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IMPORTING MODULES

```
In [1]:
         import numpy as np
         # dataa split
         from sklearn.model selection import train test split
         # model Evaluation
         from sklearn import metrics
         #navie bayesian and accuracy
         from sklearn.naive_bayes import GaussianNB
         from sklearn.metrics import accuracy score
         #pandas
         import pandas as pd
         import matplotlib.pyplot as plt
         %matplotlib inline
         plt.style.use('seaborn')
In [2]:
         import seaborn as sns
         import plotly.express as px
         # SMOTE
         from imblearn.over sampling import SMOTE
         # scaling
         from sklearn.preprocessing import StandardScaler
         from sklearn.model selection import RandomizedSearchCV
```

READING THE DATASET

```
data=pd.read_csv('dataset.csv')
           data
                        gender
                                age hypertension
                                                    heart_disease ever_married work_type Residence_type
Out[3]:
             0
                 9046
                          Male
                                  67
                                                 0
                                                                1
                                                                            Yes
                                                                                     Private
                                                                                                      Urban
                                                 0
             1
                31112
                          Male
                                  80
                                                                1
                                                                            Yes
                                                                                     Private
                                                                                                       Rural
                60182 Female
                                  49
                                                 0
                                                                0
                                                                            Yes
                                                                                     Private
                                                                                                       Urban
                                                                                       Self-
                 1665 Female
                                  79
                                                                0
             3
                                                 1
                                                                                                       Rural
                                                                            Yes
                                                                                   employed
             4
                56669
                          Male
                                  81
                                                 0
                                                                0
                                                                            Yes
                                                                                     Private
                                                                                                       Urban
                                                                                       Self-
          3421 68398
                                                                0
                                                                                                       Rural
                          Male
                                  82
                                                                            Yes
                                                                                   employed
          3422 45010 Female
                                  57
                                                                0
                                                                            Yes
                                                                                     Private
                                                                                                       Rural
                                                                                       Self-
                                                 0
                                                                0
                                                                                                      Urban
          3423 44873 Female
                                  81
                                                                            Yes
                                                                                   employed
```

In [3]:

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	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type
3424	19723	Female	35	0	0	Yes	Self- employed	Rural
3425	37544	Male	51	0	0	Yes	Private	Rural
3426 ı	rows × 1	12 colum	ns					
4								•

DATA ENCODING (PREPARATION)

```
In [4]:
         # convert string to numeric using map
         # gender
         data['gender'] = data['gender'].map({
         'Male': int(0),
         'Female':int(1),
         'Other':int(2)})
         # ever married
         data['ever married'] =data['ever married'].map({
         'Yes':int(1),
         'No':int(0)})
         # work type
         data['work type'] = data['work type'].map({
         'Private':int(3),
         'Self-employed':int(4),
         'Govt job':int(2),
         'children':int(1),
         'Never_worked':int(0)})
         # Residence_type
         data['Residence type'] = data['Residence type'].map({
         'Urban':int(2),
         'Rural':int(1)})
         # smoking status
         data['smoking status'] = data['smoking status'].map({
         'formerly smoked':int(1),
         'never smoked':int(2),
         'smokes':int(3),
         'Unknown':int(0)})
In [5]:
         ### attributes used in the classification
In [6]:
         x=data[['gender','age','hypertension','heart_disease','ever_married','work_ty
         y=data[['stroke']]
         x=x.values
         y=y.values
```

SPLIT DATASET

```
In [7]: from sklearn.model_selection import train_test_split
```

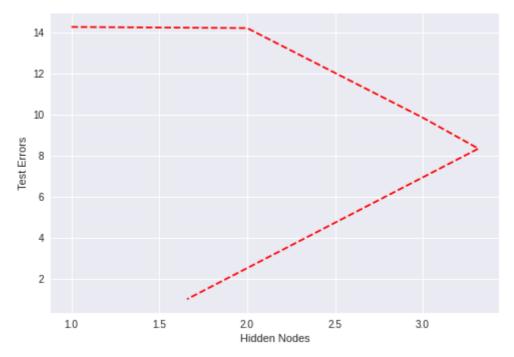
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Different numbers of hidden nodes

```
In [11]:
         import tensorflow as tf
         from keras.models import Sequential
         from keras.layers import Dense
         import matplotlib.pyplot as plt
         import math
In [12]:
         testerr=[]
In [13]:
         hiddennodes=[1,2,3,math.sqrt(11),(math.sqrt(11))/2]
In [14]:
         # define keras model
         model=tf.keras.Sequential()
         model.add(tf.keras.layers.Dense(1,activation='relu'))
         #compile keras model
         model.compile('adam', 'binary_crossentropy', metrics=['accuracy'])
         history = model.fit(X_train, y_train, validation_data=(X_test, y_test), verbos
         test_loss = history.history['val_loss']
         testerr.append(test_loss)
        cy: 0.0509 - val loss: 14.2712 - val accuracy: 0.0641
In [15]:
         # define keras model
         model=tf.keras.Sequential()
         model.add(tf.keras.layers.Dense(2,activation='relu'))
         #compile keras model
         model.compile('adam','binary_crossentropy',metrics=['accuracy'])
```

```
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), verbos
         test_loss = history.history['val_loss']
         testerr.append(test loss)
                                =======] - Os 2ms/step - loss: 14.4484 - accura
        cy: 0.3214 - val loss: 14.2156 - val accuracy: 0.4082
In [16]:
        # define keras model
        model=tf.keras.Sequential()
         model.add(tf.keras.layers.Dense(3,activation='relu'))
         #compile keras model
         model.compile('adam','binary crossentropy',metrics=['accuracy'])
         history = model.fit(X_train, y_train, validation_data=(X_test, y_test), verbos
         test loss = history.history['val loss']
         testerr.append(test loss)
        y: 0.0481 - val loss: 9.8439 - val accuracy: 0.0641
In [17]:
        # define keras model
        model=tf.keras.Sequential()
         model.add(tf.keras.layers.Dense(math.sqrt(11),activation='relu'))
         #compile keras model
         model.compile('adam','binary crossentropy',metrics=['accuracy'])
         history = model.fit(X_train, y_train, validation_data=(X_test, y_test), verbos
         test loss = history.history['val loss']
         testerr.append(test loss)
        y: 0.9519 - val loss: 8.3349 - val accuracy: 0.9359
In [18]:
        # define keras model
        model=tf.keras.Sequential()
         model.add(tf.keras.layers.Dense((math.sqrt(11))/2,activation='relu'))
         #compile keras model
         model.compile('adam','binary_crossentropy',metrics=['accuracy'])
         history = model.fit(X_train, y_train, validation_data=(X_test, y_test), verbos
         test loss = history.history['val loss']
         testerr.append(test loss)
        y: 0.9530 - val loss: 0.9894 - val accuracy: 0.9359
In [19]:
        print(testerr)
        [[14.27115249633789], [14.215579986572266], [9.843886375427246], [8.334875106
        811523], [0.9893553256988525]]
In [20]:
         plt.plot(hiddennodes, testerr, 'r--')
         plt.xlabel('Hidden Nodes')
         plt.ylabel('Test Errors')
         plt.show();
```

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INFERENCES

The above graph shows that Test error is high at Hidden node 1 and 2.

When it increases, the test error decreases.

When hidden node is half of sqrt(attributes), it even decreases.

As the process goes, the test error decreases.