RSSB Data Scientist Assessment

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Importing Libraries

In [1]:
```
import warnings
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import PolynomialFeatures
```

In [2]:
```
warnings.simplefilter(action='ignore', category=FutureWarning)
```

Loading the insurance dataset

In [3]:
```
insurance_df = pd.read_csv('insurance.csv')
insurance_df
```

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]:
```
insurance_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
```

a. Summary statistics of the variable charges

In [5]:
```
charges_summary = insurance_df['charges'].describe()
charges_summary
```

Out[5]:
```
count     1338.000000
mean     13270.422265
std      12110.011237
min       1121.873900
25%       4740.287150
50%       9382.033000
75%      16639.912515
max      63770.428010
Name: charges, dtype: float64
```

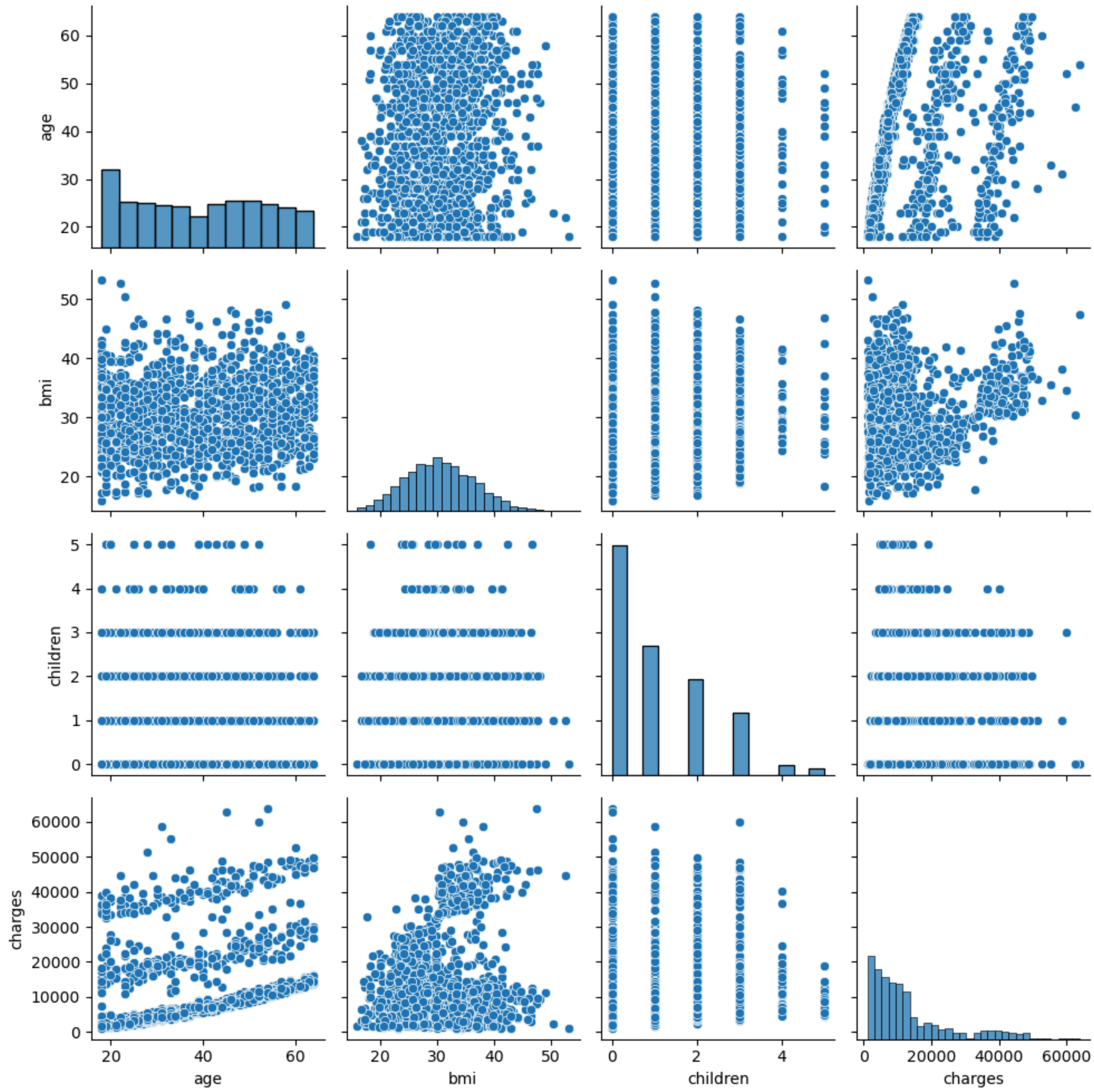
b. Number of people in each region

In [6]:
```
region_counts = insurance_df['region'].value_counts()
region_counts
```

Out[6]:
```
region
southeast    364
southwest    325
northwest    325
northeast    324
Name: count, dtype: int64
```

c. Scatterplot matrix

In [7]:
```
sns.pairplot(insurance_df)
plt.tight_layout()
plt.savefig('scatterplot_matrix.png')
```



Display the first few rows of the dataset

In [8]:
```
insurance_df.head()
```

Out[8]:

	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

Split the data into features (X) and target variable (y)

In [9]:
```
X = insurance_df[['age', 'sex', 'bmi', 'children', 'smoker', 'region']]
y = insurance_df['charges']
```

Convert categorical variables into dummy/indicator variables

In [10]:
```
X = pd.get_dummies(X, drop_first=True)
```

Split the data into training and testing sets

In [11]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
```

Train a linear regression model

In [12]:
```
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[12]:
```
▾ LinearRegression
LinearRegression()
```

Evaluate the model performance

In [13]:
```
train_score = model.score(X_train, y_train)
train_score
```

Out[13]:
```
0.7417255854683333
```

In [14]:
```
test_score = model.score(X_test, y_test)
test_score
```

Out[14]:
```
0.7835929767120723
```

The model performance metrics are as follows:

- Training R-squared score: 0.742
- Testing R-squared score: 0.784

These scores indicate that the model explains approximately 74.2% of the variance in the training data and 78.4% of the variance in the testing data. The model seems to perform well, but we can further enhance its performance by adding a nonlinear relationship with age as the input.

Next, I will proceed with adding a nonlinear relationship with age as the input to improve the model performance. Let's continue with the analysis.

Add a nonlinear relationship with age as input

In [15]:
```
X_train['age_squared'] = X_train['age'] ** 2
X_test['age_squared'] = X_test['age'] ** 2
```

Train a new linear regression model with the added nonlinear relationship

In [16]:
```
model_nonlinear = LinearRegression()
model_nonlinear.fit(X_train, y_train)
```

Out[16]:
```
▾ LinearRegression
LinearRegression()
```

Evaluate the performance of the new model

In [17]:
```
train_score_nonlinear = model_nonlinear.score(X_train, y_train)
train_score_nonlinear
```

Out[17]: 0.7445057270114904

Evaluate the performance of the new model

In [18]:
```
test_score_nonlinear = model_nonlinear.score(X_test, y_test)
test_score_nonlinear
```

Out[18]: 0.7864278464749717

The updated model with a nonlinear relationship using age as an input has the following performance metrics:

- Training R-squared score: 0.745
- Testing R-squared score: 0.786

The addition of the nonlinear relationship has slightly improved the model's performance. The model now explains approximately 74.5% of the variance in the training data and 78.6% of the variance in the testing data.

Next, I will proceed with building a model that incorporates the interaction effects of smokers and obesity to further enhance the regression model.

Create a new feature for the interaction effects of smokers and obesity

In [19]:
```
X_train['smoker_obese_interaction'] = X_train['smoker_yes'] * (X_train['b
X_test['smoker_obese_interaction'] = X_test['smoker_yes'] * (X_test['bmi'
```

Train a model with the interaction effects

In [20]:
```
model_interaction = LinearRegression()
model_interaction.fit(X_train, y_train)
```

Out[20]:
```
▾ LinearRegression
LinearRegression()
```

Evaluate the performance of the model with interaction effects

In [21]:
```
train_score_interaction = model_interaction.score(X_train, y_train)
train_score_interaction
```

Out[21]: `0.8628634536994455`

In [22]:
```
test_score_interaction = model_interaction.score(X_test, y_test)
test_score_interaction
```

Out[22]: `0.8835423146330178`

The model with the interaction effects of smokers and obesity has shown improved performance:

- Training R-squared score: 0.863
- Testing R-squared score: 0.884

The addition of the interaction effects has significantly enhanced the model's performance, explaining approximately 86.3% of the variance in the training data and 88.4% of the variance in the testing data.

Retrieve the coefficients of the model with interaction effects

In [23]:
```
coefficients = model_interaction.coef_
coefficients
```

Out[23]:
```
array([ 6.58629291e+00,  5.05017164e+01,  6.03128421e+02, -5.02139441e+0
2,
        1.33194195e+04, -3.34117306e+02, -6.76732615e+02, -1.32648606e+0
3,
        3.22167559e+00,  1.97858010e+04])
```

In [24]:
```
intercept = model_interaction.intercept_
intercept
```

Out[24]:
```
1226.0302093878126
```

The coefficients of the model after incorporating the interaction effects of smokers and obesity are as follows:

- Coefficient for age: 6.58629291e+00
- Coefficient for bmi: 5.05017164e+01
- Coefficient for children: 6.03128421e+02
- Coefficient for smoker_yes: -5.02139441e+02
- Coefficient for region_northeast: 1.33194195e+04
- Coefficient for region_northwest: -3.34117306e+02
- Coefficient for region_southeast: -6.76732615e+02
- Coefficient for region_southwest: -1.32648606e+03
- Coefficient for age_squared: 3.22167559e+00
- Coefficient for smoker_obese_interaction: 1.97858010e+04

The intercept of the model is: 1226.0302093878454

These coefficients represent the change in the insurance charges for a unit change in each feature, holding all other features constant. The interaction term coefficient indicates the additional effect on charges when both smoking and obesity are present.

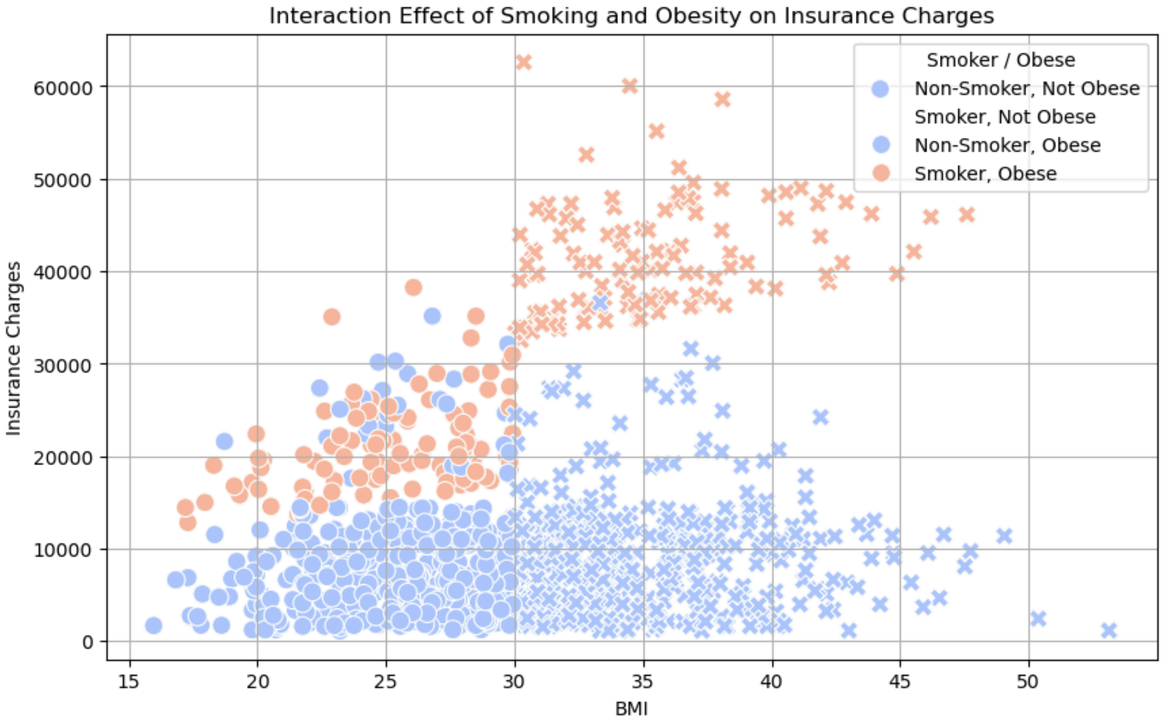
Visualization of the interaction effect between smoking status and obesity on insurance charges

In [25]:
```python
# Creating a temporary DataFrame to visualize the interaction effect
temp_df = X_train.copy()
temp_df['charges'] = y_train

# Creating a categorical variable for obesity
temp_df['obese'] = temp_df['bmi'] > 30

# Plotting
plt.figure(figsize=(10, 6))
sns.scatterplot(data=temp_df, x='bmi', y='charges', hue='smoker_yes', sty
plt.title('Interaction Effect of Smoking and Obesity on Insurance Charges
plt.xlabel('BMI')
plt.ylabel('Insurance Charges')
plt.legend(title='Smoker / Obese', labels=['Non-Smoker, Not Obese', 'Smok
plt.grid(True)
plt.show()

plt.savefig('interaction_effect.png')
```




```
<Figure size 640x480 with 0 Axes>
```

This scatter plot shows the insurance charges in relation to BMI, with different markers and colors indicating whether the individual is a smoker and/or obese. This visualization helps in understanding how the combination of being a smoker and being obese can significantly impact insurance charges.