Medical Cost / Health Insurance Prediction

- Author: Peng Shen (Dylan)
- Student ID: 57408005
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Background

- Prediction of the potential medical cost of an individual could be useful in real-world scenarios such as helping insurance company to determine the personalized premium based on client's personal information, as well as assisting health insurance bureau to make a budget.

Objective

- Perform the data analysis to explore the factors affecting the medical costs and eventually develop some predicting models for the medical costs;
- To develop a GUI that prompts for the personal profile and returns the predicted medical cost.

To achieve this objective, I need to figure out those questions below:

1. Is there a relationship between the response and predictors?
2. Deciding on important predictors to add into model.
3. Goodness of fit of the model.
4. Prediction accuracy of models.

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4. Overview of The Variables in The Dataset
5. Exploaratory Data Analysis
6. Fitting Candidate Models and Making comparisons
7. Developing a GUI for Medical Cost Prediction

1. Importing Libraries

In [1]:
```
# Basic Python Packages
import pandas as pd # for dataframes
import numpy as np # for mathmatical operations

# Matplotlib and Seaborn
import matplotlib.pyplot as plt # for data visualization
import seaborn as sns # for data visualization
%matplotlib inline

# Plotly Packages for data visulization
from plotly import tools
import plotly.plotly as py
import plotly.graph_objs as go
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)

# scikit-learn for Preprocessing of dataset and Machine Learning
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor

# Regression Modeling
import statsmodels.api as sm

# Other Libraries
import warnings
warnings.filterwarnings("ignore")
```

2. Load the dataset

- Age: age of primary beneficiary, years
- Sex: insurance contractor gender, [female, male]
- BMI: Body mass index, providing an understanding of body weights that are relatively high or low relative to height, objective index of body weight (kg / m ^ 2) using the ratio of height to weight, ideally 18.5 to 24.9, one is underweight if < 18.5, overweight if ≥ 25 and <29.9, obese if ≥ 30
- Children: Number of children covered by health insurance / Number of dependents
- Smoker: Smoking status
- Region: the beneficiary's residential area in the US, northeast, southeast, southwest, northwest.
- Charges: Individual medical costs billed by health insurance, USD

In [2]:
```
df = pd.read_csv('insurance.csv')
original_df = df.copy()
```

In [3]:
```
# Get the genenal infomation of the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
age         1338 non-null int64
sex         1338 non-null object
bmi         1338 non-null float64
children    1338 non-null int64
smoker      1338 non-null object
region      1338 non-null object
charges     1338 non-null float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.2+ KB
```

In [4]:
```
# Display the first 5 rows of the dataset
df.head()
```

Out[4]:

	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. Data Preparation

In [5]:
```
# Checking missing data
df.isna().sum()
```

Out[5]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

In [6]:
```
# Checking duplicated data
df.duplicated().sum()
```

Out[6]: 1

In [7]:
```
df.duplicated().shape
```

Out[7]: (1338,)

In [8]:
```
df[df.duplicated(keep = 'first')]
```

Out[8]:

	age	sex	bmi	children	smoker	region	charges
581	19	male	30.59	0	no	northwest	1639.5631

In [9]:
```
df[df.duplicated(keep = 'last')]
```

Out[9]:

	age	sex	bmi	children	smoker	region	charges
195	19	male	30.59	0	no	northwest	1639.5631

In [10]:
```
# Remove the duplicated data
df.drop_duplicates(keep = 'first').shape
```

Out[10]: (1337, 7)

In [11]:
```
df_1 = df.drop_duplicates(keep = 'first')
```

In [12]:
```
df_1.shape
```

Out[12]: (1337, 7)

4. Overview of the variables in the dataset

In [13]:
```
# 4 out of 7 varaibles are quatitative variable
df_1.describe()
```

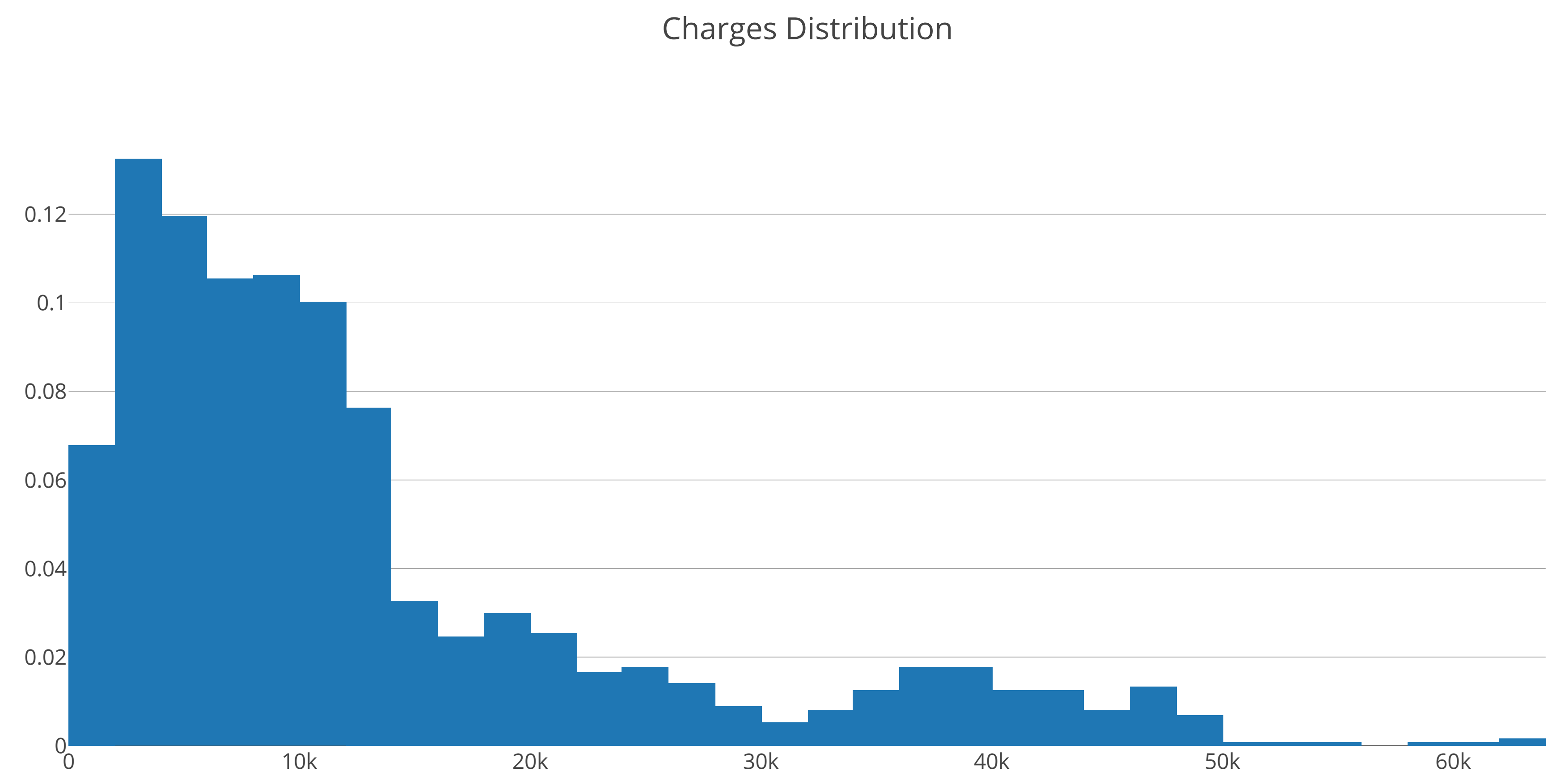
Out[13]:

	age	bmi	children	charges
count	1337.000000	1337.000000	1337.000000	1337.000000
mean	39.222139	30.663452	1.095737	13279.121487
std	14.044333	6.100468	1.205571	12110.359656
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.290000	0.000000	4746.344000
50%	39.000000	30.400000	1.000000	9386.161300
75%	51.000000	34.700000	2.000000	16657.717450
max	64.000000	53.130000	5.000000	63770.428010

4.1 Medical Charges

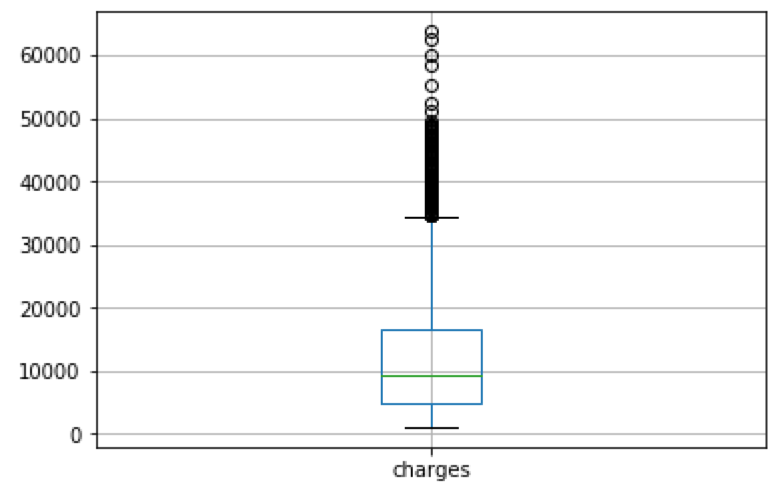
In [14]:
```
# Medical charges is the response variable of interest, which is a continuous numerical variable, so making
# prediction of this is a regression problem
```

In [15]:
```
# Distribution of Charges
charges_dist = df_1["charges"].values
charges_hist = go.Histogram(x=charges_dist, histnorm='probability', name="Charges Distribution")
data = [charges_hist]
layout = go.Layout(title="Charges Distribution")
fig = go.Figure(data=data, layout=layout)
iplot(fig, filename="Charges Distribution")

# From the histogram we can observe a positive skewed distribution of charges
```

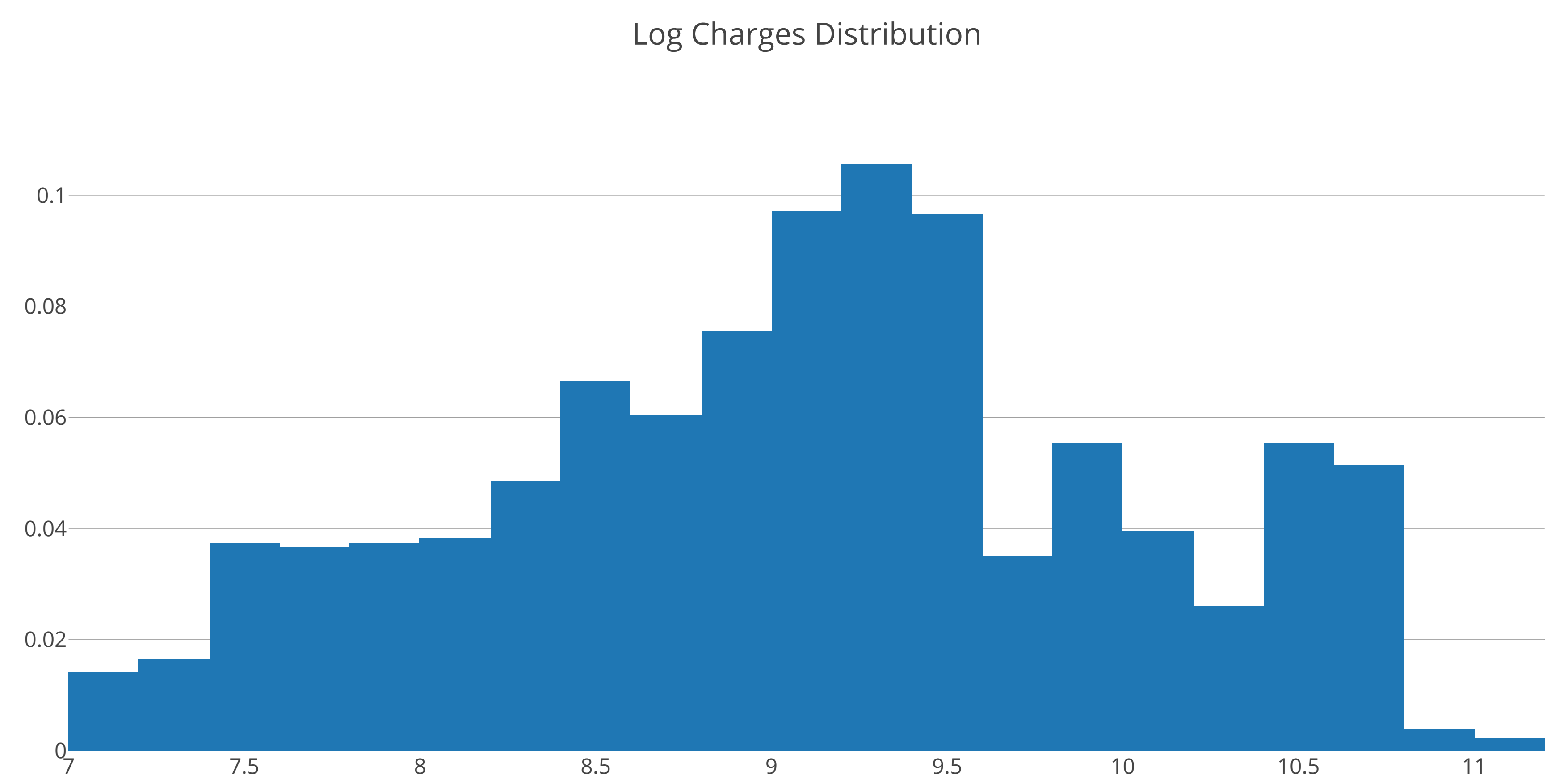


In [16]:
```
df_1.boxplot(column = 'charges')
```

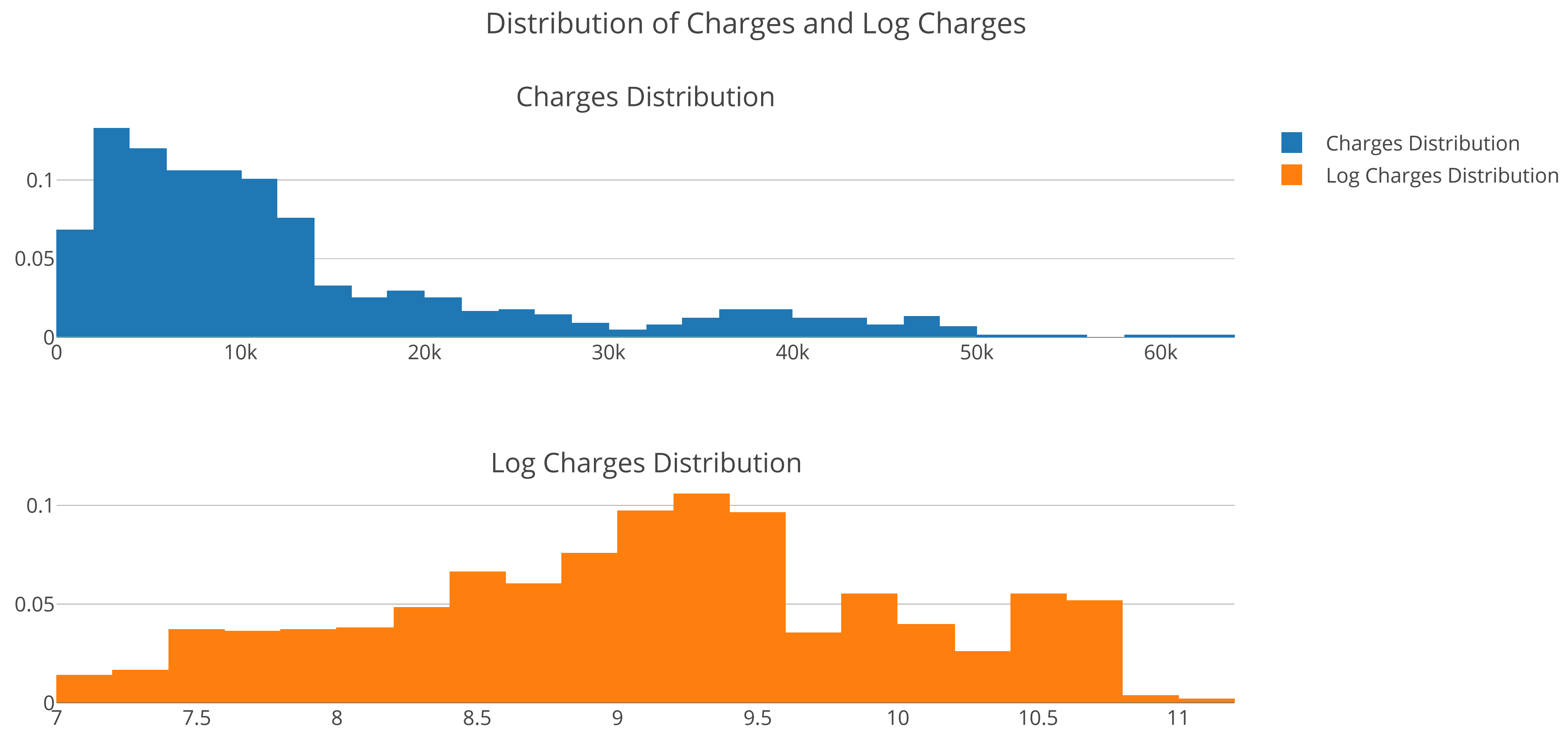
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1ce76cf8>



In [17]:
```
# Log Transformation of Charges and Distribution of Log Charges
logcharges_dist = np.log(df_1["charges"])
logcharges_hist = go.Histogram(x=logcharges_dist, histnorm='probability', name="Log Charges Distribution")
data = [logcharges_hist]
layout = go.Layout(title="Log Charges Distribution")
fig = go.Figure(data=data, layout=layout)
iplot(fig, filename="Log Charges Distribution")
```

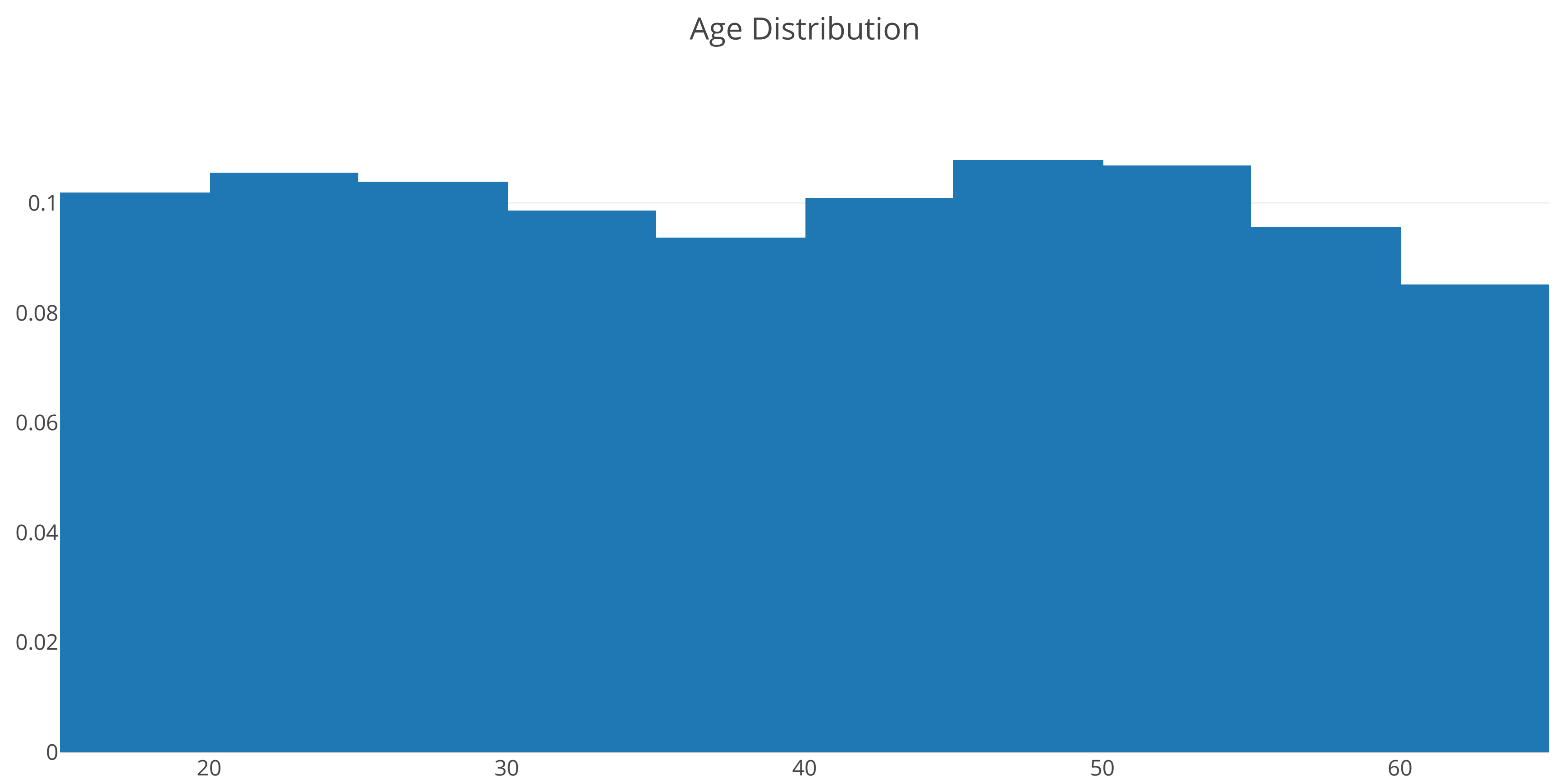


In [18]:
```
# Plotting charges and log charges on one graph
fig = tools.make_subplots(rows=2, cols=1,
                          subplot_titles=("Charges Distribution", "Log Charges Distribution"),
                         print_grid=False)
fig.append_trace(charges_hist, 1, 1)
fig.append_trace(logcharges_hist, 2, 1)
fig['layout'].update(showlegend=True, title="Distribution of Charges and Log Charges")
iplot(fig, filename="Distribution of Charges and Log Charges")
```



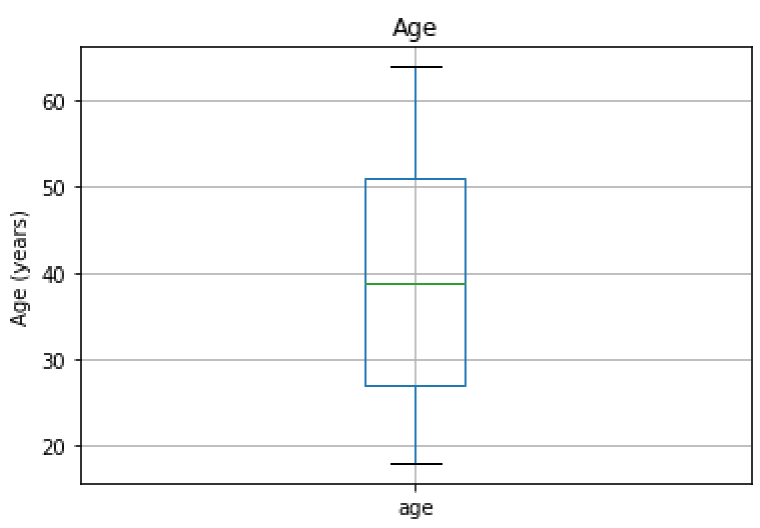
4.2 Age

In [19]:
```
# Distribution of Age (continuous variable)
age_dist = df_1["age"].values
age_hist = go.Histogram(x = age_dist,
                        histnorm = "probability",
                        xbins=dict(start=15,end=65,size=5),
                        name = "Distribution of Age"
                       )
data = [age_hist]
layout = go.Layout(title="Age Distribution")
fig = go.Figure(data=data, layout=layout)
iplot(fig, filename = "Distribution of Age")
```



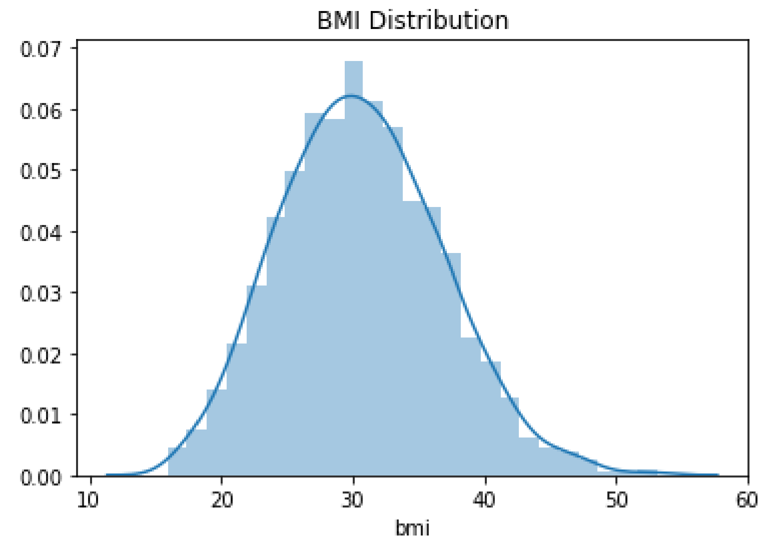
In [20]:
```
# Boxplot can help to indentify outliers
age_boxplot = df_1.boxplot(column = 'age')
plt.title("Age")
plt.ylabel("Age (years)")
plt.xlabel("")
```

Out[20]: `Text(0.5, 0, '')`



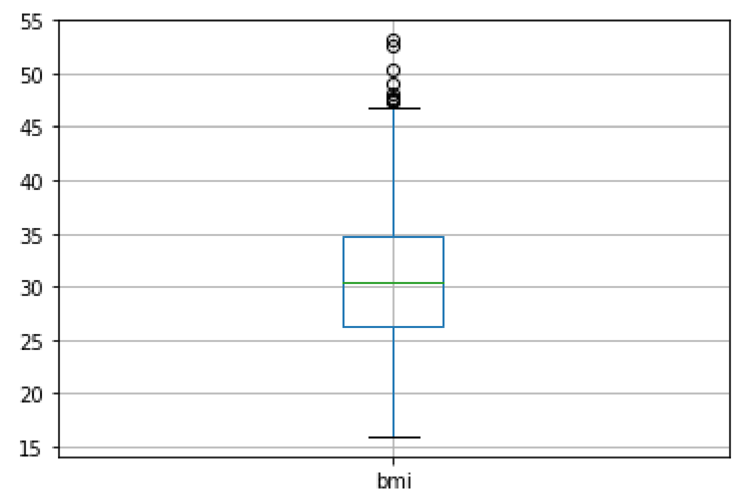
4.3 Body Mass Index (BMI)

In [21]:
```
# Distribution of continuous feature BMI
distPlot = sns.distplot(df_1['bmi'])
plt.title("BMI Distribution")
plt.show(distPlot)
```



In [22]:
```
# Boxplot can help to indentify outliers
df_1.boxplot(column = 'bmi')
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2115cf60>



4.4 Number of Children

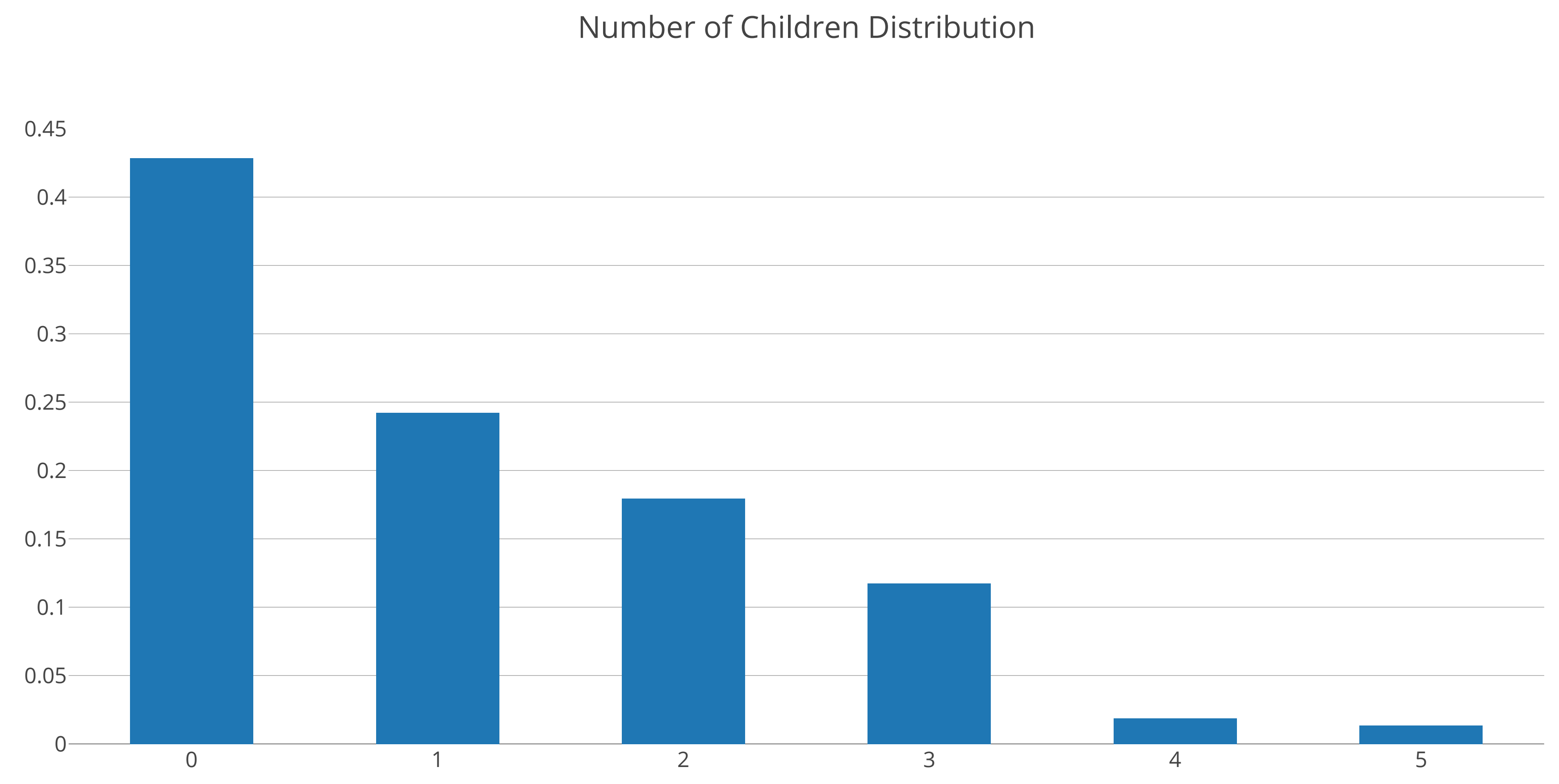
In [23]:
```
# Number of Children covered by insurance is an discrete variable
df_1.children.unique()
```

Out[23]: array([0, 1, 3, 2, 5, 4])

In [24]:
```
df_1.children.value_counts()
```

Out[24]:
```
0    573
1    324
2    240
3    157
4     25
5     18
Name: children, dtype: int64
```

In [25]:
```
# Bar Chart Displaying the Distribution of the number of children covered by insurance
children_dist = df_1["children"].values
children_hist = go.Histogram(x=children_dist, histnorm='probability', name="Number of Chlildren Distribution")
data = [children_hist]
layout = go.Layout(title="Number of Children Distribution", bargap=0.5)
fig = go.Figure(data=data,layout=layout)
iplot(fig, filename="Number of Children Distribution")
```



4.5 Sex

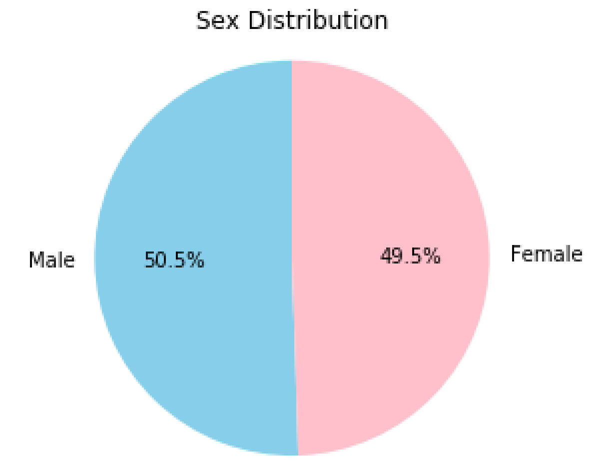
In [26]:
```
# Gender is a binary variable
df_1.sex.unique()
```

Out[26]: array(['female', 'male'], dtype=object)

In [27]:
```
df_1.sex.value_counts()
```

Out[27]:
```
male      675
female    662
Name: sex, dtype: int64
```

In [28]:
```
# Pie chart
labels = ['Male', 'Female']
sizes = [675, 662]
colors = ['skyblue', 'pink']

plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', shadow=False, startangle=90)
plt.title("Sex Distribution")
plt.axis('equal')
plt.show()
```



4.6 Smoking Status

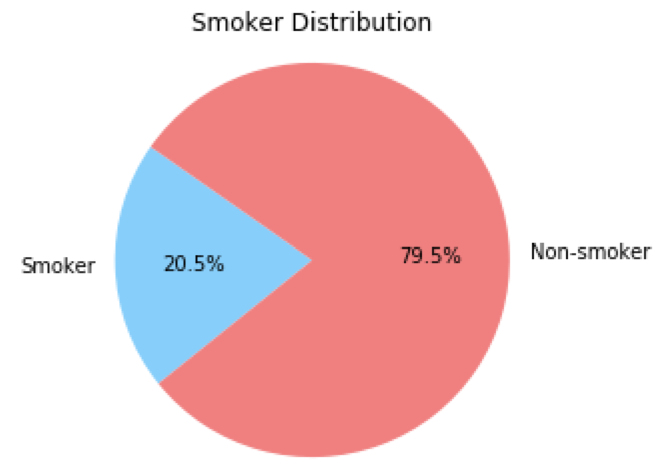
In [29]:
```
# Smoking status is a categorical and a binary variable
df_1.smoker.unique()
```

Out[29]:
```
array(['yes', 'no'], dtype=object)
```

In [30]:
```
df_1.smoker.value_counts()
```

Out[30]:
```
no      1063
yes      274
Name: smoker, dtype: int64
```

In [31]:
```
# Pie chart
labels = ['Smoker', 'Non-smoker']
sizes = [274, 1063]
colors = ['lightskyblue', 'lightcoral']

plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', shadow=False, startangle=145)
plt.title("Smoker Distribution")
plt.axis('equal')
plt.show()
```



4.7 Living Region

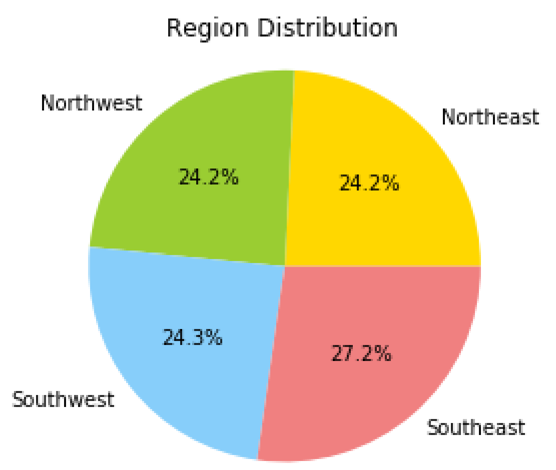
In [32]:
```
# Living Region is a categorical variable
df_1.region.unique()
```

Out[32]:
```
array(['southwest', 'southeast', 'northwest', 'northeast'], dtype=object)
```

In [33]:
```
df_1.region.value_counts()
```

Out[33]:
```
southeast    364
southwest    325
northeast    324
northwest    324
Name: region, dtype: int64
```

In [34]:
```
# Pie chart
labels = ['Northeast', 'Northwest', 'Southwest', 'Southeast']
sizes = [324, 324, 325, 364]
colors = ['gold', 'Yellowgreen', 'lightskyblue', 'lightcoral']

plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', shadow=False, startangle=0)
plt.title("Region Distribution")

plt.axis('equal')
plt.show()
```

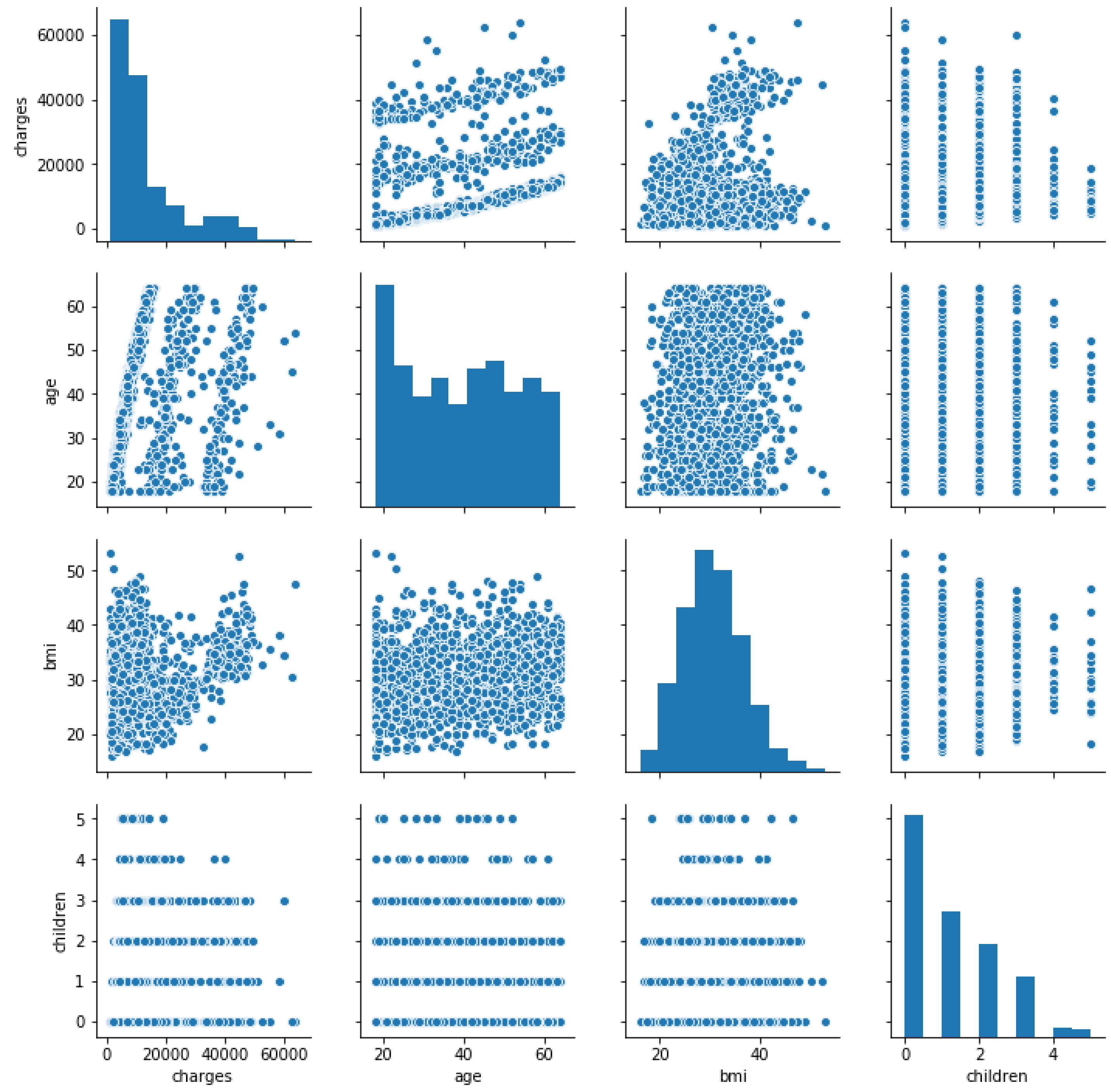


5. Exploratory Analysis

- To figure out which features/columns are important for prediction of medical charges

5.1 Relationship of Charges to Numerical features

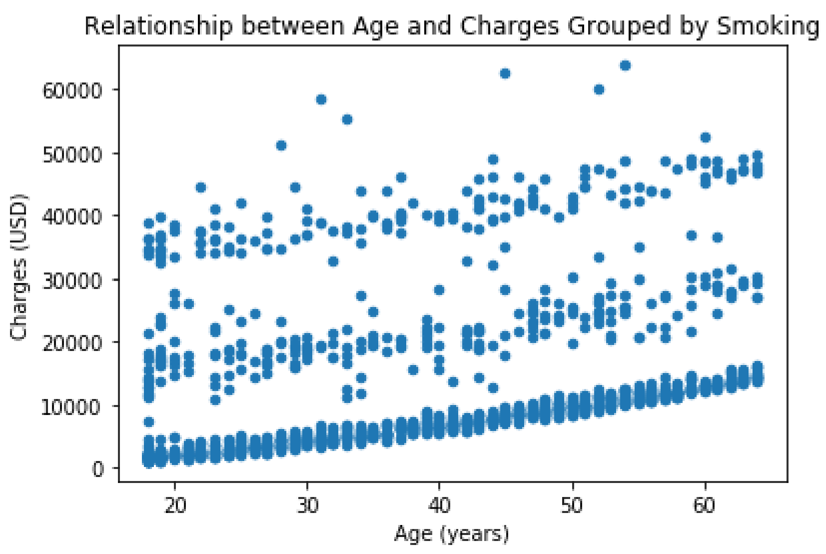
In [35]:
```
pairPlot = sns.pairplot(df_1[["charges", "age", "bmi", "children"]])
```



5.1.1 Relationship between Charges and Age

In [36]:
```
df_1.plot.scatter(x='age', y='charges')
plt.title("Relationship between Age and Charges Grouped by Smoking")
plt.ylabel("Charges (USD)")
plt.xlabel("Age (years)")
```

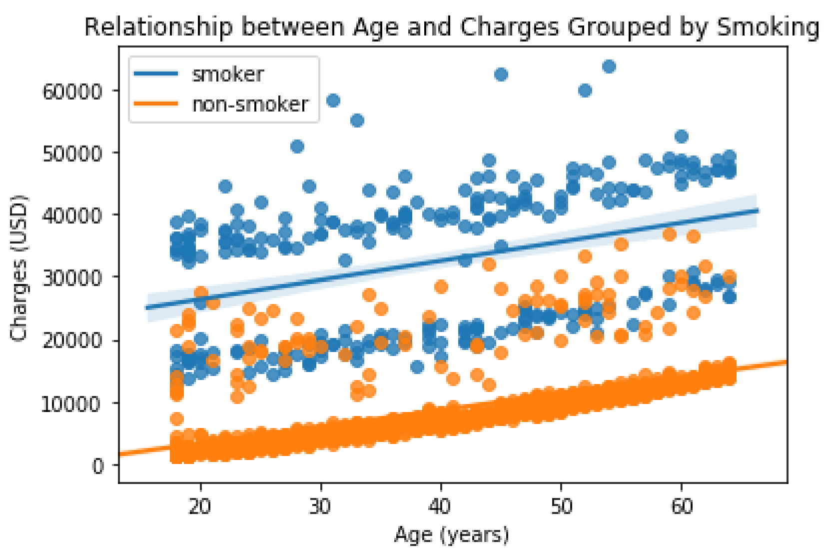
Out[36]: `Text(0.5, 0, 'Age (years)')`



- We can observe an upper trend of charges as age increases, and there seems to be three distinctive groups/clusters. Each of the clusters exhibit a linear form, so a simple least-square regression between Age and Charges may not be good. A more complicated model would be needed. It's worth trying to displaying this plot by one important feature Smoker, to see if this pattern has anything to do with this factor.

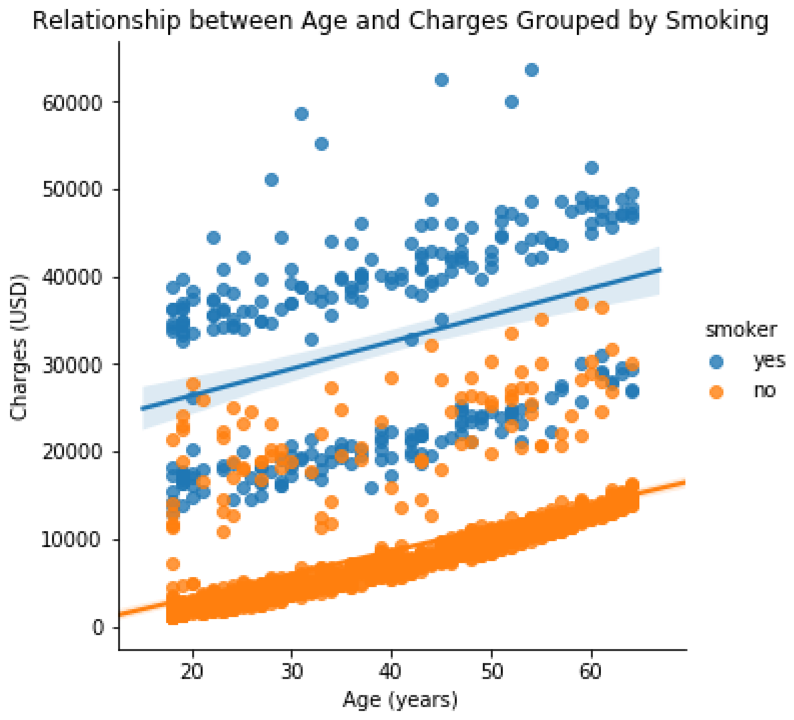
In [37]:
```
# Create Age vs. Charges scatter plots grouped by smoker and non-smoker
fig = sns.regplot(x='age', y='charges', data=df_1.loc[df_1['smoker'] == 'yes'])
fig = sns.regplot(x='age', y='charges', data=df_1.loc[df_1['smoker'] == 'no'])
fig.set_title("Relationship between Age and Charges Grouped by Smoking")
fig.legend(('smoker', 'non-smoker'))
fig.set_ylabel("Charges (USD)")
fig.set_xlabel("Age (years)")
```

Out[37]: `Text(0.5, 0, 'Age (years)')`



In [38]:
```
# Create Age vs. Charges scatter plots grouped by smoker and non-smoker
fig = sns.lmplot(x='age', y='charges', data=df_1, hue='smoker')
plt.title("Relationship between Age and Charges Grouped by Smoking")
plt.ylabel("Charges (USD)")
plt.xlabel("Age (years)")
```

Out[38]: Text(0.5, 20.80000000000002, 'Age (years)')



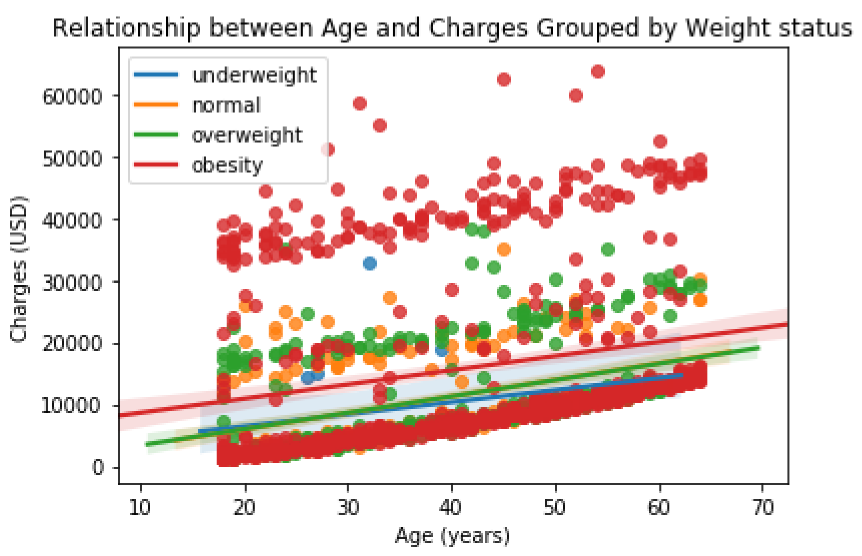
In [39]:
```
# Transform BMI to an ordinal variable and create a new column called 'weight_status' in the dataframe
df_1['weight_status'] = 'default'
df_1.loc[df_1['bmi'] < 18.5,['weight_status']] = 'underweight'
df_1.loc[(df_1['bmi'] >= 18.5)&(df_1['bmi'] < 25),['weight_status']] = 'normal'
df_1.loc[(df_1['bmi'] >= 25)&(df_1['bmi'] < 30),['weight_status']] = 'overweight'
df_1.loc[df_1['bmi'] >= 30,['weight_status']] = 'obese'
df_1.head()
```

Out[39]:

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

In [40]:
```
# Create Age vs. Charges scatter plots grouped by weight status
fig = sns.regplot(x='age', y='charges', data=df_1.loc[df_1['weight_status'] == 'underweight'])
fig = sns.regplot(x='age', y='charges', data=df_1.loc[df_1['weight_status'] == 'normal'])
fig = sns.regplot(x='age', y='charges', data=df_1.loc[df_1['weight_status'] == 'overweight'])
fig = sns.regplot(x='age', y='charges', data=df_1.loc[df_1['weight_status'] == 'obese'])
fig.set_title("Relationship between Age and Charges Grouped by Weight status")
fig.legend(('underweight', 'normal', 'overweight', 'obesity'))
fig.set_ylabel("Charges (USD)")
fig.set_xlabel("Age (years)")
```

Out[40]: Text(0.5, 0, 'Age (years)')

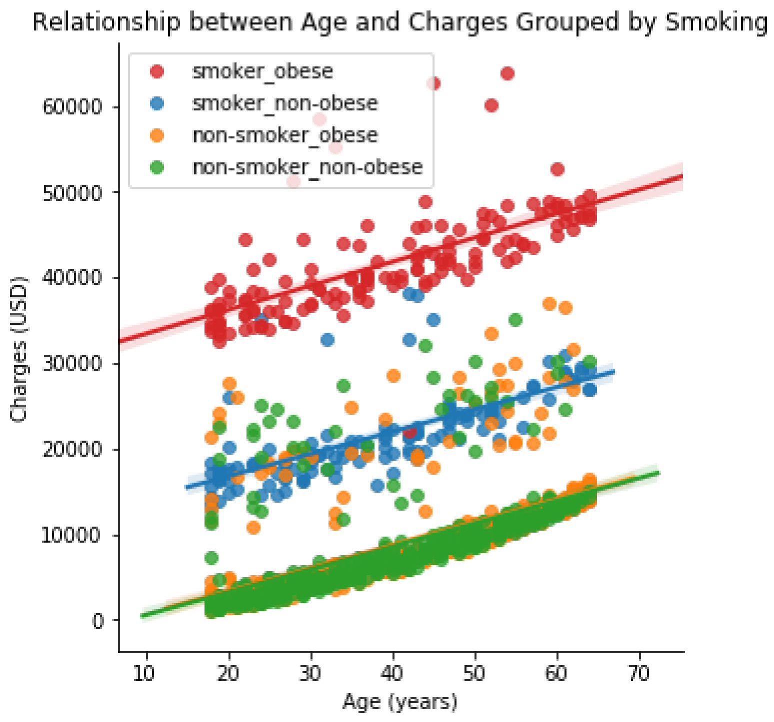


In [41]:
```
# Creat a new column 'weight_smoking_status'
df_1['smoking_weight_status'] = 'default'
df_1.loc[(df_1['weight_status'] != 'obese')&(df_1['smoker']=='yes'),['smoking_weight_status']] = 'smoker_non-obese'
df_1.loc[(df_1['weight_status'] == 'obese')&(df_1['smoker']=='yes'),['smoking_weight_status']] = 'smoker_obese'
df_1.loc[(df_1['weight_status'] != 'obese')&(df_1['smoker']=='no'),['smoking_weight_status']] = 'non-smoker_non-obese'
df_1.loc[(df_1['weight_status'] == 'obese')&(df_1['smoker']=='no'),['smoking_weight_status']] = 'non-smoker_obese'
df_1.head()
```

Out[41]:

	age	sex	bmi	children	smoker	region	charges	weight_status	smoking_weight_status
0	19	female	27.900	0	yes	southwest	16884.92400	overweight	smoker_non-obese
1	18	male	33.770	1	no	southeast	1725.55230	obese	non-smoker_obese
2	28	male	33.000	3	no	southeast	4449.46200	obese	non-smoker_obese
3	33	male	22.705	0	no	northwest	21984.47061	normal	non-smoker_non-obese
4	32	male	28.880	0	no	northwest	3866.85520	overweight	non-smoker_non-obese

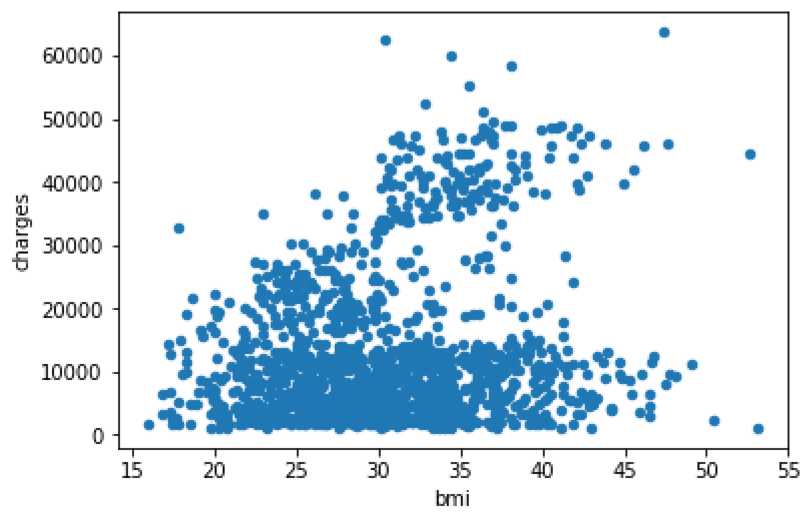
In [42]:
```
# Create Age vs. Charges scatter plots grouped by smoking and obesity
fig = sns.lmplot(x='age', y='charges', data=df_1, hue='smoking_weight_status', legend=False)
plt.title("Relationship between Age and Charges Grouped by Smoking")
plt.ylabel("Charges (USD)")
plt.xlabel("Age (years)")
# Change the order of legend
handles, labels = plt.gca().get_legend_handles_labels()
order = [3,0,1,2]
plt.legend([handles[idx] for idx in order],[labels[idx] for idx in order])
# Save the plot to as a file
plt.savefig('smoking_weight_age_charges', dpi=None, facecolor='w', edgecolor='w',
        orientation='portrait', papertype=None, format=None,
        transparent=False, bbox_inches='tight', pad_inches=None,
        frameon=None, metadata=None)
```



5.1.2 Relationship between Charges and BMI

In [43]:
```
df_1.plot.scatter(x='bmi', y='charges')
```

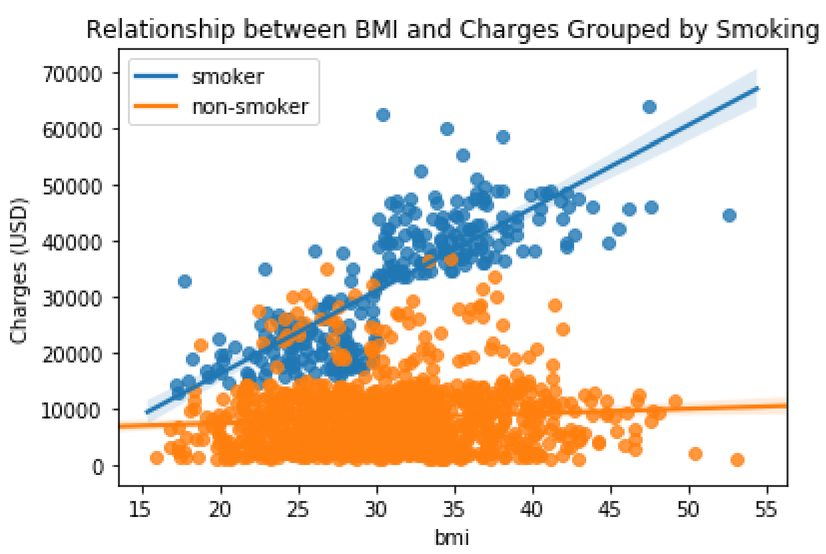
Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x1c21766ac8>



- We can observe more people charged higher when bmi > 30, and there seems to be two groups/clusters indicating other underlying factors.

In [44]:
```
# Create BMI vs. Charges scatter plots grouped by smoker and non-smoker
fig = sns.regplot('bmi', 'charges', df_1.loc[df_1['smoker'] == 'yes'])
fig = sns.regplot('bmi', 'charges', df_1.loc[df_1['smoker'] == 'no'])
fig.set_title("Relationship between BMI and Charges Grouped by Smoking")
fig.legend(('smoker', 'non-smoker'))
fig.set_ylabel("BMI (kg/m²)")
fig.set_ylabel("Charges (USD)")
```

Out[44]: Text(0, 0.5, 'Charges (USD)')

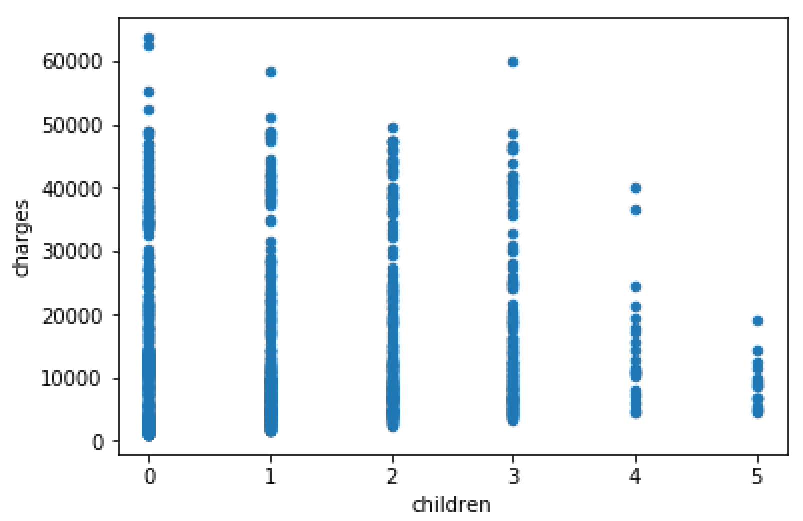


- BMI seems to have no effect on charges for non-smokers, while there is an upper trend of charges as bmi increases for smokers.

5.1.5 Relationship between Charges and Children

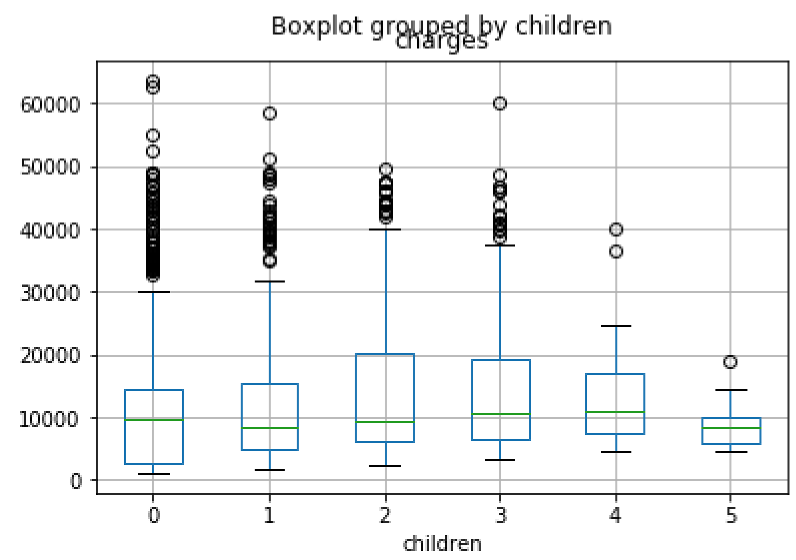
In [45]:
```
df_1.plot.scatter(x='children', y='charges')
```

Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x1c21627940>



In [46]:
```
df_1.boxplot(column = 'charges', by = 'children')
```

Out[46]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1cfaa9b0>
```



- People with 4 or 5 children seem to pay less charge.

5.2 Relationship of Charges to the Categorical Features

- In all instances charges demonstrate a right skewed distribution

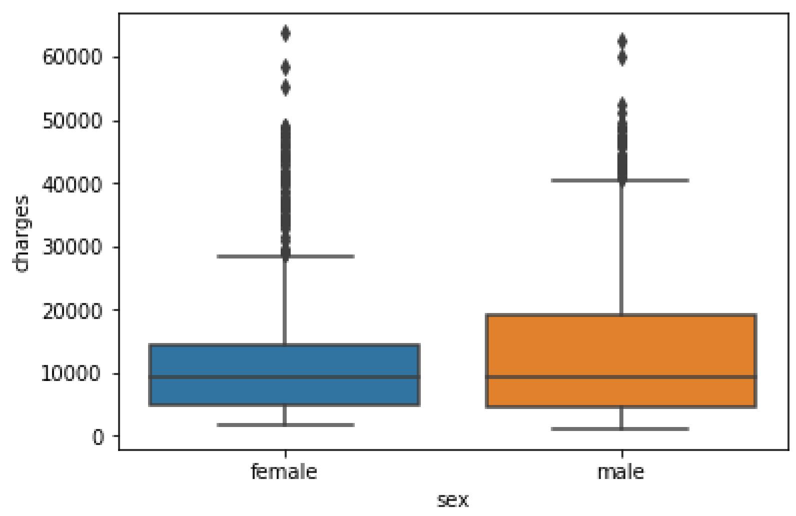
In [47]:
```
# define a funtion to make boxplot
def making_boxplot(data, group, feature):
    """function to produce boxplot using seaborn"""
    sns.boxplot(x = group, y = feature, data = data)
```

5.2.1 Relationship between Charges and Sex

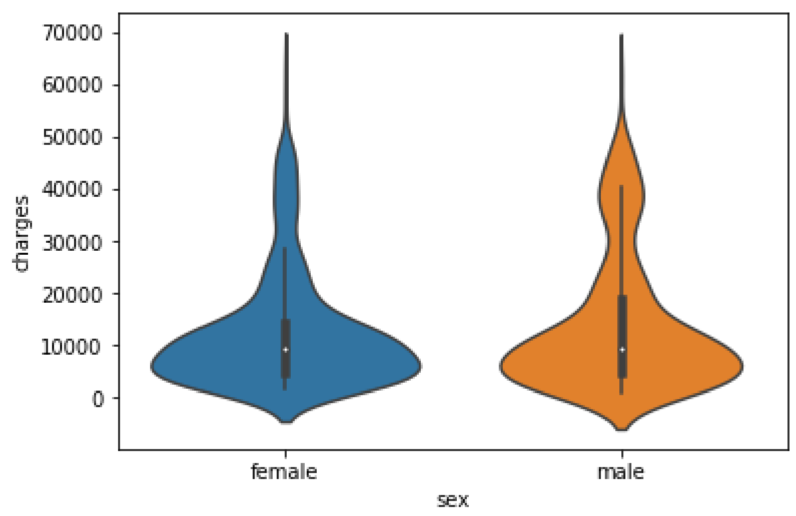
In [48]:
```
# Average charges for different gender
meanChargeGender = df_1.groupby(by = 'sex')['charges'].mean()
print(meanChargeGender)
```

```
sex
female    12569.578844
male      13974.998864
Name: charges, dtype: float64
```

In [49]:
```
# Boxplot
making_boxplot(df_1, 'sex', 'charges')
```



In [50]:
```
# Violin plot
violinPlot = sns.violinplot(x = 'sex', y = 'charges', data = df_1)
```

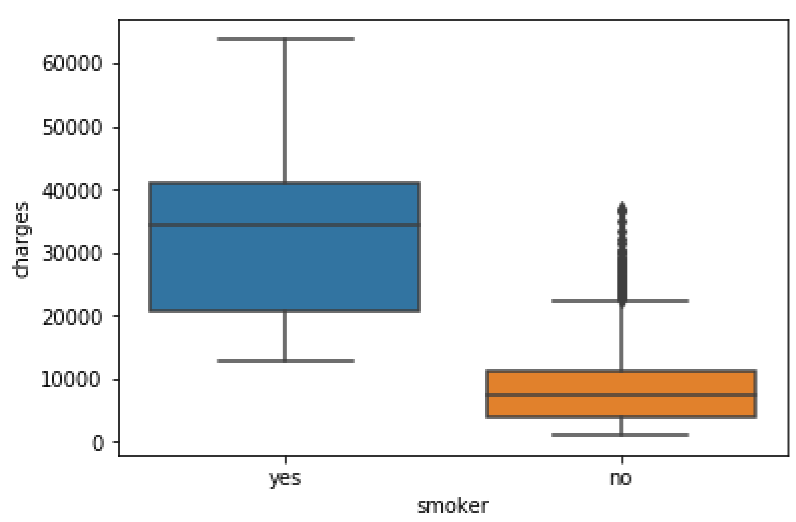


- There isn't much difference between male and female regarding their medical cost.

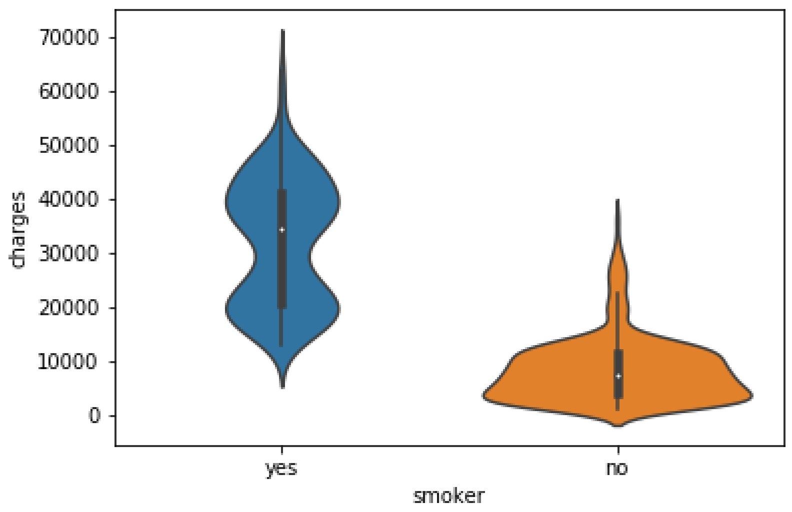
5.2.2 Relationship between Charges and Smoker

In [51]:
```
# Average charges for smoker and non-smoker
meanChargeSmoker = df_1.groupby(by = 'smoker')['charges'].mean()
print(meanChargeSmoker)
# Box plot
boxPlot = sns.boxplot(x = 'smoker', y = 'charges', data = df_1)
```

```
smoker
no      8440.660307
yes    32050.231832
Name: charges, dtype: float64
```



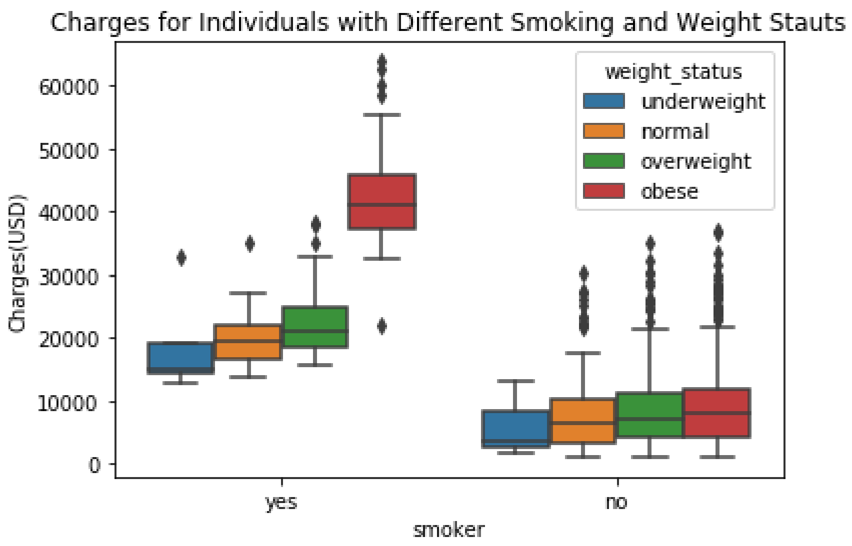
In [52]:
```python
# ViolinPlot
violinPlot = sns.violinplot(x = 'smoker', y = 'charges', data = df_1)
```



- We can observe a obvious higher charges paid by smokers compared to non-smokers.

In [53]:
```python
# Average charges for smoker and non-smoker
meanChargeSmoker = df_1.groupby(by = 'smoking_weight_status')['charges'].mean()
print(meanChargeSmoker)
# Box plot
boxPlot = sns.boxplot(x='smoker', y='charges', hue='weight_status', data=df_1, hue_order=('underweight','normal',
                                                                                          'overweight', 'obese'))
plt.title("Charges for Individuals with Different Smoking and Weight Stauts")
plt.ylabel("Charges(USD)")
# Save the plot as a file
plt.savefig('smoking_weight_charges', dpi=None, facecolor='w', edgecolor='w',
        orientation='portrait', papertype=None, format=None,
        transparent=False, bbox_inches='tight', pad_inches=None,
        frameon=None, metadata=None)
```

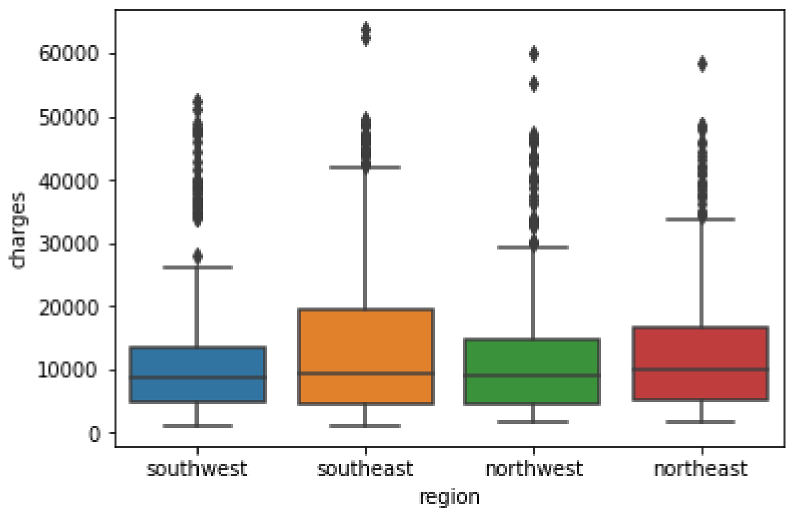
```
smoking_weight_status
non-smoker_non-obese     7977.029520
non-smoker_obese         8855.531349
smoker_non-obese        21363.217016
smoker_obese            41557.989840
Name: charges, dtype: float64
```



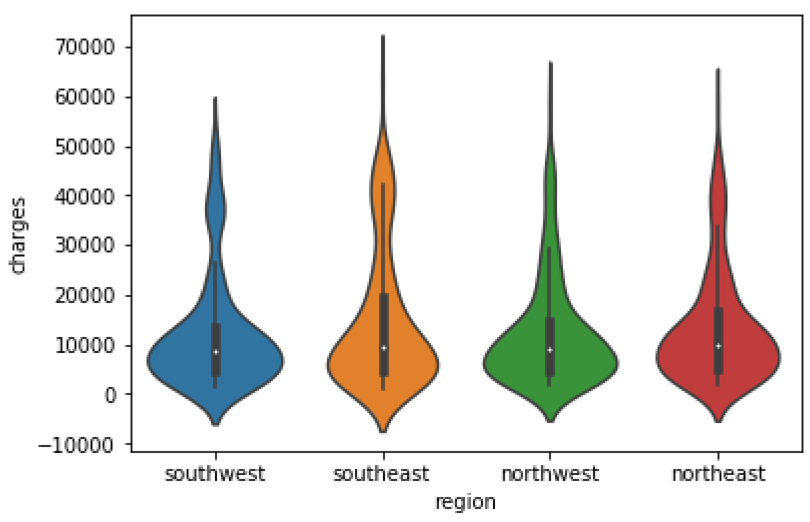
5.2.3 Relationship between Charges and Region

In [54]:
```python
meanChargeRegion = df_1.groupby(by = 'region')['charges'].mean()
print(meanChargeRegion)
boxPlot = sns.boxplot(x = 'region', y = 'charges', data = df_1)
```

```
region
northeast    13406.384516
northwest    12450.840844
southeast    14735.411438
southwest    12346.937377
Name: charges, dtype: float64
```



In [55]:
```python
violinPlot = sns.violinplot(x = 'region', y = 'charges', data = df_1)
```



- There isn't much difference of medical charges among different regions.

5.3 Quantifying the correlation pattern observed in data visualization

Based on the visualization of the relationship between charges and other predictors above, we can make some hypothesis:

- There is no significant difference of charges between different sex or regions
- Smokers are charged significantly higher than those who don't smoke
- The charge increases as the benificiary gets older
- There is a distinctive group of people with BMI larger than 30 charged significantly high, which might indicate some confounding factors
- The charges are relatively low for those with 4 or 5 children

Simple linear regression will be used to quantify the correlation of the numerical predictors to Charges

5.3.1 Simple linear regression using Age as a predictor

In [56]:
```
# Simple linear regression using age as a predictor
Y = df_1['charges']
X = df_1['age']
X = sm.add_constant(X)
SimpleLinear = sm.OLS(Y, X).fit()
print(SimpleLinear.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.089
Model:                            OLS   Adj. R-squared:                  0.088
Method:                 Least Squares   F-statistic:                     130.4
Date:                Sun, 26 May 2019   Prob (F-statistic):           6.98e-29
Time:                        02:29:55   Log-Likelihood:                -14405.
No. Observations:                1337   AIC:                         2.881e+04
Df Residuals:                    1335   BIC:                         2.882e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       3190.0217    938.396      3.399      0.001    1349.130    5030.913
age          257.2297     22.526     11.419      0.000     213.040     301.419
==============================================================================
Omnibus:                      398.876   Durbin-Watson:                   2.034
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              861.815
Skew:                           1.731   Prob(JB):                    7.23e-188
Kurtosis:                       4.865   Cond. No.                         124.
==============================================================================

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

- The P value of regression coefficient is <0.001 which is significant.
- The R-square is 0.089, meaning that fitted model explains 8.9% of the variation of charges.
- The P value of the F-statistic is <0.001 indicating that the model is significantly improved than just taking the mean charges.

5.3.2 Simple linear regression using BMI as a predictor

In [57]:
```
# Simple linear regression using BMI as a predictor
Y = df_1['charges']
X = df_1['bmi']
X = sm.add_constant(X)
SimpleLinear = sm.OLS(Y, X).fit()
print(SimpleLinear.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.039
Model:                            OLS   Adj. R-squared:                  0.039
Method:                 Least Squares   F-statistic:                     54.70
Date:                Sun, 26 May 2019   Prob (F-statistic):           2.47e-13
Time:                        02:29:55   Log-Likelihood:                -14440.
No. Observations:                1337   AIC:                         2.888e+04
Df Residuals:                    1335   BIC:                         2.889e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       1202.1404   1664.857      0.722      0.470   -2063.880    4468.161
bmi          393.8559     53.252      7.396      0.000     289.390     498.322
==============================================================================
Omnibus:                      260.633   Durbin-Watson:                   1.985
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              430.246
Skew:                           1.296   Prob(JB):                     3.74e-94
Kurtosis:                       4.002   Cond. No.                         160.
==============================================================================

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

- The P value of regression coefficient is < 0.001, which is significant.
- The R-square is 0.039, meaning that fitted model explains 3.9% of the variation of charges.
- The P value of the F-statistic is <0.001 indicating that the model is significantly improved than just taking the mean charges.

5.3.3 Simple linear regression using Children as a predictor

In [58]:
```
# Simple linear regression using children as a predictor
Y = df_1['charges']
X = df_1['children']
X = sm.add_constant(X)
SimpleLinear = sm.OLS(Y, X).fit()
print(SimpleLinear.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.005
Model:                            OLS   Adj. R-squared:                  0.004
Method:                 Least Squares   F-statistic:                     6.090
Date:                Sun, 26 May 2019   Prob (F-statistic):             0.0137
Time:                        02:29:55   Log-Likelihood:                -14464.
No. Observations:                1337   AIC:                         2.893e+04
Df Residuals:                    1335   BIC:                         2.894e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       1.254e+04    446.786     28.061      0.000    1.17e+04    1.34e+04
children     676.9481    274.306      2.468      0.014     138.831    1215.066
==============================================================================
Omnibus:                      340.596   Durbin-Watson:                   2.004
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              665.347
Skew:                           1.527   Prob(JB):                    3.33e-145
Kurtosis:                       4.617   Cond. No.                         2.65
==============================================================================

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

- The P value of regression coefficient is <0.05, statistically significant.
- The R-square is 0.005, meaning that fitted model only explains 0.6% of the variation of charges.

- The P value of the F-statistic is <0.05 indicating that the model is significantly improved than just taking the mean charges.

5.3.4 Simple linear regression using Sex as a predictor

In [59]:
```
# Dummify categorical variables sex
df_1 = pd.get_dummies(df_1, columns = ['sex'])
print(df_1.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1337 entries, 0 to 1337
Data columns (total 10 columns):
age                      1337 non-null int64
bmi                      1337 non-null float64
children                 1337 non-null int64
smoker                   1337 non-null object
region                   1337 non-null object
charges                  1337 non-null float64
weight_status            1337 non-null object
smoking_weight_status    1337 non-null object
sex_female               1337 non-null uint8
sex_male                 1337 non-null uint8
dtypes: float64(2), int64(2), object(4), uint8(2)
memory usage: 136.6+ KB
None
```

In [60]:
```
# Simple linear regression using sex as a predictor
Y = df_1['charges']
X = df_1['sex_male']
X = sm.add_constant(X)
SimpleLinear = sm.OLS(Y, X).fit()
print(SimpleLinear.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.003
Model:                            OLS   Adj. R-squared:                  0.003
Method:                 Least Squares   F-statistic:                     4.513
Date:                Sun, 26 May 2019   Prob (F-statistic):             0.0338
Time:                        02:29:55   Log-Likelihood:                -14465.
No. Observations:                1337   AIC:                         2.893e+04
Df Residuals:                    1335   BIC:                         2.894e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       1.257e+04    470.065     26.740      0.000    1.16e+04    1.35e+04
sex_male    1405.4200    661.564      2.124      0.034     107.603    2703.238
==============================================================================
Omnibus:                      330.969   Durbin-Watson:                   2.012
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              635.251
Skew:                           1.495   Prob(JB):                    1.14e-138
Kurtosis:                       4.570   Cond. No.                         2.63
==============================================================================

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

- The P value of regression coefficient is 0.034 < 0.05, which is significant.
- The R-square is 0.003, meaning that fitted model only explains 0.3% of the variation of charges.
- The P value of the F-statistic is <0.05 indicating that the model is significantly improved than just taking the mean charges.

5.3.5 Simple linear regression using Smoker as a predictor

In [61]:
```
# Dummify categorical variables smoker
df_1 = pd.get_dummies(df_1, columns=['smoker'])
print(df_1.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1337 entries, 0 to 1337
Data columns (total 11 columns):
age                      1337 non-null int64
bmi                      1337 non-null float64
children                 1337 non-null int64
region                   1337 non-null object
charges                  1337 non-null float64
weight_status            1337 non-null object
smoking_weight_status    1337 non-null object
sex_female               1337 non-null uint8
sex_male                 1337 non-null uint8
smoker_no                1337 non-null uint8
smoker_yes               1337 non-null uint8
dtypes: float64(2), int64(2), object(3), uint8(4)
memory usage: 128.8+ KB
None
```

In [62]:
```
# Simple linear regression using smoker as a predictor
Y = df_1['charges']
X = df_1['smoker_yes']
X = sm.add_constant(X)
SimpleLinear = sm.OLS(Y, X).fit()
print(SimpleLinear.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.620
Model:                            OLS   Adj. R-squared:                  0.619
Method:                 Least Squares   F-statistic:                     2176.
Date:                Sun, 26 May 2019   Prob (F-statistic):          1.41e-282
Time:                        02:29:55   Log-Likelihood:                -13820.
No. Observations:                1337   AIC:                         2.764e+04
Df Residuals:                    1335   BIC:                         2.766e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       8440.6603    229.137     36.837      0.000    7991.153    8890.167
smoker_yes  2.361e+04    506.157     46.645      0.000    2.26e+04    2.46e+04
==============================================================================
Omnibus:                      135.799   Durbin-Watson:                   2.025
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              211.849
Skew:                           0.727   Prob(JB):                     9.95e-47
Kurtosis:                       4.299   Cond. No.                         2.60
==============================================================================

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

- The P value of regression coefficient <0.001, which is significant.
- The R-square is 0.620, meaning that fitted model explains 62% of the variation of charges.

- The P value of the F-statistic is <0.001 indicating that the model is significantly improved than just taking the mean charges.

5.3.6 Simple linear regression using Region as a predictor

In [63]:
```
# Dummify categorical variables region
df_1 = pd.get_dummies(df_1, columns = ['region'])
print(df_1.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1337 entries, 0 to 1337
Data columns (total 14 columns):
age                      1337 non-null int64
bmi                      1337 non-null float64
children                 1337 non-null int64
charges                  1337 non-null float64
weight_status            1337 non-null object
smoking_weight_status    1337 non-null object
sex_female               1337 non-null uint8
sex_male                 1337 non-null uint8
smoker_no                1337 non-null uint8
smoker_yes               1337 non-null uint8
region_northeast         1337 non-null uint8
region_northwest         1337 non-null uint8
region_southeast         1337 non-null uint8
region_southwest         1337 non-null uint8
dtypes: float64(2), int64(2), object(2), uint8(8)
memory usage: 123.6+ KB
None
```

In [64]:
```
# Simple linear regression using region_northeast as a predictor
Y = df_1['charges']
X = df_1['region_northeast']
X = sm.add_constant(X)
SimpleLinear = sm.OLS(Y, X).fit()
print(SimpleLinear.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                   0.04719
Date:                Sun, 26 May 2019   Prob (F-statistic):              0.828
Time:                        02:29:56   Log-Likelihood:                -14467.
No. Observations:                1337   AIC:                         2.894e+04
Df Residuals:                    1335   BIC:                         2.895e+04
Df Model:                           1
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const             1.324e+04    380.634     34.780      0.000    1.25e+04     1.4e+04
region_northeast   167.9671    773.215      0.217      0.828   -1348.882    1684.816
==============================================================================
Omnibus:                      336.970   Durbin-Watson:                   2.004
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              653.866
Skew:                           1.515   Prob(JB):                    1.03e-142
Kurtosis:                       4.598   Cond. No.                         2.50
==============================================================================

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

- The P value of the regression coefficient is >0.05, not significant.
- The R-square is 0.000, meaning that fitted model doesn't explain the variation of charges.
- The P value of the F-statistic is >0.05 indicating that the model is not significantly improved than just taking the mean charges. So Region_northeast has no correlation with Charges.

In [65]:
```
# Simple linear regression using Region_northwest as a predictor
Y = df_1['charges']
X = df_1['region_northwest']
X = sm.add_constant(X)
SimpleLinear = sm.OLS(Y, X).fit()
print(SimpleLinear.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     2.002
Date:                Sun, 26 May 2019   Prob (F-statistic):              0.157
Time:                        02:29:56   Log-Likelihood:                -14466.
No. Observations:                1337   AIC:                         2.894e+04
Df Residuals:                    1335   BIC:                         2.895e+04
Df Model:                           1
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const             1.354e+04    380.355     35.609      0.000    1.28e+04    1.43e+04
region_northwest -1093.1996    772.650     -1.415      0.157   -2608.940     422.541
==============================================================================
Omnibus:                      334.118   Durbin-Watson:                   1.999
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              644.601
Skew:                           1.506   Prob(JB):                    1.06e-140
Kurtosis:                       4.579   Cond. No.                         2.50
==============================================================================

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

- The P value of the regression coefficient is >0.05, not significant.
- The R-square is 0.001, meaning that fitted model only explains 0.1% of the variation of charges.
- The P value of the F-statistic is >0.05 indicating that the model is not significantly improved than just taking the mean charges. So Region_northwest has no correlation with Charges.

In [66]:
```
# Simple linear regression using Region_southeast as a predictor
Y = df_1['charges']
X = df_1['region_southeast']
X = sm.add_constant(X)
SimpleLinear = sm.OLS(Y, X).fit()
print(SimpleLinear.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.005
Model:                            OLS   Adj. R-squared:                  0.005
Method:                 Least Squares   F-statistic:                     7.267
Date:                Sun, 26 May 2019   Prob (F-statistic):            0.00711
Time:                        02:29:56   Log-Likelihood:                -14463.
No. Observations:                1337   AIC:                         2.893e+04
Df Residuals:                    1335   BIC:                         2.894e+04
Df Model:                           1
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const             1.273e+04    387.333     32.877      0.000     1.2e+04    1.35e+04
region_southeast  2001.0891    742.334      2.696      0.007     544.821    3457.358
==============================================================================
Omnibus:                      325.680   Durbin-Watson:                   2.001
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              617.702
Skew:                           1.480   Prob(JB):                    7.37e-135
Kurtosis:                       4.524   Cond. No.                         2.45
==============================================================================

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

- The P value of the regression coefficient is <0.01, significant.
- The R-square is 0.005, meaning that fitted model only explains 0.7% of the variation of charges.
- The P value of the F-statistic is <0.05 indicating that the model is significantly improved than just taking the mean charges.

In [67]:
```
# Simple linear regression using Region_southwest as a predictor
Y = df_1['charges']
X = df_1['region_southwest']
X = sm.add_constant(X)
SimpleLinear = sm.OLS(Y, X).fit()
print(SimpleLinear.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     2.547
Date:                Sun, 26 May 2019   Prob (F-statistic):              0.111
Time:                        02:29:56   Log-Likelihood:                -14466.
No. Observations:                1337   AIC:                         2.894e+04
Df Residuals:                    1335   BIC:                         2.895e+04
Df Model:                           1
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const             1.358e+04    380.466     35.689      0.000    1.28e+04    1.43e+04
region_southwest -1231.5515    771.684     -1.596      0.111   -2745.397     282.294
==============================================================================
Omnibus:                      335.945   Durbin-Watson:                   2.009
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              650.771
Skew:                           1.511   Prob(JB):                    4.86e-142
Kurtosis:                       4.595   Cond. No.                         2.50
==============================================================================

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

- The P value of regression coefficient is >0.05, not significant.
- The R-square is 0.004, meaning that Region_southwest only explains 0.4% of the variation of charges.
- The Pvaluse of the F-statistic is <0.05 indicating that the model is significantly improved than just taking the mean charges.

5.3.7 Correlation Metrix for the whole variables in the dataset

In [68]:
```
df_1.corr()
```

Out[68]:

	age	bmi	children	charges	sex_female	sex_male	smoker_no	smoker_yes	region_northeast	region_northwest	region_southeast	region_southwest
age	1.000000	0.109344	0.041536	0.298308	0.019814	-0.019814	0.025587	-0.025587	0.001868	0.001495	-0.012311	0.009415
bmi	0.109344	1.000000	0.012755	0.198401	-0.046397	0.046397	-0.003746	0.003746	-0.138178	-0.136138	0.270057	-0.006211
children	0.041536	0.012755	1.000000	0.067389	-0.017848	0.017848	-0.007331	0.007331	-0.023202	0.026044	-0.023492	0.021538
charges	0.298308	0.198401	0.067389	1.000000	-0.058044	0.058044	-0.787234	0.787234	0.005945	-0.038695	0.073578	-0.043637
sex_female	0.019814	-0.046397	-0.017848	-0.058044	1.000000	-1.000000	0.076596	-0.076596	0.002008	0.012482	-0.017578	0.003767
sex_male	-0.019814	0.046397	0.017848	0.058044	-1.000000	1.000000	-0.076596	0.076596	-0.002008	-0.012482	0.017578	-0.003767
smoker_no	0.025587	-0.003746	-0.007331	-0.787234	0.076596	-0.076596	1.000000	-1.000000	-0.002597	0.036321	-0.068282	0.037168
smoker_yes	-0.025587	0.003746	0.007331	0.787234	-0.076596	0.076596	-1.000000	1.000000	0.002597	-0.036321	0.068282	-0.037168
region_northeast	0.001868	-0.138178	-0.023202	0.005945	0.002008	-0.002008	-0.002597	0.002597	1.000000	-0.319842	-0.345909	-0.320493
region_northwest	0.001495	-0.136138	0.026044	-0.038695	0.012482	-0.012482	0.036321	-0.036321	-0.319842	1.000000	-0.345909	-0.320493
region_southeast	-0.012311	0.270057	-0.023492	0.073578	-0.017578	0.017578	-0.068282	0.068282	-0.345909	-0.345909	1.000000	-0.346614
region_southwest	0.009415	-0.006211	0.021538	-0.043637	0.003767	-0.003767	0.037168	-0.037168	-0.320493	-0.320493	-0.346614	1.000000

From above correlation results from simple linear regression and correlation metrix, we can observe the strength of correlation between predictors and Charges in descending order as follows:

- Smoker - 0.79, strong correlation
- Age - 0.30, moderate correlation
- BMI - 0.20, weak correlation
- Children - 0.07, very weak correlation
- Sex - 0.06, very weak correlation
- Region - nearly no correlation

6. Fitting Candidate Models and Making comparisons

Linear models:

```
1.Multiple Linear Regression
2.Ridge Regression
3.Lasso
```

Tree-based models:

4.Regression Tree
5.Random Forests
6.Boosting for Regression Tree (Adaboost & Gradient Boosting Regression Tree)

6.1 Exploring the optimal multiple linear regression model using Backward Elimination Stepwise Method

There are several ways to decide on the order about putting variables in the model

- Hierarchical or blockwise entry: the predictors are based on past work and the researcher decides in which order the variables are entered in the model. This order should be based on the importance of the variables. The most important variable is entered first and so on. Than the new predictors can be entered.
- Forced entry: all the predictors are put in the model at once
- Stepwise methods: the order in which the predictors are entered in the model are based on mathematical criteria. You can use a forward and a backward method. In a forward method the first variable that in entered in the model, is the one that explains most of the variation of the outcome variable, the next variable entered in the model explains the largest part of the remaining variation and so on. In a backward method all the variables are entered in the model and one by one the variables are removed that explain the smallest part of the variation. To avoid overfitting it is important to cross-validate the model.
- All sub-sets method

In [69]:
```
df_1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1337 entries, 0 to 1337
Data columns (total 14 columns):
age                      1337 non-null int64
bmi                      1337 non-null float64
children                 1337 non-null int64
charges                  1337 non-null float64
weight_status            1337 non-null object
smoking_weight_status    1337 non-null object
sex_female               1337 non-null uint8
sex_male                 1337 non-null uint8
smoker_no                1337 non-null uint8
smoker_yes               1337 non-null uint8
region_northeast         1337 non-null uint8
region_northwest         1337 non-null uint8
region_southeast         1337 non-null uint8
region_southwest         1337 non-null uint8
dtypes: float64(2), int64(2), object(2), uint8(8)
memory usage: 123.6+ KB
```

6.1.1 Multiple Linear Regression Model with all predictors added

In [70]:
```
# Putting all predictors into the model
X = df_1[['age','bmi','children','sex_male','smoker_yes','region_northeast','region_northwest','region_southeast']]
Y = df_1.iloc[:, 3]

# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)

# Fit the model
x_train = sm.add_constant(x_train) # add an intercept (beta_0) to the model
MultiLinear_1 = sm.OLS(y_train, x_train).fit() # Fit a multiple linear regression model

#Print the statistics of the above model
print(MultiLinear_1.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                charges   R-squared:                       0.752
Model:                            OLS   Adj. R-squared:                  0.750
Method:                 Least Squares   F-statistic:                     375.9
Date:                Sun, 26 May 2019   Prob (F-statistic):          3.05e-294
Time:                        02:29:56   Log-Likelihood:                -10128.
No. Observations:                1002   AIC:                         2.027e+04
Df Residuals:                     993   BIC:                         2.032e+04
Df Model:                           8                                         
Covariance Type:            nonrobust                                         
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const            -1.185e+04   1167.295    -10.155      0.000   -1.41e+04   -9563.389
age                244.3788     13.448     18.171      0.000     217.988     270.770
bmi                305.1715     32.483      9.395      0.000     241.427     368.916
children           483.6063    155.005      3.120      0.002     179.431     787.782
sex_male            27.4955    378.049      0.073      0.942    -714.372     769.363
smoker_yes        2.393e+04    473.115     50.581      0.000      2.3e+04    2.49e+04
region_northeast  1155.9896    542.239      2.132      0.033      91.924    2220.055
region_northwest   884.7692    537.354      1.647      0.100    -169.711    1939.249
region_southeast   322.9083    534.796      0.604      0.546    -726.552    1372.369
==============================================================================
Omnibus:                      257.309   Durbin-Watson:                   2.027
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              728.361
Skew:                           1.293   Prob(JB):                    6.89e-159
Kurtosis:                       6.281   Cond. No.                         328.
==============================================================================

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

- R-square is 0.752, which means model_1 can explain 75.2% of the variation of charges.
- Sex has a P value of 0.942, which is not significant and hence we want to remove it first.

6.1.2 Multiple Linear Regression after dropping predictor Sex

- As the P value of coefficient for Sex_male is 0.942.

In [71]:
```
# Droppin Sex from the model
X = df_1[['age','bmi','children','smoker_yes','region_northeast','region_northwest','region_southeast']]
Y = df_1['charges']

# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)

# Calculate the linear correlation coefficient between charges and predictors
x_train = sm.add_constant(x_train) # add an intercept (beta_0) to the model
MultiLinear_2 = sm.OLS(y_train, x_train).fit() # Fit a multiple linear regression model

# Print out the statistics
print(MultiLinear_2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.752
Model:                            OLS   Adj. R-squared:                  0.750
Method:                 Least Squares   F-statistic:                     430.1
Date:                Sun, 26 May 2019   Prob (F-statistic):          1.42e-295
Time:                        02:29:56   Log-Likelihood:                -10128.
No. Observations:                1002   AIC:                         2.027e+04
Df Residuals:                     994   BIC:                         2.031e+04
Df Model:                           7
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const            -1.184e+04   1156.956    -10.236      0.000   -1.41e+04   -9572.725
age                244.3516     13.437     18.186      0.000     217.984     270.719
bmi                305.2554     32.447      9.408      0.000     241.583     368.927
children           483.9135    154.870      3.125      0.002     180.004     787.823
smoker_yes        2.393e+04    472.138     50.690      0.000      2.3e+04    2.49e+04
region_northeast  1156.9015    541.822      2.135      0.033      93.655    2220.148
region_northwest   885.2554    537.043      1.648      0.100    -168.614    1939.125
region_southeast   323.2139    534.512      0.605      0.546    -725.688    1372.115
==============================================================================
Omnibus:                      257.310   Durbin-Watson:                   2.027
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              728.292
Skew:                           1.293   Prob(JB):                    7.14e-159
Kurtosis:                       6.280   Cond. No.                         325.
==============================================================================

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

- R-square is 0.752, model_2 can explain 75.2% of the variation of charges.
- The P value of Region is not significant so we will remove Region from the model.

6.1.3 Muliple Linear Regression dropping predictor Sex and Region_southeast

- As the P value of the regression coefficient for Region_southeast is 0.546, not significant.

In [72]:
```
# Dropping Sex and Region
X = df_1[['age','bmi','children','smoker_yes','region_northeast','region_northwest']]
Y = df_1.iloc[:,3]
# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)
# Calculate the linear correlation coefficient between charges and predictors
x_train = sm.add_constant(x_train)
MultiLinear_3 = sm.OLS(y_train, x_train).fit()
# Print out the statistics
print(MultiLinear_3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.752
Model:                            OLS   Adj. R-squared:                  0.750
Method:                 Least Squares   F-statistic:                     502.0
Date:                Sun, 26 May 2019   Prob (F-statistic):          7.30e-297
Time:                        02:29:56   Log-Likelihood:                -10128.
No. Observations:                1002   AIC:                         2.027e+04
Df Residuals:                     995   BIC:                         2.031e+04
Df Model:                           6
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const            -1.178e+04   1152.570    -10.225      0.000    -1.4e+04   -9523.077
age                244.2233     13.431     18.184      0.000     217.868     270.579
bmi                308.7746     31.910      9.676      0.000     246.155     371.394
children           479.8525    154.675      3.102      0.002     176.326     783.379
smoker_yes        2.395e+04    470.707     50.889      0.000      2.3e+04    2.49e+04
region_northeast  1000.5494    475.994      2.102      0.036      66.481    1934.617
region_northwest   729.6390    471.217      1.548      0.122    -195.054    1654.332
==============================================================================
Omnibus:                      258.698   Durbin-Watson:                   2.026
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              735.269
Skew:                           1.298   Prob(JB):                    2.18e-160
Kurtosis:                       6.297   Cond. No.                         321.
==============================================================================

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

- R-squared is 0.750, which means 75% of the variation of charges can be explained by model_3

6.1.4 Muliple Linear Regression dropping predictor Sex, Region_southeast, and Region_northwest

- As the P value of the coefficient for Region_northwest is 0.1, not significant.

In [73]:
```
# Dropping Sex and Region
X = df_1[['age','bmi','children','smoker_yes','region_northeast']]
Y = df_1['charges']
# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)
# Calculate the linear correlation coefficient between charges and predictors
x_train = sm.add_constant(x_train)
MultiLinear_4 = sm.OLS(y_train, x_train).fit()
# Print out the statistics
print(MultiLinear_4.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.751
Model:                            OLS   Adj. R-squared:                  0.750
Method:                 Least Squares   F-statistic:                     601.1
Date:                Sun, 26 May 2019   Prob (F-statistic):          9.36e-298
Time:                        02:29:56   Log-Likelihood:                -10130.
No. Observations:                1002   AIC:                         2.027e+04
Df Residuals:                     996   BIC:                         2.030e+04
Df Model:                           5
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const            -1.125e+04   1100.511    -10.223      0.000   -1.34e+04   -9091.112
age                244.5827     13.438     18.201      0.000     218.213     270.953
bmi                298.8465     31.281      9.553      0.000     237.461     360.232
children           481.0207    154.782      3.108      0.002     177.285     784.757
smoker_yes        2.393e+04    470.862     50.830      0.000      2.3e+04    2.49e+04
region_northeast   746.1613    447.057      1.669      0.095    -131.120    1623.442
==============================================================================
Omnibus:                      261.229   Durbin-Watson:                   2.025
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              750.017
Skew:                           1.307   Prob(JB):                    1.37e-163
Kurtosis:                       6.337   Cond. No.                         302.
==============================================================================

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

6.1.5 Muliple Linear Regression dropping predictor Sex, Region_southeast, Region_northwest, and Region_northeast

- As the P value of the coefficient for Region_northeast is 0.095, not significant.

In [74]:
```
# Dropping Sex and Region
X = df_1[['age','bmi','children','smoker_yes', 'region_southwest']]
Y = df_1['charges']
# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)
# Calculate the linear correlation coefficient between charges and predictors
x_train = sm.add_constant(x_train)
MultiLinear_5 = sm.OLS(y_train, x_train).fit()
# Print out the statistics
print(MultiLinear_5.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.751
Model:                            OLS   Adj. R-squared:                  0.750
Method:                 Least Squares   F-statistic:                     601.4
Date:                Sun, 26 May 2019   Prob (F-statistic):          7.75e-298
Time:                        02:29:56   Log-Likelihood:                -10129.
No. Observations:                1002   AIC:                         2.027e+04
Df Residuals:                     996   BIC:                         2.030e+04
Df Model:                           5
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const            -1.066e+04   1082.543     -9.848      0.000   -1.28e+04   -8536.191
age                245.0131     13.432     18.241      0.000     218.654     271.372
bmi                291.1697     30.976      9.400      0.000     230.384     351.955
children           488.5251    154.846      3.155      0.002     184.663     792.387
smoker_yes         2.39e+04    471.331     50.702      0.000      2.3e+04    2.48e+04
region_southwest  -775.0603    435.533     -1.780      0.075   -1629.728      79.607
==============================================================================
Omnibus:                      256.439   Durbin-Watson:                   2.027
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              722.405
Skew:                           1.290   Prob(JB):                    1.35e-157
Kurtosis:                       6.263   Cond. No.                         296.
==============================================================================

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

6.1.6 Muliple Linear Regression dropping predictor Sex and Regions

- As the P value of the regression coefficient for Region_southwest is 0.075, not significant.

In [75]:
```
# Dropping Sex and Region
X = df_1[['age','bmi','children','smoker_yes']]
Y = df_1['charges']
# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)
# Calculate the linear correlation coefficient between charges and predictors
x_train = sm.add_constant(x_train)
MultiLinear_6 = sm.OLS(y_train, x_train).fit()
# Print out the statistics
print(MultiLinear_6.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.750
Model:                            OLS   Adj. R-squared:                  0.749
Method:                 Least Squares   F-statistic:                     749.3
Date:                Sun, 26 May 2019   Prob (F-statistic):          1.29e-298
Time:                        02:29:56   Log-Likelihood:                -10131.
No. Observations:                1002   AIC:                         2.027e+04
Df Residuals:                     997   BIC:                         2.030e+04
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -1.087e+04   1077.385    -10.088      0.000    -1.3e+04   -8754.282
age          245.0751     13.447     18.226      0.000     218.688     271.462
bmi          291.6229     31.008      9.405      0.000     230.774     352.472
children     478.5799    154.913      3.089      0.002     174.586     782.574
smoker_yes  2.394e+04    471.275     50.796      0.000      2.3e+04    2.49e+04
==============================================================================
Omnibus:                      261.037   Durbin-Watson:                   2.023
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              744.486
Skew:                           1.309   Prob(JB):                    2.17e-162
Kurtosis:                       6.314   Cond. No.                         294.
==============================================================================

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

In [76]:
```
# The prediction by model_6
x_test = sm.add_constant(x_test)
multiple_linear_pred = MultiLinear_6.predict(x_test)
```

I will stop here since all the variables left in model_6 are with a significant P value of regression coefficient. The optimal multiple linear regression model would be model_6.

6.2 Ridge Regression

In [77]:
```
# Using 'age', 'bmi', 'children' and 'smoking' as predictors as stated in model_6 of multiple linear regression
# The training set and testing set will be the same

# Fit the Ridge model with training set
ridge_model = Ridge().fit(x_train, y_train)
# Predicting the testing set
ridge_pred = ridge_model.predict(x_test)
```

6.3 Lasso

In [78]:
```
# Using 'age', 'bmi', 'children' and 'smoking' as predictors as stated in model_6 of multiple linear regression
# The training set and testing set will be the same

# Fit the Ridge model with training set
lasso_model = Lasso().fit(x_train, y_train)
# Predicting the testing set
lasso_pred = lasso_model.predict(x_test)
```

In [79]:
```
# Comparing prediction accuracy

# define a function to get the root mean sqaured error of the model
def rmse(y_test, y_pred):
    """function to return root mean squared error"""
    mse = metrics.mean_squared_error(y_test, y_pred)
    return mse ** (1/2)
```

6.4 Regression Tree

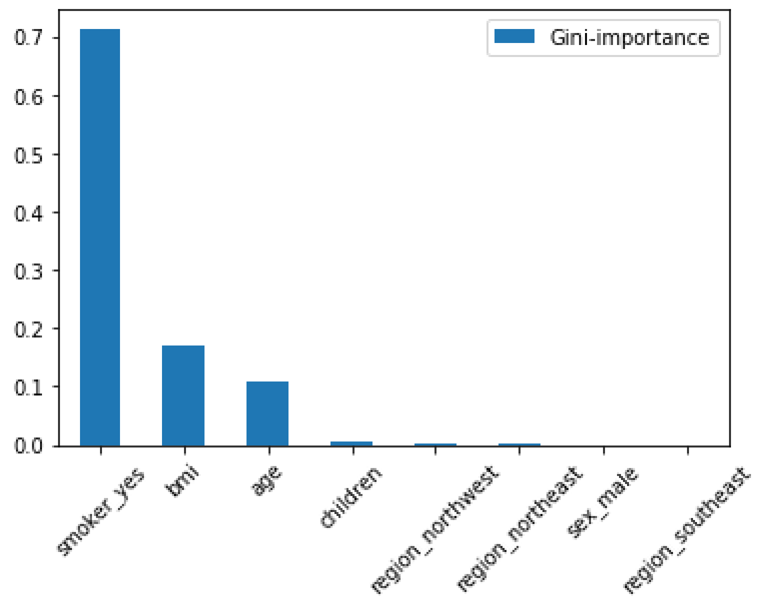
In [80]:
```
# First I will define two functions to help me get the optimized estimator parameters and the importance of features
def show_optimized_parameters(model, params_tree, x_train, y_train):
    """function that takes a model, a dictionary of parameters of tree model, and traing x and y as parameters and
    print the optimized parameters
    """
    grid_tree = GridSearchCV(model, params_tree)
    grid_tree.fit(x_train, y_train)
    print(grid_tree.best_estimator_)

def show_feature_importance(fitted_model, x_train):
    """function that takes a fitted model and training features as parameters and print a table and a graph showing
    feature Gini-importance rank
    """
    feats = {}
    for feature, importance in zip(x_train.columns, rt_model.feature_importances_):
        feats[feature] = importance #add the name/value pair
    importances = pd.DataFrame.from_dict(feats, orient='index').rename(columns={0: 'Gini-importance'})
    importances.sort_values(by='Gini-importance',ascending=False).plot(kind='bar', rot=45)
    print(importances.sort_values(by='Gini-importance',ascending=False))
    plt.show()
```

In [81]:
```
# Including all variables
X = df_1[['age','bmi','children','sex_male','smoker_yes','region_northeast','region_northwest','region_southeast']]
Y = df_1.iloc[:, 3]

# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)

# Exploring the optimized parameters for the regression tree
tree = DecisionTreeRegressor()
params_tree = {"max_depth":np.arange(2,6)
              }
show_optimized_parameters(tree, params_tree, x_train, y_train)
```

```
DecisionTreeRegressor(criterion='mse', max_depth=3, max_features=None,
           max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           presort=False, random_state=None, splitter='best')
```

In [82]:
```
# We will use the optimized parameters obtained above: mean squered error == varince as spliting criteria,
# max_depth=5 with others parameters set as default
tree = DecisionTreeRegressor(criterion="mse", max_depth=5)

# Fit the model with
rt_model = tree.fit(x_train,y_train)

# Make predictions on testing set
rt_pred = rt_model.predict(x_test)

# Show the importance of features
show_feature_importance(rt_model, x_train)

# Show the test RMSE
rmse(y_test,rt_pred)
```

```
                  Gini-importance
smoker_yes               0.711836
bmi                      0.169455
age                      0.110036
children                 0.005412
region_northwest         0.001911
region_northeast         0.001350
sex_male                 0.000000
region_southeast         0.000000
```



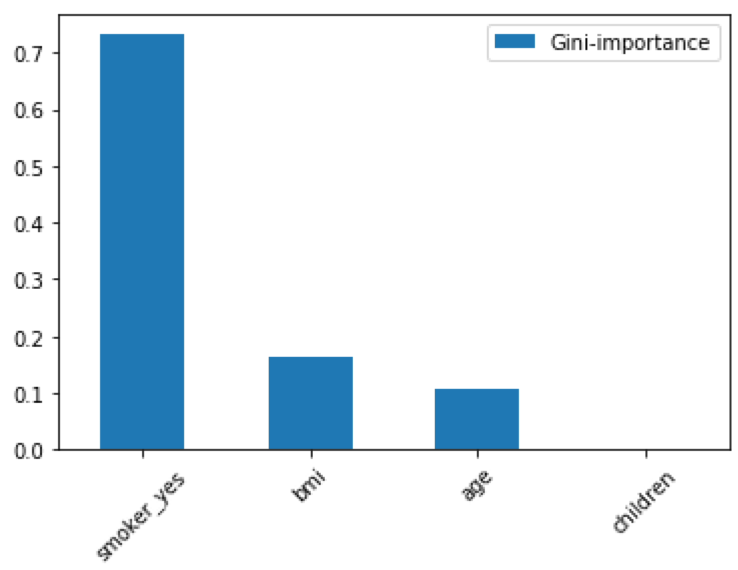
Out[82]: 5174.06371948571

In [83]:
```
# 'gender' and 'region' are of no importance as shown above, so I will drop these features.

# Using 'age', 'bmi', 'children' and 'smoking' as predictors as stated in model_6 of multiple linear regression
X = df_1[['age','bmi','children','smoker_yes']]
Y = df_1['charges']

# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)

# Exploring the optimized parameters for the regression tree
tree = DecisionTreeRegressor()
params_tree = {"max_depth":np.arange(2,10),
              }
show_optimized_parameters(tree, params_tree, x_train, y_train)
```

```
DecisionTreeRegressor(criterion='mse', max_depth=3, max_features=None,
           max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           presort=False, random_state=None, splitter='best')
```

In [84]:
```
# Set the regression tree to the opitimized parameters obtained above
tree = DecisionTreeRegressor(criterion="mse",max_depth=3)

#Fit the model
rt_model = tree.fit(x_train,y_train)

#Make predictions on testing set
rt_pred = rt_model.predict(x_test)

#Show the importance of features
show_feature_importance(rt_model, x_train)

# Calculate the root mean squared error
rmse(y_test,rt_pred)
```

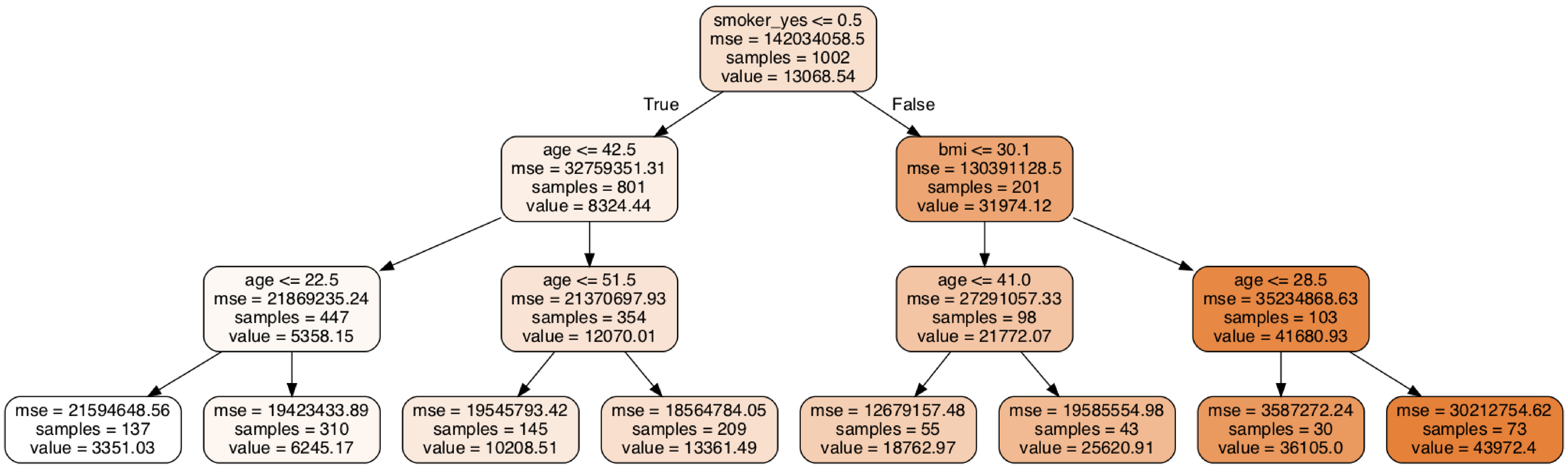
```
            Gini-importance
smoker_yes         0.732004
bmi                0.162130
age                0.105866
children           0.000000
```



Out[84]: 5198.212590616661

In [85]:
```
# Visualizing the regression tree

# Create DOT data
from sklearn.tree import export_graphviz
dot_data = export_graphviz(rt_model, out_file=None, feature_names = x_train.columns,
                rounded = True, proportion = False, precision = 2, filled = True)

# Draw graph
import pydotplus
graph = pydotplus.graph_from_dot_data(dot_data)


# Show graph
from IPython.display import Image
Image(graph.create_png())
```

Out[85]:



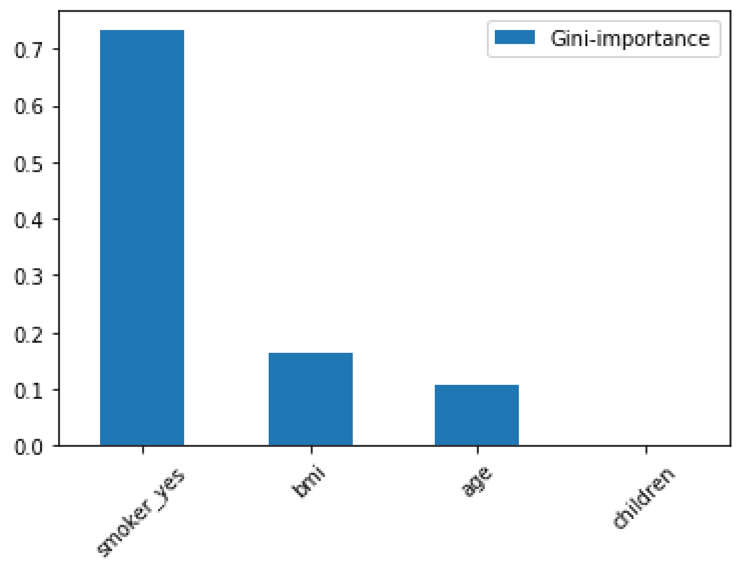
6.5 Random Forests

In [86]:
```
# Still using 'age', 'bmi', 'children' and 'smoking' as predictors.
X = df_1[['age','bmi','children','smoker_yes']]
Y = df_1['charges']

# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)

# Exploring the optimized parameters for the regression tree
rf=RandomForestRegressor()
params_tree = {"n_estimators":np.arange(10,100),
               "min_samples_leaf":np.arange(1,8)
               }
show_optimized_parameters(rf, params_tree, x_train, y_train)
```

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=7, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=54, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
```

In [103]:
```
#Call training model, B=54, m=auto
rf = RandomForestRegressor(n_estimators=54, oob_score=True, min_samples_leaf=7)
rf_model=rf.fit(x_train, y_train)

#Make predictions on testing set
rf_pred = rf_model.predict(x_test)

#Show the importance of features
show_feature_importance(rf_model, x_train)

# Check rmse
rmse(y_test, rf_pred)
```

	Gini-importance
smoker_yes	0.732004
bmi	0.162130
age	0.105866
children	0.000000



Out[103]: 4894.150435558846

6.6 Boosting for regression trees

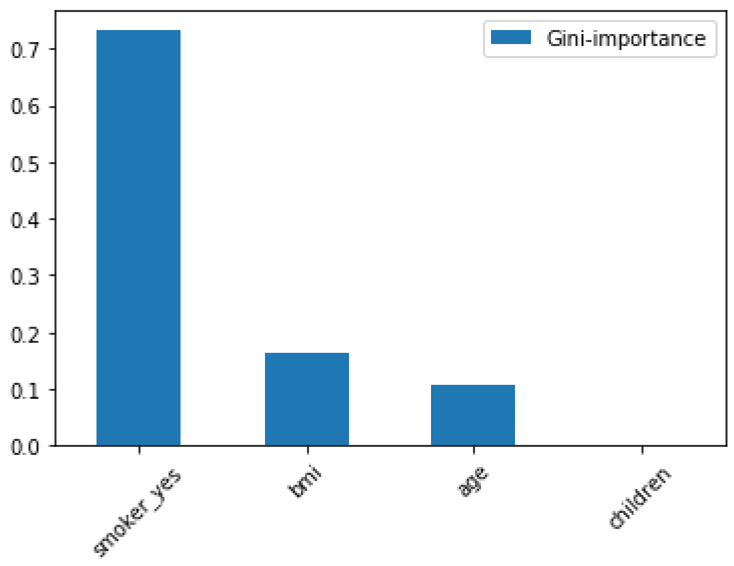
Adaboost regression tree

In [88]:
```
##### Adaboost model

# Using 'age', 'bmi', 'children' and 'smoking' as predictors.
X = df_l[['age','bmi','children','smoker_yes']]
Y = df_l['charges']

# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)

# Exploring the optimized parameters for the regression tree
adaboost = AdaBoostRegressor()
params_tree = {"n_estimators":np.arange(10,100),
               "learning_rate":(1, 0.01, 0.001)
              }
show_optimized_parameters(adaboost, params_tree, x_train, y_train)
```

```
AdaBoostRegressor(base_estimator=None, learning_rate=0.001, loss='linear',
         n_estimators=55, random_state=None)
```

In [106]:
```
#Call training model, B=55, λ=0.001, d=1
adaboost = AdaBoostRegressor(n_estimators=55, learning_rate=0.001)
adaboost_model=adaboost.fit(x_train, y_train)

#Make predictions on testing set
adaboost_pred = adaboost_model.predict(x_test)

#Show the importance of features
show_feature_importance(adaboost_model, x_train)

# Check rmse
rmse(y_test, adaboost_pred)
```

	Gini-importance
smoker_yes	0.732004
bmi	0.162130
age	0.105866
children	0.000000



Out[106]: 5087.88396578332

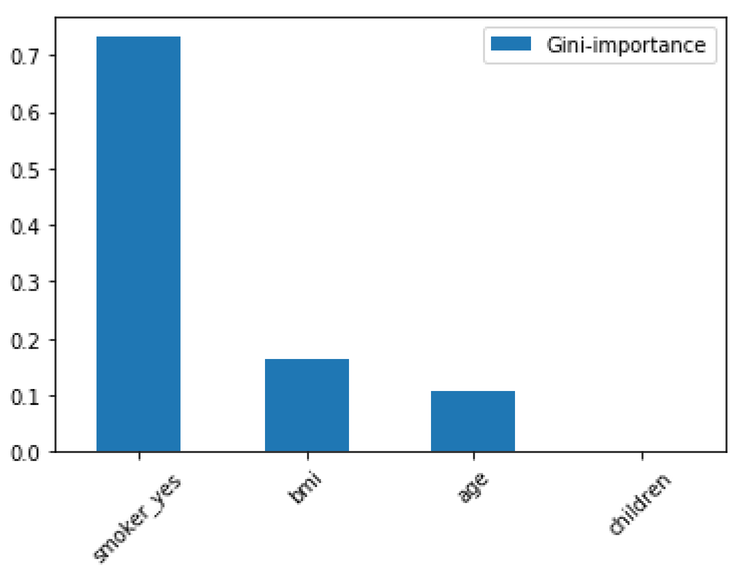
Gradient Boosting Regression Tree

In [90]:
```
# Gradient Boosting Regression Tree

# Using 'age', 'bmi', 'children' and 'smoking' as predictors.
X = df_l[['age','bmi','children','smoker_yes']]
Y = df_l['charges']

# Splitting the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state = 0)

# Exploring the optimized parameters for the regression tree
gbrt = GradientBoostingRegressor()
params_tree = {"n_estimators":np.arange(10,500),
               "learning_rate":(0.01, 0.001)
              }
show_optimized_parameters(gbrt, params_tree, x_train, y_train)
```

```
GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
             learning_rate=0.01, loss='ls', max_depth=3, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=1,
             min_samples_split=2, min_weight_fraction_leaf=0.0,
             n_estimators=389, n_iter_no_change=None, presort='auto',
             random_state=None, subsample=1.0, tol=0.0001,
             validation_fraction=0.1, verbose=0, warm_start=False)
```

In [107]:
```
#Call training model, B=389, λ=0.01, d=1
gbrt = GradientBoostingRegressor(n_estimators=389, learning_rate=0.01)
gbrt_model=gbrt.fit(x_train, y_train)

#Make predictions on testing set
gbrt_pred = gbrt_model.predict(x_test)

#Show the importance of features
show_feature_importance(gbrt_model, x_train)

# Check rmse
rmse(y_test, gbrt_pred)
```

	Gini-importance
smoker_yes	0.732004
bmi	0.162130
age	0.105866
children	0.000000



Out[107]: 4906.556648513094

6.7 Comparison of the models

In [108]:
```
# Generating a dataframe of each model's residual mean squared error
performanceModel = pd.DataFrame({"model":["multiple linear regression",
                                          "ridge regression",
                                          "lasso",
                                          "regression tree",
                                          "randomforests",
                                          "adaboost regression tree",
                                          "gradient boosting regression tree"],
                                 "rmse":[rmse(y_test, multiple_linear_pred),
                                        rmse(y_test, ridge_pred),
                                        rmse(y_test, lasso_pred),
                                        rmse(y_test, rt_pred),
                                        rmse(y_test, rf_pred),
                                        rmse(y_test, adaboost_pred),
                                        rmse(y_test, gbrt_pred )]
                                })
print(performanceModel)
```

```
                               model         rmse
0         multiple linear regression  6392.679054
1                   ridge regression  6391.266016
2                              lasso  6392.622143
3                    regression tree  5198.212591
4                      randomforests  4894.150436
5           adaboost regression tree  5087.883966
6  gradient boosting regression tree  4906.556649
```

Random forests model and gradient boostting regression tree both show lowerer test mean squared error compared to others.

7. GUI for Medical Cost Prediction

In [109]:

```
# Medical Cost Prediction Tool
"""Widgets:
            Title - Label
            Age - Entry
            Height - Entry
            Weight - Entry
            Smoker - CheckButton
            Number of children - Entry
            Generate result - Button
            Result - Label
"""

from tkinter import *
from tkinter.ttk import *

TEMPLATE = "The medical cost is: {0:.2f} USD (predicted by '{1}' with the test RMSE of {2:.2f})."

class PredGui():
    """Define the Prediction Interface"""

    def __init__(self, window):
        """GUI constructor"""

        # Label widget showing the title/function of GUI
        self.name_label = Label(window, text='Medical Cost / Health Insurance Prediction', font=("Arial", 22))
        self.name_label.grid(row=0, column=0, columnspan=2, pady=10)

        # Entry and Checkbutton Widgets prompting the inputs
        self.age_label = Label(window, text='Age:')
        self.age_label.grid(row=1, column=0, pady=5)
        self.age = IntVar()
        self.age_entry = Entry(window, textvariable=self.age)
        self.age_entry.grid(row=1, column=1, pady=5)

        self.height_label = Label(window, text='Height(m):')
        self.height_label.grid(row=2, column=0, pady=5)
        self.height = DoubleVar()
        self.height_entry = Entry(window, textvariable=self.height)
        self.height_entry.grid(row=2, column=1, pady=5)

        self.weight_label = Label(window, text='Weight(kg):')
        self.weight_label.grid(row=3, column=0, pady=5)
        self.weight = DoubleVar()
        self.weight_entry = Entry(window, textvariable=self.weight)
        self.weight_entry.grid(row=3, column=1, pady=5)

        self.children_label = Label(window, text='The number of children:')
        self.children_label.grid(row=4, column=0, pady=5)
        self.children = IntVar()
        self.children_entry = Entry(window, textvariable=self.children)
        self.children_entry.grid(row=4, column=1, pady=5)

        self.smoker = IntVar()
        self.smoker_button = Checkbutton(window,
                                         text='A current or previous smoker?',
                                         variable=self.smoker,
                                         onvalue=1,
                                         offvalue=0)
        self.smoker_button.grid(row=5, column=0, columnspan=2, pady=5)

        # Button widgets generating result
        self.pred_button = Button(window, text='Predict', command=self.predict)
        self.pred_button.grid(row=6, column=0, columnspan=2, pady=5,ipady=10, ipadx=10)

        # Label widgets showing result
        self.mlr_result_label = Label(window)
        self.mlr_result_label.grid(row=7, column=0, columnspan=2, pady=5, sticky='W')
        self.ridge_result_label = Label(window)
        self.ridge_result_label.grid(row=8, column=0, columnspan=2, pady=5, sticky='W')
        self.lasso_result_label = Label(window)
        self.lasso_result_label.grid(row=9, column=0, columnspan=2, pady=5, sticky='W')
        self.rt_result_label = Label(window)
        self.rt_result_label.grid(row=10, column=0, columnspan=2, pady=5, sticky='W')
        self.rf_result_label = Label(window)
        self.rf_result_label.grid(row=11, column=0, columnspan=2, pady=5, sticky='W')
        self.adaboost_result_label = Label(window)
        self.adaboost_result_label.grid(row=12, column=0, columnspan=2, pady=5, sticky='W')
        self.gbrt_result_label = Label(window)
        self.gbrt_result_label.grid(row=13, column=0, columnspan=2, pady=5, sticky='W')

        # Further adjusting the layout
        window.columnconfigure(0, weight=1)
        window.columnconfigure(1, weight=1)
        window.rowconfigure((0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13), weight=1)


    def predict(self):
        """Method to predict based on input from the user"""
        age = self.age.get()
        height = self.height.get()
        weight = self.weight.get()
        bmi =  weight / height ** 2
        children = self.children.get()
        smoker = self.smoker.get()
        data_lm = [(1, age, bmi, children, smoker)]
        df_lm = pd.DataFrame(data_lm, columns = ['const','age', 'bmi', 'children', 'smoker'])
        x_test_lm = df_lm[['const','age','bmi','children','smoker']]
        data = [(age, bmi, children, smoker)]
        df = pd.DataFrame(data, columns = ['age', 'bmi', 'children', 'smoker'])
        x_test = df[['age','bmi','children','smoker']]
        mlr_prediction = MultiLinear_6.predict(x_test_lm)
        ridge_prediction = ridge_model.predict(x_test_lm)
        lasso_prediction = lasso_model.predict(x_test_lm)
        rt_prediction = rt_model.predict(x_test)
        rf_prediction = rf_model.predict(x_test)
        adaboost_prediction = adaboost_model.predict(x_test)
        gbrt_prediction = gbrt_model.predict(x_test)
        self.mlr_result_label['text'] = TEMPLATE.format(list(mlr_prediction)[0],
                                                        "Multiple Linear Regression",
                                                        rmse(y_test, multiple_linear_pred))
        self.ridge_result_label['text'] = TEMPLATE.format(list(ridge_prediction)[0],
                                                          "Ridge Regression",
                                                          rmse(y_test, ridge_pred))
        self.lasso_result_label['text'] = TEMPLATE.format(list(lasso_prediction)[0],
                                                          "Lasso",
                                                         rmse(y_test, lasso_pred))
        self.rt_result_label['text'] = TEMPLATE.format(list(rt_prediction)[0],
                                                       "Regression Tree",
                                                       rmse(y_test, rt_pred))
        self.rf_result_label['text'] = TEMPLATE.format(list(rf_prediction)[0],
                                                       "Random Forests",
                                                       rmse(y_test, rf_pred))
        self.adaboost_result_label['text'] = TEMPLATE.format(list(adaboost_prediction)[0],
                                                             "Adaboost Regression Tree",
                                                                rmse(y_test, adaboost_pred))
        self.gbrt_result_label['text'] = TEMPLATE.format(list(gbrt_prediction)[0],
```

```
                                                              "Gradient Boosting Regression Tree",
                                                             rmse(y_test, gbrt_pred))


def main():
    """Setup the GUI"""
    window = Tk()
    prediction = PredGui(window)
    window.mainloop()
```

In [110]:

```
# Run the GUI
main()
```

In [ ]: