

```

import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
import numpy as np
import sklearn.metrics
from pylab import rcParams
%matplotlib inline
pd.set_option('display.max_columns', 500)
pd.set_option('display.max_rows', 500)

```

## Business case

Claim related fraud is a huge problem in the insurance industry. It is quite complex and difficult to identify those unwanted claims. With Random Forest Non-Parametric Machine Learning Algorithm, I am trying to troubleshoot and help the General Insurance industry with this problem.

The data that I have is from Automobile Insurance. I will be creating a predictive model that predicts if an insurance claim is fraudulent or not. The answer between YES/NO, is a Binary Classification task. A comparison study has been performed to understand which ML algorithm suits best to the dataset.

```

#load & view raw data
df = pd.read_csv('insurance_claims.csv')
df.head(10)

```

	months_as_customer	age	policy_number	policy_bind_date	policy_state
0	328	48	521585	2014-10-17	OH
1	228	42	342868	2006-06-27	IN
2	134	29	687698	2000-09-06	OH
3	256	41	227811	1990-05-25	IL
4	228	44	367455	2014-06-06	IL
5	256	39	104594	2006-10-12	OH
6	137	34	413978	2000-06-04	IN
7	165	37	429027	1990-02-03	IL
8	27	33	485665	1997-02-05	IL
9	212	42	636550	2011-07-25	IL

	policy_csl	policy_deductable	policy_annual_premium	umbrella_limit	
\					
0	250/500	1000	1406.91	0	
1	250/500	2000	1197.22	5000000	
2	100/300	2000	1413.14	5000000	
3	250/500	2000	1415.74	6000000	
4	500/1000	1000	1583.91	6000000	
5	250/500	1000	1351.10	0	
6	250/500	1000	1333.35	0	
7	100/300	1000	1137.03	0	
8	100/300	500	1442.99	0	
9	100/300	500	1315.68	0	
	insured_zip	insured_sex	insured_education_level	insured_occupation	
\					
0	466132	MALE	MD	craft-repair	
1	468176	MALE	MD	machine-op-inspct	
2	430632	FEMALE	PhD	sales	
3	608117	FEMALE	PhD	armed-forces	
4	610706	MALE	Associate	sales	
5	478456	FEMALE	PhD	tech-support	
6	441716	MALE	PhD	prof-specialty	
7	603195	MALE	Associate	tech-support	
8	601734	FEMALE	PhD	other-service	
9	600983	MALE	PhD	priv-house-serv	
	insured_hobbies	insured_relationship	capital-gains	capital-loss	\
0	sleeping	husband	53300	0	
1	reading	other-relative	0	0	
2	board-games	own-child	35100	0	

3	board-games	unmarried	48900	-62400
4	board-games	unmarried	66000	-46000
5	bungee-jumping	unmarried	0	0
6	board-games	husband	0	-77000
7	base-jumping	unmarried	0	0
8	golf	own-child	0	0
9	camping	wife	0	-39300

	incident_date	incident_type	collision_type	incident_severity
0	2015-01-25	Single Vehicle Collision	Side Collision	Major Damage
1	2015-01-21	Vehicle Theft	?	Minor Damage
2	2015-02-22	Multi-vehicle Collision	Rear Collision	Minor Damage
3	2015-01-10	Single Vehicle Collision	Front Collision	Major Damage
4	2015-02-17	Vehicle Theft	?	Minor Damage
5	2015-01-02	Multi-vehicle Collision	Rear Collision	Major Damage
6	2015-01-13	Multi-vehicle Collision	Front Collision	Minor Damage
7	2015-02-27	Multi-vehicle Collision	Front Collision	Total Loss
8	2015-01-30	Single Vehicle Collision	Front Collision	Total Loss
9	2015-01-05	Single Vehicle Collision	Rear Collision	Total Loss

	authorities_contacted	incident_state	incident_city	incident_location
0	Police	SC	Columbus	9935 4th Drive
1	Police	VA	Riverwood	6608 MLK Hwy
2	Police	NY	Columbus	7121 Francis Lane
3	Police	OH	Arlington	6956 Maple Drive
4	None	NY	Arlington	3041 3rd Ave
5	Fire	SC	Arlington	8973 Washington St
6	Police	NY	Springfield	5846 Weaver Drive
7	Police	VA	Columbus	3525 3rd Hwy

8	Police	WV	Arlington	4872 Rock
9	Other	NC	Hillsdale	3066 Francis
Ave				

incident_hour_of_the_day	number_of_vehicles_involved	property_damage \
0	5	1
YES		
1	8	1
?		
2	7	3
NO		
3	5	1
?		
4	20	1
NO		
5	19	3
NO		
6	0	3
?		
7	23	3
?		
8	21	1
NO		
9	14	1
NO		

bodily_injuries	witnesses	police_report_available	total_claim_amount \
0	1	2	YES
71610			
1	0	0	?
5070			
2	2	3	NO
34650			
3	1	2	NO
63400			
4	0	1	NO
6500			
5	0	2	NO
64100			
6	0	0	?
78650			
7	2	2	YES
51590			
8	1	1	YES
27700			
9	2	1	?

42300

	injury_claim	property_claim	vehicle_claim	auto_make	auto_model
\					
0	6510	13020	52080	Saab	92x
1	780	780	3510	Mercedes	E400
2	7700	3850	23100	Dodge	RAM
3	6340	6340	50720	Chevrolet	Tahoe
4	1300	650	4550	Accura	RSX
5	6410	6410	51280	Saab	95
6	21450	7150	50050	Nissan	Pathfinder
7	9380	9380	32830	Audi	A5
8	2770	2770	22160	Toyota	Camry
9	4700	4700	32900	Saab	92x

	auto_year	fraud_reported	_c39
0	2004	Y	NaN
1	2007	Y	NaN
2	2007	N	NaN
3	2014	Y	NaN
4	2009	N	NaN
5	2003	Y	NaN
6	2012	N	NaN
7	2015	N	NaN
8	2012	N	NaN
9	1996	N	NaN

df.dtypes

months_as_customer	int64
age	int64
policy_number	int64
policy_bind_date	object
policy_state	object
policy_csl	object
policy_deductable	int64
policy_annual_premium	float64
umbrella_limit	int64
insured_zip	int64
insured_sex	object
insured_education_level	object

insured_occupation	object
insured_hobbies	object
insured_relationship	object
capital-gains	int64
capital-loss	int64
incident_date	object
incident_type	object
collision_type	object
incident_severity	object
authorities_contacted	object
incident_state	object
incident_city	object
incident_location	object
incident_hour_of_the_day	int64
number_of_vehicles_involved	int64
property_damage	object
bodily_injuries	int64
witnesses	int64
police_report_available	object
total_claim_amount	int64
injury_claim	int64
property_claim	int64
vehicle_claim	int64
auto_make	object
auto_model	object
auto_year	int64
fraud_reported	object
_c39	float64

dtype: object

df.columns

```
Index(['months_as_customer', 'age', 'policy_number',
      'policy_bind_date',
      'policy_state', 'policy_csl', 'policy_deductable',
      'policy_annual_premium', 'umbrella_limit', 'insured_zip',
      'insured_sex',
      'insured_education_level', 'insured_occupation',
      'insured_hobbies',
      'insured_relationship', 'capital-gains', 'capital-loss',
      'incident_date', 'incident_type', 'collision_type',
      'incident_severity',
      'authorities_contacted', 'incident_state', 'incident_city',
      'incident_location', 'incident_hour_of_the_day',
      'number_of_vehicles_involved', 'property_damage',
      'bodily_injuries',
      'witnesses', 'police_report_available', 'total_claim_amount',
      'injury_claim', 'property_claim', 'vehicle_claim', 'auto_make',
      'auto_model', 'auto_year', 'fraud_reported', '_c39'],
      dtype='object')
```

```
df.shape
```

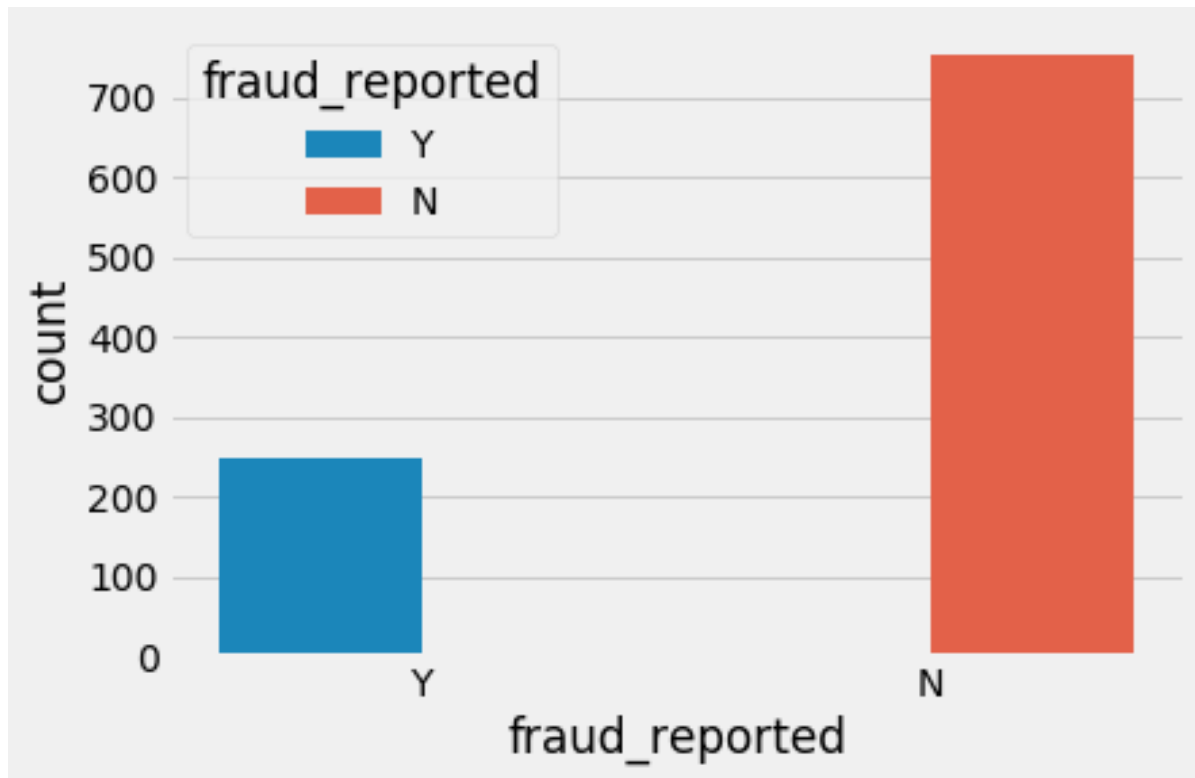
```
(1000, 40)
```

```
df.nunique()
```

```
months_as_customer    391
age                   46
policy_number         1000
policy_bind_date      951
policy_state           3
policy_csl             3
policy_deductable      3
policy_annual_premium  991
umbrella_limit        11
insured_zip           995
insured_sex            2
insured_education_level  7
insured_occupation     14
insured_hobbies        20
insured_relationship    6
capital-gains          338
capital-loss           354
incident_date          60
incident_type           4
collision_type          4
incident_severity       4
authorities_contacted   5
incident_state          7
incident_city           7
incident_location      1000
incident_hour_of_the_day  24
number_of_vehicles_involved  4
property_damage         3
bodily_injuries         3
witnesses              4
police_report_available  3
total_claim_amount     763
injury_claim           638
property_claim         626
vehicle_claim          726
auto_make              14
auto_model             39
auto_year              21
fraud_reported          2
_c39                   0
dtype: int64
```

```
plt.style.use('fivethirtyeight')
```

```
ax = sns.countplot(x='fraud_reported', data=df, hue='fraud_reported')
```



From above plot, like most fraud datasets, the label distribution is skewed.

```
df['fraud_reported'].value_counts() # Count number of frauds vs non-frauds
```

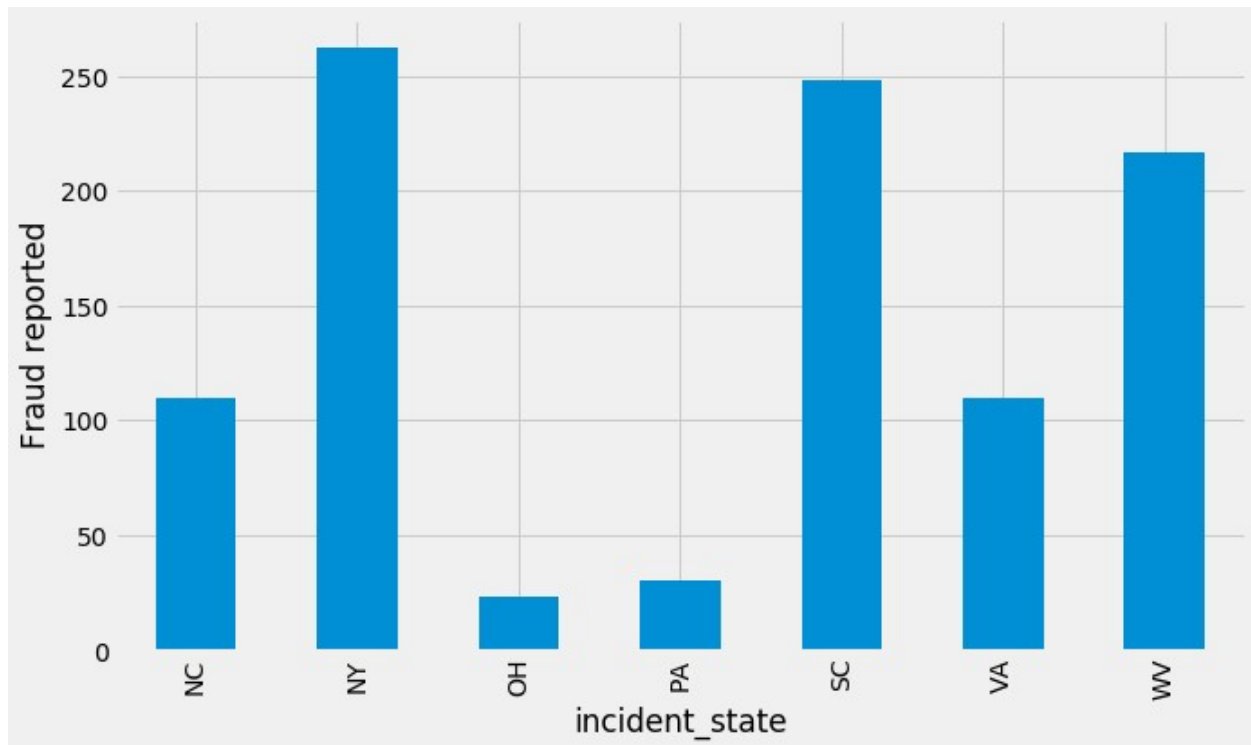
```
N    753
Y    247
Name: fraud_reported, dtype: int64
```

```
df['incident_state'].value_counts()
```

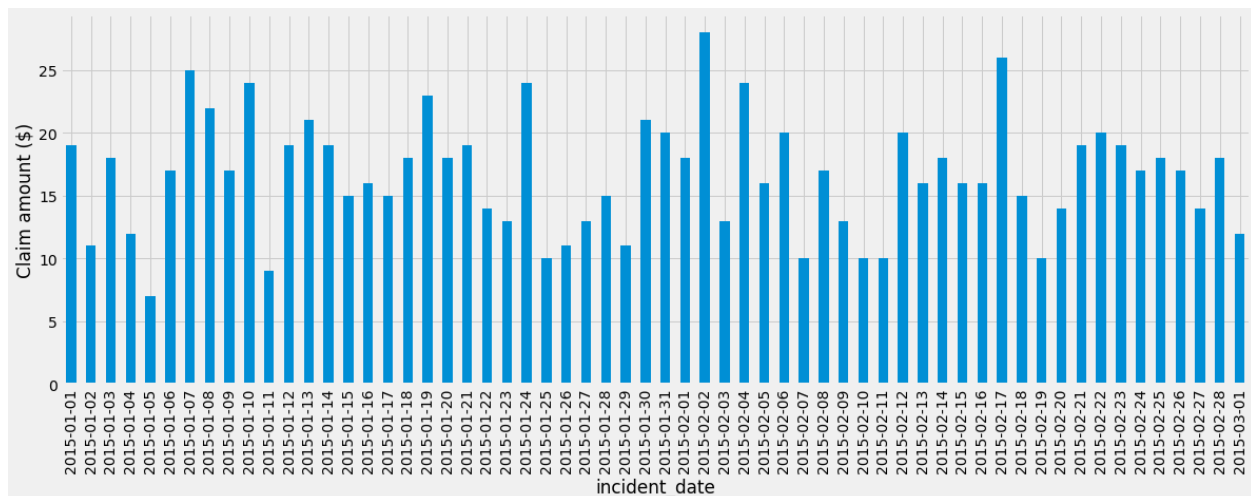
```
NY    262
SC    248
WV    217
VA    110
NC    110
PA     30
OH     23
Name: incident_state, dtype: int64
```

```
plt.style.use('fivethirtyeight')
fig = plt.figure(figsize=(10,6))
ax =
df.groupby('incident_state').fraud_reported.count().plot.bar(ylim=0)
ax.set_ylabel('Fraud reported')
plt.show()
```





```
plt.style.use('fivethirtyeight')
fig = plt.figure(figsize=(18,6))
ax =
df.groupby('incident_date').total_claim_amount.count().plot.bar(ylim=0
)
ax.set_ylabel('Claim amount ($)')
plt.show()
```



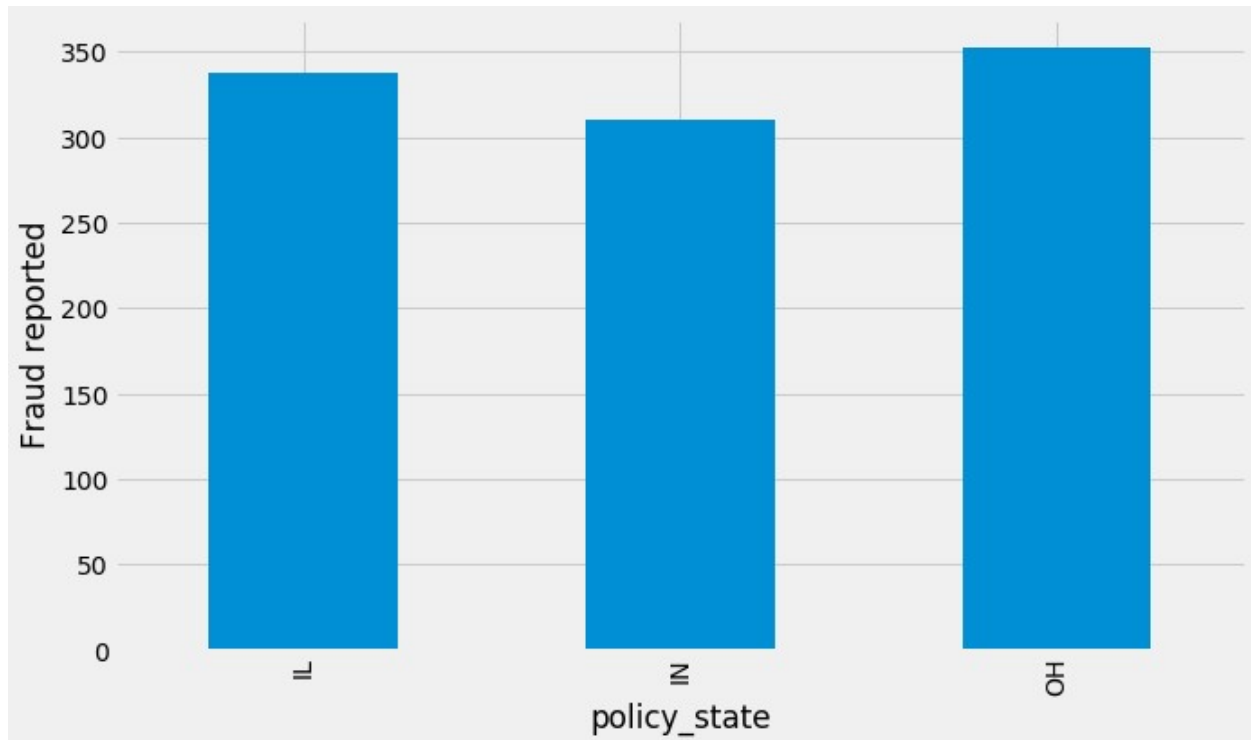
We see that, all the cases in above plot are for the months of January and February 2015

```
plt.style.use('fivethirtyeight')
fig = plt.figure(figsize=(10,6))
```

```

ax =
df.groupby('policy_state').fraud_reported.count().plot.bar(ylim=0)
ax.set_ylabel('Fraud reported')
plt.show()

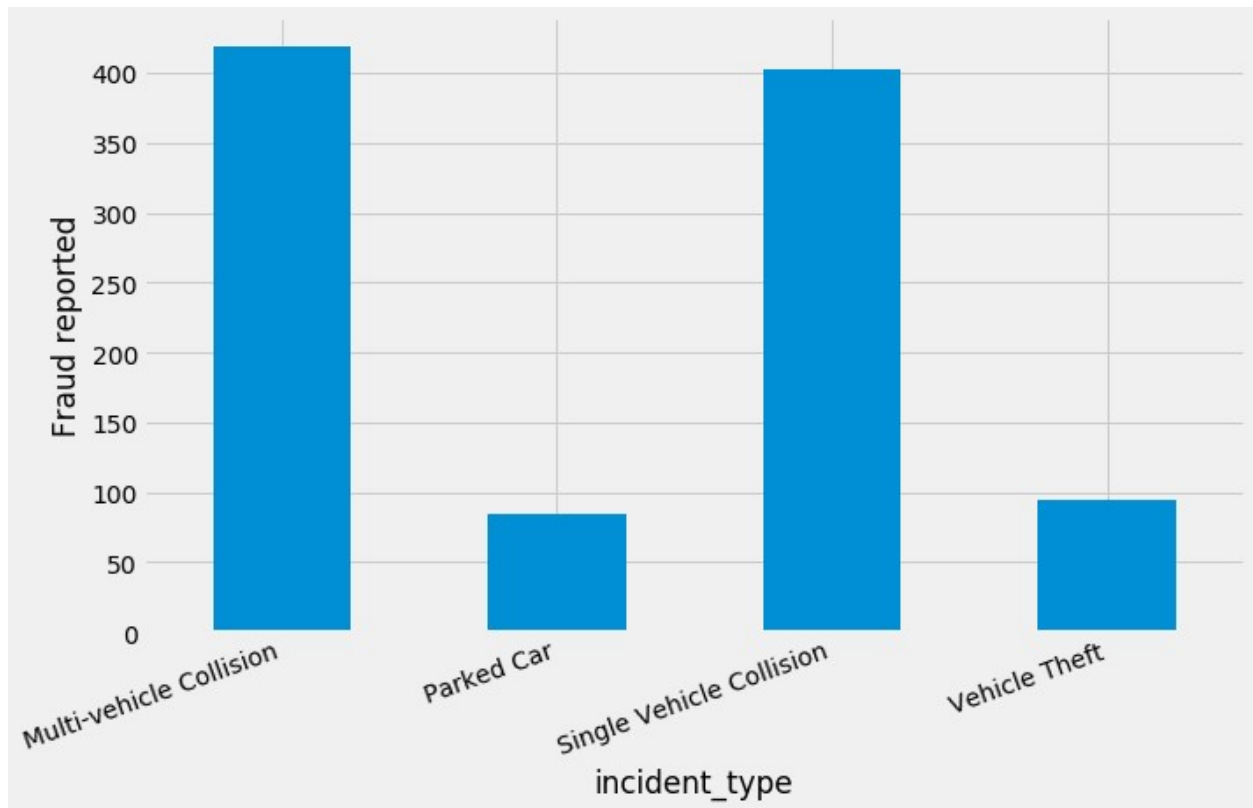
```



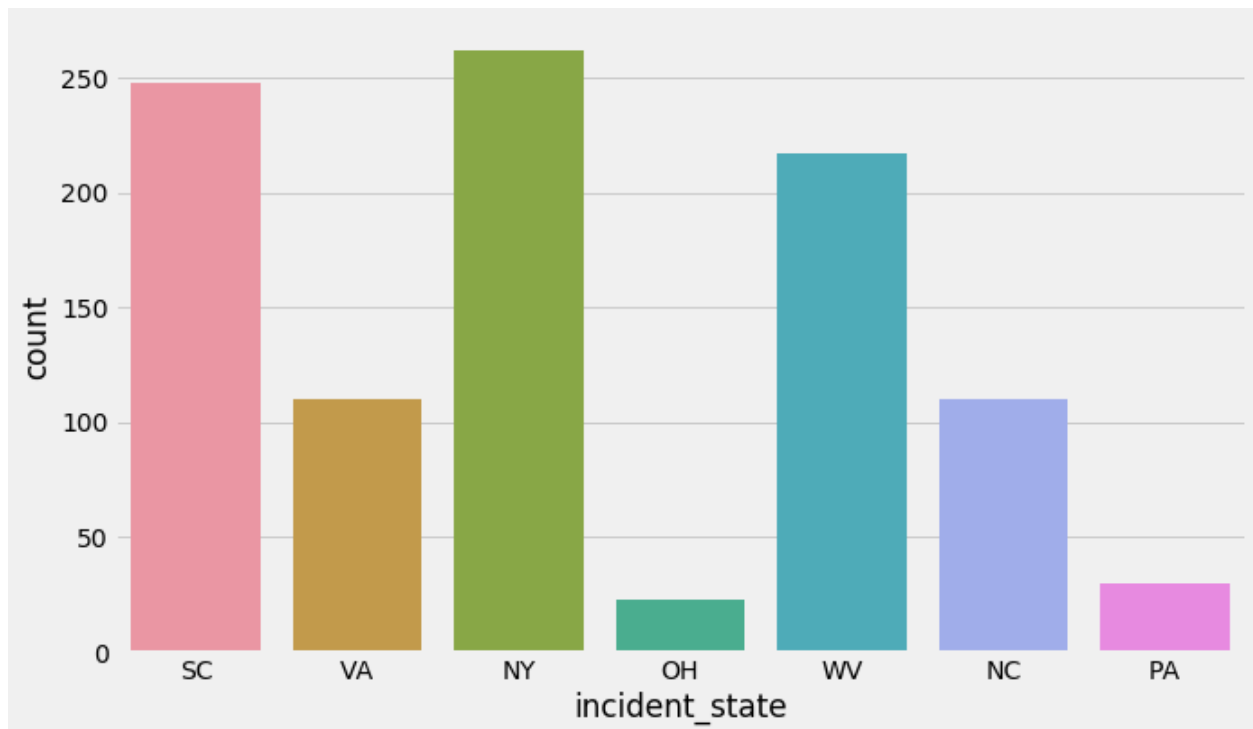
```

plt.style.use('fivethirtyeight')
fig = plt.figure(figsize=(10,6))
ax =
df.groupby('incident_type').fraud_reported.count().plot.bar(ylim=0)
ax.set_xticklabels(ax.get_xticklabels(), rotation=20, ha="right")
ax.set_ylabel('Fraud reported')
plt.show()

```

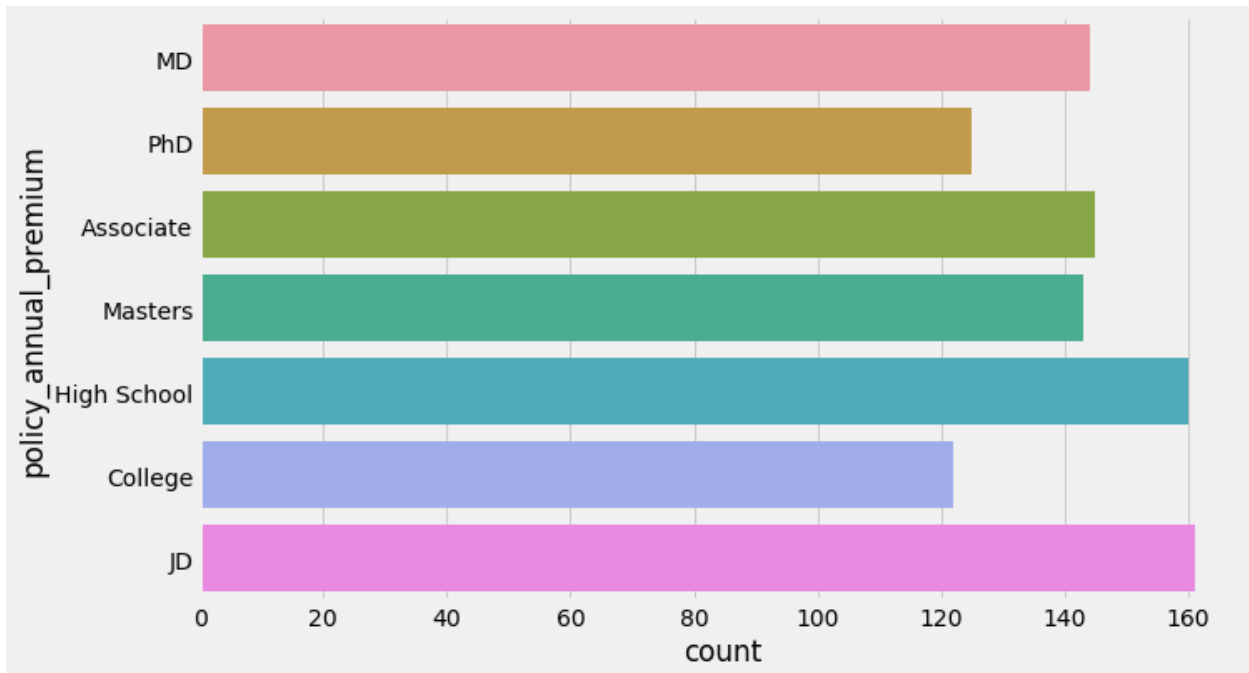


```
plt.style.use('fivethirtyeight')
fig = plt.figure(figsize=(10,6))
ax = sns.countplot(x='incident_state', data=df)
```



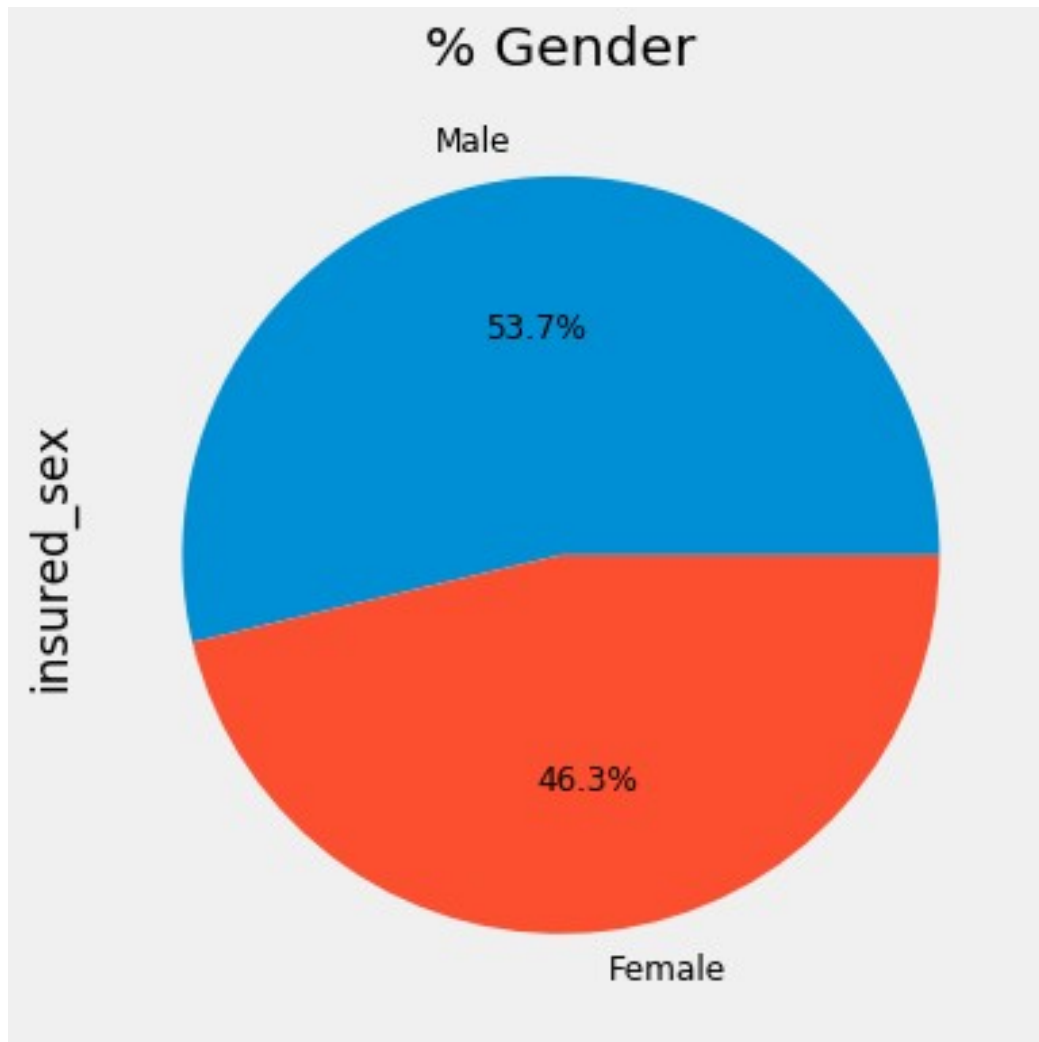
```
fig = plt.figure(figsize=(10,6))
ax = sns.countplot(y = 'insured_education_level', data=df)
ax.set_ylabel('policy_annual_premium')
plt.show()
```

*# # Breakdown of Average Vehicle claim by insured's education level, grouped by fraud reported*



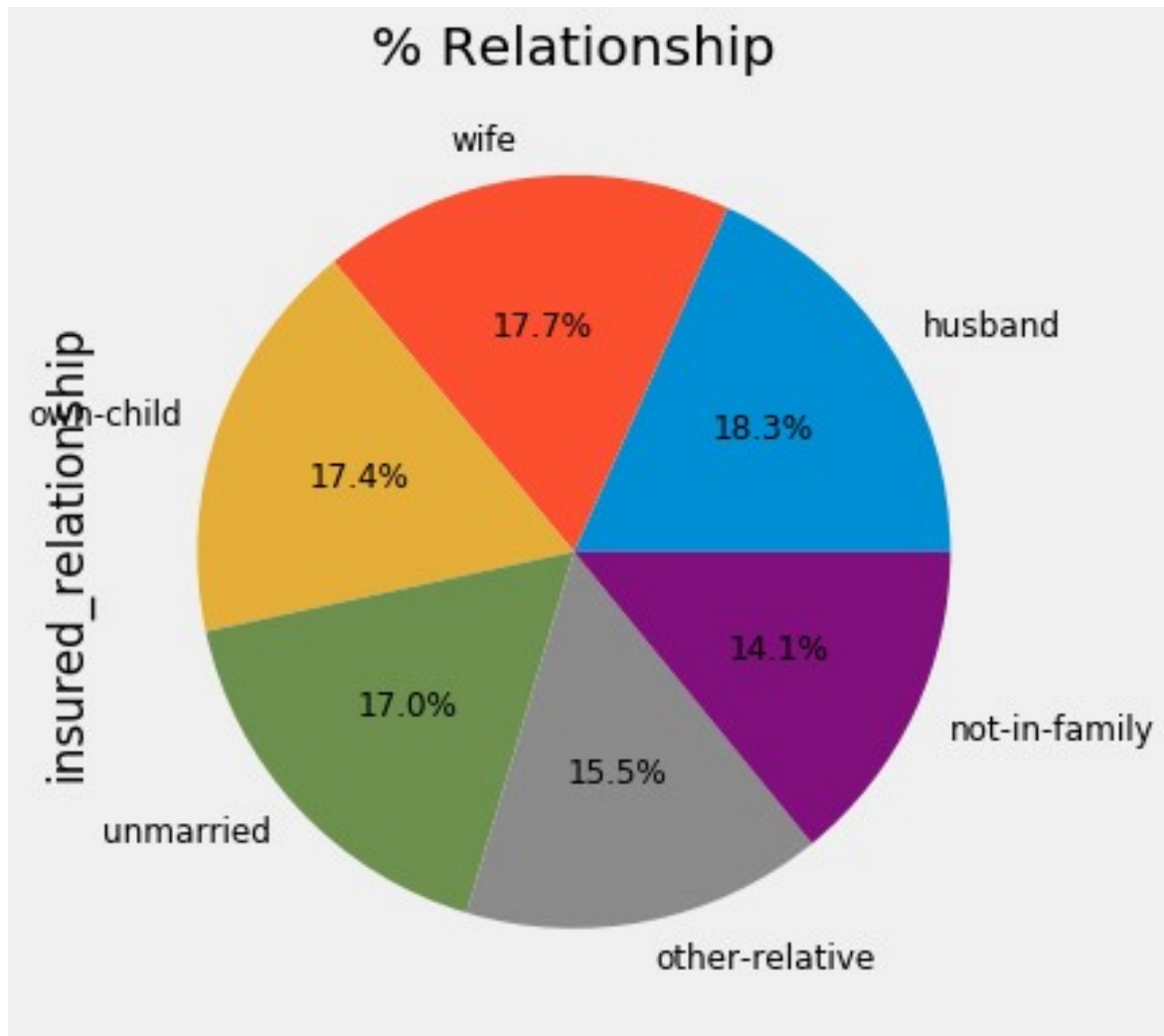
```
fig = plt.figure(figsize=(10,6))
ax = (df['insured_sex'].value_counts()*100.0 / len(df))\
.plot.pie(autopct='%1f%%', labels = ['Male', 'Female'], fontsize=12)

ax.set_title('% Gender')
plt.show()
```

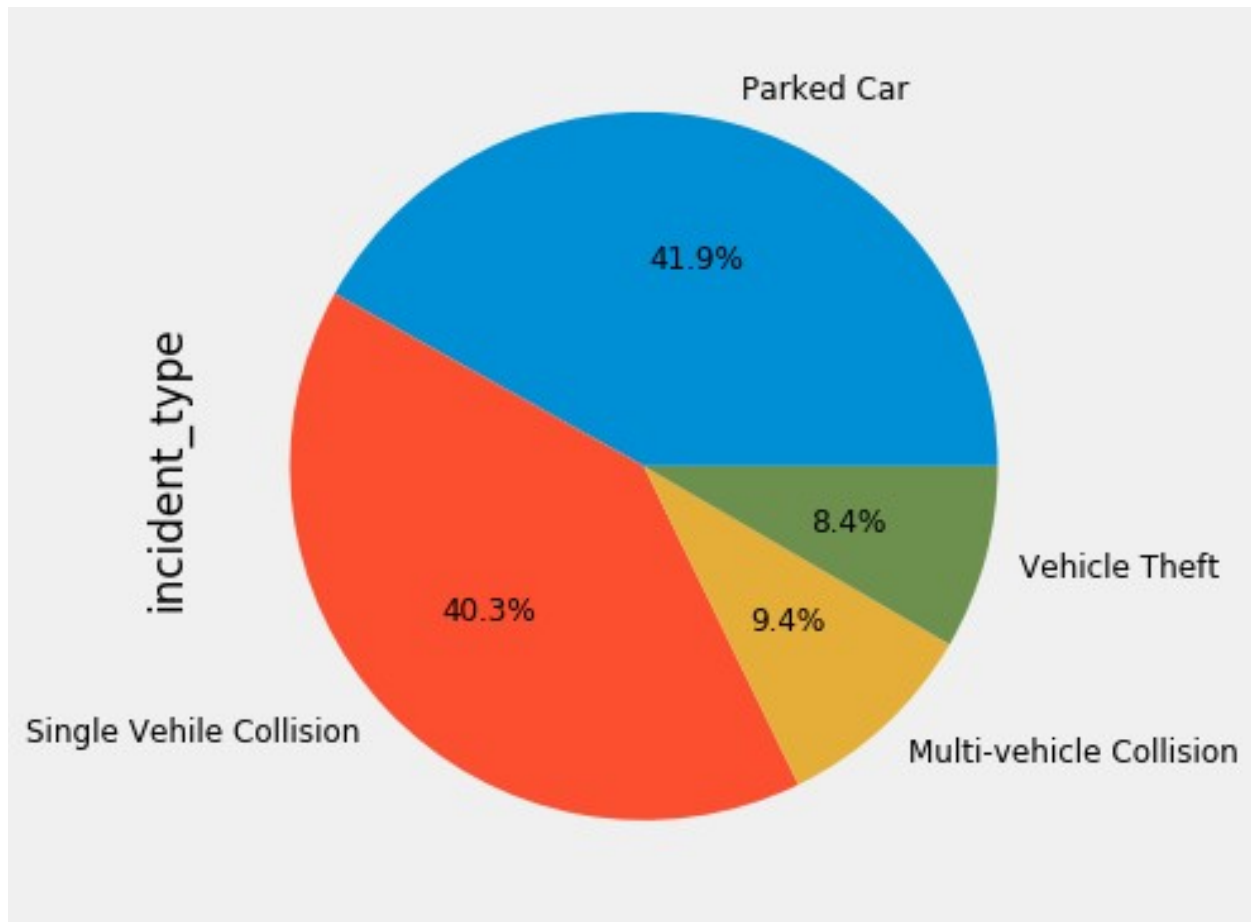


```
fig = plt.figure(figsize=(10,6))
ax = (df['insured_relationship'].value_counts()*100.0 / len(df))\
.plot.pie(autopct='%1f%%', labels = ['husband', 'wife', 'own-child',
'unmarried', 'other-relative', 'not-in-family'],
         fontsize=12)

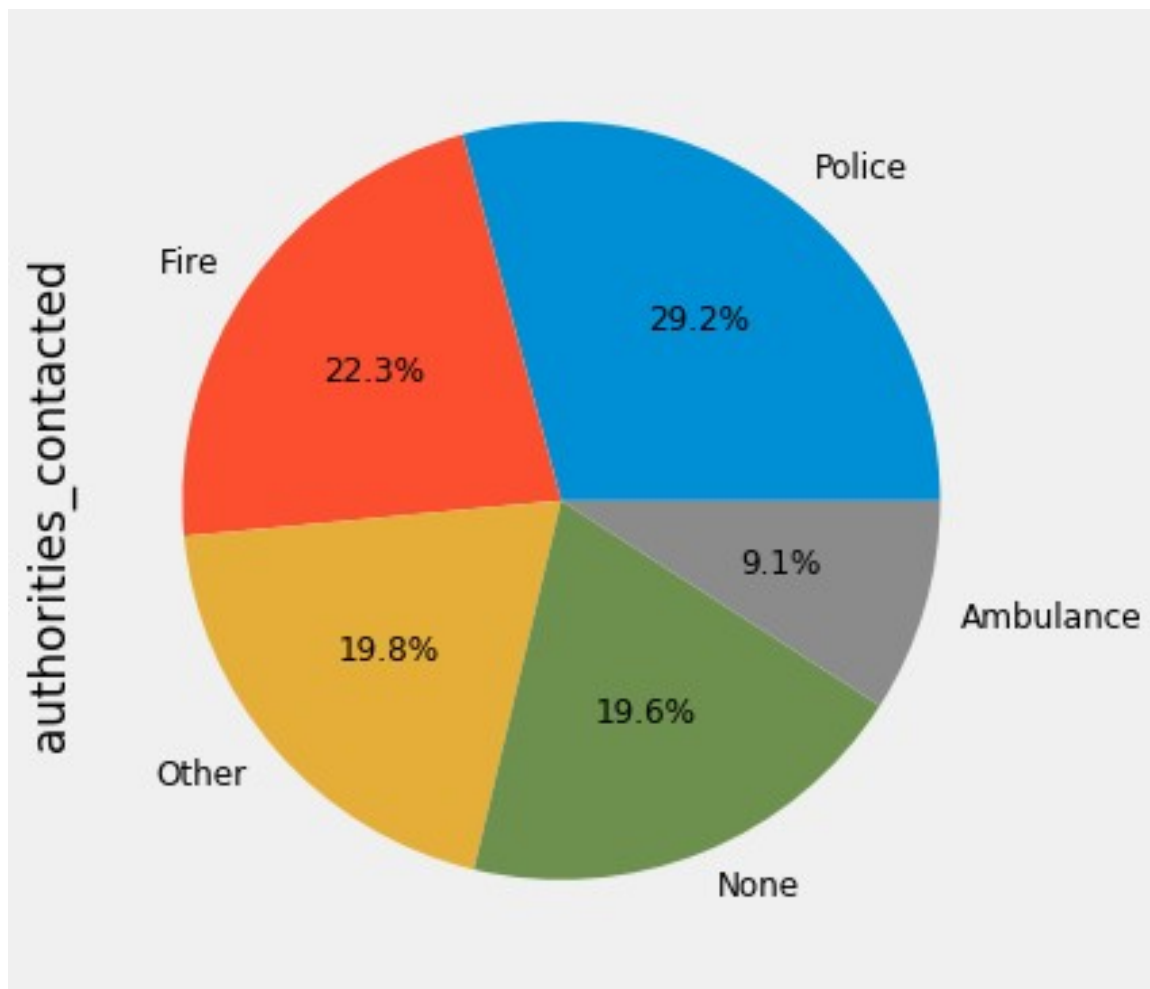
ax.set_title('% Relationship')
plt.show()
```



```
fig = plt.figure(figsize=(10,6))
ax = (df['incident_type'].value_counts()*100.0 /len(df))\
.plot.pie(autopct='%1f%%', labels = ['Parked Car', 'Single Vehile
Collision', 'Multi-vehicle Collision', 'Vehicle Theft'],
        fontsize=12)
```

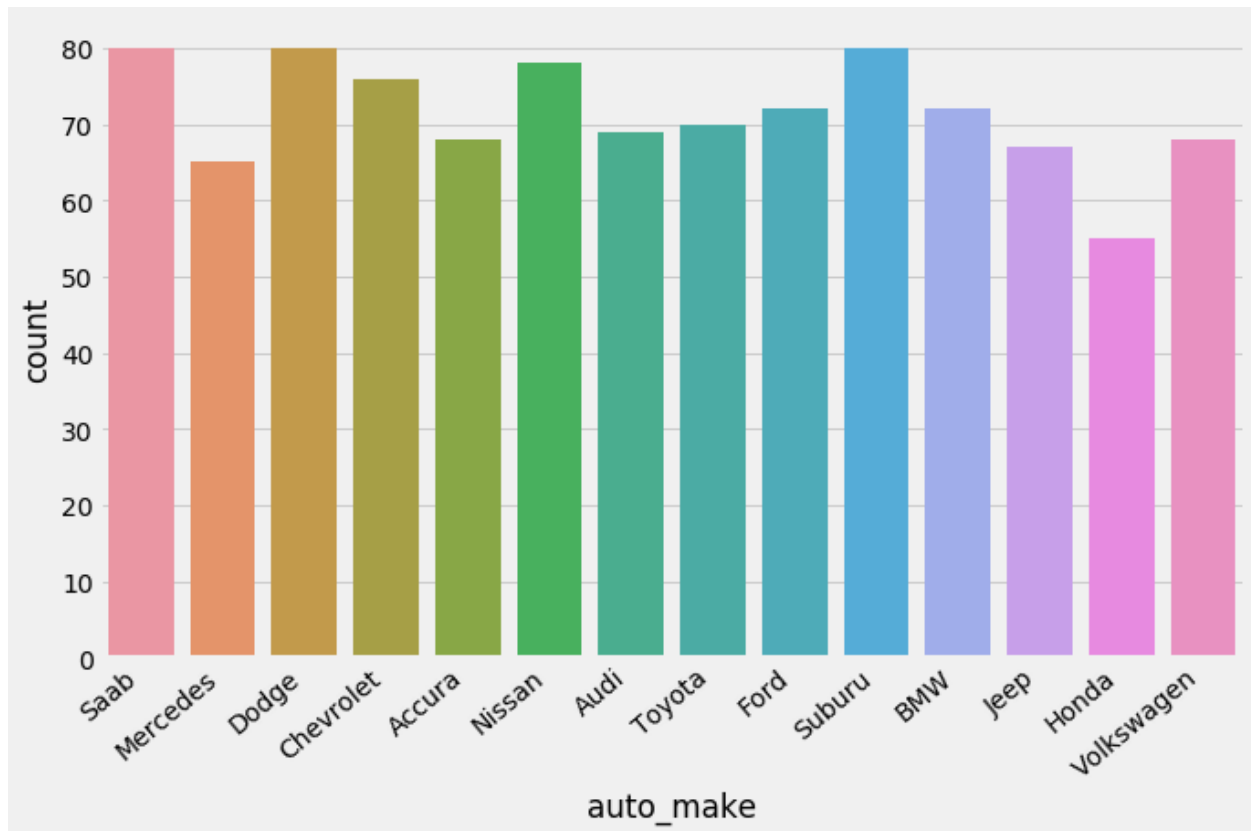


```
fig = plt.figure(figsize=(10,6))
ax = (df['authorities_contacted'].value_counts()*100.0 /len(df))\
.plot.pie(autopct='%1f%%', labels = ['Police', 'Fire', 'Other',
'None', 'Ambulance'],
        fontsize=12)
```

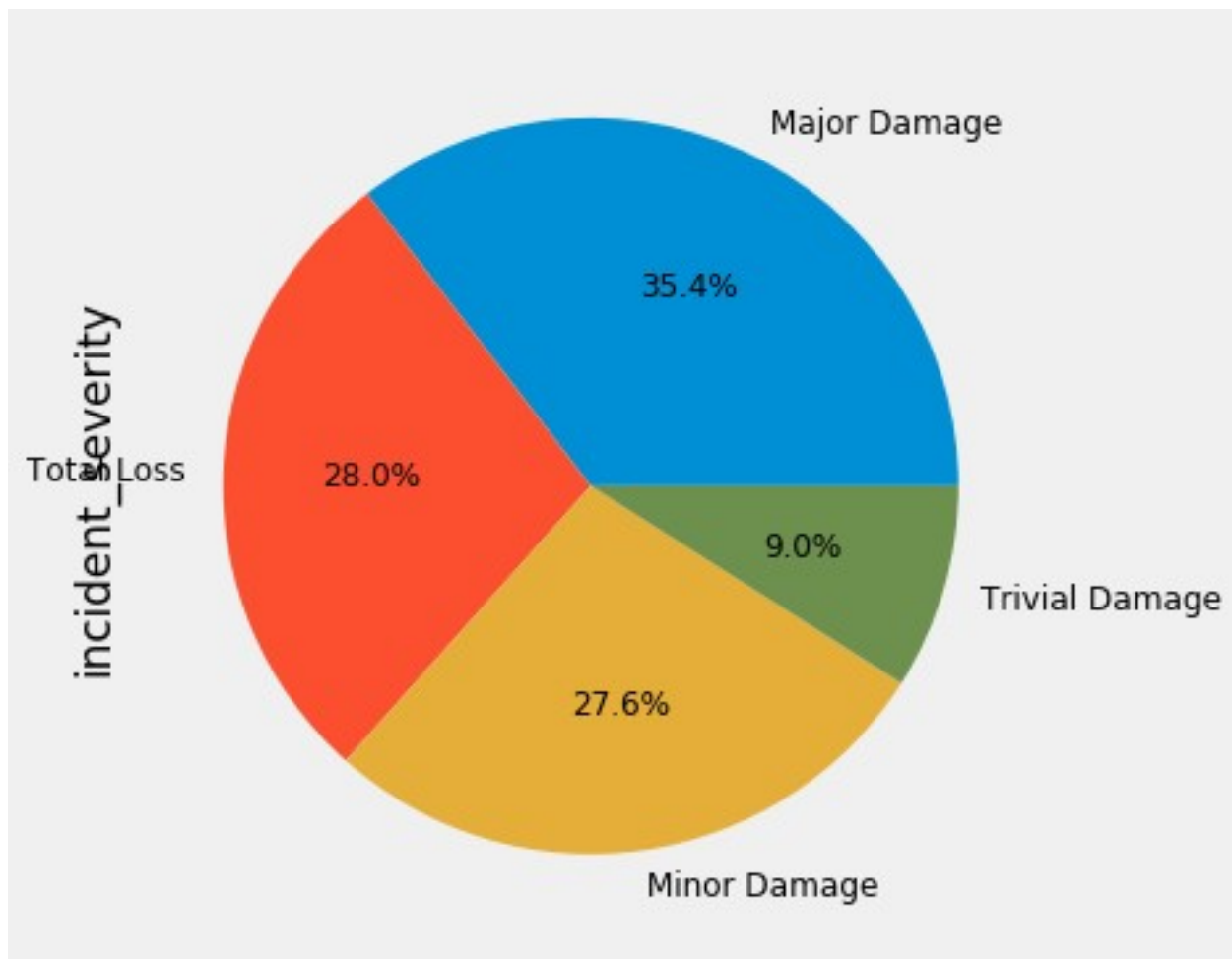


```
fig = plt.figure(figsize=(10,6))  
ax = sns.countplot(x='auto_make', data=df)  
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")  
plt.show()
```

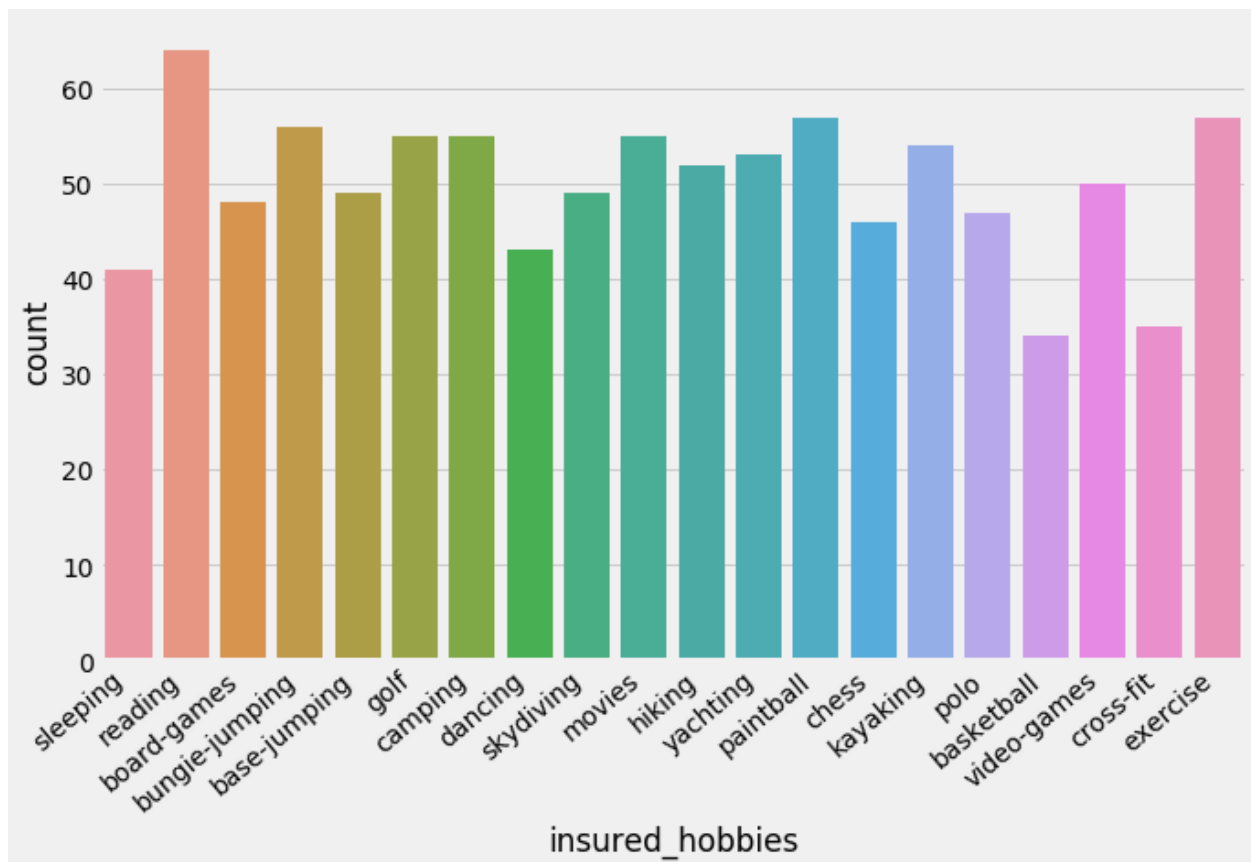




```
fig = plt.figure(figsize=(10,6))
ax = (df['incident_severity'].value_counts()*100.0 /len(df))\
.plot.pie(autopct='%.1f%%', labels = ['Major Damage', 'Total Loss',
'Minor Damage', 'Trivial Damage'],
        fontsize=12)
```



```
fig = plt.figure(figsize=(10,6))
ax = sns.countplot(x='insured_hobbies', data=df)
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
plt.show()
```

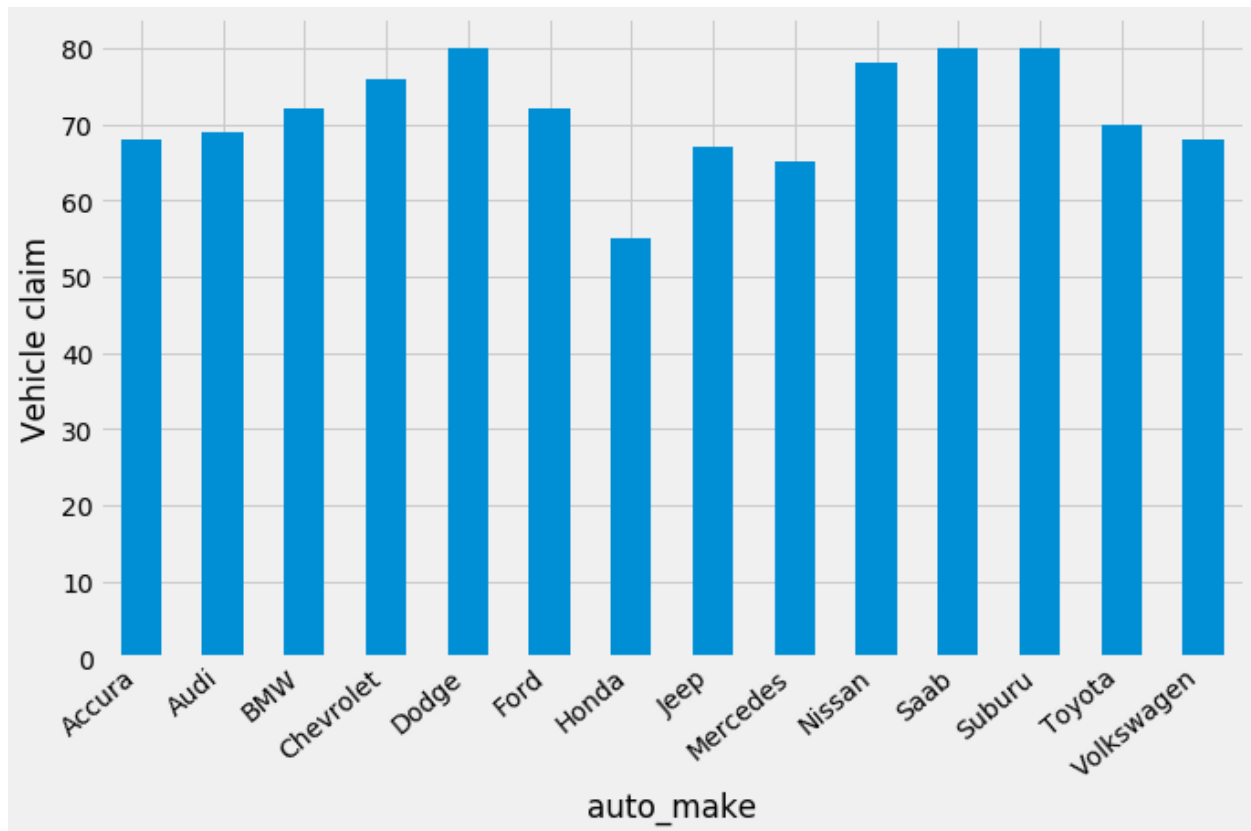


```
df["insured_occupation"].value_counts()
```

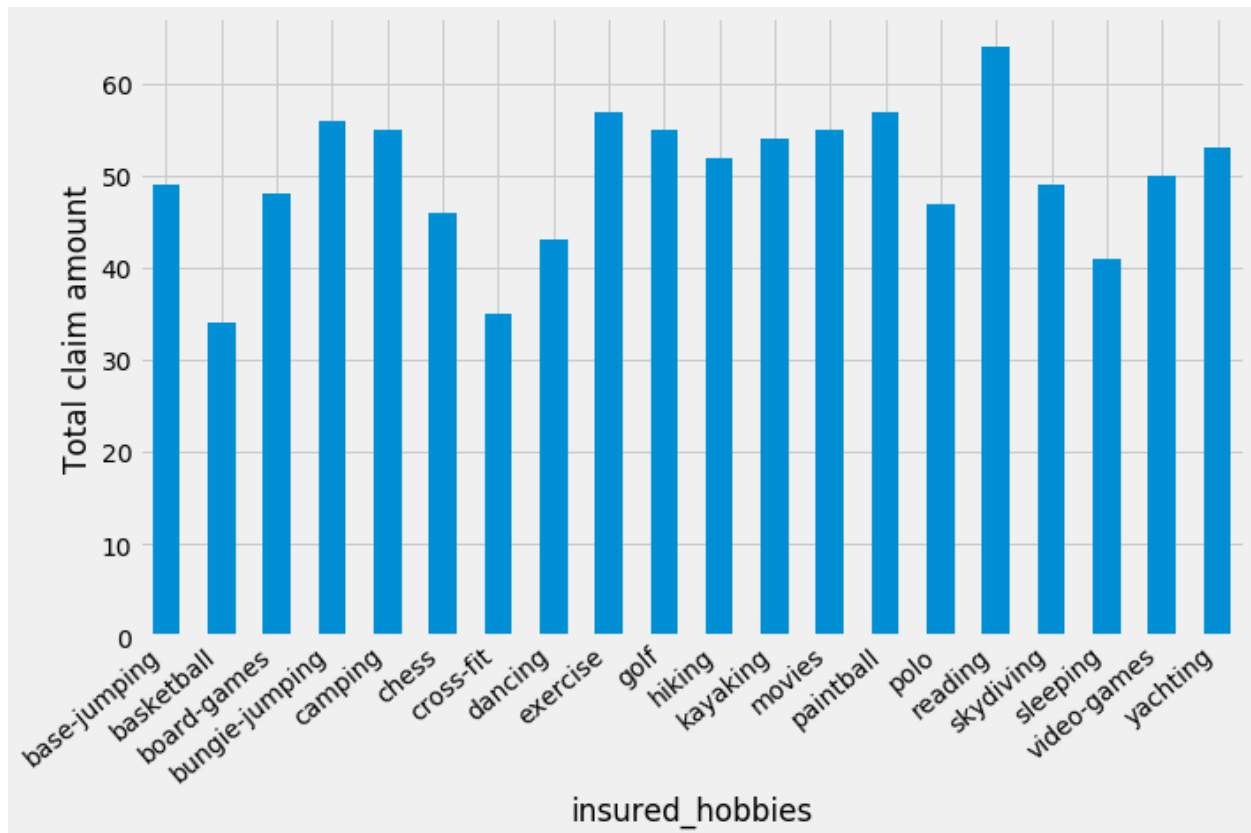
```
machine-op-inspct    93
prof-specialty       85
tech-support         78
exec-managerial      76
sales                76
craft-repair         74
transport-moving     72
priv-house-serv      71
other-service        71
armed-forces         69
adm-clerical         65
protective-serv      63
handlers-cleaners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

```
Name: insured_occupation, dtype: int64
```

```
plt.style.use('fivethirtyeight')
fig = plt.figure(figsize=(10,6))
ax= df.groupby('auto_make').vehicle_claim.count().plot.bar(ylim=0)
ax.set_ylabel('Vehicle claim')
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
plt.show()
```



```
plt.style.use('fivethirtyeight')
fig = plt.figure(figsize=(10,6))
ax=
df.groupby('insured_hobbies').total_claim_amount.count().plot.bar(ylim
=0)
ax.set_ylabel('Total claim amount')
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
plt.show()
```



## Data Processing

Cleaning up the data and prepare it for machine learning model.

```
df['fraud_reported'].replace(to_replace='Y', value=1, inplace=True)
df['fraud_reported'].replace(to_replace='N', value=0, inplace=True)
df.head()
```

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

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

1	250/500	2000	1197.22	5000000
2	100/300	2000	1413.14	5000000
3	250/500	2000	1415.74	6000000
4	500/1000	1000	1583.91	6000000

	insured_zip	insured_sex	insured_education_level	insured_occupation
0	466132	MALE	MD	craft-repair
1	468176	MALE	MD	machine-op-inspct
2	430632	FEMALE	PhD	sales
3	608117	FEMALE	PhD	armed-forces
4	610706	MALE	Associate	sales

	insured_hobbies	insured_relationship	capital-gains	capital-loss	\
0	sleeping	husband	53300	0	
1	reading	other-relative	0	0	
2	board-games	own-child	35100	0	
3	board-games	unmarried	48900	-62400	
4	board-games	unmarried	66000	-46000	

	incident_date	incident_type	collision_type	incident_severity	\
0	2015-01-25	Single Vehicle Collision	Side Collision	Major Damage	
1	2015-01-21	Vehicle Theft	?	Minor Damage	
2	2015-02-22	Multi-vehicle Collision	Rear Collision	Minor Damage	
3	2015-01-10	Single Vehicle Collision	Front Collision	Major Damage	
4	2015-02-17	Vehicle Theft	?	Minor Damage	

	authorities_contacted	incident_state	incident_city	incident_location	\
0	Police	SC	Columbus	9935 4th Drive	
1	Police	VA	Riverwood	6608 MLK Hwy	
2	Police	NY	Columbus	7121 Francis Lane	

3	Police	OH	Arlington	6956 Maple
Drive				
4	None	NY	Arlington	3041 3rd
Ave				
	incident_hour_of_the_day	number_of_vehicles_involved		
property_damage \				
0	5	1		
YES				
1	8	1		
?				
2	7	3		
NO				
3	5	1		
?				
4	20	1		
NO				
	bodily_injuries	witnesses	police_report_available	
total_claim_amount \				
0	1	2	YES	
71610				
1	0	0	?	
5070				
2	2	3	NO	
34650				
3	1	2	NO	
63400				
4	0	1	NO	
6500				
	injury_claim	property_claim	vehicle_claim	auto_make
auto_model \				
0	6510	13020	52080	Saab 92x
1	780	780	3510	Mercedes E400
2	7700	3850	23100	Dodge RAM
3	6340	6340	50720	Chevrolet Tahoe
4	1300	650	4550	Accura RSX
	auto_year	fraud_reported	_c39	
0	2004	1	NaN	
1	2007	1	NaN	
2	2007	0	NaN	
3	2014	1	NaN	
4	2009	0	NaN	

```
df[['insured_zip']] = df[['insured_zip']].astype(object)
```

```
df.describe()
```

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

	policy_annual_premium	umbrella_limit	capital-gains	capital-loss
count	1000.000000	1.000000e+03	1000.000000	
mean	1256.406150	1.101000e+06	25126.100000	-
std	244.167395	2.297407e+06	27872.187708	
min	433.330000	-1.000000e+06	0.000000	-
25%	1089.607500	0.000000e+00	0.000000	-
50%	1257.200000	0.000000e+00	0.000000	-
75%	1415.695000	0.000000e+00	51025.000000	
max	2047.590000	1.000000e+07	100500.000000	

	incident_hour_of_the_day	number_of_vehicles_involved
count	1000.000000	1000.000000
mean	11.644000	1.83900
std	6.951373	1.01888



min	0.000000	0.000000	1.000000
0.000000			
25%	6.000000	1.000000	
0.000000			
50%	12.000000	1.000000	
1.000000			
75%	17.000000	3.000000	
2.000000			
max	23.000000	4.000000	
2.000000			

	witnesses	total_claim_amount	injury_claim	
property_claim \				
count	1000.000000	1000.000000	1000.000000	1000.000000
mean	1.487000	52761.94000	7433.420000	7399.570000
std	1.111335	26401.53319	4880.951853	4824.726179
min	0.000000	100.00000	0.000000	0.000000
25%	1.000000	41812.50000	4295.000000	4445.000000
50%	1.000000	58055.00000	6775.000000	6750.000000
75%	2.000000	70592.50000	11305.000000	10885.000000
max	3.000000	114920.00000	21450.000000	23670.000000

	vehicle_claim	auto_year	fraud_reported	_c39
count	1000.000000	1000.000000	1000.000000	0.0
mean	37928.950000	2005.103000	0.247000	NaN
std	18886.252893	6.015861	0.431483	NaN
min	70.000000	1995.000000	0.000000	NaN
25%	30292.500000	2000.000000	0.000000	NaN
50%	42100.000000	2005.000000	0.000000	NaN
75%	50822.500000	2010.000000	0.000000	NaN
max	79560.000000	2015.000000	1.000000	NaN

Some variables such as 'policy\_bind\_date', 'incident\_date', 'incident\_location' and 'insured\_zip' contain very high number of level. We will remove these columns for our purposes.

```
df.auto_year.value_counts() # check the spread of years to decide on further action.
```

```
1995    56
1999    55
2005    54
2011    53
2006    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

```

auto\_year has 21 levels, and the number of records for each of the levels are quite significant considering dataset size is not so large. We will do some feature engineering using this variable considering, the year of manufacturing of automobile indicates the age of the vehicle and may contain valuable information for insurance premium or fraud is concerned.

```

df['vehicle_age'] = 2018 - df['auto_year'] # Deriving the age of the
vehicle based on the year value
df['vehicle_age'].head(10)

```

```

0    14
1    11
2    11
3     4
4     9
5    15
6     6
7     3
8     6
9    22
Name: vehicle_age, dtype: int64

```

```

bins = [-1, 3, 6, 9, 12, 17, 20, 24] # Factorize according to the
time period of the day.
names = ["past_midnight", "early_morning", "morning", "fore-noon",
'afternoon', 'evening', 'night']
df['incident_period_of_day'] = pd.cut(df.incident_hour_of_the_day,
bins, labels=names).astype(object)
df[['incident_hour_of_the_day', 'incident_period_of_day']].head(20)

```

```

incident_hour_of_the_day  incident_period_of_day
0                        5      early_morning
1                        8        morning
2                        7        morning

```

3	5	early_morning
4	20	evening
5	19	evening
6	0	past_midnight
7	23	night
8	21	night
9	14	afternoon
10	22	night
11	21	night
12	9	morning
13	5	early_morning
14	12	fore-noon
15	12	fore-noon
16	0	past_midnight
17	9	morning
18	19	evening
19	8	morning

*# Check on categorical variables:*

```
df.select_dtypes(include=['object']).columns # checking categorcial columns
```

```
Index(['policy_bind_date', 'policy_state', 'policy_csl',
      'insured_zip',
      'insured_sex', 'insured_education_level', 'insured_occupation',
      'insured_hobbies', 'insured_relationship', 'incident_date',
      'incident_type', 'collision_type', 'incident_severity',
      'authorities_contacted', 'incident_state', 'incident_city',
      'incident_location', 'property_damage',
      'police_report_available',
      'auto_make', 'auto_model', 'incident_period_of_day'],
      dtype='object')
```

*# dropping unimportant columns*

```
df = df.drop(columns = [
    'policy_number',
    'insured_zip',
    'policy_bind_date',
    'incident_date',
    'incident_location',
    '_c39',
    'auto_year',
    'incident_hour_of_the_day'])
```

```
df.head(2)
```

	months_as_customer	age	policy_state	policy_csl	policy_deductable
0	328	48	OH	250/500	1000

1	228	42	IN	250/500	2000
---	-----	----	----	---------	------

	policy_annual_premium	umbrella_limit	insured_sex
	insured_education_level \		
0	1406.91	0	MALE
MD			
1	1197.22	5000000	MALE
MD			

	insured_occupation	insured_hobbies	insured_relationship	capital-gains \
0	craft-repair	sleeping	husband	
53300				
1	machine-op-inspct	reading	other-relative	
0				

	capital-loss	incident_type	collision_type
	incident_severity \		
0	0	Single Vehicle Collision	Side Collision
Major Damage			
1	0	Vehicle Theft	?
Minor Damage			

	authorities_contacted	incident_state	incident_city \
0	Police	SC	Columbus
1	Police	VA	Riverwood

	number_of_vehicles_involved	property_damage	bodily_injuries
witnesses \			
0	1	YES	1
2			
1	1	?	0
0			

	police_report_available	total_claim_amount	injury_claim
	property_claim \		
0	YES	71610	6510
13020			
1	?	5070	780
780			

	vehicle_claim	auto_make	auto_model	fraud_reported	vehicle_age \
0	52080	Saab	92x	1	14
1	3510	Mercedes	E400	1	11

	incident_period_of_day
0	early_morning
1	morning

```
# identify variables with '?' values
unknowns = {}
for i in list(df.columns):
    if (df[i]).dtype == object:
        j = np.sum(df[i] == "?")
        unknowns[i] = j
unknowns = pd.DataFrame.from_dict(unknowns, orient = 'index')
print(unknowns)
```

```

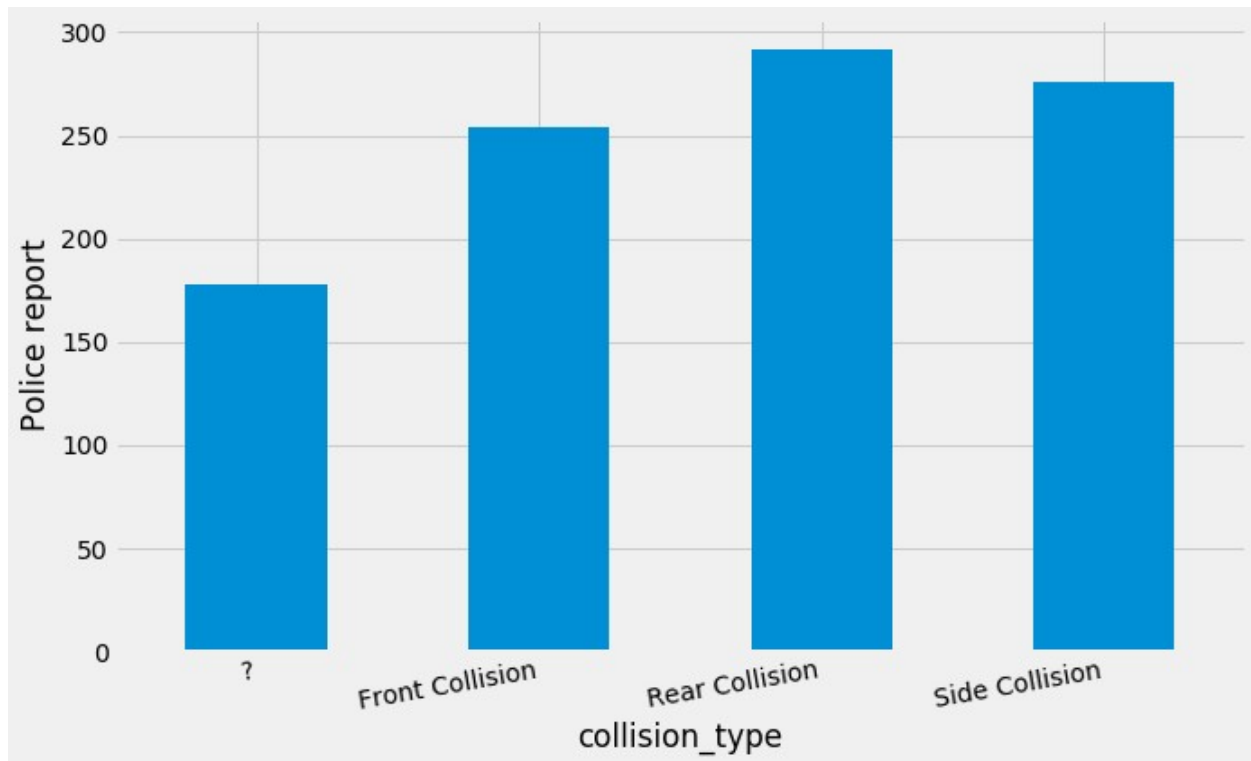
                                0
policy_state                    0
policy_csl                      0
insured_sex                     0
insured_education_level         0
insured_occupation              0
insured_hobbies                 0
insured_relationship            0
incident_type                   0
collision_type                  178
incident_severity               0
authorities_contacted           0
incident_state                  0
incident_city                   0
property_damage                 360
police_report_available         343
auto_make                      0
auto_model                     0
incident_period_of_day          0
```

collision\_type, property\_damage, police\_report\_available contain many missing values. So, first isolate these variables, inspect these individually for spread of category values.

```
df.collision_type.value_counts()
```

```
Rear Collision      292
Side Collision      276
Front Collision     254
?                  178
Name: collision_type, dtype: int64
```

```
plt.style.use('fivethirtyeight')
fig = plt.figure(figsize=(10,6))
ax=
df.groupby('collision_type').police_report_available.count().plot.bar(
ylim=0)
ax.set_ylabel('Police report')
ax.set_xticklabels(ax.get_xticklabels(), rotation=10, ha="right")
plt.show()
```



```
df.property_damage.value_counts()
```

```
?      360
```

```
NO      338
```

```
YES     302
```

```
Name: property_damage, dtype: int64
```

```
plt.style.use('fivethirtyeight')
```

```
fig = plt.figure(figsize=(10,6))
```

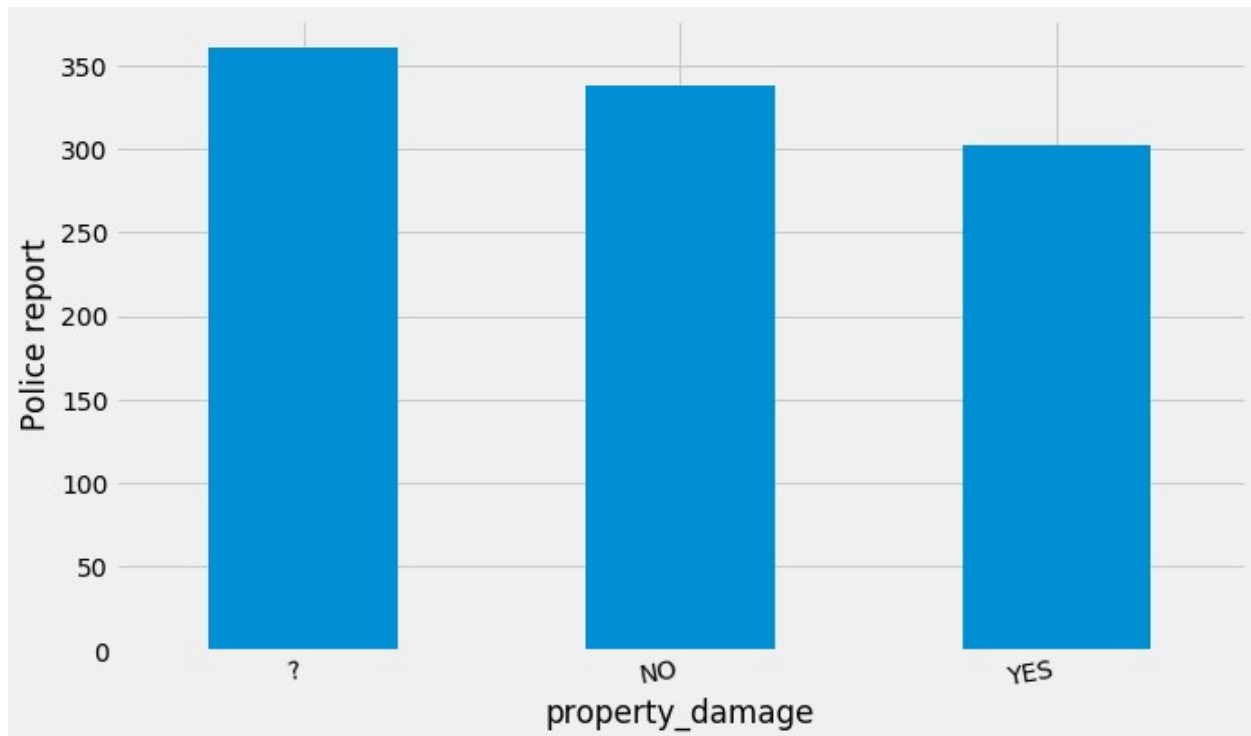
```
ax=
```

```
df.groupby('property_damage').police_report_available.count().plot.bar  
(ylim=0)
```

```
ax.set_ylabel('Police report')
```

```
ax.set_xticklabels(ax.get_xticklabels(), rotation=10, ha="right")
```

```
plt.show()
```



```
df.police_report_available.value_counts()
```

```
?      343
```

```
NO      343
```

```
YES     314
```

```
Name: police_report_available, dtype: int64
```

```
df.columns
```

```
Index(['months_as_customer', 'age', 'policy_state', 'policy_csl',
      'policy_deductable', 'policy_annual_premium', 'umbrella_limit',
      'insured_sex', 'insured_education_level', 'insured_occupation',
      'insured_hobbies', 'insured_relationship', 'capital-gains',
      'capital-loss', 'incident_type', 'collision_type',
      'incident_severity',
      'authorities_contacted', 'incident_state', 'incident_city',
      'number_of_vehicles_involved', 'property_damage',
      'bodily_injuries',
      'witnesses', 'police_report_available', 'total_claim_amount',
      'injury_claim', 'property_claim', 'vehicle_claim', 'auto_make',
      'auto_model', 'fraud_reported', 'vehicle_age',
      'incident_period_of_day'],
      dtype='object')
```

```
df._get_numeric_data().head() # Checking numeric columns
```

```
  months_as_customer  age  policy_deductable
policy_annual_premium \
```

0	328	48	1000	1406.91
1	228	42	2000	1197.22
2	134	29	2000	1413.14
3	256	41	2000	1415.74
4	228	44	1000	1583.91

	umbrella_limit	capital-gains	capital-loss
number_of_vehicles_involved \			
0	0	53300	0
1			
1	5000000	0	0
1			
2	5000000	35100	0
3			
3	6000000	48900	-62400
1			
4	6000000	66000	-46000
1			

	bodily_injuries	witnesses	total_claim_amount	injury_claim \
0	1	2	71610	6510
1	0	0	5070	780
2	2	3	34650	7700
3	1	2	63400	6340
4	0	1	6500	1300

	property_claim	vehicle_claim	fraud_reported	vehicle_age
0	13020	52080	1	14
1	780	3510	1	11
2	3850	23100	0	11
3	6340	50720	1	4
4	650	4550	0	9

```
df._get_numeric_data().columns
```

```
Index(['months_as_customer', 'age', 'policy_deductable',
      'policy_annual_premium', 'umbrella_limit', 'capital-gains',
      'capital-loss', 'number_of_vehicles_involved',
      'bodily_injuries',
      'witnesses', 'total_claim_amount', 'injury_claim',
      'property_claim',
      'vehicle_claim', 'fraud_reported', 'vehicle_age'],
      dtype='object')
```

```
df.select_dtypes(include=['object']).columns # checking categorcial
columns
```



```
Index(['policy_state', 'policy_csl', 'insured_sex',
      'insured_education_level',
      'insured_occupation', 'insured_hobbies',
      'insured_relationship',
      'incident_type', 'collision_type', 'incident_severity',
      'authorities_contacted', 'incident_state', 'incident_city',
      'property_damage', 'police_report_available', 'auto_make',
      'auto_model',
      'incident_period_of_day'],
      dtype='object')
```

Applying one-hot encoding to convert all categorical variables except out target variables

'collision\_type', 'property\_damage', 'police\_report\_available', 'fraud\_reported'

```
dummies = pd.get_dummies(df[[
    'policy_state',
    'policy_csl',
    'insured_sex',
    'insured_education_level',
    'insured_occupation',
    'insured_hobbies',
    'insured_relationship',
    'incident_type',
    'incident_severity',
    'authorities_contacted',
    'incident_state',
    'incident_city',
    'auto_make',
    'auto_model',
    'incident_period_of_day']])
```

```
dummies = dummies.join(df[[
    'collision_type',
    'property_damage',
    'police_report_available',
    "fraud_reported"]])
```

```
dummies.head()
```

	policy_state_IL	policy_state_IN	policy_state_OH
policy_csl_100/300	\		
0	0	0	1
0			
1	0	1	0
0			
2	0	0	1
1			

3	1	0	0
0			
4	1	0	0
0			
	policy_csl_250/500	policy_csl_500/1000	insured_sex_FEMALE \
0	1	0	0
1	1	0	0
2	0	0	1
3	1	0	1
4	0	1	0
	insured_sex_MALE	insured_education_level_Associate	\
0	1	0	
1	1	0	
2	0	0	
3	0	0	
4	1	1	
	insured_education_level_College	insured_education_level_High	
School \			
0		0	
0			
1		0	
0			
2		0	
0			
3		0	
0			
4		0	
0			
	insured_education_level_JD	insured_education_level_MD	\
0	0	1	
1	0	1	
2	0	0	
3	0	0	
4	0	0	
	insured_education_level_Masters	insured_education_level_PhD	\
0	0	0	
1	0	0	
2	0	1	
3	0	1	
4	0	0	
	insured_occupation_adm-clerical	insured_occupation_armed-forces	\
0	0	0	
1	0	0	
2	0	0	

3	0	1
4	0	0

	insured_occupation_craft-repair	insured_occupation_exec-managerial
\		
0	1	0
1	0	0
2	0	0
3	0	0
4	0	0

	insured_occupation_farming-fishing	insured_occupation_handlers-cleaners
\		
0	0	
0		
1	0	
0		
2	0	
0		
3	0	
0		
4	0	
0		

	insured_occupation_machine-op-inspct	insured_occupation_other-service
\		
0	0	
0		
1	1	
0		
2	0	
0		
3	0	
0		
4	0	
0		

	insured_occupation_priv-house-serv	insured_occupation_prof-specialty
\		
0	0	
0		
1	0	
0		
2	0	
0		

3	0
0	
4	0
0	

	insured_occupation_protective-serv	insured_occupation_sales \
0	0	0
1	0	0
2	0	1
3	0	0
4	0	1

	insured_occupation_tech-support	insured_occupation_transport-moving \
0	0	
0		
1	0	
0		
2	0	
0		
3	0	
0		
4	0	
0		

	insured_hobbies_base-jumping	insured_hobbies_basketball \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

	insured_hobbies_board-games	insured_hobbies_bungee-jumping \
0	0	0
1	0	0
2	1	0
3	1	0
4	1	0

	insured_hobbies_camping	insured_hobbies_chess
	insured_hobbies_cross-fit \	
0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0

0

insured\_hobbies\_dancing insured\_hobbies\_exercise

insured\_hobbies\_golf \

0 0 0

0

1 0 0

0

2 0 0

0

3 0 0

0

4 0 0

0

insured\_hobbies\_hiking insured\_hobbies\_kayaking

insured\_hobbies\_movies \

0 0 0

0

1 0 0

0

2 0 0

0

3 0 0

0

4 0 0

0

insured\_hobbies\_paintball insured\_hobbies\_polo

insured\_hobbies\_reading \

0 0 0

0

1 0 0

1

2 0 0

0

3 0 0

0

4 0 0

0

insured\_hobbies\_skydiving insured\_hobbies\_sleeping \

0 0 1

1 0 0

2 0 0

3 0 0

4 0 0

insured\_hobbies\_video-games insured\_hobbies\_yachting \

0 0 0

1	0	0
2	0	0
3	0	0
4	0	0
insured_relationship_husband insured_relationship_not-in-family \		
0	1	0
1	0	0
2	0	0
3	0	0
4	0	0
insured_relationship_other-relative insured_relationship_own-child		
\		
0	0	0
1	1	0
2	0	1
3	0	0
4	0	0
insured_relationship_unmarried insured_relationship_wife \		
0	0	0
1	0	0
2	0	0
3	1	0
4	1	0
incident_type_Multi-vehicle Collision incident_type_Parked Car \		
0	0	0
1	0	0
2	1	0
3	0	0
4	0	0
incident_type_Single Vehicle Collision incident_type_Vehicle Theft		
\		
0	1	0
1	0	1
2	0	0
3	1	0
4	0	1

	incident_severity_Major Damage	incident_severity_Minor Damage	\
0	1	0	
1	0	1	
2	0	1	
3	1	0	
4	0	1	

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

	authorities_contacted_Ambulance	authorities_contacted_Fire	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

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

	authorities_contacted_Police	incident_state_NC	incident_state_NY	\
0	1	0	0	
1	1	0	0	
2	1	0	1	
3	1	0	0	
4	0	0	1	

	incident_state_OH	incident_state_PA	incident_state_SC	incident_state_VA	\
0	0	0	1		
0					
1	0	0	0		
1					
2	0	0	0		
0					

3	1	0	0
0			
4	0	0	0
0			

	incident_state_WV	incident_city_Arlington	incident_city_Columbus
\			
0	0	0	1
1	0	0	0
2	0	0	1
3	0	1	0
4	0	1	0

	incident_city_Hillsdale	incident_city_Northbend
incident_city_Northbrook \		
0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
0		

	incident_city_Riverwood	incident_city_Springfield
auto_make_Accura \		
0	0	0
0		
1	1	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
1		

	auto_make_Audi	auto_make_BMW	auto_make_Chevrolet	auto_make_Dodge
\				
0	0	0	0	0
1	0	0	0	0



2	0	0	0	1
3	0	0	1	0
4	0	0	0	0

	auto_make_Ford	auto_make_Honda	auto_make_Jeep	auto_make_Mercedes
\				
0	0	0	0	0
1	0	0	0	1
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	auto_make_Nissan	auto_make_Saab	auto_make_Suburu
auto_make_Toyota \			
0	0	1	0
0			
1	0	0	0
0			
2	0	0	0
0			
3	0	0	0
0			
4	0	0	0
0			

	auto_make_Volkswagen	auto_model_3 Series	auto_model_92x
auto_model_93 \			
0	0	0	1
0			
1	0	0	0
0			
2	0	0	0
0			
3	0	0	0
0			
4	0	0	0
0			

	auto_model_95	auto_model_A3	auto_model_A5	auto_model_Accord	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	

3	0	0	0	0
4	0	0	0	0

	auto_model_C300	auto_model_CRV	auto_model_Camry	auto_model_Civic
\				
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	auto_model_Corolla	auto_model_E400	auto_model_Escape
auto_model_F150	\		
0	0	0	0
0			
1	0	1	0
0			
2	0	0	0
0			
3	0	0	0
0			
4	0	0	0
0			

	auto_model_Forester	auto_model_Fusion	auto_model_Grand Cherokee
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	auto_model_Highlander	auto_model_Impreza	auto_model_Jetta	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	auto_model_Legacy	auto_model_M5	auto_model_MDX	auto_model_ML350
\				

0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	auto_model_Malibu	auto_model_Maxima	auto_model_Neon
auto_model_Passat \			
0	0	0	0
0			
1	0	0	0
0			
2	0	0	0
0			
3	0	0	0
0			
4	0	0	0
0			

	auto_model_Pathfinder	auto_model_RAM	auto_model_RSX \
0	0	0	0
1	0	0	0
2	0	1	0
3	0	0	0
4	0	0	1

	auto_model_Silverado	auto_model_TL	auto_model_Tahoe
auto_model_Ultima \			
0	0	0	0
0			
1	0	0	0
0			
2	0	0	0
0			
3	0	0	1
0			
4	0	0	0
0			

	auto_model_Wrangler	auto_model_X5	auto_model_X6 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

```

    incident_period_of_day_afternoon
incident_period_of_day_early_morning \
0 0
1
1 0
0
2 0
0
3 0
1
4 0
0

    incident_period_of_day_evening incident_period_of_day_fore-noon \
0 0 0
1 0 0
2 0 0
3 0 0
4 1 0

    incident_period_of_day_morning incident_period_of_day_night \
0 0 0
1 1 0
2 1 0
3 0 0
4 0 0

    incident_period_of_day_past_midnight collision_type
property_damage \
0 0 Side Collision
YES
1 0 ?
?
2 0 Rear Collision
NO
3 0 Front Collision
?
4 0 ?
NO

    police_report_available fraud_reported
0 YES 1
1 ? 1
2 NO 0
3 NO 1
4 NO 0

X = dummies.iloc[:, 0:-1]
y = dummies.iloc[:, -1]

```

```
len(X.columns)
```

```
145
```

```
X.head(2)
```

	policy_state_IL	policy_state_IN	policy_state_OH
policy_csl_100/300 \			
0	0	0	1
0			
1	0	1	0
0			

	policy_csl_250/500	policy_csl_500/1000	insured_sex_FEMALE	\
0	1	0	0	
1	1	0	0	

	insured_sex_MALE	insured_education_level_Associate	\
0	1	0	
1	1	0	

	insured_education_level_College School	insured_education_level_High	\
0		0	
0			
1		0	
0			

	insured_education_level_JD	insured_education_level_MD	\
0	0	1	
1	0	1	

	insured_education_level_Masters	insured_education_level_PhD	\
0	0	0	
1	0	0	

	insured_occupation_adm-clerical	insured_occupation_armed-forces	\
0	0	0	
1	0	0	

	insured_occupation_craft-repair	insured_occupation_exec-managerial	\
0		1	0
1		0	0

	insured_occupation_farming-fishing cleaners	insured_occupation_handlers-	\
0		0	
0			

1	0
0	
insured_occupation_machine-op-inspct	insured_occupation_other-service \
0	0
0	
1	1
0	
insured_occupation_priv-house-serv	insured_occupation_prof-specialty \
0	0
0	
1	0
0	
insured_occupation_protective-serv	insured_occupation_sales \
0	0
1	0
insured_occupation_tech-support	insured_occupation_transport-moving \
0	0
0	
1	0
0	
insured_hobbies_base-jumping	insured_hobbies_basketball \
0	0
1	0
insured_hobbies_board-games	insured_hobbies_bungee-jumping \
0	0
1	0
insured_hobbies_camping	insured_hobbies_chess
insured_hobbies_cross-fit \	
0	0
0	
1	0
0	
insured_hobbies_dancing	insured_hobbies_exercise
insured_hobbies_golf \	
0	0
0	
1	0
0	

insured_hobbies_hiking	insured_hobbies_kayaking
insured_hobbies_movies \	
0	0
0	
1	0
0	
insured_hobbies_paintball	insured_hobbies_polo
insured_hobbies_reading \	
0	0
0	
1	0
1	
insured_hobbies_skydiving	insured_hobbies_sleeping \
0	0
1	0
insured_hobbies_video-games	insured_hobbies_yachting \
0	0
1	0
insured_relationship_husband	insured_relationship_not-in-family \
0	1
1	0
insured_relationship_other-relative	insured_relationship_own-child
\	
0	0
1	1
insured_relationship_unmarried	insured_relationship_wife \
0	0
1	0
incident_type_Multi-vehicle Collision	incident_type_Parked Car \
0	0
1	0
incident_type_Single Vehicle Collision	incident_type_Vehicle Theft
\	
0	1
1	0
incident_severity_Major Damage	incident_severity_Minor Damage \
0	1
	0

1	0	1
incident_severity_Total Loss	incident_severity_Trivial Damage \	
0	0	0
1	0	0
authorities_contacted_Ambulance	authorities_contacted_Fire \	
0	0	0
1	0	0
authorities_contacted_None	authorities_contacted_Other \	
0	0	0
1	0	0
authorities_contacted_Police	incident_state_NC	incident_state_NY
\		
0	1	0
1	1	0
incident_state_OH	incident_state_PA	incident_state_SC
incident_state_VA \		
0	0	1
0		
1	0	0
1		
incident_state_WV	incident_city_Arlington	incident_city_Columbus
\		
0	0	1
1	0	0
incident_city_Hillsdale	incident_city_Northbend	
incident_city_Northbrook \		
0	0	0
0		
1	0	0
0		
incident_city_Riverwood	incident_city_Springfield	
auto_make_Accura \		
0	0	0
0		
1	1	0
0		
auto_make_Audi	auto_make_BMW	auto_make_Chevrolet
		auto_make_Dodge



\				
0	0	0	0	0
1	0	0	0	0

	auto_make_Ford	auto_make_Honda	auto_make_Jeep	auto_make_Mercedes
\				
0	0	0	0	0
1	0	0	0	1

	auto_make_Nissan	auto_make_Saab	auto_make_Suburu
auto_make_Toyota	\		
0	0	1	0
0			
1	0	0	0
0			

	auto_make_Volkswagen	auto_model_3 Series	auto_model_92x
auto_model_93	\		
0	0	0	1
0			
1	0	0	0
0			

	auto_model_95	auto_model_A3	auto_model_A5	auto_model_Accord	\
0	0	0	0	0	
1	0	0	0	0	

	auto_model_C300	auto_model_CRV	auto_model_Camry	auto_model_Civic
\				
0	0	0	0	0
1	0	0	0	0

	auto_model_Corolla	auto_model_E400	auto_model_Escape
auto_model_F150	\		
0	0	0	0
0			
1	0	1	0
0			

	auto_model_Forestor	auto_model_Fusion	auto_model_Grand Cherokee
\			
0	0	0	0
1	0	0	0

	auto_model_Highlander	auto_model_Impreza	auto_model_Jetta	\
0	0	0	0	
1	0	0	0	

	auto_model_Legacy	auto_model_M5	auto_model_MDX	auto_model_ML350
\				
0	0	0	0	0
1	0	0	0	0

	auto_model_Malibu	auto_model_Maxima	auto_model_Neon
auto_model_Passat	\		
0	0	0	0
0			
1	0	0	0
0			

	auto_model_Pathfinder	auto_model_RAM	auto_model_RSX	\
0	0	0	0	
1	0	0	0	

	auto_model_Silverado	auto_model_TL	auto_model_Tahoe
auto_model_Ultima	\		
0	0	0	0
0			
1	0	0	0
0			

	auto_model_Wrangler	auto_model_X5	auto_model_X6	\
0	0	0	0	
1	0	0	0	

	incident_period_of_day_afternoon
incident_period_of_day_early_morning	\
0	0
1	
1	0
0	

	incident_period_of_day_evening	incident_period_of_day_fore-noon	\
0	0	0	
1	0	0	

	incident_period_of_day_morning	incident_period_of_day_night	\
0	0	0	
1	1	0	

	incident_period_of_day_past_midnight	collision_type
--	--------------------------------------	----------------

```

property_damage \
0                0 Side Collision
YES
1
0                ?                ?

  police_report_available
0                YES
1                ?

y.head()

0    1
1    1
2    0
3    1
4    0
Name: fraud_reported, dtype: int64

```

### Label encoding

```

from sklearn.preprocessing import LabelEncoder
X['collision_en'] =
LabelEncoder().fit_transform(dummies['collision_type'])
X[['collision_type', 'collision_en']]

```

	collision_type	collision_en
0	Side Collision	3
1	?	0
2	Rear Collision	2
3	Front Collision	1
4	?	0
5	Rear Collision	2
6	Front Collision	1
7	Front Collision	1
8	Front Collision	1
9	Rear Collision	2
10	Front Collision	1
11	Front Collision	1
12	Rear Collision	2
13	?	0
14	Rear Collision	2
15	Side Collision	3
16	Rear Collision	2
17	Side Collision	3
18	Side Collision	3
19	Side Collision	3
20	Rear Collision	2
21	Side Collision	3
22	Rear Collision	2

23	Front Collision	1
24	Rear Collision	2
25	Rear Collision	2
26	?	0
27	?	0
28	Side Collision	3
29	Rear Collision	2
30	Side Collision	3
31	Side Collision	3
32	Front Collision	1
33	Front Collision	1
34	Side Collision	3
35	Front Collision	1
36	Rear Collision	2
37	?	0
38	Rear Collision	2
39	Front Collision	1
40	Rear Collision	2
41	Side Collision	3
42	Side Collision	3
43	Rear Collision	2
44	Front Collision	1
45	Rear Collision	2
46	Rear Collision	2
47	Front Collision	1
48	?	0
49	Rear Collision	2
50	Front Collision	1
51	?	0
52	?	0
53	Side Collision	3
54	?	0
55	Rear Collision	2
56	Front Collision	1
57	?	0
58	Front Collision	1
59	Side Collision	3
60	Rear Collision	2
61	Side Collision	3
62	Side Collision	3
63	Front Collision	1
64	Rear Collision	2
65	Front Collision	1
66	Side Collision	3
67	Side Collision	3
68	Front Collision	1
69	?	0
70	Side Collision	3
71	Front Collision	1

72	Rear Collision	2
73	Rear Collision	2
74	Side Collision	3
75	Front Collision	1
76	Front Collision	1
77	Front Collision	1
78	?	0
79	Rear Collision	2
80	Side Collision	3
81	?	0
82	?	0
83	?	0
84	Side Collision	3
85	Front Collision	1
86	Front Collision	1
87	Side Collision	3
88	?	0
89	Side Collision	3
90	Front Collision	1
91	Side Collision	3
92	?	0
93	Front Collision	1
94	Rear Collision	2
95	?	0
96	Side Collision	3
97	Rear Collision	2
98	?	0
99	?	0
100	Rear Collision	2
101	Side Collision	3
102	Front Collision	1
103	?	0
104	Side Collision	3
105	?	0
106	Rear Collision	2
107	Front Collision	1
108	Front Collision	1
109	Rear Collision	2
110	Rear Collision	2
111	Front Collision	1
112	Rear Collision	2
113	Side Collision	3
114	?	0
115	Side Collision	3
116	Rear Collision	2
117	Side Collision	3
118	Rear Collision	2
119	Rear Collision	2
120	Side Collision	3

121	Front Collision	1
122	Front Collision	1
123	Front Collision	1
124	Rear Collision	2
125	Rear Collision	2
126	Side Collision	3
127	?	0
128	Front Collision	1
129	Front Collision	1
130	Front Collision	1
131	Front Collision	1
132	Front Collision	1
133	Side Collision	3
134	Side Collision	3
135	Rear Collision	2
136	?	0
137	Rear Collision	2
138	Rear Collision	2
139	Front Collision	1
140	Rear Collision	2
141	?	0
142	?	0
143	Rear Collision	2
144	Rear Collision	2
145	Front Collision	1
146	Side Collision	3
147	Front Collision	1
148	Rear Collision	2
149	Side Collision	3
150	Side Collision	3
151	Rear Collision	2
152	Rear Collision	2
153	Rear Collision	2
154	Rear Collision	2
155	Front Collision	1
156	Rear Collision	2
157	?	0
158	Front Collision	1
159	?	0
160	?	0
161	Front Collision	1
162	Side Collision	3
163	Front Collision	1
164	Rear Collision	2
165	Side Collision	3
166	Rear Collision	2
167	Front Collision	1
168	?	0
169	?	0

170	Rear Collision	2
171	Rear Collision	2
172	Rear Collision	2
173	Front Collision	1
174	?	0
175	Rear Collision	2
176	Front Collision	1
177	Rear Collision	2
178	Front Collision	1
179	?	0
180	Side Collision	3
181	Side Collision	3
182	Side Collision	3
183	Rear Collision	2
184	Front Collision	1
185	Front Collision	1
186	Front Collision	1
187	?	0
188	Rear Collision	2
189	Rear Collision	2
190	?	0
191	Side Collision	3
192	Front Collision	1
193	?	0
194	Rear Collision	2
195	Side Collision	3
196	?	0
197	?	0
198	Front Collision	1
199	?	0
200	?	0
201	Rear Collision	2
202	?	0
203	Rear Collision	2
204	Rear Collision	2
205	Rear Collision	2
206	Rear Collision	2
207	Side Collision	3
208	Side Collision	3
209	?	0
210	?	0
211	?	0
212	Side Collision	3
213	Side Collision	3
214	Side Collision	3
215	Side Collision	3
216	Front Collision	1
217	?	0
218	Rear Collision	2

219	Side Collision	3
220	Front Collision	1
221	Front Collision	1
222	Side Collision	3
223	Side Collision	3
224	Side Collision	3
225	Front Collision	1
226	Rear Collision	2
227	Front Collision	1
228	Front Collision	1
229	Rear Collision	2
230	Side Collision	3
231	Side Collision	3
232	Side Collision	3
233	Rear Collision	2
234	Front Collision	1
235	Side Collision	3
236	Front Collision	1
237	Rear Collision	2
238	Side Collision	3
239	Front Collision	1
240	Front Collision	1
241	Front Collision	1
242	?	0
243	Rear Collision	2
244	?	0
245	Rear Collision	2
246	Side Collision	3
247	Rear Collision	2
248	?	0
249	Rear Collision	2
..	...	...
750	?	0
751	Side Collision	3
752	Rear Collision	2
753	Rear Collision	2
754	Side Collision	3
755	Side Collision	3
756	Rear Collision	2
757	Rear Collision	2
758	Front Collision	1
759	Front Collision	1
760	Side Collision	3
761	Rear Collision	2
762	Rear Collision	2
763	Front Collision	1
764	Rear Collision	2
765	Rear Collision	2
766	Rear Collision	2



767	Front Collision	1
768	Rear Collision	2
769	Side Collision	3
770	Front Collision	1
771	Side Collision	3
772	Front Collision	1
773	Rear Collision	2
774	Side Collision	3
775	?	0
776	Front Collision	1
777	Rear Collision	2
778	Front Collision	1
779	Rear Collision	2
780	Front Collision	1
781	Front Collision	1
782	?	0
783	?	0
784	Front Collision	1
785	Front Collision	1
786	Rear Collision	2
787	Front Collision	1
788	Front Collision	1
789	Rear Collision	2
790	?	0
791	Rear Collision	2
792	Rear Collision	2
793	Side Collision	3
794	Front Collision	1
795	Side Collision	3
796	Rear Collision	2
797	Side Collision	3
798	Side Collision	3
799	?	0
800	Rear Collision	2
801	Rear Collision	2
802	Front Collision	1
803	Rear Collision	2
804	?	0
805	Rear Collision	2
806	Side Collision	3
807	Rear Collision	2
808	Side Collision	3
809	Rear Collision	2
810	Side Collision	3
811	?	0
812	Front Collision	1
813	?	0
814	Front Collision	1
815	Rear Collision	2

816	Side Collision	3
817	Rear Collision	2
818	?	0
819	Side Collision	3
820	?	0
821	Side Collision	3
822	Front Collision	1
823	Front Collision	1
824	Rear Collision	2
825	Front Collision	1
826	Front Collision	1
827	Side Collision	3
828	Rear Collision	2
829	Side Collision	3
830	Side Collision	3
831	Rear Collision	2
832	?	0
833	Rear Collision	2
834	?	0
835	?	0
836	Rear Collision	2
837	?	0
838	Side Collision	3
839	Rear Collision	2
840	?	0
841	Rear Collision	2
842	?	0
843	Front Collision	1
844	Side Collision	3
845	Side Collision	3
846	Side Collision	3
847	Side Collision	3
848	Side Collision	3
849	?	0
850	Side Collision	3
851	Side Collision	3
852	Side Collision	3
853	Front Collision	1
854	Side Collision	3
855	Rear Collision	2
856	Side Collision	3
857	Front Collision	1
858	Side Collision	3
859	Side Collision	3
860	Rear Collision	2
861	Side Collision	3
862	Rear Collision	2
863	Front Collision	1
864	Front Collision	1

865	Rear Collision	2
866	Front Collision	1
867	Rear Collision	2
868	Front Collision	1
869	Rear Collision	2
870	Front Collision	1
871	?	0
872	Side Collision	3
873	Rear Collision	2
874	Side Collision	3
875	Side Collision	3
876	?	0
877	Front Collision	1
878	Rear Collision	2
879	Front Collision	1
880	Front Collision	1
881	Rear Collision	2
882	Rear Collision	2
883	Side Collision	3
884	Front Collision	1
885	Rear Collision	2
886	Front Collision	1
887	?	0
888	Rear Collision	2
889	Side Collision	3
890	Side Collision	3
891	Rear Collision	2
892	?	0
893	?	0
894	?	0
895	Front Collision	1
896	?	0
897	Front Collision	1
898	Rear Collision	2
899	?	0
900	Side Collision	3
901	Side Collision	3
902	Side Collision	3
903	Side Collision	3
904	Side Collision	3
905	Side Collision	3
906	Rear Collision	2
907	Front Collision	1
908	?	0
909	Rear Collision	2
910	Side Collision	3
911	Front Collision	1
912	Rear Collision	2
913	Side Collision	3

914	Front Collision	1
915	Rear Collision	2
916	?	0
917	Side Collision	3
918	Front Collision	1
919	Rear Collision	2
920	Rear Collision	2
921	Rear Collision	2
922	?	0
923	Rear Collision	2
924	Rear Collision	2
925	?	0
926	Front Collision	1
927	Front Collision	1
928	?	0
929	Side Collision	3
930	Rear Collision	2
931	Side Collision	3
932	Side Collision	3
933	Side Collision	3
934	Rear Collision	2
935	Side Collision	3
936	Front Collision	1
937	Front Collision	1
938	Front Collision	1
939	Rear Collision	2
940	?	0
941	Side Collision	3
942	?	0
943	Front Collision	1
944	Side Collision	3
945	Front Collision	1
946	Side Collision	3
947	Side Collision	3
948	Front Collision	1
949	Side Collision	3
950	?	0
951	Side Collision	3
952	Front Collision	1
953	?	0
954	Rear Collision	2
955	Side Collision	3
956	Side Collision	3
957	Rear Collision	2
958	Front Collision	1
959	?	0
960	Rear Collision	2
961	?	0
962	Rear Collision	2

963		?	0
964		?	0
965	Front	Collision	1
966	Rear	Collision	2
967	Rear	Collision	2
968	Side	Collision	3
969		?	0
970	Side	Collision	3
971	Front	Collision	1
972	Rear	Collision	2
973	Rear	Collision	2
974	Side	Collision	3
975	Rear	Collision	2
976	Side	Collision	3
977	Side	Collision	3
978	Front	Collision	1
979	Rear	Collision	2
980	Rear	Collision	2
981	Front	Collision	1
982	Front	Collision	1
983		?	0
984	Side	Collision	3
985	Side	Collision	3
986	Rear	Collision	2
987	Side	Collision	3
988	Rear	Collision	2
989	Rear	Collision	2
990	Rear	Collision	2
991	Rear	Collision	2
992	Front	Collision	1
993	Side	Collision	3
994		?	0
995	Front	Collision	1
996	Rear	Collision	2
997	Side	Collision	3
998	Rear	Collision	2
999		?	0

[1000 rows x 2 columns]

```

X['property_damage'].replace(to_replace='YES', value=1, inplace=True)
X['property_damage'].replace(to_replace='NO', value=0, inplace=True)
X['property_damage'].replace(to_replace='?', value=0, inplace=True)
X['police_report_available'].replace(to_replace='YES', value=1,
inplace=True)
X['police_report_available'].replace(to_replace='NO', value=0,
inplace=True)
X['police_report_available'].replace(to_replace='?', value=0,
inplace=True)

```

```
X.head(10)
```

	policy_state_IL	policy_state_IN	policy_state_OH
0	0	0	1
1	0	1	0
2	0	0	1
3	1	0	0
4	1	0	0
5	0	0	1
6	0	1	0
7	1	0	0
8	1	0	0
9	1	0	0

	policy_csl_250/500	policy_csl_500/1000	insured_sex_FEMALE
0	1	0	0
1	1	0	0
2	0	0	1
3	1	0	1
4	0	1	0
5	1	0	1
6	1	0	0
7	0	0	0
8	0	0	1
9	0	0	0

	insured_sex_MALE	insured_education_level_Associate
0	1	0
1	1	0
2	0	0
3	0	0
4	1	1
5	0	0
6	1	0
7	1	1
8	0	0
9	1	0

	insured_education_level_College	insured_education_level_High
School \		
0	0	
0		
1	0	
0		
2	0	
0		
3	0	
0		
4	0	
0		
5	0	
0		
6	0	
0		
7	0	
0		
8	0	
0		
9	0	
0		
	insured_education_level_JD	insured_education_level_MD \
0	0	1
1	0	1
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	0	0
8	0	0
9	0	0
	insured_education_level_Masters	insured_education_level_PhD \
0	0	0
1	0	0
2	0	1
3	0	1
4	0	0
5	0	1
6	0	1
7	0	0
8	0	1
9	0	1
	insured_occupation_adm-clerical	insured_occupation_armed-forces \
0	0	0
1	0	0

2	0	0
3	0	1
4	0	0
5	0	0
6	0	0
7	0	0
8	0	0
9	0	0

	insured_occupation_craft-repair	insured_occupation_exec-managerial
\		
0	1	0
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	0	0
8	0	0
9	0	0

	insured_occupation_farming-fishing	insured_occupation_handlers-cleaners
\		
0	0	
0		
1	0	
0		
2	0	
0		
3	0	
0		
4	0	
0		
5	0	
0		
6	0	
0		
7	0	
0		



8	0
0	
9	0
0	
insured_occupation_machine-op-inspct	
service \	
0	0
0	
1	1
0	
2	0
0	
3	0
0	
4	0
0	
5	0
0	
6	0
0	
7	0
0	
8	0
1	
9	0
0	
insured_occupation_priv-house-serv	
specialty \	
0	0
0	
1	0
0	
2	0
0	
3	0
0	
4	0
0	
5	0
0	
6	0
1	
7	0
0	
8	0
0	
9	1

0

	insured_occupation_protective-serv	insured_occupation_sales	\
--	------------------------------------	--------------------------	---

0	0	0
1	0	0
2	0	1
3	0	0
4	0	1
5	0	0
6	0	0
7	0	0
8	0	0
9	0	0

	insured_occupation_tech-support	insured_occupation_transport-moving	\
--	---------------------------------	-------------------------------------	---

0	0
0	
1	0
0	
2	0
0	
3	0
0	
4	0
0	
5	1
0	
6	0
0	
7	1
0	
8	0
0	
9	0
0	

	insured_hobbies_base-jumping	insured_hobbies_basketball	\
--	------------------------------	----------------------------	---

0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	1	0
8	0	0
9	0	0

	insured_hobbies_board-games	insured_hobbies_bungee-jumping	\
--	-----------------------------	--------------------------------	---

0	0	0
1	0	0
2	1	0
3	1	0
4	1	0
5	0	1
6	1	0
7	0	0
8	0	0
9	0	0

	insured_hobbies_camping	insured_hobbies_chess
insured_hobbies_cross-fit \		

0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
0		
5	0	0
0		
6	0	0
0		
7	0	0
0		
8	0	0
0		
9	1	0
0		

	insured_hobbies_dancing	insured_hobbies_exercise
insured_hobbies_golf \		

0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
0		
5	0	0
0		
6	0	0

0		
7	0	0
0		
8	0	0
1		
9	0	0
0		

	insured_hobbies_hiking	insured_hobbies_kayaking
insured_hobbies_movies \		
0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
0		
5	0	0
0		
6	0	0
0		
7	0	0
0		
8	0	0
0		
9	0	0
0		

	insured_hobbies_paintball	insured_hobbies_polo
insured_hobbies_reading \		
0	0	0
0		
1	0	0
1		
2	0	0
0		
3	0	0
0		
4	0	0
0		
5	0	0
0		
6	0	0
0		
7	0	0
0		

8	0	0
0		
9	0	0
0		

	insured_hobbies_skydiving	insured_hobbies_sleeping	\
0	0	1	
1	0	0	
2	0	0	
3	0	0	
4	0	0	
5	0	0	
6	0	0	
7	0	0	
8	0	0	
9	0	0	

	insured_hobbies_video-games	insured_hobbies_yachting	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	
5	0	0	
6	0	0	
7	0	0	
8	0	0	
9	0	0	

	insured_relationship_husband	insured_relationship_not-in-family	\
0	1	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	
5	0	0	
6	1	0	
7	0	0	
8	0	0	
9	0	0	

	insured_relationship_other-relative	insured_relationship_own-child	\
0	0	0	
1	1	0	
2	0	1	
3	0	0	

4	0	0
5	0	0
6	0	0
7	0	0
8	0	1
9	0	0

	insured_relationship_unmarried	insured_relationship_wife \
0	0	0
1	0	0
2	0	0
3	1	0
4	1	0
5	1	0
6	0	0
7	1	0
8	0	0
9	0	1

	incident_type_Multi-vehicle Collision	incident_type_Parked Car \
0	0	0
1	0	0
2	1	0
3	0	0
4	0	0
5	1	0
6	1	0
7	1	0
8	0	0
9	0	0

	incident_type_Single Vehicle Collision	incident_type_Vehicle Theft
\		
0	1	0
1	0	1
2	0	0
3	1	0
4	0	1
5	0	0

6	0	0
7	0	0
8	1	0
9	1	0

	incident_severity_Major Damage	incident_severity_Minor Damage \
0	1	0
1	0	1
2	0	1
3	1	0
4	0	1
5	1	0
6	0	1
7	0	0
8	0	0
9	0	0

	incident_severity_Total Loss	incident_severity_Trivial Damage \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	1	0
8	1	0
9	1	0

	authorities_contacted_Ambulance	authorities_contacted_Fire \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	0	1
6	0	0
7	0	0
8	0	0
9	0	0

	authorities_contacted_None	authorities_contacted_Other \
0	0	0
1	0	0
2	0	0

3	0	0
4	1	0
5	0	0
6	0	0
7	0	0
8	0	0
9	0	1

	authorities_contacted_Police	incident_state_NC	incident_state_NY
\			
0	1	0	0
1	1	0	0
2	1	0	1
3	1	0	0
4	0	0	1
5	0	0	0
6	1	0	1
7	1	0	0
8	1	0	0
9	0	1	0

	incident_state_OH	incident_state_PA	incident_state_SC
incident_state_VA			
0	0	0	1
0			
1	0	0	0
1			
2	0	0	0
0			
3	1	0	0
0			
4	0	0	0
0			
5	0	0	1
0			
6	0	0	0
0			
7	0	0	0
1			
8	0	0	0
0			



9	0	0	0
0			
	incident_state_WV	incident_city_Arlington	incident_city_Columbus
\			
0	0	0	1
1	0	0	0
2	0	0	1
3	0	1	0
4	0	1	0
5	0	1	0
6	0	0	0
7	0	0	1
8	1	1	0
9	0	0	0

	incident_city_Hillsdale	incident_city_Northbend
incident_city_Northbrook	\	
0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
0		
5	0	0
0		
6	0	0
0		
7	0	0
0		
8	0	0
0		
9	1	0
0		

incident\_city\_Riverwood   incident\_city\_Springfield

auto\_make\_Accura \

0	0	0
0		
1	1	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
1		
5	0	0
0		
6	0	1
0		
7	0	0
0		
8	0	0
0		
9	0	0
0		

auto\_make\_Audi auto\_make\_BMW auto\_make\_Chevrolet auto\_make\_Dodge

\				
0	0	0	0	0
1	0	0	0	0
2	0	0	0	1
3	0	0	1	0
4	0	0	0	0
5	0	0	0	0
6	0	0	0	0
7	1	0	0	0
8	0	0	0	0
9	0	0	0	0

auto\_make\_Ford auto\_make\_Honda auto\_make\_Jeep auto\_make\_Mercedes

\				
0	0	0	0	0
1	0	0	0	1

2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
5	0	0	0	0
6	0	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0

	auto_make_Nissan	auto_make_Saab	auto_make_Suburu
auto_make_Toyota \			
0	0	1	0
0			
1	0	0	0
0			
2	0	0	0
0			
3	0	0	0
0			
4	0	0	0
0			
5	0	1	0
0			
6	1	0	0
0			
7	0	0	0
0			
8	0	0	0
1			
9	0	1	0
0			

	auto_make_Volkswagen	auto_model_3 Series	auto_model_92x
auto_model_93 \			
0	0	0	1
0			
1	0	0	0
0			
2	0	0	0
0			
3	0	0	0
0			

4	0	0	0
0			
5	0	0	0
0			
6	0	0	0
0			
7	0	0	0
0			
8	0	0	0
0			
9	0	0	1
0			

	auto_model_95	auto_model_A3	auto_model_A5	auto_model_Accord	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	
5	1	0	0	0	
6	0	0	0	0	
7	0	0	1	0	
8	0	0	0	0	
9	0	0	0	0	

	auto_model_C300	auto_model_CRV	auto_model_Camry	auto_model_Civic	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	
5	0	0	0	0	
6	0	0	0	0	
7	0	0	0	0	
8	0	0	1	0	
9	0	0	0	0	

auto\_model\_Corolla   auto\_model\_E400   auto\_model\_Escape  
 auto\_model\_F150   \

0	0	0	0
0			
1	0	1	0
0			
2	0	0	0
0			
3	0	0	0
0			
4	0	0	0
0			
5	0	0	0
0			
6	0	0	0
0			
7	0	0	0
0			
8	0	0	0
0			
9	0	0	0
0			

	auto_model_Forrestor	auto_model_Fusion	auto_model_Grand Cherokee
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0

	auto_model_Highlander	auto_model_Impreza	auto_model_Jetta	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

5	0	0	0	
6	0	0	0	
7	0	0	0	
8	0	0	0	
9	0	0	0	
	auto_model_Legacy	auto_model_M5	auto_model_MDX	auto_model_ML350
\				
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
5	0	0	0	0
6	0	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0
	auto_model_Malibu	auto_model_Maxima	auto_model_Neon	
auto_model_Passat	\			
0	0	0	0	
0				
1	0	0	0	
0				
2	0	0	0	
0				
3	0	0	0	
0				
4	0	0	0	
0				
5	0	0	0	
0				
6	0	0	0	
0				
7	0	0	0	
0				
8	0	0	0	
0				
9	0	0	0	

0

	auto_model_Pathfinder	auto_model_RAM	auto_model_RSX	\
0	0	0	0	
1	0	0	0	
2	0	1	0	
3	0	0	0	
4	0	0	1	
5	0	0	0	
6	1	0	0	
7	0	0	0	
8	0	0	0	
9	0	0	0	

	auto_model_Silverado	auto_model_TL	auto_model_Tahoe	
auto_model_Ultima	\			
0	0	0	0	
0				
1	0	0	0	
0				
2	0	0	0	
0				
3	0	0	1	
0				
4	0	0	0	
0				
5	0	0	0	
0				
6	0	0	0	
0				
7	0	0	0	
0				
8	0	0	0	
0				
9	0	0	0	
0				

	auto_model_Wrangler	auto_model_X5	auto_model_X6	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
5	0	0	0	
6	0	0	0	
7	0	0	0	
8	0	0	0	
9	0	0	0	

incident\_period\_of\_day\_afternoon

	incident_period_of_day_early_morning \
--	--

0	0
1	
1	0
0	
2	0
0	
3	0
1	
4	0
0	
5	0
0	
6	0
0	
7	0
0	
8	0
0	
9	1
0	

	incident_period_of_day_evening	incident_period_of_day_fore-noon \
--	--------------------------------	------------------------------------

0	0	0
1	0	0
2	0	0
3	0	0
4	1	0
5	1	0
6	0	0
7	0	0
8	0	0
9	0	0

	incident_period_of_day_morning	incident_period_of_day_night \
--	--------------------------------	--------------------------------

0	0	0
1	1	0
2	1	0
3	0	0
4	0	0
5	0	0
6	0	0
7	0	1
8	0	1
9	0	0

	incident_period_of_day_past_midnight	collision_type
--	--------------------------------------	----------------

property_damage \		
0	0	Side Collision
1		



1		0	?
0			
2		0	Rear Collision
0			
3		0	Front Collision
0			
4		0	?
0			
5		0	Rear Collision
0			
6		1	Front Collision
0			
7		0	Front Collision
0			
8		0	Front Collision
0			
9		0	Rear Collision
0			

	police_report_available	collision_en
0	1	3
1	0	0
2	0	2
3	0	1
4	0	0
5	0	2
6	0	1
7	1	1
8	1	1
9	0	2

```
X = X.drop(columns = ['collision_type'])
X.head(2)
```

	policy_state_IL	policy_state_IN	policy_state_OH
policy_csl_100/300 \			
0	0	0	1
0			
1	0	1	0
0			

	policy_csl_250/500	policy_csl_500/1000	insured_sex_FEMALE	\
0	1	0	0	
1	1	0	0	

	insured_sex_MALE	insured_education_level_Associate	\
0	1	0	
1	1	0	

	insured_education_level_College	insured_education_level_High
--	---------------------------------	------------------------------

School \		
0		0
0		
1		0
0		

insured_education_level_JD	insured_education_level_MD \
0	0 1
1	0 1

insured_education_level_Masters	insured_education_level_PhD \
0	0 0
1	0 0

insured_occupation_adm-clerical	insured_occupation_armed-forces \
0	0 0
1	0 0

insured_occupation_craft-repair	insured_occupation_exec-managerial \
0	1 0
1	0 0

insured_occupation_farming-fishing	insured_occupation_handlers-cleaners \
0	0
0	
1	0
0	

insured_occupation_machine-op-inspct	insured_occupation_other-service \
0	0
0	
1	1
0	

insured_occupation_priv-house-serv	insured_occupation_prof-specialty \
0	0
0	
1	0
0	

insured_occupation_protective-serv	insured_occupation_sales \
0	0 0
1	0 0

insured_occupation_tech-support	insured_occupation_transport-
moving \	

0	0
---	---

0
---

1	0
---	---

0
---

insured_hobbies_base-jumping	insured_hobbies_basketball \
------------------------------	------------------------------

0	0	0
---	---	---

1	0	0
---	---	---

insured_hobbies_board-games	insured_hobbies_bungee-jumping \
-----------------------------	----------------------------------

0	0	0
---	---	---

1	0	0
---	---	---

insured_hobbies_camping	insured_hobbies_chess
-------------------------	-----------------------

insured_hobbies_cross-fit \	
-----------------------------	--

0	0	0
---	---	---

0
---

1	0	0
---	---	---

0
---

insured_hobbies_dancing	insured_hobbies_exercise
-------------------------	--------------------------

insured_hobbies_golf \	
------------------------	--

0	0	0
---	---	---

0
---

1	0	0
---	---	---

0
---

insured_hobbies_hiking	insured_hobbies_kayaking
------------------------	--------------------------

insured_hobbies_movies \	
--------------------------	--

0	0	0
---	---	---

0
---

1	0	0
---	---	---

0
---

insured_hobbies_paintball	insured_hobbies_polo
---------------------------	----------------------

insured_hobbies_reading \	
---------------------------	--

0	0	0
---	---	---

0
---

1	0	0
---	---	---

1
---

insured_hobbies_skydiving	insured_hobbies_sleeping \
---------------------------	----------------------------

0	0	1
---	---	---

1	0	0
---	---	---

insured_hobbies_video-games	insured_hobbies_yachting \
-----------------------------	----------------------------

0	0	0
---	---	---

1	0	0
---	---	---

	insured_relationship_husband	insured_relationship_not-in-family	\
0	1	0	
1	0	0	

	insured_relationship_other-relative	insured_relationship_own-child	
\			
0	0	0	
1	1	0	

	insured_relationship_unmarried	insured_relationship_wife	\
0	0	0	
1	0	0	

	incident_type_Multi-vehicle Collision	incident_type_Parked Car	\
0	0	0	
1	0	0	

	incident_type_Single Vehicle Collision	incident_type_Vehicle Theft	
\			
0	1	0	
1	0	1	

	incident_severity_Major Damage	incident_severity_Minor Damage	\
0	1	0	
1	0	1	

	incident_severity_Total Loss	incident_severity_Trivial Damage	\
0	0	0	
1	0	0	

	authorities_contacted_Ambulance	authorities_contacted_Fire	\
0	0	0	
1	0	0	

	authorities_contacted_None	authorities_contacted_Other	\
0	0	0	
1	0	0	

	authorities_contacted_Police	incident_state_NC	incident_state_NY	
\				
0	1	0	0	
1	1	0	0	

	incident_state_OH	incident_state_PA	incident_state_SC	
--	-------------------	-------------------	-------------------	--

incident_state_VA	\			
0	0	0	1	
0				
1	0	0	0	
1				

incident_state_WV	incident_city_Arlington	incident_city_Columbus	
\			
0	0	0	1
1	0	0	0

incident_city_Hillsdale	incident_city_Northbend	
incident_city_Northbrook	\	
0	0	0
0		
1	0	0
0		

incident_city_Riverwood	incident_city_Springfield	
auto_make_Accura	\	
0	0	0
0		
1	1	0
0		

auto_make_Audi	auto_make_BMW	auto_make_Chevrolet	auto_make_Dodge
\			
0	0	0	0
1	0	0	0

auto_make_Ford	auto_make_Honda	auto_make_Jeep	auto_make_Mercedes
\			
0	0	0	0
1	0	0	1

auto_make_Nissan	auto_make_Saab	auto_make_Suburu
auto_make_Toyota	\	
0	0	1
0		0
1	0	0
0		0

auto_make_Volkswagen	auto_model_3 Series	auto_model_92x
auto_model_93	\	

0	0	0	1
0			
1	0	0	0
0			

	auto_model_95	auto_model_A3	auto_model_A5	auto_model_Accord	\
0	0	0	0	0	
1	0	0	0	0	

	auto_model_C300	auto_model_CRV	auto_model_Camry	auto_model_Civic	\
0	0	0	0	0	
1	0	0	0	0	

	auto_model_Corolla	auto_model_E400	auto_model_Escape
auto_model_F150	\		
0	0	0	0
0			
1	0	1	0
0			

	auto_model_Forester	auto_model_Fusion	auto_model_Grand Cherokee
\			
0	0	0	0
1	0	0	0

	auto_model_Highlander	auto_model_Impreza	auto_model_Jetta	\
0	0	0	0	
1	0	0	0	

	auto_model_Legacy	auto_model_M5	auto_model_MDX	auto_model_ML350
\				
0	0	0	0	0
1	0	0	0	0

	auto_model_Malibu	auto_model_Maxima	auto_model_Neon
auto_model_Passat	\		
0	0	0	0
0			
1	0	0	0
0			

	auto_model_Pathfinder	auto_model_RAM	auto_model_RSX	\
0	0	0	0	
1	0	0	0	

	auto_model_Silverado	auto_model_TL	auto_model_Tahoe
auto_model_Ultima \			
0	0	0	0
0			
1	0	0	0
0			

	auto_model_Wrangler	auto_model_X5	auto_model_X6 \
0	0	0	0
1	0	0	0

	incident_period_of_day_afternoon
incident_period_of_day_early_morning \	
0	0
1	
1	0
0	

	incident_period_of_day_evening	incident_period_of_day_fore-noon \
0	0	0
1	0	0

	incident_period_of_day_morning	incident_period_of_day_night \
0	0	0
1	1	0

	incident_period_of_day_past_midnight	property_damage \
0	0	1
1	0	0

	police_report_available	collision_en
0	1	3
1	0	0

```
X = pd.concat([X, df._get_numeric_data()], axis=1) # joining numeric
columns
X.head(2)
```

	policy_state_IL	policy_state_IN	policy_state_OH
policy_csl_100/300 \			
0	0	0	1
0			
1	0	1	0
0			

	policy_csl_250/500	policy_csl_500/1000	insured_sex_FEMALE \
0	1	0	0
1	1	0	0

	insured_sex_MALE	insured_education_level_Associate \
--	------------------	-------------------------------------

0	1	0
1	1	0

insured_education_level_College School \	insured_education_level_High
0	0
0	
1	0
0	

insured_education_level_JD	insured_education_level_MD \
0	0 1
1	0 1

insured_education_level_Masters	insured_education_level_PhD \
0	0 0
1	0 0

insured_occupation_adm-clerical	insured_occupation_armed-forces \
0	0 0
1	0 0

insured_occupation_craft-repair	insured_occupation_exec-managerial
\	
0	1 0
1	0 0

insured_occupation_farming-fishing	insured_occupation_handlers- cleaners \
0	0
0	
1	0
0	

insured_occupation_machine-op-inspct	insured_occupation_other- service \
0	0
0	
1	1
0	

insured_occupation_priv-house-serv	insured_occupation_prof- specialty \
0	0
0	
1	0
0	



	insured_occupation_protective-serv	insured_occupation_sales	\
0	0	0	
1	0	0	

	insured_occupation_tech-support	insured_occupation_transport-moving	\
0	0		
0			
1	0		
0			

	insured_hobbies_base-jumping	insured_hobbies_basketball	\
0	0	0	
1	0	0	

	insured_hobbies_board-games	insured_hobbies_bungee-jumping	\
0	0	0	
1	0	0	

	insured_hobbies_camping	insured_hobbies_chess
	insured_hobbies_cross-fit	\
0	0	0
0		
1	0	0
0		

	insured_hobbies_dancing	insured_hobbies_exercise
	insured_hobbies_golf	\
0	0	0
0		
1	0	0
0		

	insured_hobbies_hiking	insured_hobbies_kayaking
	insured_hobbies_movies	\
0	0	0
0		
1	0	0
0		

	insured_hobbies_paintball	insured_hobbies_polo
	insured_hobbies_reading	\
0	0	0
0		
1	0	0
1		

	insured_hobbies_skydiving	insured_hobbies_sleeping	\
0	0	1	
1	0	0	

	insured_hobbies_video-games	insured_hobbies_yachting	\
0	0	0	
1	0	0	

	insured_relationship_husband	insured_relationship_not-in-family	\
0	1	0	
1	0	0	

	insured_relationship_other-relative	insured_relationship_own-child	
\			
0	0	0	
1	1	0	

	insured_relationship_unmarried	insured_relationship_wife	\
0	0	0	
1	0	0	

	incident_type_Multi-vehicle Collision	incident_type_Parked Car	\
0	0	0	
1	0	0	

	incident_type_Single Vehicle Collision	incident_type_Vehicle Theft	
\			
0	1	0	
1	0	1	

	incident_severity_Major Damage	incident_severity_Minor Damage	\
0	1	0	
1	0	1	

	incident_severity_Total Loss	incident_severity_Trivial Damage	\
0	0	0	
1	0	0	

	authorities_contacted_Ambulance	authorities_contacted_Fire	\
0	0	0	
1	0	0	

	authorities_contacted_None	authorities_contacted_Other	\
0	0	0	
1	0	0	

	authorities_contacted_Police	incident_state_NC	incident_state_NY	
\				
0	1	0	0	

1		1		0		0
---	--	---	--	---	--	---

	incident_state_OH		incident_state_PA		incident_state_SC	
incident_state_VA	\					
0	0		0		1	
0						
1	0		0		0	
1						

	incident_state_WV		incident_city_Arlington		incident_city_Columbus	
\						
0	0		0		1	
1	0		0		0	

	incident_city_Hillsdale		incident_city_Northbend	
incident_city_Northbrook	\			
0	0		0	
0				
1	0		0	
0				

	incident_city_Riverwood		incident_city_Springfield	
auto_make_Accura	\			
0	0		0	
0				
1	1		0	
0				

	auto_make_Audi		auto_make_BMW		auto_make_Chevrolet		auto_make_Dodge
\							
0	0		0		0		0
1	0		0		0		0

	auto_make_Ford		auto_make_Honda		auto_make_Jeep		auto_make_Mercedes
\							
0	0		0		0		0
1	0		0		0		1

	auto_make_Nissan		auto_make_Saab		auto_make_Suburu
auto_make_Toyota	\				
0	0		1		0
0					
1	0		0		0
0					

auto_make_Volkswagen	auto_model_3 Series	auto_model_92x
auto_model_93 \		
0	0	1
0		
1	0	0
0		

auto_model_95	auto_model_A3	auto_model_A5	auto_model_Accord \
0	0	0	0
1	0	0	0

auto_model_C300	auto_model_CRV	auto_model_Camry	auto_model_Civic
\			
0	0	0	0
1	0	0	0

auto_model_Corolla	auto_model_E400	auto_model_Escape
auto_model_F150 \		
0	0	0
0		
1	0	1
0		0

auto_model_Forester	auto_model_Fusion	auto_model_Grand Cherokee
\		
0	0	0
1	0	0

auto_model_Highlander	auto_model_Impreza	auto_model_Jetta \
0	0	0
1	0	0

auto_model_Legacy	auto_model_M5	auto_model_MDX	auto_model_ML350
\			
0	0	0	0
1	0	0	0

auto_model_Malibu	auto_model_Maxima	auto_model_Neon
auto_model_Passat \		
0	0	0
0		
1	0	0
0		

	auto_model_Pathfinder	auto_model_RAM	auto_model_RSX	\
0	0	0	0	
1	0	0	0	

	auto_model_Silverado	auto_model_TL	auto_model_Tahoe	
auto_model_Ultima	\			
0	0	0	0	
0				
1	0	0	0	
0				

	auto_model_Wrangler	auto_model_X5	auto_model_X6	\
0	0	0	0	
1	0	0	0	

	incident_period_of_day_afternoon	
incident_period_of_day_early_morning	\	
0	0	
1		
1	0	
0		

	incident_period_of_day_evening	incident_period_of_day_fore-noon	\
0	0	0	
1	0	0	

	incident_period_of_day_morning	incident_period_of_day_night	\
0	0	0	
1	1	0	

	incident_period_of_day_past_midnight	property_damage	\
0	0	1	
1	0	0	

	police_report_available	collision_en	months_as_customer	age	\
0	1	3	328	48	
1	0	0	228	42	

	policy_deductable	policy_annual_premium	umbrella_limit	capital-
gains	\			
0	1000	1406.91	0	
53300				
1	2000	1197.22	5000000	
0				

	capital-loss	number_of_vehicles_involved	bodily_injuries	
witnesses	\			
0	0	1	1	
2				
1	0	1	0	

```

0
  total_claim_amount  injury_claim  property_claim  vehicle_claim \
0                71610           6510           13020           52080
1                5070            780            780            3510

  fraud_reported  vehicle_age
0                1           14
1                1           11
X.columns
Index(['policy_state_IL', 'policy_state_IN', 'policy_state_OH',
      'policy_csl_100/300', 'policy_csl_250/500',
      'policy_csl_500/1000',
      'insured_sex_FEMALE', 'insured_sex_MALE',
      'insured_education_level_Associate',
      'insured_education_level_College',
      ...,
      'capital-loss', 'number_of_vehicles_involved',
      'bodily_injuries',
      'witnesses', 'total_claim_amount', 'injury_claim',
      'property_claim',
      'vehicle_claim', 'fraud_reported', 'vehicle_age'],
      dtype='object', length=161)

X = X.drop(columns = ['fraud_reported'])
X.columns
Index(['policy_state_IL', 'policy_state_IN', 'policy_state_OH',
      'policy_csl_100/300', 'policy_csl_250/500',
      'policy_csl_500/1000',
      'insured_sex_FEMALE', 'insured_sex_MALE',
      'insured_education_level_Associate',
      'insured_education_level_College',
      ...,
      'capital-gains', 'capital-loss', 'number_of_vehicles_involved',
      'bodily_injuries', 'witnesses', 'total_claim_amount',
      'injury_claim',
      'property_claim', 'vehicle_claim', 'vehicle_age'],
      dtype='object', length=160)

```

We now have a dataset that we could use to evaluate an algorithm sensitive to missing values like LDA.

```

from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score

# evaluate an LDA model on the dataset using k-fold cross validation
model = LinearDiscriminantAnalysis()

```

```
kfold = KFold(n_splits=5, random_state=7)
result = cross_val_score(model, X, y, cv=kfold, scoring='accuracy')
print(result.mean())
```

```
C:\Users\Sarit\Anaconda3\envs\python\lib\site-packages\sklearn\
discriminant_analysis.py:388: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
C:\Users\Sarit\Anaconda3\envs\python\lib\site-packages\sklearn\
discriminant_analysis.py:388: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
C:\Users\Sarit\Anaconda3\envs\python\lib\site-packages\sklearn\
discriminant_analysis.py:388: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
C:\Users\Sarit\Anaconda3\envs\python\lib\site-packages\sklearn\
discriminant_analysis.py:388: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
```

0.841

```
C:\Users\Sarit\Anaconda3\envs\python\lib\site-packages\sklearn\
discriminant_analysis.py:388: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
```

84.1% accuracy without standardizing the data. This looks good to go for Random Forest Classification method. Random Forest is a tree-based model and hence does not require feature scaling. The convergence and numerical precision issues, which can sometimes trip up the algorithms used in logistic and linear regression, as well as neural networks, aren't so important in case of random forest.

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
train_size=0.8, random_state=1234)
print('length of X_train and X_test: ', len(X_train), len(X_test))
print('length of y_train and y_test: ', len(y_train), len(y_test))
```

```
length of X_train and X_test: 800 200
length of y_train and y_test: 800 200
```

## Random Forest Classification

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, recall_score,
classification_report, cohen_kappa_score
from sklearn import metrics

# Baseline Random forest based Model
rfc = RandomForestClassifier(criterion = 'gini', n_estimators=1000,
verbose=1, n_jobs = -1,
                           class_weight = 'balanced', max_features =
'auto')
rfcg = rfc.fit(X_train,y_train) # fit on training data
predictions = rfcg.predict(X_test)
```

```

print('Baseline: N_features: ', len(list(X.columns)))
print('Baseline: Accuracy: ', round(accuracy_score(y_test,
predictions)*100, 2))
print('Cohen Kappa: ' + str(np.round(cohen_kappa_score(y_test,
predictions),3)))
print('Baseline: Recall: ', round(recall_score(y_test,
predictions)*100, 2))
print('\n Classification Report:\n',
classification_report(y_test,predictions))

```

```

[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 8
concurrent workers.

```

```

[Parallel(n_jobs=-1)]: Done 34 tasks      | elapsed:    0.0s
[Parallel(n_jobs=-1)]: Done 184 tasks    | elapsed:    0.2s
[Parallel(n_jobs=-1)]: Done 434 tasks    | elapsed:    0.5s
[Parallel(n_jobs=-1)]: Done 784 tasks    | elapsed:    1.0s
[Parallel(n_jobs=-1)]: Done 1000 out of 1000 | elapsed:    1.3s
finished

```

```

[Parallel(n_jobs=8)]: Using backend ThreadingBackend with 8 concurrent
workers.

```

```

[Parallel(n_jobs=8)]: Done 34 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 184 tasks    | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 434 tasks    | elapsed:    0.0s

```

```

Baseline: N_features: 160
Baseline: Accuracy: 72.5
Cohen Kappa: 0.201
Baseline: Recall: 21.31

```

```

Classification Report:

```

	precision	recall	f1-score	support
0	0.73	0.95	0.83	139
1	0.65	0.21	0.32	61
accuracy			0.73	200
macro avg	0.69	0.58	0.57	200
weighted avg	0.71	0.72	0.67	200

```

[Parallel(n_jobs=8)]: Done 784 tasks      | elapsed:    0.1s
[Parallel(n_jobs=8)]: Done 1000 out of 1000 | elapsed:    0.2s
finished

```

```

rfcg

```

```

RandomForestClassifier(bootstrap=True, class_weight='balanced',
                        criterion='gini', max_depth=None,
max_features='auto',
                        max_leaf_nodes=None, min_impurity_decrease=0.0,

```



```

        min_impurity_split=None, min_samples_leaf=1,
        min_samples_split=2,
min_weight_fraction_leaf=0.0,
        n_estimators=1000, n_jobs=-1, oob_score=False,
        random_state=None, verbose=1, warm_start=False)

from sklearn.metrics import confusion_matrix

import itertools

#Evaluation of Model - Confusion Matrix Plot
def plot_confusion_matrix(cm, classes, title = 'Confusion matrix',
normalize=False, cmap = plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    print('Confusion matrix')

    print(cm)

    fig = plt.figure(figsize=(10,6))
    plt.style.use('fivethirtyeight')
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]),
range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()

# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, predictions)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Fraud

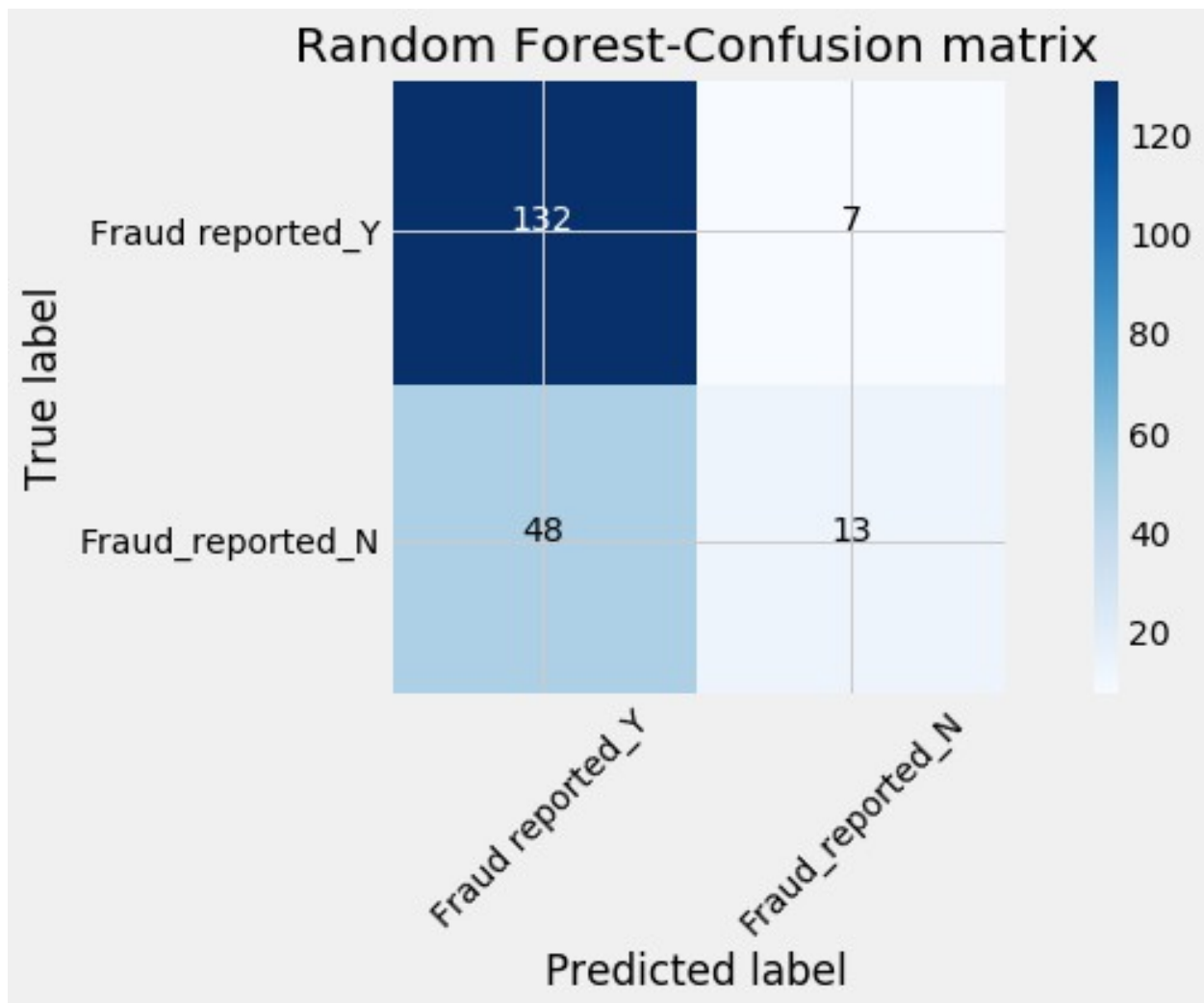
```

```
reported_Y', 'Fraud_reported_N'],
      title='Random Forest-Confusion matrix')
```

Confusion matrix

```
[[132  7]
 [ 48 13]]
```

<Figure size 432x288 with 0 Axes>



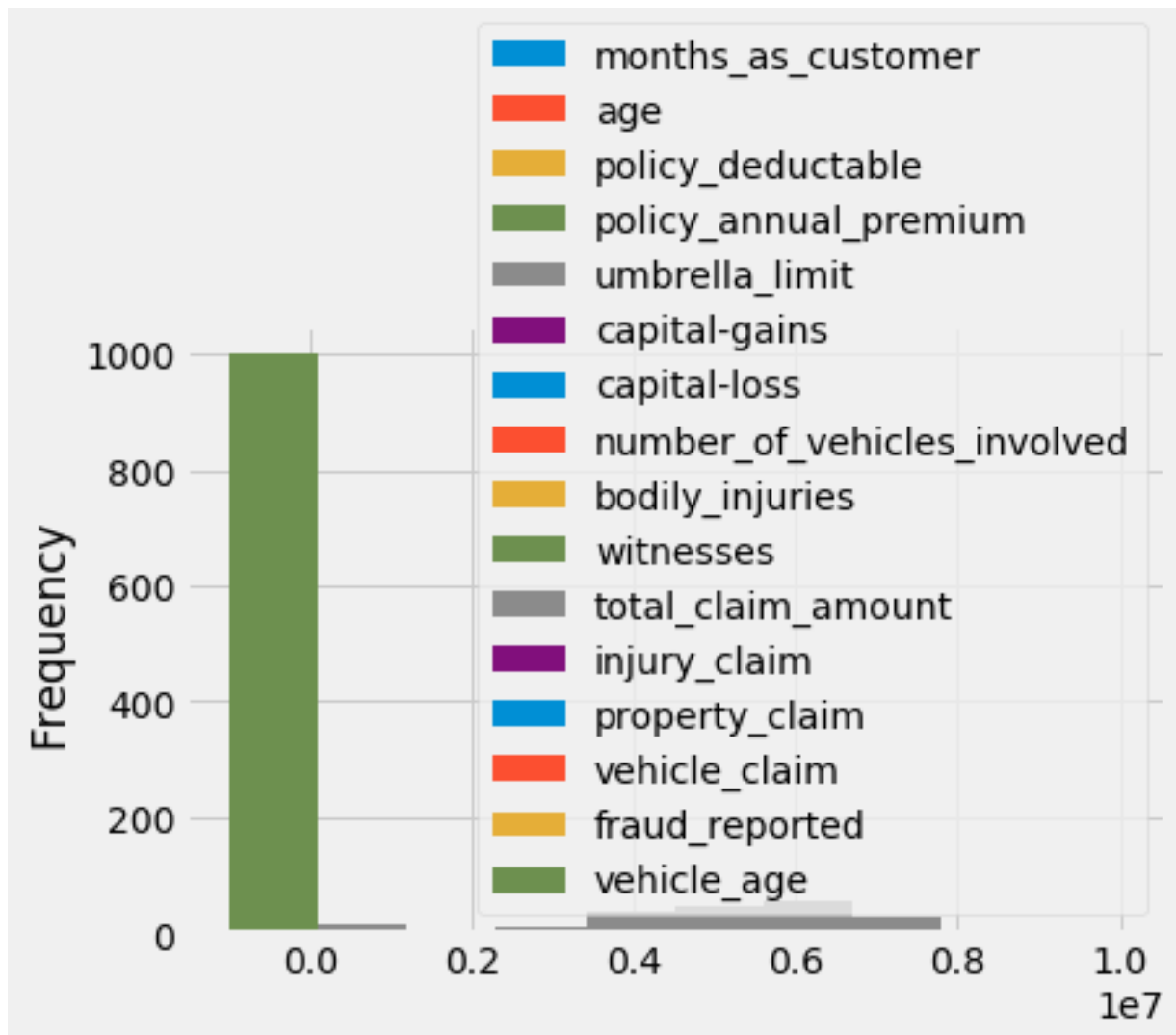
With 72.5% accuracy, we take a closer look at the confusion matrix:

- 132 transactions were classified as valid that were actually valid
- 7 transactions were classified as fraud that were actually valid (type 1 error)
- 48 transactions were classified as valid that were fraud (type 2 error)
- 13 transactions were classified as fraud.

$$\text{Err} = ((\text{FP} + \text{FN}) / (\text{TP} + \text{TN} + \text{FN} + \text{FP})) = \{(48 + 7) / (132 + 7 + 48 + 13)\} * 100 = 0.275$$

So, the algorithm misclassified 27.5% fraudulent transactions. We looked at other measures too like the Cohen Kappa, Recall, and F1 score. In each case, the scores are closer to 1.

```
# Generate a Histogram plot for anomaly detection
df.plot(kind='hist')
plt.show()
```



```
# Minimum and maximum premium
print('Minimum premium ' + str(df['policy_annual_premium'].min()))
print('Maximum premium ' + str(df['policy_annual_premium'].max()))
```

```
Minimum premium 433.33
Maximum premium 2047.59
```

```
# Minimum and maximum age of vehicle
print('Vehicle age-minimum ' + str(df['vehicle_age'].min()))
print('Vehicle Age-maximum ' + str(df['vehicle_age'].max()))
```

```
Vehicle age-minimum 3
Vehicle Age-maximum 23
```

```

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler(with_mean=False)
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

```

The 10-fold cross validation procedure is used to evaluate each algorithm, importantly configured with the same random seed to ensure that the same splits to the training data are performed and that each algorithms is evaluated in precisely the same way.

```

from xgboost import XGBClassifier
from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LogisticRegressionCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.ensemble import AdaBoostClassifier

xgb = XGBClassifier()
logreg2= LogisticRegressionCV(solver='lbfgs', cv=10)
knn = KNeighborsClassifier(5)
svcl = SVC()
adb = AdaBoostClassifier()
dtclf = DecisionTreeClassifier(max_depth=5)
rfclf = RandomForestClassifier()

# prepare configuration for cross validation test harness
seed = 7
# prepare models
models = []
models.append(('LR', LogisticRegressionCV(solver='lbfgs',
max_iter=5000, cv=10)))
models.append(('XGB', XGBClassifier()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('DT', DecisionTreeClassifier()))
models.append(('SVM', SVC(gamma='auto')))
models.append(('RF', RandomForestClassifier(n_estimators=100)))
models.append(('ADA', AdaBoostClassifier(n_estimators=100)))

# evaluate each model in turn
results = []
names = []
scoring = 'accuracy'
for name, model in models:
    kfold = model_selection.KFold(n_splits=10, random_state=seed)
    cv_results = model_selection.cross_val_score(model,
X_train_scaled, y_train, cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())

```

```
print(msg)
```

```
# boxplot algorithm comparison
```

```
fig = plt.figure()
```

```
fig.suptitle('Algorithm Comparison')
```

```
ax = fig.add_subplot(111)
```

```
plt.boxplot(results)
```

```
ax.set_xticklabels(names)
```

```
plt.show()
```

```
LR: 0.812500 (0.034460)
```

```
XGB: 0.807500 (0.023184)
```

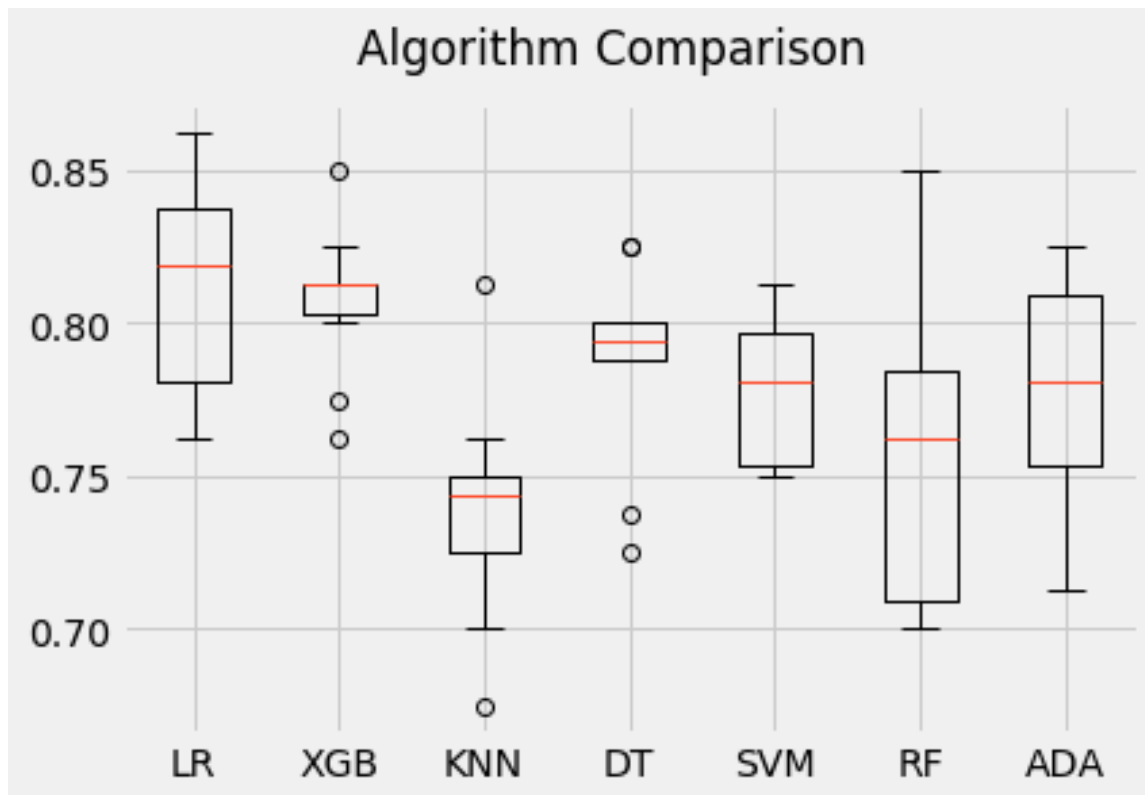
```
KNN: 0.738750 (0.035111)
```

```
DT: 0.787500 (0.031125)
```

```
SVM: 0.777500 (0.022220)
```

```
RF: 0.756250 (0.045843)
```

```
ADA: 0.778750 (0.034483)
```



Above a list of each algorithm, the mean accuracy and the standard deviation accuracy and a box & whisker plot showing the spread of the accuracy scores across each cross validation fold for each algorithm.

It is clear that the LR or LDA is good enough for both feature selection (81% and 84% accuracy with 100 features) as well as model selection.

I will analyse both both logistic regression and linear discriminate analysis further on this problem.

