Project: Investigate a Dataset - No-show

Table of Contents

- Introduction
- Data Wrangling
- Exploratory Data Analysis
- Conclusions

Introduction

Dataset Summary

No-show appointments (original source on <a href="Kaggle_(https://www.google.com/url?ge=https://www.kaggle.com/joniarroba/noshowappointments&sa=D&ust=1532469042118000)): This dataset collects information from 100k medical appointments in Brazil and is focused on the question of whether or not patients show up for their appointment. A number of characteristics about the patient are included in each row.

Columns Description

01 - PatientId

Identification of a patient

02 - AppointmentID

Identification of each appointment

03 - Gender

Male or Female . Female is the greater proportion, woman takes way more care of they health in comparison to man.

04 - ScheduledDay

The day of the actual appointment, when they have to visit the doctor.

05 - AppointmentDay

The day someone called or registered the appointment, this is before appointment of course.

06 - Age

How old is the patient.

07 - Neighbourhood

Where the appointment takes place.

08 - Scholarship

True (1) of False (0) . Observation, this is a broad topic, consider reading this article https://en.wikipedia.org/wiki/Bolsa_Fam%C3%ADlia (https://en.wikipedia.org/wiki/Bolsa_Fam%C3%ADlia)

09 - Hipertension

True (1) of False (0)

10 - Diabetes

True (1) of False (0)

Alcoholism

True (1) of False (0)

Handcap

True (1) of False (0)

SMS received

1 or more messages sent to the patient.

No-show

True (1) of False (0) - Please note, True means that the patient did not show up

Question(s) for Analysis

Tip: at least one dependent variable and three independent variables.

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

Data Wrangling

General Properties

In [129]:

```
# Use this cell to set up import statements for all of the packages that you
# plan to use.

# Remember to include a 'magic word' so that your visualizations are plotted
# inline with the notebook. See this page for more:
# http://ipython.readthedocs.io/en/stable/interactive/magics.html

%matplotlib inline
%config InlineBackend.figure_format = 'retina'

import matplotlib
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.ticker as mtick
import matplotlib as mpl
```

In [3]:

```
# 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-kagglev2-may-2016.csv')
df.info() #To get info about any null cells, type and also a good overview of title
df.describe()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype
		110527 11	
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
d+vn	es• float64(1)	int64(8) object(5.)

dtypes: float64(1), int64(8), object(5)

memory usage: 11.8+ MB

Out[3]:

	PatientId	AppointmentID	Age	Scholarship	Hipertension	Diabete
count	1.105270e+05	1.105270e+05	110527.000000	110527.000000	110527.000000	110527.00000
mean	1.474963e+14	5.675305e+06	37.088874	0.098266	0.197246	0.07186
std	2.560949e+14	7.129575e+04	23.110205	0.297675	0.397921	0.25826
min	3.921784e+04	5.030230e+06	-1.000000	0.000000	0.000000	0.00000
25%	4.172614e+12	5.640286e+06	18.000000	0.000000	0.000000	0.00000
50%	3.173184e+13	5.680573e+06	37.000000	0.000000	0.000000	0.00000
75%	9.439172e+13	5.725524e+06	55.000000	0.000000	0.000000	0.00000
max	9.999816e+14	5.790484e+06	115.000000	1.000000	1.000000	1.00000

In [4]:

```
#get column titles for copy paste into introduction paragraoh
for col in df.columns:
    print(col)
```

PatientId
AppointmentID
Gender
ScheduledDay
AppointmentDay
Age
Neighbourhood
Scholarship
Hipertension
Diabetes
Alcoholism
Handcap
SMS_received
No-show

In [5]:

df.shape # In it's own cell, because the result did not print when in same cell as

Out[5]:

(110527, 14)

In [6]:

df.head()

Out[6]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood
0	2.987250e+13	5642903	F	2016-04- 29T18:38:08Z	2016-04- 29T00:00:00Z	62	JARDIM DA PENHA
1	5.589978e+14	5642503	М	2016-04- 29T16:08:27Z	2016-04- 29T00:00:00Z	56	JARDIM DA PENHA
2	4.262962e+12	5642549	F	2016-04- 29T16:19:04Z	2016-04- 29T00:00:00Z	62	MATA DA PRAIA
3	8.679512e+11	5642828	F	2016-04- 29T17:29:31Z	2016-04- 29T00:00:00Z	8	PONTAL DE CAMBURI
4	8.841186e+12	5642494	F	2016-04- 29T16:07:23Z	2016-04- 29T00:00:00Z	56	JARDIM DA PENHA

In [7]:

```
sum(df.duplicated()) #check for duplicates
```

Out[7]:

0

```
In [8]:

df['AppointmentID'].nunique() # Checking if Appointment ID is a true identifier show
Out[8]:
110527
```

Result from Data Wrangling

- · There are no nulls, the dataset seems to be intact
- · Appointment ID is the true identifier
- No duplications
- There is a strange lowest age -1
- TODO 1: Convert patient_id float64 to int for better readability
- TODO 2: Rewrite titles to correct syntax. Title names should be lowercase and with underscore where appropriate to follow Python syntax. Rewrite No-show to show_ups in preparation of TODO 4
- TODO 3: Schedule day and Appointment day are dates and needs to be set to type datetime
- TODO 4: Flip yes/no so that Yes is for Show ups and No for No Show
- TODO 5: Drop age -1

```
In [9]:
# TODO 1: Starting process changing float64 to int
df['PatientId'].nunique() # Checking Patient ID unique
Out[9]:
62299
In [10]:
df['PatientId'] = df['PatientId'].astype(int) # Converting Patient ID to Integer
In [11]:
df['PatientId'].nunique() # Checking if Patient ID is still unique, should be same out[11]:
62299
```

In [12]:

df.head() # Checking result

Out[12]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourho
0	29872499824296	5642903	F	2016-04- 29T18:38:08Z	2016-04- 29T00:00:00Z	62	JARDIM PEN
1	558997776694438	5642503	М	2016-04- 29T16:08:27Z	2016-04- 29T00:00:00Z	56	JARDIM PEN
2	4262962299951	5642549	F	2016-04- 29T16:19:04Z	2016-04- 29T00:00:00Z	62	MATA DA PRA
3	867951213174	5642828	F	2016-04- 29T17:29:31Z	2016-04- 29T00:00:00Z	8	PONTAL CAMBI
4	8841186448183	5642494	F	2016-04- 29T16:07:23Z	2016-04- 29T00:00:00Z	56	JARDIM PEN

In [13]:

Out[13]:

	patient_id	appointment_id	gender	scheduled_day	appointment_day	age	neighbourh
0	29872499824296	5642903	F	2016-04- 29T18:38:08Z	2016-04- 29T00:00:00Z	62	JARDIM PEI
1	558997776694438	5642503	М	2016-04- 29T16:08:27Z	2016-04- 29T00:00:00Z	56	JARDIM PEI
2	4262962299951	5642549	F	2016-04- 29T16:19:04Z	2016-04- 29T00:00:00Z	62	MATA PF
3	867951213174	5642828	F	2016-04- 29T17:29:31Z	2016-04- 29T00:00:00Z	8	PONTAL CAMB
4	8841186448183	5642494	F	2016-04- 29T16:07:23Z	2016-04- 29T00:00:00Z	56	Jardim Pet

In [14]:

```
# TODO 3a Convert scheduled_day to datetime

df['scheduled_day'] = pd.to_datetime(df['scheduled_day'])
```

```
In [15]:
```

```
# TODO 3b Convert appointment_day to datetime

df['appointment_day'] = pd.to_datetime(df['appointment_day'])
```

In [16]:

```
df['scheduled_day'].dt.day_name() #checking that the convertion worked
Out[16]:
0
             Friday
             Friday
1
2
             Friday
3
             Friday
             Friday
             . . .
110522
            Tuesday
110523
            Tuesday
110524
          Wednesday
110525
          Wednesday
110526
          Wednesday
Name: scheduled_day, Length: 110527, dtype: object
In [17]:
df['appointment day'].dt.day name() #checking that the convertion worked
Out[17]:
           Friday
0
1
           Friday
2
           Friday
```

```
1 Friday
2 Friday
3 Friday
4 Friday
...
110522 Tuesday
110523 Tuesday
110524 Tuesday
110525 Tuesday
110526 Tuesday
```

Name: appointment day, Length: 110527, dtype: object

In [18]:

```
# TODO 4: Flipping yes/no
df['show_ups'].value_counts() # Checking count of Yes and No
```

Out[18]:

```
No 88208
Yes 22319
```

Name: show_ups, dtype: int64

```
In [19]:
```

```
df = df.replace('No', 'Coco') # Changing No to something completely different first,
df['show_ups'].value_counts() # Checking I am doing the right thing :P
```

Out[19]:

```
Coco 88208
Yes 22319
```

Name: show ups, dtype: int64

In [20]:

```
df = df.replace('Yes', 'No') # Now changing Yes to No
df['show_ups'].value_counts()
```

Out[20]:

Coco 88208 No 22319

Name: show_ups, dtype: int64

In [21]:

```
df = df.replace('Coco','Yes')# Now changing Coco to Yes
df['show_ups'].value_counts() # If correct Yes is No, and No is Yes
```

Out[21]:

```
Yes 88208
No 22319
```

Name: show_ups, dtype: int64

In [121]:

```
# TODO 5 Drop -1

df = df.drop(df[df.age == -1].index)
df.describe() # check min age changed from -1 to 0
```

Out[121]:

	patient_id	appointment_id	age	scholarship	hipertension	diabet
count	1.105260e+05	1.105260e+05	110526.000000	110526.000000	110526.000000	110526.0000
mean	1.474934e+14	5.675304e+06	37.089219	0.098266	0.197248	0.0718
std	2.560943e+14	7.129544e+04	23.110026	0.297676	0.397923	0.2582
min	3.921700e+04	5.030230e+06	0.000000	0.000000	0.000000	0.0000
25%	4.172536e+12	5.640285e+06	18.000000	0.000000	0.000000	0.0000
50%	3.173184e+13	5.680572e+06	37.000000	0.000000	0.000000	0.0000
75%	9.438963e+13	5.725523e+06	55.000000	0.000000	0.000000	0.0000
max	9.999816e+14	5.790484e+06	115.000000	1.000000	1.000000	1.0000

Exploratory Data Analysis

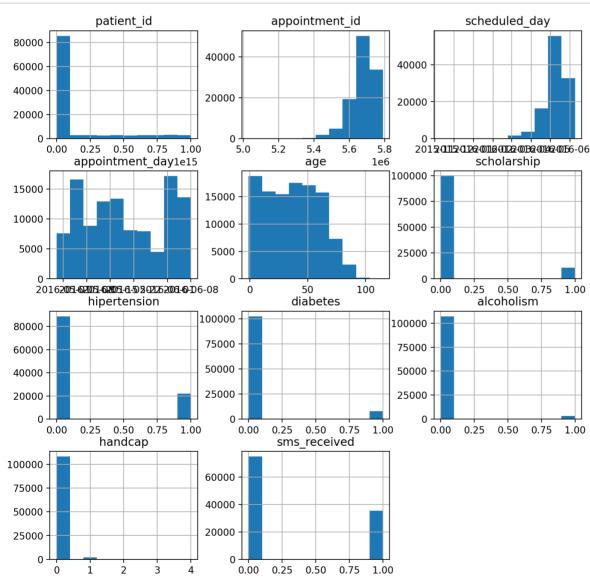
What factors are important for us to know in order to predict if a patient will show up for their scheduled appointment?

This is a very broad question and for this course I will narrow to look at a selection of factors:

- 1. How many appointments of all appointments are No shows. To get an understanding of proportions.
- 2. There seems to be about 2 appointments per patient. I would like to investigate if there are the same patients that do not show. It might be the statistic becomes misleading because of some few people pushing the numbers to either side.
- 3. How important is age, gender?
- 4. Is there a correlation between human difficulties such as Hipertension, Diabetes, Handcap and not showing up?
- 5. Does weekday or time at the day matter
- 6. Does neighbourhoud matter

In [22]:

0. Hist exploring - just to see what happens df.hist(figsize= (10,10));



1. How many appointments of all appointments are No shows. To get an understanding of proportions.

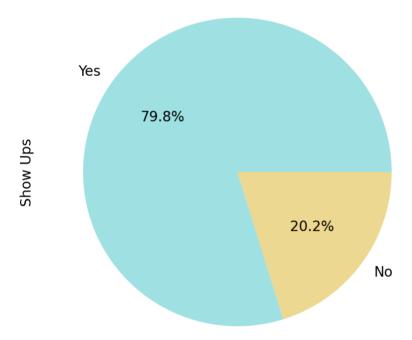
In [176]:

```
# 1. How many appointments of all appointments are No shows.
# To get an understanding of proportions.
colors = ['#9fele3','#edd891'] # colors for my plotting theme
df['show_ups'].value_counts().plot.pie(ylabel='Show Ups', autopct='%1.1f%%', figsize
plt.title('Portion between Yes / No shows')
```

Out[176]:

Text(0.5, 1.0, 'Portion between Yes / No shows')

Portion between Yes / No shows



Result of question number 1:

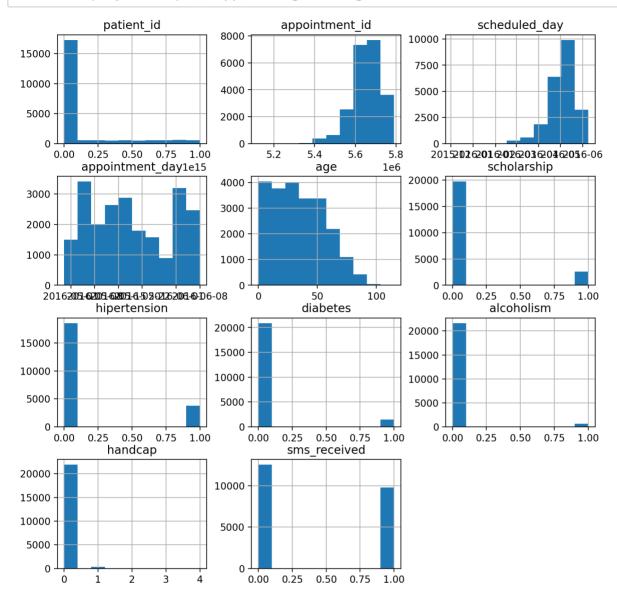
Most people, almost 80% do show up which should be seen as positive.

In [24]:

1b. wanting to see why people not showing up, so I remove all yes and focus on no
nodf = df.drop(df[df.show_ups == 'Yes'].index)

In [25]:

nodf.hist(figsize= (10,10)); # a quick explore



2. There seems to be about 2 appointments per patient. I would like to investigate if there are the same patients that do not show. It might be the statistic becomes misleading because of some few people pushing the numbers to either side.

In [26]:

```
# groupby patient ID and count number of Show ups equal to 'No'
df_count = df.groupby('patient_id')['show_ups'].apply(lambda x: (x=='No').sum()).res
count the count = df count.groupby('count')['count'].count()
# view results
count the count # Note for later: look at the relation to how many scheduled appoint
```

Out[26]:

count

```
0
       44636
       14437
1
2
        2418
3
          516
4
          162
           58
5
           33
6
7
           13
            9
8
9
            3
10
11
12
            1
13
            1
            1
14
15
            1
16
            1
18
            1
Name: count, dtype: int64
```

In [29]:

```
patient df = pd.DataFrame()
patient_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 0 entries
Empty DataFrame
```

In [30]:

```
# Count of appointments per patient
patient s = df.groupby('patient id')['appointment id'].count()
patient s.value counts()
```

```
Out[30]:
```

```
1
       37920
2
       13895
3
        5500
4
        2367
5
        1119
6
         553
7
         306
8
         202
         104
9
           85
10
           63
11
12
           36
13
           35
           22
14
15
           15
           10
17
16
           10
20
            8
18
            8
19
            6
62
            4
21
            3
            2
42
            2
34
46
            2
            2
23
38
            2
30
            2
84
            1
54
            1
            1
33
40
            1
57
            1
88
            1
29
            1
24
            1
22
            1
65
70
            1
            1
37
35
            1
55
            1
51
            1
50
Name: appointment_id, dtype: int64
```

Result of question number 2:

Most patients 44 636 have never missed an appointment . Those who have missed 1 or 2 are also quite common but from it drops significantly. Look at dropouts here. Yet there are single patients having up to 18 scheduled appointments. Lets look at the ratio of them. Looking at number of appointments per patients it is most common with one appointment and relatively common with up to five. But without going deeper it's not possible if they really correlate. It would be interesting to see if there is a connection between having many appointments and also not showing up and by this also look at any potential pattern with alcoholism, scholarship and diseases.

3. How important is age, gender?

For this I decided to add a column with age-groups to get an easier overview of patterns

```
In [125]:
#first a little count
g = df['gender'].value_counts()
a = pd.DataFrame(df['age'].value counts())
ag = df['age group'].value counts()
print('Gender count: \n','-'*40, '\n',g,'\n')
print('Age count:\n','-'*40, '\n',a.head(103),'\n')
print('Age groups count:\n' ,'-'*40, '\n',ag,'\n')
Gender count:
    71839
    38687
М
Name: gender, dtype: int64
Age count:
 _____
      age
    3539
0
```

```
2273
1
52
    1746
49
     1652
53
     1651
. .
98
       6
       5
115
100
        4
102
       2
99
       1
```

[103 rows x 1 columns]

Age groups count:

_____ 22592 20-35 22122 22100 51-65 35-50 10449 66-80 13-19 9375 7-12 7784 2-6 7440 infant 5812 81-2852 Name: age group, dtype: int64

In [32]:

```
# adding age_group
df.loc[df['age'] <=1, 'age_group'] = 'infant'
df.loc[df['age'].between(2,6), 'age_group'] = '2-6'
df.loc[df['age'].between(7,12), 'age_group'] = '7-12'
df.loc[df['age'].between(13,19), 'age_group'] = '13-19'
df.loc[df['age'].between(20,35), 'age_group'] = '20-35'
df.loc[df['age'].between(36,50), 'age_group'] = '35-50'
df.loc[df['age'].between(51,65), 'age_group'] = '51-65'
df.loc[df['age'].between(66,80), 'age_group'] = '66-80'
df.loc[df['age']>=81, 'age_group'] = '81-'
```

Out[32]:

	patient_id	appointment_id	gender	scheduled_day	appointment_day	age	neighbourh
0	29872499824296	5642903	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	62	JARDIM PEI
1	558997776694438	5642503	М	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	56	JARDIM PEI
2	4262962299951	5642549	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	62	MATA PF
3	867951213174	5642828	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	8	PONTAL CAMB
4	8841186448183	5642494	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	56	JARDIM PEN

In [40]:

```
# Creating a series for count for yes or no shows devided in main category age group
# and minor category gender.
showup_age_gender_counts_s = df.groupby(['show_ups' , 'age_group', 'gender']).count(
showup_age_gender_counts_s
```

Out[40]:

show_ups	age grou	p geno	ler
No	13-19	F	1540
210	10 15	M	894
	2-6	F	695
	2 0	M	752
	20-35	F	3938
		M	1421
	35-50	F	3136
		М	1356
	51-65	F	2532
		М	1129
	66-80	F	1082
		М	515
	7-12	F	834
		M	972
	81-	F	316
		М	153
	infant	F	521
		M	533
Yes	13-19	\mathbf{F}	4515
		M	2426
	2-6	F	2853
		M	3140
	20-35	F	12559
		M	4674
	35-50	F	12123
		M	5485
	51-65	F	12547
		M	5914
	66-80	F	5916
		M	2936
	7-12	\mathbf{F}	2831
		M	3147
	81-	F	1613
		M	770
	infant	F	2289
		M	2470
Mama nat	ion+ id	d+1700 •	in+61

Name: patient_id, dtype: int64

In [41]:

```
showup_age_counts_s = df.groupby(['show_ups' , 'age_group']).count()['patient_id']
showup_age_counts_s
```

Out[41]:

show_ups	age_grou	p
No	13-19	2434
	2-6	1447
	20-35	5359
	35-50	4492
	51-65	3661
	66-80	1597
	7-12	1806
	81-	469
	infant	1054
Yes	13-19	6941
	2-6	5993
	20-35	17233
	35-50	17608
	51-65	18461
	66-80	8852
	7-12	5978
	81-	2383
	infant	4759
		11

Name: patient_id, dtype: int64

In [46]:

```
su_count_df = pd.DataFrame(showup_age_counts_s)
```

Out[46]:

patient_id

age_group	show_ups	
13-19	No	2434
2-6		1447
20-35		5359
35-50		4492
51-65		3661

In [135]:

```
# Making a new dataframe based on the showup_counts series for plotting.
# There are probably many faster ways to do this
Showups = ['No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes',
Agegroups = ['13-19', '2-6', '20-35', '35-50', '51-65', '66-80', '7-12', '81-', 'inf
Nopatients = [2434, 1447, 5359, 4492, 3661, 1597, 1806, 469, 1054]
Yespatients = [6941, 5993, 17233, 17608, 18461, 8852, 5978, 2383, 4759]
su_count_df['show_ups2'] = Showups
new_df = pd.DataFrame()
new_df['age_group'] = pd.DataFrame(Agegroups)
new_df['no_patients'] = pd.DataFrame(Nopatients)
new_df['yes_patients'] = pd.DataFrame(Yespatients)
```

In [136]:

```
# Store the new_df in a more namy df. Now the original is intact and I can feel more
yesno_count = new_df
yesno_count
```

Out[136]:

	age_group	no_patients	yes_patients
0	13-19	2434	6941
1	2-6	1447	5993
2	20-35	5359	17233
3	35-50	4492	17608
4	51-65	3661	18461
5	66-80	1597	8852
6	7-12	1806	5978
7	81-	469	2383
8	infant	1054	4759

In [137]:

```
yesno_count.iloc[3] = ['36-50', 4492, 17608] #fixing 35 --> 36
```

```
In [152]:
```

```
# this cell has previously been used to fix order of age group in yesno_count before
# yesno_count.iloc[2], yesno_count.iloc[3] = yesno_count.iloc[3], yesno_count.iloc[2]
# User defined function that takes yesno_count and put out right order if the order
# then no need to do it manually via iloc

def ageorder(ag):
    if ag == '13-19':

        data = [['infant', 1054, 4759], ['2-6', 1447, 5993], ['7-12', 1806, 5978], [
        ['20-35', 5359, 17233], ['36-50', 4492, 17608], ['51-65', 3661, 18461], ['66-
        yesno_count_order = pd.DataFrame(data, columns=['age_group', 'no_patients',
        yesno_count = yesno_count_order

    return yesno_count
```

In [156]:

```
ageorder('13-19') #testing function
```

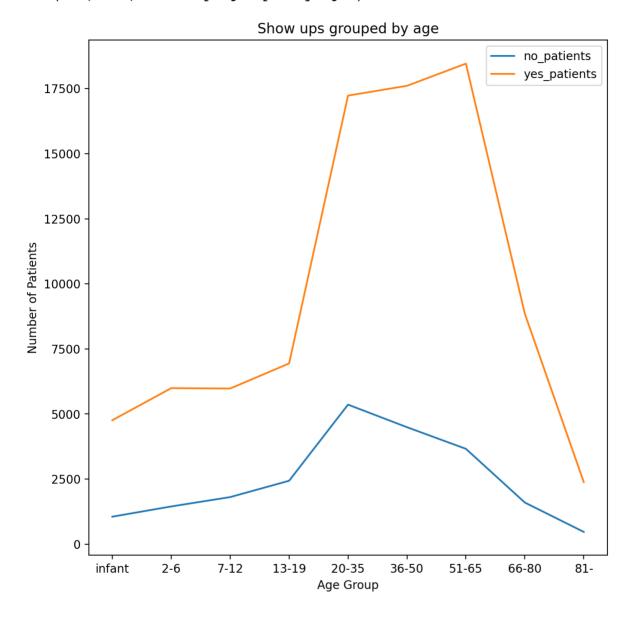
Out[156]:

age_group	no_patients	yes_patients
infant	1054	4759
2-6	1447	5993
7-12	1806	5978
13-19	2434	6941
20-35	5359	17233
36-50	4492	17608
51-65	3661	18461
66-80	1597	8852
81-	469	2383
	infant 2-6 7-12 13-19 20-35 36-50 51-65 66-80	2-6 1447 7-12 1806 13-19 2434 20-35 5359 36-50 4492 51-65 3661 66-80 1597

In [173]:

Out[173]:

Text(0.5, 1.0, 'Show ups grouped by age')



```
In [49]:
```

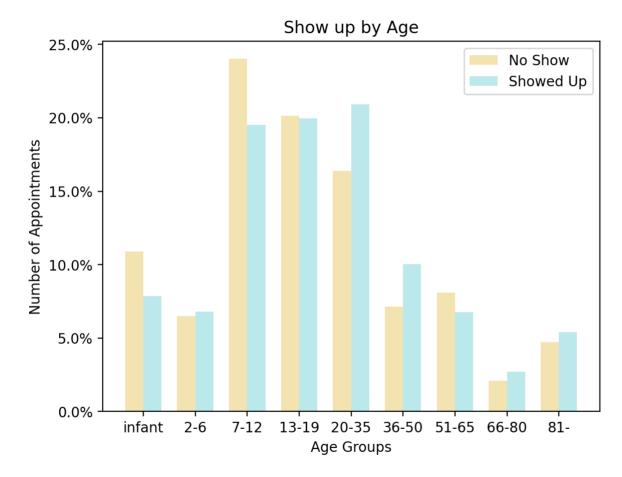
```
# Start of alternative plotting about age vs no/yes show ups
# Get total counts for each no shows
showup totals = df.groupby('show_ups').count()['appointment_id']
showup totals
Out[49]:
show_ups
No
       22319
       88208
Yes
Name: appointment id, dtype: int64
In [54]:
# gGt proportions by dividing no rating counts by total # of no samples
no proportions = showup age counts s['No'] / showup totals['No']
no_proportions
Out[54]:
age group
13-19
          0.109055
          0.064833
2-6
20-35
          0.240109
35-50
          0.201263
          0.164031
51-65
66-80
          0.071553
7-12
          0.080918
81-
          0.021013
          0.047224
infant.
Name: patient_id, dtype: float64
In [55]:
# Get proportions by dividing yes rating counts by total # of yes samples
yes_proportions = showup_age_counts_s['Yes'] / showup_totals['Yes']
yes proportions
Out[55]:
age group
          0.078689
13-19
2-6
          0.067942
20 - 35
          0.195368
35-50
          0.199619
51-65
          0.209289
66-80
          0.100354
7-12
          0.067772
          0.027016
81_
infant
          0.053952
Name: patient_id, dtype: float64
In [56]:
ind = np.arange(len(no_proportions)) # the x locations for the groups
width = 0.35
                   # the width of the bars
```

In [57]:

```
# plot bars
no_bars = plt.bar(ind, no_proportions, width, color='#edd891', alpha=.7, label='No s
yes_bars = plt.bar(ind + width, yes_proportions, width, color='#9fele3', alpha=.7, l
# title and labels
plt.ylabel('Number of Appointments')
plt.xlabel('Age Groups')
locations = ind + width / 2 # xtick locations
labels = ['infant', '2-6', '7-12', '13-19', '20-35', '36-50', '51-65', '66-80', '81-
plt.xticks(locations, labels)
plt.gca().yaxis.set_major_formatter(mtick.PercentFormatter(xmax=1.0)) # percentage
# legend
plt.legend()
```

Out[57]:

<matplotlib.legend.Legend at 0x7f9e92a3a350>



Result of question number 3:

There are almost double amount of women that has an appointment 71 840 female vs 38 687 male. Age: Newborn babies are the single largest group of patients but looking at age-groups majority of patients are between 20-65. Looking at compare age group combined with gender in a list or just age group shows similarities with the total yes/no portions. It would require to calculate and visualises each age group + gender to be really sure this is not a significant factor for predicting if the patient might not show up or not. When plotting age group it is though clear that age group 20-35 has the most amount of no shows, but they are also the largest group so relatively smaller and actually more likely to show up than the younger generation that are the ones most likely not to show up. Relatively the age group 51-65 are the ones showing up more.

4. Is there a correlation between human difficulties such as Hipertension, Diabetes, Handcap and not showing up?

```
In [58]:
```

```
# filter using query to get no_showups
no_showups = df.query('show_ups =="No"')
no_showups.head()
```

Out[58]:

	patient_id	appointment_id	gender	scheduled_day	appointment_day	age	neighbour
6	733688164476661	5630279	F	2016-04-27 15:05:12+00:00	2016-04-29 00:00:00+00:00	23	GOIABE
7	3449833394123	5630575	F	2016-04-27 15:39:58+00:00	2016-04-29 00:00:00+00:00	39	GOIABE
11	7542951368435	5620163	М	2016-04-26 08:44:12+00:00	2016-04-29 00:00:00+00:00	29	PALES
17	14794966191172	5633460	F	2016-04-28 09:28:57+00:00	2016-04-29 00:00:00+00:00	40	CONQL
20	622257462899397	5626083	F	2016-04-27 07:51:14+00:00	2016-04-29 00:00:00+00:00	30	PALES

In [59]:

```
# Start of series of cells to count number of No shows depending on one or
# combination of hipertension, diabetes and handcap
hdc = no_showups[['hipertension', 'diabetes', 'handcap']] # series to count
hdc_count = hdc[(hdc.hipertension >= 1) & (hdc.diabetes >= 1) & (hdc.handcap >=1)].s
```

In [60]:

```
hdc_count # double check outcome
```

Out[60]:

55

In [61]:

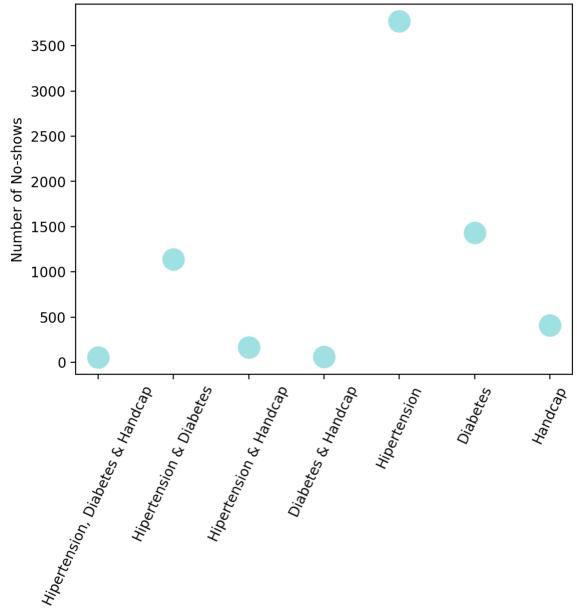
```
hd = no_showups[['hipertension', 'diabetes']]
hd_count = hd[(hd.hipertension >= 1) & (hd.diabetes >= 1)].sum(axis=1).count()
```

```
In [62]:
hd count
Out[62]:
1141
In [63]:
hc = no_showups[['hipertension', 'handcap']]
hc count = hc[(hc.hipertension >= 1) & (hc.handcap >= 1)].sum(axis=1).count()
In [64]:
hc count
Out[64]:
164
In [65]:
dc = no showups[['diabetes', 'handcap']]
dc count = dc[(dc.diabetes >= 1) & (dc.handcap >= 1)].sum(axis=1).count()
In [66]:
dc count
Out[66]:
59
In [67]:
h = no showups[['hipertension']]
h_count = h[(h.hipertension >= 1)].sum(axis=1).count()
d = no_showups[['diabetes']]
d count = d[(d.diabetes >= 1)].sum(axis=1).count()
c = no showups[['handcap']]
c_count = c[(c.handcap >= 1)].sum(axis=1).count()
In [68]:
print(h_count)
print(d count)
print(c_count)
3772
1430
407
```

In [69]:

In [170]:





Human Difficulties

In [72]:

```
# Human Difficulty-percentage of total no-show
sum_hd = human_diff['no_counts'].sum()
no_total = no_showups['show_ups'].count()

percentage = sum_hd / no_total * 100

percentage
```

Out[72]:

31.488865988619562

Result of question number 4:

Hipertension alone is a big portion of not showing up. And all human difficulties together is 31 % of the total no shows indicating this is an important factor.

5. Does weekday or time at the day matter

In [73]:

```
# 5. Does weekday or time at the day matter for no shows?
# starting looking att weekday
weekdays_noshow = pd.DataFrame(no_showups['scheduled_day'].dt.day_name())
weekdays_noshow['scheduled_day'].value_counts()
```

Out[73]:

```
Tuesday 5291
Wednesday 4879
Monday 4561
Friday 3887
Thursday 3700
Saturday 1
Name: scheduled_day, dtype: int64
```

In [74]:

```
# looking at hours
hours_noshow_s = no_showups['scheduled_day'].dt.hour
hours_noshow_s.value_counts()
```

```
Out[74]:
7
       2911
8
       2804
9
       2526
10
       2440
14
       2070
11
       1928
13
       1891
15
       1873
16
       1317
12
       1104
17
        722
6
        303
18
        285
19
        114
         30
20
Name: scheduled day, dtype: int64
```

Result of question number 5:

Weekday does not seem to matter that much but most no shows is happening on Tuesdays, least at Thursdays. There is also 1 no show on Saturday but this might be wrong data as when the other days the numbers varies between 5291 and 3700. Looking at time people are more likely to show really early or late. This might be because of working hours and could be a factor. Would be interesting to look on this in combination with age group

6. Does neighbourhoud matter?

```
In [127]:
```

```
df['neighbourhood'] = df['neighbourhood'].str.title() #fixing nicer reading for plot
neigh_counts_s = df.groupby(['show_ups', 'neighbourhood']).count()['patient_id']
neigh_counts_s
```

Out[127]:

show_u	ıps neighbourhood		
No	Aeroporto	1	
	Andorinhas	521	
	Antônio Honório	50	
	Ariovaldo Favalessa	62	
	Barro Vermelho	91	
Yes	São José	1549	
	São Pedro	1933	
	Tabuazeiro	2559	
	Universitário	120	
	Vila Rubim	710	
Name:	patient_id, Length: 160	, dtype:	int64
	No Yes	No Aeroporto Andorinhas Antônio Honório Ariovaldo Favalessa Barro Vermelho Yes São José São Pedro Tabuazeiro Universitário Vila Rubim	No Aeroporto 1 Andorinhas 521 Antônio Honório 50 Ariovaldo Favalessa 62 Barro Vermelho 91 Yes São José 1549 São Pedro 1933 Tabuazeiro 2559 Universitário 120

In [178]:

```
# Plotting
ax = neigh_counts_s.unstack(level=0).plot(kind='bar', xlabel='Number of scheduled ar
plt.tight_layout()
plt.title('Count of No and Yes shows per neighbourhood')
```

Out[178]:

Text(0.5, 1.0, 'Count of No and Yes shows per neighbourhood')

Result of question number 6:

Neighbourhood: seem to matter. It would need to do perceptual comparison to see the actual correlation.

Conclusions

Human difficulties are an significant factor for not showing up. Also where you live seems important. I have not looked into several nested datasets which would have shown more. I have not looked alcoholism or scholarship which might also be an important factors in combination with age and neighbourhood.

Comment

I would like to investigate so much more and dig deeper but not time in this course to do more. I'm too still quite new and every look up taking quite some time.

```
In [ ]:
```

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