Final Project Submission

Please fill out:

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- Student pace: Part time
- Scheduled project review date/time: 26/02/2023
- Instructor name: Hardik Idnani

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

# Ignores warnings
import warnings
warnings.filterwarnings('ignore')
import statsmodels.api as sm
import statsmodels.formula.api as smf
import scipy.stats as stats
import statsmodels.stats.api as sms
from statsmodels.formula.api import ols
import pylab

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_squared_error, make_scorer
from sklearn.model_selection import cross_val_score
from sklearn import metrics
```

Column Names and descriptions for Insurance Data Set

age: age of primary beneficiary

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

children: Number of children covered by health insurance / Number of dependents

smoker: Smoking

region: the beneficiary's residential area in the US, northeast, southeast, southwest, northwest.

charges: Individual medical costs billed by health insurance

Base Model

In [2]:
```
dfi=pd.read_csv('insurance_prl.csv')
```

In [3]:
```
dfi
```

Out[3]:

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

1338 rows × 7 columns

In [4]:
```
dfi.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
```

In [5]:
```
dfi.isnull().sum()
```

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

In [6]:
```
df=dfi.drop_duplicates()
```

In [7]:
```
df.describe()
```

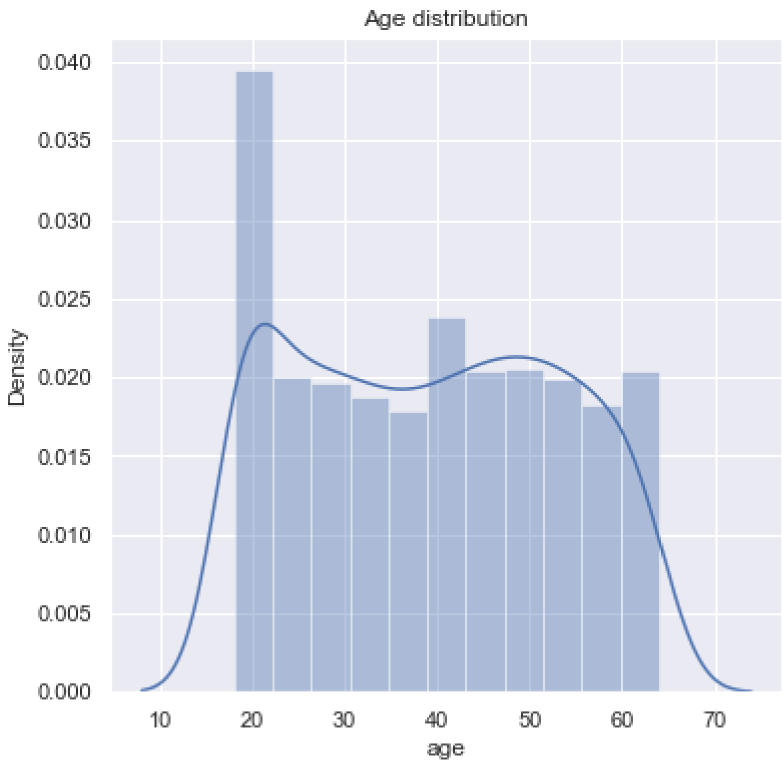
Out[7]:

	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

	age	bmi	children	charges
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

Visualization of data and checking outliners

In [8]:
```
sns.set()
plt.figure(figsize=(6,6))
sns.distplot(df['age'])
plt.title('Age distribution')
plt.show()
```

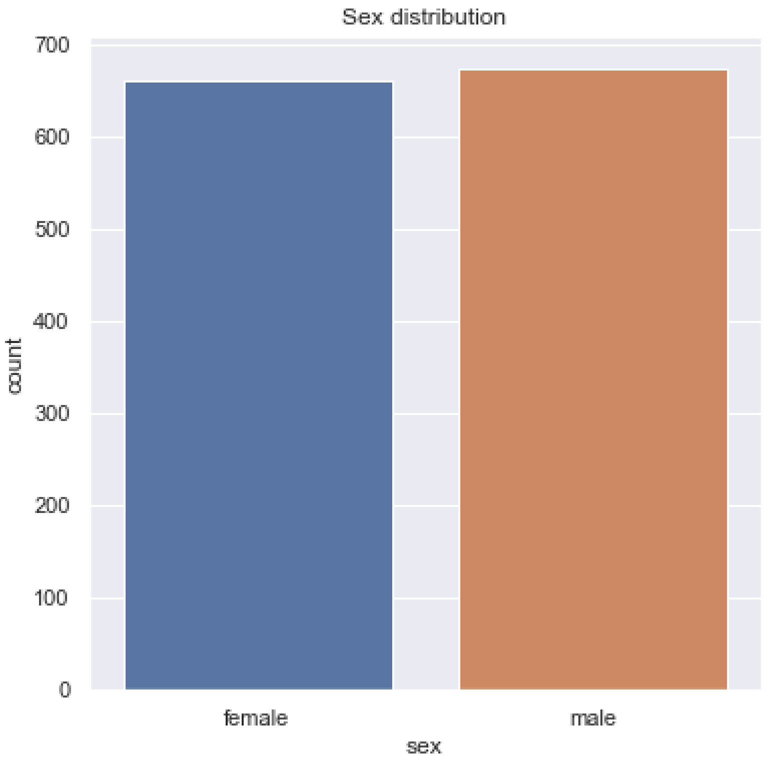


Here we can see most of our age group in our dataset is between 20-30 age group

In [9]:
```
df['sex'].value_counts()
```

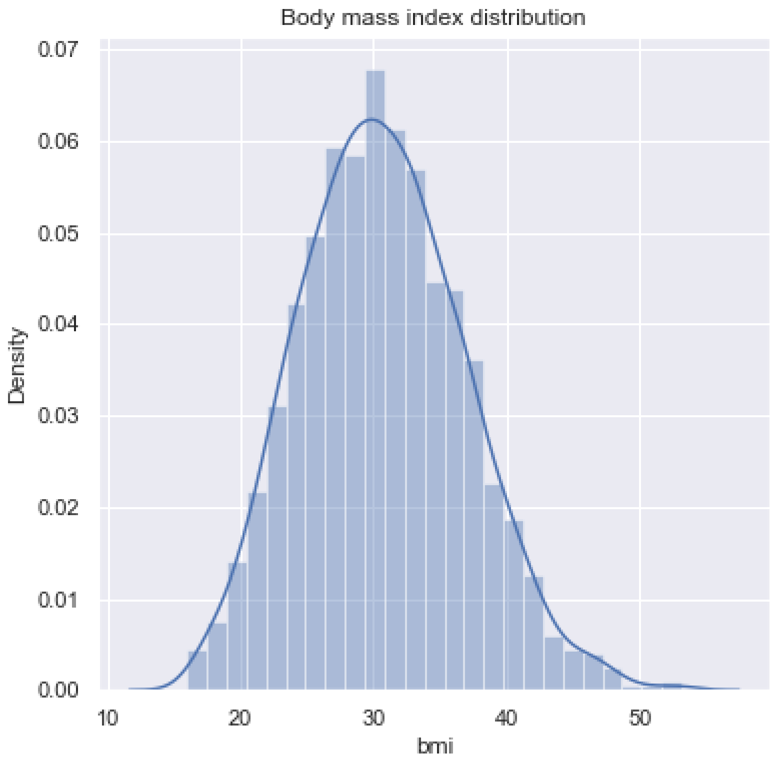
Out[9]:
```
male      675
female    662
Name: sex, dtype: int64
```

In [10]:
```
plt.figure(figsize=(6,6))
sns.countplot(x='sex',data=df)
plt.title('Sex distribution')
plt.show()
```



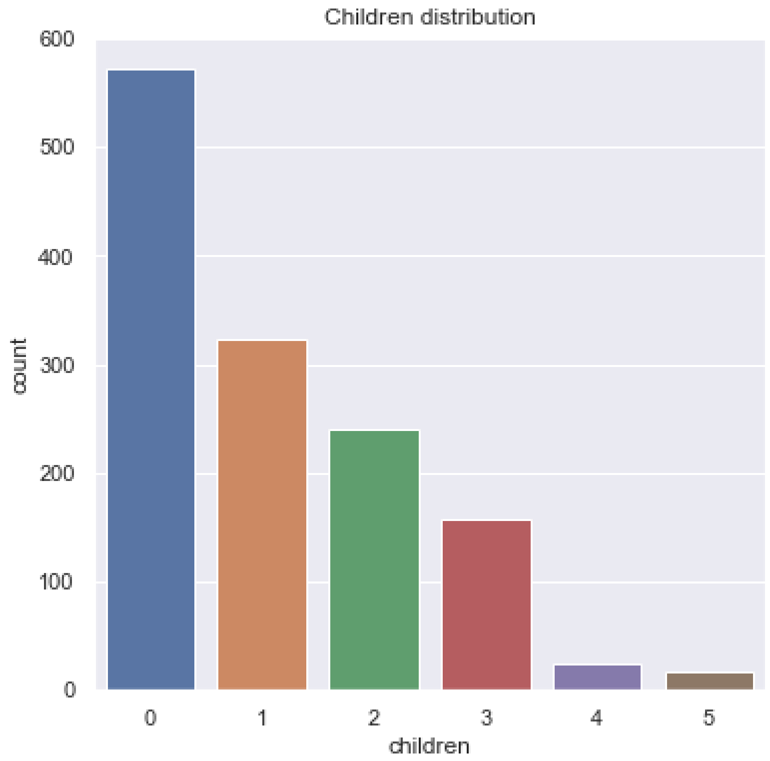
Here we can see the no of male is between 650 t0 700

In [11]:
```
sns.set()
plt.figure(figsize=(6,6))
sns.distplot(df['bmi'])
plt.title('Body mass index distribution')
plt.show()
```



Here we can see it is normally disrtibution and there is outliner

In [12]:
```
plt.figure(figsize=(6,6))
sns.countplot(x='children',data=df)
plt.title('Children distribution')
plt.show()
```



Here we can see there are more number of peole who no children

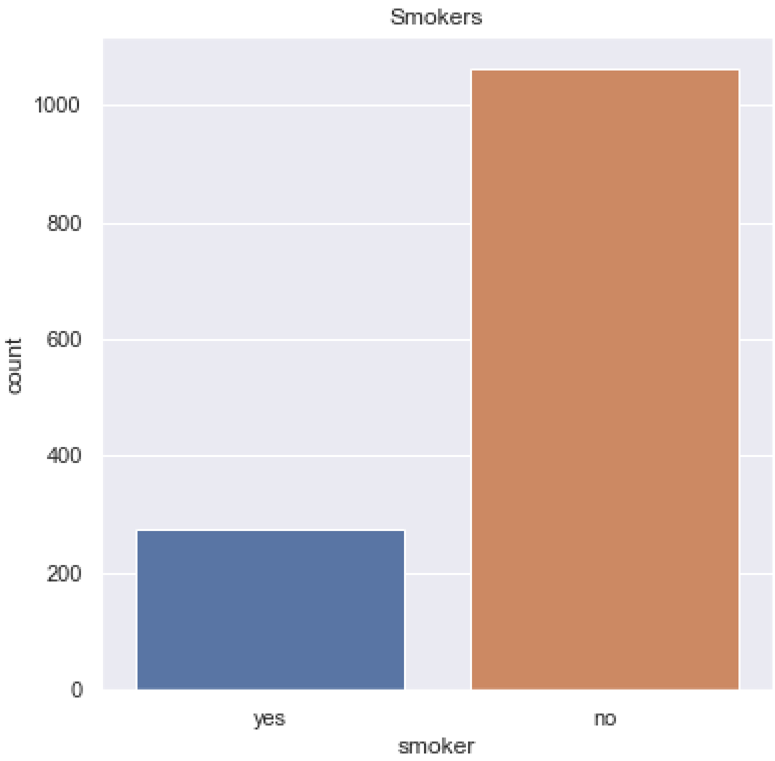
In [13]:
```
df['children'].value_counts()
```

Out[13]:
```
0    573
1    324
2    240
3    157
4     25
5     18
Name: children, dtype: int64
```

In [14]:
```
df['smoker'].value_counts()
```

Out[14]:
```
no     1063
yes     274
Name: smoker, dtype: int64
```

In [15]:
```
plt.figure(figsize=(6,6))
sns.countplot(x='smoker',data=df)
plt.title('Smokers')
plt.show()
```

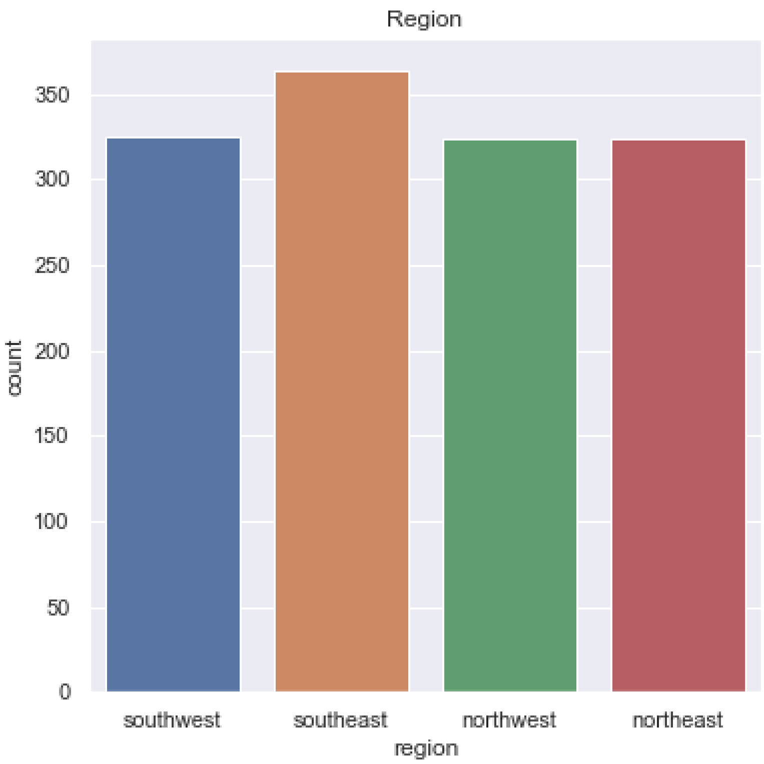


Here we can see there are less no:of smokers

In [16]:
```
df['region'].value_counts()
```

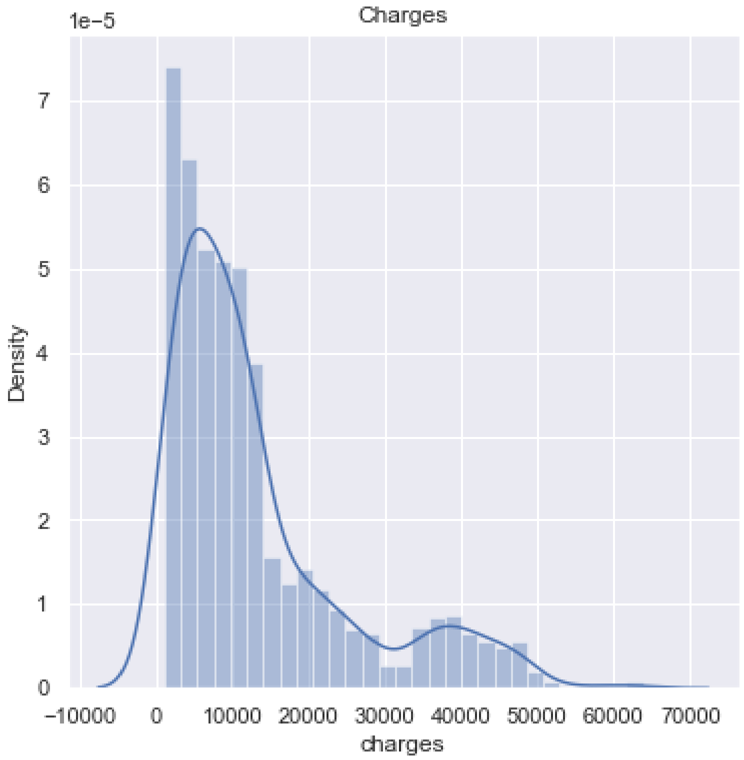
Out[16]:
```
southeast    364
southwest    325
northeast    324
northwest    324
Name: region, dtype: int64
```

In [17]:
```
plt.figure(figsize=(6,6))
sns.countplot(x='region',data=df)
plt.title('Region')
plt.show()
```



In [18]:

```
sns.set()
plt.figure(figsize=(6,6))
sns.distplot(df['charges'])
plt.title('Charges')
plt.show()
```



There are three catogorical columns- smokers, region and sex Here we will replace the values to numerical values

In [19]:

```
#Changing the catagorical variable to numerical variable

df.replace({'sex':{'male':0,'female':1}},inplace=True)
df.replace({'smoker':{'yes':0,'no':1}},inplace=True)
df.replace({'region':{'southwest':1,'southeast':2,'northwest':3,'northeast':4}},inpl
```

In [20]:

```
df
```

Out[20]:

	age	sex	bmi	children	smoker	region	charges
0	19	1	27.900	0	0	1	16884.92400
1	18	0	33.770	1	1	2	1725.55230
2	28	0	33.000	3	1	2	4449.46200
3	33	0	22.705	0	1	3	21984.47061
4	32	0	28.880	0	1	3	3866.85520
...	...	...	...	...	...	...	...
1333	50	0	30.970	3	1	3	10600.54830
1334	18	1	31.920	0	1	4	2205.98080
1335	18	1	36.850	0	1	2	1629.83350
1336	21	1	25.800	0	1	1	2007.94500
1337	61	1	29.070	0	0	3	29141.36030

1337 rows × 7 columns

In [21]:
```
outcome = 'charges'
x_cols = df.drop('charges',axis=1)
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=df).fit()
model.summary()
```

Out[21]:

OLS Regression Results

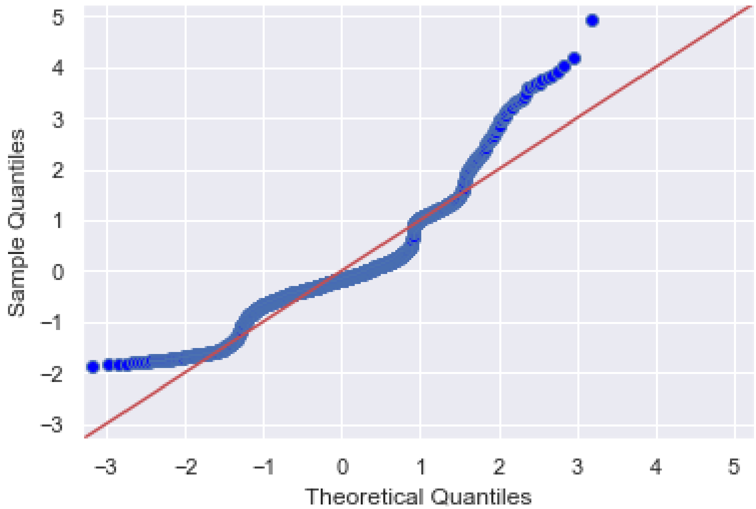
Dep. Variable:	charges	**R-squared:**	0.751
Model:	OLS	**Adj. R-squared:**	0.749
Method:	Least Squares	**F-statistic:**	667.0
Date:	Sun, 26 Feb 2023	**Prob (F-statistic):**	0.00
Time:	21:07:09	**Log-Likelihood:**	-13539.
No. Observations:	1337	**AIC:**	2.709e+04
Df Residuals:	1330	**BIC:**	2.713e+04
Df Model:	6		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	1.046e+04	1126.526	9.287	0.000	8252.296	1.27e+04
age	257.2032	11.899	21.616	0.000	233.861	280.546
sex	129.4009	333.059	0.389	0.698	-523.978	782.779
bmi	332.5957	27.733	11.993	0.000	278.191	387.000
children	478.7717	137.732	3.476	0.001	208.576	748.967
smoker	-2.382e+04	412.051	-57.806	0.000	-2.46e+04	-2.3e+04
region	354.0097	151.995	2.329	0.020	55.834	652.185

Omnibus:	298.466	**Durbin-Watson:**	2.088
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	711.712
Skew:	1.206	**Prob(JB):**	2.84e-155
Kurtosis:	5.637	**Cond. No.**	352.

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

In [22]:
```
# Q-Q plot and Regression plot
model=smf.ols(formula,data=df).fit()
fig = sm.graphics.qqplot(model.resid, line='45',fit=True);
```



Creating Dummies

In [23]:
```
dummy_1= pd.get_dummies(data=df, columns=['sex'],prefix='s', drop_first=True)
dummy_1
dummy_2= pd.get_dummies(data=dummy_1, columns=['smoker'],prefix='sm', drop_first=Tru
dummy_2
dummy_3= pd.get_dummies(data=dummy_2, columns=['children'],prefix='ch', drop_first=T
dummy_3
dummy_4= pd.get_dummies(data=dummy_3, columns=['region'],prefix='reg', drop_first=Tr
dummy_4
```

Out[23]:

	age	bmi	charges	s_1	sm_1	ch_1	ch_2	ch_3	ch_4	ch_5	reg_2	reg_3	reg_4
0	19	27.900	16884.92400	1	0	0	0	0	0	0	0	0	0
1	18	33.770	1725.55230	0	1	1	0	0	0	0	1	0	0
2	28	33.000	4449.46200	0	1	0	0	1	0	0	1	0	0
3	33	22.705	21984.47061	0	1	0	0	0	0	0	0	1	0
4	32	28.880	3866.85520	0	1	0	0	0	0	0	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1333	50	30.970	10600.54830	0	1	0	0	1	0	0	0	1	0
1334	18	31.920	2205.98080	1	1	0	0	0	0	0	0	0	1
1335	18	36.850	1629.83350	1	1	0	0	0	0	0	1	0	0
1336	21	25.800	2007.94500	1	1	0	0	0	0	0	0	0	0
1337	61	29.070	29141.36030	1	0	0	0	0	0	0	0	1	0

1337 rows × 13 columns

In [24]:
```
outcome = 'charges'
x_cols = dummy_4.drop('charges',axis=1)
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=dummy_4).fit()
model.summary()
```

Out[24]:

OLS Regression Results

Dep. Variable:	charges	**R-squared:**	0.752

Model:	OLS	**Adj. R-squared:**	0.750
Method:	Least Squares	**F-statistic:**	334.1
Date:	Sun, 26 Feb 2023	**Prob (F-statistic):**	0.00
Time:	21:07:10	**Log-Likelihood:**	-13535.
No. Observations:	1337	**AIC:**	2.710e+04
Df Residuals:	1324	**BIC:**	2.716e+04
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.083e+04	1077.752	10.050	0.000	8716.671	1.29e+04
age	257.1083	11.928	21.556	0.000	233.709	280.507
bmi	336.9626	28.624	11.772	0.000	280.809	393.116
s_1	126.4424	333.085	0.380	0.704	-526.990	779.875
sm_1	-2.384e+04	414.334	-57.527	0.000	-2.46e+04	-2.3e+04
ch_1	389.0683	421.630	0.923	0.356	-438.068	1216.205
ch_2	1633.7392	466.970	3.499	0.000	717.657	2549.822
ch_3	962.4373	548.394	1.755	0.079	-113.378	2038.253
ch_4	2945.1623	1239.673	2.376	0.018	513.225	5377.099
ch_5	1114.2598	1456.578	0.765	0.444	-1743.193	3971.712
reg_2	-80.4056	470.732	-0.171	0.864	-1003.867	843.056
reg_3	576.4105	478.999	1.203	0.229	-363.270	1516.091
reg_4	952.9217	478.328	1.992	0.047	14.558	1891.285

Omnibus:	293.461	**Durbin-Watson:**	2.085
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	693.568
Skew:	1.190	**Prob(JB):**	2.48e-151
Kurtosis:	5.604	**Cond. No.**	454.

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

In [25]:
```
dff1=dummy_4.drop(['s_1','ch_1','ch_5','reg_2','reg_3','reg_4'],axis=1)
dff1
```

Out[25]:

	age	bmi	charges	sm_1	ch_2	ch_3	ch_4
0	19	27.900	16884.92400	0	0	0	0
1	18	33.770	1725.55230	1	0	0	0
2	28	33.000	4449.46200	1	0	1	0

	age	bmi	charges	sm_1	ch_2	ch_3	ch_4
3	33	22.705	21984.47061	1	0	0	0
4	32	28.880	3866.85520	1	0	0	0
...	...	...	...	...	...	...	...
1333	50	30.970	10600.54830	1	0	1	0
1334	18	31.920	2205.98080	1	0	0	0
1335	18	36.850	1629.83350	1	0	0	0
1336	21	25.800	2007.94500	1	0	0	0
1337	61	29.070	29141.36030	0	0	0	0

1337 rows × 7 columns

In [26]:

```
outcome = 'charges'
x_cols = dff1.drop('charges',axis=1)
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=dff1).fit()
model.summary()
```

Out[26]:

OLS Regression Results

Dep. Variable:	charges	**R-squared:**	0.750
Model:	OLS	**Adj. R-squared:**	0.749
Method:	Least Squares	**F-statistic:**	666.4
Date:	Sun, 26 Feb 2023	**Prob (F-statistic):**	0.00
Time:	21:07:10	**Log-Likelihood:**	-13539.
No. Observations:	1337	**AIC:**	2.709e+04
Df Residuals:	1330	**BIC:**	2.713e+04
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.184e+04	986.732	12.004	0.000	9908.977	1.38e+04
age	258.1182	11.913	21.667	0.000	234.748	281.489
bmi	319.6454	27.372	11.678	0.000	265.948	373.343
sm_1	-2.378e+04	411.730	-57.763	0.000	-2.46e+04	-2.3e+04
ch_2	1477.7344	440.236	3.357	0.001	614.101	2341.367
ch_3	848.3077	525.419	1.615	0.107	-182.433	1879.049
ch_4	2834.1479	1229.852	2.304	0.021	421.486	5246.810

Omnibus:	295.108	**Durbin-Watson:**	2.082
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	697.275
Skew:	1.197	**Prob(JB):**	3.88e-152

Kurtosis:	5.605	**Cond. No.**	381.

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

In [27]:
```
dff2=dff1.drop(['ch_3'],axis=1)
dff2
```

Out[27]:

	age	bmi	charges	sm_1	ch_2	ch_4
0	19	27.900	16884.92400	0	0	0
1	18	33.770	1725.55230	1	0	0
2	28	33.000	4449.46200	1	0	0
3	33	22.705	21984.47061	1	0	0
4	32	28.880	3866.85520	1	0	0
...	...	...	...	...	...	...
1333	50	30.970	10600.54830	1	0	0
1334	18	31.920	2205.98080	1	0	0
1335	18	36.850	1629.83350	1	0	0
1336	21	25.800	2007.94500	1	0	0
1337	61	29.070	29141.36030	0	0	0

1337 rows × 6 columns

In [28]:
```
outcome = 'charges'
x_cols = dff2.drop('charges',axis=1)
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=dff2).fit()
model.summary()
```

Out[28]:

OLS Regression Results

Dep. Variable:	charges	**R-squared:**	0.750
Model:	OLS	**Adj. R-squared:**	0.749
Method:	Least Squares	**F-statistic:**	798.2
Date:	Sun, 26 Feb 2023	**Prob (F-statistic):**	0.00
Time:	21:07:10	**Log-Likelihood:**	-13540.
No. Observations:	1337	**AIC:**	2.709e+04
Df Residuals:	1331	**BIC:**	2.712e+04
Df Model:	5		
Covariance Type:	nonrobust		

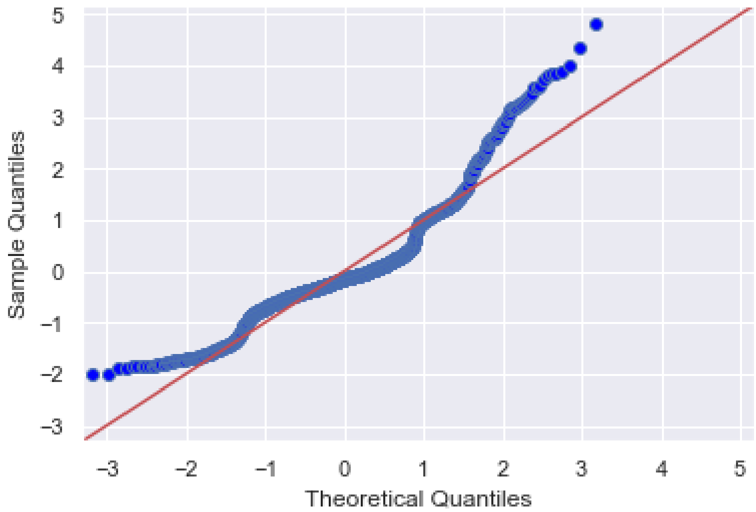
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.195e+04	985.355	12.123	0.000	1e+04	1.39e+04

age	259.3494	11.896	21.802	0.000	236.013	282.686
bmi	319.6190	27.389	11.670	0.000	265.889	373.349
sm_1	-2.381e+04	411.564	-57.859	0.000	-2.46e+04	-2.3e+04
ch_2	1352.3495	433.594	3.119	0.002	501.748	2202.951
ch_4	2712.5801	1228.286	2.208	0.027	302.993	5122.167

Omnibus:	291.437	**Durbin-Watson:**	2.077
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	681.388
Skew:	1.187	**Prob(JB):**	1.09e-148
Kurtosis:	5.568	**Cond. No.**	380.

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

In [29]:
```
# Q-Q plot and Regression plot
model=smf.ols(formula,data=dff2).fit()
fig = sm.graphics.qqplot(model.resid, line='45',fit=True);
```



In [30]:
```
#Independent varialbe
X=dff2.drop(columns='charges',axis=1)
#Dependent variable
y=dff2['charges']
```

In [31]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=1
```

In [32]:
```
lm=LinearRegression()
lm.fit(X_train,y_train)
```

Out[32]:
```
LinearRegression()
```

In [33]:
```
y_predict_train= lm.predict(X_train)
y_predict_train
```

Out[33]:
```
array([11296.01066886,  5381.7702395 , 15554.13010863, ...,
       13686.1410004 ,  5677.50932887,  9294.23709869])
```

In [34]:
```
y_predict_test= lm.predict(X_test)
acc_linreg=metrics.r2_score(y_test,y_predict_test)
y_predict_test
```

Out[34]:
```
array([ 9962.96020182,  2690.26793395,  3696.1971618 , 14225.13322934,
        8423.72214909,   243.3035617 , 15105.77784165,  6503.95195717,
       10602.82309429,  5735.97605701, 10235.48391501, 11493.15417901,
       14767.69728615, 12615.5202823 ,  9502.85753452, 37487.76580082,
        8550.34207778, 12674.03465875, 15550.27572744, 14292.34665875,
         275.22994067, 28695.83887208, 33253.25727924, 13393.12018563,
       26798.19559806, 25612.52096597, 11805.44977087, 13351.37059694,
        6443.20106603,  6098.73224034,  5670.78798593,  8880.97267559,
        3047.14150664,  3296.8691343 ,   333.39929453,  5225.15399356,
        8161.54212612, 10979.21829894, 14077.8079138 ,   410.05234148,
       10763.64161513, 33509.32265766,  9062.90694622,  9714.56788731,
       31287.60949181,  6537.59437036, 28030.42592099,  2949.18832429,
       33632.96263595,  2151.02885014,  -410.9894361 ,  3052.82491072,
        7069.43401588,  9291.62894163,  3462.1844332 , 14168.5460435 ,
       30423.42321427, 10701.07365093, 11004.76835756,  2378.36788409,
       11857.63834638,  7416.90654063, 29899.89902952, 13437.94502133,
       15714.12184699, 16016.76666492,  4311.29820855,  6151.4264754 ,
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       13142.99701597, 38952.61106996,  2002.76376345,  2921.17879576,
       14296.25155936,  6021.97815456, 11781.92507058,  7390.50175558,
        7880.29561132,  7336.74413507,  5125.90289445, -2119.24848178,
        5583.3628794 ,  8029.28931278,  5869.90920609,  2480.27648648,
        6104.61197986,  7501.11966283, 36066.53484173,  4087.91172351,
        3215.96616416, 34561.15035856,  4984.96415117, 10221.28871471,
       12071.73390101,  8191.70195145,  5433.76247957,  8683.58231058,
       12732.50138689, 38859.94574967, 11921.05986382, 14632.97305306,
       24447.01036271, 12473.19740437,  5270.4368405 ,  9403.16154719,
       27467.16842717,  7308.82082444, 10674.53330176, 12771.64281852,
       29130.40343059,  5817.17640144,  4570.06991175, 12763.78536899,
       12180.79391363, 14765.95448117,  8019.79917581, 14336.59156683,
        2402.93052325, 12126.09652198,  4479.4804692 , 11778.82320379,
        4412.11835265, 11729.43912079, 29498.85496781, 29265.63332322,
        9919.08708709,  5571.99607126,  5898.32622645,  9221.2897458 ,
        3225.15892684,  3875.0533143 ,  3244.38318451, 37498.08272027,
        9703.20107917,  9203.74582386, 36778.10794166, 14815.57346921,
       11147.79610159,  3030.09129443, 14503.8221065 ,  6066.35979995,
       39016.8593699 ,  6612.86445585,  6182.10663023, 11512.97318524,
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        7885.57152357, 32216.89762254,  7896.69147685,  8107.72086318,
        5005.1786994 , 12846.46684259, 30457.63375624,  2536.07258833,
       18993.67919057, 32008.37535443,  4894.22602147, 14063.57414392,
       14653.12513206,  3684.83035366,  1500.19469153, 10715.6524434 ,
       13557.64440052,  1999.25440484,  5095.68192406,  8825.27474147,
        8810.2618374 , 30709.42531181, 29603.51754329, 13268.92402838,
         317.23833405,  7690.40572344,  4307.14645307, 35569.25363187,
        1360.72682552, 12636.91858544,  4900.20679982, 27256.53171172,
       30260.67750283, 27380.82890781, 16554.62278727, 12467.74890534,
       27937.11820384,  9383.93728951, 28949.42088093,  4707.31321288,
       14878.68566256, 34606.81679769,  2311.15445469, 11867.17613164,
       11178.83322883, 11830.90166175, 11383.93235623, 12690.73984838,
        4422.20036706, 25181.31707893, 10794.38136809,   220.56994542,
        6342.92227995,  6233.84914431, 11247.52778741, 14583.58897005,
        5828.54320958, 26467.13375977, 11699.98416156,  4430.50387802,
        1985.71355123, 10696.97241487, 16924.29664899,  7411.71684628,
        9472.69770919, 11613.11236289,  9101.34351174,  7686.99453255,
        4892.34935029,  1976.52078855, 12758.94069723,  9900.44275704,
        4106.7909586 ,  6600.76903294,  5940.52070337,  8798.73439229,
       10512.28130004,  7955.10768557, 12899.14912783, 33015.14331459,
       11312.22214877,  3180.82780086, 11878.1116993 ,  5326.46784739,
        4168.07412907, 13577.56157448,  4188.63369989,  4954.86679508,
       16138.93746385,  5614.44765495, 10768.54588502,  2431.64491789,
       15387.43184828,  9167.47135397,  2609.21627666,  6824.14356816,
       11659.90295878,  5070.77426231,  9216.64428059,  6066.85350968,
```

```
10338.13308198, 13126.74983759, 31075.49164719,  3684.92852138,
 1296.87406758, 34673.14097536, 28911.97173486, 13584.67845943,
14989.78415652,  -391.71465901, 28065.2192617 , 12504.86497865])
```

In [35]:

```
#model evaluation
print('R^2:',metrics.r2_score(y_train, y_predict_train))
print('Adjusted R^2:',1 - (1-metrics.r2_score(y_train, y_predict_train))*(len(y_trai
print('MAE:',metrics.mean_absolute_error(y_train, y_predict_train))
print('MSE:',metrics.mean_squared_error(y_train, y_predict_train))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_train, y_predict_train)))
```

```
R^2: 0.7475991591346649
Adjusted R^2: 0.7464119491588166
MAE: 4242.39872111041
MSE: 36658430.20228838
RMSE: 6054.620566335134
```

In [36]:

```
#model evaluation-testing prediction

print('R^2:',acc_linreg)
print('Adjusted R^2:', 1- (1-metrics.r2_score(y_test,y_predict_test))*(len(y_test)-1
print('MAE:',metrics.mean_absolute_error(y_test, y_predict_test))
print('MSE:',metrics.mean_squared_error(y_test, y_predict_test))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test, y_predict_test)))
```

```
R^2: 0.7559022400879338
Adjusted R^2: 0.7512438858911387
MAE: 4099.324686626276
MSE: 37035796.83181868
RMSE: 6085.704300392739
```

In [37]:

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

y_hat_train = linreg.predict(X_train)
y_hat_test = linreg.predict(X_test)
```

In [38]:

```
from sklearn.metrics import mean_squared_error

train_mse = mean_squared_error(y_train, y_hat_train)
test_mse = mean_squared_error(y_test, y_hat_test)
variance=train_mse-test_mse
print('Train Mean Squared Error:', train_mse)
print('Test Mean Squared Error:', test_mse)
print('Variance:',variance)
```

```
Train Mean Squared Error: 36658430.20228838
Test Mean Squared Error: 37035796.83181868
Variance: -377366.62953029573
```

In [39]:

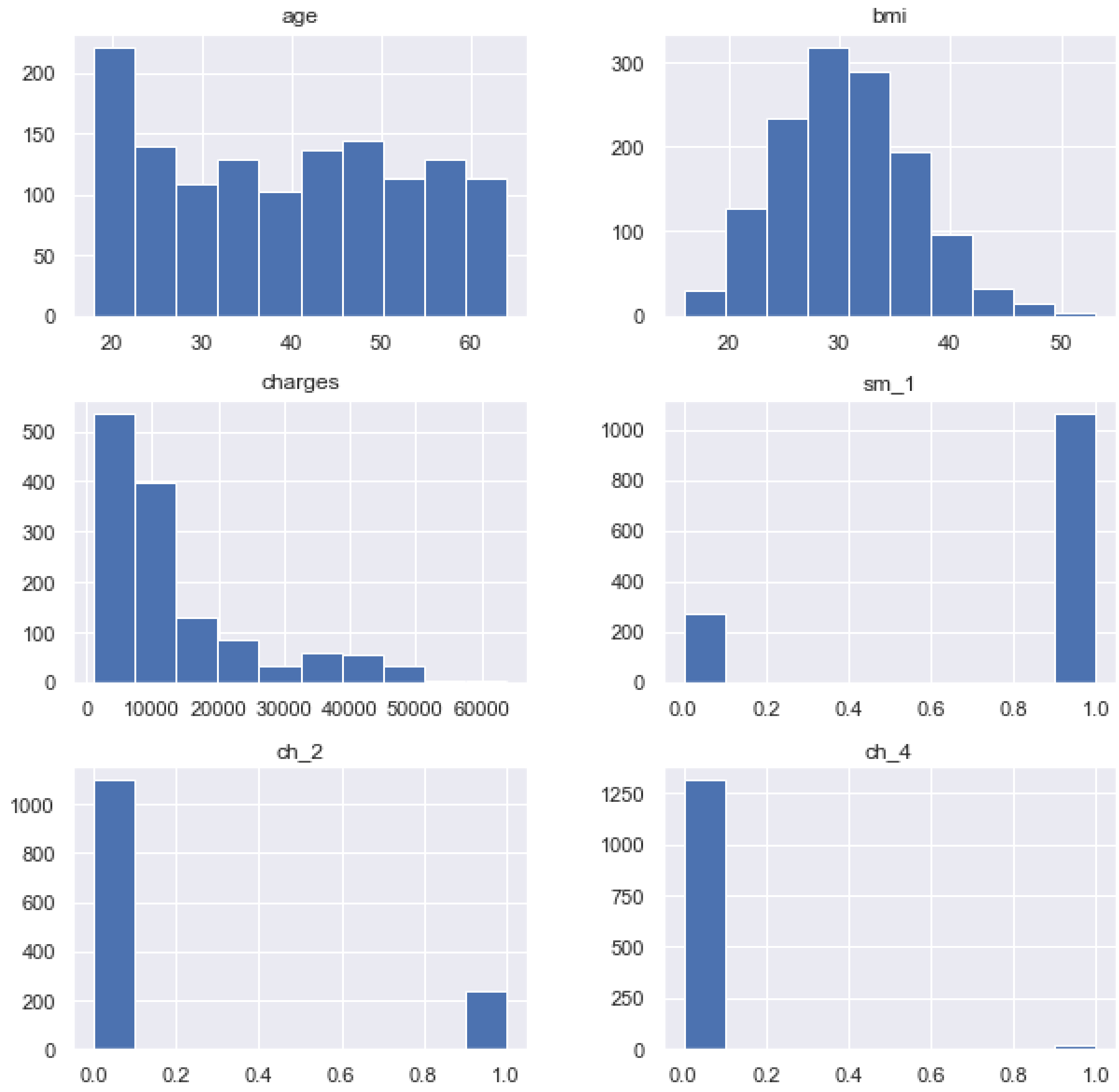
```
variance=train_mse-test_mse
print('Variance:',variance)
```

```
Variance: -377366.62953029573
```

Iteration 1-Log transform

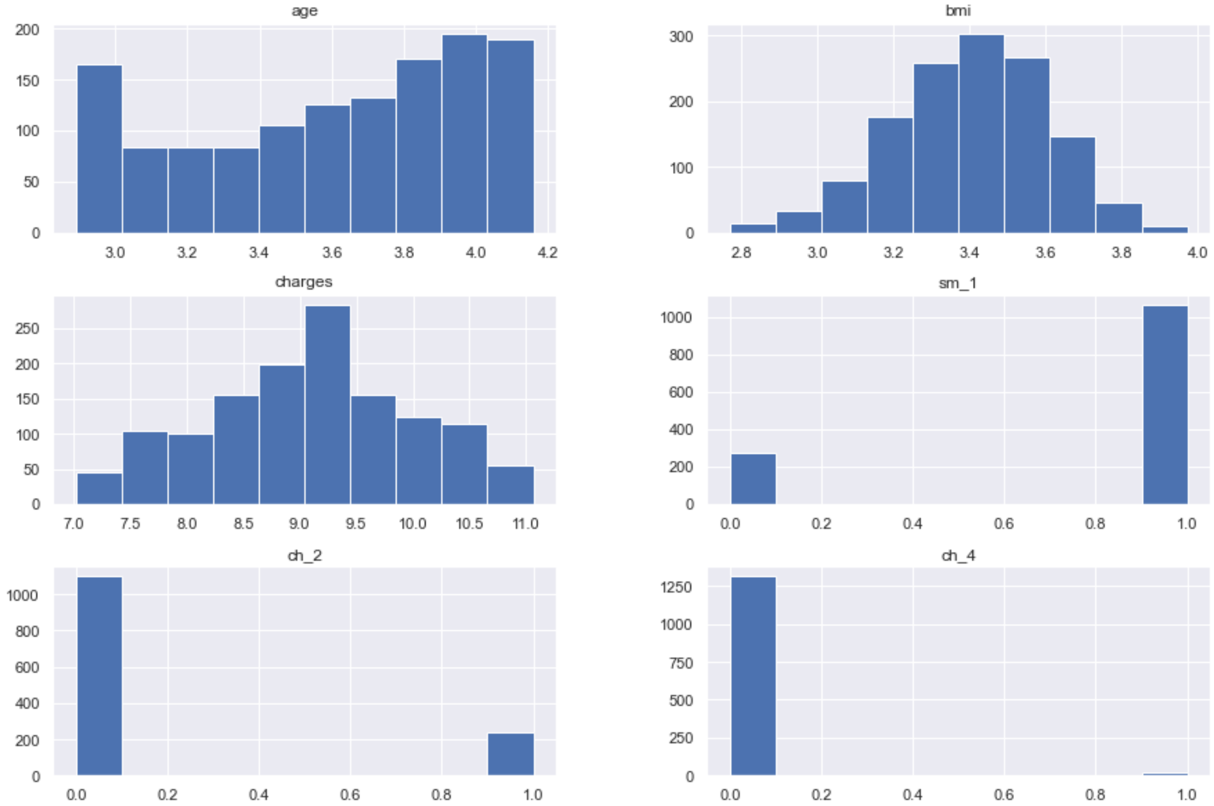
In [40]:

```
#Histogram for each features -before log transform
dff2.hist(bins=10,figsize=(10,10))
plt.show()
```



In [41]:
```
d_log = dff2
d_log['age'] = np.log(dff2['age'])
d_log['bmi'] = np.log(dff2['bmi'])
d_log['charges']=np.log(dff2['charges'])

d_log.hist(figsize  = [15,10 ]);
```



In [42]:
```
d_log
```

Out[42]:

	age	bmi	charges	sm_1	ch_2	ch_4
0	2.944439	3.328627	9.734176	0	0	0
1	2.890372	3.519573	7.453302	1	0	0
2	3.332205	3.496508	8.400538	1	0	0
3	3.496508	3.122585	9.998092	1	0	0
4	3.465736	3.363149	8.260197	1	0	0
...	...	...	...	...	...	...
1333	3.912023	3.433019	9.268661	1	0	0
1334	2.890372	3.463233	7.698927	1	0	0
1335	2.890372	3.606856	7.396233	1	0	0
1336	3.044522	3.250374	7.604867	1	0	0
1337	4.110874	3.369707	10.279914	0	0	0

1337 rows × 6 columns

In [43]:
```
outcome = 'charges'
x_cols = d_log.drop('charges',axis=1)
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=d_log).fit()
model.summary()
```

Out[43]:

OLS Regression Results

Dep. Variable:	charges	**R-squared:**	0.759
Model:	OLS	**Adj. R-squared:**	0.758

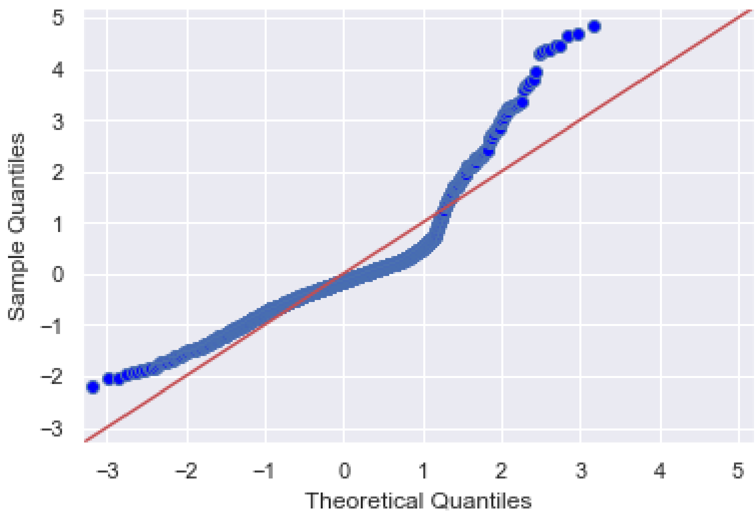
Method:	Least Squares	**F-statistic:**	836.3
Date:	Sun, 26 Feb 2023	**Prob (F-statistic):**	0.00
Time:	21:07:13	**Log-Likelihood:**	-833.25
No. Observations:	1337	**AIC:**	1679.
Df Residuals:	1331	**BIC:**	1710.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	4.5500	0.229	19.896	0.000	4.101	4.999
age	1.2680	0.032	39.726	0.000	1.205	1.331
bmi	0.3465	0.061	5.636	0.000	0.226	0.467
sm_1	-1.5427	0.031	-50.292	0.000	-1.603	-1.483
ch_2	0.1563	0.032	4.834	0.000	0.093	0.220
ch_4	0.3954	0.092	4.318	0.000	0.216	0.575

Omnibus:	444.157	**Durbin-Watson:**	2.036
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1499.450
Skew:	1.630	**Prob(JB):**	0.00
Kurtosis:	7.035	**Cond. No.**	97.5

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

In [44]:
```
# Q-Q plot and Regression plot
model=smf.ols(formula,data=d_log).fit()
fig = sm.graphics.qqplot(model.resid, line='45',fit=True);
```



In [45]:
```
#Independent varialbe
X=d_log.drop(columns='charges',axis=1)
```

```
#Dependent variable
```

In [46]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import FunctionTransformer, OneHotEncoder
from sklearn.linear_model import LinearRegression
```

In [47]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=1
```

In [48]:
```
lm=LinearRegression()
lm.fit(X_train,y_train)
```

Out[48]:
```
LinearRegression()
```

In [49]:
```
c=lm.intercept_
c
```

Out[49]:
```
4.598806931019106
```

In [50]:
```
m=lm.coef_
m
```

Out[50]:
```
array([ 1.23655022,  0.36351017, -1.53079084,  0.11761011,  0.3077766 ])
```

In [51]:
```
y_predict_train= lm.predict(X_train)
y_predict_train
```

Out[51]:
```
array([9.07591817, 7.96707418, 9.28732684, ..., 9.34942685, 7.97533613,
       9.10578018])
```

In [52]:
```
y_predict_test= lm.predict(X_test)
acc_linreg=metrics.r2_score(y_test,y_predict_test)
y_predict_test
```

Out[52]:
```
array([ 8.87917035,  7.99373076,  8.54168683,  9.33687136,  8.40812205,
        7.78173189,  9.43357484,  8.71337841,  9.12614768,  8.48200713,
        8.99873967,  9.20455436,  9.53135396,  9.34981267,  8.97472451,
       10.93310237,  8.98179742,  9.21008851,  9.38922698,  9.33882572,
        7.7832309 ,  9.92408523, 10.64227963,  9.35324766,  9.54775699,
        9.44974326,  9.25844095,  9.24385575,  8.88829429,  8.870431  ,
        7.97515043,  8.95668957,  7.95241225,  8.01583899,  7.84099951,
        8.46382784,  8.9830919 ,  9.13913985,  9.4250687 ,  7.89601487,
        9.21865237, 10.54643085,  9.14067529,  9.07748955, 10.36444483,
        8.16900164,  9.9001964 ,  8.23042504, 10.38989959,  8.19537767,
        7.80335408,  7.89447636,  8.61053429,  8.80934581,  7.96679962,
        9.42817516, 10.44405701,  9.19006761,  8.90837988,  7.92796022,
        9.13156255,  8.99231848, 10.24162272,  9.24962347,  9.58613086,
        9.41688529,  8.32273775,  8.29587212,  9.52191844, 10.92657611,
        9.48402547, 10.04875688,  8.02819349,  8.04702261,  8.63327831,
       10.58567739,  9.30386751, 10.9886214 ,  8.10811072,  8.2214692 ,
        9.43250271,  7.98472849,  9.25758893,  8.58350626,  8.89282596,
        8.89650649,  8.20225296,  7.64906022,  8.74229864,  8.86356109,
        8.6637966 ,  8.45226263,  8.45947038,  8.66745413, 10.77173488,
        7.92854236,  8.15805697, 10.38777908,  8.12377348,  9.21813441,
        9.31773276,  9.04128425,  8.36217041,  8.86366024,  9.36519559,
       11.0220574 ,  9.36575998,  9.38926456,  9.34552658,  9.19841784,
        8.51080476,  8.93275392, 10.17289321,  8.87669146,  8.99444157,
        9.29181393,  9.97542201,  8.686354  ,  8.33221528,  9.37682568,
        9.11045929,  9.39641816,  8.43943865,  9.39672598,  7.98276982,
        9.10016116,  8.49775505,  9.13634627,  8.32645973,  9.22764207,
       10.25136919,  9.86219766,  9.1130218 ,  8.77958894,  8.52088224,
        8.88112956,  8.31611371,  8.2672516 ,  7.90102627, 10.93047588,
        9.10831401,  9.05783556, 10.85424685,  9.33788701,  9.24631859,
        8.10553802,  9.38856144,  8.5267172 , 11.01533982,  8.60813947,
        8.88865757,  9.33233523,  9.23821022,  8.86709712, 10.93411115,
```

```
        9.36286011,  8.93739541, 10.5613385 ,  8.95527794,  8.68656418,
        8.60253695,  9.23225848,  9.85193874,  8.08615501,  9.50411891,
       10.54580249,  8.12094785,  9.37497166,  9.43227609,  8.58555134,
        7.83652276,  9.07712013,  9.28613559,  7.85617674,  8.50386529,
        9.0099603 ,  8.66490003, 10.21824916, 10.25378939,  9.40650295,
        7.78519392,  8.9780623 ,  8.151323  , 10.60942305,  7.83083476,
        9.1143142 ,  8.48414779,  9.44975884, 10.38544463, 10.185673  ,
        9.50157896,  9.23686289, 10.02805499,  9.09546779,  9.71962014,
        8.00683127,  9.4633262 , 10.62134116,  7.92540926,  8.98145553,
        9.29094844,  9.21607895,  9.20074794,  9.32900467,  8.32682984,
        9.37578177,  9.13281778,  7.97831456,  7.99326629,  8.25879869,
        9.01117399,  9.44205535,  8.63617482, 10.047876  ,  9.28003821,
        8.57706668,  8.22422207,  9.28499879,  9.51173354,  8.91745073,
        8.9124896 ,  9.10978493,  8.90051686,  8.70229753,  8.66818891,
        8.06287514,  9.13800528,  9.10058692,  8.04340556,  8.74421832,
        8.7183384 ,  8.76515526,  8.75374984,  8.92181393,  8.92901186,
       10.53051789,  9.28681782,  8.34822493,  9.23578296,  8.23133171,
        8.23674481,  9.33200205,  8.31815735,  8.34586677,  9.50233896,
        8.19289091,  9.06164452,  8.20808831,  9.45497202,  9.18826145,
        7.8788391 ,  8.98160384,  9.23950075,  8.76299371,  8.92661741,
        8.29906844,  9.10960262,  9.35831384, 10.30958861,  8.36999851,
        7.82820062, 10.6940567 ,  9.64663967,  9.35958812,  9.21525331,
        7.98325463, 10.08951516,  9.30977085])
```

In [53]:

```python
#model evaluation
print('R^2:',metrics.r2_score(y_train, y_predict_train))
print('Adjusted R^2:',1 - (1-metrics.r2_score(y_train, y_predict_train))*(len(y_trai
print('MAE:',metrics.mean_absolute_error(y_train, y_predict_train))
print('MSE:',metrics.mean_squared_error(y_train, y_predict_train))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_train, y_predict_train)))
```

```
R^2: 0.7508321808748831
Adjusted R^2: 0.7496601779627237
MAE: 0.30139369976041896
MSE: 0.20785598472780825
RMSE: 0.45591225551394016
```

In [54]:

```python
#model evaluation-testing prediction

print('R^2:',acc_linreg)
print('Adjusted R^2:', 1- (1-metrics.r2_score(y_test,y_predict_test))*(len(y_test)-1
print('MAE:',metrics.mean_absolute_error(y_test, y_predict_test))
print('MSE:',metrics.mean_squared_error(y_test, y_predict_test))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test, y_predict_test)))
```

```
R^2: 0.7842170604969696
Adjusted R^2: 0.7800990654682858
MAE: 0.2926671482776501
MSE: 0.18956530099829216
RMSE: 0.4353909748700496
```

In [55]:

```python
print(X.shape,X_train.shape,X_test.shape)
```

```
(1337, 5) (1069, 5) (268, 5)
```

In [56]:

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

y_hat_train = linreg.predict(X_train)
y_hat_test = linreg.predict(X_test)
```

In [57]:

```python
from sklearn.metrics import mean_squared_error

train_mse = mean_squared_error(y_train, y_hat_train)
test_mse = mean_squared_error(y_test, y_hat_test)
variance=train_mse-test_mse
```

```
print('Train Mean Squared Error:', train_mse)
print('Test Mean Squared Error:', test_mse)
print('Variance:',variance)
```

```
Train Mean Squared Error: 0.20785598472780825
Test Mean Squared Error: 0.18956530099829216
Variance: 0.01829068372951609
```

In [58]:
```
variance= train_mse - test_mse
variance
```

Out[58]:
```
0.01829068372951609
```

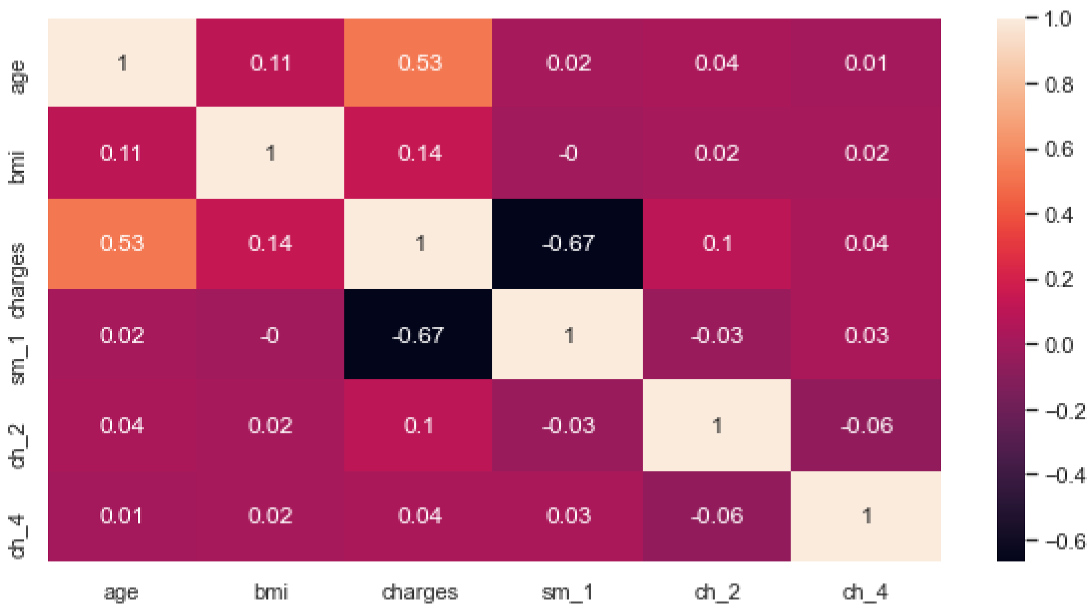
In [59]:
```
d_log.corr()
```

Out[59]:

	age	bmi	charges	sm_1	ch_2	ch_4
age	1.000000	0.109659	0.533992	0.023274	0.035445	0.005170
bmi	0.109659	1.000000	0.138222	-0.000399	0.017343	0.022925
charges	0.533992	0.138222	1.000000	-0.665718	0.101015	0.038944
sm_1	0.023274	-0.000399	-0.665718	1.000000	-0.028077	0.029046
ch_2	0.035445	0.017343	0.101015	-0.028077	1.000000	-0.064566
ch_4	0.005170	0.022925	0.038944	0.029046	-0.064566	1.000000

In [60]:
```
plt.figure(figsize=(10,5))
sns.heatmap(d_log.corr().round(2),annot=True)
```

Out[60]:
```
<AxesSubplot:>
```



Polynomial Regression

In [61]:
```
from sklearn.model_selection import train_test_split as holdout
from sklearn.preprocessing import PolynomialFeatures
x = d_log.drop(['charges'], axis = 1)
y = d_log.charges
pol = PolynomialFeatures (degree = 2)
x_pol = pol.fit_transform(x)
x_train, x_test, y_train, y_test = holdout(x_pol, y, test_size=0.2, random_state=0)
Pol_reg = LinearRegression()
```

```
Pol_reg.fit(x_train, y_train)
y_train_pred = Pol_reg.predict(x_train)
y_test_pred = Pol_reg.predict(x_test)
print(Pol_reg.intercept_)
print(Pol_reg.coef_)
print(Pol_reg.score(x_test, y_test))
```

```
-0.5338604523150714
[ 0.          0.32116891  4.08356927 -0.23954045  1.01578563  0.34267336
  0.05912651 -0.0963124   1.13628595 -0.42315143 -0.9938306  -0.32837518
 -1.51787556 -0.12906876  0.78398916 -0.23954045  0.11804948  0.69483672
  1.01578563  0.          0.34267336]
0.8370466230055339
```

In [62]:

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_train, y_train_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_train, y_train_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_train, y_trai
```

```
Mean Absolute Error: 0.22463884111700938
Mean Squared Error: 0.1501548127586702
Root Mean Squared Error: 0.38749814549062067
```

In [63]:

```
##Evaluating the performance of the algorithm
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_test_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_test_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_test_
```

```
Mean Absolute Error: 0.23740596949324314
Mean Squared Error: 0.14656285738843813
Root Mean Squared Error: 0.3828352875434005
```

In [64]:

```
##Predicting the charges
y_test_charges = Pol_reg.predict(x_test)
##Comparing the actual output values with the predicted values
dfp = pd.DataFrame({'Actual': y_test, 'Predicted': y_test_pred,'Variance':y_test-y_t
dfp
```

Out[64]:

	Actual	Predicted	Variance
1248	7.398763	7.663362	-0.264599
610	9.053417	9.142139	-0.088723
393	9.136709	9.205100	-0.068391
503	10.390482	10.063189	0.327292
198	9.174117	9.210311	-0.036194
...	...	...	...
809	8.104641	8.153760	-0.049120
726	8.804578	8.926495	-0.121916
938	7.742403	8.166279	-0.423876
474	10.141807	10.199920	-0.058113
1084	9.617122	9.546027	0.071095

268 rows × 3 columns

In [65]:

```
##Predicting the charges
y_train_charges = Pol_reg.predict(x_train)
##Comparing the actual output values with the predicted values
dfp1 = pd.DataFrame({'Actual': y_train, 'Predicted': y_train_pred,'variance':y_train
dfp1
```

Out[65]:

	Actual	Predicted	variance
896	9.893339	9.768671	0.124668
194	7.036562	7.675671	-0.639110
240	10.558716	10.655066	-0.096350
1257	9.333083	9.364757	-0.031674
575	9.411066	9.480065	-0.068998
...	...	...	...
764	9.115488	9.191096	-0.075608
836	8.389867	8.721590	-0.331722
1217	8.308474	8.633651	-0.325177
559	7.406364	7.753048	-0.346684
685	9.327623	9.380907	-0.053283

1069 rows × 3 columns

The End