Project: Database_No_show_appointments

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Introduction

This dataset collects information from 100k medical appointments in Brazil and is focused on the question of whether patients show up for their appointment or not. Several characteristics about the patient are included in each row.

‘ScheduledDay’ tells us on what day the patient set up their appointment. ‘Neighborhood’ indicates the location of the hospital. ‘Scholarship’ indicates whether or not the patient is enrolled in Brasilian welfare program Bolsa Familia. Be careful about the encoding of the last column: it says ‘No’ if the patient showed up to their appointment, and ‘Yes’ if they did not show up.

question:

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

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

I used head and tail for my dataset to quick look at some of the first data and last data in my dataset. it helps me to have general view about data.

In [2]:
```
data=pd.read_csv("KaggleV2-May-2016.csv")
data.head()
```

Out[2]:

	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

by using data.info() I can understand type of my data and number of missing data as we see in this dataset, we do not have any missing data. the number of Non-Null in each field is equal to total rows

In [4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   PatientId       110527 non-null  float64
 1   AppointmentID   110527 non-null  int64
 2   Gender          110527 non-null  object
 3   ScheduledDay    110527 non-null  object
 4   AppointmentDay  110527 non-null  object
 5   Age             110527 non-null  int64
 6   Neighbourhood   110527 non-null  object
 7   Scholarship     110527 non-null  int64
 8   Hipertension    110527 non-null  int64
 9   Diabetes        110527 non-null  int64
 10  Alcoholism      110527 non-null  int64
 11  Handcap         110527 non-null  int64
 12  SMS_received    110527 non-null  int64
 13  No-show         110527 non-null  object
dtypes: float64(1), int64(8), object(5)
memory usage: 11.8+ MB
```

Now, we need to check duplicated rows if we find any duplicated rows, we remove them by data.drop_duplicates()

In [37]:
```
data.duplicated().sum()
```

Out[37]: 0

Like missing value, we do not have any duplicated values.

Exploratory Data Analysis

Research Question 1 (what properties of patients are important to predict they will show up or not??)
First of all we need to use mask for Yes and No in "No-show" field to write program better

In [6]:
```
not_show=data["No-show"]=="Yes"
show=data["No-show"]=="No"
```

Then we want to analysis Age of patients. We interested to know average of patients age who show up and average of patients age who not show up.

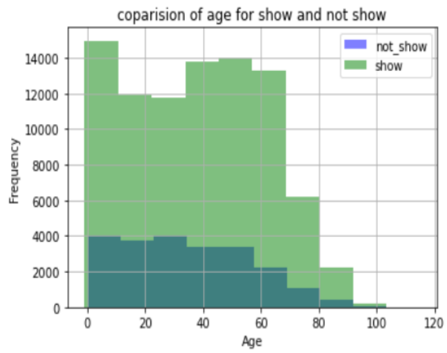
In [7]:
```
data["Age"][not_show].mean(),data["Age"][show].mean()
```

Out[7]: (34.31766656212196, 37.790064393252315)

Mean of patients age who show up is more than mean of patients not show up.

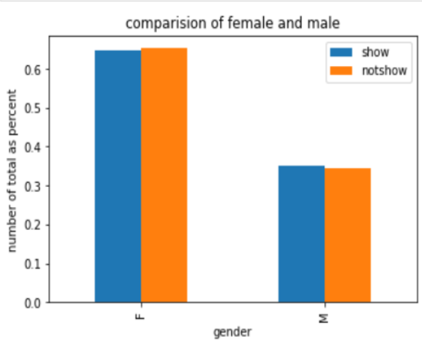
We can draw histogram for age in each group:

In [25]:
```
data.Age[not_show].hist(alpha=0.5,color="b",label="not_show")
data.Age[show].hist(alpha=0.5,color="g",label="show")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.title("coparision of age for show and not show")
plt.legend()
plt.show()
```



In the next step, we are interested in analyzing the trend of Gender can be changed from show to not show ,in other words, we want to know for example number of men increase from show up to not show up or not

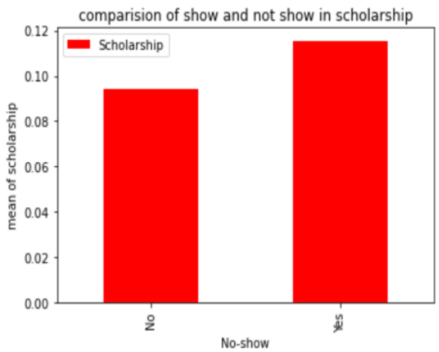
In [26]:
```
total_show=data[show].Age.count()
total_notshow=data[not_show].Age.count()
percent_show=data[show].groupby("Gender").count().Age/total_show
percent_notshow=data[not_show].groupby("Gender").count().Age/total_notshow
percent_notshow
pd.DataFrame({"show":percent_show,"notshow":percent_notshow},index=["F","M"]).plot(kind="bar")
plt.xlabel("gender")
plt.ylabel("number of total as percent")
plt.title("comparision of female and male")
plt.show()
```



This chart illustrates percent of female is increased from show to not show, conversely for male is decreased. Thus, female have more effect for the patients who not show up.

effect of Scholarship on showing up:

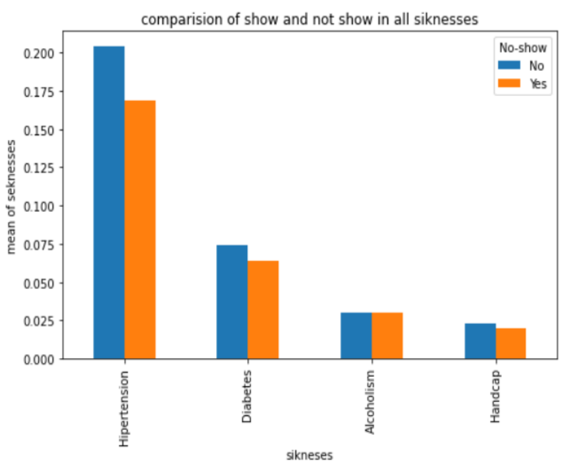
In [28]:
```
data.groupby("No-show").mean()["Scholarship"].plot.bar(color="r",label="Scholarship");
plt.legend()
plt.ylabel("mean of scholarship")
plt.title("comparision of show and not show in scholarship")
plt.show()
```



This chart indicates patients who are not show up, more enrolled in Brasilian welfare program.

At this time we need to focus of these field: "Hypertension", "Diabetes", "Alcoholism", "Handicap".

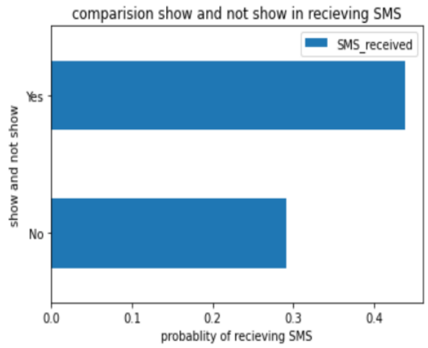
In [31]:
```
d1=data.groupby("No-show").mean()[["Hipertension","Diabetes","Alcoholism","Handcap"]].round(3)
pd.DataFrame(d1.values.T,index=d1.columns,columns=d1.index).plot.bar(figsize=(8,5));
plt.xlabel("sikneses")
plt.ylabel("mean of seknesses")
plt.title("comparision of show and not show in all siknesses")
plt.show()
```



In this chart we can easily compare any sickness in two state of show and not show up. the average of patients who show up and not in Alcoholism is the same. but for other three sickness this average is decreased from patients who show up to not show up.

Next step, we need to consider processing of SMS

```
In [32]:
data.groupby("No-show").mean()["SMS_received"].plot.barh(label="SMS_received")
plt.xlabel("probablity of recieving SMS")
plt.ylabel("show and not show")
plt.legend()
plt.title("comparision show and not show in recieving SMS")
plt.show()
```



This chart shows us people who do not show up received SMS more than people show up. Thus, receiving SMS could not be useful action to inform them about their appointment.

```
In [15]:
d2=data.groupby(["No-show","Gender"]).mean()["SMS_received"]
d2
```

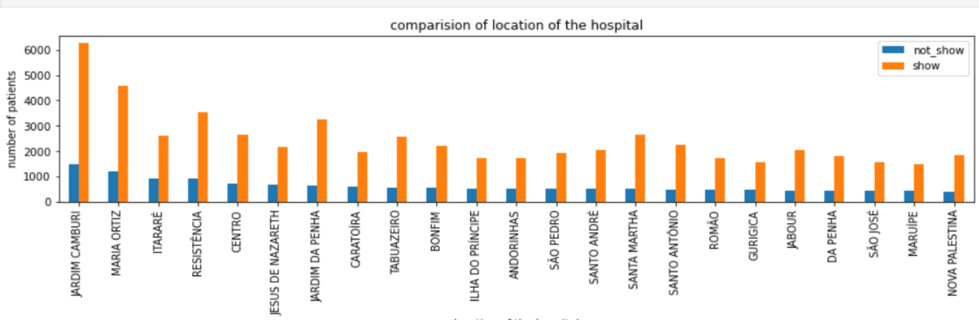
```
Out[15]: No-show  Gender
         No       F         0.305384
                  M         0.265358
         Yes      F         0.460463
                  M         0.396634
         Name: SMS_received, dtype: float64
```

Prior report illustrates average of receiving SMS in female people who do not show up is more than others.

As we know ‘Neighborhood’ indicates the location of the hospital we have lots of locations. We want to compare number of patients who show up and patients who are not show up in each location to know which locations patients who not show up increased (because of the number of location is a lot, we analyse for locations where have at least 400 patients)

```
In [33]:
d2=data["Neighbourhood"][not_show].value_counts()[data["Neighbourhood"][not_show].value_counts()>400]
d0=data["Neighbourhood"][show].value_counts()
d1=d0[d2.index]

pd.DataFrame({"not_show":d2,"show":d1},index=d2.index).plot.bar(figsize=(15,3))
plt.legend()
plt.xlabel("location of the hospital")
plt.ylabel("number of patients")
plt.title("comparision of location of the hospital")
plt.show()
```



As we see in this chart, we should to find some locations that patients who show up increased from one location to another, while, patients who not show up decreased in this situation. For example, from JESUD DE NAZARETH to JARDIM DA PENHA.

Finally, we need to check out duration of time between schedule time and appointment time. it seems for one patient that happen a long duration time between schedule and appointment time, he does not show up. we need to change format of these columns from string to timestamp then calculate difference them. Finally, we get total hours between schedule time and appointment time these value could be added to dataframe to get new report using it.

In [18]:
```
data["ScheduledDay"]=data["ScheduledDay"].apply(lambda x: pd.to_datetime(x))
data["AppointmentDay"]=data["AppointmentDay"].apply(lambda x: pd.to_datetime(x))
data["hours_diff"]=(data["ScheduledDay"]-data["AppointmentDay"]).apply(lambda diff: abs(diff.days*24+int(str(diff)[-8:-6])))
```

we need to check to confirm that this field added or not

In [19]:
```
data.head(2)
```

Out[19]:

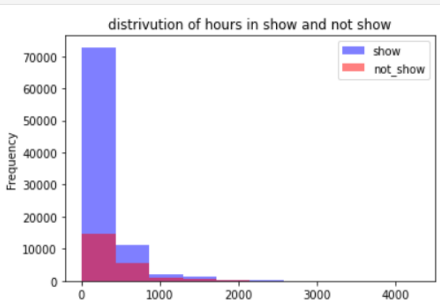
	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_received	No-show
0	2.987250e+13	5642903	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	62	JARDIM DA PENHA	0	1	0	0	0	0	No
1	5.589978e+14	5642503	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	0	0	0	0	0	0	No

In [20]:
```
data.groupby("No-show").mean()["hours_diff"]
```

Out[20]:
```
No-show
No     207.943871
Yes    370.476634
Name: hours_diff, dtype: float64
```

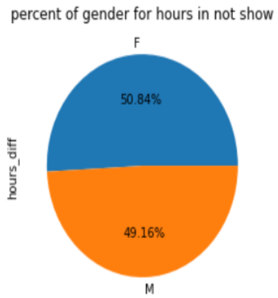
By this value, we understand, when calculates duration between scheduled date and appointment date by hours, patients will prefer to not show up if this duration takes a long time. Thus, we can just consider patients who those dates are close together (schedule date and appointment date).

In [35]:
```
data["hours_diff"][show].hist(label="show",color="b",alpha=0.5)
data["hours_diff"][not_show].hist(label="not_show",color="r",alpha=0.5)
plt.grid(False)
plt.legend()
plt.title("distrivution of hours in show and not show")
plt.xlabel("hours")
plt.ylabel("Frequency")
data["hours_diff"][not_show].count()
plt.show()
```



By this top graph, hours around 0 to 400 between schedule date and appointment date for both show up and not show up is really a lot and they gradually decreased.

In [36]:
```
data[not_show].groupby("Gender").mean()["hours_diff"].plot(kind="pie",autopct="%1.2f%%");
plt.title("percent of gender for hours in not show")
plt.show()
```



This chart displays that hours between schedule date and appointment date for female who not show up are more than male who are not show up.

Conclusions

1. Age of patients who show and patients do not show are really close together and there is no big difference between them.
2. Number of female and male from show up state to no show up have a little changed.
3. There is big difference between patients who received SMS and show up versus patients received SMS and not show up.
4. Patients who have disease ("Hypertension", "Diabetes", "Handicap") are more likely show up than not show up.
5. There is high proportion of percentage (upper than 75%) in average of duration between schedule date and appointment date for patients who not show up against show up.