Project 3: Predict attendance at a medical appointment based on different variables.

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Source of data (Kaggle): Get Data

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Introduction

The goal of this project is determinate and know if are there factors to predict if a patient will show up for their scheduled appointment?

The dataset used to this project collects information from 100k medical appointments in Brazil and is focused on the question of whether or not patients show up for their appointment. The following characteristics about the patient are included in each row.

- 'PatientId' is the ID of patient that request a medical appointment.
- 'AppointmentID' is the ID of Appointment used by the system or application of medical center.
- 'Gender' of the patient.
- 'ScheduledDay' tells us on what day the patient set up their appointment.
- 'Age' of the patient.
- 'Neighborhood' indicates the location of the hospital.
- 'Scholarship' indicates whether or not the patient is enrolled in Brasilian welfare program Bolsa Família.
- 'Hipertension, Diabetes, Alcoholism, Handcap' are atributes inherits to a each patient.
- 'SMS_received' is a message sent to each patient about an appointment.
- Be careful about the encoding of the last column: it says 'No' if the patient showed up to their appointment, and 'Yes' if they did not show up.

In [1]:
```
# Use this cell to set up import statements for all of the packages that you
#   plan to use.

# Remember to include a 'magic word' so that your visualizations are plotted
#   inline with the notebook. See this page for more:
#   http://ipython.readthedocs.io/en/stable/interactive/magics.html

import numpy as np
import pandas as pd
```

```
import matplotlib.pyplot as plt
import seaborn as sns

dayOfWeek={0:'Monday', 1:'Tuesday', 2:'Wednesday', 3:'Thursday', 4:'Friday', 5:'
```

Data Wrangling

General Properties

In [2]:
```
# Read the CSV file using pandas

data = pd.read_csv('noshowappointments-kagglev2-may-2016.csv')

data.head()
#We can appreciate a print preview of data.
```

Out[2]:

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

Data Cleaning

In [3]:
```
data.duplicated().sum()
```

Out[3]: 0

It's important to know that we don't have duplicated records.

In [4]:
```
data.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
```

We can appreciate datatypes, non null values and records quantity. In my opinion is better change the following atributes to datetime format.

In [5]:
```
data['PatientId']      = data['PatientId'].astype('int64')  #Avoid scientific no
data['ScheduledDay']   = pd.to_datetime(data['ScheduledDay'])
data['AppointmentDay'] = pd.to_datetime(data['AppointmentDay'])
```

We change datatypes from object to datetime

In [6]:
```
data.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  int64
 1   AppointmentID   110527 non-null  int64
 2   Gender          110527 non-null  object
 3   ScheduledDay    110527 non-null  datetime64[ns, UTC]
 4   AppointmentDay  110527 non-null  datetime64[ns, UTC]
 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: datetime64[ns, UTC](2), int64(9), object(3)
memory usage: 11.8+ MB
```

In [7]:
```
data.head()
```

Out[7]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourh
0	29872499824296	5642903	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	62	JARDIN PE
1	558997776694438	5642503	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	56	JARDIN PE
2	4262962299951	5642549	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	62	MATA DA PI
3	867951213174	5642828	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	8	PONTA CAME
4	8841186448183	5642494	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	56	JARDIN PE

We can appreciate the dataframe has fourteen columns and over one houndred and ten thousand records. In my opinion the columns PatientId and AppointmentID are not relevant to

our analysis. Before drop off both columns we are goint to test a few considerations (Duplicated records, nulls).

In [8]:
```
data['DateDiff'] = data['AppointmentDay'] - data['ScheduledDay']
data['Anticipated_hours'] = data['DateDiff'].astype('timedelta64[h]')
data['Anticipated_days'] = round(data['Anticipated_hours'] / 24, 0).astype(int)
```

We are adding two new columns to see how far in advance the appointment was scheduled.

In [9]:
```
data.head(100)
```

Out[9]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbou
0	29872499824296	5642903	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	62	JARD F
1	558997776694438	5642503	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	56	JARD F
2	4262962299951	5642549	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	62	MATA DA
3	867951213174	5642828	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	8	PONT CAI
4	8841186448183	5642494	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	56	JARD F
...	...	...	...	...	...	...	
95	198624862183842	5640307	M	2016-04-29 10:28:54+00:00	2016-04-29 00:00:00+00:00	1	B(
96	79376248773989	5623692	M	2016-04-26 14:28:39+00:00	2016-04-29 00:00:00+00:00	3	B(
97	5253342488842	5565493	F	2016-04-11 09:00:00+00:00	2016-04-29 00:00:00+00:00	35	B(
98	372596436556933	5571906	F	2016-04-12 09:44:42+00:00	2016-04-29 00:00:00+00:00	51	B(
99	124621344153	5641893	F	2016-04-29 14:38:28+00:00	2016-04-29 00:00:00+00:00	1	B(

100 rows × 17 columns

In [10]:
```
print('Shape=', str(data.shape));

Qty_Records = data.shape[0]

print('Quantity of records=', Qty_Records);
```

```
Shape= (110527, 17)
Quantity of records= 110527
```

In [11]:
```
data.isnull().sum()
```

Out[11]:
```
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
DateDiff             0
Anticipated_hours    0
Anticipated_days     0
dtype: int64
```

It's important to know that we don't have a null values

In [12]:
```
data['AppointmentID'].duplicated().sum()
```

Out[12]:
```
0
```

It's important to know that we don't have a duplicated records that we affect our analysis.

In [13]:
```
data['AppointmentID'].describe()
```

Out[13]:
```
count    1.105270e+05
mean     5.675305e+06
std      7.129575e+04
min      5.030230e+06
25%      5.640286e+06
50%      5.680573e+06
75%      5.725524e+06
max      5.790484e+06
Name: AppointmentID, dtype: float64
```

In [14]:
```
Min_AppointmentID = data['AppointmentID'].min()
Max_AppointmentID = data['AppointmentID'].max()

Qty_AppointmentID = Max_AppointmentID - Min_AppointmentID

print('Min AppID= {0}, Max AppID= {1}, Qty AppID= {2}'.format(Min_AppointmentID,
```

```
Min AppID= 5030230, Max AppID= 5790484, Qty AppID= 760254
```

In terms of database records of capture the system, between the min and max Appointmend ID, we got 760254 records. It's a important things because our dataframe only have 110527 records.

In [15]:
```
Diff_Records = Qty_AppointmentID - Qty_Records
print('Diff_records= {0}'.format(Diff_Records))

Data_gathered = Qty_Records / Qty_AppointmentID
print('% of data gathered= {0}%'.format( round(Data_gathered * 100, 2) ))
```

```
Diff_records= 649727
% of data gathered= 14.54%
```

We only got a 14.54% of total amount of record of appointments. Probably they had a issue with the capture of data.

In [16]:
```
data.drop(['AppointmentID'], axis=1, inplace=True)
```

The AppointmentID is not relevant to our Analysis.

In [17]:
```
data.head()
```

Out[17]:

	PatientId	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarshi
0	29872499824296	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	62	JARDIM DA PENHA	(
1	558997776694438	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	(
2	4262962299951	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	62	MATA DA PRAIA	(
3	867951213174	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	8	PONTAL DE CAMBURI	(
4	8841186448183	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	(

In [18]:
```
print(data.shape)
```

```
(110527, 16)
```

In [19]:
```
data.describe()
```

Out[19]:

	PatientId	Age	Scholarship	Hipertension	Diabetes	Alcoholism
count	1.105270e+05	110527.000000	110527.000000	110527.000000	110527.000000	110527.000000
mean	1.474963e+14	37.088874	0.098266	0.197246	0.071865	0.030400
std	2.560949e+14	23.110205	0.297675	0.397921	0.258265	0.171686
min	3.921700e+04	-1.000000	0.000000	0.000000	0.000000	0.000000
25%	4.172614e+12	18.000000	0.000000	0.000000	0.000000	0.000000
50%	3.173184e+13	37.000000	0.000000	0.000000	0.000000	0.000000
75%	9.439172e+13	55.000000	0.000000	0.000000	0.000000	0.000000
max	9.999816e+14	115.000000	1.000000	1.000000	1.000000	1.000000

In [20]:
```
data['PatientId'].value_counts()
```

Out[20]:
```
822145925426128    88
99637671331        84
26886125921145     70
33534783483176     65
6264198675331      62
                   ..
2886912523138       1
68129842443312      1
99264711372         1
2212945531847       1
57863365759569      1
Name: PatientId, Length: 62299, dtype: int64
```

Indentify how many time one patient request a appointment

In [21]:
```
data['Gender'].value_counts()
```

Out[21]:
```
F    71840
M    38687
Name: Gender, dtype: int64
```

In [22]:
```
data.Gender.nunique()
```

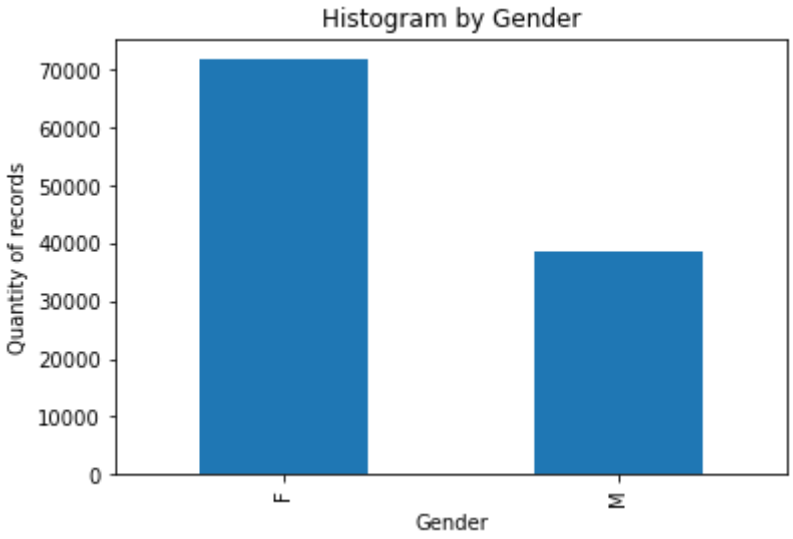
Out[22]:
```
2
```

The variable 'Gender' (F = Female, M = Male) is fine because you only have two correct choices. We don't need to do anything. It can be seen that there are more requirements for women than for men.

In [23]:
```
#data.Gender.hist();

data.groupby('Gender').size().plot(kind='bar', title='Histogram by Gender', xlab
```

Out[23]:
```
<AxesSubplot:title={'center':'Histogram by Gender'}, xlabel='Gender', ylabel='Qu
antity of records'>
```



Basic way to make a histogram. It's easy to appreciate there are more female than male appointment.

In [24]:
```
data.query('Gender == "F"')['Gender'].size
```

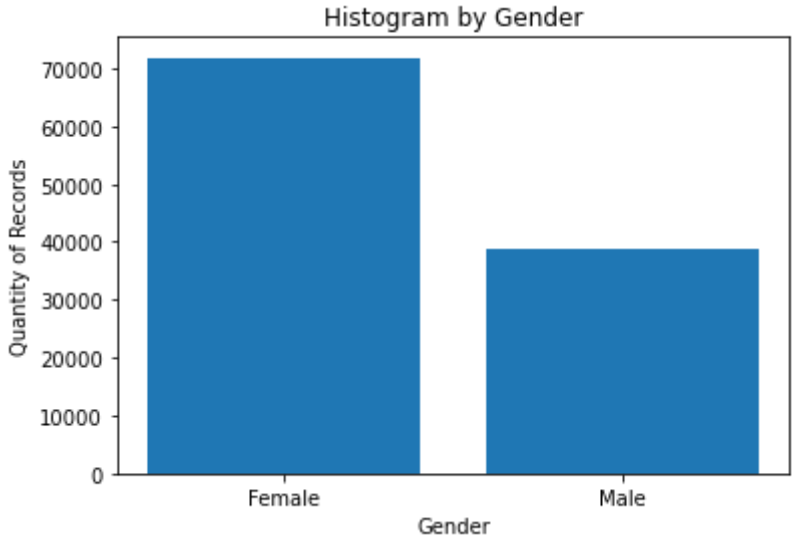
Out[24]:
```
71840
```

In [25]:
```
# Histogram by Gender
locations = [1, 2]

Female_Qty = data.query('Gender == "F"')['Gender'].size;
Male_Qty   = data.query('Gender == "M"')['Gender'].size;

heights = [Female_Qty, Male_Qty]
labels = ['Female', 'Male']
plt.bar(locations, heights, tick_label=labels)
plt.title('Histogram by Gender')
```

```
plt.xlabel('Gender')
plt.ylabel('Quantity of Records');
```



Other way to plot.

In [26]:
```
data['Weekday_ScheduledDay'] = data['ScheduledDay'].dt.dayofweek.map(dayOfWeek)
```

In [27]:
```
data.head()
```

Out[27]:

	PatientId	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarshi
0	29872499824296	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	62	JARDIM DA PENHA	(
1	558997776694438	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	(
2	4262962299951	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	62	MATA DA PRAIA	(
3	867951213174	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	8	PONTAL DE CAMBURI	(
4	8841186448183	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	(

In [28]:
```
data.ScheduledDay.min()
```

Out[28]:
```
Timestamp('2015-11-10 07:13:56+0000', tz='UTC')
```

In [29]:
```
data.ScheduledDay.max()
```

Out[29]:
```
Timestamp('2016-06-08 20:07:23+0000', tz='UTC')
```

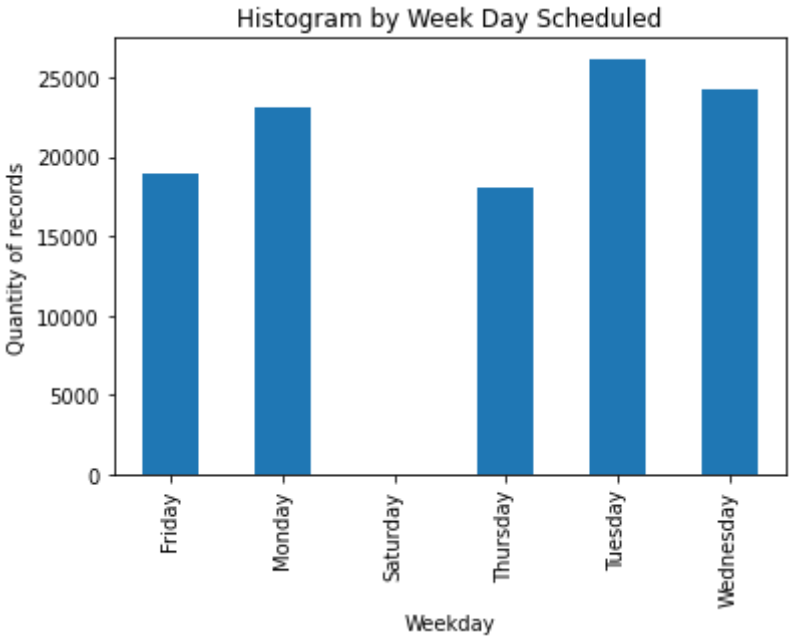
The time window available with the dataset covers about 7 months. It would be ideal to have much more information, hopefully at least twelve months to have a better understanding of the model considering the seasonal effects.

In [30]:
```
data['Weekday_ScheduledDay'].value_counts()
```

Out[30]:
```
Tuesday      26168
Wednesday    24262
Monday       23085
Friday       18915
Thursday     18073
Saturday        24
Name: Weekday_ScheduledDay, dtype: int64
```

In [31]:
```
data.groupby('Weekday_ScheduledDay').size().plot(kind='bar', title='Histogram by
```

Out[31]:
```
<AxesSubplot:title={'center':'Histogram by Week Day Scheduled'}, xlabel='Weekda
y', ylabel='Quantity of records'>
```



Scheduled Day with more Appointments

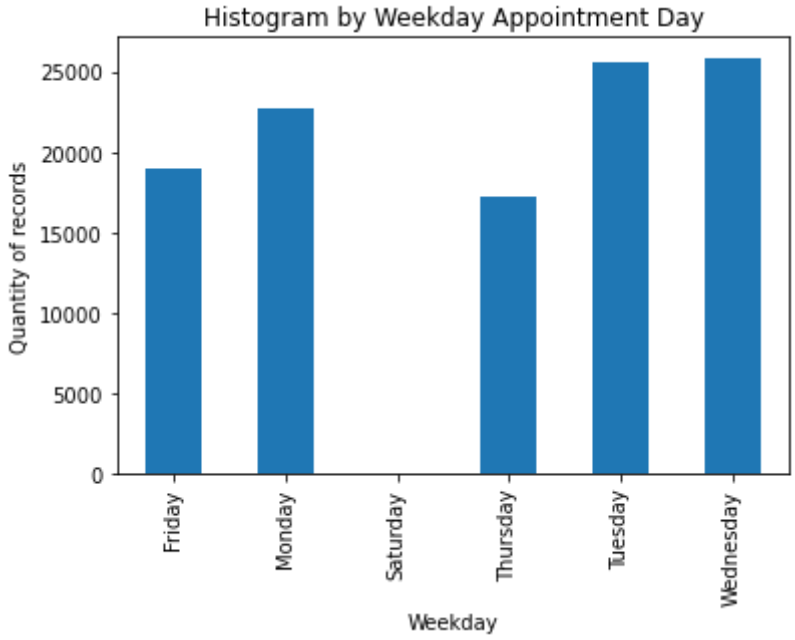
In [32]:
```
data['Weekday_AppointmentDay'] = data['AppointmentDay'].dt.dayofweek.map(dayOfWe
```

In [33]:
```
data['Weekday_AppointmentDay'].value_counts()
```

Out[33]:
```
Wednesday    25867
Tuesday      25640
Monday       22715
Friday       19019
Thursday     17247
Saturday        39
Name: Weekday_AppointmentDay, dtype: int64
```

In [34]:
```
data.groupby('Weekday_AppointmentDay').size().plot(kind='bar', title='Histogram
                                                   xlabel='Weekday', ylabel='Qua
```

Out[34]:
```
<AxesSubplot:title={'center':'Histogram by Weekday Appointment Day'}, xlabel='We
ekday', ylabel='Quantity of records'>
```



Appointment days more requested.

In [35]:
```
data['Age'].value_counts()
```

Out[35]:
```
0      3539
1      2273
52     1746
49     1652
53     1651
       ...
115       5
100       4
102       2
99        1
-1        1
Name: Age, Length: 104, dtype: int64
```

In [36]:
```
data['Age'].describe()
```

Out[36]:
```
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
```

in the Age variable we will assume that:

- -1: refers to pregnant woman
- 0: refers to a baby who is not yet one year old
- 1: refers to a one year old baby
- 2 onwards, the patient's age

In [37]:
```
pregnant = data.query('Age == -1')
pregnant['Gender'].value_counts()
```

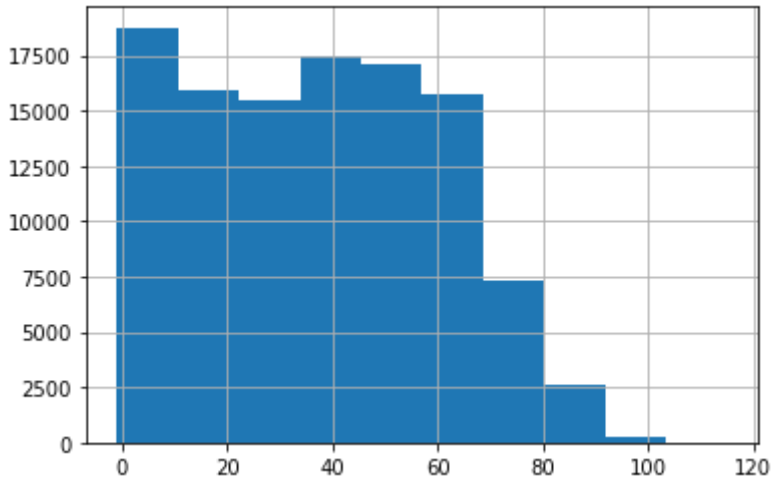
Out[37]:
```
F    1
Name: Gender, dtype: int64
```

Other way to ask the same: pregnant = data.query('Age == -1')
pregnant['Gender'].value_counts()

It is ok that the Gender of pregnant women was female.

In [38]:
```
data.Age.hist()
```

Out[38]:
```
<AxesSubplot:>
```



In [39]:
```
data.query('Age > 100')
```

Out[39]:

	PatientId	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Schola
58014	976294799775439	F	2016-05-03 09:14:53+00:00	2016-05-03 00:00:00+00:00	102	CONQUISTA	
63912	31963211613981	F	2016-05-16 09:17:44+00:00	2016-05-19 00:00:00+00:00	115	ANDORINHAS	
63915	31963211613981	F	2016-05-16 09:17:44+00:00	2016-05-19 00:00:00+00:00	115	ANDORINHAS	
68127	31963211613981	F	2016-04-08 14:29:17+00:00	2016-05-16 00:00:00+00:00	115	ANDORINHAS	
76284	31963211613981	F	2016-05-30 09:44:51+00:00	2016-05-30 00:00:00+00:00	115	ANDORINHAS	
90372	234283596548	F	2016-05-31 10:19:49+00:00	2016-06-02 00:00:00+00:00	102	MARIA ORTIZ	
97666	748234579244724	F	2016-05-19 07:57:56+00:00	2016-06-03 00:00:00+00:00	115	SÃO JOSÉ	

It is strange to have records over 100 years old, but the following link indicates that it is possible

https://www.guinnessworldrecords.com/world-records/oldest-person#:~:text=Share&text=The%20greatest%20fully%20authenticated%20age,France%20on%20

In [40]:
```
# Bin edges that will be used to "cut" the data into groups
bin_edges = [-1, 18, 37, 55, 115]
```

In [41]:
```
# Labels for quantity anticipated groups
bin_names = ['<18', '19 - 37', '38 - 55', '> 56'] # Name each Age range category
```

In [42]:
```
data['Age_groups'] = pd.cut(data['Age'], bin_edges, labels=bin_names)
```

We add a new column to create a category groups by Age that could help to improve our Analysis.

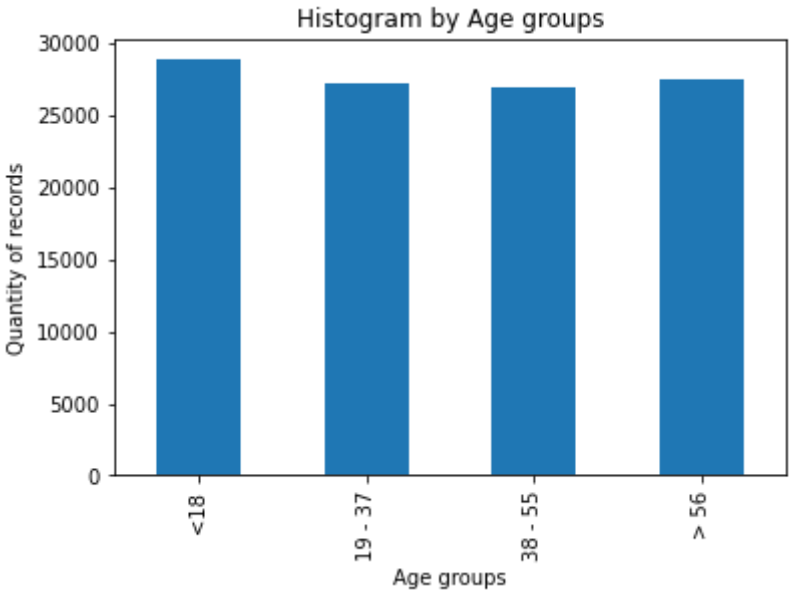
In [43]:
```
data.head()
```

Out[43]:

	PatientId	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarshi
0	29872499824296	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	62	JARDIM DA PENHA	(
1	558997776694438	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	(
2	4262962299951	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	62	MATA DA PRAIA	(
3	867951213174	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	8	PONTAL DE CAMBURI	(
4	8841186448183	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	(

In [44]:
```
data.groupby('Age_groups').size().plot(kind='bar', title='Histogram by Age group
                                       xlabel='Age groups', ylabel='
```

Out[44]:
```
<AxesSubplot:title={'center':'Histogram by Age groups'}, xlabel='Age groups', yl
abel='Quantity of records'>
```

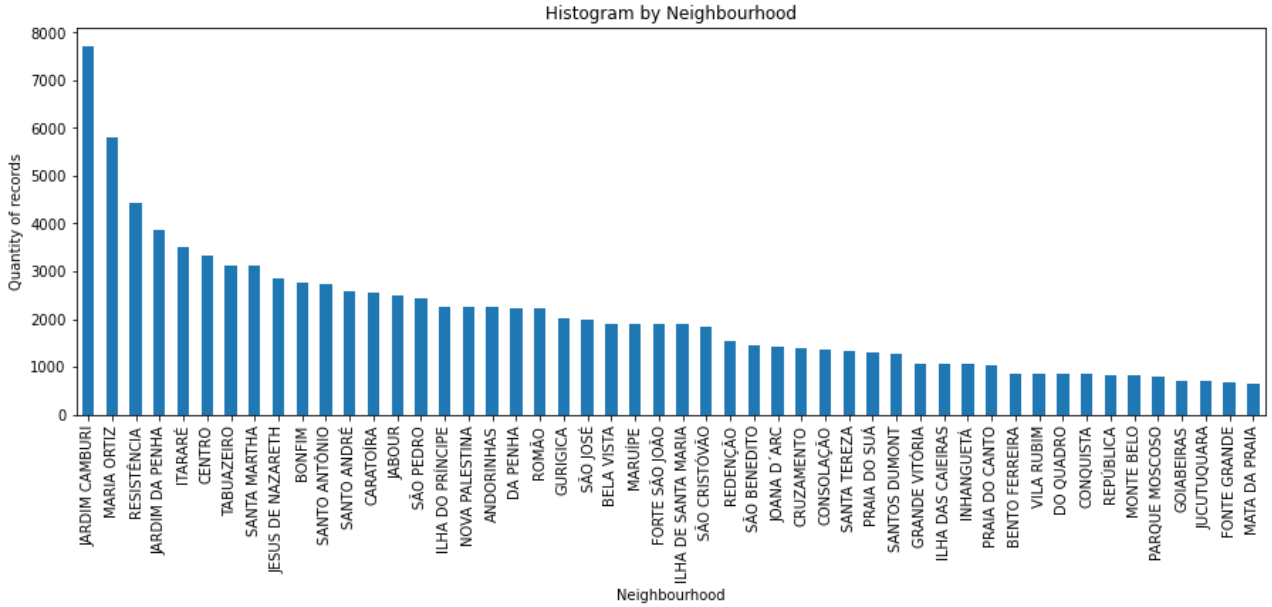


We have a very homogeneous groups by Age

In [45]:
```
data.Neighbourhood.value_counts().head(50).plot(kind='bar', figsize=(15,5), titl
                                                xlabel='Neighbourhood', ylabe
```

Out[45]:
```
<AxesSubplot:title={'center':'Histogram by Neighbourhood'}, xlabel='Neighbourhoo
```

```
d', ylabel='Quantity of records'>
```



The top 50 Neighbourhood

In [46]:
```
data['Scholarship'].value_counts()
```

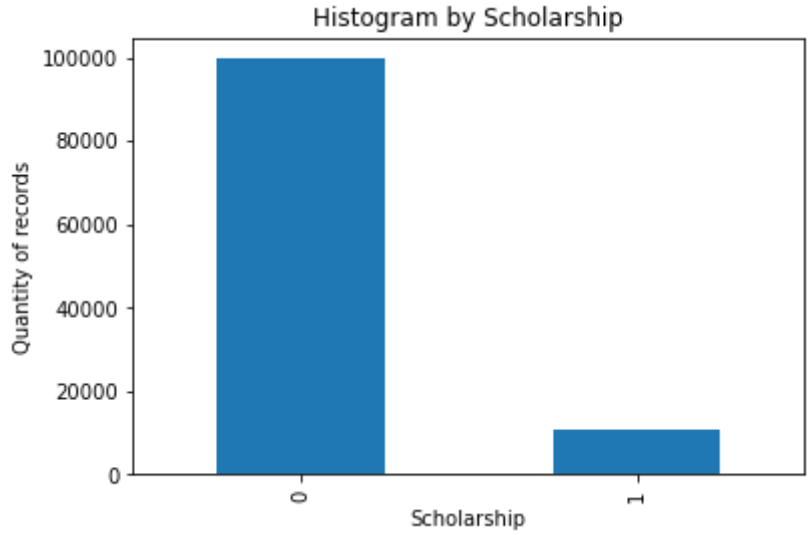
Out[46]:
```
0    99666
1    10861
Name: Scholarship, dtype: int64
```

in the Scholarship variable we will assume that:

- 1: The people has Scholarship.
- 0: The people hasn't Scholarship, **majority case**.

In [47]:
```
data.groupby('Scholarship').size().plot(kind='bar', title='Histogram by Scholars
                                                    xlabel='Scholarship', ylabel=
```

Out[47]:
```
<AxesSubplot:title={'center':'Histogram by Scholarship'}, xlabel='Scholarship',
ylabel='Quantity of records'>
```



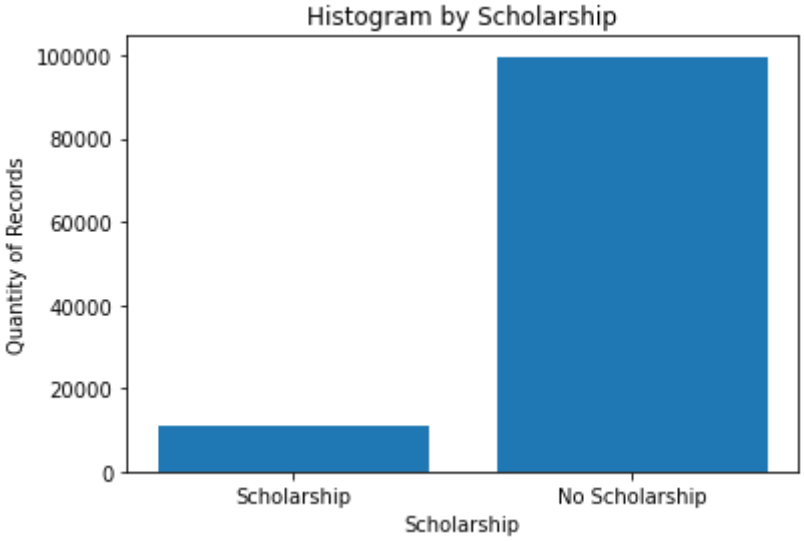
In [48]:
```
#data.Scholarship.hist();

# Histogram by Scholarship
```

```
locations = [1, 2]

Sch_Qty = data.query('Scholarship == "1"')['Scholarship'].size;
nSch_Qty   = data.query('Scholarship == "0"')['Scholarship'].size;

heights = [Sch_Qty, nSch_Qty]
labels = ['Scholarship', 'No Scholarship']
plt.bar(locations, heights, tick_label=labels)
plt.title('Histogram by Scholarship')
plt.xlabel('Scholarship')
plt.ylabel('Quantity of Records');
```



In [49]:
```
data['Hipertension'].value_counts()
```

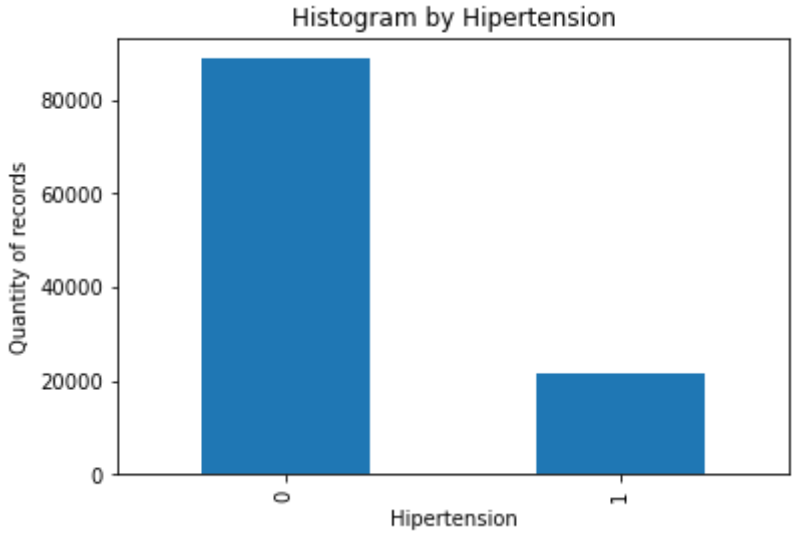
Out[49]:
```
0    88726
1    21801
Name: Hipertension, dtype: int64
```

in the Hipertension variable we will assume that:

- 1: The people has Hipertension.
- 0: The people hasn't Hipertension, **majority case**.

In [50]:
```
data.groupby('Hipertension').size().plot(kind='bar', title='Histogram by Hiperte
                                                    xlabel='Hipertension', ylabel
```

Out[50]:
```
<AxesSubplot:title={'center':'Histogram by Hipertension'}, xlabel='Hipertensio
n', ylabel='Quantity of records'>
```



In [51]:
```
data['Diabetes'].value_counts()
```

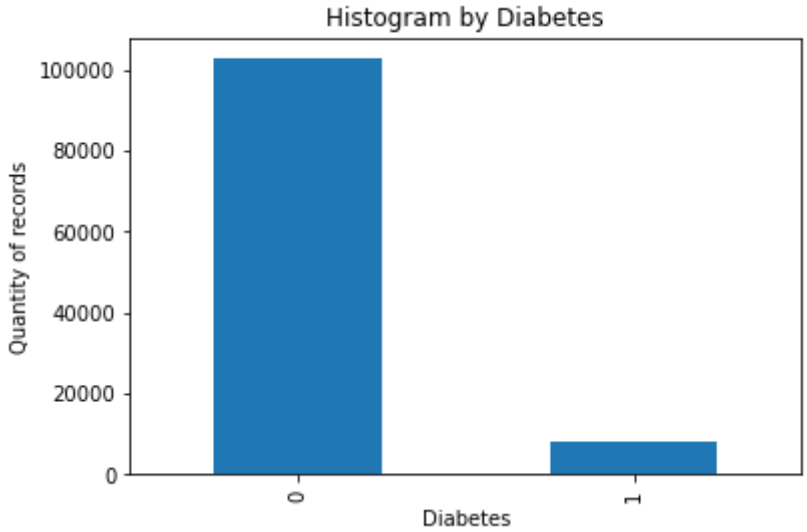
Out[51]:
```
0    102584
1      7943
Name: Diabetes, dtype: int64
```

in the Diabetes variable we will assume that:

- 1: The people has Diabetes.
- 0: The people hasn't Diabetes, **majority case**.

In [52]:
```
data.groupby('Diabetes').size().plot(kind='bar', title='Histogram by Diabetes',
                                     xlabel='Diabetes', ylabel='Qu
```

Out[52]:
```
<AxesSubplot:title={'center':'Histogram by Diabetes'}, xlabel='Diabetes', ylabel
='Quantity of records'>
```



In [53]:
```
data['Alcoholism'].value_counts()
```

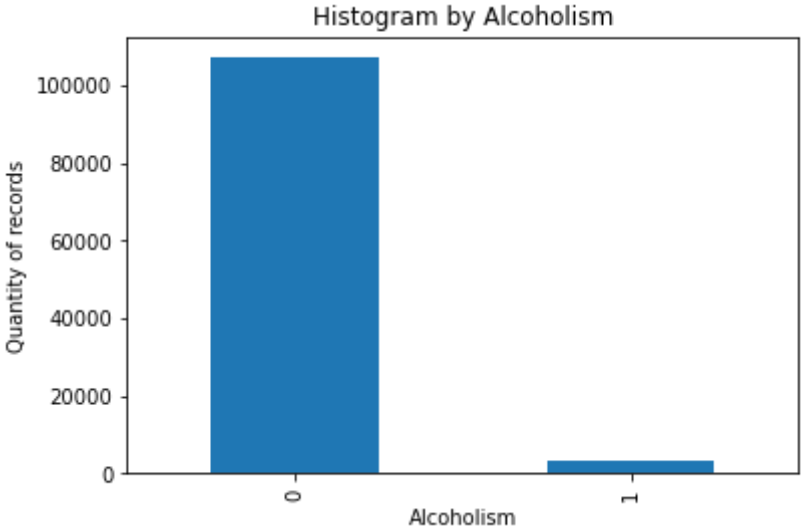
Out[53]:
```
0    107167
1      3360
Name: Alcoholism, dtype: int64
```

in the Alcoholism variable we will assume that:

- 1: The people has Alcoholism.
- 0: The people hasn't Alcoholism, **majority case**.

In [54]:
```
data.groupby('Alcoholism').size().plot(kind='bar', title='Histogram by Alcoholis
                                       xlabel='Alcoholism', ylabel='
```

Out[54]:
```
<AxesSubplot:title={'center':'Histogram by Alcoholism'}, xlabel='Alcoholism', yl
abel='Quantity of records'>
```



In [55]:
```
data['Handcap'].value_counts()
```

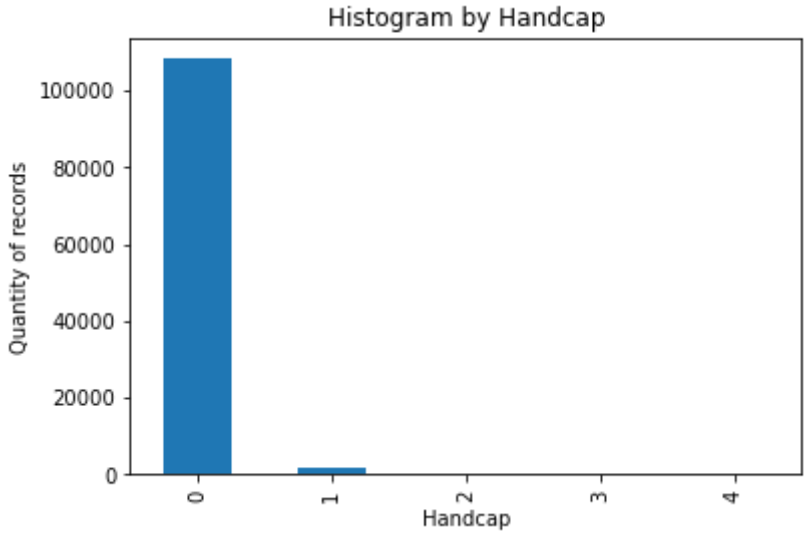
Out[55]:
```
0    108286
1      2042
2       183
3        13
4         3
Name: Handcap, dtype: int64
```

in the Handcap variable we will assume that:

- 1: The people has any kind of Handcap
- 0: The people hasn't any kind of Handcap, **majority case**.

In [56]:
```
data.groupby('Handcap').size().plot(kind='bar', title='Histogram by Handcap',
                                    xlabel='Handcap', ylabel='Quanti
```

Out[56]:
```
<AxesSubplot:title={'center':'Histogram by Handcap'}, xlabel='Handcap', ylabel
='Quantity of records'>
```



In [57]:
```
data['SMS_received'].value_counts()
```

Out[57]:
```
0    75045
1    35482
Name: SMS_received, dtype: int64
```

in the SMS_received variable we will assume that:

- 1: The people did receive a SMS.
- 0: The people didn't, receive a SMS, **majority case**.

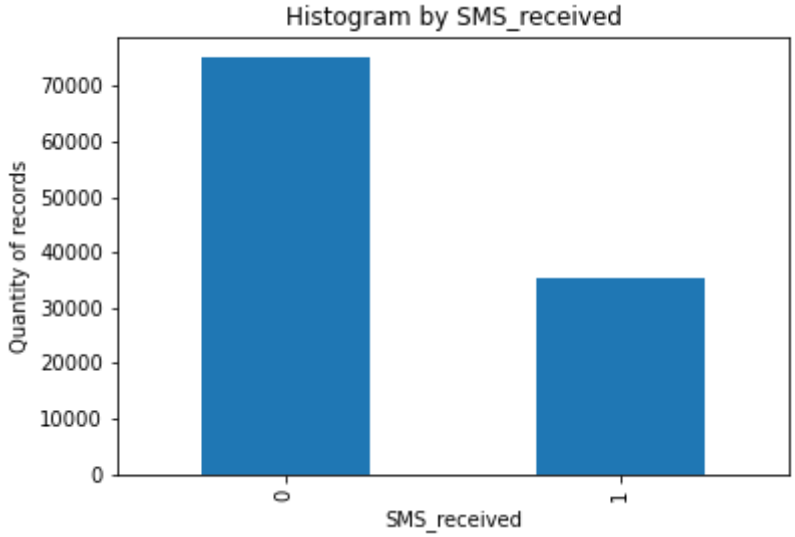
In [58]:
```
data['SMS_received'].value_counts()/Qty_Records*100
```

Out[58]:
```
0    67.897437
1    32.102563
Name: SMS_received, dtype: float64
```

Only 32,1% de SMS were received.

In [59]:
```
data.groupby('SMS_received').size().plot(kind='bar', title='Histogram by SMS_rec
                                         xlabel='SMS_received', ylabel='Quantity
```

Out[59]:
```
<AxesSubplot:title={'center':'Histogram by SMS_received'}, xlabel='SMS_receive
d', ylabel='Quantity of records'>
```



In [60]:
```
data['No-show'].value_counts()
```

Out[60]:
```
No     88208
Yes    22319
Name: No-show, dtype: int64
```

in the No-show variable we will assume that:

- No: If the patient showed up to their appointment, **majority case**.
- Yes: If they did not show up.

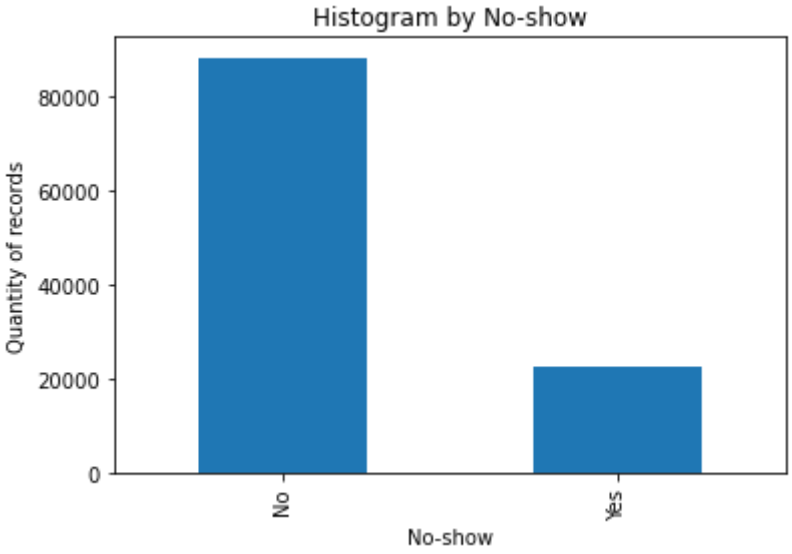
In [61]:
```
data['No-show'].value_counts()/Qty_Records*100
```

Out[61]:
```
No     79.806744
Yes    20.193256
Name: No-show, dtype: float64
```

We got a 79,80% in the effectiveness in the appointment. In my opinion is a good performance indicator.

In [62]:
```
data.groupby('No-show').size().plot(kind='bar', title='Histogram by No-show',
                                    xlabel='No-show', ylabel='Quantity of record
```

Out[62]:
```
<AxesSubplot:title={'center':'Histogram by No-show'}, xlabel='No-show', ylabel
='Quantity of records'>
```



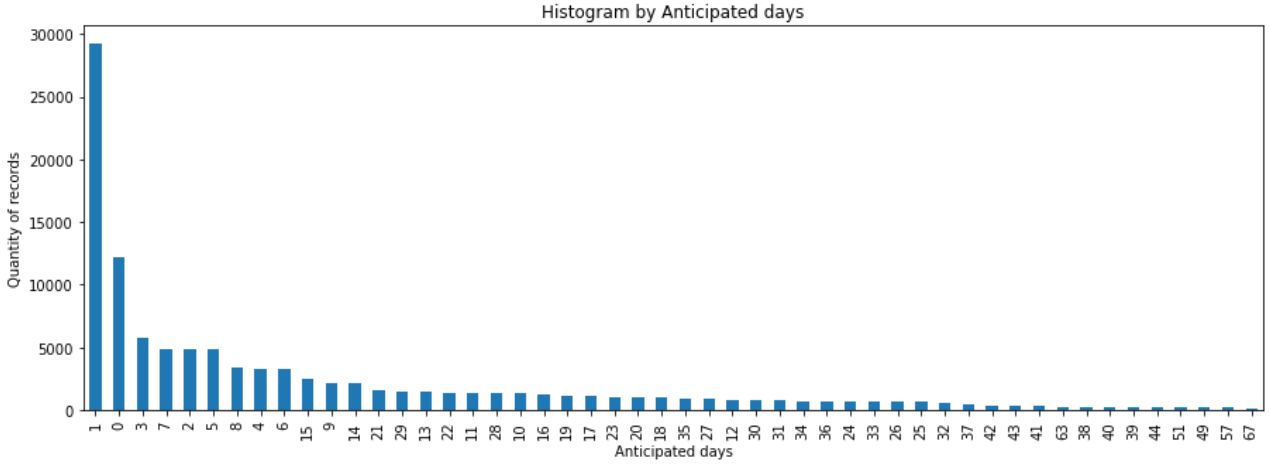
In [63]:
```
data.Anticipated_days.value_counts().head(50)
```

Out[63]:
```
1     29210
0     12158
3      5774
7      4910
2      4891
5      4849
8      3397
4      3301
6      3254
15     2442
9      2176
14     2136
21     1630
29     1482
13     1473
```

```
22     1393
11     1377
28     1366
10     1315
16     1229
19     1138
17     1107
23     1077
20     1072
18     1061
35      918
27      915
12      831
30      786
31      761
34      713
36      708
24      701
33      693
26      648
25      643
32      554
37      477
42      368
43      347
41      297
63      235
38      229
40      225
39      196
44      195
51      189
49      178
57      177
67      165
Name: Anticipated_days, dtype: int64
```

In [64]:
```
data.Anticipated_days.value_counts().head(50).plot(kind='bar', figsize=(15,5), t
                                    xlabel='Anticipated days', ylabel='Quantity
```

Out[64]:
```
<AxesSubplot:title={'center':'Histogram by Anticipated days'}, xlabel='Anticipat
ed days', ylabel='Quantity of records'>
```



Top 50 requested Appointment by anticipated days

In [65]:
```
data.Anticipated_days.describe()
```

Out[65]:
```
count    110527.000000
```

```
mean          10.779755
std           15.229088
min           -6.000000
25%            1.000000
50%            4.000000
75%           15.000000
max          180.000000
Name: Anticipated_days, dtype: float64
```

In [66]:
```
# Bin edges that will be used to "cut" the data into groups
bin_edges = [-6, 1, 4, 15, 180] # Fill in this list with five values you just fo
```

In [67]:
```
# Labels for quantity anticipated groups
bin_names = ['Urgent', 'Close', 'Regular', 'Scheduled'] # Name each group catego
```

In [68]:
```
data['Anticipated_group'] = pd.cut(data['Anticipated_days'], bin_edges, labels=b
```

In [69]:
```
data.head()
```

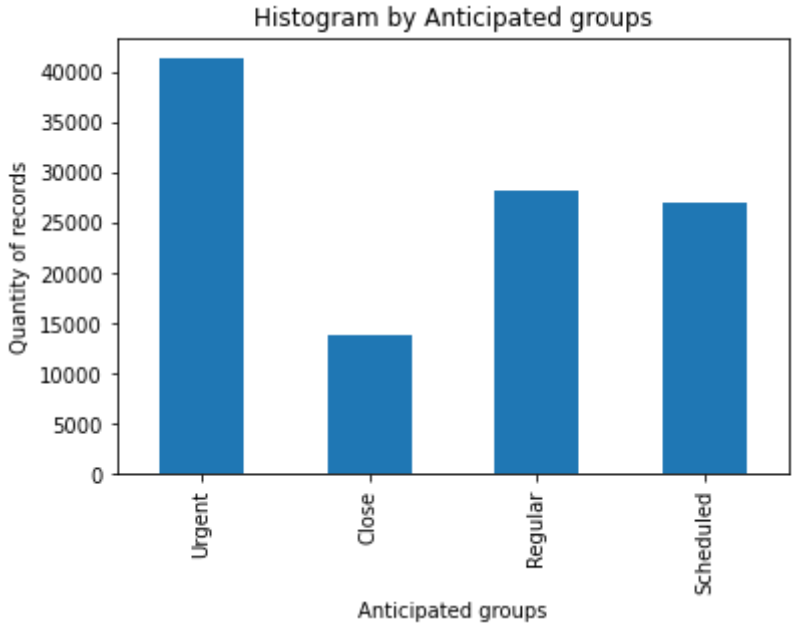
Out[69]:

	PatientId	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarshi
0	29872499824296	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	62	JARDIM DA PENHA	(
1	558997776694438	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	(
2	4262962299951	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	62	MATA DA PRAIA	(
3	867951213174	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	8	PONTAL DE CAMBURI	(
4	8841186448183	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	(

In [70]:
```
data.drop(['PatientId', 'ScheduledDay', 'AppointmentDay', 'Neighbourhood', 'Date
          axis=1, inplace=True)
```

In [71]:
```
data.groupby('Anticipated_group').size().plot(kind='bar', title='Histogram by An
                                    xlabel='Anticipated groups', ylabel='Quantit
```

Out[71]:
```
<AxesSubplot:title={'center':'Histogram by Anticipated groups'}, xlabel='Anticip
ated groups', ylabel='Quantity of records'>
```



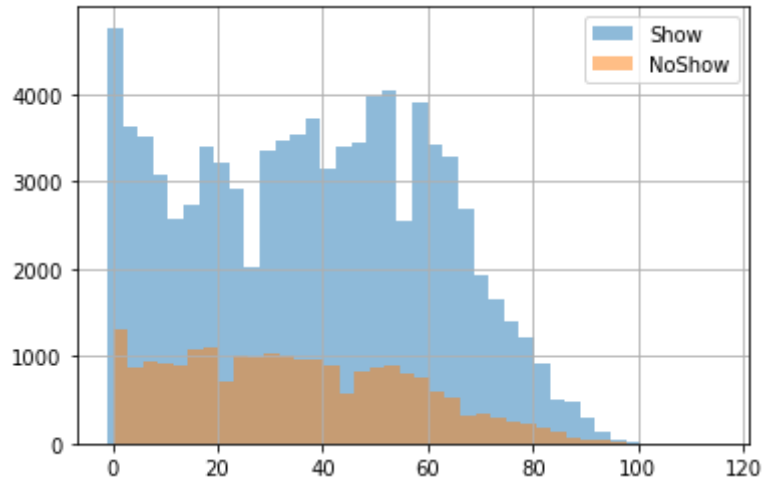
IMPORTANT: It is important to note that the dependent variable is 'No-show'. It could depend on all the other variables. For example: Gender, Scheduled Day, Appointment Day, Age, Neighborhood, Scholarship, Hypertension, Diabetes, Alcoholism, Handcap, SMS_received.

In [72]:
```
Show = data['No-show'] == 'No'
NoShow = data['No-show'] == 'Yes'
```

In [73]:
```
data.groupby(['Gender'])['No-show'].value_counts()
```

Out[73]:
```
Gender  No-show
F       No         57246
        Yes        14594
M       No         30962
        Yes         7725
Name: No-show, dtype: int64
```

In [74]:
```
data.Age[Show].hist(alpha=0.5, bins=40, label='Show')
data.Age[NoShow].hist(alpha=0.5, bins=40, label='NoShow')
plt.legend();
```



This graph gives us an overview, but through exploratory data analysis we will be able to review

our concerns in more detail.

Before start EDA, we are cleaning the data frame with irrelevant columns.

In [75]:
```
data.head()
```

Out[75]:

	Gender	Age	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_received	No-show
0	F	62	0	1	0	0	0	0	No
1	M	56	0	0	0	0	0	0	No
2	F	62	0	0	0	0	0	0	No
3	F	8	0	0	0	0	0	0	No
4	F	56	0	1	1	0	0	0	No

In [76]:
```
data.head()
```

Out[76]:

	Gender	Age	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_received	No-show
0	F	62	0	1	0	0	0	0	No
1	M	56	0	0	0	0	0	0	No
2	F	62	0	0	0	0	0	0	No
3	F	8	0	0	0	0	0	0	No
4	F	56	0	1	1	0	0	0	No

Exploratory Data Analysis

Research Question 1 (How much a person's gender influences their responsibility to show up for the scheduled appointment ?)

In [77]:
```
#Will be the Gender a relevant factor to no show.

data.groupby(['Gender'])['No-show'].value_counts()
```

Out[77]:
```
Gender  No-show
F       No         57246
        Yes        14594
M       No         30962
        Yes         7725
Name: No-show, dtype: int64
```

In [78]:
```
data.Gender.value_counts()
```

Out[78]:
```
F    71840
M    38687
Name: Gender, dtype: int64
```

In [79]:
```
Gender_NoShow = pd.crosstab(index=data['Gender'], columns=data['No-show'])
Gender_NoShow
```

Out[79]:

Gender	No-show No	Yes
F	57246	14594
M	30962	7725

It is a better way to compare both variables with crosstab function

In [80]:
```
Gender_NoShow = round(pd.crosstab(index=data['Gender'], columns=data['No-show'],
Gender_NoShow
```

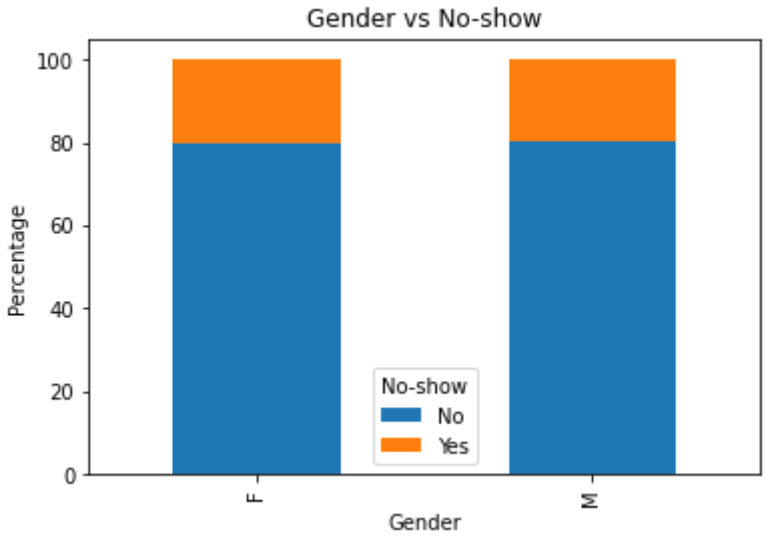
Out[80]:

Gender	No-show No	Yes
F	79.69	20.31
M	80.03	19.97

Now, other way to present the information using percentages

In [81]:
```
Gender_NoShow.plot(kind='bar', title='Gender vs No-show', stacked = True,
                                xlabel='Gender', ylabel='Percentage')
```

Out[81]:
```
<AxesSubplot:title={'center':'Gender vs No-show'}, xlabel='Gender', ylabel='Perc
entage'>
```



In my opinion, we don't have a significant difference between gender and No-show.

Research Question 2 (How much help to send an SMS message to remind the user that they have a planned visit to the hospital ?)

In [82]:
```
data.groupby(['SMS_received'])['No-show'].value_counts()
```

Out[82]:
```
SMS_received  No-show
0             No         62510
              Yes        12535
1             No         25698
              Yes         9784
Name: No-show, dtype: int64
```

In [83]:
```
data.SMS_received.value_counts()
```

Out[83]:
```
0    75045
1    35482
Name: SMS_received, dtype: int64
```

In [84]:
```
SMS_received_NoShow = pd.crosstab(index=data['SMS_received'], columns=data['No-s
SMS_received_NoShow
```

Out[84]:

No-show	No	Yes
SMS_received		
0	62510	12535
1	25698	9784

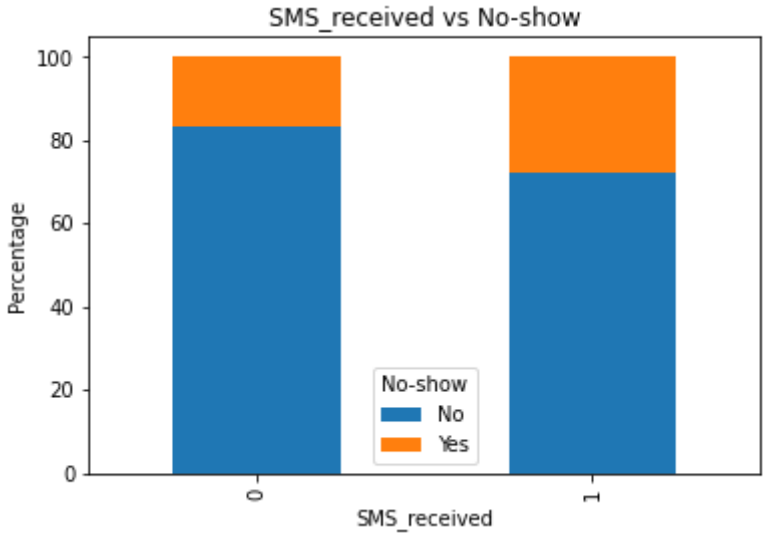
In [85]:
```
SMS_received_NoShow = round(pd.crosstab(index=data['SMS_received'], columns=data
SMS_received_NoShow
```

Out[85]:

No-show	No	Yes
SMS_received		
0	83.30	16.70
1	72.43	27.57

In [86]:
```
SMS_received_NoShow.plot(kind='bar', title='SMS_received vs No-show', stacked =
                                 xlabel='SMS_received', ylabel='Percentage')
```

Out[86]:
```
<AxesSubplot:title={'center':'SMS_received vs No-show'}, xlabel='SMS_received',
ylabel='Percentage'>
```



In this case is strange to see that a SMS-received don't help to improve the Show up in an Appointment. At the beginning of the analysis I would have opted for a different result.

Research Question 3 (There is a relationship between the Scholarship and the responsibility to show up at the planned appointment ?)

In [87]:
```
data.groupby(['Scholarship'])['No-show'].value_counts()
```

Out[87]:
```
Scholarship  No-show
0            No         79925
             Yes        19741
1            No          8283
             Yes         2578
Name: No-show, dtype: int64
```

In [88]:
```
data.Scholarship.value_counts()
```

Out[88]:
```
0    99666
1    10861
Name: Scholarship, dtype: int64
```

In [89]:
```
Scholarship_NoShow = pd.crosstab(index=data['Scholarship'], columns=data['No-sho
Scholarship_NoShow
```

Out[89]:

No-show	No	Yes
Scholarship		
0	79925	19741
1	8283	2578

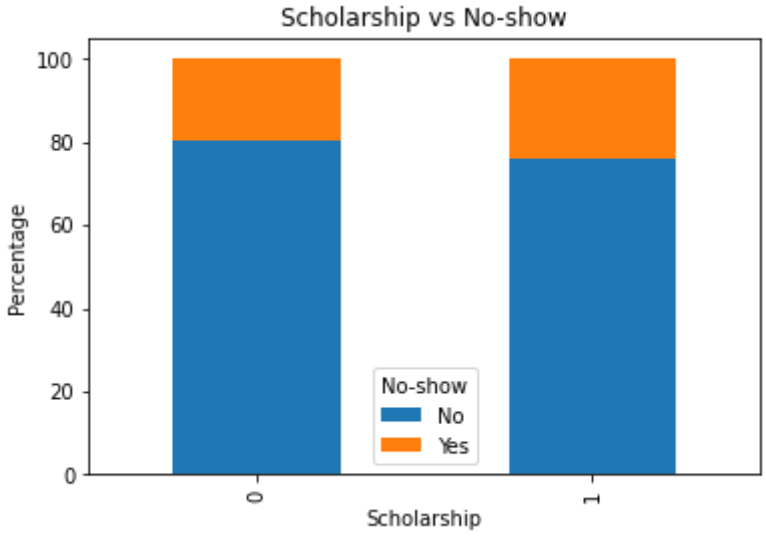
In [90]:
```
Scholarship_NoShow = round(pd.crosstab(index=data['Scholarship'], columns=data['
Scholarship_NoShow
```

Out[90]:

No-show	No	Yes
Scholarship		
0	80.19	19.81
1	76.26	23.74

In [91]:
```
Scholarship_NoShow.plot(kind='bar', title='Scholarship vs No-show', stacked = Tr
                                xlabel='Scholarship', ylabel='Percentage')
```

Out[91]:
```
<AxesSubplot:title={'center':'Scholarship vs No-show'}, xlabel='Scholarship', yl
abel='Percentage'>
```



In this case is strange to see that a Scholarship don't help to improve the Show up in an Appointment. At the beginning of the analysis I would have opted for a different result.

Research Question 4 (How much age influences the responsibility to attend a planned appointment ?)

In [92]:
```
data.groupby(['Age'])['No-show'].value_counts()
```

Out[92]:
```
Age   No-show
-1    No            1
 0    No         2900
      Yes         639
 1    No         1858
      Yes         415
                 ...
 99   No            1
 100  No            4
 102  No            2
 115  Yes           3
      No            2
Name: No-show, Length: 204, dtype: int64
```

In [93]:
```
data.Age.value_counts()
```

Out[93]:
```
0      3539
1      2273
52     1746
49     1652
53     1651
       ...
115       5
100       4
102       2
99        1
-1        1
Name: Age, Length: 104, dtype: int64
```

In [94]:
```
Age_NoShow = pd.crosstab(index=data['Age'], columns=data['No-show'])
Age_NoShow
```

Out[94]:

No-show	No	Yes
Age		
-1	1	0
0	2900	639
1	1858	415
2	1366	252
3	1236	277
...	...	...
98	5	1
99	1	0
100	4	0
102	2	0
115	2	3

104 rows × 2 columns

In [95]:
```
Age_NoShow = round(pd.crosstab(index=data['Age'], columns=data['No-show'], norma
Age_NoShow
```

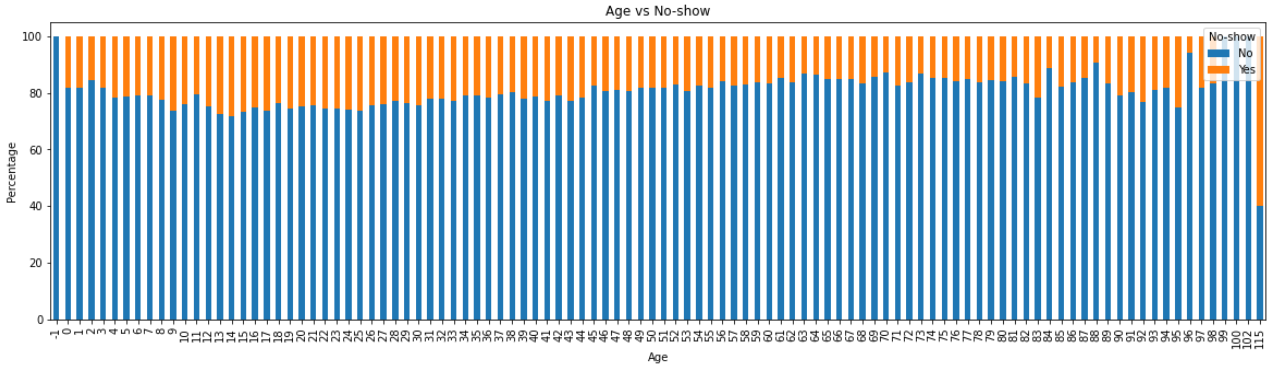
Out[95]:

No-show	No	Yes
Age		
-1	100.00	0.00
0	81.94	18.06
1	81.74	18.26
2	84.43	15.57
3	81.69	18.31
...	...	...
98	83.33	16.67
99	100.00	0.00
100	100.00	0.00
102	100.00	0.00
115	40.00	60.00

104 rows × 2 columns

In [96]:
```
Age_NoShow.plot(kind='bar', title='Age vs No-show', stacked = True, figsize=(20,
                            xlabel='Age', ylabel='Percentage')
```

Out[96]:
```
<AxesSubplot:title={'center':'Age vs No-show'}, xlabel='Age', ylabel='Percentag
e'>
```



It's not easy to see between what range of age is better to improve the indicator of show up an a Appointment. Using different groups could be a better option.

In [97]:
```
Age_groups_NoShow = pd.crosstab(index=data['Age_groups'], columns=data['No-show'
Age_groups_NoShow
```

Out[97]:

No-show	No	Yes
Age_groups		
<18	22519	6347
19 - 37	20836	6414

No-show	No	Yes
Age_groups		
38 - 55	21651	5255
> 56	23201	4303

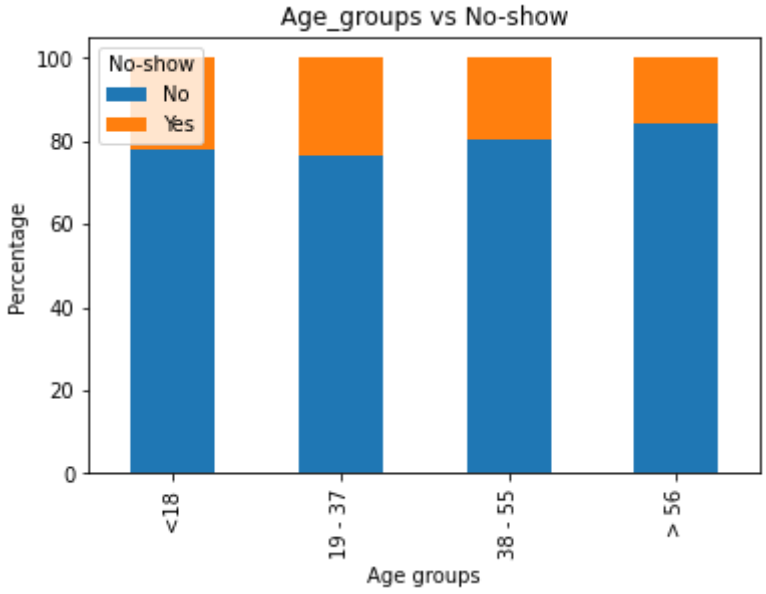
In [98]:
```
Age_groups_NoShow = round(pd.crosstab(index=data['Age_groups'], columns=data['No
Age_groups_NoShow
```

Out[98]:

No-show	No	Yes
Age_groups		
<18	78.01	21.99
19 - 37	76.46	23.54
38 - 55	80.47	19.53
> 56	84.36	15.64

In [99]:
```
Age_groups_NoShow.plot(kind='bar', title='Age_groups vs No-show', stacked = True
                       xlabel='Age groups', ylabel='Percentage')
```

Out[99]:
```
<AxesSubplot:title={'center':'Age_groups vs No-show'}, xlabel='Age groups', ylab
el='Percentage'>
```



In this case is easy to see that in the range > 56 increase the show up an a Appointment.

Research Question 5 (There is a relationship between the Hipertension and the responsibility to show up at the planned appointment ?)

In [100…
```
data.groupby(['Hipertension'])['No-show'].value_counts()
```

Out[100…
```
Hipertension  No-show
0             No         70179
              Yes        18547
1             No         18029
```

```
                Yes          3772
Name: No-show, dtype: int64
```

In [101…
```
data.Hipertension.value_counts()
```

Out[101…
```
0    88726
1    21801
Name: Hipertension, dtype: int64
```

In [102…
```
Hipertension_NoShow = pd.crosstab(index=data['Hipertension'], columns=data['No-s
Hipertension_NoShow
```

Out[102…

No-show	No	Yes
Hipertension		
0	70179	18547
1	18029	3772

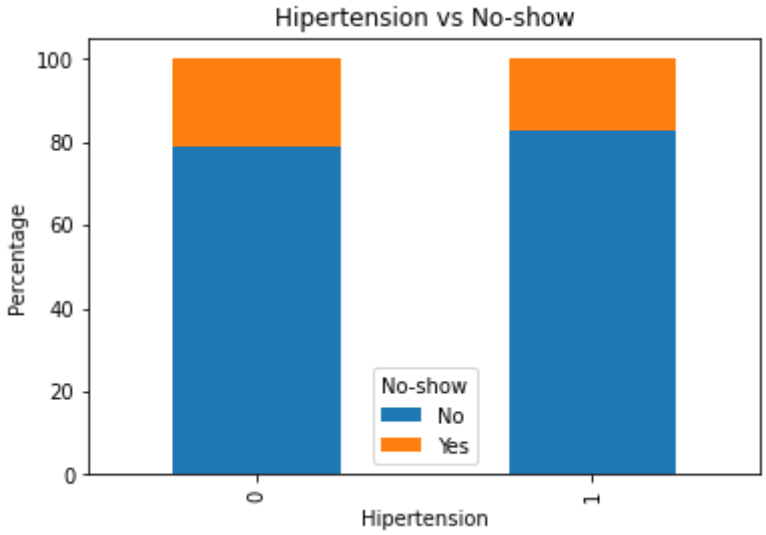
In [103…
```
Hipertension_NoShow = round(pd.crosstab(index=data['Hipertension'], columns=data
Hipertension_NoShow
```

Out[103…

No-show	No	Yes
Hipertension		
0	79.1	20.9
1	82.7	17.3

In [104…
```
Hipertension_NoShow.plot(kind='bar', title='Hipertension vs No-show', stacked =
                         xlabel='Hipertension', ylabel='Percentage')
```

Out[104…
```
<AxesSubplot:title={'center':'Hipertension vs No-show'}, xlabel='Hipertension',
ylabel='Percentage'>
```



In this case the people with Hipertension have a better indicator for show up an a Appointment.

Research Question 6 (There is a relationship between the Diabetes and the responsibility to show up at the planned appointment ?)

In [105…
```
data.groupby(['Diabetes'])['No-show'].value_counts()
```

Out[105…
```
Diabetes  No-show
0         No          81695
          Yes         20889
1         No           6513
          Yes          1430
Name: No-show, dtype: int64
```

In [106…
```
data.Diabetes.value_counts()
```

Out[106…
```
0    102584
1      7943
Name: Diabetes, dtype: int64
```

In [107…
```
Diabetes_NoShow = pd.crosstab(index=data['Diabetes'], columns=data['No-show'])
Diabetes_NoShow
```

Out[107…

No-show	No	Yes
Diabetes		
0	81695	20889
1	6513	1430

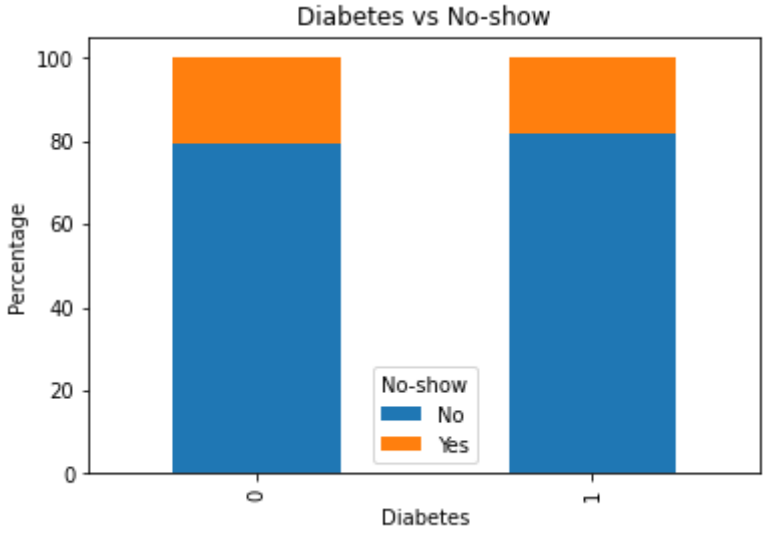
In [108…
```
Diabetes_NoShow = round(pd.crosstab(index=data['Diabetes'], columns=data['No-sho
Diabetes_NoShow
```

Out[108…

No-show	No	Yes
Diabetes		
0	79.64	20.36
1	82.00	18.00

In [109…
```
Diabetes_NoShow.plot(kind='bar', title='Diabetes vs No-show', stacked = True,
                     xlabel='Diabetes', ylabel='Percentage')
```

Out[109…
```
<AxesSubplot:title={'center':'Diabetes vs No-show'}, xlabel='Diabetes', ylabel
='Percentage'>
```



In this case the people with Diabetes have a better indicator for show up an a Appointment.

Research Question 7 (There is a relationship between the Alcoholism and the responsibility to show up at the planned appointment ?)

In [110…
```
data.groupby(['Alcoholism'])['No-show'].value_counts()
```

Out[110…
```
Alcoholism  No-show
0           No         85525
            Yes        21642
1           No          2683
            Yes          677
Name: No-show, dtype: int64
```

In [111…
```
data.Alcoholism.value_counts()
```

Out[111…
```
0    107167
1      3360
Name: Alcoholism, dtype: int64
```

In [112…
```
Alcoholism_NoShow = pd.crosstab(index=data['Alcoholism'], columns=data['No-show'
Alcoholism_NoShow
```

Out[112…

No-show	No	Yes
Alcoholism		
0	85525	21642
1	2683	677

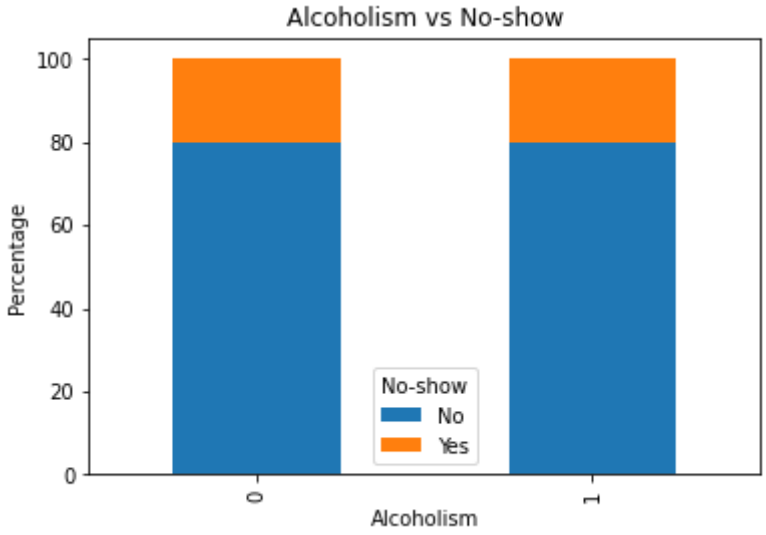
In [113…
```
Alcoholism_NoShow = round(pd.crosstab(index=data['Alcoholism'], columns=data['No
Alcoholism_NoShow
```

Out[113…

No-show	No	Yes
Alcoholism		
0	79.81	20.19
1	79.85	20.15

In [114…
```
Alcoholism_NoShow.plot(kind='bar', title='Alcoholism vs No-show', stacked = True
                       xlabel='Alcoholism', ylabel='Percentage')
```

Out[114…
```
<AxesSubplot:title={'center':'Alcoholism vs No-show'}, xlabel='Alcoholism', ylab
el='Percentage'>
```



In my opinion, we don't have a significant difference between Alcoholism and No-show. This variable not affect show up an a Appointment.

Research Question 8 (There is a relationship between the Handcap and the responsibility to show up at the planned appointment ?)

)

In [115…
```
data.groupby(['Handcap'])['No-show'].value_counts()
```

Out[115…
```
Handcap  No-show
0        No         86374
         Yes        21912
1        No          1676
         Yes          366
2        No           146
         Yes           37
3        No            10
         Yes            3
4        No             2
         Yes            1
Name: No-show, dtype: int64
```

In [116…
```
data.Handcap.value_counts()
```

Out[116…
```
0    108286
1      2042
2       183
3        13
4         3
Name: Handcap, dtype: int64
```

In [117…
```
Handcap_NoShow = pd.crosstab(index=data['Handcap'], columns=data['No-show'])
Handcap_NoShow
```

Out[117…

No-show	No	Yes
Handcap		
0	86374	21912
1	1676	366

No-show	No	Yes
Handcap		
2	146	37
3	10	3
4	2	1

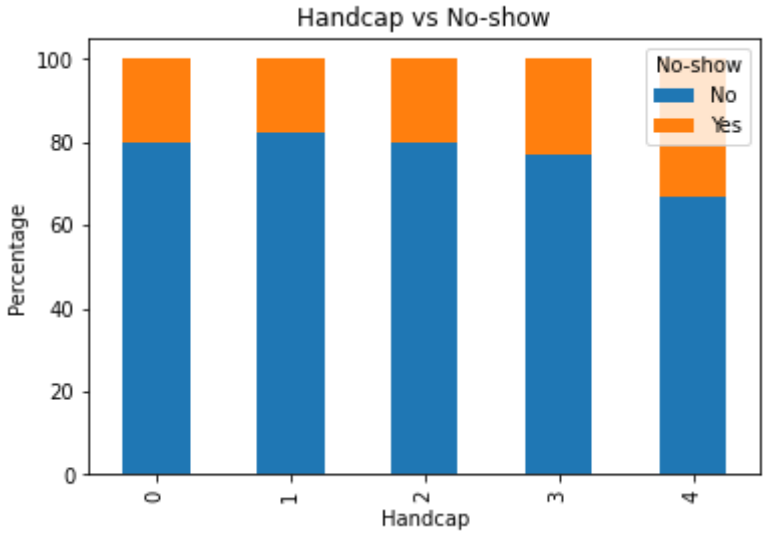
In [118…
```
Handcap_NoShow = round(pd.crosstab(index=data['Handcap'], columns=data['No-show'
Handcap_NoShow
```

Out[118…

No-show	No	Yes
Handcap		
0	79.76	20.24
1	82.08	17.92
2	79.78	20.22
3	76.92	23.08
4	66.67	33.33

In [119…
```
Handcap_NoShow.plot(kind='bar', title='Handcap vs No-show', stacked = True,
                    xlabel='Handcap', ylabel='Percentage')
```

Out[119…
```
<AxesSubplot:title={'center':'Handcap vs No-show'}, xlabel='Handcap', ylabel='Pe
rcentage'>
```



In this case the people with more Handcap decrease the indicator for show up an a Appointment.

Research Question 9 (There is a relationship between the Antipated days and the responsibility to show up at the planned appointment ?)

In [120…
```
data.groupby(['Anticipated_days'])['No-show'].value_counts()
```

Out[120…
```
Anticipated_days  No-show
```

```
-6                Yes            1
-1                Yes            2
 0                No         11562
                  Yes          596
 1                No         27418
                               ...
 176              Yes            4
 177              No             6
                  Yes            2
 180              No             8
                  Yes            2
Name: No-show, Length: 243, dtype: int64
```

In [121…
```
data.Anticipated_days.value_counts()
```

Out[121…
```
1      29210
0      12158
3       5774
7       4910
2       4891
       ...
108        1
102        1
101        1
152        1
127        1
Name: Anticipated_days, Length: 136, dtype: int64
```

In [122…
```
Anticipated_days_NoShow = pd.crosstab(index=data['Anticipated_days'], columns=da
Anticipated_days_NoShow
```

Out[122…

No-show	No	Yes
Anticipated_days		
-6	0	1
-1	0	2
0	11562	596
1	27418	1792
2	3774	1117
…	…	…
162	9	2
169	7	1
176	4	4
177	6	2
180	8	2

136 rows × 2 columns

In [123…
```
Anticipated_days_NoShow = round(pd.crosstab(index=data['Anticipated_days'], colu
Anticipated_days_NoShow
```

Out[123…

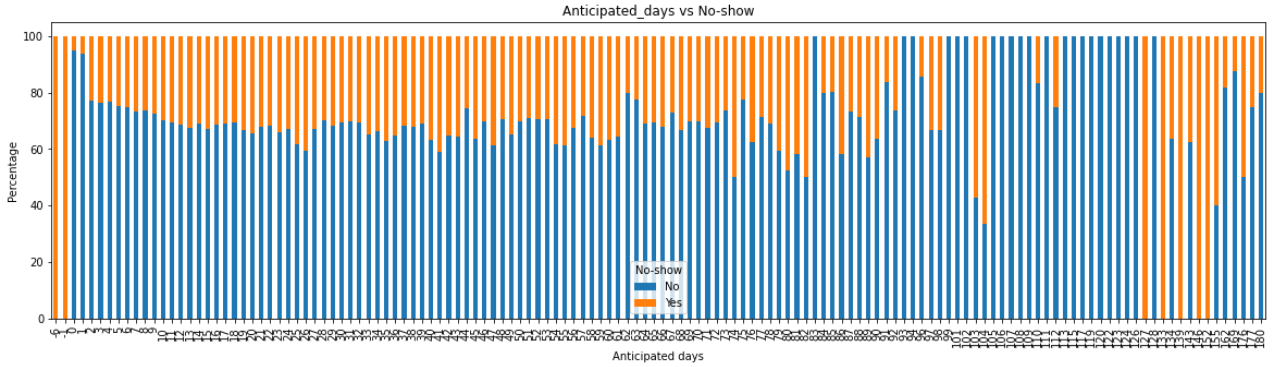
No-show	No	Yes

Anticipated_days	No-show	No	Yes
Anticipated_days			
-6		0.00	100.00
-1		0.00	100.00
0		95.10	4.90
1		93.87	6.13
2		77.16	22.84
...		...	...
162		81.82	18.18
169		87.50	12.50
176		50.00	50.00
177		75.00	25.00
180		80.00	20.00

136 rows × 2 columns

In [124…
```
Anticipated_days_NoShow.plot(kind='bar', title='Anticipated_days vs No-show', st
                             figsize=(20,5), xlabel='Anticipated days', ylabel='
```

Out[124…
```
<AxesSubplot:title={'center':'Anticipated_days vs No-show'}, xlabel='Anticipated
days', ylabel='Percentage'>
```



It's not easy to see if Anticipated days is better to improve the indicator of show up an a Appointment. Using different groups could be a better option.

In [125…
```
data.groupby(['Anticipated_group'])['No-show'].value_counts()
```

Out[125…
```
Anticipated_group  No-show
Urgent             No         38980
                   Yes         2390
Close              No         10711
                   Yes         3255
Regular            No         20303
                   Yes         7857
Scheduled          No         18214
                   Yes         8816
Name: No-show, dtype: int64
```

In [126…
```
data.Anticipated_group.value_counts()
```

Out[126…
```
Urgent       41370
Regular      28160
Scheduled    27030
Close        13966
Name: Anticipated_group, dtype: int64
```

In [127…
```
Anticipated_group_NoShow = pd.crosstab(index=data['Anticipated_group'], columns=
Anticipated_group_NoShow
```

Out[127…

No-show	No	Yes
Anticipated_group		
Urgent	38980	2390
Close	10711	3255
Regular	20303	7857
Scheduled	18214	8816

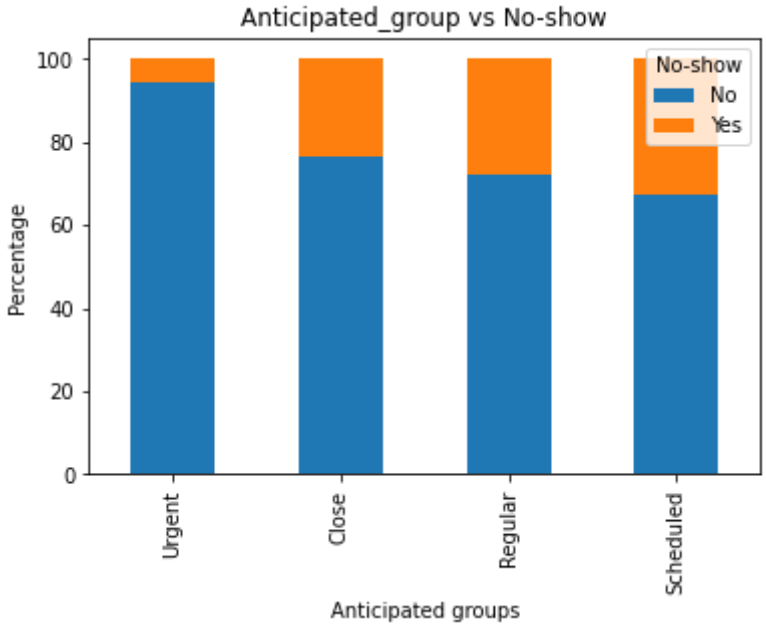
In [128…
```
Anticipated_group_NoShow = round(pd.crosstab(index=data['Anticipated_group'], co
Anticipated_group_NoShow
```

Out[128…

No-show	No	Yes
Anticipated_group		
Urgent	94.22	5.78
Close	76.69	23.31
Regular	72.10	27.90
Scheduled	67.38	32.62

In [129…
```
Anticipated_group_NoShow.plot(kind='bar', title='Anticipated_group vs No-show',
                              xlabel='Anticipated groups', ylabel='Percentage')
```

Out[129…
```
<AxesSubplot:title={'center':'Anticipated_group vs No-show'}, xlabel='Anticipate
d groups', ylabel='Percentage'>
```



In this case, it is easy to observe that as the appointment is closer to the current date, a better performance indicator is obtained in the presentation of an appointment.

Research Question 10 (There is a relationship between the Weekday Appointment Day and the responsibility to show up at the planned appointment ?)

In [130…
```
data.groupby(['Weekday_AppointmentDay'])['No-show'].value_counts()
```

Out[130…
```
Weekday_AppointmentDay  No-show
Friday                  No         14982
                        Yes         4037
Monday                  No         18025
                        Yes         4690
Saturday                No           30
                        Yes           9
Thursday                No         13909
                        Yes         3338
Tuesday                 No         20488
                        Yes         5152
Wednesday               No         20774
                        Yes         5093
Name: No-show, dtype: int64
```

In [131…
```
data.Weekday_AppointmentDay.value_counts()
```

Out[131…
```
Wednesday    25867
Tuesday      25640
Monday       22715
Friday       19019
Thursday     17247
Saturday        39
Name: Weekday_AppointmentDay, dtype: int64
```

In [132…
```
Weekday_AppointmentDay_NoShow = pd.crosstab(index=data['Weekday_AppointmentDay']
Weekday_AppointmentDay_NoShow
```

Out[132…

No-show	No	Yes

Weekday_AppointmentDay	No-show	No	Yes

Weekday_AppointmentDay		
Friday	14982	4037
Monday	18025	4690
Saturday	30	9
Thursday	13909	3338
Tuesday	20488	5152
Wednesday	20774	5093

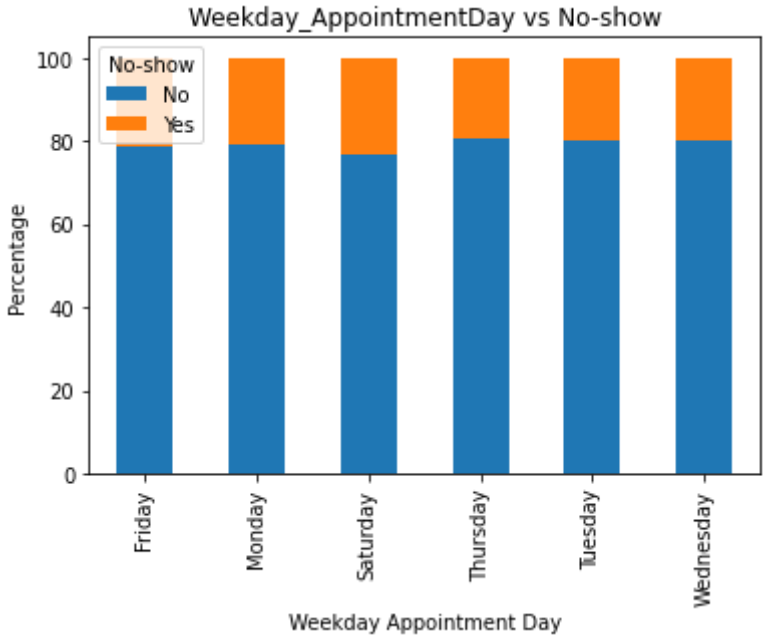
In [133…
```
Weekday_AppointmentDay_NoShow = round(pd.crosstab(index=data['Weekday_Appointmen
                                normalize='index')*100, 2)
Weekday_AppointmentDay_NoShow
```

Out[133…

No-show	No	Yes
Weekday_AppointmentDay		
Friday	78.77	21.23
Monday	79.35	20.65
Saturday	76.92	23.08
Thursday	80.65	19.35
Tuesday	79.91	20.09
Wednesday	80.31	19.69

In [134…
```
Weekday_AppointmentDay_NoShow.plot(kind='bar', title='Weekday_AppointmentDay vs
                                   stacked = True, xlabel='Weekday Appointment D
```

Out[134…
```
<AxesSubplot:title={'center':'Weekday_AppointmentDay vs No-show'}, xlabel='Weekd
ay Appointment Day', ylabel='Percentage'>
```



According to the previous graph, Saturday is the day that has the worst indicator of compliance with a scheduled appointment. Looks good.

Limitations

(1) In my opinion always is better have the maximum amount of data that allows the best possible analysis of the data. Unfortunately in this case we observe that there is not all the data available according to the capture IDs of the system and perhaps this inconvenience could produce adverse effects in the present prediction model.

Certain independent variables, such as Scholarship and SMS-received appear to be erratic and may lead us to misunderstand the data from this analysis.

Taking as a reference the "In [14] [15]", In terms of database records of capture the system, between the min and max Appointmend ID, we got 760254 records. It's a important things because our dataframe only have 110527 records.

We only got a 14.54% of total amount of record of appointments. Probably they had a issue with the capture of data.

(2) The time window available with the dataset covers about 7 months. It would be ideal to have much more information, hopefully at least twelve months to have a better understanding of the model considering the seasonal effects.

(3) Although the dataset contains many relevant variables, perhaps new variables could be incorporated that allow a better understanding of how to make the delivery of medical hours more efficient. For example, the absenteeism history of the same patients in previous opportunities.

Conclusions

It is surprising that many times the initial hypotheses that one can make, based on perception, can lead us to make bad decisions. The importance of this project, and in the analysis based on the evidence of the data, can help to better interpret the environment variables associated with a particular problem.

- In my opinion, we don't have a significant difference between gender and No-show.
- It's strange to see that a SMS-received don't help to improve the Show up in an Appointment. At the beginning of the analysis I would have opted for a different result.
- It's strange to see that a Scholarship don't help to improve the Show up in an Appointment. At the beginning of the analysis I would have opted for a different result.
- We don't have a significant difference between Alcoholism and No-show. This variable not affect show up an a Appointment.
- According to the previous graph, Saturday is the day that has the worst indicator of compliance with a scheduled appointment. Looks good.

In a positive way, we can affirm that the following variables positively affect the presentation to a previously scheduled medical appointment.

- The Age range > 56 years old, increase the show up an a Appointment.
- The people with Hipertension, Diabetes and less Handcap have a better indicator.
- If the appointment is closer to the current date, we get a better performance indicator.

Finally, the conjunction of all the previous variables will significantly improve attendance at medical hours, making the entire process more efficient and producing economic and social benefits for the community near the medical center.

In [ ]: