Dharavath Ramdas

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Domain: Insurence

Project Title: Insurance Premium Prediction

Machine Learning Technology

Show code

Problem Statement:

The goal of this project is to give people an estimate of how much they need based on their individual health situation. After that, customers can work with any health insurance carrier and its plans and perks while keeping the projected cost from our study in mind. This can assist a person in concentrating on the health side of an insurance policy rather han the ineffective part.

Approach:

The classical machine learning tasks like Data Exploration, Data Cleaning, Feature Engineering, Model Building and Model Testing. Try out different machine learning algorithms that's best fit for the above case. Some Famous Algorithms: - Multiple Linear Regression, Decision tree Regression and Gradient Boosting, Decision tree, Regression

Results:

You have to build a solution that should able to predict the premium of the personal for health insurance

Dataset Link:

https://raw.githubusercontent.com/dharavathramdas101/Machine-Learning-Algorithms/main/insurence_data/insurance.csv

```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import warnings
```

Read Data

```
df = pd.read_csv(r"https://raw.githubusercontent.com/dharavathramdas101/Machine-Learning-A
```

```
df.head()
```

	age	sex	bmi	children	smoker	region	expenses
0	19	female	27.9	0	yes	southwest	16884.92
1	18	male	33.8	1	no	southeast	1725.55
2	28	male	33.0	3	no	southeast	4449.46
3	33	male	22.7	0	no	northwest	21984.47
4	32	male	28.9	0	no	northwest	3866.86

```
# Check rows and columns of data
```

```
df.shape
```

```
(1338, 7)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       1338 non-null   int64  
 1   sex       1338 non-null   object 
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64  
 4   smoker    1338 non-null   object 
 5   region    1338 non-null   object 
 6   expenses  1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

```
df.describe()
```

	age	bmi	children	expenses
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.665471	1.094918	13270.422414
std	14.049960	6.098382	1.205493	12110.011240
min	18.000000	16.000000	0.000000	1121.870000
25%	27.000000	26.300000	0.000000	4740.287500
50%	39.000000	30.400000	1.000000	9382.030000
75%	51.000000	34.700000	2.000000	16639.915000
max	64.000000	53.100000	5.000000	63770.430000

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%
age	1338.0	39.207025	14.049960	18.00	27.0000	39.00	51.000
bmi	1338.0	30.665471	6.098382	16.00	26.3000	30.40	34.700
children	1338.0	1.094918	1.205493	0.00	0.0000	1.00	2.000
expenses	1338.0	13270.422414	12110.011240	1121.87	4740.2875	9382.03	16639.915

63

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

	age	sex	bmi	children	smoker	region	expenses
0	19	female	27.9	0	yes	southwest	16884.92
1	18	male	33.8	1	no	southeast	1725.55

```
# Checking the male and female
```

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

```
male      676
female    662
Name: sex, dtype: int64
```

```
# Checking the region
```

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

```
southeast    364
southwest    325
northwest    325
northeast    324
Name: region, dtype: int64
```

```
# Checking the age
```

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

```
18    69
19    68
50    29
51    29
47    29
46    29
45    29
20    29
48    29
52    29
22    28
49    28
54    28
53    28
21    28
26    28
24    28
25    28
28    28
27    28
23    28
43    27
29    27
30    27
41    27
42    27
44    27
31    27
40    27
32    26
33    26
56    26
34    26
```

```
55    26
57    26
37    25
59    25
58    25
36    25
38    25
35    25
39    25
61    23
60    23
63    23
62    23
64    22
Name: age, dtype: int64
```

```
# Check unique values of target variables

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

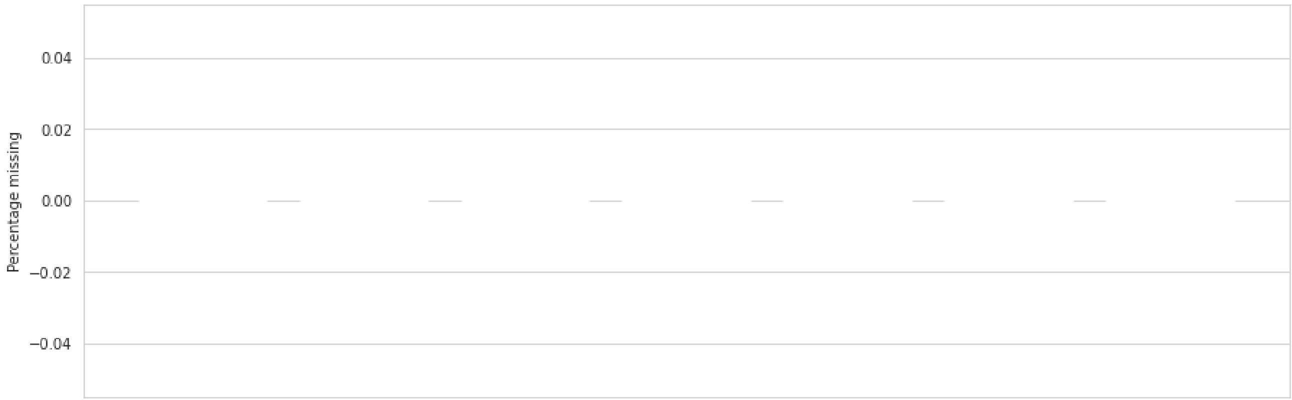
```
1639.56     2
16884.92    1
29330.98    1
2221.56     1
19798.05    1
           ..
7345.08     1
26109.33    1
28287.90    1
1149.40     1
29141.36    1
Name: expenses, Length: 1337, dtype: int64
```

```
# define numerical and categorical columns

numerical_fea = [fea for fea in df.columns if df[fea].dtype != 'O']
categorical_fea = [fea for fea in df.columns if df[fea].dtype == 'O']

# print columns

print('we have {} numerical features : {}'.format(len(numerical_fea),numerical_fea))
print()
print('we have {} categorical features : {}'.format(len(categorical_fea),categorical_fea))
```

```
we have 4 numerical features : ['age', 'bmi', 'children', 'expenses']

we have 3 categorical features : ['sex', 'smoker', 'region']
```

```
# Checking missing values
```

