Investigate No_Show_Appointment-Copy1

August 15, 2022

1 Project: Investigating the Noshow/Show of Patients to their medical appointments using the dataset; No_Show_Appointment

1.1 Table of Contents

Introduction

1.1.1 Dataset Description

This dataset collects information from 110,527 medical appointments in Brazil and is focused on the question of whether or not patients show up for their appointment. A number of characteristics about the patient are included in each column, they are;

PatientId: Identification of a patient
AppointmentID: Identification of each appointment
Gender: Male or Female
AppointmentDay: The day of the actual appointment, when they have to visit the doctor
ScheduledDay: The day someone called or registered the appointment, this is before appointme
Age: How old is the patient
Neighbourhood: Where the appointment takes place
Scholarship: 1 or 0 representing True of False. This shows if the patient is on welfare or n
Hipertension: 1 or 0 representing True or False
Diabetes: 1 or 0 representing True or False
Alcoholism: 1 or 0 representing True or False
Handcap: 0, 1, 2, 3, 4 representing levels of handicap
SMS_received: 1 or 0 messages sent to the patient
No-show: True or False

Question

1) What factors are important for us to know inorder to predict if a patient will show up for their scheduled medical appointment?

1.1.2 Importing the necessary Libraries

```
In [1]: import pandas as pd
        import numpy as np
        from numpy.random import seed, randint
        seed(100)
        import matplotlib.pyplot as plt
        import seaborn as sns
        % matplotlib inline
        import datetime
```

Data Wrangling

1.1.3 Loading the dataset

```
In [2]: ls
```

```
Database_Ncis_and_Census_data/  Database_TMDb_movie_data/
Database_No_show_appointments/  Investigate No_Show_Appointment-Copy1.ipynb
Database_Soccer/
```

```
In [3]: cd"Database_No_show_appointments"
```

```
/home/workspace/Database_No_show_appointments
```

```
In [4]: #Loading the dataset from the Database
        df = pd.read_csv("noshowappointments-kagglev2-may-2016.csv")

In [5]: df.head()
```

```
Out[5]:       PatientId  AppointmentID Gender          ScheduledDay  \
        0  2.987250e+13        5642903      F  2016-04-29T18:38:08Z
        1  5.589978e+14        5642503      M  2016-04-29T16:08:27Z
        2  4.262962e+12        5642549      F  2016-04-29T16:19:04Z
        3  8.679512e+11        5642828      F  2016-04-29T17:29:31Z
        4  8.841186e+12        5642494      F  2016-04-29T16:07:23Z

                 AppointmentDay  Age      Neighbourhood  Scholarship  Hipertension  \
        0  2016-04-29T00:00:00Z   62    JARDIM DA PENHA            0             1
        1  2016-04-29T00:00:00Z   56    JARDIM DA PENHA            0             0
        2  2016-04-29T00:00:00Z   62      MATA DA PRAIA            0             0
        3  2016-04-29T00:00:00Z    8  PONTAL DE CAMBURI            0             0
        4  2016-04-29T00:00:00Z   56    JARDIM DA PENHA            0             1

           Diabetes  Alcoholism  Handcap  SMS_received No-show
        0         0           0        0             0      No
        1         0           0        0             0      No
        2         0           0        0             0      No
        3         0           0        0             0      No
        4         1           0        0             0      No
```

```
In [6]: #Getting the shape (number of rows and columns) of the dataset
        df.shape
```

```
Out[6]: (110527, 14)
```

This shows us that the dataset has "110527" rows and "14" columns

```
In [7]: #Getting the describtion of the dataset
        df.describe()
```

```
Out[7]:           PatientId  AppointmentID            Age    Scholarship  \
        count  1.105270e+05   1.105270e+05  110527.000000  110527.000000
        mean   1.474963e+14   5.675305e+06      37.088874       0.098266
        std    2.560949e+14   7.129575e+04      23.110205       0.297675
        min    3.921784e+04   5.030230e+06      -1.000000       0.000000
        25%    4.172614e+12   5.640286e+06      18.000000       0.000000
        50%    3.173184e+13   5.680573e+06      37.000000       0.000000
        75%    9.439172e+13   5.725524e+06      55.000000       0.000000
        max    9.999816e+14   5.790484e+06     115.000000       1.000000

                Hipertension       Diabetes     Alcoholism        Handcap  \
        count  110527.000000  110527.000000  110527.000000  110527.000000
        mean        0.197246       0.071865       0.030400       0.022248
        std         0.397921       0.258265       0.171686       0.161543
        min         0.000000       0.000000       0.000000       0.000000
        25%         0.000000       0.000000       0.000000       0.000000
        50%         0.000000       0.000000       0.000000       0.000000
        75%         0.000000       0.000000       0.000000       0.000000
        max         1.000000       1.000000       1.000000       4.000000

                SMS_received
        count  110527.000000
        mean        0.321026
        std         0.466873
        min         0.000000
        25%         0.000000
        50%         0.000000
        75%         1.000000
        max         1.000000
```

```
In [8]: #Checking the information about the dataset
        df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
PatientId         110527 non-null float64
AppointmentID     110527 non-null int64
Gender            110527 non-null object
```

```
ScheduledDay      110527 non-null object
AppointmentDay    110527 non-null object
Age               110527 non-null int64
Neighbourhood     110527 non-null object
Scholarship       110527 non-null int64
Hipertension      110527 non-null int64
Diabetes          110527 non-null int64
Alcoholism        110527 non-null int64
Handcap           110527 non-null int64
SMS_received      110527 non-null int64
No-show           110527 non-null object
dtypes: float64(1), int64(8), object(5)
memory usage: 11.8+ MB
```

In [9]:
```python
#Checking if there is any empty(null) cell
df.isnull().sum()
```

Out[9]:
```
PatientId         0
AppointmentID     0
Gender            0
ScheduledDay      0
AppointmentDay    0
Age               0
Neighbourhood     0
Scholarship       0
Hipertension      0
Diabetes          0
Alcoholism        0
Handcap           0
SMS_received      0
No-show           0
dtype: int64
```

There are no null cell in the dataset

In [10]:
```python
#Checking for Duplicates
df.duplicated().sum()
```

Out[10]: 0

There are no duplicates

In [11]:
```python
#Finding the unique count for each charateristics
df.nunique()
```

Out[11]:
```
PatientId          62299
AppointmentID     110527
Gender                 2
```

```
ScheduledDay      103549
AppointmentDay        27
Age                  104
Neighbourhood         81
Scholarship            2
Hipertension           2
Diabetes               2
Alcoholism             2
Handcap                5
SMS_received           2
No-show                2
dtype: int64
```

This gives us the number of unique values contained in each column

1.1.4 Data Cleaning

From visual inspection of the loaded dataset, some problems were observed, which will need to be cleaned. These problems includes;

Some column names were wronly spelt, and will need to be corrected to avoid issues of remembering the odd spellings during analysis

PatientId supposed to be an integer and not a float, so we will convert it to integer64

Datatype of ScheduledDay and AppointmentDay are object, so they will be converted to datatime datatype

The AppointmentDay time is set to 00:00:00 which does not make any sense, therefore, we will ignore it

1.1.5 Correcting the above listed problems

```
In [12]: #Correcting the wrongly spelt Column names
         df.rename(columns={"Hipertension":"Hypertension", "Handcap":"Handicap", "SMS_received":
```

```
In [13]: #Converting the datatype for the column "PatientId" from "Object" to "Integer64"
         df["PatientId"] = df["PatientId"].astype("int64")
```

```
In [14]: #Converting the datatype for scheduledDay to "datetime"
         df.ScheduledDay = df.ScheduledDay.apply(np.datetime64)
```

```
In [15]: #Converting the datatype for AppointmentDay to "datetime"
         df.AppointmentDay = df.AppointmentDay.apply(np.datetime64)
```

```
In [16]: #Printing out few lines to check for comformity of corrections
         df.head()
```

```
Out[16]:          PatientId  AppointmentID Gender        ScheduledDay AppointmentDay  \
         0   29872499824296        5642903      F 2016-04-29 18:38:08     2016-04-29
         1  558997776694438        5642503      M 2016-04-29 16:08:27     2016-04-29
         2    4262962299951        5642549      F 2016-04-29 16:19:04     2016-04-29
         3     867951213174        5642828      F 2016-04-29 17:29:31     2016-04-29
```

```
4    8841186448183        5642494      F 2016-04-29 16:07:23     2016-04-29

   Age      Neighbourhood  Scholarship  Hypertension  Diabetes  Alcoholism  \
0   62    JARDIM DA PENHA            0             1         0           0
1   56    JARDIM DA PENHA            0             0         0           0
2   62      MATA DA PRAIA            0             0         0           0
3    8  PONTAL DE CAMBURI            0             0         0           0
4   56    JARDIM DA PENHA            0             1         1           0

   Handicap  SMSreceived NoShow
0         0            0     No
1         0            0     No
2         0            0     No
3         0            0     No
4         0            0     No
```

In [17]:
```
#Getting the unique values of the columns
df.columns.unique()
```

Out[17]:
```
Index(['PatientId', 'AppointmentID', 'Gender', 'ScheduledDay',
       'AppointmentDay', 'Age', 'Neighbourhood', 'Scholarship', 'Hypertension',
       'Diabetes', 'Alcoholism', 'Handicap', 'SMSreceived', 'NoShow'],
      dtype='object')
```

In [18]:
```
#Getting the Unique values of "Age"
df["Age"].unique()
```

Out[18]:
```
array([ 62,  56,   8,  76,  23,  39,  21,  19,  30,  29,  22,  28,  54,
        15,  50,  40,  46,   4,  13,  65,  45,  51,  32,  12,  61,  38,
        79,  18,  63,  64,  85,  59,  55,  71,  49,  78,  31,  58,  27,
         6,   2,  11,   7,   0,   3,   1,  69,  68,  60,  67,  36,  10,
        35,  20,  26,  34,  33,  16,  42,   5,  47,  17,  41,  44,  37,
        24,  66,  77,  81,  70,  53,  75,  73,  52,  74,  43,  89,  57,
        14,   9,  48,  83,  72,  25,  80,  87,  88,  84,  82,  90,  94,
        86,  91,  98,  92,  96,  93,  95,  97, 102, 115, 100,  99,  -1])
```

From the above array, it is obvious that "Age" contains some unrelialistic values like; "-1" which cannot be. There we replace them using the mean "Age"

In [19]:
```
#Finding the mean "Age"
mean_age = df["Age"].mean()
mean_age
```

Out[19]: 37.088874211731067

In [20]:
```
#Looping through all values in the "Age" column
#  if the value is <= (less than, or equals to) 0(zero)
#  we will replace it with the mean "Age"
for x in df.index:
```

```
            if df.loc[x, "Age"] < 0:
                df.loc[x, "Age"] = 37
```

```
In [21]: #Checking the result
         df["Age"].unique()
```

```
Out[21]: array([ 62,  56,   8,  76,  23,  39,  21,  19,  30,  29,  22,  28,  54,
                15,  50,  40,  46,   4,  13,  65,  45,  51,  32,  12,  61,  38,
                79,  18,  63,  64,  85,  59,  55,  71,  49,  78,  31,  58,  27,
                 6,   2,  11,   7,   0,   3,   1,  69,  68,  60,  67,  36,  10,
                35,  20,  26,  34,  33,  16,  42,   5,  47,  17,  41,  44,  37,
                24,  66,  77,  81,  70,  53,  75,  73,  52,  74,  43,  89,  57,
                14,   9,  48,  83,  72,  25,  80,  87,  88,  84,  82,  90,  94,
                86,  91,  98,  92,  96,  93,  95,  97, 102, 115, 100,  99])
```

The values have been change accordingly

1.2 The columns "PatientId" and "AppointmentID"are just patients unique identifiers and are of no use in answering the question posed by this analysis. Therefore, we will drop them

```
In [22]: #dropping the column "PatientId" and "AppointmentID"
         df.drop(["PatientId", "AppointmentID"], axis=1, inplace=True)
```

```
In [23]: #Printing few lines from the dataset for check
         df.head()
```

```
Out[23]:   Gender        ScheduledDay AppointmentDay  Age      Neighbourhood  \
         0      F 2016-04-29 18:38:08     2016-04-29   62    JARDIM DA PENHA
         1      M 2016-04-29 16:08:27     2016-04-29   56    JARDIM DA PENHA
         2      F 2016-04-29 16:19:04     2016-04-29   62      MATA DA PRAIA
         3      F 2016-04-29 17:29:31     2016-04-29    8  PONTAL DE CAMBURI
         4      F 2016-04-29 16:07:23     2016-04-29   56    JARDIM DA PENHA

            Scholarship  Hypertension  Diabetes  Alcoholism  Handicap  SMSreceived  \
         0            0             1         0           0         0            0
         1            0             0         0           0         0            0
         2            0             0         0           0         0            0
         3            0             0         0           0         0            0
         4            0             1         1           0         0            0

           NoShow
         0     No
         1     No
         2     No
         3     No
         4     No
```

The columns have been dropped
Exploratory Data Analysis

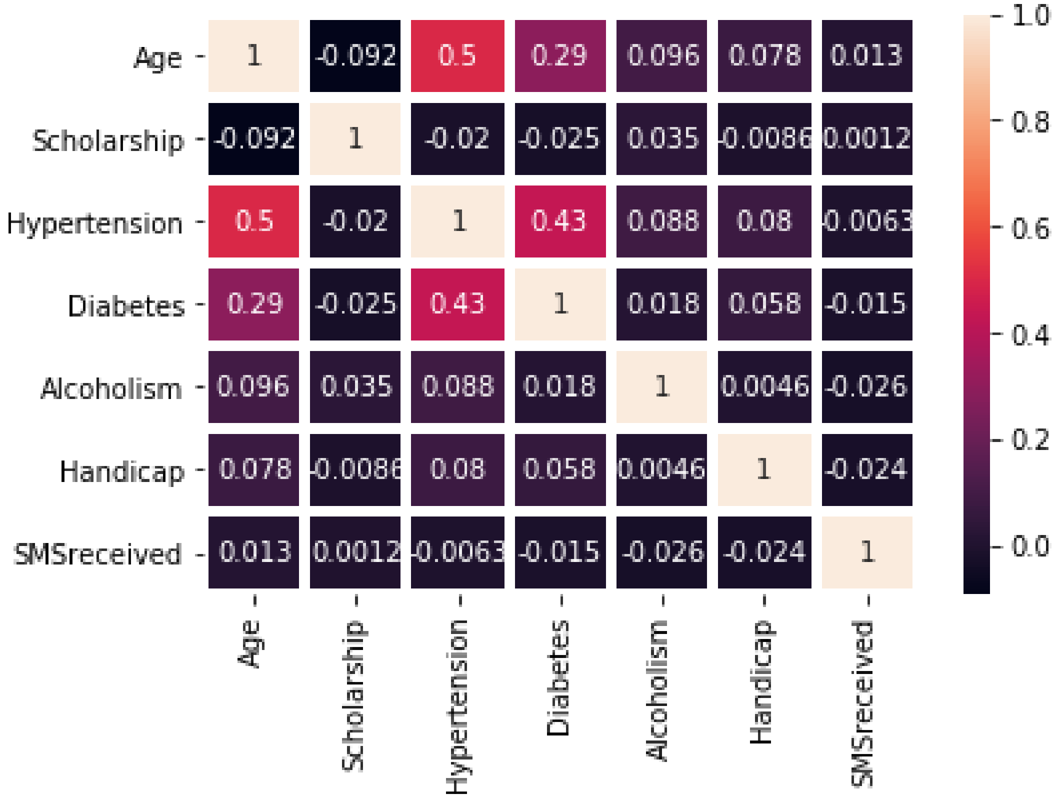
1.2.1 Ques: What factors are important for us to know inorder to predict if a patient will show up for their scheduled appointment?

For us to be able to answer this question, a heuristic exploration and statistical analysis needs to be carried out on the various characteristics of the dataset inoder to know their correlation to a patient showing up to appointment or not.

1.3 First, lets find out the level of correlation between the various dataset characteristics using a heat map

First lets get the correlation between the various characteristics of the dataset using a heatmap

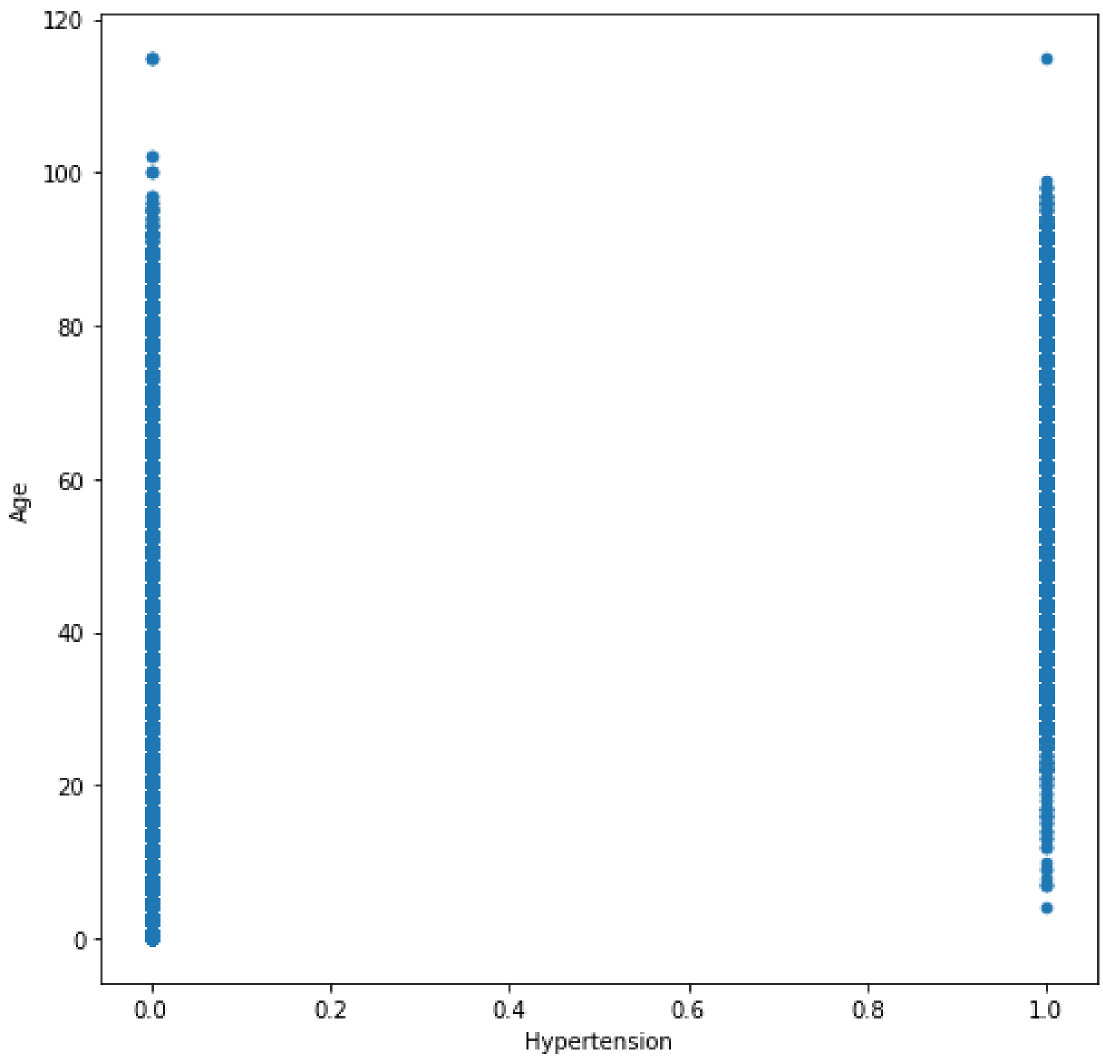
```
In [24]: sns.heatmap(df.corr(), annot=True, linewidths= 3.0);
```



From the correlation plot, we can see that "Hypertension" and "Age" have a positive correlation. This implies that as a patients Age increases, the patient will stand a chance of having an increased level of Hypertension and vise versa. Therefore, we will keep a keen eye on this two dataset characteristics, because both are likely to have similar correlation to a patients show up to appointment

1.3.1 Plotting a scatter plot of "Hypertension" and "Age"

```
In [25]: #Scatter plot of "Hypertension and "Age"
         df.plot(kind= "scatter", x= "Hypertension", y= "Age", figsize= (8,8));
```



From the plot, we can see that the scatter points forms a vertical linear pattern, and the points for patients with Hypertension and those without Hypertension peaks almost at the same Age. This attest to the fact that both Hypertension and Age have a position correlation.

1.3.2 Finding the date range for "ScheduledDay"

```
In [26]: ScheduledDay_Range = df.ScheduledDay.unique()
```

```
In [27]: #Loading the data
         ScheduledDay_Range
```

```
Out[27]: array(['2016-04-29T18:38:08.000000000', '2016-04-29T16:08:27.000000000',
                '2016-04-29T16:19:04.000000000', ...,
                '2016-04-27T16:03:52.000000000', '2016-04-27T15:09:23.000000000',
                '2016-04-27T13:30:56.000000000'], dtype='datetime64[ns]')
```

It can be seen that the ScheduleDay ranges from 2015-11-10 to 2016-06-08. This is about 7 months

1.3.3 Finding the Date Range of AppointmentDay

```
In [28]: AppointmentDayRange = df.AppointmentDay.unique()
```

```
In [29]: AppointmentDayRange
```

```
Out[29]: array(['2016-04-29T00:00:00.000000000', '2016-05-03T00:00:00.000000000',
                '2016-05-10T00:00:00.000000000', '2016-05-17T00:00:00.000000000',
                '2016-05-24T00:00:00.000000000', '2016-05-31T00:00:00.000000000',
                '2016-05-02T00:00:00.000000000', '2016-05-30T00:00:00.000000000',
                '2016-05-16T00:00:00.000000000', '2016-05-04T00:00:00.000000000',
                '2016-05-19T00:00:00.000000000', '2016-05-12T00:00:00.000000000',
                '2016-05-06T00:00:00.000000000', '2016-05-20T00:00:00.000000000',
                '2016-05-05T00:00:00.000000000', '2016-05-13T00:00:00.000000000',
                '2016-05-09T00:00:00.000000000', '2016-05-25T00:00:00.000000000',
                '2016-05-11T00:00:00.000000000', '2016-05-18T00:00:00.000000000',
                '2016-05-14T00:00:00.000000000', '2016-06-02T00:00:00.000000000',
                '2016-06-03T00:00:00.000000000', '2016-06-06T00:00:00.000000000',
                '2016-06-07T00:00:00.000000000', '2016-06-01T00:00:00.000000000',
                '2016-06-08T00:00:00.000000000'], dtype='datetime64[ns]')
```

It can be seen that the AppointmentDay lapses between 2016-04-29 to 2016-06-08. This is about 1 month.

1.3.4 Finding the Total Number of patients that Showed-Up and the number of those that didn't show in the Dataset

```
In [30]: #Getting the unique value count
         NoShow_Value = df.NoShow.value_counts()
```

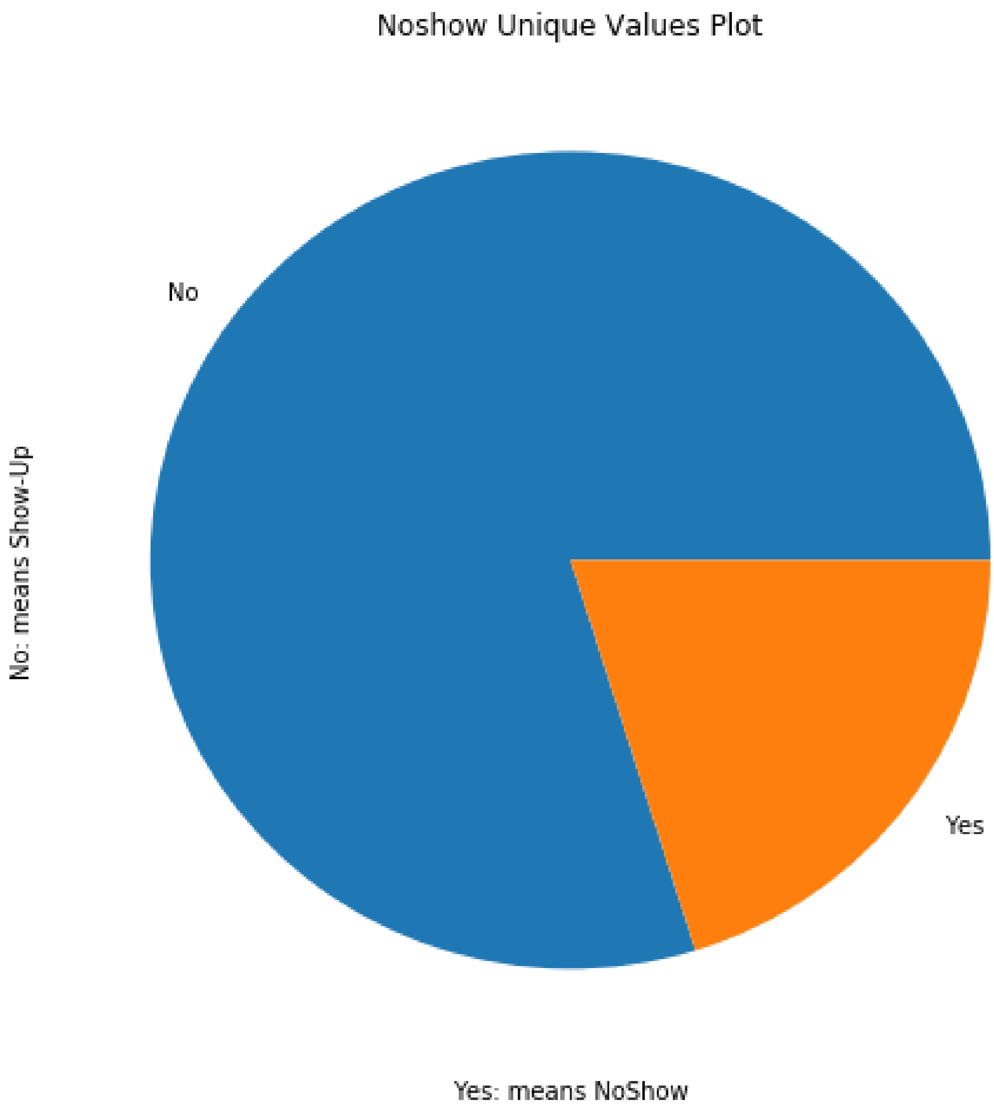
```
In [31]: NoShow_Value
```

```
Out[31]: No      88208
         Yes     22319
         Name: NoShow, dtype: int64
```

From this result, it can be seen that the number of people that came for their appointment is; "88,208" while "22,319" didnt show up

Bar Plot of Unique Values of NoShow

```
In [32]: ax = NoShow_Value.plot(kind= "pie", title="Noshow Unique Values Plot", figsize= (8,8))
         ax.set_xlabel("Yes: means NoShow")
         ax.set_ylabel("No: means Show-Up");
```



This chart gives us a clear visualization of the spread of patients Show_up and NoShow population. "No" represents those that showed up, while "Yes" represents those that didnt show up.

```
In [33]: #Finding the percentage representation of this values
         df.NoShow.value_counts("%")*100

Out[33]: No     79.806744
         Yes    20.193256
         Name: NoShow, dtype: float64
```

The above shows us that 79.8% of appointments showed up, while 20.2% didnt show up

1.4 We will now use groupby and query function to see the correlation of various characteristics to NoShow

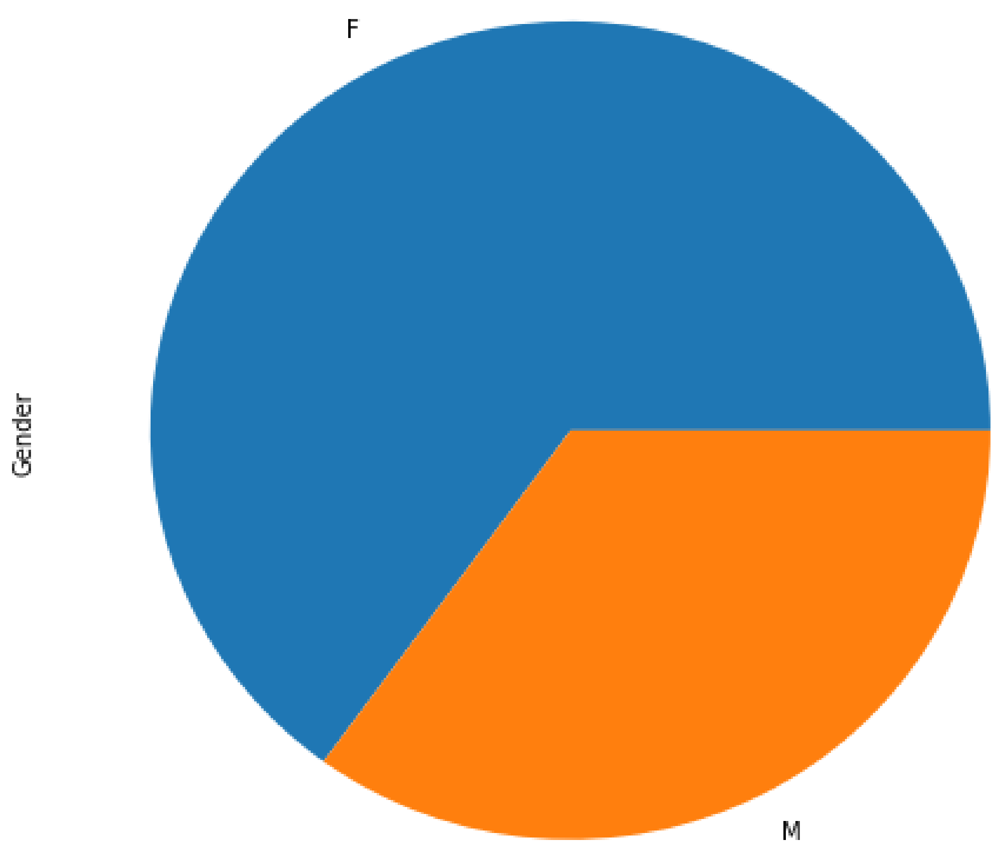
1.4.1 Getting the Correlation of "Gender" and "NoShow"

```
In [34]: #Extracting the unique value count of Gender
         df.Gender.value_counts()
```

```
Out[34]: F    71840
         M    38687
         Name: Gender, dtype: int64
```

This shows us that 71,840(65%) of the patients are Females, while 38,687(35%) are male

```
In [35]: #Visualizing the Gender value count with a pie chart
         df.Gender.value_counts().plot(kind= "pie", figsize= (8,8));
```



As we can see, Females(F) spans a greater area of the chart than Males(M), showing that females have more number than males

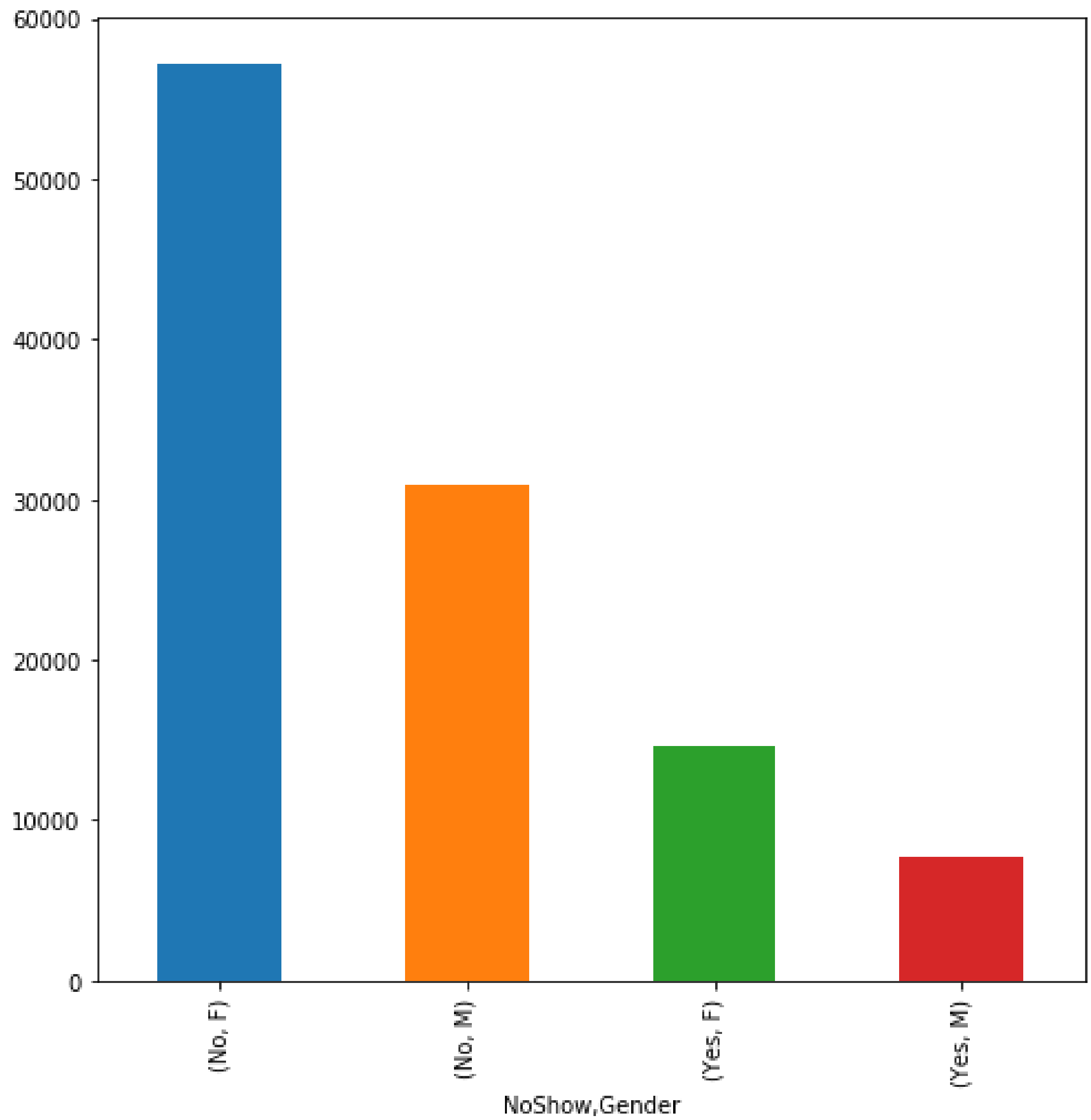
In [36]:
```
#Getting the correleration between Gender and NoShow using groupby
Gender_NoShow = df.groupby("NoShow")["Gender"]
```

In [37]:
```
gen = Gender_NoShow.value_counts()
```

In [38]:
```
gen
```

Out[38]:
```
NoShow  Gender
No      F         57246
        M         30962
Yes     F         14594
        M          7725
Name: Gender, dtype: int64
```

In [39]:
```
#Plotting a bar plot of correlation of the Unique values of Gender to NoShow
gen.plot(kind="bar", figsize=(8,8),);
```



From the data above, it can be seen that;
79.69%(57,246) of the Female patients showed up for their appointments
80.03%(30,962) of the Male patients showed up for their appointment
Since these values are approximately equal, we can conclude that "Gender" is not a determinant or predictor to "Noshow/Show-up" to appointment among patients.

1.5 Getting the correlation of "Neighbourhood" to "NoShow"

In [40]:
```
#Getting the unique value of "Neigbourhood"
df.Neighbourhood.unique()
```

Out[40]:
```
array(['JARDIM DA PENHA', 'MATA DA PRAIA', 'PONTAL DE CAMBURI',
       'REPÚBLICA', 'GOIABEIRAS', 'ANDORINHAS', 'CONQUISTA',
```

```
       'NOVA PALESTINA', 'DA PENHA', 'TABUAZEIRO', 'BENTO FERREIRA',
       'SÃO PEDRO', 'SANTA MARTHA', 'SÃO CRISTÓVÃO', 'MARUÍPE',
       'GRANDE VITÓRIA', 'SÃO BENEDITO', 'ILHA DAS CAIEIRAS',
       'SANTO ANDRÉ', 'SOLON BORGES', 'BONFIM', 'JARDIM CAMBURI',
       'MARIA ORTIZ', 'JABOUR', 'ANTÔNIO HONÓRIO', 'RESISTÊNCIA',
       'ILHA DE SANTA MARIA', 'JUCUTUQUARA', 'MONTE BELO',
       'MÁRIO CYPRESTE', 'SANTO ANTÔNIO', 'BELA VISTA', 'PRAIA DO SUÁ',
       'SANTA HELENA', 'ITARARÉ', 'INHANGUETÁ', 'UNIVERSITÁRIO',
       'SÃO JOSÉ', 'REDENÇÃO', 'SANTA CLARA', 'CENTRO', 'PARQUE MOSCOSO',
       'DO MOSCOSO', 'SANTOS DUMONT', 'CARATOÍRA', 'ARIOVALDO FAVALESSA',
       'ILHA DO FRADE', 'GURIGICA', 'JOANA D´ARC', 'CONSOLAÇÃO',
       'PRAIA DO CANTO', 'BOA VISTA', 'MORADA DE CAMBURI', 'SANTA LUÍZA',
       'SANTA LÚCIA', 'BARRO VERMELHO', 'ESTRELINHA', 'FORTE SÃO JOÃO',
       'FONTE GRANDE', 'ENSEADA DO SUÁ', 'SANTOS REIS', 'PIEDADE',
       'JESUS DE NAZARETH', 'SANTA TEREZA', 'CRUZAMENTO',
       'ILHA DO PRÍNCIPE', 'ROMÃO', 'COMDUSA', 'SANTA CECÍLIA',
       'VILA RUBIM', 'DE LOURDES', 'DO QUADRO', 'DO CABRAL', 'HORTO',
       'SEGURANÇA DO LAR', 'ILHA DO BOI', 'FRADINHOS', 'NAZARETH',
       'AEROPORTO', 'ILHAS OCEÂNICAS DE TRINDADE', 'PARQUE INDUSTRIAL'], dtype=object)
```

In [41]:
```
#Getting the unique count of Neighbourhood
df.Neighbourhood.nunique()
```

Out[41]:
```
81
```

This tells us that there are 81 unique Neigghbourhoods in the dataset

In [42]:
```
#Getting the value count to "NoShow" info using groupby (by percentage)
Neigh_NoShow = df.groupby("Neighbourhood")["NoShow"].value_counts("%")
```

In [43]:
```
Neigh_NoShow
```

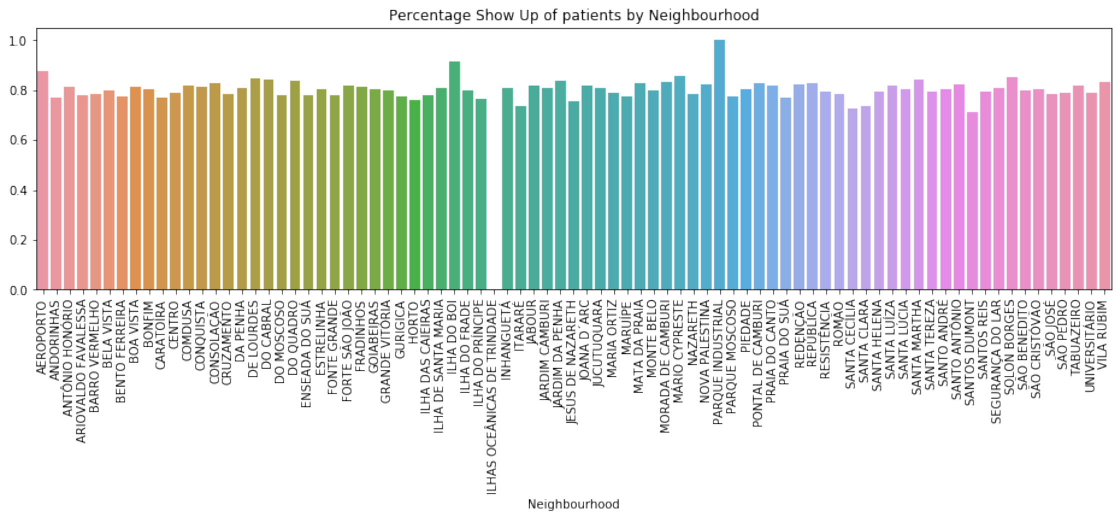
Out[43]:
```
Neighbourhood        NoShow
AEROPORTO            No        0.875000
                     Yes       0.125000
ANDORINHAS           No        0.769673
                     Yes       0.230327
ANTÔNIO HONÓRIO      No        0.815498
                     Yes       0.184502
ARIOVALDO FAVALESSA  No        0.780142
                     Yes       0.219858
BARRO VERMELHO       No        0.784870
                     Yes       0.215130
BELA VISTA           No        0.798637
                     Yes       0.201363
BENTO FERREIRA       No        0.775058
                     Yes       0.224942
BOA VISTA            No        0.814103
                     Yes       0.185897
```

```
BONFIM               No        0.801659
                     Yes       0.198341
CARATOÍRA            No        0.769591
                     Yes       0.230409
CENTRO               No        0.789142
                     Yes       0.210858
COMDUSA              No        0.819355
                     Yes       0.180645
CONQUISTA            No        0.811543
                     Yes       0.188457
CONSOLAÇÃO           No        0.827762
                     Yes       0.172238
CRUZAMENTO           No        0.782546
                     Yes       0.217454
                                  ...
SANTA MARTHA         No        0.841584
                     Yes       0.158416
SANTA TEREZA         No        0.795796
                     Yes       0.204204
SANTO ANDRÉ          No        0.802412
                     Yes       0.197588
SANTO ANTÔNIO        No        0.823744
                     Yes       0.176256
SANTOS DUMONT        No        0.710815
                     Yes       0.289185
SANTOS REIS          No        0.795247
                     Yes       0.204753
SEGURANÇA DO LAR     No        0.806897
                     Yes       0.193103
SOLON BORGES         No        0.852878
                     Yes       0.147122
SÃO BENEDITO         No        0.800556
                     Yes       0.199444
SÃO CRISTÓVÃO        No        0.802288
                     Yes       0.197712
SÃO JOSÉ             No        0.783510
                     Yes       0.216490
SÃO PEDRO            No        0.789624
                     Yes       0.210376
TABUAZEIRO           No        0.817050
                     Yes       0.182950
UNIVERSITÁRIO        No        0.789474
                     Yes       0.210526
VILA RUBIM           No        0.834313
                     Yes       0.165687
Name: NoShow, Length: 160, dtype: float64
```

Plotting a bar plot to visualize the above percentage representation for "NoShow = No" only.

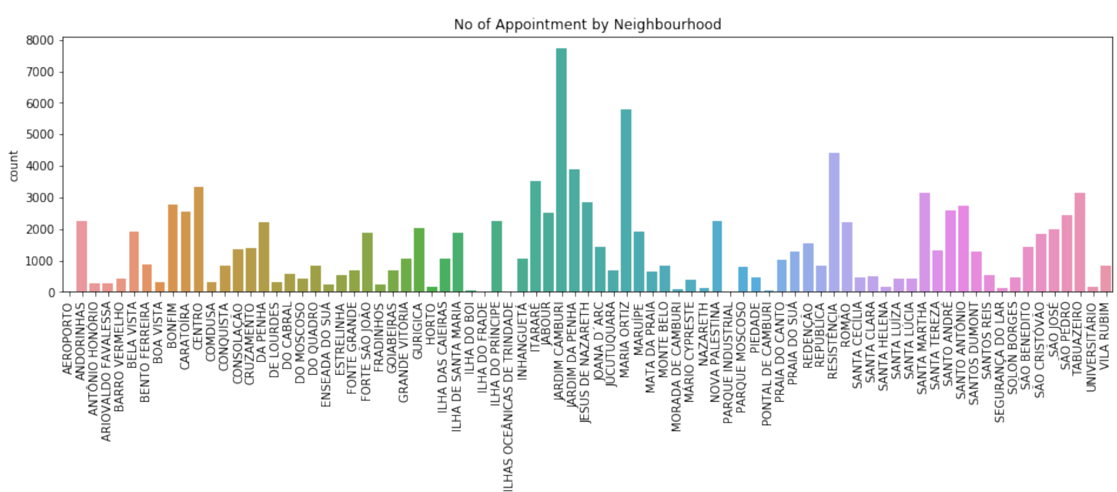
```
In [44]: df_perc = df[df.NoShow == "No"].groupby(["Neighbourhood"]).size()/df.groupby(["Neighbou
```

```
In [45]: plt.figure(figsize=(16,4))
         plt.xticks(rotation=90)
         ax = sns.barplot(x=df_perc.index, y=df_perc)
         ax.set_title("Percentage Show Up of patients by Neighbourhood")
         plt.show()
```



Plotting a graph of Number of Appointment by Neighbourhood

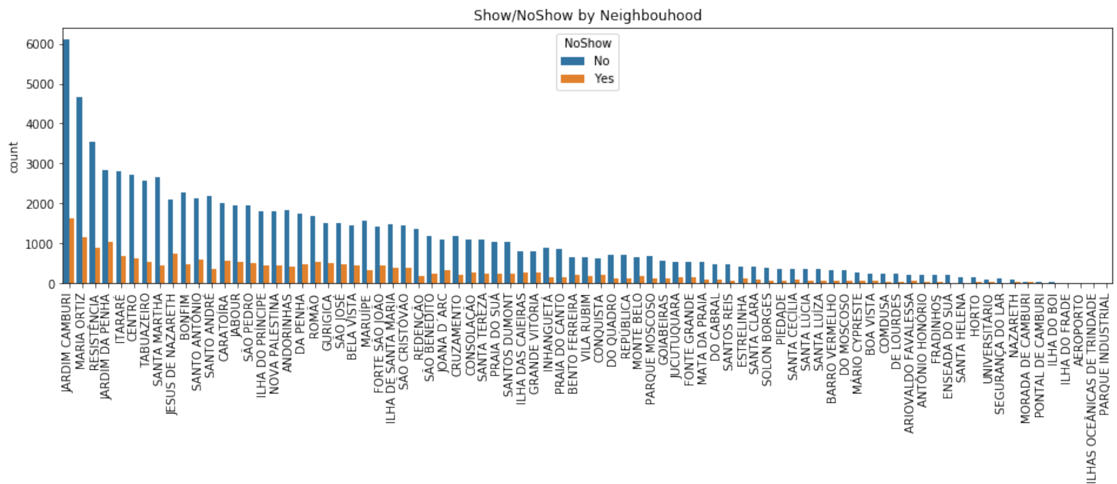
```
In [46]: #Plotting a bar plot of Number of Appointment by Neighbourhood
         plt.figure(figsize=(16,4))
         plt.xticks(rotation=90)
         ax = sns.countplot(x=np.sort(df.Neighbourhood))
         ax.set_title("No of Appointment by Neighbourhood")
         plt.show()
```



From the plot above, we can see that few Neighbourhoods have high number of appointment.

Plotting a bar plot of NoShow/Show by Neighbourhood

```
In [47]: plt.figure(figsize=(16,4))
         plt.xticks(rotation=90)
         ax = sns.countplot(x=np.sort(df.Neighbourhood), hue=df.NoShow, order=df.Neighbourhood.v
         ax.set_title("Show/NoShow by Neighbouhood")
         plt.show()
```



From the above statistics and plots. it is worth to note that;

The percentage Show-Up of patients for all the Neighbourhoods lies within the same range

Therefore, Since its obvious that the appointment Show-Up does not depend on the appointment Neighbourhood. Neighbourhood is not a determinant/predictor of Show-up to appointment.

1.6 Getting the correlation of "Age" to "NoShow"

```
In [48]: Age_NoShow = df.groupby("NoShow")["Age"]
```

```
In [49]: AgeNo = Age_NoShow.value_counts()
```

```
In [50]: #Getting the "NoShow" for patients below "Age" 11
         AgeNoShow1 = df.query("Age < 11").NoShow.value_counts()
```

```
In [51]: AgeNoShow1
```

```
Out[51]: No      14961
         Yes      3788
         Name: NoShow, dtype: int64
```

```
In [52]: #Getting the "NoShow" for patients between "Age" 11-25
         AgeNoShow2 = df.query("Age >= 11" and "Age <= 25").NoShow.value_counts()
```

```
In [53]: AgeNoShow2
```

```
Out[53]: No      29781
         Yes      8818
         Name: NoShow, dtype: int64
```

```
In [54]: #Getting the "NoShow" for patients between "Age" 26-55
         AgeNoShow3 = df.query("Age >= 26" and "Age <= 55").NoShow.value_counts()
```

```
In [55]: AgeNoShow3
```

```
Out[55]: No      65007
         Yes     18016
         Name: NoShow, dtype: int64
```

```
In [56]: #Getting the "NoShow" for patients from "Age" 55 and above
         AgeNoShow4 = df.query("Age > 55").NoShow.value_counts()
```

```
In [57]: AgeNoShow4
```

```
Out[57]: No      23201
         Yes      4303
         Name: NoShow, dtype: int64
```

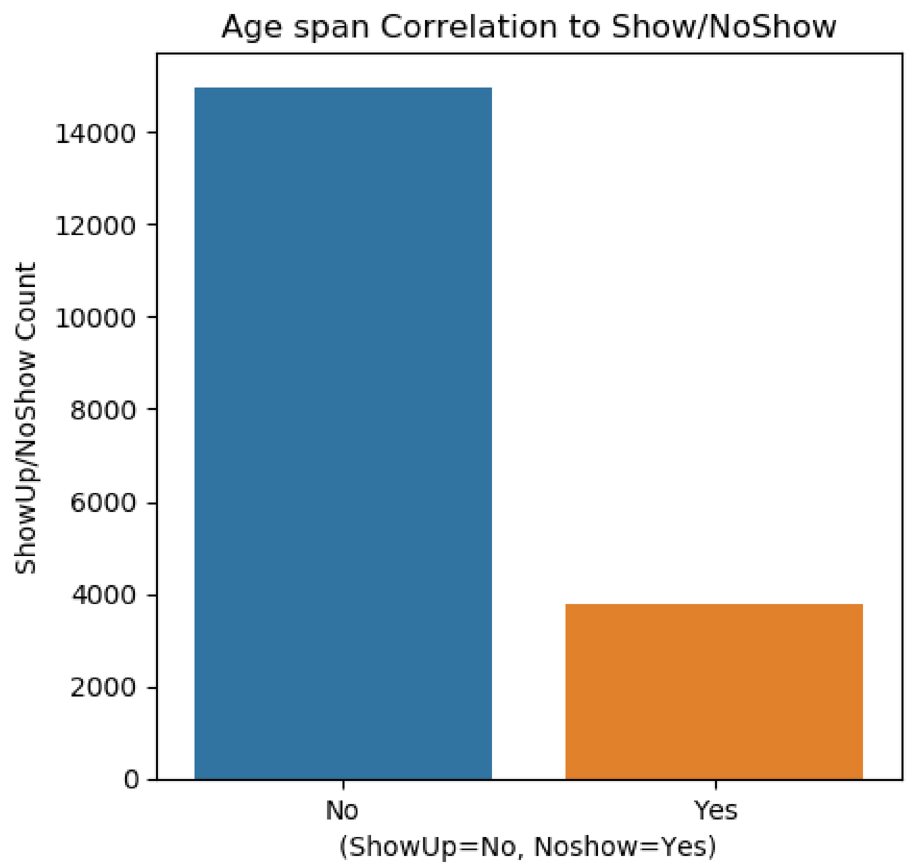
1.6.1 Visualizing the "NoShow" by "Age Span" using Bar plot

This will be done by "Defining a Function" that will be called upon to plot the various plots. This is necessary to avoid code repititions.

```
In [58]: #Defining a Function that will be called upon for bar plot of the various Age spans
         def gnd(ds):
             plt.figure(figsize= (5,5), dpi=100)
             sns.barplot(x=ds.index, y=ds)
             plt.title("Age span Correlation to Show/NoShow")
             plt.ylabel("ShowUp/NoShow Count")
             plt.xlabel("(ShowUp=No, Noshow=Yes)");
         plt.show()
```

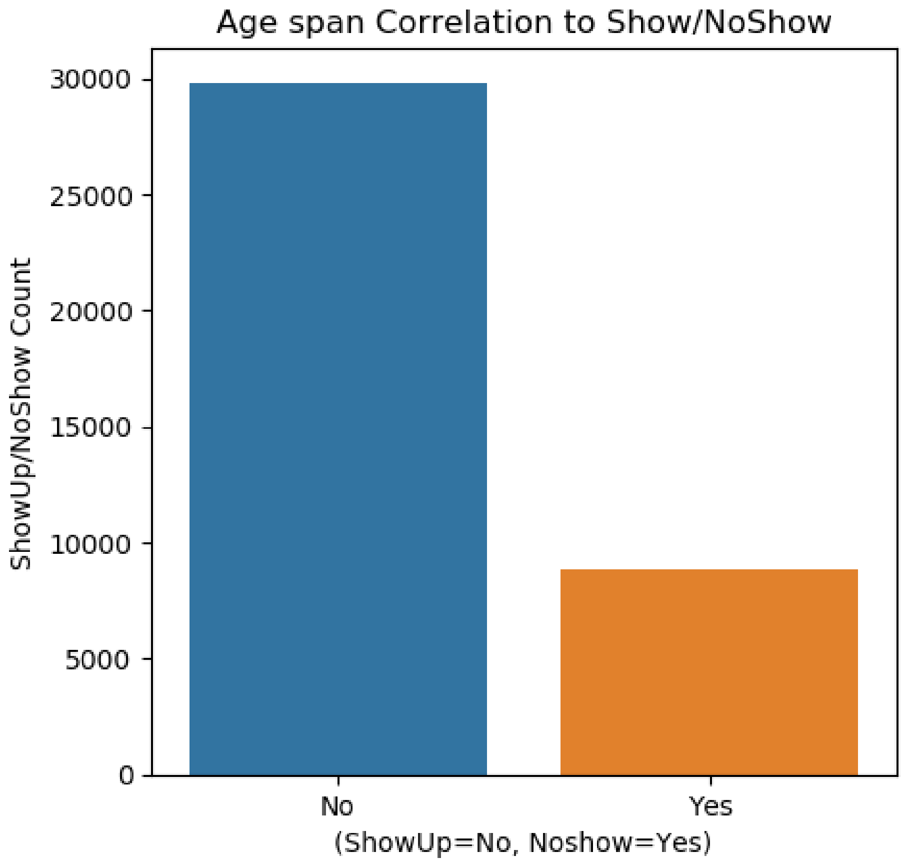
Plotting a Bar plot of NoShow/Show Appointment for "Age" 0-10yrs

```
In [59]: #Calling the function with the variable AgeNoShow1
         gnd(AgeNoShow1)
```



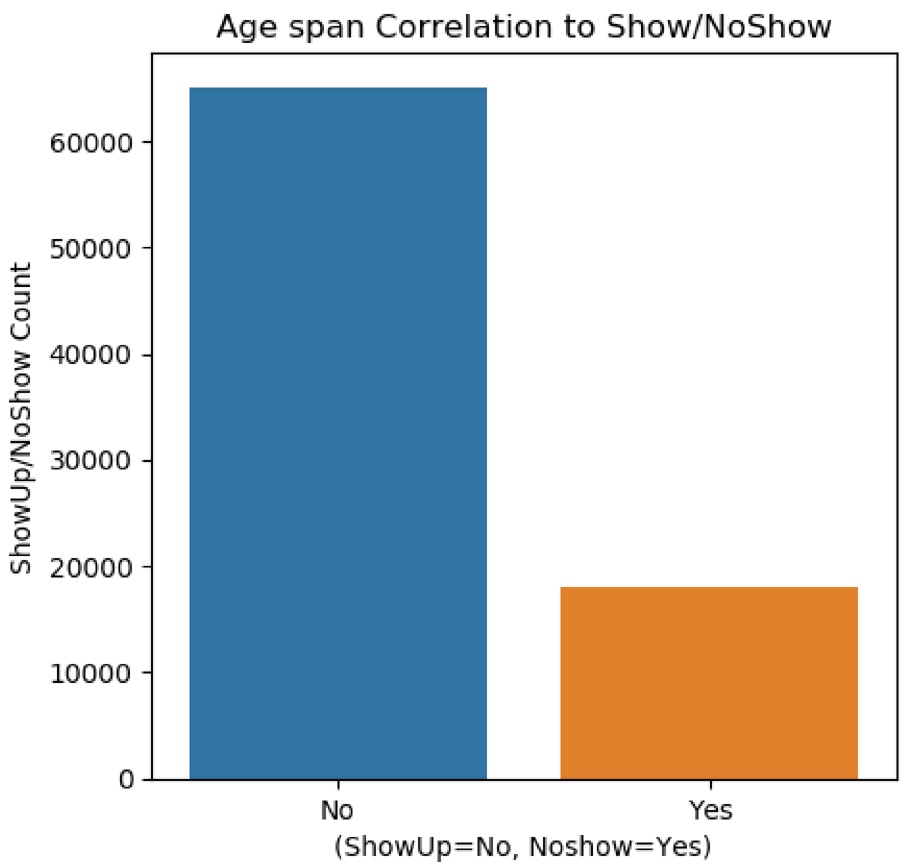
Plotting a Bar plot of NoShow/Show Appointment for "Age" 11-25yrs

```
In [60]: #Calling the function with the variable AgeNoShow2
         gnd(AgeNoShow2)
```



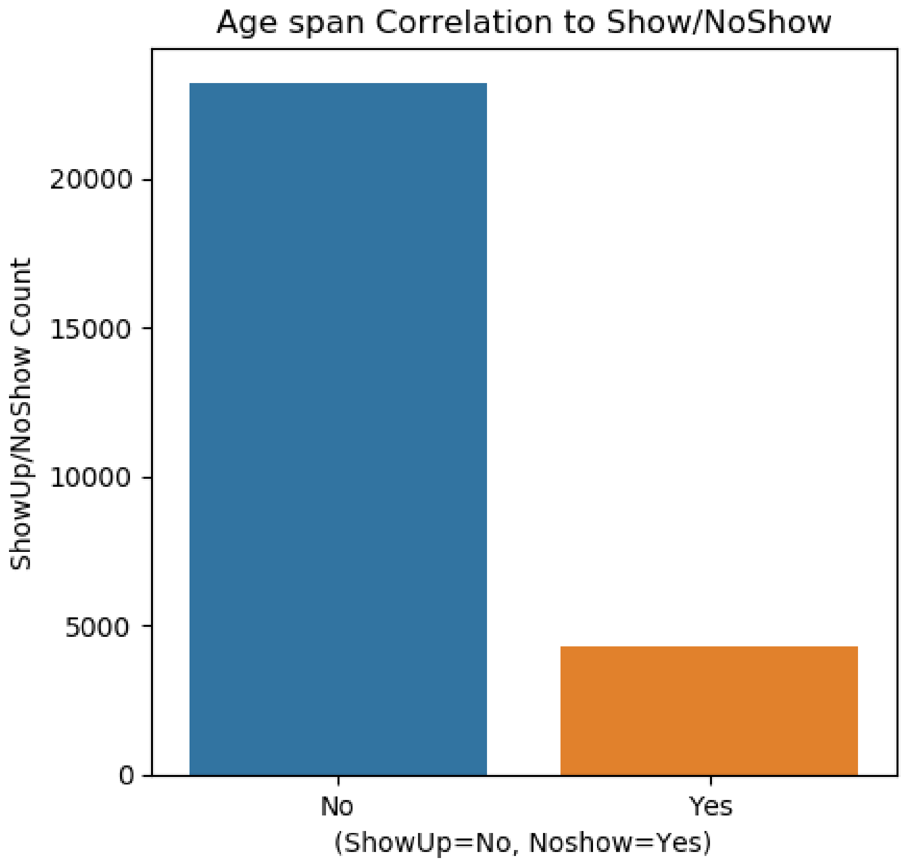
Plotting a Bar plot of NoShow/Show Appointment for "Age" 26-55yrs

```
In [61]: #Calling the function with the variable AgeNoShow3
         gnd(AgeNoShow3)
```



Plotting a Bar plot of NoShow/Show Appointment for "Age" above 55

In [62]:
```
#Calling the function with the variable AgeNoShow4
gnd(AgeNoShow4)
```



From the statistics and plots above, we can see that for Age;

Age 0-10: 79.9% of patients showed up
Age 11-25: 77.15% of the patients showed up
Age 26-55: 78.3% of the patients showed up
Age 55 and above: 84.36% of the patients showed up

It's obvious from the above listed statistics that all the various age ranges have a high rate of turn-up, but patients that are above 50yrs of age have the highest turn-up percentage. This can be as a result of older individuals being susceptible or prone to diseases as a result of weakened Immune-system and the need for proper medical attention at this stage of their lives.

Thus, we can say that "Gender" is a determinant/predictor of NoShow/Show-up of patients to their appointments.

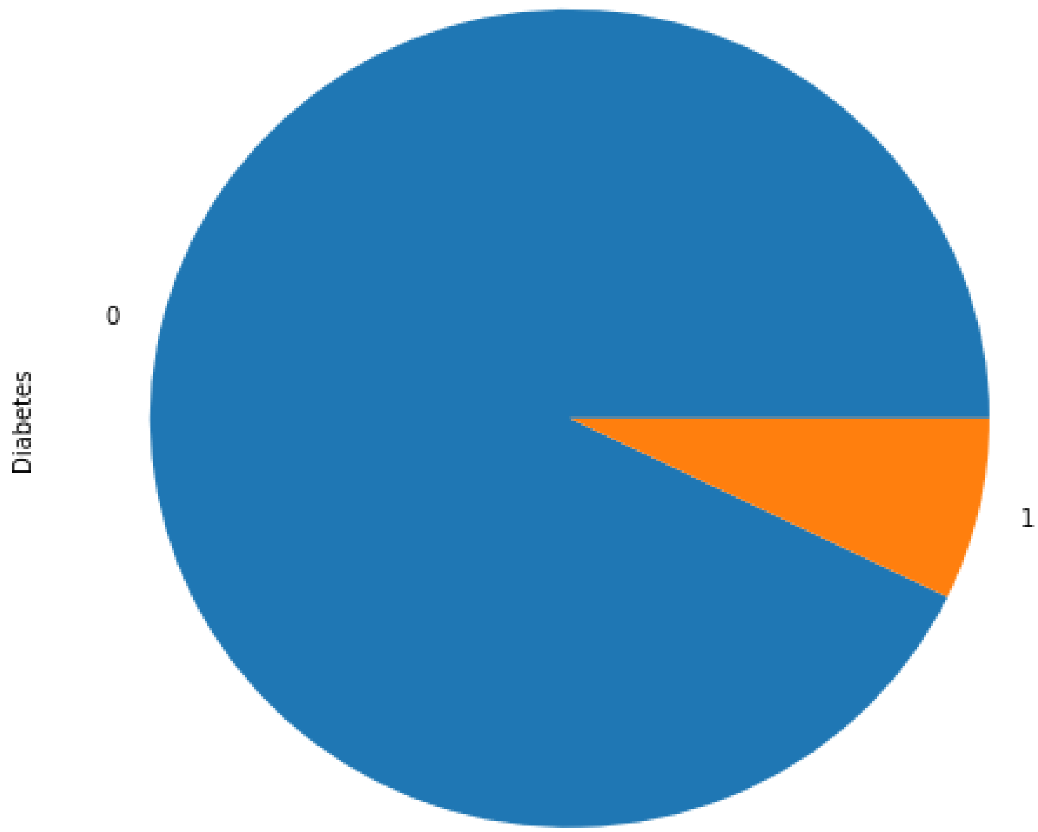
1.7 Getting The Correlation of "Diabetes" to "NoShow"

```
In [63]: #Extracting information about the unique value count of "Diabetes"
         diabetes = df.Diabetes.value_counts()
```

```
In [64]: #Loading the result
         diabetes
```

```
Out[64]: 0    102584
         1      7943
         Name: Diabetes, dtype: int64
```

```
In [65]: #Plotting a Pie plot of the above result for diabetes
         diabetes.plot(kind ="pie", figsize=(8,8));
```



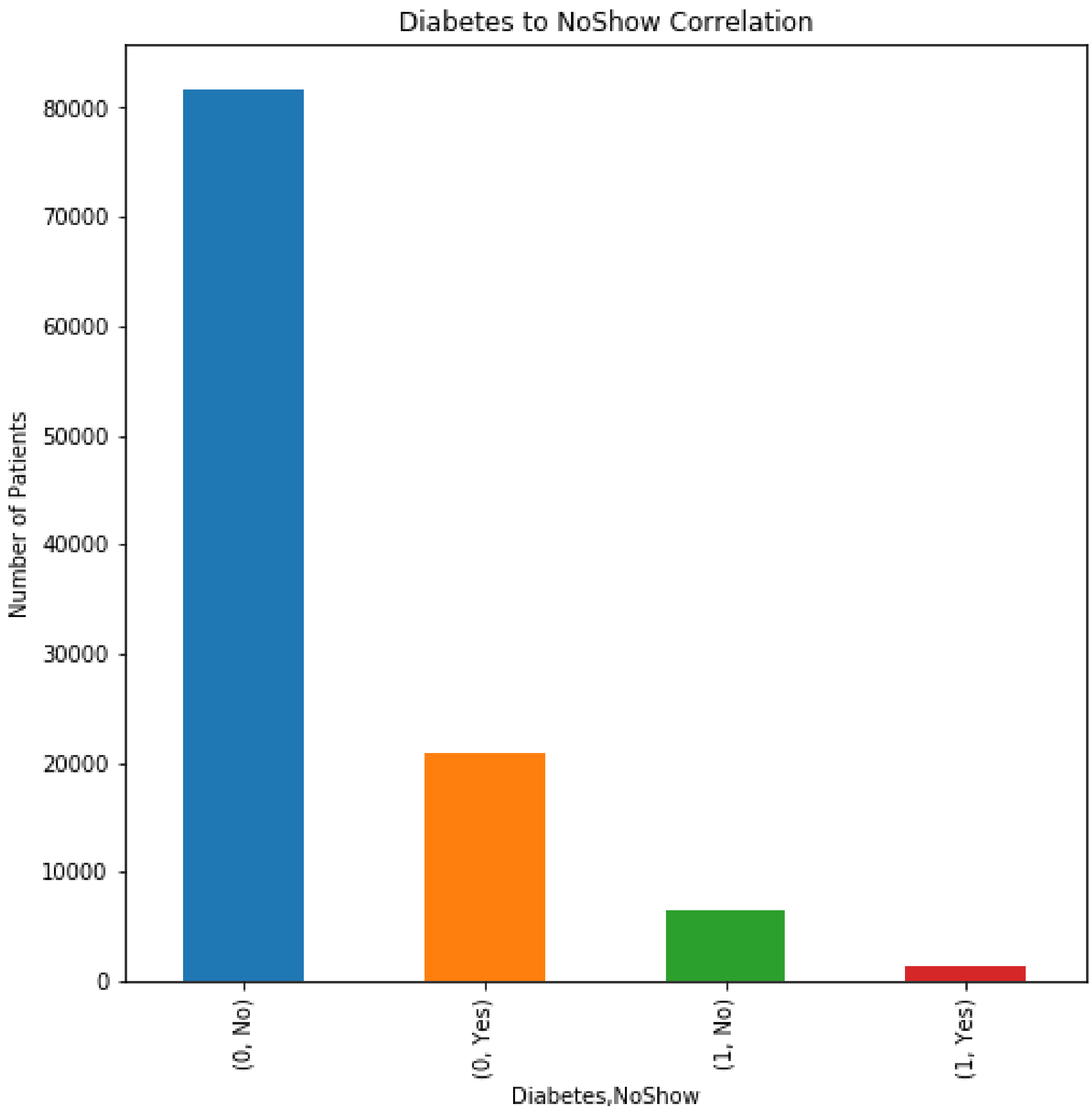
The above results shows us that; patients without "Diabetes" are 102,584 while those with "Diabetes" are 7,943

```
In [66]: #Using groupby to get the corresponding "NoShow" result for each unique value of "Diabe
         Diabetes_NoShow = df.groupby("Diabetes")["NoShow"].value_counts()
```

```
In [67]: #Loading the data
         Diabetes_NoShow
```

```
Out[67]: Diabetes  NoShow
         0         No        81695
                   Yes       20889
         1         No         6513
                   Yes        1430
         Name: NoShow, dtype: int64
```

```
In [68]: #Plotting a Bar plot "Diabetes,NoShow" against "Number of Patients"
         ax = Diabetes_NoShow.plot(kind= "bar", title="Diabetes to NoShow Correlation", figsize=
         ax.set_xlabel("Diabetes,NoShow")
         ax.set_ylabel("Number of Patients");
```



From the Bar plot above, it can be seen that;
Patients without Diabetes and Showed-up for their appointment have the highest number

Patients with Diabetes that showed up for their appointment are fewer

Thus, we can say that; Diabetes is not a strong determinant that a patient will show up their appointment

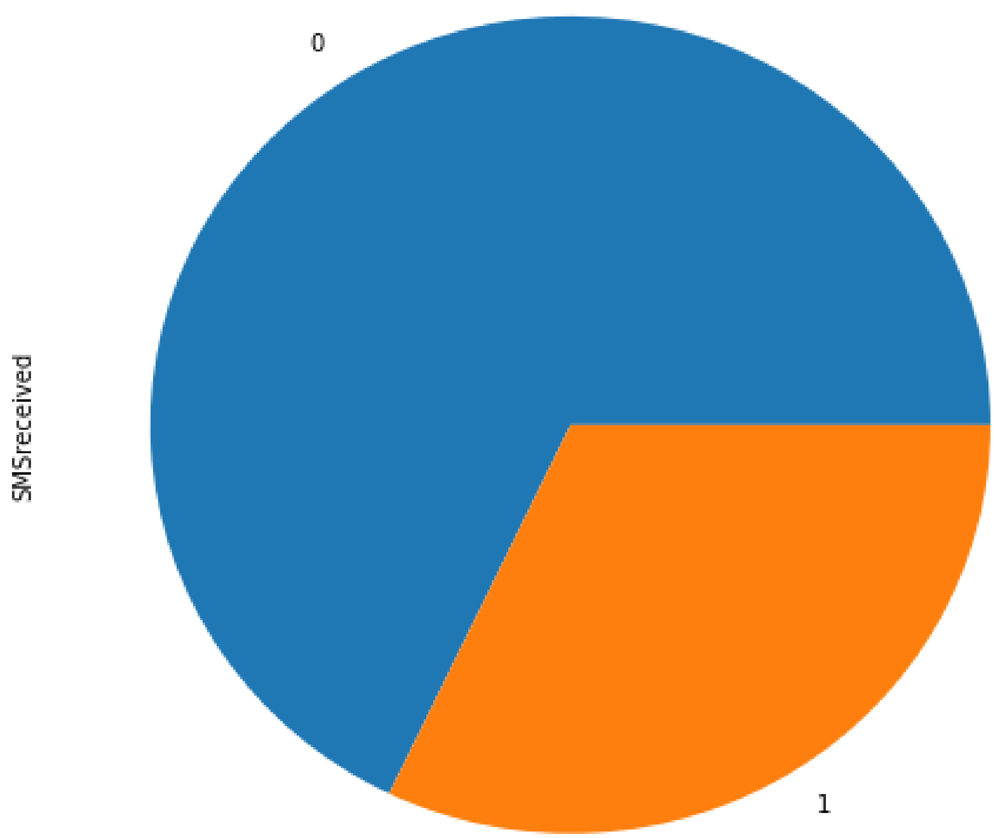
1.8 Getting the Correlation of "SMSreceived" to "NoShow"

In [69]:
```
#Extracting information about the unique value counts of "SMSreceived"
sms_received = df["SMSreceived"].value_counts()
```

In [70]:
```
#Loading the result for sms_received
sms_received
```

Out[70]:
```
0    75045
1    35482
Name: SMSreceived, dtype: int64
```

In [71]:
```
#Visualizing the result using a pie chart
sms_received.plot(kind= "pie", figsize= (8,8));
```



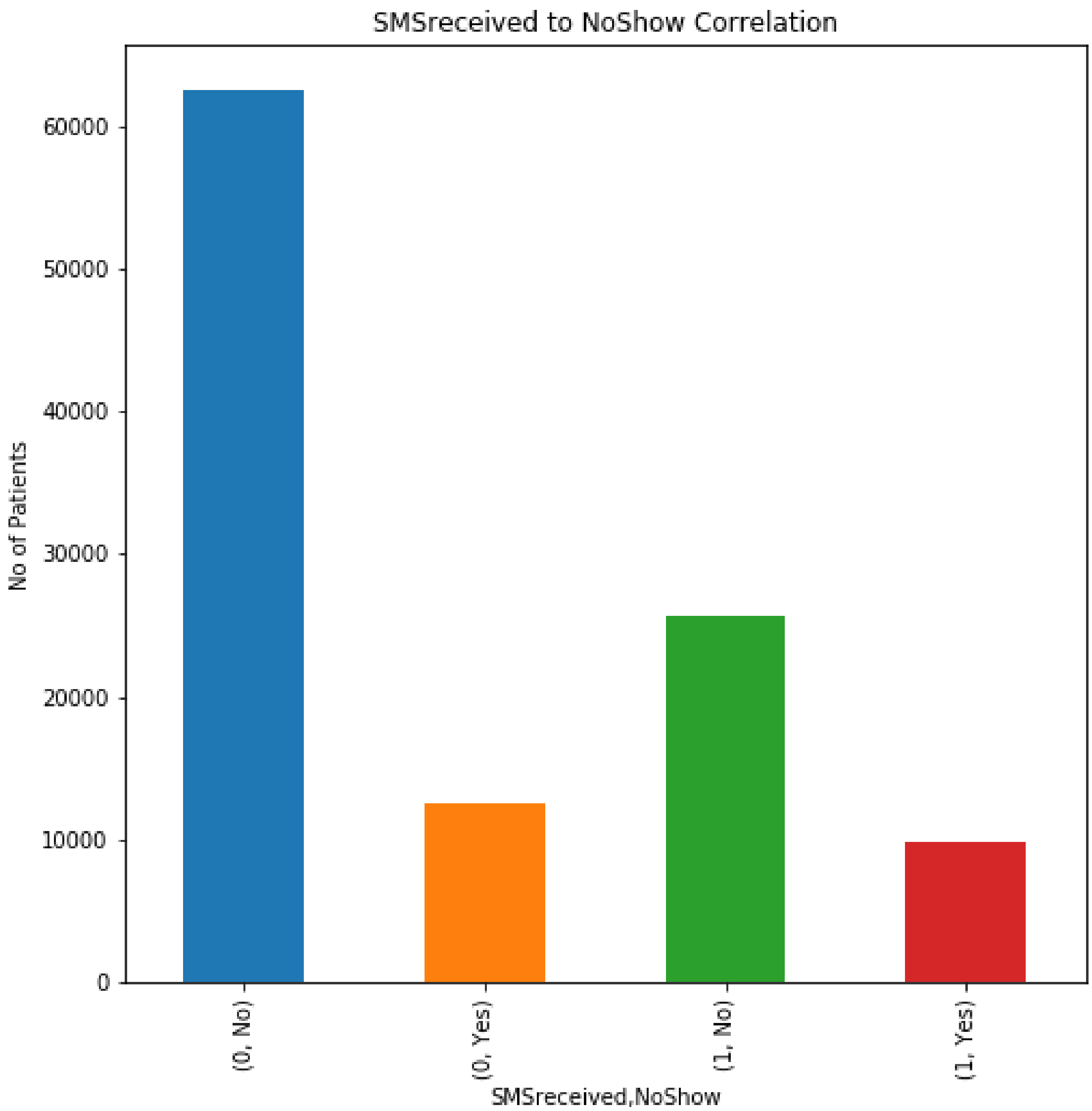
The above results shows us that; patients that received SMS are 35,482(32.1%), while those that receive SMS are 75,045(67.9%)

In [72]:
```
#Using groupby to get the corresponding value of "NoShow" for each unique value of "SMS
SMS_NoShow = df.groupby("SMSreceived")["NoShow"].value_counts()
```

In [73]:
```
SMS_NoShow
```

Out[73]:
```
SMSreceived  NoShow
0            No        62510
             Yes       12535
1            No        25698
             Yes        9784
Name: NoShow, dtype: int64
```

In [74]:
```
#Plotting a Bar Plot of the Correlation
ax = SMS_NoShow.plot(kind ="bar", title="SMSreceived to NoShow Correlation", figsize= (
ax.set_xlabel("SMSreceived,NoShow")
ax.set_ylabel("No of Patients");
```



From the information above, it can be deduced that;

Out of the 35,482 patients that received SMS, 72.43% showed up for there appointment, while 16.7% didnt show up

Out of the 75,045 that didnt receive SMS, 83.3% showed for their appointment, while 16.7% didnt show up

Thus, since those that didnt receive SMS have a higher percentage of show up than those that received, "SMSreceived" is not a strong predictor of appointment show-up.

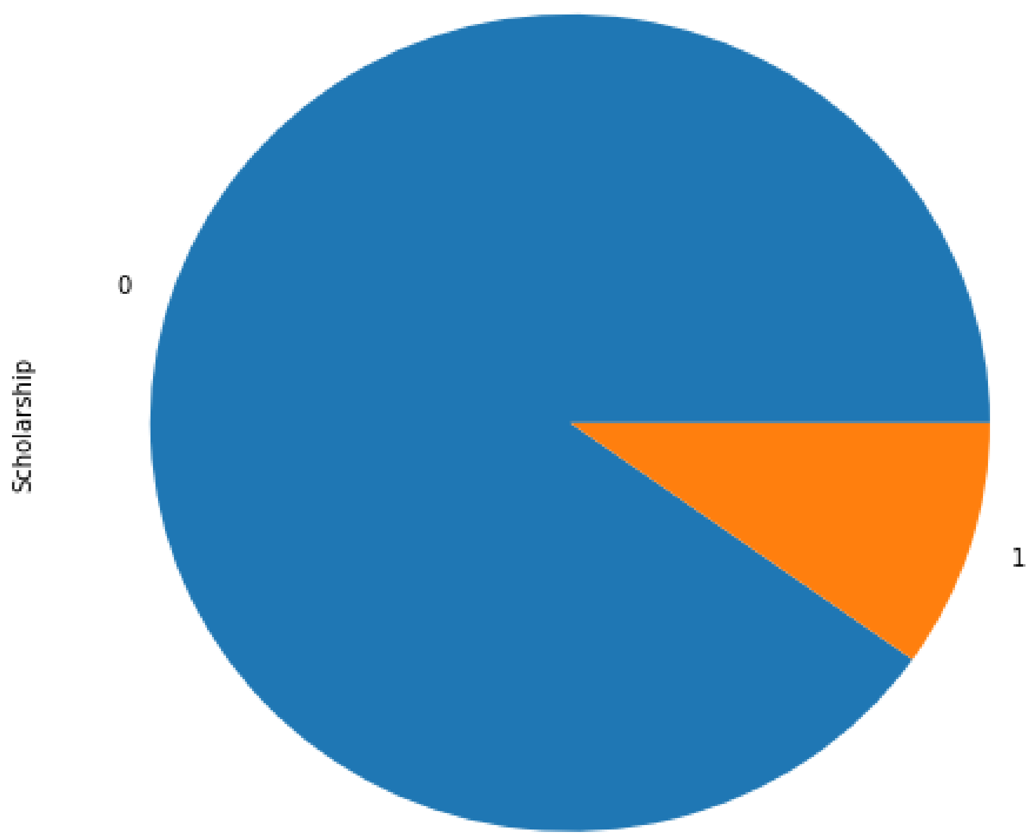
1.9 Getting the Correlation of "Scholarship" to "NoShow"

In [75]:
```
#Extracting information on unique value count of "Scholarship"
scholarship = df["Scholarship"].value_counts()
```

In [76]:
```
#Loading the result
scholarship
```

Out[76]:
```
0    99666
1    10861
Name: Scholarship, dtype: int64
```

In [77]:
```
#visualizing the result using pie chart
scholarship.plot(kind = "pie", figsize= (8,8));
```



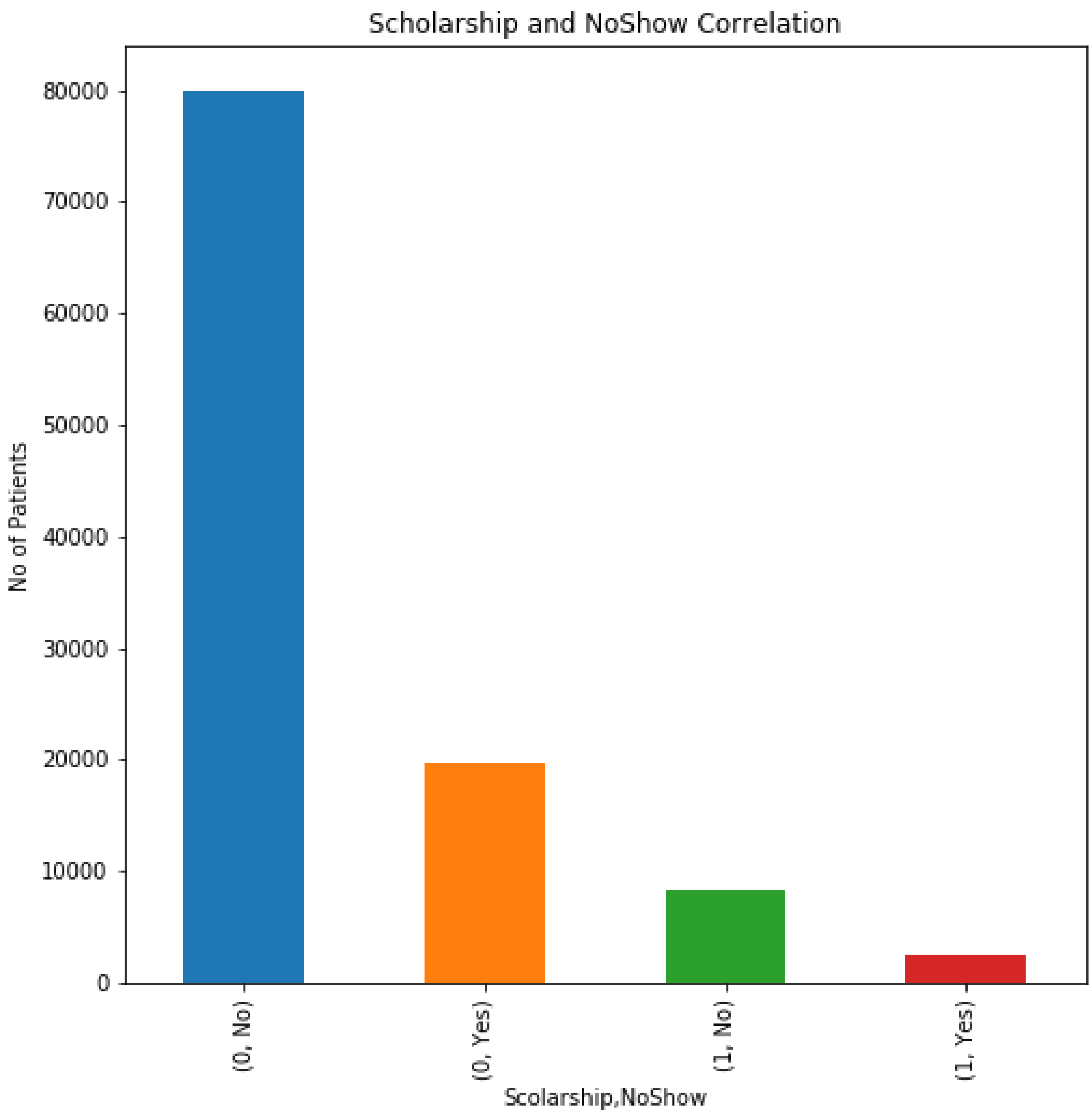
This tells us that there are 99,666 patients without Scholarships and 10,861 with Scholarship

In [78]:
```
#Using groupby to get the corresponding value of "NoShow"
Scholarship_NoShow = df.groupby("Scholarship")["NoShow"].value_counts()
```

In [79]:
```
Scholarship_NoShow
```

```
Out[79]: Scholarship  NoShow
         0            No        79925
                      Yes       19741
         1            No         8283
                      Yes        2578
         Name: NoShow, dtype: int64
```

```
In [80]: #Plotting a Bar plot of the correlation
         ax = Scholarship_NoShow.plot(kind= "bar", title="Scholarship and NoShow Correlation", f
         ax.set_xlabel("Scolarship,NoShow")
         ax.set_ylabel("No of Patients");
```



From the statistics above, it can be seen that;

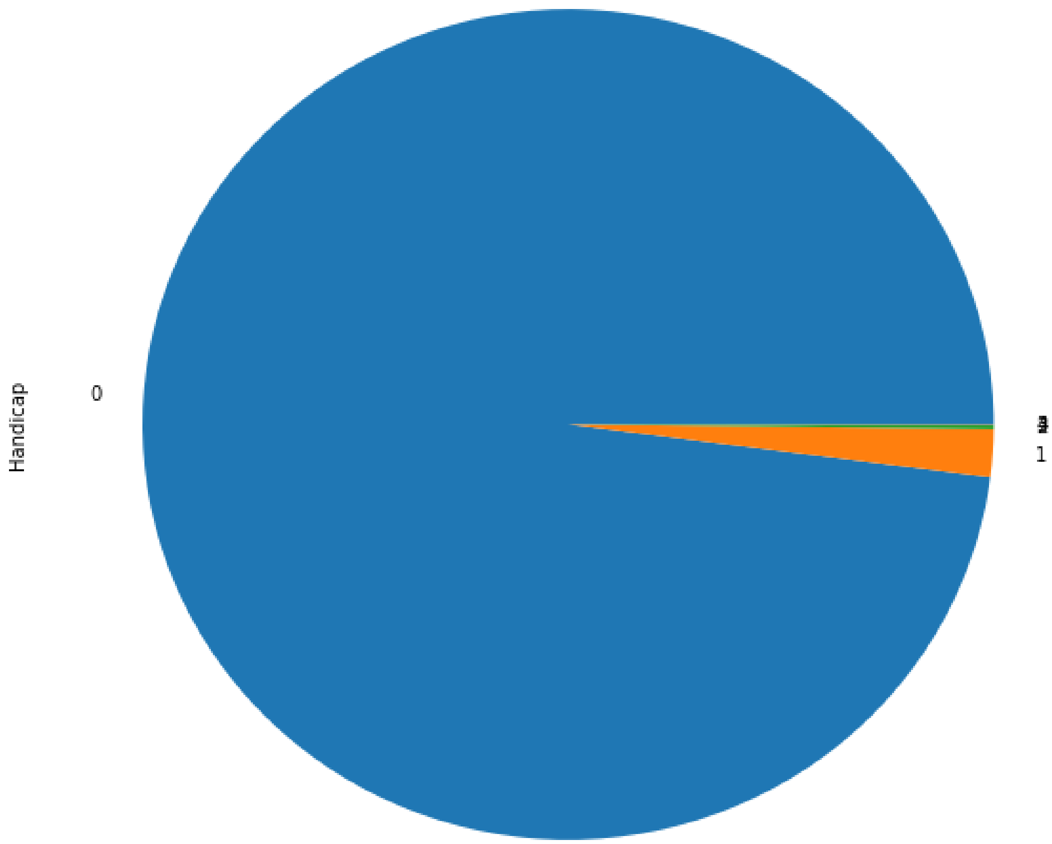
Out of the 10,861 patients that have Scholarship, 76.26% showed up to their appointment, while 23.74% didnt show up

Out of the 99,666 patients that didnt receive Scholarship, 80.19% showed up for their appointment, while 19.81% didnt show up

Thus, since the percentage of Show-up for people that didnt receive the Scholarship is greater than that of those that received Scholarship, it can be concluded that Scholarship is not a strong determinant for showup, because even a greater percentage of patients that didnt receive Scholarship still showed up for their appointment. This meant that some other factor was a major contributor to Show-Up rather than Scholarship.

1.10 Getting the Correlation of "Handicap" to "NoShow"

```
In [81]: #Extracting information on unique value counts for "Handicap"
         df["Handicap"].unique()

Out[81]: array([0, 1, 2, 3, 4])

In [82]: #Getting the value counts for the various levels of handicap
         handicap = df["Handicap"].value_counts()

In [83]: #Loading the result
         handicap

Out[83]: 0    108286
         1      2042
         2       183
         3        13
         4         3
         Name: Handicap, dtype: int64

In [84]: #Visualizing the result using a pie chart
         handicap.plot(kind= "pie", figsize=(10,10));
```



This results shows us that; patients with 0(zero) handicap are 108,286(97.97%), those with 1(one) handicap are 2,042(1.85%), those with 2 handicaps are 183(0.17%), those with 3(three) handicaps are 13(0.012%), while those with 4(four) handicaps are 3(0.0027%)

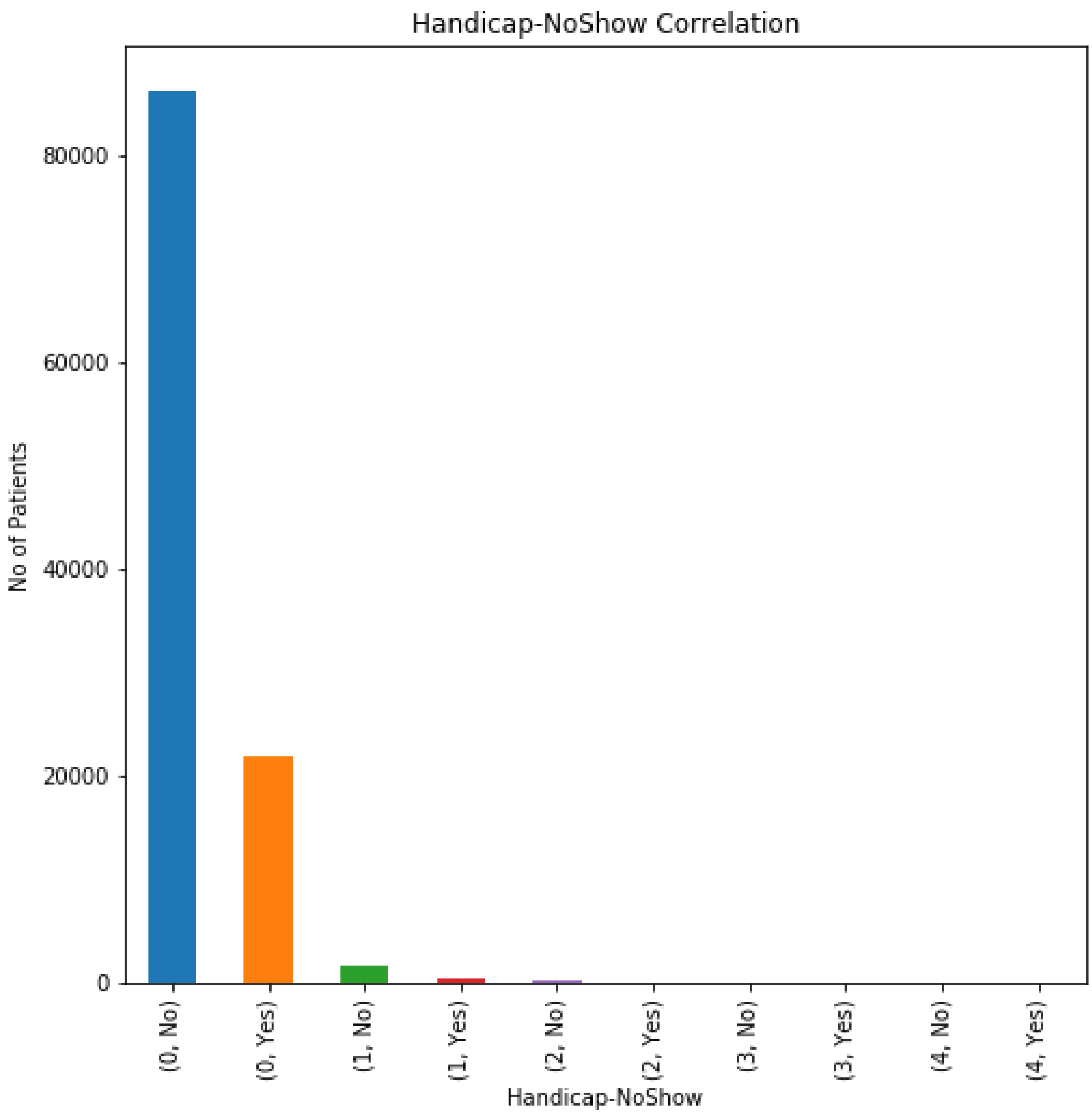
In [85]:
```
#Getting the correlation with "Noshow" using groupby
Handicap_NoShow = df.groupby("Handicap")["NoShow"].value_counts()
```

In [86]:
```
#Loading the data
Handicap_NoShow
```

Out[86]:
```
Handicap  NoShow
0         No        86374
          Yes       21912
1         No         1676
          Yes         366
2         No          146
```

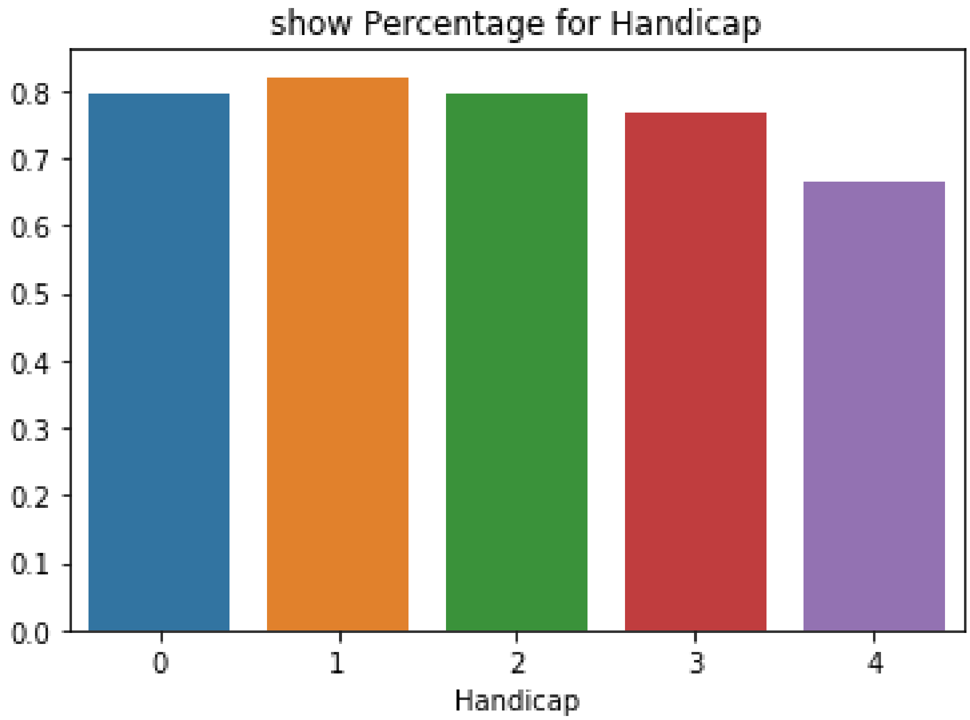
```
            Yes          37
3           No           10
            Yes           3
4           No            2
            Yes           1
Name: NoShow, dtype: int64
```

In [87]:
```
#plotting a Bar plot of the Correlation
ax = Handicap_NoShow.plot(kind= "bar", title="Handicap-NoShow Correlation", figsize= (8
ax.set_xlabel("Handicap-NoShow")
ax.set_ylabel("No of Patients");
```



In [88]:
```
#Getting the Percentage Handicap
df_new = df[df.NoShow == "No"].groupby(['Handicap']).size()/df.groupby(["Handicap"]).si
```

```
ax = sns.barplot(x=df_new.index, y=df_new)
ax.set_title("show Percentage for Handicap");
```



From the above statistics and plots;

97.97% of the patients are not Handicap and out of this, 79.76% showed up for their appointment

Of the 2241 patients that have 1-4 type of handicap, 81.84% showed up for their appointments

From the Handicap Percentage Bar plot, it can be seen that each level of Handicap has a distinct percentage which signify its share of the patient count

From the points highlighted above, its obvious that "Handicap" is a predictor and determinant for Show-Up/No-Show to appointments.

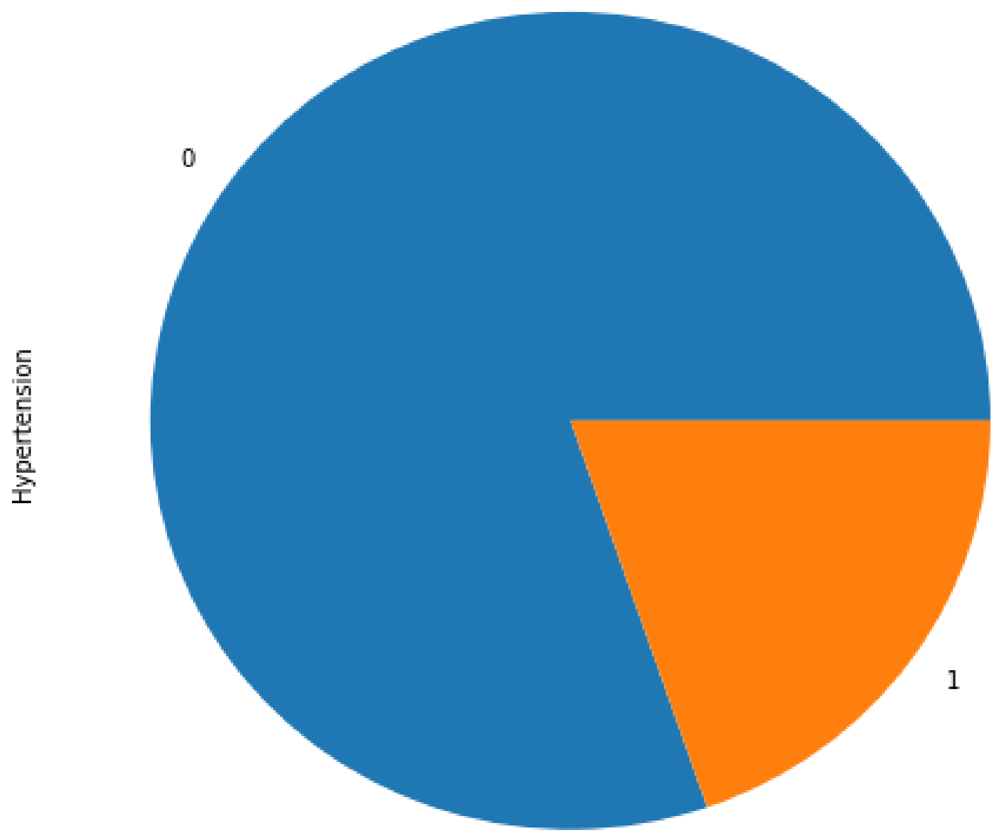
1.11 Getting the Correlation of "Hypertension" to "NoShow"

```
In [89]: #Extracting information on unique values count of "Hypertension"
         hypertension = df.Hypertension.value_counts()
```

```
In [90]: #Loading the result
         hypertension
```

```
Out[90]: 0    88726
         1    21801
         Name: Hypertension, dtype: int64
```

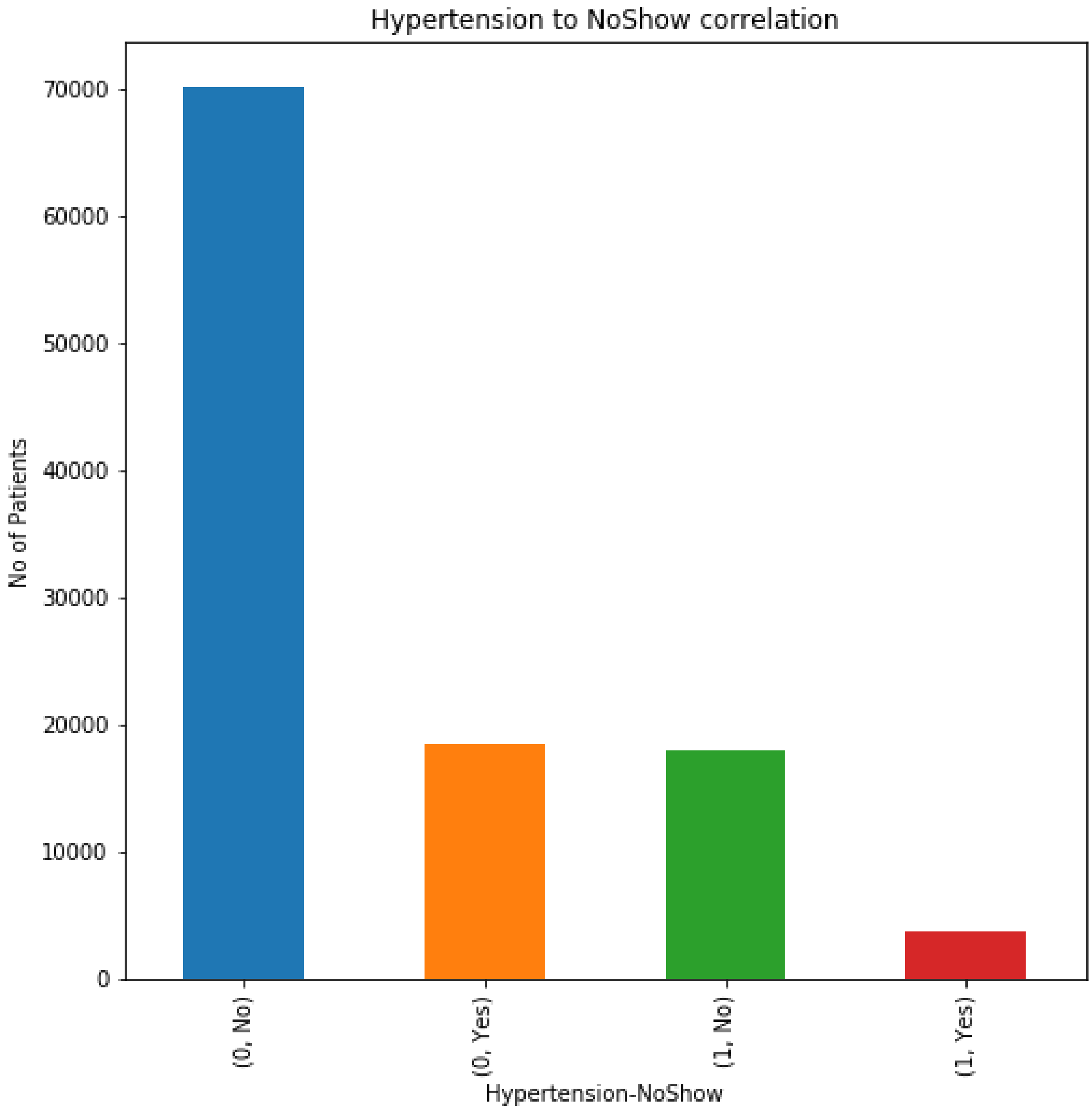
```
In [91]: #Visualizing the result using a piechart
         hypertension.plot(kind ="pie", figsize =(8,8));
```



This tells us that 88,726(80.28%) patients does not have Hypertension, while 21,801(19.72%) have Hypertension

```
In [92]: #Getting the Correlation with "NoShow" using groupby() method
         Hyper_NoShow = df.groupby("Hypertension")["NoShow"].value_counts()

In [93]: #Loading the data
         Hyper_NoShow

Out[93]: Hypertension  NoShow
         0             No        70179
                       Yes       18547
         1             No        18029
                       Yes        3772
         Name: NoShow, dtype: int64
```

```
In [94]: #Plotting a Bar Plot of the Correlation
         ax = Hyper_NoShow.plot(kind ="bar", title="Hypertension to NoShow correlation", figsize
         ax.set_xlabel("Hypertension-NoShow")
         ax.set_ylabel("No of Patients");
```



From the above derived information;

The percentage of patients with Hypertension that showed up for their appointment is 82.7%

The percentage of patients without Hypertension that showed up for their appointment is 79.1%

From the above listed points, it can be seen that the percentage of a "patient with Hypertension" showing up for appointment is greater than the percentage of a "patient without Hypertension" showing up for their appointment. Thus, Hypertension is a predictor and determinant of Show-Up to an appointment.

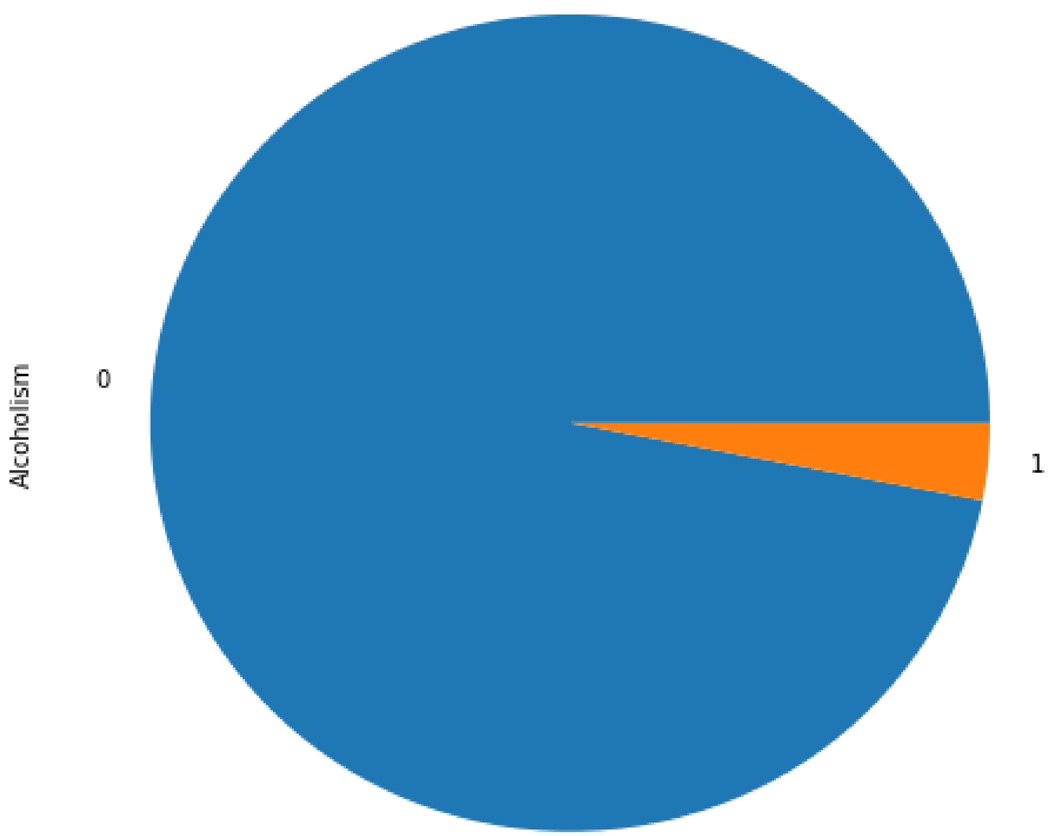
1.12 Getting the Correlation of "Alcoholism" to "NoShow"

```
In [95]: #Extracting information about the unique values of "Alcohoism"
         alcoholism = df["Alcoholism"].value_counts()
```

```
In [96]: #Loading the result
         alcoholism
```

```
Out[96]: 0    107167
         1      3360
         Name: Alcoholism, dtype: int64
```

```
In [97]: #Visualizing the result using a pie chart
         alcoholism.plot(kind ="pie", figsize= (8,8));
```



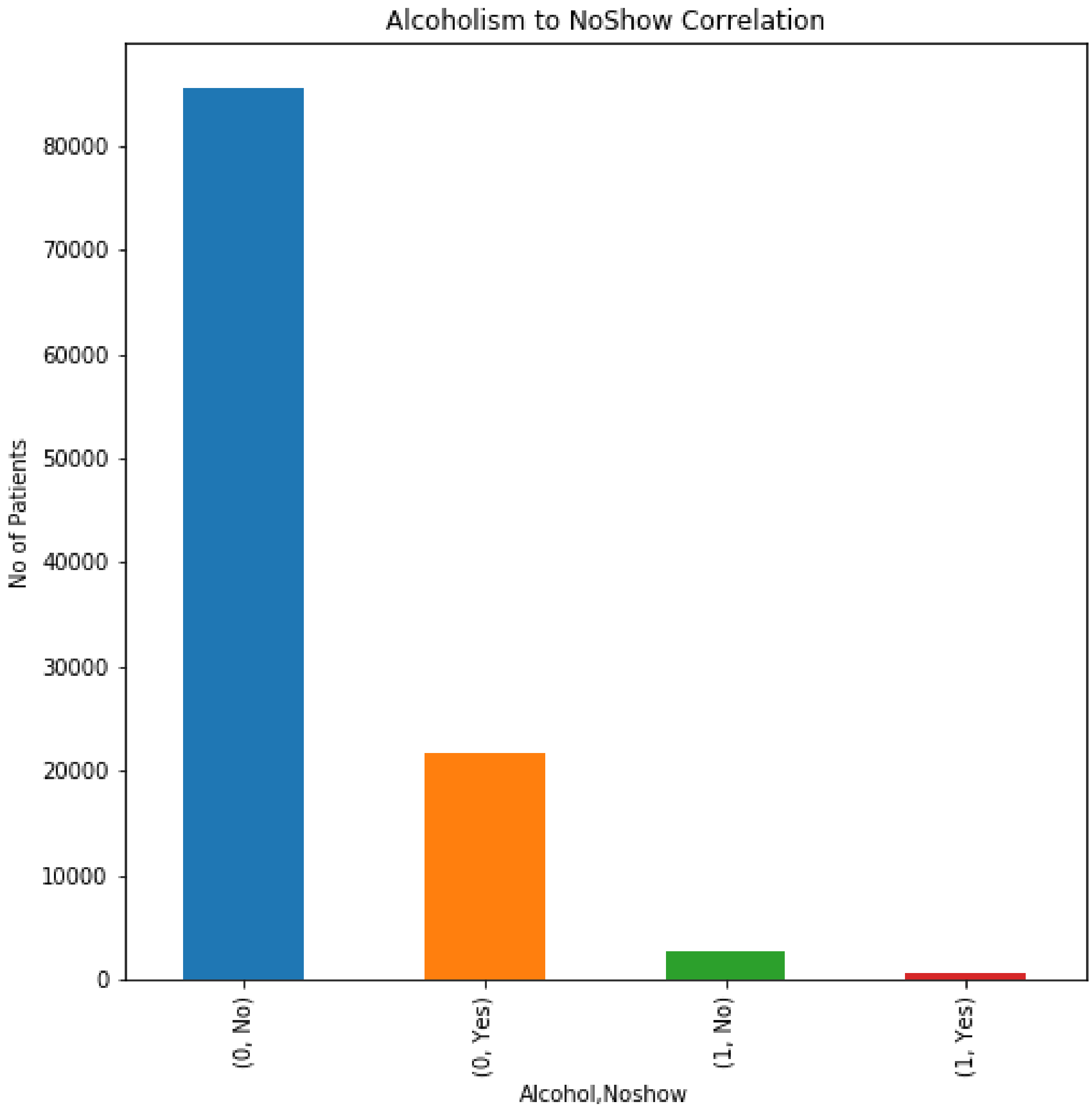
This tells us that there are 107,167(96.96%) patients without alcoholism issues, while 3,360(3.04%) do have alcoholism issues

In [98]:
```
#Getting the Correlation with NoShow
Alcohol_NoShow = df.groupby("Alcoholism")["NoShow"].value_counts()
```

In [99]:
```
#Loading the data
Alcohol_NoShow
```

Out[99]:
```
Alcoholism  NoShow
0           No        85525
            Yes       21642
1           No         2683
            Yes         677
Name: NoShow, dtype: int64
```

In [100]:
```
#Plotting a Bar Plot of the Correleration
ax = Alcohol_NoShow.plot(kind= "bar", title="Alcoholism to NoShow Correlation", figsiz
ax.set_xlabel("Alcohol,Noshow")
ax.set_ylabel("No of Patients");
```



From the above information;

```
<li>The percentage of patients with Alcoholism that showed up to their appointment is 79.85%</li
<li>The percentage of patients without Alcoholism that showed up to their appointments is 79.81%
```

From the above highlighted points, we can see that patients with Alcolism and those without Alcoholism have the same Show Up percentage.

Therefore, Alcoholism is not a predictor and determinant of appointment Show-up

Conclusions

From the conclusions derived for each unique corellation analysis, we can conclude that:

Characteristics like Hypertension, Handicap, Gender, Age are all important factors in predicting if a patient will show up to an appointment.

Limitations

There are observed limitations of the dataset and this includes:

The distance to the appointment Neighbourhood from the patients location was not provided. This would have helped to give more insight about the Show_Up/No-Show population, by exploring the distance between the patients location to the appointment Neighbourhood and analyzing the correlation between distance to Show/NoSow, thereby knowing if distance to the Show/NoShow

AppointmentDay spans only for about a month, compared to ScheduledDay that spans to about 7 months. This but represents a glimpse of the data and its analysis does not make a true representation of the whole data

The reason for the scheduled appointment was not given. The reason for the appointment would have told us if the reason is a serious one that a No-Show would have been odd. Or if the scheduled appointment was just for a minor complaint that wouldnt be odd if the patient didnt show up.

The AppointmentDay time was set to 00:00:00. This time would have given us another insight on whether there is a correlation between the time of appointment to show up to the appointment

In [101]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

Out[101]: 255