Treatment_Costs_Prediction

November 12, 2023

0.1 Introduction

Linear regression is one of the most important algorithms under the supervised learning category in Machine Learning. It is also the commonly used model for predictive analysis. This project using this machine learning method to explore the personal health dataset and predict treatment and insurance costs.

0.2 Model Implementation

0.2.1 1. Import Data

[3]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

[4]:
```
# Read the data
df=pd.read_csv("insurance.csv")

# Browse the sample data
df.head()
```

[4]:

	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

0.2.2 2. Preprocessing the data

[5]:
```
# Check for overall data information include the data types & nulls
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
```

[6]:
```python
# double check the NULL
df.isnull().sum()
```

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

[7]:
```python
# Calculating some statistical data
df.describe()
```

[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

[8]:
```python
# Getting the data columns
df.describe().columns
```

[8]:
```
Index(['age', 'bmi', 'children', 'charges'], dtype='object')
```

[9]:
```python
# Separating numerical and categorical data
df_num = df[['age','bmi','children','charges']]
df_cat = df[['sex','smoker','region']]
```

[10]:
```python
# Use one hot enconding to converting the categorical data into numeric data
df1 = pd.get_dummies(df_cat)
df1
```

[10]:
```
      sex_female  sex_male  smoker_no  smoker_yes  region_northeast  \
0           True     False      False        True             False
1          False      True       True       False             False
2          False      True       True       False             False
3          False      True       True       False             False
4          False      True       True       False             False
…            …         …          …          …                …
1333       False      True       True       False             False
1334        True     False       True       False              True
1335        True     False       True       False             False
1336        True     False       True       False             False
1337        True     False      False        True             False

      region_northwest  region_southeast  region_southwest
0                False             False              True
1                False              True             False
2                False              True             False
3                 True             False             False
4                 True             False             False
…                  …                 …                …
1333              True             False             False
1334             False             False             False
1335             False              True             False
1336             False             False              True
1337              True             False             False

[1338 rows x 8 columns]
```

[11]:
```python
# Concatenating the encoded categorical and numerical data to form the dataset.
data = pd.concat([df_num,df1], axis=1)
data
```

[11]:
```
      age     bmi  children      charges  sex_female  sex_male  smoker_no  \
0      19  27.900         0  16884.92400        True     False      False
1      18  33.770         1   1725.55230       False      True       True
2      28  33.000         3   4449.46200       False      True       True
3      33  22.705         0  21984.47061       False      True       True
4      32  28.880         0   3866.85520       False      True       True
…    …      …       …            …           …         …
1333   50  30.970         3  10600.54830       False      True       True
1334   18  31.920         0   2205.98080        True     False       True
1335   18  36.850         0   1629.83350        True     False       True
1336   21  25.800         0   2007.94500        True     False       True
```

```
1337   61  29.070         0  29141.36030        True      False       False

      smoker_yes  region_northeast  region_northwest  region_southeast  \
0           True             False             False             False
1          False             False             False              True
2          False             False             False              True
3          False             False              True             False
4          False             False              True             False
…            …                …                 …                 …
1333       False             False              True             False
1334       False              True             False             False
1335       False             False             False              True
1336       False             False             False             False
1337        True             False              True             False

      region_southwest
0                 True
1                False
2                False
3                False
4                False
…                  …
1333             False
1334             False
1335             False
1336              True
1337             False

[1338 rows x 12 columns]
```

0.2.3 3. Exploratory Data Analysis

[12]:
```python
# The correlation between the features
data.corr()
```

[12]:
```
                       age       bmi  children   charges  sex_female  \
age               1.000000  0.109272  0.042469  0.299008    0.020856
bmi               0.109272  1.000000  0.012759  0.198341   -0.046371
children          0.042469  0.012759  1.000000  0.067998   -0.017163
charges           0.299008  0.198341  0.067998  1.000000   -0.057292
sex_female        0.020856 -0.046371 -0.017163 -0.057292    1.000000
sex_male         -0.020856  0.046371  0.017163  0.057292   -1.000000
smoker_no         0.025019 -0.003750 -0.007673 -0.787251    0.076185
smoker_yes       -0.025019  0.003750  0.007673  0.787251   -0.076185
region_northeast  0.002475 -0.138156 -0.022808  0.006349    0.002425
region_northwest -0.000407 -0.135996  0.024806 -0.039905    0.011156
```

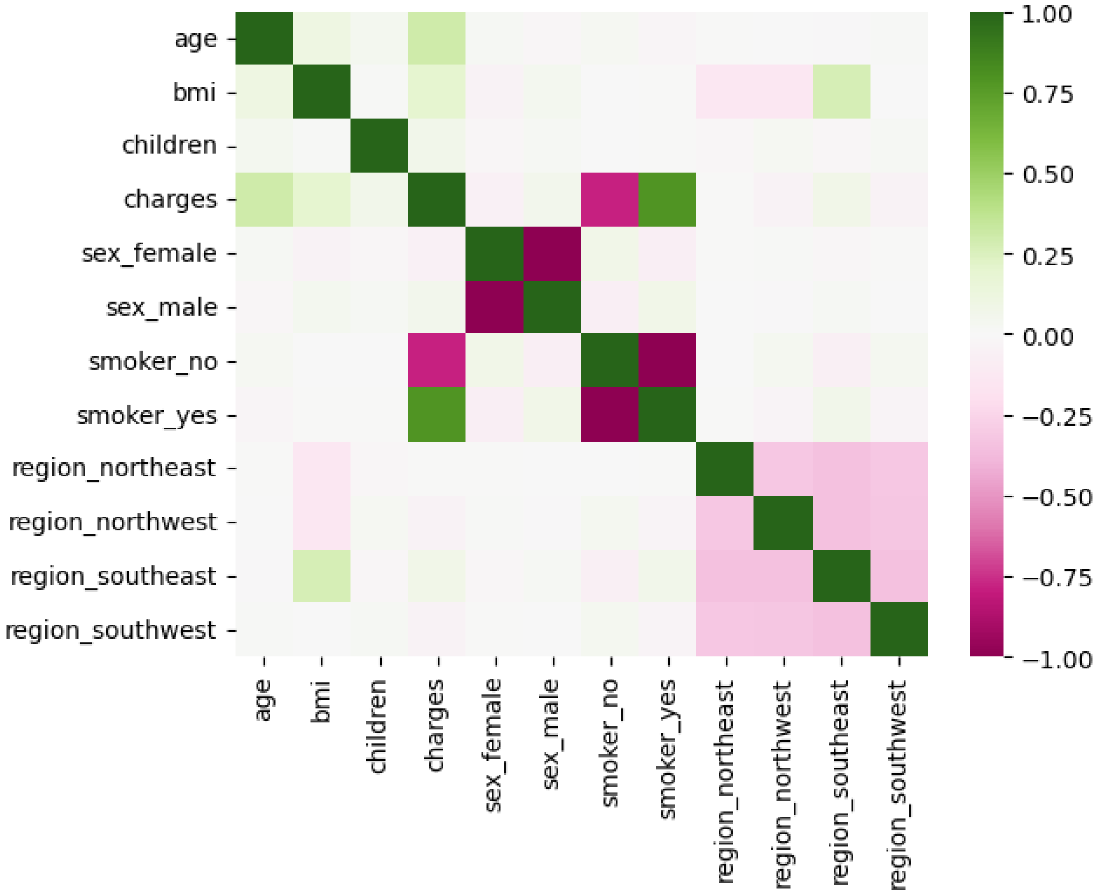
```
region_southeast -0.011642  0.270025 -0.023066  0.073982   -0.017117
region_southwest  0.010016 -0.006205  0.021914 -0.043210    0.004184

                  sex_male  smoker_no  smoker_yes  region_northeast  \
age              -0.020856   0.025019   -0.025019          0.002475
bmi               0.046371  -0.003750    0.003750         -0.138156
children          0.017163  -0.007673    0.007673         -0.022808
charges           0.057292  -0.787251    0.787251          0.006349
sex_female       -1.000000   0.076185   -0.076185          0.002425
sex_male          1.000000  -0.076185    0.076185         -0.002425
smoker_no        -0.076185   1.000000   -1.000000         -0.002811
smoker_yes        0.076185  -1.000000    1.000000          0.002811
region_northeast -0.002425  -0.002811    0.002811          1.000000
region_northwest -0.011156   0.036945   -0.036945         -0.320177
region_southeast  0.017117  -0.068498    0.068498         -0.345561
region_southwest -0.004184   0.036945   -0.036945         -0.320177

                  region_northwest  region_southeast  region_southwest
age                      -0.000407         -0.011642          0.010016
bmi                      -0.135996          0.270025         -0.006205
children                  0.024806         -0.023066          0.021914
charges                  -0.039905          0.073982         -0.043210
sex_female                0.011156         -0.017117          0.004184
sex_male                 -0.011156          0.017117         -0.004184
smoker_no                 0.036945         -0.068498          0.036945
smoker_yes               -0.036945          0.068498         -0.036945
region_northeast         -0.320177         -0.345561         -0.320177
region_northwest          1.000000         -0.346265         -0.320829
region_southeast         -0.346265          1.000000         -0.346265
region_southwest         -0.320829         -0.346265          1.000000
```

[13]:
```
# Heatmap to visualize the correlation
sns.heatmap(data.corr(), cmap='PiYG')
```

[13]:
```
<Axes: >
```



From this heatmap we find the following observations:

1. Strong correlation between charges and smoker_yes.
2. Weak correlation between charges and age.
3. Weak correlation between charges and bmi.
4. Weak correlation between bmi and region_southeast.

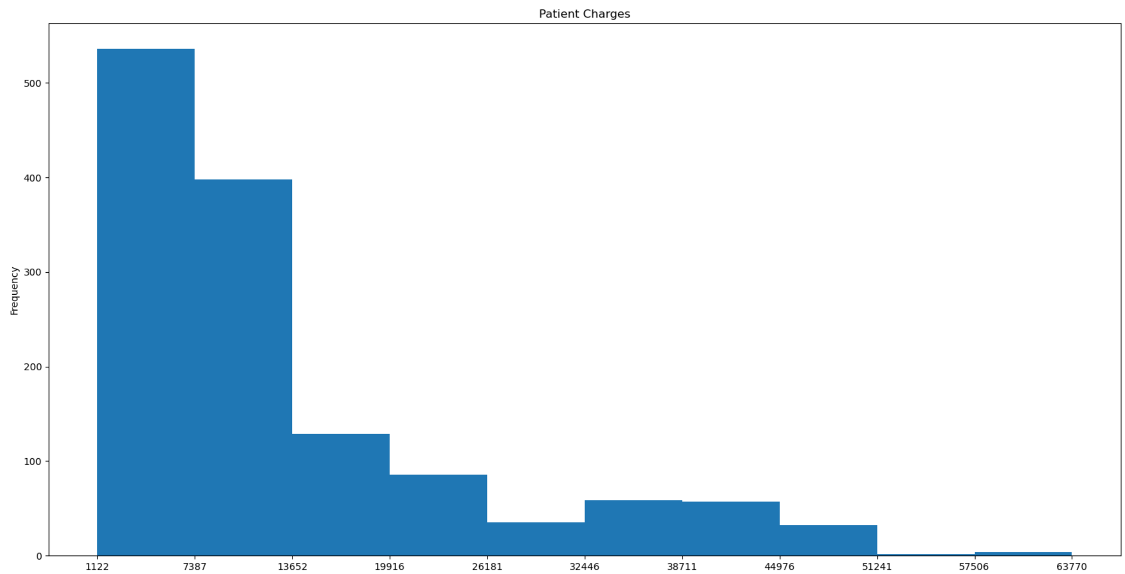
Since the values for the weak correlations are less than 0.5 so we term them as insignificant and drop them

[14]:
```
# Correlation between charges and the other features.
data.corr()['charges'].sort_values()
```

[14]:
```
smoker_no          -0.787251
sex_female         -0.057292
region_southwest   -0.043210
region_northwest   -0.039905
region_northeast    0.006349
sex_male            0.057292
children            0.067998
```

```
region_southeast    0.073982
bmi                 0.198341
age                 0.299008
smoker_yes          0.787251
charges             1.000000
Name: charges, dtype: float64
```

[15]:
```python
# Graph showing the min and maximum charges
count, bin_edges = np.histogram(data['charges'])
data['charges'].plot(kind='hist', xticks=bin_edges, figsize=(20,10))
plt.title("Patient Charges")
plt.show()
```



0.2.4 4. Model Building

Use sklearn package to split the test and train data then use statsmodels to build a simple linear regression to predict insurance charges with the help of the other features.

[16]:
```python
from sklearn.model_selection import train_test_split

import statsmodels.api as sm
from statsmodels.formula.api import ols
```

0.2.5 5. Model fitting

For this model, we split the dataset into training and test set. We use 30% of the dataset for testing (test_size=0.3) and then take the dataset without the charges column as the predictor variables and the charges as response/target variable.

```
[25]: x = data.drop(['charges'], axis = 1)
y = data['charges']

x_train,x_test,y_train,y_test = train_test_split(x,y, test_size=0.3,␣
↪random_state = 0)
#lr = LinearRegression().fit(x_train,y_train)

boolean_columns = ['sex_female', 'sex_male', 'smoker_no', 'smoker_yes',␣
↪'region_northeast', 'region_northwest', 'region_southeast',␣
↪'region_southwest']
x_train[boolean_columns] = x_train[boolean_columns].astype(int)
x_test[boolean_columns] = x_test[boolean_columns].astype(int)
```

```
[36]: # Fit the OLS model using the training data
model_tr = sm.OLS(y_train, x_train)
results_tr = model_tr.fit()
```

0.2.6 6. Model prediction

```
[39]: # Make predictions on the test set
y_pred = results_tr.predict(x_test)

print(r2_score(y_test,y_pred))
```

```
0.7909160991789904
```

Looks like the basic linear regression model predicting the cost of treatment look good and the score value is 0.79.

0.3 Model Evaluation

```
[33]: from sklearn.metrics import r2_score,mean_squared_error
```

0.3.1 1. Statistical Analysis:

From the summary table below, we can see that the F-statistic is 314.8 which means there are strong evidence that at least one of the independent variables in this model is related to the dependent variable "charges." And the p-value associated with the F-statistic is very close to zero (3.47e-258) suggests that the overall model is statistically significant. While the overall model might be significant, it's also essential to look at the significance of individual coefficients for a more detailed understanding of the contribution of each variable. In this summary table, the statistical significance of each coefficient is indicated by the "P>|t|" column. This column represents the p-value associated with the t-test for each coefficient. Therefore, the age, bmi, smoker_no, smoker_yes, and childeren are statistically significant variables for this liner regression model.

[38]:
```python
# Print the summary of the train OLS regression
print(results_tr.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                charges   R-squared:                       0.731
Model:                            OLS   Adj. R-squared:                  0.729
Method:                 Least Squares   F-statistic:                     314.8
Date:                Sun, 12 Nov 2023   Prob (F-statistic):          3.47e-258
Time:                        18:26:10   Log-Likelihood:                -9495.3
No. Observations:                 936   AIC:                         1.901e+04
Df Residuals:                     927   BIC:                         1.905e+04
Df Model:                           8
Covariance Type:            nonrobust
================================================================================
====
                       coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----
age                256.4354     14.628     17.531      0.000     227.728
285.143
bmi                335.3691     34.437      9.738      0.000     267.785
402.954
children           472.7098    168.734      2.802      0.005     141.565
803.854
sex_female        -268.2715    504.493     -0.532      0.595   -1258.353
721.810
sex_male          -315.8182    509.105     -0.620      0.535   -1314.950
683.314
smoker_no        -1.201e+04    514.978    -23.321      0.000     -1.3e+04
-1.1e+04
smoker_yes        1.143e+04    543.118     21.038      0.000     1.04e+04
1.25e+04
region_northeast   443.0023    411.075      1.078      0.281    -363.742
1249.747
region_northwest  -118.8989    406.077     -0.293      0.770    -915.835
678.037
region_southeast  -551.7464    467.462     -1.180      0.238   -1469.153
365.661
region_southwest  -356.4467    419.488     -0.850      0.396   -1179.702
466.809
```

```
==============================================================================
Omnibus:                      232.849   Durbin-Watson:                   2.048
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              571.734
Skew:                           1.309   Prob(JB):                    7.07e-125
Kurtosis:                       5.794   Cond. No.                     4.39e+17
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.29e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

0.3.2 2. the model performance

From the results below, the MSE means the squared difference between predicted and actual values is approximately 33,342,497.83 and the R-squared for test data means that the accuracy of our model is around 80% on the test data. Overall, the model is performing reasonably well on the test set, as indicated by the relatively low MSE and the high R-squared value. This is enough to conclude our model is appropriate to predict patient charges based on their personal health data

[50]:
```
# Evaluate the model performance, using metrics like Mean Squared Error (MSE)␣
↪and R^2
mse = mean_squared_error(y_test, y_pred)
#mse2 = mean_squared_error(y_train,y_pred)
print(f'Mean Squared Error on Test Set: {mse}')
print(f'R2 for test data: {r2_score(y_test,y_pred)}')
```

```
Mean Squared Error on Test Set: 33342497.82695458
R2 for test data: 0.7909160991789904
```

0.4 References

1. Miri Choi, Medical Cost Personal Datasets (2013), Kaggle, https://www.kaggle.com/datasets/mirichoi0218/insurance
2. Thomas George, Predicting Patient treatment costs (2020), Medium, https://medium.com/analytics-vidhya/

[ ]:
```
```