In [1]:

```
#libraries used
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn
import missingno as msno
from scipy import stats
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

In [2]:

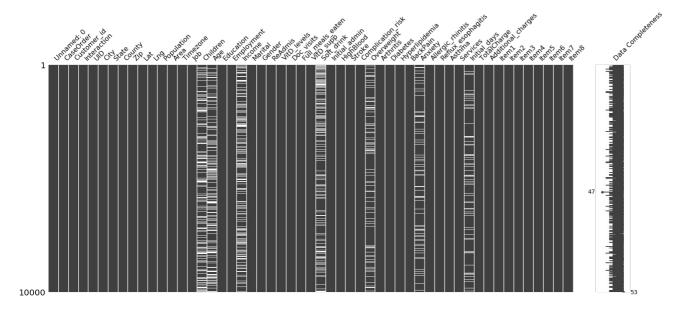
```
#import datafile
data = pd.read_csv('C:/Users/ericy/Desktop/medical_raw_data.csv')
```

In [3]:

```
# Graph variables to visualize missing data
msno.matrix(data, labels=True)
```

Out[3]:

<matplotlib.axes. subplots.AxesSubplot at 0x1f8228e9a08>



In [4]:

```
#find out shape, create 'Index' variable, Drop 'Unnamed:0'.
data.shape
data['Index'] = pd.Series(range(0, 10000))
#Note https://appdividend.com/2020/06/01/pandas-dataframe-drop-method-in-python/ for .drop() method in PA
data.drop(['Unnamed: 0'], axis=1, inplace=True)
#Move 'Index' to beginning of data.
column_to_move = data.pop('Index')
data.insert(0, 'Index', column_to_move)
data.head()
```

Out[4]:

	Index	CaseOrder	Customer_id	Interaction	UID	City	State	County	Zip	Lat	 Т
0	0	1	C412403	8cd49b13- f45a-4b47- a2bd- 173ffa932c2f	3a83ddb66e2ae73798bdf1d705dc0932	Eva	AL	Morgan	35621	34.34960	 3
1	1	2	Z919181	d2450b70- 0337-4406- bdbb- bc1037f1734c	176354c5eef714957d486009feabf195	Marianna	FL	Jackson	32446	30.84513	 4
2	2	3	F995323	a2057123- abf5-4a2c- abad- 8ffe33512562	e19a0fa00aeda885b8a436757e889bc9	Sioux Falls	SD	Minnehaha	57110	43.54321	 2
3	3	4	A879973	1dec528d- eb34-4079- adce- 0d7a40e82205	cd17d7b6d152cb6f23957346d11c3f07	New Richland	MN	Waseca	56072	43.89744	 2
4	4	5	C544523	5885f56b- d6da-43a3- 8760- 83583af94266	d2f0425877b10ed6bb381f3e2579424a	West Point	VA	King William	23181	37.59894	 1

5 rows × 53 columns

In [5]:

#Double check which variables have null values
data.isnull().any()

Out[5]:

False Index CaseOrder False Customer id False Interaction False UID False City False State False County False False Zip Lat False Lng False Population False Area False Timezone False Job False Children True Age True Education False Employment False Income True Marital False Gender False ReAdmis False VitD_levels False Doc_visits
Full_meals_eaten False False VitD_supp False Soft_drink True Initial admin False HighBlood False Stroke False Complication_risk False Overweight True Arthritis False Diabetes False Hyperlipidemia False BackPain False Anxiety True Allergic_rhinitis False Reflux_esophagitis False Asthma False Services False Initial days True TotalCharge False Additional charges False Item1 False Item2 False Item3 False Item4 False Item5 False Item6 False Item7 False Item8 False

dtype: bool

In [6]:

#Total null cases in each variable
data.isnull().sum()
#Variables to address with null values: Children, Age, Income, Soft_drink, Overweight, Anxiety, Initial_days.

Out[6]:

0 Index 0 CaseOrder Customer id 0 Interaction 0 UID City 0 State 0 County 0 0 Zip Lat 0 0 Lng Population 0 Area 0 Timezone 0 Job Children 2588 2414 Aae Education 0 Employment 0 2464 Income Marital 0 Gender 0 ReAdmis 0 VitD levels 0 Doc_visits 0 Full_meals_eaten 0 0 VitD supp Soft drink 2467 Initial_admin 0 0 HighBlood Stroke 0 Complication risk 0 982 Overweight Arthritis 0 0 Diabetes Hyperlipidemia 0 BackPain Anxiety 984 Allergic_rhinitis 0 Reflux_esophagitis Asthma 0 Services 0 1056 Initial days TotalCharge 0 Additional_charges Item1 0 Ttem2 0 Item3 Item4 0 Item5 0 Ttem6 0 Item7 0 0 Ttem8 dtype: int64

In [7]:

```
#Rename Item1-Item8 variables to names provided in data's supplemental PDF.
#Also rename 'CaseOrder', 'ReAdmis', 'HighBlood', 'BackPain', and 'TotalCharge' to have the same syntax in variab
le naming across the dataset
#Note https://re-thought.com/guide-to-renaming-columns-with-python-pandas/ for .rename() method
data.rename(columns={'CaseOrder':'Case_order','ReAdmis':'Readmis','HighBlood':'High_blood','BackPain':'Back_pain'
,'TotalCharge':'Total_charge','Item1':'Timely_admission', 'Item2':'Timely_treatment', 'Item3':'Timely_visits', 'I
tem4':'Reliability', 'Item5':'Options', 'Item6':'Hours', 'Item7':'Courteous', 'Item8':'Active_listen'}, inplace=T
rue)
```

#Check that variables were correctly renamed
data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 53 columns):
     Column
                         Non-Null Count Dtype
#
- - -
                          -----
0
     Index
                         10000 non-null int64
                         10000 non-null int64
     Case order
 1
 2
     Customer id
                          10000 non-null
                                         object
     Interaction
                         10000 non-null
 3
                                         object
 4
                          10000 non-null
     UID
                                         object
 5
     City
                         10000 non-null
                                          obiect
 6
     State
                         10000 non-null
                                          obiect
 7
     County
                         10000 non-null
                                          object
 8
                          10000 non-null
     Zip
                         10000 non-null
 9
     Lat
                                          float64
 10
     Lng
                          10000 non-null
                                          float64
                         10000 non-null
 11
     Population
                                          int64
 12
                          10000 non-null
     Area
                                          object
 13
                          10000 non-null
     Timezone
                                          object
 14
     Job
                          10000 non-null
                                          object
 15
     Children
                          7412 non-null
                                          float64
 16
                          7586 non-null
                                          float64
     Aae
 17
     Education
                          10000 non-null
                                          obiect
 18
     Employment
                         10000 non-null
                                          object
 19
                         7536 non-null
     Income
                                          float64
 20
    Marital
                         10000 non-null
                                          object
 21
     Gender
                          10000 non-null
                                          obiect
 22
     Readmis
                          10000 non-null
                                          object
 23
     VitD levels
                          10000 non-null
                                          float64
 24
     Doc visits
                          10000 non-null
                                          int64
 25
     Full meals eaten
                          10000 non-null
                                          int64
 26
     VitD supp
                          10000 non-null
                                          int64
 27
     Soft drink
                          7533 non-null
                                          object
 28
     Initial_admin
                          10000 non-null
                                          object
 29
     High blood
                          10000 non-null
                                          object
 30
     Stroke
                          10000 non-null
                                          object
     Complication risk
 31
                          10000 non-null
                                          obiect
 32
     Overweight
                          9018 non-null
                                          float64
 33
     Arthritis
                          10000 non-null
                                          object
 34
     Diabetes
                          10000 non-null
                                          object
     Hyperlipidemia
 35
                          10000 non-null
                                          object
 36
     Back pain
                          10000 non-null
                                         object
 37
                          9016 non-null
     Anxiety
                                          float64
                          10000 non-null
 38
     Allergic_rhinitis
                                          object
 39
     Reflux_esophagitis
                         10000 non-null
                                          object
                          10000 non-null
 40
     Asthma
                                          object
 41
     Services
                          10000 non-null
                                          object
 42
     Initial_days
                          8944 non-null
                                          float64
 43
                          10000 non-null
     Total charge
                                         float64
 44
                         10000 non-null
     Additional_charges
                                         float64
 45
                          10000 non-null
     Timely admission
                                          int64
 46
     Timely treatment
                          10000 non-null int64
 47
     Timely visits
                          10000 non-null int64
                          10000 non-null int64
 48
    Reliability
 49
                          10000 non-null
     Options
                                         int64
                         10000 non-null int64
 50
    Hours
 51 Courteous
                          10000 non-null int64
                         10000 non-null int64
52 Active listen
dtypes: float64(11), int64(15), object(27)
memory usage: 4.0+ MB
```

In [9]:

```
#Address missing values in 'Soft_drink'
print(data['Soft_drink'])
data['Soft_drink'].fillna(0, inplace=True)
data.isnull().sum()
```

```
3
         No
4
        Yes
9995
         No
9996
         No
9997
        Yes
9998
         No
9999
         No
Name: Soft_drink, Length: 10000, dtype: object
Out[9]:
                           0
Index
                           0
{\tt Case\_order}
Customer id
                           0
Interaction
                           0
UID
                           0
                           0
City
State
                           0
                           0
County
                           0
Zip
                           0
Lat
Lng
                           0
Population
                           0
Area
                           0
                           0
Timezone
                           0
Job
Children
                        2588
                        2414
Age
Education
                           0
                           0
Employment
                        2464
Income
Marital
                           0
Gender
                           0
Readmis
                           0
VitD levels
                           0
Doc_visits
Full_meals_eaten
                           0
VitD_supp
                           0
Soft drink
                           0
                           0
Initial_admin
High blood
                           0
Stroke
                           0
Complication_risk
                           0
Overweight
                         982
Arthritis
                           0
                           0
Diabetes
Hyperlipidemia
                           0
                           0
Back_pain
Anxiety
                         984
Allergic rhinitis
                           0
Reflux_esophagitis
                           0
Asthma
Services
                           0
                        1056
{\tt Initial\_days}
Total_charge
                           0
Additional_charges
Timely_admission
Timely_treatment
                           0
                           0
Timely visits
                           0
Reliability
                           0
Options
                           0
                           0
Hours
Courteous
                           0
                           0
Active_listen
dtype: int64
```

In [10]:

0

1

2

NaN

No

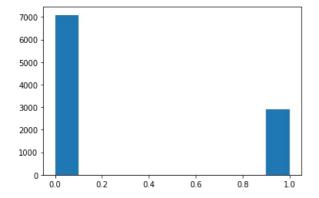
No

#Address missing values in 'Anxiety'

In [11]:

```
data['Anxiety'].fillna(0, inplace=True)
plt.hist(data['Anxiety'])
```

Out[11]:



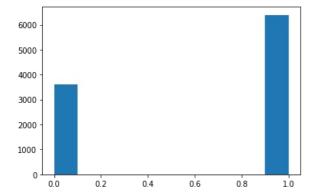
In [12]:

#Address missing values in 'Overweight'

In [13]:

```
data['Overweight'].fillna(0, inplace=True)
plt.hist(data['Overweight'])
```

Out[13]:



In [14]:

Check for null values data.isnull().sum()

Out[14]:

Index ${\tt Case_order}$ 0 Customer_id 0 0 Interaction UID 0 City 0 State 0 County 0 Zip 0 0 Lat Lng 0 Population 0 Area 0 Timezone 0 Job 0 2588 Children Age 2414 0 Education Employment 0 2464 Income Marital 0 0 Gender Readmis 0 VitD_levels 0 Doc visits 0 0 Full_meals_eaten VitD_supp Soft_drink 0 0 Initial admin 0 High_blood 0 Stroke 0 ${\tt Complication_risk}$ 0 Overweight 0 Arthritis 0 0 Diabetes Hyperlipidemia 0 Back pain 0 0 Anxiety Allergic_rhinitis 0 Reflux_esophagitis 0 0 Asthma Services 0 Initial_days 1056 Total_charge 0 Additional charges 0 0 Timely_admission Timely_treatment
Timely_visits 0 0 Reliability 0 Options 0 Hours 0 0 Courteous 0 Active_listen

In [15]:

dtype: int64

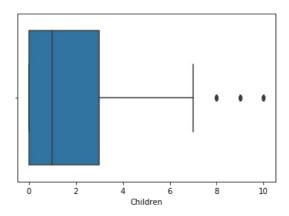
#Address null values in 'Children'.

In [16]:

seaborn.boxplot(data['Children'])

Out[16]:

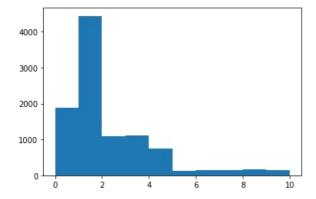
<matplotlib.axes. subplots.AxesSubplot at 0x1f822f5b4c8>



In [17]:

```
data['Children'].fillna(data['Children'].median(), inplace=True)
plt.hist(data['Children'])
```

Out[17]:



In [18]:

```
data.isnull().sum()
```

Out[18]:

Index	0
Case order	0
Customer id	0
Interaction	0
UID	0
	0
City	
State	0
County	0
Zip	0
Lat	0
Lng	0
Population	0
Area	0
Timezone	0
Job	0
Children	0
Age	2414
Education	0
Employment	Ö
Income	2464
Marital	2404
Gender	0
Readmis	0
VitD_levels	0
Doc_visits	0
Full_meals_eaten	0
VitD_supp	0
Soft_drink	0
<pre>Initial_admin</pre>	0
High blood	0
Stroke	0
Complication risk	0
0verweight	0
Arthritis	0
Diabetes	0
Hyperlipidemia	0
Back pain	0
Anxiety	0
Allergic_rhinitis	0
Reflux esophagitis	0
	0
Asthma	
Services	0
<pre>Initial_days</pre>	1056
Total_charge	0
Additional_charges	0
Timely_admission	Θ
Timely_treatment	0
Timely_visits	0
Reliability	0
Options	0
Hours	0
Courteous	0
Active_listen	0
dtype: int64	

In [19]:

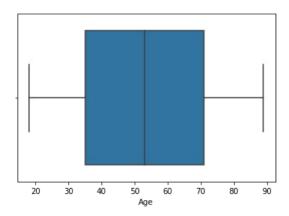
#Address null values in 'Age'.

In [20]:

```
seaborn.boxplot(data['Age'])
```

Out[20]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f82246f508>



In [21]:

```
data['Age'].fillna(method='backfill', inplace=True)
data.isnull().sum()
data['Age'].fillna(method='ffill', inplace=True)
data.isnull().sum()
```

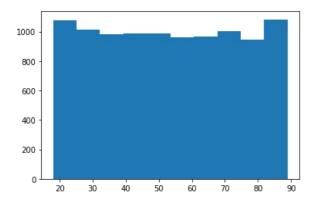
Out[21]:

0 Index Case order 0 0 Customer id 0 Interaction 0 UID 0 City State 0 0 County 0 Zip Lat 0 Lng 0 Population 0 0 Area 0 Timezone 0 Job Children 0 Age 0 Education 0 **Employment** 0 2464 Income Marital 0 Gender 0 Readmis 0 0 VitD_levels Doc_visits
Full_meals_eaten 0 0 VitD_supp 0 Soft_drink Initial admin 0 High_blood 0 Stroke 0 ${\tt Complication_risk}$ Overweight 0 0 Arthritis Diabetes 0 Hyperlipidemia 0 Back_pain 0 0 Anxiety Allergic_rhinitis 0 Reflux_esophagitis Asthma 0 0 Services Initial days 1056 0 Total_charge Additional charges 0 Timely_admission 0 Timely_treatment 0 Timely_visits 0 Reliability 0 Options 0 Hours 0 0 Courteous Active_listen 0 dtype: int64

In [22]:

```
plt.hist(data['Age'])
```

Out[22]:

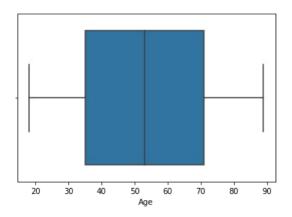


In [23]:

seaborn.boxplot(data['Age'])

Out[23]:

<matplotlib.axes. subplots.AxesSubplot at 0x1f823f98648>



In [24]:

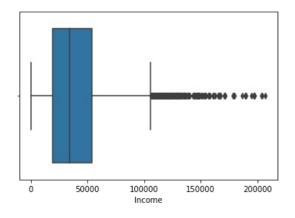
#Address null values in 'Income'

In [25]:

```
seaborn.boxplot(data['Income'])
```

Out[25]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f82400db48>



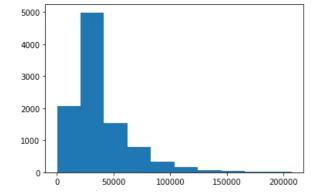
In [26]:

data['Income'].fillna(data['Income'].median(), inplace=True)

In [27]:

```
plt.hist(data['Income'])
```

Out[27]:

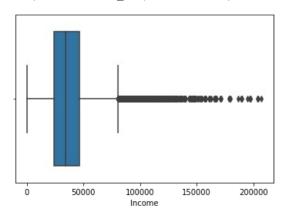


In [28]:

seaborn.boxplot(data['Income'])

Out[28]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f82446c808>



In [29]:

#Check data for null values.
data.isnull().sum()

Out[29]:

out[25].	
Index Case_order Customer_id Interaction UID City State County Zip Lat Lng Population Area Timezone Job Children Age Education Employment Income Marital Gender Readmis VitD_levels Doc_visits Full_meals_eaten VitD_supp Soft_drink Initial_admin High_blood Stroke Complication_risk Overweight Arthritis Diabetes Hyperlipidemia Back_pain Anxiety Allergic_rhinitis Reflux_esophagitis Asthma Services Inital_days Total_charge Additional_charges	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Allergic_rhinitis	
Reflux_esophagitis	0
Asthma	0
	0
Initial days	1056
Total charge	0
Additional charges	0
Timely admission	0
Timely_treatment	0
Timely_visits	0
	0
Reliability	
Options	0
Hours	0
Courteous	0
Active_listen	0
dtype: int64	

In [30]:

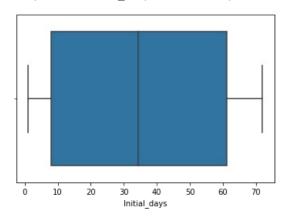
#Begin analyzing 'Initial_days'

In [31]:

```
seaborn.boxplot(data['Initial_days'])
```

Out[31]:

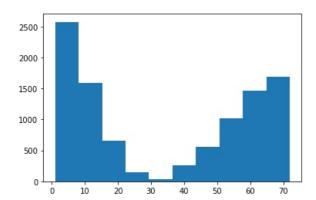
<matplotlib.axes. subplots.AxesSubplot at 0x1f8258b7b88>



In [32]:

```
data['Initial_days'].fillna(method='backfill', inplace=True)
plt.hist(data['Initial_days'])
```

Out[32]:

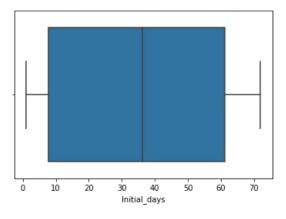


In [33]:

```
seaborn.boxplot(data['Initial_days'])
```

Out[33]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f82596da88>

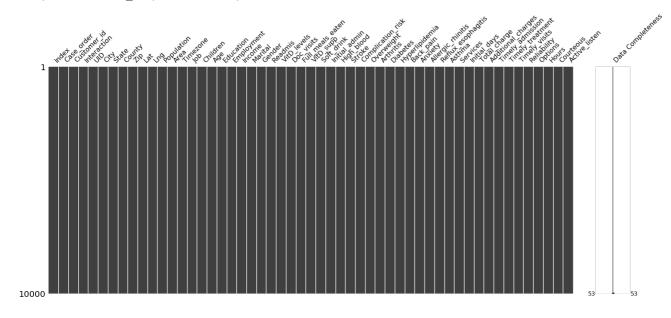


In [34]:

msno.matrix(data, labels=True)

Out[34]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f8260755c8>



In [35]:

data.isnull().sum()

Out[35]:

0 Index Case order 0 Customer_id 0 Interaction 0 UID 0 City 0 State 0 County 0 0 Zip Lat 0 0 Lng Population 0 Area 0 Timezone 0 Job 0 Children 0 Age 0 Education 0 Employment Income 0 Marital 0 Gender 0 Readmis 0 VitD_levels 0 Doc_visits
Full_meals_eaten 0 0 VitD_supp 0 Soft_drink Initial admin 0 High_blood 0 Stroke Complication_risk 0 Overweight 0 Arthritis 0 Diabetes Hyperlipidemia 0 Back_pain 0 0 Anxiety Allergic_rhinitis Reflux_esophagitis 0 Asthma 0 Services 0 Initial days Total_charge 0 Additional charges 0 Timely_admission 0 Timely_treatment Timely_visits 0 Reliability 0 Options 0 Hours 0 Courteous 0 Active_listen 0 dtype: int64

In [36]:

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 53 columns):

Data	columns (total 53 d		
#	Column	Non-Null Count	Dtype
0	Index	10000 non-null	int64
1	Case order	10000 non-null	int64
2	Customer id	10000 non-null	object
3	Interaction	10000 non-null	object
4	UID	10000 non-null	object
5	City	10000 non-null	object
6	State	10000 non-null	object
7	County	10000 non-null	object
8	Zip	10000 non-null	int64
9	Lat	10000 non-null	float64
10	Lng	10000 non-null	float64
11	Population		int64
12	•		
	Area	10000 non-null	object
13	Timezone	10000 non-null	object
14	Job	10000 non-null	object
15	Children	10000 non-null	float64
16	Age	10000 non-null	float64
17	Education	10000 non-null	object
18	Employment	10000 non-null	object
19	Income	10000 non-null	float64
20	Marital	10000 non-null	object
21	Gender	10000 non-null	object
22	Readmis	10000 non-null	object
23	VitD levels	10000 non-null	float64
24	Doc visits	10000 non-null	int64
25	Full meals eaten	10000 non-null	int64
26	VitD supp	10000 non-null	int64
27	Soft drink	10000 non-null	object
28	Initial admin	10000 non-null	object
29	High blood	10000 non-null	object
30	Stroke	10000 non-null	object
31	Complication risk	10000 non-null	object
32	Overweight	10000 non-null	float64
33	Arthritis	10000 non-null	object
34	Diabetes	10000 non-null	object
35	Hyperlipidemia	10000 non-null	object
36	Back_pain	10000 non-null	object
37	Anxiety	10000 non-null	float64
38	Allergic_rhinitis	10000 non-null	object
39	Reflux_esophagitis	10000 non-null	object
40	Asthma	10000 non-null	object
41	Services	10000 non-null	object
42	Initial_days	10000 non-null	float64
43	Total_charge	10000 non-null	float64
44	Additional_charges	10000 non-null	float64
45	Timely_admission	10000 non-null	int64
46	Timely_treatment	10000 non-null	int64
47	Timely_visits	10000 non-null	int64
48	Reliability	10000 non-null	int64
49	Options	10000 non-null	int64
50	Hours	10000 non-null	int64
51	Courteous	10000 non-null	int64
52	Active listen	10000 non-null	int64
dtype	es: flo \overline{a} t64(11), int		7)
	ry usage: 4.0+ MB	· ·	
	- 5		

In [37]:

data.head()

Out[37]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat	1
0	0	1	C412403	8cd49b13- f45a-4b47- a2bd- 173ffa932c2f	3a83ddb66e2ae73798bdf1d705dc0932	Eva	AL	Morgan	35621	34.34960	
1	1	2	Z919181	d2450b70- 0337-4406- bdbb- bc1037f1734c	176354c5eef714957d486009feabf195	Marianna	FL	Jackson	32446	30.84513	
2	2	3	F995323	a2057123- abf5-4a2c- abad- 8ffe33512562	e19a0fa00aeda885b8a436757e889bc9	Sioux Falls	SD	Minnehaha	57110	43.54321	
3	3	4	A879973	1dec528d- eb34-4079- adce- 0d7a40e82205	cd17d7b6d152cb6f23957346d11c3f07	New Richland	MN	Waseca	56072	43.89744	
4	4	5	C544523	5885f56b- d6da-43a3- 8760- 83583af94266	d2f0425877b10ed6bb381f3e2579424a	West Point	VA	King William	23181	37.59894	

5 rows × 53 columns

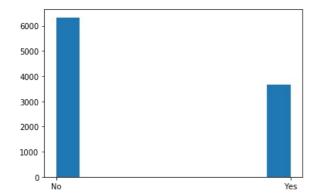
4

In [38]:

```
plt.hist(data['Readmis'])
```

Out[38]:

```
(array([6331., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
      3669.]),
array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
<a list of 10 Patch objects>)
```



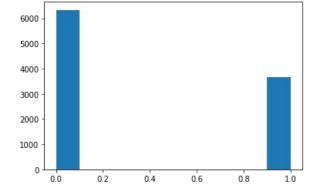
In [39]:

```
#Reexpression of 'Readmis' data as numeric
data['Readmis'] = data['Readmis'].astype(str)
data['Readmis'].replace(('Yes','No'), (1,0), inplace=True)
```

```
In [40]:
```

```
plt.hist(data['Readmis'])
```

Out[40]:



In [41]:

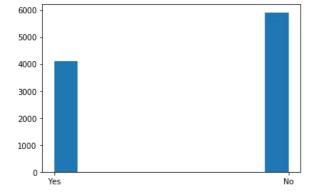
```
#Reexpression of 'Soft_drink' data as numeric
data['Soft_drink'] = data['Soft_drink'].astype(str)
data['Soft_drink'].replace(('Yes','No'), (1,0), inplace=True)
```

In []:

In [42]:

```
plt.hist(data['High_blood'])
```

Out[42]:



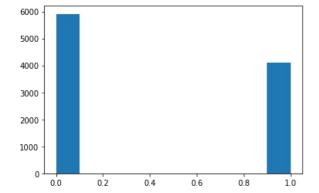
In [43]:

```
#Reexpression of 'High_blood' data as numeric
data['High_blood'] = data['High_blood'].astype(str)
data['High_blood'].replace(('Yes','No'), (1,0), inplace=True)
```

In [44]:

```
plt.hist(data['High_blood'])
```

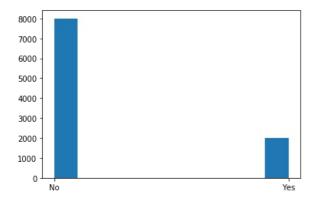
Out[44]:



In [45]:

```
#Reexpression of 'Stroke' data as numeric
plt.hist(data['Stroke'])
```

Out[45]:



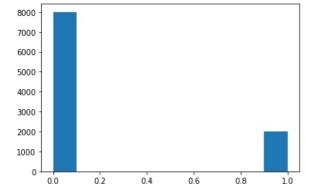
In [46]:

```
#Reexpression of 'Stroke' data as numeric
data['Stroke'] = data['Stroke'].astype(str)
data['Stroke'].replace(('Yes','No'), (1,0), inplace=True)
```

In [47]:

```
plt.hist(data['Stroke'])
```

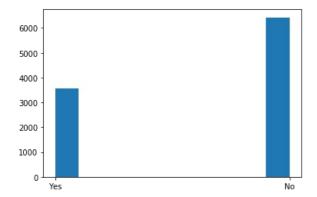
Out[47]:



In [48]:

```
#Reexpression of 'Arthritis' data as numeric
plt.hist(data['Arthritis'])
```

Out[48]:



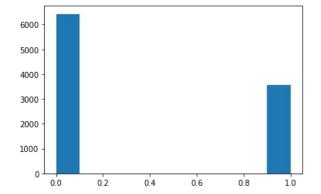
In [49]:

```
#Reexpression of 'Arthritis' data as numeric
data['Arthritis'] = data['Arthritis'].astype(str)
data['Arthritis'].replace(('Yes','No'), (1,0), inplace=True)
```

In [50]:

```
plt.hist(data['Arthritis'])
```

Out[50]:

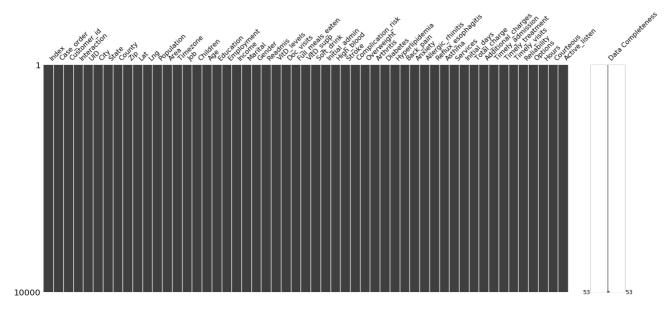


In [51]:

```
msno.matrix(data, labels=True)
```

Out[51]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f825fdbb48>



In [52]:

data.info()

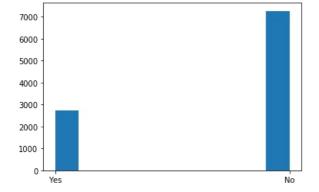
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 53 columns):

Data	columns (total 53 d		
#	Column	Non-Null Count	Dtype
0	Index	10000 non-null	int64
1	Case order	10000 non-null	int64
2	Customer id	10000 non-null	object
3	Interaction	10000 non-null	object
4	UID	10000 non-null	object
5	City	10000 non-null	object
6	State	10000 non-null	object
7		10000 non-null	
	County		object
8	Zip	10000 non-null	int64
9	Lat	10000 non-null	float64
10	Lng	10000 non-null	float64
11	Population	10000 non-null	int64
12	Area	10000 non-null	object
13	Timezone	10000 non-null	object
14	Job	10000 non-null	object
15	Children	10000 non-null	float64
16	Age	10000 non-null	float64
17	Education	10000 non-null	object
18	Employment	10000 non-null	obiect
19	Income	10000 non-null	float64
20	Marital	10000 non-null	object
21	Gender	10000 non-null	object
22	Readmis	10000 non-null	int64
23	VitD levels	10000 non-null	float64
24	Doc visits	10000 non-null	int64
25	Full meals eaten	10000 non-null	
			int64
26	VitD_supp	10000 non-null	int64
27	Soft_drink	10000 non-null	object
28	Initial_admin	10000 non-null	object
29	High_blood	10000 non-null	int64
30	Stroke	10000 non-null	int64
31	Complication_risk	10000 non-null	object
32	Overweight	10000 non-null	float64
33	Arthritis	10000 non-null	int64
34	Diabetes	10000 non-null	object
35	Hyperlipidemia	10000 non-null	object
36	Back pain	10000 non-null	object
37	Anxiety	10000 non-null	float64
38	Allergic_rhinitis	10000 non-null	object
39	Reflux esophagitis	10000 non-null	object
40	Asthma	10000 non-null	object
41	Services	10000 non-null	object
42	Initial_days	10000 non-null	float64
			float64
43	Total_charge		
44	Additional_charges	10000 non-null	float64
45	Timely_admission	10000 non-null	int64
46	Timely_treatment	10000 non-null	int64
47	Timely_visits	10000 non-null	int64
48	Reliability	10000 non-null	int64
49	Options	10000 non-null	int64
50	Hours	10000 non-null	int64
51	Courteous	10000 non-null	int64
52	Active listen	10000 non-null	int64
dtype	es: flo \overline{a} t64(11), int	64(19), object(2	3)
	ry usage: 4.0+ MB	, ,	
	- 5		

```
In [53]:
```

```
plt.hist(data['Diabetes'])
```

Out[53]:



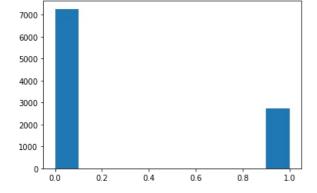
In [54]:

```
#Reexpression of 'Diabetes' data as numeric
data['Diabetes'] = data['Diabetes'].astype(str)
data['Diabetes'].replace(('Yes','No'), (1,0), inplace=True)
```

In [55]:

```
plt.hist(data['Diabetes'])
```

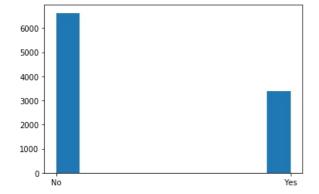
Out[55]:



In [56]:

```
#Reexpression of 'Hyperlipidemia' data as numeric
plt.hist(data['Hyperlipidemia'])
```

Out[56]:



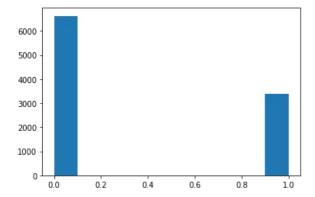
In [57]:

```
data['Hyperlipidemia'] = data['Hyperlipidemia'].astype(str)
data['Hyperlipidemia'].replace(('Yes','No'), (1,0), inplace=True)
```

In [58]:

```
plt.hist(data['Hyperlipidemia'])
```

Out[58]:



In [59]:

```
#Reexpression of 'Back_pain' data as numeric
plt.hist(data['Back_pain'])
```

Out[59]:



In [60]:

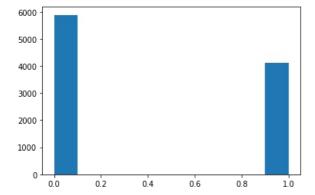
```
data['Back_pain'] = data['Back_pain'].astype(str)
data['Back_pain'].replace(('Yes','No'), (1,0), inplace=True)
```

In [61]:

```
plt.hist(data['Back_pain'])
```

Out[61]:

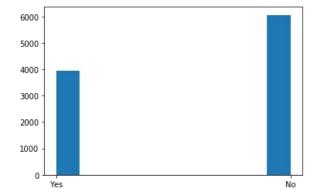
```
(array([5886., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
      4114.]),
array([0., 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.]),
<a list of 10 Patch objects>)
```



In [62]:

```
#Reexpression of 'Allergic_rhinitis' as numeric
plt.hist(data['Allergic_rhinitis'])
```

Out[62]:



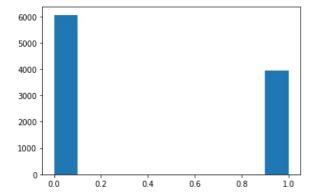
In [63]:

```
data['Allergic_rhinitis'] = data['Allergic_rhinitis'].astype(str)
data['Allergic_rhinitis'].replace(('Yes','No'), (1,0), inplace=True)
```

In [64]:

```
plt.hist(data['Allergic_rhinitis'])
```

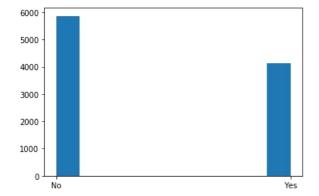
Out[64]:



In [65]:

```
#Reexpression of 'Reflux_esophagitis' data as numeric
plt.hist(data['Reflux_esophagitis'])
```

Out[65]:



In [66]:

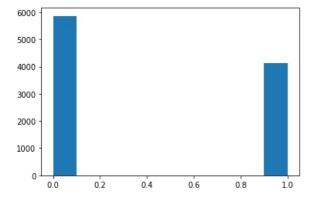
```
data['Reflux_esophagitis'] = data['Reflux_esophagitis'].astype(str)
data['Reflux_esophagitis'].replace(('Yes','No'), (1,0), inplace=True)
```

In [67]:

```
plt.hist(data['Reflux_esophagitis'])
```

Out[67]:

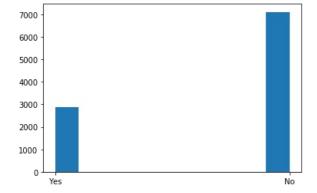
```
(array([5865., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
      4135.]),
array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
<a list of 10 Patch objects>)
```



In [68]:

```
#Reexpression of 'Asthma' data as numeric.
plt.hist(data['Asthma'])
```

Out[68]:



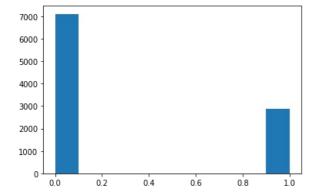
In [69]:

```
data['Asthma'] = data['Asthma'].astype(str)
data['Asthma'].replace(('Yes','No'), (1,0), inplace=True)
```

In [70]:

```
plt.hist(data['Asthma'])
```

Out[70]:

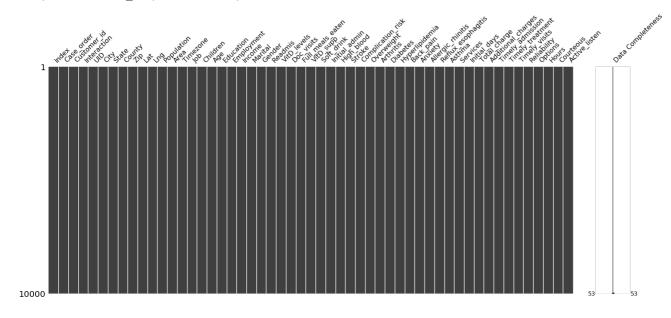


In [71]:

msno.matrix(data, labels=True)

Out[71]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f827311c08>



In [72]:

data.info()

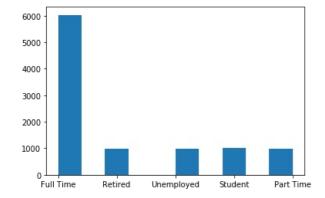
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 53 columns):

	Column (total 53 C		Dtymo
#	Column	Non-Null Count	Dtype
0	Index	10000 non-null	int64
1	Case_order	10000 non-null	int64
2	Customer_id	10000 non-null	object
3	Interaction	10000 non-null	object
4	UID	10000 non-null	object
5	City	10000 non-null	object
6	State	10000 non-null	object
7	County	10000 non-null	object
8	Zip	10000 non-null	int64
9	Lat	10000 non-null	float64
10	Lng	10000 non-null	float64
11	Population	10000 non-null	int64
12	Area	10000 non-null	object
13	Timezone	10000 non-null	object
14	Job	10000 non-null	object
15	Children	10000 non-null	float64
16	Age	10000 non-null	float64
17	Education	10000 non-null	object
18	Employment	10000 non-null	object
19	Income	10000 non-null	float64
20	Marital	10000 non-null	object
21	Gender	10000 non-null	object
22	Readmis	10000 non-null	int64
23	VitD_levels	10000 non-null	float64
24	Doc_visits	10000 non-null	int64
25	Full_meals_eaten	10000 non-null	int64
26	VitD_supp	10000 non-null	int64
27	Soft_drink	10000 non-null	object
28	Initial_admin	10000 non-null	object
29	High_blood	10000 non-null	int64
30	Stroke	10000 non-null	int64
31	Complication_risk	10000 non-null	object
32	0verweight	10000 non-null	float64
33	Arthritis	10000 non-null	int64
34	Diabetes	10000 non-null	int64
35	Hyperlipidemia	10000 non-null	int64
36	Back_pain	10000 non-null	int64
37	Anxiety	10000 non-null	float64
38	Allergic_rhinitis	10000 non-null	int64
39	Reflux_esophagitis	10000 non-null	int64
40	Asthma	10000 non-null	int64
41	Services	10000 non-null	object
42	<pre>Initial_days</pre>	10000 non-null	float64
43	Total_charge	10000 non-null	float64
44	Additional_charges	10000 non-null	float64
45	Timely_admission	10000 non-null	int64
46	Timely_treatment	10000 non-null	int64
47	Timely_visits	10000 non-null	int64
48	Reliability	10000 non-null	int64
49	Options	10000 non-null	int64
50	Hours	10000 non-null	int64
51	Courteous	10000 non-null	int64
52	Active_listen	10000 non-null	int64
	es: float64(11), int	64(25), object(1	7)
memo	ry usage: 4.0+ MB		

In [73]:

```
#Reexpress 'Employment' data as numeric.
plt.hist(data['Employment'])
```

Out[73]:



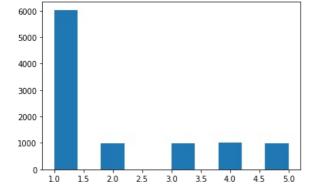
In [74]:

```
data['Employment'] = data['Employment'].astype(str)
data['Employment'].replace(('Full Time','Retired', 'Unemployed', 'Student', 'Part Time'), (1, 2, 3, 4, 5), inplac
e=True)
```

In [75]:

```
plt.hist(data['Employment'])
```

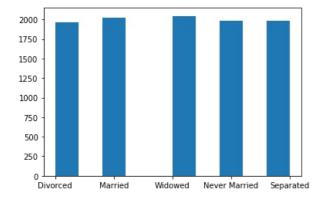
Out[75]:



In [76]:

```
#Reexpress 'Marital' data as numeric
plt.hist(data['Marital'])
```

Out[76]:



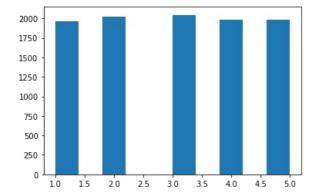
In [77]:

```
data['Marital'] = data['Marital'].astype(str)
data['Marital'].replace(('Divorced','Married', 'Widowed', 'Never Married', 'Separated'), (1, 2, 3, 4, 5), inplace
=True)
```

In [78]:

```
plt.hist(data['Marital'])
```

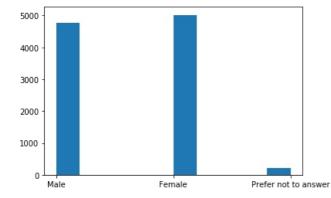
Out[78]:



In [79]:

```
#Reexpress 'Gender' data as numeric
plt.hist(data['Gender'])
```

Out[79]:



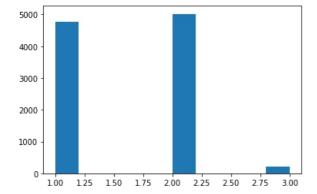
In [80]:

```
data['Gender'] = data['Gender'].astype(str)
data['Gender'].replace(('Male','Female', 'Prefer not to answer'), (1, 2, 3), inplace=True)
```

In [81]:

```
plt.hist(data['Gender'])
```

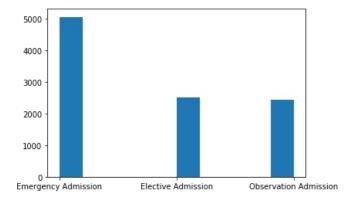
Out[81]:



In [82]:

```
#Reexpress 'Initial_admin' as numeric data plt.hist(data['Initial_admin'])
```

Out[82]:



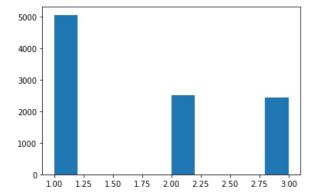
In [83]:

```
data['Initial_admin'] = data['Initial_admin'].astype(str)
data['Initial_admin'].replace(('Emergency Admission', 'Elective Admission', 'Observation Admission'), (1, 2, 3), i
nplace=True)
```

In [84]:

```
plt.hist(data['Initial admin'])
```

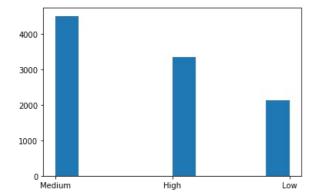
Out[84]:



In [85]:

```
#Reexpress 'Complication_risk' data as numeric
plt.hist(data['Complication_risk'])
```

Out[85]:



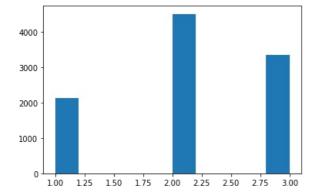
In [86]:

```
data['Complication_risk'] = data['Complication_risk'].astype(str)
data['Complication_risk'].replace(('Low', 'Medium', 'High'), (1, 2, 3), inplace=True)
```

In [87]:

```
plt.hist(data['Complication_risk'])
```

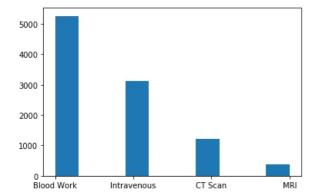
Out[87]:



In [88]:

```
#Reexpress 'Services' data as numeric
plt.hist(data['Services'])
```

Out[88]:



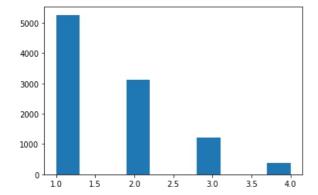
In [89]:

```
data['Services'] = data['Services'].astype(str)
data['Services'].replace(('Blood Work','Intravenous', 'CT Scan', 'MRI'), (1, 2, 3, 4), inplace=True)
```

In [90]:

```
plt.hist(data['Services'])
```

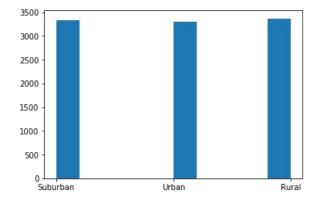
Out[90]:



In [91]:

```
#Reexpress 'Area' data as numeric
plt.hist(data['Area'])
```

Out[91]:



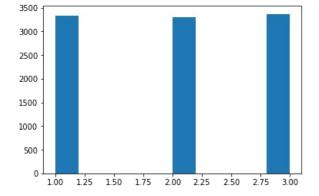
In [92]:

```
data['Area'] = data['Area'].astype(str)
data['Area'].replace(('Suburban', 'Urban', 'Rural'), (1, 2, 3), inplace=True)
```

In [93]:

```
plt.hist(data['Area'])
```

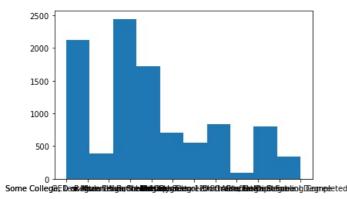
Out[93]:



In [94]:

```
#Reexpress 'Education' data as numeric
plt.hist(data['Education'])
```

Out[94]:



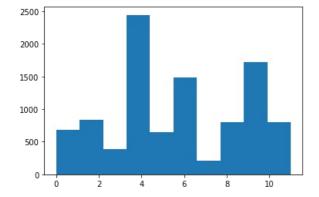
In [95]:

```
data['Education'] = data['Education'].astype(str)
data['Education'].replace(('No Schooling Completed', 'Nursery School to 8th Grade', '9th Grade to 12th Grade, No
Diploma', 'GED or Alternative Credential', 'Regular High School Diploma', 'Some College, Less than 1 Year', 'Some
College, 1 or More Years, No Degree', 'Professional School Degree', 'Associate\'s Degree', 'Bachelor\'s Degree',
'Master\'s Degree', 'Doctorate Degree'), (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11), inplace=True)
```

In [96]:

```
plt.hist(data['Education'])
```

Out[96]:



In [97]:

```
data['Education'].unique()
```

Out[97]:

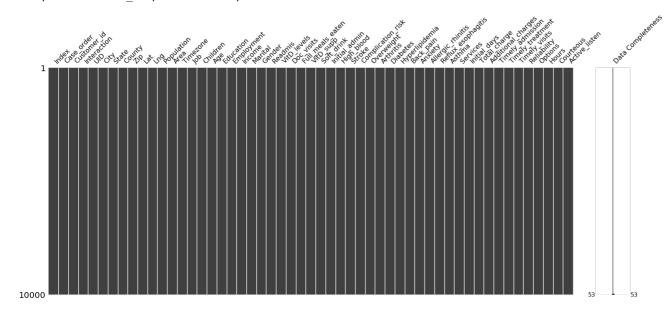
```
array([5, 6, 3, 4, 9, 10, 1, 2, 11, 8, 7, 0], dtype=int64)
```

In [98]:

msno.matrix(data, labels=True)

Out[98]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f82916b5c8>



In [99]:

data.info()

```
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 53 columns):
#
     Column
                         Non-Null Count
                                          Dtype
- - -
 0
                          10000 non-null
     Index
                                          int64
                          10000 non-null
 1
     Case order
                                          int64
 2
     Customer id
                          10000 non-null
                                          object
     Interaction
                          10000 non-null
 3
                                          object
 4
                          10000 non-null
     UTD
                                          object
 5
                         10000 non-null
     City
                                          object
 6
     State
                          10000 non-null
                                          object
                          10000 non-null
 7
     County
                                          object
 8
     Zip
                          10000 non-null
                                          int64
 9
     Lat
                          10000 non-null
                                          float64
                          10000 non-null
 10
     Lng
                                          float64
     Population
                          10000 non-null
 11
                                          int64
                          10000 non-null
 12
     Area
                                          int64
 13
                          10000 non-null
     Timezone
                                          object
 14
                          10000 non-null
     Job
                                          object
 15
                          10000 non-null
     Children
                                          float64
 16
     Age
                          10000 non-null
                                          float64
                          10000 non-null
 17
     Education
                                          int64
     Employment
                          10000 non-null
                          10000 non-null
 19
     Income
                                          float64
 20
     Marital
                          10000 non-null
                                          int64
 21
     Gender
                          10000 non-null int64
 22
     Readmis
                          10000 non-null int64
 23
     VitD levels
                          10000 non-null
                                          float64
 24
     Doc visits
                          10000 non-null
                                          int64
                         10000 non-null
     Full meals_eaten
 25
                                          int64
 26
     VitD_supp
                          10000 non-null
                                          int64
 27
     Soft_drink
                          10000 non-null
                                          object
 28
     Initial_admin
                          10000 non-null
                                          int64
 29
     High blood
                          10000 non-null
                                          int64
 30
     Stroke
                          10000 non-null
                                          int64
 31
                          10000 non-null
     Complication risk
                                          int64
 32
     Overweight
                          10000 non-null
                                          float64
     Arthritis
                          10000 non-null
 33
                                          int64
 34
    Diabetes
                          10000 non-null int64
 35
     Hyperlipidemia
                         10000 non-null
                                          int64
 36
    Back pain
                          10000 non-null
                                          int64
 37
     Anxiety
                          10000 non-null
                                          float64
                          10000 non-null int64
 38
     Allergic rhinitis
 39
     Reflux_esophagitis
                         10000 non-null
                                          int64
 40
     Asthma
                          10000 non-null
                                          int64
 41
     Services
                          10000 non-null
                                          int64
 42
     Initial days
                          10000 non-null
                                          float64
 43
     Total charge
                          10000 non-null
                                          float64
                         10000 non-null
 44
     Additional charges
                                          float64
                          10000 non-null
 45
     Timely_admission
                          10000 non-null
 46
    Timely_treatment
                                          int64
 47
     Timely_visits
                          10000 non-null
                                          int64
                          10000 non-null
 48
    Reliability
                                          int64
                          10000 non-null int64
 49
     Options
                          10000 non-null int64
 50
    Hours
                          10000 non-null
 51
    Courteous
                                          int64
                         10000 non-null int64
52 Active_listen
dtypes: float64(11), int64(33), object(9)
memory usage: 4.0+ MB
In [ ]:
In [100]:
data.to csv('C:/Users/ericy/Desktop/D206 clean.csv')
In [101]:
#Round 'Income' case entries
data['Income'].round()
data['Income'] = data['Income'].astype('int64')
```

<class 'pandas.core.frame.DataFrame'>

```
In [102]:
data['Income'].head()
Out[102]:
0
     86575
1
     46805
2
     14370
     39741
      1209
Name: Income, dtype: int64
In [103]:
#Round 'VitD levels' case entries
data['VitD_levels'].round()
data['VitD levels'] = data['VitD levels'].astype('int64')
data['VitD_levels'].head()
Out[103]:
0
     17
1
     18
     17
2
3
     17
4
     16
Name: VitD_levels, dtype: int64
In [104]:
#Round 'Initial_days' case entries
data['Initial_days'].round()
data['Initial_days'] = data['Initial_days'].astype('int64')
data['Initial_days'].head()
Out[104]:
0
     10
1
     15
2
      4
3
      1
4
      1
Name: Initial_days, dtype: int64
In [105]:
#Round 'Total charge' case entries
data['Total_charge'].round()
data['Total charge'] = data['Total charge'].astype('int64')
data['Total charge'].head()
Out[105]:
0
     3191
     4214
2
     2177
3
     2465
     1885
Name: Total charge, dtype: int64
In [106]:
#Round 'Additional_charges' case entries
data['Additional charges'].round()
data['Additional_charges'] = data['Additional_charges'].astype('int64')
data['Additional_charges'].head()
Out[106]:
0
     17939
     17612
1
2
     17505
3
     12993
```

4

3716

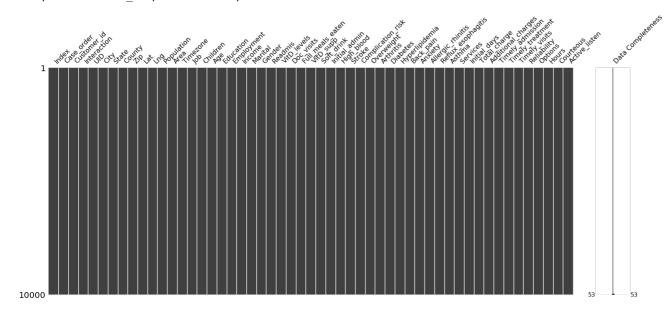
Name: Additional_charges, dtype: int64

In [107]:

msno.matrix(data, labels=True)

Out[107]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f829306d88>



In [108]:

data.info()

```
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 53 columns):
#
     Column
                         Non-Null Count Dtype
- - -
 0
     Index
                         10000 non-null
                                         int64
 1
     Case order
                         10000 non-null int64
     Customer id
                         10000 non-null object
                         10000 non-null object
 3
     Interaction
 4
     UTD
                         10000 non-null
                                         object
 5
                         10000 non-null object
     City
 6
     State
                         10000 non-null object
 7
                         10000 non-null object
     County
 8
     Zip
                         10000 non-null
                                         int64
 9
     Lat
                         10000 non-null
                                         float64
                         10000 non-null float64
 10
     Lng
     Population
                         10000 non-null int64
 11
                         10000 non-null
 12
     Area
                                          int64
                         10000 non-null
 13
     Timezone
                                         obiect
 14
                         10000 non-null
                                          object
 15
                         10000 non-null float64
     Children
 16
     Age
                         10000 non-null
                                          float64
 17
                         10000 non-null int64
     Education
     Employment
                         10000 non-null int64
                         10000 non-null int64
 19
     Income
 20
                         10000 non-null
     Marital
                                         int64
 21
     Gender
                         10000 non-null int64
                         10000 non-null int64
 22
    Readmis
                         10000 non-null int64
 23
    VitD levels
 24
     Doc visits
                         10000 non-null
    Full meals_eaten
                         10000 non-null int64
 25
 26
                         10000 non-null int64
     VitD_supp
                         10000 non-null
     {\tt Soft\_drink}
 27
                                         object
 28
     Initial_admin
                         10000 non-null
                                          int64
 29
     High blood
                         10000 non-null int64
 30
     Stroke
                         10000 non-null int64
                         10000 non-null int64
 31
     Complication risk
 32
     Overweight
                         10000 non-null
                                          float64
                         10000 non-null int64
 33
     Arthritis
 34
    Diabetes
                         10000 non-null int64
                         10000 non-null int64
10000 non-null int64
 35
    Hyperlipidemia
 36
    Back pain
 37
     Anxietv
                         10000 non-null float64
                         10000 non-null int64
 38
    Allergic rhinitis
 39
     Reflux_esophagitis
                         10000 non-null
                                         int64
 40
     Asthma
                         10000 non-null
                                          int64
 41
     Services
                         10000 non-null int64
 42
     Initial days
                         10000 non-null int64
 43
                         10000 non-null
                                         int64
     Total charge
                         10000 non-null int64
 44
     Additional charges
     Timely_admission
 45
                         10000 non-null int64
                         10000 non-null int64
 46
    Timely_treatment
                         10000 non-null
 47
     Timely_visits
                                         int64
 48
    Reliability
                         10000 non-null
                                         int64
                         10000 non-null int64
 49
     Options
                         10000 non-null int64
 50
    Hours
 51
    Courteous
                         10000 non-null
                                         int64
52 Active_listen
                         10000 non-null int64
dtypes: float64(6), int64(38), object(9)
memory usage: 4.0+ MB
In [109]:
data.to csv('C:/Users/ericy/Desktop/D206 clean.csv')
```

<class 'pandas.core.frame.DataFrame'>

In [110]:

```
#Convert 'Children', 'Age', 'Education', 'Readmis', 'Soft_drink', 'High_blood', 'Stroke',
#'Overweight', 'Arthritis', 'Diabetes', and 'Anxiety' to int64 datatype
data['Children'] = data['Children'].astype('int64')
data['Age'] = data['Age'].astype('int64')
data['Education'] = data['Education'].astype('int64')
data['Readmis'] = data['Readmis'].astype('int64')
data['Soft_drink'] = data['Soft_drink'].astype('int64')
data['High_blood'] = data['High_blood'].astype('int64')
data['Stroke'] = data['Stroke'].astype('int64')
data['Overweight'] = data['Overweight'].astype('int64')
data['Arthritis'] = data['Arthritis'].astype('int64')
data['Diabetes'] = data['Diabetes'].astype('int64')
data['Anxiety'] = data['Anxiety'].astype('int64')
```

In [111]:

data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 53 columns):
                         Non-Null Count Dtype
#
     Column
_ _ _
                         -----
0
     Index
                         10000 non-null int64
     Case_order
 1
                         10000 non-null int64
                         10000 non-null object
     Customer_id
 2
 3
     Interaction
                         10000 non-null
                                         object
                         10000 non-null
 4
     UTD
                                         obiect
 5
     City
                         10000 non-null
                                         object
                         10000 non-null
 6
     State
                                         obiect
 7
     County
                         10000 non-null
                                          object
 8
     7in
                         10000 non-null
                                         int64
 9
                         10000 non-null float64
 10
     Lng
                         10000 non-null
                                          float64
 11
     Population
                         10000 non-null
                                          int64
                         10000 non-null
                                         int64
 12
     Area
 13
     Timezone
                         10000 non-null
                                          object
 14
                         10000 non-null
     Job
                                          object
 15
     Children
                         10000 non-null
                                          int64
 16
     Age
                         10000 non-null
                                         int64
 17
     Education
                         10000 non-null int64
 18
     Employment
                         10000 non-null
                                         int64
 19
     Income
                         10000 non-null
                                          int64
 20
    Marital
                         10000 non-null int64
 21
     Gender
                         10000 non-null int64
                         10000 non-null
 22
     Readmis
                                          int64
                         10000 non-null
 23
     VitD levels
                                          int64
 24
     Doc visits
                         10000 non-null
                                          int64
 25
     Full_meals_eaten
                         10000 non-null
                                          int64
 26
     VitD supp
                         10000 non-null
                                          int64
 27
     Soft drink
                         10000 non-null
                                          int64
                         10000 non-null
 28
     Initial admin
                                         int64
 29
     High_blood
                         10000 non-null
                                          int64
                         10000 non-null
 30
     Stroke
                                          int64
                         10000 non-null
 31
     Complication_risk
                                         int64
 32
     Overweight
                         10000 non-null
                                         int64
                         10000 non-null
 33
     Arthritis
                                          int64
 34
     Diabetes
                         10000 non-null
                                          int64
    Hyperlipidemia
 35
                         10000 non-null
                                         int64
                         10000 non-null int64
 36
     Back pain
                         10000 non-null int64
     Anxiety
 37
 38
     Allergic rhinitis
                         10000 non-null
                                          int64
 39
                         10000 non-null int64
     Reflux_esophagitis
                         10000 non-null int64
 40
     Asthma
 41
                         10000 non-null int64
     Services
 42
     Initial days
                         10000 non-null
                                          int64
                         10000 non-null
 43
     Total_charge
                                          int64
 44
                         10000 non-null
     Additional charges
 45
     Timely_admission
                         10000 non-null
                                         int64
 46
     Timely_treatment
                         10000 non-null
                                          int64
     Timely_visits
 47
                         10000 non-null int64
 48
     Reliability
                         10000 non-null int64
                         10000 non-null int64
 49
    Options
 50
    Hours
                         10000 non-null
                                         int64
                         10000 non-null int64
 51 Courteous
 52 Active listen
                         10000 non-null int64
dtypes: float64(2), int64(43), object(8)
memory usage: 4.0+ MB
```

In [112]:

```
data.to_csv('C:/Users/ericy/Desktop/D206_clean.csv', index=False)
data.to_csv('C:/Users/ericy/Desktop/data_z.csv', index=False)
data.to_csv('C:/Users/ericy/Desktop/PCA_Ready.csv', index=False)
```

```
#Calculate Z-Scores for all quantitative variables
dataz = pd.read_csv('C:/Users/ericy/Desktop/data_z.csv')
dataz.info()
dataz['Age_z'] = stats.zscore(data['Age'])
Agez = dataz.query('Age_z > 3 | Age_z < -3')
Agez.head()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 53 columns):
                         Non-Null Count Dtype
#
     Column
 0
     Tndex
                         10000 non-null
                                         int64
 1
     Case order
                         10000 non-null
                                         int64
 2
     Customer id
                         10000 non-null object
     Interaction
 3
                         10000 non-null object
 4
                         10000 non-null
     UID
                                         object
 5
     City
                         10000 non-null
                                          object
 6
                         10000 non-null
     State
                                         object
 7
     County
                         10000 non-null
                                          object
 8
                         10000 non-null
     Zip
                                          int64
 9
     Lat
                         10000 non-null
                                          float64
 10
     Lna
                         10000 non-null
                                          float64
 11
     Population
                         10000 non-null int64
                         10000 non-null
 12
     Area
                                         int64
 13
     Timezone
                         10000 non-null
                                          object
 14
                         10000 non-null
     Job
                                         obiect
 15
     Children
                         10000 non-null
                                         int64
 16
     Aae
                         10000 non-null
                                         int64
 17
     Education
                         10000 non-null
                                          int64
 18
     Employment
                         10000 non-null
                                         int64
 19
     Income
                         10000 non-null
                                          int64
 20
    Marital
                         10000 non-null
                                          int64
 21
     Gender
                         10000 non-null
                                          int64
 22
     Readmis
                         10000 non-null
                                         int64
 23
    VitD_levels
                         10000 non-null
                                          int64
                         10000 non-null
 24
     Doc_visits
                                          int64
 25
                         10000 non-null
     Full_meals_eaten
                                          int64
 26
     VitD supp
                         10000 non-null
                                         int64
                         10000 non-null
 27
     Soft drink
                                          int64
 28
     Initial admin
                         10000 non-null
                                          int64
    High blood
                         10000 non-null
 29
                                         int64
                         10000 non-null int64
 30
     Stroke
                         10000 non-null int64
 31
     Complication risk
                         10000 non-null
 32
     Overweight
                                         int64
                         10000 non-null
 33
     Arthritis
                                         int64
 34
     Diabetes
                         10000 non-null int64
                         10000 non-null int64
 35
    Hyperlipidemia
 36
     Back pain
                         10000 non-null
                                          int64
                         10000 non-null
 37
     Anxiety
                                          int64
     Allergic rhinitis
                         10000 non-null
 38
                         10000 non-null
 39
     Reflux_esophagitis
                                         int64
 40
                         10000 non-null
     Asthma
 41
     Services
                         10000 non-null int64
                         10000 non-null int64
 42
     Initial days
                         10000 non-null int64
 43
    Total_charge
     Additional charges
                         10000 non-null
 44
 45
                         10000 non-null int64
    Timely admission
 46
    Timely treatment
                         10000 non-null int64
                         10000 non-null int64
 47
    Timely_visits
 48
     Reliability
                         10000 non-null
                                          int64
 49
     Options 0
                         10000 non-null int64
 50
    Hours
                         10000 non-null int64
                         10000 non-null int64
 51
    Courteous
    Active_listen
                         10000 non-null
dtypes: float64(2), int64(43), object(8)
memory usage: 4.0+ MB
```

#Assign variable to dataset for calculating z scores

Out[113]:

Index Case_order Customer_id Interaction UID City State County Zip Lat ... Additional_charges Timely_admission Timely_treat

In [114]:

```
dataz['Children_z'] = stats.zscore(dataz['Children'])
Childrenz = dataz.query('Children_z > 3 | Children_z < -3')
Childrenz.sort_values(['Children_z'], ascending = False)</pre>
```

Out[114]:

Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	La
16	17	O377757	7faf0261- bc66-489a- a8ba- fec333485254	728333940561457a9feba1e1dc763258	Blythe	CA	Riverside	92225	33.7464
1093	1094	U798396	ded17fc4- 27d2-4fce- a7e4- c3b27427ff0b	9d56a350bcbd02ad66629ce06080ef32	Rock Hill	SC	York	29730	34.8867 ⁻
6484	6485	A961890	00730262- 8847-4a35- 9a79- f8d247ee57e8	ef304b3a546a70fb216abde377fbe688	Loomis	CA	Placer	95650	38.81284
2124	2125	T948257	17f13f8d- 8c16-47eb- 9e6c- c5635f97dcc8	672cf906ec22dbec40674cb78f837e44	Mullen	NE	Hooker	69152	42.1092
2121	2122	E859932	2d86af54- e54e-485f- 8d06- 01de27a966d9	432f2a96712dfd4d2f56965c4805bb68	Madison	AR	St. Francis	72359	35.02289
6112	6113	Z417502	05902a2c- b76f-4ab6- b46d- 857c58cf6da7	30695977947a77889822d153007e8eb2	Chicago	IL	Cook	60653	41.8192
6174	6175	M717683	14ea5131- 9ce6-4417- 8e3f- 99467287ff45	47525dc30f2e86cabbaad3e3bd4a7406	Plainview	AR	Yell	72857	34.8577
2524	2525	A541545	78c32463- 77cd-4121- 8d1c- e6764c6757fa	1c3e490f7ad5a81bf8f8ba7937e2221b	Lonsdale	MN	Rice	55046	44.44867
2487	2488	L515011	e5b1b81c- 917f-434f- 84ae- ed6ffb281020	fced486b7771e55cfb7d800cb0e0fc04	Beavercreek	OR	Clackamas	97004	45.2511!
9999	10000	1569847	bc482c02- f8c9-4423- 99de- 3db5e62a18d5	95663a202338000abdf7e09311c2a8a1	Coraopolis	PA	Allegheny	15108	40.4999
	16 1093 6484 2124 2121 6112 6174 22524	16 17 1093 1094 6484 6485 2124 2125 2121 2122 6112 6113 6174 6175 2524 2525 2487 2488	1093 1094 U798396 6484 6485 A961890 2124 2125 T948257 2121 2122 E859932 6112 6113 Z417502 6174 6175 M717683 2524 2525 A541545 2487 2488 L515011	16 17 O377757 Tfaf0261-bc66-489a-a8ba-fec333485254 1093 1094 U798396 ded17fc4-27d2-4fce-a7e4-c3b27427ff0b 6484 6485 A961890 00730262-8847-4a35-9a79-f8d247ee57e8 2124 2125 T948257 17f13f8d-8c16-47eb-9e6c-c5635f97dcc8 2121 2122 E859932 2d86af54-e54e-485f-8d06-01de27a966d9 6112 6113 Z417502 b76f-4ab6-b46d-857c58cf6da7 6174 6175 M717683 9002a2c-b76f-4ab6-b46d-857c58cf6da7 2524 2525 A541545 78c32463-77cd-4121-8d1c-947c4121-8d1c-947c4121-8d1c-96764c675ffa 2487 2488 L515011 e5b1b81c-91f-434f-8dae-ed6ffb281020 9999 10000 1569847 90de-423-99de-28f629-423-99de-28f629-423-99de-28f629-423-99de-28f6-28f6-28f6-28f6-28f6-28f6-28f6-28f6	Triaff0261-bc66-489a-a8ba-fec333485254 1093	Tario	Transport	Triant	Trialization

In [115]:

```
dataz['Income_z'] = stats.zscore(dataz['Income'])
Incomez = dataz.query('Income_z > 3 | Income_z < -3')
Incomez.sort_values(['Income_z'], ascending = False)</pre>
```

Out[115]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	L
8386	8386	8387	C817840	41770631- ff8b-4e71- 9631- f369b04d2125	f81e41a00a41c04266e666361ad49a33	Phoenix	AZ	Maricopa	85044	33.342
841	841	842	F304162	cbd20767- 266b-470b- 9bd7- 9b8aab96da38	3424165edc18b296b6ec24d69101a2a9	Galloway	WV	Barbour	26349	39.235 ⁻
8598	8598	8599	C730234	bb1cdec6- 187d-40ac- bcb2- 1544f5bb4b1d	609d3ae46250dffa60021c1f62169869	Haywood	VA	Madison	22722	38.461
6406	6406	6407	J423842	fe003dd7- d9b2-4cc0- b446- fc0c48cdabea	b481a4d89ab6871d664e7f917393a5ba	Scranton	PA	Lackawanna	18504	41.425
1778	1778	1779	T848406	3c57ca24- c58c-45b0- a96f- 928187a615d0	73fffc542bdeb8f39051413f55972023	Mowrystown	ОН	Highland	45155	39.039
7697	7697	7698	S906499	2d880cc6- 37c3-4b7c- 90d7- 6fc3074d19eb	c4a72a9475c3d22d40ae6d483e8a5867	Lynnfield	MA	Essex	1940	42.534
3702	3702	3703	D875126	736613d8- eb00-488f- 8e93- 2c3f7d939c0f	0e9eb923d8ddf8ecca0db017fa1e99d8	Byron	MN	Olmsted	55920	44.013
86	86	87	E681129	78216a6f- 87fe-45a8- 8e76- a8abbe2adff2	ad555647d06822a4a1259340c2e21c5f	Caroleen	NC	Rutherford	28019	35.280
3017	3017	3018	Y624229	b920591f- 01cb-4320- af69- d62ca61ae8e2	886eb2d72c29fe788232f6b36bd37f08	Sulphur Springs	AR	Benton	72768	36.476!
2507	2507	2508	S453939	004cdcae- 763f-4fe8- 82c9- 46bab6bf7011	37a0b6995354a733063ab3566e171a67	Selma	NC	Johnston	27576	35.582
180 rd	ows × 50	6 columns								

In [116]:

```
dataz['VitD_levels_z'] = stats.zscore(dataz['VitD_levels'])
VitD_levels_z = dataz.query('VitD_levels_z > 3 | VitD_levels_z < -3')
VitD_levels_z.sort_values(['VitD_levels_z'], ascending = False)</pre>
```

Out[116]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat	
1963	1963	1964	J288779	d643d57b- cebb-4556- ac38- 8b339b85175d	7305ac02547eb73b8a5e30855b602e99	Jean	NV	Clark	89019	35.76620	
3473	3473	3474	Y739652	6dbae289- 4c4d-4157- 9fbf- 4bc4665c12fd	0f46805163c147c5bc70ef76b46be56a	Concord	CA	Contra Costa	94521	37.95603	
2615	2615	2616	S997798	8888fd85- 4442-48f6- 924d- 858c30e733d0	4876750cae50b72e92b19e2213b1371c	Harris	МО	Sullivan	64645	40.29741	••
7157	7157	7158	L397900	85cc282c- 0b16-404b- 8f15- 6b7ac633c2d6	2b091704732658b36d1a37c3674e69a0	Jobstown	NJ	Burlington	8041	40.03788	
1306	1306	1307	B77596	e19f375b- b1ea-44b9- a0e3- bcf3bf4b4bc1	bcd4395e7916ffa8e6659f9c563f56ea	Holualoa	ні	Hawaii	96725	19.62925	
786	786	787	U179768	1ca91d4f- 9f12-4095- 907a- 3c81afb93207	266a7c39f532ce5455c4ac68a615d003	Hatteras	NC	Dare	27943	35.21097	
7270	7270	7271	M212963	b9e0709b- a602-41a5- b3b4- 229576f57952	758d7f97dea2ebe1c585733bd100e86f	Augusta	GA	Richmond	30905	33.41474	
5688	5688	5689	Q71266	2179cd1f- a3b0-4ee7- a53a- 35a3632bf291	ba620f7005481bb1641cbac29720efea	Duarte	CA	Los Angeles	91010	34.14074	
2946	2946	2947	T519902	50542ca6- d2bb-4ead- a3c1- d8194eaab696	23bc2fc77e42f0a89e7bbef583f9cd9d	Dayton	WA	Columbia	99328	46.25660	
8197	8197	8198	U547343	6150f8d8- e206-462b- bd81- 930c7fb8aef1	cf0e28edb667f9e5166f0287a7e5ef07	Old Bethpage	NY	Nassau	11804	40.75874	
500 rc	ows × 5	7 columns									

In [117]:

```
dataz['Doc_visits_z'] = stats.zscore(dataz['Doc_visits'])
Doc_visits_z = dataz.query('Doc_visits_z > 3 | Doc_visits_z < -3')
Doc_visits_z.sort_values(['Doc_visits_z'], ascending = False)</pre>
```

Out[117]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat	
962	962	963	A518996	a38c4ad7- 323f-41f2- 9a08- ff17743aaa53	4112b686f622313e4d247da0b9a2afb4	Uvalde	TX	Uvalde	78801	29.35664	
2766	2766	2767	N924859	5a334d2f- a78d-4165- aa83- d368bb82fa48	a18d1b5abef353e496b4d25926c0d213	Walton	OR	Lane	97490	44.00425	
5645	5645	5646	H849940	d5b2f306- 7c65-4ad0- 8d9b- 3b144bd20c34	e5e3073cdab4a0e7ba03a174660cb5b2	Faber	VA	Nelson	22938	37.86065	
5756	5756	5757	Q856766	abf1c636- 143b-4f87- a663- 82c1ac92bbd2	5046bbcc46fbcccf4f6b76c7e5b71082	Toronto	ОН	Jefferson	43964	40.48617	
6017	6017	6018	Z448538	a44eb330- 7119-4c47- a0c0- 356b2d481587	42e4405346a43a9c60a2acf63718f235	Collins	WI	Manitowoc	54207	44.08782	
6498	6498	6499	D695903	7e305136- 22ea-4d2d- a92d- 39132c1bf66b	994f0adf59f7a7d9bb53bb296058be3b	Douglas	ОК	Garfield	73733	36.25360	
6942	6942	6943	W120936	2d981e21- 86cd-4880- b731- a5c0d5a2c2bb	2fd0a3063b109969d378e61c19c081c0	Noonan	ND	Divide	58765	48.87743	
7143	7143	7144	K252805	dc0772b4- e146-492f- 8537- 8c02679d553f	bf9248b12adbe35b728debdf7f00b68e	El Paso	TX	El Paso	79907	31.70750	

8 rows × 58 columns

In [118]:

```
dataz['Full_mealz'] = stats.zscore(dataz['Full_meals_eaten'])
Full_mealz = dataz.query('Full_mealz > 3 | Full_mealz < -3')
Full_mealz.sort_values(['Full_mealz'], ascending = False)</pre>
```

Out[118]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	
958	958	959	Y657696	c7a8a8b7- 5d61-4d95- 872f- 58f3bb589c09	30703ca82ae5ed6da3addcd421777c38	Sebastopol	CA	Sonoma	95472	38.3
4709	4709	4710	F767195	7da332b0- bc0f-4486- a973- c960376154aa	bda40730190467bcfc2b4ce70b727a71	Leopold	МО	Bollinger	63760	37.2
9986	9986	9987	Z630066	1ed0ed27- 4965-4252- 85ea- dd7ed73bd51a	f132eca4af3b1c955d89a213096ef88a	Perry	IA	Dallas	50220	41.8
7217	7217	7218	M529189	73802f3c- f978-4b67- ba2c- 844140ac7e41	b200ab915ceeee74bceab2dc0ad39121	Ashton	IA	Osceola	51232	43.3
6068	6068	6069	Z447871	56d5bab6- 25c0-4c30- a3f9- 822ff27def3e	2db6d1a15351eaa51b4370872cafab51	Constableville	NY	Lewis	13325	43.5
1231	1231	1232	J394932	e625f515- a366-4b95- 8e88- 9dc3afda79d8	ea252a0d3bcd2272a60a658b7cf21b29	Bay Shore	NY	Suffolk	11706	40.7
2184	2184	2185	H40270	30bfc529- 4c99-4244- b3fa- b1828e591622	e8b301a00be4e22f809745e50b684b28	Waynesville	GA	Brantley	31566	31.1

8144	8144	8145	G557244	25861106- d9bf-4744- 8f7f- 952bdef14ace	eff4a060f579f85142c6ea7ca3884435	Mangham	LA	Richland	71259	32.2
6083	6083	6084	T927706	1d3b5fc2- 3a3b-4138- a2f8- b65e93d26125	cb97fffaa14fa2a4499cdaf32ae81f22	Highland	MI	Oakland	48356	42.6
6694	6694	6695	C327638	e9cfdc20- d85d-4c1f- 9e35- a0714c341760	64b2d0f9910d479999267b0ecc142da2	Davison	MI	Genesee	48423	43.0
6802	6802	6803	G952688	1f4bf3cd- 6419-4b0e- b1e1- 91b44601ff79	10fb646b9851135d5578c03983ce924c	Hillpoint	WI	Sauk	53937	43.3
8326	8326	8327	P966922	ba29b074- 2909-4ac0- ae8c- 3d98132c1bb5	a0aefe75fb9316a55e02d0f11bed7c73	Hillsboro	MD	Caroline	21641	38.9
5859	5859	5860	1304713	a2a1010e- bdd1-4d85- 95f8- ca765bd1777d	d01e611cc208e9b2ed5306fc36bba740	Lincoln	NE	Lancaster	68510	40.8
8902	8902	8903	L332623	65bd9f6f-5f20- 4e8b-b155- c448edb96e4f	d6d5dab162b78d68aa561e09a763f5a8	Virginia Beach	VA	Virginia Beach	23456	36.7
8994	8994	8995	N415828	e089be60- b2ba-4d32- a086- 77c5895e6516	c5367056ea7b4fcdcd2907135bee3e79	Odessa	TX	Ector	79766	31.7
9067	9067	9068	1917390	962d0ec6- 27e9-4010- b59a- af649d02a475	3ed7b9e4969092fd2b6d49c3b421d494	Canaseraga	NY	Allegany	14822	42.4
9220	9220	9221	C513727	91d192f4- 9f40-47d3- 8a35- 4d6c0b4dcb0a	0c5424d0c0c4877f43d9129966ba4a81	East Montpelier	VT	Washington	5651	44.2
6026	6026	6027	M688413	fc55b7d4- 5d5f-47ce- 872d- 19b28001adf4	2eb28fd3fae40faeb134019216fe4f9b	Huger	SC	Berkeley	29450	33.0
550	550	551	K368670	ee6e63d6- b073-4f56- 9751- 5933049da455	8d4f1906f9ce5eff77b1d790fa7ed95f	Fort Covington	NY	Franklin	12937	44.9
5711	5711	5712	G268057	3abc06f2- a987-4242- a08d- ff8cadf45365	e6825550973f181bca9c8a8e5f02ef81	Mercer Island	WA	King	98040	47.5
5597	5597	5598	V944194	38f18892- 2a10-41c2- 8e11- 49bf96c4bd1f	99679c97db9658487cdea25b37a173f9	Bradford	VT	Orange	5033	44.0
697	697	698	F454155	1592fb46- 79d4-4b63- 8ce9- f25374e8c8d4	467b7a7e36f1a274388dfe83f47fb2ba	Diamond	МО	Newton	64840	37.0
5367	5367	5368	O11669	0ae8ebb4- 846a-4c59- acc5- 7e2c90640cfe	6c43df9bb0d357055173d45dd8907ecf	Rumely	MI	Alger	49826	46.3
4902	4902	4903	X275889	46cca6f8- 5e68-4662- 8b41- a82c03d97719	084fc0fd364584d5f88ac080fac3f087	Aurora	MN	St. Louis	55705	47.4
4345	4345	4346	Q413439	46264e69- 39c9-41af- 9876- 02ee2159ad63	2a86f887f3306f030dc96d91f57b07ba	Grand Lake	СО	Grand	80447	40.2
2919	2919	2920	Y483255	3af744a4- 3e8f-4baa- b3fe- 402953395fef	a67c72e0926293aaa5ec33727f37a7e5	Laotto	IN	Noble	46763	41.2
2877	2877	2878	1684405	4f10c57b- d053-4ea6- b52c- 0313f3f130b2	6330a5d3563e97a21e3ed67cf941f7a7	Tranquillity	CA	Fresno	93668	36.6
2746	2746	2747	M406925	3d584b8b- 8269-4ef5- 8f9c- 4e2d934eabea	c97a081eb0f5d3bf57b64eba126732e9	Kent	ОН	Portage	44243	41.1

2652	2652	2653	B388915	4eec34de- c681-4901- b640- 854cc7f32ebe	df2c4002e9d0dcb589b326b997d9c762	Boonville	CA	Mendocino	95415	39.0
2315	2315	2316	E105778	234af304- 1c20-4578- 9251- 0648e8126ead	4814abcb5f4f0f2fe482feb98ac27f98	Crawford	WV	Lewis	26343	38.8
1456	1456	1457	V65457	e8c0a2d8- 05df-4c82- a3c5- e93ee72ac9b5	a131bb7a298e31324f6a7f99c2714d24	Syracuse	NY	Onondaga	13214	43.0
1148	1148	1149	F466335	bfa9aa23- ec57-4b95- abbf- 4402007b0a5b	755781fcb9b85ed2e5e675895fa810bb	Spring Glen	NY	Ulster	12483	41.6
5543	5543	5544	C451388	3e4e410f- f60e-4966- a3bd- 1f604dafbf35	431621904d47fb4feee40a28bd421c0a	San Antonio	TX	Comal	78266	29.6
33 row	s × 59 colum	nns								

In [119]:

```
dataz['VitD_suppz'] = stats.zscore(dataz['VitD_supp'])
VitD_suppz = dataz.query('VitD_suppz > 3 | VitD_suppz < -3')
VitD_suppz.sort_values(['VitD_suppz'], ascending = False)</pre>
```

Out[119]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	
3131	3131	3132	A693543	c2eef231- ba8b-4f2a- b7bb- 5722189fbe4b	19716f3f690b579b5dcdb771550f9b5c	Washington	KS	Washington	66968	39.82
2715	2715	2716	P60898	f66b928a- 6de9-4043- b2d2- 8cf0bfac0b34	52e8f2a6e67c326ce495e89cf8e3391a	Bainbridge	IN	Putnam	46105	39.764
9091	9091	9092	A771264	4676ed64- 981d-48c8- bf78- 6706c592e4fd	f77af82fc41b30951e69e437feb63ca5	Rio Nido	CA	Sonoma	95471	38.524
1342	1342	1343	X97640	c6680d61- 0228-44dc- bac6- 7f71492b5daf	15fc59be69381309db87a023bce971cd	Franklin Square	NY	Nassau	11010	40.700
2533	2533	2534	H623137	7dffab81- 3be0-4a66- 8aad- 4d04a9e08ed9	c7b63686ec434c9059203bb28fe3cea1	Lonsdale	MN	Rice	55046	44.44{
4398	4398	4399	P241002	c43abb2f- d03f-4f94- b85c- b94f9b87ba8e	1a1d72d68cbe08b21e7a2e69b0db05a6	Honolulu	НІ	Honolulu	96816	21.292
4406	4406	4407	Y884211	6559cede- c035-452a- a0cf- 41f6ea72ffda	fd9e9c25844f187a3903254ac48a87b4	Glasco	NY	Ulster	12432	42.044
4567	4567	4568	M822122	3824bf42- 5578-4c6a- bddf- e7c653e57fd8	10f56b5cfa41d592fca272b95903a775	Oklahoma City	OK	Oklahoma	73107	35.48 ⁻
4844	4844	4845	L06840	07c93832- d655-440e- b039- 030796cb9d72	48bbbf13517022e7f004b71473afddcf	Hartford	SD	Minnehaha	57033	43.619
9982	9982	9983	O64996	07ffe436- a1a2-4b37- 96b0- 2602ffb1ad6f	b0df4c12776c7d9efceb9fcc67d0262e	Atlantic City	NJ	Atlantic	8401	39.379
70 rov	vs x 60	columns								

In [120]:

```
dataz['Initial_days_z'] = stats.zscore(dataz['Initial_days'])
Initial_days_z = dataz.query('Initial_days_z > 3 | Initial_days_z < -3')
Initial_days_z.sort_values(['Initial_days_z'], ascending = False)</pre>
```

Out[120]:

Index Case_order Customer_id Interaction UID City State County Zip Lat ... Courteous Active_listen Age_z Children_z Incom

0 rows × 61 columns

In [121]:

```
dataz['Total_charge_z'] = stats.zscore(dataz['Total_charge'])
Total_charge_z = dataz.query('Total_charge_z > 3 | Total_charge_z < -3')
Total_charge_z.sort_values(['Total_charge_z'], ascending = False)</pre>
```

Out[121]:

	Zip	County	State	City	UID	Interaction	Customer_id	Case_order	Index	
30.96	70787	West Feliciana	LA	Weyanoke	815273eb63baa4ef16b596d02cfb92de	3fc45464- 51e3-4182- ba05- 0e960ddff205	1804892	8801	8800	8800
36.55	65681	Stone	МО	Lampe	331b2187466de52359ae522cb8b48f8f	56066f7f- 5a32-4732- 965a- 9e92af4ffb0b	G175531	9006	9005	9005
32.34	31025	Houston	GA	Elko	00a99d284dcb8bafd8bae0ee83314e77	11e8adb4- b54b-4672- b122- 16b2efd33943	Y654860	5245	5244	5244
43.42	3233	Merrimack	NH	Elkins	cf2d345d5c28fd232a947fff963496c7	3af75e11- a617-493d- aef8- c799d51ad04b	N354417	5454	5453	5453
32.80	75182	Dallas	TX	Sunnyvale	c6f3559b9c756e76dabad184af795a4e	d4613a36- 798a-4258- 9106- e7769c8b9e13	G163318	9160	9159	9159
35.76	89019	Clark	NV	Jean	7305ac02547eb73b8a5e30855b602e99	d643d57b- cebb-4556- ac38- 8b339b85175d	J288779	1964	1963	1963
42.88	3826	Rockingham	NH	East Hampstead	ede05577efbb3df8b43befa16a7fb9bf	0d02edda- 1ffe-4388- a126- a9f073151711	V552831	3000	2999	2999
39.75	47872	Parke	IN	Rockville	7a4b3164770176c1f1df08872cf835d3	9beaf0ae- 8bb0-4788- baf7- 9b1936f94e5a	E836671	1848	1847	1847
40.56	61776	McLean	IL	Towanda	b34915d6185285bb08a88575c22176fe	7f6cd69d- 9319-4ac2- b7de- 8a011a9525c5	M549619	3351	3350	3350
45.40	97267	Clackamas	OR	Portland	512e1a052e1043902a81b535e80ae309	39114acf-c2f5- 4971-8fbc- 88d830367e98	1117310	528	527	527

In [122]:

```
dataz['Additional_charges_z'] = stats.zscore(dataz['Additional_charges'])
Additional_charges_z = dataz.query('Additional_charges_z > 3 | Additional_charges_z < -3')
Additional_charges_z.sort_values(['Additional_charges_z'], ascending = False)</pre>
```

Out[122]:

Index Case_order Customer_id Interaction UID City State County Zip Lat ... Age_z Children_z Income_z VitD_levels_z Doc

U LUME x 83 columns

In [123]:

```
dataz['Population_z'] = stats.zscore(dataz['Population'])
Population_z = dataz.query('Population_z > 3 | Population_z < -3')
Population_z.sort_values(['Population_z'], ascending = False)</pre>
```

Out[123]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat
3024	3024	3025	W840448	7c8ccd98- 1619-4492- 99a7- b1dd82a713be	02cd4f72ff3415f684ab0847e47feffd	Katy	тх	Harris	77449	29.83556
9662	9662	9663	Y770582	7096d230- 358f-4244- b05c- 70aa3143572f	be3f3df437c3b7b114dc7d24b1a48bfc	Katy	TX	Harris	77449	29.83556
5965	5965	5966	Q787284	121150ca- a1fc-4ba7- aa48- 6b7893d0eb0e	8356f8d77795cf648b1f66b4af5f1577	Houston	TX	Harris	77084	29.82641
767	767	768	E632881	e7758807- cc96-4396- a8c5- ff54d26882cc	3008f82476a1bca85459d1b3270a3f8f	Pacoima	CA	Los Angeles	91331	34.25563
7686	7686	7687	N145589	9ec70eec- 90f7-4ba5- a266- df39435d1cd2	6b797b8b5e27596ef3475e8f57156ead	Pacoima	CA	Los Angeles	91331	34.25563
3185	3185	3186	T770780	21bd9512- ce0a-4dad- aae7- ada9c372032c	16c3b9e31c642011e9b28d4e8b091722	Kalispell	MT	Flathead	59901	48.22816
3819	3819	3820	R649606	ef1c915b- 6122-43e1- a288- 81fdb6adc8cb	b298e046e927404b221d90dce841db2a	Kalispell	MT	Flathead	59901	48.22816
6796	6796	6797	N911416	f2b9a623- b285-48c4- b0ea- af4d2224a904	e96e51aef8bb754c395bea931debcaeb	Mason	ОН	Warren	45040	39.35199
964	964	965	U840422	3a1e8fac- deea-4914- 87b4- e24a4c37233f	29198a8aad2c9d4f6b66429f61f1cf40	West Chester	PA	Chester	19382	39.92809
288	288	289	Q451442	77d2a41e- 8515-4c2c- 8fcb- 0bc170b2cbe2	115c7675bbc8d7adb2ffe728a8a06403	Fort Washington	MD	Prince George's	20744	38.75403

218 rows × 64 columns

In [124]:

```
dataz['Zip_z'] = stats.zscore(dataz['Zip'])
Zip_z = dataz.query('Zip_z > 3 | Zip_z < -3')
Zip_z.sort_values(['Zip_z'], ascending = False)</pre>
```

Out[124]:

Index Case_order Customer_id Interaction UID City State County Zip Lat ... Income_z VitD_levels_z Doc_visits_z Full_meal_

In [125]:

```
dataz['Lat_z'] = stats.zscore(dataz['Lat'])
Lat_z = dataz.query('Lat_z > 3 | Lat_z < -3')
Lat_z.sort_values(['Lat_z'], ascending = False)</pre>
```

Out[125]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat
960	960	961	L207471	3f59f2e7- e47d-41f5- 9c69- a28435694872	8bd4402de2b9aaa9d398ddc2834f694a	Atqasuk	AK	North Slope	99791	70.56099
2282	2282	2283	Z462873	fef4cded- 5810-4c43- b849- 49ede612900c	292e98f84603bfcbbb8ab779578df8c3	Anchorage	AK	North Slope	99510	70.13850
4772	4772	4773	S598156	c8f0beab- fbe6-4c6e- 96b1- 04f973b16a8d	17301ae1a06453897f5863e10637ebd3	Venetie	AK	Yukon- Koyukuk	99781	67.47706
3836	3836	3837	M299873	b88c011f- aa2f-41dc- 8633- 5072c27a181b	d1b3b5734eca4799a52f296afdc93f81	Ambler	AK	Northwest Arctic	99786	67.17316
9141	9141	9142	P944084	ec4415b4- b579-490a- a7af- 50e195f79efe	9de234b2402c0d5365f66861c99bc292	Bettles Field	AK	Yukon- Koyukuk	99726	67.11836
2013	2013	2014	D675480	30eae952- c151-4c25- 9858- 10ece8691ca2	62f14eded5c5606c559d00af81a5b057	Guayanilla	PR	Guayanilla	656	18.05280
2249	2249	2250	E748476	26b84dcf- ae87-4ea1- 8cb7- 4a9566877a26	76e8858db9fe7ad330140776f0b4e524	Ponce	PR	Ponce	730	18.03091
944	944	945	1293001	c5314d07- 5984-4572- b727- cb484d00b67e	cdf21e87d6f3fe781ee55d08278d5132	Salinas	PR	Salinas	751	18.01023
5813	5813	5814	Q527299	3cca64fe- 7391-48e4- b7a3- 8e0a72d14561	5fa7855743b0bcec3db78d7a13f2e6b7	Boqueron	PR	Cabo Rojo	622	17.99174
4873	4873	4874	B702637	5066e481- 8c4d-4e4d- 988f- 80135e832d0f	f1b458365728af1ea3392e965436559c	Aguirre	PR	Salinas	704	17.96719
144 rc	ows × 6	6 columns								

In [126]:

```
dataz['Lng_z'] = stats.zscore(dataz['Lng'])
Lng_z = dataz.query('Lng_z > 3 | Lng_z < -3')
Lng_z.sort_values(['Lng_z'], ascending = False)</pre>
```

Out[126]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat	
378	378	379	U534288	6ceb0811- 1275-44aa- 8299- a9dd9d5ceab1	84d5d4366a34af0dfab077b864ccf94d	Yakutat	AK	Yakutat	99689	59.52058	_
5611	5611	5612	1630264	a25209fd- 76aa-44b3- 86b8- 90c267e4f164	c1fce98dfc966e6d942561864ff64926	Northway	AK	Southeast Fairbanks	99764	63.38147	
627	627	628	C106587	0bfad232- 90c5-4073- 8ec7- f5ea37f8dc3c	2f73f44bbab256a40c98564ae3127121	Central	AK	Yukon- Koyukuk	99730	65.61511	
4772	4772	4773	S598156	c8f0beab- fbe6-4c6e- 96b1- 04f973b16a8d	17301ae1a06453897f5863e10637ebd3	Venetie	AK	Yukon- Koyukuk	99781	67.47706	
6760	6760	6761	1277334	e09b15f3- c030-4fc2- a836- 683d7903c01a	f38746b1cc1d220ec70e086bcde4fb6f	Cordova	AK	Valdez- Cordova	99574	60.63146	
8841	8841	8842	R937496	91a6430c- 84d2-41c3- bca0- afe9fa0cd27a	a528a4e8683ad5fa167ad4410a6b8a78	Brevig Mission	AK	Nome	99785	65.34195	
1150	1150	1151	M44338	3f241261- 2e26-4597- ac3c- 230396f60da0	26ae468de550e93a8fb0dd8c5992605d	Brevig Mission	AK	Nome	99785	65.34195	
65	65	66	Q660046	3ade4df3- 2168-40df- 9929- 66b232d3a8a3	e81f2ce7a34173a2e91ea2914648290c	Savoonga	AK	Nome	99769	63.67959	
965	965	966	W154018	ba7dc969- 1349-415d- 9fe7- 8878e9a80434	3093ad47d782be083a1ebcae81481d1d	Gambell	AK	Nome	99742	63.75233	
7336	7336	7337	N152385	06d49f7f- b2d7-49c6- ad52- dd900f46d977	35bf54f7d86d864180701408820875df	Atka	AK	Aleutians West	99547	52.22953	

98 rows × 67 columns

In [127]:

```
dataz['Options_z'] = stats.zscore(dataz['Options'])
Options_z = dataz.query('Options_z > 3 | Options_z < -3')
Options_z.sort_values(['Options_z'], ascending = False)</pre>
```

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat
371	371	372	V913617	6a9f9ede- dce6-4941- aec4- f0d9a960cf1c	7575470a2ba3f0559cd44366c66b1854	Rocky Ford	CO	Otero	81067	37.93805
2444	2444	2445	G520259	5af62758- 6ef8-4fc9- 87e0- 0eb8e6c3e1d1	806f7f7d0ea6cb96b677f21155914b05	Tuttle	ND	Kidder	58488	47.17813
2751	2751	2752	C510896	6d3ca2ab- ff80-4312- a022- f5c1cdf97e1c	e0313ac2c67615ed26ac09ff85844277	Duncans Mills	CA	Sonoma	95430	38.46139
2901	2901	2902	M319118	a6b42670- d106-4294- bcf4- ef73404bb837	fd2f7b6a79b6c107c6a58d80ab2f93e2	Knox	PA	Clarion	16232	41.22118
3784	3784	3785	W908780	0af8874a- 9626-4d8c- 8622- d8472d5bbd05	c42b740687893082d4d1138a8301c99c	Newry	SC	Oconee	29665	34.72472
4322	4322	4323	C969452	2b3d7773- 2381-413a- a900- 043f47866d5c	ba9c8eabdd06457a3663e0c0cb73e52d	Columbus	GA	Muscogee	31903	32.41475
4754	4754	4755	A11402	363a9ecc- abe0-4a65- 873c- 78c1951a2494	e6eeaf589832325a9030ce3f1145158c	Miami	FL	Miami- Dade	33178	25.85803
4881	4881	4882	G449875	09208922- 733e-4204- 8933- 6aaa8be4e705	2afac6a1d982922dd1f717d4a6634595	Lebanon	VA	Russell	24266	36.86436
5209	5209	5210	G807667	a9e2a880- 2624-4bae- b79f- 810eb8b05317	3b3cab0e4ba8ebe3ed6f7cf75973eb10	Avon	СТ	Hartford	6001	41.79071
5992	5992	5993	E395420	a418c42c- e7e0-4405- ae49- 1fa7871fc14a	d5b67f3c0d5527c9dfca6a21848be574	Warrendale	PA	Allegheny	15086	40.66541
7227	7227	7228	A751122	9b3b0e27- 28a1-44e8- a8a9- 16027b5f6af3	a222c4a72bf61f4bc01c528707005d24	Pasadena	TX	Harris	77503	29.70217
8100	8100	8101	Z697522	d2d2fd80- a1b0-4991- a4c0- d2df1e35d9fc	0973f36b623000e861747c5d3b18e97f	Cardwell	МО	Dunklin	63829	36.03861
8151	8151	8152	Q252120	fe3bb0ad- 7432-4a8a- 8102- 81b099200ae5	7607342de1d353f3f3e7e9360b1a5874	Winter Garden	FL	Orange	34787	28.48236
13 rov	vs × 68	columns								

In [128]:

```
dataz['Timely_admission_z'] = stats.zscore(dataz['Timely_admission'])
Timely_admission_z = dataz.query('Timely_admission_z > 3 | Options_z < -3')
Timely_admission_z.sort_values(['Timely_admission_z'], ascending = False)</pre>
```

Out[128]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	La
6790	6790	6791	C605737	3d3ed28d- f5df-494b- bd11- cd27c77093d3	50c72f0c71254a277cedc7d19336ee69	Pe Ell	WA	Lewis	98572	46.55120
116	116	117	Q253368	de7c4cbc- 75a8-45ca- 871b- fbd377786202	961865602af02e4cfeb19e4e67ba1bf7	Kittanning	PA	Armstrong	16201	40.80912
420	420	421	130274	b5f9cc4d- c321-4d66- a04c- 4eab054a39b6	62ec6ebc42411a51bcc19efcfbcf67ea	Faucett	МО	Buchanan	64448	39.59986
2356	2356	2357	L130335	6aa7c824- 8804-4c2d- ba17- fe9c15686edf	9163bfdc3c246f323a899122f82f2359	Trinidad	СО	Las Animas	81082	37.17862
3772	3772	3773	Z199638	c62b19e0- 1701-4c6a- 81d8- 3720875d458c	5309a64c2a22a27d6951843b7566a7cf	Mc Intosh	FL	Marion	32664	29.44557
5016	5016	5017	R426838	e3615fee- cc1e-4cea- abd7- 5d6182fa3813	9c036eb794dc11c924a12760a3f302f7	Indianapolis	IN	Marion	46254	39.84896
5298	5298	5299	H509222	86e7bd57- 33fc-499a- 9b4c- 7e5edbcdd169	b9a6ac0eda10b24ccdd0d59f13a0e8e0	Skyforest	CA	San Bernardino	92385	34.21475
5375	5375	5376	U499841	9a159a22- d40d-4b9b- 9c47- c646dd9ecb89	a3ee73d52d794f63a01dceca701a3c98	Lima	ОН	Allen	45806	40.67520
5949	5949	5950	Y669279	ce23eb44- 1118-4449- b02c- b2db863e068a	7aa2d9e58477acae0acf56b48d3cb75c	Chugwater	WY	Platte	82210	41.74660
6488	6488	6489	J302887	c92e8738- f1a4-4f2c- 81ba- 72d2c8ec6dfb	497602cac02a66b78bc74089098cd212	Alma	KS	Wabaunsee	66401	38.97012
7431	7431	7432	R89456	5861dc08- c0ef-4c11- a0b9- 8bd9fb8f5d93	dfd40be8f524c0a7212b149a952d414b	Waukegan	IL	Lake	60087	42.40344

11 rows × 69 columns

In [129]:

```
dataz['Timely_treatment_z'] = stats.zscore(dataz['Timely_treatment'])
Timely_treatment_z = dataz.query('Timely_treatment_z > 3 | Options_z < -3')
Timely_treatment_z.sort_values(['Timely_treatment_z'], ascending = False)</pre>
```

Out[129]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	La
501	501	502	1780387	635e0f1f- 1535-4b1d- 9898- 8339acdea07a	0b522fa019f9c845ab508d1107670413	Dublin	ОН	Franklin	43016	40.0985
1764	1764	1765	N221105	d08c7a9d- 11d7-4923- 9d0a- c29c5fa47050	326a6a697b2873e5c84c3e8ff988a779	Greeleyville	SC	Williamsburg	29056	33.6051
5016	5016	5017	R426838	e3615fee- cc1e-4cea- abd7- 5d6182fa3813	9c036eb794dc11c924a12760a3f302f7	Indianapolis	IN	Marion	46254	39.8489
5247	5247	5248	K348432	fa2b59a9- f62e-4b99- a436- f48056aaba05	bf488781a1c46f8634685e3754017d23	Dearborn Heights	MI	Wayne	48125	42.2779
5298	5298	5299	H509222	86e7bd57- 33fc-499a- 9b4c- 7e5edbcdd169	b9a6ac0eda10b24ccdd0d59f13a0e8e0	Skyforest	CA	San Bernardino	92385	34.2147
6000	6000	6001	W425417	0ea98b00- 1c7d-4f83- a0be- d6803f1d70b5	5712e1276c2d0df9c87c814557130ee7	Fort Irwin	CA	San Bernardino	92310	35.2614
7431	7431	7432	R89456	5861dc08- c0ef-4c11- a0b9- 8bd9fb8f5d93	dfd40be8f524c0a7212b149a952d414b	Waukegan	IL	Lake	60087	42.4034
8326	8326	8327	P966922	ba29b074- 2909-4ac0- ae8c- 3d98132c1bb5	a0aefe75fb9316a55e02d0f11bed7c73	Hillsboro	MD	Caroline	21641	38.9177
8376	8376	8377	O962318	f3427c5f-7c7d- 4ebc-926b- a66c8761c047	8e5566f675e2add9866ca24d88bdb879	Welda	KS	Anderson	66091	38.1739
9113	9113	9114	C804661	dc1b957c- 348b-41f7- 88d2- d6366e8bf0b6	c3d926798a7c16afdfc9abc2ebe345c1	Bayview	ID	Kootenai	83803	48.0363
9352	9352	9353	B573266	e031c243- b356-41ae- 92ee- 46a1f3a8d793	f70d725f7037eafce1b89ab1000710d8	Encinitas	CA	San Diego	92024	33.0561
9763	9763	9764	T741340	39753426- 4e17-4d66- a135- 87a4367840ad	8b253260c77c08fcaa54aea8e2f91d70	Nicholson	PA	Lackawanna	18446	41.6450
12 rou	vo v 70	oolumno								

12 rows × 70 columns

In [130]:

```
dataz['Timely_visits_z'] = stats.zscore(dataz['Timely_visits'])
Timely_visits_z = dataz.query('Timely_visits_z > 3 | Timely_visits_z < -3')
Timely_visits_z.sort_values(['Timely_visits_z'], ascending = False)</pre>
```

Out[130]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat
8822	8822	8823	H579237	33326e08- 9f62-4159- 8d6a- d66545d8f4c5	f526923b83632e506fb60fb12e0e2e5f	Hoisington	KS	Barton	67544	38.58229
1028	1028	1029	E875190	999b36db- 926b-4b88- 894d- ecaa90dee332	b7e732e4a621c935ed640d6b46cc5a0a	Battle Creek	MI	Calhoun	49015	42.27127
1642	1642	1643	D685434	496fb29f- 7556-430d- a720- 7f4d24c4b75f	7cfcb06672f5b69c126fa537e2e80646	Eola	IL	DuPage	60519	41.77789
2939	2939	2940	F633638	f991a423- 956e-47b3- 8688- 70ad78315bb6	3e4b4f0b30b7cd50d3cb71fe6350d348	Wyncote	PA	Montgomery	19095	40.08597
3805	7ab39276- 865f-4445- 8fe3- 366fb7043dc4		f508f7c105d64011562326584f6e4e89	Cass Lake	MN	Cass	56633	47.31969		
4050	4050	4051	C64476	2a818f63- e4bc-407b- 8ae7- dd36f3578230	b01fac561a372c34255d2d607569fd14	Horatio	SC	Sumter	29062	33.99475
4407	4407	4408	H470636	c0994b61- 454e-4c42- 8617- 26304aa9d717	c57d48f888a7783080049f4246196487	Mine Hill	NJ	Morris	7803	40.87768
6686	6686	6687	R295268	6ea0af09- 7536-41ff- 9800- c09fbc6a668b	33129b04dbe49d9623900e922ffe1e55	Sylmar	CA	Los Angeles	91342	34.31515
8964	8964	8965	R85226	e3703132- 3e0a-46a1- 9250- 1824d2c7ad55	eca777ec1754a973bc33e553c9b0d055	Norwich	СТ	New London	6360	41.54884
9113	9113	9114	C804661	dc1b957c- 348b-41f7- 88d2- d6366e8bf0b6	c3d926798a7c16afdfc9abc2ebe345c1	Bayview	ID	Kootenai	83803	48.03638
9528	9528	9529	O612221	a1e51d59- d286-4d7c- a310- f61354ea0ae3	09e5eac102d16fe00214670cff2f281e	Brookfield	МО	Linn	64628	39.79720
9827	9827	9828	V442531	7e0ff2ee- 5b10-426b- 8d7c- 0f9cecf0dbaa	cfaee561a749c8b9348a674e96fff4bc	Hurley	NY	Ulster	12443	41.93393
12 rov	vs × 71	columns								

In [131]:

```
dataz['Reliability_z'] = stats.zscore(dataz['Reliability'])
Reliability_z = dataz.query('Reliability_z > 3 | Reliability_z < -3')
Reliability_z.sort_values(['Reliability_z'], ascending = False)</pre>
```

Out[131]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat
448	448	449	X12279	791a7ee3- 0c9b-4b43- 9c24- 2b33d43bbe6f	34127cd5ef45302ae320eb5c4cd1818f	Eastlake Weir	FL	Marion	32133	29.02018
2101	2101	2102	1382969	df50efa2- 6a57-4501- 8230- d72650de2c52	4506338ab2653e7ef05edb1df50d1374	Columbia	MD	Howard	21046	39.17356
3178	3178	3179	B356505	8cda92fd- 73c7-4074- 8f1e- 00cacd66538e	94cc5113be1dae40d7a06b76499d4cb6	Paul	ID	Minidoka	83347	42.73392
3225	3225	3226	X349857	b15f90d5- 2def-4729- 9a96- 7e73e5a9b184	60bdc5a688500d47c205bdf4ae6d87f7	Deer Park	TX	Harris	77536	29.69839
4211	4211	4212	M801409	47e2d486- cbd5-4219- 8270- b8ac05a831d7	8a62458f602cbebeb69774ec0172f9ed	Dixie	WV	Fayette	25059	38.23311
4776	4776	4777	E632070	a82d11e2- 68b8-475d- bbab- 322fda5b882b	7d77e330fbafe63f9088310532c27d5e	Columbus	TX	Colorado	78934	29.69375
5300	5300	5301	F18171	c4d5dff8-cabe- 4839-aff4- 9e6fdbfeafd5	4d492e879a993a3d12711b2370c1d0be	Torrance	CA	Los Angeles	90504	33.86682
6461	6461	6462	M335375	56dcfbe9- d2b6-432d- a3f2- ee53be0ede3e	c1cc82e04b82f27848576181f7337602	Olney	MT	Flathead	59927	48.57210
6983	6983	6984	U605143	1d5bb548- aefc-4895- b20a- c8a6baf60b48	eeed90779ca7d42bc79169c9014bfb45	Pembroke Township	IL	Kankakee	60958	41.06492
7585	7585	7586	S186662	da77edc9- 494f-42c8- a439- c60d962cfe86	7cc42283a16ad06f41222c90101fbfe4	Pleasureville	KY	Henry	40057	38.38941
9708	9708	9709	1863574	c61ad302- 84d7-498b- b744- f02cfae51a0e	1545a4a865cfa40dc797acd623f5bd37	Gordon	GA	Twiggs	31031	32.87127
9798	9798	9799	X960973	6494dcf6- 0e77-4093- 9687- 9598ae0f7e50	b84cc9a7f1028b58b10e02b6461c7529	Axis	AL	Mobile	36505	30.94264
4.0										

12 rows × 72 columns

In [132]:

```
dataz['Hours_z'] = stats.zscore(dataz['Hours'])
Hours_z = dataz.query('Hours_z > 3 | Hours_z < -3')
Hours_z.sort_values(['Hours_z'], ascending = False)</pre>
```

Out[132]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat											
565	565	566	D442431	f7c46c99- 70fe-4d6c- bdf5- 67349d4e7ef7	20cc938a8b12edfd67faddf51db079e4	Burnside	IA	Webster	50521	42.34623											
1755	1755	1756	P17573	f3addeec- cdbc-455b- 972d- a53ca3e1ec88	4504b498855a2c2a64f1f455244336aa	Winnsboro	SC	Fairfield	29180	34.36739											
1952	1952	1953	Q450603	a8a6aa7d- 3bb0-46e7- 9b1a- c52180587d63	e443edee809fd9937a2167b060af46b3	Nanjemoy	MD	Charles	20662	38.43516											
2574	2574	2575	F525478	6a38e9cb- b2fd-4044- 8f71- 2793507c28e5	66e1f4663fe790b3ec24c900ebf0edb3	Beaver Bay	MN	Lake	55601	47.23577											
2871	2871	2872	L172909	cb794d21- e46a-4f93- 8071- 431d8f8857f4	864b1053b47da42f8439efb5ec2e6b0b	Fayetteville	GA	Fayette	30214	33.4917(
4141	4141	4142	D232618	80e82d9f- 5ceb-460f- 8cb5- 610ac12927cc	32a5fbdf11647d8cf4ca3903d5371d51	Conway	NC	Northampton	27820	36.41563											
4808	4808	4809	1840751	463c85ed- 291f-4e56- a036- 5dc319bfdb08	35814159827104bc8d42fe74a3c74837	Little Neck	NY	Queens	11363	40.77268											
6790	6790	6791	C605737	3d3ed28d- f5df-494b- bd11- cd27c77093d3	50c72f0c71254a277cedc7d19336ee69	Pe Ell	WA	Lewis	98572	46.55120											
7359	7359	7360	S363644	6fd69439- 6c22-4e89- a13e- 68349730c50d	08ab920b9c49d1263bfe4203b0251cac	Vero Beach	FL	Indian River	32968	27.58700											
7553	7553	7554	R463541	98f8f4af-679c- 4f63-a578- 91f1818f407d	d9cfcc2c206eaa0f5343e3cd1d176f13	Rutherford	TN	Gibson	38369	36.13228											
10 rov	vs × 73	columns								10 rows × 73 columns											

In [133]:

```
dataz['Courteous_z'] = stats.zscore(dataz['Courteous'])
Courteous_z = dataz.query('Courteous_z > 3 | Courteous_z < -3')
Courteous_z.sort_values(['Courteous_z'], ascending = False)</pre>
```

Out[133]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	Lat
599	599	600	T536145	e4fe184f- c28a-416a- 816c- b9f1898f7d73	d8c1c6ac065390f252cdb698708233df	Hawthorn	PA	Clarion	16230	41.02099
2010	2010	2011	T101729	7ba6e56a- 01bb-4ebb- a630- a394d2c730d6	f43629df63b8350dc12a8586bf35c690	Caldwell	ID	Canyon	83607	43.70795
3790	3790	3791	E382593	82eb36cd- 68b4-41a5- 92c2- a92824d2ce8d	384cb41d65137a4e243abaa659eeb543	Hampton	VA	Hampton	23664	37.07528
4850	4850	4851	E444065	6a02074b- e1bb-4685- a767- 3df69665a270	d64310eb316104566c7cd992783f3431	Tatitlek	AK	Valdez- Cordova	99677	60.89214
6646	6646	6647	Z03012	44b36d8d- 7ac5-4368- 919f- b33144ad9542	c55ce718a887e70b8ccbf845c58584c8	Roseland	NJ	Essex	7068	40.82071
7527	7527	7528	Q775427	44a210d6- c9f0-490d- b544- 55fce9e8f50a	2729d115709a2096811a62e42c6e04f1	Horton	AL	Marshall	35980	34.17625
7843	7843	7844	E472114	22957ec2- 6c15-4bbf- bc0e- 2f4a2f7a6f05	9de913184e45ee14815a8dbd467f102b	East Bridgewater	MA	Plymouth	2333	42.03515
8142	8142	8143	C831750	0c68fb1f-8acc- 4d23-a4c7- 9db30c5976ce	be947f4225d7856c32d58286bb1b463a	Charleston	sc	Charleston	29414	32.83802
8165	8165	8166	1670859	e9dec8d8- c2e1-4ed4- 91ae- 390090dc45b2	440b7ad9e4e5bf020215b7ed6d7f670d	Springfield	IL	Sangamon	62701	39.80082
8209	8209	8210	J805835	5ba4461e- d984-4d40- 979a- e7433bfce4ef	7b193c59128eaa3b856febd43dca4222	Hamburg	NJ	Sussex	7419	41.15321
8720	8720	8721	U975030	8ef249c1- 5b93-42d6- b105- 2b7c93a49ea5	53ac1f6c55358c8352a3b8d05680c525	Algoma	WI	Kewaunee	54201	44.62083
11 rov	vs × 74	columns								

11 rows × 74 columns

In [134]:

```
dataz['Active_listen_z'] = stats.zscore(dataz['Active_listen'])
Active_listen_z = dataz.query('Active_listen_z > 3 | Active_listen_z < -3')
Active_listen_z.sort_values(['Active_listen_z'], ascending = False)</pre>
```

Out[134]:

	Index	Case_order	Customer_id	Interaction	UID	City	State	County	Zip	
248	248	249	F210779	e9693fd1- 0d38-494a- 8961- 038d929066ee	3820c94c0e8e198124716e61e4a0f674	Oklahoma City	ОК	Oklahoma	73102	35.47
898	898	899	S435495	4d71a2be- b91c-40a7- 9db0- a0b973154826	6a90d9c6b5cf447735de5bae988dcef6	Harviell	МО	Butler	63945	36.60
1096	1096	1097	O879050	3ea27c2a- 3a58-43a2- bde2- 52a5a1a2b014	8e4e762fa2f47dc5cdfc42e49fb2688e	Gadsden	AL	Etowah	35903	34.02
1402	1402	1403	Z958874	6a3115dc- e21f-4fe4- ad62- 1dbf4d7d8e9f	40ca6a31050d74f2eaef8bc217311d4c	Fleming	PA	Centre	16835	40.90
2054	2054	2055	M400514	5f863a0c- 008e-4933- be8a- 95ae7ff7c1fa	542cfb80a4610dbb641a4d8e7995f924	Hague	VA	Westmoreland	22469	38.07
2736	2736	2737	M174545	44d3b166- 135f-4f8e- a546- d489a7cc2b29	eed6c940042850d71911cb55a61aa0c0	Sylvania	ОН	Lucas	43560	41.7(
3300	3300	3301	V574050	1ca7a786- bd34-44ea- 8051- c4a746ec9e62	9cea7c94a4ee90ceb62b74ead6315f6a	South Bloomingville	ОН	Hocking	43152	39.39
3395	3395	3396	U246066	d579c126- 57e0-40ef- 9343- 52bf53f71f93	b0e56f03b1aae1846c3966bde3b4f0a5	Coloma	WI	Waushara	54930	44.02
5949	5949	5950	Y669279	ce23eb44- 1118-4449- b02c- b2db863e068a	7aa2d9e58477acae0acf56b48d3cb75c	Chugwater	WY	Platte	82210	41.74
6508	6508	6509	T191666	b9de5930- e19e-46a9- b0ce- 7311bb4e9ca7	5aef9f1f998d472b7db14e77564228f2	Seymour	МО	Webster	65746	37.14
8326	8326	8327	P966922	ba29b074- 2909-4ac0- ae8c- 3d98132c1bb5	a0aefe75fb9316a55e02d0f11bed7c73	Hillsboro	MD	Caroline	21641	38.9°
9799	9799	9800	Z246842	4afec6c9- 9a63-4710- b72f- 898f65fdd4e9	158ae21bf8d8ba5501015416cdc6ee9d	Normal	IL	McLean	61761	40.52

12 rows × 75 columns

In [135]:

```
dataz.to_csv('C:/Users/ericy/Desktop/data_z.csv')
```

In [136]:

dataz.shape

Out[136]:

(10000, 75)

In [137]:

dataz.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 75 columns):

Data #	columns (total 75 columns		Dtype
#	Column	Non-Null Count	Dtype
0	Index	10000 non-null	int64
1	Case_order	10000 non-null	int64
2 3	Customer_id Interaction	10000 non-null 10000 non-null	object
3 4	UID	10000 non-null	object object
5	City	10000 non-null	object
6	State	10000 non-null	object
7	County	10000 non-null	object
8	Zip	10000 non-null	int64
9 10	Lat Lng	10000 non-null 10000 non-null	float64 float64
11	Population	10000 non-null	int64
12	Area	10000 non-null	int64
13	Timezone	10000 non-null	object
14	Job	10000 non-null	object
15 16	Children	10000 non-null	int64
16 17	Age Education	10000 non-null 10000 non-null	int64 int64
18	Employment	10000 non-null	int64
19	Income	10000 non-null	int64
20	Marital	10000 non-null	int64
21	Gender	10000 non-null	int64
22 23	Readmis VitD levels	10000 non-null 10000 non-null	int64 int64
24	Doc visits	10000 non-null	int64
25	Full meals eaten	10000 non-null	int64
26	VitD_supp	10000 non-null	int64
27	Soft_drink	10000 non-null	int64
28	Initial_admin	10000 non-null	int64
29 30	High_blood Stroke	10000 non-null 10000 non-null	int64 int64
31	Complication_risk	10000 non-null	int64
32	Overweight	10000 non-null	int64
33	Arthritis	10000 non-null	int64
34	Diabetes	10000 non-null	int64
35	Hyperlipidemia	10000 non-null	int64
36 37	Back_pain Anxiety	10000 non-null 10000 non-null	int64 int64
38	Allergic rhinitis	10000 non-null	int64
39	Reflux_esophagitis	10000 non-null	int64
40	Asthma	10000 non-null	int64
41	Services	10000 non-null 10000 non-null	int64
42 43	<pre>Initial_days Total charge</pre>	10000 non-null	int64 int64
44	Additional charges	10000 non-null	int64
45	Timely_admission	10000 non-null	int64
46	Timely_treatment	10000 non-null	int64
47	Timely_visits	10000 non-null	int64
48 49	Reliability Options	10000 non-null 10000 non-null	int64 int64
50	Hours	10000 non-null	int64
51	Courteous	10000 non-null	int64
52	Active_listen	10000 non-null	int64
53	Age_z	10000 non-null	float64
54 55	Children_z Income z	10000 non-null 10000 non-null	float64 float64
56	VitD_levels_z	10000 non-null	float64
57	Doc visits z	10000 non-null	float64
58	Full_mealz	10000 non-null	float64
59	VitD_suppz	10000 non-null	float64
60	<pre>Initial_days_z</pre>	10000 non-null	float64
61 62	Total_charge_z Additional charges z	10000 non-null 10000 non-null	float64 float64
63	Population z	10000 non-null	float64
64	Zip_z	10000 non-null	float64
65	Lat_z	10000 non-null	float64
66	Lng_z	10000 non-null	float64
67 68	Options_z	10000 non-null	float64
68 69	Timely_admission_z Timely_treatment_z	10000 non-null 10000 non-null	float64 float64
70	Timely_visits_z	10000 non-null	float64
71	Reliability_z	10000 non-null	float64
72	Hours_z	10000 non-null	float64
73	Courteous_z	10000 non-null	float64
74 dtvpe	<pre>Active_listen_z es: float64(24), int64</pre>	10000 non-null (43). object(8)	float64
> PC		,,,	

dtypes: float64(24), int64(43), object(8)
memory usage: 5.7+ MB

```
In [138]:
med = pd.read_csv('C:/Users/ericy/Desktop/pca_1.csv')
In [139]:
med.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
     Column
                         Non-Null Count Dtype
#
                         10000 non-null
 0
     Doc_visits
                                          int64
     VitD supp
                         10000 non-null
 1
                                         int64
 2
                         10000 non-null
     Initial_days
                                         int64
                         10000 non-null
     Total charge
                                          int64
     Additional_charges
                         10000 non-null
                                          int64
     Timely admission
                         10000 non-null
                                         int64
 6
     Timely_treatment
                         10000 non-null
                                         int64
 7
     Timely_visits
                         10000 non-null
                                          int64
 8
     Reliability
                         10000 non-null
                                         int64
     Options
                         10000 non-null int64
                         10000 non-null int64
 10
    Hours
 11
     Courteous
                         10000 non-null
                                         int64
 12 Active listen
                         10000 non-null int64
dtypes: int64(13)
memory usage: 1015.8 KB
In [140]:
#Define variables for PCA
med = med[['Doc_visits','VitD_supp','Initial_days','Total_charge','Additional_charges','Timely_admission','Timely
_treatment','Timely_visits','Reliability','Options','Hours','Courteous','Active_listen']]
In [141]:
#Normalize data - scales data
med_normalized = (med-med.mean())/med.std()
In [142]:
pca = PCA(n components=med.shape[1])
In [143]:
pca.fit(med_normalized)
Out[143]:
PCA(n components=13)
In [144]:
med pca = pd.DataFrame(pca.transform(med normalized),
                      columns=['PC1','PC2','PC3','PC4','PC5','PC6','PC7','PC8','PC9','PC10','PC11','PC12','PC13']
```

In [145]:

Out[145]:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
Doc_visits	0.007069	-0.002075	-0.013897	0.551134	-0.750294	0.362101	-0.019941	-0.026724	-0.025656	0.007265	-0.010368
VitD_supp	-0.004949	0.019578	0.034108	0.545353	0.650617	0.524840	0.030928	0.030766	0.013852	-0.003816	0.010258
Initial_days	-0.016866	0.425164	0.562897	-0.043657	-0.030162	0.021512	-0.011771	-0.006577	0.000766	-0.007445	0.031354
Total_charge	-0.014241	0.440002	0.552356	-0.010146	-0.022778	-0.003120	-0.000712	-0.014128	0.000295	0.011957	-0.028224
Additional_charges	0.003986	0.034518	0.020067	0.629137	0.092341	-0.768731	0.004383	-0.041244	0.005803	0.014262	-0.015063
Timely_admission	0.454784	-0.232816	0.184023	0.002111	0.007337	-0.003075	-0.095714	-0.076403	-0.010802	0.086216	0.181731
Timely_treatment	0.428496	-0.226595	0.186167	0.004032	0.004817	-0.002444	-0.146858	-0.134481	-0.062202	0.102062	0.625524
Timely_visits	0.395301	-0.228728	0.188430	-0.004630	0.027615	0.010274	-0.204619	-0.212429	-0.238900	-0.433423	-0.620798
Reliability	0.152243	0.437651	-0.346530	-0.019568	0.047671	0.027333	-0.365196	-0.361566	-0.387968	0.483537	-0.113822
Options	-0.190134	-0.463555	0.355510	-0.004262	-0.000015	0.000493	0.124501	0.058344	-0.132365	0.694576	-0.307619
Hours	0.410398	0.134827	-0.093755	-0.005404	-0.014136	0.013554	-0.050728	0.061982	0.796740	0.266844	-0.274555
Courteous	0.356642	0.150254	-0.089585	0.013667	-0.017869	-0.029628	0.035179	0.846287	-0.335176	0.068621	-0.060967
Active_listen	0.312688	0.137892	-0.094741	-0.018968	-0.013051	0.008766	0.879324	-0.270498	-0.151259	0.040836	-0.037450
4											b

In [146]:

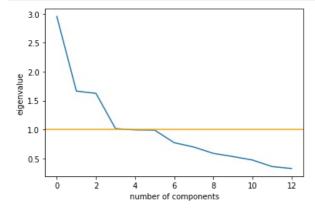
```
cov matrix = np.dot(med normalized.T, med normalized) / med.shape[0]
```

In [147]:

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

In [148]:

```
plt.plot(eigenvalues)
plt.xlabel('number of components')
plt.ylabel('eigenvalue')
plt.axhline(y=1, color='orange')
plt.show()
```



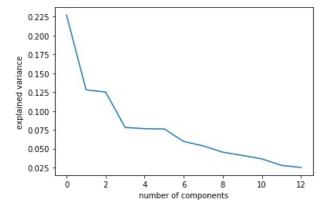
In [149]:

```
print(eigenvalues)
```

 $[2.953561847701104, \ 1.664527005604655, \ 1.6253016059708472, \ 1.015751765687237, \ 0.9944920712433167, \ 0.9897973674624058, \ 0.7730497224229762, \ 0.698131569259065, \ 0.588691460987571, \ 0.5337901719644559, \ 0.4736831400386705, \ 0.361101692090996, \ 0.3268205795665951]$

In [150]:

```
plt.plot(pca.explained_variance_ratio_)
plt.xlabel('number of components')
plt.ylabel('explained variance')
plt.show()
```



In []: