Medical_Insurance_Prediction

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Anthony Adungo Machine Learning Project.

1 Project Description

This project focuses on predicting medical insurance premiums using a publicly available dataset. The dataset includes key attributes such as demographics, health-related factors, and personal habits, which influence the cost of insurance premiums. The primary objective is to develop machine-learning models capable of accurately forecasting premium amounts. This involves identifying the most significant factors affecting premiums and providing actionable insights to refine pricing strategies, enabling insurers to optimize their offerings and enhance customer satisfaction.

2 Key Objectives

Data Exploration and Preprocessing.

Perform exploratory data analysis (EDA) to understand the dataset's structure. Clean the data by handling missing values, addressing outliers, and encoding categorical variables where necessary.

Feature Engineering.

Develop and refine features to enhance model performance by identifying relationships between demographic, behavioral, and other relevant factors.

Model Development

Utilize machine learning algorithms, including Multiple Linear Regression, Random Forest Regressor, and XGBoost Regressor, to predict medical insurance premiums. Compare the performance of these models to determine the best approach for accurate predictions.

Model Evaluation

Evaluate each model's performance using metrics such as R^2, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Ensure the models are robust and capable of generalizing well to unseen data.

Insights and Recommendations

Analyze model outputs to identify the most influential factors affecting insurance premiums. Provide actionable insights for insurers to optimize premium pricing strategies and enhance customer satisfaction.

3 Tools and Technologies

Programming: Python (Pandas, NumPy, Scikit-learn, XGBoost) Environment: Jupyter Notebooks Visualization: Matplotlib, Seaborn Machine Learning: Multiple Linear Regression, Random Forest Regressor, XGBoost Regressor

4 Part 1: Data Pre-processing

I) Importing the dataset and exploring its properties.

[95]:
```
#Importing all the necessary libraries.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from scipy import stats
```

[96]:
```
df = pd.read_csv('insurance.csv')
df.sample(5)
```

[96]:

	age	sex	bmi	children	smoker	region	charges
1245	28	male	24.300	5	no	southwest	5615.36900
908	63	male	39.800	3	no	southwest	15170.06900
319	32	male	37.335	1	no	northeast	4667.60765
462	62	female	38.095	2	no	northeast	15230.32405
729	41	female	36.080	1	no	southeast	6781.35420

[97]:
```
df.shape
```

[97]: (1338, 7)

[98]:
```
df.columns
```

[98]:
```
Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'],
dtype='object')
```

[99]:
```
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
```

[100]:
```
#Finding the statistical summary of the dataset.
df.describe().transpose()
```

[100]:
```
           count          mean           std        min         25%       50%  \
age       1338.0     39.207025     14.049960    18.0000    27.00000    39.000
bmi       1338.0     30.663397      6.098187    15.9600    26.29625    30.400
children  1338.0      1.094918      1.205493     0.0000     0.00000     1.000
charges   1338.0  13270.422265  12110.011237  1121.8739  4740.28715  9382.033

                   75%          max
age          51.000000     64.00000
bmi          34.693750     53.13000
children      2.000000      5.00000
charges   16639.912515  63770.42801
```

[101]:
```
print(df.dtypes)
```

```
age           int64
sex          object
bmi         float64
children      int64
smoker       object
region       object
charges     float64
dtype: object
```

[102]:
```
#Finding the categorical variables.
df.select_dtypes(include='object').columns
```

[102]: `Index(['sex', 'smoker', 'region'], dtype='object')`

[103]:
```
len(df.select_dtypes(include='object').columns)
```

[103]: 3

[104]:
```
df.select_dtypes(include=['float64','int64']).columns
```

[104]: `Index(['age', 'bmi', 'children', 'charges'], dtype='object')`

[105]:
```
len(df.select_dtypes(include=['float64','int64']).columns)
```

[105]: 4

II) Dealing with missing values.

[106]:
```
missing_data = df.isnull()
print(missing_data.head())
for column in missing_data.columns.values.tolist():
    print(column)
    print(missing_data[column].value_counts())
    print(" ")
```

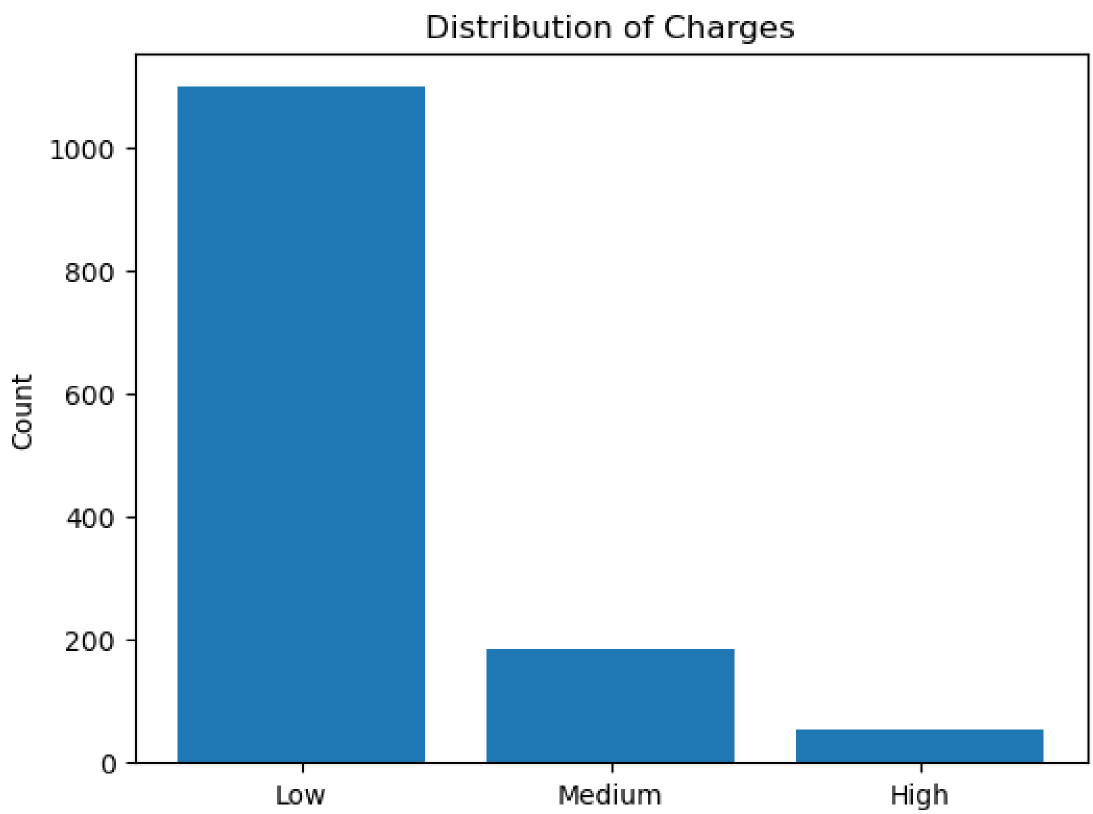
```
     age    sex    bmi  children  smoker  region  charges
0  False  False  False     False   False   False    False
1  False  False  False     False   False   False    False
2  False  False  False     False   False   False    False
3  False  False  False     False   False   False    False
4  False  False  False     False   False   False    False
age
age
False    1338
Name: count, dtype: int64

sex
sex
False    1338
Name: count, dtype: int64

bmi
bmi
False    1338
Name: count, dtype: int64

children
children
False    1338
Name: count, dtype: int64

smoker
smoker
False    1338
Name: count, dtype: int64

region
region
False    1338
Name: count, dtype: int64

charges
charges
False    1338
```

```
Name: count, dtype: int64
```

III) Creating bins to see the distribution of the charges.

[107]:
```python
bins = np.linspace(min(df['charges']), max(df['charges']),4)
group_names = ["Low","Medium","High"]
df["charges_binned"] = pd.cut(df["charges"], bins, labels = group_names,␣
↪include_lowest= True)
plt.bar(group_names,df["charges_binned"].value_counts())
plt.title("Distribution of Charges")
plt.ylabel("Count")
```

[107]:
```
Text(0, 0.5, 'Count')
```



IV) Grouping the dataset by 'sex','smoker' and 'region'.

[108]:
```python
df.groupby('sex').mean(numeric_only=True)
```

[108]:

	age	bmi	children	charges
sex				
female	39.503021	30.377749	1.074018	12569.578844

```
male    38.917160  30.943129  1.115385  13956.751178
```

[109]:
```python
df.groupby('smoker').mean(numeric_only=True)
```

[109]:
```
              age        bmi  children       charges
smoker
no      39.385338  30.651795  1.090226   8434.268298
yes     38.514599  30.708449  1.113139  32050.231832
```

[110]:
```python
''' There is a huge disparity between charges for smokers and non-smokers.␣
↪Smokers on average pay 4 times as much as non-smokers.'''
```

[110]: ' There is a huge disparity between charges for smokers and non-smokers. Smokers on average pay 4 times as much as non-smokers.'

[111]:
```python
df.groupby('region').mean(numeric_only=True)
```

[111]:
```
                 age        bmi  children       charges
region
northeast  39.268519  29.173503  1.046296  13406.384516
northwest  39.196923  29.199785  1.147692  12417.575374
southeast  38.939560  33.355989  1.049451  14735.411438
southwest  39.455385  30.596615  1.141538  12346.937377
```

[112]:
```python
pearson_coef, p_value = stats.pearsonr(df['bmi'],df["charges"])
print(pearson_coef, p_value)
```

```
0.19834096883362912 2.459085535116604e-13
```

[113]:
```python
'''There is a statistically significant relationship between the bmi and␣
↪charges.'''
```

[113]: 'There is a statistically significant relationship between the bmi and charges.'

V) Feature Engineering.

[114]:
```python
for column in df.select_dtypes(include='object').columns.tolist():
    print(df[column].unique())
```

```
['female' 'male']
['yes' 'no']
['southwest' 'southeast' 'northwest' 'northeast']
```

[115]:
```python
df = df.drop(columns = "charges_binned")
```

[116]:
```python
df.head()
```

[116]:
```
   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
```

[117]:
```
dataset = pd.get_dummies(data = df,drop_first=True)
```

[118]:
```
dataset.head()
```

[118]:
```
   age     bmi  children      charges  sex_male  smoker_yes  region_northwest  \
0   19  27.900         0  16884.92400     False        True             False
1   18  33.770         1   1725.55230      True       False             False
2   28  33.000         3   4449.46200      True       False             False
3   33  22.705         0  21984.47061      True       False              True
4   32  28.880         0   3866.85520      True       False              True

   region_southeast  region_southwest
0             False              True
1              True             False
2              True             False
3             False             False
4             False             False
```

[119]:
```
dataset.shape
```

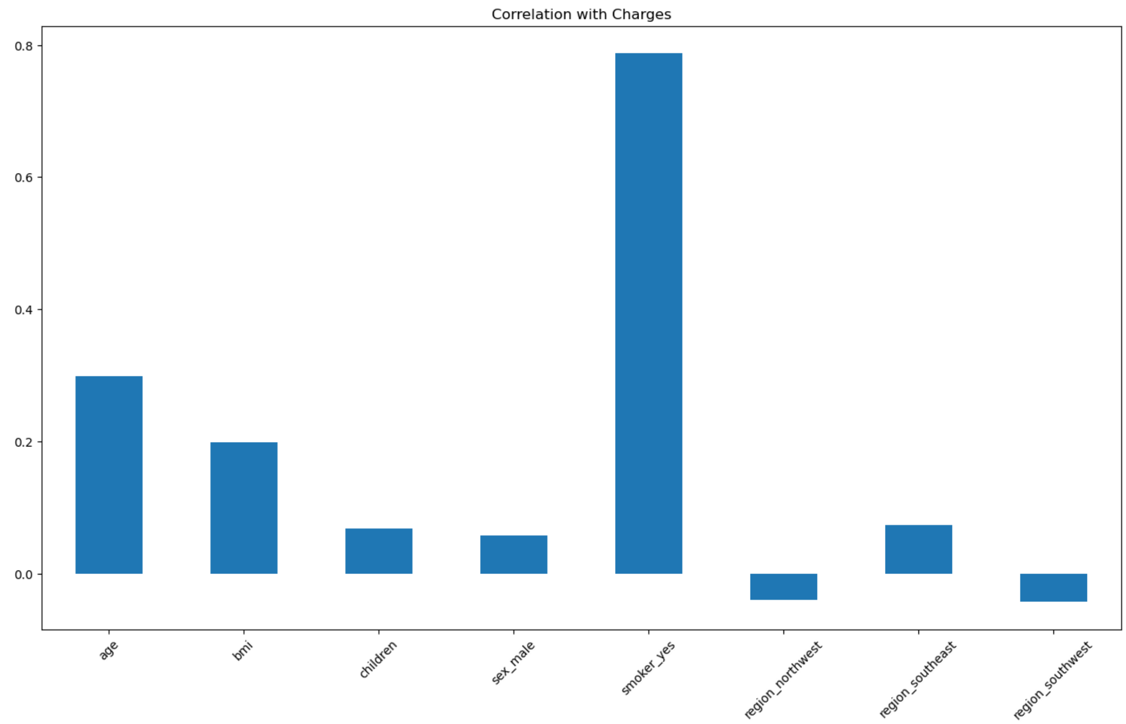
[119]:
```
(1338, 9)
```

V) Correlation matrix.

[120]:
```
dataset_2 = dataset.drop(columns = 'charges')
```

[121]:
```
dataset_2.corrwith(dataset['charges']).plot.bar(
    figsize = (16,9),
    title = "Correlation with Charges",
rot=45)
```

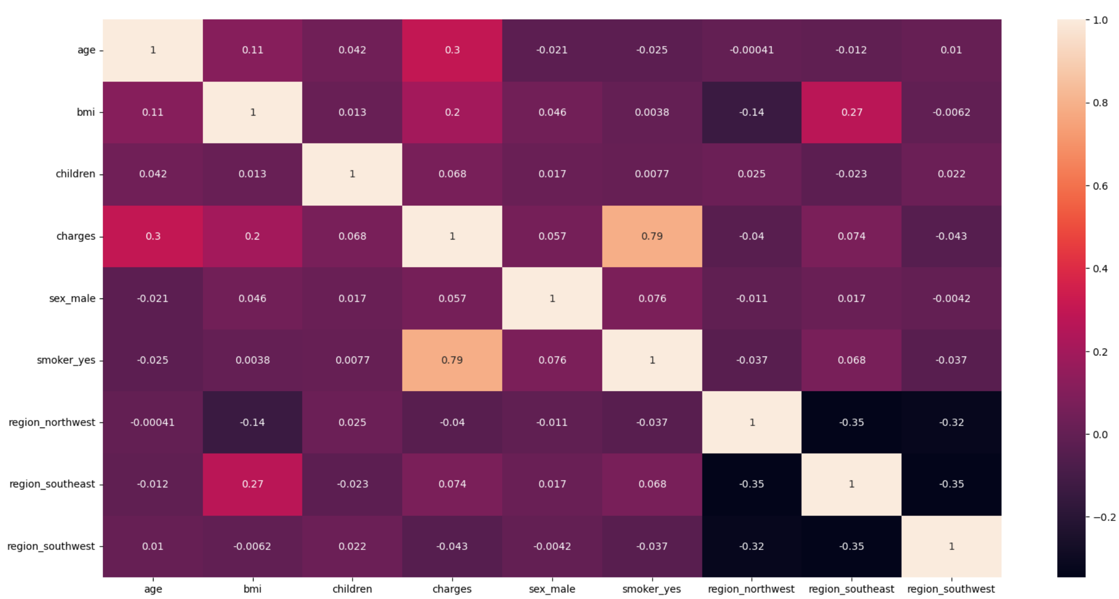
[121]:
```
<Axes: title={'center': 'Correlation with Charges'}>
```



[122]:
```
corr = dataset.corr()
```

[123]:
```
plt.figure(figsize=(20,10))
sns.heatmap(corr, annot= True)
```

[123]: <Axes: >



VI) Splitting the dataset.

[124]:
```
#Independent variable.
X = dataset.drop(columns= 'charges')
```

[125]:
```
X.shape
```

[125]: (1338, 8)

[126]:
```
#Dependent variable.
y = dataset['charges']
```

[127]:
```
y.shape
```

[127]: (1338,)

[128]:
```
from sklearn.model_selection import train_test_split
```

[129]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=101)
```

[130]:
```
X_train.shape
```

[130]: (1070, 8)

[131]:
```
X_test.shape
```

[131]: (268, 8)

VI) Feature Scaling.

[132]:
```
from sklearn.preprocessing import StandardScaler
```

[133]:
```
scaler = StandardScaler()
```

[134]:
```
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

[135]:
```
X_train
```

[135]:
```
array([[-1.15786012, -0.68882801, -0.92785237, …, -0.56943606,
          1.64390454, -0.57087511],
        [-1.51663179,  1.24518419, -0.92785237, …, -0.56943606,
          1.64390454, -0.57087511],
        [ 0.77950689,  2.31160214, -0.09635988, …, -0.56943606,
          1.64390454, -0.57087511],
        …,
```

```
[ 1.28178723,  0.5435502 , -0.92785237, …,  1.75612342,
 -0.60830783, -0.57087511],
[ 0.92301556,  1.12112479,  0.73513261, …,  1.75612342,
 -0.60830783, -0.57087511],
[-0.22505378, -1.78235828, -0.92785237, …, -0.56943606,
 -0.60830783, -0.57087511]])
```

[136]:
```
X_test
```

[136]:
```
array([[-0.08154511,  1.04307417, -0.09635988, …, -0.56943606,
        -0.60830783, -0.57087511],
       [-1.37312312, -0.31500662, -0.92785237, …, -0.56943606,
        -0.60830783, -0.57087511],
       [ 1.06652423, -0.86136096, -0.09635988, …, -0.56943606,
        -0.60830783, -0.57087511],
       …,
       [-1.15786012, -2.1882215 , -0.09635988, …,  1.75612342,
        -0.60830783, -0.57087511],
       [ 1.35354156,  0.39402164, -0.92785237, …, -0.56943606,
        -0.60830783,  1.75169662],
       [ 1.28178723, -0.03402439, -0.92785237, …,  1.75612342,
        -0.60830783, -0.57087511]])
```

5 Part 2: Building the models.

I) Multiple Linear Regression.

[137]:
```
from sklearn.linear_model import LinearRegression
```

[138]:
```
model_lr = LinearRegression()
model_lr.fit(X_train, y_train)
```

[138]:
```
LinearRegression()
```

[139]:
```
y_pred = model_lr.predict(X_test)
```

[140]:
```
from sklearn.metrics import r2_score
```

[141]:
```
score = r2_score(y_test, y_pred)
```

[142]:
```
score
```

[142]:
```
0.760837110132396
```

II) Random Forest Regressor.

[143]:
```
from sklearn.ensemble import RandomForestRegressor
regressor_rf = RandomForestRegressor(random_state=0)
```

```
regressor_rf.fit(X_train, y_train)
```

[143]:
```
RandomForestRegressor(random_state=0)
```

[144]:
```
y_pred = regressor_rf.predict(X_test)
```

[145]:
```
score = r2_score(y_test, y_pred)
```

[146]:
```
score
```

[146]:
```
0.8409756227354694
```

III) XB Boost Regressor

[147]:
```
from xgboost import XGBRegressor
```

[148]:
```
regressor_xgb = XGBRegressor()
regressor_xgb.fit(X_train, y_train)
```

[148]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=None, n_jobs=None,
             num_parallel_tree=None, random_state=None, …)
```

[149]:
```
y_pred = regressor_xgb.predict(X_test)
```

[150]:
```
score = r2_score(y_test, y_pred)
```

[151]:
```
score
```

[151]:
```
0.8274000763370111
```

6 Part 3: Predict charges for a new customer.

[152]:
```
new_customer1_obsv = [[40, 45.5, 4, 1, 1, 0, 0, 0]]
```

[153]:
```
regressor_xgb.predict(scaler.transform(new_customer1_obsv))
```

[153]:
```
array([44938.145], dtype=float32)
```

[154]:
```
new_customer_2 = [[22, 23.5, 4, 1, 1, 0, 0, 0]]
```

[155]:
```
regressor_xgb.predict(scaler.transform(new_customer_2))
```

[155]:
```
array([16239.731], dtype=float32)
```

[ ]:
```
```