Appointments

May 28, 2022

1 Project: Hospital Data Analysis

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Introduction > This analysis focuses on examining the **No-Show appointments** data from Kaggle. In the dataset, about 100,000 medical appointment records from Brazil have been featured. The information captured in the dataset include the patient's **id, Appointment Id, Gender, ScheduledDay, AppointmentDay, Age, Neighbourhood, Scholarship, Hipertension, Diabetes, Alcoholism, Handcap, SMS_received, No-show** > ### Definition of important variables. » *Gender*: Describes whether the patient is **male** or **female**. » *ScheduledDay*: Tells us on what day the patient set up their appointment. » *Age*: Indicates the patients age. » *Neighbourhood*: Indicates the location of the hospital. » *Scholarship*: Indicates whether or not the patient is enrolled in Brasilian welfare program Bolsa Família. » *Hipertension*: Indicates whether a patient has Hipertension or not » *Diabetes*: Indicates whether a patient is diabetic or not. » *Alcoholism*: Indicates whether a patient alcoholic or not. » *Handcap*: Indicates whether a patient is Handcapped or not. » *SMS_received*: Indicates whether a patient received sms notifications about the appointment or not. » *No-show*: Indicates whether a patient showed up for their appointment or not. »> #### Important Points to Note: »» 1. For the *Scholarship*, *Hipertension*, *Diabetes*, *Alcoholism*, *Handcap*, and *SMS_received* fields, **1 = Yes** and **0 = No** »» 2. For the *No-show* field, **No = The patient showed up for the appointment** and **yes = The patient did not show up for the appointment** > ### Questions to be answered. » Q1: Do patients of particular age groups book appointments more frequently than others? » Q2: Are male patients more likely to show up for an appointment as compared to female patients? » Q3: Are older patients more likely to show up for an appointment as compared to the younger patients? » Q4: How do the location of a hospital affect appointment attendance? » Q5: Are patients who are enrolled in Brasilian welfare program more likely to show up for scheduled appointments? » Q6: How do positive diagnosis of health conditions such as hipertension, Diabetes, Alcoholism, and Handcap affect appointment attendance?

[1]:
```
# Import the required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from pandas import Series
from matplotlib.pyplot import figure

%matplotlib inline
```

Data Wrangling

1.2 General Properties

[2]:
```
# Loading the data and set the 'AppointmentID' as the index
df = pd.read_csv('Dataset/appointments_data.csv')

# Verify that the data was loaded successfully
df.head()
```

[2]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_received	No-show
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	0	1	0	0	0	0	No
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	0	0	0	0	0	No
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	0	0	0	0	0	0	No
3	8.679512e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	0	0	0	0	0	0	No
4	8.841186e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	1	1	0	0	0	No

[3]:
```
# Examine the datatypes of the data in every column in the dataset
df.dtypes
```

[3]:
```
PatientId         float64
AppointmentID       int64
Gender             object
ScheduledDay       object
AppointmentDay     object
Age                 int64
Neighbourhood      object
Scholarship         int64
Hipertension        int64
Diabetes            int64
```

```
Alcoholism          int64
Handcap             int64
SMS_received        int64
No-show            object
dtype: object
```

All the numerical columns in the dataset are set as integers while the columns with text data are set to string as required.

[4]:
```
# Descrptive summary for patient ages
df.Age.describe()
```

[4]:
```
count    110527.000000
mean         37.088874
std          23.110205
min          -1.000000
25%          18.000000
50%          37.000000
75%          55.000000
max         115.000000
Name: Age, dtype: float64
```

This summary indicates that the minimum age entry is -1 years while the maximum age entry is 115 years. **-1 is not a reasonable age and therefore needs some cleaning attention**

[5]:
```
# Examine the number of columns and rows in the data
df.shape
```

[5]:
```
(110527, 14)
```

The dataset has 14 columns and 110527 entries

[6]:
```
# Check whether the data has any duplicated records
df.duplicated().sum()
```

[6]:
```
0
```

The dataset has no duplicated records

[7]:
```
# check for records with null values.
df.isnull().sum()
```

[7]:
```
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 values in the dataset.

[8]:
```
# Check the number of unique appointments record by appointment id
df['AppointmentID'].nunique()
```

[8]:
```
110527
```

There are 110527 unique appoint records in the dataset

[9]:
```
# How many unique patients are captured in the dataset?
df['PatientId'].nunique()
```

[9]:
```
62299
```

62,299 unique patients have been captured in the dataset. - This shows that some patients set more than one appointments.

[10]:
```
# How many appointments were made by patients with hipertension in the dataset?
df['Hipertension'].value_counts()
```

[10]:
```
0    88726
1    21801
Name: Hipertension, dtype: int64
```

Of all the appointments that were recorded, 21,810 appointments were made by patients who had hipertension.

[11]:
```
# How many appointments were made by patients with Scholarship?
df['Scholarship'].value_counts()
```

[11]:
```
0    99666
1    10861
Name: Scholarship, dtype: int64
```

Of all the appointments that were recorded, 10861 appointments were made by patients who had enrolled in Brasilian welfare program Bolsa Família.

[12]:
```
# How many appointments were made by patients with alcoholism?
df.Alcoholism.value_counts()
```

[12]:
```
0    107167
1      3360
Name: Alcoholism, dtype: int64
```

Of the appointments that were made, 3360 from patients with alcoholism.

[13]:
```
# How many appointments were made by patients who had received SMS?
df.SMS_received.value_counts()
```

[13]:
```
0    75045
1    35482
Name: SMS_received, dtype: int64
```

Of all the appointments that were made, 35,482 were made by individuals who received SMS

1.2.1 *Cleaning Remarks:* The dataset :-

1. Does not have any duplicated records.
2. Has no null values.
3. Has all the columns set to the correct datatypes
4. Has one erroneous age entry, **-1**, which needs to be removed.
5. Has the last column named **No-show** instead of **No_show**. This needs to be addressed
6. Has some columns that we may not be needed in the analysis process.
7. Needs to have the `AppointmentId` field set as the index. **In the data cleaning step, we need to address remarks 4, 5, 6, and 7**

1.3 Data cleaning

[14]:
```
# Make a copy of the original dataset
df_new = df.copy()

# Verify that the data was copied successfully
df_new.head(3)
```

[14]:

	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	

	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	

```
   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
```

[15]:
```
# Display all the columns for ease of reference
df_new.columns
```

[15]:
```
Index(['PatientId', 'AppointmentID', 'Gender', 'ScheduledDay',
       'AppointmentDay', 'Age', 'Neighbourhood', 'Scholarship', 'Hipertension',
       'Diabetes', 'Alcoholism', 'Handcap', 'SMS_received', 'No-show'],
      dtype='object')
```

We need to drop the `AppointmentDay` column.

1.3.1 Dropping the `AppointmentDay` column

[16]:
```
# Drop the columns
df_new.drop(columns='AppointmentDay', axis=1, inplace=True)

# Verify that the columns were dropped successfully
df_new.columns
```

[16]:
```
Index(['PatientId', 'AppointmentID', 'Gender', 'ScheduledDay', 'Age',
       'Neighbourhood', 'Scholarship', 'Hipertension', 'Diabetes',
       'Alcoholism', 'Handcap', 'SMS_received', 'No-show'],
      dtype='object')
```

1.3.2 Dropping the record with an erroneous age entry

[17]:
```
# View the Record
odd_age = df_new.query('Age < 0')
odd_age
```

[17]:
```
          PatientId  AppointmentID Gender          ScheduledDay  Age  \
99832  4.659432e+14        5775010      F  2016-06-06T08:58:13Z   -1

      Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
99832         ROMÃO            0             0         0           0        0

       SMS_received No-show
99832             0      No
```

[18]:
```
# Drop the Record
df_new.drop(odd_age.index, inplace=True)

# Verify that the entry was dropped
df_new.query('Age < 0') # This should return an empty dataset if the drop was␣
 ↪successful
```

[18]:
```
Empty DataFrame
Columns: [PatientId, AppointmentID, Gender, ScheduledDay, Age, Neighbourhood,
Scholarship, Hipertension, Diabetes, Alcoholism, Handcap, SMS_received, No-show]
Index: []
```

1.3.3 Set `AppointmentID` as the index column

[19]:
```
df_new.set_index('AppointmentID', inplace=True)

# Confirm that the index was changed successfully
df_new.head(1)
```

[19]:
```
                  PatientId Gender          ScheduledDay  Age  \
AppointmentID
5642903        2.987250e+13      F  2016-04-29T18:38:08Z   62

                Neighbourhood  Scholarship  Hipertension  Diabetes  \
AppointmentID
5642903        JARDIM DA PENHA            0             1         0

                Alcoholism  Handcap  SMS_received No-show
AppointmentID
5642903                  0        0             0      No
```

1.3.4 Rename the column named `No-show` to `No_show`

[20]:
```
#df_new['N-show']=df_new['No_show']
df_new.rename(columns={'No-show':'No_show'}, inplace = True)
df_new.columns
```

[20]:
```
Index(['PatientId', 'Gender', 'ScheduledDay', 'Age', 'Neighbourhood',
       'Scholarship', 'Hipertension', 'Diabetes', 'Alcoholism', 'Handcap',
       'SMS_received', 'No_show'],
      dtype='object')
```

1.3.5 Save the cleaned dataset in a new csv file.

[21]:
```
df_new.to_csv('Dataset/clean_data.csv', index=True)
```

Exploratory Data Analysis (EDA)

[22]:
```
# Load the cleaned dataset.
df_clean = pd.read_csv('Dataset/clean_data.csv')

# Verify that the data was loaded successfully
df_clean.head(1)
```

[22]:
```
   AppointmentID     PatientId Gender          ScheduledDay  Age  \
0        5642903  2.987250e+13      F  2016-04-29T18:38:08Z   62

     Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
0  JARDIM DA PENHA            0             1         0           0        0

   SMS_received No_show
0             0      No
```

For this EDA process, when analyzing the data to come up with solutions for the raised questions, we will be needing to work with proportions in multiple occassions. To avoid repetition, it is elegant to define a function that we can invoke any time we want to calculate a proportion. The cell below defines a `proportion function`

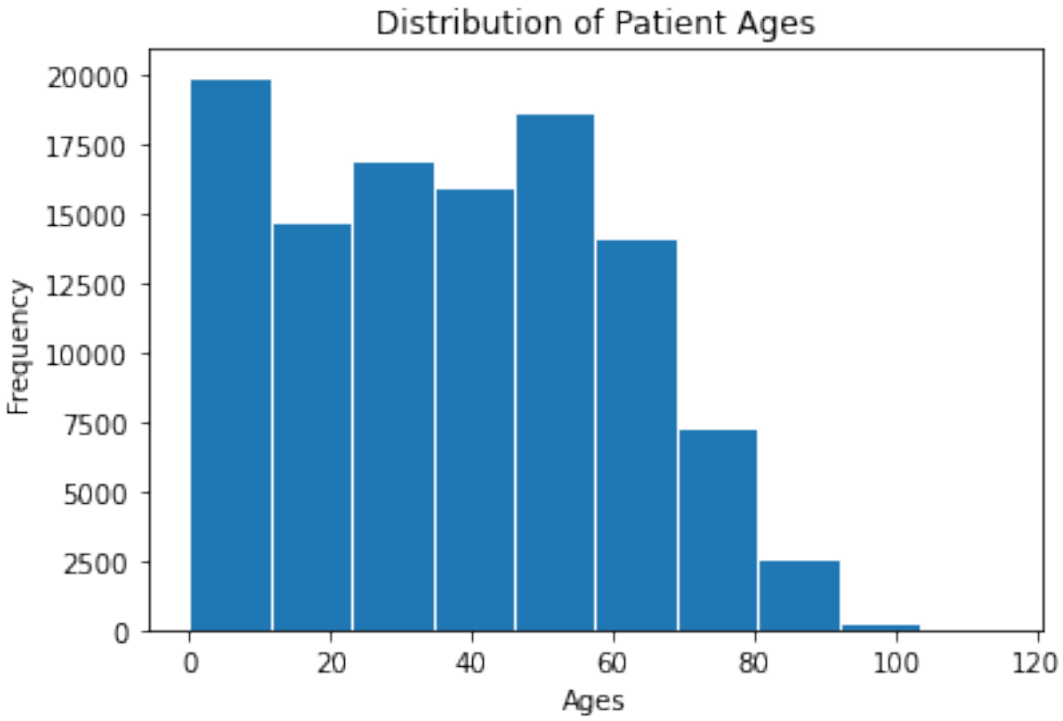
[23]:
```
# Defining the proportion funtion
def proportion(total, interest_items):
    """
    Description: This is a function that calculates the proportion of items of␣
 ↪interest

    Inputs:
        total: This is the total number of items to be considered in␣
 ↪calculating the proportions
        interest_items: This is the number of items of interest whose␣
 ↪proportion needs to be calculated.
    Results:
        prop: This is the result obtained after dividing the interest_items by␣
 ↪the total
    """
    if interest_items > total:
        result = "Items of interest must be less than or equal to the total␣
 ↪number of items"
    else:
        result = interest_items/total
    return(result)
```

1.4 Research Question 1: Do patients of particular age groups book appointments more frequently than others?

To Respond to this question, we need to examine how the ages of the patients who booked appointments in all hospitals are distributed. To do this, we need to visualize the ages using a histogram

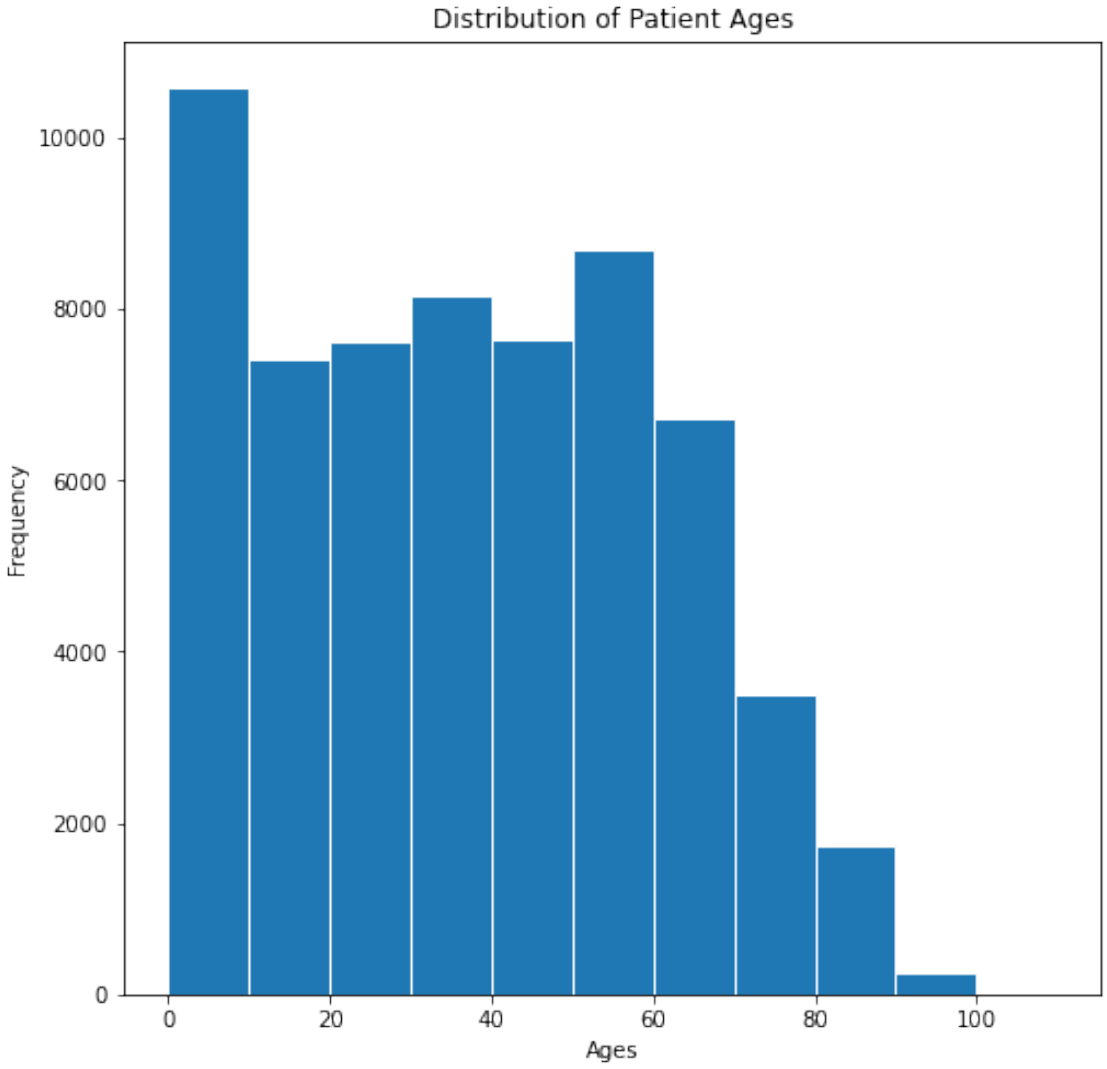
[24]:
```
# Check the distribution of the ages of the patients
df_clean.Age.plot(kind= 'hist', edgecolor='white')
plt.title('Distribution of Patient Ages')
plt.xlabel('Ages')
```

```
plt.ylabel('Frequency');
```



This does not give a clear picture of the distribution of the patient ages because as initially established, several patients made more than one appointment. To get a more accurate visualization, we need to plot the histogram using ages for the unique patients only.

[25]:
```
# Extract the data for the unique patients
unique_patients = df_clean.drop_duplicates(subset='PatientId', keep='first')

# Use the ages in this new dataset to examine the distribution of patient ages.
# unique_patients['Age'].plot(kind='hist')
ages = unique_patients['Age']
bins = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110]
fig, ax = plt.subplots(figsize = (8,8))
ax.hist(ages, bins, edgecolor='white')
plt.title('Distribution of Patient Ages')
plt.xlabel('Ages')
plt.ylabel('Frequency');
```



1.4.1 Question 1 Response:

1.5 Research Question 2: Are male patients more likely to show up for an appointment as compared to female patients?

To arrive at a conclusive and valid question for this research question, we need to compare the proportion of male patients who showed up for the appointment and the proportion of women who showed up for the appointment

1.5.1 Step 1: separate the data into two dataframes

male_df = Dataframe with only the appointments booked by male patients
female_df = Dataframe with only the appointments booked by female patients

[26]:
```
# Extract the appointments booked by males
male_df = df_clean.query('Gender == "M"')
male_df.head(2)
```

[26]:
```
    AppointmentID     PatientId Gender          ScheduledDay  Age  \
1         5642503  5.589978e+14      M  2016-04-29T16:08:27Z   56
11        5620163  7.542951e+12      M  2016-04-26T08:44:12Z   29

      Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
1   JARDIM DA PENHA            0             0         0           0        0
11   NOVA PALESTINA            0             0         0           0        0

    SMS_received No_show
1              0      No
11             1     Yes
```

[27]:
```
# Verify that there are no Female entries in the male dataframe
male_df.query('Gender == "F"')
# This should display an empty dataset if there are no entries that have gender␣
 ↪set as female.
```

[27]:
```
Empty DataFrame
Columns: [AppointmentID, PatientId, Gender, ScheduledDay, Age, Neighbourhood,
Scholarship, Hipertension, Diabetes, Alcoholism, Handcap, SMS_received, No_show]
Index: []
```

[28]:
```
# Extract the appointments booked by males
female_df = df_clean.query('Gender == "F"')
female_df.head(2)
```

[28]:
```
   AppointmentID     PatientId Gender          ScheduledDay  Age  \
0        5642903  2.987250e+13      F  2016-04-29T18:38:08Z   62
2        5642549  4.262962e+12      F  2016-04-29T16:19:04Z   62

     Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
0  JARDIM DA PENHA            0             1         0           0        0
2    MATA DA PRAIA            0             0         0           0        0

   SMS_received No_show
0             0      No
2             0      No
```

[29]:
```
# Verify that there are no male entries in the female dataframe
female_df.query('Gender == "M"')
# This should display an empty dataset if there are no entries that have gender␣
 ↪set as male.
```

[29]:
```
Empty DataFrame
Columns: [AppointmentID, PatientId, Gender, ScheduledDay, Age, Neighbourhood,
Scholarship, Hipertension, Diabetes, Alcoholism, Handcap, SMS_received, No_show]
Index: []
```

1.5.2 Step 2: Calculate the proportion of male patients who showed up for the appointment

Based on the description of the proportion function defined above, we need to obtain the **total number of male patients** and **the number of male patients who showed up for the appointments**

[30]:
```
# Find the total number of male patients who made appointments
total_males_appointments = male_df.AppointmentID.value_counts().sum()

# Find the number of male patients who showed up for the appointments
No_of_males_who_attended = male_df.query('No_show == "No"').value_counts().sum()

# Print out the obtained values
print(total_males_appointments)
print(No_of_males_who_attended)
```

```
38687
30962
```

[31]:
```
# Invoke the proportion function to calculate the proportion of male patients␣
 ↪who showed up for the appointments
prop_M_who_showed = proportion(total_males_appointments,␣
 ↪No_of_males_who_attended)
prop_M_who_showed
```

[31]:
```
0.8003205211052808
```

1.5.3 Step 3: Calculate the proportion of female patients who showed up for the appointment

This follows the same procedure as step 2 above

[32]:
```
# Find the total number of female patients who made appointments
total_females_appointments = female_df.AppointmentID.value_counts().sum()

# Find the number of female patients who showed up for the appointments
No_of_females_who_attended = female_df.query('No_show == "No"').value_counts().
 ↪sum()
```

```
# Print out the obtained values
print(total_females_appointments)
print(No_of_females_who_attended)
```

```
71839
57245
```

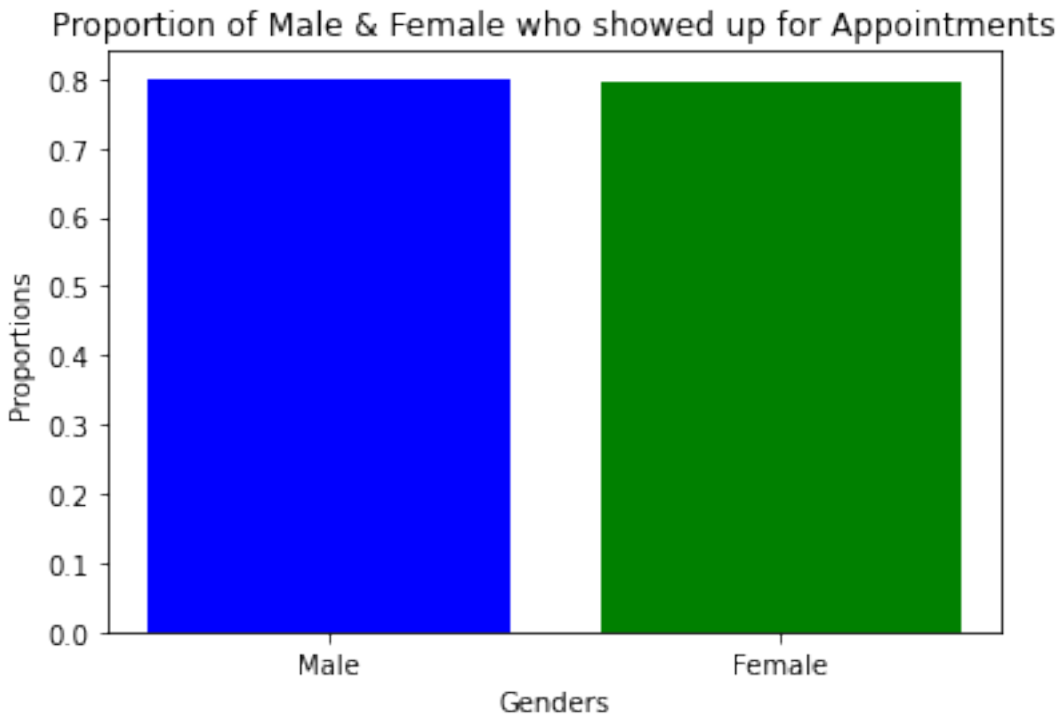
[33]:
```
# Invoke the proportion function to calculate the proportion
prop_F_who_showed = proportion(total_females_appointments,␣
 ↪No_of_females_who_attended)
prop_F_who_showed
```

[33]:
```
0.7968512924734475
```

Comparing the results from step 2 and 3, we can tell that the proportion of male patients who showed up for their appointments is slightly higher than that of the female patients. To get a clear picture of how these two proportions vary, we need to visualize them using a bar graph.

1.5.4 Step 4: Visualize the proportions

[34]:
```
genders = ['Male','Female']
props = [prop_M_who_showed, prop_F_who_showed]
colors = ['blue','Green']
plt.bar(genders, props, color = colors)
plt.title('Proportion of Male & Female who showed up for Appointments')
plt.xlabel('Genders')
plt.ylabel('Proportions')

plt.show();
```



1.5.5 Question 2 Response

The visualization above shows that the proportion of males who showed up for the appointment is almost equal to the proportion of the females who showed up for the appointment

1.6 Research Question 3: Are older patients more likely to show up for an appointment as compared to the younger patients?

To respond to this question, we need to divide the cleaned dataset into two datasets, one to hold appointments for the older patients and one to hold the records for the younger patients. The young patients are those whose age is less than or equal to the median age while the older patients are those whose age falls above the median age. > **young_df** : Dataframe for the young patients > **older_df** : Datafram for the older patients

1.6.1 Step 1: Determine the median age

[35]:
```
median_age = df_clean['Age'].median()
median_age
```

[35]:
```
37.0
```

1.6.2 Step 2: Separate the dataset

[36]:
```
# The young patients
young_df = df_clean.query('Age <= {}'.format(median_age))
young_df.head(2)
```

[36]:
```
   AppointmentID     PatientId Gender          ScheduledDay  Age  \
3        5642828  8.679512e+11      F  2016-04-29T17:29:31Z    8
6        5630279  7.336882e+14      F  2016-04-27T15:05:12Z   23

       Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  \
3  PONTAL DE CAMBURI            0             0         0           0
6         GOIABEIRAS            0             0         0           0

   Handcap  SMS_received No_show
3        0             0      No
6        0             0     Yes
```

[37]:
```
# The older patients
older_df = df_clean.query('Age > {}'.format(median_age))
older_df.head(2)
```

[37]:
```
   AppointmentID     PatientId Gender          ScheduledDay  Age  \
0        5642903  2.987250e+13      F  2016-04-29T18:38:08Z   62
1        5642503  5.589978e+14      M  2016-04-29T16:08:27Z   56

     Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
0  JARDIM DA PENHA            0             1         0           0        0
1  JARDIM DA PENHA            0             0         0           0        0

   SMS_received No_show
0             0      No
1             0      No
```

[38]:
```
# Verify that the two dataframes are disjoint
(older_df.AppointmentID.value_counts().sum())+(young_df.AppointmentID.
 ↪value_counts().sum()) == df_clean.AppointmentID.value_counts().sum()
# This should return True if the two datasets are disjoint.
```

[38]:
```
True
```

1.6.3 Step 3: Find the proportion of young patients who showed up for appointments

[39]:
```
# Find the total number of young patients
total_young = young_df.AppointmentID.value_counts().sum()
total_young
```

[39]: 56116

[40]:
```
# Find the number of young patients who showed up for their appointments
Num_Young_showed_up = young_df.query('No_show == "No"').value_counts().sum()
Num_Young_showed_up
```

[40]: 43355

[41]:
```
# Invoke the Proportion function to calculate the proportion of young patients␣
↪who showed up for the appointment
prop_young = proportion(total_young, Num_Young_showed_up)
prop_young
```

[41]: 0.7725960510371374

1.6.4 Step 4: Find the proportion of older patients who showed up for appointments

[42]:
```
# Find the total number of older patients
total_older = older_df.AppointmentID.value_counts().sum()
total_older
```

[42]: 54410

[43]:
```
# Find the number of young patients who showed up for their appointments
Num_Older_showed_up = older_df.query('No_show == "No"').value_counts().sum()
Num_Older_showed_up
```

[43]: 44852

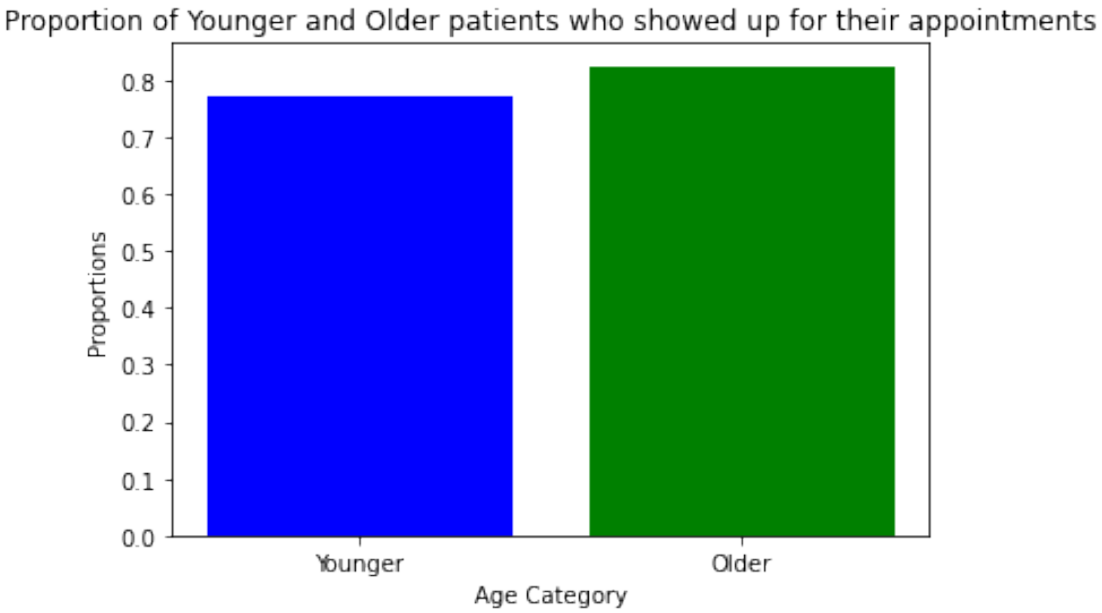
[44]:
```
# Invoke the Proportion function to calculate the proportion of older patients␣
↪who showed up for the appointment
prop_old = proportion(total_older, Num_Older_showed_up)
prop_old
```

[44]: 0.8243337621760706

Comparing the results obtained in step 3 and step 4, it is evident that the proportion of older patients who showed up for their appointment is higher than that of the younger patients who showed up for the appointment. **For better clarity, it is important to visualize these results**

1.6.5 Step 5: Visualize the results

[45]:
```
ages = ['Younger', 'Older']
age_proportions = [prop_young, prop_old]
colors = ['Blue', 'Green']
plt.bar(ages, age_proportions, color=colors)
plt.title('Proportion of Younger and Older patients who showed up for their␣
 ↪appointments')
plt.xlabel('Age Category')
plt.ylabel('Proportions')

plt.show();
```



The visualization clearly shows that the proportion of older patients who showed up for their appointments was a bit higher as compared to that of the younger patients

1.7 Research Question 4: How do the location of a hospital affect appointment attendance?

- To effectively respond to this question, it is necessary to identify the counts of the number of appointments made to hospitals in the varous neighbourhoods.

- It is also necessary to identify the total number of attended appointments in hospitals in every neighbourhood.

[46]:
```
# Find the total number of appointments made for every neighbourhood
total_appointments_by_nbd = df_clean['Neighbourhood'].value_counts()
total_appointments_by_nbd
```

[46]:
```
JARDIM CAMBURI                 7717
MARIA ORTIZ                    5805
RESISTÊNCIA                    4431
JARDIM DA PENHA                3877
ITARARÉ                        3514
                               ...
ILHA DO BOI                      35
ILHA DO FRADE                    10
AEROPORTO                         8
ILHAS OCEÂNICAS DE TRINDADE       2
PARQUE INDUSTRIAL                 1
Name: Neighbourhood, Length: 81, dtype: int64
```

[47]:
```
# Find the total number of attended appointments for every neighbourhood
total_attendants_by_nbd = df_clean.query('No_show == "No"')['Neighbourhood'].
 ↪value_counts()
total_attendants_by_nbd
```

[47]:
```
JARDIM CAMBURI       6252
MARIA ORTIZ          4586
RESISTÊNCIA          3525
JARDIM DA PENHA      3246
SANTA MARTHA         2635
                     ...
PONTAL DE CAMBURI      57
ILHA DO BOI            32
ILHA DO FRADE           8
AEROPORTO               7
PARQUE INDUSTRIAL       1
Name: Neighbourhood, Length: 80, dtype: int64
```

Comparing the two results above: **Note**: *In the total number of appointments made for every neighbourhood, there are 81 neighbourhoods while in the total number of attended appointments for every neighbourhood, there are 80 neighbourhoods.* This is evident that there is one neighbourhood where some appointments were made, but none of the patients who filed for appointments showed up on the appointment day. **Let's check which neighbourhood it is**

[48]:
```
# Check the neighbourhood where patients filed for appointments but never␣
 ↪showed up
for i in total_appointments_by_nbd.index:
```

```
    if i not in total_attendants_by_nbd.index:
        print(i)
```

```
ILHAS OCEÂNICAS DE TRINDADE
```

> Patients in ILHAS OCEÂNICAS DE TRINDADE booked some appointments but did not show up. >To avoid errors during analysis, we need to add this neighbourhood in the series holding results of the number of appointments made per neighbourhood, and assign a value **0** for this neighbourhood.

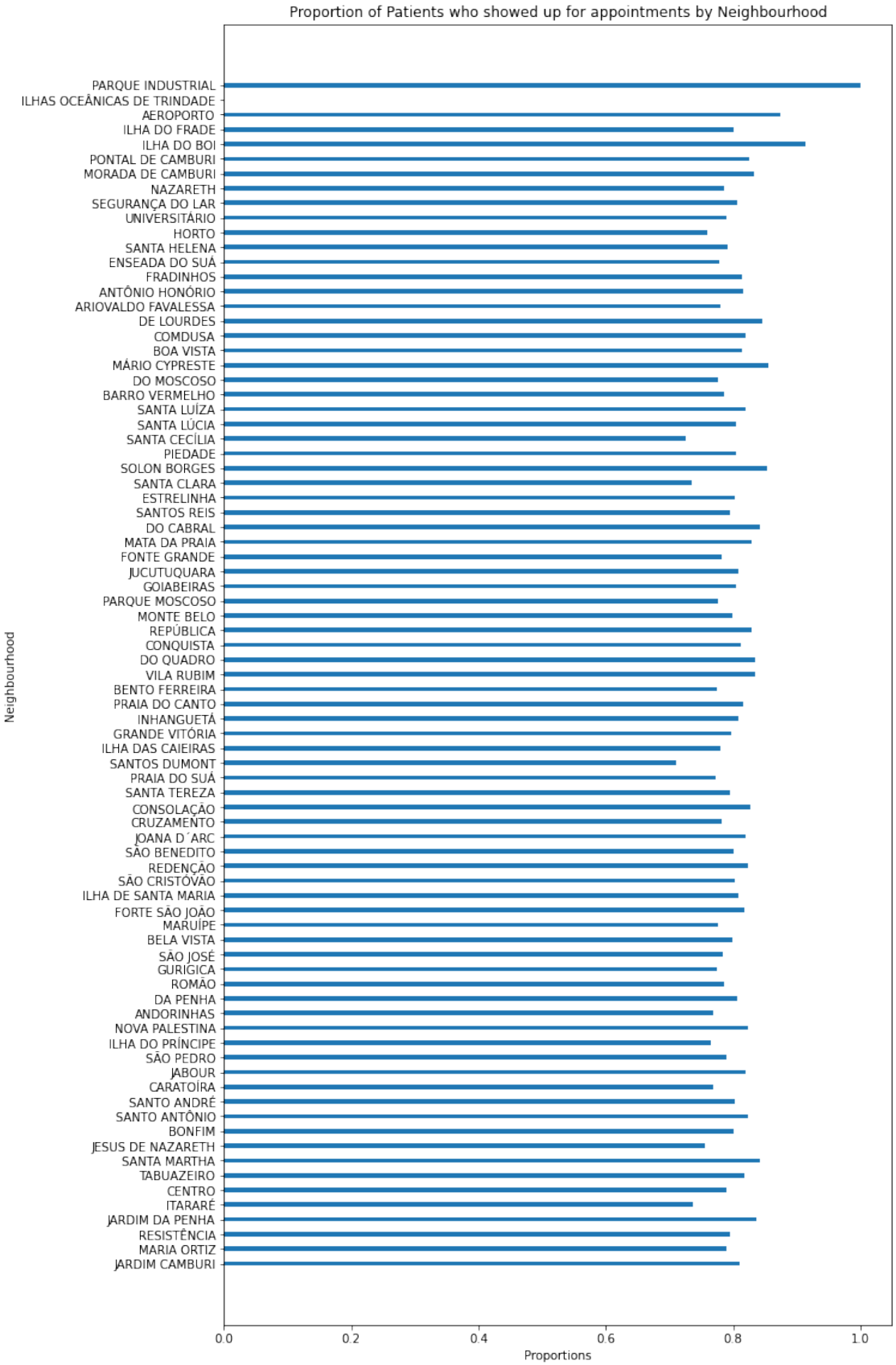
[49]:
```
# Data to add
add_data = Series([0], index=['ILHAS OCEÂNICAS DE TRINDADE'])

# Make the update
total_attendants_by_nbd = pd.concat([total_attendants_by_nbd, add_data])

# Verify that the new record was entered successfully
total_attendants_by_nbd.count() == total_appointments_by_nbd.count() # Should␣
 ↪return True
```

[49]:
```
True
```

[50]:
```
# Use the indexs to identify entries from similar neighbourhoods and use them␣
 ↪to calculated the proportions as required
# att_props : attendance proportion for every neighbourhood

neighbourhood = [] # Holds the list of Neighbourhoods
attendance_proportion = [] # Holds the Patient proportion that showed up for␣
 ↪the appointments
for i in total_appointments_by_nbd.index:
    for x in total_attendants_by_nbd.index:
        if x == i:
            att_props =␣
 ↪proportion(total_appointments_by_nbd[i],total_attendants_by_nbd[x])

    #print(i, att_props)
    neighbourhood.append(i)
    attendance_proportion.append(att_props)
```

[51]:
```
figure(figsize=(10,20))
plt.barh(neighbourhood, attendance_proportion, height=0.3)
plt.rcParams['font.size']='10'
plt.title('Proportion of Patients who showed up for appointments by␣
 ↪Neighbourhood')
plt.xlabel('Proportions')
plt.ylabel('Neighbourhood');
```

```
#plt.yticks(fontsize=20)
```


Proportion of Patients who showed up for appointments by Neighbourhood
Neighbourhood
PARQUE INDUSTRIAL
ILHAS OCEÂNICAS DE TRINDADE
AEROPORTO
ILHA DO FRADE
ILHA DO BOI
PONTAL DE CAMBURI
MORADA DE CAMBURI
NAZARETH
SEGURANÇA DO LAR
UNIVERSITÁRIO
HORTO
SANTA HELENA
ENSEADA DO SUÁ
FRADINHOS
ANTÔNIO HONÓRIO
ARIOVALDO FAVALESSA
DE LOURDES
COMDUSA
BOA VISTA
MÁRIO CYPRESTE
DO MOSCOSO
BARRO VERMELHO
SANTA LUÍZA
SANTA LÚCIA
SANTA CECÍLIA
PIEDADE
SOLON BORGES
SANTA CLARA
ESTRELINHA
SANTOS REIS
DO CABRAL
MATA DA PRAIA
FONTE GRANDE
JUCUTUQUARA
GOIABEIRAS
PARQUE MOSCOSO
MONTE BELO
REPÚBLICA
CONQUISTA
DO QUADRO
VILA RUBIM
BENTO FERREIRA
PRAIA DO CANTO
INHANGUETÁ
GRANDE VITÓRIA
ILHA DAS CAIEIRAS
SANTOS DUMONT
PRAIA DO SUÁ
SANTA TEREZA
CONSOLAÇÃO
CRUZAMENTO
JOANA D´ARC
SÃO BENEDITO
REDENÇÃO
SÃO CRISTÓVÃO
ILHA DE SANTA MARIA
FORTE SÃO JOÃO
MARUÍPE
BELA VISTA
SÃO JOSÉ
GURIGICA
ROMÃO
DA PENHA
ANDORINHAS
NOVA PALESTINA
ILHA DO PRÍNCIPE
SÃO PEDRO
JABOUR
CARATOÍRA
SANTO ANDRÉ
SANTO ANTÔNIO
BONFIM
JESUS DE NAZARETH
SANTA MARTHA
TABUAZEIRO
CENTRO
ITARARÉ
JARDIM DA PENHA
RESISTÊNCIA
MARIA ORTIZ
JARDIM CAMBURI
0.0
0.2
0.4
0.6
0.8
1.0
Proportions

[52]:
```
min(attendance_proportion)
```

[52]:
```
0.0
```

Note: For the neighbourhood with a proportion of patients who showed up for the appointment after booking as 0, only **two** patient had book for the appointment. We can ignore this when considering the lowest proportion of turn out since the bookings for this neighbourhood are very low

[53]:
```
# remove 0 from the list of proportions
attendance_proportion.remove(0.0)
min(attendance_proportion)
```

[53]:
```
0.7108150470219435
```

1.7.1 Question 4 Results

The visualization above shows that for hospitals located in some neighbourhoods, the proportion of patients who showed up for the appointment they booked was higher than in others. In almost all the neighbourhoods, the patient turn out after booking an appointment is more than 70%

1.8 Research Question 5: Are patients who are enrolled in Brasilian welfare program more likely to show up for scheduled appointments?

To respond to this question, we need to divide the cleaned dataset into two separate datasets, one holding the records who were enrolled in the Brasilian welfare program and the other holding the records for patients who were not enrolled in the program > **enrolled_df** : Dataset holding records for the enrolled patients > **n_enrolled_df** : Dataset holding records for the patients who were not enrolled

After separating the data, we will calculate the respective proportions

1.8.1 Step 1: Separate the dataset

[54]:
```
df_clean.columns
```

[54]:
```
Index(['AppointmentID', 'PatientId', 'Gender', 'ScheduledDay', 'Age',
       'Neighbourhood', 'Scholarship', 'Hipertension', 'Diabetes',
       'Alcoholism', 'Handcap', 'SMS_received', 'No_show'],
      dtype='object')
```

[55]:
```
# Separating the dataset
enrolled_df = df_clean.query('Scholarship == 1')
n_enrolled_df = df_clean.query('Scholarship == 0')
```

[56]:
```
# View the enrolled patients data
enrolled_df.head(2)
```

[56]:
```
    AppointmentID     PatientId Gender          ScheduledDay  Age  \
12        5634718  5.666548e+14      F  2016-04-28T11:33:51Z   22
17        5633460  1.479497e+13      F  2016-04-28T09:28:57Z   40

     Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
12  NOVA PALESTINA            1             0         0           0        0
17       CONQUISTA            1             0         0           0        0

    SMS_received No_show
12             0      No
17             0     Yes
```

[57]:
```
# View the un-enrolled patients data
n_enrolled_df.head(2)
```

[57]:
```
   AppointmentID     PatientId Gender          ScheduledDay  Age  \
0        5642903  2.987250e+13      F  2016-04-29T18:38:08Z   62
1        5642503  5.589978e+14      M  2016-04-29T16:08:27Z   56

     Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
0  JARDIM DA PENHA            0             1         0           0        0
1  JARDIM DA PENHA            0             0         0           0        0

   SMS_received No_show
0             0      No
1             0      No
```

1.8.2 Step 2: Find the proportion of the enrolled patients who showed up for the appointment

[58]:
```
# find the total number of enrolled patients
tt_enrolled = enrolled_df.AppointmentID.value_counts().sum()
tt_enrolled
```

[58]:
```
10861
```

[59]:
```
# find the total number of enrolled patients who showed up for their␣
 ↪appointment
tt_enrolled_show = enrolled_df.query('No_show == "No"').value_counts().sum()
tt_enrolled_show
```

[59]:
```
8283
```

[60]:
```
# Calculate the proportion of enrolled patients who showed up for the␣
 ↪appointments
# Invoke the proportion function
enrolled_prop = proportion(tt_enrolled, tt_enrolled_show)
enrolled_prop
```

[60]:
```
0.7626369579228433
```

1.8.3 Step 3: Find the proportion of the patients who were not enrolled who showed up for the appointment

[61]:
```
# find the total number of patients who were not enrolled in the program
tt_n_enrolled = n_enrolled_df.AppointmentID.value_counts().sum()
tt_n_enrolled
```

[61]:
```
99665
```

[62]:
```
# find the total number of patients who were not enrolled in the program who␣
 ↪showed up for their appointment
tt_n_enrolled_show = n_enrolled_df.query('No_show == "No"').value_counts().sum()
tt_n_enrolled_show
```

[62]:
```
79924
```

[63]:
```
# Calculate the proportion of patients who were not enrolled in the program who␣
 ↪showed up for the appointments
# Invoke the proportion function
n_enrolled_prop = proportion(tt_n_enrolled, tt_n_enrolled_show)
n_enrolled_prop
```

[63]:
```
0.8019264536196258
```

1.8.4 Question 5 Response

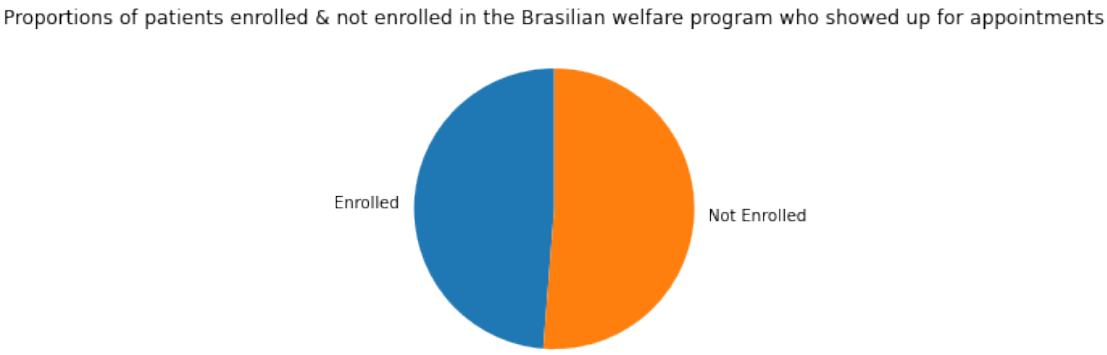
comparing the results in step 2 and 3 above, we can conclude that patients who were not enrolled in the Brasilian welfare program were less likely to show up for appointments as compared to those who were not enrolled

1.8.5 Step 4: Visualizing the Results

To show the difference in the proportions, we will use the a pie chart

1.8.6 Question 5 Visual Response

[64]:
```
plot_proportions = [enrolled_prop, n_enrolled_prop]
m_labels = ['Enrolled', 'Not Enrolled']
# m_colors = ['Blue', 'Green']
plt.pie(plot_proportions, labels= m_labels, startangle=90)
plt.title('Proportions of patients enrolled & not enrolled in the Brasilian␣
 ↪welfare program who showed up for appointments')
plt.show();
```



This pie chart shows that the proportion of the patients who were enrolled in the Brasilian welfare program were less likely to show up for appointments as compared to the patients who were not enrolled in the program

1.9 Research Question 6: How do positive diagnosis of health conditions such as hipertension, Diabetes, Alcoholism, and Handcap affect appointment attendance?

For this question, we will begin by examining how each individual health condition affects appointment attendance. Thereafter, we will check to see how the four conditions compare in terms of affecting whether the patients show up for appointments or not.

Research Question 6A: How do positive diagnosis of hipertension affect appointment attendance?

Split the clean dataset into two datasets, one with records of patients who had High Blood Pressure (HBP), and another with records of patients who did not have HBP

hbp_df : records of patients with Hipertension **n_hbp_df** : records of patients with no Hipertension

[65]:
```
# Split the data
hbp_df = df_clean.query('Hipertension == 1')
n_hbp_df = df_clean.query('Hipertension == 0')
```

[66]:
```
hbp_df.head(2)
```

[66]:
```
   AppointmentID     PatientId Gender          ScheduledDay  Age  \
0        5642903  2.987250e+13      F  2016-04-29T18:38:08Z   62
4        5642494  8.841186e+12      F  2016-04-29T16:07:23Z   56

     Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
0  JARDIM DA PENHA            0             1         0           0        0
4  JARDIM DA PENHA            0             1         1           0        0

   SMS_received No_show
0             0      No
4             0      No
```

[67]:
```
n_hbp_df.head(2)
```

[67]:
```
   AppointmentID     PatientId Gender          ScheduledDay  Age  \
1        5642503  5.589978e+14      M  2016-04-29T16:08:27Z   56
2        5642549  4.262962e+12      F  2016-04-29T16:19:04Z   62

     Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
1  JARDIM DA PENHA            0             0         0           0        0
2    MATA DA PRAIA            0             0         0           0        0

   SMS_received No_show
1             0      No
2             0      No
```

Step 1: Find the proportion of patients with hipertension who showed up for the appointment

[68]:
```
# Find the total number of patients who were diagnosed with hipertension/High␣
 ↪Blood Pressure (HBP)
tt_HBP_patient = hbp_df['AppointmentID'].value_counts().sum()
tt_HBP_patient
```

[68]:
```
21801
```

[69]:
```
# Find the number of patients with hipertension who showed up for the␣
 ↪appointment
tt_HBP_patient_show = hbp_df.query('No_show == "No"').value_counts().sum()
tt_HBP_patient_show
```

[69]:
```
18029
```

[70]:
```
# proportion of patients with hipertension who showed up for the appointment
prop_HBP_patient_show = proportion(tt_HBP_patient, tt_HBP_patient_show)
prop_HBP_patient_show
```

[70]:
```
0.8269804137424889
```

Step 2: Find the proportion of patients with no hipertension who showed up for the appointment

[71]:
```
# Find the total number of patients who did not have hipertension/High Blood␣
 ↪Pressure (HBP)
n_tt_HBP_patient = n_hbp_df['AppointmentID'].value_counts().sum()
n_tt_HBP_patient
```

[71]:
```
88725
```

[72]:
```
# Find the number of patients with no hipertension who showed up for the␣
 ↪appointment
n_tt_HBP_patient_show = n_hbp_df.query('No_show == "No"').value_counts().sum()
n_tt_HBP_patient_show
```

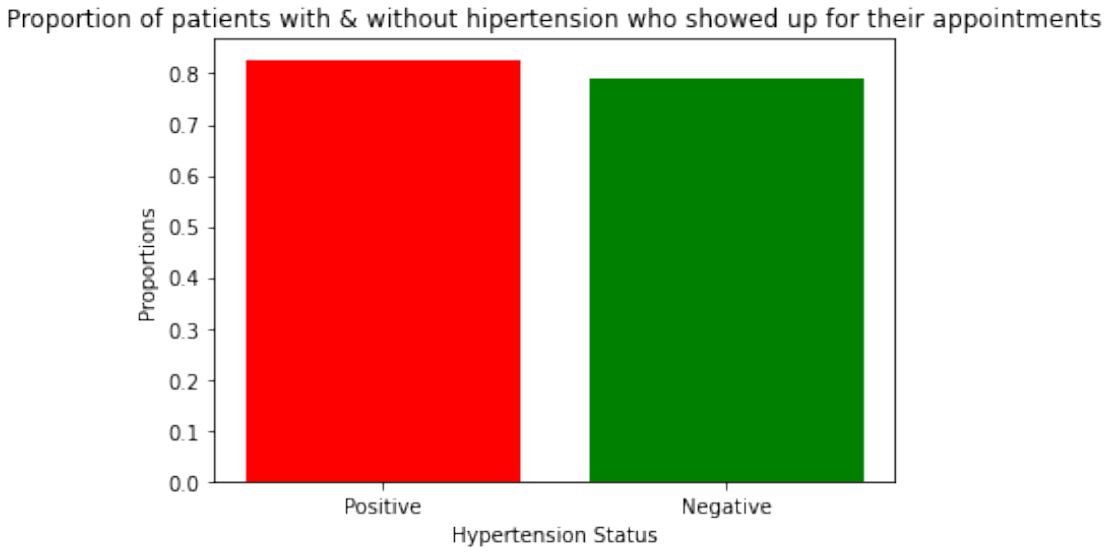
[72]:
```
70178
```

[73]:
```
# proportion of patients with no hipertension who showed up for the appointment
prop_n_HBP_patient_show = proportion(n_tt_HBP_patient, n_tt_HBP_patient_show)
prop_n_HBP_patient_show
```

[73]:
```
0.7909608340377571
```

Step 3: Visualize the results

[74]:
```
hbp_status = ['Positive', 'Negative']
hbp_proportions = [prop_HBP_patient_show, prop_n_HBP_patient_show]
colors = ['Red', 'Green']
plt.bar(hbp_status, hbp_proportions, color=colors)
plt.title('Proportion of patients with & without hipertension who showed up for␣
 ↪their appointments')
plt.xlabel('Hypertension Status')
plt.ylabel('Proportions')

plt.show();
```



Question 6A Response

The data indicates that the proportion of patients with hipertension who showed up for the appointment was higher than the proportion of patients without hipertension who showed up for the appointment.

Research Question 6b: How do positive diagnosis of Diabetes affect appointment attendance?

Step 1: Split the dataset

diabetic_df : appointment records of diabetic patients **n_diabetic_df** : appointment records of patients who did not have diabetes

[75]:
```
# Split the data
diabetic_df = df_clean.query('Diabetes == 1')
n_diabetic_df = df_clean.query('Diabetes == 0')
```

[76]:
```
diabetic_df.head(1)
```

[76]:
```
    AppointmentID     PatientId Gender          ScheduledDay  Age  \
4         5642494  8.841186e+12      F  2016-04-29T16:07:23Z   56

      Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
4  JARDIM DA PENHA            0             1         1           0        0

   SMS_received No_show
4             0      No
```

[77]:
```
n_diabetic_df.head(1)
```

[77]:
```
    AppointmentID     PatientId Gender          ScheduledDay  Age  \
0         5642903  2.987250e+13      F  2016-04-29T18:38:08Z   62

      Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
0  JARDIM DA PENHA            0             1         0           0        0

   SMS_received No_show
0             0      No
```

Step 2: Find the proportion of the diabetic patients who showed up for the appointment

[78]:
```
# Total number of diabetic patients
tt_diabetic = diabetic_df.AppointmentID.value_counts().sum()
tt_diabetic
```

[78]:
```
7943
```

[79]:
```
# Number of diabetic patients who showed up for the appointment
tt_diabetic_show = diabetic_df.query('No_show == "No"').value_counts().sum()
tt_diabetic_show
```

[79]:
```
6513
```

[80]:
```
# Proportion of diabetic patients who showed up for the appointments
prop_diabetic_show = proportion(tt_diabetic, tt_diabetic_show)
prop_diabetic_show
```

[80]:
```
0.8199672667757774
```

Step 3: Find the proportion of the non-diabetic patients who showed up for the appointment

[81]:
```
# Total number of non diabetic patients
tt_n_diabetic = n_diabetic_df.AppointmentID.value_counts().sum()
tt_n_diabetic
```

[81]:
```
102583
```

[82]:
```
# Number of diabetic non-patients who showed up for the appointment
n_diabetic_show = n_diabetic_df.query('No_show == "No"').value_counts().sum()
n_diabetic_show
```

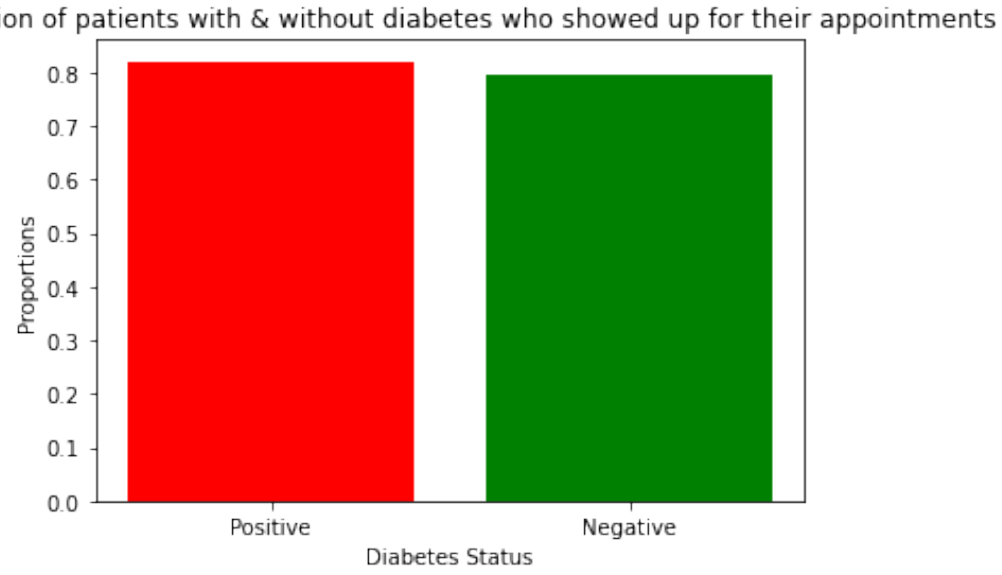
[82]:
```
81694
```

[83]:
```
# Proportion of non_diabetic patients who showed up for the appointments
prop_n_diabetic_show = proportion(tt_n_diabetic, n_diabetic_show)
prop_n_diabetic_show
```

[83]:
```
0.7963697688700857
```

Step 4: Visualize the results

[84]:
```
diabetes_status = ['Positive', 'Negative']
diabetes_proportions = [prop_diabetic_show, prop_n_diabetic_show]
colors = ['Red', 'Green']
plt.bar(diabetes_status, diabetes_proportions, color=colors)
plt.title('Proportion of patients with & without diabetes who showed up for␣
 ↪their appointments')
plt.xlabel('Diabetes Status')
plt.ylabel('Proportions')

plt.show();
```



`Question 6B Results`

This shows that the proportion of patients with diabetes who showed up for the appointment was higher than the proportion of patients without diabetes who showed up for the appointment

Research Question 6c: How do Alcoholism affect appointment attendance?

Step 1: Split the dataset

alcoholic_df : appointment records of alcoholic patients **n_alcoholic_df** : appointment records of patients who did not have alcoholism

[85]:
```
# Split the data
alcoholic_df = df_clean.query('Alcoholism == 1')
n_alcoholic_df = df_clean.query('Alcoholism == 0')
```

[86]:
```
alcoholic_df.head(1)
```

[86]:
```
    AppointmentID     PatientId Gender          ScheduledDay  Age  \
46        5615608  1.379437e+11      M  2016-04-25T12:44:36Z   58

    Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
46  SÃO CRISTÓVÃO            0             1         0           1        0

    SMS_received No_show
46             1      No
```

[87]:
```
n_alcoholic_df.head(1)
```

[87]:
```
   AppointmentID     PatientId Gender          ScheduledDay  Age  \
0        5642903  2.987250e+13      F  2016-04-29T18:38:08Z   62

     Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
0  JARDIM DA PENHA            0             1         0           0        0

   SMS_received No_show
0             0      No
```

Step 2: Find the proportion of the alcoholic patients who showed up for the appointment

[88]:
```
# Total number of alcoholic patients
tt_alcoholic = alcoholic_df.AppointmentID.value_counts().sum()
tt_alcoholic
```

[88]:
```
3360
```

[89]:
```
# Number of alcoholic patients who showed up for the appointment
tt_alcoholic_show = alcoholic_df.query('No_show == "No"').value_counts().sum()
tt_alcoholic_show
```

[89]:
```
2683
```

[90]:
```
# Proportion of diabetic patients who showed up for the appointments
prop_alcoholic_show = proportion(tt_alcoholic, tt_alcoholic_show)
prop_alcoholic_show
```

[90]:
```
0.7985119047619048
```

Step 3: Find the proportion of the non-alcoholic patients who showed up for the appointment

[91]:
```
# Total number of non alcoholic patients
tt_n_alcoholic = n_alcoholic_df.AppointmentID.value_counts().sum()
tt_n_alcoholic
```

[91]:
```
107166
```

[92]:
```
# Number of diabetic non-alcoholic who showed up for the appointment
n_alcoholic_show = n_alcoholic_df.query('No_show == "No"').value_counts().sum()
n_alcoholic_show
```

[92]:
```
85524
```

[93]:
```
# Proportion of non_diabetic patients who showed up for the appointments
prop_n_alcoholic_show = proportion(tt_n_alcoholic, n_alcoholic_show)
prop_n_alcoholic_show
```

[93]:
```
0.7980516208498964
```

Step 4: Visualize the results

[94]:
```
diabetes_status = ['Alcoholic', 'Non-Alcoholic']
diabetes_proportions = [prop_alcoholic_show, prop_n_alcoholic_show]
colors = ['Red', 'Green']
plt.bar(diabetes_status, diabetes_proportions, color=colors)
plt.title('Proportion of patients with & without Alcoholism who showed up for␣
 ↪their appointments')
plt.xlabel('Alcoholism Status')
plt.ylabel('Proportions')

plt.show();
```

`Research question 6C Results`

Since there is no significant difference between the proportion of alcoholic patients who showed up for appointments and the non-alcoholic patients who showed up

for the appointments, We can conclude that Alcoholism does not significantly affect whether an individiual shows up for an appointment or not.

Research Question 6D: How do being HandCapped affect appointment attendance?

Step 1: Split the dataset

handcap_df : appointment records of HandCapped patients **n_handcap_df** : appointment records of patients who are not HandCapped

[95]:
```
# Split the data
handcap_df = df_clean.query('Handcap == 1')
n_handcap_df = df_clean.query('Handcap == 0')
```

[96]:
```
handcap_df.head(1)
```

[96]:
```
     AppointmentID     PatientId Gender          ScheduledDay  Age  \
147        5639200  2.984854e+14      F  2016-04-29T08:48:03Z   65

     Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
147  UNIVERSITÁRIO            0             1         0           0        1

     SMS_received No_show
147             0      No
```

[97]:
```
n_handcap_df.head(1)
```

[97]:
```
   AppointmentID     PatientId Gender          ScheduledDay  Age  \
0        5642903  2.987250e+13      F  2016-04-29T18:38:08Z   62

     Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  \
0  JARDIM DA PENHA            0             1         0           0        0

   SMS_received No_show
0             0      No
```

Step 2: Find the proportion of the handcap patients who showed up for the appointment

[98]:
```
# Total number of handcap patients
tt_handcap = handcap_df.AppointmentID.value_counts().sum()
tt_handcap
```

[98]:
```
2042
```

[99]:
```
# Number of handcap patients who showed up for the appointment
tt_handcap_show = handcap_df.query('No_show == "No"').value_counts().sum()
tt_handcap_show
```

[99]:
```
1676
```

[100]:
```
# Proportion of handcap patients who showed up for the appointments
prop_handcap_show = proportion(tt_handcap, tt_handcap_show)
```

```
prop_handcap_show
```

[100]: 0.8207639569049952

Step 3: Find the proportion of the non-handcap patients who showed up for the appointment

[101]:
```
# Total number of non handcap patients
tt_n_handcap = n_handcap_df.AppointmentID.value_counts().sum()
tt_n_handcap
```

[101]: 108285

[102]:
```
# Number of diabetic non-handcap who showed up for the appointment
n_handcap_show = n_handcap_df.query('No_show == "No"').value_counts().sum()
n_handcap_show
```

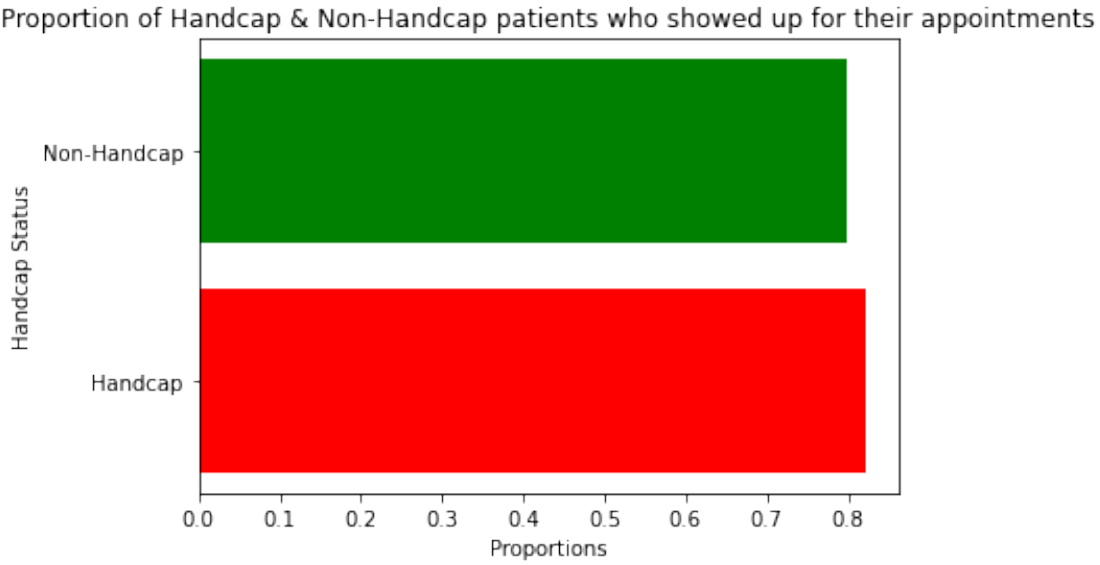
[102]: 86373

[103]:
```
# Proportion of non_handcap patients who showed up for the appointments
prop_n_handcap_show = proportion(tt_n_handcap, n_handcap_show)
prop_n_handcap_show
```

[103]: 0.7976451031998891

Step 4: Visualize the results

[104]:
```
handcap_status = ['Handcap', 'Non-Handcap']
handcap_proportions = [prop_handcap_show, prop_n_handcap_show]
colors = ['Red', 'Green']
plt.barh(handcap_status, handcap_proportions, color=colors)
plt.title('Proportion of Handcap & Non-Handcap patients who showed up for their␣
 ↪appointments')
plt.xlabel('Proportions')
plt.ylabel('Handcap Status')

plt.show();
```



`Research question 6D Results`

This analysis shows that the handcapped patients are more likely to show up for appointments as compared to the non-handcap patients

Conclusion

Findings: Based on the analysis done on the dataset:- > 1. Patients aged between 0 to 10 years book a higher number of appointments as compared to the other age groups. The number of appointments booked by patients aged between 90 years and 100 years is disproportionately low as compared to the other age groups. > 2. The proportion of males who showed up for the appointment is almost equal to the proportion of the females who showed up for the appointment. > 3. The proportion of older patients who showed up for their appointment is higher than that of the younger patients who showed up for the appointment. > 4. For hospitals located in some neighbourhoods, the proportion of patients who showed up for the appointment they booked was higher than in others. However, in all neighbourhoods, more than 70% of the patients who booked appointments showed up on for the appointment. > 5. The proportion of the patients who were enrolled in the Brasilian welfare program and showed up for appointments was slightly lower compared to the proportion of patients who were not enrolled in the program and showed up for the appointments. > 6. > a. The proportion of patients with hipertension who showed up for the appointment was higher than the proportion of patients without hipertension who showed up for the appointment. b. The proportion of patients with diabetes who showed up for the appointment was higher than the proportion of patients without diabetes who showed up for the appointment. c. Since there is no significant difference between the proportion of alcoholic patients who showed up for appointments and the non-alcoholic patients who

showed up for the appointments, We can conclude that Alcoholism does not significantly affect whether an individiual shows up for an appointment or not. d. The proportion of Handcap patients who showed up for the appointment was higher than the proportion of patients who are not handcap who showed up for the appointment.

Challenges > 1. *This analysis only focused on correlation between the variables. Causation was not addressed* > 2. *Writing python functions to replace some repetitive tasks was challenging*

[ ]: