Untitled

January 21, 2019

1 Dataset : Hospital No-show Analysis

1.1 Step 0: Importing Libraries

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

1.2 Step 1: Questions

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

1.3 Step 2: Wrangle Data

```
In [2]: df = pd.read_csv('data.csv', parse_dates=['ScheduledDay', 'AppointmentDay'])
        df.head()
```

```
Out[2]:       PatientId  AppointmentID Gender        ScheduledDay AppointmentDay  Age  \
        0  2.987250e+13        5642903      F 2016-04-29 18:38:08     2016-04-29   62
        1  5.589978e+14        5642503      M 2016-04-29 16:08:27     2016-04-29   56
        2  4.262962e+12        5642549      F 2016-04-29 16:19:04     2016-04-29   62
        3  8.679512e+11        5642828      F 2016-04-29 17:29:31     2016-04-29    8
        4  8.841186e+12        5642494      F 2016-04-29 16:07:23     2016-04-29   56

             Neighbourhood  Scholarship  Hipertension  Diabetes  Alcoholism  \
        0    JARDIM DA PENHA            0             1         0           0
        1    JARDIM DA PENHA            0             0         0           0
        2      MATA DA PRAIA            0             0         0           0
        3  PONTAL DE CAMBURI            0             0         0           0
        4    JARDIM DA PENHA            0             1         1           0

           Handcap  SMS_received No-show
        0        0             0      No
        1        0             0      No
        2        0             0      No
```

```
3        0              0      No
4        0              0      No
```

In [3]: df.describe()

Out[3]:

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

        Hipertension       Diabetes     Alcoholism        Handcap  \
count  110527.000000  110527.000000  110527.000000  110527.000000
mean        0.197246       0.071865       0.030400       0.022248
std         0.397921       0.258265       0.171686       0.161543
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.000000       0.000000       0.000000
max         1.000000       1.000000       1.000000       4.000000

        SMS_received
count  110527.000000
mean        0.321026
std         0.466873
min         0.000000
25%         0.000000
50%         0.000000
75%         1.000000
max         1.000000
```

1.3.1 No data is missing in the dataset

In [4]: df.info()

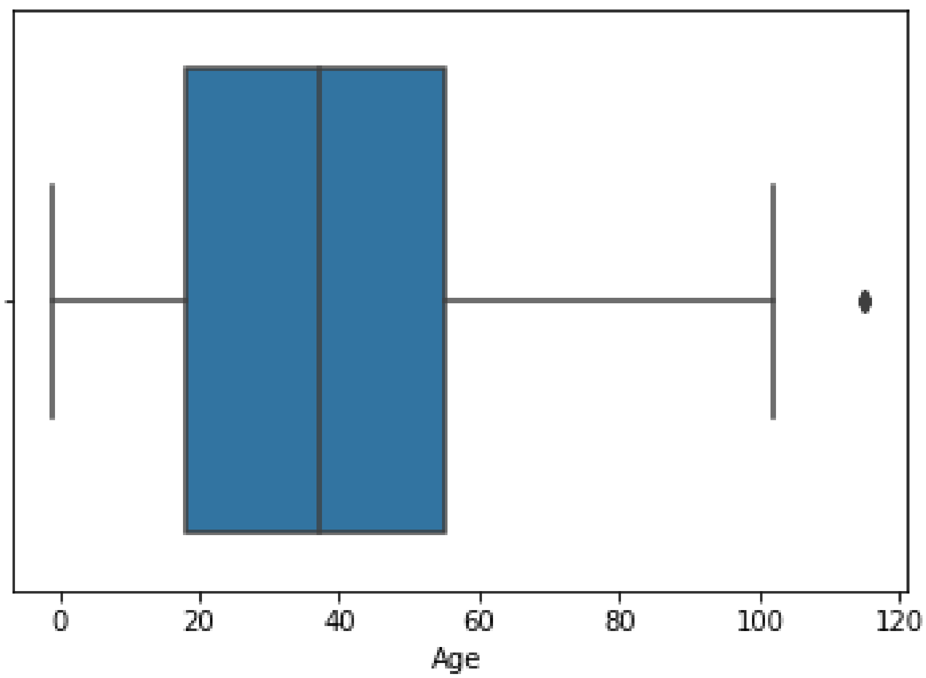
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
PatientId         110527 non-null float64
AppointmentID     110527 non-null int64
Gender            110527 non-null object
ScheduledDay      110527 non-null datetime64[ns]
AppointmentDay    110527 non-null datetime64[ns]
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: datetime64[ns](2), float64(1), int64(8), object(3)
memory usage: 11.8+ MB
```

1.3.2 Removing irrelevant values for Age

In [5]:
```
sns.boxplot(df['Age'])
```

Out[5]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb48db068d0>
```



In [6]:
```
df = df[ (df['Age'] <=100) & (df['Age']>0)]
```

1.4 Step 3: EDA

1.4.1 Defining one function that calculates the probability of No-show given a group by on a particular column

In [7]:
```
def findProb(groupby ,  df, return_dict=False):
```

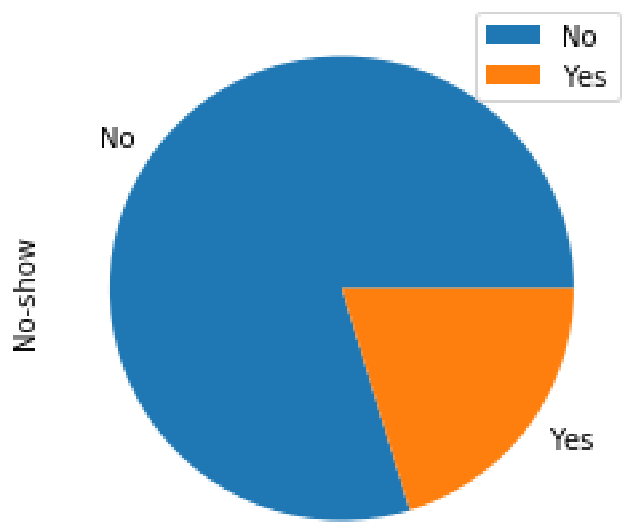
```
        groupby.append('No-show')
        lst = []
        lst_key= {}
        df_temp = df.groupby(groupby).count()
        #print(df_temp)
        for i in range(0,len(df_temp),2):
            #print(df_temp['PatientId'][i+1] , df_temp['PatientId'][i])
            #print(df_temp.index[i][0])
            lst.append(df_temp['PatientId'].iloc[i+1] / (df_temp['PatientId'].iloc[i]+df_tem
            lst_key[df_temp.index[i][0]] = df_temp['PatientId'].iloc[i+1] / (df_temp['Patien
            #i = i+2
        if(return_dict):
            return lst_key
        return lst
```

In [8]:
```
df_count = df['No-show'].value_counts()
df_count
```

Out[8]:
```
No     85303
Yes    21677
Name: No-show, dtype: int64
```

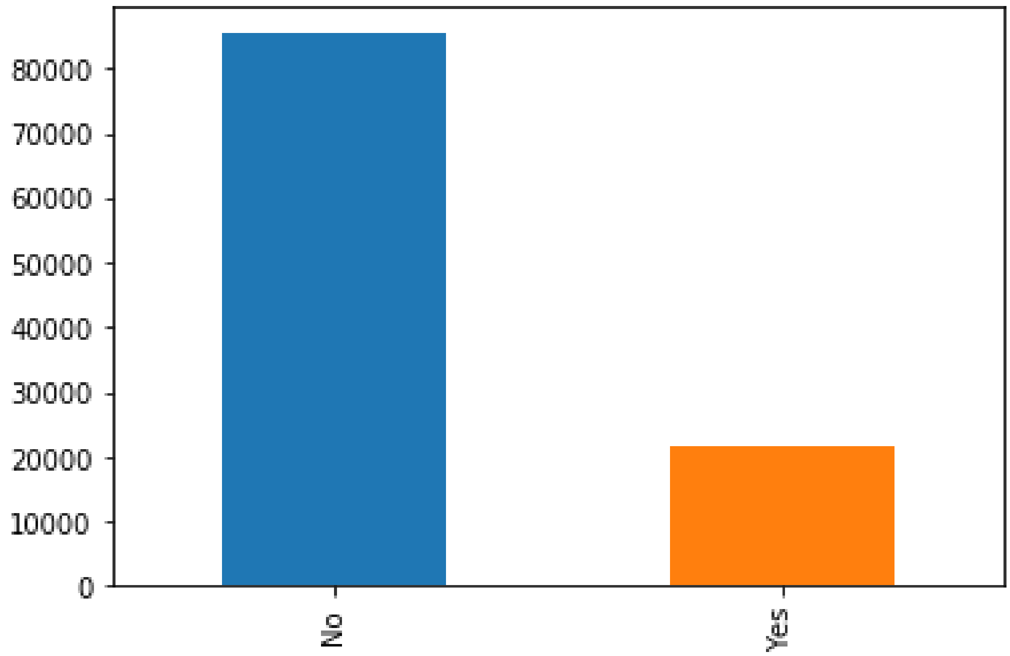
In [9]:
```
df_count.plot(kind='pie', legend=True, figsize=(4,4))
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48dddd860>



In [10]:
```
df_count.plot(kind='bar')
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48e09fda0>



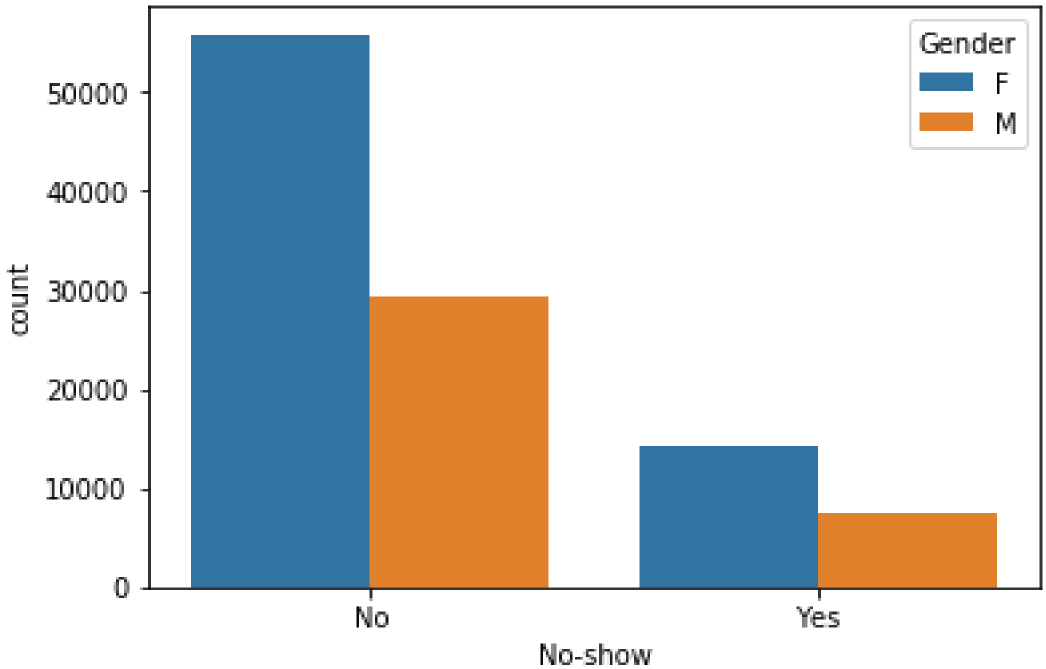
1.4.2 Analysis based on Gender

```
In [11]: count_gender = findProb(['Gender'],df, True)
```

1.4.3 Women see doctor more often than men

```
In [12]: sns.countplot(df['No-show'], hue=df['Gender'])
```

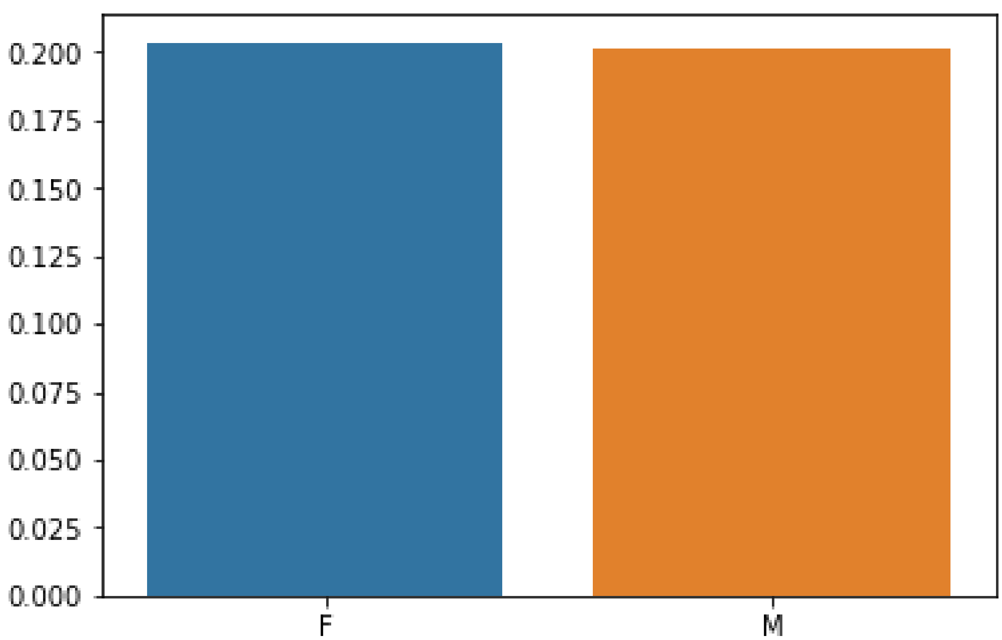
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48e017668>



1.4.4 20 % of the people don't show up on Appointments on Average be it a Male or a Female

```
In [13]: sns.barplot(x= np.array(list(count_gender.keys())), y = np.array(list(count_gender.valu
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48e09f278>
```



1.4.5 Conclusion: Not related to gender any ways

1.4.6 Analysis based on the day of the week Appointment was scheduled

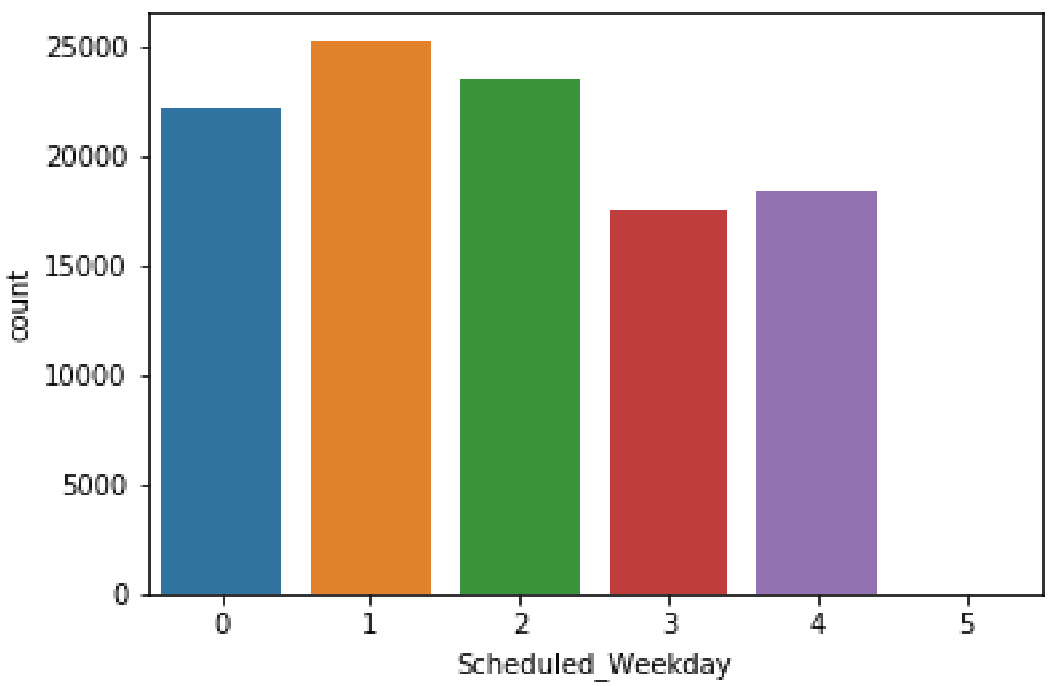
```
In [14]: weekday = []
         for i in enumerate(df.ScheduledDay):
             weekday.append(i[1].weekday())
```

```
In [15]: df["Scheduled_Weekday"] = weekday
```

1.4.7 Most of the appointments are scheduled on Tuesday

```
In [16]: sns.countplot( df['Scheduled_Weekday'])
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48daf4e48>
```

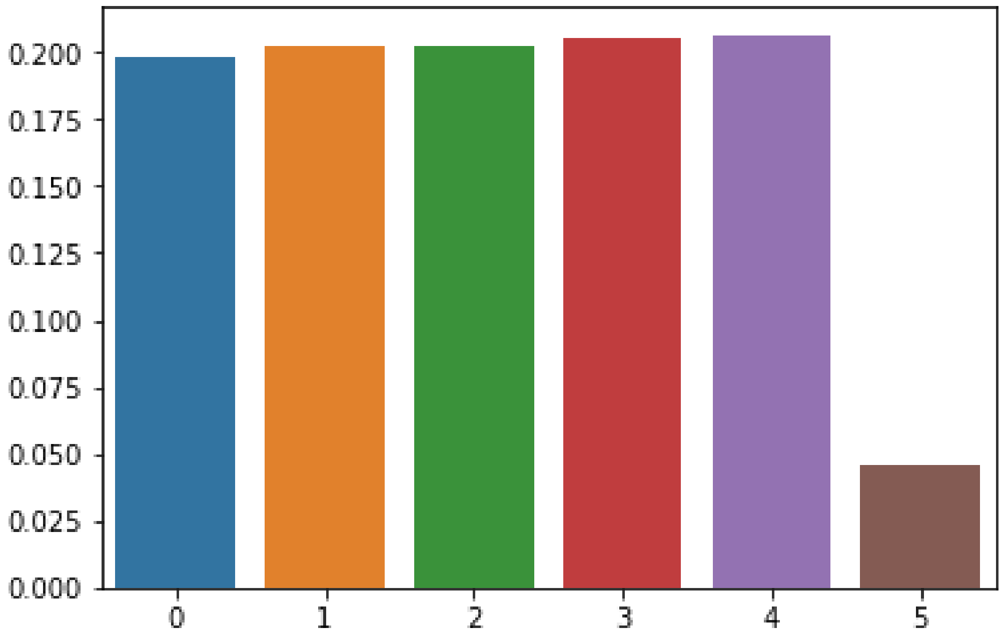



```
In [17]: count = findProb(['Scheduled_Weekday'] ,df, True)
```

1.4.8 Most of the appointments scheduled on Friday have a less probability of cancelling

```
In [18]: sns.barplot(x= np.array(list(count.keys())), y = np.array(list(count.values())))
```

```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48dfdd940>
```



1.4.9 Conclusion: It does not really matters on which day the appointment was booked, Friday comes out to be a day where there is low chance of No-show but we do not have enough data for friday to support this claim

1.4.10 Analysis based on the day of the week Actual Appointment was scheduled

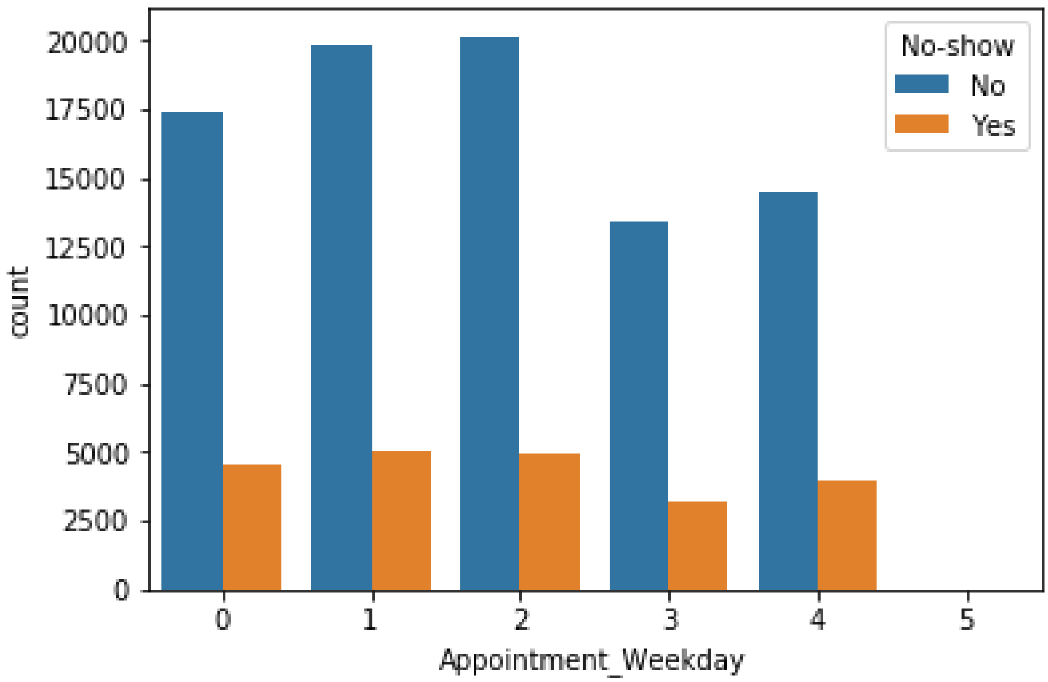
```
In [19]: weekday_a = []
         for i in enumerate(df.AppointmentDay):
             weekday_a.append(i[1].weekday())

In [20]: df['Appointment_Weekday'] = weekday_a
```

1.4.11 Most of the appointments are scheduled on Tuesday, Wednesday

```
In [21]: sns.countplot( df['Appointment_Weekday'], hue=df['No-show'])

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48de7e940>
```

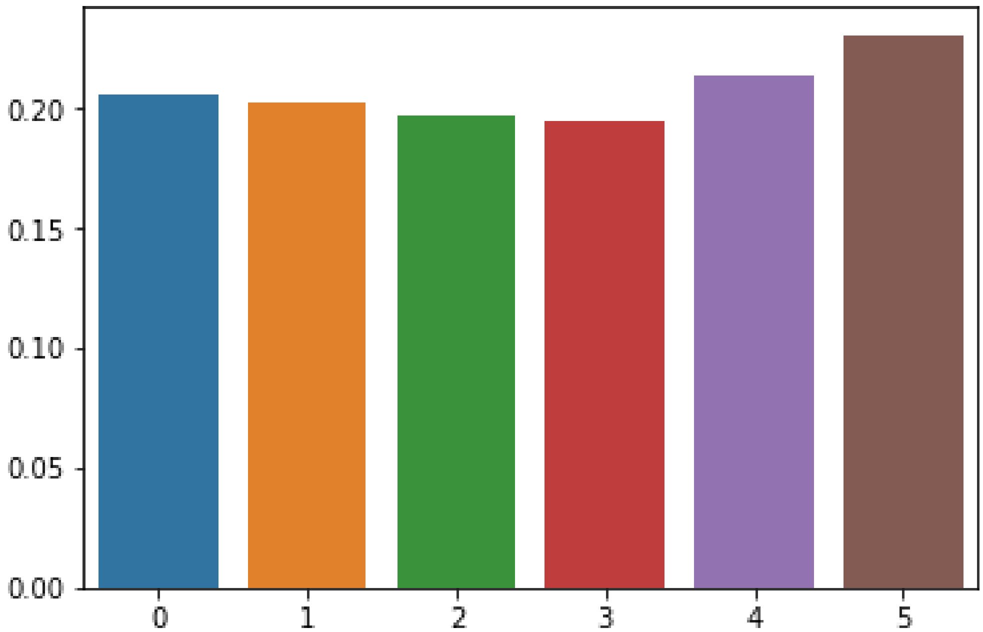



```
In [22]: count_week = findProb(['Appointment_Weekday'], df, True)
         count_week

Out[22]: {0: 0.20610931007716543,
          1: 0.20233588401127667,
          2: 0.1972100438421682,
          3: 0.1946445725264169,
          4: 0.21338821490467938,
          5: 0.23076923076923078}

In [23]: sns.barplot(x = np.array(list(count_week.keys())) , y=np.array(list(count_week.values()

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48ddb30b8>
```



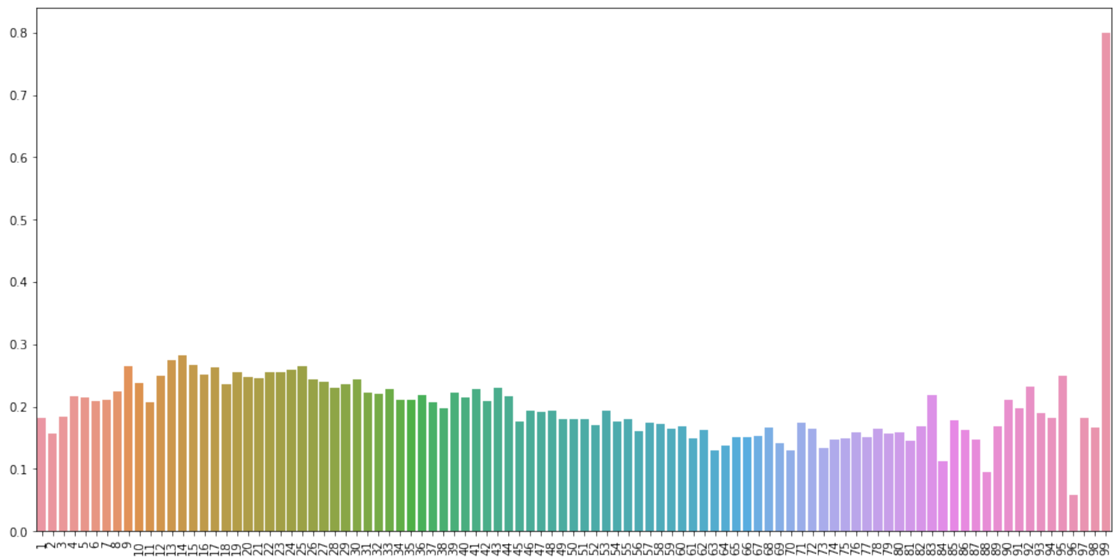
1.4.12 Looks like friday is the day when people miss most appointments but we do not have enough data to support this claim

1.4.13 Analysis based on the age

```
In [24]: count_age = findProb(['Age'], df, True)
```

```
In [25]: fig, ax = plt.subplots(figsize=(16,8))

         sns.barplot(x = np.array(list(count_age.keys())) , y=np.array(list(count_age.values()))
         plt.xticks(rotation=90);
```



1.4.14 Conclusion: People close to 99 are more vulnerable to miss an appointment. Also in the age group of 13-15 they are more likely to miss an appointment

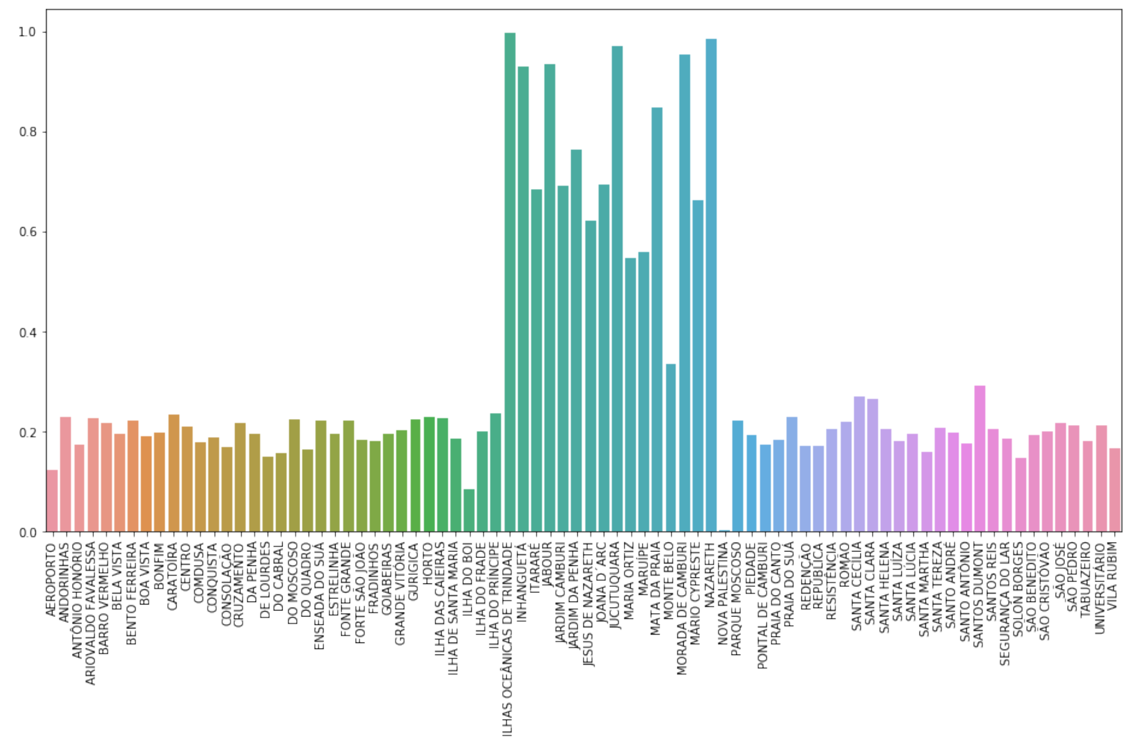
1.4.15 Analysis based on the Neighbourhood

```
In [26]: count_hood = findProb(['Neighbourhood'], df, True)

In [27]: count_hood;

In [28]: fig, ax = plt.subplots(figsize=(16,8))

         sns.barplot(x = np.array(list(count_hood.keys())) , y=np.array(list(count_hood.values()
         plt.xticks(rotation=90);
```



1.4.16 Conclusion People having Appointment in ILHAS OCEÂNICAS DE TRINDADE,

1.4.17 INHANGUETÁ': 0.9311111111111111, 'JABOUR': 0.9344063164287884,

1.4.18 'JARDIM DA PENHA': 0.7651685393258427,'JESUS DE NAZARETH': 0.6227678571428571,

1.4.19 'JOANA Dt'ARC': 0.6940581542351454,'JUCUTUQUARA': 0.9706666666666667

1.4.20 have greater chances of no show.

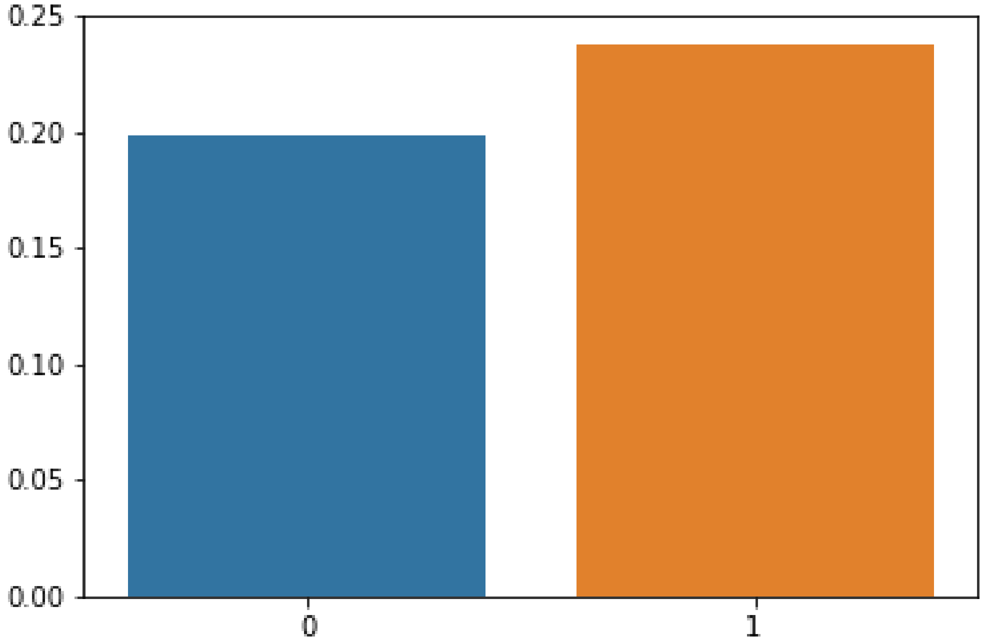
1.4.21 Clearly the Neighbourhood matters a lot

1.4.22 Analysis based on Scholarship

```
In [29]: count_scholar = findProb(['Scholarship'], df, True)


         sns.barplot(x = np.array(list(count_scholar.keys())) , y=np.array(list(count_scholar.va
```

```
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48d644080>
```



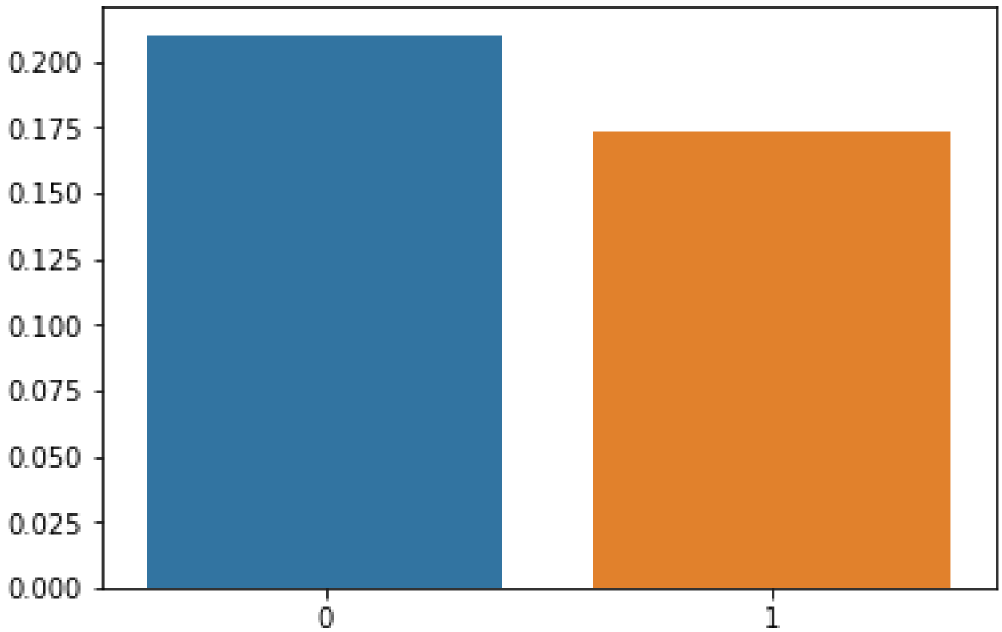
1.4.23 Not much of a difference, people who do not have a scholarship are more likely to not miss an appointment

1.4.24 Analysis based on Various Diseases

In [30]:
```
count_hyper = findProb(['Hipertension'], df, True)


sns.barplot(x = np.array(list(count_hyper.keys())) , y=np.array(list(count_hyper.values
```

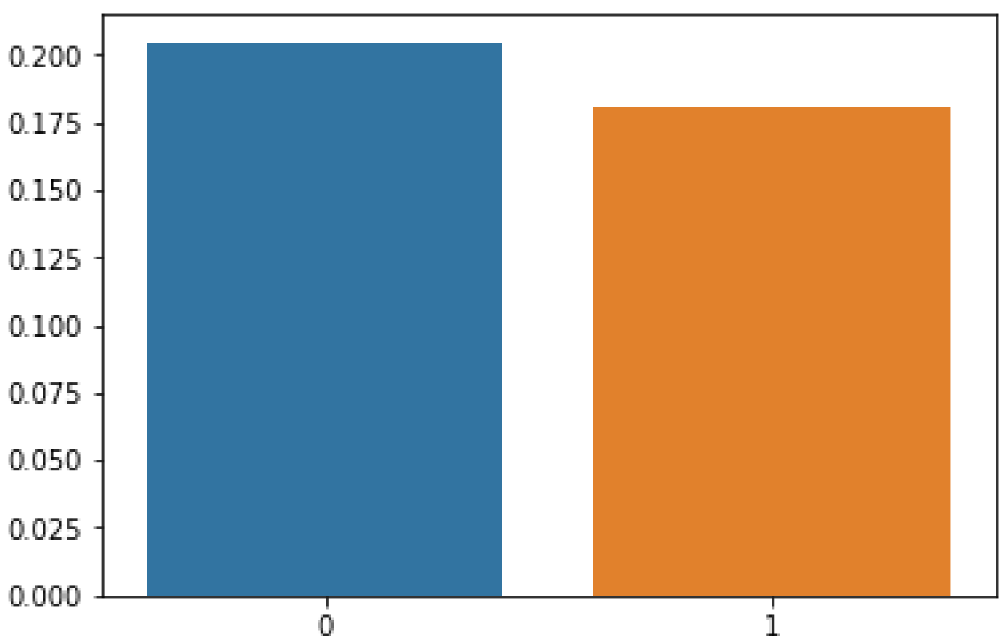
Out[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb48dd39240>
```




```
In [31]: count_dia = findProb(['Diabetes'], df, True)


         sns.barplot(x = np.array(list(count_dia.keys())) , y=np.array(list(count_dia.values()))
```

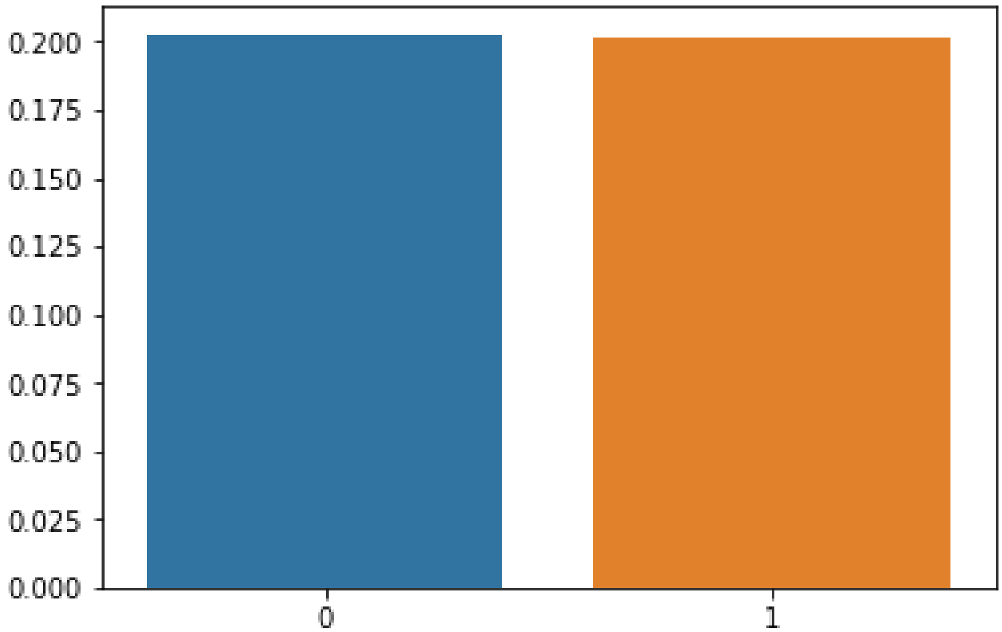
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48dc369e8>



```
In [32]: count_alcohal = findProb(['Alcoholism'], df, True)


         sns.barplot(x = np.array(list(count_alcohal.keys())) , y=np.array(list(count_alcohal.va
```

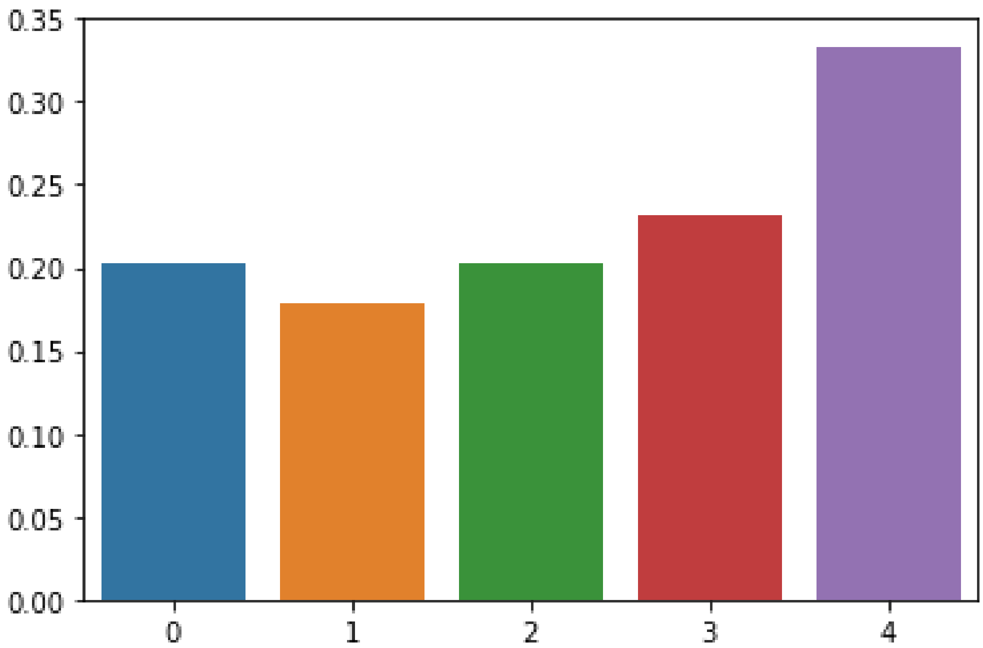
```
Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48db5dda0>
```




```
In [33]: count_handi = findProb(['Handcap'], df, True)


         sns.barplot(x = np.array(list(count_handi.keys())) , y=np.array(list(count_handi.values
```

```
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb48dbf0780>
```



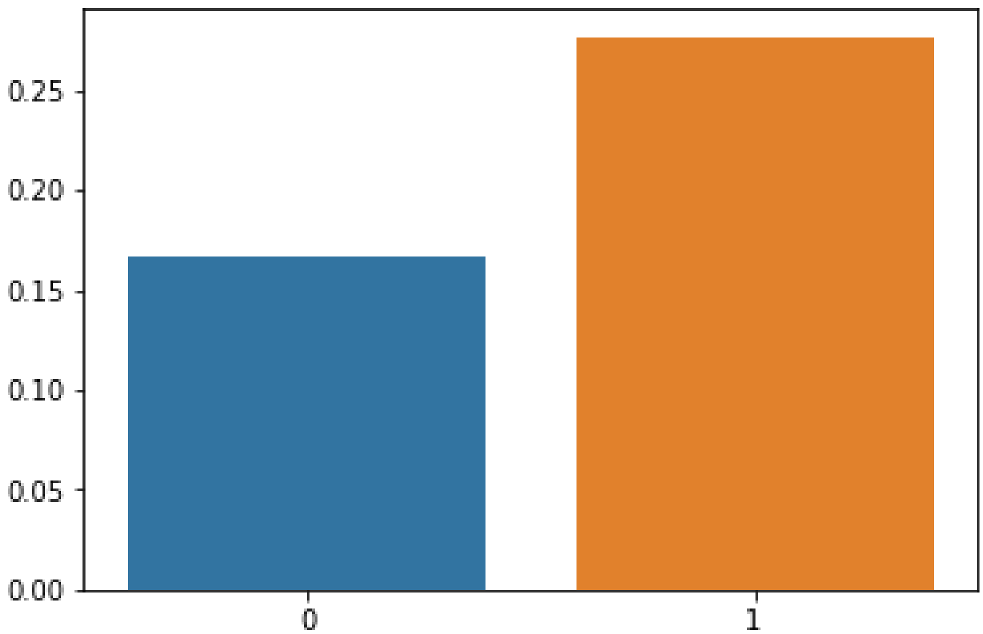
1.4.25 Conclusion: It does not matters for what a person is showing up to doctor but if a person is handicapped in level 4 then there is a 34% probability that he won't show up

1.4.26 Analysis based on the SMS

In [34]:
```
count_sms = findProb(['SMS_received'], df, True)


sns.barplot(x = np.array(list(count_sms.keys())) , y=np.array(list(count_sms.values()))
```

Out[34]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb48d819898>
```



1.4.27 Conclusion: It is so interesting to see that people who did not receive the SMS are less likely to miss an appointment as compared to people who received SMS. There is a probabilty that 28% of the people who received an SMS will not show up. Interesting, I was not expecting this

1.4.28 Finding Correlation between various Variables

```
In [35]: modified_df = df
         modified_df['No-show'] = modified_df['No-show'].map({'Yes':1,'No':0})
         modified_df.corr()
```

```
Out[35]:                     PatientId  AppointmentID       Age  Scholarship  \
         PatientId            1.000000       0.004193 -0.003060    -0.002162
         AppointmentID        0.004193       1.000000 -0.023450     0.022384
         Age                 -0.003060      -0.023450  1.000000    -0.112668
         Scholarship         -0.002162       0.022384 -0.112668     1.000000
         Hipertension        -0.006195       0.012086  0.502307    -0.024534
         Diabetes             0.001882       0.022509  0.290793    -0.027629
         Alcoholism           0.011367       0.033162  0.090461     0.033523
         Handcap             -0.007888       0.014000  0.073400    -0.009824
         SMS_received        -0.008495      -0.254696  0.005332    -0.000019
         No-show             -0.001037      -0.161565 -0.067183     0.029384
         Scheduled_Weekday   -0.001762      -0.006973  0.007592    -0.005592
         Appointment_Weekday -0.001380      -0.051602  0.000526    -0.000778

                             Hipertension  Diabetes  Alcoholism   Handcap  \
```

```
PatientId              -0.006195  0.001882   0.011367 -0.007888
AppointmentID           0.012086  0.022509   0.033162  0.014000
Age                     0.502307  0.290793   0.090461  0.073400
Scholarship            -0.024534 -0.027629   0.033523 -0.009824
Hipertension            1.000000  0.430836   0.085459  0.078377
Diabetes                0.430836  1.000000   0.016870  0.056477
Alcoholism              0.085459  0.016870   1.000000  0.003897
Handcap                 0.078377  0.056477   0.003897  1.000000
SMS_received           -0.008851 -0.016143  -0.027409 -0.025018
No-show                -0.037253 -0.015919  -0.000510 -0.006699
Scheduled_Weekday      -0.000702 -0.001164   0.006252  0.000375
Appointment_Weekday     0.002683  0.006281   0.002460  0.004260

                     SMS_received   No-show  Scheduled_Weekday  \
PatientId              -0.008495 -0.001037          -0.001762
AppointmentID          -0.254696 -0.161565          -0.006973
Age                     0.005332 -0.067183           0.007592
Scholarship            -0.000019  0.029384          -0.005592
Hipertension           -0.008851 -0.037253          -0.000702
Diabetes               -0.016143 -0.015919          -0.001164
Alcoholism             -0.027409 -0.000510           0.006252
Handcap                -0.025018 -0.006699           0.000375
SMS_received            1.000000  0.127300           0.078584
No-show                 0.127300  1.000000           0.006100
Scheduled_Weekday       0.078584  0.006100           1.000000
Appointment_Weekday    -0.092653  0.002076           0.324949

                     Appointment_Weekday
PatientId                      -0.001380
AppointmentID                  -0.051602
Age                             0.000526
Scholarship                    -0.000778
Hipertension                    0.002683
Diabetes                        0.006281
Alcoholism                      0.002460
Handcap                         0.004260
SMS_received                   -0.092653
No-show                         0.002076
Scheduled_Weekday               0.324949
Appointment_Weekday             1.000000
```

1.4.29 Removing ID variables as they not contribute at all in deciding whether a patient will turn up or not

```
In [36]: modified_df.drop(columns=['PatientId', 'AppointmentID'], inplace=True)
```

```
In [37]: modified_df.corr()
```

```
Out[37]:                        Age  Scholarship  Hipertension  Diabetes  \
```

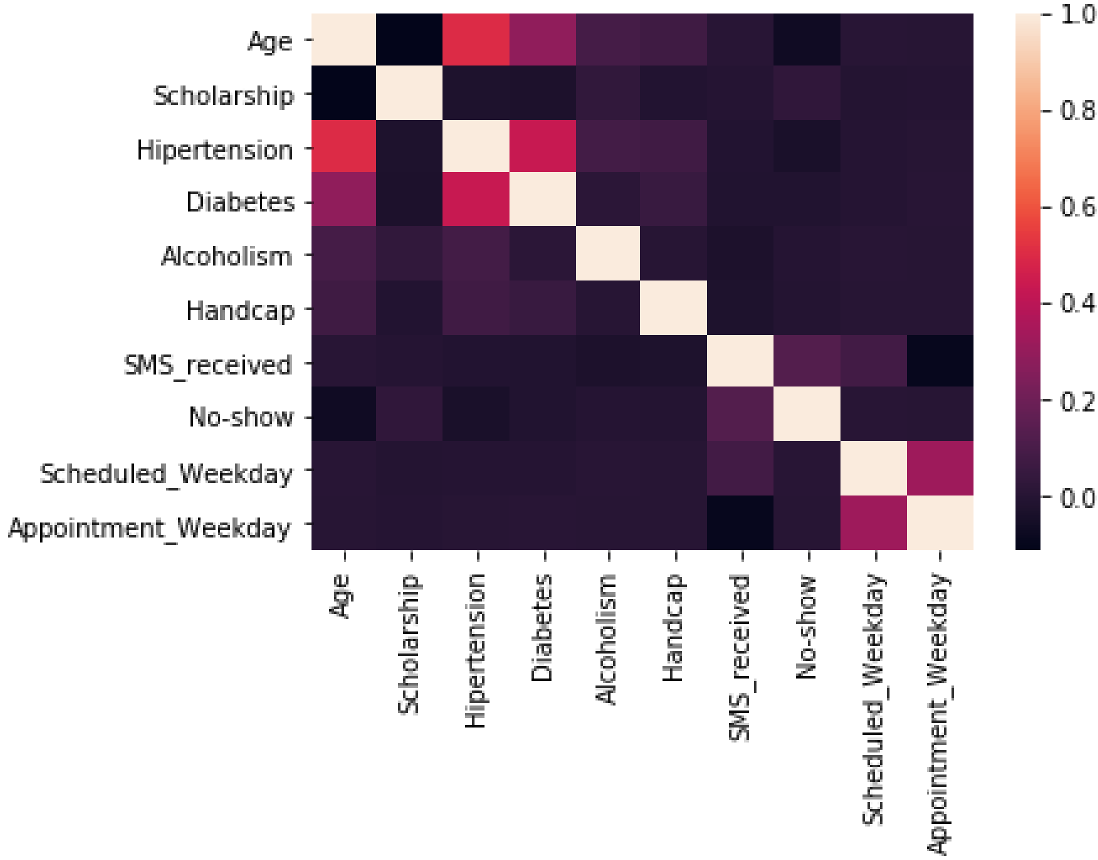
```
Age                  1.000000    -0.112668       0.502307  0.290793
Scholarship         -0.112668     1.000000      -0.024534 -0.027629
Hipertension         0.502307    -0.024534       1.000000  0.430836
Diabetes             0.290793    -0.027629       0.430836  1.000000
Alcoholism           0.090461     0.033523       0.085459  0.016870
Handcap              0.073400    -0.009824       0.078377  0.056477
SMS_received         0.005332    -0.000019      -0.008851 -0.016143
No-show             -0.067183     0.029384      -0.037253 -0.015919
Scheduled_Weekday    0.007592    -0.005592      -0.000702 -0.001164
Appointment_Weekday  0.000526    -0.000778       0.002683  0.006281

                     Alcoholism   Handcap  SMS_received   No-show  \
Age                    0.090461  0.073400      0.005332 -0.067183
Scholarship            0.033523 -0.009824     -0.000019  0.029384
Hipertension           0.085459  0.078377     -0.008851 -0.037253
Diabetes               0.016870  0.056477     -0.016143 -0.015919
Alcoholism             1.000000  0.003897     -0.027409 -0.000510
Handcap                0.003897  1.000000     -0.025018 -0.006699
SMS_received          -0.027409 -0.025018      1.000000  0.127300
No-show               -0.000510 -0.006699      0.127300  1.000000
Scheduled_Weekday      0.006252  0.000375      0.078584  0.006100
Appointment_Weekday    0.002460  0.004260     -0.092653  0.002076

                     Scheduled_Weekday  Appointment_Weekday
Age                           0.007592             0.000526
Scholarship                  -0.005592            -0.000778
Hipertension                 -0.000702             0.002683
Diabetes                     -0.001164             0.006281
Alcoholism                    0.006252             0.002460
Handcap                       0.000375             0.004260
SMS_received                  0.078584            -0.092653
No-show                       0.006100             0.002076
Scheduled_Weekday             1.000000             0.324949
Appointment_Weekday           0.324949             1.000000
```

In [38]:
```
sns.heatmap(modified_df.corr())
```

Out[38]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb48d56e7f0>
```

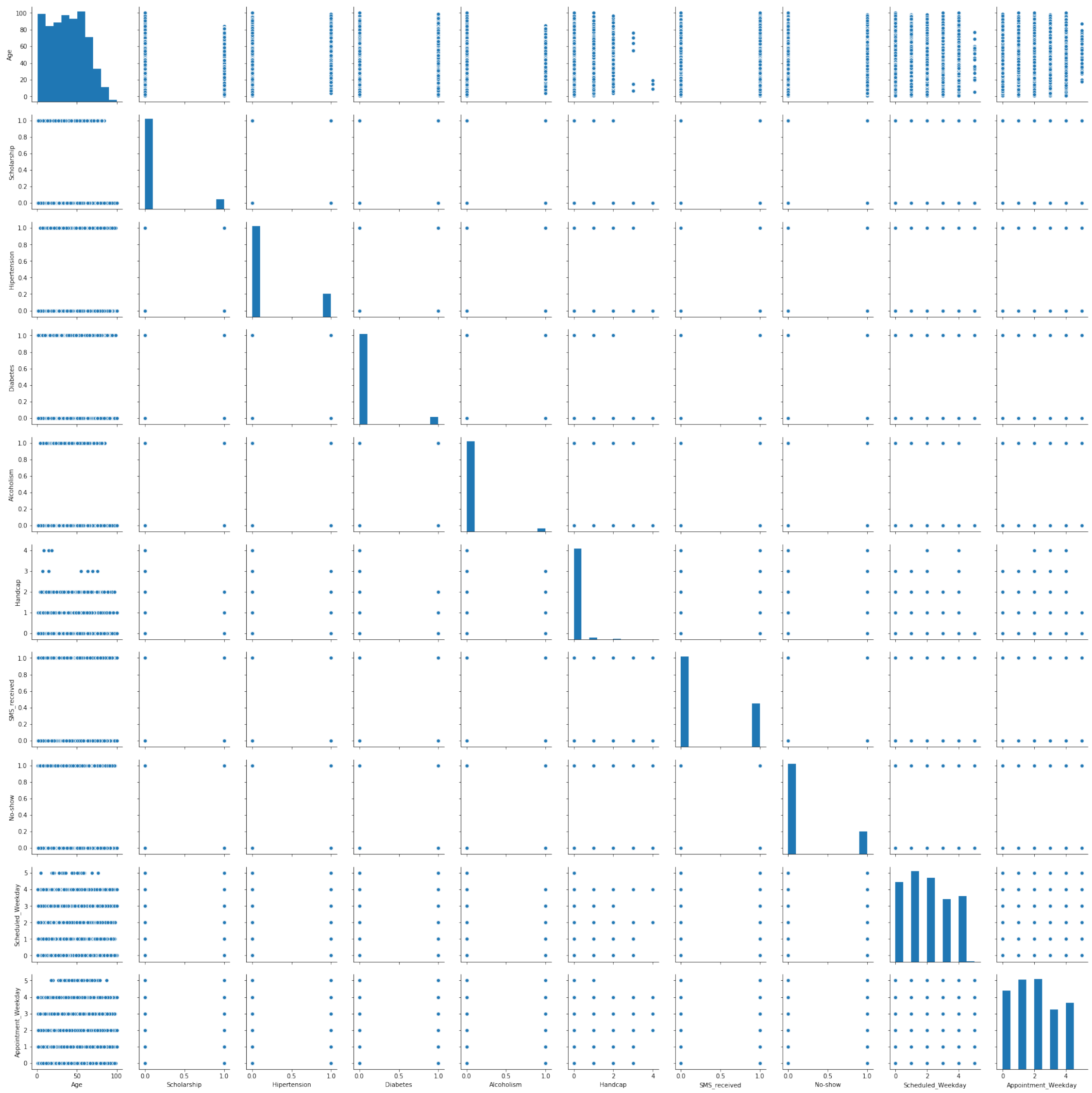


1.4.30 Conclusion: It turns out that Hypertension and Diabetes are closely related to each other

1.4.31 Also Hypertension and Age have a positive correlation which means that as the person gets old, he has 50 %chance of getting Hypertension

```
In [39]: sns.pairplot(modified_df)

Out[39]: <seaborn.axisgrid.PairGrid at 0x7fb48d56e3c8>
```


Age
Scholarship
Hipertension
Diabetes
Alcoholism
Handcap
SMS_received
No-show
Scheduled_Weekday
Appointment_Weekday