intresting variablas distrabution - bar plots, chi^2 test, common distrabution

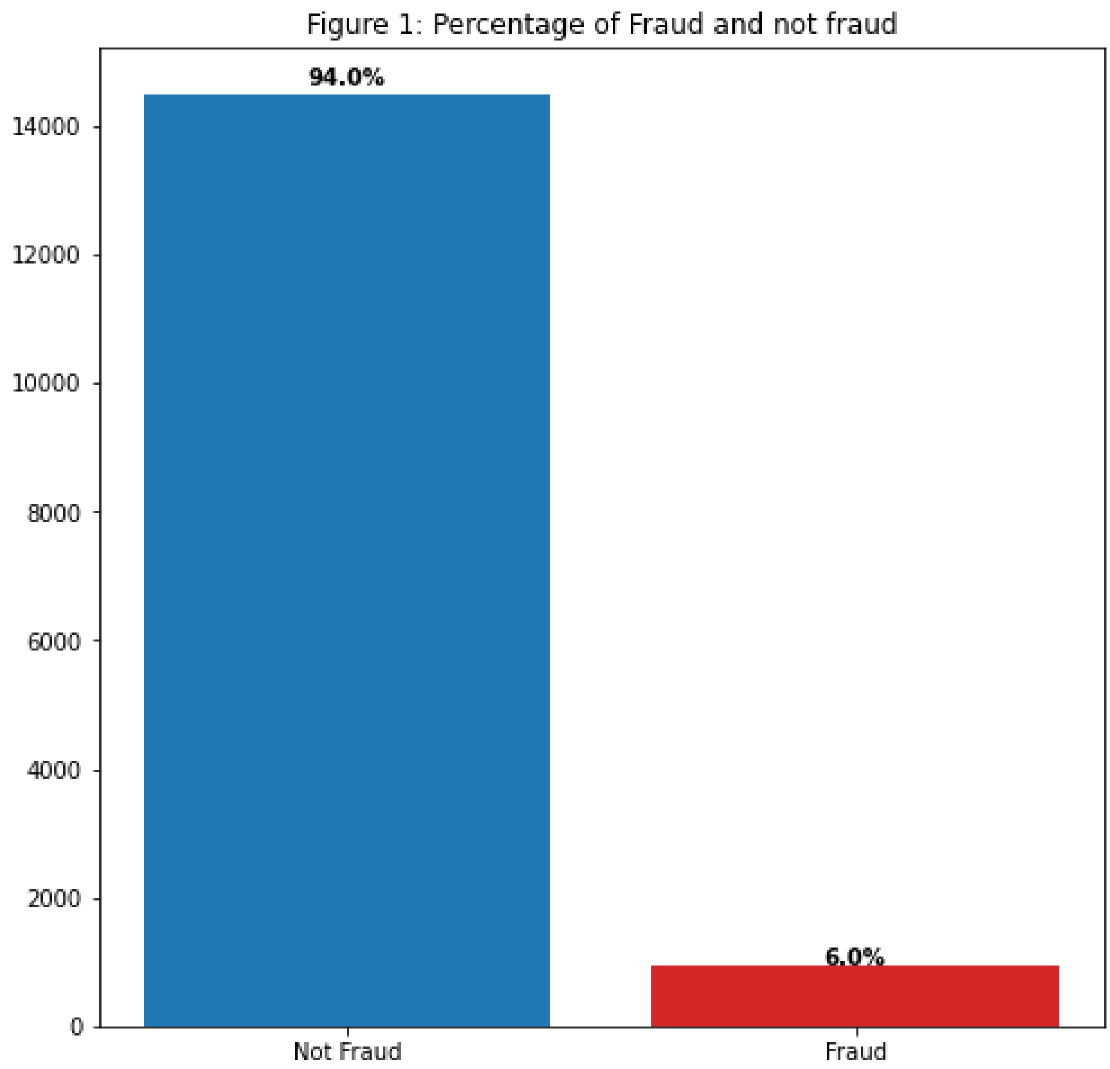
```
[ ]: print(dataset['FraudFound_P'].value_counts(),'\n') # 923 frauds and 14497 not␣
      ↪fraud - outcome
     print(dataset['AgeOfPolicyHolder'].value_counts(),'\n')
     print(dataset['WitnessPresent'].value_counts(), '\n')
     print(dataset['PoliceReportFiled'].value_counts())
```

```
0    14497
1      923
Name: FraudFound_P, dtype: int64

31 to 35    5593
36 to 40    4043
41 to 50    2828
51 to 65    1392
26 to 30     613
over 65      508
16 to 17     320
21 to 25     108
```

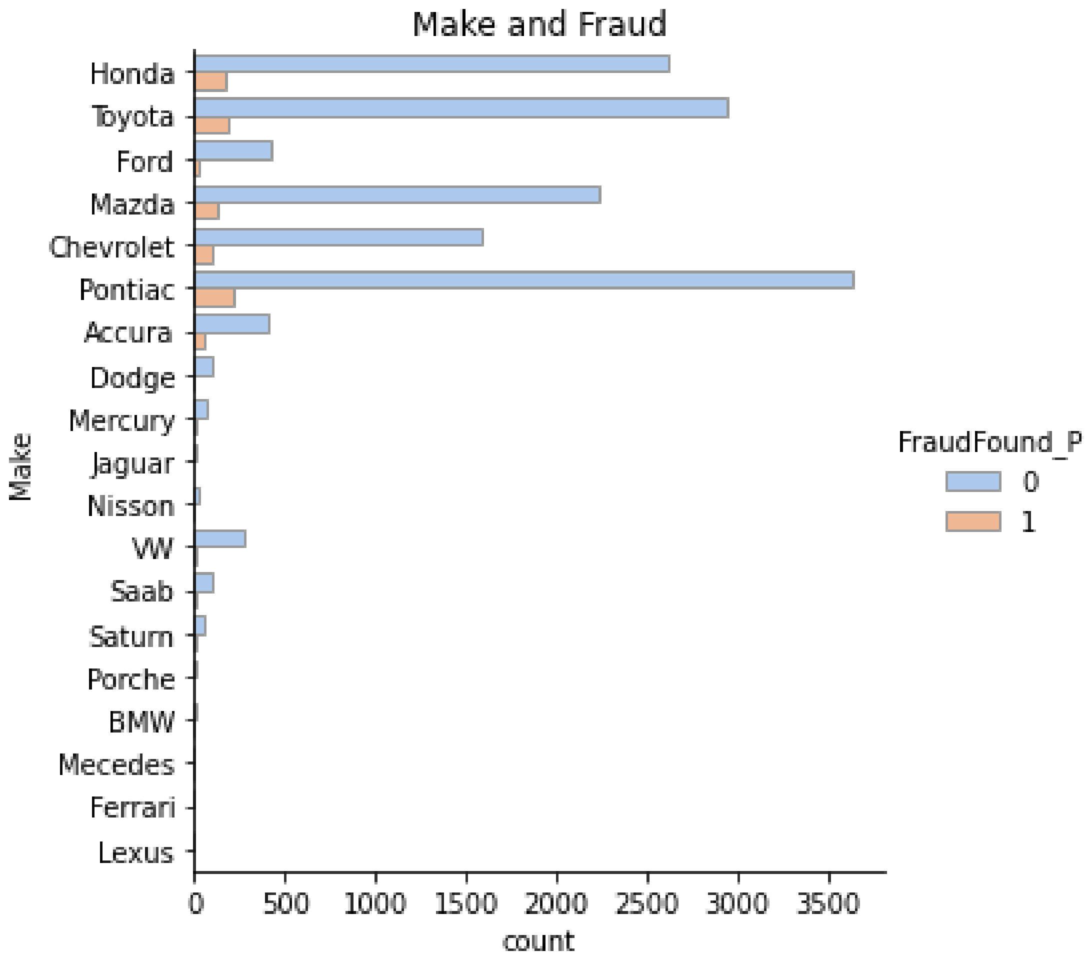
```
18 to 20      15
Name: AgeOfPolicyHolder, dtype: int64

No     15333
Yes       87
Name: WitnessPresent, dtype: int64

No     14992
Yes      428
Name: PoliceReportFiled, dtype: int64
```

**bar plots**

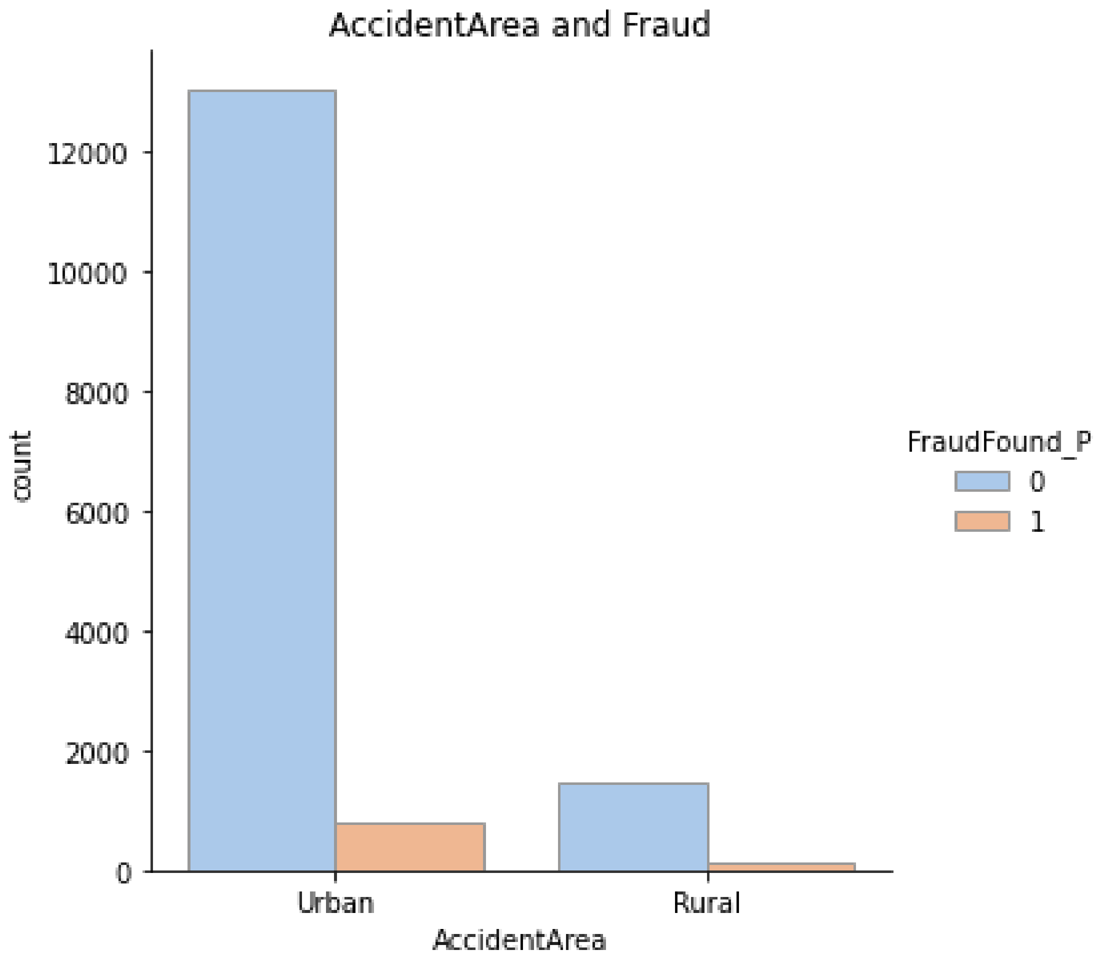
[ ]:
```
# creating data for the plot
data_FraudFound_P = pd.DataFrame({'category':['Not Fraud', 'Fraud'],
                     'counts': dataset['FraudFound_P'].value_counts().values,
                     'percentage': [round(sum(dataset.FraudFound_P == 0)/
 ↪len(dataset), 3)*100 ,
                                    round(sum(dataset.FraudFound_P == 1)/
 ↪len(dataset), 3)*100]
                    })


plt.figure(figsize=(8,8))
colors_list = ['tab:blue', 'tab:red']
graph = plt.bar(data_FraudFound_P.category,data_FraudFound_P.counts, color =␣
 ↪colors_list)
plt.title("Figure 1: Percentage of Fraud and not fraud")

i = 0
for p in graph:
    width = p.get_width()
    height = p.get_height()
    x, y = p.get_xy()
    plt.text(x+width/2,
             y+height*1.01,
             str(data_FraudFound_P.percentage[i])+'%',
             ha='center',
             weight='bold')
    i+=1
plt.show()
```



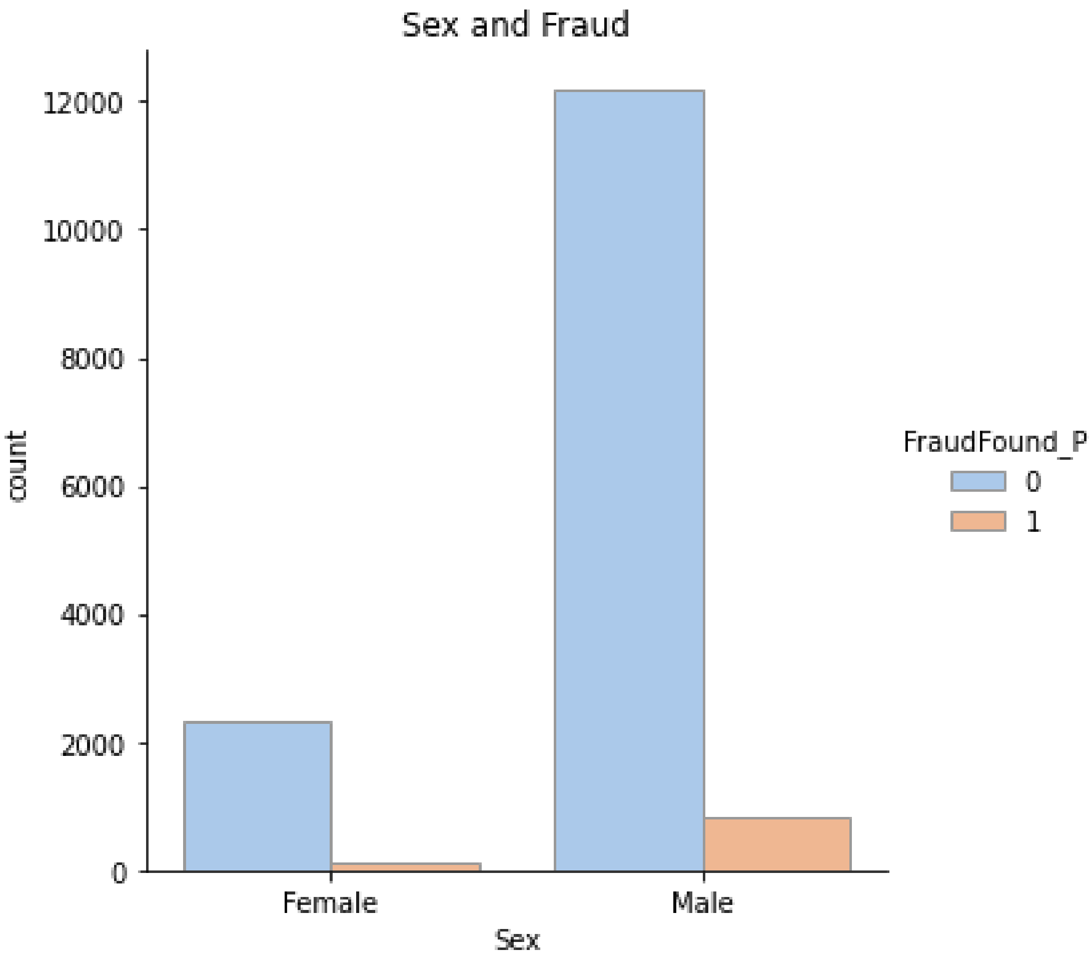

[ ]:
```
sns.catplot(y="Make", hue="FraudFound_P", kind="count",
            palette="pastel", edgecolor=".6",
            data=dataset).set(title = "Make and Fraud")
plt.show()
```



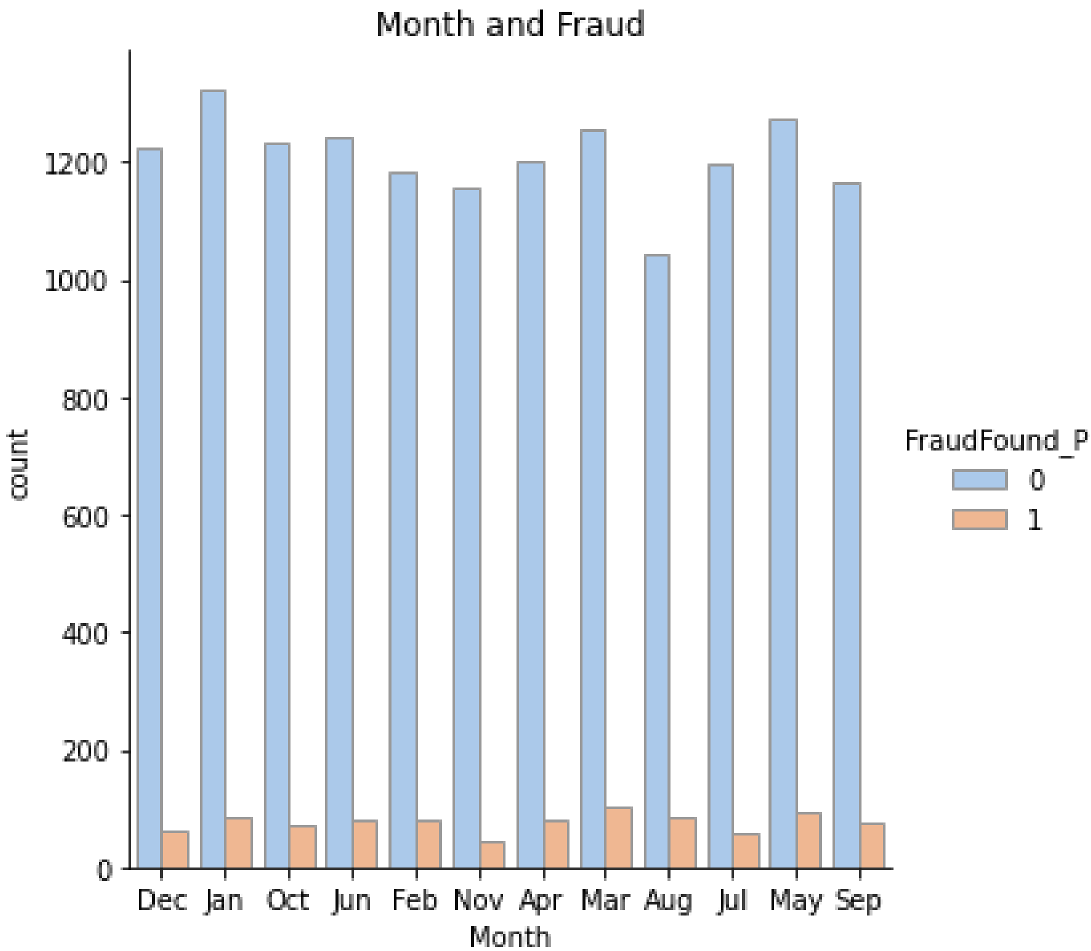

[ ]:
```
sns.catplot(x="AccidentArea", hue="FraudFound_P", kind="count",
            palette="pastel", edgecolor=".6",
            data=dataset).set(title = "AccidentArea and Fraud")
plt.show()
```



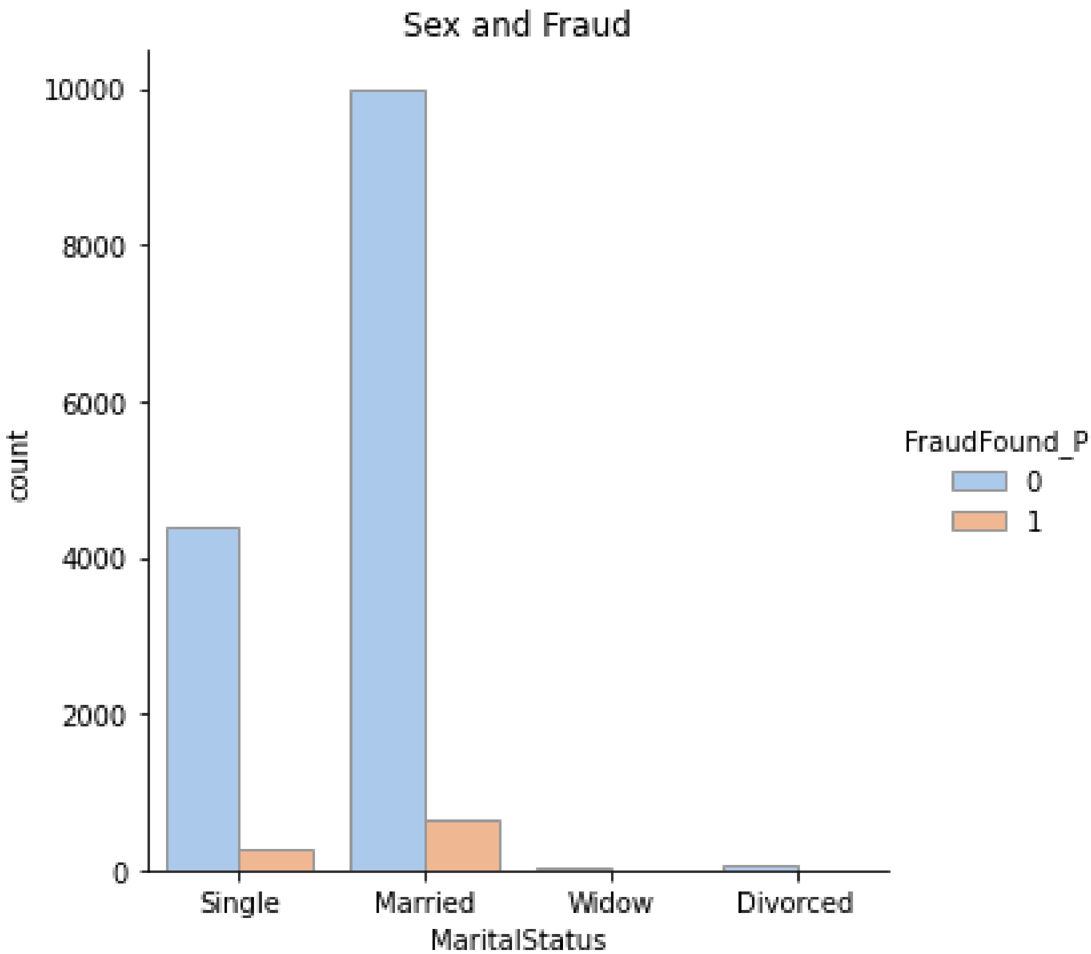

[ ]:
```
sns.catplot(x="Sex", hue="FraudFound_P", kind="count",
            palette="pastel", edgecolor=".6",
            data=dataset).set(title = "Sex and Fraud")
plt.show()
```



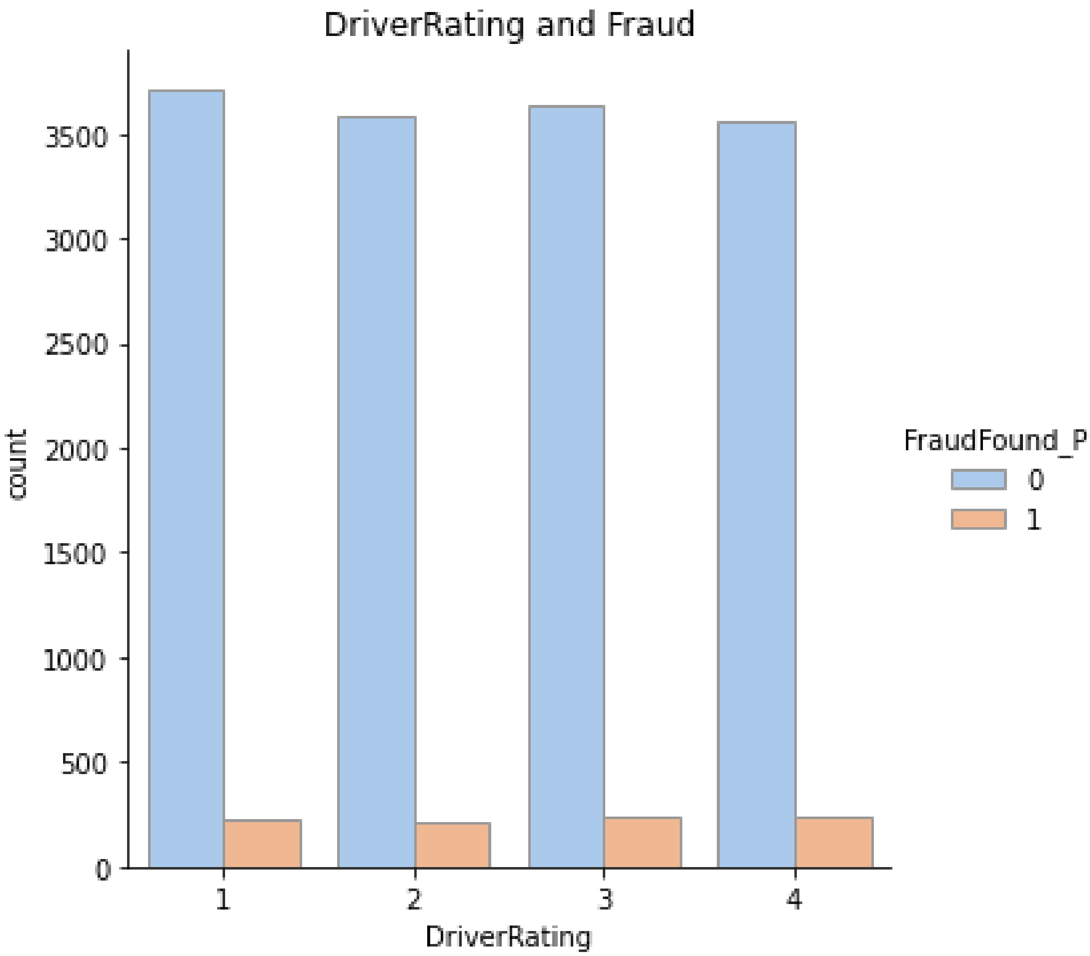

[ ]:
```
sns.catplot(x="Month", hue="FraudFound_P", kind="count",
            palette="pastel", edgecolor=".6",
            data=dataset).set(title = "Month and Fraud")
plt.show()
```



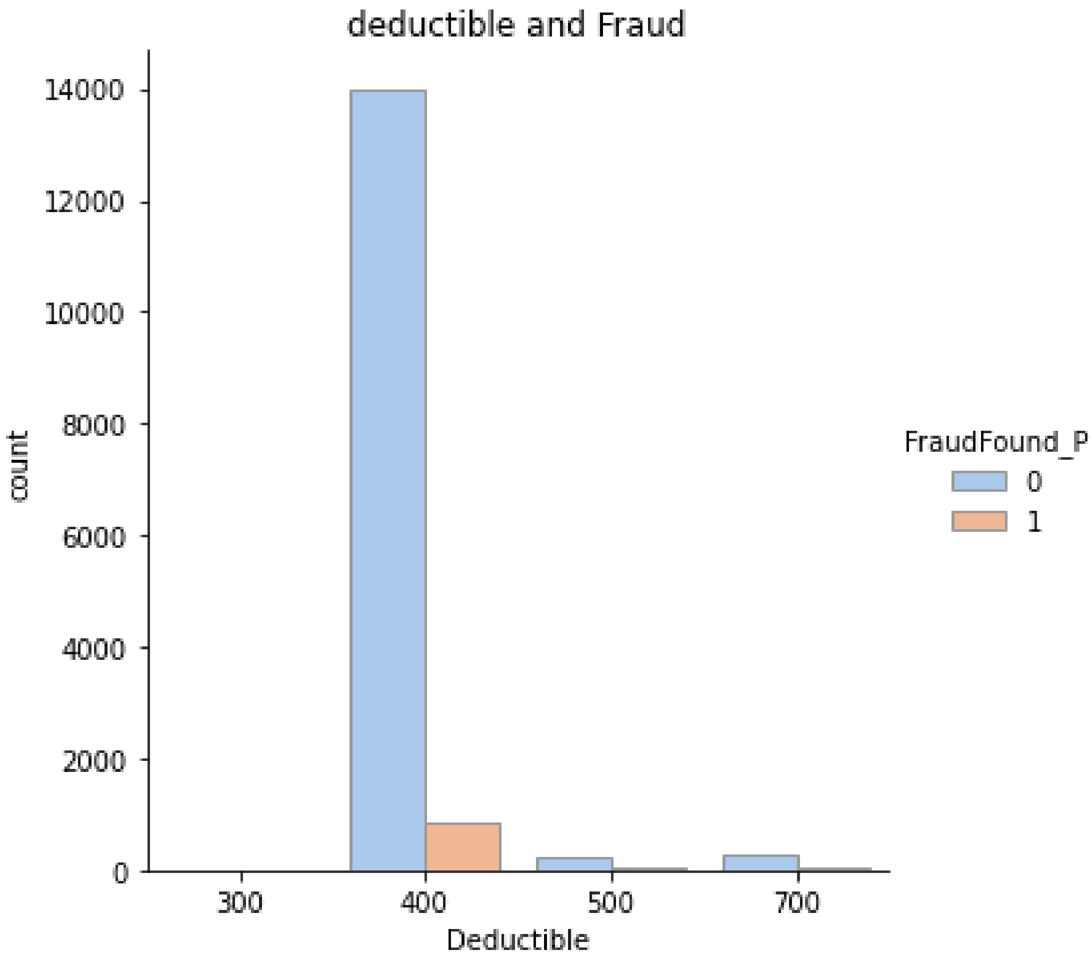

[ ]:
```
sns.catplot(x="MaritalStatus", hue="FraudFound_P", kind="count",
            palette="pastel", edgecolor=".6",
            data=dataset).set(title = "Sex and Fraud")
plt.show()
```



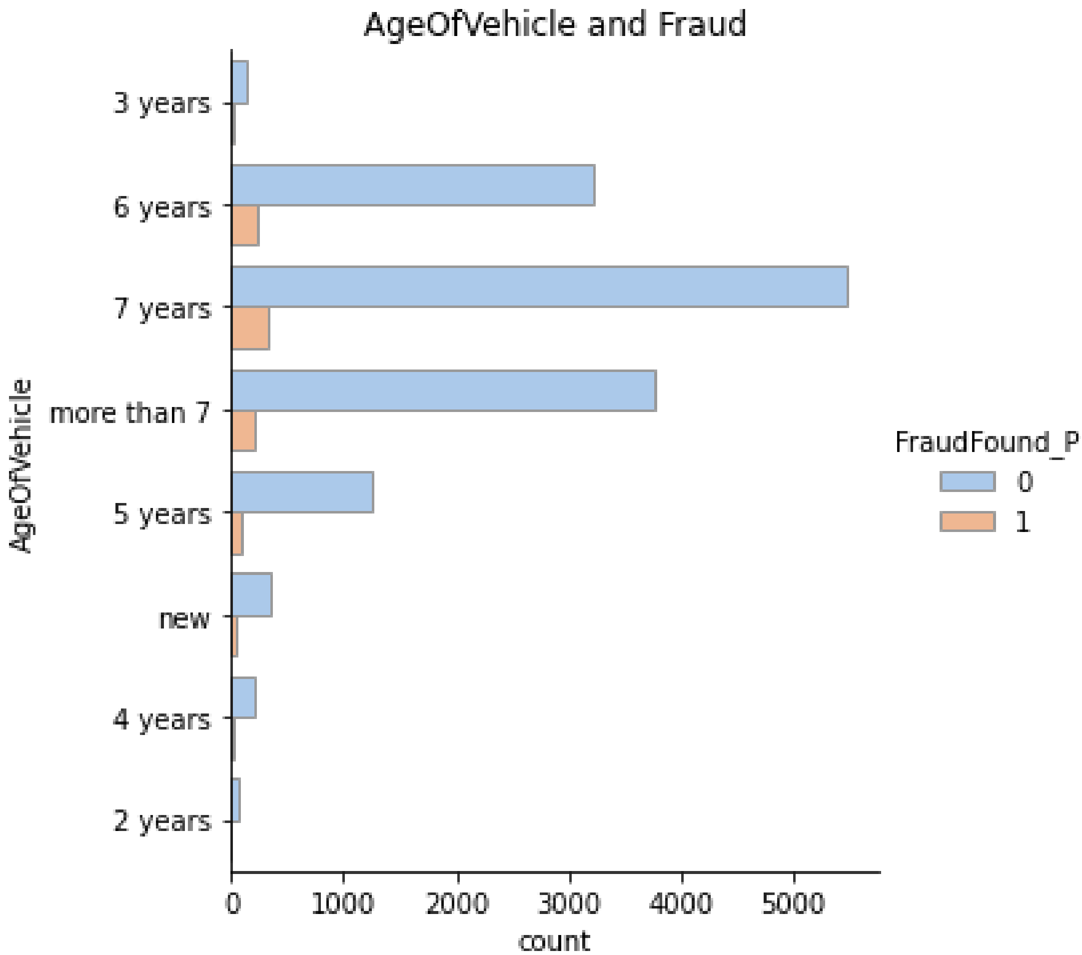

```
[ ]: sns.catplot(x="DriverRating", hue="FraudFound_P", kind="count",
                 palette="pastel", edgecolor=".6",
                 data=dataset).set(title = "DriverRating and Fraud")
     plt.show()
```



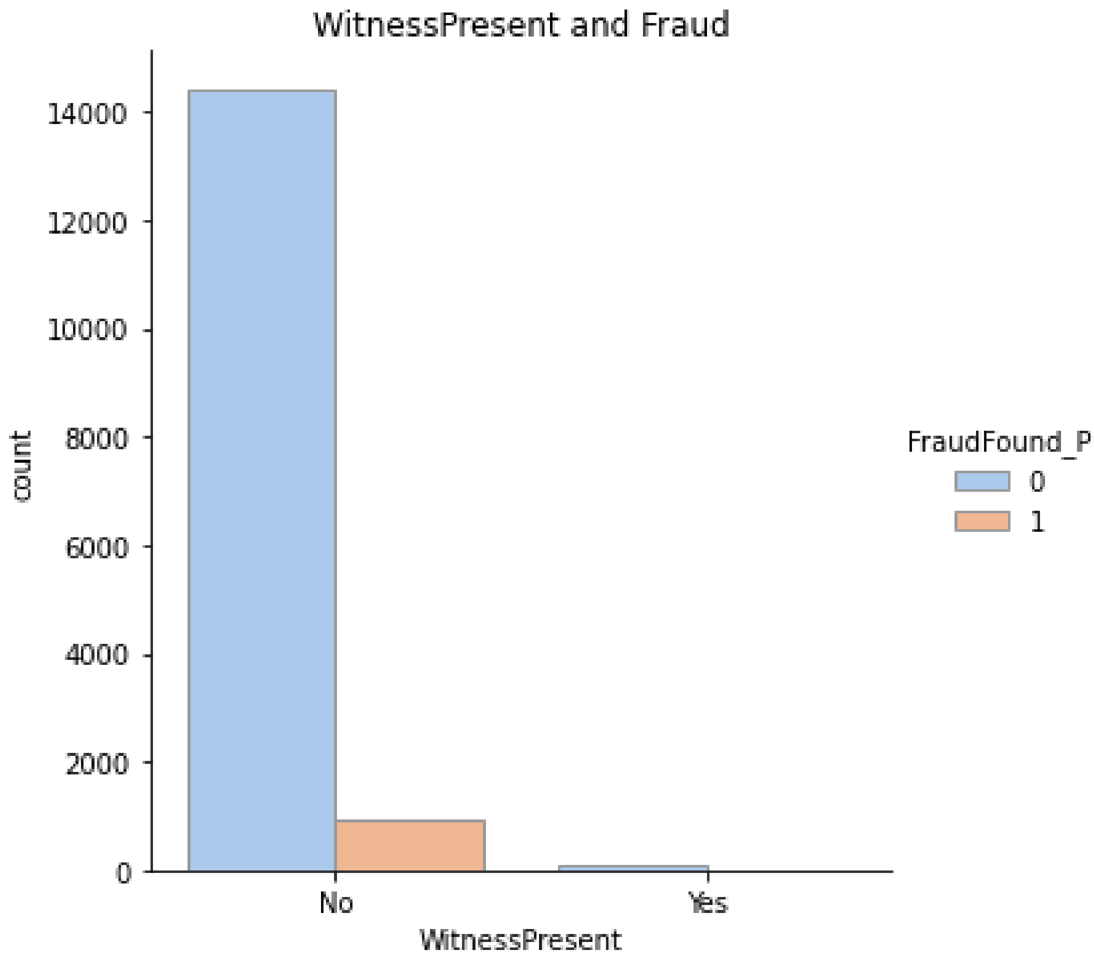

```
[ ]: sns.catplot(x="Deductible", hue="FraudFound_P", kind="count",
                 palette="pastel", edgecolor=".6",
                 data=dataset).set(title = "deductible and Fraud")
     plt.show()
```



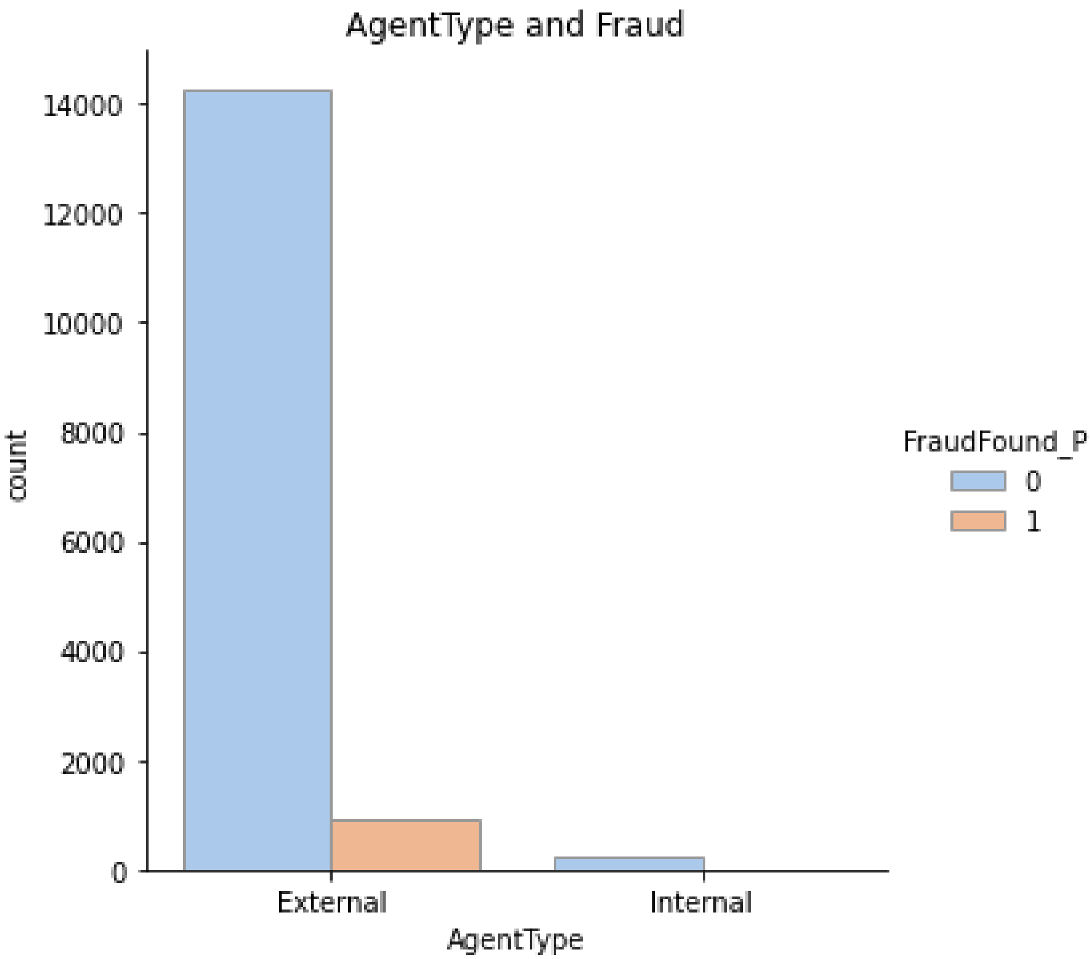

```
[ ]: sns.catplot(y="AgeOfVehicle", hue="FraudFound_P", kind="count",
                 palette="pastel", edgecolor=".6",
                 data=dataset).set(title = "AgeOfVehicle and Fraud")
     plt.show()
```



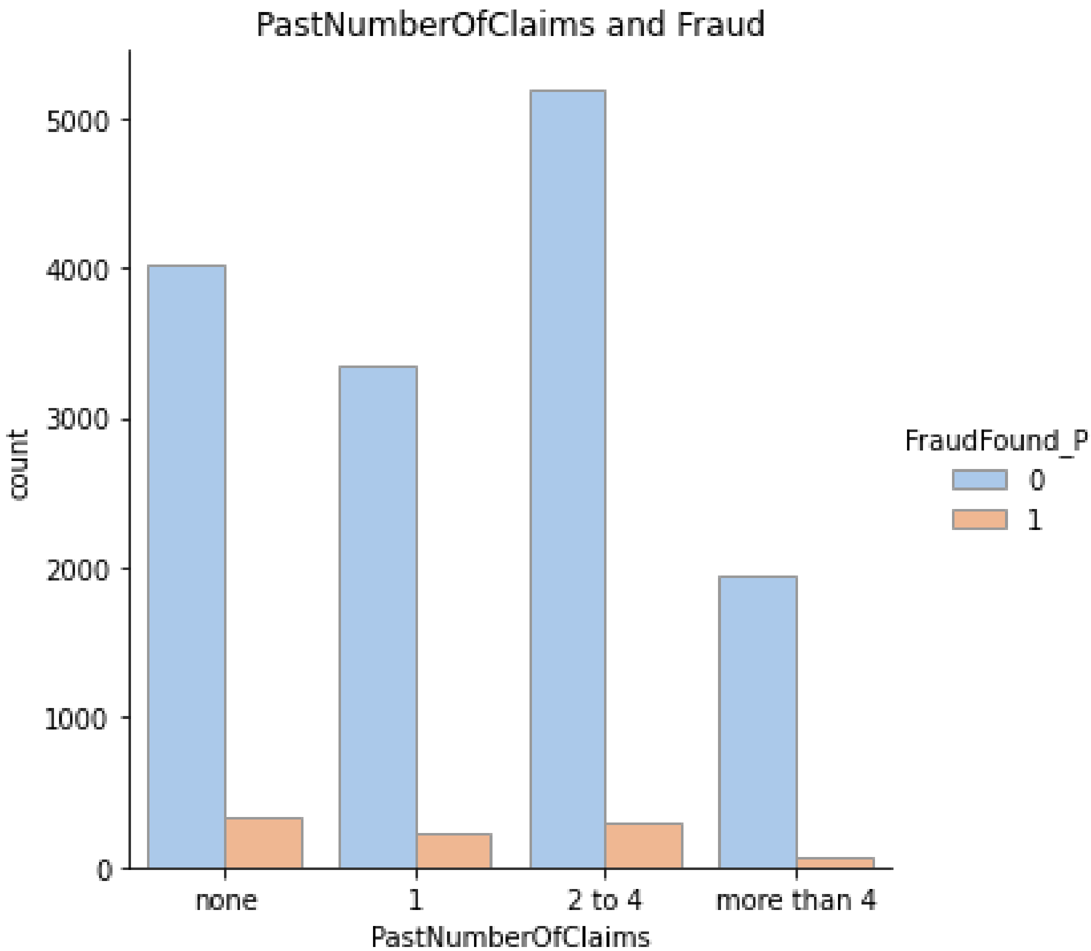

[ ]:
```
sns.catplot(x="WitnessPresent", hue="FraudFound_P", kind="count",
            palette="pastel", edgecolor=".6",
            data=dataset).set(title = "WitnessPresent and Fraud")
plt.show()
```



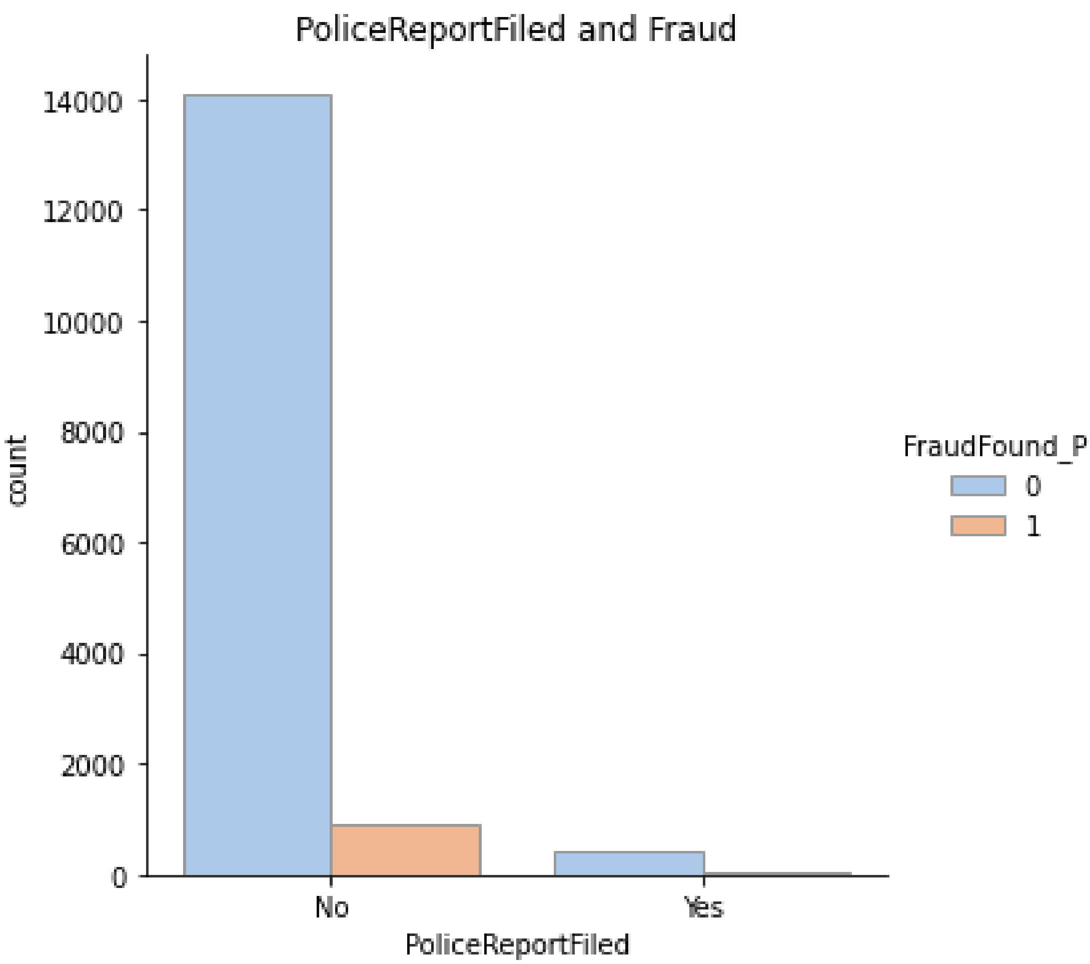

[ ]:
```
sns.catplot(x="AgentType", hue="FraudFound_P", kind="count",
            palette="pastel", edgecolor=".6",
            data=dataset).set(title = "AgentType and Fraud")
plt.show()
```




[ ]:
```
sns.catplot(x="PastNumberOfClaims", hue="FraudFound_P", kind="count",
            palette="pastel", edgecolor=".6",
            data=dataset).set(title = "PastNumberOfClaims and Fraud")
plt.show()
```




[ ]:
```
sns.catplot(x="PoliceReportFiled", hue="FraudFound_P", kind="count",
            palette="pastel", edgecolor=".6",
            data=dataset).set(title = "PoliceReportFiled and Fraud")
plt.show()
```




```
[ ]: dataset.columns[~dataset.columns.isin(["Age", 'Month'])]
```

```
[ ]: Index(['WeekOfMonth', 'DayOfWeek', 'Make', 'AccidentArea', 'DayOfWeekClaimed',
           'MonthClaimed', 'WeekOfMonthClaimed', 'Sex', 'MaritalStatus', 'Fault',
           'PolicyType', 'VehicleCategory', 'VehiclePrice', 'FraudFound_P',
           'PolicyNumber', 'RepNumber', 'Deductible', 'DriverRating',
           'Days_Policy_Accident', 'Days_Policy_Claim', 'PastNumberOfClaims',
           'AgeOfVehicle', 'AgeOfPolicyHolder', 'PoliceReportFiled',
           'WitnessPresent', 'AgentType', 'NumberOfSuppliments',
           'AddressChange_Claim', 'NumberOfCars', 'Year', 'BasePolicy'],
          dtype='object')
```

**⌒2 test**

```
[ ]: col_names = dataset.columns[~dataset.columns.isin(['Age', 'FraudFound_P'])]
     for i in dataset.columns[~dataset.columns.isin(['Age', 'FraudFound_P'])]:
         col_names = col_names[col_names != i]
```

```python
    for j in col_names:
        crosstab, test_results, expected = rp.crosstab(dataset[i], dataset[j],
                                                       test= "chi-square",
                                                       expected_freqs= True,
                                                       prop= "cell")
        if test_results['results'][1] < 0.05:
            print(i + ' ' + j + ':')
            print(test_results)
            print('\n')
    print('****** new ******')
```

```
Month WeekOfMonth:
                 Chi-square test   results
0  Pearson Chi-square ( 44.0) =   149.1212
1                      p-value =    0.0000
2                   Cramer's V =    0.0492


Month DayOfWeek:
                 Chi-square test   results
0  Pearson Chi-square ( 66.0) =   201.1752
1                      p-value =    0.0000
2                   Cramer's V =    0.0466


Month DayOfWeekClaimed:
                 Chi-square test   results
0  Pearson Chi-square ( 77.0) =   199.4474
1                      p-value =    0.0000
2                   Cramer's V =    0.0430


Month MonthClaimed:
                  Chi-square test     results
0  Pearson Chi-square ( 132.0) =   94726.2341
1                       p-value =      0.0000
2                    Cramer's V =      0.7473


Month WeekOfMonthClaimed:
                 Chi-square test   results
0  Pearson Chi-square ( 44.0) =   234.5356
1                      p-value =    0.0000
2                   Cramer's V =    0.0617
```

```
Month PolicyType:
                 Chi-square test   results
0  Pearson Chi-square ( 88.0) =   127.0620
1                     p-value =     0.0041
2                  Cramer's V =     0.0321
```

```
Month VehiclePrice:
                 Chi-square test  results
0  Pearson Chi-square ( 55.0) =   78.5796
1                     p-value =    0.0201
2                  Cramer's V =    0.0319
```

```
Month AgeOfVehicle:
                 Chi-square test   results
0  Pearson Chi-square ( 77.0) =   269.3303
1                     p-value =     0.0000
2                  Cramer's V =     0.0500
```

```
Month AgeOfPolicyHolder:
                 Chi-square test   results
0  Pearson Chi-square ( 88.0) =   212.3422
1                     p-value =     0.0000
2                  Cramer's V =     0.0415
```

```
Month PoliceReportFiled:
                 Chi-square test  results
0  Pearson Chi-square ( 11.0) =   46.8558
1                     p-value =    0.0000
2                  Cramer's V =    0.0551
```

```
Month NumberOfCars:
                 Chi-square test   results
0  Pearson Chi-square ( 44.0) =   265.3381
1                     p-value =     0.0000
2                  Cramer's V =     0.0656
```

```
Month Year:
                 Chi-square test   results
0  Pearson Chi-square ( 22.0) =   113.4837
1                     p-value =     0.0000
2                  Cramer's V =     0.0607
```

```
Month BasePolicy:
                 Chi-square test  results
0  Pearson Chi-square ( 22.0) =   44.5829
1                     p-value =    0.0030
2                  Cramer's V =    0.0380


****** new ******
WeekOfMonth DayOfWeek:
                 Chi-square test  results
0  Pearson Chi-square ( 24.0) =   39.4612
1                     p-value =    0.0244
2                  Cramer's V =    0.0253


WeekOfMonth MonthClaimed:
                 Chi-square test   results
0  Pearson Chi-square ( 48.0) =   121.6322
1                     p-value =     0.0000
2                  Cramer's V =     0.0444


WeekOfMonth WeekOfMonthClaimed:
                 Chi-square test    results
0  Pearson Chi-square ( 16.0) =   9935.7556
1                     p-value =      0.0000
2                  Cramer's V =      0.4014


WeekOfMonth Fault:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =   10.1096
1                    p-value =    0.0386
2                 Cramer's V =    0.0256


WeekOfMonth PolicyType:
                 Chi-square test  results
0  Pearson Chi-square ( 32.0) =   67.2744
1                     p-value =    0.0003
2                  Cramer's V =    0.0330


WeekOfMonth VehicleCategory:
                Chi-square test  results
0  Pearson Chi-square ( 8.0) =   17.3118
1                    p-value =    0.0270
```

```
2                 Cramer's V =    0.0237


WeekOfMonth Days_Policy_Accident:
                 Chi-square test  results
0  Pearson Chi-square ( 16.0) =   29.0664
1                     p-value =    0.0235
2                  Cramer's V =    0.0217


****** new ******
DayOfWeek AccidentArea:
                Chi-square test  results
0  Pearson Chi-square ( 6.0) =   14.9448
1                    p-value =    0.0207
2                 Cramer's V =    0.0311


DayOfWeek DayOfWeekClaimed:
                 Chi-square test    results
0  Pearson Chi-square ( 42.0) =   1959.6262
1                     p-value =      0.0000
2                  Cramer's V =      0.1455


DayOfWeek MaritalStatus:
                 Chi-square test  results
0  Pearson Chi-square ( 18.0) =   30.9558
1                     p-value =    0.0291
2                  Cramer's V =    0.0259


DayOfWeek Fault:
                Chi-square test  results
0  Pearson Chi-square ( 6.0) =   29.0767
1                    p-value =    0.0001
2                 Cramer's V =    0.0434


DayOfWeek PolicyType:
                 Chi-square test   results
0  Pearson Chi-square ( 48.0) =   127.6210
1                     p-value =     0.0000
2                  Cramer's V =     0.0371


DayOfWeek VehicleCategory:
                 Chi-square test  results
```

```
0  Pearson Chi-square ( 12.0) =   96.8021
1                    p-value =    0.0000
2                 Cramer's V =    0.0560
```

```
DayOfWeek VehiclePrice:
                 Chi-square test  results
0  Pearson Chi-square ( 30.0) =   51.9935
1                    p-value =    0.0076
2                 Cramer's V =    0.0260
```

```
DayOfWeek Deductible:
                 Chi-square test  results
0  Pearson Chi-square ( 18.0) =   32.2414
1                    p-value =    0.0206
2                 Cramer's V =    0.0264
```

```
DayOfWeek PastNumberOfClaims:
                 Chi-square test  results
0  Pearson Chi-square ( 18.0) =   29.6607
1                    p-value =    0.0409
2                 Cramer's V =    0.0253
```

```
DayOfWeek AgeOfPolicyHolder:
                 Chi-square test  results
0  Pearson Chi-square ( 48.0) =   92.4484
1                    p-value =    0.0001
2                 Cramer's V =    0.0316
```

```
DayOfWeek BasePolicy:
                 Chi-square test  results
0  Pearson Chi-square ( 12.0) =   69.4465
1                    p-value =    0.0000
2                 Cramer's V =    0.0475
```

```
****** new ******
Make AccidentArea:
                 Chi-square test  results
0  Pearson Chi-square ( 18.0) =   50.7382
1                    p-value =    0.0001
2                 Cramer's V =    0.0574
```

```
Make Sex:
                 Chi-square test   results
0  Pearson Chi-square ( 18.0) =   100.7645
1                    p-value =     0.0000
2                 Cramer's V =     0.0808
```

```
Make MaritalStatus:
                 Chi-square test   results
0  Pearson Chi-square ( 54.0) =   265.6970
1                    p-value =     0.0000
2                 Cramer's V =     0.0758
```

```
Make Fault:
                 Chi-square test  results
0  Pearson Chi-square ( 18.0) =   51.6409
1                    p-value =    0.0000
2                 Cramer's V =    0.0579
```

```
Make PolicyType:
                  Chi-square test    results
0  Pearson Chi-square ( 144.0) =   3508.2304
1                     p-value =      0.0000
2                  Cramer's V =      0.1686
```

```
Make VehicleCategory:
                 Chi-square test    results
0  Pearson Chi-square ( 36.0) =   1174.8102
1                    p-value =      0.0000
2                 Cramer's V =      0.1952
```

```
Make VehiclePrice:
                 Chi-square test    results
0  Pearson Chi-square ( 90.0) =   5307.6281
1                    p-value =      0.0000
2                 Cramer's V =      0.2624
```

```
Make PastNumberOfClaims:
                 Chi-square test   results
0  Pearson Chi-square ( 54.0) =   106.7208
1                    p-value =     0.0000
2                 Cramer's V =     0.0480
```

```
Make AgeOfVehicle:
                 Chi-square test    results
0  Pearson Chi-square ( 126.0) =   2147.2538
1                      p-value =      0.0000
2                   Cramer's V =      0.1410


Make AgeOfPolicyHolder:
                 Chi-square test    results
0  Pearson Chi-square ( 144.0) =   1924.9858
1                      p-value =      0.0000
2                   Cramer's V =      0.1249


Make AgentType:
                Chi-square test  results
0  Pearson Chi-square ( 18.0) =   35.1848
1                     p-value =    0.0090
2                  Cramer's V =    0.0478


Make NumberOfSuppliments:
                Chi-square test   results
0  Pearson Chi-square ( 54.0) =   173.2723
1                     p-value =     0.0000
2                  Cramer's V =     0.0612


Make NumberOfCars:
                Chi-square test   results
0  Pearson Chi-square ( 72.0) =   117.1254
1                     p-value =     0.0006
2                  Cramer's V =     0.0436


Make BasePolicy:
                Chi-square test   results
0  Pearson Chi-square ( 36.0) =   438.5126
1                     p-value =     0.0000
2                  Cramer's V =     0.1192


****** new ******
AccidentArea DayOfWeekClaimed:
               Chi-square test  results
0  Pearson Chi-square ( 7.0) =   17.2348
1                    p-value =    0.0159
```

```
2                  Cramer's V =    0.0334
```

```
AccidentArea MonthClaimed:
                 Chi-square test  results
0  Pearson Chi-square ( 12.0) =   24.7296
1                   p-value =    0.0162
2                 Cramer's V =    0.0400
```

```
AccidentArea Sex:
                Chi-square test  results
0  Pearson Chi-square ( 1.0) =   17.6210
1                  p-value =    0.0000
2              Cramer's phi =    0.0338
```

```
AccidentArea PolicyType:
                Chi-square test  results
0  Pearson Chi-square ( 8.0) =   78.5019
1                  p-value =    0.0000
2                Cramer's V =    0.0714
```

```
AccidentArea VehicleCategory:
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =   65.1495
1                  p-value =    0.0000
2                Cramer's V =    0.0650
```

```
AccidentArea Days_Policy_Claim:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =    9.3663
1                  p-value =    0.0248
2                Cramer's V =    0.0246
```

```
AccidentArea PastNumberOfClaims:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =   60.8933
1                  p-value =    0.0000
2                Cramer's V =    0.0628
```

```
AccidentArea WitnessPresent:
                Chi-square test  results
0  Pearson Chi-square ( 1.0) =   12.4043
```

```
1                   p-value =    0.0004
2              Cramer's phi =    0.0284


AccidentArea AddressChange_Claim:
               Chi-square test  results
0  Pearson Chi-square ( 4.0) =   13.8445
1                   p-value =    0.0078
2                Cramer's V =    0.0300


AccidentArea BasePolicy:
               Chi-square test  results
0  Pearson Chi-square ( 2.0) =   50.1098
1                   p-value =    0.0000
2                Cramer's V =    0.0570


****** new ******
DayOfWeekClaimed MonthClaimed:
                Chi-square test     results
0  Pearson Chi-square ( 84.0) =   15649.1595
1                    p-value =       0.0000
2                 Cramer's V =       0.3808


DayOfWeekClaimed WeekOfMonthClaimed:
                Chi-square test   results
0  Pearson Chi-square ( 28.0) =   102.6120
1                    p-value =     0.0000
2                 Cramer's V =     0.0408


DayOfWeekClaimed PolicyType:
                Chi-square test   results
0  Pearson Chi-square ( 56.0) =   140.5674
1                    p-value =     0.0000
2                 Cramer's V =     0.0361


DayOfWeekClaimed VehicleCategory:
                Chi-square test  results
0  Pearson Chi-square ( 14.0) =   26.3675
1                    p-value =    0.0232
2                 Cramer's V =    0.0292


DayOfWeekClaimed RepNumber:
```

```
                 Chi-square test   results
0  Pearson Chi-square ( 105.0) =   132.0635
1                     p-value =     0.0381
2                  Cramer's V =     0.0350


DayOfWeekClaimed Days_Policy_Claim:
                Chi-square test     results
0  Pearson Chi-square ( 21.0) =   15438.0791
1                    p-value =       0.0000
2                 Cramer's V =       0.5777


DayOfWeekClaimed AgeOfVehicle:
                Chi-square test  results
0  Pearson Chi-square ( 49.0) =   90.7528
1                    p-value =    0.0003
2                 Cramer's V =    0.0290


DayOfWeekClaimed AgeOfPolicyHolder:
                Chi-square test   results
0  Pearson Chi-square ( 56.0) =   113.5637
1                    p-value =     0.0000
2                 Cramer's V =     0.0324


DayOfWeekClaimed AgentType:
               Chi-square test  results
0  Pearson Chi-square ( 7.0) =   14.5105
1                   p-value =    0.0428
2                Cramer's V =    0.0307


****** new ******
MonthClaimed WeekOfMonthClaimed:
                Chi-square test   results
0  Pearson Chi-square ( 48.0) =   288.3509
1                    p-value =     0.0000
2                 Cramer's V =     0.0684


MonthClaimed PolicyType:
                Chi-square test   results
0  Pearson Chi-square ( 96.0) =   133.4310
1                    p-value =     0.0069
2                 Cramer's V =     0.0329
```

```
MonthClaimed VehiclePrice:
                 Chi-square test   results
0  Pearson Chi-square ( 60.0) =   107.1590
1                    p-value =     0.0002
2                 Cramer's V =     0.0373


MonthClaimed Days_Policy_Claim:
                 Chi-square test     results
0  Pearson Chi-square ( 36.0) =   15435.2169
1                    p-value =       0.0000
2                 Cramer's V =       0.5776


MonthClaimed PastNumberOfClaims:
                 Chi-square test  results
0  Pearson Chi-square ( 36.0) =   57.4361
1                    p-value =    0.0131
2                 Cramer's V =    0.0352


MonthClaimed AgeOfVehicle:
                 Chi-square test   results
0  Pearson Chi-square ( 84.0) =   354.1054
1                    p-value =     0.0000
2                 Cramer's V =     0.0573


MonthClaimed AgeOfPolicyHolder:
                 Chi-square test   results
0  Pearson Chi-square ( 96.0) =   340.5870
1                    p-value =     0.0000
2                 Cramer's V =     0.0525


MonthClaimed PoliceReportFiled:
                 Chi-square test  results
0  Pearson Chi-square ( 12.0) =   64.2098
1                    p-value =    0.0000
2                 Cramer's V =    0.0645


MonthClaimed AgentType:
                 Chi-square test  results
0  Pearson Chi-square ( 12.0) =   22.7712
1                    p-value =    0.0297
2                 Cramer's V =    0.0384
```

```
MonthClaimed NumberOfCars:
                 Chi-square test   results
0  Pearson Chi-square ( 48.0) =   151.7854
1                    p-value =     0.0000
2                 Cramer's V =     0.0496


MonthClaimed Year:
                 Chi-square test   results
0  Pearson Chi-square ( 24.0) =   113.5557
1                    p-value =     0.0000
2                 Cramer's V =     0.0607


MonthClaimed BasePolicy:
                 Chi-square test  results
0  Pearson Chi-square ( 24.0) =   57.1723
1                    p-value =    0.0002
2                 Cramer's V =    0.0431


****** new ******
WeekOfMonthClaimed VehicleCategory:
                Chi-square test  results
0  Pearson Chi-square ( 8.0) =   16.5586
1                   p-value =    0.0350
2                Cramer's V =    0.0232


WeekOfMonthClaimed VehiclePrice:
                 Chi-square test  results
0  Pearson Chi-square ( 20.0) =   35.3163
1                    p-value =    0.0185
2                 Cramer's V =    0.0239


WeekOfMonthClaimed PastNumberOfClaims:
                 Chi-square test  results
0  Pearson Chi-square ( 12.0) =   22.6916
1                    p-value =    0.0305
2                 Cramer's V =    0.0221


WeekOfMonthClaimed PoliceReportFiled:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =   12.3583
```

```
1                  p-value =    0.0149
2               Cramer's V =    0.0283


****** new ******
Sex MaritalStatus:
                Chi-square test   results
0  Pearson Chi-square ( 3.0) =   377.0490
1                  p-value =     0.0000
2               Cramer's V =     0.1564


Sex PolicyType:
                Chi-square test   results
0  Pearson Chi-square ( 8.0) =   138.8970
1                  p-value =     0.0000
2               Cramer's V =     0.0949


Sex VehicleCategory:
                Chi-square test   results
0  Pearson Chi-square ( 2.0) =   106.8475
1                  p-value =     0.0000
2               Cramer's V =     0.0832


Sex VehiclePrice:
                Chi-square test   results
0  Pearson Chi-square ( 5.0) =   336.3477
1                  p-value =     0.0000
2               Cramer's V =     0.1477


Sex AgeOfVehicle:
                Chi-square test   results
0  Pearson Chi-square ( 7.0) =   700.5206
1                  p-value =     0.0000
2               Cramer's V =     0.2131


Sex AgeOfPolicyHolder:
                Chi-square test   results
0  Pearson Chi-square ( 8.0) =   289.7156
1                  p-value =     0.0000
2               Cramer's V =     0.1371


Sex BasePolicy:
```

```
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =   75.2780
1                    p-value =    0.0000
2                 Cramer's V =    0.0699


****** new ******
MaritalStatus PolicyType:
                 Chi-square test   results
0  Pearson Chi-square ( 24.0) =   113.2053
1                     p-value =     0.0000
2                  Cramer's V =     0.0495


MaritalStatus VehicleCategory:
                Chi-square test  results
0  Pearson Chi-square ( 6.0) =   67.2819
1                    p-value =    0.0000
2                 Cramer's V =    0.0467


MaritalStatus VehiclePrice:
                 Chi-square test   results
0  Pearson Chi-square ( 15.0) =   245.7704
1                     p-value =     0.0000
2                  Cramer's V =     0.0729


MaritalStatus Deductible:
                Chi-square test  results
0  Pearson Chi-square ( 9.0) =   25.6227
1                    p-value =    0.0024
2                 Cramer's V =    0.0235


MaritalStatus Days_Policy_Accident:
                 Chi-square test  results
0  Pearson Chi-square ( 12.0) =   30.1381
1                     p-value =    0.0027
2                  Cramer's V =    0.0255


MaritalStatus PastNumberOfClaims:
                Chi-square test  results
0  Pearson Chi-square ( 9.0) =   17.7580
1                    p-value =    0.0381
2                 Cramer's V =    0.0196
```

```
MaritalStatus AgeOfVehicle:
                 Chi-square test    results
0  Pearson Chi-square ( 21.0) =   3288.8123
1                    p-value =      0.0000
2                 Cramer's V =      0.2666


MaritalStatus AgeOfPolicyHolder:
                 Chi-square test    results
0  Pearson Chi-square ( 24.0) =   4299.7930
1                    p-value =      0.0000
2                 Cramer's V =      0.3049


MaritalStatus NumberOfSuppliments:
                Chi-square test  results
0  Pearson Chi-square ( 9.0) =   29.1260
1                   p-value =    0.0006
2                Cramer's V =    0.0251


MaritalStatus BasePolicy:
                Chi-square test  results
0  Pearson Chi-square ( 6.0) =   47.3191
1                   p-value =    0.0000
2                Cramer's V =    0.0392


****** new ******
Fault PolicyType:
                Chi-square test  results
0  Pearson Chi-square ( 8.0) =   895.858
1                   p-value =     0.000
2                Cramer's V =     0.241


Fault VehicleCategory:
                Chi-square test   results
0  Pearson Chi-square ( 2.0) =   544.8769
1                   p-value =     0.0000
2                Cramer's V =     0.1880


Fault VehiclePrice:
                Chi-square test  results
0  Pearson Chi-square ( 5.0) =   37.5873
1                   p-value =    0.0000
```

```
2                 Cramer's V =    0.0494


Fault Days_Policy_Accident:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =   17.8731
1                    p-value =    0.0013
2                 Cramer's V =    0.0340


Fault Days_Policy_Claim:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =    7.8594
1                    p-value =    0.0490
2                 Cramer's V =    0.0226


Fault PastNumberOfClaims:
                Chi-square test   results
0  Pearson Chi-square ( 3.0) =   250.4110
1                    p-value =     0.0000
2                 Cramer's V =     0.1274


Fault AgeOfVehicle:
                Chi-square test  results
0  Pearson Chi-square ( 7.0) =   36.1858
1                    p-value =    0.0000
2                 Cramer's V =    0.0484


Fault AgeOfPolicyHolder:
                Chi-square test  results
0  Pearson Chi-square ( 8.0) =   55.2858
1                    p-value =    0.0000
2                 Cramer's V =    0.0599


Fault PoliceReportFiled:
                Chi-square test  results
0  Pearson Chi-square ( 1.0) =   11.4467
1                    p-value =    0.0007
2               Cramer's phi =    0.0272


Fault WitnessPresent:
                Chi-square test  results
0  Pearson Chi-square ( 1.0) =   57.4464
```

```
1                   p-value =    0.0000
2              Cramer's phi =    0.0610


Fault NumberOfSuppliments:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =   12.9618
1                   p-value =    0.0047
2                 Cramer's V =    0.0290


Fault BasePolicy:
                Chi-square test   results
0  Pearson Chi-square ( 2.0) =   659.5151
1                   p-value =     0.0000
2                 Cramer's V =     0.2068


****** new ******
PolicyType VehicleCategory:
                 Chi-square test  results
0  Pearson Chi-square ( 16.0) =   30840.0
1                    p-value =       0.0
2                  Cramer's V =       1.0


PolicyType VehiclePrice:
                 Chi-square test    results
0  Pearson Chi-square ( 40.0) =   5558.1464
1                    p-value =      0.0000
2                  Cramer's V =      0.2685


PolicyType Deductible:
                 Chi-square test    results
0  Pearson Chi-square ( 24.0) =   1943.0273
1                    p-value =      0.0000
2                  Cramer's V =      0.2049


PolicyType Days_Policy_Accident:
                 Chi-square test  results
0  Pearson Chi-square ( 32.0) =   48.6201
1                    p-value =    0.0301
2                  Cramer's V =    0.0281


PolicyType PastNumberOfClaims:
```

```
                 Chi-square test    results
0  Pearson Chi-square ( 24.0) =   2506.1265
1                    p-value =      0.0000
2                 Cramer's V =      0.2328
```

```
PolicyType AgeOfVehicle:
                 Chi-square test   results
0  Pearson Chi-square ( 56.0) =   810.0619
1                    p-value =     0.0000
2                 Cramer's V =     0.0866
```

```
PolicyType AgeOfPolicyHolder:
                 Chi-square test    results
0  Pearson Chi-square ( 64.0) =   1459.5007
1                    p-value =      0.0000
2                 Cramer's V =      0.1088
```

```
PolicyType PoliceReportFiled:
                Chi-square test  results
0  Pearson Chi-square ( 8.0) =   34.2248
1                   p-value =    0.0000
2                Cramer's V =    0.0471
```

```
PolicyType WitnessPresent:
                Chi-square test  results
0  Pearson Chi-square ( 8.0) =   40.1169
1                   p-value =    0.0000
2                Cramer's V =    0.0510
```

```
PolicyType AgentType:
                Chi-square test   results
0  Pearson Chi-square ( 8.0) =   153.7383
1                   p-value =     0.0000
2                Cramer's V =     0.0999
```

```
PolicyType NumberOfSuppliments:
                 Chi-square test   results
0  Pearson Chi-square ( 24.0) =   136.2349
1                    p-value =     0.0000
2                 Cramer's V =     0.0543
```

```
PolicyType AddressChange_Claim:
                 Chi-square test   results
0  Pearson Chi-square ( 32.0) =   107.6380
1                    p-value =     0.0000
2                 Cramer's V =     0.0418


PolicyType NumberOfCars:
                 Chi-square test  results
0  Pearson Chi-square ( 32.0) =   55.0367
1                    p-value =    0.0069
2                 Cramer's V =    0.0299


PolicyType Year:
                 Chi-square test  results
0  Pearson Chi-square ( 16.0) =   32.2181
1                    p-value =    0.0094
2                 Cramer's V =    0.0323


PolicyType BasePolicy:
                 Chi-square test  results
0  Pearson Chi-square ( 16.0) =   30840.0
1                    p-value =       0.0
2                 Cramer's V =       1.0


****** new ******
VehicleCategory VehiclePrice:
                 Chi-square test    results
0  Pearson Chi-square ( 10.0) =   2530.6226
1                    p-value =      0.0000
2                 Cramer's V =      0.2865


VehicleCategory Days_Policy_Accident:
                Chi-square test  results
0  Pearson Chi-square ( 8.0) =   18.8717
1                   p-value =    0.0156
2                Cramer's V =    0.0247


VehicleCategory PastNumberOfClaims:
                Chi-square test    results
0  Pearson Chi-square ( 6.0) =   1744.3221
1                   p-value =      0.0000
2                Cramer's V =      0.2378
```

```
VehicleCategory AgeOfVehicle:
                 Chi-square test   results
0  Pearson Chi-square ( 14.0) =   153.6338
1                   p-value =     0.0000
2                Cramer's V =     0.0706


VehicleCategory AgeOfPolicyHolder:
                 Chi-square test   results
0  Pearson Chi-square ( 16.0) =   193.5867
1                   p-value =     0.0000
2                Cramer's V =     0.0792


VehicleCategory PoliceReportFiled:
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =   25.2812
1                  p-value =    0.0000
2               Cramer's V =    0.0405


VehicleCategory WitnessPresent:
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =   11.8448
1                  p-value =    0.0027
2               Cramer's V =    0.0277


VehicleCategory AgentType:
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =   30.1847
1                  p-value =    0.0000
2               Cramer's V =    0.0442


VehicleCategory NumberOfSuppliments:
                Chi-square test  results
0  Pearson Chi-square ( 6.0) =   28.4876
1                  p-value =    0.0001
2               Cramer's V =    0.0304


VehicleCategory BasePolicy:
                Chi-square test     results
0  Pearson Chi-square ( 4.0) =   14293.1690
1                  p-value =       0.0000
```

```
2                 Cramer's V =       0.6808


****** new ******
VehiclePrice Days_Policy_Accident:
                  Chi-square test  results
0  Pearson Chi-square ( 20.0) =   34.7076
1                    p-value =    0.0217
2                 Cramer's V =    0.0237


VehiclePrice PastNumberOfClaims:
                  Chi-square test   results
0  Pearson Chi-square ( 15.0) =   392.2822
1                    p-value =     0.0000
2                 Cramer's V =     0.0921


VehiclePrice AgeOfVehicle:
                  Chi-square test    results
0  Pearson Chi-square ( 35.0) =   2886.6801
1                    p-value =      0.0000
2                 Cramer's V =      0.1935


VehiclePrice AgeOfPolicyHolder:
                  Chi-square test    results
0  Pearson Chi-square ( 40.0) =   2499.9984
1                    p-value =      0.0000
2                 Cramer's V =      0.1801


VehiclePrice AgentType:
                 Chi-square test   results
0  Pearson Chi-square ( 5.0) =   148.2960
1                   p-value =     0.0000
2                Cramer's V =     0.0981


VehiclePrice NumberOfSuppliments:
                  Chi-square test   results
0  Pearson Chi-square ( 15.0) =   153.5315
1                    p-value =     0.0000
2                 Cramer's V =     0.0576


VehiclePrice Year:
                  Chi-square test  results
```

```
0  Pearson Chi-square ( 10.0) =   37.7982
1                     p-value =    0.0000
2                  Cramer's V =    0.0350


VehiclePrice BasePolicy:
                 Chi-square test    results
0  Pearson Chi-square ( 10.0) =   1294.7487
1                     p-value =      0.0000
2                  Cramer's V =      0.2049


****** new ******
****** new ******
RepNumber AgeOfVehicle:
                  Chi-square test   results
0  Pearson Chi-square ( 105.0) =   144.5109
1                      p-value =     0.0064
2                   Cramer's V =     0.0366


RepNumber AgeOfPolicyHolder:
                  Chi-square test   results
0  Pearson Chi-square ( 120.0) =   148.6219
1                      p-value =     0.0392
2                   Cramer's V =     0.0347


****** new ******
Deductible AgeOfVehicle:
                 Chi-square test   results
0  Pearson Chi-square ( 21.0) =   296.7951
1                     p-value =     0.0000
2                  Cramer's V =     0.0801


Deductible AgeOfPolicyHolder:
                 Chi-square test   results
0  Pearson Chi-square ( 24.0) =   147.9834
1                     p-value =     0.0000
2                  Cramer's V =     0.0566


Deductible AddressChange_Claim:
                 Chi-square test     results
0  Pearson Chi-square ( 12.0) =   13202.0328
1                     p-value =       0.0000
2                  Cramer's V =       0.5342
```

```
Deductible NumberOfCars:
                 Chi-square test  results
0  Pearson Chi-square ( 12.0) =   62.1425
1                    p-value =    0.0000
2                 Cramer's V =    0.0367


****** new ******
****** new ******
Days_Policy_Accident Days_Policy_Claim:
                 Chi-square test    results
0  Pearson Chi-square ( 12.0) =   7675.3042
1                    p-value =      0.0000
2                 Cramer's V =      0.4073


Days_Policy_Accident PastNumberOfClaims:
                 Chi-square test  results
0  Pearson Chi-square ( 12.0) =   52.2123
1                    p-value =    0.0000
2                 Cramer's V =    0.0336


Days_Policy_Accident AgeOfVehicle:
                 Chi-square test   results
0  Pearson Chi-square ( 28.0) =   102.2116
1                    p-value =     0.0000
2                 Cramer's V =     0.0407


Days_Policy_Accident AgeOfPolicyHolder:
                 Chi-square test  results
0  Pearson Chi-square ( 32.0) =   52.1698
1                    p-value =    0.0136
2                 Cramer's V =    0.0291


Days_Policy_Accident WitnessPresent:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =   49.1640
1                   p-value =    0.0000
2                Cramer's V =    0.0565


Days_Policy_Accident NumberOfSuppliments:
                 Chi-square test   results
```

```
0  Pearson Chi-square ( 12.0) =   148.1611
1                    p-value =     0.0000
2                 Cramer's V =     0.0566


Days_Policy_Accident NumberOfCars:
                 Chi-square test   results
0  Pearson Chi-square ( 16.0) =   165.0298
1                    p-value =     0.0000
2                 Cramer's V =     0.0517


Days_Policy_Accident BasePolicy:
                Chi-square test  results
0  Pearson Chi-square ( 8.0) =   26.0831
1                   p-value =    0.0010
2                Cramer's V =    0.0291


****** new ******
Days_Policy_Claim PastNumberOfClaims:
                Chi-square test  results
0  Pearson Chi-square ( 9.0) =   38.2365
1                   p-value =    0.0000
2                Cramer's V =    0.0287


Days_Policy_Claim AgeOfVehicle:
                 Chi-square test  results
0  Pearson Chi-square ( 21.0) =   74.7111
1                    p-value =    0.0000
2                 Cramer's V =    0.0402


Days_Policy_Claim AgeOfPolicyHolder:
                 Chi-square test  results
0  Pearson Chi-square ( 24.0) =   75.9610
1                    p-value =    0.0000
2                 Cramer's V =    0.0405


Days_Policy_Claim NumberOfSuppliments:
                Chi-square test  results
0  Pearson Chi-square ( 9.0) =   70.1265
1                   p-value =    0.0000
2                Cramer's V =    0.0389
```

```
Days_Policy_Claim BasePolicy:
                Chi-square test  results
0  Pearson Chi-square ( 6.0) =   14.1933
1                  p-value =    0.0275
2               Cramer's V =    0.0215


****** new ******
PastNumberOfClaims AgeOfVehicle:
                 Chi-square test  results
0  Pearson Chi-square ( 21.0) =   83.7227
1                   p-value =    0.0000
2                Cramer's V =    0.0425


PastNumberOfClaims AgeOfPolicyHolder:
                 Chi-square test  results
0  Pearson Chi-square ( 24.0) =   69.7237
1                   p-value =    0.0000
2                Cramer's V =    0.0388


PastNumberOfClaims AgentType:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =   11.4980
1                  p-value =    0.0093
2               Cramer's V =    0.0273


PastNumberOfClaims NumberOfSuppliments:
                Chi-square test   results
0  Pearson Chi-square ( 9.0) =   210.2259
1                  p-value =     0.0000
2               Cramer's V =     0.0674


PastNumberOfClaims BasePolicy:
                Chi-square test    results
0  Pearson Chi-square ( 6.0) =   2197.7416
1                  p-value =      0.0000
2               Cramer's V =      0.2670


****** new ******
AgeOfVehicle AgeOfPolicyHolder:
                 Chi-square test     results
0  Pearson Chi-square ( 56.0) =   30849.6640
1                   p-value =       0.0000
```

```
2                  Cramer's V =       0.5346


AgeOfVehicle WitnessPresent:
                Chi-square test  results
0  Pearson Chi-square ( 7.0) =   18.8519
1                   p-value =    0.0087
2                Cramer's V =    0.0350


AgeOfVehicle NumberOfSuppliments:
                 Chi-square test   results
0  Pearson Chi-square ( 21.0) =   631.7692
1                    p-value =     0.0000
2                 Cramer's V =     0.1169


AgeOfVehicle BasePolicy:
                 Chi-square test   results
0  Pearson Chi-square ( 14.0) =   295.9225
1                    p-value =     0.0000
2                 Cramer's V =     0.0980


****** new ******
AgeOfPolicyHolder NumberOfSuppliments:
                 Chi-square test   results
0  Pearson Chi-square ( 24.0) =   440.4423
1                    p-value =     0.0000
2                 Cramer's V =     0.0976


AgeOfPolicyHolder Year:
                 Chi-square test  results
0  Pearson Chi-square ( 16.0) =   32.3318
1                    p-value =    0.0091
2                 Cramer's V =    0.0324


AgeOfPolicyHolder BasePolicy:
                 Chi-square test   results
0  Pearson Chi-square ( 16.0) =   404.3574
1                    p-value =     0.0000
2                 Cramer's V =     0.1145


****** new ******
PoliceReportFiled WitnessPresent:
```

```
                Chi-square test   results
0  Pearson Chi-square ( 1.0) =   605.1143
1                  p-value =     0.0000
2             Cramer's phi =     0.1981
```

```
PoliceReportFiled AgentType:
                Chi-square test  results
0  Pearson Chi-square ( 1.0) =    8.3486
1                  p-value =    0.0039
2             Cramer's phi =    0.0233
```

```
PoliceReportFiled NumberOfSuppliments:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =    8.4281
1                  p-value =    0.0379
2               Cramer's V =    0.0234
```

```
PoliceReportFiled NumberOfCars:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =   11.6517
1                  p-value =    0.0201
2               Cramer's V =    0.0275
```

```
PoliceReportFiled Year:
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =    8.2065
1                  p-value =    0.0165
2               Cramer's V =    0.0231
```

```
PoliceReportFiled BasePolicy:
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =   29.3742
1                  p-value =    0.0000
2               Cramer's V =    0.0436
```

```
****** new ******
WitnessPresent Year:
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =    6.0565
1                  p-value =    0.0484
2               Cramer's V =    0.0198
```

```
WitnessPresent BasePolicy:
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =   23.8709
1                  p-value =    0.0000
2               Cramer's V =    0.0393


****** new ******
AgentType NumberOfSuppliments:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =   17.6963
1                  p-value =    0.0005
2               Cramer's V =    0.0339


AgentType AddressChange_Claim:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =   11.2244
1                  p-value =    0.0242
2               Cramer's V =    0.0270


AgentType NumberOfCars:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =   14.6981
1                  p-value =    0.0054
2               Cramer's V =    0.0309


AgentType Year:
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =    6.0853
1                  p-value =    0.0477
2               Cramer's V =    0.0199


AgentType BasePolicy:
                Chi-square test   results
0  Pearson Chi-square ( 2.0) =   106.9915
1                  p-value =     0.0000
2               Cramer's V =     0.0833


****** new ******
NumberOfSuppliments BasePolicy:
                Chi-square test  results
0  Pearson Chi-square ( 6.0) =   43.5975
```

```
1                   p-value =    0.0000
2                Cramer's V =    0.0376


****** new ******
AddressChange_Claim NumberOfCars:
                 Chi-square test     results
0  Pearson Chi-square ( 16.0) =   13501.6367
1                    p-value =       0.0000
2                 Cramer's V =       0.4679


****** new ******
****** new ******
Year BasePolicy:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =   10.9377
1                   p-value =    0.0273
2                Cramer's V =    0.0188


****** new ******
****** new ******
```

[ ]:

```python
for i in dataset.columns[~dataset.columns.isin(['Age', 'FraudFound_P'])]:
    crosstab, test_results, expected = rp.crosstab(dataset[i],␣
 ↪dataset['FraudFound_P'],
                                                   test= "chi-square",
                                                   expected_freqs= True,
                                                   prop= "cell")

    if test_results['results'][1] < 0.05:
        print(i + ':')
        print(test_results)
        print('\n')
```

```
Month:
                 Chi-square test  results
0  Pearson Chi-square ( 11.0) =   29.7964
1                    p-value =    0.0017
2                 Cramer's V =    0.0440


Make:
                 Chi-square test  results
0  Pearson Chi-square ( 18.0) =   59.8100
1                    p-value =    0.0000
```

```
2                  Cramer's V =    0.0623
```

```
AccidentArea:
                Chi-square test  results
0  Pearson Chi-square ( 1.0) =   17.3045
1                  p-value =    0.0000
2               Cramer's phi =    0.0335
```

```
MonthClaimed:
                 Chi-square test  results
0  Pearson Chi-square ( 12.0) =   42.2667
1                   p-value =    0.0000
2                 Cramer's V =    0.0524
```

```
Sex:
                Chi-square test  results
0  Pearson Chi-square ( 1.0) =   13.8348
1                  p-value =    0.0002
2               Cramer's phi =    0.0300
```

```
Fault:
                Chi-square test   results
0  Pearson Chi-square ( 1.0) =   266.1974
1                  p-value =     0.0000
2               Cramer's phi =     0.1314
```

```
PolicyType:
                Chi-square test   results
0  Pearson Chi-square ( 8.0) =   437.4019
1                  p-value =     0.0000
2                Cramer's V =     0.1684
```

```
VehicleCategory:
                Chi-square test   results
0  Pearson Chi-square ( 2.0) =   290.9421
1                  p-value =     0.0000
2                Cramer's V =     0.1374
```

```
VehiclePrice:
                Chi-square test  results
0  Pearson Chi-square ( 5.0) =   67.7683
```

```
1                   p-value =    0.0000
2                Cramer's V =    0.0663
```

```
Deductible:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =   72.4152
1                   p-value =    0.0000
2                Cramer's V =    0.0685
```

```
Days_Policy_Accident:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =   11.5716
1                   p-value =    0.0208
2                Cramer's V =    0.0274
```

```
PastNumberOfClaims:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =   53.5008
1                   p-value =    0.0000
2                Cramer's V =    0.0589
```

```
AgeOfVehicle:
                Chi-square test  results
0  Pearson Chi-square ( 7.0) =   21.9290
1                   p-value =    0.0026
2                Cramer's V =    0.0377
```

```
AgeOfPolicyHolder:
                Chi-square test  results
0  Pearson Chi-square ( 8.0) =   33.0033
1                   p-value =    0.0001
2                Cramer's V =    0.0463
```

```
PoliceReportFiled:
                Chi-square test  results
0  Pearson Chi-square ( 1.0) =    3.9512
1                   p-value =    0.0468
2              Cramer's phi =    0.0160
```

```
AgentType:
                Chi-square test  results
```

```
0  Pearson Chi-square ( 1.0) =    8.1417
1                    p-value =    0.0043
2               Cramer's phi =    0.0230


NumberOfSuppliments:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =   18.1406
1                    p-value =    0.0004
2                 Cramer's V =    0.0343


AddressChange_Claim:
                Chi-square test   results
0  Pearson Chi-square ( 4.0) =   104.7338
1                    p-value =     0.0000
2                 Cramer's V =     0.0824


Year:
                Chi-square test  results
0  Pearson Chi-square ( 2.0) =    9.5780
1                    p-value =    0.0083
2                 Cramer's V =    0.0249


BasePolicy:
                Chi-square test   results
0  Pearson Chi-square ( 2.0) =   402.8519
1                    p-value =     0.0000
2                 Cramer's V =     0.1616
```

[ ]:
```
for i in dataset.columns[~dataset.columns.isin(['Age', 'FraudFound_P'])]:
    crosstab, test_results, expected = rp.crosstab(dataset[i],␣
 ↪dataset['FraudFound_P'],
                                               test= "chi-square",
                                               expected_freqs= True,
                                               prop= "cell")

    if test_results['results'][1] > 0.05:
        print(i + ':')
        print(test_results)
        print('\n')
```

```
WeekOfMonth:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =    2.4474
```

```
1                 p-value =    0.6541
2              Cramer's V =    0.0126
```

```
DayOfWeek:
                Chi-square test  results
0  Pearson Chi-square ( 6.0) =   10.1506
1                 p-value =    0.1185
2              Cramer's V =    0.0257
```

```
DayOfWeekClaimed:
                Chi-square test  results
0  Pearson Chi-square ( 7.0) =    5.1596
1                 p-value =    0.6405
2              Cramer's V =    0.0183
```

```
WeekOfMonthClaimed:
                Chi-square test  results
0  Pearson Chi-square ( 4.0) =    3.3723
1                 p-value =    0.4976
2              Cramer's V =    0.0148
```

```
MaritalStatus:
                Chi-square test  results
0  Pearson Chi-square ( 3.0) =    1.0135
1                 p-value =    0.7980
2              Cramer's V =    0.0081
```

```
PolicyNumber:
                    Chi-square test     results
0  Pearson Chi-square ( 15419.0) =   15420.0000
1                     p-value =       0.4962
2                  Cramer's V =       1.0000
```

```
RepNumber:
                 Chi-square test  results
0  Pearson Chi-square ( 15.0) =   11.8196
1                  p-value =    0.6926
2               Cramer's V =    0.0277
```

```
DriverRating:
                Chi-square test  results
```

```
0  Pearson Chi-square ( 3.0) =    1.6494
1                   p-value =    0.6482
2                Cramer's V =    0.0103


Days_Policy_Claim:
                 Chi-square test  results
0  Pearson Chi-square ( 3.0) =    4.8812
1                   p-value =    0.1807
2                Cramer's V =    0.0178


WitnessPresent:
                 Chi-square test  results
0  Pearson Chi-square ( 1.0) =    1.0011
1                   p-value =    0.3171
2              Cramer's phi =    0.0081


NumberOfCars:
                 Chi-square test  results
0  Pearson Chi-square ( 4.0) =    2.4161
1                   p-value =    0.6597
2                Cramer's V =    0.0125
```

**common distrabution**

[ ]:
```
pd.crosstab(dataset.Sex, dataset.FraudFound_P)
```

[ ]:
```
FraudFound_P      0    1
Sex
Female         2315  105
Male          12182  818
```

[ ]:
```
pd.crosstab(dataset.Sex, dataset.FraudFound_P, normalize = 'columns')
```

[ ]:
```
FraudFound_P         0         1
Sex
Female        0.159688  0.113759
Male          0.840312  0.886241
```

[ ]:
```
pd.crosstab(dataset.AccidentArea, dataset.FraudFound_P)
```

[ ]:
```
FraudFound_P      0    1
AccidentArea
Rural          1465  133
```

```
Urban          13032  790
```

[ ]:
```
pd.crosstab(dataset.AccidentArea, dataset.FraudFound_P, normalize = 'columns')
```

[ ]:
```
FraudFound_P          0         1
AccidentArea
Rural          0.101055  0.144095
Urban          0.898945  0.855905
```

[ ]:
```
pd.crosstab(dataset.VehicleCategory, dataset.FraudFound_P)
```

[ ]:
```
FraudFound_P        0    1
VehicleCategory
Sedan            8876  795
Sport            5274   84
Utility           347   44
```

[ ]:
```
pd.crosstab(dataset.VehicleCategory, dataset.FraudFound_P, normalize =␣
 ↪'columns')
```

[ ]:
```
FraudFound_P            0         1
VehicleCategory
Sedan            0.612265  0.861322
Sport            0.363799  0.091008
Utility          0.023936  0.047671
```

[ ]:
```
pd.crosstab(dataset.VehicleCategory, dataset.FraudFound_P, normalize =␣
 ↪'columns')
```

[ ]:
```
FraudFound_P            0         1
VehicleCategory
Sedan            0.612265  0.861322
Sport            0.363799  0.091008
Utility          0.023936  0.047671
```

[ ]:
```
for i in dataset.columns[~dataset.columns.isin(['Age', 'FraudFound_P'])]:
    print(pd.crosstab(dataset[i], dataset.FraudFound_P))
    print(pd.crosstab(dataset[i], dataset.FraudFound_P, normalize = 'columns'))
```

```
FraudFound_P     0    1
Month
Apr           1200   80
Aug           1043   84
Dec           1223   62
Feb           1184   82
Jan           1324   87
```

```
Jul            1197   60
Jun            1241   80
Mar            1258  102
May            1273   94
Nov            1155   46
Oct            1235   70
Sep            1164   76
FraudFound_P          0         1
Month
Apr            0.082776  0.086674
Aug            0.071946  0.091008
Dec            0.084362  0.067172
Feb            0.081672  0.088841
Jan            0.091329  0.094258
Jul            0.082569  0.065005
Jun            0.085604  0.086674
Mar            0.086777  0.110509
May            0.087811  0.101842
Nov            0.079672  0.049837
Oct            0.085190  0.075840
Sep            0.080292  0.082340
FraudFound_P      0    1
WeekOfMonth
1              2987  200
2              3333  225
3              3425  215
4              3206  192
5              1546   91
FraudFound_P          0         1
WeekOfMonth
1              0.206043  0.216685
2              0.229910  0.243770
3              0.236256  0.232936
4              0.221149  0.208017
5              0.106643  0.098592
FraudFound_P      0    1
DayOfWeek
Friday         2291  154
Monday         2456  160
Saturday       1850  132
Sunday         1623  122
Thursday       2053  120
Tuesday        2180  120
Wednesday      2044  115
FraudFound_P          0         1
DayOfWeek
Friday         0.158033  0.166847
Monday         0.169414  0.173348
```

```
Saturday       0.127613  0.143012
Sunday         0.111954  0.132178
Thursday       0.141616  0.130011
Tuesday        0.150376  0.130011
Wednesday      0.140995  0.124594
FraudFound_P      0     1
Make
Accura          413    59
BMW              14     1
Chevrolet      1587    94
Dodge           107     2
Ferrari           2     0
Ford            417    33
Honda          2622   179
Jaguar            6     0
Lexus             1     0
Mazda          2231   123
Mecedes           3     1
Mercury          77     6
Nisson           29     1
Pontiac        3624   213
Porche            5     0
Saab             97    11
Saturn           52     6
Toyota         2935   186
VW              275     8
FraudFound_P          0          1
Make
Accura         0.028489  0.063922
BMW            0.000966  0.001083
Chevrolet      0.109471  0.101842
Dodge          0.007381  0.002167
Ferrari        0.000138  0.000000
Ford           0.028765  0.035753
Honda          0.180865  0.193933
Jaguar         0.000414  0.000000
Lexus          0.000069  0.000000
Mazda          0.153894  0.133261
Mecedes        0.000207  0.001083
Mercury        0.005311  0.006501
Nisson         0.002000  0.001083
Pontiac        0.249983  0.230769
Porche         0.000345  0.000000
Saab           0.006691  0.011918
Saturn         0.003587  0.006501
Toyota         0.202456  0.201517
VW             0.018969  0.008667
FraudFound_P       0     1
```

```
AccidentArea
Rural          1465  133
Urban         13032  790
FraudFound_P         0         1
AccidentArea
Rural         0.101055  0.144095
Urban         0.898945  0.855905
FraudFound_P         0    1
DayOfWeekClaimed
0                    1    0
Friday            2333  164
Monday            3541  216
Saturday           117   10
Sunday              49    3
Thursday          2516  144
Tuesday           3177  198
Wednesday         2763  188
FraudFound_P             0         1
DayOfWeekClaimed
0                 0.000069  0.000000
Friday            0.160930  0.177681
Monday            0.244257  0.234020
Saturday          0.008071  0.010834
Sunday            0.003380  0.003250
Thursday          0.173553  0.156013
Tuesday           0.219149  0.214518
Wednesday         0.190591  0.203684
FraudFound_P     0    1
MonthClaimed
0                1    0
Apr           1189   82
Aug           1034   92
Dec           1097   49
Feb           1209   78
Jan           1354   92
Jul           1169   56
Jun           1215   78
Mar           1251   97
May           1309  102
Nov           1239   46
Oct           1266   73
Sep           1164   78
FraudFound_P         0         1
MonthClaimed
0             0.000069  0.000000
Apr           0.082017  0.088841
Aug           0.071325  0.099675
Dec           0.075671  0.053088
```

```
Feb           0.083397  0.084507
Jan           0.093399  0.099675
Jul           0.080637  0.060672
Jun           0.083810  0.084507
Mar           0.086294  0.105092
May           0.090295  0.110509
Nov           0.085466  0.049837
Oct           0.087328  0.079090
Sep           0.080292  0.084507
FraudFound_P           0    1
WeekOfMonthClaimed
1                   3230  220
2                   3512  208
3                   3362  221
4                   3224  209
5                   1169   65
FraudFound_P               0         1
WeekOfMonthClaimed
1                   0.222805  0.238353
2                   0.242257  0.225352
3                   0.231910  0.239437
4                   0.222391  0.226436
5                   0.080637  0.070423
FraudFound_P      0    1
Sex
Female         2315  105
Male          12182  818
FraudFound_P         0         1
Sex
Female        0.159688  0.113759
Male          0.840312  0.886241
FraudFound_P      0    1
MaritalStatus
Divorced         73    3
Married        9986  639
Single         4406  278
Widow            32    3
FraudFound_P          0         1
MaritalStatus
Divorced       0.005036  0.003250
Married        0.688832  0.692308
Single         0.303925  0.301192
Widow          0.002207  0.003250
FraudFound_P       0    1
Fault
Policy Holder  10344  886
Third Party     4153   37
FraudFound_P          0         1
```

```
Fault
Policy Holder  0.713527  0.959913
Third Party    0.286473  0.040087
FraudFound_P            0    1
PolicyType
Sedan - All Perils    3676  411
Sedan - Collision     5200  384
Sedan - Liability     4951   36
Sport - All Perils      22    0
Sport - Collision      300   48
Sport - Liability        1    0
Utility - All Perils   299   41
Utility - Collision     27    3
Utility - Liability     21    0
FraudFound_P                0         1
PolicyType
Sedan - All Perils    0.253570  0.445287
Sedan - Collision     0.358695  0.416035
Sedan - Liability     0.341519  0.039003
Sport - All Perils    0.001518  0.000000
Sport - Collision     0.020694  0.052004
Sport - Liability     0.000069  0.000000
Utility - All Perils  0.020625  0.044420
Utility - Collision   0.001862  0.003250
Utility - Liability   0.001449  0.000000
FraudFound_P       0    1
VehicleCategory
Sedan            8876  795
Sport            5274   84
Utility           347   44
FraudFound_P            0         1
VehicleCategory
Sedan            0.612265  0.861322
Sport            0.363799  0.091008
Utility          0.023936  0.047671
FraudFound_P       0    1
VehiclePrice
20000 to 29000   7658  421
30000 to 39000   3358  175
40000 to 59000    430   31
60000 to 69000     83    4
less than 20000   993  103
more than 69000  1975  189
FraudFound_P            0         1
VehiclePrice
20000 to 29000   0.528247  0.456121
30000 to 39000   0.231634  0.189599
40000 to 59000   0.029661  0.033586
```

```
60000 to 69000   0.005725  0.004334
less than 20000  0.068497  0.111593
more than 69000  0.136235  0.204767
FraudFound_P  0  1
PolicyNumber
1             1  0
2             1  0
3             1  0
4             1  0
5             1  0
…          .. ..
15416         0  1
15417         1  0
15418         0  1
15419         1  0
15420         0  1

[15420 rows x 2 columns]
FraudFound_P         0         1
PolicyNumber
1             0.000069  0.000000
2             0.000069  0.000000
3             0.000069  0.000000
4             0.000069  0.000000
5             0.000069  0.000000
…                  …         …
15416         0.000000  0.001083
15417         0.000069  0.000000
15418         0.000000  0.001083
15419         0.000069  0.000000
15420         0.000000  0.001083

[15420 rows x 2 columns]
FraudFound_P    0   1
RepNumber
1             924  63
2             901  55
3             889  60
4             862  50
5             935  52
6             876  66
7             995  74
8             879  52
9             934  65
10            920  66
11            892  56
12            930  47
13            834  58
```

```
14             884  57
15             928  49
16             914  53
FraudFound_P          0         1
RepNumber
1              0.063737  0.068256
2              0.062151  0.059588
3              0.061323  0.065005
4              0.059461  0.054171
5              0.064496  0.056338
6              0.060426  0.071506
7              0.068635  0.080173
8              0.060633  0.056338
9              0.064427  0.070423
10             0.063461  0.071506
11             0.061530  0.060672
12             0.064151  0.050921
13             0.057529  0.062839
14             0.060978  0.061755
15             0.064013  0.053088
16             0.063048  0.057421
FraudFound_P       0    1
Deductible
300                6    2
400            13982  856
500              216   47
700              293   18
FraudFound_P          0         1
Deductible
300            0.000414  0.002167
400            0.964475  0.927411
500            0.014900  0.050921
700            0.020211  0.019502
FraudFound_P      0    1
DriverRating
1              3712  232
2              3587  214
3              3642  242
4              3556  235
FraudFound_P          0         1
DriverRating
1              0.256053  0.251354
2              0.247431  0.231853
3              0.251224  0.262189
4              0.245292  0.254605
FraudFound_P               0    1
Days_Policy_Accident
1 to 7                    13    1
```

```
15 to 30               46    3
8 to 15                50    5
more than 30        14342  905
none                   46    9
FraudFound_P                0         1
Days_Policy_Accident
1 to 7              0.000897  0.001083
15 to 30            0.003173  0.003250
8 to 15             0.003449  0.005417
more than 30        0.989308  0.980498
none                0.003173  0.009751
FraudFound_P          0    1
Days_Policy_Claim
15 to 30             50    6
8 to 15              18    3
more than 30      14428  914
none                  1    0
FraudFound_P             0         1
Days_Policy_Claim
15 to 30          0.003449  0.006501
8 to 15           0.001242  0.003250
more than 30      0.995240  0.990249
none              0.000069  0.000000
FraudFound_P          0    1
PastNumberOfClaims
1                  3351  222
2 to 4             5191  294
more than 4        1942   68
none               4013  339
FraudFound_P              0         1
PastNumberOfClaims
1                  0.231151  0.240520
2 to 4             0.358074  0.318527
more than 4        0.133959  0.073673
none               0.276816  0.367281
FraudFound_P     0    1
AgeOfVehicle
2 years         70    3
3 years        139   13
4 years        208   21
5 years       1262   95
6 years       3220  228
7 years       5482  325
more than 7   3775  206
new            341   32
FraudFound_P         0         1
AgeOfVehicle
2 years       0.004829  0.003250
```

```
3 years       0.009588  0.014085
4 years       0.014348  0.022752
5 years       0.087052  0.102925
6 years       0.222115  0.247021
7 years       0.378147  0.352113
more than 7   0.260399  0.223185
new           0.023522  0.034670
FraudFound_P          0    1
AgeOfPolicyHolder
16 to 17            289   31
18 to 20             13    2
21 to 25             92   16
26 to 30            580   33
31 to 35           5233  360
36 to 40           3806  237
41 to 50           2684  144
51 to 65           1322   70
over 65             478   30
FraudFound_P              0         1
AgeOfPolicyHolder
16 to 17           0.019935  0.033586
18 to 20           0.000897  0.002167
21 to 25           0.006346  0.017335
26 to 30           0.040008  0.035753
31 to 35           0.360971  0.390033
36 to 40           0.262537  0.256771
41 to 50           0.185142  0.156013
51 to 65           0.091191  0.075840
over 65            0.032972  0.032503
FraudFound_P           0    1
PoliceReportFiled
No                 14085  907
Yes                  412   16
FraudFound_P             0         1
PoliceReportFiled
No                 0.97158  0.982665
Yes                0.02842  0.017335
FraudFound_P        0    1
WitnessPresent
No              14413  920
Yes                84    3
FraudFound_P           0        1
WitnessPresent
No              0.994206  0.99675
Yes             0.005794  0.00325
FraudFound_P      0    1
AgentType
External      14260  919
```

```
Internal        237    4
FraudFound_P         0         1
AgentType
External      0.983652  0.995666
Internal      0.016348  0.004334
FraudFound_P            0    1
NumberOfSuppliments
1 to 2               2330  159
3 to 5               1920   97
more than 5          3672  195
none                 6575  472
FraudFound_P                0         1
NumberOfSuppliments
1 to 2               0.160723  0.172264
3 to 5               0.132441  0.105092
more than 5          0.253294  0.211268
none                 0.453542  0.511376
FraudFound_P             0    1
AddressChange_Claim
1 year                 159   11
2 to 3 years           240   51
4 to 8 years           598   33
no change            13499  825
under 6 months           1    3
FraudFound_P                0         1
AddressChange_Claim
1 year               0.010968  0.011918
2 to 3 years         0.016555  0.055255
4 to 8 years         0.041250  0.035753
no change            0.931158  0.893824
under 6 months       0.000069  0.003250
FraudFound_P      0    1
NumberOfCars
1 vehicle     13466  850
2 vehicles      666   43
3 to 4          343   29
5 to 8           20    1
more than 8       2    0
FraudFound_P         0         1
NumberOfCars
1 vehicle     0.928882  0.920910
2 vehicles    0.045941  0.046587
3 to 4        0.023660  0.031419
5 to 8        0.001380  0.001083
more than 8   0.000138  0.000000
FraudFound_P     0    1
Year
1994          5733  409
```

```
1995           4894  301
1996           3870  213
FraudFound_P          0         1
Year
1994           0.395461  0.443120
1995           0.337587  0.326111
1996           0.266952  0.230769
FraudFound_P      0     1
BasePolicy
All Perils     3997  452
Collision      5527  435
Liability      4973   36
FraudFound_P          0         1
BasePolicy
All Perils     0.275712  0.489707
Collision      0.381251  0.471289
Liability      0.343036  0.039003
```

