Part I: Research Question

A. Question

Can we identify the variables most influential in the readmittance of patients following a visit at our hospital?

B. Variables

CaseOrder: Integer that maintains initial order of raw data Customer_id: String that provides unique key to patient Interaction: String that provides unique key for patient transactions, procedures, and admissions UID: String that provides unique key for patient transactions, procedures, and admissions City: String that indicates patient city of residence on billing statement State: String that indicates patient state of residence on billing statement County: String that indicates patient county of residence on billing statement Zip: Integer that indicates patient zip code of residence on billing statement Lat: Float that indicates Latitude based on billing statement address Lng: Float that indicates Longitude based on billing statement address Population: Integer that indicates population based on census data within one-mile radius of address Area: String that indicates area type based on census Timezone: String that indicates timezone based on patient provided residence Job: String that indicates patient job as provided by admissions information Children: Float that indicates number of children provided by admissions information Age: Float that indicates age of patient provided by admissions information Education: String that indicates highest earned level of education provided by admissions information Employment: String that indicates current employment status provided by admissions information Income: Float that indicates annual income of patient (or primary insurance holder) provided by admissions information Marital: String that indicates current marital status of patient (or primary insurance holder) provided by admissions information Gender: String that indicates self-identified gender ReAdmis: String that indicates whether the patient was readmitted within a month of relevant visit VitD_levels: Float that indicates patient vitamin D levels measured in ng/ml Doc_visits: Integer that indicates the number of times that the PCP (Primary Care Physician) visited the patient during their initial stay Full_meals_eaten: Integer that indicates the number of full meals the patient ate during hospitilization (partial = 0) VitD_supp: Integer that indicates the number of times vitamin D supplements were administered to patient Soft_drink: String that indicates if a patient drinks 3 or more sodas in a day frequently Initial_admin: String that indicates the route in which a patient was admitted into the hospital HighBlood: String that indicates if the patient has high blood pressure Stroke: String that indicates if the patient has had a stroke Complication_risk: String that indicates the level of risk for complication associated with the patient Overweight: Float that indicates if the patient is overweight Arthritis: String that indicates if the patient has arthritis Diabetes: String that indicates if the patient has diabetes Hyperlipidemia: String that indicates if the patient has hyperlipidemia BackPain: String that indicates if the patient has chronic back pain Anxiety: Float that indicates if the patient has an anxiety disorder Allergic_rhinitis: String that indicates if the patient has allergic rhinitis Reflux_esophagitis: String that indicates if the patient has reflux esophagitis Asthma: String that indicates if the patient if the patient has asthma Services: String that indicates the primary service a patient received during their stay Initial_days: Float that indicates the number of days the patient stayed during the initial visit TotalCharge: Float that indicates the average cost per day (Total Cost/# of days) Additional_charges: Float that indicates the average cost of miscellaneous services received during stay Item1: Integer that indicates survey answer about the importance of "Timely Admission" (Scale of 1 most - 8 least) Item2: Integer that indicates survey answer about the importance of "Timely Treatment" (Scale of 1 most - 8 least) Item3: Integer that indicates survey answer about the importance of "Timely Visits" (Scale of 1 most - 8 least) Item4: Integer that indicates survey answer about the importance of "Reliability" (Scale of 1 most - 8 least) Item5: Integer that indicates survey answer about the importance of "Options" (Scale of 1 most - 8 least) Item6: Integer that indicates survey answer about the importance of "Hours of Treatment" (Scale of 1 most - 8 least) Item7: Integer that indicates survey answer about the importance of "Courteous Staff" (Scale of 1 most - 8 least) Item8: Integer that indicates survey answer about the importance of "Evidence of Active Listening from Doctor" (Scale of 1 most - 8 least)

Part II: Data-Cleaning Plan

C. Plan Explanation

C1.

- Orient Myself to the data
- Value Counts
- Missing Values
- Standardized numeric columns
- Categorical variables to Numeric
- Histograms and Boxplots (Outlier Detection)
- PCA

C2.

This data cleaning plan is based up on the Data Preparation Phase explained in the text "Data Science Using Python and R." I have added a few pieces to be more specific about my process that is based on my experience as a full-time Data Analyst.

The first time is orienting myself to the data. In general - this is just the step where I am going to look at the raw data itself. What is my initial input and what stands out? What are the data types I am working with? etc.

The second step is value counts. In general - this will help me to identify unique identifier columns that may not be beneficial in a model. This will also give me a high level view of distributions for both categorical and numeric values.

Missing values is the step in which I will utilize multiple imputation to address missing values. ML models typically do not account for missing data (there is nuance in this), so you need to assign values in every row of every column. I will use IterativeImputer from sklearn to fill in our missing measures. IterativeImputer is similar to MICE within R. It is going to iterate through the dataset multiple times and establish estimations of the missing value based upon the other variables. (Scikit-learn)

Standardized numeric columns will be two fold - there will be some mapping and then standardizing the columns with sklearns standardscaler. This module will center distributions around 0 as the mean. This will be necessary for PCA and will be easier to evaluate outliers and distribution since the scale will be standardized. (Larose, 2019)

Converting categorical variables to numeric is necessary on a couple levels. We need this for our IterativeImputer so that categorical variables can be evaluated as a part of that model. Also - again this will be necessary in future ML applications. (Larose, 2019)

Histograms and boxplots will allow me to visualize the distributions and outliers in a graphic format. This will help to inform decisions on how to deal with outliers. Do certain observations need to be excluded?

PCA is really the end goal of this project. PCA is a form of dimensionality reduction. "Principla components analysis (PCA) seeks to account for the correlation structure of a set of predictor variables, using a smaller set of uncorrelated linear combinations of these variables, called components," (Larose, 2019). I find that the easiest way to conceptualize this is as the vector transformation along a single line to explain the maximal variance. With this method - we can reduce our necessity for all variables and explain most of the variance in a dataset.

C3.

I am utilizing Python as my programming language of choice in this project. Python is a highly flexible programming language that handles data really well. It is consistently one of the most used programming languages in the world (Eastwood, 2020). In thinking of long-term strategy - it is much simpler to put a Python built model into production within an existing application environment. This allows the data analyst to not just be putting together presentations and visuals, but to truly contribute in production. R is great at statistical programming - it is very often used in research, because it is built for that very implementation. So, there is certainly in argument for its utilization in any project like this. But, I prefer Python for its flexibility. You can create web applications, desktop applications, api's and the list goes on. So, if we ever needed to pivot this analysis into a different domain - it would be far easier to do in Python than R.

As for packages - I am using several. Pandas is one of the most popular packages in Python and it deals with tabular data. It effectively allows you to interact with the data in a format we are traditionally used to - with column headers and row numbers. Numpy is a package that I will use for some calculations and also interacting with the data at certain points as an array. Matplotlib is the package that will be used for visualizations. Sklearn is a scientific package for Python meant to implement the various stages of Machine Learning. So, sklearn will be used in imputation, transformation, and ultimately PCA. Bioinfokit is an additional package that I will be using for some visualization of PCA.

In [397…

```
#Package imports
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from matplotlib import pyplot
from sklearn import preprocessing
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

In [398…

```
#Read in dataset and set index to first column that already has indexes. It also 0 inde

Med_df = pd.read_csv(r'C:\Users\jacob.colp.UNITY\Downloads\Medical Data Raw\medical_raw

Med_df = Med_df.reset_index(drop = True)
```

In [399…

```
#Show relevant statistical information about numeric columns.

Med_df.describe()
```

Out[399…

	CaseOrder	Zip	Lat	Lng	Population	Children	Age
count	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	7412.000000	7586.000000
mean	5000.50000	50159.323900	38.751099	-91.243080	9965.253800	2.098219	53.295676
std	2886.89568	27469.588208	5.403085	15.205998	14824.758614	2.155427	20.659182
min	1.00000	610.000000	17.967190	-174.209690	0.000000	0.000000	18.000000
25%	2500.75000	27592.000000	35.255120	-97.352982	694.750000	0.000000	35.000000
50%	5000.50000	50207.000000	39.419355	-88.397230	2769.000000	1.000000	53.000000
75%	7500.25000	72411.750000	42.044175	-80.438050	13945.000000	3.000000	71.000000
max	10000.00000	99929.000000	70.560990	-65.290170	122814.000000	10.000000	89.000000

8 rows × 25 columns

In [400…

```
#Convert yes/no columns to binary. I also converted Complication Risk to ordinal values

for x in Med_df.columns:
    if Med_df[x].dtype == object:
        Med_df[x].replace({'Yes':1,'yes':1,'No':0,'no':0}, inplace = True)

Med_df.Complication_risk.replace({'High':3, 'Medium':2, 'Low':1}, inplace = True)

Med_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 52 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   CaseOrder           10000 non-null  int64  
 1   Customer_id         10000 non-null  object 
 2   Interaction         10000 non-null  object 
 3   UID                 10000 non-null  object 
 4   City                10000 non-null  object 
 5   State               10000 non-null  object 
 6   County              10000 non-null  object 
 7   Zip                 10000 non-null  int64  
 8   Lat                 10000 non-null  float64
 9   Lng                 10000 non-null  float64
 10  Population          10000 non-null  int64  
 11  Area                10000 non-null  object 
 12  Timezone            10000 non-null  object 
 13  Job                 10000 non-null  object 
 14  Children            7412 non-null   float64
 15  Age                 7586 non-null   float64
 16  Education           10000 non-null  object 
 17  Employment          10000 non-null  object 
 18  Income              7536 non-null   float64
 19  Marital             10000 non-null  object 
 20  Gender              10000 non-null  object 
 21  ReAdmis             10000 non-null  int64  
 22  VitD_levels         10000 non-null  float64
 23  Doc_visits          10000 non-null  int64  
 24  Full_meals_eaten    10000 non-null  int64  
 25  VitD_supp           10000 non-null  int64  
 26  Soft_drink          7533 non-null   float64
 27  Initial_admin       10000 non-null  object 
 28  HighBlood           10000 non-null  int64  
 29  Stroke              10000 non-null  int64  
 30  Complication_risk   10000 non-null  int64  
 31  Overweight          9018 non-null   float64
 32  Arthritis           10000 non-null  int64  
 33  Diabetes            10000 non-null  int64  
 34  Hyperlipidemia      10000 non-null  int64  
 35  BackPain            10000 non-null  int64  
 36  Anxiety             9016 non-null   float64
 37  Allergic_rhinitis   10000 non-null  int64  
 38  Reflux_esophagitis  10000 non-null  int64  
 39  Asthma              10000 non-null  int64  
 40  Services            10000 non-null  object 
 41  Initial_days        8944 non-null   float64
 42  TotalCharge         10000 non-null  float64
 43  Additional_charges  10000 non-null  float64
 44  Item1               10000 non-null  int64  
 45  Item2               10000 non-null  int64  
 46  Item3               10000 non-null  int64  
 47  Item4               10000 non-null  int64  
 48  Item5               10000 non-null  int64  
 49  Item6               10000 non-null  int64  
 50  Item7               10000 non-null  int64  
 51  Item8               10000 non-null  int64  
dtypes: float64(12), int64(25), object(15)
memory usage: 4.0+ MB
```

In [401…

```
#This will tell me the number of null values in each column

Med_df.isnull().sum()
```

Out[401…

```
CaseOrder                0
Customer_id              0
Interaction              0
UID                      0
City                     0
State                    0
County                   0
Zip                      0
Lat                      0
Lng                      0
Population               0
Area                     0
Timezone                 0
Job                      0
Children              2588
Age                   2414
Education                0
Employment               0
Income                2464
Marital                  0
Gender                   0
ReAdmis                  0
VitD_levels              0
Doc_visits               0
Full_meals_eaten         0
VitD_supp                0
Soft_drink            2467
Initial_admin            0
HighBlood                0
Stroke                   0
Complication_risk        0
Overweight             982
Arthritis                0
Diabetes                 0
Hyperlipidemia           0
BackPain                 0
Anxiety                984
Allergic_rhinitis        0
Reflux_esophagitis       0
Asthma                   0
Services                 0
Initial_days          1056
TotalCharge              0
Additional_charges       0
Item1                    0
Item2                    0
Item3                    0
Item4                    0
Item5                    0
Item6                    0
Item7                    0
Item8                    0
dtype: int64
```

In [402…

```
#Find unique columns
for x in Med_df:
```

```
    print(x+': '+str(Med_df[x].is_unique))
```

```
CaseOrder: True
Customer_id: True
Interaction: True
UID: True
City: False
State: False
County: False
Zip: False
Lat: False
Lng: False
Population: False
Area: False
Timezone: False
Job: False
Children: False
Age: False
Education: False
Employment: False
Income: False
Marital: False
Gender: False
ReAdmis: False
VitD_levels: True
Doc_visits: False
Full_meals_eaten: False
VitD_supp: False
Soft_drink: False
Initial_admin: False
HighBlood: False
Stroke: False
Complication_risk: False
Overweight: False
Arthritis: False
Diabetes: False
Hyperlipidemia: False
BackPain: False
Anxiety: False
Allergic_rhinitis: False
Reflux_esophagitis: False
Asthma: False
Services: False
Initial_days: False
TotalCharge: True
Additional_charges: False
Item1: False
Item2: False
Item3: False
Item4: False
Item5: False
Item6: False
Item7: False
Item8: False
```

In [403…

```
#I am dropping Job, Income, and Marital Status because those all may not relate to the 

Med_df.drop(['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'Job', 'Income', 'Marita

#Rename all Item survey columns to their question topic.
```

```
Med_df.rename({'Item1':'Survey_Timely_Admission', 'Item2':'Survey_Timely_Treatment', 'I
           'Item7':'Survey_Courteous_Staff', 'Item8':'Survey_Evidence_of_Active_Listeni

Med_df.columns
```

Out[403…

```
Index(['City', 'State', 'County', 'Zip', 'Lat', 'Lng', 'Population', 'Area',
       'Timezone', 'Children', 'Age', 'Education', 'Employment', 'Gender',
       'ReAdmis', 'VitD_levels', 'Doc_visits', 'Full_meals_eaten', 'VitD_supp',
       'Soft_drink', 'Initial_admin', 'HighBlood', 'Stroke',
       'Complication_risk', 'Overweight', 'Arthritis', 'Diabetes',
       'Hyperlipidemia', 'BackPain', 'Anxiety', 'Allergic_rhinitis',
       'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',
       'TotalCharge', 'Additional_charges', 'Survey_Timely_Admission',
       'Survey_Timely_Treatment', 'Survey_Timely_Visits', 'Survey_Reliability',
       'Survey_Options', 'Survey_Hours_of_Treatment', 'Survey_Courteous_Staff',
       'Survey_Evidence_of_Active_Listening'],
      dtype='object')
```

In [404…

```
#I am converting categorical values into the "category" datatype from pandas. This will

categorical_variables = ['City', 'State', 'County', 'Zip', 'Area', 'Timezone', 'Educati

for x in categorical_variables:
    Med_df[x] = Med_df[x].astype('category')

Med_df.dtypes
```

Out[404…

```
City                                   category
State                                  category
County                                 category
Zip                                    category
Lat                                     float64
Lng                                     float64
Population                                int64
Area                                   category
Timezone                               category
Children                                float64
Age                                     float64
Education                              category
Employment                             category
Gender                                 category
ReAdmis                                   int64
VitD_levels                             float64
Doc_visits                                int64
Full_meals_eaten                          int64
VitD_supp                                 int64
Soft_drink                              float64
Initial_admin                          category
HighBlood                                 int64
Stroke                                    int64
Complication_risk                         int64
Overweight                              float64
Arthritis                                 int64
Diabetes                                  int64
Hyperlipidemia                            int64
BackPain                                  int64
Anxiety                                 float64
Allergic_rhinitis                         int64
Reflux_esophagitis                        int64
```

```
Asthma                                  int64
Services                             category
Initial_days                          float64
TotalCharge                           float64
Additional_charges                    float64
Survey_Timely_Admission                 int64
Survey_Timely_Treatment                 int64
Survey_Timely_Visits                    int64
Survey_Reliability                      int64
Survey_Options                          int64
Survey_Hours_of_Treatment               int64
Survey_Courteous_Staff                  int64
Survey_Evidence_of_Active_Listening     int64
dtype: object
```

In [405…

```
#This code gives me the value counts for each value of each column. I can roughly see d

for x in Med_df:
    print(Med_df[x].value_counts())
```

```
Houston          36
San Antonio      26
Springfield      22
Miami            21
New York         21
                 ..
Hollenberg        1
Hollandale        1
Holland Patent    1
Holcombe          1
Zumbro Falls      1
Name: City, Length: 6072, dtype: int64
TX    553
CA    550
PA    547
NY    514
IL    442
OH    383
MO    328
FL    304
VA    287
IA    276
MI    273
MN    267
NC    254
GA    247
KS    220
WI    214
KY    210
WV    207
OK    207
IN    195
TN    194
AL    194
WA    191
AR    190
NE    185
CO    179
NJ    176
LA    173
```

```
MA    149
MS    134
MD    131
SC    128
SD    123
OR    122
ME    122
MT    112
NM    110
ID    109
ND    108
AZ    108
CT     80
NH     79
UT     72
AK     70
VT     60
NV     51
WY     51
PR     43
HI     34
DE     17
RI     14
DC     13
Name: State, dtype: int64
Jefferson      118
Washington     100
Franklin        93
Los Angeles     88
Montgomery      80
              ...
Churchill        1
Republic         1
Cimarron         1
St. Martin       1
Lamoille         1
Name: County, Length: 1607, dtype: int64
24136    4
88345    4
77663    4
38330    4
37324    4
        ..
37146    1
37144    1
37138    1
37134    1
99929    1
Name: Zip, Length: 8612, dtype: int64
36.06702    4
33.34798    4
35.25512    4
39.38610    4
37.86890    4
           ..
41.00911    1
39.20560    1
46.36035    1
34.96563    1
40.49998    1
Name: Lat, Length: 8588, dtype: int64
```

```
-121.28753    4
-82.35159     4
-85.99134     4
-105.68001    4
-89.03658     4
             ..
-74.87894     1
-99.17911     1
-91.81854     1
-106.83727    1
-80.19959     1
Name: Lng, Length: 8601, dtype: int64
0        109
195       14
115       11
178       11
285       11
        ...
8092       1
11147      1
27175      1
7371       1
41524      1
Name: Population, Length: 5951, dtype: int64
Rural       3369
Suburban    3328
Urban       3303
Name: Area, dtype: int64
America/New_York                  3889
America/Chicago                   3771
America/Los_Angeles                937
America/Denver                     612
America/Detroit                    262
America/Indiana/Indianapolis       151
America/Phoenix                    100
America/Boise                       86
America/Anchorage                   50
America/Puerto_Rico                 43
Pacific/Honolulu                    34
America/Menominee                   14
America/Nome                        12
America/Indiana/Vincennes            8
America/Sitka                        6
America/Kentucky/Louisville          6
America/Toronto                      5
America/Indiana/Tell_City            3
America/Indiana/Marengo              3
America/North_Dakota/Beulah          2
America/Indiana/Winamac              1
America/Indiana/Vevay                1
America/North_Dakota/New_Salem       1
America/Indiana/Knox                 1
America/Yakutat                      1
America/Adak                         1
Name: Timezone, dtype: int64
0.0     1880
1.0     1858
3.0     1113
2.0     1094
4.0      739
8.0      157
```

```
7.0      154
6.0      145
5.0      126
9.0       83
10.0      63
Name: Children, dtype: int64
30.0    126
47.0    124
74.0    123
38.0    123
40.0    122
       ...
75.0     90
82.0     90
63.0     90
51.0     89
36.0     85
Name: Age, Length: 72, dtype: int64
Regular High School Diploma                 2444
Bachelor's Degree                           1724
Some College, 1 or More Years, No Degree    1484
9th Grade to 12th Grade, No Diploma          832
Associate's Degree                           797
Master's Degree                              701
Some College, Less than 1 Year               642
Nursery School to 8th Grade                  552
GED or Alternative Credential                389
Professional School Degree                   208
No Schooling Completed                       133
Doctorate Degree                              94
Name: Education, dtype: int64
Full Time     6029
Student       1017
Part Time      991
Unemployed     983
Retired        980
Name: Employment, dtype: int64
Female                  5018
Male                    4768
Prefer not to answer     214
Name: Gender, dtype: int64
0    6331
1    3669
Name: ReAdmis, dtype: int64
17.802330    1
18.423248    1
15.954743    1
19.566698    1
19.221626    1
            ..
18.107325    1
17.331743    1
49.013013    1
18.292722    1
20.421883    1
Name: VitD_levels, Length: 10000, dtype: int64
5    3823
6    2436
4    2385
7     634
3     595
```

```
8      61
2      58
1       6
9       2
Name: Doc_visits, dtype: int64
0    3715
1    3615
2    1856
3     612
4     169
5      25
6       6
7       2
Name: Full_meals_eaten, dtype: int64
0    6702
1    2684
2     544
3      64
4       5
5       1
Name: VitD_supp, dtype: int64
0.0    5589
1.0    1944
Name: Soft_drink, dtype: int64
Emergency Admission      5060
Elective Admission       2504
Observation Admission    2436
Name: Initial_admin, dtype: int64
0    5910
1    4090
Name: HighBlood, dtype: int64
0    8007
1    1993
Name: Stroke, dtype: int64
2    4517
3    3358
1    2125
Name: Complication_risk, dtype: int64
1.0    6395
0.0    2623
Name: Overweight, dtype: int64
0    6426
1    3574
Name: Arthritis, dtype: int64
0    7262
1    2738
Name: Diabetes, dtype: int64
0    6628
1    3372
Name: Hyperlipidemia, dtype: int64
0    5886
1    4114
Name: BackPain, dtype: int64
0.0    6110
1.0    2906
Name: Anxiety, dtype: int64
0    6059
1    3941
Name: Allergic_rhinitis, dtype: int64
0    5865
1    4135
```

```
Name: Reflux_esophagitis, dtype: int64
0    7107
1    2893
Name: Asthma, dtype: int64
Blood Work     5265
Intravenous    3130
CT Scan        1225
MRI             380
Name: Services, dtype: int64
10.585770    1
64.630142    1
48.772686    1
67.036508    1
63.334689    1
            ..
9.216747     1
1.021594     1
10.261690    1
17.170461    1
70.850592    1
Name: Initial_days, Length: 8944, dtype: int64
3191.048774     1
7329.393066     1
8498.290160     1
8451.833926     1
7530.770634     1
               ..
2065.518265     1
3409.593273     1
15289.590000    1
4383.419018     1
8700.856021     1
Name: TotalCharge, Length: 10000, dtype: int64
8013.787149     5
22000.064780    4
3241.339760     4
11303.682330    4
8755.123303     4
               ..
20461.526600    1
13357.949060    1
5316.329223     1
24412.109160    1
11643.189930    1
Name: Additional_charges, Length: 8888, dtype: int64
4    3455
3    3404
5    1377
2    1315
6     225
1     213
7      10
8       1
Name: Survey_Timely_Admission, dtype: int64
3    3439
4    3351
5    1421
2    1360
1     213
6     204
7      12
```

```
Name: Survey_Timely_Treatment, dtype: int64
4    3464
3    3379
5    1358
2    1356
6     220
1     211
7      11
8       1
Name: Survey_Timely_Visits, dtype: int64
3    3422
4    3394
5    1388
2    1346
6     231
1     207
7      12
Name: Survey_Reliability, dtype: int64
4    3446
3    3423
2    1380
5    1308
6     219
1     211
7      13
Name: Survey_Options, dtype: int64
4    3464
3    3371
5    1403
2    1319
6     220
1     213
7      10
Name: Survey_Hours_of_Treatment, dtype: int64
4    3487
3    3456
2    1345
5    1274
1     215
6     212
7      11
Name: Survey_Courteous_Staff, dtype: int64
3    3401
4    3337
5    1429
2    1391
6     221
1     209
7      12
Name: Survey_Evidence_of_Active_Listening, dtype: int64
```

In [406…

```
#Encode categorical variables for multiple imputation in IterativeImputer. Original var

label_encode = preprocessing.LabelEncoder()

for x in Med_df[categorical_variables]:
    encode_column = str(x)+'_Encoded'
    Med_df[encode_column] = label_encode.fit_transform(Med_df[x])

Med_df_cat = Med_df[categorical_variables]
```

```
Med_df.drop(categorical_variables, axis = 1, inplace = True)
```

In [407…

```
#Use IterativeImputer from Sklearn to impute missing values in the dataset. Again, this

It_Imp = IterativeImputer(skip_complete = True, min_value = 0)

Med_df_fill = np.round(It_Imp.fit_transform(Med_df))

Med_df_fill = pd.DataFrame(Med_df_fill)

Med_df_fill.isna().sum()
```

Out[407…

```
0     0
1     0
2     0
3     0
4     0
5     0
6     0
7     0
8     0
9     0
10    0
11    0
12    0
13    0
14    0
15    0
16    0
17    0
18    0
19    0
20    0
21    0
22    0
23    0
24    0
25    0
26    0
27    0
28    0
29    0
30    0
31    0
32    0
33    0
34    0
35    0
36    0
37    0
38    0
39    0
40    0
41    0
42    0
43    0
44    0
dtype: int64
```

In [408…

```
#This renames all of my columns in my newly formed DF to match their original names for

for x, y in enumerate(It_Imp.feature_names_in_):
    Med_df_fill.rename(columns= {x:y}, inplace = True)

for x in categorical_variables:
    cat_var = str(x)+'_Encoded'
    Med_df_fill[cat_var] = Med_df_fill[cat_var].astype('category')

Med_df_fill.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 45 columns):
 #   Column                              Non-Null Count  Dtype   
---  ------                              --------------  -----   
 0   Lat                                 10000 non-null  float64 
 1   Lng                                 10000 non-null  float64 
 2   Population                          10000 non-null  float64 
 3   Children                            10000 non-null  float64 
 4   Age                                 10000 non-null  float64 
 5   ReAdmis                             10000 non-null  float64 
 6   VitD_levels                         10000 non-null  float64 
 7   Doc_visits                          10000 non-null  float64 
 8   Full_meals_eaten                    10000 non-null  float64 
 9   VitD_supp                           10000 non-null  float64 
 10  Soft_drink                          10000 non-null  float64 
 11  HighBlood                           10000 non-null  float64 
 12  Stroke                              10000 non-null  float64 
 13  Complication_risk                   10000 non-null  float64 
 14  Overweight                          10000 non-null  float64 
 15  Arthritis                           10000 non-null  float64 
 16  Diabetes                            10000 non-null  float64 
 17  Hyperlipidemia                      10000 non-null  float64 
 18  BackPain                            10000 non-null  float64 
 19  Anxiety                             10000 non-null  float64 
 20  Allergic_rhinitis                   10000 non-null  float64 
 21  Reflux_esophagitis                  10000 non-null  float64 
 22  Asthma                              10000 non-null  float64 
 23  Initial_days                        10000 non-null  float64 
 24  TotalCharge                         10000 non-null  float64 
 25  Additional_charges                  10000 non-null  float64 
 26  Survey_Timely_Admission             10000 non-null  float64 
 27  Survey_Timely_Treatment             10000 non-null  float64 
 28  Survey_Timely_Visits                10000 non-null  float64 
 29  Survey_Reliability                  10000 non-null  float64 
 30  Survey_Options                      10000 non-null  float64 
 31  Survey_Hours_of_Treatment           10000 non-null  float64 
 32  Survey_Courteous_Staff              10000 non-null  float64 
 33  Survey_Evidence_of_Active_Listening 10000 non-null  float64 
 34  City_Encoded                        10000 non-null  category
 35  State_Encoded                       10000 non-null  category
 36  County_Encoded                      10000 non-null  category
 37  Zip_Encoded                         10000 non-null  category
 38  Area_Encoded                        10000 non-null  category
 39  Timezone_Encoded                    10000 non-null  category
 40  Education_Encoded                   10000 non-null  category
 41  Employment_Encoded                  10000 non-null  category
 42  Gender_Encoded                      10000 non-null  category
 43  Initial_admin_Encoded               10000 non-null  category
 44  Services_Encoded                    10000 non-null  category
```

```
dtypes: category(11), float64(34)
memory usage: 3.3 MB
```

In [409…

```
#Create hold df for our target variable and then drop it from our working DF

Target = Med_df_fill.ReAdmis

Med_df_fill.drop(columns='ReAdmis', axis = 1, inplace=True)

Target
```

Out[409…

```
0       0.0
1       0.0
2       0.0
3       0.0
4       0.0
       ...
9995    0.0
9996    1.0
9997    1.0
9998    1.0
9999    1.0
Name: ReAdmis, Length: 10000, dtype: float64
```

In [410…

```
#Temporarily add back in categorical values for cleaned data set

Med_df_fill =  Med_df_fill.merge(Med_df_cat, left_index=True, right_index=True)
```

In [411…

```
#Export clean dataset and then drop non-numeric categorical values

Med_df_fill.to_csv(r'C:\Users\jacob.colp.UNITY\Downloads\Medical Data Raw\medical_raw_d

for x in Med_df_cat:
    Med_df_fill.drop(x, axis=1, inplace=True)
```

In [412…

```
#This scales all of the numeric values relative to their mean.

Standard_Scaler = StandardScaler()

Scaled_Med_df = Standard_Scaler.fit_transform(Med_df_fill)

Scaled_Med_df = pd.DataFrame(Scaled_Med_df)

for x, y in enumerate(Standard_Scaler.feature_names_in_):
    Scaled_Med_df.rename(columns = {x:y}, inplace = True)

#Getting rid of qualitative variables

Scaled_Med_df = Scaled_Med_df.drop(columns=['City_Encoded', 'County_Encoded', 'State_En

Scaled_Med_df.describe()
```

Out[412…

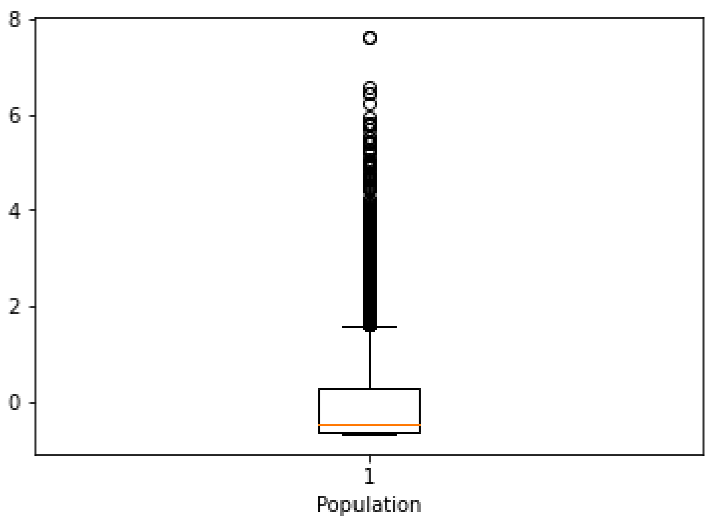
	Population	Children	Age	VitD_levels	Doc_visits	Full_meals_eaten	
count	1.000000e+04	1.000000e+04	1.000000e+04	1.000000e+04	1.000000e+04	1.000000e+04	1.0

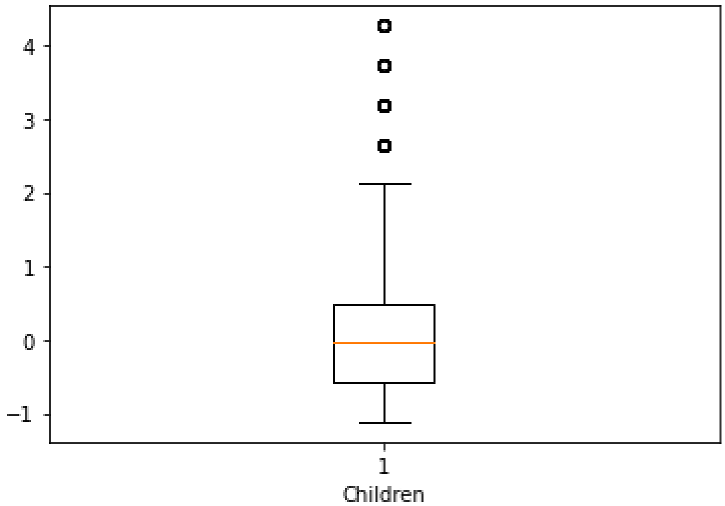
	Population	Children	Age	VitD_levels	Doc_visits	Full_meals_eaten	
mean	-1.207923e-17	1.065814e-17	-1.353584e-16	2.405187e-16	3.161915e-17	-7.815970e-17	3.6
std	1.000050e+00	1.000050e+00	1.000050e+00	1.000050e+00	1.000050e+00	1.000050e+00	1.0
min	-6.722371e-01	-1.116784e+00	-2.276538e+00	-1.397478e+00	-3.836921e+00	-9.933869e-01	-
25%	-6.253705e-01	-5.780035e-01	-8.081510e-01	-3.576545e-01	-9.679806e-01	-9.933869e-01	-
50%	-4.854456e-01	-3.922320e-02	-2.501152e-02	-2.091084e-01	-1.166703e-02	-1.388797e-03	-
75%	2.684661e-01	4.995571e-01	8.193108e-01	8.798388e-02	9.446465e-01	9.906093e-01	9.5
max	7.612562e+00	4.271019e+00	2.275461e+00	4.990006e+00	3.813587e+00	5.950600e+00	7.3

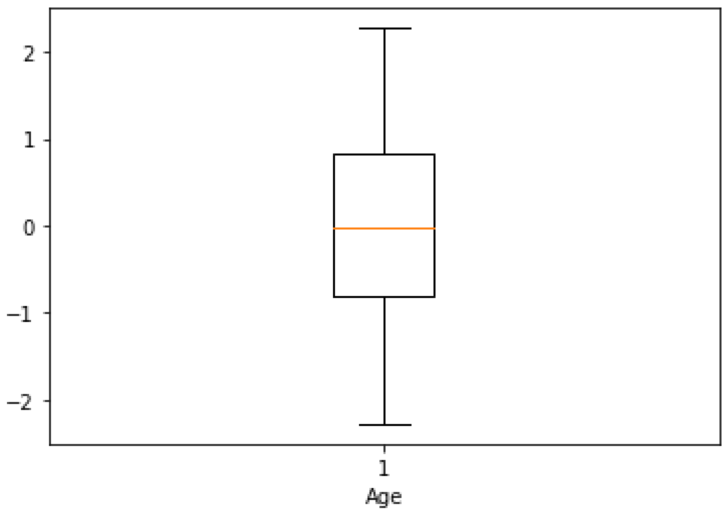
8 rows × 31 columns

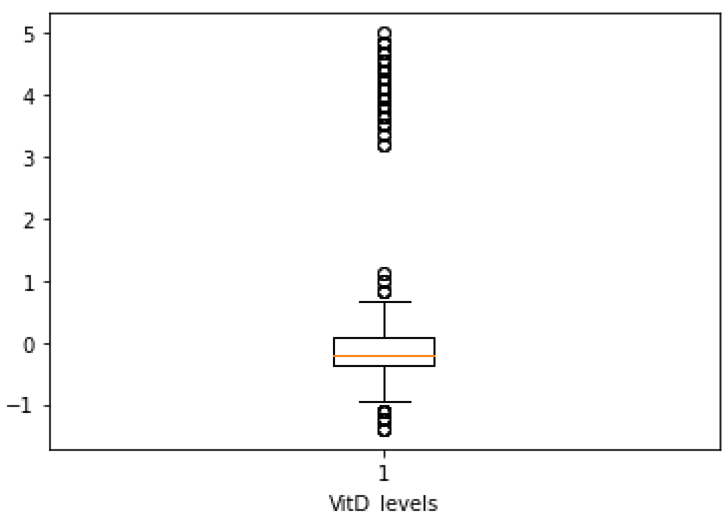
In [413…

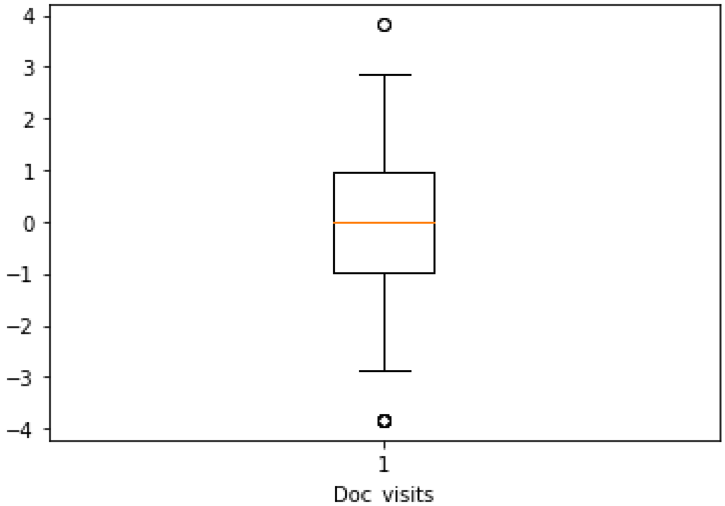
```
#Print boxplots for all non-categorical variables

for x in Scaled_Med_df:
        pyplot.boxplot(Scaled_Med_df[x])
        pyplot.xlabel(x)
        pyplot.show()
```

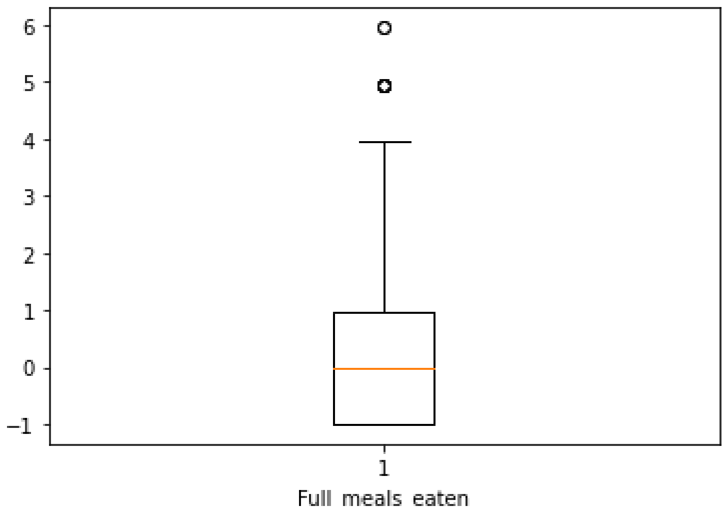


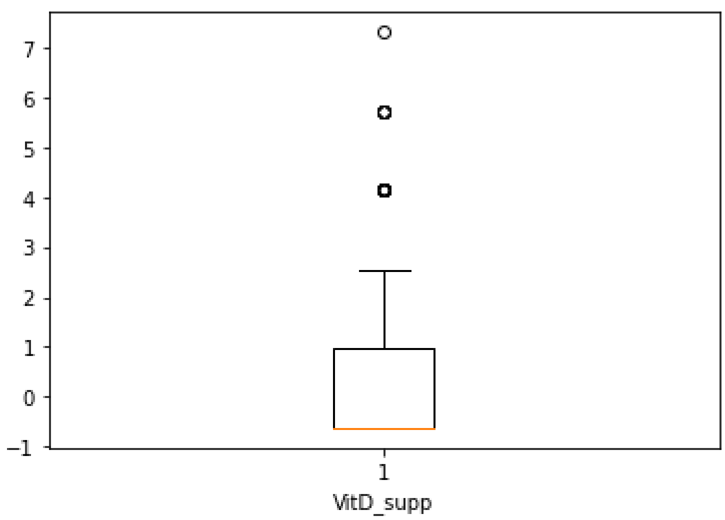

4
3
2
1
0
−1
1
Children

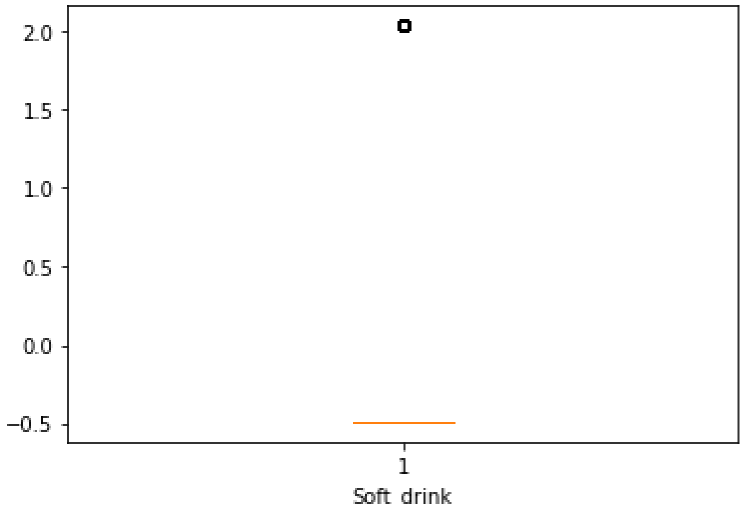

2
1
0
−1
−2
1
Age

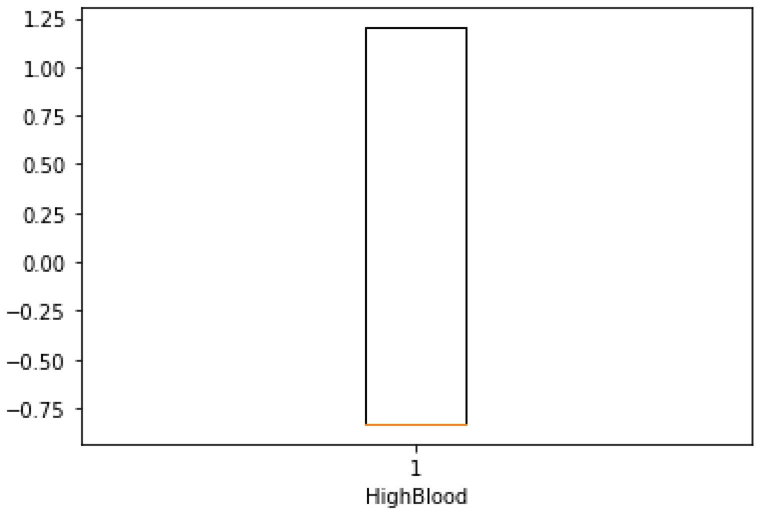

5
4
3
2
1
0
−1
1
VitD_levels

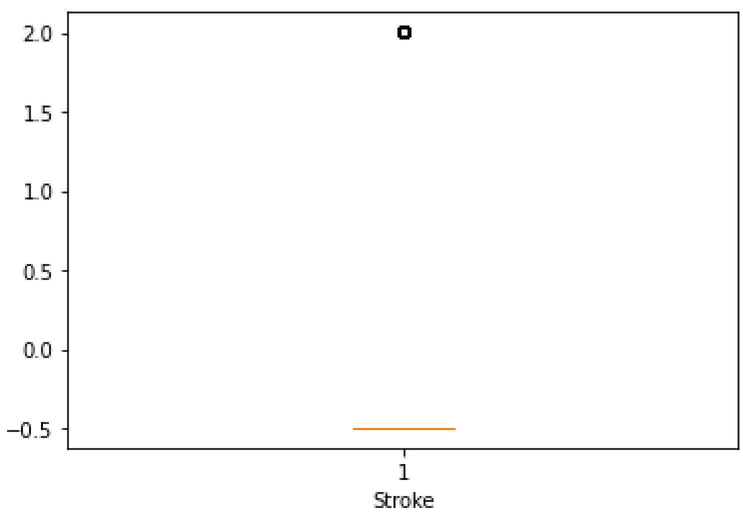

4
3
2
1
0
−1
−2
−3
−4
1
Doc_visits

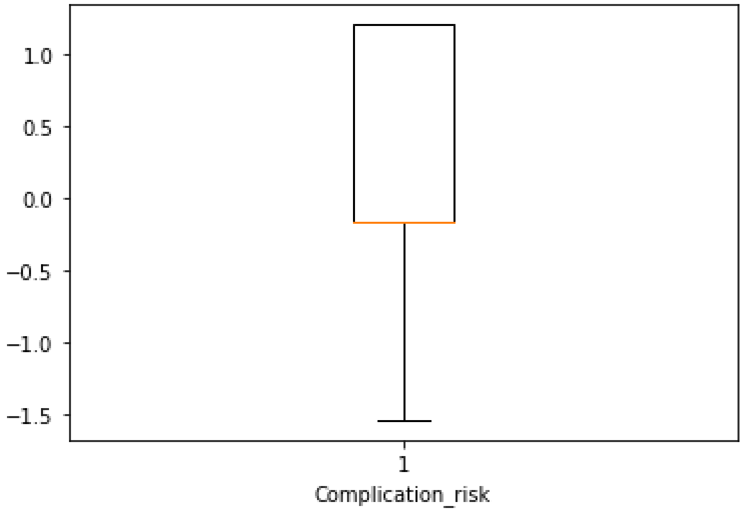

6
5
4
3
2
1
0
−1
1
Full_meals_eaten

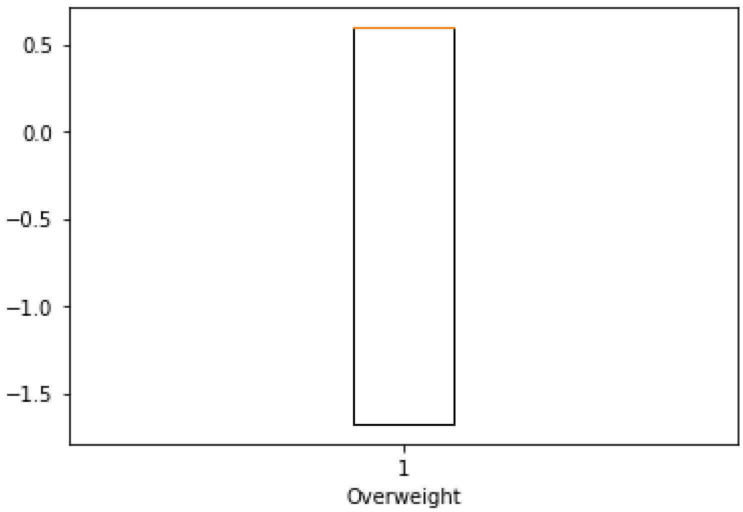

7
6
5
4
3
2
1
0
−1
1
VitD_supp

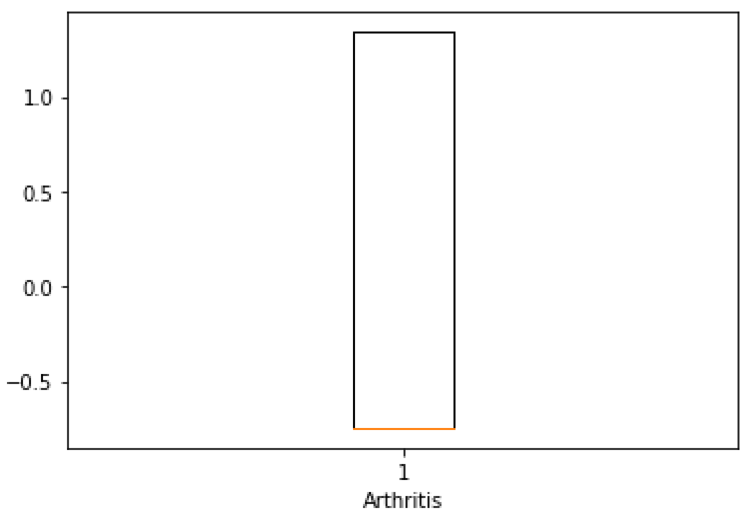

2.0
1.5
1.0
0.5
0.0
−0.5
1
Soft_drink

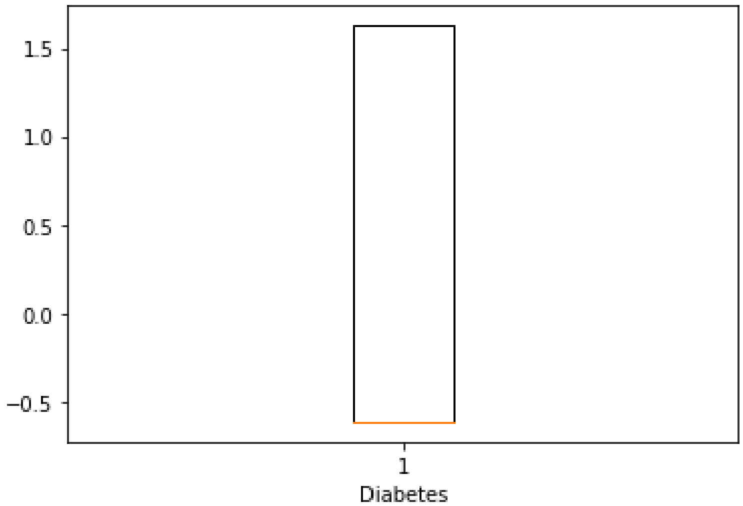

1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
1
HighBlood

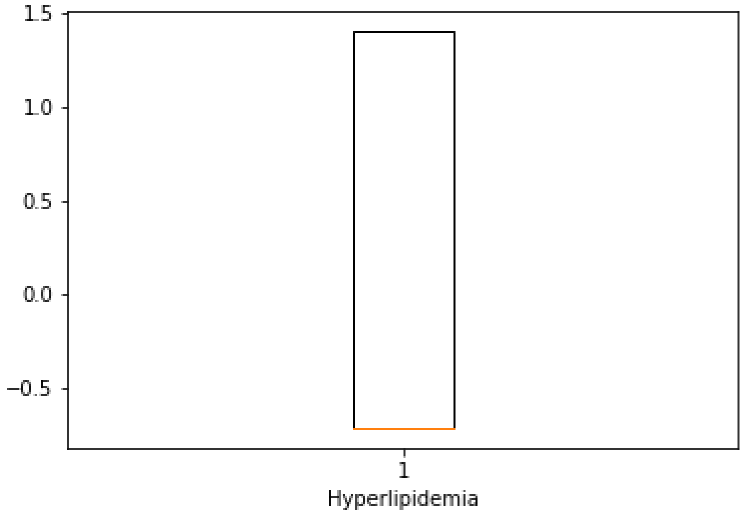

2.0
1.5
1.0
0.5
0.0
−0.5
1
Stroke

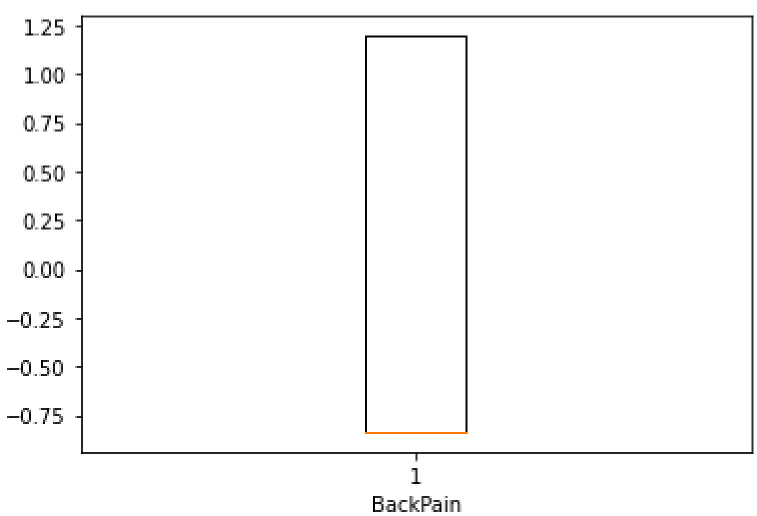

1.0
0.5
0.0
−0.5
−1.0
−1.5
1
Complication_risk


0.5
0.0
−0.5
−1.0
−1.5
1
Overweight

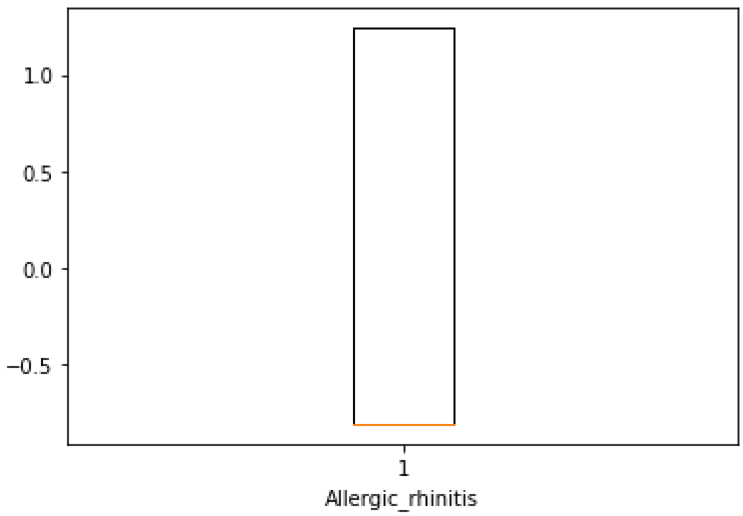

1.0
0.5
0.0
−0.5
1
Arthritis

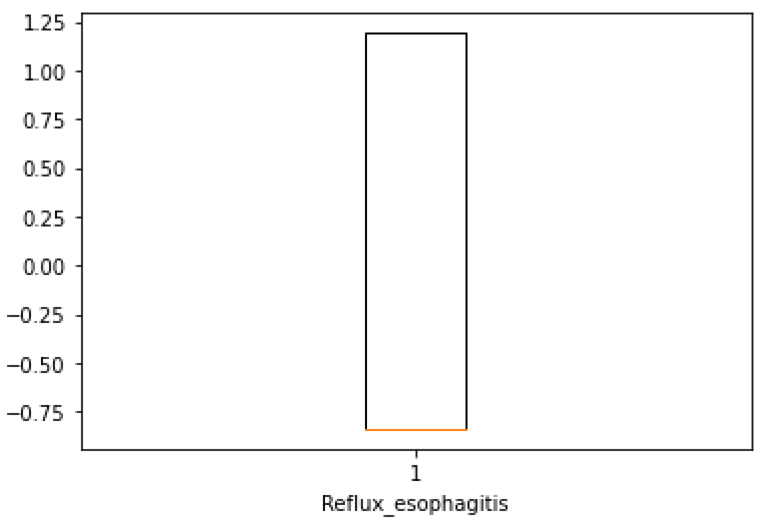

1.5
1.0
0.5
0.0
−0.5
1
Diabetes

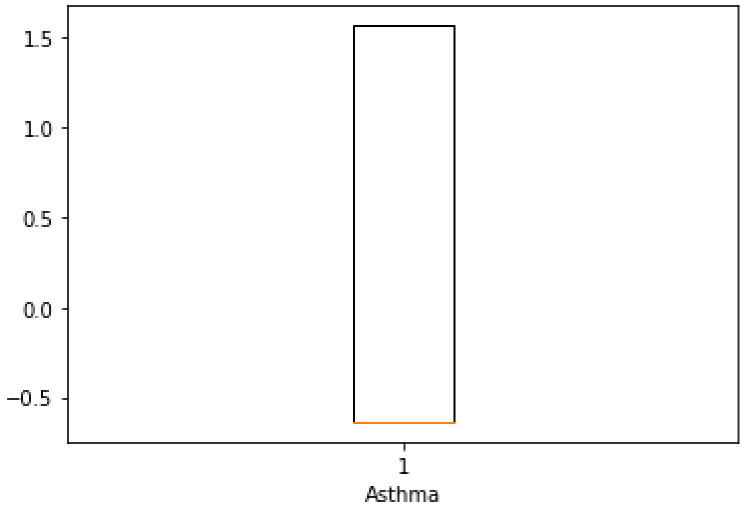

1.5
1.0
0.5
0.0
−0.5
1
Hyperlipidemia

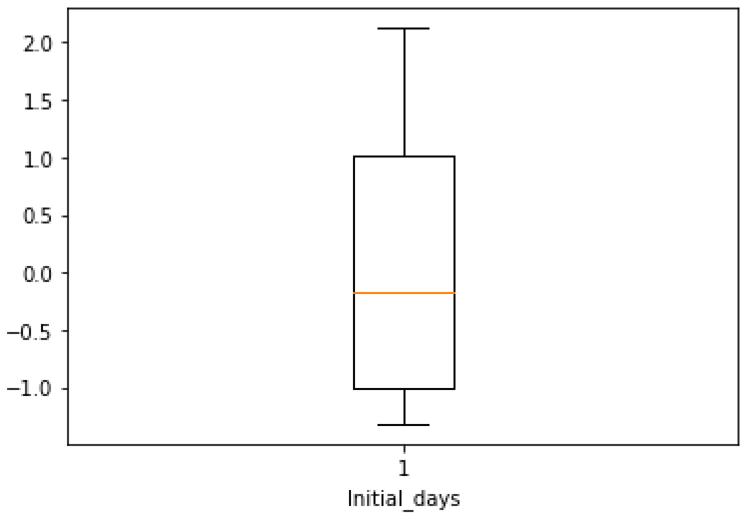

1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
1
BackPain

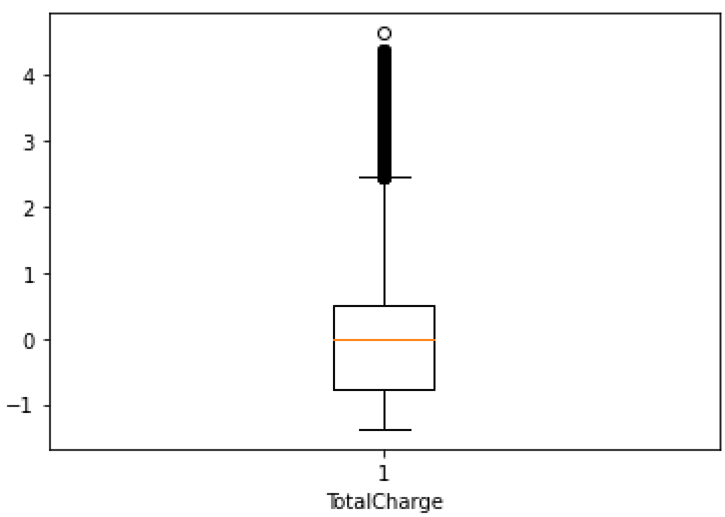

1.5
1.0
0.5
0.0
−0.5
1
Anxiety

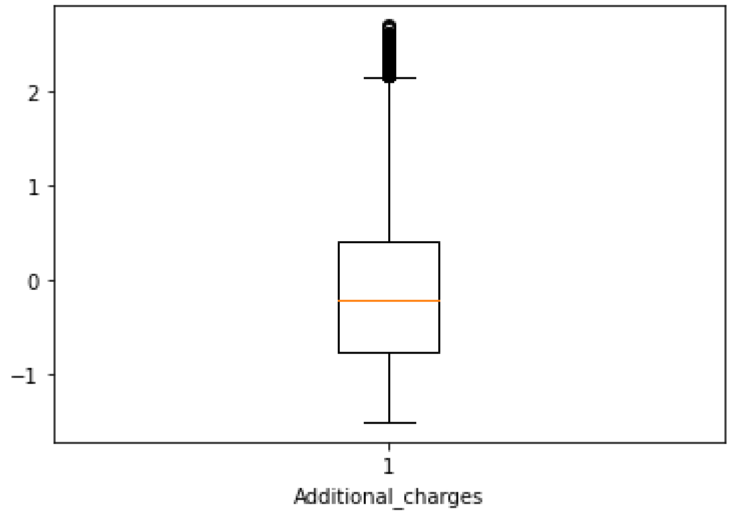

1.0
0.5
0.0
−0.5
1
Allergic_rhinitis

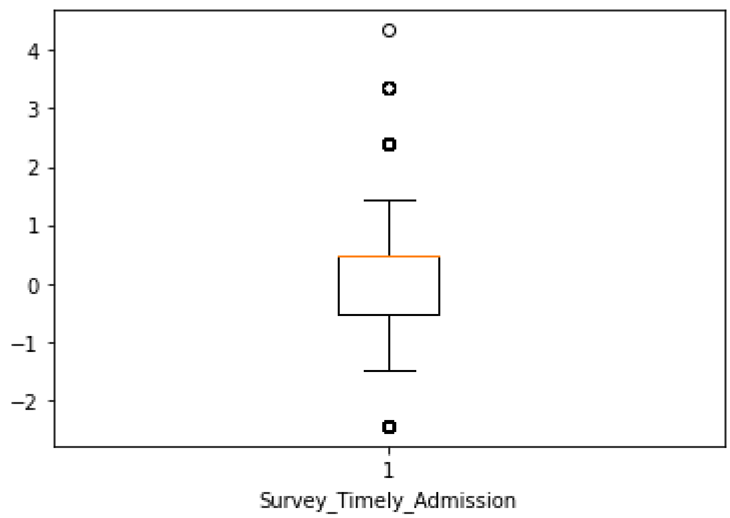

1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
1
Reflux_esophagitis

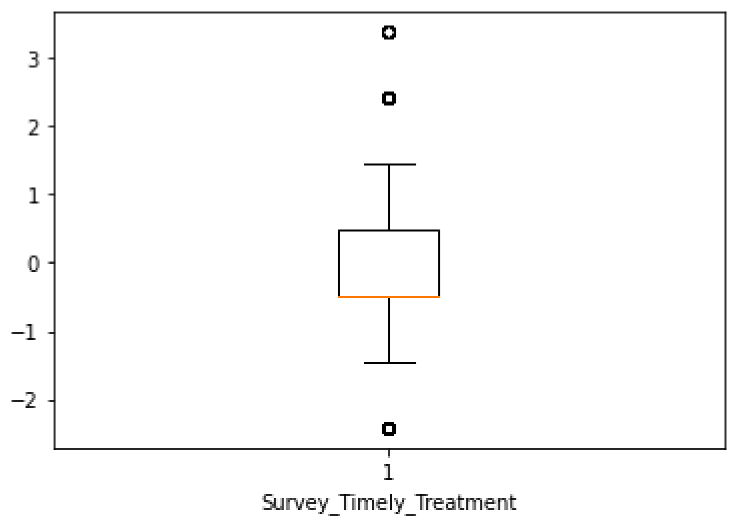

1.5
1.0
0.5
0.0
−0.5
1
Asthma

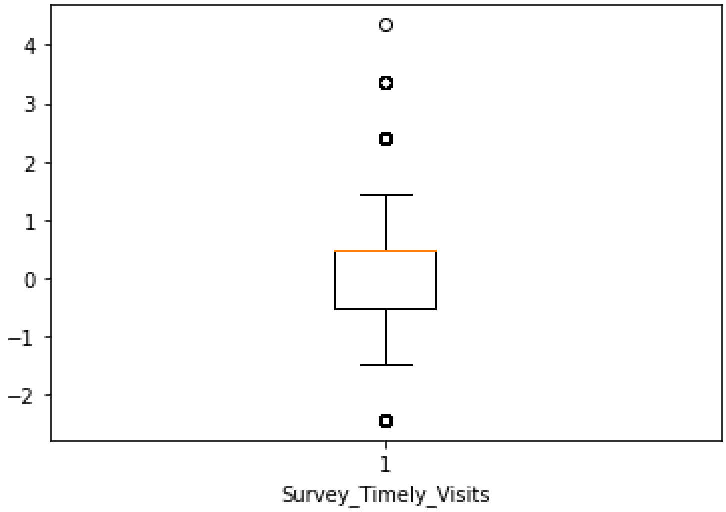

2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
1
Initial_days

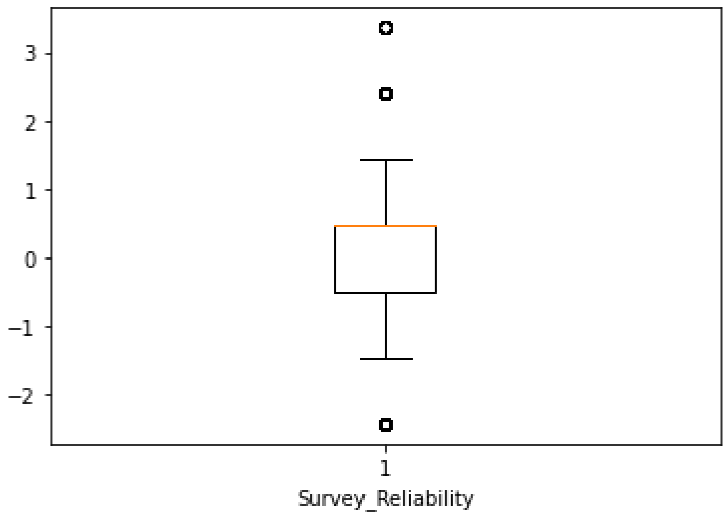

4
3
2
1
0
−1
1
TotalCharge

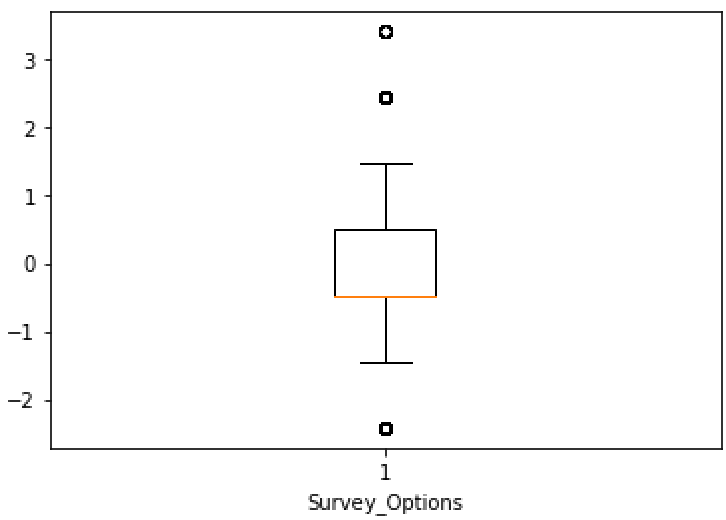

2
1
0
−1
1
Additional_charges

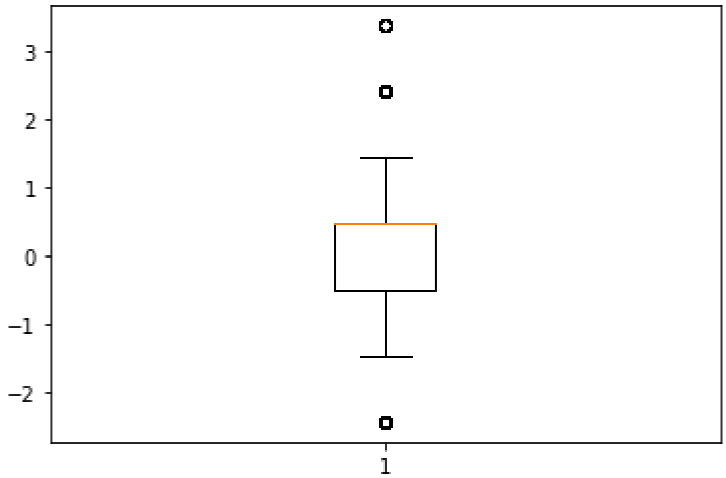

4
3
2
1
0
−1
−2
1
Survey_Timely_Admission

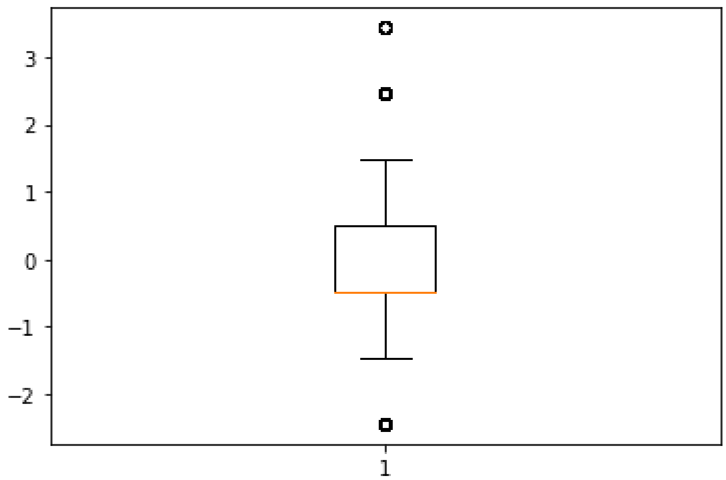

3
2
1
0
−1
−2
1
Survey_Timely_Treatment

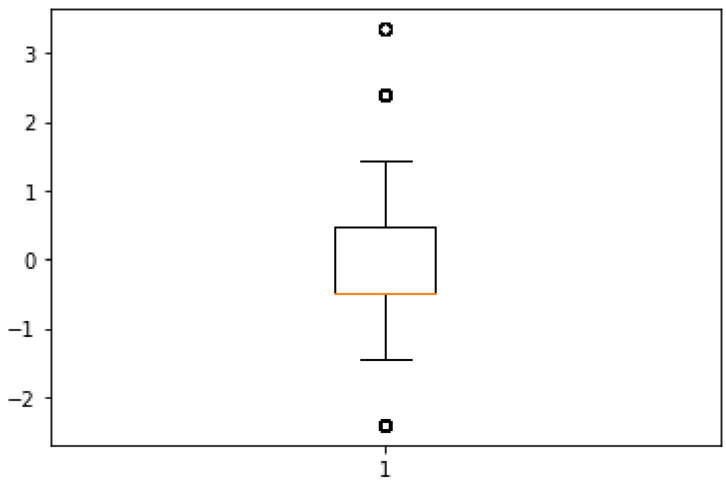

4
3
2
1
0
−1
−2
1
Survey_Timely_Visits


3
2
1
0
−1
−2
1
Survey_Reliability


3
2
1
0
−1
−2
1
Survey_Options

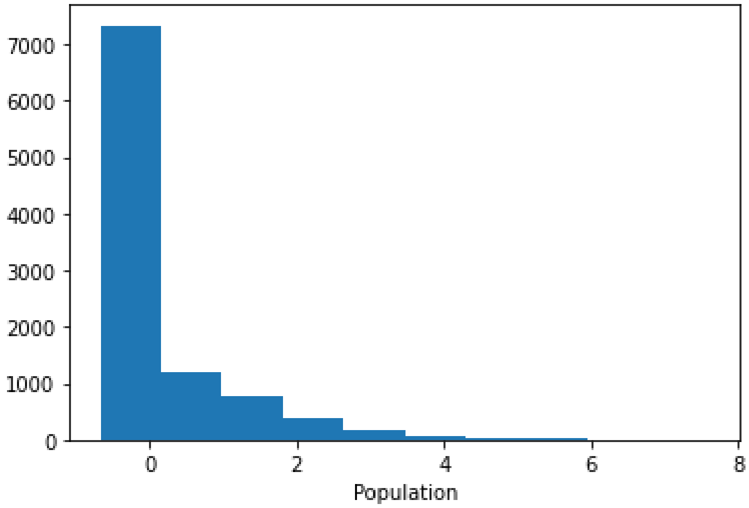


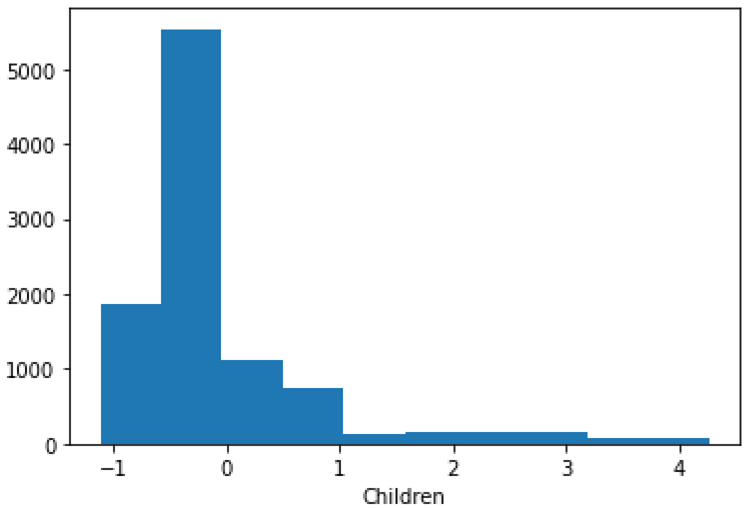


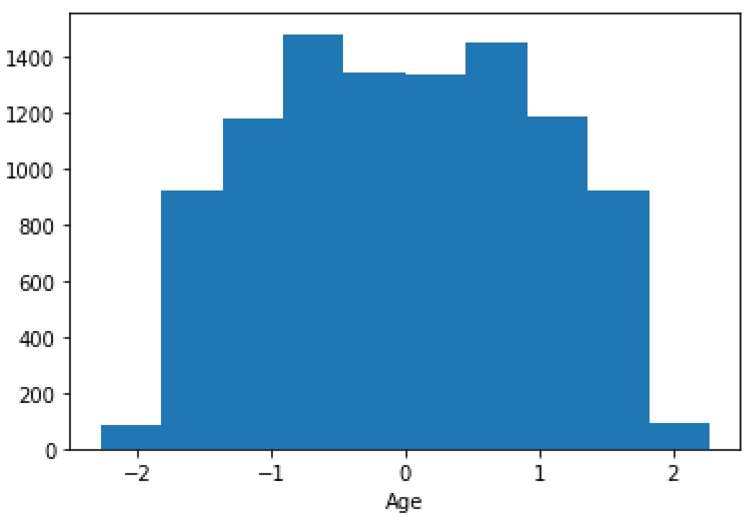


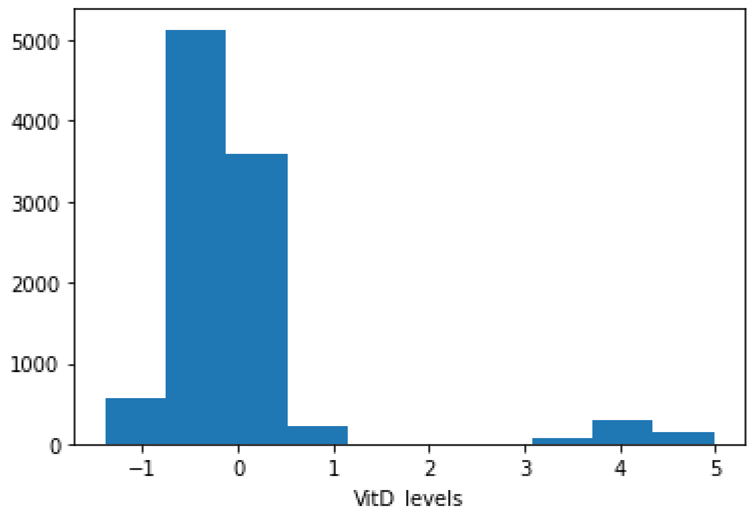
In [414…

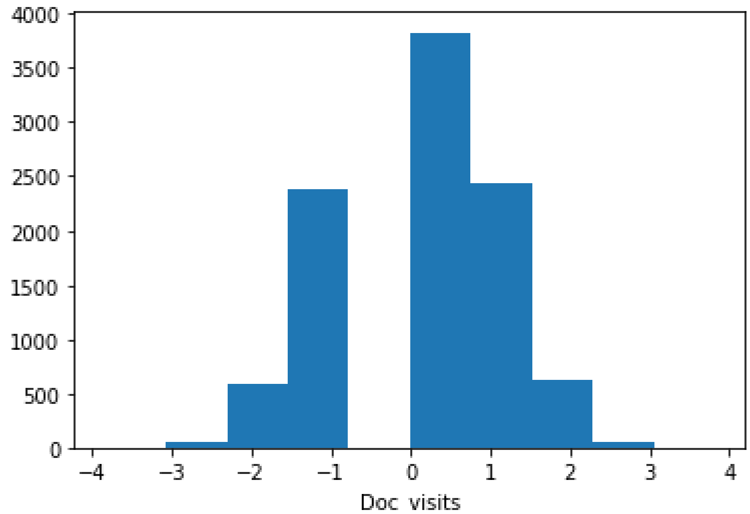
```
#Print histograms for all non-categorical variables

for x in Scaled_Med_df:
    pyplot.hist(Scaled_Med_df[x])
    pyplot.xlabel(x)
    pyplot.show()
```

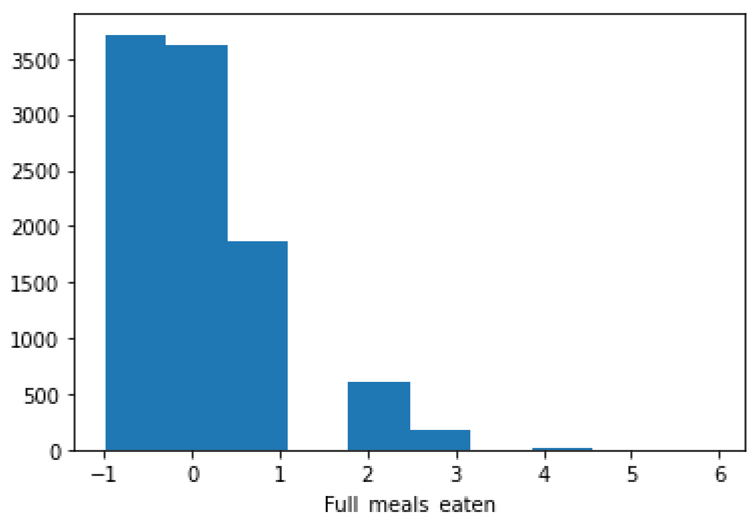

7000
6000
5000
4000
3000
2000
1000
0
0
2
4
6
8
Population

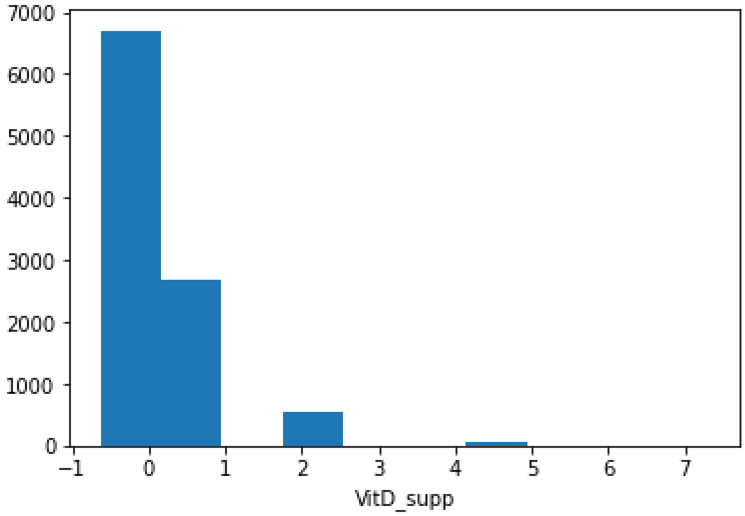

5000
4000
3000
2000
1000
0
−1
0
1
2
3
4
Children


1400
1200
1000
800
600
400
200
0
−2
−1
0
1
2
Age

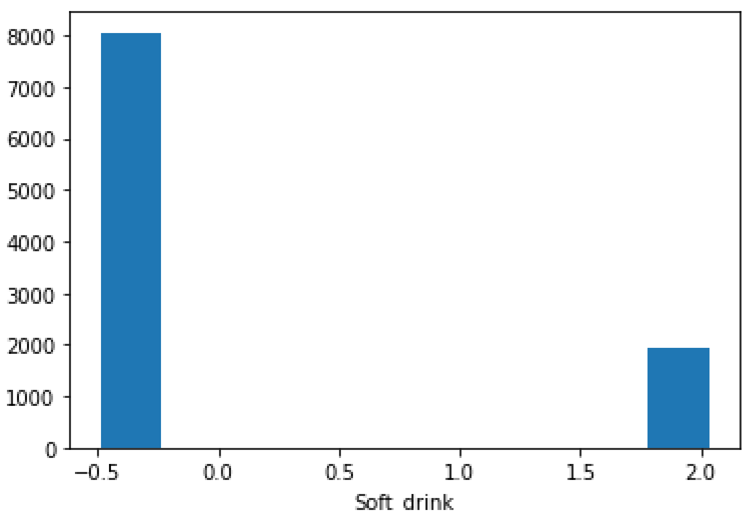

5000
4000
3000
2000
1000
0
−1
0
1
2
3
4
5
VitD_levels


4000
3500
3000
2500
2000
1500
1000
500
0
−4
−3
−2
−1
0
1
2
3
4
Doc_visits

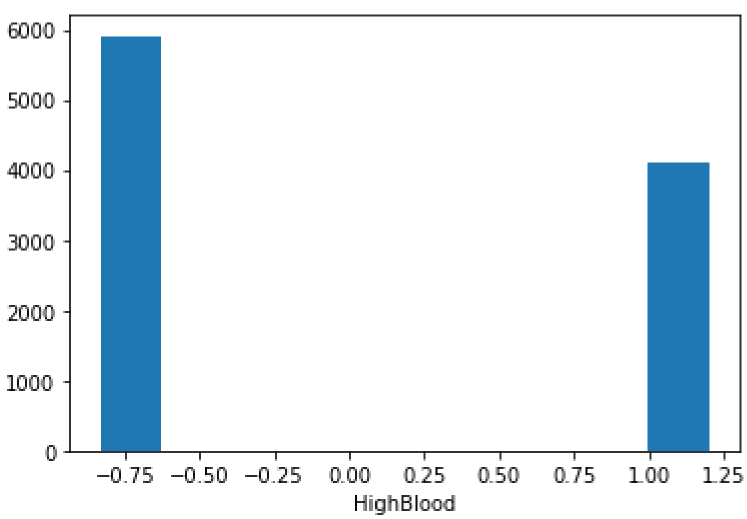

3500
3000
2500
2000
1500
1000
500
0
−1
0
1
2
3
4
5
6
Full_meals_eaten



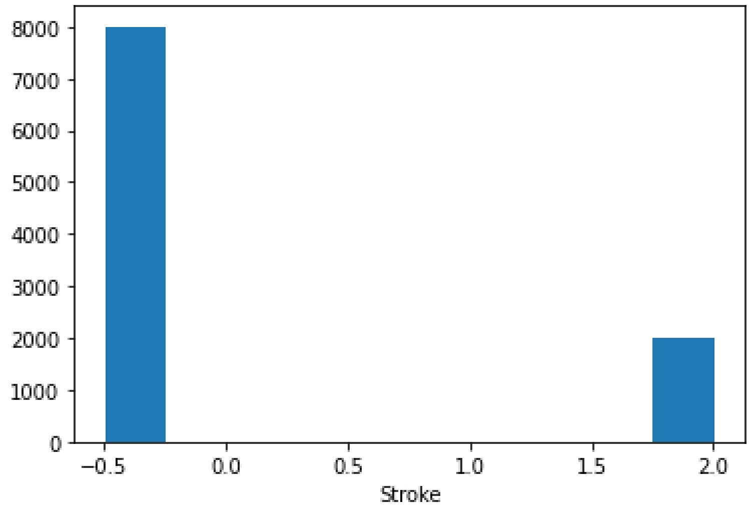
7000
6000
5000
4000
3000
2000
1000
0
−1
0
1
2
3
4
5
6
7
VitD_supp

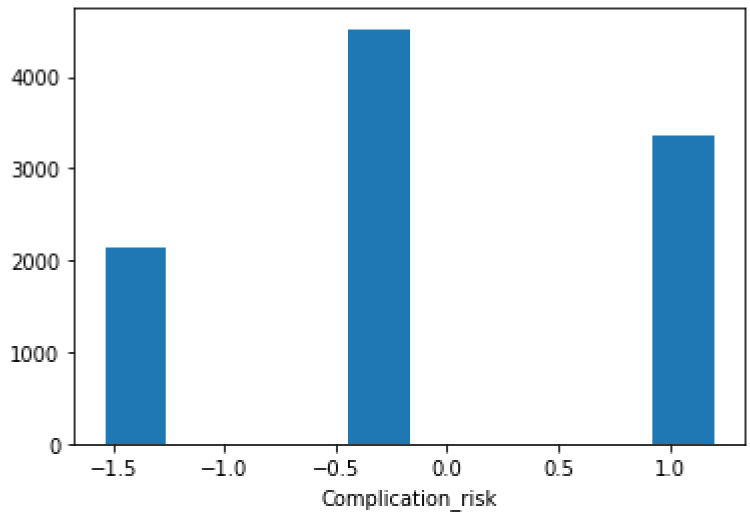


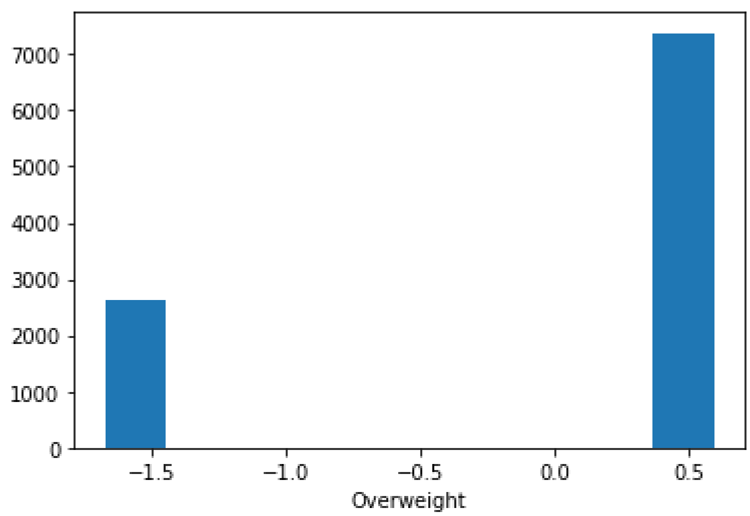
8000
7000
6000
5000
4000
3000
2000
1000
0
−0.5
0.0
0.5
1.0
1.5
2.0
Soft_drink

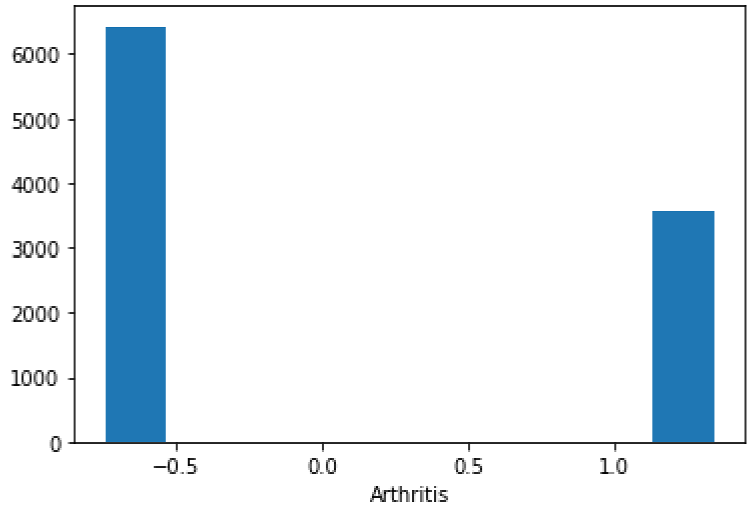


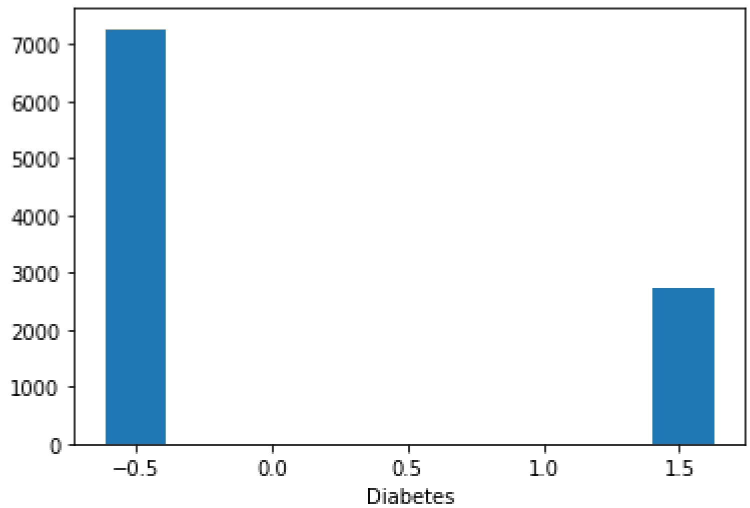
6000
5000
4000
3000
2000
1000
0
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
HighBlood

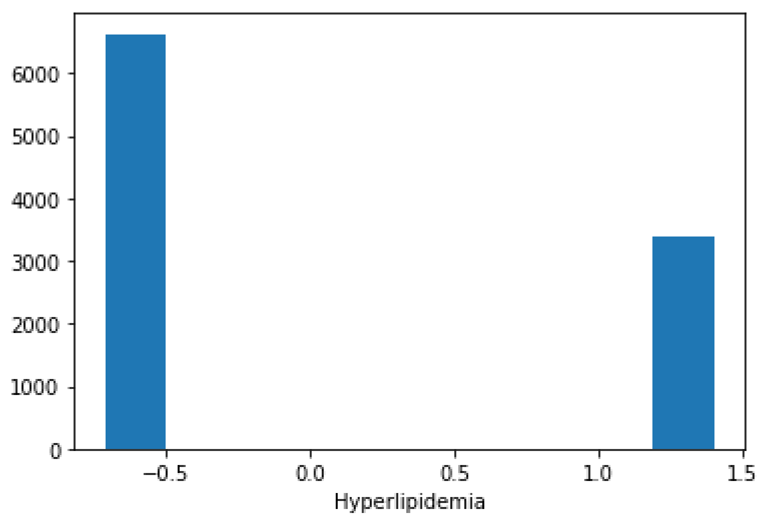

8000
7000
6000
5000
4000
3000
2000
1000
0
−0.5
0.0
0.5
1.0
1.5
2.0
Stroke

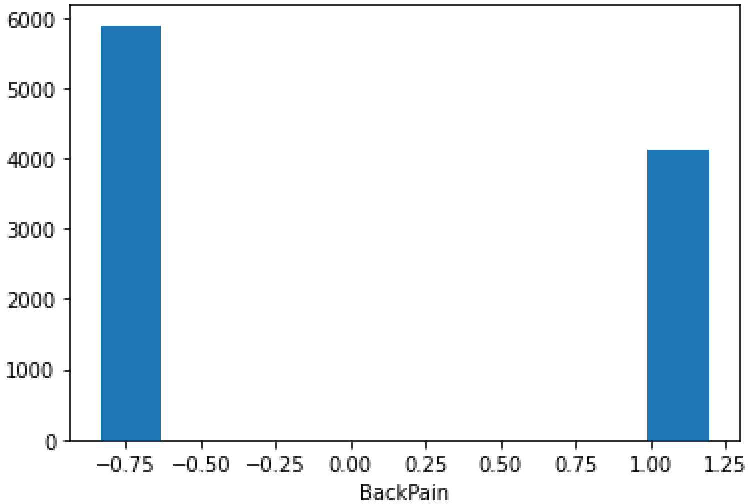

4000
3000
2000
1000
0
−1.5
−1.0
−0.5
0.0
0.5
1.0
Complication_risk

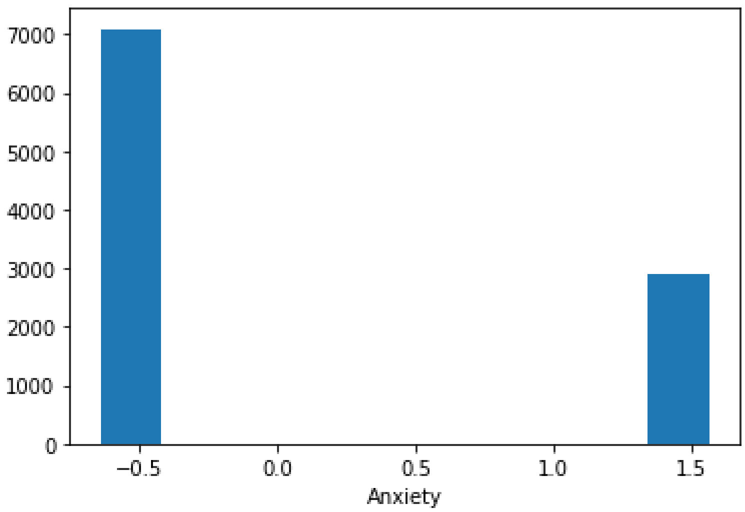

7000
6000
5000
4000
3000
2000
1000
0
−1.5
−1.0
−0.5
0.0
0.5
Overweight

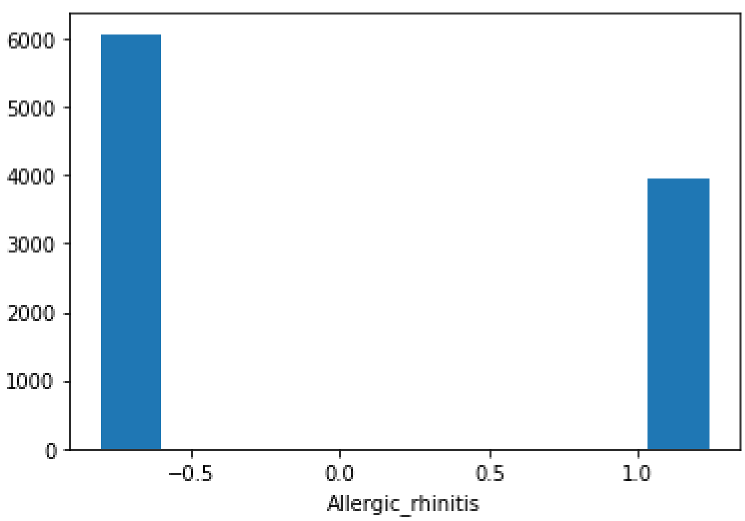

6000
5000
4000
3000
2000
1000
0
−0.5
0.0
0.5
1.0
Arthritis

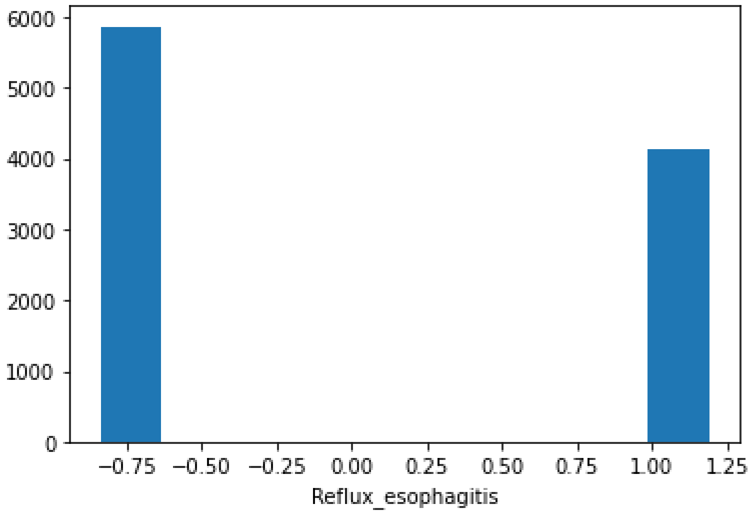

7000
6000
5000
4000
3000
2000
1000
0
−0.5
0.0
0.5
1.0
1.5
Diabetes

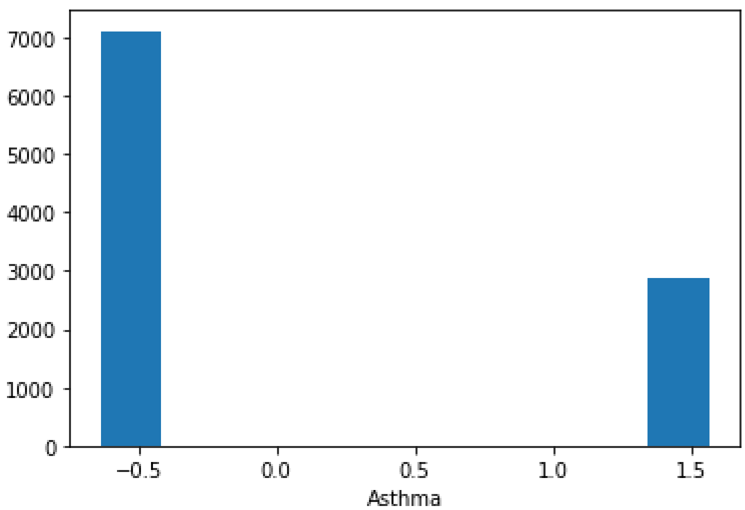

6000
5000
4000
3000
2000
1000
0
−0.5
0.0
0.5
1.0
1.5
Hyperlipidemia

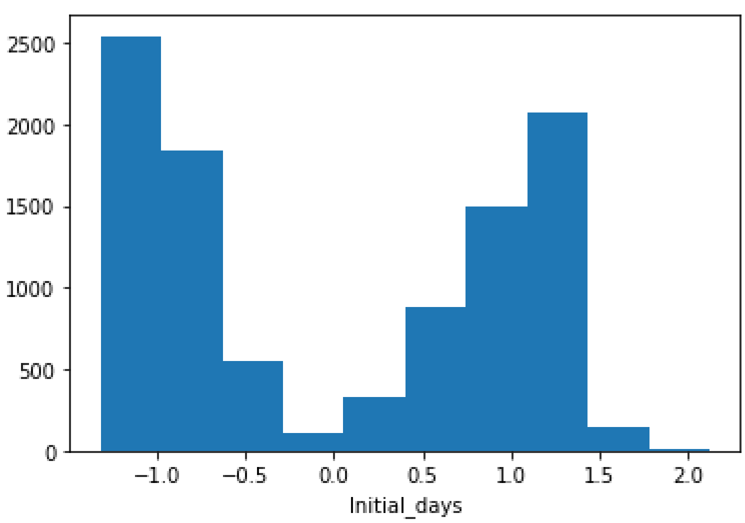

6000
5000
4000
3000
2000
1000
0
−0.75 −0.50 −0.25 0.00 0.25 0.50 0.75 1.00 1.25
BackPain

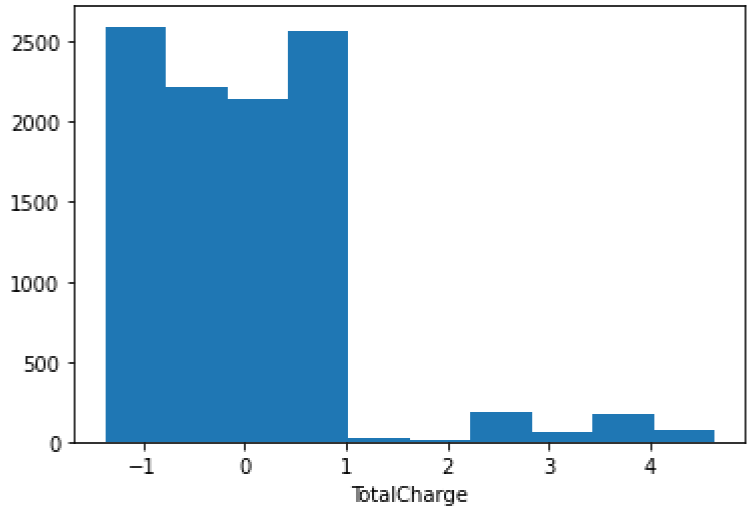

7000
6000
5000
4000
3000
2000
1000
0
−0.5 0.0 0.5 1.0 1.5
Anxiety

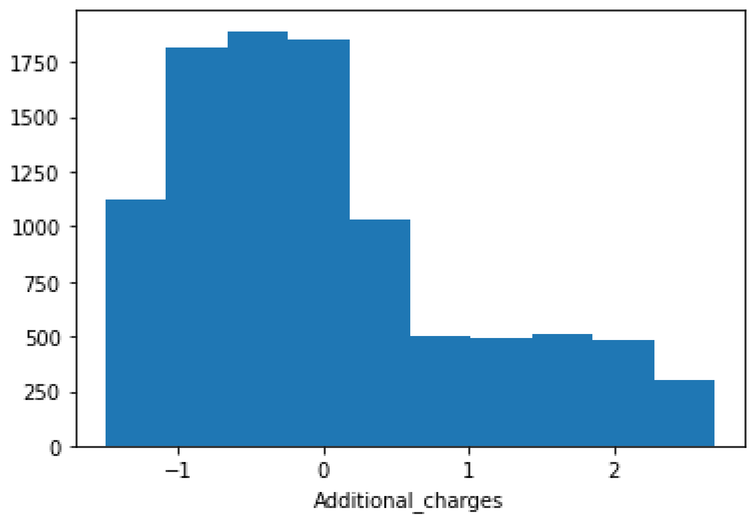

6000
5000
4000
3000
2000
1000
0
−0.5 0.0 0.5 1.0
Allergic_rhinitis

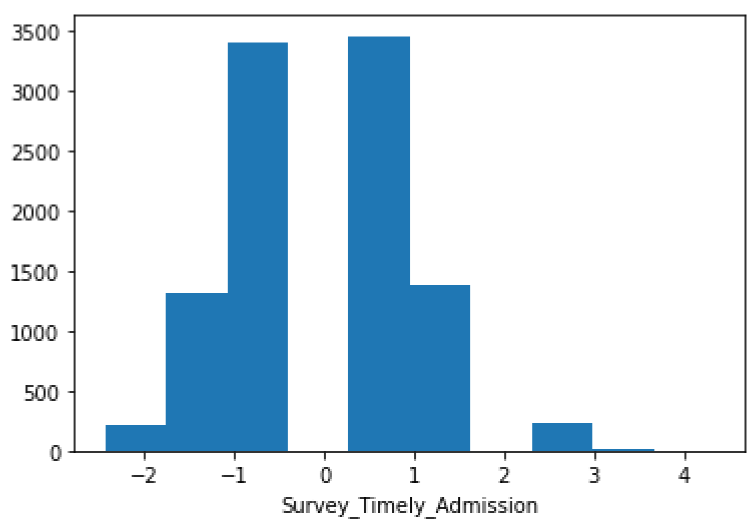

6000
5000
4000
3000
2000
1000
0
−0.75 −0.50 −0.25 0.00 0.25 0.50 0.75 1.00 1.25
Reflux_esophagitis

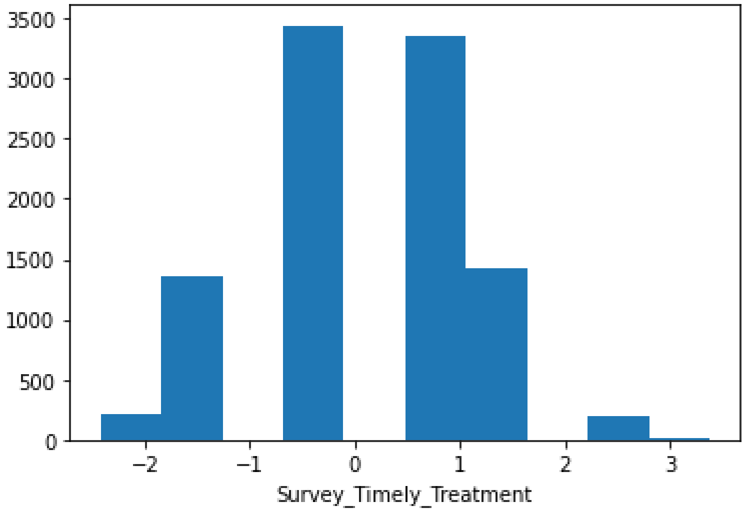

7000
6000
5000
4000
3000
2000
1000
0
−0.5 0.0 0.5 1.0 1.5
Asthma


2500
2000
1500
1000
500
0
−1.0 −0.5 0.0 0.5 1.0 1.5 2.0
Initial_days

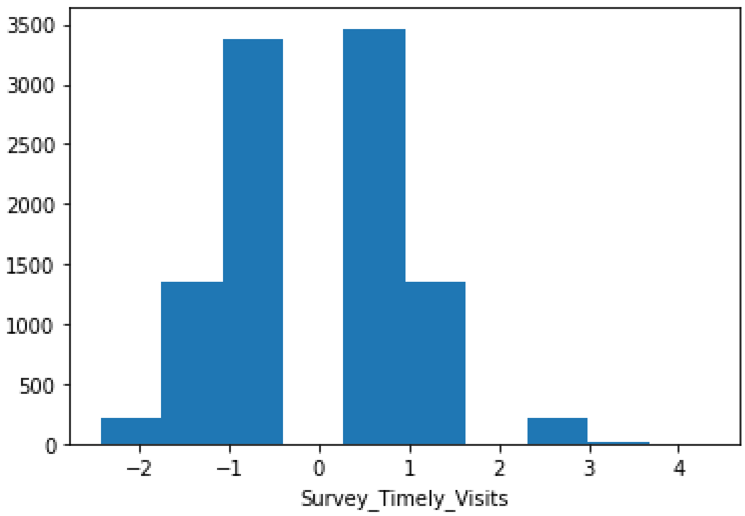

2500
2000
1500
1000
500
0
−1
0
1
2
3
4
TotalCharge


1750
1500
1250
1000
750
500
250
0
−1
0
1
2
Additional_charges

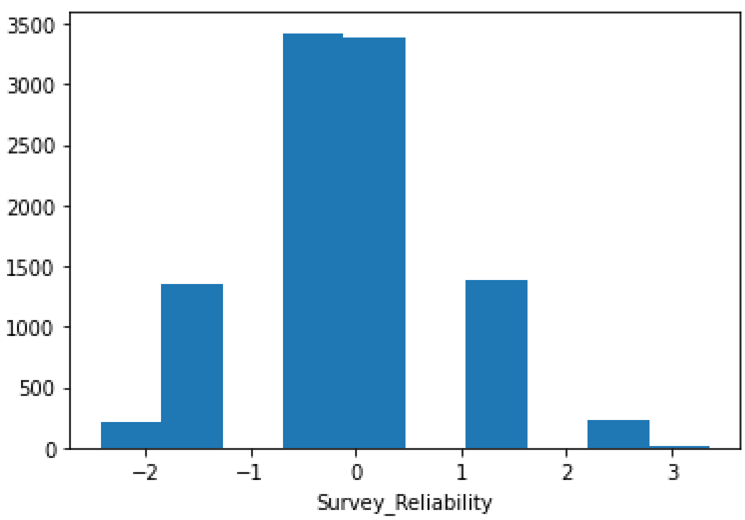

3500
3000
2500
2000
1500
1000
500
0
−2
−1
0
1
2
3
4
Survey_Timely_Admission



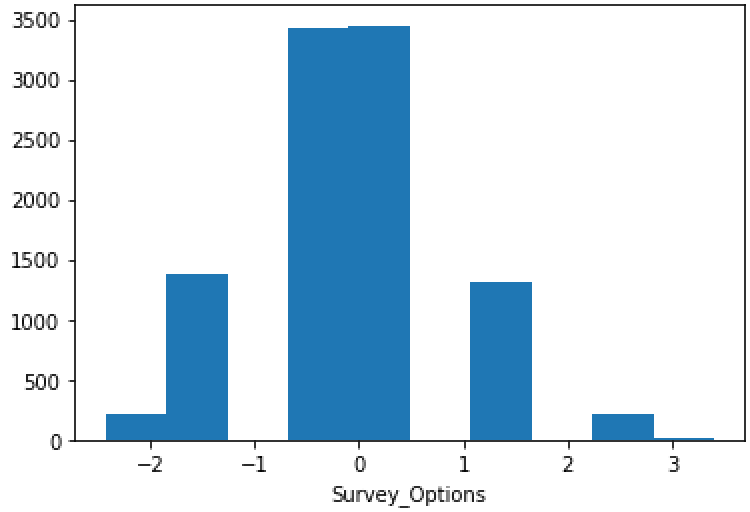
3500
3000
2500
2000
1500
1000
500
0
−2
−1
0
1
2
3
Survey_Timely_Treatment

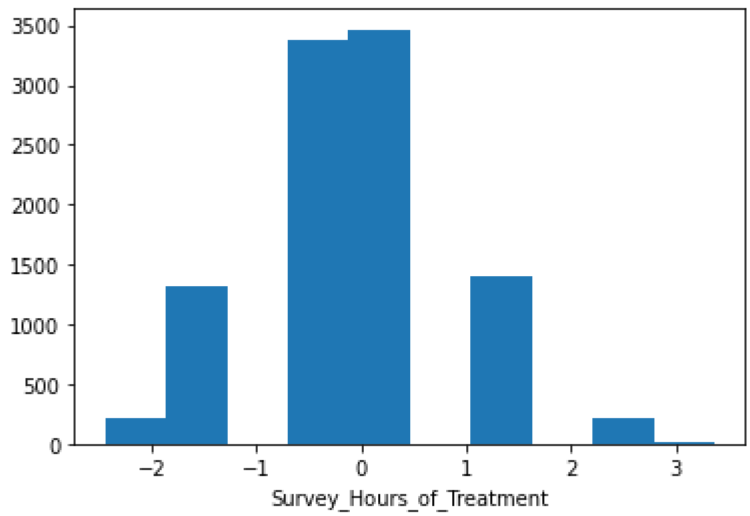


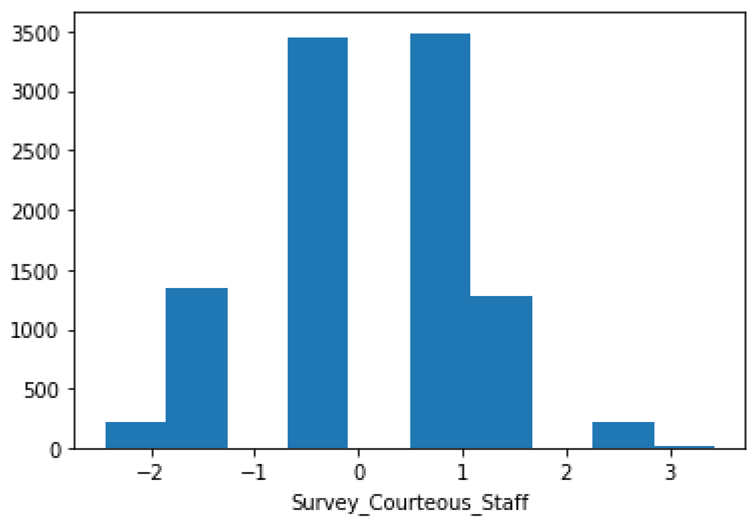
3500
3000
2500
2000
1500
1000
500
0
−2
−1
0
1
2
3
4
Survey_Timely_Visits

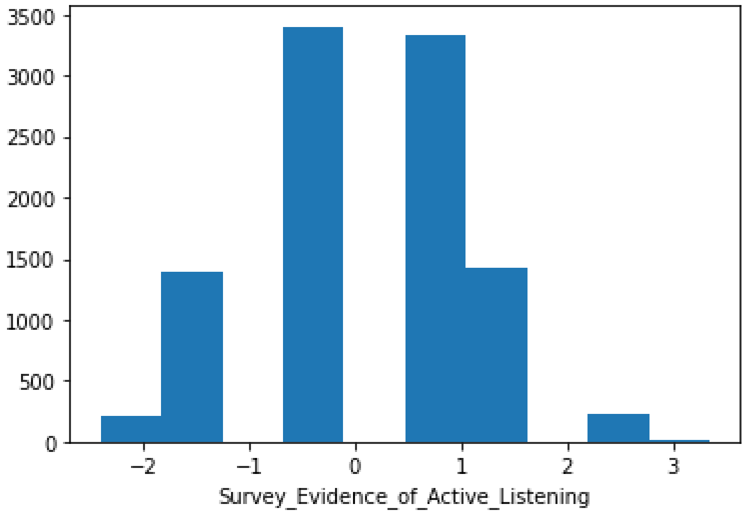


3500
3000
2500
2000
1500
1000
500
0
−2
−1
0
1
2
3
Survey_Reliability


3500
3000
2500
2000
1500
1000
500
0
−2
−1
0
1
2
3
Survey_Options


3500
3000
2500
2000
1500
1000
500
0
−2
−1
0
1
2
3
Survey_Hours_of_Treatment


3500
3000
2500
2000
1500
1000
500
0
−2
−1
0
1
2
3
Survey_Courteous_Staff



Part III: Data-Cleaning

D. Data-Cleaning Process Summary

- Orient Myself to the data
- Value Counts
- Missing Values
- Standardized numeric columns
- Categorical variables to Numeric
- Histograms and Boxplots (Outlier Detection)

D1.

I am choosing not remove any outliers. I believe that all anomilies are a normal part of our studied population. As noted in "Guidelines for Removing and Handling Outliers in Data" - anomalies should be removed when they are either the result of an error, or they cease to represent our studied population. I do not believe any outliers to be indicative of either of those things. Therefore - I am maintaining all values. To be fair - anomalies do exist within the data. To name a few - income, education, and population. As we are evaluating a hospital - it is reasonable to expect that you are going to have broad variations on these factors. Were our research question to be centered around the readmission of low income/low education individuals, or low population areas - we could certainly scrub our data of extremely high anomalies, but as this is an evaluation of an inclusive hospital population - these will be retained.

D2.

As I have chosen to leave all data intact - there are no mitigation methods to be justified. However, these could have been dealt with using some kind of normalization. Perhaps reassigning these outliers to more representative values, or dropping them all together.

D3.

The first data cleaning step was familiarizing myself with the data. The ultimate outcome of this was me being able to identify data types and their general statistical values.

The second step was value counts. This really helps me be able to identify the unique columns that will not aid in the ultimate goal of dimensionality reduction, and gives me a general idea of what exists in each column.

Third was dealing with missing values. I utilized IterativeImputer from the sklearn package. This iterates over the data multiple times to train a model that will impute missing values based upon that variables relationship to other columns. Ultimately - this helps us to infer missing data points and provide a complete dataset to future models.

Standardized numeric columns was the fourth step that normalized all of our values around a mean of 0. This has multiple functions - it does help in scale for viewing outliers. It is also a necessary step in PCA that will be performed below. It gives the model values to recognize variance across the whole dataset.

Fifth was converting categorical variables to numeric. This is a necessity for our imputation performed above. The iterativeimputer module requires numeric values. It would also help if they were needed for another future model down the line where we wanted to evaluate their impact. Of course we would need to define that there is no ordinal value so that a model would not infer that, but again it was a necessary part of what we were doing now as well.

Finally - we have histograms and boxplots. This helps the user to be able to visually identify distribution and outliers. To me - distributions look as to be expected. And, outliers are believed to be a normal part of our studied population.

D4.

Code can be found above this section of commentary.

D5.

Cleaned data was exported above this section and will be found in project submission.

D6.

There are certainly limitations within my approach to data cleaning in this project. Ideally - with missing values, I would have preferred to have conversations with the client around potential reasons as to why they were missing in the first place. I had to make the assumption that there was nothing to correct in the process of data gathering and those values needed to be imputed. I also chose to leave anomalies as a part of my analysis moving forward. This of course could be misinterpreted by a model the line, but I again could not have a conversation with the client to determine if these were true values or the result of an error. So, I chose to err on the side of caution and include under the assumption that they were true observations. I do believe that this is ethically correct based upon the intended outcome of the project.

D7.

So, how could the limitations of my approach impact analysis? Imputation could certainly lead to a misrepresentation of the truth. Is there any 100% guarantee that the imputed values are going to be indicative of reality? No. I cannot say with 100% certainty that the imputed values are correct, however that is the nature of imputation and the nature of dealing with missing values. There is no way of getting back to truth unless you go back and confirm that observation. I believe that the ultimate impact of this is mitigated, because the total number of missing values is small relative to the total number of observations, but it is certainly context to be aware of when communicating this to stakeholders.

As for the non-action on anomalies - this could lead to the outliers impacting our model by providing extremes. However, as they are assumed-to-be-true values - they need to be included as to have accurate information relative to our population. So, while this may lead to some differences in the model compared to their exclusion - it does fall in line with best practices.

In [415…

```
#This is our correlation matrix to show the relationship between variables

Scaled_Med_df.corr()
```

Out[415…

	Population	Children	Age	VitD_levels	Doc_visits	Full_meals_
Population	1.000000	0.007205	-0.018371	0.002124	0.012646	-0.0
Children	0.007205	1.000000	0.005393	-0.002391	-0.004734	-0.0
Age	-0.018371	0.005393	1.000000	0.019033	0.005166	0.0
VitD_levels	0.002124	-0.002391	0.019033	1.000000	0.001367	0.0
Doc_visits	0.012646	-0.004734	0.005166	0.001367	1.000000	-0.0
Full_meals_eaten	-0.025608	-0.000856	0.010050	0.009170	-0.002767	1.0
VitD_supp	0.009781	-0.000463	0.008860	0.009991	0.005681	-0.0
Soft_drink	0.004115	0.007961	0.004361	-0.000697	0.017951	0.0
HighBlood	0.009764	0.004411	0.010891	0.004970	0.008967	0.0
Stroke	-0.001690	0.004573	0.013436	-0.009912	-0.002230	0.0
Complication_risk	0.015936	-0.003008	-0.000490	0.005316	0.012306	0.0
Overweight	0.000367	-0.021073	-0.007507	-0.007787	0.001087	-0.0
Arthritis	0.000055	0.004476	0.008995	-0.000469	-0.000719	0.0
Diabetes	-0.009975	0.018689	0.005136	-0.023462	0.012781	0.0
Hyperlipidemia	-0.006222	-0.009856	0.003964	0.000824	-0.026730	0.0
BackPain	0.006437	-0.023047	0.019881	-0.003450	0.008514	-0.0
Anxiety	-0.012899	0.005274	0.008150	0.014533	-0.002834	0.0
Allergic_rhinitis	0.007681	-0.019174	0.014716	-0.002394	0.002920	0.0
Reflux_esophagitis	0.014340	0.004483	-0.016896	-0.007717	-0.005330	-0.0
Asthma	-0.001510	0.005987	0.009301	0.011450	-0.017989	0.0

	Population	Children	Age	VitD_levels	Doc_visits	Full_meals_
Initial_days	0.019087	0.010640	0.016488	0.008069	-0.007615	-0.0
TotalCharge	0.013751	0.003058	0.024185	0.727561	-0.004515	-0.0
Additional_charges	-0.004820	0.009551	0.728847	0.016425	0.008072	0.0
Survey_Timely_Admission	0.014312	0.005446	0.004909	-0.004335	0.003680	0.0
Survey_Timely_Treatment	0.023612	0.010784	0.002969	-0.017683	0.006024	-0.0
Survey_Timely_Visits	-0.001248	0.002291	0.004855	-0.012496	-0.002718	0.0
Survey_Reliability	-0.004660	0.005824	0.005639	0.012671	-0.006538	-0.0
Survey_Options	0.008705	0.006133	-0.007860	-0.012255	-0.009434	0.0
Survey_Hours_of_Treatment	0.008159	-0.002160	-0.000156	0.007350	0.012530	0.0
Survey_Courteous_Staff	0.010034	0.005558	0.010302	0.001992	0.008589	0.0
Survey_Evidence_of_Active_Listening	-0.000220	-0.011324	-0.003642	0.004033	0.004571	-0.0

31 rows × 31 columns

In [416…

```
#Initiating PCA
#Reference: (Kindsonthegenius, 2020)
Med_PCA = PCA()

Med_PCA_FT = Med_PCA.fit_transform(Scaled_Med_df)

Med_PCA_FT = pd.DataFrame(Med_PCA_FT)

Med_PCA_FT
```

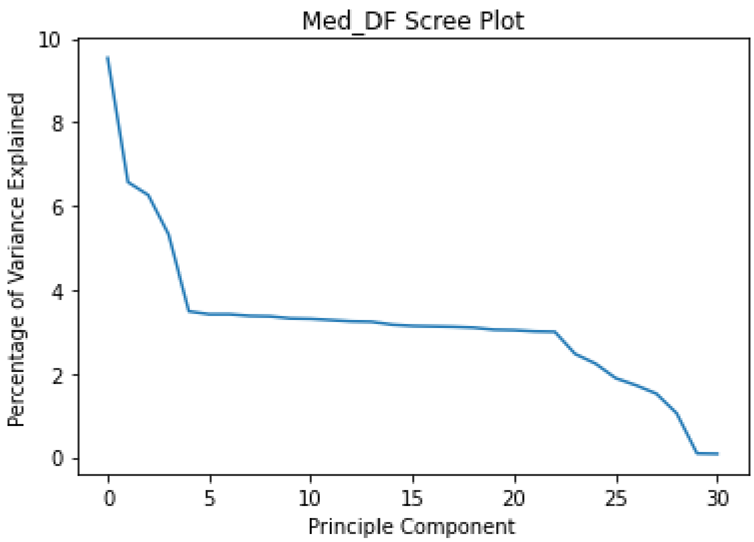
Out[416…

	0	1	2	3	4	5	6	7	8
0	-1.606819	0.087476	-1.603797	0.352726	1.125682	-0.824507	0.640937	-1.515131	0.697186
1	-0.325365	0.219360	-1.222288	-0.104782	-0.962116	-0.164027	-1.638954	0.928217	0.414256
2	-0.201751	-0.355915	-1.831390	-0.660291	0.278594	-0.051720	-1.148161	0.144641	0.345984
3	2.345966	-0.854095	-1.201547	0.391742	1.022480	0.349036	-0.389637	-0.557362	-0.722921
4	-2.372715	-2.752463	0.395789	-0.337430	-0.334034	1.333370	0.521480	1.905066	-1.221259
...	...	...	...	...	...	...	...	...	...
9995	-2.107126	-0.304723	0.550835	-0.270944	-0.520516	-0.188865	-1.047018	-0.071344	0.030868
9996	-0.703980	2.668207	-1.576351	1.724087	1.016712	0.329201	-0.810658	-1.916748	0.112562
9997	-1.880049	0.880328	0.037438	0.261843	0.846171	-0.806931	-0.263213	0.499075	0.946759
9998	0.796273	-0.095912	1.684987	0.896192	-0.497747	-0.143362	0.280589	0.528423	-0.508669
9999	0.676988	0.715358	1.253763	0.224172	-0.985252	2.139548	-1.036507	-1.679030	-0.553948

10000 rows × 31 columns

In [417…

```
percent_variance = np.round(Med_PCA.explained_variance_ratio_*100, decimals=2)

pyplot.plot(Med_PCA_FT.columns, percent_variance)
pyplot.title('Med_DF Scree Plot')
pyplot.xlabel('Principle Component')
pyplot.ylabel('Percentage of Variance Explained')
plt.show()
```

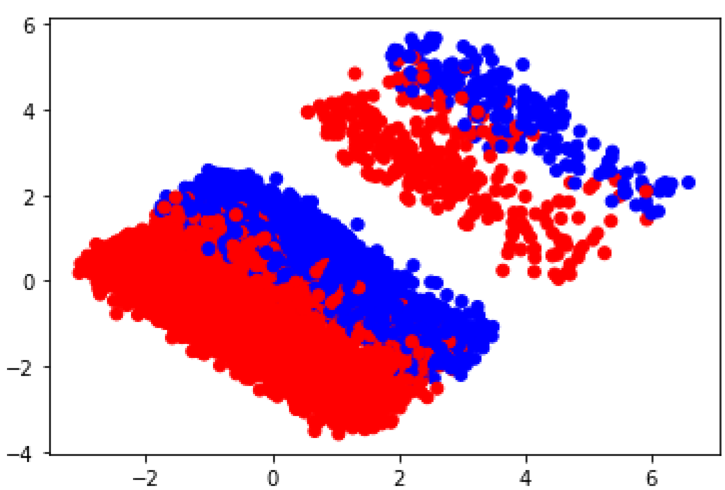


In [418…

```
Med_PCA_FT = Med_PCA_FT.merge(Target, left_index=True, right_index=True)

Med_PCA_FT['Color']= Med_PCA_FT['ReAdmis'].replace({0:'r', 1:'b'})

pyplot.scatter(Med_PCA_FT[1], Med_PCA_FT[2], c = Med_PCA_FT.Color)
```

Out[418…

```
<matplotlib.collections.PathCollection at 0x2218b651e50>
```



In [419…

```
for x, y in zip(Med_PCA_FT.columns, np.cumsum(Med_PCA.explained_variance_ratio_)):
    print(x, y)
```

```
0 0.09537300264151131
1 0.1611225273178129
```

```
2 0.2237484613314441
3 0.2769622917197733
4 0.3118530427783067
5 0.34609321081467875
6 0.38024913482062234
7 0.41407433387307635
8 0.44781038979305654
9 0.4810487349915523
10 0.5141275727512862
11 0.5468873589467472
12 0.5793946548583053
13 0.611750188981412
14 0.6434984437742507
15 0.6749148229595627
16 0.7061959206457349
17 0.7374189541249802
18 0.7683845215516597
19 0.7988632337291206
20 0.8292759952287545
21 0.8593506065006781
22 0.8893644401291758
23 0.9140778533385729
24 0.9364863689582283
25 0.9554105521881042
26 0.9725630552530493
27 0.9877610200006122
28 0.9983011849043533
29 0.9992245607476545
30 1.0000000000000002
```

In [420…

```
#This gives me all our initial variables and their loadings in each principle component

loadings = pd.DataFrame(Med_PCA.components_.T*100, index= Scaled_Med_df.columns)

loadings
```

Out[420…

	0	1	2	3	4	
Population	1.026974	0.665143	2.180759	2.527812	-38.867162	9.32201
Children	0.252623	1.025776	-0.351872	1.369559	17.525652	40.57281
Age	0.625204	38.748640	-35.165643	2.854789	12.690066	17.42189
VitD_levels	-0.957820	36.082300	38.019565	3.446524	12.190871	-23.28975
Doc_visits	0.706793	0.613241	-1.351132	-0.533841	-13.355231	-3.77970
Full_meals_eaten	-0.051667	1.052641	-2.852055	2.213620	42.384042	-20.99512
VitD_supp	-0.467146	2.892635	1.281249	0.797140	-35.693543	18.59583
Soft_drink	0.689039	-0.001508	-0.066078	1.389166	25.409101	9.80328
HighBlood	-0.340725	33.691132	-33.268180	0.445878	-15.031272	-15.87263
Stroke	-0.235984	1.392486	-3.759940	1.544252	-2.891159	11.73140
Complication_risk	1.285496	4.839999	-0.920201	-0.953717	-15.346986	-10.70158
Overweight	0.426311	-0.103823	-2.925938	1.157815	-18.473379	-50.03268
Arthritis	-1.422671	2.196020	0.959379	-0.741561	9.220582	1.10043

	0	1	2	3	4	
Diabetes	-0.295194	-1.237835	-1.666642	3.139808	35.350400	20.05220
Hyperlipidemia	1.707249	0.334629	1.237430	-1.475862	11.077778	21.05807
BackPain	-1.299412	2.929841	0.178080	-0.655148	-12.771244	-6.91411
Anxiety	-0.075996	3.347648	1.315573	-2.262854	20.985467	-4.94182
Allergic_rhinitis	0.481664	2.343741	-1.145508	1.778240	-2.767455	-25.23259
Reflux_esophagitis	0.632136	-0.241043	2.315297	-1.112417	-11.421476	21.44813
Asthma	-1.063100	0.931665	-1.676664	2.043914	28.676481	-29.09239
Initial_days	-1.986170	31.075724	34.955306	6.561606	-11.140513	24.07338
TotalCharge	-1.854153	48.252981	50.801088	6.605548	1.330958	-1.51388
Additional_charges	0.505671	51.079931	-48.241300	2.715812	-0.857136	2.31586
Survey_Timely_Admission	45.453775	-2.177145	-0.479634	29.500934	-0.139541	0.42481
Survey_Timely_Treatment	42.822559	-2.234316	-0.597632	29.182524	-1.840905	1.04289
Survey_Timely_Visits	39.516046	-2.408963	-0.202250	29.369536	0.238986	0.01781
Survey_Reliability	15.205224	4.398749	2.833105	-55.460947	1.262114	3.34240
Survey_Options	-18.994090	-5.919344	-2.362698	57.951343	0.370184	-0.36436
Survey_Hours_of_Treatment	41.003413	1.808836	2.106847	-16.146311	1.997520	0.88180
Survey_Courteous_Staff	35.636388	3.445278	1.404365	-16.893725	2.500745	0.73984
Survey_Evidence_of_Active_Listening	31.204330	1.960899	2.029133	-16.537068	-1.907401	-7.31687

31 rows × 31 columns

Part III: Data Cleaing (Continued)

E. Principle Component Analysis

E1., E2., E3.

I have printed out the results of PCA in the above code. I will choose to maintain 20 of the principle components as to explain 80% of the total variance in the data moving forward. You can tell this by looking at their cumulative explained variance in combination with the above scree plot. This allows me to have reasonable dimensionality reduction while maintaining the majority of what is being communicated in the data set. PC1 explains about 10% of the total variance and it's variables with highest correlation are:

Timely_Admission Timely_Treatment Hours_of_Treatment Timely_Visits

All of these variables are highly positively correlated to the variance explained in PC1.

So, how can an organization benefit from this analysis? Ultimately - these would be identified as the areas that they should focus research on. Ideally - they would want to reach out to the patients that answered to the extremes within these survey questions. Theoretically - they could define additional areas of concerns and provide that as a part of the dataset for deeper evaluation. Really what this is going to do is give them areas to focus in on for further evaluation. You can see the relationship of the first two principle components to our target in the scatter plot found above.

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