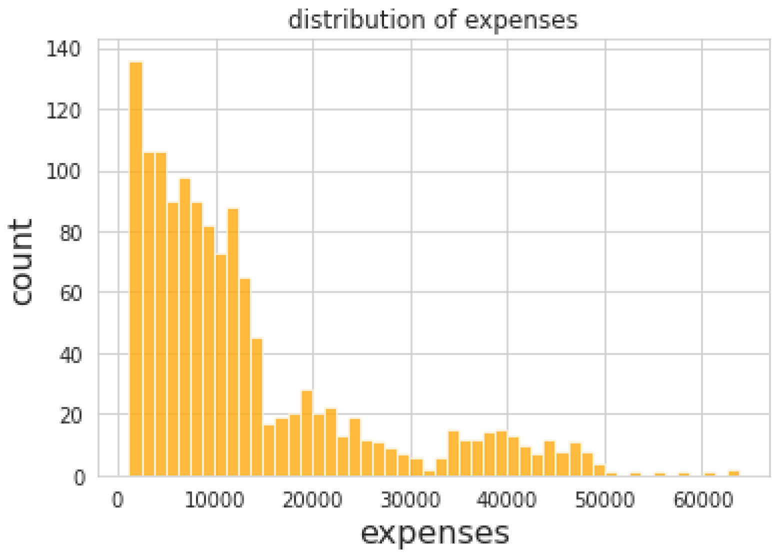
```
# plotting the missing values count for each column


fig, ax = plt.subplots(figsize=(15,5))

missing = df.isna().sum().div(df.shape[0]).mul(100).to_frame().sort_values(by=0, ascending

ax.bar(missing.index, missing.values.T[0])
plt.xticks([])
plt.ylabel("Percentage missing")
plt.show()
```



report: No Null values

```
plt.title("distribution of expenses")
p = sns.histplot(x='expenses',data=df,bins=50,color='orange')
p.set_xlabel("expenses", fontsize=16)
p.set_ylabel("count",fontsize=16)
```

```
Text(0, 0.5, 'count')
```




```
df.head(3)
```

```
df.head(3)
```

	age	sex	bmi	children	smoker	region	expenses
0	19	female	27.9	0	yes	southwest	16884.92
1	18	male	33.8	1	no	southeast	1725.55
2	28	male	33.0	3	no	southeast	4449.46

Creating dummy variables

```
one_hot_data = pd.get_dummies(df[categorical_fea])
```

```
one_hot_data.head(3)
```

	sex_female	sex_male	smoker_no	smoker_yes	region_northeast	region_northwest	r
0	1	0	0	1	0	0	
1	0	1	1	0	0	0	
2	0	1	1	0	0	0	

```
df = pd.concat([df[numerical_fea],one_hot_data],axis = 1)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   age               1338 non-null   int64  
 1   bmi               1338 non-null   float64
 2   children          1338 non-null   int64  
 3   expenses          1338 non-null   float64
 4   sex_female        1338 non-null   uint8  
 5   sex_male          1338 non-null   uint8  
 6   smoker_no         1338 non-null   uint8  
 7   smoker_yes        1338 non-null   uint8  
 8   region_northeast  1338 non-null   uint8  
 9   region_northwest  1338 non-null   uint8  
 10  region_southeast  1338 non-null   uint8  
 11  region_southwest  1338 non-null   uint8  
dtypes: float64(2), int64(2), uint8(8)
memory usage: 52.4 KB
```

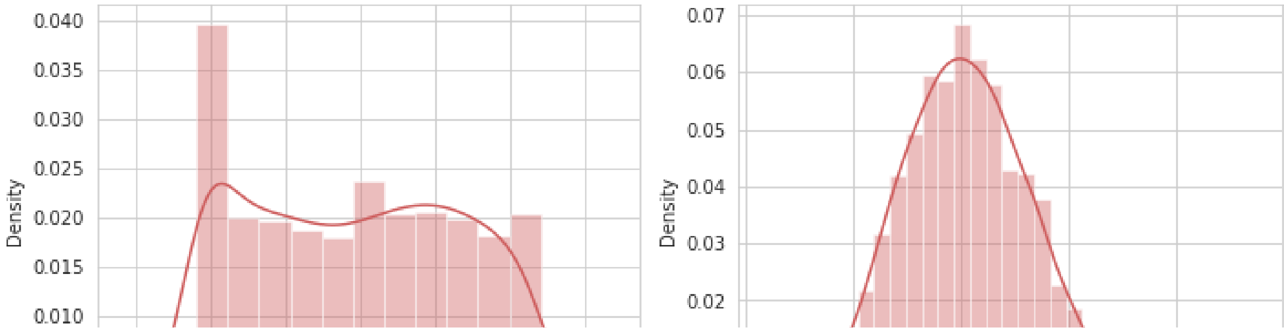
```
df
```

	age	bmi	children	expenses	sex_female	sex_male	smoker_no	smoker_yes	regi
0	19	27.9	0	16884.92	1	0	0	1	
1	18	33.8	1	1725.55	0	1	1	0	
2	28	33.0	3	4449.46	0	1	1	0	
3	33	22.7	0	21984.47	0	1	1	0	
4	32	28.9	0	3866.86	0	1	1	0	
...	...	...	...	...	...	...	...	...	
1333	50	31.0	3	10600.55	0	1	1	0	
1334	18	31.9	0	2205.98	1	0	1	0	
1335	18	36.9	0	1629.83	1	0	1	0	
1336	21	25.8	0	2007.95	1	0	1	0	
1337	61	29.1	0	29141.36	1	0	0	1	

Plot distribution of all independent Numerical variables

```
plt.figure(figsize=(10,15))
for i,col in enumerate(numerical_fea):
    plt.subplot(4,2,i+1)
    sns.distplot(x=df[col],color='indianred')
    plt.xlabel(col,weight='bold')
    plt.tight_layout()
```

```
/usr/local/lib/python3.9/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.9/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.9/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.9/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
```

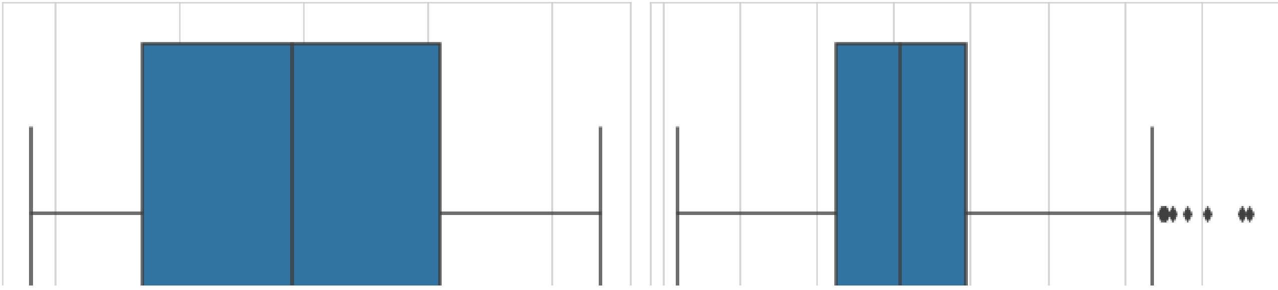


Report:

. Asper the above plot most of the features are not normally distributed

Boxplot (Numerical fea)

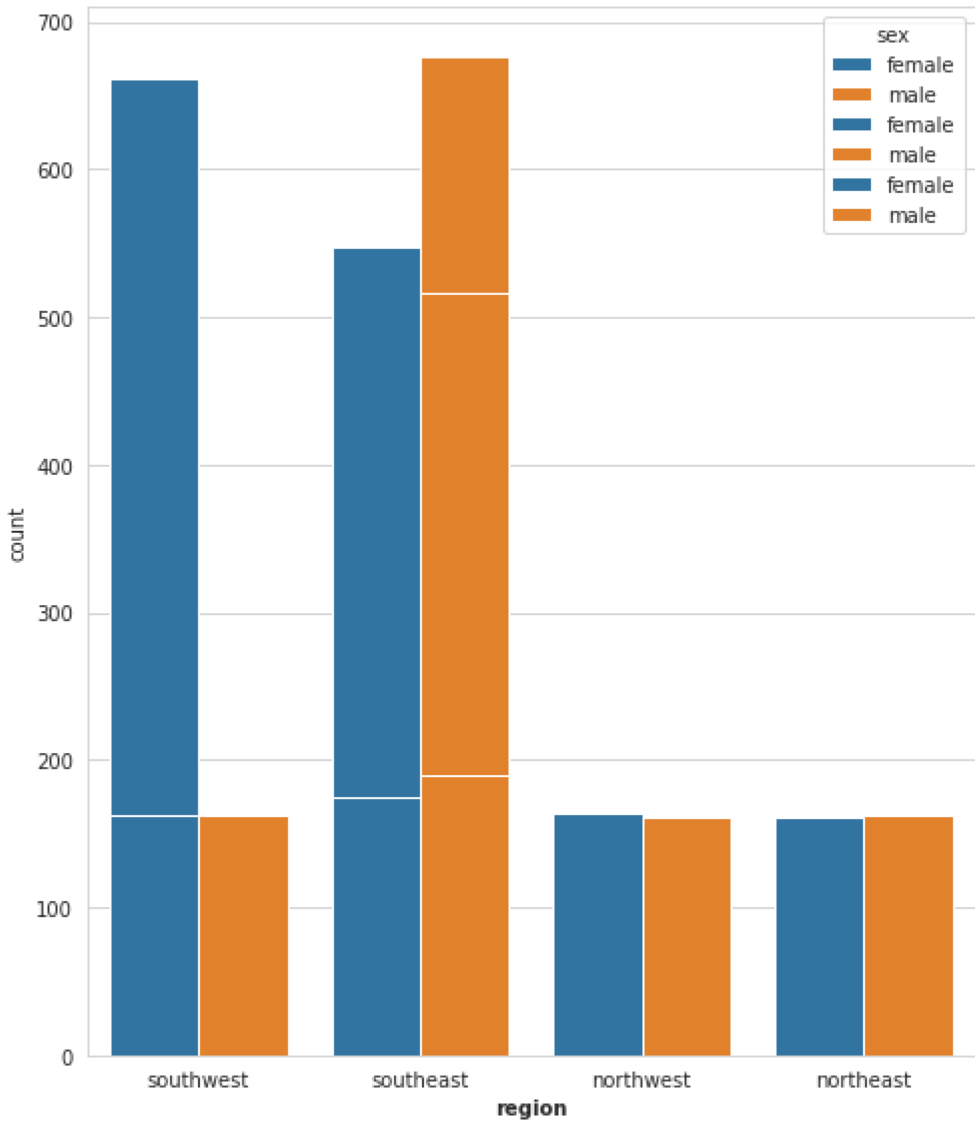

```
plt.figure(figsize=(10,15))
for i,col in enumerate(numerical_fea):
    plt.subplot(4,2,i+1)
    sns.boxplot(x=df[col])
    plt.xlabel(col,weight='bold')
    plt.tight_layout()
```



Countplot (categorical fea)

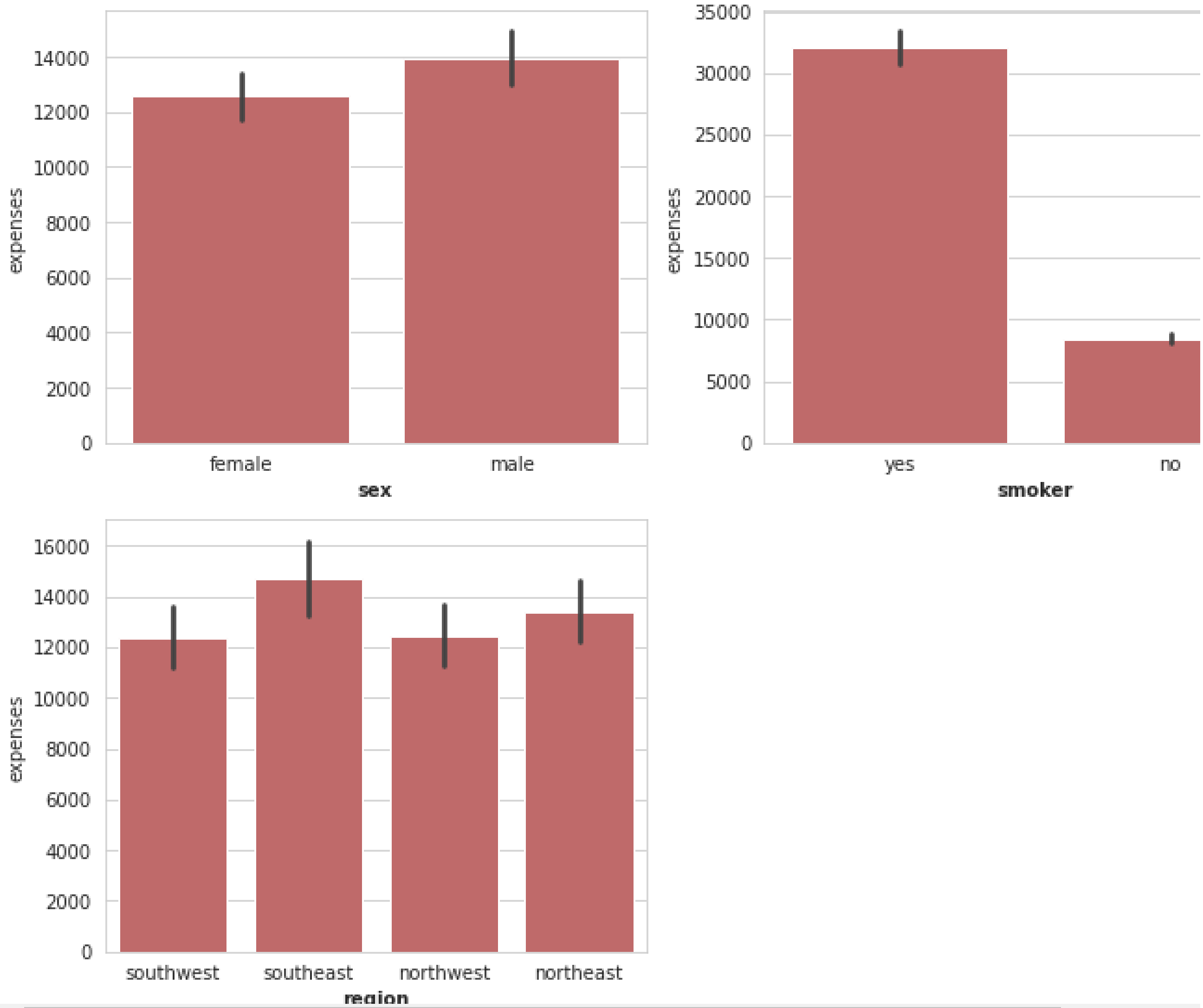
```
# Countplot
```

```
plt.figure(figsize=(7,8))
for i,col in enumerate(categorical_fea):
    plt.plot(3,1,i+1)
    sns.countplot(x=df[col],hue=df['sex'])
    plt.xlabel(col,weight='bold')
    plt.tight_layout()
```



Barplot (categorical fea)

```
plt.figure(figsize=(10,15))
for i,col in enumerate(categorical_fea):
    plt.subplot(4,2,i+1)
    sns.barplot(x=df[col],y=df['expenses'],color='indianred')
    plt.xlabel(col,weight='bold')
    plt.tight_layout()
```

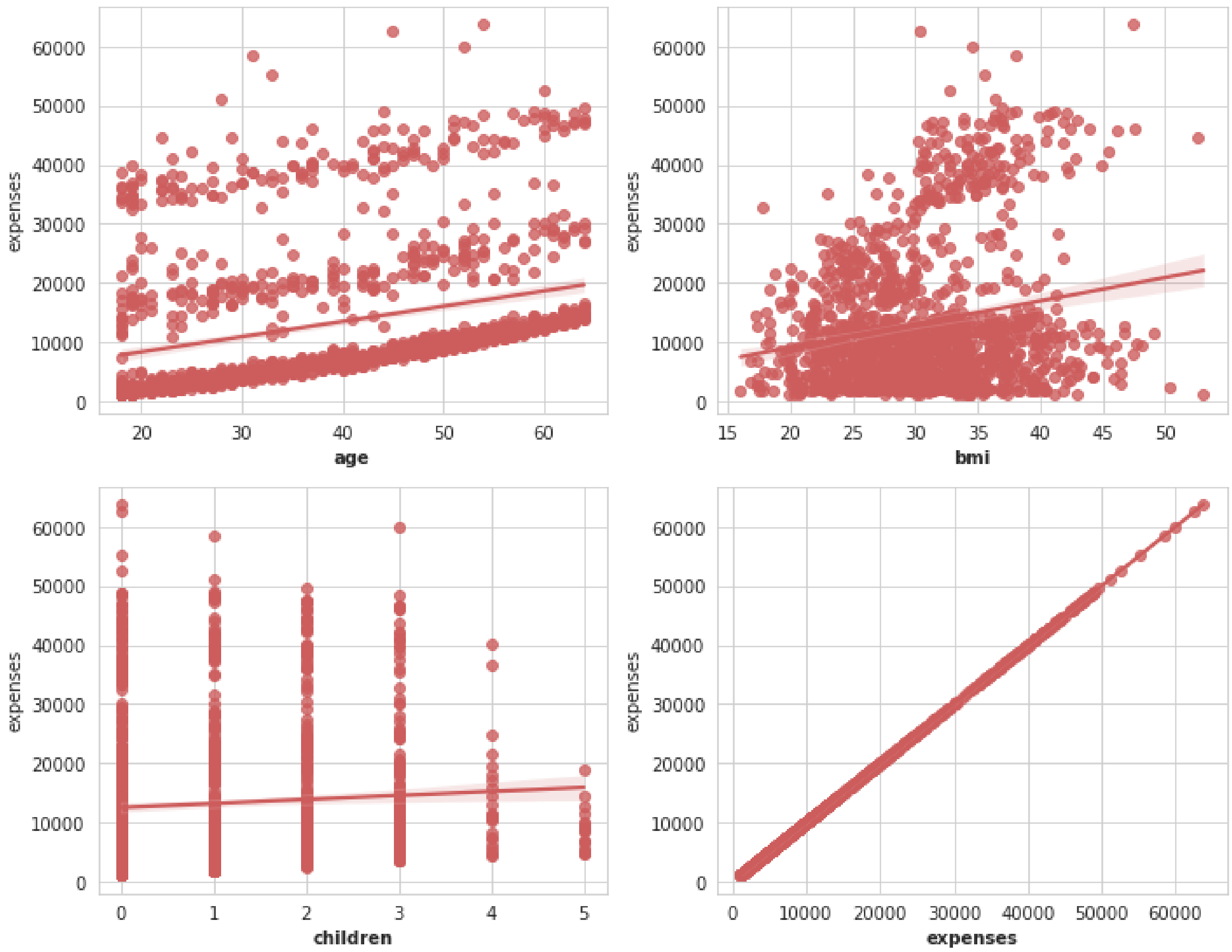


Regression Plot (numerical fea)

```
# Regression Plot
```

```
plt.figure(figsize=(10,15))
for i,col in enumerate(numerical_fea):
    plt.subplot(4,2,i+1)
    sns.regplot(x=df[col],y=df['expenses'],color='indianred')
```

```
    plt.xlabel(col,weight='bold')
    plt.tight_layout()
```

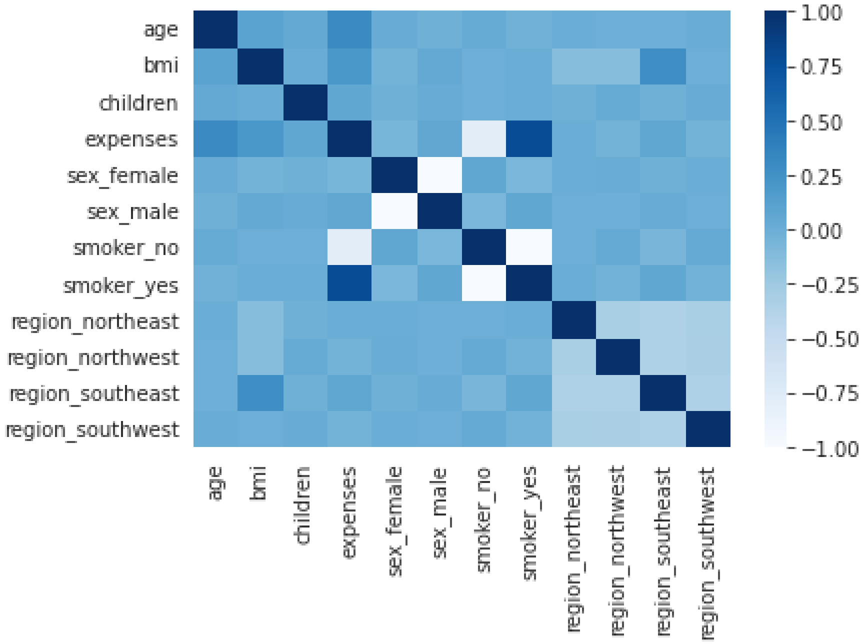



```
df.corr()
```

	age	bmi	children	expenses	sex_female	sex_male	smok
age	1.000000	0.109341	0.042469	0.299008	0.020856	-0.020856	0.0
bmi	0.109341	1.000000	0.012645	0.198576	-0.046380	0.046380	-0.0
children	0.042469	0.012645	1.000000	0.067998	-0.017163	0.017163	-0.0
expenses	0.299008	0.198576	0.067998	1.000000	-0.057292	0.057292	-0.7

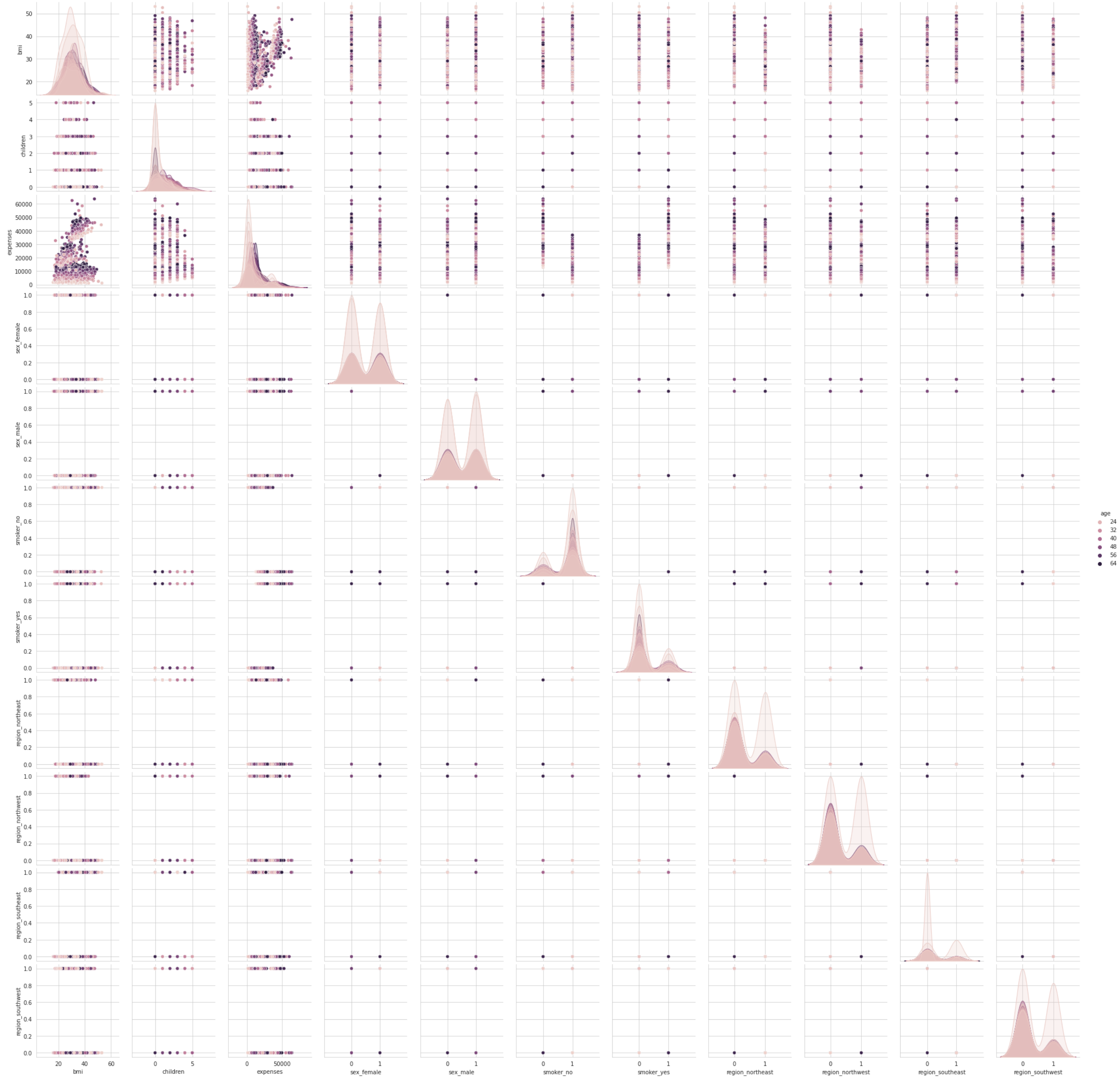
```
sns.heatmap(df.corr(),cmap='Blues')
```

```
<AxesSubplot:>
```




```
sns.pairplot(data=df,hue='age')
```

```
<seaborn.axisgrid.PairGrid at 0x7f3a85249ca0>
```



Evaluate Model on Different experiments

```
# spliting X and y for all experiments
```

```
X =df.drop('expenses',axis=1)
y = df['expenses']
```

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split (X,y,test_size=0.3, random_state=42)
```

```
print(X_train.shape, y_train.shape)
```

```
(936, 11) (936,)
```

```
print(X_test.shape, y_test.shape)
```

```
(402, 11) (402,)
```

Standardize or feature scalling the dataset

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler
```

```
▾ StandardScaler
StandardScaler()
```

```
X_train = scaler.fit_transform(X_train)
```

```
X_test = scaler.transform(X_test)
```

```
X_train
```

```
array([[ 1.54446486,  0.10949025, -0.91501097, ...,  1.75708174,
        -0.59380229, -0.55760593],
       [ 0.48187425, -0.49119089, -0.91501097, ..., -0.56912549,
        -0.59380229,  1.79338122],
       [ 1.04858924,  0.22628936,  1.56027883, ..., -0.56912549,
         1.68406222, -0.55760593],
       ...,
       [ 1.33194673, -0.89164499, -0.91501097, ..., -0.56912549,
        -0.59380229, -0.55760593],
       [-0.15568012,  2.84592657,  0.73518223, ..., -0.56912549,
        -0.59380229,  1.79338122],
```

```
       [ 1.11942861, -0.10742238, -0.91501097, ..., -0.56912549,
        -0.59380229,  1.79338122]])
```

```
X_test
```

```
array([[ 0.41103487, -0.89164499,  0.73518223, ..., -0.56912549,
        -0.59380229, -0.55760593],
       [-0.22651949, -0.09073679, -0.91501097, ...,  1.75708174,
        -0.59380229, -0.55760593],
       [ 1.75698298, -0.60799   , -0.91501097, ...,  1.75708174,
        -0.59380229, -0.55760593],
       ...,
       [-1.50162823, -0.39107737, -0.91501097, ..., -0.56912549,
        -0.59380229, -0.55760593],
       [ 1.33194673,  0.92708403, -0.91501097, ..., -0.56912549,
         1.68406222, -0.55760593],
       [-1.35994948, -1.42558378, -0.08991437, ..., -0.56912549,
        -0.59380229,  1.79338122]])
```

Model Training

```
from sklearn.linear_model import LinearRegression
```

```
regression = LinearRegression()
```

```
regression
```

```
▾ LinearRegression
LinearRegression()
```

```
regression.fit(X_train,y_train)
```

```
▾ LinearRegression
LinearRegression()
```

Coefficient and intercept

```
print("coefficient ",regression.coef_)
```

```
coefficient  [3.66259502e+03 2.21576698e+03 4.77319913e+02 5.11462776e+15
 5.11462776e+15 2.21478562e+17 2.21478562e+17 3.94494645e+17
 3.87853431e+17 3.96084775e+17 3.83765370e+17]
```

```
print("intercept ",regression.intercept_)
```

```
intercept  13372.684473585865
```

```
# prediction for the test data
reg_pred = regression.predict(X_test)
reg_pred
```

```
            13500.68447359,  4508.68447359,  2236.68447359, 31580.68447359,
            25148.68447359, 18076.68447359, 24860.68447359,  9468.68447359,
            36924.68447359,  -707.31552641,  6332.68447359,  8124.68447359,
             4668.68447359,  4636.68447359,  6460.68447359,  4540.68447359,
            15420.68447359, 10972.68447359,  7740.68447359,  2620.68447359,
             1468.68447359, 32188.68447359, 16924.68447359, 11932.68447359,
              476.68447359, 12604.68447359,  1596.68447359,  8892.68447359,
             1052.68447359, 33212.68447359, 11420.68447359,  2300.68447359,
            24668.68447359, 25372.68447359,  9212.68447359,   860.68447359,
            13820.68447359,  1084.68447359, 10812.68447359, 10140.68447359,
```

```
       32796.68447359, 39100.68447359, 12220.68447359,  7708.68447359,
       16508.68447359, 15356.68447359, 10300.68447359, 10044.68447359,
        8284.68447359,  3132.68447359, 10812.68447359,  3548.68447359,
       10812.68447359, 16700.68447359,  6812.68447359,  2236.68447359,
       14908.68447359,   572.68447359])
```

```
# Mean_squared_error, Mean_absolute_error

from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,reg_pred))
print(mean_absolute_error(y_test,reg_pred))
print(np.sqrt(mean_squared_error(y_test,reg_pred)))
```

```
34410879.61966635
4261.460898113474
5866.0787260031175
```

```
# Performance metrics
# R squared and adjusted R square
# R squared
from sklearn.metrics import r2_score
linear_score=r2_score(y_test,reg_pred)
print(linear_score)

# Adjusted R Squared
#### adjusted R square
#### display adjusted R-squared
print(1 - (1-linear_score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1))
```

```
0.7653125879883471
0.7586931994444287
```

```
def model_det(model, model_name, cvn=20): # Default value for cvn = 20
    print(model_name)
    print()
    # train, test Model pred
    y_pred_model_train = model.predict(X_train)
    y_pred_model_test = model.predict(X_test)
    print()
```

```
    print("MSE MAE RMSE")
    # MSE MAE RMSE
    print("Mean Square Error ",mean_squared_error(y_test,y_pred_model_test))
    print("Mean Absolute Error ",mean_absolute_error(y_test,y_pred_model_test))
    print("Root Mean Square Error ",np.sqrt(mean_squared_error(y_test,y_pred_model_test)))
    print()
    print("R2Score Model")
    # train, test R2Score model
    R2Score_model_train = r2_score(y_train, y_pred_model_train)
    print("Training R2 Score: ", R2Score_model_train)
    R2Score_model_test = r2_score(y_test, y_pred_model_test)
    print("Testing R2 Score: ",  R2Score_model_test)
    print( )
    print("Adj_R2Score Model")
    # train, test Adj_R2Score model
    Adj_R2Score_model_train = 1 - (1-R2Score_model_train)*(len(y_test)-1)/(len(y_test)-X_t
    print("Training Adj_R2 Score: ", Adj_R2Score_model_train)
    Adj_R2Score_model_test = 1 - (1-R2Score_model_test)*(len(y_test)-1)/(len(y_test)-X_tes
    print("Testing Adj_R2 Score: ",  Adj_R2Score_model_test)


    RMSE_model_train = sqrt(mean_squared_error(y_train, y_pred_model_train))
    print("RMSE for Training Data: ", RMSE_model_train)
    RMSE_model_test = sqrt(mean_squared_error(y_test, y_pred_model_test))
    print("RMSE for Testing Data: ", RMSE_model_test)
#     if model == polynomial_reg:
#         polynomial_features = PolynomialFeatures(degree=3)
#         y_pred_cv_PR = cross_val_predict(model, polynomial_features.fit_transform(X), y,
#     else:
    y_pred_cv_model = cross_val_predict(model, X, y, cv=cvn)
    accuracy_cv_model = r2_score(y, y_pred_cv_model)
    print("Accuracy for", cvn,"- Fold Cross Predicted: ", accuracy_cv_model)
```

```
from sklearn.linear_model import LinearRegression
regressor=LinearRegression()
regressor.fit(X_train,y_train)
LinearRegression()
```

```
▾ LinearRegression
LinearRegression()
```

```
model_det(regressor,"multilinear regression")
```

```
multilinear regression


MSE MAE RMSE
Mean Square Error  34410879.61966635
Mean Absolute Error  4261.460898113474
Root Mean Square Error  5866.0787260031175

R2Score Model
Training R2 Score:  0.7410211674946332
```

```
Testing R2 Score:  0.7653125879883471

Adj_R2Score Model
Training Adj_R2 Score:  0.7337166363214049
Testing Adj_R2 Score:  0.7586931994444287
RMSE for Training Data:  6158.913329477451
RMSE for Testing Data:  5866.0787260031175
Accuracy for 20 - Fold Cross Predicted:  0.7466981000116759
```

Ridge Regression

```
from sklearn.linear_model import Ridge
ridgeR = Ridge(alpha=.99)
ridgeR.fit(X_train,y_train)
model_det(ridgeR,"Ridge Regression ")
```

```
Ridge Regression


MSE MAE RMSE
Mean Square Error  33777649.6874477
Mean Absolute Error  4145.265733644485
Root Mean Square Error  5811.85423831738

R2Score Model
Training R2 Score:  0.7424099901263734
Testing R2 Score:  0.7696313120559464

Adj_R2Score Model
Training Adj_R2 Score:  0.7351446308735275
Testing Adj_R2 Score:  0.7631337336780372
RMSE for Training Data:  6142.3769650745835
RMSE for Testing Data:  5811.85423831738
Accuracy for 20 - Fold Cross Predicted:  0.7467015687862073
```

Lasso Regression

```
from sklearn.linear_model import Lasso

lasso = Lasso(alpha = 0.05)
lasso.fit(X_train,y_train)
model_det(lasso,"Lasso Regression ")
```

```
Lasso Regression


MSE MAE RMSE
Mean Square Error  33777095.326205276
Mean Absolute Error  4144.883992759768
```

```
Root Mean Square Error  5811.806545834546

R2Score Model
Training R2 Score:  0.7424103108697158
Testing R2 Score:  0.7696350928836015

Adj_R2Score Model
Training Adj_R2 Score:  0.735144960663477
Testing Adj_R2 Score:  0.7631376211444211
RMSE for Training Data:  6142.373140921752
RMSE for Testing Data:  5811.806545834546
Accuracy for 20 - Fold Cross Predicted:  0.7466988392107343
```

ElasticNet Regression

```
from sklearn.linear_model import ElasticNet
# Train the model
el_net = ElasticNet(alpha=.02,l1_ratio=.2)
el_net.fit(X_train,y_train)

model_det(el_net,"ElasticNet Regression ")
```

```
ElasticNet Regression


MSE MAE RMSE
Mean Square Error  33795730.807521895
Mean Absolute Error  4151.193272231395
Root Mean Square Error  5813.409568189902

R2Score Model
Training R2 Score:  0.7423384467073105
Testing R2 Score:  0.7695079960778782

Adj_R2Score Model
Training Adj_R2 Score:  0.7350710695631577
Testing Adj_R2 Score:  0.7630069395569978
RMSE for Training Data:  6143.22990215194
RMSE for Testing Data:  5813.409568189902
Accuracy for 20 - Fold Cross Predicted:  0.7454076349180764
```

Decision Tree

```
from sklearn.tree import DecisionTreeRegressor


decision_tree_reg = DecisionTreeRegressor(max_depth=5, random_state=13)
decision_tree_reg.fit(X_train, y_train)
model_det(decision_tree_reg, "Decision_Tree_Regression")
```

```
Decision_Tree_Regression
```

```
MSE MAE RMSE
Mean Square Error  20957331.492411833
Mean Absolute Error  2672.988410615133
Root Mean Square Error  4577.917811889138

R2Score Model
Training R2 Score:  0.8779410468755883
Testing R2 Score:  0.8570678243338631

Adj_R2Score Model
Training Adj_R2 Score:  0.8744983584541305
Testing Adj_R2 Score:  0.8530364039945618
RMSE for Training Data:  4228.2122353167215
RMSE for Testing Data:  4577.917811889138
Accuracy for 20 - Fold Cross Predicted:  0.8517265048084235
```

Random Forest

```
from sklearn.ensemble import RandomForestRegressor
```

```
random_forest_reg = RandomForestRegressor()
random_forest_reg.fit(X_train,y_train)

model_det(random_forest_reg,"Random Forest Regression")
```

```
Random Forest Regression


MSE MAE RMSE
Mean Square Error  21786559.065425057
Mean Absolute Error  2598.504051990051
Root Mean Square Error  4667.607424090533

R2Score Model
Training R2 Score:  0.9747584169173479
Testing R2 Score:  0.851412366663785

Adj_R2Score Model
Training Adj_R2 Score:  0.9740464748304013
Testing Adj_R2 Score:  0.8472214334158404
RMSE for Training Data:  1922.782907436925
RMSE for Testing Data:  4667.607424090533
Accuracy for 20 - Fold Cross Predicted:  0.8384891650642876
```

XGBoost

```
import xgboost as xgb
```

```
xgb_r = xgb.XGBRegressor(objective ='reg:linear',
                  n_estimators = 10, seed = 123,verbosity=0)

# Fitting the model
xgb_r.fit(X_train, y_train)


model_det(xgb_r,"Xg_boost")
```

```
Xg_boost


MSE MAE RMSE
Mean Square Error  19869941.834197562
Mean Absolute Error  2284.9122612280394
Root Mean Square Error  4457.571293226566

R2Score Model
Training R2 Score:  0.9186233222453871
Testing R2 Score:  0.8644839865347471

Adj_R2Score Model
Training Adj_R2 Score:  0.9163280826164109
Testing Adj_R2 Score:  0.8606617400011118
RMSE for Training Data:  3452.4065827653408
RMSE for Testing Data:  4457.571293226566
Accuracy for 20 - Fold Cross Predicted:  0.8505018200770418
```

GradientBoostRegression

```
from sklearn.ensemble import GradientBoostingRegressor


Gb_reg = GradientBoostingRegressor(random_state=0)
Gb_reg.fit(X_train, y_train)

model_det(Gb_reg,"Gradient Boost Regression ")
```

```
Gradient Boost Regression


MSE MAE RMSE
Mean Square Error  19526203.71601384
Mean Absolute Error  2465.016758597356
Root Mean Square Error  4418.846423673699

R2Score Model
Training R2 Score:  0.902543197053236
Testing R2 Score:  0.8668283325746603

Adj_R2Score Model
Training Adj_R2 Score:  0.8997944154316606
Testing Adj_R2 Score:  0.8630722086216379
RMSE for Training Data:  3778.139926965801
```

```
RMSE for Testing Data:  4418.846423673699
Accuracy for 20 - Fold Cross Predicted:  0.8583036254288966
```

KNN Reg

```
from sklearn.neighbors import KNeighborsRegressor
```

```
knn_reg = KNeighborsRegressor(n_neighbors=2)
knn_reg.fit(X_train, y_train)

model_det(knn_reg,"KNeighborsRegressor")
```

```
KNeighborsRegressor


MSE MAE RMSE
Mean Square Error  31812365.96961033
Mean Absolute Error  3326.8291542288557
Root Mean Square Error  5640.2452047415745

R2Score Model
Training R2 Score:  0.9229412884951933
Testing R2 Score:  0.7830348447382174

Adj_R2Score Model
Training Adj_R2 Score:  0.9207678376578783
Testing Adj_R2 Score:  0.7769153147180132
RMSE for Training Data:  3359.5633102213233
RMSE for Testing Data:  5640.2452047415745
Accuracy for 20 - Fold Cross Predicted:  0.2634474484014062
```

```
from sklearn.ensemble import AdaBoostRegressor
```

```
ada_regr = AdaBoostRegressor(random_state=0, n_estimators=100)
ada_regr.fit(X_train, y_train)

model_det(ada_regr,"AdaBoostRegressor")
```

```
AdaBoostRegressor


MSE MAE RMSE
Mean Square Error  28439196.703686614
Mean Absolute Error  4322.124202716974
Root Mean Square Error  5332.841334943935

R2Score Model
Training R2 Score:  0.822399376746681
Testing R2 Score:  0.8060403701431665
```