Investigate_a_Dataset

November 18, 2021

1 Project: Investigate a Dataset (No-show appointments)

1.1 Table of Contents

1.1.1 Business Understanding

A person makes a doctor appointment, receives all the instructions and no-show. Who to blame?

This dataset collects information from 110527 medical appointments in Brazil from ('2016-04-29') to ('2016-06-08') and is focused on the question of whether or not patients show up for their appointment.

Problem: Many patients book the appointment with doctor then didn't show up on scheduled day.

Objective of the analysis: Investigate What factors are important for us to know in order to predict if a patient will show up for their scheduled appointment?.

1.1.2 Features :

- PatientId: Identification of the patient
- AppointmentID: Identification of the appointment
- Gender: M=>Male & F=>Female.
- AppointmentDay: The day of Appointment.
- ScheduledDay: Tells us on what day the patient set up their appointment.
- Age: Patient's age.
- Neighborhood: indicates the location of the hospital.
- Scholarship: indicates whether or not the patient is enrolled in Brasilian welfare program

- Hipertension: True or False
- Diabetes: True or False
- Alcoholism: True or False
- Handcap: handicap rate (0 to 4)
- SMS_received: True or False.
- No-show: True or False.

Data set url noshowappointments

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

        sns.set()
```

2 Custom Functions

- Drop columns from data frame in place:

```
In [2]: def drop_df_columns(df,cols_list):
            df.drop(columns=cols_list,inplace=True)
```

- To DateTime FataFrame Columns Converting

```
In [3]: def df_columns_to_datetime(df,cols_list):
            for i in cols_list:
                df[i]=pd.to_datetime(df[i])
```

- Rename DataFrame Columns

```
In [4]: def df_rename_cols(df,col_name_dict):
            df.rename(columns=col_name_dict,inplace=True)
```

1- Asking Questions
Q1 Is there any Correlation between features and patient's show up?
Q2 Is SMS_received , gender and scholarship affect the patient's show up?
Q3 Is any deseases (Hipertension , Diabetes or Handcap) affect the patient's show up?
Q4 Is Appointment Day of the week and the month affect the patient's show up?
Q5 Is Alcoholism affect the patient's show up?
Q6 Is the average of age affect the patient's show up?
Q7 Is the waiting days affect the patient's show up?
Q8 What factors areimportant for us to know in order to predict if a patient will show up for their scheduled appointment up?

2- Data Wrangling
Gathering Data
Assessing Data
Cleaning Data
a) Gathering Data

- As mentiond before in introduction DataSet downloaded from noshowappointments

```
In [5]: df=pd.read_csv(r'noshowappointments-KaggleV2-May-2016.csv')
        df.head()
```

Out[5]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_received	No-show
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	0	1	0	0	0	0	No
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	0	0	0	0	0	No
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	0	0	0	0	0	0	No
3	8.679512e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	0	0	0	0	0	0	No
4	8.841186e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	1	1	0	0	0	No

b) Assessing Data

```
In [6]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
PatientId         110527 non-null float64
AppointmentID     110527 non-null int64
Gender            110527 non-null object
ScheduledDay      110527 non-null object
AppointmentDay    110527 non-null object
Age               110527 non-null int64
Neighbourhood     110527 non-null object
Scholarship       110527 non-null int64
Hipertension      110527 non-null int64
Diabetes          110527 non-null int64
```

```
Alcoholism        110527 non-null int64
Handcap           110527 non-null int64
SMS_received      110527 non-null int64
No-show           110527 non-null object
dtypes: float64(1), int64(8), object(5)
memory usage: 11.8+ MB
```

- as we can see there are 14 feature columns and 110527 row with out any null values.
- PatientId and AppointmentID features hasn't predict power because so:
  - remove PatientId column.
  - remove AppointmentID column.
- some data types need to be converted :
  - ScheduledDay to datetime
  - AppointmentDay to datetime
- Check duplicated rows.

```
In [7]: df.duplicated().sum()

Out[7]: 0
```

- there is no dublicated rows

```
In [8]: df['Gender'].value_counts()

Out[8]: F    71840
        M    38687
        Name: Gender, dtype: int64
```

- map M to male and F to female is better representive

```
In [9]: df['No-show'].value_counts()

Out[9]: No     88208
        Yes    22319
        Name: No-show, dtype: int64
```

- Convert No-show to is show to reduse confusion:
  - this required map yes to 0 and no to 1 and then convert column data type to int
- rename all columns to lower case and split tow sections word by _

```
In [10]: df['Age'].describe()
```

```
Out[10]: 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 [11]: df[df['Age']==0]['Age'].count()

Out[11]: 3539
```

- removing data with age < 0 but we will accept the max value 115 because it is possible
- 3539 with age zero acceptable because my born up to 11 month ago.

```
In [12]: df.describe()

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

                Hipertension       Diabetes     Alcoholism        Handcap  \
         count  110527.000000  110527.000000  110527.000000  110527.000000
         mean        0.197246       0.071865       0.030400       0.022248
         std         0.397921       0.258265       0.171686       0.161543
         min         0.000000       0.000000       0.000000       0.000000
         25%         0.000000       0.000000       0.000000       0.000000
         50%         0.000000       0.000000       0.000000       0.000000
         75%         0.000000       0.000000       0.000000       0.000000
         max         1.000000       1.000000       1.000000       4.000000

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

```
In [13]: df.Handcap.value_counts()
```

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

- rename Handcap column to handicap

2.0.1 Assess conclusions:

- Remove PatientId column.
- Remove AppointmentID column.
- Convert ScheduledDay column datatype to datetime
- Convert AppointmentDay column datatype to datetime
- map M to male and F to female better representive
- Convert No-show to is show to reduse confusion and map yes to 0 and no to 1 and then convert column data type to int.
- rename all columns to lower case and split tow sections word by _
- removing data with age < 0
- rename Handcap column to handicap

b) Cleaning Data

steps: 1- Copy data fram to new one

```
In [14]: df_new=df.copy()
```

2- Remove un needed columns PatientId and AppointmentID

```
In [15]: drop_df_columns(df_new,['PatientId','AppointmentID'])
         df_new.head()
```

```
Out[15]:   Gender          ScheduledDay        AppointmentDay  Age      Neighbourhood  \
         0      F  2016-04-29T18:38:08Z  2016-04-29T00:00:00Z   62    JARDIM DA PENHA
         1      M  2016-04-29T16:08:27Z  2016-04-29T00:00:00Z   56    JARDIM DA PENHA
         2      F  2016-04-29T16:19:04Z  2016-04-29T00:00:00Z   62      MATA DA PRAIA
         3      F  2016-04-29T17:29:31Z  2016-04-29T00:00:00Z    8  PONTAL DE CAMBURI
         4      F  2016-04-29T16:07:23Z  2016-04-29T00:00:00Z   56    JARDIM DA PENHA

            Scholarship  Hipertension  Diabetes  Alcoholism  Handcap  SMS_received  \
         0            0             1         0           0        0             0
         1            0             0         0           0        0             0
         2            0             0         0           0        0             0
         3            0             0         0           0        0             0
         4            0             1         1           0        0             0
```

```
  No-show
0      No
1      No
2      No
3      No
4      No
```

3- Convert ScheduledDay and AppointmentDay to datatime data type

```
In [16]: df_columns_to_datetime(df_new,['ScheduledDay','AppointmentDay'])
         df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 12 columns):
Gender            110527 non-null object
ScheduledDay      110527 non-null datetime64[ns]
AppointmentDay    110527 non-null datetime64[ns]
Age               110527 non-null int64
Neighbourhood     110527 non-null object
Scholarship       110527 non-null int64
Hipertension      110527 non-null int64
Diabetes          110527 non-null int64
Alcoholism        110527 non-null int64
Handcap           110527 non-null int64
SMS_received      110527 non-null int64
No-show           110527 non-null object
dtypes: datetime64[ns](2), int64(7), object(3)
memory usage: 10.1+ MB
```

4 - map M to male and F to female

```
In [17]: df_new['Gender']=df_new['Gender'].map({'M':'male','F':'female'})
         df_new['Gender'].value_counts()
```

```
Out[17]: female    71840
         male      38687
         Name: Gender, dtype: int64
```

```
In [18]: df_new.shape
```

```
Out[18]: (110527, 12)
```

4 - removing data with age less than 0

```
In [19]: df_new=df_new[df_new['Age']>=0]
         df_new.shape
```

```
Out[19]: (110526, 12)
```

5 rename columns: - rename all columns to lower case and split tow sections word by _ - rename Handcap column to handicap

```
In [20]: df_new.columns.values

Out[20]: array(['Gender', 'ScheduledDay', 'AppointmentDay', 'Age', 'Neighbourhood',
                'Scholarship', 'Hipertension', 'Diabetes', 'Alcoholism', 'Handcap',
                'SMS_received', 'No-show'], dtype=object)

In [21]: df_rename_cols(df_new,lambda x:x.lower().replace('-','_'))
         df_new.columns.values

Out[21]: array(['gender', 'scheduledday', 'appointmentday', 'age', 'neighbourhood',
                'scholarship', 'hipertension', 'diabetes', 'alcoholism', 'handcap',
                'sms_received', 'no_show'], dtype=object)

In [22]: df_rename_cols(df_new,{'scheduledday':'scheduled_day','appointmentday':'appointment_day
         df_new.columns.values

Out[22]: array(['gender', 'scheduled_day', 'appointment_day', 'age',
                'neighbourhood', 'scholarship', 'hipertension', 'diabetes',
                'alcoholism', 'handicap', 'sms_received', 'no_show'], dtype=object)
```

6 - Convert No-show to is show to reduse confusion and map yes to 0 and no to 1 and then convert column data type to int.

```
In [23]: df_new['no_show']=df_new['no_show'].map({'Yes':0,'No':1})
         df_rename_cols(df_new,{'no_show':'show'})
         df_new['show']=df_new['show'].astype(int)
         df_new['show'].value_counts()

Out[23]: 1    88207
         0    22319
         Name: show, dtype: int64
```

7 - adding new column to diffrence between Scheduled Day and Appointment Day

```
In [24]: df_new['waiting_days']=df_new['appointment_day']-df_new['scheduled_day']
         df_new['waiting_days'].describe()

Out[24]: count                      110526
         mean       9 days 17:08:42.047952
         std       15 days 05:51:31.240428
         min             -7 days +10:10:40
         25%             -1 days +15:41:32
         50%               3 days 11:22:33
         75%       14 days 07:41:37.750000
         max             178 days 13:19:01
         Name: waiting_days, dtype: object
```

```
In [25]: df_new['waiting_days']=df_new['waiting_days'].astype(str).apply(lambda x:x.split()[0]).
         df_new['waiting_days'].describe()

Out[25]: count    110526.000000
         mean          9.183794
         std          15.255034
         min          -7.000000
         25%          -1.000000
         50%           3.000000
         75%          14.000000
         max         178.000000
         Name: waiting_days, dtype: float64
```

- as we see min waiting_days is -7 and Q1 is -1 day so we need to drop this invalid data because appointment_day must be greater than or equal to scheduled_day

```
In [26]: df_new=df_new[df_new['waiting_days'] >=0]

In [27]: df_new.describe(include='all')

Out[27]:         gender        scheduled_day      appointment_day            age  \
         count    71959                71959                71959  71959.000000
         unique       2                68666                   27           NaN
         top     female  2016-04-25 17:18:27  2016-06-06 00:00:00           NaN
         freq     48070                   22                 3073           NaN
         first      NaN  2015-11-10 07:13:56  2016-04-29 00:00:00           NaN
         last       NaN  2016-06-07 19:03:57  2016-06-08 00:00:00           NaN
         mean       NaN                  NaN                  NaN     38.502564
         std        NaN                  NaN                  NaN     22.925421
         min        NaN                  NaN                  NaN      0.000000
         25%        NaN                  NaN                  NaN     19.000000
         50%        NaN                  NaN                  NaN     39.000000
         75%        NaN                  NaN                  NaN     57.000000
         max        NaN                  NaN                  NaN    115.000000

                 neighbourhood   scholarship  hipertension      diabetes  \
         count           71959  71959.000000  71959.000000  71959.000000
         unique             80           NaN           NaN           NaN
         top     JARDIM CAMBURI           NaN           NaN           NaN
         freq             5213           NaN           NaN           NaN
         first             NaN           NaN           NaN           NaN
         last              NaN           NaN           NaN           NaN
         mean              NaN      0.092706      0.208897      0.074723
         std               NaN      0.290021      0.406523      0.262946
         min               NaN      0.000000      0.000000      0.000000
         25%               NaN      0.000000      0.000000      0.000000
         50%               NaN      0.000000      0.000000      0.000000
         75%               NaN      0.000000      0.000000      0.000000
         max               NaN      1.000000      1.000000      1.000000
```

	alcoholism	handicap	sms_received	show	waiting_days
count	71959.000000	71959.000000	71959.000000	71959.000000	71959.000000
unique	NaN	NaN	NaN	NaN	NaN
top	NaN	NaN	NaN	NaN	NaN
freq	NaN	NaN	NaN	NaN	NaN
first	NaN	NaN	NaN	NaN	NaN
last	NaN	NaN	NaN	NaN	NaN
mean	0.025320	0.020025	0.493086	0.714810	14.642018
std	0.157096	0.154072	0.499956	0.451508	16.494334
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	3.000000
50%	0.000000	0.000000	0.000000	1.000000	8.000000
75%	0.000000	0.000000	1.000000	1.000000	21.000000
max	1.000000	4.000000	1.000000	1.000000	178.000000

8- split appointment_day and scheduled_day into date , time , hour and day of the week to make more analysis

```
In [28]: df_new['appointment_date']=df_new['appointment_day'].dt.date
         df_new['appointment_time']=df_new['appointment_day'].dt.time
         df_new['appointment_dow']=df_new['appointment_day'].dt.day_name()
         df_new['appointment_hour']=df_new['appointment_day'].dt.hour
         df_new['appointment_month']=df_new['appointment_day'].dt.month_name()
```

```
In [29]: df_new.sample(10)
```

Out[29]:

	gender	scheduled_day	appointment_day	age	neighbourhood	\
12930	female	2016-04-05 08:24:32	2016-05-31	67	MONTE BELO	
88648	female	2016-05-16 10:27:53	2016-06-03	59	PRAIA DO CANTO	
9956	female	2016-04-28 07:29:03	2016-05-04	39	ROMÃO	
5609	female	2016-05-13 14:52:06	2016-05-16	35	ILHA DO PRÍNCIPE	
63377	female	2016-05-11 11:51:47	2016-05-19	36	JARDIM DA PENHA	
28237	male	2016-04-26 17:21:21	2016-05-24	30	REPÚBLICA	
107608	female	2016-06-06 12:01:13	2016-06-07	9	NAZARETH	
44407	female	2016-04-29 09:56:52	2016-05-17	27	JABOUR	
100842	male	2016-05-16 16:34:04	2016-06-01	41	BENTO FERREIRA	
46876	female	2016-04-19 07:26:08	2016-05-10	52	SANTA CECÍLIA	

	scholarship	hipertension	diabetes	alcoholism	handicap	\
12930	0	1	1	0	0	
88648	0	1	1	0	0	
9956	0	0	0	0	0	
5609	0	0	0	0	0	
63377	0	0	0	0	0	
28237	0	0	0	0	0	
107608	0	0	0	0	0	
44407	1	0	0	0	0	
100842	0	0	0	0	0	

```
46876             0             1         0           0         0

        sms_received  show  waiting_days appointment_date appointment_time  \
12930              1     1            55       2016-05-31         00:00:00
88648              1     0            17       2016-06-03         00:00:00
9956               0     1             5       2016-05-04         00:00:00
5609               0     1             2       2016-05-16         00:00:00
63377              0     1             7       2016-05-19         00:00:00
28237              1     1            27       2016-05-24         00:00:00
107608             0     1             0       2016-06-07         00:00:00
44407              0     0            17       2016-05-17         00:00:00
100842             1     1            15       2016-06-01         00:00:00
46876              0     1            20       2016-05-10         00:00:00

       appointment_dow  appointment_hour appointment_month
12930          Tuesday                0               May
88648           Friday                0              June
9956         Wednesday                0               May
5609            Monday                0               May
63377         Thursday                0               May
28237           Tuesday                0               May
107608          Tuesday                0              June
44407           Tuesday                0               May
100842        Wednesday                0              June
46876           Tuesday                0               May
```

```
In [30]: df_new['appointment_time'].nunique()
```

```
Out[30]: 1
```

9- Drop it and appointment_hour because all rows with the same appointment_time .

```
In [31]: drop_df_columns(df_new,['appointment_time','appointment_hour'])
         df_new.sample(10)
```

```
Out[31]:         gender       scheduled_day appointment_day  age    neighbourhood  \
35178   female 2016-04-26 08:02:08      2016-05-06   34   ENSEADA DO SUÁ
39434   female 2016-05-12 16:42:09      2016-05-17   49      MARIA ORTIZ
107174  female 2016-04-05 15:16:56      2016-06-01   39        FRADINHOS
50148     male 2016-04-05 15:14:18      2016-05-03   64  JARDIM DA PENHA
13882   female 2016-05-24 07:56:19      2016-05-30    6     SANTA TEREZA
31037   female 2016-05-05 09:55:32      2016-05-06   31           CENTRO
57278   female 2016-04-26 07:28:56      2016-05-30    9       CRUZAMENTO
24569   female 2016-05-06 08:02:47      2016-05-10   60      SANTO ANDRÉ
21139   female 2016-05-17 07:06:42      2016-05-19   63          MARUÍPE
44120   female 2016-04-18 10:03:22      2016-05-10    1        SÃO PEDRO

        scholarship  hipertension  diabetes  alcoholism  handicap  \
35178             0             0         0           0         0
```

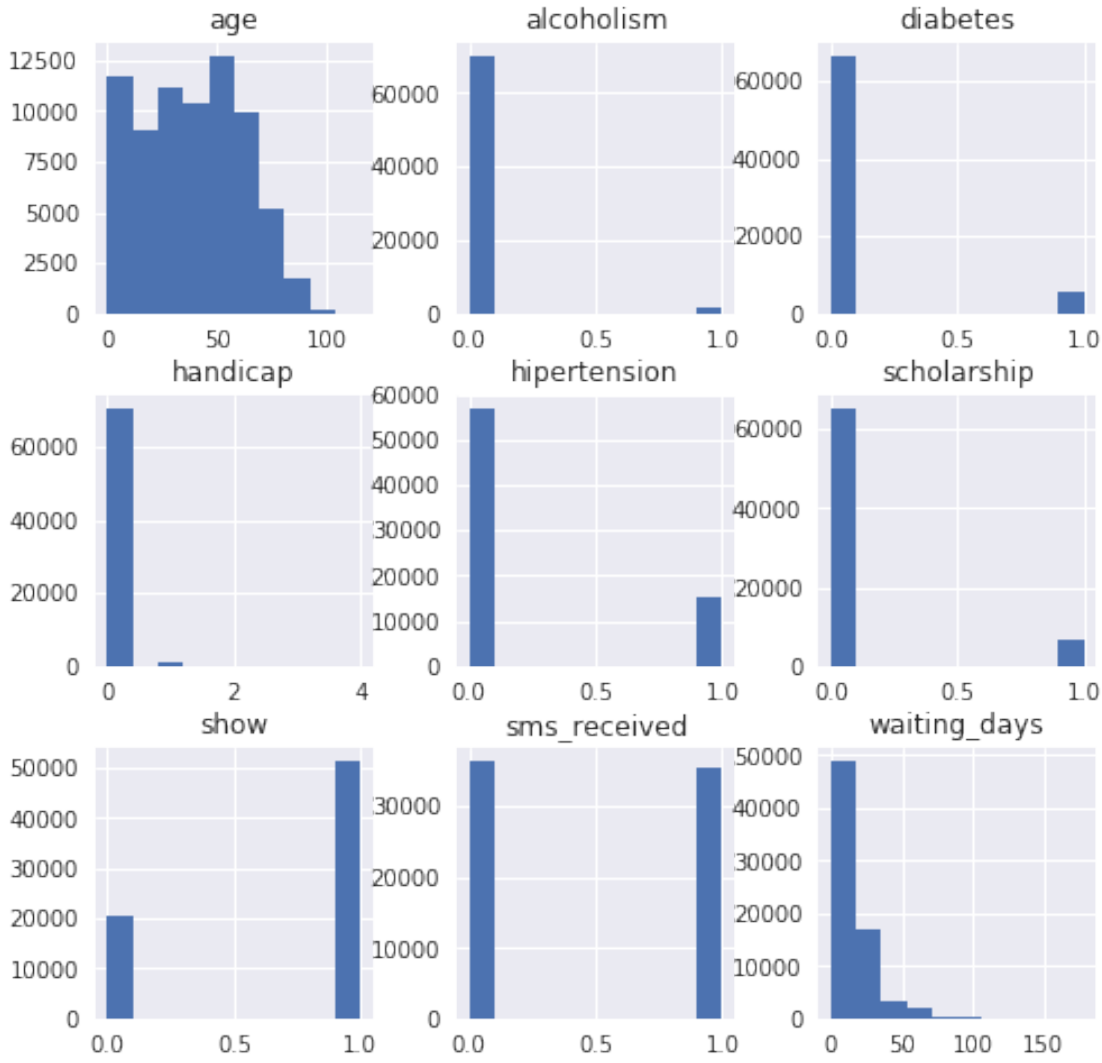
```
39434             0             0         0          0         0
107174            0             0         0          0         0
50148             0             1         0          0         0
13882             0             0         0          0         0
31037             0             0         0          0         0
57278             0             0         0          0         0
24569             0             1         0          0         0
21139             0             0         0          0         0
44120             0             0         0          0         0

        sms_received  show  waiting_days appointment_date appointment_dow  \
35178              1     0             9       2016-05-06          Friday
39434              0     1             4       2016-05-17         Tuesday
107174             1     0            56       2016-06-01       Wednesday
50148              1     1            27       2016-05-03         Tuesday
13882              1     1             5       2016-05-30          Monday
31037              0     1             0       2016-05-06          Friday
57278              1     1            33       2016-05-30          Monday
24569              1     1             3       2016-05-10         Tuesday
21139              0     0             1       2016-05-19        Thursday
44120              1     1            21       2016-05-10         Tuesday

       appointment_month
35178                May
39434                May
107174              June
50148                May
13882                May
31037                May
57278                May
24569                May
21139                May
44120                May
```

- now , we finished cleaning data so save data to csv and then start EDA

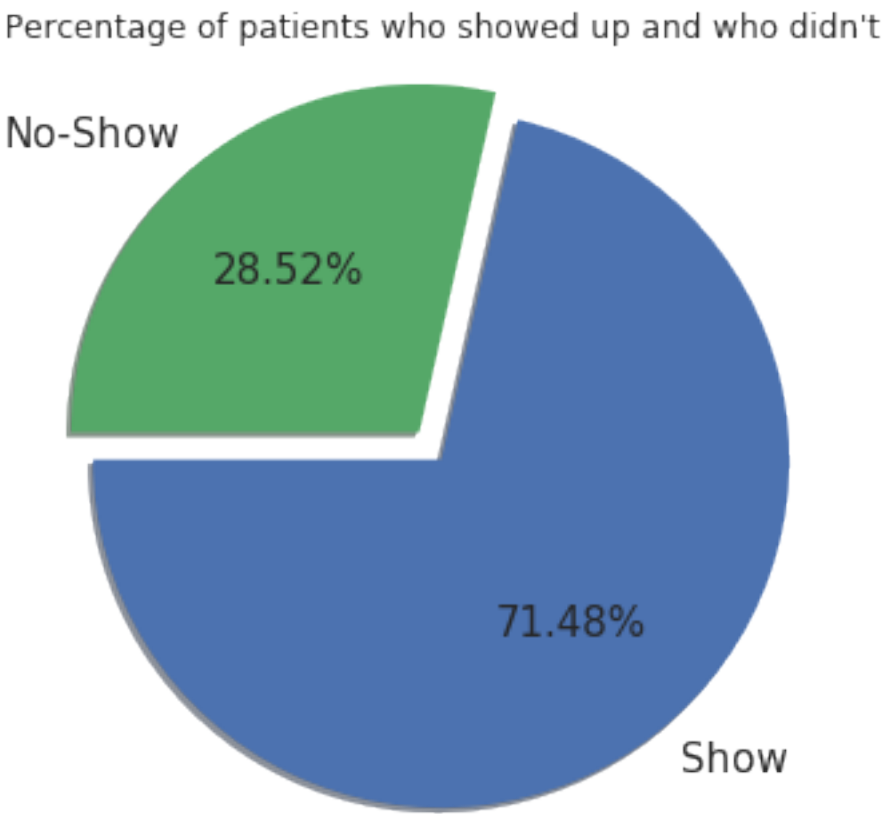
```
In [32]: df_new.to_csv('noshowappointments_cleaned.csv',index=False)
```

Exploratory Data Analysis

```
In [33]: df_cleaned=pd.read_csv(r'noshowappointments_cleaned.csv')
         df_cleaned.hist(figsize=(8,8));
```

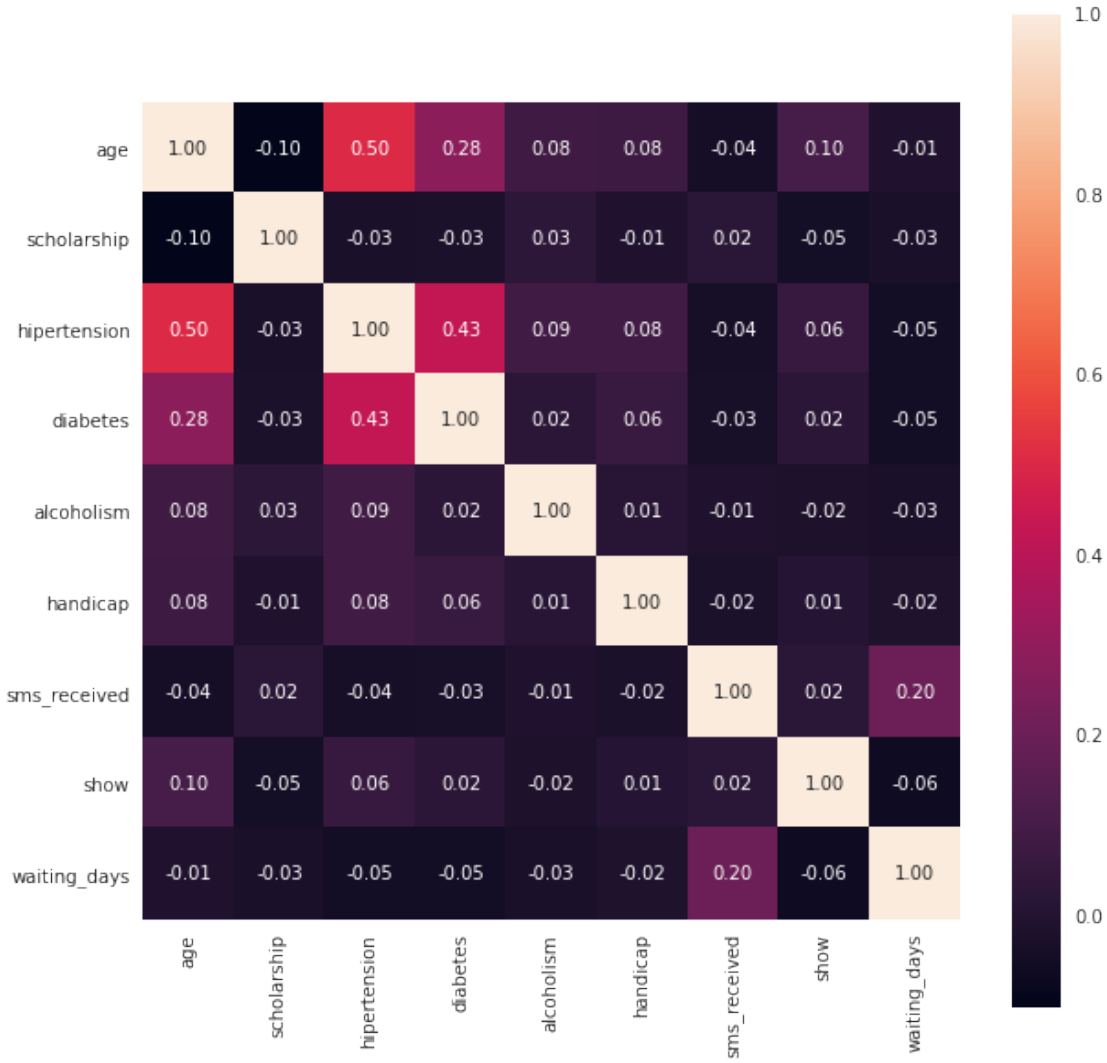



```
In [34]: label_Names = ["Show", "No-Show"]
         data = [df_cleaned.query('show == 1').count()[0], df_cleaned.query('show == 0').count()
         explode = (0, 0.15)
         plt.axis('equal');
         plt.pie(data,radius=1.5,shadow=True ,labels = label_Names,explode=explode, startangle=1
         plt.title("Percentage of patients who showed up and who didn't",y=1.2);
```



