Udacity's Data Analyst Nanodegree

Project 2 - The Data Analysis Process

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In this project we will analyze the No-Show Database.

Importing necessary libraries:

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

Loading database and performing initial checks:

In [2]:
```
df = pd.read_csv('noshowappointments-kagglev2-may-2016.csv')
df.head()
```

Out[2]:

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

In [3]:
```
df.dtypes
```

Out[3]:
```
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
dtype: object
```

The datatypes seem to be in order. It's noteworthy that Hipertension, Diabetes, Alcoholism, Handcap and SMS_received follow binary encoding ('yes'= 1 and 'no'=0).

In [4]:
```
df.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
```

All the info seems to be available, without NaNs whatsoever.

In [5]:

```
print(f"Are there duplicated patient ids? {'Yes' if any(df.PatientId.duplicated()) else 'No'}")
print(f"Are there duplicated appointment ids? {'Yes' if any(df.AppointmentID.duplicated()) else 'No'}")
```

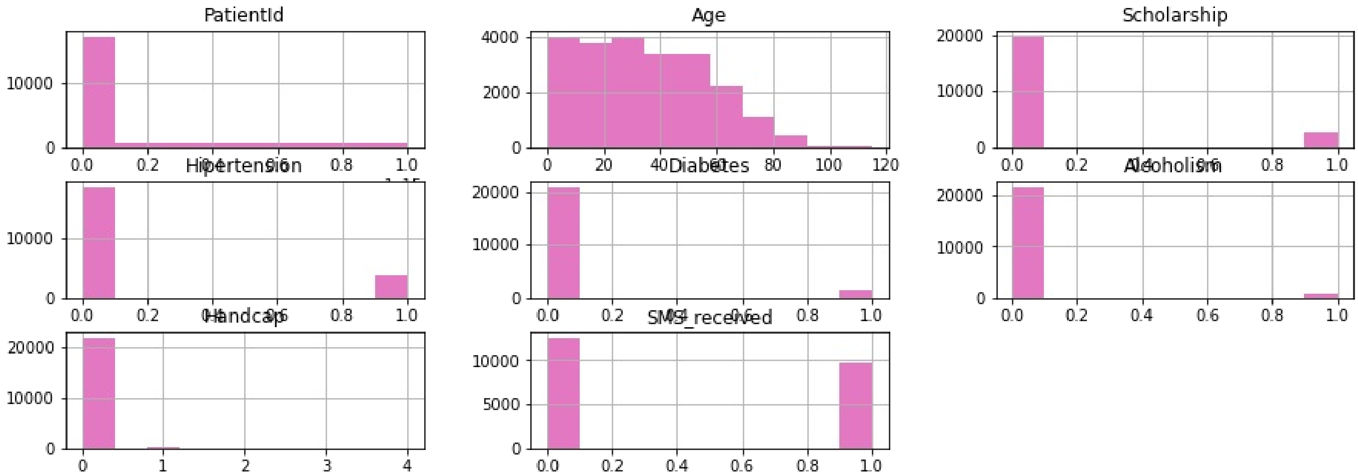
```
Are there duplicated patient ids? Yes
Are there duplicated appointment ids? No
```

In [6]:

```
# There are no duplicated Appointment ID rows, thus we can drop them, assuming
# they won't contribute to the analysis.
df.drop(['AppointmentID'],axis = 1, inplace = True)
```

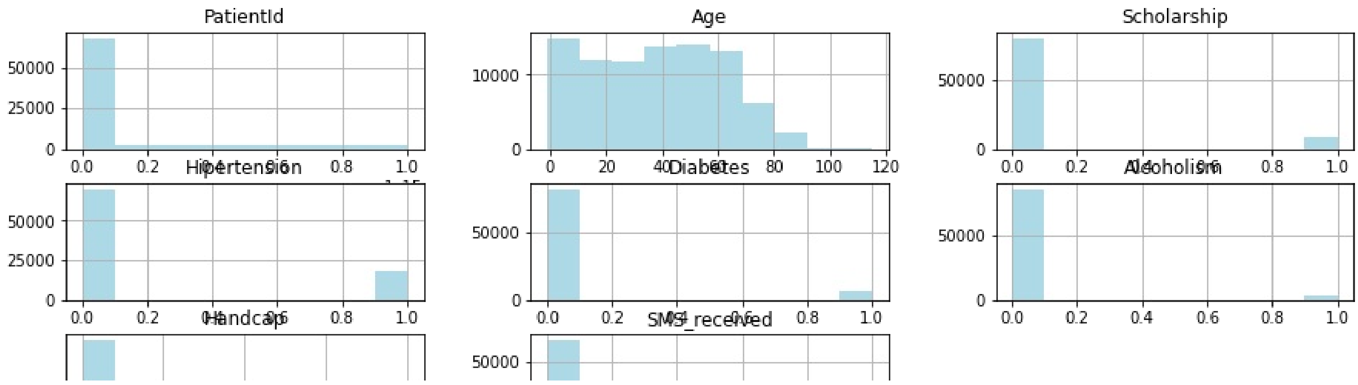
In [7]:

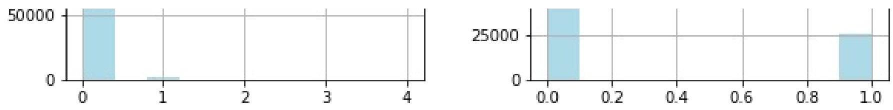
```
no_show = df['No-show'] == 'Yes' # patient did not show
yes_show = df['No-show'] == 'No' # patient did not show

df[no_show].hist(figsize=(15,5), color='tab:pink');
plt.show();
```



In [8]:

```
df[yes_show].hist(figsize=(15,5), color='lightblue');
plt.show();
```





Apart from age, the majority of above charted features are in binary. Meaning they can either be present or not for each appointment and individual. Therefore:

- The majority of variables all seem to have the same distribution both in the show and no-show appointments

Which is reinforced by the statistics below:

In [9]:

```
df[no_show].describe()
```

Out[9]:

	PatientId	Age	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_received
count	2.231900e+04	22319.000000	22319.000000	22319.000000	22319.000000	22319.000000	22319.000000	22319.000000
mean	1.467523e+14	34.317667	0.115507	0.169004	0.064071	0.030333	0.020297	0.438371
std	2.549905e+14	21.965941	0.319640	0.374764	0.244885	0.171505	0.156670	0.496198
min	5.628261e+06	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	4.176779e+12	16.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	3.156794e+13	33.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	9.454270e+13	51.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000
max	9.996585e+14	115.000000	1.000000	1.000000	1.000000	1.000000	4.000000	1.000000

In [10]:

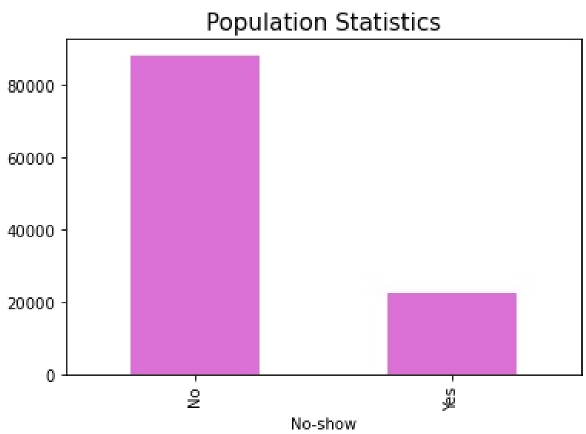
```
df[yes_show].describe()
```

Out[10]:

	PatientId	Age	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_received
count	8.820800e+04	88208.000000	88208.000000	88208.000000	88208.000000	88208.000000	88208.000000	88208.000000
mean	1.476845e+14	37.790064	0.093903	0.204392	0.073837	0.030417	0.022742	0.291334
std	2.563747e+14	23.338878	0.291695	0.403259	0.261507	0.171732	0.162750	0.454380
min	3.921784e+04	-1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	4.168386e+12	18.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	3.176184e+13	38.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	9.433715e+13	56.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000
max	9.999816e+14	115.000000	1.000000	1.000000	1.000000	1.000000	4.000000	1.000000

In [11]:

```
df.groupby('No-show')['PatientId'].count().plot(kind = 'bar',color = 'orchid'); plt.title('Population Statistics'
```



In [12]:

```
overall = pd.pivot_table(df, index = 'No-show',values=['Scholarship',   'Hipertension', 'Diabetes',     'Alcoholi
overall.reset_index(inplace=True)
overall
```

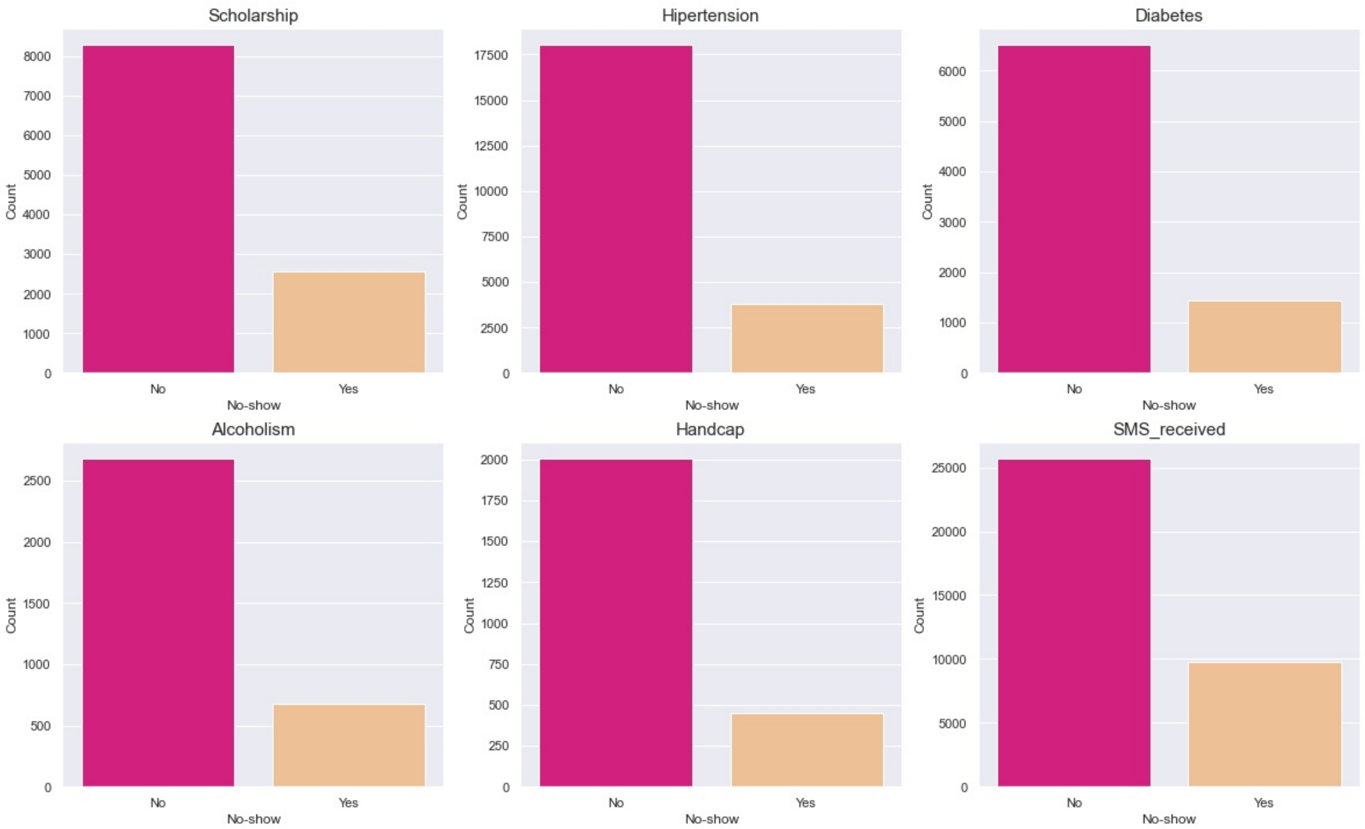
Out[12]:

	No-show	Alcoholism	Diabetes	Handcap	Hipertension	SMS_received	Scholarship
0	No	2683	6513	2006	18029	25698	8283

1	Yes	677	1430	453	3772	9784	2578

In [13]:

```
sns.set()
plt.figure(figsize=(20,12))
l = ['Scholarship',     'Hipertension', 'Diabetes',     'Alcoholism',    'Handcap',      'SMS_received']
for i in l:
    n = l.index(i)+1
    plt.subplot(2,3,n)
    sns.barplot(x='No-show',y=i,data=overall,palette='Accent_r')
    # plt.xticks(['yes','no'])
    plt.title(i, fontsize = 15);

    plt.ylabel('Count');
```



From the initial exploratory analysis above it seems like there is no clear relationship between not showing up and any of the above variables. Apparently, they all follow pretty much the same distribution from the population regardless of whether the patient showed up or not.

Having the scholarship (welfare program aid) and received sms seems to slightly increase the volume of no-shows.

Delving deeper

Is there any particular feature more associated with not showing up?

In [14]:

```
df.head()
```

Out[14]:

	PatientId	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SM
0	2.987250e+13	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	0	1	0	0	0	
1	5.589978e+14	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	0	0	0	0	
2	4.262962e+12	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	0	0	0	0	0	
3	8.679512e+11	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	0	0	0	0	0	
4	8.841186e+12	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	1	1	0	0	

But first, let's check how many of the no-shows were patients that have a tendency to be late:

In [15]:
```
df[df.PatientId.duplicated()]
```

Out[15]:

	PatientId	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap
27	1.215484e+13	F	2016-04-27T10:51:45Z	2016-04-29T00:00:00Z	4	CONQUISTA	0	0	0	0	(
154	1.925263e+10	F	2016-04-28T16:38:34Z	2016-04-29T00:00:00Z	30	ITARARÉ	0	0	0	0	(
288	2.246214e+13	M	2016-03-31T12:39:06Z	2016-04-29T00:00:00Z	43	CARATOÍRA	0	0	0	0	(
290	7.222383e+12	M	2016-04-11T09:50:18Z	2016-04-29T00:00:00Z	7	CARATOÍRA	0	0	0	0	(
316	1.756579e+13	F	2016-04-14T10:01:09Z	2016-04-29T00:00:00Z	1	JOANA D´ARC	0	0	0	0	(
...	...	...	...	...	...	...	...	...	...	...	..
110521	3.635534e+13	F	2016-05-03T08:23:40Z	2016-06-07T00:00:00Z	53	MARIA ORTIZ	0	0	0	0	(
110522	2.572134e+12	F	2016-05-03T09:15:35Z	2016-06-07T00:00:00Z	56	MARIA ORTIZ	0	0	0	0	(
110523	3.596266e+12	F	2016-05-03T07:27:33Z	2016-06-07T00:00:00Z	51	MARIA ORTIZ	0	0	0	0	(
110525	9.213493e+13	F	2016-04-27T15:09:23Z	2016-06-07T00:00:00Z	38	MARIA ORTIZ	0	0	0	0	(
110526	3.775115e+14	F	2016-04-27T13:30:56Z	2016-06-07T00:00:00Z	54	MARIA ORTIZ	0	0	0	0	(

48228 rows × 13 columns

In [16]:
```
top = df[no_show].groupby(['PatientId'], as_index=False)['No-show'].count()
top.sort_values('No-show', ascending = False)
```

Out[16]:

	PatientId	No-show
3067	1.421987e+12	18
15734	5.635135e+14	16
5146	5.587790e+12	15
15814	5.811973e+14	14
11288	6.575144e+13	13
...	...	...
6460	8.286429e+12	1
6461	8.287416e+12	1
6462	8.293317e+12	1
6463	8.294383e+12	1
17662	9.996585e+14	1

17663 rows × 2 columns

As we can infer from the table above, there is a number of patients that tend not to show up. The biggest no-show offensor not having showed up 18 times.

Therefore, it is tentative to affirm that not having showed up before may be a red flag for the likelihood of not showing up again.

But, is it though? If we only look at absolute values we could end up not taking into account people who miss more appointments simply because they schedule more total appointments (for instance, people with poor health).

In [17]:
```
# Getting relative count of no-shows x total appointments per patient:
pat = df.groupby(['PatientId','No-show'], as_index=False)['Age'].count()

pat['per'] = pat.groupby('PatientId')['Age'].transform(lambda x: x/x.sum())
pat.rename(columns={'Age':'Count'},inplace = True)
```

In [18]:
```
# Considering top 10 offenders of the no-show criteria and comparing how many appointments they missed x not miss
top_10 = top.sort_values('No-show', ascending = False).head(10)['PatientId'].values
pat[pat.PatientId.isin(top_10)].sort_values('PatientId')
```

Out[18]:

	PatientId	No-show	Count	per
6811	4.768616e+11	No	1	0.083333
6812	4.768616e+11	Yes	11	0.916667
11863	1.198157e+12	No	11	0.478261
11864	1.198157e+12	Yes	12	0.521739
12368	1.421987e+12	Yes	18	1.000000
15119	2.728422e+12	No	4	0.266667
15120	2.728422e+12	Yes	11	0.733333
20937	5.587790e+12	No	5	0.250000
20938	5.587790e+12	Yes	15	0.750000
29349	9.715136e+12	No	9	0.450000
29350	9.715136e+12	Yes	11	0.550000
45796	6.575144e+13	Yes	13	1.000000
58174	2.491637e+14	No	7	0.388889
58175	2.491637e+14	Yes	11	0.611111
63896	5.635135e+14	Yes	16	1.000000
64219	5.811973e+14	Yes	14	1.000000

As we can see from the table above, the top 10 patients with highest amount of no-shows seem to have a tendency to miss appointments consistently.

All of the above have missed more than they have attended. Some of them have not showed up even once, despite the amount of missed appointments (such as the Patient 1.421987e+12 who has missed a total of 18 appointments in a row without ever showing up).

Therefore, it is tentative to conclude that missing appointments in the past might be a good indicator of missing them again in the future, thus an **autoregressive relation** of sorts might be adequate.

In [19]:
```
nei = df.groupby(['Neighbourhood','No-show'], as_index=False)['Age'].count()

nei['per'] = nei.groupby('Neighbourhood')['Age'].transform(lambda x: x/x.sum())
nei.rename(columns={'Age':'Count'},inplace = True)

tot_nei = nei.copy()
nei[nei['No-show']=='Yes'].sort_values('Count', ascending = False)
```

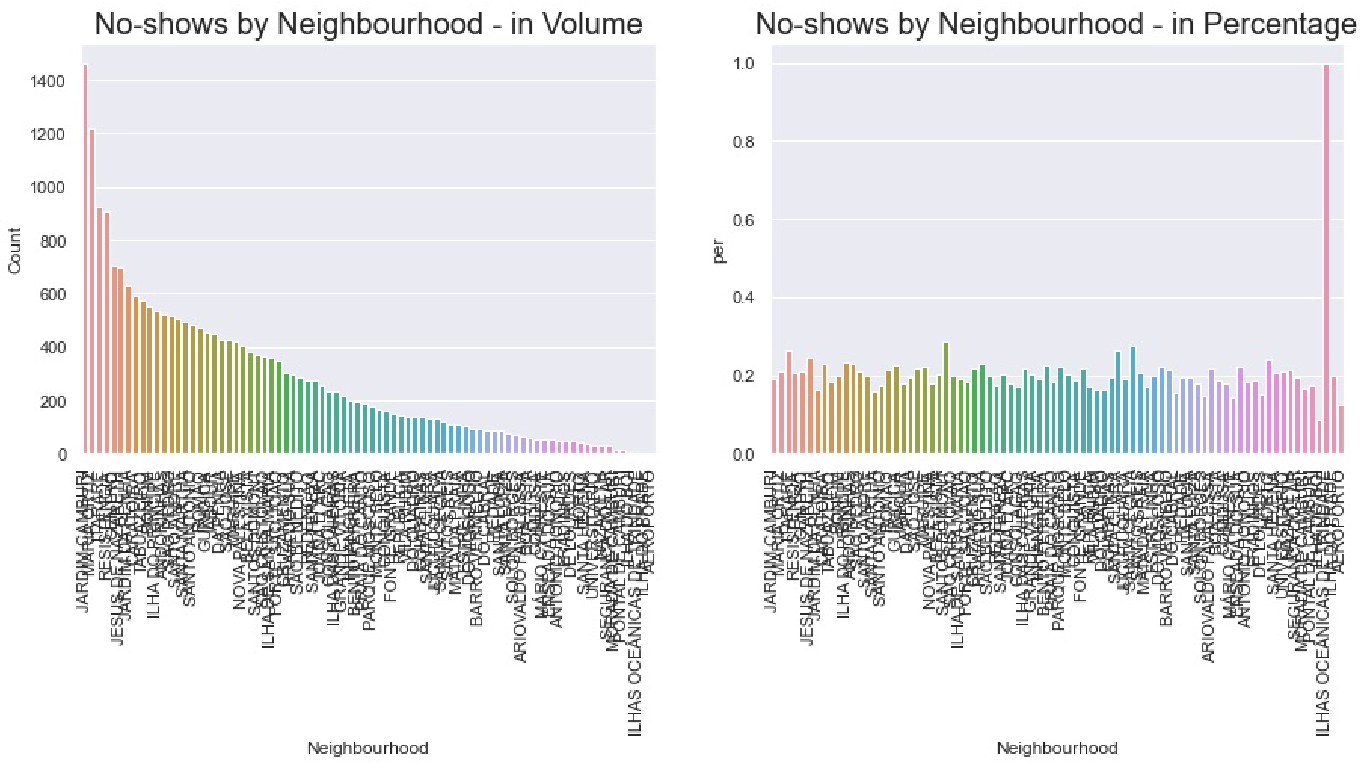
Out[19]:

	Neighbourhood	No-show	Count	per
76	JARDIM CAMBURI	Yes	1465	0.189841
86	MARIA ORTIZ	Yes	1219	0.209991
72	ITARARÉ	Yes	923	0.262664
117	RESISTÊNCIA	Yes	906	0.204469
21	CENTRO	Yes	703	0.210858
...	...	...	...	...
107	PONTAL DE CAMBURI	Yes	12	0.173913
63	ILHA DO BOI	Yes	3	0.085714
68	ILHAS OCEÂNICAS DE TRINDADE	Yes	2	1.000000
65	ILHA DO FRADE	Yes	2	0.200000
1	AEROPORTO	Yes	1	0.125000

80 rows × 4 columns

In [20]:
```
nei = nei[nei['No-show']=='Yes'].sort_values('Count', ascending = False)
nei.sort_values('Count', ascending = False, inplace = True)
plt.figure(figsize=(15,5))
sns.set()
plt.subplot(121)
sns.barplot(x='Neighbourhood', y ='Count', data = nei, ci = None);
```

```python
plt.xticks(rotation=90);
plt.title("No-shows by Neighbourhood - in Volume", fontsize=20)
plt.subplot(122)
sns.barplot(x='Neighbourhood', y ='per', data = nei,ci = None);
plt.xticks(rotation=90);
plt.title("No-shows by Neighbourhood - in Percentage", fontsize=20);
```



The neighbourhood feature represents the location of the hospital.

When looking exclusively at volume, it would seem like JARDIM CAMBURI has the most no-shows, but, in reality, it simply has the highest volume of visits. Hence, the importance of checking no-shows relative to total appointments (right chart). From the left chart we can infer only the volumes and, perhaps, that the neighbourhoods to the left are located in more densely populated areas, therefore boasting of a higher volume of appointments.

As we can see in the right chart the majority of hospitals tend to have a no-show rate in the neighbourhood of 20-30%, with an obvious outlier being the hospital in ILHAS OCEANICAS DE TRINDADE. Let's check it out next:

In [21]:

```python
tot_nei[tot_nei.Neighbourhood == 'ILHAS OCEÂNICAS DE TRINDADE']
```

Out[21]:

	Neighbourhood	No-show	Count	per
68	ILHAS OCEÂNICAS DE TRINDADE	Yes	2	1.0

It is not an aberrant observation at all: it only has 2 appointments in the database, both no-shows.

Does it have anything to do with **age**?

In [22]:

```python
df[no_show].groupby('Age')['No-show'].count().sort_values(ascending=False).head(10)
```

Out[22]:

```
Age
0     639
1     415
17    396
19    394
30    369
9     364
21    355
20    355
16    353
25    352
Name: No-show, dtype: int64
```

As seem above, the 2 ages with higher no-show volumes are 0 and 1. But what about no-show percentage relative to total per age cohorts?

In [23]:

```
age = df.groupby(['Age','No-show'], as_index=False)['PatientId'].count()

age['per'] = age.groupby('Age')['PatientId'].transform(lambda x: x/x.sum())
age.rename(columns={'PatientId':'Count'},inplace = True)

tot_age = age.copy()
age[age['No-show']=='Yes'].sort_values('Count', ascending = False)
```

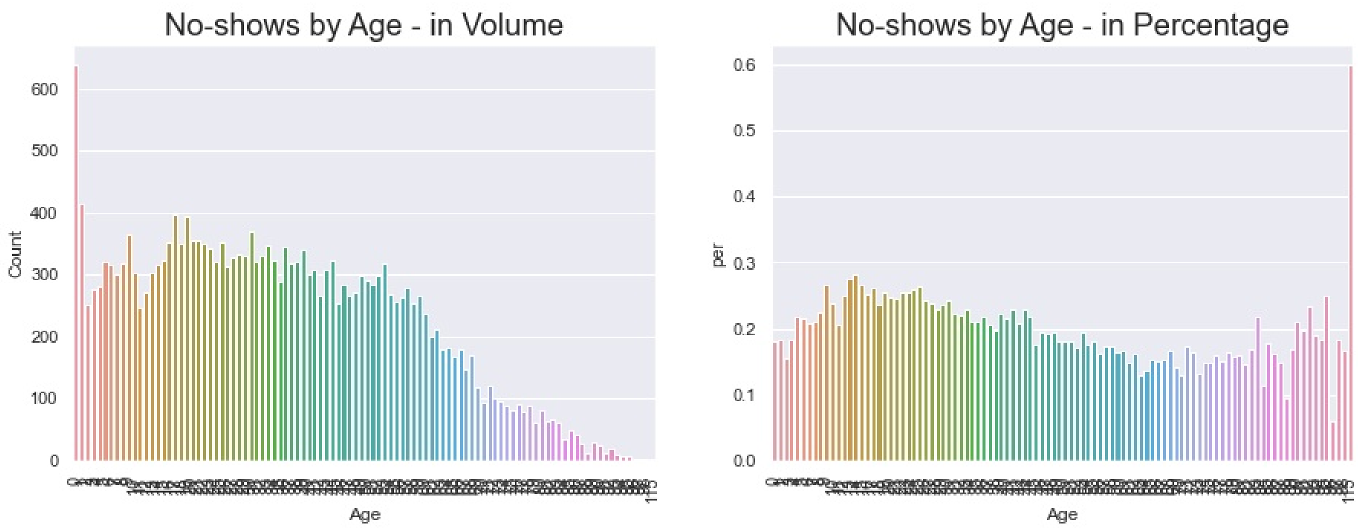
Out[23]:

	Age	No-show	Count	per
2	0	Yes	639	0.180559
4	1	Yes	415	0.182578
36	17	Yes	396	0.262425
40	19	Yes	394	0.255016
62	30	Yes	369	0.242604
...	...	...	...	...
192	95	Yes	6	0.250000
203	115	Yes	3	0.600000
196	97	Yes	2	0.181818
194	96	Yes	1	0.058824
198	98	Yes	1	0.166667

100 rows × 4 columns

In [24]:

```
age = age[age['No-show']=='Yes'].sort_values('Age', ascending = True)
age.sort_values('Count', ascending = False, inplace = True)
plt.figure(figsize=(15,5))
sns.set()
plt.subplot(121)
sns.barplot(x='Age', y ='Count', data = age, ci = None);
plt.xticks(rotation=90);
plt.title("No-shows by Age - in Volume", fontsize=20)
plt.subplot(122)
sns.barplot(x='Age', y ='per', data = age,ci = None);
plt.xticks(rotation=90);
plt.title("No-shows by Age - in Percentage", fontsize=20);
```



The total amount of no-shows is bigger for newborns. However, when taking into account the number of appointments, it is made clear that is so simply due to the sheer amount of appointments for newborn patients (which makes sense). When considering percentage of no-shows per total appointments per age cohort, it is clear that adolescents and young adults tend to miss the appointments more often, in contrast to the elderly missing less appointments, but the difference is not stark. Also, there is an outlier at the 115 years old cohort. Let's delve deeper into that:

In [25]:

```
tot_age[tot_age.Age == 115]
```

Out[25]:

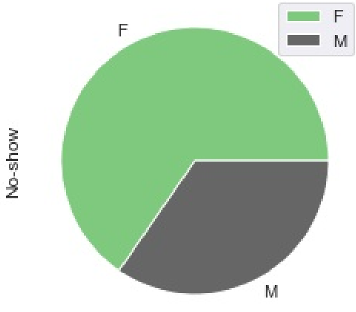
Age	No-show	Count	per

202	115	No	2	0.4
203	115	Yes	3	0.6

Once more we can not draw conclusions about the 115 age cohort because there are way too few observations available.

Maybe it is a matter of **gender**?

In [26]:
```
gend=df[no_show].groupby('Gender')[['No-show']].count().plot(kind='pie',subplots=True,cmap='Accent');
```



At first glance, there seems the majority of no-shows are from women.

In [27]:
```
df.groupby('Gender')[['No-show']].count()
```

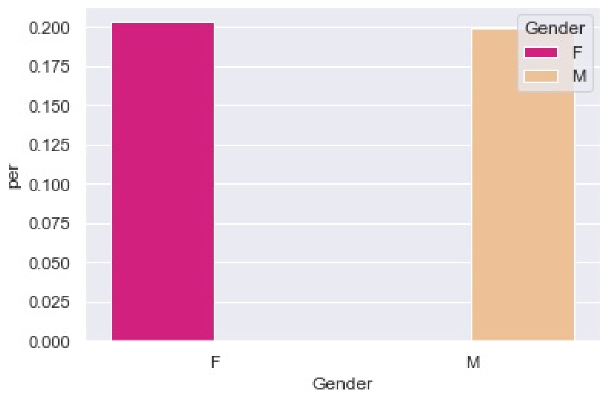
Out[27]:

	No-show
Gender	
F	71840
M	38687

However, when checking the whole sample we can see there are clearly more women than men, regardless of showing up or not. The amount of female patients is almost twofold the amount of male patients.

Which makes sense, considering in Brazil it is a well-known statistic / fact that women tend to care better for their health.

In [28]:
```
gend = df.groupby(['Gender','No-show'], as_index=False)['PatientId'].count()

gend['per'] = gend.groupby('Gender')['PatientId'].transform(lambda x: x/x.sum())
gend.rename(columns={'PatientId':'Count'},inplace = True)
sns.barplot(data = gend[gend['No-show']=='Yes'][['Gender','per']], x='Gender',hue ='Gender', y='per',palette ='Ac
```



When taking into consideration the gender totals we get that both genders have approximately 20% of no-shows. Therefore, when it comes to showing up/not , gender seems to be irrelevant.

Binary Features Analysis

Chronic Disease

Let us assume a strong *a priori* that people with grave chronic disease tend to be more dilligent with their healthcare. Therefore, we'll investigate whether people with that have each of them tend to show up more often.

In [29]:
```
df['No-show'] = df.copy()['No-show'].map({'Yes': 1,'No': 0})
df_dis = df[['Hipertension','Diabetes','No-show']]
df_dis
```

Out[29]:

	Hipertension	Diabetes	No-show
0	1	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	1	1	0
...	...	...	...
110522	0	0	0
110523	0	0	0
110524	0	0	0
110525	0	0	0
110526	0	0	0

110527 rows × 3 columns

In [30]:
```
hipertension = df.groupby(['Hipertension','No-show'], as_index=False)['PatientId'].count()
hipertension['per'] = hipertension.groupby('Hipertension')['PatientId'].transform(lambda x: x/x.sum())
hipertension.rename(columns={'PatientId':'Volume'}, inplace = True)
hipertension
```

Out[30]:

	Hipertension	No-show	Volume	per
0	0	0	70179	0.790963
1	0	1	18547	0.209037
2	1	0	18029	0.826980
3	1	1	3772	0.173020

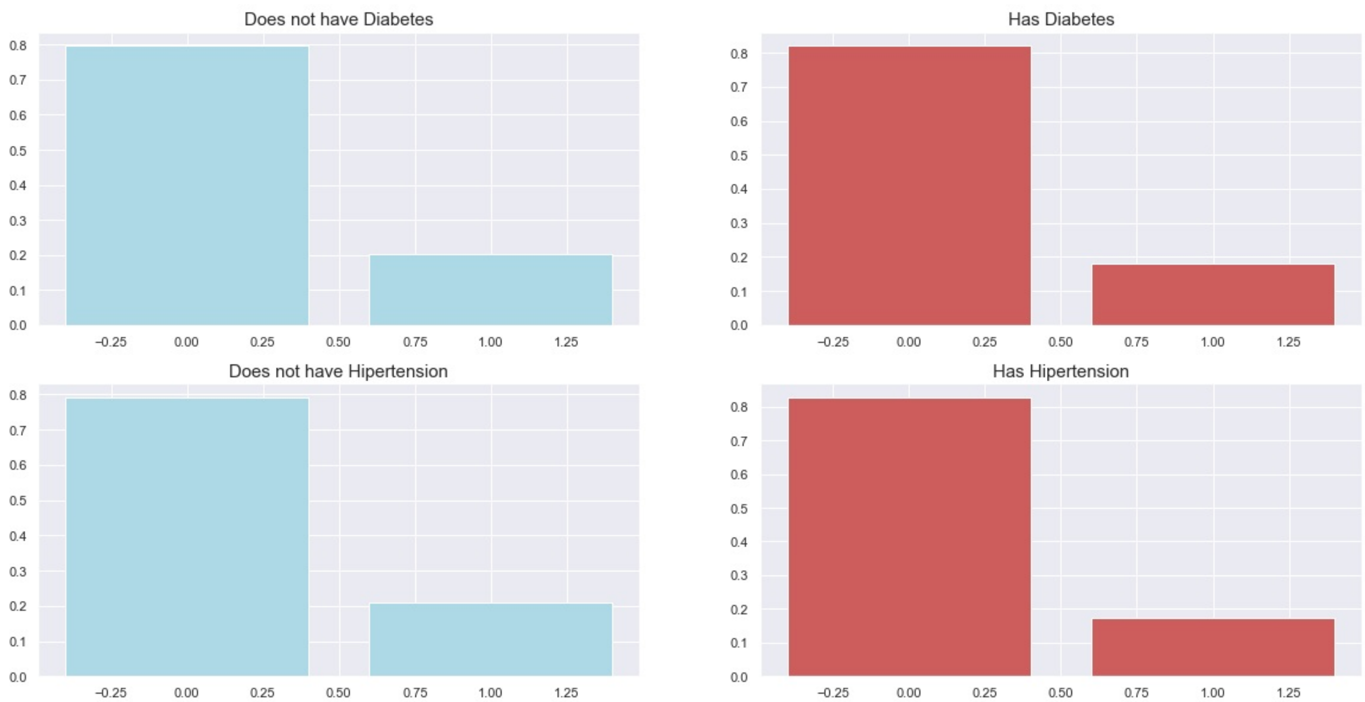
In [31]:
```
diabetes = df.groupby(['Diabetes','No-show'], as_index=False)['PatientId'].count()
diabetes['per'] = diabetes.groupby('Diabetes')['PatientId'].transform(lambda x: x/x.sum())
diabetes.rename(columns={'PatientId':'Volume'}, inplace = True)
diabetes
```

Out[31]:

	Diabetes	No-show	Volume	per
0	0	0	81695	0.796372
1	0	1	20889	0.203628
2	1	0	6513	0.819967
3	1	1	1430	0.180033

In [32]:
```
# Diabetes:
plt.figure(figsize=(20,10))
plt.subplot(221)
plt.bar(x = diabetes[diabetes['Diabetes']==0]['No-show'], height = diabetes[diabetes['Diabetes']==0]['per'], colo
plt.title('Does not have Diabetes',fontsize=15)
plt.subplot(222)
plt.bar(x = diabetes[diabetes['Diabetes']==1]['No-show'], height = diabetes[diabetes['Diabetes']==1]['per'], colo
plt.title('Has Diabetes',fontsize=15);

# Hipertension:
plt.subplot(223)
```

```
plt.bar(x = hipertension[hipertension['Hipertension']==0]['No-show'], height = hipertension[hipertension['Hiperte
plt.title('Does not have Hipertension',fontsize=15)
plt.subplot(224)
plt.bar(x = hipertension[hipertension['Hipertension']==1]['No-show'], height = hipertension[hipertension['Hiperte
plt.title('Has Hipertension',fontsize=15);
```



Above we have percentual comparison for the two chronic diseases. Neither seems to impact no-show volume so much: only a small decrease in missed appointments is made evident by the charts above (percentage of total was used to ascertain both groups would be comparable).

Let us check the correlation table.

In [33]:

```
df_dis[['Hipertension','Diabetes','No-show']].corr()
```

Out[33]:

	Hipertension	Diabetes	No-show
Hipertension	1.000000	0.433086	-0.035701
Diabetes	0.433086	1.000000	-0.015180
No-show	-0.035701	-0.015180	1.000000

From the Pearson linear correlations above we can see that there is indeed a negative correlation between having any of the diseases and not showing up. Thus, to a small extent, those afflicted tend to miss slightly less appointments.

It is important to observe that a strong positive correlation between Hipertension and Diabetes is shown, which sheds light to the possibility that having either of those increases the likelihood of having the other as well.

In [34]:

```
df.head()
```

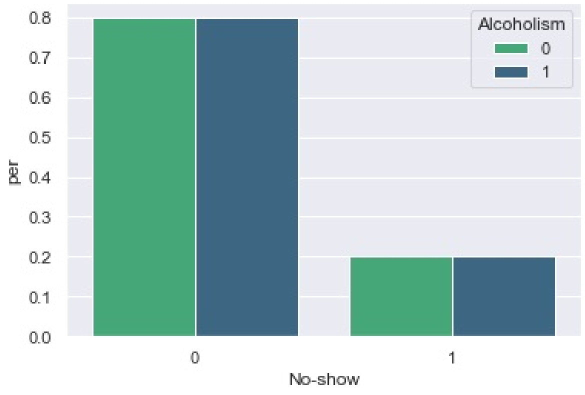
Out[34]:

	PatientId	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SM
0	2.987250e+13	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	0	1	0	0	0	
1	5.589978e+14	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	0	0	0	0	
2	4.262962e+12	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	0	0	0	0	0	
3	8.679512e+11	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	0	0	0	0	0	
4	8.841186e+12	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	1	1	0	0	

Alcoholism

Do alcoholics miss more appointments?

In [35]:
```
alco = df.groupby(['Alcoholism','No-show'], as_index=False)['PatientId'].count()
alco['per'] = alco.groupby('Alcoholism')['PatientId'].transform(lambda x: x/x.sum())
alco.rename(columns={'PatientId':'Volume'}, inplace = True)
sns.barplot(data = alco, x = 'No-show', y = 'per', hue ='Alcoholism', palette='viridis_r');
```

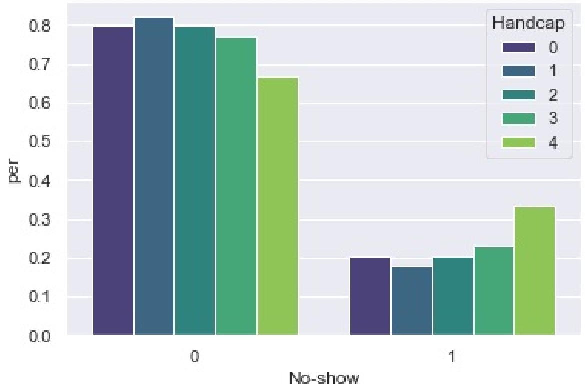


Alcoholism does not seem to play any part in missing appointments whatsoever.

Handcap

Do hadcapped people miss more / less appointments?

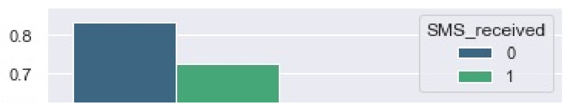
In [36]:
```
hand = df.groupby(['Handcap','No-show'], as_index=False)['PatientId'].count()
hand['per'] = hand.groupby('Handcap')['PatientId'].transform(lambda x: x/x.sum())
hand.rename(columns={'PatientId':'Volume'}, inplace = True)
sns.barplot(data = hand, x = 'No-show', y = 'per', hue ='Handcap', palette='viridis');
```

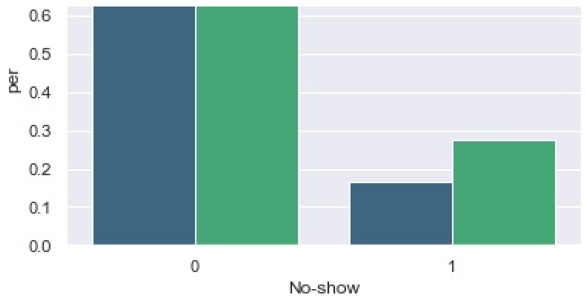


It seems like the volume of missed appointments increases with the severity of the handcap. People with less severe handcaps (1,2) tend to be more dilligent with their appointments than people who don't have any (0), but from handcap =3 to 4 both the no-shows amount increases. Maybe it is due to how hard it is for people in these cohorts to travel to the hospital (having more physical restrictions).

SMS - received

In [37]:
```
sms = df.groupby(['SMS_received','No-show'], as_index=False)['PatientId'].count()
sms['per'] = sms.groupby('SMS_received')['PatientId'].transform(lambda x: x/x.sum())
sms.rename(columns={'PatientId':'Volume'}, inplace = True)
sns.barplot(data = sms, x = 'No-show', y = 'per', hue ='SMS_received', palette='viridis');
```





The above is counter-intuitive: the percentage of no-shows increases from around 18% (for people who did not receive sms) to 28% (for people who did).

In [38]:

```
df[['SMS_received','No-show']].corr()
```

Out[38]:

	SMS_received	No-show
SMS_received	1.000000	0.126431
No-show	0.126431	1.000000

It is further shown from the linear correlation table above that there is a significant positive correlation between receiving sms and not showing up.

Maybe people simply don't like being bothered? (͡° ͜ʖ ͡°)

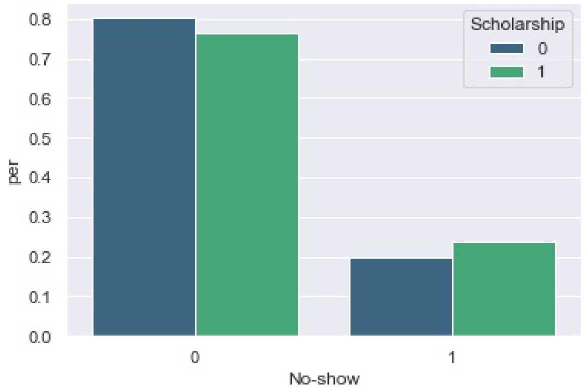
Scholarship

Health and receiving welfare doesn't seem to compete.

Although maybe, if we consider receiving welfare as a proxy for poverty (which is the case for Bolsa Familia), we can test whether people with less means are more likely to miss apointments or not.

In [39]:

```
welf = df.groupby(['Scholarship','No-show'], as_index=False)['PatientId'].count()
welf['per'] = welf.groupby('Scholarship')['PatientId'].transform(lambda x: x/x.sum())
welf.rename(columns={'PatientId':'Volume'}, inplace = True)
sns.barplot(data = welf, x = 'No-show', y = 'per', hue ='Scholarship', palette='viridis');
```



In [40]:

```
df[['Scholarship','No-show']].corr()
```

Out[40]:

	Scholarship	No-show
Scholarship	1.000000	0.029135
No-show	0.029135	1.000000

Once again, a small impact: receiving Bolsa Familia aid increases by a small margin the no-show volume.

Conclusion for Binary Variables: 'Scholarship', 'Hipertension', 'Diabetes', 'Handcap' & 'SMS_received' all seem to impact attendance by a small amount, as seem above, with each having small correlations to attendance. The only binary feature that does not seem to impact attendance at all is Alcoholism.

Appointment and Schedule Dates Analysis

In [41]:
```
days = df[['ScheduledDay','AppointmentDay','No-show']]
days
```

Out[41]:

	ScheduledDay	AppointmentDay	No-show
0	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	0
1	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	0
2	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	0
3	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	0
4	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	0
...	...	...	...
110522	2016-05-03T09:15:35Z	2016-06-07T00:00:00Z	0
110523	2016-05-03T07:27:33Z	2016-06-07T00:00:00Z	0
110524	2016-04-27T16:03:52Z	2016-06-07T00:00:00Z	0
110525	2016-04-27T15:09:23Z	2016-06-07T00:00:00Z	0
110526	2016-04-27T13:30:56Z	2016-06-07T00:00:00Z	0

110527 rows × 3 columns

From the looks of it we have:

- date AND hour for when the appointment was scheduled.
- just date for the appointment date

Therefore, we can't make assumptions about traffic during rush hours and such, as the actual appointments scheduled hour is absent.

In [42]:
```
days['app_day'] = pd.to_datetime(days['AppointmentDay']).dt.day_name()
days['wait_time'] = pd.to_datetime(days['AppointmentDay']).dt.date - pd.to_datetime(days['ScheduledDay']).dt.date
days
```

```
<ipython-input-42-0c058ec4a846>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retur
ning-a-view-versus-a-copy
  days['app_day'] = pd.to_datetime(days['AppointmentDay']).dt.day_name()
<ipython-input-42-0c058ec4a846>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retur
ning-a-view-versus-a-copy
  days['wait_time'] = pd.to_datetime(days['AppointmentDay']).dt.date - pd.to_datetime(days['ScheduledDay']).dt.da
te
```

Out[42]:

	ScheduledDay	AppointmentDay	No-show	app_day	wait_time
0	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	0	Friday	0 days
1	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	0	Friday	0 days
2	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	0	Friday	0 days
3	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	0	Friday	0 days
4	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	0	Friday	0 days
...	...	...	...	...	...
110522	2016-05-03T09:15:35Z	2016-06-07T00:00:00Z	0	Tuesday	35 days
110523	2016-05-03T07:27:33Z	2016-06-07T00:00:00Z	0	Tuesday	35 days
110524	2016-04-27T16:03:52Z	2016-06-07T00:00:00Z	0	Tuesday	41 days
110525	2016-04-27T15:09:23Z	2016-06-07T00:00:00Z	0	Tuesday	41 days
110526	2016-04-27T13:30:56Z	2016-06-07T00:00:00Z	0	Tuesday	41 days

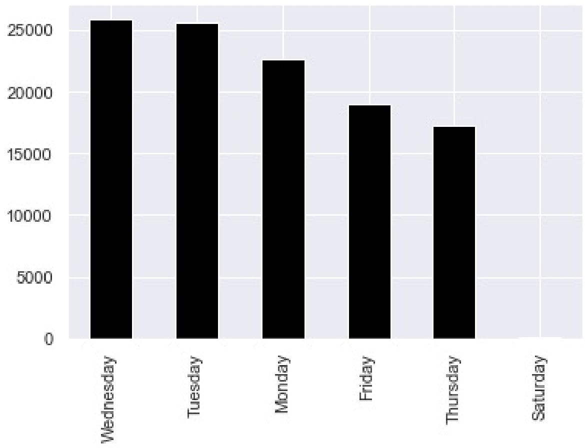
110527 rows × 5 columns

Above we added both the day of the appointment and the time (in days) between schedule date and appointment.

The goal here is to:

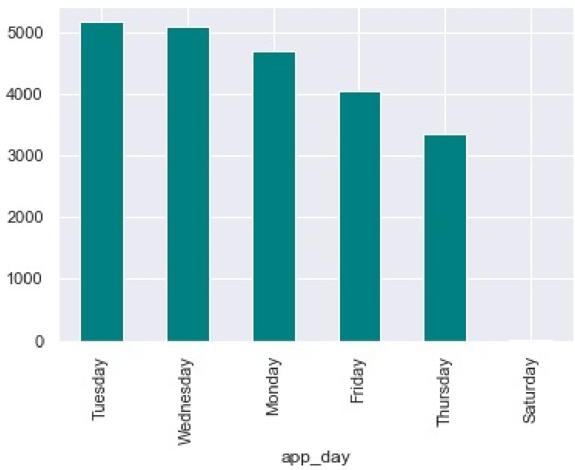
- **check whether there is a specific day of the week related to more missed appointments**
- **check if people forget their appointments. More days between schedule and appointment should be correlated to more missed apointments.**

In [43]:
```
days['app_day'].value_counts().plot(kind = 'bar', color = 'black');
```



There are no appointments on Saturdays. The day with highest number of appointments is Wednesday.

In [44]:
```
days.groupby('app_day')['No-show'].sum().sort_values(ascending=False).plot(kind = 'bar', color = 'teal');
```



Although the top two days reverse when it comes to no-show volume, the amount is proportional to the volume (black chart), displaying more or less the same shape through the days.

Therefore, the day of the week does not seem to influence missed appointments volume.

In [45]:
```
#converting wait time in a discrete int number:
days['wait_time'] = days['wait_time'].astype('timedelta64[D]')
days = days[days.wait_time >=0] # To remove errors (there can't be negative wait times, logically impossible)
days[['No-show', 'wait_time']].corr()
```

```
<ipython-input-45-7e108013fdf7>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retur
```

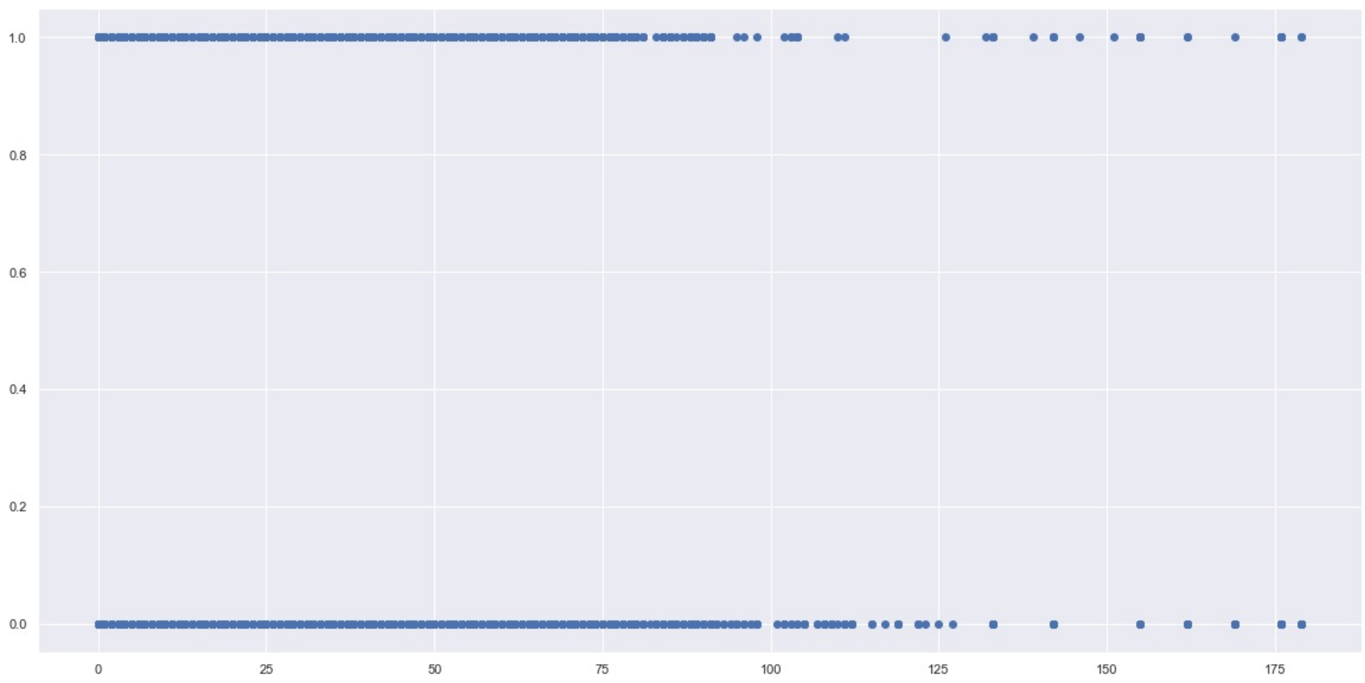
```
ning-a-view-versus-a-copy
  days['wait_time'] = days['wait_time'].astype('timedelta64[D]')
```

Out[45]:

	No-show	wait_time
No-show	1.000000	0.186322
wait_time	0.186322	1.000000

In [46]:

```
plt.figure(figsize=(20,10))
plt.scatter(days['wait_time'], days['No-show']);
```

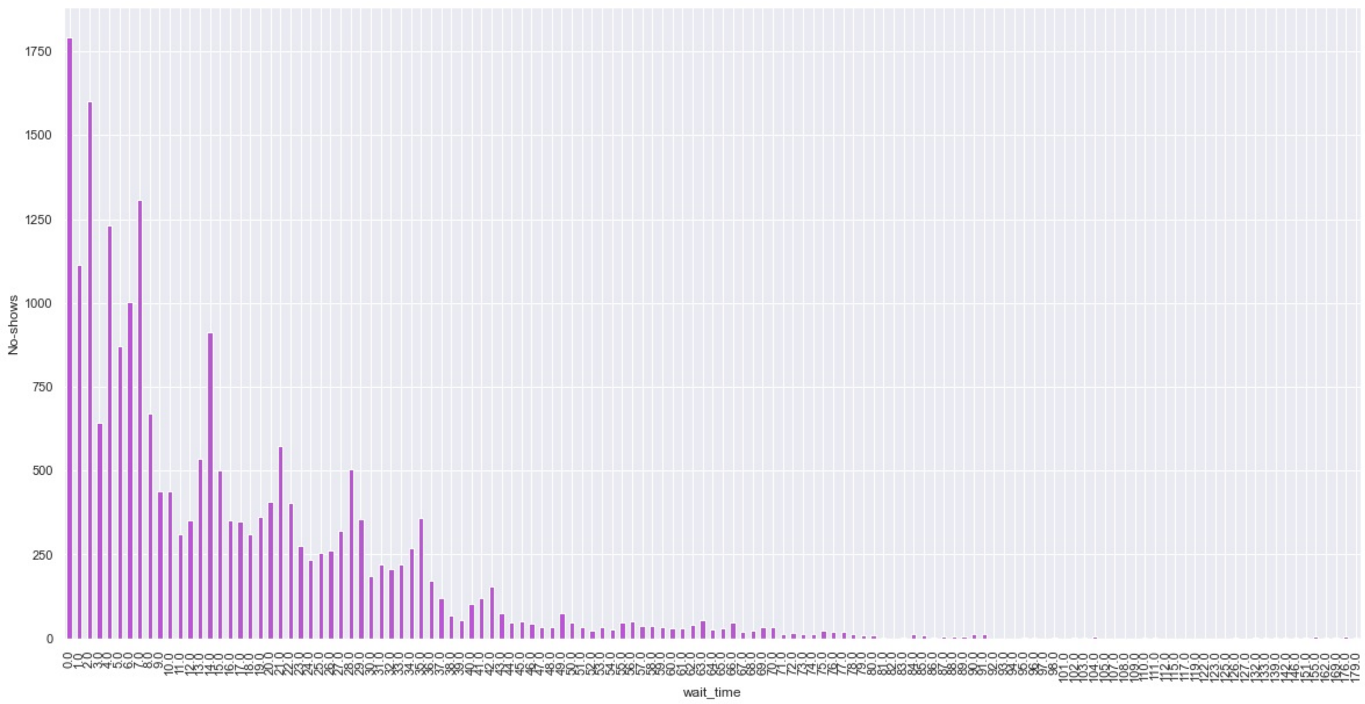


We can conclude that, although week day does not have importance related to no-shows, the wait time does.

A significant positive correlation is seem above and further reinforced by the spreadchart

In [47]:

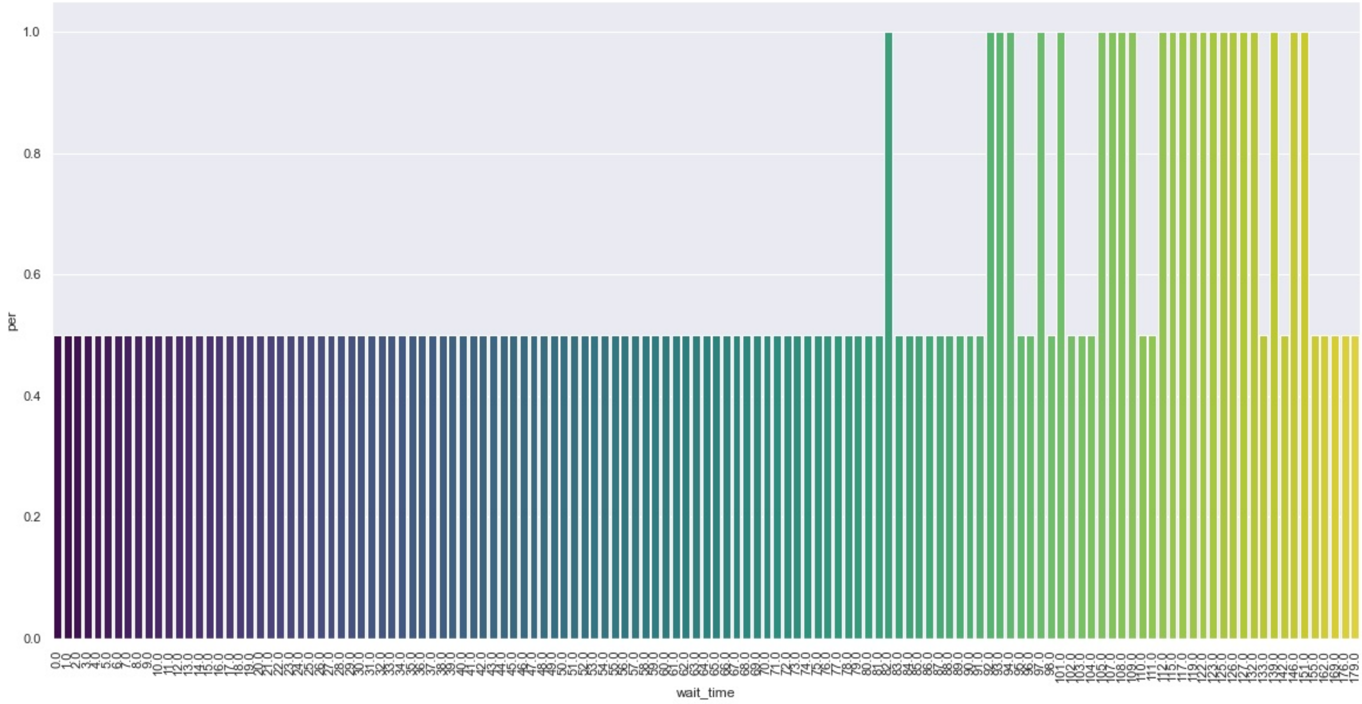
```
plt.figure(figsize=(20,10))
days.groupby('wait_time')['No-show'].sum().plot(kind='bar', color='mediumorchid');
plt.ylabel('No-shows');
```



In volume there are more no-shows registered for appointments scheduled in the same day (wait time = 0). But that just goes to show that the

In volume there are more no-shows registered for appointments scheduled in the same day (wait time = 0). But that just goes to show that the majority of appointments are scheduled in the nick of time.

In [48]:
```
plt.figure(figsize=(20,10))
wait = days.groupby(['wait_time','No-show'], as_index=False)['app_day'].count()
wait['per'] = wait.groupby('wait_time')['app_day'].transform(lambda x: x/x.sum())
sns.barplot(data = wait, x = 'wait_time', y = 'per', palette='viridis', ci = False);
plt.xticks(rotation = 90);
```



When taking into account the percentage of no-shows per total appointments per wait time we get the exact same conclusion as the correlations table and scatterplot above:

In [49]:
```
wait.sort_values('per', ascending = False)
```

Out[49]:

	wait_time	No-show	app_day	per
190	97.0	0	2	1.000000
164	82.0	0	1	1.000000
184	93.0	0	2	1.000000
220	139.0	1	1	1.000000
185	94.0	0	2	1.000000
...	...	...	...	...
228	162.0	1	2	0.181818
172	86.0	1	1	0.166667
230	169.0	1	1	0.125000
166	83.0	1	1	0.125000
1	0.0	1	1792	0.046469

235 rows × 4 columns

Conclusions:

In [50]:
```
df.head(0)
```

Out[50]:

PatientId	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_rec

- **Disease and Hipertension**: strongly correlated amongst themselves. Hence, if an individual has one he could likely have the other as well. The presence of any seems to be negative correlated to missing appointments, to a small extent.
- **Gender, Neighbourhood & Alcoholism**: all proved to be irrelevant to predict no-shows. Specially when analyzing in percentual terms.
- **Handcap**: the presence of handcap does not affect attendance for the low levels of severity. However, from Handcap = 3 to 4 the attendence reduces considerably, shedding light on how hard it must be for those afflicted to move to the appointment and make it in time.
- **Scholarship & SMS_received**: both behaved the opposite of what we expected, as both increase in percentual terms the no-shows. Hence, financially challenged people tend to miss more appointments (maybe it has to do with the public transport system) and those who receive SMS reminders also tend to miss their appointments more frequently.
- **Age, Wait Time, PatientId**: all of these proved to be significant for predicting no-shows. The elderly tend to miss less apointments on average (they might take better care of their health). We used appointment and scheduled day to obtain wait_time, which also seems to play a part in explaining missed appointments: the longer the wait, the more likely it is the patient forgets the appointment, hence the higher the no-show rates. Employing PatientId as a proxy to get the repeat offenders of the no-show statistic, we found that some people simply tend to miss more appointments. Perhaps previous unattendances might be considered as red flags, signaling that said individual is prone to miss his / her appointments.

If we were to train a model in this project, we would go with the following features to explain no-shows: Age, Wait Time, Repeated Offenders, SMS (after understanding the variable more in-depth, as it is it is way too dubious) and Handcap.