# Data Mining - Lasso Regression

Data Mining I expands predictive modeling into nonlinear dimensions, enhancing the capabilities and effectiveness of the data analytics lifecycle. In this course, learners implement supervised models—specifically classification and prediction data mining models—to unearth relationships among variables that are not apparent with more surface-level techniques. The course provides frameworks for assessing models' sensitivity and specificity.

## Competencies

**Classification Data Mining Models**
Applies observations to appropriate classes and categories using classification models.

**Predictive Data Mining Models**
Implements prediction data mining models to find hard-to-spot relationships among variables.

**Data Mining Model Performance**
Evaluates data mining model performance for precision, accuracy, and model comparison.

## Write Up

**Research Question**
Can Lasso Regression be used to predict total charges for this specific hospital chain?

**Goal**
One goal of the data analysis is to determine if lasso regression method can produce a model that can predict total charge.

**Explanation of Classification Method**
The prediction method I chose is Lasso regression. Lasso regression helps to reduce model complexity, prevent overfitting, and help with feature selection. This prediction method will analyze the data set by looking at the coefficients of less important features and shrinking them to zero while the more important features are focused on. (Bowne-Anderson, n.d.) The expected outcome will be a model that can make accurate predictions for the target continuous variable total charges.

**Summary of Method Assumption**
One assumption of the lasso regression prediction method has the same assumptions as linear models which includes linearity. (Elleh, 2022) Linearity is assuming that the relationship between the predictor variables (X) and the target variables (y) are linear.

## Code

In [1]:
```
# Importing packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import missingno as msno
import seaborn as sns
```

In [2]:
```
# Importing medical data CSV and creating the medical_data DataFrame
medical_data = pd.read_csv("C:/Users/Makayla Avendano/Desktop/medical_clean.csv")
```

In [3]:
```
# Looking at columns, non-null counts and data types
medical_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 50 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            10000 non-null  int64  
 15  Age                 10000 non-null  int64  
 16  Income              10000 non-null  float64
 17  Marital             10000 non-null  object 
 18  Gender              10000 non-null  object 
 19  ReAdmis             10000 non-null  object 
 20  VitD_levels         10000 non-null  float64
 21  Doc_visits          10000 non-null  int64  
 22  Full_meals_eaten    10000 non-null  int64  
 23  vitD_supp           10000 non-null  int64  
 24  Soft_drink          10000 non-null  object 
 25  Initial_admin       10000 non-null  object 
 26  HighBlood           10000 non-null  object 
 27  Stroke              10000 non-null  object 
 28  Complication_risk   10000 non-null  object 
 29  Overweight          10000 non-null  object 
 30  Arthritis           10000 non-null  object 
 31  Diabetes            10000 non-null  object 
 32  Hyperlipidemia      10000 non-null  object 
 33  BackPain            10000 non-null  object 
 34  Anxiety             10000 non-null  object 
 35  Allergic_rhinitis   10000 non-null  object 
 36  Reflux_esophagitis  10000 non-null  object 
 37  Asthma              10000 non-null  object 
 38  Services            10000 non-null  object 
 39  Initial_days        10000 non-null  float64
 40  TotalCharge         10000 non-null  float64
 41  Additional_charges  10000 non-null  float64
 42  Item1               10000 non-null  int64  
 43  Item2               10000 non-null  int64  
 44  Item3               10000 non-null  int64  
 45  Item4               10000 non-null  int64  
 46  Item5               10000 non-null  int64  
 47  Item6               10000 non-null  int64  
 48  Item7               10000 non-null  int64  
 49  Item8               10000 non-null  int64  
dtypes: float64(7), int64(16), object(27)
memory usage: 3.8+ MB
```

In [4]:
```python
# Drop columns that are not needed
medical_data = medical_data.drop(columns=['Interaction', 'UID', 'City', 'State', 'Cour
```

In [5]:
```
# Updated data frame
medical_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 27 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Children            10000 non-null  int64  
 1   Age                 10000 non-null  int64  
 2   Income              10000 non-null  float64
 3   Gender              10000 non-null  object 
 4   ReAdmis             10000 non-null  object 
 5   VitD_levels         10000 non-null  float64
 6   Doc_visits          10000 non-null  int64  
 7   Full_meals_eaten    10000 non-null  int64  
 8   vitD_supp           10000 non-null  int64  
 9   Soft_drink          10000 non-null  object 
 10  Initial_admin       10000 non-null  object 
 11  HighBlood           10000 non-null  object 
 12  Stroke              10000 non-null  object 
 13  Complication_risk   10000 non-null  object 
 14  Overweight          10000 non-null  object 
 15  Arthritis           10000 non-null  object 
 16  Diabetes            10000 non-null  object 
 17  Hyperlipidemia      10000 non-null  object 
 18  BackPain            10000 non-null  object 
 19  Anxiety             10000 non-null  object 
 20  Allergic_rhinitis   10000 non-null  object 
 21  Reflux_esophagitis  10000 non-null  object 
 22  Asthma              10000 non-null  object 
 23  Services            10000 non-null  object 
 24  Initial_days        10000 non-null  float64
 25  TotalCharge         10000 non-null  float64
 26  Additional_charges  10000 non-null  float64
dtypes: float64(5), int64(5), object(17)
memory usage: 2.1+ MB
```

In [6]:
```
# Duplicates
medical_duplicates = medical_data.duplicated()
print(medical_duplicates.value_counts())
```

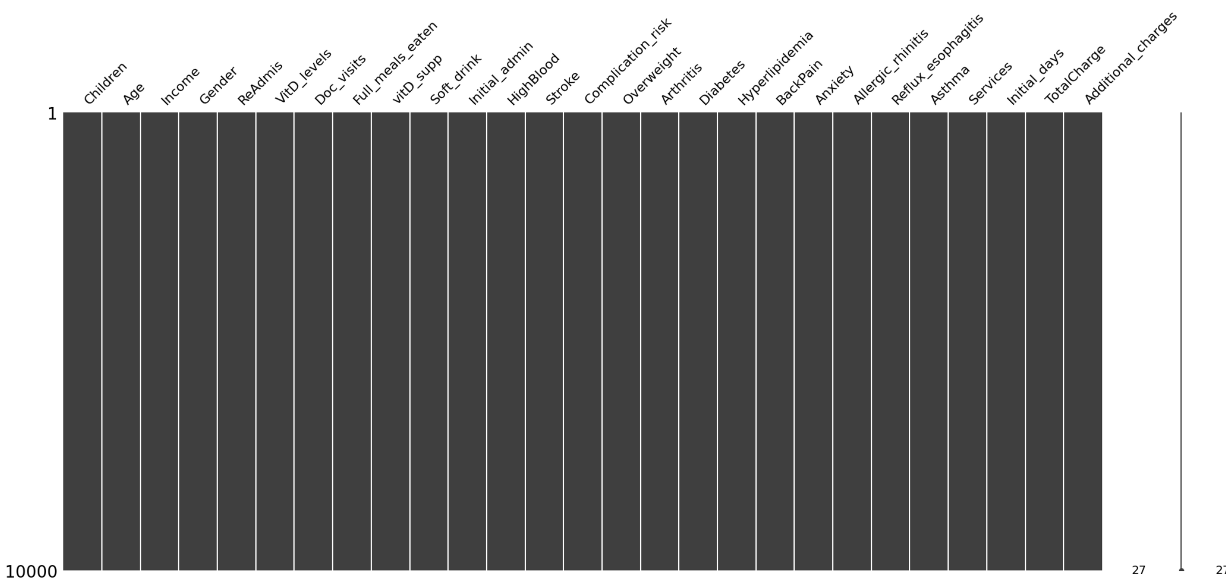
```
False    10000
Name: count, dtype: int64
```

In [7]:
```
# Missing Values
# Sum of all null values within each column
medical_data.isnull().sum()
```

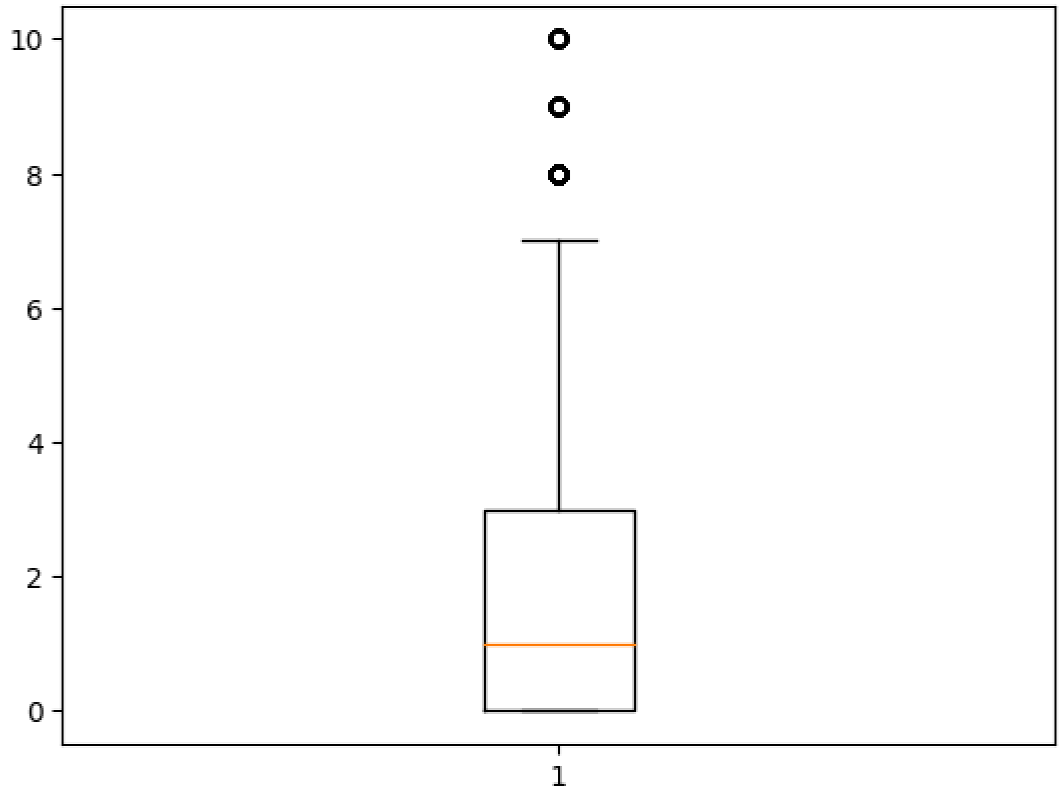
Out[7]:
```
Children              0
Age                   0
Income                0
Gender                0
ReAdmis               0
VitD_levels           0
Doc_visits            0
Full_meals_eaten      0
vitD_supp             0
Soft_drink            0
Initial_admin         0
HighBlood             0
Stroke                0
Complication_risk     0
Overweight            0
Arthritis             0
Diabetes              0
Hyperlipidemia        0
BackPain              0
Anxiety               0
Allergic_rhinitis     0
Reflux_esophagitis    0
Asthma                0
Services              0
Initial_days          0
TotalCharge           0
Additional_charges    0
dtype: int64
```

In [8]:
```
# Double checking no missing values
msno.matrix(medical_data)
```

Out[8]:
```
<Axes: >
```




In [9]:
```
# Outliers
ChildrenPlot = plt.boxplot(x='Children', data = medical_data)
```

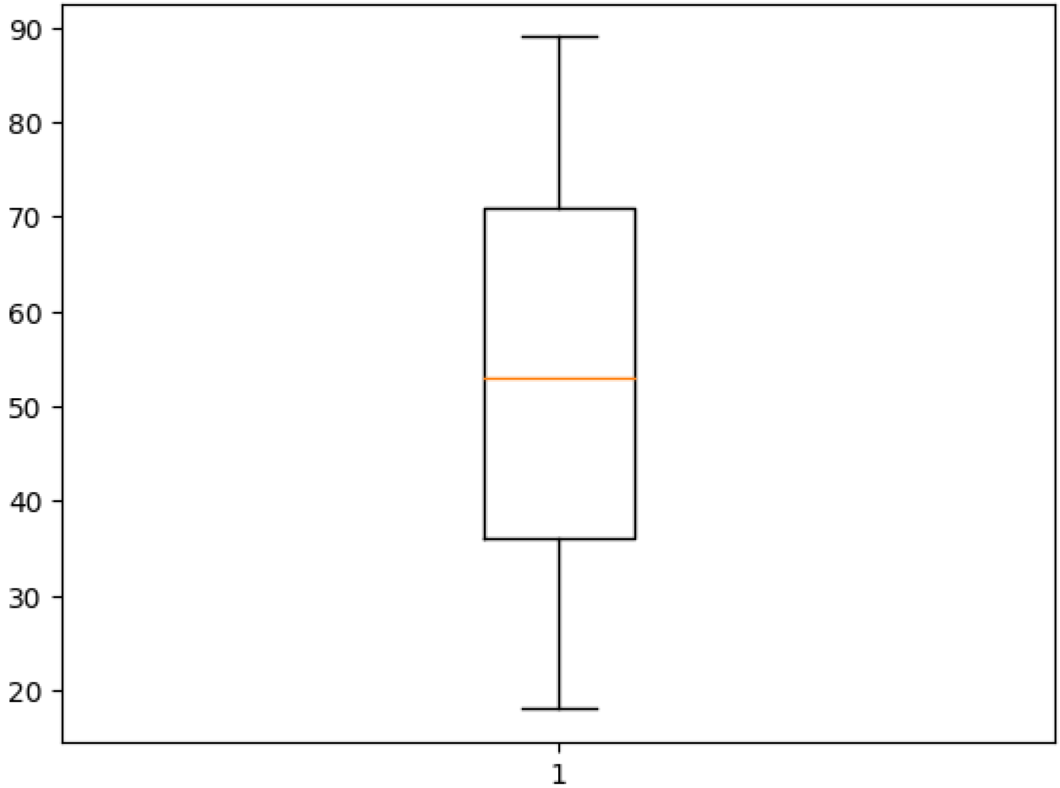



In [10]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_children = np.percentile(medical_data['Children'], 75)
Q1_children = np.percentile(medical_data['Children'], 25)
IQR_children = Q3_children - Q1_children
Max_children = Q3_children + (1.5 * IQR_children)
print(Max_children)
```

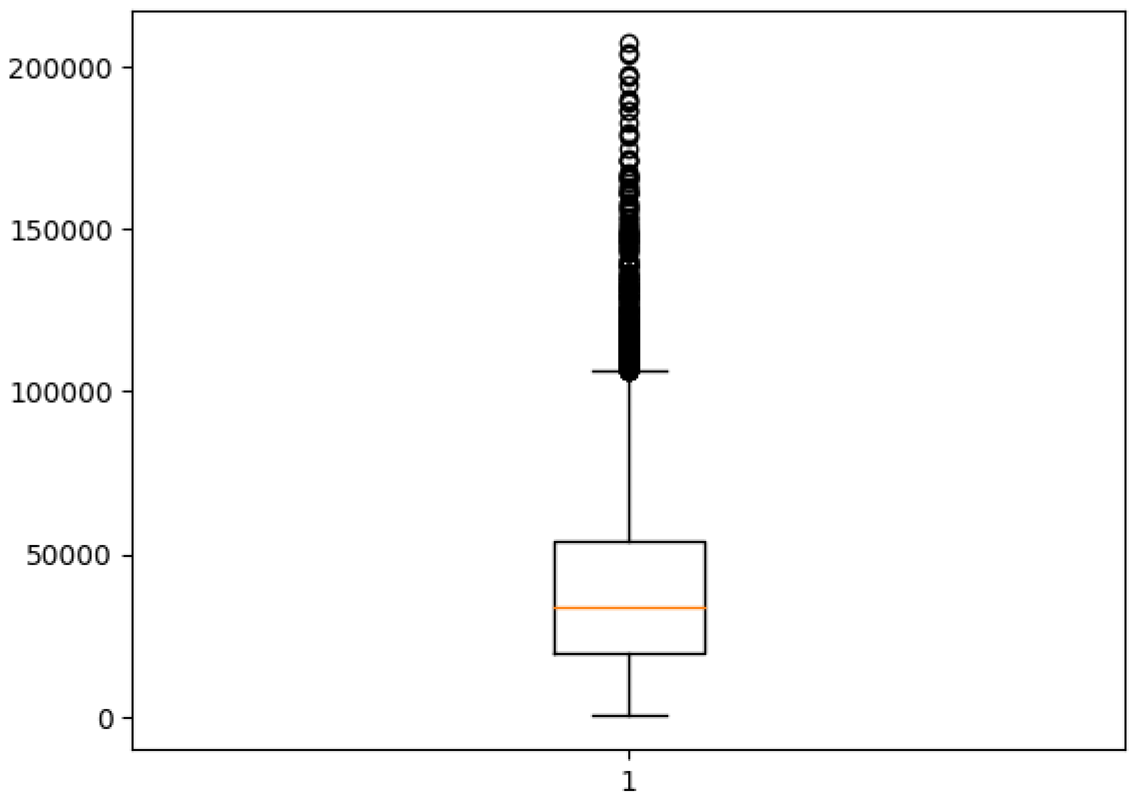
```
7.5
```

In [11]:
```
# Replacing with the median
median = float(medical_data['Children'].median())
medical_data['Children'] = np.where(medical_data['Children'] > Max_children, median, r
```

In [12]:
```
AgePlot = plt.boxplot(x='Age', data = medical_data)
```




In [13]:
```
IncomePlot = plt.boxplot(x='Income', data = medical_data)
```



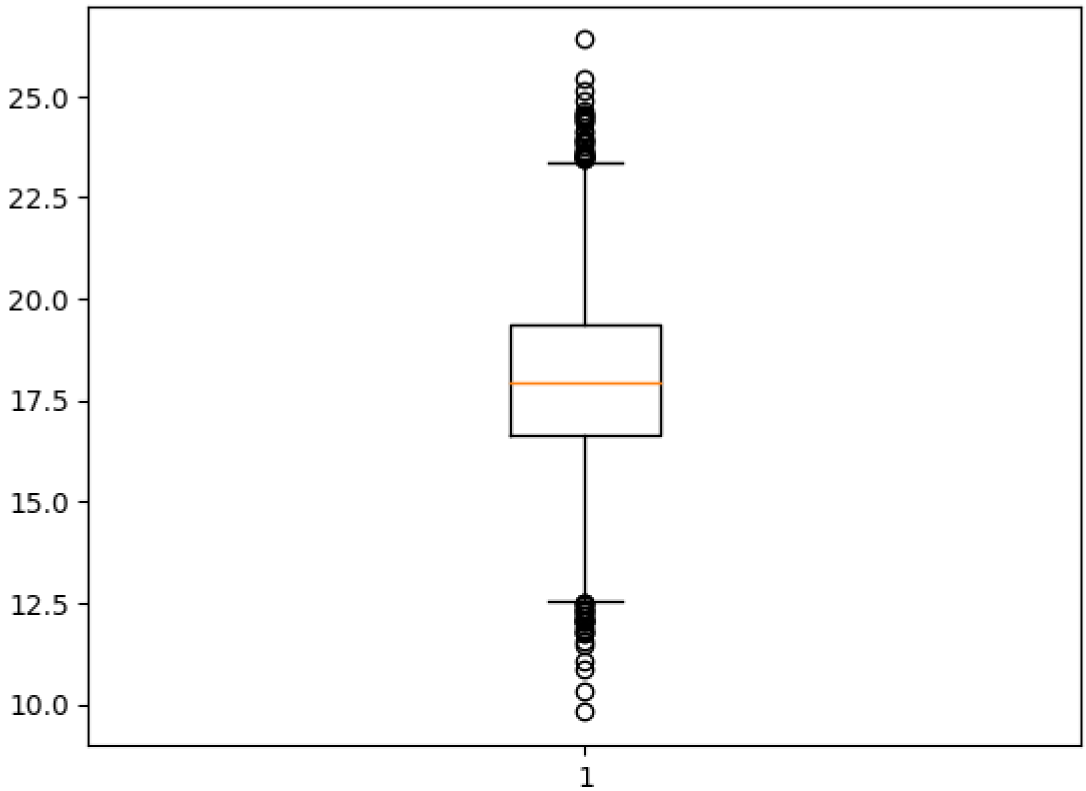

In [14]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_income = np.percentile(medical_data['Income'], 75)
Q1_income = np.percentile(medical_data['Income'], 25)
IQR_income = Q3_income - Q1_income
```

```
Max_income = Q3_income + (1.5 * IQR_income)
print(Max_income)
```

106342.84374999999

In [15]:
```
# Replacing with the median
median = float(medical_data['Income'].median())
medical_data['Income'] = np.where(medical_data['Income'] > Max_income, median, medical
```

In [16]:
```
VitDlevelsplot = plt.boxplot(x='VitD_levels', data = medical_data)
```




In [17]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_vitd = np.percentile(medical_data['VitD_levels'], 75)
Q1_vitd = np.percentile(medical_data['VitD_levels'], 25)
IQR_vitd = Q3_vitd - Q1_vitd
Max_vitd = Q3_vitd + (1.5 * IQR_vitd)
rounded_max_vitd = round(Max_vitd,1)
print(rounded_max_vitd)
```

23.4

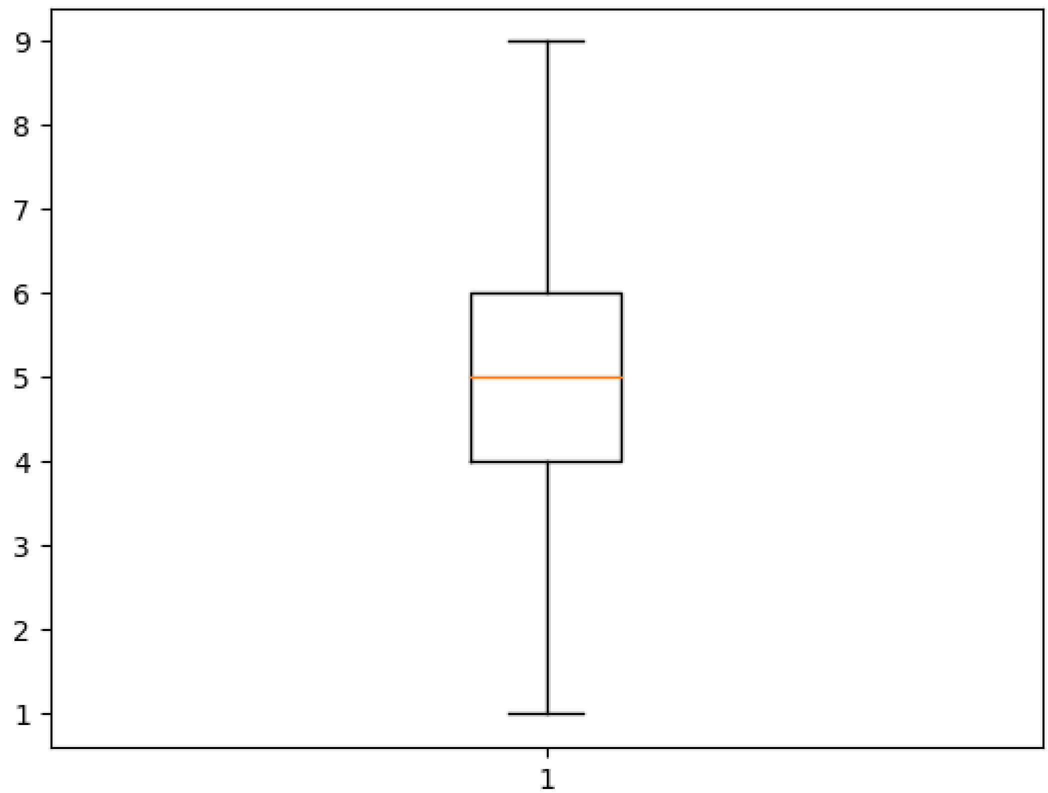
In [18]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (lower
Q3_vitd = np.percentile(medical_data['VitD_levels'], 75)
Q1_vitd = np.percentile(medical_data['VitD_levels'], 25)
IQR_vitd = Q3_vitd - Q1_vitd
Min_vitd = Q1_vitd - (1.5 * IQR_vitd)
rounded_min_vitd = round(Min_vitd,1)
print(rounded_min_vitd)
```

12.5

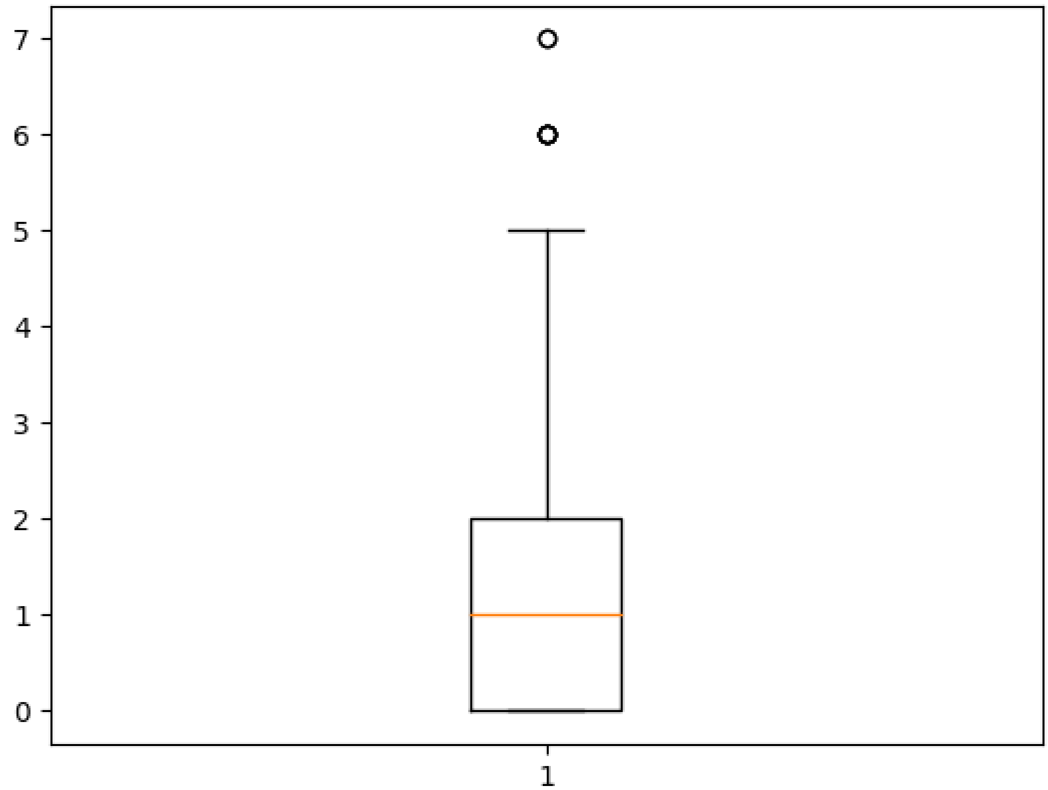
In [19]:
```
# Replacing with the median
median = float(medical_data['VitD_levels'].median())
medical_data['VitD_levels'] = np.where(medical_data['VitD_levels'] > rounded_max_vitd,
```

In [20]:
```
# Replacing with the median
median = float(medical_data['VitD_levels'].median())
medical_data['VitD_levels'] = np.where(medical_data['VitD_levels'] < rounded_min_vitd,
```

In [21]:
```
Docvisitsplot = plt.boxplot(x='Doc_visits', data = medical_data)
```




In [22]:
```
Fullsmealseatenplot = plt.boxplot(x='Full_meals_eaten', data = medical_data)
```

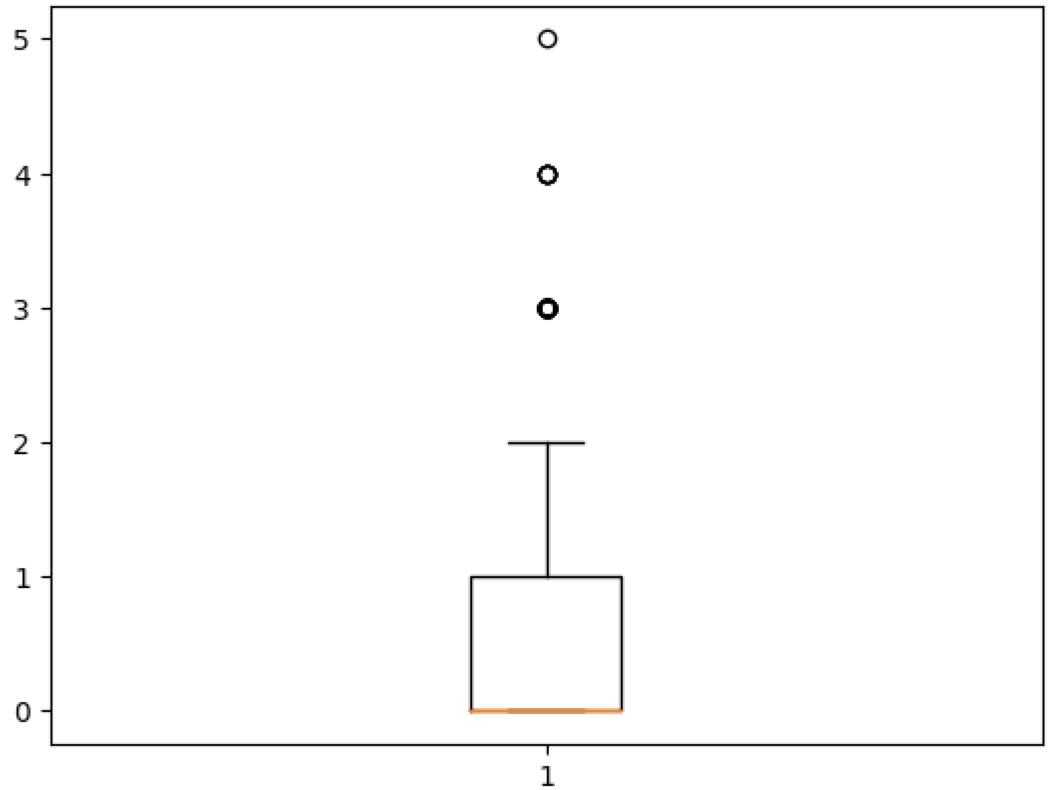



In [23]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_meals = np.percentile(medical_data['Full_meals_eaten'], 75)
Q1_meals = np.percentile(medical_data['Full_meals_eaten'], 25)
IQR_meals = Q3_vitd - Q1_vitd
Max_meals = Q3_vitd + (1.5 * IQR_vitd)
rounded_max_meals = round(Max_meals,1)
print(rounded_max_meals)
```

```
23.4
```

In [24]:
```
# Replacing with the median
median = float(medical_data['Full_meals_eaten'].median())
medical_data['Full_meals_eaten'] = np.where(medical_data['Full_meals_eaten'] > roundec
```

In [25]:
```
VitDSuppplot = plt.boxplot(x='vitD_supp', data = medical_data)
```

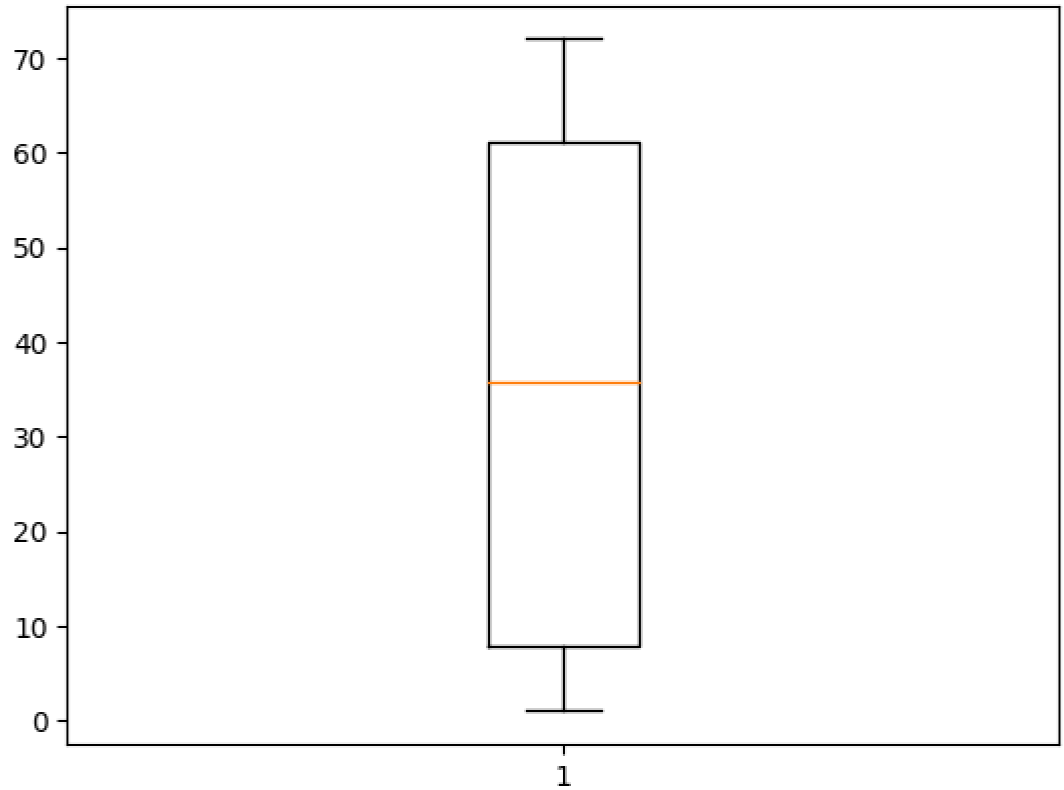



In [26]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_supp = np.percentile(medical_data['vitD_supp'], 75)
Q1_supp = np.percentile(medical_data['vitD_supp'], 25)
IQR_supp = Q3_supp - Q1_supp
Max_supp = Q3_supp + (1.5 * IQR_supp)
rounded_max_supp = round(Max_supp,1)
print(rounded_max_supp)
```

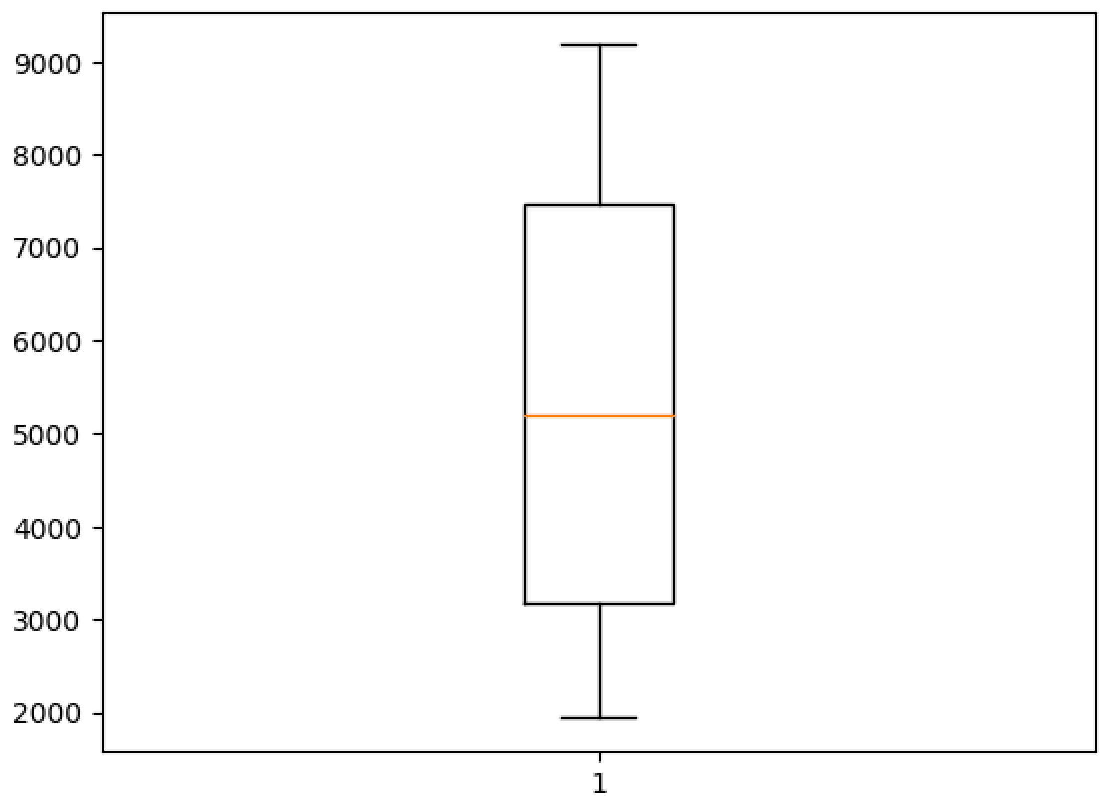
```
2.5
```

In [27]:
```
# Replacing with the median
median = float(medical_data['vitD_supp'].median())
medical_data['vitD_supp'] = np.where(medical_data['vitD_supp'] > rounded_max_supp, mec
```

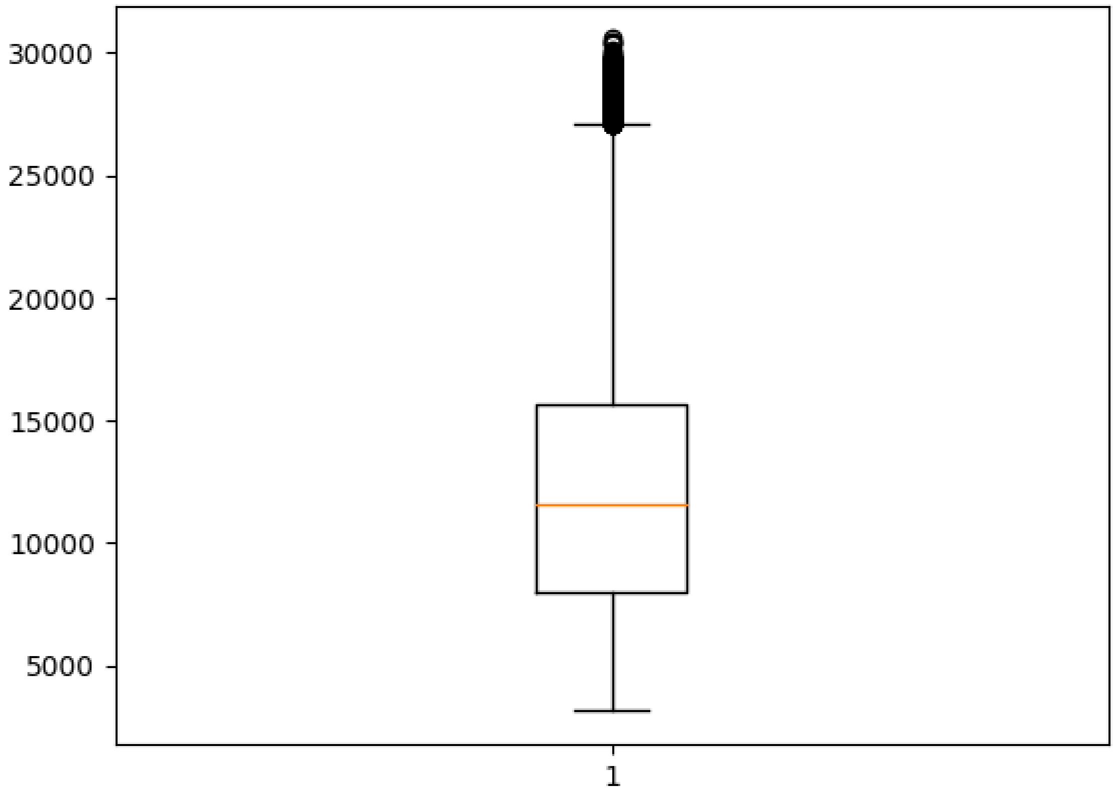
In [28]:
```
Initialdaysplot = plt.boxplot(x='Initial_days', data = medical_data)
```




In [29]:
```
TotalChargePlot = plt.boxplot(x='TotalCharge', data = medical_data)
```




In [30]:
```
AddPlot = plt.boxplot(x='Additional_charges', data = medical_data)
```




In [31]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_add = np.percentile(medical_data['Additional_charges'], 75)
Q1_add = np.percentile(medical_data['Additional_charges'], 25)
IQR_add = Q3_add - Q1_add
Max_add = Q3_add + (1.5 * IQR_add)
rounded_max_add = round(Max_add,1)
print(rounded_max_add)
```

```
27086.5
```

In [32]:
```
# Replacing with the median
median = float(medical_data['Additional_charges'].median())
medical_data['Additional_charges'] = np.where(medical_data['Additional_charges'] > rou
```

In [33]:
```
# Exploratory
# EDA - Looking at descriptive statistics
medical_data.describe()
```

Out[33]:

| | Children | Age | Income | VitD_levels | Doc_visits | Full_meals_eaten | vi |
|---|---|---|---|---|---|---|---|
| **count** | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 1000 |
| **mean** | 1.779900 | 53.511700 | 37355.193095 | 17.958778 | 5.012200 | 1.001400 | |
| **std** | 1.673361 | 20.638538 | 22986.930317 | 1.962375 | 1.045734 | 1.008117 | |
| **min** | 0.000000 | 18.000000 | 154.080000 | 12.507730 | 1.000000 | 0.000000 | |
| **25%** | 0.000000 | 36.000000 | 19598.775000 | 16.642449 | 4.000000 | 0.000000 | |
| **50%** | 1.000000 | 53.000000 | 33766.005000 | 17.951074 | 5.000000 | 1.000000 | |
| **75%** | 3.000000 | 71.000000 | 51024.942500 | 19.325515 | 6.000000 | 2.000000 | |
| **max** | 7.000000 | 89.000000 | 106220.500000 | 23.363658 | 9.000000 | 7.000000 | |

In [34]:

```
# Qualitative/categorical descriptive data
medical_data.describe(include='object')
```

Out[34]:

| | Gender | ReAdmis | Soft_drink | Initial_admin | HighBlood | Stroke | Complication_risk | Overweigh |
|---|---|---|---|---|---|---|---|---|
| **count** | 10000 | 10000 | 10000 | 10000 | 10000 | 10000 | 10000 | 1000 |
| **unique** | 3 | 2 | 2 | 3 | 2 | 2 | 3 | |
| **top** | Female | No | No | Emergency Admission | No | No | Medium | Ye |
| **freq** | 5018 | 6331 | 7425 | 5060 | 5910 | 8007 | 4517 | 709 |

In [35]:

```
# Data Wrangling
# 1. Create new column to input into
medical_data['ReAdmis_numeric'] = medical_data['ReAdmis']
# 2. Create dictionary for the values
dict_readmis = {"ReAdmis_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dict_readmis, inplace = True)
```

In [36]:

```
# Data Wrangling
# 1. Create new column to input into
medical_data['HighBlood_numeric'] = medical_data['HighBlood']
# 2. Create dictionary for the values
dict_highblood = {"HighBlood_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dict_highblood, inplace = True)
```

In [37]:

```
# Data Wrangling
# 1. Create new column to input into
medical_data['Soft_drink_numeric'] = medical_data['Soft_drink']
# 2. Create dictionary for the values
dict_soft = {"Soft_drink_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dict_soft, inplace = True)
```

In [38]:

```
# Data Wrangling
# 1. Create new column to input into
medical_data['Stroke_numeric'] = medical_data['Stroke']
# 2. Create dictionary for the values
```

```
dictstroke = {"Stroke_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictstroke, inplace = True)
```

In [39]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Overweight_numeric'] = medical_data['Overweight']
# 2. Create dictionary for the values
dictover = {"Overweight_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictover, inplace = True)
```

In [40]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Arthritis_numeric'] = medical_data['Arthritis']
# 2. Create dictionary for the values
dictarth = {"Arthritis_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictarth, inplace = True)
```

In [41]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Diabetes_numeric'] = medical_data['Diabetes']
# 2. Create dictionary for the values
dictdib = {"Diabetes_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictdib, inplace = True)
```

In [42]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Hyperlipidemia_numeric'] = medical_data['Hyperlipidemia']
# 2. Create dictionary for the values
dicthyp = {"Hyperlipidemia_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dicthyp, inplace = True)
```

In [43]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['BackPain_numeric'] = medical_data['BackPain']
# 2. Create dictionary for the values
dictback = {"BackPain_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictback, inplace = True)
```

In [44]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Anxiety_numeric'] = medical_data['Anxiety']
# 2. Create dictionary for the values
dictanx = {"Anxiety_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictanx, inplace = True)
```

In [45]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Allergic_rhinitis_numeric'] = medical_data['Allergic_rhinitis']
# 2. Create dictionary for the values
dictallerg = {"Allergic_rhinitis_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictallerg, inplace = True)
```

In [46]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Reflux_esophagitis_numeric'] = medical_data['Reflux_esophagitis']
# 2. Create dictionary for the values
```

```
dictreflux = {"Reflux_esophagitis_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictreflux, inplace = True)
```

In [47]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Asthma_numeric'] = medical_data['Asthma']
# 2. Create dictionary for the values
dictasthma = {"Asthma_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictasthma, inplace = True)
```

In [48]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Complication_risk_numeric'] = medical_data['Complication_risk']
# 2. Create dictionary for the values
dictcompl = {"Complication_risk_numeric": {"High": 2, "Medium": 1, "Low": 0}}
medical_data.replace(dictcompl, inplace = True)
```

In [49]:
```
medical_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 41 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Children                     10000 non-null  float64
 1   Age                          10000 non-null  int64  
 2   Income                       10000 non-null  float64
 3   Gender                       10000 non-null  object 
 4   ReAdmis                      10000 non-null  object 
 5   VitD_levels                  10000 non-null  float64
 6   Doc_visits                   10000 non-null  int64  
 7   Full_meals_eaten             10000 non-null  float64
 8   vitD_supp                    10000 non-null  float64
 9   Soft_drink                   10000 non-null  object 
 10  Initial_admin                10000 non-null  object 
 11  HighBlood                    10000 non-null  object 
 12  Stroke                       10000 non-null  object 
 13  Complication_risk            10000 non-null  object 
 14  Overweight                   10000 non-null  object 
 15  Arthritis                    10000 non-null  object 
 16  Diabetes                     10000 non-null  object 
 17  Hyperlipidemia               10000 non-null  object 
 18  BackPain                     10000 non-null  object 
 19  Anxiety                      10000 non-null  object 
 20  Allergic_rhinitis            10000 non-null  object 
 21  Reflux_esophagitis           10000 non-null  object 
 22  Asthma                       10000 non-null  object 
 23  Services                     10000 non-null  object 
 24  Initial_days                 10000 non-null  float64
 25  TotalCharge                  10000 non-null  float64
 26  Additional_charges           10000 non-null  float64
 27  ReAdmis_numeric              10000 non-null  int64  
 28  HighBlood_numeric            10000 non-null  int64  
 29  Soft_drink_numeric           10000 non-null  int64  
 30  Stroke_numeric               10000 non-null  int64  
 31  Overweight_numeric           10000 non-null  int64  
 32  Arthritis_numeric            10000 non-null  int64  
 33  Diabetes_numeric             10000 non-null  int64  
 34  Hyperlipidemia_numeric       10000 non-null  int64  
 35  BackPain_numeric             10000 non-null  int64  
 36  Anxiety_numeric              10000 non-null  int64  
 37  Allergic_rhinitis_numeric    10000 non-null  int64  
 38  Reflux_esophagitis_numeric   10000 non-null  int64  
 39  Asthma_numeric               10000 non-null  int64  
 40  Complication_risk_numeric    10000 non-null  int64  
dtypes: float64(8), int64(16), object(17)
memory usage: 3.1+ MB
```

In [50]:

```python
# Drop all categorical variables that were re-expressed
medical_data = medical_data.drop(columns=['HighBlood','Stroke','Complication_risk','Ov
```

In [51]:

```python
medical_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 27 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Children                     10000 non-null  float64
 1   Age                          10000 non-null  int64  
 2   Income                       10000 non-null  float64
 3   Gender                       10000 non-null  object 
 4   VitD_levels                  10000 non-null  float64
 5   Doc_visits                   10000 non-null  int64  
 6   Full_meals_eaten             10000 non-null  float64
 7   vitD_supp                    10000 non-null  float64
 8   Initial_admin                10000 non-null  object 
 9   Services                     10000 non-null  object 
 10  Initial_days                 10000 non-null  float64
 11  TotalCharge                  10000 non-null  float64
 12  Additional_charges           10000 non-null  float64
 13  ReAdmis_numeric              10000 non-null  int64  
 14  HighBlood_numeric            10000 non-null  int64  
 15  Soft_drink_numeric           10000 non-null  int64  
 16  Stroke_numeric               10000 non-null  int64  
 17  Overweight_numeric           10000 non-null  int64  
 18  Arthritis_numeric            10000 non-null  int64  
 19  Diabetes_numeric             10000 non-null  int64  
 20  Hyperlipidemia_numeric       10000 non-null  int64  
 21  BackPain_numeric             10000 non-null  int64  
 22  Anxiety_numeric              10000 non-null  int64  
 23  Allergic_rhinitis_numeric    10000 non-null  int64  
 24  Reflux_esophagitis_numeric   10000 non-null  int64  
 25  Asthma_numeric               10000 non-null  int64  
 26  Complication_risk_numeric    10000 non-null  int64  
dtypes: float64(8), int64(16), object(3)
memory usage: 2.1+ MB
```

In [52]:
```python
# Using get dummies pandas function to get numerical values for the 3 nominal categori
medical_data = pd.get_dummies(medical_data, columns=['Services', 'Gender', 'Initial_ad
medical_data.head()
```

Out[52]:

| | Children | Age | Income | VitD_levels | Doc_visits | Full_meals_eaten | vitD_supp | Initial_days | TotalCha |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1.0 | 53 | 86575.93 | 19.141466 | 6 | 0.0 | 0.0 | 10.585770 | 3726.702 |
| **1** | 3.0 | 51 | 46805.99 | 18.940352 | 4 | 2.0 | 1.0 | 15.129562 | 4193.190 |
| **2** | 3.0 | 53 | 14370.14 | 18.057507 | 4 | 1.0 | 0.0 | 4.772177 | 2434.234 |
| **3** | 0.0 | 78 | 39741.49 | 16.576858 | 4 | 1.0 | 0.0 | 1.714879 | 2127.830 |
| **4** | 1.0 | 22 | 1209.56 | 17.439069 | 5 | 0.0 | 2.0 | 1.254807 | 2113.073 |

5 rows × 34 columns

In [53]:
```python
medical_data.info()
```

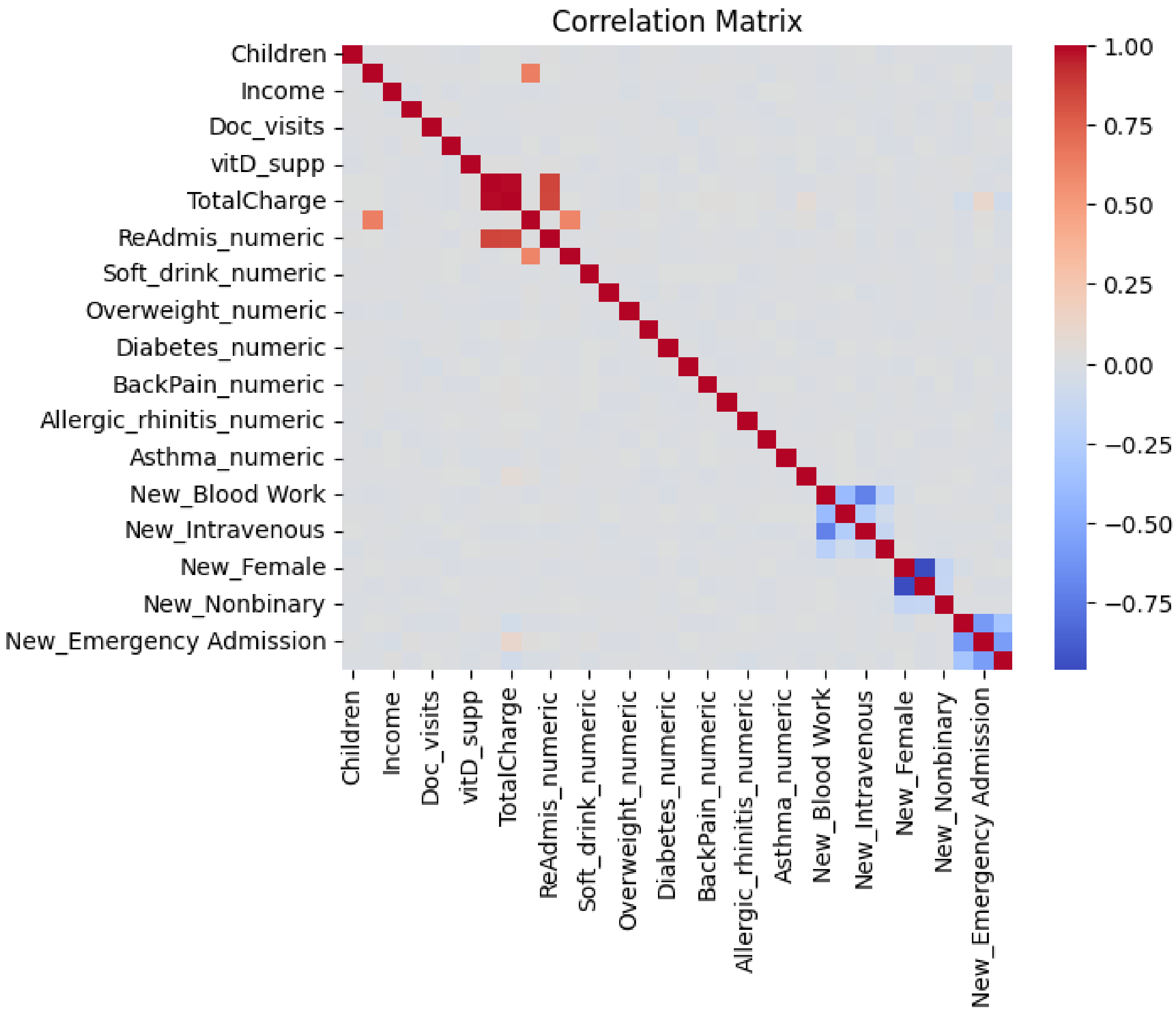
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 34 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Children                     10000 non-null  float64
 1   Age                          10000 non-null  int64
 2   Income                       10000 non-null  float64
 3   VitD_levels                  10000 non-null  float64
 4   Doc_visits                   10000 non-null  int64
 5   Full_meals_eaten             10000 non-null  float64
 6   vitD_supp                    10000 non-null  float64
 7   Initial_days                 10000 non-null  float64
 8   TotalCharge                  10000 non-null  float64
 9   Additional_charges           10000 non-null  float64
 10  ReAdmis_numeric              10000 non-null  int64
 11  HighBlood_numeric            10000 non-null  int64
 12  Soft_drink_numeric           10000 non-null  int64
 13  Stroke_numeric               10000 non-null  int64
 14  Overweight_numeric           10000 non-null  int64
 15  Arthritis_numeric            10000 non-null  int64
 16  Diabetes_numeric             10000 non-null  int64
 17  Hyperlipidemia_numeric       10000 non-null  int64
 18  BackPain_numeric             10000 non-null  int64
 19  Anxiety_numeric              10000 non-null  int64
 20  Allergic_rhinitis_numeric    10000 non-null  int64
 21  Reflux_esophagitis_numeric   10000 non-null  int64
 22  Asthma_numeric               10000 non-null  int64
 23  Complication_risk_numeric    10000 non-null  int64
 24  New_Blood Work               10000 non-null  int32
 25  New_CT Scan                  10000 non-null  int32
 26  New_Intravenous              10000 non-null  int32
 27  New_MRI                      10000 non-null  int32
 28  New_Female                   10000 non-null  int32
 29  New_Male                     10000 non-null  int32
 30  New_Nonbinary                10000 non-null  int32
 31  New_Elective Admission       10000 non-null  int32
 32  New_Emergency Admission      10000 non-null  int32
 33  New_Observation Admission    10000 non-null  int32
dtypes: float64(8), int32(10), int64(16)
memory usage: 2.2 MB
```

In [54]:

```
# Export CSV file
medical_data.to_csv("C:/Users/Makayla Avendano/Desktop/new_med_data_209_task2.csv")
```

In [55]:

```
# Correlation matrix
corr_matrix = medical_data.corr()
sns.heatmap(corr_matrix, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```




In [56]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Lasso
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# Define variables
X = medical_data.drop('TotalCharge',axis=1)
y = medical_data['TotalCharge']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2, random_state=4
```

In [57]:
```
# Export train/test sets
X_train.to_csv("C:/Users/Makayla Avendano/Desktop/X_train.csv")
X_test.to_csv("C:/Users/Makayla Avendano/Desktop/X_test.csv")
y_train.to_csv("C:/Users/Makayla Avendano/Desktop/y_train.csv")
y_test.to_csv("C:/Users/Makayla Avendano/Desktop/y_test.csv")
```

In [58]:
```
# Define variables
X = medical_data.drop('TotalCharge',axis=1).values
y = medical_data['TotalCharge'].values

# Normalize data
scaler = StandardScaler()
```

```
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# Define grid of candidate alpha values
param_grid = {"alpha": 10.0 ** np.arange(-5,6)}

# Create the model
lasso = Lasso()

# GridSearchCV for hyperparameter tuning
grid_search_lasso = GridSearchCV(estimator=lasso, param_grid=param_grid)
grid_search_lasso.fit(X_train,y_train)

# Alpha parameter results
best_alpha = grid_search_lasso.best_params_['alpha']
best_score = grid_search_lasso.best_score_

# Training the model
lasso = Lasso(alpha=best_alpha)
lasso.fit(X_train, y_train)
lasso_pred = lasso.predict(X_test)


# Evaluating the model
train_score = lasso.score(X_train, y_train)
test_score = lasso.score(X_test, y_test)
print(f"Training Set Score (R-squared): {train_score:.4f}")
print(f"Test Set Score (R-squared): {test_score:.4f}")
```

```
Training Set Score (R-squared): 0.9978
Test Set Score (R-squared): 0.9978
```

In [59]:

```
# Alpha parameter results
print(f"Best Alpha: {best_alpha}")
print(f"Best Score: {best_score}")
```

```
Best Alpha: 0.1
Best Score: 0.9978233805905405
```

In [60]:

```
# MSE, RMSE, R-squared
mse = mean_squared_error(y_test, lasso_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, lasso_pred)

print(f"Mean Squared Error (MSE): {mse:.4f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
print(f"R-squared (R2): {r2:.4f}")
```

```
Mean Squared Error (MSE): 10334.9392
Root Mean Squared Error (RMSE): 101.6609
R-squared (R2): 0.9978
```

In [61]:

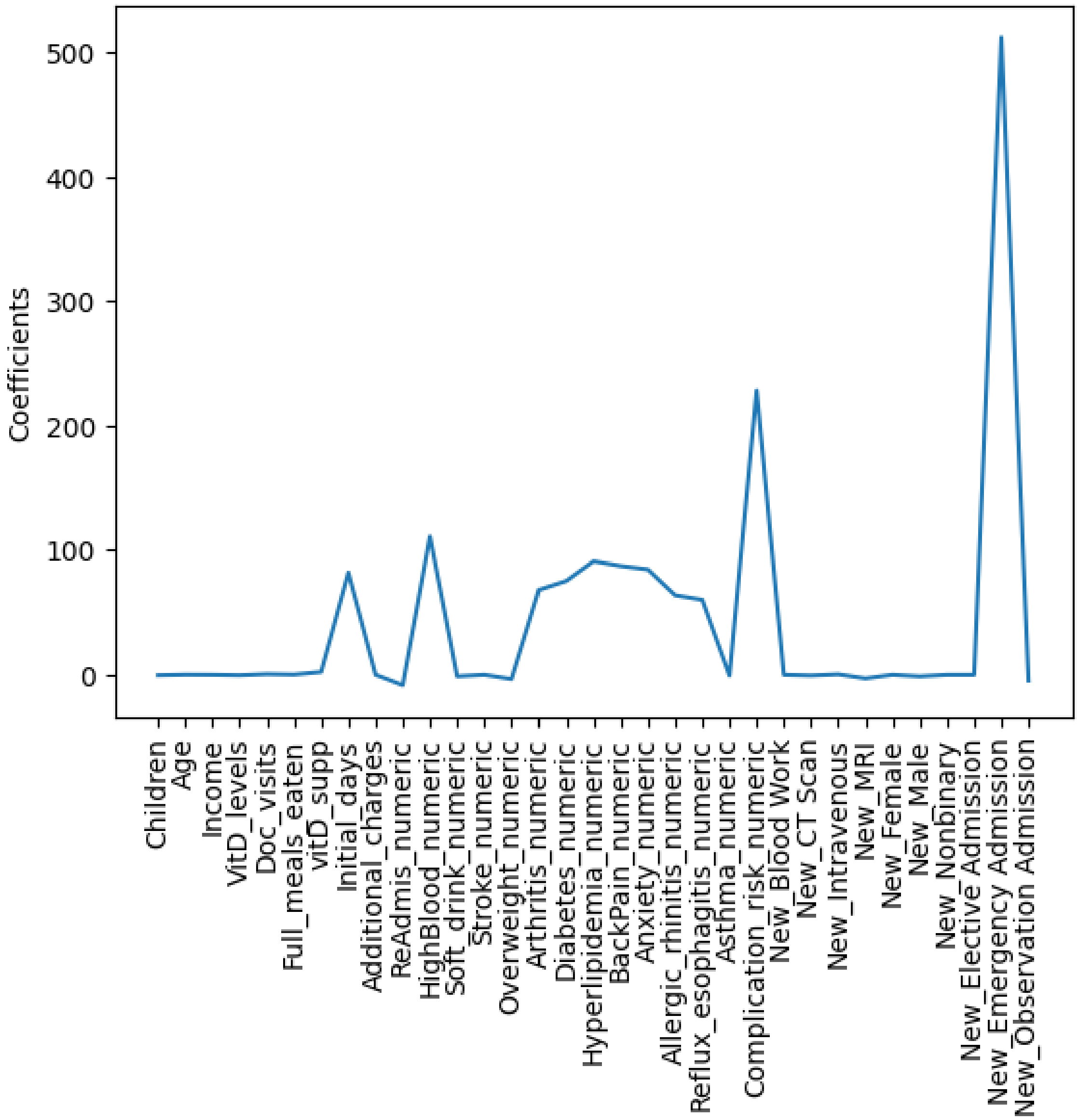
```
lasso_coef = lasso.coef_
feature_names = medical_data.drop('TotalCharge', axis=1).columns

print("Lasso Coefficients:")
for feature, coefficient in zip(feature_names, lasso_coef):
    print(f"{feature}: {coefficient:.4f}")
```

```
Lasso Coefficients:
Children: -0.7603
Age: 1.6111
Income: 0.7337
VitD_levels: -1.0187
Doc_visits: 0.7649
Full_meals_eaten: 0.3418
vitD_supp: 1.6220
Initial_days: 2162.7771
Additional_charges: -2.7147
ReAdmis_numeric: -3.7415
HighBlood_numeric: 54.9430
Soft_drink_numeric: -0.0000
Stroke_numeric: -0.0000
Overweight_numeric: -1.6087
Arthritis_numeric: 32.4999
Diabetes_numeric: 33.2649
Hyperlipidemia_numeric: 43.6299
BackPain_numeric: 42.4945
Anxiety_numeric: 38.8821
Allergic_rhinitis_numeric: 31.7058
Reflux_esophagitis_numeric: 30.2119
Asthma_numeric: 0.0000
Complication_risk_numeric: 166.3628
New_Blood Work: 0.0000
New_CT Scan: -0.4777
New_Intravenous: 0.6160
New_MRI: -1.1968
New_Female: 1.5904
New_Male: -0.0000
New_Nonbinary: -0.0487
New_Elective Admission: -87.4865
New_Emergency Admission: 154.7731
New_Observation Admission: -90.0343
```

In [62]:

```
# Lasso feature selection visualization
features = medical_data.drop('TotalCharge',axis=1).columns
lasso = Lasso(alpha=0.1)
lasso_coef = lasso.fit(X,y).coef_
plt.plot(range(len(features)),lasso_coef)
plt.xticks(range(len(features)), features, rotation=90)
plt.ylabel('Coefficients')
plt.show()
```




## Explanation of Steps

The analysis technique that was used to analyze the data was lasso regression. The first calculation performed to prepare the model was the imputation of outliers using the median. The maximum value was calculated using the equation Q3 + (1.5 *IQR) and the minimum was calculated using the equation Q1 – (1.5* IQR). These calculations were performed and then the where function was used to replace all values above the maximum and below the minimum with the median.

Next, the re-expression of ordinal categorical variables. A new column to input data into was created, a dictionary was created where yes was equal to one and no was equal to zero (except for complication risk), and the data was then inputted into the new column. Then, the re-expression of nominal categorical variables using the get dummies function in pandas.

The data was then split into 80% training set and 20% for the test set. Next, the model was developed. Variables were indicated first and then the data was normalized using

StandardScaler. The parameter grid for grid search cross validation was defined and the lasso model was created. Grid search cross validation was performed and then we began to train the model. Lastly, the model was evaluated. The best alpha parameter results were calculated from the grid search cross validation. Mean squared error, the root mean squared error, and r-squared were then calculated to determine the accuracy of the prediction model. The lasso coefficients were then shown looking at the coefficient values and an added visual.

# Data Summary and Implications

Mean Squared Error (MSE): 10334.9392 Root Mean Squared Error (RMSE): 101.6609 R-squared (R2): 0.9978

The mean squared error (MSE), “is the sum of squares differences between the predicted values and the actual values. It determines how good the estimate is based on the algorithm analysis.” (Elleh, 2022) The root mean squared error (RMSE) is the square root of the MSE and has the same units as our dependent variable total charges making this value easier to interpret. The RMSE of around 102 indicates that the predicted total charges and the actual total charges have an error of around 102. The MSE and RMSE can reveal the degree of error and how significant it is in reference to the model. The R-squared, “metric tells how well a model fits the data. It ranges between 0 and 1. Higher R-squared, the better the model fits the data.” (Elleh, 2022) The R-squared for our model is almost 1 meaning the model fits the data extremely well.

Lasso Regression was used for this analysis. The model that was developed had an R-squared of 0.99 which indicates that our model fits our data very well. The root mean square (RMSE) was 102 which is relatively high and indicates that predictions of total charges are inaccurate by $102. Even though the RMSE is 102, if we compare it to the median value of total charges (5312) it is still relatively small indicating a smaller prediction error. Instead of using SelectKBest for feature selection, lasso regression uses shrinkage to shrink the coefficients that are of less importance. In contrast, the coefficients that are most importance will get larger like Initial_days with a value of 2162.8 and Complication_risk with a value of 166.4.

GridSearchCV is the hyperparameter tuning method that was used to determine the best alpha value. The alpha value that was determined was 0.1 and with this value of alpha the highest model score would be 0.99. Due to the score being high, we can assume that hyperparameter tuning worked efficiently and reduced the risk of overfitting the model. (Bowne-Anderson, n.d) Another thing to note would be that the best alpha value was 0.1 which is on the lower end meaning that the model had a lower complexity value. (Bowne-Anderson, n.d).

# Limitations

One important limitation of lasso regression is instability with correlated features. “What usually happens is that one of the features gets selected somewhat arbitrarily and all of the other features that are highly correlated with that feature get effectively dropped from the model.”

(Ellis, 2021) This means that if there is any correlation within the data, the automatic feature selection built within lasso could potentially misinterpret these correlated features.

## Course of Action

With the results indicated in E2, I believe that this model can be used to predict total charges within this hospital. Although the RMSE is 102, this value is relatively small compared to the median value of total charges which is 5312. This hospital can use this model to focus on those high value lasso coefficients to determine which variables are the most influential on total charges. This model can also give the hospital good insight into the hospital’s income and adjust it as necessary.

In [ ]:

```

```