Kaggle-No-show-Analysis

January 22, 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 [64]: df = pd.read_csv('data.csv', parse_dates=['ScheduledDay', 'AppointmentDay'])
         df.head()
```

```
Out[64]:       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 [65]: df.describe()

```
Out[65]:          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 [66]: df.info()

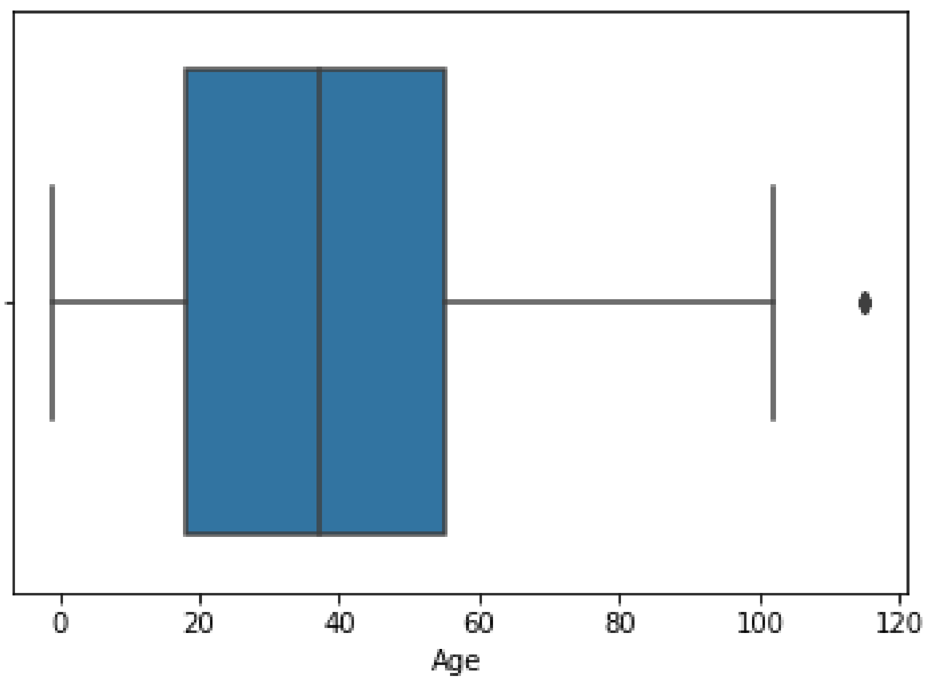
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
PatientId         110527 non-null float64
AppointmentID     110527 non-null int64
Gender            110527 non-null object
ScheduledDay      110527 non-null datetime64[ns]
AppointmentDay    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 [67]: sns.boxplot(df['Age'])
```

```
Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb481715f60>
```




```
In [68]: 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 [69]: def findProb(groupby ,  df, return_dict=False):
```

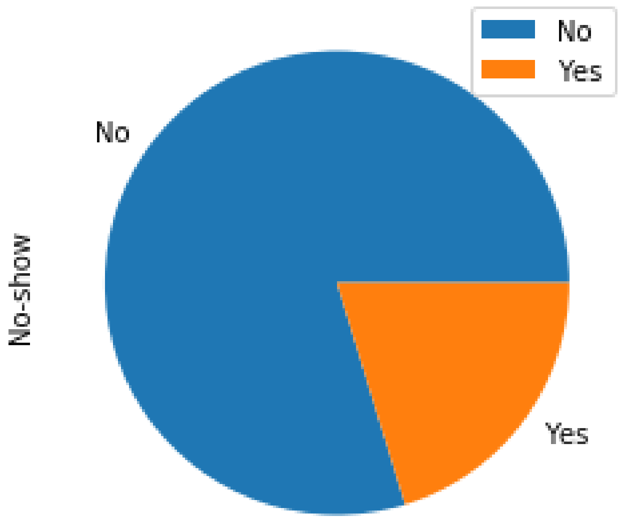
```
        groupby.append('No-show')
        lst = []
        lst_key= {}
        df_temp = df.groupby(groupby).count()
        #print(df_temp)
        for i in range(0,len(df_temp),2):
            #print(df_temp['PatientId'][i+1] , df_temp['PatientId'][i])
            #print(df_temp.index[i][0])
 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

```
In [70]: df_count = df['No-show'].value_counts()
         df_count
```

```
Out[70]: No     85303
         Yes    21677
         Name: No-show, dtype: int64
```

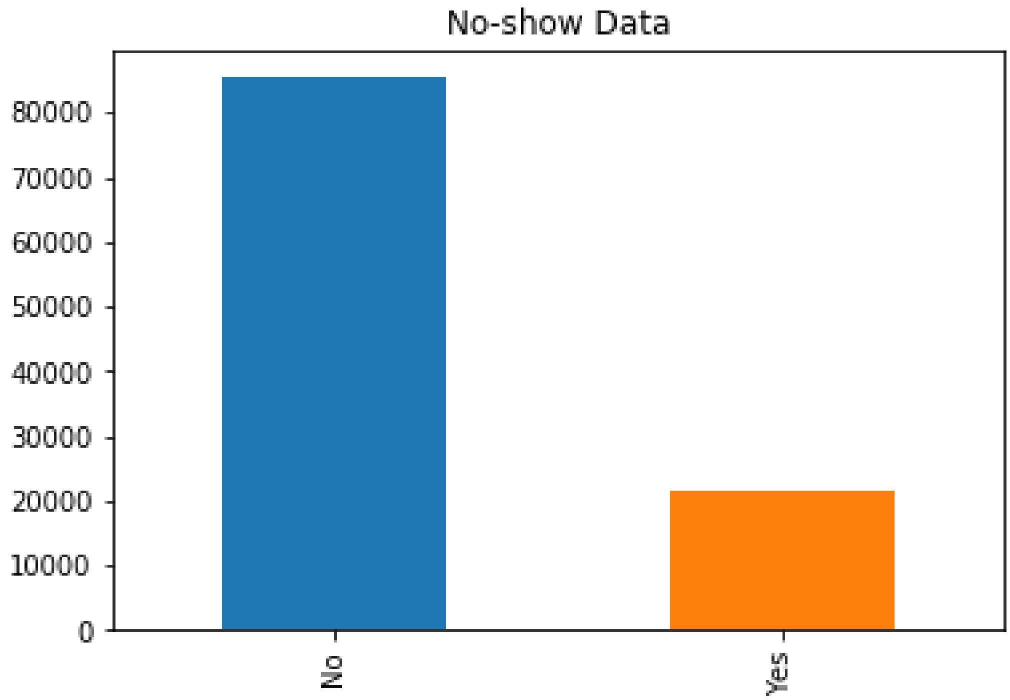
```
In [71]: df_count.plot(kind='pie', legend=True, figsize=(4,4))
```

```
Out[71]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb47fa60ef0>
```




```
In [72]: df_count.plot(kind='bar',title="No-show Data")
```

Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb4816a59e8>



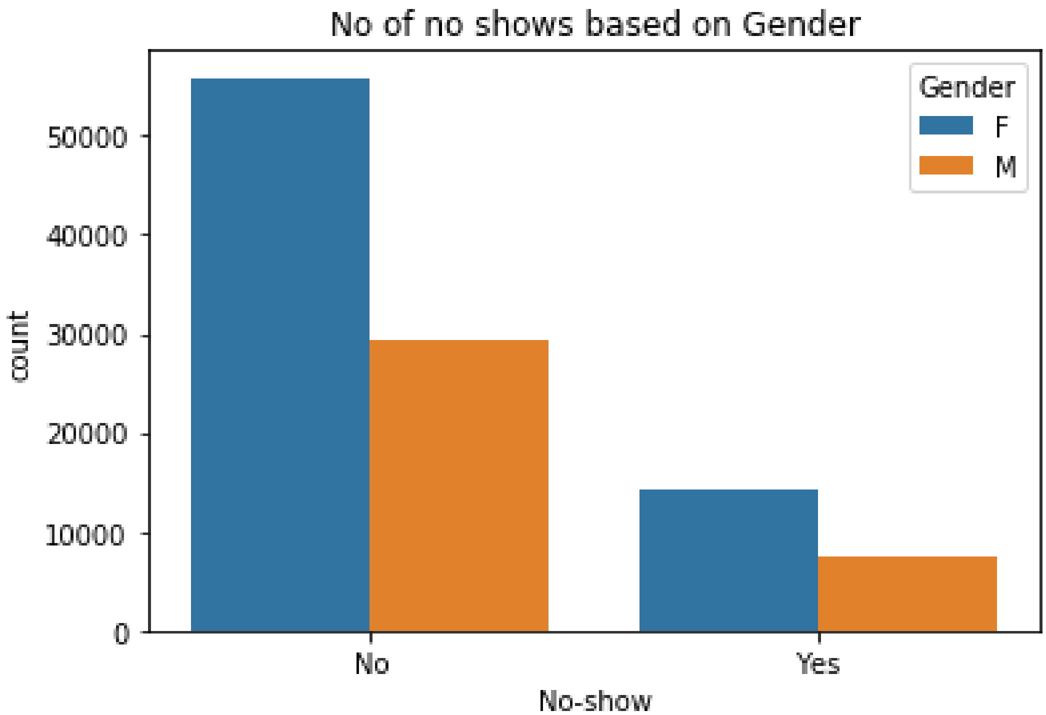
1.4.2 Analysis based on Gender

```
In [73]: count_gender = findProb(['Gender'],df, True)
```

1.4.3 Women see doctor more often than men

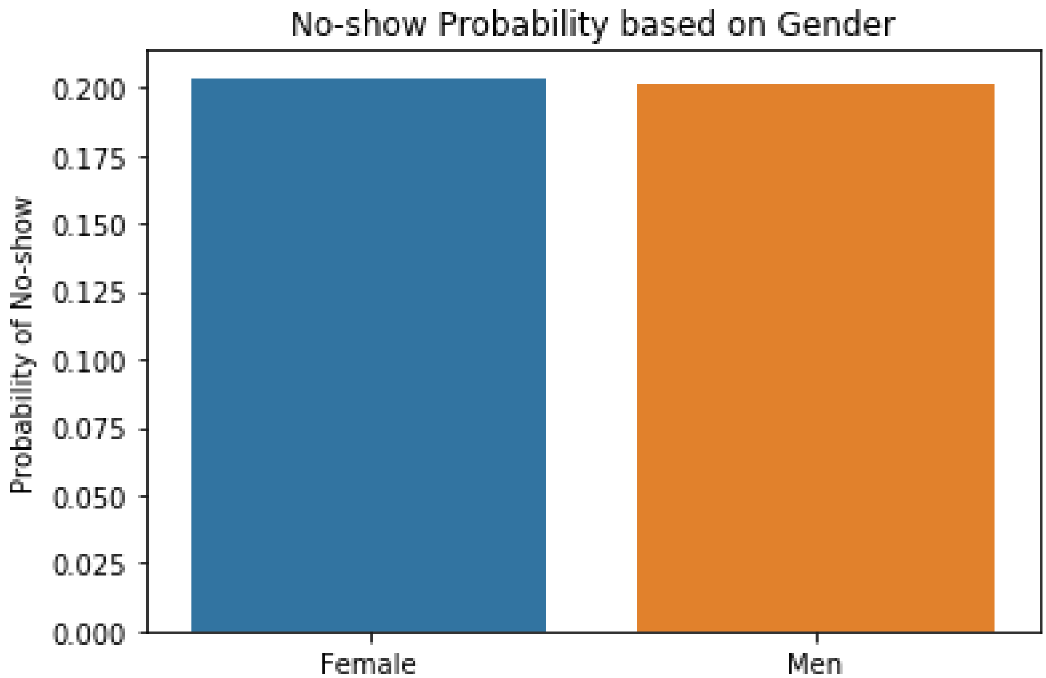
```
In [74]: sns.countplot(df['No-show'], hue=df['Gender'])
         plt.title('No of no shows based on Gender')
```

```
Out[74]: Text(0.5, 1.0, 'No of no shows based on Gender')
```



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

```
In [75]: sns.barplot(x= ['Female','Men'], y = np.array(list(count_gender.values())))
         plt.title('No-show Probability based on Gender');
         plt.ylabel('Probability of No-show');
```



1.4.5 Conclusion: Not related to gender any ways

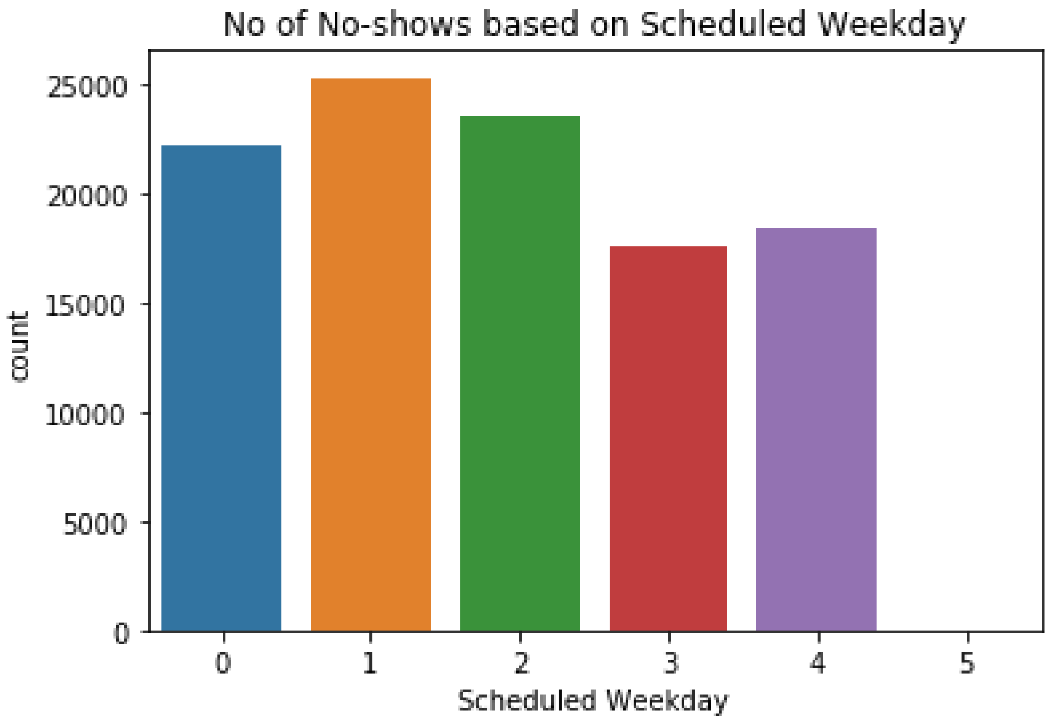
1.4.6 Analysis based on the day of the week Appointment was scheduled

```
In [76]: weekday = []
         for i in enumerate(df.ScheduledDay):
             weekday.append(i[1].weekday())
```

```
In [77]: df["Scheduled_Weekday"] = weekday
```

1.4.7 Most of the appointments are scheduled on Tuesday

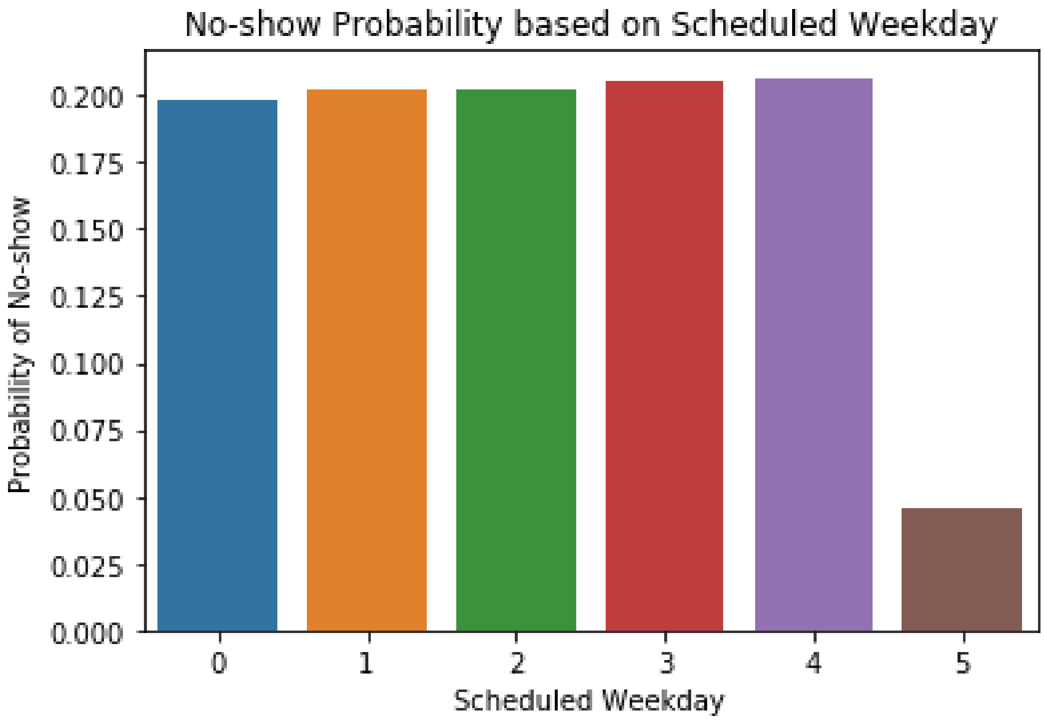
```
In [78]: sns.countplot( df['Scheduled_Weekday'])
         plt.title('No of No-shows based on Scheduled Weekday')
         plt.xlabel('Scheduled Weekday')

Out[78]: Text(0.5, 0, 'Scheduled Weekday')
```




```
In [79]: count = findProb(['Scheduled_Weekday'] ,df, True)
```

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

```
In [80]: sns.barplot(x= np.array(list(count.keys())), y = np.array(list(count.values())))
         plt.title('No-show Probability based on Scheduled Weekday');
         plt.xlabel('Scheduled Weekday')
         plt.ylabel('Probability of No-show');
```



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

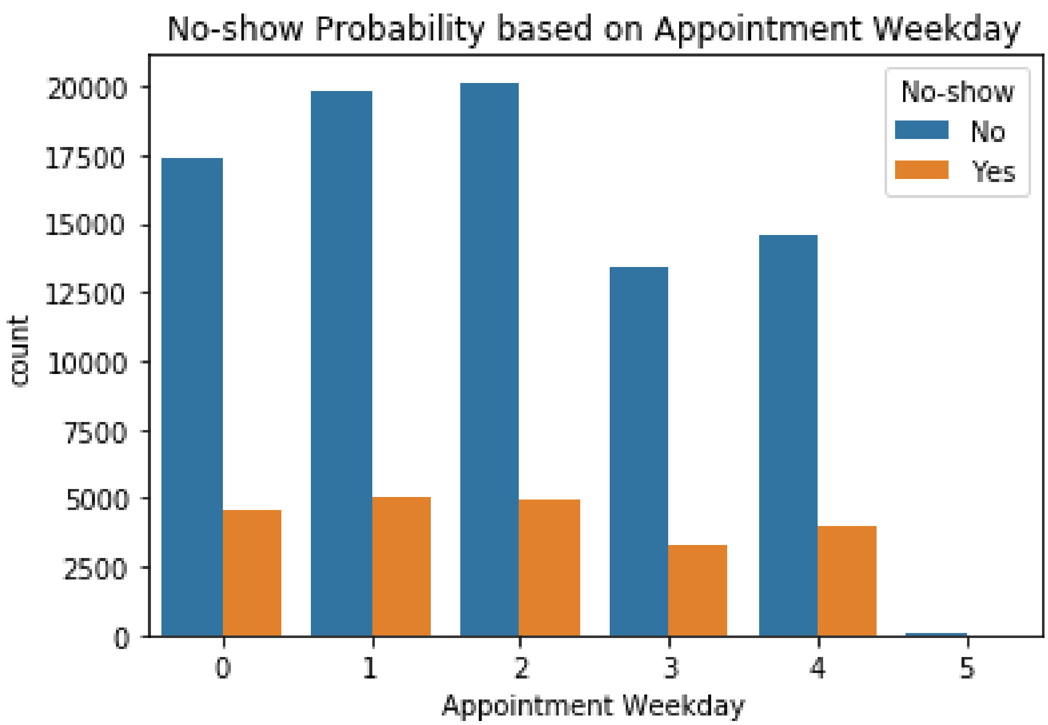
1.4.10 Analysis based on the day of the week Actual Appointment was scheduled

```
In [81]: weekday_a = []
         for i in enumerate(df.AppointmentDay):
             weekday_a.append(i[1].weekday())
```

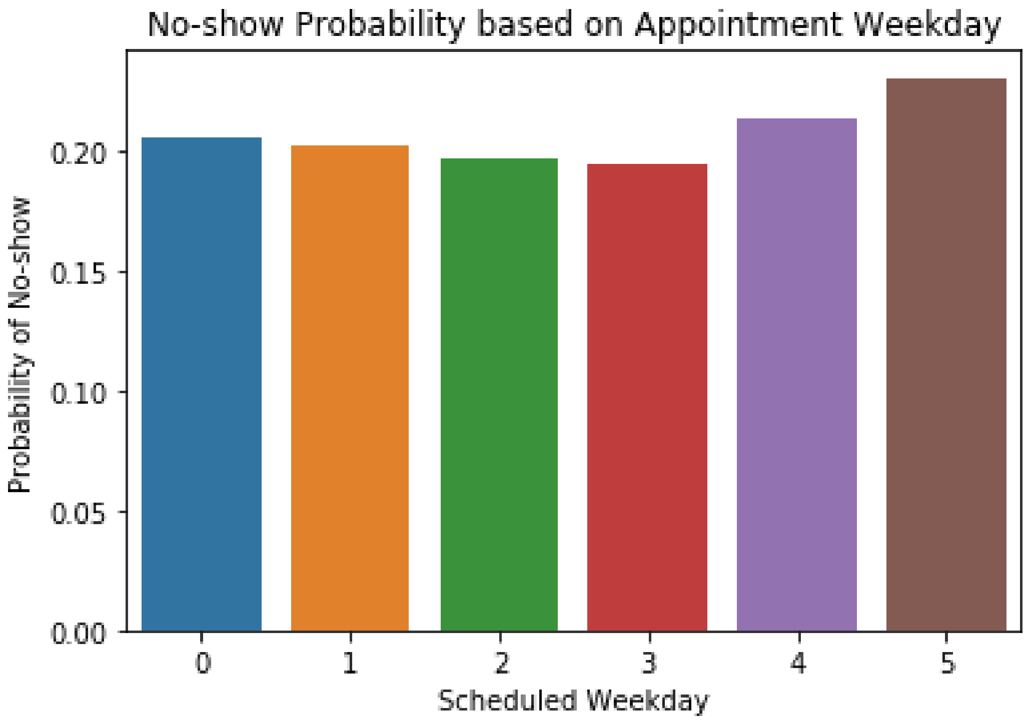
```
In [82]: df['Appointment_Weekday'] = weekday_a
```

1.4.11 Most of the appointments are scheduled on Tuesday, Wednesday

```
In [105]: sns.countplot( df['Appointment_Weekday'], hue=df['No-show'])

          plt.title('No-show Probability based on Appointment Weekday');
          plt.xlabel('Appointment Weekday');
```




```
In [84]: count_week = findProb(['Appointment_Weekday'], df, True)
         count_week

Out[84]: {0: 0.20610931007716543,
          1: 0.20233588401127667,
          2: 0.1972100438421682,
          3: 0.1946445725264169,
          4: 0.21338821490467938,
          5: 0.23076923076923078}

In [85]: sns.barplot(x = np.array(list(count_week.keys())) , y=np.array(list(count_week.values()
         plt.title('No-show Probability based on Appointment Weekday');
         plt.xlabel('Scheduled Weekday')
         plt.ylabel('Probability of No-show');
```



1.4.12 Looks like Saturday 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 [86]: count_age = findProb(['Age'], df, True)
```

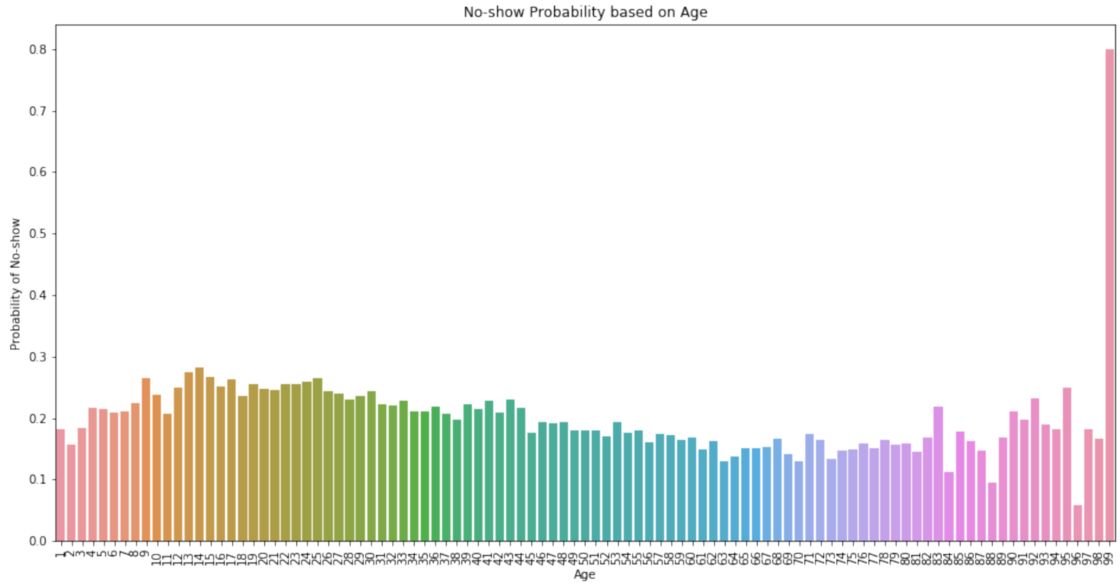
```
In [87]: count_age
```

```
Out[87]: {1: 0.1825780906291245,
          2: 0.1557478368355995,
          3: 0.1830799735624587,
          4: 0.21709006928406466,
          5: 0.21490933512424445,
          6: 0.20775805391190005,
          7: 0.2109320252277505 4,
          8: 0.22331460674157302,
          9: 0.2653061224489796,
          10: 0.23861852433281006,
          11: 0.20669456066945607,
          12: 0.2490842490842491,
          13: 0.2747053490480508,
          14: 0.2826475849731664,
          15: 0.2658959537572254,
```

```
16: 0.25178316690442226,
17: 0.2624254473161034,
18: 0.23537323470073973,
19: 0.2550161812297735,
20: 0.24704244954766874,
21: 0.24449035812672176,
22: 0.2550872093023256,
23: 0.2542624166048925,
24: 0.2584541062801932,
25: 0.26426426426426425,
26: 0.24318004676539362,
27: 0.23892519970951343,
28: 0.2292817679558011,
29: 0.23521026372059872,
30: 0.24260355029585798,
31: 0.22237665045170257,
32: 0.21993355481727575,
33: 0.2283464566929134,
34: 0.21100917431192662,
35: 0.20972423802612483,
36: 0.21772151898734177,
37: 0.20678408349641225,
38: 0.19643953345610804,
39: 0.22135416666666666,
40: 0.21469329529243938,
41: 0.2288261515601783,
42: 0.20833333333333334,
43: 0.22991071428571427,
44: 0.2172158708809684,
45: 0.17549896765313144,
46: 0.19383561643835617,
47: 0.1915351506456241,
48: 0.1937097927090779,
49: 0.18038740920096852,
50: 0.18040917544947302,
51: 0.18059987236758138,
52: 0.17010309278350516,
53: 0.19321623258631132,
54: 0.17516339869281045,
55: 0.18035087719298246,
56: 0.16085626911314985,
57: 0.17342482844666252,
58: 0.17222600408441116,
59: 0.1644088669950739,
60: 0.16725726435152374,
61: 0.14892032762472077,
62: 0.16158536585365854,
63: 0.13027656477438138,
```

```
 64: 0.13673929376408714,
 65: 0.1516802906448683,
 66: 0.15080033698399326,
 67: 0.15210688591983557,
 68: 0.16699604743083005,
 69: 0.14182692307692307,
 70: 0.1298342541436464,
 71: 0.17410071942446043,
 72: 0.16422764227642275,
 73: 0.13241379310344828,
 74: 0.1478405315614618,
 75: 0.1488970588235294,
 76: 0.159369527145359,
 77: 0.14990512333965844,
 78: 0.1645101663585952,
 79: 0.1564102564102564,
 80: 0.15851272015655576,
 81: 0.14516129032258066,
 82: 0.1683673469387755,
 83: 0.21785714285714286,
 84: 0.11254019292604502,
 85: 0.1781818181818182,
 86: 0.16153846153846155,
 87: 0.14673913043478262,
 88: 0.09523809523809523,
 89: 0.1676300578034682,
 90: 0.21100917431192662,
 91: 0.19696969696969696,
 92: 0.23255813953488372,
 93: 0.18867924528301888,
 94: 0.18181818181818182,
 95: 0.25,
 96: 0.058823529411764705,
 97: 0.18181818181818182,
 98: 0.16666666666666666,
 99: 0.8}
```

In [88]:
```
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);
plt.title('No-show Probability based on Age');
plt.xlabel('Age')
plt.ylabel('Probability of No-show');
```



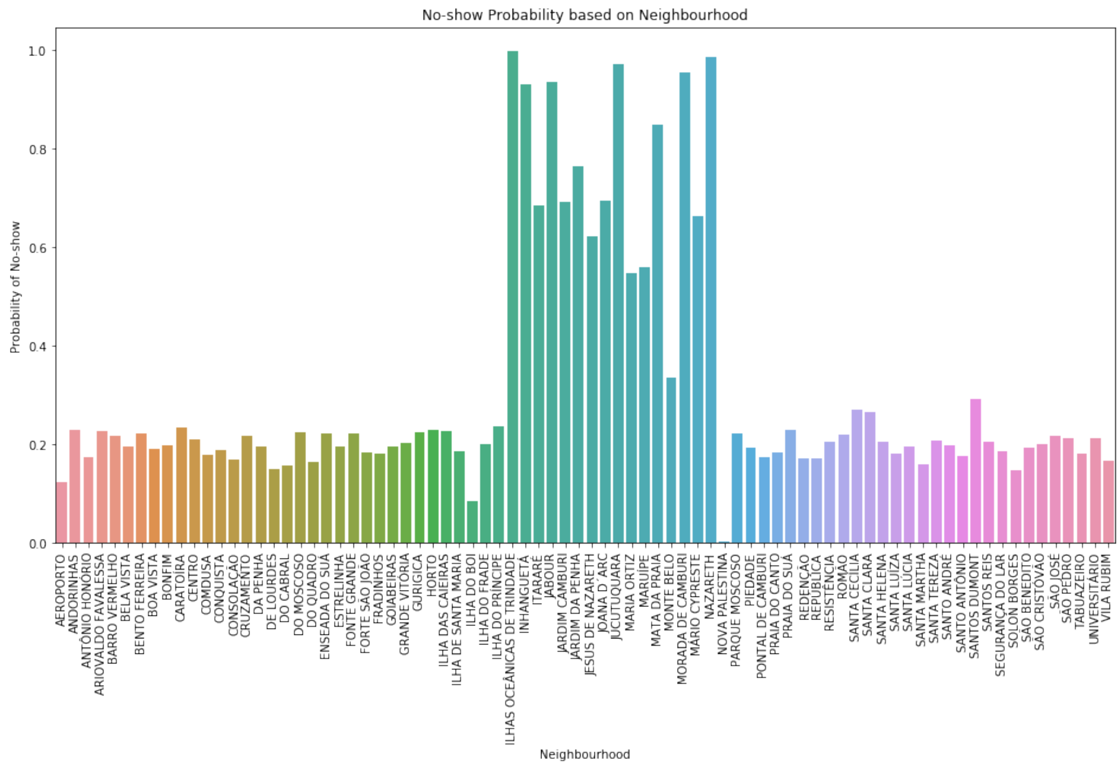
1.4.14 Conclusion: People close to 99 are more vulnerable to miss an appointment but there is only one record to support this claim, hence not a valid conclusion. Also in the age group of 13-17 and 22-25 they are more likely to miss an appointment

1.4.15 Analysis based on the Neighbourhood

```
In [89]: count_hood = findProb(['Neighbourhood'], df, True)
```

```
In [90]: count_hood;
```

```
In [91]: 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);
         plt.title('No-show Probability based on Neighbourhood');
         plt.xlabel('Neighbourhood')
         plt.ylabel('Probability of No-show');
```



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,

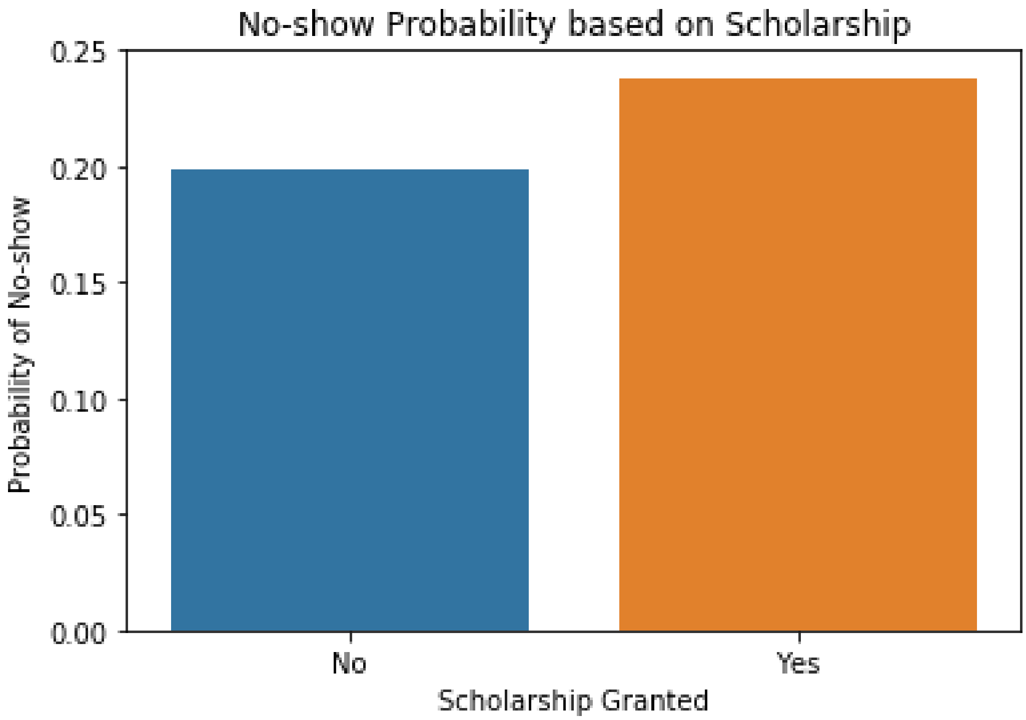
1.4.19 'JOANA Dť'ARC': 0.6940581542351454,'JUCUTUQUARA': 0.9706666666666667

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 [92]: count_scholar = findProb(['Scholarship'], df, True)


         sns.barplot(x = ['No','Yes'] , y=np.array(list(count_scholar.values())))
         plt.title('No-show Probability based on Scholarship');
         plt.xlabel('Scholarship Granted')
         plt.ylabel('Probability of No-show');
```



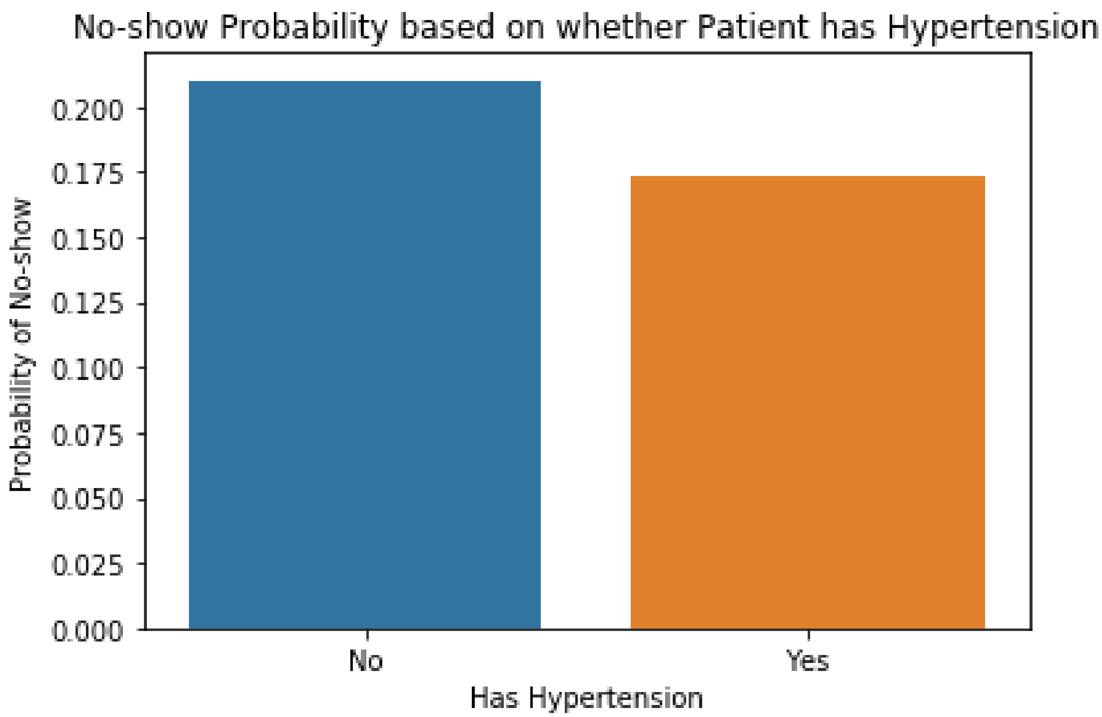
In [101]:
```
df.groupby('Scholarship').count()
```

Out[101]:
```
             PatientId  AppointmentID  Gender  ScheduledDay  AppointmentDay  \
Scholarship
0                96171          96171   96171         96171           96171
1                10809          10809   10809         10809           10809

               Age  Neighbourhood  Hipertension  Diabetes  Alcoholism  \
Scholarship
0            96171          96171         96171     96171       96171
1            10809          10809         10809     10809       10809

             Handcap  SMS_received  No-show  Scheduled_Weekday  \
Scholarship
0              96171         96171    96171              96171
1              10809         10809    10809              10809

             Appointment_Weekday
Scholarship
0                          96171
1                          10809
```

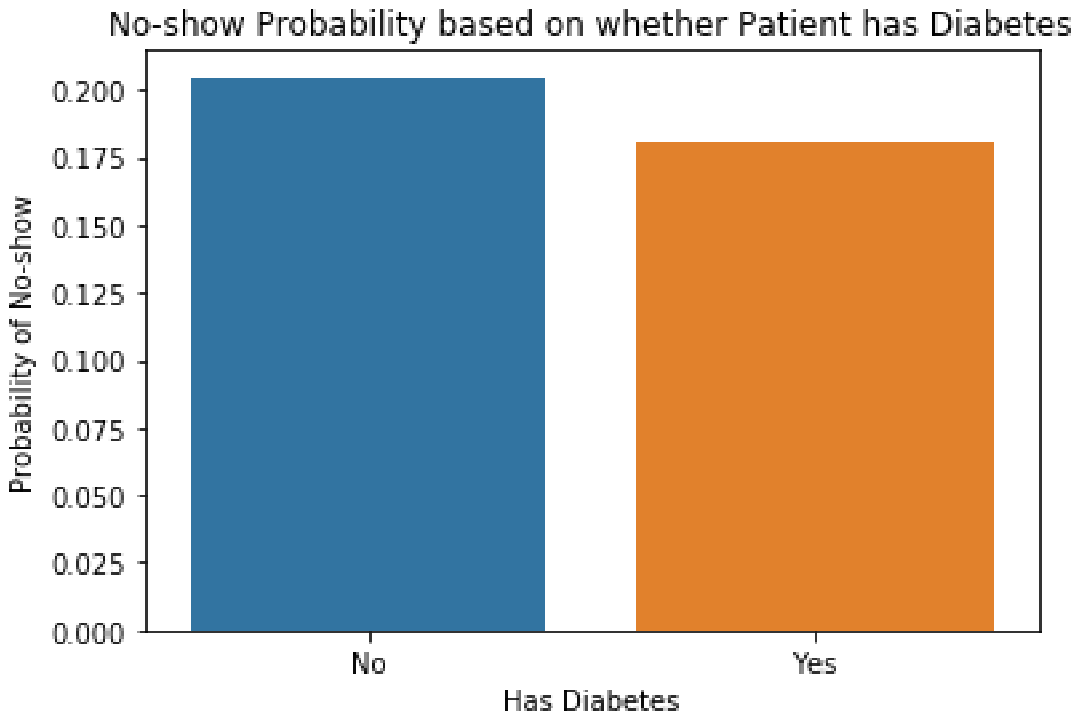
1.4.23 Not much of a difference, people who do not have a scholarship are more likely to not miss an appointment

1.4.24 Analysis based on Various Diseases

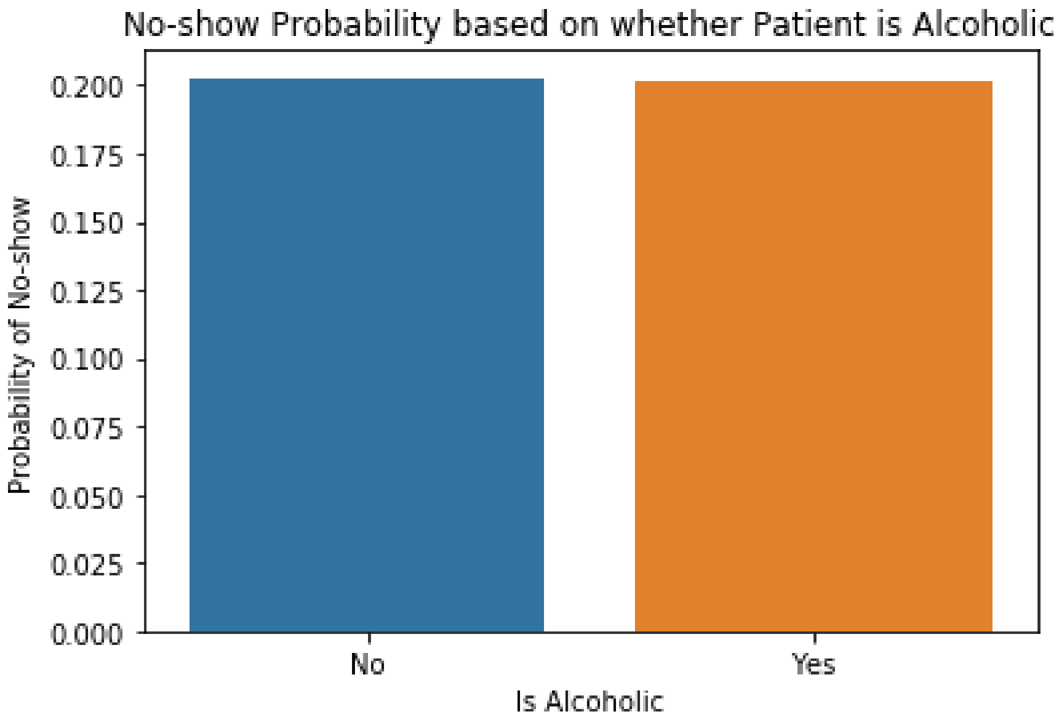
In [94]:
```
count_hyper = findProb(['Hipertension'], df, True)


sns.barplot(x = ['No','Yes'], y=np.array(list(count_hyper.values())))
plt.title('No-show Probability based on whether Patient has Hypertension');
plt.xlabel('Has Hypertension')
plt.ylabel('Probability of No-show');
```



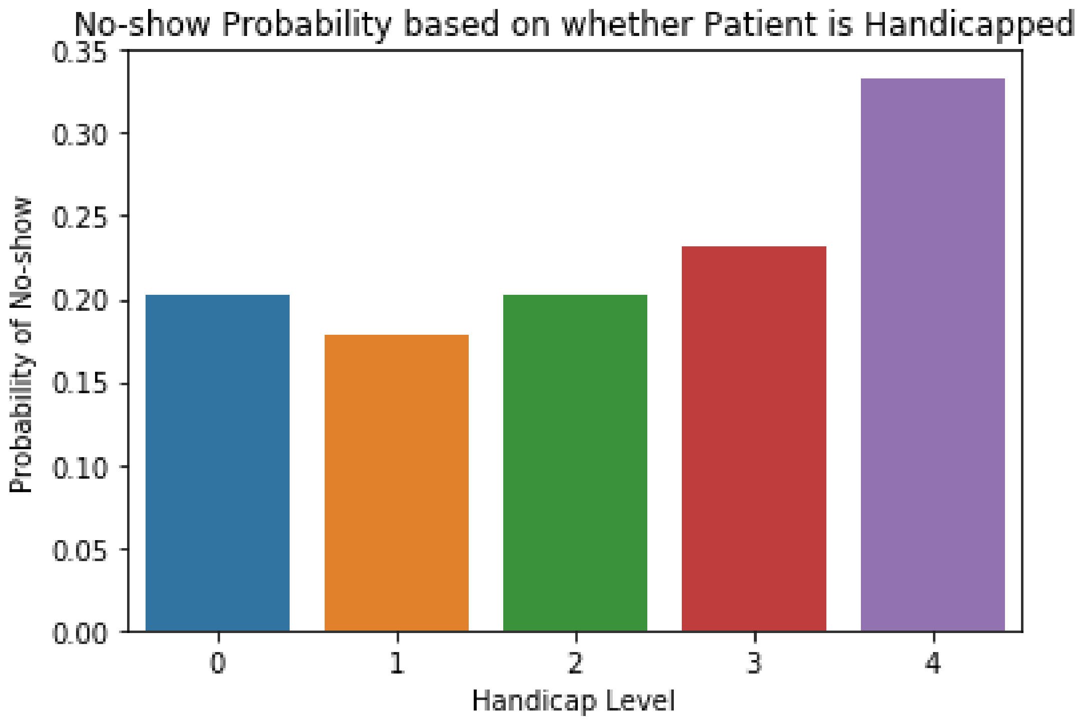
In [97]:
```
count_dia = findProb(['Diabetes'], df, True)


sns.barplot(x =['No', 'Yes'] , y=np.array(list(count_dia.values())))
plt.title('No-show Probability based on whether Patient has Diabetes');
plt.xlabel('Has Diabetes')
plt.ylabel('Probability of No-show');
```



In [96]:
```
count_alcohal = findProb(['Alcoholism'], df, True)


sns.barplot(x = ['No', 'Yes'] , y=np.array(list(count_alcohal.values())))
plt.title('No-show Probability based on whether Patient is Alcoholic');
plt.xlabel('Is Alcoholic')
plt.ylabel('Probability of No-show');
```




```
In [98]: count_handi = findProb(['Handcap'], df, True)


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

         plt.title('No-show Probability based on whether Patient is Handicapped');
         plt.xlabel('Handicap Level')
         plt.ylabel('Probability of No-show');
```



In [100]: df.groupby('Handcap').count()

Out[100]:

Handcap	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay
0	104744	104744	104744	104744	104744
1	2037	2037	2037	2037	2037
2	183	183	183	183	183
3	13	13	13	13	13
4	3	3	3	3	3

Handcap	Age	Neighbourhood	Scholarship	Hipertension	Diabetes
0	104744	104744	104744	104744	104744
1	2037	2037	2037	2037	2037
2	183	183	183	183	183
3	13	13	13	13	13
4	3	3	3	3	3

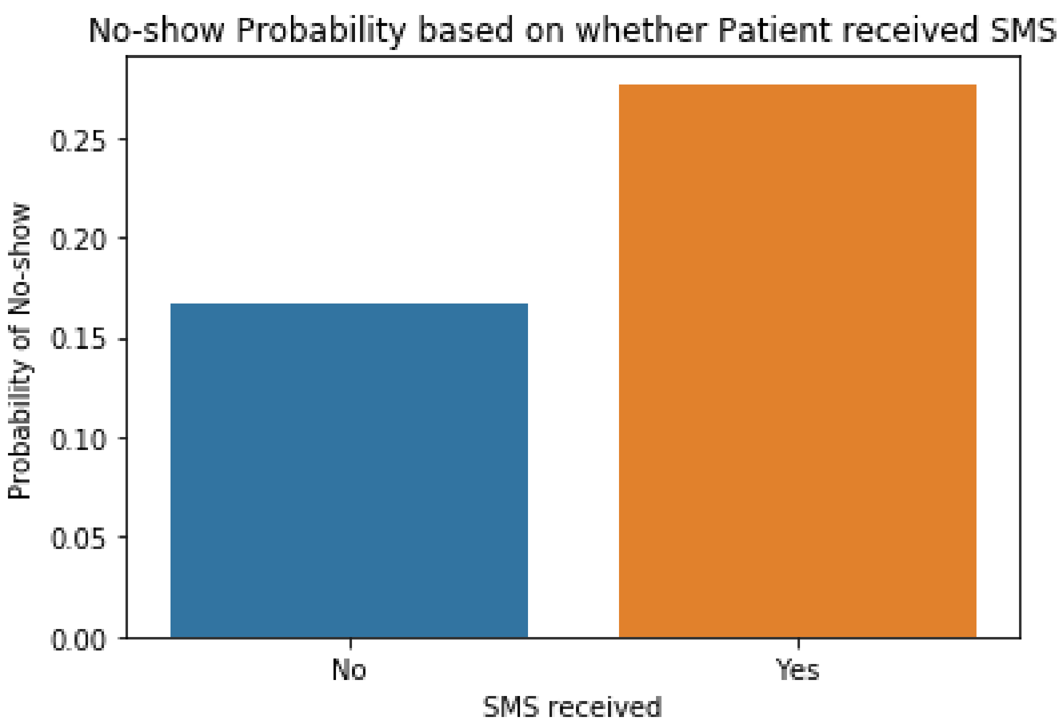
Handcap	Alcoholism	SMS_received	No-show	Scheduled_Weekday
0	104744	104744	104744	104744
1	2037	2037	2037	2037
2	183	183	183	183
3	13	13	13	13

```
4                  3             3        3                   3

         Appointment_Weekday
Handcap
0                     104744
1                       2037
2                        183
3                         13
4                          3
```

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 but we do not have enough data to support this claim

1.4.26 Analysis based on the SMS

```
In [102]: count_sms = findProb(['SMS_received'], df, True)


          sns.barplot(x = ['No', 'Yes'] , y=np.array(list(count_sms.values())))

          plt.title('No-show Probability based on whether Patient received SMS');
          plt.xlabel('SMS received')
          plt.ylabel('Probability of No-show');
```



```
In [103]: df.groupby('SMS_received').count()
```

```
Out[103]:               PatientId  AppointmentID  Gender  ScheduledDay  AppointmentDay  \
          SMS_received
          0                 72396          72396   72396         72396           72396
          1                 34584          34584   34584         34584           34584

                          Age  Neighbourhood  Scholarship  Hipertension  Diabetes  \
          SMS_received
          0             72396          72396        72396         72396     72396
          1             34584          34584        34584         34584     34584

                        Alcoholism  Handcap  No-show  Scheduled_Weekday  \
          SMS_received
          0                  72396    72396    72396              72396
          1                  34584    34584    34584              34584

                        Appointment_Weekday
          SMS_received
          0                           72396
          1                           34584
```

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)
```

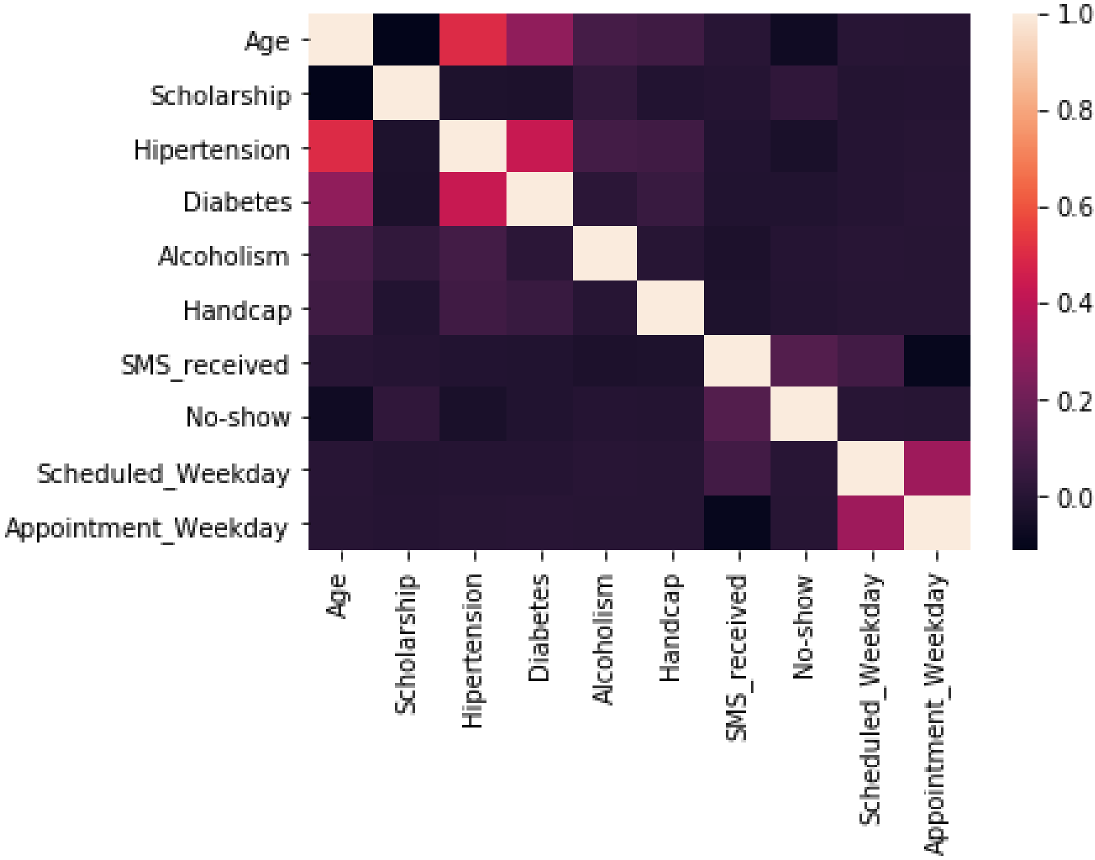
In [37]:
```
modified_df.corr()
```

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>
```

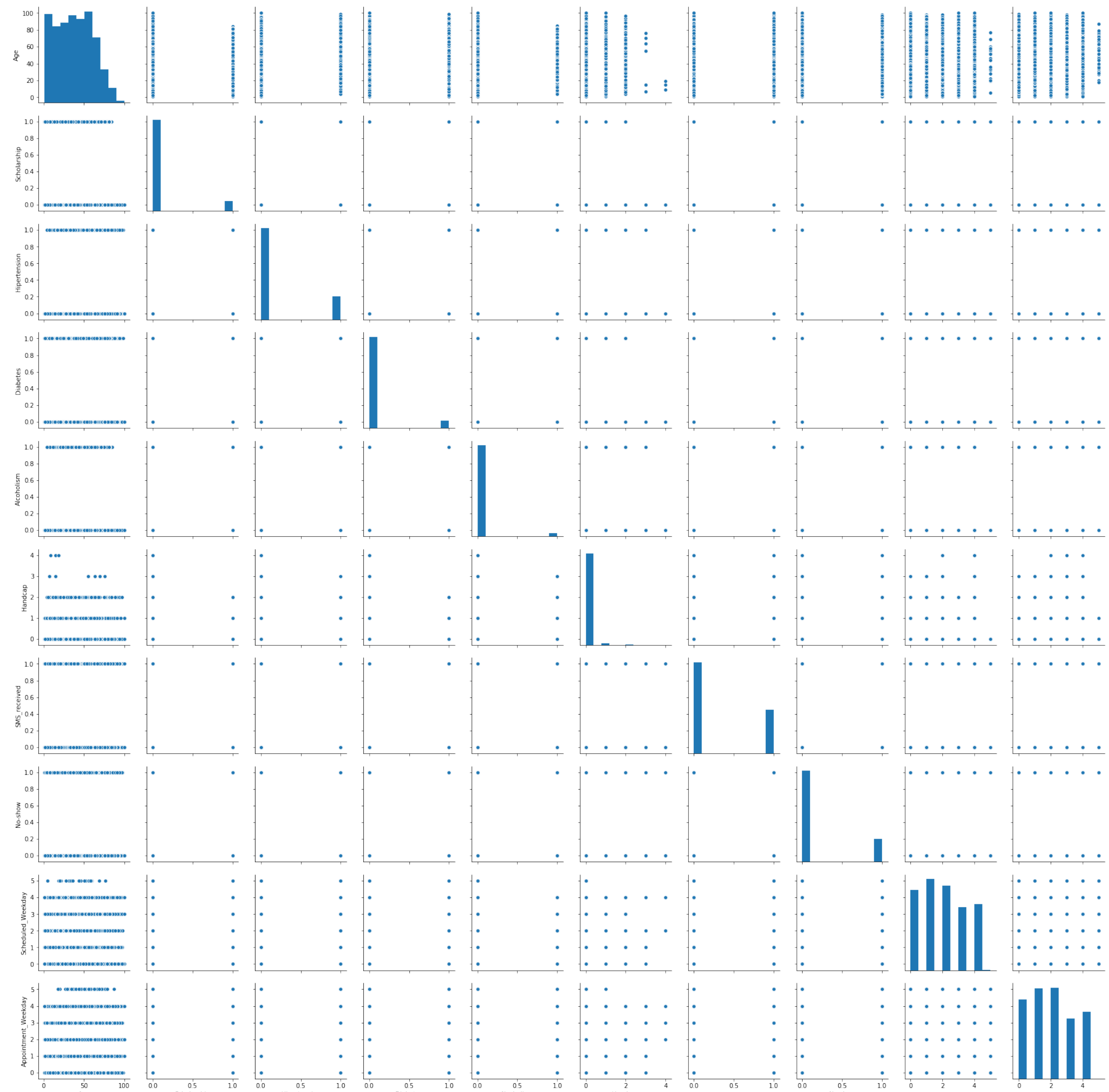


1.4.30 Conclusion: It turns out that Hypertension and Diabetes are closely related to each other

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>
```



1.5 Step 4: Conclusions and Limitations

Limitations:

1. The dataset is not balanced with respect to No-show labels. That is the dataset containes currently 25% people who did not show up on appointment. It is good if we have dataset balanced in equal propotions i.e. 50% each for show and Non-show

2. To understand this problem more on gender basis, the dataset is not balanced. It is clear from here that women show doctores more often than men but until the dataset is balanced it does not provides the clear picture.

Conclusions:

Without Limitations: 1. People tend to miss more appointments on weekends i.e. Fridays. 2. People in the age group 13-17 and 22-25 are more likely to miss appointments 3. There are >75% chances that People having Appointments in ILHAS OCEÂNICAS DE TRINDADE, INHANGUETÁ, JABOUR, JARDIM DA PENHA, JESUS DE NAZARETH, JOANA Dt’ARC , JUCUTUQUARA will not show up 4. People who have scholarhsips tend to miss appointments more than people who don’t have 5. People who have no hypertension are more likely to miss appointment than people who have. 6. People who have not received SMS are more likely to show up than the people who received SMS!!

With Limitations:

1. Women see more often than men, but gender does no contributes in any case if the person will show up or not
2. Most of the appointments are scheduled on Tuesday but the weekday of scheduling does not directly relates to No-show. Although on If Scheduled on Friday there are less chances of Cancellation but this is not conclusive as we don’t have enough data
3. There asre greater chances that people don’t turn up on Friday’s and Saturday but we don’t have enough data to prove for Saturday.
4. People of age 99 miss the appointment but there is only 1 record to support this claim. Hence it may or maynot be valid
5. People who are handicapped with Level 3 and above are more likely to miss appointment but we do not have enough data to support this claim