CLAIM AMOUNT PREDICTIONS FOR JOHNSON INSURANCE PLC

1. Problem Statement

- Building a predictive model that can provide the total amount of claim by a customer in seconds

2. Hypothesis Generation

a. Policy Deductable: The monthly contributions on the policy might have the effect on the total amount of the claim by the customer

b. Incident Hour oF The Day: Some insurance covers regulates the times which are covered by the insurance, this might be one of the affector determing the amount to beclaims

c. Number of Vehicles involved: The third party claims will result in higher amounts to be paid to the client, if there is no a third party the amount will be less.

e. Property Damage: The type of property involved will result in higher claims.

f. Policy Annual Premium: The overall contributions by the client might determine how much they client will claim per incident

g. Umbrella Limit: Claim limits can determine the number of times that a client can claim with a direct influence on the total claim amount

h. incident_type : The type of the incident will determine the saverity and the amounts of damages, which will have an impact on whether the total claim is less or high.

i. collision_type: Losses will play the same role as capital gains, with direct impact to the amount paid to clients

j. Months as Customer: - Loyal customers who have spent many years with the company and contributed more towards their insurance covers could be the ones who's claims are processed quicker

k. Incident Severity: The severity of the incident will determine the level of damages which will directly determine the costs and the total claim amount

j. Authorities Contacted: Customers who file claims without reporting their incidents to obtain the incident report and case number will determine whether claims will be paid or not.

k. Witnesses: Claims that have witnesses can strengthen the filed claim they also guarantee that the claim will be paid and the total amount paid wont have any penalties.

l. Auto Make: The make of the vehicle will influence the total amount of the claim to be paid to the client.

m. Auto Model: The model of the car will also determine the amount of claim

n. Auto Year: The age of the car will affect the amount to be paid to the client, cars that are still 1 to few years old will result in higher claim amounts

o. Police Report Available: Claims that do not have the police report might end up not be paid which will result in zero amount being paid, or the amount paid could be higher or accurate without penalties if there is a report

3. Loading Packages and Data

In [2626]:

```
#importing modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline


import warnings #to ignore warnings
warnings.filterwarnings('ignore');
```

DATA

It consists of the training dataset and testing dataset

Training Data: Will be used to train and test the model accuracy
Testing Data: will be used for submission

In [2627]:

```
#creating dataframes
load_train = pd.read_csv('train.csv', na_values=["?"]) #na_values will replace "?" with
NaN
load_test = pd.read_csv('test.csv', na_values=["?"])
load_submission = pd.read_csv('sample_submission.csv')

#making copies to protect the original data
train_original = load_train.copy()
test_original = load_test.copy()
submission_originial = load_submission.copy()

train = load_train
test = load_test
sumbission = load_submission
```

4. Understandng the Data

- We check the structure of the train and test data.
- Look at the features present in the datasets

In [2628]:

```
#print first five rows and columns
train.head()
```

Out[2628]:

	Customer_ID	months_as_customer	age	insured_sex	insured_education_level	insured_o
0	Customer_541	239	41	FEMALE	JD	farm
1	Customer_440	108	31	MALE	Masters	prote
2	Customer_482	116	30	MALE	JD	handler
3	Customer_422	8	21	MALE	High School	handler
4	Customer_778	161	38	MALE	PhD	priv-h

5 rows × 37 columns

In [2629]:

```
#shapes of the data
f'train: {train.shape}, test: {test.shape}'
```

Out[2629]:

```
'train: (700, 37), test: (300, 36)'
```

The training data contains 700 observations and the test contains 300 observations

In [2630]:

```
#features of training set
train.columns, len(train.columns)
```

Out[2630]:

```
(Index(['Customer_ID', 'months_as_customer', 'age', 'insured_sex',
        'insured_education_level', 'insured_occupation', 'insured_hobbie
s',
        'insured_relationship', 'capital-gains', 'capital-loss',
        'policy_number', 'policy_bind_date', 'policy_state', 'policy_csl',
        'policy_deductable', 'incident_location', 'incident_hour_of_the_da
y',
        'number_of_vehicles_involved', 'property_damage', 'bodily_injurie
s',
        'policy_annual_premium', 'umbrella_limit', 'insured_zip',
        'incident_date', 'incident_type', 'collision_type', 'incident_seve
rity',
        'authorities_contacted', 'incident_state', 'incident_city', 'witne
sses',
        'police_report_available', 'auto_make', 'auto_model', 'auto_year',
        '_c39', 'total_claim_amount'],
       dtype='object'), 37)
```

In [2631]:

```
#print the data types
train.dtypes
```

Out[2631]:

```
Customer_ID                    object
months_as_customer              int64
age                             int64
insured_sex                    object
insured_education_level        object
insured_occupation             object
insured_hobbies                object
insured_relationship           object
capital-gains                   int64
capital-loss                    int64
policy_number                   int64
policy_bind_date               object
policy_state                   object
policy_csl                     object
policy_deductable               int64
incident_location              object
incident_hour_of_the_day        int64
number_of_vehicles_involved     int64
property_damage                object
bodily_injuries                 int64
policy_annual_premium         float64
umbrella_limit                  int64
insured_zip                     int64
incident_date                  object
incident_type                  object
collision_type                 object
incident_severity              object
authorities_contacted          object
incident_state                 object
incident_city                  object
witnesses                       int64
police_report_available        object
auto_make                      object
auto_model                     object
auto_year                       int64
_c39                          float64
total_claim_amount            float64
dtype: object
```

In [2632]:

```
train.total_claim_amount
```

Out[2632]:

```
0       14386.67000
1       76440.00000
2       79560.00000
3      121680.00000
4       80640.00000
           ...
695    106400.00000
696    113733.33000
697     78466.67000
698     97866.67000
699     38400.00000
Name: total_claim_amount, Length: 700, dtype: float64
```

The data consists of the following types

Independent Categorical Data
7-Objects:

- Customer_ID, insured_sex, insured_education_level, insured_occupation, insured_hobbies, insured_relationship
- policy_bind_date, policy_state, incident_location, property_damage, incident_date, incident_type, auto_model, policy_csl
- collision_type, incident_severity, authorities_contacted, incident_state, incident_city, police_report_available, auto_make

Indepentent Numerical Data

Nominal Data

- number_of_vehicles_involved
- bodily_injuries

13-Int64:

- months_as_customer, age, capital-gains, capital-loss, policy_number, policy_deductable, incident_hour_of_the_day
- policy_annual_premium, umbrella_limit, insured_zip, witnesses, auto_year

3-Float

- _c39
- policy_annual_premium

Dependent/Target Variable
1- float

- total_claim_amount (target variable)

Target Variable

- total_claim_amount (target variable)

5. Exploratory Data Analysis

5.1 Univariables Analysis

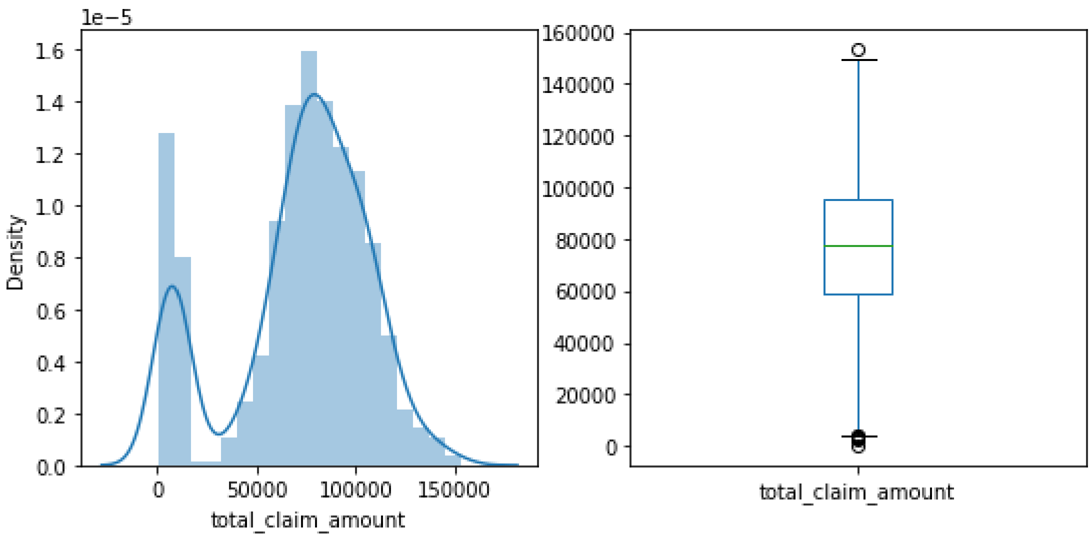
We look at the analysis of each variable:

- Categorical: Frequency table, Percentage distribution and Bar-plot
- Numerical: Probability density plot

- **Target Variable: total_claim_amount**

In [2633]:

```
#density distribution of total_claim_amount
plt.figure(1)

plt.subplot(121)
sns.distplot(train.total_claim_amount); #density distribution

plt.subplot(122)
train.total_claim_amount.plot.box(figsize = (9, 4))
plt.show()
```

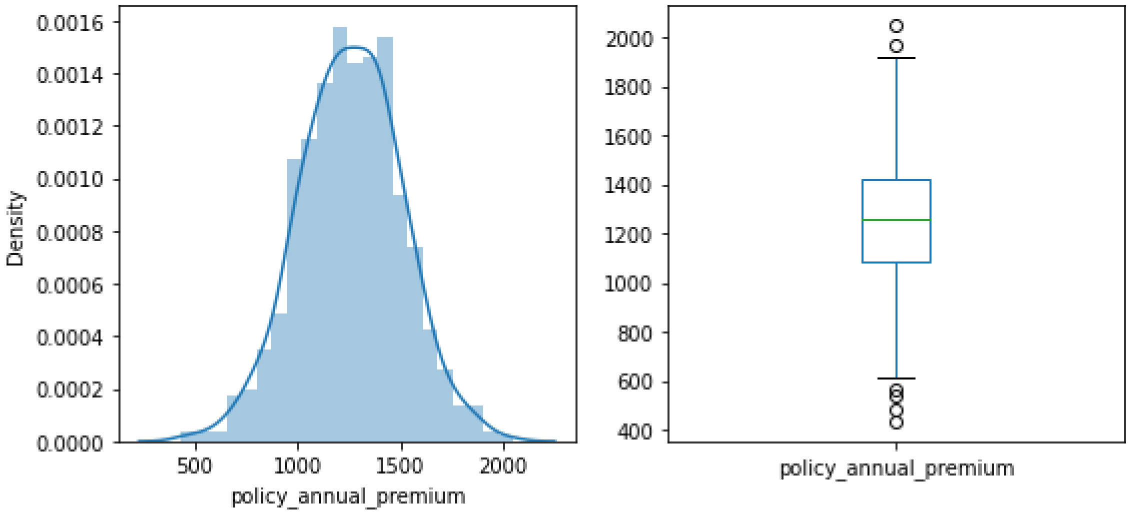


- The train.total_claim_amount does not have any extreme values, the distribution is normal, majority of the claims where paid between 50k to 150k.

- **policy_annual_premium**

In [2634]:

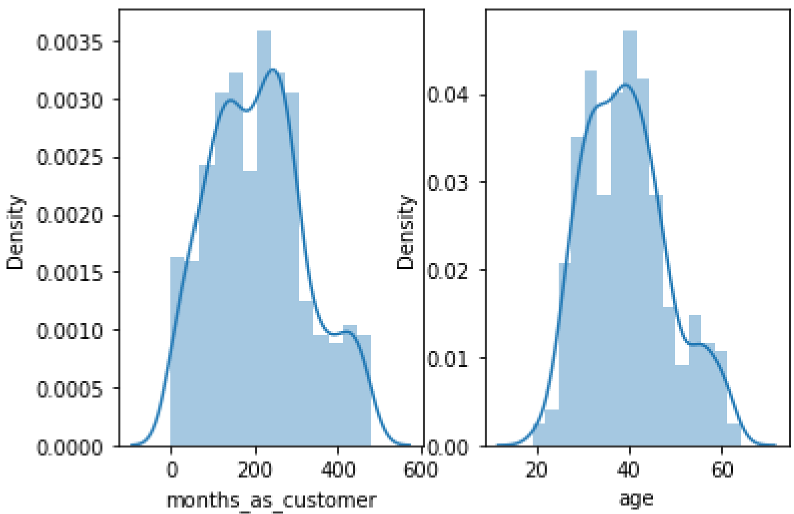
```
# distribution of policy_annual_premium
plt.figure(1)
plt.subplot(121)
sns.distplot(train.policy_annual_premium)
plt.subplot(122)
train.policy_annual_premium.plot.box(figsize = (9, 4))
plt.show()
```



- **months_as_customer and age**

In [2635]:

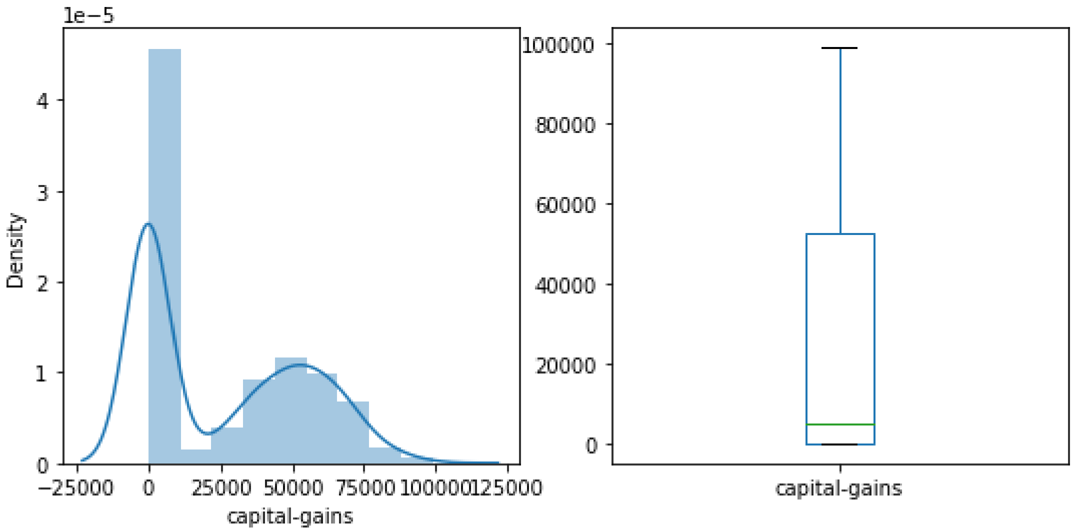
```
# distribution of months_as_customer
plt.figure(1)
plt.subplot(121)
sns.distplot(train.months_as_customer)
plt.subplot(122)
sns.distplot(train.age)
plt.show()
```



- **capital-gains**

In [2636]:

```
plt.figure(1)
plt.subplot(121)
sns.distplot(train['capital-gains'])
plt.subplot(122)
train['capital-gains'].plot.box(figsize = (9, 4))
plt.show()
```



In [2637]:

```
train['capital-gains'].head()
```

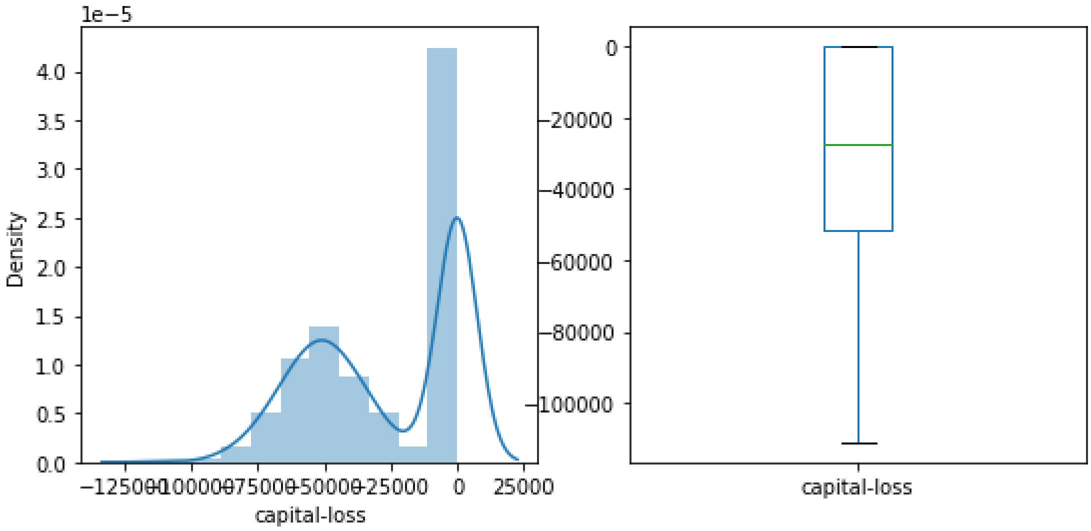
Out[2637]:

```
0    51400
1        0
2        0
3        0
4    60200
Name: capital-gains, dtype: int64
```

- **capital-loss**

In [2638]:

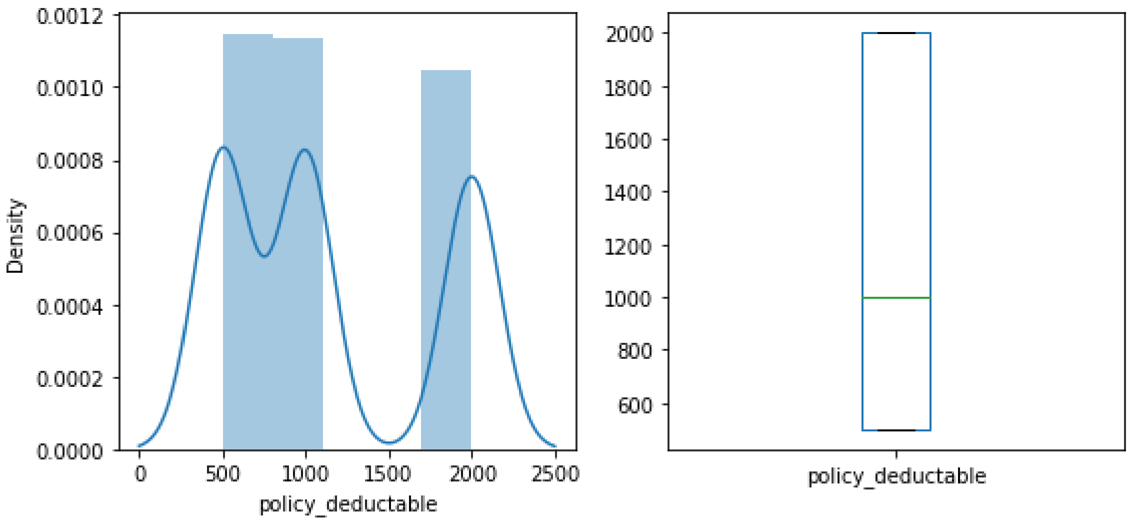
```
plt.figure(1)
plt.subplot(121)
sns.distplot(train['capital-loss'])
plt.subplot(122)
train['capital-loss'].plot.box(figsize = (9, 4))
plt.show()
```

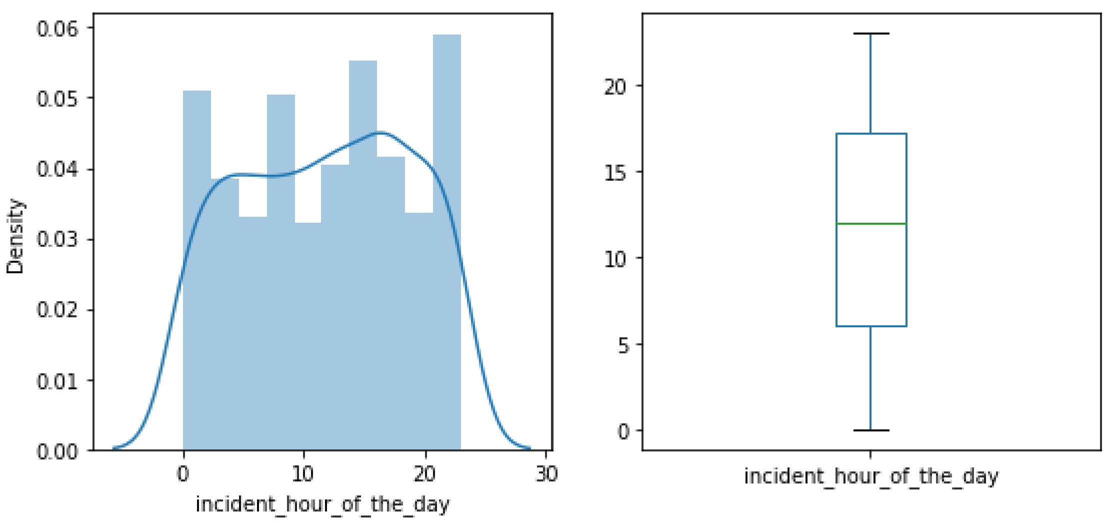


- **policy_deductable and incident_hour_of_the_day**

In [2639]:

```
plt.figure(1)
plt.subplot(121)
sns.distplot(train['policy_deductable'])
plt.subplot(122)
train['policy_deductable'].plot.box(figsize = (9, 4))
plt.show()

plt.figure(2)
plt.subplot(121)
sns.distplot(train.incident_hour_of_the_day)
plt.subplot(122)
train['incident_hour_of_the_day'].plot.box(figsize = (9, 4))
plt.show()
```

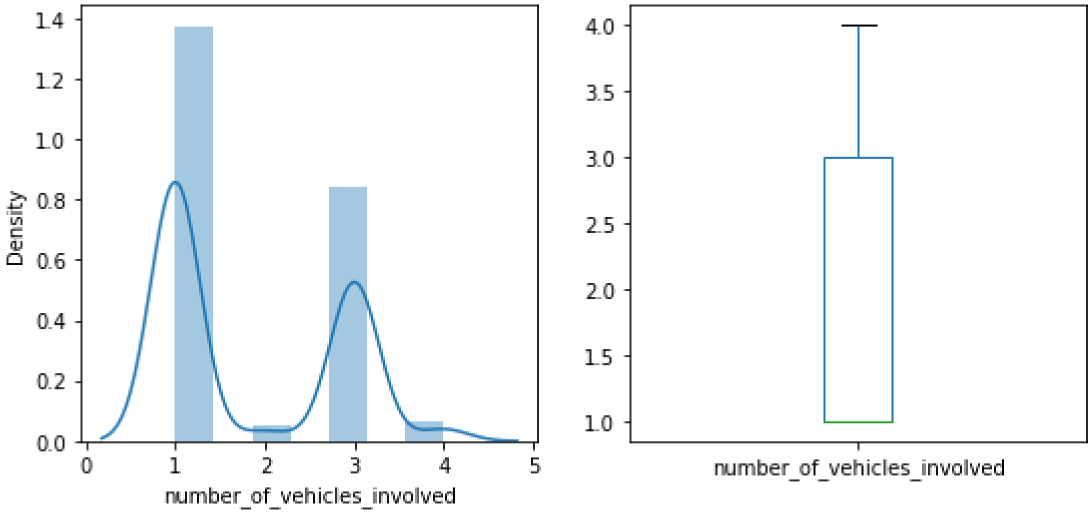




- **number_of_vehicles_involved**

In [2640]:

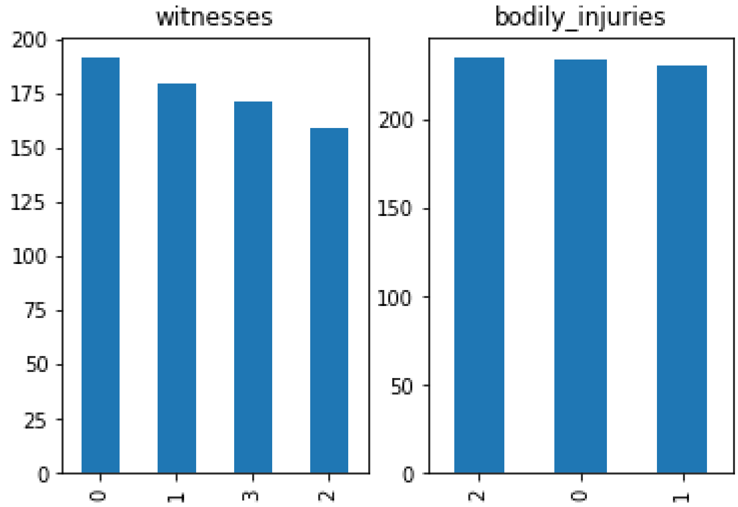
```
plt.figure(2)
plt.subplot(121)
sns.distplot(train.number_of_vehicles_involved)
plt.subplot(122)
train['number_of_vehicles_involved'].plot.box(figsize = (9, 4))
plt.show()
```

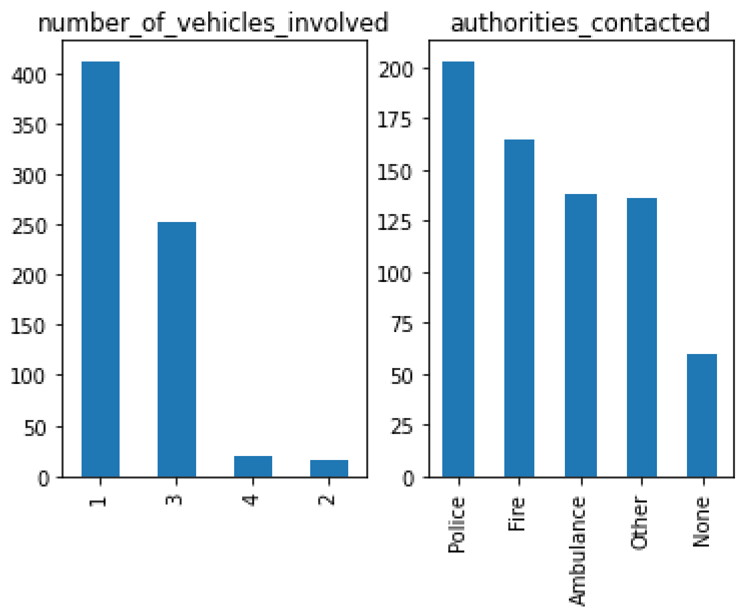


- **bodily_injuries**
- **number_of_vehicles_involved, witnesses**
- **authorities_contacted**

In [2641]:

```
#bar plot
plt.figure(1)
plt.subplot(121)
train['witnesses'].value_counts().plot.bar(title = 'witnesses');
plt.subplot(122)
#bar plot
train.bodily_injuries.value_counts().plot.bar(title = 'bodily_injuries')
plt.figure(2)
plt.subplot(121)
train.number_of_vehicles_involved.value_counts().plot.bar(title = 'number_of_vehicles_i
nvolved')
plt.subplot(122)
train.authorities_contacted.value_counts().plot.bar(title = 'authorities_contacted')
plt.show()
```

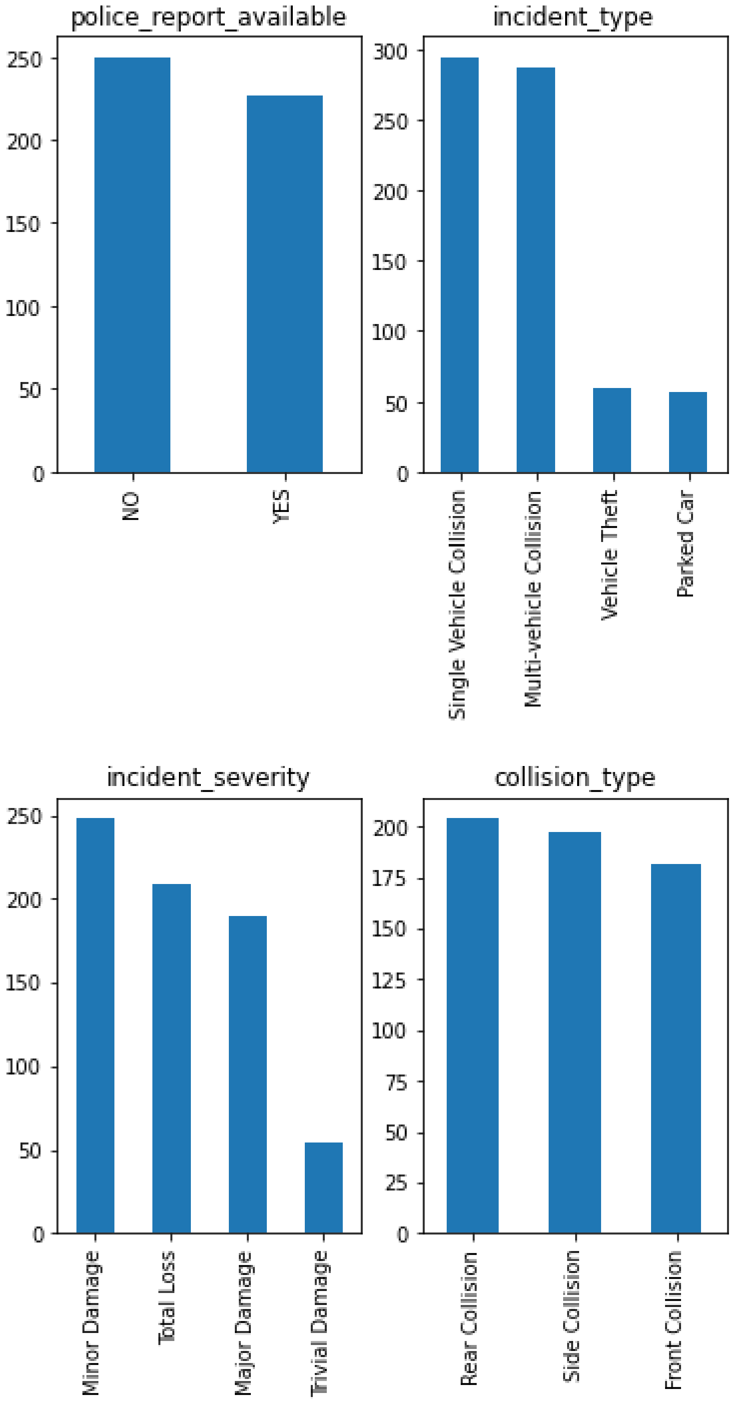




- **police_report_available**
- **police_report_available**
- **incident_severity**
- **collision_type**

In [2642]:

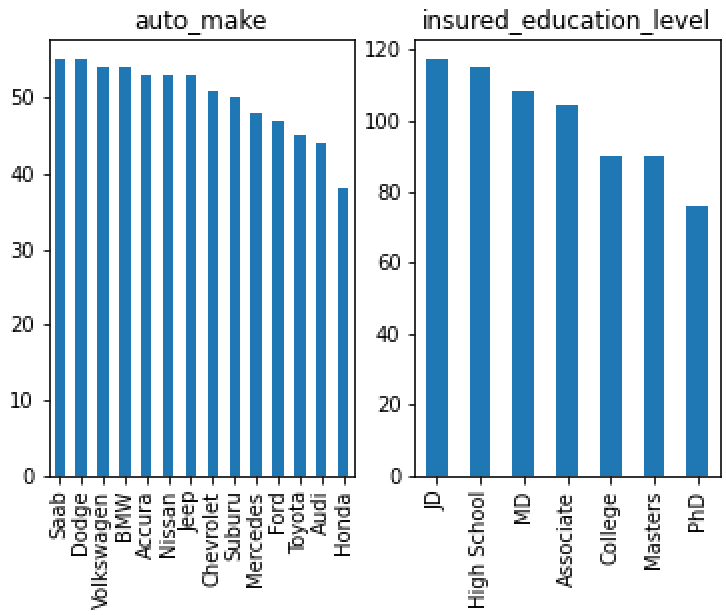
```
#bar plot
plt.figure(1)
plt.subplot(121)
train['police_report_available'].value_counts().plot.bar(title = 'police_report_availab
le');
plt.subplot(122)
#bar plot
train.incident_type.value_counts().plot.bar(title = 'incident_type')

plt.figure(2)
plt.subplot(121)
train['incident_severity'].value_counts().plot.bar(title = 'incident_severity');
plt.subplot(122)
#bar plot
train.collision_type.value_counts().plot.bar(title = 'collision_type')
plt.show()
```

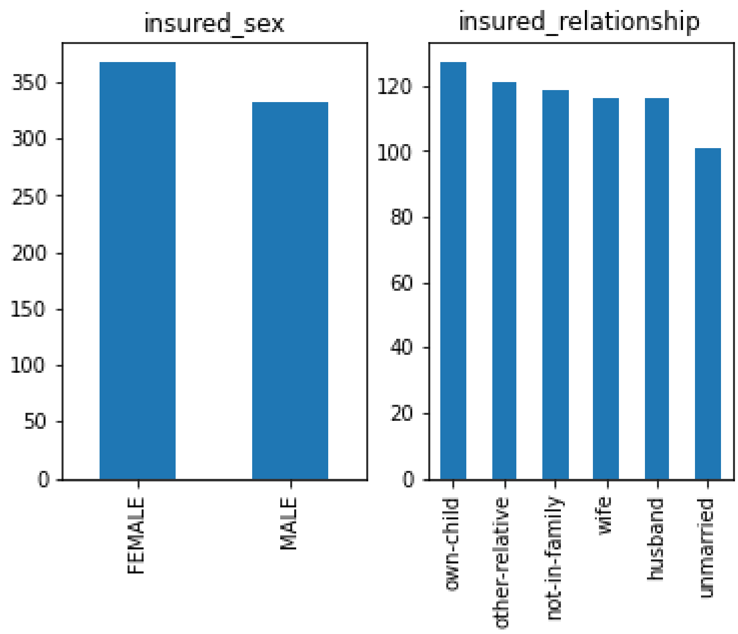


- **auto_make**
- **insured_sex**
- **insured_relationship**
- **insured_education_level**

In [2643]:

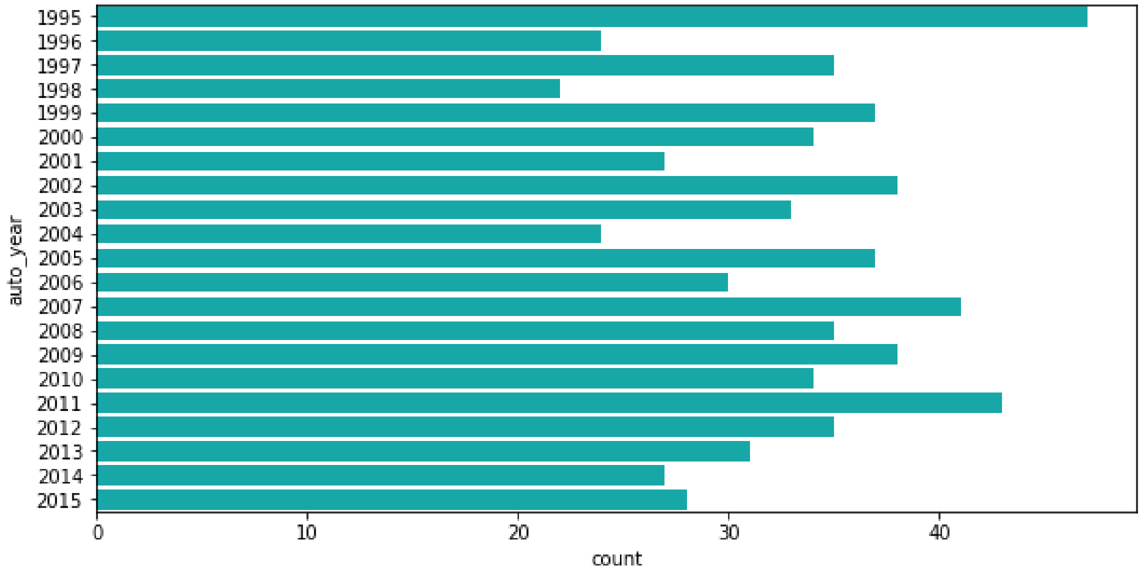
```
#bar plot
plt.figure(1)
plt.subplot(121)
#bar plot
train['auto_make'].value_counts().plot.bar(title = 'auto_make')
plt.subplot(122)
train['insured_education_level'].value_counts().plot.bar(title = 'insured_education_lev
el')
plt.show()

plt.figure(2)
plt.subplot(121)
train.insured_sex.value_counts().plot.bar(title = 'insured_sex')
plt.subplot(122)
train.insured_relationship.value_counts().plot.bar(title = 'insured_relationship')

plt.show()
```





In [2644]:

```
#visualize auto year
f, ax = plt.subplots(figsize=(10, 5))
sns.countplot(y="auto_year", data=train, color="c");
```



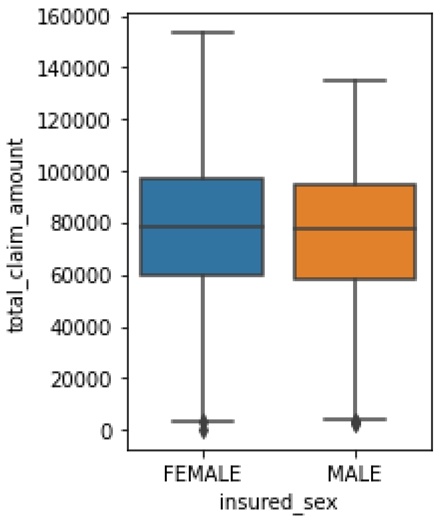
5.2 Bivariable Analysis

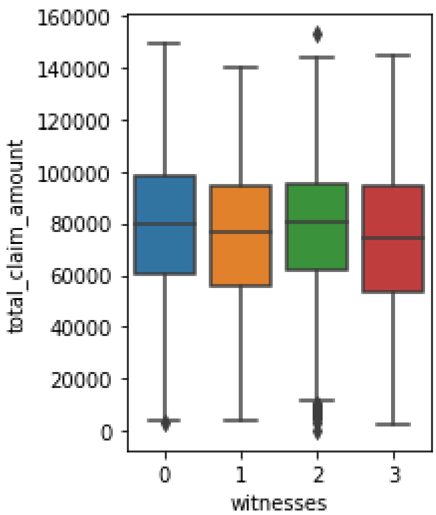
Analysis will be based on Independent variables and target variable to see the relationship between them

- **Insured Sex vs Total Claim Amount**

In [2645]:

```
plt.figure(1)
plt.subplot(121)
sns.boxplot(x = 'insured_sex', y = 'total_claim_amount', data = train)
plt.show()

plt.figure(2)
plt.subplot(121)
sns.boxplot(x = 'witnesses', y = 'total_claim_amount', data = train);
plt.show()
```

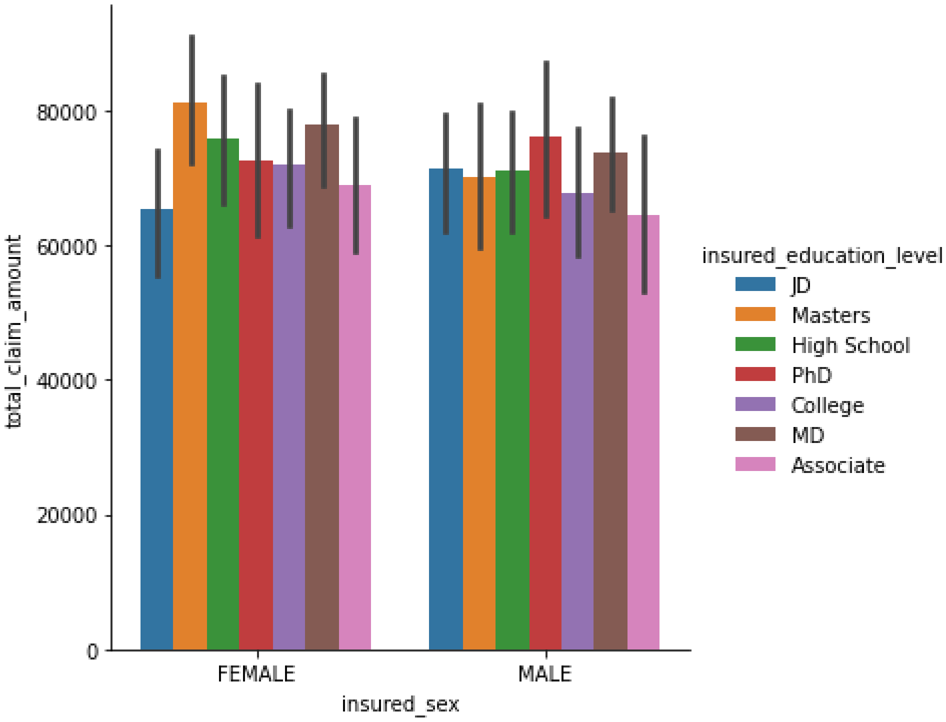




- **visualize insured_sex**
- **total_claim_amount**
- **insured_education_level**

In [2646]:

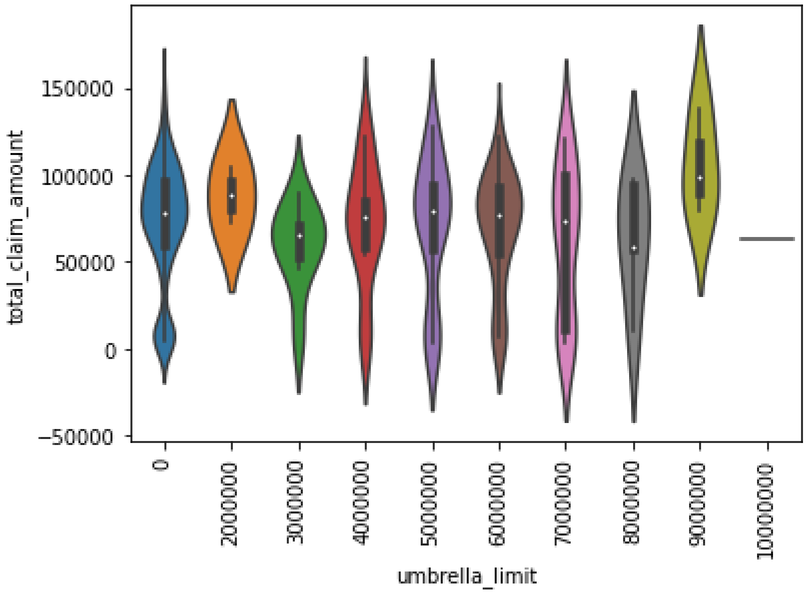
```
#visualize insured_sex
#total_claim_amount
#insured_education_level
sns.catplot(x="insured_sex", y="total_claim_amount", hue="insured_education_level", kin
d="bar", data=train);
```



- **umbrella_limit**
- **total_claim_amount**

In [2647]:

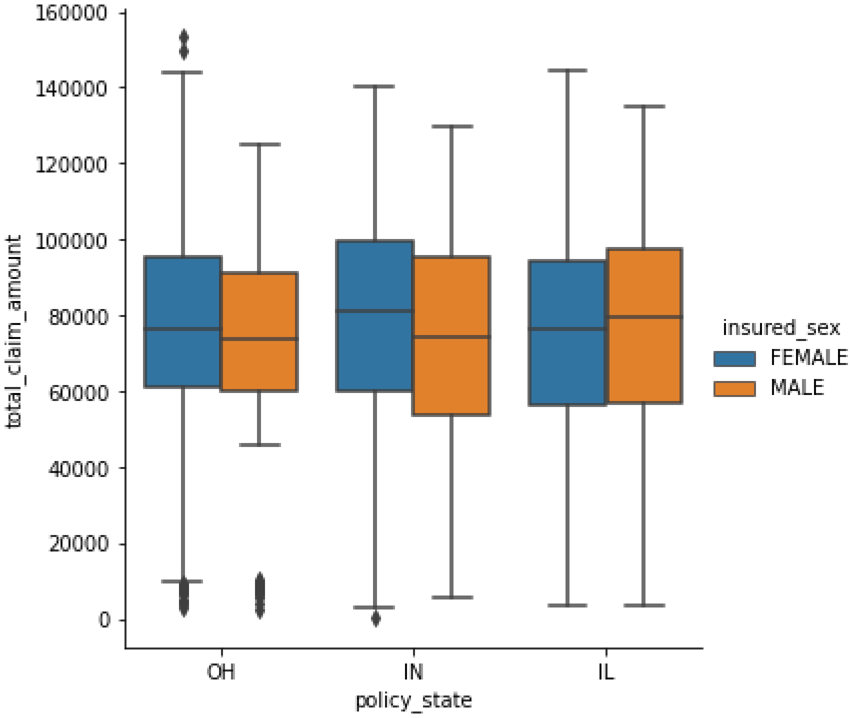
```
#Using violin to plot the item types as well
plt.xticks(rotation = 90)
sns.violinplot(x = train.umbrella_limit, y= train.total_claim_amount);
```



- **incident_type**
- **age**
- **policy_state**

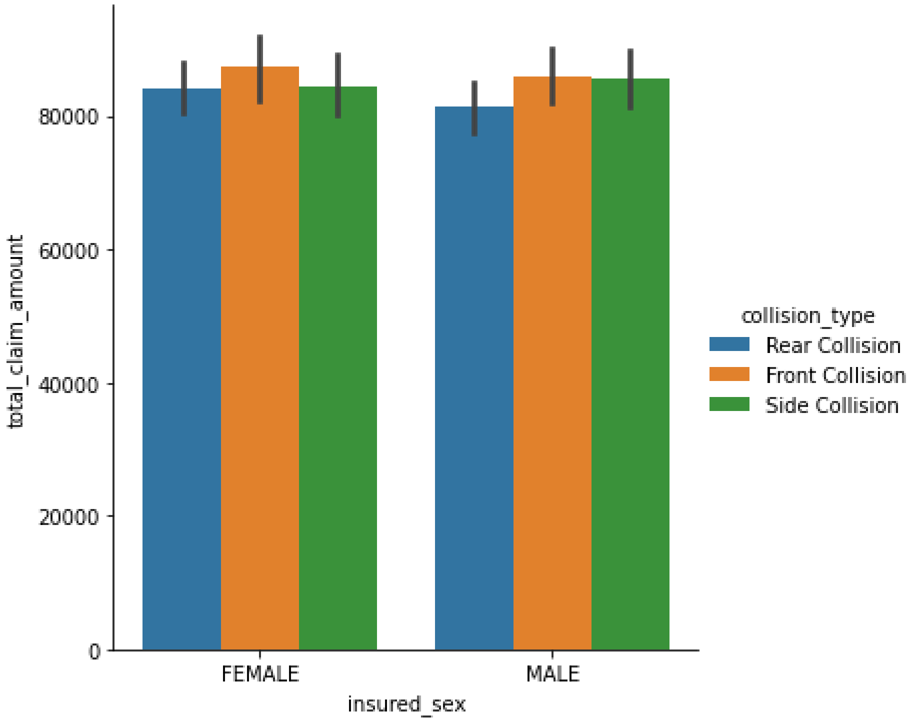
In [2648]:

```
#visuallize with Item_Type and Outlet_Size
sns.catplot(x="policy_state", y="total_claim_amount", hue="insured_sex",  kind="box", d
ata= train);
```

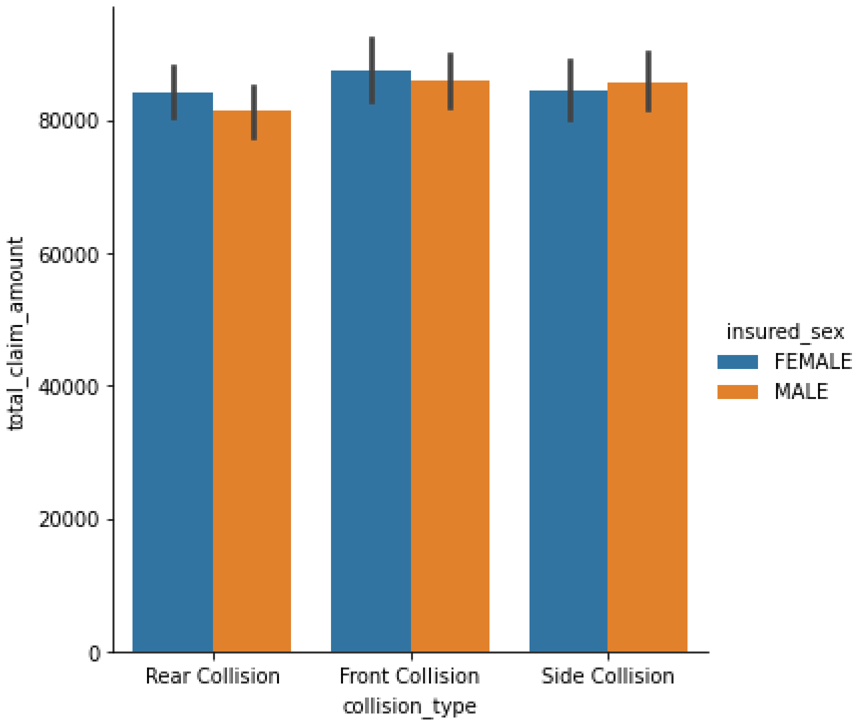


In [2649]:

```
#collision type, total_claim_amount, gender
sns.catplot(x="insured_sex", y="total_claim_amount", hue="collision_type", kind="bar",
data=train);
sns.catplot(x="collision_type", y="total_claim_amount", hue="insured_sex", kind="bar",
data=train);
```



0
20000
40000
60000
80000
total_claim_amount
FEMALE
MALE
insured_sex
collision_type
Rear Collision
Front Collision
Side Collision



0
20000
40000
60000
80000
total_claim_amount
Rear Collision
Front Collision
Side Collision
collision_type
insured_sex
FEMALE
MALE

6. Hanlding Missing Values and Outliers

In [2650]:

```
#sorting missing values columns and filtering 0 missing value cols
missing_value_cols = train.isnull().sum()
missing_value_cols = missing_value_cols[missing_value_cols != 0]
missing_value_cols.sort_values(ascending = False)
```

Out[2650]:

```
_c39                      700
property_damage           255
police_report_available   224
collision_type            117
dtype: int64
```

In [2651]:

```
def clean_data(df):
    #Replace missing values with the mode for categorical and or mean/median for numeri
cal
    #train dataset
    df['property_damage'].fillna(df['property_damage'].mode()[0], inplace = True)
    df['police_report_available'].fillna(df['police_report_available'].mode()[0], inpla
ce = True)
    df['collision_type'].fillna(df['collision_type'].mode()[0], inplace = True)

    #drop the _c39 column since it consists of nan only
    df = df.drop(['_c39'], axis = 'columns')

    return df
```

In [2652]:

```
#clean the datasets
train = clean_data(train)
test = clean_data(test)
```

In [2653]:

```
#sorting missing values columns and filtering 0 missing value cols
missing_value_cols = train.isnull().sum()
missing_value_cols = missing_value_cols[missing_value_cols != 0]
missing_value_cols.sort_values(ascending = False)
```

Out[2653]:

```
Series([], dtype: int64)
```

In [2654]:

```
#property damage
train.property_damage.value_counts()
```

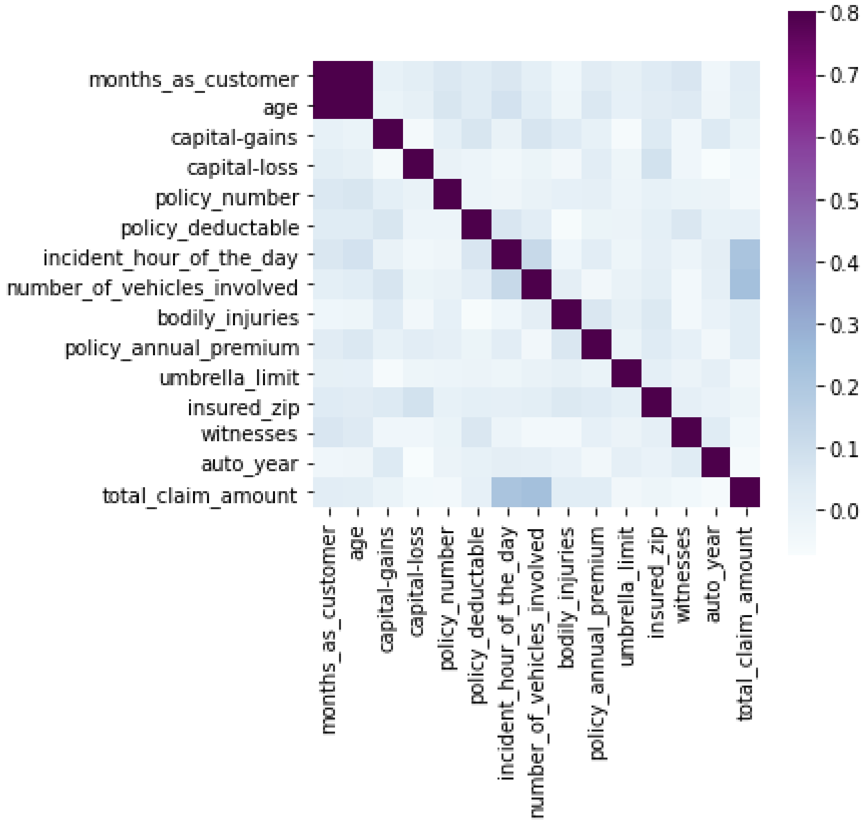
Out[2654]:

```
NO     479
YES    221
Name: property_damage, dtype: int64
```

Correlations on Data

In [2655]:

```
#view Correlations
matrix = train.corr()
f, ax = plt.subplots(figsize = (5, 5))
sns.heatmap(matrix, vmax = 0.8, square = True, cmap = 'BuPu');
```

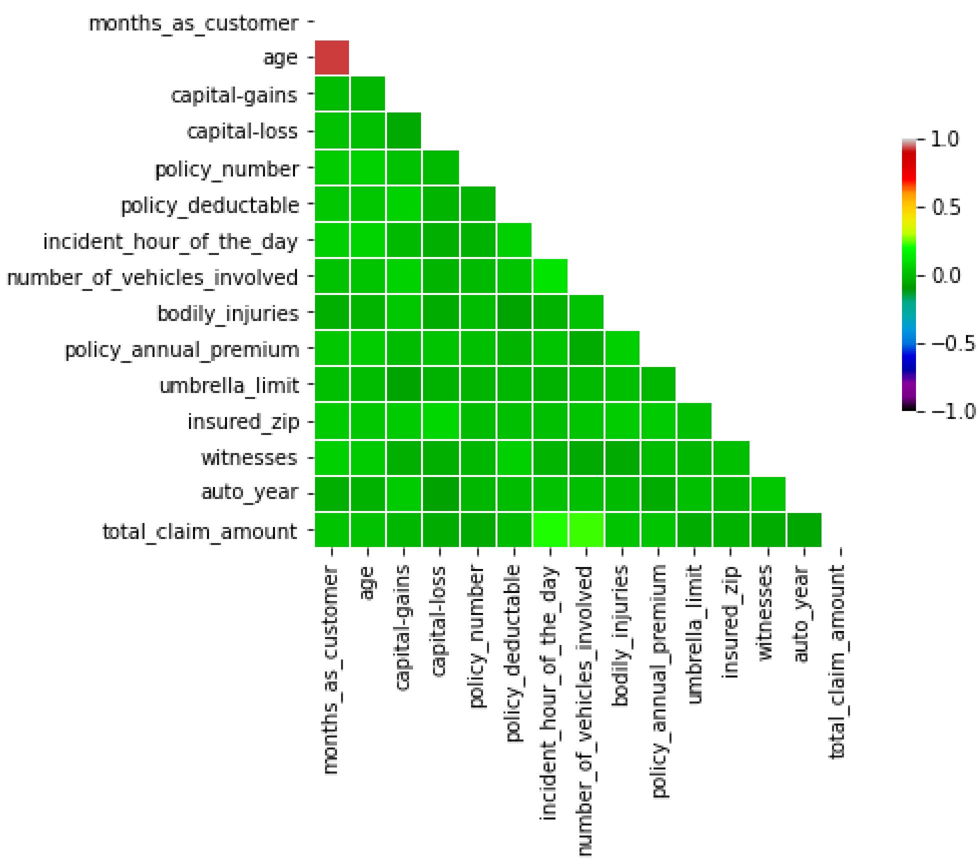


In [2656]:

```
#Compute the correlation matrix
corr = train.corr()
# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=bool))
# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(8, 5))
# Generate a custom diverging colormap
cmap = 'nipy_spectral'
# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax= 1, vmin = -1, center=0,square=True, linew
idths=.5, cbar_kws={"shrink": .5})
```

Out[2656]:

```
<AxesSubplot:>
```



In [2657]:

```
#creates shorth cut for training purposes
train_ = train.copy()
test_ = test.copy()
```

In [2713]:

```
#copy copies for training purposes
train = train_
test = test_
```

In [2714]:

```
#verify if deleted Customer ID is reinstated
assert 'Customer_ID' in train.columns
```

7. Pre-Processing Data

7.1 One Hot Encoding

In [2715]:

```
def one_hot_encoding(df):
    #import the library
    from sklearn.preprocessing import LabelEncoder
    le = LabelEncoder()
    #set targets
    columns_to_fit = [ 'insured_sex', 'insured_occupation', 'insured_relationship',
                      'policy_state', 'property_damage',  'witnesses', 'police_report_a
vailable',
                      'incident_state', 'auto_model', 'auto_make','authorities_contacte
d', 'months_as_customer',
                      'insured_hobbies', 'incident_city', 'witnesses', 'insured_educati
on_level' ]
    #removed
    #movded 'collision_type', 'collision_type'
    #loop df and apply encoding
    for col in df.columns:
        if col in columns_to_fit:
            df[col] = le.fit_transform(df[col])
    return df
```

In [2716]:

```
train.authorities_contacted.unique()
```

Out[2716]:

```
array([4, 1, 3, 0, 2])
```

In [2717]:

```
#apply one hot encoding
train = one_hot_encoding(train)
test = one_hot_encoding(test)
```

In [2718]:

```
f'Education_Level: {train.insured_education_level[0]}'
```

Out[2718]:

```
'Education_Level: 3'
```

7.2 Feature Engineering

In [2719]:

```
def auto_age(df):

    #calculate the years of the auto_year or car
    from datetime import datetime
    current_date_time = datetime.now()
    #replace the YYYY date with number of years
    df['auto_age'] = (current_date_time.year - df['auto_year'])
    #add the years_as_customer
    df['years_as_customer'] = df.months_as_customer//12
    #add the months_out_of_12_as_customer
    df['no_months_as_customer'] = df.months_as_customer%12

    return df
```

In [2720]:

```
#apply feature engineering on the datasets
train = auto_age(train)
test = auto_age(test)
```

In [2721]:

```
#verify processing: years and months of customer 1
f'ID: {train.Customer_ID[0]}, Years: {train.years_as_customer[0]}, Months: {train.no_mo
nths_as_customer[0]}'
```

Out[2721]:

```
'ID: Customer_541, Years: 16, Months: 7'
```

In [2722]:

```
def preprocessing_datasets(df):
    #add policy period by the time of the incident
    #use copy df to create it and add to the original df
    dftr = df.copy()
    dftr['incident_date'] = pd.to_datetime(dftr['incident_date'])
    dftr['policy_bind_date'] = pd.to_datetime(dftr['policy_bind_date'])
    df['policy_period'] = (dftr.incident_date - dftr.policy_bind_date)
    #Convert days in policy_period from dtype timedelta to int64
    df['policy_period'] = df['policy_period'].dt.days
     #convert string float fractions in policy_csl into floats
    df_ = df.copy()
    df_[["numerator", "denominator"]] = df_["policy_csl"].str.split("/", expand=True)
    df["policy_csl_float"] = df_["numerator"].astype(float) / df_["denominator"].astype
(float)

    return df
```

In [2723]:

```
#convtert the dates
train = preprocessing_datasets(train)
test = preprocessing_datasets(test)
```

In [2724]:

```
#confirm processing: policy_period is the number of days of the policy when the acciden
t took place
f'ID: {train.Customer_ID[0]}, Policy period: {test.policy_period[0]} days , Policy CLS:
{train.policy_csl_float[0]}'
```

Out[2724]:

```
'ID: Customer_541, Policy period: 182 days , Policy CLS: 0.5'
```

7.3 Drop unwanted columns

In [2725]:

```
#appply function to delete columns
def drop_columns(df):

    #set targets
    columns_to_filter = [ 'Customer_ID','policy_csl','incident_location', 'policy_numbe
r', 'policy_bind_date', 'incident_city', 'incident_state', 'incident_date', 'months_as_
customer',
                        'auto_year', 'policy_period', 'insured_zip']


    #loop df and delete columns
    for col in df.columns:
        if col in  columns_to_filter:
            df = df.drop(col, axis = 1)

    return df
```

In [2726]:

```
#drop unwanted columns
train = drop_columns(train)
test = drop_columns(test)
```

In [2727]:

```
#verify dropped columns
assert 'Customer_ID' not in train.columns
```

In [2728]:

```
#copy data
df_train = train.copy()
df_test = test.copy()
```

8. Building The Model

In [2729]:

```
#drop target variable: total_claim_amount and assign it to y
X = train.drop('total_claim_amount', axis = 1)
y = train.total_claim_amount
```

In [2730]:

```
#Creating Dummies
X = pd.get_dummies(X)
train = pd.get_dummies(train)
test = pd.get_dummies(test)
```

In [2731]:

```
#split the data into train and test
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state =
42)
```

In [2732]:

```
#import the libraries
#import lib and mod
from math import sqrt
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import GridSearchCV

#instantiate the model
model = LinearRegression()
#set parameters
parameters = {'fit_intercept':[True,False], 'normalize':[True,False], 'copy_X':[True, F
alse]}
grid = GridSearchCV(model,parameters, cv=None)

#fit/train the model
grid.fit(X_train, y_train);
```

In [2734]:

```
#predict the X_test
y_pred_1 = grid.predict(X_test)
rmse = sqrt(mean_squared_error(y_test, y_pred_1))
print(f'Grid Model RMSE:{rmse}')
```

```
Grid Model RMSE:20878.17626758436
```

Model 2

In [2736]:

```
from sklearn.ensemble import GradientBoostingRegressor #For Regression
#Instantiate the model
regress_2 = GradientBoostingRegressor(n_estimators=100, learning_rate=1.0, max_depth=1)
#fit the model
regress_2.fit(X_train, y_train);
```

In [2737]:

```
#prediction with GB
y_pred_2 = regress_2.predict(X_test)

#root mean square error and mean squeare error of both models
MSE = np.square(np.subtract(y_test,y_pred_2)).mean()
rmse = sqrt(mean_squared_error(y_test, y_pred_2))
print(f'Regress_2 Model RMSE: {rmse}, MSE: {MSE}')
```

```
Regress_2 Model RMSE: 21789.521358081238, MSE: 474783241.0142782
```

Model 3: GradientBoostingRegressor and AdaBoostRegressor

In [2738]:

```
#import libraries
from sklearn  import ensemble #can also use sklearn.ensemble import GradientBoostRegres
sor
#set parameters
params = {'n_estimators': 500,
          'max_depth': 4,
          'min_samples_split': 5,
          'learning_rate': 0.01,
          'loss': 'ls'}
#fit GBR
reg_ = ensemble.GradientBoostingRegressor(**params)
reg_.fit(X_train, y_train);
```

In [2739]:

```
#fit adaboost classifier
reg_1=ensemble.AdaBoostRegressor()
reg_1.fit(X_train, y_train);
```

In [2740]:

```
#prediction with GB and AB
reg_pred = reg_.predict(X_test)
reg1_pred = reg_1.predict(X_test)

#root mean square error
rmse = sqrt(mean_squared_error(y_test, reg_pred))
rmse1 = sqrt(mean_squared_error(y_test,reg1_pred))
rmse, rmse1
```

Out[2740]:

```
(21052.63579053497, 20725.649978770918)
```

Randomized Search

In [2741]:

```
from sklearn.model_selection import GridSearchCV
from scipy.stats import uniform as sp_rand
from sklearn.linear_model import Ridge
from sklearn.model_selection import RandomizedSearchCV

#instantiate the model
model = LinearRegression()
#set parameters
parameters = {'fit_intercept':[True,False], 'normalize':[True,False], 'copy_X':[True, F
alse]}
grid = GridSearchCV(model,parameters, cv=None)

#fit/train the model
grid.fit(X_train, y_train);
```

In [2744]:

```
# prepare a uniform distribution to sample for the alpha parameter
param_grid = {'alpha': sp_rand()}
# create and fit a ridge regression model, testing random alpha values
model = Ridge()
rsearch = RandomizedSearchCV(estimator=model, param_distributions=param_grid, n_iter=10
0)
rsearch.fit(X_train, y_train);
print(rsearch)
# summarize the results of the random parameter search
print(rsearch.best_score_)
print(rsearch.best_estimator_.alpha);
```

```
RandomizedSearchCV(cv='warn', error_score='raise-deprecating',
                   estimator=Ridge(alpha=1.0, copy_X=True, fit_intercept=T
rue,
                                   max_iter=None, normalize=False,
                                   random_state=None, solver='auto',
                                   tol=0.001),
                   iid='warn', n_iter=100, n_jobs=None,
                   param_distributions={'alpha': <scipy.stats._distn_infra
structure.rv_frozen object at 0x261C0170>},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring=None, verbose=0)
0.6618540252818471
0.4678099547970791
```

In [2745]:

```
#prediction with GB and AB
rs_pred = rsearch.predict(X_test)
grid_pred = grid.predict(X_test)
#root mean square error
rmse = sqrt(mean_squared_error(y_test, rs_pred))
rmse1 = sqrt(mean_squared_error(y_test, grid_pred))
rmse, rmse1
```

Out[2745]:

```
(20774.645553056802, 20878.17626758436)
```

Polynomial and Linear Regression

In [2746]:

```
#Importing Linear Regression
from sklearn.linear_model import LinearRegression

# Training Model
lm=LinearRegression()
lm.fit(X_train,y_train)
```

Out[2746]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=F
alse)
```

In [2747]:

```
# importing libraries for polynomial transform
from sklearn.preprocessing import PolynomialFeatures
# for creating pipeline
from sklearn.pipeline import Pipeline

# creating pipeline and fitting it on data
Input=[('polynomial',PolynomialFeatures(degree=2)),('modal',LinearRegression())]

pipe=Pipeline(Input)
pipe.fit(X_train,y_train);
```

In [2748]:

```
#predict wit linear
linear_pred=lm.predict(X_test)
#predict with polynomial
poly_pred=pipe.predict(X_test)
```

In [2749]:

```
print('RMSE for Polynomial Regression=>',np.sqrt(mean_squared_error(y_test,poly_pred)))
print('RMSE for Linear Regression=>',np.sqrt(mean_squared_error(y_test,linear_pred)))
```

```
RMSE for Polynomial Regression=> 137711.7309840463
RMSE for Linear Regression=> 20756.684446860014
```

Ordinary Least Squares

In [2750]:

```
#import libraries
import statsmodels.api as sm
# adding a constants
X_train = sm.add_constant(X_train)
X_test = sm.add_constant(X_test)
#train the model
model = sm.OLS(y_train, X_train).fit()
```

In [2751]:

```
#prediction with GB and AB
ols_pred = model.predict(X_test)
#root mean square error
rmse = sqrt(mean_squared_error(y_test, ols_pred))
rmse
```

Out[2751]:

```
20756.684446091116
```

Simplified LinearRegression Model

LRM

In [2752]:

```
#import mse
from sklearn.metrics import mean_squared_error

#Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state
=42)
lin_reg_mod = LinearRegression()
#fit the model
lin_reg_mod.fit(X_train, y_train)
```

Out[2752]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=F
alse)
```

In [2753]:

```
#make a prediction
final_pred = lin_reg_mod.predict(X_test)
#RMSE
rmse = (sqrt(mean_squared_error(y_test, final_pred))
rmse
```

Out[2753]:

```
20756.684446860014
```

In [2754]:

```
final_pred = lin_reg_mod.predict(test)
#Adds total_claim_amout column and fill it
submission = pd.read_csv('sample_submission.csv')
submission['total_claim_amount'] = final_pred
#Adds Customer_ID and fill it
submission['Customer_ID'] = test_original['Customer_ID']
#Convert submission to .csv file format
submission.to_csv('final_pred_model.csv', index = False)
```

Complex Linear Regression Models

In [2755]:

```
#split test and training dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state
=42)

# import necessary libraries
from random import random
from random import randint
from random import seed
from numpy import arange
from numpy import mean
from numpy import std
from numpy import absolute
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedKFold
from matplotlib import pyplot


# 1. evaluate a model
def evaluate_model(X, y, model):
    # define model evaluation method
    cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
    # evaluate model
    scores = cross_val_score(model, X, y, scoring='neg_mean_absolute_error', cv=cv, n_j
obs=-1)
    # force scores to be positive
    return absolute(scores)
```

In [2756]:

```
# 2. plot the dataset and the model's line of best fit
def best_fit(X, y, model):
    #fits the model to the training data
    model.fit(X, y)
    #return the fitted model
    return model

# 3. define the model, evalutate and fit it
model = LinearRegression()
# evaluate model
results = evaluate_model(X_test, y_test, model)
#predict results
print(f'Mean MAE:{mean(results)}, STD: {std(results)}')
# fit the model
fitted_model = best_fit(X_train, y_train, model)
```

```
Mean MAE:19407.932341490352, STD: 3897.1101134635887
```

In [2757]:

```
# 3. define the model, evalutate and fit it
model = LinearRegression()
# evaluate model
results = evaluate_model(X_test, y_test, model)
#predict results
print(f'Mean MAE:{mean(results)}, STD: {std(results)}')
# fit the model
fitted_model = best_fit(X_train, y_train, model)
#predict the target
pred_results = fitted_model.predict(X_test)
#RMSE
rmse = (sqrt(mean_squared_error(y_test, pred_results)))
rmse
```

```
Mean MAE:19407.932341490352, STD: 3897.1101134635887
```

Out[2757]:

```
20756.684446860014
```

Linear Regression with QuantileTransformer

In [2759]:

```
#import libraries
from sklearn.compose import TransformedTargetRegressor
from sklearn.preprocessing import QuantileTransformer


transformer = QuantileTransformer(output_distribution = 'normal')
regressor = LinearRegression()
regression_model_3 = TransformedTargetRegressor(regressor = regressor, transformer = tr
ansformer)
#Model3 with transformed target variable
regression_model_3.fit(X_train, y_train);
```

In [2760]:

```
#predict and measure RMSE
y_pred_3 = regression_model_3.predict(X_test)
rmse = sqrt(mean_squared_error(y_test, y_pred_3))
f'Root Mean Square Error: {rmse}'
```

Out[2760]:

```
'Root Mean Square Error: 20701.980818671047'
```

In [ ]:

```

```