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1 D206 Data Cleaning Performance Assessment

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2 Part I: Research Question

2.1 A1: QUESTION OR DECISION

For this performance assessment, I propose the following research question:

'What patient factors influence hospital readmission rates?'

Hospital readmission rates are an important metric tracked by medical institutions. Since readmission indicates a failure to accomplish the intended outcome of the initial hospital visit, it is seen as a sign that substandard care was administered (CMS Office of Minority Health, 2020). For this reason, and due to disproportionate readmission rates for vulnerable populations, federal government organizations penalize hospitals for readmissions. This system incentivizes medical businesses to reduce readmission rates, making an analysis of the root causes relevant to medical business financial interests. The dataset that will be cleaned to analyze this research question comes from a chain of hospitals and provides many vital variables necessary to answer such a question.

2.2 A2: REQUIRED VARIABLES

The table below contains the information for every variable within the data file, indicating its data type, describing the variable, and presenting an example of the variable. Note that each example is from the same row of data.

2.2.1 Code for accessing examples

[238]:
```
#the examples in the below table were generated with this line of code
import pandas as pd
data_df = pd.read_csv('/content/medical_raw_data.csv', index_col=0)
data_df.dropna(how='any').iloc[10,:];
```

Variable	Data type	Description	Example
CaseOrder	Quantitative	Serial primary key	10
Customer_id	Qualitative	ID of patient	Z229385

Variable	Data type	Description	Example
Interaction	Qualitative	ID for patient-related activities	5acd5dd3-f0ae-41c7-9540-cf3e4ecb2e27
UID	Qualitative	ID for patient-related activities	687e7ba1b80022c310fa2d4b00db199a
City	Qualitative	Patient city	Paynesville
State	Qualitative	Patient state	MN
County	Qualitative	Patient county	Stearns
Zip	Qualitative	Patient zip code	56362
Lat	Quantitative	Latitude of patient residence	45.40325
Lng	Quantitative	Longitutde of patient residence	-94.71424
Population	Quantitative	Population within 1-mile of patient residence	5840
Area	Qualitative	Development classification	Urban
Timezone	Qualitative	Patient time-zone	America/Chicago
Job	Qualitative	Patient job (or primary insurance holder)	Production assistant, radio
Children	Quantitative	Patient children	2.0
Age	Quantitative	Patient age	78.0
Education	Qualitative	Patient education	Some College, 1 or More Years, No Degree
Employment	Qualitative	Patient employment status	Full Time
Income	Quantitative	Patient annual income (or primary insurance holder)	38965.22
Marital	Qualitative	Patient marital status (or primary insurance holder)	Never Married
Gender	Qualitative	Patient gender	Female
ReAdmis	Qualitative	Was patient readmitted within a month of discharge?	No
VitD_levels	Quantitative	Patient vitamin D levels (ng/mL)	19.628554
Doc_visits	Quantitative	Primary physician visits during initial hospital stay	7
Full_meals_eaten	Quantitative	Full meals eaten while hospitalized	1

Variable	Data type	Description	Example
VitD_supp	Quantitative	Vitamin D supplements given during stay	2
Soft_drink	Qualitative	Does the patient regularly drink 3 or greater sodas per day?	No
Initial_admin	Qualitative	Patient's intial admission type	Emergency Admission
HighBlood	Qualitative	Does the patient have high blood pressure?	Yes
Stroke	Qualitative	Has the patient had a stroke?	No
Complication_risk	Qualitative	Patient complication risk level	High
Overweight	Qualitative	Is the patient considered overweight for their height, gender, and age?	1.0
Arthritis	Qualitative	Does the patient have arthritis?	No
Diabetes	Qualitative	Does the patient have diabetes?	No
Hyperlipidemia	Qualitative	Does the patient have hyperlipidemia?	No
BackPain	Qualitative	Does the patient have chronic back pain?	No
Anxiety	Qualitative	Does the patient have an anxiety disorder?	0.0
Allergic_rhinitis	Qualitative	Does the patient have allergic rhinitis?	Yes
Reflux_esophagitis	Qualitative	Does the patient have reflux esophagitis?	Yes
Asthma	Qualitative	Does the patient have asthma?	Yes
Services	Qualitative	Patient primary service received	Blood Work
Initial_days	Quantitative	Length of patient's intial stay (days)	1.632554

Variable	Data type	Description	Example
TotalCharge	Quantitative	Average daily charge to the patient during their hospital stay, excluding specialized treatments	3709.547665
Additional_charges	Quantitative	Average cost billed to the patient for various procedures, anesthesiology, medications, treatments, etc.	26225.98991
Item1	Quantitative	Patient's importance rating (1=most important, 8= least) for: Timely admission	5
Item2	Quantitative	Patient's importance rating (1=most important, 8= least) for: Timely treatment	5
Item3	Quantitative	Patient's importance rating (1=most important, 8= least) for: Timely visits	5
Item4	Quantitative	Patient's importance rating (1=most important, 8= least) for: Reliability	3
Item5	Quantitative	Patient's importance rating (1=most important, 8= least) for: Options	4
Item6	Quantitative	Patient's importance rating (1=most important, 8= least) for: Hours of treatment	2
Item7	Quantitative	Patient's importance rating (1=most important, 8= least) for: Courteous staff	3

Variable	Data type	Description	Example
Item8	Quantitative	Patient's importance rating (1=most important, 8= least) for: Evidence of active listening from doctor	2

3 Part II: Data-Cleaning Plan

3.1 B1: PLAN TO ASSESS QUALITY OF DATA

Below I detail my plan to access data qualitiy issues in four areas: 1. Re-expression of catergorical variables 2. Duplicates 3. Missing values 4. Outliers

3.1.1 Re-expression of catergorical variables

To access data quality issues in the qualitative variables, I will select all the qualitative variables and examine their distinct values. I will examine the distinct values and correct any variables that deviate from the majority standard by replacing the values with the ones of the standard. I will exclude the location-related variables (*City*, *State*, *Lat*, etc.) from this investigation and further data quality investigations since they should be verified on another lookup system that specilizes in location vertfication.

The methods I will use to accomplish this is to load the data file into Python utilizing the pandas package. The pandas package has the `value_counts()` function which returns the unique values and their number of counts within each catergory. We can use a loop to go through every qualititative variable, printing out the distinct values and counts:

```
for every qualitative column in the data file
  print column.value_counts()
```

This will allow us to investigate if their are any inconsitencies in the catergorical variables.

3.1.2 Duplicates

To examine any data quality issues due to duplicates, I will explore the data frame to see if there are any duplicate rows. This will be accomplished using the `duplicated().sum()` chain of pandas functions. `duplicated()` returns a pandas column, called a series, that contains boolean entries indicating `True` or `False` whether or not that row has a duplicate somewhere else in the data frame. Chaining this with the `sum()` will count all the `True` entries in the series. We will know if there are duplicate rows if the results are nonzero.

I will then check the quantitative columns to see if they contain duplicates. To accomplish this task, we will use a very similar method as we used for the re-expression of categorical variables, namely:

```
for every quantitative column in the data file
  print column.value_counts()
```

We only look at the quantitative columns because the qualitative columns will have duplicates. Again, I will exclude the location-specific variables from this investigation. I will also not investigate the survey questions, as they are expected to contain duplicate entries. Depending on the context, the duplicates in the quantitative columns may or may not be an issue. For example, we expect *Children* to have duplicates, but maybe not *Income*, except if some rounding is applied.

If any columns do come back as having duplicate entries, we will then further investigate these entries by pulling up side by side the rows with the same entries in the column under investigation. Doing this will allow us to determine if we need to drop these entries due to some mistake in the data-entry phase, or if they are legitimate entries with expected repeated values.

One way to accomplish this is to call the pandas `groupby()` function followed by the `filter()` function. Within the `filter()` call, we can use Python's `lambda` anonymous function to generate a quick boolean series where only groups returned by the `groupby` with more than 1 entry are presented. The pseudocode would look like this:

```
grouped = data.groupby(column of interest).filter(lambda x: len(x) > 1)
```

From where we will sort the values using pandas `sort_values()` function. The result could then be printed and examined to see if any duplicates appear erroneous.

3.1.3 Missing values

To handle data quality issues caused by missing values, I will begin by looking at the NA values for each column. By investigating the qualitative variables, I already understand that the categorical variables do not contain missing values, so using the built-in `info()` pandas function will be sufficient. I will then take note of which columns have NA values.

Because the missing data may have some pattern, we must ask ourselves: Are these missing values in the same row? Is there some pattern to these missing values? To answer these questions, I will plot the number of missing data values in each row using `data.isna().sum(axis=1).plot()`. This code first uses `isna()` to return a DataFrame of Boolean entries, `True` or `False` depending on whether or not the entry is Not a Number (NaN). Calling `sum(axis=1)` adds up all the `True` values for every row, returning a series of numbers representing the number of NaN values in each row. `plot()` is then pandas' call to matplotlib to plot the series, with the series index as the x-axis and the series values as the y-axis. What I will do is call this chain of functions for every column that does not have NaN entries, sorting the results by that column like so:

```
for every column without NaN:
  data.isna().sum(axis=1).sort_values(column).plot()
```

Using this method, we can visually see if the missing values are clustered around any specific relationship with another column.

Before we consider using imputation methods, I will examine if any rows or columns should be dropped. If any column contains more than 60% NaN values, it will be dropped, and if the rows with NaN values comprise 5% or less of the total number of rows, they will be dropped. To determine these values, we can use the following pseudocode:

```
missing_pct_cols = data.isnull().sum() / len(data)

missing_pct_rows = (data_df.isnull().sum(axis=1) >= 1).sum() / len(data)
```

We include the `>=1` because `data_df.isnull().sum(axis=1)` returns a count of NaNs in each row, and we only care whether there is any NaN at all.

Should columns remain with NaN values after the above check, we then want to examine the columns with NaN values to determine what imputation method we should use. We will do this by plotting the distribution of each of our columns with NaN values:

```
for every column with NaN values:
  plot column histogram
```

We can get the histogram for numeric columns using pandas' `hist()` function. We can use univariate methods, such as mean, median, or mode, to impute the distributions based on whether a distribution is normal, skewed, or bimodal, respectively. These investigations will inform our imputation methods accordingly. We would not want to use univariate methods if we found some pattern in the missing values, as these would disregard the relationship between the missing values and the other values in the row.

3.1.4 Outliers

To assess the impact of outliers on data quality, we must first determine if outliers exist. Outliers can be defined as values that fall outside the expected range. Their inclusion in the dataset can lead to data quality issues. For instance, they might skew results so significantly that other aspects of the data become obscured. This could occur due to a very high value that distorts the average, causing a divergence between the median and average values.

While these can cause issues, it's important to note that values far from expectations are not always outliers. In my view, a more stringent criterion for defining outliers is needed. Specifically, outliers should be values that deviate significantly from the rest of the data and have an erroneous source.

By this definition, a value higher than the majority of the data but has a legitimate source and is significant to the research question would not be considered an outlier.

To find outliers, I will employ two methods: examination of Z-scores and histogram distributions. The first thing we will do to detect outliers is to examine Z-scores for each column. Z-scores are simply the number of standard deviations away from the mean of any value in the dataset. One rule of thumb is that if a value has a Z-score of $\pm$ 3, aka if it is 3 or more standard deviations away from the mean, it is considered an outlier. Using pandas functions `std()` and `mean()`, we can easily find the Z-scores that meet this definition:

```
z_scores = (data - data.mean()) / data.std()
outliers = z_scores > 3 OR z_scores < -3
```

Using these functions, pandas will compute the Z-score for each column using only the column-specific mean and standard deviation. It uses the index, so we don't need loops. We then can examine these results and determine if this determination of outliers is reasonable. However, this method assumes that the investigated data is normally distributed. This is because if the data is normally distributed, only 0.03% of the data is expected to be found beyond the 3 Z-score threshold (Investopedia, n.d.). However, if this assumption is not met, the Z-score method can be a decent starting place but is not the end-all-be-all.

For this reason, I will also plot a histogram for each quantitative data column using the methods discussed earlier. In addition to the histogram, it would be beneficial to visualize the Z-scores and have a representative normal distribution curve. This will allow us to investigate,

1. How well did the Z-score method perform in selecting outliers?
2. Compare the frequency of values flagged as outliers to the frequency we would expect at those extremes if the data followed a normal distribution.

To do this, I will employ the following plan:

1. For each column with outliers, plot a histogram highlighting the bins that contain outliers.
2. Generate and plot a normal distribution curve for comparison.

For 2. I will use the SciPy package and the stats module to call `norm.pdf(x-axis value, mean, standard deviation)` which will generate a normal distribution curve that meets the specified inputs. My pseudocode is as follows:

```
for each column in outliers:

 calculate mean and standard deviation of the column

 plot histogram of the column

 identify bins with values beyond 3 standard deviations from mean

 highlight outlier bins in the histogram

 generate a normal distribution with the same mean and standard deviation

 plot the normal distribution curve on the histogram
```

The above method will allow us to locate suspected outliers using the Z-score and histogram. However, before declaring these as outliers, it's necessary to determine if they have an erroneous source or hold significance to the research question. These values could be a good predictor of patient readmission, which is significant to our research question. Therefore, we would not want to drop these outliers from the dataset, which would significantly influence our predictive capabilities. A final step to check if the suspected outliers are significant to the research question is to examine the frequency of re-admission rates for patients falling into these outlier ranges. We can use the histogram to determine our investigation range and then calculate the percentage of readmissions for these patients using *ReAdmis*. This can then be compared to the majority of the data.

Pseudocode for this final step of outlier verification:

```
outlier_readmin_rate = data[
  (data[column] > outlier_range)
  ]['ReAdmis'].value_counts(normalize=True)

nonoutlier_readmin_rate = data[
  ~(data[column] > outlier_range)
  ]['ReAdmis'].value_counts(normalize=True)

print('outlier_readmin_rate:\n', outlier_readmin_rate)
print('nonoutlier_readmin_rate:\n', nonoutlier_readmin_rate)
```

This final step will give us a good sense of the quality of these suspected outliers and provide us with the information needed to determine how best to handle them.

3.2 B2: JUSTIFICATION OF APPROACH

Below, I justify my approach to assessing data quality issues.

One of the characteristics of the dataset is that it contains many qualitative variables. Because of this, I decided to assess whether or not I needed to examine the categorical variables to determine whether or not they need to be re-expressed. I included this in my approach to determine if any of the categorical values were expressed as numbers or numeric variables. This would cause these variables to be included in numeric calculations, such as calculating means or medians of data columns. To avoid this and to strictly limit qualitative variables to string type or object type columns, I decided it best to include these in my data cleaning plan to re-express them if I located them.

I decided to check for duplicates when building my data cleaning plan because this dataset contains many unique ID rows, which is one of the characteristics of this data, and I wanted to ensure none of these unique IDs were repeated. If these were to be repeated, they would cause issues in answering our research question. We do not want to give undue weight to any patient's experience. Because quite a few of the variables are expected to contain duplicated values, they are categorical variables with limited distinct values, so this data characteristic needed to be accounted for in the data cleaning plan.

My approach to handling missing values can be justified because the data is held in a pandas data frame, which provides many excellent features for detecting and handling NaN values. In fact, when ingesting the data into a data frame using pandas, pandas will automatically detect and recharacterize NaN values so they are all in the same format. So knowing this, we can utilize some of these built-in pandas methods. We do want to, however, be mindful of just how missing values are dispersed, as when we arrive at data imputation methods if we unknowingly fill in values that skew the results very significantly, we can really influence the ability of the dataset to answer the research question. So, knowing this, my approach is cautious in distinguishing just how the missing values are laid out.

I especially wanted to take a careful, considerate approach to assessing outliers. To detect outliers, we focus on the quantitative variables. Because readmission rates can only impact a subset of the patients profiled, it is possible that a variable with outliers has outliers related to the outlier issue of readmission rates. So, it's essential in this context to be thorough. For this reason, I used both the Z-score and the histogram method to detect outliers. But I also included an evaluation of the relationship between suspected outliers and the predictive variable of interest, as this ultimately is the most important part and will make sure we don't miss anything during data analysis.

3.3 B3: JUSTIFICATION OF TOOLS

Python has been used to assess the quality of and clean the data required for this research question. Python was chosen as the tool for these tasks because it offers powerful methods and visualizations that aid in accomplishing these tasks. Compared to other tools such as Excel, a relational database, or a text editor, Python enables efficient data quality investigations and cleaning. For example, utilizing Python, I can quickly loop through the columns in a data file, adjusting or selecting certain features, while at the same time handling different data types using conditionals or try-except blocks.

Beyond Python, I chose to operate exclusively within the Google Colab Jupyter notebook Python environment. This tool offers several advantages over a typical Python IDE, including cloud access from any machine, the ability to isolate code blocks for execution and investigation, as well as the ability to use markdown text cells. However, one of the most significant reasons to choose Google Colab over a typical Jupyter notebook is the ease of use regarding package installation, as no local files need to be accessed to use Colab, enabling speedy data cleaning from any machine.

I chose Python as my language over other languages designed for statistical analysis, such as R, because while R can be used in Google Colab, it is primarily used for Python. The main reason to emphasize Google Colab is to democratize the coding and data analysis journey, as any user can access the code I have written in this notebook, and execute it at will, from any machine. This is a key advantage that R and RStudio cannot easily replicate.

From specific packages, I primarily used pandas, which is the main package to load in data files into what is called a dataframe, or table. It allows certain aspects of the table to be selected, as well as providing many additional functions that make data cleaning very efficient. It comes with plotting functions for visualization purposes. Pandas is also built upon the NumPy package, as are many Python packages. NumPy offers data array manipulation, which are like vectors or matrices in mathematics. NumPy offers many of the mathematical tools that are needed in data cleaning such as vector multiplication or data reduction, such as mean, median, or standard deviation calculations. For visualization, pandas is also built upon matplotlib, which is the primary library for Python visualizations. I also used SciPy, specifically the stats module, which is a package that offers many of the more niche yet widely used statistical tools not offered in NumPy. Also utilized is the Scikit-learn package, which also builds upon NumPy and SciPy, offering many machine learning tools such as PCA.

These tools are ideal for cleaning this data as they offer a wide range of functionalities that are not readily available in other tools. For instance, the pandas library provides a flexible and efficient DataFrame object for data manipulation which is not available in Excel or a text editor. Similarly, the NumPy and SciPy libraries offer various mathematical and statistical functions unavailable in a relational database. The Google Colab environment, on the other hand, provides a convenient and accessible platform for executing and sharing the code, which is not easily replicable in R or RStudio.

4 Part III: Data Cleaning

4.1 C1: CLEANING FINDINGS

4.1.1 Re-expression of catergorical variables

[239]:
```
# Select all the qualitative variables
qual_vars = ['Customer_id',
             'Interaction',
             'UID',
             'Job',
             'Education',
             'Employment',
```

```
              'Marital',
              'Gender',
              'ReAdmis',
              'Soft_drink',
              'Initial_admin',
              'HighBlood',
              'Stroke',
              'Complication_risk',
              'Overweight',
              'Arthritis',
              'Diabetes',
              'Hyperlipidemia',
              'BackPain',
              'Anxiety',
              'Allergic_rhinitis',
              'Reflux_esophagitis',
              'Asthma',
              'Services']

# Print the distinct values and their counts for each selected column
for col in data_df[qual_vars]:
  print(data_df[col].value_counts())
  print("\n") # Add an empty line for better readability
```

```
Customer_id
C412403    1
D294364    1
B203210    1
C20177     1
K216020    1
          ..
J694995    1
N704840    1
A197688    1
H115454    1
I569847    1
Name: count, Length: 10000, dtype: int64


Interaction
8cd49b13-f45a-4b47-a2bd-173ffa932c2f    1
dc1799a6-61d1-44a3-9b94-b89584baddfc    1
dc6bab10-659b-4c78-ba87-87ffa3def32f    1
1cb70cc8-47b7-4192-8bed-faad0f27ab3b    1
06d0da86-5600-472d-a35d-7632775b5cd7    1
                                       ..
2d5c049d-0431-443f-a9d7-46f875998599    1
```

```
4ccc7838-5c2c-4a3c-9e3b-2a646cec157e    1
4767cd0e-626d-4c5a-834e-a948aba315c2    1
8b1e1ea3-e596-4a97-b2cb-7f9926e9fbee    1
bc482c02-f8c9-4423-99de-3db5e62a18d5    1
Name: count, Length: 10000, dtype: int64


UID
3a83ddb66e2ae73798bdf1d705dc0932    1
5d85418e862aab28ed18975446153694    1
28970195a839f74e572d2f43bd7fcb71    1
24665d1c5070b579d0c190324599ca6d    1
2d42fd6803d96fcffe64d3fcaab430dc    1
                                   ..
ce28b38948f9737918e240d8ce6b275f    1
d98f314ddd12ca99e05858219127a06e    1
43e47521f56f27d0fc8e00ba7141de1b    1
ffd9be64812b5e36ba9367abe51be705    1
95663a202338000abdf7e09311c2a8a1    1
Name: count, Length: 10000, dtype: int64


Job
Outdoor activities/education manager     29
Exhibition designer                      27
Theatre director                         27
Scientist, audiological                  26
Toxicologist                             25
                                         ..
Government social research officer        6
Phytotherapist                            6
Engineer, control and instrumentation     6
Public relations account executive        6
Licensed conveyancer                      6
Name: count, Length: 639, dtype: int64


Education
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: count, dtype: int64
```

```
Employment
Full Time     6029
Student       1017
Part Time      991
Unemployed     983
Retired        980
Name: count, dtype: int64
```

```
Marital
Widowed          2045
Married          2023
Separated        1987
Never Married    1984
Divorced         1961
Name: count, dtype: int64
```

```
Gender
Female                  5018
Male                    4768
Prefer not to answer     214
Name: count, dtype: int64
```

```
ReAdmis
No     6331
Yes    3669
Name: count, dtype: int64
```

```
Soft_drink
No     5589
Yes    1944
Name: count, dtype: int64
```

```
Initial_admin
Emergency Admission      5060
Elective Admission       2504
Observation Admission    2436
Name: count, dtype: int64
```

```
HighBlood
No     5910
Yes    4090
Name: count, dtype: int64


Stroke
No     8007
Yes    1993
Name: count, dtype: int64


Complication_risk
Medium    4517
High      3358
Low       2125
Name: count, dtype: int64


Overweight
1.0    6395
0.0    2623
Name: count, dtype: int64


Arthritis
No     6426
Yes    3574
Name: count, dtype: int64


Diabetes
No     7262
Yes    2738
Name: count, dtype: int64


Hyperlipidemia
No     6628
Yes    3372
Name: count, dtype: int64


BackPain
No     5886
Yes    4114
Name: count, dtype: int64
```

```
Anxiety
0.0    6110
1.0    2906
Name: count, dtype: int64


Allergic_rhinitis
No     6059
Yes    3941
Name: count, dtype: int64


Reflux_esophagitis
No     5865
Yes    4135
Name: count, dtype: int64


Asthma
No     7107
Yes    2893
Name: count, dtype: int64


Services
Blood Work     5265
Intravenous    3130
CT Scan        1225
MRI             380
Name: count, dtype: int64
```

Examining the output above, I see that the columns *Anxiety* and *Overweight* need to be corrected as their distinct values are *1* and *0*. In contrast, they should be set to *Yes* and *No* to align with the other variables. None of the different qualitative variables appear to have data quality issues.

4.1.2 Duplicates

Next, let's move on to investigating duplicate records in our data.

[240]:
```
#count the number of rows that are identical
data_df.duplicated().sum()
```

[240]: 0

From the above result, we can see zero duplicate rows in our data. Next, let's look at the quantitative columns. We only look at the quantitative columns because the qualitative columns will have duplicates. I will however include the ID columns, as these should be distinct. Again, I will exclude the location-specific variables from this investigation. I will also not investigate the survey questions, as they are expected to contain duplicate entries.

[241]:
```
# Select all quantitative variables
quan_cols = [
    'Customer_id',
    'Interaction',
    'UID',
    "CaseOrder",
    "Population",
    "Children",
    "Age",
    "Income",
    "VitD_levels",
    "Doc_visits",
    "Full_meals_eaten",
    "VitD_supp",
    "Initial_days",
    "TotalCharge",
    "Additional_charges",
]

# Print the distinct values and their counts for each selected column
for col in quan_cols:
  print(data_df[col].value_counts())
  print("\n") # Add an empty line for better readability
```

```
Customer_id
C412403    1
D294364    1
B203210    1
C20177     1
K216020    1
          ..
J694995    1
N704840    1
A197688    1
H115454    1
I569847    1
Name: count, Length: 10000, dtype: int64


Interaction
8cd49b13-f45a-4b47-a2bd-173ffa932c2f    1
dc1799a6-61d1-44a3-9b94-b89584baddfc    1
dc6bab10-659b-4c78-ba87-87ffa3def32f    1
```

```
1cb70cc8-47b7-4192-8bed-faad0f27ab3b    1
06d0da86-5600-472d-a35d-7632775b5cd7    1
                                       ..
2d5c049d-0431-443f-a9d7-46f875998599    1
4ccc7838-5c2c-4a3c-9e3b-2a646cec157e    1
4767cd0e-626d-4c5a-834e-a948aba315c2    1
8b1e1ea3-e596-4a97-b2cb-7f9926e9fbee    1
bc482c02-f8c9-4423-99de-3db5e62a18d5    1
Name: count, Length: 10000, dtype: int64


UID
3a83ddb66e2ae73798bdf1d705dc0932    1
5d85418e862aab28ed18975446153694    1
28970195a839f74e572d2f43bd7fcb71    1
24665d1c5070b579d0c190324599ca6d    1
2d42fd6803d96fcffe64d3fcaab430dc    1
                                   ..
ce28b38948f9737918e240d8ce6b275f    1
d98f314ddd12ca99e05858219127a06e    1
43e47521f56f27d0fc8e00ba7141de1b    1
ffd9be64812b5e36ba9367abe51be705    1
95663a202338000abdf7e09311c2a8a1    1
Name: count, Length: 10000, dtype: int64


CaseOrder
1        1
6671     1
6664     1
6665     1
6666     1
        ..
3334     1
3335     1
3336     1
3337     1
10000    1
Name: count, Length: 10000, dtype: int64


Population
0        109
195       14
115       11
178       11
285       11
        …
```

```
8092       1
11147      1
27175      1
7371       1
41524      1
Name: count, Length: 5951, dtype: int64


Children
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: count, dtype: int64


Age
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: count, Length: 72, dtype: int64


Income
14572.40    2
37132.97    2
55506.92    2
20474.03    2
26915.85    2
           ..
35093.92    1
41900.29    1
13511.95    1
```

```
34015.88    1
62682.63    1
Name: count, Length: 7531, dtype: int64


VitD_levels
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: count, Length: 10000, dtype: int64


Doc_visits
5    3823
6    2436
4    2385
7     634
3     595
8      61
2      58
1       6
9       2
Name: count, dtype: int64


Full_meals_eaten
0    3715
1    3615
2    1856
3     612
4     169
5      25
6       6
7       2
Name: count, dtype: int64


VitD_supp
0    6702
1    2684
```

```
2     544
3      64
4       5
5       1
Name: count, dtype: int64


Initial_days
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: count, Length: 8944, dtype: int64


TotalCharge
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: count, Length: 10000, dtype: int64


Additional_charges
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: count, Length: 8888, dtype: int64
```

Investigating the results above, the *Population* column appears strange. It indicates several patients with identical numbers of people living within a mile radius; for example, 14 patients have a *Population* value of 195. However, it is possible to have multiple residences with the same number of people within a 1-mile radius. Likewise, the 109 zero values also seem odd, but this could be possible in rural areas. I will leave it to the corporate location lookup to investigate these values further. Besides *Population*, the *Income* and the *Additional_charges* columns also appear to have duplicates despite being floating point values. This seems unlikely to have occurred by chance and warrants further investigation.

First, I want to note that it is possible that the same income for multiple patients was used since it is the income of the primary insurance holder that is entered, and if a family came in, they would all have the same income. With the *Additional_charges*, this too could be possible due to the same services having identical costs. We will pull up these rows to investigate further.

[242]:
```python
# Group the DataFrame by 'Income' and filter groups with more than one row
grouped = data_df.groupby('Income').filter(lambda x: len(x) > 1)

# Sort the grouped DataFrame by 'Income'
grouped = grouped.sort_values('Income')



# Select what columns to examine

cols_to_view =  ['City', 'State',
                'Job', 'Children', 'Age', 'Education',
                 'Employment', 'Income', ]
grouped[cols_to_view]
```

[242]:
```
                City State                             Job  Children   Age  \
3630      Kure Beach    NC                     Tax adviser       3.0  41.0
6786 Running Springs    CA               Designer, graphic       1.0  40.0
3756          Belpre    OH                            Make       NaN  18.0
9954       Charlotte    NC           Merchandiser, retail        NaN   NaN
7982     Perronville    MI            Commissioning editor      10.0  47.0
8014         Mahopac    NY   Garment/textile technologist       0.0  83.0
5247     Idaho Falls    ID  Chartered certified accountant       3.0  68.0
5979           Grant    OK              Magazine journalist       1.0  76.0
2107         Vincent    IA                      Aid worker       8.0   NaN
3965  Fairless Hills    PA            Clinical embryologist       1.0   NaN

                          Education Employment    Income
3630    Some College, Less than 1 Year  Full Time  14572.40
6786         Professional School Degree  Part Time  14572.40
```

```
3756                         Associate's Degree   Full Time  20474.03
9954  Some College, 1 or More Years, No Degree     Student  20474.03
7982                     No Schooling Completed   Full Time  26915.85
8014             GED or Alternative Credential  Unemployed  26915.85
5247               Nursery School to 8th Grade   Part Time  37132.97
5979                          Bachelor's Degree     Retired  37132.97
2107                          Bachelor's Degree   Full Time  55506.92
3965                          Bachelor's Degree   Full Time  55506.92
```

Investigating the above for *Income*, there does not appear to be any similarities between the other values for the duplicated income values. Without further information, this leads to the conclusion that these values are similar because the incomes are the same for the patients.

Let's next look at the *Additional_charges* column.

[243]:
```python
# Group the DataFrame by 'Additional_charges'
# Filter groups with more than one row
grouped = data_df.groupby('Additional_charges').filter(lambda x: len(x) > 1)

# Drop rows with missing values in 'Additional_charges'
grouped = grouped.dropna(subset=['Additional_charges'])

# Sort the grouped DataFrame by 'Additional_charges'
grouped = grouped.sort_values('Additional_charges')

# Select columns to view
cols_to_view =  ['ReAdmis', 'VitD_levels', 'Doc_visits', 'Full_meals_eaten',
       'VitD_supp', 'Soft_drink', 'Initial_admin', 'HighBlood',
       'Complication_risk',  'Diabetes',
       'Hyperlipidemia', 'BackPain', 'Anxiety', 'Allergic_rhinitis',
       'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',
       'TotalCharge', 'Additional_charges',]
# Print the grouped DataFrame with headers
grouped[cols_to_view]
```

[243]:
```
     ReAdmis  VitD_levels  Doc_visits  Full_meals_eaten  VitD_supp Soft_drink  \
2415      No    13.885272           6                 1          0         No
1478      No    18.616349           6                 2          0         No
3515      No    16.820644           6                 1          1         No
4232      No    15.516329           6                 2          1        NaN
478       No    22.002974           4                 2          0         No
…       …          …         …                 …        …         …
5591      No    20.788480           6                 1          0         No
21        No    19.968337           6                 2          2         No
6939     Yes    51.216965           4                 0          2         No
2785      No    17.929633           6                 1          0         No
3654      No    16.138054           7                 2          0        NaN
```

```
               Initial_admin HighBlood Complication_risk Diabetes  \
2415  Observation Admission        No               Low       No
1478  Observation Admission        No               Low       No
3515  Observation Admission        No               Low       No
4232  Observation Admission        No               Low       No
478   Observation Admission        No               Low       No
…                      …       …                …      …
5591  Observation Admission       Yes              High       No
21      Emergency Admission       Yes              High       No
6939    Emergency Admission       Yes              High       No
2785    Emergency Admission       Yes              High      Yes
3654    Emergency Admission       Yes              High      Yes

     Hyperlipidemia BackPain  Anxiety Allergic_rhinitis Reflux_esophagitis  \
2415             No      Yes      0.0                No                 No
1478            Yes       No      1.0                No                Yes
3515             No      Yes      NaN                No                 No
4232            Yes       No      1.0                No                 No
478              No       No      1.0                No                 No
…             …      …      …                 …                …
5591             No       No      1.0               Yes                 No
21               No       No      0.0                No                Yes
6939            Yes       No      1.0               Yes                 No
2785            Yes      Yes      1.0                No                 No
3654            Yes       No      1.0               Yes                Yes

     Asthma     Services  Initial_days   TotalCharge  Additional_charges
2415     No   Blood Work           NaN   3103.259193         3132.259990
1478     No  Intravenous      8.625293   2376.546409         3132.259990
3515     No   Blood Work           NaN   3041.617173         3139.049369
4232    Yes   Blood Work      5.992014   3120.725616         3139.049369
478      No  Intravenous      6.271732   2577.008347         3241.339760
…       …          …           …           …                 …
5591     No   Blood Work     56.411105   7716.801405        28783.690590
21       No   Blood Work      7.094503   3772.156911        28788.080310
6939    Yes   Blood Work     64.315721  19931.182170        28788.080310
2785     No   Blood Work      1.929441   2888.314977        29527.827700
3654    Yes  Intravenous      2.890621   3362.456590        29527.827700

[2079 rows x 20 columns]
```

There are many entries with duplicate additional charges. Because these values may be standard prices for services offered, I need additional information to conclude that these values are to be expected to be duplicated.

So overall, my plan for handling the duplicates in the data is to retain them, as, without further information, they are not causing any data quality issues.

4.1.3 Missing values

Determining if there is a pattern in the missing values

[244]:
```
# Begin by looking at the NA values
data_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 10000 entries, 1 to 10000
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  object
 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   object
 27  Initial_admin       10000 non-null  object
 28  HighBlood           10000 non-null  object
 29  Stroke              10000 non-null  object
 30  Complication_risk   10000 non-null  object
 31  Overweight          9018 non-null   float64
 32  Arthritis           10000 non-null  object
 33  Diabetes            10000 non-null  object
 34  Hyperlipidemia      10000 non-null  object
 35  BackPain            10000 non-null  object
 36  Anxiety             9016 non-null   float64
```

```
 37  Allergic_rhinitis   10000 non-null  object
 38  Reflux_esophagitis  10000 non-null  object
 39  Asthma              10000 non-null  object
 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(11), int64(14), object(27)
memory usage: 4.0+ MB
```

There appear to be critical columns with NA values.

1. Children
2. Age
3. Income
4. Soft_drink
5. Overweight
6. Anxiety
7. Initial_days

Are these in the same row? Is there some pattern to these values? I think we should find out.

[245]:
```
# Istall a plotting style package that produces nice plots
!pip install scienceplots
```

```
Requirement already satisfied: scienceplots in /usr/local/lib/python3.10/dist-
packages (2.1.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-
packages (from scienceplots) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->scienceplots) (1.2.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-
packages (from matplotlib->scienceplots) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->scienceplots) (4.53.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->scienceplots) (1.4.5)
Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.10/dist-
packages (from matplotlib->scienceplots) (1.25.2)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->scienceplots) (24.1)
```

```
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-
packages (from matplotlib->scienceplots) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->scienceplots) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->scienceplots) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.7->matplotlib->scienceplots) (1.16.0)
```

[246]:
```
import matplotlib.pyplot as plt
import scienceplots
plt.style.use(['science','notebook'])
```

[247]:
```
# Visualize how NAs look across the rows
na_cols =␣
 ↪['Children','Age','Income','Soft_drink','Overweight','Anxiety','Initial_days']
data_df[na_cols].isna().sum(axis=1).plot(
    title ='Number of missing values across the rows of the data file',
    style='.', color='red',ylabel='Number of NAs',xlabel='row number');
```

From the above plot, it appears that in the default order of the rows, there is no pattern in the NA values. However, we may see a pattern if sorted by some other value.

Let's sort the data frame by the columns and see if some pattern in the NA values appears.

[248]:
```
import numpy as np

# Select all the non NA columns
non_na_cols = [col for col in data_df.columns if not data_df[col].isna().any()]

# Determine the layout of the subplots
num_cols = 6
num_rows = np.ceil(len(non_na_cols) / num_cols)

# Create a figure and a grid of subplots
fig, axs = plt.subplots(
    int(num_rows),
    num_cols,
    figsize=(num_cols*5, num_rows*5),sharex=True,sharey=True)

# Flatten the array of axes
axs = axs.flatten()

# Plot each column in a subplot
for i, col in enumerate(non_na_cols):
    axs[i].plot(
        data_df.sort_values(col).isna().sum(axis=1).values,
        marker='.', linewidth=0)
    axs[i].set_title(col,fontsize=25)

# Remove unused subplots
for ax in axs[len(non_na_cols):]:
    ax.remove()

plt.tight_layout()
plt.show()
```

Investigating the results of the non-NA plots, we found that there does not appear to be any pattern in the NA values, leading us to conclude that these errors are random.

Based on the above results, imputation methods should be used to elminate these missing values.

Determining if columns or rows need to be dropped Before considering data-imputation techniques for handling missing data, let's examine the missing data to determine if any columns or rows should be dropped from the data set.

[249]:
```
# Calculate the percentage of missing values for each column
missing_percentage_cols = (
    (data_df.isnull().sum() / len(data_df)) * 100
    # Sorted from high to low, selecting the top 8 columns
    ).sort_values(ascending=False)[:8]

print("Percentage of missing values per column:\n", missing_percentage_cols)

# Calculate the percentage of missing values for each row
missing_percentage_rows = (
    # Select only those rows with 1 or more NaN
    data_df.isnull().sum(axis=1)>=1
    ).sum()/len(data_df) * 100
print(
    f"\nPercentage of rows with a missing value: {missing_percentage_rows:.2f}%"
    )
```

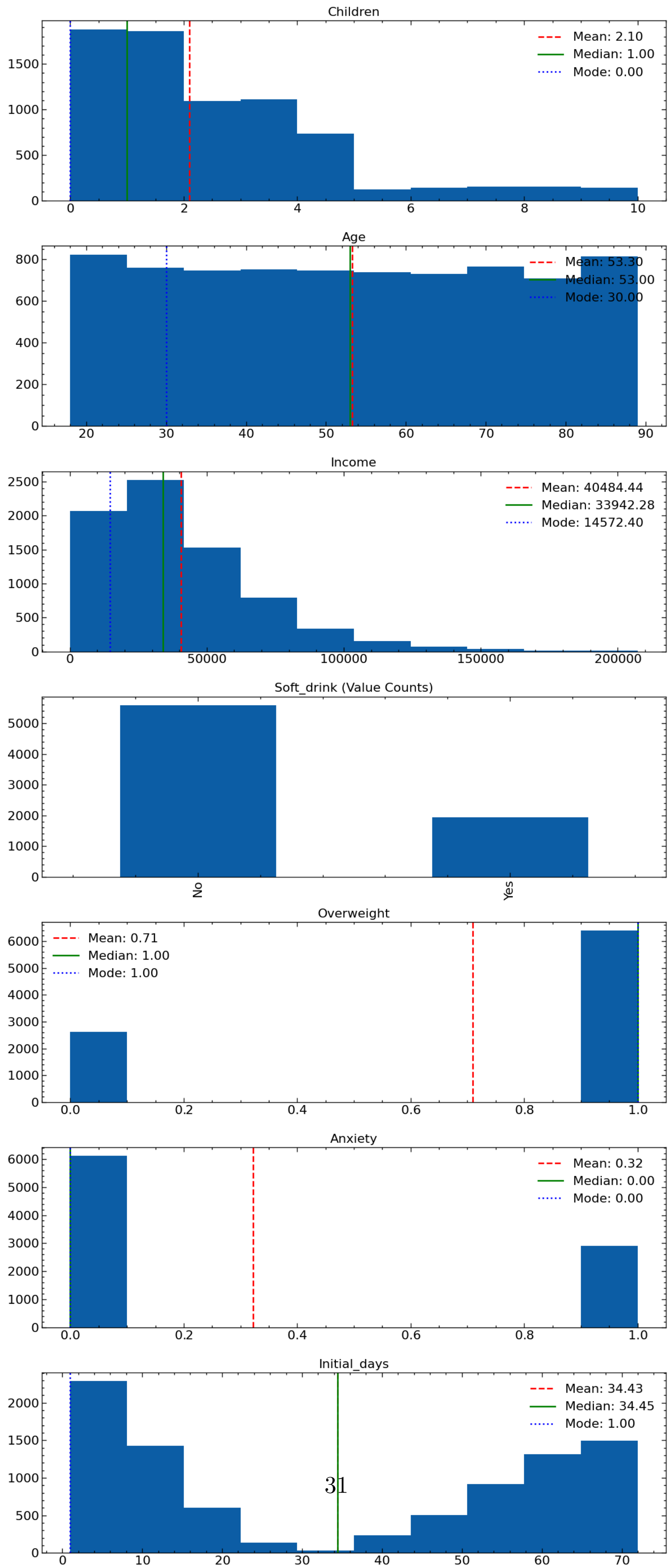
```
Percentage of missing values per column:
 Children             25.88
Soft_drink          24.67
Income              24.64
Age                 24.14
Initial_days        10.56
Anxiety              9.84
Overweight           9.82
Complication_risk    0.00
dtype: float64

Percentage of rows with a missing value: 76.87%
```

Based on the results above, none of the columns meet the 60% missing data threshold to be dropped. Also, a significant amount of rows contain missing values, failing to meet the threshold of 5% or less of rows containing missing values necessary for consideration of deleting rows with missing values. What this means is that we have a majority of our rows containing missing values while at the same time having columns with many non-missing values. So we need to determine some way to fill in these missing values, since deletion is not an option, as this would leave us with no data to answer our research question.

Determining data imputation method Next, let's review the distribution for each column with NA values and identify what approach we might take for each column for data imputation.

[250]:

```
# Create a figure and a grid of subplots
na_cols =␣
↪['Children','Age','Income','Soft_drink','Overweight','Anxiety','Initial_days']
fig, axs = plt.subplots(7, 1, figsize=(12, 28))
axs = axs.flatten()

# Iterate over columns with NA values
for i, col in enumerate(na_cols):
    ax = axs[i]

    # Handle different data types
    if data_df[col].dtype == 'object':
        # For string columns, plot value counts
        data_df[col].value_counts().plot(kind='bar', ax=ax,xlabel='')
        ax.set_title(f"{col} (Value Counts)")
    else:
        # For numeric columns, plot histogram
        data_df[col].hist(ax=ax, grid=False)
        ax.set_title(col)

        # Calculate and display mean, median, and mode
        mean = data_df[col].mean()
        median = data_df[col].median()
        mode = data_df[col].mode()[0]  # Mode might return multiple values,␣
↪take the first
        ax.axvline(mean, color='r', linestyle='--', label=f"Mean: {mean:.2f}")
        ax.axvline(median, color='g', linestyle='-', label=f"Median: {median:.
↪2f}")
        ax.axvline(mode, color='b', linestyle=':', label=f"Mode: {mode:.2f}")
        ax.legend()


plt.tight_layout()
```


Children
Mean: 2.10
Median: 1.00
Mode: 0.00
0
500
1000
1500
0
2
4
6
8
10
Age
Mean: 53.30
Median: 53.00
Mode: 30.00
0
200
400
600
800
20
30
40
50
60
70
80
90
Income
Mean: 40484.44
Median: 33942.28
Mode: 14572.40
0
500
1000
1500
2000
2500
0
50000
100000
150000
200000
Soft_drink (Value Counts)
0
1000
2000
3000
4000
5000
No
Yes
Overweight
Mean: 0.71
Median: 1.00
Mode: 1.00
0
1000
2000
3000
4000
5000
6000
0.0
0.2
0.4
0.6
0.8
1.0
Anxiety
Mean: 0.32
Median: 0.00
Mode: 0.00
0
1000
2000
3000
4000
5000
6000
0.0
0.2
0.4
0.6
0.8
1.0
Initial_days
Mean: 34.43
Median: 34.45
Mode: 1.00
0
500
1000
1500
2000
0
10
20
30
40
50
60
70

From the above charts, we see several distributions for each column with missing values. *Children* and *Age* both appear right-skewed, so using the median as a univariate method for imputation would be more appropriate in this case. *Intial_days*, on the other hand, appears to have a bimodal distribution, but this data is comprised of float values, and thus, pandas can not find a single mode value as all values in the column are different. To handle this column as well as the binary columns, *Soft_drink*, *Overweight*, and *Anxiety*, we will need to find some other method that fills in the missing values without introducing information that is not meant to be there. We also have a uniform distribution in the *Age* column. We could use univariate methods for all of these columns, but this may distort the distribution for each column and ignore the relationships between the other variables in any row. For example, say there is a solid positive relationship between *Age* and the *Education* column; if we utilize the mean for the *Age* column, we may distort that relationship. Therefore, we would like to use some more sophisticated imputation method that attempts to account for these inter-variable relationships. For this reason I will use Multiple Imputation methods.

4.1.4 Outliers

The first thing we will do to detect outliers is to examine Z-scores for each column.

[251]:
```
quan_cols = ['CaseOrder', 'Population',
             'Children', 'Age',
             'Income',  'VitD_levels',
             'Doc_visits', 'Full_meals_eaten',
             'VitD_supp', 'Initial_days',
             'TotalCharge', 'Additional_charges',
             'Item1', 'Item2',
             'Item3', 'Item4',
             'Item5', 'Item6',
             'Item7', 'Item8']

# Calculate z-scores for quantitative columns
data_quan_df = data_df[quan_cols]

data_z_scores = (
    data_quan_df - data_quan_df.mean(numeric_only=True
                                     )) / data_quan_df.std(numeric_only=True)

# Identify outliers
outlier_z_df = data_z_scores.abs() > 3

# Print outliers for each column
outliers = data_quan_df[outlier_z_df].dropna(how='all').dropna(how='all',axis=1)
outliers
```

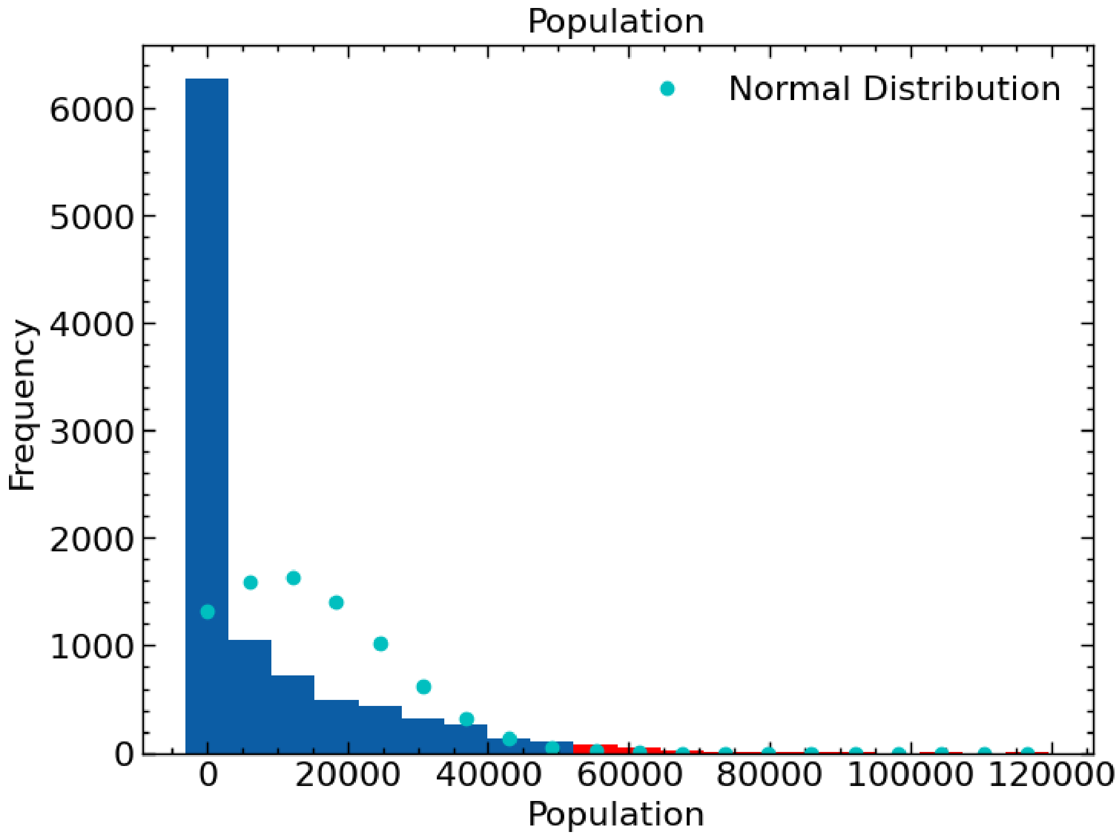
[251]:
```
      Population  Children     Income  VitD_levels  Doc_visits  \
12           NaN       NaN        NaN    47.813476         NaN
```

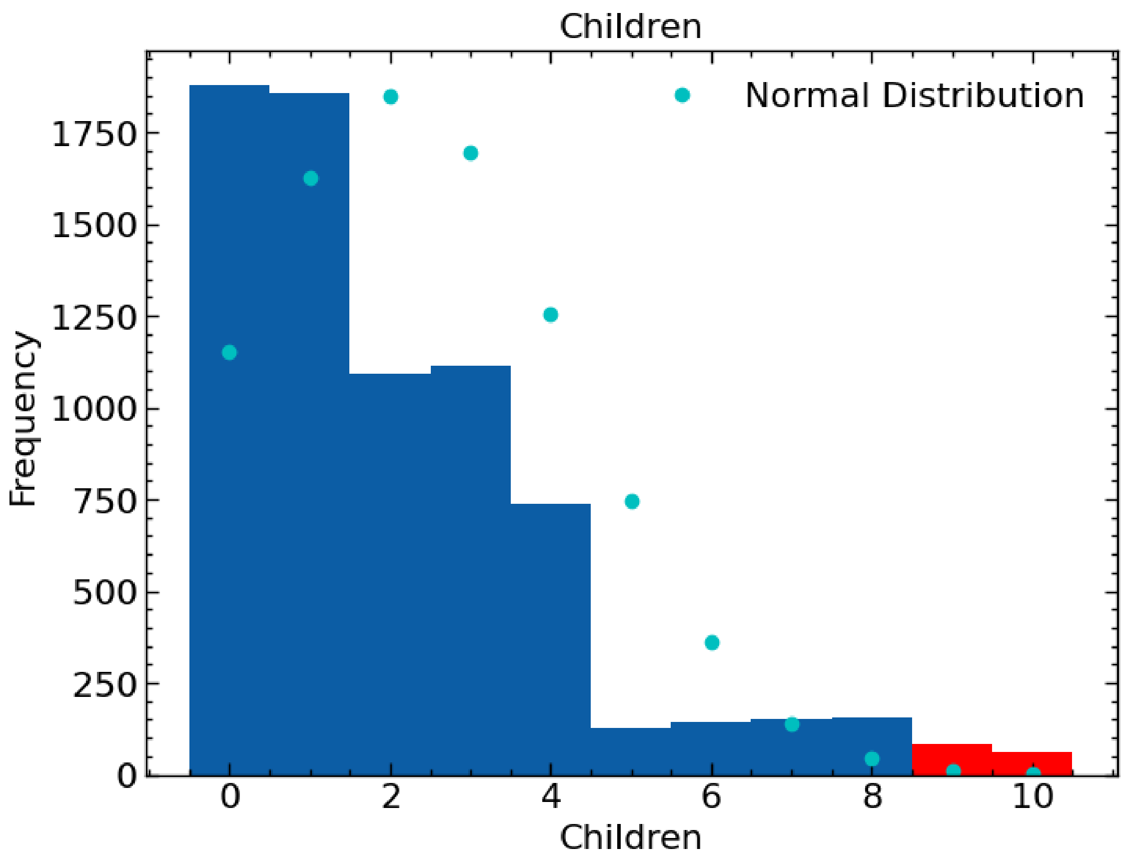
```
17            NaN      10.0         NaN          NaN          NaN
31            NaN       NaN   167105.10          NaN          NaN
59            NaN       NaN   132963.95          NaN          NaN
63            NaN       NaN         NaN          NaN          NaN
…          …       …        …          …         …
9930          NaN       NaN         NaN    44.494793          NaN
9934          NaN       NaN         NaN    45.440725          NaN
9974          NaN       NaN         NaN    47.439599          NaN
9983          NaN       NaN         NaN          NaN          NaN
9987          NaN       NaN         NaN          NaN          NaN

      Full_meals_eaten  VitD_supp  TotalCharge  Item1  Item2  Item3  Item4  \
12                 NaN        NaN          NaN    NaN    NaN    NaN    NaN
17                 NaN        NaN          NaN    NaN    NaN    NaN    NaN
31                 NaN        NaN          NaN    NaN    NaN    NaN    NaN
59                 NaN        NaN          NaN    NaN    NaN    NaN    NaN
63                 NaN        3.0          NaN    NaN    NaN    NaN    NaN
…                 …        …          …    …    …    …    …
9930               NaN        NaN  18847.70517    NaN    NaN    NaN    NaN
9934               NaN        NaN  19409.18352    NaN    NaN    NaN    NaN
9974               NaN        NaN  18579.48149    NaN    NaN    NaN    NaN
9983               NaN        3.0          NaN    NaN    NaN    NaN    NaN
9987               6.0        NaN          NaN    NaN    NaN    NaN    NaN

      Item5  Item6  Item7  Item8
12      NaN    NaN    NaN    NaN
17      NaN    NaN    NaN    NaN
31      NaN    NaN    NaN    NaN
59      NaN    NaN    NaN    NaN
63      NaN    NaN    NaN    NaN
…     …    …    …    …
9930    NaN    NaN    NaN    NaN
9934    NaN    NaN    NaN    NaN
9974    NaN    NaN    NaN    NaN
9983    NaN    NaN    NaN    NaN
9987    NaN    NaN    NaN    NaN

[1108 rows x 16 columns]
```

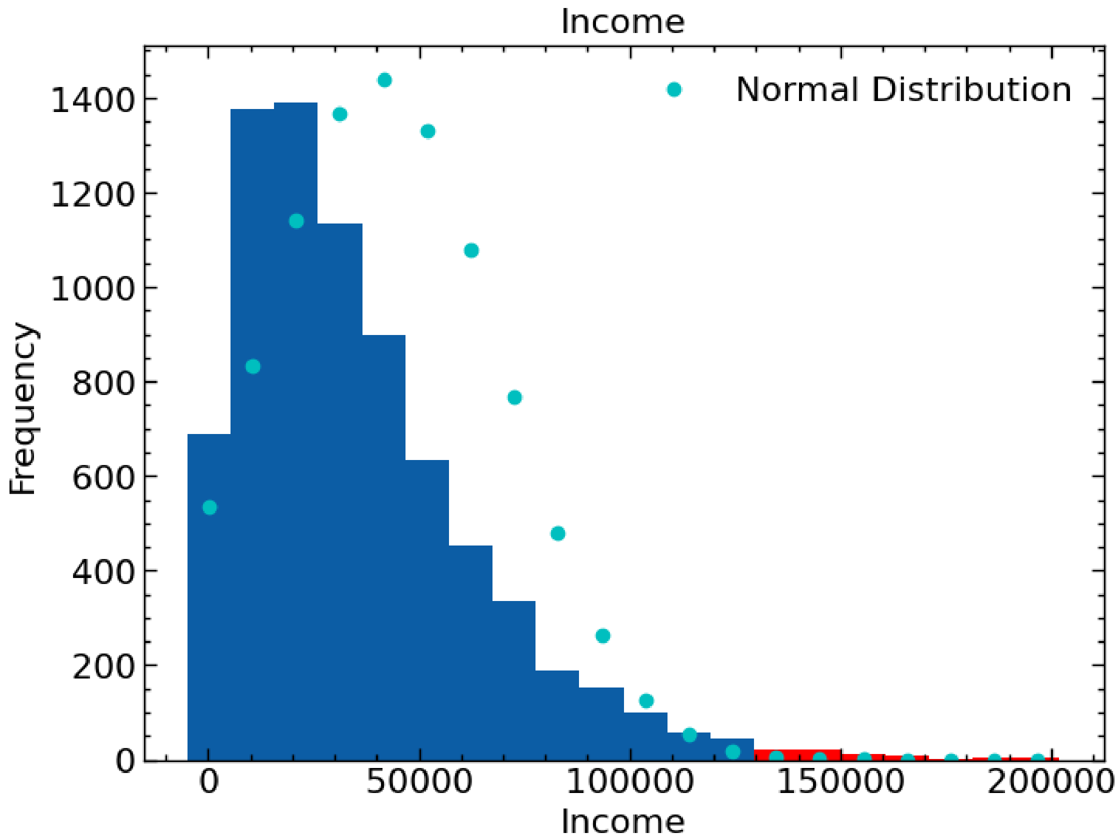
It would also help to visualize the outliers.

[252]:
```python
import scipy.stats as stats

# Plot histograms for columns with outliers, highlighting outlier bins
for col in outliers.columns:
    data = data_quan_df[col]
```

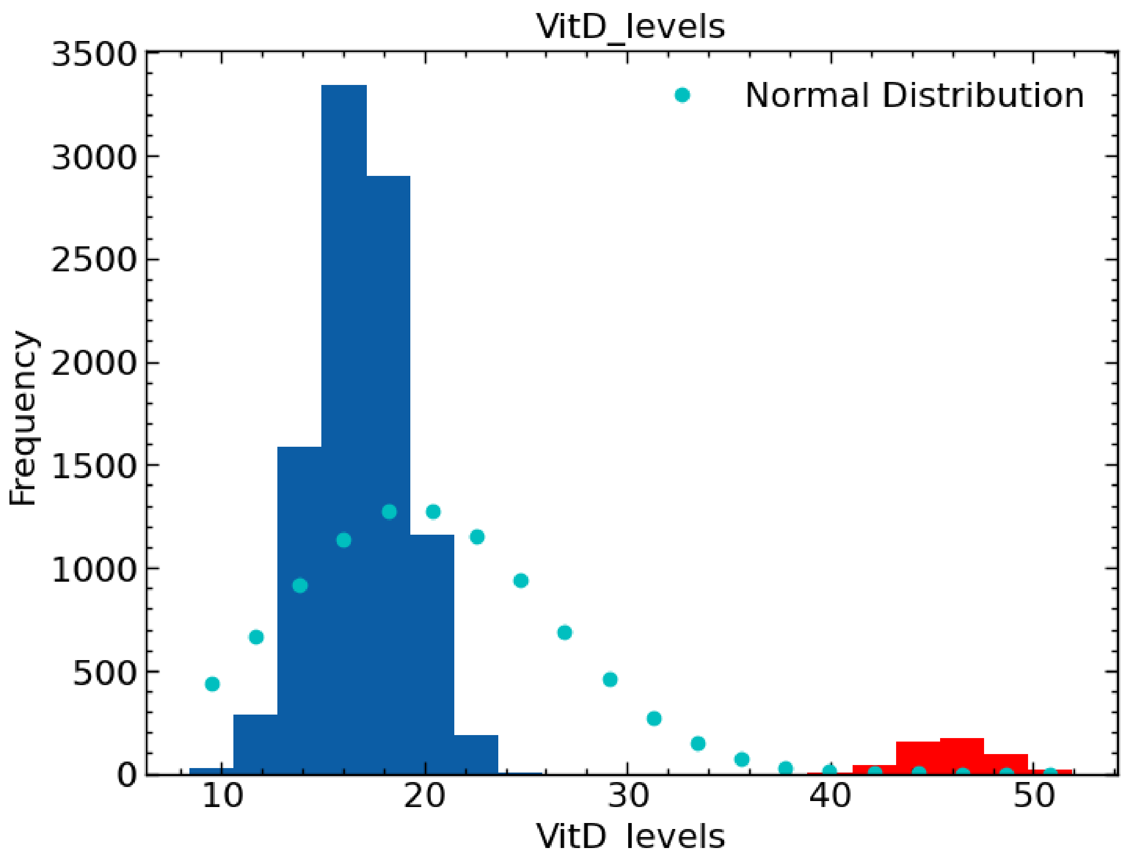
```
# Determine the number of unique values in the column
unique_values = data.nunique()

# Define bin edges
# Use 20 bins for columns with more than 20 unique values
if unique_values > 20:
    bins = 20
else:  # Use bins of width 1 for columns with 20 or fewer unique values
    # + 2 for range to include the rightmost edge
    bins = np.arange(data.min(), data.max() + 2 )

fig, ax = plt.subplots()
_, bins, patches = ax.hist(data, bins=bins, align='left')

# Calculate mean and standard deviation
mean = data.mean()
std_dev = data.std()

# Identify outlier bins
outlier_bins = np.where(np.abs((bins[:-1] - mean) / std_dev) > 3)[0]
#select all but the last bin since bins is greater than patches by 1

# Color outlier bins differently
for i in outlier_bins:
    patches[i].set_facecolor('red')

# Calculate the values of the normal distribution
p = stats.norm.pdf(bins[:-1], mean, std_dev)
#scale the distribution to match the bin width
p *= data.size * np.diff(bins)

# Plot the values of the normal distribution
ax.plot(bins[:-1],
                 p, 'co', label='Normal Distribution')

ax.legend()
ax.set_title(f'{col}')
ax.set_xlabel(col)
ax.set_ylabel('Frequency')
plt.show()
```

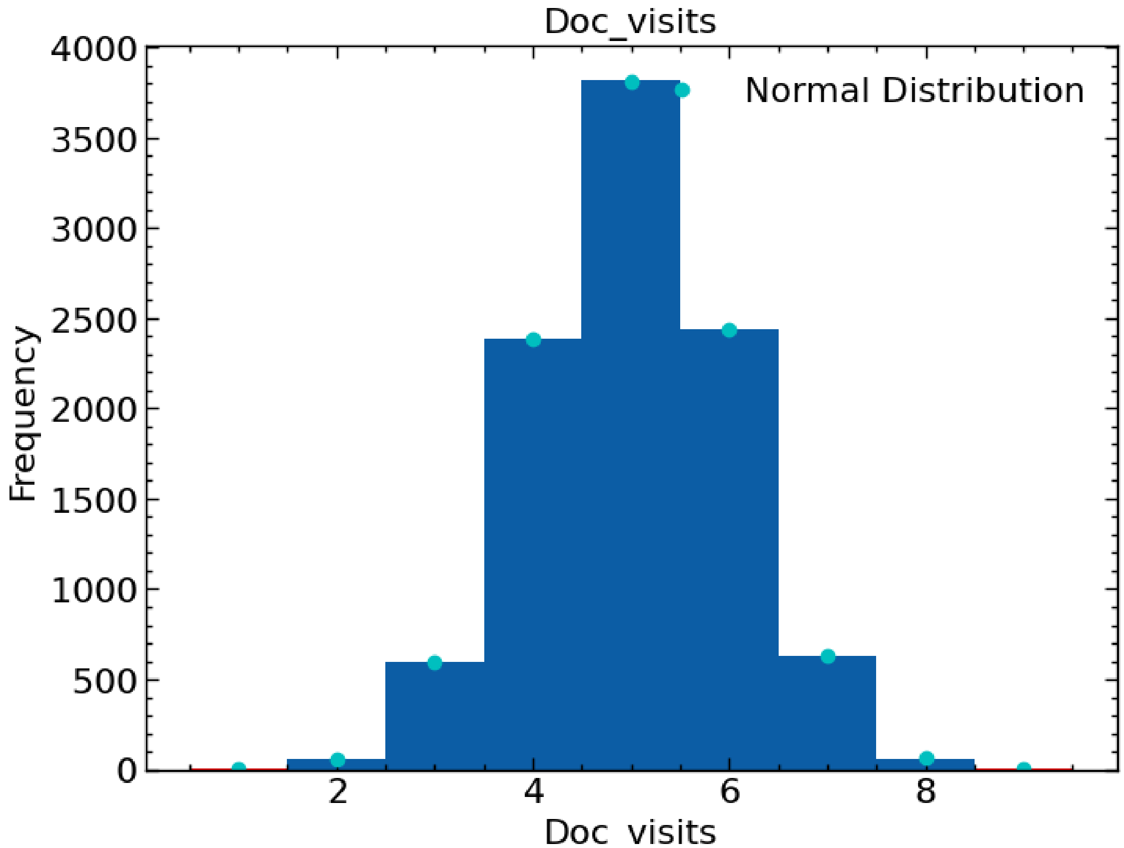

Population
Normal Distribution
6000
5000
4000
3000
2000
1000
0
Frequency
0
20000
40000
60000
80000
100000
120000
Population

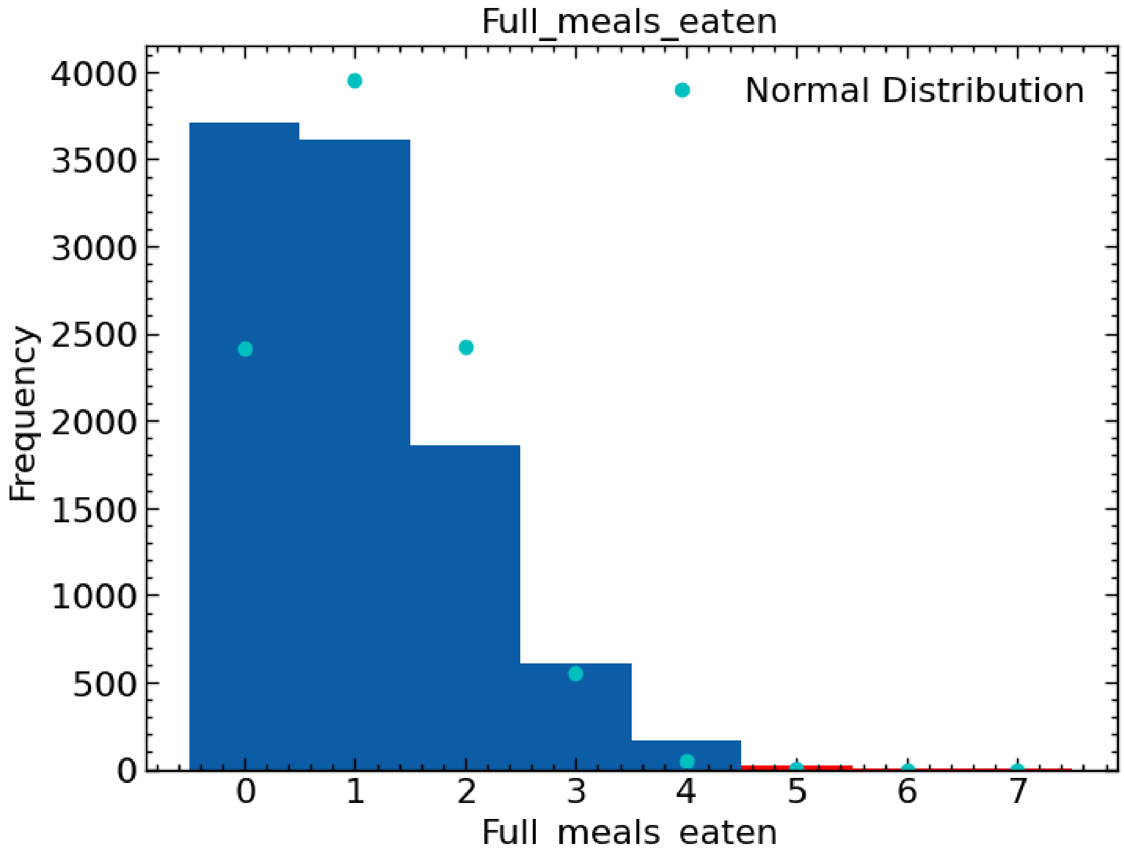

Children
Normal Distribution
1750
1500
1250
1000
750
500
250
0
Frequency
0
2
4
6
8
10
Children

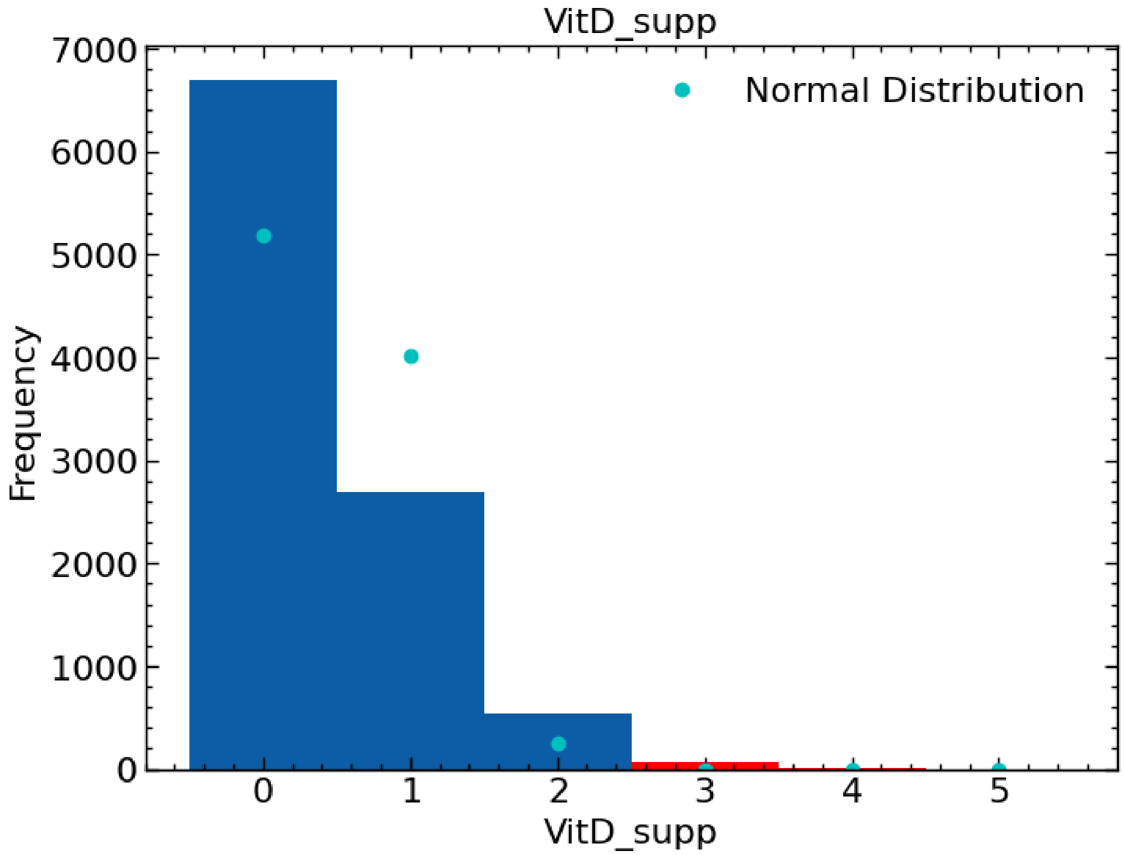


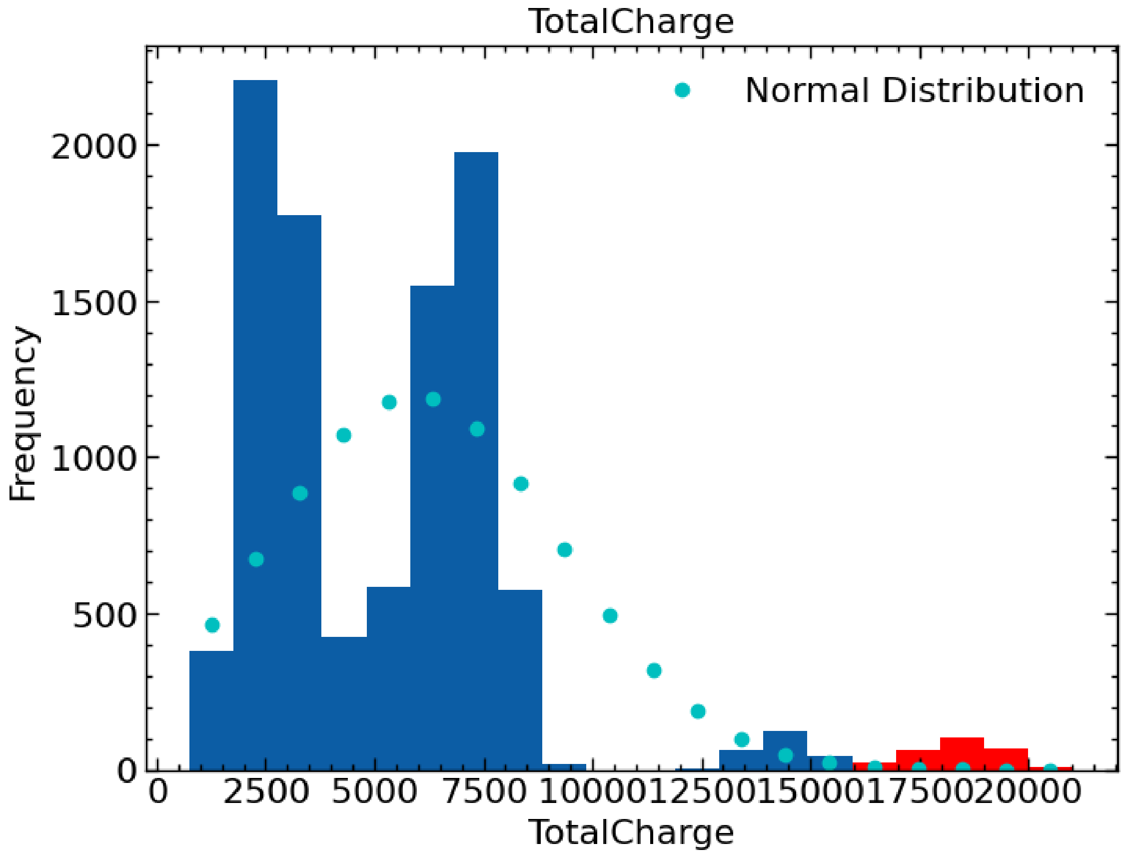
Income
Normal Distribution
1400
1200
1000
800
600
400
200
0
Frequency
0
50000
100000
150000
200000
Income

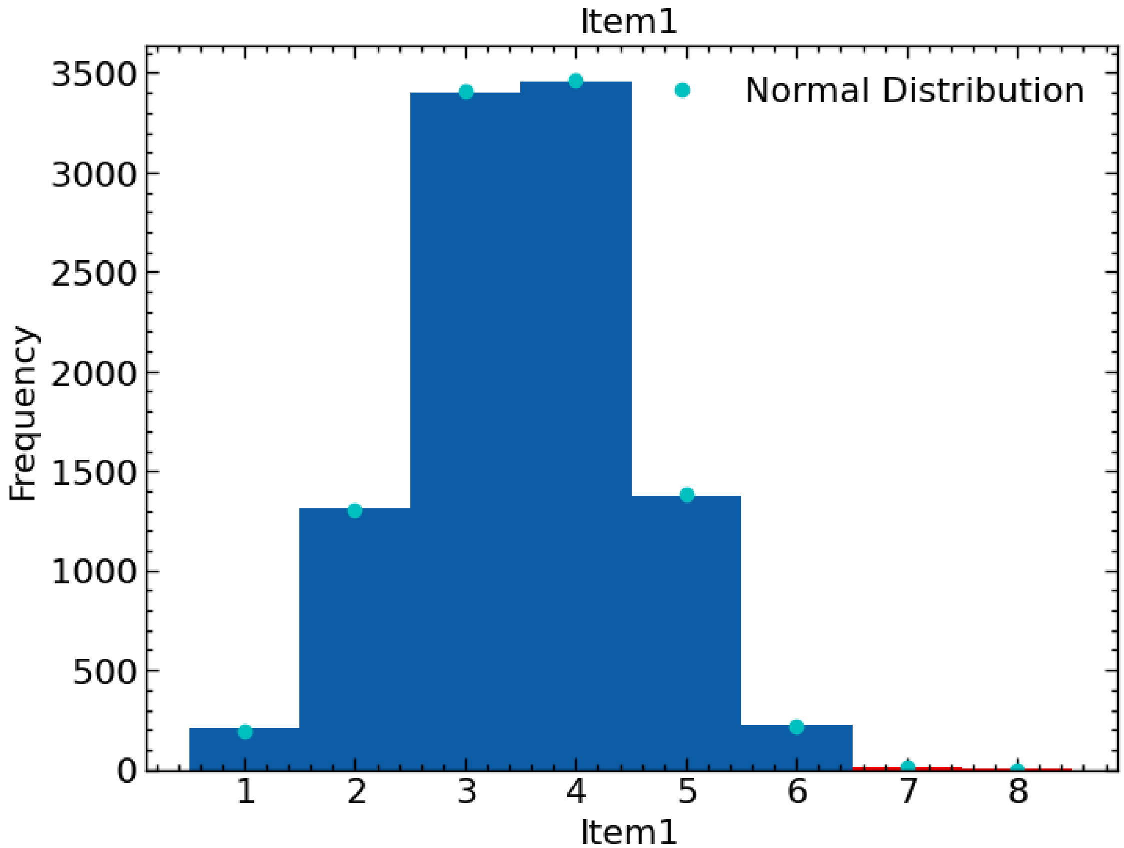

VitD_levels
Normal Distribution
3500
3000
2500
2000
1500
1000
500
0
Frequency
10
20
30
40
50
VitD_levels

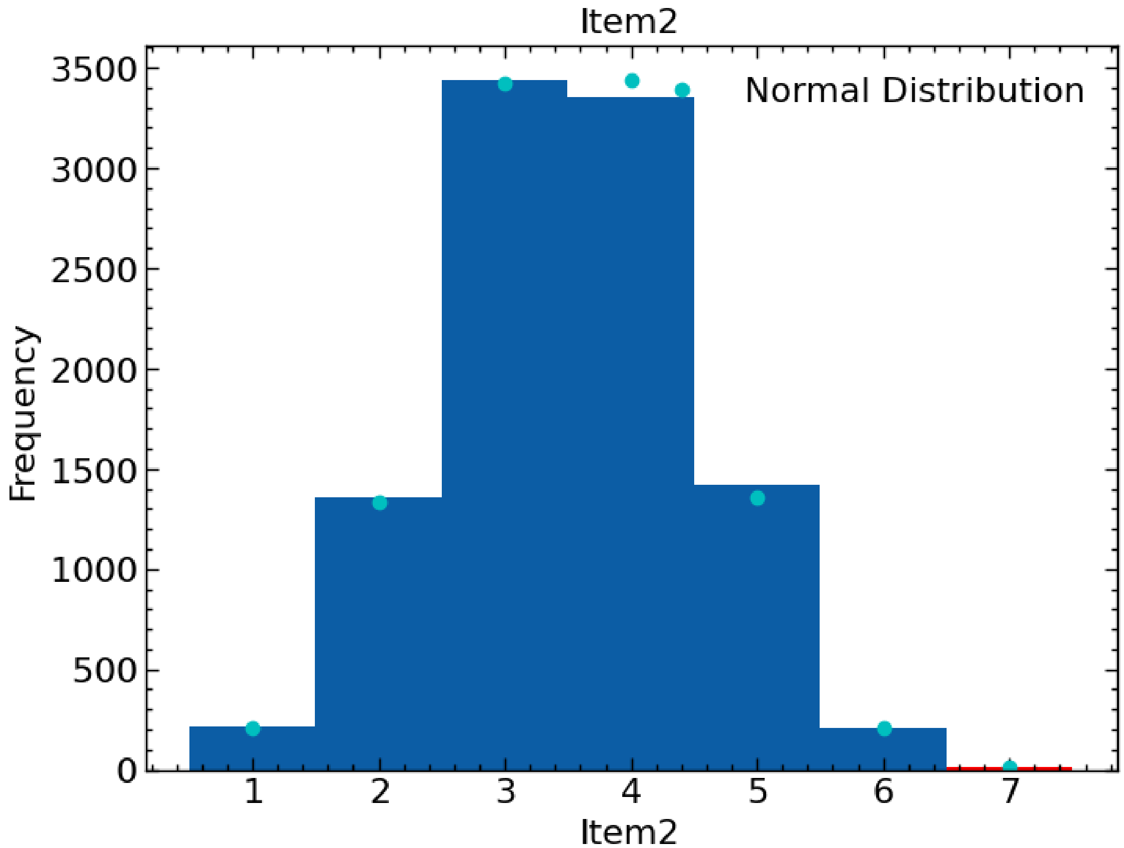

Doc_visits
Normal Distribution
Frequency
4000
3500
3000
2500
2000
1500
1000
500
0
2
4
6
8
Doc_visits


Full_meals_eaten
Normal Distribution
Frequency
4000
3500
3000
2500
2000
1500
1000
500
0
0
1
2
3
4
5
6
7
Full_meals_eaten

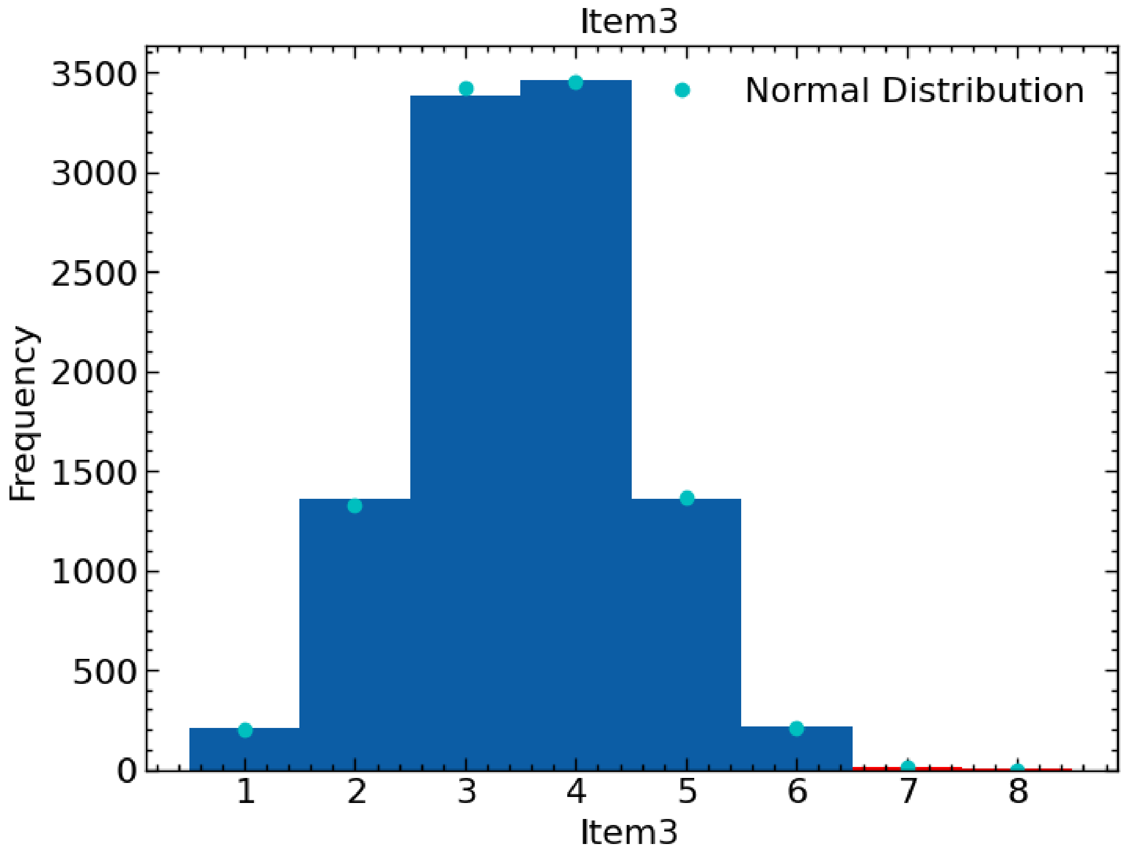

VitD_supp
Normal Distribution
Frequency
7000
6000
5000
4000
3000
2000
1000
0
0
1
2
3
4
5
VitD_supp

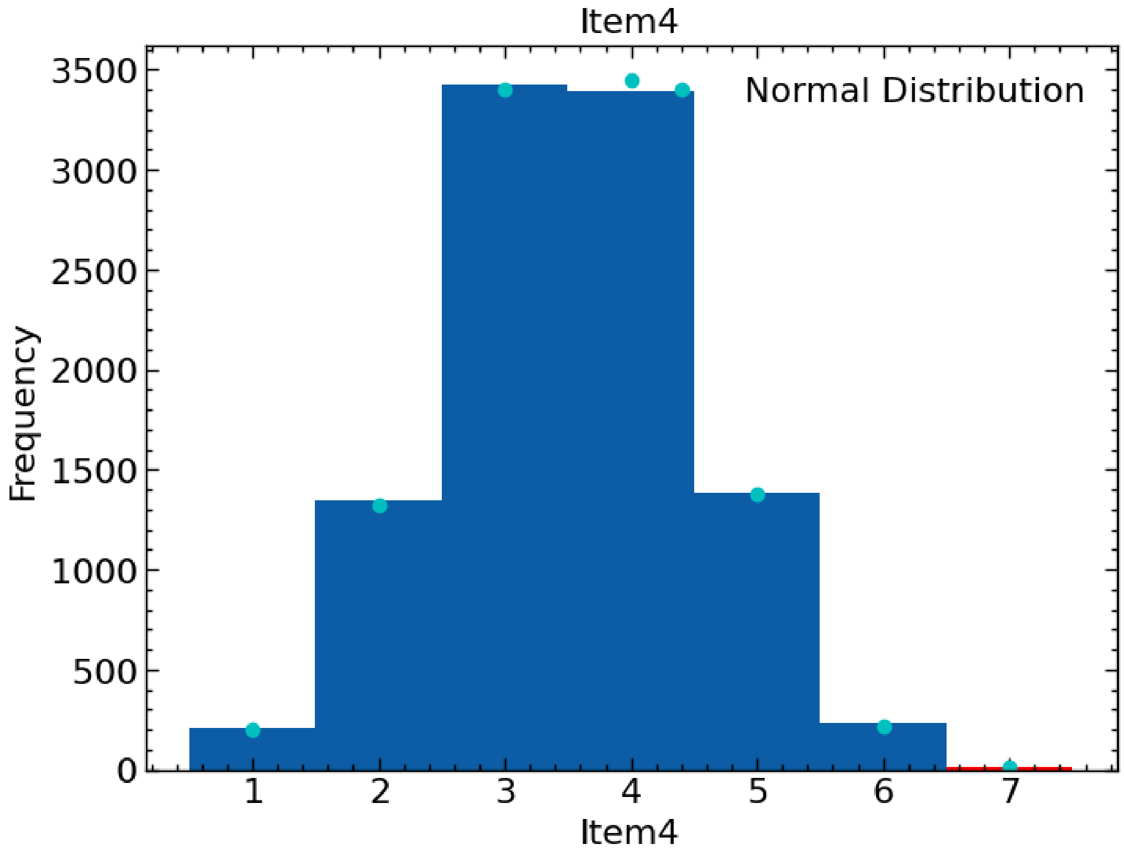

TotalCharge
Normal Distribution
2000
1500
1000
500
0
Frequency
0
2500
5000
7500
10000
12500
15000
17500
20000
TotalCharge

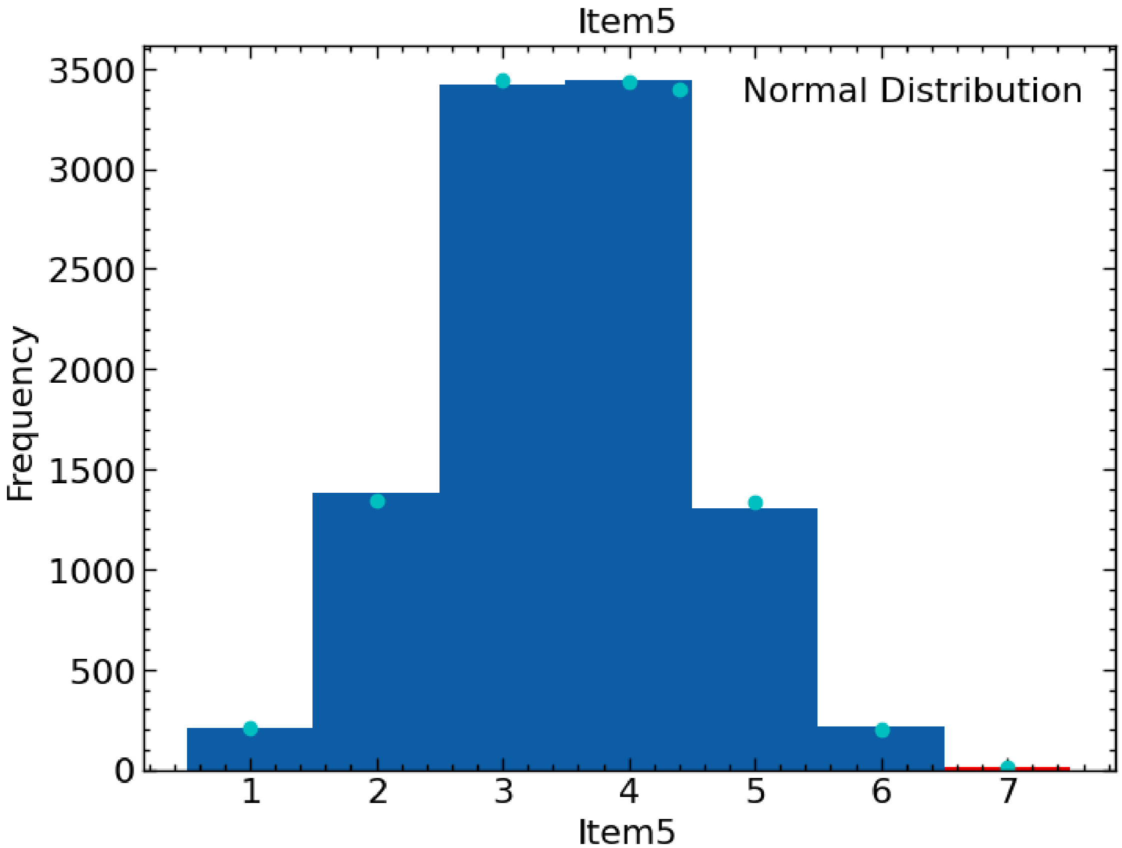

Item1
Normal Distribution
Frequency
0
500
1000
1500
2000
2500
3000
3500
1
2
3
4
5
6
7
8
Item1

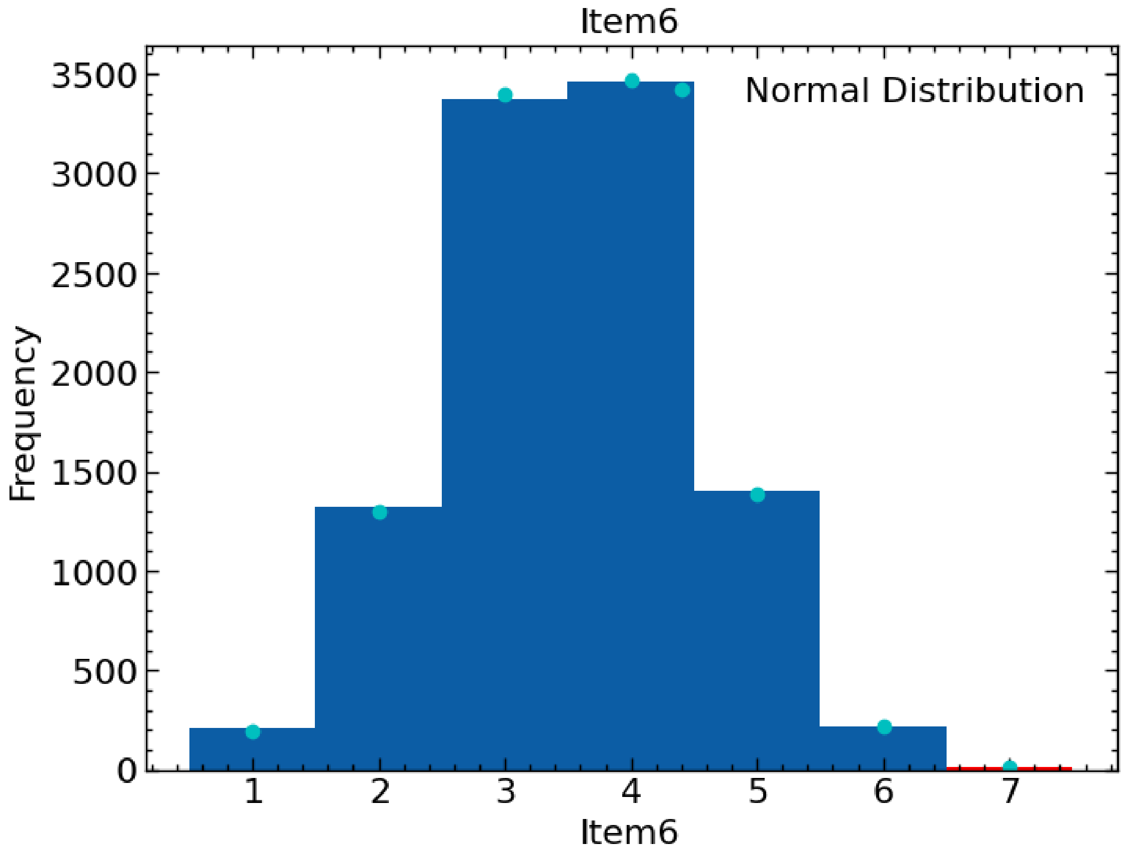


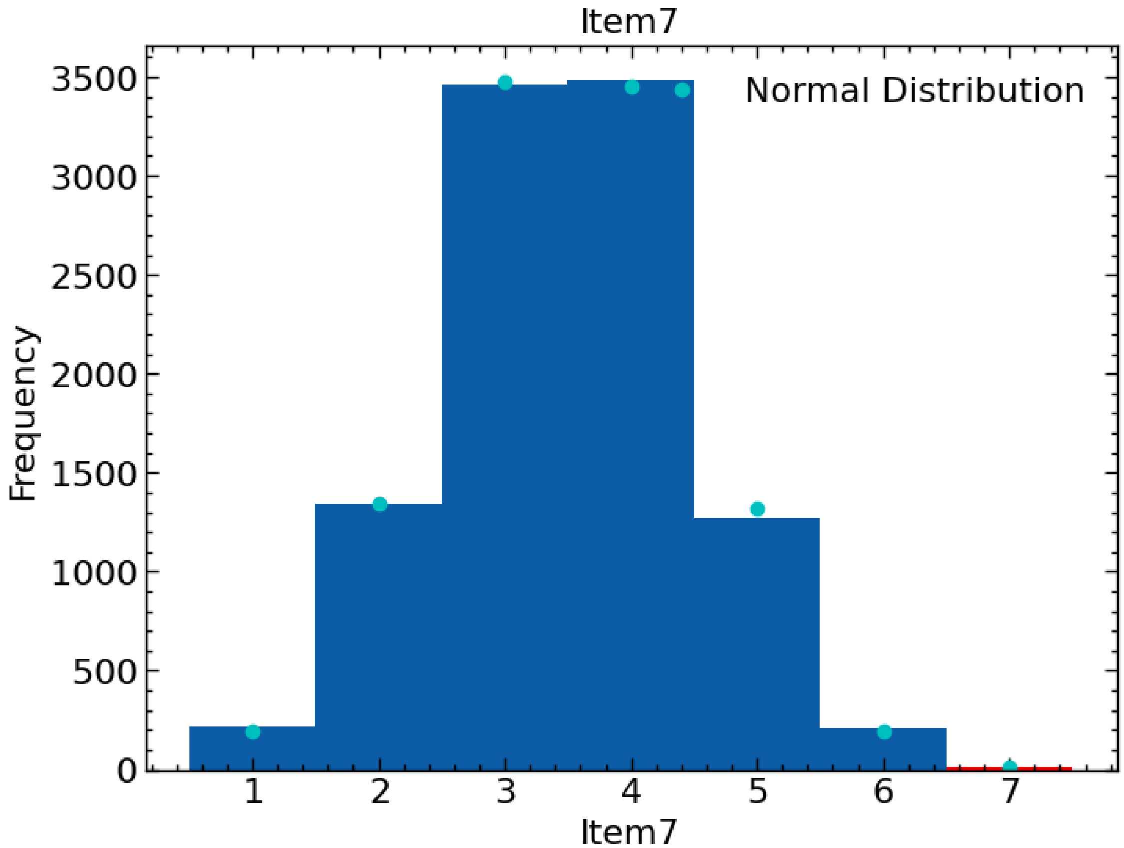
Item2
Normal Distribution
Frequency
0
500
1000
1500
2000
2500
3000
3500
1
2
3
4
5
6
7
Item2

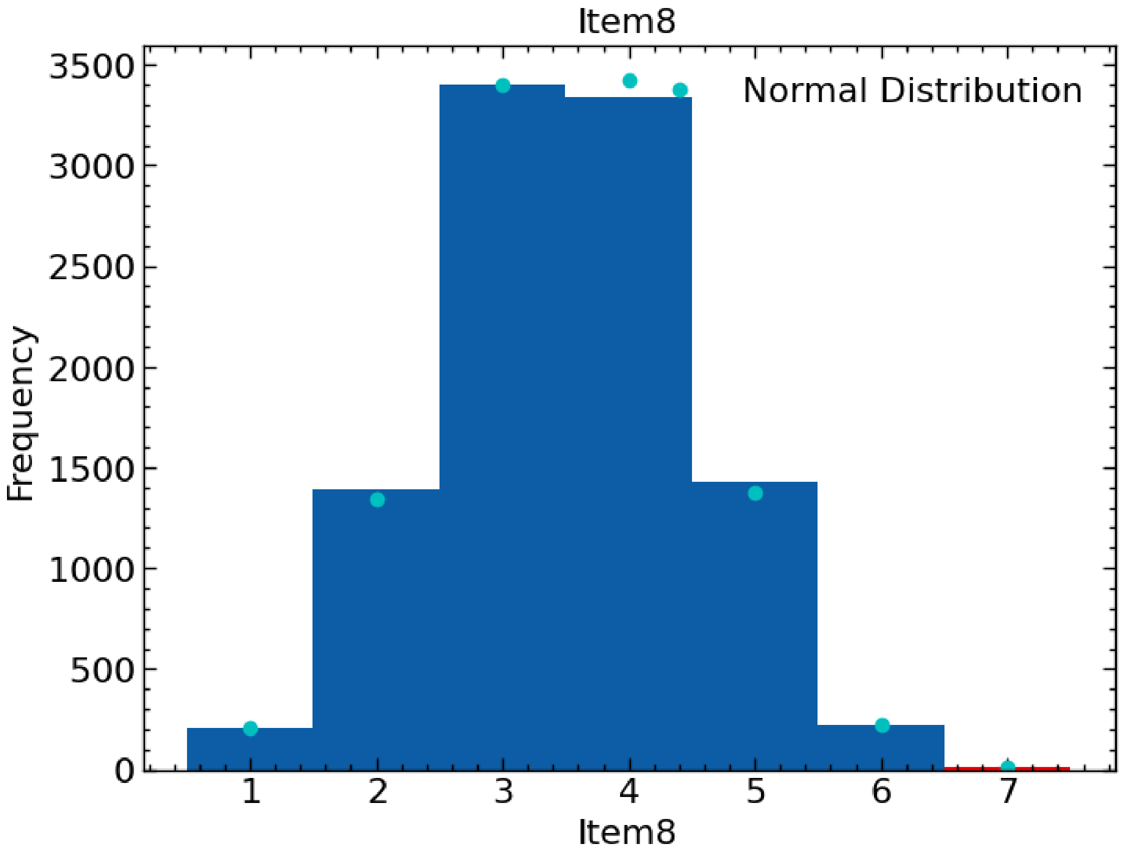

Item3
Frequency
3500
3000
2500
2000
1500
1000
500
0
Normal Distribution
1
2
3
4
5
6
7
8
Item3


Item4
Normal Distribution
Frequency
3500
3000
2500
2000
1500
1000
500
0
1
2
3
4
5
6
7
Item4


Item5
Normal Distribution
Frequency
0
500
1000
1500
2000
2500
3000
3500
1
2
3
4
5
6
7
Item5


Item6
Normal Distribution
Frequency
3500
3000
2500
2000
1500
1000
500
0
1
2
3
4
5
6
7
Item6


Item7
Normal Distribution
Frequency
3500
3000
2500
2000
1500
1000
500
0
1
2
3
4
5
6
7
Item7



From the above plots, it's evident that some points tagged as outliers are genuinely part of the data. They appear infrequently and in quantities that align with what we expect for rare values. This can be seen from the overlaid normal distributions, which provide a sense of what values we would expect if the distribution was normal. However, it's important to note that not all these distributions are normal, highlighting a key limitation of the Z-score method.

By combining the Z-score method and the histogram, we can refine our results more effectively. Both *VitD_levels* and *TotalCharge* appear to have outliers, although the Z-score method does not capture all of them. Before declaring these as outliers, it's necessary to determine if they have an erroneous source or if they hold significance to the research question.

For instance, *VitD_levels* could be a bimodal distribution, and the distribution labeled as outliers might actually indicate a significant relationship. These values could be a good predictor of patient readmission, which is significant to our research question. Therefore, we would not want to drop these outliers from the dataset, as that would significantly influence our predictive capabilities.

Similarly, with *TotalCharge*, this distribution is multi-modal, and it may be the case that the distribution is comprised of four distributions. Without further investigation, it would be ill-advised to declare these as outliers.

Since *ReAdmis* is the critical variable in our research question, a step to check if the suspected outliers for *TotalCharge* and *VitD_levels* are significant to the research question is to examine the frequency of re-admission rates for patients falling into these outlier ranges. We can use the histogram to determine our investigation range and then calculate the percentage of readmissions for these patients using *ReAdmis*. This can then be compared to the majority of the data.

[253]:
```python
# Declare the suspected outlier cutoff values as determined from the histograms
TotalCharge_outlier_range = 11000
VitD_outlier_range =  30

# Split the suspected outlier columns at the cutoff values, returning the counts
# for ReAdmis column (Yes or No)

TC_outlier_readmin_rate = data_df[
    (data_df['TotalCharge'] > TotalCharge_outlier_range)
    ]['ReAdmis'].value_counts(normalize=True)

TC_nonoutlier_readmin_rate = data_df[
    ~(data_df['TotalCharge'] > TotalCharge_outlier_range)
    ]['ReAdmis'].value_counts(normalize=True)

VitD_outlier_readmin_rate = data_df[
    (data_df['VitD_levels'] > VitD_outlier_range)
    ]['ReAdmis'].value_counts(normalize=True)

VitD_nonoutlier_readmin_rate = data_df[
    ~(data_df['VitD_levels'] > VitD_outlier_range)
    ]['ReAdmis'].value_counts(normalize=True)

# Print the results
print('TC_outlier_readmin_rate:\n', TC_outlier_readmin_rate)
print('TC_nonoutlier_readmin_rate:\n', TC_nonoutlier_readmin_rate)
print('VitD_outlier_readmin_rate:\n', VitD_outlier_readmin_rate)
print('VitD_nonoutlier_readmin_rate:\n', VitD_nonoutlier_readmin_rate)
```

```
TC_outlier_readmin_rate:
 ReAdmis
No     0.592
Yes    0.408
Name: proportion, dtype: float64
TC_nonoutlier_readmin_rate:
 ReAdmis
No     0.635263
Yes    0.364737
Name: proportion, dtype: float64
VitD_outlier_readmin_rate:
 ReAdmis
No     0.592
Yes    0.408
Name: proportion, dtype: float64
VitD_nonoutlier_readmin_rate:
```

```
 ReAdmis
No     0.635263
Yes    0.364737
Name: proportion, dtype: float64
```

The above results lead us to believe that these suspected outliers' readmission rates are twice as high. Additional statistical testing could be done when conducting the analysis required to answer the research question. However, at this stage, this is enough to remark that these suspected outliers should NOT be discarded but instead retained in the dataset. Also, we notice that these patients appear to have the same rates, indicating that every suspected *VitD_levels* outlier patient is the same *TotalCharge* suspected outlier patient. This gives further credence to the argument NOT to discard these values. Further in-depth analysis can investigate this relationship further, but this is sufficient for data cleaning.

Based on this investigation, my recommendation for handling outliers in the data is to retain all records.

4.2 C2: JUSTIFICATION OF MITIGATION METHODS

4.2.1 Re-expression of catergorical variables

To correct the variables that need to be recategorized, I will run the following code:

[ ]:
```
# Replace the number values in the trouble columns with strings
data_df['Anxiety'] = data_df['Anxiety'].replace({1.0: 'Yes', 0.0: 'No'})
data_df['Overweight'] = data_df['Overweight'].replace({1.0: 'Yes', 0.0: 'No'})
```

After running the above code, all qualitative variables will have been recategorized appropriately. I justify this method as it will replace all the categorical variables in the dataset with numeric values to a consistent standard that matches all the other categorical variables. The dictionary in the `replace()` command will find all the values that meet the `1.0` or `0.0` value, and the dictionary will use those as keys to access the values to replace them with. Using this will make all categorical variables in the dataset non-numeric, which was my intention.

4.2.2 Duplicates

Based on my investigation of the duplicates in the data file, I have decided to retain all duplicate entries. My justification for this method is that these duplicates are not redundant or erroneous data but rather a reflection of the reality that the data is trying to capture. For instance, multiple customers can have the same income, live in areas with the same population, or have the same number of doctor visits. The *Population* column indicates the number of people living within a mile radius, and it's possible for multiple residences to have the same number of people within a 1-mile radius. The *Income* column might have duplicates because it is possible for multiple people to earn the same amount of money. The *Additional_charges* column could have duplicates because the same services might have identical costs. Therefore, retaining the duplicates without further information is reasonable as they are not causing data quality issues. If any of these assumptions do not hold, I might need to reconsider my strategy for handling duplicates.

4.2.3 Missing values

Based on my investigation of the data file, I have decided to use multiple imputation methods to clean the missing values. Multiple imputation methods begin using a univariate method, such as the mean and then update the value through successive iterations that consider the other columns in the data set (DataCamp, n.d.). According to DataCamp, multiple imputation assumes that the data is missing at random (MAR). MAR can be defined as a situation where data is missing randomly within the data's columns without a pattern, whereas between columns, there is a definite characteristic to the missing data. This is exactly the situation we have with this data. Since, through my investigation, we determined that there is no pattern to the missing data within each column, but that only a select few columns actually have missing data, this data meets the definition of MAR, and can then use multiple imputation methods. This will hopefully retain the characteristics of the data set while filling in the missing values. Moreover, multiple imputation methods can handle both quantitative and qualitative types of variables and different patterns of missingness. This is useful because three columns with missing values are categorical: *Overweight*, *Soft_drink*, and *Anxiety*. Therefore, given the nature of the missing data in our dataset and the advantages of multiple imputation, this method is the most appropriate choice for handling the missing values in this context.

4.2.4 Outliers

Based on my investigation of the high and low values in the data file, I have decided that no values in the columns are outliers. Thus, I will keep all values the same while cleaning the data for outliers. I justify this through my investigation, in which the values initially tagged as outliers by the Z-score method were genuinely part of the data. These values, although infrequent, align with what we expect for rare but significant observations.

Using the Z-score method and histogram plots, I determined that columns such as *VitD_levels* and *TotalCharge* appeared to have outliers. However, further analysis showed that these distributions were bimodal or multimodal, indicating that the outliers might have significant relationships relevant to the research question, particularly regarding patient readmission rates. For example, patients with high *VitD_levels* or *TotalCharge* exhibited twice the readmission rates compared to others, which is critical for our analysis.

Therefore, my handling of outliers in the data is to keep all records, making sure that significant patterns and relationships are preserved for accurate analysis.

4.3 C3: SUMMARY OF THE OUTCOMES

4.3.1 Re-expression of categorical variables

The below code will re-express the categorical variables that need addressing. Notably, it will change the number values `1.0` and `0.0` to the string values `Yes` and `No` for the *Anxiety* and *Overweight* columns. To do this, I will use the `replace()` function of the pandas package, which takes in a dictionary with the original values to select as keys.

[254]:
```
# Replace the number values in the trouble columns with strings
data_df['Anxiety'] = data_df['Anxiety'].replace({1.0: 'Yes', 0.0: 'No'})
data_df['Overweight'] = data_df['Overweight'].replace({1.0: 'Yes', 0.0: 'No'})
```

We can examine the qualitative variables again and verify that all categorical variables contain strings.

[255]:
```
# Select all the qualitative variables
qual_vars = ['Customer_id',
             'Interaction',
             'UID',
             'Job',
             'Education',
             'Employment',
             'Marital',
             'Gender',
             'ReAdmis',
             'Soft_drink',
             'Initial_admin',
             'HighBlood',
             'Stroke',
             'Complication_risk',
             'Overweight',
             'Arthritis',
             'Diabetes',
             'Hyperlipidemia',
             'BackPain',
             'Anxiety',
             'Allergic_rhinitis',
             'Reflux_esophagitis',
             'Asthma',
             'Services']

# Print the distinct values and their counts for each selected column
for col in data_df[qual_vars]:
  print(col)
  print(data_df[col].unique())
  print("\n") # Add an empty line for better readability
```

```
Customer_id
['C412403' 'Z919181' 'F995323' … 'R778890' 'E344109' 'I569847']


Interaction
['8cd49b13-f45a-4b47-a2bd-173ffa932c2f'
 'd2450b70-0337-4406-bdbb-bc1037f1734c'
 'a2057123-abf5-4a2c-abad-8ffe33512562' …
 '1d79569d-8e0f-4180-a207-d67ee4527d26'
 'f5a68e69-2a60-409b-a92f-ac0847b27db0'
 'bc482c02-f8c9-4423-99de-3db5e62a18d5']
```

```
UID
['3a83ddb66e2ae73798bdf1d705dc0932' '176354c5eef714957d486009feabf195'
 'e19a0fa00aeda885b8a436757e889bc9' … '41b770aeee97a5b9e7f69c906a8119d7'
 '2bb491ef5b1beb1fed758cc6885c167a' '95663a202338000abdf7e09311c2a8a1']


Job
['Psychologist, sport and exercise' 'Community development worker'
 'Chief Executive Officer' 'Early years teacher'
 'Health promotion specialist' 'Corporate treasurer' 'Hydrologist'
 'Psychiatric nurse' 'Computer games developer'
 'Production assistant, radio' 'Contractor'
 'Surveyor, planning and development'
 'English as a second language teacher' 'Actuary' 'Media planner'
 'Fast food restaurant manager' 'Horticulturist, commercial'
 'Secretary, company' 'Designer, graphic' 'Personnel officer'
 'Telecommunications researcher' 'Restaurant manager, fast food'
 'Surveyor, minerals' 'Architectural technologist'
 'Therapist, speech and language' 'Accounting technician'
 'Glass blower/designer' 'Travel agency manager' 'Illustrator'
 'Police officer' 'Accountant, chartered public finance'
 'Sport and exercise psychologist' 'Pensions consultant'
 'Community education officer' 'Radio producer'
 'Designer, television/film set' 'Conference centre manager'
 'Advertising account executive' 'Civil Service fast streamer'
 'Training and development officer' 'Buyer, retail' 'Event organiser'
 'IT technical support officer'
 'Historic buildings inspector/conservation officer'
 'Research scientist (physical sciences)' 'Games developer'
 'Manufacturing engineer' 'Embryologist, clinical' 'Merchant navy officer'
 'Television floor manager' 'Web designer' 'Industrial buyer' 'Aid worker'
 'Systems developer' 'Probation officer'
 'Scientific laboratory technician' 'Environmental health practitioner'
 'Prison officer' 'Naval architect' 'Pilot, airline'
 'Medical sales representative' 'Learning disability nurse'
 'Agricultural engineer' 'Multimedia programmer' 'Cartographer'
 'Company secretary' 'Operations geologist' 'Conservation officer, nature'
 'Therapist, art' 'Therapist, sports' 'Oncologist'
 'Armed forces logistics/support/administrative officer' 'Podiatrist'
 'Translator' 'Geochemist' 'Engineer, technical sales'
 'Production designer, theatre/television/film' 'Site engineer'
 'Teacher, primary school' 'Clinical molecular geneticist'
 'Armed forces operational officer' 'Careers information officer'
 'Camera operator' 'Engineer, aeronautical' 'Learning mentor'
 'Neurosurgeon' 'Clothing/textile technologist' 'Financial controller'
 'Education officer, museum' 'Set designer'
 'Accountant, chartered certified' 'Solicitor' 'Forensic psychologist'
 'Outdoor activities/education manager' 'Heritage manager'
```

```
'Hospital doctor' 'Engineer, chemical' 'Musician'
'Engineer, control and instrumentation' 'Engineer, mining'
'Editor, commissioning' 'Sports development officer' 'Teacher, music'
"Nurse, children's" 'Editor, film/video' 'Acupuncturist' 'Data scientist'
'Tax inspector' 'Engineer, maintenance' 'Radiographer, therapeutic'
'Surveyor, commercial/residential' 'Engineer, civil (contracting)'
'Therapist, nutritional' 'Public affairs consultant' 'Warehouse manager'
'Consulting civil engineer' 'Museum/gallery exhibitions officer'
'Risk manager' 'Air traffic controller' 'Health service manager'
'Teacher, adult education' 'Theatre stage manager'
'Designer, fashion/clothing' 'Engineer, site' 'Psychologist, counselling'
'Product/process development scientist' 'Financial adviser'
'Quarry manager' 'Librarian, public' 'Presenter, broadcasting'
'Structural engineer' 'Trade mark attorney' 'Amenity horticulturist'
'Building services engineer' 'Primary school teacher' 'Network engineer'
'Psychotherapist, child' 'Archaeologist' 'Publishing rights manager'
'Economist' 'Herbalist' 'Legal secretary'
'Engineer, manufacturing systems' 'Psychologist, occupational'
'Journalist, broadcasting' 'Lexicographer' 'Clinical psychologist'
'Scientist, water quality'
'Chartered legal executive (England and Wales)' 'Statistician'
'Chartered accountant' 'Operational investment banker'
'Nutritional therapist' 'Actor' 'Ecologist' 'Conservator, furniture'
'Archivist' 'Industrial/product designer' 'Air broker' 'Sports coach'
'Chief Technology Officer' 'Arts administrator' 'Restaurant manager'
'Editorial assistant' 'Cytogeneticist' 'Scientist, marine'
'Surveyor, quantity' 'Designer, exhibition/display' 'Curator'
'Human resources officer' 'Osteopath' 'Therapist, music'
'Volunteer coordinator' 'Office manager' 'Research officer, government'
'Quality manager' 'Artist' 'Museum education officer'
'Exercise physiologist'
'Administrator, charities/voluntary organisations' 'Purchasing manager'
'Therapeutic radiographer' 'Farm manager' 'Tour manager' 'Writer'
'Designer, industrial/product' 'Science writer' 'Engineer, biomedical'
'Development worker, international aid' 'Journalist, newspaper'
'Multimedia specialist' 'Dealer' 'Water engineer'
'Scientist, clinical (histocompatibility and immunogenetics)'
'Special effects artist' 'Engineer, agricultural'
'Corporate investment banker' 'Best boy'
'Production assistant, television' 'Chiropractor' 'Jewellery designer'
'Energy engineer' 'Scientist, forensic' 'Biomedical engineer'
'Insurance account manager' 'Occupational psychologist'
'Diagnostic radiographer' 'Banker' 'Medical technical officer'
'Quantity surveyor' 'Biochemist, clinical' 'Broadcast engineer'
'Chartered management accountant' 'Theatre manager' 'Animal technologist'
'Animator' 'Producer, radio' 'Chiropodist' 'Exhibition designer'
'Occupational therapist' 'Database administrator'
'Arts development officer' 'Health and safety inspector'
```

'Press photographer' 'Recruitment consultant'
'Dance movement psychotherapist' 'Audiological scientist'
'Soil scientist' 'Equities trader' 'Orthoptist' 'Engineer, materials'
'Regulatory affairs officer' 'Trade union research officer'
'Research scientist (maths)' 'Television production assistant'
'Chief of Staff' 'Advertising copywriter'
'Programme researcher, broadcasting/film/video'
'Technical sales engineer' 'Music therapist' 'Electronics engineer'
'Waste management officer' 'Plant breeder/geneticist'
'Operational researcher' 'Further education lecturer'
'Electrical engineer' 'Television camera operator'
'Runner, broadcasting/film/video' 'Pharmacist, community'
'Ophthalmologist' 'Wellsite geologist' 'Psychologist, educational'
'Advertising account planner' 'Sports therapist'
'Surveyor, building control' 'Engineer, land' 'Clinical embryologist'
'Marine scientist' 'Teacher, secondary school' 'Chief Financial Officer'
'Landscape architect' 'Community pharmacist' 'Product manager'
'Financial risk analyst' 'Administrator' 'Civil engineer, contracting'
'Engineer, maintenance (IT)' 'Scientist, audiological'
'Management consultant' 'Dentist' 'Barrister' 'Surveyor, insurance'
'Customer service manager' 'Clinical cytogeneticist'
'Forest/woodland manager' 'Insurance underwriter'
'Speech and language therapist' 'Trading standards officer'
'Surveyor, building' 'Engineering geologist' 'Investment analyst'
'Research scientist (life sciences)' 'Firefighter'
'Higher education careers adviser' 'Theatre director'
'Passenger transport manager' 'English as a foreign language teacher'
'Research officer, trade union'
'Conservation officer, historic buildings'
'Scientist, product/process development' 'Air cabin crew'
'Colour technologist' 'Research officer, political party'
'Chemist, analytical' 'Hydrogeologist' 'Music tutor' 'Therapist, drama'
'Health physicist' 'Lecturer, higher education' 'Records manager'
'Scientist, research (medical)' 'Field trials officer'
'Adult guidance worker' 'Fine artist'
'Social research officer, government' 'Interior and spatial designer'
'Freight forwarder' 'Production engineer' 'Accommodation manager'
'Retail banker' 'Research scientist (medical)' 'Occupational hygienist'
'Diplomatic Services operational officer' "Barrister's clerk"
'Call centre manager' 'Tourism officer' 'Agricultural consultant'
'Armed forces technical officer' "Politician's assistant"
'Geographical information systems officer' 'Chief Operating Officer'
'Higher education lecturer' 'Therapist, occupational' 'Land'
'Print production planner' 'Tree surgeon' 'Physiological scientist'
'Producer, television/film/video' 'Facilities manager'
'Designer, blown glass/stained glass' 'Location manager'
'Maintenance engineer' 'Meteorologist' 'Local government officer'
'Energy manager' 'Estate agent' 'Counsellor' 'Dispensing optician'

```
'Geophysical data processor' 'Adult nurse' 'Educational psychologist'
'Mental health nurse' 'IT sales professional' 'Water quality scientist'
'Advice worker' 'Intelligence analyst' 'Community arts worker'
'Optometrist' 'Patent examiner' 'Psychotherapist, dance movement'
'Gaffer' 'Risk analyst' 'Financial trader'
'Sales promotion account executive' 'Equality and diversity officer'
'Administrator, education' 'Medical secretary'
'Claims inspector/assessor' 'Child psychotherapist' 'Immigration officer'
'Metallurgist' 'Education administrator' 'Fitness centre manager'
'Chief Strategy Officer' 'Public librarian'
'Furniture conservator/restorer' 'Photographer' 'Production manager'
'Nature conservation officer' 'Phytotherapist' 'Therapist, horticultural'
'Aeronautical engineer' 'Engineer, civil (consulting)'
'Television/film/video producer' 'Solicitor, Scotland'
'Psychologist, forensic' 'Development worker, community'
'Engineer, manufacturing' 'Garment/textile technologist'
'Charity officer' 'Insurance risk surveyor' 'Broadcast presenter'
'Secretary/administrator' 'Civil Service administrator'
'Surveyor, hydrographic' 'Loss adjuster, chartered'
'Secondary school teacher' 'Teacher, special educational needs'
'Engineer, petroleum' 'Surveyor, rural practice'
'Information systems manager' 'Designer, furniture' 'Engineer, energy'
'Conservator, museum/gallery' 'Environmental consultant'
'Doctor, general practice' 'Nurse, mental health' 'Graphic designer'
'Investment banker, corporate' 'Astronomer' 'Data processing manager'
'Stage manager' 'Textile designer' 'Drilling engineer'
'Scientist, research (life sciences)' 'Furniture designer'
'Ambulance person' 'Buyer, industrial' 'Copywriter, advertising'
'Academic librarian' 'Scientist, research (maths)'
'International aid/development worker' 'Engineer, structural'
'Lecturer, further education' 'Interpreter' 'Chief Marketing Officer'
'Transport planner' 'Pharmacist, hospital' 'Toxicologist' 'Proofreader'
'Contracting civil engineer' 'Psychologist, clinical' 'Retail manager'
'Manufacturing systems engineer' 'Art therapist'
'Chartered certified accountant' 'Sales professional, IT'
'Dramatherapist' 'Designer, interior/spatial'
'Administrator, Civil Service' 'Printmaker' 'Engineer, electrical'
'Planning and development surveyor' 'Paediatric nurse'
'Designer, multimedia' 'Herpetologist' 'Mudlogger' 'Engineer, water'
'Arboriculturist' 'Sub' 'Sports administrator' 'Mechanical engineer'
'Physicist, medical' 'Armed forces training and education officer'
'Marketing executive' 'Magazine features editor' 'Ergonomist'
'Mining engineer' 'Dancer' 'Optician, dispensing' 'Designer, textile'
'Ranger/warden' 'Psychiatrist' 'Bonds trader' 'Technical brewer'
'Engineer, building services' 'Field seismologist'
'Engineer, electronics' 'Medical illustrator' 'Architect'
'Engineer, production' 'Licensed conveyancer' 'Surveyor, mining'
'Applications developer' 'Museum/gallery curator' 'Market researcher'
```

'Radiation protection practitioner'
'Control and instrumentation engineer' 'Programmer, applications'
'Advertising art director'
'Clinical scientist, histocompatibility and immunogenetics'
'Professor Emeritus' 'Horticulturist, amenity' 'Physiotherapist'
'Race relations officer' 'Surveyor, land/geomatics' 'Youth worker'
'Horticultural therapist' 'IT consultant' 'Make'
'Public relations account executive' 'Private music teacher'
'Fashion designer' 'Hospital pharmacist' 'Tax adviser'
'Engineer, broadcasting (operations)' 'Commercial art gallery manager'
'Legal executive' 'Visual merchandiser' 'Commercial/residential surveyor'
'Personal assistant' 'Insurance claims handler' 'Financial manager'
'Tourist information centre manager' 'Scientist, physiological'
'Designer, ceramics/pottery' 'Accountant, chartered management'
'Psychotherapist' 'Health visitor' 'Pharmacologist'
'Special educational needs teacher' 'Public relations officer'
'Town planner' 'Animal nutritionist' 'Building control surveyor'
'Engineer, automotive' 'Information officer'
'Senior tax professional/tax inspector' 'Film/video editor' 'Cabin crew'
'Radiographer, diagnostic' 'Warden/ranger' 'Video editor' 'Airline pilot'
'Newspaper journalist' 'Education officer, community'
'Geologist, engineering' 'Librarian, academic' 'Paramedic'
'Recycling officer' 'Merchandiser, retail' 'Retail merchandiser'
'Administrator, local government' 'Counselling psychologist'
'Estate manager/land agent' 'Oceanographer' 'Haematologist'
'Scientist, research (physical sciences)' 'Medical physicist'
'Communications engineer' 'Surgeon' 'Homeopath' 'Charity fundraiser'
'Theme park manager' 'Barista' 'Chartered public finance accountant'
'Teaching laboratory technician' 'Microbiologist'
'Programmer, multimedia' 'Automotive engineer' 'Holiday representative'
'Systems analyst' 'Product designer' 'Forensic scientist'
'Museum/gallery conservator' 'Patent attorney' 'Ship broker'
'Technical author' 'Pension scheme manager' 'Ceramics designer'
'Careers adviser' 'Building surveyor' 'Public house manager'
'Environmental education officer' 'Journalist, magazine'
'Magazine journalist' 'Analytical chemist'
'Teacher, English as a foreign language'
'Lighting technician, broadcasting/film/video' 'Teacher, early years/pre'
'Commercial horticulturist' 'Publishing copy' 'Clinical biochemist'
'IT trainer' 'Programmer, systems' 'Logistics and distribution manager'
'Horticultural consultant' 'Hotel manager' 'Associate Professor'
'Nurse, learning disability' 'Hydrographic surveyor' 'Nurse, adult'
'Fisheries officer' 'Administrator, sports' 'Insurance broker'
'Veterinary surgeon' 'Designer, jewellery' 'Lobbyist' 'Chemical engineer'
'Chartered loss adjuster' 'Social researcher' 'Petroleum engineer'
'Social worker' 'Education officer, environmental' 'Futures trader'
'Fish farm manager' 'Lawyer' 'Seismic interpreter' 'TEFL teacher'
'Immunologist' 'Engineer, drilling'

```
 'Emergency planning/management officer' 'Pathologist'
 'Broadcast journalist' 'Geologist, wellsite'
 'Investment banker, operational' 'Biomedical scientist' 'Bookseller'
 'Copy' 'Midwife' 'Media buyer' 'Geneticist, molecular'
 'Housing manager/officer' 'Geophysicist/field seismologist'
 'Art gallery manager' 'Food technologist' 'Land/geomatics surveyor'
 'Radio broadcast assistant' 'Psychologist, prison and probation services'
 'Dietitian' 'Civil engineer, consulting' 'Sales executive'
 'Leisure centre manager' 'Scientist, biomedical'
 'Exhibitions officer, museum/gallery' 'Engineer, communications'
 'Catering manager' 'Administrator, arts' 'Software engineer'
 'Medical laboratory scientific officer' 'Commissioning editor'
 'Geoscientist' 'Materials engineer' 'Financial planner'
 'Brewing technologist' 'Minerals surveyor' 'Editor, magazine features'
 'General practice doctor' 'Health and safety adviser' 'Doctor, hospital'
 'Environmental manager' 'Clinical research associate'
 'Sound technician, broadcasting/film/video' 'Press sub' 'Retail buyer'
 'Comptroller' 'Government social research officer'
 'Rural practice surveyor' 'Accountant, chartered']


Education
['Some College, Less than 1 Year'
 'Some College, 1 or More Years, No Degree'
 'GED or Alternative Credential' 'Regular High School Diploma'
 "Bachelor's Degree" "Master's Degree" 'Nursery School to 8th Grade'
 '9th Grade to 12th Grade, No Diploma' 'Doctorate Degree'
 "Associate's Degree" 'Professional School Degree'
 'No Schooling Completed']


Employment
['Full Time' 'Retired' 'Unemployed' 'Student' 'Part Time']


Marital
['Divorced' 'Married' 'Widowed' 'Never Married' 'Separated']


Gender
['Male' 'Female' 'Prefer not to answer']


ReAdmis
['No' 'Yes']


Soft_drink
```

```
[nan 'No' 'Yes']


Initial_admin
['Emergency Admission' 'Elective Admission' 'Observation Admission']


HighBlood
['Yes' 'No']


Stroke
['No' 'Yes']


Complication_risk
['Medium' 'High' 'Low']


Overweight
['No' 'Yes' nan]


Arthritis
['Yes' 'No']


Diabetes
['Yes' 'No']


Hyperlipidemia
['No' 'Yes']


BackPain
['Yes' 'No']


Anxiety
['Yes' nan 'No']


Allergic_rhinitis
['Yes' 'No']


Reflux_esophagitis
```

```
['No' 'Yes']


Asthma
['Yes' 'No']


Services
['Blood Work' 'Intravenous' 'CT Scan' 'MRI']
```

4.3.2 Missing values

The below code will impute the missing values using Multiple Imputation by Chained Equations (MICE).

[256]:
```
# Code source: (DataCamp, n.d.).
!pip install miceforest
from miceforest import ImputationKernel
```

```
Requirement already satisfied: miceforest in /usr/local/lib/python3.10/dist-
packages (5.7.0)
Requirement already satisfied: lightgbm>=3.3.1 in
/usr/local/lib/python3.10/dist-packages (from miceforest) (4.1.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from miceforest) (1.25.2)
Requirement already satisfied: blosc in /usr/local/lib/python3.10/dist-packages
(from miceforest) (1.11.2)
Requirement already satisfied: dill in /usr/local/lib/python3.10/dist-packages
(from miceforest) (0.3.8)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
(from lightgbm>=3.3.1->miceforest) (1.11.4)
```

[257]:
```
# We first need to convert the 'object' datatypes to 'category' for MICE to work
for col in data_df.columns:
    if data_df[col].dtype == 'object':
        data_df[col] = data_df[col].astype('category')
```

[258]:
```
# We dont want to select some columns that may just slow down the imputation
# These columns will not help in predicting the NA values
cols_to_exclude =␣
 ↪['Customer_id','Interaction','UID','City','State','County','Timezone','Job']
mice_kernel = ImputationKernel(
data = data_df.drop(columns=cols_to_exclude),
save_all_iterations = True,
random_state = 2023
)
```

[259]:
```python
#run for one iteration
mice_kernel.mice(1)
mice_imputation = mice_kernel.complete_data()
```

Now all NA values in the dataframe should be gone. Let's check the results:

[260]:
```python
# Calculate the number of missing values in each column of the original␣
↪DataFrame
na_cols_original = data_df.drop(columns=cols_to_exclude).isna().sum()

# Calculate the number of missing values in each column of the imputed DataFrame
na_cols_imputed = mice_imputation.isna().sum()

# Compare the results
comparison_df = pd.DataFrame({
    "Original Missing Values": na_cols_original,
    "Imputed Missing Values": na_cols_imputed
})

print(comparison_df)
```

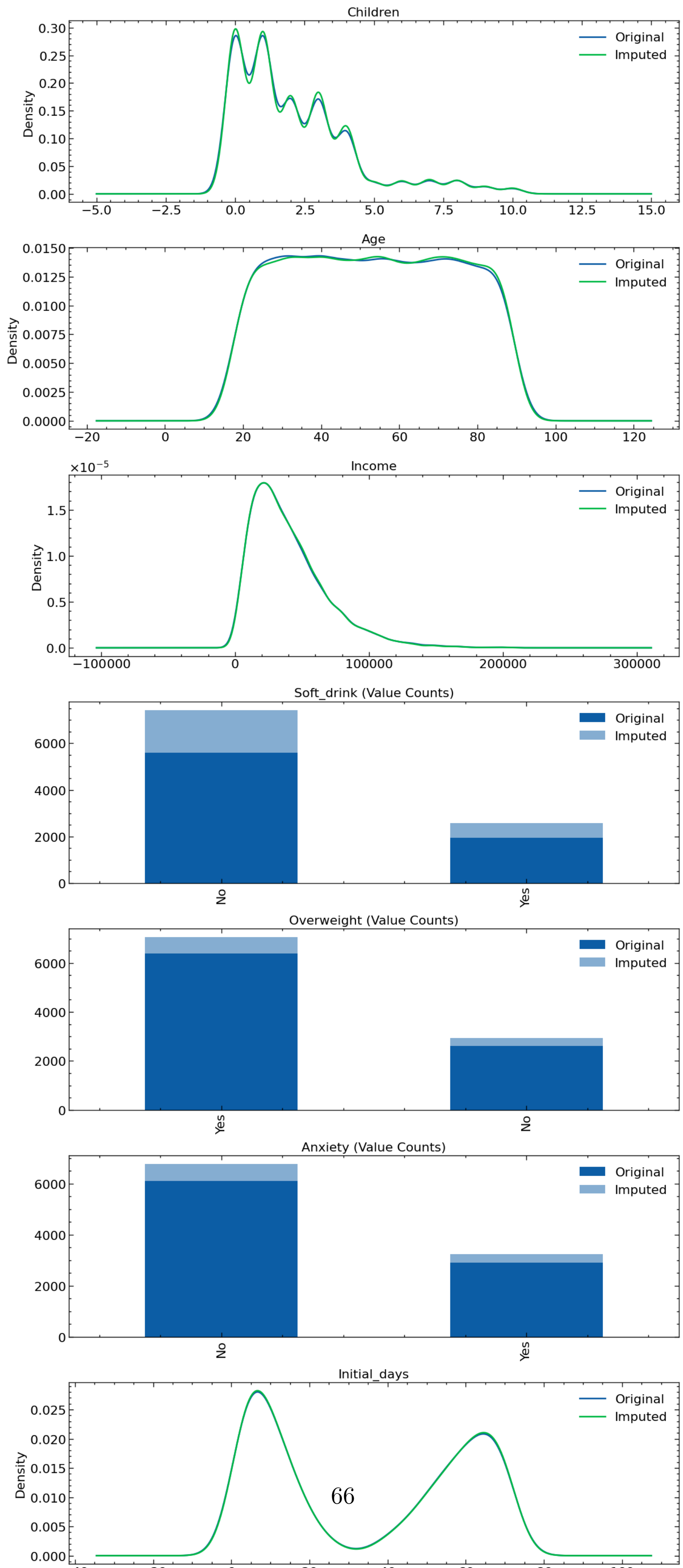
```
                    Original Missing Values  Imputed Missing Values
CaseOrder                                 0                       0
Zip                                       0                       0
Lat                                       0                       0
Lng                                       0                       0
Population                                0                       0
Area                                      0                       0
Children                               2588                       0
Age                                    2414                       0
Education                                 0                       0
Employment                                0                       0
Income                                 2464                       0
Marital                                   0                       0
Gender                                    0                       0
ReAdmis                                   0                       0
VitD_levels                               0                       0
Doc_visits                                0                       0
Full_meals_eaten                          0                       0
VitD_supp                                 0                       0
Soft_drink                             2467                       0
Initial_admin                             0                       0
HighBlood                                 0                       0
Stroke                                    0                       0
Complication_risk                         0                       0
Overweight                              982                       0
Arthritis                                 0                       0
Diabetes                                  0                       0
```

```
Hyperlipidemia                    0          0
BackPain                          0          0
Anxiety                         984          0
Allergic_rhinitis                 0          0
Reflux_esophagitis                0          0
Asthma                            0          0
Services                          0          0
Initial_days                   1056          0
TotalCharge                       0          0
Additional_charges                0          0
Item1                             0          0
Item2                             0          0
Item3                             0          0
Item4                             0          0
Item5                             0          0
Item6                             0          0
Item7                             0          0
Item8                             0          0
```

Just as expected, we see no more NA values. Now, to confirm that we chose the correct imputation method, let's examine how the distribution of the original data compares to the imputed data.

[261]:
```python
# Create a figure and a grid of subplots
fig, axs = plt.subplots(len(na_cols), 1, figsize=(12, 28))
axs = axs.flatten()

# Iterate over columns with NA values
for i, col in enumerate(na_cols):
    ax = axs[i]

    # Handle different data types
    if data_df[col].dtype == 'category':
        # For string columns, plot value counts
        data_df[col].value_counts().plot(kind='bar',
                                         ax=ax,
                                         alpha=1,
                                         label='Original',
                                         xlabel='')
        mice_imputation[col].value_counts().plot(kind='bar',
                                                 ax=ax,
                                                 alpha=.5,
                                                 label='Imputed',
                                                 xlabel='')
        ax.set_title(f"{col} (Value Counts)")
        ax.legend()
    else:
        # For numeric columns, plot KDE
        data_df[col].plot(kind='kde', ax=ax,  label='Original',title=col)
```

```
        mice_imputation[col].plot(kind='kde', ax=ax, label='Imputed')
        ax.legend()
plt.tight_layout()
```


Children
Original
Imputed
Density
Age
Original
Imputed
Density
Income
×10^-5
Original
Imputed
Density
Soft_drink (Value Counts)
Original
Imputed
No
Yes
Overweight (Value Counts)
Original
Imputed
Yes
No
Anxiety (Value Counts)
Original
Imputed
No
Yes
Initial_days
Original
Imputed
Density

Even after just 1 itteration, the orginal and imputed data curves are nearly indistinguishable. We have preserved the original distribution and hopefully the inter-variable relationships.

The last step is to complete the process by overwriting the old columns.

[262]:
```
#overwrite the old columns with NA values with the new columns
data_df[na_cols] = mice_imputation[na_cols]
```

Let's confirm our work.

[263]:
```
#count every instance of a missing value
data_df.isna().sum().sum()
```

[263]: 0

There are no more missing values in our data frame.

In summary, through our cleaning process, we have recategorized two columns, ensuring they were strings, and eliminated all missing values through MICE. This data is now cleaned and prepared for analysis!

4.4 C4: LIMITATIONS

Let's quickly summarize how we approached data cleaning for this file:

- Ensured all categorical variables were comprised of string data types
- Imputed missing values using MICE
- Did not remove any outliers
- Did not remove any duplicates

Now, let's address the limitations of each of these decisions.

Categorical Variables:

Limitation: The recategorization of qualitative variables could have been better served by employing the One-Hot method. By not taking this approach, should this dataset be used later for machine learning approaches, this step will need to be taken, requiring additional data cleaning.

Imputation with MICE:

Limitation: Imputing values using MICE is less straightforward than univariate methods and is somewhat of a black box. While it seems to have achieved the desired outcome based on distributions, it's not immediately clear how it did so. This could introduce spurious relationships that may surface later. Additionally, without proper documentation, the information on which values were imputed may be lost, complicating future analyses.

Outliers:

Limitation: Declaring that this dataset contains no outliers may have been applied too liberally. We used the Z-score and histogram approach, comparing values tagged as outliers to the distribution density of the data. However, we did not account for non-normal distributions or use a quantitative method. There may have been outliers that should have been removed, potentially causing issues in further calculations.

Duplicates:

Limitation: By deciding to remove no duplicates, we assumed that without additional information, plausible duplicates should be kept. However, if these duplicates are spurious, we allowed incorrect data to pass to the analysis stage, negatively influencing the results.

4.5 C5: IMPACT OF LIMITATIONS

Categorical Variables:

Impact: The need for additional data cleaning (One-Hot encoding) for machine learning purposes means future analyses could be delayed or compromised by the need to reformat the data. This extra step could introduce errors or inconsistencies, potentially impacting the accuracy of machine learning models.

Imputation with MICE:

Impact: The 'black box' nature of MICE imputation means future analysts may not fully understand how missing values were filled, leading to potential mistrust or misuse of the data. Spurious relationships introduced could skew analyses, leading to incorrect conclusions. Lack of documentation on which values were imputed could further complicate data use.

Outliers:

Impact: The decision not to remove outliers could result in analyses influenced by extreme values, potentially leading to misleading conclusions. Since non-normal distributions were not accounted for, some legitimate outliers might still be present, affecting the robustness of statistical analyses and models.

Duplicates:

Impact: Allowing potential duplicates to remain in the dataset could lead to biased or inaccurate results. If these duplicates are spurious, they could distort summary statistics and analyses, leading to incorrect interpretations and decisions. This could be particularly problematic in decision-making processes where accuracy is critical, such as in medical or financial contexts.

4.6 D1: MITIGATION CODE

See code attached in file: *d206_linehan.ipynb*.

4.7 D2: CLEAN DATA

[264]:
```
#export data
data_df.to_csv('/content/medical_cleaned_data.csv', index=False)
```

See attached file: *medical_cleaned_data.csv*.

4.8 E1: PRINCIPAL COMPONENTS

[265]:
```
# Import necessary packages
from sklearn.decomposition import PCA
```

[266]:
```
# Select numeric columns, excluding categorical and variables with limited range
data_numeric = data_df.select_dtypes(include=np.number).drop(columns=
                                                              [
                                                               'CaseOrder',
                                                               'Zip',
                                                               'Item1',
                                                               'Item2',
                                                               'Item3',
                                                               'Item4',
                                                               'Item5',
                                                               'Item6',
                                                               'Item7',
                                                               'Item8',
                                                              ]
                                                               )
# Normalize columns
data_numeric = (
    data_numeric - data_numeric.mean(numeric_only=True)
    ) / data_numeric.std(numeric_only=True)
print(
    f'Number of principal components: {data_numeric.shape[1]}'
)
print(
    f'Columns used:'
    f'{data_numeric.columns.tolist()}'
)
```

```
Number of principal components: 13
Columns used:['Lat', 'Lng', 'Population', 'Children', 'Age', 'Income',
'VitD_levels', 'Doc_visits', 'Full_meals_eaten', 'VitD_supp', 'Initial_days',
'TotalCharge', 'Additional_charges']
```

[267]:
```
# Intialize PCA
pca = PCA(n_components=data_numeric.shape[1])
# Fit PCA
pca.fit(data_numeric)
# Transform into dataframe
data_pca_df = pd.DataFrame(pca.transform(data_numeric),
                           columns=[
                               f'PC{i+1}' for i in range(data_numeric.shape[1])
                               ]
                           )
```

Display PCA loadings table

[268]:
```
loadings = pd.DataFrame(
    pca.components_.T,
    columns=[f'PC{i+1}' for i in range(data_numeric.shape[1])],
    index=data_numeric.columns
)
loadings
```

[268]:
```
                        PC1       PC2       PC3       PC4       PC5  \
Lat               -0.017308  0.003348 -0.717694  0.039960 -0.069918
Lng               -0.005424  0.007386  0.277088 -0.594107  0.211054
Population         0.020464 -0.029520  0.623464  0.299590 -0.162122
Children           0.035266  0.047942 -0.053724  0.520471 -0.198721
Age                0.130867  0.693001  0.012392 -0.027205 -0.013895
Income            -0.035476 -0.002283  0.055269  0.436389  0.522534
VitD_levels        0.519258 -0.096507 -0.037034 -0.049947  0.369183
Doc_visits        -0.004613  0.015264  0.021549  0.174710  0.435478
Full_meals_eaten  -0.006619  0.030063 -0.099327  0.030808  0.375056
VitD_supp          0.029546  0.012288  0.030928  0.240233 -0.003910
Initial_days       0.461097 -0.092051  0.012818  0.042625 -0.379766
TotalCharge        0.692698 -0.128052 -0.016701 -0.011005  0.026771
Additional_charges 0.128904  0.693568  0.015312 -0.001233  0.000668

                        PC6       PC7       PC8       PC9      PC10  \
Lat               -0.103167 -0.076826  0.052907 -0.020547 -0.020017
Lng               -0.191302  0.312876 -0.411330 -0.143037 -0.242550
Population         0.138388 -0.195594  0.243993  0.073882 -0.036011
Children           0.175924  0.298102 -0.331929 -0.391208 -0.545616
Age               -0.011683 -0.018688  0.015000 -0.002235  0.033209
Income            -0.099158  0.225159 -0.275456 -0.174336  0.590127
VitD_levels        0.096758  0.103448  0.437774 -0.256801 -0.151742
Doc_visits        -0.374039 -0.664261 -0.199062  0.054190 -0.388064
Full_meals_eaten   0.611724  0.112676 -0.164018  0.626832 -0.191656
VitD_supp         -0.599533  0.486205  0.238922  0.497821 -0.197049
Initial_days      -0.098855 -0.129333 -0.516197  0.283856  0.202677
TotalCharge        0.002080 -0.006494 -0.010381 -0.003292  0.026042
Additional_charges 0.000678 -0.015326  0.019306 -0.002383  0.038555

                       PC11      PC12      PC13
Lat                0.676648  0.009884 -0.000815
Lng                0.377678 -0.004326  0.000953
Population         0.608245  0.017536  0.000219
Children          -0.049074  0.005560 -0.004591
Age               -0.001273  0.706673 -0.018170
Income             0.129848  0.017075  0.001892
VitD_levels       -0.004089  0.019422  0.528978
```

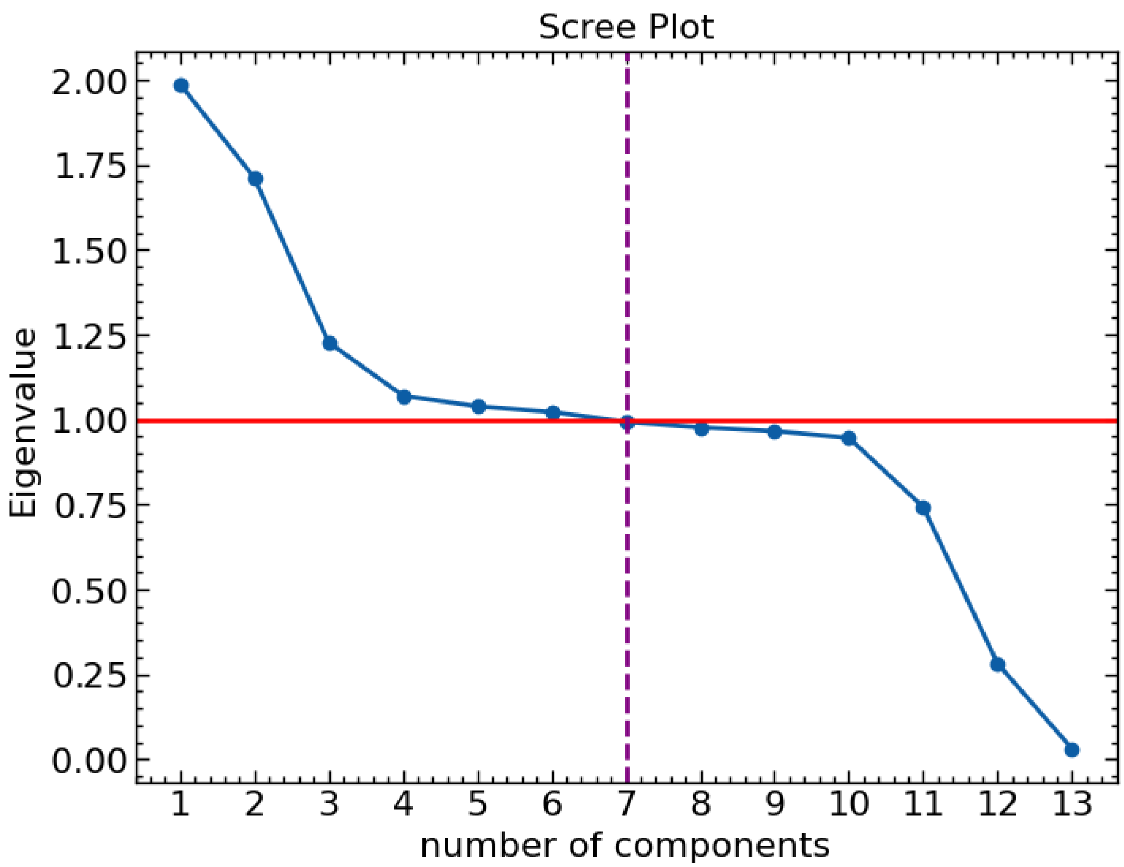
```
Doc_visits          -0.069370 -0.000475 -0.001079
Full_meals_eaten     0.063371  0.009658 -0.002548
VitD_supp           -0.026687 -0.000164  0.002619
Initial_days         0.009750  0.008126  0.466841
TotalCharge          0.004579 -0.021656 -0.708041
Additional_charges   0.024515 -0.706301  0.023410
```

4.9 E2: CRITERIA USED

[269]:
```
# Code source:
# Video 1: Getting Started with D206 | Principal Component Analysis (PCA)
cov_matrix = np.dot(
    data_numeric.T, data_numeric
) / data_numeric.shape[0]

eigenvalues = [
    np.dot(eigenvector.T, np.dot(cov_matrix, eigenvector))
    for eigenvector in pca.components_
]
```

[270]:
```
plt.plot(eigenvalues,marker='o',)
plt.title('Scree Plot')
plt.xlabel('number of components')
plt.ylabel('Eigenvalue')
plt.axhline(y=1,
            color='red',
            )
plt.xticks(range(data_numeric.shape[1]),
           labels=range(1, data_numeric.shape[1]+1));
plt.axvline(x=6, color='purple',linestyle='--')
```

[270]: <matplotlib.lines.Line2D at 0x793c2a58bb20>



[271]:
```
# Examine eigenvalues between PC6 and PC7.
print(f'Eigenvalue of PC6: {eigenvalues[5]:.2f}')
print(f'Eigenvalue of PC7: {eigenvalues[6]:.2f}')
```

```
Eigenvalue of PC6: 1.02
Eigenvalue of PC7: 0.99
```

[272]:
```
loadings.iloc[:,np.where(np.array(eigenvalues) >= 1)[0]]
```

[272]:

	PC1	PC2	PC3	PC4	PC5	PC6
Lat	-0.017308	0.003348	-0.717694	0.039960	-0.069918	-0.103167
Lng	-0.005424	0.007386	0.277088	-0.594107	0.211054	-0.191302
Population	0.020464	-0.029520	0.623464	0.299590	-0.162122	0.138388
Children	0.035266	0.047942	-0.053724	0.520471	-0.198721	0.175924
Age	0.130867	0.693001	0.012392	-0.027205	-0.013895	-0.011683
Income	-0.035476	-0.002283	0.055269	0.436389	0.522534	-0.099158
VitD_levels	0.519258	-0.096507	-0.037034	-0.049947	0.369183	0.096758
Doc_visits	-0.004613	0.015264	0.021549	0.174710	0.435478	-0.374039
Full_meals_eaten	-0.006619	0.030063	-0.099327	0.030808	0.375056	0.611724
VitD_supp	0.029546	0.012288	0.030928	0.240233	-0.003910	-0.599533

```
Initial_days        0.461097 -0.092051  0.012818  0.042625 -0.379766 -0.098855
TotalCharge         0.692698 -0.128052 -0.016701 -0.011005  0.026771  0.002080
Additional_charges  0.128904  0.693568  0.015312 -0.001233  0.000668  0.000678
```

Based on the above scree-plot, select components PC1 through PC6. From the scree-plot, these components all have eigenvalues above 1, and according to the Kaiser rule, these would be the components we would select. Additionally, according to the scree plot test, we would choose those just above the elbow, which would be components four and below, so selecting up to 6 still reduces our number of components by half, but while providing the variability explained.

4.10 E3: BENEFITS

There are several benefits to using Principal Component Analysis (PCA). One significant advantage is its ability to prevent overfitting. Overfitting occurs when a model is too specialized due to the inclusion of an excessive number of variables, rendering it ineffective at accurately predicting new scenarios. By eliminating certain components, the risk of overfitting is reduced. However, the question arises: which components are best to eliminate? This is where PCA proves invaluable. It provides an effective method for reducing the number of variables in combination with selection methods such as the Kaiser rule. Implementing this strategy allows the model to adapt more flexibly to new scenarios, thereby enhancing its predictive accuracy.

5 F: VIDEO

Video can be located at the following link:

https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=abe9f85a-0231-4f37-93fc-b1b801693178

6 G: SOURCES OF THIRD-PARTY CODE

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