Medical Appointments No-Show Case Study: Appointments Data Analysis

Table of Contents

Introduction

In this report we will investigate 110,527 medical appointments & its 14 associated variables.

The following is the data description that is found on Kaggle (https://www.kaggle.com/joniarroba/noshowappointments).

- PatientId: Identification of a patient.
- AppointmentID: Identification of each appointment.
- Gender: Male or Female.
- Schedule day : the day the patient set up an appointment day.
- Appointment day: the day the patient was expected to show up.
- Age: How old is the patient.
- Neighbourhood: Where the appointment takes place.
- Scholarship: True of False.
- Hipertension: True or False.
- Diabetes: True or False.
- Alcoholism: True or False.
- Handcap: True or False.
- SMS_received: 1 or 0.
- No-show: 1 or 0.

In [4]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
```

Data Wrangling

In [5]:
```
df=pd.read_csv('noshowappointments-kagglev2-may-2016.csv')
df.sample(5)
```

Out[5]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourho
65588	5.317250e+14	5607053	F	2016-04-20T11:01:47Z	2016-05-02T00:00:00Z	1	S CRISTÓV
81903	9.259660e+14	5596877	F	2016-04-18T15:28:38Z	2016-05-30T00:00:00Z	45	ITARA
80181	1.897260e+12	5702473	M	2016-05-16T12:25:16Z	2016-05-18T00:00:00Z	62	JARI CAMBI
9513	7.319190e+13	5514078	F	2016-03-28T10:40:40Z	2016-05-02T00:00:00Z	19	ROM
91071	7.367380e+14	5698883	M	2016-05-16T07:57:46Z	2016-06-08T00:00:00Z	57	DO CABF

In [6]:
```
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
```

So we have around 110,527 entries , none of them has null values which is good.
However, is there any duplicates or unqiues among `patientID` and `AppointmentID` ? possibaly we can use one of them as an index to our data set?

For the sake of convenience , i'll lower the cases for all column names and use underscores to seperate between two words.

In [7]:
```
df.rename(str.lower, axis='columns' ,inplace=True)
df.rename({'no-show':'no_show'}, axis='columns' ,inplace=True)
df.head()
```

Out[7]:

	patientid	appointmentid	gender	scheduledday	appointmentday	age	neighbourhood	sc
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	
1	5.589980e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	
2	4.262960e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	
3	8.679510e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	
4	8.841190e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	

In [8]:
```
print('patient id duplicates:',df.patientid.duplicated().sum())
print('appointment id duplicates:',df.appointmentid.duplicated().sum())
```

```
patient id duplicates: 48783
appointment id duplicates: 0
```

Looks like `AppointmentID` has no duplicates so we can use it as an index.
`PatientID` duplicating make sense , it means that the same patient had several appointments.

In [9]:
```
df.set_index('appointmentid' , inplace=True)
df.sample(1)
```

Out[9]:

	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scho
appointmentid							
5663412	7.652490e+14	F	2016-05-05T09:59:31Z	2016-05-06T00:00:00Z	2	FORTE SÃO JOÃO	

In [10]:
```
print('Number of Patients with unique ID:',len(df.patientid.unique()))
print('Number of Appointments:',df.patientid.value_counts().sum())
```

```
Number of Patients with unique ID: 61744
Number of Appointments: 110527
```

Data Cleaning

Do duplicate entries exist among our data set?

In [11]:
```
print('Number of entries before removing dulicates:',df.shape[0])
print('Duplicated entries:',df.duplicated().sum())
df.drop_duplicates(inplace=True)
print('Number of entries after removing dulicates:',df.shape[0])
```

```
Number of entries before removing dulicates: 110527
Duplicated entries: 618
Number of entries after removing dulicates: 109909
```

Now lets check the unique values for each column to verify **data integrity**.

In [12]:
```
for column in df.columns.drop(['patientid','scheduledday','appointmentday','neighbourhood']):
    print(f'{column}:{df[column].unique()}\n')
print(f'Value Counts:{df[df.age==-1].age.value_counts()}')
```

```
gender:['F' 'M']

age:[ 62  56   8  76  23  39  21  19  30  29  22  28  54  15  50  40  46   4
  13  65  45  51  32  12  61  38  79  18  63  64  85  59  55  71  49  78
  31  58  27   6   2  11   7   0   3   1  69  68  60  67  36  10  35  20
  26  34  33  16  42   5  47  17  41  44  37  24  66  77  81  70  53  75
  73  52  74  43  89  57  14   9  48  83  72  25  80  87  88  84  82  90
  94  86  91  98  92  96  93  95  97 102 115 100  99  -1]

scholarship:[0 1]

hipertension:[1 0]

diabetes:[0 1]

alcoholism:[0 1]

handcap:[0 1 2 3 4]

sms_received:[0 1]

no_show:['No' 'Yes']

Value Counts:-1    1
Name: age, dtype: int64
```

I noticed multiple issues with columns' unique values and they are:

- There is one unique value in `age` which is `-1` , that doesnt make any sense.
- Why does `handcap` column has unique values from `0` to `4` ? , my first intial thought was it would be a binary stating if patient is handicaped or not as in 1 and 0.
- `sms_recieved` column has `0` and `1` values only indicating that its binary , however on the data description, it states that it can varry from `0` to `5` indicating number of `sms_recieved` , was it swapped out with `handcap` column?

- My intial thought that `-1` might had been a misentry , a 1 year old kid is less likely to have `hipertension` , `diabetes` & `alchololism` issues , the following cells show clearly the sum of 1 year old kids and how many of them suffer from certain issues , my fix would be is changing the `-1` into `1`

In [13]:
```python
print("sum of people older than 1 year who suffer from:")
print(df[df.age!=1].iloc[:,7:11].sum())
print("sum of people that are 1 year old who suffer from")
print(df[df.age==1].iloc[:,7:11].sum())
```

```
sum of people older than 1 year who suffer from:
hipertension    21678
diabetes         7892
alcoholism       3344
handcap          2431
dtype: int64
sum of people that are 1 year old who suffer from
hipertension    0
diabetes        1
alcoholism      0
handcap         1
dtype: int64
```

In [14]:
```python
df.loc[df.age == -1,'age'] = 1
df[df.age == -1]
```

Out[14]:

	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scholarsh
appointmentid							

- After doing a little research on kaggle , i found this message (https://www.kaggle.com/joniarroba/noshowappointments/discussion/29699#229356) from the data set creator stating that the numbers in `handcap` column refers to the amount of disabilities that the patient is suffering from. so nothing to be changed.

In [15]:
```python
print('number of unique values')
df.handcap.value_counts()
```

```
number of unique values
```

Out[15]:
```
0    107690
1      2023
2       182
3        11
4         3
Name: handcap, dtype: int64
```

- Prior to the previous markdown cell , it clearly states that `0` means No sms recieved and `1` means message sent , so i will change nothing.

In [16]:
```
df.sms_received.value_counts()
print('Number ofduplicates:',df.duplicated().sum())
```

```
Number ofduplicates: 0
```

Timestamp segregation

In [17]:
```
df['ap_year']=pd.to_datetime(df.appointmentday).dt.year
df['ap_month']=pd.to_datetime(df.appointmentday).dt.month
df['ap_dom']=pd.to_datetime(df.appointmentday).dt.day
df['ap_dow']=pd.to_datetime(df.appointmentday).dt.dayofweek
df['ap_doy']=pd.to_datetime(df.appointmentday).dt.dayofyear
df['ap_hr']=pd.to_datetime(df.appointmentday).dt.hour
df.appointmentday=pd.to_datetime(df.appointmentday).dt.date
df['sc_year']=pd.to_datetime(df.scheduledday).dt.year
df['sc_month']=pd.to_datetime(df.scheduledday).dt.month
df['sc_dom']=pd.to_datetime(df.scheduledday).dt.day
df['sc_dow']=pd.to_datetime(df.scheduledday).dt.dayofweek
df['sc_doy']=pd.to_datetime(df.scheduledday).dt.dayofyear
df['sc_hr']=pd.to_datetime(df.scheduledday).dt.hour
df.scheduledday=pd.to_datetime(df.scheduledday).dt.date
df.head(1)
print('Number ofduplicates:',df.duplicated().sum())
```

```
Number ofduplicates: 1613
```

Notice how duplicates re-emerged, we will address this later.

Setting up a new column (waiting_days) to describe how many days between:

- Schedule day : the day the patient set up an appointment day in the future.
- Appointment day: the day the patient was expected to show up.

In [18]:
```
df['waiting_days']=df.appointmentday - df.scheduledday
df['waiting_days']=df.waiting_days.dt.days
df.waiting_days.value_counts().sort_index().head()
```

Out[18]:
```
-6        1
-1        4
 0    38495
 1     5162
 2     6698
Name: waiting_days, dtype: int64
```

Looks like we have 5 invalid entries, one (-6 days) and four (-1 days) , I'm not sure why they exist , but I decided to remove them.

In [19]:
```
df=df.drop(df[df.waiting_days< 0].index)
df.waiting_days.value_counts().sort_index().head()
```

Out[19]:
```
0    38495
1     5162
2     6698
3     2711
4     5269
Name: waiting_days, dtype: int64
```

`waiting_days` looks good to go now!

In [20]:
```
df.head()
```

Out[20]:

	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scho
appointmentid							
5642903	2.987250e+13	F	2016-04-29	2016-04-29	62	JARDIM DA PENHA	
5642503	5.589980e+14	M	2016-04-29	2016-04-29	56	JARDIM DA PENHA	
5642549	4.262960e+12	F	2016-04-29	2016-04-29	62	MATA DA PRAIA	
5642828	8.679510e+11	F	2016-04-29	2016-04-29	8	PONTAL DE CAMBURI	
5642494	8.841190e+12	F	2016-04-29	2016-04-29	56	JARDIM DA PENHA	

5 rows × 26 columns

Outlier removal

In [21]:
```python
def get_num_vars(data):
    """ a function that returns a list of a numeric non binary "0" or "1" vari
ables in dataframe
    Args:
        data (pandas dataframe): supplied only with dataframes
    Returns:
        list (list): returns a list with numeric non binary variables
    """
    num_vars=[]
    numeric_vars=data.dtypes[data.dtypes!= 'object'].index
    for numeric_var in numeric_vars:
        condition= (len(data[numeric_var].unique()) == 2) & (data[numeric_var]
.unique().sum() == 1)
        if not condition:
            num_vars.append(numeric_var)
        else:
          print(numeric_var,data[numeric_var].unique())
    return(num_vars)
```

In [22]:
```python
# extracting numerical variables from dataset
numeric_vars=get_num_vars(df)
numeric_vars.index('patientid')
numeric_vars.pop(0)
numeric_vars
```

```
scholarship [0 1]
hipertension [1 0]
diabetes [0 1]
alcoholism [0 1]
sms_received [0 1]
```

Out[22]:
```
['age',
 'handcap',
 'ap_year',
 'ap_month',
 'ap_dom',
 'ap_dow',
 'ap_doy',
 'ap_hr',
 'sc_year',
 'sc_month',
 'sc_dom',
 'sc_dow',
 'sc_doy',
 'sc_hr',
 'waiting_days']
```

In [23]:
```
numeric_vars=get_num_vars(df)
numeric_vars.pop(numeric_vars.index('patientid'))
Q1 = df[numeric_vars].quantile(0.25) # 1st quartile for all numerical vars
Q3 = df[numeric_vars].quantile(0.75) # 3rt quartile for all numerical vars
IQR = Q3 - Q1                         # Inter quartile range for all numerical
 vars
lower_fence=Q1-1.5*IQR                # lower fence
upper_fence=Q3+1.5*IQR                # upper fence
print(lower_fence)
print(upper_fence)
```

```
scholarship [0 1]
hipertension [1 0]
diabetes [0 1]
alcoholism [0 1]
sms_received [0 1]
age              -37.5
handcap            0.0
ap_year         2016.0
ap_month           5.0
ap_dom           -16.0
ap_dow            -2.0
ap_doy            97.0
ap_hr              0.0
sc_year         2016.0
sc_month           2.5
sc_dom           -18.0
sc_dow            -2.0
sc_doy            88.5
sc_hr              0.5
waiting_days     -22.5
dtype: float64
age              110.5
handcap            0.0
ap_year         2016.0
ap_month           5.0
ap_dom            40.0
ap_dow             6.0
ap_doy           185.0
ap_hr              0.0
sc_year         2016.0
sc_month           6.5
sc_dom            46.0
sc_dow             6.0
sc_doy           172.5
sc_hr             20.5
waiting_days      37.5
dtype: float64
```

In [24]:
```python
# using this cell to build up the query statement, which we will evaulate late
r.
cond=[]
tot='2'
# Outlier removal statment according to lower fencer and upper fence
for var, fence in lower_fence.items():
    condi=f'(df["{var}"] >= {fence})'
    cond.append(condi)

for var, fence in upper_fence.items():
    condi = f'(df["{var}"] <= {fence})'
    cond.append(condi)

cond=' & '.join(cond)
cond
```

Out[24]:
```
'(df["age"] >= -37.5) & (df["handcap"] >= 0.0) & (df["ap_year"] >= 2016.0) &
(df["ap_month"] >= 5.0) & (df["ap_dom"] >= -16.0) & (df["ap_dow"] >= -2.0) &
(df["ap_doy"] >= 97.0) & (df["ap_hr"] >= 0.0) & (df["sc_year"] >= 2016.0) &
(df["sc_month"] >= 2.5) & (df["sc_dom"] >= -18.0) & (df["sc_dow"] >= -2.0) &
(df["sc_doy"] >= 88.5) & (df["sc_hr"] >= 0.5) & (df["waiting_days"] >= -22.5)
& (df["age"] <= 110.5) & (df["handcap"] <= 0.0) & (df["ap_year"] <= 2016.0) &
(df["ap_month"] <= 5.0) & (df["ap_dom"] <= 40.0) & (df["ap_dow"] <= 6.0) & (d
f["ap_doy"] <= 185.0) & (df["ap_hr"] <= 0.0) & (df["sc_year"] <= 2016.0) & (d
f["sc_month"] <= 6.5) & (df["sc_dom"] <= 46.0) & (df["sc_dow"] <= 6.0) & (df
["sc_doy"] <= 172.5) & (df["sc_hr"] <= 20.5) & (df["waiting_days"] <= 37.5)'
```

In [25]:
```python
med=df[eval(cond)].copy()
med
```

Out[25]:

	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scho
appointmentid							
5530556	4.983940e+13	F	2016-03-31	2016-05-03	49	MARIA ORTIZ	
5549661	8.957750e+13	F	2016-04-06	2016-05-10	73	MARIA ORTIZ	
5613929	4.661450e+11	F	2016-04-25	2016-05-17	51	MARIA ORTIZ	
5731976	8.678120e+13	F	2016-05-24	2016-05-24	20	MARIA ORTIZ	
5739155	5.811740e+13	F	2016-05-25	2016-05-31	37	MARIA ORTIZ	
...	...	...	...	...	...	...	
5670576	3.292130e+11	F	2016-05-06	2016-05-06	15	BONFIM	
5559647	8.481724e+10	M	2016-04-08	2016-05-11	19	BONFIM	
5574248	7.481600e+13	M	2016-04-12	2016-05-11	64	BONFIM	
5574252	7.481600e+13	M	2016-04-12	2016-05-11	64	BONFIM	
5594435	8.521460e+12	M	2016-04-18	2016-05-24	48	BONFIM	

74726 rows × 26 columns

In [26]:
```
#creating age groups
med['age_group']=pd.cut(med['age'],bins=[0,3,16,40,60,103],right=False,
                            labels=['Baby 0-2','Teen 3-15', 'Young Adults 16-3
9','Middle-aged 40-59', 'Elderly 60+'])
med['age_group'].value_counts().sort_index()
```

Out[26]:
```
Baby 0-2               5259
Teen 3-15             11678
Young Adults 16-39    24045
Middle-aged 40-59     20152
Elderly 60+           13592
Name: age_group, dtype: int64
```

In [27]:
```
print('Number of entries after removing outliers:',med.shape[0])
```

```
Number of entries after removing outliers: 74726
```

Exploratory Data Analysis

Univariate Exploration

In [28]:
```
med['no_show_bin']=pd.get_dummies(med['no_show'],drop_first=True)
```

In [29]:
```
med.describe()
```

Out[29]:

	patientid	age	scholarship	hipertension	diabetes	alcoholism	har
count	7.472600e+04	74726.000000	74726.000000	74726.000000	74726.000000	74726.000000	74
mean	1.474372e+14	36.435899	0.101504	0.192477	0.069507	0.030940	
std	2.562173e+14	22.937845	0.301997	0.394248	0.254316	0.173156	
min	9.380000e+04	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	4.192338e+12	17.000000	0.000000	0.000000	0.000000	0.000000	
50%	3.172600e+13	36.000000	0.000000	0.000000	0.000000	0.000000	
75%	9.445998e+13	55.000000	0.000000	0.000000	0.000000	0.000000	
max	9.999820e+14	102.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 22 columns

```
In [30]: med.patientid.value_counts()
```

```
Out[30]: 8.221460e+14    62
9.963767e+10    59
6.264200e+12    50
2.688610e+13    47
3.353480e+13    47
                ..
4.999710e+13     1
9.139710e+12     1
1.534727e+10     1
4.476740e+12     1
4.983940e+13     1
Name: patientid, Length: 46666, dtype: int64
```

We have atleast 46666 unqiue patients, and some of them had up to 62 appointments, quite strange, lets check patient ID 8.221460e+14

```
In [31]: inspection=med[med.patientid==8.221460e+14].sort_values('appointmentid')
inspection[['patientid','scheduledday','sc_hr','ap_doy','sms_received','no_sho
w']]
```

Out[31]:

	patientid	scheduledday	sc_hr	ap_doy	sms_received	no_show
appointmentid						
5645183	8.221460e+14	2016-05-02	9	123	0	No
5649058	8.221460e+14	2016-05-02	17	123	0	No
5649163	8.221460e+14	2016-05-02	17	123	0	No
5655382	8.221460e+14	2016-05-03	16	124	0	No
5657205	8.221460e+14	2016-05-04	9	125	0	No
...	...	...	...	...	...	...
5747258	8.221460e+14	2016-05-30	15	151	0	No
5748219	8.221460e+14	2016-05-30	17	151	0	No
5752932	8.221460e+14	2016-05-31	13	152	0	No
5753275	8.221460e+14	2016-05-31	13	152	0	No
5754261	8.221460e+14	2016-05-31	15	152	0	No

62 rows × 6 columns

I've discovered something interesting, it seems there is **rescheduling phenomenon** occuring during same day, here is a sequence of appointments for patient number `8221460`

In [32]:
```
inspection.loc[5667980:5673265,['patientid','scheduledday','sc_hr','waiting_da
ys','ap_doy','sms_received','no_show']]
```

Out[32]:

	patientid	scheduledday	sc_hr	waiting_days	ap_doy	sms_received	no_sho
appointmentid							
5667980	8.221460e+14	2016-05-06	8	0	127	0	I
5668887	8.221460e+14	2016-05-06	9	0	127	0	I
5671341	8.221460e+14	2016-05-06	16	0	127	0	I
5671588	8.221460e+14	2016-05-06	19	4	131	1	Y
5673265	8.221460e+14	2016-05-09	9	0	130	0	I

Unfortunately, everytime this happens, a new `appointmentID` is generated, infact, there should be less appointments in the dataset after this fact check,I will be removing all appointments scheduled in the same day for every unique `patientid` and keeping last chronological entry only in `med` data set, but also, I'll make a new data set called `re_med` to investigate the rescheduling phenomenon.

In [33]:
```
re_med=med.copy()
```

In [34]:
```
print('Total number of rescheduls in dataset: ',med.duplicated(subset=['patien
tid','scheduledday']).sum())
```

```
Total number of rescheduls in dataset:  6976
```

In [35]:
```
#Re-ordering dataset according to appointmentid , assuming the increase in its
value is chronological
med=med.sort_values('appointmentid')
med.drop_duplicates(subset=['patientid','scheduledday'],keep='last',inplace=Tr
ue)
med.duplicated().sum()
```

Out[35]: 0

In [36]:
```
print('Number of entries after removing reschedules:',med.shape[0])
```

```
Number of entries after removing reschedules: 67750
```

In [37]:
```
med.patientid.value_counts()
```

Out[37]:
```
6.264200e+12    20
3.353480e+13    19
2.584240e+11    19
2.688610e+13    19
8.713750e+14    18
                ..
9.243360e+12     1
4.587950e+13     1
2.199480e+14     1
4.583990e+14     1
7.333670e+12     1
Name: patientid, Length: 46666, dtype: int64
```

Now these values are more realistic, 20 appointments is more digestable than 62 appointments in 3 month period (to be discovered later on).

In [38]:
```
inspection=med[med.patientid==6.264200e+12]
inspection[:10]
```

Out[38]:

appointmentid	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scho
5601038	6.264200e+12	M	2016-04-19	2016-05-10	59	JESUS DE NAZARETH	
5627939	6.264200e+12	M	2016-04-27	2016-05-17	59	JESUS DE NAZARETH	
5649053	6.264200e+12	M	2016-05-02	2016-05-02	59	JESUS DE NAZARETH	
5660590	6.264200e+12	M	2016-05-04	2016-05-04	59	JESUS DE NAZARETH	
5664515	6.264200e+12	M	2016-05-05	2016-05-05	59	JESUS DE NAZARETH	
5671328	6.264200e+12	M	2016-05-06	2016-05-06	59	JESUS DE NAZARETH	
5677173	6.264200e+12	M	2016-05-09	2016-05-09	59	JESUS DE NAZARETH	
5682204	6.264200e+12	M	2016-05-10	2016-05-10	59	JESUS DE NAZARETH	
5685804	6.264200e+12	M	2016-05-11	2016-05-18	59	JESUS DE NAZARETH	
5693047	6.264200e+12	M	2016-05-12	2016-05-12	59	JESUS DE NAZARETH	

10 rows × 28 columns

In [39]:
```
med.duplicated().sum()
```
Out[39]: 0

Rescheduling Phenomenon Investigation

In [40]:
```
#aquiring desired columns for analysis and sorting the values
re_meds=re_med.sort_values(['patientid','scheduledday','sc_hr'])[['patientid',
'scheduledday','sc_doy','sc_hr','waiting_days','ap_doy','no_show_bin']]
```

In [41]:
```
res=re_meds[re_meds.duplicated(subset=['patientid','scheduledday'],keep=False
)]
res
```
Out[41]:

	patientid	scheduledday	sc_doy	sc_hr	waiting_days	ap_doy	no_show_bin
appointmentid							
5722094	2.699191e+08	2016-05-20	141	7	0	141	0
5722676	2.699191e+08	2016-05-20	141	7	0	141	0
5647331	4.288349e+08	2016-05-02	123	13	11	134	0
5647345	4.288349e+08	2016-05-02	123	13	1	124	0
5624326	5.225847e+08	2016-04-26	117	15	20	137	1
...	...	...	...	...	...	...	...
5650930	9.988820e+14	2016-05-03	124	8	0	124	0
5664282	9.992780e+14	2016-05-05	126	11	0	126	0
5664279	9.992780e+14	2016-05-05	126	11	0	126	0
5615134	9.994790e+14	2016-04-25	116	11	7	123	1
5615162	9.994790e+14	2016-04-25	116	11	14	130	0

12846 rows × 7 columns

In [42]:
```
#Calculating the number of scheduling attempts for each patient for every day
per_day=res.groupby(['patientid','sc_doy'])['no_show_bin'].count().sort_values
().reset_index().rename({'no_show_bin':'re_scds per day'},axis='columns')
#removing the 1 count from the calculation to reflect reschedeuling attempts p
er patient per day
per_day['re_scds per day']-=1
per_day
```

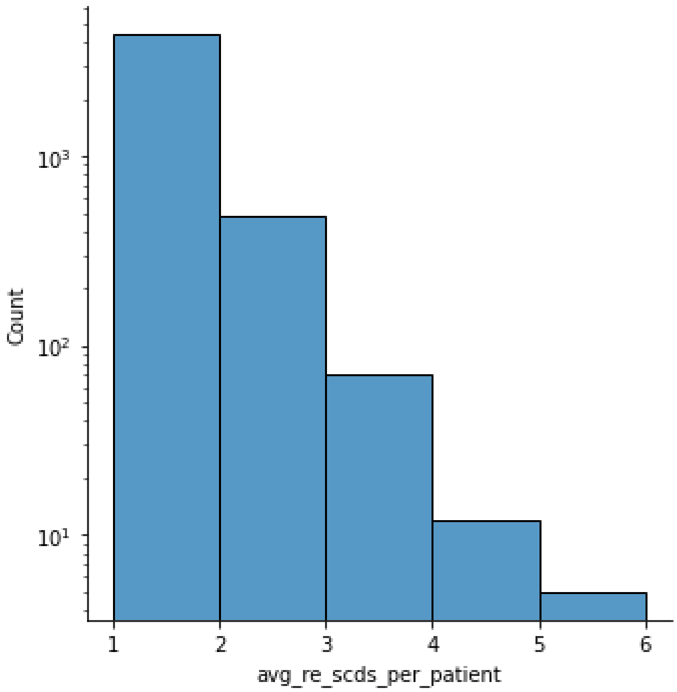
Out[42]:

	patientid	sc_doy	re_scds per day
0	2.699191e+08	141	1
1	6.683760e+13	116	1
2	6.681260e+13	124	1
3	6.681220e+13	118	1
4	6.663390e+13	134	1
...	...	...	...
5865	9.338860e+13	119	5
5866	4.768620e+11	119	5
5867	4.551840e+12	140	6
5868	7.194940e+12	146	6
5869	3.699500e+13	134	6

5870 rows × 3 columns

In [43]:
```
#calculating the average rescheduels per day for every unqiue patient
re_scds=per_day.groupby('patientid')['re_scds per day'].mean().reset_index().s
ort_values('re_scds per day').rename({'re_scds per day':'avg_re_scds_per_patie
nt'},axis='columns')
# Rounding values to be 1,2,3,4,5 or 6
re_scds['avg_re_scds_per_patient'] = re_scds['avg_re_scds_per_patient'].round(
0)
```

In [44]:
```
sns.displot(data=re_scds,x='avg_re_scds_per_patient',bins=5)
plt.yscale('log');
```



In [45]:
```python
#Merging med dataset with a new feature "avg_re_scds_per_patient"
med=pd.merge(med,re_scds,how='left',left_on='patientid',right_on='patientid')
# filling empty entires in the new feature with 0, indicating its
med.avg_re_scds_per_patient.fillna(0,inplace=True)
med.isna().sum()
```

Out[45]:
```
patientid                  0
gender                     0
scheduledday               0
appointmentday             0
age                        0
neighbourhood              0
scholarship                0
hipertension               0
diabetes                   0
alcoholism                 0
handcap                    0
sms_received               0
no_show                    0
ap_year                    0
ap_month                   0
ap_dom                     0
ap_dow                     0
ap_doy                     0
ap_hr                      0
sc_year                    0
sc_month                   0
sc_dom                     0
sc_dow                     0
sc_doy                     0
sc_hr                      0
waiting_days               0
age_group                  0
no_show_bin                0
avg_re_scds_per_patient    0
dtype: int64
```

How does age distribution look like?

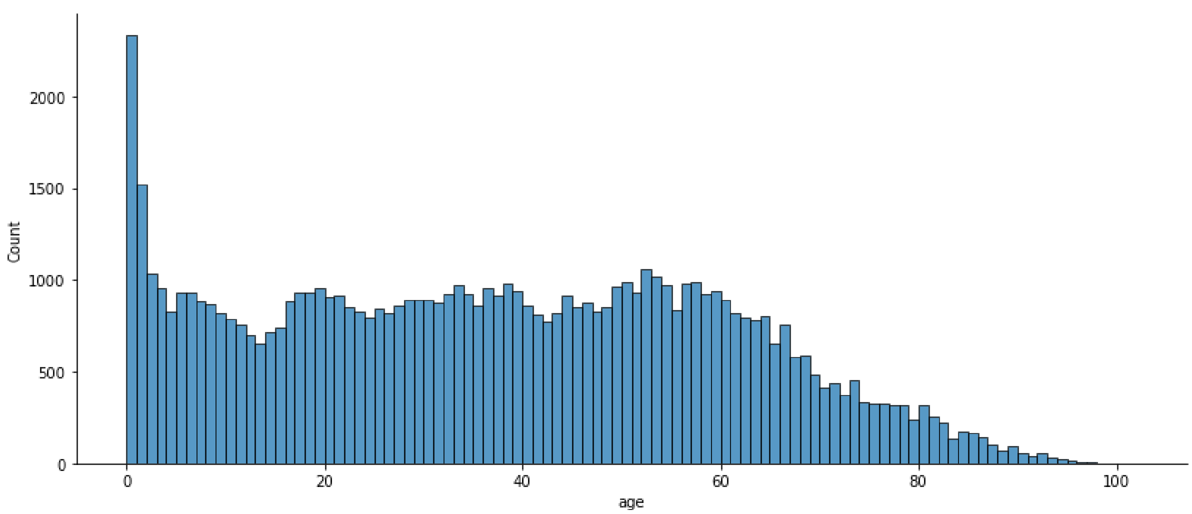
In [46]:
```
med.age.value_counts()
```

Out[46]:
```
0      2334
1      1523
52     1057
2      1031
53     1019
       ...
95       14
96        9
97        7
98        1
102       1
Name: age, Length: 100, dtype: int64
```

In [47]:
```
med.age.describe()
```

Out[47]:
```
count    67750.000000
mean        36.525373
std         23.072912
min          0.000000
25%         17.000000
50%         36.000000
75%         55.000000
max        102.000000
Name: age, dtype: float64
```

In [48]:
```
bins = np.arange(0, med['age'].max()+1, 1)
# plt.hist(data=med, x='age', bins=bins,edgecolor='black');
sns.displot(data=med, x='age', bins=bins,height=5,aspect=2.3);
```

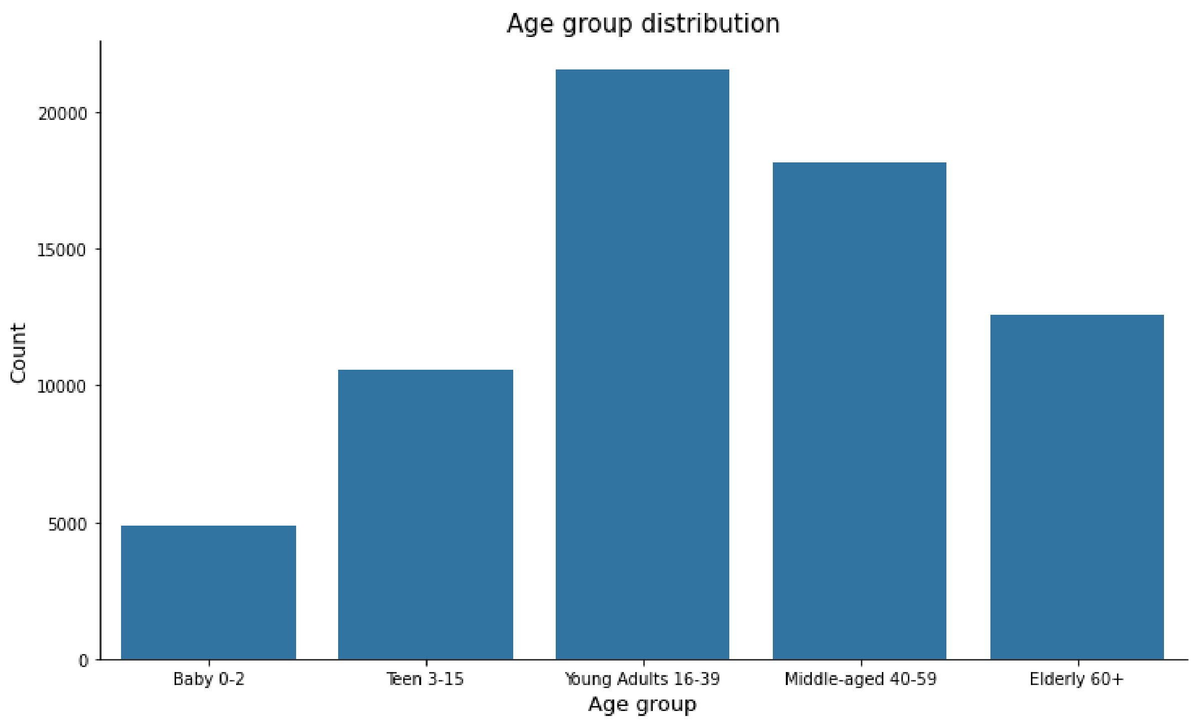


Age distribution is multimodel, peaks are around 0, 20, 40 and 55

In [49]:
```
base_color = sns.color_palette()[0]
alt=sns.color_palette()[7]
```

How does age group distripution look like?

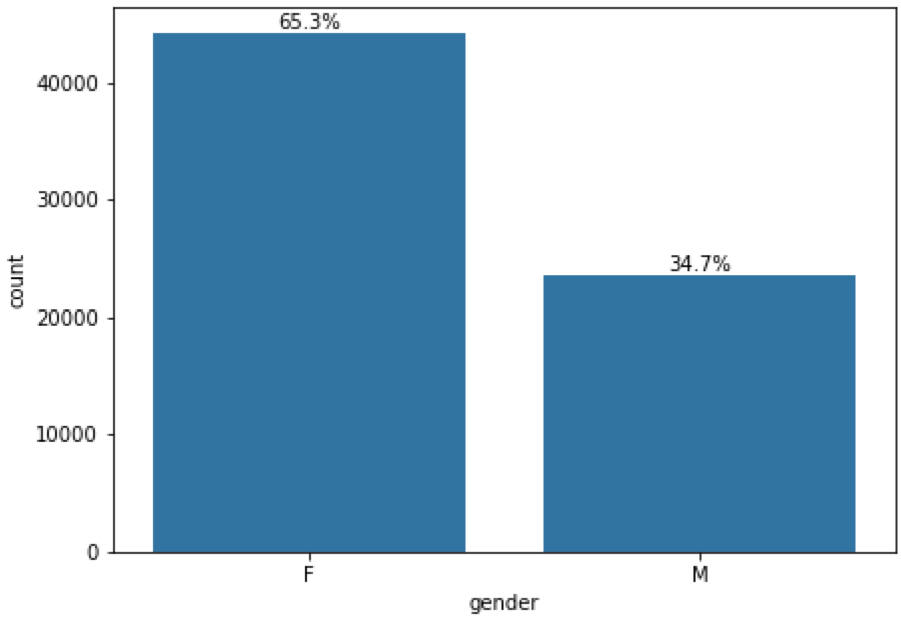
In [50]:
```
plt.figure(figsize=(12,7))
sns.countplot(data=med,x='age_group',color=base_color);
plt.xlabel('Age group',fontsize=13)
plt.ylabel('Count',fontsize=13)
plt.title('Age group distribution',fontsize=15);
sns.despine()
```



What is gender distripution?

In [51]:
```
def bar_data(d,var):
    counts=d[var].value_counts().sort_index()
    idx=d[var].value_counts().sort_index().index
    pct=d[var].value_counts(normalize=True).sort_index()
    txt = ['{:0.1f}%'.format(v) for v in pct*100]
    return counts,idx,txt
```

In [52]:
```
counts,idx,txt = bar_data(med,'gender')
fig=plt.figure(figsize=(7,5))
g=sns.countplot(data=med ,x='gender' ,color=base_color)

for i in range (len(counts)):
    plt.text(i,                              # x axis co-ordinate
             counts[i],                      # y axis co-ordinate
             txt[i],                         # text names to be displayed
             ha='center',                    # horizontal aligment
             va='bottom')
```



What is the distripution of scheduled day and appointment day?

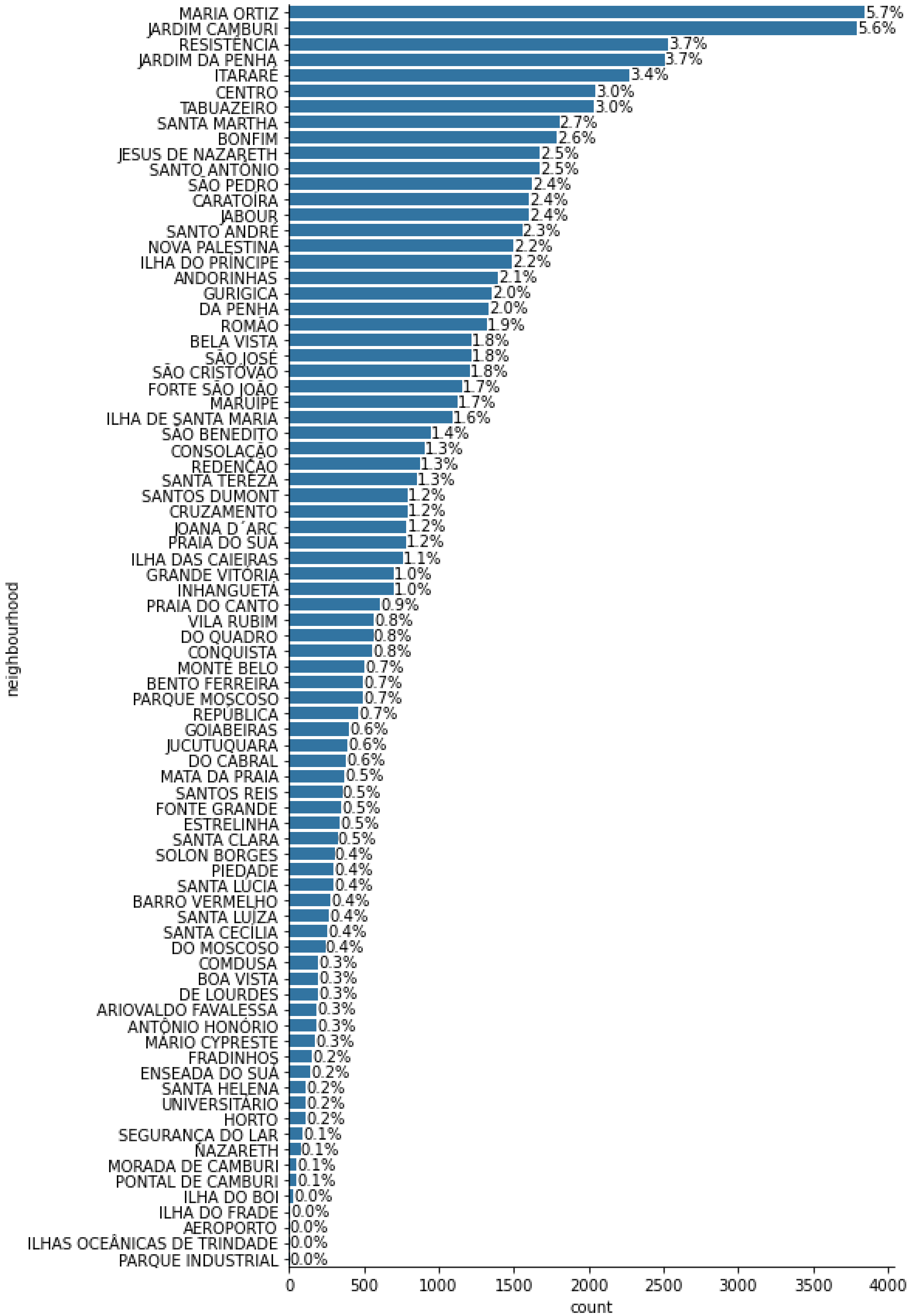
In [53]:
```
med.appointmentday.describe()
```

Out[53]:
```
count          67750
unique            20
top       2016-05-16
freq            3844
Name: appointmentday, dtype: object
```

What does the distribution for neighbourhoods look like?

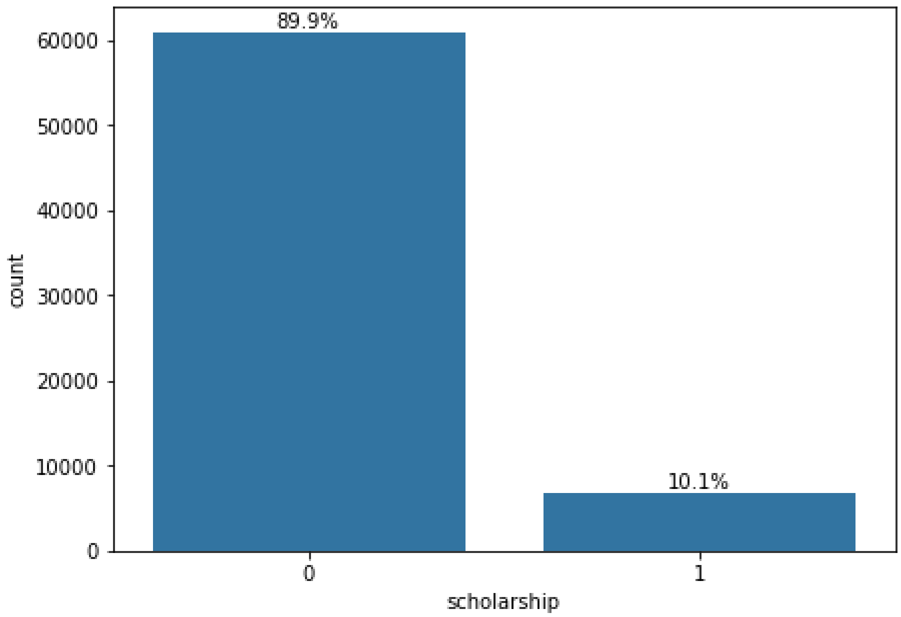
In [55]:

```
nbd_counts=med.neighbourhood.value_counts()
nbd_idx=med.neighbourhood.value_counts().index
nbd_pct=med.neighbourhood.value_counts(normalize=True)
nbd_txt = ['{:0.1f}%'.format(v) for v in nbd_pct*100]
plt.figure(figsize = [7, 15])
sns.countplot(data=med,y='neighbourhood',color=base_color,order=nbd_idx)
plt.xlabel('count')
sns.despine()
for i in range (nbd_counts.shape[0]):
    plt.text(nbd_counts.values[i],  # x axis co-ordinate
             i,                      # y axis co-ordinate
             nbd_txt[i],       # text names to be displayed
             ha='left',              # horizontal aligment
             va='center')
```



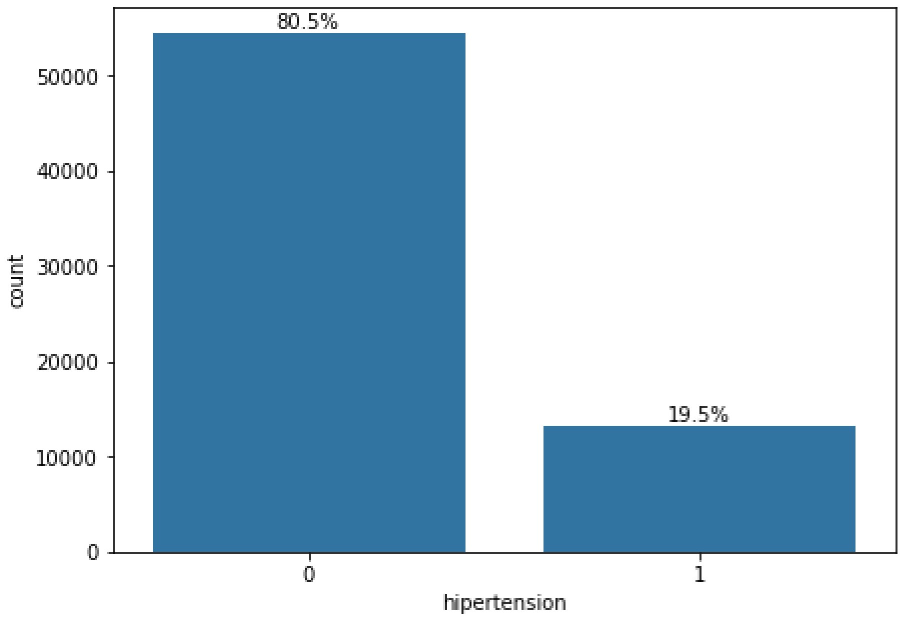
How many appointments had someone with scholarship program?

In [56]:
```
counts,idx,txt = bar_data(med,'scholarship')
fig=plt.figure(figsize=(7,5))
g=sns.countplot(data=med ,x='scholarship' ,color=base_color)

for i in range (len(counts)):
    plt.text(i,                                   # x axis co-ordinate
             counts[i],# y axis co-ordinate
             txt[i],                       # text names to be displayed
             ha='center',                         # horizontal aligment
             va='bottom')
```



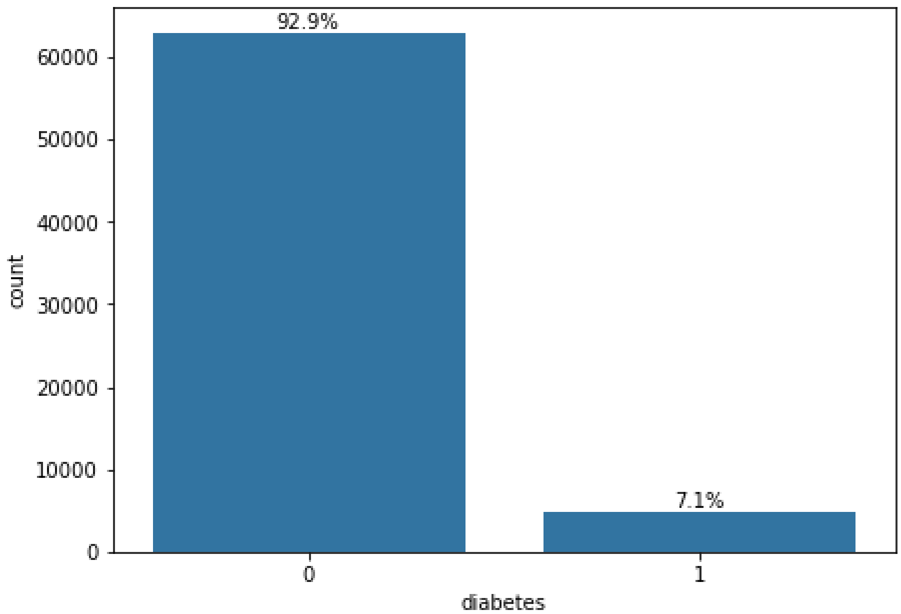
How many appointments involved someone with hipertension disease?

In [57]:
```
counts,idx,txt = bar_data(med,'hipertension')
fig=plt.figure(figsize=(7,5))
g=sns.countplot(data=med ,x='hipertension' ,color=base_color)

for i in range (len(counts)):
    plt.text(i,                                 # x axis co-ordinate
             counts[i],# y axis co-ordinate
             txt[i],                  # text names to be displayed
             ha='center',                       # horizontal aligment
             va='bottom')
```



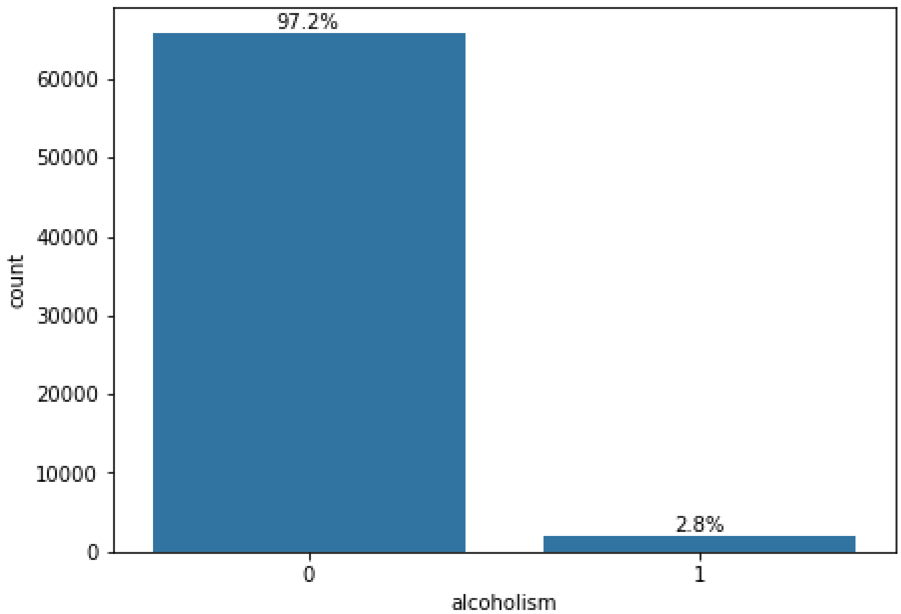
How many appointments involved someone with diabetes disease?

In [58]:
```
counts,idx,txt = bar_data(med,'diabetes')
fig=plt.figure(figsize=(7,5))
g=sns.countplot(data=med ,x='diabetes' ,color=base_color)

for i in range (len(counts)):
    plt.text(i,                                  # x axis co-ordinate
             counts[i],# y axis co-ordinate
             txt[i],                   # text names to be displayed
             ha='center',                        # horizontal aligment
             va='bottom')
```



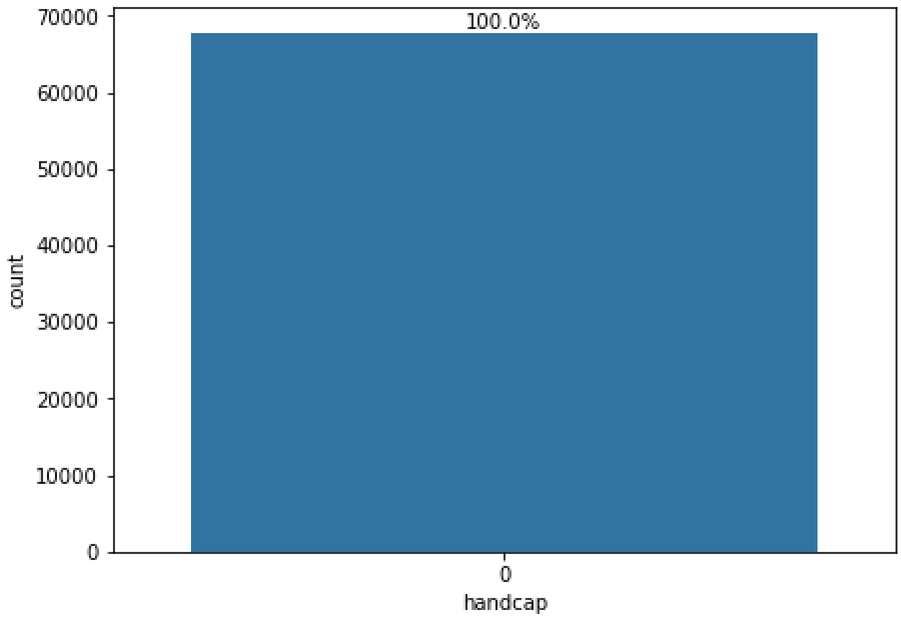
How many appointments involved someone with alcoholism issues?

In [59]:
```
counts,idx,txt = bar_data(med,'alcoholism')
fig=plt.figure(figsize=(7,5))
g=sns.countplot(data=med ,x='alcoholism' ,color=base_color)

for i in range (len(counts)):
    plt.text(i,                                # x axis co-ordinate
             counts[i],# y axis co-ordinate
             txt[i],                    # text names to be displayed
             ha='center',                      # horizontal aligment
             va='bottom')
```



How many appointments involved a handicaped patient?

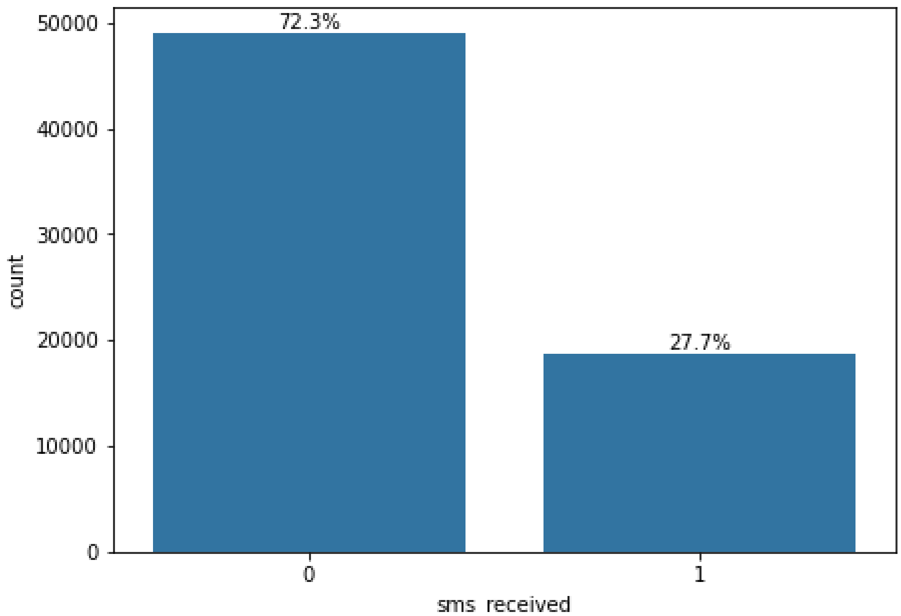
In [60]:
```
counts,idx,txt = bar_data(med,'handcap')
fig=plt.figure(figsize=(7,5))
g=sns.countplot(data=med ,x='handcap' ,color=base_color)

for i in range (len(counts)):
    plt.text(i,                                # x axis co-ordinate
             counts[i],# y axis co-ordinate
             txt[i],                    # text names to be displayed
             ha='center',                      # horizontal aligment
             va='bottom')
```



All the handicaped patients were removed in the outlier removal process.

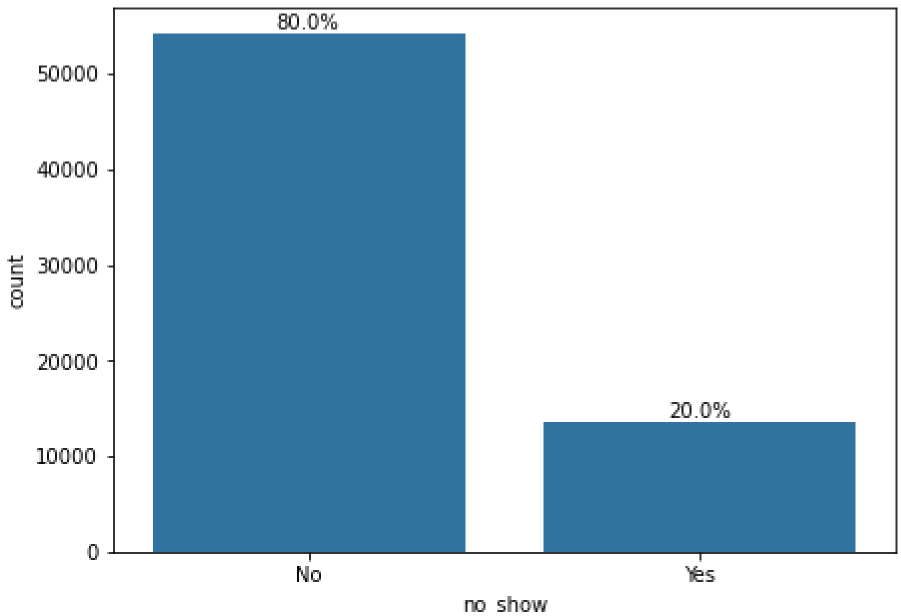
How many appointments patients were sent a SMS?

```
In [61]: counts,idx,txt = bar_data(med,'sms_received')
fig=plt.figure(figsize=(7,5))
g=sns.countplot(data=med ,x='sms_received' ,color=base_color)

for i in range (len(counts)):
    plt.text(i,                                 # x axis co-ordinate
             counts[i],# y axis co-ordinate
             txt[i],                    # text names to be displayed
             ha='center',                       # horizontal aligment
             va='bottom')
```



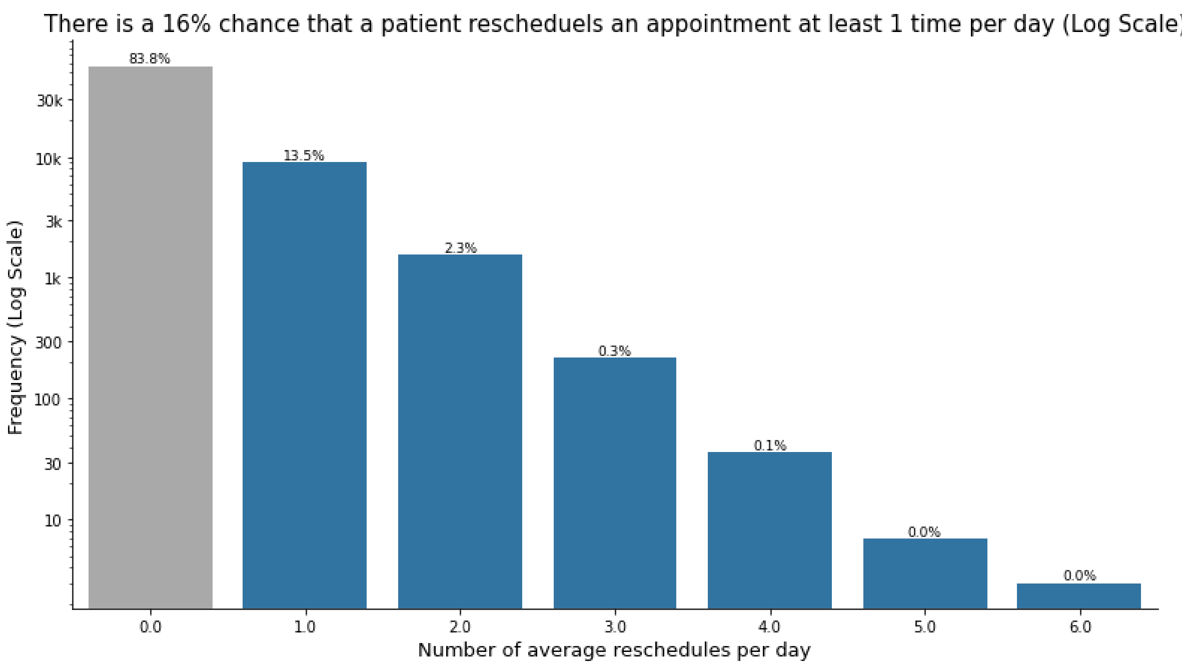
How many appointments patients did not show up for?

In [62]:
```
counts,idx,txt = bar_data(med,'no_show')
fig=plt.figure(figsize=(7,5))
g=sns.countplot(data=med ,x='no_show' ,color=base_color,order=med.no_show.valu
e_counts().index)

for i in range (len(counts)):
    plt.text(i,                                  # x axis co-ordinate
             counts[i],# y axis co-ordinate
             txt[i],                      # text names to be displayed
             ha='center',                        # horizontal aligment
             va='bottom')
```



Do patients tend to reschedule their appointments?

In [63]:
```
counts,idx,txt=bar_data(med,'avg_re_scds_per_patient')
plt.figure(figsize=(13,7))
colors = [base_color if (index in idx[1:]) else '#A9A9A9' for index in idx ]
g=sns.countplot(data=med ,x='avg_re_scds_per_patient' ,palette=colors)
[plt.text(i, counts[idx[i]],txt[i], ha='center',va='bottom',size=9) for i in range(len(counts))];
plt.yscale('log')
plt.yticks([10,30,100,300,1000,3000,10000,30000],['10','30','100','300','1k','3k','10k','30k'])
plt.xlabel("Number of average reschedules per day",fontsize=13)
plt.ylabel('Frequency (Log Scale)',fontsize=13);
plt.title("There is a 16% chance that a patient reschedeuls an appointment at least 1 time per day (Log Scale)",fontsize=15)
sns.despine();
```



Timestamp analysis

Year distribution

In [64]:
```
med.sc_year.value_counts()
# All occurences happened in 2016
```

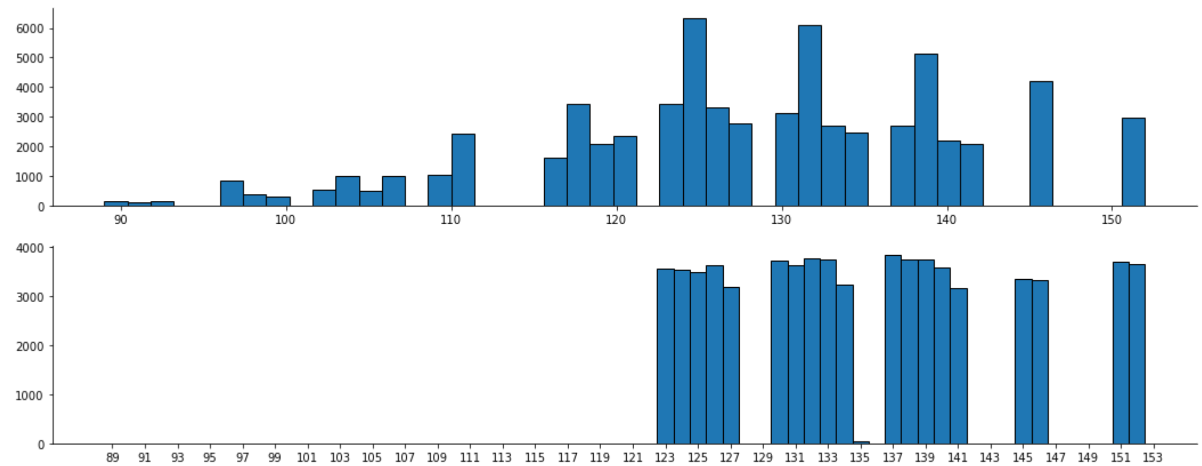
Out[64]:
```
2016    67750
Name: sc_year, dtype: int64
```

In [65]:
```
med.ap_year.value_counts()
# All occurences happened in 2016
```

Out[65]:
```
2016    67750
Name: ap_year, dtype: int64
```

Day of Year Distribution

In [67]:
```
fig=plt.subplots(2,1,figsize=(18,7))
plt.subplot(2,1,1)
plt.hist(data=med,x='sc_doy',bins=45,edgecolor='black')
# plt.xticks(np.arange(0,43+1,1),[date.strftime('%d-%m') for date in idx],rota
tion=-45);
plt.subplot(2,1,2)
ax2=plt.hist(data=med, x='ap_doy',bins=np.arange(88.5, 152.5+1, 1),edgecolor=
'black')
plt.xticks(np.arange(89, 152+2, 2),np.arange(89, 152+2, 2));
sns.despine()
```

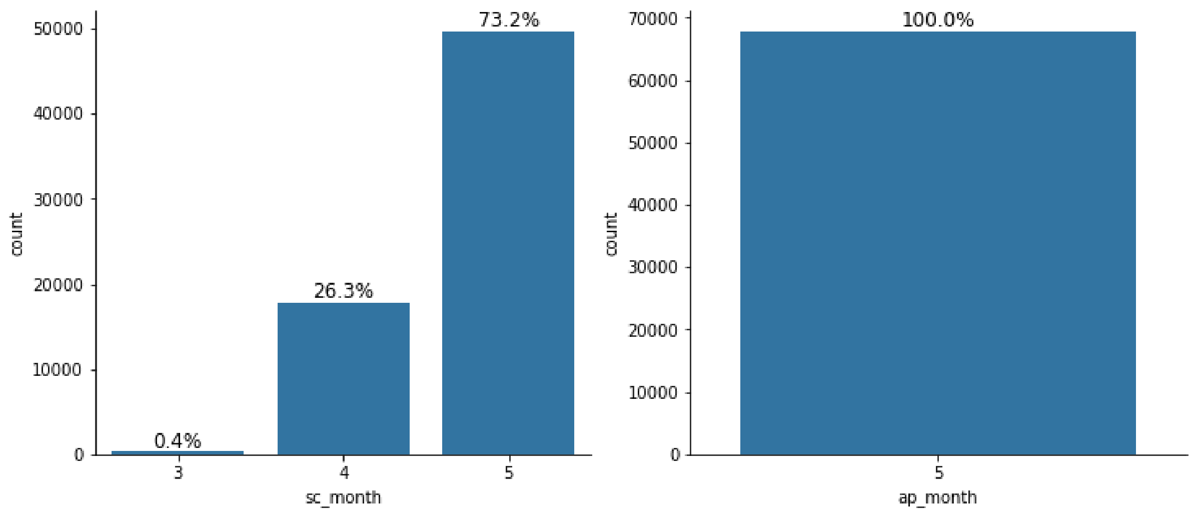


Although gaps should represent Days off on saturday and sunday, some gaps seem to be **bigger** than two days. To investigate this phenomenon,I'm using [Days of Year calender (https://asd.gsfc.nasa.gov/Craig.Markwardt/doy2016.html)](https://asd.gsfc.nasa.gov/Craig.Markwardt/doy2016.html) and [official brazil holidays in 2016 (https://www.timeanddate.com/holidays/brazil/2016#:~:text=20%20Mar,Government%20Holiday)](https://www.timeanddate.com/holidays/brazil/2016#:~:text=20%20Mar,Government%20Holiday) to explain the reasoning behind these wide gaps.

- 93 Saturday
- 94 Sunday
- 95 Mon (4-april-2016) **unclear**
- 100 Saturday
- 101 Sunday
- 107 Saturday
- 108 Sunday
- 112 Thu (21-april-2016) Tiradentes Day (https://www.calendarlabs.com/holidays/brazil/2016#:~:text=Apr%2021%2C%202016-,Tiradentes%20Day,-Sunday)
- 113 Fri (22-april-2016) **unclear** possibly to link with Saturday
- 114 Saturday
- 115 Sunday
- 121 Saturday
- 122 Sunday
- 135 Saturday
- 136 Sunday
- 142 Saturday
- 143 Sunday
- 144 Mon (23-May-2016) **unclear**
- 147 Thu (26-May-2016) Corpus Christi (https://www.calendarlabs.com/holidays/brazil/2016#:~:text=May%2026%2C%202016-,Corpus%20Christi,-Wednesday)
- 148 Fri (27-May-2016) **unclear** possibly to link with Saturday
- 149 Saturday
- 150 Sunday

Month distribution

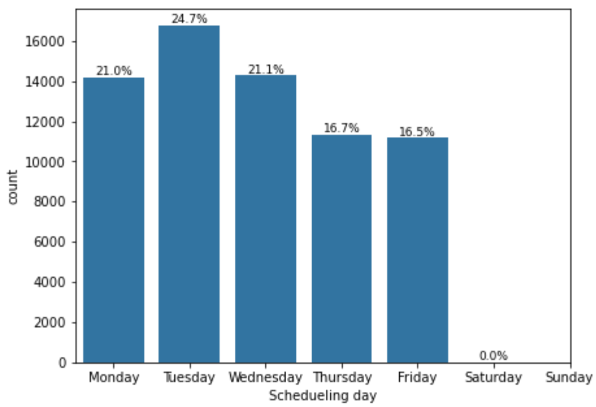
In [68]:
```
fig=plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
counts,idx,txt = bar_data(med,'sc_month')
sns.countplot(data=med ,x='sc_month',order=idx,color=base_color)
[plt.text(i, counts[idx[i]],txt[i], ha='center',va='bottom',size=12) for i in
range (len(counts))];
plt.subplot(1,2,2)
counts,idx,txt = bar_data(med,'ap_month')
sns.countplot(data=med ,x='ap_month',order=idx,color=base_color);
[plt.text(i, counts[idx[i]],txt[i], ha='center',va='bottom',size=12) for i in
range (len(counts))];
sns.despine()
```

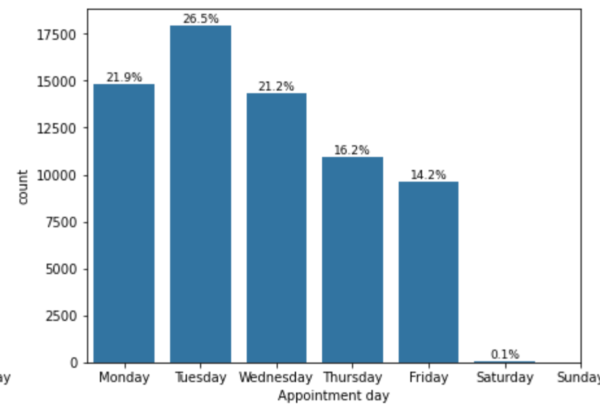


Most of the schedueled appointments happened in may and less over the preceding months.

In [69]:
```
week_names=['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sun
day']
```

In [70]:
```
fig=plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
counts,idx,txt = bar_data(med,'sc_dow')
g = sns.countplot(data=med ,x='sc_dow',color=base_color)
[plt.text(i, counts[idx[i]],txt[i], ha='center',va='bottom',size=9) for i in range(len(counts))];
plt.xticks(np.arange(0,7,1),week_names);
plt.xlabel('Schedueling day');
plt.subplot(1,2,2)
counts,idx,txt = bar_data(med,'ap_dow')
g = sns.countplot(data=med ,x='ap_dow',color=base_color)
[plt.text(i, counts[idx[i]],txt[i], ha='center',va='bottom',size=9) for i in range(len(counts))];
plt.xticks(np.arange(0,7,1),week_names);
plt.xlabel('Appointment day');
```



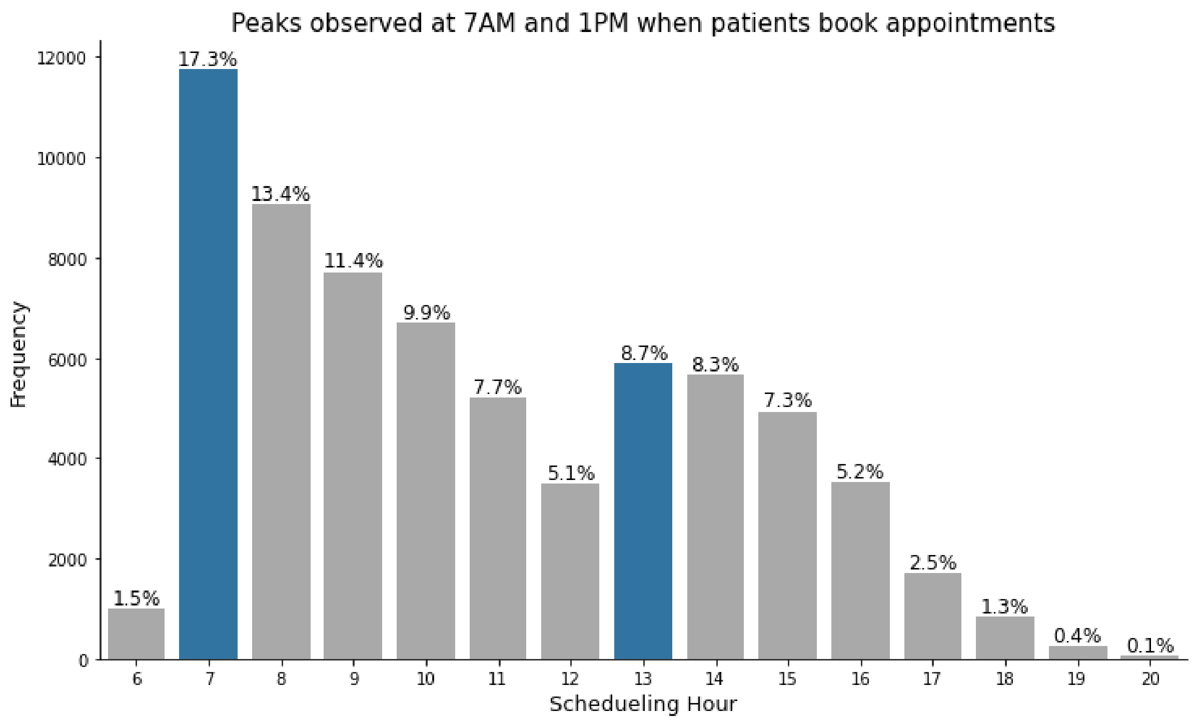


looks like no schedueling rendezvous occur on saturday and sunday... Day off maybe? There is also Higher engagement on Tuesday followed by less engagment in the other days

Appointments that are schedueled to happen peaks also at Tuesday, following the same trend like graph on the left

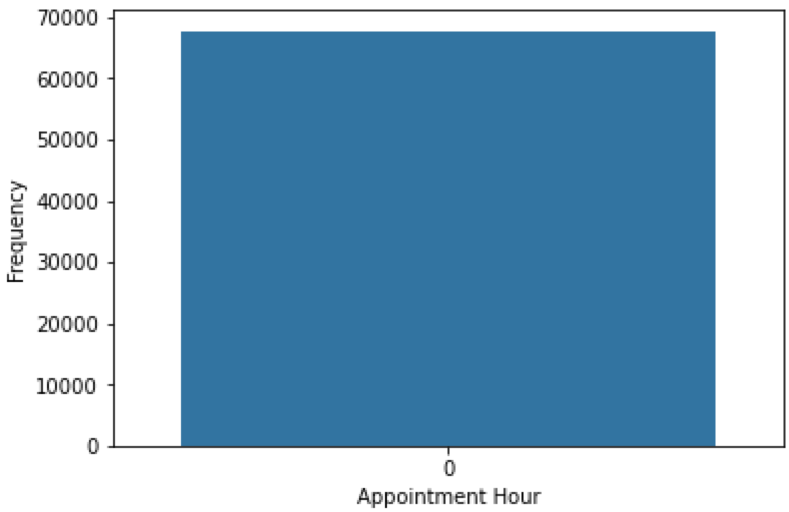
What are the congested hours for scheduling appointments?

In [71]:
```
counts,idx,txt = bar_data(med,'sc_hr')
fig = plt.figure(figsize=(12,7))
colors = [base_color if (hour in [7,13]) else '#A9A9A9' for hour,value in coun
ts.items() ]
g = sns.countplot(data=med ,x='sc_hr',palette=colors)
[plt.text(i, counts[idx[i]],txt[i], ha='center',va='bottom',size=12) for i in
range(len(counts))];
# plt.xticks(np.arange(0,7,1),week_names);
plt.xlabel('Schedueling Hour',size=13);
plt.ylabel('Frequency',size=13);
plt.title("Peaks observed at 7AM and 1PM when patients book appointments",size
=15);
sns.despine()
```



Scheduling rendezvous peaks at 7AM and gradually decreases till 12PM ,Peaks again at 1PM & 2PM and gradually decreases again till 10PM

In [72]:
```
counts,idx,txt = bar_data(med,'ap_hr')
# colors = [base_color if (hour in [7,13]) else alt for hour,value in counts.i
tems() ]
g = sns.countplot(data=med ,x='ap_hr')
# [plt.text(i, counts[idx[i]],txt[i], ha='center',va='bottom',size=9) for i in
range(len(counts))];
# plt.xticks(np.arange(0,7,1),week_names);
plt.xlabel('Appointment Hour');
plt.ylabel('Frequency');
```



Looks like when Appointments get scheduled they don't get assigned a specific hour.

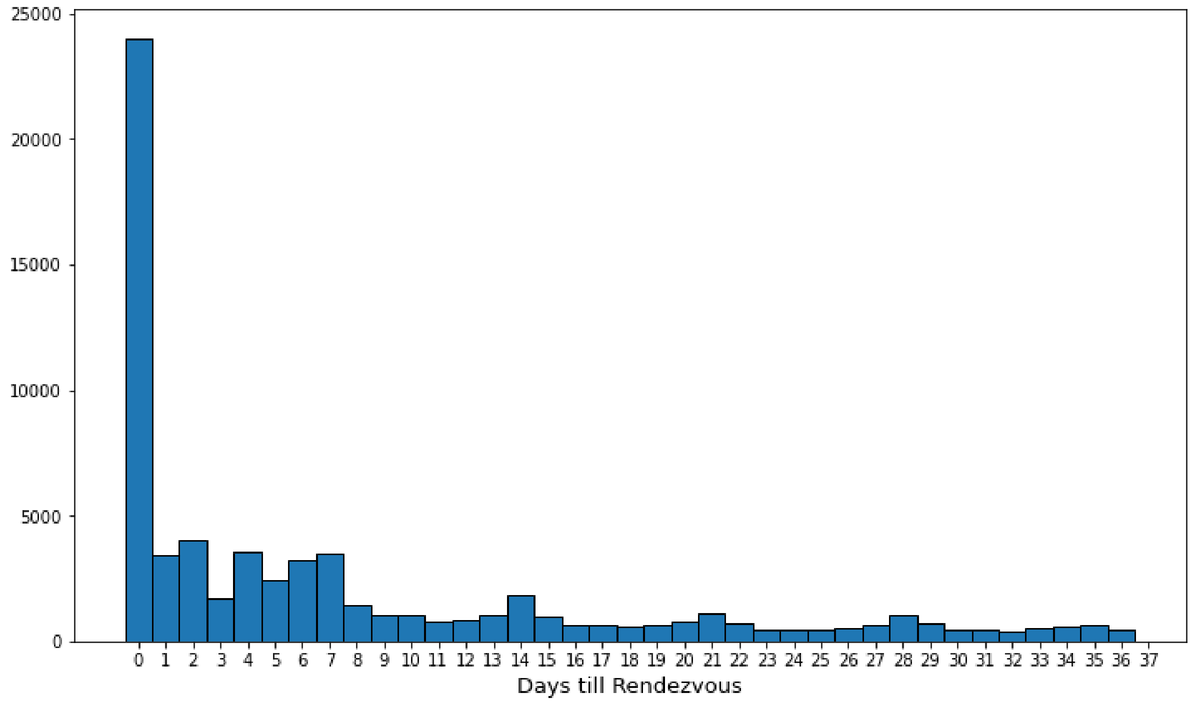
In [73]:
```
med.columns
```

Out[73]:
```
Index(['patientid', 'gender', 'scheduledday', 'appointmentday', 'age',
       'neighbourhood', 'scholarship', 'hipertension', 'diabetes',
       'alcoholism', 'handcap', 'sms_received', 'no_show', 'ap_year',
       'ap_month', 'ap_dom', 'ap_dow', 'ap_doy', 'ap_hr', 'sc_year',
       'sc_month', 'sc_dom', 'sc_dow', 'sc_doy', 'sc_hr', 'waiting_days',
       'age_group', 'no_show_bin', 'avg_re_scds_per_patient'],
      dtype='object')
```

Are there any particular waiting days associated with more pre-schedueled appointments?

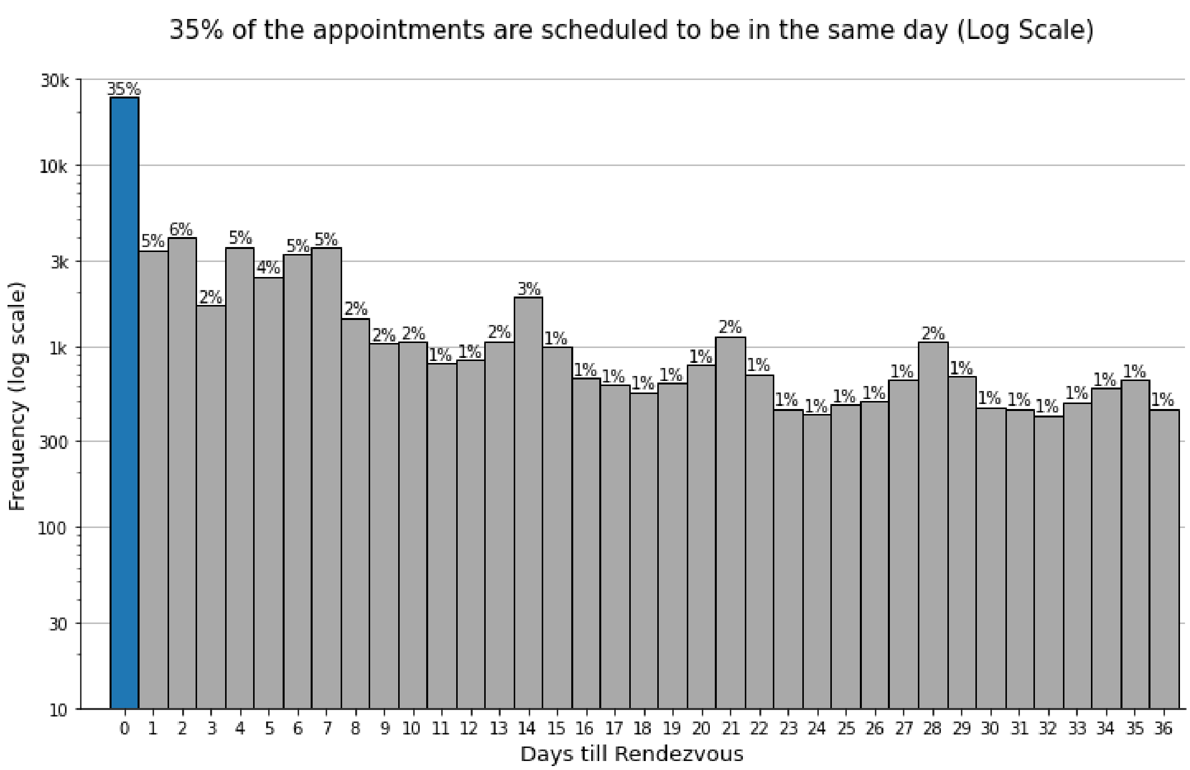
In [206]:

```
fig=plt.figure(figsize=(12,7))
bins = np.arange(0, med['waiting_days'].max()+1, 1)
freq, bins, patches =plt.hist(data=med, x='waiting_days', bins=bins,edgecolor=
'black');
plt.xticks(np.arange(0.5,med['waiting_days'].max()+1.5,1),np.arange(0,med['wai
ting_days'].max()+1,1));
plt.xlabel('Days till Rendezvous',size=13);
```



In [205]:

```
fig=plt.figure(figsize=(12,7))
ax = fig.add_subplot(1,1,1)
ax.grid(zorder=0)
ax.xaxis.grid(color='#A9A9A9', linestyle='-')
bins = np.arange(0, med['waiting_days'].max()+1, 1)

freq, bins, patches =plt.hist(data=med, x='waiting_days', bins=bins,edgecolor=
'black',zorder=3);
bin_centers = np.diff(bins)*0.5 + bins[:-1]
plt.yscale('log')
patches[20].set_fc('#A9A9A9')
for n,(fr, x, patch) in enumerate(zip(freq, bin_centers, patches)):
  patches[n].set_fc('#A9A9A9')
  height = int(freq[n])
  plt.annotate("{:.0%}".format(height/len(med)),xy = (x, height),xytext = (0,
0.2),textcoords = "offset points",
               ha = 'center', va = 'bottom')
patches[0].set_fc(base_color)
plt.xticks(np.arange(0.5,med['waiting_days'].max()+1.5,1),np.arange(0,med['wai
ting_days'].max()+1,1));
plt.ylabel('Frequency (log scale)');
plt.yticks([10,30,100,300,1000,3000,10000,30000],['10','30','100','300','1k',
'3k','10k','30k']);
plt.ylabel('Frequency (log scale)',size=13);
plt.xlabel('Days till Rendezvous',size=13);
plt.title('35% of the appointments are scheduled to be in the same day (Log Sc
ale)',y=1.05,size=15);
plt.xlim(-1,37.25)
sns.despine()
```



In [77]:
```
# the % of the appointments scheduled to happen in the same day
med.groupby('waiting_days')['no_show'].value_counts(normalize=True)[0]*100
```

Out[77]:
```
no_show
No     95.790396
Yes     4.209604
Name: no_show, dtype: float64
```

35% of all the appointments are scheduled to happen in the same day, but around 4% of those appointments, their patients don't show up.

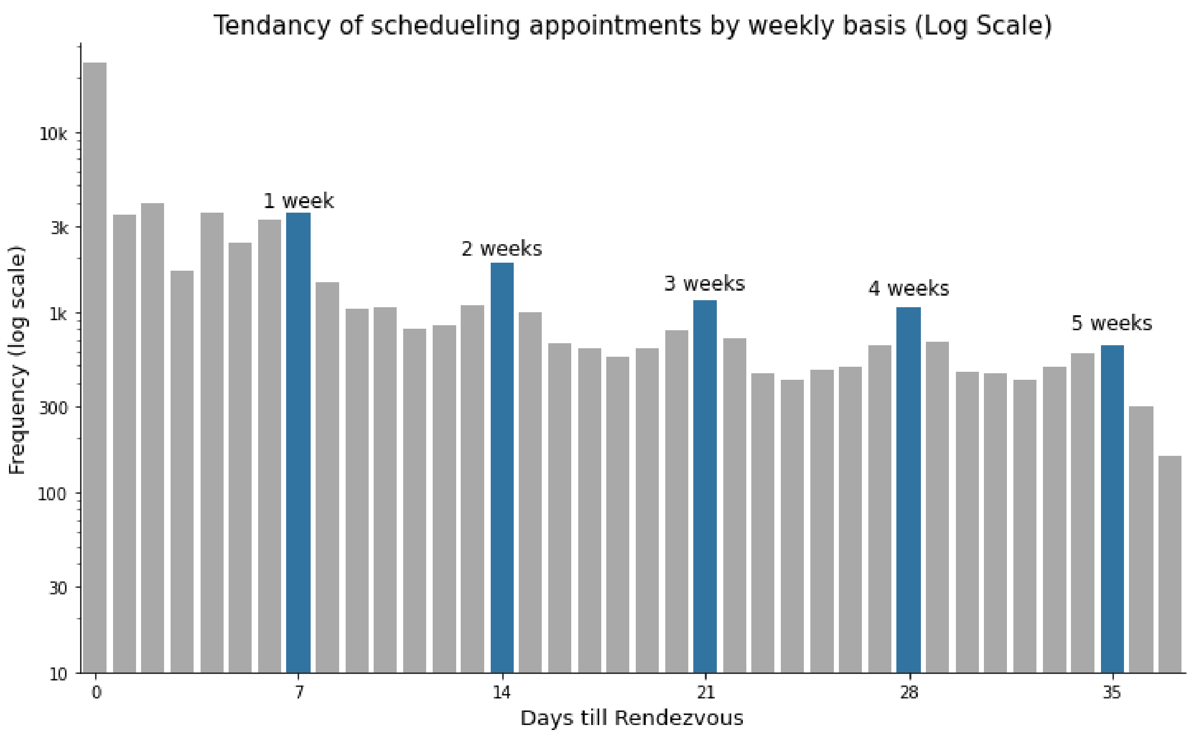
There is also an interesting multimodal pattern!

In [78]:
```
wd_counts = med.waiting_days.value_counts().sort_index()
highlights =  med.waiting_days.value_counts()[[7,14,21,28,35]]
week_txt= [f"{int(ind/7)} weeks" for ind in highlights.index ]
week_txt[0]='1 week'
week= pd.Series(week_txt,index=[7,14,21,28,35])
```

What do the peaks represent in the waiting days distribution?

In [79]:

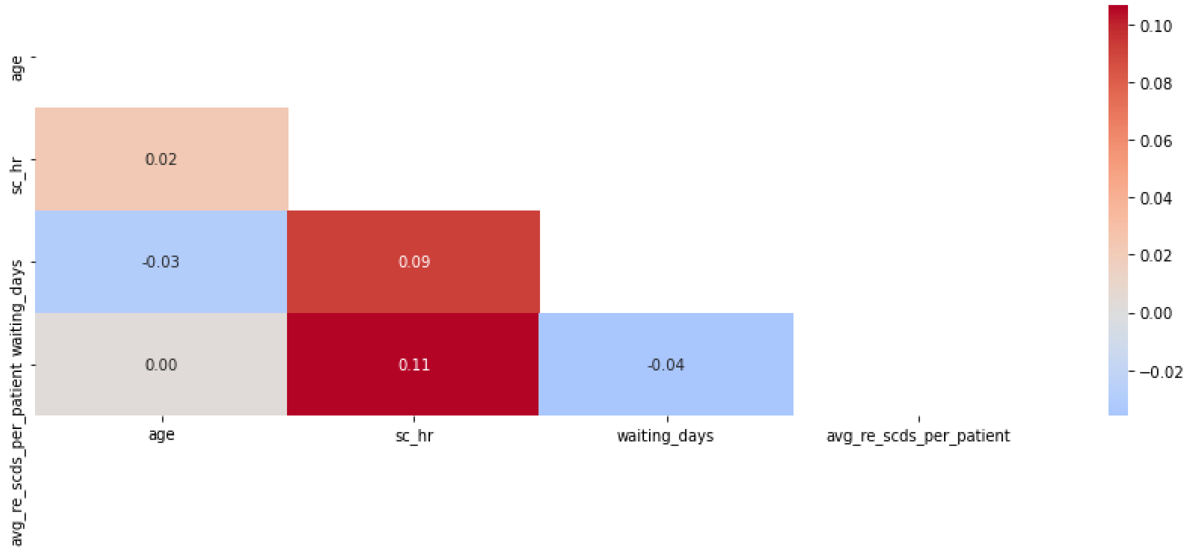
```
colors = [base_color if (index in highlights.index) else '#A9A9A9' for index,v
alue in wd_counts.items() ]
counts,idx,txt = bar_data(med,'waiting_days')
fig = plt.figure(figsize=(12,7))
g = sns.countplot(data=med ,x='waiting_days' ,palette=colors)
[plt.text(index,value+100,week[index], ha='center',va='bottom',size=12) for in
dex,value in highlights.items() ]

plt.yscale('log')
plt.yticks([10,30,100,300,1000,3000,10000],['10','30','100','300','1k','3k','1
0k']);
plt.xticks(np.arange(idx.min(),idx.max()+7,7),np.arange(idx.min(),idx.max()+7,
7));
plt.ylabel('Frequency (log scale)',size=13);
plt.xlabel('Days till Rendezvous',size=13);
plt.title('Tendancy of schedueling appointments by weekly basis (Log Scale)',s
ize=15);
plt.xlim(-0.5,37.5)
sns.despine()
```



While `waiting days` 0, 2 & 4 have higher frequencies than other days, It looks like the peaks in the distribution corresponds exactly to weekly standard counts, 7 days is 1 week, 14 days is 2 weeks .... and so on, so "patients" or "staff" tend to schedule appointments more by weekly basis, assuming they don't schedule during the 1st week.

Bivariate Exploration

In [80]:
```python
corr=med[['age','sc_hr','waiting_days','avg_re_scds_per_patient']].corr()
mask = np.triu(np.ones_like(corr, dtype=bool))
plt.figure(figsize=(15,5))
sns.heatmap(corr, annot = True,
            fmt = '.2f', cmap = 'coolwarm',
            mask=mask, center = 0);
```



It doesn't look like there is any strong linear correlation between any of these numeric variables.

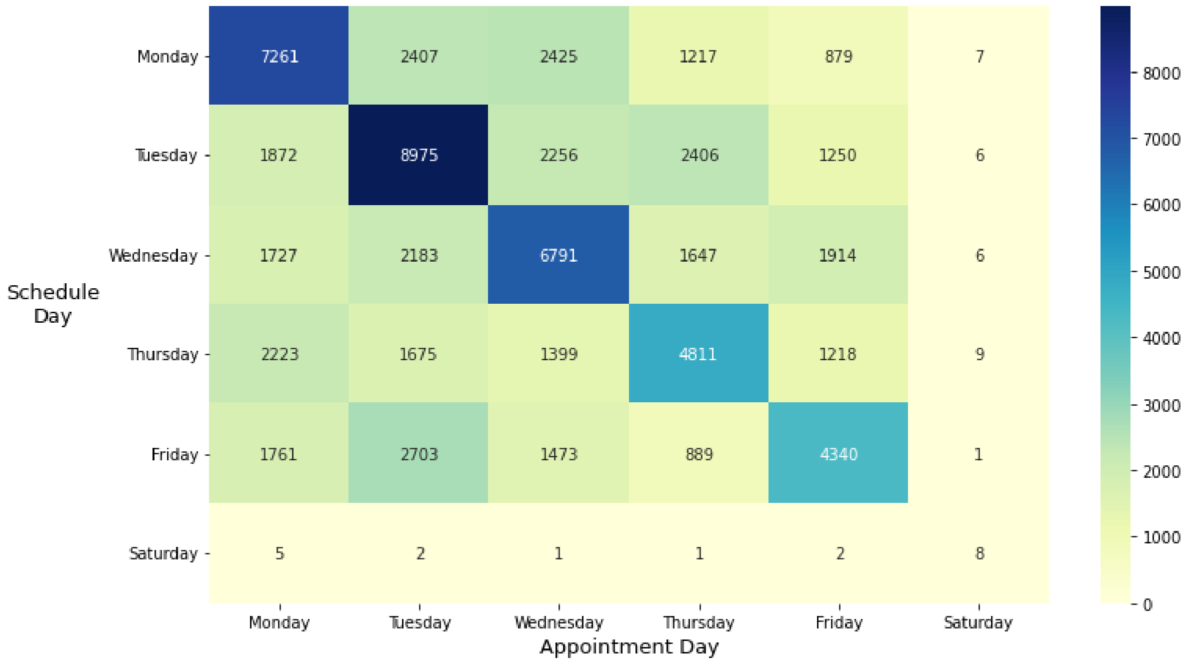
Do specific schedule weekdays associate with certain appointment weekdays?

In [196]:
```python
data=med.groupby(['sc_dow','ap_dow']).size().reset_index(name='count')
data_pivot=data.pivot(index='sc_dow',columns='ap_dow',values='count')
data_pivot
```

Out[196]:

ap_dow	0	1	2	3	4	5
sc_dow						
0	7261	2407	2425	1217	879	7
1	1872	8975	2256	2406	1250	6
2	1727	2183	6791	1647	1914	6
3	2223	1675	1399	4811	1218	9
4	1761	2703	1473	889	4340	1
5	5	2	1	1	2	8

In [207]:
```
plt.figure(figsize=[12,7])
sns.heatmap(data_pivot,annot=True,fmt='d',cmap='YlGnBu',vmin=0)
plt.xticks(np.arange(0.5,5.5+1,1),week_names)
plt.yticks(np.arange(0.5,5.5+1,1),week_names,va='center',rotation=0)
plt.ylabel('Schedule\nDay',size=13,rotation=0,ha='center',va='center',labelpad
=35);
plt.xlabel('Appointment Day',size=13);
```



Again, since the diagonal has the highest counts, the heat map depicts the tendancy to schedule appointments by weekly basis, as shown before in the univariate analysis for the waiting days.

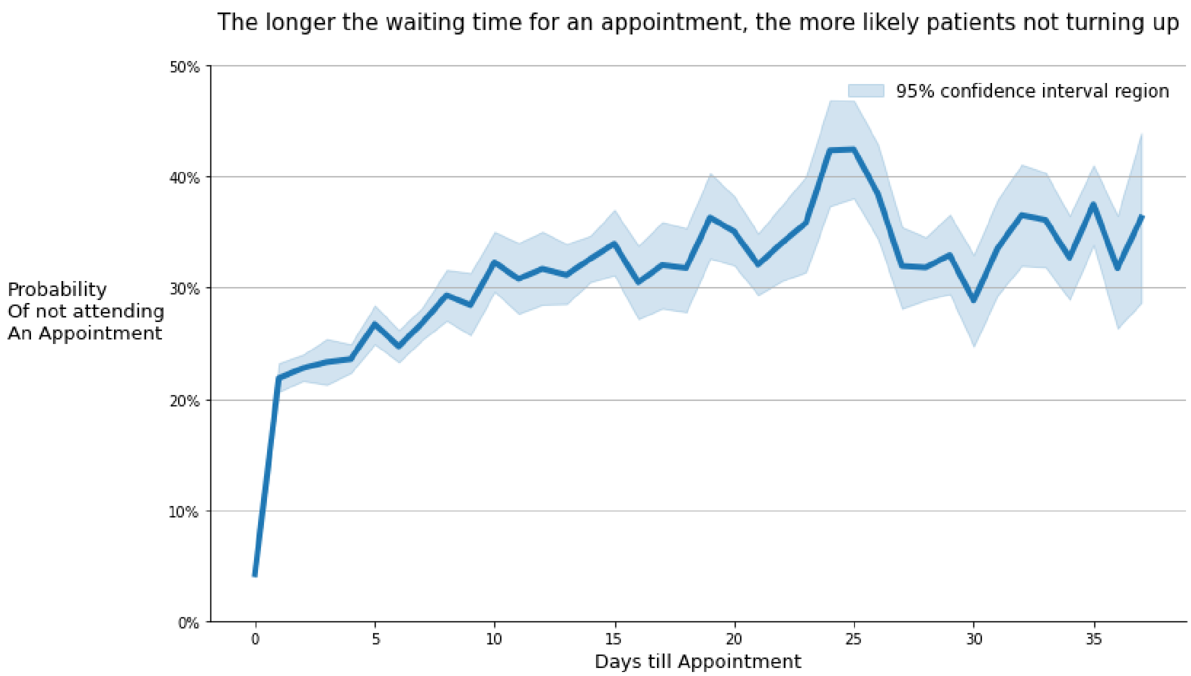
In [603]:
```
med[['sc_dow','no_show_bin']].describe()
```

Out[603]:

	sc_dow	no_show_bin
count	67750.000000	67750.000000
mean	1.831277	0.199720
std	1.373423	0.399792
min	0.000000	0.000000
25%	1.000000	0.000000
50%	2.000000	0.000000
75%	3.000000	0.000000
max	5.000000	1.000000

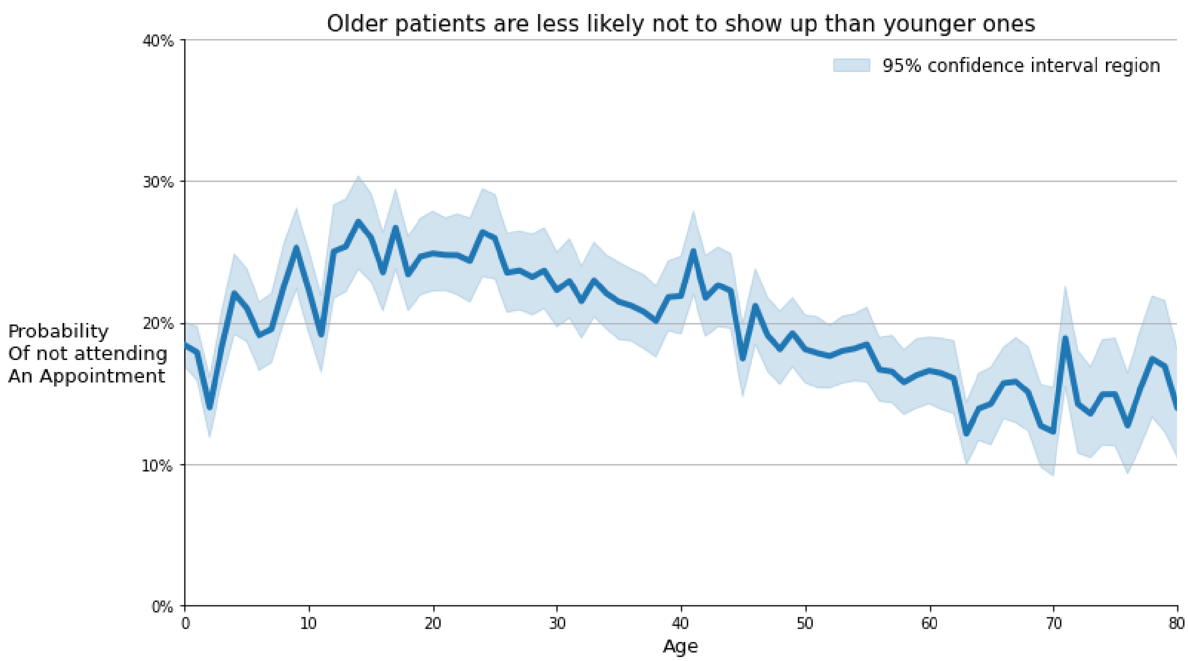
Does waiting more days relates to not attending appointments?

In [210]:
```
import warnings
warnings.filterwarnings('ignore')
fig =plt.figure(figsize=(12,7))
ax = fig.add_subplot(1,1,1)
ax.grid(zorder=0)
ax.xaxis.grid(color='gray', linestyle='-')
sns.lineplot(data=med, x='waiting_days',y='no_show_bin',lw=4,ax=ax,zorder=3)
plt.ylabel('Probability\nOf not attending\nAn Appointment',size=13,rotation=0,
ha='left',va='bottom',labelpad=110);
plt.xlabel('Days till Appointment',size=13)
plt.yticks(plt.yticks()[0],pd.DataFrame(["{:.0%}".format(yy) for yy in plt.yti
cks()[0]])[0].values)
plt.title('The longer the waiting time for an appointment, the more likely pat
ients not turning up',size=15,y=1.05)
plt.legend(['_','95% confidence interval region'],frameon=False,prop={'size':1
2},loc='best');
sns.despine()
```



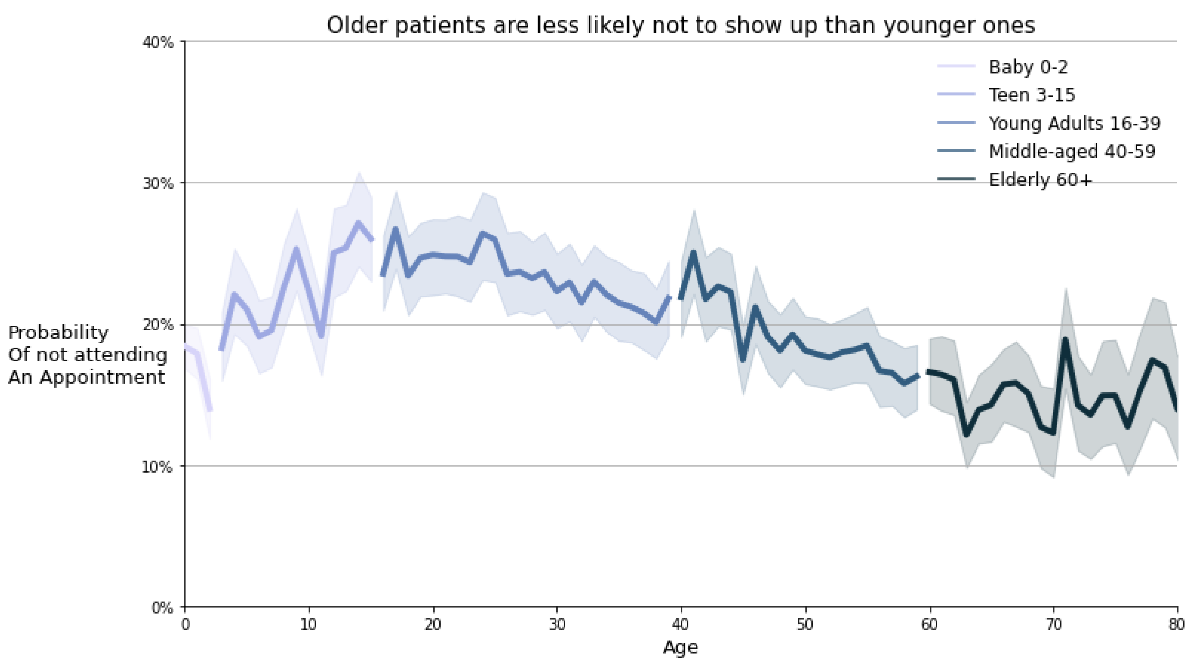
Is age related to not showing up for appointments?

In [211]:
```
fig=plt.figure(figsize=(12,7))
ax = fig.add_subplot(1,1,1)
ax.grid(zorder=0)
ax.xaxis.grid(color='gray', linestyle='-')
g=sns.lineplot(data=med, x='age',y='no_show_bin',lw=4,palette=[base_color],zor
der=3)
plt.xlim(0, 80)
plt.title('Older patients are less likely not to show up than younger ones',si
ze=15);
plt.ylabel('Probability\nOf not attending\nAn Appointment',size=13,rotation=0,
va='top',ha='left',labelpad=90);
plt.yticks(plt.yticks()[0],pd.DataFrame(["{:.0%}".format(yy) for yy in plt.yti
cks()[0]])[0].values)
plt.xlabel('Age',size=13);
plt.ylim(0,0.4);
plt.legend(['_','95% confidence interval region'],frameon=False,prop={'size':1
2},loc='best');
sns.despine()
```



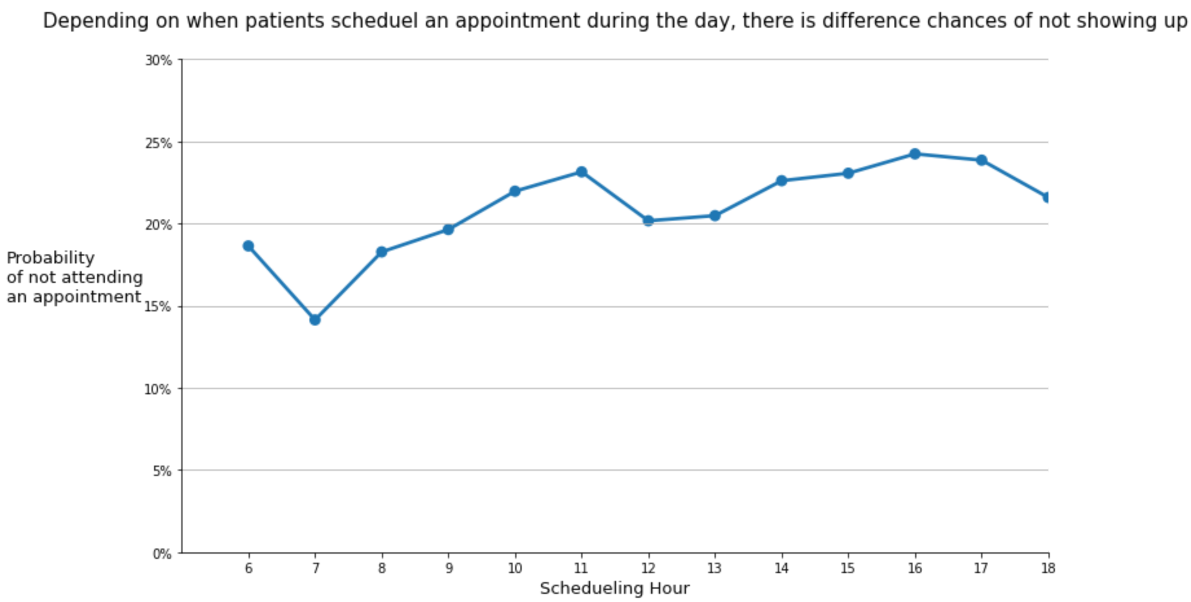
In [213]:

```
fig=plt.figure(figsize=(12,7))
ax = fig.add_subplot(1,1,1)
ax.grid(zorder=0)
ax.xaxis.grid(color='gray', linestyle='-')
g=sns.lineplot(data=med, x='age',y='no_show_bin',lw=4,zorder=3,hue='age_group'
,
    hue_order=['Baby 0-2','Teen 3-15','Young Adults 16-39','Middle-aged 40-59'
, 'Elderly 60+'],
    palette=sns.cubehelix_palette(5,start=2.5,rot=0.2,hue=1))
plt.xlim(0, 80)
plt.title('Older patients are less likely not to show up than younger ones',si
ze=15);
plt.ylabel('Probability\nOf not attending\nAn Appointment',size=13,rotation=0,
va='top',ha='left',labelpad=90);
plt.yticks(plt.yticks()[0],pd.DataFrame(["{:.0%}".format(yy) for yy in plt.yti
cks()[0]])[0].values)
plt.xlabel('Age',size=13);
plt.ylim(0,0.4);
plt.legend(title=False,frameon=False,prop={'size':12})
sns.despine()
```



Does the time of scheduling an appointment during the day , influence the likelihood of not turning up?

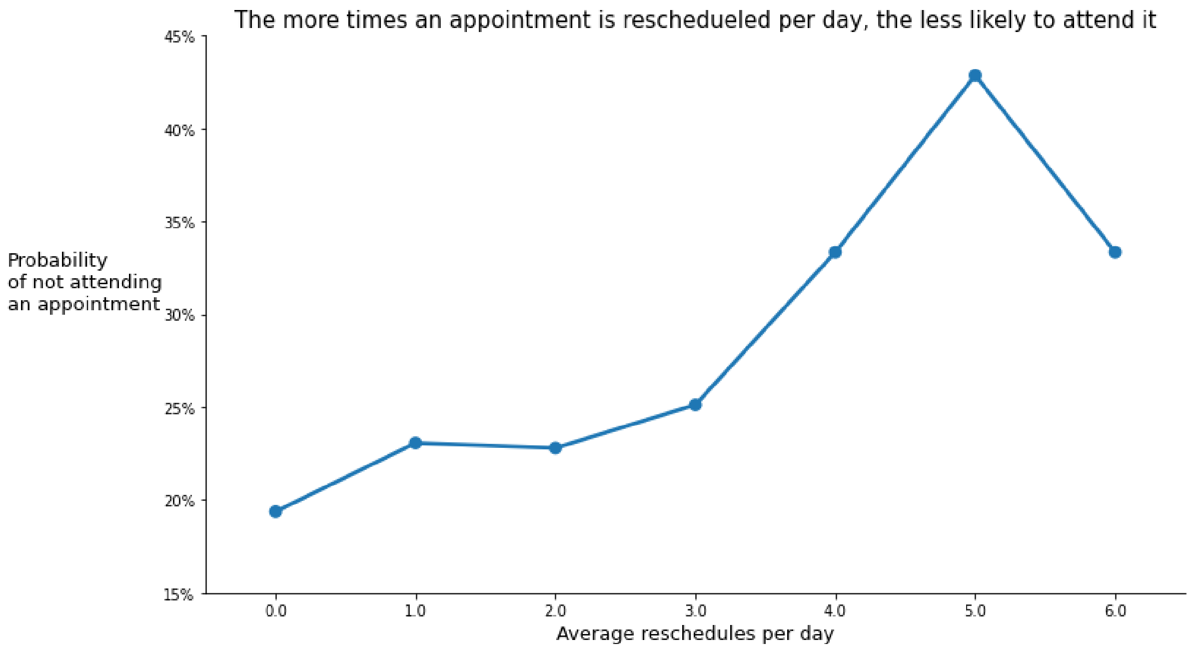
In [607]:
```
fig=plt.figure(figsize=(12,7))
ax = fig.add_subplot(1,1,1)
ax.grid(zorder=0)
ax.xaxis.grid(color='#', linestyle='-')
sns.pointplot(data=med,x='sc_hr',y='no_show_bin',ci=False,ax=ax,zorder=3)
plt.xlabel('Schedeuling Hour',size=13);
plt.ylabel('Probability\nof not attending\nan appointment',size=13,rotation=0,
ha='left',labelpad=106);
plt.title("Depending on when patients scheduel an appointment during the day,
 there is difference chances of not showing up",size=15,y=1.05);
plt.ylim(0,0.3)
plt.yticks(plt.yticks()[0],pd.DataFrame(["{:.0%}".format(yy) for yy in plt.yti
cks()[0]])[0].values)
plt.xlim(-1,12)
sns.despine()
```



While the change in the likelihood of not showing up for an appointment **isn't significant**, we can spot a positive correlation between 7AM and 11AM , and between 1PM and 4PM

Do patients that reschedule their appointments during the day are more likely not to show up?

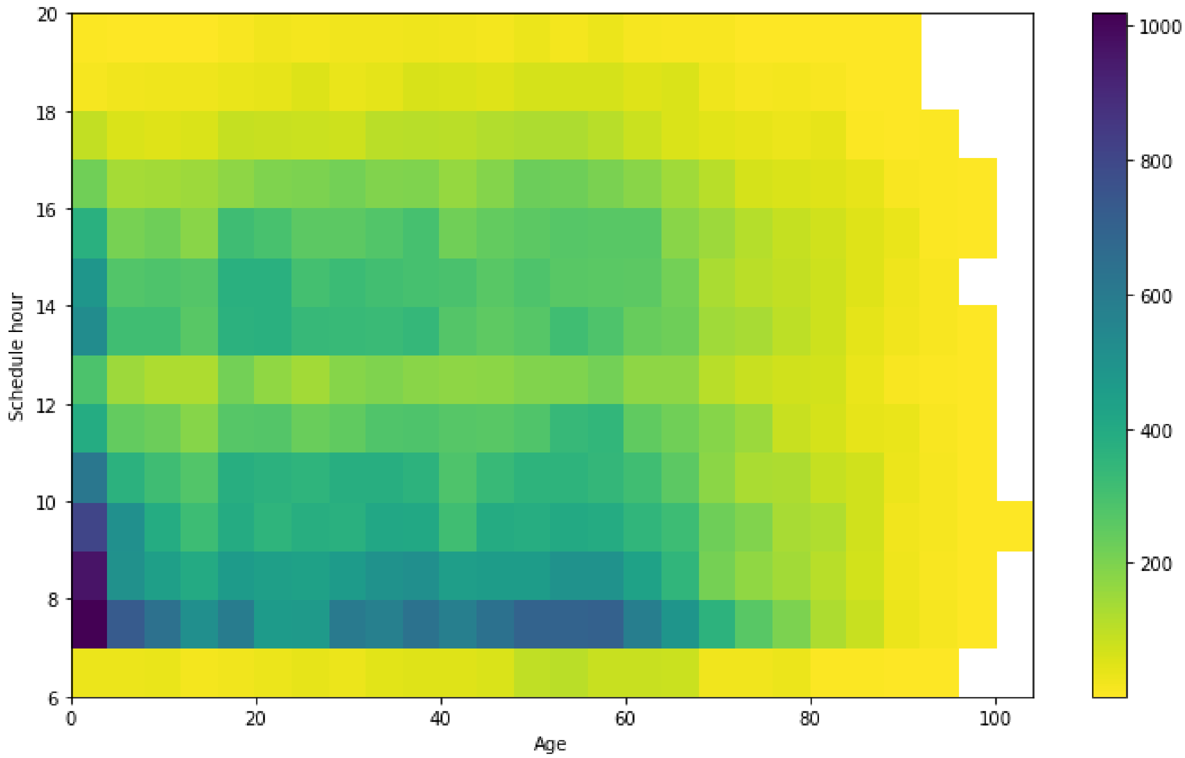
In [608]:
```
fig=plt.figure(figsize=(12,7))
sns.pointplot(data=med,x='avg_re_scds_per_patient',y='no_show_bin',ci=False)
plt.xlabel("Average reschedules per day",fontsize=13)
plt.ylabel('Probability\nof not attending\nan appointment',size=13,rotation=0,
ha='left',labelpad=106);
plt.title("The more times an appointment is reschedueled per day, the less lik
ely to attend it",size=15);
plt.yticks(plt.yticks()[0],pd.DataFrame(["{:.0%}".format(yy) for yy in plt.yti
cks()[0]])[0].values)
sns.despine()
```



Are there certain hourly scheduling times associated with a specific age group?

In [609]:

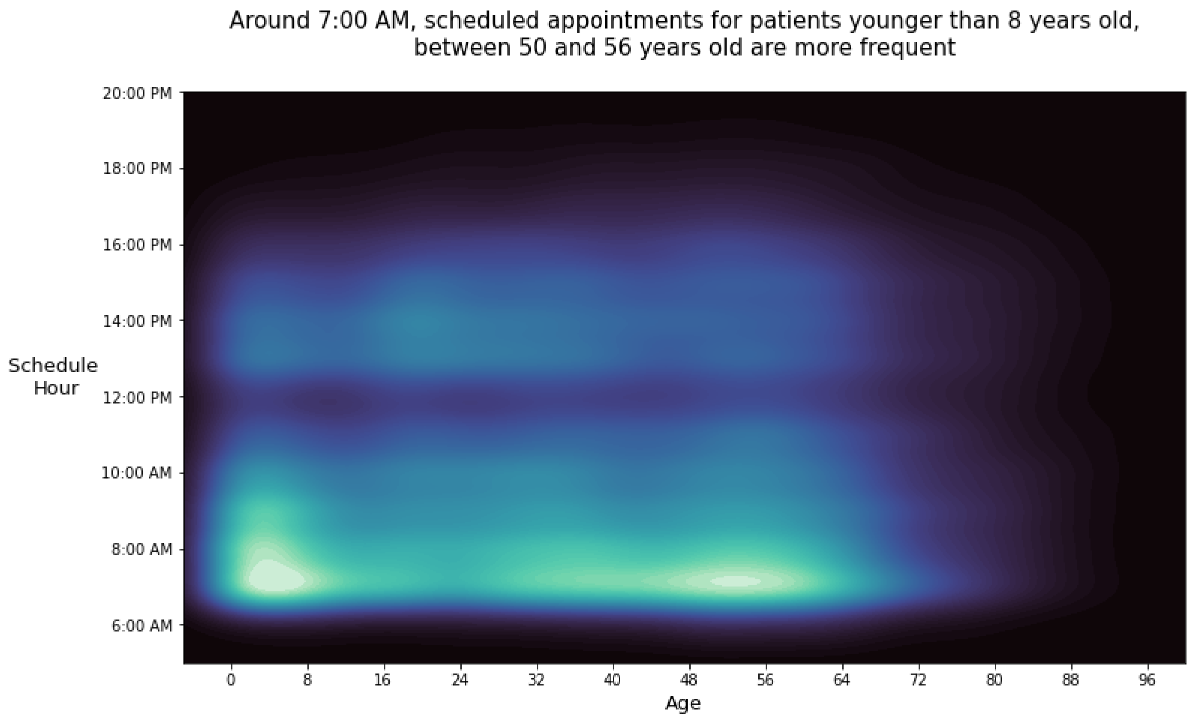
```
fig = plt.figure(figsize=(12,7))

bins_x = np.arange(0, 102+4, 4)
bins_y = np.arange(6, 20+1, 1)
# Use cmin to set a minimum bound of counts
# Use cmap to reverse the color map.
h2d = plt.hist2d(data = med, x = 'age', y = 'sc_hr', cmin=0.5, cmap='viridis_
r', bins = [bins_x, bins_y])
#plt.xticks(np.arange(89, 152+3, 3),np.arange(89, 152+3, 3))
#plt.yticks(np.arange(123, 152+3, 3),np.arange(123, 152+3, 3))
plt.colorbar()
plt.xlabel('Age')
plt.ylabel('Schedule hour');
```



In [610]:

```
def minu(t):
    t=str(t).split('.')
    if t[1]== '5':
        t[1]='30'
    else:
        t[1]='00'
    if int(t[0]) < 12:
        out= t[0]+':'+t[1]+" AM"
    else:
        out= t[0]+':'+t[1]+" PM"
    return out
```

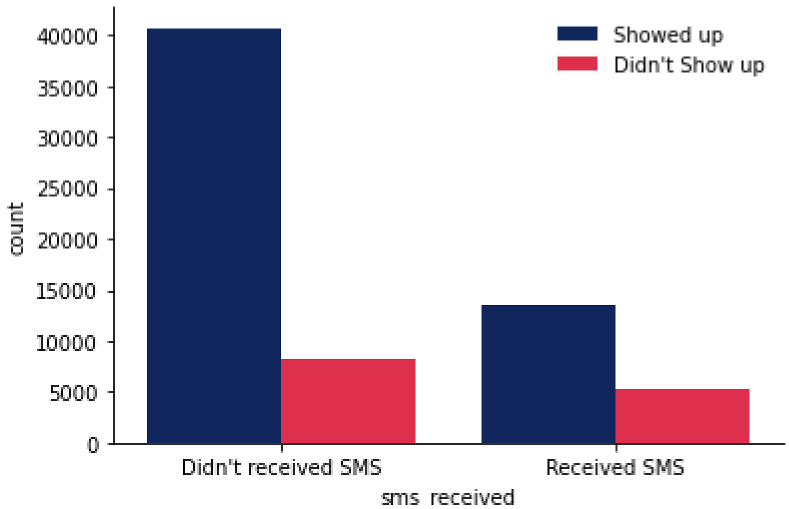
In [611]:
```
fig=plt.figure(figsize=(12,7))
sns.kdeplot(data=med, y="sc_hr", x="age", fill=True, thresh=0, levels=100, cma
p="mako");
plt.xlabel('Age',size=13);
plt.xticks(np.arange(0,102+8,8),np.arange(0,102+8,8))
plt.title('Around 7:00 AM, scheduled appointments for patients younger than 8
 years old,\nbetween 50 and 56 years old are more frequent',y=1.05,size=15)
plt.ylabel('Schedule \nHour',size=13,rotation=0,va='center',labelpad=30);
plt.yticks(plt.yticks()[0],pd.DataFrame([minu(yy) for yy in plt.yticks()[0]])[
0].values);
plt.ylim(5,20)
plt.xlim(-5,100);
```



Concentrations observed around 7AM schedule time for appointments. they are associated with patients of age less than 8 years old and between 50 and 56 years old

Do the patients who didn't reveive SMS messages are more likely not to show up?

In [612]:
```
sns.countplot(data=med,x='sms_received',palette=['#042069','#fb1239'],hue='no_
show_bin',dodge=True)
plt.xticks([0,1],["Didn't received SMS",'Received SMS']);
plt.legend(labels=['Showed up',"Didn't Show up"],title=False,frameon=False)
sns.despine()
```



In [613]:
```
sms_counts=med.groupby('sms_received')['no_show_bin'].value_counts()
no_sms_r=sms_counts[0][1]/sms_counts[0].sum()
sms_r=sms_counts[1][1]/sms_counts[1].sum()
print('no sms no show rate:',f'{no_sms_r:.1%}')
print('sms no show rate:',f'{sms_r:.1%}')
f'{(sms_r - no_sms_r):.1%}'
```

```
no sms no show rate: 16.9%
sms no show rate: 27.9%
```

Out[613]: `'10.9%'`

It's hard to tell, because the quantity of patients who recieved SMS compared to ones who didn't isn't balanced, and the results are **counterintuitive**, in an ideal case we would need the same amount people to receive SMS , and then perfom A/B test to see if the difference is statistically significant to indicate whether `no_shows` are associated with more or less patients who recieved SMS.

$$H_0 : P_{sms} \leq P_{nosms}$$
$$H_1 : P_{sms} > P_{nosms}$$

Rephrased into:

$$H_0 : P_{sms} - P_{nosms} \leq 0$$
$$H_1 : P_{sms} - P_{nosms} > 0$$

Where P is the probabilty of not showing up

Conclusion

- Around 16% of the patients reschedule their appointment atleast 1 time per day.
- Several workdays (4-April_2016, 23-May-2016) had an unexplained inactivity.
- Tuesday is the busiest day for appointments while Thursday and Friday are the quietest, disregarding days off.
- Tuesday is the busiest day for scheduling appointments while Friday is the quietest, disregarding days off.
- Peak times where scheduling takes place are 7 AM and 1 PM.
- 35% of all the appointments are scheduled to happen in the same day, but around 4% of those appointments, their patients don't show up.
- There is a tendancy for scheduling appointments by weekly basis since they are represented as peaks in the `waiting_days` distribution.
- The likelehood of not showing up for an appointment increases, the longer the patient wait for his/her particular appointment.
- Older patients are more likely to show up for an appointment than younger ones.
- The more times a patient rescheduel his/her appointment the less likely he/she show up.
- Concentrations observed around 7AM schedule time for appointments. they are associated with patients of age less than 8 years old and between 50 and 56 years old.

Limitations

- One thing that i found to be strange , the fact that majority of data samples comes from scheduel day after march 2016, with earliest record at november 2015, this is a 5 months difference and thats huge , during this period there are 402 appointments only, why there wasn't more appointments during this period, i find it also weird that after march 2016 it shows significant growth for appointments. was the selection process for the sample biased?, if so this could mean that calculations above are insignificant and could be wrong.
- Most of the data attributes like `diabetes` , `no_show` , `sms_received` , `hipertension` and `scholarship` are imbalanced, and it is difficult to do classification based on them.
- One of these imbalance issues is demonstrated regarding `sms_received` and `no_show` attributes, and at some point it shows that the `no_show` rate for the group who recieved SMS is high than that of the group who didn't receive an SMS, which is counterintuitive.
- There is a large portion of the data numerically considered as outliers, and after removing the reschedules to analyse the actual appointments, we're down from 110,527 to 67,750 entries, which make certain categories in some attributes of the data set more or less at a critical state to run analysis on.