Problem Statement:

Business case: Insurance fraud is a huge problem in the industry. It's difficult to identify fraud claims. Machine Learning is in a unique position to help the Auto Insurance industry with this problem. In this project, you are provided a dataset which has the details of the insurance policy along with the customer details. It also has the details of the accident on the basis of which the claims have been made.

Importing Required Library

In [204]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import zscore
import scikitplot as skplt
from imblearn.over_sampling import SMOTE
import pickle
pd.set_option('display.max_columns',None) # For display maximum columns
from sklearn.model_selection import train_test_split, cross_val_score,GridSearchC
from sklearn.preprocessing import MinMaxScaler, OrdinalEncoder
from sklearn.metrics import classification_report, roc_auc_score, roc_curve, plot
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier
from sklearn.linear_model import LogisticRegression
import xgboost as xgb
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Reading Data

In [2]:
```
df = pd.read_csv(r"C:\Users\Kushal Arya\Desktop\csv file\Automobile_insurance_fra
df.head()
```

Out[2]:

	months_as_customer	age	policy_number	policy_bind_date	policy_state	policy_csl	policy_ded
0	328	48	521585	17-10-2014	OH	250/500	
1	228	42	342868	27-06-2006	IN	250/500	
2	134	29	687698	06-09-2000	OH	100/300	
3	256	41	227811	25-05-1990	IL	250/500	
4	228	44	367455	06-06-2014	IL	500/1000	

Check no of row and column

In [3]:
```
print('No of Rows and Columns ----->', df.shape )
```

```
No of Rows and Columns -----> (1000, 40)
```

Checking for Null values

In [4]:
```python
print('================================\n')
print(df.isnull().sum())
print('\n================================')
```

```
================================

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

================================
```

There is null value

Information about dataset

In [5]:

```python
print('==================================================\n')
print(df.info())
print('====================================================')
```

```
==================================================

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 40 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   months_as_customer           1000 non-null   int64  
 1   age                          1000 non-null   int64  
 2   policy_number                1000 non-null   int64  
 3   policy_bind_date             1000 non-null   object 
 4   policy_state                 1000 non-null   object 
 5   policy_csl                   1000 non-null   object 
 6   policy_deductable            1000 non-null   int64  
 7   policy_annual_premium        1000 non-null   float64
 8   umbrella_limit               1000 non-null   int64  
 9   insured_zip                  1000 non-null   int64  
 10  insured_sex                  1000 non-null   object 
 11  insured_education_level      1000 non-null   object 
 12  insured_occupation           1000 non-null   object 
 13  insured_hobbies              1000 non-null   object 
 14  insured_relationship         1000 non-null   object 
 15  capital-gains                1000 non-null   int64  
 16  capital-loss                 1000 non-null   int64  
 17  incident_date                1000 non-null   object 
 18  incident_type                1000 non-null   object 
 19  collision_type               822 non-null    object 
 20  incident_severity            1000 non-null   object 
 21  authorities_contacted        1000 non-null   object 
 22  incident_state               1000 non-null   object 
 23  incident_city                1000 non-null   object 
 24  incident_location            1000 non-null   object 
 25  incident_hour_of_the_day     1000 non-null   int64  
 26  number_of_vehicles_involved  1000 non-null   int64  
 27  property_damage              640 non-null    object 
 28  bodily_injuries              1000 non-null   int64  
 29  witnesses                    1000 non-null   int64  
 30  police_report_available      657 non-null    object 
 31  total_claim_amount           1000 non-null   int64  
 32  injury_claim                 1000 non-null   int64  
 33  property_claim               1000 non-null   int64  
 34  vehicle_claim                1000 non-null   int64  
 35  auto_make                    1000 non-null   object 
 36  auto_model                   1000 non-null   object 
 37  auto_year                    1000 non-null   int64  
 38  fraud_reported               1000 non-null   object 
 39  _c39                         0 non-null      float64
dtypes: float64(2), int64(17), object(21)
memory usage: 312.6+ KB
None
====================================================
```

Categorical data present in our data set

Drop unwanted column

In [6]:
```
df = df.drop('_c39', axis = 1)
df.head(2)
```

Out[6]:

	months_as_customer	age	policy_number	policy_bind_date	policy_state	policy_csl	policy_ded
0	328	48	521585	17-10-2014	OH	250/500	
1	228	42	342868	27-06-2006	IN	250/500	

We drop the '_c39' column

Fill NaN

In [7]:
```
df = df.apply(lambda x:x.fillna(x.mean())if x.dtype == 'int64' else x.fillna(x.va
```

```python
In [8]: print('================================\n')
        print(df.isnull().sum())
        print('\n================================')
```

```
================================

months_as_customer             0
age                            0
policy_number                  0
policy_bind_date               0
policy_state                   0
policy_csl                     0
policy_deductable              0
policy_annual_premium          0
umbrella_limit                 0
insured_zip                    0
insured_sex                    0
insured_education_level        0
insured_occupation             0
insured_hobbies                0
insured_relationship           0
capital-gains                  0
capital-loss                   0
incident_date                  0
incident_type                  0
collision_type                 0
incident_severity              0
authorities_contacted          0
incident_state                 0
incident_city                  0
incident_location              0
incident_hour_of_the_day       0
number_of_vehicles_involved    0
property_damage                0
bodily_injuries                0
witnesses                      0
police_report_available        0
total_claim_amount             0
injury_claim                   0
property_claim                 0
vehicle_claim                  0
auto_make                      0
auto_model                     0
auto_year                      0
fraud_reported                 0
dtype: int64

================================
```

There is no null value left

Statistics of Data

In [9]:
```
df.describe()
```

Out[9]:

	months_as_customer	age	policy_number	policy_deductable	policy_annual_premiu
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000
mean	203.954000	38.948000	546238.648000	1136.000000	1256.40615
std	115.113174	9.140287	257063.005276	611.864673	244.16739
min	0.000000	19.000000	100804.000000	500.000000	433.33000
25%	115.750000	32.000000	335980.250000	500.000000	1089.60750
50%	199.500000	38.000000	533135.000000	1000.000000	1257.20000
75%	276.250000	44.000000	759099.750000	2000.000000	1415.69500
max	479.000000	64.000000	999435.000000	2000.000000	2047.59000

Features Engineering

Incident Date column

In [10]:
```
df.head(2)
```

Out[10]:

	months_as_customer	age	policy_number	policy_bind_date	policy_state	policy_csl	policy_ded
0	328	48	521585	17-10-2014	OH	250/500	
1	228	42	342868	27-06-2006	IN	250/500	

In [11]:
```
df['incident_date'].value_counts()
```

Out[11]:
```
02-02-2015    28
17-02-2015    26
07-01-2015    25
10-01-2015    24
04-02-2015    24
24-01-2015    24
19-01-2015    23
08-01-2015    22
30-01-2015    21
13-01-2015    21
22-02-2015    20
31-01-2015    20
12-02-2015    20
06-02-2015    20
01-01-2015    19
14-01-2015    19
21-01-2015    19
12-01-2015    19
23-02-2015    19
21-02-2015    19
01-02-2015    18
03-01-2015    18
14-02-2015    18
20-01-2015    18
25-02-2015    18
18-01-2015    18
28-02-2015    18
08-02-2015    17
24-02-2015    17
26-02-2015    17
06-01-2015    17
09-01-2015    17
16-02-2015    16
15-02-2015    16
16-01-2015    16
13-02-2015    16
05-02-2015    16
28-01-2015    15
15-01-2015    15
17-01-2015    15
18-02-2015    15
20-02-2015    14
22-01-2015    14
27-02-2015    14
09-02-2015    13
03-02-2015    13
27-01-2015    13
23-01-2015    13
01-03-2015    12
04-01-2015    12
26-01-2015    11
29-01-2015    11
02-01-2015    11
11-02-2015    10
```

```
07-02-2015    10
10-02-2015    10
25-01-2015    10
19-02-2015    10
11-01-2015     9
05-01-2015     7
Name: incident_date, dtype: int64
```

In [12]:
```
df['IncidentMonth&Year'] = df['incident_date'].str[3:]
df.head(2)
```

Out[12]:

	months_as_customer	age	policy_number	policy_bind_date	policy_state	policy_csl	policy_ded
0	328	48	521585	17-10-2014	OH	250/500	
1	228	42	342868	27-06-2006	IN	250/500	

In [13]:
```
df['IncidentMonth&Year'].value_counts()
```

Out[13]:
```
01-2015    516
02-2015    472
03-2015     12
Name: IncidentMonth&Year, dtype: int64
```

Policy Bind Date column

In [14]:
```
df['policy_bind_date'].value_counts()
```

Out[14]:
```
05-08-1992    3
28-04-1992    3
01-01-2006    3
22-08-1991    2
07-07-1996    2
             ..
11-06-2008    1
11-12-1994    1
19-06-2008    1
16-03-1998    1
19-04-2002    1
Name: policy_bind_date, Length: 951, dtype: int64
```

In [15]:
```
df['PolicyBindMonth&year'] = df['policy_bind_date'].str[3:]
df.head(2)
```

Out[15]:

	months_as_customer	age	policy_number	policy_bind_date	policy_state	policy_csl	policy_ded
0	328	48	521585	17-10-2014	OH	250/500	
1	228	42	342868	27-06-2006	IN	250/500	

In [16]:
```
df['PolicyBindMonth&year'].value_counts()
```

Out[16]:
```
11-1991    9
07-1996    8
03-2007    8
08-1994    8
12-1995    8
          ..
02-2012    1
07-1998    1
04-1997    1
01-2000    1
09-1998    1
Name: PolicyBindMonth&year, Length: 286, dtype: int64
```

In [17]:
```
df['Incident_Pincode'] = df['incident_location'].str[0:4]
df['Incident_Pincode'] = df['Incident_Pincode'].astype('int64')
df.head(2)
```

Out[17]:

	months_as_customer	age	policy_number	policy_bind_date	policy_state	policy_csl	policy_ded
0	328	48	521585	17-10-2014	OH	250/500	
1	228	42	342868	27-06-2006	IN	250/500	

To Get Details With Pincode ¶

In [18]:
```python
import pgeocode

nomi = pgeocode.Nominatim('in')
nomi.query_postal_code('801503')
```

Out[18]:
```
postal_code                                                  801503
country_code                                                     IN
place_name        Jamsaut, Sherpur, Ganghara, Sadikpur, Dalip Ch...
state_name                                                    Bihar
state_code                                                       34
county_name                                                   Patna
county_code                                                   230.0
community_name                                              Danapur
community_code                                                  NaN
latitude                                                      25.61
longitude                                                 84.978713
accuracy                                                          4
Name: 0, dtype: object
```

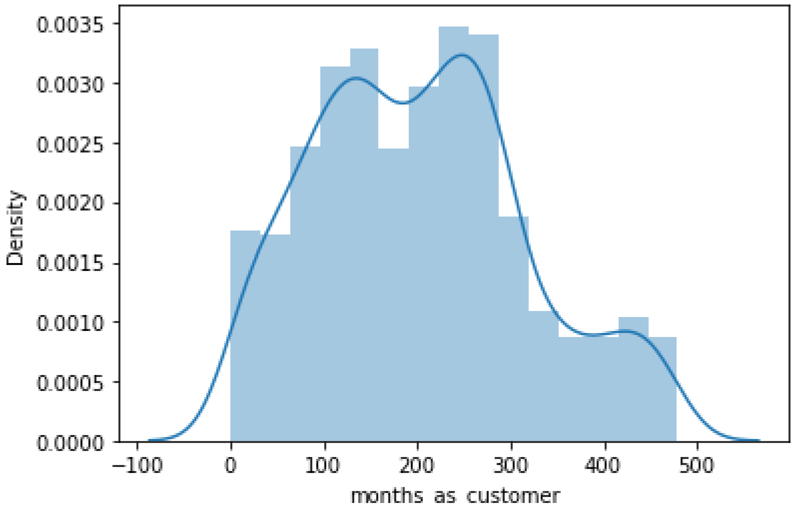
Analysis of Data

Months as customer column

In [19]:
```python
df['months_as_customer'].value_counts()
```

Out[19]:
```
194    8
254    7
210    7
101    7
140    7
      ..
312    1
62     1
309    1
308    1
0      1
Name: months_as_customer, Length: 391, dtype: int64
```

In [20]:
```
sns.distplot(df['months_as_customer'], kde = True, hist = True)
plt.show()
```



Months as customer has skewed

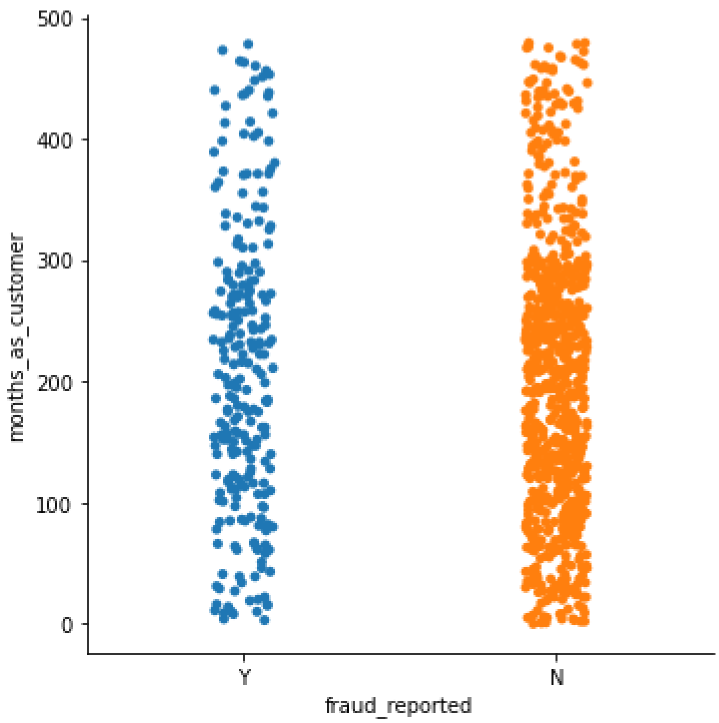
In [21]:
```
df['fraud_reported'].value_counts()
```

Out[21]:
```
N    753
Y    247
Name: fraud_reported, dtype: int64
```

In [22]:
```
m = df.groupby('months_as_customer')['fraud_reported'].value_counts()
m
```

Out[22]:
```
months_as_customer  fraud_reported
0                   N                 1
1                   N                 3
2                   N                 2
3                   N                 1
                    Y                 1
                                     ..
475                 N                 2
476                 N                 1
478                 N                 1
                    Y                 1
479                 N                 2
Name: fraud_reported, Length: 532, dtype: int64
```

In [23]:
```
sns.catplot(y = 'months_as_customer', x = 'fraud_reported', data = df)
plt.show()
```



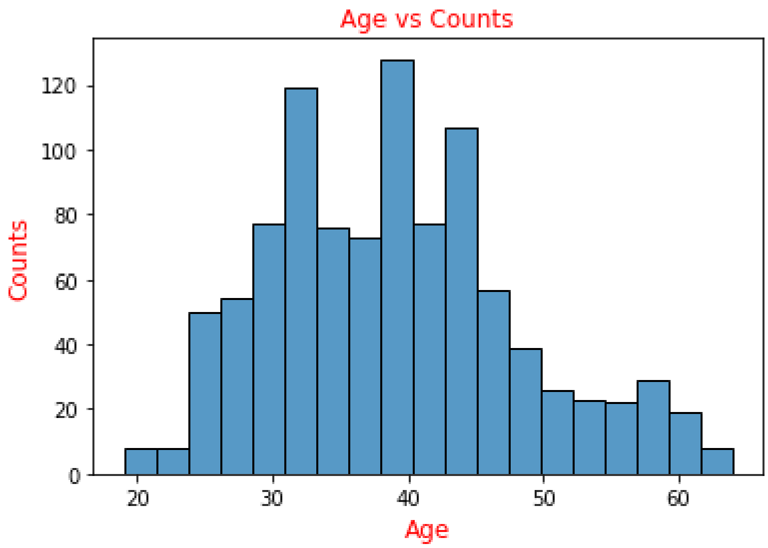
Above plot shows who is less preriod of time customer is changes of fraud is high

Age column

In [24]:
```
df['age'].value_counts()
```

Out[24]:
```
43    49
39    48
41    45
34    44
38    42
30    42
31    42
37    41
33    39
40    38
32    38
29    35
46    33
35    32
44    32
36    32
42    32
28    30
45    26
26    26
48    25
47    24
27    24
57    16
55    14
25    14
49    14
50    13
53    13
24    10
54    10
61    10
51     9
60     9
56     8
58     8
23     7
21     6
59     5
52     4
62     4
63     2
64     2
20     1
22     1
19     1
Name: age, dtype: int64
```

In [25]:
```
sns.histplot( x="age", data=df)
plt.xlabel('Age', c = 'r', fontsize = 12)
plt.ylabel('Counts', c = 'r', fontsize = 12)
plt.title('Age vs Counts', c = 'r', fontsize = 12)
plt.show()
```



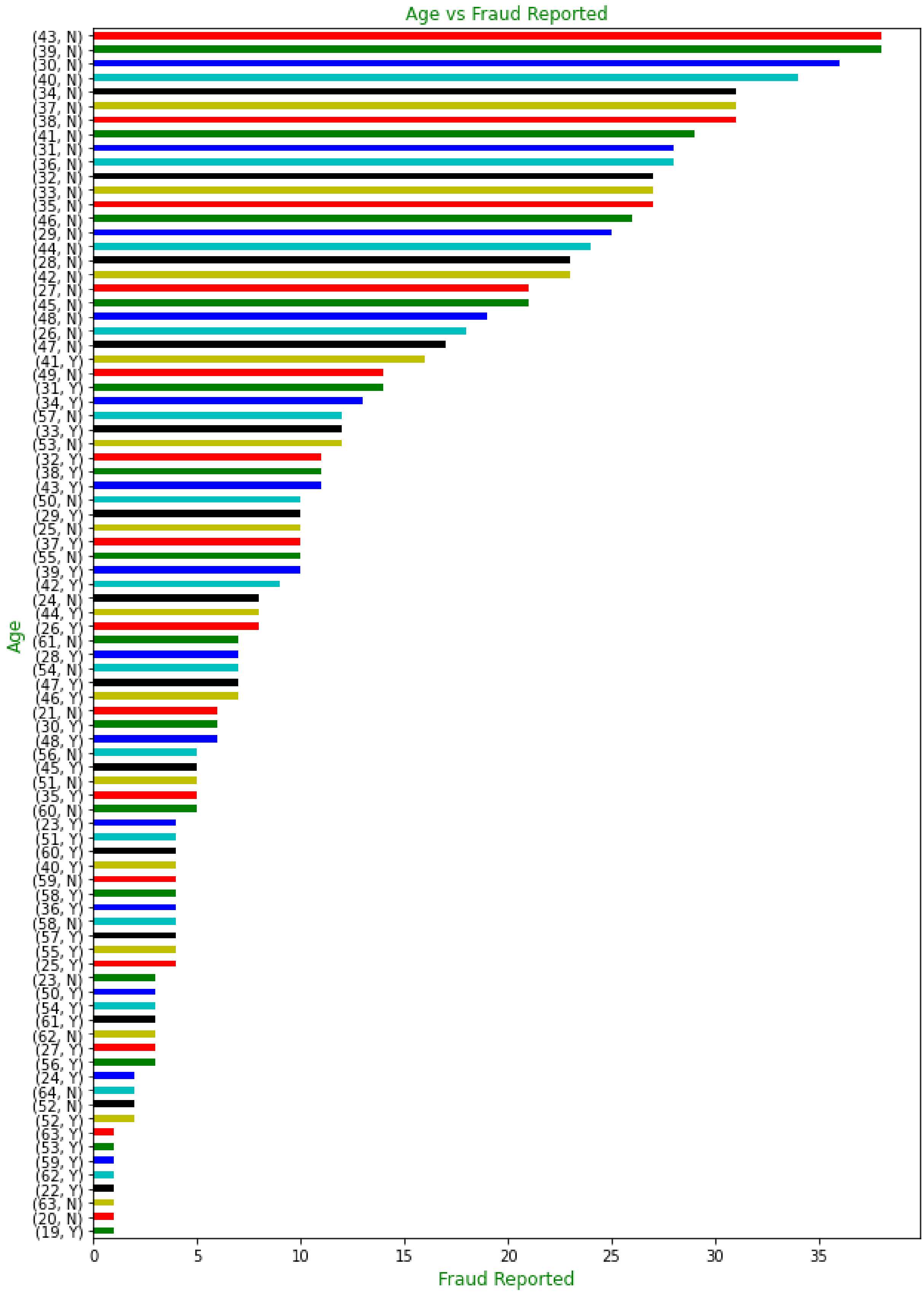
Age 39 to 43 is highest counts

In [26]:
```
a = df.groupby('age')['fraud_reported'].value_counts().sort_values()
a
```

Out[26]:
```
age  fraud_reported
19   Y                  1
20   N                  1
63   N                  1
22   Y                  1
62   Y                  1
                       ..
34   N                 31
40   N                 34
30   N                 36
39   N                 38
43   N                 38
Name: fraud_reported, Length: 86, dtype: int64
```

In [27]:
```
sns.catplot(y = 'age', x = 'fraud_reported', data = df)
plt.ylabel('Age', c = 'b', fontsize = 12)
plt.xlabel('Fraud Reported', c = 'b', fontsize = 12 )
plt.title('Age vs Fraud Reported', c = 'b', fontsize = 12)
plt.show()
```

In [28]:
```
a.plot.barh(figsize = (10,15), rot = 360, color = ['g','r','y','k','c','b'])
plt.ylabel('Age', c = 'g', fontsize = 12)
plt.xlabel('Fraud Reported', c = 'g', fontsize = 12 )
plt.title('Age vs Fraud Reported', c = 'g', fontsize = 12)
plt.show()
```



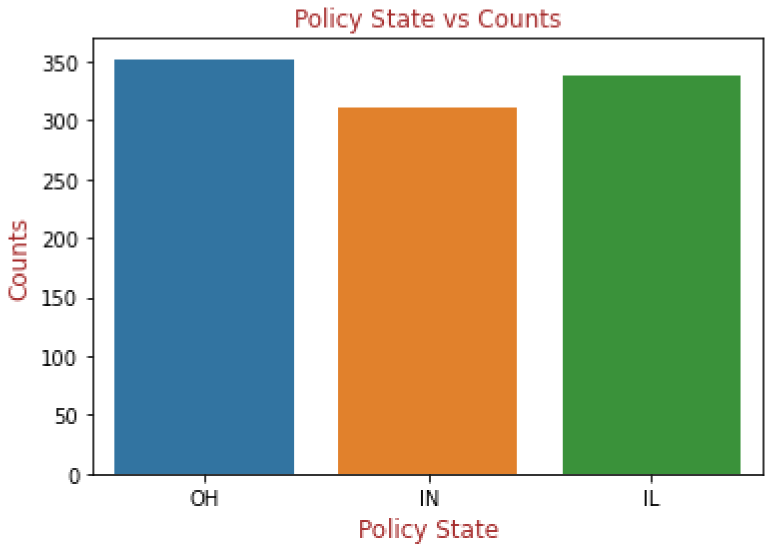
Age group 31 to 41 highest Fraud Reported

Policy State

In [29]:
```
df['policy_state'].value_counts()
```

Out[29]:
```
OH    352
IL    338
IN    310
Name: policy_state, dtype: int64
```

In [30]:
```
sns.countplot( x="policy_state", data=df)
plt.xlabel('Policy State', c = 'brown', fontsize = 12)
plt.ylabel('Counts', c = 'brown', fontsize = 12)
plt.title('Policy State vs Counts', c = 'brown', fontsize = 12)
plt.show()
```



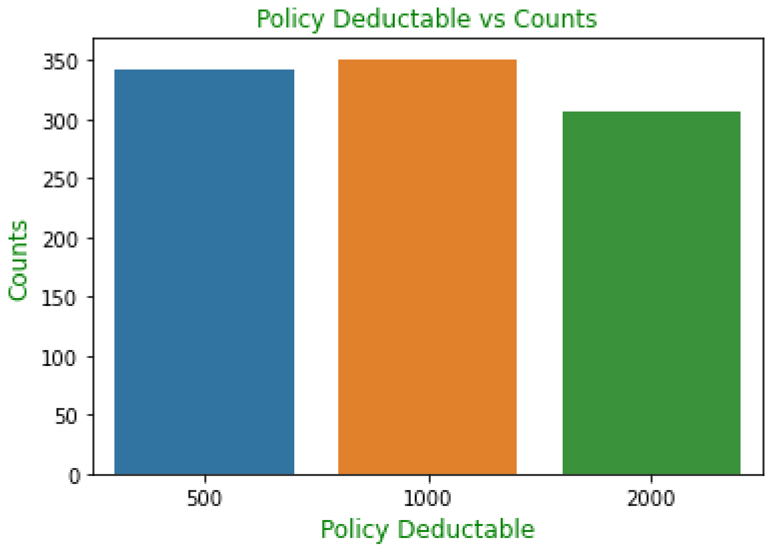
OH highest counts

Policy Deductable

In [31]:
```
df['policy_deductable'].value_counts()
```

Out[31]:
```
1000    351
500     342
2000    307
Name: policy_deductable, dtype: int64
```

In [32]:
```
sns.countplot( x="policy_deductable", data=df)
plt.xlabel('Policy Deductable', c = 'g', fontsize = 12)
plt.ylabel('Counts', c = 'g', fontsize = 12)
plt.title('Policy Deductable vs Counts', c = 'g', fontsize = 12)
plt.show()
```



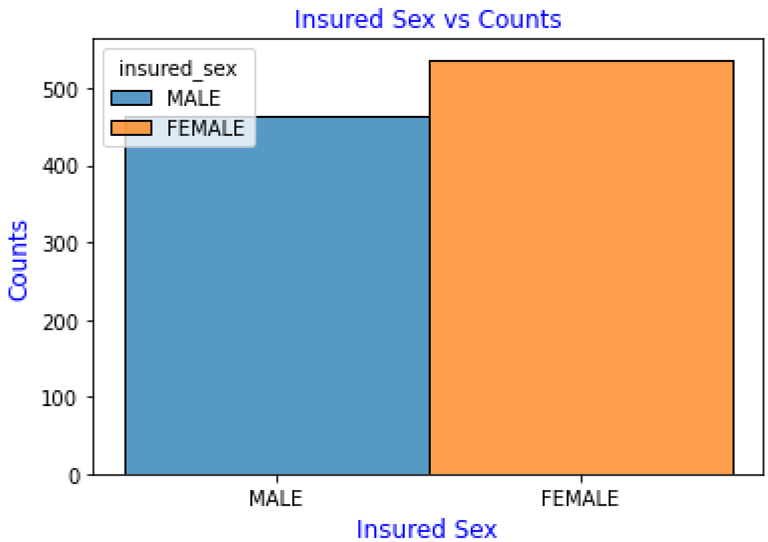
1000 policy deductable highest counts

Insured Sex Columns

In [33]:
```
df['insured_sex'].value_counts()
```

Out[33]:
```
FEMALE    537
MALE      463
Name: insured_sex, dtype: int64
```

In [34]:
```
sns.histplot(binwidth=0.5, x="insured_sex", hue="insured_sex", data=df, stat="cou
plt.xlabel('Insured Sex', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Insured Sex vs Counts', c = 'b', fontsize = 12)
plt.show()
```

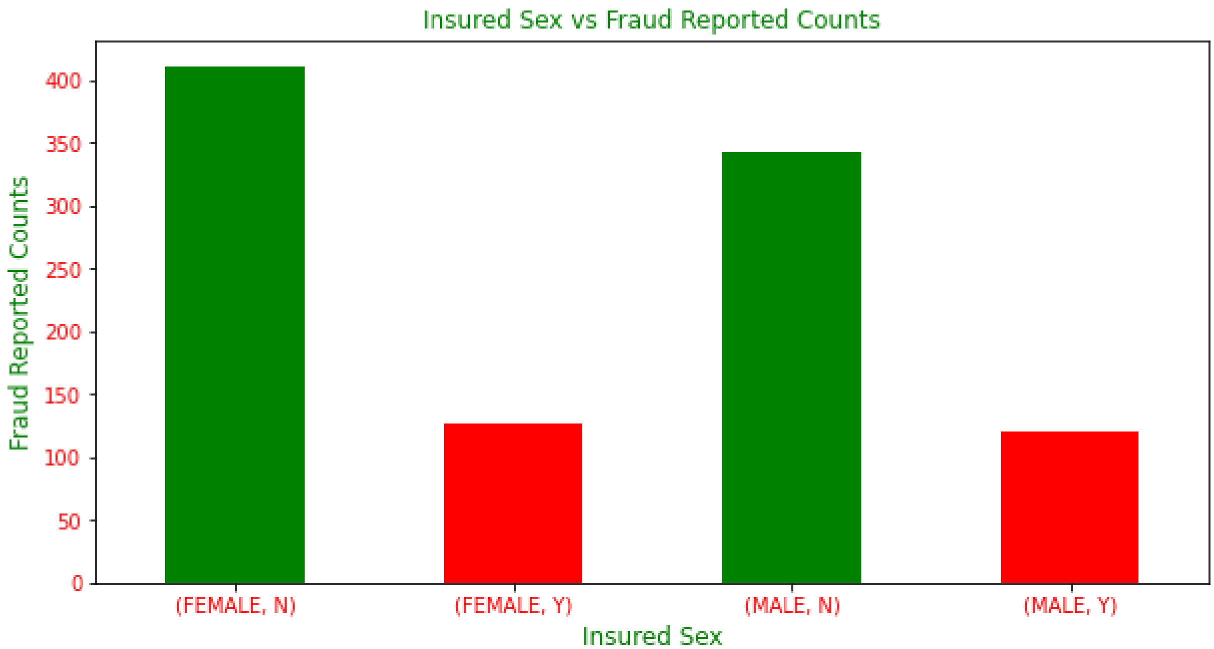


Female is highest in counts

In [35]:
```
s = df.groupby('insured_sex')['fraud_reported'].value_counts()
s
```

Out[35]:
```
insured_sex  fraud_reported
FEMALE       N                 411
             Y                 126
MALE         N                 342
             Y                 121
Name: fraud_reported, dtype: int64
```

In [36]:
```
s.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Insured Sex', c = 'g', fontsize = 12)
plt.ylabel('Fraud Reported Counts', c = 'g', fontsize = 12 )
plt.title('Insured Sex vs Fraud Reported Counts', c = 'g', fontsize = 12)
plt.xticks(c = 'r')
plt.yticks(c = 'r')
plt.show()
```



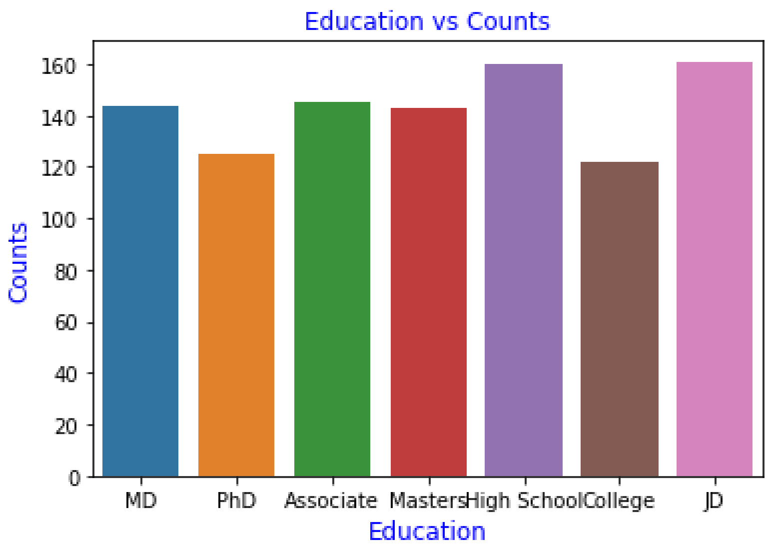
In female highest no of fraud reported

Insured Education Level counts

In [37]:
```
df['insured_education_level'].value_counts()
```

Out[37]:
```
JD             161
High School    160
Associate      145
MD             144
Masters        143
PhD            125
College        122
Name: insured_education_level, dtype: int64
```

In [38]:
```
sns.countplot( x="insured_education_level", data=df)
plt.xlabel('Education', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Education vs Counts', c = 'b', fontsize = 12)
plt.show()
```

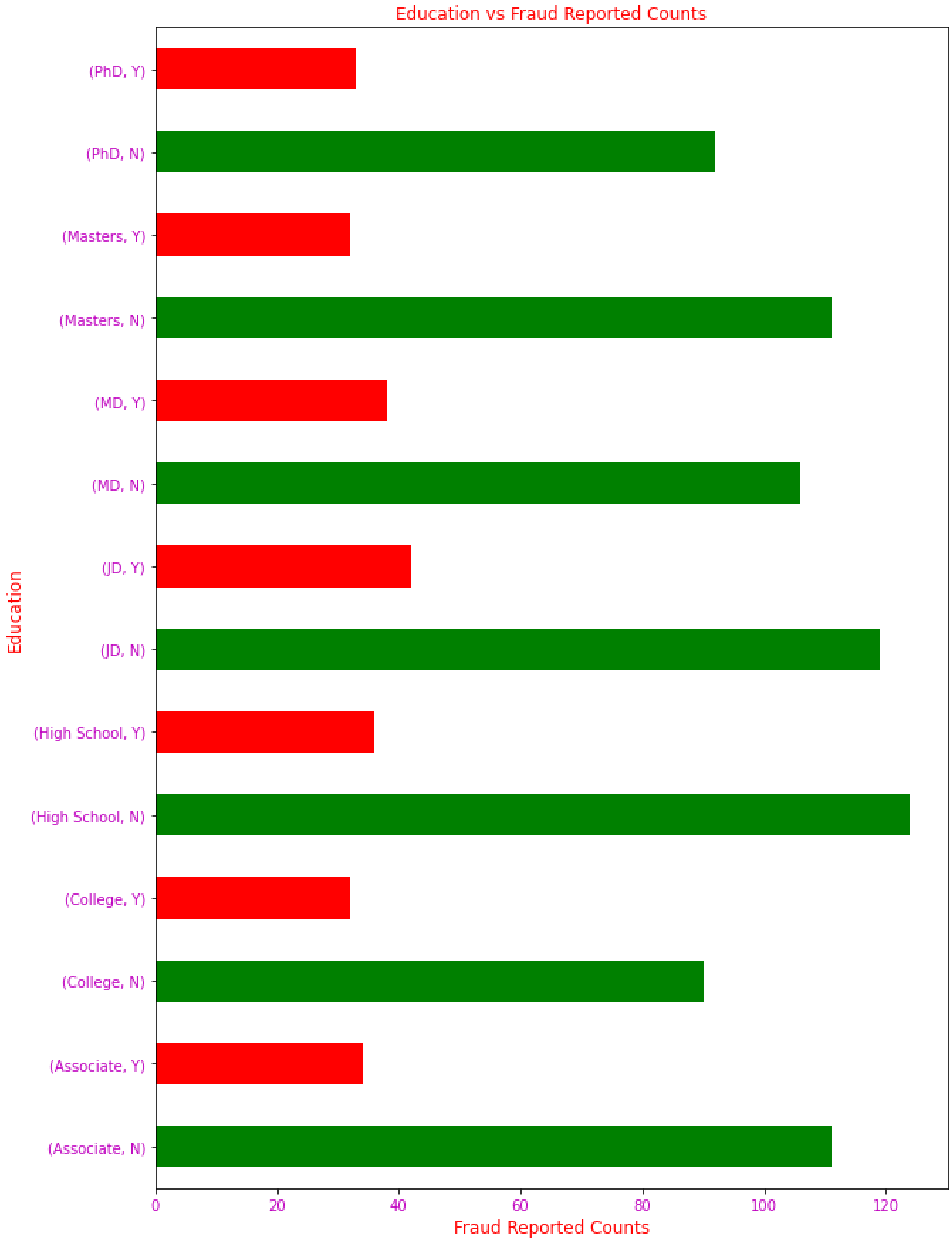


In education JD is highest counts

In [39]:
```
e = df.groupby('insured_education_level')['fraud_reported'].value_counts()
e
```

Out[39]:
```
insured_education_level  fraud_reported
Associate                N                 111
                         Y                  34
College                  N                  90
                         Y                  32
High School              N                 124
                         Y                  36
JD                       N                 119
                         Y                  42
MD                       N                 106
                         Y                  38
Masters                  N                 111
                         Y                  32
PhD                      N                  92
                         Y                  33
Name: fraud_reported, dtype: int64
```

In [40]:
```
e.plot.barh(figsize = (10,15), color = ['g','r'])
plt.ylabel('Education', c = 'r', fontsize = 12)
plt.xlabel('Fraud Reported Counts', c = 'r', fontsize = 12 )
plt.title('Education vs Fraud Reported Counts', c = 'r', fontsize = 12)
plt.xticks(c = 'm')
plt.yticks(c = 'm')
plt.show()
```



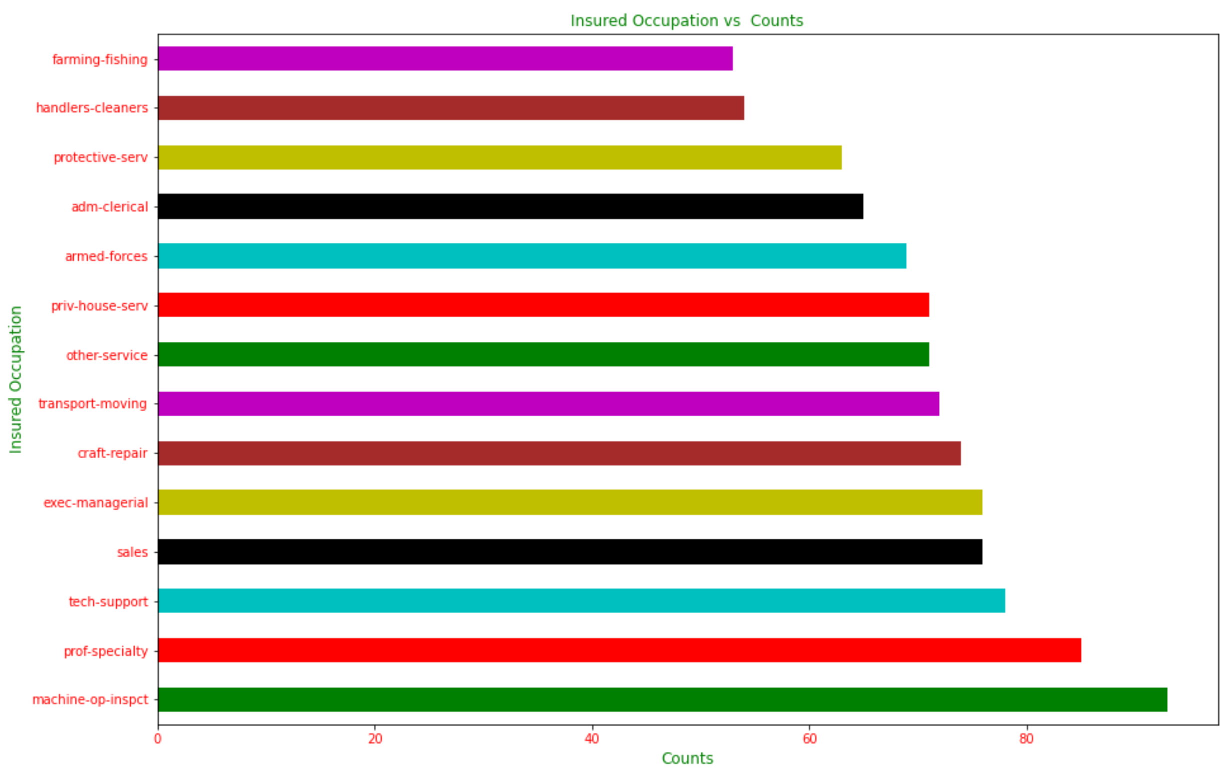
JD has highest fraud reported

Insured Occupation Columns

In [41]:
```
o = df['insured_occupation'].value_counts()
o
```

Out[41]:
```
machine-op-inspct    93
prof-specialty       85
tech-support         78
sales                76
exec-managerial      76
craft-repair         74
transport-moving     72
other-service        71
priv-house-serv      71
armed-forces         69
adm-clerical         65
protective-serv      63
handlers-cleaners    54
farming-fishing      53
Name: insured_occupation, dtype: int64
```

In [42]:
```
o.plot.barh( figsize = (15,10),  color = ['g','r','c','k','y', 'brown', 'm'])
plt.xlabel('Counts', c = 'g', fontsize = 12)
plt.ylabel('Insured Occupation', c = 'g', fontsize = 12 )
plt.title('Insured Occupation vs  Counts', c = 'g', fontsize = 12)
plt.xticks(c = 'r')
plt.yticks(c = 'r')
plt.show()
```

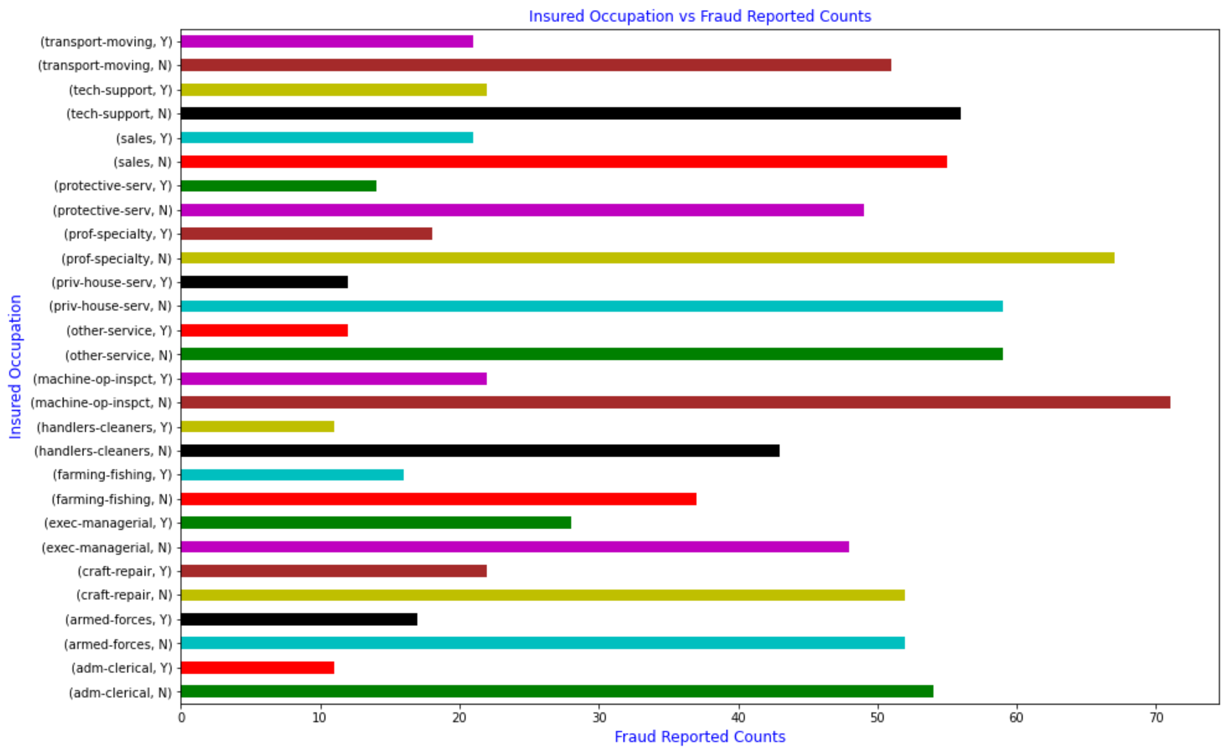


Machine-op-inspct highest counts

In [43]:
```python
op = df.groupby('insured_occupation')['fraud_reported'].value_counts()
op
```

Out[43]:
```
insured_occupation  fraud_reported
adm-clerical        N                 54
                    Y                 11
armed-forces        N                 52
                    Y                 17
craft-repair        N                 52
                    Y                 22
exec-managerial     N                 48
                    Y                 28
farming-fishing     N                 37
                    Y                 16
handlers-cleaners   N                 43
                    Y                 11
machine-op-inspct   N                 71
                    Y                 22
other-service       N                 59
                    Y                 12
priv-house-serv     N                 59
                    Y                 12
prof-specialty      N                 67
                    Y                 18
protective-serv     N                 49
                    Y                 14
sales               N                 55
                    Y                 21
tech-support        N                 56
                    Y                 22
transport-moving    N                 51
                    Y                 21
Name: fraud_reported, dtype: int64
```

In [44]:
```
op.plot.barh(figsize = (15,10),color = ['g','r','c','k','y', 'brown', 'm'])
plt.ylabel('Insured Occupation', c = 'b', fontsize = 12)
plt.xlabel('Fraud Reported Counts', c = 'b', fontsize = 12 )
plt.title('Insured Occupation vs Fraud Reported Counts', c = 'b', fontsize = 12)
plt.show()
```



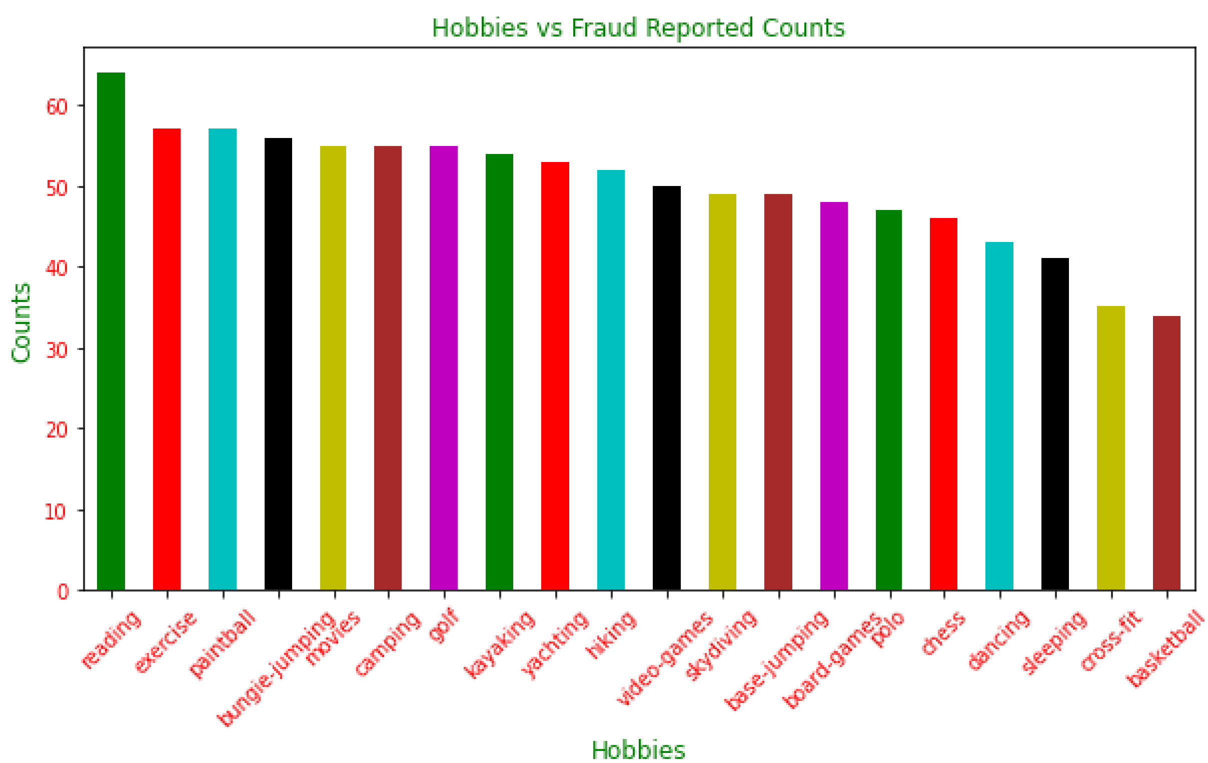
Exec-managerial occupation has highest fraud reported counts

Insured Hobbies Columns

```
In [45]: h = df['insured_hobbies'].value_counts()
         h
```

```
Out[45]: reading           64
         exercise          57
         paintball         57
         bungie-jumping    56
         movies            55
         camping           55
         golf              55
         kayaking          54
         yachting          53
         hiking            52
         video-games       50
         skydiving         49
         base-jumping      49
         board-games       48
         polo              47
         chess             46
         dancing           43
         sleeping          41
         cross-fit         35
         basketball        34
         Name: insured_hobbies, dtype: int64
```

```
In [46]: h.plot.bar(figsize = (10,5), rot = 45, color = ['g','r','c','k','y', 'brown', 'm'
         plt.xlabel('Hobbies', c = 'g', fontsize = 12)
         plt.ylabel('Counts', c = 'g', fontsize = 12 )
         plt.title('Hobbies vs Fraud Reported Counts', c = 'g', fontsize = 12)
         plt.xticks(c = 'r')
         plt.yticks(c = 'r')
         plt.show()
```



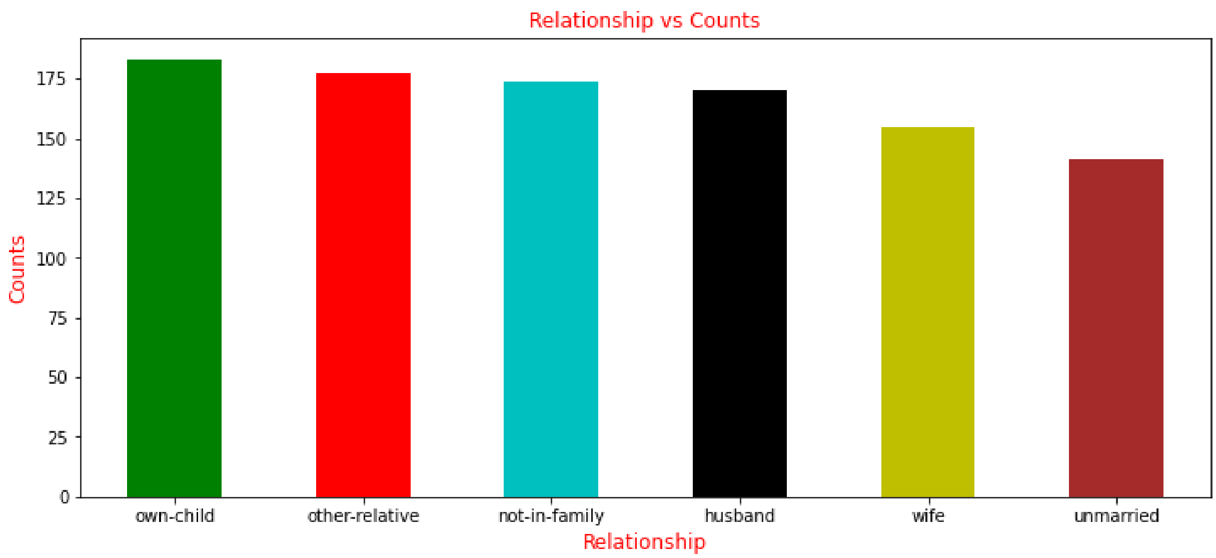
Reading is highest hobbies

Insured Relationship Column

In [47]:
```
r = df['insured_relationship'].value_counts()
r
```

Out[47]:
```
own-child         183
other-relative    177
not-in-family     174
husband           170
wife              155
unmarried         141
Name: insured_relationship, dtype: int64
```

In [48]:
```
r.plot.bar(figsize = (12,5), rot = 360, color = ['g','r','c','k','y', 'brown', 'r
plt.xlabel('Relationship', c = 'r', fontsize = 12)
plt.ylabel('Counts', c = 'r', fontsize = 12)
plt.title('Relationship vs Counts', c = 'r', fontsize = 12)
plt.show()
```

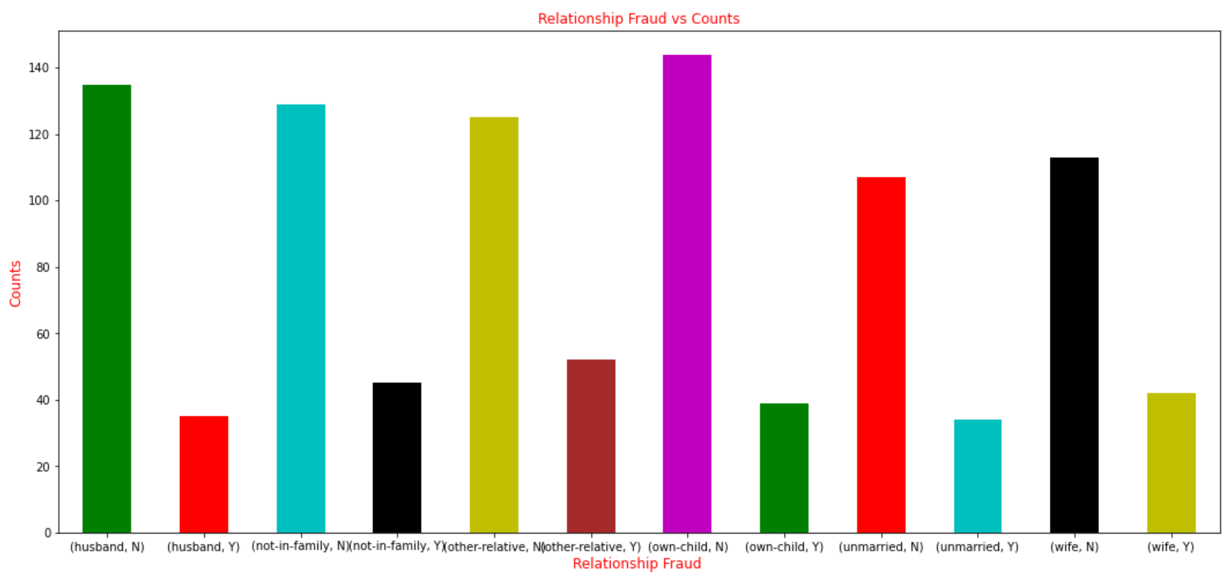


Own child has highest counts

In [49]:
```
re = df.groupby('insured_relationship')['fraud_reported'].value_counts()
re
```

Out[49]:
```
insured_relationship  fraud_reported
husband               N                 135
                      Y                  35
not-in-family         N                 129
                      Y                  45
other-relative        N                 125
                      Y                  52
own-child             N                 144
                      Y                  39
unmarried             N                 107
                      Y                  34
wife                  N                 113
                      Y                  42
Name: fraud_reported, dtype: int64
```

In [50]:
```
re.plot.bar(figsize = (18,8), rot = 360, color = ['g','r','c','k','y', 'brown', '
plt.xlabel('Relationship Fraud ', c = 'r', fontsize = 12)
plt.ylabel('Counts', c = 'r', fontsize = 12)
plt.title('Relationship Fraud vs Counts', c = 'r', fontsize = 12)
plt.show()
```



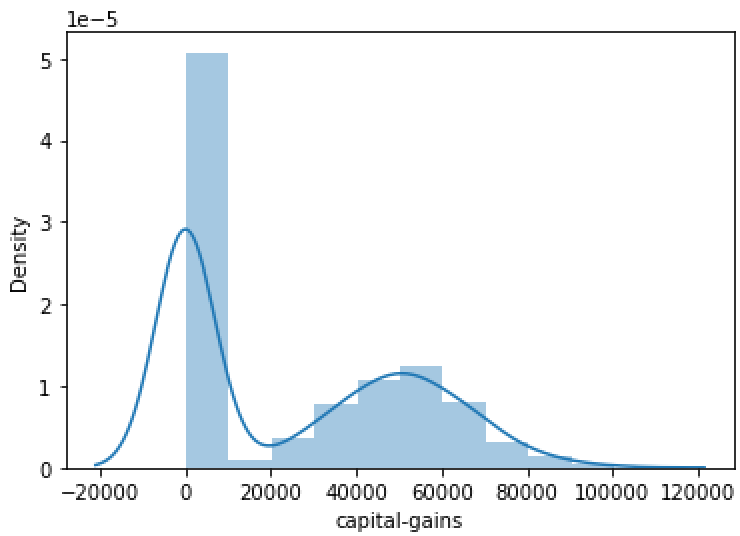
Other relative highest fraud counts

Capital Gains Column

In [51]:
```
df['capital-gains'].value_counts()
```

Out[51]:
```
0        508
46300      5
68500      4
51500      4
45500      3
        ...
54700      1
40100      1
33200      1
37300      1
72700      1
Name: capital-gains, Length: 338, dtype: int64
```

In [52]:
```
sns.distplot(df['capital-gains'], kde = True, hist = True)
plt.show()
```



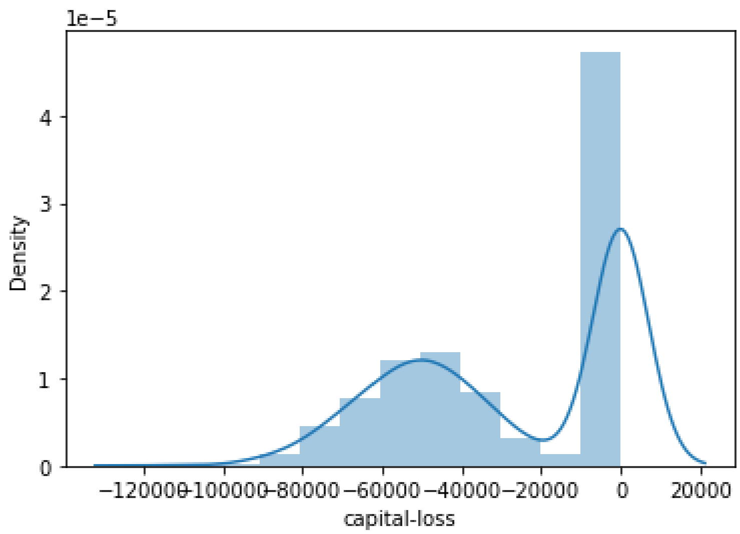
Capital Gains has skwed

Capital Loss Column

In [53]:
```
df['capital-loss'].value_counts()
```

Out[53]:
```
 0        475
-53700      5
-50300      5
-31700      5
-51000      4
         ...
-43300      1
-66100      1
-55900      1
-66500      1
-48000      1
Name: capital-loss, Length: 354, dtype: int64
```

In [54]:
```
sns.distplot(df['capital-loss'], kde = True, hist = True)
plt.show()
```



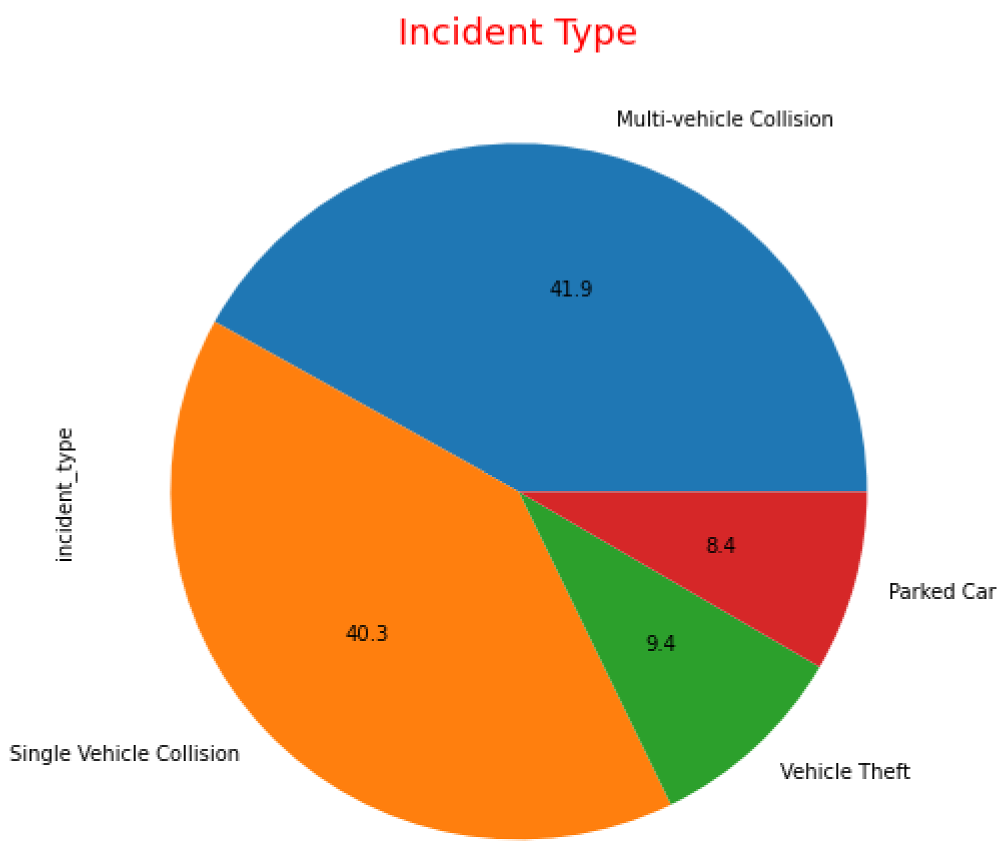
Capital loss has skwed

Incident Type Column

In [55]:
```
i = df['incident_type'].value_counts()
i
```

Out[55]:
```
Multi-vehicle Collision     419
Single Vehicle Collision    403
Vehicle Theft                94
Parked Car                   84
Name: incident_type, dtype: int64
```

In [56]:
```
i.plot.pie(figsize = (8,8),autopct = '%.1f')
plt.title('Incident Type', c = 'r', fontsize = 18)
plt.show()
```

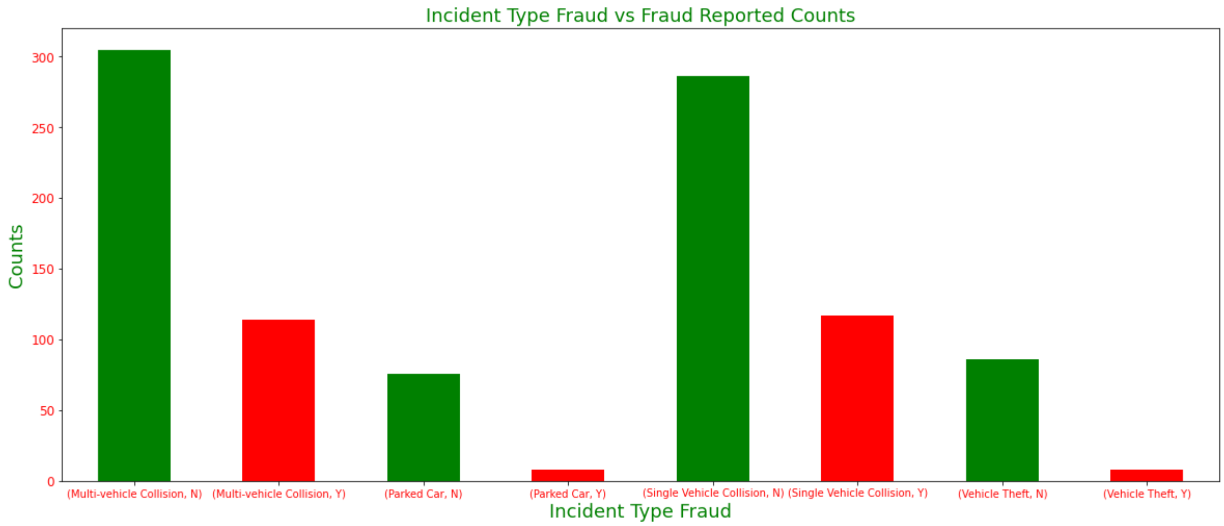


Multi Vehicle Collision Highest Counts

In [57]:
```
ig = df.groupby('incident_type')['fraud_reported'].value_counts()
ig
```

Out[57]:
```
incident_type             fraud_reported
Multi-vehicle Collision   N                 305
                          Y                 114
Parked Car                N                  76
                          Y                   8
Single Vehicle Collision  N                 286
                          Y                 117
Vehicle Theft             N                  86
                          Y                   8
Name: fraud_reported, dtype: int64
```

In [58]:
```
ig.plot.bar(figsize = (20,8), rot = 360, color = ['g','r'])
plt.xlabel('Incident Type Fraud', c = 'g', fontsize = 18)
plt.ylabel('Counts', c = 'g', fontsize = 18 )
plt.title('Incident Type Fraud vs Fraud Reported Counts', c = 'g', fontsize = 18)
plt.xticks(c = 'r', fontsize = 10)
plt.yticks(c = 'r', fontsize = 12)
plt.show()
```



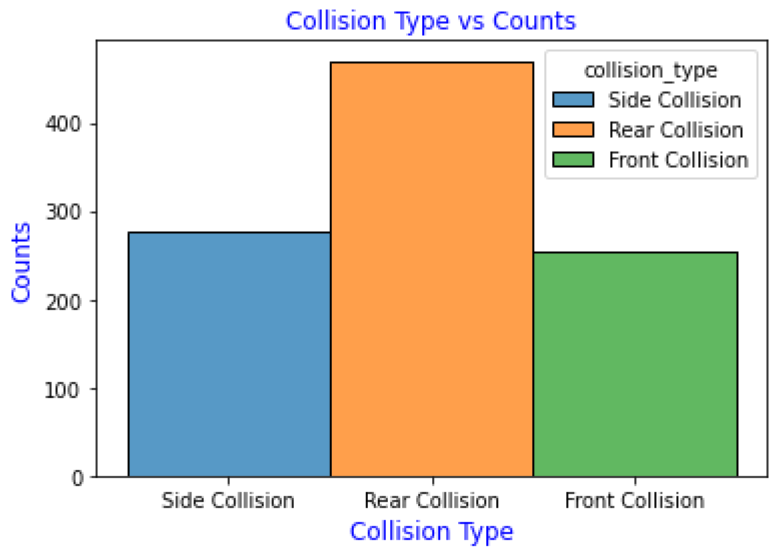
Single Vehicle Collision Highest Fraud Counts

Collision Type Counts

In [59]:
```
df['collision_type'].value_counts()
```

Out[59]:
```
Rear Collision     470
Side Collision     276
Front Collision    254
Name: collision_type, dtype: int64
```

In [60]:
```
sns.histplot(binwidth=0.5, x="collision_type", hue="collision_type", data=df, sta
plt.xlabel('Collision Type', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Collision Type vs Counts', c = 'b', fontsize = 12)
plt.show()
```

