investigate-a-dataset-Submission-2-Kinnaird

February 27, 2018

1 Project: Investigate the Misuse of Healthcare Resources Through Missed Appointments

1.1 Table of Contents

Introduction

According to the World Bank analysis of World Health Organization Global Health Expenditure data, annual health expenditure per capita significantly increased from 1995-2014. Within this 10 year period, expenditures increased from $461 to $1,058 per person. This 130% increase outpaces growth in international GDP per capita by 30% (1995: $5,403, 2014: $10,871, World Bank Data).

As healthcare expenditures increase, healthcare resources must be strategic utilized. In order to understand the use and misuse of healthcare resources, 100,000 medical appointments in Brazil will be analyzed. The purpose of the analysis is to understand what characterstics are commonly associated with a "no-show appointment," which is when an appointment is scheduled and the patient does not arrive for the appointment, and what hospitals do patients with these characteristics visit.

The dependent variable considered is whether or not the patient arrives for the appointment. The independent variables to be considered are age-group (0-18, 19-44, 45-64, 65-84, and 85 and over; these age bins reflect the same bins used by the Centers for Medicare and Medicaid Services "Health Expenditures by Age and Gender" study),"Scholarship"(whether the patient receives federal assistance or does not receive federal assistance), and general well-being (whether the patient has hypertension, diabetes, alcoholism, or handicap or none of these conditions).

Once the initial analysis is complete, the above indpendent variables will then be grouped by neighborhood, the next dependent variable to be analyzed. Grouping by neighborhood will create profiles for each neighborhood based on age-groups, scholarship, and general well-being.

Combining the results from each analysis will provide initial conclusions for understanding which group(s) based on age, scholarship, and general well-being, misuse healthcare resources and in which neighborhoods these groups are concentrated.

All data provided by JoniHoppen from the "Medical Appointment No Shows" dataset.

```
In [97]: # Import statements for all of the packages used.
         import pandas as pd
```

```
import numpy as np
import matplotlib.pyplot as plt
% matplotlib inline
```

Data Wrangling

1.1.1 General Properties

In [98]:
```
# Load data
df = pd.read_csv('noshowappointments-kagglev2-may-2016.csv')
# Inspect data types
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
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
```

In [99]:
```
# Visually inspect data rows
df.head()
```

Out[99]:
```
      PatientId  AppointmentID Gender          ScheduledDay  \
0  2.987250e+13        5642903      F  2016-04-29T18:38:08Z
1  5.589978e+14        5642503      M  2016-04-29T16:08:27Z
2  4.262962e+12        5642549      F  2016-04-29T16:19:04Z
3  8.679512e+11        5642828      F  2016-04-29T17:29:31Z
4  8.841186e+12        5642494      F  2016-04-29T16:07:23Z

         AppointmentDay  Age      Neighbourhood  Scholarship  Hipertension  \
0  2016-04-29T00:00:00Z   62    JARDIM DA PENHA            0             1
1  2016-04-29T00:00:00Z   56    JARDIM DA PENHA            0             0
2  2016-04-29T00:00:00Z   62      MATA DA PRAIA            0             0
3  2016-04-29T00:00:00Z    8  PONTAL DE CAMBURI            0             0
```

```
4  2016-04-29T00:00:00Z   56    JARDIM DA PENHA             0              1

   Diabetes  Alcoholism  Handcap  SMS_received No-show
0         0           0        0             0      No
1         0           0        0             0      No
2         0           0        0             0      No
3         0           0        0             0      No
4         1           0        0             0      No
```

In [100]:
```
# Inspect data count
df.count()
```

Out[100]:
```
PatientId         110527
AppointmentID     110527
Gender            110527
ScheduledDay      110527
AppointmentDay    110527
Age               110527
Neighbourhood     110527
Scholarship       110527
Hipertension      110527
Diabetes          110527
Alcoholism        110527
Handcap           110527
SMS_received      110527
No-show           110527
dtype: int64
```

In [101]:
```
# Find duplicate rows
df[df.duplicated(keep=False)].count()[0]
```

Out[101]:
```
0
```

The data inspection revealed a data frame with 14 columns (PatientId, AppointmentID, Gender, ScheduledDay, AppointmentDay, Age, Neighbourhood, Scholarship, Hipertension, Diabetes, Alcoholism, Handcap, SMS_received, No-show) and 110527 rows with no duplicates. Looking at the first 5 rows shows several of the columns to be binary values.

1.1.2 Data Cleaning

The data cleaning of the dataframe will require the renaming of columns to correct spelling, the deletion of columns to focus on data for this study, and further examination of the remaining columns.

In [102]:
```
#Drop columns not to be used in this study
df = df.drop(['PatientId','Gender','ScheduledDay','AppointmentDay','SMS_received'], a
```

In [103]:
```
# Inspect updated df
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 9 columns):
AppointmentID    110527 non-null int64
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
No-show          110527 non-null object
dtypes: int64(7), object(2)
memory usage: 7.6+ MB
```

In [104]:
```python
# Inspect number of unique values in each column
df.nunique()
```

Out[104]:
```
AppointmentID    110527
Age                 104
Neighbourhood        81
Scholarship           2
Hipertension          2
Diabetes              2
Alcoholism            2
Handcap               5
No-show               2
dtype: int64
```

In [105]:
```python
# Correct mispelling, change regional spelling of column names, add '_' to 'appointm
df = df.rename(index=str, columns={'AppointmentID': 'appointment_id',"Neighbourhood"
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 110527 entries, 0 to 110526
Data columns (total 9 columns):
appointment_id    110527 non-null int64
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
no_show           110527 non-null object
dtypes: int64(7), object(2)
memory usage: 8.4+ MB
```

In [106]:
```
# For consistency, convert all remaining columns to lowercase
df.columns = map(str.lower, df.columns)
```

In [107]:
```
# For consistency, convert all values in the column 'neighboorhood' to lowercase
df['neighborhood'] = df['neighborhood'].str.lower()
```

In [108]:
```
df.head()
```

Out[108]:
```
   appointment_id  age       neighborhood  scholarship  hypertension  \
0         5642903   62    jardim da penha            0             1
1         5642503   56    jardim da penha            0             0
2         5642549   62      mata da praia            0             0
3         5642828    8  pontal de camburi            0             0
4         5642494   56    jardim da penha            0             1

   diabetes  alcoholism  handicap no_show
0         0           0         0      No
1         0           0         0      No
2         0           0         0      No
3         0           0         0      No
4         1           0         0      No
```

In [109]:
```
# Further inspect each column
df['age'].max()
```

Out[109]: 115

In [110]:
```
df['age'].min()
```

Out[110]: -1

In [111]:
```
# Identify which row contains an age of -1, because -1 is not a real age.
df[df['age']==-1]
```

Out[111]:
```
       appointment_id  age neighborhood  scholarship  hypertension  diabetes  \
99832         5775010   -1        romão            0             0         0

       alcoholism  handicap no_show
99832           0         0      No
```

In [112]:
```
# Drop the row associated with 'age' = -1
drop_age = df[df['age']==-1].index[0]
df = df.drop([drop_age])
```

In [113]:
```
# Confirm drop of row associated with 'age' = -1
df['age'].min()
```

Out[113]: 0

In [114]:
```
# Investigage list of 'neighborhood' values
sorted(df['neighborhood'].unique())
```

```
Out[114]: ['aeroporto',
           'andorinhas',
           'antônio honório',
           'ariovaldo favalessa',
           'barro vermelho',
           'bela vista',
           'bento ferreira',
           'boa vista',
           'bonfim',
           'caratoíra',
           'centro',
           'comdusa',
           'conquista',
           'consolação',
           'cruzamento',
           'da penha',
           'de lourdes',
           'do cabral',
           'do moscoso',
           'do quadro',
           'enseada do suá',
           'estrelinha',
           'fonte grande',
           'forte são joão',
           'fradinhos',
           'goiabeiras',
           'grande vitória',
           'gurigica',
           'horto',
           'ilha das caieiras',
           'ilha de santa maria',
           'ilha do boi',
           'ilha do frade',
           'ilha do príncipe',
           'ilhas oceânicas de trindade',
           'inhanguetá',
           'itararé',
           'jabour',
           'jardim camburi',
           'jardim da penha',
           'jesus de nazareth',
           'joana dťarc',
           'jucutuquara',
           'maria ortiz',
           'maruípe',
           'mata da praia',
           'monte belo',
           'morada de camburi',
```

```
            'mário cypreste',
            'nazareth',
            'nova palestina',
            'parque industrial',
            'parque moscoso',
            'piedade',
            'pontal de camburi',
            'praia do canto',
            'praia do suá',
            'redenção',
            'república',
            'resistência',
            'romão',
            'santa cecília',
            'santa clara',
            'santa helena',
            'santa luíza',
            'santa lúcia',
            'santa martha',
            'santa tereza',
            'santo andré',
            'santo antônio',
            'santos dumont',
            'santos reis',
            'segurança do lar',
            'solon borges',
            'são benedito',
            'são cristóvão',
            'são josé',
            'são pedro',
            'tabuazeiro',
            'universitário',
            'vila rubim']
```

```
In [115]: # Verify all columns 'scholarship', 'hypertension', 'diabetes', 'alcoholism', 'handi
          # only contain binary data
          df['scholarship'].unique()

Out[115]: array([0, 1])

In [116]: df['hypertension'].unique()

Out[116]: array([1, 0])

In [117]: df['diabetes'].unique()

Out[117]: array([0, 1])

In [118]: df['alcoholism'].unique()
```

Out[118]: array([0, 1])

In [119]: df['handicap'].unique()

Out[119]: array([0, 1, 2, 3, 4])

In [120]: df['no_show'].unique()

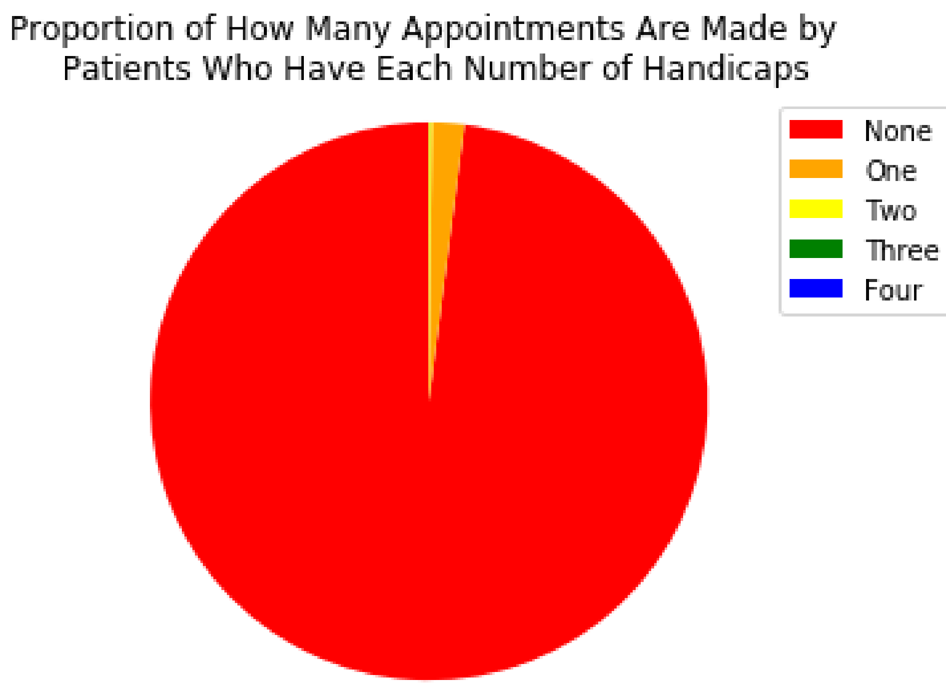
Out[120]: array(['No', 'Yes'], dtype=object)

Inspection of the 'handicap' column displays 5 values: 0,1,2,3,4. According to JoniHoppen, who provided the data, "the handcap refers to the number of desabilites a person has. For example, if the person is blind and can't walk the total is 2."

In [121]:
```
# Proportion of how many patients have each number of handicaps
zero_handicap = df[df['handicap']==0].count()[0]/(df.nunique()[0])
one_handicap = df[df['handicap']==1].count()[0]/(df.nunique()[0])
two_handicap = df[df['handicap']==2].count()[0]/(df.nunique()[0])
three_handicap = df[df['handicap']==3].count()[0]/(df.nunique()[0])
four_handicap = df[df['handicap']==4].count()[0]/(df.nunique()[0])
print(zero_handicap, one_handicap, two_handicap, three_handicap, four_handicap)
```

```
0.979724227784 0.0184752908818 0.00165571901634 0.000117619383674 2.71429346941e-05
```

In [122]:
```
# Pie chart of proportion of how many patients have each number of handicaps
labels = ['None', 'One', 'Two', 'Three', 'Four']
sizes = [zero_handicap, one_handicap, two_handicap, three_handicap, four_handicap]
colors = ['red', 'orange', 'yellow', 'green', 'blue']
patches, texts = plt.pie(sizes, colors=colors, startangle=90)
plt.legend(patches, labels, loc="best")
plt.title('Proportion of How Many Appointments Are Made by \n Patients Who Have Each
# Set aspect ratio to be equal so that pie is drawn as a circle.
plt.axis('equal')
plt.tight_layout()
plt.show()
```



Becuase 97.9% of patients have 0 handicaps, all patients with 1 or more handicaps will be considered handicapped as indicated by a 1.

```
In [123]: # Convert all handicap values greater than 1 to 1.
          df['handicap'] = np.where(df['handicap'] >= 1, 1, 0)

In [124]: # Verify column 'handicap' only includes binary data
          df['handicap'].unique()

Out[124]: array([0, 1])
```

The data wrangling up to this point motivated the decision to combine 'Hypertension','Diabetes','Alcoholism', 'Handicap' into one column named 'Existing_condition'. Future exploratory data analysis may reveal the value of exploring each condition individually.

```
In [125]: # Combine 'hypertension','diabetes','alcoholism', 'handicap' into one column named '
          # any patient with 1 or more "Existing Condition"and a 0 for patients with "No Exist
          df['existing_condition'] = np.where(((df['hypertension']>=1) | (df['diabetes']>=1) |
          # Verify results of the creation of 'existing_condition' column.
          df[df['existing_condition']==1]

Out[125]:    appointment_id  age     neighborhood  scholarship  hypertension  \
          0         5642903   62  jardim da penha            0             1
          4         5642494   56  jardim da penha            0             1
          5         5626772   76        república            0             1
```

25	5624020	46	conquista	0	1
26	5641781	45	bento ferreira	0	1
32	5637908	61	são cristóvão	0	1
34	5637963	79	são cristóvão	0	1
36	5637975	63	são cristóvão	0	1
37	5637986	64	tabuazeiro	1	1
38	5609446	85	são cristóvão	0	1
41	5633339	71	maruípe	0	0
43	5641620	49	são cristóvão	0	1
44	5635414	78	são cristóvão	0	1
46	5615608	58	são cristóvão	0	1
47	5633116	39	maruípe	0	1
68	5552915	69	jardim da penha	0	1
73	5552934	68	república	0	1
85	5623102	69	resistência	0	1
102	5634093	54	mário cypreste	0	1
105	5639399	51	bela vista	0	1
106	5639773	54	santo antônio	0	1
111	5574534	56	santo antônio	0	1
112	5594665	59	santo antônio	0	1
115	5641363	54	santo antônio	0	1
122	5642643	46	bela vista	0	1
125	5542592	36	mário cypreste	0	1
126	5633576	67	praia do suá	0	0
127	5561194	42	praia do suá	0	1
131	5637150	29	praia do suá	0	0
133	5580520	69	praia do suá	0	0
...	...	...	...	...	...
110202	5767693	91	cruzamento	0	0
110305	5752701	56	bento ferreira	0	1
110359	5762836	70	resistência	0	1
110363	5624922	54	resistência	0	1
110383	5582577	48	resistência	0	1
110386	5582576	48	resistência	0	1
110398	5751672	75	resistência	0	1
110399	5692938	17	resistência	0	1
110421	5763871	34	resistência	0	0
110433	5627262	63	resistência	0	0
110434	5627263	63	resistência	0	0
110436	5784368	21	resistência	0	0
110439	5784366	34	resistência	0	0
110448	5756082	40	resistência	0	1
110450	5746688	49	resistência	0	1
110452	5701786	39	resistência	0	1
110453	5772475	86	resistência	0	1
110455	5772215	52	resistência	0	0
110456	5772107	79	resistência	0	1
110459	5770574	61	resistência	0	1

110468	5763322	76	resistência	0	1
110471	5781360	84	resistência	0	1
110475	5779726	54	resistência	0	1
110476	5678369	80	resistência	0	1
110477	5673472	67	resistência	0	0
110483	5769404	60	praia do canto	0	1
110492	5786741	33	maria ortiz	0	1
110496	5779046	37	maria ortiz	0	1
110499	5757697	66	maria ortiz	0	1
110515	5778621	33	maria ortiz	0	1

	diabetes	alcoholism	handicap	no_show	existing_condition
0	0	0	0	No	1
4	1	0	0	No	1
5	0	0	0	No	1
25	0	0	0	No	1
26	0	0	0	No	1
32	0	0	0	No	1
34	0	0	0	No	1
36	1	0	0	No	1
37	1	0	0	No	1
38	0	0	0	No	1
41	1	0	0	No	1
43	0	0	0	No	1
44	1	0	0	Yes	1
46	0	1	0	No	1
47	1	0	0	No	1
68	0	0	0	No	1
73	1	0	0	No	1
85	0	0	0	No	1
102	0	0	0	No	1
105	0	0	0	No	1
106	0	0	0	No	1
111	0	0	0	No	1
112	1	0	0	No	1
115	0	0	0	No	1
122	0	0	0	No	1
125	0	0	0	No	1
126	1	0	0	Yes	1
127	1	0	0	No	1
131	0	1	0	Yes	1
133	1	1	0	No	1
...	...	...	...	...	...
110202	0	0	1	Yes	1
110305	1	0	0	No	1
110359	1	0	0	No	1
110363	0	0	0	Yes	1
110383	0	0	0	Yes	1

```
110386          0          0          0    Yes               1
110398          0          0          0     No               1
110399          0          0          0    Yes               1
110421          0          0          1     No               1
110433          1          0          0     No               1
110434          1          0          0     No               1
110436          0          0          1     No               1
110439          0          0          1     No               1
110448          1          0          0     No               1
110450          0          0          0     No               1
110452          0          0          0     No               1
110453          0          0          0     No               1
110455          0          0          1     No               1
110456          1          0          0     No               1
110459          0          0          0     No               1
110468          1          0          0     No               1
110471          0          0          0     No               1
110475          0          0          0     No               1
110476          0          0          0     No               1
110477          1          0          0     No               1
110483          0          0          0     No               1
110492          0          0          0    Yes               1
110496          0          0          0    Yes               1
110499          1          0          0     No               1
110515          0          0          0    Yes               1

[26412 rows x 10 columns]
```

In [126]:
```python
# Verify results of the creation of 'existing_condition' column.
df[df['existing_condition']==0]
```

Out[126]:
```
        appointment_id  age       neighborhood  scholarship  hypertension  \
1              5642503   56    jardim da penha            0             0
2              5642549   62      mata da praia            0             0
3              5642828    8  pontal de camburi            0             0
6              5630279   23         goiabeiras            0             0
7              5630575   39         goiabeiras            0             0
8              5638447   21         andorinhas            0             0
9              5629123   19          conquista            0             0
10             5630213   30     nova palestina            0             0
11             5620163   29     nova palestina            0             0
12             5634718   22     nova palestina            1             0
13             5636249   28     nova palestina            0             0
14             5633951   54     nova palestina            0             0
15             5620206   15     nova palestina            0             0
16             5633121   50     nova palestina            0             0
17             5633460   40          conquista            1             0
18             5621836   30     nova palestina            1             0
```

19	5640433	46	da penha	0	0
20	5626083	30	nova palestina	0	0
21	5628338	4	conquista	0	0
22	5616091	13	conquista	0	0
23	5634142	46	conquista	0	0
24	5641780	65	tabuazeiro	0	0
27	5628345	4	conquista	0	0
28	5642400	51	são pedro	0	0
29	5642186	32	santa martha	0	0
30	5628068	46	nova palestina	0	0
31	5628907	12	nova palestina	1	0
33	5616921	38	são cristóvão	1	0
35	5637968	18	são cristóvão	0	0
39	5639644	59	são cristóvão	0	0
...	...	...	...	...	...
110494	5779073	38	maria ortiz	0	0
110495	5759838	40	maria ortiz	0	0
110497	5757745	76	maria ortiz	0	0
110498	5787655	59	maria ortiz	0	0
110500	5787233	59	maria ortiz	0	0
110501	5758133	44	maria ortiz	0	0
110502	5787937	22	goiabeiras	0	0
110503	5759473	64	solon borges	0	0
110504	5788052	4	maria ortiz	0	0
110505	5758455	55	maria ortiz	0	0
110506	5758779	5	maria ortiz	0	0
110507	5786918	0	maria ortiz	0	0
110508	5757656	59	maria ortiz	0	0
110509	5786750	33	maria ortiz	0	0
110510	5757587	64	solon borges	0	0
110511	5786742	14	maria ortiz	0	0
110512	5786368	41	maria ortiz	0	0
110513	5785964	2	antônio honório	0	0
110514	5786567	58	maria ortiz	0	0
110516	5780205	37	maria ortiz	0	0
110517	5780122	19	maria ortiz	0	0
110518	5630375	50	maria ortiz	0	0
110519	5630447	22	maria ortiz	0	0
110520	5650534	42	maria ortiz	0	0
110521	5651072	53	maria ortiz	0	0
110522	5651768	56	maria ortiz	0	0
110523	5650093	51	maria ortiz	0	0
110524	5630692	21	maria ortiz	0	0
110525	5630323	38	maria ortiz	0	0
110526	5629448	54	maria ortiz	0	0

	diabetes	alcoholism	handicap	no_show	existing_condition
1	0	0	0	No	0

2	0	0	0	No	0
3	0	0	0	No	0
6	0	0	0	Yes	0
7	0	0	0	Yes	0
8	0	0	0	No	0
9	0	0	0	No	0
10	0	0	0	No	0
11	0	0	0	Yes	0
12	0	0	0	No	0
13	0	0	0	No	0
14	0	0	0	No	0
15	0	0	0	No	0
16	0	0	0	No	0
17	0	0	0	Yes	0
18	0	0	0	No	0
19	0	0	0	No	0
20	0	0	0	Yes	0
21	0	0	0	Yes	0
22	0	0	0	Yes	0
23	0	0	0	No	0
24	0	0	0	No	0
27	0	0	0	No	0
28	0	0	0	No	0
29	0	0	0	No	0
30	0	0	0	No	0
31	0	0	0	Yes	0
33	0	0	0	No	0
35	0	0	0	No	0
39	0	0	0	No	0
...	...	...	...	...	...
110494	0	0	0	No	0
110495	0	0	0	No	0
110497	0	0	0	No	0
110498	0	0	0	No	0
110500	0	0	0	No	0
110501	0	0	0	No	0
110502	0	0	0	No	0
110503	0	0	0	No	0
110504	0	0	0	No	0
110505	0	0	0	No	0
110506	0	0	0	No	0
110507	0	0	0	No	0
110508	0	0	0	No	0
110509	0	0	0	No	0
110510	0	0	0	No	0
110511	0	0	0	No	0
110512	0	0	0	No	0
110513	0	0	0	No	0

```
110514          0          0         0      No                  0
110516          0          0         0     Yes                  0
110517          0          0         0      No                  0
110518          0          0         0      No                  0
110519          0          0         0      No                  0
110520          0          0         0      No                  0
110521          0          0         0      No                  0
110522          0          0         0      No                  0
110523          0          0         0      No                  0
110524          0          0         0      No                  0
110525          0          0         0      No                  0
110526          0          0         0      No                  0

[84114 rows x 10 columns]
```

Columns 'hypertension','diabetes','alcoholism', 'handicap' will no longer be used; therfore, these columns will be dropped.

```
In [127]: # Drop 'hypertension','diabetes','alcoholism', 'handicap'
          df = df.drop(['hypertension','diabetes','alcoholism', 'handicap'], axis = 1);
          # Verify results of drop
          df.head()
```

```
Out[127]:    appointment_id  age        neighborhood  scholarship no_show  \
          0         5642903   62     jardim da penha            0      No
          1         5642503   56     jardim da penha            0      No
          2         5642549   62       mata da praia            0      No
          3         5642828    8   pontal de camburi            0      No
          4         5642494   56     jardim da penha            0      No

             existing_condition
          0                   1
          1                   0
          2                   0
          3                   0
          4                   1
```

Althought not necessary for the analysis in this report, in consideration of later analysis, the values in column 'no-show' will be converted to 1 and 0. 0 in the 'no_show' column represents a patient who missed an appointment. 1 in the 'no_show' column represents a patient who attended an appointment.

```
In [128]: # Convert values 'Yes' and 'No' in the 'no_show' appointment column to 0 for 'Yes'.
          df['no_show'] = df['no_show'].replace('Yes', 0)
```

```
In [129]: # Convert values 'Yes' and 'No' in the 'no_show' appointment column to and 1 for 'No
          df['no_show'] = df['no_show'].replace('No', 1)
```

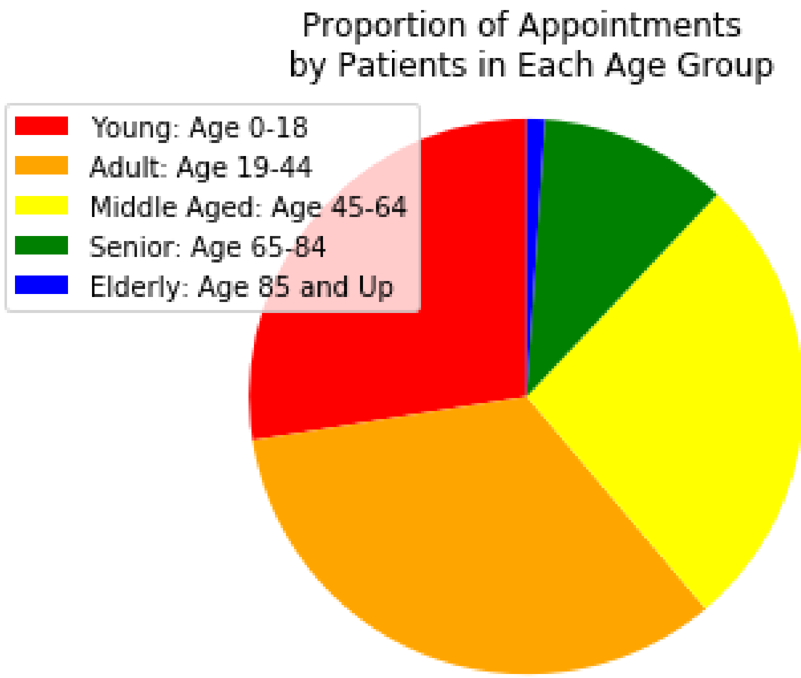
```
In [130]: df.head()
```

```
Out[130]:    appointment_id  age        neighborhood  scholarship  no_show  \
          0         5642903   62    jardim da penha            0        1
          1         5642503   56    jardim da penha            0        1
          2         5642549   62      mata da praia            0        1
          3         5642828    8  pontal de camburi            0        1
          4         5642494   56    jardim da penha            0        1

             existing_condition
          0                   1
          1                   0
          2                   0
          3                   0
          4                   1
```

The age columns will be divided into the following age-groups: 0-18 as 'young', 19-44 as 'adult', 45-64 as 'middle_aged', 65-84 as 'aging', and 85 and over as 'elderly'.

```
In [131]: # Create bins for each age-group divide
          bin_edges = [(df['age'].min()),19,45,65,85,(df['age'].max())]

In [132]: # Create names for each age-group divide
          bin_names = ['young','adult','middle_aged','senior','elderly']

In [133]: # Creates age_group column
          df['age_group'] = pd.cut(df['age'], bin_edges, labels=bin_names, include_lowest=True

In [134]: # Inspect results of adding age_group column
          df['age_group'].unique()

Out[134]: [middle_aged, young, senior, adult, elderly]
          Categories (5, object): [young < adult < middle_aged < senior < elderly]

In [135]: # Proportion in each 'age_group'
          p_young = df[df['age_group'] == 'young'].count()[0]/(df.count()[0])
          p_adult = df[df['age_group'] == 'adult'].count()[0]/(df.count()[0])
          p_middle_aged = df[df['age_group'] == 'middle_aged'].count()[0]/(df.count()[0])
          p_senior = df[df['age_group'] == 'senior'].count()[0]/(df.count()[0])
          p_elderly = df[df['age_group'] == 'elderly'].count()[0]/(df.count()[0])
          print(p_young, p_adult, p_middle_aged, p_senior, p_elderly)

0.275147928994 0.336337151439 0.268172194778 0.109847456707 0.0104952680817

In [136]: # Pie chart of proportion in each 'age_group'
          labels = ['Young: Age 0-18', 'Adult: Age 19-44', 'Middle Aged: Age 45-64', 'Senior:
          sizes = [p_young, p_adult, p_middle_aged, p_senior, p_elderly]
          colors = ['red', 'orange', 'yellow', 'green', 'blue']
          patches, texts = plt.pie(sizes, colors=colors, startangle=90)
          plt.legend(patches, labels, loc="best")
```

```
plt.title('Proportion of Appointments \n by Patients in Each Age Group')
# Set aspect ratio to be equal so that pie is drawn as a circle.
plt.axis('equal')
plt.tight_layout()
plt.show()
```



The pie chart above shows the proportion of appointments made by patients in each age group. Three age groups make up a comparatively large amount of all appointments: "Young", "Adult", and "Middle Aged." The age groups "Senior" and "Elderly" account for a small percentage, only 12%, of all appointments.

In [137]:
```
# Drop age column
df = df.drop(['age'], axis = 1)
df.head()
```

Out[137]:
```
   appointment_id       neighborhood  scholarship  no_show  \
0         5642903     jardim da penha            0        1
1         5642503     jardim da penha            0        1
2         5642549       mata da praia            0        1
3         5642828   pontal de camburi            0        1
4         5642494     jardim da penha            0        1

   existing_condition    age_group
0                   1  middle_aged
1                   0  middle_aged
```

```
2                       0  middle_aged
3                       0        young
4                       1  middle_aged
```

Data cleaning is now complete. To clarify, neighborhood reflects the neighborhood in which a hospital is located, not necessarily the hospital's name. Efforts have been made to clarify this distinction throughout this investigation.

Exploratory Data Analysis

The purpose of the analysis is to understand what patient characterstics are commonly associated with a "no-show" appointment, which is when an appointment is scheduled and the patient does not arrive for the appointment. Once these characteristics have been explored, the neighborhoods, i.e. hospitals, most frequntend by these patients will be analyzed.

1.1.3 What group of patients are most commonly "No-Shows," i.e. miss the most appointments?

The dependent variable considered is column 'no_show' (1 if a patient is not a 'no_show', i.e. the patient arrives for the appointment, and 0 if a patients is a 'no_show', i.e. the patient does not arrive for the appointment). The independent variables to be considered are column 'age-group' ('young', 'adult', 'middle_aged', 'senior', and 'elderly'), 'scholarship' (1 if a patient receives 'scholarship' and 0 if a patient does not receive 'schlarship'), and 'existing_condition' (1 if a patient has any of 'hypertension','diabetes','alcoholism', 'handicap' and 0 if a patient does not have any of those "Existing Conditions"). The intent of the analysis is to understand what group of patients is most commonly associated with a 'no-show' appointment.

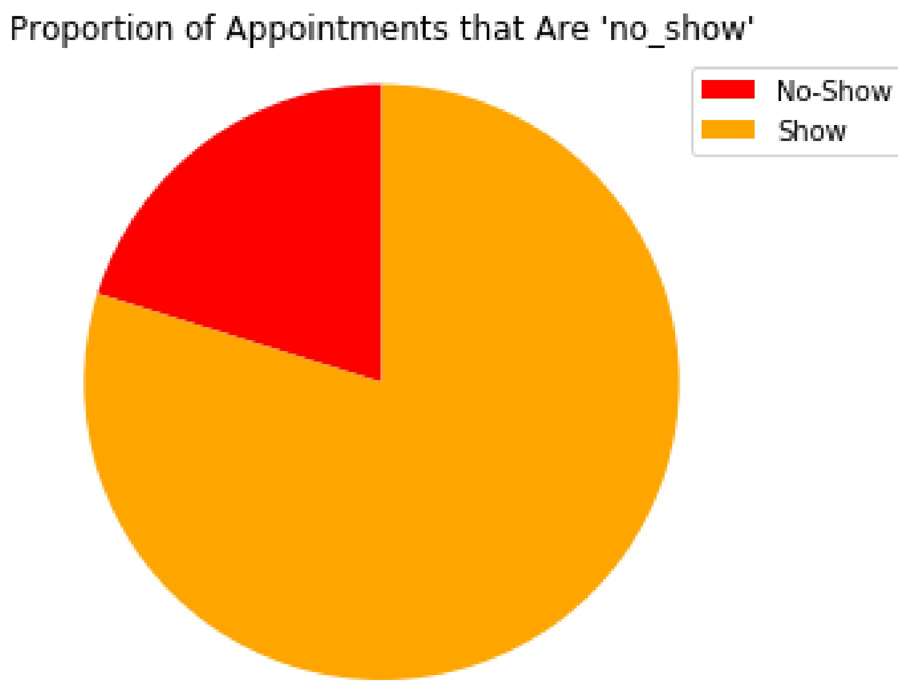
In [138]:
```python
# Number of appointments that are 'no_show', i.e. 0 in column 'no_show'
df[df['no_show'] == 0].count()[0]
```

Out[138]:
```
22319
```

In [139]:
```python
# Proportion of appointments that are 'no_show', i.e. 0 in column 'no_show'
p_all_no_show = 1 - df['no_show'].mean()
print(p_all_no_show)
```

```
0.20193438647919948
```

In [140]:
```python
# Pie chart of proportion of appointments that are 'no_show', i.e. 0 in column 'no_s
labels = ['No-Show', 'Show']
sizes = [p_all_no_show, (1-p_all_no_show)]
colors = ['red', 'orange']
patches, texts = plt.pie(sizes, colors=colors, startangle=90)
plt.legend(patches, labels, loc="best")
plt.title("Proportion of Appointments that Are 'no_show'")
# Set aspect ratio to be equal so that pie is drawn as a circle.
plt.axis('equal')
plt.tight_layout()
plt.show()
```



22,319 appointments were missed, representing 21% of appointments. This value is encouraging as the vast majority of appointments are kept.

```
In [141]: # Create a new dataframe named 'df_no_show' containing only data on 'no-show' appoin
          df_no_show = df[df['no_show'] == 0]
          # Verify column 'no_show' in 'df_no_show' includes only 0
          df_no_show['no_show'].unique()
```

```
Out[141]: array([0])
```

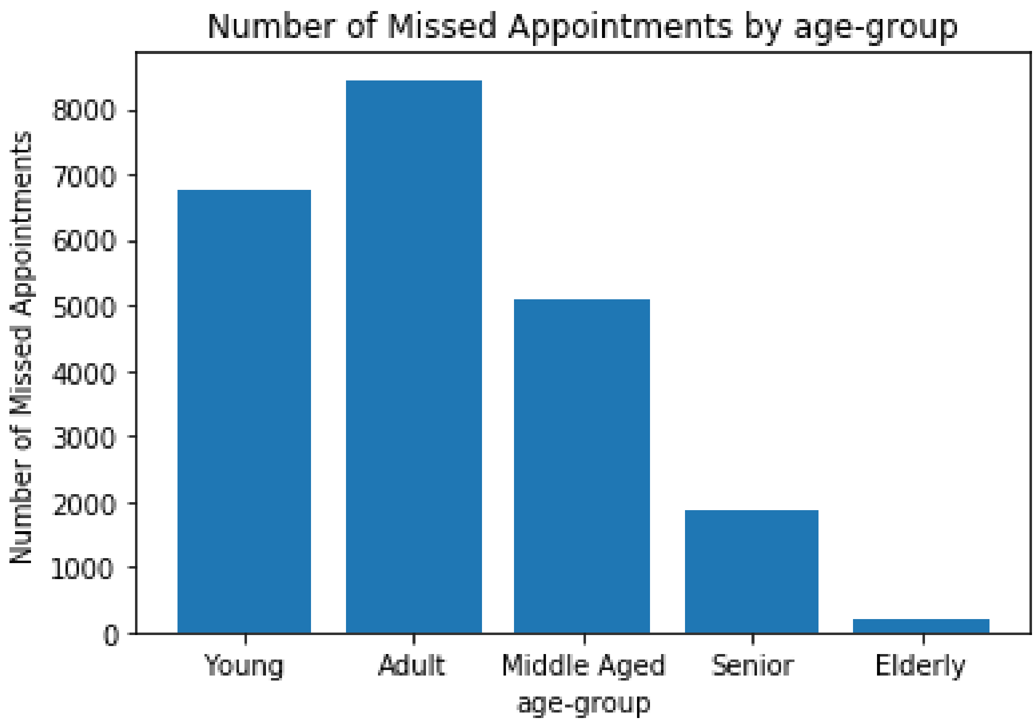
With the creation of the new dataframe 'df_no_show', characteristics of a "no-show" patient can be analyzed.

First, what age-group has the laregest number of "no-show" patients?

```
In [142]: # Count "no-shows" by 'age_group'
          c_young_no_show = df_no_show[df_no_show['age_group'] == 'young'].count()[0]
          c_adult_no_show = df_no_show[df_no_show['age_group'] == 'adult'].count()[0]
          c_middle_aged_no_show = df_no_show[df_no_show['age_group'] == 'middle_aged'].count()
          c_senior_no_show = df_no_show[df_no_show['age_group'] == 'senior'].count()[0]
          c_elderly_no_show = df_no_show[df_no_show['age_group'] == 'elderly'].count()[0]
          print(c_young_no_show, c_adult_no_show, c_middle_aged_no_show, c_senior_no_show, c_el
```

```
6741 8441 5071 1871 195
```

In [143]:
```
# Bar chart of results from count of "no-shows" by 'age_group'
c_a_locations = [1, 2, 3, 4, 5]
c_a_heights = [c_young_no_show, c_adult_no_show, c_middle_aged_no_show, c_senior_no_s
c_a_labels = ['Young', 'Adult', 'Middle Aged', 'Senior', 'Elderly']
plt.bar(c_a_locations, c_a_heights, tick_label=c_a_labels)
plt.title('Number of Missed Appointments by age-group')
plt.xlabel('age-group')
plt.ylabel('Number of Missed Appointments');
```



In [144]:
```
# Range of count of "no-shows"
max(c_young_no_show, c_adult_no_show, c_middle_aged_no_show, c_senior_no_show, c_elde
```

Out[144]: 8246

According to these preliminary results, the "Young" and "Adult" age-groups missed the most appointments. After the "Adult" age-group, as age-groups increase in age the number of missed appointments decreases. The range of values is 8,246 appointments, with Adults missing the most and Elderly missing the fewest.

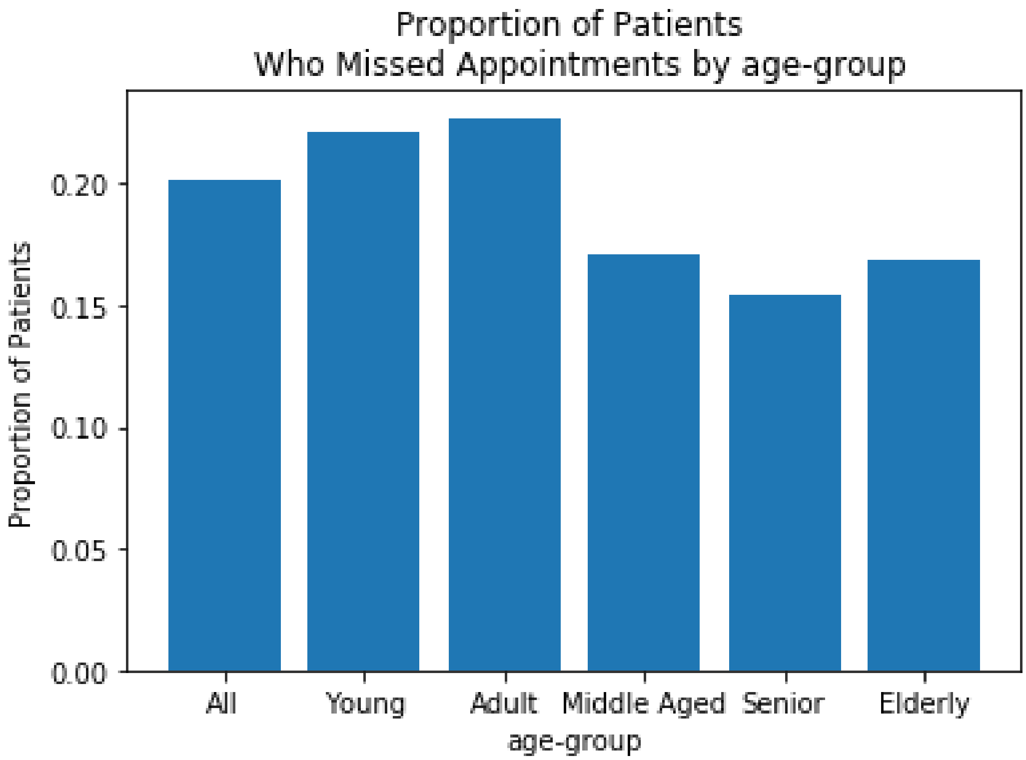
In order to understand if the number of missed appointments relates to the number of appointments overall, the number of missed appointments by age-group will be compared to the total number of appointments by age-group.

In [145]:
```
# Proportion of 'no-shows' by 'age_group' when compared to the total number of appoi
p_young_no_show = df_no_show[df_no_show['age_group'] == 'young'].count()[0]/(df[df['a
```

```
p_adult_no_show = df_no_show[df_no_show['age_group'] == 'adult'].count()[0]/(df[df['a
p_middle_aged_no_show = df_no_show[df_no_show['age_group'] == 'middle_aged'].count()
p_senior_no_show = df_no_show[df_no_show['age_group'] == 'senior'].count()[0]/(df[df
p_elderly_no_show = df_no_show[df_no_show['age_group'] == 'elderly'].count()[0]/(df[d
print(p_young_no_show, p_adult_no_show, p_middle_aged_no_show, p_senior_no_show, p_el
```

```
0.221663213969 0.227067305106 0.171086369771 0.154105922082 0.168103448276
```

In [146]:
```
# Bar chart of results from proportion of "no-shows" by 'age_group' when compared to
# appointments by the age-group
p_a_locations = [1, 2, 3, 4, 5,6]
p_a_heights = [p_all_no_show, p_young_no_show, p_adult_no_show, p_middle_aged_no_show
p_a_labels = ['All','Young', 'Adult', 'Middle Aged', 'Senior', 'Elderly']
plt.bar(p_a_locations, p_a_heights, tick_label=p_a_labels)
plt.title('Proportion of Patients \n Who Missed Appointments by age-group')
plt.xlabel('age-group')
plt.ylabel('Proportion of Patients');
```



In [147]:
```
# Create array of the difference between proportion of "no-shows" by 'age_group' whe
# appointments by the age-group and proportion of all appointments that are 'no_show
p_a_heights_difference = np.array(p_a_heights) - p_all_no_show
```

```
In [148]: # Create df to display 'p_a_heights_difference'
          df_p_a_heights = pd.DataFrame(data = p_a_heights_difference, index = p_a_labels, colu
          df_p_a_heights
```

```
Out[148]:              p_diff_age_group
          All                  0.000000
          Young                0.019729
          Adult                0.025133
          Middle Aged         -0.030848
          Senior              -0.047828
          Elderly             -0.033831
```

```
In [149]: # Range of proportion differences of 'no-shows'
          df_p_a_heights['p_diff_age_group'].max() - df_p_a_heights['p_diff_age_group'].min()
```

```
Out[149]: 0.072961383023518234
```

The analysis of the number of "no-shows" by age-group when compared to the total number of appointments by the respective age-group agrees with the earlier results in that the "Adult" age-groups misses the most appointments proportionally.

The range for the difference between the mean of all "no-show" appointments and the mean of each age-group is 7.29%. Furthermore, the "Adult" age-group's proportion of "no-show" appointments is 2.5% greater than the average for all appointments. In contrast, the "Senior" age-group had the lowest proportion of "no-show" appointments: 4.78% lower than the average of all appointments.

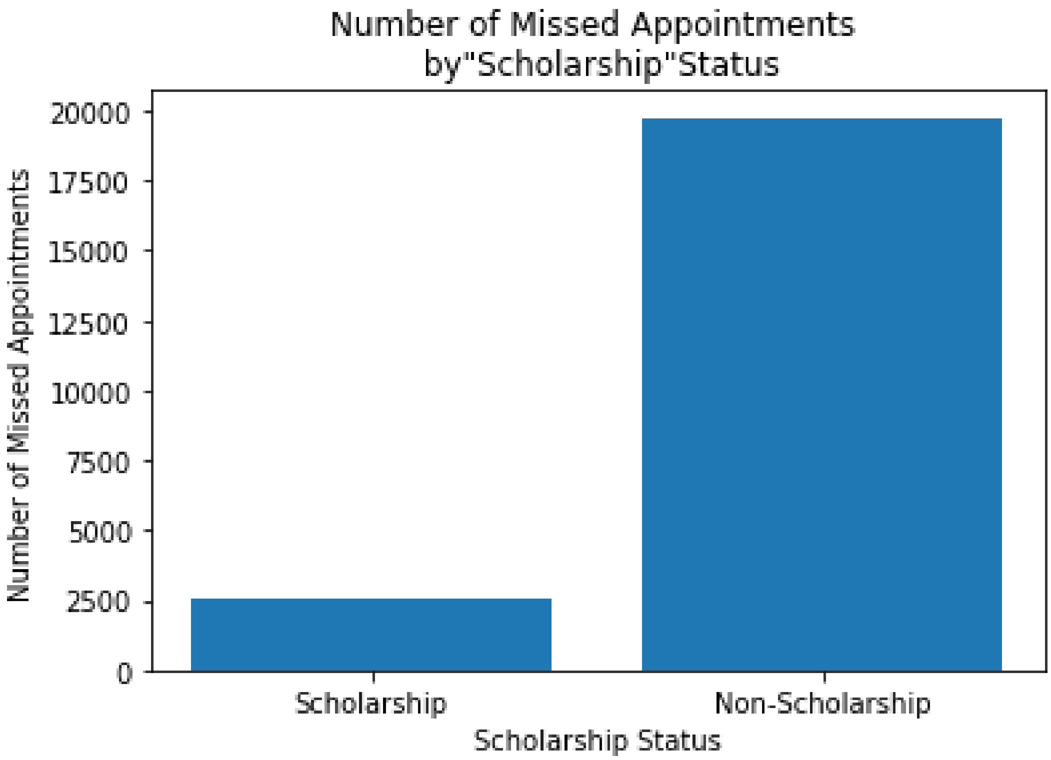
Preliminary conclusions imply the "Adult" age-group, ages 19-44, has the most "no-show" appointments.

The next question is which group has more "no-show" appointments, patients who receive "Scholarship" or patients who do not receive "Scholarship"?

```
In [150]: # Count "no-shows" by 'scholarship'
          c_s_no_show = df_no_show[df_no_show['scholarship'] == 1].count()[0]
          c_no_s_no_show = df_no_show[df_no_show['scholarship'] == 0].count()[0]
          print(c_s_no_show, c_no_s_no_show)
```

```
2578 19741
```

```
In [151]: # Bar chart of results from count of "no-shows" by 'scholarship'
          c_s_locations = [1, 2]
          c_s_heights = [c_s_no_show, c_no_s_no_show]
          c_s_labels = ['Scholarship', 'Non-Scholarship']
          plt.bar(c_s_locations, c_s_heights, tick_label=c_s_labels)
          plt.title('Number of Missed Appointments \n by"Scholarship"Status')
          plt.xlabel('Scholarship Status')
          plt.ylabel('Number of Missed Appointments');
```



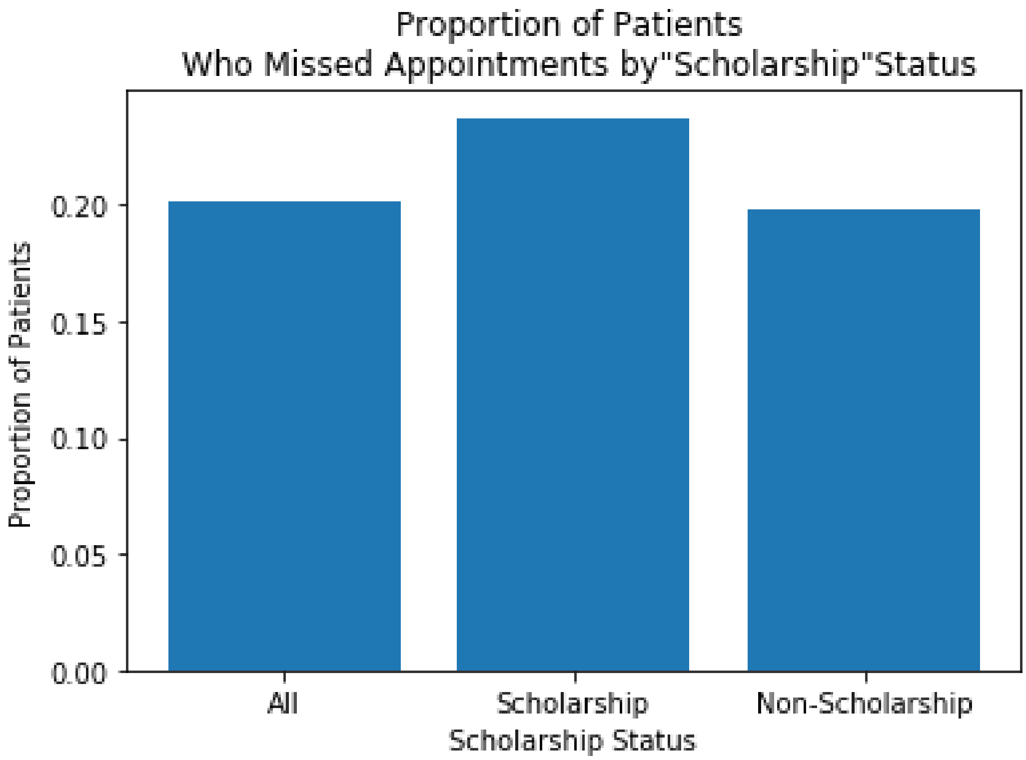
According to these preliminary results, the "Non-Scholarship" group missed the most appointments.

In order to understand if the number of missed appointments relates to the number of appointments overall, the number of missed appointments by"Scholarship"status will be compared to the total number of appointments by"Scholarship"status.

```
In [152]: # Proportion of 'no-shows' by 'scholarship' when compared to the total number of app
          # sub-group
          p_s_no_show = df_no_show[df_no_show['scholarship'] == 1].count()[0]/(df[df['scholarsh
          p_no_s_no_show = df_no_show[df_no_show['scholarship'] == 0].count()[0]/(df[df['schola
          print(p_s_no_show, p_no_s_no_show)
```

```
0.237363042077 0.19807354638
```

```
In [153]: # Bar chart of results from proportion of "no-shows" by 'scholarship' when compared
          # appointments by"Scholarship"status
          p_s_locations = [1, 2,3]
          p_s_heights = [p_all_no_show, p_s_no_show, p_no_s_no_show]
          p_s_labels = ['All','Scholarship', 'Non-Scholarship']
          plt.bar(p_s_locations, p_s_heights, tick_label=p_s_labels)
          plt.title('Proportion of Patients \n Who Missed Appointments by"Scholarship"Status')
          plt.xlabel('Scholarship Status')
          plt.ylabel('Proportion of Patients');
```



In [154]:
```
# Create array of the difference between proportion of 'no-shows' by 'scholarhsip' wh
# appointments by the"Scholarship"and proportion of all appointments that are 'no_sho
p_s_heights_difference = np.array(p_s_heights) - p_all_no_show
```

In [155]:
```
# Create df to display 'p_s_heights_difference'
df_p_s_heights = pd.DataFrame(data = p_s_heights_difference, index = p_s_labels, colu
df_p_s_heights
```

Out[155]:

	p_diff_scholarship
All	0.000000
Scholarship	0.035429
Non-Scholarship	-0.003861

In [156]:
```
# Range of proportion differences of "no-shows"
df_p_s_heights['p_diff_scholarship'].max() - df_p_s_heights['p_diff_scholarship'].min
```

Out[156]: 0.039289495696782556

The analysis of the number of "no-shows" by "Scholarship" status when compared to the total number of appointments by the respective "Scholarship" status contrasts with the earlier results in that the "Scholarship" group misses the most appointments proportionally.

The range for the difference between the mean of all "no-show" appointments and the mean of each "Scholarship" group is 3.93%. Furthermore, the "Scholarship" group's proportion of "no-show" appointments is 3.54% greater than the average for all appointments. In contrast, the 'Non-scholarship' group's proportion of "no-show" appointments is 0.38% lower than the average of all appointments.

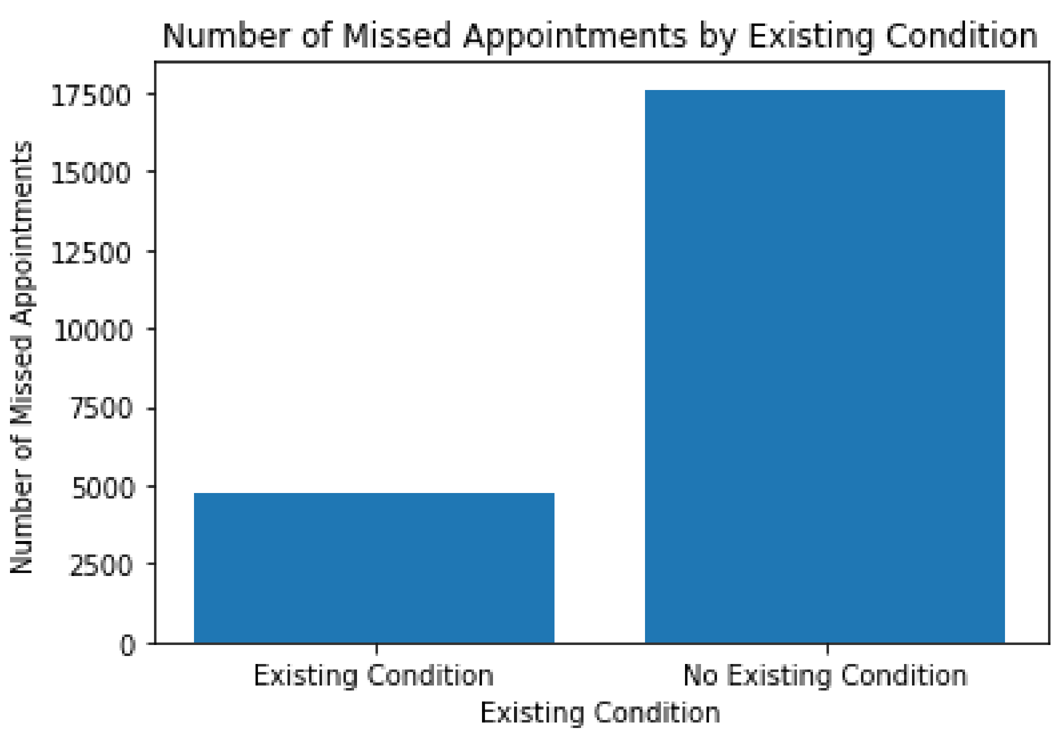
Preliminary conclusions imply the 'Scholarship' group proportionally has more "no-show" appointments.

The next question is which group has more "no-show" appointments, patients with "Existing Conditions" or patients without "Existing Conditions"?

```
In [157]: # Count 'no-shows' by 'existing_condition'
          c_e_no_show = df_no_show[df_no_show['existing_condition'] == 1].count()[0]
          c_no_e_no_show = df_no_show[df_no_show['existing_condition'] == 0].count()[0]
          print(c_e_no_show, c_no_e_no_show)
```

```
4716 17603
```

```
In [158]: # Bar chart of results from count of 'no-shows' by 'existing_condition'
          c_e_locations = [1, 2]
          c_e_heights = [c_e_no_show, c_no_e_no_show]
          c_e_labels = ['Existing Condition', 'No Existing Condition']
          plt.bar(c_e_locations, c_e_heights, tick_label=c_e_labels)
          plt.title('Number of Missed Appointments by Existing Condition')
          plt.xlabel('Existing Condition')
          plt.ylabel('Number of Missed Appointments');
```



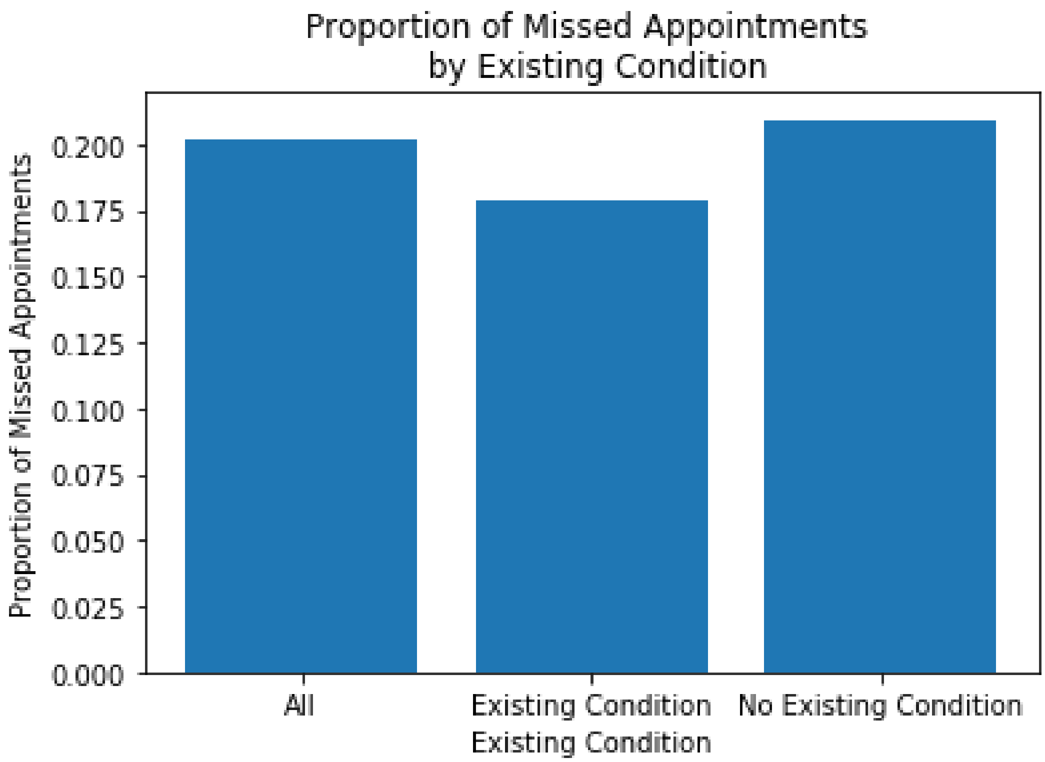
According to these preliminary results, the "No Existing Condition" group missed the most appointments.

In order to understand if the number of missed appointments relates to the number of appointments overall, the number of missed appointments by "Existing Condition" will be compared to the total number of appointments by "Existing Condition".

In [159]:
```
# Proportion of 'no-shows' by 'existing_condition' when compared to the total number
# by patients with an 'existing_condition'
p_e_no_show = df_no_show[df_no_show['existing_condition'] == 1].count()[0]/(df[df['e
p_no_e_no_show = df_no_show[df_no_show['existing_condition'] == 0].count()[0]/(df[df
print(p_e_no_show, p_no_e_no_show)
```

```
0.178555202181 0.20927550705
```

In [160]:
```
# Bar chart of results from proportion of 'no-shows' by 'existing_condition' when co
# appointments by patients with an 'existing_condition'
p_e_locations = [1, 2,3]
p_e_heights = [p_all_no_show, p_e_no_show, p_no_e_no_show]
p_e_labels = ['All','Existing Condition', 'No Existing Condition']
plt.bar(p_e_locations, p_e_heights, tick_label=p_e_labels)
plt.title('Proportion of Missed Appointments \n by Existing Condition')
plt.xlabel('Existing Condition')
plt.ylabel('Proportion of Missed Appointments');
```



```
In [161]: # Create array of the difference between proportion of "no-shows" by 'existing_condi
          # total number of appointments by patients in each 'existing_condition' group and pr
          # that are 'no_show', i.e. 0 in column 'no_show'
          p_e_heights_difference = np.array(p_e_heights) - p_all_no_show
```

```
In [162]: # Create df to display 'p_e_heights_difference'
          df_p_e_heights = pd.DataFrame(data = p_e_heights_difference, index = p_e_labels, colu
          df_p_e_heights
```

Out[162]:

	p_diff_existing_condition
All	0.000000
Existing Condition	-0.023379
No Existing Condition	0.007341

```
In [163]: # Range of proportion differences of "no-shows"
          df_p_e_heights['p_diff_existing_condition'].max() - df_p_e_heights['p_diff_existing_c
```

```
Out[163]: 0.030720304869129106
```

The analysis of the number of "no-shows" by patients' "Existing Condition" group when compared to the total number of appointments by the respective patients agrees with the earlier results in that the patients with an exisiting condition miss the most appointments proportionally.

The range for the difference between the mean of all "no-show" appointments and the mean of each group of patients is 3.07%. Furthermore, the "No Existing Condition" group's proportion of "no-show" appointments is 0.07% greater than the average for all appointments. In contrast, the "Existing Condition" group's proportion of "no-show" appointments is 2.34% lower than the average of all appointments.

Preliminary conclusions imply the "No Existing Condition" group proportionally has more "no-show" appointments.

This analysis will be used for the next section to see which hospital receives the most of each group with the highest proportion of "no-show" appointments: Adults, Scholarship, and No Exisiting Condition.

1.1.4 Which hospital sees the largest proportion of the group of patients who are most commonly "No-Shows," i.e. miss the most appointments?

With the initial analysis is complete, the above indpendent variables will be grouped by neighborhood, the next dependent variable to be analyzed. Grouping by neighborhood will create profiles for each neighborhood based on how many patients visit each neigborhood who are in the "Adult" age-group, are in the "Scholarship" group, and are in the "No Existing Condition" group.

First, the neighborhood which receives the most appointments from patients in each group will be found. This data will be compared to the proportion of the neighborhoods' total number of appointments.

Then the neighborhood which receives the most patients from all three groups combined will be found. Again, this data will be compared to the proportion of the neighborhoods' total number of appointments.

In [164]:
```
# Create dataframe of all data grouped by 'neighborhood'
df_neighborhood = df.groupby(['neighborhood']).count()
```

In [165]:
```
# Drop all columns except 'appointment_id' as count for total number of appointments
df_neighborhood = df_neighborhood.drop(['scholarship', 'no_show', 'existing_conditio
```

In [166]:
```
# Rename 'appointment_id' column to 'count_all_appointments'
df_neighborhood = df_neighborhood.rename(index=str, columns={'appointment_id': 'coun
```

In [167]:
```
# Calculate the mean of 'count_all_appointments' in each 'neighborhood'
neighborhood_m = df_neighborhood['count_all_appointments'].mean()
```

In [168]:
```
# Drop all rows in 'neighborhood' with a value in 'count_all_appointments' less than
df_neighborhood = df_neighborhood[df_neighborhood.count_all_appointments > neighborho
```

In [169]:
```
df_neighborhood.head()
```

Out[169]:

```
              count_all_appointments
neighborhood
andorinhas                      2262
bela vista                      1907
bonfim                          2773
caratoíra                       2565
centro                          3334
```

In order to focus the analysis on the largest neighborhoods, all nieghborhoods with fewer appointments than the mean are removed from the dataframe. Going forward, all caclulations will be based on this new dataframe which only includes neighborhoods with more appointments than the mean number of appointments in each neighborhood.

The first independent variable to be analyzed is the "Adult" age-group.

In [170]:
```
# Create dataframe with only 'adult' appointments in the 'age_group' column
df_adult = df[df['age_group'] == 'adult']
```

In [171]:
```
# Drop all columns except 'neighborhood' and 'age_group'
df_adult = df_adult.drop(['appointment_id', 'scholarship', 'no_show', 'existing_condi
```

In [172]:
```
# Count of number of appointments by patients with 'adult' age-group for each neighbo
df_adult = df_adult.groupby(['neighborhood']).count().sort_values(by = 'age_group', a
```

In [173]:
```
# Rename 'age_group' column to 'count_adult_appointments'
df_adult = df_adult.rename(index=str, columns={'age_group': 'count_adult_appointments
```

In [174]:
```
# Add column 'count_all_appointments' to df_adult and drop all 'NaN' columns
df_adult = df_adult.join(df_neighborhood).dropna(axis = 0)
```

In [175]:
```
# Rename df_adult to create dfc_adult for the count of 'adult'
dfc_adult = df_adult
```

In [176]:
```
dfc_adult.head(10)
```

```
Out[176]:                      count_adult_appointments  count_all_appointments
          neighborhood
          jardim camburi                           2075                  7717.0
          maria ortiz                              1924                  5805.0
          resistência                              1711                  4431.0
          itararé                                  1265                  3514.0
          jardim da penha                          1250                  3877.0
          santa martha                             1127                  3131.0
          centro                                   1121                  3334.0
          bonfim                                   1071                  2773.0
          tabuazeiro                               1044                  3132.0
          jesus de nazareth                        1000                  2853.0
```

```
In [177]: dfc_adult_m = [dfc_adult['count_adult_appointments'].mean()]
```

```
In [178]: print(dfc_adult_m)
```

```
[905.5]
```

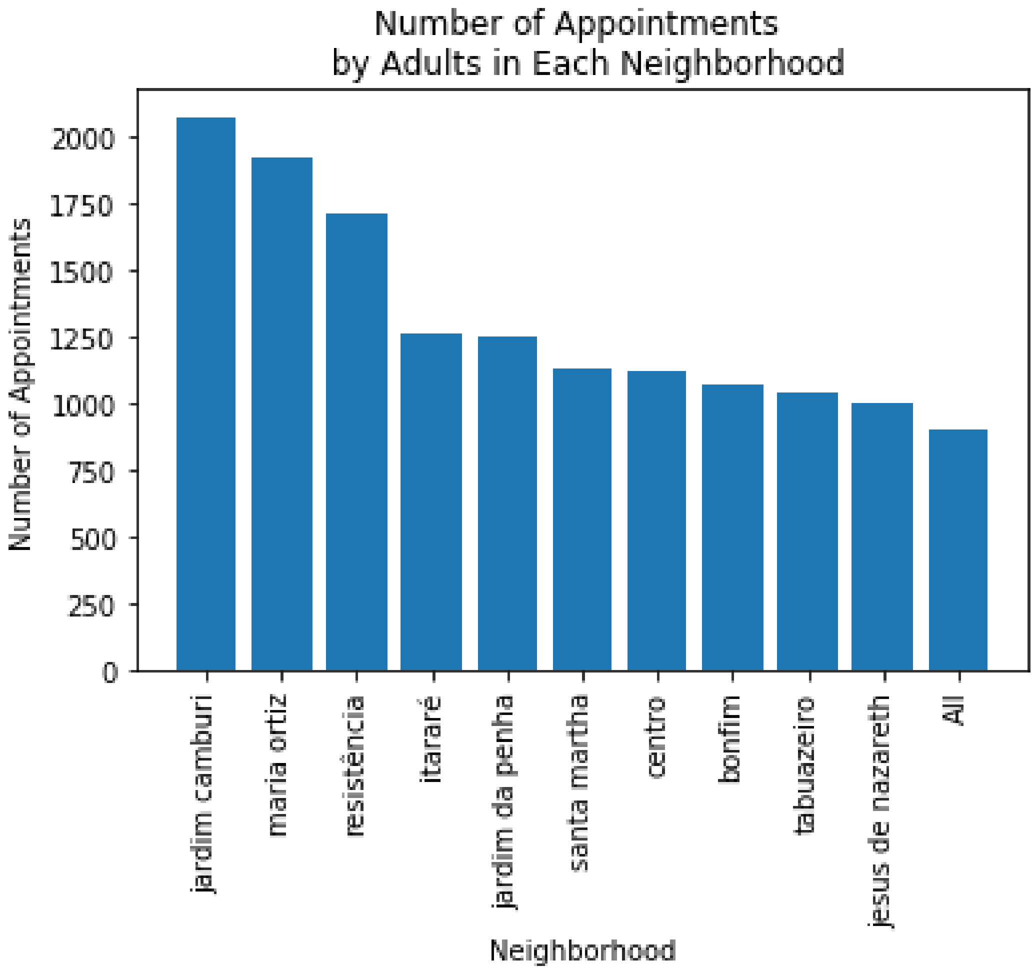
```
In [179]: c_adult_heights = dfc_adult['count_adult_appointments'].head(10).tolist()
```

```
In [180]: c_adult_heights = c_adult_heights + dfc_adult_m
```

```
In [181]: c_adult_labels = dfc_adult.index.format()[0:10]
```

```
In [182]: c_adult_labels = c_adult_labels + ['All']
```

```
In [183]: # Bar chart of results from count of "Adults" who made appointments in each 'neighbo
          c_aa_locations = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
          c_aa_heights = c_adult_heights
          c_aa_labels = c_adult_labels
          plt.bar(c_aa_locations, c_aa_heights)
          plt.title('Number of Appointments \n by Adults in Each Neighborhood')
          plt.xlabel('Neighborhood')
          plt.xticks(c_aa_locations, c_aa_labels, rotation=90)
          plt.ylabel('Number of Appointments');
```



Above is the bar chart of the 10 neighborhoods who receive the highest number of "Adults" who make appointments at each "Neighborhood." Each neighborhood receives 1,000 or more appointments for "Adult" patients.

Now, the proportion of appointments for "Adult" patients will be analyzed. The proportion of "Adult" appointments at each "Neighborhood" will be compared to the overall proportion of appointments for "Adult" patients in all "Neighborhoods."

```
In [184]: # Divide 'count_adult_appointments' by 'count_all_appointments'
          df_adult['proportion_adult_appointments'] = df_adult['count_adult_appointments'] / d
```

```
In [185]: # Rename df_adult to create dfp_adult for the proportion of 'adult'
          dfp_adult = df_adult
```

```
In [186]: # Sort values by column 'propoortion_adult_appointments'
          dfp_adult = dfp_adult.sort_values(by = 'proportion_adult_appointments', ascending = 
```

```
In [187]: dfp_adult.head(10)
```

```
Out[187]:                    count_adult_appointments  count_all_appointments  \
          neighborhood
          redenção                                653                  1553.0
          forte são joão                          756                  1889.0
          cruzamento                              550                  1398.0
          bonfim                                 1071                  2773.0
          resistência                            1711                  4431.0
          andorinhas                              868                  2262.0
          da penha                                833                  2217.0
          gurigica                                757                  2018.0
          romão                                   827                  2214.0
          são benedito                            525                  1439.0

                           proportion_adult_appointments
          neighborhood
          redenção                              0.420476
          forte são joão                        0.400212
          cruzamento                            0.393419
          bonfim                                0.386224
          resistência                           0.386143
          andorinhas                            0.383731
          da penha                              0.375733
          gurigica                              0.375124
          romão                                 0.373532
          são benedito                          0.364837
```

```
In [188]: dfp_adult_m = [dfp_adult['proportion_adult_appointments'].mean()]
```

```
In [189]: print(dfp_adult_m)
```

```
[0.3458778710357711]
```

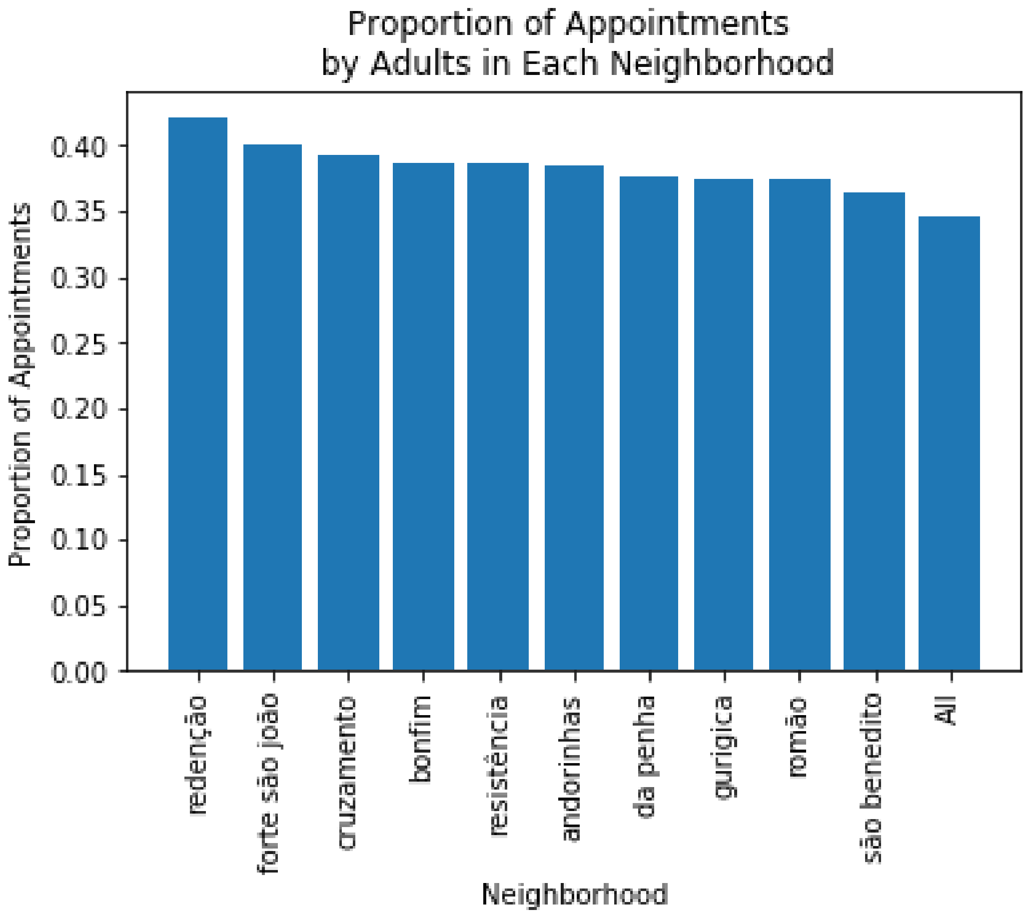
```
In [190]: p_adult_heights = dfp_adult['proportion_adult_appointments'].head(10).tolist()
```

```
In [191]: p_adult_heights = p_adult_heights + dfp_adult_m
```

```
In [192]: p_adult_labels = dfp_adult.index.format()[0:10]
```

```
In [193]: p_adult_labels = p_adult_labels + ['All']
```

```
In [194]: # Bar chart of results the proportion of "Adults" who made appointments in each 'nei
          p_aa_locations = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
          p_aa_heights = p_adult_heights
          p_aa_labels = p_adult_labels
          plt.bar(p_aa_locations, p_aa_heights)
          plt.title('Proportion of Appointments \n by Adults in Each Neighborhood')
          plt.xlabel('Neighborhood')
          plt.xticks(p_aa_locations, p_aa_labels, rotation=90)
          plt.ylabel('Proportion of Appointments');
```



Preliminary analysis suggests resources to understand and limit "no-show" appointments may be well utilized at the neighborhood Resistência. Resistência ranks 3rd in the number of adult patient appointments with 1,711 compared to an average of 906 and 5th in the proportion of adult patients with 38.6% compared to an average of 34.6%.

Next, the neighborhood which receives the most appointments from patients in the "Scholarship" group will be found. This data will be compared to the proportion of the neighborhoods' total number of appointments.

In [195]:
```
# Create dataframe with only patients who receive scholarship in the 'scholarship' c
df_scholarship = df[df['scholarship'] == 1]
```

In [196]:
```
# Drop all columns except 'neighborhood' and 'scholarship'
df_scholarship = df_scholarship.drop(['appointment_id', 'no_show', 'existing_conditi
```

In [197]:
```
# Count of number of appointments by patients who receive 'scholarship' in each 'nei
df_scholarship = df_scholarship.groupby(['neighborhood']).count().sort_values(by = '
```

In [198]:
```
# Rename 'scholarship' column to 'count_scholarship_appointments'
df_scholarship = df_scholarship.rename(index=str, columns={'scholarship': 'count_scho
```

In [199]:
```python
# Add column 'count_all_appointments' to df_scholarship and drop all 'NaN' columns
df_scholarship = df_scholarship.join(df_neighborhood).dropna(axis = 0)
```

In [200]:
```python
# Rename df_scholarship to create dfc_scholarship for the count of 'scholarship'
dfc_scholarship = df_scholarship
```

In [201]:
```python
dfc_scholarship.head(10)
```

Out[201]:

neighborhood	count_scholarship_appointments	count_all_appointments
ilha do príncipe	579	2266.0
tabuazeiro	537	3132.0
resistência	468	4431.0
caratoíra	456	2565.0
santa martha	441	3131.0
gurigica	422	2018.0
são benedito	404	1439.0
bonfim	373	2773.0
santo andré	334	2571.0
andorinhas	323	2262.0

In [202]:
```python
dfc_scholarship_m = [dfc_scholarship['count_scholarship_appointments'].mean()]
```

In [203]:
```python
print(dfc_scholarship_m)
```

```
[265.03125]
```

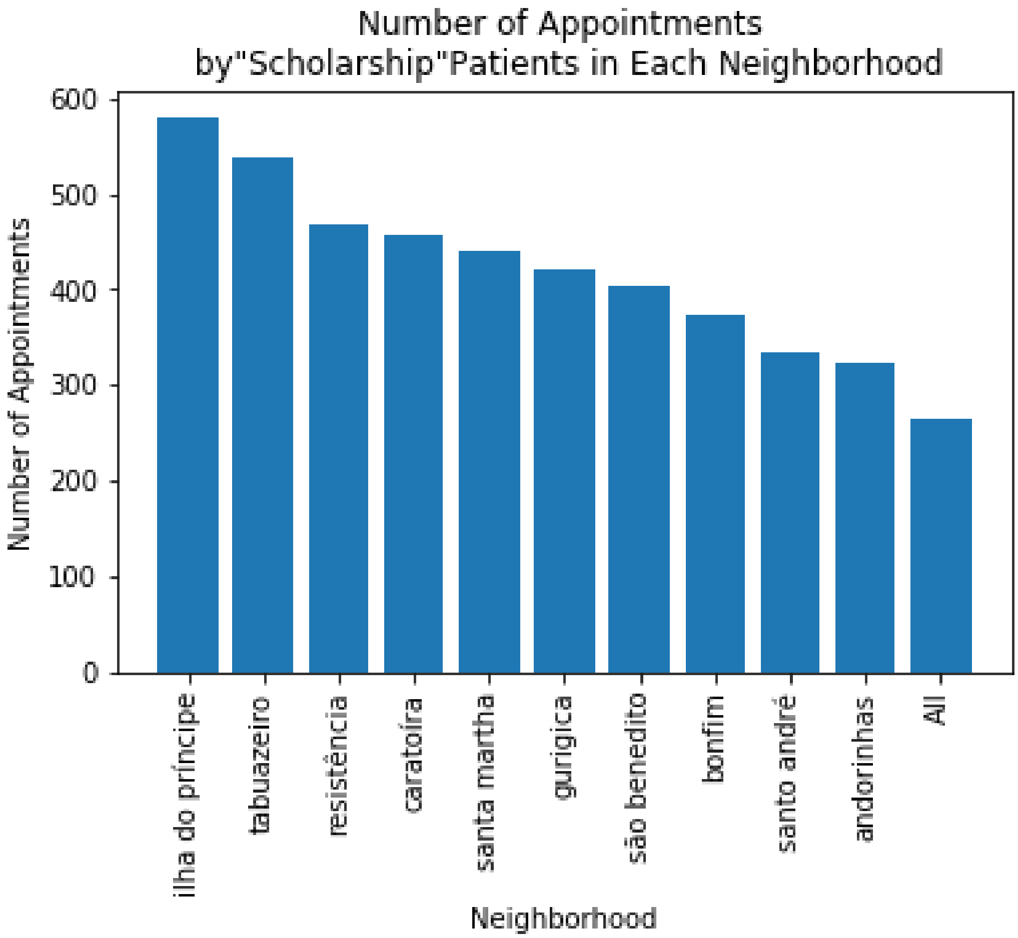
In [204]:
```python
c_scholarship_heights = dfc_scholarship['count_scholarship_appointments'].head(10).to
```

In [205]:
```python
c_scholarship_heights = c_scholarship_heights + dfc_scholarship_m
```

In [206]:
```python
c_scholarship_labels = dfc_scholarship.index.format()[0:10]
```

In [207]:
```python
c_scholarship_labels = c_scholarship_labels + ['All']
```

In [208]:
```python
# Bar chart of results from count of 'scholarship' patients who made appointments in
c_sa_locations = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
c_sa_heights = c_scholarship_heights
c_sa_labels = c_scholarship_labels
plt.bar(c_sa_locations, c_sa_heights)
plt.title('Number of Appointments \n by"Scholarship"Patients in Each Neighborhood')
plt.xlabel('Neighborhood')
plt.xticks(c_sa_locations, c_sa_labels, rotation=90)
plt.ylabel('Number of Appointments');
```



Above is the chart of the 10 neighborhoods who receive the highest number of "Scholarship" patients who make appointments in each "Neighborhood." Each neighborhood receives 300 or more appointments for "Scholarship" patients compared to the mean of 265 appointments by "Scholarship" patients across all neighborhoods.

Now, the proportion of appointments for "Scholarship" patients will be analyzed. The proportion of "Scholarship" appointments in each "Neighborhood" will be compared to the overall proportion of appointments for "Scholarship" patients in all "Neighborhoods."

In [209]:
```
# Divide 'count_scholarship_appointments' by 'count_all_appointments'
df_scholarship['proportion_scholarship_appointments'] = df_scholarship['count_schola
```

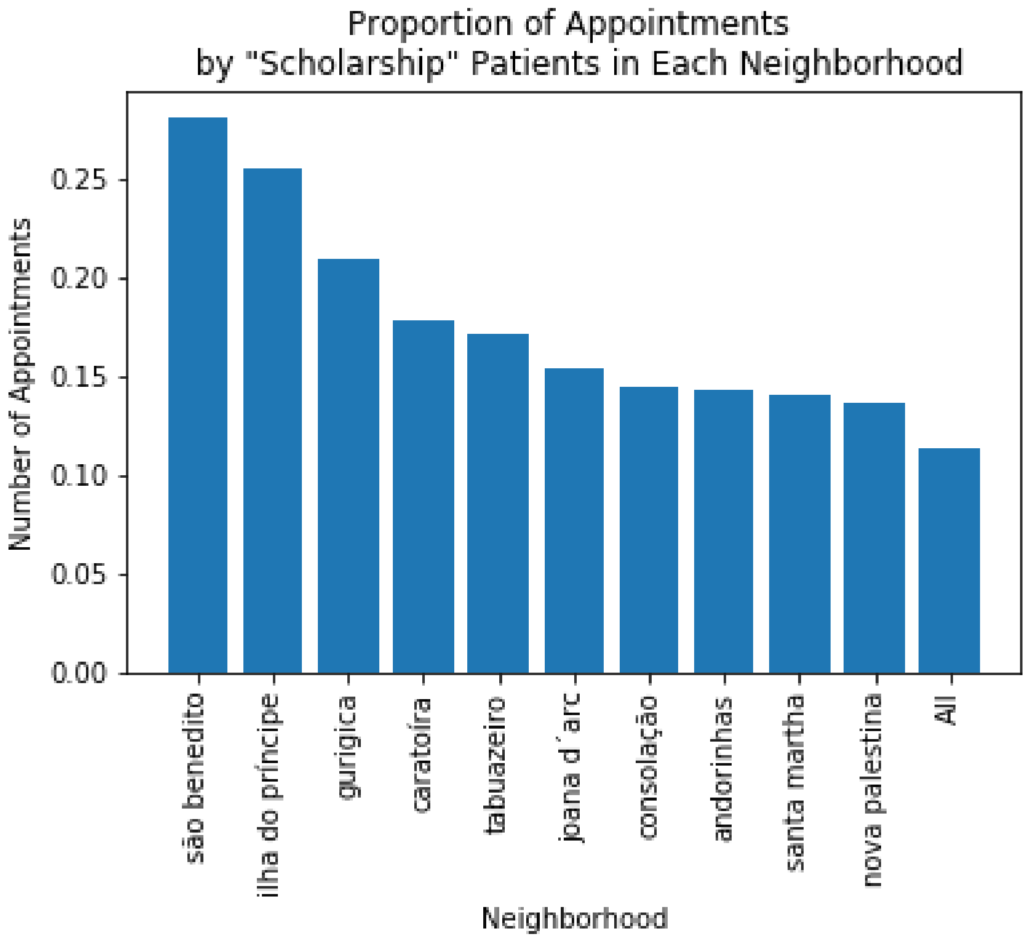
In [210]:
```
# Rename df_scholarship to create dfp_scholarship for the proportion of 'scholarship
dfp_scholarship = df_scholarship
```

In [211]:
```
# Sort values by column 'propoortion_scholarship_appointments'
dfp_scholarship = dfp_scholarship.sort_values(by = 'proportion_scholarship_appointme
```

In [212]:
```
dfp_scholarship.head(10)
```

```
Out[212]:                     count_scholarship_appointments  count_all_appointments  \
          neighborhood
          são benedito                                   404                  1439.0
          ilha do príncipe                               579                  2266.0
          gurigica                                       422                  2018.0
          caratoíra                                      456                  2565.0
          tabuazeiro                                     537                  3132.0
          joana dťarc                                    219                  1427.0
          consolação                                     199                  1376.0
          andorinhas                                     323                  2262.0
          santa martha                                   441                  3131.0
          nova palestina                                 310                  2264.0

                            proportion_scholarship_appointments
          neighborhood
          são benedito                                 0.280751
          ilha do príncipe                             0.255516
          gurigica                                     0.209118
          caratoíra                                    0.177778
          tabuazeiro                                   0.171456
          joana dťarc                                  0.153469
          consolação                                   0.144622
          andorinhas                                   0.142794
          santa martha                                 0.140850
          nova palestina                               0.136926
```

```
In [213]: dfp_scholarship_m = [dfp_scholarship['proportion_scholarship_appointments'].mean()]

In [214]: print(dfp_scholarship_m)

[0.1136161142962836]


In [215]: p_scholarship_heights = dfp_scholarship['proportion_scholarship_appointments'].head(

In [216]: p_scholarship_heights = p_scholarship_heights + dfp_scholarship_m

In [217]: p_scholarship_labels = dfp_scholarship.index.format()[0:10]

In [218]: p_scholarship_labels = p_scholarship_labels + ['All']

In [219]: # Bar chart of results from proportion of 'scholarship' patients who made appointmen
          p_sa_locations = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
          p_sa_heights = p_scholarship_heights
          p_sa_labels = p_scholarship_labels
          plt.bar(p_sa_locations, p_sa_heights)
          plt.title('Proportion of Appointments \n by "Scholarship" Patients in Each Neighborho
          plt.xlabel('Neighborhood')
          plt.xticks(p_sa_locations, p_sa_labels, rotation=90)
          plt.ylabel('Number of Appointments');
```



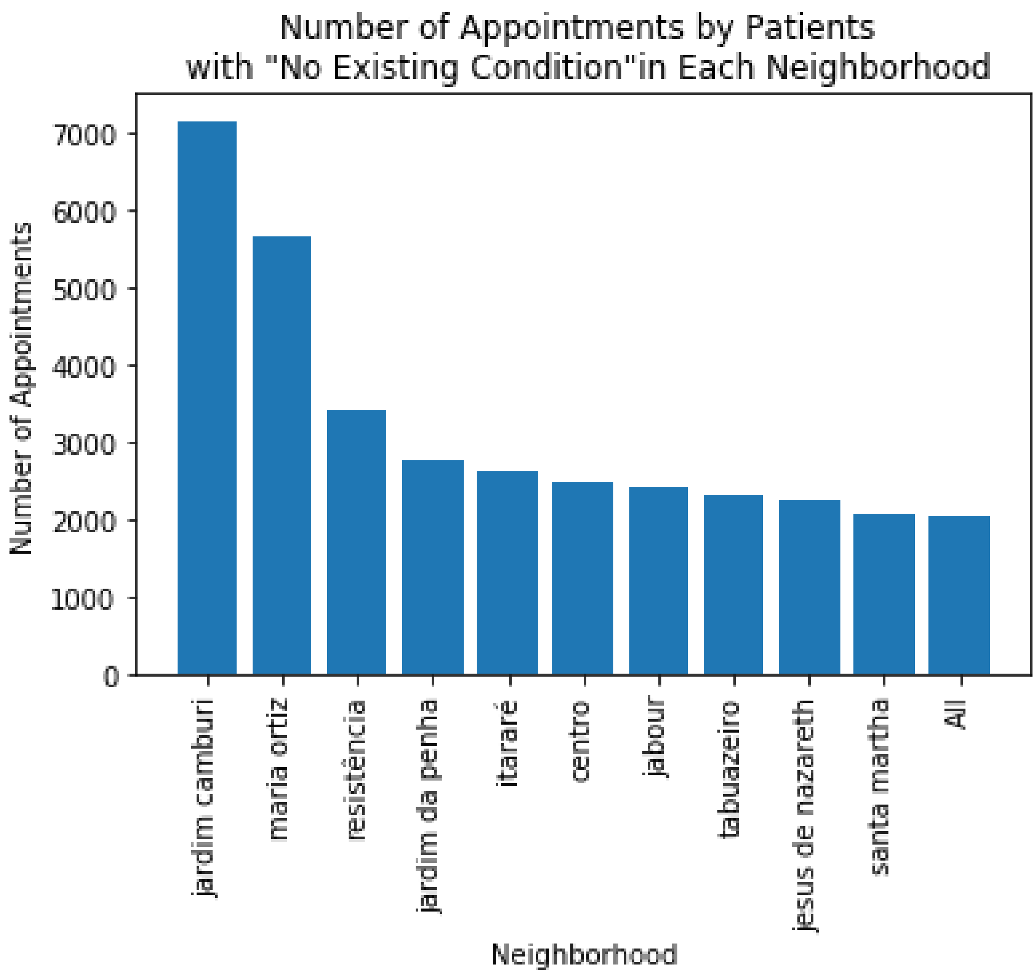
Preliminary analysis suggests resources to understand and limit "no-show" appointments may be well utilized at the neighborhood Ilha do Príncipe. Ilha do Príncipe ranks 1st in the number of "Scholarship" patient appointments with 579 compared to an average of 265 and 2nd in the proportion of adult patients with 25.6% compared to an average of 11.4%.

Next, the neighborhood which receives the most appointments from patients in the "No Existing Condition" group will be found. This data will be compared to the proportion of the neighborhoods' total number of appointments.

```
In [220]: # Create dataframe with only patients without existing conditions in the 'existing_c
          df_excon = df[df['existing_condition'] == 0]

In [221]: # Drop all columns except 'neighborhood' and 'existing_condition'
          df_excon = df_excon.drop(['appointment_id', 'no_show', 'scholarship', 'age_group'], a

In [222]: # Count of number of appointments by patients who have no 'existing_condition' in ea
          df_excon = df_excon.groupby(['neighborhood']).count().sort_values(by = 'existing_cond

In [223]: # Rename 'existing_condition' column to 'count_no_existing_condition_appointments'
          df_excon = df_excon.rename(index=str, columns={'existing_condition': 'count_no_existi
```

```
In [224]: # Add column 'count_all_appointments' to df_excon and drop all 'NaN' columns
          df_excon = df_excon.join(df_neighborhood).dropna(axis = 0)

In [225]: # Rename df_excon to create dfc_excon for the count of 'existing_condition'
          dfc_excon = df_excon

In [226]: dfc_excon.head(10)

Out[226]:                    count_no_existing_condition_appointments  \
          neighborhood
          jardim camburi                                         7143
          maria ortiz                                            5656
          resistência                                            3407
          jardim da penha                                        2774
          itararé                                                2606
          centro                                                 2481
          jabour                                                 2405
          tabuazeiro                                             2311
          jesus de nazareth                                      2230
          santa martha                                           2069

                             count_all_appointments
          neighborhood
          jardim camburi                     7717.0
          maria ortiz                        5805.0
          resistência                        4431.0
          jardim da penha                    3877.0
          itararé                            3514.0
          centro                             3334.0
          jabour                             2509.0
          tabuazeiro                         3132.0
          jesus de nazareth                  2853.0
          santa martha                       3131.0

In [227]: dfc_excon_m = [dfc_excon['count_no_existing_condition_appointments'].mean()]

In [228]: print(dfc_excon_m)

[2040.4375]


In [229]: c_excon_heights = dfc_excon['count_no_existing_condition_appointments'].head(10).tol

In [230]: c_excon_heights = c_excon_heights + dfc_excon_m

In [231]: c_excon_labels = dfc_excon.index.format()[0:10]

In [232]: c_excon_labels = c_excon_labels + ['All']
```

```
In [233]: # Bar chart of results from count of patients with no 'existing_condition' who made 
          c_ea_locations = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
          c_ea_heights = c_excon_heights
          c_ea_labels = c_excon_labels
          plt.bar(c_ea_locations, c_ea_heights)
          plt.title('Number of Appointments by Patients \n with "No Existing Condition"in Each
          plt.xlabel('Neighborhood')
          plt.xticks(c_ea_locations, c_ea_labels, rotation=90)
          plt.ylabel('Number of Appointments');
```



Above is the chart of the 10 neighborhoods who receive the highest number of patients with "No Existing Conditions" who make appointments in each neighborhood. Each neighborhood receives 2,069 or more appointments for patients with "No Existing Conditions" compared to the mean of 2,040 appointments by patients with "No Existing Conditions" across all neighborhoods. The neighborhood Jardim Camburi seems to be an outlier with 7,143 appointments made by patients with "No Existing Conditions"; further analysis should be done to consider why this neighborhood sees so many patient with "No Existing Conditions" or if this data is inaccurate.

Now, the proportion of appointments for patients with "No Existing Conditions" will be analyzed. The proportion of "No Existing Condition" appointments in each neighborhood will be compared to the overall proportion of appointments for "Existing Condition" patients in all neighborhoods.

In [234]:
```
# Divide 'count_no_existing_condition_appointments' by 'count_all_appointments'
df_excon['proportion_no_existing_condition_appointments'] = df_excon['count_no_exist
```

In [235]:
```
# Rename df_excon to create dfp_excon for the proportion of 'existing_condition'
dfp_excon = df_excon
```

In [236]:
```
# Sort values by column 'propoortion_existing_condition_appointments'
dfp_excon = dfp_excon.sort_values(by = 'proportion_no_existing_condition_appointment
```

In [237]:
```
dfp_excon.head(10)
```

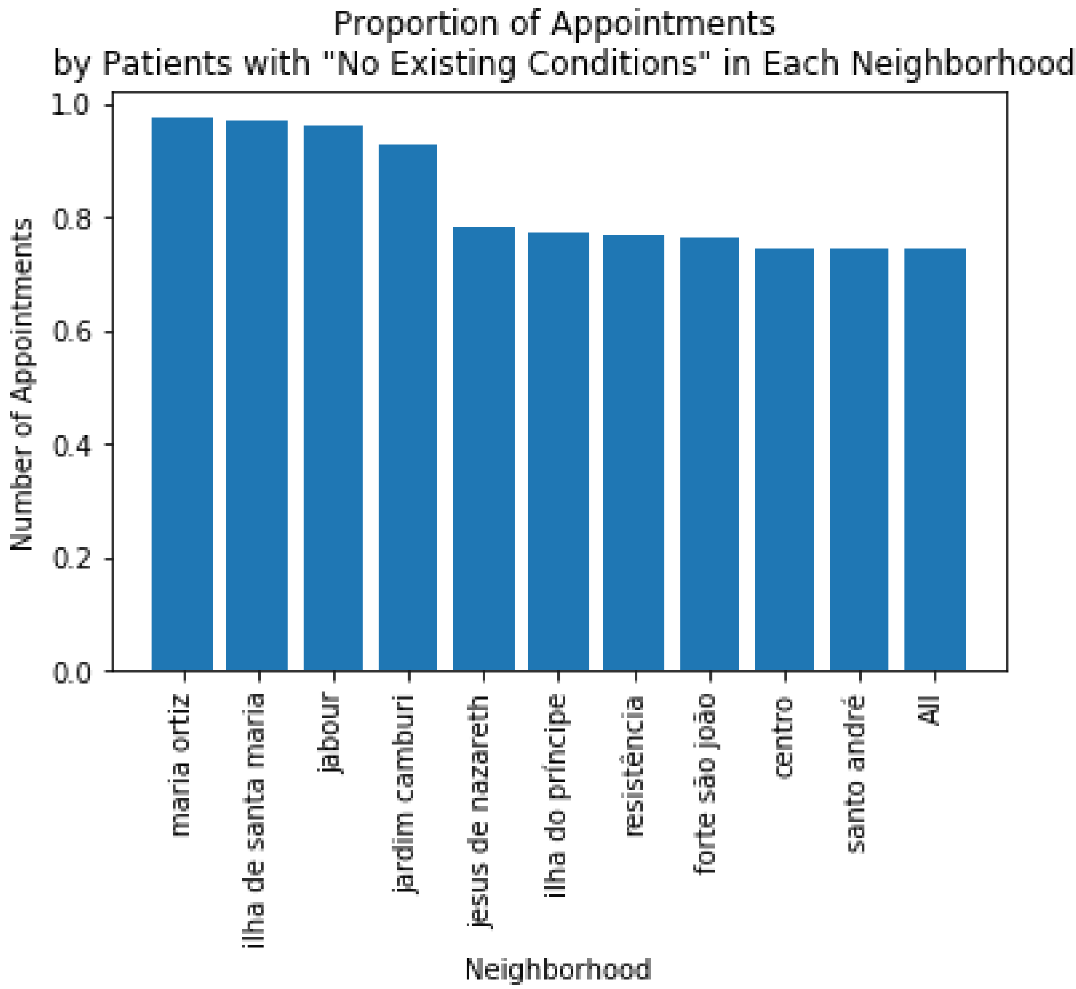
Out[237]:
```
                         count_no_existing_condition_appointments  \
neighborhood
maria ortiz                                                  5656
ilha de santa maria                                          1827
jabour                                                       2405
jardim camburi                                               7143
jesus de nazareth                                            2230
ilha do príncipe                                             1745
resistência                                                  3407
forte são joão                                               1441
centro                                                       2481
santo andré                                                  1908

                         count_all_appointments  \
neighborhood
maria ortiz                              5805.0
ilha de santa maria                      1885.0
jabour                                   2509.0
jardim camburi                           7717.0
jesus de nazareth                        2853.0
ilha do príncipe                         2266.0
resistência                              4431.0
forte são joão                           1889.0
centro                                   3334.0
santo andré                              2571.0

                         proportion_no_existing_condition_appointments
neighborhood
maria ortiz                                                   0.974332
ilha de santa maria                                           0.969231
jabour                                                        0.958549
jardim camburi                                                0.925619
jesus de nazareth                                             0.781633
```

```
ilha do príncipe                                                    0.770079
resistência                                                         0.768901
forte são joão                                                      0.762837
centro                                                              0.744151
santo andré                                                         0.742124
```

```
In [238]: dfp_excon_m = [dfp_excon['proportion_no_existing_condition_appointments'].mean()]

In [239]: print(dfp_excon_m)
```

```
[0.7441066150132695]
```

```
In [240]: p_excon_heights = dfp_excon['proportion_no_existing_condition_appointments'].head(10

In [241]: p_excon_heights = p_excon_heights + dfp_excon_m

In [242]: p_excon_labels = dfp_excon.index.format()[0:10]

In [243]: p_excon_labels = p_excon_labels + ['All']

In [244]: # Bar chart of results from count of all patients with no 'existing_condition' who m
          p_ea_locations = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
          p_ea_heights = p_excon_heights
          p_ea_labels = p_excon_labels
          plt.bar(p_ea_locations, p_ea_heights)
          plt.title('Proportion of Appointments \n by Patients with "No Existing Conditions" i
          plt.xlabel('Neighborhood')
          plt.xticks(p_ea_locations, p_ea_labels, rotation=90)
          plt.ylabel('Number of Appointments');
```



Preliminary analysis suggests resources to understand and limit "no-show" appointments may be well utilized at the neighborhood Maria Ortiz. Maria Ortiz ranks 2nd in the number of appointments by patients with "No Existing Conditions" with 5656 compared to an average of 2040 and 1st in the proportion of patients with "No Existing Conditions" with 97.4% compared to an average of 74.4%.

Finally, each "Neighborhood" will be analyzed based on the number of patients seen from all three categories: "Adult," "Scholarship," and "No Existing Condition."

```
In [245]: # Create dataframe with only 'adult', 'scholarship', and 'existing_condition' appoin
          df['asec'] = np.where(((df['age_group']=='adult') | (df['scholarship']==1) | (df['ex

In [246]: # Drop all columns except 'neighborhood' and 'asec'
          df_asec = df.drop(['appointment_id', 'scholarship', 'no_show', 'existing_condition',

In [247]: # Drop all rows without a 1 in column 'asec'
          df_asec = df_asec[df_asec.asec == 1]

In [248]: # Count of number of appointments by patients in group 'asec' in each 'neighborhood'
          df_asec = df_asec.groupby(['neighborhood']).count().sort_values(by = 'asec', ascendi
```

In [249]:
```
# Rename 'asec' column to 'count_asec_appointments'
df_asec = df_asec.rename(index=str, columns={'asec': 'count_asec_appointments'})
```

In [250]:
```
# Add column 'count_all_appointments' to df_asec and drop all 'NaN' columns
df_asec = df_asec.join(df_neighborhood).dropna(axis = 0)
```

In [251]:
```
# Rename df_asec to create dfc_asec for the count of 'adult', 'scholarship', and 'ex
dfc_asec = df_asec
```

In [252]:
```
df_asec.head(10)
```

Out[252]:

neighborhood	count_asec_appointments	count_all_appointments
jardim camburi	7182	7717.0
maria ortiz	5692	5805.0
resistência	3676	4431.0
jardim da penha	2853	3877.0
itararé	2791	3514.0
centro	2612	3334.0
tabuazeiro	2528	3132.0
jabour	2424	2509.0
jesus de nazareth	2411	2853.0
santa martha	2393	3131.0

In [253]:
```
dfc_asec_m = [dfc_asec['count_asec_appointments'].mean()]
```

In [254]:
```
print(dfc_asec_m)
```

```
[2190.0625]
```

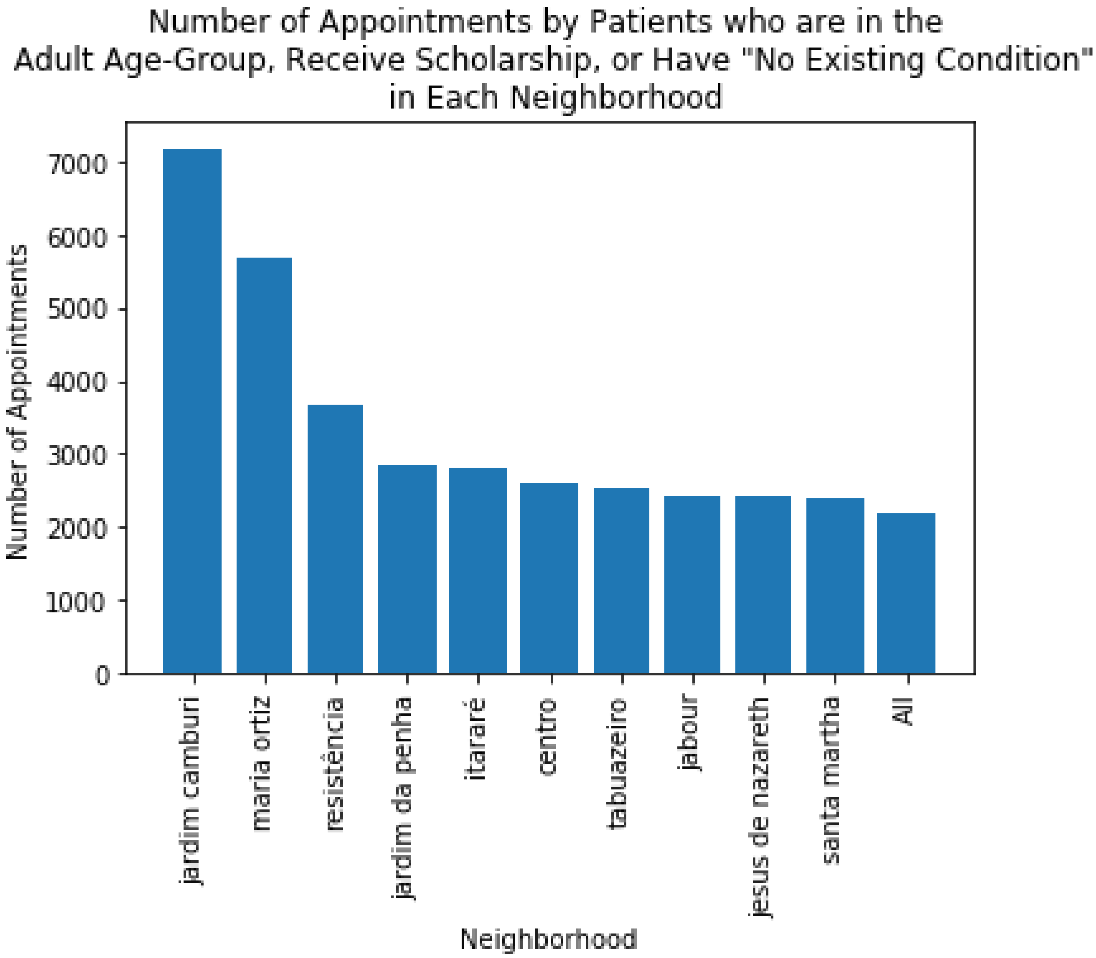
In [255]:
```
c_asec_heights = dfc_asec['count_asec_appointments'].head(10).tolist()
```

In [256]:
```
c_asec_heights = c_asec_heights + dfc_asec_m
```

In [257]:
```
c_asec_labels = dfc_asec.index.format()[0:10]
```

In [258]:
```
c_asec_labels = c_asec_labels + ['All']
```

In [259]:
```
# Bar chart of results from count of patients within 'asec' who made appointments in
c_asec_locations = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
c_asec_heights = c_asec_heights
c_asec_labels = c_asec_labels
plt.bar(c_asec_locations, c_asec_heights)
plt.title('Number of Appointments by Patients who are in the \n Adult Age-Group, Rec
plt.xlabel('Neighborhood')
plt.xticks(c_asec_locations, c_asec_labels, rotation=90)
plt.ylabel('Number of Appointments');
```



Above is the chart of the 10 neighborhoods who receive the highest number of patients who are "Adults", recive "Scholarship" or have "No Existing Conditions" who make appointments in each "Neighborhood." Each "Neighborhood" receives 2,393 or more appointments for patients in this group compared to the mean of 2,190 appointments by patients with in these groups across all "Neighborhoods".

Now, the proportion of appointments for patients in all these groups will be analyzed. The proportion of appointments by patients in these groups in each "Neighborhood" will be compared to the overall proportion of appointments for these patients in all "Neighborhoods."

```
In [260]: # Divide 'count_asec_appointments' by 'count_all_appointments'
          df_asec['proportion_asec_appointments'] = df_asec['count_asec_appointments'] / df_asc
```

```
In [261]: # Rename df_asec to create dfc_asec for the proportion of 'adult', 'scholarship', and
          dfp_asec = df_asec
```

```
In [262]: # Sort values by column 'propoortion_asec_appointments'
          dfp_asec = dfp_asec.sort_values(by = 'proportion_asec_appointments', ascending = Fals
```

```
In [263]: dfp_asec.head(10)
```

```
Out[263]:                      count_asec_appointments  count_all_appointments  \
          neighborhood
          maria ortiz                             5692                  5805.0
          ilha de santa maria                     1845                  1885.0
          jabour                                  2424                  2509.0
          jardim camburi                          7182                  7717.0
          jesus de nazareth                       2411                  2853.0
          forte são joão                          1589                  1889.0
          gurigica                                1680                  2018.0
          resistência                             3676                  4431.0
          são benedito                            1191                  1439.0
          santo andré                             2124                  2571.0

                               proportion_asec_appointments
          neighborhood
          maria ortiz                              0.980534
          ilha de santa maria                      0.978780
          jabour                                   0.966122
          jardim camburi                           0.930673
          jesus de nazareth                        0.845075
          forte são joão                           0.841186
          gurigica                                 0.832507
          resistência                              0.829610
          são benedito                             0.827658
          santo andré                              0.826138
```

```
In [264]: dfp_asec_m = [dfp_asec['proportion_asec_appointments'].mean()]
```

```
In [265]: print(dfp_asec_m)
```

```
[0.808276283639208]
```

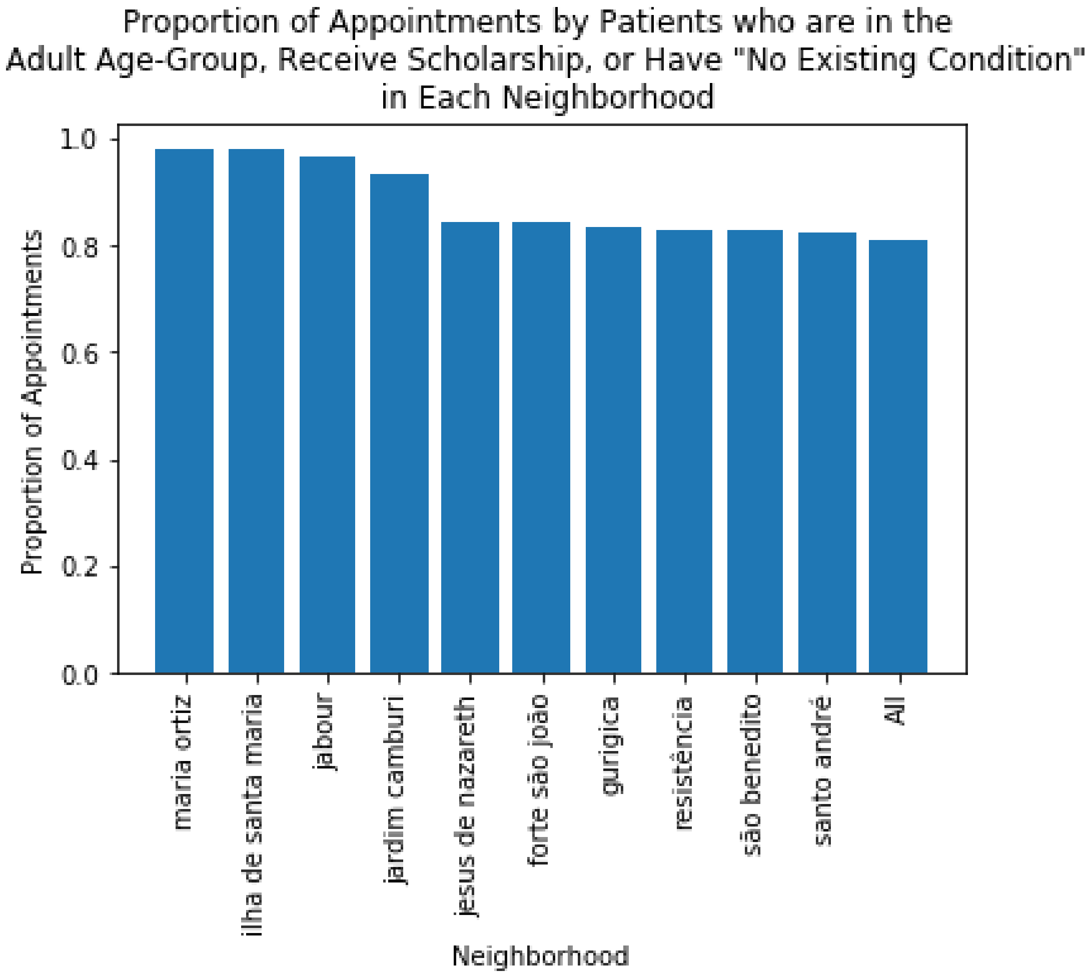
```
In [266]: p_asec_heights = dfp_asec['proportion_asec_appointments'].head(10).tolist()
```

```
In [267]: p_asec_heights = p_asec_heights + dfp_asec_m
```

```
In [268]: p_asec_labels = dfp_asec.index.format()[0:10]
```

```
In [269]: p_asec_labels = p_asec_labels + ['All']
```

```
In [270]: # Bar chart of results from proportion of patients within 'asec' group who made appo
          p_asec_locations = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
          p_asec_heights = p_asec_heights
          p_asec_labels = p_asec_labels
          plt.bar(p_asec_locations, p_asec_heights)
          plt.title('Proportion of Appointments by Patients who are in the \n Adult Age-Group,
          plt.xlabel('Neighborhood')
          plt.xticks(p_asec_locations, p_asec_labels, rotation=90)
          plt.ylabel('Proportion of Appointments');
```



Preliminary analysis of all three independent variables ("Adult", "Scholarship", "No Existing Condition") combined suggests resources to understand and limit "no-show" appointments may be well utilized at the neighborhood Maria Ortiz. Maria Ortiz ranks 2nd in the number of appointments by patients with any of the three variables with 5,692 compared to an average of 2,190 and 1st in proportion with 98.1% compared to an average of 80.8%. Maria Ortiz is the highest rank neighborhood which appears in the top 10 values of count and proportion of patients.

Finally, all 8 data sets analyzed so far will be concatonated to see which "Neighborhood" appeared most frequently on within the top 10 of all "Neighborhood" count and proportion tables.

```
In [271]: # Table of neighborhoods who appeared in the top 10 of more than 1 list
          dfc_asec = dfc_asec.head(10)
          dfc_excon = dfc_excon.head(10)
          dfc_scholarship = dfc_scholarship.head(10)
          dfc_adult = dfc_adult.head(10)
          dfp_asec = dfp_asec.head(10)
          dfp_excon = dfp_excon.head(10)
          dfp_scholarship = dfp_scholarship.head(10)
          dfp_adult = dfp_adult.head(10)
```

```
In [272]: # Table of neighborhoods who appeared in the top 10 of more than 1 list
          df_all = dfc_asec.append([dfc_excon, dfc_scholarship, dfc_adult, dfp_asec, dfp_excon

In [273]: df_all = df_all[['neighborhood']]

In [274]: df_all = df_all.neighborhood.value_counts().to_frame().reset_index()

In [275]: df_all = df_all.rename(index=str, columns={'index': 'neighborhood', "neighborhood": 

In [276]: df_all.head(10)

Out[276]:          neighborhood  count
          0         resistência      7
          1          tabuazeiro      5
          2   jesus de nazareth      5
          3         santa martha      5
          4          maria ortiz      5
          5      jardim camburi      5
          6            gurigica      4
          7              centro      4
          8              jabour      4
          9         são benedito      4
```

According to the table above, the "Neighborhood" Resistência appeared most frequently within the top 10 for all variables considered.

Conclusions

The groups which stood out for further investigation are patients who are in the age-group "Adults", patients who receive "Scholarship", and patients who have "No Existing Condition." More elaborate statistical models should be used to confirm whether or not these traits can be associated with a "no-show" appointment.

The neighborhood where these three groups most often schedule appointments was examined. The hospital located in the "Neighborhood" Resistência stood out among others as the strongest candidate for further study and potential experimental intervention in the prevention of "no-shows." Resistência appeared 7 times within the top 10 of neighborhoods who scheduled the most appointments for the groups identified earlier as potentially being associated with "no-show" appointments.

Further investigation must be done to fully understand the data analyzed within this report. Care must be given to critique the data associated with the column 'existing_condition' as this variable heavy weighed the final analysis.

"No-show" appointments misappropriate resources resulting in the mis-use of healthcare funds. In order limit the misuse of medical practicitioners' time and healthcare providers' resources, preliminary analysis of "no-show" data was conducted. While causation cannot be drawn from this analysis, patterns arose which warrant further statistical investigation.

1.2 Resources

- https://www.kaggle.com/joniarroba/noshowappointments
- https://data.worldbank.org/indicator/SH.XPD.PCAP?end=2014&start=1995&view=chart
- https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?view=chart

- https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Age-and-Gender.html
- https://stackoverflow.com/
- http://pandas.pydata.org/
- https://matplotlib.org/
- https://docs.scipy.org/doc/
- https://chrisalbon.com/