medical_appointment_EDA

October 26, 2020

1 Project: Investigate a Dataset of Medical Appointment

1.1 Table of Contents

Introduction

Data Wrangling

Exploratory Data Analysis

Final Conclusions

1.2 Introduction

This is project intends to investigate a dataset with No-show appointment, which is avaiable in Kaggle, in this link. As we will see in further, there is a relevant percentage of No-show in appointment and, one of the subject is analyze data and try to find out reasons and what could be done to decrease this rate.

[1]:
```
#importing libralies

import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

sns.set_style('darkgrid')
```

1.3 Data Wrangling

In this section of the report, it will be loaded data and take a overview. We are looking for inconsistencies, missing and/or duplicate data to trim and clean to set the dataset ready to analysis.
All manipulation will be described bellow

1.3.1 General Properties

[44]:
```
# Load your data and print out a few lines. Perform operations to inspect data

df = pd.read_csv('./data_bases/noshowappointments-kagglev2-may-2016.csv')
df.head()
```

[44]:
```
      PatientId  AppointmentID Gender          ScheduledDay  \
0  2.987250e+13        5642903      F  2016-04-29T18:38:08Z
1  5.589978e+14        5642503      M  2016-04-29T16:08:27Z
2  4.262962e+12        5642549      F  2016-04-29T16:19:04Z
3  8.679512e+11        5642828      F  2016-04-29T17:29:31Z
4  8.841186e+12        5642494      F  2016-04-29T16:07:23Z

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

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

[3]:
```
# Show some statistics information about dataset
df.describe()
```

[3]:
```
          PatientId  AppointmentID            Age    Scholarship  \
count  1.105270e+05   1.105270e+05  110527.000000  110527.000000
mean   1.474963e+14   5.675305e+06      37.088874       0.098266
std    2.560949e+14   7.129575e+04      23.110205       0.297675
min    3.921784e+04   5.030230e+06      -1.000000       0.000000
25%    4.172614e+12   5.640286e+06      18.000000       0.000000
50%    3.173184e+13   5.680573e+06      37.000000       0.000000
75%    9.439172e+13   5.725524e+06      55.000000       0.000000
max    9.999816e+14   5.790484e+06     115.000000       1.000000

        Hipertension       Diabetes     Alcoholism        Handcap  \
count  110527.000000  110527.000000  110527.000000  110527.000000
mean        0.197246       0.071865       0.030400       0.022248
std         0.397921       0.258265       0.171686       0.161543
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
```

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

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

In quick view we found two inconsistencies: **There is no possible that someone with -1 year old. Same for 115 year old, it's strange**. For now, just keep it on mind to check later. Let's see some general information about this dataset

[4]:
```
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
```

Theres no missing values in this dataframe, which means less manipulation.

1.3.2 Vizualizing and Manipulating Data

Now that we made a quick view, let's go further and check some features to understand what it is about and determine if is relevant to analysis or not.

Irrelevant columns will be droped.

[5]:
```
#Let's check if we have duplicated appointment in the dataframe

df['AppointmentID'].nunique() == df.shape[0]
```

[5]:
```
True
```

Before to start netx step, I want do split schedule and appointment into year, month and day (hour could not be useful now) - since these columns are in string format.
Therefore, it will be created six new columns.

[6]:
```
#Create splited columns to scheduled day
df['S_year'] = df['ScheduledDay'].apply(lambda x: x[:4])
df['S_month'] = df['ScheduledDay'].apply(lambda x: x[5:7])

#Create splited columns to appointment day
df['A_year'] = df['AppointmentDay'].apply(lambda x: x[:4])
df['A_month'] = df['AppointmentDay'].apply(lambda x: x[5:7])

#Reorder columns
df = df[['PatientId', 'AppointmentID', 'Gender', 'ScheduledDay', 'S_year',␣
↪'S_month', 'AppointmentDay',
    'A_year', 'A_month', 'Age', 'Neighbourhood', 'Scholarship', 'Hipertension',␣
↪'Diabetes',
    'Alcoholism', 'Handcap', 'SMS_received', 'No-show',
   ]]
```

Other point to confirm it's appointment hour - first five record have ”00:00:00”, so let's check if we have some different values:

[7]:
```
#List row wich appointment day contain other value
df[~df['AppointmentDay'].str.contains("00:00:00")]
```

[7]:
```
Empty DataFrame
Columns: [PatientId, AppointmentID, Gender, ScheduledDay, S_year, S_month,
AppointmentDay, A_year, A_month, Age, Neighbourhood, Scholarship, Hipertension,
Diabetes, Alcoholism, Handcap, SMS_received, No-show]
Index: []
```

Since there no values different than 00:00:00, this information will not be important to further analysis.
In this case, I will cut hour from ScheduledDay and AppointmentDay and convert to datatime type:

[8]:
```
columns_to_change = ['ScheduledDay', 'AppointmentDay']

for i in columns_to_change:
```

```
    df[i] = df[i].apply(lambda x: x[:10]).astype('datetime64')

df[['ScheduledDay', 'AppointmentDay']].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 2 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   ScheduledDay    110527 non-null  datetime64[ns]
 1   AppointmentDay  110527 non-null  datetime64[ns]
dtypes: datetime64[ns](2)
memory usage: 1.7 MB
```

Aditionally, we are create a new colum with timedelta between appointment day and scheduled day to measure waiting time.

[9]:
```
df['Waiting_time'] = (df['AppointmentDay'] - df['ScheduledDay'])
df['Waiting_time'].describe()
```

[9]:
```
count                         110527
mean      10 days 04:24:31.828602965
std       15 days 06:07:11.673762786
min                -6 days +00:00:00
25%                  0 days 00:00:00
50%                  4 days 00:00:00
75%                 15 days 00:00:00
max                179 days 00:00:00
Name: Waiting_time, dtype: object
```

We have negative values, that's impossible, in data cleaning session we will find and drop these ones.
Now let's check year and month range of dataset:

[10]:
```
year_columns = ['S_year', 'A_year']
month_columns = ['S_month', 'A_month']

for year in year_columns:
        print(year, ':\n', df[year].value_counts().sort_index(), '\n')

for month in month_columns:
    print(month, ':\n',df[month].value_counts().sort_index(), '\n')
```

```
S_year :
 2015        62
2016    110465
Name: S_year, dtype: int64

A_year :
```

```
 2016    110527
Name: A_year, dtype: int64

S_month :
 01       60
02       281
03      3614
04     25339
05     67421
06     13750
11         1
12        61
Name: S_month, dtype: int64

A_month :
 04      3235
05     80841
06     26451
Name: A_month, dtype: int64
```

We have some appointment scheduled in 2015, but all appointment was in 2016, starting in April and ending in June. That means waiting time in day it's going to be greate.
It's just 62 rows, this sample is too small to be significant, so I will drop these rows and focus analysis in 2016 record.

Finally, these columns that contain desease are represented by boolean and I'm not sure if they will be important.
Just to check, let's see if they have correlation between themselves. To do that, I will add column with No-show, in boolean.

[11]:
```
#if No-show are Yes, it's mean the patient missed the appointment
#than in apply function receive the value 1

df['No-show-boolean'] = df['No-show'].apply(lambda x: 1 if x == "Yes" else 0)
df.corr()
```

[11]:
```
                 PatientId  AppointmentID       Age  Scholarship  \
PatientId         1.000000       0.004039 -0.004139    -0.002880
AppointmentID     0.004039       1.000000 -0.019126     0.022615
Age              -0.004139      -0.019126  1.000000    -0.092457
Scholarship      -0.002880       0.022615 -0.092457     1.000000
Hipertension     -0.006441       0.012752  0.504586    -0.019729
Diabetes          0.001605       0.022628  0.292391    -0.024894
Alcoholism        0.011011       0.032944  0.095811     0.035022
Handcap          -0.007916       0.014106  0.078033    -0.008586
SMS_received     -0.009749      -0.256618  0.012643     0.001194
No-show-boolean  -0.001461      -0.162602 -0.060319     0.029135
```

```
                 Hipertension  Diabetes  Alcoholism   Handcap  SMS_received  \
PatientId           -0.006441  0.001605    0.011011 -0.007916     -0.009749
AppointmentID        0.012752  0.022628    0.032944  0.014106     -0.256618
Age                  0.504586  0.292391    0.095811  0.078033      0.012643
Scholarship         -0.019729 -0.024894    0.035022 -0.008586      0.001194
Hipertension         1.000000  0.433086    0.087971  0.080083     -0.006267
Diabetes             0.433086  1.000000    0.018474  0.057530     -0.014550
Alcoholism           0.087971  0.018474    1.000000  0.004648     -0.026147
Handcap              0.080083  0.057530    0.004648  1.000000     -0.024161
SMS_received        -0.006267 -0.014550   -0.026147 -0.024161      1.000000
No-show-boolean     -0.035701 -0.015180   -0.000196 -0.006076      0.126431

                 No-show-boolean
PatientId              -0.001461
AppointmentID          -0.162602
Age                    -0.060319
Scholarship             0.029135
Hipertension           -0.035701
Diabetes               -0.015180
Alcoholism             -0.000196
Handcap                -0.006076
SMS_received            0.126431
No-show-boolean         1.000000
```

No one of these columns has strong correlation, so we can just drop them.

1.3.3 Data Cleaning

First, let's take a look in data with strange ages.
For strange age, I'm considering age under zero or more than a hundred:

[12]:
```
# Locate in the dataset row wich contain age under zero or a hundred
df.loc[(df['Age'] < 0) |
       (df['Age'] > 100)]
```

[12]:
```
          PatientId  AppointmentID Gender ScheduledDay S_year S_month  \
58014  9.762948e+14        5651757      F   2016-05-03   2016      05
63912  3.196321e+13        5700278      F   2016-05-16   2016      05
63915  3.196321e+13        5700279      F   2016-05-16   2016      05
68127  3.196321e+13        5562812      F   2016-04-08   2016      04
76284  3.196321e+13        5744037      F   2016-05-30   2016      05
90372  2.342836e+11        5751563      F   2016-05-31   2016      05
97666  7.482346e+14        5717451      F   2016-05-19   2016      05
99832  4.659432e+14        5775010      F   2016-06-06   2016      06

      AppointmentDay A_year A_month  Age Neighbourhood  Scholarship  \
```

```
58014      2016-05-03   2016       05  102      CONQUISTA            0
63912      2016-05-19   2016       05  115     ANDORINHAS            0
63915      2016-05-19   2016       05  115     ANDORINHAS            0
68127      2016-05-16   2016       05  115     ANDORINHAS            0
76284      2016-05-30   2016       05  115     ANDORINHAS            0
90372      2016-06-02   2016       06  102    MARIA ORTIZ            0
97666      2016-06-03   2016       06  115       SÃO JOSÉ            0
99832      2016-06-06   2016       06   -1          ROMÃO            0

       Hipertension  Diabetes  Alcoholism  Handcap  SMS_received No-show  \
58014             0         0           0        0             0      No
63912             0         0           0        1             0     Yes
63915             0         0           0        1             0     Yes
68127             0         0           0        1             0     Yes
76284             0         0           0        1             0      No
90372             0         0           0        0             0      No
97666             1         0           0        0             1      No
99832             0         0           0        0             0      No

      Waiting_time  No-show-boolean
58014       0 days                0
63912       3 days                1
63915       3 days                1
68127      38 days                1
76284       0 days                0
90372       2 days                0
97666      15 days                0
99832       0 days                0
```

These rows wich age is 115 refers to a single (See the PatientID it's the same for all record). Although that seems strange for me, I'll keep those and drop just the row wich age are negative.

[13]:
```
#Drop row by index
df.drop(axis=0, index=99832, inplace=True)
```

[14]:
```
#Check quantity of unique patients
df['PatientId'].nunique()
```

[14]: 62298

[15]:
```
#Check how many Neighbourhood have in dataset
print('This dataset have {} Neibourhood \n'.format(df['Neighbourhood'].
 ↪nunique()),
      'relative frequence: \n',
      df['Neighbourhood'].value_counts(normalize=True)*100
     )
```

```
This dataset have 81 Neibourhood
```

```
 relative frequence:
 JARDIM CAMBURI                6.982068
MARIA ORTIZ                   5.252158
RESISTÊNCIA                   4.009011
JARDIM DA PENHA               3.507772
ITARARÉ                       3.179342
                                …
ILHA DO BOI                   0.031667
ILHA DO FRADE                 0.009048
AEROPORTO                     0.007238
ILHAS OCEÂNICAS DE TRINDADE   0.001810
PARQUE INDUSTRIAL             0.000905
Name: Neighbourhood, Length: 81, dtype: float64
```

We have great number of neighbourhoods, and they are very distributed in dataset, so we are not going to use them.

Finally, let's drop columns that we are not going to use in this analysis.

[16]:
```
df.drop(['AppointmentID', 'Neighbourhood', 'Scholarship', 'Hipertension',␣
 ↪'Diabetes', 'Alcoholism', 'Handcap'], axis=1, inplace=True)
df
```

[16]:
```
           PatientId Gender ScheduledDay S_year S_month AppointmentDay A_year  \
0       2.987250e+13      F   2016-04-29   2016      04     2016-04-29   2016
1       5.589978e+14      M   2016-04-29   2016      04     2016-04-29   2016
2       4.262962e+12      F   2016-04-29   2016      04     2016-04-29   2016
3       8.679512e+11      F   2016-04-29   2016      04     2016-04-29   2016
4       8.841186e+12      F   2016-04-29   2016      04     2016-04-29   2016
…                …     …           …      …      …              …      …
110522  2.572134e+12      F   2016-05-03   2016      05     2016-06-07   2016
110523  3.596266e+12      F   2016-05-03   2016      05     2016-06-07   2016
110524  1.557663e+13      F   2016-04-27   2016      04     2016-06-07   2016
110525  9.213493e+13      F   2016-04-27   2016      04     2016-06-07   2016
110526  3.775115e+14      F   2016-04-27   2016      04     2016-06-07   2016

       A_month  Age  SMS_received No-show Waiting_time  No-show-boolean
0           04   62             0      No       0 days                0
1           04   56             0      No       0 days                0
2           04   62             0      No       0 days                0
3           04    8             0      No       0 days                0
4           04   56             0      No       0 days                0
…          …    …           …      …          …               …
110522      06   56             1      No      35 days                0
110523      06   51             1      No      35 days                0
110524      06   21             1      No      41 days                0
110525      06   38             1      No      41 days                0
110526      06   54             1      No      41 days                0
```

```
[110526 rows x 13 columns]
```

Drop all appointment scheduled in 2015:

```
[17]: appointment_of_2005 = df.query('`S_year` == "2015"').index
      df.drop(appointment_of_2005, axis=0, inplace=True)
```

```
[18]: df.query('`S_year` == "2015"')
```

```
[18]: Empty DataFrame
      Columns: [PatientId, Gender, ScheduledDay, S_year, S_month, AppointmentDay,
      A_year, A_month, Age, SMS_received, No-show, Waiting_time, No-show-boolean]
      Index: []
```

```
[19]: #Drop all row with negative waiting time
      negative_waiting_days = df.query('`Waiting_time` < "0"').index
      df.drop(negative_waiting_days, axis=0, inplace=True)
```

```
[20]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 110459 entries, 0 to 110526
Data columns (total 13 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   PatientId        110459 non-null  float64
 1   Gender           110459 non-null  object
 2   ScheduledDay     110459 non-null  datetime64[ns]
 3   S_year           110459 non-null  object
 4   S_month          110459 non-null  object
 5   AppointmentDay   110459 non-null  datetime64[ns]
 6   A_year           110459 non-null  object
 7   A_month          110459 non-null  object
 8   Age              110459 non-null  int64
 9   SMS_received     110459 non-null  int64
 10  No-show          110459 non-null  object
 11  Waiting_time     110459 non-null  timedelta64[ns]
 12  No-show-boolean  110459 non-null  int64
dtypes: datetime64[ns](2), float64(1), int64(3), object(6), timedelta64[ns](1)
memory usage: 11.8+ MB
```

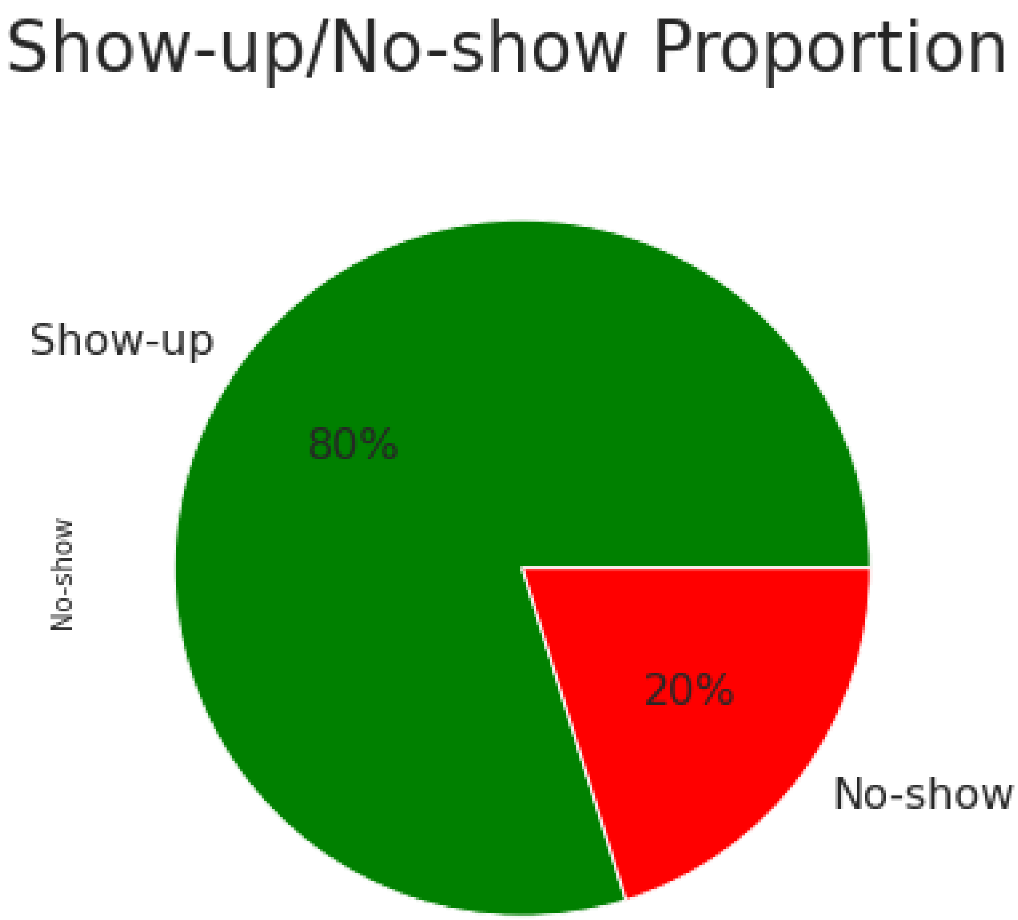
1.4 Exploratory Data Analysis

1.4.1 First findings

let's extract the firsts information, such as proportion of show-up/no-show and amount of appointment per month.

Proportion

[21]:
```
sup_nshow = df['No-show'].value_counts()

labels = ['Show-up', 'No-show']
plt.figure(figsize=(6, 6))
plt.suptitle('Show-up/No-show Proportion', fontsize=26)
sup_nshow.plot(
    kind='pie', labels=labels, autopct='%1.f%%', colors=['g', 'r'],
    fontsize=16)
plt.show()
print(sup_nshow)
```



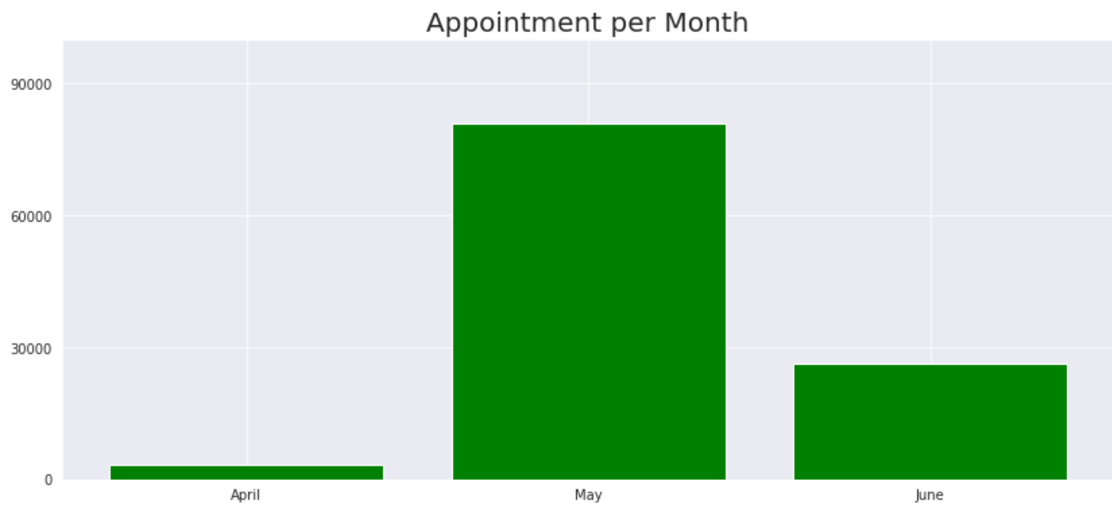

```
No      88164
Yes     22295
Name: No-show, dtype: int64
```

We have 22,319 no-show appointment, wich represent 20% of all data.
In the next session we will try to find out the reasons

Appointments per Month

[22]:
```
#Creating index and Series to plot bar chart
#The series was sort by index to be orded by month
index = ['April', 'May', 'June']
appointment_per_month = df['A_month'].value_counts().sort_index()

plt.figure(figsize=(14,6))
plt.title('Appointment per Month', fontsize=20)
```

```
plt.bar(index, appointment_per_month, color='g')
plt.ylim(0, 100000)
plt.yticks(np.arange(0, 100000, step=30000))
plt.show()

print(appointment_per_month)
```

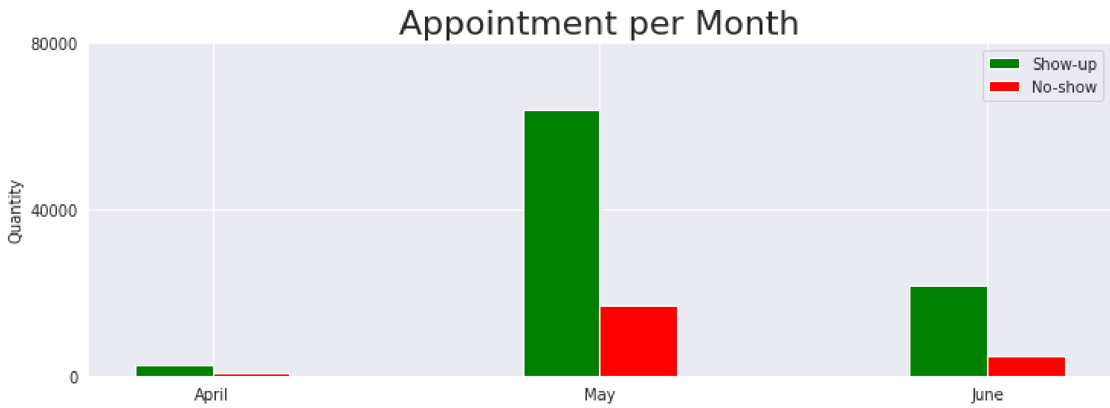



```
04      3235
05     80799
06     26425
Name: A_month, dtype: int64
```

[23]:
```
#Query to separate dataframe into show-up and no-show, grouping by appointment␣
↪month to plot further

n_show = df.query('`No-show` == "Yes"')['A_month'].value_counts().sort_index()
y_show = df.query('`No-show` == "No"')['A_month'].value_counts().sort_index()
```

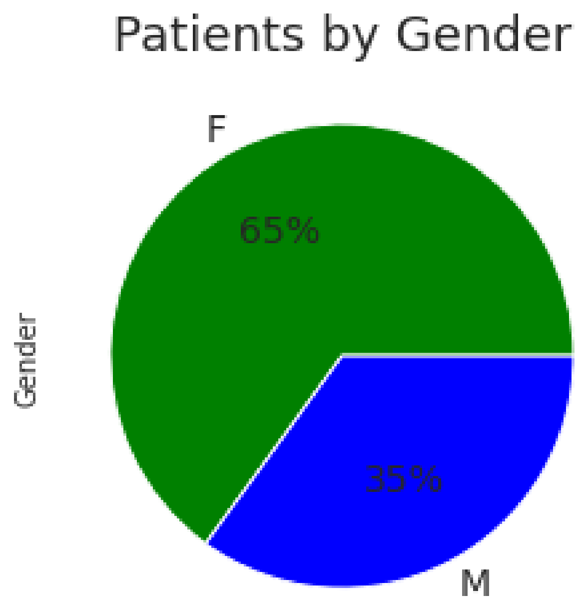
[24]:
```
_index = np.arange(len(index))
plt.figure(figsize=(12, 4))
plt.ylim(0, 80000)
plt.title('Appointment per Month', fontsize=22)


plt.bar(_index-0.1, y_show, color='g', width=0.2, align='center')
plt.bar(_index+0.1, n_show, color='r', width=0.2, align='center')


plt.yticks(np.arange(0, 90000, step=40000))
plt.xticks(_index, index)
```

```
plt.ylabel('Quantity')
plt.legend(['Show-up', 'No-show'])
plt.show()
```



Patients by gender As we can see below, woman represent 65% of patients:

[25]:
```
labels = ['Female', 'Male']
gender = df['Gender'].value_counts()

gender.plot(kind='pie', fontsize=14, autopct='%1.f%%', colors=['g', 'b'])
plt.title('Patients by Gender', fontsize=18)
plt.show()

print(gender)
```




```
F    71791
M    38668
Name: Gender, dtype: int64
```

1.4.2 Research Question 1 - What gender tend to miss more appointment?

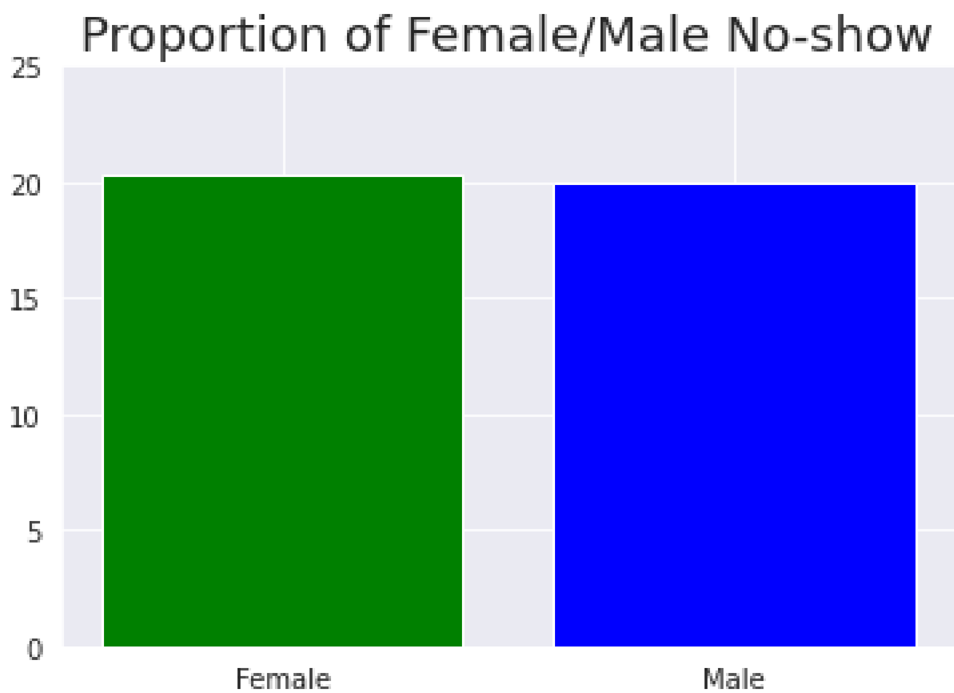
To Answer that question, it's not fair to use absolute value, since we have much more female record than male. Therefore, it's necessary to divide each value by total of no-show.
For the record, see below the absolute value.

[26]:
```
df.query('`No-show` == "Yes"')['Gender'].value_counts()
```

[26]:
```
F    14580
M     7715
Name: Gender, dtype: int64
```

[27]:
```
#total of no-show using mask, selecting any column, just to count
female_total = df.query('`Gender` == "F"').shape[0]
male_total = df.query('`Gender` == "M"').shape[0]
total = df.shape[0]

#calculating proportional values
nshow_female = (df[(df['No-show'] == 'Yes') & (df['Gender'] == 'F')]['Gender'].
 ↪count() / female_total) * 100
```

```
nshow_male = (df[(df['No-show'] == 'Yes') & (df['Gender'] == 'M')]['Gender'].
 ↪count() / male_total) * 100

plt.ylim(0, 25)
plt.title('Proportion of Female/Male No-show', fontsize=18)
plt.bar('Female', nshow_female, color='g')
plt.bar('Male', nshow_male, color='b')
plt.show()
print('Female proportion: {:.2f} \n Male proportion: {:.2f}'.
 ↪format(nshow_female, nshow_male))
```

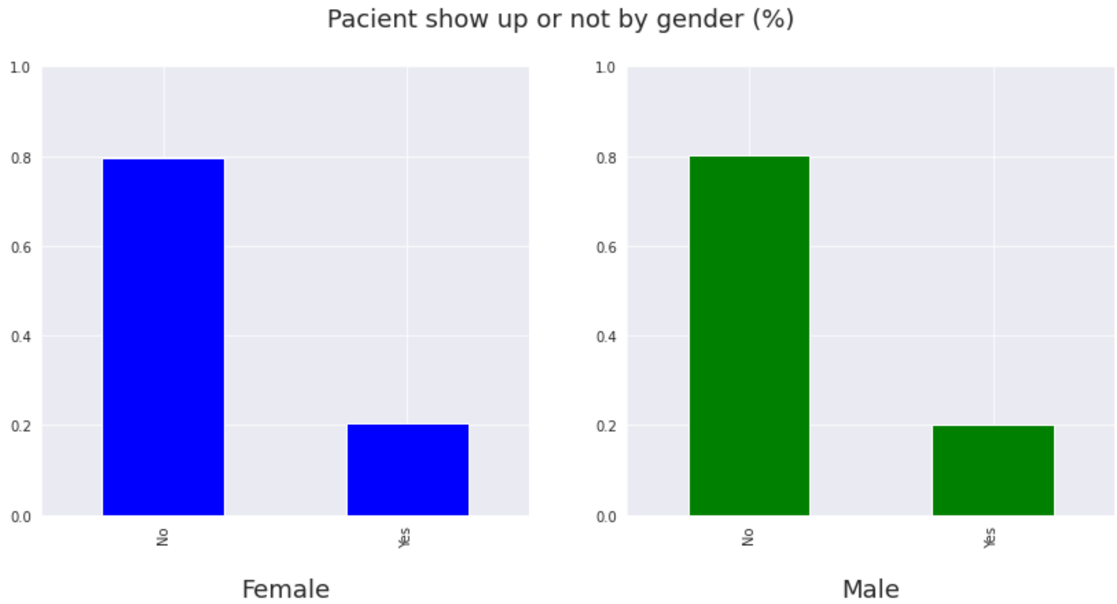



```
Female proportion: 20.31
 Male proportion: 19.95
```

As we can see woman proportion is slightly higher than man.
That maybe happens because even calculating separating by gender, proportion are similar:

[28]:
```
female = df.query('Gender == "F"')['No-show'].value_counts(normalize=True)
male = df.query('Gender == "M"')['No-show'].value_counts(normalize=True)

plt.figure(figsize=(14,6))
ticks = np.arange(0, 1.2, 0.2)

plt.suptitle('Pacient show up or not by gender (%)', fontsize=18)
```

```
plt.subplot(1, 2, 1)
female.plot(kind="bar", color='b')
plt.title('Female', fontsize=18, y=-0.2)
plt.yticks(ticks)

plt.subplot(1, 2, 2)
male.plot(kind="bar", color='g')
plt.title('Male', fontsize=18, y=-0.2)
plt.yticks(ticks)

plt.show()

# print value of queries
print('Female: \n', female, '\n\n', 'Male: \n', male)
```




```
Female:
 No     0.79691
Yes    0.20309
Name: No-show, dtype: float64

 Male:
 No     0.800481
Yes    0.199519
Name: No-show, dtype: float64
```

Conclusion Since the differente are insignificant, **we can't affirm wich gender miss more appointment**.

1.4.3 Research Question 2 - Are SMS reminder efficient to avoid no-show?

In the dataset we have information if patient received sms to reminder about appointment (1 if received and 0 if not).
To calculate correlation between no-show and sms, we'are going to apply pandas corr function:

[29]:
```
df.corr()
```

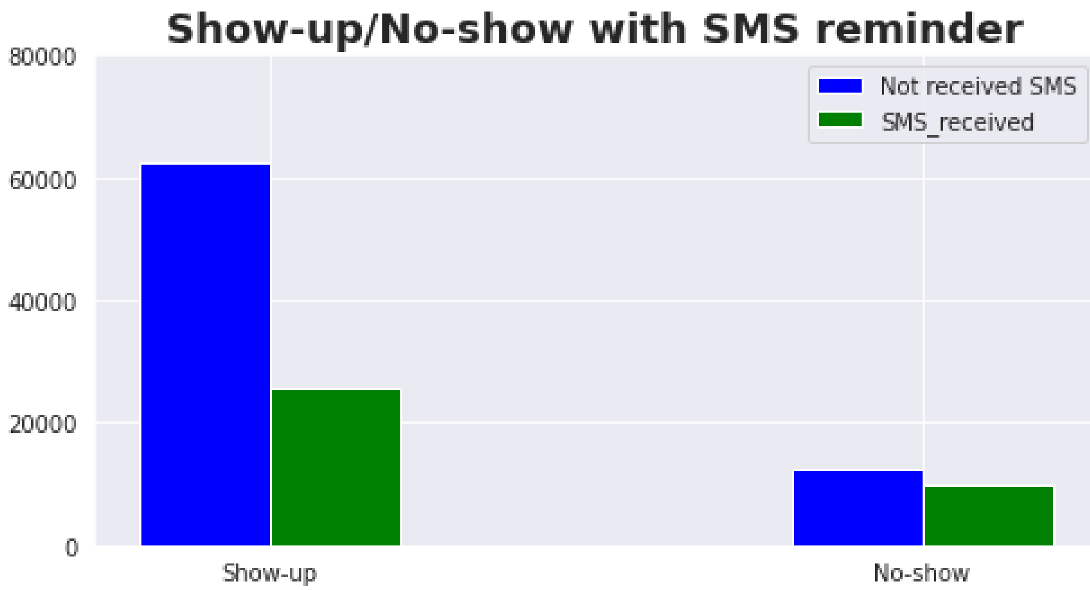
[29]:

	PatientId	Age	SMS_received	No-show-boolean
PatientId	1.000000	-0.004274	-0.009630	-0.001452
Age	-0.004274	1.000000	0.012219	-0.060547
SMS_received	-0.009630	0.012219	1.000000	0.126452
No-show-boolean	-0.001452	-0.060547	0.126452	1.000000

At first there is no strong correlation between sms and no-show, since the value are 0.12.
Correlation can variate since -1 until 1, values closer in these indicate strong correlation.
Let's just calculate how efficient was send sms to remind about appointment.

[30]:
```
sms_rec = df.query("`SMS_received` == 1").groupby('No-show').count()['Age']
sms_not_received = df.query("`SMS_received` == 0").groupby('No-show').
 ↪count()['Age']
```

[31]:
```
index = ['Show-up', 'No-show']
_index = np.arange(len(index))


font = {
    'size': 18,
    'weight': 'bold',
}

plt.figure(figsize=(8,4))

plt.bar(_index-0.1, sms_not_received, width=0.2, color='b')
plt.bar(_index+0.1, sms_rec, width=0.2, color='g')

plt.ylim(0, 80001)
plt.yticks(np.arange(0, 80001, step=20000))
plt.xticks(_index, index)


plt.title('Show-up/No-show with SMS reminder', fontdict=font)
plt.legend(['Not received SMS', 'SMS_received'])
plt.show()
```

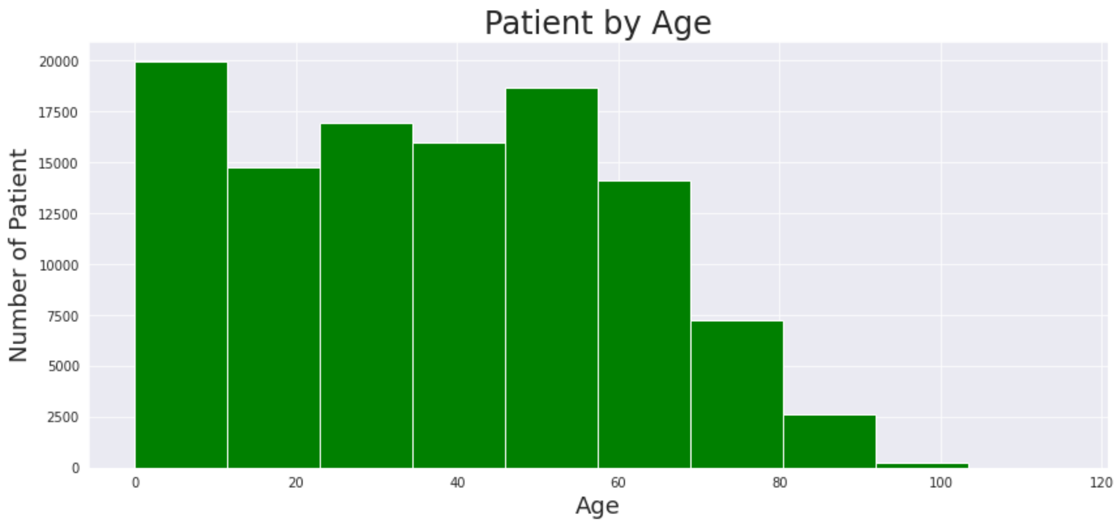


Conclusion Send SMS **it's not efficient to avoid no-show appointment**.

1.4.4 Research Question 3 - What's age range miss more appointment?

As we saw before, in this dataset we have people from 0 until 115 year. Here, a chart with

[32]:
```
plt.figure(figsize=(14, 6))
plt.hist(df['Age'], color='g')

plt.title('Patient by Age', fontsize=24)
plt.xlabel('Age', fontsize=18)
plt.ylabel('Number of Patient', fontsize=18)

plt.show()
```



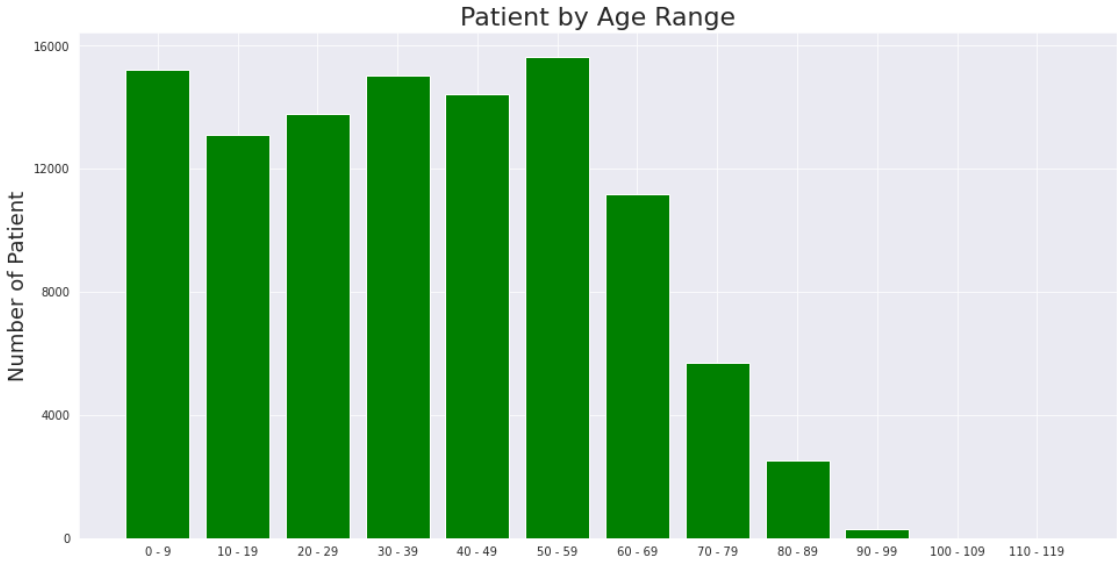
To see better how distribute are the age of patient, let's categorize:

[33]:
```
#Create labels of age range
labels = ["{0} - {1}".format(i, i + 9) for i in range(0, 120, 10)]

#Create a new column and classify age range using pandas cut method.
df['Age_range'] = pd.cut(df['Age'], range(0, 130, 10), right=True,␣
↪labels=labels)

#age range count
norm_age_range = df['Age_range'].value_counts().sort_index()
norm_age_range
```

[33]:
```
0 - 9        15209
10 - 19      13098
20 - 29      13780
30 - 39      15047
40 - 49      14413
50 - 59      15648
60 - 69      11175
70 - 79       5707
80 - 89       2535
90 - 99        301
100 - 109        2
110 - 119        5
Name: Age_range, dtype: int64
```

[34]:
```
plt.figure(figsize=(16, 8))
plt.bar(labels, norm_age_range, color='g')
plt.title('Patient by Age Range', fontsize=22)
```

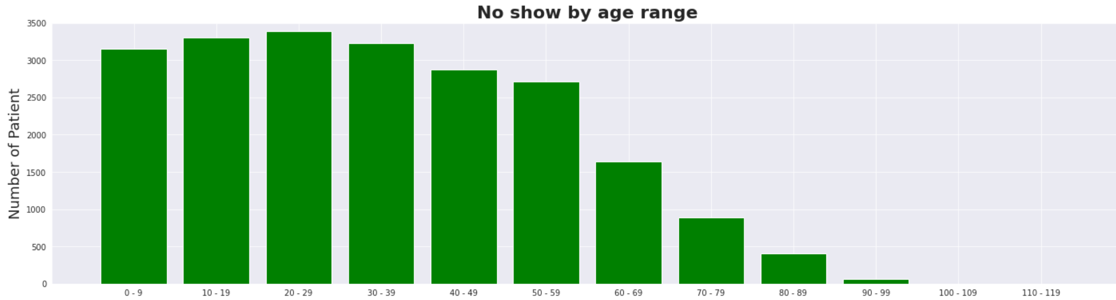
```
plt.ylabel('Number of Patient', fontsize=18)
plt.yticks(np.arange(0, 16001, step=4000))
plt.show()
```



Looking this categories, we can see that childrens and teenage represent over 25%. That could be the reason to send sms not be efficient, since most of those persons may not have access to cell phones.
Now let's plot no-show per age rage

[35]:
```
nshow = df.query('`No-show` == "Yes"')
showup = df.query('`No-show` == "No"')

nshow_per_age_rage = nshow.groupby('Age_range').count()['Age']
```

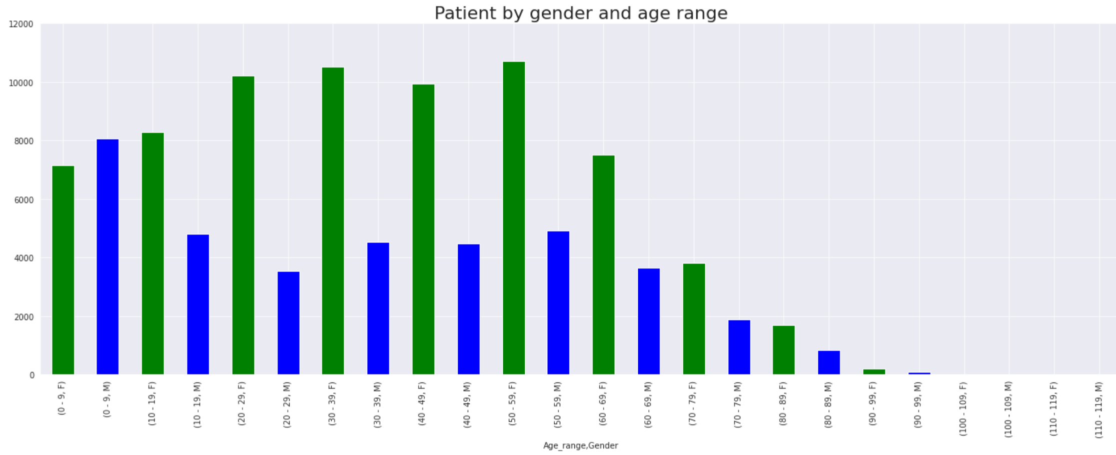
[36]:
```
plt.figure(figsize=(24,6))

plt.bar(labels, nshow_per_age_rage, color='g')
plt.ylim(0, 3500)

plt.title('No show by age range', fontsize=(22), weight='bold')
plt.ylabel('Number of Patient', fontsize=18)
plt.show()

print(nshow_per_age_rage)
```




```
Age_range
0 - 9         3148
10 - 19       3307
20 - 29       3392
30 - 39       3230
40 - 49       2869
50 - 59       2717
60 - 69       1644
70 - 79        884
80 - 89        403
90 - 99         59
100 - 109        0
110 - 119        3
Name: Age, dtype: int64
```

Just to know, let's check age range by gender too.

[37]:
```
gender_by_age_range = df.groupby(['Age_range', 'Gender']).count()['Age']

plt.figure(figsize=(24, 8))
plt.ylim(0, 12000)
plt.yticks(np.arange(0, 12001, step=2000))
plt.title("")
plt.grid(b=True, which='minor')
gender_by_age_range.plot(kind='bar', color=['g', 'b'])
plt.title('Patient by gender and age range', fontsize=22)
plt.show()
```



Conclusion Person with age between 20 to 29 miss more appointment than others age range. It's interesting to notice that no-show rate increase until that age range, and after this one rate are decreasing.

1.4.5 Research Question 4 - Is wainting time related with no show-rate?

Firts let's check some information about this column:

[38]:
```
df['Waiting_time'].describe()
```

[38]:
```
count                          110459
mean      10 days 02:19:30.222435473
std       14 days 19:16:40.291861651
min                   0 days 00:00:00
25%                   0 days 00:00:00
50%                   4 days 00:00:00
75%                  15 days 00:00:00
max                 146 days 00:00:00
Name: Waiting_time, dtype: object
```

[39]:
```
#Creating masks to further manipulations
nshow_waiting = df.query('`No-show` == "Yes"')['Waiting_time']
showup_waiting = df.query('`No-show` == "No"')['Waiting_time']
```

[40]:
```
nshow_waiting.describe()
```

[40]:
```
count                           22295
mean      15 days 17:00:22.121551917
std       16 days 00:43:04.432820586
min                   0 days 00:00:00
```

```
25%                  4 days 00:00:00
50%                 11 days 00:00:00
75%                 23 days 00:00:00
max                146 days 00:00:00
Name: Waiting_time, dtype: object
```

[41]:
```
showup_waiting.describe()
```

[41]:
```
count                          88164
mean       8 days 16:16:00.391996733
std       14 days 03:04:08.440778715
min                  0 days 00:00:00
25%                  0 days 00:00:00
50%                  2 days 00:00:00
75%                 12 days 00:00:00
max                133 days 00:00:00
Name: Waiting_time, dtype: object
```

[42]:
```
print('Average waiting time to no show appointment: {} \nAverage waiting time␣
↪to show up appointment: {}'.format(nshow_waiting.mean(), showup_waiting.
↪mean()))
```

```
Average waiting time to no show appointment: 15 days 17:00:22.121551917
Average waiting time to show up appointment: 8 days 16:16:00.391996733
```

[43]:
```
df.query('`No-show` == "Yes"').shape
```

[43]:
```
(22295, 14)
```

Conclusion Average waiting time in no show appointment it almost double, so **we can affirm some correlation between no-show and waiting time**

1.5 Final Conclusions

In this report, it was analyzed medical appointment and show up/no show rate in 2016. See below some findings: * No show rate are 20%; * Send SMS seems to be not very effective to increase this rate; * That could be because childrens and teenagers (0 - 19 year old) represent 28% of all miss - These pacient may not have cel phone to receive SMS; * There are more woman appointment than man - woman represent 65% of dataset; * Despite this proportion, woman and man miss appointment in same proportion;