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


warnings.filterwarnings("ignore", category=FutureWarning, message="is_categorical_d
```

Datatypes of the columns

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

Out[2]:
```
age           int64
sex          object
bmi         float64
children      int64
smoker       object
region       object
charges     float64
dtype: object
```

Categorical Variables:

- sex (object)
- smoker (object)
- region (object)

Total categorical variables: 3

Numerical Variables:

- age (int64)
- bmi (float64)
- children (int64)
- charges (float64)

Total numerical variables: 4

Shape of the data

In [3]:
```
data.shape
```

Out[3]:
```
(1338, 7)
```

Shape of data:

- 1338 (raws)
- 7 (columns)

Dealing with missing value

In [4]:
```
data.isna().sum()
```

Out[4]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

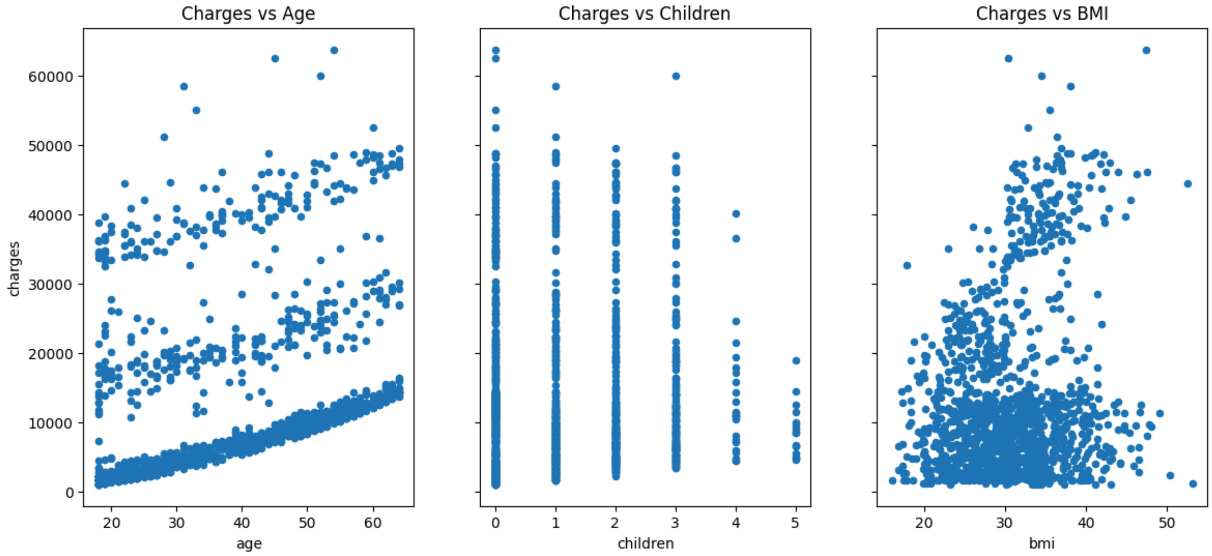
The dataset is clean with no missing data

Exploring the relationship between the feature and target column

age,bmi,children and charges are numerical columns so we'll perform on them scatter plot

In [5]:
```
fig,axs = plt.subplots(1,3,sharey = True)
data.plot(kind = 'scatter',x='age',y='charges',ax=axs[0],figsize=(14,6))
data.plot(kind = 'scatter',x='children',y='charges',ax=axs[1])
data.plot(kind = 'scatter',x='bmi',y='charges',ax=axs[2])

axs[0].set_title('Charges vs Age')
axs[1].set_title('Charges vs Children')
axs[2].set_title('Charges vs BMI')
```

Out[5]:
```
Text(0.5, 1.0, 'Charges vs BMI')
```



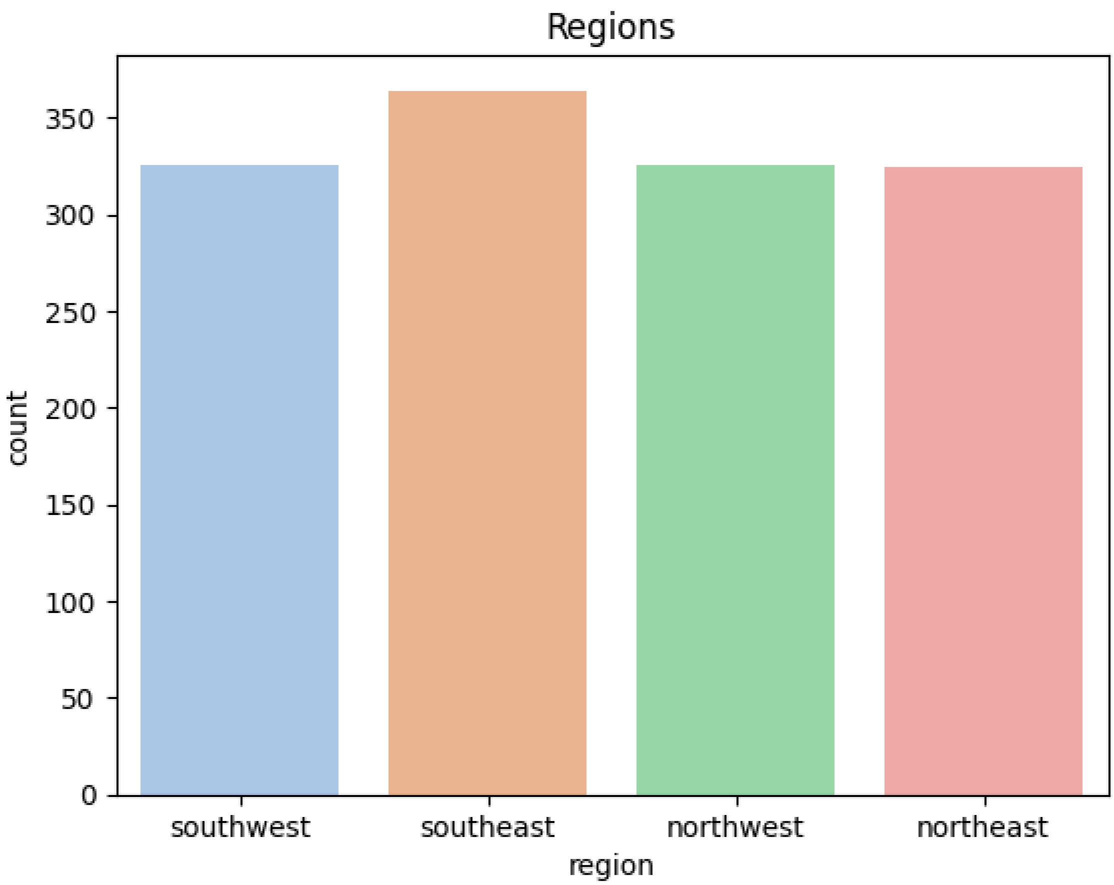
There is a positive correlation between age and charges,as age increases,charges tend to increase.

There isn’t a clear trend between the number of children and the charges. The points are widely scattered, showing that the number of children doesn’t affects charges.

There seems to be a moderate positive correlation between BMI and charges, where higher BMI values are linked with higher charges.

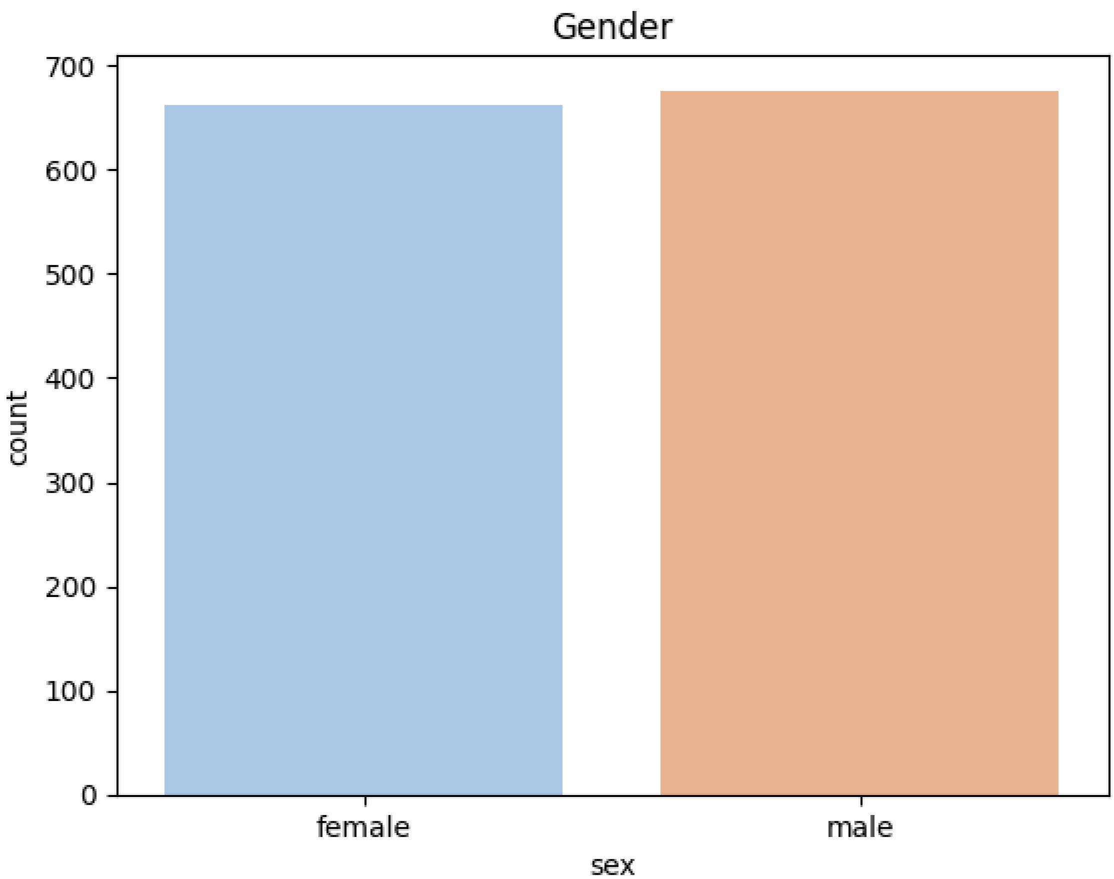
sex,smoker and region are categorical columns so we'll perform on them count plot

In [6]:
```
sns.countplot(data=data,x='region',palette='pastel')
plt.title('Regions')
plt.show()
```



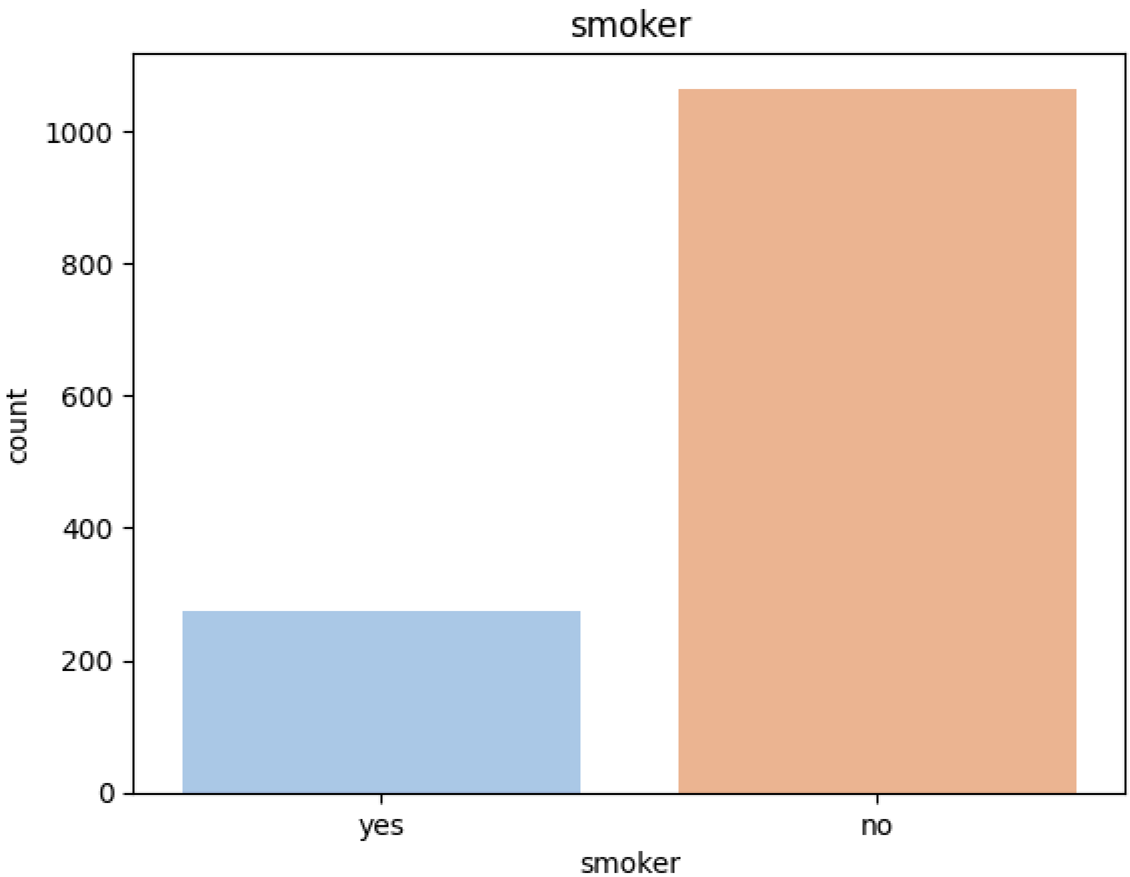
Southeast Region is the most region in the data

In [7]:
```
sns.countplot(data=data,x='sex',palette='pastel')
plt.title('Gender')
plt.show()
```



Males and females are almost equal

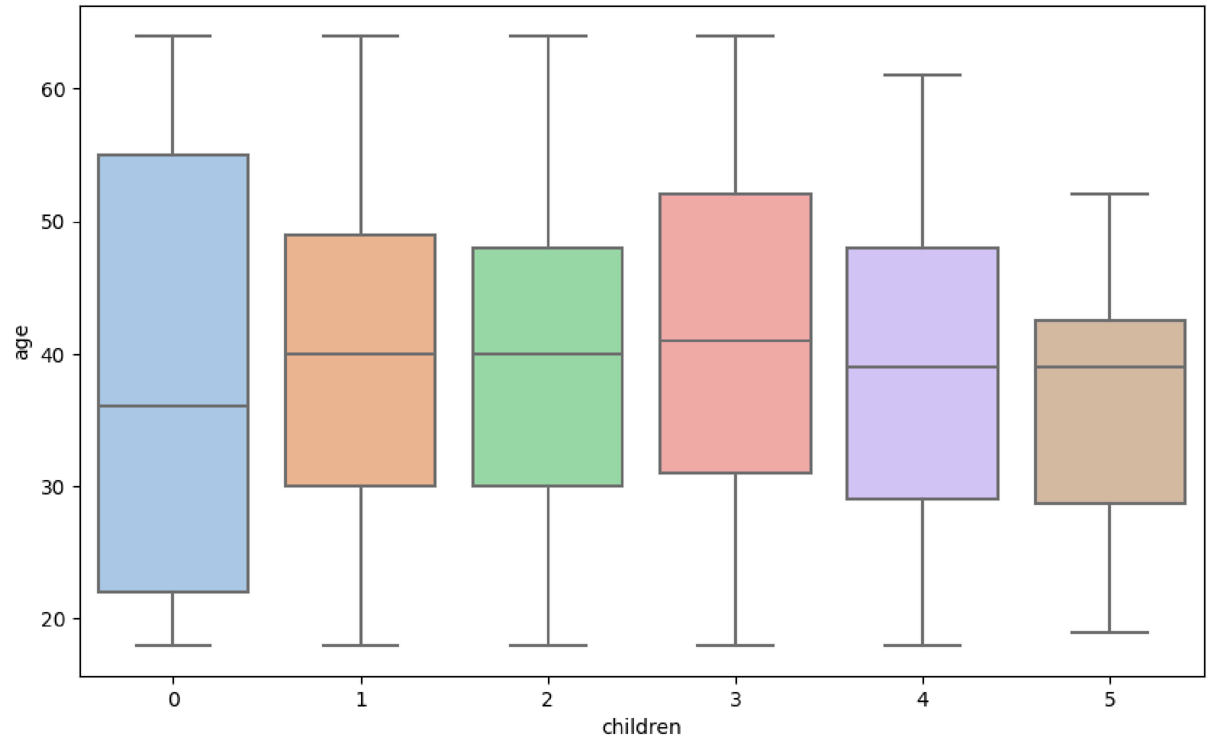
In [8]:
```
sns.countplot(data=data,x='smoker',palette='pastel')
plt.title('smoker')
plt.show()
```



Smokers are less than non smokers

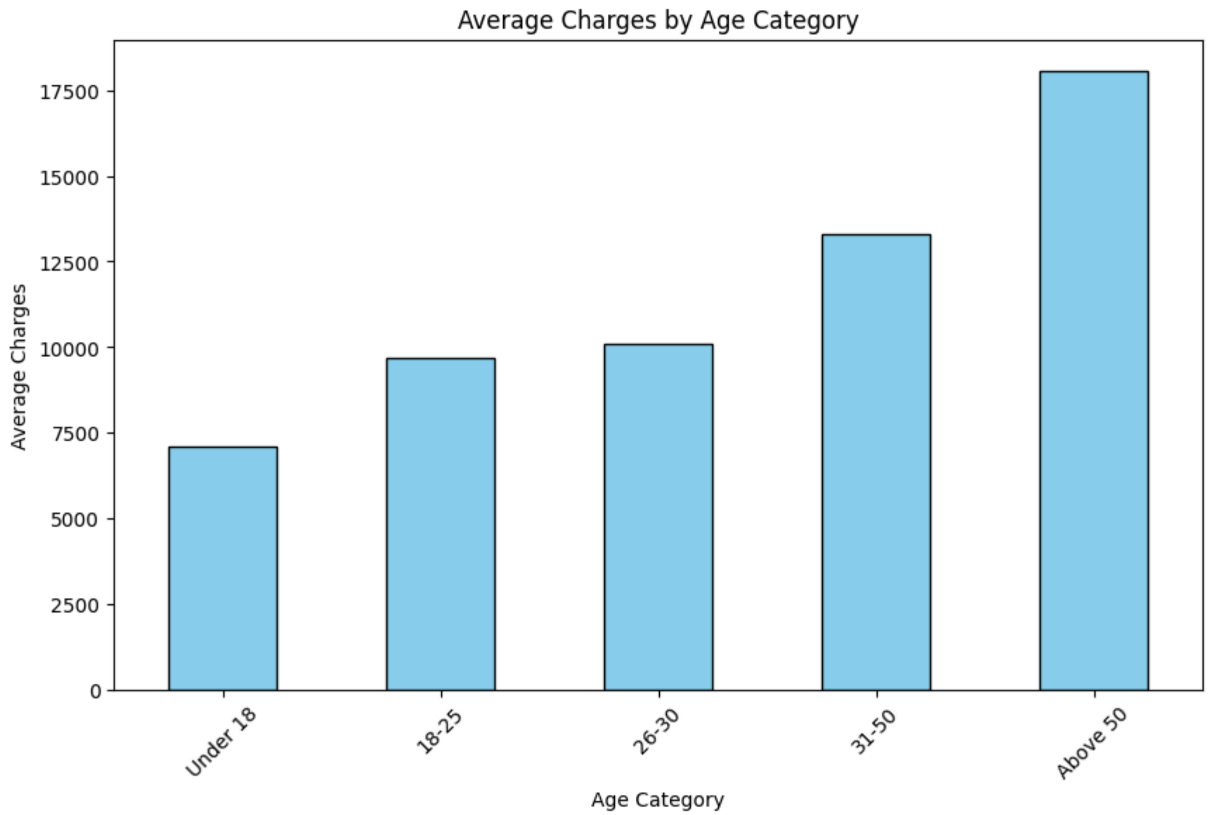
Plotting of Feature vs Feature Plots

In [9]:
```
plt.figure(figsize=(10,6))
sns.boxplot(x='children',y='age',data=data,palette='pastel')
plt.show()
```



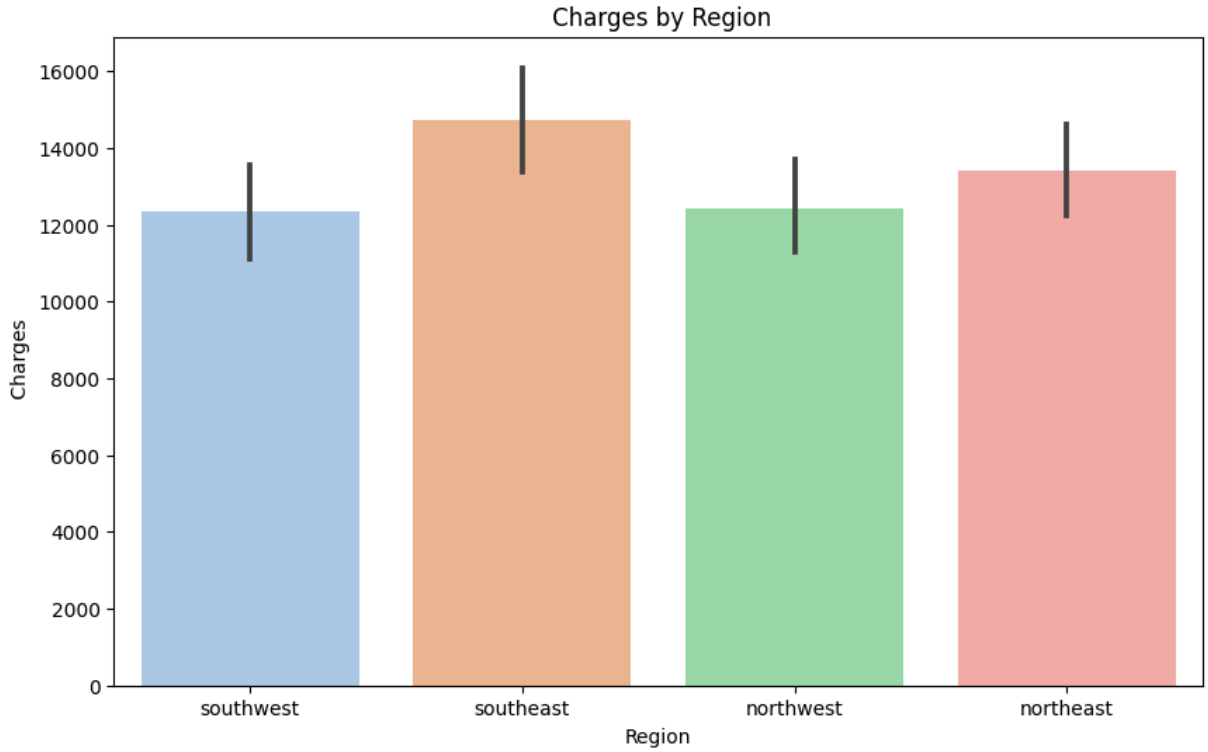
In [10]:
```
bins = [0, 18.5, 25, 30, 50, 100]
labels = ['Under 18', '18-25', '26-30', '31-50', 'Above 50']

data['age_category'] = pd.cut(data['age'], bins=bins, labels=labels)

age_category_avg_charges = data.groupby('age_category')['charges'].mean()


plt.figure(figsize=(10, 6))
age_category_avg_charges.plot(kind='bar', color='skyblue', edgecolor='black')
plt.xlabel('Age Category')
plt.ylabel('Average Charges')
plt.title('Average Charges by Age Category')
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\khi00\AppData\Local\Temp\ipykernel_29264\342903545.py:6: FutureWarning: The
default of observed=False is deprecated and will be changed to True in a future vers
ion of pandas. Pass observed=False to retain current behavior or observed=True to ad
opt the future default and silence this warning.
  age_category_avg_charges = data.groupby('age_category')['charges'].mean()
```

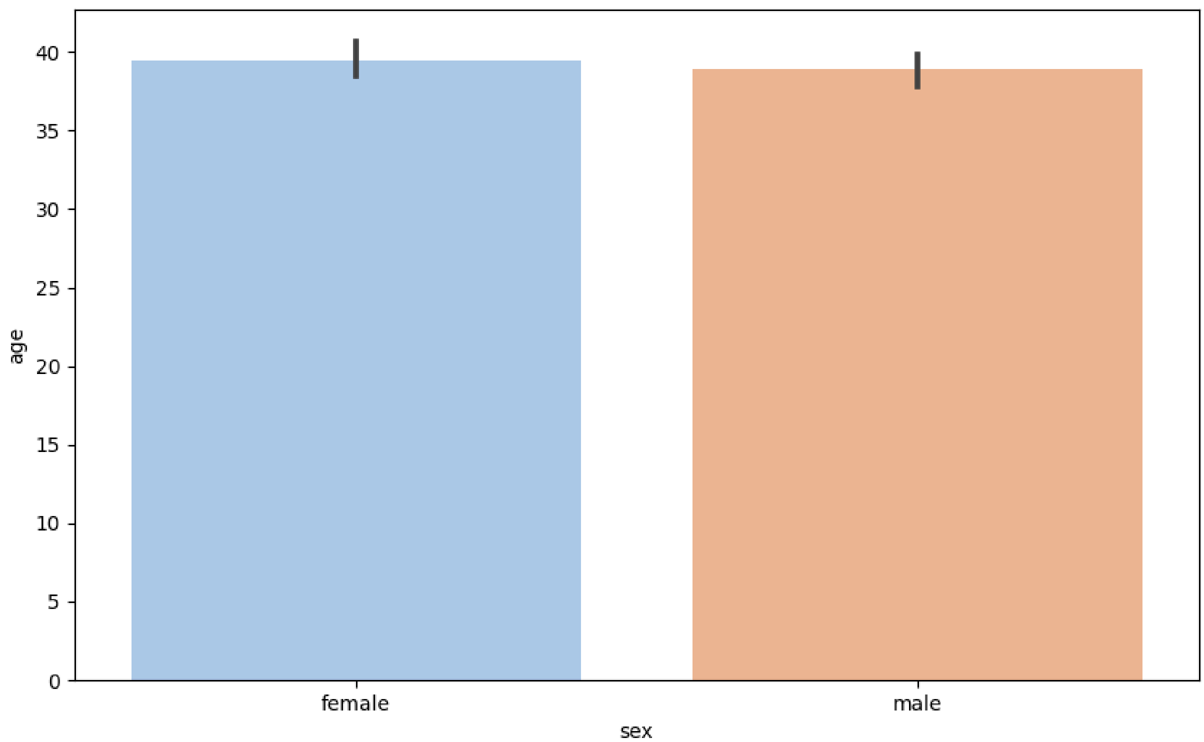


There is a positive relationship between age and Charges,
with higher age categories generally leading to higher average charges.

In [11]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x='region', y='charges', data=data, palette='pastel')
plt.xlabel('Region')
plt.ylabel(' Charges')
plt.title(' Charges by Region')
plt.show()
```



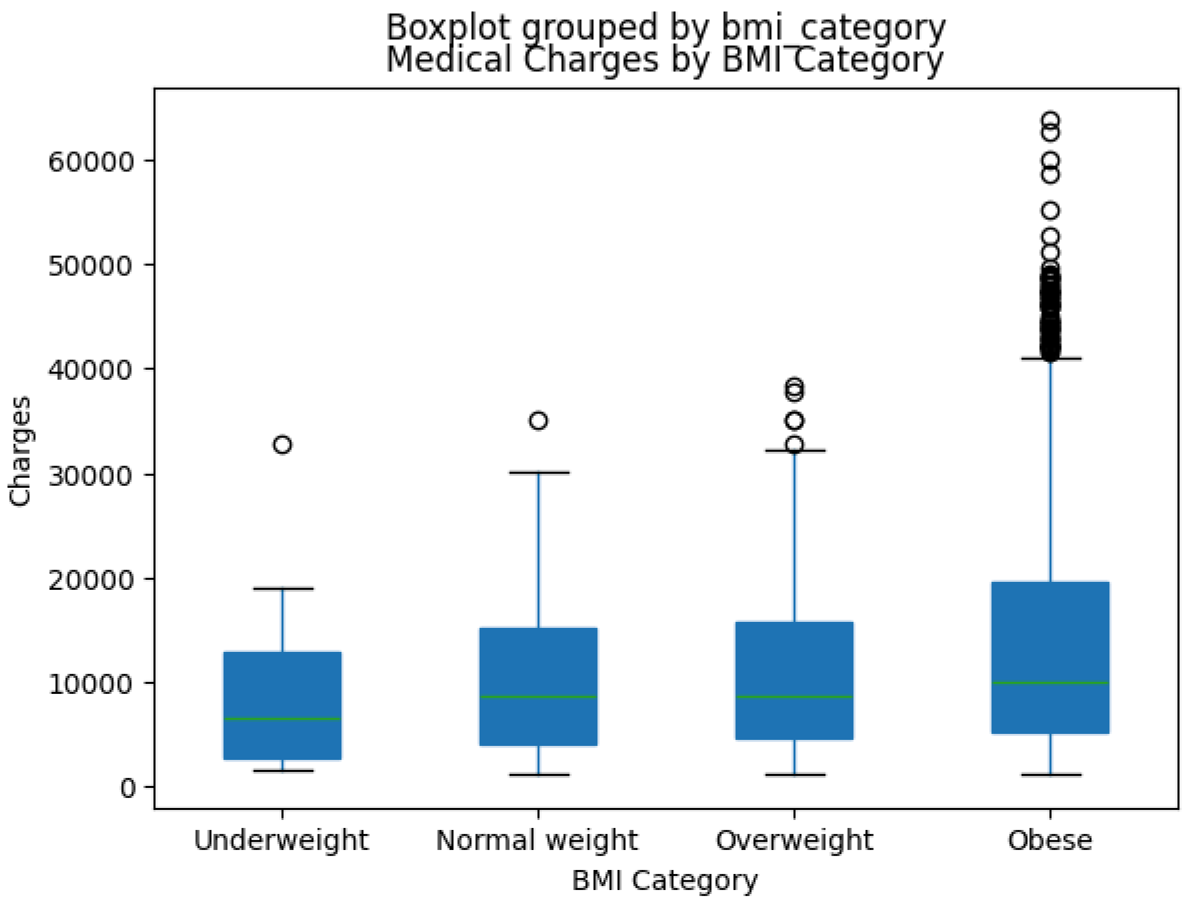
In [12]:
```
plt.figure(figsize=(10,6))
sns.barplot(x='sex',y='age',data=data,palette='pastel')
plt.show()
```



In [13]:
```
bins = [0, 18.5, 25, 30, 50]
labels = ['Underweight', 'Normal weight', 'Overweight', 'Obese']
data['bmi_category'] = pd.cut(data['bmi'], bins=bins, labels=labels)

plt.figure(figsize=(8, 5))
```

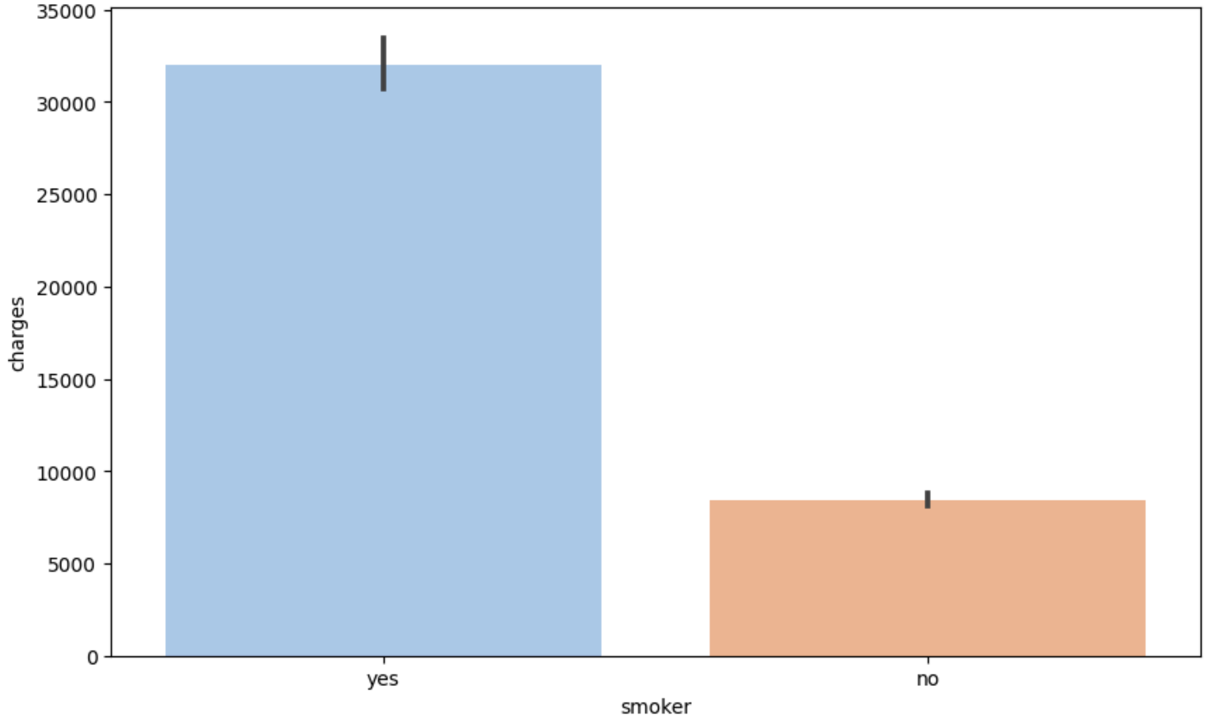
```
data.boxplot(column='charges', by='bmi_category', grid=False, patch_artist=True)
plt.xlabel('BMI Category')
plt.ylabel('Charges')
plt.title('Medical Charges by BMI Category')
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```



There is a positive relationship between BMI and Charges,
with higher BMI categories generally resulting higher average charges.

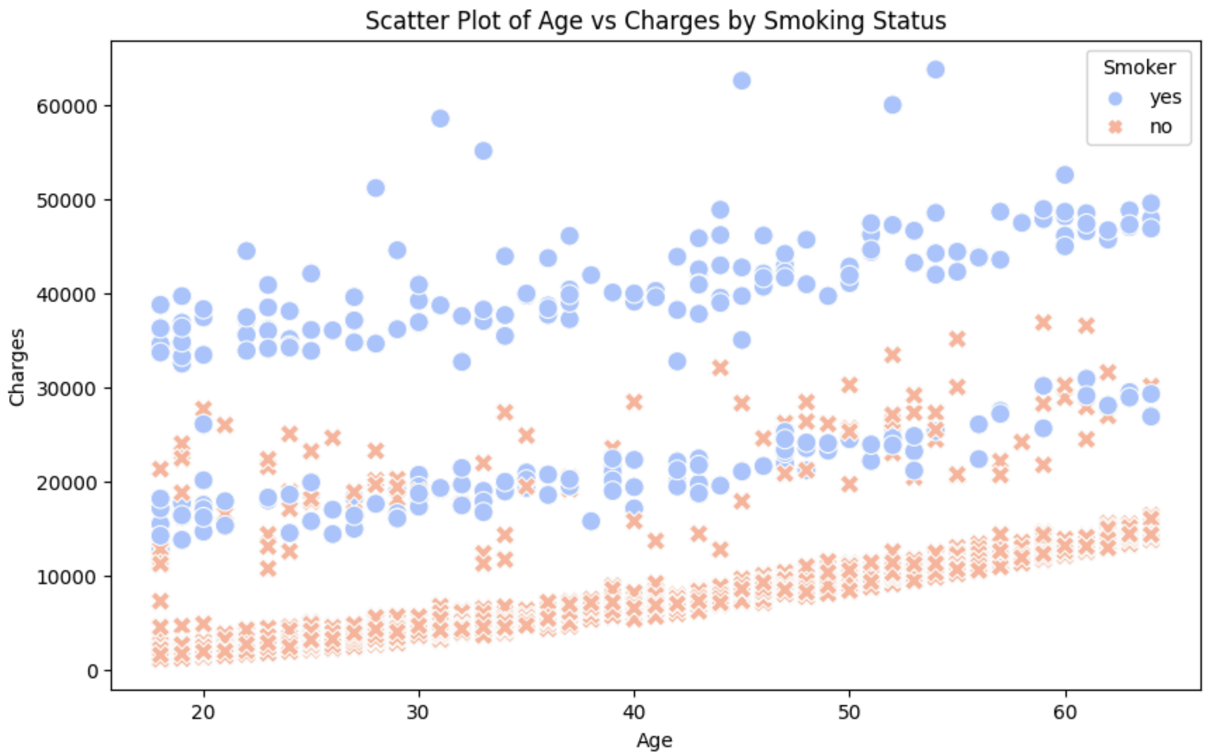
In [14]:
```
plt.figure(figsize=(10,6))
sns.barplot(x='smoker',y='charges',data=data,palette='pastel')
plt.show()
```



There is a positive relationship between Smoker and Charges, with higher smokers reflect higher cost charges.

In [15]:
```
data_filtered = data[['age', 'charges', 'smoker']]
```

In [16]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='age', y='charges', hue='smoker', data=data_filtered, palette='co
plt.xlabel('Age')
plt.ylabel('Charges')
plt.title('Scatter Plot of Age vs Charges by Smoking Status')
plt.legend(title='Smoker')
plt.show()
```



As insurance holders are smokers the amount of charges is becoming higher with respect to age increase

In [17]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

In [18]:
```
X = data[['age', 'smoker']]
y = data['charges']


preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), ['age']),
        ('cat', OneHotEncoder(), ['smoker'])
    ])


model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
])

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Fit the model
```

```
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)




# Print results
print(f"Mean Squared Error: {mse}")
print(f"R Sqaured: {r2}")
```

```
Mean Squared Error: 38274699.675041825
R Sqaured: 0.7534620778716639
```

Making prediction

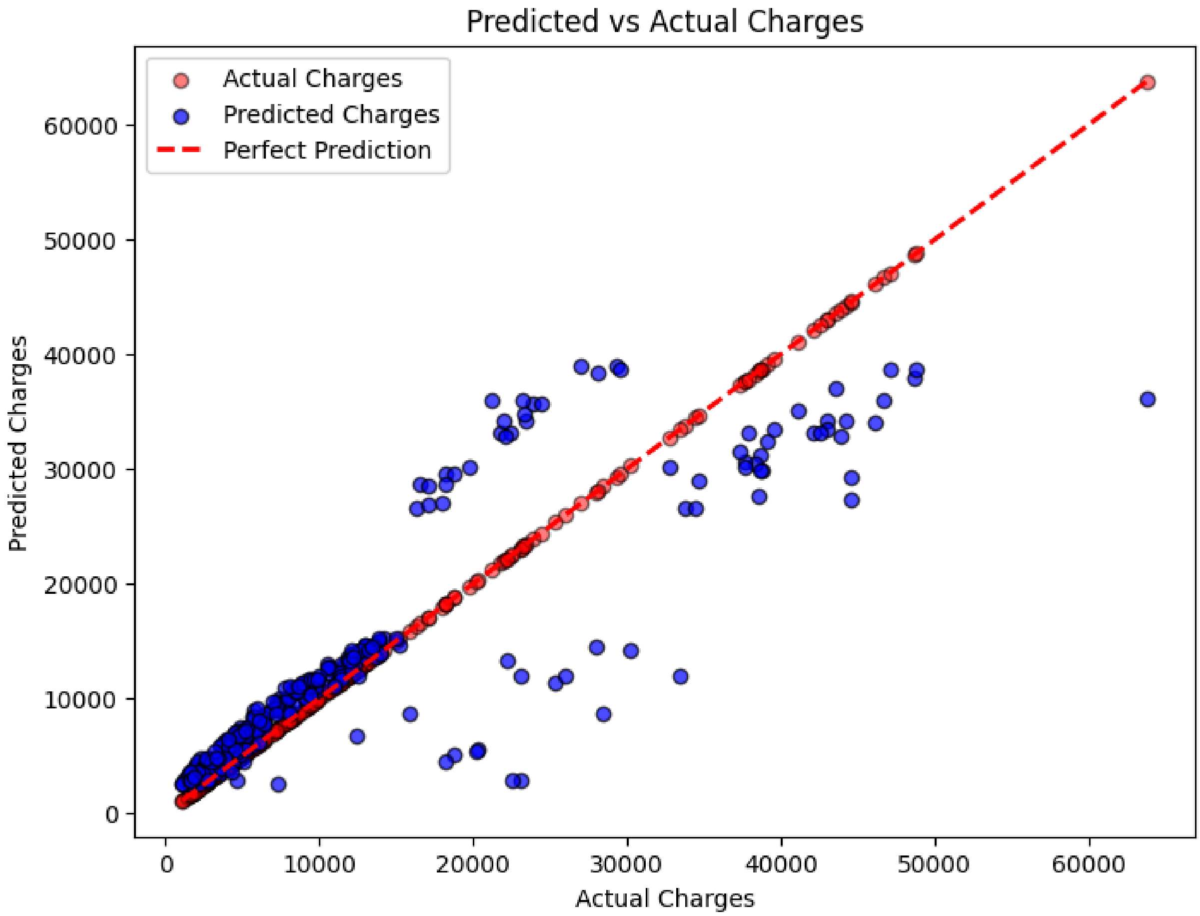
In [19]:

```
new_data = pd.DataFrame({'age': [19], 'smoker': ['yes']})
predicted_charges = model.predict(new_data)

print(f"Predicted Charges for new data: {predicted_charges[0]}")
```

```
Predicted Charges for new data: 26545.412779517086
```

In [20]:

```
import matplotlib.pyplot as plt

# Plot predicted vs actual values
plt.figure(figsize=(8, 6))

# Scatter plot for actual values
plt.scatter(y_test, y_test, color='red', label='Actual Charges', alpha=0.5, edgecol

# Scatter plot for predicted values
plt.scatter(y_test, y_pred, color='blue', label='Predicted Charges', alpha=0.7, edg

# diagonal line for perfect prediction
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2, l

# Add labels and title
plt.xlabel('Actual Charges')
plt.ylabel('Predicted Charges')
plt.title('Predicted vs Actual Charges')
plt.legend()

# Show plot
plt.show()
```



After applying linear regression the predicted values become far from diagonal line which proves as a poor model

Apply polynamial Regression and adding new variable bmi

In [21]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder, PolynomialFeatures
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_squared_error, r2_score



# Define features and target
X = data[['age', 'smoker','bmi']]
y = data['charges']

# Preprocessing
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), ['age','bmi']),
        ('cat', OneHotEncoder(drop='first'), ['smoker'])  # drop='first' avoids the
    ])
```

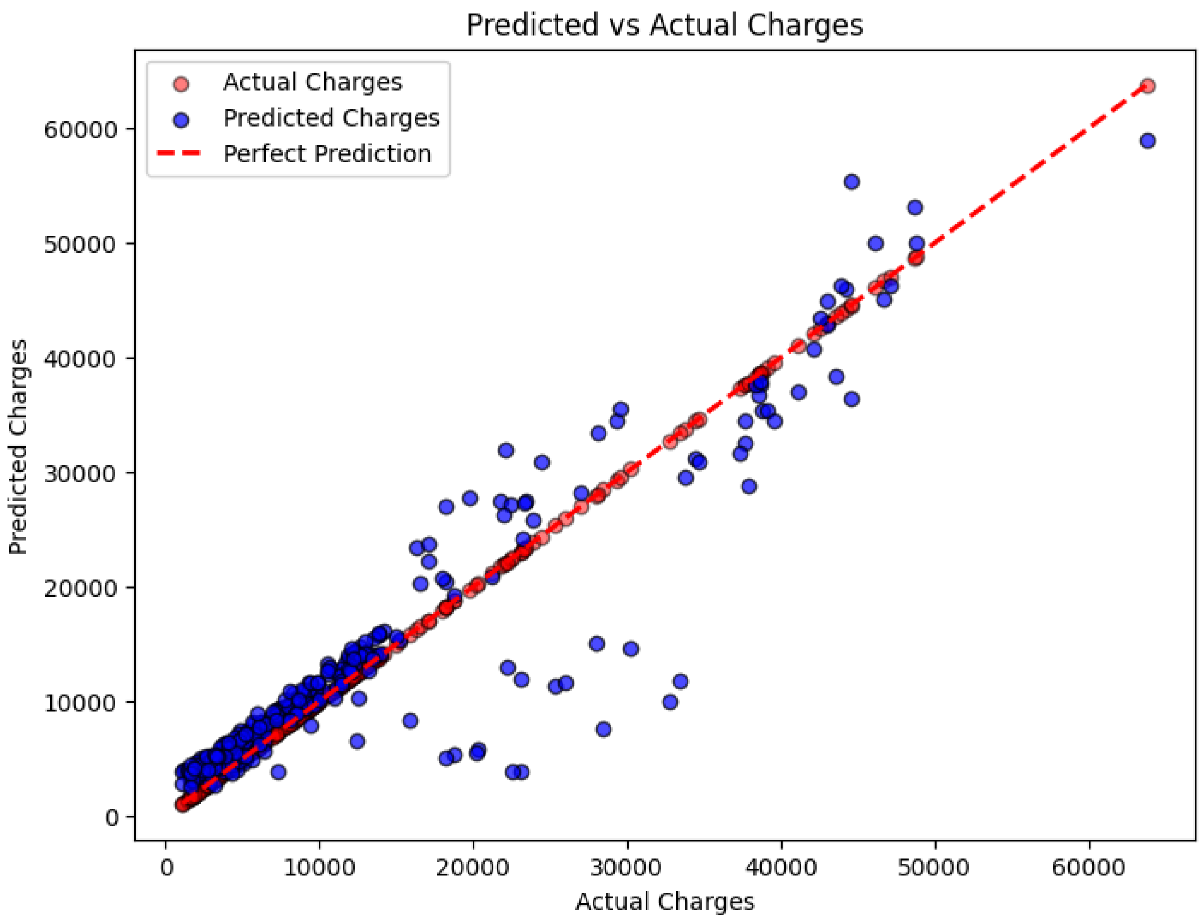
```
# Create Polynomial Features
poly_features = PolynomialFeatures(degree=2, include_bias=False)

# Create and train the Ridge regression model
model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('poly', poly_features),
    ('regressor', Ridge(alpha=1.0))  # alpha is the regularization parameter
])

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Fit the model
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error: {mse}")
print(f"R^2 Score: {r2}")

# Example of making a new prediction
new_data = pd.DataFrame({'age': [19], 'smoker': ['yes'],'bmi':[29]})
predicted_charges = model.predict(new_data)
print(f"Predicted Charges for new data: {predicted_charges[0]}")
```

```
Mean Squared Error: 21539421.75531167
R^2 Score: 0.8612586296303939
Predicted Charges for new data: 25316.399937213057
```

In [22]:

```
import matplotlib.pyplot as plt

# Plot predicted vs actual values
plt.figure(figsize=(8, 6))

# Scatter plot for actual values
plt.scatter(y_test, y_test, color='red', label='Actual Charges', alpha=0.5, edgecol

# Scatter plot for predicted values
plt.scatter(y_test, y_pred, color='blue', label='Predicted Charges', alpha=0.7, edg

# diagonal line for perfect prediction
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2, l

# Add labels and title
plt.xlabel('Actual Charges')
plt.ylabel('Predicted Charges')
plt.title('Predicted vs Actual Charges')
plt.legend()
```

```
# Show plot
plt.show()
```



After applying polynomial regression the predicted values become closer to diagonal line which proves as a good model