# final_eda_cs2

October 2, 2021

[ ]:
```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

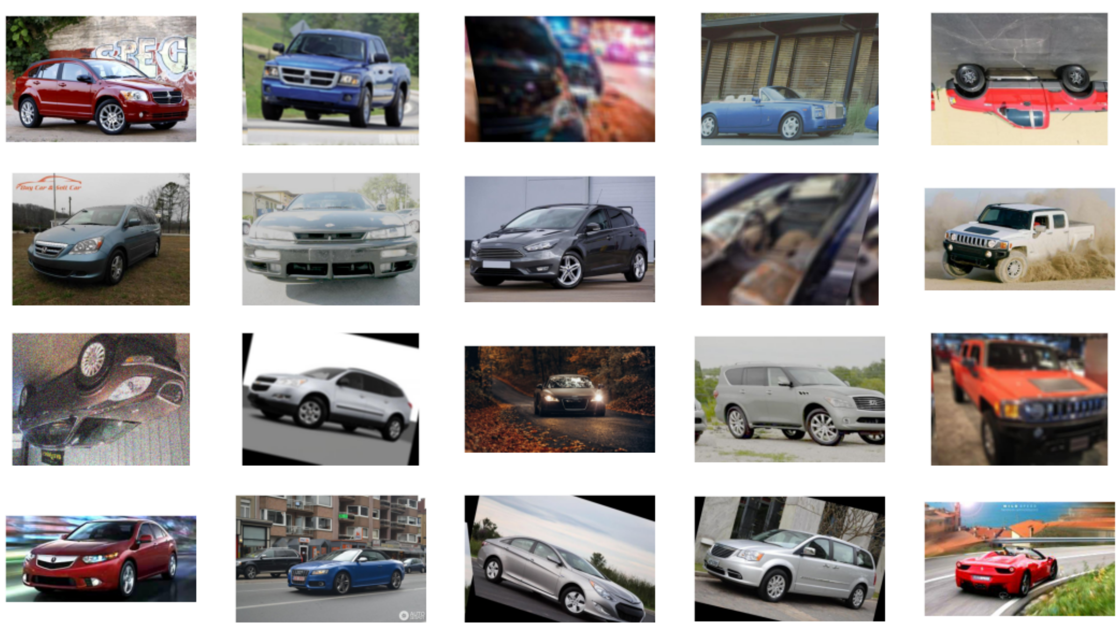
[ ]:
```
import pandas as pd
import numpy as np
import glob
import os
import cv2
from IPython.display import Image
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import *
from tensorflow.keras.models import *
from tensorflow.keras.preprocessing import image
from sklearn.preprocessing import *
import xgboost as xgb
import warnings
warnings.filterwarnings('ignore')

from scipy import stats
from datetime import *
import datetime
```

[ ]:
```
train_data = pd.read_csv('/content/gdrive/MyDrive/cs2/data/train.csv')
train_data
```

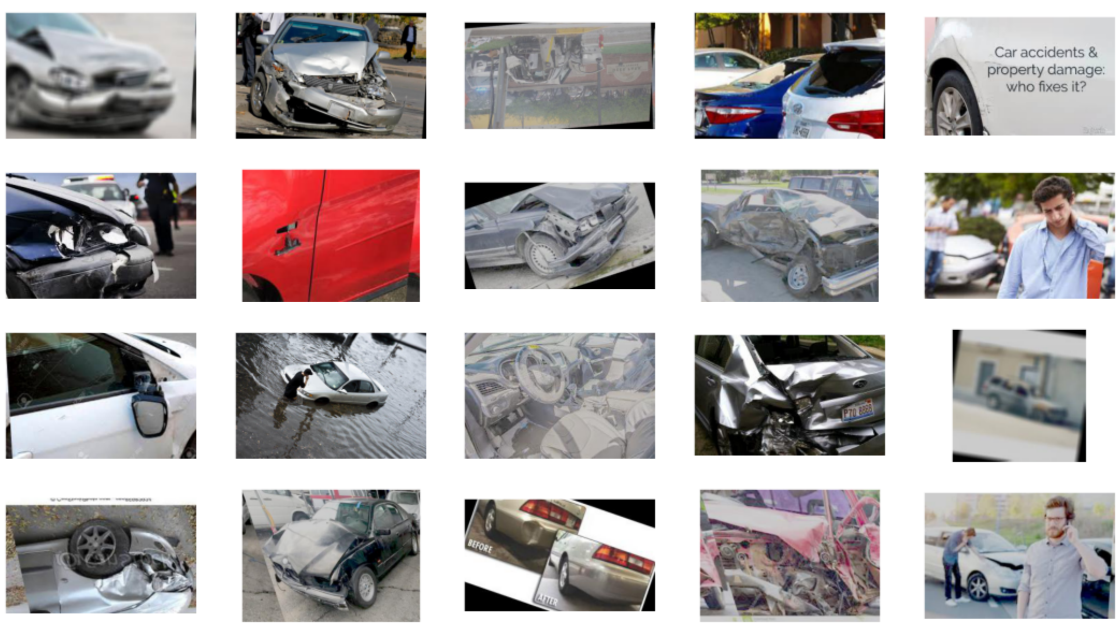
[ ]:
```
           Image_path Insurance_company  …  Condition  Amount
0     img_4513976.jpg                BQ  …          0     0.0
1     img_7764995.jpg                BQ  …          1  6194.0
2      img_451308.jpg                 A  …          0     0.0
3     img_7768372.jpg                 A  …          1  7699.0
4     img_7765274.jpg                AC  …          1  8849.0
…                 …               …  …        …      …
1394  img_4637237.jpg                DA  …          1  4565.0
1395  img_4637000.jpg                BQ  …          1  3363.0
```

```
1396   img_4637503.jpg              AA  …          1  5336.0
1397   img_4515101.jpg               A  …          1  8734.0
1398   img_4636333.jpg               B  …          1     NaN

[1399 rows x 8 columns]
```

[ ]:
```python
#vehicle pics with undamaged condition
path = '/content/gdrive/MyDrive/cs2/data/trainImages/'
for i,img in enumerate(train_data.loc[train_data['Condition']==0,'Image_path']):

    if i < 0:
       continue

    fig = plt.gcf()
    fig.set_size_inches(18.5, 10.5)
    plt.subplot(4,5,i+1)
    img = plt.imread(path+str(img))

    plt.imshow(img)
    plt.xticks([])
    plt.yticks([])
    i+=1
    if i == 20:
        break
plt.show()
```



[ ]:
```
#vehicle pics with damage condition
path = '/content/gdrive/MyDrive/cs2/data/trainImages/'
for i,img in enumerate(train_data.loc[train_data['Condition']==1,'Image_path']):

    if i < 0:
       continue

    fig = plt.gcf()
    fig.set_size_inches(18.5, 10.5)
    plt.subplot(4,5,i+1)
    img = plt.imread(path+str(img))

    plt.imshow(img)
    plt.xticks([])
    plt.yticks([])
    i+=1
    if i == 20:
        break
plt.show()
```




#1. EDA

[ ]:
```
train_data[train_data['Amount'] > train_data['Max_coverage']]
```

[ ]:

| | Image_path | Insurance_company | … | Condition | Amount |
|---|---|---|---|---|---|
| 4 | img_7765274.jpg | AC | … | 1 | 8849.0 |
| 10 | img_4516058.jpg | DA | … | 1 | 9634.0 |

```
39     img_4634526.jpg                BQ  …           1  10598.0
51     img_4516363.jpg                 O  …           1   9093.0
85     img_4637399.jpg                RE  …           1   8488.0
…            …                   …   …        …       …
1324   img_7767995.jpg                AA  …           1  59844.0
1351   img_4514501.jpg                 O  …           1   8636.0
1359   img_4635588.jpg                AA  …           1   6448.0
1364   img_4635842.jpg                 B  …           1   6166.0
1397   img_4515101.jpg                 A  …           1   8734.0

[91 rows x 8 columns]
```

[ ]:
```python
train_data[(train_data['Amount'] > train_data['Max_coverage']) &␣
↪train_data['Condition']==1]
```

[ ]:
```
           Image_path Insurance_company  …  Condition   Amount
4      img_7765274.jpg                AC  …           1   8849.0
10     img_4516058.jpg                DA  …           1   9634.0
39     img_4634526.jpg                BQ  …           1  10598.0
51     img_4516363.jpg                 O  …           1   9093.0
85     img_4637399.jpg                RE  …           1   8488.0
…            …                   …   …        …       …
1324   img_7767995.jpg                AA  …           1  59844.0
1351   img_4514501.jpg                 O  …           1   8636.0
1359   img_4635588.jpg                AA  …           1   6448.0
1364   img_4635842.jpg                 B  …           1   6166.0
1397   img_4515101.jpg                 A  …           1   8734.0

[91 rows x 8 columns]
```

[ ]:
```python
train_data[(train_data['Amount'] > train_data['Max_coverage']) &␣
↪train_data['Condition']==1].isnull().sum()
```

[ ]:
```
Image_path           0
Insurance_company    0
Cost_of_vehicle      0
Min_coverage         0
Expiry_date          0
Max_coverage         0
Condition            0
Amount               0
dtype: int64
```

**OBSERVATIONS**

1. from the official given description/instruction it is not clear Amount column represents what, whether it is insurance premium amount or insurance claim amount or insurance sum assured amount, since this dataset have majority of damaged vehicle is seen from its distribution so we go

with Amount as insurance claim amount.

2. since it is insurance claim amount, so claim cannot be greater than cost of vehicle and maximum insurance coverage amount, so we have to perform imputation on Amount column which are greater than cost_of_vehicle and Amount(insurance claim amount).

3. since dataset mention Max_coverage : Represents maximum coverage provided by insurance company, it is not clear whether this add-ons added or not on this Max_coverage.

[ ]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1399 entries, 0 to 1398
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Image_path         1399 non-null   object
 1   Insurance_company  1399 non-null   object
 2   Cost_of_vehicle    1310 non-null   float64
 3   Min_coverage       1310 non-null   float64
 4   Expiry_date        1399 non-null   object
 5   Max_coverage       1310 non-null   float64
 6   Condition          1399 non-null   int64
 7   Amount             1388 non-null   float64
dtypes: float64(4), int64(1), object(3)
memory usage: 87.6+ KB
```

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

[ ]:

| | Cost_of_vehicle | Min_coverage | Max_coverage | Condition | Amount |
|---|---|---|---|---|---|
| count | 1310.000000 | 1310.000000 | 1310.000000 | 1399.000000 | 1388.000000 |
| mean | 37454.274809 | 936.356870 | 11242.925160 | 0.929235 | 4117.144092 |
| std | 8921.428143 | 223.035704 | 7163.735952 | 0.256523 | 3151.516223 |
| min | 11100.000000 | 277.500000 | 2853.000000 | 0.000000 | -999.000000 |
| 25% | 29800.000000 | 745.000000 | 7603.000000 | 1.000000 | 1641.750000 |
| 50% | 37300.000000 | 932.500000 | 9678.000000 | 1.000000 | 4070.000000 |
| 75% | 45175.000000 | 1129.375000 | 11703.000000 | 1.000000 | 6039.500000 |
| max | 53500.000000 | 1337.500000 | 46495.680000 | 1.000000 | 59844.000000 |

[ ]:
```
train_data[train_data['Amount']<0]
```

[ ]:

| | Image_path | Insurance_company | … | Condition | Amount |
|---|---|---|---|---|---|
| 641 | img_7766741.jpg | O | … | 1 | -999.0 |

[1 rows x 8 columns]

**OBSERVATION**

1. train data, amount column value at min statitics, have negative value which is not possible, so we will be doing imputation based on its category to which insurance company this belongs

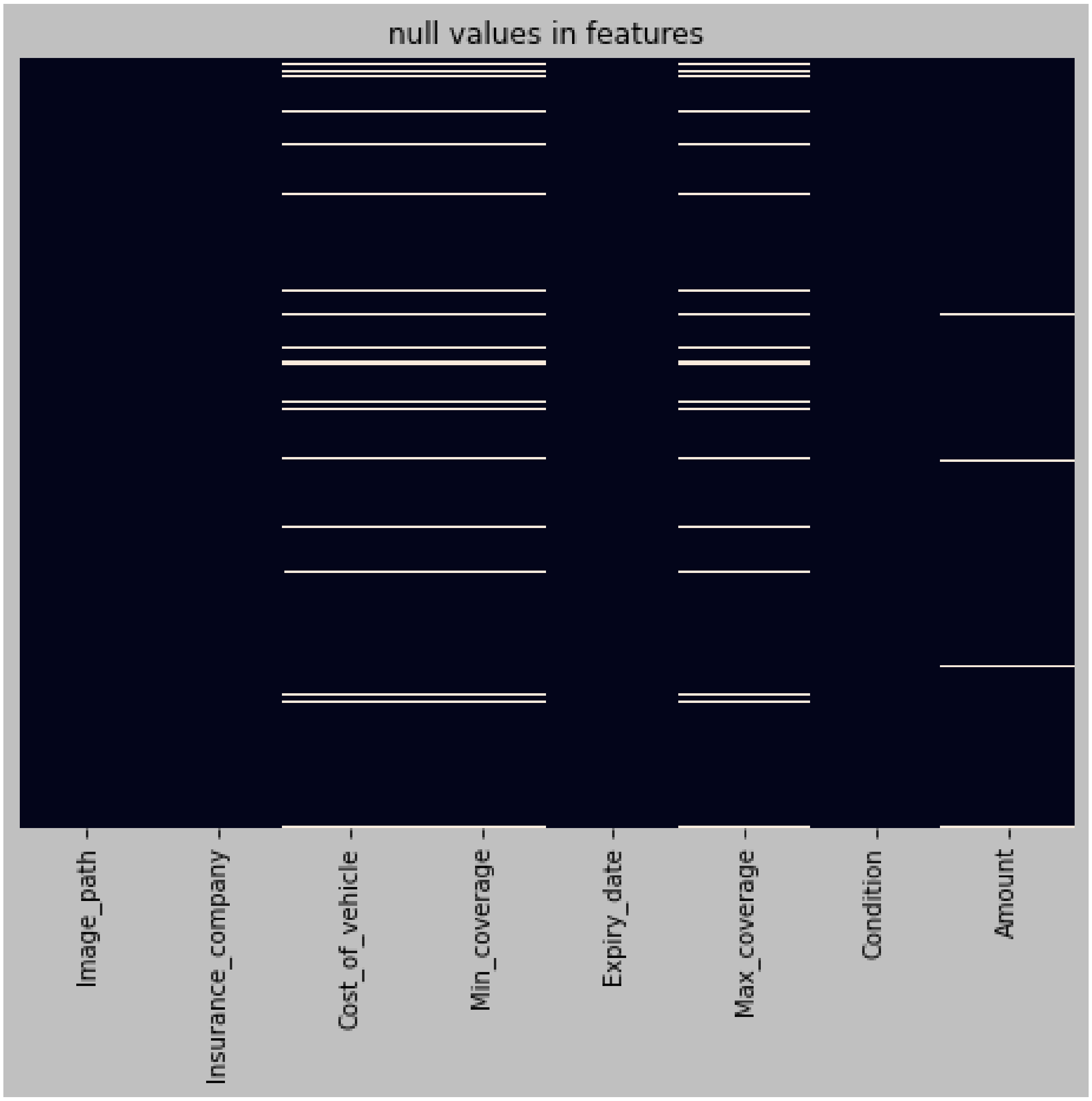
here it is O. ——- 1

##1.1 CHECK NULL

[ ]:
```
train_data.isnull().sum()
```

[ ]:
```
Image_path            0
Insurance_company     0
Cost_of_vehicle      89
Min_coverage         89
Expiry_date           0
Max_coverage         89
Condition             0
Amount               11
dtype: int64
```

[ ]:
```
def check_plot_null(data):
  fig = plt.figure(figsize=(8,6))
  fig.patch.set_facecolor('silver')
  sns.heatmap(data.isnull(), cbar=False, yticklabels=False)
  plt.title('null values in features')
  plt.show()

check_plot_null(train_data)
```




**OBSERVATION**

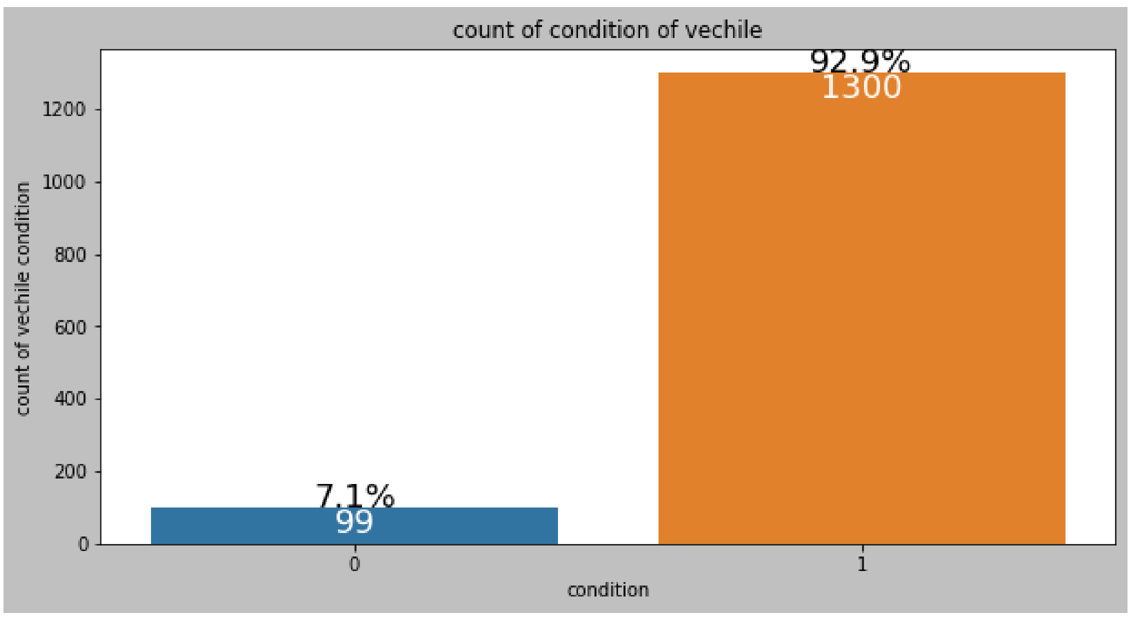
1. from above plot we see there is null value in cost of vehicle (89), minimum coverage (89), maximum coverage (89), amount (11).

2. we will not be droping the null data since we have very less data (1399 rows).

##1.2 VEHICLE CONDITION DISTRIBUTION

[ ]:
```
def vech_cond_distribution(data, column):

  fig = plt.figure(figsize=(10,5))
  fig.patch.set_facecolor('silver')
```

```
  total = data.shape[0]

  ax = sns.countplot(x=column, data=data)
  for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x()+0.4, p.get_height()+1.4),␣
↪ha='center', va='top', color='white', size=18)
    percentage = '{:.1f}%'.format(100 * p.get_height()/total)
    ax.annotate(percentage, (p.get_x()+0.4, p.get_height()), ha='center',␣
↪size=18)

  plt.xlabel('condition')
  plt.ylabel('count of vechile condition')
  plt.title('count of condition of vechile')
  plt.show()

vech_cond_distribution(train_data, 'Condition')
```



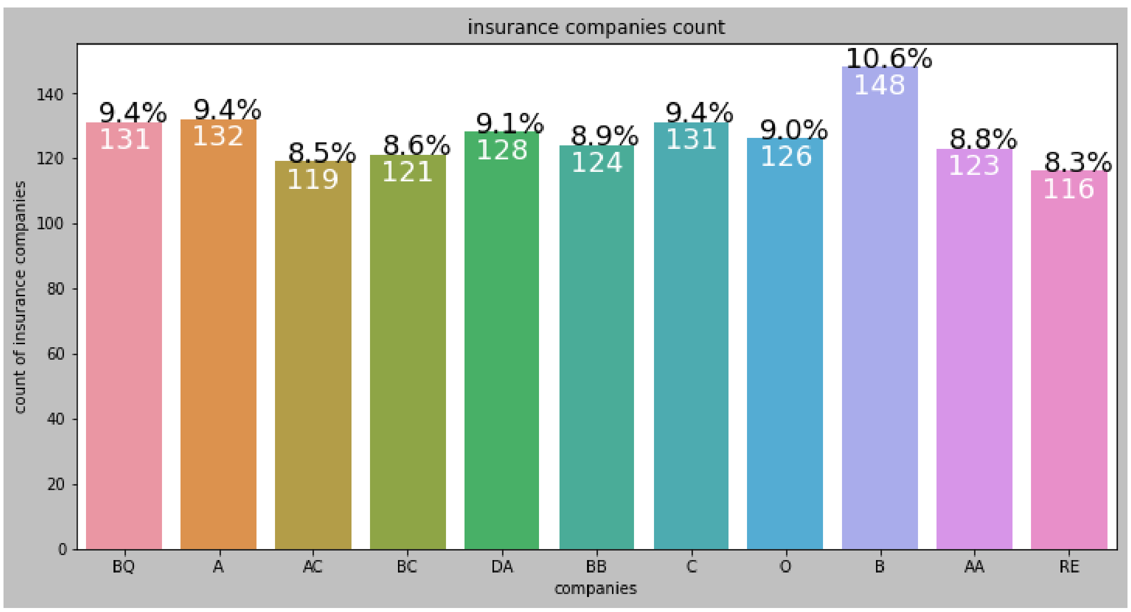

**OBSERVATION**

1. out of 1399 train data points, 1300 vechiles data points are damaged (1), which makes 92.9% of data, where as 99 vechiles data points are not damaged (0), which makes 7.1% of data.

##1.3 VEHICLE DISTRIBUION IN EACH INSURANCE COMPANY

[ ]:
```
def company_count(data, column):

  '''takes data : train data,
         column : insurance comapny column
```

```
        returns : number of data points in each insurance comapany with overall␣
↪percentage data'''


    fig = plt.figure(figsize=(12,6))
    fig.patch.set_facecolor('silver')

    total = data.shape[0]

    ax = sns.countplot(x=column, data=data)
    for p in ax.patches:
      ax.annotate(f'{p.get_height()}', (p.get_x()+0.4, p.get_height()-1.4),␣
↪ha='center', va='top', color='white', size=18)
      percentage = '{:.1f}%'.format(100 * p.get_height()/total)
      ax.annotate(percentage, (p.get_x()+0.5, p.get_height()), ha='center',␣
↪size=18)

    plt.xlabel('companies')
    plt.ylabel('count of insurance companies')
    plt.title('insurance companies count')
    plt.show()

company_count(train_data, 'Insurance_company')
```



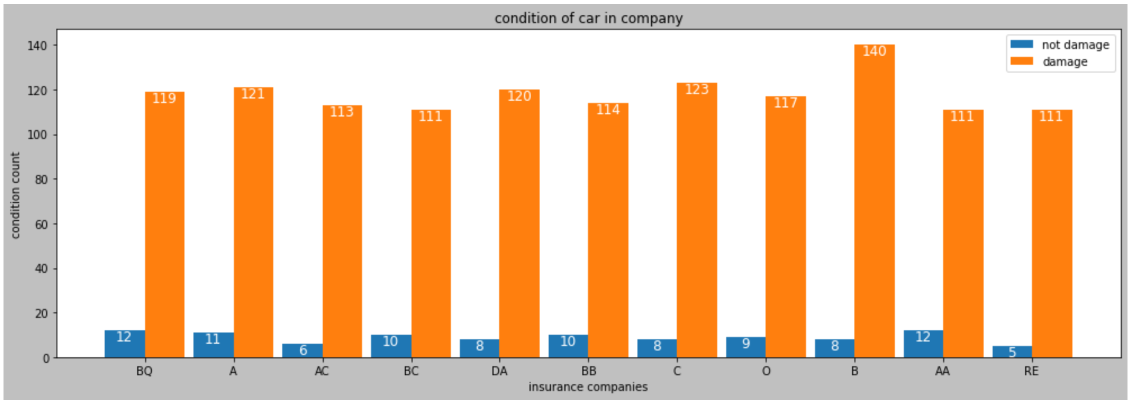

**OBSERVATION**

1. almost every insurance company have nearly same percentage share, with highest being insurance company 'B' (10.6%), lowest share of insurance company 'RE' (8.3%).

##1.4 CONDITION OF VEHICLE IN EACH INSURNACE COMPANY

[ ]:
```python
def vech_condition_in_insurance_company(data, column, condition):

    '''takes data : train data,
          column : insurance comapny column,
       condition : damage(1) or not damage(0)
         returns : condition of vehicle (damage/not damge) in each insurance␣
 ↪comapany'''

    labels = data[column].unique()

    zeros_lst = []
    ones_lst = []

    for i in labels:
        pt = data[data[column]==i].groupby(condition).agg({condition: ['count']})
        zeros_lst.append(pt.values.flatten()[0])
        ones_lst.append(pt.values.flatten()[1])


    x = np.arange(len(labels))  # the label locations
    width = 0.45                # the width of the bars

    fig, ax = plt.subplots(figsize=(14,5))
    fig.patch.set_facecolor('silver')


    rects1 = ax.bar(x - width/2, zeros_lst, width, label='not damage')
    rects2 = ax.bar(x + width/2, ones_lst, width, label='damage')
    for p in ax.patches:
        ax.annotate(f'{p.get_height()}', (p.get_x()+.22, p.get_height()+0.5),␣
 ↪ha='center', va='top', color='white', size=12)

    # Add some text for labels, title and custom x-axis tick labels, etc.
    ax.set_ylabel('condition count')
    ax.set_title('condition of car in company')
    ax.set_xlabel('insurance companies')
    ax.set_xticks(x)
    ax.set_xticklabels(labels)
    ax.legend()

    fig.tight_layout()

    plt.show()
```

```
vech_condition_in_insurance_company(train_data, 'Insurance_company',␣
↪'Condition')
```




**OBSERVATION**

1. from above data it is clear that every insurance company have very few data which is being not damage, but inrsurance comapny 'B' have highest (140), and 'BC', 'AA', 'RE' have lowest (111) each.
2. this imbalance is being in line with statement, as we want to predict the price of claim to be paid based on damaged condition.

##1.5 IMPUTATAION

[ ]:
```
def imputation_null_ins_cmpny(data, column, aggby, name):

  '''takes data : train data,
           column : insurance comapny column,
           aggby  : column name by which to aggregate,
             name : final reanamed column,
       returns : condition of vehicle (damage/not damge) in each insurance␣
↪comapany'''

  labels = data[column].unique()
  df = pd.DataFrame()

  for i in labels:
    pt = data[data[column]==i].groupby(column).agg({aggby: ['median']})
    df = df.append({column : pt.index[0], name : round(pt.iloc[:,0].
↪values[0],4)}, ignore_index=True)

  return df
```

[ ]:
```
impute_data_cost_vech = imputation_null_ins_cmpny(train_data,␣
↪'Insurance_company', 'Cost_of_vehicle','mead_cost_vehicle')
impute_data_cost_vech
```

[ ]:
```
   Insurance_company  mead_cost_vehicle
0                 BQ            40000.0
1                  A            38600.0
2                 AC            37300.0
3                 BC            37500.0
4                 DA            36700.0
5                 BB            36700.0
6                  C            35900.0
7                  O            36900.0
8                  B            36000.0
9                 AA            36500.0
10                RE            38900.0
```

[ ]:
```
impute_data_min_covrg = imputation_null_ins_cmpny(train_data,␣
↪'Insurance_company', 'Min_coverage','mead_min_coverage')
impute_data_min_covrg
```

[ ]:
```
   Insurance_company  mead_min_coverage
0                 BQ             1000.0
1                  A              965.0
2                 AC              932.5
3                 BC              937.5
4                 DA              917.5
5                 BB              917.5
6                  C              897.5
7                  O              922.5
8                  B              900.0
9                 AA              912.5
10                RE              972.5
```

[ ]:
```
impute_data_max_covrg = imputation_null_ins_cmpny(train_data,␣
↪'Insurance_company', 'Max_coverage','mead_max_coverage')
impute_data_max_covrg
```

[ ]:
```
   Insurance_company  mead_max_coverage
0                 BQ            10403.0
1                  A             9828.0
2                 AC             9690.5
3                 BC             9778.0
4                 DA             9403.0
5                 BB             9478.0
6                  C             9165.5
7                  O             9353.0
```

```
8                    B            9428.0
9                   AA            9428.0
10                  RE            9853.0
```

[ ]:
```python
impute_data_mead_amt = imputation_null_ins_cmpny(train_data,␣
↪'Insurance_company', 'Amount','mead_amount')
impute_data_mead_amt
```

[ ]:
```
   Insurance_company  mead_amount
0                 BQ       3757.0
1                  A       4349.0
2                 AC       4013.0
3                 BC       4221.0
4                 DA       4156.5
5                 BB       3931.0
6                  C       3389.0
7                  O       3853.0
8                  B       4481.0
9                 AA       4048.0
10                RE       4487.0
```

[ ]:
```python
def impute_columns(data, column, col, condition, impute_data):

  '''takes data : train dataframe,
         column : insurance company column,
         col    : column which has null value,
      condition : condition od vehicle damage(0) or not damage(1),
    impute data : median value of column based on insurance company cat.
        return  : dataframe'''

  for i in impute_data[column].tolist():
    if col == 'Amount':
      ind = data.loc[(data[column]==i) & (data[condition]==1) & (data[col].
↪isnull())].index
    else:
      ind = data.loc[((data[column]==i) & (data[col].isnull()))].index

    for j in ind:
      data.loc[j, col] = impute_data.loc[(impute_data[column] == i)].
↪values[0][-1]

  return data
```

[ ]:
```python
impute_columns(train_data, 'Insurance_company', 'Amount',␣
↪'Condition',impute_data_mead_amt)
```

```
[ ]:            Image_path Insurance_company  ...  Condition  Amount
     0      img_4513976.jpg                BQ  ...          0     0.0
     1      img_7764995.jpg                BQ  ...          1  6194.0
     2       img_451308.jpg                 A  ...          0     0.0
     3      img_7768372.jpg                 A  ...          1  7699.0
     4      img_7765274.jpg                AC  ...          1  8849.0
     ...                ...               ...  ...        ...     ...
     1394   img_4637237.jpg                DA  ...          1  4565.0
     1395   img_4637000.jpg                BQ  ...          1  3363.0
     1396   img_4637503.jpg                AA  ...          1  5336.0
     1397   img_4515101.jpg                 A  ...          1  8734.0
     1398   img_4636333.jpg                 B  ...          1  4481.0

     [1399 rows x 8 columns]
```

```
[ ]: train_data.loc[train_data['Condition']==0]['Amount'].value_counts()
```

```
[ ]: 0.0    99
     Name: Amount, dtype: int64
```

```
[ ]: impute_columns(train_data, 'Insurance_company', 'Cost_of_vehicle', _,␣
     ↪impute_data_cost_vech)
```

```
[ ]:            Image_path Insurance_company  ...  Condition  Amount
     0      img_4513976.jpg                BQ  ...          0     0.0
     1      img_7764995.jpg                BQ  ...          1  6194.0
     2       img_451308.jpg                 A  ...          0     0.0
     3      img_7768372.jpg                 A  ...          1  7699.0
     4      img_7765274.jpg                AC  ...          1  8849.0
     ...                ...               ...  ...        ...     ...
     1394   img_4637237.jpg                DA  ...          1  4565.0
     1395   img_4637000.jpg                BQ  ...          1  3363.0
     1396   img_4637503.jpg                AA  ...          1  5336.0
     1397   img_4515101.jpg                 A  ...          1  8734.0
     1398   img_4636333.jpg                 B  ...          1  4481.0

     [1399 rows x 8 columns]
```

```
[ ]: impute_columns(train_data, 'Insurance_company', 'Max_coverage', _,␣
     ↪impute_data_max_covrg)
```

```
[ ]:            Image_path Insurance_company  ...  Condition  Amount
     0      img_4513976.jpg                BQ  ...          0     0.0
     1      img_7764995.jpg                BQ  ...          1  6194.0
     2       img_451308.jpg                 A  ...          0     0.0
     3      img_7768372.jpg                 A  ...          1  7699.0
     4      img_7765274.jpg                AC  ...          1  8849.0
```

```
…                …                 …  …        …      …
1394   img_4637237.jpg                DA  …           1  4565.0
1395   img_4637000.jpg                BQ  …           1  3363.0
1396   img_4637503.jpg                AA  …           1  5336.0
1397   img_4515101.jpg                 A  …           1  8734.0
1398   img_4636333.jpg                 B  …           1  4481.0

[1399 rows x 8 columns]
```

[ ]:
```
impute_columns(train_data, 'Insurance_company', 'Min_coverage', _,␣
↪impute_data_min_covrg)
```

[ ]:
```
           Image_path Insurance_company  …  Condition  Amount
0      img_4513976.jpg                BQ  …           0     0.0
1      img_7764995.jpg                BQ  …           1  6194.0
2       img_451308.jpg                 A  …           0     0.0
3      img_7768372.jpg                 A  …           1  7699.0
4      img_7765274.jpg                AC  …           1  8849.0
…                …                 …  …        …      …
1394   img_4637237.jpg                DA  …           1  4565.0
1395   img_4637000.jpg                BQ  …           1  3363.0
1396   img_4637503.jpg                AA  …           1  5336.0
1397   img_4515101.jpg                 A  …           1  8734.0
1398   img_4636333.jpg                 B  …           1  4481.0

[1399 rows x 8 columns]
```

[ ]:
```
train_data.isnull().sum()
```

[ ]:
```
Image_path           0
Insurance_company    0
Cost_of_vehicle      0
Min_coverage         0
Expiry_date          0
Max_coverage         0
Condition            0
Amount               0
dtype: int64
```

##1.6 PDF AND CDF OF FEATURES

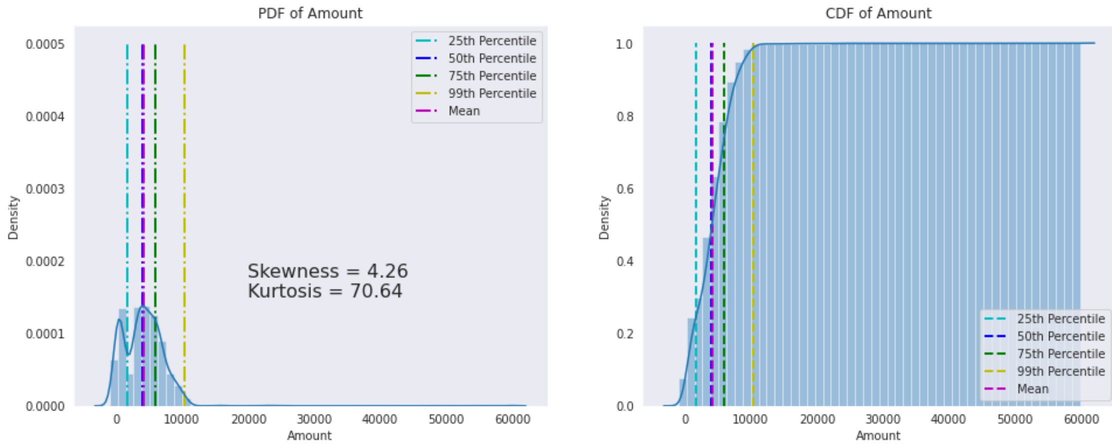
[ ]:
```
def percentile_line(data, column):

  percentile25 = np.percentile(data[column].tolist(), 25)
  percentile50 = np.percentile(data[column].tolist(), 50)
  percentile75 = np.percentile(data[column].tolist(), 75)
  percentile99 = np.percentile(data[column].tolist(), 99)
```

```
    mean          = data[column].mean()

    return percentile25, percentile50, percentile75, percentile99, mean
```

[ ]:
```
percentile25, percentile50, percentile75, percentile99, mean =␣
↪percentile_line(train_data, 'Amount')
```

