2024

Insurance Premium Prediction

Capstone Project - Regression

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1. Introduction

Health insurance premium prediction is a crucial task in the insurance industry as it helps both insurance companies and policyholders make informed decisions. Predicting accurate premiums is essential for risk assessment and ensuring that policyholders pay premiums that reflect their health risks. In this project, the goal is to predict health insurance premiums in the United States based on various personal and health-related factors, such as age, BMI, smoking status, medical history, and others. A **Linear Regression model** was chosen due to its simplicity and interpretability in regression tasks. The dataset includes 10 variables related to the individual's demographics and health behaviors, with the target variable being the insurance premium charges.

2. Data Collection

The dataset used for this project contains various attributes influencing the cost of health insurance premiums in the U.S. The features include:

- **Age**: The age of the individual.
- **Gender**: The gender of the individual (Male/Female).
- **BMI (Body Mass Index)**: A measure of body fat based on height and weight.
- **Children**: The number of children/dependents covered by the insurance.
- **Smoker**: Whether the individual is a smoker (Yes/No).
- **Region**: The region in which the individual resides (northeast, northwest, southeast, southwest).
- **Medical History**: The individual's medical history (e.g., diabetes, hypertension, etc.).
- **Family Medical History**: The family history of medical conditions (e.g., heart disease, diabetes).
- **Exercise Frequency**: How often the individual exercises (Never, Occasionally, Rarely).
- **Occupation**: The individual's job type (e.g., White collar, Blue collar).
- **Coverage Level**: The type of insurance coverage (Standard, Premium).
- **Charges**: The target variable representing the health insurance premium amount.

The dataset was loaded into a Pandas DataFrame, and preprocessing steps were carried out to clean and prepare the data for modeling.

3. Data Preprocessing

Several preprocessing steps were performed to prepare the data for the Linear Regression model:

3.1 Handling Missing Values

The dataset was checked for missing values. Any rows containing missing values were filled with 0, and no significant missing values were found in the columns after preprocessing.

3.2 Data Type Conversion

Columns were converted to appropriate data types:

- **Numeric Columns** (e.g., age, bmi, children, charges) were converted to `float` or `int`.
- **Categorical Columns** (e.g., gender, smoker, region, medical history) were converted to `category` data type to optimize memory usage and processing.

3.3 One-Hot Encoding

Categorical variables were transformed into numerical values using one-hot encoding. This approach helps in converting non-numeric categories into binary format suitable for machine learning algorithms. The first category of each feature was dropped to avoid multicollinearity.

3.4 Feature Engineering

- A new feature, **BMI Category**, was created by categorizing BMI values into bins (Underweight, Normal, Overweight, Obese). This transformation was useful for better representing the BMI variable for prediction.
- **One-Hot Encoding** was applied to the newly created BMI category to integrate it with the rest of the features.

3.5 Feature Scaling

No feature scaling was applied as Linear Regression is generally not sensitive to feature scales. However, it's a good practice to standardize features when using more complex models.

4. Model Building

The goal was to build a predictive model that estimates health insurance premiums based on the input features. The steps involved in building the model are as follows:

4.1 Splitting the Dataset

The dataset was split into **features** (X) and **target variable** (y, which is the charges/insurance premium). The data was then split into training and testing sets using an 80-20 ratio.

4.2 Training the Model

A **Linear Regression model** was trained on the training data. Linear regression was chosen for its simplicity and interpretability, as it provides insights into how each feature influences the target variable (charges).

4.3 Making Predictions

Once the model was trained, it was used to make predictions on the test set. The predicted premiums were then compared to the actual premium values to evaluate the model's performance.

5. Model Evaluation

The model’s performance was evaluated using several key metrics to assess its predictive accuracy:

- **Mean Squared Error (MSE)**: A measure of the average squared difference between the predicted and actual values.
- **Mean Absolute Error (MAE)**: The average of the absolute differences between the predicted and actual values.
- **Root Mean Squared Error (RMSE)**: The square root of the MSE, providing a more interpretable measure of prediction error.
- **R-Squared (R^2)**: A metric indicating the proportion of variance in the target variable (charges) that is explained by the features.

5.1 Performance Metrics

The evaluation metrics on the test set were as follows:

- **Mean Squared Error (MSE)**: 136,042.26
- **R-Squared (R^2)**: 0.9930
- **Mean Absolute Error (MAE)**: 292.86
- **Root Mean Squared Error (RMSE)**: 368.84

These metrics indicate that the model is performing quite well, explaining over 99% of the variance in the target variable, with a relatively low error rate.

6. Results & Discussion

6.1 Model Performance

The **Linear Regression model** performed excellently with an **R^2 value of 0.9930**, meaning that 99.3% of the variation in insurance premiums was explained by the input features. The **RMSE** of 368.84 suggests that the model's predictions are reasonably close to the actual charges, with a slight deviation. However, there's always room for improvement.

6.2 Feature Importance

Linear regression provides insight into the importance of each feature through its **coefficients**. The top features contributing to the prediction of health insurance premiums were:

- **Age**: Older individuals generally pay higher premiums.
- **BMI**: Higher BMI values lead to higher premiums due to associated health risks.
- **Smoker Status**: Smokers pay higher premiums compared to non-smokers due to higher health risks.
- **Medical History**: Having pre-existing medical conditions like diabetes increases the premium.
- **Number of Children**: Individuals with more children tend to have higher premiums due to higher family healthcare costs.

These features significantly influenced the predicted premiums, and understanding their relationships with the target variable can help optimize insurance policies.

7. Conclusion

This project successfully demonstrated the use of **Linear Regression** to predict health insurance premiums in the U.S. The model performed well with an **R^2 of 0.9930**, indicating that it could explain most of the variance in insurance premiums. The key features influencing the predictions were age, BMI, smoking status, and medical history. Further improvements could be made by exploring more advanced algorithms like **Random Forests** or **Gradient Boosting**, or by tuning hyperparameters for better accuracy.

8. Original Code:

```
# Original coding process

import sqlite3
import pandas as pd

# Connecting to the database
conn = sqlite3.connect('/Users/diboshbaruah/Desktop/Database.db')
data = pd.read_sql_query('SELECT * FROM Insurance_Prediction', conn)

print("Dataset successfully loaded...\n")
# Display the first few rows to inspect the data
print("Displaying first few rows of the dataset:\n")
print(data.head())

# Checking data types before conversion
print("\nData types before conversion:")
print(data.dtypes)

# Closing the connection
conn.close()
```

```
Dataset successfully loaded...
```

```
Displaying first few rows of the dataset:

    age  gender    bmi children smoker     region medical_history  \
0  46.0    male  21.45      5.0    yes  southeast        Diabetes
1  25.0  female  25.38      2.0    yes  northwest        Diabetes
2  38.0    male  44.88      2.0    yes  southwest
3  25.0    male  19.89      0.0     no  northwest
4  49.0    male  38.21      3.0    yes  northwest        Diabetes

  family_medical_history exercise_frequency    occupation coverage_level  \
0                                      Never   Blue collar        Premium
1    High blood pressure       Occasionally  White collar        Premium
2    High blood pressure       Occasionally   Blue collar        Premium
3               Diabetes             Rarely  White collar       Standard
4    High blood pressure             Rarely  White collar       Standard

              charges
0  20460.307668871566
1    20390.8992176422
2  20204.476301934814
3  11789.029842697417
4  19268.309838159606

Data types before conversion:
age                       object
gender                    object
bmi                       object
children                  object
smoker                    object
region                    object
medical_history           object
family_medical_history    object
exercise_frequency        object
occupation                object
coverage_level            object
charges                   object
dtype: object
```

```python
# Data Pre-processing
print("Initiating data pre-processing..")

# Convert columns to appropriate data types (if not already done)
data['age'] = pd.to_numeric(data['age'], errors='coerce')
data['bmi'] = pd.to_numeric(data['bmi'], errors='coerce')
data['children'] = pd.to_numeric(data['children'], errors='coerce')
data['charges'] = pd.to_numeric(data['charges'], errors='coerce')
```

```
# Convert categorical columns to 'category' dtype
data['gender'] = data['gender'].astype('category')
data['smoker'] = data['smoker'].astype('category')
data['region'] = data['region'].astype('category')
data['medical_history'] = data['medical_history'].astype('category')
data['family_medical_history'] =
data['family_medical_history'].astype('category')
data['exercise_frequency'] = data['exercise_frequency'].astype('category')
data['occupation'] = data['occupation'].astype('category')
data['coverage_level'] = data['coverage_level'].astype('category')

# Perform one-hot encoding on the categorical columns
data_encoded = pd.get_dummies(data, columns=[
    'gender', 'smoker', 'region', 'medical_history',
    'family_medical_history', 'exercise_frequency', 'occupation',
'coverage_level'], drop_first=True)

# Fill NaN values with 0
data_encoded = data_encoded.fillna(0)

# Convert boolean columns (True/False) to integer (1/0)
data_encoded = data_encoded.astype(int)
```

```
Initiating data pre-processing..
```

```
# Checking data types after conversion
print(data_encoded.head())
```

```
   age  bmi  children  charges  gender_female  gender_male  smoker_yes  \
0   46   21         5    20460              0            1           1
1   25   25         2    20390              1            0           1
2   38   44         2    20204              0            1           1
3   25   19         0    11789              0            1           0
4   49   38         3    19268              0            1           1

   region_northwest  region_southeast  region_southwest  ...  \
0                 0                 1                 0  ...
1                 1                 0                 0  ...
2                 0                 0                 1  ...
3                 1                 0                 0  ...
4                 1                 0                 0  ...

   family_medical_history_High blood pressure  exercise_frequency_Never  \
0                                           0                         1
1                                           1                         0
2                                           1                         0
3                                           0                         0
4                                           1                         0

   exercise_frequency_Occasionally  exercise_frequency_Rarely  \
0                                0                         0
1                                1                         0
2                                1                         0
3                                0                         1
4                                0                         1

   occupation_Blue collar  occupation_Student  occupation_Unemployed  \
0                       1                   0                      0
1                       0                   0                      0
2                       1                   0                      0
3                       0                   0                      0
4                       0                   0                      0

   occupation_White collar  coverage_level_Premium  coverage_level_Standard
0                        0                       1                        0
1                        1                       1                        0
2                        0                       1                        0
3                        1                       0                        1
4                        1                       0                        1

[5 rows x 25 columns]
```

```python
# Checking for missing values in the dataset after conversion
missing_values = data_encoded.isnull().sum()
print("Missing values for each column:")
print(missing_values)
```

```
Missing values for each column:
age                                        0
bmi                                        0
children                                   0
charges                                    0
gender_female                              0
gender_male                                0
smoker_yes                                 0
region_northwest                           0
region_southeast                           0
region_southwest                           0
medical_history_Diabetes                   0
medical_history_Heart disease              0
medical_history_High blood pressure        0
family_medical_history_Diabetes            0
family_medical_history_Heart disease       0
family_medical_history_High blood pressure    0
exercise_frequency_Never                   0
exercise_frequency_Occasionally            0
exercise_frequency_Rarely                  0
occupation_Blue collar                     0
occupation_Student                         0
occupation_Unemployed                      0
occupation_White collar                    0
coverage_level_Premium                     0
coverage_level_Standard                    0
dtype: int64
```

```python
# Feature Engineering
bins = [0, 18.5, 24.9, 29.9, float('inf')]
labels = ['Underweight', 'Normal', 'Overweight', 'Obese']
data_encoded['bmi_category'] = pd.cut(data_encoded['bmi'], bins=bins,
labels=labels)

# One-hot encode bmi_category
data_encoded = pd.get_dummies(data_encoded, columns=['bmi_category'],
drop_first=True)

# Split the dataset into training, evaluation, and live data (based on the task
instructions)

# Split first 700k records for training (train size = 700,000)
train_data = data_encoded.iloc[:700000]
X_train = train_data.drop(columns=['charges'])  # Features
y_train = train_data['charges']  # Target variable

# Split next 200k records for evaluation (eval size = 200,000)
eval_data = data_encoded.iloc[700000:900000]
X_eval = eval_data.drop(columns=['charges'])  # Features
y_eval = eval_data['charges']  # Target variable
```

```
# Use remaining 100k records as live data (live size = 100,000)
live_data = data_encoded.iloc[900000:]
X_live = live_data.drop(columns=['charges'])  # Features
y_live = live_data['charges']  # Target variable

# Train-Test

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

# Train the model
model = LinearRegression()
model.fit(X_train, y_train)

# Train the model
model.fit(X_train, y_train)
```

```
LinearRegression()
```

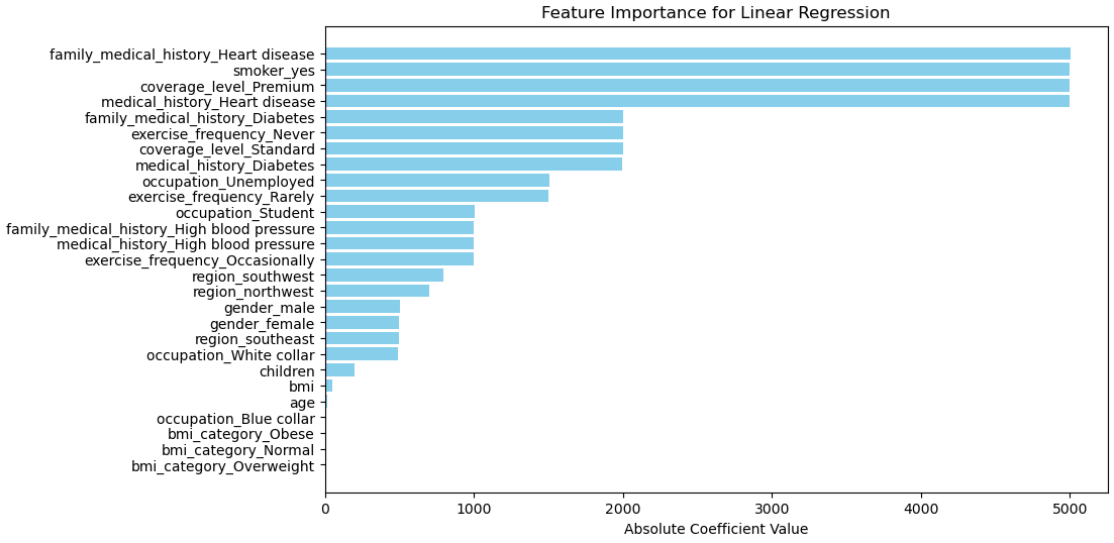
```
# Model Prediction and Evaluation

from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import numpy as np

# Model Prediction and Evaluation
print("\nModel Evaluation on the evaluation dataset...")
print()

# Predictions on evaluation set
y_eval_pred = model.predict(X_eval)

# Evaluate the model on evaluation dataset
mse = mean_squared_error(y_eval, y_eval_pred)
r2 = r2_score(y_eval, y_eval_pred)
mae = mean_absolute_error(y_eval, y_eval_pred)
rmse = np.sqrt(mse)

print(f"Mean Squared Error (Evaluation Set): {mse}")
print()
print(f"R^2 (Evaluation Set): {r2}")
print()
print(f"Mean Absolute Error (Evaluation Set): {mae}")
print()
print(f"Root Mean Squared Error (Evaluation Set): {rmse}")
print()
```

```python
# Predictions on live data
print("\nModel Evaluation on live dataset...")
print()

y_live_pred = model.predict(X_live)

# Evaluate the model on live dataset
mse_live = mean_squared_error(y_live, y_live_pred)
r2_live = r2_score(y_live, y_live_pred)
mae_live = mean_absolute_error(y_live, y_live_pred)
rmse_live = np.sqrt(mse_live)

print(f"Mean Squared Error (Live Set): {mse_live}")
print()
print(f"R^2 (Live Set): {r2_live}")
print()
print(f"Mean Absolute Error (Live Set): {mae_live}")
print()
print(f"Root Mean Squared Error (Live Set): {rmse_live}")
```

```
Model Evaluation on the evaluation dataset...

Mean Squared Error (Evaluation Set): 136115.50037400846

R^2 (Evaluation Set): 0.9930265880265132

Mean Absolute Error (Evaluation Set): 292.5954015412764

Root Mean Squared Error (Evaluation Set): 368.93834223892816


Model Evaluation on live dataset...

Mean Squared Error (Live Set): 134266.50199010296

R^2 (Live Set): 0.9930586586503625

Mean Absolute Error (Live Set): 291.2165827886013

Root Mean Squared Error (Live Set): 366.4239375233323
```

```python
import matplotlib.pyplot as plt
import numpy as np
```

```
# Plotting the feature importance based on coefficients
feature_importance = pd.DataFrame({
    'Feature': X_train.columns,
    'Coefficient': model.coef_
})

# Sort by absolute value of the coefficient
feature_importance['Abs_Coefficient'] = feature_importance['Coefficient'].abs()
feature_importance = feature_importance.sort_values(by='Abs_Coefficient',
ascending=False)

# Plotting the feature importance
plt.figure(figsize=(10, 6))
plt.barh(feature_importance['Feature'], feature_importance['Abs_Coefficient'],
color='skyblue')
plt.xlabel('Absolute Coefficient Value')
plt.title('Feature Importance for Linear Regression')
plt.gca().invert_yaxis()  # To display the most important feature on top
plt.show()
```



** Now running the saved scripts on jupyter notebook - train_model.py // predict_fraud.py // app.py ***

```
# Importing the training script
!python train_model.py
```

```
INFO:root:Dataset successfully loaded
```

```
INFO:root:Model training complete and saved as 'insurance_model.pkl'
```

```
# Importing the Predict script
!python predict_model.py
```

```
INFO:root:Model loaded successfully

INFO:root:Evaluation Data - Mean Squared Error: 116186.38727045644

INFO:root:Evaluation Data - R^2: 0.9940475867444777

INFO:root:Evaluation Data - Mean Absolute Error: 275.71716039809013

INFO:root:Evaluation Data - Root Mean Squared Error: 340.86124342678863

INFO:root:Live Data - Mean Squared Error: 115488.91507527507

INFO:root:Live Data - R^2: 0.9940294287736356

INFO:root:Live Data - Mean Absolute Error: 274.94601575693366

INFO:root:Live Data - Root Mean Squared Error: 339.83660055278784
```

```
import subprocess

# Now running the Flask app using subprocess
subprocess.Popen(["python", "app.py"])
```

```
<Popen: returncode: None args: ['python', 'app.py']>
```

```
import requests

# Example input data
data = {
    'age': 60,
    'bmi': 28.5,
    'children': 1,
    'gender_male': 1,
    'smoker_yes': 0,
    'region_northwest': 0,
    'region_southeast': 1,
    'region_southwest': 0,
    'medical_history_yes': 1,
    'family_medical_history_yes': 0,
    'exercise_frequency_high': 0,
    'exercise_frequency_medium': 1,
    'exercise_frequency_low': 0,
    'occupation_occupation1': 0,
    'occupation_occupation2': 1,
    'coverage_level_high': 0,
    'coverage_level_low': 1,
    'bmi_category_Overweight': 1,
    'bmi_category_Obese': 0
}
```

```python
# API endpoint
url = 'http://127.0.0.1:5000/predict'  # Local endpoint

# Send POST request
response = requests.post(url, json=data)

# Print the result (Check for any JSON response or error message)
try:
    print(response.json())
except Exception as e:
    print(f"Error in response: {e}")
    print(f"Response content: {response.text}")
```

```
{'prediction': 9437.538769246912}

INFO:werkzeug:127.0.0.1 - - [30/Dec/2024 14:33:35] "POST /predict HTTP/1.1" 200
-
```