insurance_charges_linear_regression

November 22, 2020

1 Coursera/IBM Supervised Learning: Regression

Kaggle Dataset (https://www.kaggle.com/mirichoi0218/insurance)

Main objective of the analysis that specifies whether your model will be focused on prediction or interpretation. * The model will focus on both predicting the charges and being able to address the magnitude of the features, hence interpretabilty.

Brief description of the data set you chose and a summary of its attributes. * The data provided from Kaggle, referenced above, was tidy. Thus, no cleaning was needed. Furthermore, many factors that affect how much you pay for health insurance are not within your control. Nonetheless, it's good to have an understanding of what they are. Here are some factors that affect how much health insurance premiums cost:

```
* **age:** Age of primary beneficiary.
* **sex:** Insurance contractor gender: Female or Male.
* **bmi:** Body mass index, providing an understanding of body, weights that are relatively hig
* **children:** Number of children covered by health insurance / Number of dependents.
* **smoker:** Insurance contractor smoker: Yes or No.
* **region:** The beneficiary's residential area in the US: Northeast, Southeast, Southwest, o
```

Brief summary of data exploration and actions taken for data cleaning and feature engineering. * As aforementioned the data did not need cleaning, however in terms of feature engineering: * Applied the natural log to the right skewed distribution of charges graph. * Looked at the charges by region. * Looked at sex, smoking, and having children by region. * Analyzed medical charges by age, bmi, and children according to the smoking factor. * Converted objects labels (Sex, Smoker, and Region) into categorical. * Converted category labels (Sex, Smoker, and Region) into numerical using LabelEncoder.

Summary of training at least three linear regression models which should be variations that cover using a simple linear regression as a baseline, adding polynomial effects, and using a regularization regression. Preferably, all use the same training and test splits, or the same cross-validation method. * The baseline linear regression model resulted in a R^2 Train Score: 0.7417 & **R^2 Test Score: 0.7833**. * The OLS model resulted in a R^2 Train Score: 0.7123 & **R^2 Test Score: 0.7570**. * The Ridge model resulted in a R^2 Train Score: 0.7417 & **R^2 Test Score: 0.7833**. * The Lasso model resulted in a R^2 Train Score: 0.7417 & **R^2 Test Score: 0.7833**. * The 3rd degree Polynomial model resulted in a R^2 Train Score: 0.8415 & **R^2 Test Score: 0.8690**.

A paragraph explaining which of your regressions you recommend as a final model that best fits your needs in terms of accuracy and explainability. * The best regression model was the 3rd degree **Polynomial Regression model** with an **R^2 test score of 0.8670**. The 1st degree polynomial regression was an underfit model, high bias and low variance. While the 3rd degree polynomial regression was an overfit model, low bias and high variance. Moreover, the Training Root Mean Squared Error: 4781.9091 & the Testing Rooot Mean Squared Error: 4508.7727.

Summary Key Findings and Insights, which walks your reader through the main drivers of your model and insights from your data derived from your linear regression model. * In conclusion smoking is the greatest factor that affects medical cost charges, followed by children and bmi, respectively. Moreover, the Polynomial Regression model turned out to be the best model.

Suggestions for next steps in analyzing this data, which may include suggesting revisiting this model adding specific data features to achieve a better explanation or a better prediction. * In order to further analyze this data I would like to implement different machine learning models such as; Logistic Regression and Random Forest. Moreover, I would like to gather more information from these beneficiaries if possible.

1.1 Import Libraries and Data

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns

import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
df = pd.read_csv("insurance.csv")
df.head()
```

[2]:

	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

[3]:
```
df.shape
```

[3]: (1338, 7)

[4]:
```
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
```

[5]:
```
df.describe()
```

[5]:

	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

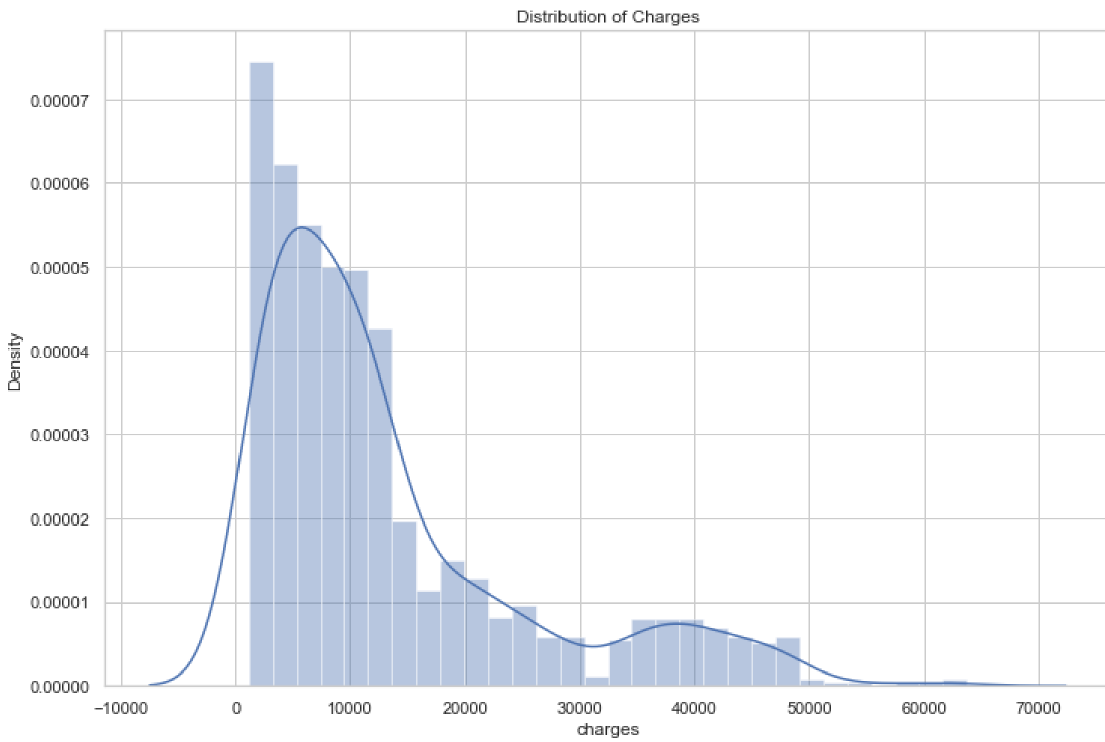
[6]:
```
# There are 0 missing values.
df.isnull().sum()
```

[6]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

1.2 EDA

[7]:
```
sns.set(style='whitegrid')
plt.subplots(1,1, figsize=(12, 8))
sns.distplot(df['charges'], kde = True, color = 'b')
plt.title('Distribution of Charges')
```

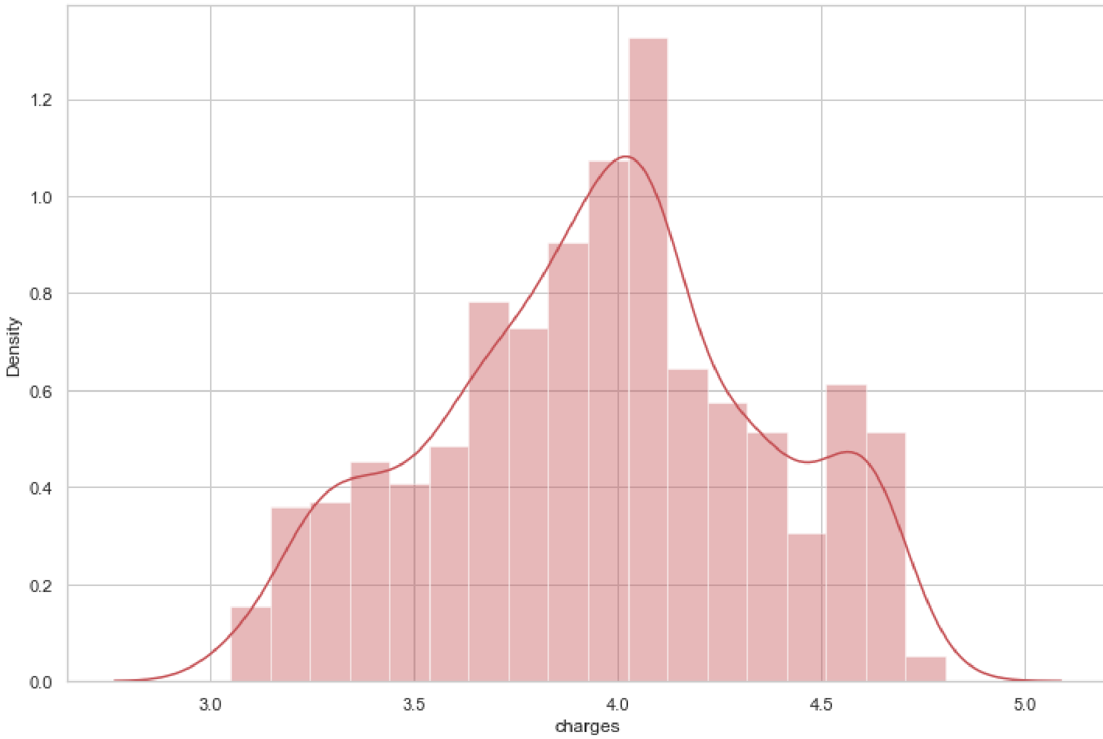
[7]:
```
Text(0.5, 1.0, 'Distribution of Charges')
```



This distribution is right-skewed. To make it closer to normal I will apply the natural log.

[8]:
```
plt.subplots(1, 1, figsize=(12, 8))
sns.distplot(np.log10(df['charges']), kde = True, color = 'r' )
```

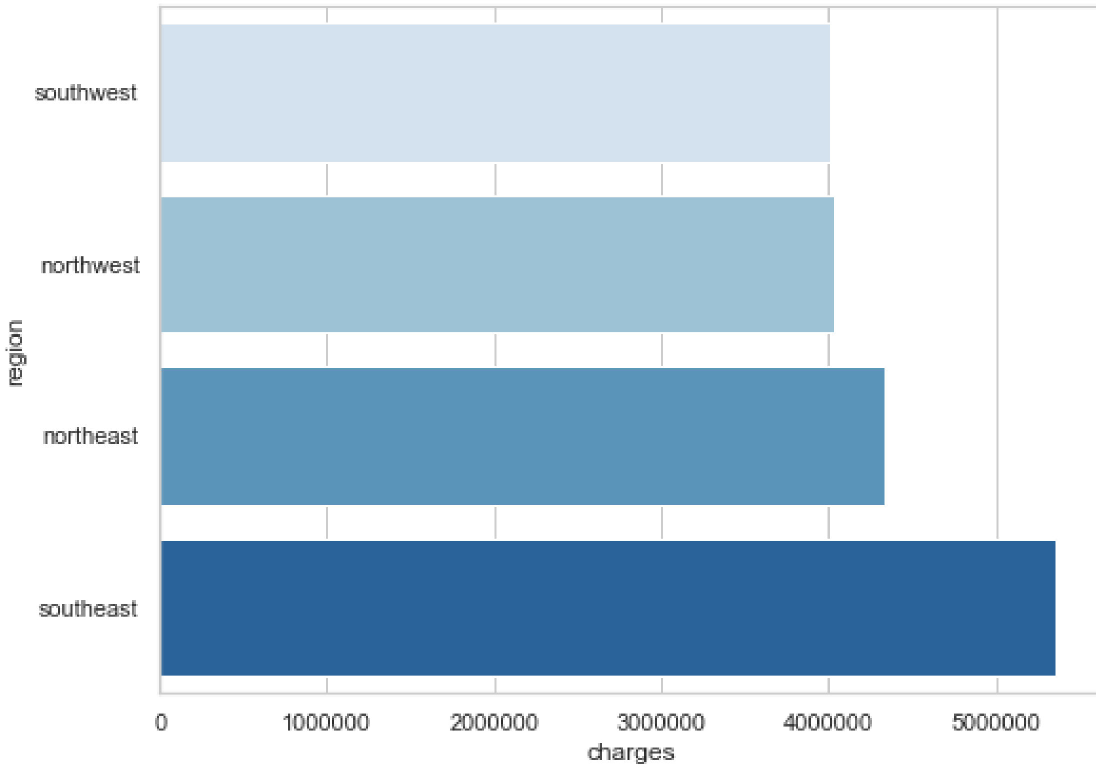
[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7fae5ff94150>



Now let's look at the charges by region.

[9]:
```
charges = df['charges'].groupby(df.region).sum().sort_values(ascending = True)
plt.subplots(1, 1, figsize=(8, 6))
sns.barplot(charges.head(), charges.head().index, palette='Blues')
```

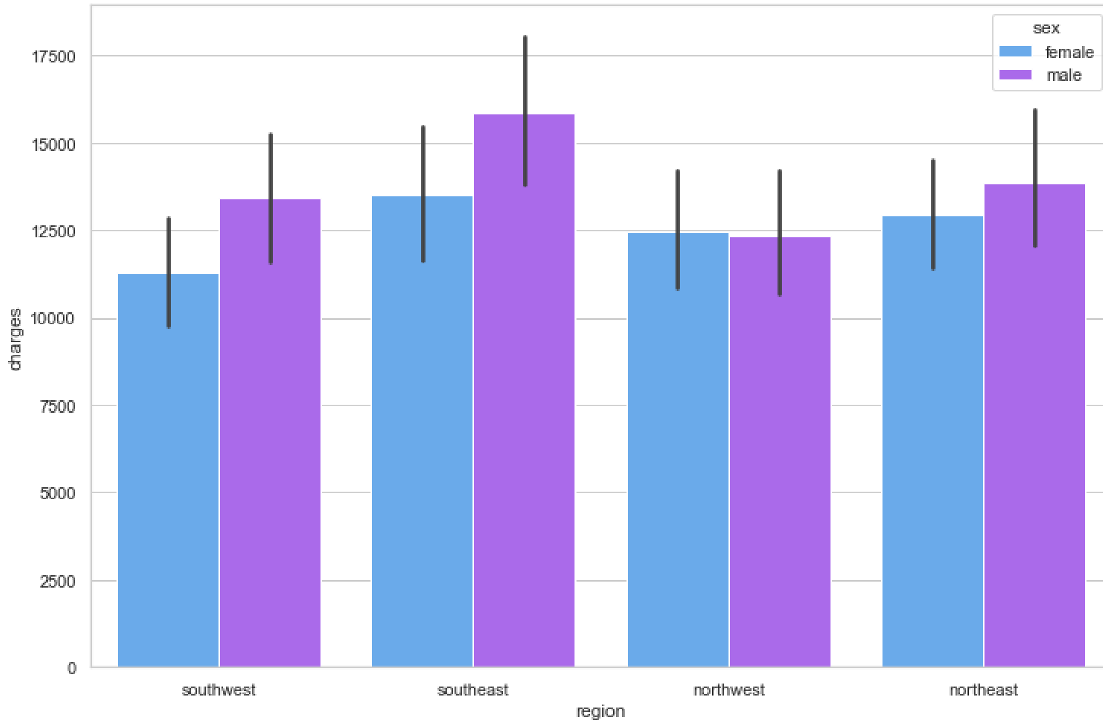
[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fae635086d0>
```



The highest medical charges are in the Southeast and the lowest are in the Southwest. Taking into account certain factors (sex, smoking, having children) let's see how it changes by region.

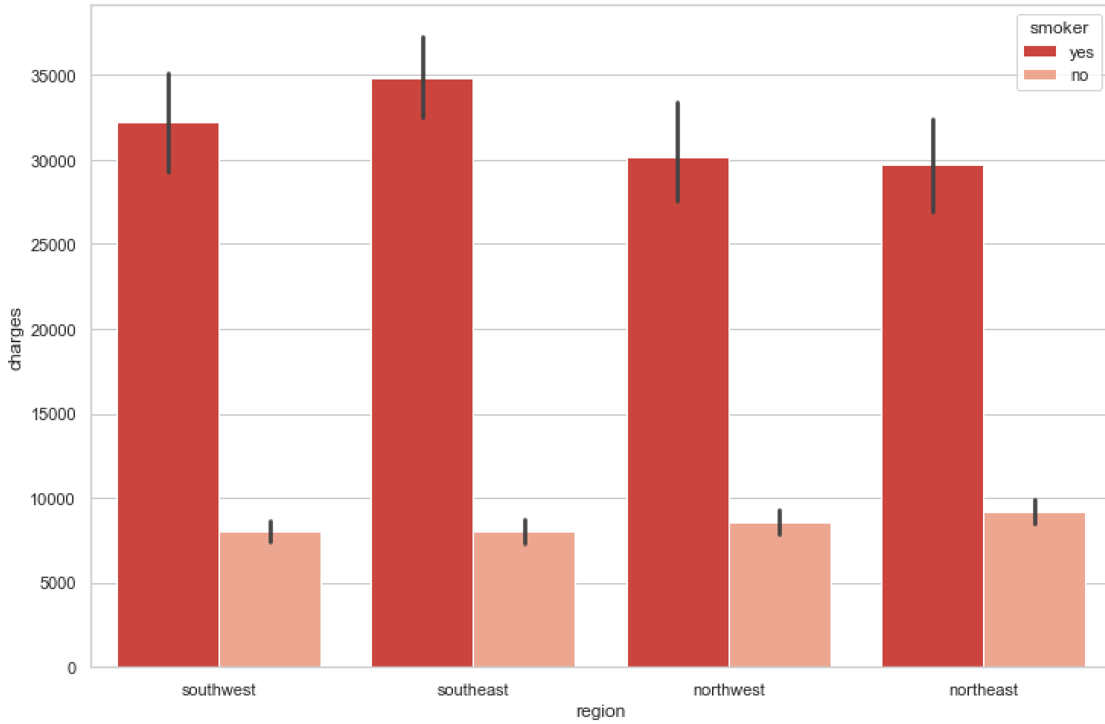
[10]:
```
plt.subplots(1, 1, figsize=(12, 8))
sns.barplot(x='region', y='charges', hue='sex', data=df, palette='cool')
```

[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7fae62f3c890>



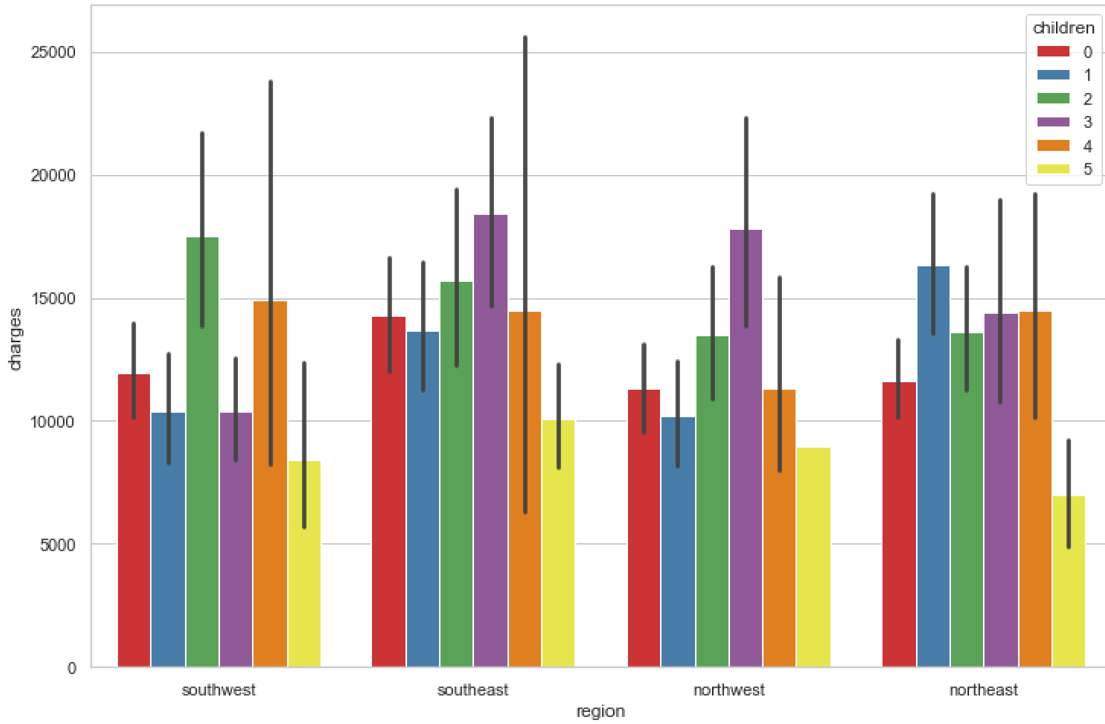
[11]:
```
plt.subplots(1,1, figsize=(12,8))
sns.barplot(x = 'region', y = 'charges',
            hue='smoker', data=df, palette='Reds_r')
```

[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7fae63840590>



[12]:
```
plt.subplots(1, 1, figsize=(12, 8))
sns.barplot(x='region', y='charges', hue='children', data=df, palette='Set1')
```

[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7fae63a485d0>

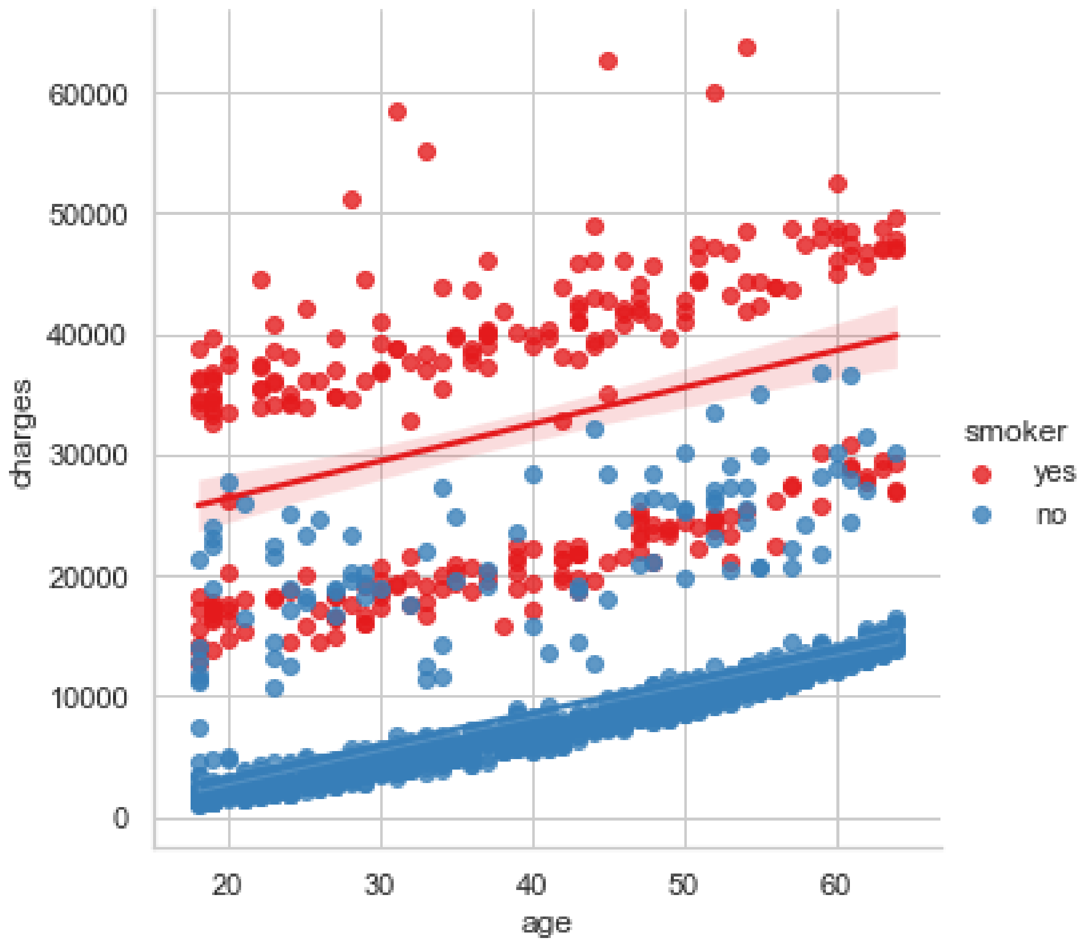


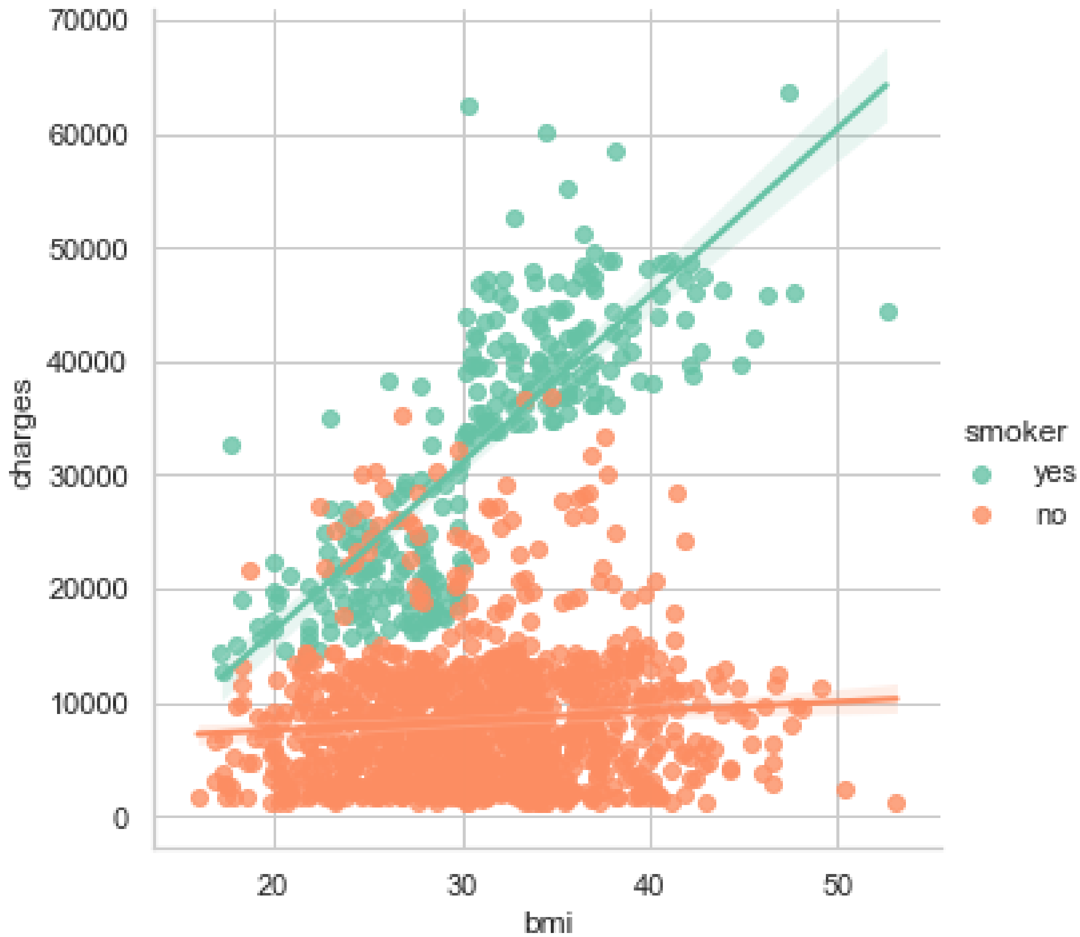
As we can see from these barplots the highest charges due to smoking are still in the Southeast but the lowest are in the Northeast. People in the Southwest generally smoke more than people in the Northeast, but people in the Northeast have higher charges by gender than in the Southwest and Northwest overall. And people with children tend to have higher medical costs overall as well.

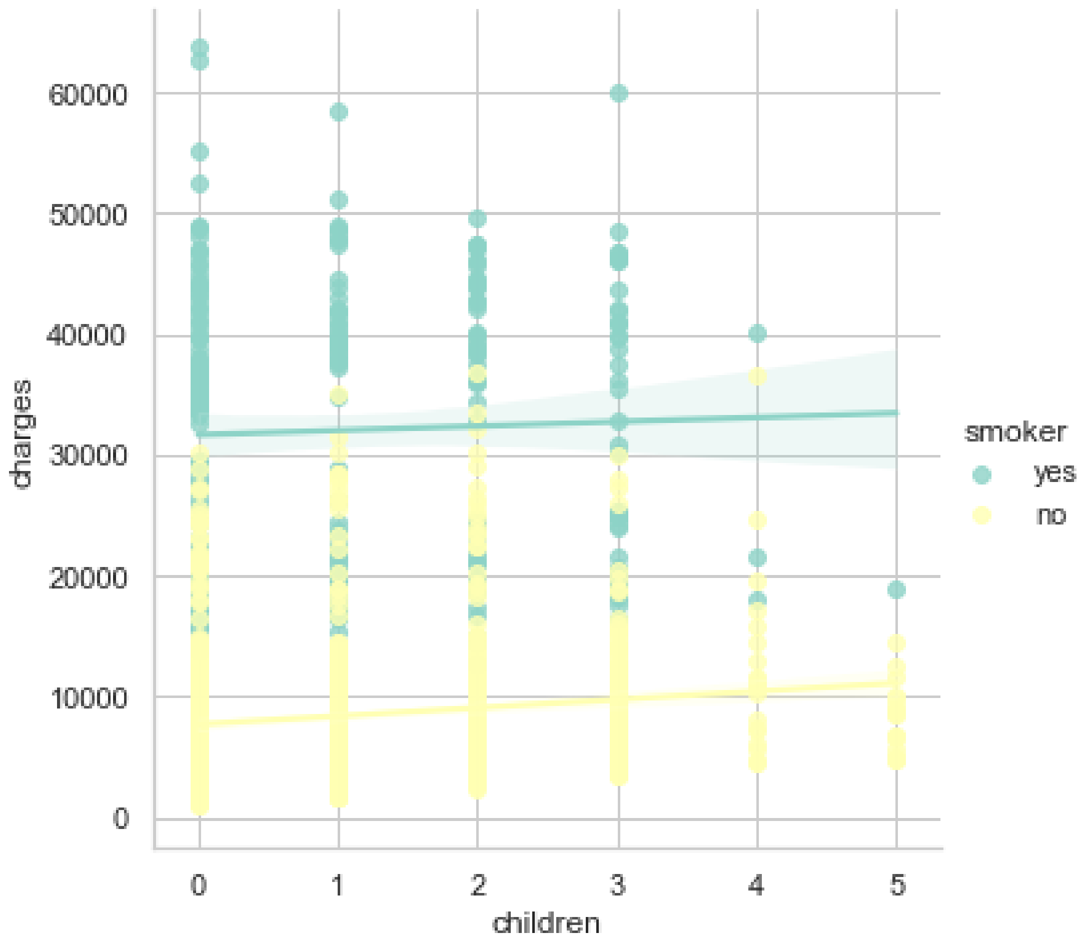
Now let's analyze the medical charges by age, bmi, and children according to the smoking factor.

[13]:
```
sns.lmplot(x = 'age', y = 'charges', data=df, hue='smoker', palette='Set1')
sns.lmplot(x = 'bmi', y = 'charges', data=df, hue='smoker', palette='Set2')
sns.lmplot(x = 'children', y = 'charges', data=df, hue='smoker', palette='Set3')
```

[13]: <seaborn.axisgrid.FacetGrid at 0x7fae623ea2d0>


60000
50000
40000
30000
20000
10000
0
charges
20
30
40
50
60
age
smoker
yes
no

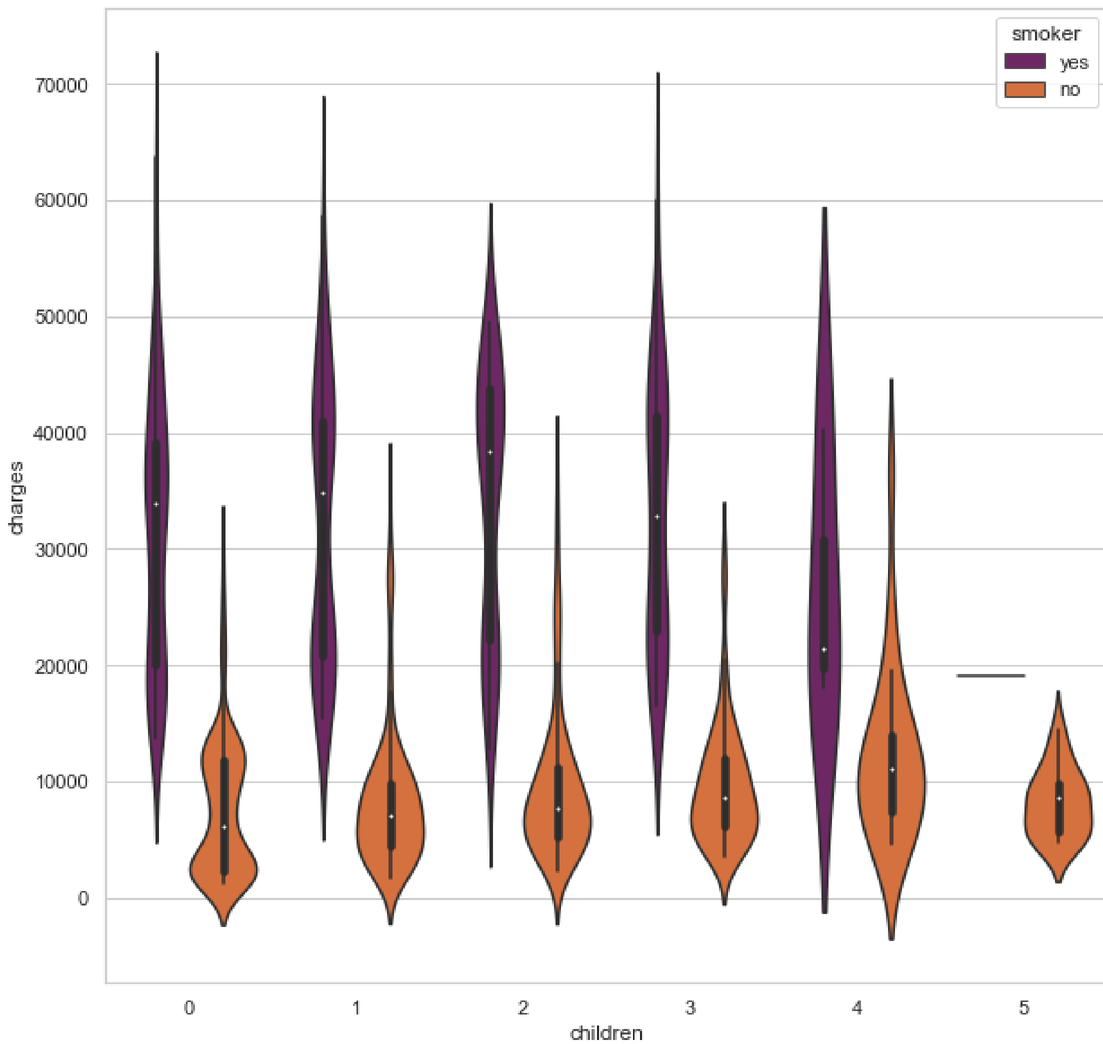

70000
60000
50000
40000
30000
20000
10000
0
charges
20
30
40
50
bmi
smoker
yes
no



Smoking has the highest impact on medical costs; even though the costs are growing with age, bmi, and children. Also people who have children generally smoke less, which the following violinplots shows as well.

[14]:
```
plt.subplots(1, 1, figsize=(10, 10))
sns.violinplot(x = 'children', y = 'charges', data=df,
               orient='v', hue='smoker', palette='inferno')
```

[14]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fae640dfa50>
```



[15]:
```
# Converting objects labels into categorical
df[['sex', 'smoker', 'region']] = df[['sex', 'smoker', 'region']].
 ↪astype('category')
df.dtypes
```

[15]:
```
age            int64
sex         category
bmi          float64
children       int64
smoker      category
region      category
charges      float64
dtype: object
```

[16]:
```
# Converting category labels into numerical using LabelEncoder
from sklearn.preprocessing import LabelEncoder
label = 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.dtypes
```

[16]:
```
age           int64
sex           int64
bmi         float64
children      int64
smoker        int64
region        int64
charges     float64
dtype: object
```

[17]:
```
plt.subplots(1, 1, figsize=(10, 10))
sns.heatmap(df.corr(), annot=True)
```

[17]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fae64748510>
```

No significant correlations, except for smoker feature.

1.3 Linear Regression

[18]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics

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

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,␣
 ↪random_state=42)

Lin_reg = LinearRegression()
Lin_reg.fit(X_train, y_train)

print(Lin_reg.intercept_)
print(Lin_reg.coef_)
print(Lin_reg.score(X_test, y_test))
```

```
-11946.606567263048
[ 2.57056264e+02 -1.87914567e+01  3.35781491e+02  4.25091456e+02
  2.36478181e+04 -2.71284266e+02]
0.7833463107364539
```

[19]:
```
y_train_pred_lr = Lin_reg.predict(X_train)
y_pred_lr = Lin_reg.predict(X_test)

train_rmse_lr = np.sqrt(metrics.mean_squared_error(y_train, y_train_pred_lr))
test_rmse_lr = np.sqrt(metrics.mean_squared_error(y_test, y_pred_lr))

print('Training Root Mean Squared Error:' , train_rmse_lr)
print("Testing Rooot Mean Squared Error:" , test_rmse_lr)

# print ("R^2 Score:", ridge.score(y_train, y_train_pred))
print ("R^2 Train Score:", metrics.r2_score(y_train, (y_train_pred_lr)))
print("R^2 Test Score:", metrics.r2_score(y_test, y_pred_lr))
```

```
Training Root Mean Squared Error: 6105.789320191615
Testing Rooot Mean Squared Error: 5799.587091438356
R^2 Train Score: 0.7417049283233981
R^2 Test Score: 0.7833463107364539
```

[20]:
```
# Predicting the charges
# Comparing the actual output values with the predicted values
df_lr = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_lr})
df_lr
```

[20]:

	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
…	…	…
109	47055.53210	39116.968669
575	12222.89830	11814.555568

```
535    6067.12675   7638.107736
543   63770.42801  40959.081722
846    9872.70100  12258.228529

[268 rows x 2 columns]
```

The baseline result was good, but improvements can be made by reducing unimportant features.

2 OLS

[21]:
```python
import statsmodels.api as stats
model = stats.OLS(y_train, X_train)
ols = model.fit()
print(ols.summary())
```

```
                                 OLS Regression Results
================================================================================
=======
Dep. Variable:                charges   R-squared (uncentered):
0.871
Model:                            OLS   Adj. R-squared (uncentered):
0.871
Method:                 Least Squares   F-statistic:
1200.
Date:                Sun, 22 Nov 2020   Prob (F-statistic):
0.00
Time:                        22:30:27   Log-Likelihood:
-10903.
No. Observations:                1070   AIC:
2.182e+04
Df Residuals:                    1064   BIC:
2.185e+04
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
age          201.0509     13.132     15.310      0.000     175.284     226.818
sex         -676.4918    391.303     -1.729      0.084   -1444.305      91.322
bmi           60.1496     20.376      2.952      0.003      20.168     100.131
children     197.1493    161.418      1.221      0.222    -119.585     513.883
smoker      2.315e+04    488.390     47.397      0.000    2.22e+04    2.41e+04
region      -451.8044    178.872     -2.526      0.012    -802.787    -100.822
==============================================================================
Omnibus:                      215.934   Durbin-Watson:                   2.046
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              476.342
Skew:                           1.117   Prob(JB):                    3.66e-104
```

```
Kurtosis:                       5.386   Cond. No.                       128.
==============================================================================

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

[22]:
```
y_train_pred_ols = ols.predict(X_train)
y_pred_ols = ols.predict(X_test)

train_rmse_ols = np.sqrt(metrics.mean_squared_error(y_train, y_train_pred_ols))
test_rmse_ols = np.sqrt(metrics.mean_squared_error(y_test, y_pred_ols))

print('Training Root Mean Squared Error:' , train_rmse_ols)
print("Testing Rooot Mean Squared Error:" , test_rmse_ols)

# print ("R^2 Score:", ridge.score(y_train, y_train_pred))
print ("R^2 Train Score:", metrics.r2_score(y_train, (y_train_pred_ols)))
print("R^2 Test Score:", metrics.r2_score(y_test, y_pred_ols))
```

```
Training Root Mean Squared Error: 6443.398770567204
Testing Rooot Mean Squared Error: 6142.028799493614
R^2 Train Score: 0.7123512376362529
R^2 Test Score: 0.7570059516022006
```

[23]:
```
# Predicting the charges
# Comparing the actual output values with the predicted values
df_ols = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_ols})
df_ols
```

[23]:

	Actual	Predicted
764	9095.06825	10955.856940
887	5272.17580	8591.720285
890	29330.98315	37180.579963
1293	9301.89355	10260.046289
259	33750.29180	27759.648979
…	…	…
109	47055.53210	36344.760268
575	12222.89830	12843.414675
535	6067.12675	8846.285607
543	63770.42801	35952.836541
846	9872.70100	11152.450265

[268 rows x 2 columns]

2.1 Ridge Regression

[24]:
```
from sklearn.linear_model import Ridge

Ridge = Ridge(alpha=0.001, fit_intercept=True, normalize=False, random_state=42)
Ridge.fit(X_train, y_train)

y_train_pred_ridge = Ridge.predict(X_train)
y_pred_ridge = Ridge.predict(X_test)

train_rmse_ridge = np.sqrt(metrics.mean_squared_error(y_train,␣
 ↪y_train_pred_ridge))
test_rmse_ridge = np.sqrt(metrics.mean_squared_error(y_test, y_pred_ridge))

print('Training Root Mean Squared Error:' , train_rmse_ridge)
print("Testing Rooot Mean Squared Error:" , test_rmse_ridge)

# print ("R^2 Score:", ridge.score(y_train, y_train_pred))
print ("R^2 Train Score:", metrics.r2_score(y_train, (y_train_pred_ridge)))
print("R^2 Test Score:", metrics.r2_score(y_test, y_pred_ridge))
```

```
Training Root Mean Squared Error: 6105.789320438454
Testing Rooot Mean Squared Error: 5799.590353421407
R^2 Train Score: 0.7417049283025138
R^2 Test Score: 0.783346067022255
```

[25]:
```
# Predicting the charges
# Comparing the actual output values with the predicted values
df_ridge = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_ridge})
df_ridge
```

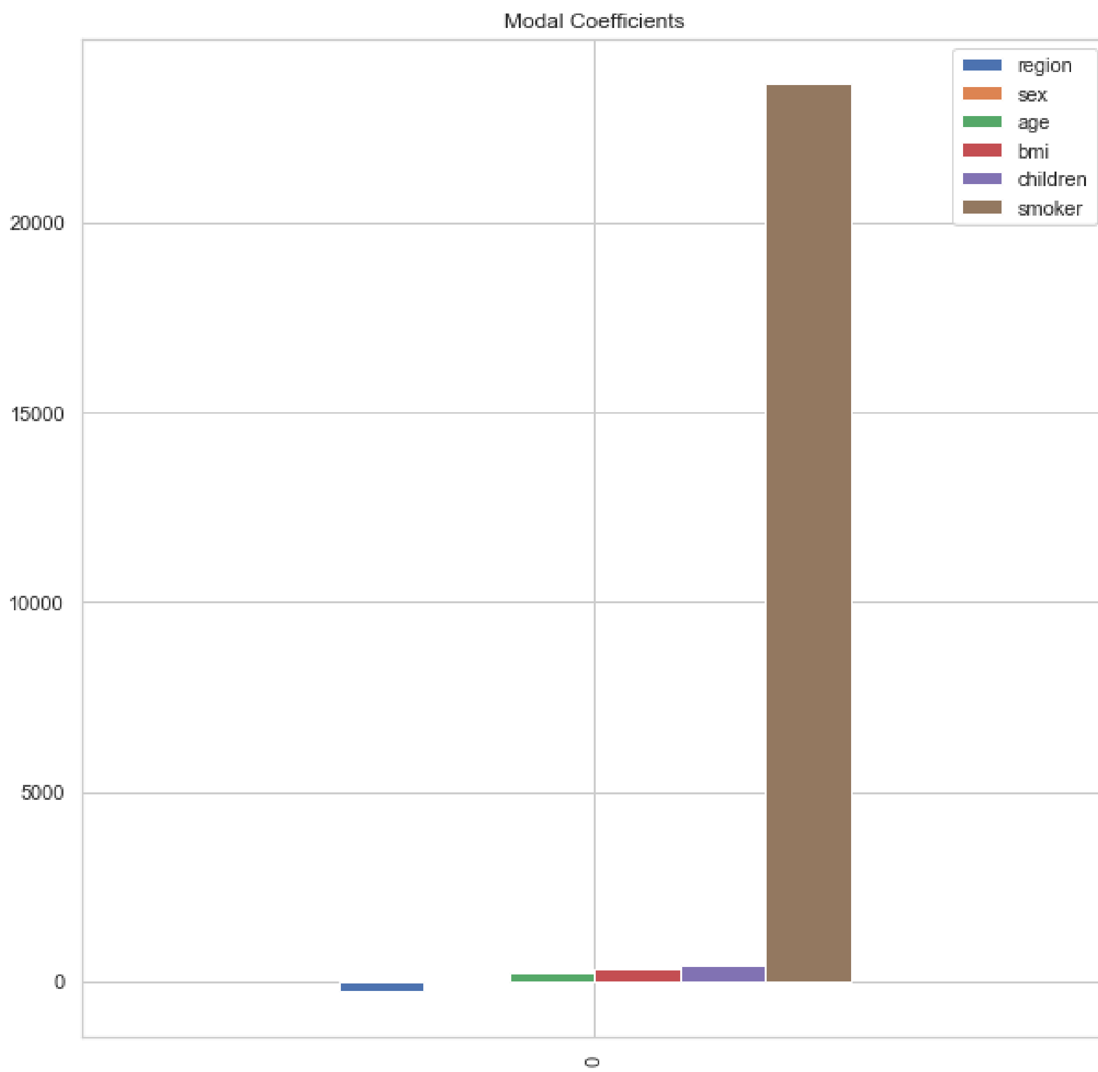
[25]:

	Actual	Predicted
764	9095.06825	8924.430756
887	5272.17580	7116.319338
890	29330.98315	36908.895655
1293	9301.89355	9507.906077
259	33750.29180	27013.249268
…	…	…
109	47055.53210	39116.858732
575	12222.89830	11814.575330
535	6067.12675	7638.140081
543	63770.42801	40958.965983
846	9872.70100	12258.249886

[268 rows x 2 columns]

[26]:
```
ridge_coef01 = pd.DataFrame(data=Ridge.coef_).T
ridge_coef01.columns = X_train.columns
ridge_coef01 = ridge_coef01.T.sort_values(by=0).T
ridge_coef01.plot(kind='bar', title='Modal Coefficients', legend=True,␣
↪figsize=(10,10))
```

[26]: <matplotlib.axes._subplots.AxesSubplot at 0x7fae641ad9d0>



2.2 Lasso Regression

[27]:
```
from sklearn.linear_model import Lasso

Lasso = Lasso(alpha=0.001, fit_intercept=True, normalize=False, random_state=42)
```

```
Lasso.fit(X_train, y_train)

y_train_pred_lasso = Lasso.predict(X_train)
y_pred_lasso = Lasso.predict(X_test)
train_rmse_lasso = np.sqrt(metrics.mean_squared_error(y_train,␣
 ↪y_train_pred_lasso))
test_rmse_lasso = np.sqrt(metrics.mean_squared_error(y_test, y_pred_lasso))

print('Training Root Mean Squared Error:' , train_rmse_lasso)
print("Testing Rooot Mean Squared Error:" , test_rmse_lasso)

# print ("R^2 Score:", lasso.score(y_train, y_train_pred))
print ("R^2 Train Score:", metrics.r2_score(y_train, (y_train_pred_lasso)))
print("R^2 Test Score:", metrics.r2_score(y_test, y_pred_lasso))
```

```
Training Root Mean Squared Error: 6105.789320192639
Testing Rooot Mean Squared Error: 5799.58744633592
R^2 Train Score: 0.7417049283233114
R^2 Test Score: 0.7833462842208183
```

[28]:
```
# Predicting the charges
# Comparing the actual output values with the predicted values
df_lasso = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_lasso})
df_lasso
```

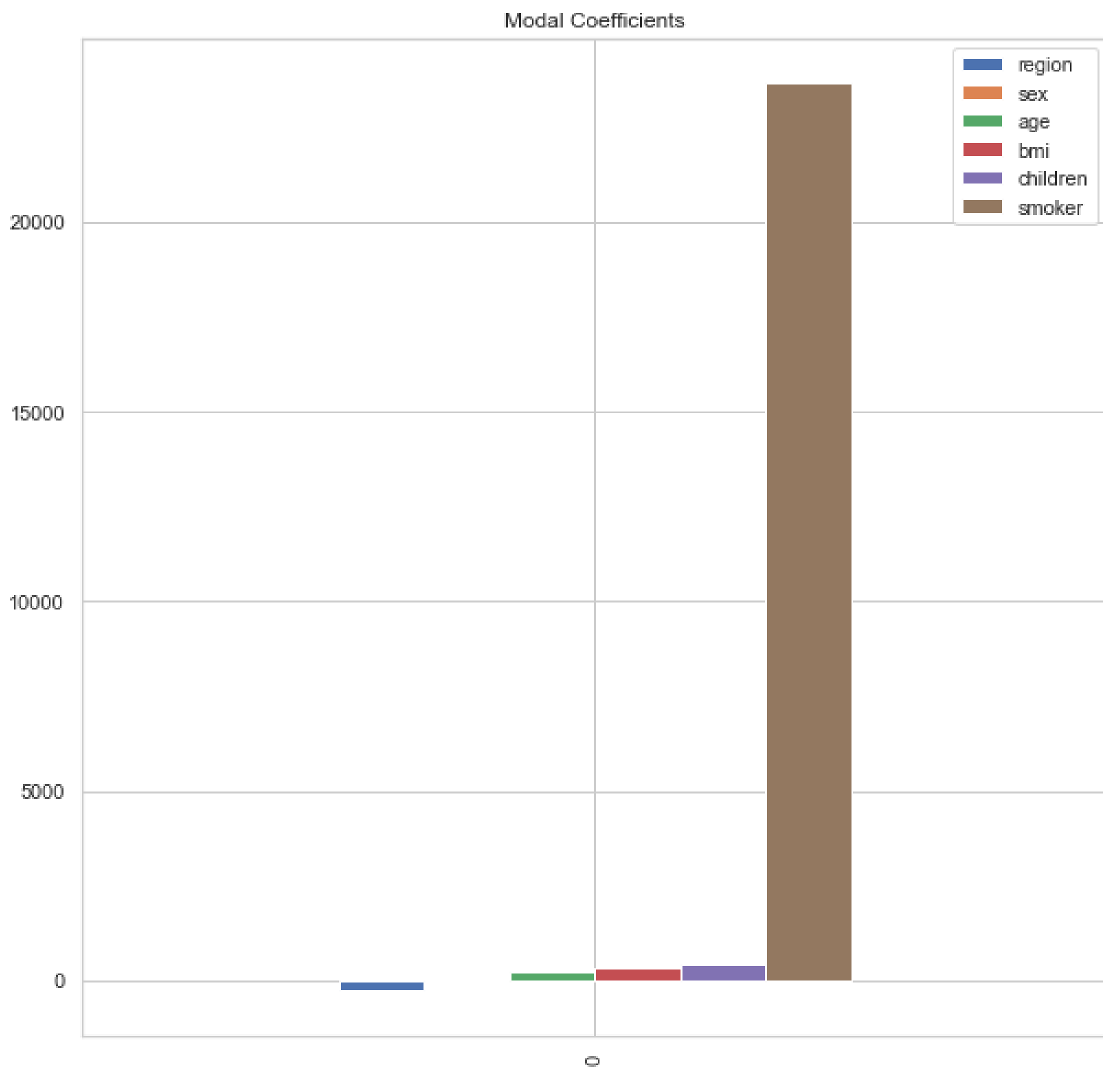
[28]:

	Actual	Predicted
764	9095.06825	8924.404696
887	5272.17580	7116.294427
890	29330.98315	36909.006482
1293	9301.89355	9507.876740
259	33750.29180	27013.347373
…	…	…
109	47055.53210	39116.966446
575	12222.89830	11814.555020
535	6067.12675	7638.110168
543	63770.42801	40959.074365
846	9872.70100	12258.228652

[268 rows x 2 columns]

[29]:
```
lasso_coef01 = pd.DataFrame(data=Lasso.coef_).T
lasso_coef01.columns = X_train.columns
lasso_coef01 = lasso_coef01.T.sort_values(by=0).T
lasso_coef01.plot(kind='bar', title='Modal Coefficients', legend=True,␣
 ↪figsize=(10,10))
```

[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7fae65e0bc90>



2.3 Polynomial Regression

[30]:
```
from sklearn.preprocessing import PolynomialFeatures

X = df.drop(['charges', 'sex', 'region'], axis=1)
y = df.charges

pol = PolynomialFeatures (degree = 3)

X_pol = pol.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_pol, y, test_size=0.20,␣
↪random_state=42)
```

```
Pol_reg = LinearRegression()
Pol_reg.fit(X_train, y_train)

y_train_pred_plr = Pol_reg.predict(X_train)
y_test_pred_plr = Pol_reg.predict(X_test)

print(Pol_reg.intercept_)
print(Pol_reg.coef_)
print(Pol_reg.score(X_test, y_test))
```

```
34288.949821339884
[ 3.15464039e-07 -4.99528746e+01 -3.41482037e+03  5.90926806e+03
 -1.24245357e+04  5.05325736e+00  4.65623016e+00 -2.46091361e+02
  2.44947375e+01  1.10673636e+02  4.15759857e+01  1.27441657e+03
 -7.49957293e+02 -5.72818911e+02 -1.24245357e+04 -3.26821468e-02
  4.68016415e-02  2.11634627e+00 -3.45467953e+00 -1.74142394e-01
  1.41208405e+00  7.02992932e+00  8.56161155e+00  1.04997464e+01
  2.44947375e+01 -1.10286704e+00 -1.38494598e+00 -2.10765215e+01
 -3.07716685e-01 -3.23811939e+01  1.27441657e+03  5.28380416e+01
  4.05878013e+02 -5.72818911e+02 -1.24245357e+04]
0.8690550878813432
```

[31]:
```
# Evaluating the performance of the algorithm

print('Mean Absolute Error:', metrics.mean_absolute_error(y_test,␣
 ↪y_test_pred_plr))
print('Mean Squared Error:', metrics.mean_squared_error(y_test,␣
 ↪y_test_pred_plr))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_test_pred_plr)))
```

```
Mean Absolute Error: 2745.538146157703
Mean Squared Error: 20329031.50172321
Root Mean Squared Error: 4508.772726776458
```

[32]:
```
train_rmse_plr = np.sqrt(metrics.mean_squared_error(y_train, y_train_pred_plr))
test_rmse_plr = np.sqrt(metrics.mean_squared_error(y_test, y_test_pred_plr))

print('Training Root Mean Squared Error:' , train_rmse_plr)
print("Testing Rooot Mean Squared Error:" , test_rmse_plr)

# print ("R^2 Score:", lasso.score(y_train, y_train_pred))
print ("R^2 Train Score:", metrics.r2_score(y_train, (y_train_pred_plr)))
print("R^2 Test Score:", metrics.r2_score(y_test, y_test_pred_plr))
```

```
Training Root Mean Squared Error: 4781.909147452257
Testing Rooot Mean Squared Error: 4508.772726776458
R^2 Train Score: 0.8415708357607841
```

```
R^2 Test Score: 0.8690550878813433
```

[33]:
```python
# Predicting the charges
# Comparing the actual output values with the predicted values
df_plr = pd.DataFrame({'Actual': y_test, 'Predicted': y_test_pred_plr})
df_plr
```

[33]:

	Actual	Predicted
764	9095.06825	9279.796983
887	5272.17580	6107.265474
890	29330.98315	32187.304034
1293	9301.89355	9704.430992
259	33750.29180	29384.071123
…	…	…
109	47055.53210	46254.120517
575	12222.89830	12972.531736
535	6067.12675	7312.001844
543	63770.42801	54536.136234
846	9872.70100	11848.379471

[268 rows x 2 columns]

[ ]: