Project: Investigate a Dataset (Medical Appointment No Shows)

Name: Ashinze Emmanuel Chidi

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Section I: Introduction

Dataset: No-show appointments

Description: This dataset collects 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.

Columns Description

- `PatientId` : The patient's ID(Identification Number)
- `AppointmentID` : Appointment ID(Identification Nunber) this field should be unique for each appointment
- `Gender` : Patient's gender (Male/Female)
- `ScheduledDay` : The day of the actuall appointment, when they have to visit the doctor.
- `AppointmentDay` : The day someone called or registered the appointment, this is before appointment of course.
- `Age` : How old is the patient
- `Neighborhood` : Where the appointment takes place(Health Center Location)
- `Scholarship` : Shows whether or not the patient is enrolled in Brasilian welfare program Bolsa Família.(1 if true, 0 if False)
- `Hipertension` : Tells if the patient is experiencing Hypertension.(1 if true, 0 if False)
- `Diabetes` :Tells if the patient is experiencing Diabetes.(1 if true, 0 if False)
- `Alcoholism` :Tells if thepatient is experiencing Alcoholism.(1 if true, 0 if False)
- `Handcap` : Tells if the patient is with special needs.(Ranking from 0-4 to show the level of special needs)
- `SMS_received` : Tells if the patient has received a reminder text message and the number of messages received(1 if true, 0 if False)
- `Show-up` : ‘No’ if the patient showed up to their appointment, and ‘Yes’ if they did not show up.

We will be investigating the dataset to uncover the following:

1. What factors are important for us to know in order to predict if a patient will show up for their scheduled appointment?

2. How do the Factors vary with Each Other?

Research Areas

1. `Target Variable(Absent)` : studying the trends in the absent study overall proportions to help in the analysis with other variables
2. `Univariate Analysis` : Studying each variable to uncover patterns and how they relate with the target variable. How does `Age` , `Gender` , `Neighbourhood` and `Scholarship` influence a patient from attending the Hospital appointment.
3. `Multivariate Analysis` : Studyying how the variables relate with one another and how they can help in predicting the target variable. How do the variables affect each other(Correlation) and affects the target variable.

LIMITATIONS

1. Time was set to 00:00:00 for all cases, analysis was only carried in days. Cases of Having an appointment and schedule on the same day could not be used for the analysis
2. The data was not totally consistent, some unusual forms of data and irregularities were found which could have affected the analysis because it was dropped.
3. Most of the columns are categorical, hence the use of Bar charts and Pie charts, Only Age was quantitative and could be visualised with appropraite means.
4. The Neighbourhood Data should have included the gographical coordinates for better analysis as to how a location can affect the choice of the patient

In [100…

```
#Importing all the required libraries and includin a 'magic word' so that visualizations are plotted
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

In [101…

```
#reading the dataset with pandas
df = pd.read_csv("C:/Users/ashin/Downloads/noshowappointments-kagglev2-may-2016.csv")
```

Section II: Data Wrangling

Data wrangling is the process of cleaning and unifying messy and complex data sets for easy access and analysis

1. General Properties (Dataset dimensions, columns/ rows/ data types)

In [102…

```
#checking for the basic properties of the Dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   PatientId       110527 non-null  float64
 1   AppointmentID   110527 non-null  int64  
 2   Gender          110527 non-null  object 
 3   ScheduledDay    110527 non-null  object 
 4   AppointmentDay  110527 non-null  object 
 5   Age             110527 non-null  int64  
 6   Neighbourhood   110527 non-null  object 
 7   Scholarship     110527 non-null  int64  
 8   Hipertension    110527 non-null  int64  
 9   Diabetes        110527 non-null  int64  
 10  Alcoholism      110527 non-null  int64  
 11  Handcap         110527 non-null  int64  
 12  SMS_received    110527 non-null  int64  
 13  No-show         110527 non-null  object 
dtypes: float64(1), int64(8), object(5)
memory usage: 11.8+ MB
```

This Dataset has 14 columns and 110527 rows

In [103…

```
df.head()
#checking the first 5 rows
```

Out[103]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	H
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	0	
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	0	
3	8.679512e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	0	
4	8.841186e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	

In [104…

```
df.tail()
#display the last 5 rows
```

Out[104]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarsl
110522	2.572134e+12	5651768	F	2016-05-03T09:15:35Z	2016-06-07T00:00:00Z	56	MARIA ORTIZ	
110523	3.596266e+12	5650093	F	2016-05-03T07:27:33Z	2016-06-07T00:00:00Z	51	MARIA ORTIZ	

110524	1.557663e+13	5630692	F	2016-04-27T16:03:52Z	2016-06-07T00:00:00Z	21	MARIA ORTIZ
110525	9.213493e+13	5630323	F	2016-04-27T15:09:23Z	2016-06-07T00:00:00Z	38	MARIA ORTIZ
110526	3.775115e+14	5629448	F	2016-04-27T13:30:56Z	2016-06-07T00:00:00Z	54	MARIA ORTIZ

In [105…

```
df.dtypes
# Checking the data types
```

Out[105]:

```
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
```

In [106…

```
df.describe(include='all')
# describing the data using the describw function.
```

Out[106]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood
count	1.105270e+05	1.105270e+05	110527	110527	110527	110527.000000	110527
unique	NaN	NaN	2	103549	27	NaN	81
top	NaN	NaN	F	2016-05-06T07:09:54Z	2016-06-06T00:00:00Z	NaN	JARDIM CAMBURI
freq	NaN	NaN	71840	24	4692	NaN	7717
mean	1.474963e+14	5.675305e+06	NaN	NaN	NaN	37.088874	NaN
std	2.560949e+14	7.129575e+04	NaN	NaN	NaN	23.110205	NaN
min	3.921784e+04	5.030230e+06	NaN	NaN	NaN	-1.000000	NaN
25%	4.172614e+12	5.640286e+06	NaN	NaN	NaN	18.000000	NaN
50%	3.173184e+13	5.680573e+06	NaN	NaN	NaN	37.000000	NaN
75%	9.439172e+13	5.725524e+06	NaN	NaN	NaN	55.000000	NaN
max	9.999816e+14	5.790484e+06	NaN	NaN	NaN	115.000000	NaN

Looking at the dataset, we have Quantitative and Categorical Variables and the nature of variables will affect the nature of analysis

1. **Categorical Data:** `Gender, Diabetes, Alcoholism, Handcap, SMS_received, No-show`

2. **Quantitative Data:** `PatientId, AppointmentID, Age, ScheduledDay, AppointmentDay`

The Dataset is not in the best form for analysis as we need to clean it to make it appropraite for analysis. We have to:

1. Check for missing Values
2. Duplicates
3. Data Validation(Checking for unusual data)
4. Data Cleaning

1.Missing values

In [107…

```
# Check if there is any missing values


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

Out[107]:

```
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 missing values in the dataset

2.Duplicates

In [108…

```
# Check for duplicate rows
df.duplicated().sum()
```

Out[108]:

```
0
```

There are no duplicate rows in the dataset

In [109…

```
 # checking if there are duplicates in each column
def check_column_duplicates():
    column_list = list(df.columns)
    for column in column_list:
        print(f'{column}   has   {sum(df[column].duplicated())}   duplicates
\n')
check_column_duplicates()
```

```
PatientId   has   48228   duplicates
```

```
AppointmentID   has   0   duplicates

Gender   has   110525   duplicates

ScheduledDay   has   6978   duplicates

AppointmentDay   has   110500   duplicates

Age   has   110423   duplicates

Neighbourhood   has   110446   duplicates

Scholarship   has   110525   duplicates

Hipertension   has   110525   duplicates

Diabetes   has   110525   duplicates

Alcoholism   has   110525   duplicates

Handcap   has   110522   duplicates

SMS_received   has   110525   duplicates

No-show   has   110525   duplicates
```

It is noticed that there are duplicates in the columns but it is easily understandable as the Categorical variables are repeated. The Variable of interest is the `PatientID` as it shows if a patient has multiple appointments. Also,we can confirm that `AppointmentID` is unique, meaning each appointment is unique

In [110…

```
#Checking the first 10 patients with most appointments
df.PatientId.value_counts().head(10)
```

Out[110]:

```
8.221459e+14    88
9.963767e+10    84
2.688613e+13    70
3.353478e+13    65
6.264199e+12    62
2.584244e+11    62
8.713749e+14    62
7.579746e+13    62
6.684488e+13    57
8.722785e+11    55
Name: PatientId, dtype: int64
```

3. Data Validation(Checking for unusual data)

Data validation is the process of ensuring data has undergone data cleansing to ensure they have data quality, that is, that they are both correct and useful.

In [111…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
```

```
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   PatientId       110527 non-null  float64
 1   AppointmentID   110527 non-null  int64  
 2   Gender          110527 non-null  object 
 3   ScheduledDay    110527 non-null  object 
 4   AppointmentDay  110527 non-null  object 
 5   Age             110527 non-null  int64  
 6   Neighbourhood   110527 non-null  object 
 7   Scholarship     110527 non-null  int64  
 8   Hipertension    110527 non-null  int64  
 9   Diabetes        110527 non-null  int64  
 10  Alcoholism      110527 non-null  int64  
 11  Handcap         110527 non-null  int64  
 12  SMS_received    110527 non-null  int64  
 13  No-show         110527 non-null  object 
dtypes: float64(1), int64(8), object(5)
memory usage: 11.8+ MB
```

In [112…

```
#checking the PatientID
df.query('PatientId <= 0')
```

Out[112]:

PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hiperte

The `PatientId` colunmn has no values that is zero or negative

In [113…

```
#checking the AppointmentID
df.query('AppointmentID <= 0')
```

Out[113]:

PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hiperte

The `AppointmentId` colunmn has no values that is zero or negative

In [114…

```
#checking the Gender column
df['Gender'].unique()
```

Out[114]:

```
array(['F', 'M'], dtype=object)
```

The Gender Column has two unique values,Male and Female

In [115…

```
#Checking the ScheduledDay Column
df['ScheduledDay'].unique()
```

Out[115]:

```
array(['2016-04-29T18:38:08Z', '2016-04-29T16:08:27Z',
       '2016-04-29T16:19:04Z', ..., '2016-04-27T16:03:52Z',
       '2016-04-27T15:09:23Z', '2016-04-27T13:30:56Z'], dtype=object)
```

In [116…

```
#Checking the AppointmentDay Column
df['AppointmentDay'].unique()
```

```
array(['2016-04-29T00:00:00Z', '2016-05-03T00:00:00Z',
```

Out[116]:
```
'2016-05-10T00:00:00Z', '2016-05-17T00:00:00Z',
       '2016-05-24T00:00:00Z', '2016-05-31T00:00:00Z',
       '2016-05-02T00:00:00Z', '2016-05-30T00:00:00Z',
       '2016-05-16T00:00:00Z', '2016-05-04T00:00:00Z',
       '2016-05-19T00:00:00Z', '2016-05-12T00:00:00Z',
       '2016-05-06T00:00:00Z', '2016-05-20T00:00:00Z',
       '2016-05-05T00:00:00Z', '2016-05-13T00:00:00Z',
       '2016-05-09T00:00:00Z', '2016-05-25T00:00:00Z',
       '2016-05-11T00:00:00Z', '2016-05-18T00:00:00Z',
       '2016-05-14T00:00:00Z', '2016-06-02T00:00:00Z',
       '2016-06-03T00:00:00Z', '2016-06-06T00:00:00Z',
       '2016-06-07T00:00:00Z', '2016-06-01T00:00:00Z',
       '2016-06-08T00:00:00Z'], dtype=object)
```

In [117…
```
#check the age for negative values
df.query('Age < 0')
```

Out[117]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarshi
99832	4.659432e+14	5775010	F	2016-06-06T08:58:13Z	2016-06-06T00:00:00Z	-1	ROMÃO	

There are negative values in the Age which suggests that this is an unusual value, it is not possible to have negative age, it will be addressed in the data cleaning section

In [118…
```
#Checking the Neighbourhood column
print(df['Neighbourhood'].unique(),df['Neighbourhood'].nunique())
```

```
['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'] 81
```

The Neighbourhood column has 81 unique values. There are people from 81 distinct neighbourhood in dataset

In [119…
```
#checking the Scholarship Column
df['Scholarship'].unique()
```

Out[119]:
```
array([0, 1], dtype=int64)
```

The Scholarship column has two unique values. Binary Categorical Variable

In [120…

```
#Checking the Hipertension Column
df['Hipertension'].unique()
```

Out[120]:

```
array([1, 0], dtype=int64)
```

The Hipertension column has two unique values. Binary Categorical Variable

In [121…

```
df['Diabetes'].unique()
```

Out[121]:

```
array([0, 1], dtype=int64)
```

The Diabetes column has two unique values. Binary Categorical Variable

In [122…

```
df['Alcoholism'].unique()
```

Out[122]:

```
array([0, 1], dtype=int64)
```

The Alcoholism column has two unique values. Binary Categorical Variable

In [123…

```
df['Handcap'].unique()
```

Out[123]:

```
array([0, 1, 2, 3, 4], dtype=int64)
```

The Handcap column has 5 unique values.Categorical Variable

In [124…

```
df['SMS_received'].unique()
```

Out[124]:

```
array([0, 1], dtype=int64)
```

The SMS_received column has two unique values. Binary Categorical Variable

In [125…

```
df['No-show'].unique()
```

Out[125]:

```
array(['No', 'Yes'], dtype=object)
```

The No-show column has two unique values. Binary Categorical Variable

Summary

After exploring the columns, we noticed some irregularities in the data that will addressed in the next section

4.Data Cleaning

In [126…

```
#Renaming Columns
df.columns = ['PatientID', 'AppointmentID', 'Gender', 'ScheduledDay',
       'AppointmentDay', 'Age', 'Neighbourhood', 'Scholarship',
```

```
'Hypertension',
       'Diabetes', 'Alcoholism', 'Handicap', 'SMS_received', 'Absent']
```

In [127…

```
df.head()
```

Out[127]:

	PatientID	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	H
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	0	
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	0	
3	8.679512e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	0	
4	8.841186e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	

In [128…

```
#Convert  PatientID to int64
df['PatientID'] = df['PatientID'].astype('int64')
```

In [129…

```
#Change ApppointmentDay column to the day and date of appointment
df['AppointmentDate'] = pd.to_datetime(df['AppointmentDay']).dt.date
df['Appointmentday'] = pd.to_datetime(df['AppointmentDay']).dt.day_name()
df.drop('AppointmentDay',axis=1, inplace = True)
```

In [130…

```
#checking the data set to confirm changes
df
```

Out[130]:

	PatientID	AppointmentID	Gender	ScheduledDay	Age	Neighbourhood	Scholarship	Hypertensi
0	29872499824296	5642903	F	2016-04-29T18:38:08Z	62	JARDIM DA PENHA	0	
1	558997776694438	5642503	M	2016-04-29T16:08:27Z	56	JARDIM DA PENHA	0	
2	4262962299951	5642549	F	2016-04-29T16:19:04Z	62	MATA DA PRAIA	0	
3	867951213174	5642828	F	2016-04-29T17:29:31Z	8	PONTAL DE CAMBURI	0	
4	8841186448183	5642494	F	2016-04-29T16:07:23Z	56	JARDIM DA PENHA	0	
...	...	...	...	...	...	...	...	
110522	2572134369293	5651768	F	2016-05-03T09:15:35Z	56	MARIA ORTIZ	0	
110523	3596266328735	5650093	F	2016-05-03T07:27:33Z	51	MARIA ORTIZ	0	
110524	15576631729893	5630692	F	2016-04-27T16:03:52Z	21	MARIA ORTIZ	0	

110525	92134931435557	5630323	F	2016-04-27T15:09:23Z	38	MARIA ORTIZ	0	
110526	377511518121127	5629448	F	2016-04-27T13:30:56Z	54	MARIA ORTIZ	0	

110527 rows × 15 columns

In [131…

```
#Change the ScheduledDay  to date
df['ScheduledDate'] = pd.to_datetime(df['ScheduledDay']).dt.date
df.drop('ScheduledDay',axis=1, inplace = True)
```

In [132…

```
df
#checking the data set to confirm changes
```

Out[132]:

	PatientID	AppointmentID	Gender	Age	Neighbourhood	Scholarship	Hypertension	Diabetes
0	29872499824296	5642903	F	62	JARDIM DA PENHA	0	1	0
1	558997776694438	5642503	M	56	JARDIM DA PENHA	0	0	0
2	4262962299951	5642549	F	62	MATA DA PRAIA	0	0	0
3	867951213174	5642828	F	8	PONTAL DE CAMBURI	0	0	0
4	8841186448183	5642494	F	56	JARDIM DA PENHA	0	1	1
...	...	...	...	...	...	...	...	...
110522	2572134369293	5651768	F	56	MARIA ORTIZ	0	0	0
110523	3596266328735	5650093	F	51	MARIA ORTIZ	0	0	0
110524	15576631729893	5630692	F	21	MARIA ORTIZ	0	0	0
110525	92134931435557	5630323	F	38	MARIA ORTIZ	0	0	0
110526	377511518121127	5629448	F	54	MARIA ORTIZ	0	0	0

110527 rows × 15 columns

Creating a new feature `Waiting interval` for better analysis

In [133…

```
#create waiting interval by getting difference between appointment and schedule date
df['WaitingInterval'] = df.AppointmentDate - df.ScheduledDate
```

In [134…

```
df.head()
#checking the data set to confirm changes
```

Out[134]:

	PatientID	AppointmentID	Gender	Age	Neighbourhood	Scholarship	Hypertension	Diabetes	Alcohc
0	29872499824296	5642903	F	62	JARDIM DA PENHA	0	1	0	

1	558997776694438	5642503	M	56	JARDIM DA PENHA	0	0	0
2	4262962299951	5642549	F	62	MATA DA PRAIA	0	0	0
3	867951213174	5642828	F	8	PONTAL DE CAMBURI	0	0	0
4	8841186448183	5642494	F	56	JARDIM DA PENHA	0	1	1

In [135…

```
#check for patients with negative waiting interval
df[df['WaitingInterval'] < '0 days']
```

Out[135]:

	PatientID	AppointmentID	Gender	Age	Neighbourhood	Scholarship	Hypertension	Diabetes	A
27033	7839272661752	5679978	M	38	RESISTÊNCIA	0	0	0	
55226	7896293967868	5715660	F	19	SANTO ANTÔNIO	0	0	0	
64175	24252258389979	5664962	F	22	CONSOLAÇÃO	0	0	0	
71533	998231581612122	5686628	F	81	SANTO ANTÔNIO	0	0	0	
72362	3787481966821	5655637	M	7	TABUAZEIRO	0	0	0	

In [136…

```
#removing instances with negative waiting instances from the dataset
df = df[df['AppointmentDate'] >= df['ScheduledDate']]
df.shape
```

Out[136]:

```
(110522, 16)
```

In [137…

```
#removing negative age instance from the analysis
df = df[df.Age != -1]
df.shape
```

Out[137]:

```
(110521, 16)
```

In [138…

```
df
```

Out[138]:

	PatientID	AppointmentID	Gender	Age	Neighbourhood	Scholarship	Hypertension	Diabetes
0	29872499824296	5642903	F	62	JARDIM DA PENHA	0	1	0
1	558997776694438	5642503	M	56	JARDIM DA PENHA	0	0	0
2	4262962299951	5642549	F	62	MATA DA PRAIA	0	0	0
3	867951213174	5642828	F	8	PONTAL DE CAMBURI	0	0	0
4	8841186448183	5642494	F	56	JARDIM DA PENHA	0	1	1
...	...	...	...	...	...	...	...	...

110522	2572134369293	5651768	F	56	MARIA ORTIZ	0	0	0
110523	3596266328735	5650093	F	51	MARIA ORTIZ	0	0	0
110524	15576631729893	5630692	F	21	MARIA ORTIZ	0	0	0
110525	92134931435557	5630323	F	38	MARIA ORTIZ	0	0	0
110526	377511518121127	5629448	F	54	MARIA ORTIZ	0	0	0

110521 rows × 16 columns

In [139…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 110521 entries, 0 to 110526
Data columns (total 16 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   PatientID         110521 non-null  int64
 1   AppointmentID     110521 non-null  int64
 2   Gender            110521 non-null  object
 3   Age               110521 non-null  int64
 4   Neighbourhood     110521 non-null  object
 5   Scholarship       110521 non-null  int64
 6   Hypertension      110521 non-null  int64
 7   Diabetes          110521 non-null  int64
 8   Alcoholism        110521 non-null  int64
 9   Handicap          110521 non-null  int64
 10  SMS_received      110521 non-null  int64
 11  Absent            110521 non-null  object
 12  AppointmentDate   110521 non-null  object
 13  Appointmentday    110521 non-null  object
 14  ScheduledDate     110521 non-null  object
 15  WaitingInterval   110521 non-null  timedelta64[ns]
dtypes: int64(9), object(6), timedelta64[ns](1)
memory usage: 14.3+ MB
```

In [ ]:

```

```

Exploratory Data Analysis

Exploratory Data Analysis refers to the critical process of performing initial investigations on data so as to discover patterns,to spot anomalies,to test hypothesis and to check assumptions with the help of summary statistics and graphical representations. We are going to be exploring the data with these questions in mind

1. What factors are important for us to know in order to predict if a patient will show up for their scheduled appointment?
2. How do the Factors vary with Each Other?

Research Areas

1. `Target Variable(Absent)` : studying the trends in the absent study overall proportions to help in the analysis with other variables

2. `Univariate Analysis` : Studying each variable to uncover patterns and how they relate with the target variable. How does `Age` , `Gender` , `Neighbourhood` and `Scholarship` influence a patient from attending the Hospital appointment.
3. `Multivariate Analysis` : Studyying how the variables relate with one another and how they can help in predicting the target variable. How do the variables affect each other(Correlation) and affects the target variable.

Gender vs Scholarship

AgeGroup vs Scholarsip

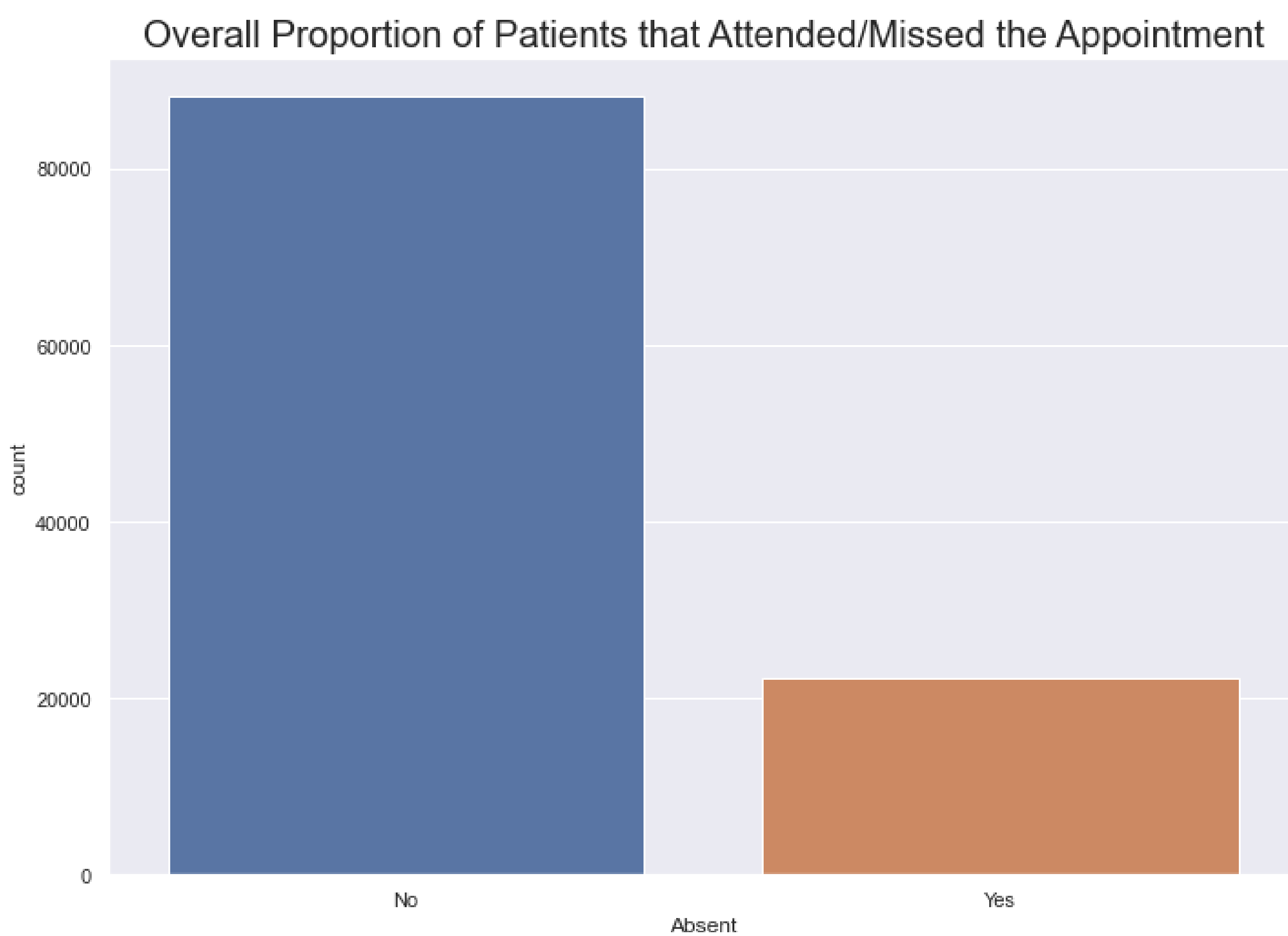
These will be done with the appropraite analysis and visualisations.

1. **Target Variable**

`Absent` This shows if a patient shows up for a scheduled appointment, `Yes` if absent and `No` if Present

In [149…

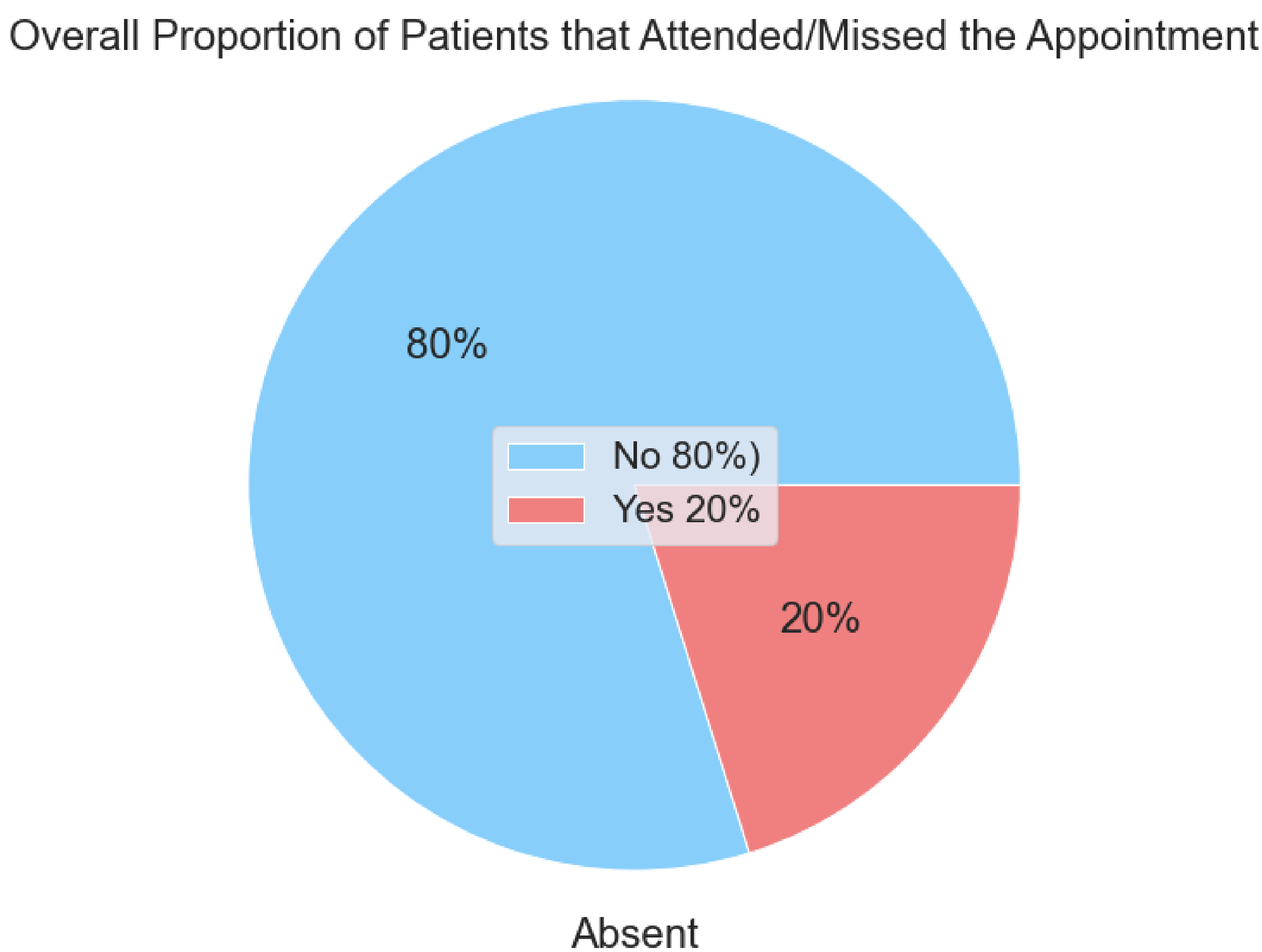
```
#plot a countplot with seaborn
sns.countplot(x='Absent',data=df)

sns.set(font_scale=1.7)

plt.title("Overall Proportion of Patients that Attended/Missed the Appointment");
```



It can be seen from the bar plot that a huge proportion of the patients did not miss their hospital appointmnent.

In [150…

```
#plot piechart with seaborn
labels = [r'No 80%)',r'Yes 20%']
sizes =df['Absent'].value_counts()
colors = ['lightskyblue', 'lightcoral']
sns.set(font_scale=2)
patches, texts = plt.pie(sizes, colors=colors)
plt.legend(patches, labels, loc="center")
plt.pie(df['Absent'].value_counts(),autopct ='%.0f%%',colors=colors)
plt.title("Overall Proportion of Patients that Attended/Missed the
Appointment")
plt.xlabel('Absent')
plt.axis('equal')
plt.tight_layout()
plt.show()
```



The pie chart shows us that only 20% of the patients missed their hospital appointment. We will be investigating the patterns in other features in the data set to be able to answer the research questions.

In [ ]:

```
```

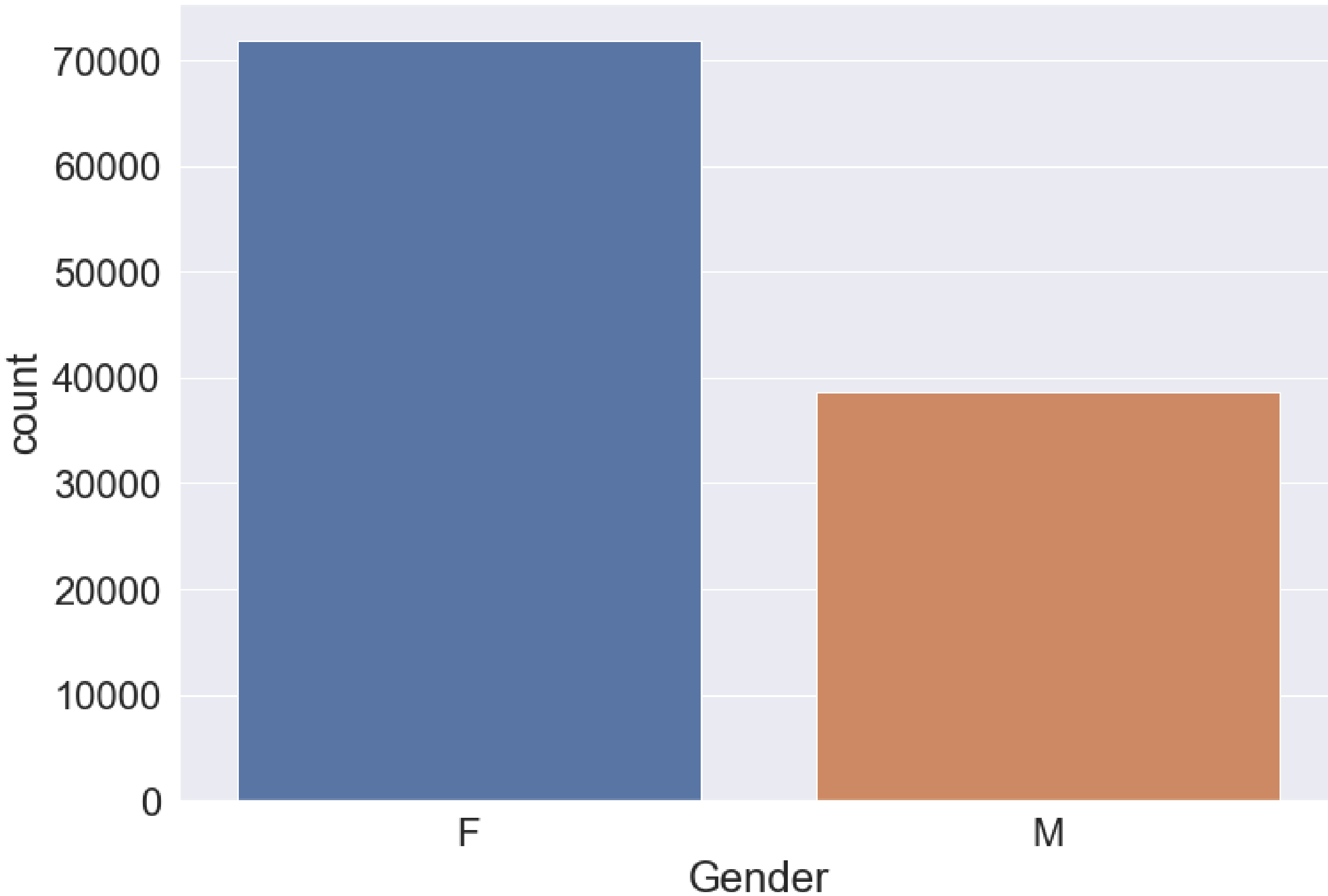
Univariate Analysis

1. Gender

The gender indicates the sex of the patient. It is a categorical variable. We will observe the trends by cheching the proportion

In [151…

```
#plot countplot with seaborn
df['Gender'].value_counts()
sns.set(font_scale=2)
sns.countplot(x='Gender',data=df);
```

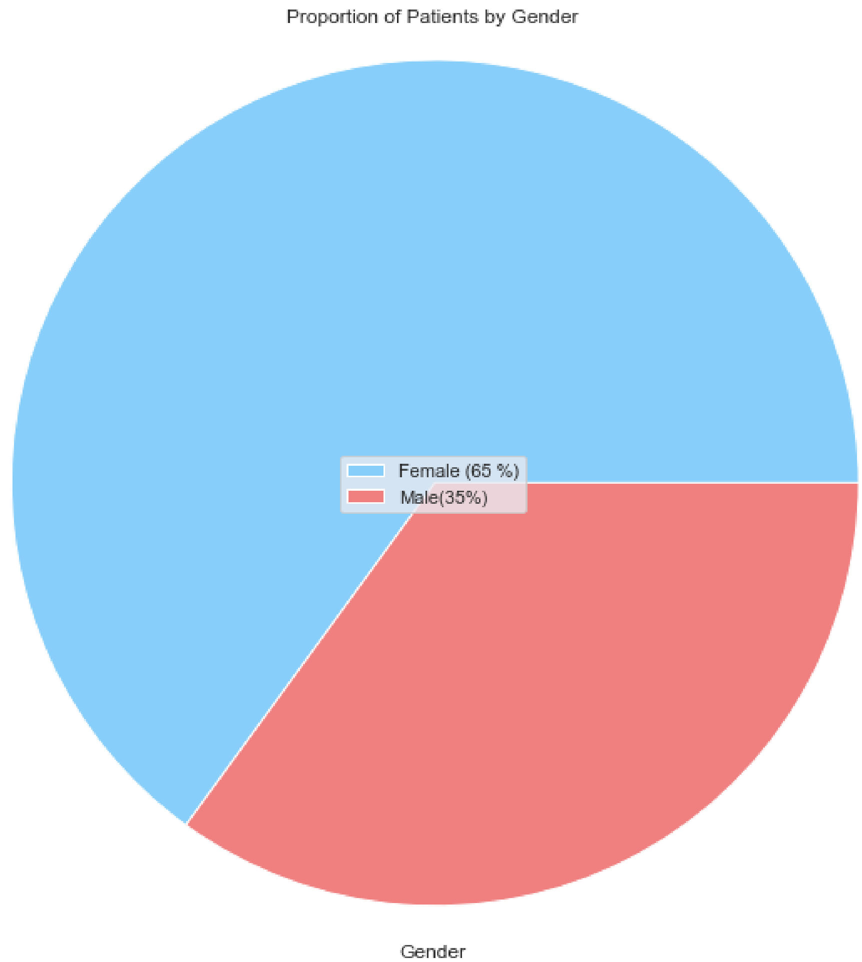


A huge proportion of all patients are Females. Over 70000 females and about 40000 males.

In [152…

```
#create piechart with seaborn
labels = [r'Female (65 %)',r'Male(35%)' ]
sizes = df['Gender'].value_counts()
sns.set(font_scale=2)
sns.set(rc={'figure.figsize':(11.7,8.27)})
colors = ['lightskyblue', 'lightcoral']
patches, texts = plt.pie(sizes, colors=colors)
plt.legend(patches, labels, loc="center")
plt.title("Proportion of Patients by Gender")
plt.xlabel('Gender')
```

```
# Set aspect ratio to be equal so that pie is drawn as a circle.
plt.axis('equal')
plt.tight_layout()
plt.show()
```

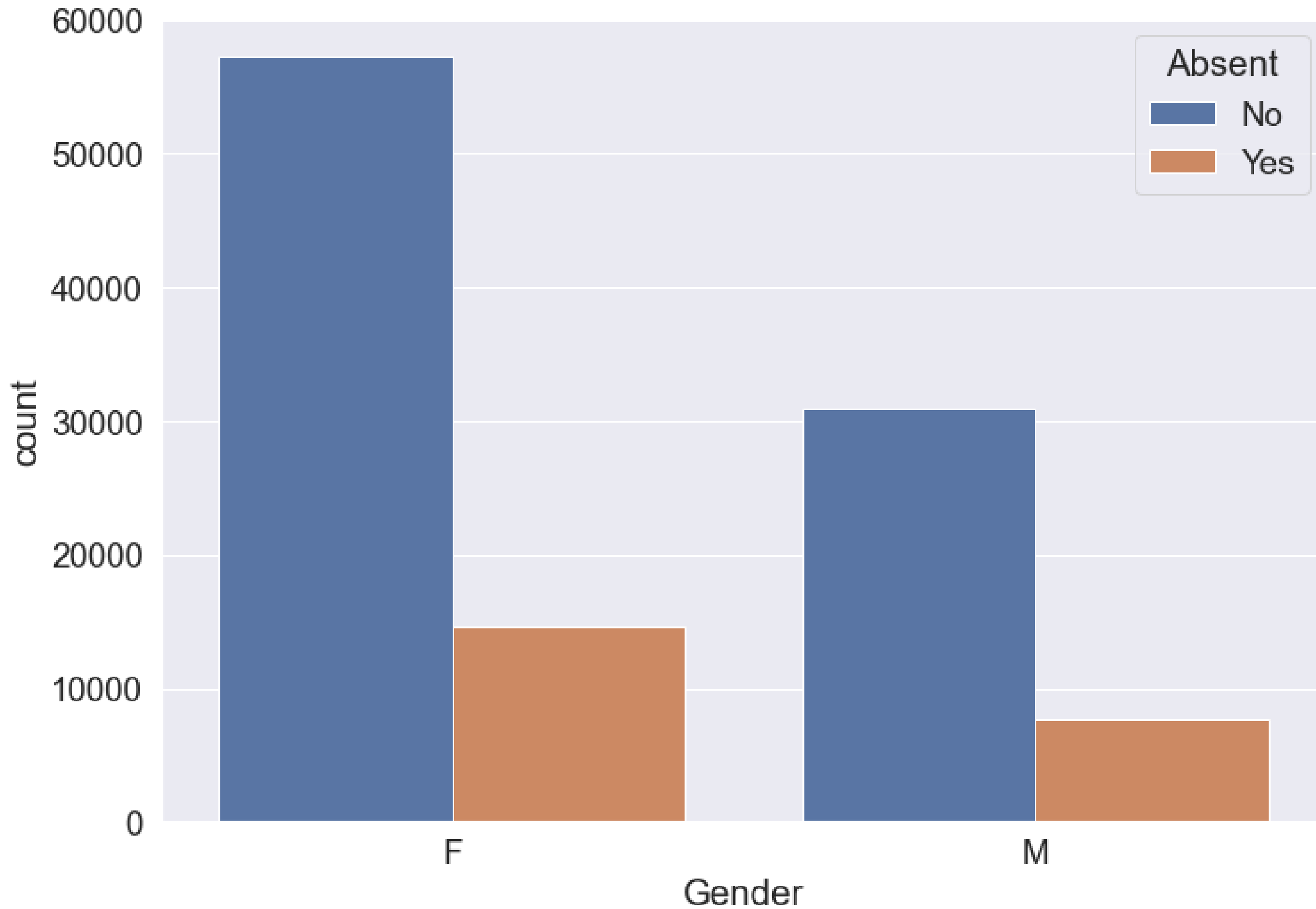


65% of the patients are Females and Males account for 35%. This means that Females dominate the dataset

Does Gender Relate to Missing hospital Appointment?

In [153…

```
#create countplot with seaborn
sns.set(font_scale=1.7)
sns.countplot(x='Gender',data =df,hue ='Absent');
```



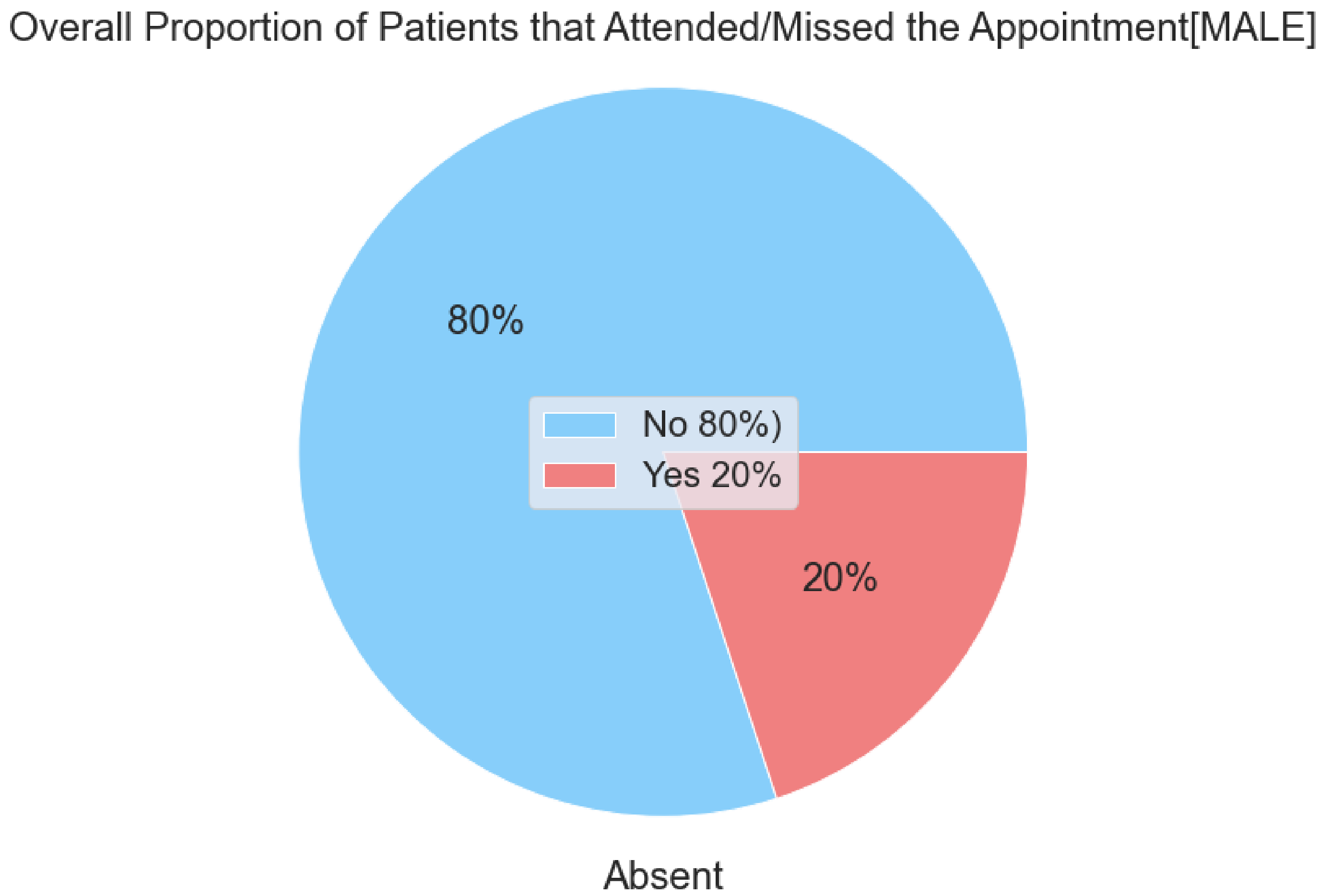
As seen from the overall proportion, a huge percentage of each gender did not miss the hospital appointment. Well Show the percentages with a pie chart.

In [154…

```
#filterring the dataset according to gender
df_male = df[df.Gender == 'M']
df_female = df[df.Gender == 'F']
```

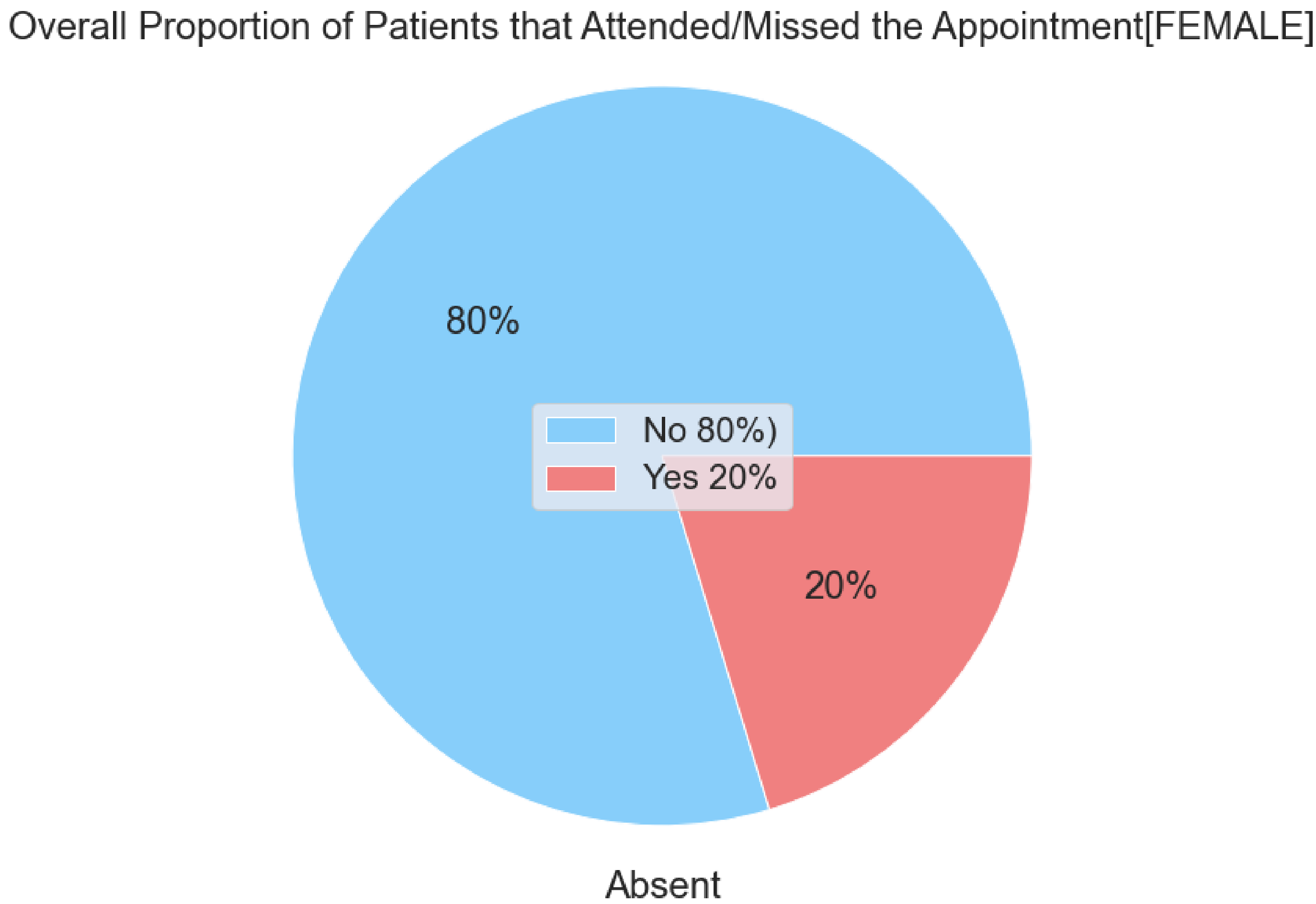
In [155…

```
#plot a piechart with sns and matplotlib
labels = [r'No 80%)',r'Yes 20%']
sizes =df_male['Absent'].value_counts()
colors = ['lightskyblue', 'lightcoral']
sns.set(font_scale=2)
patches, texts = plt.pie(sizes, colors=colors)
plt.legend(patches, labels, loc="center")
plt.pie(df_male['Absent'].value_counts(),autopct ='%.0f%%',colors=colors)
plt.title("Overall Proportion of Patients that Attended/Missed the
Appointment[MALE]")
plt.xlabel('Absent')
plt.axis('equal')
plt.tight_layout()
plt.show()
```



In [156…

```
#plot a piechart with sns and matplotlib
labels = [r'No 80%)',r'Yes 20%']
sizes =df_female['Absent'].value_counts()
colors = ['lightskyblue', 'lightcoral']
sns.set(font_scale=2)
patches, texts = plt.pie(sizes, colors=colors)
plt.legend(patches, labels, loc="center")
plt.pie(df_female['Absent'].value_counts(),autopct ='%.0f%%',colors=colors)
plt.title("Overall Proportion of Patients that Attended/Missed the Appointment[FEMALE]")
plt.axis('equal')
plt.tight_layout()
plt.xlabel('Absent')
plt.show()
```



The proportion of Males and females that did not miss the hospital appointment are almost the same.

In [ ]:

```

```

In [ ]:

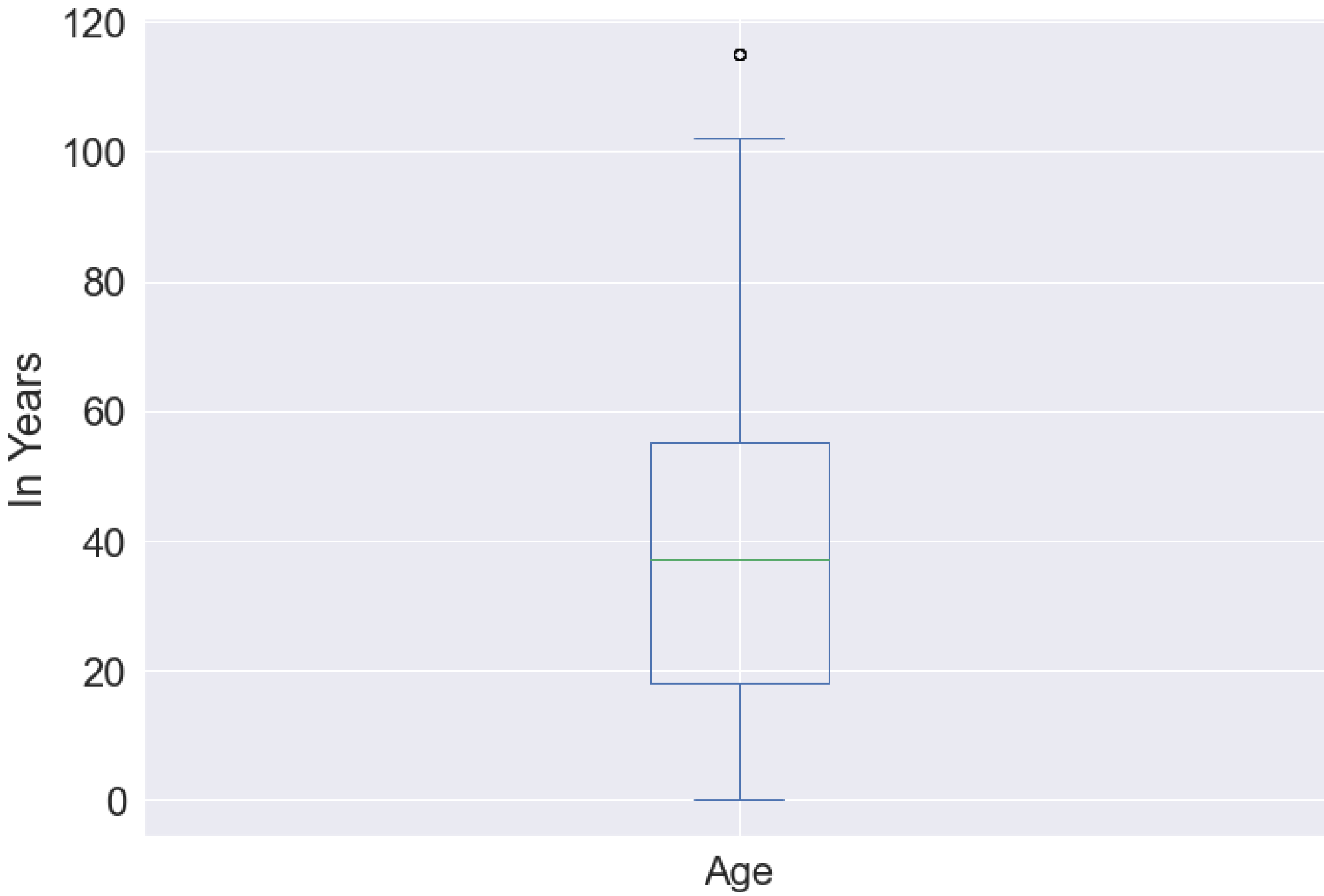
```

```

2. Age

Indicates how Old the patient is. It is a quantitative variable.

In [157…

```
#creating a box plot
df['Age'].plot(kind ='box')
plt.ylabel('In Years');
```



In [158…

```
df['Age'].describe()
#getting info about the Age variable
```

Out[158]:

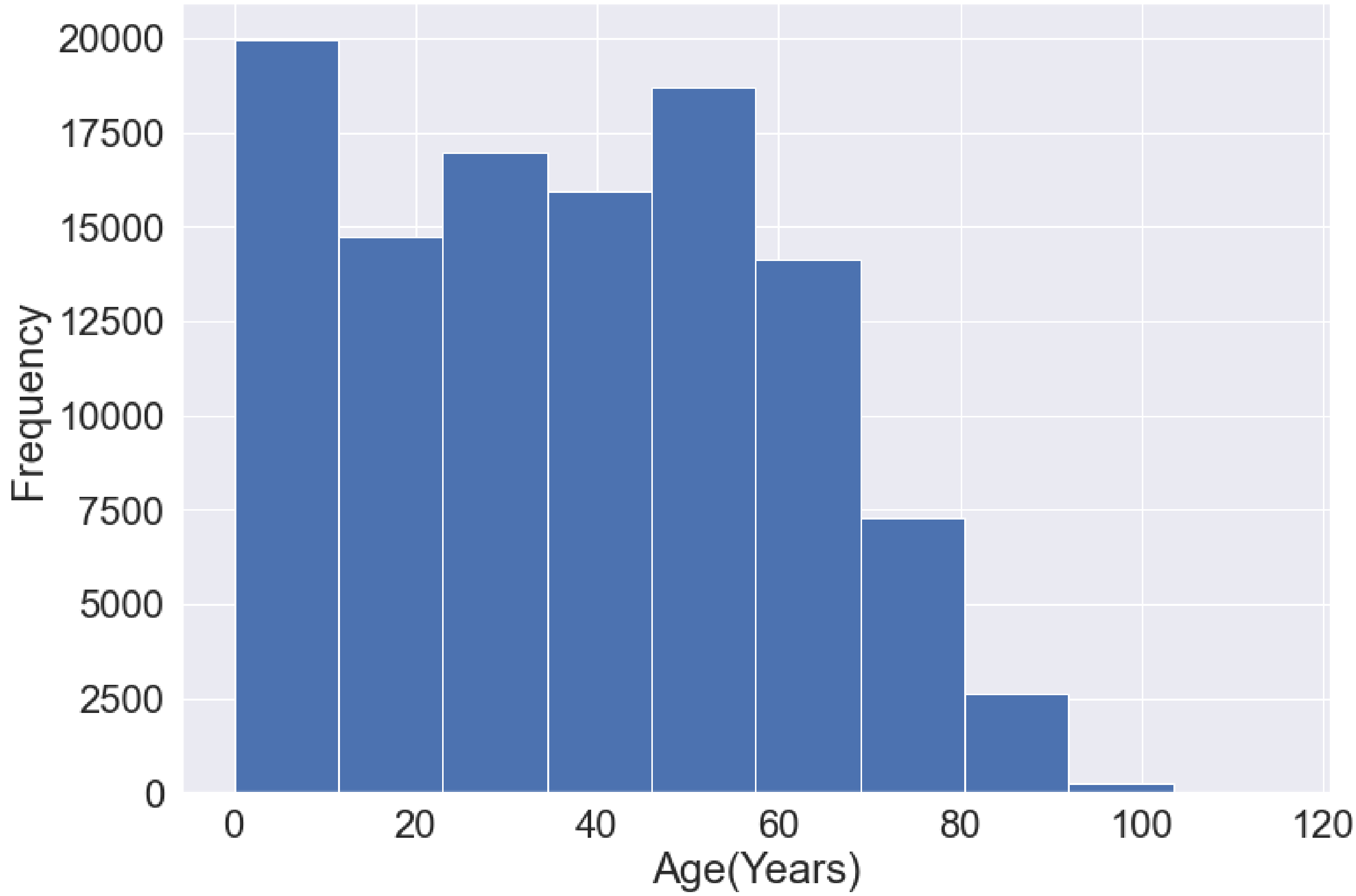
```
count    110521.000000
mean         37.089386
std          23.109885
min           0.000000
25%          18.000000
50%          37.000000
75%          55.000000
max         115.000000
Name: Age, dtype: float64
```

In [159…

```
#plot an histogram with matplotlib
df['Age'].plot(kind='hist');
plt.xlabel('Age(Years)')
```

Out[159]:

```
Text(0.5, 0, 'Age(Years)')
```



The distribution of the age is positively skewed with a median age of 37 years old. The range is 0-115 years with the prescence of a high outlier(one patient is very old). To gain better insights, we will analyse the Age according to age groups.

In [160…

```
#dividing age into age groups using the pandas cut function
df['Agegroup'] = pd.cut(x=df['Age'], bins=[0, 20, 40, 60, 80, 100,120],
                    labels=['0 - 20 years', '21 - 40 years', '41 - 60 years',
                            '61 - 80 years', '81- 100 years','100-120
years'])
```

In [161…

```
#check the dataset to confirm changes
df
```

Out[161]:

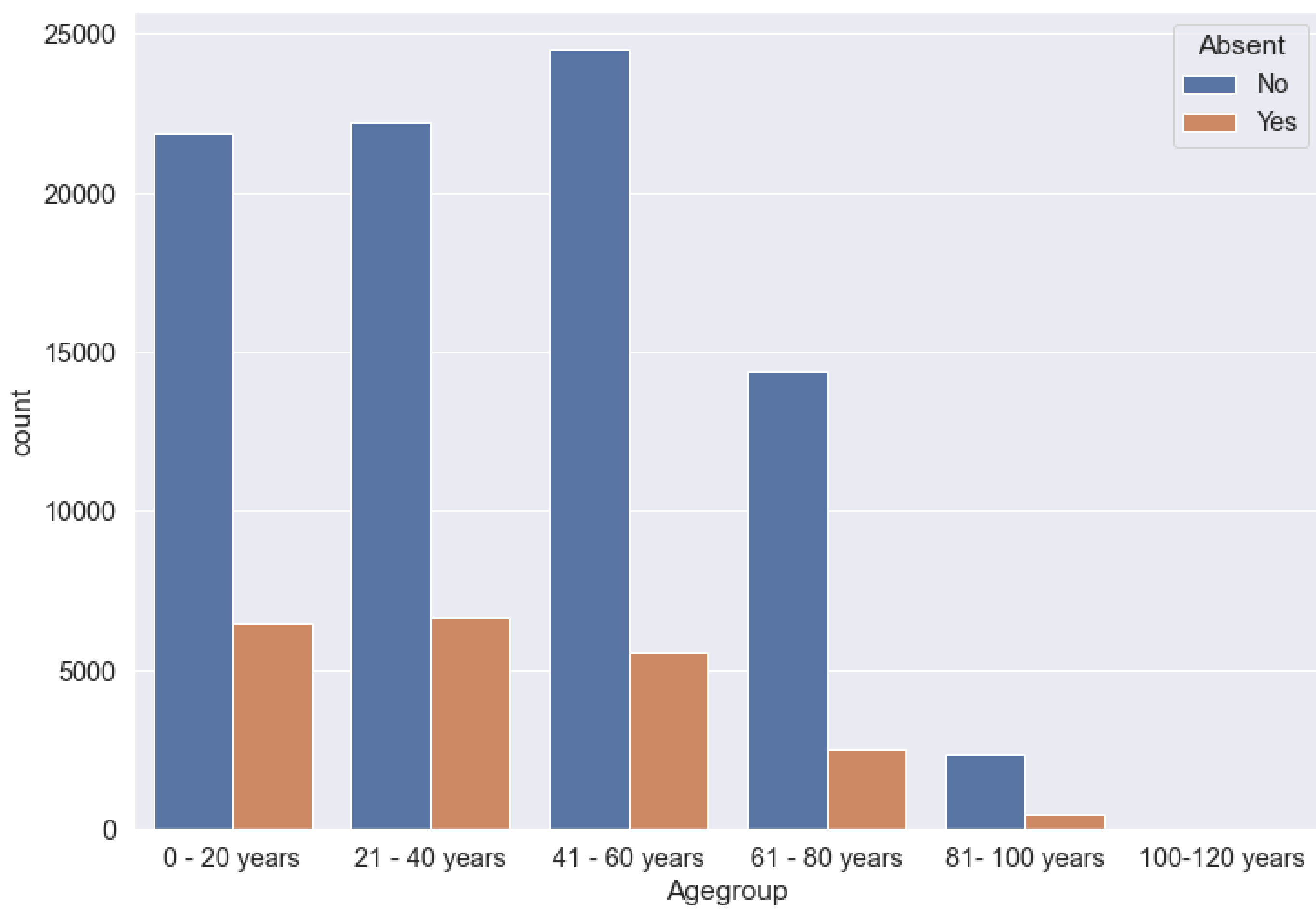
	PatientID	AppointmentID	Gender	Age	Neighbourhood	Scholarship	Hypertension	Diabetes
0	29872499824296	5642903	F	62	JARDIM DA PENHA	0	1	0
1	558997776694438	5642503	M	56	JARDIM DA PENHA	0	0	0
2	4262962299951	5642549	F	62	MATA DA PRAIA	0	0	0
3	867951213174	5642828	F	8	PONTAL DE CAMBURI	0	0	0
4	8841186448183	5642494	F	56	JARDIM DA PENHA	0	1	1

...	...	...	...	...	...	...	...	...
110522	2572134369293	5651768	F	56	MARIA ORTIZ	0	0	0
110523	3596266328735	5650093	F	51	MARIA ORTIZ	0	0	0
110524	15576631729893	5630692	F	21	MARIA ORTIZ	0	0	0
110525	92134931435557	5630323	F	38	MARIA ORTIZ	0	0	0
110526	377511518121127	5629448	F	54	MARIA ORTIZ	0	0	0

110521 rows × 17 columns

In [163…

```
#plot a countplot with multiple variables
sns.countplot(x='Agegroup',data=df,hue='Absent')
sns.set(font_scale=1.3)
```



Across all age groups have a common trend of a larger proportion not missing the hospital appointments.

In [ ]:

```

```

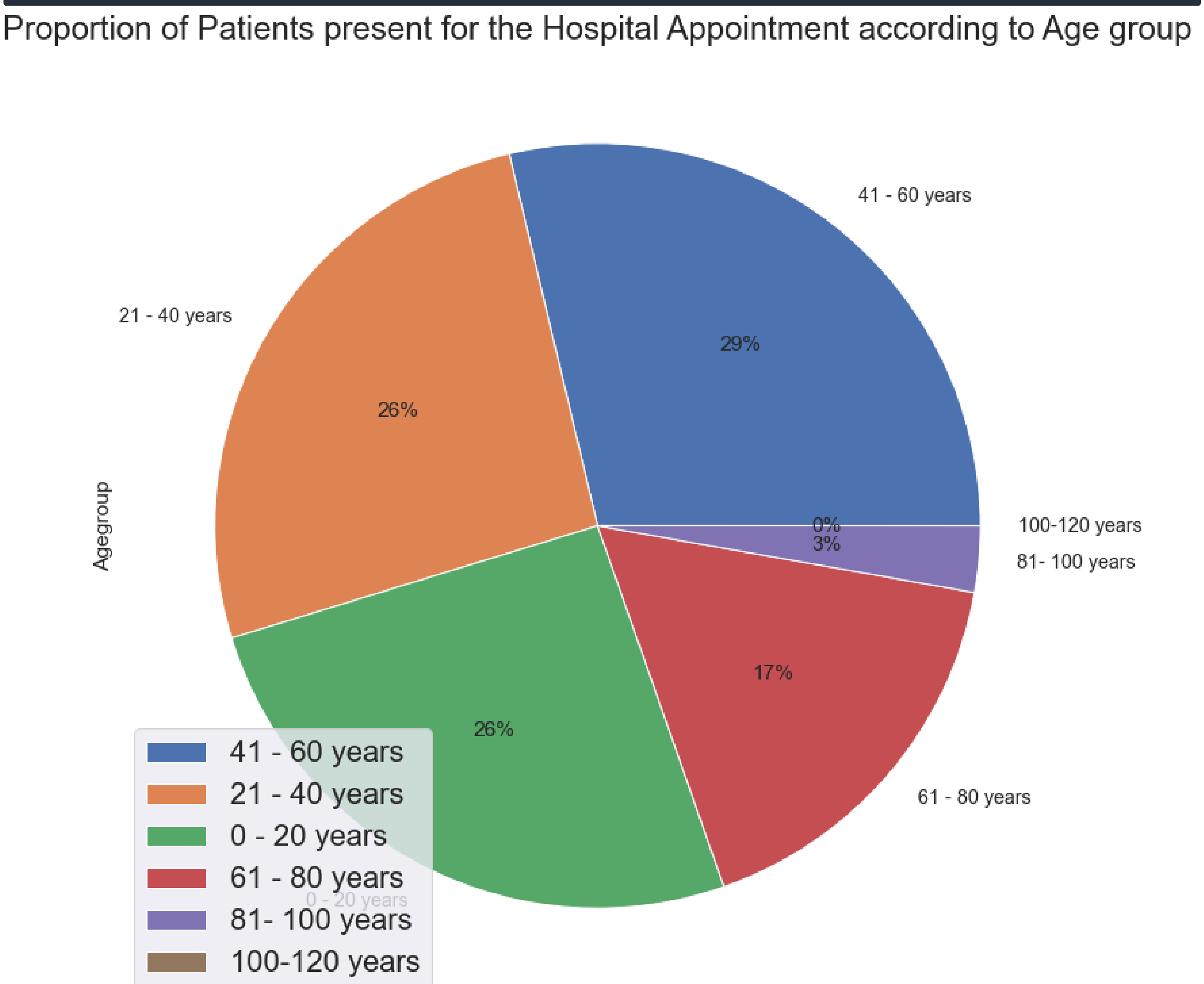
In [164…

```
#splitting the Absent column into two
df_show = df[df.Absent == 'No']
df_noshow =df[df.Absent == 'Yes']
```

```
#plot a piechart with sns and matplotlib
df_show['Agegroup'].value_counts().plot(kind='pie',autopct ='%.0f%%',figsize=
(15,13))
sns.set(font_scale=2)
plt.legend(loc ='lower left')
plt.title('Proportion of Patients present for the Hospital Appointment
according to Age group')
```

Out[164]:

```
Text(0.5, 1.0, 'Proportion of Patients present for the Hospital Appointment according to
Age group')
```



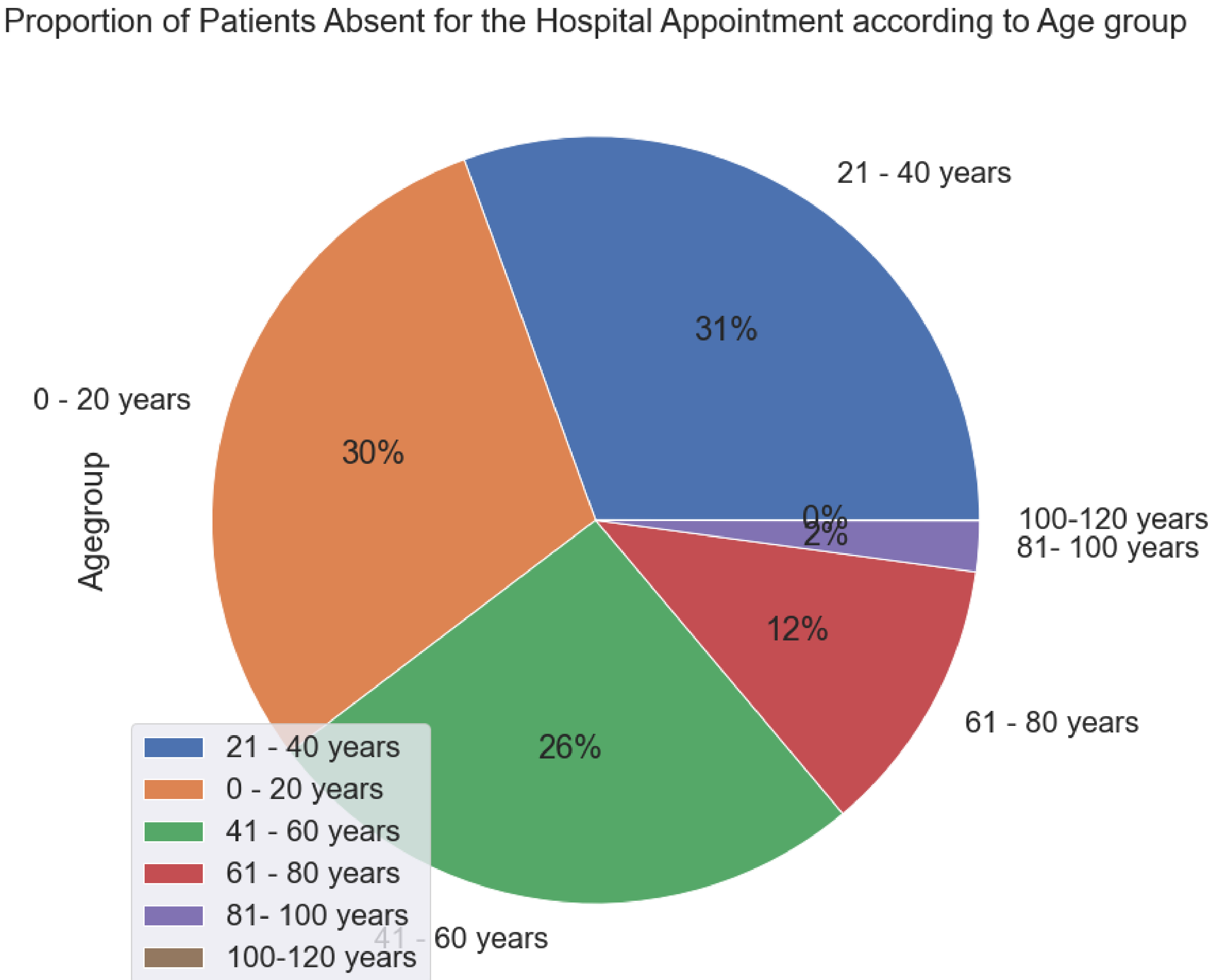
The largest percentage of Patients not missing the hospital appointment is from the 41-60 years age group. This is as a result of people around that age group being prone to high risk diseases. In upcoming sections, age group will be analysed with some high risk diseases.

In [165…

```
df_show = df[df.Absent == 'No']
df_noshow =df[df.Absent == 'Yes']
#plot a piechart with sns and matplotlib
df_noshow['Agegroup'].value_counts().plot(kind='pie',autopct
='%.0f%%',figsize=(15,13))
sns.set(font_scale=2)
```

```
plt.legend(loc ='lower left')
plt.title('Proportion of Patients Absent for the Hospital Appointment according to Age group')
```

Out[165]:
```
Text(0.5, 1.0, 'Proportion of Patients Absent for the Hospital Appointment according to Age group')
```



The largest percentage of Patients missing the hospital appointment is from the 21-40 years age group. This is as a result of people around that age group having to work for hours/lots of commitments or picking up habits like alcoholism that will not allow them attend.In upcoming sections, age group will some of this behaviours.

In [ ]:
```

```

3. Neighbourhood

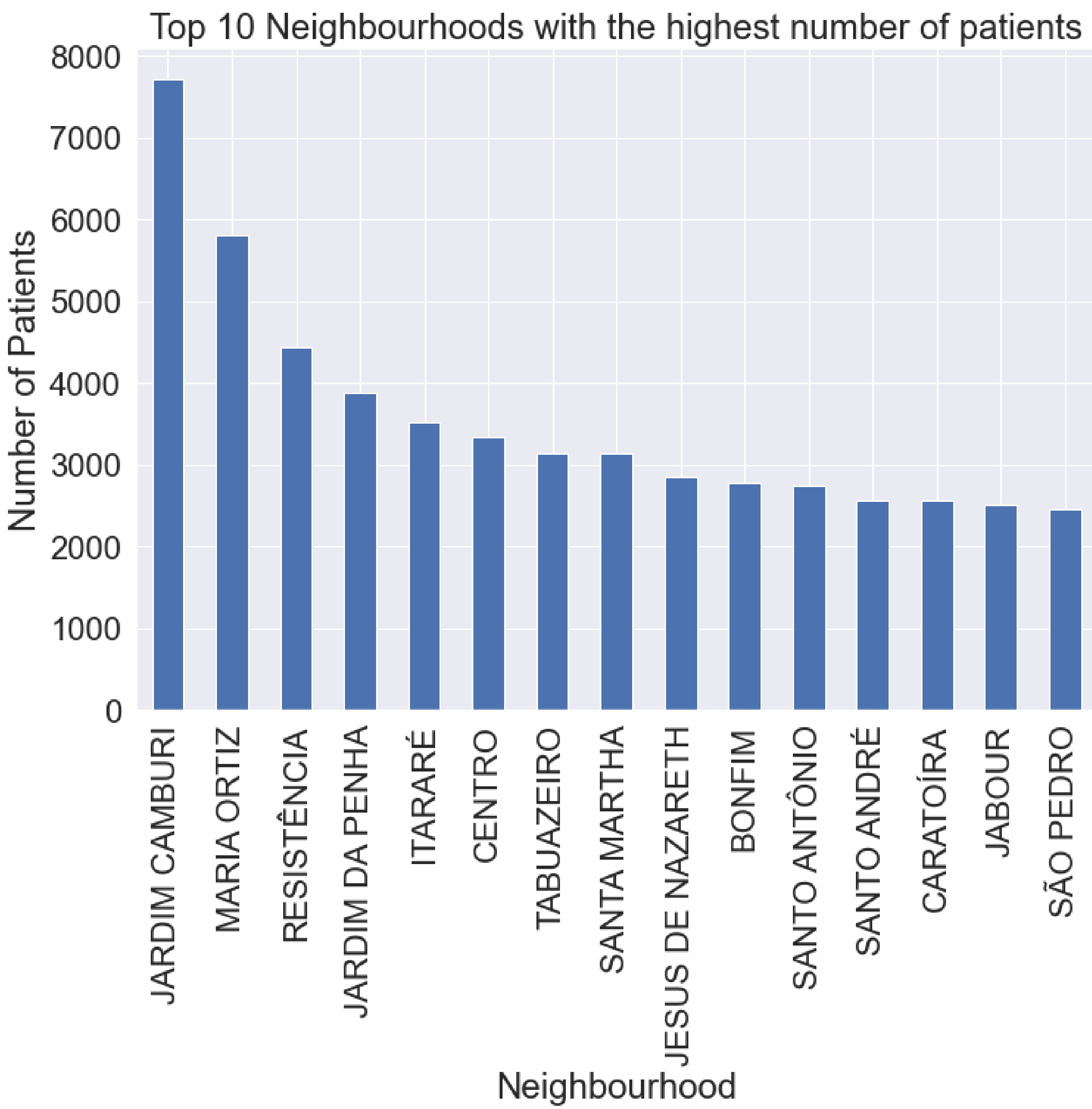
Where the appointment takes place(Health Center Location). A categorical variable with 81 unique values.

In [166…
```
#Top 10 Neighbourhoods with the highest number of patients

df['Neighbourhood'].value_counts().sort_values(ascending=False)
[0:15].plot(kind ='bar')
```

```
plt.title('Top 10 Neighbourhoods with the highest number of patients')
plt.xlabel('Neighbourhood')
plt.ylabel('Number of Patients')
```

Out[166]:

```
Text(0, 0.5, 'Number of Patients')
```



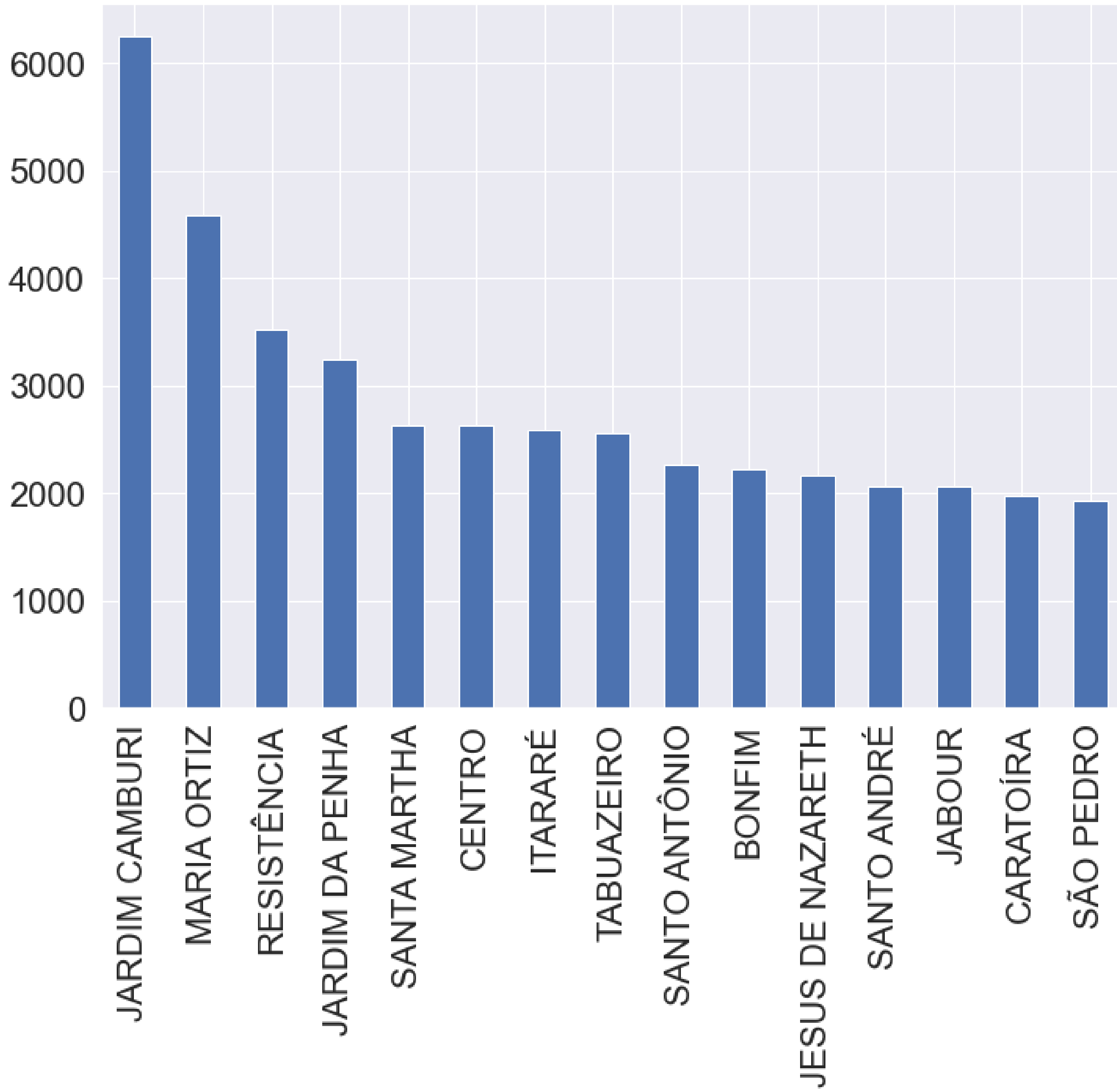
The JARDIM CAMBURI Neighbourhood has the highest number of patients with about 8000 patients.

In [167…

```
#checking the patients present for the appointment
df_show['Neighbourhood'].value_counts().sort_values(ascending=False)
[0:15].plot(x='Neighbourhood',y='Absent',kind ='bar')
```

Out[167]:

```
<AxesSubplot:>
```



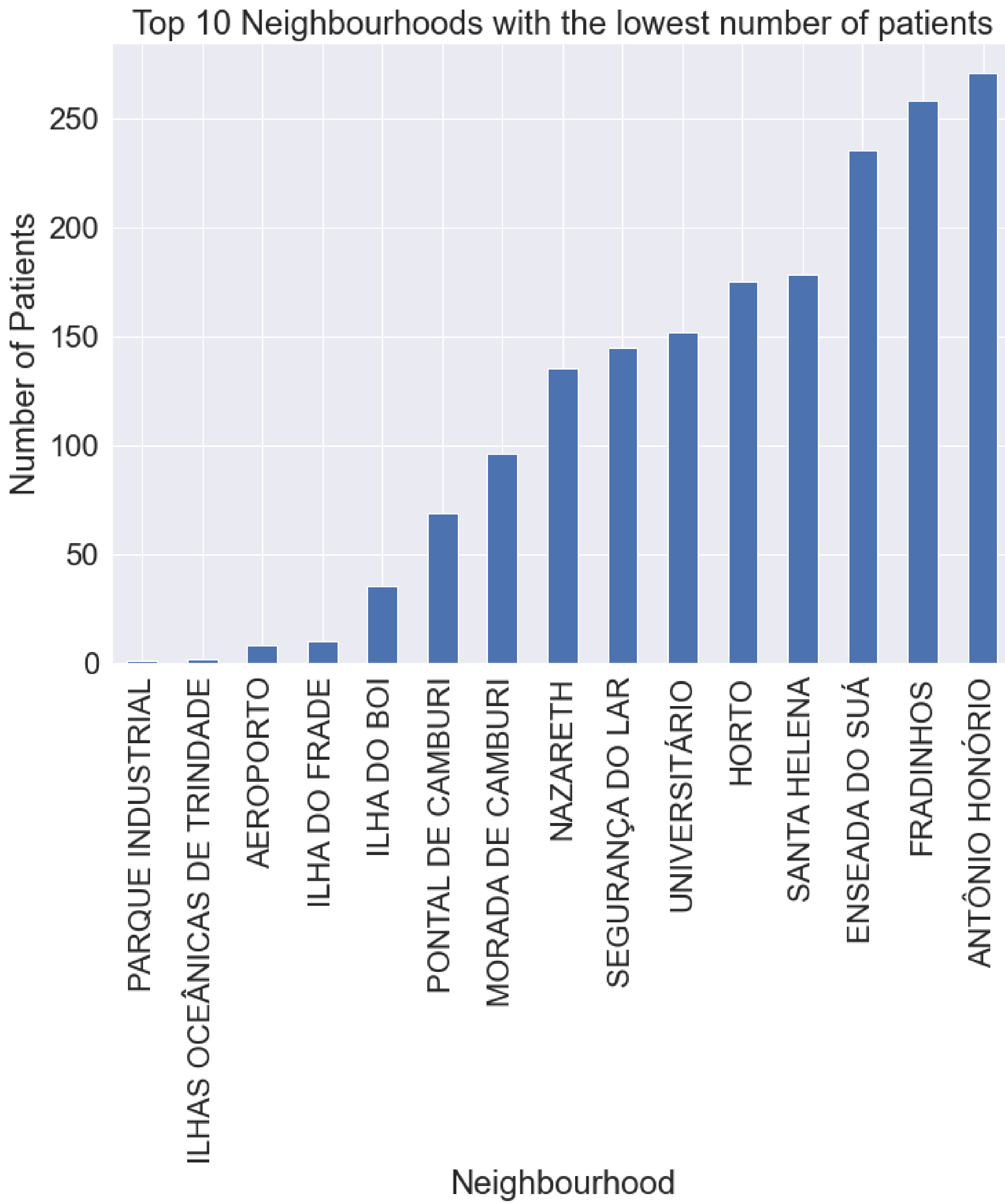
THE JARDIM CAMBURI neighbourhood also has the highest attendance. This could be due to its access to facilities

In [168…

```
#Top 10 Neighbourhoods with the lowest number of patients

df['Neighbourhood'].value_counts().sort_values()[0:15].plot(kind ='bar')
plt.title('Top 10 Neighbourhoods with the lowest number of patients')
plt.xlabel('Neighbourhood')
plt.ylabel('Number of Patients')
```

Out[168]:

```
Text(0, 0.5, 'Number of Patients')
```



The PARQUE INDUSTRIAL has the lowest number of patients and attendance rate. This could be due to the location.

In [ ]:

In [ ]:

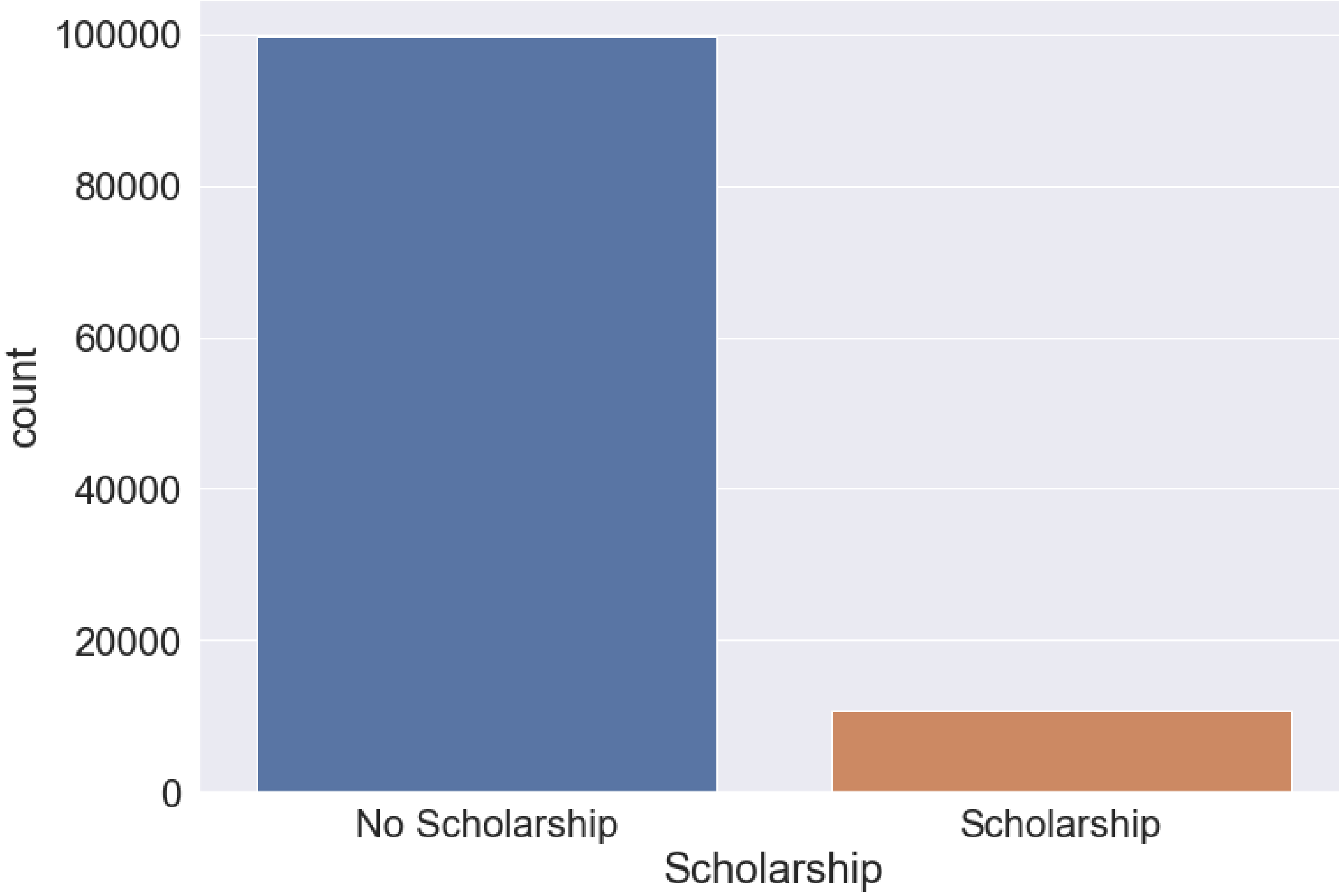
4.. Scholarship

Shows whether or not the patient is enrolled in Brasilian welfare program Bolsa Família.(1 if true, 0 if False)

In [169…

```
#plot a countplot with multiple variables
df['Scholarship'] = df.Scholarship.astype('category')
df.Scholarship.cat.rename_categories(['No Scholarship','Scholarship'],
inplace = True);
sns.countplot(x='Scholarship',data=df)
sns.set(font_scale=1.3)
```

```
C:\Users\ashin\anaconda3\lib\site-packages\pandas\core\arrays\categorical.py:2631: FutureWarning: The `inplace` parameter in pandas.Categorical.rename_categories is deprecated and will be removed in a future version. Removing unused categories will always return a new Categorical object.
  res = method(*args, **kwargs)
```

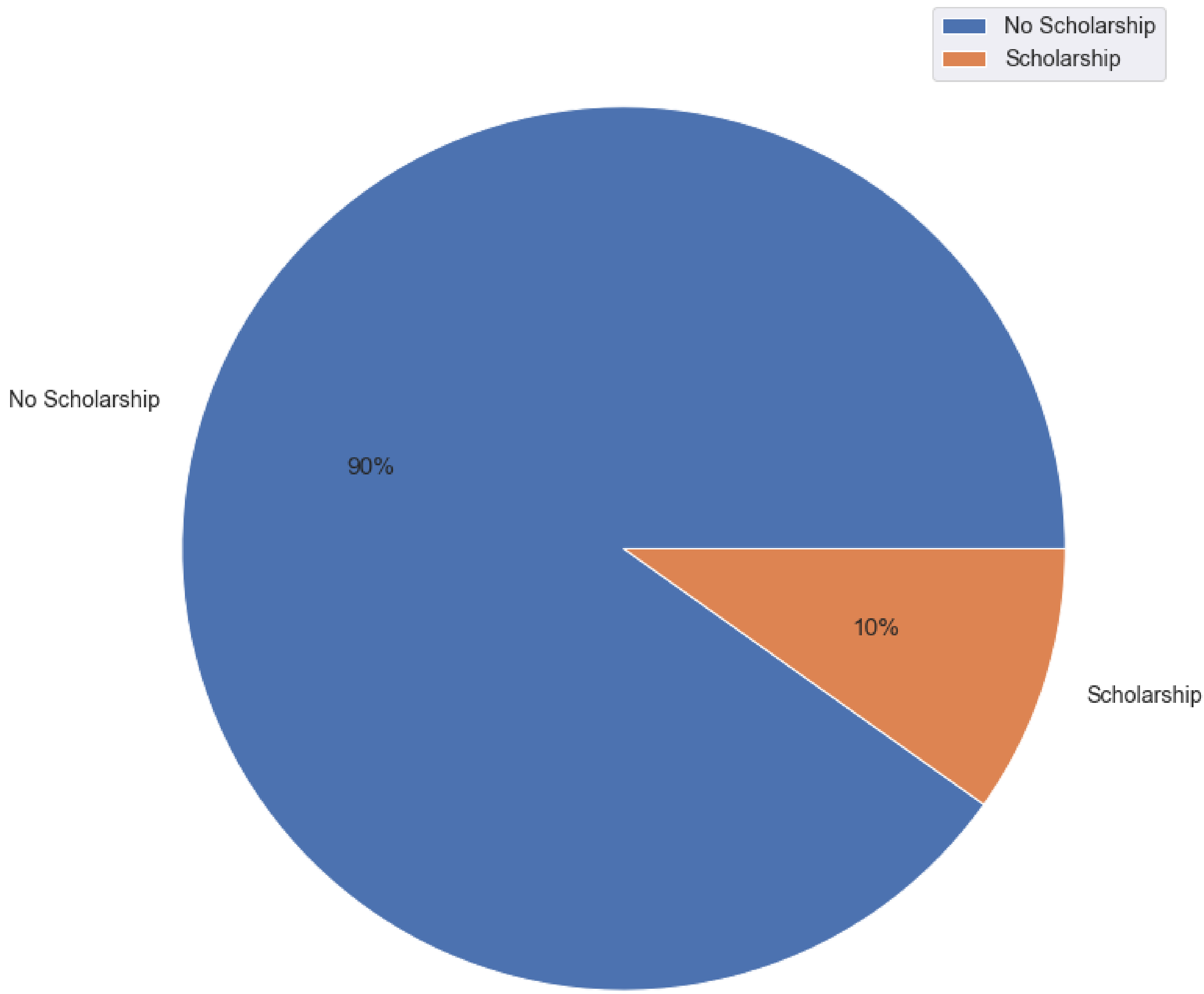


A huge proportion of the patients are not under the scholarship program.

In [170…

```
df['Scholarship'].value_counts().plot(kind='pie',autopct ='%.0f%%',figsize=
(15,13))
plt.ylabel('')
plt.legend()
plt.title('Proportion of Patients with Health care Scholarship ');
```

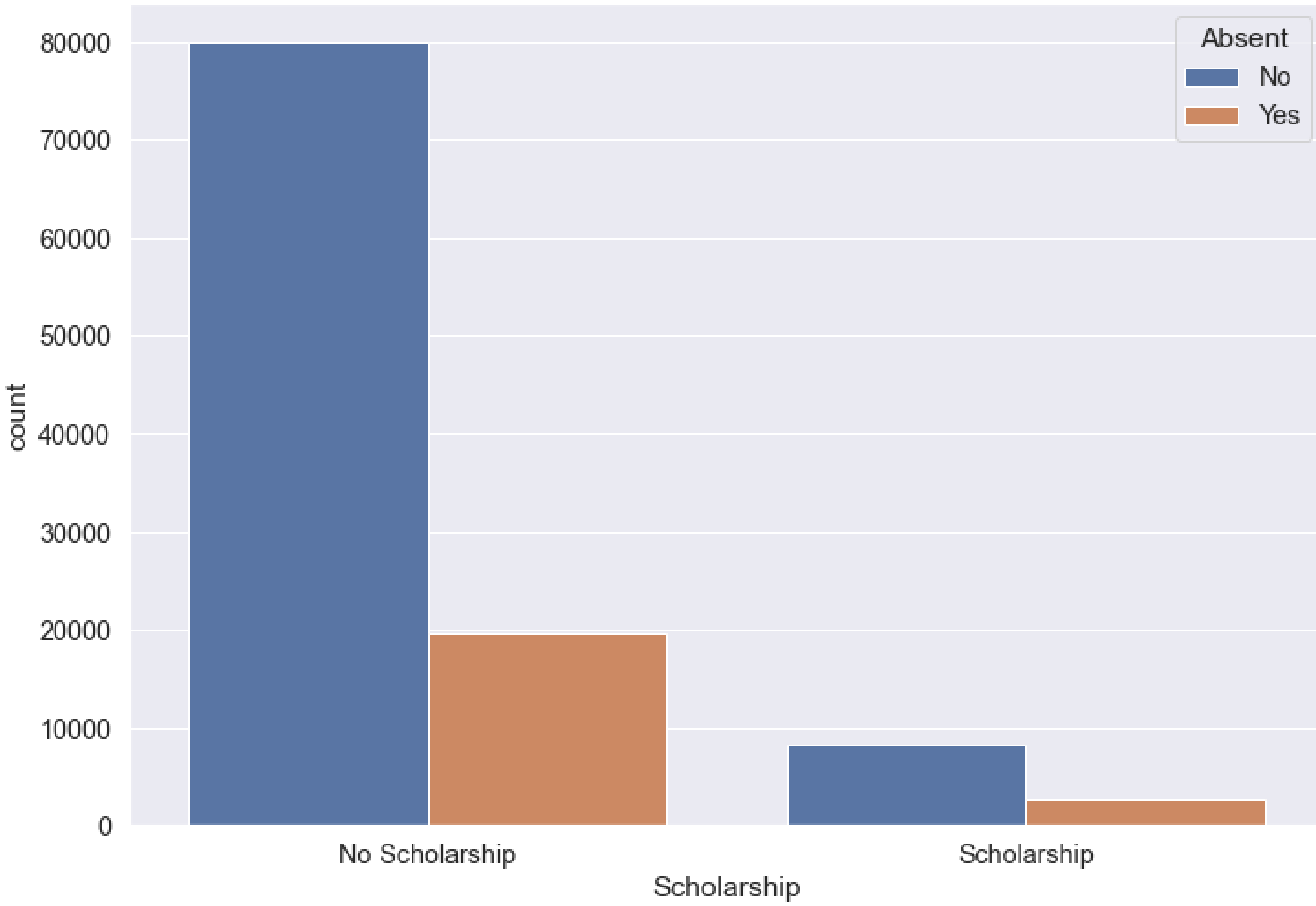
Proportion of Patients with Health care Scholarship



Only 10% of the patients are on the health welfare program

In [171…

```
sns.countplot(x='Scholarship',data=df,hue='Absent')
sns.set(font_scale=1.3)
```



The Scholarship also follows a common trend of a huge percentage attending the hospital appointment

In [ ]:

Multivariate Analysis

Studying how the variables relate with one another and how they can help in predicting the target variable. How do the variables affect each other(Correlation) and affects the target variable.

Gender vs Scholarship

Scholarship vs Agegroup

Plotting a Correlogram

In [172…

```
#insppecting the dataset
df.head()
```

Out[172]:

	PatientID	AppointmentID	Gender	Age	Neighbourhood	Scholarship	Hypertension	Diabetes	Alcoho
0	29872499824296	5642903	F	62	JARDIM DA PENHA	No Scholarship	1	0	
1	558997776694438	5642503	M	56	JARDIM DA PENHA	No Scholarship	0	0	
2	4262962299951	5642549	F	62	MATA DA PRAIA	No Scholarship	0	0	

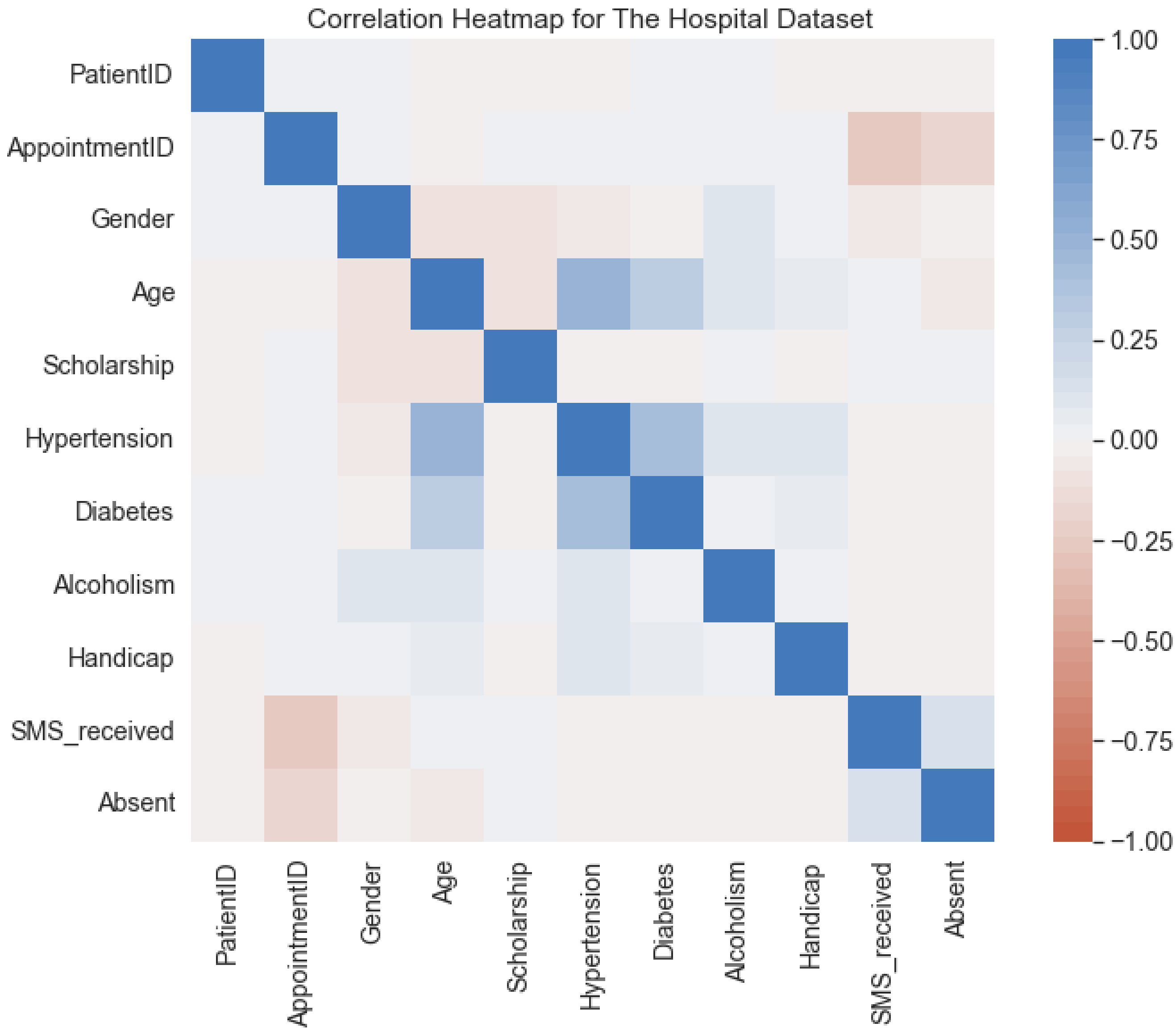
3	867951213174	5642828	F	8	PONTAL DE CAMBURI	No Scholarship	0	0
4	8841186448183	5642494	F	56	JARDIM DA PENHA	No Scholarship	1	1

In [173…

```
#changing the categorical variables to numbers so it can be read by the
computer
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
df_corr =df.copy()
df_corr['Absent']=le.fit_transform(df_corr['Absent'].astype(str))
df_corr['Gender']=le.fit_transform(df_corr['Gender'].astype(str))
df_corr['Scholarship']=le.fit_transform(df_corr['Scholarship'].astype(str))
```

In [174…

```
#plotting a correlation heat map
sns.heatmap(
df_corr.corr(),
vmin=-1, vmax=1, center=0,
cmap=sns.diverging_palette(20, 250, n=50),
square=True
);
plt.title('Correlation Heatmap for The Hospital Dataset ');
```



In [ ]:

```
```

In [ ]:

```
```

1. Gender vs Scholarship

We noticed that female patients attend hospital appointments better than the males. Could that be because the females are favoured under the scholarship program.

In [175…

```
df['Scholarship'] = df.Scholarship.astype('category')
df.Scholarship.cat.rename_categories(['No Scholarship','Scholarship'],
inplace = True);
sns.countplot(x='Scholarship',hue='Gender',data=df);
```

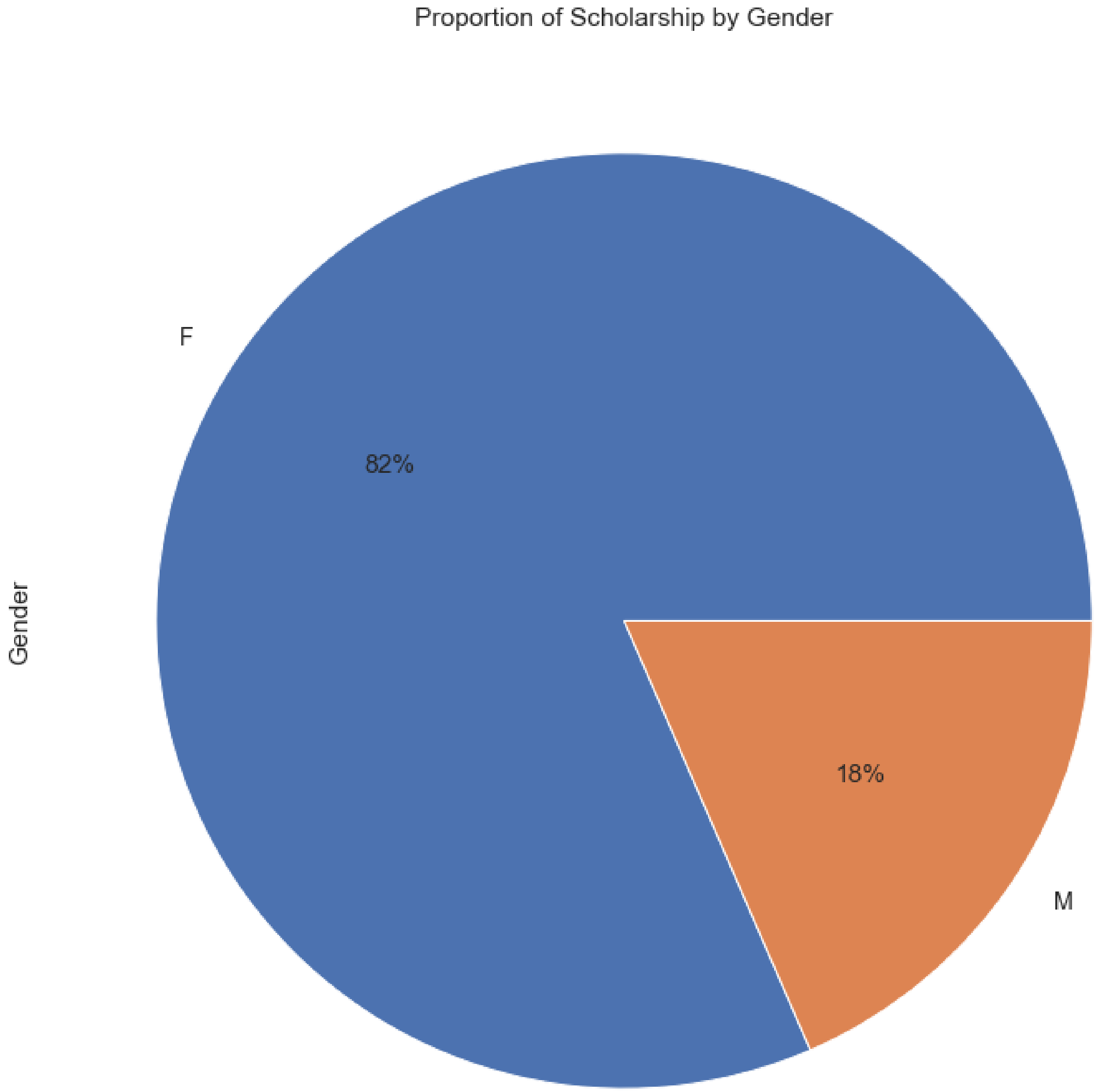
```
C:\Users\ashin\anaconda3\lib\site-packages\pandas\core\arrays\categorical.py:2631: FutureWarning: The `inplace` parameter in pandas.Categorical.rename_categories is deprecated and will be removed in a future version. Removing unused categories will always return a new Categorical object.
  res = method(*args, **kwargs)
```

In [176…

```
df_sch = df[df.Scholarship == 'Scholarship']
df_sch
df_sch['Gender'].value_counts().plot(kind='pie',autopct ='%.0f%%',figsize=
(15,13))
plt.title('Proportion of Scholarship by Gender')
```

Out[176]:

```
Text(0.5, 1.0, 'Proportion of Scholarship by Gender')
```

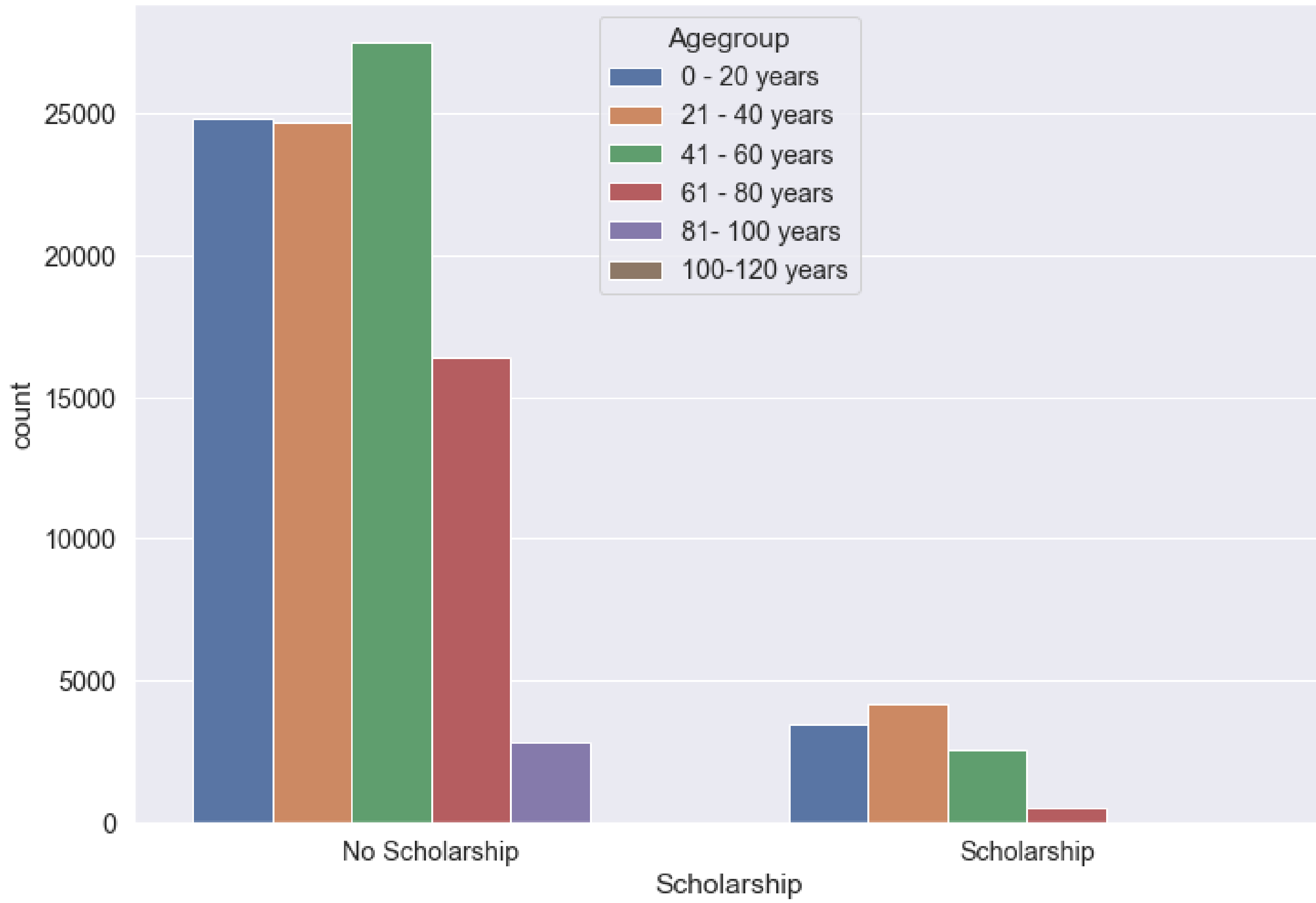


Looking at the Scholarship Program, only 18% are males which means they may not have been favoured by the program

2. Age vs Scholarship Tocheck if Old or young people are favoured by the scholarship program

In [177…

```
sns.countplot(x='Scholarship',hue='Agegroup',data=df)
sns.set(rc={'figure.figsize':(15,13)})
```

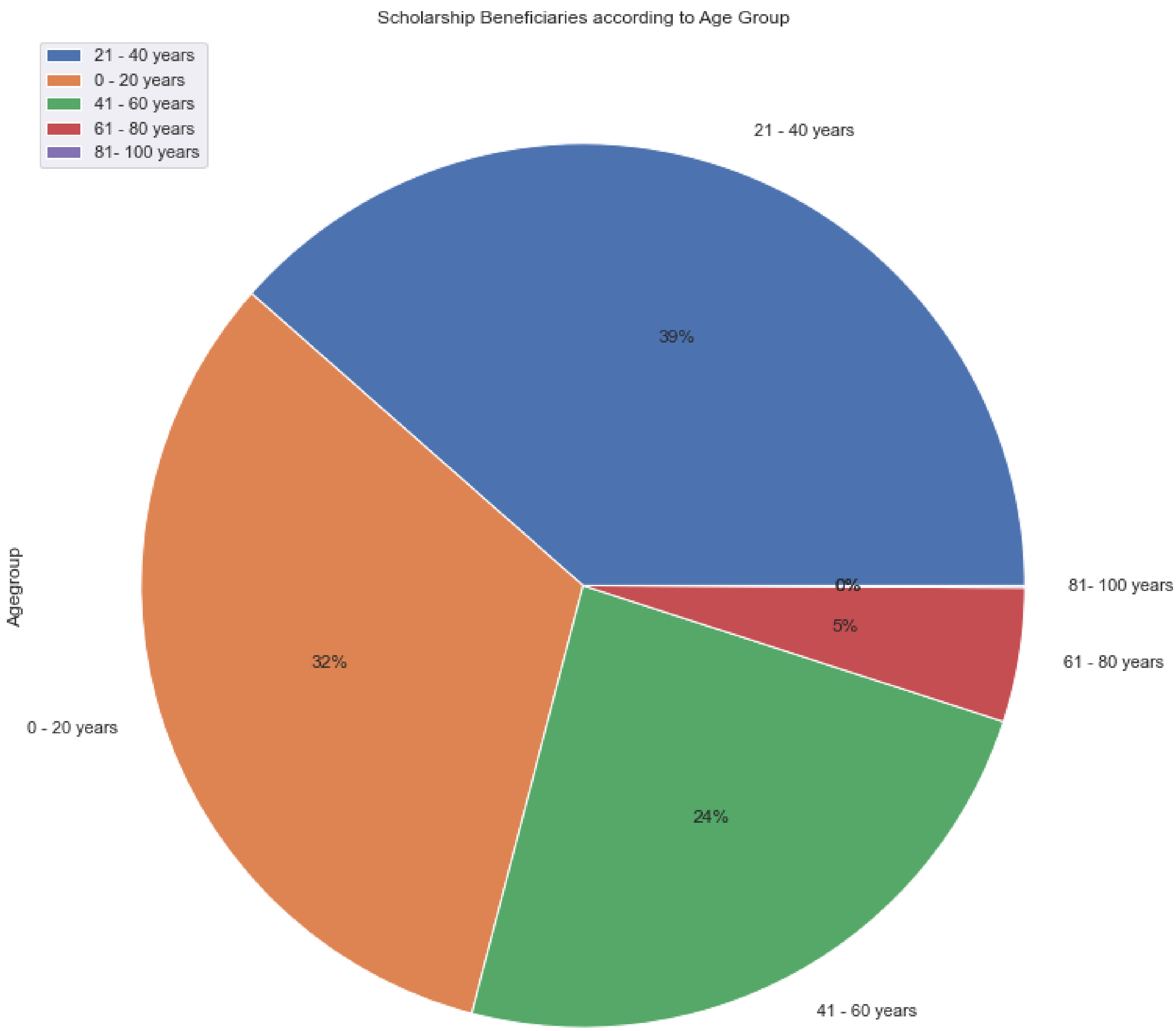


In [178…

```
df_sch['Agegroup'].value_counts().plot(kind='pie',autopct ='%.0f%%',figsize=
(15,13))
plt.title('Scholarship Beneficiaries according to Age Group')
plt.legend()
```

Out[178]:

```
<matplotlib.legend.Legend at 0x11e0048ffa0>
```



The Scholarship program favours Young people as the people aged from 0-40 years accounts for more than 70 % of the beneficiaries

In [ ]:

In [ ]:

Conclusion

A brief Recap of the Research Questions

1. What factors are important for us to know in order to predict if a patient will show up for their scheduled appointment?
2. How do the Factors vary with Each Other?

Research Areas

1. `Target Variable(Absent)` : studying the trends in the absent study overall proportions to help in the analysis with other variables
2. `Univariate Analysis` : Studying each variable to uncover patterns and how they relate with the target variable. How does `Age` , `Gender` , `Neighbourhood` and `Scholarship` influence a patient from attending the Hospital appointment.
3. `Multivariate Analysis` : Studyying how the variables relate with one another and how they can help in predicting the target variable. How do the variables affect each other(Correlation) and affects the target variable.

Gender vs Scholarship

AgeGroup vs Scholarsip

In [ ]:

```

```

Age

The distribution of the age is positively skewed with a median age of 37 years old. The range is 0-115 years with the prescence of a high outlier(one patient is very old). Across all age groups, there's a common trend of most patients attending their hospital appointments with people aged 41-60 years having the highest attendance. The largest percentage of Patients missing the hospital appointment is from the 21-40 years age group. This is as a result of people around that age group having to work for hours/lots of commitments or picking up habits like alcoholism that will not allow them attend

In [ ]:

```

```

Gender

A huge proportion of all patients are Females. Over 70000 females and about 40000 males.65% of the patients are Females and Males account for 35%. A huge percentage of each gender did not miss the hospital appointment. The proportion of Males and females that did not miss the hospital appointment are almost the same, 80%

In [ ]:

```

```

Neighbourhood

The JARDIM CAMBURI Neighbourhood has the highest number of patients with about 8000 patients and highest attendance rate. The PARQUE INDUSTRIAL has the lowest number of patients and attendance rate. This could be due to the location.

In [ ]:

```

```

Scholarship

A huge proportion of the patients are not under the scholarship program. Only 10% of the patients are on the health welfare program The Scholarship Beneficiaries also follows a common trend of a huge percentage of patients attending the hospital appointment.

In [ ]:

Gender vs Scholarship

Looking at the Scholarship Program, only 18% are males which means they may not have been favoured by the program. This could be one of the factors affecting the total population proportion of males missing hospital appointments.

In [ ]:

Age vs Scholarship

The Scholarship program favours Young people as the people aged from 0-40 years accounts for more than 70% of the beneficiaries.

In [ ]:

LIMITATIONS

1. Time was set to 00:00:00 for all cases, analysis was only carried in days. Cases of Having an appointment and schedule on the same day could not be used for the analysis
2. The data was not totally consistent, some unusual forms of data and irregularities were found which could have affected the analysis because it was dropped.
3. Most of the columns are categorical, hence the use of Bar charts and Pie charts, Only Age was quantitative and could be visualised with appropraite means.
4. The Neighbourhood Data should have included the gographical coordinates for better analysis as to how a location can affect the choice of the patient

In [ ]:

References

1.https://www.geeksforgeeks.org/how-to-create-a-seaborn-correlation-heatmap-in-python/
2.https://www.analyticsvidhya.com/blog/2022/02/exploratory-data-analysis-in-python/
3.https://mugekuskon.medium.com/how-to-perform-exploratory-data-analysis-5c3d944c13ff
4.https://towardsdatascience.com/exploratory-data-analysis-8fc1cb20fd15
5.https://towardsdatascience.com/exploratory-analysis-python-kaggle-data-b0afb6ec1788

In [ ]: