Insurance Claims Fraud Detection

In [1]:
```
# Importing Necessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv('insurance_claim_fraud.csv')
df
```

Out[2]:

	months_as_customer	age	policy_number	policy_bind_date	policy_state	policy_csl	policy_
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	
...	...	...	...	...	...	...	
995	3	38	941851	16-07-1991	OH	500/1000	
996	285	41	186934	05-01-2014	IL	100/300	
997	130	34	918516	17-02-2003	OH	250/500	
998	458	62	533940	18-11-2011	IL	500/1000	
999	456	60	556080	11-11-1996	OH	250/500	

1000 rows × 40 columns

So here we have 1000 rows and 40 columns in data

- fraud_reported is our target variable

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 40 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   months_as_customer           1000 non-null   int64  
 1   age                          1000 non-null   int64  
 2   policy_number                1000 non-null   int64  
 3   policy_bind_date             1000 non-null   object 
 4   policy_state                 1000 non-null   object 
 5   policy_csl                   1000 non-null   object 
 6   policy_deductable            1000 non-null   int64  
 7   policy_annual_premium        1000 non-null   float64
 8   umbrella_limit               1000 non-null   int64  
 9   insured_zip                  1000 non-null   int64  
 10  insured_sex                  1000 non-null   object 
 11  insured_education_level      1000 non-null   object 
 12  insured_occupation           1000 non-null   object 
 13  insured_hobbies              1000 non-null   object 
 14  insured_relationship         1000 non-null   object 
 15  capital-gains                1000 non-null   int64  
 16  capital-loss                 1000 non-null   int64  
 17  incident_date                1000 non-null   object 
 18  incident_type                1000 non-null   object 
 19  collision_type               1000 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              1000 non-null   object 
 28  bodily_injuries              1000 non-null   int64  
 29  witnesses                    1000 non-null   int64  
 30  police_report_available      1000 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
```

- Here we have 19 numerical and 21 object columns present in the dataset.

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
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
_c39                           1000
dtype: int64
```

- There is no null value present in the columns except _c39 column so dropping it

In [5]:
```
# droping _c39 column so dropping it.
df.drop('_c39',axis=1,inplace=True)
```

In [6]:
```
df.shape
```

Out[6]:
```
(1000, 39)
```

```
In [7]: # printing all data type  and their unique values
        for column in df.columns:
            if df[column].dtype==object:
                print(df[column].value_counts())
                print('***************************************************************'
```

```
05-08-1992    3
01-01-2006    3
28-04-1992    3
29-01-1998    2
21-12-2002    2
             ..
25-11-1994    1
12-02-2009    1
28-03-2001    1
17-12-2003    1
10-12-2014    1
Name: policy_bind_date, Length: 951, dtype: int64
***************************************************************
OH    352
IL    338
IN    310
Name: policy_state, dtype: int64
***************************************************************
250/500     351
```

```
In [8]: # replacing '?' with No Info
        df=df.replace('?','No Info')
```

- Some of the rows having ? sign replacing them with No Info

```
In [9]: # printing all data type  and their unique values
        for column in df.columns:
            if df[column].dtype==object:
                print(df[column].value_counts())
                print('************************************************************'
```

```
05-08-1992    3
01-01-2006    3
28-04-1992    3
29-01-1998    2
21-12-2002    2
             ..
25-11-1994    1
12-02-2009    1
28-03-2001    1
17-12-2003    1
10-12-2014    1
Name: policy_bind_date, Length: 951, dtype: int64
***************************************************************
OH    352
IL    338
IN    310
Name: policy_state, dtype: int64
***************************************************************
250/500     351
100/300     349
500/1000    300
Name: policy_csl, dtype: int64
***************************************************************
FEMALE    537
MALE      463
Name: insured_sex, dtype: int64
***************************************************************
JD             161
High School    160
Associate      145
MD             144
Masters        143
PhD            125
College        122
Name: insured_education_level, dtype: int64
***************************************************************
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
***************************************************************
reading           64
paintball         57
exercise          57
bungie-jumping    56
camping           55
```

```
golf              55
movies            55
kayaking          54
yachting          53
hiking            52
video-games       50
base-jumping      49
skydiving         49
board-games       48
polo              47
chess             46
dancing           43
sleeping          41
cross-fit         35
basketball        34
Name: insured_hobbies, dtype: int64
***************************************************************
own-child         183
other-relative    177
not-in-family     174
husband           170
wife              155
unmarried         141
Name: insured_relationship, dtype: int64
***************************************************************
02-02-2015    28
17-02-2015    26
07-01-2015    25
24-01-2015    24
10-01-2015    24
04-02-2015    24
19-01-2015    23
08-01-2015    22
30-01-2015    21
13-01-2015    21
12-02-2015    20
31-01-2015    20
22-02-2015    20
06-02-2015    20
21-01-2015    19
14-01-2015    19
21-02-2015    19
01-01-2015    19
12-01-2015    19
23-02-2015    19
14-02-2015    18
20-01-2015    18
18-01-2015    18
03-01-2015    18
01-02-2015    18
28-02-2015    18
25-02-2015    18
09-01-2015    17
24-02-2015    17
06-01-2015    17
08-02-2015    17
26-02-2015    17
```

```
15-02-2015    16
16-02-2015    16
05-02-2015    16
16-01-2015    16
13-02-2015    16
15-01-2015    15
28-01-2015    15
17-01-2015    15
18-02-2015    15
27-02-2015    14
22-01-2015    14
20-02-2015    14
23-01-2015    13
09-02-2015    13
03-02-2015    13
27-01-2015    13
01-03-2015    12
04-01-2015    12
26-01-2015    11
29-01-2015    11
02-01-2015    11
07-02-2015    10
10-02-2015    10
11-02-2015    10
19-02-2015    10
25-01-2015    10
11-01-2015     9
05-01-2015     7
Name: incident_date, dtype: int64
***************************************************************
Multi-vehicle Collision     419
Single Vehicle Collision    403
Vehicle Theft                94
Parked Car                   84
Name: incident_type, dtype: int64
***************************************************************
Rear Collision     292
Side Collision     276
Front Collision    254
No Info            178
Name: collision_type, dtype: int64
***************************************************************
Minor Damage      354
Total Loss        280
Major Damage      276
Trivial Damage     90
Name: incident_severity, dtype: int64
***************************************************************
Police       292
Fire         223
Other        198
Ambulance    196
None          91
Name: authorities_contacted, dtype: int64
***************************************************************
NY    262
SC    248
```

```
WV    217
NC    110
VA    110
PA     30
OH     23
Name: incident_state, dtype: int64
***************************************************************
Springfield    157
Arlington      152
Columbus       149
Northbend      145
Hillsdale      141
Riverwood      134
Northbrook     122
Name: incident_city, dtype: int64
***************************************************************
8983 Tree St           1
1589 Best Ave          1
3847 Elm Hwy           1
4780 Best Drive        1
8689 Maple Hwy         1
                      ..
5783 Oak Ave           1
3790 Andromedia Hwy    1
1507 Solo Ave          1
4629 Elm Ridge         1
6484 Tree Drive        1
Name: incident_location, Length: 1000, dtype: int64
***************************************************************
No Info    360
NO         338
YES        302
Name: property_damage, dtype: int64
***************************************************************
No Info    343
NO         343
YES        314
Name: police_report_available, dtype: int64
***************************************************************
Suburu        80
Saab          80
Dodge         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
***************************************************************
RAM                43
Wrangler           42
```

```
A3                 37
Neon               37
MDX                36
Jetta              35
Passat             33
Legacy             32
A5                 32
Pathfinder         31
Malibu             30
Forrestor          28
92x                28
Camry              28
F150               27
95                 27
E400               27
93                 25
Grand Cherokee     25
Escape             24
Maxima             24
Tahoe              24
Ultima             23
X5                 23
Highlander         22
Silverado          22
Civic              22
Fusion             21
TL                 20
Corolla            20
CRV                20
Impreza            20
ML350              20
3 Series           18
C300               18
X6                 16
M5                 15
Accord             13
RSX                12
Name: auto_model, dtype: int64
***************************************************************
N    753
Y    247
Name: fraud_reported, dtype: int64
***************************************************************
```

Description of Dataset

In [10]:
```
# statisticla summary of numerical columns
df.describe()
```

Out[10]:

	months_as_customer	age	policy_number	policy_deductable	policy_annual_premiu
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.0000
mean	203.954000	38.948000	546238.648000	1136.000000	1256.4061
std	115.113174	9.140287	257063.005276	611.864673	244.1673
min	0.000000	19.000000	100804.000000	500.000000	433.3300
25%	115.750000	32.000000	335980.250000	500.000000	1089.6075
50%	199.500000	38.000000	533135.000000	1000.000000	1257.2000
75%	276.250000	44.000000	759099.750000	2000.000000	1415.6950
max	479.000000	64.000000	999435.000000	2000.000000	2047.5900

This gives the statistical information of the numerical columns . The summary of this dataset looks perfect

From the above description we can observe the following things.

- The count of all the columns are same which means there are no missing values in the dataset.
- The mean value is greater than the median(50%) in most of the columns which means the data is skewed to right in these columns
- The data in the few columns have mean value less than median that means the data is skewed to left
- By summerising the data we can observe there is huge difference between 75% and max in most of the columns hence there are outliers present in the data which we will remove them leter on using approprate methods.
- We can also notice the Standard deviation , min, 25% percentile values from this describe method.

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

Out[11]:
```
 0           798
 6000000      57
 5000000      46
 4000000      39
 7000000      29
 3000000      12
 8000000       8
 9000000       5
 2000000       3
 10000000      2
-1000000       1
Name: umbrella_limit, dtype: int64
```

- We can see there is one row in negative value must be the mistake or not sure so dropping the row

In [12]:
```
df.loc[df['umbrella_limit']== -1000000]
```

Out[12]:

	months_as_customer	age	policy_number	policy_bind_date	policy_state	policy_csl	policy_
290	284	42	526039	04-05-1995	OH	100/300	

1 rows × 39 columns

In [13]:
```
# droping that value row(one row only)
df.drop(df[df['umbrella_limit']== -1000000].index,inplace=True)
```

In [14]:
```
# dividing ['incident_data'] into three other columns
df['incident_Date']=df['incident_date'].str.split('-').str[0]
df['incident_Month']=df['incident_date'].str.split('-').str[1]
df['incident_Year']=df['incident_date'].str.split('-').str[2]
```

In [15]:
```
# in incident data all the incident is from 2015 so droping the incident_year
df['incident_Year'].value_counts()
df.drop('incident_Year',axis=1,inplace=True)
```

In [16]:
```
# dividing policy_bind_date into three other columns
df['policy_bind_Date']=df['policy_bind_date'].str.split('-').str[0]
df['policy_bind_Month']=df['policy_bind_date'].str.split('-').str[1]
df['policy_bind_Year']=df['policy_bind_date'].str.split('-').str[2]

# droping policy_bind_date column
df.drop('policy_bind_date',axis=1,inplace=True)
```

In [17]:
```
df.head()
```

Out[17]:

	months_as_customer	age	policy_number	policy_state	policy_csl	policy_deductable	policy_a
0	328	48	521585	OH	250/500	1000	
1	228	42	342868	IN	250/500	2000	
2	134	29	687698	OH	100/300	2000	
3	256	41	227811	IL	250/500	2000	
4	228	44	367455	IL	500/1000	1000	

5 rows × 43 columns

In [18]:
```
# droping the policy_number and other useless columns as well
df.drop(['policy_number','insured_zip','incident_location'],axis=1,inplace=True
```

In [19]:
```
df.head()
```

Out[19]:

	months_as_customer	age	policy_state	policy_csl	policy_deductable	policy_annual_premium
0	328	48	OH	250/500	1000	1406.91
1	228	42	IN	250/500	2000	1197.22
2	134	29	OH	100/300	2000	1413.14
3	256	41	IL	250/500	2000	1415.74
4	228	44	IL	500/1000	1000	1583.91

5 rows × 40 columns

In [20]:
```
df.shape
```

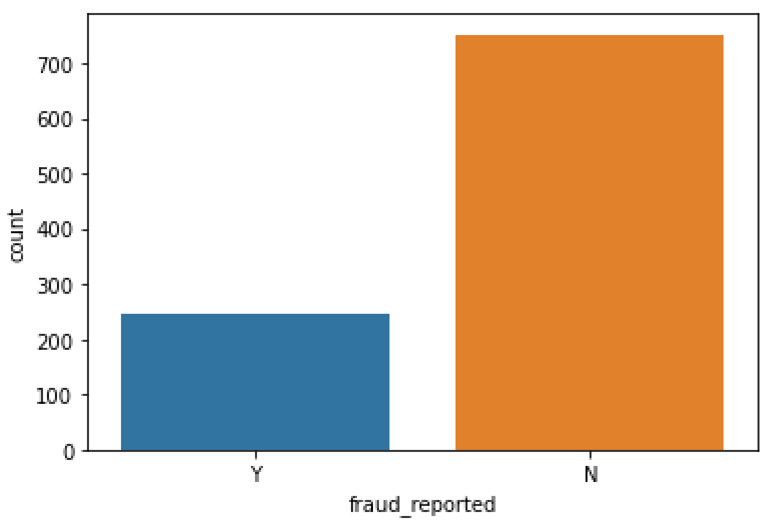
Out[20]:
```
(999, 40)
```

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

Out[21]:
```
N    752
Y    247
Name: fraud_reported, dtype: int64
```

In [22]:
```
sns.countplot(df['fraud_reported'])
```

Out[22]:
```
<AxesSubplot:xlabel='fraud_reported', ylabel='count'>
```



- We can notice data is imbalance we chave to deal with it.

EDA

In [23]:
```python
df.head()
```

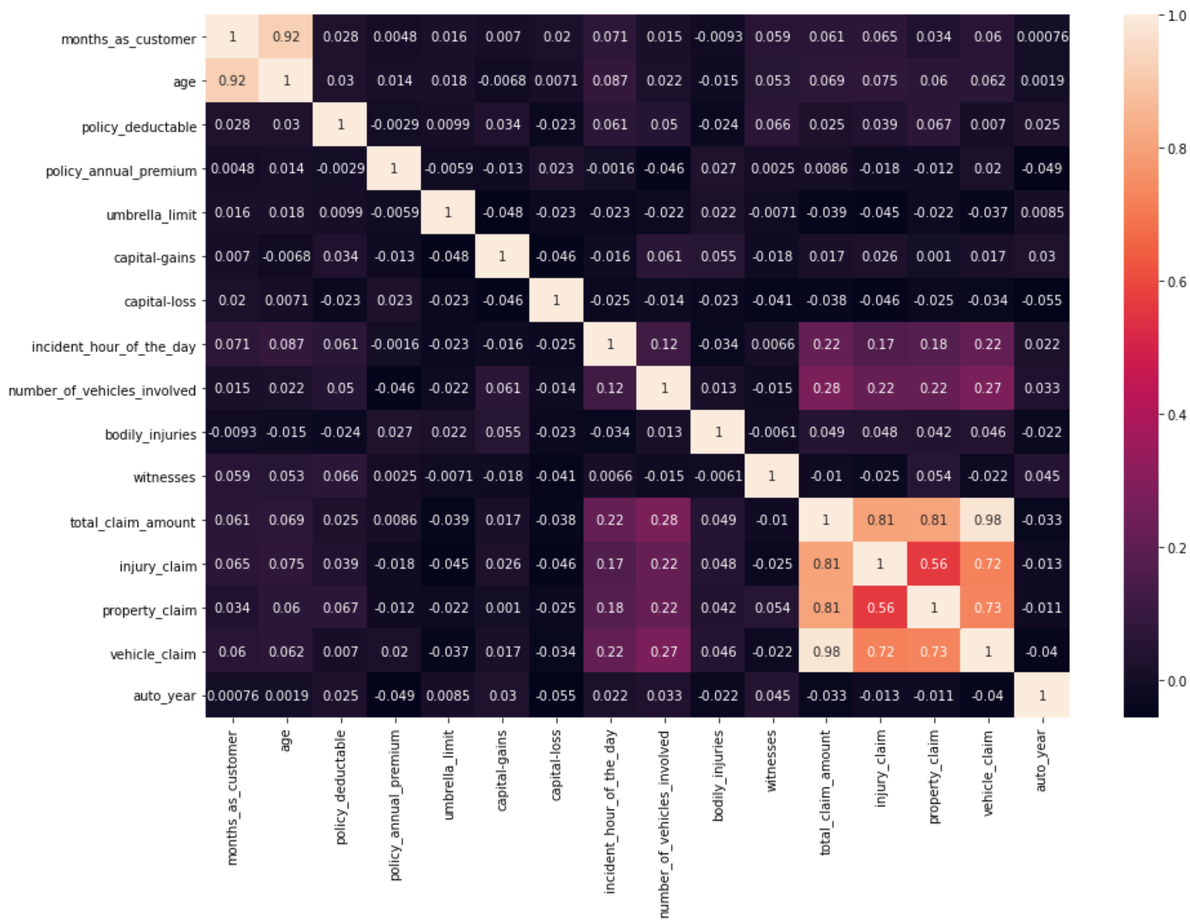
Out[23]:

	months_as_customer	age	policy_state	policy_csl	policy_deductable	policy_annual_premium
0	328	48	OH	250/500	1000	1406.91
1	228	42	IN	250/500	2000	1197.22
2	134	29	OH	100/300	2000	1413.14
3	256	41	IL	250/500	2000	1415.74
4	228	44	IL	500/1000	1000	1583.91

5 rows × 40 columns

In [24]:
```python
plt.figure(figsize=(15,10))
sns.heatmap(df.corr(),annot=True)
```

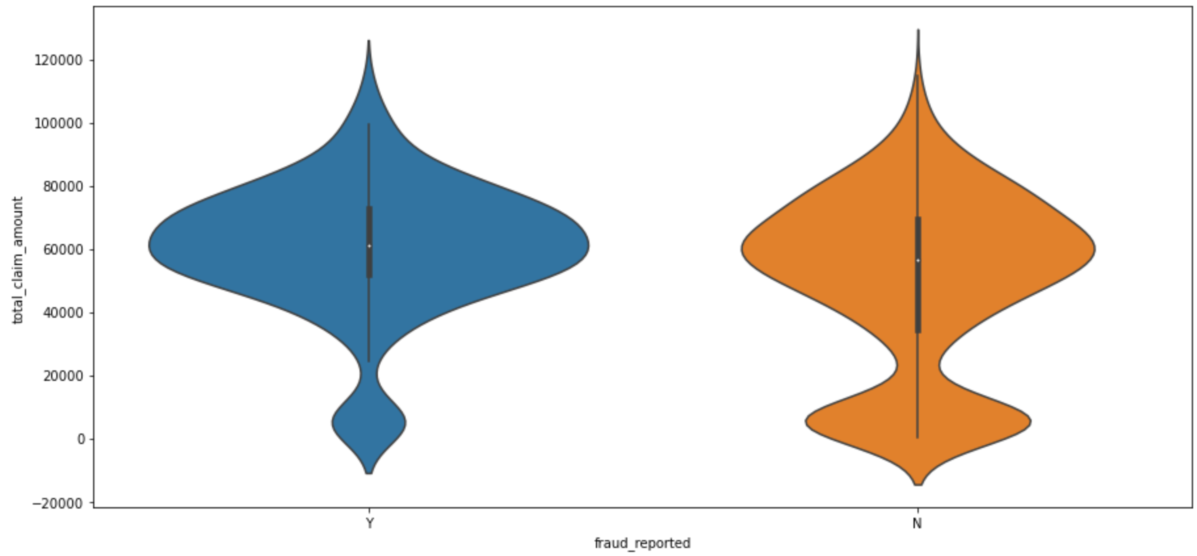
Out[24]: <AxesSubplot:>



- We can notice total_claim_amount, injury_claim, property_claim and vehicle_claim are highly correlated with each other .
- All other columns are very least correlated with each other.

In [25]:
```
plt.figure(figsize=(15,7))
sns.violinplot(y='total_claim_amount',x='fraud_reported',data=df)
```

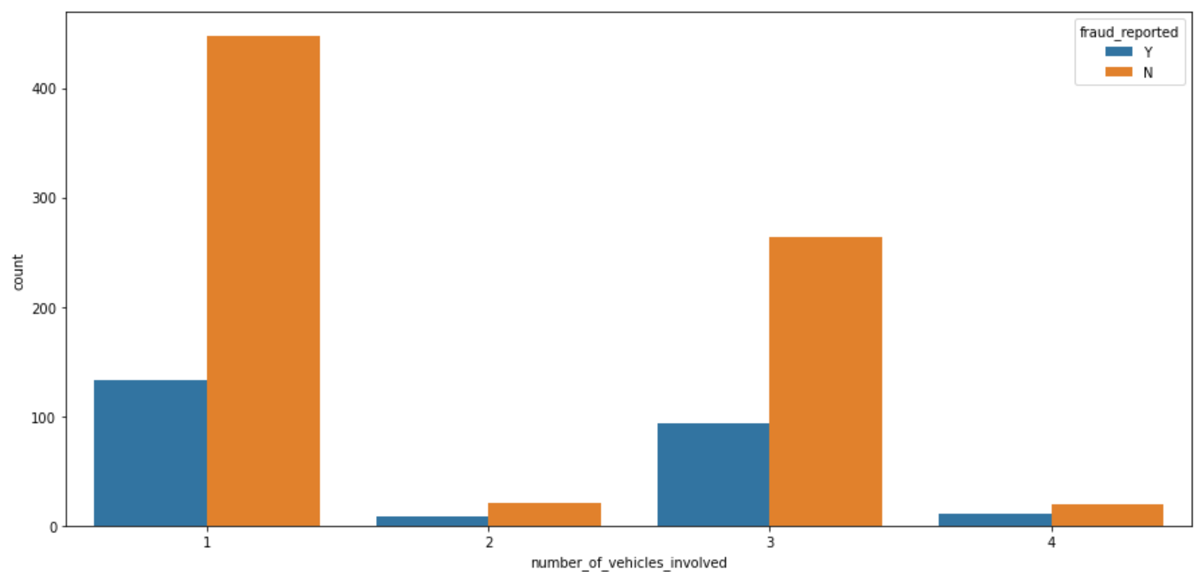
Out[25]: <AxesSubplot:xlabel='fraud_reported', ylabel='total_claim_amount'>



- Most of fraud reported found where total claimed amount 50000 to 70000

In [26]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='number_of_vehicles_involved',hue='fraud_reported',data=df)
```

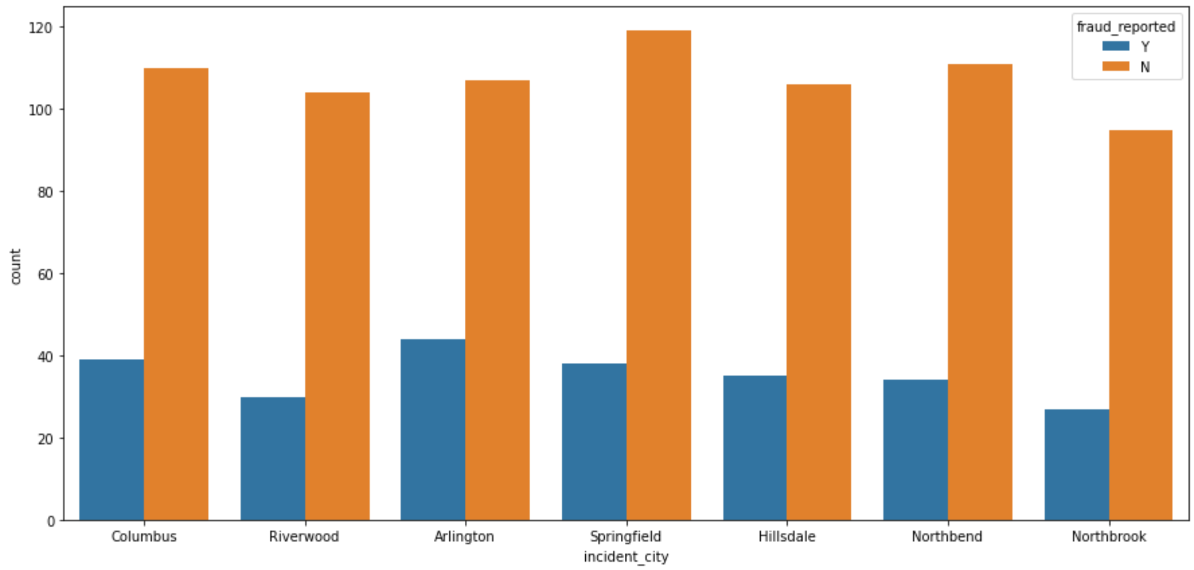
Out[26]: <AxesSubplot:xlabel='number_of_vehicles_involved', ylabel='count'>



- Most of the fraud report were found where number_of_vehicles_involved more than 1

In [27]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='incident_city',hue='fraud_reported',data=df)
```

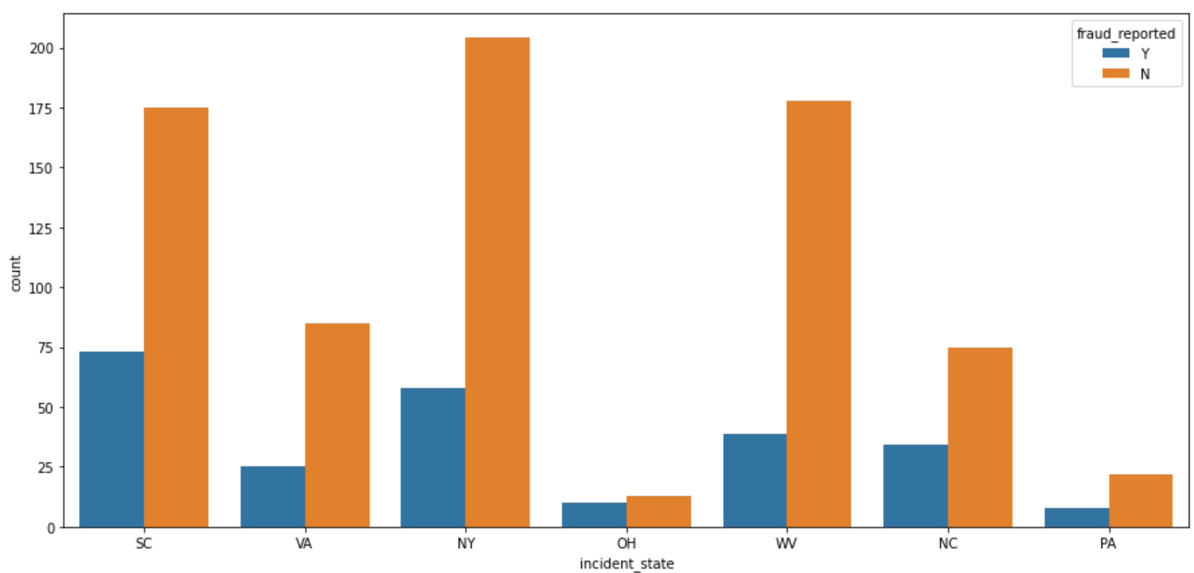
Out[27]: <AxesSubplot:xlabel='incident_city', ylabel='count'>



- In all cities fraud reported counts are almost same.

In [28]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='incident_state',hue='fraud_reported',data=df)
```

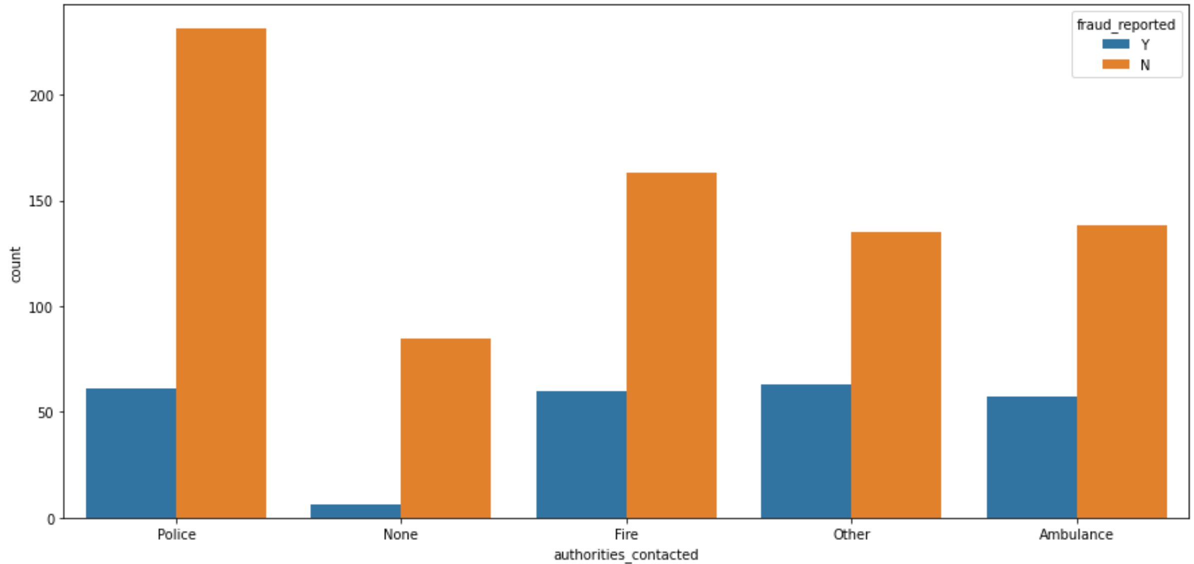
Out[28]: <AxesSubplot:xlabel='incident_state', ylabel='count'>



- Most of the fraud reported were fonund where incident state was SC, NY, OH, NC and PA

In [29]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='authorities_contacted',hue='fraud_reported',data=df)
```

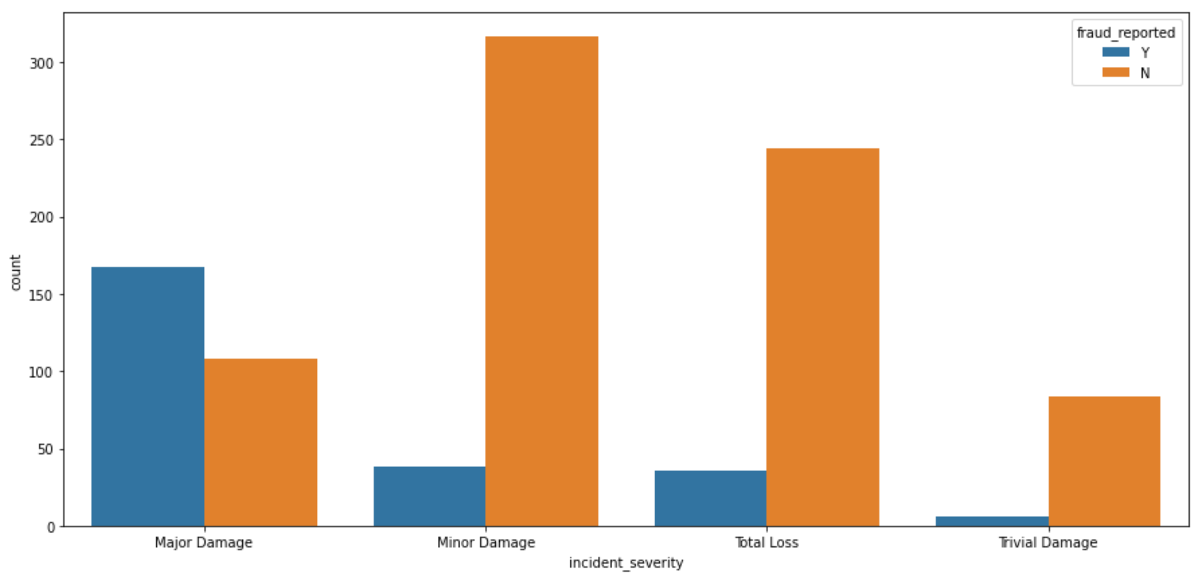
Out[29]: <AxesSubplot:xlabel='authorities_contacted', ylabel='count'>



- Most of the fraud founded where cx have contacted authorities_contacted of Fire, Other and Ambulance

In [30]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='incident_severity',hue='fraud_reported',data=df)
```

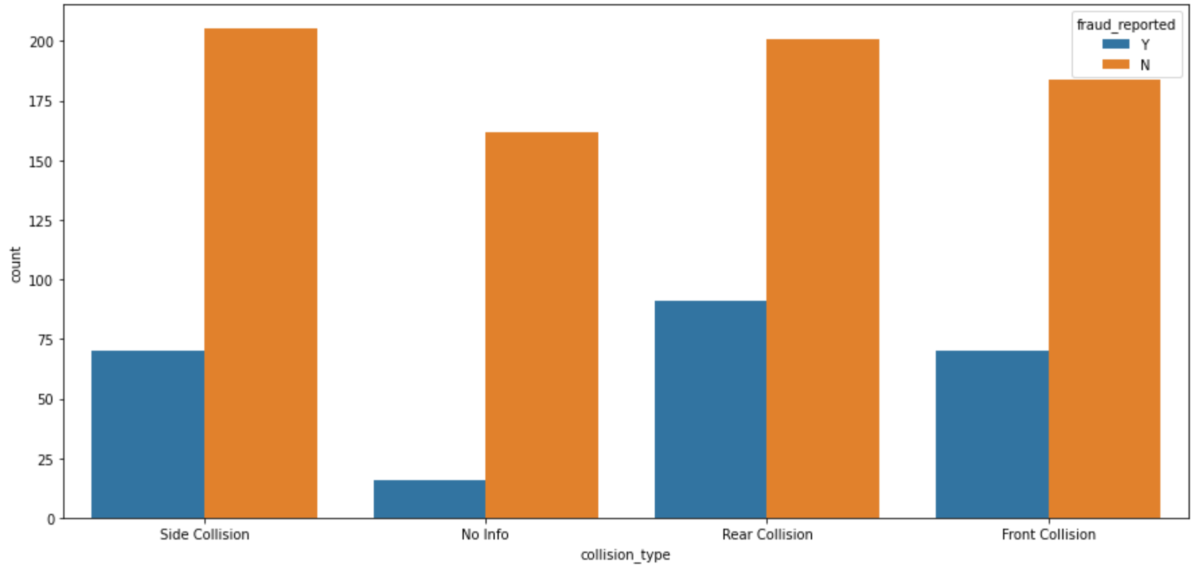
Out[30]: <AxesSubplot:xlabel='incident_severity', ylabel='count'>



- Most of fraud reported claim are Major Damage , most of them are counted as fraud
- There are very fraud report in Trivial damage.

```
In [31]: plt.figure(figsize=(15,7))
         sns.countplot(x='collision_type',hue='fraud_reported',data=df)
```

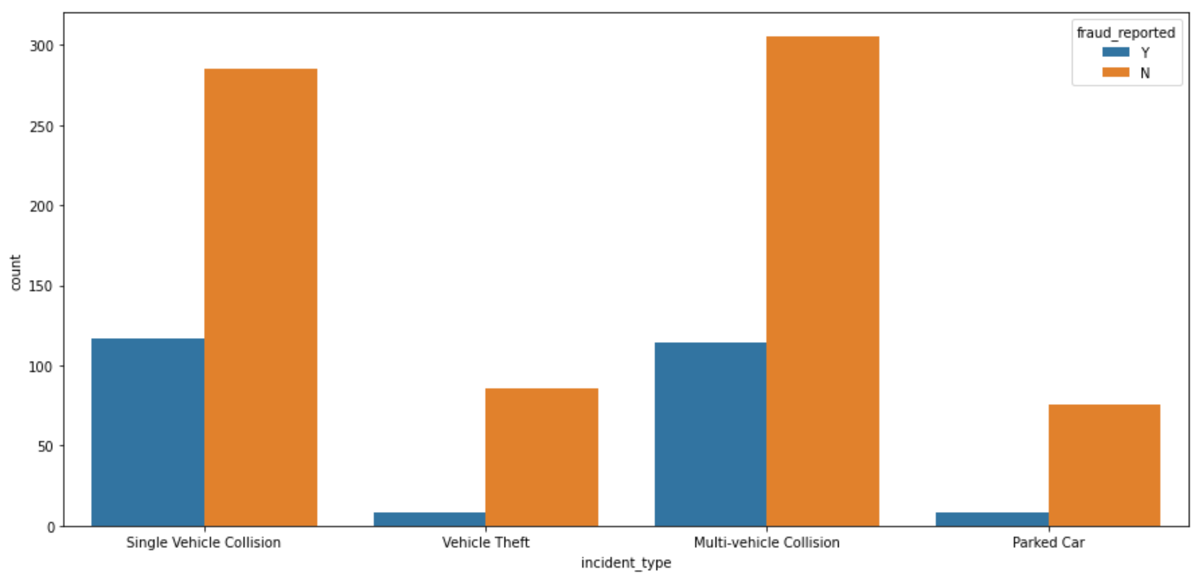
```
Out[31]: <AxesSubplot:xlabel='collision_type', ylabel='count'>
```



- Most of fraud reported claims in Side Collision, Rear Collision and Front Collision.
- Some of reported claim we have those are in no info of collision type

```
In [32]: plt.figure(figsize=(15,7))
         sns.countplot(x='incident_type',hue='fraud_reported',data=df)
```

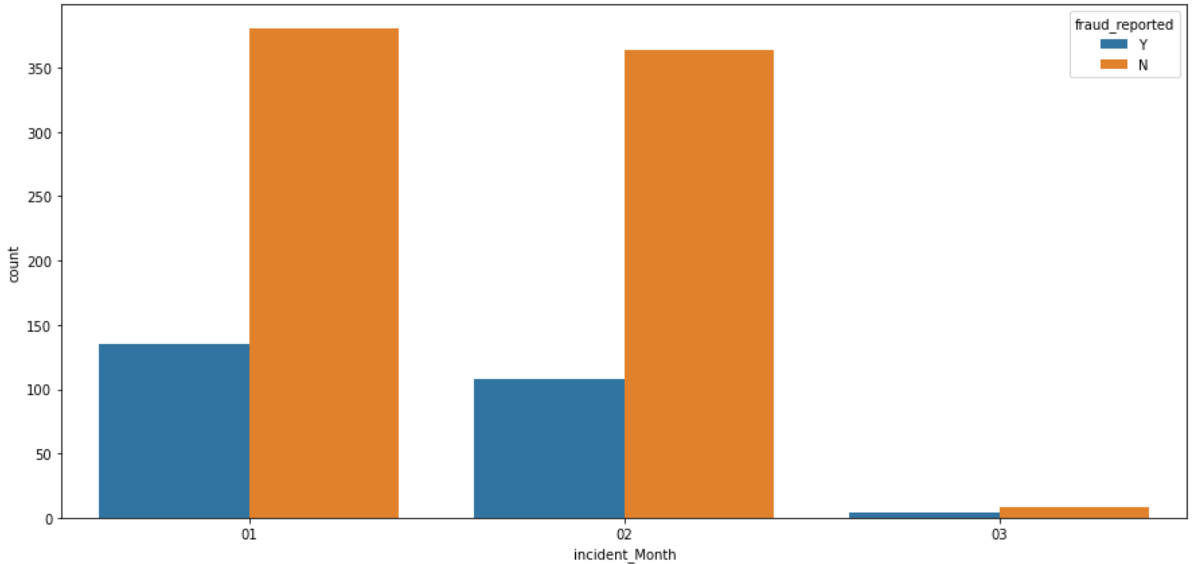
```
Out[32]: <AxesSubplot:xlabel='incident_type', ylabel='count'>
```



- We have most claim reported and fraud reported in Single vehicle collision and multi-vehicle collision incident type.
- In other two incident type vehicle theft an dparked car are very less fraud report.

In [33]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='incident_Month',hue='fraud_reported',data=df)
```

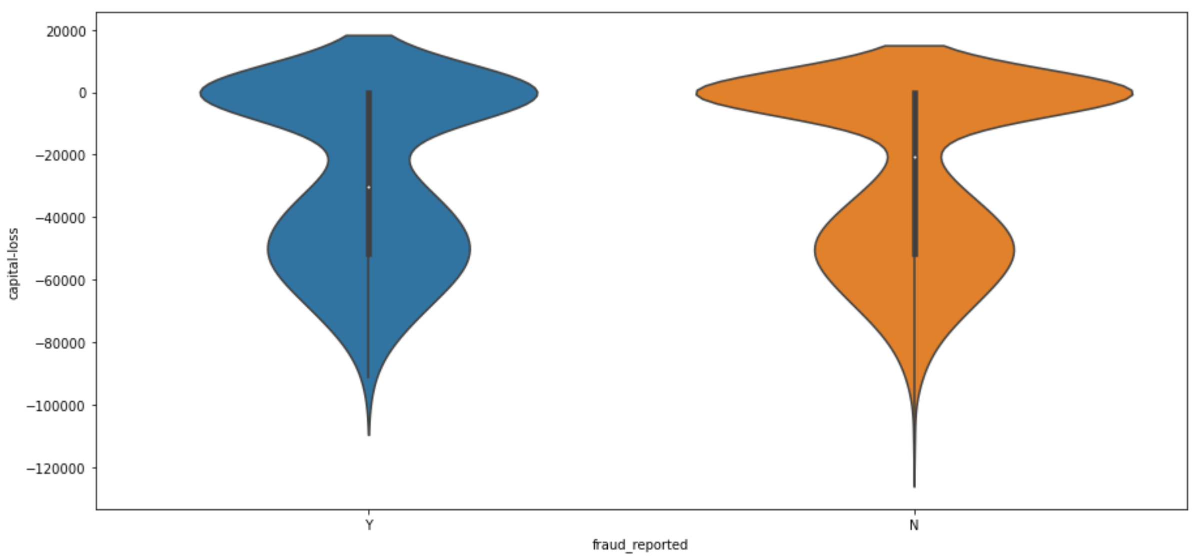
Out[33]: <AxesSubplot:xlabel='incident_Month', ylabel='count'>



- Most of the data we have reported in month 1 and 2 fraud reported are also around same in both months.

In [34]:
```
plt.figure(figsize=(15,7))
sns.violinplot(y='capital-loss',x='fraud_reported',data=df)
```

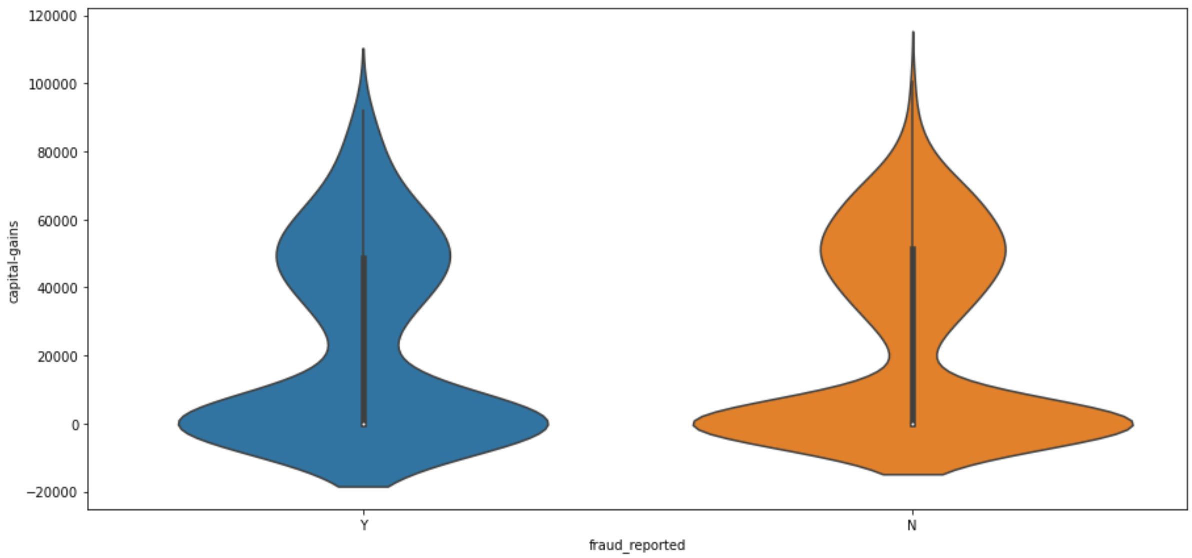
Out[34]: <AxesSubplot:xlabel='fraud_reported', ylabel='capital-loss'>



- Most of fraud reported we see in cx those capital loss are and -40000 to -60000

In [35]:
```
plt.figure(figsize=(15,7))
sns.violinplot(y='capital-gains',x='fraud_reported',data=df)
```

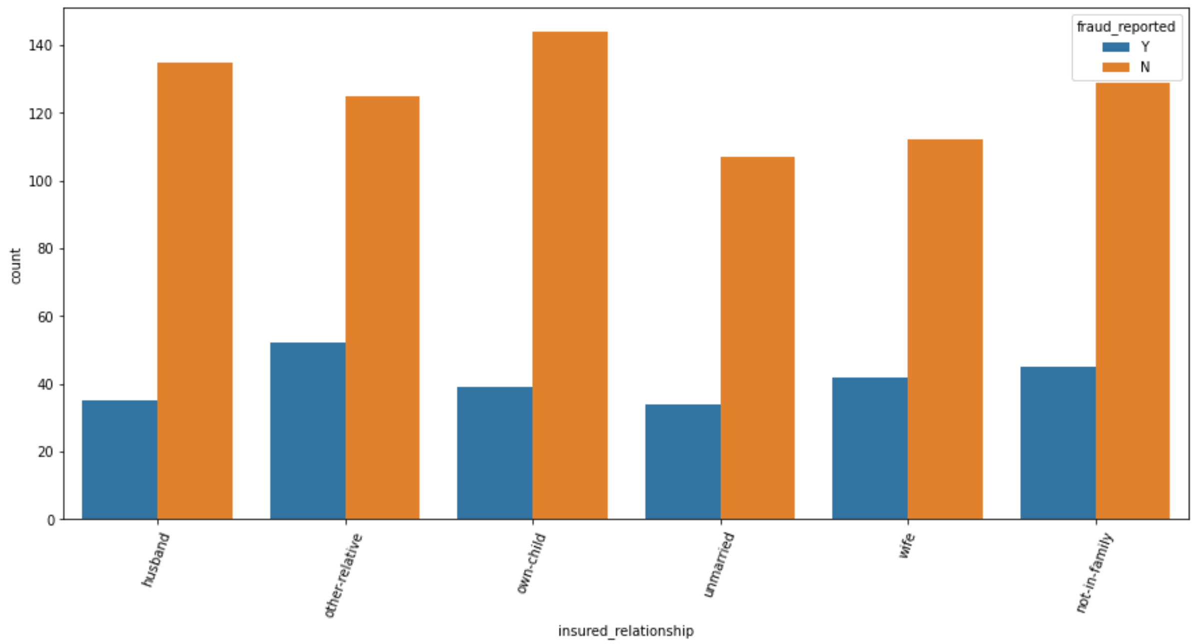
Out[35]: <AxesSubplot:xlabel='fraud_reported', ylabel='capital-gains'>



- Most of the fraud reported are in cx those capital gains are 0 and around 50000

In [36]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='insured_relationship',hue='fraud_reported',data=df)
plt.xticks(rotation=70)
```

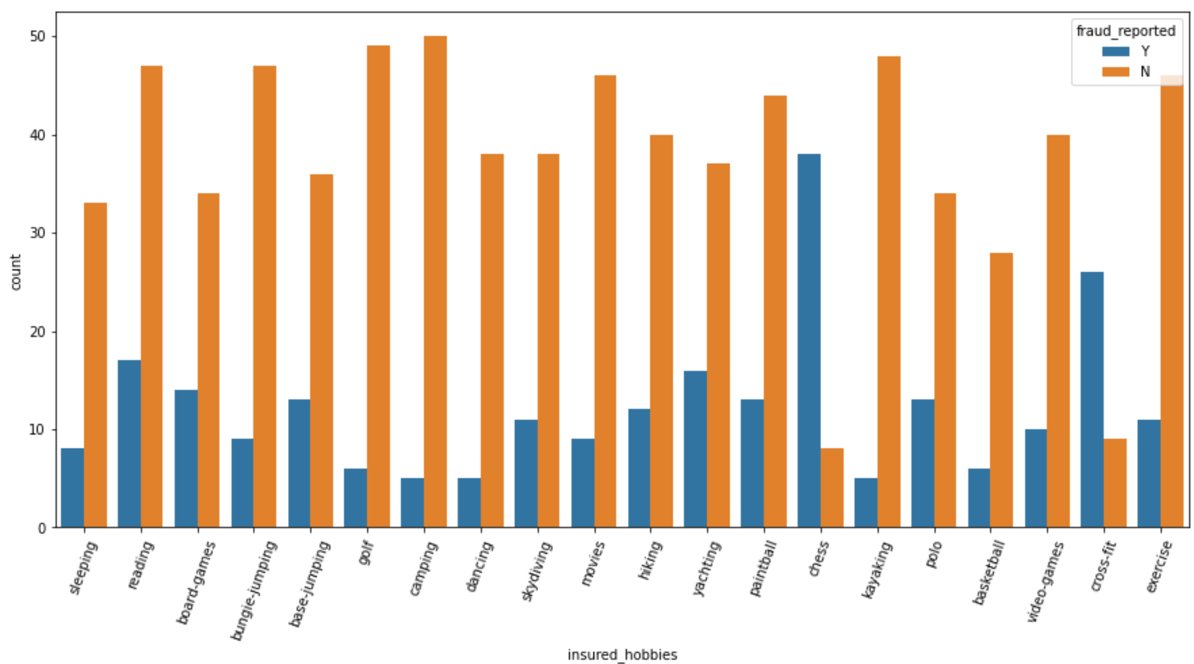
Out[36]:
```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'husband'),
  Text(1, 0, 'other-relative'),
  Text(2, 0, 'own-child'),
  Text(3, 0, 'unmarried'),
  Text(4, 0, 'wife'),
  Text(5, 0, 'not-in-family')])
```



- According to the data info, cx those having insured relationship with other relative and wife are most reported than others.

In [37]:
```python
plt.figure(figsize=(15,7))
sns.countplot(x='insured_hobbies',hue='fraud_reported',data=df)
plt.xticks(rotation=70)
```

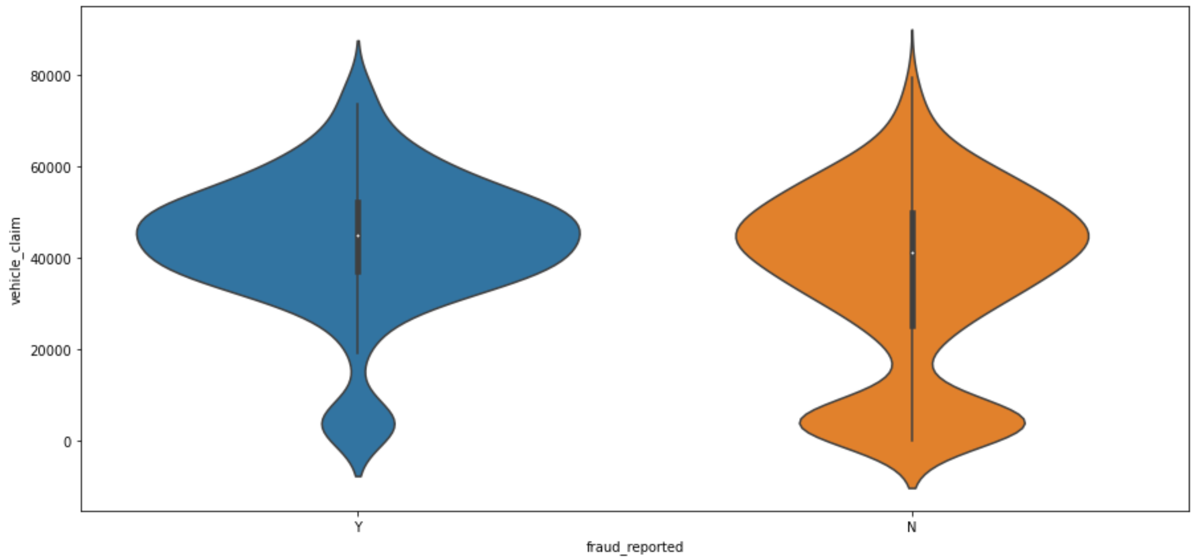
Out[37]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19]),
 [Text(0, 0, 'sleeping'),
  Text(1, 0, 'reading'),
  Text(2, 0, 'board-games'),
  Text(3, 0, 'bungie-jumping'),
  Text(4, 0, 'base-jumping'),
  Text(5, 0, 'golf'),
  Text(6, 0, 'camping'),
  Text(7, 0, 'dancing'),
  Text(8, 0, 'skydiving'),
  Text(9, 0, 'movies'),
  Text(10, 0, 'hiking'),
  Text(11, 0, 'yachting'),
  Text(12, 0, 'paintball'),
  Text(13, 0, 'chess'),
  Text(14, 0, 'kayaking'),
  Text(15, 0, 'polo'),
  Text(16, 0, 'basketball'),
  Text(17, 0, 'video-games'),
  Text(18, 0, 'cross-fit'),
  Text(19, 0, 'exercise')])
```



- Here we can see the cx those hobbies are Chess, are most fraud reported cx.
- Here we can see the cx those hobbies are cross-fit , are also most fraud reported cx
- After that cx those hobbies are reading, board games, base-jumping, yechting, painball, polo and etc also most fraud report cx than others

```
In [38]: plt.figure(figsize=(15,7))
         sns.violinplot(y='vehicle_claim',x='fraud_reported',data=df)
```

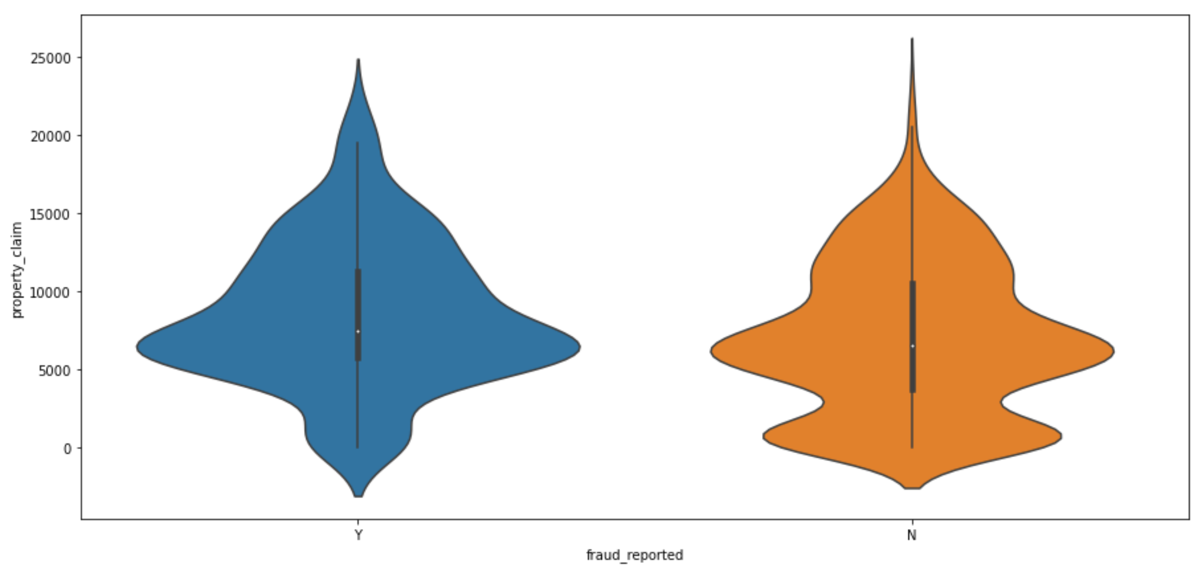
Out[38]: <AxesSubplot:xlabel='fraud_reported', ylabel='vehicle_claim'>



- In vehicle_claim most of the cx are between 100 to 6500
- Fraud report is higher in cx are between 3500 to 5500 vehicle_claim

```
In [39]: plt.figure(figsize=(15,7))
         sns.violinplot(y='property_claim',x='fraud_reported',data=df)
```

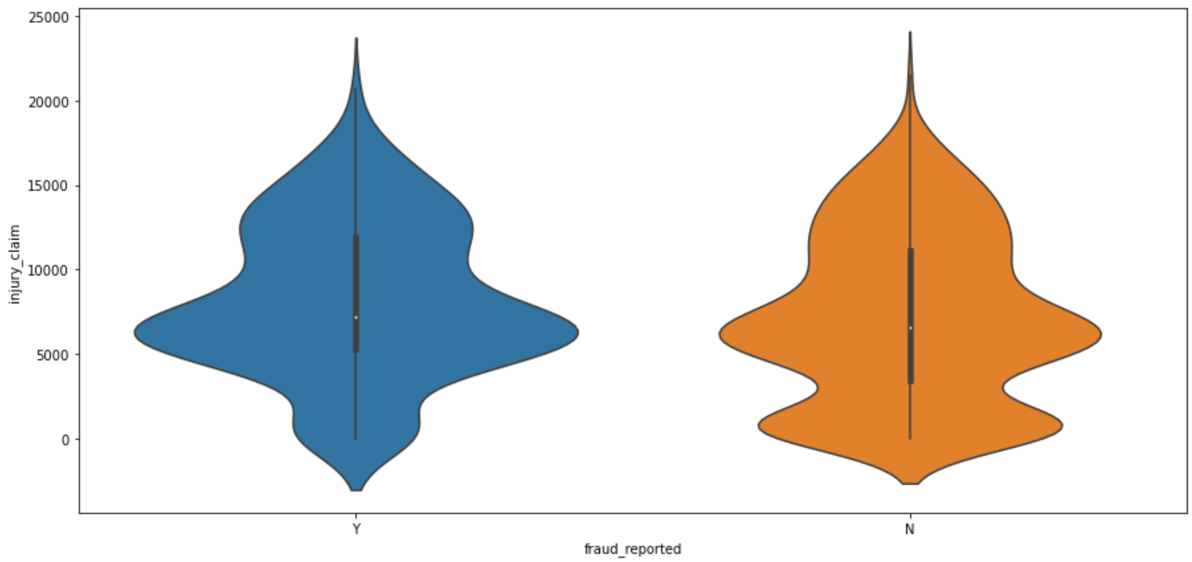
Out[39]: <AxesSubplot:xlabel='fraud_reported', ylabel='property_claim'>



- In Property claim fraud reported is higher in cx claimed of 5000 to 8000

In [40]:
```
plt.figure(figsize=(15,7))
sns.violinplot(y='injury_claim',x='fraud_reported',data=df)
```

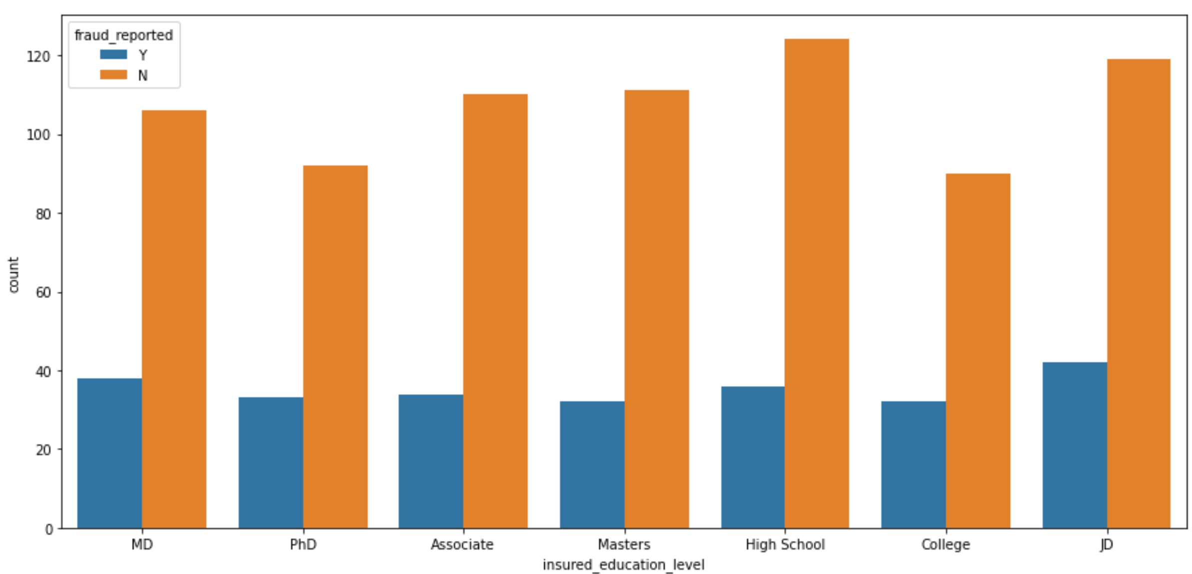
Out[40]: <AxesSubplot:xlabel='fraud_reported', ylabel='injury_claim'>



- Most of the cx injury claim is 100 to 15000
- Most fraud reported cx are between 5000 to 8000 injury claim

In [41]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='insured_education_level', hue='fraud_reported',data=df)
```

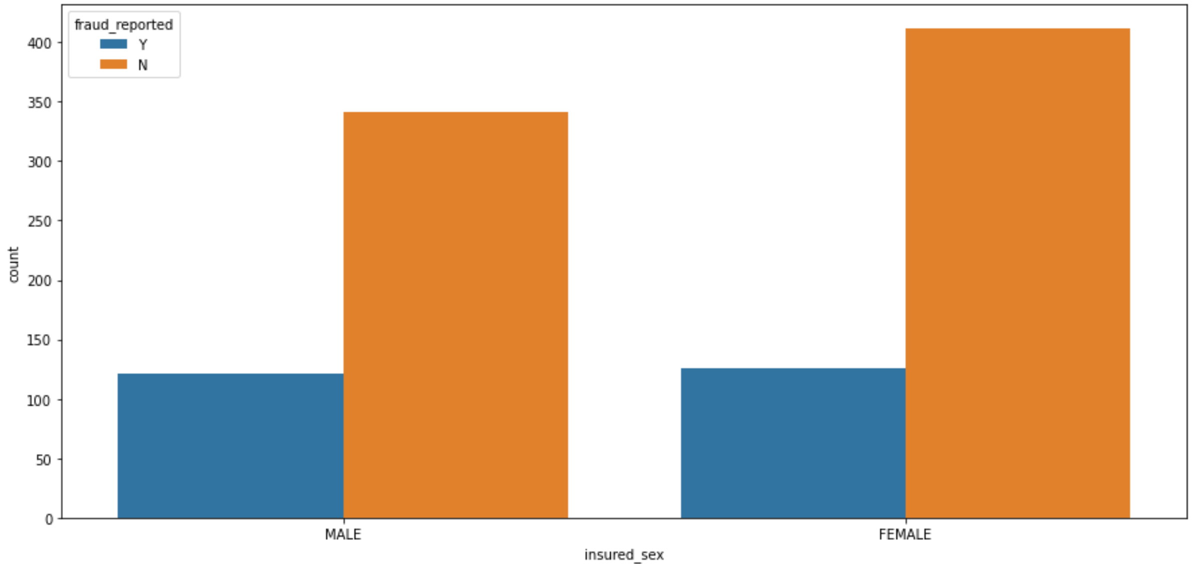
Out[41]: <AxesSubplot:xlabel='insured_education_level', ylabel='count'>



- We higher cx those are education level is High School and least cx in PhD and College
- There is very little difference in fraud report in all kind of cx
- Fraud report is little higher in cx those education level is JD, MD, PhD, and College than others.

In [42]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='insured_sex', hue='fraud_reported', data=df)
```

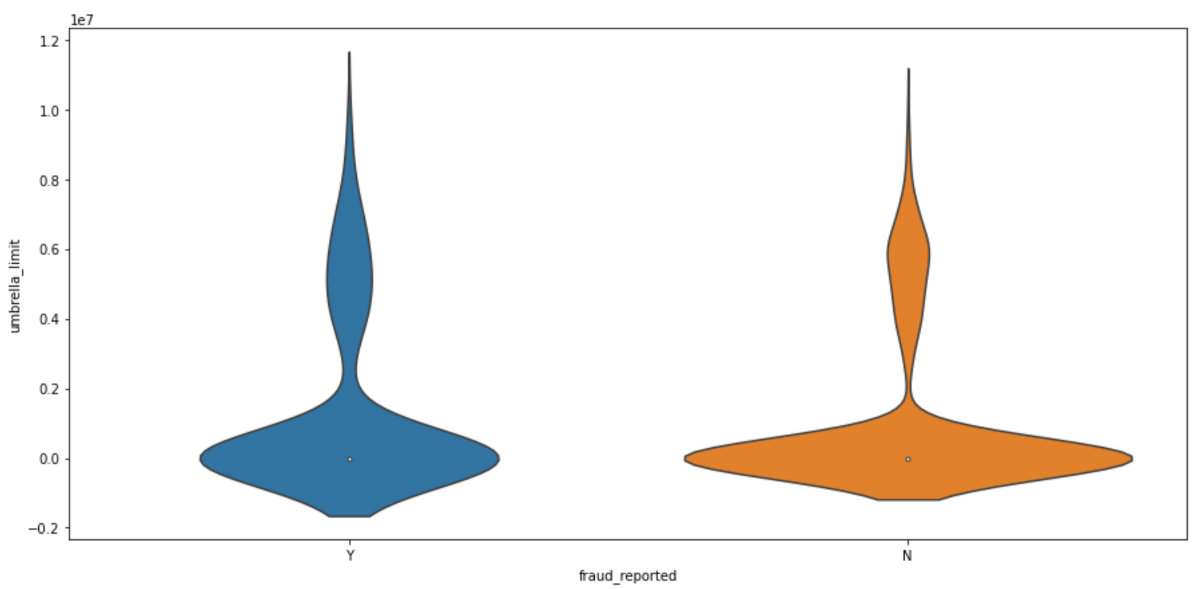
Out[42]: <AxesSubplot:xlabel='insured_sex', ylabel='count'>



- We have more cx in Female than the Male
- But fraud reported is little high Male cx

In [43]:
```
plt.figure(figsize=(15,7))
sns.violinplot(x='fraud_reported',y='umbrella_limit',data=df)
```

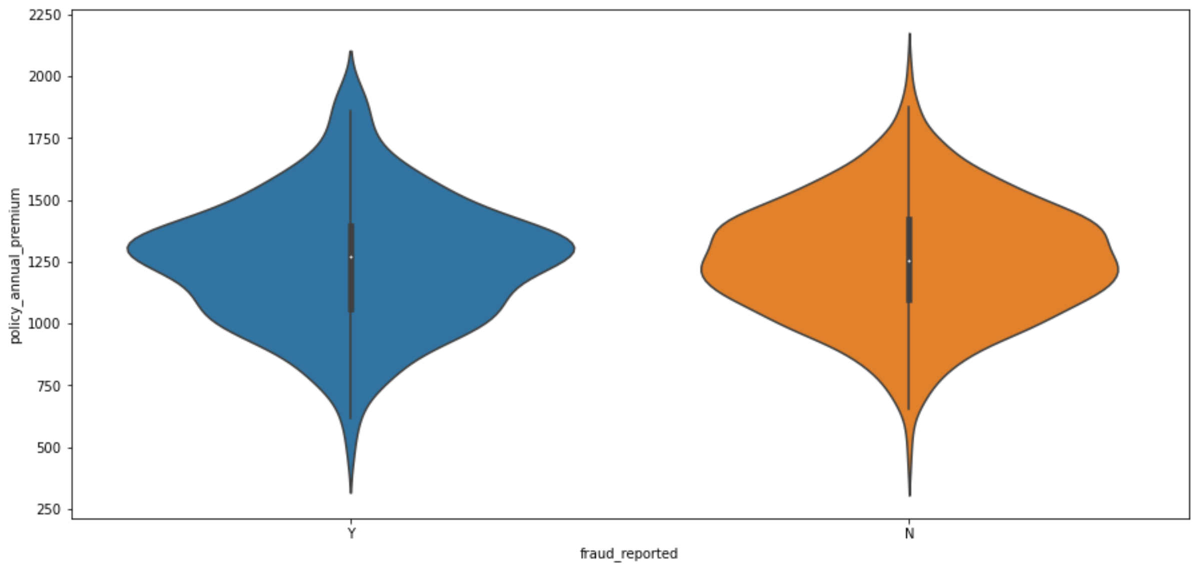
Out[43]: <AxesSubplot:xlabel='fraud_reported', ylabel='umbrella_limit'>



- Most of cx we have their umbrella limit is 0
- fraud reported is also high those cx

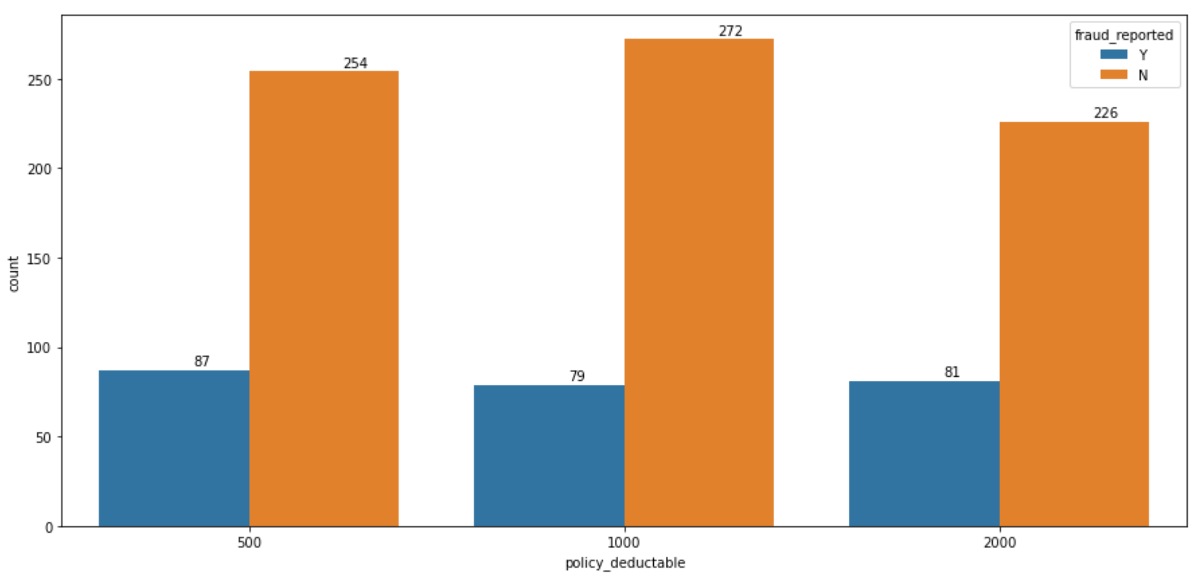
In [44]:
```
plt.figure(figsize=(15,7))
sns.violinplot(x='fraud_reported',y='policy_annual_premium',data=df)
```

Out[44]: <AxesSubplot:xlabel='fraud_reported', ylabel='policy_annual_premium'>



- Most of cx we have 1000 to 1500 of premiums payers
- Most of the fraud reported we found in those premium is 1250 to 1300

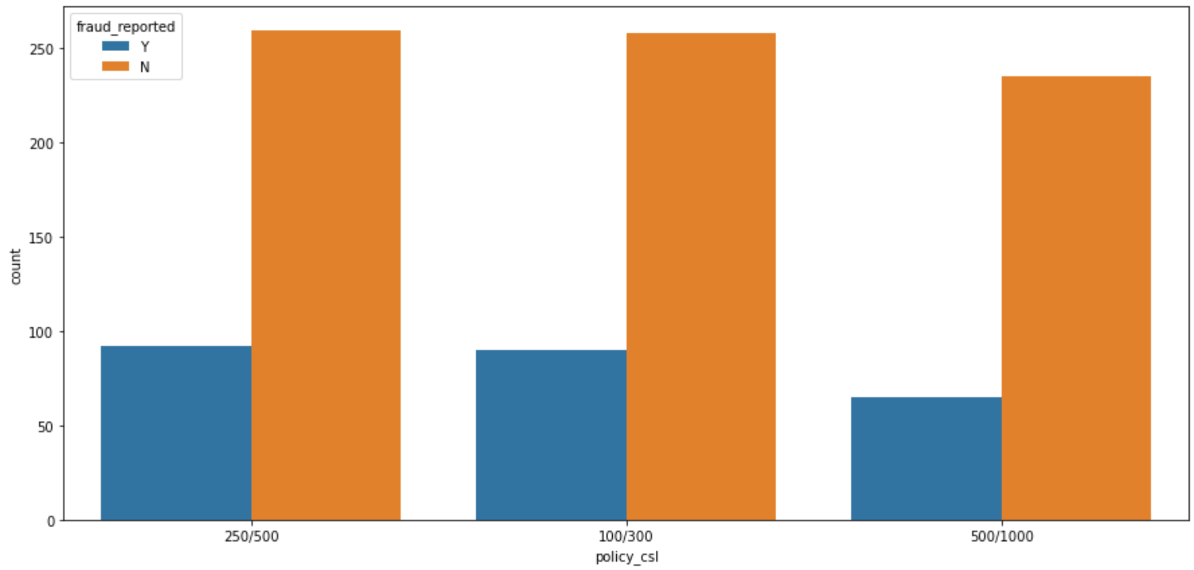
In [45]:
```
plt.figure(figsize=(15,7))
ax=sns.countplot(x='policy_deductable',hue='fraud_reported',data=df)
for p in ax.patches:
    ax.annotate(int(p.get_height()), (p.get_x()+0.25, p.get_height()+1), va='bo
                color= 'black')
```



- Here we notice here according to count fraud report high in cx of 2000 policy_deductable

In [46]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='policy_csl',hue='fraud_reported',data=df)
```

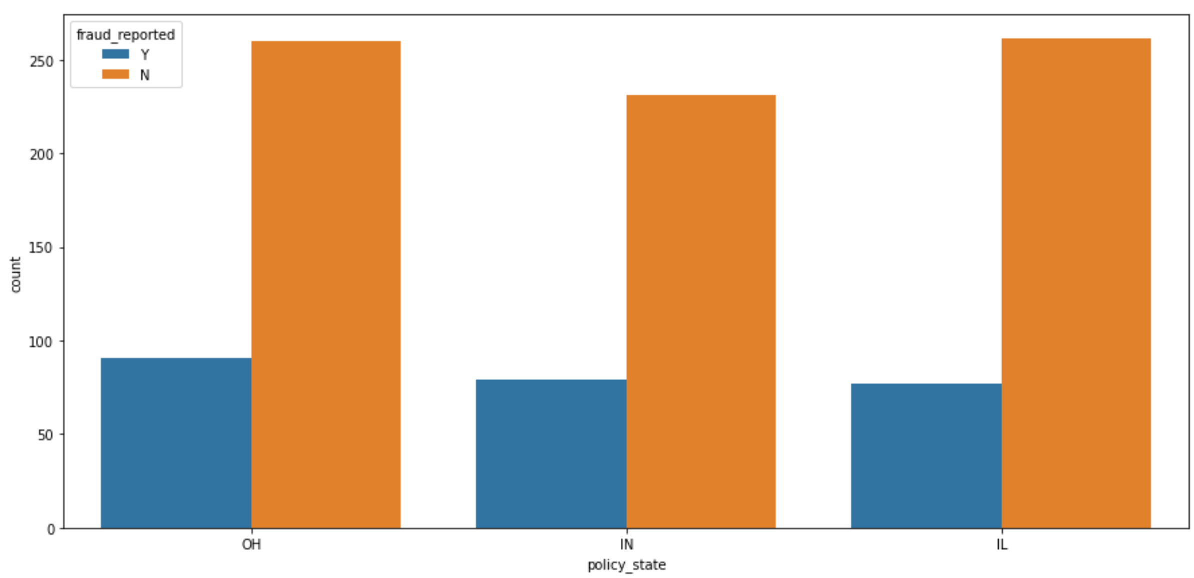
Out[46]: <AxesSubplot:xlabel='policy_csl', ylabel='count'>



- In all three csl we same kind of similarity fraud report is also common in all policy_csl

In [47]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='policy_state',hue='fraud_reported',data=df)
```

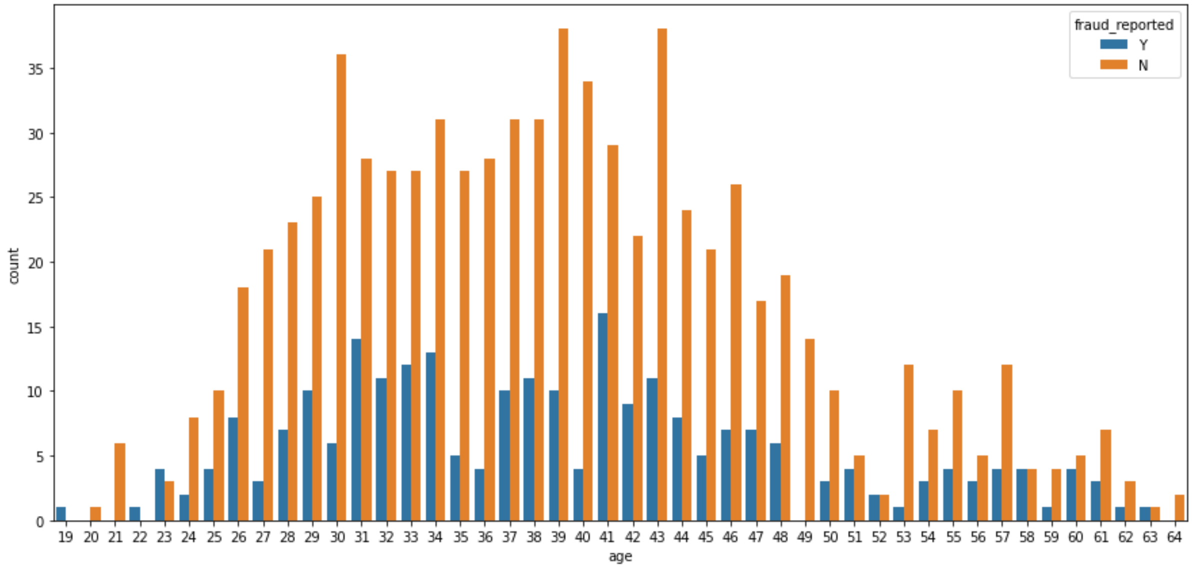
Out[47]: <AxesSubplot:xlabel='policy_state', ylabel='count'>



- We have cx from three stats and fraud report almost common in all three states.

In [48]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='age',hue='fraud_reported',data=df)
```

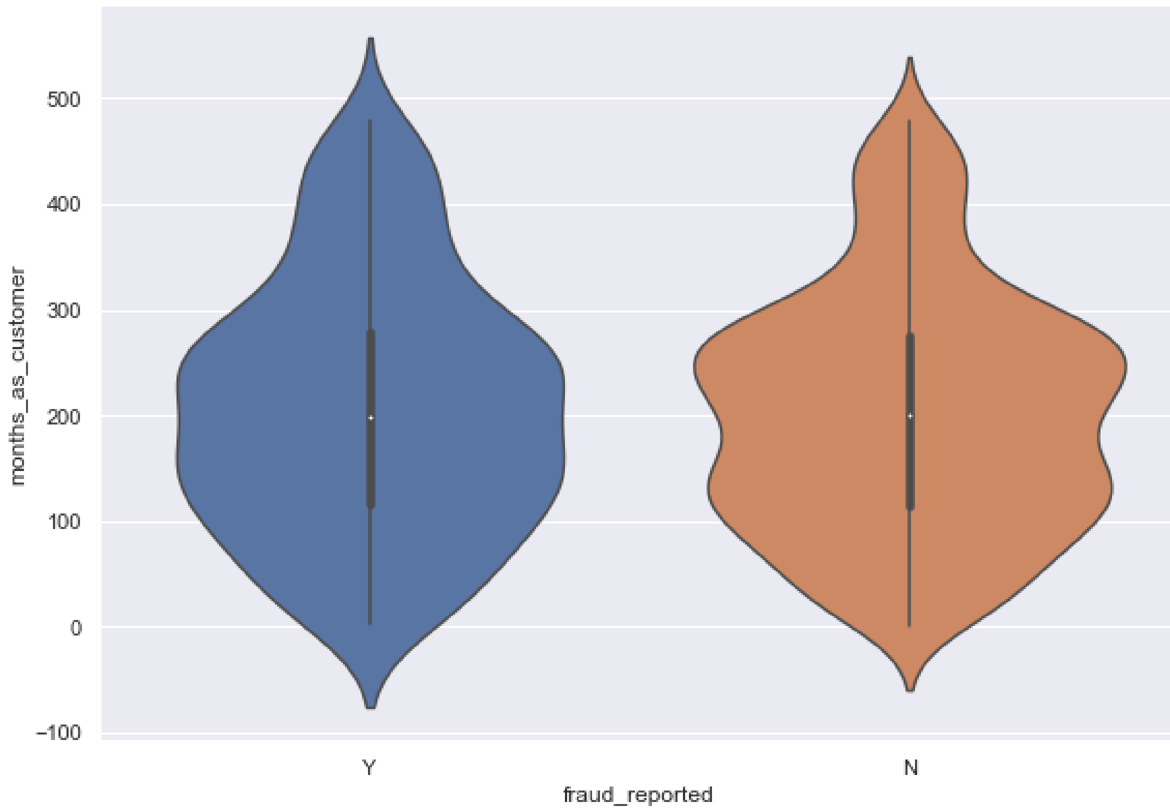
Out[48]: <AxesSubplot:xlabel='age', ylabel='count'>



- We see most of the cx are age of 26 to 50
- Fraud reported is higher in cx 26 to 50 of age.

In [49]:
```
plt.figure(figsize=(10,7))
sns. set(color_codes=True)
sns.violinplot(y='months_as_customer',x='fraud_reported',data=df)
```

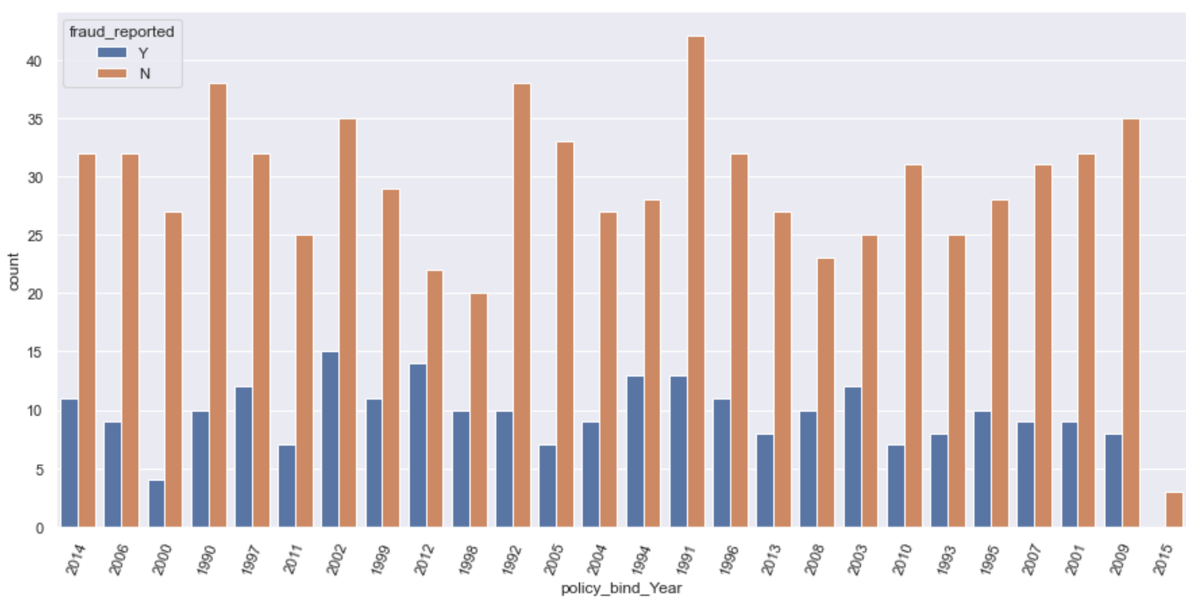
Out[49]: <AxesSubplot:xlabel='fraud_reported', ylabel='months_as_customer'>



- Most of the cx are 100 to 300 months old
- We can notice here fraud reort is high in cx between 100 to 250 months old

In [50]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='policy_bind_Year',hue='fraud_reported',data=df)
plt.xticks(rotation =70,)
```

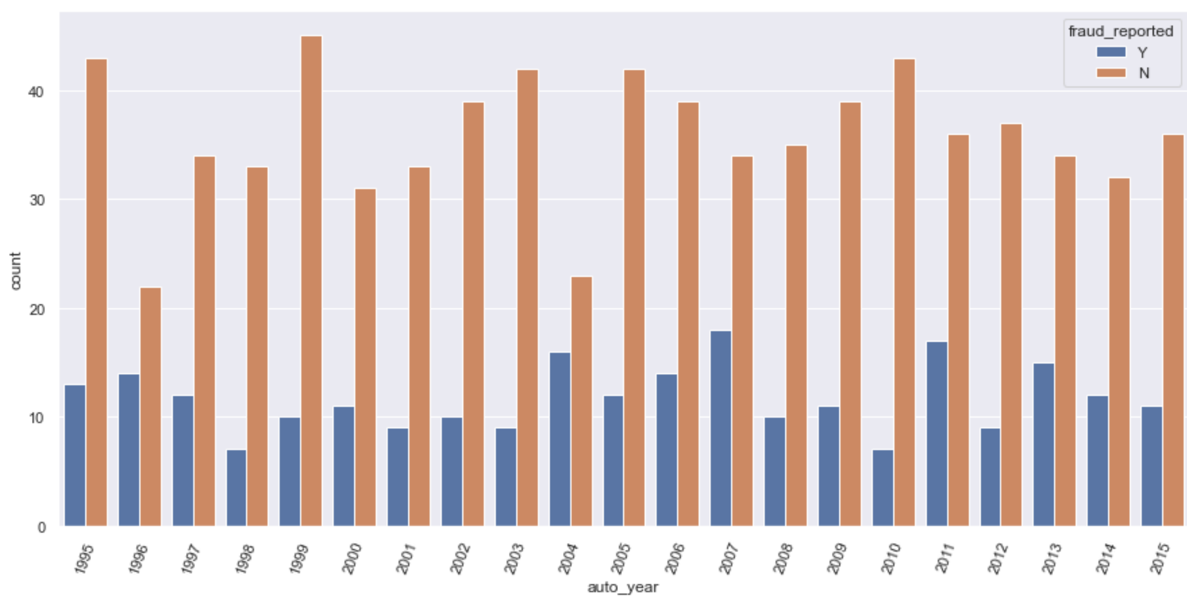
Out[50]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25]),
 [Text(0, 0, '2014'),
  Text(1, 0, '2006'),
  Text(2, 0, '2000'),
  Text(3, 0, '1990'),
  Text(4, 0, '1997'),
  Text(5, 0, '2011'),
  Text(6, 0, '2002'),
  Text(7, 0, '1999'),
  Text(8, 0, '2012'),
  Text(9, 0, '1998'),
  Text(10, 0, '1992'),
  Text(11, 0, '2005'),
  Text(12, 0, '2004'),
  Text(13, 0, '1994'),
  Text(14, 0, '1991'),
  Text(15, 0, '1996'),
  Text(16, 0, '2013'),
  Text(17, 0, '2008'),
  Text(18, 0, '2003'),
  Text(19, 0, '2010'),
  Text(20, 0, '1993'),
  Text(21, 0, '1995'),
  Text(22, 0, '2007'),
  Text(23, 0, '2001'),
  Text(24, 0, '2009'),
  Text(25, 0, '2015')])
```



- Here we notice fraud report is high in policy_vind_Year of 2014, 2006, 1990, 1997, 2002, 1999, 2012, 1998, 1994, 2008, 2003 and etc thanothers

In [51]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='auto_year',hue='fraud_reported',data=df)
plt.xticks(rotation =70,)
```

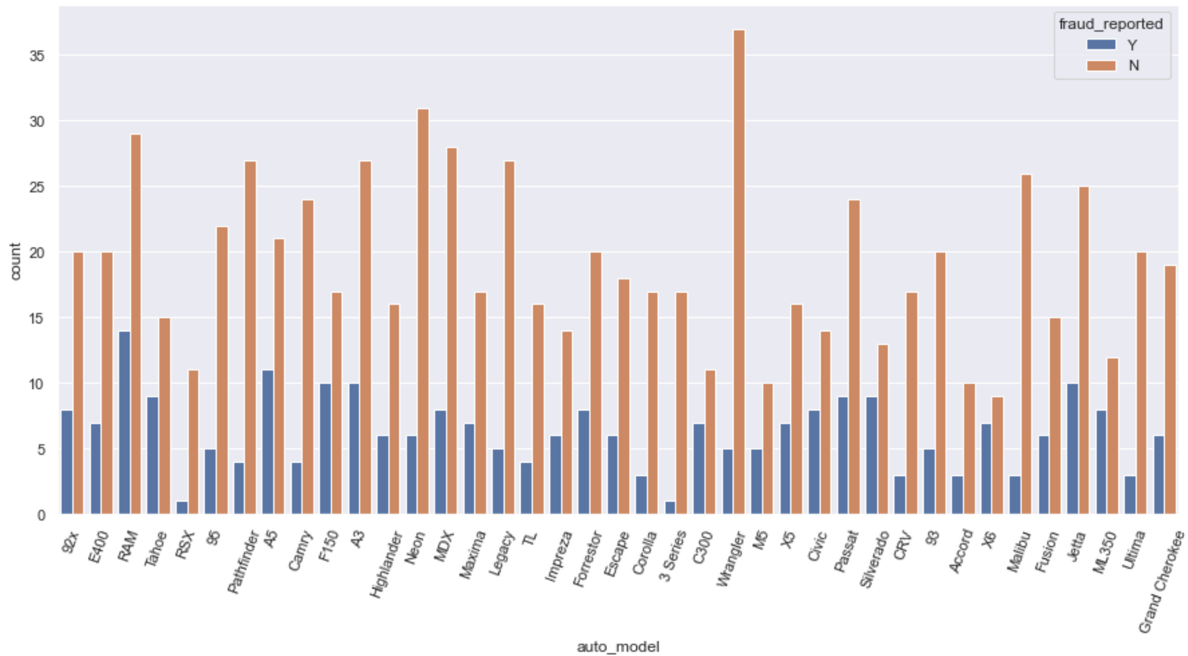
Out[51]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20]),
 [Text(0, 0, '1995'),
  Text(1, 0, '1996'),
  Text(2, 0, '1997'),
  Text(3, 0, '1998'),
  Text(4, 0, '1999'),
  Text(5, 0, '2000'),
  Text(6, 0, '2001'),
  Text(7, 0, '2002'),
  Text(8, 0, '2003'),
  Text(9, 0, '2004'),
  Text(10, 0, '2005'),
  Text(11, 0, '2006'),
  Text(12, 0, '2007'),
  Text(13, 0, '2008'),
  Text(14, 0, '2009'),
  Text(15, 0, '2010'),
  Text(16, 0, '2011'),
  Text(17, 0, '2012'),
  Text(18, 0, '2013'),
  Text(19, 0, '2014'),
  Text(20, 0, '2015')])
```



- We can notice we have less vehicle from 1998 and 20010 auto year
- According to vehicle count fraud reported is higher in vehicle of 1996, 2004, 2007, 2011, 2013, 2014 and etc auto year than others

In [52]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='auto_model',hue='fraud_reported',data=df)
plt.xticks(rotation =70,)
```

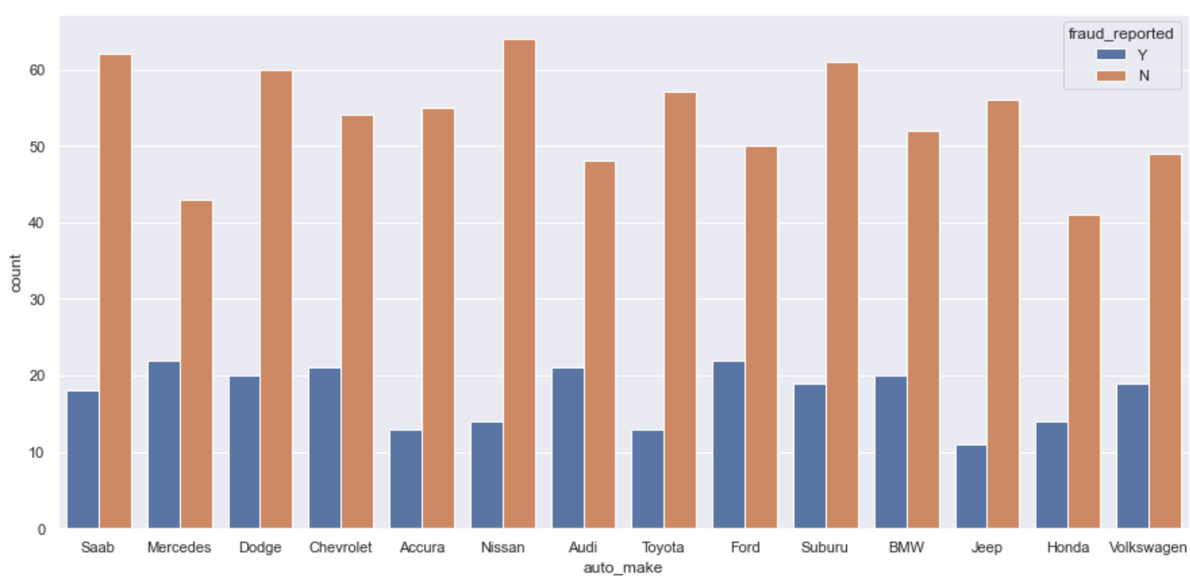
Out[52]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37, 38]),
 [Text(0, 0, '92x'),
  Text(1, 0, 'E400'),
  Text(2, 0, 'RAM'),
  Text(3, 0, 'Tahoe'),
  Text(4, 0, 'RSX'),
  Text(5, 0, '95'),
  Text(6, 0, 'Pathfinder'),
  Text(7, 0, 'A5'),
  Text(8, 0, 'Camry'),
  Text(9, 0, 'F150'),
  Text(10, 0, 'A3'),
  Text(11, 0, 'Highlander'),
  Text(12, 0, 'Neon'),
  Text(13, 0, 'MDX'),
  Text(14, 0, 'Maxima'),
  Text(15, 0, 'Legacy'),
  Text(16, 0, 'TL'),
  Text(17, 0, 'Impreza'),
  Text(18, 0, 'Forrestor'),
  Text(19, 0, 'Escape'),
  Text(20, 0, 'Corolla'),
  Text(21, 0, '3 Series'),
  Text(22, 0, 'C300'),
  Text(23, 0, 'Wrangler'),
  Text(24, 0, 'M5'),
  Text(25, 0, 'X5'),
  Text(26, 0, 'Civic'),
  Text(27, 0, 'Passat'),
  Text(28, 0, 'Silverado'),
  Text(29, 0, 'CRV'),
  Text(30, 0, '93'),
  Text(31, 0, 'Accord'),
  Text(32, 0, 'X6'),
  Text(33, 0, 'Malibu'),
  Text(34, 0, 'Fusion'),
  Text(35, 0, 'Jetta'),
  Text(36, 0, 'ML350'),
  Text(37, 0, 'Ultima'),
  Text(38, 0, 'Grand Cherokee')])
```



- Most of auto_model we see in Wrangler, RAM , Pathfinder, Neon and etc.
- We can notice Fraud report is higher in 92x, RAM, E400, Tahore, A5, F150, X5, C300, M5, CIVIC, SILVERADOX6 ML300 and etc auto_models

In [53]:
```
plt.figure(figsize=(15,7))
sns.countplot(x='auto_make',hue='fraud_reported',data=df)
```

Out[53]: <AxesSubplot:xlabel='auto_make', ylabel='count'>



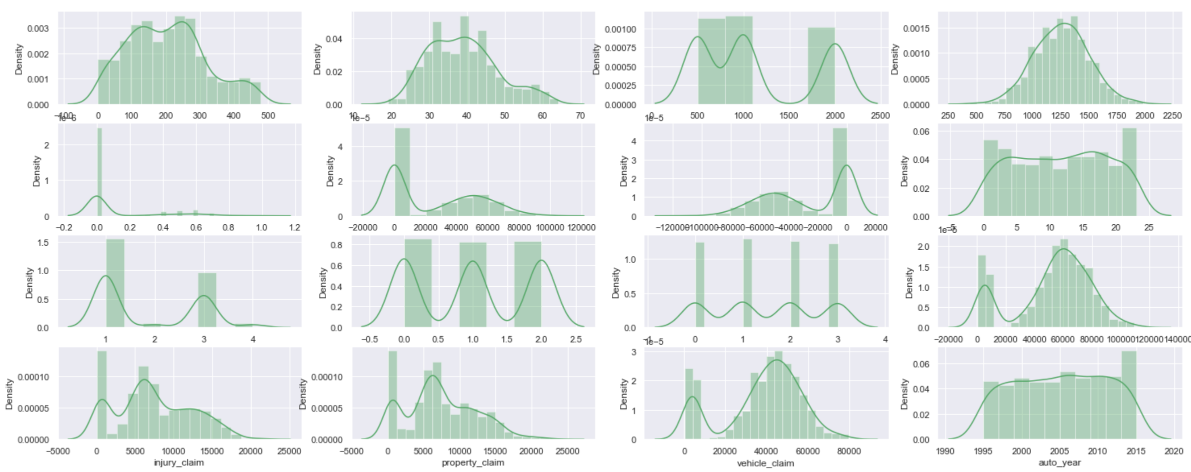
- Fraud reported claim is higher in Saab, Merceded, Dodge, Chevrolet, Audi , Ford, Suburu BMW and volkswagen auto_make
- In Other Auto_make brand is less than other.

Have done the analysis of all important features, some of features don't have much information to define

Skewness Handling

Skew and Outliers will be handel in numerical columns only

In [54]:
```
# ploting for numerical columns only
plt.figure(figsize=(25,20))
for i in enumerate(df.select_dtypes(include=['int64','float','int32'])):
    plt.subplot(8,4,i[0]+1)
    sns.distplot(df[i[1]],color='g')
```



In [55]:
```
df.select_dtypes(include=['int64','float','int32']).skew()
```

Out[55]:
```
months_as_customer             0.364014
age                            0.479796
policy_deductable              0.476426
policy_annual_premium          0.005374
umbrella_limit                 1.806100
capital-gains                  0.477220
capital-loss                  -0.389813
incident_hour_of_the_day      -0.034990
number_of_vehicles_involved    0.501009
bodily_injuries                0.012940
witnesses                      0.018399
total_claim_amount            -0.595646
injury_claim                   0.265382
property_claim                 0.378121
vehicle_claim                 -0.622627
auto_year                     -0.049502
dtype: float64
```

Skewness more than +/-0.5 will we treated

Object and target variable columns will not be treated

we can see here most of the columns are skewed

will only deal with numerical columns

- umbrella_limit
- total_claim_amount
- vehicle_claim

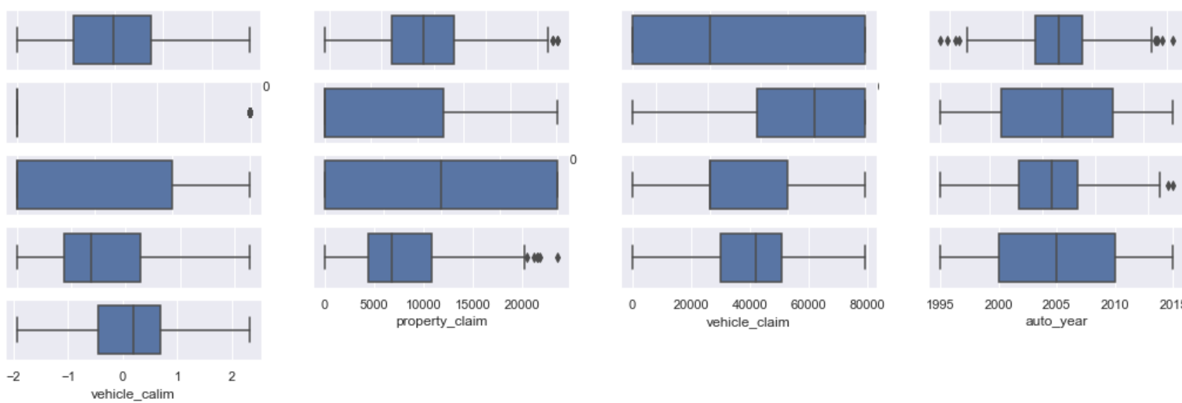
will be treated

In [56]:
```
from sklearn.preprocessing import power_transform

df[['umbrella_limit','total_claim_amount','vehicle_calim']]=power_transform(
     df[['umbrella_limit','total_claim_amount','vehicle_claim']],method='yeo-jo
```

Outliers Handling

In [57]:
```
plt.figure(figsize=(18,10))
for i in enumerate(df.select_dtypes(include=['int64','float','int32'])):
    plt.subplot(9,4,i[0]+1)
    sns.boxplot(df[i[1]])
```



- Only some of columns seems having outliers after skewness removed

Outliers Removal

ZSCORE Method

In [58]:
```
from scipy.stats import zscore

z=np.abs(zscore(df.select_dtypes(include=['int64','float','int32'])))

print(np.where(z>3))
```

```
(array([229, 248, 499, 762, 806], dtype=int64), array([ 3,  3, 13,  3,  6], d
type=int64))
```

In [59]:
```
df_1=df[(z<3).all(axis=1)]
print(("with outliers::",df.shape))
print("After removing outliers::",df_1.shape)
```

```
('with outliers::', (999, 41))
After removing outliers:: (994, 41)
```

- After using zscore method we only lose 5 rows from data

IQR Method

In [60]:
```
from scipy import stats
IQR = stats.iqr(df.select_dtypes(include=['int64','float','int32']))
IQR
```

Out[60]:
```
1997.574235635032
```

In [61]:
```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)

df_out = df.select_dtypes(include=['int64','float','int32'])[~((df.select_dtype
print(df_out.shape)
```

```
(311, 17)
```

choosing Zscore because there is huge dataloss in IQR

In [62]:
```
df= df_1
```

Using LabelEncoder for convering categorical to numerical

In [63]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 994 entries, 0 to 999
Data columns (total 41 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   months_as_customer           994 non-null    int64  
 1   age                          994 non-null    int64  
 2   policy_state                 994 non-null    object 
 3   policy_csl                   994 non-null    object 
 4   policy_deductable            994 non-null    int64  
 5   policy_annual_premium        994 non-null    float64
 6   umbrella_limit               994 non-null    float64
 7   insured_sex                  994 non-null    object 
 8   insured_education_level      994 non-null    object 
 9   insured_occupation           994 non-null    object 
 10  insured_hobbies              994 non-null    object 
 11  insured_relationship         994 non-null    object 
 12  capital-gains                994 non-null    int64  
 13  capital-loss                 994 non-null    int64  
 14  incident_date                994 non-null    object 
 15  incident_type                994 non-null    object 
 16  collision_type               994 non-null    object 
 17  incident_severity            994 non-null    object 
 18  authorities_contacted        994 non-null    object 
 19  incident_state               994 non-null    object 
 20  incident_city                994 non-null    object 
 21  incident_hour_of_the_day     994 non-null    int64  
 22  number_of_vehicles_involved  994 non-null    int64  
 23  property_damage              994 non-null    object 
 24  bodily_injuries              994 non-null    int64  
 25  witnesses                    994 non-null    int64  
 26  police_report_available      994 non-null    object 
 27  total_claim_amount           994 non-null    float64
 28  injury_claim                 994 non-null    int64  
 29  property_claim               994 non-null    int64  
 30  vehicle_claim                994 non-null    int64  
 31  auto_make                    994 non-null    object 
 32  auto_model                   994 non-null    object 
 33  auto_year                    994 non-null    int64  
 34  fraud_reported               994 non-null    object 
 35  incident_Date                994 non-null    object 
 36  incident_Month               994 non-null    object 
 37  policy_bind_Date             994 non-null    object 
 38  policy_bind_Month            994 non-null    object 
 39  policy_bind_Year             994 non-null    object 
 40  vehicle_calim                994 non-null    float64
dtypes: float64(4), int64(13), object(24)
memory usage: 326.2+ KB
```

In [64]:
```
from sklearn.preprocessing import LabelEncoder
```

In [65]:
```
# encoding  object columns into Numeric values in df
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
categ_data = df.select_dtypes(exclude=['int64','float','int32'])
for val in categ_data:
    df[val]=le.fit_transform(df[val].astype(str))
```

In [66]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 994 entries, 0 to 999
Data columns (total 41 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   months_as_customer           994 non-null    int64  
 1   age                          994 non-null    int64  
 2   policy_state                 994 non-null    int32  
 3   policy_csl                   994 non-null    int32  
 4   policy_deductable            994 non-null    int64  
 5   policy_annual_premium        994 non-null    float64
 6   umbrella_limit               994 non-null    float64
 7   insured_sex                  994 non-null    int32  
 8   insured_education_level      994 non-null    int32  
 9   insured_occupation           994 non-null    int32  
 10  insured_hobbies              994 non-null    int32  
 11  insured_relationship         994 non-null    int32  
 12  capital-gains                994 non-null    int64  
 13  capital-loss                 994 non-null    int64  
 14  incident_date                994 non-null    int32  
 15  incident_type                994 non-null    int32  
 16  collision_type               994 non-null    int32  
 17  incident_severity            994 non-null    int32  
 18  authorities_contacted        994 non-null    int32  
 19  incident_state               994 non-null    int32  
 20  incident_city                994 non-null    int32  
 21  incident_hour_of_the_day     994 non-null    int64  
 22  number_of_vehicles_involved  994 non-null    int64  
 23  property_damage              994 non-null    int32  
 24  bodily_injuries              994 non-null    int64  
 25  witnesses                    994 non-null    int64  
 26  police_report_available      994 non-null    int32  
 27  total_claim_amount           994 non-null    float64
 28  injury_claim                 994 non-null    int64  
 29  property_claim               994 non-null    int64  
 30  vehicle_claim                994 non-null    int64  
 31  auto_make                    994 non-null    int32  
 32  auto_model                   994 non-null    int32  
 33  auto_year                    994 non-null    int64  
 34  fraud_reported               994 non-null    int32  
 35  incident_Date                994 non-null    int32  
 36  incident_Month               994 non-null    int32  
 37  policy_bind_Date             994 non-null    int32  
 38  policy_bind_Month            994 non-null    int32  
 39  policy_bind_Year             994 non-null    int32  
 40  vehicle_calim                994 non-null    float64
dtypes: float64(4), int32(24), int64(13)
memory usage: 233.0 KB
```

- All columns are converted into numerical now

Dividing data into X and Y

In [67]:
```
x = df.drop(['fraud_reported'],axis=1)
y = df['fraud_reported']
```

In [68]:
```
x.shape
```

Out[68]:
```
(994, 40)
```

In [69]:
```
y.shape
```

Out[69]:
```
(994,)
```

Here are the dimension of x and y

Scaling X values

In [70]:
```
from sklearn.preprocessing import MinMaxScaler

sc=MinMaxScaler()
x=sc.fit_transform(x)
```

In [71]:
```
pd.DataFrame(x).isnull().sum()
```

Out[71]:
```
0     0
1     0
2     0
3     0
4     0
5     0
6     0
7     0
8     0
9     0
10    0
11    0
12    0
13    0
14    0
15    0
16    0
17    0
18    0
19    0
20    0
21    0
22    0
23    0
24    0
25    0
26    0
27    0
28    0
29    0
30    0
31    0
32    0
33    0
34    0
35    0
36    0
37    0
38    0
39    0
dtype: int64
```

So here we can see there is no null value present in the dataset.

In [72]:
```
pd.DataFrame(x).describe()
```

Out[72]:

	0	1	2	3	4	5	6	
count	994.000000	994.000000	994.000000	994.000000	994.000000	994.000000	994.000000	994.(
mean	0.426698	0.443975	0.507042	0.474849	0.424883	0.502476	0.201896	0.4
std	0.240313	0.203319	0.415523	0.402499	0.408046	0.168078	0.401223	0.4
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.(
25%	0.242171	0.288889	0.000000	0.000000	0.000000	0.385783	0.000000	0.(
50%	0.417537	0.422222	0.500000	0.500000	0.333333	0.502305	0.000000	0.(
75%	0.577766	0.572222	1.000000	1.000000	1.000000	0.613049	0.000000	1.(
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.(

8 rows × 40 columns

Here we can see the data have been scalled.

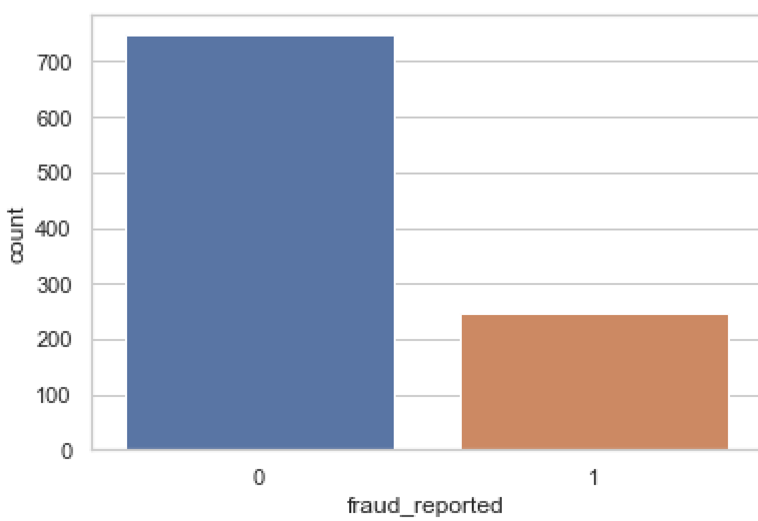
Imbalanced learn

Using Oversampling BoarderlineSMOTE

- because there is less data in Churn for yes

In [73]:
```
sns.set_style("whitegrid")
sns.countplot(x='fraud_reported',data=df)
```

Out[73]:
```
<AxesSubplot:xlabel='fraud_reported', ylabel='count'>
```



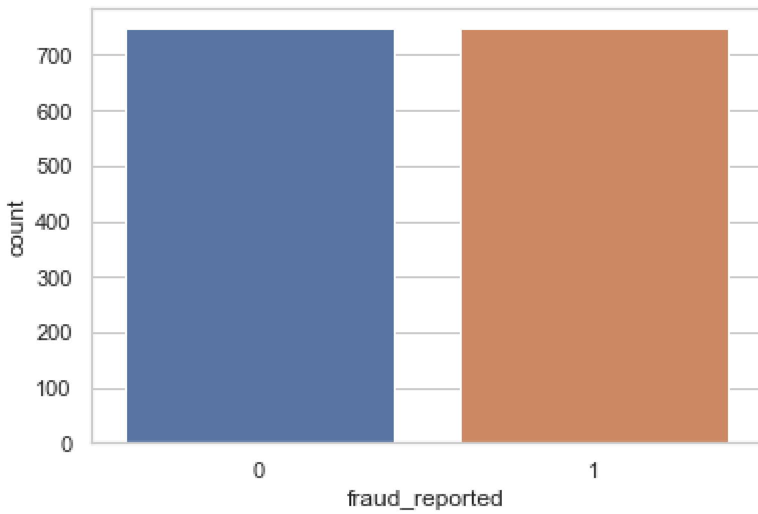
In [74]:
```
from imblearn.over_sampling import BorderlineSMOTE

x_rus, y_rus = BorderlineSMOTE().fit_resample(x,y)
print('Original Target dataset shape:',y.shape)
print('Resample Target dataset shape',y_rus.shape)
```

```
Original Target dataset shape: (994,)
Resample Target dataset shape (1496,)
```

In [75]:
```
sns.set_style("whitegrid")
sns.countplot(y_rus)
```

Out[75]: <AxesSubplot:xlabel='fraud_reported', ylabel='count'>



- Now we have balanced data for model training.

Spliting Train and Test data

In [76]:
```
from sklearn.model_selection import train_test_split
```

In [77]:
```
x_train,x_test,y_train,y_test = train_test_split(x_rus,y_rus,test_size=.27,ranc
```

In [78]:
```
x_train.shape
```

Out[78]: (1092, 40)

In [79]:
```
y_train.shape
```

Out[79]: (1092,)

In [80]:
```
x_test.shape
```

Out[80]: (404, 40)

In [81]:
```
y_test.shape
```
Out[81]:
```
(404,)
```

So her we sucessfully split train and test data , now move on for model building

Model Building

In [82]:
```
# importing necessary libraries

from sklearn.linear_model import LogisticRegression

from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import GradientBoostingClassifier

from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix,classification_repo
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

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

Logistic Regression

In [83]:
```
logreg = LogisticRegression()
logreg_score=cross_val_score(logreg,x_rus,y_rus,cv=5,scoring='accuracy')
print("Cross validation score for logreg:",np.mean(logreg_score))
```
```
Cross validation score for logreg: 0.7446688963210703
```

In [84]:
```
logreg.fit(x_train,y_train)
LR_predicted=logreg.predict(x_test)

print(accuracy_score(y_test,LR_predicted))
print(confusion_matrix(y_test,LR_predicted))
print(classification_report(y_test,LR_predicted))

print("Training accuracy::",logreg.score(x_train,y_train))
print("Test accuracy::",logreg.score(x_test,y_test))
```

```
0.7128712871287128
[[122  64]
 [ 52 166]]
              precision    recall  f1-score   support

           0       0.70      0.66      0.68       186
           1       0.72      0.76      0.74       218

    accuracy                           0.71       404
   macro avg       0.71      0.71      0.71       404
weighted avg       0.71      0.71      0.71       404

Training accuracy:: 0.7628205128205128
Test accuracy:: 0.7128712871287128
```

Decision Tree Classifier

In [85]:
```
dtc = DecisionTreeClassifier()
dtc_score=cross_val_score(dtc,x_rus,y_rus,cv=5,scoring='accuracy')
print("Cross validation score for dtc:",np.mean(dtc_score))
```

```
Cross validation score for dtc: 0.8369654403567447
```

In [86]:
```
dtc.fit(x_train,y_train)
predicted_dtc=dtc.predict(x_test)

print(accuracy_score(y_test,predicted_dtc))
print(confusion_matrix(y_test,predicted_dtc))
print(classification_report(y_test,predicted_dtc))

print("Training accuracy::",dtc.score(x_train,y_train))
print("Test accuracy::",dtc.score(x_test,y_test))
```

```
0.806930693069307
[[141  45]
 [ 33 185]]
              precision    recall  f1-score   support

           0       0.81      0.76      0.78       186
           1       0.80      0.85      0.83       218

    accuracy                           0.81       404
   macro avg       0.81      0.80      0.80       404
weighted avg       0.81      0.81      0.81       404

Training accuracy:: 1.0
Test accuracy:: 0.806930693069307
```

KNeighbors Classifier

In [87]:
```
knn = KNeighborsClassifier()
knn_score=cross_val_score(knn,x_rus,y_rus,cv=5,scoring='accuracy')
print("Cross validation score for knn :",np.mean(knn_score))
```

```
Cross validation score for knn : 0.6597703455964326
```

In [88]:
```
knn.fit(x_train,y_train)
predicted_knn=knn.predict(x_test)

print(accuracy_score(y_test,predicted_knn))
print(confusion_matrix(y_test,predicted_knn))
print(classification_report(y_test,predicted_knn))

print("Training accuracy::",knn.score(x_train,y_train))
print("Test accuracy::",knn.score(x_test,y_test))
```

```
0.6633663366336634
[[ 61 125]
 [ 11 207]]
              precision    recall  f1-score   support

           0       0.85      0.33      0.47       186
           1       0.62      0.95      0.75       218

    accuracy                           0.66       404
   macro avg       0.74      0.64      0.61       404
weighted avg       0.73      0.66      0.62       404

Training accuracy:: 0.7261904761904762
Test accuracy:: 0.6633663366336634
```

Random Forest Classifier

In [89]:
```
rfc = RandomForestClassifier()
rfc_score=cross_val_score(rfc,x_rus,y_rus,cv=5,scoring='accuracy')
print("Cross validation score for rfc :",np.mean(rfc_score))
```

```
Cross validation score for rfc : 0.8744147157190636
```

In [90]:
```
rfc.fit(x_train,y_train)
predicted_rfc=rfc.predict(x_test)

print(accuracy_score(y_test,predicted_rfc))
print(confusion_matrix(y_test,predicted_rfc))
print(classification_report(y_test,predicted_rfc))

print("Training accuracy::",rfc.score(x_train,y_train))
print("Test accuracy::",rfc.score(x_test,y_test))
```

```
0.844059405940594
[[157  29]
 [ 34 184]]
              precision    recall  f1-score   support

           0       0.82      0.84      0.83       186
           1       0.86      0.84      0.85       218

    accuracy                           0.84       404
   macro avg       0.84      0.84      0.84       404
weighted avg       0.84      0.84      0.84       404

Training accuracy:: 1.0
Test accuracy:: 0.844059405940594
```

Ensemble Technique

1. AdaBoost Classifier

In [91]:
```
adb = AdaBoostClassifier()
adb_score=cross_val_score(adb,x_rus,y_rus,cv=5,scoring='accuracy')
print("Cross validation score for adb :",np.mean(adb_score))
```

```
Cross validation score for adb : 0.8383389074693424
```

In [92]:
```
adb.fit(x_train,y_train)
predicted_adb=adb.predict(x_test)

print(accuracy_score(y_test,predicted_adb))
print(confusion_matrix(y_test,predicted_adb))
print(classification_report(y_test,predicted_adb))

print("Training accuracy::",adb.score(x_train,y_train))
print("Test accuracy::",adb.score(x_test,y_test))
```

```
0.8193069306930693
[[152  34]
 [ 39 179]]
              precision    recall  f1-score   support

           0       0.80      0.82      0.81       186
           1       0.84      0.82      0.83       218

    accuracy                           0.82       404
   macro avg       0.82      0.82      0.82       404
weighted avg       0.82      0.82      0.82       404

Training accuracy:: 0.8946886446886447
Test accuracy:: 0.8193069306930693
```

2. Bagging Classifier

In [93]:
```
bgc = BaggingClassifier()
bgc_score=cross_val_score(bgc,x_rus,y_rus,cv=5,scoring='accuracy')
print("Cross validation score for bgc :",np.mean(bgc_score))
```

```
Cross validation score for bgc : 0.8730479375696767
```

In [94]:
```
bgc.fit(x_train,y_train)
predicted_bgc=bgc.predict(x_test)

print(accuracy_score(y_test,predicted_bgc))
print(confusion_matrix(y_test,predicted_bgc))
print(classification_report(y_test,predicted_bgc))

print("Training accuracy::",bgc.score(x_train,y_train))
print("Test accuracy::",bgc.score(x_test,y_test))
```

```
0.8564356435643564
[[155  31]
 [ 27 191]]
              precision    recall  f1-score   support

           0       0.85      0.83      0.84       186
           1       0.86      0.88      0.87       218

    accuracy                           0.86       404
   macro avg       0.86      0.85      0.86       404
weighted avg       0.86      0.86      0.86       404

Training accuracy:: 0.9935897435897436
Test accuracy:: 0.8564356435643564
```

3. Gradient Boosting Classifier

In [95]:
```
grbc = GradientBoostingClassifier()
grbc_score=cross_val_score(grbc,x_rus,y_rus,cv=5,scoring='accuracy')
print("Cross validation score for grbc :",np.mean(grbc_score))
```

```
Cross validation score for grbc : 0.8790858416945374
```

In [96]:
```
grbc.fit(x_train,y_train)
predicted_grbc=grbc.predict(x_test)

print(accuracy_score(y_test,predicted_grbc))
print(confusion_matrix(y_test,predicted_grbc))
print(classification_report(y_test,predicted_grbc))

print("Training accuracy::",grbc.score(x_train,y_train))
print("Test accuracy::",grbc.score(x_test,y_test))
```

```
0.8910891089108911
[[156  30]
 [ 14 204]]
              precision    recall  f1-score   support

           0       0.92      0.84      0.88       186
           1       0.87      0.94      0.90       218

    accuracy                           0.89       404
   macro avg       0.89      0.89      0.89       404
weighted avg       0.89      0.89      0.89       404

Training accuracy:: 0.9734432234432234
Test accuracy:: 0.8910891089108911
```

Observation :

```
Choosing :-

    - Gradietn  Boostin Classifier as final model for Hyper Parameter
Tuning because both train and test accuracies are close and highest as
well
    - Rest of the models having huge difference between train and test
accuracies so no considering them.
```

Hyper Parameter Tuning : GradietnBoostingClassifier

In [97]:
```
adb=GradientBoostingClassifier()
param_grid={
    'criterion' :['mse','mae'],
    'n_estimators' :[100,200],
    'learning_rate' :[0.1,0.5,1.0],
     'random_state' :[5],
}
```

In [98]:
```
adb_grid=GridSearchCV(GradientBoostingClassifier(),param_grid,cv=4,scoring='acc
```

In [99]:
```
adb_grid.fit(x_train,y_train)
adb_pred=adb_grid.best_estimator_.predict(x_test)
print("Accuracy after parameter tuning::",accuracy_score(y_test,adb_pred))
```

```
Fitting 4 folds for each of 12 candidates, totalling 48 fits
Accuracy after parameter tuning:: 0.8589108910891089
```

In [100]:
```
adb_grid.best_params_
```

Out[100]:
```
{'criterion': 'mse',
 'learning_rate': 1.0,
 'n_estimators': 200,
 'random_state': 5}
```

Model Training with best parameters

In [101]:
```
best_param={
    'criterion' :['mse'],
    'n_estimators' :[200],
    'learning_rate' :[0.1],
     'random_state' :[5],
}
```

In [102]:
```
best_adb_grid=GridSearchCV(GradientBoostingClassifier(),best_param,cv=4,scoring
```

In [103]:
```
best_adb_grid.fit(x_train,y_train)
best_adb_pred=best_adb_grid.best_estimator_.predict(x_test)
print("Accuracy after parameter tuning::",accuracy_score(y_test,best_adb_pred))
```

```
Fitting 4 folds for each of 1 candidates, totalling 4 fits
Accuracy after parameter tuning:: 0.8910891089108911
```

As we notice after Hyper Parameter Tuning models accuracy score got increased

Report of GradientBoostingClassifier

In [104]:
```python
print("Classification Report::\n",classification_report(y_test,best_adb_pred))
```

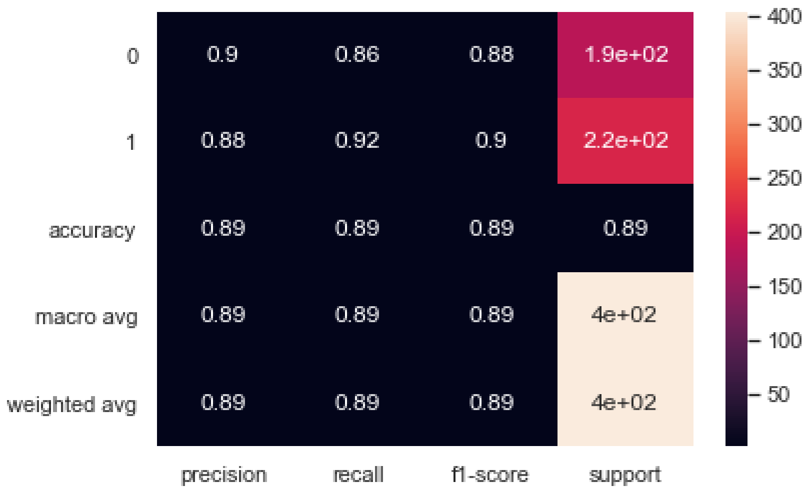
```
Classification Report::
               precision    recall  f1-score   support

           0       0.90      0.86      0.88       186
           1       0.88      0.92      0.90       218

    accuracy                           0.89       404
   macro avg       0.89      0.89      0.89       404
weighted avg       0.89      0.89      0.89       404
```

In [105]:
```python
clsf_repo = classification_report(y_test,best_adb_pred,output_dict=True)
sns.heatmap(pd.DataFrame(clsf_repo).T, annot=True)
```

Out[105]: <AxesSubplot:>



Plotting AUC ROC curve

In [106]:
```python
from sklearn.metrics import roc_auc_score
```

In [107]:
```python
print("roc auc score::",roc_auc_score(y_test,best_adb_pred))
```

```
roc auc score:: 0.8888231232119956
```

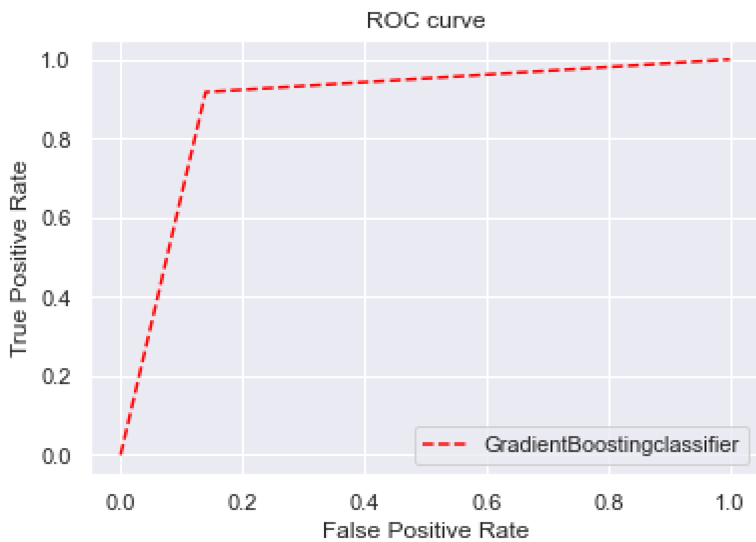
In [108]:
```python
from sklearn.metrics import roc_curve
```

In [109]:
```python
fpr1, tpr1, thresh1 = roc_curve(y_test, best_adb_pred, pos_label=1)
```

In [110]:
```python
# plotting ROC CURVE
sns.set_theme(style="darkgrid")
plt.plot(fpr1, tpr1,linestyle='--',color='red', label='GradientBoostingclassifi

plt.title("ROC curve")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='best')
```

Out[110]: <matplotlib.legend.Legend at 0x1667102ef40>



Saving the Model

In [111]:
```python
import joblib
joblib.dump(best_adb_grid.best_estimator_,'InsuranceClaims-FraudDetection.obj')
```

Out[111]: ['InsuranceClaims-FraudDetection.obj']

So here save the best model using joblib library.

Prediction Result

In [112]:
```python
# Loading the saved model
model=joblib.load("InsuranceClaims-FraudDetection.obj")

# Prediction
prediction = model.predict(x_test)
prediction
```

Out[112]:
```
array([0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1,
       1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1,
       0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1,
       0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1,
       1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0,
       1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0,
       1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1,
       0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1,
       0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0,
       0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1,
       0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0,
       1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0,
       1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1,
       1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1,
       1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0,
       0, 1, 1, 0, 1, 1, 0, 0])
```

In [115]:
```python
pd.DataFrame([model.predict(x_test)[:],y_test[:]],index=["Predicted","Original"
```

Out[115]:

	Predicted	Original
0	0	0
1	1	1
2	1	1
3	0	0
4	0	1
...	...	...
399	0	0
400	1	1
401	1	1
402	0	0
403	0	1

404 rows × 2 columns

So here we can observe that the actual predicted values are almost same, that means our model worked well.