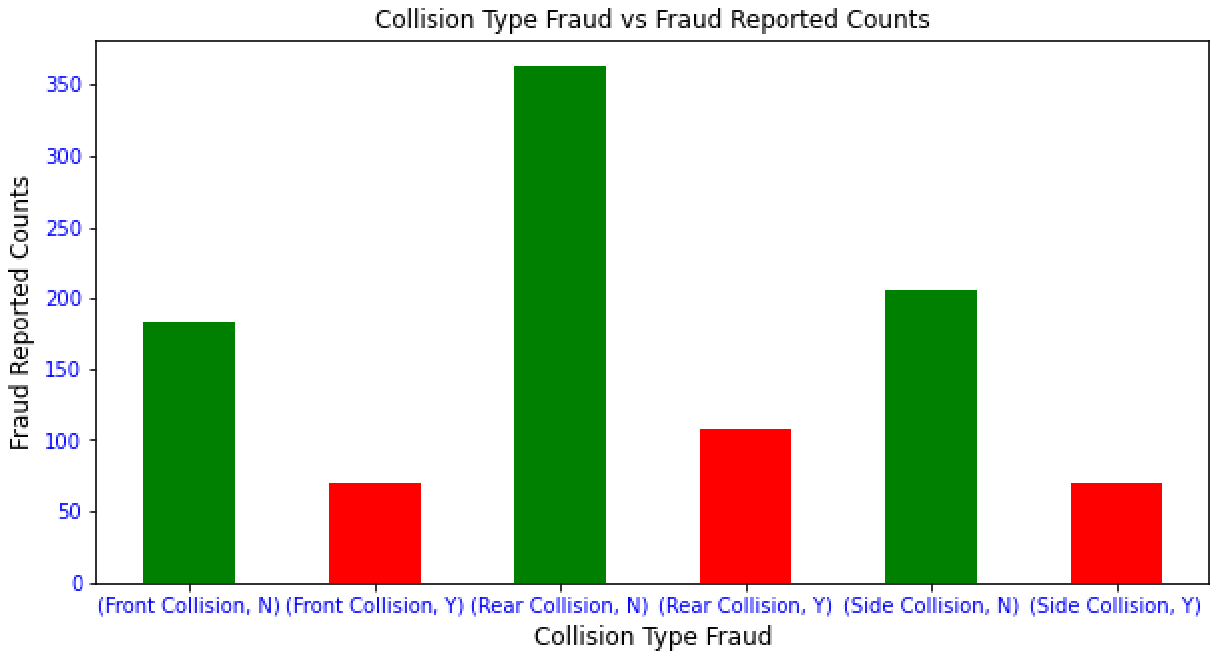


Rear Collision Has Highest Counts

In [61]:
```
ct = df.groupby('collision_type')['fraud_reported'].value_counts()
ct
```

Out[61]:
```
collision_type   fraud_reported
Front Collision  N                 184
                 Y                  70
Rear Collision   N                 363
                 Y                 107
Side Collision   N                 206
                 Y                  70
Name: fraud_reported, dtype: int64
```

In [62]:
```
ct.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Collision Type Fraud', c = 'k', fontsize = 12)
plt.ylabel('Fraud Reported Counts', c = 'k', fontsize = 12 )
plt.title('Collision Type Fraud vs Fraud Reported Counts', c = 'k', fontsize = 12
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```



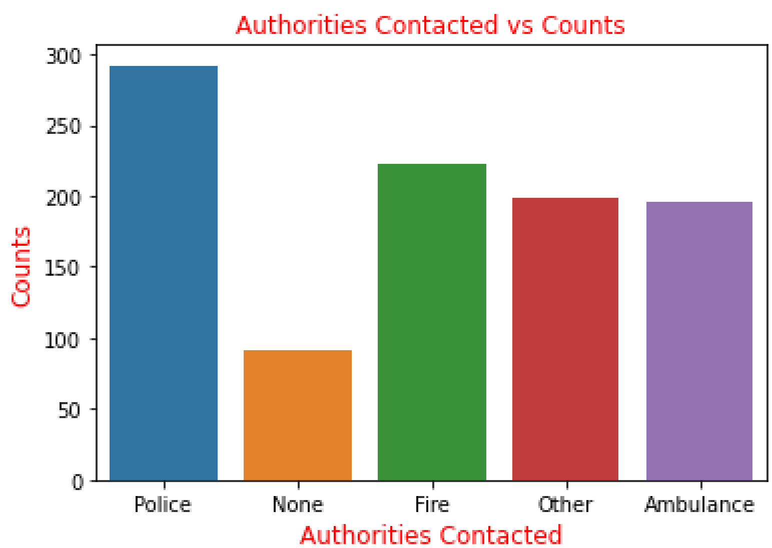
Rear Collision Has Highest Fraud Reported Counts

Authorities Contacted Column

In [63]:
```
df['authorities_contacted'].value_counts()
```

Out[63]:
```
Police       292
Fire         223
Other        198
Ambulance    196
None          91
Name: authorities_contacted, dtype: int64
```

In [64]:
```
sns.countplot(x="authorities_contacted", data=df)
plt.xlabel('Authorities Contacted', c = 'r', fontsize = 12)
plt.ylabel('Counts', c = 'r', fontsize = 12)
plt.title('Authorities Contacted vs Counts', c = 'r', fontsize = 12)
plt.show()
```

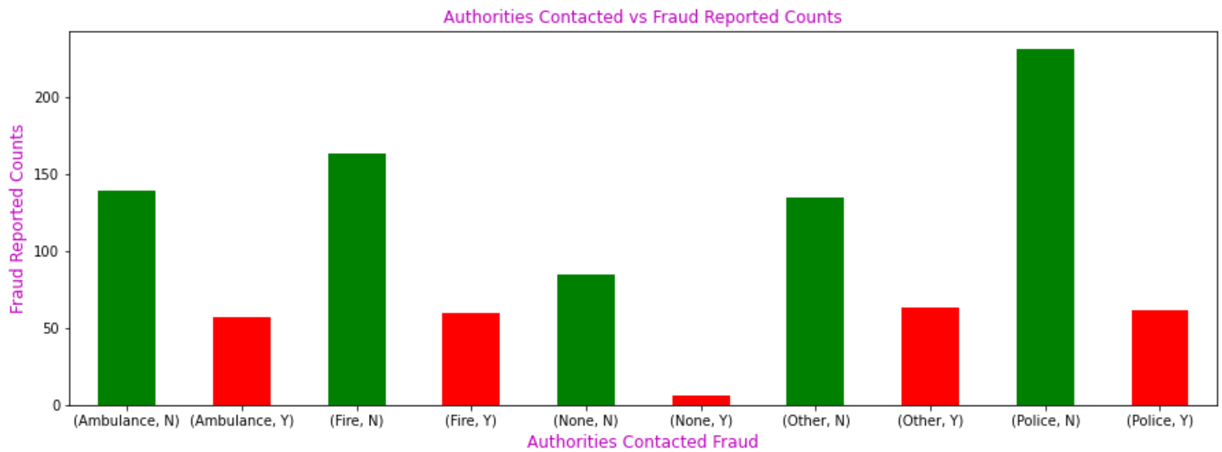


Police Has Highest Counts

In [65]:
```
au = df.groupby('authorities_contacted')['fraud_reported'].value_counts()
au
```

Out[65]:
```
authorities_contacted  fraud_reported
Ambulance              N                 139
                       Y                  57
Fire                   N                 163
                       Y                  60
None                   N                  85
                       Y                   6
Other                  N                 135
                       Y                  63
Police                 N                 231
                       Y                  61
Name: fraud_reported, dtype: int64
```

In [66]:
```
au.plot.bar(figsize = (15,5), rot = 360, color = ['g','r'])
plt.xlabel('Authorities Contacted Fraud', c = 'm', fontsize = 12)
plt.ylabel('Fraud Reported Counts', c = 'm', fontsize = 12 )
plt.title('Authorities Contacted vs Fraud Reported Counts', c = 'm', fontsize = 1
plt.show()
```



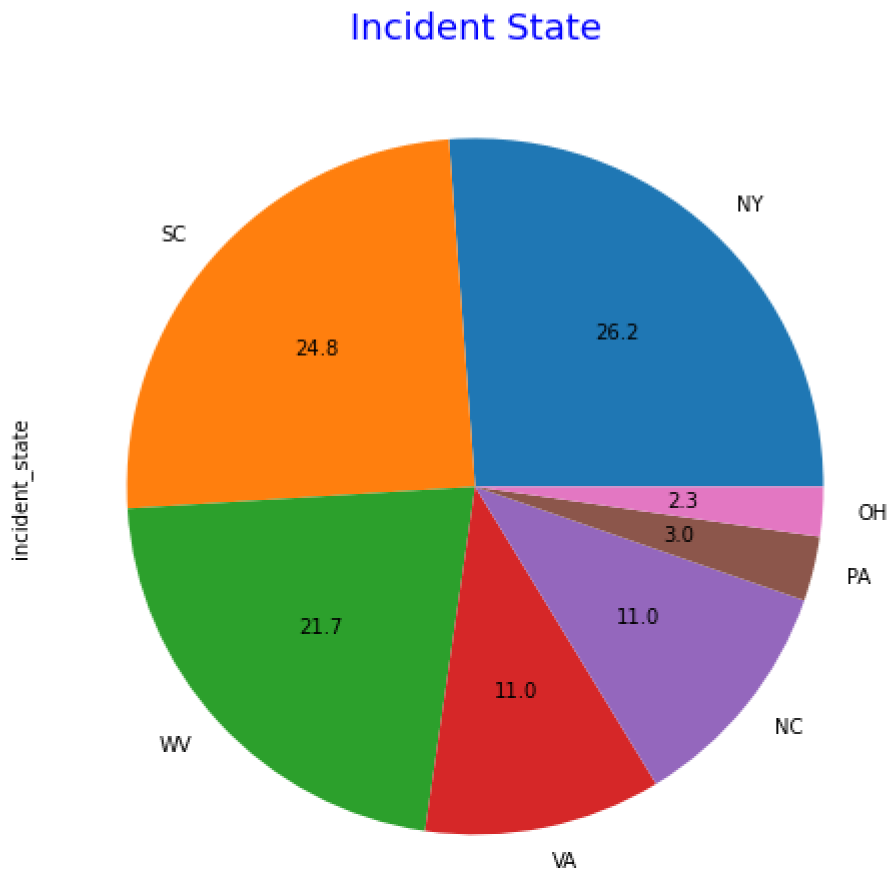
Other has highest no of fraud reported

Incident State Column

In [67]:
```
ist =df['incident_state'].value_counts()
ist
```

Out[67]:
```
NY    262
SC    248
WV    217
VA    110
NC    110
PA     30
OH     23
Name: incident_state, dtype: int64
```

In [68]:
```
ist.plot.pie(figsize = (8,8),autopct = '%.1f')
plt.title('Incident State', c ='b', fontsize = 18)
plt.show()
```

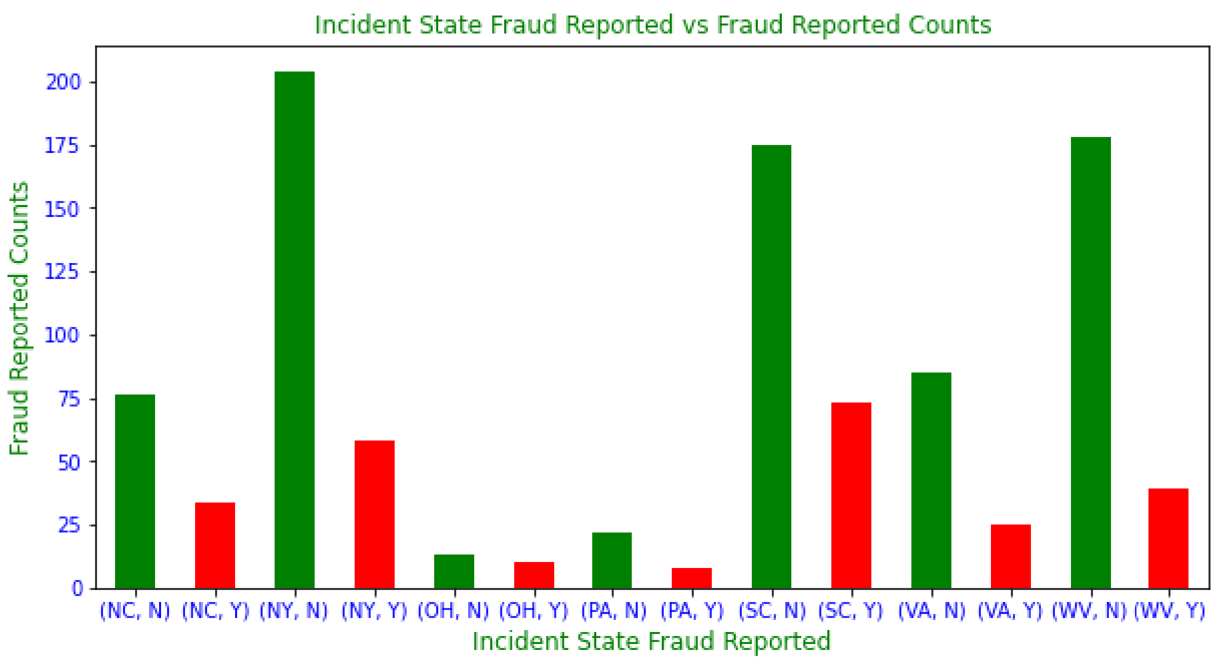


NY state has highest counts

In [69]:
```
sf = df.groupby('incident_state')['fraud_reported'].value_counts()
sf
```

Out[69]:
```
incident_state  fraud_reported
NC              N                  76
                Y                  34
NY              N                 204
                Y                  58
OH              N                  13
                Y                  10
PA              N                  22
                Y                   8
SC              N                 175
                Y                  73
VA              N                  85
                Y                  25
WV              N                 178
                Y                  39
Name: fraud_reported, dtype: int64
```

In [70]:
```
sf.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Incident State Fraud Reported', c = 'g', fontsize = 12)
plt.ylabel('Fraud Reported Counts', c = 'g', fontsize = 12 )
plt.title('Incident State Fraud Reported vs Fraud Reported Counts', c = 'g', font
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```



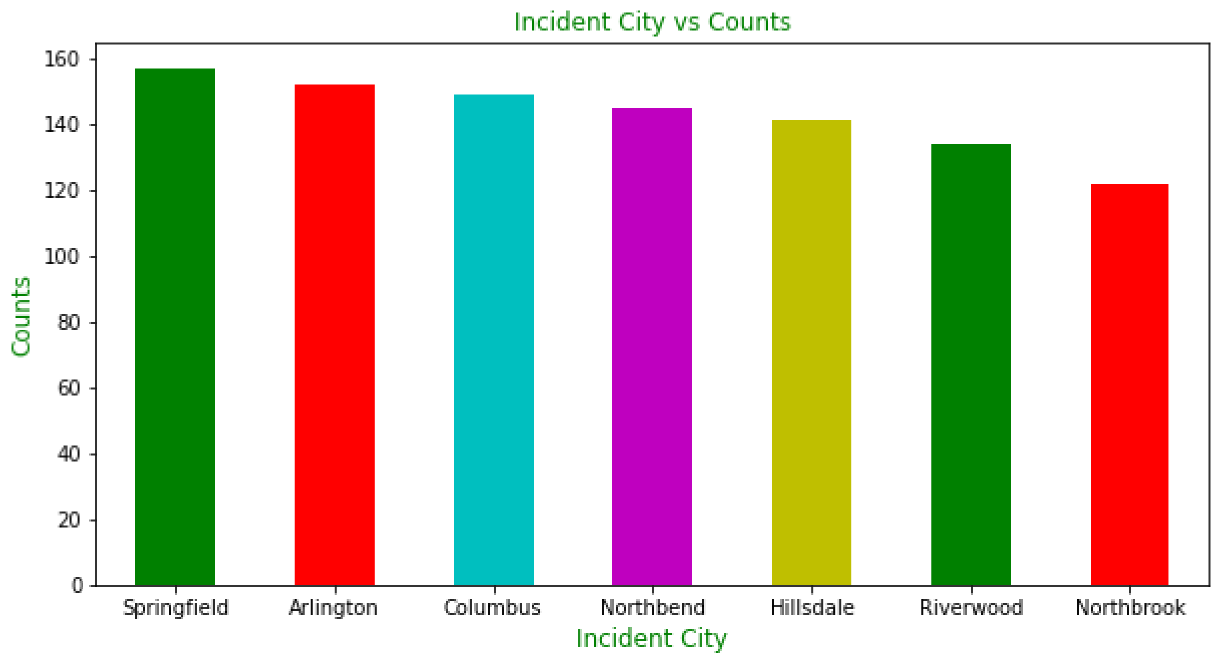
SC state highest fraud reported counts

Incident City Column

In [71]:
```
ic = df['incident_city'].value_counts()
ic
```

Out[71]:
```
Springfield    157
Arlington      152
Columbus       149
Northbend      145
Hillsdale      141
Riverwood      134
Northbrook     122
Name: incident_city, dtype: int64
```

In [72]:
```
ic.plot.bar(figsize = (10,5), rot = 360, color = ['g','r','c','m','y'])
plt.xlabel('Incident City', c = 'g', fontsize = 12)
plt.ylabel('Counts', c = 'g', fontsize = 12 )
plt.title('Incident City vs Counts', c = 'g', fontsize = 12)
plt.show()
```

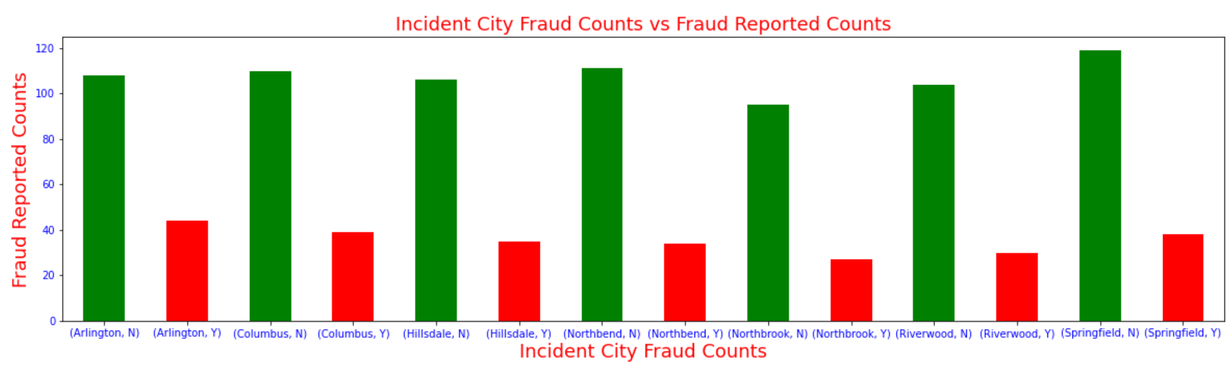


Springfield City has highest counts

In [73]:
```
c = df.groupby('incident_city')['fraud_reported'].value_counts()
c
```

Out[73]:
```
incident_city  fraud_reported
Arlington      N                 108
               Y                  44
Columbus       N                 110
               Y                  39
Hillsdale      N                 106
               Y                  35
Northbend      N                 111
               Y                  34
Northbrook     N                  95
               Y                  27
Riverwood      N                 104
               Y                  30
Springfield    N                 119
               Y                  38
Name: fraud_reported, dtype: int64
```

In [74]:
```
c.plot.bar(figsize = (20,5), rot = 360, color = ['g','r'])
plt.xlabel('Incident City Fraud Counts', c = 'r', fontsize = 18)
plt.ylabel('Fraud Reported Counts', c = 'r', fontsize = 18 )
plt.title('Incident City Fraud Counts vs Fraud Reported Counts', c = 'r', fontsiz
plt.xticks(c = 'b', fontsize = 10)
plt.yticks(c = 'b', fontsize = 10)
plt.show()
```



Arlington city highest fraud reported counts

Incident Hour Of The Day Column

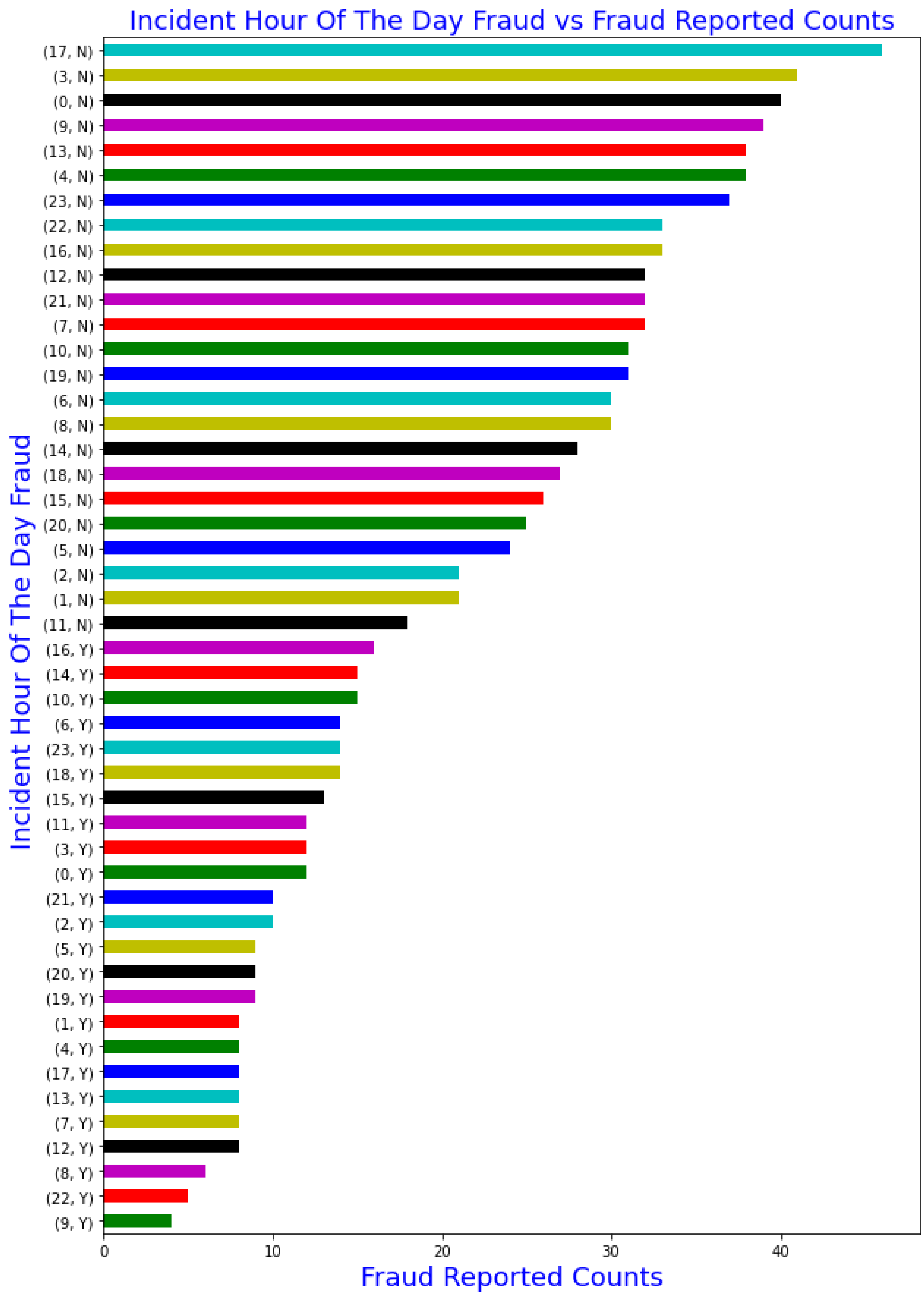
In [75]:
```
df['incident_hour_of_the_day'].value_counts()
```

Out[75]:
```
17    54
3     53
0     52
23    51
16    49
4     46
10    46
13    46
6     44
14    43
9     43
21    42
18    41
7     40
19    40
12    40
15    39
22    38
8     36
20    34
5     33
2     31
11    30
1     29
Name: incident_hour_of_the_day, dtype: int64
```

In [76]:
```
hr = df.groupby('incident_hour_of_the_day')['fraud_reported'].value_counts().sort
hr
```

Out[76]:
```
incident_hour_of_the_day  fraud_reported
9                         Y                  4
22                        Y                  5
8                         Y                  6
12                        Y                  8
7                         Y                  8
13                        Y                  8
17                        Y                  8
4                         Y                  8
1                         Y                  8
19                        Y                  9
20                        Y                  9
5                         Y                  9
2                         Y                 10
21                        Y                 10
0                         Y                 12
3                         Y                 12
11                        Y                 12
15                        Y                 13
18                        Y                 14
23                        Y                 14
6                         Y                 14
10                        Y                 15
14                        Y                 15
16                        Y                 16
11                        N                 18
1                         N                 21
2                         N                 21
5                         N                 24
20                        N                 25
15                        N                 26
18                        N                 27
14                        N                 28
8                         N                 30
6                         N                 30
19                        N                 31
10                        N                 31
7                         N                 32
21                        N                 32
12                        N                 32
16                        N                 33
22                        N                 33
23                        N                 37
4                         N                 38
13                        N                 38
9                         N                 39
0                         N                 40
3                         N                 41
17                        N                 46
Name: fraud_reported, dtype: int64
```

In [77]:
```
hr.plot.barh(figsize = (10,15), rot = 360, color = ['g','r','m','k','y','c','b'])
plt.ylabel('Incident Hour Of The Day Fraud ', c = 'b', fontsize = 18)
plt.xlabel('Fraud Reported Counts', c = 'b', fontsize = 18 )
plt.title('Incident Hour Of The Day Fraud vs Fraud Reported Counts', c = 'b', for
plt.show()
```



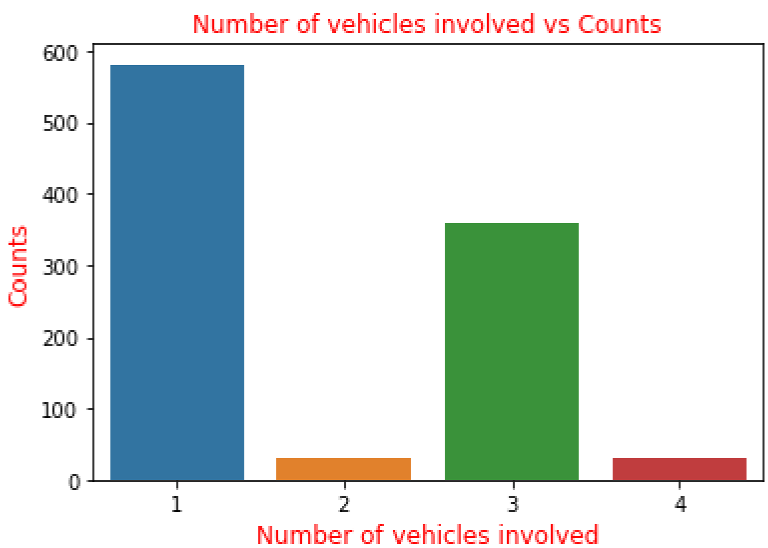
In a day highest 16 fraud case reported

Number Of Vehicles Involved Column

In [78]:
```
df['number_of_vehicles_involved'].value_counts()
```

Out[78]:
```
1    581
3    358
4     31
2     30
Name: number_of_vehicles_involved, dtype: int64
```

In [79]:
```
sns.countplot( x="number_of_vehicles_involved", data=df)
plt.xlabel('Number of vehicles involved', c = 'r', fontsize = 12)
plt.ylabel('Counts', c = 'r', fontsize = 12)
plt.title('Number of vehicles involved vs Counts', c = 'r', fontsize = 12)
plt.show()
```

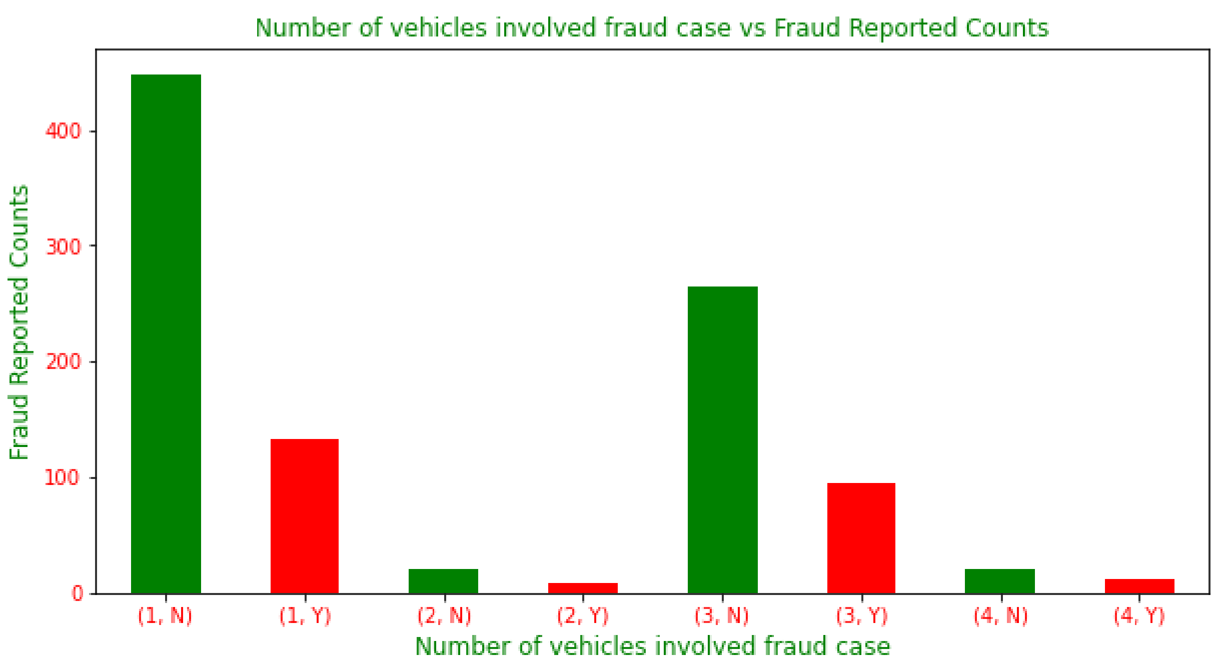


One vehicles involved fraud case highest

In [80]:
```
v = df.groupby('number_of_vehicles_involved')['fraud_reported'].value_counts()
v
```

Out[80]:
```
number_of_vehicles_involved  fraud_reported
1                            N                 448
                             Y                 133
2                            N                  21
                             Y                   9
3                            N                 264
                             Y                  94
4                            N                  20
                             Y                  11
Name: fraud_reported, dtype: int64
```

In [81]:
```
v.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Number of vehicles involved fraud case', c = 'g', fontsize = 12)
plt.ylabel('Fraud Reported Counts', c = 'g', fontsize = 12 )
plt.title('Number of vehicles involved fraud case vs Fraud Reported Counts', c =
plt.xticks(c = 'r')
plt.yticks(c = 'r')
plt.show()
```



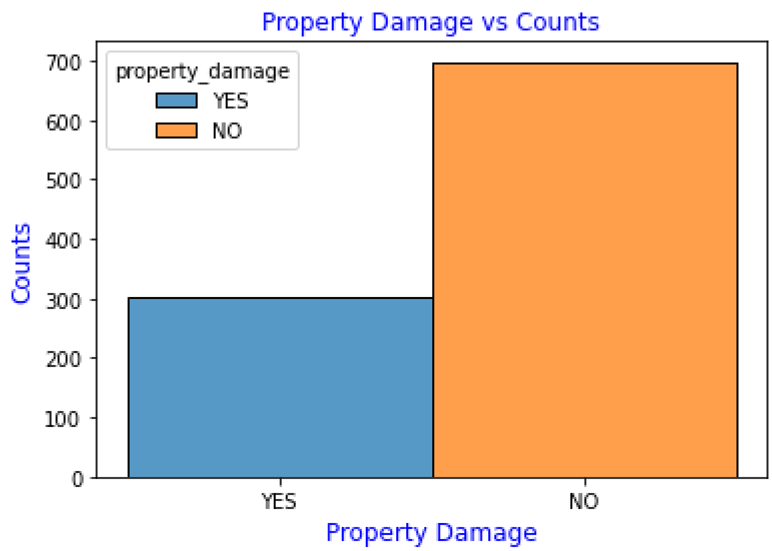
One vehicles involved fraud case highest

Property Damage

In [82]:
```
df['property_damage'].value_counts()
```

Out[82]:
```
NO     698
YES    302
Name: property_damage, dtype: int64
```

In [83]:
```
sns.histplot(binwidth=0.5, x="property_damage", hue="property_damage", data=df, s
plt.xlabel('Property Damage', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Property Damage vs Counts', c = 'b', fontsize = 12)
plt.show()
```



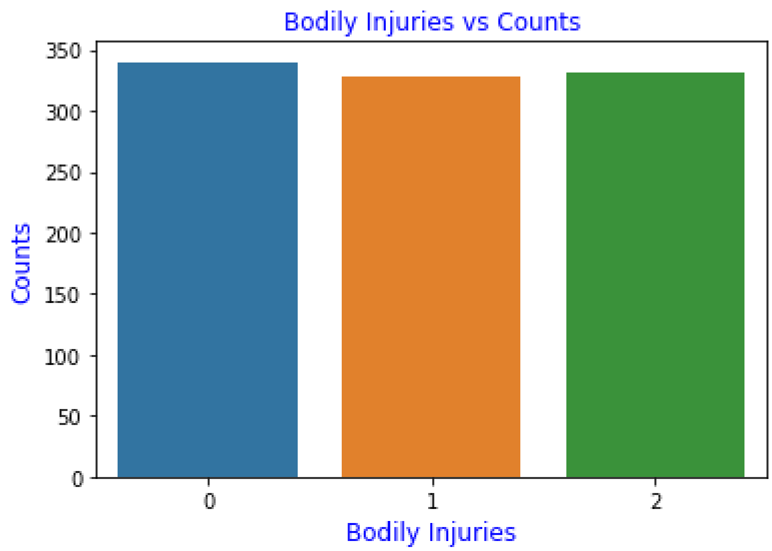
Property Damage cases are low

Bodily Injuries Column

In [84]:
```
df['bodily_injuries'].value_counts()
```

Out[84]:
```
0    340
2    332
1    328
Name: bodily_injuries, dtype: int64
```

In [85]:
```
sns.countplot( x="bodily_injuries", data=df)
plt.xlabel('Bodily Injuries', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Bodily Injuries vs Counts', c = 'b', fontsize = 12)
plt.show()
```



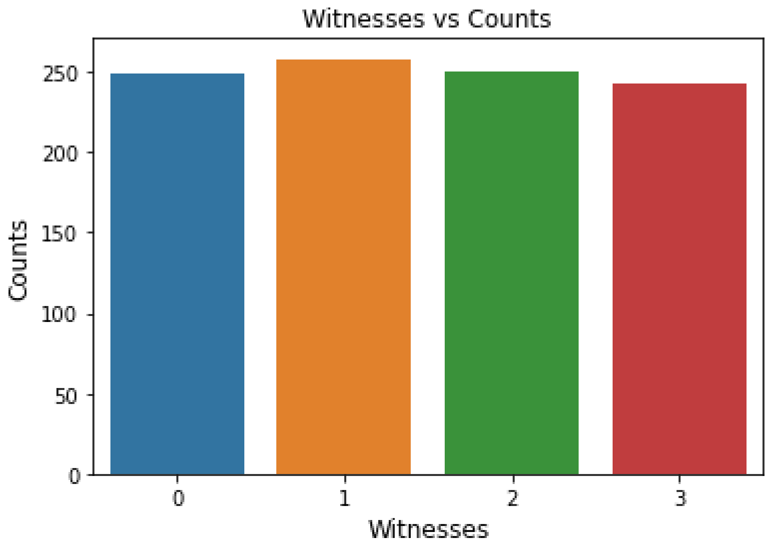
Zero has highest counts

Witnesses Column

In [86]:
```
df['witnesses'].value_counts()
```

Out[86]:
```
1    258
2    250
0    249
3    243
Name: witnesses, dtype: int64
```

In [87]:
```
sns.countplot( x="witnesses", data=df)
plt.xlabel('Witnesses', c = 'k', fontsize = 12)
plt.ylabel('Counts', c = 'k', fontsize = 12)
plt.title('Witnesses vs Counts', c = 'k', fontsize = 12)
plt.show()
```



One witnesses counts is highest

Total Claim Amount Column

In [88]:
```
print('Maximum Claim Amount------------>',df['total_claim_amount'].max())
```

```
Maximum Claim Amount------------> 114920
```

In [89]:
```
print('Minimum Claim Amount------------>',df['total_claim_amount'].min())
```

```
Minimum Claim Amount------------> 100
```

Injury Claim Column

In [90]:
```
print('Maximum Injury Claim Amount------------>',df['injury_claim'].max())
```

```
Maximum Injury Claim Amount------------> 21450
```

In [91]:
```
print('Minimum Injury Claim Amount------------>',df['injury_claim'].min())
```

```
Minimum Injury Claim Amount------------> 0
```

Property Claim Column

In [92]:
```python
print('Maximum Property Claim ------------>',df['property_claim'].max())
```

```
Maximum Property Claim ------------> 23670
```

In [93]:
```python
print('Minimum Property Claim ------------>',df['property_claim'].min())
```

```
Minimum Property Claim ------------> 0
```

Vehicle Claim Column

In [94]:
```python
print('Maximum Vehicle Claim ------------>',df['vehicle_claim'].max())
```

```
Maximum Vehicle Claim ------------> 79560
```

In [95]:
```python
print('Minimum Vehicle Claim ------------>',df['vehicle_claim'].min())
```

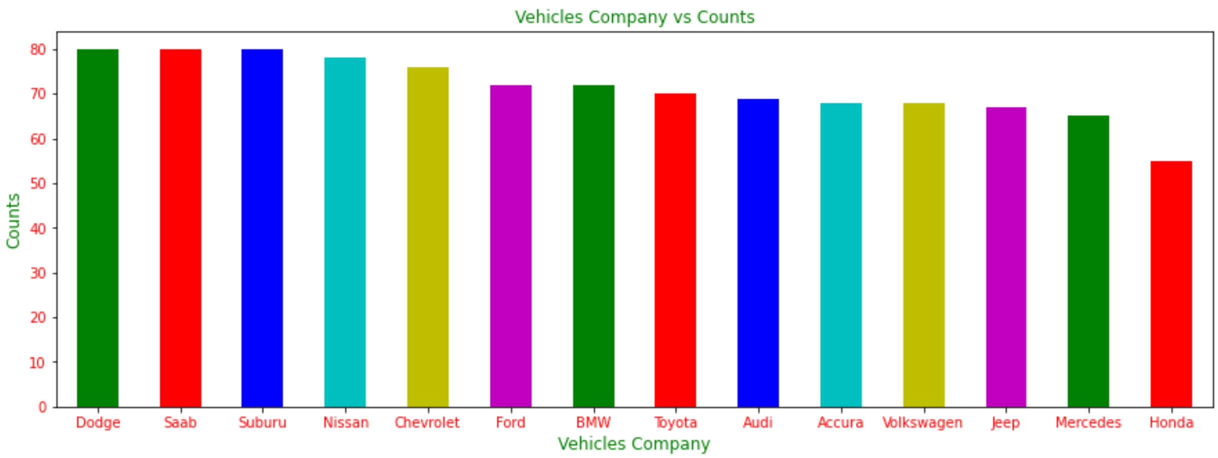
```
Minimum Vehicle Claim ------------> 70
```

Auto Make Column

In [96]:
```python
au = df['auto_make'].value_counts()
au
```

Out[96]:
```
Dodge         80
Saab          80
Suburu        80
Nissan        78
Chevrolet     76
Ford          72
BMW           72
Toyota        70
Audi          69
Accura        68
Volkswagen    68
Jeep          67
Mercedes      65
Honda         55
Name: auto_make, dtype: int64
```

In [97]:
```
au.plot.bar(figsize = (15,5), rot = 360, color = ['g','r','b','c','y','m'])
plt.xlabel('Vehicles Company', c = 'g', fontsize = 12)
plt.ylabel('Counts', c = 'g', fontsize = 12 )
plt.title('Vehicles Company vs Counts', c = 'g', fontsize = 12)
plt.xticks(c = 'r')
plt.yticks(c = 'r')
plt.show()
```

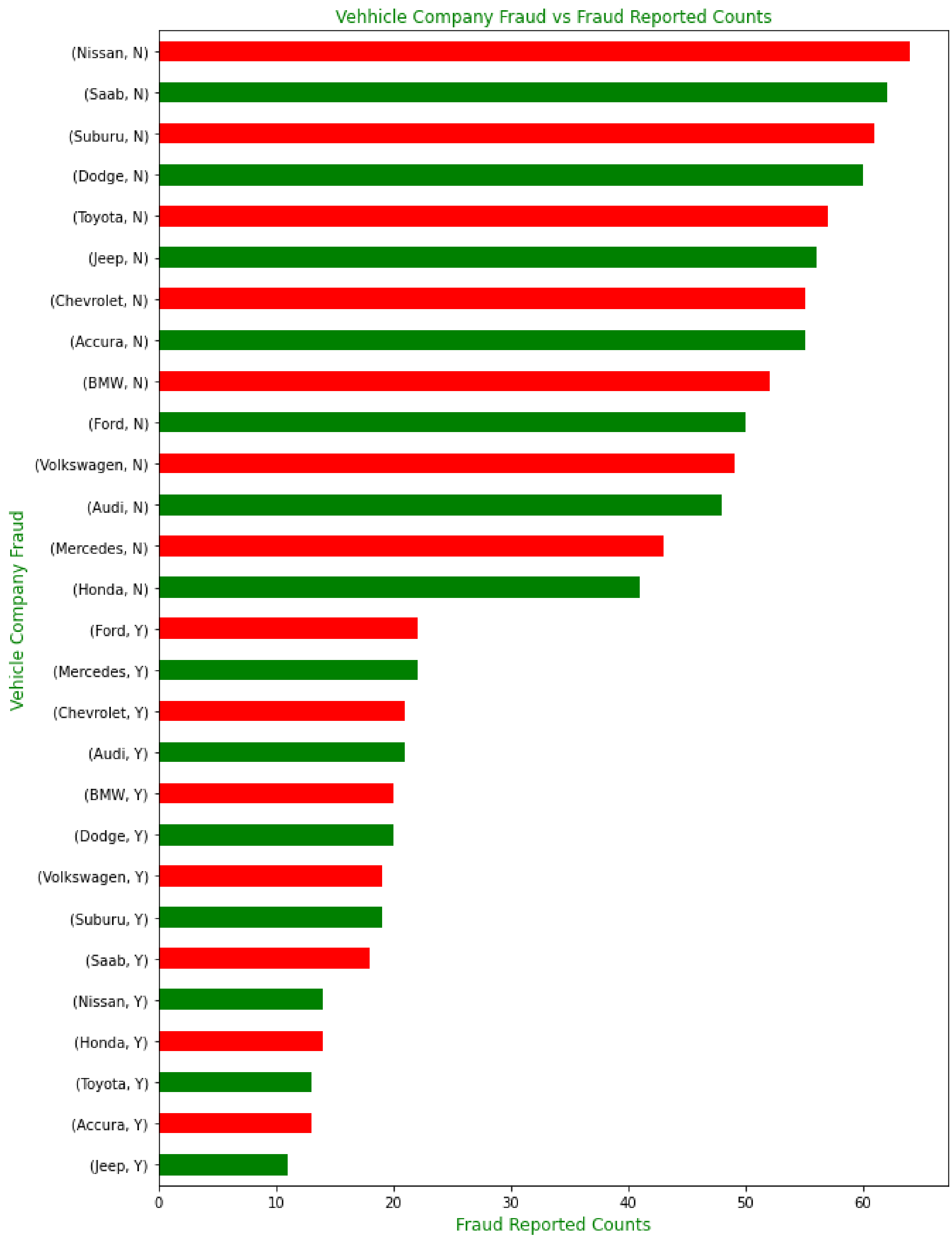


Dodge is highest counts and Honda is lowest

In [98]:
```python
am = df.groupby('auto_make')['fraud_reported'].value_counts().sort_values()
am
```

Out[98]:
```
auto_make   fraud_reported
Jeep        Y                 11
Accura      Y                 13
Toyota      Y                 13
Honda       Y                 14
Nissan      Y                 14
Saab        Y                 18
Suburu      Y                 19
Volkswagen  Y                 19
Dodge       Y                 20
BMW         Y                 20
Audi        Y                 21
Chevrolet   Y                 21
Mercedes    Y                 22
Ford        Y                 22
Honda       N                 41
Mercedes    N                 43
Audi        N                 48
Volkswagen  N                 49
Ford        N                 50
BMW         N                 52
Accura      N                 55
Chevrolet   N                 55
Jeep        N                 56
Toyota      N                 57
Dodge       N                 60
Suburu      N                 61
Saab        N                 62
Nissan      N                 64
Name: fraud_reported, dtype: int64
```

```
In [99]: am.plot.barh(figsize = (10,15), rot = 360, color = ['g','r'])
         plt.ylabel('Vehicle Company Fraud', c = 'g', fontsize = 12)
         plt.xlabel('Fraud Reported Counts', c = 'g', fontsize = 12 )
         plt.title('Vehhicle Company Fraud vs Fraud Reported Counts', c = 'g', fontsize =
         plt.show()
```



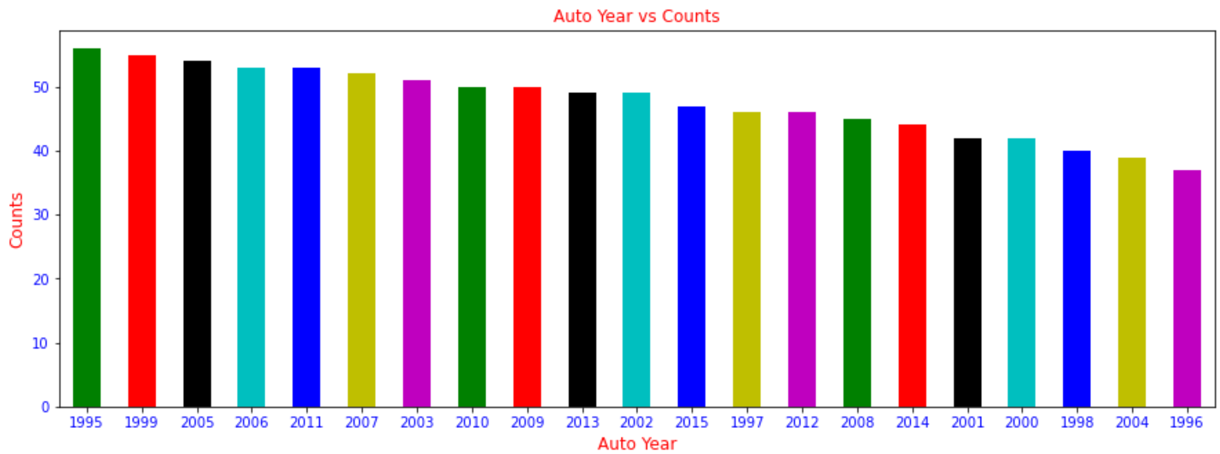
Mercedes and Ford has highest fraud reported

Auto Year Column

In [100]:
```
y = df['auto_year'].value_counts()
y
```

Out[100]:
```
1995    56
1999    55
2005    54
2006    53
2011    53
2007    52
2003    51
2010    50
2009    50
2013    49
2002    49
2015    47
1997    46
2012    46
2008    45
2014    44
2001    42
2000    42
1998    40
2004    39
1996    37
Name: auto_year, dtype: int64
```

In [101]:
```
y.plot.bar(figsize = (15,5), rot = 360, color = ['g','r','k','c','b','y','m'])
plt.xlabel('Auto Year', c = 'r', fontsize = 12)
plt.ylabel('Counts', c = 'r', fontsize = 12 )
plt.title('Auto Year vs Counts', c = 'r', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```

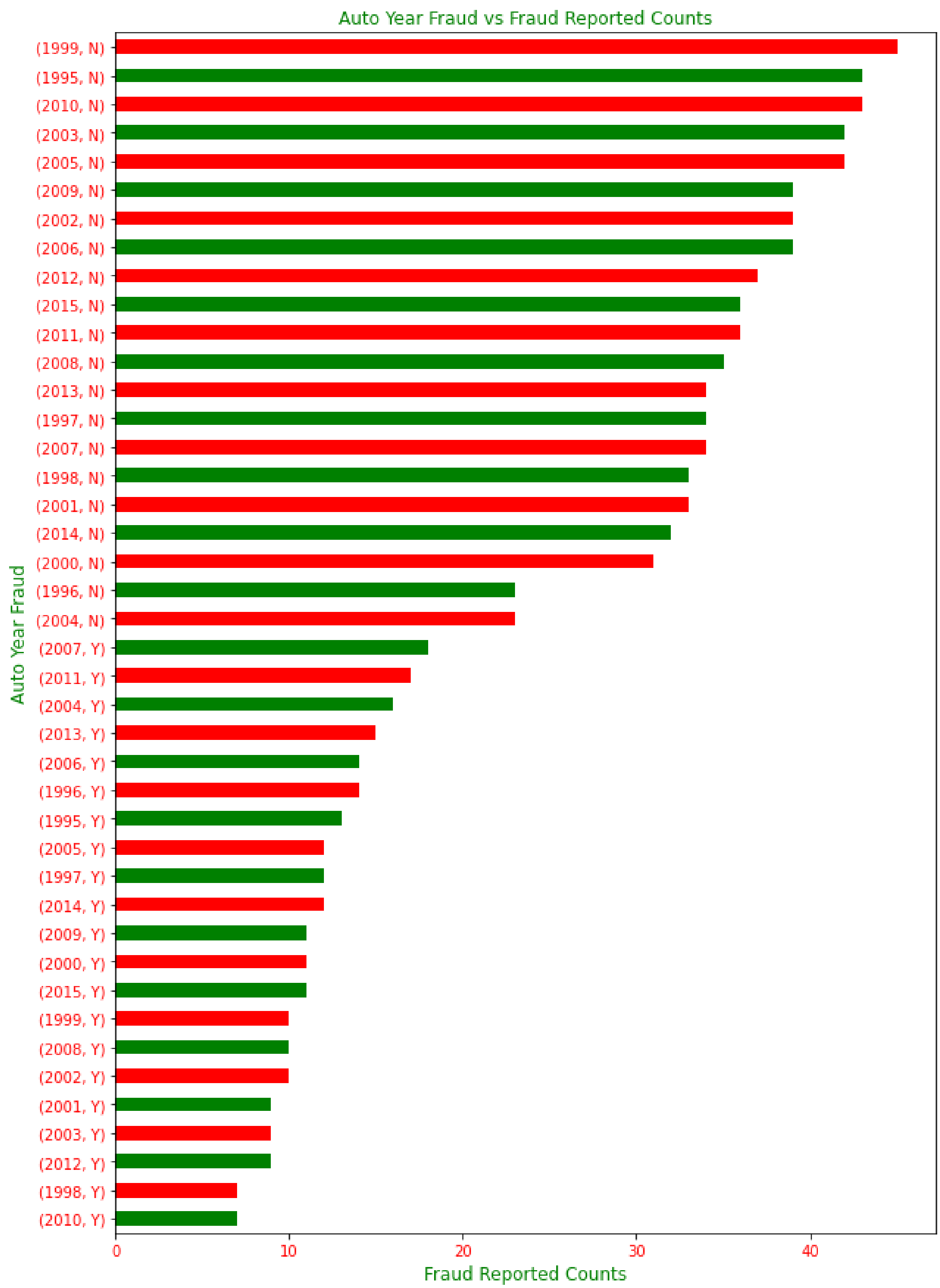


1995 highest sell of auto

```
In [102]: ay = df.groupby('auto_year')['fraud_reported'].value_counts().sort_values()
          ay
```

```
Out[102]: auto_year  fraud_reported
          2010       Y                  7
          1998       Y                  7
          2012       Y                  9
          2003       Y                  9
          2001       Y                  9
          2002       Y                 10
          2008       Y                 10
          1999       Y                 10
          2015       Y                 11
          2000       Y                 11
          2009       Y                 11
          2014       Y                 12
          1997       Y                 12
          2005       Y                 12
          1995       Y                 13
          1996       Y                 14
          2006       Y                 14
          2013       Y                 15
          2004       Y                 16
          2011       Y                 17
          2007       Y                 18
          2004       N                 23
          1996       N                 23
          2000       N                 31
          2014       N                 32
          2001       N                 33
          1998       N                 33
          2007       N                 34
          1997       N                 34
          2013       N                 34
          2008       N                 35
          2011       N                 36
          2015       N                 36
          2012       N                 37
          2006       N                 39
          2002       N                 39
          2009       N                 39
          2005       N                 42
          2003       N                 42
          2010       N                 43
          1995       N                 43
          1999       N                 45
          Name: fraud_reported, dtype: int64
```

```
In [103]: ay.plot.barh(figsize = (10,15), rot = 360, color = ['g','r'])
          plt.ylabel('Auto Year Fraud', c = 'g', fontsize = 12)
          plt.xlabel('Fraud Reported Counts', c = 'g', fontsize = 12 )
          plt.title('Auto Year Fraud vs Fraud Reported Counts', c = 'g', fontsize = 12)
          plt.xticks(c = 'r')
          plt.yticks(c = 'r')
          plt.show()
```



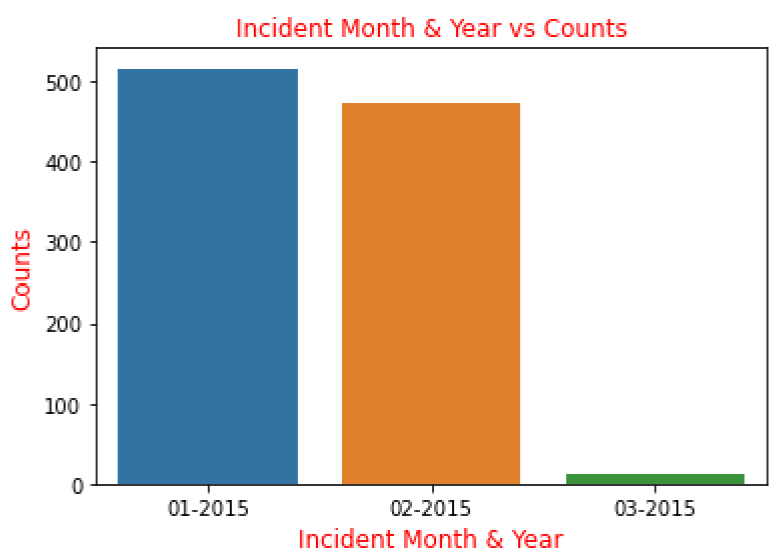
Year 2007 highest fraud reported counts

Incident Month & Year Column

In [104]:
```
df['IncidentMonth&Year'].value_counts()
```

Out[104]:
```
01-2015    516
02-2015    472
03-2015     12
Name: IncidentMonth&Year, dtype: int64
```

In [105]:
```
sns.countplot( x="IncidentMonth&Year", data=df)
plt.xlabel('Incident Month & Year', c = 'r', fontsize = 12)
plt.ylabel('Counts', c = 'r', fontsize = 12)
plt.title('Incident Month & Year vs Counts', c = 'r', fontsize = 12)
plt.show()
```

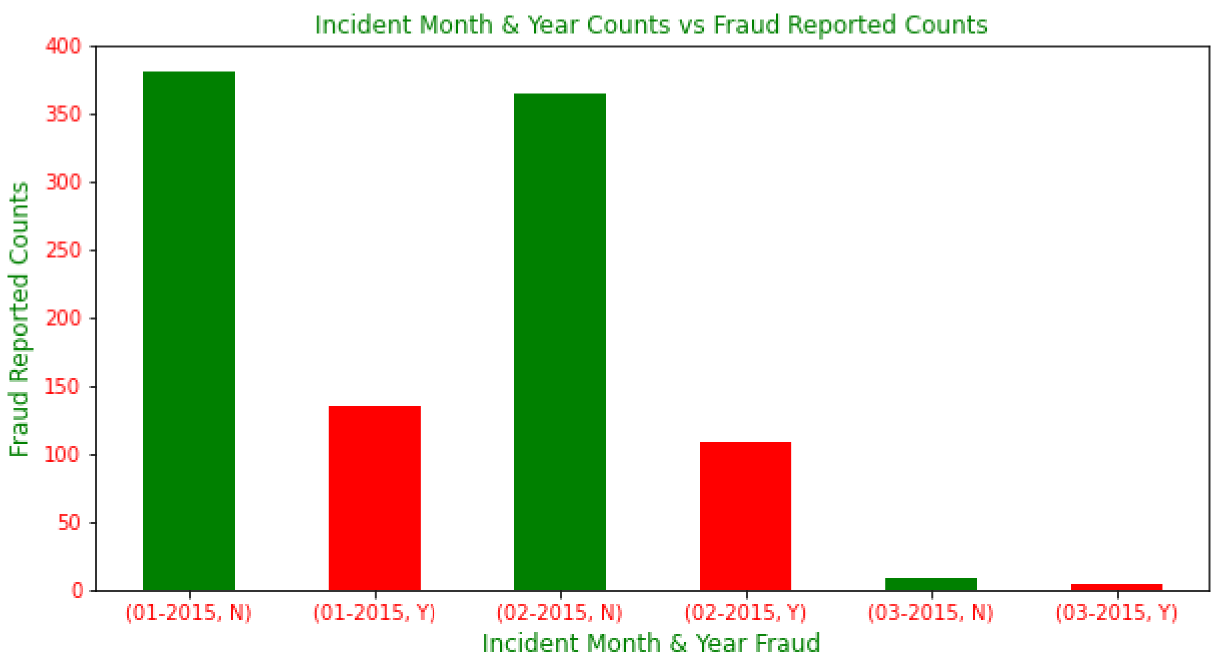


In 2015 first month highest incident counts

In [106]:
```
imy = df.groupby('IncidentMonth&Year')['fraud_reported'].value_counts()
imy
```

Out[106]:
```
IncidentMonth&Year  fraud_reported
01-2015             N                 381
                    Y                 135
02-2015             N                 364
                    Y                 108
03-2015             N                   8
                    Y                   4
Name: fraud_reported, dtype: int64
```

In [107]:
```
imy.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Incident Month & Year Fraud', c = 'g', fontsize = 12)
plt.ylabel('Fraud Reported Counts', c = 'g', fontsize = 12 )
plt.title('Incident Month & Year Counts vs Fraud Reported Counts', c = 'g', fonts
plt.xticks(c = 'r')
plt.yticks(c = 'r')
plt.show()
```



In 2015 first month highest fraud reported counts

Drop Columns

In [108]:
```
col = ['policy_bind_date', 'incident_date', 'incident_location']
```

In [109]:
```
df = df.drop(col, axis = 1)
df.head(2)
```

Out[109]:

	months_as_customer	age	policy_number	policy_state	policy_csl	policy_deductable	policy_an
0	328	48	521585	OH	250/500	1000	
1	228	42	342868	IN	250/500	2000	

In [110]:
```
print('No of Rows and Columns after removing columns ----->', df.shape )
```

```
No of Rows and Columns after removing columns -----> (1000, 39)
```

Encoding Categorical Column

In [111]:
```
oe = OrdinalEncoder()
```

In [112]:
```
for i in df.columns:
    if df[i].dtypes == 'object':
        df[i] = oe.fit_transform(df[i].values.reshape(-1,1))
df.head(2)
```

Out[112]:

	months_as_customer	age	policy_number	policy_state	policy_csl	policy_deductable	policy_an
0	328	48	521585	2.0	1.0	1000	
1	228	42	342868	1.0	1.0	2000	

In [113]:
```python
print('==================================================\n')
print(df.info())
print('====================================================')
```

```
==================================================

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 39 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   months_as_customer           1000 non-null   int64  
 1   age                          1000 non-null   int64  
 2   policy_number                1000 non-null   int64  
 3   policy_state                 1000 non-null   float64
 4   policy_csl                   1000 non-null   float64
 5   policy_deductable            1000 non-null   int64  
 6   policy_annual_premium        1000 non-null   float64
 7   umbrella_limit               1000 non-null   int64  
 8   insured_zip                  1000 non-null   int64  
 9   insured_sex                  1000 non-null   float64
 10  insured_education_level      1000 non-null   float64
 11  insured_occupation           1000 non-null   float64
 12  insured_hobbies              1000 non-null   float64
 13  insured_relationship         1000 non-null   float64
 14  capital-gains                1000 non-null   int64  
 15  capital-loss                 1000 non-null   int64  
 16  incident_type                1000 non-null   float64
 17  collision_type               1000 non-null   float64
 18  incident_severity            1000 non-null   float64
 19  authorities_contacted        1000 non-null   float64
 20  incident_state               1000 non-null   float64
 21  incident_city                1000 non-null   float64
 22  incident_hour_of_the_day     1000 non-null   int64  
 23  number_of_vehicles_involved  1000 non-null   int64  
 24  property_damage              1000 non-null   float64
 25  bodily_injuries              1000 non-null   int64  
 26  witnesses                    1000 non-null   int64  
 27  police_report_available      1000 non-null   float64
 28  total_claim_amount           1000 non-null   int64  
 29  injury_claim                 1000 non-null   int64  
 30  property_claim               1000 non-null   int64  
 31  vehicle_claim                1000 non-null   int64  
 32  auto_make                    1000 non-null   float64
 33  auto_model                   1000 non-null   float64
 34  auto_year                    1000 non-null   int64  
 35  fraud_reported               1000 non-null   float64
 36  IncidentMonth&Year           1000 non-null   float64
 37  PolicyBindMonth&year         1000 non-null   float64
 38  Incident_Pincode             1000 non-null   int64  
dtypes: float64(21), int64(18)
memory usage: 304.8 KB
None
====================================================
```

All categorical columns are encoded

All categorical columns are encoded

Data distribution

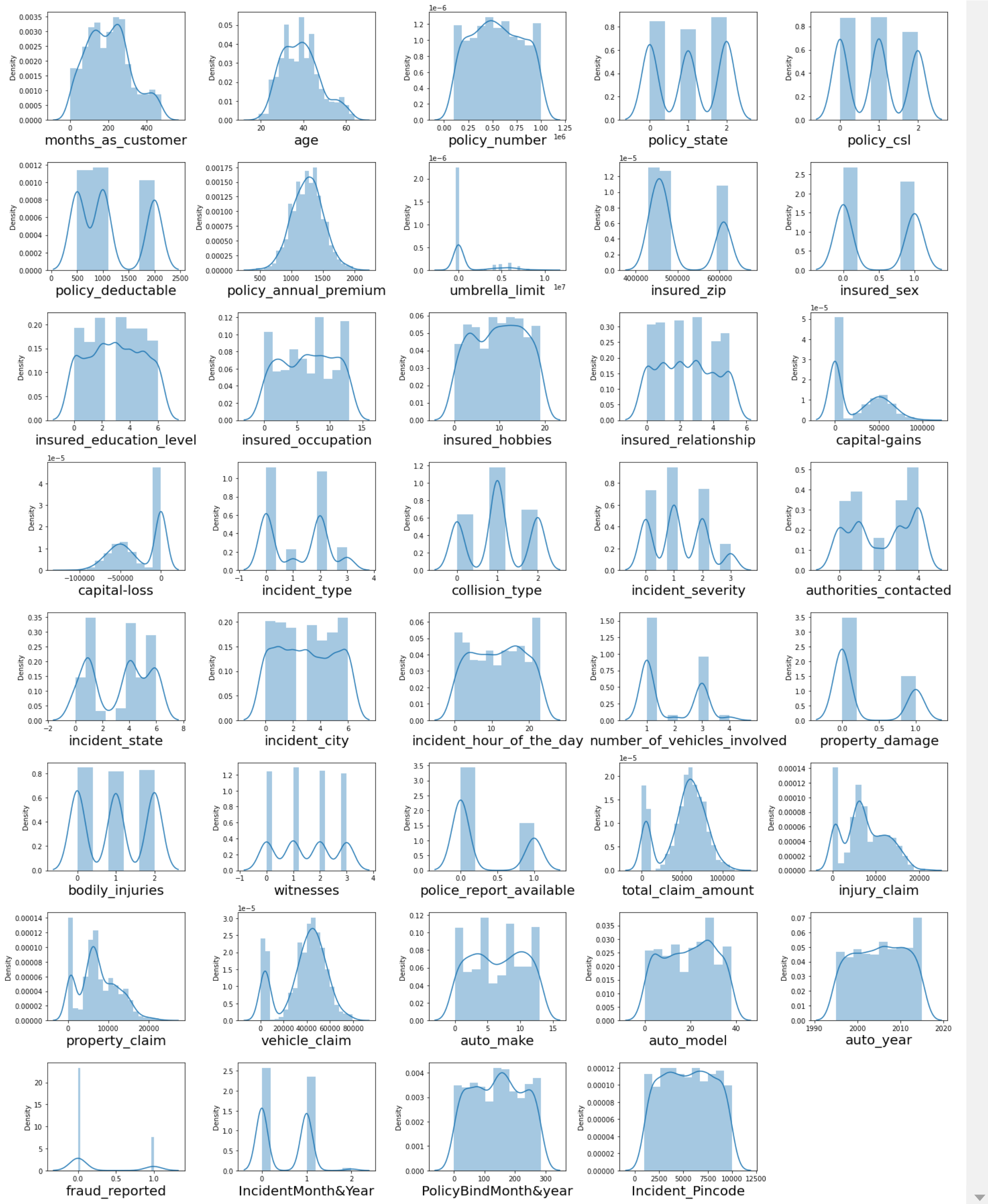
In [114]:

```
print('---------------------')
print('Distribution Plot :- ')
print('---------------------')

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

for column in df:
    if plotnumber <=40:
        ax = plt.subplot(8,5, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column, fontsize = 20)
    plotnumber +=1
plt.tight_layout()
```

```
---------------------
Distribution Plot :-
---------------------
```



Some columns are little skewed

Check skweness

In [115]:
```python
print('========================================')
print(df.skew())
print('========================================')
```

```
========================================
months_as_customer             0.362177
age                            0.478988
policy_number                  0.038991
policy_state                  -0.026177
policy_csl                     0.088928
policy_deductable              0.477887
policy_annual_premium          0.004402
umbrella_limit                 1.806712
insured_zip                    0.816554
insured_sex                    0.148630
insured_education_level       -0.000148
insured_occupation            -0.058881
insured_hobbies               -0.061563
insured_relationship           0.077488
capital-gains                  0.478850
capital-loss                  -0.391472
incident_type                  0.101507
collision_type                -0.033682
incident_severity              0.279016
authorities_contacted         -0.121744
incident_state                -0.148865
incident_city                  0.049531
incident_hour_of_the_day      -0.035584
number_of_vehicles_involved    0.502664
property_damage                0.863806
bodily_injuries                0.014777
witnesses                      0.019636
police_report_available        0.802728
total_claim_amount            -0.594582
injury_claim                   0.264811
property_claim                 0.378169
vehicle_claim                 -0.621098
auto_make                     -0.018797
auto_model                    -0.080773
auto_year                     -0.048289
fraud_reported                 1.175051
IncidentMonth&Year             0.267378
PolicyBindMonth&year          -0.001113
Incident_Pincode               0.002897
dtype: float64
========================================
```

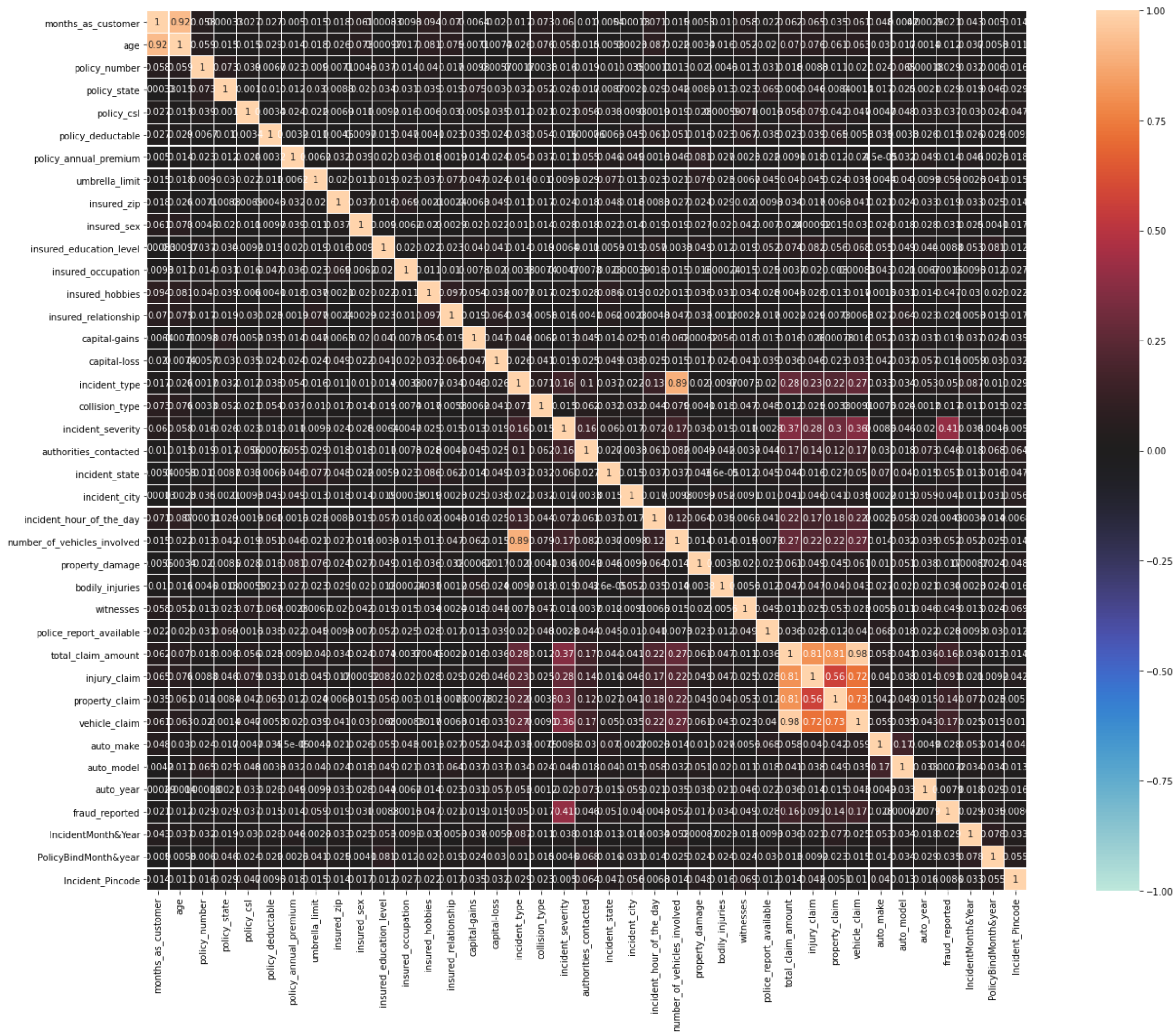
Skewness present in our dataset

Corelation of Feature vs Label using Heat map

In [116]:
```
print('-----------')
print('Heat Map :-')
print('-----------')
df_corr = df.corr().abs()

plt.figure(figsize = (22,16))
sns.heatmap(df_corr, vmin = -1, annot = True, square = True, center = 0, fmt = '
plt.tight_layout()
```

```
-----------
Heat Map :-
-----------
```



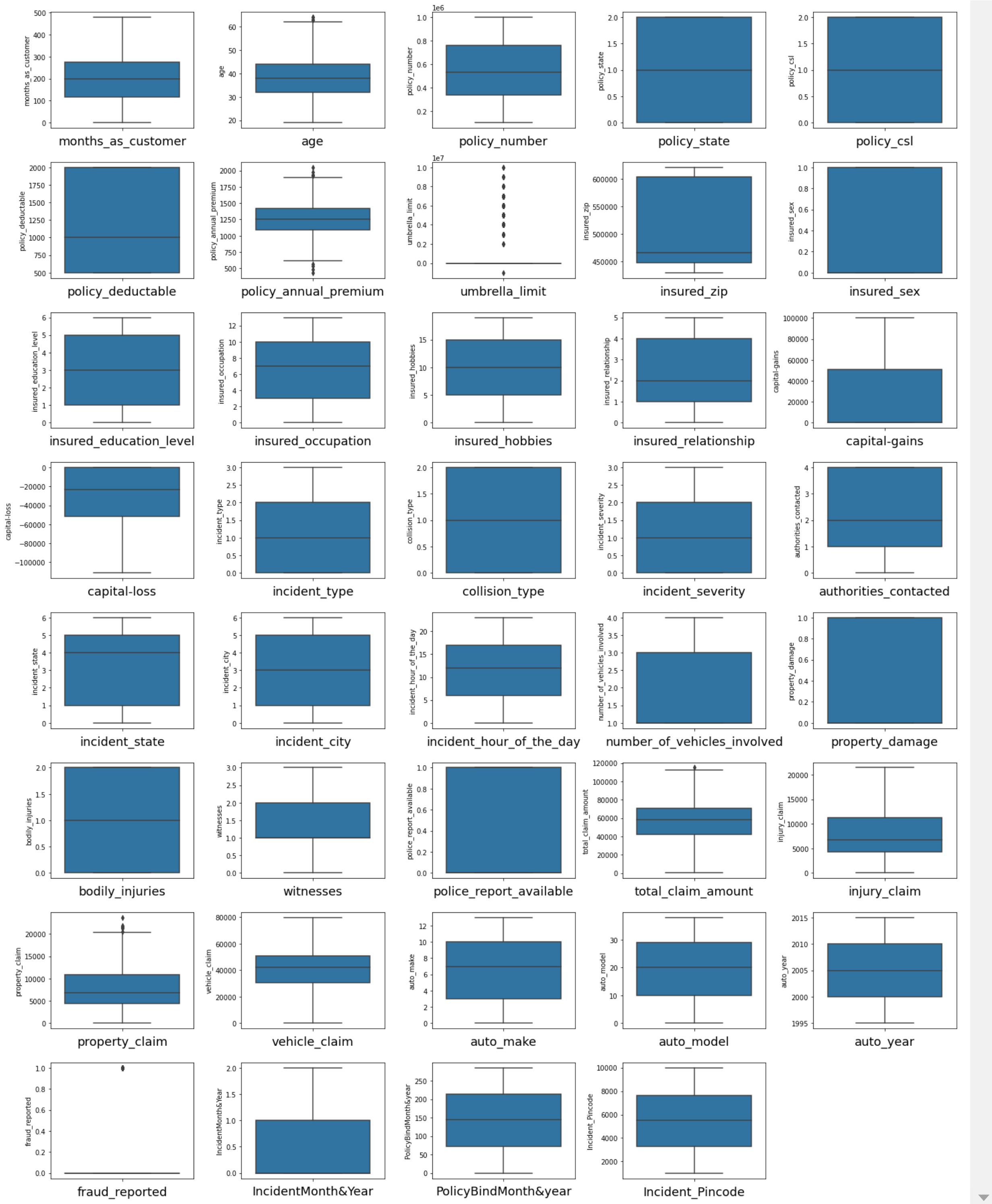
Vehicle Claim highest corelation

Checking Outliers

In [117]:
```
print('===========')
print('Box Plot :-')
print('===========')

plt.figure(figsize = (20,25), facecolor = 'white')
plotnumber = 1
for column in df:
    if plotnumber <=40:
        ax = plt.subplot(8,5, plotnumber)
        sns.boxplot(y=df[column]) # It is the axis for vertical set as y
        plt.xlabel(column, fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
===========
Box Plot :-
===========
```



There are outliers presents in dataset

Removing Outliers

In [118]:
```python
# with std 3 Lets see the stats

z_score = zscore(df[['age', 'umbrella_limit', 'total_claim_amount', 'property_cla
abs_z_score = np.abs(z_score)

filtering_entry = (abs_z_score < 3).all(axis = 1)

df = df[filtering_entry]
df.describe()
```

Out[118]:

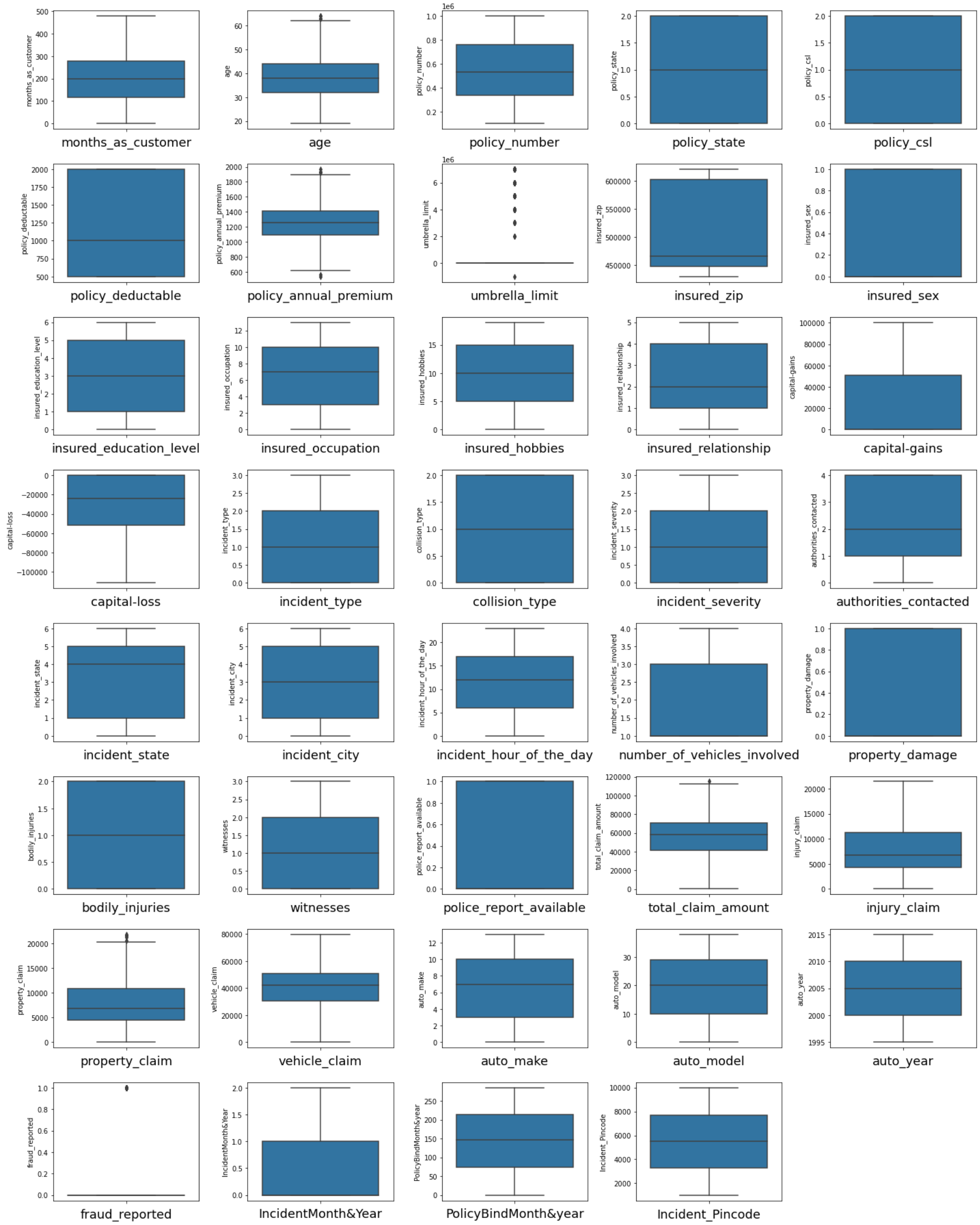
	months_as_customer	age	policy_number	policy_state	policy_csl	policy_deductabl
count	981.000000	981.000000	981.000000	981.000000	981.000000	981.00000
mean	204.594292	38.972477	545930.544343	1.020387	0.945973	1138.12436
std	115.362802	9.179406	257515.314276	0.830289	0.804412	611.56719
min	0.000000	19.000000	100804.000000	0.000000	0.000000	500.00000
25%	116.000000	32.000000	335780.000000	0.000000	0.000000	500.00000
50%	200.000000	38.000000	533940.000000	1.000000	1.000000	1000.00000
75%	278.000000	44.000000	760179.000000	2.000000	2.000000	2000.00000
max	479.000000	64.000000	999435.000000	2.000000	2.000000	2000.00000

In [119]:

```
# Let' see outliers are removed in columns or not.
print('===========')
print('Box Plot :-')
print('===========')

plt.figure(figsize = (20,25), facecolor = 'white')
plotnumber = 1
for column in df:
    if plotnumber <=40:
        ax = plt.subplot(8,5, plotnumber)
        sns.boxplot(y=df[column]) # It is the axis for vertical set as y
        plt.xlabel(column, fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
===========
Box Plot :-
===========
```



In [120]:
```
df.shape # Here we check shape of remaining data after removal of outliers.
```
Out[120]: (981, 39)

Outliers are removed

Spliting Dataset into features and label

In [121]:
```
x = df.drop('fraud_reported', axis = 1)
y = df. fraud_reported
print('Data has been splited')
```

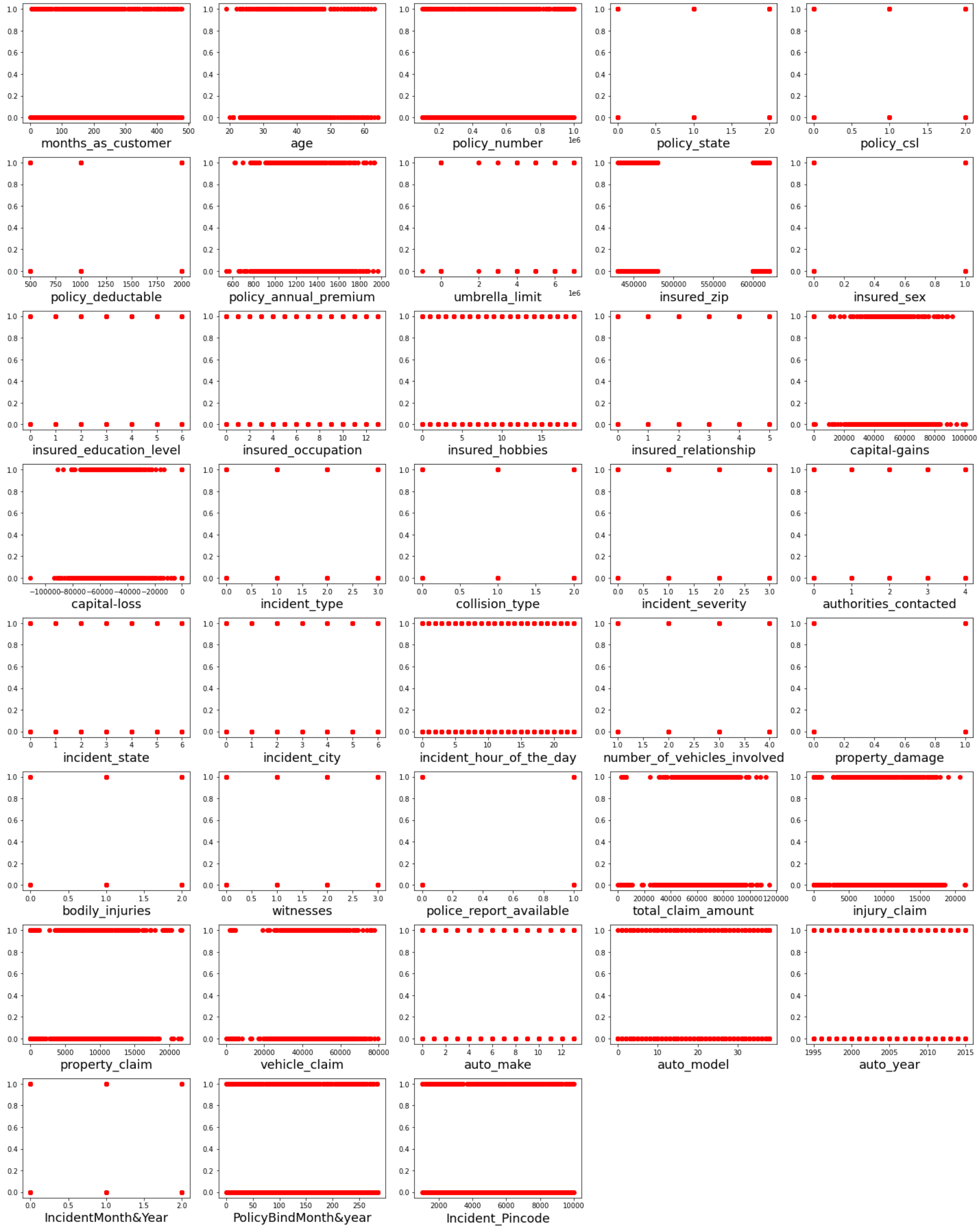
```
Data has been splited
```

In [122]:

```
# Let' see relation between features and label.
print('-----------------')
print('Scatter Plot :-')
print('-----------------')

plt.figure(figsize = (20,25), facecolor = 'white')
plotnumber = 1
for column in x:
    if plotnumber <=40:
        ax = plt.subplot(8,5, plotnumber)
        plt.scatter(x[column],y, c = 'r')
        plt.xlabel(column, fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
-----------------
Scatter Plot :-
-----------------
```



Positive relation in feature and label

Checking for class imbalance

In [123]:
```python
df['fraud_reported'].value_counts()
```

Out[123]:
```
0.0    741
1.0    240
Name: fraud_reported, dtype: int64
```

Class are not balance

Handling Class Imbalance

In [124]:
```python
sm = SMOTE()
x_over, y_over = sm.fit_resample(x,y)
```

In [125]:
```python
print('---------------------')
print('Class are balanced :-')
print('---------------------')
print(y_over.value_counts())
print('---------------------')
```

```
---------------------
Class are balanced :-
---------------------
0.0    741
1.0    741
Name: fraud_reported, dtype: int64
---------------------
```

Data Scaling

In [170]:
```python
scaler = MinMaxScaler()
x_scaled = scaler.fit_transform(x)
x_scaled
```

Out[170]:
```
array([[0.68475992, 0.64444444, 0.4682467 , ..., 0.        , 0.82807018,
        0.99409537],
       [0.47599165, 0.51111111, 0.26936974, ..., 0.        , 0.47368421,
        0.62344029],
       [0.27974948, 0.22222222, 0.65309788, ..., 0.5       , 0.69122807,
        0.68059269],
       ...,
       [0.27139875, 0.33333333, 0.90995303, ..., 0.        , 0.13333333,
        0.73718806],
       [0.95615866, 0.95555556, 0.48199539, ..., 0.5       , 0.90175439,
        0.56996435],
       [0.9519833 , 0.91111111, 0.50663287, ..., 0.5       , 0.85263158,
        0.04500891]])
```

Data has been scaled

Split data into train and test. Model will be bulit on training data and tested on test data

In [171]:
```
x_train, x_test, y_train, y_test = train_test_split(x_over, y_over, test_size = 0
print('Data has been splited.')
```

```
Data has been splited.
```

Model Bulding

Decision Tree model instantiaing, training and evaluating

In [172]:
```
bag_dt = BaggingClassifier(DecisionTreeClassifier(), n_estimators = 30, max_sampl
                          random_state= 3, oob_score = True)
```

In [173]:
```
bag_dt.oob_score
```

Out[173]:
```
True
```

In [174]:
```
bag_dt.fit(x_train, y_train)
print('Bagging DT score ------->', bag_dt.score(x_test, y_test))
```

```
Bagging DT score -------> 0.8598382749326146
```

In [175]:
```
y_pred = bag_dt.predict(x_test)
```

In [176]:
```
print('-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------\n')
```

```
-------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.85      0.88      0.87       191
         1.0       0.87      0.83      0.85       180

    accuracy                           0.86       371
   macro avg       0.86      0.86      0.86       371
weighted avg       0.86      0.86      0.86       371

------------------------------------------------------------
```

Conclusion : Decision Tree model has 86% score

Cross Validation score to check if the model is overfitting

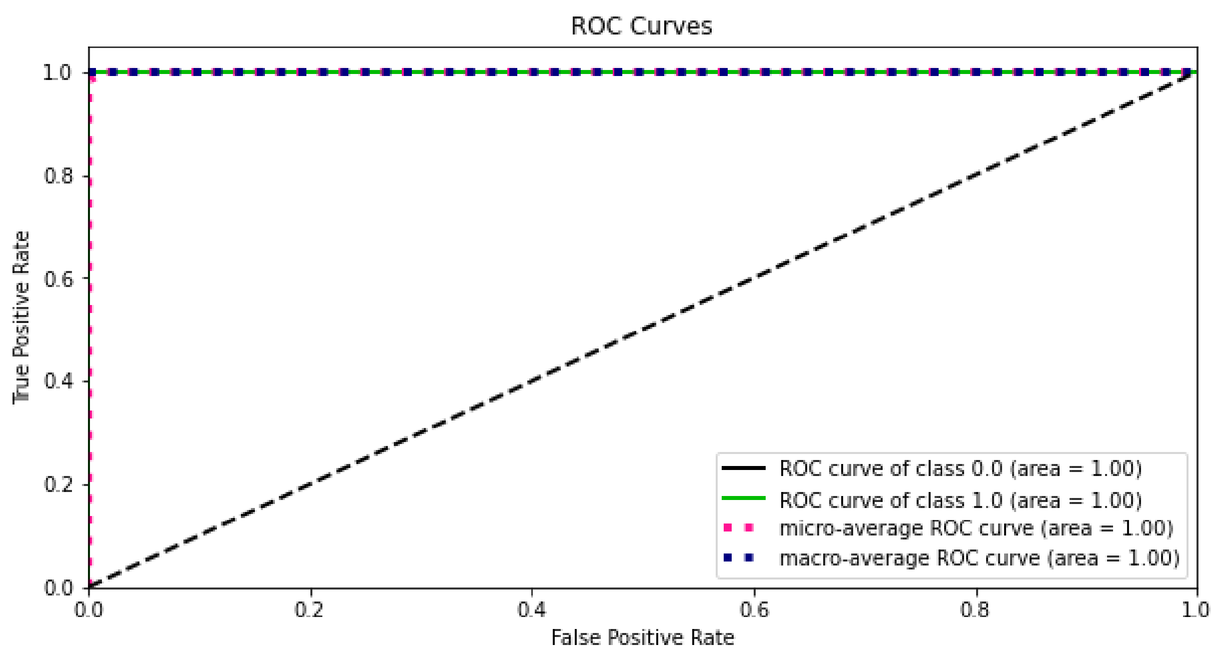
In [177]:
```
cv = cross_val_score(bag_dt, x, y, cv = 5)
print('Cross Validation score of Decision Tree model --->', cv.mean())
```

```
Cross Validation score of Decision Tree model ---> 0.8318398425359993
```

Conclusion : Decision Tree model has 83% Cross Validation score

ROC, AUC Curve

In [178]:
```
prob = bag_dt.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



XGBoost model instantiaing, training and evaluating

In [179]:
```
bag_xgb = BaggingClassifier(xgb.XGBClassifier(eval_metric = 'mlogloss'), n_estima
                            random_state= 3, oob_score = True)
```

In [180]:
```
bag_xgb.oob_score
```

Out[180]:
```
True
```

In [181]:
```
bag_xgb.fit(x_train, y_train)
print('Bagging XGBoost score ------->', bag_xgb.score(x_test, y_test))
```

```
Bagging XGBoost score -------> 0.8814016172506739
```

In [182]:
```
y_pred = bag_xgb.predict(x_test)
```

In [183]:
```
print('-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------\n')
```

```
-------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.90      0.86      0.88       191
         1.0       0.86      0.90      0.88       180

    accuracy                           0.88       371
   macro avg       0.88      0.88      0.88       371
weighted avg       0.88      0.88      0.88       371

------------------------------------------------------------
```

Conclusion : XGBoost model has 88% score

Cross Validation score to check if the model is overfitting

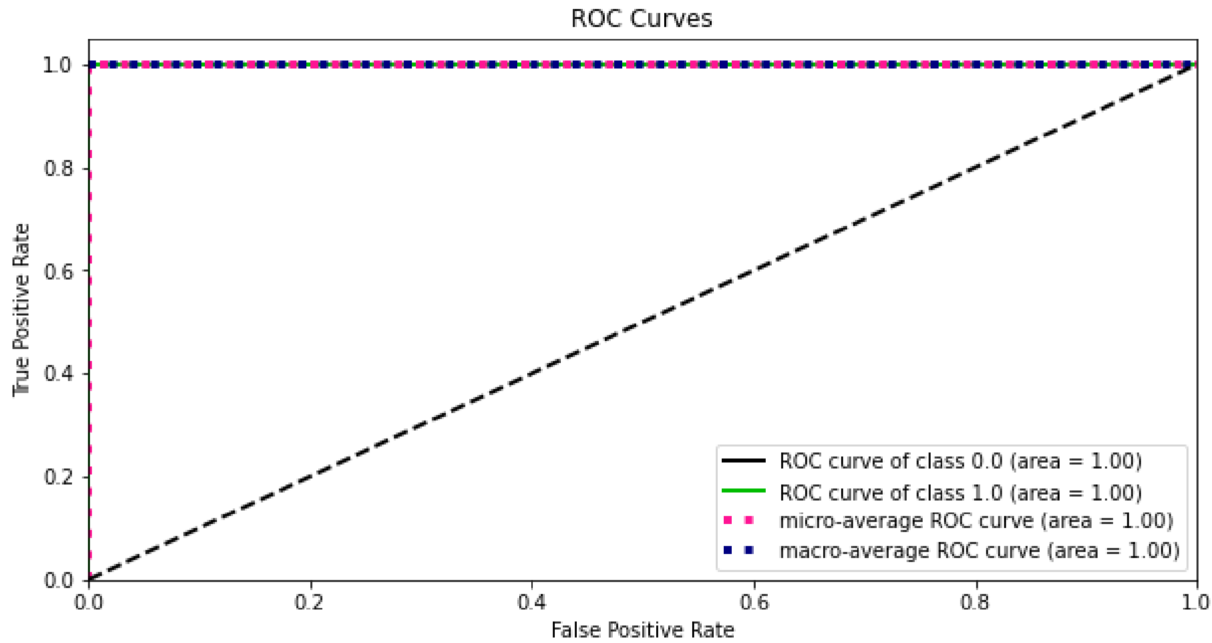
In [184]:
```
cv = cross_val_score(bag_xgb, x, y, cv = 5)
print('Cross Validation score of XGBoost model --->', cv.mean())
```

```
Cross Validation score of XGBoost model ---> 0.8256863151351912
```

Conclusion : XGBoost model has 82% Cross Validation score

ROC, AUC Curve

In [141]:
```
prob = bag_xgb.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Knn model instantiaing, training and evaluating

In [185]:
```
bag_Knn = BaggingClassifier(KNeighborsClassifier(n_neighbors = 5), n_estimators =
                            random_state= 3, oob_score = True)
```

In [186]:
```
bag_Knn.oob_score
```

Out[186]: True

In [187]:
```
bag_Knn.fit(x_train, y_train)
print('Bagging KNN score ------->', bag_Knn.score(x_test, y_test))
```

```
Bagging KNN score -------> 0.6630727762803235
```

In [188]:
```
y_pred = bag_dt.predict(x_test)
```

In [189]:
```
print('------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------\n')
```

```
------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.85      0.88      0.87       191
         1.0       0.87      0.83      0.85       180

    accuracy                           0.86       371
   macro avg       0.86      0.86      0.86       371
weighted avg       0.86      0.86      0.86       371

------------------------------------------------------------
```

Conclusion : KNN model has 86% score

Cross Validation score to check if the model is overfitting

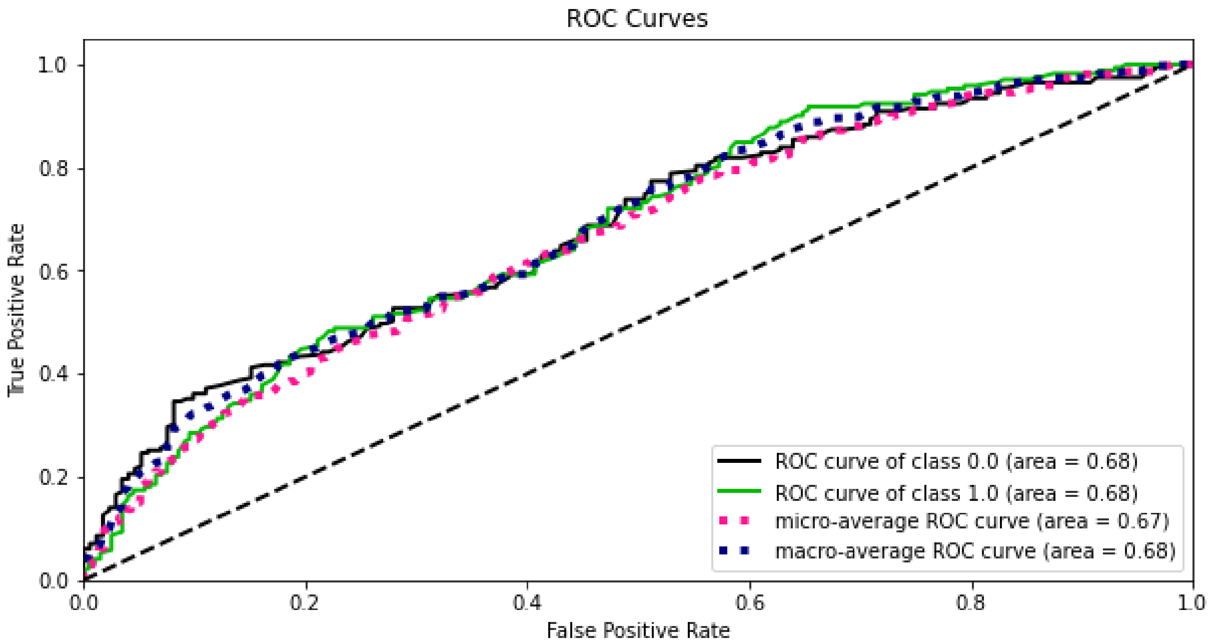
In [190]:
```
cv = cross_val_score(bag_Knn, x, y, cv = 5)
print('Cross Validation score of Knn model --->', cv.mean())
```

```
Cross Validation score of Knn model ---> 0.7451362270796643
```

Conclusion : Knn model has 74% Cross Validation score

ROC, AUC Curve

In [148]:
```
prob = bag_Knn.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Random Forest model instantiaing, training and evaluating

In [191]:
```
bag_Rn = BaggingClassifier(RandomForestClassifier(), n_estimators = 30, max_sampl
                                          random_state= 3, oob_score = True)
```

In [192]:
```
bag_Rn.oob_score
```

Out[192]:
```
True
```

In [193]:
```
bag_Rn.fit(x_train, y_train)
print('Bagging Random Forest score ------->', bag_Rn.score(x_test, y_test))
```

```
Bagging Random Forest score -------> 0.8706199460916442
```

In [194]:
```
y_pred = bag_Rn.predict(x_test)
```

In [195]:
```
print('-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------\n')
```

```
-------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.87      0.87      0.87       191
         1.0       0.87      0.87      0.87       180

    accuracy                           0.87       371
   macro avg       0.87      0.87      0.87       371
weighted avg       0.87      0.87      0.87       371

------------------------------------------------------------
```

Conclusion : Random Forest model has 87% score

Cross Validation score to check if the model is overfitting

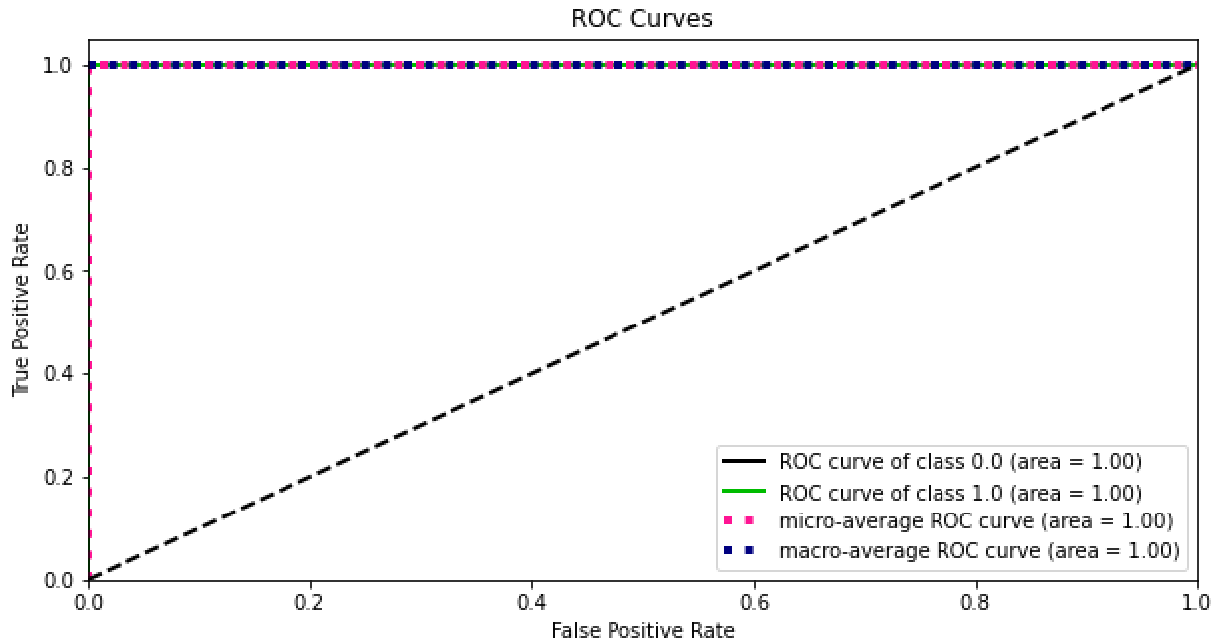
In [196]:
```
cv = cross_val_score(bag_Rn, x, y, cv = 5)
print('Cross Validation score of Rn model --->', cv.mean())
```

```
Cross Validation score of Rn model ---> 0.7573604060913706
```

Conclusion : Random Forest model has 75% Cross Validation score

ROC, AUC Curve

In [155]:
```
prob = bag_Rn.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Logistic Regression model instantiaing, training and evaluating

In [197]:
```
bag_Lr = BaggingClassifier(LogisticRegression(), n_estimators = 30, max_samples =
                           random_state= 3, oob_score = True)
```

In [198]:
```
bag_Lr.oob_score
```

Out[198]: True

In [199]:
```
bag_Lr.fit(x_train, y_train)
print('Bagging Logostic Regression score ------->', bag_Lr.score(x_test, y_test))
```

Bagging Logostic Regression score -------> 0.5498652291105122

In [200]:
```
y_pred = bag_Lr.predict(x_test)
```

In [201]:
```
print('------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-----------------------------------------------------------\n')
```

```
------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.57      0.52      0.54       191
         1.0       0.53      0.58      0.55       180

    accuracy                           0.55       371
   macro avg       0.55      0.55      0.55       371
weighted avg       0.55      0.55      0.55       371

-----------------------------------------------------------
```

Conclusion : Logistic Regression model has 55% score

Cross Validation score to check if the model is overfitting

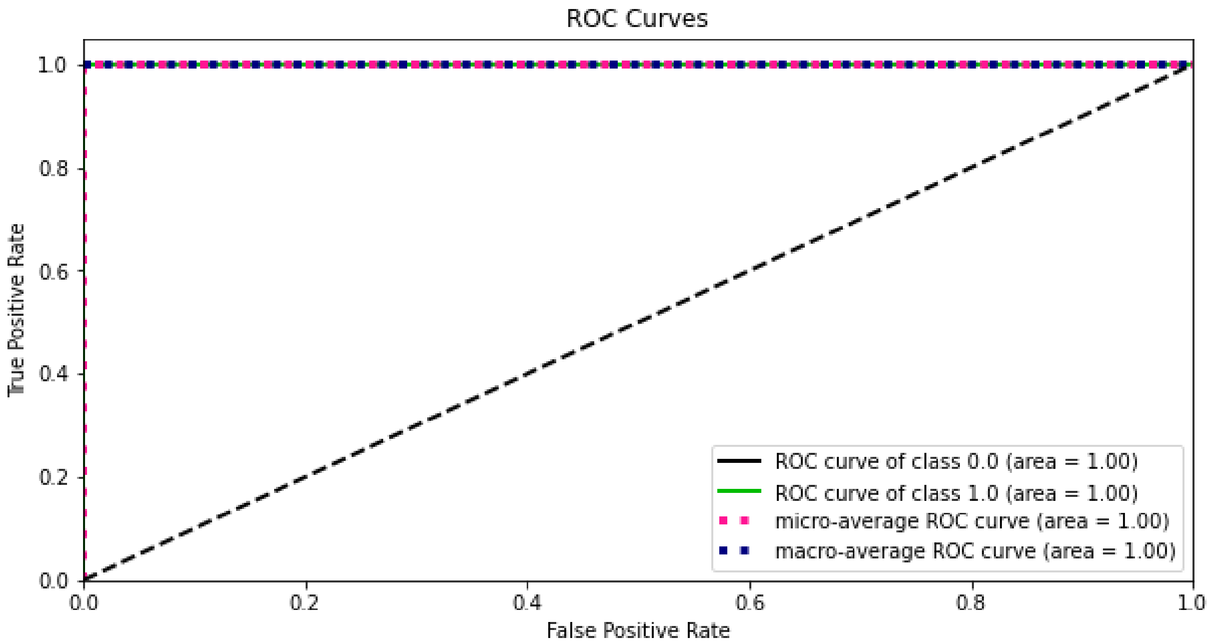
In [202]:
```
cv = cross_val_score(bag_Lr, x, y, cv = 5)
print('Cross Validation score of Logistic regression model --->', cv.mean())
```

```
Cross Validation score of Logistic regression model ---> 0.7553506681860561
```

Conclusion : Logistic Regression model has 75% Cross Validation score

ROC, AUC Curve

In [203]:
```
prob = bag_Lr.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Let's find ROC, AUC score

In [205]:
```
# DecisionTreeClassifier
roc_auc_score(y_test, bag_dt.predict(x_test))
```

Out[205]: 0.8590750436300175

In [206]:
```
# XGBoostClassifier
roc_auc_score(y_test, bag_xgb.predict(x_test))
```

Out[206]: 0.881937172774869

In [207]:
```
# KNeighborsClassifier
roc_auc_score(y_test, bag_Knn.predict(x_test))
```

Out[207]: 0.6660558464223385

In [208]:
```
# RandomForestClassifier
roc_auc_score(y_test, bag_Rn.predict(x_test))
```

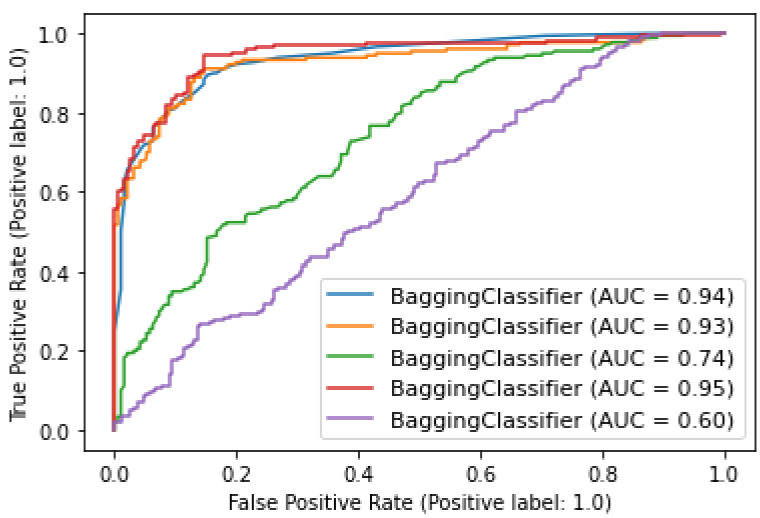
Out[208]: 0.8705061082024432

In [209]:
```
# LogisticRegressionClassifier
roc_auc_score(y_test, bag_Lr.predict(x_test))
```

Out[209]: 0.5506689936009308

Let's check ROC, AUC Curve for the fitted model

In [210]:
```
dis = plot_roc_curve(bag_dt, x_test, y_test)
plot_roc_curve(bag_Rn, x_test, y_test, ax = dis.ax_) # ax_ = Axes with confusion
plot_roc_curve(bag_Knn, x_test, y_test, ax = dis.ax_)
plot_roc_curve(bag_xgb, x_test, y_test, ax = dis.ax_)
plot_roc_curve(bag_Lr, x_test, y_test, ax = dis.ax_)
plt.legend(prop = {'size':11}, loc = 'lower right')
plt.show()
```



Looking ROC, AUC Curve we found Random Forest has best model so we do Hyperparameter Tuning on it.

In [213]:
```
param = {'n_estimators': [50,100], 'max_samples': [1.0], 'bootstrap': [True]}
```

In [216]:
```
grid_search = GridSearchCV(estimator = bag_Rn, param_grid = param, cv = 5 , n_jot
```

In [217]:
```
grid_search.fit(x_train, y_train)
```

Out[217]:
```
GridSearchCV(cv=5,
             estimator=BaggingClassifier(base_estimator=RandomForestClassifier
(),
                                         max_samples=0.5, n_estimators=30,
                                         oob_score=True, random_state=3),
             n_jobs=-1,
             param_grid={'bootstrap': [True], 'max_samples': [1.0],
                         'n_estimators': [50, 100]})
```

In [218]:
```
best_parameters = grid_search.best_params_
print(best_parameters)
```

```
{'bootstrap': True, 'max_samples': 1.0, 'n_estimators': 50}
```

In [219]:
```
hRn = BaggingClassifier(base_estimator=RandomForestClassifier(),max_samples = 1.0
hRn.fit(x_train, y_train)
hRn.score(x_test, y_test)
```

Out[219]:
```
0.8679245283018868
```

In [220]:
```
y_pred = hRn.predict(x_test)
```

In [221]:
```
print('-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-------------------------------------------------------------\n')
```

```
--------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.88      0.86      0.87       191
         1.0       0.86      0.87      0.87       180

    accuracy                           0.87       371
   macro avg       0.87      0.87      0.87       371
weighted avg       0.87      0.87      0.87       371

------------------------------------------------------------
```

After Hyperparameter Tuning model accuracy score 87%.

Saving The Model

In [222]:
```python
# saving the model to the Local file system
filename = 'Insurance Claims Fraud Detection.pickle'
pickle.dump(hRn, open(filename, 'wb'))
```

Predict Insurance Claims Fraud Detection

In [223]:
```python
model = pickle.load(open('Insurance Claims Fraud Detection.pickle', 'rb'))
result = model.score(x_test, y_test)
print('Predicted Score --------->', result)
```

```
Predicted Score ---------> 0.8679245283018868
```

In [224]:
```python
Prediction = pd.DataFrame([model.predict(x_test)[:], y_test[:]], index = ['Predic
Prediction
```

Out[224]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Predicted	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0	1.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0
Orginal	0.0	0.0	1.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0

Saving the predicted result in CSV file

In [225]:
```python
Prediction.to_csv('Insurance Claims Fraud Detection.csv')
```

Final Conclusion : Random Forest is our best model.

In [ ]: