Eric Yarger, Classification Analysis

In [2]:
```python
# Import Libraries

import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
import missingno as msno
from scipy import stats
from scipy.stats import zscore
from sklearn.feature_selection import SelectKBest, chi2
```

In [3]:
```python
# Jupyter environment version
!jupyter --version
```

```
jupyter core     : 4.6.3
jupyter-notebook : 6.0.3
qtconsole        : 4.7.2
ipython          : 7.13.0
ipykernel        : 5.1.4
jupyter client   : 6.1.2
jupyter lab      : 1.2.6
nbconvert        : 5.6.1
ipywidgets       : 7.5.1
nbformat         : 5.0.4
traitlets        : 4.3.3
```

In [4]:
```python
# Python Environment version
import platform
print(platform.python_version())
```

```
3.7.7
```

In [ ]:

Data Preparation

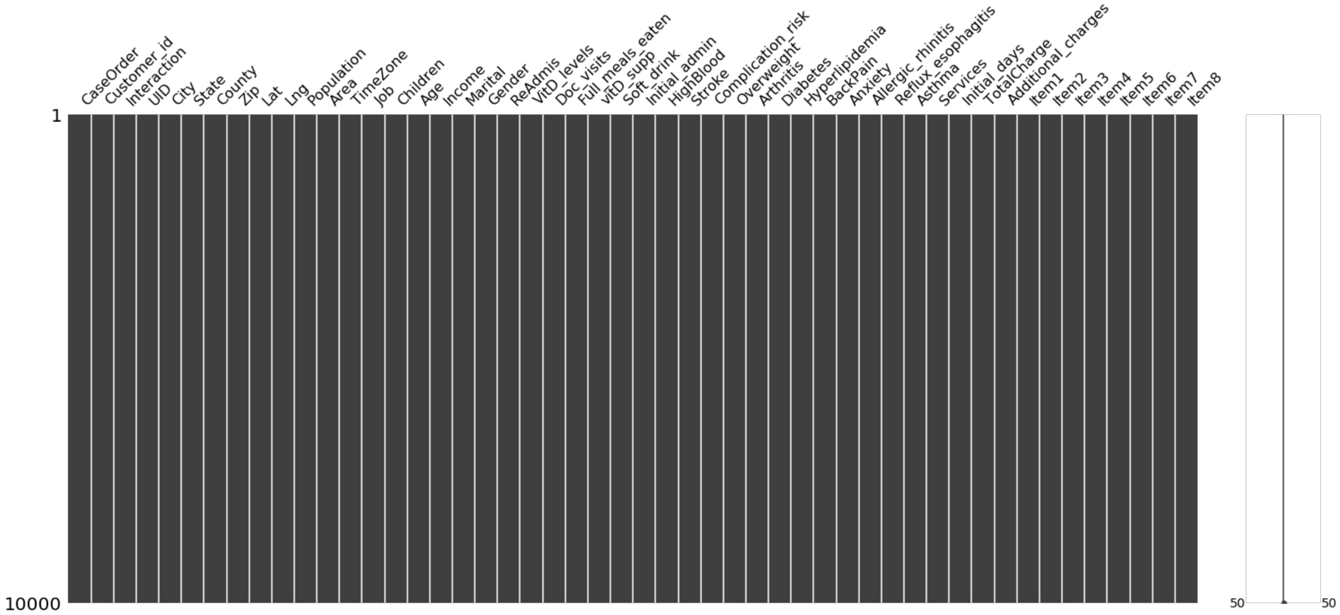
Step 1 : Load the Data and initial visualization

In [5]:
```python
df = pd.read_csv('C:/Users/ericy/Desktop/medical_clean.csv')
```

In [ ]:

In [6]:
```python
msno.matrix(df)
```

Out[6]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5e73ae888>
```



In [7]:
```python
df.hist(figsize=(20,20))
```

Out[7]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E6CBFDC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7891D08>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E78CACC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7901DC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E793AEC8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7973FC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E79B0148>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E79EA248>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E79F0E08>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7A27FC8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7A95508>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7ACD608>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7B05748>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7B3E848>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7B76908>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7BAE9C8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7BE9AC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7C22BC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7C59D08>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7C92E08>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7CCBEC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7CF4FC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7D30108>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7D6A208>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5E7DA2408>]],
      dtype=object)
```

In [ ]:

In [ ]:

In [ ]:

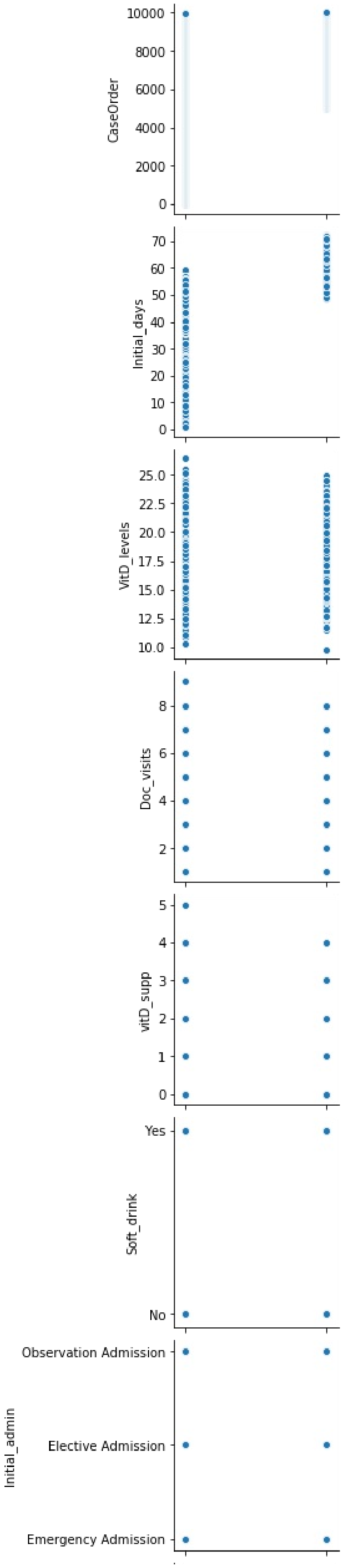
In [ ]:

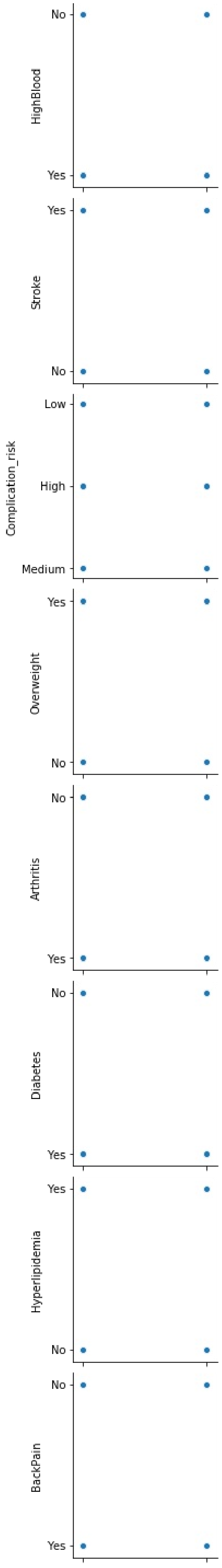
Step 2 : Rename columns and create Pairplots

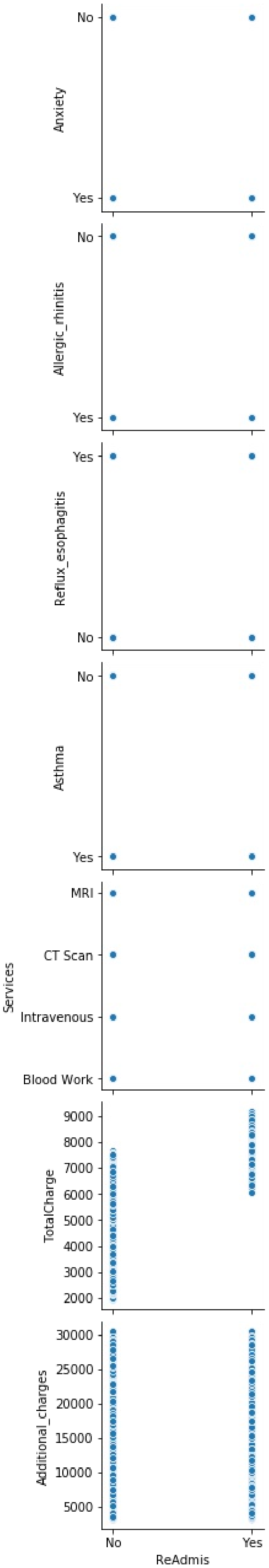
In [8]:
```
df.rename(columns={'Item1':'Timely_admis','Item2':'Timely_treat','Item3':'Timely_vis','Item4':'Reliability','It
```

In [9]:
```
sns.pairplot(df, x_vars=['ReAdmis'], y_vars=['CaseOrder','Initial_days','VitD_levels','Doc_visits','vitD_supp',
```

Out[9]:
```
<seaborn.axisgrid.PairGrid at 0x2b5e9d700c8>
```

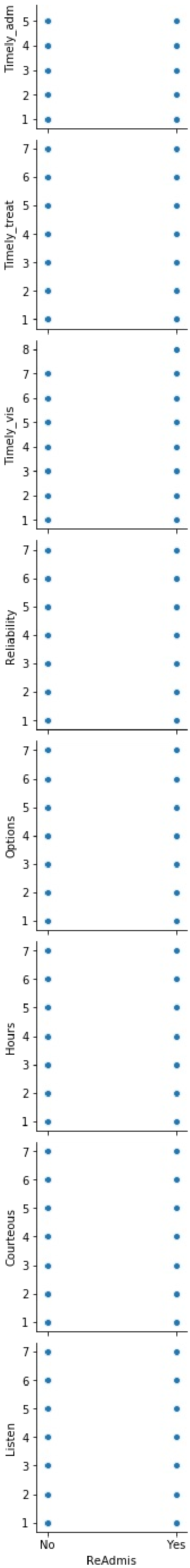



No
HighBlood
Yes
Yes
Stroke
No
Low
Complication_risk
High
Medium
Yes
Overweight
No
No
Arthritis
Yes
No
Diabetes
Yes
Yes
Hyperlipidemia
No
No
BackPain
Yes



In [10]:
```
sns.pairplot(df, x_vars=['ReAdmis'], y_vars=['Timely_admis','Timely_treat','Timely_vis','Reliability','Options'
```

Out[10]: <seaborn.axisgrid.PairGrid at 0x2b5ebbed308>



Step 3 : Address missing data, duplicates, and outliers. ReAdmis replace Yes/No with 1/0

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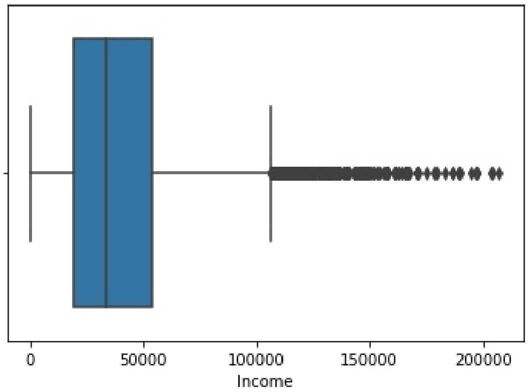
In [11]:
```
# Calculate Z-scores, remove Outliers Z > 3

#df.isnull().sum()
```

In [12]:
```
df.duplicated().any()
```

Out[12]:
```
False
```

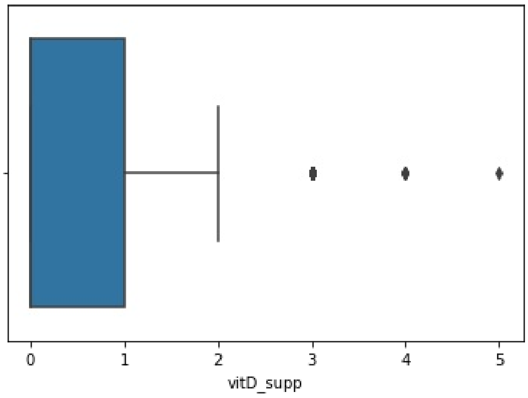
In [13]:
```
sns.boxplot(df['Income'])
```

Out[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5ec362688>
```



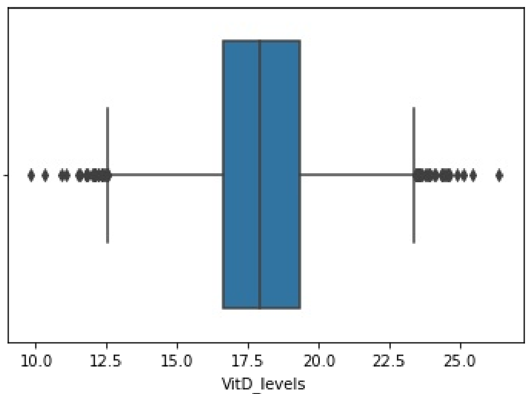
In [14]:
```
sns.boxplot(df['vitD_supp'])
```

Out[14]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5ed3915c8>
```



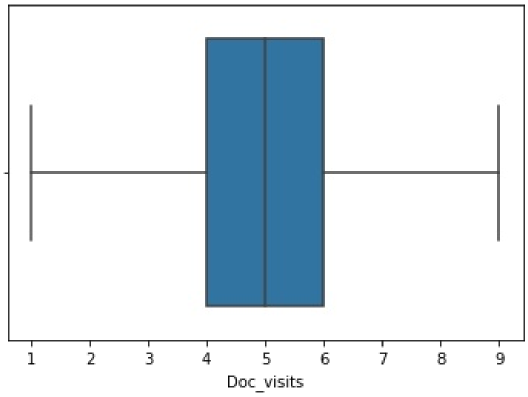
In [15]:
```
sns.boxplot(df['VitD_levels'])
```

Out[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5ed3fdbc8>
```



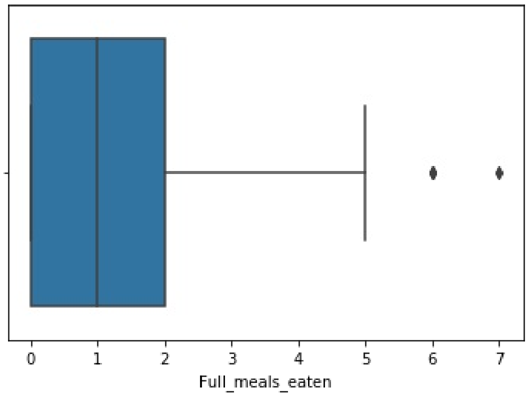
In [16]:
```
sns.boxplot(df['Doc_visits'])
```

Out[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5ed469d48>
```



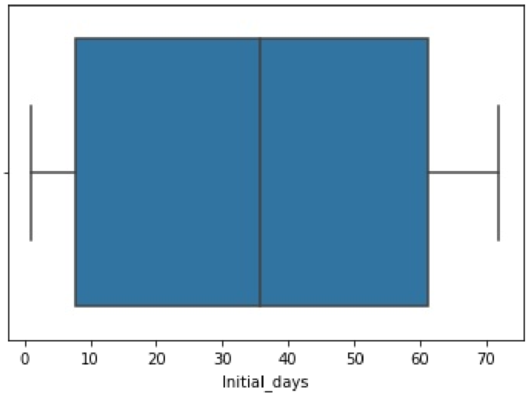
In [17]:
```
sns.boxplot(df['Full_meals_eaten'])
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5ec320088>



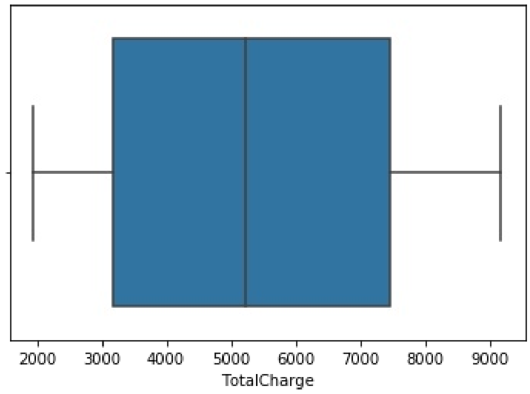
In [18]:
```
sns.boxplot(df['Initial_days'])
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5ed51a5c8>



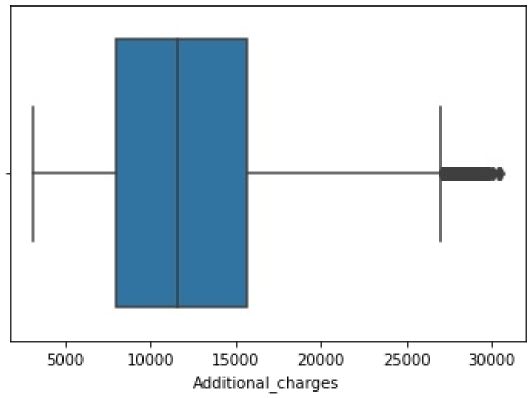
In [19]:
```
sns.boxplot(df['TotalCharge'])
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5ed58bdc8>



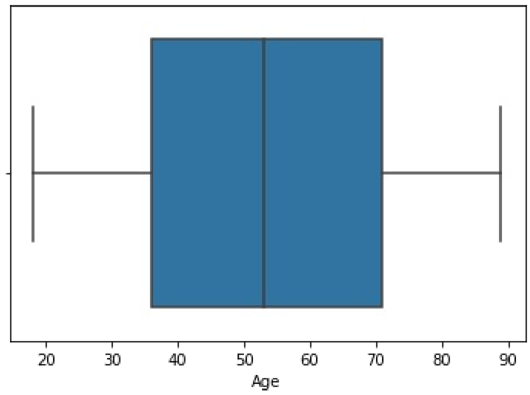
In [20]:
```
sns.boxplot(df['Additional_charges'])
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5ed5fae88>



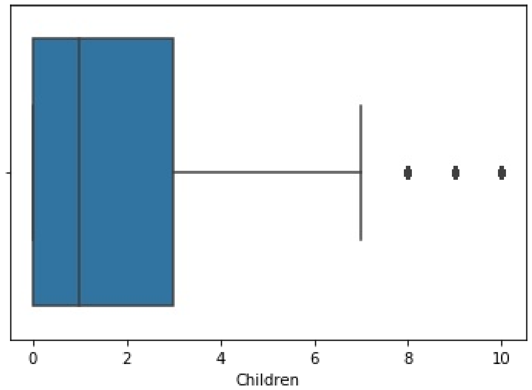
In [21]:
```
sns.boxplot(df['Age'])
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5ed65a2c8>

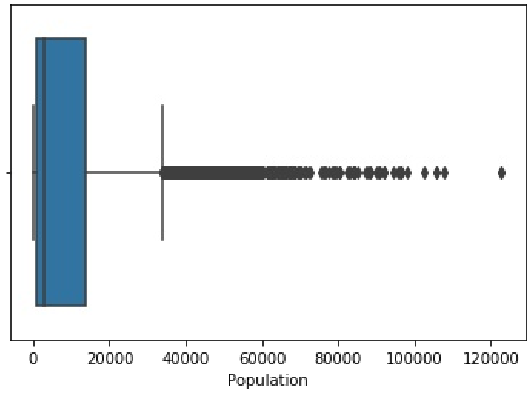


In [22]:
```
sns.boxplot(df['Children'])
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5ed6c8fc8>



In [23]:
```
sns.boxplot(df['Population'])
```
Out[23]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5dde87a88>
```



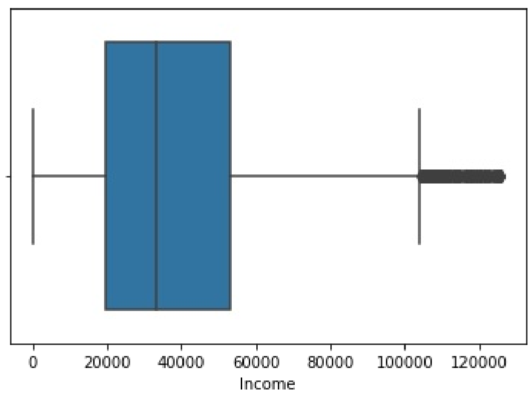
In [ ]:
```

```

In [24]:
```
# Outlier removal method via Z-score, Code reference (Bushmanov, 2019)

num_data = df.select_dtypes(include=['number'])
cat_data = df.select_dtypes(exclude=['number'])
```

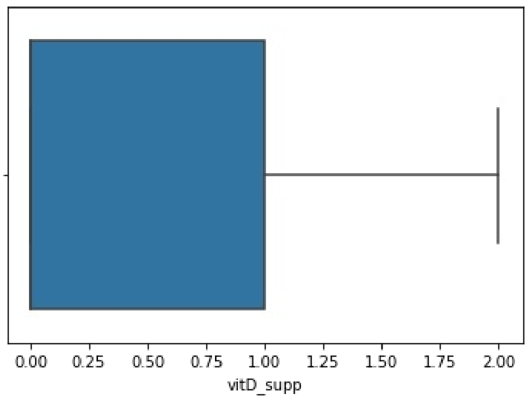
In [25]:
```
idx = np.all(stats.zscore(num_data) <3, axis=1)
```

In [26]:
```
df = pd.concat([num_data.loc[idx], cat_data.loc[idx]], axis=1)
```

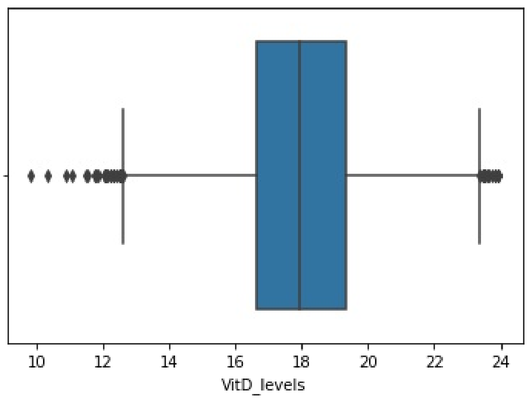
In [27]:
```
sns.boxplot(df['Income'])
```
Out[27]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5ed7c0c08>
```



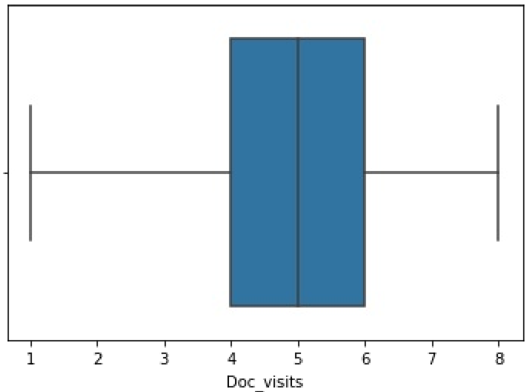
In [28]:
```
sns.boxplot(df['vitD_supp'])
```
Out[28]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5ed6c37c8>
```



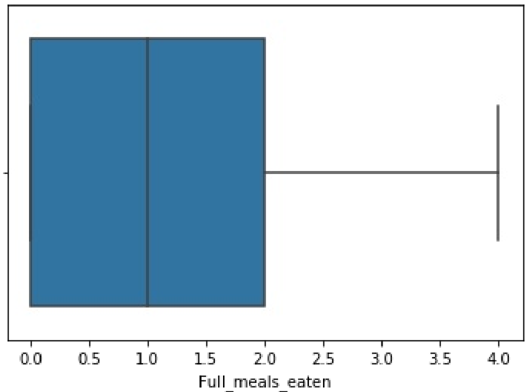
In [29]:
```
sns.boxplot(df['VitD_levels'])
```
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5edbd91c8>



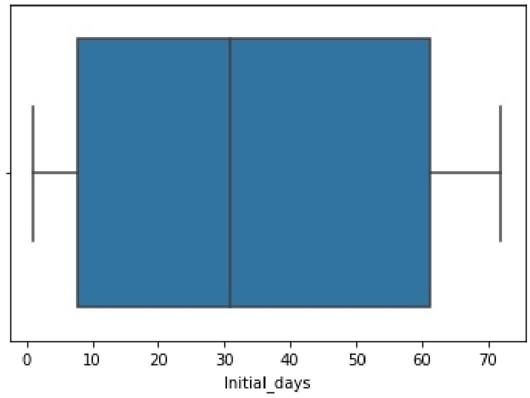
In [30]:
```
sns.boxplot(df['Doc_visits'])
```
Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5edc4b648>



In [31]:
```
sns.boxplot(df['Full_meals_eaten'])
```
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5edcb4e88>

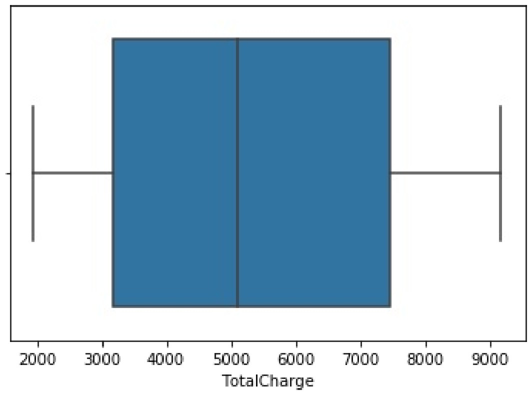


In [32]:
```
sns.boxplot(df['Initial_days'])
```
Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5edd1e6c8>



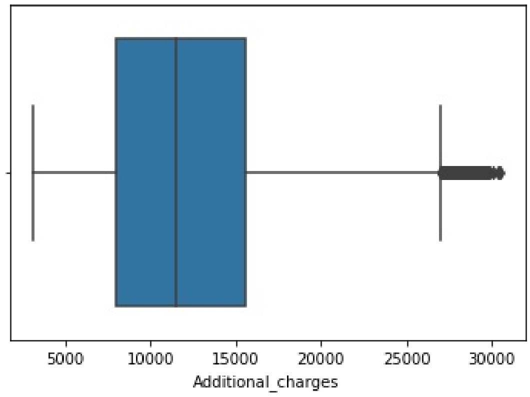
In [33]:
```
sns.boxplot(df['TotalCharge'])
```

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5edc535c8>



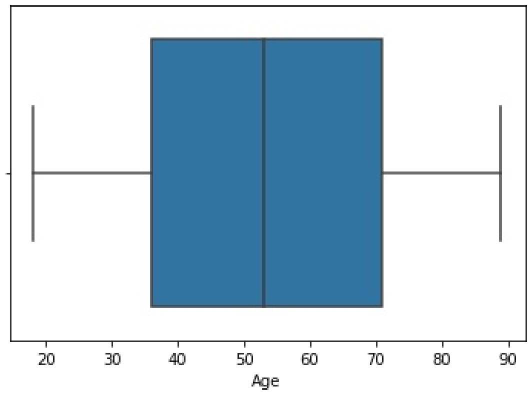
In [34]:
```
sns.boxplot(df['Additional_charges'])
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5eddff908>



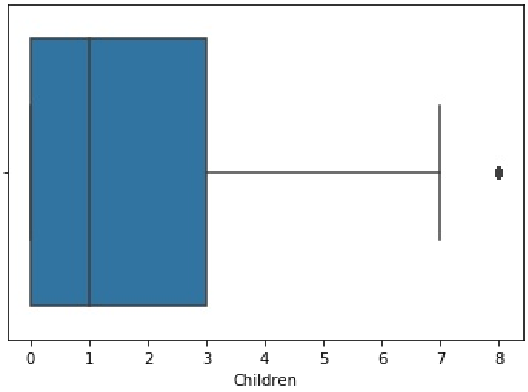
In [35]:
```
sns.boxplot(df['Age'])
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5ee097608>



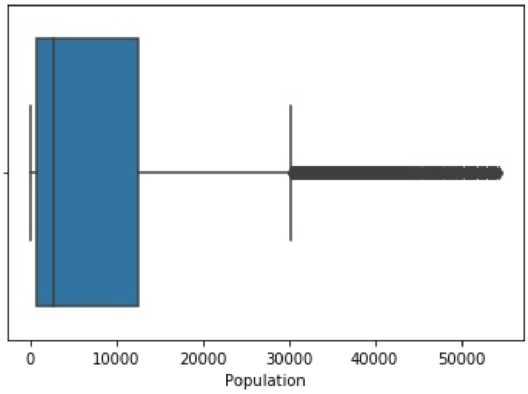
In [36]:
```
sns.boxplot(df['Children'])
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x2b5ee105048>



In [37]:
```
sns.boxplot(df['Population'])
```

Out[37]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5ee16f248>
```



In [ ]:

In [38]:
```
# replace yes/no with 1/0 ReAdmis

df['ReAdmis'].replace(('Yes','No'), (1,0), inplace=True)
```

In [39]:
```
df.duplicated().sum()
```

Out[39]:
```
0
```

Step 4 : Look at correlation between variables

In [40]:
```
df.corr()
```

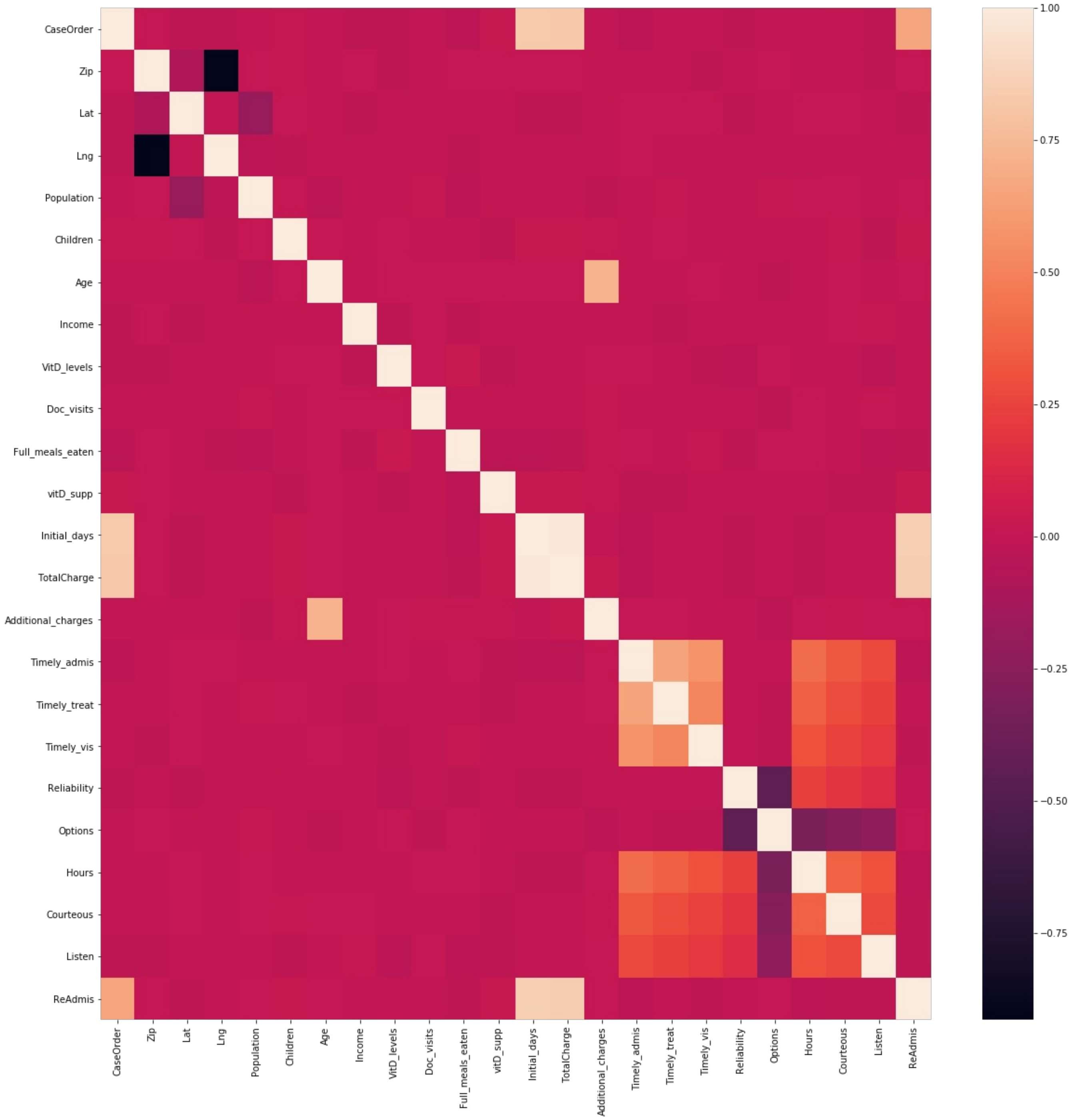
Out[40]:

	CaseOrder	Zip	Lat	Lng	Population	Children	Age	Income	VitD_levels	Doc_visits	...	Additi
CaseOrder	1.000000	0.010465	-0.012946	-0.012081	0.001489	0.017027	-0.003011	-0.012265	-0.015026	-0.006920	...	
Zip	0.010465	1.000000	-0.084258	-0.913573	0.012947	0.014307	-0.003327	0.010507	-0.010747	0.000257	...	
Lat	-0.012946	-0.084258	1.000000	0.001062	-0.187334	0.005874	-0.000132	-0.015414	-0.005158	0.004689	...	
Lng	-0.012081	-0.913573	0.001062	1.000000	-0.018263	-0.014141	0.002780	-0.008175	0.000931	0.002417	...	
Population	0.001489	0.012947	-0.187334	-0.018263	1.000000	0.007810	-0.018884	0.002162	0.004719	0.016088	...	
Children	0.017027	0.014307	0.005874	-0.014141	0.007810	1.000000	0.006050	0.003951	0.006542	-0.003467	...	
Age	-0.003011	-0.003327	-0.000132	0.002780	-0.018884	0.006050	1.000000	-0.003218	0.008795	0.010819	...	
Income	-0.012265	0.010507	-0.015414	-0.008175	0.002162	0.003951	-0.003218	1.000000	-0.015684	0.011179	...	
VitD_levels	-0.015026	-0.010747	-0.005158	0.000931	0.004719	0.006542	0.008795	-0.015684	1.000000	0.010297	...	
Doc_visits	-0.006920	0.000257	0.004689	0.002417	0.016088	-0.003467	0.010819	0.011179	0.010297	1.000000	...	
Full_meals_eaten	-0.020805	0.013077	-0.001353	-0.013120	-0.025711	-0.005112	0.008499	-0.012628	0.032606	-0.004586	...	
vitD_supp	0.026011	0.009348	0.005225	-0.001817	0.004134	-0.010125	0.009336	0.001478	-0.015671	0.002755	...	
Initial_days	0.831426	0.011103	-0.009938	-0.006659	0.004435	0.022122	0.009943	-0.006543	-0.007267	-0.008363	...	
TotalCharge	0.821397	0.010493	-0.012843	-0.005866	0.004758	0.022909	0.010785	-0.008523	-0.004403	-0.005363	...	
Additional_charges	-0.003178	0.001545	-0.001433	0.003290	-0.011835	0.014076	0.716409	-0.005190	0.006120	0.014611	...	
Timely_admis	-0.016607	-0.008630	0.008075	0.011933	0.004194	0.004097	0.005614	-0.004194	0.010499	0.003984	...	
Timely_treat	-0.005508	-0.002475	0.009184	-0.002521	0.016837	0.006169	0.004382	-0.012371	0.003697	0.004377	...	
Timely_vis	-0.006320	-0.010277	0.010924	0.002614	-0.004754	-0.002485	0.006990	-0.007394	-0.011930	-0.003794	...	
Reliability	-0.016204	0.001231	-0.011577	0.000283	-0.008892	-0.001091	0.003407	-0.003532	-0.016650	-0.006303	...	
Options	-0.004709	0.006290	0.000179	-0.002771	0.013720	0.003409	-0.013980	-0.005088	0.007878	-0.011124	...	
Hours	-0.006087	-0.001406	0.009542	-0.004637	0.007970	-0.002796	0.003434	0.003083	0.004610	0.009226	...	
Courteous	0.005102	-0.004203	0.009071	0.002070	0.010529	0.015894	0.009339	0.008516	-0.007461	0.005322	...	
Listen	-0.012319	-0.010159	0.004348	0.003871	-0.005522	-0.011509	0.002873	0.020238	-0.024347	0.006145	...	
ReAdmis	0.661462	0.009519	-0.012324	-0.004241	0.007563	0.023890	0.011880	-0.008669	0.002858	-0.002226	...	

24 rows × 24 columns

In [41]:

```
fig_dims = (20, 20)
fig, ax = plt.subplots(figsize=fig_dims)
sns.heatmap(df.corr(), ax=ax)
plt.show()
```

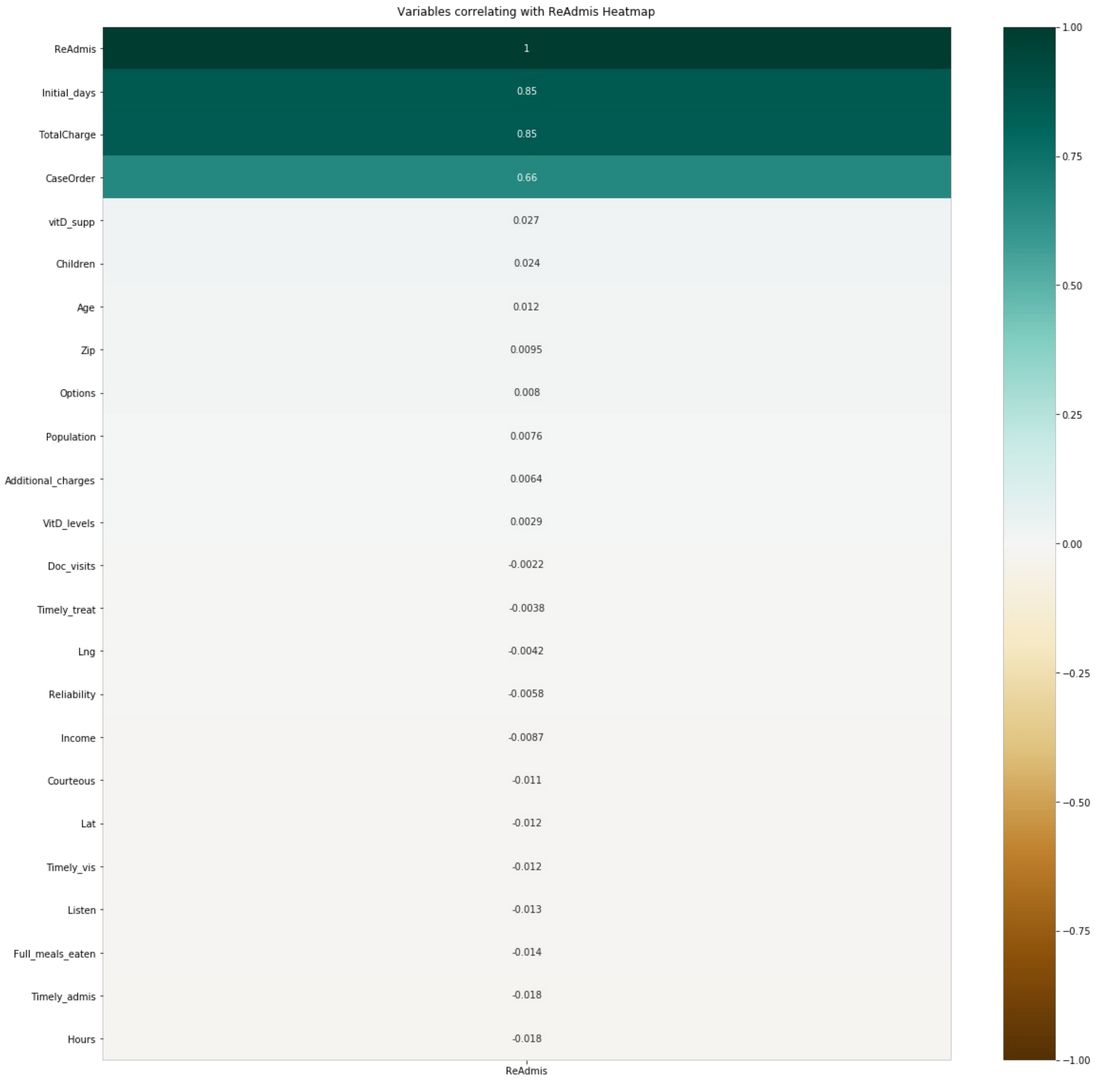


In [42]:

```
# Heatmap code reference (Seaborn.heatmap, N.d.)

plt.figure(figsize=(20,20))
heatmap = sns.heatmap(df.corr()[['ReAdmis']].sort_values(by='ReAdmis', ascending=False), vmin=-1, vmax=1, annot
heatmap.set_title('Variables correlating with ReAdmis Heatmap',pad=12)
```

Out[42]:

```
Text(0.5, 1, 'Variables correlating with ReAdmis Heatmap')
```



Step 5 : Create dummy variables (ensure n = k number of varibles) & rename any necessary features

In [43]:
```
#Get dummies code reference (Pandas.get_dummies, N.d.)

df = pd.get_dummies(df, columns=['Children','Marital','Gender','Doc_visits','vitD_supp','Soft_drink','Initial_a
```

In [44]:
```
df.rename(columns={'Services_CT Scan':'Services_CT_Scan','Marital_Never Married':'Marital_Never_Married','Initi
```

Step 6 drop demographic features that won't be used in the analysis

In [45]:
```
df.drop(['CaseOrder','Customer_id','Interaction','UID','City','State','County','Area','TimeZone','Job','Lng','L
```

Step 7 Create variables y = ReAdmis, X = df with ReAdmis dropped.

In [46]:
```
y = df.ReAdmis
X = df.drop(columns = 'ReAdmis')
X
```

Out[46]:

	Zip	Age	Income	VitD_levels	Full_meals_eaten	Initial_days	TotalCharge	Additional_charges	Timely_admis	Timely_treat	...	Alle
0	35621	53	86575.93	19.141466	0	10.585770	3726.702860	17939.403420	3	3	...	
1	32446	51	46805.99	18.940352	2	15.129562	4193.190458	17612.998120	3	4	...	
2	57110	53	14370.14	18.057507	1	4.772177	2434.234222	17505.192460	2	4	...	
3	56072	78	39741.49	16.576858	1	1.714879	2127.830423	12993.437350	3	5	...	
4	23181	22	1209.56	17.439069	0	1.254807	2113.073274	3716.525786	2	1	...	
...	...	...	...	...	...	...	...	...	...	...	...	
9995	27563	25	45967.61	16.980860	2	51.561220	6850.942000	8927.642000	3	2	...	
9996	8340	87	14983.02	18.177020	0	68.668240	7741.690000	28507.150000	3	3	...	
9997	37171	45	65917.81	17.129070	2	70.154180	8276.481000	15281.210000	3	3	...	
9998	57775	43	29702.32	19.910430	2	63.356900	7644.483000	7781.678000	5	5	...	
9999	15108	70	62682.63	18.388620	0	70.850590	7887.553000	11643.190000	4	3	...	

9206 rows × 78 columns

Step 8 Min/Max scale features

In [47]:
```
#Min-Max scaling

X = (X - X.min()) / (X.max() - X.min())
X
```

Out[47]:

	Zip	Age	Income	VitD_levels	Full_meals_eaten	Initial_days	TotalCharge	Additional_charges	Timely_admis	Timely_treat
0	0.353850	0.492958	0.686851	0.660419	0.00	0.135022	0.246933	0.539851	0.4	0.4
1	0.321761	0.464789	0.370773	0.646191	0.50	0.199037	0.311343	0.527956	0.4	0.6
2	0.571036	0.492958	0.112984	0.583732	0.25	0.053117	0.068475	0.524027	0.2	0.6
3	0.560545	0.845070	0.314627	0.478981	0.25	0.010044	0.026168	0.359607	0.4	0.8
4	0.228121	0.056338	0.008389	0.539980	0.00	0.003562	0.024130	0.021531	0.2	0.0
...	...	...	...	...	...	...	...	...	...	...
9995	0.272409	0.098592	0.364110	0.507563	0.50	0.712308	0.678314	0.211438	0.4	0.2
9996	0.078126	0.971831	0.117855	0.592188	0.00	0.953321	0.801304	0.924967	0.4	0.4
9997	0.369516	0.380282	0.522667	0.518049	0.50	0.974256	0.875146	0.442979	0.4	0.4
9998	0.577757	0.352113	0.234839	0.714821	0.50	0.878492	0.787882	0.169676	0.8	0.8
9999	0.146529	0.732394	0.496955	0.607158	0.00	0.984067	0.821444	0.310400	0.6	0.4

9206 rows × 78 columns

Step 9 SelectKBest feature selection

In [48]:
```
# SelectKBest technique code reference (Bprasad26, 2022) and (Sklearn.feature_selection.SelectKBest, n.d.)

select_class = SelectKBest(k=10, score_func=chi2)
select_class.fit(X, y)
Xnew = select_class.transform(X)
print("Num Features before:", X.shape[1])
print("Num Features after:", Xnew.shape[1])
```

```
Num Features before: 78
Num Features after: 10
```

In [49]:
```
#Get column names for selected features

dfs = X.iloc[:,select_class.get_support()]
```

```
dfs
```

Out[49]:

	Initial_days	TotalCharge	Children_1	Children_4	Children_6	Marital_Divorced	vitD_supp_1	vitD_supp_2	Services_CT_Scan	Services_
0	0.135022	0.246933	1.0	0.0	0.0	1.0	0.0	0.0	0.0	
1	0.199037	0.311343	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
2	0.053117	0.068475	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.010044	0.026168	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.003562	0.024130	1.0	0.0	0.0	0.0	0.0	1.0	1.0	
...	...	...	...	...	...	...	...	...	...	
9995	0.712308	0.678314	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
9996	0.953321	0.801304	0.0	1.0	0.0	0.0	0.0	0.0	1.0	
9997	0.974256	0.875146	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
9998	0.878492	0.787882	0.0	0.0	0.0	1.0	1.0	0.0	0.0	
9999	0.984067	0.821444	0.0	0.0	0.0	0.0	1.0	0.0	0.0	

9206 rows × 10 columns

Step 10 ReJoin ReAdmis and Selected Features for prepared data set.

In [50]:
```
dfn = pd.concat([y, dfs], axis=1)
```

In [51]:
```
dfn.to_excel('C:/Users/ericy/Desktop/d209.1_prepared.xlsx')
```

Step 11 Summary stats for selected features and ReAdmis

In [52]:
```
dfn
```

Out[52]:

	ReAdmis	Initial_days	TotalCharge	Children_1	Children_4	Children_6	Marital_Divorced	vitD_supp_1	vitD_supp_2	Services_CT_Scan
0	0	0.135022	0.246933	1.0	0.0	0.0	1.0	0.0	0.0	0.0
1	0	0.199037	0.311343	0.0	0.0	0.0	0.0	1.0	0.0	0.0
2	0	0.053117	0.068475	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0	0.010044	0.026168	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0	0.003562	0.024130	1.0	0.0	0.0	0.0	0.0	1.0	1.0
...	...	...	...	...	...	...	...	...	...	...
9995	0	0.712308	0.678314	0.0	0.0	0.0	0.0	1.0	0.0	0.0
9996	1	0.953321	0.801304	0.0	1.0	0.0	0.0	0.0	0.0	1.0
9997	1	0.974256	0.875146	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9998	1	0.878492	0.787882	0.0	0.0	0.0	1.0	1.0	0.0	0.0
9999	1	0.984067	0.821444	0.0	0.0	0.0	0.0	1.0	0.0	0.0

9206 rows × 11 columns

In [53]:
```
dfn.isnull().sum()
```

Out[53]:
```
ReAdmis                 0
Initial_days            0
TotalCharge             0
Children_1              0
Children_4              0
Children_6              0
Marital_Divorced        0
vitD_supp_1             0
vitD_supp_2             0
Services_CT_Scan        0
Services_Intravenous    0
dtype: int64
```

In [54]:
```
dfn.describe()
```

Out[54]:

	ReAdmis	Initial_days	TotalCharge	Children_1	Children_4	Children_6	Marital_Divorced	vitD_supp_1	vitD_supp_2	Services_C
count	9206.000000	9206.000000	9206.000000	9206.000000	9206.00000	9206.000000	9206.000000	9206.000000	9206.000000	9206
mean	0.366935	0.470530	0.465055	0.256137	0.10189	0.019335	0.194330	0.269933	0.054204	0
std	0.481995	0.370886	0.301177	0.436522	0.30252	0.137708	0.395705	0.443949	0.226432	0
min	0.000000	0.000000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0
25%	0.000000	0.096921	0.171211	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0
50%	0.000000	0.420396	0.436588	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0
75%	1.000000	0.847510	0.762208	1.000000	0.00000	0.000000	0.000000	1.000000	0.000000	0
max	1.000000	1.000000	1.000000	1.000000	1.00000	1.000000	1.000000	1.000000	1.000000	1

In [55]:
```
dfn.corr()
```

Out[55]:

	ReAdmis	Initial_days	TotalCharge	Children_1	Children_4	Children_6	Marital_Divorced	vitD_supp_1	vitD_supp_2	Se
ReAdmis	1.000000	0.852064	0.845034	-0.025936	0.022959	0.015853	-0.021329	0.016839	0.018813	
Initial_days	0.852064	1.000000	0.987666	-0.035131	0.021351	0.016965	-0.024673	0.015574	0.016912	
TotalCharge	0.845034	0.987666	1.000000	-0.033019	0.021048	0.017821	-0.025384	0.016072	0.017946	
Children_1	-0.025936	-0.035131	-0.033019	1.000000	-0.197647	-0.082396	-0.008320	-0.000281	0.013395	
Children_4	0.022959	0.021351	0.021048	-0.197647	1.000000	-0.047295	-0.001163	-0.005013	-0.017197	
Children_6	0.015853	0.016965	0.017821	-0.082396	-0.047295	1.000000	-0.003171	-0.017855	0.001225	
Marital_Divorced	-0.021329	-0.024673	-0.025384	-0.008320	-0.001163	-0.003171	1.000000	-0.014786	-0.007239	
vitD_supp_1	0.016839	0.015574	0.016072	-0.000281	-0.005013	-0.017855	-0.014786	1.000000	-0.145567	
vitD_supp_2	0.018813	0.016912	0.017946	0.013395	-0.017197	0.001225	-0.007239	-0.145567	1.000000	
Services_CT_Scan	0.026087	0.010723	0.013805	0.004024	0.004116	0.012332	0.015231	-0.002455	-0.000445	
Services_Intravenous	-0.018757	-0.013546	-0.014466	0.008071	0.009326	0.000371	-0.000971	0.010679	0.001678	

In [56]:
```
dfn.mean()
```

Out[56]:
```
ReAdmis                 0.366935
Initial_days            0.470530
TotalCharge             0.465055
Children_1              0.256137
Children_4              0.101890
Children_6              0.019335
Marital_Divorced        0.194330
vitD_supp_1             0.269933
vitD_supp_2             0.054204
Services_CT_Scan        0.122855
Services_Intravenous    0.313383
dtype: float64
```

In [57]:
```
dfn.median()
```

Out[57]:
```
ReAdmis                 0.000000
Initial_days            0.420396
TotalCharge             0.436588
Children_1              0.000000
Children_4              0.000000
Children_6              0.000000
Marital_Divorced        0.000000
vitD_supp_1             0.000000
vitD_supp_2             0.000000
Services_CT_Scan        0.000000
Services_Intravenous    0.000000
dtype: float64
```

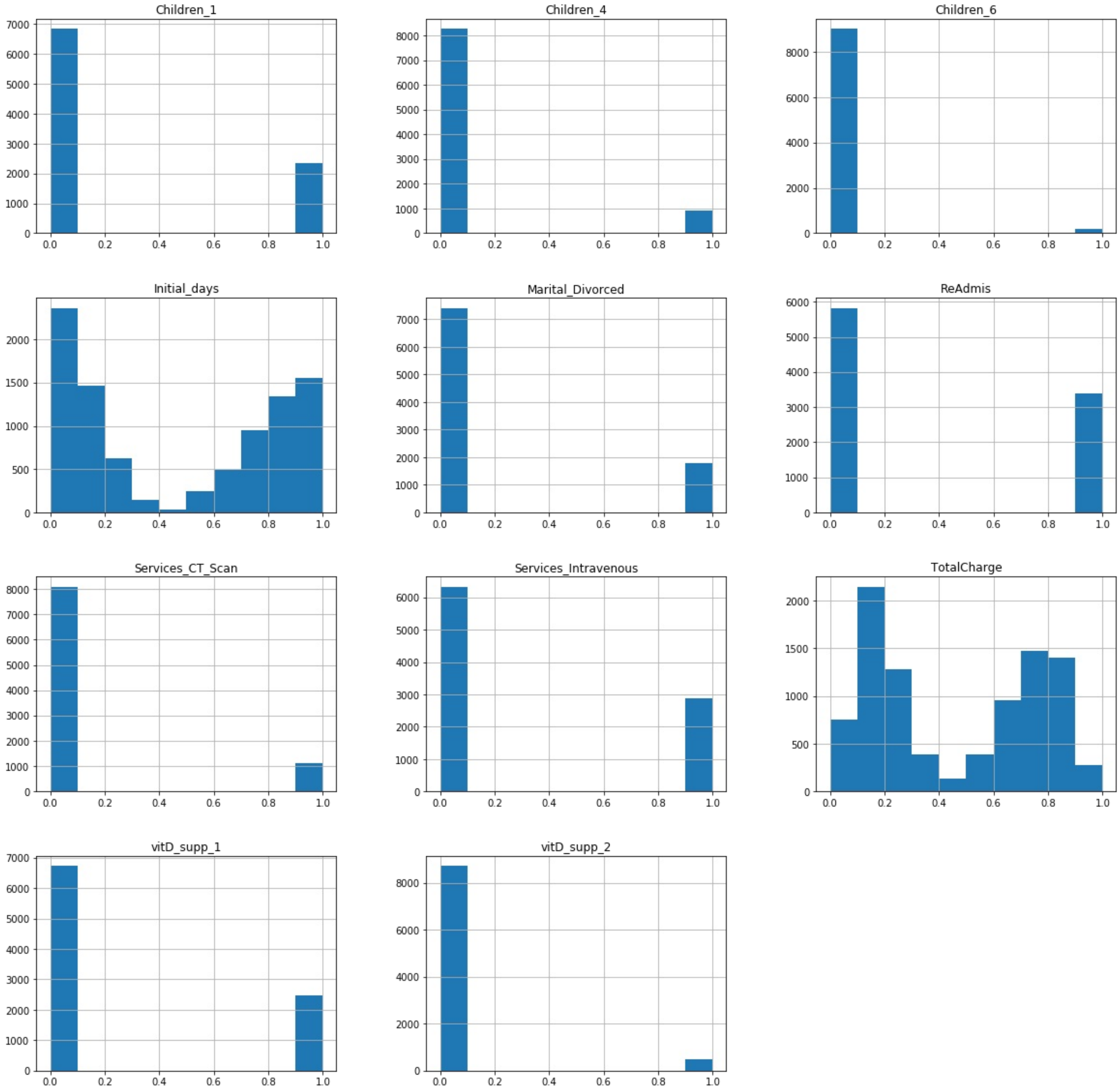
In [58]:
```
dfn.mode()
```

Out[58]:

	ReAdmis	Initial_days	TotalCharge	Children_1	Children_4	Children_6	Marital_Divorced	vitD_supp_1	vitD_supp_2	Services_CT_Scan	Se
0	0.0	0.935755	0.775589	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	NaN	0.976668	0.832094	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

In [59]:
```
dfn.hist(figsize=(20,20))
```

Out[59]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000002B5EDF95A08>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5F153F8C8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5F158E5C8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002B5EFC6B6C8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5F1271808>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5F18B6908>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002B5F17C19C8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5F16C8B08>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5F16BB708>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002B5F138A8C8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5F07BDE48>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002B5F19DCE88>]],
      dtype=object)
```



In [60]:
```
dfn.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9206 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   ReAdmis               9206 non-null   int64  
 1   Initial_days          9206 non-null   float64
 2   TotalCharge           9206 non-null   float64
 3   Children_1            9206 non-null   float64
 4   Children_4            9206 non-null   float64
 5   Children_6            9206 non-null   float64
 6   Marital_Divorced      9206 non-null   float64
 7   vitD_supp_1           9206 non-null   float64
 8   vitD_supp_2           9206 non-null   float64
 9   Services_CT_Scan      9206 non-null   float64
 10  Services_Intravenous  9206 non-null   float64
dtypes: float64(10), int64(1)
memory usage: 863.1 KB
```

Step 12 .replace() and .astype() ReAdmis - ensure feature is binary categorical, int32

In [61]:
```
dfn.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9206 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   ReAdmis              9206 non-null   int64  
 1   Initial_days         9206 non-null   float64
 2   TotalCharge          9206 non-null   float64
 3   Children_1           9206 non-null   float64
 4   Children_4           9206 non-null   float64
 5   Children_6           9206 non-null   float64
 6   Marital_Divorced     9206 non-null   float64
 7   vitD_supp_1          9206 non-null   float64
 8   vitD_supp_2          9206 non-null   float64
 9   Services_CT_Scan     9206 non-null   float64
 10  Services_Intravenous  9206 non-null   float64
dtypes: float64(10), int64(1)
memory usage: 863.1 KB
```

In [62]:
```
#dfn = pd.get_dummies(dfn, columns=['ReAdmis'])

dfn.astype({'ReAdmis': 'int8', 'Children_1':'int8','Children_4':'int8','Children_6':'int8','Marital_Divorced':'
```

Out[62]:
```
ReAdmis                    int8
Initial_days            float64
TotalCharge             float64
Children_1                 int8
Children_4                 int8
Children_6                 int8
Marital_Divorced           int8
vitD_supp_1                int8
vitD_supp_2                int8
Services_CT_Scan           int8
Services_Intravenous       int8
dtype: object
```

In [63]:
```
dfn.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9206 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   ReAdmis              9206 non-null   int64  
 1   Initial_days         9206 non-null   float64
 2   TotalCharge          9206 non-null   float64
 3   Children_1           9206 non-null   float64
 4   Children_4           9206 non-null   float64
 5   Children_6           9206 non-null   float64
 6   Marital_Divorced     9206 non-null   float64
 7   vitD_supp_1          9206 non-null   float64
 8   vitD_supp_2          9206 non-null   float64
 9   Services_CT_Scan     9206 non-null   float64
 10  Services_Intravenous  9206 non-null   float64
dtypes: float64(10), int64(1)
memory usage: 863.1 KB
```

Step 13 Assign prepared features to y = ReAdmis, X = Prepared independent features.

In [63]:
```
y = dfn.ReAdmis
X = dfn.drop(columns = 'ReAdmis')
```

Step 14 import necessary libraries for KNN Classification

split data into test and train sets.

In [64]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score
from sklearn import metrics
```

In [65]:
```
#Stratify code reference (Parameter "stratify" from method "train_test_split" (scikit learn), n.d.)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, random_state = 1, stratify=y)
```

In [66]:
```
X_train.to_excel('C:/Users/ericy/Desktop/d209.1.X_train.xlsx')
```

In [67]:
```
X_test.to_excel('C:/Users/ericy/Desktop/d209.1.X_test.xlsx')
```

In [68]:
```
y_train.to_excel('C:/Users/ericy/Desktop/d209.1.y_train.xlsx')
```

In [69]:
```
y_test.to_excel('C:/Users/ericy/Desktop/d209.1.y_test.xlsx')
```

In [ ]:

In [ ]:

In [ ]:

Section D: Data Analysis

In [70]:
```
# Import GridSearchCV for cross validation of model
# Code reference (Okamura, 2020).

paramgrid = {'n_neighbors': np.arange(1, 50)}
knc = KNeighborsClassifier()
knccv = GridSearchCV(knc , paramgrid, cv=5)

# Fit the model to training data.
knccv.fit(X_train, y_train)

print('The best n_neighbors for the model: {}'.format(knccv.best_params_))
```

```
The best n_neighbors for the model: {'n_neighbors': 4}
```

In [71]:
```
# Print ot the best score for classification model
print('The best classification score for the model: {:.6f}'.format(knccv.best_score_))
```

```
The best classification score for the model: 0.970981
```

In [ ]:

In [72]:
```
# KneighborsClassifier code method reference (Klein, 2022)

knc = KNeighborsClassifier(n_neighbors=4)

knc.fit(X_train,y_train)
```

Out[72]:
```
KNeighborsClassifier(n_neighbors=4)
```

In [73]:
```
y_pred = knc.predict(X_test)
```

In [74]:
```
print('KNN model accuracy:', accuracy_score(y_test, y_pred))
```

```
KNN model accuracy: 0.9670528602461984
```

In [75]:
```
print( classification_report(y_test, y_pred))
```

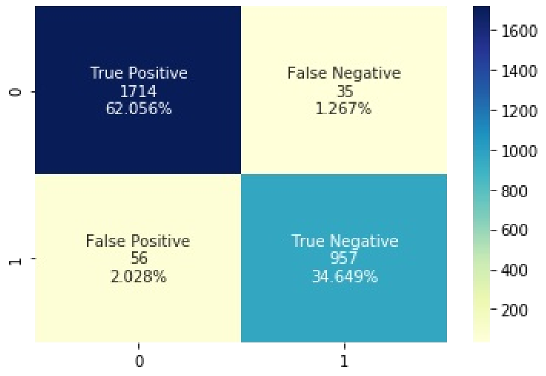
```
              precision    recall  f1-score   support

           0       0.97      0.98      0.97      1749
           1       0.96      0.94      0.95      1013

    accuracy                           0.97      2762
   macro avg       0.97      0.96      0.96      2762
weighted avg       0.97      0.97      0.97      2762
```

In [76]:
```
confmatrix = confusion_matrix(y_test, y_pred)
print(confmatrix)
```

```
[[1714   35]
 [  56  957]]
```

In [77]:
```
# Confusion matrix visualization reference (Aruchamy, 2021).

matnames = ['True Positive', 'False Negative', 'False Positive', 'True Negative']
matcounts = ["{0:0.0f}".format(value) for value in confmatrix.flatten()]
matpercent = ["{0:.3%}".format(value) for value in confmatrix.flatten()/np.sum(confmatrix)]
labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in zip(matnames, matcounts, matpercent)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(confmatrix, annot=labels, fmt='', cmap='YlGnBu')
```

Out[77]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x190834423c8>
```



In [78]:
```
# Computing cross-val scores
# Code reference (Allwright, 2022)
crossauc = cross_val_score(knccv, X, y, cv=4)
print("Cross val scores computed using 4-fold cross-validation: {}".format(crossauc))
```

```
Cross val scores computed using 4-fold cross-validation: [0.97263249 0.97219809 0.97088223 0.53628857]
```

In [ ]:

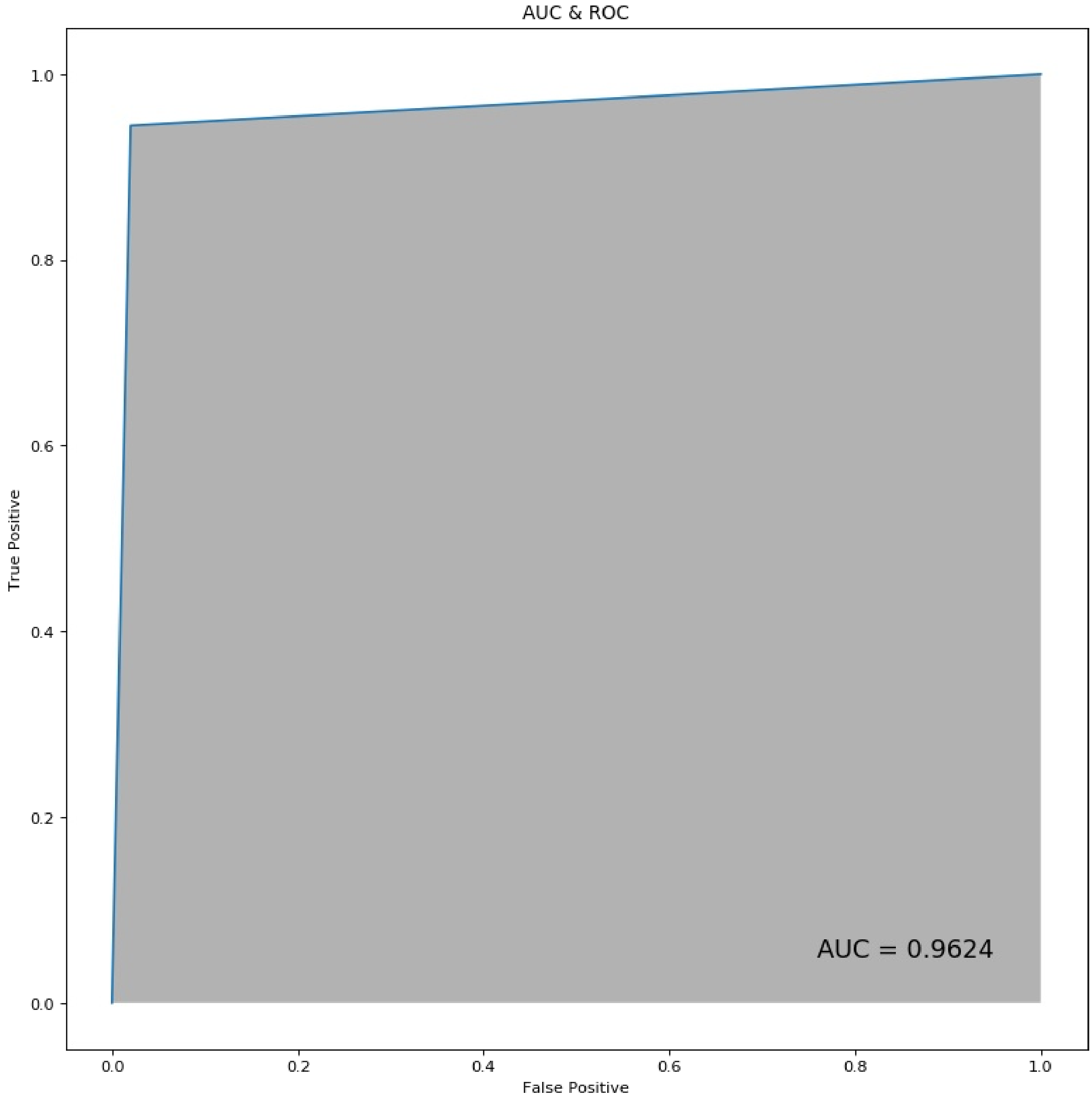
In [ ]:

Section E1

In [ ]:

In [ ]:

In [79]:
```
# AUC and ROC Curve
# code reference (Kharwal, 2022) and (Zach, 2021)
auc = metrics.roc_auc_score(y_test, y_pred)

false_positive_rate, true_positive_rate, thresolds = metrics.roc_curve(y_test, y_pred)


plt.figure(figsize=(12, 12), dpi=80)
plt.plot(false_positive_rate, true_positive_rate)
plt.xlim([0, 1])
plt.ylim([0, 1])

plt.axis('scaled')
plt.fill_between( false_positive_rate,true_positive_rate,facecolor='grey',alpha=0.6)
plt.text(0.95, 0.05, 'AUC = %0.4f' % auc, ha='right', fontsize=16, weight='normal', color='black')

plt.title("AUC & ROC")
plt.xlabel("False Positive")
plt.ylabel("True Positive")

plt.show()
```



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