

Project: Investigate a Dataset - [Medical Appointment No Shows]

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Introduction

Dataset Description

Dataset Variables

- **PatientId**: Identification of a patient
- **AppointmentID**: Identification of each appointment
- **Gender**: Male or Female . Female is the greater proportion, woman takes way more care of they health in comparison to man.
- **ScheduledDay**: The day of the actual appointment, when they have to visit the doctor.
- **AppointmentDay**: The day someone called or registered the appointment, this is before appointment of course.
- **Age**: How old is the patient.
- **Neighbourhood**: Where the appointment takes place.
- **Scholarship**: True or False.
- **Hipertension**: True or False.
- **Diabetes**: True or False.
- **Alcoholism**: True or False.
- **Handcap**: True or False.
- **SMS_received**: True or False.
- **No-show**: True or False.

Question(s) for Analysis

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

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

Data Wrangling

Importing The Datasets

```
In [2]: 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	

Investigating the data

```
In [3]: df.shape #checking number of rows and columns in the dataset
```

```
Out[3]: (110527, 14)
```

The data has 110527 rows and 14 columns

```
In [4]: df.info() #checking data types of the variables and if there is any missing values
```

```
<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 [5]: df.describe() #seeing some statistical information about the dataset
```

```
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]: df.nunique() #checking number of unique values for each variable
```

```
Out[6]:
```

PatientId	62299
AppointmentID	110527
Gender	2
ScheduledDay	103549
AppointmentDay	27
Age	104
Neighbourhood	81
Scholarship	2
Hipertension	2
Diabetes	2
Alcoholism	2
Handcap	5
SMS_received	2
No-show	2

dtype: int64

```
In [7]: df.duplicated(['PatientId','No-show']).sum() #number of patients in the dataset that hav
#we will need to drop the duplicates in order to have more accurate results
```

```
Out[7]: 38710
```

```
In [8]: df.duplicated().sum() #checking the number of duplicate rows in our dataset
```

```
Out[8]: 0
```

The data has no duplicate rows

```
In [9]: df.isna().sum() #checking the number of NaN values in our dataset
```

```
Out[9]:
```

PatientId	0
AppointmentID	0
Gender	0
ScheduledDay	0
AppointmentDay	0

```

Age          0
Neighbourhood 0
Scholarship  0
Hipertension  0
Diabetes      0
Alcoholism    0
Handcap       0
SMS_received  0
No-show       0
dtype: int64

```

The data has no missing values

Checking unique values of columns

```
In [10]: df['No-show'].unique()
```

```
Out[10]: array(['No', 'Yes'], dtype=object)
```

```
In [11]: df['Gender'].unique()
```

```
Out[11]: array(['F', 'M'], dtype=object)
```

```
In [12]: df['Age'].unique()
```

```
Out[12]: array([ 62,  56,   8,  76,  23,  39,  21,  19,  30,  29,  22,  28,  54,
                15,  50,  40,  46,   4,  13,  65,  45,  51,  32,  12,  61,  38,
                79,  18,  63,  64,  85,  59,  55,  71,  49,  78,  31,  58,  27,
                 6,   2,  11,   7,   0,   3,   1,  69,  68,  60,  67,  36,  10,
                35,  20,  26,  34,  33,  16,  42,   5,  47,  17,  41,  44,  37,
                24,  66,  77,  81,  70,  53,  75,  73,  52,  74,  43,  89,  57,
                 14,   9,  48,  83,  72,  25,  80,  87,  88,  84,  82,  90,  94,
                86,  91,  98,  92,  96,  93,  95,  97, 102, 115, 100,  99, -1],
                dtype=int64)
```

```
In [13]: df.query('Age < 0') #removing invalid input of age
```

```
Out[13]:
```

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

```
In [14]: df['Handcap'].unique() # we need to convert all the values > than 1 to 1 because they me
```

```
Out[14]: array([0, 1, 2, 3, 4], dtype=int64)
```

```
In [15]: df['Alcoholism'].unique()
```

```
Out[15]: array([0, 1], dtype=int64)
```

```
In [16]: df['Diabetes'].unique()
```

```
Out[16]: array([0, 1], dtype=int64)
```

```
In [17]: df['Hipertension'].unique()
```

```
Out[17]: array([1, 0], dtype=int64)
```

```
In [18]: df['Scholarship'].unique()
```

```
Out[18]: array([0, 1], dtype=int64)
```

```
In [19]: df.Handcap.value_counts()
```

```
Out[19]: 0    108286
1      2042
2       183
3        13
4         3
Name: Handcap, dtype: int64
```

Data Cleaning

```
In [20]: df.drop(index=99832, inplace=True)
```

```
In [21]: df.rename(columns={'No-show': 'no_show'}, inplace = True) #renaming columns for easier acc
df.rename(columns = lambda x: x.lower(), inplace=True) #convering column names to lower c
```

```
In [22]: df.drop_duplicates(['patientid', 'no_show'], inplace=True) #dropping the number of patient
```

```
In [23]: df.columns
df.drop(['patientid', 'appointmentid', 'scheduledday', 'appointmentday'], axis=1, inplace=T
```

```
In [24]: df.columns #checking if the columns have been renamed
```

```
Out[24]: Index(['gender', 'age', 'neighbourhood', 'scholarship', 'hipertension',
              'diabetes', 'alcoholism', 'handcap', 'sms_received', 'no_show'],
              dtype='object')
```

```
In [25]: df['handcap'] = df['handcap'].apply(lambda x: True if (x >= 1) else False) #converting a
```

```
In [26]: df['no_show'] = df['no_show'].apply(lambda x: True if (x == 'Yes') else False) #converтин
```

```
In [27]: df['no_show'].unique() #checking if the values have been changed
```

```
Out[27]: array([False,  True])
```

```
In [28]: df['no_show'] = df['no_show'].astype(int) #converting all bool values to int True -> 1 ,
```

```
In [29]: df['handcap'] = df['handcap'].astype(int) #converting all bool values to int True -> 1 ,
```

```
In [30]: df.dtypes #checking variables data types after the change
```

```
Out[30]: gender          object
age              int64
neighbourhood    object
scholarship      int64
hipertension     int64
diabetes         int64
alcoholism       int64
handcap          int32
sms_received     int64
no_show          int32
dtype: object
```

The no_show column and handicap column have been changed successfully

Exploratory Data Analysis

Research Question (What factors are important for us to know in order to predict if a patient will show up for their scheduled appointment?)

```
In [31]: showed = df.no_show == 0 #getting the subset of data where the patient had showed  
        didnt_show = df.no_show == 1 #getting the subset of data where the patient didn't show
```

```
In [32]: df.groupby(['no_show', 'gender']).mean() #Checking the mean of the variables grouped by t
```

```
Out[32]:
```

		age	scholarship	hipertension	diabetes	alcoholism	handcap	sms_received
no_show	gender							
0	F	39.130292	0.115160	0.219765	0.078518	0.013558	0.016276	0.307609
	M	33.766269	0.047934	0.172302	0.062575	0.041890	0.023863	0.278331
1	F	36.065010	0.137146	0.183817	0.069181	0.020337	0.013993	0.471059
	M	31.220400	0.054734	0.146825	0.057496	0.046451	0.019003	0.419522

```
In [33]: df.groupby('sms_received').mean() #Checking the mean of the variables grouped by sms rec
```

```
Out[33]:
```

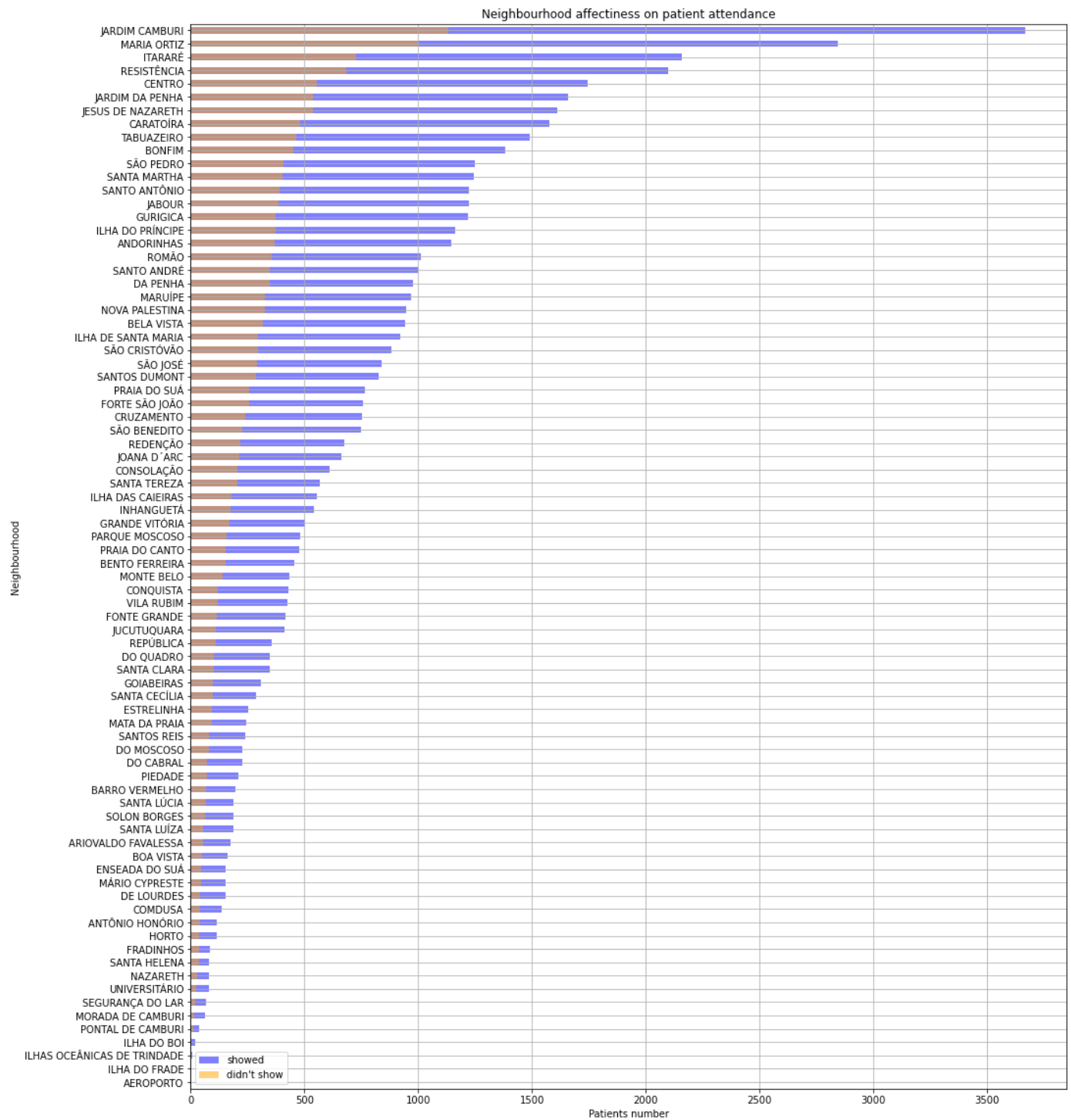
	age	scholarship	hipertension	diabetes	alcoholism	handcap	no_show	
sms_received								
0		36.233711	0.095019	0.197330	0.074166	0.026217	0.020161	0.202444
		37.109216	0.096560	0.190589	0.064608	0.022698	0.014233	0.332088

people who received an sms has a lower attendance rate than the one who didn't maybe there is a problem in sms system

Making a function to make bar plots

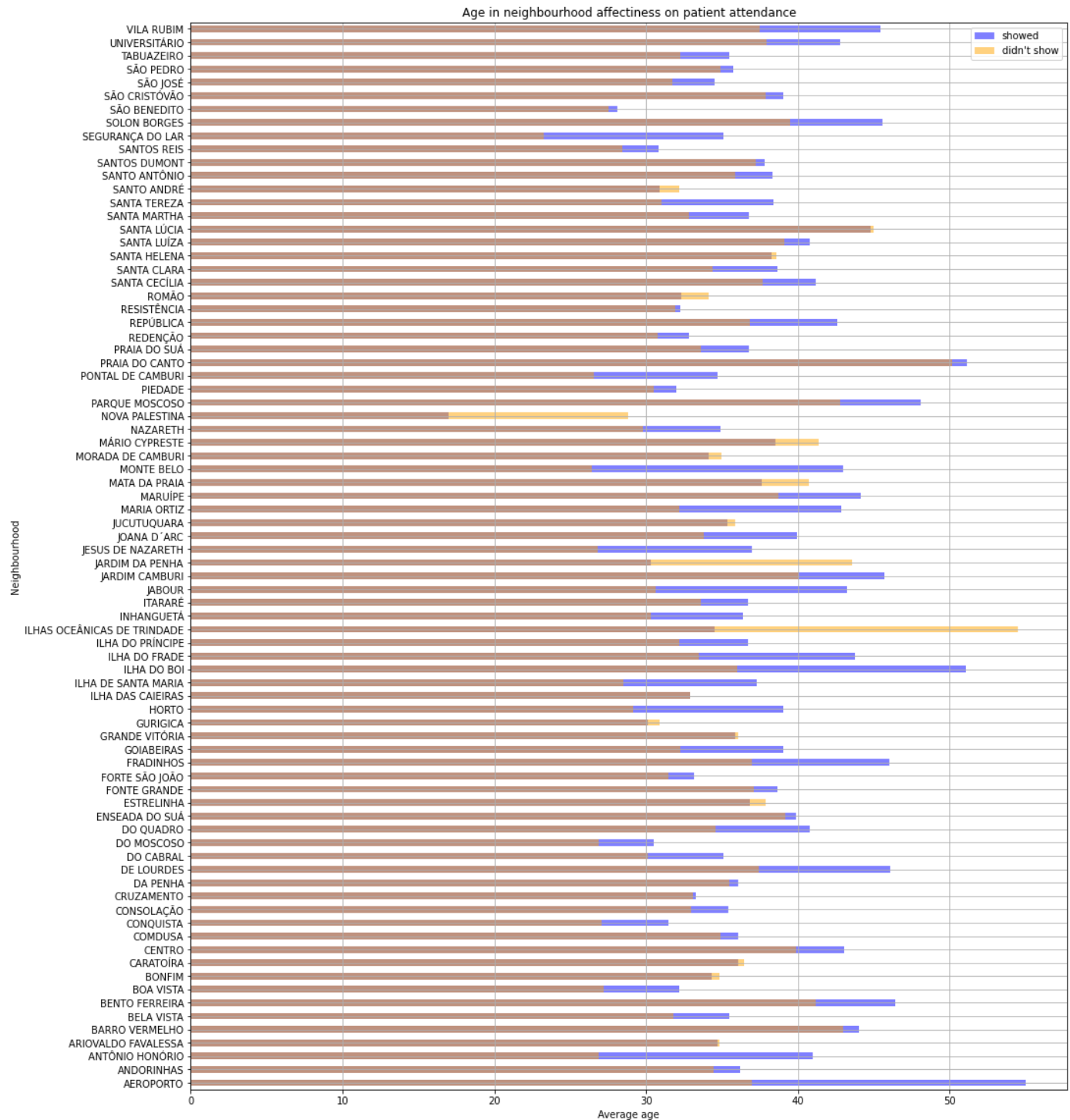
```
In [34]: def plot_bar(data,col,showed,didnt_show,title,xlab,ylab):  
        """  
        plot a bar for a specific col in the dataset to compare people who showed vs. people  
        parameters:  
  
        data: the dataframe  
        col: the specific column  
        showed: the sample who showed  
        didnt_show: the sample who didn't show  
        title: the title you want to give to the plot  
        xlab: the x-axis label you want to give to the plot  
        ylab: the y-axis label you want to give to the plot  
  
        """  
        plt.figure(figsize=(16,20))  
        data[col][showed].value_counts().sort_values(ascending=True).plot(kind='barh', alpha  
        data[col][didnt_show].value_counts().sort_values(ascending=True).plot(kind='barh', a  
        plt.title(title)  
        plt.xlabel(xlab)  
        plt.ylabel(ylab)  
        plt.grid(True)  
        plt.legend()  
        plt.show();
```

```
In [35]: plot_bar(df, 'neighbourhood', showed, didnt_show, 'Neighbourhood affectiness on patient atte  
         'Patients number', 'Neighbourhood')
```



As we can see that the neighbourhood has correlation of attending or not

```
In [36]: plt.figure(figsize=(16,20))
df[showed].groupby('neighbourhood').age.mean().plot(kind='barh', alpha=0.5, color='blue')
df[didn't_show].groupby('neighbourhood').age.mean().plot(kind='barh', alpha=0.5, color='orange')
plt.title('Age in neighbourhood affectiness on patient attendance')
plt.xlabel('Average age')
plt.ylabel('Neighbourhood')
plt.grid(True)
plt.legend()
plt.show();
```



Making a function to make histogram plots

```
In [37]: def plot_hist(data,col,showed,didnt_show,title,xlab,ylab):
    """
    plot a histogram for a specific col in the dataset to compare people who showed vs.
    parameters:

    data: the dataframe
    col: the specific column
    showed: the sample who showed
    didnt_show: the sample who didn't show
    title: the title you want to give to the plot
    xlab: the x-axis label you want to give to the plot
    ylab: the y-axis label you want to give to the plot

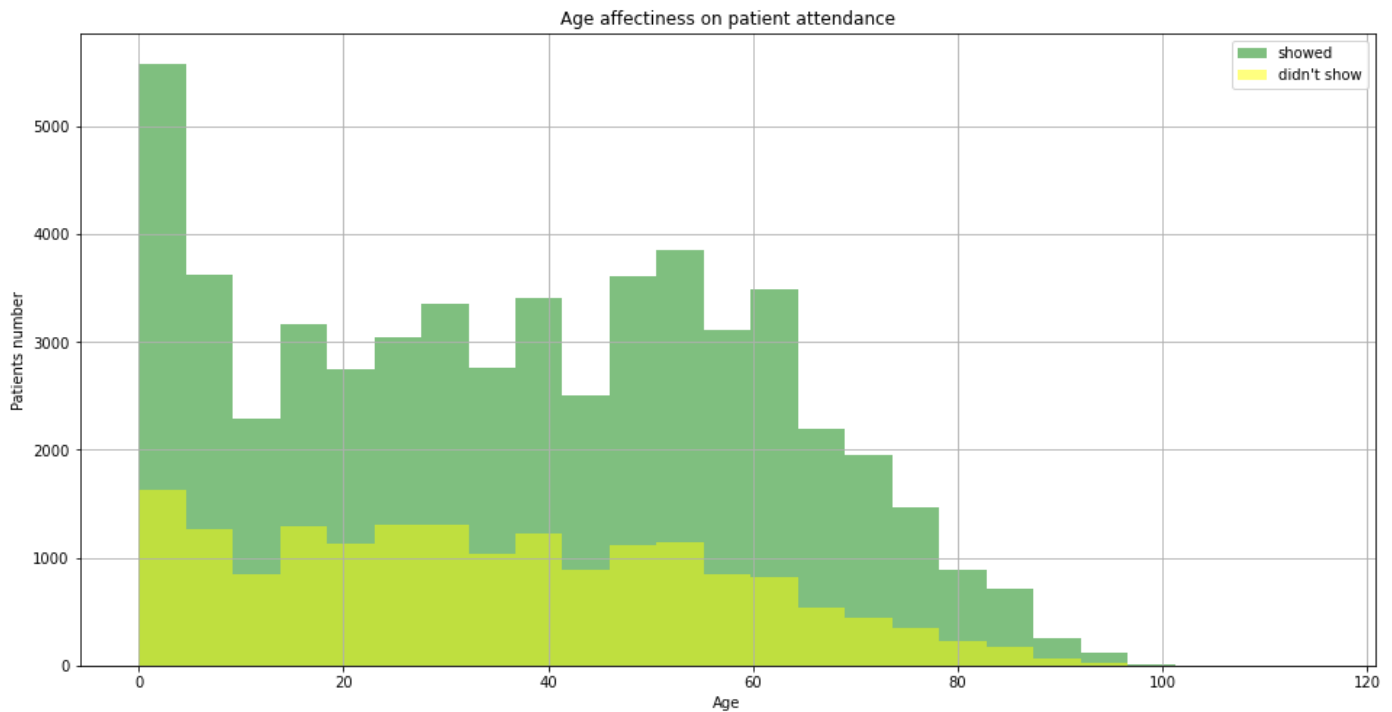
    """
```



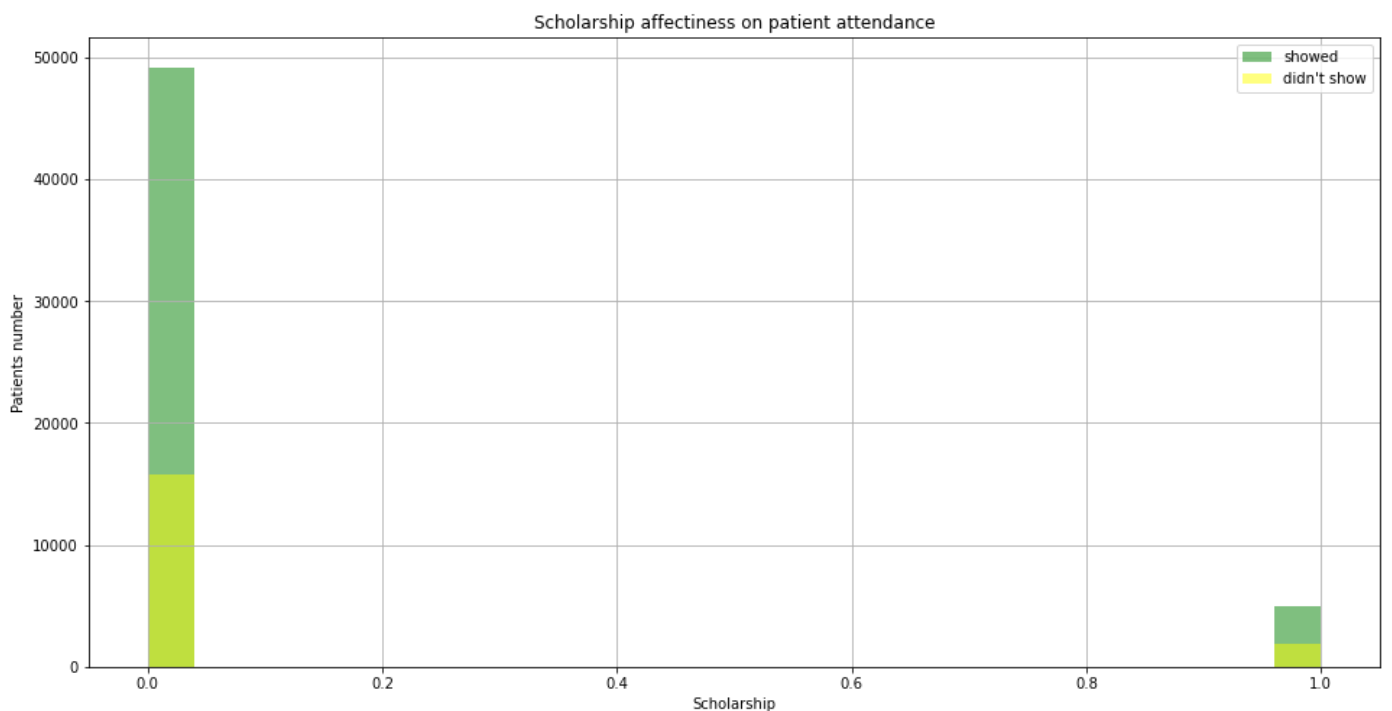
```
plt.figure(figsize=(16,8))
data[col][showed].hist(alpha=0.5, bins=25, label='showed', color='green');
data[col][didn't_show].hist(alpha=0.5, bins=25, label='didn\'t show', color='yellow')
plt.title(title)
plt.xlabel(xlab)
plt.ylabel(ylab)
plt.grid(True)
plt.legend()
plt.show();
```

Making a histogram of the different variables in order to see relations

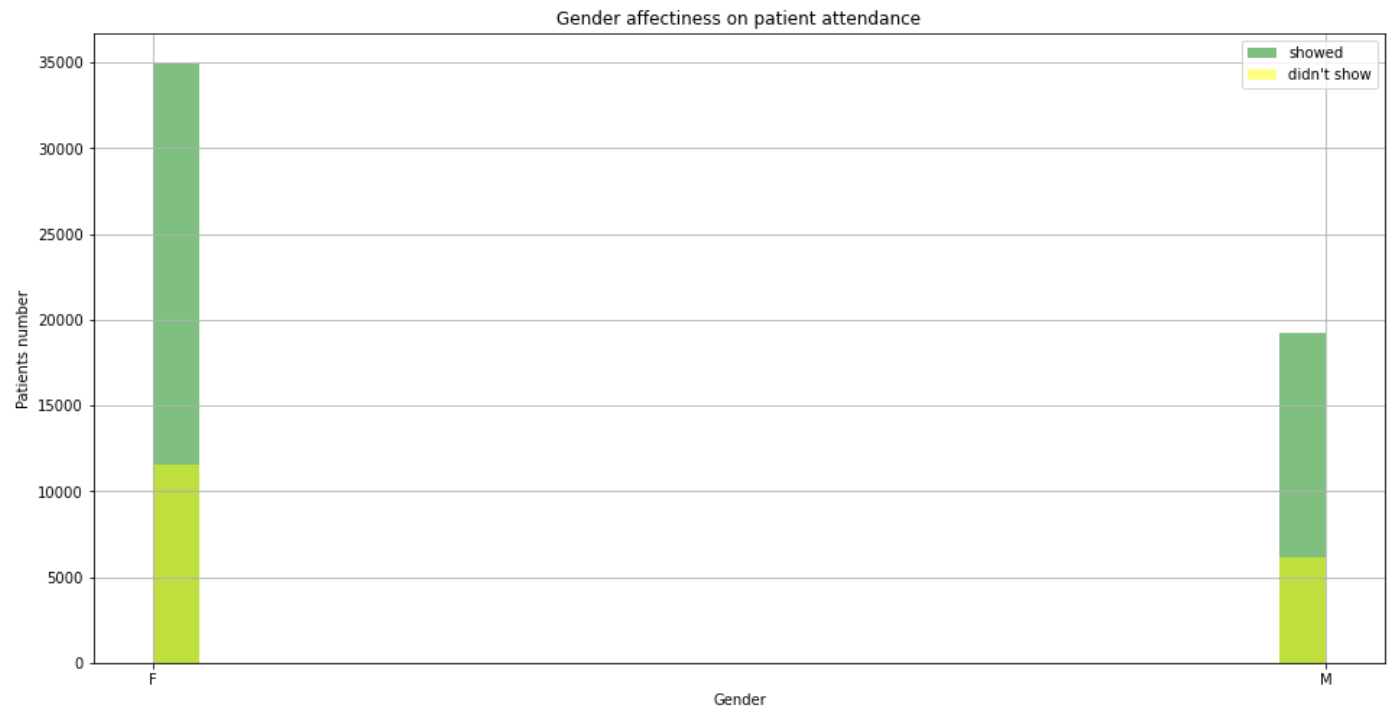
In [38]: `plot_hist(df, 'age', showed, didnt_show, 'Age affectiness on patient attendance', 'Age', 'Pati`



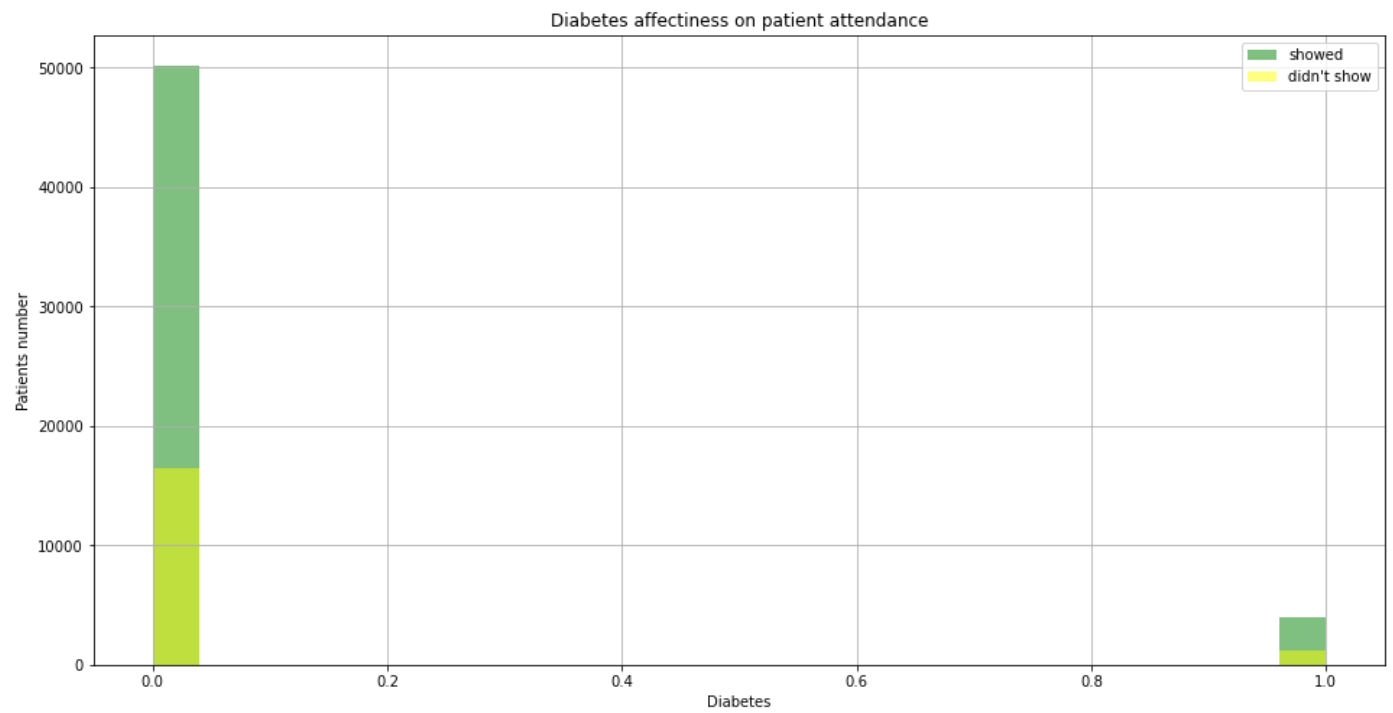
In [39]: `plot_hist(df, 'scholarship', showed, didnt_show, 'Scholarship affectiness on patient attenda`



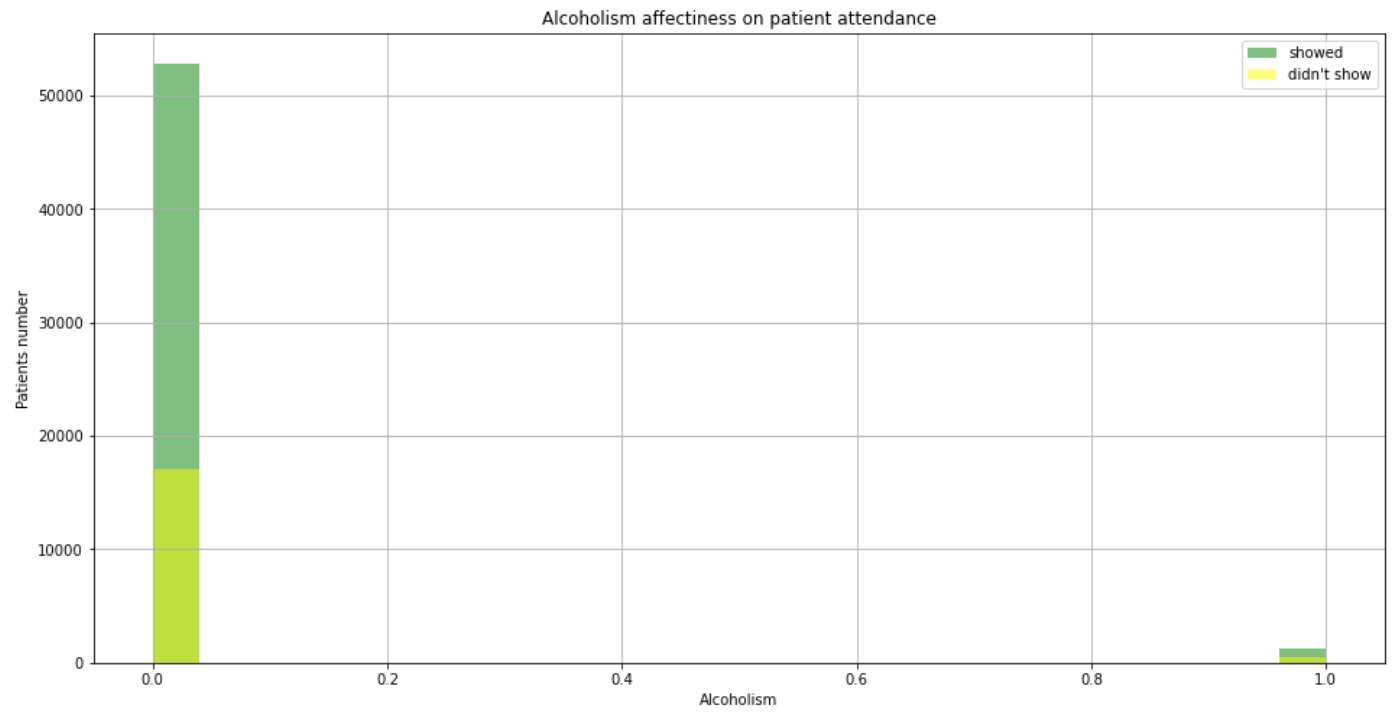
In [40]: `plot_hist(df, 'gender', showed, didnt_show, 'Gender affectiness on patient attendance', 'Gend`



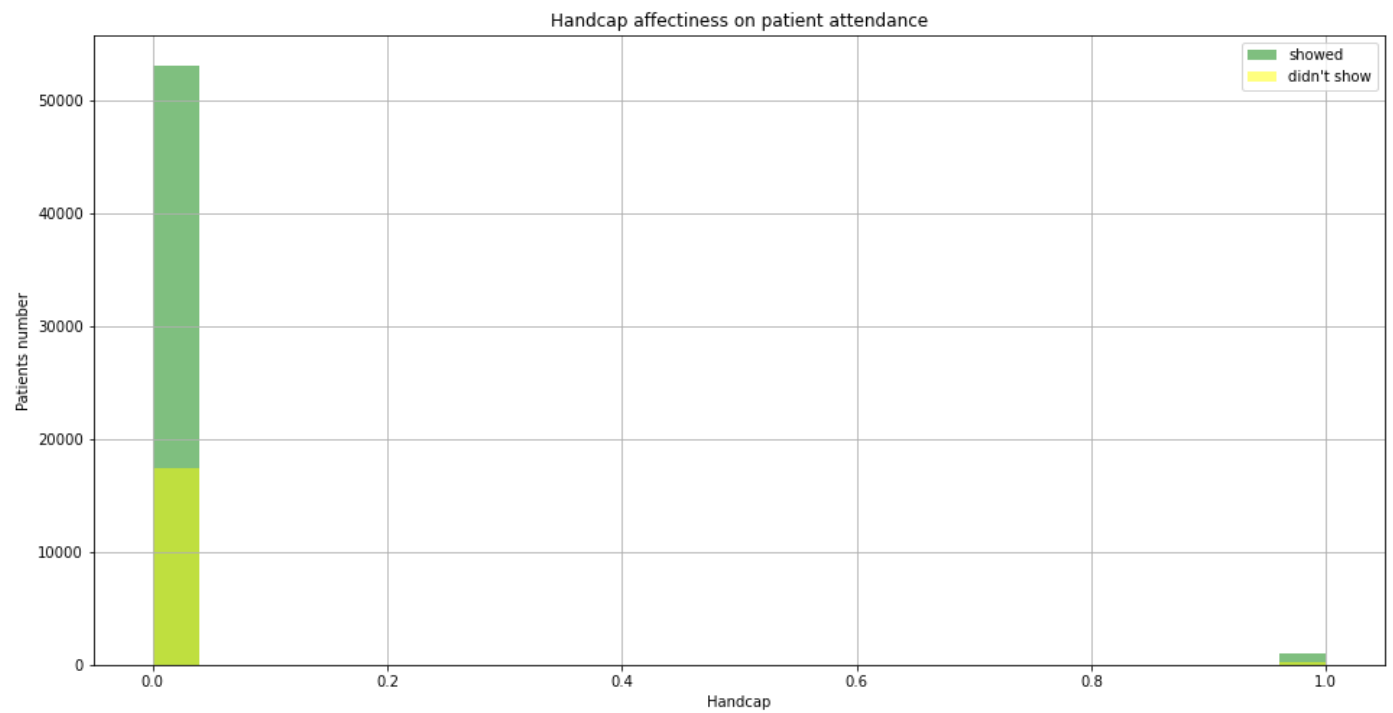
```
In [41]: plot_hist(df, 'diabetes', showed, didnt_show, 'Diabetes affectiness on patient attendance', '
```



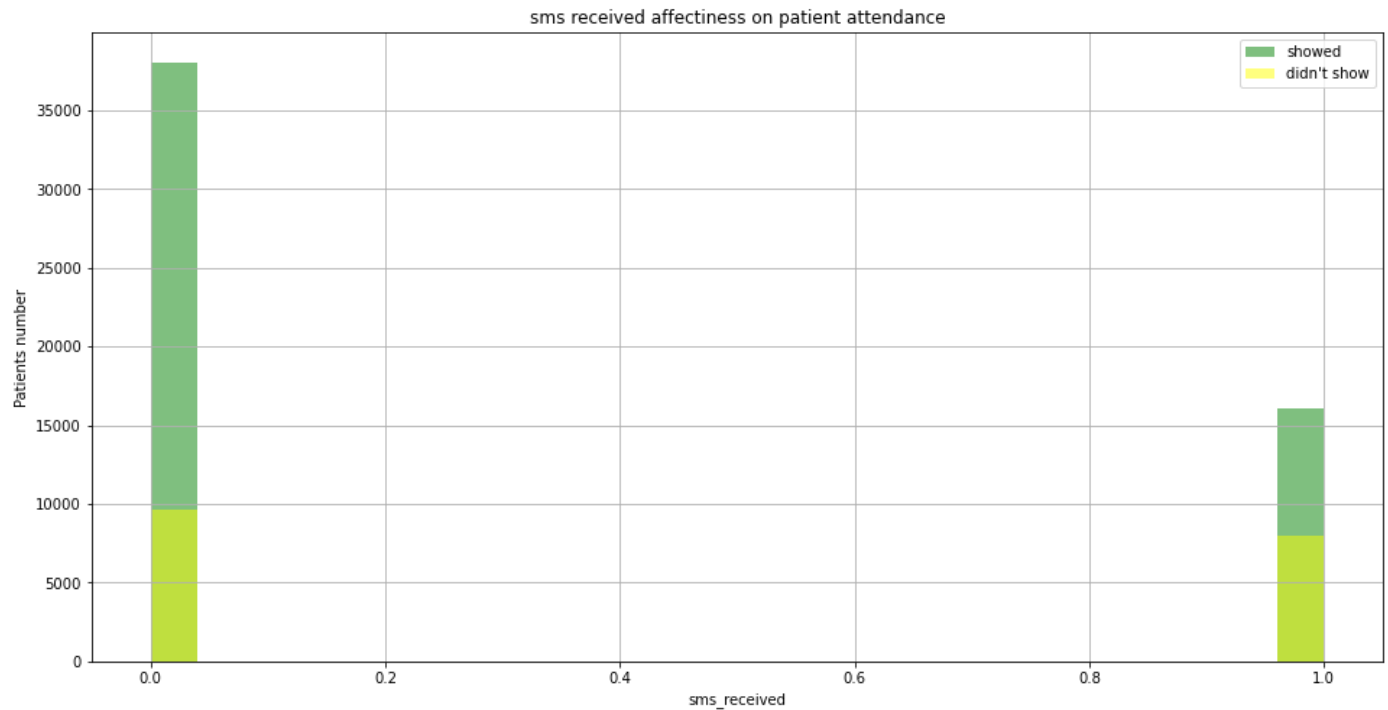
```
In [42]: plot_hist(df, 'alcoholism', showed, didnt_show, 'Alcoholism affectiness on patient attendance', '
```



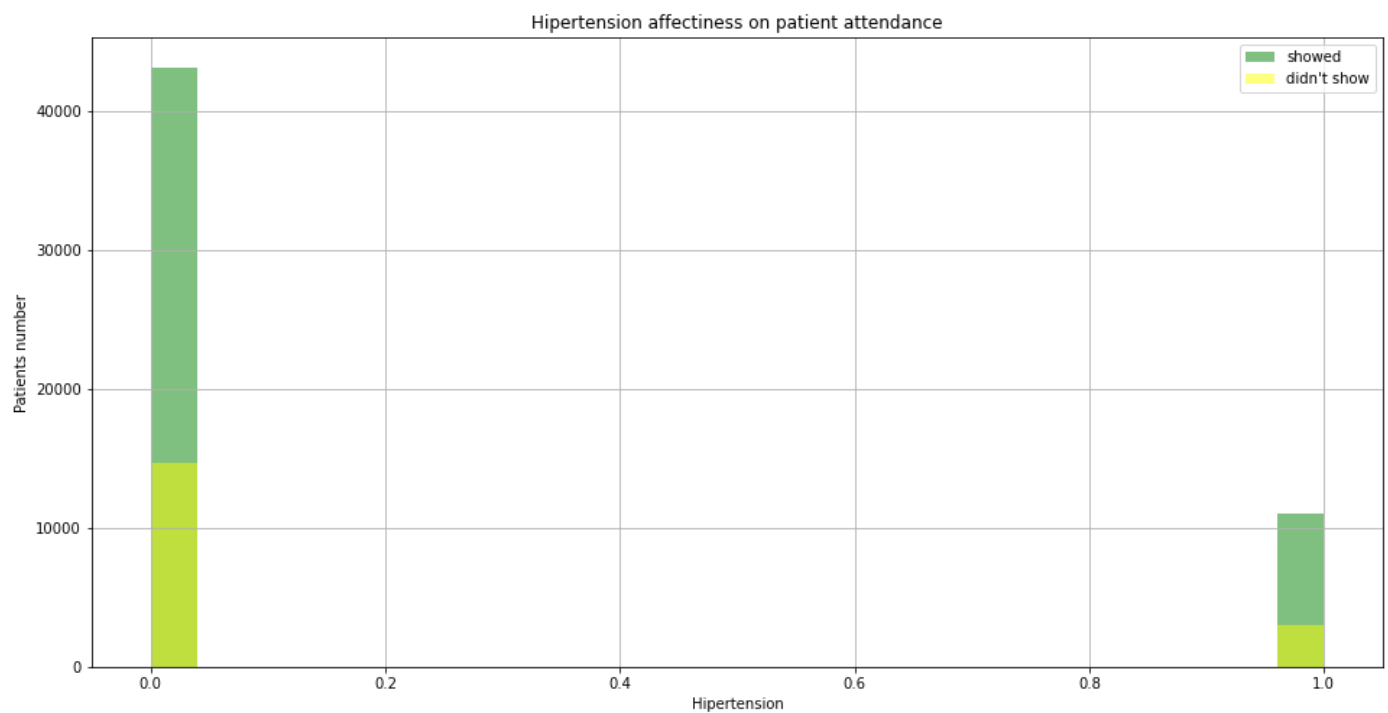
```
In [43]: plot_hist(df, 'handcap', showed, didnt_show, 'Handcap affectiness on patient attendance', 'Ha
```



```
In [44]: plot_hist(df, 'sms_received', showed, didnt_show, 'sms received affectiness on patient atten
```



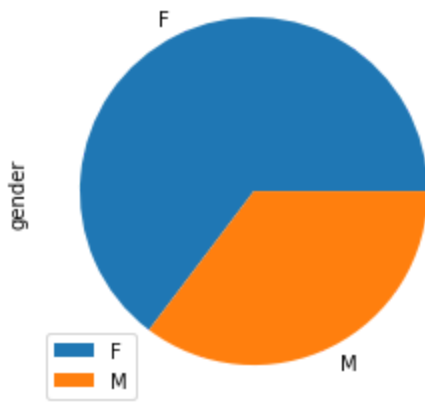
```
In [45]: plot_hist(df, 'hipertension', showed, didnt_show, 'Hipertension affectiness on patient atten
```



Ploting a pie chart to see the difference of number between genders in the dataset

```
In [46]: df.gender.value_counts().plot(kind='pie')
plt.legend();
plt.title('Number of Females vs. Males');
```

Number of Females vs. Males



As we can see female patients are more than the males in this dataset

Conclusions

- People who didnt recieve an sms has more attendance than the one who got one
- There is a correlation between the neighbourhood and patient attending and the most attending neighbourhood is JARDIM CAMBURI
- Maybe the most attending neighbourhood is close to the hospital and least attending are far from it (we cant be sure of that because we dont have the neighbourhood of the hospital)
- The most people attending between the age of (0-8) and then (51-65) and the least is (80-115)
- We cant assume that females attend more than males because the number of females in the dataset is almost the double of number of males
- Handcap people attend less than other people

Limitations

- There is no direct correlation other than neighbourhood in the dateset to predict if a patient will show up for their scheduled appointment