LINEAR REGRESSION MODEL

- Linear regression is a type of supervised machine learning algorithm that computes the linear relationship between a dependent variable and one or more independent features.
- The goal of the algorithm is to find the best linear equation that can predict the value of the dependent variable based on the independent variables

Assumption for Linear Regression Model

- **Linearity**: The independent and dependent variables have a linear relationship with one another. This implies that changes in the dependent variable follow those in the independent variable(s) in a linear fashion.
- **Independence**: The observations in the dataset are independent of each other. This means that the value of the dependent variable for one observation does not depend on the value of the dependent variable for another observation.
- **Homoscedasticity**: Across all levels of the independent variable(s), the variance of the errors is constant. This indicates that the amount of the independent variable(s) has no impact on the variance of the errors.
- **Normality**: The errors in the model are normally distributed.
- **No multicollinearity**: There is no high correlation between the independent variables. This indicates that there is little or no correlation between the independent variables.

Purpose of the Project

- Exploratory data analysis (EDA) is one of the most significant methods which is conducted using various statistical and data visualization techniques to understand the structure and characteristics of the data before applying more complex modeling or hypothesis testing.
- Implementing Multiple Linear Regression on the dataset for future prediction.
- Regularization techniques used to address over-fitting
- Gradient Descent is an optimization algorithm is used to minimize the cost function as far as possible

Life cycle of the Project

- Collect/Extract Data
- Preprocess the Data
- Divide data into Independent and Dependent Variable
- Split the data inti tarining and test data where training is for building linear regression model and predicting the test data.
- Build Model- Linear Regression Model
- Validate the test data

Import Necessary Libraries

In [1]:
```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
%matplotlib inline

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

Import Dataset

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

In [3]:
```
df.head()
```

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

In [4]:
```
df.info()
```

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

Check and Remove duplicate rows

In [5]:
```
df.duplicated().sum()
```

Out[5]:
```
1
```

In [6]:
```
#we got duplicated values in this dataset, so we have to remove one dulpiacted
```

In [7]:
```
df.drop_duplicates(inplace=True)
```

Dopping Non-Significant Columns:

- Here there is no non significant column, so no need to drop

Data Preprocessing

1. Null Value Treatment

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

In [9]:
```
#No null values so no need to treat
```

2.Checking Outliers

In [10]:
```
df.describe()
```

Out[10]:

	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

In [11]:
```
df['bmi'].describe()
```

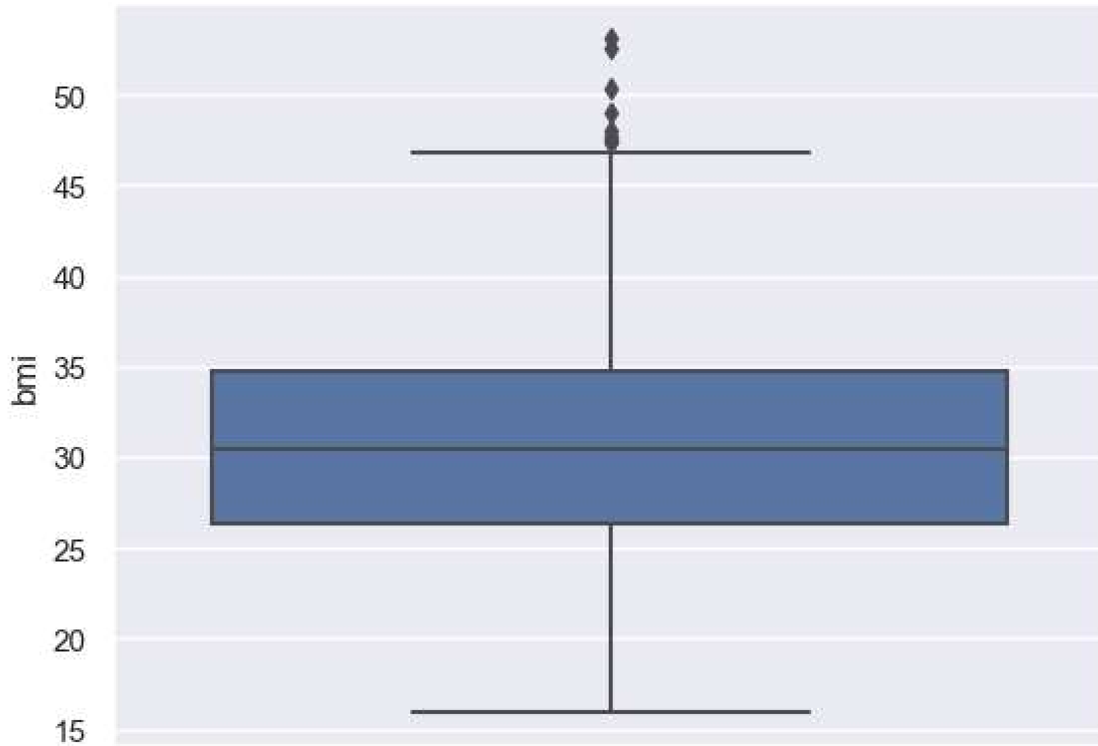
Out[11]:
```
count    1337.000000
mean       30.663452
std         6.100468
min        15.960000
25%        26.290000
50%        30.400000
75%        34.700000
max        53.130000
Name: bmi, dtype: float64
```

In [12]:
```
df['children'].value_counts()
```

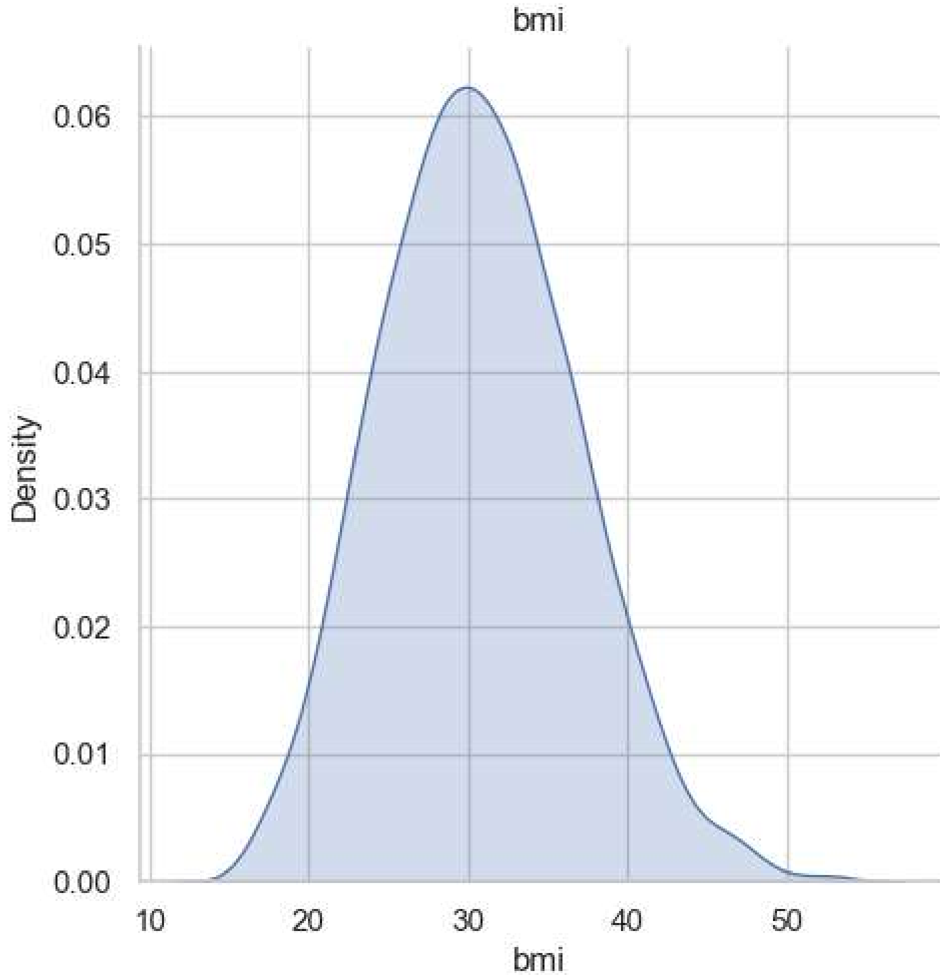
Out[12]:
```
0    573
1    324
2    240
3    157
4     25
5     18
Name: children, dtype: int64
```

In [13]:
```
#This column does not need any outlier treatment
```

In [14]:
```
sns.boxplot(y='bmi', data= df)
plt.show()
```



In [15]:
```
sns.set(style="whitegrid")  # Optional, sets the style of the plots
sns.displot(data=df, x='bmi', kind='kde', fill=True)
plt.title("bmi")
plt.show()
```



- So we need to do outlier treatment in this column

ENCODING

In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1337 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       1337 non-null   int64  
 1   sex       1337 non-null   object 
 2   bmi       1337 non-null   float64
 3   children  1337 non-null   int64  
 4   smoker    1337 non-null   object 
 5   region    1337 non-null   object 
 6   charges   1337 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 115.9+ KB
```

In [17]:
```
df['sex'].value_counts()
```

Out[17]:
```
male      675
female    662
Name: sex, dtype: int64
```

In [18]:
```
df['sex']= df['sex'].astype('category')
df['sex']= df['sex'].cat.codes
```

In [19]:
```
df['smoker'].value_counts()
```

Out[19]:
```
no     1063
yes     274
Name: smoker, dtype: int64
```

In [20]:
```
df['smoker']= df['smoker'].astype('category')
df['smoker']= df['smoker'].cat.codes
```

In [21]:
```
df['region'].value_counts()
```

Out[21]:
```
southeast    364
southwest    325
northwest    324
northeast    324
Name: region, dtype: int64
```

In [22]:
```
df=pd.get_dummies( df,columns=['region'])
```

In [23]:
```
df= df.drop(['region_northeast'],axis=1)
```

In [24]:
```
df.head()
```

Out[24]:

	age	sex	bmi	children	smoker	charges	region_northwest	region_southeast	region_
0	19	0	27.900	0	1	16884.92400	0	0	
1	18	1	33.770	1	0	1725.55230	0	1	
2	28	1	33.000	3	0	4449.46200	0	1	
3	33	1	22.705	0	0	21984.47061	1	0	
4	32	1	28.880	0	0	3866.85520	1	0	

Treating Outliers

- Only for bmi column

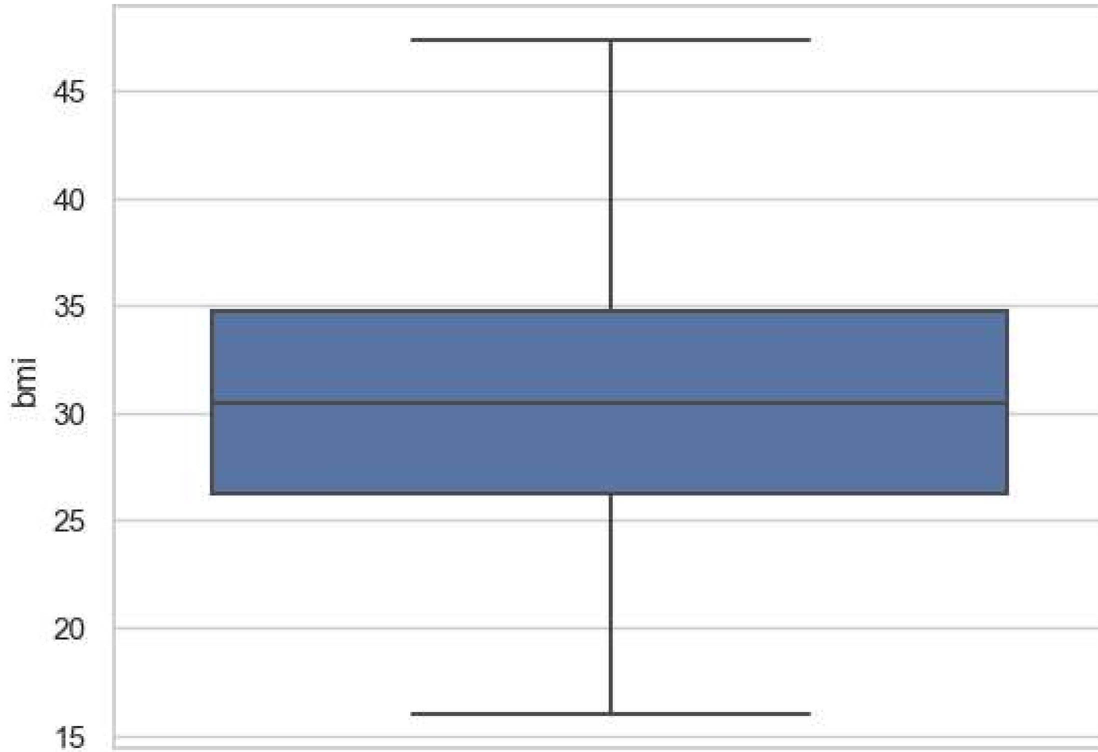
In [25]:
```
new_df=df.copy()
```

In [26]:
```
bmi_q1=new_df['bmi'].quantile(0.25)
bmi_q3=new_df['bmi'].quantile(0.75)
bmi_iqr= bmi_q3 - bmi_q1

bmi_upper= bmi_q3 + 1.5*bmi_iqr
bmi_lower= bmi_q1 - 1.5*bmi_iqr
```

In [27]:
```
new_df['bmi']= np.where(new_df['bmi']>bmi_upper,bmi_upper,
                                np.where(new_df['bmi']<bmi_lower,bmi_lower,
                                         new_df['bmi']))
```

In [28]:
```
sns.boxplot(y='bmi', data= new_df)
plt.show()
```



- There are no more outliers

Feature Scaling

In [29]:
```
i=5
x = new_df.iloc[:, [col for col in range(new_df.shape[1]) if col != i]]  #this
y= new_df['charges']
```

In [30]:
```
x.head()
```

Out[30]:

	age	sex	bmi	children	smoker	region_northwest	region_southeast	region_southwest
0	19	0	27.900	0	1	0	0	1
1	18	1	33.770	1	0	0	1	0
2	28	1	33.000	3	0	0	1	0
3	33	1	22.705	0	0	1	0	0
4	32	1	28.880	0	0	1	0	0

In [31]:
```
y.head()
```

Out[31]:
```
0    16884.92400
1     1725.55230
2     4449.46200
3    21984.47061
4     3866.85520
Name: charges, dtype: float64
```

In [32]:
```
from sklearn.preprocessing import StandardScaler
sc= StandardScaler()
sc_x= sc.fit_transform(x)
pd.DataFrame(sc_x)
```

Out[32]:

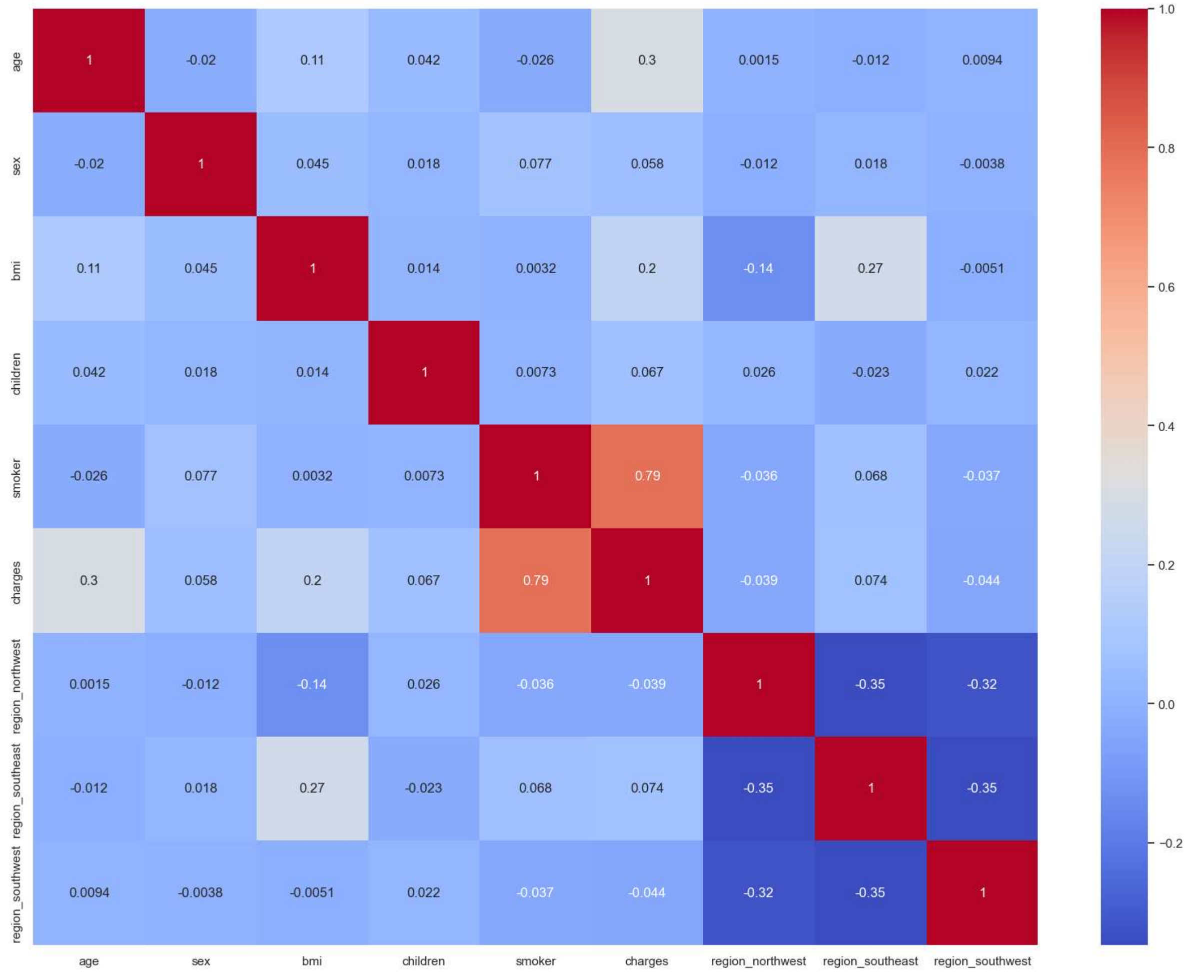
	0	1	2	3	4	5	6	7
0	-1.440418	-1.009771	-0.454032	-0.909234	1.969660	-0.565546	-0.611638	1.764609
1	-1.511647	0.990324	0.515033	-0.079442	-0.507702	-0.565546	1.634955	-0.566698
2	-0.799350	0.990324	0.387915	1.580143	-0.507702	-0.565546	1.634955	-0.566698
3	-0.443201	0.990324	-1.311662	-0.909234	-0.507702	1.768203	-0.611638	-0.566698
4	-0.514431	0.990324	-0.292246	-0.909234	-0.507702	1.768203	-0.611638	-0.566698
...	...	...	...	...	...	...	...	...
1332	0.767704	0.990324	0.052787	1.580143	-0.507702	1.768203	-0.611638	-0.566698
1333	-1.511647	-1.009771	0.209621	-0.909234	-0.507702	-0.565546	-0.611638	-0.566698
1334	-1.511647	-1.009771	1.023503	-0.909234	-0.507702	-0.565546	1.634955	-0.566698
1335	-1.297958	-1.009771	-0.800716	-0.909234	-0.507702	-0.565546	-0.611638	1.764609
1336	1.551231	-1.009771	-0.260879	-0.909234	1.969660	1.768203	-0.611638	-0.566698

1337 rows × 8 columns

HEATMAP Visualization to check the Multi-collinearity

- By visualizing the heatmap we can check corelation between dependent variables and independent variables
- We have to notice two thing
  - if the value is coming more than 0.75 or 0.8 we have to remove that variables
  - if between independent variables two or more values have same value, we have to drop one of them.

In [33]:
```
plt.figure(figsize=(20,15))
corr= new_df.corr()
sns.heatmap(corr, annot= True, cmap='coolwarm')
plt.show()
```



Variance Inflation Factor- VIF

- One of the stat method to chech the multi-collinearity
- if any feature vif value is greater than 5 then there is a multi-collinearity

In [34]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
variable= sc_x

vif= pd.DataFrame()

vif['Variance Inflation Factor'] = [variance_inflation_factor(variable,i) for

vif['Features']= x.columns
```

In [35]:
```
vif
```

Out[35]:

	Variance Inflation Factor	Features
0	1.017435	age
1	1.008800	sex
2	1.106541	bmi
3	1.004040	children
4	1.012110	smoker
5	1.517673	region_northwest
6	1.651039	region_southeast
7	1.529201	region_southwest

In [36]:
```
# So there is no multi-collinearity
```

Split the data into Train and Test

Approach-1 (Linear Regression Method)

In [37]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, rand

print(x_train.shape , x_test.shape, y_train.shape, y_test.shape)
```

```
(1002, 8) (335, 8) (1002,) (335,)
```

Building Linear Regression Model

In [38]:
```
from sklearn.linear_model import LinearRegression
lm= LinearRegression()
lm.fit(x_train, y_train)
```

Out[38]:
```
▾ LinearRegression
LinearRegression()
```

predict the price by using lm model with test dataset

In [39]:
```
y_pred_price=lm.predict(x_test)
y_pred_price_train=lm.predict(x_train)
```

Validate the actual price with the predicted price

In [40]:
```
from sklearn.metrics import r2_score
r2_score(y_test,y_pred_price)
```

Out[40]:
```
0.7509443198322774
```

In [41]:
```
r2_score(y_train,y_pred_price_train)
```

Out[41]:
```
0.7494256286283418
```

Approach-2 (OLS Method)

In [42]:
```
from statsmodels.regression.linear_model import OLS
import statsmodels.regression.linear_model as smf
```

In [43]:
```
reg_model= smf.OLS(endog = y_train , exog = x_train).fit()
```

In [44]:
```
reg_model.summary()
```

Out[44]:

OLS Regression Results

Dep. Variable:	charges	**R-squared (uncentered):**	0.875
Model:	OLS	**Adj. R-squared (uncentered):**	0.874
Method:	Least Squares	**F-statistic:**	867.8
Date:	Fri, 21 Jul 2023	**Prob (F-statistic):**	0.00
Time:	12:44:35	**Log-Likelihood:**	-10203.
No. Observations:	1002	**AIC:**	2.042e+04
Df Residuals:	994	**BIC:**	2.046e+04
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
age	191.4127	13.431	14.251	0.000	165.056	217.769
sex	-462.0753	404.736	-1.142	0.254	-1256.310	332.160
bmi	79.5710	22.438	3.546	0.000	35.540	123.602
children	307.0506	169.470	1.812	0.070	-25.509	639.610
smoker	2.27e+04	491.602	46.173	0.000	2.17e+04	2.37e+04
region_northwest	-1905.5176	569.885	-3.344	0.001	-3023.833	-787.202
region_southeast	-1075.0157	599.043	-1.795	0.073	-2250.550	100.519
region_southwest	-1910.0682	591.157	-3.231	0.001	-3070.128	-750.009

Omnibus:	199.495	**Durbin-Watson:**	1.803
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	416.190
Skew:	1.124	**Prob(JB):**	4.22e-91
Kurtosis:	5.216	**Cond. No.**	213.

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [ ]:

Approach-3 (Regularization Method)

Lasso Model

In [45]:
```
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=0.1)
lasso.fit(x_train, y_train)
print("Lasso Model :", (lasso.coef_))
```

```
Lasso Model : [  247.90454386    42.70282668   354.30666359   475.60461309
 23211.47865099  -417.66679968  -715.35196294  -826.59425113]
```

In [46]:
```
y_pred_train_lasso = lasso.predict(x_train)
y_pred_test_lasso = lasso.predict(x_test)
```

In [47]:
```
print("Training Accuracy :", r2_score(y_train, y_pred_train_lasso))
print()
print("Test Accuracy :", r2_score(y_test, y_pred_test_lasso))
```

```
Training Accuracy : 0.749425624265386

Test Accuracy : 0.750939616420311
```

Ridge Model

In [48]:
```
from sklearn.linear_model import Ridge
ridge = Ridge(alpha=0.3)
ridge.fit(x_train, y_train)
print("Ridge Model :", (ridge.coef_))
```

```
Ridge Model : [  247.89120385    45.73552846   354.19869159   475.93527165
 23170.85496598  -417.16593991  -711.35102432  -825.99100007]
```

In [49]:
```
y_pred_train_ridge = ridge.predict(x_train)
y_pred_test_ridge = ridge.predict(x_test)
```

In [50]:
```
print("Training Accuracy :", r2_score(y_train, y_pred_train_ridge))
print()
print("Test Accuracy :", r2_score(y_test, y_pred_test_ridge))
```

```
Training Accuracy : 0.7494236637733178

Test Accuracy : 0.7507137627091925
```

In [ ]:

ElasticNet

In [51]:
```
from sklearn.linear_model import ElasticNet
elastic = ElasticNet(alpha=0.3, l1_ratio=0.1)
elastic.fit(x_train, y_train)
```

Out[51]:
```
ElasticNet
ElasticNet(alpha=0.3, l1_ratio=0.1)
```

In [52]:
```
y_pred_train_elastic = elastic.predict(x_train)
y_pred_test_elastic = elastic.predict(x_test)
```

In [53]:
```
print("Training Accuracy :", r2_score(y_train, y_pred_train_elastic))
print()
print("Test Accuracy :", r2_score(y_test, y_pred_test_elastic))
```

```
Training Accuracy : 0.5143658694292714

Test Accuracy : 0.48133319032716915
```

Approach-4 (Gradient Descent Method)

In [54]:
```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(sc_x, y, test_size=0.25, r

print(x_train.shape, x_test.shape, y_train.shape, y_test.shape)
```

```
(1002, 8) (335, 8) (1002,) (335,)
```

In [55]:
```
from sklearn.linear_model import SGDRegressor
```

In [56]:
```
gd_model = SGDRegressor()
gd_model.fit(x_train, y_train)
```

Out[56]:
```
SGDRegressor
SGDRegressor()
```

In [57]:
```
y_pred_gd_train = gd_model.predict(x_train)

y_pred_gd_test = gd_model.predict(x_test)
```

In [58]:
```
print("GD Training Accuracy :", r2_score(y_train, y_pred_gd_train))

print()

print("GD Test Accuracy :", r2_score(y_test, y_pred_gd_test))
```

```
GD Training Accuracy : 0.749326155350849

GD Test Accuracy : 0.7529170146365437
```

Polynominal Regression Model

In [59]:
```
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
```

In [60]:
```
poly = PolynomialFeatures()
x_train_trans = poly.fit_transform(x_train)
x_test_trans = poly.fit_transform(x_test)
```

In [61]:
```
lr = LinearRegression()
lr.fit(x_train_trans, y_train)
```

Out[61]:
```
▾ LinearRegression
LinearRegression()
```

In [62]:
```
y_pred_poly_train = lr.predict(x_train_trans)
y_pred_poly_test = lr.predict(x_test_trans)
```

In [63]:
```
print("Poly Training Accuracy :", r2_score(y_train, y_pred_poly_train))

print()

print("Poly Test Accuracy :", r2_score(y_test, y_pred_poly_test))
```

```
Poly Training Accuracy : 0.8558617888209539

Poly Test Accuracy : 0.8192166992170076
```

Performance matrix

Mean Absolute Error (MAE)

In [64]:
```
from sklearn import metrics
```

In [65]:
```
print("MAE :", metrics.mean_absolute_error(y_test, y_pred_price))
```

```
MAE : 4086.8466832149925
```

Mean Absolute Percent Error (MAPE)

In [66]:
```
print("MAPE :", metrics.mean_absolute_error(y_test, y_pred_price)/100)
```

```
MAPE : 40.86846683214993
```

Mean Squared Error (MSE)

In [67]:
```
print("MSE :", metrics.mean_squared_error(y_test, y_pred_price))
```

```
MSE : 36535029.98449478
```

Root Mean Squared Error (RMSE)

In [68]:
```
print("RMSE :", np.sqrt(metrics.mean_squared_error(y_test, y_pred_price)))
```

```
RMSE : 6044.421393689787
```

Random Forest Regression

In [69]:
```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor()
rf.fit(x_train, y_train)
```

Out[69]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

In [77]:
```
y_pred_train_rm = rf.predict(x_train)
y_pred_test_rm = rf.predict(x_test)
```

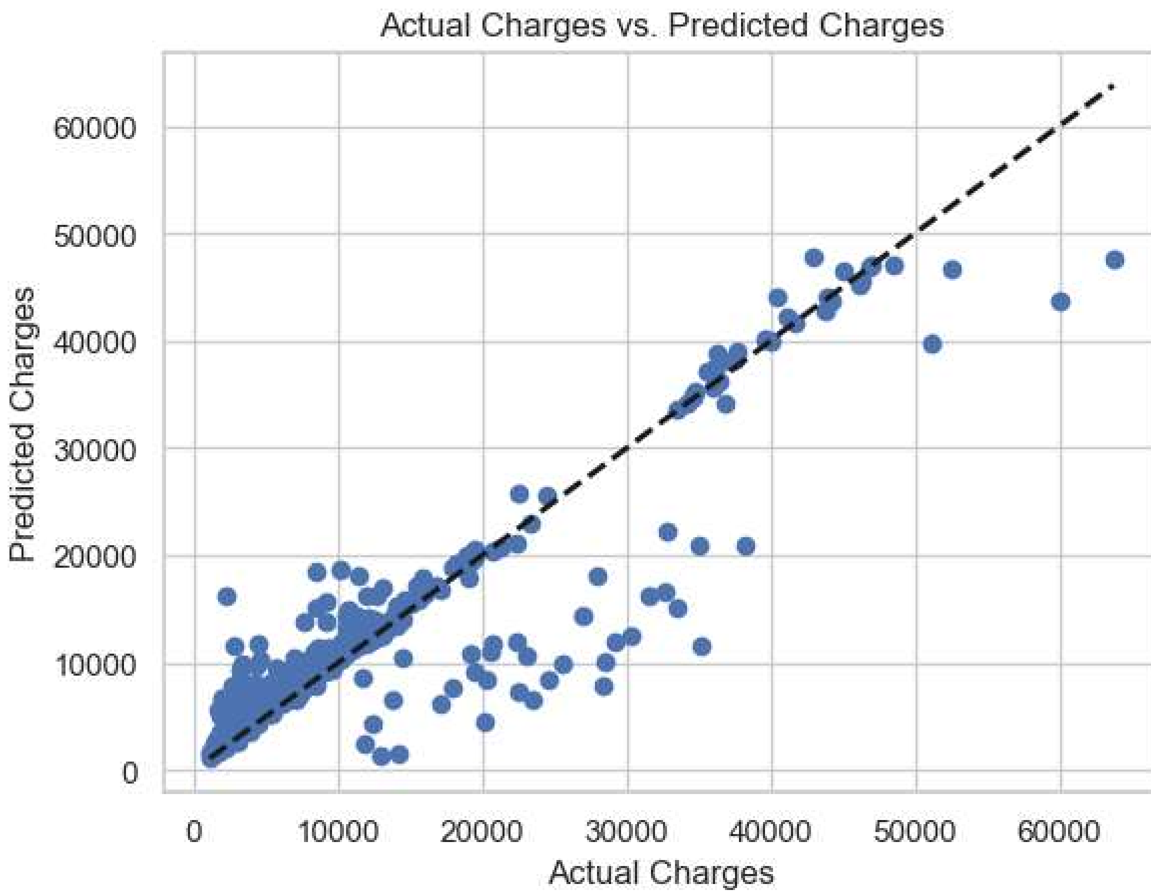
In [78]:
```
print(r2_score(y_train, y_pred_train_rm))
print()
print(r2_score(y_test, y_pred_test_rm))
```

```
0.977938281661721

0.8240442887939176
```

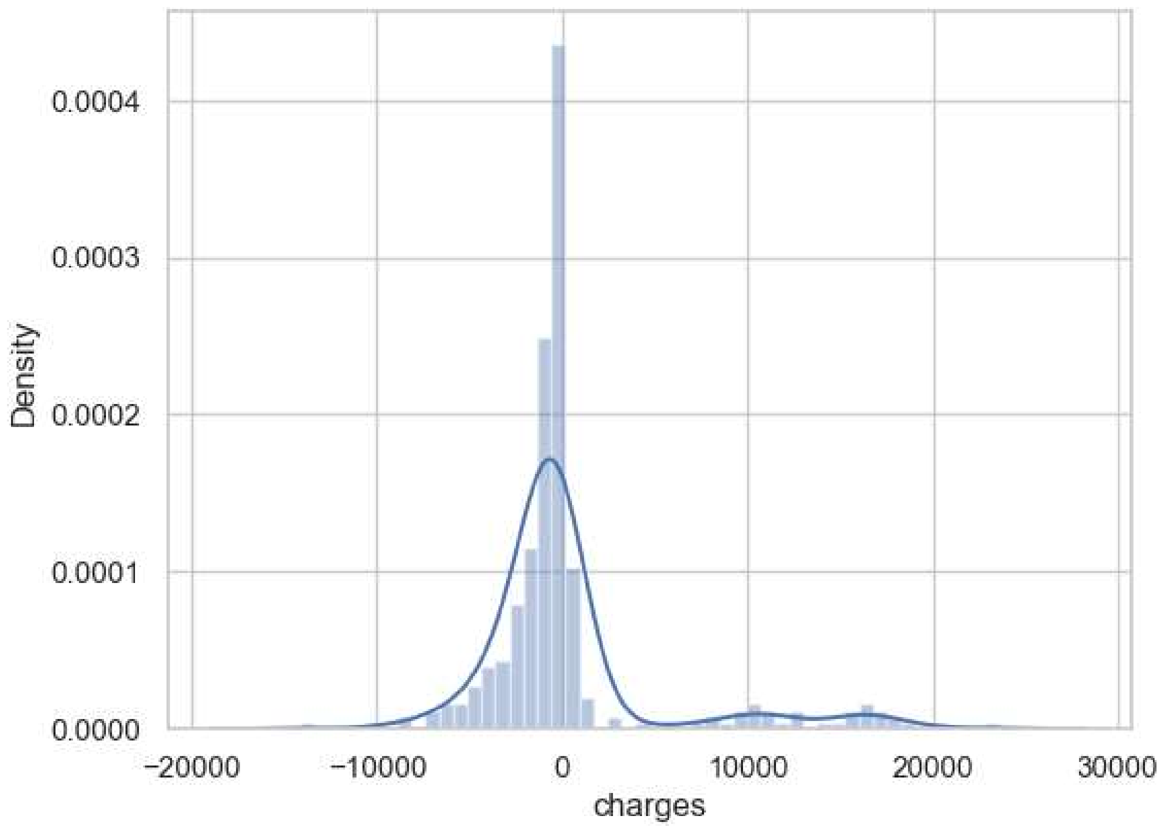
Check linearity

In [86]:
```
plt.scatter(y_test, y_pred_test_rm)
plt.plot([y.min(), y.max()], [y.min(), y.max()], 'k--', lw=2)  # Linearity cur
plt.xlabel('Actual Charges')
plt.ylabel('Predicted Charges')
plt.title('Actual Charges vs. Predicted Charges')
plt.show()
```



In [87]:
```
# Normality of Residual

sns.distplot((y_test - y_pred_test_rm), bins=50)
plt.show()
```



Conclusion:

- 1. Linearity - **Satisfied**
- 2. Normality of Residuals- **Satisfied**
- 3. Homoscedasticity - **Satisfied (there is no outlier and residual is normaly distributed)**
- 4. No autocorrelation - **Satisfied**
- 5. No or little Multicollinearity - **Satisfied**
- 6. No endogenity problem - **Satisfied**

In [ ]: