

# Project: Investigate a Dataset (No Show Appointments )

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## Introduction

This dataset collects information from 110k 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, we will try in this analysis to know What are the factors that important in order to predict if a patient will show up for their scheduled appointment?

```
In [1]: # adding import statements for all of the packages in this notebook

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from datetime import datetime
```

## Data Wrangling

In this section of the report, data will be loaded, checked for cleanliness, and then trimed and cleaned to be prepared for analysis.

## General Properties

```
In [2]: # Loading the data and checking its content
# first thing to be cleaned are the names of the columes to lowercase them and fix minor
df=pd.read_csv("noshowappointments.csv")
df.head()
```

```
Out[2]:
```

	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 [3]:

```
#using info function to inspect the data
#we can inspect that the ScheduledDay and AppointmentDay are set as object which need to
#also we can be certain that we have no null values in our 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
```

In [4]:

```
#checking for the number of duplicated values, and from this we can see we have no null
sum(df.duplicated())
```

Out[4]: 0

In [5]:

```
#from here we can see some abnormalities with Age having min as -1 and max as 115, also
#which can be changed to 0 and 1 to represent having a handicap or not
df.describe()
```

Out[5]:

	PatientId	AppointmentID	Age	Scholarship	Hipertension	Diabetes	Alcoholism
count	1.105270e+05	1.105270e+05	110527.000000	110527.000000	110527.000000	110527.000000	110527.000000
mean	1.474963e+14	5.675305e+06	37.088874	0.098266	0.197246	0.071865	0.030400
std	2.560949e+14	7.129575e+04	23.110205	0.297675	0.397921	0.258265	0.171686
min	3.921784e+04	5.030230e+06	-1.000000	0.000000	0.000000	0.000000	0.000000
25%	4.172614e+12	5.640286e+06	18.000000	0.000000	0.000000	0.000000	0.000000
50%	3.173184e+13	5.680573e+06	37.000000	0.000000	0.000000	0.000000	0.000000
75%	9.439172e+13	5.725524e+06	55.000000	0.000000	0.000000	0.000000	0.000000
max	9.999816e+14	5.790484e+06	115.000000	1.000000	1.000000	1.000000	1.000000



In [6]:

```
#from the below boxplot, we can see that -1 and 115 are considered as outliers which mo
```

*#and could affect our data analysis,so they will be dropped*

```
fig, ax = plt.subplots()
bp = ax.boxplot(df["Age"])
ax.set_title('Age Distrubtion')
ax.set_ylabel('Age')
plt.show()
```



In [7]: *#we can see here that there is no direct -positive or negative- correlation between the*  
`df.corr()`

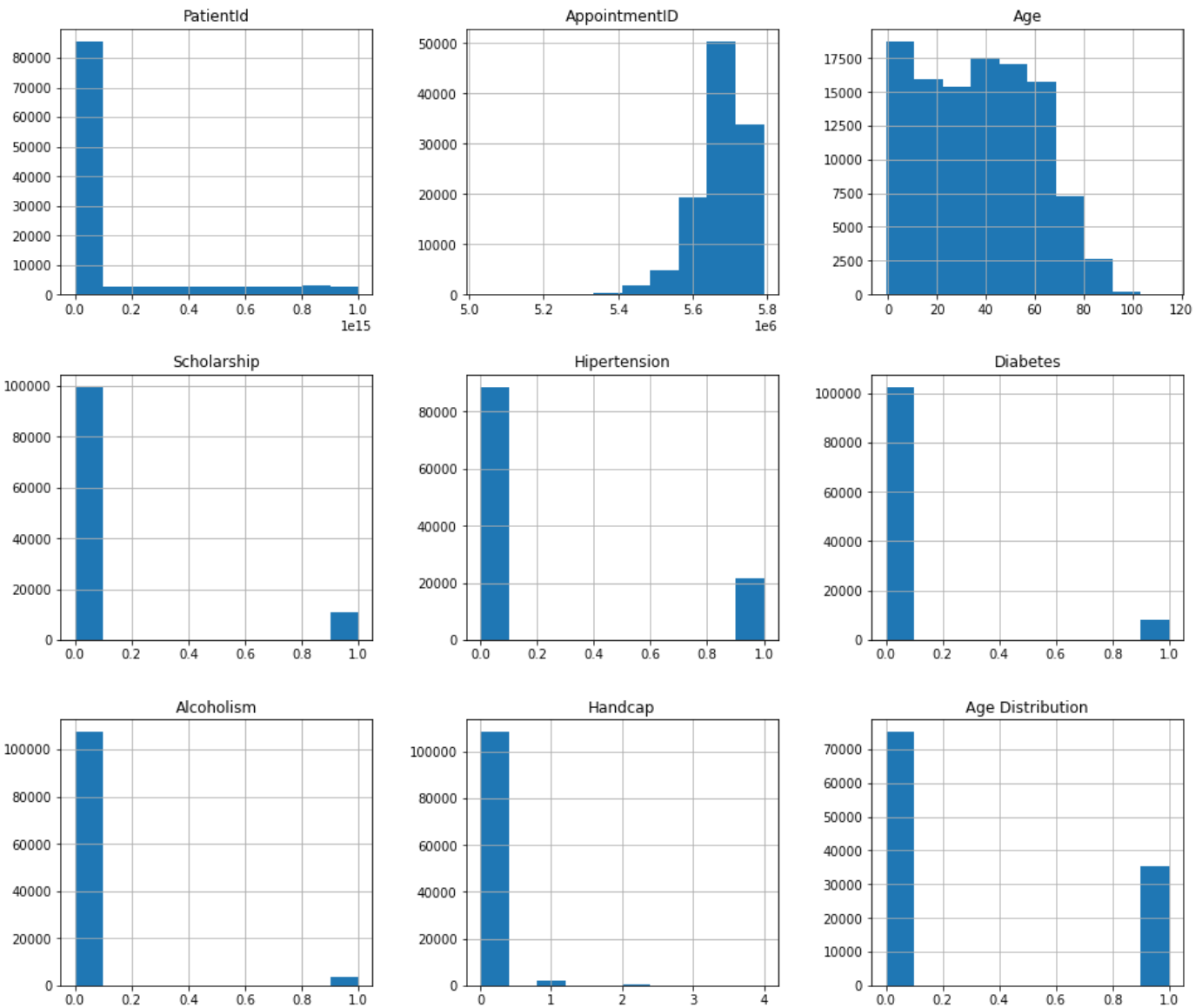
Out[7]:

	PatientId	AppointmentID	Age	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap
PatientId	1.000000	0.004039	-0.004139	-0.002880	-0.006441	0.001605	0.011011	-0.007916
AppointmentID	0.004039	1.000000	-0.019126	0.022615	0.012752	0.022628	0.032944	0.014106
Age	-0.004139	-0.019126	1.000000	-0.092457	0.504586	0.292391	0.095811	0.078033
Scholarship	-0.002880	0.022615	-0.092457	1.000000	-0.019729	-0.024894	0.035022	-0.008586
Hipertension	-0.006441	0.012752	0.504586	-0.019729	1.000000	0.433086	0.087971	0.080083
Diabetes	0.001605	0.022628	0.292391	-0.024894	0.433086	1.000000	0.018474	0.057530
Alcoholism	0.011011	0.032944	0.095811	0.035022	0.087971	0.018474	1.000000	0.004648
Handcap	-0.007916	0.014106	0.078033	-0.008586	0.080083	0.057530	0.004648	1.000000
SMS_received	-0.009749	-0.256618	0.012643	0.001194	-0.006267	-0.014550	-0.026147	-0.024161

In [8]: *# from the below histograms, we can see the followings:*  
*#Age:we have alot of young patients(age 0,1) but the rest of the patients age*  
*#is distributed evenly with less patients older than 60 years.*  
*#Alcoholism: Most of the patients are not alcoholics.*  
*#Handicap: There are 4 handicap categories but most of the patients aren't handicaped*  
*#Diabetes: Most of the patients don't have diabetes but it slightly more than alcoholics*  
*#Scholarship:Most of the patients didn't receive Scholarship but it slightly more than*

```
df.hist(figsize=(16,14));
plt.title('Age Distribution')
```

Out[8]: Text(0.5, 1.0, 'Age Distribution')



## Initial Observations:

- The dataset size is 14 columns by 110527 rows, there are neither null nor duplicated values
- All of the columns names need to be in lower case and to be corrected from slight mistakes
- Changing the columns type to correct type e.g. scheduled\_day to datetime
- Age: we have a lot of young patients (age 0,1) but the rest of the patients' age is distributed evenly with less patients older than 60 years.
- Alcoholism: Most of the patients are not alcoholics.
- Handicap: There are 4 handicap categories but most of the patients aren't handicapped
- Diabetes: Most of the patients don't have diabetes but it's slightly more than alcoholics ratio and handicap.
- Scholarship: Most of the patients didn't receive Scholarship but it's slightly more than alcoholics ratio and handicap
- fixing age outliers (Age < 0 & > 100) and changing handicap to bool

In the next section, data will be cleaned as per the above observations to get it ready for analysis

## Data Cleaning phase

```
In [9]: # Starting the cleaning phase with renaming the dataset columns
```

```
df_cleaned=df.rename(columns={"PatientId":"patient_id", "AppointmentID":"appointment_id",
})
df_cleaned.head()
```

Out[9]:

	patient_id	appointment_id	gender	scheduled_day	appointment_day	age	neighbourhood	scholarship	hy
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 [10]:

```
# the next step will be to change scheduled_day and appointment_day to datetime, as it v
#with days and hours and we can pin point the highest no-show day, hour
#to do this we have to convert them to the following format '%Y-%m-%dT%H:%M:%SZ'
df_cleaned["scheduled_day"]=pd.to_datetime(df_cleaned["scheduled_day"], format='%Y-%m-%dT%H:%M:%SZ')
df_cleaned["appointment_day"]=pd.to_datetime(df_cleaned["appointment_day"], format='%Y-%m-%dT%H:%M:%SZ')
df_cleaned.insert(4, "scheduled_hour",pd.to_datetime(df_cleaned["scheduled_day"]).astype(str).str[11:16])
df_cleaned.head()
```

Out[10]:

	patient_id	appointment_id	gender	scheduled_day	scheduled_hour	appointment_day	age	neighbourhood	scholarship
0	2.987250e+13	5642903	F	2016-04-29 18:38:08	18	2016-04-29	62	JARDIM DA PENHA	0
1	5.589978e+14	5642503	M	2016-04-29 16:08:27	16	2016-04-29	56	JARDIM DA PENHA	0
2	4.262962e+12	5642549	F	2016-04-29 16:19:04	16	2016-04-29	62	MATA DA PRAIA	0
3	8.679512e+11	5642828	F	2016-04-29 17:29:31	17	2016-04-29	8	PONTAL DE CAMBURI	0
4	8.841186e+12	5642494	F	2016-04-29 16:07:23	16	2016-04-29	56	JARDIM DA PENHA	0

In [11]:

```
df_cleaned.drop(list(df_cleaned.index[df_cleaned["age"] > 102])+list(df_cleaned.index[df_cleaned["age"] < 5]))
```

In [12]:

```
#checking the values before changing it to bool to make sure all the data is transferred
df_cleaned["handicap"].value_counts()
```

Out[12]:

```
0    104746
1     2037
2     183
3      13
4       3
Name: handicap, dtype: int64
```

In [13]:

```
#changing handicap to boolean will make it easier to detect its effect on the no-show
df_cleaned["handicap"] = df_cleaned["handicap"].astype('bool')
```

```
In [14]: df_cleaned["handicap"].value_counts()
```

```
Out[14]: False    104746
         True      2236
         Name: handicap, dtype: int64
```

```
In [15]: #checking the values before changing it to bool to make sure all the data is transferred
df_cleaned["no_show"].value_counts()
```

```
Out[15]: No      85305
         Yes     21677
         Name: no_show, dtype: int64
```

```
In [16]: #changing no_show to boolean will make it easier to work with
df_cleaned["no_show"].replace({'No': 0, 'Yes': 1}, inplace = True)

df_cleaned["no_show"] = df_cleaned["no_show"].astype('bool')
```

```
In [17]: df_cleaned["no_show"].value_counts()
```

```
Out[17]: False    85305
         True     21677
         Name: no_show, dtype: int64
```

with this cleaning is completed, In the next section, data set will be analyzed to discover the patterns behind the no-show problem

## Exploratory Data Analysis

Now that the data is cleaned, it is ready for exploration. if we looked at the different columns, we can see 3 categories

- 1-Demographics Features(Gender,Age,Neighborhood)
- 2-Diseases / chronic or harmful Personal Features
- 3-Season / time Feature

Any of the above features could have affected the missed appointments ratio For example, a certain hour/day of the week or certain location might be the reason, in the following section we will explore all of these questions. but before that, lets first find the total number of the missed appointments

```
In [18]: #I also find taking a copy the data into a new variable after every step for safekeeping
#a mistake happened and we wanted to return to the cleaned version
df_ready=df_cleaned
df_ready.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 106982 entries, 0 to 110526
Data columns (total 15 columns):
#   Column                Non-Null Count  Dtype
---  -
0   patient_id            106982 non-null float64
```

```

1 appointment_id 106982 non-null int64
2 gender          106982 non-null object
3 scheduled_day   106982 non-null datetime64[ns]
4 scheduled_hour  106982 non-null int64
5 appointment_day 106982 non-null datetime64[ns]
6 age            106982 non-null int64
7 neighbourhood   106982 non-null object
8 scholarship     106982 non-null int64
9 hypertension    106982 non-null int64
10 diabetes       106982 non-null int64
11 alcoholism     106982 non-null int64
12 handicap       106982 non-null bool
13 sms_received   106982 non-null int64
14 no_show        106982 non-null bool
dtypes: bool(2), datetime64[ns](2), float64(1), int64(8), object(2)
memory usage: 11.6+ MB

```

In [19]:

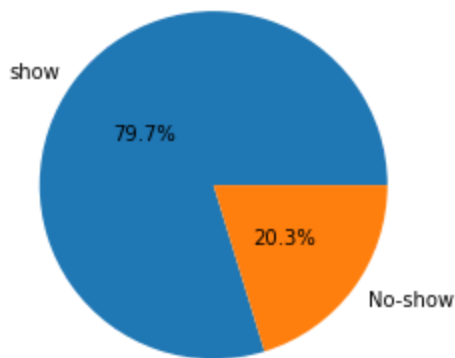
```

#from the below pie chart, we can see that 20% of the appointments are missed
print("The number of missed appointments is {}".format(df_ready.query("no_show==1")["no_s
labels=["show", "No-show"]
plt.pie(df_ready["no_show"].value_counts(), autopct='%0.1f%%', labels=labels, pctdistance=0.8)
plt.title("Percentage of no-show in appointments", fontsize=14);
plt.show()

```

The number of missed appointments is 21677

### Percentage of no-show in appointments



From the above pie chart, we can see that 20% of the appointments are missed

## Research Question 1 (Demographics Features effect) (Does Age, Gender and neighbourhood affect the no-show ratio)

In [20]:

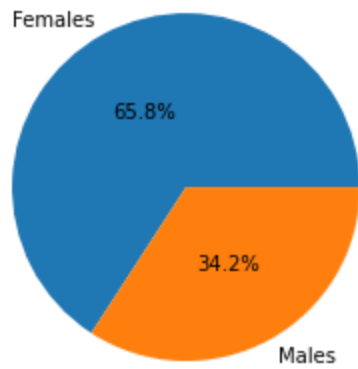
```

# lets calculate the percentage of males to females
#from the below pie, we can see that, out of the 22K, around 14.5 are females and the rest are males
df_gender=df_ready.query("no_show==1")["gender"].value_counts()
print("The number of the females whom missed appointments is {}".format(df_gender.query("gender=='F'").value_counts().sum()))
#from the below pie chart, we can see that 20% of the appointments are missed
labels=["Females", "Males"]
plt.pie(df_gender, autopct='%0.1f%%', labels=labels, pctdistance=0.5)
plt.title("Percentage of males/females in missed appointments", fontsize=14);
plt.show()

```

The number of the females whom missed appointments is [14272]

## Percentage of males/females in missed appointments



From the above pie chart, we can see that, out of the 22K, around 14.5 are females and the rest are males

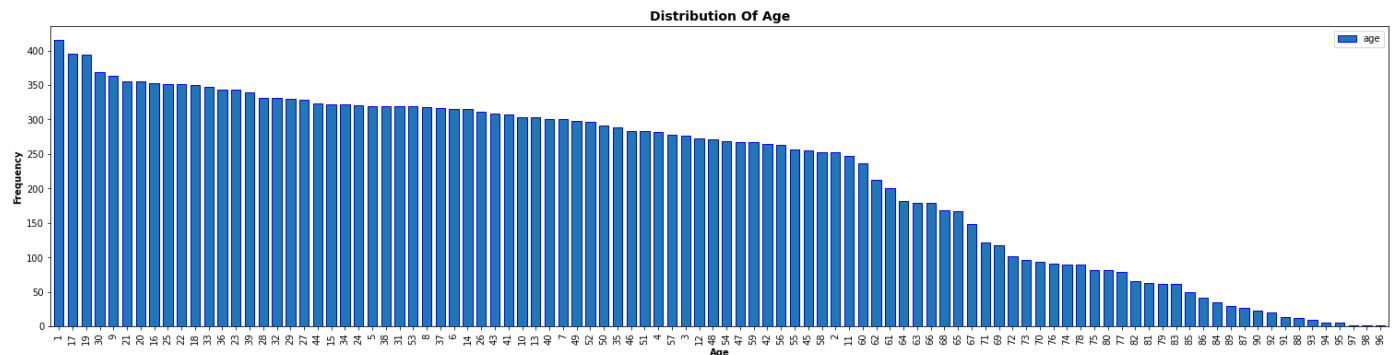
```
In [21]: # since we will create alot of bar plots to visualize our data, it is best practice to c
#to avoid repeating code every time

def myBarPlot(df,Xvar,Xvalue="",normalize=False):
    #calling plot function
    df[Xvar].value_counts(normalize=normalize).plot.bar(edgecolor="blue",figsize=[26,6],
    #adding x axis title
    if(Xvar=="no_show"):
        Xvar=Xvalue

    plt.xlabel(Xvar.title(),fontsize=10,weight="bold")
    plt.xticks(rotation=90)
    #adding y axis title
    plt.ylabel("Frequency".title(),fontsize=10,weight="bold")
    #adding plot title
    plt.title(f"Distribution of {Xvar}".title(),fontsize=14,weight="bold")
    plt.legend();
```

```
In [22]: # lets check our patients by age
# we can see from the below bar chart that there is a huge peak in the infants(0-1 years)
#the ratio decrease till it make left skewed plot

#calling our custom function to plot the bar plot
myBarPlot(df_ready.query("no_show==1"),"age")
```



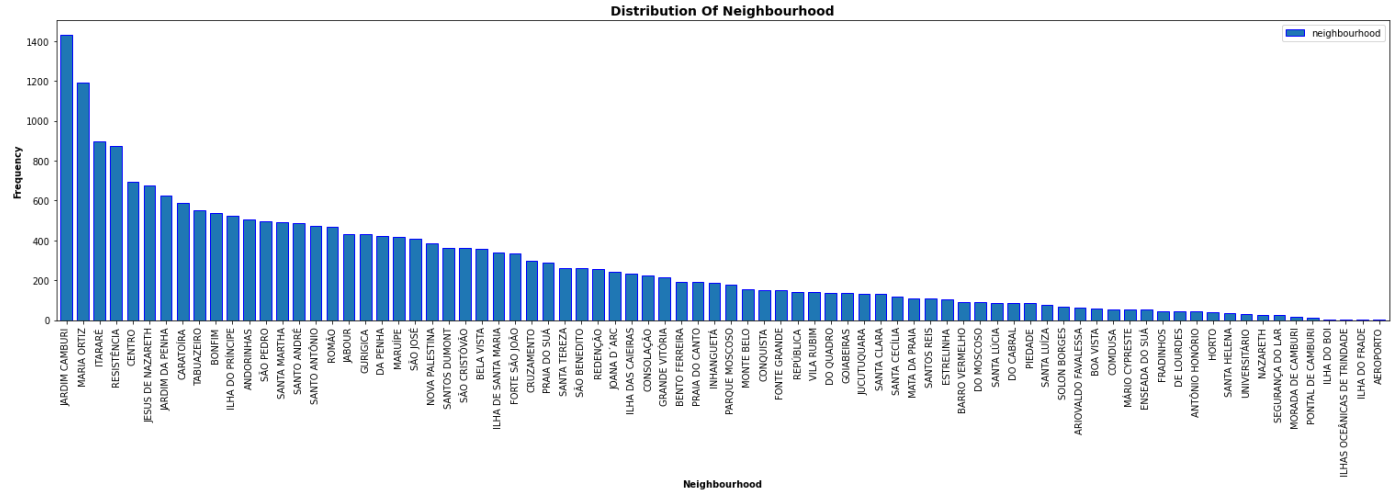
we can see from the above bar chart that there is a huge peak in the infants(0-1 years) and as the age goes up the ratio decrease till it make left skewed plot



In [23]:

```
# lets check our patients by neighbourhood
# we can see from the below bar chart that there is a huge peak in JARDIM CAMBURI and MARIA ORTIZ
# the ratio decrease till it make right skewed plot

# calling our custom function to plot the bar plot
myBarPlot(df_ready.query("no_show==1"), "neighbourhood")
```



we can see from the below bar chart that there is a huge peak in JARDIM CAMBURI and MARIA ORTIZ the ratio decrease till it make right skewed plot

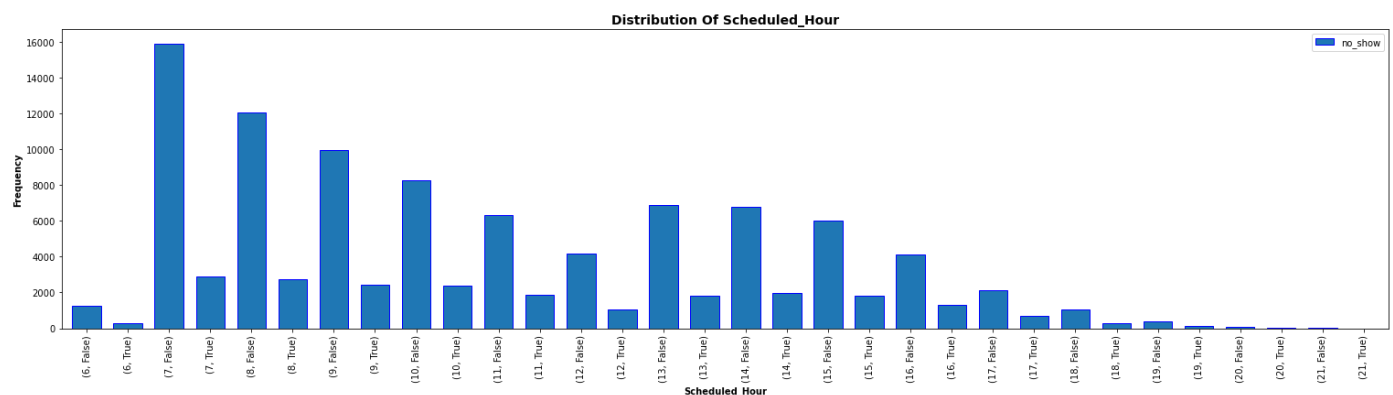
## Research Question 2 (Season/Time effect) (Is the time of the appointments can affect the no\_show ratio)

We can see that most of the dataset occurred during May 2016, so we won't be able to judge season effect on the data set, instead the time of appointments will be inspected

In [24]:

```
# lets take a look at time of the appointments and see if it will affect the ratio
# we can see from the below bar chart that, in the early morning the number of no-show
# it decrease a bit in mid day then raise again (13:00-14:00) and fall back down

# calling our custom function to plot the bar plot
myBarPlot(df_ready.groupby(["scheduled_hour"]), "no_show", "scheduled_hour")
```



We can see from the below bar chart that, in the early morning the number of no-show is higher (7-10 am), it decrease a bit in mid day then raise again (13:00-14:00) and fall back down. so this could indicate that maybe we can add more staff in morning shift or make the clinic work longer hour since it closes down at 9 pm as there is no data after that

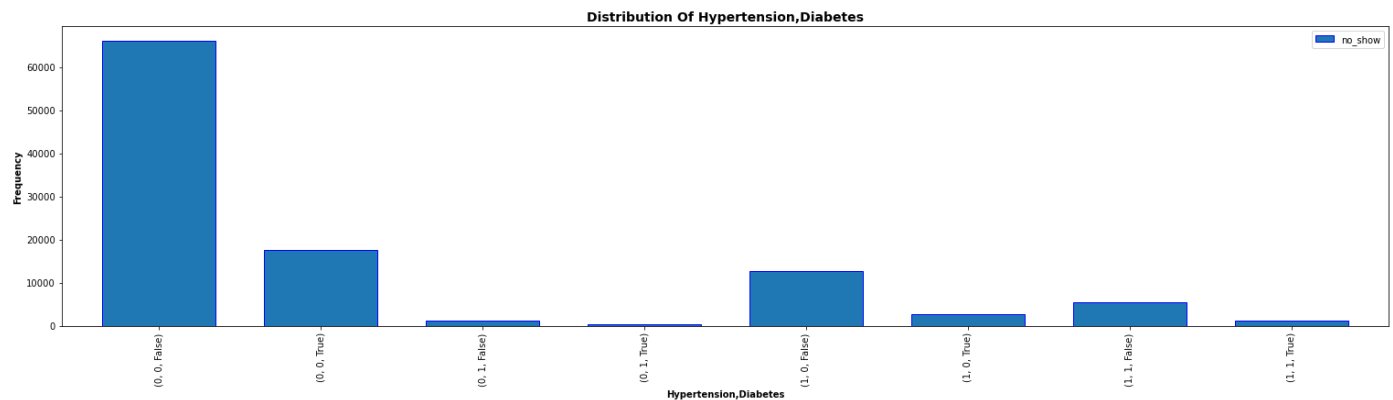
## Research Question 3 (Diseases/Chronic effect) (does having a chronic disease factor in showing up)

## In this section, we will check the effect of Diseases/Chronic illness on the no-show ratio

In [25]:

```
# lets take a look at chronic diseases columns (hypertension, diabetes) and see if it w
#from the below graph, we can see that either the patient has chronic disease or not, 80

#calling our custom function to plot the bar plot
myBarPlot(df_ready.groupby(["hypertension","diabetes"]), "no_show", "hypertension,diabetes"
```



From the above graph, we can see that either the patient has chronic disease or not, 80% will go to the appointments

In [26]:

```
#after finishing our analysis, we will save the data frame in a new csv
df_ready.to_csv("no_show_cleaned.csv")
```

## Conclusions

After cleaning and doing data exploratory analysis, I can list the most important finding as below:

- Out of 110K only 22K didn't show up in the period from 29-4-16 till 8-6-16
- out of the 22K, 14.5k are females and 7.7K are males (as seen in pie chart)
- The columns -Features- can be divided into 3 sections (Demographics Features, alignment Personal Features and Season / time Feature )
- Most of the patients aren't alcoholics. (Only 3% are alcoholics)
- Most of the patients don't have a handicap. (Only 2% suffer from handicap)
- The younger the age, the higher the ratio of no-show but it gets uniformed as the age goes up
- Either the patient has chronic disease or not, 80% will go to the appointments
- Some neighborhoods are higher than others like JARDIM CAMBURI (Bar chart)
- If we looked at the time of the missed appointments, we will find that most of them was in the early morning (7 am to 11 am) (bar chart) -To help in this issue, maybe we can add more staff in morning shift or make the clinic work longer hours-

### Limitations:

- The dataset duration (2 months) which is too small to get any conclusive and accurate data from, also any model built from this set won't have high accuracy
- Appointment time wasn't given, which could add more insights to the dataset
- This dataset only covers Vitória, not all of Brazil. Covering more than one state in Brazil would've been better.

- Also, the data is too old -4 years old-, maybe adding more data for the following years, could help to shed some light in understanding the elements which affect the missed Appointments
- The handicap category wasn't clear in the dataset, had to look for it in the discussions <https://www.kaggle.com/joniarroba/noshowappointments/discussion/32174>
- Looking over the dates, most of the missed Appointments are in certain days in May 2016, during this month there were many political events like the president impeachment (which may have impacted the no-show ratio) [https://en.wikipedia.org/wiki/2016\\_in\\_Brazil#May](https://en.wikipedia.org/wiki/2016_in_Brazil#May)