This dataset was taken from <a href="https://www.kaggle.com/joniarroba/noshowappointments/downloads/noshowappointments.zip/5">https://www.kaggle.com/joniarroba/noshowappointments.zip/5</a> (<a href="https://www.kaggle.com/joniarroba/noshowappointments/downloads/noshowappointments.zip/5">https://www.kaggle.com/joniarroba/noshowappointments/downloads/noshowappointments.zip/5</a>) to investigate the factors that lead to a no-show in the patients.

Here, the factors that we will explore will be

- Gender
- Age
- Neighbourhood
- Scholarship
- Types of ailments (Hypertension, Diabetes, Alcoholism, Handicap)
- If SMS is sent

#### In [10]:

```
import numpy as np
import pandas as pd
import sklearn
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

### Out[11]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hipertension	Diabetes	Alcoholisr
0	2.987250e+13	5642903	F	2016-04- 29T18:38:08Z	2016-04- 29T00:00:00Z	62	JARDIM DA PENHA	0	1	0	
1	5.589980e+14	5642503	М	2016-04- 29T16:08:27Z	2016-04- 29T00:00:00Z	56	JARDIM DA PENHA	0	0	0	
2	4.262960e+12	5642549	F	2016-04- 29T16:19:04Z	2016-04- 29T00:00:00Z	62	MATA DA PRAIA	0	0	0	
3	8.679510e+11	5642828	F	2016-04- 29T17:29:31Z	2016-04- 29T00:00:00Z	8	PONTAL DE CAMBURI	0	0	0	
4	8.841190e+12	5642494	F	2016-04- 29T16:07:23Z	2016-04- 29T00:00:00Z	56	JARDIM DA PENHA	0	1	1	

These above features are identifier which does not correlate to the patient's turn out.

Out[13]:

	Gender	Age	Neighbourhood	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_received	No-show
0	F	62	JARDIM DA PENHA	0	1	0	0	0	0	No
1	М	56	JARDIM DA PENHA	0	0	0	0	0	0	No
2	F	62	MATA DA PRAIA	0	0	0	0	0	0	No
3	F	8	PONTAL DE CAMBURI	0	0	0	0	0	0	No
4	F	56	JARDIM DA PENHA	0	1	1	0	0	0	No

### 

JARDIM DA PENHA 3877 ITARARÉ 3514 CENTRO 3334 TABUAZEIRO 3132 3131 SANTA MARTHA JESUS DE NAZARETH 2853 2773 BONFIM SANTO ANTÔNIO 2746 SANTO ANDRÉ 2571 CARATOÍRA 2565 2509 JABOUR SÃO PEDRO 2448 ILHA DO PRÍNCIPE 2266 NOVA PALESTINA 2264 **ANDORINHAS** 2262 DA PENHA 2217 ROMÃO 2214 **GURIGICA** 2018 SÃO JOSÉ 1977 BELA VISTA 1907 MARUÍPE 1902 FORTE SÃO JOÃO 1889 ILHA DE SANTA MARIA 1885 SÃO CRISTÓVÃO 1836 REDENÇÃO 1553 SÃO BENEDITO 1439 JOANA D'ARC 1427 . . . SANTOS REIS 547 538 **ESTRELINHA** 506 SANTA CLARA 469 SOLON BORGES PIEDADE 452 SANTA CECÍLIA 448 File failed to load: /extensiosANTAMELLGLA 438

428

BARRO VERMELHO	423					
DO MOSCOSO	413					
MÁRIO CYPRESTE	371					
BOA VISTA	312					
COMDUSA	310					
DE LOURDES	305					
ARIOVALDO FAVALESSA	282					
ANTÔNIO HONÓRIO	271					
FRADINHOS	258					
ENSEADA DO SUÁ	235					
SANTA HELENA	178					
HORTO	175					
UNIVERSITÁRIO	152					
SEGURANÇA DO LAR	145					
NAZARETH	135					
MORADA DE CAMBURI	96					
PONTAL DE CAMBURI	69					
ILHA DO BOI	35					
ILHA DO FRADE	10					
AEROPORTO	8					
ILHAS OCEÂNICAS DE TRINDADE	2					
PARQUE INDUSTRIAL						

Name: Neighbourhood, Length: 81, dtype: int64

Neighbourhood has 81 unique values, hence, we will drop it too.

```
In [16]:
          dataDrop['Age'].describe(include='all')
   Out[16]: count
                      110526.000000
                          37,089219
             mean
                          23.110026
             std
             min
                           0.000000
             25%
                          18.000000
             50%
                          37.000000
             75%
                          55,000000
                         115.000000
             max
             Name: Age, dtvpe: float64
         Binning the age
          ☐ dataDropScaled = dataDrop.copy()
In [17]:
             #Scaling the data columns
             dataDropScaled.loc[df['Age'] < 10, 'Age'] = 0</pre>
             dataDropScaled.loc[(df['Age'] >= 10) & (df['Age'] < 20), 'Age'] = 1
             dataDropScaled.loc[(df['Age'] >= 20) & (df['Age'] < 30), 'Age'] = 2
             dataDropScaled.loc[(df['Age'] >= 30) & (df['Age'] < 40), 'Age'] = 3
             dataDropScaled.loc[(df['Age'] >= 40) & (df['Age'] < 50), 'Age'] = 4
             dataDropScaled.loc[(df['Age'] >= 50) & (df['Age'] < 60), 'Age'] = 5</pre>
             dataDropScaled.loc[(df['Age'] >= 60) & (df['Age'] < 70), 'Age'] = 6
             dataDropScaled.loc[(df['Age'] >= 70) & (df['Age'] < 80), 'Age'] = 7
             dataDropScaled.loc[(df['Age'] >= 80) & (df['Age'] < 90), 'Age'] = 8
             dataDropScaled.loc[(df['Age'] >= 90) & (df['Age'] < 100), 'Age'] = 9
             dataDropScaled.loc[df['Age'] >= 100, 'Age'] = 10
```

Mapping the word values into numerical

## Out[21]:

	Gender	Age	Scholarship	Hipertension	Diabetes	Alcoholism	Handcap	SMS_received	No-show
Gender	1	-0.104285	-0.114296	-0.0557219	-0.0325558	0.106166	0.0228134	-0.0463025	-0.00412199
Age	-0.104285	1	-0.0972615	0.503017	0.291735	0.0953145	0.0761721	0.0119598	-0.0615148
Scholarship	-0.114296	-0.0972615	1	-0.0197303	-0.0248944	0.035022	-0.00858669	0.00119196	0.0291336
Hipertension	-0.0557219	0.503017	-0.0197303	1	0.433085	0.0879701	0.0800828	-0.00626997	-0.0357035
Diabetes	-0.0325558	0.291735	-0.0248944	0.433085	1	0.0184731	0.0575297	-0.0145518	-0.0151812
Alcoholism	0.106166	0.0953145	0.035022	0.0879701	0.0184731	1	0.00464743	-0.0261485	-0.00019685
Handcap	0.0228134	0.0761721	-0.00858669	0.0800828	0.0575297	0.00464743	1	-0.0241618	-0.00607685
SMS_received	-0.0463025	0.0119598	0.00119196	-0.00626997	-0.0145518	-0.0261485	-0.0241618	1	0.126428
No-show	-0.00412199	-0.0615148	0.0291336	-0.0357035	-0.0151812	-0.00019685	-0.00607685	0.126428	1

Here, we can see that hypertension has a strong correlation to age and diabetes, 0.50 and 0.43. Diabetes is also correlated to age with a R value of 0.29.

```
☐ dataDropScaledMap.isnull().sum()
In [22]:
   Out[22]: Gender
                             0
             Age
             Scholarship
                             0
             Hipertension
                             0
             Diabetes
             Alcoholism
                             0
             Handcap
             SMS received
             No-show
             dtype: int64
```

# **Modeling**

```
In [23]: # import train_test_split
from sklearn.model_selection import train_test_split
target = dataDropScaledMap['No-show'] # this is like the dependent variable: y
x_train, x_test, y_train, y_test = train_test_split(dataDropScaledMap, target, random_state = 42)

In [24]: # features_drop_inXTrainTest = ['No-show']
x_traincopy = x_train.drop(features_drop_inXTrainTest, axis=1)
x_testcopy = x_test.drop(features_drop_inXTrainTest, axis=1)

In [25]: # Importing Classifier Modules
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
import numpy as np

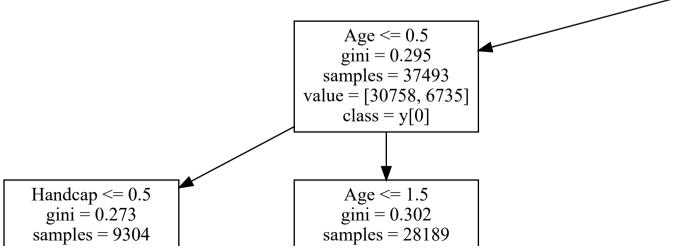
File failed to load: /extensions/MathMenujs
```

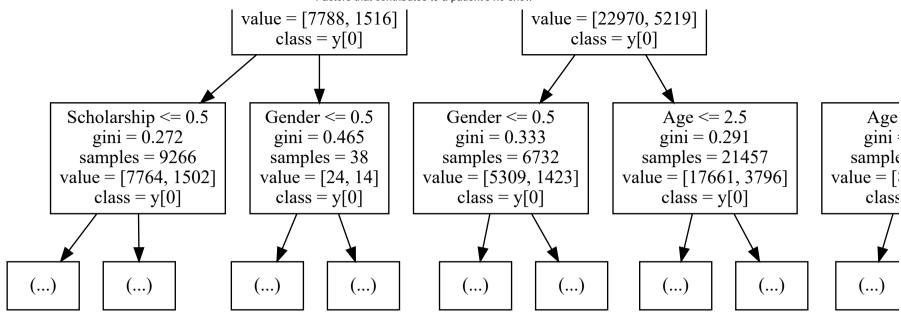
```
from sklearn.model selection import cross val score
                 k fold = KFold(n splits=10, shuffle=True, random state=0)
  In [301:
             ☐ def modeltraining(clf):
                     scoring = 'accuracy'
                     score = cross val score(clf, x traincopy, y train, cv=k fold, n jobs=1, scoring=scoring)
                     print(round(np.mean(score)*100, 2))
            modeltraining(KNeighborsClassifier(n neighbors = 13))
  In [31]:
                modeltraining(DecisionTreeClassifier())
                modeltraining(RandomForestClassifier(n estimators=13))
                modeltraining(GaussianNB())
                modeltraining(SVC(gamma='scale'))
                78.9
                79.69
                79.65
                78.99
                79.72
            SVC proves to be the best model, but it is the longest to compute. Hence, we pick the decision tree.
             □ dt = DecisionTreeClassifier()
  In [32]:
                dt.fit(x traincopy, y train)
      Out[32]: DecisionTreeClassifier(class weight=None, criterion='gini', max depth=None,
                                        max features=None, max leaf nodes=None,
                                        min impurity decrease=0.0, min impurity split=None,
                                        min samples leaf=1, min samples split=2,
                                        min weight fraction leaf=0.0, presort=False,
                                        random state=None, splitter='best')
             □ | y_pred = dt.predict(x_testcopy) # Let the model predict the test data
  In [33]:
File failed to load: /extensions/MathMenu.js
```

In [29]: ☐ **from** sklearn.model selection **import** KFold

Out[34]: 0.8004849449913144

Out[38]:





SMS Received is the first determinant for a no-show appointment, followed by Age.

Given the following patient Gender Male - 1 Age 56 - 5 Scholarship No - 0 Hipertension Yes - 1 Diabetes No - 0 Alcoholism No - 0 Handcap No - 0 SMS\_received No - 0

The output is 0 which means that he not show up with a 80% accuracy.