# 4 Part 2 - Data preproccesing

### 4.0.1 2.a drop irrelevant colmuns

Function for dropping Irrelevant_colmuns - PolicyType, PolicyNumber

[ ]:
```python
def Irrelevant_col(df , drop):
    df.drop(drop, axis=1, inplace=True)


#drop in my data set
drop = ["PolicyType","PolicyNumber"]
dataset_new = dataset
Irrelevant_col(dataset_new, drop)

dataset_new
```

[ ]:
```
      Month  WeekOfMonth  DayOfWeek     Make AccidentArea DayOfWeekClaimed  \
0       Dec            5  Wednesday    Honda        Urban          Tuesday
1       Jan            3  Wednesday    Honda        Urban           Monday
2       Oct            5     Friday    Honda        Urban         Thursday
3       Jun            2   Saturday   Toyota        Rural           Friday
4       Jan            5     Monday    Honda        Urban          Tuesday
…       …          …         …       …          …              …
15415   Nov            4     Friday   Toyota        Urban          Tuesday
15416   Nov            5   Thursday  Pontiac        Urban           Friday
15417   Nov            5   Thursday   Toyota        Rural           Friday
15418   Dec            1     Monday   Toyota        Urban         Thursday
15419   Dec            2  Wednesday   Toyota        Urban         Thursday
```

```
      MonthClaimed  WeekOfMonthClaimed     Sex MaritalStatus  …  \
0              Jan                   1  Female        Single  …
1              Jan                   4    Male        Single  …
2              Nov                   2    Male       Married  …
3              Jul                   1    Male       Married  …
4              Feb                   2  Female        Single  …
…              …                   …     …             …   …
15415          Nov                   5    Male       Married  …
15416          Dec                   1    Male       Married  …
15417          Dec                   1    Male        Single  …
15418          Dec                   2  Female       Married  …
15419          Dec                   3    Male        Single  …

       AgeOfVehicle AgeOfPolicyHolder PoliceReportFiled WitnessPresent  \
0           3 years          26 to 30                No             No
1           6 years          31 to 35               Yes             No
2           7 years          41 to 50                No             No
3       more than 7          51 to 65               Yes             No
4           5 years          31 to 35                No             No
…               …               …                 …              …
15415       6 years          31 to 35                No             No
15416       6 years          31 to 35                No             No
15417       5 years          26 to 30                No             No
15418       2 years          31 to 35                No             No
15419       5 years          26 to 30                No             No

       AgentType  NumberOfSuppliments  AddressChange_Claim  NumberOfCars  \
0       External                 none               1 year        3 to 4
1       External                 none            no change     1 vehicle
2       External                 none            no change     1 vehicle
3       External          more than 5            no change     1 vehicle
4       External                 none            no change     1 vehicle
…            …                  …                  …             …
15415   External                 none            no change     1 vehicle
15416   External          more than 5            no change        3 to 4
15417   External               1 to 2            no change     1 vehicle
15418   External          more than 5            no change     1 vehicle
15419   External               1 to 2            no change     1 vehicle

       Year  BasePolicy
0      1994   Liability
1      1994   Collision
2      1994   Collision
3      1994   Liability
4      1994   Collision
…      …          …
15415  1996   Collision
```

```
15416  1996   Liability
15417  1996   Collision
15418  1996  All Perils
15419  1996   Collision

[15420 rows x 31 columns]
```

**2.b dealing non available values** changing the zero values to nan values in columns: Age, DayOfWeekClaimed, weekclaimed

```
[ ]: #Age
     print(sum(dataset['Age']  == 0))
     dataset.loc[dataset['Age'] == 0, 'Age'] = np.nan

     #DayOfWeekClaimed
     print(dataset['DayOfWeekClaimed'].unique())
     dataset[dataset['DayOfWeekClaimed'] == '0'] # obs 1516 has a
     dataset.loc[dataset['DayOfWeekClaimed'] == 0, 'DayOfWeekClaimed'] = np.nan

     #MonthClaimed
     print(sum(dataset['MonthClaimed']  == '0'))
     dataset.loc[dataset['MonthClaimed'] == '0', 'DayOfWeekClaimed'] = np.nan
```

```
320
['Tuesday' 'Monday' 'Thursday' 'Friday' 'Wednesday' 'Saturday' 'Sunday'
 '0']
1
```

Null values of age, day of week - replacing with mean

```
[ ]: # removing rows
     dataset_new_rem = dataset_new.dropna(subset = ['Age'])
     dataset_new_rem = dataset_new_rem.dropna(subset =['MonthClaimed'␣
      ↪,'DayOfWeekClaimed'])
     #print(dataset_new_rem.isnull().sum())

     # avereging
     imputer = SimpleImputer(missing_values=np.NaN, strategy='mean')
     # We instantiated a SimpleImputer object looking for missing values that are␣
      ↪represented
     #by np.NaN and asking Scikit-Learn to use the 'mean' as its strategy.
     #This means that any np.NaN values will be imputed by the columns mean.

     dataset_new_avg = dataset_new
     imputer=imputer.fit(dataset_new_avg[['Age']])
     dataset_new_avg[['Age']]=imputer.transform(dataset_new_avg[['Age']])
```

```
dataset_new_avg = dataset_new_avg.dropna(subset =['MonthClaimed'␣
 ↪,'DayOfWeekClaimed'])
#print(dataset_new_avg.isnull().sum())
```

### 4.0.2 2.c Dealing with categorials features

[ ]:
```
dataset_new.dtypes # can we see most of the variabales are categorial
```

[ ]:
```
Month                     object
WeekOfMonth                int64
DayOfWeek                 object
Make                      object
AccidentArea              object
DayOfWeekClaimed          object
MonthClaimed              object
WeekOfMonthClaimed         int64
Sex                       object
MaritalStatus             object
Age                      float64
Fault                     object
VehicleCategory           object
VehiclePrice              object
FraudFound_P               int64
RepNumber                  int64
Deductible                 int64
DriverRating               int64
Days_Policy_Accident      object
Days_Policy_Claim         object
PastNumberOfClaims        object
AgeOfVehicle              object
AgeOfPolicyHolder         object
PoliceReportFiled         object
WitnessPresent            object
AgentType                 object
NumberOfSuppliments       object
AddressChange_Claim       object
NumberOfCars              object
Year                       int64
BasePolicy                object
dtype: object
```

[ ]:
```
#make a copy of the data for making changes
y =  dataset_new.FraudFound_P.copy()
X = dataset_new.drop('FraudFound_P', axis = 1, inplace=False ).copy()
```

Binary variables zero one coding:

[ ]:
```
cols = ['AccidentArea', 'Sex', 'Fault', 'PoliceReportFiled', 'WitnessPresent',␣
 ↪'AgentType']
y_val = ['Urban','Female','Policy Holder', 'Yes', 'Yes','External']
x_val = ['Rural', 'Male', 'Third Party', 'No', 'No', 'Internal']

for i in range(len(cols)):
    X_idx1 = X[cols[i]]==y_val[i]
    X_idx2 = X[cols[i]]==x_val[i]

    X.loc[list(X_idx1),cols[i]]=1
    X.loc[list(X_idx2),cols[i]]=0

for i in range(len(cols)):
    X[cols[i]] = X[cols[i]].astype('int')

X.dtypes
```

[ ]:
```
Month                   object
WeekOfMonth              int64
DayOfWeek               object
Make                    object
AccidentArea             int64
DayOfWeekClaimed        object
MonthClaimed            object
WeekOfMonthClaimed       int64
Sex                      int64
MaritalStatus           object
Age                    float64
Fault                    int64
VehicleCategory         object
VehiclePrice            object
RepNumber                int64
Deductible               int64
DriverRating             int64
Days_Policy_Accident    object
Days_Policy_Claim       object
PastNumberOfClaims      object
AgeOfVehicle            object
AgeOfPolicyHolder       object
PoliceReportFiled        int64
WitnessPresent           int64
AgentType                int64
NumberOfSuppliments     object
AddressChange_Claim     object
NumberOfCars            object
Year                     int64
BasePolicy              object
```

```
dtype: object
```

Ordianal categorial featurs:

```
[ ]: col_ordering = [{'col':'Month','mapping':{'Jan':1,'Feb':2,'Mar':3,'Apr':4,'May':
     ↪5,'Jun':6,'Jul':7,'Aug':8,'Sep':9,'Oct':10,'Nov':11,'Dec':12}},
         {'col':'DayOfWeek','mapping':{'Monday':1,'Tuesday':2,'Wednesday':
     ↪3,'Thursday':4,'Friday':5,'Saturday':6,'Sunday':7}},
         {'col':'DayOfWeekClaimed','mapping':{'Monday':1,'Tuesday':2,'Wednesday':
     ↪3,'Thursday':4,'Friday':5,'Saturday':6,'Sunday':7}},
         {'col':'MonthClaimed','mapping':{'Jan':1,'Feb':2,'Mar':3,'Apr':4,'May':
     ↪5,'Jun':6,'Jul':7,'Aug':8,'Sep':9,'Oct':10,'Nov':11,'Dec':12}},
         {'col':'PastNumberOfClaims','mapping':{'none':0 ,'1':1,'2 to 4':2,'more␣
     ↪than 4':5 }},
         {'col':'NumberOfSuppliments','mapping':{'none':0,'1 to 2':1,'3 to 5':
     ↪3,'more than 5':6}},
         {'col':'VehiclePrice','mapping':{'more than 69000':69001,'20000 to 29000':
     ↪24500,'30000 to 39000':34500,'less than 20000':19999,
                                         '40000 to 59000':49500,'60000 to 69000':
     ↪64500}},
         {'col':'AgeOfVehicle','mapping':{'3 years':3,'6 years':6,'7 years':7,'more␣
     ↪than 7':8,'5 years':5,'new':0,'4 years':4,'2 years':2}},
     ]
     ord_encoder = OrdinalEncoder(mapping = col_ordering, return_df=True)
     X2 = ord_encoder.fit_transform(X)
     X2.loc[X2["DayOfWeekClaimed"] == -1.0,"DayOfWeekClaimed"] = 0
     X2.loc[X2["MonthClaimed"] == -1.0,"MonthClaimed"] = 0
```

ordianal categorial featurs - taking the avg for each category

```
[ ]: col_map = [{'Days_Policy_Accident':{'more than 30': 31,'15 to 30': 22.5,'none':␣
     ↪0,'1 to 7': 4,'8 to 15': 11.5}},
         {'Days_Policy_Claim':{'more than 30': 31,'15 to 30': 22.5,'8 to 15': 11.
     ↪5,'none': 0}},
         {'AgeOfPolicyHolder':{'26 to 30':28,'31 to 35':33,'41 to 50':45.5,'51 to␣
     ↪65':58,'21 to 25':23,'36 to 40':38,'16 to 17':16.5,
                                              'over 65':66,'18 to 20':19}},
         {'AddressChange_Claim':{'1 year':1,'no change':0,'4 to 8 years':6,'2 to 3␣
     ↪years':2.5,'under 6 months':0.5}},
         {'NumberOfCars':{'3 to 4':3.5,'1 vehicle':1,'2 vehicles':2,'5 to 8':6.
     ↪5,'more than 8':9}},
     ]

     X3 = X2.copy()
     for i in range(len(col_map)):
         X3.replace(col_map[i], inplace=True)
```

```
X3.dtypes
```

[ ]:
```
Month                        int64
WeekOfMonth                  int64
DayOfWeek                    int64
Make                        object
AccidentArea                 int64
DayOfWeekClaimed           float64
MonthClaimed               float64
WeekOfMonthClaimed           int64
Sex                          int64
MaritalStatus               object
Age                        float64
Fault                        int64
VehicleCategory             object
VehiclePrice                 int64
RepNumber                    int64
Deductible                   int64
DriverRating                 int64
Days_Policy_Accident       float64
Days_Policy_Claim          float64
PastNumberOfClaims           int64
AgeOfVehicle                 int64
AgeOfPolicyHolder          float64
PoliceReportFiled            int64
WitnessPresent               int64
AgentType                    int64
NumberOfSuppliments          int64
AddressChange_Claim        float64
NumberOfCars               float64
Year                         int64
BasePolicy                  object
dtype: object
```

One hot encoder for the categorial features

[ ]:
```
#implementing one-hot encoding
one_hot_encoder = OneHotEncoder(cols =␣
 ↪['Make','MaritalStatus','VehicleCategory','BasePolicy'],use_cat_names=True,␣
 ↪return_df=True)

#implementing label encoding, with random assignment of integers to each label
# assumes no natrual underlying order to the feature labels
ord_encoder1 = OrdinalEncoder(cols =␣
 ↪['Make','MaritalStatus','VehicleCategory','BasePolicy'],return_df=True)

#implementing binary encoding
```

```
#represents the data
bi_encoder = BinaryEncoder(cols =␣
↪['Make','MaritalStatus','VehicleCategory','BasePolicy'], return_df=True)

#implimented a simple switch to change how I wanted to encode the variables
#Allowed for a updating the independet variables quickly and not missing a code␣
↪box

switch_val = 0
if switch_val ==0:
    X4 = one_hot_encoder.fit_transform(X3)
elif switch_val==1:
    X4 = ord_encoder1.fit_transform(X3)
else:
    X4 = bi_encoder.fit_transform(X3)

X4.dtypes
```

[ ]:
```
Month                         int64
WeekOfMonth                   int64
DayOfWeek                     int64
Make_Honda                    int64
Make_Toyota                   int64
Make_Ford                     int64
Make_Mazda                    int64
Make_Chevrolet                int64
Make_Pontiac                  int64
Make_Accura                   int64
Make_Dodge                    int64
Make_Mercury                  int64
Make_Jaguar                   int64
Make_Nisson                   int64
Make_VW                       int64
Make_Saab                     int64
Make_Saturn                   int64
Make_Porche                   int64
Make_BMW                      int64
Make_Mecedes                  int64
Make_Ferrari                  int64
Make_Lexus                    int64
AccidentArea                  int64
DayOfWeekClaimed            float64
MonthClaimed                float64
WeekOfMonthClaimed            int64
Sex                           int64
MaritalStatus_Single          int64
MaritalStatus_Married         int64
```

```
MaritalStatus_Widow           int64
MaritalStatus_Divorced        int64
Age                         float64
Fault                         int64
VehicleCategory_Sport         int64
VehicleCategory_Utility       int64
VehicleCategory_Sedan         int64
VehiclePrice                  int64
RepNumber                     int64
Deductible                    int64
DriverRating                  int64
Days_Policy_Accident        float64
Days_Policy_Claim           float64
PastNumberOfClaims            int64
AgeOfVehicle                  int64
AgeOfPolicyHolder           float64
PoliceReportFiled             int64
WitnessPresent                int64
AgentType                     int64
NumberOfSuppliments           int64
AddressChange_Claim         float64
NumberOfCars                float64
Year                          int64
BasePolicy_Liability          int64
BasePolicy_Collision          int64
BasePolicy_All Perils         int64
dtype: object
```

[ ]:
```python
print(pearsonr(X4.Age, X4.AgeOfPolicyHolder))
print(pearsonr(X4.MonthClaimed, X4.Month))
print(pearsonr(X4.BasePolicy_Liability,X4.VehicleCategory_Sport))
```

```
(0.8995052651641743, 0.0)
(0.8335242937029943, 0.0)
(0.944432189599651, 0.0)
```

[ ]:
```python
X4.corr()
```

[ ]:
```
                           Month  WeekOfMonth  DayOfWeek  Make_Honda  \
Month                   1.000000     0.031442   0.000968   -0.021027
WeekOfMonth             0.031442     1.000000  -0.013370    0.012041
DayOfWeek               0.000968    -0.013370   1.000000   -0.000321
Make_Honda             -0.021027     0.012041  -0.000321    1.000000
Make_Toyota            -0.003369     0.004741   0.002423   -0.237332
Make_Ford               0.002855    -0.004448   0.000286   -0.081684
Make_Mazda              0.005397    -0.009569  -0.000881   -0.199975
Make_Chevrolet         -0.002603    -0.004139  -0.006622   -0.164797
```

| | | | | |
|---|---|---|---|---|
| Make_Pontiac | 0.018575 | -0.001375 | 0.014497 | -0.271162 |
| Make_Accura | 0.004674 | -0.001817 | -0.013943 | -0.083719 |
| Make_Dodge | -0.004390 | 0.018664 | -0.006279 | -0.039752 |
| Make_Mercury | 0.000380 | -0.002377 | -0.001814 | -0.034659 |
| Make_Jaguar | -0.004119 | -0.004422 | 0.001915 | -0.009295 |
| Make_Nisson | -0.003285 | 0.001534 | -0.005380 | -0.020801 |
| Make_VW | 0.004612 | -0.005693 | -0.015286 | -0.064420 |
| Make_Saab | -0.005218 | -0.003121 | 0.006975 | -0.039568 |
| Make_Saturn | -0.011811 | -0.007190 | 0.001683 | -0.028949 |
| Make_Porche | 0.006266 | -0.008233 | -0.016450 | -0.008485 |
| Make_BMW | 0.003070 | 0.005124 | 0.010386 | -0.014701 |
| Make_Mecedes | -0.004136 | -0.003610 | 0.003598 | -0.007589 |
| Make_Ferrari | 0.005274 | -0.011399 | -0.013280 | -0.005366 |
| Make_Lexus | -0.010184 | 0.013832 | -0.011424 | -0.003794 |
| AccidentArea | 0.002140 | 0.009116 | -0.025699 | 0.018914 |
| DayOfWeekClaimed | -0.006647 | 0.010013 | -0.056893 | -0.006690 |
| MonthClaimed | 0.833524 | 0.013915 | -0.003859 | -0.025446 |
| WeekOfMonthClaimed | 0.053917 | 0.275400 | 0.004716 | 0.002430 |
| Sex | 0.007397 | -0.005314 | -0.000990 | -0.025704 |
| MaritalStatus_Single | -0.009206 | 0.017114 | 0.017814 | 0.094790 |
| MaritalStatus_Married | 0.009206 | -0.015966 | -0.018147 | -0.093388 |
| MaritalStatus_Widow | 0.000114 | 0.006773 | 0.000499 | -0.004799 |
| MaritalStatus_Divorced | -0.000472 | -0.011459 | 0.002622 | -0.001934 |
| Age | -0.023429 | -0.011781 | -0.004563 | -0.056550 |
| Fault | 0.003619 | -0.025456 | -0.011941 | -0.012439 |
| VehicleCategory_Sport | -0.012695 | -0.003411 | -0.049847 | 0.087863 |
| VehicleCategory_Utility | 0.011504 | -0.008759 | -0.029359 | -0.066362 |
| VehicleCategory_Sedan | 0.008761 | 0.006206 | 0.058630 | -0.064946 |
| VehiclePrice | -0.036599 | -0.004793 | -0.028024 | 0.116680 |
| RepNumber | 0.009520 | 0.005283 | 0.002350 | 0.005572 |
| Deductible | -0.003074 | -0.003993 | 0.000393 | -0.018293 |
| DriverRating | 0.008318 | -0.016817 | 0.001387 | -0.010871 |
| Days_Policy_Accident | 0.003888 | -0.032973 | 0.000707 | -0.016398 |
| Days_Policy_Claim | 0.004077 | -0.017198 | 0.018507 | -0.016439 |
| PastNumberOfClaims | -0.023655 | -0.009283 | -0.032424 | -0.000574 |
| AgeOfVehicle | 0.027530 | -0.009798 | -0.008550 | -0.280443 |
| AgeOfPolicyHolder | 0.006801 | -0.002224 | 0.002434 | -0.159659 |
| PoliceReportFiled | 0.047896 | 0.013026 | 0.015406 | -0.017145 |
| WitnessPresent | -0.001515 | 0.013713 | 0.004251 | -0.008541 |
| AgentType | -0.023576 | -0.006477 | -0.003516 | 0.014614 |
| NumberOfSuppliments | 0.024617 | 0.000177 | -0.001544 | -0.066027 |
| AddressChange_Claim | 0.001477 | 0.000147 | 0.006422 | -0.006243 |
| NumberOfCars | -0.015607 | 0.002901 | -0.010573 | -0.001082 |
| Year | 0.048852 | -0.003906 | 0.007275 | -0.008792 |
| BasePolicy_Liability | -0.011205 | -0.004198 | -0.055095 | 0.023751 |
| BasePolicy_Collision | 0.032236 | -0.004401 | 0.039266 | 0.035583 |
| BasePolicy_All Perils | -0.023067 | 0.009069 | 0.014744 | -0.062796 |

| | Make_Toyota | Make_Ford | Make_Mazda | Make_Chevrolet | \ |
|---|---|---|---|---|---|
| Month | -0.003369 | 0.002855 | 0.005397 | -0.002603 | |
| WeekOfMonth | 0.004741 | -0.004448 | -0.009569 | -0.004139 | |
| DayOfWeek | 0.002423 | 0.000286 | -0.000881 | -0.006622 | |
| Make_Honda | -0.237332 | -0.081684 | -0.199975 | -0.164797 | |
| Make_Toyota | 1.000000 | -0.087339 | -0.213818 | -0.176205 | |
| Make_Ford | -0.087339 | 1.000000 | -0.073591 | -0.060646 | |
| Make_Mazda | -0.213818 | -0.073591 | 1.000000 | -0.148470 | |
| Make_Chevrolet | -0.176205 | -0.060646 | -0.148470 | 1.000000 | |
| Make_Pontiac | -0.289933 | -0.099789 | -0.244297 | -0.201322 | |
| Make_Accura | -0.089514 | -0.030809 | -0.075424 | -0.062156 | |
| Make_Dodge | -0.042503 | -0.014629 | -0.035813 | -0.029513 | |
| Make_Mercury | -0.037058 | -0.012755 | -0.031225 | -0.025732 | |
| Make_Jaguar | -0.009939 | -0.003421 | -0.008374 | -0.006901 | |
| Make_Nisson | -0.022241 | -0.007655 | -0.018740 | -0.015444 | |
| Make_VW | -0.068879 | -0.023707 | -0.058037 | -0.047828 | |
| Make_Saab | -0.042307 | -0.014561 | -0.035647 | -0.029377 | |
| Make_Saturn | -0.030953 | -0.010653 | -0.026081 | -0.021493 | |
| Make_Porche | -0.009072 | -0.003123 | -0.007644 | -0.006300 | |
| Make_BMW | -0.015719 | -0.005410 | -0.013245 | -0.010915 | |
| Make_Mecedes | -0.008114 | -0.002793 | -0.006837 | -0.005634 | |
| Make_Ferrari | -0.005737 | -0.001975 | -0.004834 | -0.003984 | |
| Make_Lexus | -0.004057 | -0.001396 | -0.003418 | -0.002817 | |
| AccidentArea | 0.003407 | -0.016896 | 0.017126 | -0.016928 | |
| DayOfWeekClaimed | 0.000462 | 0.017840 | 0.002158 | -0.004756 | |
| MonthClaimed | 0.003542 | 0.002124 | 0.007731 | -0.000558 | |
| WeekOfMonthClaimed | -0.009855 | -0.008962 | -0.003094 | 0.005526 | |
| Sex | 0.017835 | -0.035614 | 0.036963 | 0.009259 | |
| MaritalStatus_Single | -0.014755 | -0.049172 | 0.019583 | -0.022905 | |
| MaritalStatus_Married | 0.014124 | 0.048220 | -0.018698 | 0.023701 | |
| MaritalStatus_Widow | 0.009890 | 0.024116 | -0.008878 | -0.007938 | |
| MaritalStatus_Divorced | -0.003186 | -0.012202 | 0.001025 | -0.000847 | |
| Age | -0.006317 | 0.064238 | -0.048459 | 0.031309 | |
| Fault | -0.005060 | -0.003225 | -0.014332 | -0.004318 | |
| VehicleCategory_Sport | -0.038119 | -0.020521 | 0.044325 | -0.002228 | |
| VehicleCategory_Utility | -0.080226 | 0.060265 | -0.028319 | 0.116977 | |
| VehicleCategory_Sedan | 0.063618 | 0.000615 | -0.034441 | -0.035836 | |
| VehiclePrice | -0.158961 | 0.121485 | -0.034307 | 0.115709 | |
| RepNumber | 0.006306 | 0.001385 | -0.008413 | -0.004676 | |
| Deductible | 0.012321 | 0.004673 | -0.005070 | -0.000241 | |
| DriverRating | -0.002516 | 0.018409 | -0.005847 | 0.005576 | |
| Days_Policy_Accident | 0.009426 | -0.004023 | 0.006525 | 0.006661 | |
| Days_Policy_Claim | 0.011277 | 0.007675 | 0.007660 | 0.008044 | |
| PastNumberOfClaims | -0.036762 | 0.004081 | 0.001717 | 0.033660 | |
| AgeOfVehicle | 0.036972 | 0.068598 | 0.019212 | 0.060899 | |
| AgeOfPolicyHolder | 0.024686 | 0.068059 | -0.022503 | 0.043510 | |

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|---|---|---|---|---|
| PoliceReportFiled | -0.004546 | 0.017613 | 0.010605 | 0.010567 |
| WitnessPresent | -0.007777 | 0.002372 | -0.007899 | -0.001345 |
| AgentType | 0.008820 | -0.021641 | 0.006964 | -0.023030 |
| NumberOfSuppliments | -0.004340 | 0.024850 | 0.008689 | 0.018211 |
| AddressChange_Claim | 0.003370 | -0.008070 | 0.007222 | 0.012737 |
| NumberOfCars | 0.004898 | -0.010908 | 0.002509 | -0.003452 |
| Year | 0.000350 | 0.000522 | -0.001274 | -0.003507 |
| BasePolicy_Liability | -0.015102 | -0.012486 | 0.023229 | 0.019971 |
| BasePolicy_Collision | -0.019789 | -0.027682 | 0.065110 | -0.023050 |
| BasePolicy_All Perils | 0.036880 | 0.042660 | -0.093993 | 0.004131 |

| | Make_Pontiac | Make_Accura | … | PoliceReportFiled \ |
|---|---|---|---|---|
| Month | 0.018575 | 0.004674 | … | 0.047896 |
| WeekOfMonth | -0.001375 | -0.001817 | … | 0.013026 |
| DayOfWeek | 0.014497 | -0.013943 | … | 0.015406 |
| Make_Honda | -0.271162 | -0.083719 | … | -0.017145 |
| Make_Toyota | -0.289933 | -0.089514 | … | -0.004546 |
| Make_Ford | -0.099789 | -0.030809 | … | 0.017613 |
| Make_Mazda | -0.244297 | -0.075424 | … | 0.010605 |
| Make_Chevrolet | -0.201322 | -0.062156 | … | 0.010567 |
| Make_Pontiac | 1.000000 | -0.102274 | … | 0.000456 |
| Make_Accura | -0.102274 | 1.000000 | … | 0.002061 |
| Make_Dodge | -0.048562 | -0.014993 | … | 0.004592 |
| Make_Mercury | -0.042340 | -0.013072 | … | -0.007034 |
| Make_Jaguar | -0.011355 | -0.003506 | … | -0.003334 |
| Make_Nisson | -0.025411 | -0.007846 | … | -0.007460 |
| Make_VW | -0.078697 | -0.024297 | … | 0.003368 |
| Make_Saab | -0.048337 | -0.014924 | … | -0.014190 |
| Make_Saturn | -0.035365 | -0.010919 | … | -0.010382 |
| Make_Porche | -0.010366 | -0.003200 | … | -0.003043 |
| Make_BMW | -0.017960 | -0.005545 | … | -0.005272 |
| Make_Mecedes | -0.009271 | -0.002862 | … | -0.002722 |
| Make_Ferrari | -0.006555 | -0.002024 | … | -0.001924 |
| Make_Lexus | -0.004635 | -0.001431 | … | -0.001361 |
| AccidentArea | -0.009039 | -0.003812 | … | 0.001754 |
| DayOfWeekClaimed | -0.009994 | 0.014267 | … | -0.010992 |
| MonthClaimed | 0.009767 | 0.004594 | … | 0.056724 |
| WeekOfMonthClaimed | 0.008607 | 0.001928 | … | 0.023510 |
| Sex | 0.011474 | -0.044583 | … | 0.007413 |
| MaritalStatus_Single | -0.020723 | -0.046151 | … | 0.012010 |
| MaritalStatus_Married | 0.020141 | 0.047801 | … | -0.011863 |
| MaritalStatus_Widow | -0.002235 | -0.008475 | … | 0.000237 |
| MaritalStatus_Divorced | 0.004474 | -0.007130 | … | -0.000617 |
| Age | 0.021635 | 0.034908 | … | -0.009089 |
| Fault | 0.003240 | 0.040838 | … | -0.027246 |
| VehicleCategory_Sport | -0.044810 | -0.052978 | … | -0.038732 |
| VehicleCategory_Utility | -0.014593 | 0.155737 | … | -0.007164 |

| | | | | |
|---|---|---|---|---|
| VehicleCategory_Sedan | 0.048869 | 0.001537 | … | 0.040469 |
| VehiclePrice | -0.175717 | 0.128124 | … | 0.009106 |
| RepNumber | -0.006369 | 0.004411 | … | 0.006107 |
| Deductible | 0.004569 | -0.004595 | … | 0.009005 |
| DriverRating | 0.011696 | -0.011854 | … | 0.015947 |
| Days_Policy_Accident | 0.005114 | -0.013999 | … | -0.017292 |
| Days_Policy_Claim | -0.003102 | -0.010459 | … | -0.009508 |
| PastNumberOfClaims | -0.000443 | 0.004945 | … | -0.005798 |
| AgeOfVehicle | 0.080781 | 0.057802 | … | -0.001556 |
| AgeOfPolicyHolder | 0.050527 | 0.036382 | … | -0.005590 |
| PoliceReportFiled | 0.000456 | 0.002061 | … | 1.000000 |
| WitnessPresent | 0.022733 | 0.011746 | … | 0.198096 |
| AgentType | 0.006009 | -0.004926 | … | -0.023268 |
| NumberOfSuppliments | 0.028510 | -0.004655 | … | 0.005256 |
| AddressChange_Claim | -0.009144 | -0.000589 | … | -0.007406 |
| NumberOfCars | -0.008096 | 0.004527 | … | -0.024648 |
| Year | 0.014070 | -0.011705 | … | 0.021206 |
| BasePolicy_Liability | -0.019347 | -0.043670 | … | -0.041331 |
| BasePolicy_Collision | -0.014644 | -0.044448 | … | 0.034467 |
| BasePolicy_All Perils | 0.035737 | 0.092914 | … | 0.005675 |

| | WitnessPresent | AgentType | NumberOfSuppliments | \ |
|---|---|---|---|---|
| Month | -0.001515 | -0.023576 | 0.024617 | |
| WeekOfMonth | 0.013713 | -0.006477 | 0.000177 | |
| DayOfWeek | 0.004251 | -0.003516 | -0.001544 | |
| Make_Honda | -0.008541 | 0.014614 | -0.066027 | |
| Make_Toyota | -0.007777 | 0.008820 | -0.004340 | |
| Make_Ford | 0.002372 | -0.021641 | 0.024850 | |
| Make_Mazda | -0.007899 | 0.006964 | 0.008689 | |
| Make_Chevrolet | -0.001345 | -0.023030 | 0.018211 | |
| Make_Pontiac | 0.022733 | 0.006009 | 0.028510 | |
| Make_Accura | 0.011746 | -0.004926 | -0.004655 | |
| Make_Dodge | -0.006356 | -0.008091 | 0.002071 | |
| Make_Mercury | -0.005541 | 0.009269 | 0.001484 | |
| Make_Jaguar | -0.001486 | 0.002486 | -0.003123 | |
| Make_Nisson | -0.003326 | 0.005563 | 0.005496 | |
| Make_VW | -0.010300 | -0.021724 | 0.018432 | |
| Make_Saab | 0.004056 | 0.010582 | 0.003355 | |
| Make_Saturn | -0.004628 | -0.009340 | -0.003591 | |
| Make_Porche | -0.001357 | 0.002269 | -0.009155 | |
| Make_BMW | -0.002351 | -0.012840 | 0.003464 | |
| Make_Mecedes | -0.001213 | 0.002030 | -0.013393 | |
| Make_Ferrari | -0.000858 | 0.001435 | -0.000269 | |
| Make_Lexus | -0.000607 | 0.001015 | -0.003443 | |
| AccidentArea | -0.028362 | 0.005189 | -0.018695 | |
| DayOfWeekClaimed | -0.002415 | -0.005900 | 0.003279 | |
| MonthClaimed | 0.001021 | -0.032042 | 0.034534 | |

| | | | |
|---|---|---|---|
| WeekOfMonthClaimed | 0.009369 | 0.011314 | 0.011589 |
| Sex | 0.005585 | 0.012681 | -0.010698 |
| MaritalStatus_Single | 0.010492 | -0.003176 | -0.026884 |
| MaritalStatus_Married | -0.011123 | 0.003455 | 0.029001 |
| MaritalStatus_Widow | 0.014601 | -0.015964 | -0.005530 |
| MaritalStatus_Divorced | -0.005301 | 0.008868 | -0.011388 |
| Age | -0.007501 | 0.007343 | 0.034230 |
| Fault | -0.061036 | 0.005306 | -0.011595 |
| VehicleCategory_Sport | -0.027693 | -0.044206 | 0.023742 |
| VehicleCategory_Utility | 0.004373 | 0.007021 | 0.003354 |
| VehicleCategory_Sedan | 0.025848 | 0.041248 | -0.024469 |
| VehiclePrice | 0.010224 | -0.018714 | 0.007826 |
| RepNumber | 0.007521 | -0.005630 | 0.005764 |
| Deductible | 0.000586 | 0.004244 | 0.010341 |
| DriverRating | 0.010489 | 0.000262 | 0.001989 |
| Days_Policy_Accident | -0.023680 | -0.010436 | 0.074091 |
| Days_Policy_Claim | -0.003147 | -0.008176 | 0.051378 |
| PastNumberOfClaims | -0.011111 | 0.011332 | 0.102582 |
| AgeOfVehicle | -0.008419 | -0.020840 | 0.151374 |
| AgeOfPolicyHolder | -0.001870 | 0.003847 | 0.068239 |
| PoliceReportFiled | 0.198096 | -0.023268 | 0.005256 |
| WitnessPresent | 1.000000 | -0.011450 | -0.015419 |
| AgentType | -0.011450 | 1.000000 | -0.033347 |
| NumberOfSuppliments | -0.015419 | -0.033347 | 1.000000 |
| AddressChange_Claim | -0.005944 | 0.026692 | -0.008348 |
| NumberOfCars | -0.012535 | -0.000356 | -0.004290 |
| Year | -0.015503 | -0.018993 | 0.014884 |
| BasePolicy_Liability | -0.039307 | -0.055502 | 0.041335 |
| BasePolicy_Collision | 0.020201 | -0.021279 | -0.006172 |
| BasePolicy_All Perils | 0.018916 | 0.080241 | -0.036091 |

| | AddressChange_Claim | NumberOfCars | Year | \ |
|---|---|---|---|---|
| Month | 0.001477 | -0.015607 | 0.048852 | |
| WeekOfMonth | 0.000147 | 0.002901 | -0.003906 | |
| DayOfWeek | 0.006422 | -0.010573 | 0.007275 | |
| Make_Honda | -0.006243 | -0.001082 | -0.008792 | |
| Make_Toyota | 0.003370 | 0.004898 | 0.000350 | |
| Make_Ford | -0.008070 | -0.010908 | 0.000522 | |
| Make_Mazda | 0.007222 | 0.002509 | -0.001274 | |
| Make_Chevrolet | 0.012737 | -0.003452 | -0.003507 | |
| Make_Pontiac | -0.009144 | -0.008096 | 0.014070 | |
| Make_Accura | -0.000589 | 0.004527 | -0.011705 | |
| Make_Dodge | 0.003389 | 0.018415 | 0.006316 | |
| Make_Mercury | -0.007733 | -0.009234 | -0.002115 | |
| Make_Jaguar | 0.011178 | 0.019147 | -0.009001 | |
| Make_Nisson | -0.000738 | -0.007452 | 0.005507 | |
| Make_VW | 0.002166 | -0.001995 | 0.006489 | |

| | | | |
|---|---|---|---|
| Make_Saab | 0.004546 | 0.025127 | -0.012177 |
| Make_Saturn | -0.007866 | 0.004039 | 0.000982 |
| Make_Porche | -0.004454 | -0.004283 | -0.001490 |
| Make_BMW | -0.004330 | 0.011969 | 0.010366 |
| Make_Mecedes | 0.004210 | -0.003831 | -0.007349 |
| Make_Ferrari | -0.002816 | -0.002709 | 0.008982 |
| Make_Lexus | -0.001991 | -0.001915 | 0.001339 |
| AccidentArea | -0.017305 | -0.005518 | 0.002284 |
| DayOfWeekClaimed | -0.001619 | 0.006807 | 0.003126 |
| MonthClaimed | 0.001160 | -0.009481 | 0.053457 |
| WeekOfMonthClaimed | 0.009449 | 0.005903 | 0.012175 |
| Sex | 0.001692 | 0.001159 | -0.000413 |
| MaritalStatus_Single | 0.002666 | -0.004618 | -0.015370 |
| MaritalStatus_Married | -0.000171 | 0.002773 | 0.013732 |
| MaritalStatus_Widow | -0.011795 | -0.011344 | 0.007928 |
| MaritalStatus_Divorced | -0.008360 | 0.019707 | 0.004782 |
| Age | -0.006791 | -0.003163 | 0.016506 |
| Fault | 0.007316 | 0.009841 | -0.011158 |
| VehicleCategory_Sport | 0.001876 | -0.004146 | 0.000584 |
| VehicleCategory_Utility | 0.006275 | -0.006745 | -0.005028 |
| VehicleCategory_Sedan | -0.003887 | 0.006276 | 0.001060 |
| VehiclePrice | -0.004111 | -0.013551 | -0.031859 |
| RepNumber | -0.002964 | -0.011262 | 0.009338 |
| Deductible | 0.061006 | -0.000276 | -0.001170 |
| DriverRating | 0.007585 | 0.010840 | -0.013890 |
| Days_Policy_Accident | 0.004967 | -0.001763 | -0.006536 |
| Days_Policy_Claim | -0.001585 | -0.008215 | -0.003559 |
| PastNumberOfClaims | -0.015250 | -0.005299 | 0.013785 |
| AgeOfVehicle | -0.003621 | 0.008260 | 0.020945 |
| AgeOfPolicyHolder | -0.006269 | -0.001538 | 0.025193 |
| PoliceReportFiled | -0.007406 | -0.024648 | 0.021206 |
| WitnessPresent | -0.005944 | -0.012535 | -0.015503 |
| AgentType | 0.026692 | -0.000356 | -0.018993 |
| NumberOfSuppliments | -0.008348 | -0.004290 | 0.014884 |
| AddressChange_Claim | 1.000000 | 0.392163 | -0.000286 |
| NumberOfCars | 0.392163 | 1.000000 | -0.003109 |
| Year | -0.000286 | -0.003109 | 1.000000 |
| BasePolicy_Liability | 0.005068 | 0.000251 | 0.009971 |
| BasePolicy_Collision | 0.000856 | 0.000814 | 0.004989 |
| BasePolicy_All Perils | -0.006158 | -0.001135 | -0.015669 |

| | BasePolicy_Liability | BasePolicy_Collision | \ |
|---|---|---|---|
| Month | -0.011205 | 0.032236 | |
| WeekOfMonth | -0.004198 | -0.004401 | |
| DayOfWeek | -0.055095 | 0.039266 | |
| Make_Honda | 0.023751 | 0.035583 | |
| Make_Toyota | -0.015102 | -0.019789 | |

| | | |
|---|---|---|
| Make_Ford | -0.012486 | -0.027682 |
| Make_Mazda | 0.023229 | 0.065110 |
| Make_Chevrolet | 0.019971 | -0.023050 |
| Make_Pontiac | -0.019347 | -0.014644 |
| Make_Accura | -0.043670 | -0.044448 |
| Make_Dodge | 0.010897 | 0.014077 |
| Make_Mercury | -0.018853 | -0.007446 |
| Make_Jaguar | 0.007379 | -0.008912 |
| Make_Nisson | -0.011769 | -0.007855 |
| Make_VW | 0.026897 | -0.028196 |
| Make_Saab | -0.013421 | 0.008372 |
| Make_Saturn | -0.019999 | -0.007451 |
| Make_Porche | 0.002891 | 0.000494 |
| Make_BMW | 0.005008 | -0.007688 |
| Make_Mecedes | -0.011173 | 0.003750 |
| Make_Ferrari | -0.007900 | 0.014345 |
| Make_Lexus | -0.005586 | 0.010143 |
| AccidentArea | 0.056380 | -0.038078 |
| DayOfWeekClaimed | -0.011861 | -0.006669 |
| MonthClaimed | -0.006066 | 0.040181 |
| WeekOfMonthClaimed | 0.018027 | -0.012527 |
| Sex | 0.061632 | -0.006469 |
| MaritalStatus_Single | 0.031454 | 0.016498 |
| MaritalStatus_Married | -0.028541 | -0.019580 |
| MaritalStatus_Widow | -0.006895 | 0.015300 |
| MaritalStatus_Divorced | -0.013224 | 0.010678 |
| Age | -0.001519 | -0.104799 |
| Fault | 0.197380 | -0.057170 |
| VehicleCategory_Sport | 0.944432 | -0.482044 |
| VehicleCategory_Utility | -0.093382 | -0.102649 |
| VehicleCategory_Sedan | -0.899640 | 0.508049 |
| VehiclePrice | 0.006224 | -0.023956 |
| RepNumber | 0.003231 | -0.011935 |
| Deductible | 0.018619 | -0.016765 |
| DriverRating | -0.000548 | -0.007651 |
| Days_Policy_Accident | 0.037864 | -0.025045 |
| Days_Policy_Claim | 0.021651 | -0.018703 |
| PastNumberOfClaims | 0.357783 | -0.143489 |
| AgeOfVehicle | -0.010160 | -0.021768 |
| AgeOfPolicyHolder | -0.018736 | -0.076071 |
| PoliceReportFiled | -0.041331 | 0.034467 |
| WitnessPresent | -0.039307 | 0.020201 |
| AgentType | -0.055502 | -0.021279 |
| NumberOfSuppliments | 0.041335 | -0.006172 |
| AddressChange_Claim | 0.005068 | 0.000856 |
| NumberOfCars | 0.000251 | 0.000814 |
| Year | 0.009971 | 0.004989 |

| | | |
|---|---|---|
| BasePolicy_Liability | 1.000000 | -0.550713 |
| BasePolicy_Collision | -0.550713 | 1.000000 |
| BasePolicy_All Perils | -0.441710 | -0.505597 |

| | BasePolicy_All Perils |
|---|---|
| Month | -0.023067 |
| WeekOfMonth | 0.009069 |
| DayOfWeek | 0.014744 |
| Make_Honda | -0.062796 |
| Make_Toyota | 0.036880 |
| Make_Ford | 0.042660 |
| Make_Mazda | -0.093993 |
| Make_Chevrolet | 0.004131 |
| Make_Pontiac | 0.035737 |
| Make_Accura | 0.092914 |
| Make_Dodge | -0.026394 |
| Make_Mercury | 0.027490 |
| Make_Jaguar | 0.001951 |
| Make_Nisson | 0.020608 |
| Make_VW | 0.002504 |
| Make_Saab | 0.004874 |
| Make_Saturn | 0.028680 |
| Make_Porche | -0.003519 |
| Make_BMW | 0.003086 |
| Make_Mecedes | 0.007519 |
| Make_Ferrari | -0.007253 |
| Make_Lexus | -0.005128 |
| AccidentArea | -0.017349 |
| DayOfWeekClaimed | 0.019428 |
| MonthClaimed | -0.036919 |
| WeekOfMonthClaimed | -0.005169 |
| Sex | -0.056752 |
| MaritalStatus_Single | -0.050245 |
| MaritalStatus_Married | 0.050546 |
| MaritalStatus_Widow | -0.009319 |
| MaritalStatus_Divorced | 0.002192 |
| Age | 0.114212 |
| Fault | -0.142571 |
| VehicleCategory_Sport | -0.458081 |
| VehicleCategory_Utility | 0.206853 |
| VehicleCategory_Sedan | 0.383832 |
| VehiclePrice | 0.019315 |
| RepNumber | 0.009489 |
| Deductible | -0.001226 |
| DriverRating | 0.008790 |
| Days_Policy_Accident | -0.012219 |
| Days_Policy_Claim | -0.002277 |

```
PastNumberOfClaims                          -0.215590
AgeOfVehicle                                 0.033899
AgeOfPolicyHolder                            0.101130
PoliceReportFiled                            0.005675
WitnessPresent                               0.018916
AgentType                                    0.080241
NumberOfSuppliments                         -0.036091
AddressChange_Claim                         -0.006158
NumberOfCars                                -0.001135
Year                                        -0.015669
BasePolicy_Liability                        -0.441710
BasePolicy_Collision                        -0.505597
BasePolicy_All Perils                        1.000000

[55 rows x 55 columns]
```

Drop Make_% for avoiding sparse Matrix Drop AgePolicyHolder beacuse 0.96 corr with Age

```
[ ]: drop = ['Make_Honda', 'Make_Toyota','Make_Toyota',␣
      ↪'Make_Ford','Make_Mazda','Make_Chevrolet','Make_Pontiac',
             'Make_Accura', 'Make_Accura','Make_Dodge', 'Make_Mercury',␣
      ↪'Make_Jaguar','Make_Nisson','Make_VW','Make_Saab',
           ␣
      ↪'Make_Saturn','Make_Porche','Make_BMW','Make_BMW','Make_Mecedes','Make_Ferrari','Make_Lexus
             'AgeOfPolicyHolder']
     X5 = X4.copy()
     Irrelevant_col(X5, drop)
```

### 4.0.3 2.d splitting our data to train, validation and test sets

```
[ ]: # splitting function
     def train_val_test_split(X, y, train_ratio, validation_ratio, test_ratio):
         X_train, X_test, y_train, y_test = train_test_split(X, y,␣
      ↪test_size=test_ratio, random_state = 3)
         X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train,
                                                          test_size=␣
      ↪validation_ratio/(train_ratio+validation_ratio), random_state =2022)
         return X_train, y_train, X_valid, y_valid,  X_test, y_test
```

```
[ ]: # with out drop AgeOfPolictyHolder and Make_%
     X_train, y_train, X_valid, y_valid,  X_test, y_test = train_val_test_split(X=␣
      ↪X4, y = y, train_ratio= 0.7, validation_ratio= 0.2, test_ratio = 0.1)

     print(X_train.shape)
     print(X_test.shape)
     print(X_valid.shape)
```

```
print(y_train.shape)
print(y_test.shape)
print(y_valid.shape)
print(len(y_valid)/len(y))
```

```
(10793, 55)
(1542, 55)
(3085, 55)
(10793,)
(1542,)
(3085,)
0.20006485084306097
```

[ ]:
```
#final splitting including all preproccesing
X_train1, y_train1, X_valid1, y_valid1,  X_test1, y_test1 =␣
↪train_val_test_split(X= X5, y = y, train_ratio= 0.7, validation_ratio= 0.2,␣
↪test_ratio = 0.1)

print(X_train1.shape)
print(X_test1.shape)
print(X_valid1.shape)
print(y_train1.shape)
print(y_test1.shape)
print(y_valid1.shape)
print(len(y_valid1)/len(y))
```

```
(10793, 35)
(1542, 35)
(3085, 35)
(10793,)
(1542,)
(3085,)
0.20006485084306097
```

# 5 Part 3 - Techniques for imbalance dataset

### 5.0.1 3.a oversampling

[ ]:
```
print('Original traim shape %s' % Counter(y_train1))
sm = SMOTE(random_state=2022)
X_res1, y_res1 = sm.fit_resample(X_train1, y_train1)
print('Resampled train shape %s' % Counter(y_res1))
```

```
Original train shape Counter({0: 10131, 1: 662})
Resampled train shape Counter({0: 10131, 1: 10131})
```

### 5.0.2 3.b undersampling

[ ]:
```
undersample = NearMiss(version=1, n_neighbors=3)
# transform the dataset
X_under1, y_under1 = undersample.fit_resample(X_train1, y_train1)
# summarize the new class distribution
print('Resampled train shape %s' % Counter(y_under1))
```

```
Resampled train shape Counter({0: 662, 1: 662})
```

### 5.0.3 3.c Feature selection decompositon

[ ]:
```
# input: train sample, m - number of fetures to select, K vec of clusters for␣
↪each class, La - label for train
# K = (num_clusters_maority, num_clusters minority)
#  first phase: local clustering
    # for each class
        # kmeans_cluster(tr(class), K[class])
        # relab;e(label(class), label(new_subclass))
# 2nd_phase: feature sellect
    # select M best of mutual information method
#    return train_M_best
from sklearn.cluster import KMeans

def decomp_fs_names(X, y, k, m):
    X_majority1 = X[y == 0]
    X_minority1 = X[y == 1]
    k_cluster = KMeans(n_clusters= k, random_state=2022)
    k_cluster = k_cluster.fit(X_majority1)
    labels= k_cluster.labels_ + 2
    labels = np.append(labels, np.repeat(1, sum(y == 1)))
    X_new1= X_majority1.copy()
    X_new1= pd.concat([X_new1 , X_minority1 ])
    X_comp_filter1 = SelectKBest(mutual_info_classif, k=m).fit(X_new1, labels)
    # names chosen by compision based Feature Selection
    comp_names = X_comp_filter1.feature_names_in_[X_comp_filter1.
↪get_support(indices=True)]
    return comp_names
```

# 6 Part 4 - Build classifiers

RF - baseline

[ ]:
```
# Random forest
rf = RandomForestClassifier(n_estimators = 100, max_features ='sqrt',␣
↪random_state = 3, max_depth =5)
rf.fit(X_train1, y_train1)
```

```
rf_pred = rf.predict(X_valid1)
```

RF - SMOTH

```
[ ]: rf_smoth1 = RandomForestClassifier(n_estimators = 100, max_features ='sqrt',␣
      ↪random_state = 2022, max_depth =5)
     rf_smoth1.fit(X_res1, y_res1)
     rf_smoth1_pred = rf_smoth1.predict(X_valid1)
```

RF-NearMiss

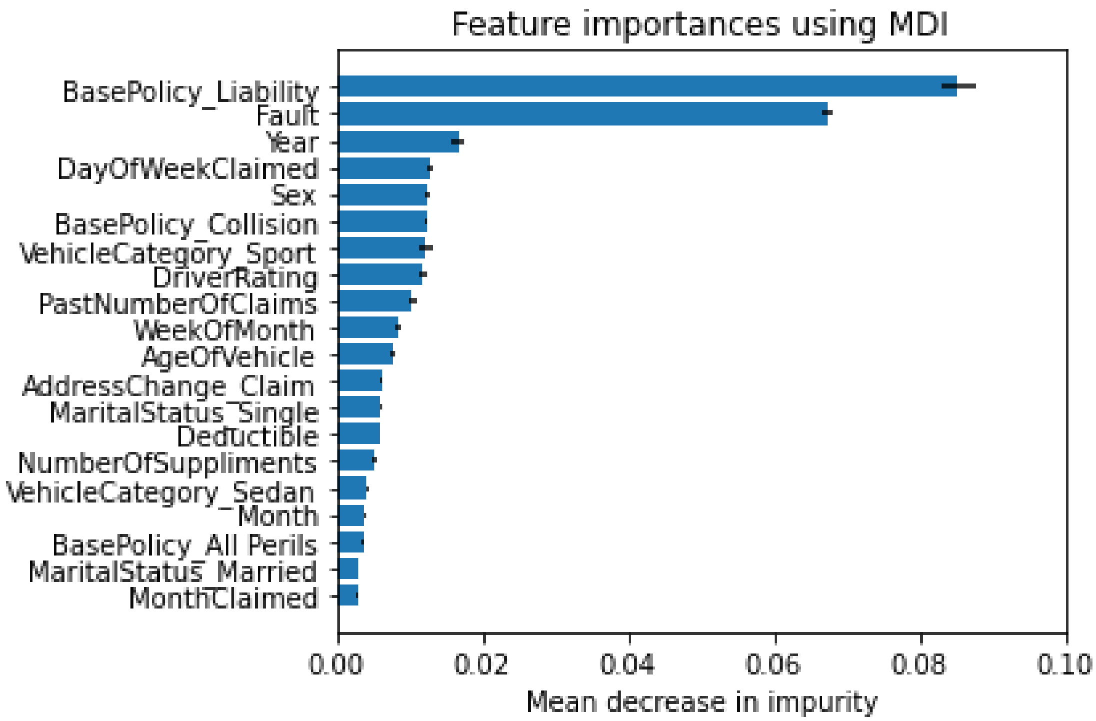
```
[ ]: rf_nearmiss1 = RandomForestClassifier(n_estimators = 100, max_features ='sqrt',␣
      ↪random_state = 2022, max_depth =5)
     rf_nearmiss1.fit(X_under1, y_under1)
     rf_nearmiss1_pred = rf_nearmiss1.predict(X_valid1)
```

RF- CS

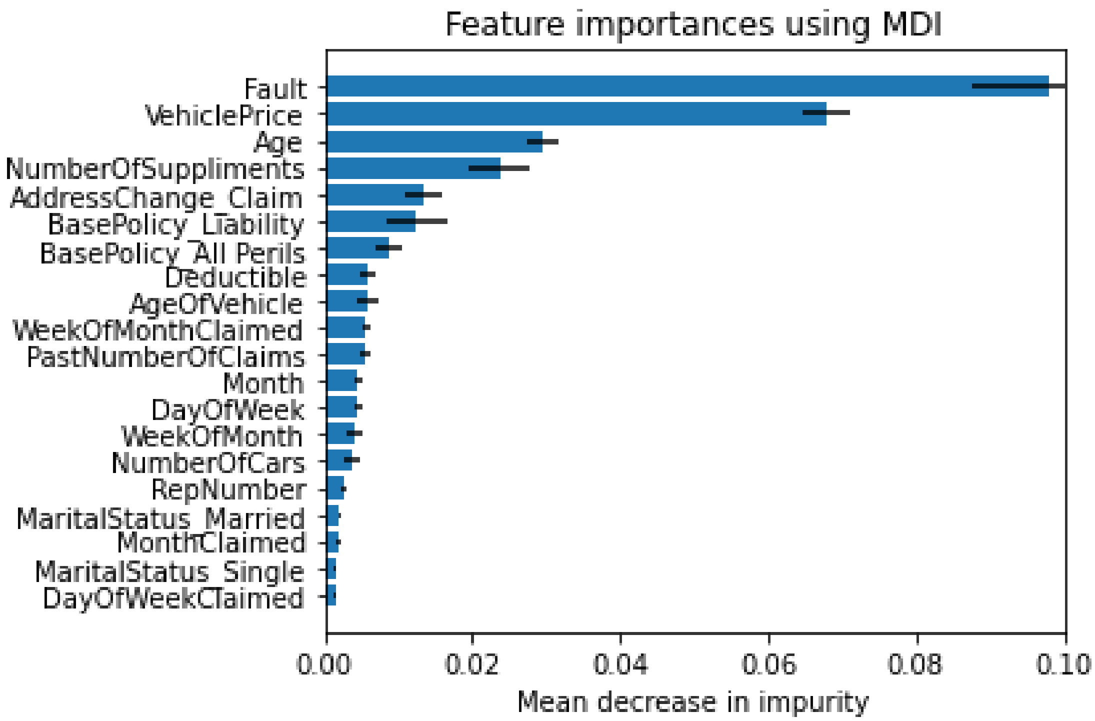
```
[ ]: rf_cs1 = RandomForestClassifier(n_estimators = 100, max_features ='sqrt',␣
      ↪random_state = 2022, max_depth =5,
                                        class_weight={0: 1 ,1:16})
     rf_cs1.fit(X_train1, y_train1)
     rf_cs1_pred = rf_cs1.predict(X_valid1)
```

feature importance for RF classifiers

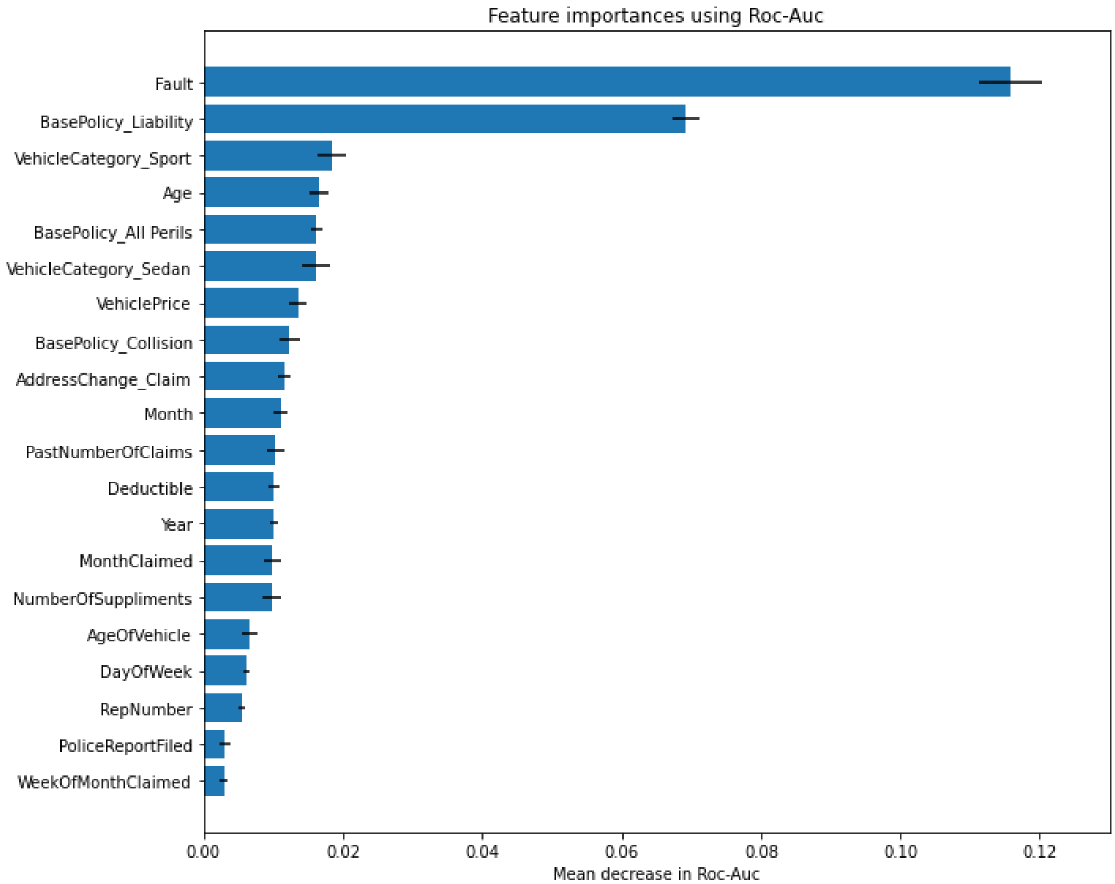
```
[ ]: # RF-SMOTH-X5
     feature_names = [f"feature {i}" for i in range(X_res1.shape[1])]
     results = permutation_importance(rf_smoth1, X_res1, y_res1, scoring='roc_auc')
     # get importance
     importance = results.importances_mean
     std = results.importances_std
     std = pd.Series(std, index = X_res1.columns)
     forest_importances = pd.Series(importance, index=X_res1.columns)
     forest_importances = forest_importances.sort_values(ascending=False)
     std = std[forest_importances.index[0:20]]
     fig, ax = plt.subplots()
     ax.barh(forest_importances.index[0:20], forest_importances[0:20], xerr=std,␣
      ↪align='center')
     ax.invert_yaxis()  # labels read top-to-bottom
     ax.set_title("Feature importances using MDI")
     ax.set_xlabel("Mean decrease in impurity")
     plt.xlim(0,0.1)
     fig.tight_layout()
```




[ ]:
```
# RF-NearMiss-X5
feature_names = [f"feature {i}" for i in range(X_under1.shape[1])]
results = permutation_importance(rf_nearmiss1, X_under1, y_under1,
    scoring='roc_auc')
# get importance
importance = results.importances_mean
std = results.importances_std
std = pd.Series(std, index = X_under1.columns)
forest_importances = pd.Series(importance, index=X_under1.columns)
forest_importances = forest_importances.sort_values(ascending=False)
std = std[forest_importances.index[0:20]]
fig, ax = plt.subplots()
ax.barh(forest_importances.index[0:20], forest_importances[0:20], xerr=std,
    align='center')
ax.invert_yaxis()  # labels read top-to-bottom
ax.set_title("Feature importances using MDI")
ax.set_xlabel("Mean decrease in impurity")
plt.xlim(0,0.1)
fig.tight_layout()
```




[ ]:
```
# RF-CS-X5
feature_names = [f"feature {i}" for i in range(X_train1.shape[1])]
results = permutation_importance(rf_cs1, X_train1, y_train1, scoring='roc_auc')
# get importance
importance = results.importances_mean
std = results.importances_std
std = pd.Series(std, index = X_train1.columns)
forest_importances = pd.Series(importance, index=X_train1.columns)
forest_importances = forest_importances.sort_values(ascending=False)
std = std[forest_importances.index[0:20]]
fig, ax = plt.subplots(figsize=(10,8))
ax.barh(forest_importances.index[0:20], forest_importances[0:20], xerr=std,␣
↪align='center')
ax.invert_yaxis()  # labels read top-to-bottom
ax.set_title("Feature importances using Roc-Auc")
ax.set_xlabel("Mean decrease in Roc-Auc")
plt.xlim(0,0.13)
fig.tight_layout()
```




NB- SMOTH

[ ]:
```
random.seed(2022)
mutual_filter = SelectKBest(mutual_info_classif, k=11)
naiv_b = BernoulliNB(alpha=1)
nb_smoth1 = make_pipeline(mutual_filter, StandardScaler(), naiv_b)
nb_smoth1.fit(X_res1, y_res1)
nb_smoth1_pred = nb_smoth1.predict(X_valid1)
mutual_filter.feature_names_in_[mutual_filter.get_support(indices=True)]
```

[ ]:
```
array(['WeekOfMonth', 'DayOfWeekClaimed', 'MonthClaimed', 'Age', 'Fault',
       'VehicleCategory_Sport', 'PastNumberOfClaims',
       'NumberOfSuppliments', 'NumberOfCars', 'Year',
       'BasePolicy_Liability'], dtype=object)
```

NB Smoth Compositon FS

[ ]:
```
comp_names1 = decomp_fs_names(X_train1, y_train1 , k = 16, m = 11)
naiv_b = BernoulliNB(alpha=1)
nb_comp_smoth1 = make_pipeline( StandardScaler(), naiv_b)
```

```
nb_comp_smoth1.fit(X_res1[comp_names1], y_res1)
nb_comp_smoth1_pred = nb_comp_smoth1.predict(X_valid1[comp_names1])
```

NB- NearMiss

[ ]:
```
np.random.seed(2022)
mutual_filter = SelectKBest(mutual_info_classif, k=11)
naiv_b = BernoulliNB(alpha=1)
nb_nearmiss1 = make_pipeline(mutual_filter, StandardScaler(), naiv_b)
nb_nearmiss1.fit(X_under1, y_under1)
nb_nearmiss1_pred = nb_nearmiss1.predict(X_valid1)
mutual_filter.feature_names_in_[mutual_filter.get_support(indices=True)]
```

[ ]:
```
array(['DayOfWeek', 'Age', 'Fault', 'VehicleCategory_Sedan',
       'VehiclePrice', 'Deductible', 'PastNumberOfClaims', 'AgeOfVehicle',
       'NumberOfSuppliments', 'AddressChange_Claim',
       'BasePolicy_Liability'], dtype=object)
```

NB NearMiss Compositon FS

[ ]:
```
np.random.seed(2022)
naiv_b = BernoulliNB(alpha=1 , )
nb_comp_nearmiss1 = make_pipeline( StandardScaler(), naiv_b)
nb_comp_nearmiss1.fit(X_under1[comp_names1], y_under1)
nb_comp_nearmiss1_pred = nb_comp_nearmiss1.predict(X_valid1[comp_names1])
```

NB- CS

[ ]:
```
train_weights1 = sklearn.utils.compute_sample_weight({0: 1, 1: 16}, y_train1)
```

[ ]:
```
np.random.seed(2022)
mutual_filter = SelectKBest(mutual_info_classif, k=11)
naiv_b = BernoulliNB(alpha=1 )
nb_cs1 = make_pipeline(mutual_filter, StandardScaler(),naiv_b)
kwargs1 = {nb_cs1.steps[-1][0] + '__sample_weight': train_weights1}
nb_cs1.fit(X_train1, y_train1, **kwargs1)
nb_cs1_pred = nb_cs1.predict(X_valid1)
mutual_filter.feature_names_in_[mutual_filter.get_support(indices=True)]
```

[ ]:
```
array(['WeekOfMonthClaimed', 'Sex', 'Fault', 'VehicleCategory_Sport',
       'VehicleCategory_Sedan', 'Deductible', 'Days_Policy_Claim',
       'PastNumberOfClaims', 'WitnessPresent', 'BasePolicy_Liability',
       'BasePolicy_All Perils'], dtype=object)
```

NB CS with compostion

[ ]:
```
np.random.seed(2022)
comp_names1 = decomp_fs_names(X_train1, y_train1 , k = 16, m = 11)
naiv_b = BernoulliNB(alpha=1)
```

```
nb_comp_cs1 = make_pipeline(StandardScaler(),naiv_b)
kwargs1 = {nb_comp_cs1.steps[-1][0] + '__sample_weight': train_weights1}
nb_comp_cs1.fit(X_train1[comp_names1], y_train1, **kwargs1)
nb_comp_cs1_pred = nb_comp_cs1.predict(X_valid1[comp_names1])
```

SVM - SMOTH

[ ]:
```
np.random.seed(2022)
mutual_filter = SelectKBest(mutual_info_classif, k=12)
svm = SVC(gamma='auto', random_state= 2022)
svm_smoth1 = make_pipeline(mutual_filter, StandardScaler(), svm)
svm_smoth1.fit(X_res1, y_res1)
svm_smoth1_pred = svm_smoth1.predict(X_valid1)
mutual_filter.feature_names_in_[mutual_filter.get_support(indices=True)]
```

[ ]:
```
array(['WeekOfMonth', 'DayOfWeekClaimed', 'MonthClaimed',
       'WeekOfMonthClaimed', 'Age', 'Fault', 'VehicleCategory_Sport',
       'PastNumberOfClaims', 'NumberOfSuppliments', 'AddressChange_Claim',
       'NumberOfCars', 'BasePolicy_Liability'], dtype=object)
```

SVM - SMOTH COMPOSITION

[ ]:
```
np.random.seed(2022)
comp_names1 = decomp_fs_names(X_train1, y_train1 , k = 16, m = 12)
svm = SVC(gamma='auto', random_state= 2022)
svm_comp_smoth1 = make_pipeline(StandardScaler(), svm)
svm_comp_smoth1.fit(X_res1[comp_names1], y_res1)
svm_comp_smoth1_pred = svm_comp_smoth1.predict(X_valid1[comp_names1])
```

**SVM - NearMiss**

[ ]:
```
np.random.seed(2022)
mutual_filter = SelectKBest(mutual_info_classif, k=14)
svm = SVC(gamma='auto', random_state= 2022)
svm_nearmiss1 = make_pipeline(mutual_filter, StandardScaler(), svm)
svm_nearmiss1.fit(X_under1, y_under1)
svm_nearmiss1_pred = svm_nearmiss1.predict(X_valid1)
mutual_filter.feature_names_in_[mutual_filter.get_support(indices=True)]
```

[ ]:
```
array(['WeekOfMonth', 'DayOfWeek', 'MaritalStatus_Single', 'Age', 'Fault',
       'VehicleCategory_Sedan', 'VehiclePrice', 'Deductible',
       'DriverRating', 'PastNumberOfClaims', 'AgeOfVehicle',
       'NumberOfSuppliments', 'AddressChange_Claim',
       'BasePolicy_Liability'], dtype=object)
```

SVM NEARMISS COMPOSITION

[ ]:
```
comp_names1 = decomp_fs_names(X_train1, y_train1 , k = 16, m = 14)
svm = SVC(gamma='auto', random_state= 2022)
```

```
svm_comp_nearmiss1 = make_pipeline( StandardScaler(), svm)
svm_comp_nearmiss1.fit(X_under1[comp_names1], y_under1)
svm_comp_nearmiss1_pred = svm_comp_nearmiss1.predict(X_valid1[comp_names1])
```

### 6.0.1 SVM - CS

[ ]:
```
np.random.seed(2022)
mutual_filter = SelectKBest(mutual_info_classif, k=14)
svm = SVC(gamma='auto', class_weight = {0:1 , 1:16}, random_state= 2022)
svm_cs1 = make_pipeline(mutual_filter, StandardScaler(), svm)
svm_cs1.fit(X_train1, y_train1)
svm_cs1_pred = svm_cs1.predict(X_valid1)
mutual_filter.feature_names_in_[mutual_filter.get_support(indices=True)]
```

[ ]:
```
array(['WeekOfMonthClaimed', 'Sex', 'Age', 'Fault',
       'VehicleCategory_Sport', 'VehicleCategory_Sedan', 'Deductible',
       'Days_Policy_Accident', 'Days_Policy_Claim', 'PastNumberOfClaims',
       'WitnessPresent', 'BasePolicy_Liability', 'BasePolicy_Collision',
       'BasePolicy_All Perils'], dtype=object)
```

SVM - CS COMPOSITION

[ ]:
```
comp_names1 = decomp_fs_names(X_train1, y_train1 , k = 16, m = 14)
svm = SVC(gamma='auto',  class_weight = {0:1 , 1:16}, random_state= 2022)
svm_comp_cs1 = make_pipeline(StandardScaler(), svm)
svm_comp_cs1.fit(X_res1[comp_names1], y_res1)
svm_comp_cs1_pred = svm_comp_cs1.predict(X_valid1[comp_names1])
```

# 7 Part 5 - Evaluating preformance, model selection

[ ]:
```
## define function for evaluating by few metrics and CM
def eval_pref(pred, y, classifier, model):
    precision, recall, thresholds = precision_recall_curve(y, pred)
    auc1 = auc(recall, precision)
    print(model,':')
    print('Accuarcy: ', round(accuracy_score(y,pred),4)*100, '%')
    print('Roc_Auc: ',round(roc_auc_score(y,pred),4)*100, '%')
    print('G-mean: ', round(geometric_mean_score(y,pred),4)*100, '%')
    print('F1-score: ',round(f1_score(y,pred),4)*100, '%')
    print('F2-score: ', round(fbeta_score(y, pred, beta=2),4)*100, '%')
    print('AUC-PR: ', round(auc1, 4)*100, '%')
    cm = confusion_matrix(y, pred, labels=classifier.classes_)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                                  display_labels=['Not Fraud', 'Fraud'])
    disp.plot()
```

[ ]:
```
eval_pref(rf_pred, y_valid1, rf, 'RF')
```

```
RF :
Accuarcy:  94.49 %
Roc_Auc:  50.0 %
G-mean:  0.0 %
F1-score:  0.0 %
F2-score:  0.0 %
AUC-PR:  52.76 %
```


[ ]:
```
eval_pref(rf_smoth1_pred, y_valid1, rf_smoth1, 'RF-SMOTH1')
```

```
RF-SMOTH1 :
Accuarcy:  75.11 %
Roc_Auc:  67.44 %
G-mean:  66.89 %
F1-score:  20.66 %
F2-score:  33.83 %
AUC-PR:  36.809999999999995 %
```


```
[ ]: eval_pref(rf_nearmiss1_pred, y_valid1, rf_nearmiss1, 'RF-NearMiss1')
```

```
RF-NearMiss1 :
Accuarcy:  52.22 %
Roc_Auc:  66.13 %
G-mean:  64.25999999999999 %
F1-score:  15.870000000000001 %
F2-score:  30.73 %
AUC-PR:  45.78 %
```


```
[ ]: eval_pref(rf_cs1_pred, y_valid1, rf_cs1, 'RF-CS')
```

```
RF-CS :
Accuarcy:  59.64 %
Roc_Auc:  75.6 %
G-mean:  73.44000000000001 %
F1-score:  20.349999999999998 %
F2-score:  38.35 %
AUC-PR:  52.65 %
```


[ ]:
```
eval_pref(svm_smoth1_pred, y_valid1, svm_smoth1, 'SVM-SMOTH1')
```

```
SVM-SMOTH1 :
Accuarcy:  72.92999999999999 %
Roc_Auc:  67.4 %
G-mean:  67.11 %
F1-score:  19.939999999999998 %
F2-score:  33.48 %
AUC-PR:  37.61 %
```


```
[ ]: eval_pref(svm_comp_smoth1_pred, y_valid1, svm_comp_smoth1, 'SVM-COMP-SMOTH1')
```

```
SVM-COMP-SMOTH1 :
Accuarcy:  78.35 %
Roc_Auc:  55.31 %
G-mean:  48.870000000000005 %
F1-score:  13.020000000000001 %
F2-score:  19.56 %
AUC-PR:  20.830000000000002 %
```


```
[ ]: eval_pref(svm_nearmiss1_pred, y_valid1, svm_nearmiss1, 'SVM-NearMiss1')
```

```
SVM-NearMiss1 :
Accuarcy:  45.96 %
Roc_Auc:  60.33 %
G-mean:  58.13 %
F1-score:  13.489999999999998 %
F2-score:  26.669999999999998 %
AUC-PR:  42.58 %
```


[ ]:
```
eval_pref(svm_comp_nearmiss1_pred, y_valid1, svm_comp_nearmiss1,␣
 ↪'SVM-COMP-NearMiss1')
```

```
SVM-COMP-NearMiss1 :
Accuarcy:  53.74 %
Roc_Auc:  53.92 %
G-mean:  53.92 %
F1-score:  11.42 %
F2-score:  21.69 %
AUC-PR:  31.52 %
```


[ ]:
```
eval_pref(svm_cs1_pred, y_valid1, svm_cs1, 'SVM-CS1')
```

```
SVM-CS1 :
Accuarcy:  60.39 %
Roc_Auc:  74.61 %
G-mean:  72.88 %
F1-score:  20.13 %
F2-score:  37.75 %
AUC-PR:  51.22 %
```


[ ]:
```
eval_pref(svm_comp_cs1_pred, y_valid1, svm_comp_cs1, 'SVM-Comp-CS1')
```

```
SVM-Comp-CS1 :
Accuarcy:  41.75 %
Roc_Auc:  63.36000000000001 %
G-mean:  58.52 %
F1-score:  14.219999999999999 %
F2-score:  28.599999999999998 %
AUC-PR:  48.03 %
```


[ ]:
```
eval_pref(nb_smoth1_pred, y_valid1, nb_smoth1, 'NB-SMOTH1')
```

```
NB-SMOTH1 :
Accuarcy:  63.4 %
Roc_Auc:  65.12 %
G-mean:  65.10000000000001 %
F1-score:  16.8 %
F2-score:  30.53 %
AUC-PR:  39.24 %
```


[ ]:
```
eval_pref(nb_comp_smoth1_pred, y_valid1, nb_comp_smoth1, 'NB-COMP-SMOTH1')
```

```
NB-COMP-SMOTH1 :
Accuarcy:  40.42 %
Roc_Auc:  63.21 %
G-mean:  57.79 %
F1-score:  14.11 %
F2-score:  28.49 %
AUC-PR:  48.55 %
```


[ ]:
```
eval_pref(nb_nearmiss1_pred, y_valid1, nb_nearmiss1, 'NB--nearmiss1')
```

```
NB--nearmiss1 :
Accuarcy:  56.730000000000004 %
Roc_Auc:  65.19 %
G-mean:  64.49000000000001 %
F1-score:  15.98 %
F2-score:  30.25 %
AUC-PR:  42.52 %
```


```
[ ]: eval_pref(nb_comp_nearmiss1_pred, y_valid1, nb_comp_nearmiss1,␣
      ↪'NB-COMP-nearmiss1')
```

```
NB-COMP-nearmiss1 :
Accuarcy:  52.349999999999994 %
Roc_Auc:  61.77 %
G-mean:  60.85 %
F1-score:  14.34 %
F2-score:  27.63 %
AUC-PR:  40.92 %
```


[ ]:
```
eval_pref(nb_cs1_pred, y_valid1, nb_cs1, 'NB-CS1')
```

```
NB-CS1 :
Accuarcy:  56.14 %
Roc_Auc:  72.36 %
G-mean:  70.03 %
F1-score:  18.54 %
F2-score:  35.47 %
AUC-PR:  50.72 %
```


```
[ ]: eval_pref(nb_comp_cs1_pred,y_valid1 , nb_comp_cs1, 'NB-Comp CS')
```

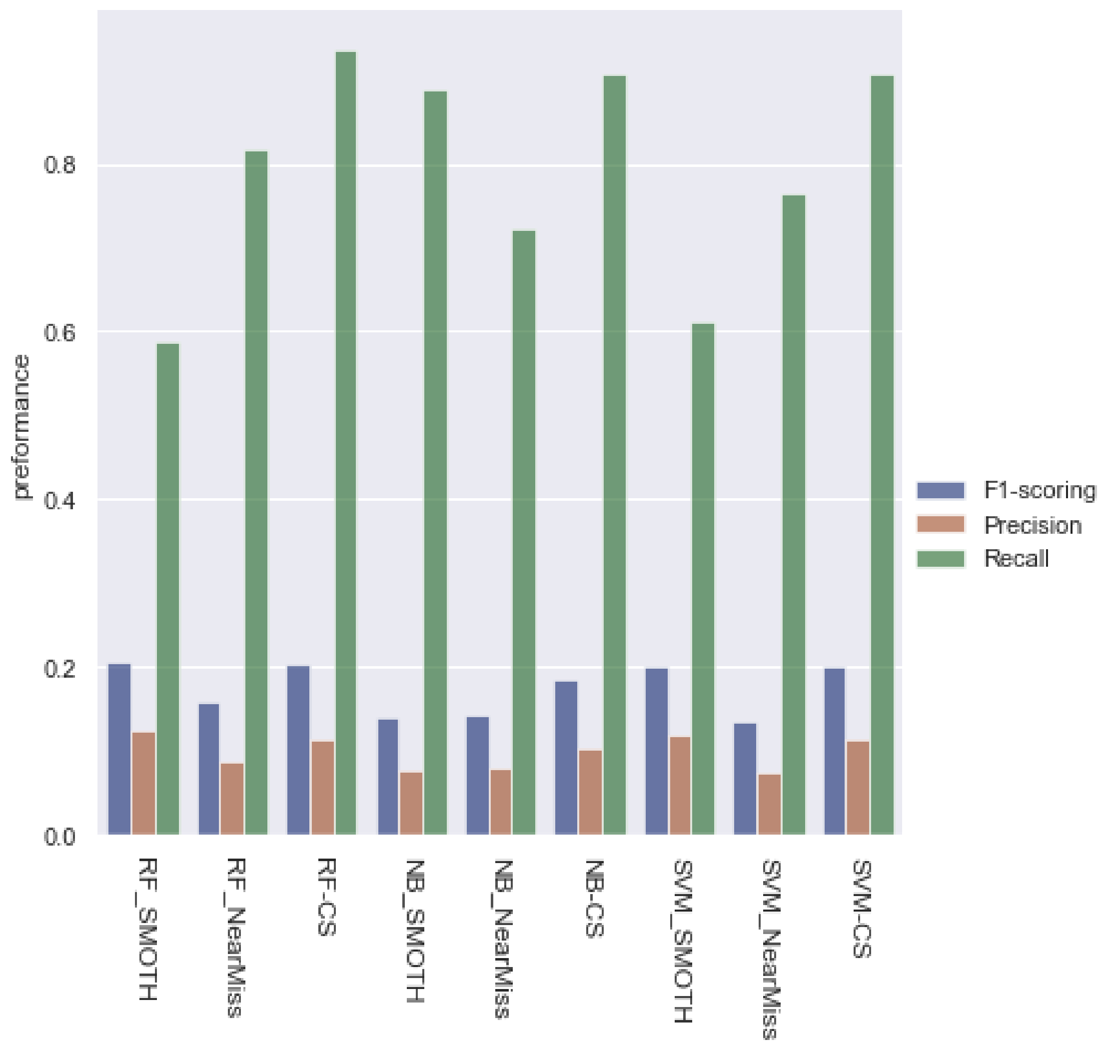
```
NB-Comp CS :
Accuarcy:  39.48 %
Roc_Auc:  63.82 %
G-mean:  57.66 %
F1-score:  14.24 %
F2-score:  28.84 %
AUC-PR:  49.69 %
```


comparison by bar plots

[ ]:
```
# presicion, recall, F1-score - without decompasition feature selection
dict_pre = {'Model':␣
 ↪['RF_SMOTH','RF_NearMiss','RF-CS','NB_SMOTH','NB_NearMiss','NB-CS','SVM_SMOTH','SVM_NearMis
 ↪'metric': np.repeat('Precision',9) ,'scoring': [] }
dict_rec = {'Model':␣
 ↪['RF_SMOTH','RF_NearMiss','RF-CS','NB_SMOTH','NB_NearMiss','NB-CS','SVM_SMOTH','SVM_NearMis
 ↪'metric': np.repeat('Recall',9), 'scoring': [] }
dict_f1 = {'Model':␣
 ↪['RF_SMOTH','RF_NearMiss','RF-CS','NB_SMOTH','NB_NearMiss','NB-CS','SVM_SMOTH','SVM_NearMis
 ↪'metric': np.repeat('F1-scoring',9), 'scoring': []  }
classifers_list = [rf_smoth1,rf_nearmiss1,rf_cs1,␣
 ↪nb_comp_smoth1,nb_comp_nearmiss1,nb_comp_cs1,svm_smoth1,svm_nearmiss1,svm_cs1]
pred_list = [rf_smoth1_pred,rf_nearmiss1_pred,rf_cs1_pred,␣
 ↪nb_comp_smoth1_pred,nb_comp_nearmiss1_pred,nb_cs1_pred,svm_smoth1_pred,svm_nearmiss1_pred,s
dict_f1['scoring'] =  [f1_score(y_valid1,pred) for pred in pred_list]
dict_pre['scoring'] = [precision_score(y_valid1,pred) for pred in pred_list]
dict_rec['scoring'] = [recall_score(y_valid1, pred) for pred in pred_list]

models_results = pd.concat([pd.DataFrame.from_dict(dict_f1),pd.DataFrame.
 ↪from_dict(dict_pre),pd.DataFrame.from_dict(dict_rec)])

sns.set_theme()
```

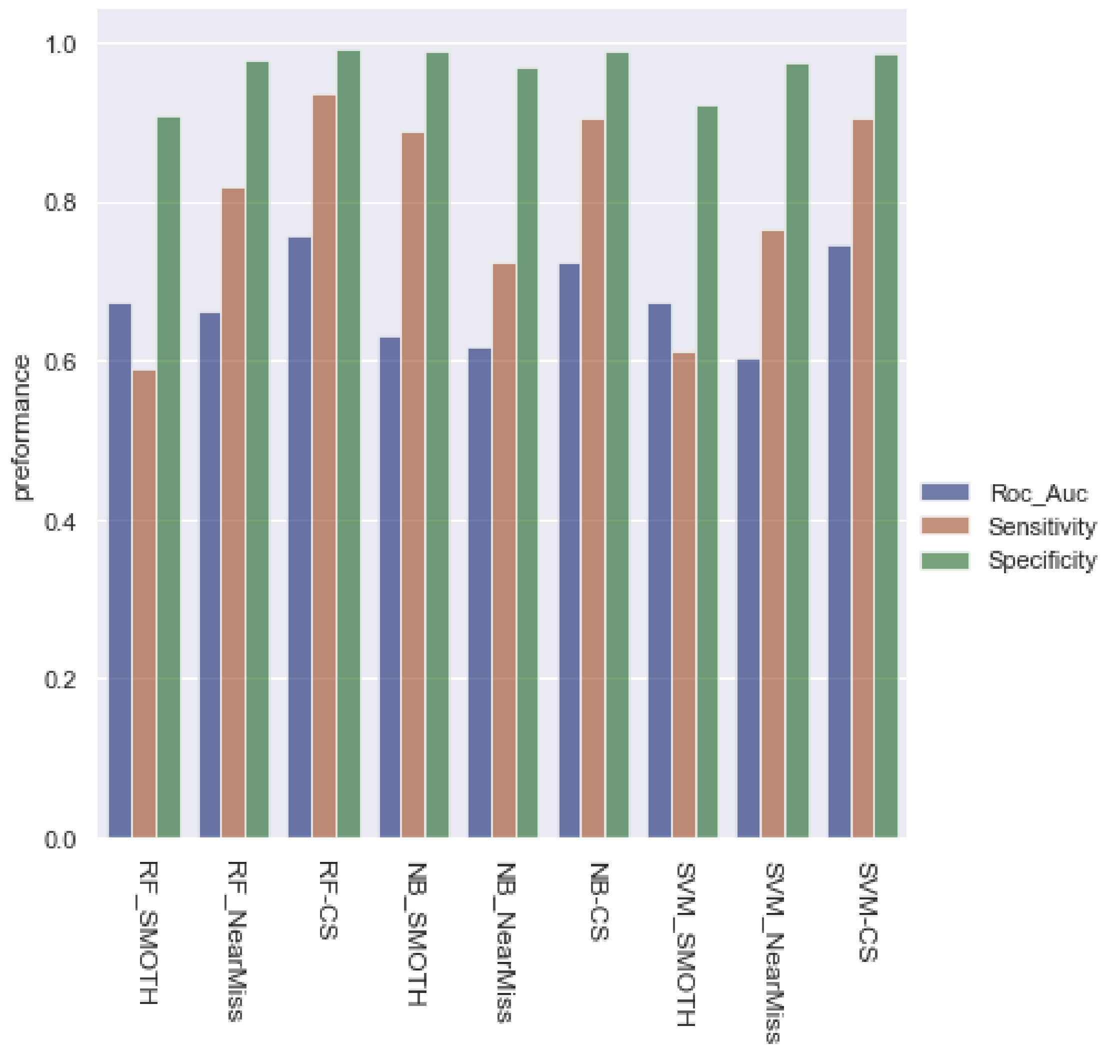
```python
# Draw a nested barplot by models and scoring
g = sns.catplot(
    data=models_results, kind="bar",
    x="Model", y="scoring", hue="metric",
    ci="sd", palette="dark", alpha=.6, height=6
)
g.despine(left=True)
g.set_axis_labels("", "preformance")
g.legend.set_title("")
g.set_xticklabels(rotation = -90, size = 12)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7f0a5c0f9810>



[ ]:
```
# senstivity, specificity, Roc Auc
dict_roc = {'Model':␣
↪['RF_SMOTH','RF_NearMiss','RF-CS','NB_SMOTH','NB_NearMiss','NB-CS','SVM_SMOTH','SVM_NearMis
↪'metric': np.repeat('Roc_Auc',9) ,'scoring': [] }
dict_sens = {'Model':␣
↪['RF_SMOTH','RF_NearMiss','RF-CS','NB_SMOTH','NB_NearMiss','NB-CS','SVM_SMOTH','SVM_NearMis
↪'metric': np.repeat('Sensitivity',9), 'scoring': [] }
dict_spec = {'Model':␣
↪['RF_SMOTH','RF_NearMiss','RF-CS','NB_SMOTH','NB_NearMiss','NB-CS','SVM_SMOTH','SVM_NearMis
↪'metric': np.repeat('Specificity',9), 'scoring': []  }
pred_list = [rf_smoth1_pred,rf_nearmiss1_pred,rf_cs1_pred,␣
↪nb_comp_smoth1_pred,nb_comp_nearmiss1_pred,nb_cs1_pred,svm_smoth1_pred,svm_nearmiss1_pred,s


dict_roc['scoring'] =  [roc_auc_score(y_valid1,pred) for pred in pred_list]
dict_spec['scoring'] = [confusion_matrix(y_valid1, pred).ravel()[1]/
↪(confusion_matrix(y_valid1, pred).ravel()[1]+confusion_matrix(y_valid1,␣
↪pred).ravel()[2]) for pred in pred_list]
dict_sens['scoring'] = [recall_score(y_valid1, pred) for pred in pred_list]

models_results = pd.concat([pd.DataFrame.from_dict(dict_roc),pd.DataFrame.
↪from_dict(dict_sens),pd.DataFrame.from_dict(dict_spec)])

sns.set_theme()


# Draw a nested barplot by models and scoring
g = sns.catplot(
    data=models_results, kind="bar",
    x="Model", y="scoring", hue="metric",
    ci="sd", palette="dark", alpha=.6, height=6
)
g.despine(left=True)
g.set_axis_labels("", "preformance")
g.legend.set_title("")
g.set_xticklabels(rotation = -90, size = 12)
```

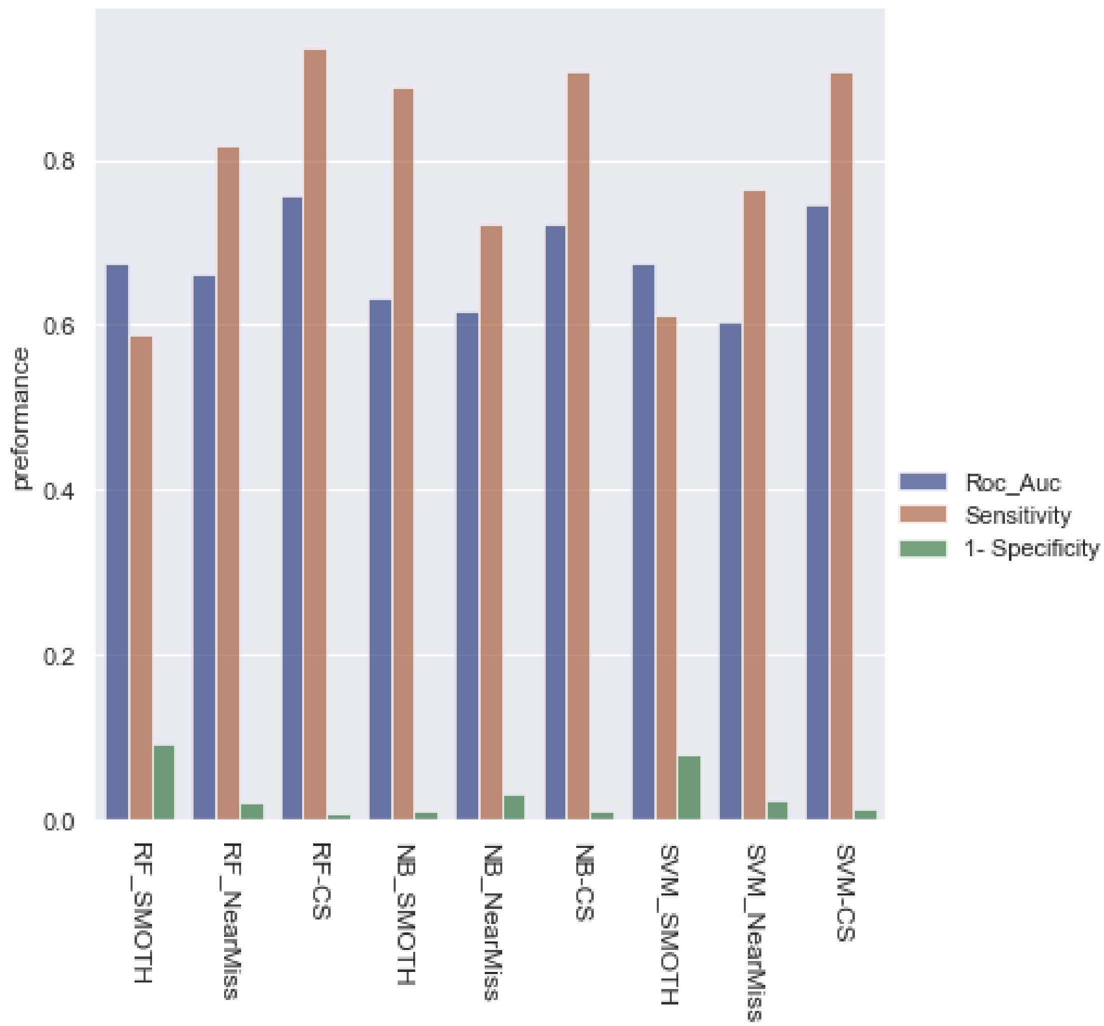
[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7f0a5c1211e0>
```




[ ]:
```
# Sensitivity, 1- Specificity, Recall
dict_roc = {'Model':␣
 ↪['RF_SMOTH','RF_NearMiss','RF-CS','NB_SMOTH','NB_NearMiss','NB-CS','SVM_SMOTH','SVM_NearMis
 ↪'metric': np.repeat('Roc_Auc',9) ,'scoring': [] }
dict_sens = {'Model':␣
 ↪['RF_SMOTH','RF_NearMiss','RF-CS','NB_SMOTH','NB_NearMiss','NB-CS','SVM_SMOTH','SVM_NearMis
 ↪'metric': np.repeat('Sensitivity',9), 'scoring': [] }
dict_1spec = {'Model':␣
 ↪['RF_SMOTH','RF_NearMiss','RF-CS','NB_SMOTH','NB_NearMiss','NB-CS','SVM_SMOTH','SVM_NearMis
 ↪'metric': np.repeat('1- Specificity',9), 'scoring': []  }
pred_list = [rf_smoth1_pred,rf_nearmiss1_pred,rf_cs1_pred,␣
 ↪nb_comp_smoth1_pred,nb_comp_nearmiss1_pred,nb_cs1_pred,svm_smoth1_pred,svm_nearmiss1_pred,s
```

```
dict_roc['scoring'] =  [roc_auc_score(y_valid1,pred) for pred in pred_list]
dict_1spec['scoring'] = [1-(confusion_matrix(y_valid1, pred).ravel()[1]/
 ↪(confusion_matrix(y_valid1, pred).ravel()[1]+confusion_matrix(y_valid1,␣
 ↪pred).ravel()[2])) for pred in pred_list]
dict_sens['scoring'] = [recall_score(y_valid1, pred) for pred in pred_list]

models_results = pd.concat([pd.DataFrame.from_dict(dict_roc),pd.DataFrame.
 ↪from_dict(dict_sens),pd.DataFrame.from_dict(dict_1spec)])

sns.set_theme()


# Draw a nested barplot by models and scoring
g = sns.catplot(
    data=models_results, kind="bar",
    x="Model", y="scoring", hue="metric",
    ci="sd", palette="dark", alpha=.6, height=6
)
g.despine(left=True)
g.set_axis_labels("", "preformance")
g.legend.set_title("")
g.set_xticklabels(rotation = -90, size = 12)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7f0a611c7730>




we can see RF-CS has the best preformance

# 8 part 6 - Test preformance of the chosen model

[ ]:
```
# what Elad did before with train data only
# rf_cs1_pred_test = rf_cs1.predict(X_test1)
# eval_pref(rf_cs1_pred_test,y_test1 , rf_cs1, 'chosen model')
```

We chose our model, we can use the combined data from train and val to get better test results (a technique we saw in the introductory kaggle course)

[ ]:
```
X_full_train = pd.concat([X_train1,X_valid1])
y_full_train = pd.concat([y_train1, y_valid1])
rf_cs_final = RandomForestClassifier(n_estimators = 100, max_features ='sqrt',␣
↪random_state = 2022, max_depth =5,
```

```
                                                class_weight={0: 1 ,1:16})

rf_cs_final.fit(X_full_train, y_full_train)
rf_cs_final_pred = rf_cs_final.predict(X_test1)
eval_pref(rf_cs_final_pred,y_test1 , rf_cs_final, 'chosen full model')
```

```
chosen full model :
Accuarcy:  62.519999999999996 %
Roc_Auc:  79.57 %
G-mean:  77.18 %
F1-score:  23.75 %
F2-score:  43.65 %
AUC-PR:  56.230000000000004 %
```