[ ]:
```
def pdf_cdf(data, column):

    sns.set_style('dark')
    plt.figure(figsize=(16,6))
    plt.subplot(1,2,1)
    sns.distplot(data[column])
    plt.text(20000, 0.00015,
             f'Skewness = {round(data[column].skew(),2)}\nKurtosis =␣
↪{round(data[column].kurtosis(),2)}',
             fontdict=dict(fontsize=16))
    plt.vlines(percentile25, 0, .0005, color='c', ls='-.', lw=2, label='25th␣
↪Percentile')
    plt.vlines(percentile50, 0, .0005, color='b', ls='-.', lw=2, label='50th␣
↪Percentile')
    plt.vlines(percentile75, 0, .0005, color='g', ls='-.', lw=2, label='75th␣
↪Percentile')
    plt.vlines(percentile99, 0, .0005, color='y', ls='-.', lw=2, label='99th␣
↪Percentile')
    plt.vlines(mean        , 0, .0005, color='m', ls='-.', lw=2, label='Mean')
    plt.title(f'PDF of {column}')
    plt.legend(loc="upper right")

    plt.subplot(1,2,2)
    sns.distplot(data[column], kde_kws={'cumulative': True},␣
↪hist_kws={'cumulative': True})
    plt.vlines(percentile25, 0, 1, color='c', ls='--', lw=2, label='25th␣
↪Percentile')
    plt.vlines(percentile50, 0, 1, color='b', ls='--', lw=2, label='50th␣
↪Percentile')
    plt.vlines(percentile75, 0, 1, color='g', ls='--', lw=2, label='75th␣
↪Percentile')
    plt.vlines(percentile99, 0, 1, color='y', ls='--', lw=2, label='99th␣
↪Percentile')
    plt.vlines(mean        , 0, 1, color='m', ls='--', lw=2, label='Mean')
    plt.title(f'CDF of {column}')
    plt.legend(loc="lower right")


    plt.show()
```

[ ]:
```
pdf_cdf(train_data, 'Amount')
```




[ ]:
```
for i in range(90, 101, 1):
    percentile = np.round(np.percentile(train_data['Amount'].tolist(), i), 4)
    print(f"{i} th Percentile \t: {percentile}")
print('\n', 35*'=', '\n')
for i in range(990, 1001, 1):
    i /= 10
    percentile = np.round(np.percentile(train_data['Amount'].tolist(), i), 4)
    print(f"{i} th Percentile \t: {percentile}")
```

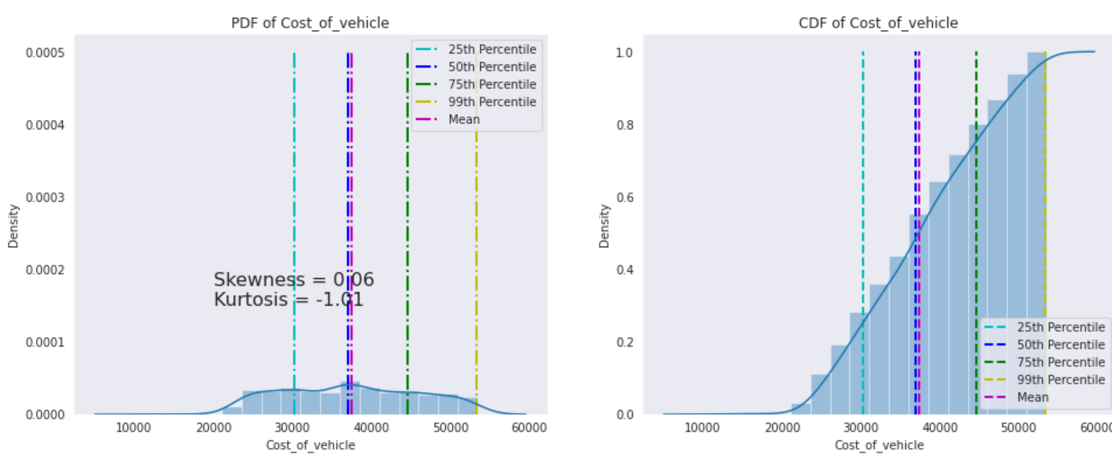
```
90 th Percentile        : 7659.0
91 th Percentile        : 7861.18
92 th Percentile        : 8060.72
93 th Percentile        : 8310.22
94 th Percentile        : 8563.44
95 th Percentile        : 8740.6
96 th Percentile        : 9074.2
97 th Percentile        : 9372.34
98 th Percentile        : 9725.64
99 th Percentile        : 10302.68
100 th Percentile       : 23000.0

 ===================================

99.0 th Percentile      : 10302.68
99.1 th Percentile      : 10374.038
99.2 th Percentile      : 10458.824
99.3 th Percentile      : 10484.782
99.4 th Percentile      : 10504.18
99.5 th Percentile      : 10524.15
99.6 th Percentile      : 10545.12
```

```
99.7 th Percentile      : 10589.464
99.8 th Percentile      : 10705.02
99.9 th Percentile      : 13795.454
100.0 th Percentile     : 23000.0
```

**OBSERVATION**

1. The Distribution is right skewed and has a long tail on the right side, indicated by the high values for Skewness and Kurtosis.
2. The PDF has a long tail on the right which means there are few samples that have large value of Amount. These samples could affect the model training.
3. It can also be seen that there is a some gap between 99 percentile and 75 percentile value, which may also confirms the presence of few outliers in the data.
4. mean and 50th percentile almost lies on one another, effect of outlier if present is negligable.
5. Also peaks can be seen in the distribution at various values of Amount which indicate multi-modal distribution.
6. Long tail on right is mainly due to single observation of 23000.

[ ]:
```python
percentile25, percentile50, percentile75, percentile99, mean = percentile_line(train_data, 'Cost_of_vehicle')
pdf_cdf(train_data, 'Cost_of_vehicle')
```




[ ]:
```python
for i in range(0, 11, 1):
    percentile = np.round(np.percentile(train_data['Cost_of_vehicle'].tolist(), i), 4)
    print(f"{i} th Percentile \t: {percentile}")
```

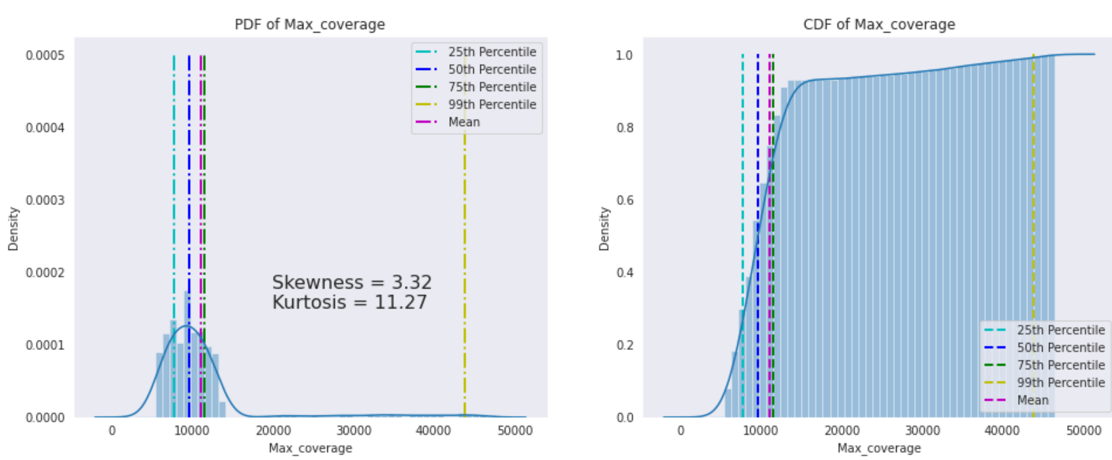
```
0 th Percentile         : 11100.0
1 th Percentile         : 22900.0
2 th Percentile         : 23296.0
3 th Percentile         : 23500.0
```

```
4 th Percentile          : 23900.0
5 th Percentile          : 24200.0
6 th Percentile          : 24488.0
7 th Percentile          : 24686.0
8 th Percentile          : 24900.0
9 th Percentile          : 25200.0
10 th Percentile         : 25500.0
```

**OBSERVATION**

1. The Distribution is left skewed and has a long tail on the left side, indicated by the low values for Skewness and Kurtosis.
2. kurtosis negative value show flatter curve.
3. The PDF has a long tail on the left which means there are few samples that have large value of Amount. These samples could affect the model training.
4. It can also be seen that there is a some gap between 0 percentile and 1 percentile value, which may also confirms the presence of few outliers in the data.
5. mean and 50th percentile almost lies on one another, effect of outlier if present is negligable.
6. Also peaks can be seen in the distribution at single values of Cost_of_vehicle which indicate single-modal distribution.
7. Long tail on left is mainly due to single observation of 11100.

[ ]:
```
percentile25, percentile50, percentile75, percentile99, mean =␣
↪percentile_line(train_data, 'Max_coverage')
pdf_cdf(train_data, 'Max_coverage')
```




[ ]:
```
for i in range(70, 99, 5):
    percentile = np.round(np.percentile(train_data['Max_coverage'].tolist(),␣
↪i), 4)
    print(f"{i} th Percentile \t: {percentile}")
```

```
#print('\n', 35*'=', '\n')
#for i in range(990, 1001, 1):
#    i /= 10
#    percentile = np.round(np.percentile(train_data['Max_coverage'].tolist(),␣
↪i), 4)
#    print(f"{i} th Percentile \t: {percentile}")
```

```
70 th Percentile         : 11203.0
75 th Percentile         : 11603.0
80 th Percentile         : 12078.0
85 th Percentile         : 12603.0
90 th Percentile         : 13178.0
95 th Percentile         : 28538.88
```

[ ]:
```
for i in range(90, 101, 1):
    percentile = np.round(np.percentile(train_data['Max_coverage'].tolist(),␣
↪i), 4)
    print(f"{i} th Percentile \t: {percentile}")
print('\n', 35*'=', '\n')
for i in range(990, 1001, 1):
    i /= 10
    percentile = np.round(np.percentile(train_data['Max_coverage'].tolist(),␣
↪i), 4)
    print(f"{i} th Percentile \t: {percentile}")
```

```
90 th Percentile         : 13178.0
91 th Percentile         : 13303.0
92 th Percentile         : 13382.0
93 th Percentile         : 13453.0
94 th Percentile         : 23238.84
95 th Percentile         : 28538.88
96 th Percentile         : 33198.6
97 th Percentile         : 35646.78
98 th Percentile         : 39535.68
99 th Percentile         : 43798.68
100 th Percentile        : 46495.68

 ===================================

99.0 th Percentile       : 43798.68
99.1 th Percentile       : 43798.68
99.2 th Percentile       : 44153.64
99.3 th Percentile       : 44407.68
99.4 th Percentile       : 44460.924
99.5 th Percentile       : 44585.16
99.6 th Percentile       : 45000.672
99.7 th Percentile       : 45314.046
```

```
99.8 th Percentile      : 45872.412
99.9 th Percentile      : 46495.68
100.0 th Percentile     : 46495.68
```

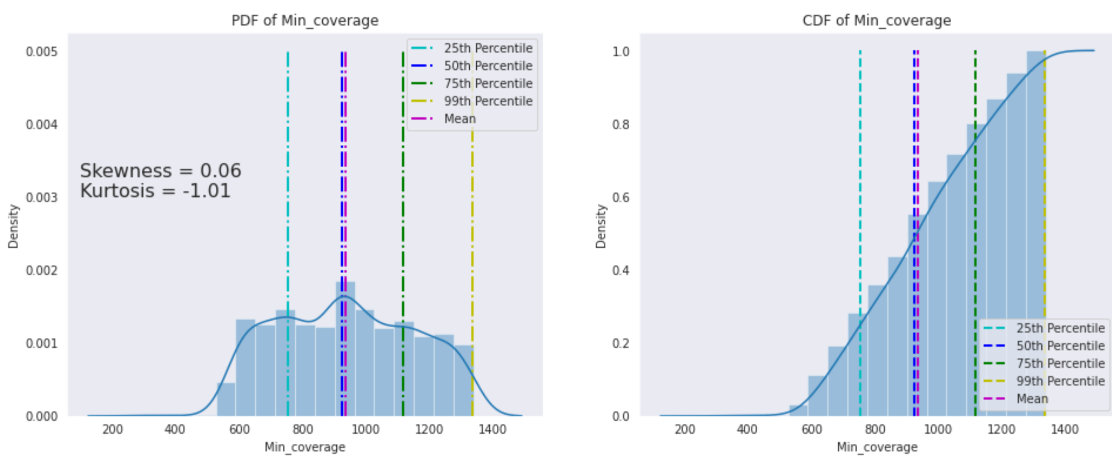
**OBSERVATION**

1. The Distribution is right skewed and has a long tail on the right side, indicated by the high values for Skewness and Kurtosis.
2. The PDF has a long tail on the right which means there are few samples that have large value of Amount. These samples could affect the model training.
3. It can also be seen that there is a some gap between 99 percentile and 75 percentile value, which may also confirms the presence of few outliers in the data.
4. mean and 50th have slight distance from one another, effect of outlier is there.
5. Also peaks can be seen in the distribution at single values of Max_coverage which indicate singlemodal distribution.
6. Long tail on right is mainly due to 75-95th percentile which approx 2.5 times.

[ ]:
```
def pdf_cdf(data, column):

  sns.set_style('dark')
  plt.figure(figsize=(16,6))
  plt.subplot(1,2,1)
  sns.distplot(data[column])
  plt.text(100, 0.003,
           f'Skewness = {round(data[column].skew(),2)}\nKurtosis =␣
↪{round(data[column].kurtosis(),2)}',
           fontdict=dict(fontsize=16))
  plt.vlines(percentile25, 0, .005, color='c', ls='-.', lw=2, label='25th␣
↪Percentile')
  plt.vlines(percentile50, 0, .005, color='b', ls='-.', lw=2, label='50th␣
↪Percentile')
  plt.vlines(percentile75, 0, .005, color='g', ls='-.', lw=2, label='75th␣
↪Percentile')
  plt.vlines(percentile99, 0, .005, color='y', ls='-.', lw=2, label='99th␣
↪Percentile')
  plt.vlines(mean        , 0, .005, color='m', ls='-.', lw=2, label='Mean')
  plt.title(f'PDF of {column}')
  plt.legend(loc="upper right")

  plt.subplot(1,2,2)
  sns.distplot(data[column], kde_kws={'cumulative': True},␣
↪hist_kws={'cumulative': True})
  plt.vlines(percentile25, 0, 1, color='c', ls='--', lw=2, label='25th␣
↪Percentile')
```

```
    plt.vlines(percentile50, 0, 1, color='b', ls='--', lw=2, label='50th␣
↪Percentile')
    plt.vlines(percentile75, 0, 1, color='g', ls='--', lw=2, label='75th␣
↪Percentile')
    plt.vlines(percentile99, 0, 1, color='y', ls='--', lw=2, label='99th␣
↪Percentile')
    plt.vlines(mean        , 0, 1, color='m', ls='--', lw=2, label='Mean')
    plt.title(f'CDF of {column}')
    plt.legend(loc="lower right")


    plt.show()
```

[ ]:
```
percentile25, percentile50, percentile75, percentile99, mean =␣
↪percentile_line(train_data, 'Min_coverage')
pdf_cdf(train_data, 'Min_coverage')
```




[ ]:
```
for i in range(0, 11, 1):
    percentile = np.round(np.percentile(train_data['Min_coverage'].tolist(),␣
↪i), 4)
    print(f"{i} th Percentile \t: {percentile}")
```

```
0 th Percentile         : 277.5
1 th Percentile         : 572.5
2 th Percentile         : 582.4
3 th Percentile         : 587.5
4 th Percentile         : 597.5
5 th Percentile         : 605.0
6 th Percentile         : 612.2
7 th Percentile         : 617.15
8 th Percentile         : 622.5
```

```
9 th Percentile          : 630.0
10 th Percentile         : 637.5
```

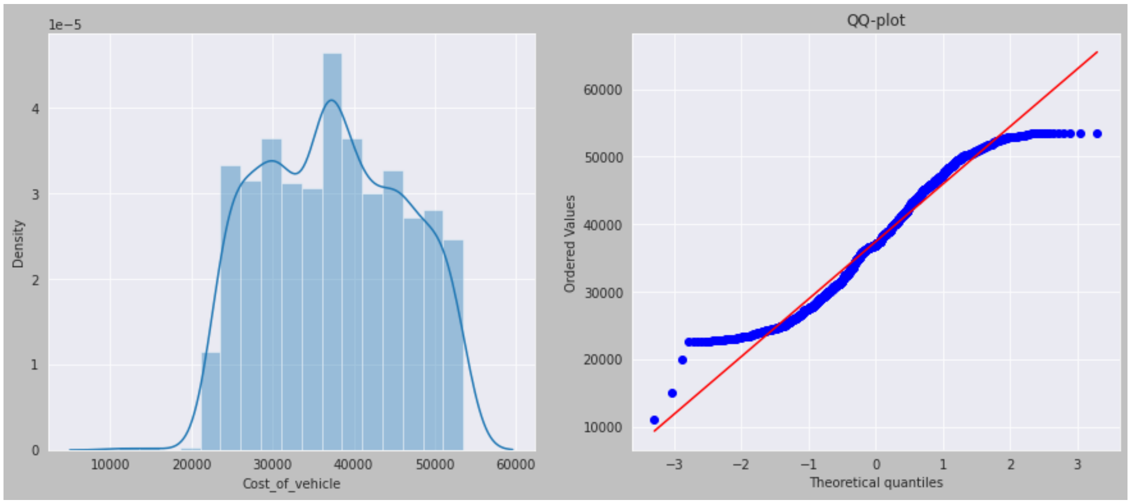
**OBSERVATION**

1. The Distribution is slight left skewed and has a long tail on the left side, indicated by the low values for Skewness and Kurtosis.
2. kurtosis negative value show somewhat flatter curve.
3. The PDF has a long tail on the left which means there are few samples that have large value of Amount. These samples could affect the model training.
4. It can also be seen that there is a some gap between 0 percentile and 1 percentile value, which may also confirms the presence of few outliers in the data.
5. mean and 50th percentile almost lies on one another, effect of outlier if present is negligable.
6. Also peaks can be seen in the distribution at single values of Min_coverage which indicate single-modal distribution.
7. Long tail on left is mainly due to single observation of 0th percentile 277.5.

##1.7 CHECKING DISTRIBUTION OF CONTINUOUS VRIABLE

[ ]:
```
def digo_plot(data, variable):
  fig = plt.figure(figsize=(15,6))
  fig.patch.set_facecolor('silver')
  sns.set_style("darkgrid")
  plt.subplot(1,2,1)

  sns.distplot(data[variable])

  plt.subplot(1,2,2)
  stats.probplot(data[variable], dist='norm', plot = plt)
  plt.title('QQ-plot')
  plt.show()
```

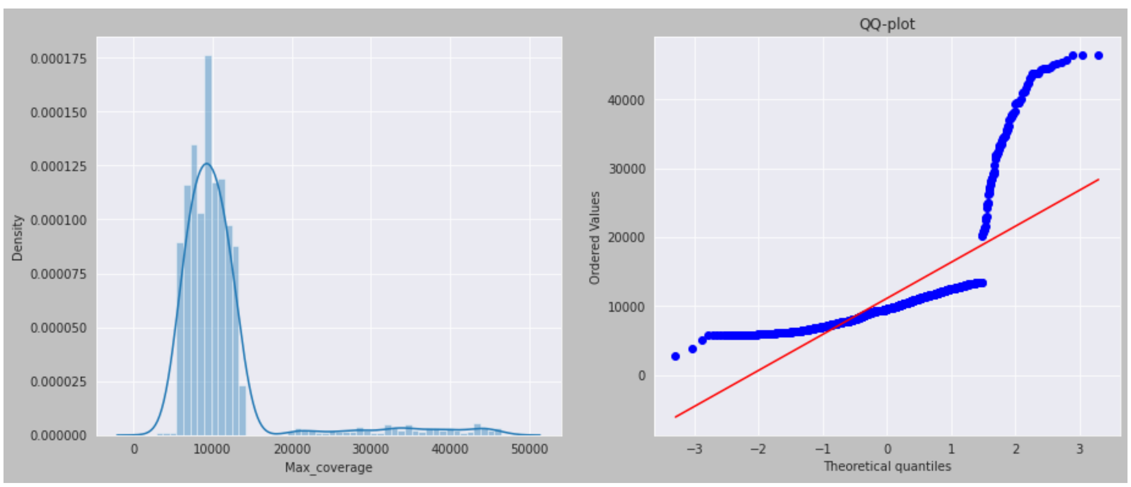
[ ]:
```
digo_plot(train_data, 'Cost_of_vehicle')
```




**OBSERVATION**

1. we have used normal distribution as base, distribution of cost_of_vehicle follows roughly normal distribution.

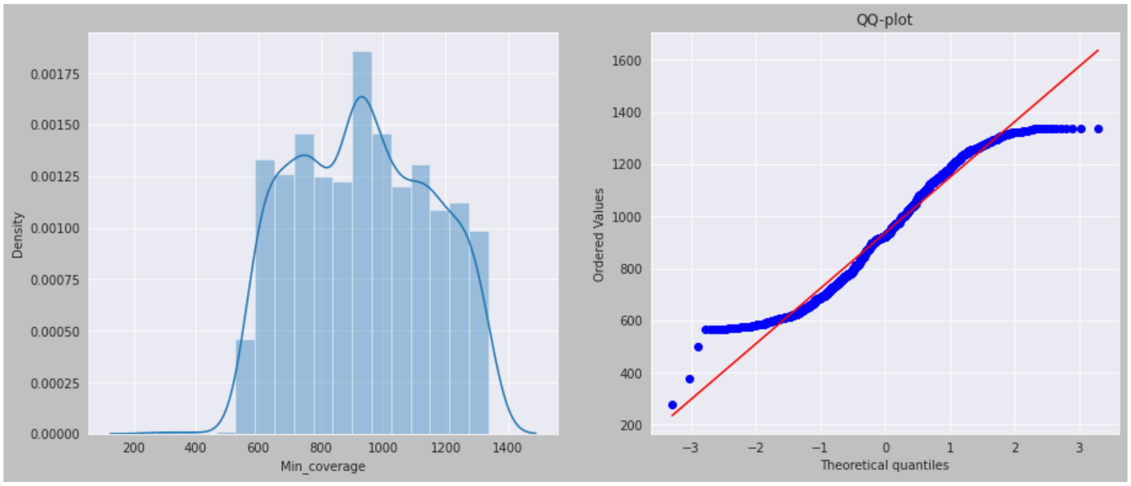
[ ]:
```
digo_plot(train_data, 'Max_coverage')
```




**OBSERVATION**

1. we have used normal distribution as base, distribution of Max_coverage do not follows roughly normal distribution.

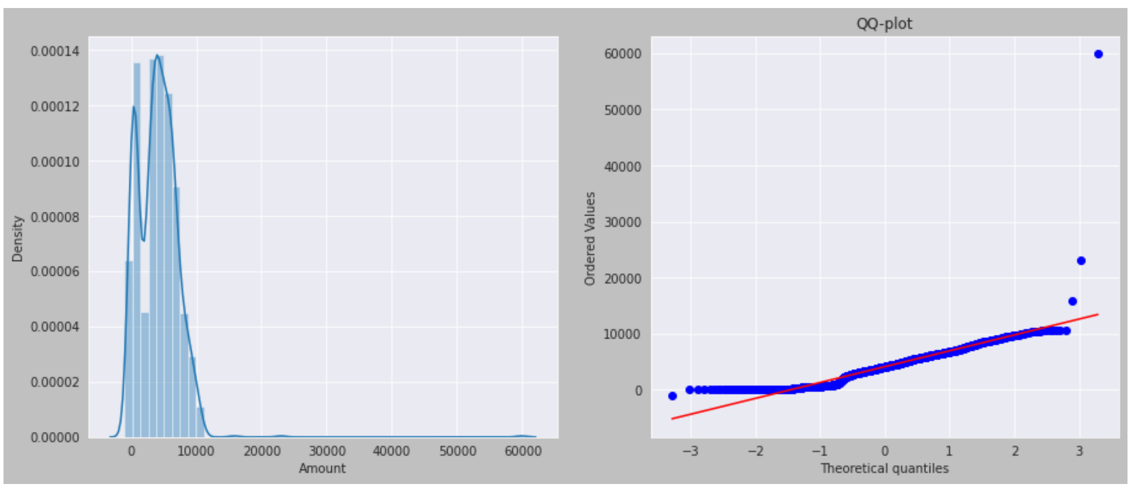
[ ]:
```
digo_plot(train_data, 'Min_coverage')
```




**OBSERVATION**

1. we have used normal distribution as base, distribution of Min_coverage follows roughly normal distribution.

```
[ ]: digo_plot(train_data, 'Amount')
```




**OBSERVATION**

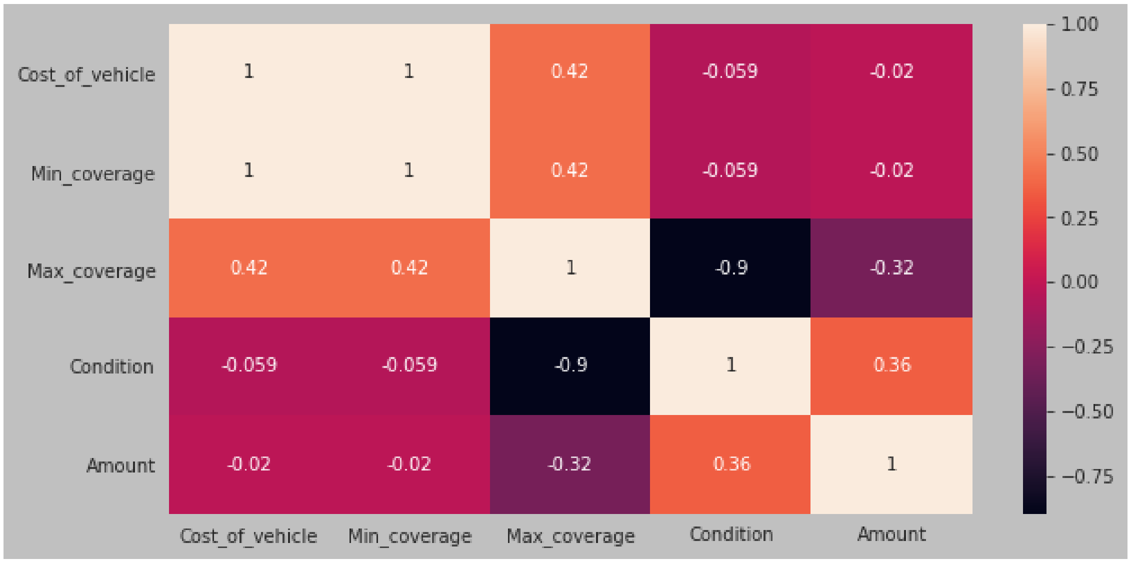
1. we have used normal distribution as base, distribution of Amount follows roughly normal distribution, with some outliers.

##1.8 CORRELATION AMONG FEATURES

```
[ ]:  def correlation_numerical(data):
        fig = plt.figure(figsize=(10,5))
        fig.patch.set_facecolor('silver')
```

```
corr_matrix = data.corr(method='pearson')
    sns.heatmap(corr_matrix, annot=True)
    plt.show()
```

[ ]:
```
correlation_numerical(train_data)
```



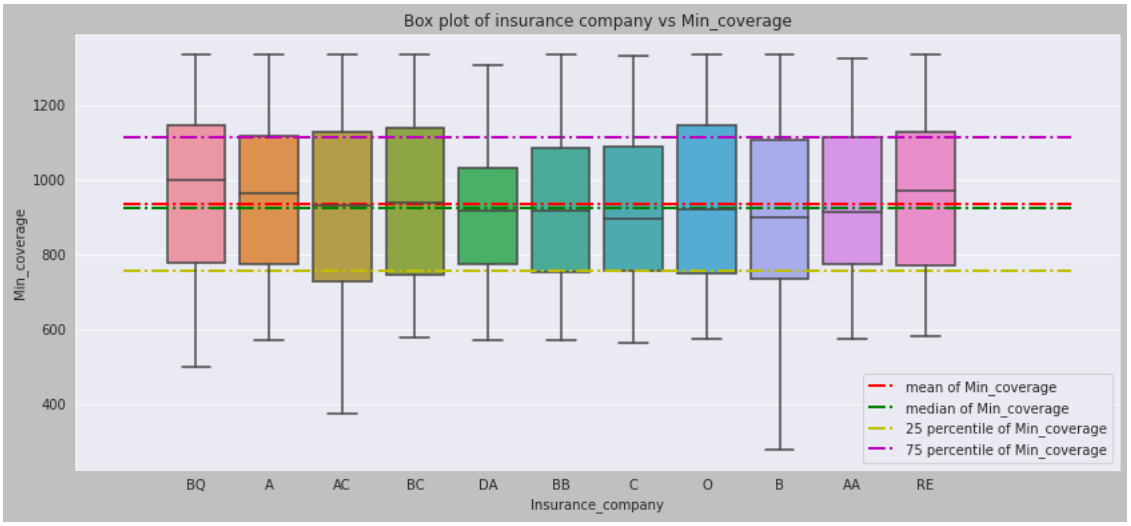

**OBSERVATION**

1. Min_coverage and Cost_of_vehicle have perfect coreelation of 1,so use either cost of vechile or min coverage.

##1.9 BOX PLOT

[ ]:
```
def box_plot(data, col1, col2):
    fig = plt.figure(figsize=(14,6))
    fig.patch.set_facecolor('silver')
    sns.boxplot(x=col1, y=col2, data=data)
    plt.hlines(np.mean(data[col2]), -1, 12, color='r', ls='-.', lw=2,␣
↪label=f'mean of {col2}')
    plt.hlines(np.median(data[col2]), -1, 12, color='g', ls='-.', lw=2,␣
↪label=f'median of {col2}')
    plt.hlines(np.percentile(data[col2],25), -1, 12, color='y', ls='-.', lw=2,␣
↪label=f'25 percentile of {col2}')
    plt.hlines(np.percentile(data[col2],75), -1, 12, color='m', ls='-.', lw=2,␣
↪label=f'75 percentile of {col2}')
    plt.title(f'Box plot of insurance company vs {col2}')
    plt.legend()
    plt.show()
```

[ ]:
```
box_plot(train_data, 'Insurance_company', 'Min_coverage')    ##cbgym
```



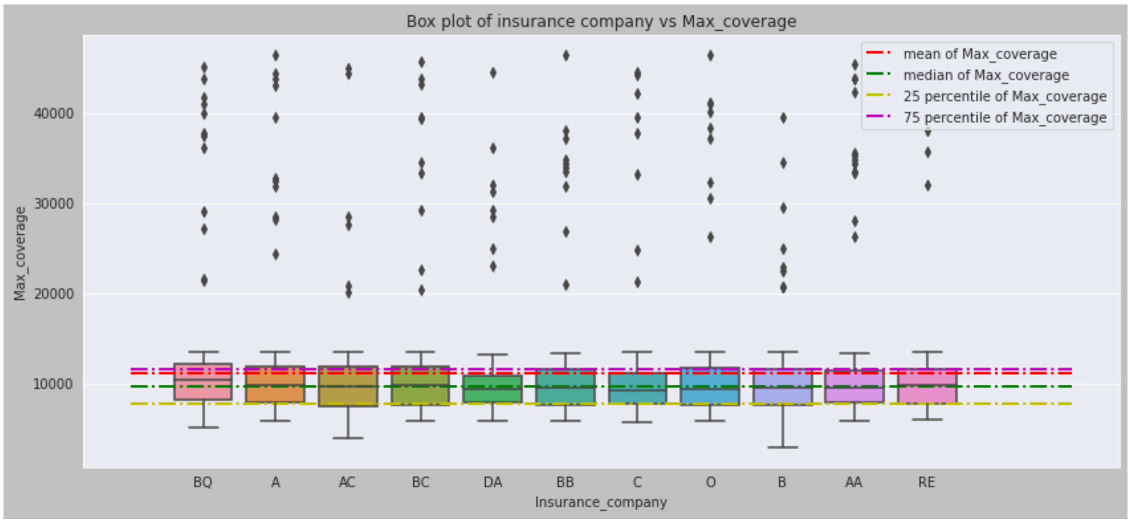

[ ]:
```
print('conclusion from above plot of Insurance_company vs Min_coverage :')
print('-'*65)
print(f'25 percentile  : {np.percentile(train_data["Min_coverage"].values,␣
 ↪25)}')
print(f'median         : {np.median(train_data["Min_coverage"].values)}')
print(f'75 percentile  : {np.percentile(train_data["Min_coverage"].values,␣
 ↪75)}')
print(' ')
print(f'iqr  : {np.percentile(train_data["Min_coverage"].values, 75) - np.
 ↪percentile(train_data["Min_coverage"].values, 25)}')
print(' ')
print(f'acc. theory  outliers : {(np.percentile(train_data["Min_coverage"].
 ↪values, 75) - np.percentile(train_data["Min_coverage"].values, 25))*1.5}')
print(' ')
print(f'range     : {max(train_data["Min_coverage"].values) -␣
 ↪min(train_data["Min_coverage"].values)}')
```

```
conclusion from above plot of Insurance_company vs Min_coverage :
-----------------------------------------------------------------
25 percentile  : 755.0
median         : 925.0
75 percentile  : 1115.0

iqr  : 360.0

acc. theory  outliers : 540.0

range     : 1060.0
```

**OBSERVATION**

1. we see that median of Min_coverage almost coinsides with median of each insurance company.
2. we see that 25 percentile of Min_coverage almost coinsides with 25 percentile of each insurance company.
3. we see that 75 percentile of Min_coverage almost coinsides with 75 percentile of each insurance company.

[ ]:
```
box_plot(train_data, 'Insurance_company', 'Max_coverage')
```

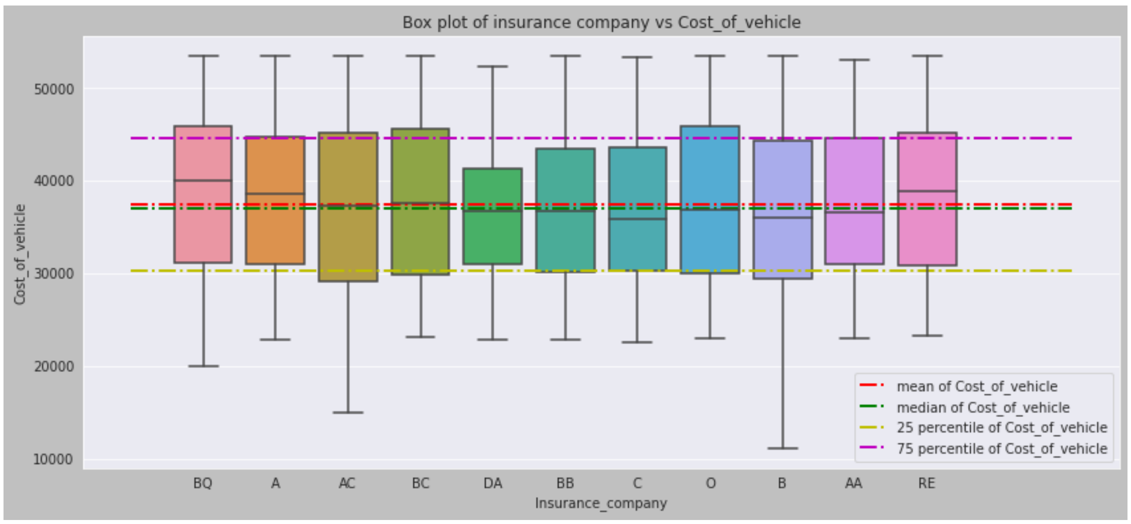



[ ]:
```
print('conclusion from above plot of Insurance_company vs Max_coverage :')
print('-'*65)
print(f'25 percentile  : {np.percentile(train_data["Max_coverage"].values,␣
↪25)}')
print(f'median         : {np.median(train_data["Max_coverage"].values)}')
print(f'75 percentile  : {np.percentile(train_data["Max_coverage"].values,␣
↪75)}')
print(' ')
print(f'iqr  : {np.percentile(train_data["Max_coverage"].values, 75) - np.
↪percentile(train_data["Max_coverage"].values, 25)}')
print(' ')
print(f'acc. theory  outliers : {(np.percentile(train_data["Max_coverage"].
↪values, 75) - np.percentile(train_data["Max_coverage"].values, 25))*1.5}')
print(' ')
print(f'range     : {max(train_data["Max_coverage"].values) -␣
↪min(train_data["Max_coverage"].values)}')
```

```
conclusion from above plot of Insurance_company vs Max_coverage :
-----------------------------------------------------------------
25 percentile  : 7728.0
```

```
median          : 9603.0
75 percentile   : 11603.0

iqr   : 3875.0

acc. theory  outliers : 5812.5

range    : 43642.68
```

[ ]:
```
box_plot(train_data, 'Insurance_company', 'Cost_of_vehicle')
```




[ ]:
```
print('conclusion from above plot of Insurance_company vs Cost_of_vehicle :')
print('-'*68)
print(f'25 percentile   : {np.percentile(train_data["Cost_of_vehicle"].values,␣
↪25)}')
print(f'median          : {np.median(train_data["Cost_of_vehicle"].values)}')
print(f'75 percentile   : {np.percentile(train_data["Cost_of_vehicle"].values,␣
↪75)}')
print(' ')
print(f'iqr   : {np.percentile(train_data["Cost_of_vehicle"].values, 75) - np.
↪percentile(train_data["Cost_of_vehicle"].values, 25)}')
print(' ')
print(f'acc. theory  outliers : {(np.percentile(train_data["Cost_of_vehicle"].
↪values, 75) - np.percentile(train_data["Cost_of_vehicle"].values, 25))*1.5}')
print(' ')
print(f'range    : {max(train_data["Cost_of_vehicle"].values) -␣
↪min(train_data["Cost_of_vehicle"].values)}')
```

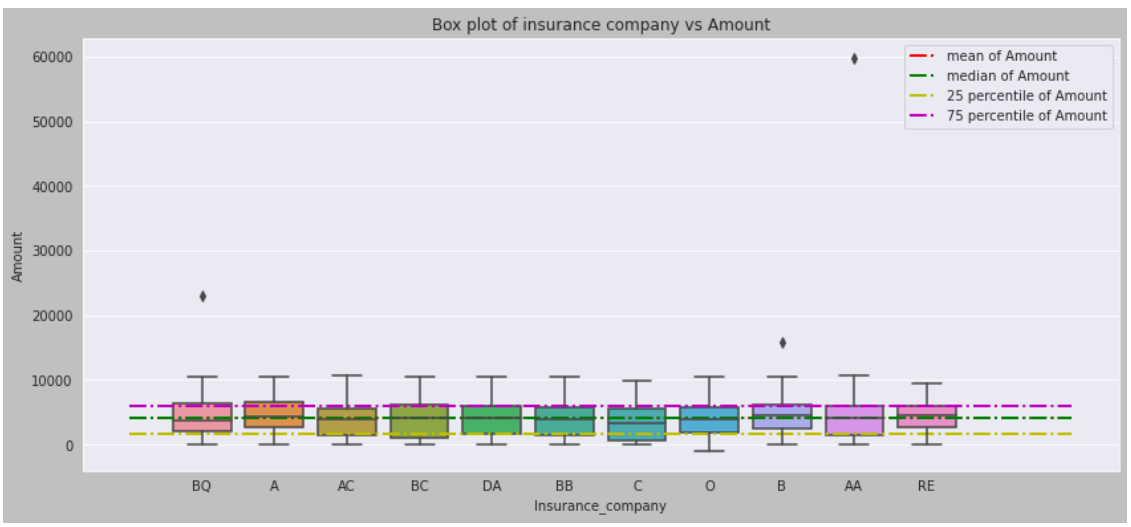
```
conclusion from above plot of Insurance_company vs Cost_of_vehicle :
--------------------------------------------------------------------
```

```
25 percentile   : 30200.0
median          : 37000.0
75 percentile   : 44600.0

iqr  : 14400.0

acc. theory  outliers : 21600.0

range    : 42400.0
```

**OBSERVATION**

1. we see that median of Cost_of_vehicle almost coinsides with median of each insurance company.
2. we see that 25 percentile of Cost_of_vehicle almost coinsides with 25 percentile of each insurance company.
3. we see that 75 percentile of Cost_of_vehicle almost coinsides with 75 percentile of each insurance company.

[ ]:
```
box_plot(train_data, 'Insurance_company', 'Amount')
```




[ ]:
```
print('conclusion from above plot of Insurance_company vs Amount :')
print('-'*60)
print(f'25 percentile   : {np.percentile(train_data["Amount"].values, 25)}')
print(f'median          : {np.median(train_data["Amount"].values)}')
print(f'75 percentile   : {np.percentile(train_data["Amount"].values, 75)}')
print(' ')
print(f'iqr  : {np.percentile(train_data["Amount"].values, 75) - np.
↪percentile(train_data["Amount"].values, 25)}')
print(' ')
```

```
print(f'acc. theory  outliers : {(np.percentile(train_data["Amount"].values,␣
↪75) - np.percentile(train_data["Amount"].values, 25))*1.5}')
print(' ')
print(f'range    : {max(train_data["Amount"].values) - min(train_data["Amount"].
↪values)}')
```

```
conclusion from above plot of Insurance_company vs Amount :
------------------------------------------------------------
25 percentile  : 1693.5
median         : 4071.0
75 percentile  : 6016.0

iqr  : 4322.5

acc. theory  outliers : 6483.75

range    : 60843.0
```

#1.10 OUTLIER TREATMENT

[ ]:
```
max(train_data['Amount'])
```

[ ]:
```
59844.0
```

[ ]:
```
train_data[train_data['Amount']>58000]  ## replace amt with aa median ammount
```

[ ]:
```
            Image_path Insurance_company  …  Condition   Amount
1324  img_7767995.jpg                AA  …          1  59844.0

[1 rows x 8 columns]
```

[ ]:
```
train_data.loc[1324,'Amount'] = 4048.0   ## replace amt with aa median ammount
```

[ ]:
```
train_data[train_data['Amount']>58000]  ## no such row
```

[ ]:
```
Empty DataFrame
Columns: [Image_path, Insurance_company, Cost_of_vehicle, Min_coverage,
Expiry_date, Max_coverage, Condition, Amount]
Index: []
```

[ ]:
```
train_data[train_data['Amount']<0]  ## replace amt with O median ammount
```

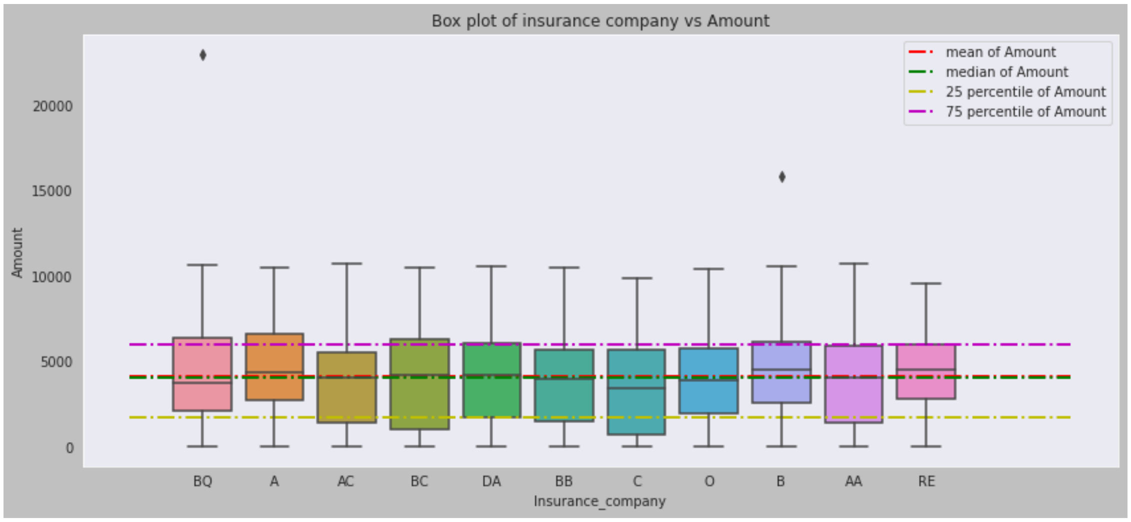
[ ]:
```
           Image_path Insurance_company  …  Condition  Amount
641  img_7766741.jpg                 O  …          1  -999.0

[1 rows x 8 columns]
```

[ ]:
```
train_data.loc[641,"Amount"] = 3853.0
```

[ ]:
```
train_data[train_data['Amount']<0]     ## no such row
```

[ ]:
```
Empty DataFrame
Columns: [Image_path, Insurance_company, Cost_of_vehicle, Min_coverage,
Expiry_date, Max_coverage, Condition, Amount]
Index: []
```

[ ]:
```
box_plot(train_data, 'Insurance_company', 'Amount')
```




[ ]:
```
print('conclusion from above plot of Insurance_company vs Amount :')
print('-'*60)
print(f'25 percentile  : {np.percentile(train_data["Amount"].values, 25)}')
print(f'median         : {np.median(train_data["Amount"].values)}')
print(f'75 percentile  : {np.percentile(train_data["Amount"].values, 75)}')
print(' ')
print(f'iqr  : {np.percentile(train_data["Amount"].values, 75) - np.
 ↪percentile(train_data["Amount"].values, 25)}')
print(' ')
print(f'acc. theory  outliers : {(np.percentile(train_data["Amount"].values,␣
 ↪75) - np.percentile(train_data["Amount"].values, 25))*1.5}')
print(' ')
print(f'range    : {max(train_data["Amount"].values) - min(train_data["Amount"].
 ↪values)}')
```

```
conclusion from above plot of Insurance_company vs Amount :
------------------------------------------------------------
25 percentile  : 1711.0
median         : 4069.0
75 percentile  : 6007.5
```

```
iqr  : 4296.5

acc. theory  outliers : 6444.75

range    : 23000.0
```

**OBSERVATION**

1. we see that median of Amount almost coinsides with median of each insurance company.
2. we see that 25 percentile of Amount almost coinsides with 25 percentile of each insurance company.
3. we see that 75 percentile of Amount almost coinsides with 75 percentile of each insurance company.

[ ]:
```
train_data[(train_data['Insurance_company']=='BQ') &␣
↪(train_data['Amount']>20000)]
```

[ ]:
```
           Image_path Insurance_company  …  Condition   Amount
786  img_7764865.jpg                BQ  …          1  23000.0

[1 rows x 8 columns]
```

[ ]:
```
train_data[(train_data['Insurance_company']=='B') &␣
↪(train_data['Amount']>10000)]
```

[ ]:
```
           Image_path Insurance_company  …  Condition   Amount
575  img_7766535.jpg                 B  …          1  10554.0
955  img_4635923.jpg                 B  …          1  15836.0

[2 rows x 8 columns]
```

**OBSERVATION**

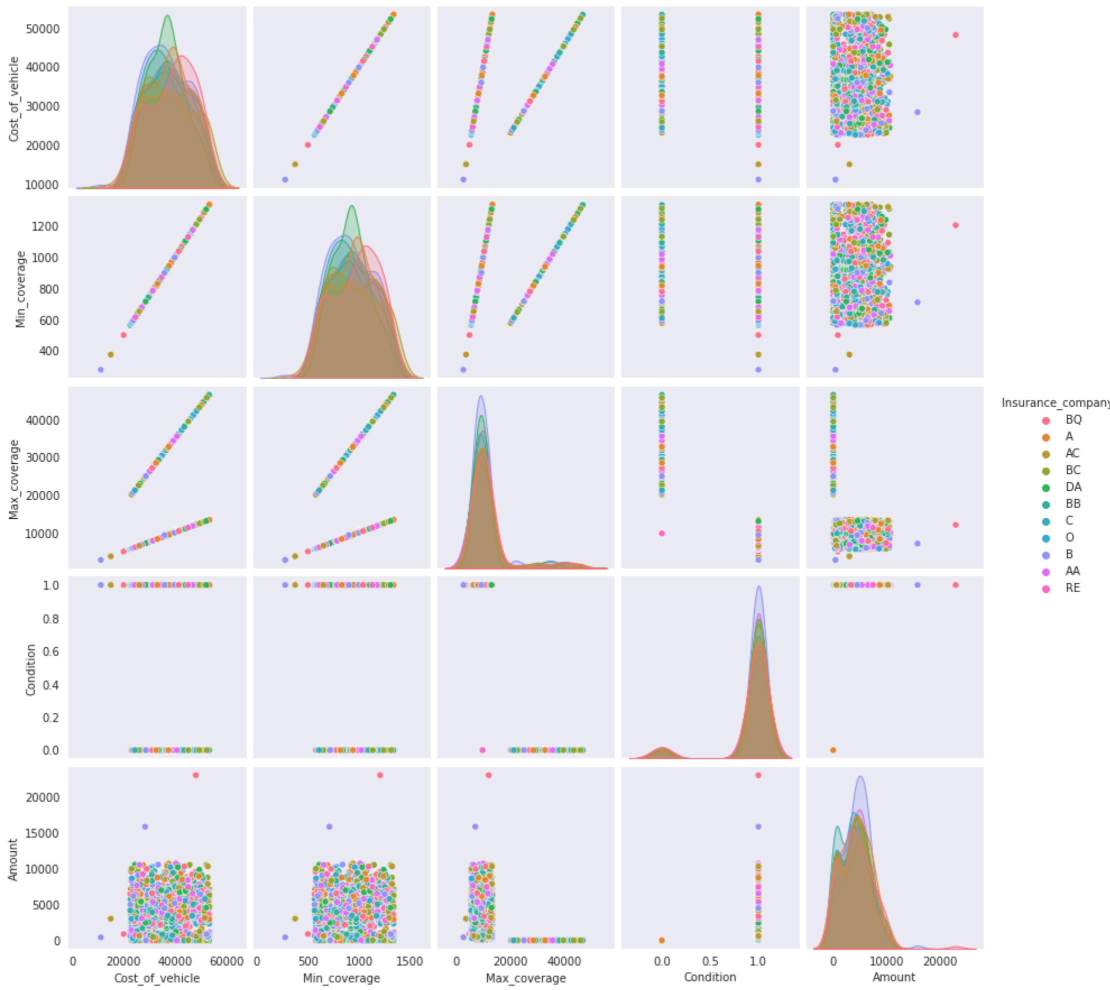
1. from above two cell we se that claim Amount is greater than Max_coverage, as of data description it is not mention whether this Max_coverage includes add-ons or not, and whether this Max_coverage before add-ons or after add-ons, for sake of generalness we assume it is without add-ons, so claim excedding max.coverage may be because of extra addons so not treating as outliers but other scenario is possible too.

##1.11 PAIR PLOT

[ ]:
```
 def pair_plt(data,column):
   fig = plt.figure(figsize=(15,15))
   fig.patch.set_facecolor('silver')
   sns.set_style('dark')
   sns.pairplot(data=data, hue=column, kind='scatter',diag_kind="kde")
   plt.show()
```

[ ]:
```
pair_plt(train_data, 'Insurance_company')
```

<Figure size 1080x1080 with 0 Axes>

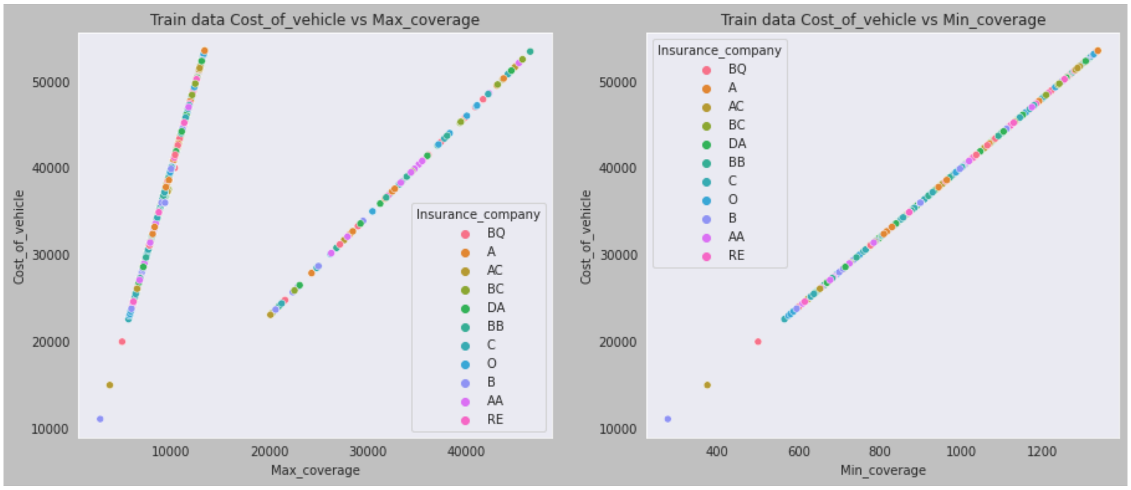



[ ]:

```python
def bi_plot(data, col, col0, col1, col2):
  fig, axes = plt.subplots(1, 2, figsize=(15, 6))
  fig.patch.set_facecolor('silver')

  plt.subplot(1, 2, 1)
  sns.scatterplot(x=col1, y=col0, data=data, hue=col)
  plt.xlabel(f'{col1}')
  plt.ylabel(f'{col0}')
  plt.title(f'Train data {col0} vs {col1}')

  plt.subplot(1, 2, 2)
  sns.scatterplot(x=col2, y=col0, data=data, hue=col)
  plt.xlabel(f'{col2}')
  plt.ylabel(f'{col0}')
  plt.title(f'Train data {col0} vs {col2}')
```

```
plt.show()
```

[ ]:
```
bi_plot(train_data, 'Insurance_company', 'Cost_of_vehicle', 'Max_coverage',␣
↪'Min_coverage')
```




[ ]:
```
train_data.loc[train_data['Max_coverage'] > 20000]['Condition'].value_counts()
```

[ ]:
```
0    97
Name: Condition, dtype: int64
```

**OBSERVATION**

1. condition on which Max_coverage is decided is based on 2 seperable categories, i.e greater than 20000 (which have almost all insurance company), do not have any damages, this helps to design a feature in feature engineering section (if Max_coverage greater than >20000 or not) i.e describe category of insurance.

#2 Feature engineering

##2.1 CHECKING TRAIN DATASET

[ ]:
```
import datetime

def feature_engg(data, col1, col2, col3, col4, col5):

   '''takes data : train/test dataframe,
      col1       : expiry_date,
      col2       : cost-of-vehicle,
      col3       : insurance company,
      col4       : max coverage
      col5       : min coverage
      returns    : newly computed feature in dataframe'''
```

```
    today = datetime.datetime(2021,9,12,0,0,0)
    luxury_seg = np.percentile(data[col2], 75)
    medium_seg = np.percentile(data[col2], 25)
    cmp_cnt = data[col3].value_counts()


    data[col1]              = data[col1].apply(pd.to_datetime)
    data['year']            = data[col1].apply(lambda x : x.year)
    data['month']           = data[col1].apply(lambda x: x.month)
    data['month_day']       = data[col1].apply(lambda x: x.day)
    data['yr_day']          = data[col1].apply(lambda x: x.dayofyear)
    data['week_day']        = data[col1].apply(lambda x: x.weekday())
    data['week_no']         = data[col1].apply(lambda x: x.week)
    data['lux_seg']         = data[col2].apply(lambda x: 1 if x>luxury_seg else 0)
    data['med_seg']         = data[col2].apply(lambda x: 1 if (x<luxury_seg and␣
↪x>medium_seg) else 0)
    data['budget_seg']      = data[col2].apply(lambda x: 1 if (x<medium_seg) else 0)
    data['age_of_insur'] = data[col1].apply(lambda x: round(abs((today-x).days)/
↪365,2))

    md_age = np.median(data['age_of_insur'])

    data['cmpny_count']        = data[col3].apply(lambda x: cmp_cnt[x])
    data['range_of_coverage'] = data[col4]-data[col5]
    data['insuran_pd']         = data['age_of_insur'].apply(lambda x: 1 if x >␣
↪md_age else 0)
    data['low_expire']         = data['age_of_insur'].apply(lambda x: 1 if x < 2␣
↪else 0)
    data['med_expire']         = data['age_of_insur'].apply(lambda x: 1 if (x > 2␣
↪and x<5) else 0)
    data['hig_expire']         = data['age_of_insur'].apply(lambda x: 1 if  x>5␣
↪else 0)
    data['cost_grt_20k']       = data[col4].apply(lambda x : 1 if x > 20000 else 0)

    return data
```

[ ]:
```
train_data_f = feature_engg(train_data, 'Expiry_date', 'Cost_of_vehicle',␣
↪'Insurance_company', 'Max_coverage', 'Min_coverage')
train_data_f
```

[ ]:

| | Image_path | Insurance_company | … | hig_expire | cost_grt_20k |
|---|---|---|---|---|---|
| 0 | img_4513976.jpg | BQ | … | 1 | 1 |
| 1 | img_7764995.jpg | BQ | … | 0 | 0 |
| 2 | img_451308.jpg | A | … | 0 | 1 |

```
3     img_7768372.jpg                  A  …            0              0
4     img_7765274.jpg                 AC  …            0              0
…             …                  …   …         …           …
1394  img_4637237.jpg                 DA  …            0              0
1395  img_4637000.jpg                 BQ  …            0              0
1396  img_4637503.jpg                 AA  …            0              0
1397  img_4515101.jpg                  A  …            0              0
1398  img_4636333.jpg                  B  …            0              0

[1399 rows x 25 columns]
```

```
[ ]: train_data_f.insert(len(train_data_f.columns)-1, 'Condition', train_data_f.
      ↪pop('Condition'))
     train_data_f.insert(len(train_data_f.columns)-1, 'Amount', train_data_f.
      ↪pop('Amount'))
```

```
[ ]: train_data_f.head()
```

```
[ ]:         Image_path Insurance_company  …  Condition  Amount
     0  img_4513976.jpg                BQ  …          0     0.0
     1  img_7764995.jpg                BQ  …          1  6194.0
     2   img_451308.jpg                 A  …          0     0.0
     3  img_7768372.jpg                 A  …          1  7699.0
     4  img_7765274.jpg                AC  …          1  8849.0

     [5 rows x 25 columns]
```

```
[ ]: import pickle
     pickle.dump((train_data_f), open('/content/gdrive/MyDrive/cs2/data/train_data_f.
      ↪pkl','wb'))
     #train_data_f = pickle.load(open('/content/gdrive/MyDrive/cs1/train_data_f.
      ↪pkl', 'rb'))
```

##2.2 CHECKING TEST DATA

```
[ ]: test_data = pd.read_csv('/content/gdrive/MyDrive/cs2/data/test.csv')
     test_data
```

```
[ ]:          Image_path Insurance_company  …  Expiry_date  Max_coverage
     0    img_4538519.jpg                 B  …   2025-04-12       5978.00
     1    img_7766002.jpg                 C  …   2028-08-24       7153.00
     2    img_4637390.jpg                AC  …   2023-11-28      11003.00
     3    img_4516108.jpg                BB  …   2028-02-04      11603.00
     4    img_4517008.jpg                BB  …   2022-01-03      10253.00
     ..              …               …   …          …            …
     595  img_7766518.jpg                 B  …   2024-10-23       7803.00
     596  img_4535713.jpg                 O  …   2025-02-21      12903.00
```

```
597  img_4511787.jpg              BQ  …   2023-07-13     23527.68
598  img_4517592.jpg              AA  …   2024-05-05     10728.00
599  img_4635378.jpg              RE  …   2025-08-07     12403.00

[600 rows x 6 columns]
```

[ ]:
```
test_data.isnull().sum()            ##no null value
```

[ ]:
```
Image_path           0
Insurance_company    0
Cost_of_vehicle      0
Min_coverage         0
Expiry_date          0
Max_coverage         0
dtype: int64
```

[ ]:
```
test_data[test_data['Max_coverage']>test_data['Cost_of_vehicle']]   ##this show␣
↪there is no such column
```

[ ]:
```
Empty DataFrame
Columns: [Image_path, Insurance_company, Cost_of_vehicle, Min_coverage,
Expiry_date, Max_coverage]
Index: []
```

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

[ ]:
```
       Cost_of_vehicle  Min_coverage  Max_coverage
count       600.000000    600.000000    600.000000
mean      38175.500000    954.387500  11281.169267
std        9181.904052    229.547601   6804.330322
min       20000.000000    500.000000   5078.000000
25%       30600.000000    765.000000   7990.500000
50%       37650.000000    941.250000   9703.000000
75%       46000.000000   1150.000000  12084.250000
max       79200.000000   1980.000000  45451.680000
```

[ ]:
```
test_data_f = feature_engg(test_data, 'Expiry_date', 'Cost_of_vehicle',␣
↪'Insurance_company', 'Max_coverage', 'Min_coverage')
test_data_f
```

[ ]:
```
          Image_path Insurance_company  …  hig_expire  cost_grt_20k
0    img_4538519.jpg                 B  …           0             0
1    img_7766002.jpg                 C  …           1             0
2    img_4637390.jpg                AC  …           0             0
3    img_4516108.jpg                BB  …           1             0
4    img_4517008.jpg                BB  …           0             0
..               …                …  …           …             …
```

```
595  img_7766518.jpg                 B  …           0           0
596  img_4535713.jpg                 O  …           0           0
597  img_4511787.jpg                BQ  …           0           1
598  img_4517592.jpg                AA  …           0           0
599  img_4635378.jpg                RE  …           0           0

[600 rows x 23 columns]
```

```
[ ]: pickle.dump((test_data_f), open('/content/gdrive/MyDrive/cs2/data/test_data_f.
      ↪pkl','wb'))
     #test_data_f = pickle.load(open('/content/gdrive/MyDrive/cs1/test_data_f.pkl',␣
      ↪'rb'))
```