2.0.2 Research Question 1 (Is there any Correlation between features and patient's show?)

```
In [35]: correlation = df_cleaned.corr()
         fig, axes = plt.subplots(figsize=(10,10))
         sns.heatmap(correlation, vmax=1, cbar=True, annot=True, square=True, fmt='.2f', annot_k
```

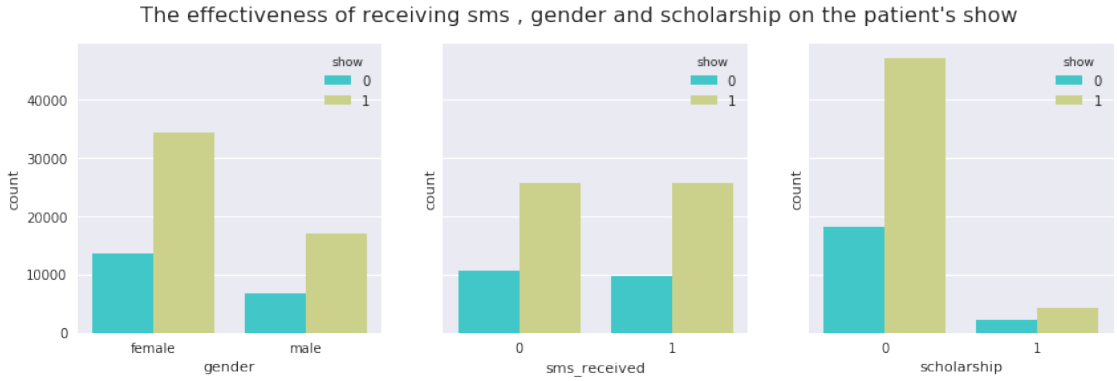


- Heatmap shows three correlations:
  - hipertension and age
  - hipertension and diabetes
  - diabetes and age
- There is no strong correlation between any feature with show

2.0.3 Research Question 2 (Is SMS_received , gender and scholarship affect the patient's show?)

```
In [36]: fig, (ax1, ax2, ax3) = plt.subplots(ncols=3, sharey=True)
         sns.countplot(x='gender', data=df_cleaned, hue='show', ax=ax1, palette='rainbow')
         sns.countplot(x='sms_received', data=df_cleaned, hue='show', ax=ax2, palette='rainbow')
```

```
sns.countplot(x='scholarship', data=df_cleaned, hue='show', ax=ax3, palette='rainbow')
fig.set_figwidth(14)
fig.set_figheight(4)
fig.suptitle("The effectiveness of receiving sms , gender and scholarship on the patien
```



- from bar chart of gender we found females percentage greatter than males

```
In [37]: df_cleaned['gender'].value_counts()
```

```
Out[37]: female    48070
         male      23889
         Name: gender, dtype: int64
```

```
In [38]: male_percentage=(df_cleaned['gender'].value_counts()[1]/df_cleaned['gender'].value_coun
         male_percentage
```

```
Out[38]: 33.198071123834403
```

```
In [39]: df_cleaned.query('show==1')['gender'].value_counts()
```

```
Out[39]: female    34396
         male      17041
         Name: gender, dtype: int64
```

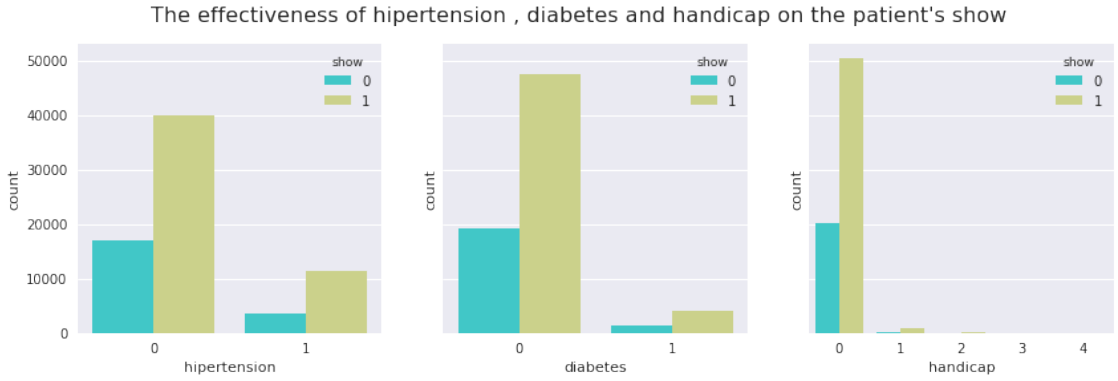
```
In [40]: male_ratio=df_cleaned.query('show==1')['gender'].value_counts()[1]/df_cleaned['gender']
         female_ratio=df_cleaned.query('show==1')['gender'].value_counts()[0]/df_cleaned['gender
         female_ratio,male_ratio
```

```
Out[40]: (0.7155398377366341, 0.71334086818200848)
```

- Both genders have same commitment to medical schedules. (71 %)
- sms doesn't affect on patient's show
- this data is imbalanced because males represent 33.2% of observations
- Number of patients who have scholarship is very small

2.0.4 Research Question 3 (are deseases like Hipertension , Diabetes and Handicap affect the patient's show?)

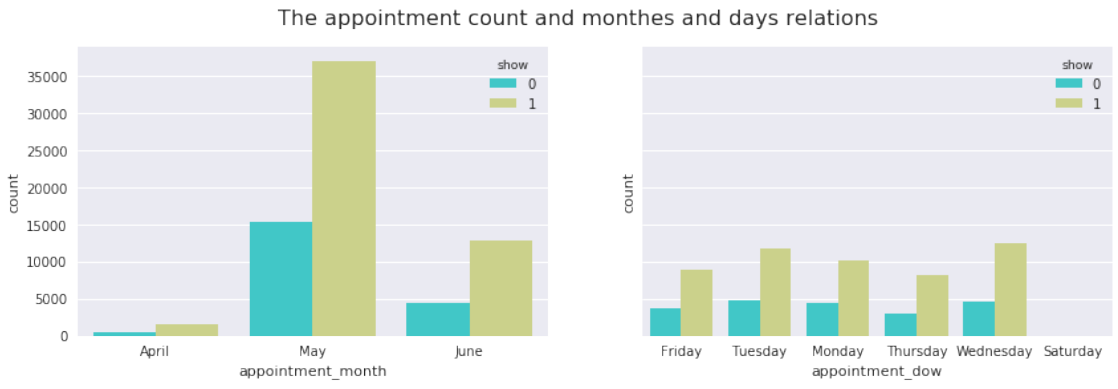
```
In [41]: fig, (ax1, ax2, ax3) = plt.subplots(ncols=3, sharey=True)
         sns.countplot(x='hipertension', data=df_cleaned, hue='show', ax=ax1, palette='rainbow')
         sns.countplot(x='diabetes', data=df_cleaned, hue='show', ax=ax2, palette='rainbow')
         sns.countplot(x='handicap', data=df_cleaned, hue='show', ax=ax3, palette='rainbow')
         fig.set_figwidth(14)
         fig.set_figheight(4)
         fig.suptitle("The effectiveness of hipertension , diabetes and handicap on the patient'
```



- hipertension has signficant effect on the patient's show up , but diabetes and handicap has insignficant effect on the patient's show up

2.0.5 Research Question 4 (Is Appointment Day of the week affect the patient's show?)

```
In [42]: fig, (ax1, ax2) = plt.subplots(ncols=2, sharey=True)
         sns.countplot(x='appointment_month', data=df_cleaned, hue='show', ax=ax1, palette='rain
         sns.countplot(x='appointment_dow', data=df_cleaned, hue='show', ax=ax2, palette='rainbo
         fig.set_figwidth(14)
         fig.set_figheight(4)
         fig.suptitle("The appointment count and monthes and days relations", fontsize=16);
```

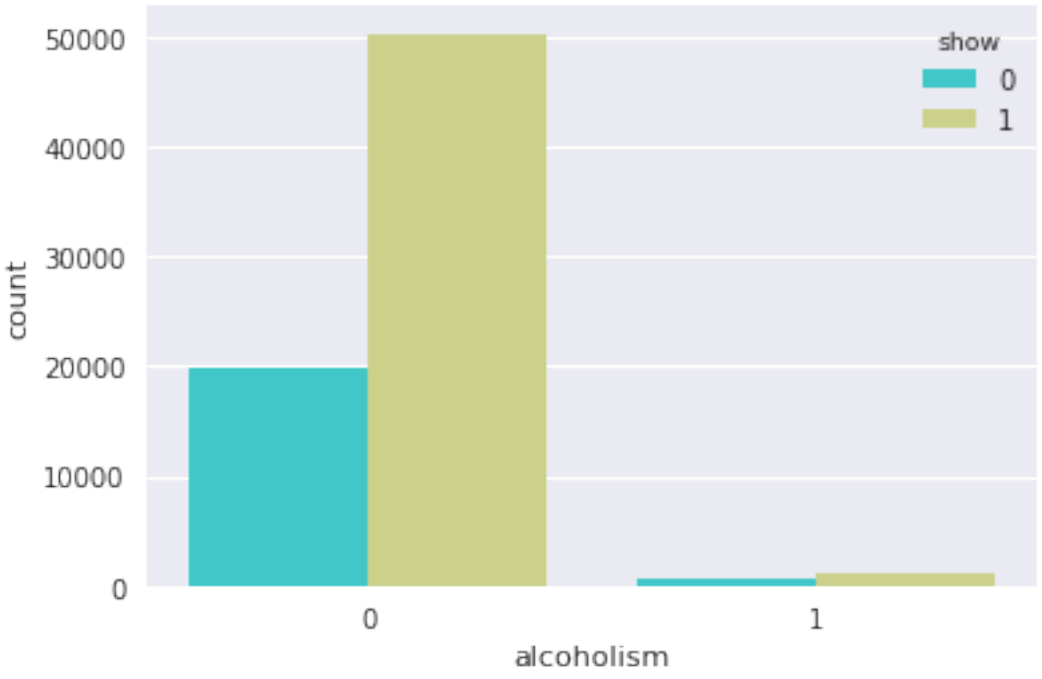


```
In [43]: df_cleaned['appointment_dow'].value_counts()

Out[43]: Wednesday    17044
         Tuesday      16462
         Monday       14581
         Friday       12516
         Thursday     11325
         Saturday        31
         Name: appointment_dow, dtype: int64

In [44]: df_cleaned['appointment_date'].min(),df_cleaned['appointment_date'].max()

Out[44]: ('2016-04-29', '2016-06-08')
```

- 'May' the highest month when patients make appointment , but data already collected from 2016-04-29 to 2016-06-08 so this chart does not give information in terms of the difference between the months
- Tuesday,Wednesday highest days when patients make appointment.
- Saturday lowest ptients appoinment

2.0.6 Research Question 5 (Is Alcoholism affect the patient's show?)

```
In [45]: sns.countplot(x='alcoholism', data=df_cleaned, hue='show', palette='rainbow')
         fig.set_figwidth(15)
         fig.set_figheight(5)
```



- alcoholism has not effect on the patient's show

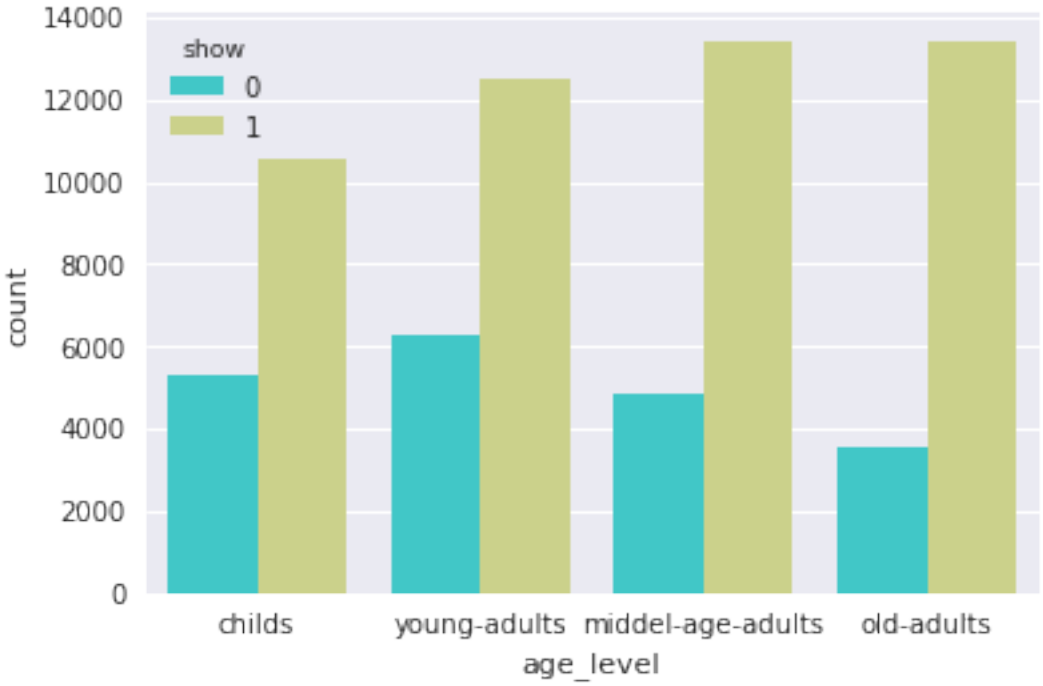
2.0.7 Research Question 6 (Is the age affect the patient's show?)

```
In [46]: df_cleaned.describe()['age']
```

```
Out[46]: count    71959.000000
         mean        38.502564
         std         22.925421
         min          0.000000
         25%         19.000000
         50%         39.000000
         75%         57.000000
         max        115.000000
         Name: age, dtype: float64
```

```
In [47]: df_age=df_cleaned.copy()
         bins=[df_cleaned.describe()['age']['min'],df_cleaned.describe()['age']['25%'],df_cleane
              df_cleaned.describe()['age']['max']]
         bins_labels=['childs','young-adults','middel-age-adults','old-adults']
         df_age['age_level']=pd.cut(df_age['age'],bins,labels=bins_labels)
```

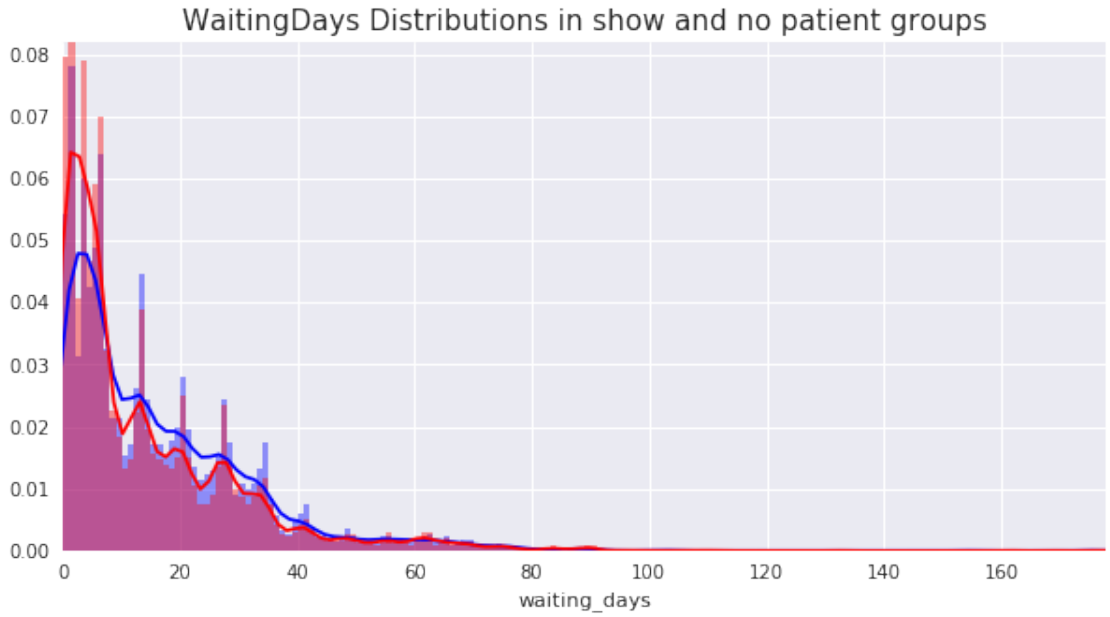
```
In [48]: sns.countplot(x='age_level', data=df_age, hue='show', palette='rainbow')
         fig.set_figwidth(15)
         fig.set_figheight(5)
```



- young adults from 19 to 39 years old are the highest missed show up

2.0.8 Research Question 7 (Is the waiting days affect the patient's show?)

```
In [49]: df_valid_waiting_days=df_cleaned.query('waiting_days >= 0').copy()
         df_valid_waiting_days.shape

Out[49]: (71959, 16)

In [50]: plt.figure(figsize=(10, 5))

         sns.distplot(df_valid_waiting_days[df_valid_waiting_days['show'] == 0]["waiting_days"],
         sns.distplot(df_valid_waiting_days[df_valid_waiting_days['show'] == 1]["waiting_days"],

         plt.title('WaitingDays Distributions in show and no patient groups', fontsize=15)
         plt.xlim(df_valid_waiting_days['waiting_days'].min(),df_valid_waiting_days['waiting_day
         plt.show()
```



- waiting days until 7 days patient show up is higher ratio after 7 days missed show up is higher ratio .

2.0.9 Research Question 8 (What factors areimportant for us to know in order to predict if a patient will show up for their scheduled appointment?)

```
In [51]: df_neighbourhood=pd.DataFrame(data=df_cleaned['neighbourhood'].value_counts())
         df_neighbourhood.reset_index(level=0, inplace=True)
```

```
df_neighbourhood.rename(columns={'neighbourhood':'appointment_count','index':'neighbour

df_neighbourhood_show =pd.DataFrame(data=df_cleaned.query('show == 1')['neighbourhood']
df_neighbourhood_show.reset_index(level=0, inplace=True)
df_neighbourhood_show.rename(columns={'neighbourhood':'show_count','index':'neighbourho
df_neighbourhood_show

df_neighbourhood_combined=df_neighbourhood.merge(df_neighbourhood_show , left_on='neigh
df_neighbourhood_combined['show_up_ratio']=df_neighbourhood_combined['show_count']/df_n
df_neighbourhood_combined
```

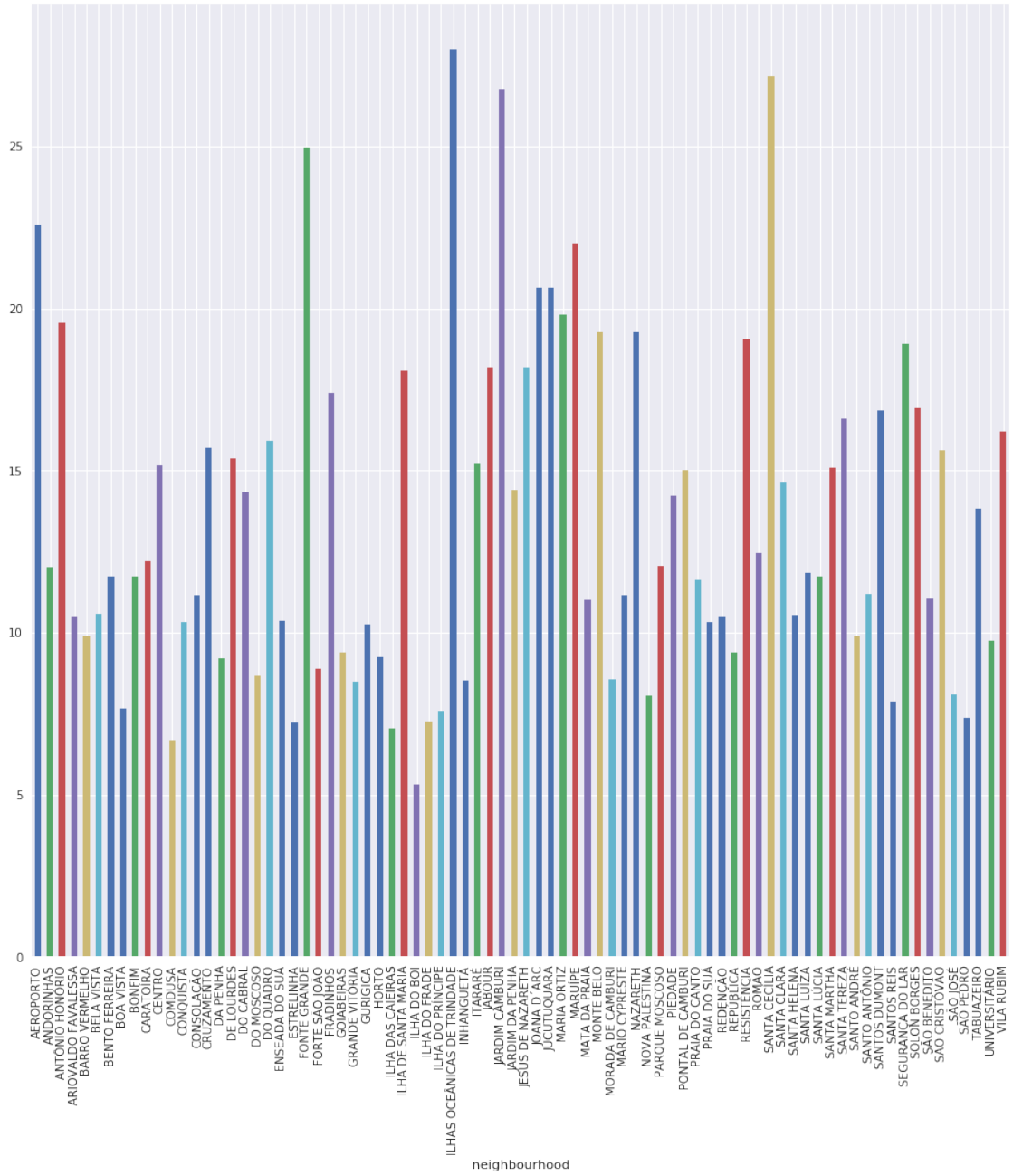
Out[51]:

	neighbourhood	appointment_count	show_count	show_up_ratio
0	JARDIM CAMBURI	5213	3854	0.739306
1	MARIA ORTIZ	3730	2592	0.694906
2	RESISTÊNCIA	2818	1961	0.695884
3	JARDIM DA PENHA	2655	2058	0.775141
4	ITARARÉ	2381	1512	0.635027
5	CENTRO	2270	1617	0.712335
6	TABUAZEIRO	1924	1398	0.726611
7	JESUS DE NAZARETH	1755	1097	0.625071
8	BONFIM	1708	1195	0.699649
9	CARATOÍRA	1691	1150	0.680071
10	JABOUR	1682	1252	0.744352
11	SANTA MARTHA	1648	1185	0.719053
12	SANTO ANTÔNIO	1621	1208	0.745219
13	SANTO ANDRÉ	1614	1140	0.706320
14	SÃO PEDRO	1584	1133	0.715278
15	ANDORINHAS	1524	1033	0.677822
16	ILHA DO PRÍNCIPE	1503	1014	0.674651
17	ROMÃO	1422	985	0.692686
18	SÃO JOSÉ	1376	1003	0.728924
19	DA PENHA	1367	984	0.719824
20	MARUÍPE	1359	956	0.703458
21	FORTE SÃO JOÃO	1293	989	0.764888
22	ILHA DE SANTA MARIA	1284	939	0.731308
23	SÃO CRISTÓVÃO	1274	928	0.728414
24	NOVA PALESTINA	1186	842	0.709949
25	BELA VISTA	1113	790	0.709793
26	GURIGICA	1105	681	0.616290
27	CRUZAMENTO	1025	743	0.724878
28	PRAIA DO SUÁ	945	664	0.702646
29	REDENÇÃO	931	674	0.723953
..	...	...	...	...
49	MATA DA PRAIA	462	361	0.781385
50	SANTA CLARA	381	252	0.661417
51	DO CABRAL	362	282	0.779006
52	SANTOS REIS	353	259	0.733711
53	SANTA CECÍLIA	349	232	0.664756

54	ESTRELINHA	344	253	0.735465
55	SOLON BORGES	337	272	0.807122
56	DO MOSCOSO	306	219	0.715686
57	SANTA LÚCIA	298	221	0.741611
58	BARRO VERMELHO	285	206	0.722807
59	SANTA LUÍZA	284	218	0.767606
60	PIEDADE	274	191	0.697080
61	COMDUSA	237	182	0.767932
62	DE LOURDES	222	177	0.797297
63	BOA VISTA	221	166	0.751131
64	FRADINHOS	193	146	0.756477
65	ANTÔNIO HONÓRIO	180	137	0.761111
66	ARIOVALDO FAVALESSA	175	118	0.674286
67	MÁRIO CYPRESTE	173	126	0.728324
68	ENSEADA DO SUÁ	163	115	0.705521
69	SANTA HELENA	126	91	0.722222
70	HORTO	114	73	0.640351
71	UNIVERSITÁRIO	112	81	0.723214
72	NAZARETH	108	79	0.731481
73	SEGURANÇA DO LAR	103	77	0.747573
74	MORADA DE CAMBURI	78	62	0.794872
75	PONTAL DE CAMBURI	41	29	0.707317
76	ILHA DO BOI	23	21	0.913043
77	ILHA DO FRADE	8	6	0.750000
78	AEROPORTO	5	4	0.800000

[79 rows x 4 columns]

In [52]:
```
df_cleaned.groupby('neighbourhood')['waiting_days'].mean().plot(kind='bar',figsize=(15,
```



- JARDIM CAMBURI the highst location of the hospital appointment that mean these hosbital in the middel of city or has Excellent doctors but because of having third highest wating days mean alot of patients missing show up.
- ILHA DO BOI has the higest show up ratio and lowest wating days mean because of patient appointment is 23.
- this is normal relation between number of appointments and wating days so they must distribute patients on hosbital accoreding Hospital Accommodation

- the important factors to know in order to predict if a patient will show up for their scheduled appointment:
  - hipertension , Age and neighbourhood

Conclusions

2.0.10 Conclusions Results:

- Percentage of patients who show up on their appointments represents 71.48%
- Percentage of patients who Don't show up on their appointments represents 28.52%
- There is no strong correlation between any feature with show up.
- Both genders have same commitment to medical schedules. (71 %)
- Sms doesn't affect on patient's show up.
- young adults from 19 to 39 years old are the highest missed show up
- Patients Who didn't show up have more than 7 days of waiting.
- Patients Who show up have less than or equal 7 days .
- Relation between wating days and show up is negative.
- JARDIM CAMBURI is the most frequent place.
- ILHA DO BOI has the higest show up ratio .
- The important factors affect patient show up are: hipertension , Age and neighbourhood ### limitations:
- Data is imbalanced because males represent 33.2% of observations.
- Data collected from 2016-04-29 to 2016-06-08 .
- some patients who marked as no show up, in real they may show up but on another day
- Data must include time of sending sms to detect if sms send before appointment day with enough time or send after appointment day.