Decision Tree and Naive Bayes(1)

November 9, 2021

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
from collections import Counter
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
```

[3]:
```python
Prudential_train = pd.read_csv("https://raw.githubusercontent.com/crisajose/
↪CIND-820-Big-Data-Analytics-Project/main/train.csv")
```

[4]:
```python
Prudential_train.head()
```

[4]:
```
   Id  Product_Info_1 Product_Info_2  Product_Info_3  Product_Info_4  \
0   2               1             D3              10        0.076923
1   5               1             A1              26        0.076923
2   6               1             E1              26        0.076923
3   7               1             D4              10        0.487179
4   8               1             D2              26        0.230769

   Product_Info_5  Product_Info_6  Product_Info_7   Ins_Age        Ht  …  \
0               2               1               1  0.641791  0.581818  …
1               2               3               1  0.059701  0.600000  …
2               2               3               1  0.029851  0.745455  …
3               2               3               1  0.164179  0.672727  …
4               2               3               1  0.417910  0.654545  …

   Medical_Keyword_40  Medical_Keyword_41  Medical_Keyword_42  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   Medical_Keyword_43  Medical_Keyword_44  Medical_Keyword_45  \
0                   0                   0                   0
```

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

   Medical_Keyword_46  Medical_Keyword_47  Medical_Keyword_48  Response
0                    0                    0                    0         8
1                    0                    0                    0         4
2                    0                    0                    0         8
3                    0                    0                    0         8
4                    0                    0                    0         8

[5 rows x 128 columns]
```

[5]:
```python
CATEGORICAL_COLUMNS = ["Product_Info_1", "Product_Info_2", "Product_Info_3",␣
 ↪"Product_Info_5", "Product_Info_6",\
                       "Product_Info_7", "Employment_Info_2",␣
 ↪"Employment_Info_3", "Employment_Info_5", "InsuredInfo_1",\
                       "InsuredInfo_2", "InsuredInfo_3", "InsuredInfo_4",␣
 ↪"InsuredInfo_5", "InsuredInfo_6", "InsuredInfo_7",\
                       "Insurance_History_1", "Insurance_History_2",␣
 ↪"Insurance_History_3", "Insurance_History_4", "Insurance_History_7",\
                       "Insurance_History_8", "Insurance_History_9",␣
 ↪"Family_Hist_1", "Medical_History_2", "Medical_History_3",\
                       "Medical_History_4", "Medical_History_5",␣
 ↪"Medical_History_6", "Medical_History_7", "Medical_History_8",\
                       "Medical_History_9", "Medical_History_11",␣
 ↪"Medical_History_12", "Medical_History_13", "Medical_History_14",\
                       "Medical_History_16", "Medical_History_17",␣
 ↪"Medical_History_18", "Medical_History_19", "Medical_History_20",\
                       "Medical_History_21", "Medical_History_22",␣
 ↪"Medical_History_23", "Medical_History_25", "Medical_History_26",\
                       "Medical_History_27", "Medical_History_28",␣
 ↪"Medical_History_29", "Medical_History_30", "Medical_History_31",\
                       "Medical_History_33", "Medical_History_34",␣
 ↪"Medical_History_35", "Medical_History_36", "Medical_History_37",\
                       "Medical_History_38", "Medical_History_39",␣
 ↪"Medical_History_40", "Medical_History_41"]
CONTINUOUS_COLUMNS = ["Product_Info_4", "Ins_Age", "Ht", "Wt", "BMI",
                      "Employment_Info_1", "Employment_Info_4",␣
 ↪"Employment_Info_6",
                      "Insurance_History_5", "Family_Hist_2", "Family_Hist_3",␣
 ↪"Family_Hist_4", "Family_Hist_5"]
DISCRETE_COLUMNS = ["Medical_History_1", "Medical_History_10",␣
 ↪"Medical_History_15", "Medical_History_24", "Medical_History_32"]
DUMMY_COLUMNS = ["Medical_Keyword_{}".format(i) for i in range(1, 48)]
```

[6]:
```python
categorical_data = Prudential_train[CATEGORICAL_COLUMNS]
```

[7]:
```python
continuous_data = Prudential_train[CONTINUOUS_COLUMNS]
```

[8]:
```python
discrete_data = Prudential_train[DISCRETE_COLUMNS]
```

[9]:
```python
dummy_data = Prudential_train[DUMMY_COLUMNS]
```

1 Variable Types

[10]:
```python
Prudential_train.dtypes
```

[10]:
```
Id                       int64
Product_Info_1           int64
Product_Info_2          object
Product_Info_3           int64
Product_Info_4         float64
                         …
Medical_Keyword_45       int64
Medical_Keyword_46       int64
Medical_Keyword_47       int64
Medical_Keyword_48       int64
Response                 int64
Length: 128, dtype: object
```

2 NULL values

[12]:
```python
Prudential_NULL = Prudential_train.isnull().any()
Prudential_NULL =[col for col in Prudential_train.columns if␣
 ↪Prudential_train[col].isnull().any()]
Prudential_NULL
```

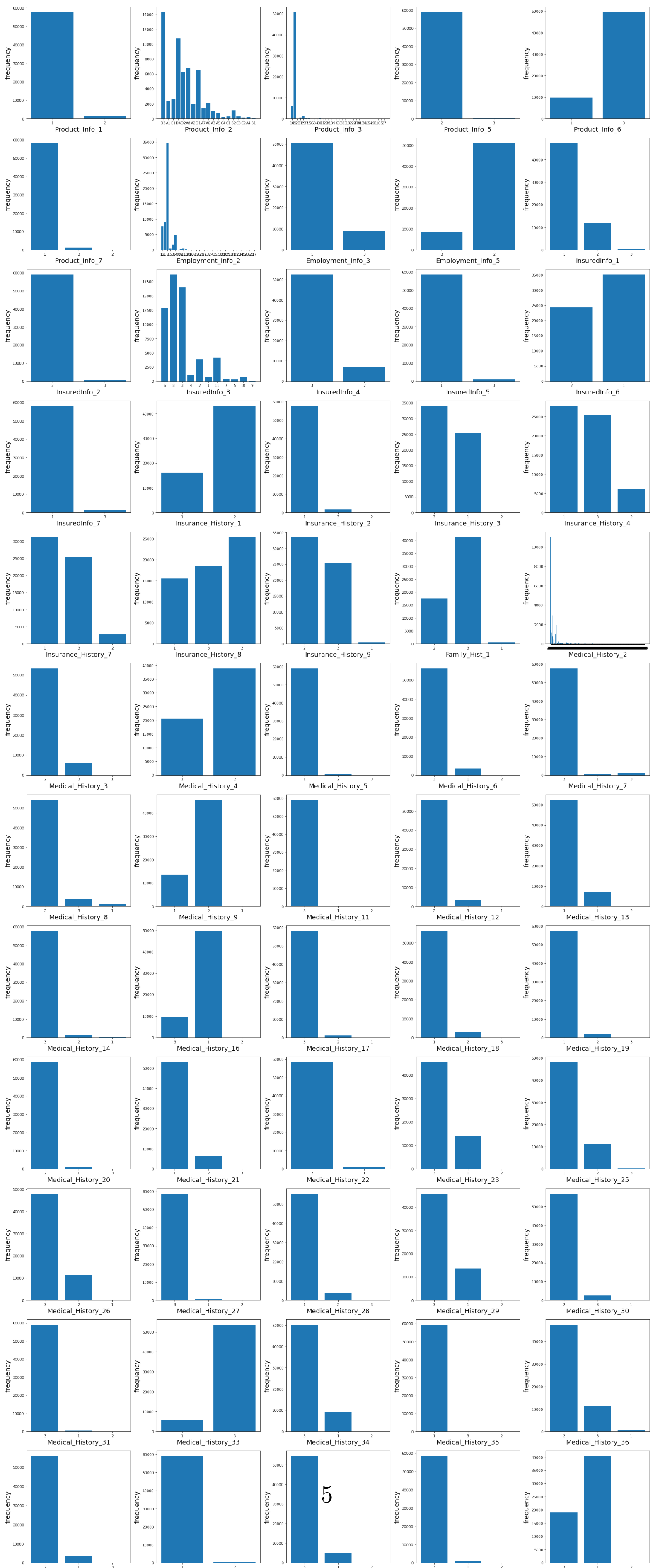
[12]:
```
['Employment_Info_1',
 'Employment_Info_4',
 'Employment_Info_6',
 'Insurance_History_5',
 'Family_Hist_2',
 'Family_Hist_3',
 'Family_Hist_4',
 'Family_Hist_5',
 'Medical_History_1',
 'Medical_History_10',
 'Medical_History_15',
```

```
 'Medical_History_24',
 'Medical_History_32']
```

