Investigate_a_Dataset

July 24, 2021

1 Project: Investigate Medical Appointment Dataset

1.1 Table of Contents

## Introduction

A person makes a doctor appointment, receives all the instructions and no-show. Who to blame? In this notebook we will try to analyze why would some patient not show up for his medical appointment and whether there are reasons for that using the data we have. We will try to find some correlation between the different attributes we have and whether the patient shows up or not.
The dataset we are going to use contains 110.527 medical appointments and its 14 associated variables (PatientId, AppointmentID, Gender, ScheduledDay, AppointmentDay, Age, Neighbourhood, Scholarship, Hipertension, Diabetes, Alcoholism, Handcap', SMS_received, No-show) #### Questions to answer * what is the percentage of noshow? * What factors are important for us to know in order to predict if a patient will show up for their scheduled appointment? - Is the time gender related to whether a patient will show or not? - Are patients with scholarship more likely to miss their appointment? - Are patients who don't recieve sms more likely to miss their appointment? - Is the time difference between the scheduling and appointment related to whether a patient will show? - Does age affect whether a patient will show up or not? - what is the percentage of patients missing their appointments for every neighbourhood

```
In [187]: #importing needed modules
          import numpy as np
          import matplotlib.pyplot as plt
          import seaborn as sns
          import pandas as pd
          #choose plots style
          sns.set_style('darkgrid')
          #make sure plots are inline with the notebook
          %matplotlib inline
```

## Data Wrangling

1.1.1 loading th dataset and checking the columns we have

```
In [188]: # Load your data and print out a few lines. Perform operations to inspect data
          #   types and look for instances of missing or possibly errant data.
          df = pd.read_csv('noshowappointments.csv')
          df.head()
```

```
Out[188]:       PatientId  AppointmentID Gender          ScheduledDay  \
          0  2.987250e+13        5642903      F  2016-04-29T18:38:08Z
          1  5.589978e+14        5642503      M  2016-04-29T16:08:27Z
          2  4.262962e+12        5642549      F  2016-04-29T16:19:04Z
          3  8.679512e+11        5642828      F  2016-04-29T17:29:31Z
          4  8.841186e+12        5642494      F  2016-04-29T16:07:23Z

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

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

```
In [189]: #get the shape and types of our data
          print(df.shape)
          pd.DataFrame(df.dtypes)
```

```
(110527, 14)
```

```
Out[189]:                     0
          PatientId       float64
          AppointmentID     int64
          Gender           object
          ScheduledDay     object
          AppointmentDay   object
          Age               int64
          Neighbourhood    object
          Scholarship       int64
          Hipertension      int64
          Diabetes          int64
          Alcoholism        int64
          Handcap           int64
          SMS_received      int64
          No-show          object
```

```
In [190]: #get some statistics about our data
          df.describe()
```

```
Out[190]:           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 [191]: #check if there is any missing values in our data
          df.info()
          df.isna().any()
```

```
<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
```

```
Out[191]: PatientId         False
          AppointmentID     False
          Gender            False
          ScheduledDay      False
          AppointmentDay    False
          Age               False
          Neighbourhood     False
          Scholarship       False
          Hipertension      False
          Diabetes          False
          Alcoholism        False
          Handcap           False
          SMS_received      False
          No-show           False
          dtype: bool
```

```
In [192]: #check if there is any duplicated rows in our data
          df.duplicated().any()
```

```
Out[192]: False
```

Notes on data exploration

we can see from the info we got from our analysis that there is some columns that needs to have its type corrected like dates. Another great finding is that our data doesn't have any duplicated or missing values. Also the column noshow can be a bit confusing and we can invert the values to make it more intuitive (show instead of noshow) and we can also turn it to integer instead of yes or no.

1.1.2 Data Cleaning

- Drop irrelevent columns
- Modify column names
- Correct data types
- Invert noshow column in to show with integer values
- Create a new column for days difference between scheduling and appointment

```
In [193]: #Drop irrelevent columns
          df.drop(['PatientId','AppointmentID'],axis=1,inplace=True)
          df.head()
```

```
Out[193]:   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
```

```
In [194]: #change all cloumns name to lower case and replace all - with _
          df.columns=df.columns.str.lower().str.replace('-','_')
          pd.DataFrame(df.columns)
```

```
Out[194]:                  0
          0           gender
          1     scheduledday
          2   appointmentday
          3              age
          4    neighbourhood
          5      scholarship
          6     hipertension
          7         diabetes
          8       alcoholism
          9          handcap
          10    sms_received
          11         no_show
```

```
In [195]: #change data columns to data type
          df['scheduledday']=pd.to_datetime(df['scheduledday'])
          df['appointmentday']=pd.to_datetime(df['appointmentday'])
```

```
In [196]: #Turn no_show column to show
          print(df.no_show.unique())
          df.no_show=df.no_show.map({'No':1,'Yes':0})
          df.rename(columns={'no_show':'show'},inplace=True)
          print(df.show.unique())
          df.head()
```

```
['No' 'Yes']
[1 0]
```

```
Out[196]:   gender        scheduledday appointmentday  age      neighbourhood  \
          0      F 2016-04-29 18:38:08     2016-04-29   62    JARDIM DA PENHA
          1      M 2016-04-29 16:08:27     2016-04-29   56    JARDIM DA PENHA
          2      F 2016-04-29 16:19:04     2016-04-29   62      MATA DA PRAIA
          3      F 2016-04-29 17:29:31     2016-04-29    8  PONTAL DE CAMBURI
          4      F 2016-04-29 16:07:23     2016-04-29   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

             show
          0     1
          1     1
          2     1
          3     1
          4     1
```

```
In [197]: #Create a new column for days difference between scheduling and appointment
          day_diff=(df.appointmentday.dt.date-df.scheduledday.dt.date).dt.days
          df.insert(3,'day_diff',day_diff)
          df.day_diff.dtype
```

```
Out[197]: dtype('int64')
```

```
In [198]: #check data one last time
          df.dtypes
```

```
Out[198]: gender                    object
          scheduledday      datetime64[ns]
          appointmentday    datetime64[ns]
          day_diff                   int64
          age                        int64
          neighbourhood             object
          scholarship                int64
          hipertension               int64
          diabetes                   int64
          alcoholism                 int64
          handcap                    int64
          sms_received               int64
          show                       int64
          dtype: object
```

Notes on data Cleaning

Now that we have our data cleaned and with the proper type for every column and also created new Time difference column we can start analyzing our data and try to find the correlation between differnt variables and the show column

## Exploratory Data Analysis

```
In [199]: #define function to get the ratio of show in different categories
          def plot_rat(x):
              df.groupby(x).show.mean().plot(kind='bar').set_ylabel('Ratio of show');
          #     plt.legend()
```

1.1.3 what is the percentage of noshow?

```
In [200]: #get some statistics about our data
          df.describe()
```

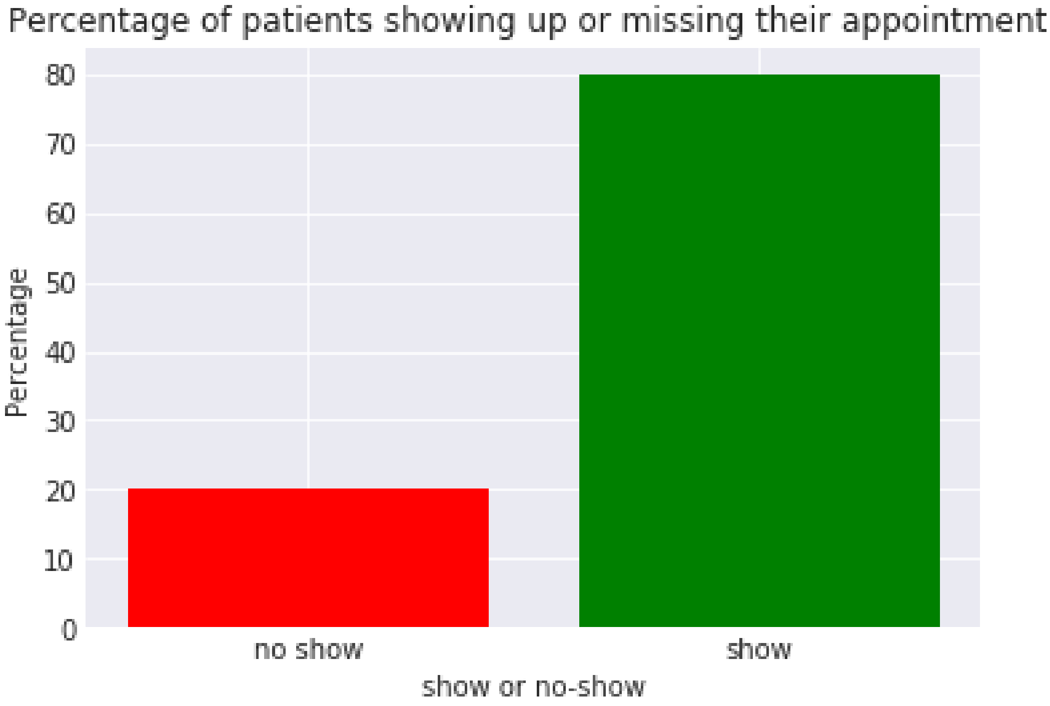
```
Out[200]:             day_diff            age    scholarship   hipertension  \
          count  110527.000000  110527.000000  110527.000000  110527.000000
          mean       10.183702      37.088874       0.098266       0.197246
          std        15.254996      23.110205       0.297675       0.397921
          min        -6.000000      -1.000000       0.000000       0.000000
          25%         0.000000      18.000000       0.000000       0.000000
          50%         4.000000      37.000000       0.000000       0.000000
          75%        15.000000      55.000000       0.000000       0.000000
          max       179.000000     115.000000       1.000000       1.000000

                      diabetes    alcoholism        handcap   sms_received  \
          count  110527.000000  110527.000000  110527.000000  110527.000000
          mean        0.071865       0.030400       0.022248       0.321026
          std         0.258265       0.171686       0.161543       0.466873
          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       1.000000
          max         1.000000       1.000000       4.000000       1.000000

                          show
          count  110527.000000
          mean        0.798067
          std         0.401444
          min         0.000000
          25%         1.000000
          50%         1.000000
          75%         1.000000
          max         1.000000
```

```
In [201]: # percentage of show and no show
          print(f"percentage of patients who didn't show up for their appointment is { (1-df.sho
          no_show=len(df[df.show==0])/len(df.show)
```

```
show=len(df[df.show==1])/len(df.show)
plt.bar(['show','no show'],[show*100,no_show*100],color=['g','r']);
plt.title('Percentage of patients showing up or missing their appointment ');
plt.ylabel('Percentage');
plt.xlabel('show or no-show');
df.groupby('show')[['show']].count()
```

```
percentage of patients who didn't show up for their appointment is 20.193255946510803 %
```

```
Out[201]:        show
          show
          0     22319
          1     88208
```



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

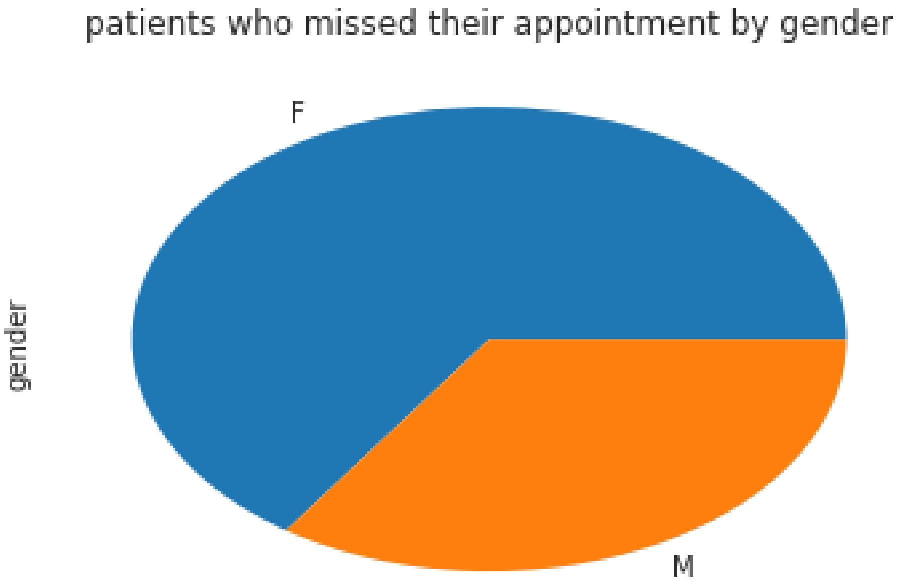
```
In [202]: #create filters for show and noshow
          show=(df.show == 1)
          noshow=(df.show == 0)
          total_miss=len(df[noshow])
          total=len(df)
```

1.1.5 Is the time gender related to whether a patient will show or not?

```
In [203]: #get the number of patients missing their appointments by gender
          noshow_gender=df[noshow]['gender'].value_counts()
          noshow_gender.plot(kind='pie');
          plt.title('patients who missed their appointment by gender');
          print('percentage of Females and Males who missed their appointment:')
          #get the percentage of patients missing their appointments by gender
          pd.DataFrame(noshow_gender*100/total)
```

```
percentage of Females and Males who missed their appointment:
```

```
Out[203]:       gender
          F  13.204013
          M   6.989242
```



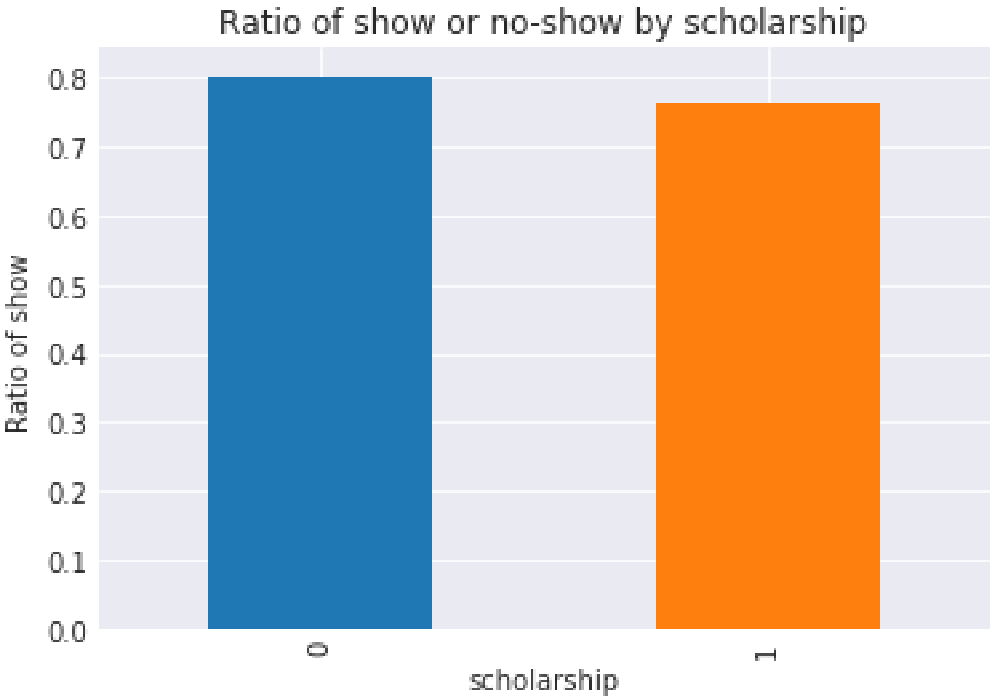
Finding

The percentage of females missing their appointment is nearly two time the males.So females are more likely to miss their appointment.

1.1.6 Are patients with scholarship more likely to miss their appointment?

```
In [204]: #what is the percentage of patients missing their appointment by scholarship
          plot_rat(df.scholarship)
          plt.title('Ratio of show or no-show by scholarship')
          df.groupby('scholarship')[['show']].mean()
```

```
Out[204]:                  show
          scholarship
          0            0.801928
          1            0.762637
```



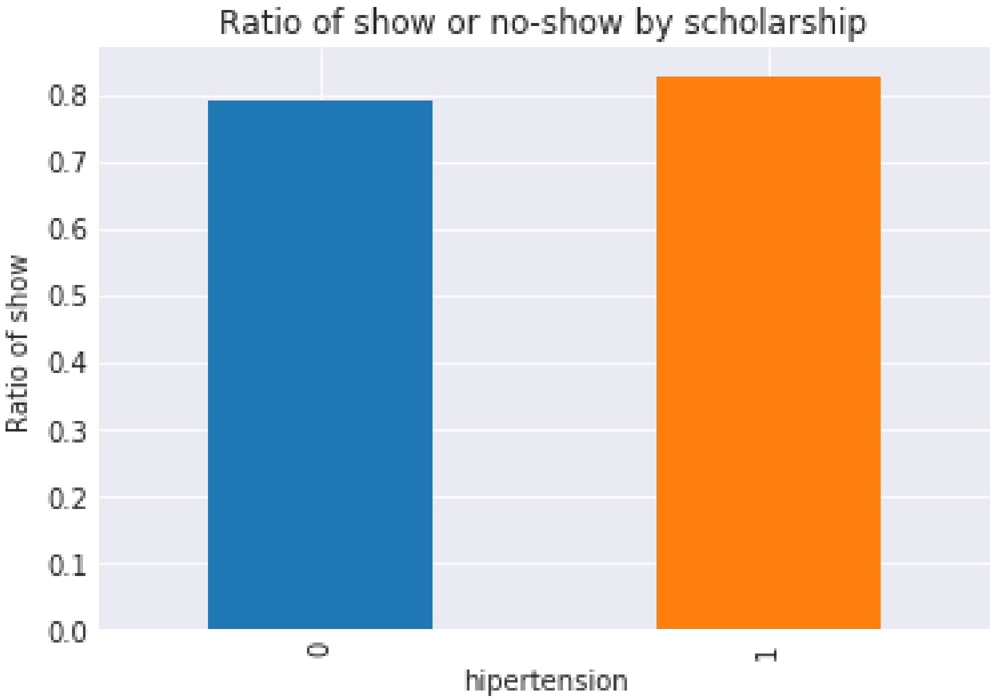
Finding

It seems that patients with scholarship are actually more likely to miss their appointment

1.1.7 Are patients with hipertension more likely to miss their appointment?

```
In [205]: #what is the percentage of patients missing their appointment by hipertension
          plot_rat(df.hipertension)
          plt.title('Ratio of show or no-show by scholarship')
          df.groupby('hipertension')[['show']].mean()
```

```
Out[205]:                  show
          hipertension
          0             0.790963
          1             0.826980
```



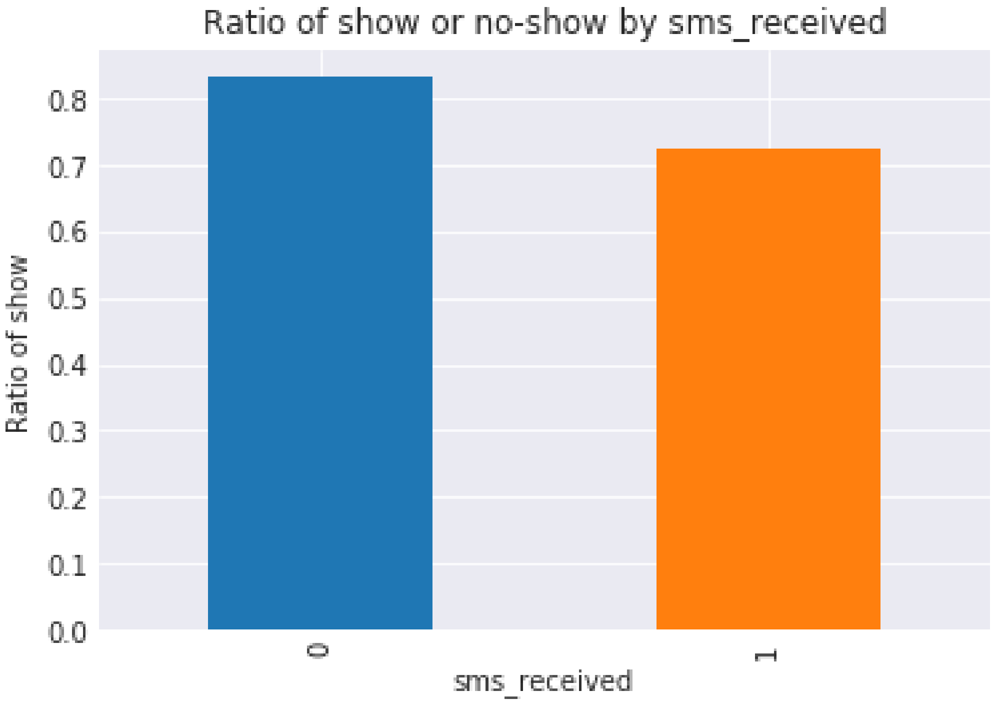
Finding

It seems that patients with hipertension are actually more likely to show up for their appointment

1.1.8 Are patients who don't recieve sms more likely to miss their appointment?

```
In [206]: #what is the percentage of patient who attended their appointment by sms_received
          plot_rat(df.sms_received)
          plt.title('Ratio of show or no-show by sms_received')
          df.groupby('sms_received')[['show']].mean()
```

```
Out[206]:                   show
          sms_received
          0             0.832967
          1             0.724255
```



Finding

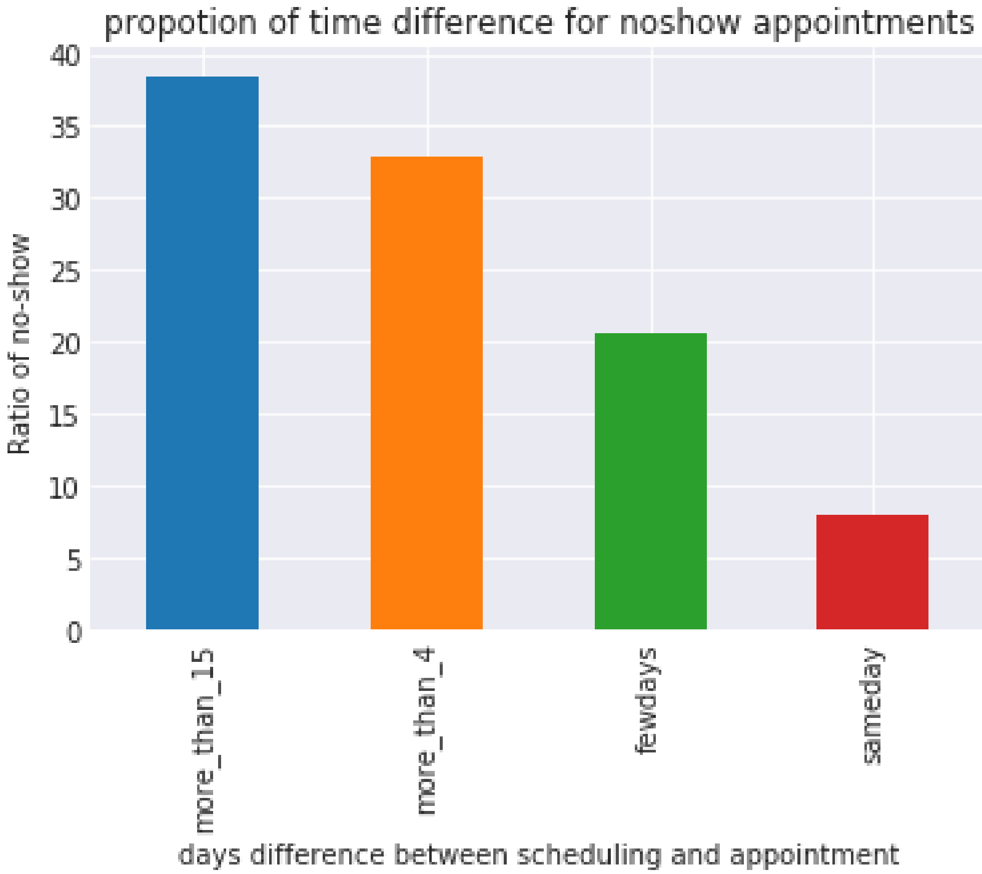
A strange finding here suggests that patients who received a sms are more likely to miss their appointment !!

1.1.9 Is the time difference between the scheduling and appointment related to whether a patient will show?

```
In [207]: #filter for positive day difference
          df1=df[df.day_diff>=0]
          # df1.day_diff.unique()
          #turn day diff into categorical column Day_diff2
          bin_edges=[-1,0,4,15,179]
          names=['sameday','fewdays','more_than_4','more_than_15']
          df['day_diff2']=pd.cut(df1.day_diff,bin_edges,labels=names)
          #filter for noshow records and count values for each category of day_diff2

          noshow_day_diff=df[noshow].day_diff2.value_counts()/len(df[noshow])*100
          noshow_day_diff.plot(kind='bar');
          plt.title('propotion of time difference for noshow appointments');
          plt.xlabel('days difference between scheduling and appointment');
          plt.ylabel('Ratio of no-show');
          print('the propotion of different time difference for patients who missed their appion
          pd.DataFrame(noshow_day_diff)
```

```
the propotion of different time difference for patients who missed their appiontments:
```

```
Out[207]:                day_diff2
          more_than_15  38.460505
          more_than_4   32.922622
          fewdays       20.565438
          sameday        8.029034
```



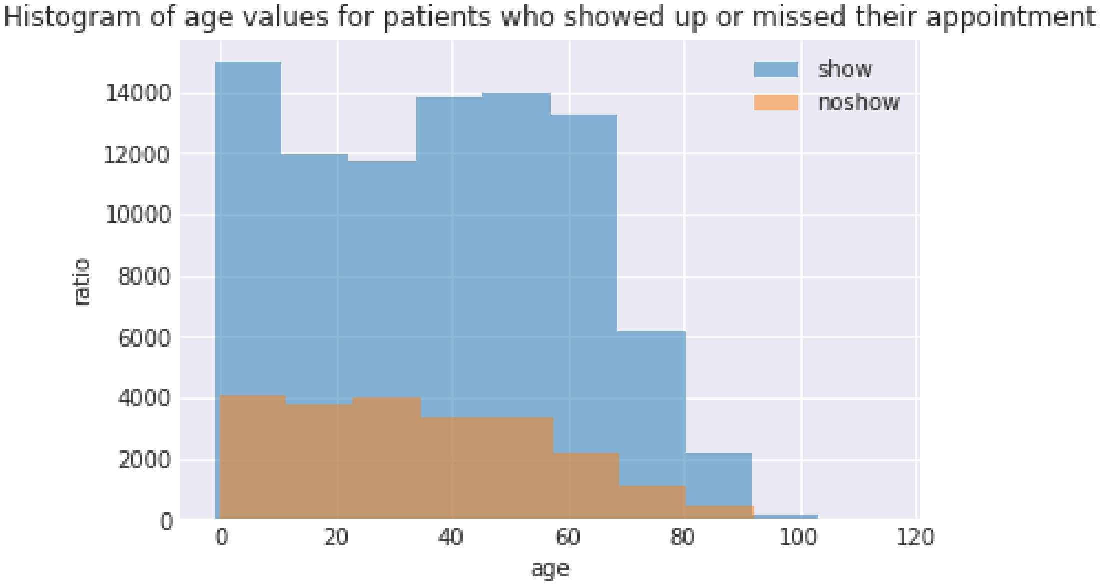
Finding

It appears that the longer the period between the scheduling and appointment the more likely the patient won't show up.

1.1.10 does age affect whether a patient will show up or not?

```
In [208]: #plot the histograns of age for patients who showed up and who didn't
          df[show].age.hist(alpha=0.5,label='show')
          df[noshow].age.hist(alpha=0.5,label='noshow')
          plt.legend()
          plt.xlabel('age')
plt.ylabel('ratio')
plt.title('Histogram of age values for patients who showed up or missed their appointm
#ger the mean age for patients who showed up and who didn't
df[noshow][['age']].describe()
```

```
Out[208]:                age
          count  22319.000000
          mean      34.317667
          std       21.965941
          min        0.000000
          25%       16.000000
          50%       33.000000
          75%       51.000000
          max      115.000000
```



Finding

there is no clear relation between the age and whether the patiens shows up or not but yonger patients are slightly more likely to miss their appointments.

1.1.11 what is the percentage of patients missing their appointments for every neighbourhood

```
In [209]: #get the number of records for each neighbourhood
          rec_neigh=df['neighbourhood'].value_counts()
          #get the number of records for patients missing their appointments for each neighbourh
          rec_neigh_noshow=df[noshow].neighbourhood.value_counts()
          #percentage of patients missing their appointments for every neighbourhood
          rec_neigh_noshow_percentage=rec_neigh_noshow/rec_neigh
          pd.DataFrame(rec_neigh_noshow_percentage.sort_values(axis=0, ascending=False))
```

```
Out[209]:                              neighbourhood
          ILHAS OCEÂNICAS DE TRINDADE       1.000000
          SANTOS DUMONT                     0.289185
          SANTA CECÍLIA                     0.274554
          SANTA CLARA                       0.264822
          ITARARÉ                           0.262664
          JESUS DE NAZARETH                 0.243954
          HORTO                             0.240000
          ILHA DO PRÍNCIPE                  0.234775
          CARATOÍRA                         0.230409
          ANDORINHAS                        0.230327
          PRAIA DO SUÁ                      0.228261
          GURIGICA                          0.225966
          BENTO FERREIRA                    0.224942
          PARQUE MOSCOSO                    0.223192
          MARUÍPE                           0.222923
          DO MOSCOSO                        0.222760
          ENSEADA DO SUÁ                    0.221277
          ARIOVALDO FAVALESSA               0.219858
          ILHA DAS CAIEIRAS                 0.219421
          FONTE GRANDE                      0.218475
          CRUZAMENTO                        0.217454
          SÃO JOSÉ                          0.216490
          BARRO VERMELHO                    0.215130
          NAZARETH                          0.214815
          ROMÃO                             0.213995
          CENTRO                            0.210858
          UNIVERSITÁRIO                     0.210526
          SÃO PEDRO                         0.210376
          MARIA ORTIZ                       0.209991
          SANTA HELENA                      0.207865
          ...                                    ...
          CONQUISTA                         0.188457
          FRADINHOS                         0.186047
          BOA VISTA                         0.185897
          ANTÔNIO HONÓRIO                   0.184502
          PRAIA DO CANTO                    0.183575
          FORTE SÃO JOÃO                    0.183166
          TABUAZEIRO                        0.182950
          JOANA DťARC                       0.180799
          COMDUSA                           0.180645
          SANTA LUÍZA                       0.179907
          JABOUR                            0.179753
          NOVA PALESTINA                    0.177562
          REDENÇÃO                          0.177077
          SANTO ANTÔNIO                     0.176256
          PONTAL DE CAMBURI                 0.173913
          CONSOLAÇÃO                        0.172238
```

```
REPÚBLICA                           0.171257
MATA DA PRAIA                       0.170807
MORADA DE CAMBURI                   0.166667
VILA RUBIM                          0.165687
DO QUADRO                           0.164900
JARDIM DA PENHA                     0.162755
SANTA MARTHA                        0.158416
DO CABRAL                           0.157143
DE LOURDES                          0.154098
SOLON BORGES                        0.147122
MÁRIO CYPRESTE                      0.145553
AEROPORTO                           0.125000
ILHA DO BOI                         0.085714
PARQUE INDUSTRIAL                        NaN

[81 rows x 1 columns]
```

## Conclusions

After analyzing the dataset here are some findings: 1- percentage of patients who didn't show up for their appointment is 20.19% .

2- The percentage of females missing their appointment is nearly two time the males.So females are more likely to miss their appointment.

3- It appears that the longer the period between the scheduling and appointment the more likely the patient won't show up.

4- It seems that patients with scholarship are actually more likely to miss their appointment.

5- A strange finding here suggests that patients who received a sms are more likely to miss their appointment !!

6- There is no clear relation between the age and whether the patients shows up or not but younger patients are slightly more likely to miss their appointments.

Analysis Shortcoming & Data Limitations

- The data doesn't state the exact hour of the appointment which would have been very useful to try to find out which hours has the most missing appointments and which doesn't. It could also be very useful to know the difference between scheduling and the appointment since many of the scheduling are on the same day.
- The data doesn't state if any day is vacation or not which can indicate if people tend to miss their appointments more on working days.
- The age column had a negative value but according to the data creator, it means a baby not porn yet (a pregnant woman).
- when calculating day difference between the scheduling and appointment days we had some negative value which make no sense and might mean that the records of questions have wrong data.

1.2 Submitting your Project

Before you submit your project, you need to create a .html or .pdf version of this notebook in the workspace here. To do that, run the code cell below. If it worked correctly, you should get a return code of 0, and you should see the generated .html file in the workspace directory (click on the orange Jupyter icon in the upper left).

Alternatively, you can download this report as .html via the **File** > **Download as** submenu, and then manually upload it into the workspace directory by clicking on the orange Jupyter icon in the upper left, then using the Upload button.

Once you've done this, you can submit your project by clicking on the "Submit Project" button in the lower right here. This will create and submit a zip file with this .ipynb doc and the .html or .pdf version you created. Congratulations!

```
In [210]: from subprocess import call
          call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])

Out[210]: 0

In [ ]:
```