Insurance claim prediction

March 19, 2024

1 Insurance claim prediction

1.1 Problem Statement :

Dataset is about Vehicle insurance claim prediction in which we have two datasets one is train and another is test data. The challenge is to predict Workers Compensation claims using the realistic data .

1.2 Independent/Predictor Variables

- ClaimNumber: Unique policy identifier
- DateTimeOfAccident: Date and time of accident
- DateReported: Date that accident was reported
- Age: Age of worker
- Gender: Gender of worker
- MaritalStatus: Martial status of worker. (M)arried, (S)ingle, (U)unknown.
- DependentChildren: The number of dependent children
- DependentsOther: The number of dependants excluding children
- WeeklyWages: Total weekly wage
- PartTimeFullTime: Binary (P) or (F)
- HoursWorkedPerWeek: Total hours worked per week
- DaysWorkedPerWeek: Number of days worked per week
- ClaimDescription: Free text description of the claim
- InitialIncurredClaimCost: Initial estimate by the insurer of the claim cost

1.3 Dependent/Target Variable

- UltimateIncurredClaimCost: Total claims payments by the insurance company.
- The Target variable 'Ultimate Incurred Claim Cost' is a continuous variable which accounts for the total claim payment by the insurance company

2 Importing Libraries

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

```python
import warnings
warnings.filterwarnings("ignore")
```

3 Data Preparation

[2]:
```python
#collecting data
df = pd.read_csv('train_SJC.csv')
df.head()
```

[2]:
```
     Unnamed: 0            Unnamed: 1          DateReported Unnamed: 3  \
0  ClaimNumber    DateTimeOfAccident                   NaN        Age
1    WC8205482  2002-04-09T07:00:00Z  2002-07-05T00:00:00Z         48
2    WC6922469  1999-01-07T11:00:00Z  1999-01-20T00:00:00Z         43
3    WC5442654  1996-03-25T00:00:00Z  1996-04-14T00:00:00Z         30
4    WC9796897  2005-06-22T13:00:00Z  2005-07-22T00:00:00Z         41

  Unnamed: 4     Unnamed: 5         Unnamed: 6  DependentsOther   Unnamed: 8  \
0     Gender  MaritalStatus  DependentChildren              NaN  WeeklyWages
1          M              M                  0              0.0          500
2          F              M                  0              0.0       509.34
3          M              U                  0              0.0        709.1
4          M              S                  0              0.0       555.46

         Unnamed: 9         Unnamed: 10  DaysWorkedPerWeek  \
0  PartTimeFullTime  HoursWorkedPerWeek                NaN
1                 F                  38                5.0
2                 F                37.5                5.0
3                 F                  38                5.0
4                 F                  38                5.0

                                         Unnamed: 12  \
0                                   ClaimDescription
1  LIFTING TYRE INJURY TO RIGHT ARM AND WRIST INJURY
2  STEPPED AROUND CRATES AND TRUCK TRAY FRACTURE …
3                  CUT ON SHARP EDGE CUT LEFT THUMB
4              DIGGING LOWER BACK LOWER BACK STRAIN

                Unnamed: 13               Unnamed: 14
0  InitialIncurredCalimsCost  UltimateIncurredClaimCost
1                       1500               4748.203388
2                       5500               6326.285819
3                       1700               2293.949087
4                      15000               17786.48717
```

[3]:
```python
#Renaming the column names in train data as it is "unnamed"
```

```
df=df.rename(columns={"Unnamed: 0":"ClaimNumber","Unnamed: 1":
↪"DateTimeOfAccident","Unnamed: 3":"Age","Unnamed: 4":"Gender",
                      "Unnamed: 5":"MaritalStatus","Unnamed: 6":
↪"DependentChildren","Unnamed: 8":"WeeklyWages",
                      "Unnamed: 9":"PartTimeFullTime","Unnamed: 10":
↪"HoursWorkedPerWeek","Unnamed: 12":"ClaimDescription",
                      "Unnamed: 13":"InitialIncurredCalimsCost","Unnamed: 14":
↪'UltimateIncurredClaimCost'},inplace=False)
```

[4]:
```
df.head()
```

[4]:
```
   ClaimNumber    DateTimeOfAccident          DateReported  Age  Gender  \
0  ClaimNumber    DateTimeOfAccident                   NaN  Age  Gender
1    WC8205482  2002-04-09T07:00:00Z  2002-07-05T00:00:00Z   48       M
2    WC6922469  1999-01-07T11:00:00Z  1999-01-20T00:00:00Z   43       F
3    WC5442654  1996-03-25T00:00:00Z  1996-04-14T00:00:00Z   30       M
4    WC9796897  2005-06-22T13:00:00Z  2005-07-22T00:00:00Z   41       M

   MaritalStatus  DependentChildren  DependentsOther  WeeklyWages  \
0  MaritalStatus  DependentChildren              NaN  WeeklyWages
1              M                  0              0.0          500
2              M                  0              0.0       509.34
3              U                  0              0.0        709.1
4              S                  0              0.0       555.46

   PartTimeFullTime  HoursWorkedPerWeek  DaysWorkedPerWeek  \
0  PartTimeFullTime  HoursWorkedPerWeek                NaN
1                 F                  38                5.0
2                 F                37.5                5.0
3                 F                  38                5.0
4                 F                  38                5.0

                                  ClaimDescription  \
0                                 ClaimDescription
1  LIFTING TYRE INJURY TO RIGHT ARM AND WRIST INJURY
2  STEPPED AROUND CRATES AND TRUCK TRAY FRACTURE …
3                    CUT ON SHARP EDGE CUT LEFT THUMB
4              DIGGING LOWER BACK LOWER BACK STRAIN

   InitialIncurredCalimsCost  UltimateIncurredClaimCost
0  InitialIncurredCalimsCost  UltimateIncurredClaimCost
1                       1500                4748.203388
2                       5500                6326.285819
3                       1700                2293.949087
4                      15000                17786.48717
```

[5]:
```python
df=df.drop(df.index[0])
df.head()
```

[5]:
```
  ClaimNumber    DateTimeOfAccident          DateReported Age Gender  \
1   WC8205482  2002-04-09T07:00:00Z  2002-07-05T00:00:00Z  48      M
2   WC6922469  1999-01-07T11:00:00Z  1999-01-20T00:00:00Z  43      F
3   WC5442654  1996-03-25T00:00:00Z  1996-04-14T00:00:00Z  30      M
4   WC9796897  2005-06-22T13:00:00Z  2005-07-22T00:00:00Z  41      M
5   WC2603726  1990-08-29T08:00:00Z  1990-09-27T00:00:00Z  36      M

  MaritalStatus DependentChildren  DependentsOther WeeklyWages  \
1             M                 0              0.0         500
2             M                 0              0.0      509.34
3             U                 0              0.0       709.1
4             S                 0              0.0      555.46
5             M                 0              0.0       377.1

  PartTimeFullTime HoursWorkedPerWeek  DaysWorkedPerWeek  \
1                F                 38                5.0
2                F               37.5                5.0
3                F                 38                5.0
4                F                 38                5.0
5                F                 38                5.0

                               ClaimDescription  \
1  LIFTING TYRE INJURY TO RIGHT ARM AND WRIST INJURY
2  STEPPED AROUND CRATES AND TRUCK TRAY FRACTURE …
3                   CUT ON SHARP EDGE CUT LEFT THUMB
4               DIGGING LOWER BACK LOWER BACK STRAIN
5  REACHING ABOVE SHOULDER LEVEL ACUTE MUSCLE STR…

  InitialIncurredCalimsCost UltimateIncurredClaimCost
1                      1500               4748.203388
2                      5500               6326.285819
3                      1700               2293.949087
4                     15000               17786.48717
5                      2800               4014.002925
```

[6]:
```python
#for training data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36176 entries, 1 to 36176
Data columns (total 15 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   ClaimNumber                36176 non-null  object
 1   DateTimeOfAccident         36176 non-null  object
```

```
 2   DateReported                 36176 non-null  object
 3   Age                          36176 non-null  object
 4   Gender                       36176 non-null  object
 5   MaritalStatus                36154 non-null  object
 6   DependentChildren            36176 non-null  object
 7   DependentsOther              36176 non-null  float64
 8   WeeklyWages                  36120 non-null  object
 9   PartTimeFullTime             36176 non-null  object
 10  HoursWorkedPerWeek           36127 non-null  object
 11  DaysWorkedPerWeek            36176 non-null  float64
 12  ClaimDescription             36176 non-null  object
 13  InitialIncurredCalimsCost    36176 non-null  object
 14  UltimateIncurredClaimCost    36176 non-null  object
dtypes: float64(2), object(13)
memory usage: 4.1+ MB
```

[7]:
```
#Checking for Categorical Data in train data
df.select_dtypes(exclude=['int64','float64']).columns
```

[7]:
```
Index(['ClaimNumber', 'DateTimeOfAccident', 'DateReported', 'Age', 'Gender',
       'MaritalStatus', 'DependentChildren', 'WeeklyWages', 'PartTimeFullTime',
       'HoursWorkedPerWeek', 'ClaimDescription', 'InitialIncurredCalimsCost',
       'UltimateIncurredClaimCost'],
      dtype='object')
```

[8]:
```
#Changing the data type for some columns in train data

df['Age'] = pd.to_numeric(df['Age'])
df['DependentChildren'] = pd.to_numeric(df['DependentChildren'])
df['DependentsOther'] = pd.to_numeric(df['DependentsOther'])
df['WeeklyWages'] = pd.to_numeric(df['WeeklyWages'])
df['HoursWorkedPerWeek'] = pd.to_numeric(df['HoursWorkedPerWeek'])
df['DaysWorkedPerWeek'] = pd.to_numeric(df['DaysWorkedPerWeek'])
df['InitialIncurredCalimsCost'] = pd.to_numeric(df['InitialIncurredCalimsCost'])
df['UltimateIncurredClaimCost'] = pd.to_numeric(df['UltimateIncurredClaimCost'])
df['DateTimeOfAccident']=pd.to_datetime(df['DateTimeOfAccident'])
df['DateReported']=pd.to_datetime(df['DateReported'])
```

[9]:
```
#To check if the data type changed or not
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36176 entries, 1 to 36176
Data columns (total 15 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   ClaimNumber                  36176 non-null  object
 1   DateTimeOfAccident           36176 non-null  datetime64[ns, UTC]
```

```
 2   DateReported                 36176 non-null  datetime64[ns, UTC]
 3   Age                          36176 non-null  int64
 4   Gender                       36176 non-null  object
 5   MaritalStatus                36154 non-null  object
 6   DependentChildren            36176 non-null  int64
 7   DependentsOther              36176 non-null  float64
 8   WeeklyWages                  36120 non-null  float64
 9   PartTimeFullTime             36176 non-null  object
 10  HoursWorkedPerWeek           36127 non-null  float64
 11  DaysWorkedPerWeek            36176 non-null  float64
 12  ClaimDescription             36176 non-null  object
 13  InitialIncurredCalimsCost    36176 non-null  int64
 14  UltimateIncurredClaimCost    36176 non-null  float64
dtypes: datetime64[ns, UTC](2), float64(5), int64(3), object(5)
memory usage: 4.1+ MB
```

[10]:

```
#checking the description of train data
df.describe()
```

[10]:

```
                Age  DependentChildren  DependentsOther   WeeklyWages  \
count  36176.000000       36176.000000     36176.000000  36120.000000
mean      33.795196           0.121296         0.009537    416.471426
std       12.114729           0.525395         0.106163    243.875364
min       13.000000           0.000000         0.000000      1.000000
25%       23.000000           0.000000         0.000000    200.000000
50%       32.000000           0.000000         0.000000    393.365000
75%       43.000000           0.000000         0.000000    500.000000
max       79.000000           9.000000         3.000000   7497.000000

       HoursWorkedPerWeek  DaysWorkedPerWeek  InitialIncurredCalimsCost  \
count        36127.000000       36176.000000               36176.000000
mean            37.766820           4.905794                7743.593874
std             12.494323           0.547077               18223.698531
min              0.000000           1.000000                   1.000000
25%             38.000000           5.000000                 700.000000
50%             38.000000           5.000000                2000.000000
75%             40.000000           5.000000                9500.000000
max            640.000000           7.000000              830000.000000

       UltimateIncurredClaimCost
count               3.617600e+04
mean                1.095282e+04
std                 3.529614e+04
min                 1.218868e+02
25%                 9.257424e+02
50%                 3.373862e+03
75%                 8.186852e+03
```

```
max                 4.027136e+06
```

[11]:
```
#Checking for duplicate values
df.duplicated().sum()
```

[11]:
```
0
```

[12]:
```
#Checking for null values
df.isnull().sum()
```

[12]:
```
ClaimNumber                  0
DateTimeOfAccident           0
DateReported                 0
Age                          0
Gender                       0
MaritalStatus               22
DependentChildren            0
DependentsOther              0
WeeklyWages                 56
PartTimeFullTime             0
HoursWorkedPerWeek          49
DaysWorkedPerWeek            0
ClaimDescription             0
InitialIncurredCalimsCost    0
UltimateIncurredClaimCost    0
dtype: int64
```

[13]:
```
#Handling null values using mean and mode imputation to treating the missing␣
 ↪values
df['WeeklyWages']=df['WeeklyWages'].fillna(df['WeeklyWages'].mean())
df['HoursWorkedPerWeek']=df['HoursWorkedPerWeek'].
 ↪fillna(df['HoursWorkedPerWeek'].mean())
df['MaritalStatus']=df['MaritalStatus'].fillna(df['MaritalStatus'].mode()[0])
```

[14]:
```
#To verify if there are any more missing values
df.isnull().sum()
```

[14]:
```
ClaimNumber                 0
DateTimeOfAccident          0
DateReported                0
Age                         0
Gender                      0
MaritalStatus               0
DependentChildren           0
DependentsOther             0
WeeklyWages                 0
PartTimeFullTime            0
```

```
HoursWorkedPerWeek           0
DaysWorkedPerWeek            0
ClaimDescription             0
InitialIncurredCalimsCost    0
UltimateIncurredClaimCost    0
dtype: int64
```

No Null values are present

Dividing the data into categorical and numerical data

[15]:
```
df_num = df[['Age', 'DependentChildren', 'DependentsOther', 'WeeklyWages',␣
 ↪'HoursWorkedPerWeek', 'DaysWorkedPerWeek',
             'InitialIncurredCalimsCost', 'UltimateIncurredClaimCost']]

df_cat = df[['ClaimNumber', 'DateTimeOfAccident', 'DateReported', 'Gender',␣
 ↪'MaritalStatus', 'PartTimeFullTime', 'ClaimDescription']]
```

[16]:
```
df['ClaimDescription'].nunique()
```

[16]:
```
20596
```

There are 20596 unique claims made.

[17]:
```
df.ClaimNumber.count()
```

[17]:
```
36176
```

The total number of claims filed is 36176.

[18]:
```
df['ClaimNumber'].nunique()
```

[18]:
```
29456
```

The total number of claims that were filed is 36176 but number of unique claims are 29456.

Data Transfromation - Data Binning

[19]:
```
df['Age'].value_counts
```

[19]:
```
<bound method IndexOpsMixin.value_counts of 1        48
2        43
3        30
4        41
5        36
         ..
36172    20
36173    35
36174    52
36175    28
36176    29
```

```
Name: Age, Length: 36176, dtype: int64>
```

[20]:
```
df['Age'].max()
```

[20]:
```
79
```

[21]:
```
df['Age'].min()
```

[21]:
```
13
```

[22]:
```
df['Age_Bin']=pd.cut(df['Age'],bins=[1,25,50,80] ,␣
↪labels=['Young','Middle-Age','Old'])
df['Age_Bin']
```

[22]:
```
1        Middle-Age
2        Middle-Age
3        Middle-Age
4        Middle-Age
5        Middle-Age
            …
36172         Young
36173    Middle-Age
36174           Old
36175    Middle-Age
36176    Middle-Age
Name: Age_Bin, Length: 36176, dtype: category
Categories (3, object): ['Young' < 'Middle-Age' < 'Old']
```

[23]:
```
df['WeeklyWages'].value_counts
```

[23]:
```
<bound method IndexOpsMixin.value_counts of 1         500.00
2          509.34
3          709.10
4          555.46
5          377.10
           …
36172      344.16
36173     1668.83
36174      204.87
36175      730.87
36176      200.00
Name: WeeklyWages, Length: 36176, dtype: float64>
```

[24]:
```
df['WeeklyWages'].max()
```

[24]:
```
7497.0
```

[25]:
```
df['WeeklyWages'].min()
```

[25]: 1.0

[26]:
```
df['WeeklyWages_Bin']=pd.
 ↪cut(df['WeeklyWages'],bins=[0,1000,2000,4000,7000,8000] ,␣
 ↪labels=['Low','Below Average','Average Wage','Above Average','High'])
df['WeeklyWages_Bin']
```

[26]:
```
1                   Low
2                   Low
3                   Low
4                   Low
5                   Low
             …
36172               Low
36173     Below Average
36174               Low
36175               Low
36176               Low
Name: WeeklyWages_Bin, Length: 36176, dtype: category
Categories (5, object): ['Low' < 'Below Average' < 'Average Wage' < 'Above
Average' < 'High']
```

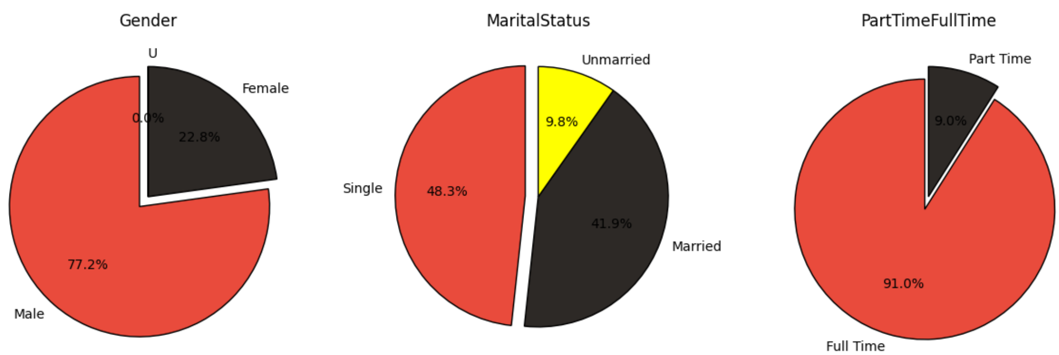
4 Exploratory Data Analysis :

4.1 Univariate Analysis

[27]:
```
Gender = df['Gender'].value_counts()
Gender = [Gender[0] / sum(Gender) * 100, Gender[1] / sum(Gender) * 100 ,␣
 ↪Gender[2] / sum(Gender) * 100]

MaritalStatus = df['MaritalStatus'].value_counts()
MaritalStatus = [MaritalStatus[0] / sum(MaritalStatus) * 100, MaritalStatus[1] /
 ↪ sum(MaritalStatus) * 100 , MaritalStatus[2] / sum(MaritalStatus) * 100]

PartTimeFullTime = df['PartTimeFullTime'].value_counts()
PartTimeFullTime = [PartTimeFullTime[0] / sum(PartTimeFullTime) * 100,␣
 ↪PartTimeFullTime[1] / sum(PartTimeFullTime) * 100 ]
```

[28]:
```
colors = ['#E94B3C','#2D2926','#FFFF00']

ax,fig = plt.subplots(nrows = 1,ncols = 3,figsize = (15,15))

plt.subplot(1,3,1)
plt.pie(Gender,labels = ['Male','Female','U'],autopct='%1.1f%%',startangle =␣
 ↪90,explode = (0.1,0,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('Gender');
```

```
plt.subplot(1,3,2)
plt.pie(MaritalStatus,labels = ['Single', 'Married','Unmarried'],autopct='%1.
 ↪1f%%',startangle = 90,explode = (0.1,0,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('MaritalStatus');

plt.subplot(1,3,3)
plt.pie(PartTimeFullTime,labels = ['Full Time','Part Time'],autopct='%1.
 ↪1f%%',startangle = 90,explode = (0.1,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('PartTimeFullTime');
```



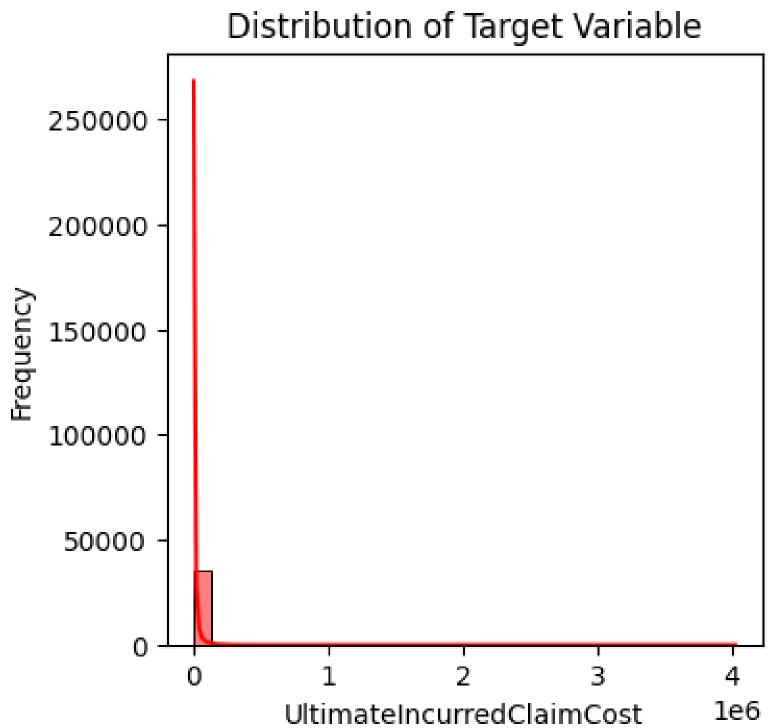
- From the above plot we can see approximately 77% people who claimed for insurance are males while 22% are females.
- We can see approximately 48% people who claimed for insurance are single while 42% are married and a very small percentage of people are unmarried.
- We can see approximately 91% of the people hold full time jobs.

[29]:
```
#Checking the target variable
df['UltimateIncurredClaimCost'].describe()
```

[29]:
```
count    3.617600e+04
mean     1.095282e+04
std      3.529614e+04
min      1.218868e+02
25%      9.257424e+02
50%      3.373862e+03
75%      8.186852e+03
max      4.027136e+06
Name: UltimateIncurredClaimCost, dtype: float64
```

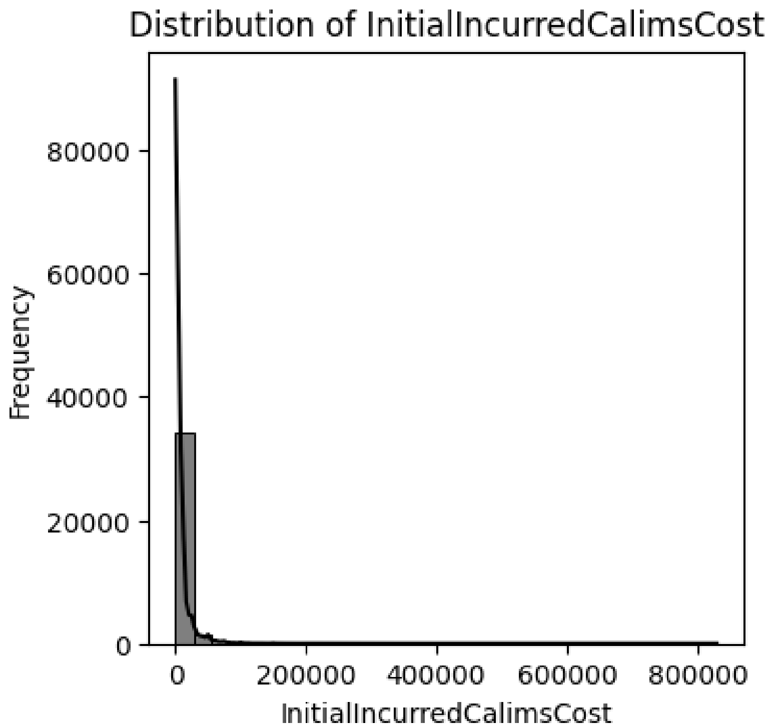
[30]:
```
#Checking the skewness of the target variable
plt.figure(figsize=(4,4))
```

```
sns.histplot(data=df, x='UltimateIncurredClaimCost', kde=True,␣
 ↪bins=30,color='red')
plt.title('Distribution of Target Variable')
plt.xlabel('UltimateIncurredClaimCost')
plt.ylabel('Frequency')
plt.show()
```