3 Categorical Variable - Plot

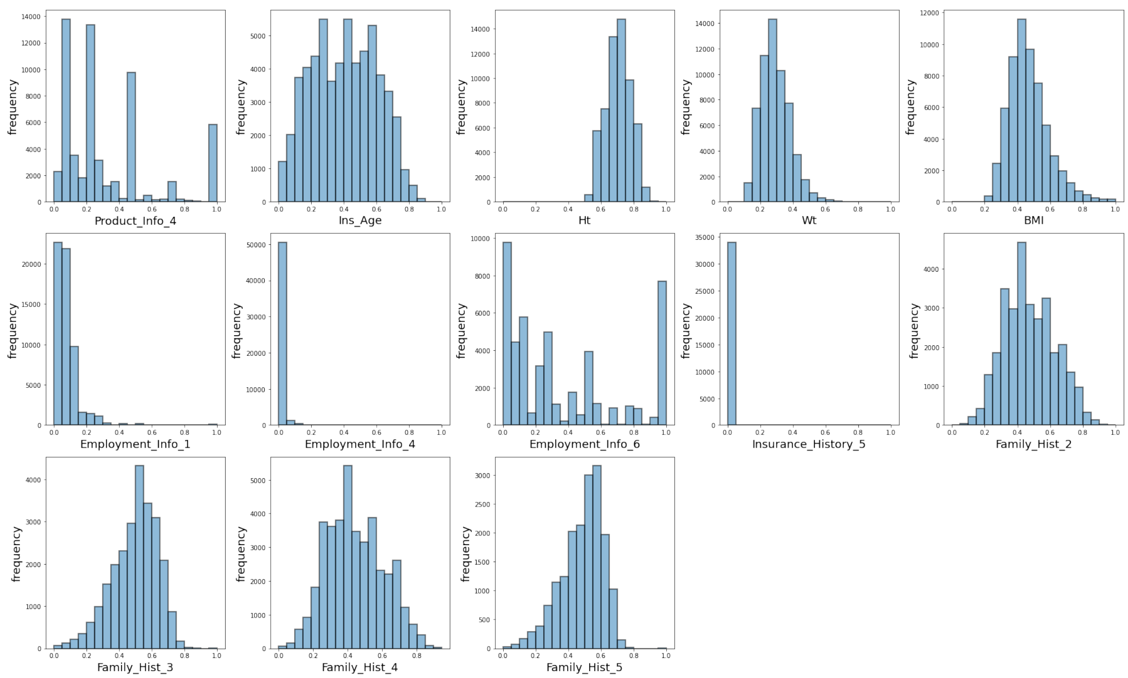
[13]:
```python
def plot_categoricals(data):
    ncols = len(data.columns)
    fig = plt.figure(figsize=(5 * 5, 5 * (ncols // 5 + 1)))
    for i, col in enumerate(data.columns):
        cnt = Counter(data[col])
        keys = list(cnt.keys())
        vals = list(cnt.values())
        plt.subplot(ncols // 5 + 1, 5, i + 1)
        plt.bar(range(len(keys)), vals, align="center")
        plt.xticks(range(len(keys)), keys)
        plt.xlabel(col, fontsize=18)
        plt.ylabel("frequency", fontsize=18)
    fig.tight_layout()
    plt.show()

plot_categoricals(categorical_data)
```


frequency
Product_Info_1
Product_Info_2
Product_Info_3
Product_Info_5
Product_Info_6
Product_Info_7
Employment_Info_2
Employment_Info_3
Employment_Info_5
InsuredInfo_1
InsuredInfo_2
InsuredInfo_3
InsuredInfo_4
InsuredInfo_5
InsuredInfo_6
InsuredInfo_7
Insurance_History_1
Insurance_History_2
Insurance_History_3
Insurance_History_4
Insurance_History_7
Insurance_History_8
Insurance_History_9
Family_Hist_1
Medical_History_2
Medical_History_3
Medical_History_4
Medical_History_5
Medical_History_6
Medical_History_7
Medical_History_8
Medical_History_9
Medical_History_11
Medical_History_12
Medical_History_13
Medical_History_14
Medical_History_16
Medical_History_17
Medical_History_18
Medical_History_19
Medical_History_20
Medical_History_21
Medical_History_22
Medical_History_23
Medical_History_25
Medical_History_26
Medical_History_27
Medical_History_28
Medical_History_29
Medical_History_30
Medical_History_31
Medical_History_33
Medical_History_34
Medical_History_35
Medical_History_36
Medical_History_37
Medical_History_38
Medical_History_39
Medical_History_40
Medical_History_41

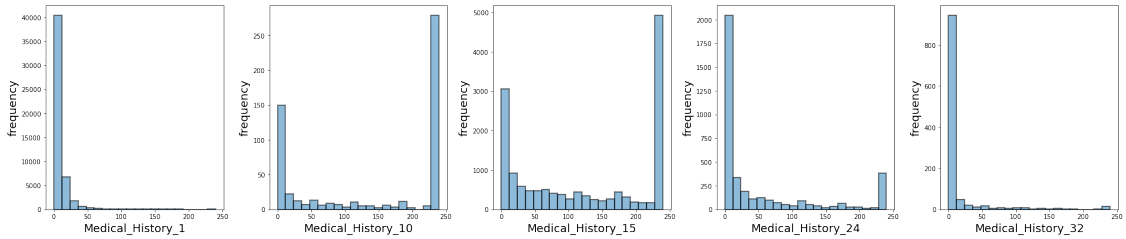
4 Continuous Variable - Plot

[14]:
```
def plot_histgrams(data):
    ncols = len(data.columns)
    fig = plt.figure(figsize=(5 * 5, 5 * (ncols // 5 + 1)))
    for i, col in enumerate(data.columns):
        X = data[col].dropna()
        plt.subplot(ncols // 5 + 1, 5, i + 1)
        plt.hist(X, bins=20, alpha=0.5, \
                 edgecolor="black", linewidth=2.0)
        plt.xlabel(col, fontsize=18)
        plt.ylabel("frequency", fontsize=18)
    fig.tight_layout()
    plt.show()
plot_histgrams(continuous_data)
```



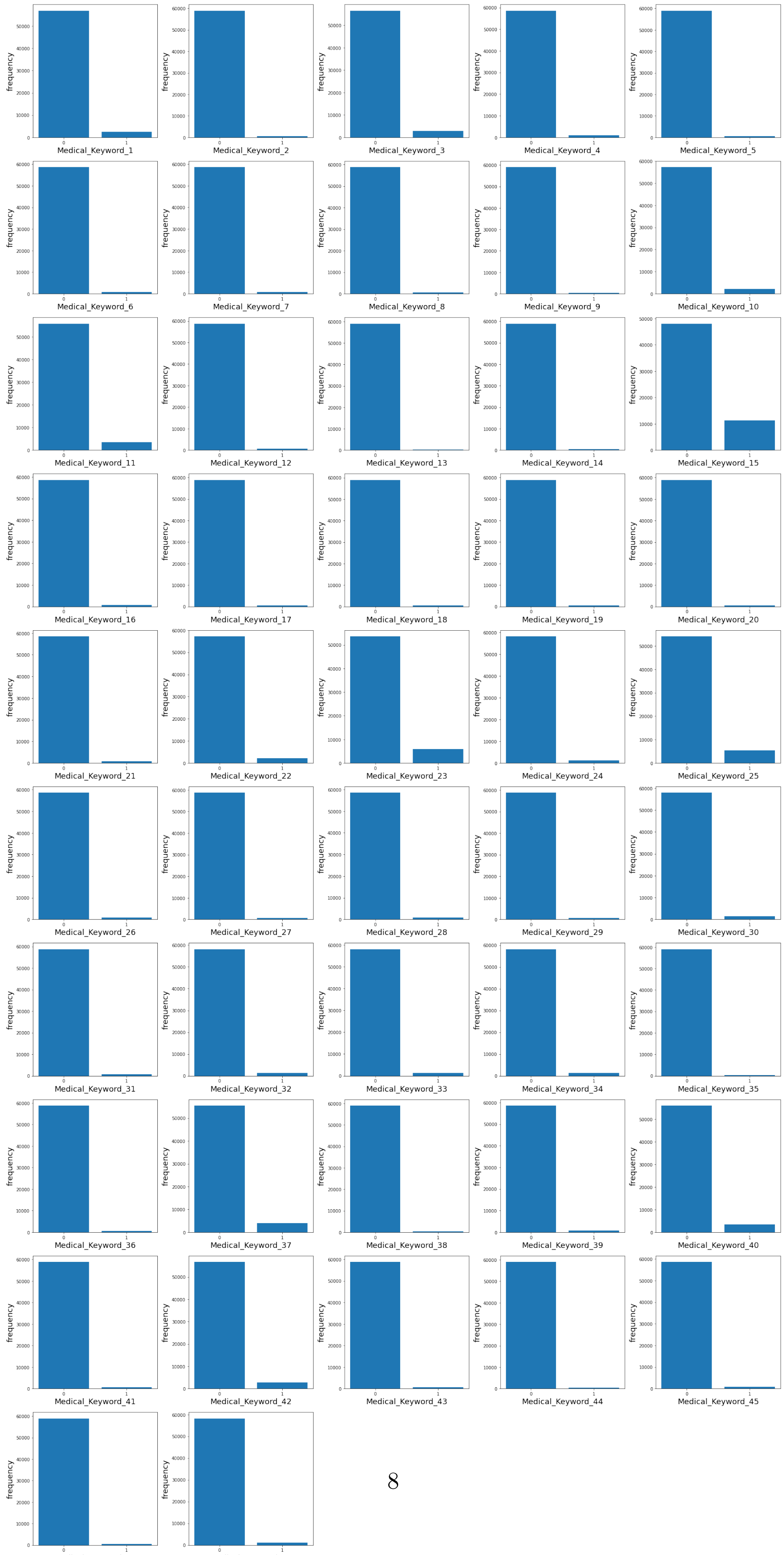
5 Discrete Variable - Plot

[16]:
```
plot_histgrams(discrete_data)
```



6 Dummy Variable - Plot

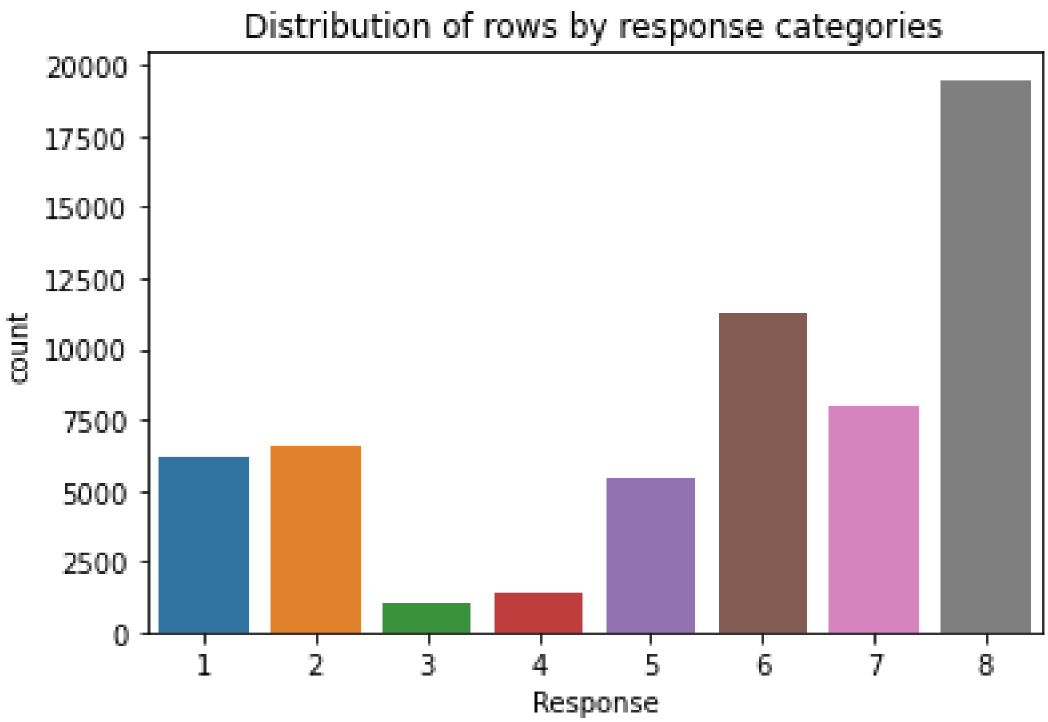
[17]:
```
plot_categoricals(dummy_data)
```


frequency
Medical_Keyword_1
Medical_Keyword_2
Medical_Keyword_3
Medical_Keyword_4
Medical_Keyword_5
Medical_Keyword_6
Medical_Keyword_7
Medical_Keyword_8
Medical_Keyword_9
Medical_Keyword_10
Medical_Keyword_11
Medical_Keyword_12
Medical_Keyword_13
Medical_Keyword_14
Medical_Keyword_15
Medical_Keyword_16
Medical_Keyword_17
Medical_Keyword_18
Medical_Keyword_19
Medical_Keyword_20
Medical_Keyword_21
Medical_Keyword_22
Medical_Keyword_23
Medical_Keyword_24
Medical_Keyword_25
Medical_Keyword_26
Medical_Keyword_27
Medical_Keyword_28
Medical_Keyword_29
Medical_Keyword_30
Medical_Keyword_31
Medical_Keyword_32
Medical_Keyword_33
Medical_Keyword_34
Medical_Keyword_35
Medical_Keyword_36
Medical_Keyword_37
Medical_Keyword_38
Medical_Keyword_39
Medical_Keyword_40
Medical_Keyword_41
Medical_Keyword_42
Medical_Keyword_43
Medical_Keyword_44
Medical_Keyword_45
Medical_Keyword_46
Medical_Keyword_47

7 Response Data Distribution

[18]:
```
sns.countplot(x=Prudential_train.Response).set_title('Distribution of rows by␣
↪response categories')
```

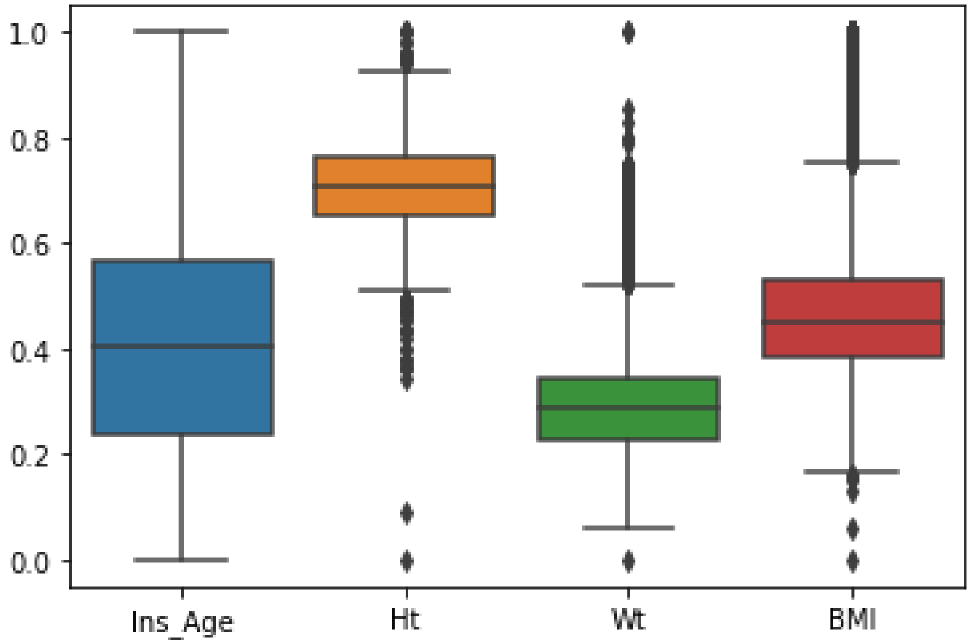
[18]: Text(0.5, 1.0, 'Distribution of rows by response categories')



8 Outliers Plot

[19]:
```
misc_cols=["Ins_Age","Ht","Wt","BMI"]
sns.boxplot(data=Prudential_train[misc_cols])
```

[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa0414a8ed0>



9 Reassign Risk Class

[20]:
```
prudential_train=Prudential_train.drop(axis=1,labels=["Product_Info_2"])
```

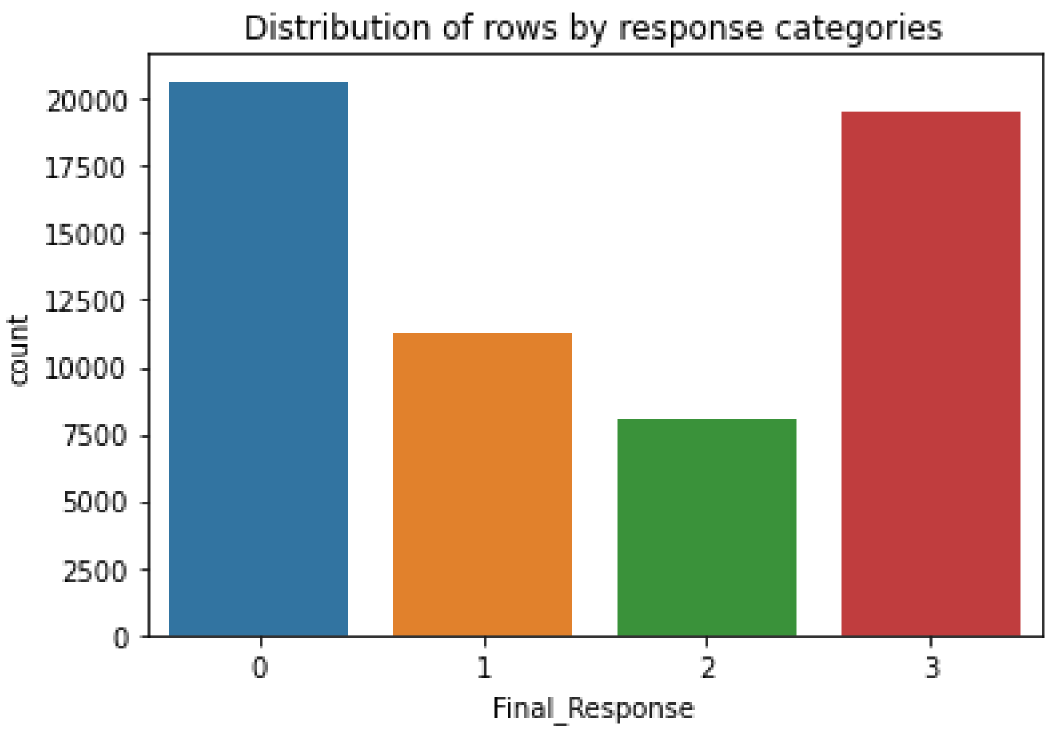
[21]:
```
prudential_train.dropna(axis=1,inplace=True)
```

[22]:
```
def new_target(row):
    if (row['Response']<=5):
        val=0
    elif (row['Response']==6):
        val=1
    elif (row['Response']==7):
        val=2
    elif (row['Response']==8):
        val=3

    else:
        val=-1
    return val
prudential_train['Final_Response']=prudential_train.apply(new_target,axis=1)
```

[23]:
```
sns.countplot(x=prudential_train.Final_Response).set_title('Distribution of␣
↪rows by response categories')
```

[23]: Text(0.5, 1.0, 'Distribution of rows by response categories')



10 Base Model

[24]:
```
y = prudential_train.Final_Response
X = prudential_train.drop(labels=['Response'],axis=1)
X = X.drop(labels=['Final_Response'],axis=1)
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=.
↪20,random_state=1)


print("Shape of X_train dataset {}".format(X_train.shape))
print("Shape of X_test dataset {}".format(X_test.shape))

print("Shape of y_train dataset {}".format(y_train.shape))
print("Shape of y_valid dataset {}".format(y_test.shape))
```

```
Shape of X_train dataset (47504, 113)
Shape of X_test dataset (11877, 113)
Shape of y_train dataset (47504,)
Shape of y_valid dataset (11877,)
```

11 Decision Tree

[25]:
```
model = DecisionTreeClassifier()
model.fit(X_train, y_train)
model_predictions = model.predict(X_test)
print("Accuracy score: {}".format(accuracy_score(y_test, model_predictions)))
print("="*80)
print(classification_report(y_test, model_predictions))
```

```
Accuracy score: 0.514018691588785
================================================================================
              precision    recall  f1-score   support

           0       0.60      0.58      0.59      4205
           1       0.32      0.34      0.33      2206
           2       0.30      0.31      0.30      1608
           3       0.64      0.62      0.63      3858

    accuracy                           0.51     11877
   macro avg       0.46      0.46      0.46     11877
weighted avg       0.52      0.51      0.52     11877
```

12 Naive Bayes

[26]:
```
model = GaussianNB()
model.fit(X_train, y_train)
model_predictions = model.predict(X_test)
print("Accuracy score: {}".format(accuracy_score(y_test, model_predictions)))
print("="*80)
print(classification_report(y_test, model_predictions))
```

```
Accuracy score: 0.428222615138503
================================================================================
              precision    recall  f1-score   support

           0       0.71      0.21      0.33      4205
           1       0.26      0.07      0.11      2206
           2       0.29      0.22      0.25      1608
           3       0.42      0.95      0.58      3858

    accuracy                           0.43     11877
   macro avg       0.42      0.36      0.32     11877
weighted avg       0.47      0.43      0.36     11877
```

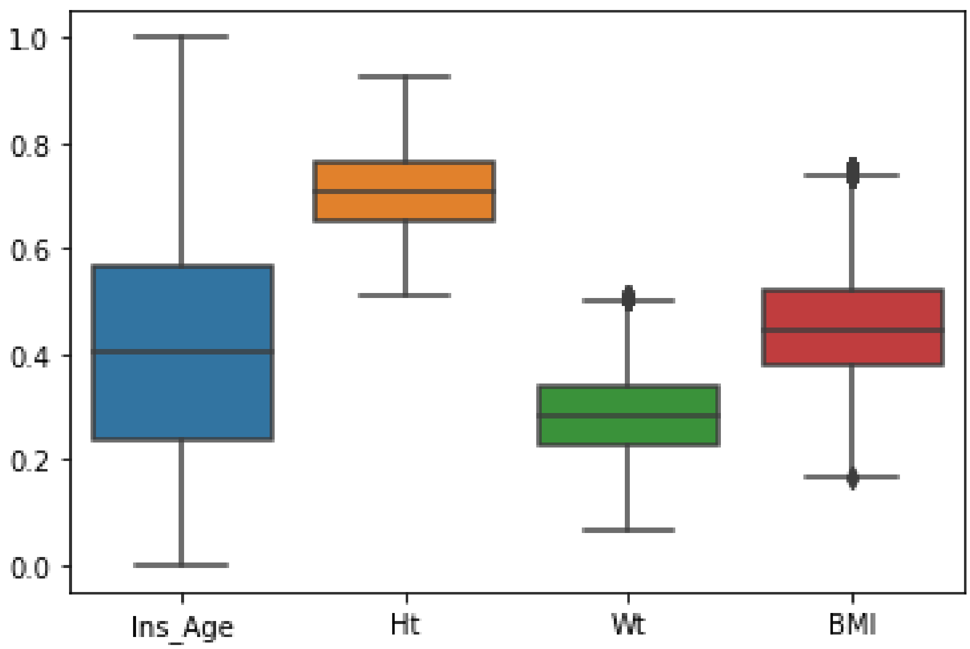
13 Treating Outliers

[29]:
```
def remove_outlier(df_in, col_name):
    q1 = df_in[col_name].quantile(0.25)
    q3 = df_in[col_name].quantile(0.75)
    iqr = q3-q1 #Interquartile range
    fence_low  = q1-1.5*iqr
    fence_high = q3+1.5*iqr
    df_out = df_in.loc[(df_in[col_name] > fence_low) & (df_in[col_name] <
 ↪fence_high)]
    return df_out


dev=remove_outlier(Prudential_train,'BMI')
dev=remove_outlier(dev,'Wt')
dev=remove_outlier(dev,'Ht')
```

[30]:
```
sns.boxplot(data=dev[misc_cols])
```

[30]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa03fe1da90>



[31]:
```
prudential_X_train = dev
```

[32]:
```
def new_target(row):
    if (row['Response']<=5):
```

```
        val=0
    elif (row['Response']==6):
        val=1
    elif (row['Response']==7):
        val=2
    elif (row['Response']==8):
        val=3

    else:
        val=-1
    return val
prudential_X_train['Final_Response']=prudential_X_train.apply(new_target,axis=1)
```

[33]:

```
medical_keyword_cols=[col for col in prudential_X_train.columns if str(col).
 ↪startswith("Medical_Keyword")]
```

[34]:

```
medical_cols=[col for col in prudential_X_train.columns if str(col).
 ↪startswith("Medical_History")]
```

[35]:

```
prudential_X_train['Total_MedKwrds']=prudential_X_train[medical_keyword_cols].
 ↪sum(axis=1)
prudential_X_train['Total_MedHist']=prudential_X_train[medical_cols].sum(axis=1)
```

[36]:

```
prudential_X_train['Total_MedKwrds']
```

[36]:

```
0        0
1        0
2        0
3        1
4        0
        ..
59376    0
59377    0
59378    1
59379    2
59380    0
Name: Total_MedKwrds, Length: 57348, dtype: int64
```

[37]:

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
prudential_X_train['Product_Info_2_en'] = le.
 ↪fit_transform(prudential_X_train['Product_Info_2'])
```

[38]:

```
prudential_X_train['Product_Info_2_en']
```

[38]:

```
0        16
1         0
```

```
2        18
3        17
4        15
         ..
59376    14
59377    16
59378    18
59379    15
59380     7
Name: Product_Info_2_en, Length: 57348, dtype: int64
```

[39]:
```
prudential_X_train = prudential_X_train.drop(axis=1,labels=['Product_Info_2'])
```

[40]:
```
prudential_X_train.Final_Response.unique()
```

[40]:
```
array([3, 0, 1, 2])
```

14 Feature Selection

[41]:
```
prudential_X_train = prudential_X_train.drop(labels = ['Response'],axis=1)
prudential_X_train = prudential_X_train.drop(labels =␣
↪['Medical_History_10'],axis=1)
prudential_X_train = prudential_X_train.drop(labels = ['Id'],axis=1)
```

15 Fill Null Values

[42]:
```
prudential_X_train = prudential_X_train.fillna(prudential_X_train.mean())
```

16 Build Model

[43]:
```
y = prudential_X_train.Final_Response
X = prudential_X_train.drop(labels=['Final_Response'],axis=1)
X = X.fillna(X.mean())

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=.
↪20,random_state=1)
print("Shape of X_train dataset {}".format(X_train.shape))
print("Shape of X_test dataset {}".format(X_test.shape))

print("Shape of y_train dataset {}".format(y_train.shape))
print("Shape of y_valid dataset {}".format(y_test.shape))
```

```
Shape of X_train dataset (45878, 127)
Shape of X_test dataset (11470, 127)
Shape of y_train dataset (45878,)
Shape of y_valid dataset (11470,)
```

17 Decision Tree - with feature selection

[44]:
```python
model = DecisionTreeClassifier()
model.fit(X_train, y_train)
model_predictions = model.predict(X_test)
print("Accuracy score: {}".format(accuracy_score(y_test, model_predictions)))
print("="*80)
print(classification_report(y_test, model_predictions))
```

```
Accuracy score: 0.5431560592850916
================================================================================
              precision    recall  f1-score   support

           0       0.60      0.59      0.59      3731
           1       0.39      0.42      0.40      2202
           2       0.35      0.35      0.35      1642
           3       0.68      0.65      0.66      3895

    accuracy                           0.54     11470
   macro avg       0.50      0.50      0.50     11470
weighted avg       0.55      0.54      0.55     11470
```

18 Naive Bayes - with feature selection

[46]:
```python
model = GaussianNB()
model.fit(X_train, y_train)
model_predictions = model.predict(X_test)
print("Accuracy score: {}".format(accuracy_score(y_test, model_predictions)))
print("="*80)
print(classification_report(y_test, model_predictions))
```

```
Accuracy score: 0.44533565823888405
================================================================================
              precision    recall  f1-score   support

           0       0.58      0.32      0.41      3731
           1       0.27      0.10      0.14      2202
           2       0.24      0.36      0.29      1642
           3       0.50      0.80      0.62      3895
```

```
    accuracy                           0.45     11470
   macro avg       0.40      0.39      0.37     11470
weighted avg       0.45      0.45      0.41     11470
```

[ ]: