week2_premium_estimator_main

June 23, 2025

0.1 Feature Engineering

The following feature engineering steps were performed:

- Created new features as required
- Transformed features, including encoding categorical variables
- Selected important features using statistical methods such as Variance Inflation Factor (VIF) and correlation analysis

0.1.1 Feature Creation - 'total_risk_score'

In this we created a new feature `total_risk_score` from `medical_history` column

[56]:
```
# Extract all distinct medical conditions listed in the dataset

df2['medical_history'].unique()
```

[56]:
```
array(['Diabetes', 'High blood pressure', 'No Disease',
       'Diabetes & High blood pressure', 'Thyroid', 'Heart disease',
       'High blood pressure & Heart disease', 'Diabetes & Thyroid',
       'Diabetes & Heart disease'], dtype=object)
```

The following risk scores, as provided by the business, will be assigned to the corresponding medical conditions:

- Heart disease: 8
- Diabetes: 6
- High blood pressure: 6
- Thyroid: 5
- No Disease: 0
- None: 0

[57]:
```
df3 = df2.copy()
df3.head()
```

[57]:
```
   age  gender     region marital_status  number_of_dependants bmi_category  \
0   26    Male  Northwest      Unmarried                     0       Normal
1   29  Female  Southeast        Married                     2      Obesity
2   49  Female  Northeast        Married                     2       Normal
3   30  Female  Southeast        Married                     3       Normal
4   18    Male  Northeast      Unmarried                     0   Overweight
```

```
  smoking_status employment_status income_level  income_lakhs  \
0     No Smoking          Salaried         <10L             6
1        Regular          Salaried         <10L             6
2     No Smoking     Self-Employed    10L - 25L            20
3     No Smoking          Salaried        > 40L            77
4        Regular     Self-Employed        > 40L            99

       medical_history insurance_plan  annual_premium_amount
0             Diabetes         Bronze                   9053
1             Diabetes         Bronze                  16339
2  High blood pressure         Silver                  18164
3           No Disease           Gold                  20303
4  High blood pressure         Silver                  13365
```

[58]:

```python
# Split the 'medical_history' column into 'disease1' and 'disease2' using '&'
↪as the delimiter

df3[['disease1','disease2']] = df3['medical_history'].str.lower().str.split(' &
↪',expand=True)
df3.head()
```

[58]:

```
   age  gender     region marital_status  number_of_dependants bmi_category  \
0   26    Male  Northwest      Unmarried                     0       Normal
1   29  Female  Southeast        Married                     2      Obesity
2   49  Female  Northeast        Married                     2       Normal
3   30  Female  Southeast        Married                     3       Normal
4   18    Male  Northeast      Unmarried                     0   Overweight

  smoking_status employment_status income_level  income_lakhs  \
0     No Smoking          Salaried         <10L             6
1        Regular          Salaried         <10L             6
2     No Smoking     Self-Employed    10L - 25L            20
3     No Smoking          Salaried        > 40L            77
4        Regular     Self-Employed        > 40L            99

       medical_history insurance_plan  annual_premium_amount  \
0             Diabetes         Bronze                   9053
1             Diabetes         Bronze                  16339
2  High blood pressure         Silver                  18164
3           No Disease           Gold                  20303
4  High blood pressure         Silver                  13365

              disease1 disease2
0             diabetes     None
1             diabetes     None
2  high blood pressure     None
```

```
3           no disease     None
4  high blood pressure     None
```

[59]:
```
# Risk Score Dictionary

risk_score_dict = {
    'heart disease' : 8,
'diabetes' : 6,
'high blood pressure' : 6,
'thyroid' : 5,
'no disease' : 0,
None : 0
}
```

[60]:
```
# Mapping each disease to its corresponding score using a predefined dictionary

df3['disease1_score'] = df3['disease1'].map(risk_score_dict)
df3['disease2_score'] = df3['disease2'].map(risk_score_dict)
df3.sample(2)
```

[60]:
```
       age gender     region marital_status  number_of_dependants  \
11647   53   Male  Southeast        Married                     3
5418    59   Male  Southeast        Married                     2

      bmi_category smoking_status employment_status income_level  \
11647      Obesity     Occasional          Salaried         <10L
5418        Normal        Regular     Self-Employed         <10L

       income_lakhs medical_history insurance_plan  annual_premium_amount  \
11647             3         Thyroid         Bronze                  15240
5418              3         Thyroid         Bronze                  14013

      disease1 disease2  disease1_score  disease2_score
11647  thyroid     None               5               0
5418   thyroid     None               5               0
```

[61]:
```
# Check if all diseases have been assigned a score and identify any missing␣
 ↪values

print('Unique Scores in Disease1 -> ',df3['disease1_score'].unique())
print('Unique Scores in Disease2 -> ',df3['disease2_score'].unique())
```

```
Unique Scores in Disease1 ->  [6 0 5 8]
Unique Scores in Disease2 ->  [0 6 8 5]
```

Since there are no NaN values, it can be concluded that all entries in the `disease1` and `disease2` columns have been successfully mapped.

[62]:
```
# Calculating the total risk score by summing 'disease1_score' and␣
↪'disease2_score'

df3['total_risk_score'] = df3['disease1_score'] + df3['disease2_score']
df3.sample(4)
```

[62]:
```
       age gender     region marital_status  number_of_dependants  \
2358    69   Male  Southeast        Married                     1
1268    60   Male  Southwest        Married                     3
9998    22   Male  Southwest        Married                     3
27335   56   Male  Southwest        Married                     5

      bmi_category smoking_status employment_status income_level  \
2358        Normal     No Smoking     Self-Employed    25L - 40L
1268        Normal     No Smoking     Self-Employed        > 40L
9998        Normal     No Smoking        Freelancer         <10L
27335       Normal        Regular          Salaried         <10L

       income_lakhs      medical_history insurance_plan  \
2358             28              Thyroid         Bronze
1268             45  High blood pressure           Gold
9998              7             Diabetes         Bronze
27335             8  High blood pressure         Silver

       annual_premium_amount             disease1 disease2  disease1_score  \
2358                   12709              thyroid     None               5
1268                   26541  high blood pressure     None               6
9998                    9001             diabetes     None               6
27335                  21654  high blood pressure     None               6

       disease2_score  total_risk_score
2358                0                 5
1268                0                 6
9998                0                 6
27335               0                 6
```

The following columns are being dropped as they are no longer needed: `medical_history`, `disease1`, `disease2`, `disease1_score`, and `disease2_score`.

[63]:
```
cols_to_drop = ['medical_history', 'disease1', 'disease2', 'disease1_score',␣
↪'disease2_score']
df4 = df3.drop(cols_to_drop,axis=1)
df4.reset_index(drop=True,inplace=True)
df4
```

[63]:
```
       age  gender     region marital_status  number_of_dependants  \
0       26    Male  Northwest      Unmarried                     0
1       29  Female  Southeast        Married                     2
```

```
2         49  Female  Northeast        Married                            2
3         30  Female  Southeast        Married                            3
4         18    Male  Northeast      Unmarried                            0
…     …     …         …           …                   …
49903     24  Female  Northwest      Unmarried                            0
49904     47  Female  Southeast        Married                            2
49905     21    Male  Northwest      Unmarried                            0
49906     18    Male  Northwest      Unmarried                            2
49907     48  Female  Southwest        Married                            3

      bmi_category smoking_status employment_status income_level  \
0           Normal     No Smoking          Salaried        <10L
1          Obesity        Regular          Salaried        <10L
2           Normal     No Smoking     Self-Employed    10L - 25L
3           Normal     No Smoking          Salaried        > 40L
4       Overweight        Regular     Self-Employed        > 40L
…              …              …                …          …
49903  Underweight     No Smoking     Self-Employed    25L - 40L
49904       Normal     No Smoking          Salaried        > 40L
49905       Normal        Regular        Freelancer    25L - 40L
49906       Normal     No Smoking          Salaried    10L - 25L
49907       Normal     Occasional     Self-Employed        <10L

       income_lakhs insurance_plan  annual_premium_amount  total_risk_score
0                 6         Bronze                   9053                 6
1                 6         Bronze                  16339                 6
2                20         Silver                  18164                 6
3                77           Gold                  20303                 0
4                99         Silver                  13365                 6
…               …              …                    …                …
49903            35         Bronze                   9111                 0
49904            82           Gold                  27076                 5
49905            32         Bronze                   8564                 0
49906            20         Bronze                   9490                 0
49907             7         Silver                  19730                 6

[49908 rows x 13 columns]
```

0.1.2 Feature Cleaning & Transformation

The following transformations were applied to the dataset features:

- Label Encoding for ordinal categorical variables (to preserve order)
- One Hot Encodingfor nominal categorical variables (to avoid introducing ordinal relationships)

[64]:
```
df5 = df4.copy()
df5.head()
```

[64]:
```
   age  gender     region marital_status  number_of_dependants bmi_category  \
0   26    Male  Northwest      Unmarried                     0       Normal
1   29  Female  Southeast        Married                     2      Obesity
2   49  Female  Northeast        Married                     2       Normal
3   30  Female  Southeast        Married                     3       Normal
4   18    Male  Northeast      Unmarried                     0   Overweight

  smoking_status employment_status income_level  income_lakhs insurance_plan  \
0     No Smoking          Salaried         <10L             6         Bronze
1        Regular          Salaried         <10L             6         Bronze
2     No Smoking     Self-Employed    10L - 25L            20         Silver
3     No Smoking          Salaried        > 40L            77           Gold
4        Regular     Self-Employed        > 40L            99         Silver

   annual_premium_amount  total_risk_score
0                   9053                 6
1                  16339                 6
2                  18164                 6
3                  20303                 0
4                  13365                 6
```

Label Encodig - 'income_level'

[65]:
```python
# Extract all distinct income levels listed in the dataset

df5.income_level.unique()
```

[65]:
```
array(['<10L', '10L - 25L', '> 40L', '25L - 40L'], dtype=object)
```

[66]:
```python
# Income level dictionary

income_level_dict =  {
        '<10L' : 1,
        '10L - 25L' : 2,
        '25L - 40L' : 3,
        '> 40L' : 4
    }
```

[67]:
```python
# Mapping each income level to a value using a predefined dictionary

df5['income_level'] = df5['income_level'].map(income_level_dict)
```

[68]:
```python
# After mapping

df5.income_level.unique()
```

[68]:
```
array([1, 2, 4, 3])
```

Label Encodig - 'insurance_plan'

[69]:
```
# Extract all distinct insurance plan listed in the dataset

df5.insurance_plan.unique()
```

[69]:
```
array(['Bronze', 'Silver', 'Gold'], dtype=object)
```

[70]:
```
# Insurance Plan dictionary

insurance_plan_dict = {
        'Bronze' : 1,
        'Silver' : 2,
        'Gold' : 3,
    }
```

[71]:
```
# Mapping each insurance plan to a value using a predefined dictionary

df5['insurance_plan'] = df5['insurance_plan'].map(insurance_plan_dict)
```

[72]:
```
# After mapping

df5.insurance_plan.unique()
```

[72]:
```
array([1, 2, 3])
```

One Hot Encoding

[73]:
```
# Selecting columns to perform one hot encoding

cols_to_encode = ['gender', 'region', 'marital_status', 'bmi_category',␣
 ↪'smoking_status', 'employment_status']
cols_to_encode
```

[73]:
```
['gender',
 'region',
 'marital_status',
 'bmi_category',
 'smoking_status',
 'employment_status']
```

[74]:
```
# Performing One Hot Encoding on df5

df6 = pd.get_dummies(df5,columns = cols_to_encode,dtype=int,drop_first=True)
```

[75]:
```
df6.sample(5)
```

[75]:
```
        age  number_of_dependants  income_level  income_lakhs  insurance_plan  \
41672   41                      1             4            72               3
```

```
1380    20                  0           3           27              1
9953    18                  2           1            7              1
7862    22                  2           3           31              1
16612   53                  2           2           10              3

       annual_premium_amount  total_risk_score  gender_Male  region_Northwest  \
41672                  21674                 0            0                 0
1380                    5773                 0            1                 0
9953                    9530                 0            1                 0
7862                    9690                 0            0                 0
16612                  29848                 6            1                 0

       region_Southeast  region_Southwest  marital_status_Unmarried  \
41672                 0                 1                         1
1380                  0                 1                         1
9953                  1                 0                         1
7862                  1                 0                         0
16612                 1                 0                         0

       bmi_category_Obesity  bmi_category_Overweight  \
41672                     0                        0
1380                      0                        0
9953                      0                        0
7862                      0                        1
16612                     0                        0

       bmi_category_Underweight  smoking_status_Occasional  \
41672                         1                          1
1380                          1                          0
9953                          1                          0
7862                          0                          0
16612                         0                          0

       smoking_status_Regular  employment_status_Salaried  \
41672                       0                           0
1380                        1                           1
9953                        0                           1
7862                        0                           0
16612                       1                           0

       employment_status_Self-Employed
41672                                1
1380                                 0
9953                                 0
7862                                 1
16612                                1
```

[76]:
```
df6.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49908 entries, 0 to 49907
Data columns (total 19 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   age                              49908 non-null  int64
 1   number_of_dependants             49908 non-null  int64
 2   income_level                     49908 non-null  int64
 3   income_lakhs                     49908 non-null  int64
 4   insurance_plan                   49908 non-null  int64
 5   annual_premium_amount            49908 non-null  int64
 6   total_risk_score                 49908 non-null  int64
 7   gender_Male                      49908 non-null  int64
 8   region_Northwest                 49908 non-null  int64
 9   region_Southeast                 49908 non-null  int64
 10  region_Southwest                 49908 non-null  int64
 11  marital_status_Unmarried         49908 non-null  int64
 12  bmi_category_Obesity             49908 non-null  int64
 13  bmi_category_Overweight          49908 non-null  int64
 14  bmi_category_Underweight         49908 non-null  int64
 15  smoking_status_Occasional        49908 non-null  int64
 16  smoking_status_Regular           49908 non-null  int64
 17  employment_status_Salaried       49908 non-null  int64
 18  employment_status_Self-Employed  49908 non-null  int64
dtypes: int64(19)
memory usage: 7.2 MB
```

[77]:
```
# Showing all the non-encoded columns and one encoded columns from each category

sampled_encoded_cols_index = [0,1,2,3,4,5,6,7,8,11,12,15,17]

df6.iloc[0:5,sampled_encoded_cols_index]
```

[77]:

	age	number_of_dependants	income_level	income_lakhs	insurance_plan	\
0	26	0	1	6	1	
1	29	2	1	6	1	
2	49	2	2	20	2	
3	30	3	4	77	3	
4	18	0	4	99	2	

	annual_premium_amount	total_risk_score	gender_Male	region_Northwest	\
0	9053	6	1	1	
1	16339	6	0	0	
2	18164	6	0	0	
3	20303	0	0	0	
4	13365	6	1	0	

```
   marital_status_Unmarried  bmi_category_Obesity  smoking_status_Occasional  \
0                         1                     0                          0
1                         0                     1                          0
2                         0                     0                          0
3                         0                     0                          0
4                         1                     0                          0

   employment_status_Salaried
0                           1
1                           1
2                           0
3                           1
4                           0
```

0.1.3 Feature Selection

- To identify the most relevant features, both pairwise correlations and multicollinearity will be analyzed.
- *Correlation* analysis will be used to detect linear relationships, while *Variance Inflation Factor (VIF)* will be employed to identify multicollinearity.
- Prior to these analyses, features will be scaled to ensure comparability across variables.

[78]:
```
# Before Scaling the features

df7 = df6.copy()
df7.sample(3)
```

[78]:
```
       age  number_of_dependants  income_level  income_lakhs  insurance_plan  \
22498   21                     3             3            28               1
6982    20                     1             3            27               1
15687   50                     3             3            26               3

       annual_premium_amount  total_risk_score  gender_Male  region_Northwest  \
22498                   8601                 0            1                 0
6982                    7292                 0            1                 0
15687                  28031                 6            1                 0

       region_Southeast  region_Southwest  marital_status_Unmarried  \
22498                 0                 1                         0
6982                  0                 1                         1
15687                 1                 0                         0

       bmi_category_Obesity  bmi_category_Overweight  \
22498                     0                        0
6982                      0                        0
```

```
15687                       0                         0

       bmi_category_Underweight  smoking_status_Occasional  \
22498                         0                          0
6982                          0                          0
15687                         1                          1

       smoking_status_Regular  employment_status_Salaried  \
22498                       0                           0
6982                        1                           0
15687                       0                           1

       employment_status_Self-Employed
22498                                0
6982                                 1
15687                                0
```

[79]:
```python
df7.columns
```

[79]:
```
Index(['age', 'number_of_dependants', 'income_level', 'income_lakhs',
       'insurance_plan', 'annual_premium_amount', 'total_risk_score',
       'gender_Male', 'region_Northwest', 'region_Southeast',
       'region_Southwest', 'marital_status_Unmarried', 'bmi_category_Obesity',
       'bmi_category_Overweight', 'bmi_category_Underweight',
       'smoking_status_Occasional', 'smoking_status_Regular',
       'employment_status_Salaried', 'employment_status_Self-Employed'],
      dtype='object')
```

The following columns will be scaled: `age`, `number_of_dependants`, `income_level`, `income_lakhs`, `insurance_plan`, `total_risk_score`.

Scaling type : Minmax scaling

[80]:
```python
# Scaling using 'MinMaxScaler'

cols_to_scale = ['age', 'number_of_dependants', 'income_level', 'income_lakhs',␣
 ↪'insurance_plan', 'total_risk_score']
mms = MinMaxScaler()
df7[cols_to_scale] = mms.fit_transform(df7[cols_to_scale])
```

Correlation

[81]:
```python
# Correlation Matrix between features

cr = df7.corr()
cr
```

[81]:
```
                                     age  number_of_dependants  income_level  \
age                             1.000000              0.415742      0.029851
```

```
number_of_dependants              0.415742              1.000000      0.006564
income_level                      0.029851              0.006564      1.000000
income_lakhs                      0.025060              0.006074      0.906830
insurance_plan                    0.496317              0.256459      0.440428
annual_premium_amount             0.767569              0.414691      0.271811
total_risk_score                  0.442773              0.371498      0.013506
gender_Male                      -0.002219             -0.003093      0.063108
region_Northwest                  0.000464              0.001693     -0.003324
region_Southeast                  0.003305              0.003620     -0.000259
region_Southwest                 -0.003424             -0.000339      0.009367
marital_status_Unmarried         -0.543104             -0.841717     -0.012994
bmi_category_Obesity              0.152496              0.115397     -0.002244
bmi_category_Overweight           0.153148              0.110451      0.007947
bmi_category_Underweight         -0.115888             -0.093881      0.000350
smoking_status_Occasional         0.066596              0.071762     -0.001340
smoking_status_Regular            0.059380              0.094829      0.020275
employment_status_Salaried       -0.008093              0.067066     -0.134032
employment_status_Self-Employed  0.314684              0.115930      0.139333

                                 income_lakhs  insurance_plan  \
age                                  0.025060        0.496317
number_of_dependants                 0.006074        0.256459
income_level                         0.906830        0.440428
income_lakhs                         1.000000        0.410753
insurance_plan                       0.410753        1.000000
annual_premium_amount                0.243058        0.834148
total_risk_score                     0.009626        0.260932
gender_Male                          0.039126        0.034211
region_Northwest                    -0.005192       -0.002821
region_Southeast                    -0.001250        0.004082
region_Southwest                     0.009929       -0.000977
marital_status_Unmarried            -0.011099       -0.316800
bmi_category_Obesity                 0.000314        0.094698
bmi_category_Overweight              0.007150        0.098639
bmi_category_Underweight            -0.000740       -0.073881
smoking_status_Occasional            0.002306        0.037351
smoking_status_Regular               0.010948        0.059587
employment_status_Salaried          -0.100510       -0.041582
employment_status_Self-Employed      0.109759        0.223947

                                 annual_premium_amount  total_risk_score  \
age                                           0.767569          0.442773
number_of_dependants                          0.414691          0.371498
income_level                                  0.271811          0.013506
income_lakhs                                  0.243058          0.009626
insurance_plan                                0.834148          0.260932
annual_premium_amount                         1.000000          0.519458
```

```
total_risk_score                          0.519458          1.000000
gender_Male                               0.064470         -0.003754
region_Northwest                         -0.005078         -0.005627
region_Southeast                          0.008235          0.002019
region_Southwest                         -0.003828         -0.000132
marital_status_Unmarried                 -0.516350         -0.433916
bmi_category_Obesity                      0.249847          0.101039
bmi_category_Overweight                   0.187103          0.102556
bmi_category_Underweight                 -0.135289         -0.087996
smoking_status_Occasional                 0.060610          0.071090
smoking_status_Regular                    0.198829          0.093822
employment_status_Salaried               -0.005442          0.059511
employment_status_Self-Employed           0.289438          0.135824

                                 gender_Male  region_Northwest  \
age                                -0.002219          0.000464
number_of_dependants               -0.003093          0.001693
income_level                        0.063108         -0.003324
income_lakhs                        0.039126         -0.005192
insurance_plan                      0.034211         -0.002821
annual_premium_amount               0.064470         -0.005078
total_risk_score                   -0.003754         -0.005627
gender_Male                         1.000000         -0.003287
region_Northwest                   -0.003287          1.000000
region_Southeast                   -0.002988         -0.368277
region_Southwest                    0.001873         -0.330654
marital_status_Unmarried            0.003944         -0.001083
bmi_category_Obesity               -0.031351         -0.002262
bmi_category_Overweight             0.080588          0.001194
bmi_category_Underweight           -0.043000         -0.002017
smoking_status_Occasional          -0.045618         -0.000669
smoking_status_Regular              0.305180         -0.000255
employment_status_Salaried          0.005559          0.004574
employment_status_Self-Employed     0.001055          0.000110

                                 region_Southeast  region_Southwest  \
age                                      0.003305         -0.003424
number_of_dependants                     0.003620         -0.000339
income_level                            -0.000259          0.009367
income_lakhs                            -0.001250          0.009929
insurance_plan                           0.004082         -0.000977
annual_premium_amount                    0.008235         -0.003828
total_risk_score                         0.002019         -0.000132
gender_Male                             -0.002988          0.001873
region_Northwest                        -0.368277         -0.330654
region_Southeast                         1.000000         -0.484271
region_Southwest                        -0.484271          1.000000
```

```
marital_status_Unmarried               -0.003980          0.004287
bmi_category_Obesity                    0.006373         -0.000934
bmi_category_Overweight                 0.002511         -0.002208
bmi_category_Underweight                0.000211         -0.000499
smoking_status_Occasional              -0.002191          0.006282
smoking_status_Regular                 -0.000401         -0.001858
employment_status_Salaried             -0.006575          0.000249
employment_status_Self-Employed         0.003287         -0.005618

                                 marital_status_Unmarried  \
age                                             -0.543104
number_of_dependants                            -0.841717
income_level                                    -0.012994
income_lakhs                                    -0.011099
insurance_plan                                  -0.316800
annual_premium_amount                           -0.516350
total_risk_score                                -0.433916
gender_Male                                      0.003944
region_Northwest                                -0.001083
region_Southeast                                -0.003980
region_Southwest                                 0.004287
marital_status_Unmarried                         1.000000
bmi_category_Obesity                            -0.118092
bmi_category_Overweight                         -0.117312
bmi_category_Underweight                         0.089315
smoking_status_Occasional                       -0.075253
smoking_status_Regular                          -0.092448
employment_status_Salaried                      -0.055285
employment_status_Self-Employed                 -0.171646

                                 bmi_category_Obesity  \
age                                          0.152496
number_of_dependants                         0.115397
income_level                                -0.002244
income_lakhs                                 0.000314
insurance_plan                               0.094698
annual_premium_amount                        0.249847
total_risk_score                             0.101039
gender_Male                                 -0.031351
region_Northwest                            -0.002262
region_Southeast                             0.006373
region_Southwest                            -0.000934
marital_status_Unmarried                    -0.118092
bmi_category_Obesity                         1.000000
bmi_category_Overweight                     -0.224205
bmi_category_Underweight                    -0.175299
smoking_status_Occasional                    0.028321
```

```
smoking_status_Regular                       0.017526
employment_status_Salaried                   0.021085
employment_status_Self-Employed              0.040750

                                 bmi_category_Overweight  \
age                                             0.153148
number_of_dependants                            0.110451
income_level                                    0.007947
income_lakhs                                    0.007150
insurance_plan                                  0.098639
annual_premium_amount                           0.187103
total_risk_score                                0.102556
gender_Male                                     0.080588
region_Northwest                                0.001194
region_Southeast                                0.002511
region_Southwest                               -0.002208
marital_status_Unmarried                       -0.117312
bmi_category_Obesity                           -0.224205
bmi_category_Overweight                         1.000000
bmi_category_Underweight                       -0.235191
smoking_status_Occasional                       0.029486
smoking_status_Regular                          0.070944
employment_status_Salaried                      0.028753
employment_status_Self-Employed                 0.035602

                                 bmi_category_Underweight  \
age                                             -0.115888
number_of_dependants                            -0.093881
income_level                                     0.000350
income_lakhs                                    -0.000740
insurance_plan                                  -0.073881
annual_premium_amount                           -0.135289
total_risk_score                                -0.087996
gender_Male                                     -0.043000
region_Northwest                                -0.002017
region_Southeast                                 0.000211
region_Southwest                                -0.000499
marital_status_Unmarried                         0.089315
bmi_category_Obesity                            -0.175299
bmi_category_Overweight                         -0.235191
bmi_category_Underweight                         1.000000
smoking_status_Occasional                       -0.023061
smoking_status_Regular                          -0.044704
employment_status_Salaried                      -0.023124
employment_status_Self-Employed                 -0.023601

                                 smoking_status_Occasional  \
```

```
age                                                    0.066596
number_of_dependants                                   0.071762
income_level                                          -0.001340
income_lakhs                                           0.002306
insurance_plan                                         0.037351
annual_premium_amount                                  0.060610
total_risk_score                                       0.071090
gender_Male                                           -0.045618
region_Northwest                                      -0.000669
region_Southeast                                      -0.002191
region_Southwest                                       0.006282
marital_status_Unmarried                              -0.075253
bmi_category_Obesity                                   0.028321
bmi_category_Overweight                                0.029486
bmi_category_Underweight                              -0.023061
smoking_status_Occasional                              1.000000
smoking_status_Regular                                -0.270923
employment_status_Salaried                             0.026424
employment_status_Self-Employed                        0.012346

                                 smoking_status_Regular  \
age                                            0.059380
number_of_dependants                           0.094829
income_level                                   0.020275
income_lakhs                                   0.010948
insurance_plan                                 0.059587
annual_premium_amount                          0.198829
total_risk_score                               0.093822
gender_Male                                    0.305180
region_Northwest                              -0.000255
region_Southeast                              -0.000401
region_Southwest                              -0.001858
marital_status_Unmarried                      -0.092448
bmi_category_Obesity                           0.017526
bmi_category_Overweight                        0.070944
bmi_category_Underweight                      -0.044704
smoking_status_Occasional                     -0.270923
smoking_status_Regular                         1.000000
employment_status_Salaried                     0.042991
employment_status_Self-Employed                0.002693

                                 employment_status_Salaried  \
age                                               -0.008093
number_of_dependants                               0.067066
income_level                                      -0.134032
income_lakhs                                      -0.100510
insurance_plan                                    -0.041582
```

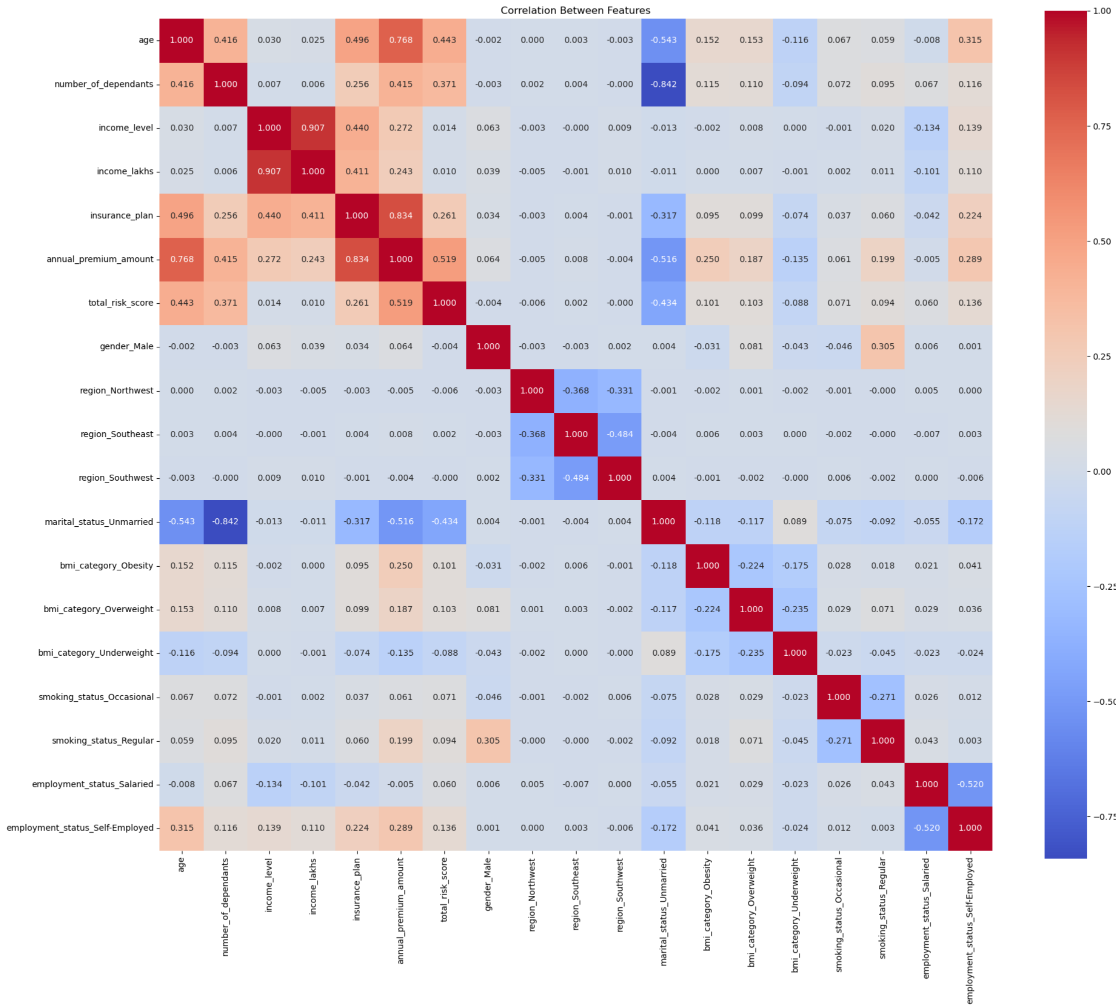
```
annual_premium_amount                        -0.005442
total_risk_score                              0.059511
gender_Male                                   0.005559
region_Northwest                              0.004574
region_Southeast                             -0.006575
region_Southwest                              0.000249
marital_status_Unmarried                     -0.055285
bmi_category_Obesity                          0.021085
bmi_category_Overweight                       0.028753
bmi_category_Underweight                     -0.023124
smoking_status_Occasional                     0.026424
smoking_status_Regular                        0.042991
employment_status_Salaried                    1.000000
employment_status_Self-Employed              -0.519576

                                 employment_status_Self-Employed
age                                                     0.314684
number_of_dependants                                    0.115930
income_level                                            0.139333
income_lakhs                                            0.109759
insurance_plan                                          0.223947
annual_premium_amount                                   0.289438
total_risk_score                                        0.135824
gender_Male                                             0.001055
region_Northwest                                        0.000110
region_Southeast                                        0.003287
region_Southwest                                       -0.005618
marital_status_Unmarried                               -0.171646
bmi_category_Obesity                                    0.040750
bmi_category_Overweight                                 0.035602
bmi_category_Underweight                               -0.023601
smoking_status_Occasional                               0.012346
smoking_status_Regular                                  0.002693
employment_status_Salaried                             -0.519576
employment_status_Self-Employed                         1.000000
```

[82]:

```
# Correlation Matrix displayed as a Heatmap

plt.figure(figsize=(20,20))
sns.heatmap(cr, annot=True, fmt='.3f', cmap='coolwarm', square=True,␣
↪cbar_kws={"shrink": 0.75})
plt.title('Correlation Between Features')
plt.tight_layout()
plt.show()
```



[83]:
```
# Display features that have a high correlation (|correlation| > 0.35) with␣
↪'annual_premium_amount'

cr[abs(cr['annual_premium_amount']) > 0.35]['annual_premium_amount']
```

[83]:
```
age                         0.767569
number_of_dependants        0.414691
insurance_plan              0.834148
annual_premium_amount       1.000000
total_risk_score            0.519458
marital_status_Unmarried   -0.516350
Name: annual_premium_amount, dtype: float64
```

[84]:
```
# Extract the feature names (index labels) that have a high correlation␣
↪(|correlation| > 0.35) with 'annual_premium_amount'
```

```
cr[abs(cr['annual_premium_amount']) > 0.35]['annual_premium_amount'].index
```

[84]:
```
Index(['age', 'number_of_dependants', 'insurance_plan',
       'annual_premium_amount', 'total_risk_score',
       'marital_status_Unmarried'],
      dtype='object')
```

Observation

Based on the correlation heatmap, a strong positive correlation with `annual_premium_amount` is observed for the features `age`, `number_of_dependants`, `insurance_plan`, and `total_risk_score`, suggesting that these variables may significantly influence premium prediction.

Additionally, a strong negative correlation is shown by `marital_status_Unmarried`, indicating that being unmarried is generally associated with lower premium amounts.

Variance Inflation Factor (VIF) The Variance Inflation Factor (VIF) will be checked to detect and address multicollinearity among the features.

[85]:
```
df7.columns
```

[85]:
```
Index(['age', 'number_of_dependants', 'income_level', 'income_lakhs',
       'insurance_plan', 'annual_premium_amount', 'total_risk_score',
       'gender_Male', 'region_Northwest', 'region_Southeast',
       'region_Southwest', 'marital_status_Unmarried', 'bmi_category_Obesity',
       'bmi_category_Overweight', 'bmi_category_Underweight',
       'smoking_status_Occasional', 'smoking_status_Regular',
       'employment_status_Salaried', 'employment_status_Self-Employed'],
      dtype='object')
```

[86]:
```
# Calculate VIF for each feature and store the results in a new DataFrame

# Initialize a dictionary to store feature names and their corresponding VIF␣
↪scores
vif_dict = {'features':[],'vif_score':[]}

# Exclude the target variable from VIF calculation
temp_df = df7.drop('annual_premium_amount',axis=1)

# Loop through each feature to compute VIF
for i,col in enumerate(temp_df.columns):
    # Calculate the Variance Inflation Factor for the current feature
    vif = variance_inflation_factor(temp_df,i)

    # Append the feature name and its VIF score to the dictionary
    vif_dict['features'].append(col)
    vif_dict['vif_score'].append(vif)
```

[87]:
```python
# Convert the VIF dictionary into a DataFrame for better readability and␣
↪analysis
vif_df = pd.DataFrame(vif_dict)

# Sort features by their VIF scores in descending order to identify highly␣
↪collinear features
vif_df.sort_values(by='vif_score',ascending=False)
```

[87]:

	features	vif_score
2	income_level	12.450675
3	income_lakhs	11.183367
0	age	4.567634
1	number_of_dependants	4.534650
4	insurance_plan	3.584752
10	marital_status_Unmarried	3.411185
8	region_Southeast	2.922414
5	total_risk_score	2.687610
9	region_Southwest	2.670666
6	gender_Male	2.421496
16	employment_status_Salaried	2.382134
17	employment_status_Self-Employed	2.137753
7	region_Northwest	2.102556
15	smoking_status_Regular	1.777089
12	bmi_category_Overweight	1.549922
11	bmi_category_Obesity	1.352806
13	bmi_category_Underweight	1.302886
14	smoking_status_Occasional	1.272745

After the Variance Inflation Factor (VIF) was calculated for all features, it was observed that both `income_level` and `income_lakhs` had VIF scores exceeding the commonly accepted threshold of 10, indicating the presence of high multicollinearity between them.

To address this issue and enhance model stability, the `income_level` feature was dropped, as it exhibited the higher VIF value of the two. This step was taken to reduce redundancy without significantly compromising the information contained in the dataset.

[88]:
```python
# Initialize a list to store highly collinear features to be removed later

high_vif_features  = []
```

[89]:
```python
# Identify the feature with the highest VIF score and add it to the removal␣
↪list 'high_vif_features'

highest_vif_feature = vif_df['features'][vif_df['vif_score'].idxmax()]
high_vif_features.append(highest_vif_feature)
print(high_vif_features)
```

```
['income_level']
```

[90]:
```
# Drop the most collinear feature from the temporary DataFrame

temp_df1 = temp_df.drop(['income_level'],axis=1).copy()
temp_df1
```

[90]:
```
            age  number_of_dependants  income_lakhs  insurance_plan  \
0      0.148148                   0.0      0.050505             0.0
1      0.203704                   0.4      0.050505             0.0
2      0.574074                   0.4      0.191919             0.5
3      0.222222                   0.6      0.767677             1.0
4      0.000000                   0.0      0.989899             0.5
…          …                    …            …              …
49903  0.111111                   0.0      0.343434             0.0
49904  0.537037                   0.4      0.818182             1.0
49905  0.055556                   0.0      0.313131             0.0
49906  0.000000                   0.4      0.191919             0.0
49907  0.555556                   0.6      0.060606             0.5

       total_risk_score  gender_Male  region_Northwest  region_Southeast  \
0              0.428571            1                 1                 0
1              0.428571            0                 0                 1
2              0.428571            0                 0                 0
3              0.000000            0                 0                 1
4              0.428571            1                 0                 0
…                   …          …                …                …
49903          0.000000            0                 1                 0
49904          0.357143            0                 0                 1
49905          0.000000            1                 1                 0
49906          0.000000            1                 1                 0
49907          0.428571            0                 0                 0

       region_Southwest  marital_status_Unmarried  bmi_category_Obesity  \
0                     0                         1                     0
1                     0                         0                     1
2                     0                         0                     0
3                     0                         0                     0
4                     0                         1                     0
…                   …                        …                    …
49903                 0                         1                     0
49904                 0                         0                     0
49905                 0                         1                     0
49906                 0                         1                     0
49907                 1                         0                     0

       bmi_category_Overweight  bmi_category_Underweight  \
0                            0                         0
1                            0                         0
```

```
2                               0                          0
3                               0                          0
4                               1                          0
…                             …                        …
49903                           0                          1
49904                           0                          0
49905                           0                          0
49906                           0                          0
49907                           0                          0

       smoking_status_Occasional  smoking_status_Regular  \
0                              0                       0
1                              0                       1
2                              0                       0
3                              0                       0
4                              0                       1
…                            …                     …
49903                          0                       0
49904                          0                       0
49905                          0                       1
49906                          0                       0
49907                          1                       0

       employment_status_Salaried  employment_status_Self-Employed
0                               1                                0
1                               1                                0
2                               0                                1
3                               1                                0
4                               0                                1
…                             …                              …
49903                           0                                1
49904                           1                                0
49905                           0                                0
49906                           1                                0
49907                           0                                1

[49908 rows x 17 columns]
```

The same process will be repeated until all VIF values are within the acceptable threshold.

[91]:
```
# Recalculate VIF scores for the updated feature set

vif_dict = {'features':[],'vif_score':[]}

for i,col in enumerate(temp_df1.columns):
    vif = variance_inflation_factor(temp_df1,i)
    vif_dict['features'].append(col)
```

```
    vif_dict['vif_score'].append(vif)

# Create a DataFrame from the updated VIF scores
vif_df = pd.DataFrame(vif_dict)

# Sort VIF scores in descending order to identify next candidates for removal
vif_df.sort_values(by='vif_score',ascending=False)
```

[91]:

	features	vif_score
0	age	4.545825
1	number_of_dependants	4.526598
3	insurance_plan	3.445682
9	marital_status_Unmarried	3.393718
7	region_Southeast	2.919775
4	total_risk_score	2.687326
8	region_Southwest	2.668314
2	income_lakhs	2.480563
5	gender_Male	2.409980
15	employment_status_Salaried	2.374628
16	employment_status_Self-Employed	2.132810
6	region_Northwest	2.100789
14	smoking_status_Regular	1.777024
11	bmi_category_Overweight	1.549907
10	bmi_category_Obesity	1.352748
12	bmi_category_Underweight	1.302636
13	smoking_status_Occasional	1.272744

All remaining features have acceptable VIF scores.

[92]:

```
# Remove the previously identified high-VIF features from the original␣
↪DataFrame.
final_df = df7.drop(high_vif_features,axis=1)

# Display the final cleaned dataset
final_df
```

[92]:

	age	number_of_dependants	income_lakhs	insurance_plan	\
0	0.148148	0.0	0.050505	0.0	
1	0.203704	0.4	0.050505	0.0	
2	0.574074	0.4	0.191919	0.5	
3	0.222222	0.6	0.767677	1.0	
4	0.000000	0.0	0.989899	0.5	
…	…	…	…	…	
49903	0.111111	0.0	0.343434	0.0	
49904	0.537037	0.4	0.818182	1.0	
49905	0.055556	0.0	0.313131	0.0	
49906	0.000000	0.4	0.191919	0.0	
49907	0.555556	0.6	0.060606	0.5	

```
       annual_premium_amount  total_risk_score  gender_Male  region_Northwest  \
0                       9053          0.428571            1                 1
1                      16339          0.428571            0                 0
2                      18164          0.428571            0                 0
3                      20303          0.000000            0                 0
4                      13365          0.428571            1                 0
…                        …                 …            …                 …
49903                   9111          0.000000            0                 1
49904                  27076          0.357143            0                 0
49905                   8564          0.000000            1                 1
49906                   9490          0.000000            1                 1
49907                  19730          0.428571            0                 0

       region_Southeast  region_Southwest  marital_status_Unmarried  \
0                     0                 0                         1
1                     1                 0                         0
2                     0                 0                         0
3                     1                 0                         0
4                     0                 0                         1
…                   …                 …                         …
49903                 0                 0                         1
49904                 1                 0                         0
49905                 0                 0                         1
49906                 0                 0                         1
49907                 0                 1                         0

       bmi_category_Obesity  bmi_category_Overweight  \
0                         0                        0
1                         1                        0
2                         0                        0
3                         0                        0
4                         0                        1
…                       …                        …
49903                     0                        0
49904                     0                        0
49905                     0                        0
49906                     0                        0
49907                     0                        0

       bmi_category_Underweight  smoking_status_Occasional  \
0                             0                          0
1                             0                          0
2                             0                          0
3                             0                          0
4                             0                          0
…                           …                          …
```

```
49903                       1                           0
49904                       0                           0
49905                       0                           0
49906                       0                           0
49907                       0                           1

       smoking_status_Regular  employment_status_Salaried  \
0                           0                           1
1                           1                           1
2                           0                           0
3                           0                           1
4                           1                           0
…                         …                         …
49903                       0                           0
49904                       0                           1
49905                       1                           0
49906                       0                           1
49907                       0                           0

       employment_status_Self-Employed
0                                    0
1                                    0
2                                    1
3                                    0
4                                    1
…                                  …
49903                                1
49904                                0
49905                                0
49906                                0
49907                                1

[49908 rows x 18 columns]
```

0.2 Model Selection

The model selection process proceeded as follows:

1. Split the dataset into training and test sets.
2. Trained different models on the training data.
3. Used cross-validation to compare model performance.
4. Tuned hyperparameters of the best model.
5. Evaluated the final model's performance on the test set.

0.2.1 Dataset Split

The dataset is divided as follows:

- Training set: 70%
- Test set: 30%

Split was done randomly with a fixed seed for reproducibility.

[93]:
```
# Separate features and target variable

features = final_df.drop(['annual_premium_amount'],axis=1)
target = final_df['annual_premium_amount']
```

[94]:
```
# Split the data into training and test sets

X_train,X_test,y_train,y_test = train_test_split(features,target,test_size=0.
  ↪3,random_state=42)
```

[95]:
```
# Display the shape of training and test sets

print(f"X_train shape: {X_train.shape}, y_train shape: {y_train.shape}")
print(f"X_test shape: {X_test.shape}, y_test shape: {y_test.shape}")
```

```
X_train shape: (34935, 17), y_train shape: (34935,)
X_test shape: (14973, 17), y_test shape: (14973,)
```

0.2.2 Model Training

Various models will be tried and training will be performed, including:

- Linear Regression
- Ridge Regression
- Lasso Regression
- Random Forest Regressor
- XGBoost Regressor

Linear Regression

[96]:
```
# Initialize and train the Linear Regression model
lr=LinearRegression()
lr.fit(X_train,y_train)

# Evaluate model performance
train_score = lr.score(X_train,y_train)
test_score = lr.score(X_test,y_test)
```

```
# Print the R² scores
print(f'Train Score : {train_score} , Test Score : {test_score} ')
```

```
Train Score : 0.9280957176093705 , Test Score : 0.9283765993531427
```

[97]:
```
# Predict on test data
y_pred = lr.predict(X_test)

# Calculate Mean Squared Error and Root Mean Squared Error
mse = mean_squared_error(y_test,y_pred)
rmse = root_mean_squared_error(y_test,y_pred)

# Print performance metrics
print(f'MSE : {mse} , RMSE : {rmse}')
```

```
MSE : 5056639.130347778 , RMSE : 2248.697207350909
```

[98]:
```
# Feature Names and Its Coefficents

print('Features -> ',lr.feature_names_in_)
print('\n','**'*50)
print('Coef -> ',lr.coef_)
```

```
Features ->  ['age' 'number_of_dependants' 'income_lakhs' 'insurance_plan'
 'total_risk_score' 'gender_Male' 'region_Northwest' 'region_Southeast'
 'region_Southwest' 'marital_status_Unmarried' 'bmi_category_Obesity'
 'bmi_category_Overweight' 'bmi_category_Underweight'
 'smoking_status_Occasional' 'smoking_status_Regular'
 'employment_status_Salaried' 'employment_status_Self-Employed']

 ********************************************************************************
********************
Coef ->  [11236.4082633   -536.61172956  -353.97067084 12515.43782972
  4846.88626348   121.53023031   -34.50219135    27.97504587
   -23.47372614  -821.78088646  3356.07750448  1613.1421694
   364.31350886   722.41051531  2261.97816483   149.57179545
   378.25130285]
```

[99]:
```
# Creating a dataframe of features and coefficients

feat_coef = {
    'features' : lr.feature_names_in_,
    'coef' : lr.coef_
}

feat_coef_df = pd.DataFrame(feat_coef)
feat_coef_df.sort_values(by=['coef'],ascending=False)
```

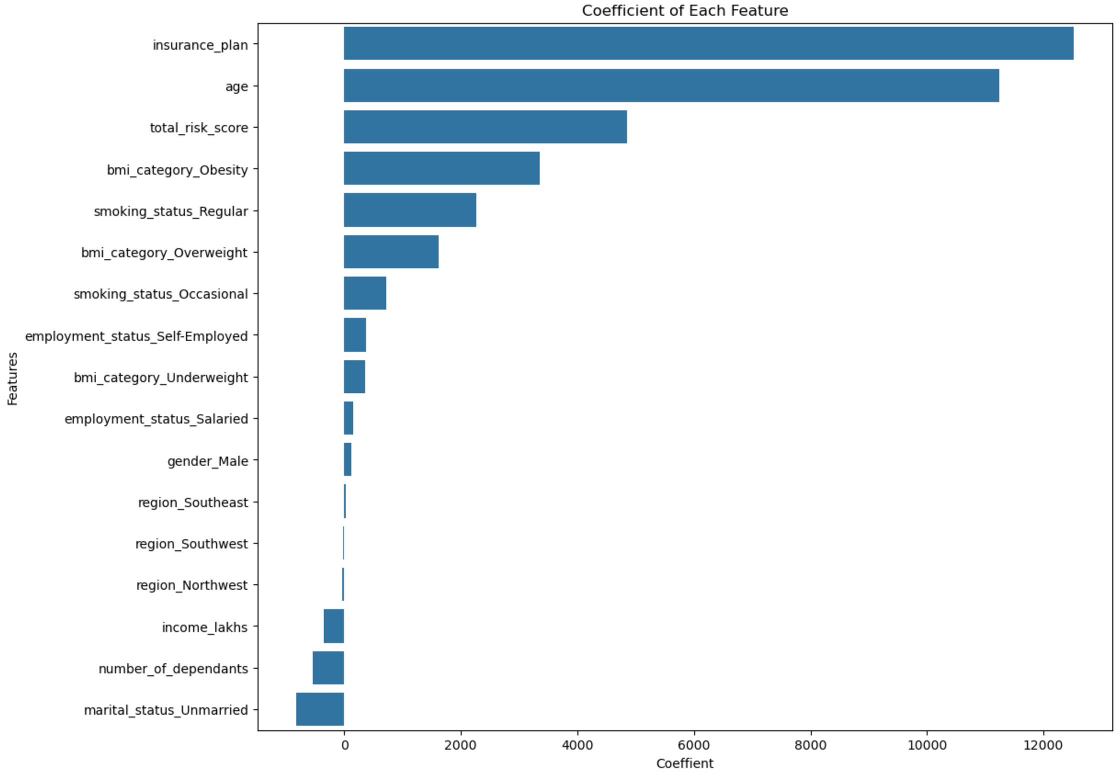
[99]:

	features	coef
3	insurance_plan	12515.437830
0	age	11236.408263
4	total_risk_score	4846.886263
10	bmi_category_Obesity	3356.077504
14	smoking_status_Regular	2261.978165
11	bmi_category_Overweight	1613.142169
13	smoking_status_Occasional	722.410515
16	employment_status_Self-Employed	378.251303
12	bmi_category_Underweight	364.313509
15	employment_status_Salaried	149.571795
5	gender_Male	121.530230
7	region_Southeast	27.975046
8	region_Southwest	-23.473726
6	region_Northwest	-34.502191
2	income_lakhs	-353.970671
1	number_of_dependants	-536.611730
9	marital_status_Unmarried	-821.780886

[100]:

```
# Plotting the features and its coefficients

plt.figure(figsize=(12,10))
sns.barplot(data=feat_coef_df.sort_values(by=['coef'],ascending=False),x =␣
↪'coef',y = 'features' )
plt.title('Coefficient of Each Feature')
plt.xlabel('Coeffient')
plt.ylabel('Features')
plt.show()
```



Lasso Regression

[101]:
```
# Initialize and train the Lasso Regression model
ls = Lasso()
ls.fit(X_train,y_train)

# Evaluate model performance
train_score = ls.score(X_train,y_train)
test_score = ls.score(X_test,y_test)

# Print the R² scores
print(f'Train Score : {train_score} , Test Score : {test_score} ')
```

```
Train Score : 0.9280927085624446 , Test Score : 0.9283637752728616
```

[102]:
```
# Predict on test data
y_pred = ls.predict(X_test)

# Calculate Mean Squared Error and Root Mean Squared Error
mse = mean_squared_error(y_test,y_pred)
rmse = root_mean_squared_error(y_test,y_pred)

# Print performance metrics
```

```
print(f'MSE : {mse} , RMSE : {rmse}')
```

```
MSE : 5057544.515257937 , RMSE : 2248.8985115513633
```

Ridge Regression

[103]:
```
# Initialize and train the Ridge Regression model
rg = Ridge()
rg.fit(X_train,y_train)

# Evaluate model performance
train_score = rg.score(X_train,y_train)
test_score = rg.score(X_test,y_test)

# Print the R² scores
print(f'Train Score : {train_score} , Test Score : {test_score} ')
```

```
Train Score : 0.9280956798900618 , Test Score : 0.9283764905001947
```

[104]:
```
# Predict on test data
y_pred = rg.predict(X_test)

# Calculate Mean Squared Error and Root Mean Squared Error
mse = mean_squared_error(y_test,y_pred)
rmse = root_mean_squared_error(y_test,y_pred)

# Print performance metrics
print(f'MSE : {mse} , RMSE : {rmse}')
```

```
MSE : 5056646.815407011 , RMSE : 2248.698916130617
```

Observation

Neither Lasso nor Ridge regression showed significant improvement over Linear Regression.

Random Forest Regressor

[105]:
```
# Initialize and train the Random Forest Regression model
rfr = RandomForestRegressor()
rfr.fit(X_train,y_train)

# Evaluate model performance
train_score = rfr.score(X_train,y_train)
test_score = rfr.score(X_test,y_test)

# Print the R² scores
print(f'Train Score : {train_score} , Test Score : {test_score} ')
```

```
Train Score : 0.9965657768248808 , Test Score : 0.9789939664693872
```

[106]:
```
# Predict on test data
y_pred = rfr.predict(X_test)

# Calculate Mean Squared Error and Root Mean Squared Error
mse = mean_squared_error(y_test,y_pred)
rmse = root_mean_squared_error(y_test,y_pred)

# Print performance metrics
print(f'MSE : {mse} , RMSE : {rmse}')
```

```
MSE : 1483033.8990467205 , RMSE : 1217.798792513246
```

Based on the R^2 score, it can be seen that this model fits the data well. The XGBoost model will be tried next.

XGboost Regressor

[107]:
```
# Initialize and train the XGboost model
xgb = XGBRegressor()
xgb.fit(X_train,y_train)

# Evaluate model performance
train_score = xgb.score(X_train,y_train)
test_score = xgb.score(X_test,y_test)

# Print the R² scores
print(f'Train Score : {train_score} , Test Score : {test_score} ')
```

```
Train Score : 0.9861041903495789 , Test Score : 0.9807721972465515
```

[108]:
```
# Predict on test data
y_pred = xgb.predict(X_test)

# Calculate Mean Squared Error and Root Mean Squared Error
mse = mean_squared_error(y_test,y_pred)
rmse = root_mean_squared_error(y_test,y_pred)

# Print performance metrics
print(f'MSE : {mse} , RMSE : {rmse}')
```

```
MSE : 1357488.75 , RMSE : 1165.1131591796875
```

Model Performance Comparison: XGBoost vs. Random Forest

Both XGBoost and Random Forest models are observed to perform well on the dataset. However, the following points are noted:

- A lower training score and a higher test score are yielded by the XGBoost model compared to Random Forest.
- This suggests that the XGBoost model generalizes better and is less prone to overfitting.
- To validate this observation, cross-validation will be used to evaluate both models more robustly using `cross_validate`.

Cross Validation - RF vs XGboost Stratified K-Fold will not be performed since this is a regression task; therefore, K-Fold cross-validation is considered sufficient.

[109]:
```
# Set up 5-fold cross-validation

kf = KFold(n_splits = 5,shuffle=True,random_state=42)
```

Cross-validation will be performed on both Random Forest and XGBoost models, with the run time also being recorded.
The `cross_validate` function is used instead of `cross_val_score` to obtain both training and testing scores.

[110]:
```
# Perform cross-validation for Random Forest Regressor

start_time = time()
cv_rfr =␣
↪cross_validate(rfr,features,target,cv=kf,return_train_score=True,scoring='r2')
end_time = time()
total_time_rfr = end_time - start_time
print(f'Total Time Taken : {round(total_time_rfr,2)} seconds')
```

```
Total Time Taken : 67.49 seconds
```

[111]:
```
# Display training scores
print("Training scores (R²):", cv_rfr['train_score'])

# Display test scores
print("Validation scores (R²):", cv_rfr['test_score'])
```

```
Training scores (R²): [0.9965103  0.99652913 0.99644755 0.99654474 0.99645785]
Validation scores (R²): [0.97901928 0.97902788 0.97945362 0.97865826 0.9794153 ]
```

[112]:
```
# Perform cross-validation for XGboost Regressor

start_time = time()
cv_xgb =␣
↪cross_validate(xgb,features,target,cv=kf,return_train_score=True,scoring='r2')
end_time = time()
total_time_xgb = end_time - start_time
print(f'Total Time Taken : {round(total_time_xgb,2)} seconds')
```

```
Total Time Taken : 0.74 seconds
```

[113]:
```
# Display training scores
print("Training scores (R²):", cv_xgb['train_score'])

# Display test scores
print("Validation scores (R²):", cv_xgb['test_score'])
```

```
Training scores (R²): [0.98580199 0.9857831  0.98563534 0.98585421 0.98580426]
Validation scores (R²): [0.9809615  0.98077649 0.98098087 0.98112887 0.98120141]
```

[114]:
```python
cv_df = pd.DataFrame(
    {
        'model' : ['Random Forest','XGboost'],
        'execution_time (seconds)' : [total_time_rfr,total_time_xgb],
        'average_train_score' : [np.mean(cv_rfr['train_score']),np.
 ↪mean(cv_xgb['train_score'])],
        'average_test_score' : [np.mean(cv_rfr['test_score']),np.
 ↪mean(cv_xgb['test_score'])]
    }
)

cv_df
```

[114]:
```
           model  execution_time (seconds)  average_train_score  \
0  Random Forest                 67.486237             0.996498
1        XGboost                  0.744500             0.985776

   average_test_score
0            0.979115
1            0.981010
```

Cross-Validation Summary: XGBoost vs. Random Forest

The cross-validation results confirm that XGBoost is consistently observed to generalize better than the Random Forest model:

- *Lower training scores* and *higher test scores* were achieved by XGBoost, indicating *better generalization* and *reduced overfitting*.
- In terms of performance, XGBoost was approximately ***83 times faster*** than Random Forest during cross-validation.

Given its superior predictive performance and computational efficiency, **XGBoost will be selected as the final model**.