Investigate_a_Dataset

July 24, 2021

1 Project: Investigate Medical Appointment Dataset

1.1 Table of Contents

Introduction
Data Wrangling
Exploratory Data Analysis
Conclusions
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 [63]: #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 [64]:
```
# 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[64]:

	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

In [65]:
```
#get the shape and types of our data
print(df.shape)
pd.DataFrame(df.dtypes)
```

```
(110527, 14)
```

Out[65]:

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

Out[66]:

	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 [67]: #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[67]: 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 [68]: #check if there is any duplicated rows in our data
         df.duplicated().any()
```

```
Out[68]: 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 [69]: #Drop irrelevent columns
         df.drop(['PatientId','AppointmentID'],axis=1,inplace=True)
         df.head()
```

Out[69]:

	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_received	No-show
0	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	0	1	0	0	0	0	No
1	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	0	0	0	0	0	No
2	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	0	0	0	0	0	0	No
3	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	0	0	0	0	0	0	No
4	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	1	1	0	0	0	No

In [70]:
```
#change all cloumns name to lower case and replace all - with _
df.columns=df.columns.str.lower().str.replace('-','_')
pd.DataFrame(df.columns)
```

Out[70]:

	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 [71]:
```
#change data columns to data type
df['scheduledday']=pd.to_datetime(df['scheduledday'])
df['appointmentday']=pd.to_datetime(df['appointmentday'])
```

In [72]:
```
#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[72]:

	gender	scheduledday	appointmentday	age	neighbourhood	scholarship	hipertension	diabetes	alcoholism	handcap	sms_received	show
0	F	2016-04-29 18:38:08	2016-04-29	62	JARDIM DA PENHA	0	1	0	0	0	0	1
1	M	2016-04-29 16:08:27	2016-04-29	56	JARDIM DA PENHA	0	0	0	0	0	0	1
2	F	2016-04-29 16:19:04	2016-04-29	62	MATA DA PRAIA	0	0	0	0	0	0	1
3	F	2016-04-29 17:29:31	2016-04-29	8	PONTAL DE CAMBURI	0	0	0	0	0	0	1
4	F	2016-04-29 16:07:23	2016-04-29	56	JARDIM DA PENHA	0	1	1	0	0	0	1

In [73]:
```
#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[73]:
```
dtype('int64')
```

In [74]:
```
#check data one last time
df.dtypes
```

Out[74]:
```
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 [75]: #define function to get the ratio of show in different categories
         def plot_rat(x):
             df.groupby(x).show.mean().plot(kind='bar',
                                            edgecolor='black',
                                            figsize=(14,8)).set_ylabel('Ratio of show');
             display(df.groupby(x)[['show']].mean())
         #     plt.legend()
```

1.1.3 what is the percentage of noshow?

```
In [76]: #get some statistics about our data
         df.describe()
```

Out[76]:

	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	

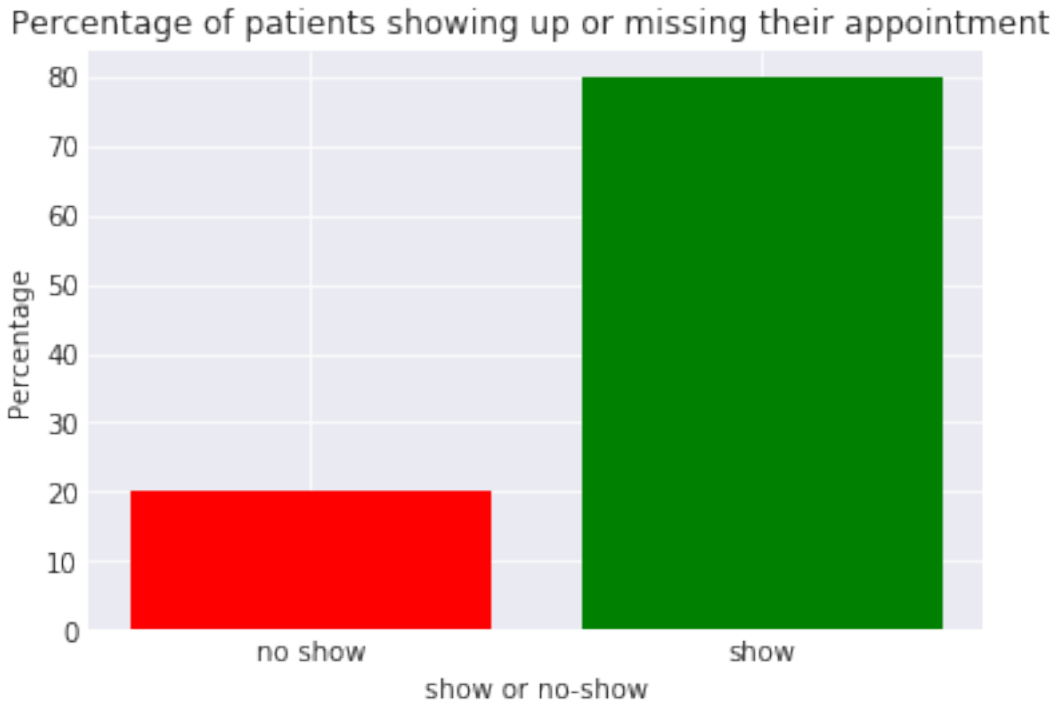
	diabetes	alcoholism	handcap	sms_received	\
count	110527.000000	110527.000000	110527.000000	110527.000000	
mean	0.071865	0.030400	0.022248	0.321026	
std	0.258265	0.171686	0.161543	0.466873	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	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 [77]:
```
# percentage of show and no show
print(f"percentage of patients who didn't show up for their appointment is { (1-df.show
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');
display(df.groupby('show')[['show']].count())
```

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

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 [78]:
```
#create filters for show and noshow
show=(df.show == 1)
```

```
noshow=(df.show == 0)
total_miss=len(df[noshow])
total=len(df)
```

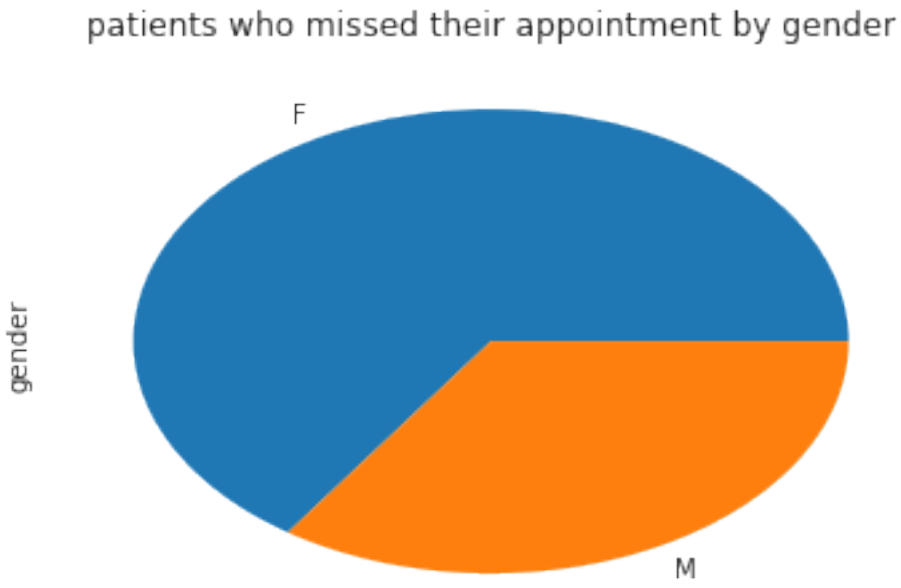
1.1.5 Is the time gender related to whether a patient will show or not?

In [79]:
```
#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)
```

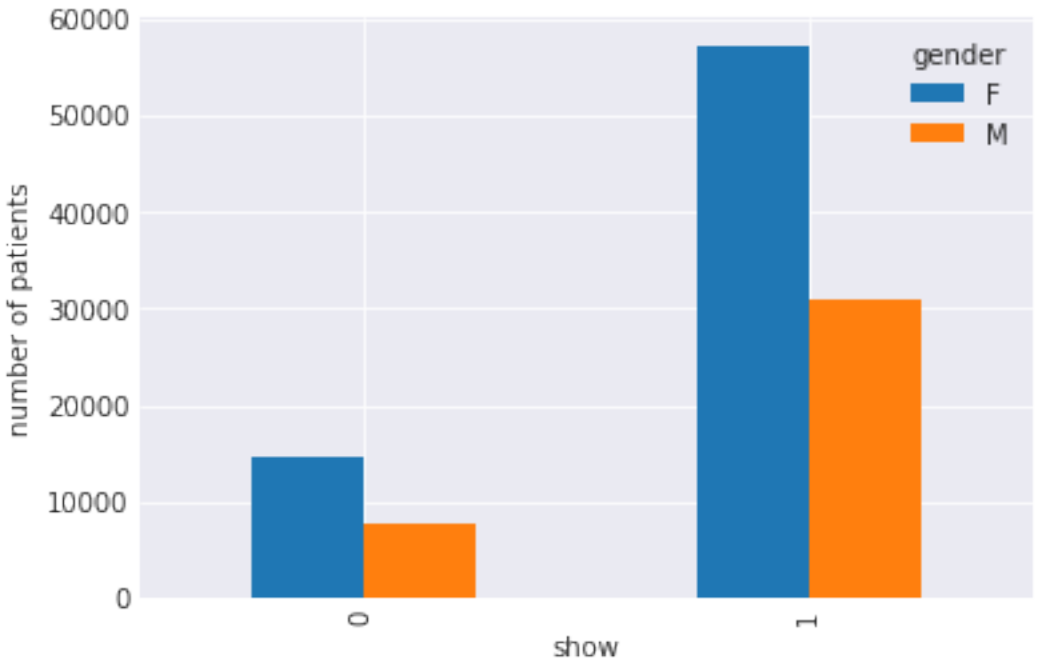
```
percentage of Females and Males who missed their appointment:
```

Out[79]:

	gender
F	13.204013
M	6.989242



In [80]:
```
df.groupby(['gender','show']).size().unstack('gender').plot(kind='bar').set_ylabel('num
```



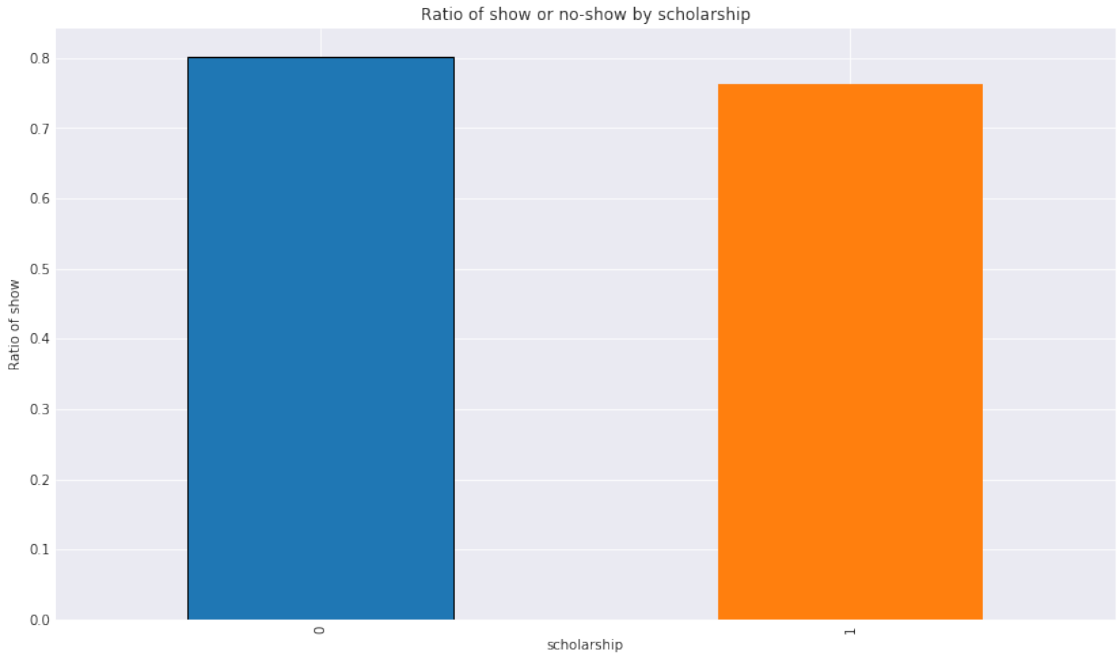
Finding

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 [81]: #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()
```

```
                show
scholarship
0            0.801928
1            0.762637
```



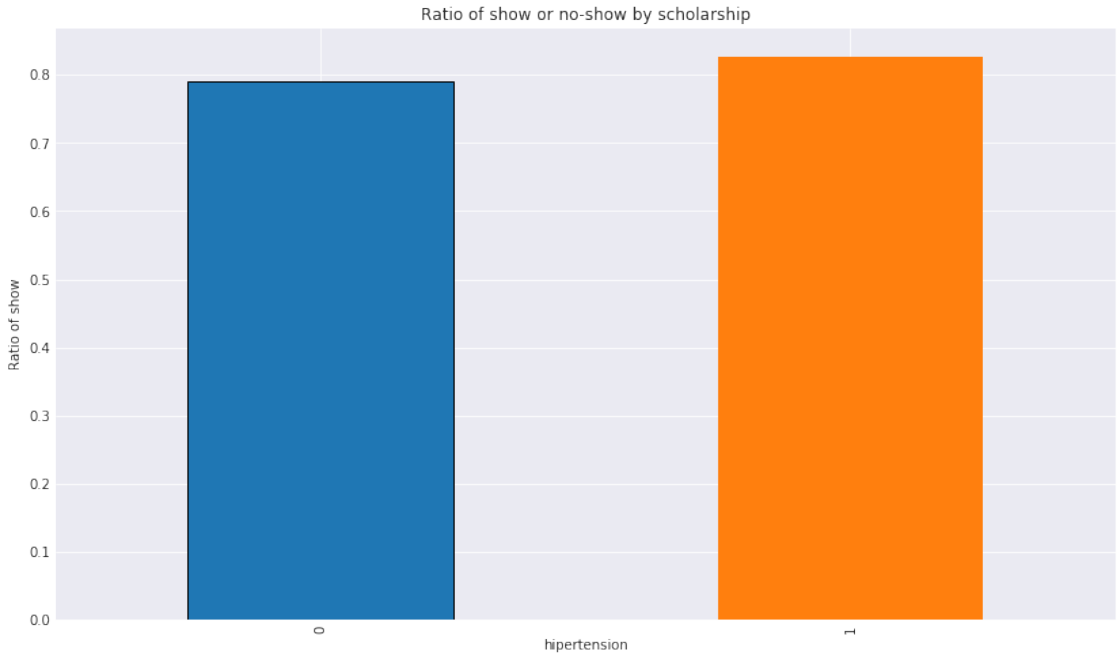
Finding

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 [82]: #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');
```

```
                show
hipertension
0           0.790963
1           0.826980
```



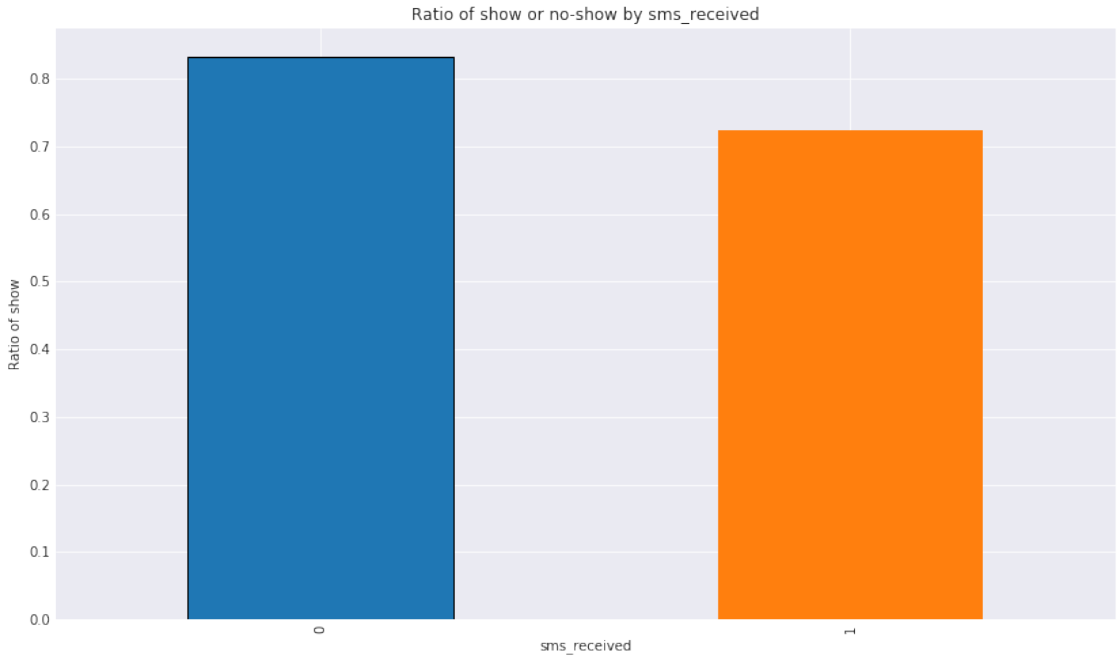
Finding

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 [83]: #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');
```

```
                  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 !!

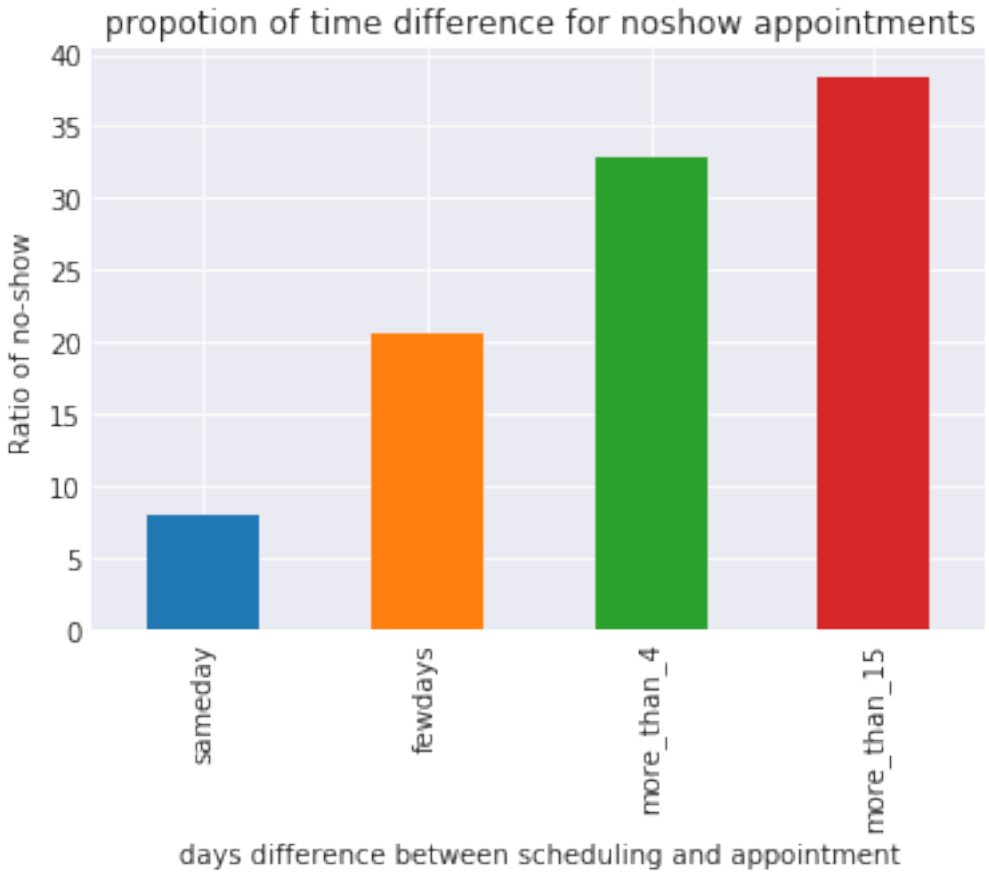
1.1.9 Is the time difference between the scheduling and appointment related to whether a patient will show?

```
In [84]: #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.reindex(names).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 appiont
         pd.DataFrame(noshow_day_diff)
```

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

Out[84]:
```
                day_diff2
more_than_15    38.460505
more_than_4     32.922622
fewdays         20.565438
sameday          8.029034
```



Finding

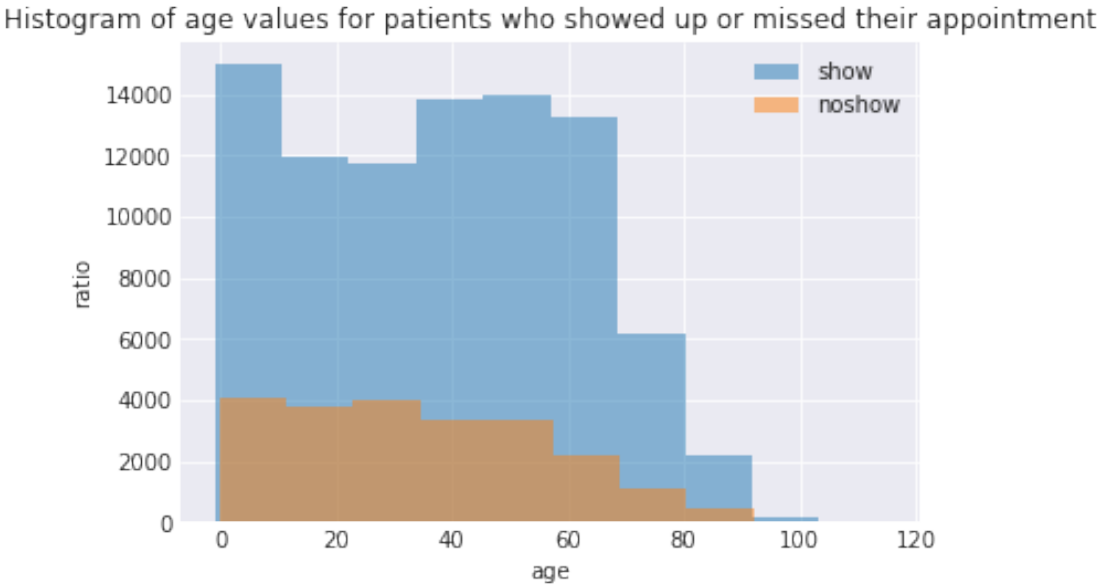
It appears that the longer the period between the scheduling and appointment the more likely the patient won't show up.

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

In [85]:
```
#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 appointme
#ger the mean age for patients who showed up and who didn't
df[noshow][['age']].describe()
```

Out[85]:

	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 [86]:
```
#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 neighbourho
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[86]:

	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 D'ARC	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.

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

```
Out[210]: 0
```

```
In [ ]:
```