In [54]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Modelling
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,AdaBoostRegressor
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression, Ridge,Lasso
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import pickle
import warnings
```

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

In [3]:
```
df.head(2)
```

Out[3]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.90	0	yes	southwest	16884.9240
1	18	male	33.77	1	no	southeast	1725.5523

In [4]:
```
df.head(2)
```

Out[4]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.90	0	yes	southwest	16884.9240
1	18	male	33.77	1	no	southeast	1725.5523

In [5]:
```
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
```

In [6]:
```
df.isnull().sum()
```

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

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

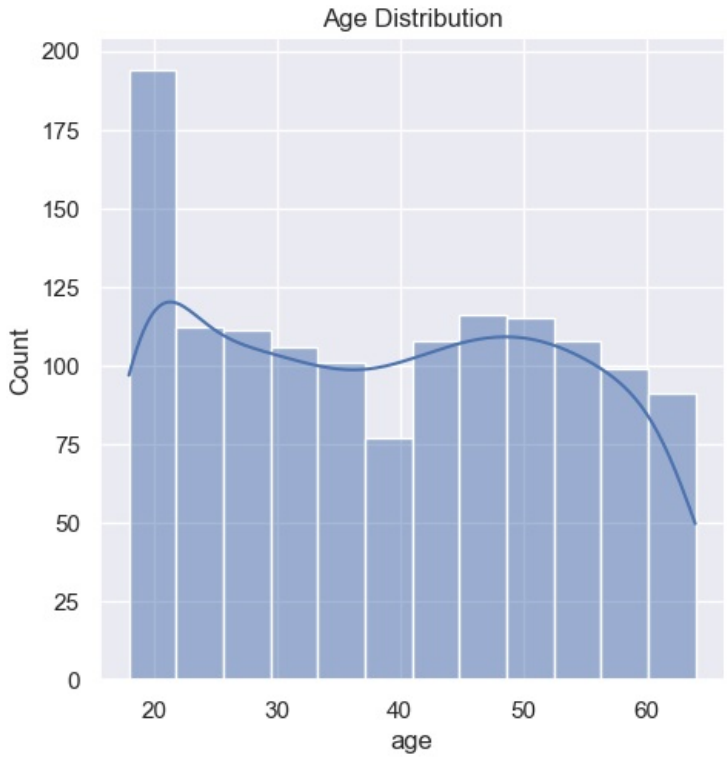
Out[7]:

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

Data Analysis

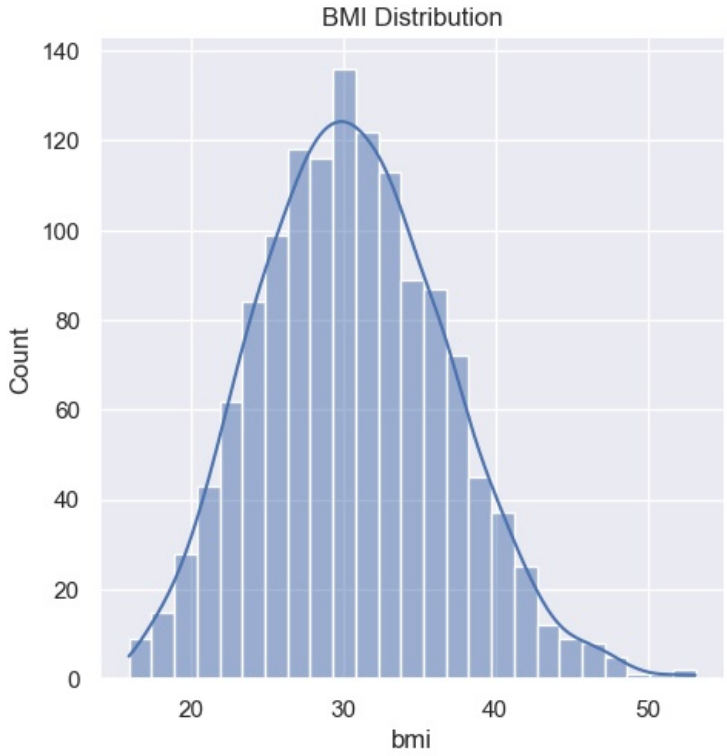
In [8]:
```
# distribution of age
sns.set()
plt.figure(figsize=(15,7))
sns.displot(df['age'],kde=True)
plt.title('Age Distribution')
plt.show()
```

```
C:\Users\nmsat\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
<Figure size 1500x700 with 0 Axes>
```



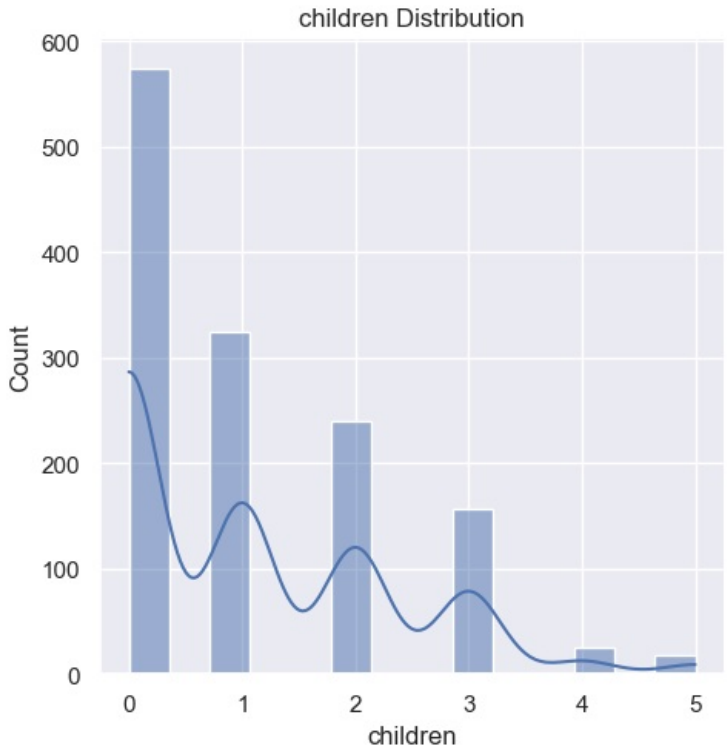
In [9]:
```
sns.set()
plt.figure(figsize=(15,7))
sns.displot(df['bmi'], kde=True)
plt.title('BMI Distribution')
plt.show()
```

```
C:\Users\nmsat\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
<Figure size 1500x700 with 0 Axes>
```



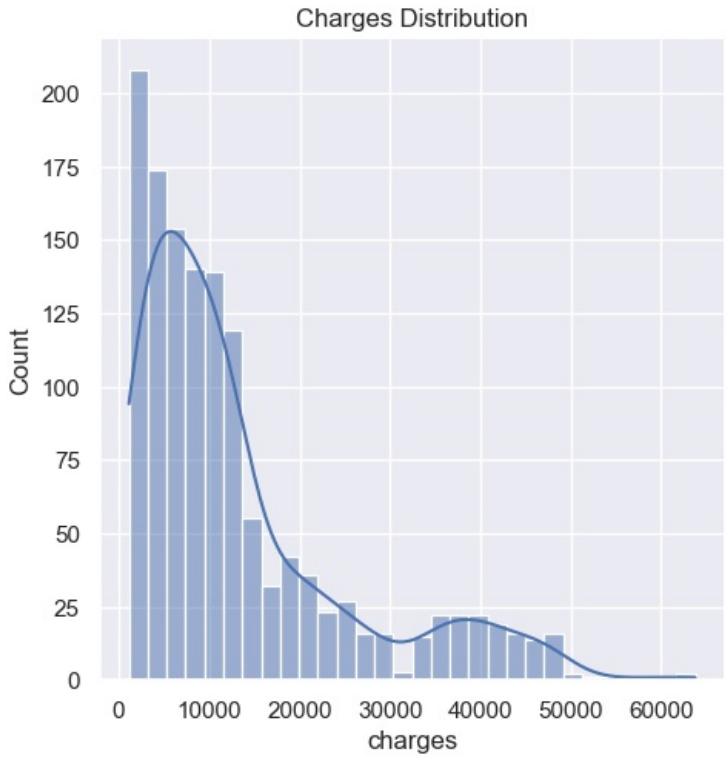
In [10]:
```
sns.set()
plt.figure(figsize=(15,7))
sns.displot(df['children'], kde=True)
plt.title('children Distribution')
plt.show()
```

```
C:\Users\nmsat\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
<Figure size 1500x700 with 0 Axes>
```



In [11]:
```
sns.set()
plt.figure(figsize=(15,7))
sns.displot(df['charges'], kde=True)
plt.title('Charges Distribution')
plt.show()
```

```
C:\Users\nmsat\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
<Figure size 1500x700 with 0 Axes>
```



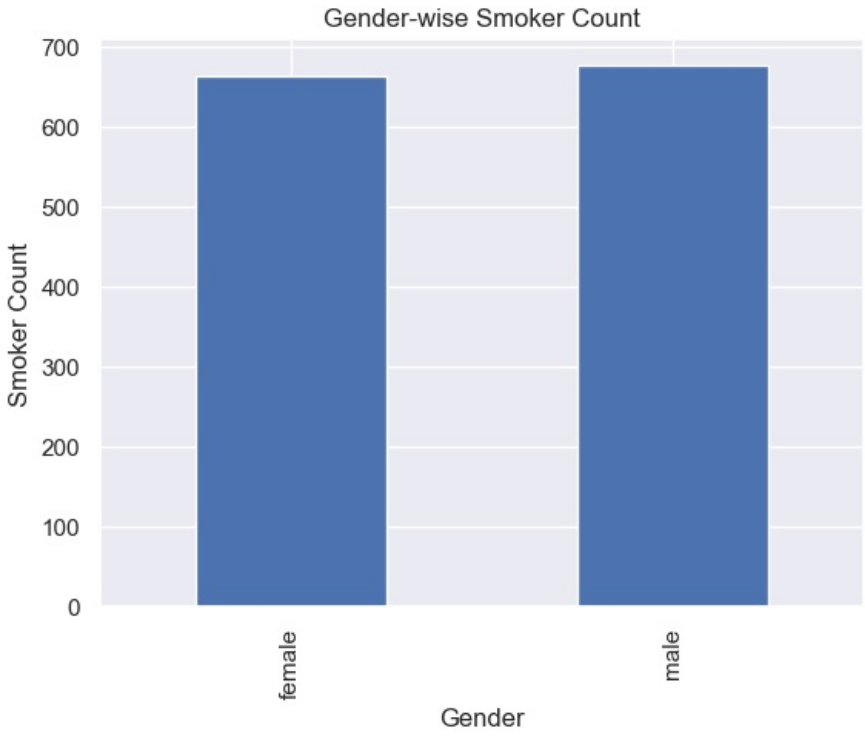
In [12]:
```
# gender wise charges
round(df.groupby('sex')['charges'].sum(),2)
```

Out[12]:
```
sex
female    8321061.19
male      9434763.80
Name: charges, dtype: float64
```

In [13]:
```
#gender wise smoker count
smoke=df.groupby('sex')['smoker'].count()
smoke
```

Out[13]:
```
sex
female    662
male      676
Name: smoker, dtype: int64
```

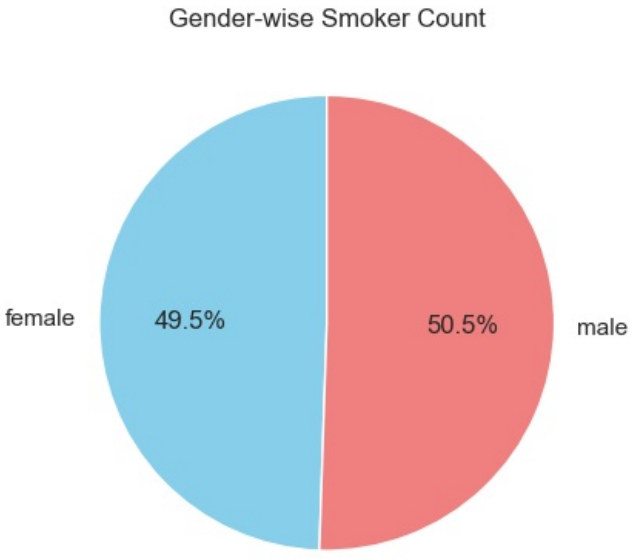
In [14]:
```
smoke.plot(kind='bar')
plt.title('Gender-wise Smoker Count')
plt.xlabel('Gender')
plt.ylabel('Smoker Count')
plt.show()
```



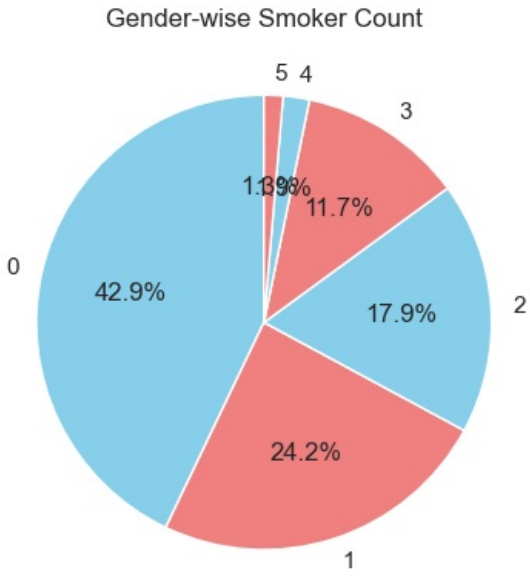
In [15]:
```
child=df['children'].value_counts()
child
```

Out[15]:
```
children
0    574
1    324
2    240
3    157
4     25
5     18
Name: count, dtype: int64
```

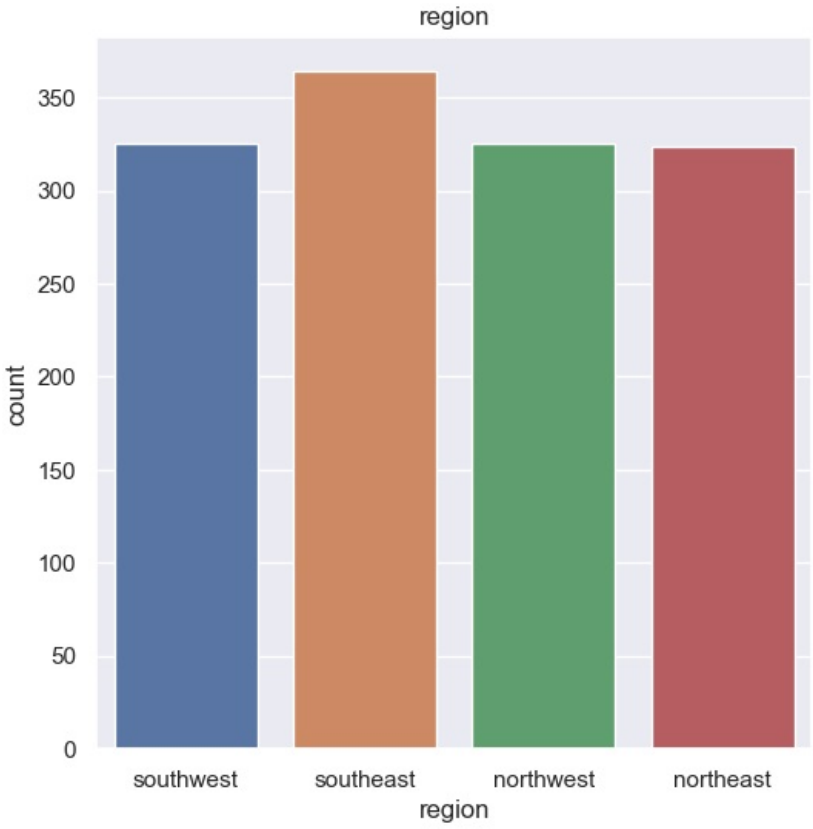
In [16]:
```
smoke.plot(kind='pie', autopct='%1.1f%%', startangle=90, colors=['skyblue', 'lightcoral'])
plt.title('Gender-wise Smoker Count')
plt.ylabel('')
plt.show()
```



In [17]:
```
child.plot(kind='pie', autopct='%1.1f%%', startangle=90, colors=['skyblue', 'lightcoral'])
plt.title('Gender-wise Smoker Count')
plt.ylabel('')  # Hides the y-label for a cleaner look
plt.show()
```



In [18]:
```
plt.figure(figsize=(6,6))
sns.countplot(x='region', data=df)
plt.title('region')
plt.show()
```



Data Preprocessing

In [19]:
```
df.head()
```

Out[19]:

	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 [20]:
```
categorical_columns = df.select_dtypes('object')
categorical_columns
```

Out[20]:

	sex	smoker	region
0	female	yes	southwest
1	male	no	southeast
2	male	no	southeast
3	male	no	northwest
4	male	no	northwest
...	...	...	...
1333	male	no	northwest
1334	female	no	northeast
1335	female	no	southeast
1336	female	no	southwest
1337	female	yes	northwest

1338 rows × 3 columns

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

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

In [22]:
```
df['smoker'] = df['smoker'].map({'yes': 1, 'no': 0})
df['sex'] =df['sex'].map({'male': 1, 'female': 0})
df['region'] = df['region'].map({'southeast': 1, 'southwest': 2,'northeast':3,'northwest':4})
```

In [23]:
```
df.head()
```

Out[23]:

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

In [24]:
```
x = df.drop('charges', axis=1)
```

In [25]:
```
y=df['charges']
```

In [26]:
```
from sklearn.model_selection import train_test_split
```

In [27]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

Create an Evaluate Function to give all metrics after model Training

In [28]:
```
def evaluate_model(true, predicted):
    mae = mean_absolute_error(true, predicted)
    mse = mean_squared_error(true, predicted)
    rmse = np.sqrt(mean_squared_error(true, predicted))
    r2_square = r2_score(true, predicted)
    return mae, rmse, r2_square
```

In [31]:
```
models = {
    "Linear Regression": LinearRegression(),
    "Lasso": Lasso(),
    "Ridge": Ridge(),
    "K-Neighbors Regressor": KNeighborsRegressor(),
    "Decision Tree": DecisionTreeRegressor(),
    "Random Forest Regressor": RandomForestRegressor(),
    "AdaBoost Regressor": AdaBoostRegressor()
}
model_list = []
r2_list =[]

for i in range(len(list(models))):
    model = list(models.values())[i]
```

```
    model.fit(x_train, y_train) # Train model

    # Make predictions
    y_train_pred = model.predict(x_train)
    y_test_pred = model.predict(x_test)

    # Evaluate Train and Test dataset
    model_train_mae , model_train_rmse, model_train_r2 = evaluate_model(y_train, y_train_pred)

    model_test_mae , model_test_rmse, model_test_r2 = evaluate_model(y_test, y_test_pred)


    print(list(models.keys())[i])
    model_list.append(list(models.keys())[i])

    print('Model performance for Training set')
    print("- Root Mean Squared Error: {:.4f}".format(model_train_rmse))
    print("- Mean Absolute Error: {:.4f}".format(model_train_mae))
    print("- R2 Score: {:.4f}".format(model_train_r2))

    print('----------------------------------')

    print('Model performance for Test set')
    print("- Root Mean Squared Error: {:.4f}".format(model_test_rmse))
    print("- Mean Absolute Error: {:.4f}".format(model_test_mae))
    print("- R2 Score: {:.4f}".format(model_test_r2))
    r2_list.append(model_test_r2)

    print('='*35)
    print('\n')
```

```
Linear Regression
Model performance for Training set
- Root Mean Squared Error: 5902.4058
- Mean Absolute Error: 4046.1716
- R2 Score: 0.7412
----------------------------------
Model performance for Test set
- Root Mean Squared Error: 6416.3459
- Mean Absolute Error: 4523.9158
- R2 Score: 0.7625
===================================


Lasso
Model performance for Training set
- Root Mean Squared Error: 5902.4069
- Mean Absolute Error: 4046.4676
- R2 Score: 0.7412
----------------------------------
Model performance for Test set
- Root Mean Squared Error: 6416.4923
- Mean Absolute Error: 4524.2995
- R2 Score: 0.7625
===================================


Ridge
Model performance for Training set
- Root Mean Squared Error: 5902.7452
- Mean Absolute Error: 4056.1826
- R2 Score: 0.7412
----------------------------------
Model performance for Test set
- Root Mean Squared Error: 6421.7215
- Mean Absolute Error: 4536.9182
- R2 Score: 0.7621
===================================


K-Neighbors Regressor
Model performance for Training set
- Root Mean Squared Error: 9288.7720
- Mean Absolute Error: 6354.6143
- R2 Score: 0.3590
----------------------------------
Model performance for Test set
- Root Mean Squared Error: 12258.6987
- Mean Absolute Error: 8551.9300
- R2 Score: 0.1330
===================================


Decision Tree
```

```
Model performance for Training set
- Root Mean Squared Error: 442.4052
- Mean Absolute Error: 20.4502
- R2 Score: 0.9985
----------------------------------
Model performance for Test set
- Root Mean Squared Error: 6953.5360
- Mean Absolute Error: 3414.9512
- R2 Score: 0.7210
==================================


Random Forest Regressor
Model performance for Training set
- Root Mean Squared Error: 1808.6768
- Mean Absolute Error: 943.6975
- R2 Score: 0.9757
----------------------------------
Model performance for Test set
- Root Mean Squared Error: 5023.1173
- Mean Absolute Error: 2716.3365
- R2 Score: 0.8544
==================================


AdaBoost Regressor
Model performance for Training set
- Root Mean Squared Error: 4753.6471
- Mean Absolute Error: 3737.0334
- R2 Score: 0.8321
----------------------------------
Model performance for Test set
- Root Mean Squared Error: 5252.0307
- Mean Absolute Error: 3995.1176
- R2 Score: 0.8409
==================================
```

In [35]:
```
pd.DataFrame(list(zip(model_list, r2_list)), columns=['Model Name', 'R2_Score']).sort_values(by=["R2_Score"],as
```

Out[35]:

	Model Name	R2_Score
5	Random Forest Regressor	0.854427
6	AdaBoost Regressor	0.840857
0	Linear Regression	0.762475
1	Lasso	0.762464
2	Ridge	0.762077
4	Decision Tree	0.721038
3	K-Neighbors Regressor	0.132994

Modelling

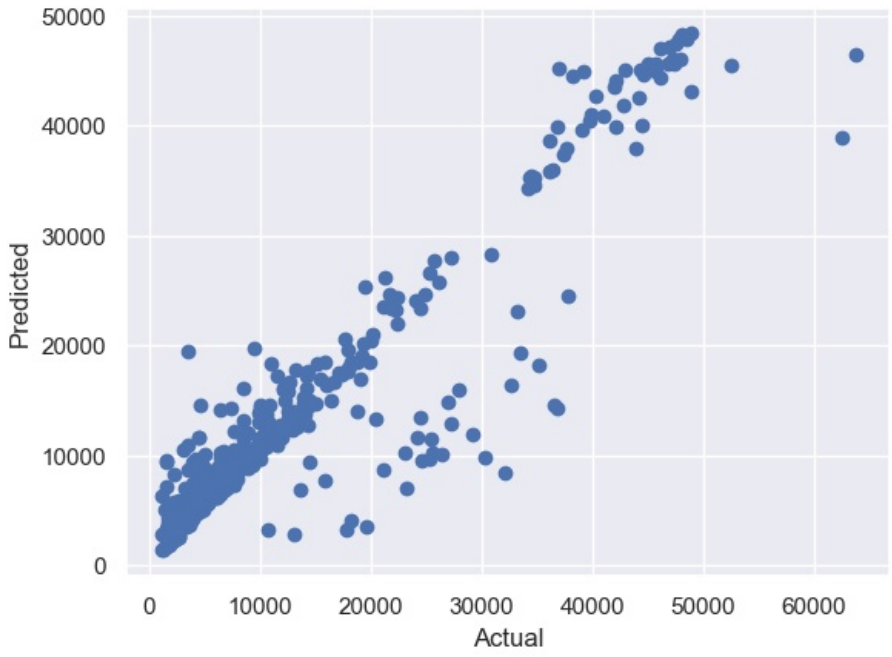
In [33]:
```
re=RandomForestRegressor()
```

In [39]:
```
rf= RandomForestRegressor()
rf =rf.fit(x_train, y_train)
y_pred = rf.predict(x_test)
score = r2_score(y_test, y_pred)*100
print(" Accuracy of the model is %.2f" %score)
```

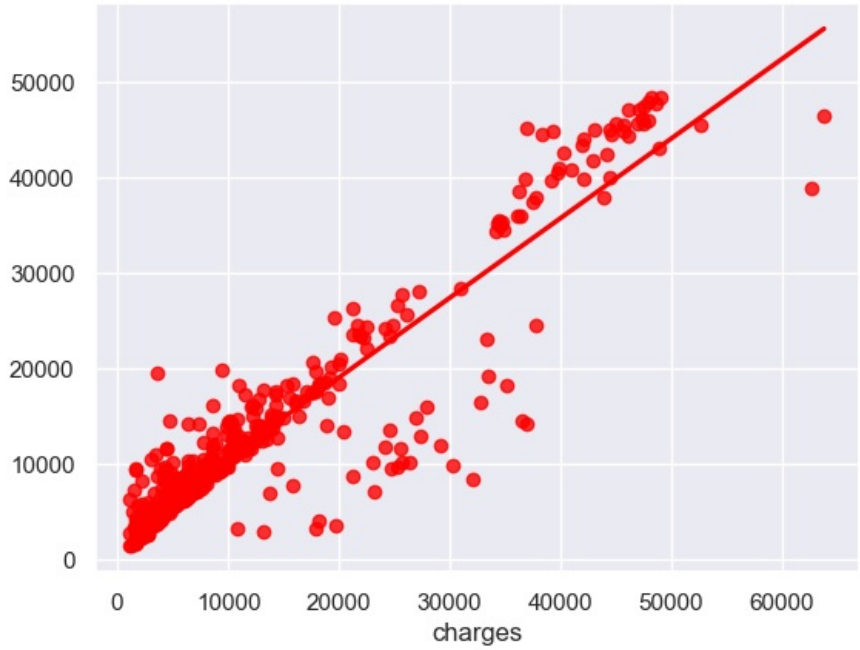
```
Accuracy of the model is 85.23
```

Plot y_pred and y_test

In [42]:
```
plt.scatter(y_test,y_pred);
plt.xlabel('Actual');
plt.ylabel('Predicted');
```



In [43]:
```
sns.regplot(x=y_test,y=y_pred,ci=None,color ='red');
```



Difference between Actual and Predicted Values

In [46]:
```
pred_df=pd.DataFrame({'Actual Value':y_test,'Predicted Value':y_pred,'Difference':y_test-y_pred})
pred_df
```

Out[46]:

	Actual Value	Predicted Value	Difference
43	6313.7590	9016.102765	-2702.343765
53	37742.5757	37933.549418	-190.973718
945	11674.1300	11916.720042	-242.590042
555	3847.6740	6453.120123	-2605.446123
874	8891.1395	8901.447535	-10.308035
...	...	...	...
852	42111.6647	44118.090149	-2006.425449
271	42856.8380	41893.316206	963.521794
563	9058.7303	9203.666005	-144.935705
1068	14349.8544	17590.965427	-3241.111027
553	11187.6567	12293.601813	-1105.945113

402 rows × 3 columns

In [55]:
```
# Load the model from the file
with open('random_forest_model.pkl', 'wb') as model_file:
    pickle.dump(rf, model_file)
```

In [ ]:
```

```