Investigate_a_Dataset

June 11, 2020

1 Project: Investigate a Dataset - Medical Appointment No Shows

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2.1 Table of Contents

Introduction

In this project, I investigated a dataset of medical appoinment records for Brasil public hospitals. The data includes some demographic information, health condition, and other components of patients. All these variables are contribute to the state of whether the patients showed up to appointments or not. The analysis is focused on the factors that influencing patients to show or not show up to appointments.

This dataset downloaded from Kaggle. The data collected information from 100k 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 row.

2.2 General Research Question

2.2.1 How do different group of patients performance no show in the appointments?

First, import all the packages will be needed in this project

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib as plt
        import matplotlib.pyplot as plt
        import csv as csv
        import seaborn as sns
        # Remember to include a 'magic word' so that your visualizations are plotted
        #   inline with the notebook. See this page for more:
        #   http://ipython.readthedocs.io/en/stable/interactive/magics.html
```

Data Wrangling

In this section of the report, I will load in the data, check for cleanliness, and then trim and clean the dataset for analysis.

2.2.2 General Properties

Read the data file and show the first several rows for reviewing. Us df.shape,df.describe,df.describe,df,info,etc to see the description information of the raw data.

```
In [2]: #Read data file
        df=pd.read_csv('noshow.csv')

In [3]: #Print out a few lines.
        df.head()
        #Rename "No-show" to "No_show"
        df=df.rename(columns={"No-show": "NoShow"})
```

The variables are:

PatientId:

Identification number of a patient

AppointmentID:

Identification number of each appointment

Gender:

Male or Female

ScheduledDay:

The day that the patient set up the appointment

AppointmentDay:

The day that the patient actually participated the appointment

Age:

How old is the patient

Neighbourhood:

Where the appointment takes place

Scholarship:

True or False, indicates if the patient is in the Brazilian welfare program - Bolsa Familia program

Hipertension:

True or False, indicates if the patient had Hipertension.

Diabetes:

True or False, indicates if the patient had Diabeties

Alcoholism:

True or False, indicates if the patient is an alcoholic

Handcap:

True or False, indicates if the patient is handicapped

SMS_received:

1 or more messages sent to the patient

No_show:

"No" indicates if the patient showed up to their appointment and "Yes" if they didn't show up

```
In [4]: df.shape
```

```
Out[4]: (110527, 14)
```

There are 110,527 subjects and 14 columns in the data.

```
In [5]: # checking for general data duplicates
        df.duplicated().sum()
        df.PatientId.duplicated().sum()
        df.AppointmentID.duplicated().sum()
```

```
Out[5]: 0
```

There is no duplicated subjects in the dataset.

```
In [6]: 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
NoShow            110527 non-null object
dtypes: float64(1), int64(8), object(5)
memory usage: 11.8+ MB
```

Initial Observations The data had 110,527 subjects in 14 variables.

df.info() told us there are no missing values for the whole dataset.

PatientId is on float data type, which should be in string. ApporintmentID, Age, Scholarship, Hipertension, Diabeties, Alcoholism, Handcap and SMS_received is on a integer data type. The rest of the data records were as the objects. Scholarship, Hipertension, Diabeties, Alcoholism, and Handcap had two data entries, such that True (1), False (0).

The appointment_day has no hour specified (it equals to 00:00:00). We will not be able to analyze if the appointment hour has anything to do with no shows.

The scheduled_day and appointment_day columns type should be changed to datetime

I decided to keep PatientID as a reference column but and I will AppointmentID, since it is useless for the analysis No-Show is the dependent variable, which indicated whether the patient attended the appointment. The rest of the variables were the independent variables, which possibly contribute to the result of dependent variable.

Check if we need to create more columns with usefull data for the exploration We can add one more column to show which day of the week of the appointment is to explore where the day of the week is also another factor.

2.2.3 Data Cleaning

1. PatientId should be converted into string data type.

```
In [7]: # formatting the patient_id column as string
        df.PatientId = df.PatientId.apply(lambda patient: str(int(patient)))
```

2. Drop AppointmentID variable.

```
In [8]: # Remove some useless columns
        # I think the AppointmentID is useless for this analysis
        df.drop(['AppointmentID'], axis=1, inplace=True)
        df.columns
```

```
Out[8]: Index(['PatientId', 'Gender', 'ScheduledDay', 'AppointmentDay', 'Age',
               'Neighbourhood', 'Scholarship', 'Hipertension', 'Diabetes',
               'Alcoholism', 'Handcap', 'SMS_received', 'NoShow'],
              dtype='object')
```

3. The scheduled_day and appointment_day columns type should be changed to datetime.

```
In [9]: # Formatting the date time 'scheduled_day' and 'appointment_day' columns

        df.ScheduledDay = pd.to_datetime(df.ScheduledDay)
        df.AppointmentDay = df.AppointmentDay.apply(np.datetime64)

        df.ScheduledDay.head(1), df.AppointmentDay.head(1)
```

```
Out[9]: (0   2016-04-29 18:38:08
         Name: ScheduledDay, dtype: datetime64[ns], 0   2016-04-29
         Name: AppointmentDay, dtype: datetime64[ns])
```

4. Add one more column as WeekDay. WeekDay: to show what day of the week the appointment was scheduled

```
In [10]: # creating the first column "appointment_week_day"
         df['WeekDay'] = df.AppointmentDay.map(lambda day: day.day_name())
         df.head()
```

```
Out[10]:          PatientId Gender        ScheduledDay AppointmentDay  Age  \
         0   29872499824296      F 2016-04-29 18:38:08     2016-04-29   62
         1  558997776694438      M 2016-04-29 16:08:27     2016-04-29   56
         2    4262962299951      F 2016-04-29 16:19:04     2016-04-29   62
         3     867951213174      F 2016-04-29 17:29:31     2016-04-29    8
         4    8841186448183      F 2016-04-29 16:07:23     2016-04-29   56

                Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  \
         0    JARDIM DA PENHA            0             1         0           0
         1    JARDIM DA PENHA            0             0         0           0
         2      MATA DA PRAIA            0             0         0           0
         3  PONTAL DE CAMBURI            0             0         0           0
         4    JARDIM DA PENHA            0             1         1           0

            Handcap  SMS_received NoShow WeekDay
         0        0             0     No  Friday
         1        0             0     No  Friday
         2        0             0     No  Friday
         3        0             0     No  Friday
         4        0             0     No  Friday
```

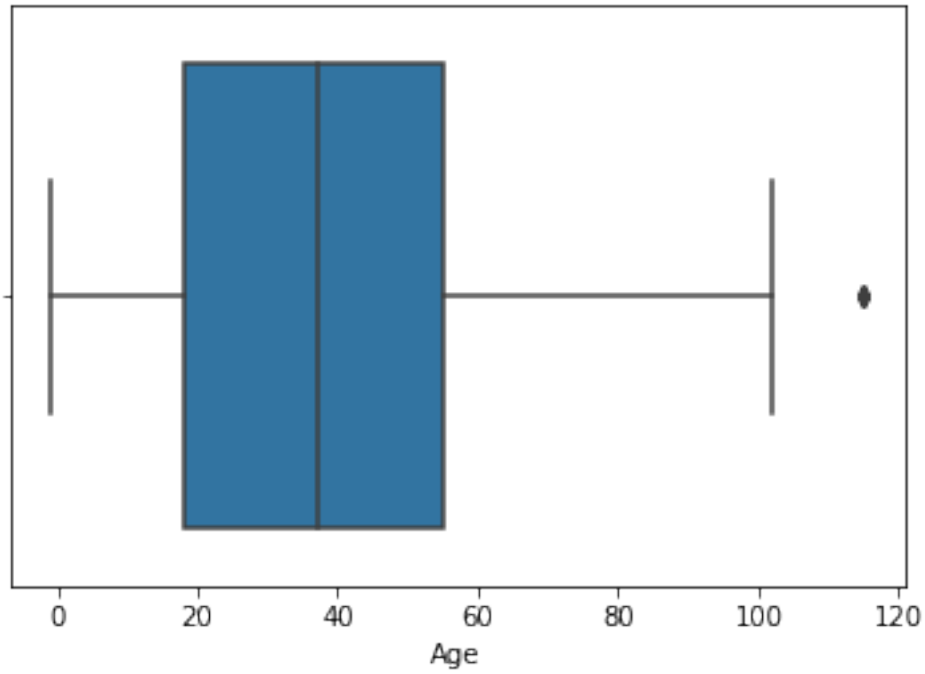
```
In [11]: #Take a look at age variable
         df.Age.value_counts()
```

```
Out[11]: 0      3539
         1      2273
         52     1746
         49     1652
         53     1651
         56     1635
         38     1629
         59     1624
         2      1618
         50     1613
         57     1603
         36     1580
         51     1567
         19     1545
         39     1536
         37     1533
         54     1530
         34     1526
         33     1524
         30     1521
         6      1521
         3      1513
         17     1509
         32     1505
         5      1489
         44     1487
         18     1487
         58     1469
         46     1460
         45     1453
                ...
         74      602
         76      571
         75      544
         78      541
         77      527
         80      511
         81      434
         82      392
         79      390
         84      311
         83      280
         85      275
         86      260
         87      184
```

```
89      173
88      126
90      109
92       86
91       66
93       53
94       33
95       24
96       17
97       11
98        6
115       5
100       4
102       2
99        1
-1        1
Name: Age, Length: 104, dtype: int64
```

```
In [12]: sns.boxplot(x=df['Age'])
```

```
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4f3977e908>
```



5. We could see Age column is having outliers of negative age and greater than 100 especially 115. Though 100+ age is possible in the real time scenario, still those are outliers and must be cleaned.

This cleaning can be done either by removing those since we have enough sample size.

```
In [13]: #clean age outliers and incorrect input.
         #I will remove the subjects with age entered as -1 and greater than 100

In [14]: df = df.drop(df[(df.Age >100) ].index)
         df = df[df.Age != -1]
```

After checking the dataset so far, it looks well cleaned and good to evaluate.

```
In [15]: df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 110519 entries, 0 to 110526
Data columns (total 14 columns):
PatientId         110519 non-null object
Gender            110519 non-null object
ScheduledDay      110519 non-null datetime64[ns]
AppointmentDay    110519 non-null datetime64[ns]
Age               110519 non-null int64
Neighbourhood     110519 non-null object
Scholarship       110519 non-null int64
Hipertension      110519 non-null int64
Diabetes          110519 non-null int64
Alcoholism        110519 non-null int64
Handcap           110519 non-null int64
SMS_received      110519 non-null int64
NoShow            110519 non-null object
WeekDay           110519 non-null object
dtypes: datetime64[ns](2), int64(7), object(5)
memory usage: 12.6+ MB


In [16]: df.describe()

Out[16]:                 Age    Scholarship   Hipertension       Diabetes  \
         count  110519.000000  110519.000000  110519.000000  110519.000000
         mean       37.084519       0.098273       0.197251       0.071870
         std        23.103165       0.297684       0.397925       0.258274
         min         0.000000       0.000000       0.000000       0.000000
         25%        18.000000       0.000000       0.000000       0.000000
         50%        37.000000       0.000000       0.000000       0.000000
         75%        55.000000       0.000000       0.000000       0.000000
         max       100.000000       1.000000       1.000000       1.000000

                   Alcoholism        Handcap   SMS_received
         count  110519.000000  110519.000000  110519.000000
         mean        0.030402       0.022213       0.321040
         std         0.171692       0.161441       0.466878
```

```
min         0.000000        0.000000        0.000000
25%         0.000000        0.000000        0.000000
50%         0.000000        0.000000        0.000000
75%         0.000000        0.000000        1.000000
max         1.000000        4.000000        1.000000
```

Now, the data had 110,519 subjects in 14 variables. The maximum age is 100 now.

3

3.1 Research Questions

3.1.1 Question 1: What is the independent variable? What is the dependent variable?

3.1.2 Question 2: What are the no show record differences between female and male?

3.1.3 Question 3: What is the distribution of age of show and no show?

3.1.4 Question 4: Which day of the week is more likely to have no-show? What is the distribution look like?

Exploratory Data Analysis

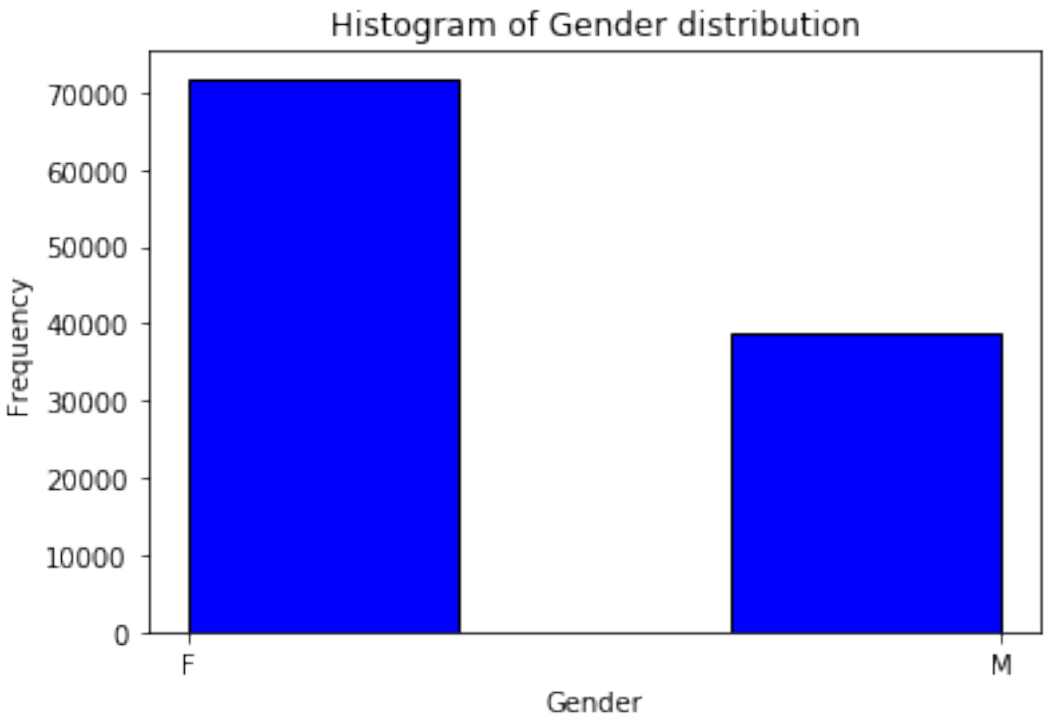
> **Tip**: Now that you've trimmed and cleaned your data, you're ready to move on to exploration. Compute statistics and create visualizations with the goal of addressing the research questions that you posed in the Introduction section. It is recommended that you be systematic with your approach. Look at one variable at a time, and then follow it up by looking at relationships between variables.

3.1.5 Question 1: What is the independent variable? What is the dependent variable?

Gender,ScheduledDay,AppointmentDay, Age, Neighbourhood, Scholarship, Hipertension, Diabetes, Alcoholism, Handcap, SMS_received and WeekDay are independent variables. Whether the patient was no-show (No-show) is the dependent variable

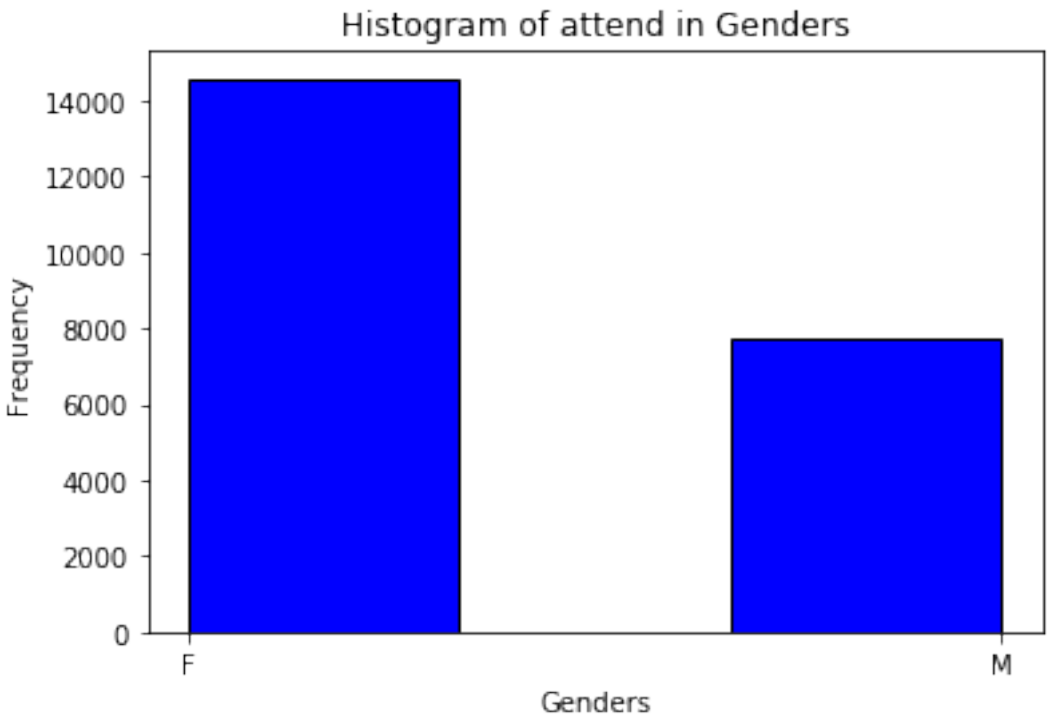
3.1.6 Question 2: What are the no show record differences between female and male?

```
In [17]: plt.hist(df['Gender'], color = 'blue', edgecolor = 'black',
                   bins = int(180/50))
         plt.title('Histogram of Gender distribution')
         plt.xlabel('Gender')
         plt.ylabel('Frequency')

Out[17]: Text(0,0.5,'Frequency')
```



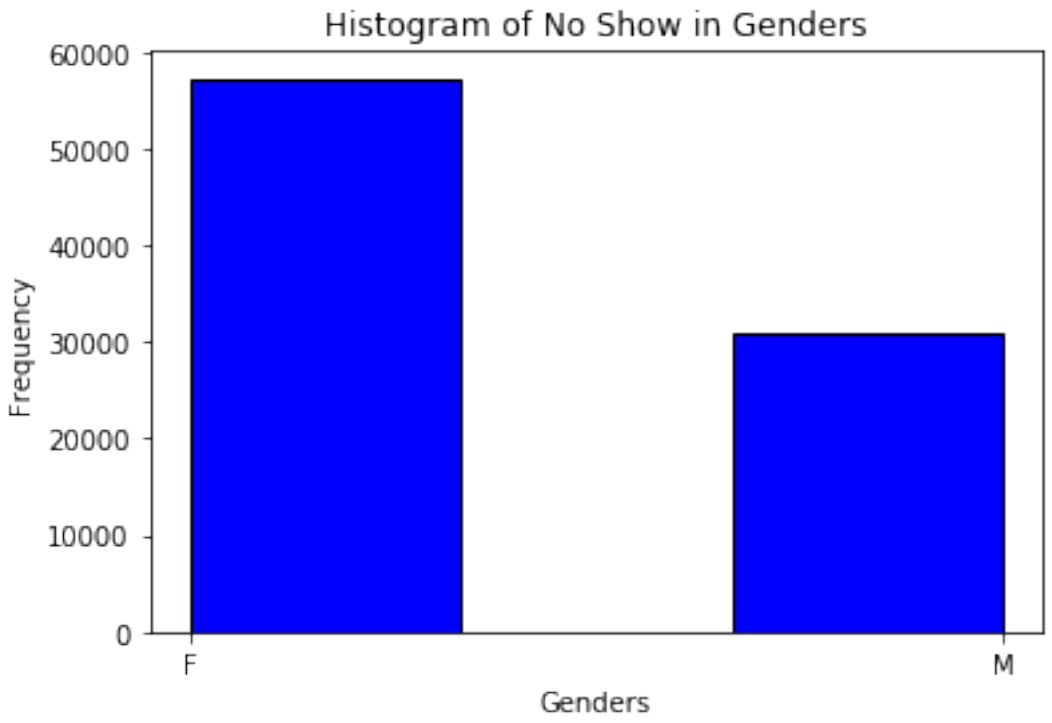
There are around 70000 female patients and 40000 male patients in the record.

```
In [18]: # name the no show records
         attend=df.NoShow=="Yes"
         not_attend=df.NoShow=="No"

In [19]: plt.hist(df.Gender[attend], color = 'blue', edgecolor = 'black',
                  bins = int(180/50))
         plt.title('Histogram of attend in Genders')
         plt.xlabel('Genders')
         plt.ylabel('Frequency')

Out[19]: Text(0,0.5,'Frequency')
```



The above histogram showed that there were more female patients attended for the appointments than male patients.

```
In [20]: plt.hist(df.Gender[not_attend], color = 'blue', edgecolor = 'black',
                  bins = int(180/50))
         plt.title('Histogram of No Show in Genders')
         plt.xlabel('Genders')
         plt.ylabel('Frequency')

Out[20]: Text(0,0.5,'Frequency')
```



The above histogram showed that there were more female patients no showed for the appointments than male patients.

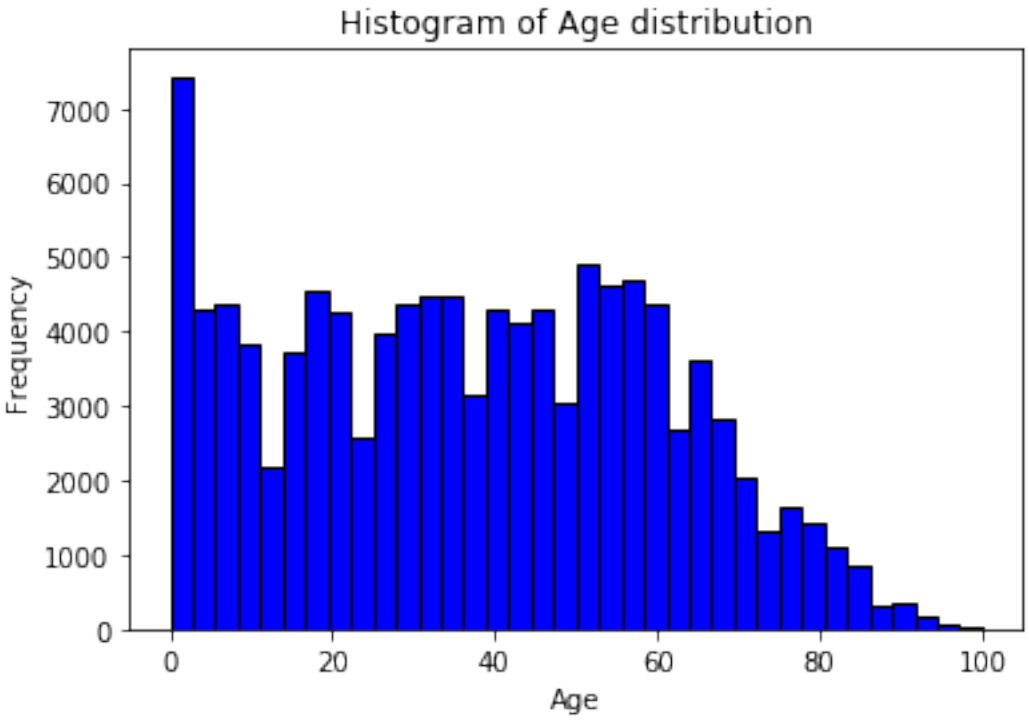
```
In [21]: #NoShow record categorized by genders
         df.groupby ('Gender')['NoShow'].value_counts()

Out[21]: Gender  NoShow
         F       No        57241
                 Yes       14591
         M       No        30962
                 Yes        7725
         Name: NoShow, dtype: int64

In [22]: #Count genders
         df.Gender.value_counts()

Out[22]: F    71832
         M    38687
         Name: Gender, dtype: int64

In [23]: #Female no show
         14591/71832

Out[23]: 0.2031267401715113

In [24]: #Male no show
         7725/38687
```

```
Out[24]: 0.19967947889471915
```

The percentage of no show in female group is slightly higher than male group. The percentage of no show in female group is 20.31%. The percentage of no show in male group is 19.67%.

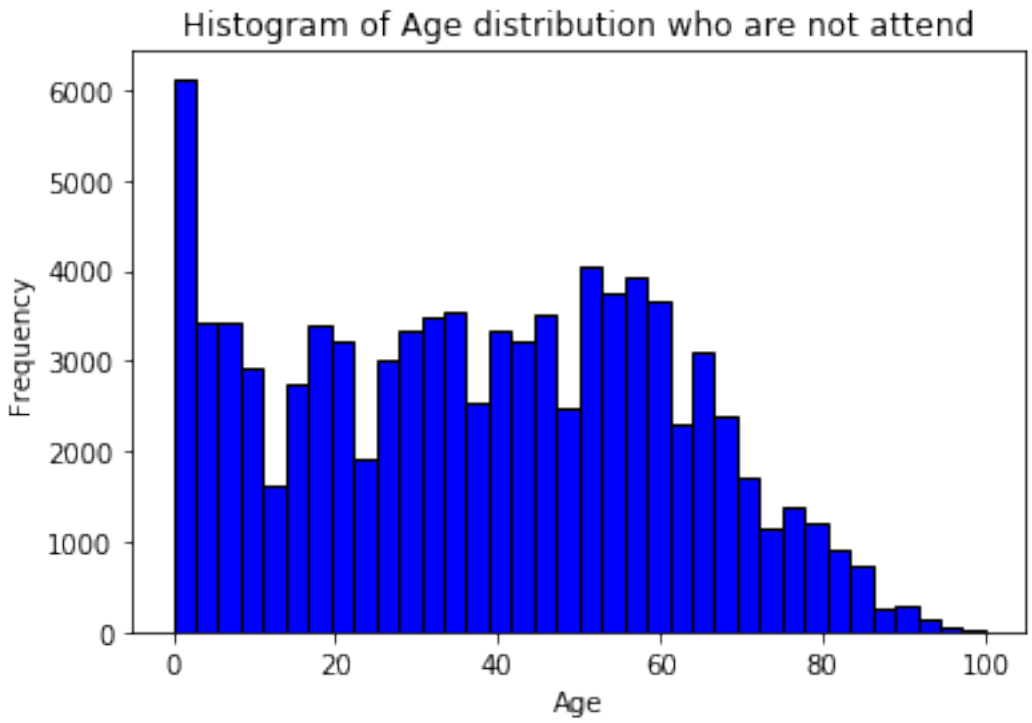
3.1.7 Question 3: What is the distribution of age of show and no show?

```
In [25]: # matplotlib histogram
         plt.hist(df['Age'], color = 'blue', edgecolor = 'black',
                  bins = int(180/5))
         plt.title('Histogram of Age distribution')
         plt.xlabel('Age')
         plt.ylabel('Frequency')

Out[25]: Text(0,0.5,'Frequency')
```



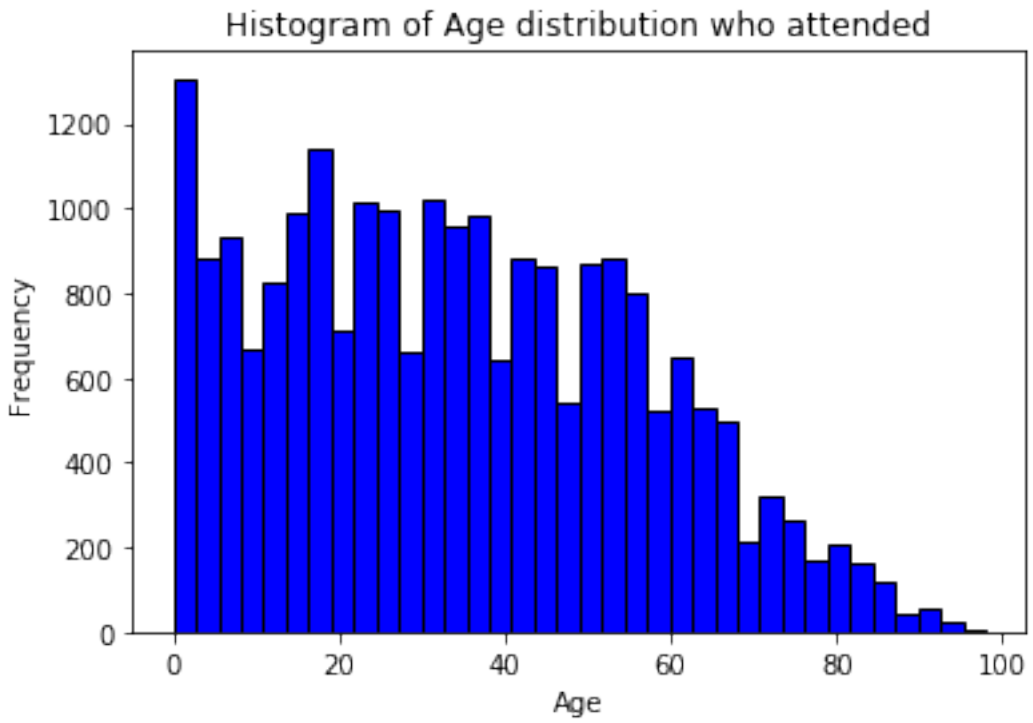
According to the above histogram, we can tell that the age distribution is skew to the right. The mode of age is at the age of baby.

```
In [26]: plt.hist(df.Age[not_attend], color = 'blue', edgecolor = 'black',
                  bins = int(180/5))
         plt.title('Histogram of Age distribution who are not attend')
         plt.xlabel('Age')
         plt.ylabel('Frequency')

Out[26]: Text(0,0.5,'Frequency')
```



According to the above histogram, we can tell that the no show record corresponding to age is skew to the right. Fewer no shows were happend the older people.

```
In [27]: plt.hist(df.Age[attend], color = 'blue', edgecolor = 'black',
                  bins = int(180/5))
         plt.title('Histogram of Age distribution who attended')
         plt.xlabel('Age')
         plt.ylabel('Frequency')

Out[27]: Text(0,0.5,'Frequency')
```

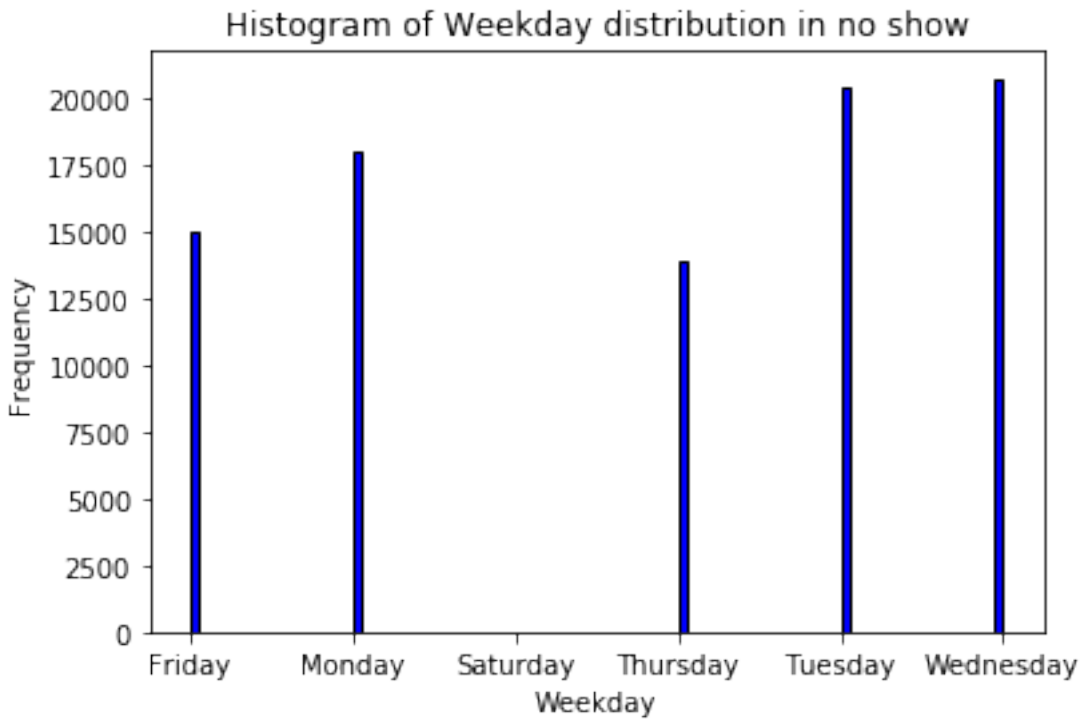


According to the above histogram, we can tell that the attended record corresponding to age is skew to the right. Fewer no shows were happend the older people. With the increase in age, the attend frequency decreased and increased until the age around 60. Then there is a sharply decrease of attended record for older people.

In [ ]:

3.1.8 Question 4: Which day of the week is more likely to have no-show? What is the distribution look like?

```
In [28]: plt.hist(df.WeekDay[not_attend], color = 'blue', edgecolor = 'black',
                  bins = int(180/2))
         plt.title('Histogram of Weekday distribution in no show')
         plt.xlabel('Weekday')
         plt.ylabel('Frequency')

Out[28]: Text(0,0.5,'Frequency')
```



According to the above histogram, only few patients are no show on Saturday's appointment. It is most likely that the patients are not showing at the appointments on Tuesday and Wednesday.

```
In [29]: df.groupby ('WeekDay')['NoShow'].value_counts()

Out[29]: WeekDay    NoShow
         Friday     No         14981
                    Yes         4037
         Monday     No         18023
                    Yes         4689
         Saturday   No            30
                    Yes            9
         Thursday   No         13908
                    Yes         3336
         Tuesday    No         20487
                    Yes         5152
         Wednesday  No         20774
                    Yes         5093
         Name: NoShow, dtype: int64

In [30]: df.WeekDay.value_counts()

Out[30]: Wednesday    25867
         Tuesday      25639
         Monday       22712
```

```
Friday       19018
Thursday     17244
Saturday        39
Name: WeekDay, dtype: int64
```

```
In [31]: #Wednesday
         print(5093/25867)
         #Tuesday
         print(5152/25639)
         #Monday
         print(4689/22712)
         #Friday
         print(4037/19018)
         #Thursday
         print(3336/17244)
         #Saturday
         print(9/39)
```

```
0.19689179263153825
0.20094387456609072
0.2064547375836562
0.21227258386791462
0.19345859429366735
0.23076923076923078
```

Although the no show frequency is lowest on Saturdays. The percentage of no show is highest on Saturdays. The percentage of no show is lowest on Thursdays which is 19.35%.

Conclusions Different categories of patients are having different performance on no show. There are more female patients than male patients in total. The percentage of no show in female group is slightly higher than male group. The percentage of no show in female group is 20.31%. The percentage of no show in male group is 19.67%.

Although the no show frequency is lowest on Saturdays. The percentage of no show is highest on Saturdays. The percentage of no show is lowest on Thursdays which is 19.35%.

```
In [32]: df.isnull().sum()
```

```
Out[32]: PatientId         0
         Gender            0
         ScheduledDay      0
         AppointmentDay    0
         Age               0
         Neighbourhood     0
         Scholarship       0
         Hipertension      0
         Diabetes          0
         Alcoholism        0
         Handcap           0
         SMS_received      0
```

```
NoShow            0
WeekDay           0
dtype: int64
```

There are some limitations in the data. There are no data is having null values or highly correlated having erroneous or missing values or imbalanced data.

Based on the age distribution, most of the patients are lying on a yonunger age range, which is a great reflection to the normal distributed age range. This will lead to wrong analysis which will lead to wrong predictions or biased analysis on no show in age.

```
In [33]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

```
Out[33]: 0
```