Project: Investigate a Dataset - Patient No-Shows for Medical Appointments

Table of Contents

Introduction

The medical appointment dataset contains information on over 100k appointments from the country of Brazil. The dataset was originally sourced from Kaggle. (https://www.kaggle.com/joniarroba/noshowappointments) It was created to study what factors were useful in predicting if patients would miss their appointments. It contains basic demographic information on the patients as well as whether or not the patient received SMS notifications. In addition, the data indicates if the patient received a scholarship for financial aid.

Questions to Investigate

- What is the overall appointment show-up vs. no-show rate?
- Does financial aid correlate with patient no-shows?
- Is age indicative of whether a patient will make their appointments?
- Do no-shows have a larger timeframe between schedule date and appointment date?
- Do some days of the week have more no-shows than others?
- Do SMS notifications coincide with fewer no-shows?
- Which neighborhoods have more no-shows than others?

The Investigation

Methodology

The general methodology followed to perform the investigation:

- Data Wrangling. Moving raw data into dataframes for manipulation.
- Data Cleaning. Transforming data to uniform format.
- Data Analysis. Exploring data and patterns.
- Data Visualization. Visualizing and drawing conclusions.

Data Wrangling

Step 1: Import data analysis packages.

This investigation makes uses of the following data analytics packages:

- Pandas. Provides flexible data structures designed to make working with “relational” or “labeled” data intuitive.
- Numpy. For adding support for large arrays, along with high-level mathematical functions to manipulate these arrays with speed.
- Matplotlib. For creating plots and visualizations with just a few lines of code.
- Datetime. For manipulating dates and times.
- Seaborn. To provide better control of output and plots.

In [121]:
```
# Import modules for working with data
import pandas as pd
import numpy as np
import datetime as dt

# Imports for better control of output and plots
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import seaborn as sns
sns.set(font_scale=1.5)

# Show plots in the notebook
%matplotlib inline
```

Step 2: Load the data into the Jupyter notebook.

In [122]:
```
# load the data file into a dataframe
df = pd.read_csv("noshowappointments-kagglev2-may-2016.csv")
```

Step 3: Integrity check to see if there is any naming or data type anomalies.

In [123]:
```
# Check data integrity for the first few rows
df.tail()
```

Out[123]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourh
110522	2.572134e+12	5651768	F	2016-05-03T09:15:35Z	2016-06-07T00:00:00Z	56	MARIA OI
110523	3.596266e+12	5650093	F	2016-05-03T07:27:33Z	2016-06-07T00:00:00Z	51	MARIA OI
110524	1.557663e+13	5630692	F	2016-04-27T16:03:52Z	2016-06-07T00:00:00Z	21	MARIA OI
110525	9.213493e+13	5630323	F	2016-04-27T15:09:23Z	2016-06-07T00:00:00Z	38	MARIA OI
110526	3.775115e+14	5629448	F	2016-04-27T13:30:56Z	2016-06-07T00:00:00Z	54	MARIA OI

Observations / Changes Needed:

- Changing column case and using underscores will make columns easier to read and manipulate.
- Changing column misspellings will make columns easier to read and manipulate.
- No-show column value is 'No' if the patient showed up to their appointment, and 'Yes' if the patient did not show up.
- Scholarship column value of 1 indicates a patient is provided financial aid by the government. Source and further information. (https://en.wikipedia.org/wiki/Bolsa_Fam%C3%ADlia)

Step 4: Data Integrity check for NULLS, and duplicates.

In [124]:
```
# Check data scructure of DataFrame
df.info()

# Check if there is any duplicates in the data
print("Number of dublicated entries: ", + sum(df.duplicated()))

# Count the number of unique patient and appointment IDs
df.loc[:, ['PatientId', 'AppointmentID']].nunique()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
PatientId         110527 non-null float64
AppointmentID     110527 non-null int64
Gender            110527 non-null object
ScheduledDay      110527 non-null object
AppointmentDay    110527 non-null object
Age               110527 non-null int64
Neighbourhood     110527 non-null object
Scholarship       110527 non-null int64
Hipertension      110527 non-null int64
Diabetes          110527 non-null int64
Alcoholism        110527 non-null int64
Handcap           110527 non-null int64
SMS_received      110527 non-null int64
No-show           110527 non-null object
dtypes: float64(1), int64(8), object(5)
memory usage: 11.8+ MB
Number of dublicated entries:  0
```

Out[124]:
```
PatientId         62299
AppointmentID    110527
dtype: int64
```

Observations / Changes Needed:

- Changing patientID data type from float to int will make the dataset easier to manipulate.
- Stripping time from the schedule_day column will make the dataset easier to manipulate.
- Stripping time from the appointment_day column will make the dataset easier to manipulate.
- No duplicate data exists. It appears some patients had multiple appointments.

Step 5: Integrity check to see a summary of statistics to look for anomalies.

In [125]:
```
# Compute a summary of statistics
df.describe()
```

Out[125]:

	PatientId	AppointmentID	Age	Scholarship	Hipertension	Diabetes
count	1.105270e+05	1.105270e+05	110527.000000	110527.000000	110527.000000	110527.000000
mean	1.474963e+14	5.675305e+06	37.088874	0.098266	0.197246	0.071865
std	2.560949e+14	7.129575e+04	23.110205	0.297675	0.397921	0.258265
min	3.921784e+04	5.030230e+06	-1.000000	0.000000	0.000000	0.000000
25%	4.172614e+12	5.640286e+06	18.000000	0.000000	0.000000	0.000000
50%	3.173184e+13	5.680573e+06	37.000000	0.000000	0.000000	0.000000
75%	9.439172e+13	5.725524e+06	55.000000	0.000000	0.000000	0.000000
max	9.999816e+14	5.790484e+06	115.000000	1.000000	1.000000	1.000000

In [126]:
```
# Check if there is an age less than 0 value
df[df["Age"] < 0]
```

Out[126]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhc
99832	4.659432e+14	5775010	F	2016-06-06T08:58:13Z	2016-06-06T00:00:00Z	-1	ROM

In [127]:
```
# Check if there is an age greater than 100 value
df[df["Age"] > 100]
```

Out[127]:

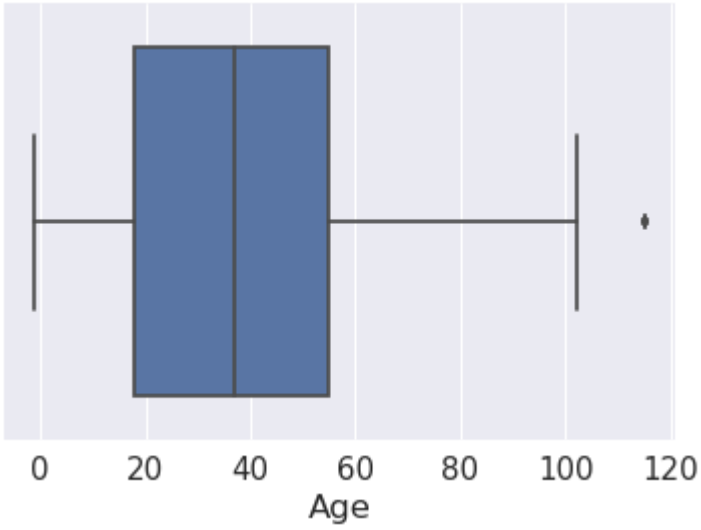
	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhc
58014	9.762948e+14	5651757	F	2016-05-03T09:14:53Z	2016-05-03T00:00:00Z	102	CONQUIS
63912	3.196321e+13	5700278	F	2016-05-16T09:17:44Z	2016-05-19T00:00:00Z	115	ANDORINH
63915	3.196321e+13	5700279	F	2016-05-16T09:17:44Z	2016-05-19T00:00:00Z	115	ANDORINH
68127	3.196321e+13	5562812	F	2016-04-08T14:29:17Z	2016-05-16T00:00:00Z	115	ANDORINH
76284	3.196321e+13	5744037	F	2016-05-30T09:44:51Z	2016-05-30T00:00:00Z	115	ANDORINH
90372	2.342836e+11	5751563	F	2016-05-31T10:19:49Z	2016-06-02T00:00:00Z	102	MARIA OR
97666	7.482346e+14	5717451	F	2016-05-19T07:57:56Z	2016-06-03T00:00:00Z	115	SÃO JC

This output exposed outliers in the age field that could potentially be errors.

The youngest person is -1 and the oldest is 115. Boxplots provide a way to visually identify outliers. Boxplots graphically display the interquartile ranges of the data, with outliers located outside of the whiskers of the plot.

In [128]:
```
# Create a boxplot of the age using seaborn
sns.boxplot(df.Age)
```

Out[128]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb6c578ed68>



Observations / Changes Needed:

- There are two patients in the data that were allegedly 115 years old. Given that "Super centurians" (https://en.wikipedia.org/wiki/List_of_the_verified_oldest_people) are very rare it is unlikely that this information is accurate. These entries along with the -1 patient will be removed to ensure no outlier affects occur.

Data Cleaning

Step 1: Fixed column mispellings, change column names, and transform no_show column data type to integer.

Making the data as easy as possible to work with by eliminating confusing inconsistencies.

In [129]:
```
# Changing the column names
new_col_names = ['patientID', 'appointmentID', 'gender', 'schedule_day', 'appo
intment_day', 'age', 'neighborhood', 'scholarship', 'hypertension', 'diabetes'
, 'alcoholism', 'handicap', 'sms_received', 'no_show']
df.columns = new_col_names

# Converting no_show field from string to int to enable plotting in charts
df["no_show"] = np.where((df.no_show=="Yes"), 1, 0)

df.tail()
```

Out[129]:

	patientID	appointmentID	gender	schedule_day	appointment_day	age	neighborhoc
110522	2.572134e+12	5651768	F	2016-05-03T09:15:35Z	2016-06-07T00:00:00Z	56	MARIA ORT
110523	3.596266e+12	5650093	F	2016-05-03T07:27:33Z	2016-06-07T00:00:00Z	51	MARIA ORT
110524	1.557663e+13	5630692	F	2016-04-27T16:03:52Z	2016-06-07T00:00:00Z	21	MARIA ORT
110525	9.213493e+13	5630323	F	2016-04-27T15:09:23Z	2016-06-07T00:00:00Z	38	MARIA ORT
110526	3.775115e+14	5629448	F	2016-04-27T13:30:56Z	2016-06-07T00:00:00Z	54	MARIA ORT

Step 2: Change schedule_day and appointment_day columns to datetime.

Converting date field from string to datetime to easily perform time calculations.

In [130]:
```
# Convert date columns data type to datetime
df.appointment_day = df.appointment_day.apply(np.datetime64)
df.schedule_day   = df.schedule_day.apply(np.datetime64)

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
patientID          110527 non-null float64
appointmentID      110527 non-null int64
gender             110527 non-null object
schedule_day       110527 non-null datetime64[ns]
appointment_day    110527 non-null datetime64[ns]
age                110527 non-null int64
neighborhood       110527 non-null object
scholarship        110527 non-null int64
hypertension       110527 non-null int64
diabetes           110527 non-null int64
alcoholism         110527 non-null int64
handicap           110527 non-null int64
sms_received       110527 non-null int64
no_show            110527 non-null int64
dtypes: datetime64[ns](2), float64(1), int64(9), object(2)
memory usage: 11.8+ MB
```

Step 3: Trim time from schedule_day and appointment_day since neither have time-level data.

Removing the time portion of schedule_day and appointment_day.

In [131]:
```
# Trim time from schedule_day and appointment_day columns
df['schedule_day'] = df['schedule_day'].apply(lambda x: x.strftime('%m-%d-%Y'
))
df['appointment_day'] = df['appointment_day'].apply(lambda x: x.strftime('%m-%
d-%Y'))

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
patientID          110527 non-null float64
appointmentID      110527 non-null int64
gender             110527 non-null object
schedule_day       110527 non-null object
appointment_day    110527 non-null object
age                110527 non-null int64
neighborhood       110527 non-null object
scholarship        110527 non-null int64
hypertension       110527 non-null int64
diabetes           110527 non-null int64
alcoholism         110527 non-null int64
handicap           110527 non-null int64
sms_received       110527 non-null int64
no_show            110527 non-null int64
dtypes: float64(1), int64(9), object(4)
memory usage: 11.8+ MB
```

Step 4: Created a appointment_dow column for day of week analysis.

Converting date fields from string to datetime, once again, to enable datetime functions, then converting date to day of week for report readability.

In [132]:
```
# Convert schedule_day and appointment_day back to datetime
df['schedule_day'] = pd.to_datetime(df['schedule_day'])
df['appointment_day'] = pd.to_datetime(df['appointment_day'])

# Convert schedule_day and appointment_day to day of week
df['schedule_dow'] = df['schedule_day'].dt.weekday_name
df['appointment_dow'] = df['appointment_day'].dt.weekday_name
df.head()
```

Out[132]:

	patientID	appointmentID	gender	schedule_day	appointment_day	age	neighborhood	sc
0	2.987250e+13	5642903	F	2016-04-29	2016-04-29	62	JARDIM DA PENHA	
1	5.589978e+14	5642503	M	2016-04-29	2016-04-29	56	JARDIM DA PENHA	
2	4.262962e+12	5642549	F	2016-04-29	2016-04-29	62	MATA DA PRAIA	
3	8.679512e+11	5642828	F	2016-04-29	2016-04-29	8	PONTAL DE CAMBURI	
4	8.841186e+12	5642494	F	2016-04-29	2016-04-29	56	JARDIM DA PENHA	

Step 5: Changed patiendID data type from float to int.

Converting patientID from float to int and remove scientific notation. It is an unnecessary format for representing a patient ID.

In [133]:
```
# Convert patientID from float to int
df['patientID'] = df['patientID'].astype(int)
df.info()
```

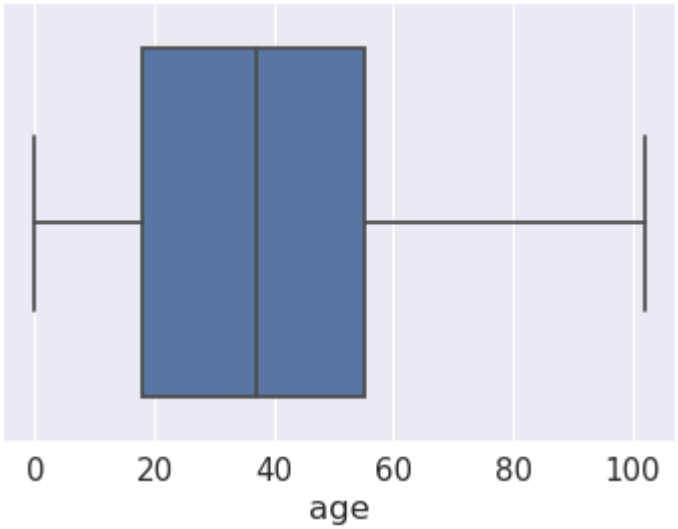
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 16 columns):
patientID          110527 non-null int64
appointmentID      110527 non-null int64
gender             110527 non-null object
schedule_day       110527 non-null datetime64[ns]
appointment_day    110527 non-null datetime64[ns]
age                110527 non-null int64
neighborhood       110527 non-null object
scholarship        110527 non-null int64
hypertension       110527 non-null int64
diabetes           110527 non-null int64
alcoholism         110527 non-null int64
handicap           110527 non-null int64
sms_received       110527 non-null int64
no_show            110527 non-null int64
schedule_dow       110527 non-null object
appointment_dow    110527 non-null object
dtypes: datetime64[ns](2), int64(10), object(4)
memory usage: 13.5+ MB
```

Step 6: Remove age outliers to ensure no outlier affects occur.

Output a boxplot to confirm the outliers are no longer present.

In [134]:
```
# Remove the outliers
df = df[(df.age > -1) & (df.age < 115)]

# Display the boxplot again to verify the outcome
sns.boxplot(df.age)
```

Out[134]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb6c43a7438>



In [135]:
```
# Double check the data was removed
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 110521 entries, 0 to 110526
Data columns (total 16 columns):
patientID          110521 non-null int64
appointmentID      110521 non-null int64
gender             110521 non-null object
schedule_day       110521 non-null datetime64[ns]
appointment_day    110521 non-null datetime64[ns]
age                110521 non-null int64
neighborhood       110521 non-null object
scholarship        110521 non-null int64
hypertension       110521 non-null int64
diabetes           110521 non-null int64
alcoholism         110521 non-null int64
handicap           110521 non-null int64
sms_received       110521 non-null int64
no_show            110521 non-null int64
schedule_dow       110521 non-null object
appointment_dow    110521 non-null object
dtypes: datetime64[ns](2), int64(10), object(4)
memory usage: 14.3+ MB
```

Step 7: Create DataFrames for reuse throughout analyses.

Create a derived column of time between schedule and appointment dates, create a reusable dataframe of all shows and no-shows records, and create a dataframe with ready-to-plot data types.

In [136]:
```
# Create a derived column of time between schedule and appointment dates
df['appointment_day'] = pd.to_datetime(df['appointment_day'])
df['schedule_day'] = pd.to_datetime(df['schedule_day'])
df['elapsed_days'] = df['appointment_day'] - df['schedule_day']
df.tail()
```

Out[136]:

	patientID	appointmentID	gender	schedule_day	appointment_day	age	neighbor
110522	2572134369293	5651768	F	2016-05-03	2016-06-07	56	MARIA C
110523	3596266328735	5650093	F	2016-05-03	2016-06-07	51	MARIA C
110524	15576631729893	5630692	F	2016-04-27	2016-06-07	21	MARIA C
110525	92134931435557	5630323	F	2016-04-27	2016-06-07	38	MARIA C
110526	377511518121127	5629448	F	2016-04-27	2016-06-07	54	MARIA C

In [137]:
```
# Create a reusable dataframe of all shows records
shows = df.query('no_show == "0"')
days = shows['elapsed_days'].mean()
timeframe_shows = days / np.timedelta64(1, 'D')
shows.head()
```

Out[137]:

	patientID	appointmentID	gender	schedule_day	appointment_day	age	neighborhood
0	29872499824296	5642903	F	2016-04-29	2016-04-29	62	JARDIM DA PENHA
1	558997776694438	5642503	M	2016-04-29	2016-04-29	56	JARDIM DA PENHA
2	4262962299951	5642549	F	2016-04-29	2016-04-29	62	MATA DA PRAIA
3	867951213174	5642828	F	2016-04-29	2016-04-29	8	PONTAL DE CAMBURI
4	8841186448183	5642494	F	2016-04-29	2016-04-29	56	JARDIM DA PENHA

In [138]:
```
# Create a reusable dataframe of all no-shows records
no_shows = df.query('no_show == "1"')
days = no_shows['elapsed_days'].mean()
timeframe_nos = days / np.timedelta64(1, 'D')
no_shows.head()
```

Out[138]:

	patientID	appointmentID	gender	schedule_day	appointment_day	age	neighborhoo
6	733688164476661	5630279	F	2016-04-27	2016-04-29	23	GOIABEIRA
7	3449833394123	5630575	F	2016-04-27	2016-04-29	39	GOIABEIRA
11	7542951368435	5620163	M	2016-04-26	2016-04-29	29	NOV PALESTIN
17	14794966191172	5633460	F	2016-04-28	2016-04-29	40	CONQUIST
20	622257462899397	5626083	F	2016-04-27	2016-04-29	30	NOV PALESTIN

In [139]:
```
# Create new seperate columns for people who showed ot not_showed
showed = df['no_show'] == 0
not_showed = df['no_show'] == 1
df['showed'] = showed
df['not_showed'] = not_showed
df.head()
```

Out[139]:

	patientID	appointmentID	gender	schedule_day	appointment_day	age	neighborhood
0	29872499824296	5642903	F	2016-04-29	2016-04-29	62	JARDIM DA PENHA
1	558997776694438	5642503	M	2016-04-29	2016-04-29	56	JARDIM DA PENHA
2	4262962299951	5642549	F	2016-04-29	2016-04-29	62	MATA DA PRAIA
3	867951213174	5642828	F	2016-04-29	2016-04-29	8	PONTAL DE CAMBURI
4	8841186448183	5642494	F	2016-04-29	2016-04-29	56	JARDIM DA PENHA

Exploratory Data Analysis

Research Question 1: What is the overall appointment show-up vs. no-show rate?

In [140]:
```
# Create a new DataFrame to show total appointments
new_df = df.groupby('no_show')['no_show'].agg(['count'])
new_df.reset_index(inplace=True)
new_df.columns = ['appt_status', 'total']
new_df.iloc[0,0] = "Show"
new_df.iloc[1,0] = "No Show"
new_df.head()
```

Out[140]:

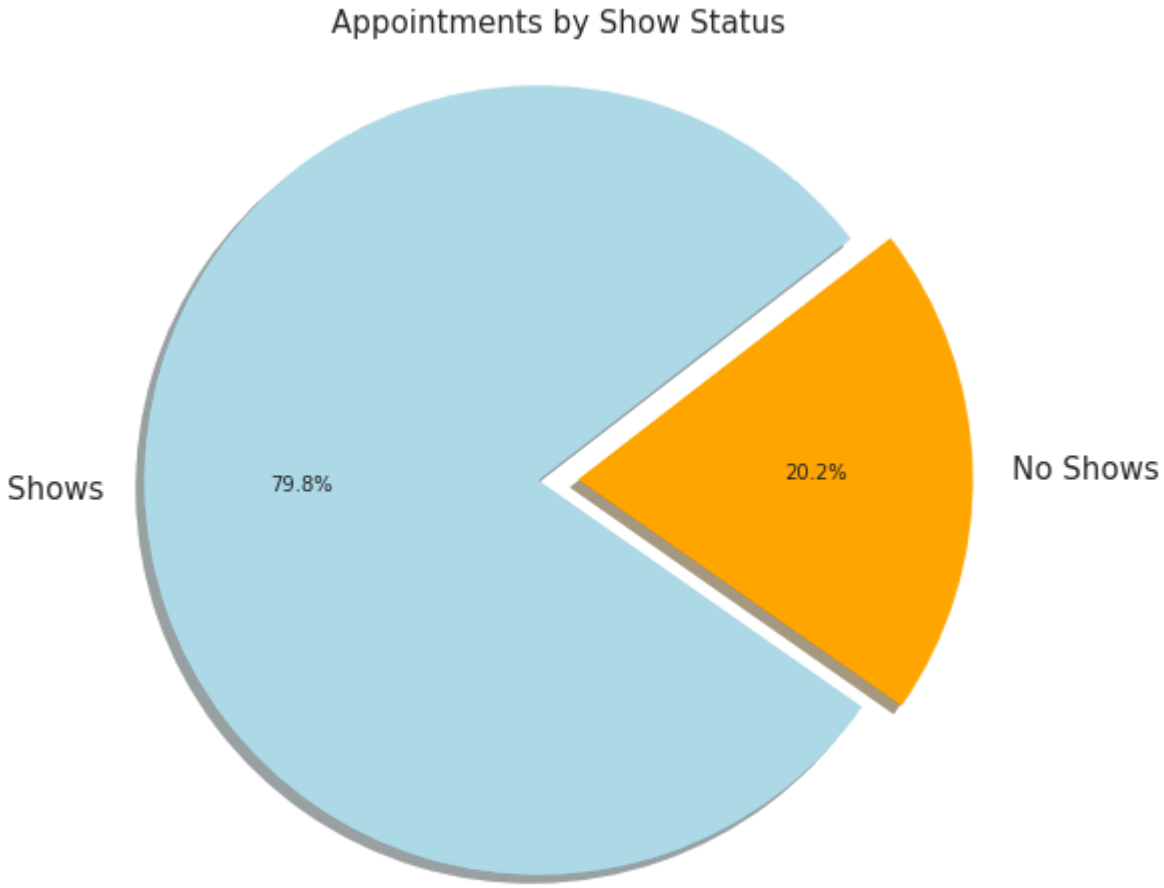
	appt_status	total
0	Show	88205
1	No Show	22316

In [141]:
```
# Create a new DataFrame to show total appointments and their propotions
shows_prop = new_df.iloc[0,1] / (new_df.iloc[0,1] + new_df.iloc[1,1])
nos_prop = new_df.iloc[1,1] / (new_df.iloc[0,1] + new_df.iloc[1,1])
new_df['proportion'] = [shows_prop, nos_prop]
new_df.head()
```

Out[141]:

	appt_status	total	proportion
0	Show	88205	0.798084
1	No Show	22316	0.201916

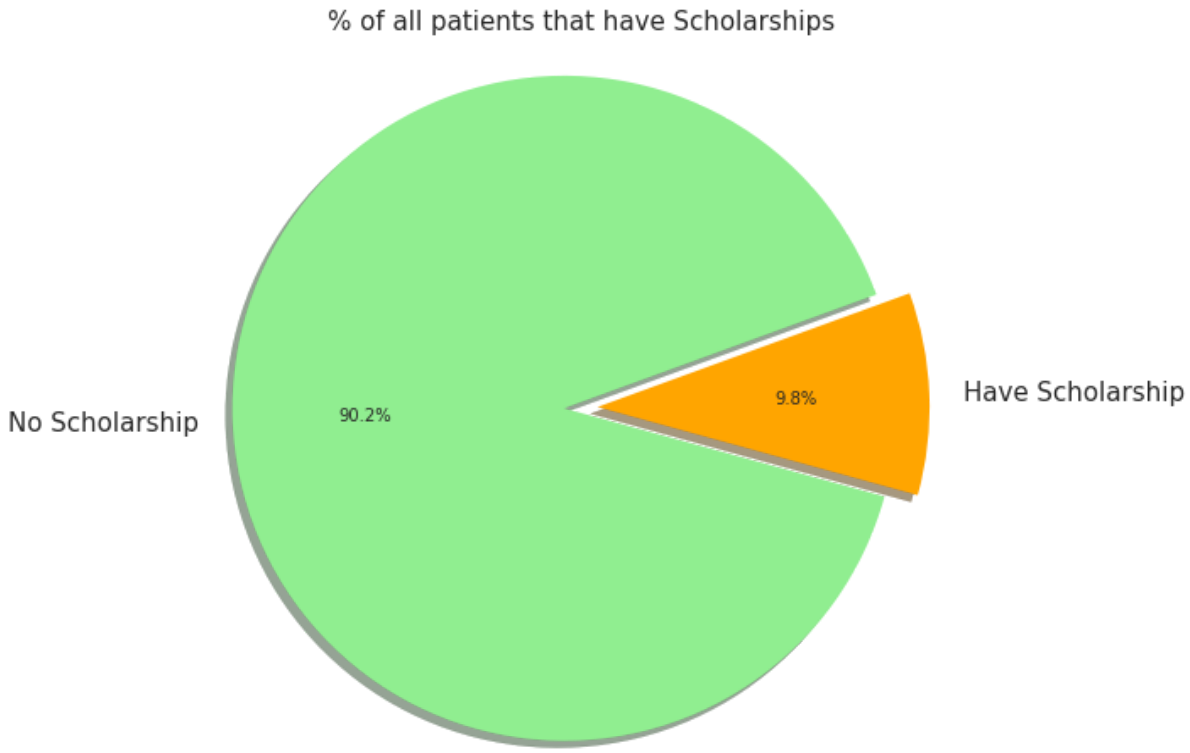
In [142]:
```
# Create a chart to show status
labels = ['No Shows', 'Shows']
sizes = [nos_prop, shows_prop]
colors = ['orange', 'lightblue']
explode = (0, 0.1)

# The plot
plt.pie(sizes, explode=explode, labels=labels, colors=colors,
        autopct='%1.1f%%', shadow=True, startangle=325)
plt.title('Appointments by Show Status', fontsize = 15)
plt.axis('equal')
fig = plt.gcf()
fig.set_size_inches(8,8);
```



Visual distribution of appointment show status.

Research Question 2: Does financial aid correlate with patient no-shows?

In [143]:
```
# Create a chart for % of patients taht have financial aid
allS = df['scholarship'].value_counts()# Data to plot
labels = ['No Scholarship', 'Have Scholarship']
colors = ['lightgreen', 'orange']
explode = (0, 0.1)

# The plot
plt.pie(allS, explode=explode, labels=labels, colors=colors,
        autopct='%1.1f%%', shadow=True, startangle=20)
plt.title('% of all patients that have Scholarships', fontsize = 15)
plt.axis('equal')
fig = plt.gcf()
fig.set_size_inches(8,8);
```

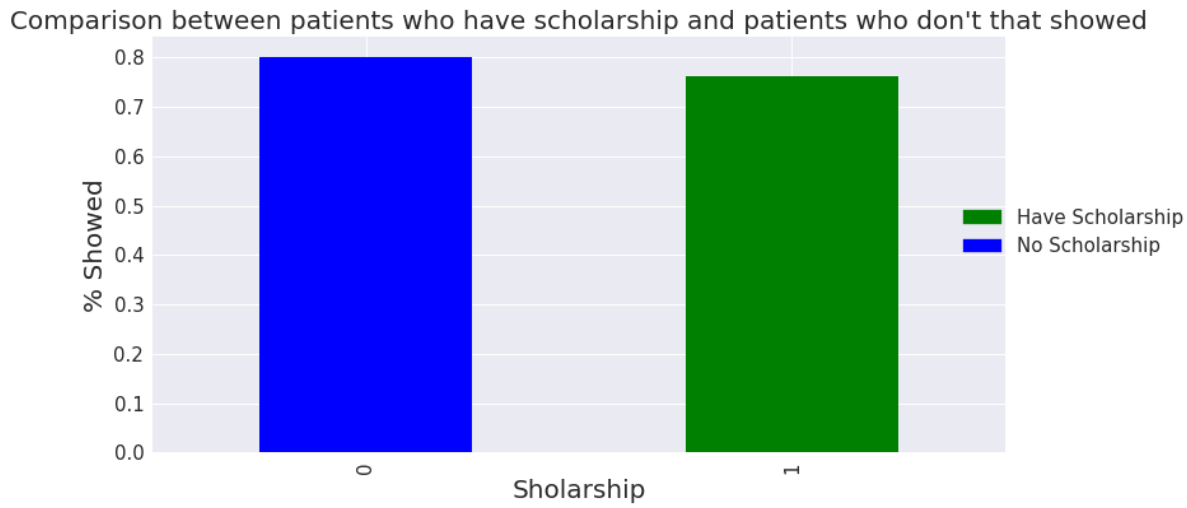


Visual distribution for patients that have a Scholarship (financial aid).

In [144]:
```
# using group by function to find relations between features
# and then see the relation between people who has scholarship and people who
 showed up and who didn't
print(df.groupby('scholarship')['showed'].mean())
print(df.groupby('scholarship')['showed'].count())

df.groupby('scholarship')['showed'].mean().plot(kind = 'bar', figsize=(12,6),
color=['blue', 'green'])
plt.xlabel("Sholarship", fontsize = 20)
plt.ylabel("% Showed", fontsize = 20)
plt.title("Comparison between patients who have scholarship and patients who d
on't that showed", fontsize = 20)

# Legend
green_patch = mpatches.Patch(color='green', label='Have Scholarship')
blue_patch = mpatches.Patch(color='blue', label='No Scholarship')

plt.legend(handles=[green_patch, blue_patch], bbox_to_anchor=(1.08, .53), loc=
'center')
```

```
scholarship
0    0.801947
1    0.762637
Name: showed, dtype: float64
scholarship
0    99660
1    10861
Name: showed, dtype: int64
```

Out[144]: <matplotlib.legend.Legend at 0x7fb6c579ed30>

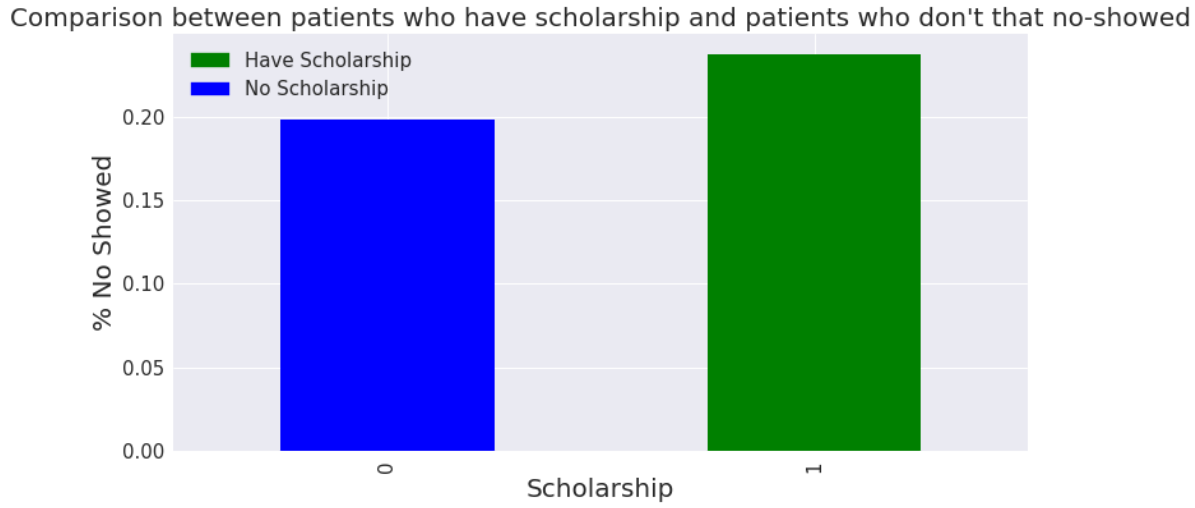


Visual comparison between patients that have financial aid and those that have none that showed.

In [145]:
```
# using group by function to find relations between features
# and then see the relation between people who has scholarship and people who
 showed up and who didn't

print(df.groupby('scholarship')['not_showed'].mean())

df.groupby('scholarship')['not_showed'].mean().plot(kind = 'bar',figsize=(12,6
), color=['blue', 'green'])
plt.xlabel("Scholarship", fontsize = 20)
plt.ylabel("% No Showed", fontsize = 20)
plt.title("Comparison between patients who have scholarship and patients who d
on't that no-showed", fontsize = 20)

# Legend
green_patch = mpatches.Patch(color='green', label='Have Scholarship')
blue_patch = mpatches.Patch(color='blue', label='No Scholarship')

plt.legend(handles=[green_patch, blue_patch])
```

```
scholarship
0    0.198053
1    0.237363
Name: not_showed, dtype: float64
```

Out[145]: <matplotlib.legend.Legend at 0x7fb6c436b438>



Visual comparison between patients that have financial aid and those that have none that no-show.

Research Question 3: Is age indicative of whether a patient will make their appointments?

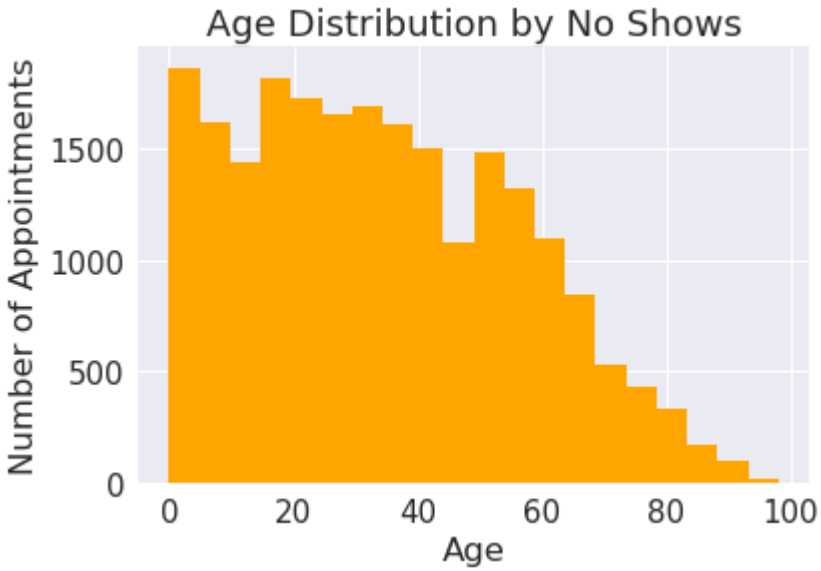
In [146]:
```
# Define a function to show probability with respect to age
def prob_show(dataset, group_by):
    df = pd.crosstab(index = dataset[group_by], columns = dataset['no_show']).
reset_index()
    # calc probability of showing up 0 means show up , 1 means missed
    df['probShowUp'] = df[0] / (df[1] + df[0])
    return df[[group_by, 'probShowUp']]
```

In [147]:
```
# Data to plot
age_df_nos = no_shows['age']
age_df_shows = shows['age']
```

In [148]:
```
# Mean age of no-shows
age_df_nos_mean = no_shows['age'].mean()


# Mean age of shows
age_df_shows_mean = shows['age'].mean()


print("Mean age of no-shows: ", age_df_nos_mean)
print("Mean age of shows: ", age_df_shows_mean)
```

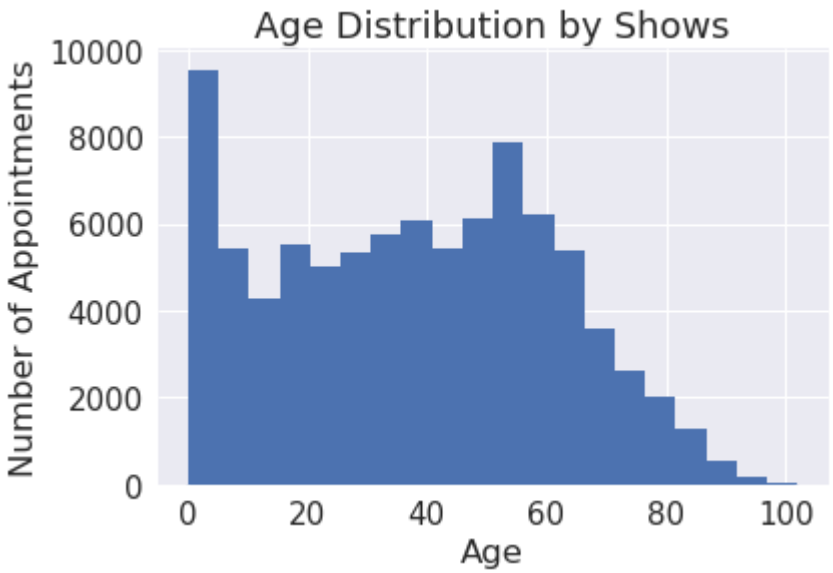
```
Mean age of no-shows:  34.3068202187
Mean age of shows:  37.788753472
```

In [149]:
```
# The histogram of no-shows
plt.hist(age_df_nos, stacked=True, bins=20, color='orange')
plt.title('Age Distribution by No Shows')
plt.xlabel('Age')
plt.ylabel('Number of Appointments');
```



Visual distribution of age for all no-shows.

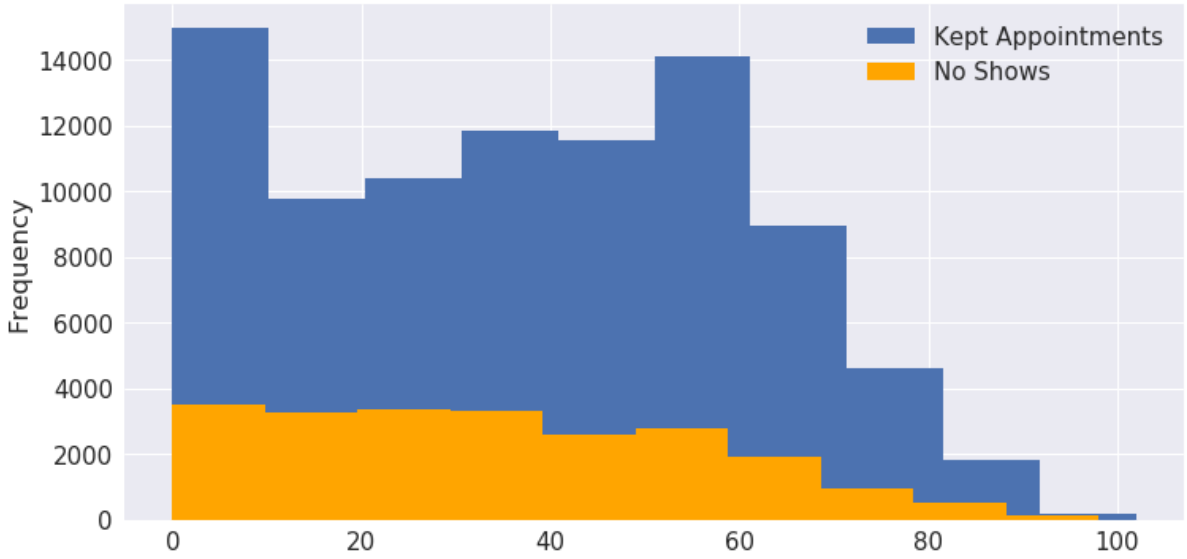
In [150]:
```
# The histogram of shows
plt.hist(age_df_shows, stacked=True, bins=20)
plt.title('Age Distribution by Shows')
plt.xlabel('Age')
plt.ylabel('Number of Appointments');
```



Visual distribution of age for all shows.

In [151]:
```
# Create an overlay histogram for shows and no-shows
kept = (df.no_show == 0)
noshows = (df.no_show == 1)

df[kept].age.plot.hist()
df[noshows].age.plot.hist(figsize=(12,6), color='orange')
plt.legend(['Kept Appointments', 'No Shows'])
```

Out[151]: <matplotlib.legend.Legend at 0x7fb6c41c50f0>

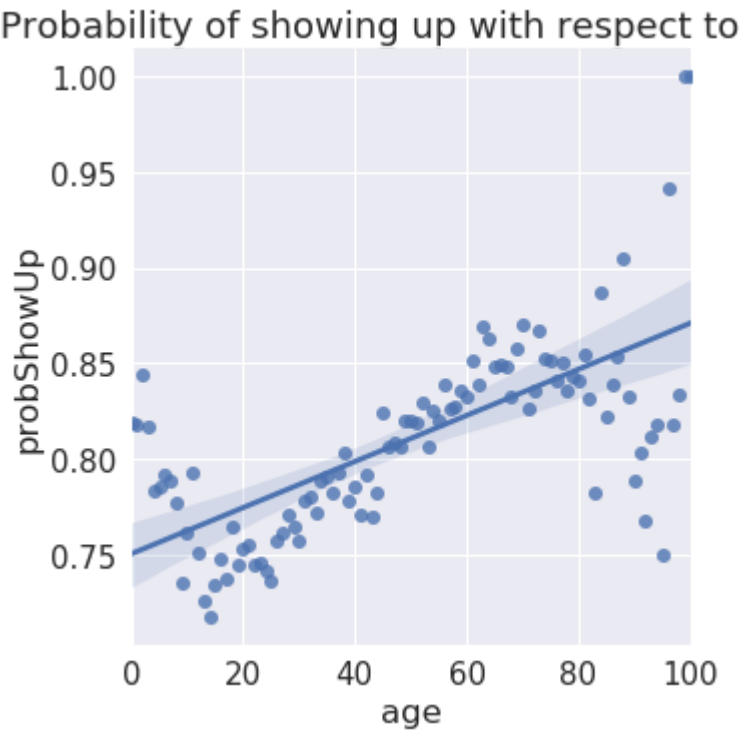


Visual distribution of kept appointments vs no-shows.

This histogram overlays the distributions of kept appointments and no shows so that they can be compared. The peak near 60 >years is much smaller for no shows.

In [152]:
```
# Dot plot of probability with respect of age
sns.lmplot(data = prob_show(df, 'age'), x = 'age', y = 'probShowUp', fit_reg = True)
plt.xlim(0, 100)
plt.title('Probability of showing up with respect to Age')
```

Out[152]: Text(0.5,1,'Probability of showing up with respect to Age')

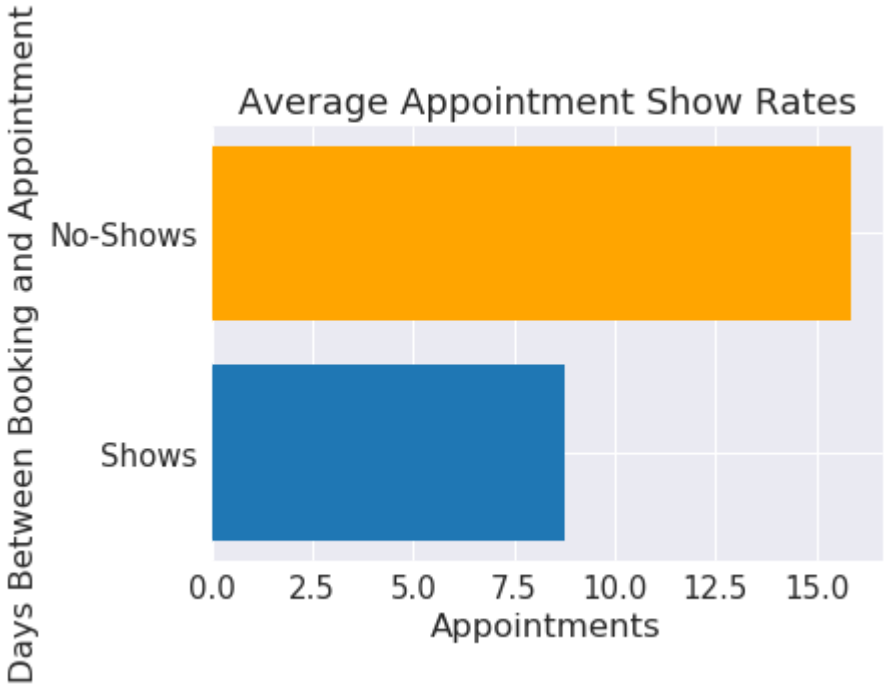


Visual distribution for probability of showing up with respect to age.

No-show rate of medical appointments is highly dependent on the age of the appointee,ages from 14 to 24 years have higher >cancellations rate. The no-show rate then decreases after around 80 year old appointees.

Research Question 4: Do no-shows have a larger timeframe between schedule date and appointment date?

In [153]:
```
# Create a horizontal bar chart to compare The plot
locations = [1, 2]
heights = [timeframe_shows, timeframe_nos]
labels = ['Shows', 'No-Shows']

plt.barh(locations, heights, tick_label=labels, color=['#1f77b4','orange'])
plt.title('Average Appointment Show Rates')
plt.xlabel('Appointments')
plt.ylabel('Days Between Booking and Appointment');
```

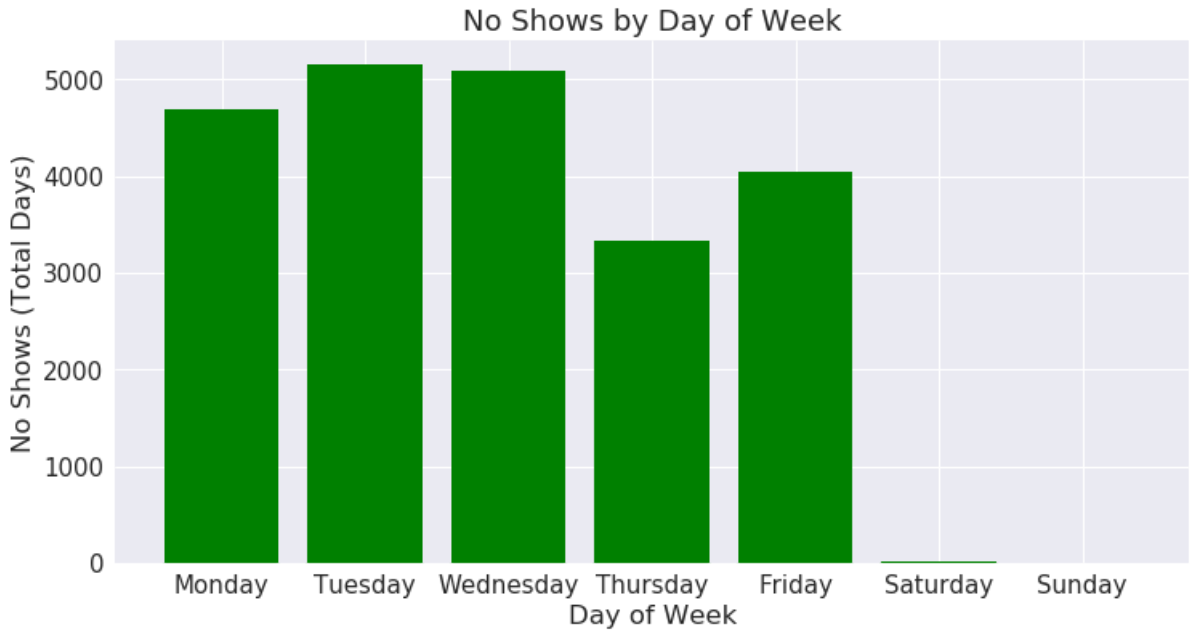


Visual distribution of mean timeframe between scheduling and appointment time.

Research Question 5: Do some days of the week have more no-shows than others?

In [154]:
```
# Days of the week data to plot
nos_mon = no_shows.query('appointment_dow == "Monday"')
nos_mon = nos_mon['appointment_dow'].count()

nos_tue = no_shows.query('appointment_dow == "Tuesday"')
nos_tue = nos_tue['appointment_dow'].count()

nos_wed = no_shows.query('appointment_dow == "Wednesday"')
nos_wed = nos_wed['appointment_dow'].count()

nos_thu = no_shows.query('appointment_dow == "Thursday"')
nos_thu = nos_thu['appointment_dow'].count()

nos_fri = no_shows.query('appointment_dow == "Friday"')
nos_fri = nos_fri['appointment_dow'].count()

nos_sat = no_shows.query('appointment_dow == "Saturday"')
nos_sat = nos_sat['appointment_dow'].count()

nos_sun = no_shows.query('appointment_dow == "Sunday"')
nos_sun = nos_sun['appointment_dow'].count()
```

In [155]:
```
# Create a bar chart to show kept appointments by day of the week
locations = [1, 2, 3, 4, 5, 6, 7]
heights = [nos_mon, nos_tue, nos_wed, nos_thu, nos_fri, nos_sat, nos_sun]
labels = ['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunda
y']
plt.bar(locations, heights, tick_label=labels, color='green')
plt.title('No Shows by Day of Week')
plt.xlabel('Day of Week')
plt.ylabel('No Shows (Total Days)')

fig = plt.gcf()
fig.set_size_inches(12,6);
```



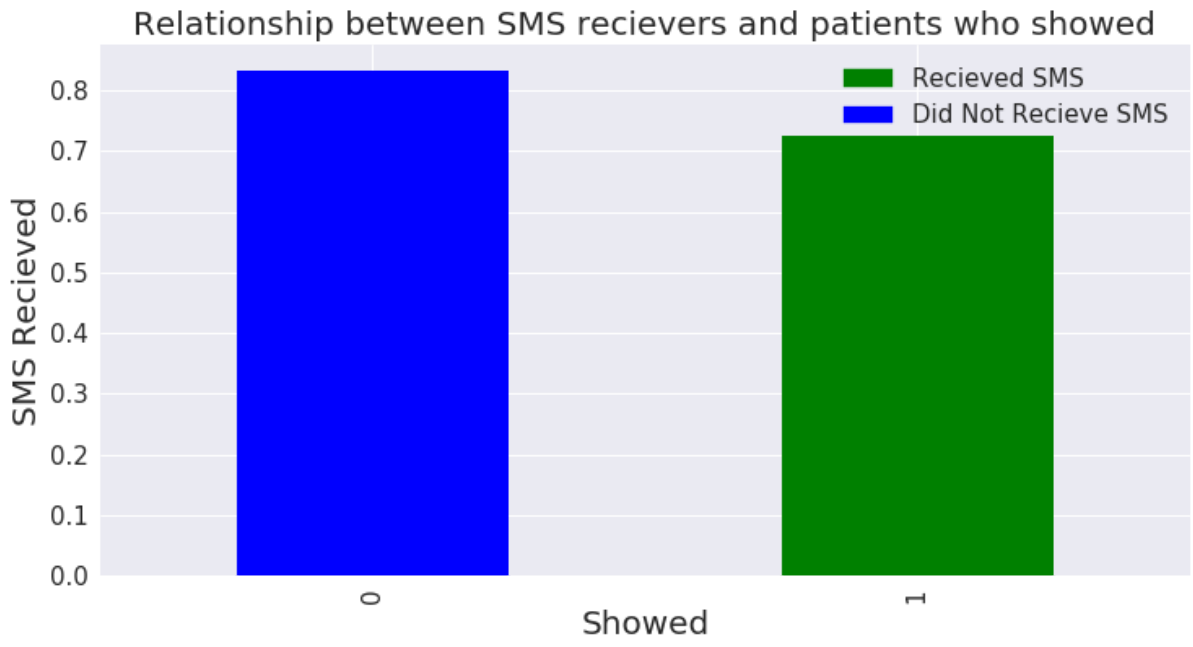
Visual distribution of no-shows by day of week.

Research Question 6: Do SMS notifications coincide with fewer no-shows?

In [156]:
```
# Using group by function to find relations between features
# and then see the relation between sms recievers and people who showed up and
who didn't
print(df.groupby('sms_received')['showed'].mean())

df.groupby('sms_received')['showed'].mean().plot(kind='bar',figsize=(12,6), co
lor=['blue', 'green']);
plt.xlabel("Showed", fontsize = 20)
plt.ylabel("SMS Recieved", fontsize = 20)
plt.title("Relationship between SMS recievers and patients who showed", fontsi
ze = 20)

# Legend
green_patch = mpatches.Patch(color='green', label='Recieved SMS')
blue_patch = mpatches.Patch(color='blue', label='Did Not Recieve SMS')

plt.legend(handles=[green_patch, blue_patch])
```

```
sms_received
0    0.832996
1    0.724247
Name: showed, dtype: float64
```

Out[156]: <matplotlib.legend.Legend at 0x7fb6c4305710>

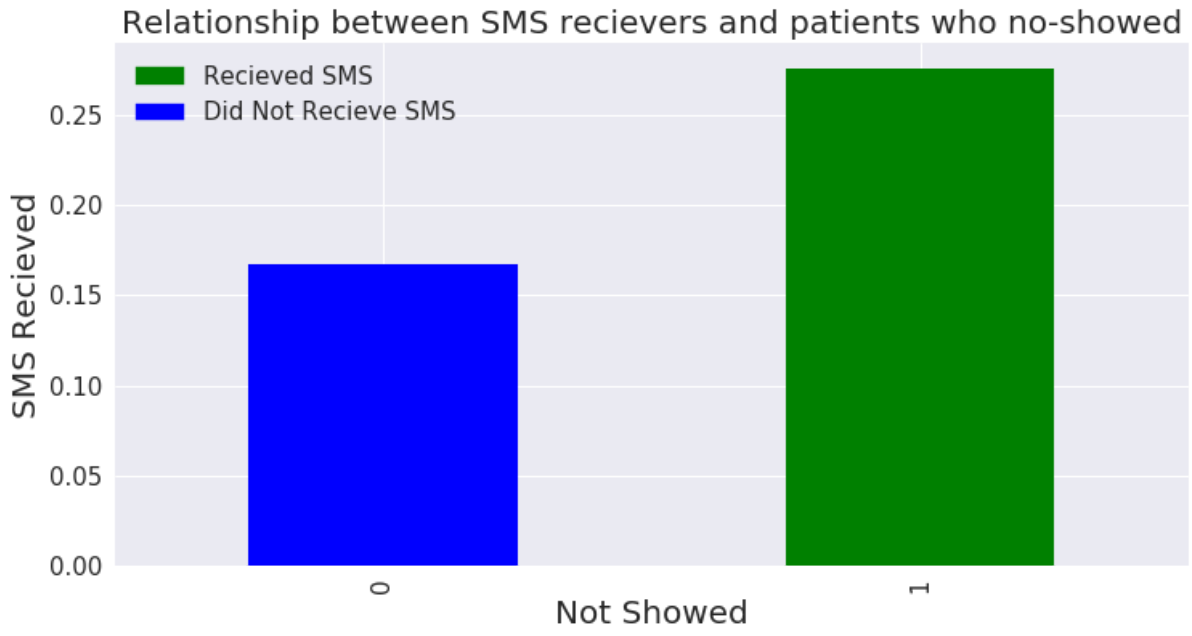


Visual comparison between patients that recieved SMS reminder and those that did not that showed.

In [157]:
```
# Using group by function to find relations between features
# and then see the relation between sms recievers and people who showed up and
who didn't
print(df.groupby('sms_received')['not_showed'].mean())

df.groupby('sms_received')['not_showed'].mean().plot(kind='bar',figsize=(12,6
), color=['blue', 'green']);
plt.xlabel("Not Showed", fontsize = 20)
plt.ylabel("SMS Recieved", fontsize = 20)
plt.title("Relationship between SMS recievers and patients who no-showed", fon
tsize = 20)

# Legend
green_patch = mpatches.Patch(color='green', label='Recieved SMS')
blue_patch = mpatches.Patch(color='blue', label='Did Not Recieve SMS')

plt.legend(handles=[green_patch, blue_patch])
```

```
sms_received
0    0.167004
1    0.275753
Name: not_showed, dtype: float64
```

Out[157]: <matplotlib.legend.Legend at 0x7fb6c40f7588>



Visual comparison between patients that recieved SMS reminder and those that did not that no-showed.

Suprisingly, the percentage of no shows is much higher when SMS messages were received.

Research Question 7: Which neighborhoods have more no-shows than others?

In [158]:
```
# Show top 10 neighboods for pts who showed
shows_by_hood = shows.groupby("neighborhood")["no_show"].count().reset_index(name="count").sort_values("count", ascending=False)
shows_by_hood.head(10)
```

Out[158]:

	neighborhood	count
37	JARDIM CAMBURI	6252
42	MARIA ORTIZ	4586
58	RESISTÊNCIA	3525
38	JARDIM DA PENHA	3246
65	SANTA MARTHA	2635
10	CENTRO	2631
35	ITARARÉ	2591
77	TABUAZEIRO	2559
68	SANTO ANTÔNIO	2262
8	BONFIM	2223

Top 10 neighborhoods by shows.

In [159]:
```
# Show top 10 neighboods for pts who no-showed
nos_by_hood = no_shows.groupby("neighborhood")["no_show"].count().reset_index(
name="count").sort_values("count", ascending=False)
nos_by_hood.head(10)
```

Out[159]:

	neighborhood	count
38	JARDIM CAMBURI	1465
43	MARIA ORTIZ	1219
36	ITARARÉ	923
58	RESISTÊNCIA	906
10	CENTRO	703
40	JESUS DE NAZARETH	696
39	JARDIM DA PENHA	631
9	CARATOÍRA	591
77	TABUAZEIRO	573
8	BONFIM	550

Top 10 neighborhoods by no-shows.

Conclusions

The following conclusions were drawn to serve as a basis for more robust analysis in the future. Approximately 80% of all patients kept their appointment while 20% of all appointments investigated were no-shows.

A trend related to age was observed where people with an age less than 35 tend to miss their appointment more than the people with age greater than 35.

There is a correlation between the number of days out an appointment was made from the scheduled date and the appointment no-show rate. The greater the number of days until the appointment, the more likely a patient would no-show.

Surprisingly sending SMS had a worse impact on whether the patient kept their appointment as the general trend shows that people who get SMS were less likely to attend their appointment as compared to those who did not.

Limitations:

- The data set explored in this analysis was over a 6 month period. Data for a longer timeframe would provide insight into how seasonality and holidays impact show rates.
- Overlaying external data sources onto this data set such as traffic, weather, or geographic data could allow us to better understand influencers on no-show rates. The current data set analysis is limited to general correlations.

Questions Answered:

What is the overall appointment show-up vs. no-show rate?

- Approximately 80% of all patients kept their appointment while 20% of all appointments investigated were no-shows.

Does financial aid correlate with patient no-shows?

- Patients with scholarships (financial aid) appeared to have a higher percentage of not attending appointments. This was unexpected and more data would be needed to find the cause of this.

Is age indicative of whether a patient will make their appointments?

- Patient age was charted to see if there was a large difference between the no-shows and shows segments. The mean age of the no-shows was 34, compared to the shows which were 38. A trend related to age could be observed where people with an age less than 35 tend to miss their appointment more than the people with age greater than 35.

Do no-shows have a larger timeframe between schedule date and appointment date?

- The timeframe between schedule date and appointment date was investigated to see if there was any correlation with kept appointments. The mean timeframe between schedule date and appointment date for no-shows was significantly higher than shows. The show rate was better if the appointment was booked fewer days from the scheduled date. There is a correlation between the number of days out an appointment was made from the scheduled date and the appointment no-show rate. The greater the number of days until the appointment, the more likely a patient would no-show.

Do some days of the week have more no-shows than others?

- Appointment no-shows occurred the most on Tuesdays and the least on Thursdays. Overall, appointments early in the week have a higher no-show rate.

Do SMS notifications coincide with fewer no-shows?

- Surprisingly sending SMS to patients had a worse impact on whether they kept their appointment. The general trend shows that patients who get SMS are less likely to attend their appointment as compared to those who did not. As can be seen, sending an SMS for the appointment is not necessarily the right option to ensure that the patient will show-up.

Which neighborhoods have more no-shows than others?

- Neighborhoods in which the appointment took place were charted to see if certain areas had higher no-show rates. JARDIM CAMBURI and MARIA ORTIZ were the Top 2 neighborhoods in both the no-shows and shows segments.

In [160]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

Out[160]:
```
0
```