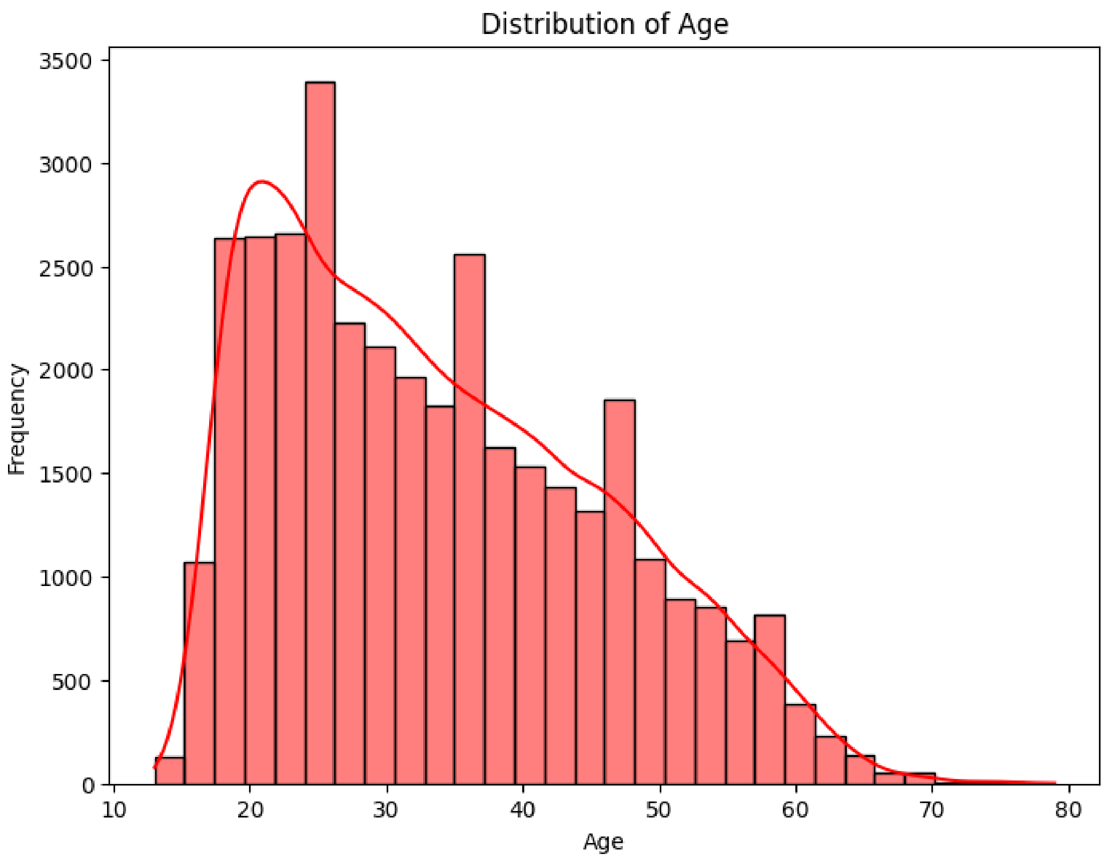
- The data for UltimateIncurredClaimCost is right skewed.

[31]:
```
plt.figure(figsize=(4,4))
sns.histplot(data=df, x='InitialIncurredCalimsCost', kde=True, bins=30,color␣
 ↪='black')
plt.title('Distribution of InitialIncurredCalimsCost')
plt.xlabel('InitialIncurredCalimsCost')
plt.ylabel('Frequency')
plt.show()
```

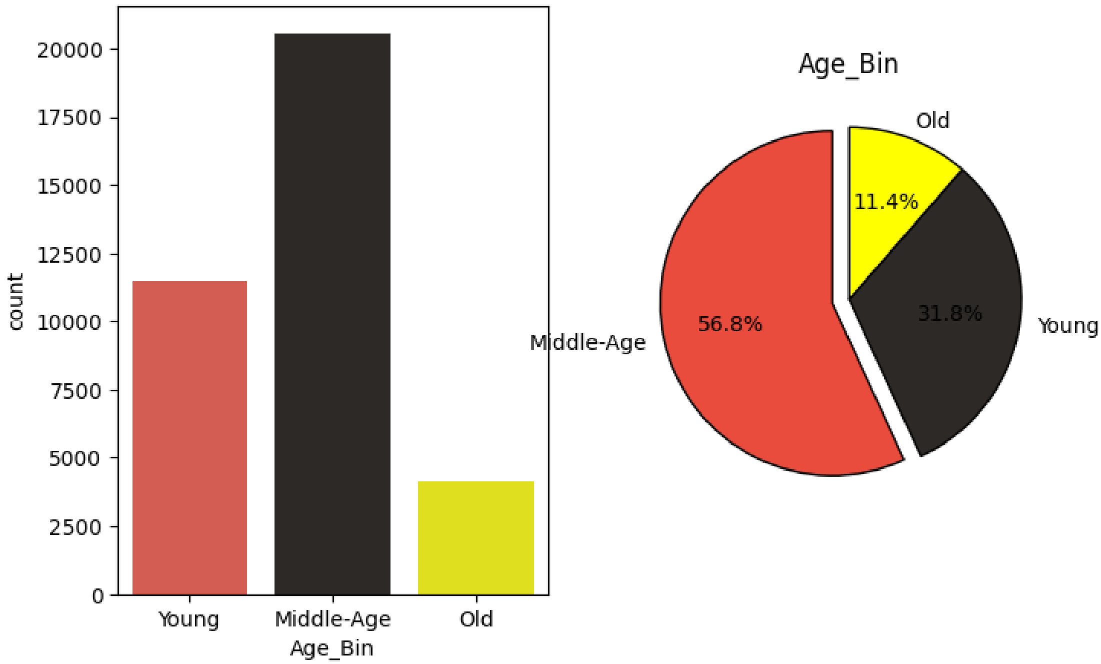


- The data for InitialIncurredClaimCost is right skewed.

[32]:
```
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x='Age', kde=True, bins=30,color='red')
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



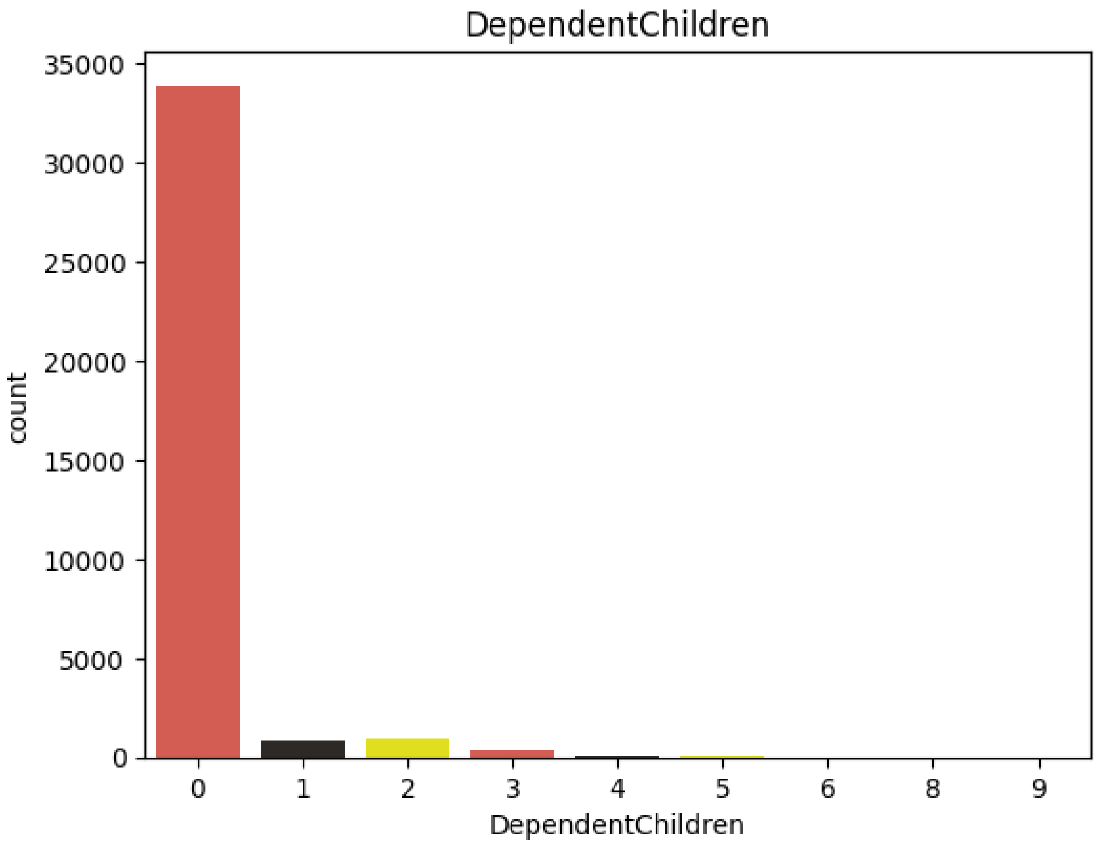
[33]:
```
Age_Bin= df['Age_Bin'].value_counts(normalize=True)*100
ax,fig = plt.subplots(nrows = 1,ncols = 3,figsize = (8,5))

plt.subplot(1,2,1)
sns.countplot(x = 'Age_Bin', data = df,palette=colors)

plt.subplot(1,2,2)
plt.pie(Age_Bin,labels = ['Middle-Age','Young','Old'],autopct='%1.
↪1f%%',startangle = 90,explode = (0.1,0,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('Age_Bin');
```



- From both the plots we can see that the claims are higher from the middle age group (25-40) which is roughly 57%.

[34]:
```
sns.countplot(x = 'DependentChildren', data = df,palette=colors)
plt.title('DependentChildren')
```

[34]: `Text(0.5, 1.0, 'DependentChildren')`



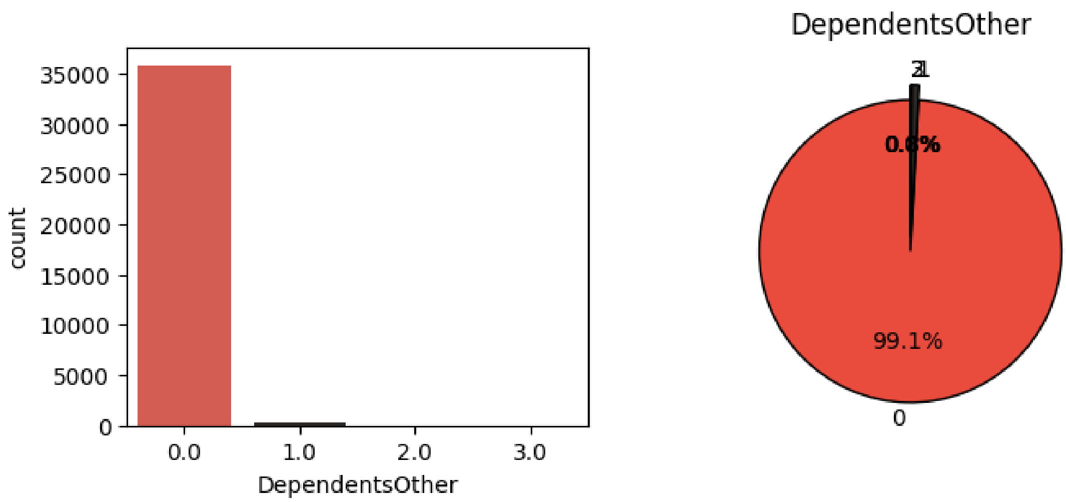
[35]:
```
df['DependentChildren'].value_counts(normalize=True)*100
```

[35]:
```
DependentChildren
0    93.703008
2     2.554180
1     2.371738
3     0.975785
4     0.284719
5     0.093985
6     0.011057
9     0.002764
8     0.002764
Name: proportion, dtype: float64
```

- The claims made from people with no children as dependents is high(Almost 94%).

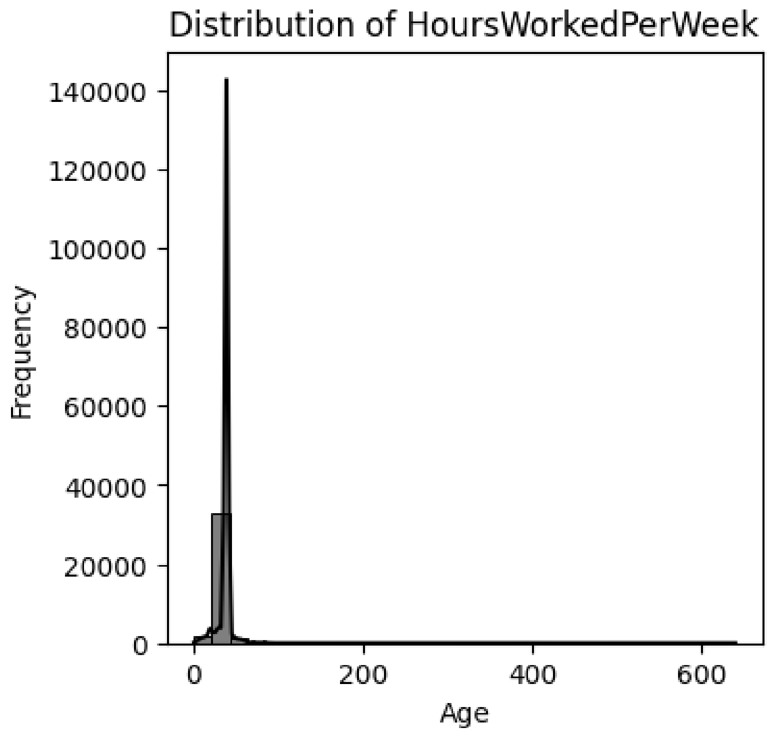
[36]:
```
DependentsOther= df['DependentsOther'].value_counts(normalize=True)*100

ax,fig = plt.subplots(nrows = 1,ncols = 3,figsize = (8,3))
```

```
plt.subplot(1,2,1)
sns.countplot(x = 'DependentsOther', data = df,palette=colors)


plt.subplot(1,2,2)
plt.pie(DependentsOther,labels = ['0','1','2','3'],autopct='%1.1f%%',startangle= 90,explode = (0.1,0,0,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('DependentsOther');
```



- The claims made from people with no dependents is high (Almost 99%).

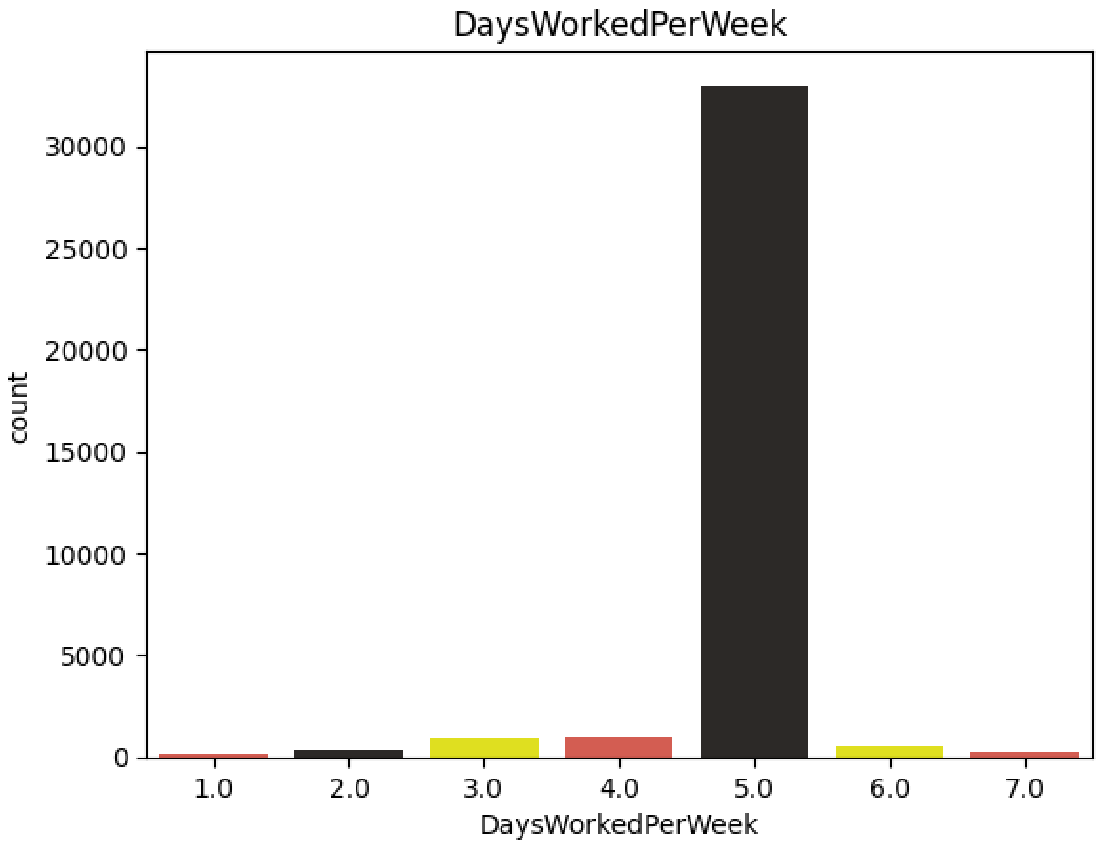
[37]:
```
plt.figure(figsize=(4,4))
sns.histplot(data=df, x='HoursWorkedPerWeek', kde=True, bins=30,color='black')
plt.title('Distribution of HoursWorkedPerWeek')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



- The data for HoursWorkedPerWeek is positively skewed.

[38]:
```
sns.countplot(x = 'DaysWorkedPerWeek', data = df , palette=colors)
plt.title('DaysWorkedPerWeek')
```

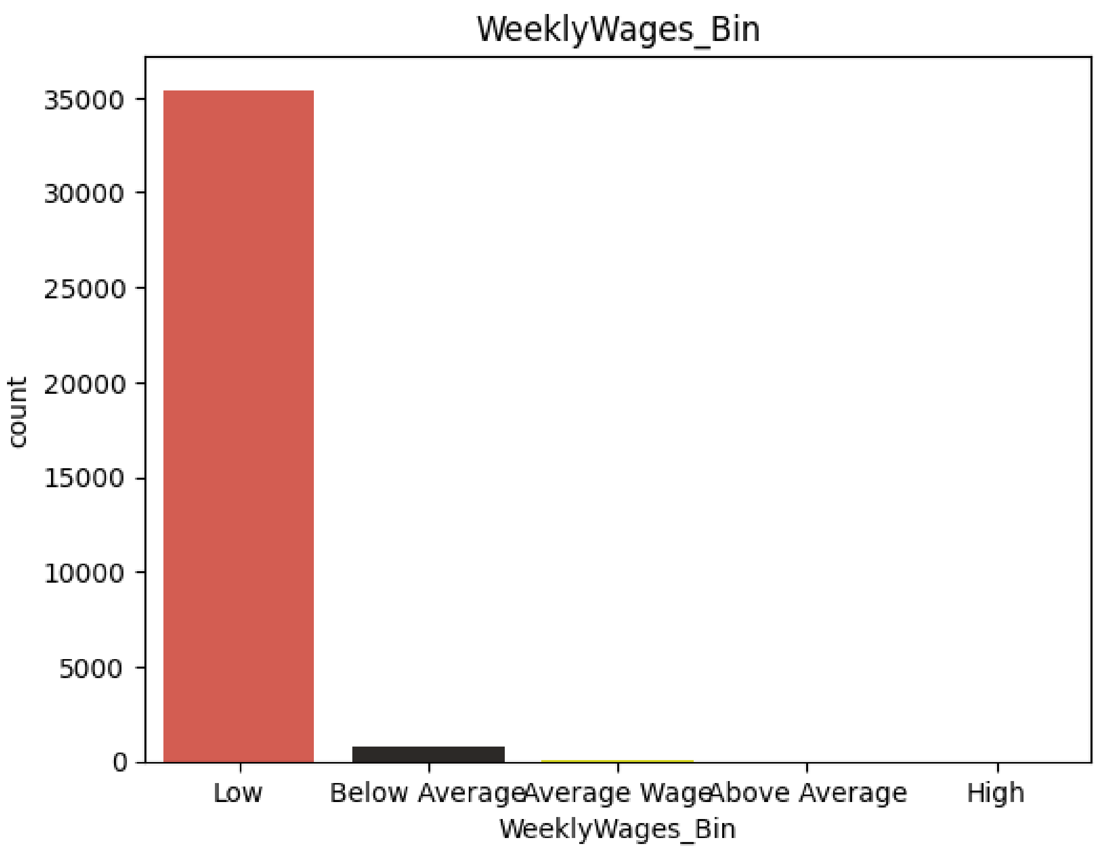
[38]: Text(0.5, 1.0, 'DaysWorkedPerWeek')



- From the above plot we can see that the people who have claimed for insurance work for 5 days a week.

[39]:
```
sns.countplot(x = 'WeeklyWages_Bin', data = df , palette=colors)
plt.title('WeeklyWages_Bin')
```

[39]: Text(0.5, 1.0, 'WeeklyWages_Bin')



[40]:
```
df['WeeklyWages_Bin'].value_counts(normalize=True)*100
```

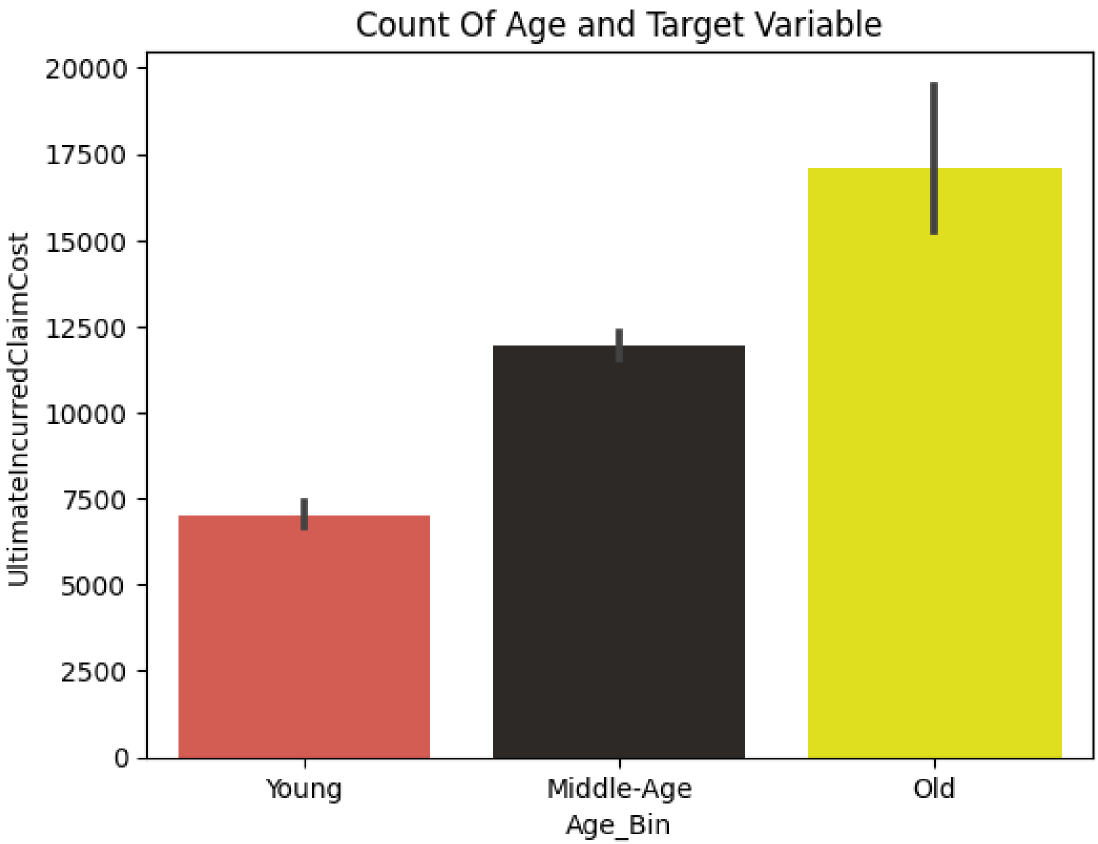
[40]:
```
WeeklyWages_Bin
Low              97.910217
Below Average     1.973684
Average Wage      0.105042
Above Average     0.008293
High              0.002764
Name: proportion, dtype: float64
```

- From the above plot we can see that most of the people who claimed for insurance have low wages

4.2 Bivariate analysis

[41]:
```
sns.barplot(x='Age_Bin',y='UltimateIncurredClaimCost',data=df , palette=colors)
plt.title('Count Of Age and Target Variable')
```

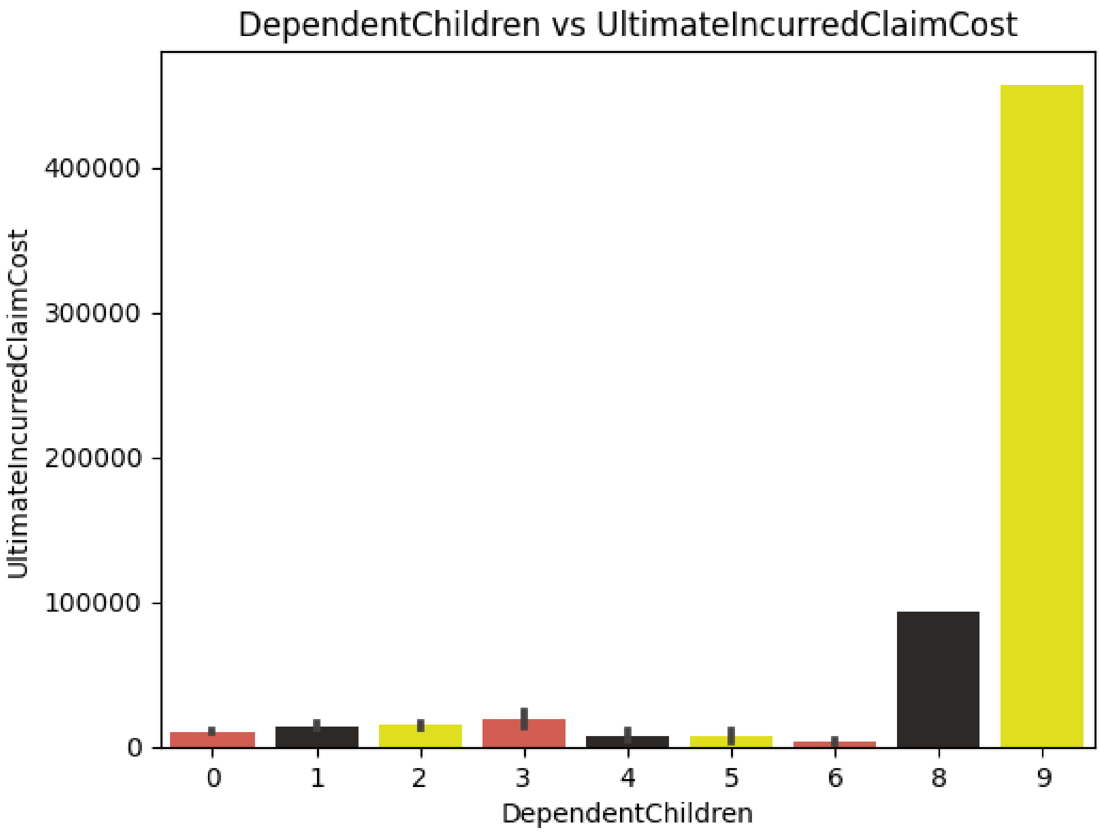
[41]:
```
Text(0.5, 1.0, 'Count Of Age and Target Variable')
```



- People who are in the old age group (50-80) got more total claims payments by the insurance company.

[42]:
```
sns.barplot(x='DependentChildren',y='UltimateIncurredClaimCost',data=df␣
 ↪,palette=colors)
plt.title('DependentChildren vs UltimateIncurredClaimCost')
```

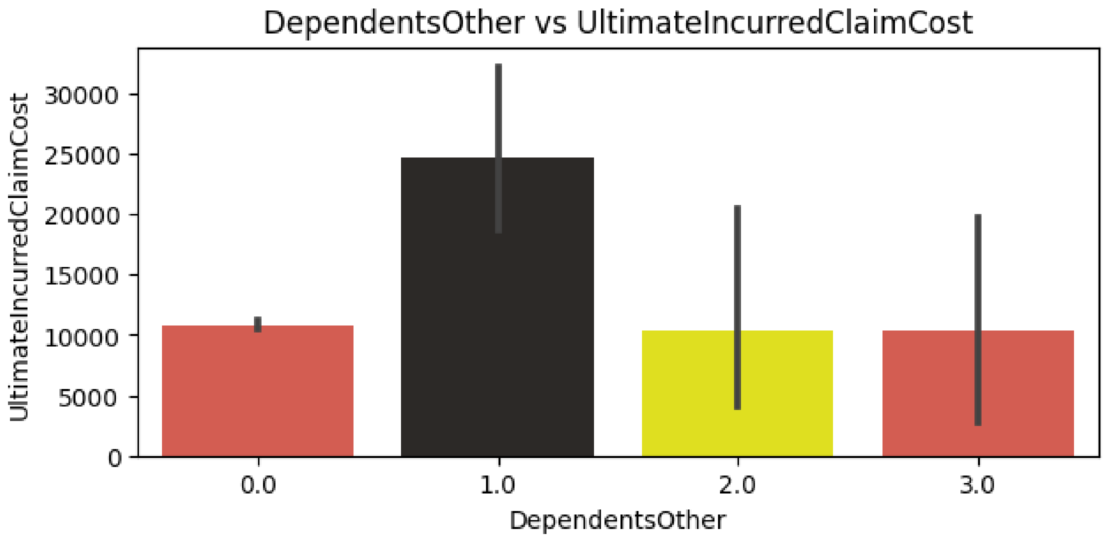
[42]: Text(0.5, 1.0, 'DependentChildren vs UltimateIncurredClaimCost')



- People who have more children as dependents got more insurance payments from the insurance company.

[43]:
```
plt.figure(figsize=(7,3))
sns.barplot(x='DependentsOther',y='UltimateIncurredClaimCost',data=df,␣
↪palette=colors)
plt.title('DependentsOther vs UltimateIncurredClaimCost')
```

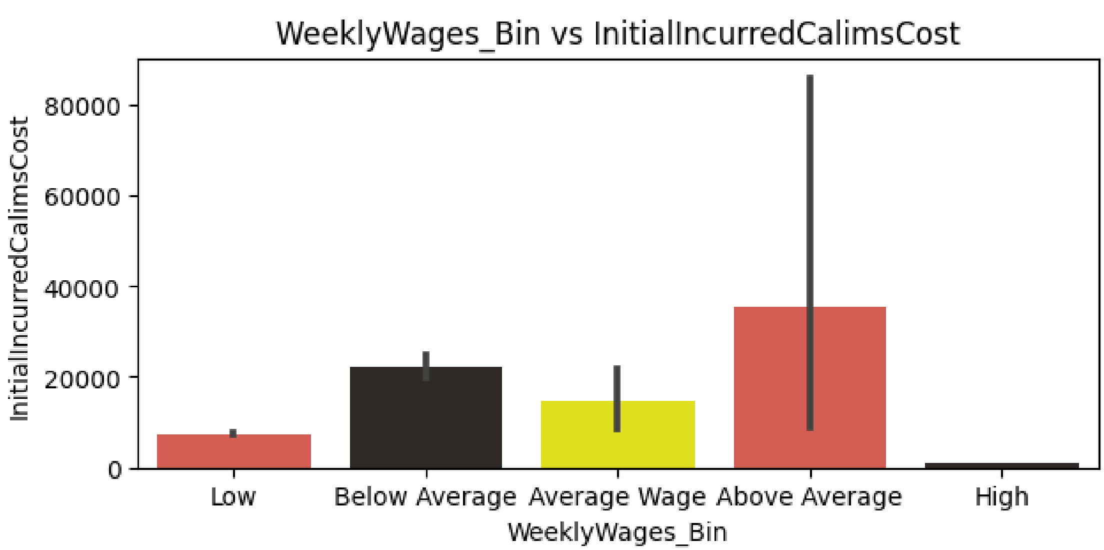
[43]:
```
Text(0.5, 1.0, 'DependentsOther vs UltimateIncurredClaimCost')
```



- People having 1 dependent person other than children has highest ultimate claimed cost.

[44]:
```
plt.figure(figsize=(7,3))
sns.
↪barplot(x='WeeklyWages_Bin',y='InitialIncurredCalimsCost',data=df,palette=colors)
plt.title('WeeklyWages_Bin vs InitialIncurredCalimsCost')
```

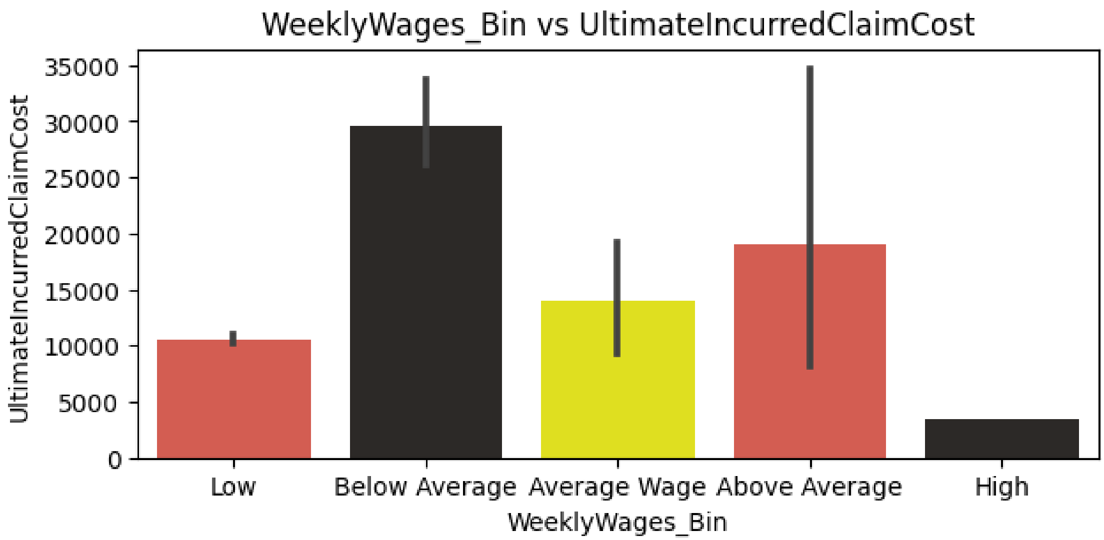
[44]:
```
Text(0.5, 1.0, 'WeeklyWages_Bin vs InitialIncurredCalimsCost')
```



- People whose wages are above average claimed for more claim cost.

[45]:
```
plt.figure(figsize=(7,3))
sns.
 ↪barplot(x='WeeklyWages_Bin',y='UltimateIncurredClaimCost',data=df,palette=colors)
plt.title('WeeklyWages_Bin vs UltimateIncurredClaimCost')
```

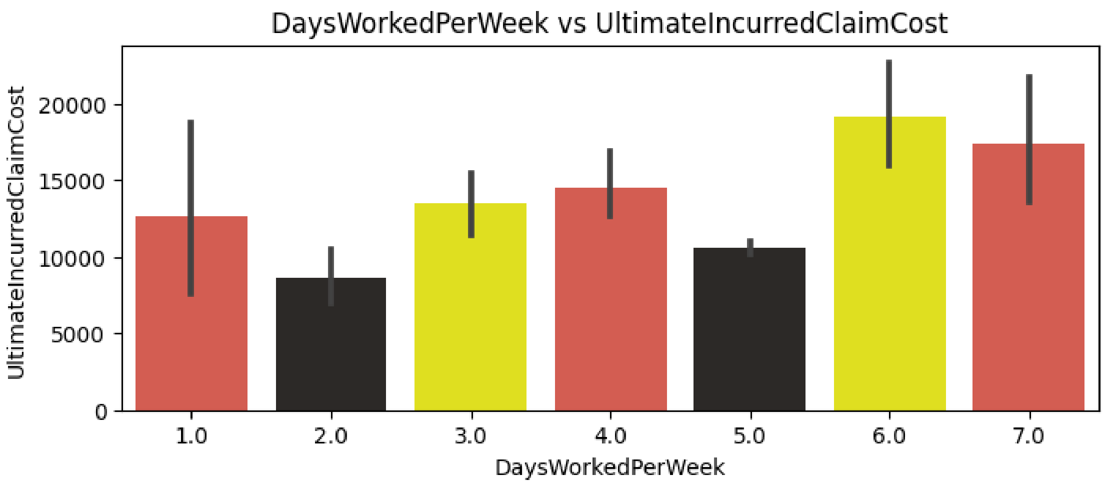
[45]: Text(0.5, 1.0, 'WeeklyWages_Bin vs UltimateIncurredClaimCost')



- People whose wages are below average and above average got more total claims payments by the insurance company.

[46]:
```
plt.figure(figsize=(8,3))
sns.
 ↪barplot(x='DaysWorkedPerWeek',y='UltimateIncurredClaimCost',data=df,palette=colors)
plt.title('DaysWorkedPerWeek vs UltimateIncurredClaimCost')
```

[46]: Text(0.5, 1.0, 'DaysWorkedPerWeek vs UltimateIncurredClaimCost')



- People who worked 6-7 days per week got more total claims payments by the insurance company.

5 Feature Engineering

[47]:
```
df['YearOfAccident']  = pd.DatetimeIndex(df['DateTimeOfAccident']).year
df['MonthOfAccident']  = pd.DatetimeIndex(df['DateTimeOfAccident']).month
df['DayOfAccident']  = pd.DatetimeIndex(df['DateTimeOfAccident']).day
df['HourOfAccident']  = pd.DatetimeIndex(df['DateTimeOfAccident']).hour
df['YearReported']  = pd.DatetimeIndex(df['DateReported']).year


df['ReportDelayInDays'] = pd.DatetimeIndex(df['DateReported']).date - pd.
 ↪DatetimeIndex(df['DateTimeOfAccident']).date
df['ReportDelayInDays'] = (df['ReportDelayInDays']  / np.timedelta64(1, 'D')).
 ↪astype(int)
df['ReportDelayInWeeks'] = np.floor(df['ReportDelayInDays'] / 7.).astype(int)
df['ReportDelayInWeeks'] = np.clip(df['ReportDelayInWeeks'], a_max=55,␣
 ↪a_min=None)
```

[48]:
```
df.reset_index(drop=True)
```

[48]:
```
      ClaimNumber         DateTimeOfAccident              DateReported  Age  \
0       WC8205482 2002-04-09 07:00:00+00:00 2002-07-05 00:00:00+00:00   48
1       WC6922469 1999-01-07 11:00:00+00:00 1999-01-20 00:00:00+00:00   43
2       WC5442654 1996-03-25 00:00:00+00:00 1996-04-14 00:00:00+00:00   30
3       WC9796897 2005-06-22 13:00:00+00:00 2005-07-22 00:00:00+00:00   41
4       WC2603726 1990-08-29 08:00:00+00:00 1990-09-27 00:00:00+00:00   36
…             …                        …                         …  …
36171   WC5624756 1996-05-29 09:00:00+00:00 1996-06-27 00:00:00+00:00   20
```

```
36172   WC8516685 2002-10-08 08:00:00+00:00 2003-02-07 00:00:00+00:00   35
36173   WC6891668 1999-09-22 09:00:00+00:00 1999-11-11 00:00:00+00:00   52
36174   WC4287842 1993-02-05 06:00:00+00:00 1993-03-19 00:00:00+00:00   28
36175   WC6368063 1998-03-06 10:00:00+00:00 1998-04-09 00:00:00+00:00   29

      Gender MaritalStatus  DependentChildren  DependentsOther  WeeklyWages  \
0          M             M                  0              0.0       500.00
1          F             M                  0              0.0       509.34
2          M             U                  0              0.0       709.10
3          M             S                  0              0.0       555.46
4          M             M                  0              0.0       377.10
…        …             …                  …                …            …
36171      F             S                  0              0.0       344.16
36172      M             M                  0              0.0      1668.83
36173      F             M                  0              0.0       204.87
36174      M             M                  0              0.0       730.87
36175      M             S                  0              0.0       200.00

      PartTimeFullTime  …  UltimateIncurredClaimCost     Age_Bin  \
0                    F  …                4748.203388  Middle-Age
1                    F  …                6326.285819  Middle-Age
2                    F  …                2293.949087  Middle-Age
3                    F  …               17786.487170  Middle-Age
4                    F  …                4014.002925  Middle-Age
…                  …  …                          …           …
36171                F  …                1343.054886       Young
36172                F  …              172876.632600  Middle-Age
36173                P  …                 632.281472         Old
36174                F  …                6714.495760  Middle-Age
36175                F  …                2588.845117  Middle-Age

      WeeklyWages_Bin  YearOfAccident  MonthOfAccident DayOfAccident  \
0                 Low            2002                4             9
1                 Low            1999                1             7
2                 Low            1996                3            25
3                 Low            2005                6            22
4                 Low            1990                8            29
…                 …               …                …           …
36171             Low            1996                5            29
36172   Below Average            2002               10             8
36173             Low            1999                9            22
36174             Low            1993                2             5
36175             Low            1998                3             6

      HourOfAccident  YearReported  ReportDelayInDays  ReportDelayInWeeks
0                  7          2002                 87                  12
1                 11          1999                 13                   1
```

2	0	1996	20	2
3	13	2005	30	4
4	8	1990	29	4
…	…	…	…	…
36171	9	1996	29	4
36172	8	2003	122	17
36173	9	1999	50	7
36174	6	1993	42	6
36175	10	1998	34	4

[36176 rows x 24 columns]

[49]:
```
numerical_features = [c for c in df.columns if df[c].dtype in ['float64',␣
↪'int64','int32'] if c not in ['Acc_Day', 'Acc_Month', 'Acc_Year']]
categorical_features = [c for c in df.columns if c not in numerical_features]
```

[50]:
```
numerical_features
```

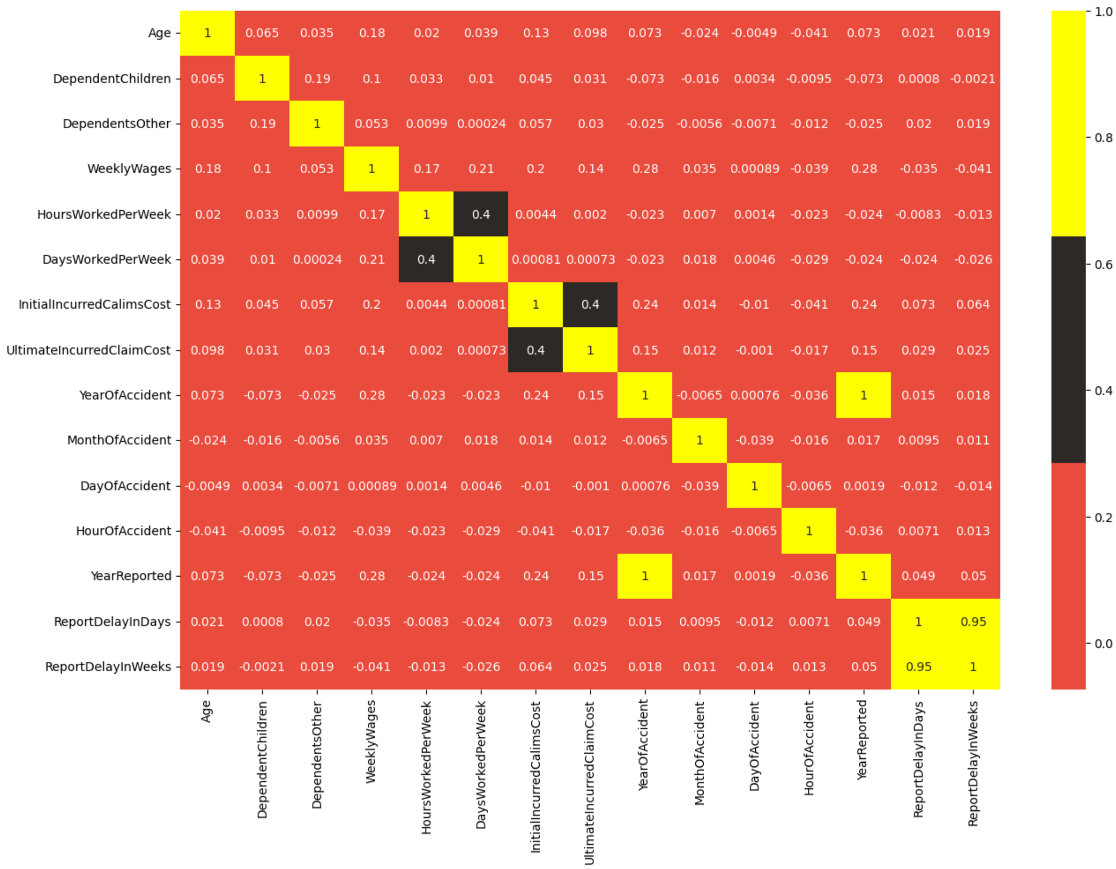
[50]:
```
['Age',
 'DependentChildren',
 'DependentsOther',
 'WeeklyWages',
 'HoursWorkedPerWeek',
 'DaysWorkedPerWeek',
 'InitialIncurredCalimsCost',
 'UltimateIncurredClaimCost',
 'YearOfAccident',
 'MonthOfAccident',
 'DayOfAccident',
 'HourOfAccident',
 'YearReported',
 'ReportDelayInDays',
 'ReportDelayInWeeks']
```

[51]:
```
categorical_features
```

[51]:
```
['ClaimNumber',
 'DateTimeOfAccident',
 'DateReported',
 'Gender',
 'MaritalStatus',
 'PartTimeFullTime',
 'ClaimDescription',
 'Age_Bin',
 'WeeklyWages_Bin']
```

5.1 Correlation

[52]:
```
plt.figure(figsize=(15,10))
sns.heatmap(df[numerical_features].corr(),annot=True , cmap=colors)
plt.show()
```

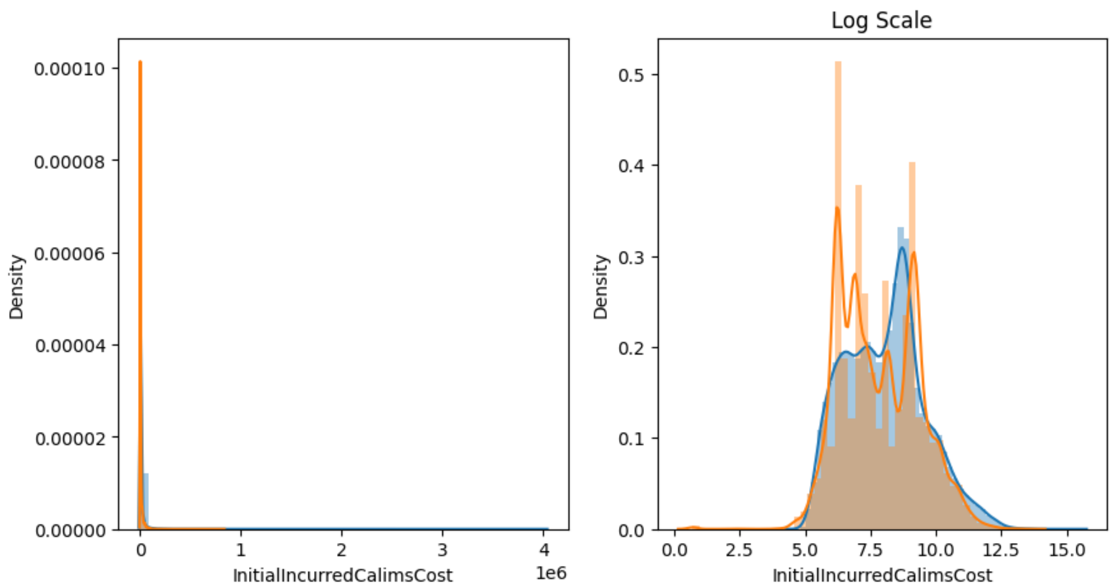


- 'DaysWorkedPerWeek' and 'HoursWorkedPerWeek' have a correlation of 0.4, which makes sense as they both refer to the time worked per week in differnt metrics. We will use either one of the 2 in our final model as they both provide the same information.
- 'InitialIncurredCalimsCost' and 'UltimateIncurredClaimCost' have a correlation of 0.4, which is good as we are trying to predict the UltimateIncurredClaimCost and the Ultimate claim cost will be dependent on the Intial claim cost.
- Log transformation is applied on 'InitialIncurredCalimsCost' and 'UltimateIncurredClaim-Cost' to transform their skewed distributions to approximately normal. This makes the interpretation much easier

[53]:
```
plt.figure(figsize = (10,5))
plt.subplot(1, 2, 1)
sns.distplot(df["UltimateIncurredClaimCost"])
```

```
sns.distplot(df['InitialIncurredCalimsCost'])
plt.subplot(1, 2, 2)
plt.title('Log Scale')
sns.distplot(np.log1p(df['UltimateIncurredClaimCost']))
sns.distplot(np.log1p(df['InitialIncurredCalimsCost']))
```

[53]: <Axes: title={'center': 'Log Scale'}, xlabel='InitialIncurredCalimsCost', ylabel='Density'>



- The above distribution plot after the log transformation can now be easily understood and interpreted. As the Initial estimate by the insurer of the claim cost increases the total claim payments to be made by the insurance company rises

5.2 Outlier Analysis and Treatment

[54]:
```
def count_outliers(df):
    # List of numeric columns
    num_cols = df.select_dtypes(include=['float64', 'int64','int32']).columns

    # Calculating quartiles and IQR
    Q1 = df[num_cols].quantile(0.25)
    Q3 = df[num_cols].quantile(0.75)
    IQR = Q3 - Q1

    print('Count of all outliers:\n')
    print(((df[num_cols] < (Q1 - 1.5 * IQR)) | (df[num_cols] > (Q3 + 1.5 *␣
↪IQR))).sum())
```

```
count_outliers(df)
```

```
Count of all outliers:

Age                           15
DependentChildren           2278
DependentsOther              318
WeeklyWages                  987
HoursWorkedPerWeek          4929
DaysWorkedPerWeek           3180
InitialIncurredCalimsCost   2889
UltimateIncurredClaimCost   4525
YearOfAccident                 0
MonthOfAccident                0
DayOfAccident                  0
HourOfAccident               916
YearReported                   0
ReportDelayInDays           3336
ReportDelayInWeeks          4273
dtype: int64
```

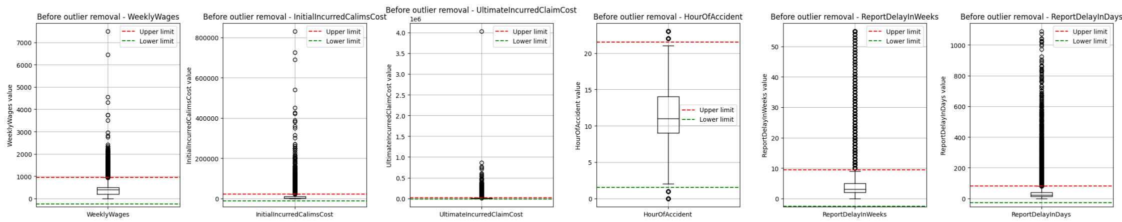
Insight:

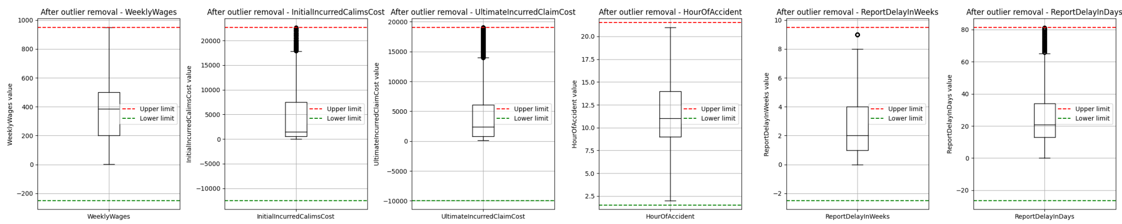
- 'Age' : has low number of outliers can be ignored
- 'DependentChildren' and 'DependentsOther': the numbers or outliers are more but removing records on the basis of these columns may result in deletion of valuable records.
- 'WeeklyWages' : outlier treatment to be performed.
- 'DaysWorkedPerWeek' and 'HoursWorkedPerWeek': removing records from one of them should handle the other column as well because they are related.
- 'InitialIncurredCalimsCost' : outlier treatment to be performed.
- 'UltimateIncurredClaimCost' : outlier treatment to be performed.

[55]:
```
# Function to calculate upper and lower bounds for outliers
def outliers_limits(df, feature):
    Q1 = df[feature].quantile(0.25)
    Q3 = df[feature].quantile(0.75)
    IQR = Q3 - Q1
    upper_limit = Q3 + 1.5 * IQR
    lower_limit = Q1 - 1.5 * IQR
    return upper_limit, lower_limit

# Function to remove outliers based on the calculated limits
def removal(df, feature, upper, lower):
    new_df = df[(df[feature] > lower) & (df[feature] < upper)]
    return new_df
```

```
# Example usage:
feature =␣
↪['WeeklyWages','InitialIncurredCalimsCost','UltimateIncurredClaimCost','HourOfAccident','Re
upper_limit, lower_limit = outliers_limits(df, feature)
cleaned_df = removal(df, feature, upper_limit, lower_limit)
```

[56]:
```
def plot_outliers(df, feature, cleaned_df, upper, lower):
    fig, axes = plt.subplots(nrows=1, ncols=len(feature), figsize=(25, 5))

    for i, feat in enumerate(feature):
        # Before removal
        df.boxplot(column=feat, ax=axes[i],color='black')
        axes[i].set_title(f'Before outlier removal - {feat}')
        axes[i].set_ylabel(f'{feat} value')
        axes[i].axhline(y=upper[feat], color='r', linestyle='--', label='Upper␣
↪limit')
        axes[i].axhline(y=lower[feat], color='g', linestyle='--', label='Lower␣
↪limit')
        axes[i].legend()

    fig.tight_layout()
    plt.show()

    fig, axes = plt.subplots(nrows=1, ncols=len(feature), figsize=(25, 5))

    for i, feat in enumerate(feature):
        # After removal
        cleaned_df.boxplot(column=feat, ax=axes[i],color='black')
        axes[i].set_title(f'After outlier removal - {feat}')
        axes[i].set_ylabel(f'{feat} value')
        axes[i].axhline(y=upper[feat], color='r', linestyle='--', label='Upper␣
↪limit')
        axes[i].axhline(y=lower[feat], color='g', linestyle='--', label='Lower␣
↪limit')
        axes[i].legend()

    fig.tight_layout()
    plt.show()



plot_outliers(df, feature, cleaned_df, upper_limit, lower_limit)
```





[57]:
```
#dropping unnecessary columns
df=df.
 ↪drop(columns=['WeeklyWages_Bin','Age_Bin','ClaimNumber','DateTimeOfAccident','DateReported'
df.head()
```

[57]:
```
   Age Gender MaritalStatus  DependentChildren  DependentsOther  WeeklyWages  \
1   48      M             M                  0              0.0       500.00
2   43      F             M                  0              0.0       509.34
3   30      M             U                  0              0.0       709.10
4   41      M             S                  0              0.0       555.46
5   36      M             M                  0              0.0       377.10

  PartTimeFullTime  HoursWorkedPerWeek  DaysWorkedPerWeek  \
1                F                38.0                5.0
2                F                37.5                5.0
3                F                38.0                5.0
4                F                38.0                5.0
5                F                38.0                5.0

   InitialIncurredCalimsCost  UltimateIncurredClaimCost  YearOfAccident  \
1                       1500                4748.203388            2002
2                       5500                6326.285819            1999
3                       1700                2293.949087            1996
4                      15000               17786.487170            2005
5                       2800                4014.002925            1990

   MonthOfAccident  DayOfAccident  HourOfAccident  YearReported  \
1                4              9               7          2002
```

```
2                 1              7              11            1999
3                 3             25               0            1996
4                 6             22              13            2005
5                 8             29               8            1990

   ReportDelayInDays  ReportDelayInWeeks
1                 87                  12
2                 13                   1
3                 20                   2
4                 30                   4
5                 29                   4
```

6 Data Loading for Test Data

[58]:
```python
df_test = pd.read_csv('Test_SJC.csv')
df_test.head()
```

[58]:
```
  ClaimNumber     DateTimeOfAccident          DateReported  Age Gender  \
0   WC8476284  2002-04-19T16:00:00Z  2002-05-13T00:00:00Z   38      M
1   WC2445024  1989-09-26T08:00:00Z  1989-10-14T00:00:00Z   38      F
2   WC4566945  1994-05-02T13:00:00Z  1994-05-17T00:00:00Z   24      M
3   WC9911299  2005-11-26T06:00:00Z  2006-01-07T00:00:00Z   21      M
4   WC9066190  2003-03-12T13:00:00Z  2003-04-10T00:00:00Z   32      M

  MaritalStatus  DependentChildren  DependentsOther  WeeklyWages  \
0             M                  0                0       500.00
1             M                  0                0       350.00
2             S                  0                0       487.50
3             S                  0                0       431.62
4             M                  3                0       480.50

  PartTimeFullTime  HoursWorkedPerWeek  DaysWorkedPerWeek  \
0                F               40.00                  5
1                P               29.75                  4
2                F               38.00                  5
3                F               40.00                  5
4                F               38.00                  5

                                 ClaimDescription  \
0  STRUCK VALVES ABRASIONS LEFT LEG LACERATED LEF…
1             LIFTING PATIENT PAIN IN LOWER BACK LEG
2               LIFTING BOXES LOWER BACK BACK INJURY
3         STRUCK LADDER BRUISED RIGHT KNEE MUSCLE RIGHT
4               FELL OFF LADDER FRACTURE RIGHT WRIST

   InitialIncurredCalimsCost
```

```
0                       1000
1                       3500
2                       7500
3                       1000
4                     111077
```

[59]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17824 entries, 0 to 17823
Data columns (total 14 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   ClaimNumber                17824 non-null  object
 1   DateTimeOfAccident         17824 non-null  object
 2   DateReported               17824 non-null  object
 3   Age                        17824 non-null  int64
 4   Gender                     17824 non-null  object
 5   MaritalStatus              17817 non-null  object
 6   DependentChildren          17824 non-null  int64
 7   DependentsOther            17824 non-null  int64
 8   WeeklyWages                17824 non-null  float64
 9   PartTimeFullTime           17824 non-null  object
 10  HoursWorkedPerWeek         17824 non-null  float64
 11  DaysWorkedPerWeek          17824 non-null  int64
 12  ClaimDescription           17824 non-null  object
 13  InitialIncurredCalimsCost  17824 non-null  int64
dtypes: float64(2), int64(5), object(7)
memory usage: 1.9+ MB
```

[60]:
```
df_test.isnull().sum()
```

[60]:
```
ClaimNumber                  0
DateTimeOfAccident           0
DateReported                 0
Age                          0
Gender                       0
MaritalStatus                7
DependentChildren            0
DependentsOther              0
WeeklyWages                  0
PartTimeFullTime             0
HoursWorkedPerWeek           0
DaysWorkedPerWeek            0
ClaimDescription             0
InitialIncurredCalimsCost    0
dtype: int64
```

[61]:
```python
#handling missing values in test data
df_test['MaritalStatus'] = df_test['MaritalStatus'].fillna('U')
```

[62]:
```python
df_test.isnull().sum()
```

[62]:
```
ClaimNumber                  0
DateTimeOfAccident           0
DateReported                 0
Age                          0
Gender                       0
MaritalStatus                0
DependentChildren            0
DependentsOther              0
WeeklyWages                  0
PartTimeFullTime             0
HoursWorkedPerWeek           0
DaysWorkedPerWeek            0
ClaimDescription             0
InitialIncurredCalimsCost    0
dtype: int64
```

[63]:
```python
# Type casting : Converting the dtype of 'DateTimeofAccident' and
 ↪'Datereported' from object to datetime64

df_test['DateTimeOfAccident']=pd.to_datetime(df_test['DateTimeOfAccident'])
df_test['DateReported']=pd.to_datetime(df_test['DateReported'])
```

[64]:
```python
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17824 entries, 0 to 17823
Data columns (total 14 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   ClaimNumber                17824 non-null  object
 1   DateTimeOfAccident         17824 non-null  datetime64[ns, UTC]
 2   DateReported               17824 non-null  datetime64[ns, UTC]
 3   Age                        17824 non-null  int64
 4   Gender                     17824 non-null  object
 5   MaritalStatus              17824 non-null  object
 6   DependentChildren          17824 non-null  int64
 7   DependentsOther            17824 non-null  int64
 8   WeeklyWages                17824 non-null  float64
 9   PartTimeFullTime           17824 non-null  object
 10  HoursWorkedPerWeek         17824 non-null  float64
 11  DaysWorkedPerWeek          17824 non-null  int64
 12  ClaimDescription           17824 non-null  object
 13  InitialIncurredCalimsCost  17824 non-null  int64
```

```
dtypes: datetime64[ns, UTC](2), float64(2), int64(5), object(5)
memory usage: 1.9+ MB
```

[65]:
```
#feature engineering for test data

df_test['YearOfAccident']  = pd.DatetimeIndex(df_test['DateTimeOfAccident']).
 ↪year
df_test['MonthOfAccident']  = pd.DatetimeIndex(df_test['DateTimeOfAccident']).
 ↪month
df_test['DayOfAccident']  = pd.DatetimeIndex(df_test['DateTimeOfAccident']).day
df_test['HourOfAccident']  = pd.DatetimeIndex(df_test['DateTimeOfAccident']).
 ↪hour
df_test['YearReported']  = pd.DatetimeIndex(df_test['DateReported']).year

df_test['ReportDelayInDays'] = pd.DatetimeIndex(df_test['DateReported']).date -␣
 ↪pd.DatetimeIndex(df_test['DateTimeOfAccident']).date
df_test['ReportDelayInDays'] = (df_test['ReportDelayInDays']  / np.
 ↪timedelta64(1, 'D')).astype(int)
df_test['ReportDelayInWeeks'] = np.floor(df_test['ReportDelayInDays'] / 7.).
 ↪astype(int)
df_test['ReportDelayInWeeks'] = np.clip(df_test['ReportDelayInWeeks'],␣
 ↪a_max=55, a_min=None)
```

[66]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17824 entries, 0 to 17823
Data columns (total 21 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   ClaimNumber                17824 non-null  object
 1   DateTimeOfAccident         17824 non-null  datetime64[ns, UTC]
 2   DateReported               17824 non-null  datetime64[ns, UTC]
 3   Age                        17824 non-null  int64
 4   Gender                     17824 non-null  object
 5   MaritalStatus              17824 non-null  object
 6   DependentChildren          17824 non-null  int64
 7   DependentsOther            17824 non-null  int64
 8   WeeklyWages                17824 non-null  float64
 9   PartTimeFullTime           17824 non-null  object
 10  HoursWorkedPerWeek         17824 non-null  float64
 11  DaysWorkedPerWeek          17824 non-null  int64
 12  ClaimDescription           17824 non-null  object
 13  InitialIncurredCalimsCost  17824 non-null  int64
 14  YearOfAccident             17824 non-null  int32
 15  MonthOfAccident            17824 non-null  int32
 16  DayOfAccident              17824 non-null  int32
 17  HourOfAccident             17824 non-null  int32
```

```
 18  YearReported                17824 non-null  int32
 19  ReportDelayInDays           17824 non-null  int32
 20  ReportDelayInWeeks          17824 non-null  int32
dtypes: datetime64[ns, UTC](2), float64(2), int32(7), int64(5), object(5)
memory usage: 2.4+ MB
```

[67]:
```
#dropping unimportant features
df_test = df_test.drop(['ClaimNumber', 'DateTimeOfAccident', 'DateReported',␣
↪'ClaimDescription'], axis=1)
```

7 Label Encoding

- Converting text in to numerical values

[68]:
```
gender_label = {'M':1, 'F':2, 'U': 3}
marital_label = {'M':1,'S':2, 'U':3}
partTime_label = {'F':1, 'P':2}

df['Gender'] = df['Gender'].map(gender_label)
df['MaritalStatus']= df['MaritalStatus'].map(marital_label)
df['PartTimeFullTime']= df['PartTimeFullTime'].map(partTime_label)
```

[69]:
```
#for test data

df_test['Gender'] = df_test['Gender'].map(gender_label)
df_test['MaritalStatus']= df_test['MaritalStatus'].map(marital_label)
df_test['PartTimeFullTime']= df_test['PartTimeFullTime'].map(partTime_label)
```

[70]:
```
df.head()
```

[70]:
```
   Age  Gender  MaritalStatus  DependentChildren  DependentsOther  \
1   48       1              1                  0              0.0
2   43       2              1                  0              0.0
3   30       1              3                  0              0.0
4   41       1              2                  0              0.0
5   36       1              1                  0              0.0

   WeeklyWages  PartTimeFullTime  HoursWorkedPerWeek  DaysWorkedPerWeek  \
1       500.00                 1                38.0                5.0
2       509.34                 1                37.5                5.0
3       709.10                 1                38.0                5.0
4       555.46                 1                38.0                5.0
5       377.10                 1                38.0                5.0

   InitialIncurredCalimsCost  UltimateIncurredClaimCost  YearOfAccident  \
1                       1500                4748.203388            2002
2                       5500                6326.285819            1999
```

3	1700	2293.949087	1996
4	15000	17786.487170	2005
5	2800	4014.002925	1990

	MonthOfAccident	DayOfAccident	HourOfAccident	YearReported	\
1	4	9	7	2002	
2	1	7	11	1999	
3	3	25	0	1996	
4	6	22	13	2005	
5	8	29	8	1990	

	ReportDelayInDays	ReportDelayInWeeks
1	87	12
2	13	1
3	20	2
4	30	4
5	29	4

[71]:
```
df_test.head()
```

[71]:

	Age	Gender	MaritalStatus	DependentChildren	DependentsOther	\
0	38	1	1	0	0	
1	38	2	1	0	0	
2	24	1	2	0	0	
3	21	1	2	0	0	
4	32	1	1	3	0	

	WeeklyWages	PartTimeFullTime	HoursWorkedPerWeek	DaysWorkedPerWeek	\
0	500.00	1	40.00	5	
1	350.00	2	29.75	4	
2	487.50	1	38.00	5	
3	431.62	1	40.00	5	
4	480.50	1	38.00	5	

	InitialIncurredCalimsCost	YearOfAccident	MonthOfAccident	DayOfAccident	\
0	1000	2002	4	19	
1	3500	1989	9	26	
2	7500	1994	5	2	
3	1000	2005	11	26	
4	111077	2003	3	12	

	HourOfAccident	YearReported	ReportDelayInDays	ReportDelayInWeeks
0	16	2002	24	3
1	8	1989	18	2
2	13	1994	15	2
3	6	2006	42	6
4	13	2003	29	4

8 Data Normalization

- Normalizing features ensures that all features have a similar scale
- Before normalization we should do train test split so that we can avoid data leakage issues.
- In order to avoid Data Leakage, it is advised to use train-test-split before any transformations. Execute the transformations according to the training data for the training as well as test data.

[72]:
```
from sklearn.model_selection import train_test_split

train , test = train_test_split(df, test_size = 0.3)

x_train = train.drop('UltimateIncurredClaimCost', axis=1)
y_train = train['UltimateIncurredClaimCost']

x_test = test.drop('UltimateIncurredClaimCost', axis = 1)
y_test = test['UltimateIncurredClaimCost']
```

[73]:
```
#for train data
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))

x_train_scaled = scaler.fit_transform(x_train)
x_train = pd.DataFrame(x_train_scaled)

x_test_scaled = scaler.transform(x_test)
x_test = pd.DataFrame(x_test_scaled)
```

[74]:
```
#for test data

df_test_scaled=scaler.fit_transform(df_test)
(df_test-df_test.min())/(df_test.max()-df_test)
scaler.fit(df_test)
scaler.transform(df_test)
```

[74]:
```
array([[0.36764706, 0.        , 0.        , …, 0.77777778, 0.02191781,
        0.05454545],
       [0.36764706, 0.5       , 0.        , …, 0.05555556, 0.01643836,
        0.03636364],
       [0.16176471, 0.        , 0.5       , …, 0.33333333, 0.01369863,
        0.03636364],
       …,
       [0.08823529, 0.        , 0.5       , …, 0.22222222, 0.0173516 ,
        0.03636364],
       [0.16176471, 0.        , 0.5       , …, 0.38888889, 0.01917808,
        0.05454545],
       [0.13235294, 0.        , 0.5       , …, 0.11111111, 0.00913242,
        0.01818182]])
```

9 Modeling

9.1 Linear regression

It is a machine learning algorithm based on supervised learning. It performs a regression task. Through linear regression we can find out the linear relationship between the target and the explanatory variables.

[75]:
```
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
```

[76]:
```
reg = LinearRegression()
reg.fit(x_train, y_train)
```

[76]:
```
LinearRegression()
```

[77]:
```
# predicting the test set results
y_pred = reg.predict(x_test)

# Calculating the r2 score
r2 = r2_score(y_test, y_pred)
print("r2 score :", r2)
```

```
r2 score : 0.10562321552454579
```

- Root Mean Squared Error (RMSE) is a metric used to evaluate a Regression Model. It tells us how accurate our predictions are and what is the amount of deviation from the actual values.

[78]:
```
print((f"Regression RMSE: {np.sqrt(mean_squared_error(y_test, y_pred))}"))
```

```
Regression RMSE: 45410.651266437555
```

[79]:
```
reg.score(x_train,y_train)
```

[79]:
```
0.24823914659803303
```

9.2 Random Forest regression

Every decision tree has high variance, but when we combine all of them together in parallel then the resultant variance is low as each decision tree gets perfectly trained on that particular sample data and hence the output doesn't depend on one decision tree but multiple decision trees.

Random Forest is an ensemble technique capable of performing both regression and classification tasks with the use of multiple decision trees and a technique called Bootstrap and Aggregation, commonly known as bagging. The basic idea behind this is to combine multiple decision trees in determining the final output rather than relying on individual decision trees.

[80]:
```
from sklearn.ensemble import RandomForestRegressor
```

[81]:
```python
rf = RandomForestRegressor()
rf.fit(x_train, y_train)
```

[81]: RandomForestRegressor()

[82]:
```python
y_pred1 = rf.predict(x_test)

# Calculating the r2 score
r2 = r2_score(y_test, y_pred1)
print("r2 score :", r2)
```

```
r2 score : 0.11344291638567794
```

[83]:
```python
print((f"Regression RMSE: {np.sqrt(mean_squared_error(y_test, y_pred1))}"))
```

```
Regression RMSE: 45211.69860023026
```

[84]:
```python
rf.score(x_train,y_train)
```

[84]: 0.8967421622463381

9.3 LGBM Regressor

LightGBM (Light Gradient Boosting Machine) Regressor is a type of gradient boosting model specifically designed for efficiency, speed, and high performance on large datasets. It is a tree-based ensemble model that builds multiple decision trees sequentially, where each tree corrects the errors of the previous one.

[85]:
```python
from lightgbm import LGBMRegressor
lgbm =LGBMRegressor()

lgbm_model = lgbm.fit(x_train, y_train)
lg_vpreds = lgbm_model.predict(x_test)

r2 = r2_score(y_test, lg_vpreds)
print("r2 score :", r2)
print((f"LGBM RMSE: {np.sqrt(mean_squared_error(y_test, lg_vpreds))}"))
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.001179 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 1154
[LightGBM] [Info] Number of data points in the train set: 25323, number of used
features: 17
[LightGBM] [Info] Start training from score 10718.897305
r2 score : 0.14521843950216928
LGBM RMSE: 44394.07834376454
```

9.4 XG Boost Regression

It is highly optimized and provides fast and accurate predictions for regression tasks. XGBoost uses a more traditional depth-wise tree growth strategy compared to LightGBM's leaf-wise strategy. It supports parallel and distributed computing, making it scalable to large datasets. XGBoost is known for its flexibility and robustness, as it provides a wide range of hyperparameters for fine-tuning and regularization.

[86]:
```python
from xgboost import XGBRegressor

xgb = XGBRegressor()
xgb_model = xgb.fit(x_train, y_train)
xg_vpreds = xgb_model.predict(x_test)

r2 = r2_score(y_test, lg_vpreds)
print("r2 score :", r2)
print((f"XGBRegressor RMSE: {np.sqrt(mean_squared_error(y_test, xg_vpreds))}"))
```

```
r2 score : 0.14521843950216928
XGBRegressor RMSE: 45382.90029449528
```

- Lower RMSE values indicate a better fit. The RMSE value for LightGBM Regression model is lower as compared to other Regression models.Hence, we go with LightGBM Regression model to predict our Target Variable and further we will do hyperparamter tuning.

9.5 Hyperparameter Tuning for LightGBM regressor

[87]:
```python
from lightgbm import LGBMRegressor
lgbm =LGBMRegressor(objective = 'regression',
               num_leaves = 4,
               learning_rate = 0.01,
               n_estimators = 10000,
               max_bin = 200,
               bagging_fraction = 0.75,
               bagging_freq = 5,
               bagging_seed = 7,
               feature_fraction = 0.2,
               feature_fraction_seed = 7,
               verbose = 1,)


lgbm_model = lgbm.fit(x_train, y_train)
lg_vpreds = lgbm_model.predict(x_test)

r2 = r2_score(y_test, lg_vpreds)
```

```
[LightGBM] [Warning] feature_fraction is set=0.2, colsample_bytree=1.0 will be
ignored. Current value: feature_fraction=0.2
[LightGBM] [Warning] bagging_fraction is set=0.75, subsample=1.0 will be
```

```
ignored. Current value: bagging_fraction=0.75
[LightGBM] [Warning] bagging_freq is set=5, subsample_freq=0 will be ignored.
Current value: bagging_freq=5
[LightGBM] [Warning] feature_fraction is set=0.2, colsample_bytree=1.0 will be
ignored. Current value: feature_fraction=0.2
[LightGBM] [Warning] bagging_fraction is set=0.75, subsample=1.0 will be
ignored. Current value: bagging_fraction=0.75
[LightGBM] [Warning] bagging_freq is set=5, subsample_freq=0 will be ignored.
Current value: bagging_freq=5
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000704 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 975
[LightGBM] [Info] Number of data points in the train set: 25323, number of used
features: 17
[LightGBM] [Info] Start training from score 10718.897305
[LightGBM] [Warning] feature_fraction is set=0.2, colsample_bytree=1.0 will be
ignored. Current value: feature_fraction=0.2
[LightGBM] [Warning] bagging_fraction is set=0.75, subsample=1.0 will be
ignored. Current value: bagging_fraction=0.75
[LightGBM] [Warning] bagging_freq is set=5, subsample_freq=0 will be ignored.
Current value: bagging_freq=5
```

[88]:
```
print("r2 score :", r2)
print((f"LGBM RMSE: {np.sqrt(mean_squared_error(y_test, lg_vpreds))}"))
```

```
r2 score : 0.13021427499593796
LGBM RMSE: 44782.01277618353
```

- Before hyperparameter -> 44394.07834376454
- After hyperparameter -> 44782.01277618353

10 Result

- Let's predict the target variable

[89]:
```
lg_vpreds =lgbm_model.predict(df_test_scaled)
```

```
[LightGBM] [Warning] feature_fraction is set=0.2, colsample_bytree=1.0 will be
ignored. Current value: feature_fraction=0.2
[LightGBM] [Warning] bagging_fraction is set=0.75, subsample=1.0 will be
ignored. Current value: bagging_fraction=0.75
[LightGBM] [Warning] bagging_freq is set=5, subsample_freq=0 will be ignored.
Current value: bagging_freq=5
```

[90]:
```
df_test = df_test
df_test['UltimateIncurredClaimCost'] = lg_vpreds
```

[91]:
```python
df_test.head()
```

[91]:

	Age	Gender	MaritalStatus	DependentChildren	DependentsOther
0	38	1	1	0	0
1	38	2	1	0	0
2	24	1	2	0	0
3	21	1	2	0	0
4	32	1	1	3	0

	WeeklyWages	PartTimeFullTime	HoursWorkedPerWeek	DaysWorkedPerWeek
0	500.00	1	40.00	5
1	350.00	2	29.75	4
2	487.50	1	38.00	5
3	431.62	1	40.00	5
4	480.50	1	38.00	5

	InitialIncurredCalimsCost	YearOfAccident	MonthOfAccident	DayOfAccident
0	1000	2002	4	19
1	3500	1989	9	26
2	7500	1994	5	2
3	1000	2005	11	26
4	111077	2003	3	12

	HourOfAccident	YearReported	ReportDelayInDays	ReportDelayInWeeks
0	16	2002	24	3
1	8	1989	18	2
2	13	1994	15	2
3	6	2006	42	6
4	13	2003	29	4

	UltimateIncurredClaimCost
0	5240.234310
1	8385.208148
2	20491.982849
3	-2365.767570
4	84406.131682

[ ]: