MUHUMMAD
HABIB

DATA SCIENCE PROJECT

MEDICAL INSURANCE COST PREDICTION

Kaggle

Github

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Medical Health Insurance Cost Prediction | Python + Regression Models

Medical Health Insurance Cost Prediction with python using Different Regression Models.

Overview

This project focuses on predicting medical health insurance costs using various regression models. The goal is to create a model that can accurately estimate the insurance costs for individuals based on their attributes. The project employs exploratory data analysis, data preprocessing, and several regression techniques to achieve this.

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Project Description

In this project, we aim to predict medical health insurance costs for individuals based on various factors such as age, sex, BMI, number of children, smoking habits, and region. The project involves the following steps:

1. **Data Loading and Overview**: The project begins by loading the dataset containing information about individuals and their insurance costs.

2. **Exploratory Data Analysis**: We analyze the dataset to gain insights into the data distribution, relationships between variables, and identify potential patterns.

3. **Data Preprocessing**: Data preprocessing steps are performed, including handling missing values, encoding categorical variables, and scaling numerical features.

4. **Regression Models**: Several regression models are implemented, including Multiple Linear Regression, Lasso Regression, Ridge Regression, ElasticNet Regressor, Random Forest Regressor, and Polynomial Regression.

5. **Model Evaluation**: The models are evaluated using metrics such as Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error. The performance of each model is compared.

6. **Conclusion**: The project concludes with a summary of key insights obtained from the analysis and suggestions for further improvement.

Requirements

1. **Python**

2. **Integrated Development Environment (IDE)**: You can use IDEs like **Jupyter Notebook**, **PyCharm**, **Visual Studio Code**, or any other of your preference.

3. **Dataset**: Collect the dataset containing medical records, including factors like age, gender, BMI, number of dependents, smoking status, region, and charges.

4. **Data Preprocessing Libraries**: You might need libraries like **Pandas** for data manipulation and cleaning, and **NumPy** for numerical operations.
5. **Data Visualization Libraries**: Consider using libraries like **Matplotlib** and **Seaborn** for visualizing the data distribution, trends, and anomalies.
6. **Statistical Libraries**: Depending on your project's needs, **Scipy** might be useful for advanced statistical operations.
7. **Machine Learning Libraries**: You will likely need **Scikit-learn** for standard machine learning algorithms and **TensorFlow** or **PyTorch** for any deep learning implementations.
8. **Regression Algorithms**: Implementing a project on insurance cost prediction will require a variety of regression algorithms such as Linear Regression, **Ridge** and **Lasso** Regression, **Decision Tree** Regression, **Random Forest** Regression, and possibly more advanced techniques based on your research.
9. **Model Evaluation Tools**: Libraries like **Scikit-learn** contain useful functions for evaluating your regression models, including metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and **R-squared**.
10. **Data Preprocessing Tools**: You might need tools like **Scikit-learn**'s `Pipeline` and `preprocessing` module for efficiently handling data preprocessing tasks.
11. **Model Deployment (Optional)**: If you plan to deploy the trained models, you might need libraries like **Flask** or **FastAPI** for creating APIs.

Dataset

The dataset used for this project contains information about individuals' attributes and their corresponding medical insurance costs. The attributes include age, sex, BMI, number of children, smoking habits, and region. The dataset is loaded and explored using Python's pandas library.

Dataset Source: https://www.kaggle.com/datasets/teertha/ushealthinsurancedataset

```
# !pip install sklearn

# !pip install scikit-learn

import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import plotly.express as px
import plotly.graph_objects as go
import plotly.figure_factory as ff
from plotly.offline import download_plotlyjs, init_notebook_mode, iplot

import warnings
warnings.filterwarnings('ignore')

# !pip install plotly
# !pip install plotly

df = pd.read_csv('insurance.csv')
```

Data Preprocessing

Data preprocessing involves handling missing values, encoding categorical variables, and scaling numerical features. Label encoding and one-hot encoding are used for categorical variables. Additionally, feature scaling is performed to ensure that numerical features are on similar scales.

```
df.head()
```

```
   age     sex     bmi  children smoker     region      charges
0   19  female  27.900         0    yes  southwest  16884.92400
1   18    male  33.770         1     no  southeast   1725.55230
2   28    male  33.000         3     no  southeast   4449.46200
3   33    male  22.705         0     no  northwest  21984.47061
4   32    male  28.880         0     no  northwest   3866.85520
```

```
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   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

```
df.describe
```

```
<bound method NDFrame.describe of       age     sex     bmi  children smoker 
region      charges
0      19  female  27.900         0    yes  southwest  16884.92400
1      18    male  33.770         1     no  southeast   1725.55230
2      28    male  33.000         3     no  southeast   4449.46200
3      33    male  22.705         0     no  northwest  21984.47061
4      32    male  28.880         0     no  northwest   3866.85520
...   ...     ...     ...       ...    ...        ...          ...
1333   50    male  30.970         3     no  northwest  10600.54830
1334   18  female  31.920         0     no  northeast   2205.98080
1335   18  female  36.850         0     no  southeast   1629.83350
1336   21  female  25.800         0     no  southwest   2007.94500
1337   61  female  29.070         0    yes  northwest  29141.36030

[1338 rows x 7 columns]>
```

```
df.describe()
```

```
               age          bmi     children       charges
count  1338.000000  1338.000000  1338.000000   1338.000000
mean     39.207025    30.663397     1.094918  13270.422265
std      14.049960     6.098187     1.205493  12110.011237
min      18.000000    15.960000     0.000000   1121.873900
25%      27.000000    26.296250     0.000000   4740.287150
50%      39.000000    30.400000     1.000000   9382.033000
75%      51.000000    34.693750     2.000000  16639.912515
max      64.000000    53.130000     5.000000  63770.428010
```

```python
df.isnull().sum()
```

```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

there's no any null values

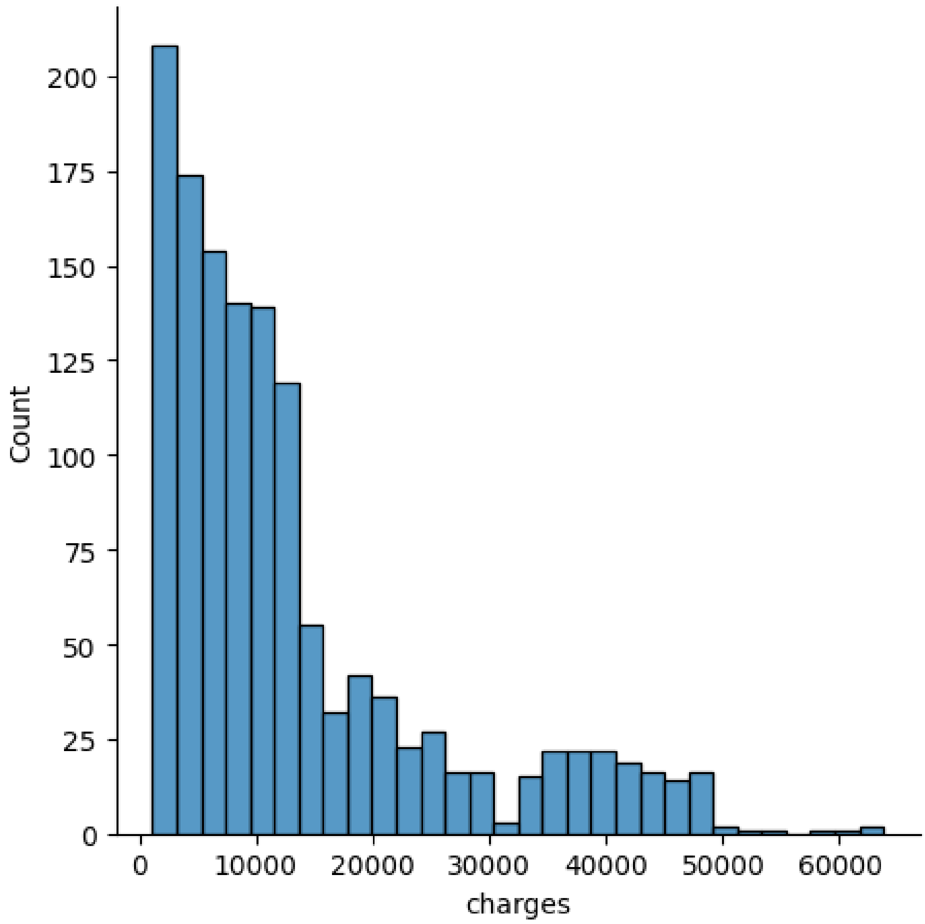
Exploratory Data Analysis

Exploratory Data Analysis (EDA) is performed to understand the distribution of variables and identify relationships. Visualizations using libraries such as seaborn, matplotlib, and plotly are used to create various plots and graphs.

```python
#WE CAN APPLY LOG TRANSFORM TO CORREST SKEWNESS
```

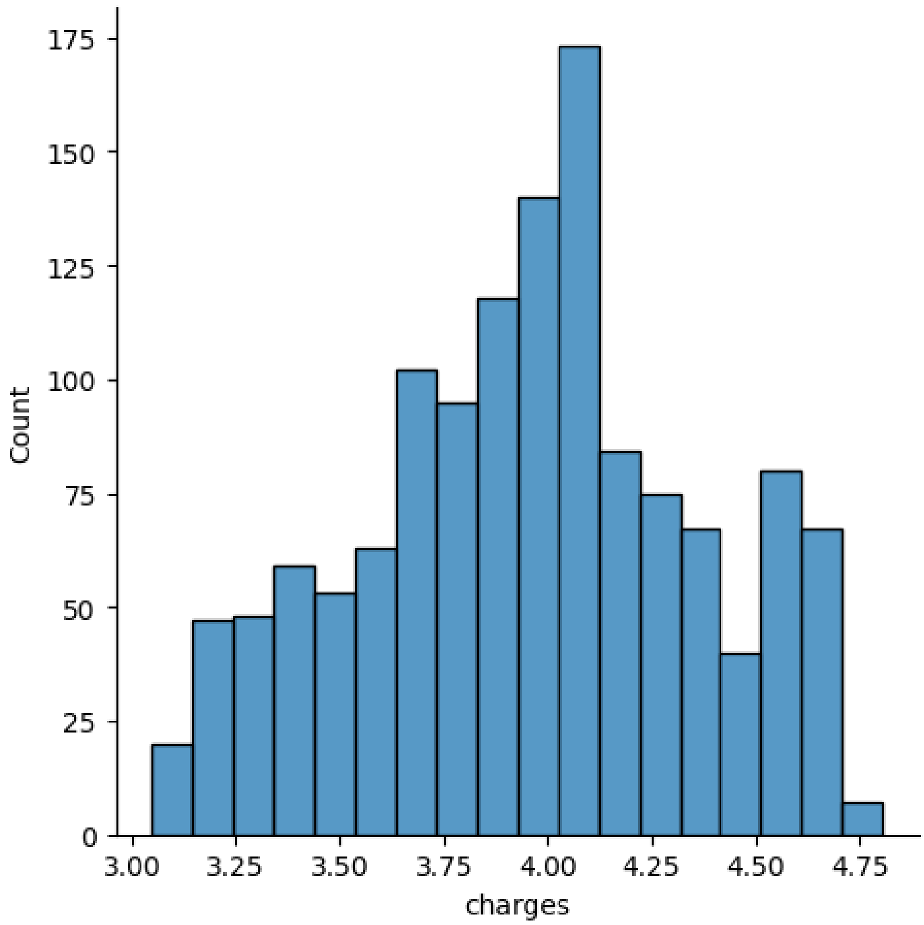
```python
skewed = sns.displot(df['charges']) #Charges is right-skewed
skewed
```

```
<seaborn.axisgrid.FacetGrid at 0x1f0a4f06040>
```




```python
log_trans = sns.displot(np.log10(df['charges'])) #skewness is corrected using log
log_trans
```

```
<seaborn.axisgrid.FacetGrid at 0x1f0ad223f10>
```




```
#CHARGES BY REGION
charges = df['charges'].groupby(df['region']).sum().sort_values(ascending = True)
charges
```

```
region
southwest    4.012755e+06
northwest    4.035712e+06
northeast    4.343669e+06
southeast    5.363690e+06
Name: charges, dtype: float64
```

```
# Ploting charges by region with plotly.express aka px

fig = px.bar(charges, title='Charges by Region', color=charges,
color_continuous_scale='plasma')
fig.update_layout(
    margin=dict(t=50, b=0, l=0, r=0),
    titlefont=dict(size=20),
    xaxis_tickangle=-45,  # Specify the angle at which x-axis labels are
displayed
)
fig.update_yaxes(showticklabels=False, title=' ')
fig.update_xaxes(title=' ')
fig.update_traces(
    texttemplate='%{y}',  # Display y values as text on the bars
    textposition='outside',  # Position the text outside the bars
    hovertemplate='<b>%{x}</b><br>Charges: %{y}',  # Customize hover template
)
fig.show()
```

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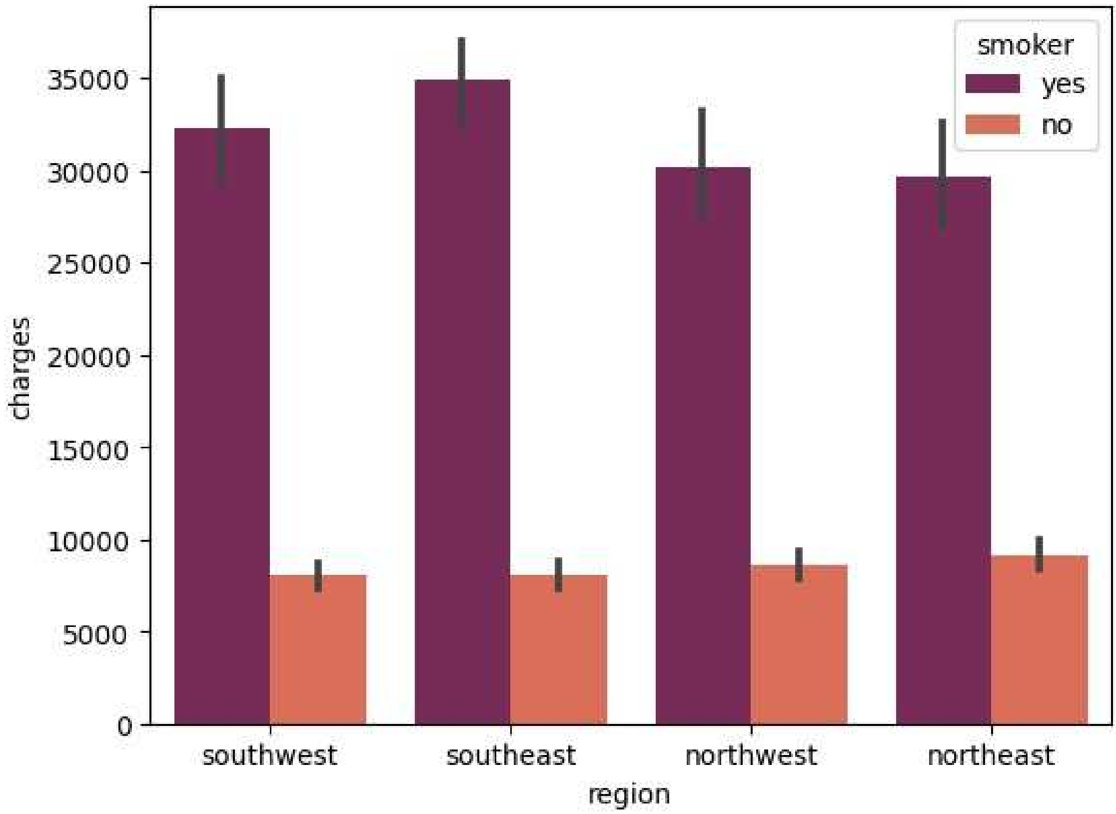
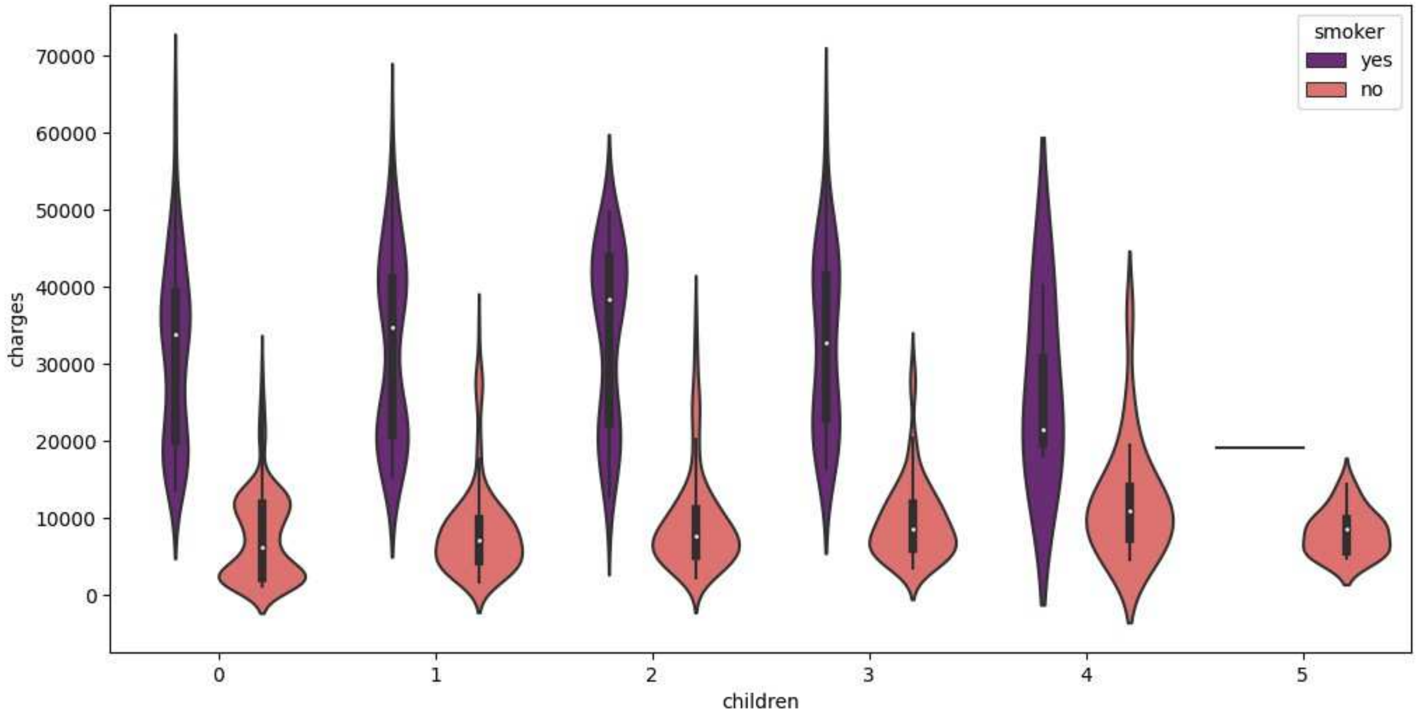
```
#WE CHECK THE CHARGES BY REGION WHO ARE SMOKERS

sns.barplot(data = df, x = 'region', y = 'charges', hue = 'smoker', palette =
'rocket' )
```

<Axes: xlabel='region', ylabel='charges'>



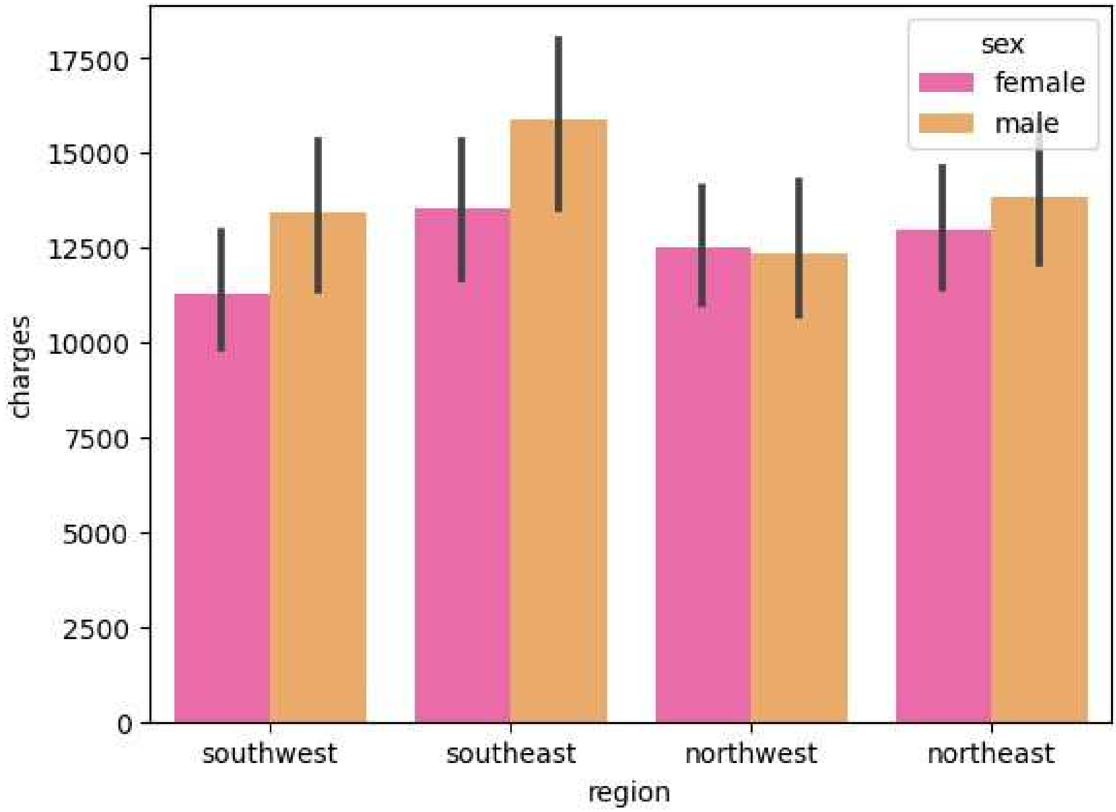

```
plt.figure(figsize=(12,6))
sns.violinplot(data = df, x = 'children', y = 'charges', hue = 'smoker', split =
False, palette = 'magma')
```

<Axes: xlabel='children', ylabel='charges'>



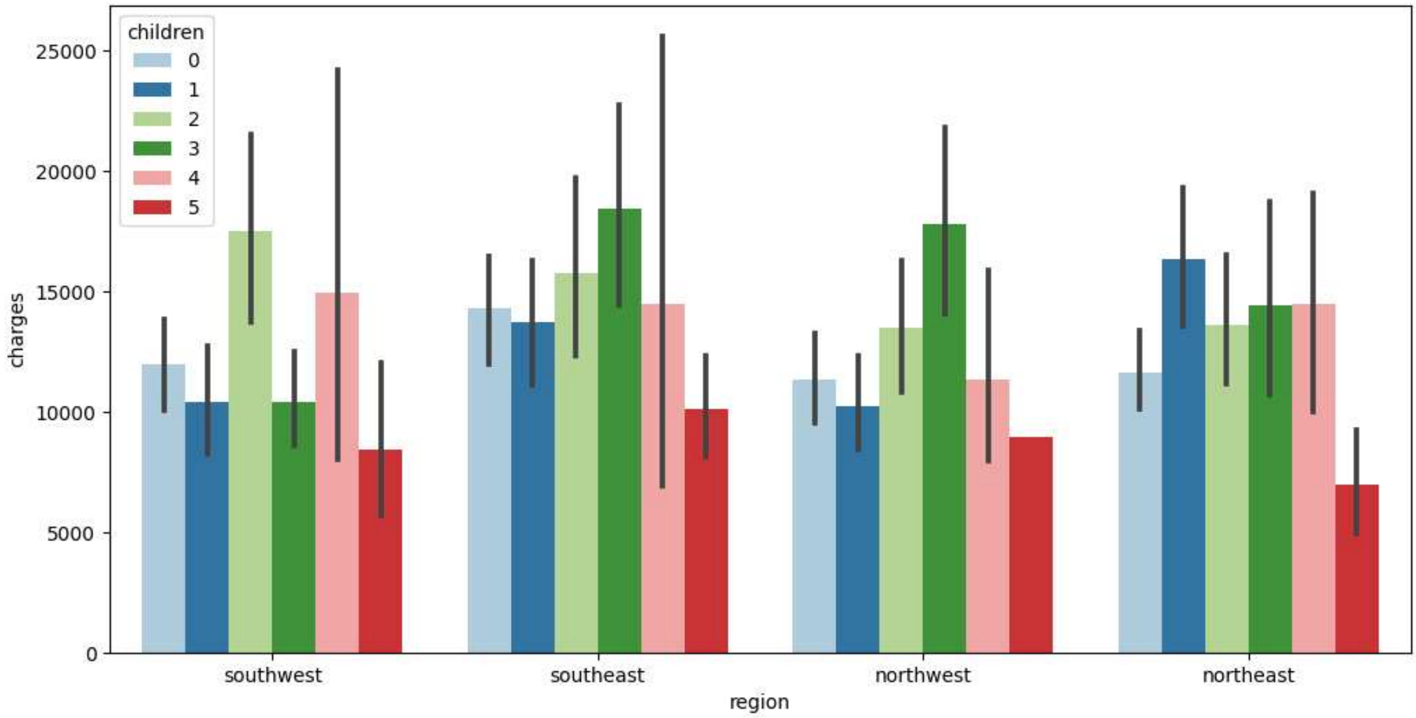

```
#WE CHECK THE CHARGES BY REGION BY THIER GENDER
sns.barplot(data = df, x='region', y='charges', hue='sex', palette='spring')
```

```
<Axes: xlabel='region', ylabel='charges'>
```



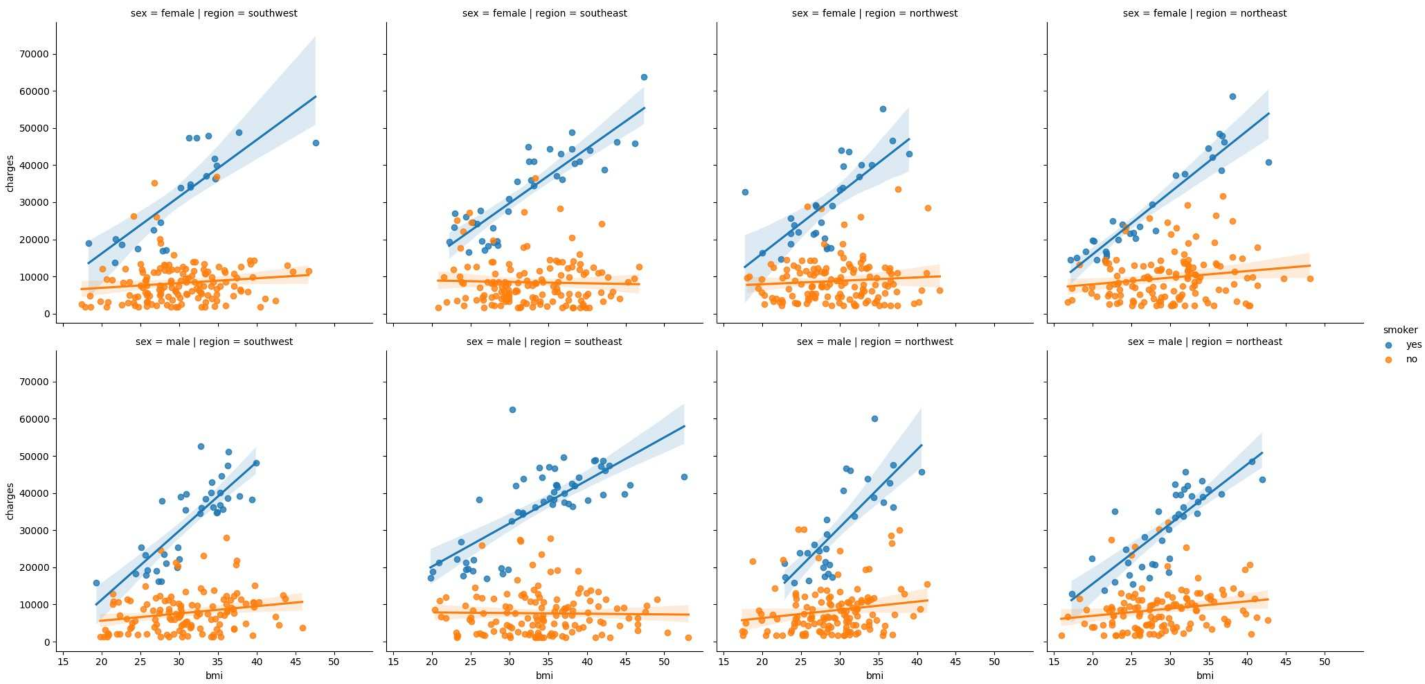

```
#WE CHECK THE CHARGES BY REGION BY THE CHILDREN AVAILABLE
plt.figure(figsize=(12,6))
sns.barplot(data = df, x = 'region', y= 'charges',  hue = 'children',
palette='Paired')
```

```
<Axes: xlabel='region', ylabel='charges'>
```



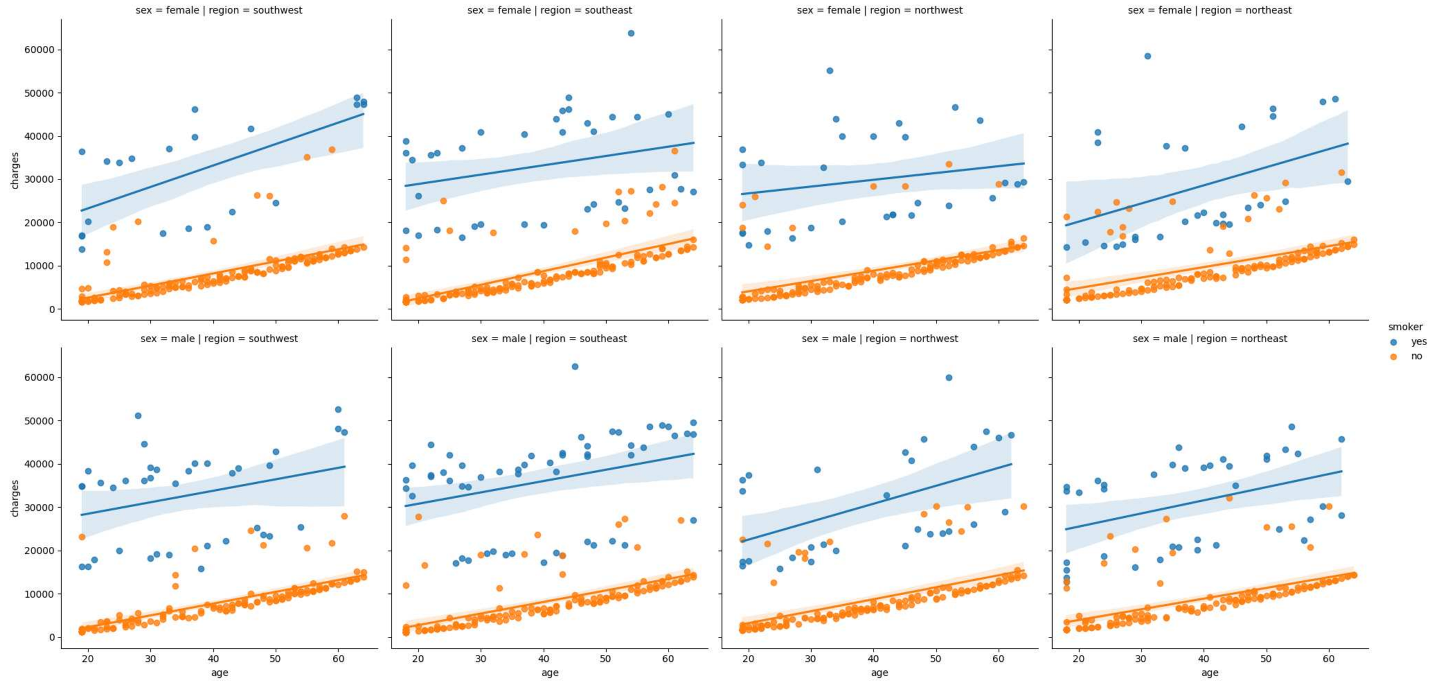

```python
#regression plot to understand the relationship between the bmi and charges considering
sns.lmplot(x = "bmi", y = "charges", row = "sex", col = "region", hue = 'smoker', data = df)
```

```
<seaborn.axisgrid.FacetGrid at 0x1f0ba646e50>
```




```python
#regression plot to understand the relationship between the Age and Charges considering
sns.lmplot(x = "age", y = "charges", row = "sex", col = "region", hue = 'smoker', data = df)
```

```
<seaborn.axisgrid.FacetGrid at 0x1f0bc80bf40>
```



From the chart above we can see that those who are smokers get a higher medical insurance charges than those that are none smoker

```
# Convert object labels to categorical data type
df[['sex', 'region', 'smoker']] = df[['sex', 'region',
'smoker']].astype('category')

# Check the updated data types
print(df.dtypes)

age            int64
sex         category
bmi          float64
children       int64
smoker      category
region      category
charges      float64
dtype: object

# Converting category labels into numerical using LabelEncoder
from sklearn import preprocessing
label = preprocessing.LabelEncoder()

label.fit(df.sex.drop_duplicates())
df.sex = label.transform(df.sex)

label.fit(df.smoker.drop_duplicates())
df.smoker = label.transform(df.smoker)

label.fit(df.region.drop_duplicates())
df.region = label.transform(df.region)

df.head()
```

	age	sex	bmi	children	smoker	region	charges
0	19	0	27.900	0	1	3	16884.92400
1	18	1	33.770	1	0	2	1725.55230
2	28	1	33.000	3	0	2	4449.46200

```
3   33    1  22.705         0       0       1  21984.47061
4   32    1  28.880         0       0       1   3866.85520
```

```
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(),cmap='coolwarm',annot=True)
```

```
<Axes: >
```


```
#we split our model
x = df.drop(['charges'], axis = 1)
y = df['charges']
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x, y, test_size = 0.2,
random_state = 42)
```

```
# !pip install statsmodels
```

```
import statsmodels.api as sm #WE GET THE STATISTICAL MODEL
#add constant to predictor variables
x2 = sm.add_constant(x_train)
```

```python
#fit linear regression model
model = sm.OLS(y_train, x2).fit()
```

```python
model.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.742
Model:                            OLS   Adj. R-squared:                  0.740
Method:                 Least Squares   F-statistic:                     508.7
Date:                Sun, 20 Aug 2023   Prob (F-statistic):          2.71e-308
Time:                        21:17:48   Log-Likelihood:                -10845.
No. Observations:                1070   AIC:                         2.170e+04
Df Residuals:                    1063   BIC:                         2.174e+04
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -1.195e+04   1086.938    -10.991      0.000   -1.41e+04   -9813.820
age          257.0563     13.452     19.109      0.000     230.661     283.451
sex          -18.7915    375.770     -0.050      0.960    -756.126     718.543
bmi          335.7815     31.655     10.607      0.000     273.668     397.895
children     425.0915    154.431      2.753      0.006     122.067     728.116
smoker      2.365e+04    465.245     50.829      0.000    2.27e+04    2.46e+04
region      -271.2843    170.373     -1.592      0.112    -605.590      63.022
==============================================================================
Omnibus:                      251.823   Durbin-Watson:                   2.085
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              611.548
Skew:                           1.251   Prob(JB):                    1.60e-133
Kurtosis:                       5.731   Cond. No.                         299.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
"""
```

Standard Errors:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

R-squared: 0.747

- The coefficient of determination.
- Proportion of variance in the response variable explained by predictor variables.
- 74.7% of the variation in exam scores explained by hours studied and prep exams taken.

F-statistic: 523.6

- Overall F-statistic for the regression model.

Prob (F-statistic): 3.16e-313

- p-value associated with the overall F-statistic.
- Determines if the regression model is statistically significant.
- p-value < 0.05 indicates a significant association of predictor variables with the response variable.

coef:

- Coefficients for each predictor variable.
- Represents average expected change in the response variable, with other predictors constant.

P>|t|:

- Individual p-values for each predictor variable.
- Indicates statistical significance.
- Statistically significant at $\alpha < 0.05$, not significant at $\alpha >= 0.05$.
- Example: "sex" not statistically significant, may be removed from the model.

Regression Models

Multiple regression models are implemented to predict insurance costs.

MULTIPLE LINEAR REGRESSION MODEL

```
from sklearn.linear_model import LinearRegression

lm = LinearRegression()


lm.fit(x_train,y_train)
```

```
LinearRegression()
```

```
print('Intercept', lm.intercept_)
print('Coefficient', lm.coef_)
print('Score', lm.score(x_test, y_test))
```

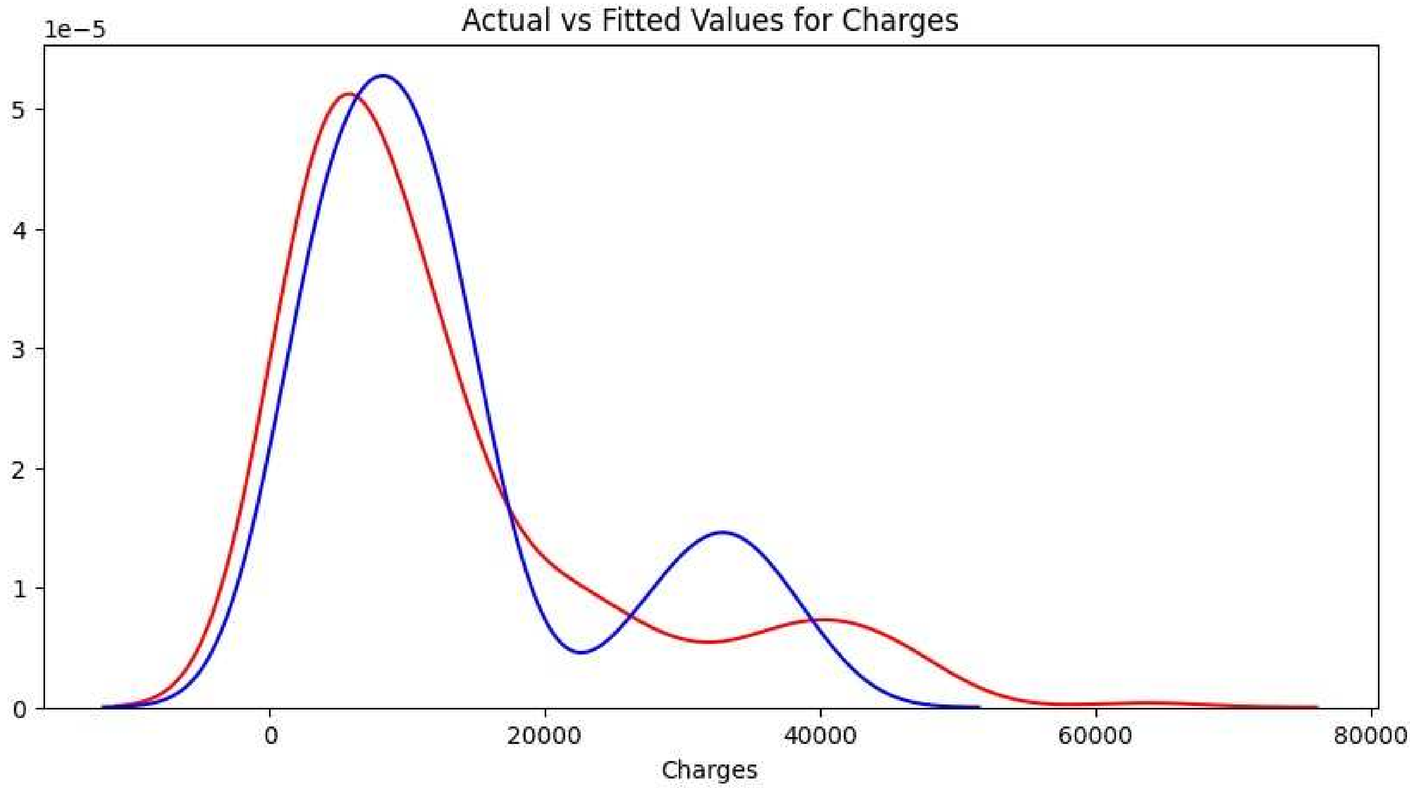
```
Intercept -11946.60656726302
Coefficient [ 2.57056264e+02 -1.87914567e+01  3.35781491e+02  4.25091456e+02
  2.36478181e+04 -2.71284266e+02]
Score 0.7833463107364539
```

```
coeff_df = pd.DataFrame(lm.coef_,x.columns,columns=['Coefficient'])
coeff_df
```

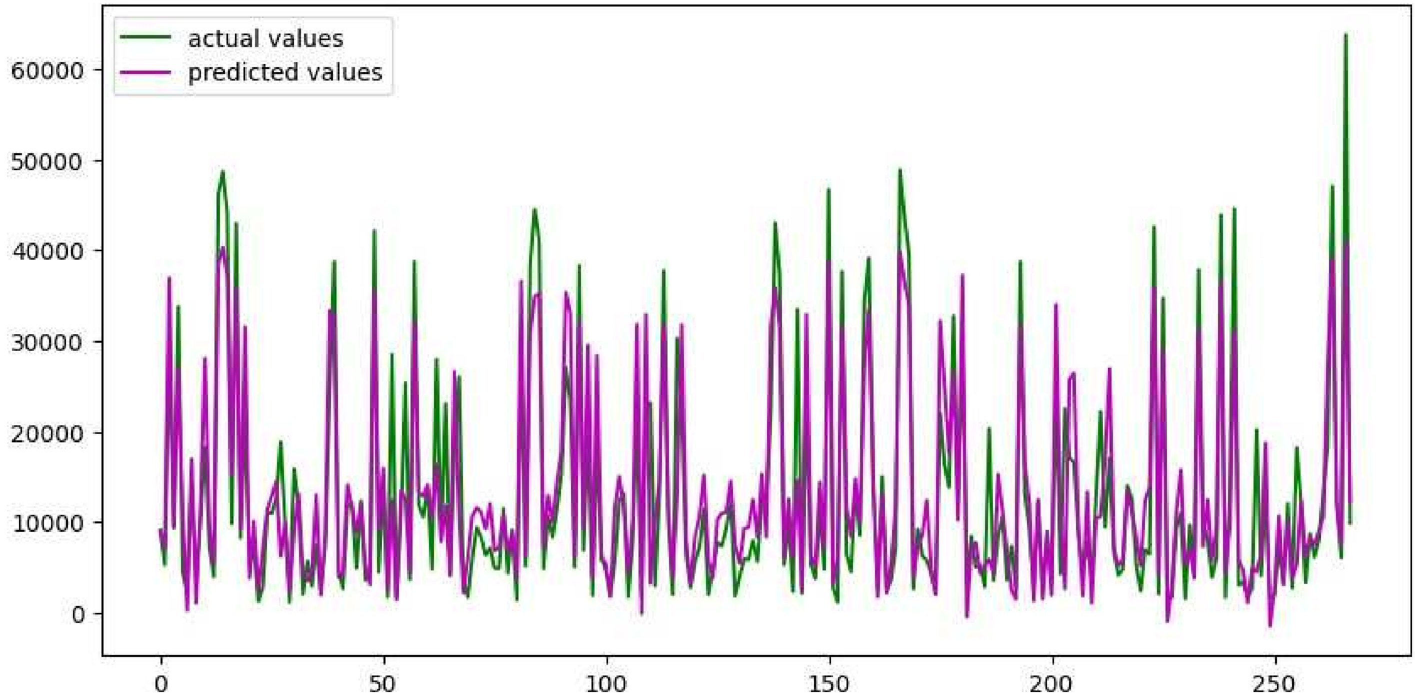
	Coefficient
age	257.056264
sex	-18.791457
bmi	335.781491
children	425.091456
smoker	23647.818096
region	-271.284266

```
#WE PREDICT OUR MODEL
y_pred1 = lm.predict(x_test)
```

```
plt.figure(figsize=(10, 5))
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred1, hist=False, color="b", label="Fitted Values" , ax=ax1)
plt.title('Actual vs Fitted Values for Charges')
plt.xlabel('Charges')
plt.ylabel('')
plt.show()
plt.close()
```




```
## ANOTHER PLOTTING TECHNIQUE

plt.figure(figsize=(10, 5))
# acutal values
plt.plot([i for i in range(len(y_test))],np.array(y_test), c='g', label="actual
values")
# predicted values
plt.plot([i for i in range(len(y_test))],y_pred1, c='m',label="predicted values")
plt.legend()
plt.show()
```




```
#DATAFRAME FOR ACTUAL AND PREDICTED VALUE
predicted1 = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred1})
predicted1.head()
```

```
            Actual      Predicted
764    9095.06825   8924.407244
887    5272.17580   7116.295018
890   29330.98315  36909.013521
1293   9301.89355   9507.874691
259   33750.29180  27013.350008
```

LASSO REGRESSION MODEL

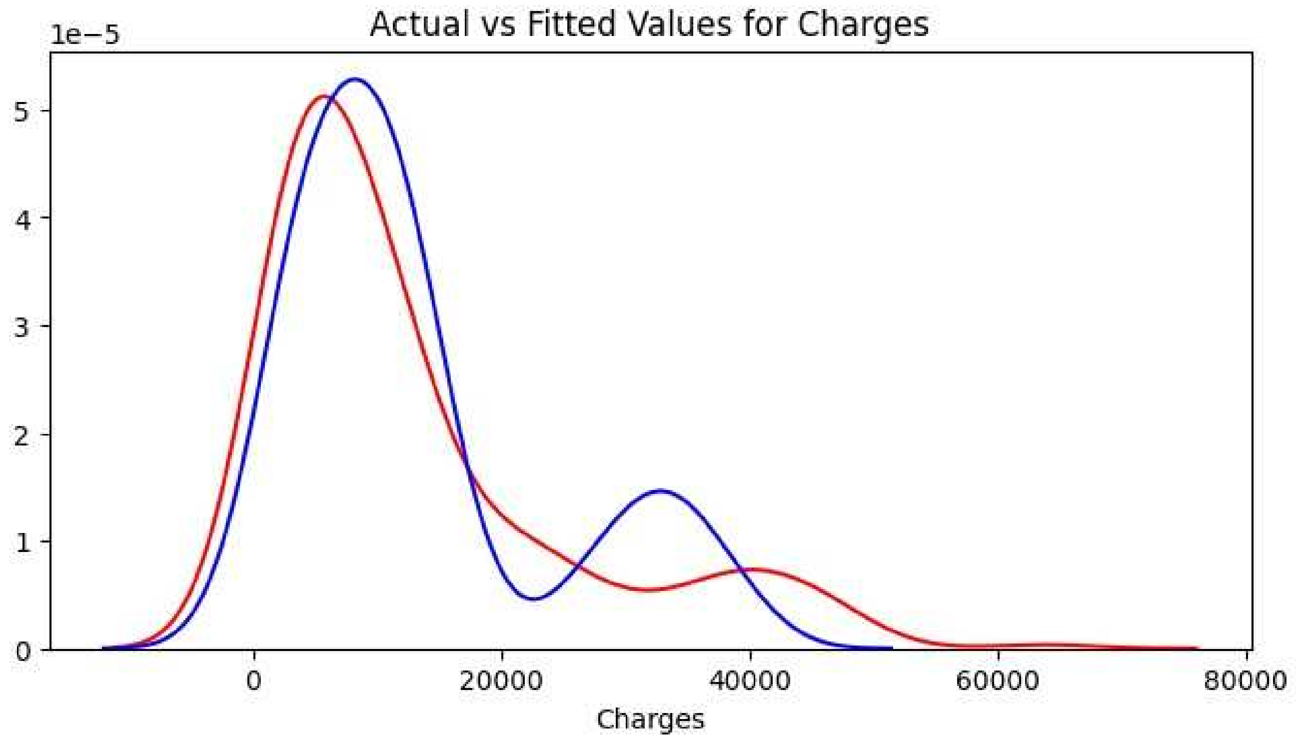
```
from sklearn.linear_model import LassoCV
from sklearn.model_selection import RepeatedKFold

#define cross-validation method to evaluate model
cv = RepeatedKFold(n_splits=10, n_repeats=4, random_state=101) #we'll use the RepeatedKF
#define model
lasso_model = LassoCV(alphas=(0.1, 1.0, 10.0), cv=cv, n_jobs=-1)
#fit model
lasso_model.fit(x_train, y_train)
```

```
LassoCV(alphas=(0.1, 1.0, 10.0),
        cv=RepeatedKFold(n_repeats=4, n_splits=10, random_state=101),
        n_jobs=-1)
```

```
print('Intercept', lm.intercept_)
print('Coefficient', lm.coef_)
print('Score', lm.score(x_test, y_test))
```

```
Intercept -11946.60656726302
Coefficient [ 2.57056264e+02 -1.87914567e+01  3.35781491e+02  4.25091456e+02
  2.36478181e+04 -2.71284266e+02]
Score 0.7833463107364539
```

```
#WE PREDICT OUR LASSOCV REGRESSION MODEL
y_pred2 = lasso_model.predict(x_test)

# Visualising the Lasso Regression results
plt.figure(figsize=(8, 4))
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred2, hist=False, color="b", label="Fitted Values" , ax=ax1)
plt.title('Actual vs Fitted Values for Charges')
plt.xlabel('Charges')
plt.ylabel('')
plt.show()
plt.close()
```




```
#DATAFRAME FOR ACTUAL AND PREDICTED VALUE
predicted2 = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred2})
predicted2.head()
```

```
           Actual     Predicted
764    9095.06825   8911.659191
887    5272.17580   7123.036794
890   29330.98315  36852.479165
1293   9301.89355   9515.428284
259   33750.29180  26976.771303
```

RIDGE REGRESSION MODEL

```
from sklearn.linear_model import Ridge
from sklearn.linear_model import RidgeCV
from sklearn.model_selection import RepeatedKFold

#define cross-validation method to evaluate model
# cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=101)

#define model
rid_model = RidgeCV(alphas=(0.1,  1.0,  10.0), cv=cv,
scoring='neg_mean_absolute_error')
#fit model
rid_model.fit(x_train, y_train)
```

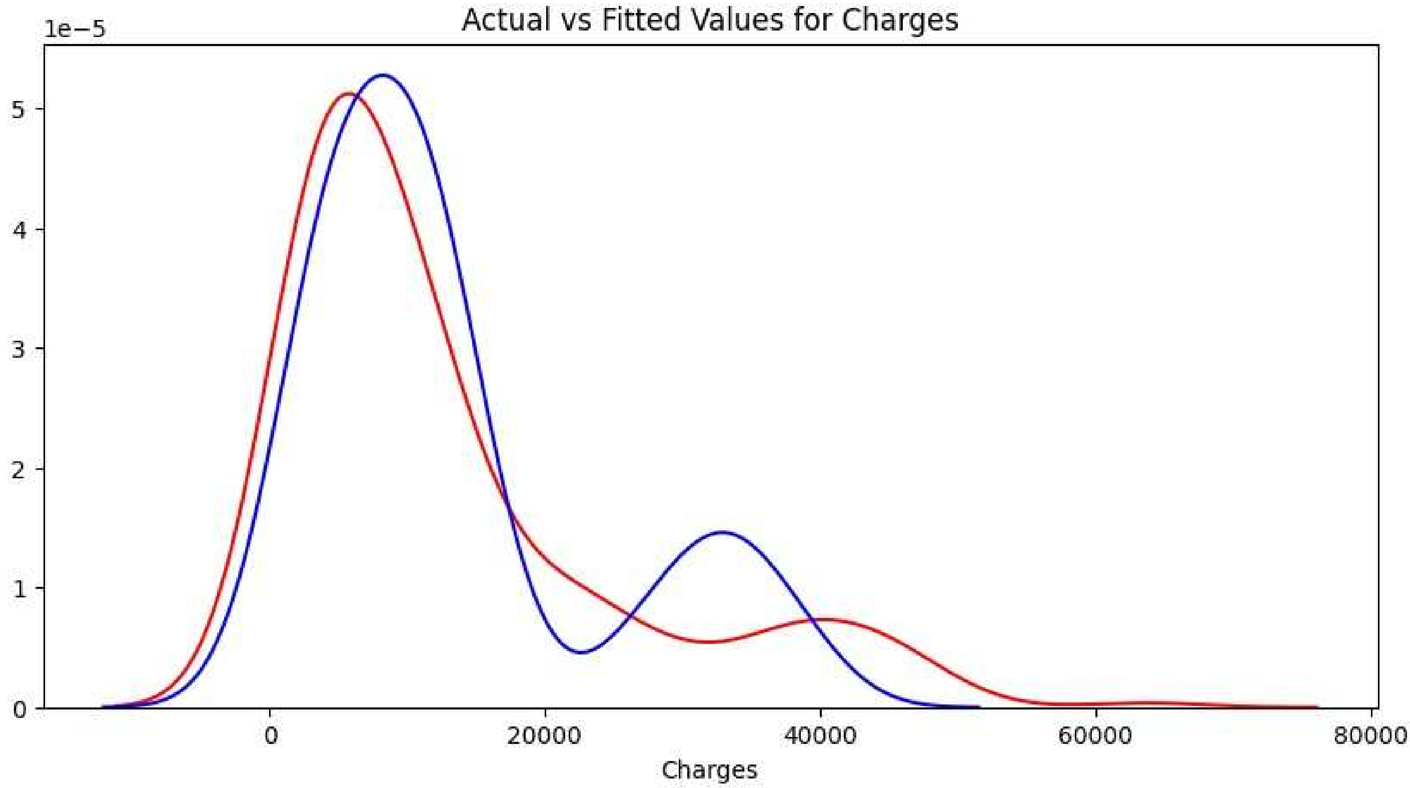
```
RidgeCV(cv=RepeatedKFold(n_repeats=4, n_splits=10, random_state=101),
        scoring='neg_mean_absolute_error')
```

```
print(rid_model.intercept_)
print(rid_model.coef_)
print(rid_model.score(x_test, y_test))
```

```
-11943.455858669686
[ 2.57035723e+02 -1.80109296e+01  3.35782790e+02  4.25136864e+02
  2.36341868e+04 -2.71303705e+02]
0.7833217621706015
```

```
#WE PREDICT OUR RIDGECV REGRESSION MODEL
y_pred3 = rid_model.predict(x_test)
```

```
# Visualising the Ridge Regression results
plt.figure(figsize=(10, 5))
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred3, hist=False, color="b", label="Fitted Values" , ax=ax1)
plt.title('Actual vs Fitted Values for Charges')
plt.xlabel('Charges')
plt.ylabel('')
plt.show()
plt.close()
```




```
#DATAFRAME FOR ACTUAL AND PREDICTED VALUE
predicted3 = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred3})
predicted3.head()
```

	Actual	Predicted
764	9095.06825	8926.757144
887	5272.17580	7118.725826
890	29330.98315	36897.233767
1293	9301.89355	9511.011287
259	33750.29180	27003.281662

ELASTICNET REGRESSOR

```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedKFold
from sklearn.linear_model import ElasticNet
```

```
#define cross-validation method to evaluate model
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
```

```
# define model
net_model = ElasticNet(alpha=0.1, l1_ratio=0.9, fit_intercept=True,
max_iter=1000, random_state=1)
```

```
# evaluate model
scores = cross_val_score(net_model, x_train,y_train,
scoring='neg_mean_absolute_error', cv=cv)

net_model.fit(x_train, y_train)
```

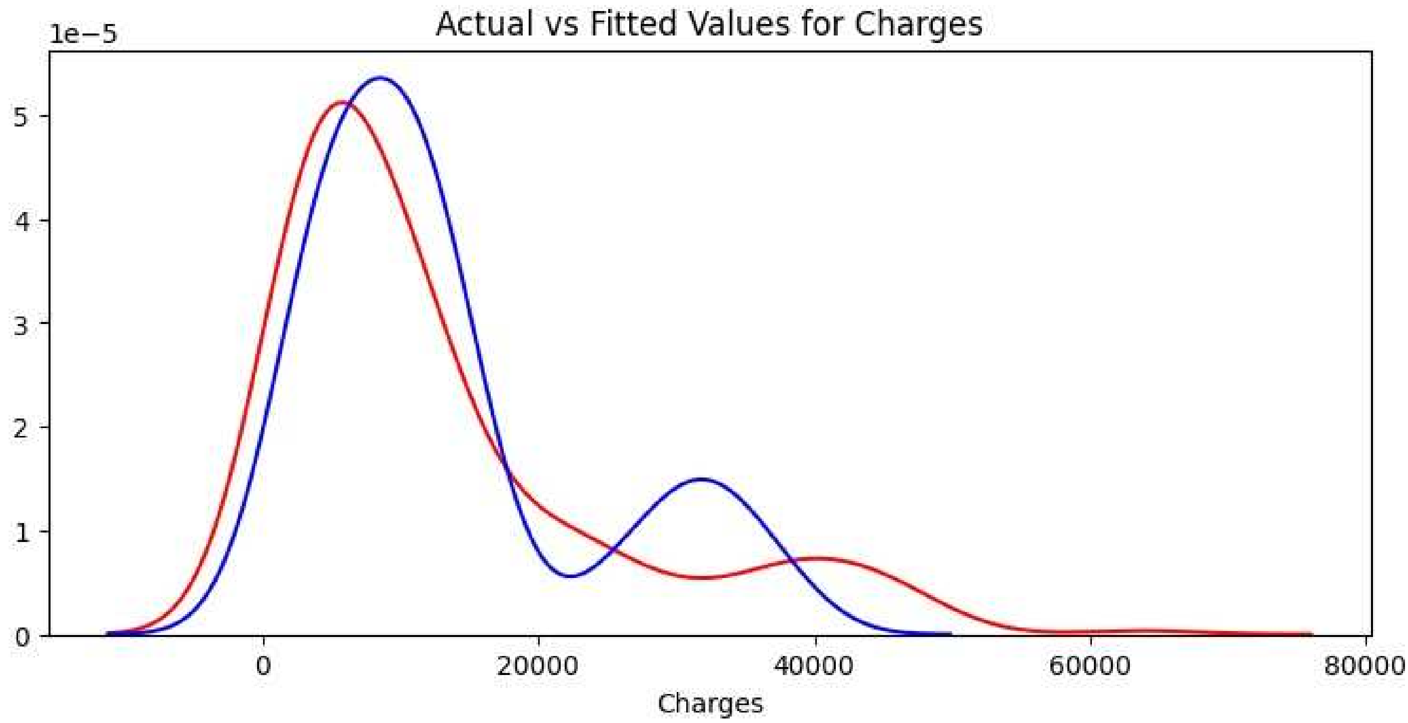
```
ElasticNet(alpha=0.1, l1_ratio=0.9, random_state=1)
```

```
print(net_model.intercept_)
print(net_model.coef_)
print(net_model.score(x_test, y_test))
```

```
-11626.875213341189
[  254.98398073    56.64093616   335.90294961   429.44085068
 22273.01597223  -273.05052278]
0.7789260673175409
```

```
y_pred4 = net_model.predict(x_test)
```

```
# Visualising the ElasticNet Regressor results
plt.figure(figsize=(9, 4))
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred4, hist=False, color="b", label="Fitted Values" , ax=ax1)
plt.title('Actual vs Fitted Values for Charges')
plt.xlabel('Charges')
plt.ylabel('')
plt.show()
plt.close()
```




```
#DATAFRAME FOR ACTUAL AND PREDICTED VALUE
predicted4 = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred4})
predicted4.head()
```

	Actual	Predicted
764	9095.06825	9162.642377
887	5272.17580	7363.304117
890	29330.98315	35722.815803
1293	9301.89355	9822.122303
259	33750.29180	25996.448958

RANDOM FOREST REGRESSOR

```
from sklearn.ensemble import RandomForestRegressor


Ram_reg = RandomForestRegressor(n_estimators=100, criterion='squared_error',
min_samples_split=2)
# fit the regressor model
Ram_reg.fit(x_train, y_train)
```

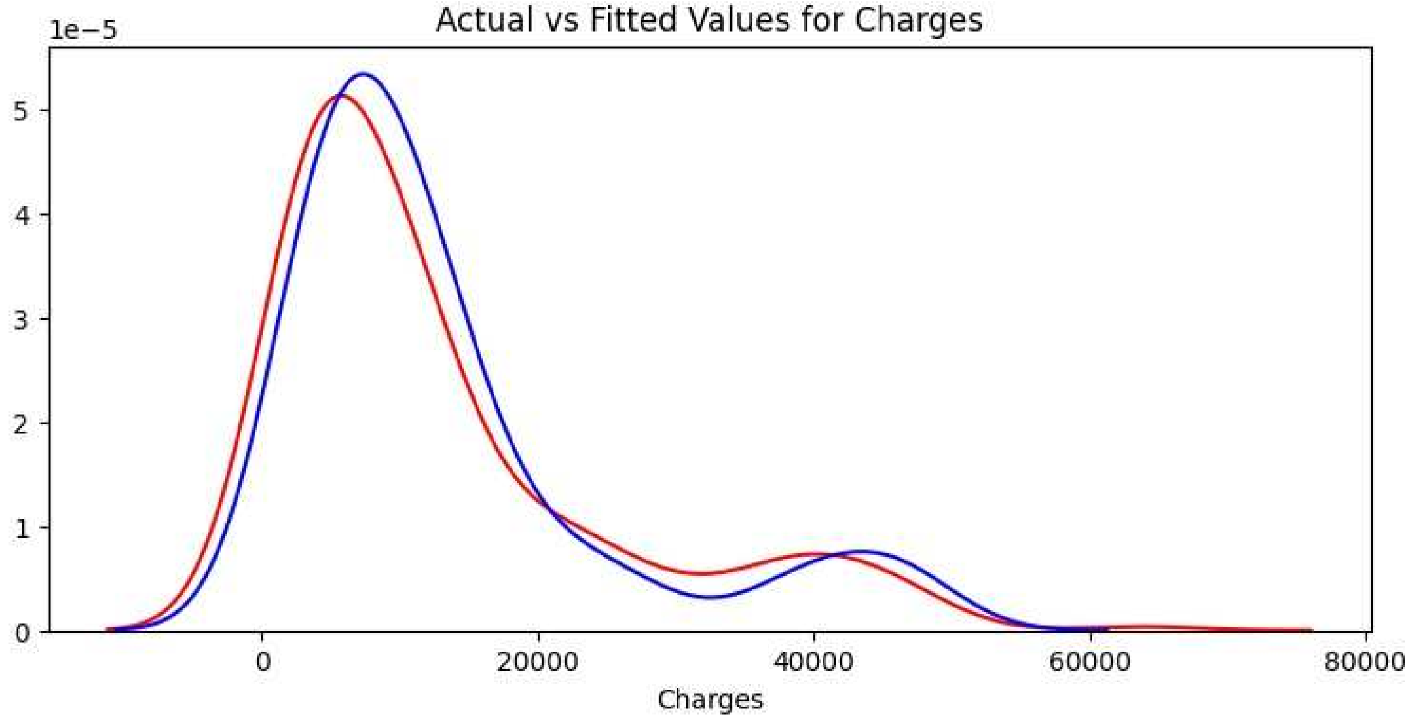
```
RandomForestRegressor()
```

```
print(Ram_reg.score(x_test, y_test))
```

```
0.8659967534430548
```

```
y_pred5 = Ram_reg.predict(x_test)
```

```
# Visualising the Random Forest Regressor results
plt.figure(figsize=(9, 4))
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred5, hist=False, color="b", label="Fitted Values" , ax=ax1)
plt.title('Actual vs Fitted Values for Charges')
plt.xlabel('Charges')
plt.ylabel('')
plt.show()
plt.close()
```

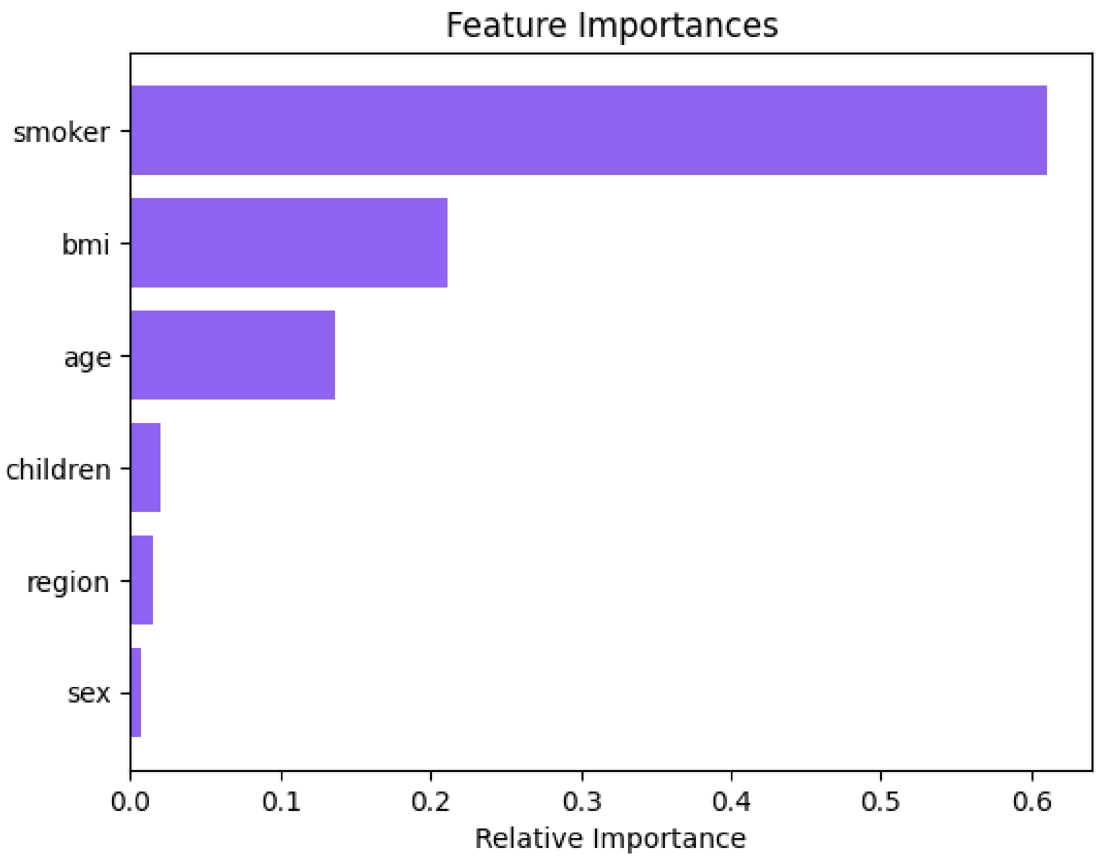



```
#DATAFRAME FOR ACTUAL AND PREDICTED VALUE
predicted5 = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred5})
predicted5.head()
```

	Actual	Predicted
764	9095.06825	10348.293849
887	5272.17580	5268.427971
890	29330.98315	28489.521986
1293	9301.89355	9908.482924
259	33750.29180	34705.577697

WE TRY SELECT THE BEST FEATURES USING FEATURE IMPORTANCE FROM RANDOM FOREST REGRESSOR

```
features = x.columns
importances = Ram_reg.feature_importances_
indices = np.argsort(importances)



plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='#8f63f4',
align='center')
plt.yticks(range(len(indices)), features[indices])
plt.xlabel('Relative Importance')
plt.show()
```



We can see that the smoker, bmi and age are more important features compared to the other features.

```
#We select the import features
x = df.drop(['charges', 'region', 'sex'], axis = 1)
y = df['charges']
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,
random_state = 0)

x
```

```
      age     bmi  children  smoker
0      19  27.900         0       1
1      18  33.770         1       0
2      28  33.000         3       0
3      33  22.705         0       0
4      32  28.880         0       0
...   ...     ...       ...     ...
1333   50  30.970         3       0
1334   18  31.920         0       0
```

```
1335   18  36.850         0       0
1336   21  25.800         0       0
1337   61  29.070         0       1

[1338 rows x 4 columns]
```

WE BUILD A MODEL USING THE POLYNOMIAL REGRESSION AFTER FEATURE IMPORTANCE

POLYNOMIAL REGRESSION MODEL

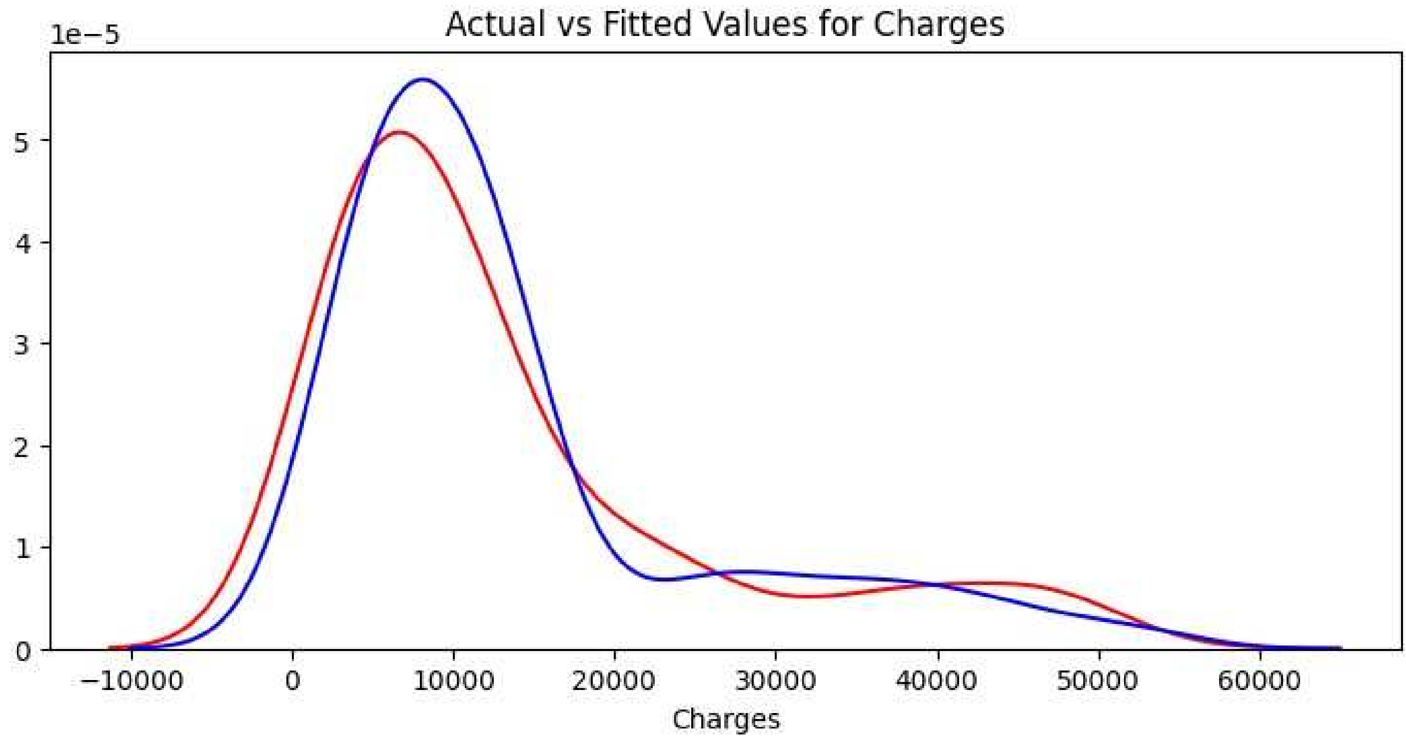
```
from sklearn.preprocessing import PolynomialFeatures


poly_reg = PolynomialFeatures(degree=2)

x_poly = poly_reg.fit_transform(x)

x_train,x_test,y_train,y_test = train_test_split(x_poly, y, test_size = 0.2,
random_state = 0)

pol_reg = LinearRegression()
pol_reg.fit(x_train, y_train)
```

```
LinearRegression()
```

```
print(pol_reg.intercept_)
print(pol_reg.coef_)
print(pol_reg.score(x_test, y_test))
```

```
-5325.881705251873
[ 0.00000000e+00 -4.01606591e+01  5.23702019e+02  8.52025026e+02
 -9.52698471e+03  3.04430186e+00  1.84508369e+00  6.01720286e+00
  4.20849790e+00 -9.38983382e+00  3.81612289e+00  1.40840670e+03
 -1.45982790e+02 -4.46151855e+02 -9.52698471e+03]
0.8812595703345225
```

```
#WE PREDICT OUR POLYNOMIAL REGRESSION MODEL
y_pred6 = pol_reg.predict(x_test)

# Visualising the Polynomial Regression results
plt.figure(figsize=(9, 4))
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred6, hist=False, color="b", label="Fitted Values" , ax=ax1)
plt.title('Actual vs Fitted Values for Charges')
plt.xlabel('Charges')
plt.ylabel('')

plt.show()
plt.close()
```



Model Evaluation

The performance of each regression model is evaluated using various metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The evaluation results provide insights into the accuracy of the models in predicting insurance costs.

```
from sklearn import metrics
from sklearn.metrics import r2_score
```

MULTIPLE LINEAR REGRESSION

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred1))
print('Mean Square Error:', metrics.mean_squared_error(y_test, y_pred1))
print('Root Mean Square Error:', np.sqrt(metrics.mean_squared_error(y_test, 
y_pred1)))
```

```
Mean Absolute Error: 10976.93032415958
Mean Square Error: 225340349.96268988
Root Mean Square Error: 15011.340711698269
```

LASSOCV REGRESSION

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred2))
print('Mean Square Error:', metrics.mean_squared_error(y_test, y_pred2))
print('Root Mean Square Error:', np.sqrt(metrics.mean_squared_error(y_test, 
y_pred2)))
```

```
Mean Absolute Error: 10968.76909663481
Mean Square Error: 224915279.3845799
Root Mean Square Error: 14997.175713599541
```

RIDGECV REGRESSION

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred3))
print('Mean Square Error:', metrics.mean_squared_error(y_test, y_pred3))
print('Root Mean Square Error:', np.sqrt(metrics.mean_squared_error(y_test, 
y_pred3)))
```

```
Mean Absolute Error: 10975.462165520717
Mean Square Error: 225254498.69396165
Root Mean Square Error: 15008.480892280926
```

ELASTICNET REGRESSION

```python
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred4))
print('Mean Square Error:', metrics.mean_squared_error(y_test, y_pred4))
print('Root Mean Square Error:', np.sqrt(metrics.mean_squared_error(y_test,
y_pred4)))
```

```
Mean Absolute Error: 10838.727060068726
Mean Square Error: 216982294.5125357
Root Mean Square Error: 14730.31888699412
```

RANDOM FOREST REGRESSOR

```python
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred5))
print('Mean Square Error:', metrics.mean_squared_error(y_test, y_pred5))
print('Root Mean Square Error:', np.sqrt(metrics.mean_squared_error(y_test,
y_pred5)))
```

```
Mean Absolute Error: 11484.288418379512
Mean Square Error: 266813319.89767018
Root Mean Square Error: 16334.421321175421
```

POLYNOMIAL REGRESSION

```python
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred6))
print('Mean Square Error:', metrics.mean_squared_error(y_test, y_pred6))
print('Root Mean Square Error:', np.sqrt(metrics.mean_squared_error(y_test,
y_pred6)))
```

```
Mean Absolute Error: 2824.49504547766
Mean Square Error: 18895160.09878044
Root Mean Square Error: 4346.856346692451
```

From the model evaluation score, we can see that polynomial regression and the Random Forest Regressor are performing well than the other models.

Key Insights

1. **Feature Importance:** After analyzing the dataset, we found that the most influential factors affecting medical insurance charges are whether the person is a smoker, their BMI (Body Mass Index), and their age.

2. **Smoking Impact:** Smokers tend to have significantly higher medical insurance charges compared to non-smokers. This is a crucial insight that highlights the importance of lifestyle choices on healthcare costs.

3. **Age and Charges:** The age of an individual is positively correlated with insurance charges. Older individuals tend to have higher medical costs, which is understandable given the increased likelihood of health issues as age advances.

4. **BMI Influence:** Higher BMI values are associated with increased medical insurance charges. This suggests that maintaining a healthy weight can positively impact healthcare costs.

5. **Model Performance:** We evaluated multiple regression models including Multiple Linear Regression, LassoCV, RidgeCV, ElasticNet, Random Forest Regressor, and Polynomial Regression. Among these, Polynomial Regression and Random Forest Regressor showed better performance in predicting medical insurance charges.

6. **Polynomial Model Advantage:** The Polynomial Regression model showed the lowest Mean Absolute Error, Mean Square Error, and Root Mean Square Error among all models, indicating its capability to better capture the underlying patterns in the data.

Suggestions

1. **Promote Healthy Lifestyles:** Encourage smoking cessation programs and awareness campaigns to reduce the number of smokers. This could lead to substantial savings in healthcare costs.

2. **Health Awareness:** Run campaigns to educate people about the impact of BMI on health and insurance costs. Promoting healthy eating and exercise can help individuals maintain a healthy weight and potentially lower their medical expenses.

3. **Targeted Insurance Plans:** Design insurance plans that cater to different age groups. Tailored plans can address the unique healthcare needs of people at various life stages.

4. **Model Refinement:** Continue refining and optimizing predictive models. This could involve exploring more advanced algorithms or techniques to improve the accuracy of predictions.

5. **Regular Data Updates:** Regularly update the dataset with new data to ensure that the models remain relevant and accurate. Healthcare trends and cost patterns may change over time.

6. **Personalized Recommendations:** Provide personalized recommendations to individuals based on their age, smoking status, and BMI to help them make informed decisions about their healthcare and insurance choices.

7. **Collaboration with Healthcare Providers:** Collaborate with healthcare providers to gather more comprehensive data that includes detailed medical history. This could further enhance the accuracy of predictive models.

8. **Continuous Monitoring:** Keep monitoring the performance of predictive models and update them as necessary. New insights or changes in the healthcare landscape could require adjustments to the models.

9. **Customer Education:** Educate customers about how their lifestyle choices and age can impact their insurance costs. This transparency can help them make healthier decisions and potentially reduce their expenses.

By implementing these insights and suggestions, the insurance industry can make informed decisions to optimize insurance plans and promote healthier lifestyles among their customers.

Conclusion

This project demonstrates the process of predicting medical health insurance costs using various regression models. The models' performances are compared using evaluation metrics, and key insights are drawn from the analysis. The project highlights the importance of data preprocessing, model selection, and evaluation for accurate predictions in the field of medical insurance cost estimation. Further improvements and refinements could be explored to enhance the models' predictive capabilities.

Feel free to reach out for further discussions or clarifications! 😊

Contact Information

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