In [4]:

```python
import pandas as pd
import numpy as np
import tensorflow as tf
```

In [5]:

```python
df = pd.read_csv("Desktop/nn/data.csv")
```

In [6]:

```python
df.head(199)
```

Out[6]:

	No.	Column1	Column2	Column3	Column4	Column5	Column6	Column7	Column8	Column9	...	Column26	Column27	Colum
0	1	119513	N	31	18.02	27.60	117.50	1013.0	0.09489	0.10360	...	139.70	1436.0	0.1
1	2	8423	N	61	17.99	10.38	122.80	1001.0	0.11840	0.27760	...	184.60	2019.0	0.1
2	3	842517	N	116	21.37	17.44	137.50	1373.0	0.08836	0.11890	...	159.10	1949.0	0.1
3	4	843483	N	123	11.42	20.38	77.58	386.1	0.14250	0.28390	...	98.87	567.7	0.2
4	5	843584	R	27	20.29	14.34	135.10	1297.0	0.10030	0.13280	...	152.20	1575.0	0.1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
193	194	942640	N	10	22.52	21.92	146.90	1597.0	0.07592	0.09162	...	162.10	1902.0	0.0
194	195	943471	N	8	15.44	31.18	101.00	740.4	0.09399	0.10620	...	112.60	929.0	0.1
195	196	94547	N	12	17.17	29.19	110.00	915.3	0.08952	0.06655	...	132.50	1295.0	0.1
196	197	947204	R	3	21.42	22.84	145.00	1440.0	0.10700	0.19390	...	198.30	2375.0	0.1
197	198	947489	N	6	16.70	28.13	110.30	885.4	0.08896	0.11310	...	128.80	1213.0	0.1

198 rows × 36 columns

In [7]:

```python
df.rename(columns={'Column1': 'ID No',
                   'Column2': 'Outcome',
                   'Column3': 'Time',
                   'Column4': 'Radius1',
                   'Column5': 'Texture1',
                   'Column6': 'Perimeter1',
                   'Column7': 'Area1',
                   'Column8': 'Smoothness1',
                   'Column9': 'Compactness1',
                   'Column10': 'Concavity1',
                   'Column11': 'ConcavePoints1',
                   'Column12': 'Symmetry1',
                   'Column13': 'FractalDim1',
                   'Column14': 'Radius2',
                   'Column15': 'Texture2',
                   'Column16': 'Perimeter2',
                   'Column17': 'Area2',
                   'Column18': 'Smoothness2',
                   'Column19': 'Compactness2',
                   'Column20': 'Concavity2',
                   'Column21': 'ConcavePoints2',
                   'Column22': 'Symmetry2',
                   'Column23': 'FractalDim2',
                   'Column24': 'Radius3',
                   'Column25': 'Texture3',
                   'Column26': 'Perimeter3',
                   'Column27': 'Area3',
                   'Column28': 'Smoothness3',
                   'Column29': 'Compactness3',
                   'Column30': 'Concavity3',
                   'Column31': 'ConcavePoints3',
```

```
                    'Column32': 'Symmetry3',
                    'Column33': 'FractalDim3',
                    'Column34': 'Tumor Diameter',
                    'Column35': 'Lymph Nodes Removed'},inplace=True)
```

In [8]:

```
df.head(199)
```

Out[8]:

	No.	ID No	Outcome	Time	Radius1	Texture1	Perimeter1	Area1	Smoothness1	Compactness1	...	Perimeter3	Area3	Smoo
0	1	119513	N	31	18.02	27.60	117.50	1013.0	0.09489	0.10360	...	139.70	1436.0	
1	2	8423	N	61	17.99	10.38	122.80	1001.0	0.11840	0.27760	...	184.60	2019.0	
2	3	842517	N	116	21.37	17.44	137.50	1373.0	0.08836	0.11890	...	159.10	1949.0	
3	4	843483	N	123	11.42	20.38	77.58	386.1	0.14250	0.28390	...	98.87	567.7	
4	5	843584	R	27	20.29	14.34	135.10	1297.0	0.10030	0.13280	...	152.20	1575.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
193	194	942640	N	10	22.52	21.92	146.90	1597.0	0.07592	0.09162	...	162.10	1902.0	
194	195	943471	N	8	15.44	31.18	101.00	740.4	0.09399	0.10620	...	112.60	929.0	
195	196	94547	N	12	17.17	29.19	110.00	915.3	0.08952	0.06655	...	132.50	1295.0	
196	197	947204	R	3	21.42	22.84	145.00	1440.0	0.10700	0.19390	...	198.30	2375.0	
197	198	947489	N	6	16.70	28.13	110.30	885.4	0.08896	0.11310	...	128.80	1213.0	

198 rows × 36 columns

In [9]:

```
## Source (unique): https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.unique.html
df['Outcome'].unique()
```

Out[9]:

```
array(['N', 'R'], dtype=object)
```

In [10]:

```
## Change 'N' (Non-Recurring) to '-1' and 'R' (Recurring) to 1

df['Outcome'] = df['Outcome'].apply(lambda x: -1 if x=='N' else 1)
```

In [11]:

```
df.head(199)
```

Out[11]:

	No.	ID No	Outcome	Time	Radius1	Texture1	Perimeter1	Area1	Smoothness1	Compactness1	...	Perimeter3	Area3	Smoo
0	1	119513	-1	31	18.02	27.60	117.50	1013.0	0.09489	0.10360	...	139.70	1436.0	
1	2	8423	-1	61	17.99	10.38	122.80	1001.0	0.11840	0.27760	...	184.60	2019.0	
2	3	842517	-1	116	21.37	17.44	137.50	1373.0	0.08836	0.11890	...	159.10	1949.0	
3	4	843483	-1	123	11.42	20.38	77.58	386.1	0.14250	0.28390	...	98.87	567.7	
4	5	843584	1	27	20.29	14.34	135.10	1297.0	0.10030	0.13280	...	152.20	1575.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
193	194	942640	-1	10	22.52	21.92	146.90	1597.0	0.07592	0.09162	...	162.10	1902.0	
194	195	943471	-1	8	15.44	31.18	101.00	740.4	0.09399	0.10620	...	112.60	929.0	

	No.	ID No	Outcome	Time	Radius1	Texture1	Perimeter1	Area1	Smoothness1	Compactness1	...	Perimeter3	Area3	Smoo
195	196	94547	-1	12	17.17	29.19	110.00	915.3	0.08952	0.06655	...	132.50	1295.0	
196	197	947204	1	3	21.42	22.84	145.00	1440.0	0.10700	0.19390	...	198.30	2375.0	
197	198	947489	-1	6	16.70	28.13	110.30	885.4	0.08896	0.11310	...	128.80	1213.0	

198 rows × 36 columns

In [12]:

```
import matplotlib.pyplot as plt
```

In [13]:

```
## Source graphs:
https://github.com/tifabi/100DaysOfMLCode/blob/55e3695ebfeefff91e2edb15bcf9c443eebc6864/ML_Algorit
ipelines/Pipeline_Example.ipynb
%matplotlib inline
plt.style.use('ggplot')
pd.DataFrame.hist(df, figsize = [20,20]);
```

In [14]:

```
# -- Preprocessing --
# We know from the column descriptions provided with the datset and from viewing the data
```

```
# that there are two non-numeric columns:
# Take a look at the data
# **Note: that the second and last column are type "object", these columns must have
#          some nonnumeric values.

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 198 entries, 0 to 197
Data columns (total 36 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   No.                  198 non-null    int64  
 1   ID No                198 non-null    int64  
 2   Outcome              198 non-null    int64  
 3   Time                 198 non-null    int64  
 4   Radius1              198 non-null    float64
 5   Texture1             198 non-null    float64
 6   Perimeter1           198 non-null    float64
 7   Area1                198 non-null    float64
 8   Smoothness1          198 non-null    float64
 9   Compactness1         198 non-null    float64
 10  Concavity1           198 non-null    float64
 11  ConcavePoints1       198 non-null    float64
 12  Symmetry1            198 non-null    float64
 13  FractalDim1          198 non-null    float64
 14  Radius2              198 non-null    float64
 15  Texture2             198 non-null    float64
 16  Perimeter2           198 non-null    float64
 17  Area2                198 non-null    float64
 18  Smoothness2          198 non-null    float64
 19  Compactness2         198 non-null    float64
 20  Concavity2           198 non-null    float64
 21  ConcavePoints2       198 non-null    float64
 22  Symmetry2            198 non-null    float64
 23  FractalDim2          198 non-null    float64
 24  Radius3              198 non-null    float64
 25  Texture3             198 non-null    float64
 26  Perimeter3           198 non-null    float64
 27  Area3                198 non-null    float64
 28  Smoothness3          198 non-null    float64
 29  Compactness3         198 non-null    float64
 30  Concavity3           198 non-null    float64
 31  ConcavePoints3       198 non-null    float64
 32  Symmetry3            198 non-null    float64
 33  FractalDim3          198 non-null    float64
 34  Tumor Diameter       198 non-null    float64
 35  Lymph Nodes Removed  198 non-null    object 
dtypes: float64(31), int64(4), object(1)
memory usage: 55.8+ KB
```

In [15]:

```
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
```

In [16]:

```
# -- Missing Values --
# The variable 'Lymph node status' was also type 'object', explore why using value_counts
# **Note: There are 4 '?'

df['Lymph Nodes Removed'].value_counts()
```

Out[16]:

```
0     87
1     35
2     17
4     10
7      6
13     6
?      4
9      4
3      4
```

```
6      3
15     3
11     3
8      2
27     2
5      2
10     2
20     2
16     1
24     1
18     1
17     1
14     1
21     1
Name: Lymph Nodes Removed, dtype: int64
```

In [17]:

```
'''
Addressing Missing Values
As mentioned previously, the WPBC dataset contains a lot of missing values (specifically in the Ly
mph Nodes Removed column). Data could be missing due to a variety of reasons. Primarily it could b
e due to

1. Missing at Random - Propensity for a data point to be missing is not related to the missing dat
a, but it is related to some of the observed data.
2. Missing Completely at Random - The fact that a certain value is missing has nothing to do with
its hypothetical value and with the values of other variables.
3. Missing not at Random - Two possible reasons are that the missing value depends on the hypothet
ical value (e.g. People with high salaries generally do not want to reveal their incomes in survey
s) or missing value is dependent on some other variable's value (e.g. Let's assume that females ge
nerally don't want to reveal their ages! Here the missing value in age variable is impacted by gen
der variable)
In the first two cases, it is safe to remove the data with missing values depending upon their occ
urrences, while in the third case removing observations with missing values can produce a bias in
the model.

Ref: https://towardsdatascience.com/how-to-handle-missing-data-8646b18db0d4
Source: https://github.com/ashnair1/Classification-using-
TensorFlow/blob/18eec28f3f2e4609d7e7c36b17911ef5044a0b8b/TF%20Classification%202%20-
%20Breast%20Cancer%20Prognosis%20.ipynb

Since it could be hypothesised that the missing values in the Lymph Nodes removed columns are miss
ing at random, we could address this issue by simply removing the record of those patients with mi
ssing values.
'''

df = df.drop(df[df['Lymph Nodes Removed']=='?'].index)
```

In [18]:

```
# Counting acctual outcomes without 4 '?'
df['Outcome'].value_counts()
```

Out[18]:

```
-1    148
 1     46
Name: Outcome, dtype: int64
```

In [19]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 194 entries, 0 to 197
Data columns (total 36 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   No.                  194 non-null    int64
 1   ID No                194 non-null    int64
 2   Outcome              194 non-null    int64
 3   Time                 194 non-null    int64
```

```
 4   Radius1              194 non-null    float64
 5   Texture1             194 non-null    float64
 6   Perimeter1           194 non-null    float64
 7   Area1                194 non-null    float64
 8   Smoothness1          194 non-null    float64
 9   Compactness1         194 non-null    float64
 10  Concavity1           194 non-null    float64
 11  ConcavePoints1       194 non-null    float64
 12  Symmetry1            194 non-null    float64
 13  FractalDim1          194 non-null    float64
 14  Radius2              194 non-null    float64
 15  Texture2             194 non-null    float64
 16  Perimeter2           194 non-null    float64
 17  Area2                194 non-null    float64
 18  Smoothness2          194 non-null    float64
 19  Compactness2         194 non-null    float64
 20  Concavity2           194 non-null    float64
 21  ConcavePoints2       194 non-null    float64
 22  Symmetry2            194 non-null    float64
 23  FractalDim2          194 non-null    float64
 24  Radius3              194 non-null    float64
 25  Texture3             194 non-null    float64
 26  Perimeter3           194 non-null    float64
 27  Area3                194 non-null    float64
 28  Smoothness3          194 non-null    float64
 29  Compactness3         194 non-null    float64
 30  Concavity3           194 non-null    float64
 31  ConcavePoints3       194 non-null    float64
 32  Symmetry3            194 non-null    float64
 33  FractalDim3          194 non-null    float64
 34  Tumor Diameter       194 non-null    float64
 35  Lymph Nodes Removed  194 non-null    object
dtypes: float64(31), int64(4), object(1)
memory usage: 56.1+ KB
```

In [20]:

```
# Handle with Data Part:


 # Getting train and test length
def get_train_n_test_len(data, percent):
        length = len(data)
        train_len = round(length * percent)
        test_len = length - train_len
        return train_len, test_len


 # Creating sets for train and test
 # train_f == train features, test_f == test features
 # from_mid == take a features (data) to test part from a middle
 # "np.ndarray": data-type object describes the format of each element in the array (its byte-orde
r, how many bytes
 # it occupies in memory, whether it is an integer, a floating point number, or something else, et
c.)
 # "np.ndarray" example:
 # np.ndarray(shape=(2,2), dtype=float, order='F') => [[0.0e+000, 0.0e+000], [ nan, 2.5e-323]]
 # Source ndarray (NumPy): https://numpy.org/doc/stable/reference/generated/numpy.ndarray.html
 # "np.vstack" example: a = [1, 2], b = [3, 4] => np.vstack(a,b) => [ [1,2], [3,4] ]
 # Source vstack (Numpy): https://numpy.org/doc/stable/reference/generated/numpy.vstack.html
 #
 # Explanation: In our example data_split() method is built to split data into 2 options:
 # Option 1: If from_mid receives a true bool value -> it take the features (data) from the middle
to part of
 # the test (from number 66 to 131, i.e. 66<= count <= 131) and everything else (the starting part
of the data,
 # where the count <= 65, and the final part of the data, where the count <= 193) take part of the
training.
 # Otherwise, (from_mid receives a false bool value) takes 128 initial features (data) (the initia
l part) to the
 # training part and the rest to the test.
def data_split(data: np.ndarray, train_len: np.int, test_len: np.int, take_from_mid: bool) \
        -> (np.ndarray, np.ndarray, np.ndarray, np.ndarray):

        train_f = np.empty((0, 33), float)
        train_diagnoses = np.array([])
```

```
        test_f = np.empty((0, 33), float)
        test_diagnoses = np.array([])

        count = 0

        # Option 1:
        if take_from_mid:
            for line in data:
                tmp_x = np.array(line[2:])
                tmp_y = line[1:2]
                # if count<66 -> take features (data) from a beginning to train part
                if count < test_len:
                    train_f = np.vstack((train_f, tmp_x))
                    train_diagnoses = np.append(train_diagnoses, [tmp_y])
                # elif 66<=count<=131 -> take features (data) from the middle to test part
                elif test_len <= count and count < test_len * 2:
                    test_f = np.vstack((test_f, tmp_x))
                    test_diagnoses = np.append(test_diagnoses, [tmp_y])
                # else (count<132) -> take the rest features (data) from the final to train part
                else:
                    train_f = np.vstack((train_f, tmp_x))
                    train_diagnoses = np.append(train_diagnoses, [tmp_y])

                count += 1

        # Option 2:
        else:
            for line in data:
                tmp_x = np.array(line[2:])
                tmp_y = line[1:2]
                # take features (data) to the train part
                if count < train_len:
                    train_f = np.vstack((train_f, tmp_x))
                    train_diagnoses = np.append(train_diagnoses, [tmp_y])
                # take the rest features (data) to the test part
                else:
                    test_f = np.vstack((test_f, tmp_x))
                    test_diagnoses = np.append(test_diagnoses, [tmp_y])

                count += 1


        return train_f, train_diagnoses, test_f, test_diagnoses


 # standardization() method to standardize values from one type to float type after values updates
(or fixing)
 # "mean()" function can be used to calculate mean/average of a given list of numbers. It returns
mean
 # of the data set passed as parameters.
 # Source "mean()" (GeeksforGeeks): https://www.geeksforgeeks.org/python-statistics-mean-function/
 # "std()" Returns the standard deviation, a measure of the spread of a distribution, of the array
elements.
 # The standard deviation is computed for the flattened array by default, otherwise over the speci
fied axis.
 # Source "std()" (NumPy): https://numpy.org/doc/stable/reference/generated/numpy.std.html
 # mat == matrix
def standardization(mat):
        mat_std = np.copy(mat)
        for i in range(0, len(mat_std[0])):
            # mat_std(i = column) = ( mat(i) - avg of mat(i) ) / standard deviation of i column of
mat(i)
            mat_std[:, i] = (mat[:, i] - mat[:, i].mean()) / mat[:, i].std()

        return mat_std


 # calc_actual() to calculate negative and positive results
 # neg == negative, pos == positive, t == targets
def calc_actual(t):
        pos = 0
        neg = 0
        for item in t:
            if item == 1:
                pos += 1
            else:
```

```
                neg += 1
        return pos, neg\


 # Calculating the prediction table
 # true_pos == true positive, false_neg == false negative, false_pos == false positive, true_neg =
= true negative
 # t == targets
 # Explanation:
 # true positive:
 # target result: The cancer had recurred | prediction: The algorithm predicted that the cancer ha
d recurred
 # false negative:
 # target result: The cancer had recurred | prediction: The algorithm predicted that the cancer ha
d Non-recurred
 # false positive:
 # target result: The cancer had Non-recurred | prediction: The algorithm predicted that the cance
r had recurred
 # true negative:
 # target result: The cancer had Non-recurred | prediction: The algorithm predicted that the cance
r had Non-recurred
def check_predictions(t, predictions):
        true_pos = 0
        false_neg = 0
        false_pos = 0
        true_neg = 0
        for i in range(0, len(predictions)):
            if t[i] == 1 and predictions[i] == 1:
                true_pos += 1
            elif t[i] == 1 and predictions[i] == -1:
                false_neg += 1
            elif t[i] == -1 and predictions[i] == 1:
                false_pos += 1
            else:
                true_neg += 1


        return true_pos, false_neg, false_pos, true_neg


 # Checking and printing the score
 # true_pos == true positive, false_neg == false negative, false_pos == false positive, true_neg =
= true negative
def check_score(true_pos, false_neg, false_pos, true_neg):

        print(f"true positive: {true_pos}")
        print(f"false negative: {false_neg}")
        print(f"false positive: {false_pos}")
        print(f"true negative: {true_neg}\n")

        total_all = true_pos + false_neg + false_pos + true_neg
        total_true = true_pos + true_neg  # total really positive
        acc = total_true / total_all
        total_pos = true_pos + false_pos  # total classified as positive
        try:
            precision = true_pos / total_pos
            recall = true_pos / (true_pos + false_neg)
            f_score = (2 * recall * precision) / (recall + precision)
            print(f"accuracy: {round(acc, 2)}")
            print(f"precision: {round(precision, 2)}")
            print(f"recall: {round(recall, 2)}")
            print(f"f_score: {round(f_score, 2)}\n")
        # Catch and throw divide by zero error
        except ZeroDivisionError:
            print("Error: The cases will predicted negative or Non-positive input data")
```

In [21]:

```
# Adaline Algorithm Part:
# f == features, t == target, w == wights, lr == alpha == learning rate


# Training data and weights and compute loss
def train_n_comp_loss(f, t, w, lr, n_epochs):
        loss_array = np.array([])
```

```
        for iteration in range(n_epochs):
            # Net input = net_inp = y_in = [Sigma(i from 1 to n) x(i)*w(i)] + w(0)
            # w(0) == bias
            net_inp = np.dot(f, w[1:]) + w[0]

            # Error sum
            squared_error = (t - net_inp)

            # Fit and Update weights and bias (w(0)) if error != 0
            # t == target
            # w(new) = w(old) + alpha * (t - y_in) * x(i)
            w[1:] += lr * np.dot(f.T, squared_error)
            # bias(new) = bias(old) + alpha * (t - y_in)
            w[0] += lr * squared_error.sum()


            # Loss: Sum of squared error : 1/2 * [Sigma(i from 1 to n) (y_in)^2]
            loss = (squared_error**2).sum() * 0.5
            # To array
            loss_array = np.append(loss_array, [loss])

        return w, loss_array

# Get predictions
def predict(f, w, threshold, pos_val, neg_val):
        # pos_val == positive value, neg_val == neagtive value
        # If y_in >= 0 -> returns 1, Otherwise -> returns -1
        return np.where(np.dot(f, w[1:]) + w[0] >= threshold, pos_val, neg_val)
```

In [22]:

```
#lst = df.drop(['No.'], axis=1)
currLst = df.drop(['No.'], axis=1)
#mylst = lst.values.tolist()
currLst
```

Out[22]:

	ID No	Outcome	Time	Radius1	Texture1	Perimeter1	Area1	Smoothness1	Compactness1	Concavity1	...	Perimeter3	Area
0	119513	-1	31	18.02	27.60	117.50	1013.0	0.09489	0.10360	0.10860	...	139.70	1436.
1	8423	-1	61	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	...	184.60	2019.
2	842517	-1	116	21.37	17.44	137.50	1373.0	0.08836	0.11890	0.12550	...	159.10	1949.
3	843483	-1	123	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	...	98.87	567
4	843584	1	27	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	...	152.20	1575.
...	...	...	...	...	...	...	...	...	...	...	...	...	.
192	9411300	-1	3	14.72	25.26	99.28	657.5	0.11740	0.21120	0.17290	...	111.60	814
193	942640	-1	10	22.52	21.92	146.90	1597.0	0.07592	0.09162	0.06862	...	162.10	1902.
194	943471	-1	8	15.44	31.18	101.00	740.4	0.09399	0.10620	0.13750	...	112.60	929
195	94547	-1	12	17.17	29.19	110.00	915.3	0.08952	0.06655	0.06583	...	132.50	1295.
197	947489	-1	6	16.70	28.13	110.30	885.4	0.08896	0.11310	0.10120	...	128.80	1213.

194 rows × 35 columns

In [23]:

```
myLst = currLst.values.tolist()
```

In [24]:

```
# Decrease the decimal number after the point
# Purpose: For easier calculation
# 1.100101 => 1.1001
for line in myLst:
        for i in range(2, len(line)):
```

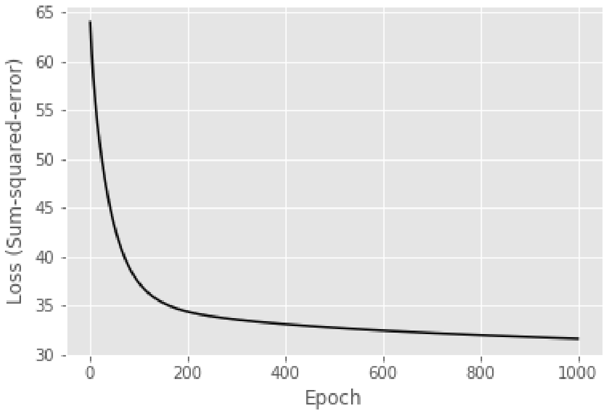
```
            if isinstance(line[i], str):
                line[i] = float(line[i])
                line[i] = round(line[i], 4)
            else:
                line[i] = float(line[i])
```

In [ ]:

```
myLst
```

In [26]:

```
import matplotlib.pyplot as plt
import time

# Implementation Adaline algorithm Part A:
# First Example: number of epochs (n_epochs) = 1000, learning rate (lr) = 0.0001
# Most recommended is that learning rate should be equal to 0.1 <= n_epochs * lr <= 1.0 -->
# 0.1/n_epochs <= lr --> 0.1 / 1000 = 0.0001 <= lr

# start time report
start = time.time()


# Calculating 66% of dataset length
train_len, test_len = get_train_n_test_len(myLst, 0.66)


# Creating sets for train and test features (datas)
# train_f == train features, test_f == test features
train_f, train_diagnoses, test_f, test_diagnoses \
    = data_split(myLst, train_len, test_len, False)
train_f = standardization(train_f)
test_f = standardization(test_f)


# Array of weights, training data and weigths
# w == weights
# Initialize the weight (to zero) for each feature (and the dummy feature, x0)
# Training the train features and diagnoses with all initial wights, learning rate and num of epoc
hs
# Getting fixed (or updated) weights and array of Loss values (training error).
w = np.zeros(1 + train_f.shape[1])
w, loss_array = train_n_comp_loss(train_f, train_diagnoses, w, 0.0001, 1000)


# Plot the training error
plt.plot(range(1, len(loss_array) + 1), loss_array, color='black')
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error)')
plt.show()


# predict target of tests features by our fixed (or updated) weights, threshold, and pos and neg v
alues
# calculate actual recurred (yes) and not recurred (no)
# get predictions of our real pos and neg results
# act_rec == actual recurred (yes), act_not_rec == actual not recurred (no)
# true_pos == true positive, false_neg == false negative, false_pos == false positive, true_neg ==
true negative
predictions = predict(test_f, w, 0.0, 1, -1)
act_rec, act_not_rec = calc_actual(test_diagnoses)
true_pos, false_neg, false_pos, true_neg = check_predictions(test_diagnoses, predictions)


# end time report
end = time.time()
print(f"Code execution time: {round(end - start, 2)} seconds")
check_score(true_pos, false_neg, false_pos, true_neg)

# Loss == t - y_in
df3 = pd.DataFrame({'Loss (Sum-squared-error)' : loss_array, 'Epoch' : range(1, len(loss_array) + 1
)})
df3
```




```
Code execution time: 0.17 seconds
true positive: 4
false negative: 10
false positive: 1
true negative: 51

accuracy: 0.83
precision: 0.8
recall: 0.29
f_score: 0.42
```

Out[26]:

	Loss (Sum-squared-error)	Epoch
0	64.000000	1
1	62.805735	2
2	61.745835	3
3	60.795017	4
4	59.933235	5
...	...	...
995	31.612313	996
996	31.610676	997
997	31.609041	998
998	31.607407	999
999	31.605775	1000

1000 rows × 2 columns

In [27]:

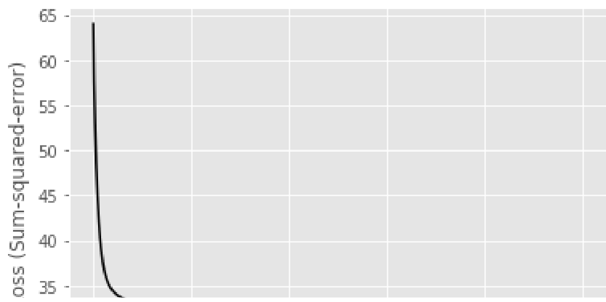
```
df2 = pd.DataFrame({'First method: 66%-33%': ['',''] ,
                    ' ':    [ "Actual: yes  ",  "Actual: no  "],
                    'Predicted: yes': [f"true positive: {round(true_pos / act_rec, 2)}%",
                                       f"false positive: {round(false_pos / act_not_rec, 2)}%"],
                    'Predicted: no': [f"false negative: {round(false_neg / act_rec, 2)}%",
                                       f"true negative: {round(true_neg / act_not_rec, 2)}%"]})

df2.head()
```

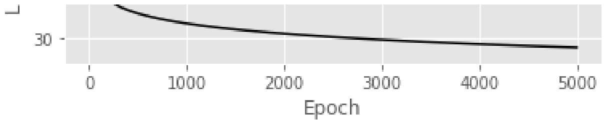
Out[27]:

	First method: 66%-33%		Predicted: yes	Predicted: no
0		Actual: yes	true positive: 0.29%	false negative: 0.71%
1		Actual: no	false positive: 0.02%	true negative: 0.98%

In [28]:

```
import matplotlib.pyplot as plt
import time

# Implementation Adaline algorithm Part A:
# Second Example: number of epochs (n_epochs) = 5000, learning rate (lr) = 0.0001
# Most recommended is that learning rate should be equal to 0.1 <= n_epochs * lr <= 1.0 -->
# 0.1/n_epochs <= lr --> 0.1 / 1000 = 0.0001 <= lr

# start time report
start = time.time()


# Calculating 66% of dataset length
train_len, test_len = get_train_n_test_len(myLst, 0.66)


# Creating sets for train and test features (datas)
# train_f == train features, test_f == test features
train_f, train_diagnoses, test_f, test_diagnoses \
    = data_split(myLst, train_len, test_len, False)
train_f = standardization(train_f)
test_f = standardization(test_f)


# Array of weights, training data and weigths
# w == weights
# Initialize the weight (to zero) for each feature (and the dummy feature, x0)
# Training the train features and diagnoses with all initial wights, learning rate and num of epoc
hs
# Getting fixed (or updated) weights and array of Loss values (training error).
w = np.zeros(1 + train_f.shape[1])
w, loss_array = train_n_comp_loss(train_f, train_diagnoses, w, 0.0001, 5000)


# Plot the training error
plt.plot(range(1, len(loss_array) + 1), loss_array, color='black')
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error)')
plt.show()


# predict target of tests features by our fixed (or updated) weights, threshold, and pos and neg v
alues
# calculate actual recurred (yes) and not recurred (no)
# get predictions of our real pos and neg results
# act_rec == actual recurred (yes), act_not_rec == actual not recurred (no)
# true_pos == true positive, false_neg == false negative, false_pos == false positive, true_neg ==
true negative
predictions = predict(test_f, w, 0.0, 1, -1)
act_rec, act_not_rec = calc_actual(test_diagnoses)
true_pos, false_neg, false_pos, true_neg = check_predictions(test_diagnoses, predictions)


# end time report
end = time.time()
print(f"Code execution time: {round(end - start, 2)} seconds")
check_score(true_pos, false_neg, false_pos, true_neg)


# Loss == t - y_in
df3 = pd.DataFrame({'Loss (Sum-squared-error)' : loss_array, 'Epoch' : range(1, len(loss_array) + 1
)})
df3
```






```
Code execution time: 0.31 seconds
true positive: 5
false negative: 9
false positive: 2
true negative: 50

accuracy: 0.83
precision: 0.71
recall: 0.36
f_score: 0.48
```

Out[28]:

	Loss (Sum-squared-error)	Epoch
0	64.000000	1
1	62.805735	2
2	61.745835	3
3	60.795017	4
4	59.933235	5
...	...	...
4995	28.928795	4996
4996	28.928467	4997
4997	28.928140	4998
4998	28.927812	4999
4999	28.927485	5000

5000 rows × 2 columns

In [29]:

```
df2 = pd.DataFrame({'First method: 66%-33%': ['',''] ,
                    ' ':    [ "Actual: yes  ",  "Actual: no  "],
                    'Predicted: yes': [f"true positive: {round(true_pos / act_rec, 2)}%",
                                        f"false positive: {round(false_pos / act_not_rec, 2)}%"],
                    'Predicted: no': [f"false negative: {round(false_neg / act_rec, 2)}%",
                                        f"true negative: {round(true_neg / act_not_rec, 2)}%"]})

df2.head()
```

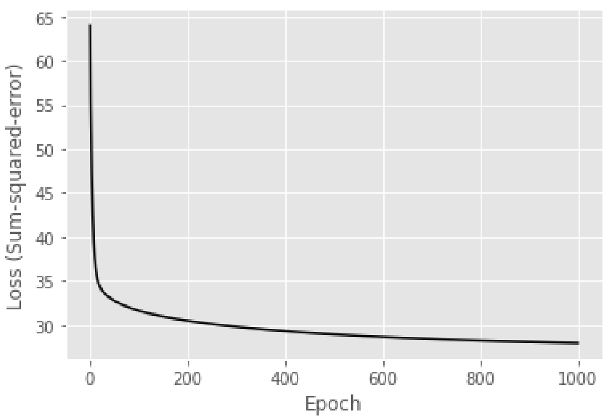
Out[29]:

	First method: 66%-33%		Predicted: yes	Predicted: no
0		Actual: yes	true positive: 0.36%	false negative: 0.64%
1		Actual: no	false positive: 0.04%	true negative: 0.96%

In [30]:

```
import matplotlib.pyplot as plt
import time

# Implementation Adaline algorithm Part A:
# Third Example: number of epochs (n_epochs) = 1000, learning rate (lr) = 0.001
# Most recommended is that learning rate should be equal to 0.1 <= n_epochs * lr <= 1.0 -->
# 0.1/n_epochs <= lr --> 0.1 / 1000 = 0.0001 <= lr

# start time report
start = time.time()
```

```
# Calculating 66% of dataset length
train_len, test_len = get_train_n_test_len(myLst, 0.66)


# Creating sets for train and test features (datas)
# train_f == train features, test_f == test features
train_f, train_diagnoses, test_f, test_diagnoses \
    = data_split(myLst, train_len, test_len, False)
train_f = standardization(train_f)
test_f = standardization(test_f)


# Array of weights, training data and weigths
# w == weights
# Initialize the weight (to zero) for each feature (and the dummy feature, x0)
# Training the train features and diagnoses with all initial wights, learning rate and num of epoc
hs
# Getting fixed (or updated) weights and array of Loss values (training error).
w = np.zeros(1 + train_f.shape[1])
w, loss_array = train_n_comp_loss(train_f, train_diagnoses, w, 0.001, 1000)


# Plot the training error
plt.plot(range(1, len(loss_array) + 1), loss_array, color='black')
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error)')
plt.show()


# predict target of tests features by our fixed (or updated) weights, threshold, and pos and neg v
alues
# calculate actual recurred (yes) and not recurred (no)
# get predictions of our real pos and neg results
# act_rec == actual recurred (yes), act_not_rec == actual not recurred (no)
# true_pos == true positive, false_neg == false negative, false_pos == false positive, true_neg ==
true negative
predictions = predict(test_f, w, 0.0, 1, -1)
act_rec, act_not_rec = calc_actual(test_diagnoses)
true_pos, false_neg, false_pos, true_neg = check_predictions(test_diagnoses, predictions)


# end time report
end = time.time()
print(f"Code execution time: {round(end - start, 2)} seconds")
check_score(true_pos, false_neg, false_pos, true_neg)


# Loss == t - y_in
df3 = pd.DataFrame({'Loss (Sum-squared-error)' : loss_array, 'Epoch' : range(1, len(loss_array) + 1
)})
df3
```




```
Code execution time: 0.17 seconds
true positive: 5
false negative: 9
false positive: 5
true negative: 47
```

```
accuracy: 0.79
precision: 0.5
recall: 0.36
f_score: 0.42
```

Out[30]:

	Loss (Sum-squared-error)	Epoch
0	64.000000	1
1	55.408282	2
2	50.852516	3
3	47.357266	4
4	44.641352	5
...	...	...
995	27.952268	996
996	27.951142	997
997	27.950017	998
998	27.948895	999
999	27.947774	1000

1000 rows × 2 columns

In [31]:

```
'''
Our onclusions:

If the number of rounds is too large -> it will take the algorithm a long time to converge and it
impairs the exact calculation of the final results

If the learning rate is too small -> the algorithm will not be able to converge on the ideal numbe
r of rounds we set (1000)

If the learning rate is too large -> the algorithm can miss the convergence point of the number of
ideal turns we have set (1000)
'''

df2 = pd.DataFrame({'First method: 66%-33%': ['',''] ,
                    ' ':    [ "Actual: yes  ",  "Actual: no  "],
                    'Predicted: yes': [f"true positive: {round(true_pos / act_rec, 2)}%",
                                        f"false positive: {round(false_pos / act_not_rec, 2)}%"],
                    'Predicted: no': [f"false negative: {round(false_neg / act_rec, 2)}%",
                                        f"true negative: {round(true_neg / act_not_rec, 2)}%"]})

df2.head()
```

Out[31]:

	First method: 66%-33%		Predicted: yes	Predicted: no
0		Actual: yes	true positive: 0.36%	false negative: 0.64%
1		Actual: no	false positive: 0.1%	true negative: 0.9%

In [32]:

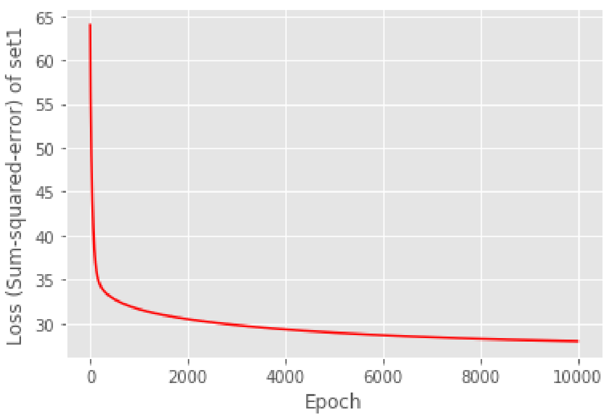
```
import matplotlib.pyplot as plt
import time

# Implementation Adaline algorithm Part B: "Cross-validation"
# Third Example: number of epochs (n_epochs) = 10000, learning rate (lr) = 0.0001
# Most recommended is that learning rate should be equal to 0.1 <= n_epochs * lr <= 1.0 -->
# 0.1/n_epochs <= lr --> 0.1 / 1000 = 0.0001 <= lr
```

```python
# start time report
start_set1 = time.time()
start_total = time.time()


# Calculating 66% of dataset length
train_len, test_len = get_train_n_test_len(myLst, 0.66)


# Creating 3 sets for train and test features (datas)
# train_f == train features, test_f == test features
train_f1, train_diagnoses1, test_f1, test_diagnoses1 \
    = data_split(myLst, train_len, test_len, False)


train_f2, train_diagnoses2, test_f2, test_diagnoses2 \
    = data_split(myLst, train_len, test_len, True)


train_f3, train_diagnoses3, test_f3, test_diagnoses3 \
    = data_split(myLst, train_len, test_len, False)


train_f1 = standardization(train_f1)
test_f1 = standardization(test_f1)


train_f2 = standardization(train_f2)
test_f2 = standardization(test_f2)


train_f3 = standardization(train_f3)
test_f3 = standardization(test_f3)
```

In [33]:

```python
## Set 1:

# Array of weights, training data and weigths of set 1
# w1 == weights of set 1,
# Initialize the weight for each feature (and the dummy feature, x0)
w1 = np.zeros(1 + train_f1.shape[1])
w1, loss_array1 = train_n_comp_loss(train_f1, train_diagnoses1, w1, 0.0001, 10000)


# predict target of tests features by our weights
# calculate real positives and negatives examples
# check prediction correctness
# true_pos1 == true positive, false_neg1 == false negative, false_pos1 == false positive,
# true_neg1 == true negative of set 1
predictions1 = predict(test_f1, w1, 0.0, 1, -1)
actual_recurred1, actual_not_recurred1 = calc_actual(test_diagnoses1)
true_pos1, false_neg1, false_pos1, true_neg1 = check_predictions(test_diagnoses1, predictions1)


print("First features set:")
check_score(true_pos1, false_neg1, false_pos1, true_neg1)



# Plot the training error
plt.plot(range(1, len(loss_array1) + 1), loss_array1, color='red')
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error) of set1')
plt.show()


end_set1 = time.time()


print(f"Code execution time of set1: {round(end_set1 - start_set1, 2)} seconds")
# Loss == t - y_in
df3_1 = pd.DataFrame({'Loss (Sum-squared-error)' : loss_array1, 'Epoch' : range(1, len(loss_array1)
+ 1)})
df3_1
```

```
First features set:
true positive: 5
false negative: 9
false positive: 5
true negative: 47

accuracy: 0.79
precision: 0.5
recall: 0.36
f_score: 0.42
```




```
Code execution time of set1: 6.13 seconds
```

Out[33]:

	Loss (Sum-squared-error)	Epoch
0	64.000000	1
1	62.805735	2
2	61.745835	3
3	60.795017	4
4	59.933235	5
...	...	...
9995	27.947683	9996
9996	27.947571	9997
9997	27.947460	9998
9998	27.947348	9999
9999	27.947236	10000

10000 rows × 2 columns

In [34]:

```
df2_1 = pd.DataFrame({'First method: 66%-33%': ['',''] ,
                      ' ':    [ "Actual: yes  ",  "Actual: no  "],
                      'Predicted: yes': [f"true positive: {round(true_pos1 / actual_recurred1, 2)}%",
                                         f"false positive: {round(false_pos1 / actual_not_recurred1, 2
}%"],
                      'Predicted: no': [f"false negative: {round(false_neg1 / actual_recurred1, 2)}%",

                                         f"true negative: {round(true_neg1 / actual_not_recurred1, 2)}
"]})

df2_1.head()
```

Out[34]:

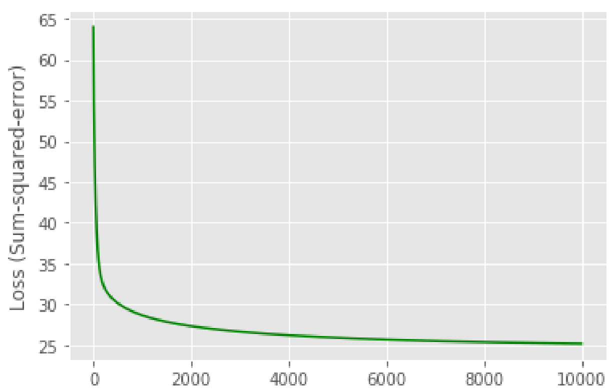
First method: 66%-33%		Predicted: yes	Predicted: no

			Predicted: yes	Predicted: no
0	First method: 66%-33%	Actual: yes	true positive: 0.36%	false negative: 0.64%
1		Actual: no	false positive: 0.1%	true negative: 0.9%

In [35]:

```
## Set 2:

start_set2 = time.time()


# Array of weights, training data and weigths of set 2
# w2 == weights of set 2,
# Initialize the weight for each feature (and the dummy feature, x0)
w2 = np.zeros(1 + train_f2.shape[1])
w2, loss_array2= train_n_comp_loss(train_f2, train_diagnoses2, w2, 0.0001, 10000)


# predict target of tests features by our weights
# calculate real positives and negatives examples
# check prediction correctness
# true_pos2 == true positive, false_neg2 == false negative, false_pos2 == false positive,
# true_neg2 == true negative of set 2
predictions2 = predict(test_f2, w2, 0.0, 1, -1)
actual_recurred2, actual_not_recurred2 = calc_actual(test_diagnoses2)
true_pos2, false_neg2, false_pos2, true_neg2 = check_predictions(test_diagnoses2, predictions2)


print("Second features set:")
check_score(true_pos2, false_neg2, false_pos2, true_neg2)


# Plot the training error
plt.plot(range(1, len(loss_array2) + 1), loss_array2, color='green')
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error)')
plt.show()


end_set2 = time.time()


print(f"Code execution time of set2: {round(end_set2 - start_set2, 2)} seconds")
# Loss == t - y_in
df3_2 = pd.DataFrame({'Loss (Sum-squared-error)' : loss_array2, 'Epoch' : range(1, len(loss_array2)
+ 1)})
df3_2.head()
```

```
Second features set:
true positive: 9
false negative: 6
false positive: 7
true negative: 44

accuracy: 0.8
precision: 0.56
recall: 0.6
f_score: 0.58
```



Epoch

```
Code execution time of set2: 0.72 seconds
```

Out[35]:

	Loss (Sum-squared-error)	Epoch
0	64.000000	1
1	62.992992	2
2	62.059908	3
3	61.188883	4
4	60.370505	5

In [36]:

```
df2_2 = pd.DataFrame({'First method: 66%-33%': ['',''] ,
                      ' ':    [ "Actual: yes  ",  "Actual: no  "],
                      'Predicted: yes': [f"true positive: {round(true_pos2 / actual_recurred2, 2)}%",
                                         f"false positive: {round(false_pos2 / actual_not_recurred2, 2
}%"],
                      'Predicted: no': [f"false negative: {round(false_neg2 / actual_recurred2, 2)}%",

                                         f"true negative: {round(true_neg2 / actual_not_recurred2, 2)}
"]})

df2_2.head()
```

Out[36]:

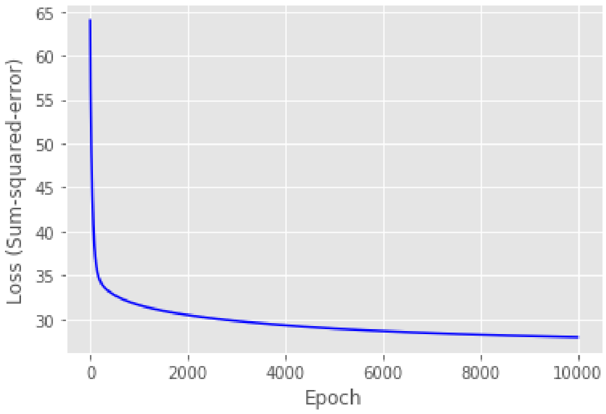
	First method: 66%-33%		Predicted: yes	Predicted: no
0		Actual: yes	true positive: 0.6%	false negative: 0.4%
1		Actual: no	false positive: 0.14%	true negative: 0.86%

In [37]:

```
## Set 3:

start_set3 = time.time()


# Array of weights, training data and weigths of set 3
# w3 == weights of set 3,
# Initialize the weight for each feature (and the dummy feature, x0)
w3 = np.zeros(1 + train_f3.shape[1])
w3, loss_array3= train_n_comp_loss(train_f3, train_diagnoses3, w3, 0.0001, 10000)


# predict target of tests features by our weights
# calculate real positives and negatives examples
# check prediction correctness
# true_pos3 == true positive, false_neg3 == false negative, false_pos3 == false positive,
# true_neg3 == true negative of set 3
predictions3 = predict(test_f3, w3, 0.0, 1, -1)
actual_recurred3, actual_not_recurred3 = calc_actual(test_diagnoses3)
true_pos3, false_neg3, false_pos3, true_neg3 = check_predictions(test_diagnoses3, predictions3)


print("Third features set:")
check_score(true_pos3, false_neg3, false_pos3, true_neg3)


# Plot the training error
plt.plot(range(1, len(loss_array3) + 1), loss_array3, color='blue')
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error)')
plt.show()
```

```
end_set3 = time.time()


print(f"Code execution time of set3: {round(end_set3 - start_set3, 2)} seconds")
# Loss == t - y_in
df3_3 = pd.DataFrame({'Loss (Sum-squared-error)' : loss_array3, 'Epoch' : range(1, len(loss_array3)
+ 1)})
df3_3
```

```
Third features set:
true positive: 5
false negative: 9
false positive: 5
true negative: 47

accuracy: 0.79
precision: 0.5
recall: 0.36
f_score: 0.42
```




```
Code execution time of set3: 0.52 seconds
```

Out[37]:

	Loss (Sum-squared-error)	Epoch
0	64.000000	1
1	62.805735	2
2	61.745835	3
3	60.795017	4
4	59.933235	5
...	...	...
9995	27.947683	9996
9996	27.947571	9997
9997	27.947460	9998
9998	27.947348	9999
9999	27.947236	10000

10000 rows × 2 columns

In [38]:

```
df2_3 = pd.DataFrame({'First method: 66%-33%': ['',''] ,
                      ' ':    [ "Actual: yes  ",  "Actual: no  "],
                      'Predicted: yes': [f"true positive: {round(true_pos3 / actual_recurred3, 2)}%",
                                         f"false positive: {round(false_pos3 / actual_not_recurred3, 2
}%"],
                      'Predicted: no': [f"false negative: {round(false_neg3 / actual_recurred3, 2)}%",
```

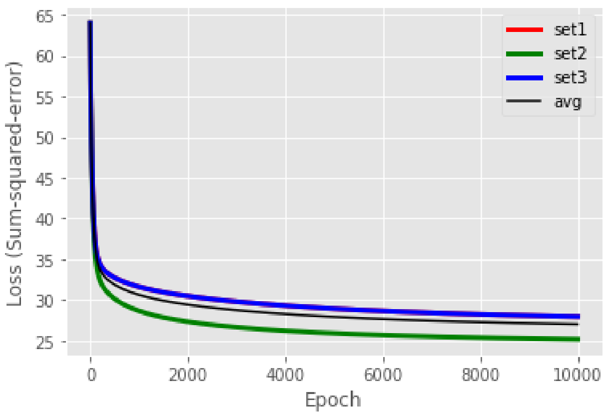
```
                                        f"true negative: {round(true_neg3 / actual_not_recurred3, 2)}
"]})

df2_3.head()
```

Out[38]:

First method: 66%-33%		Predicted: yes	Predicted: no
0	Actual: yes	true positive: 0.36%	false negative: 0.64%
1	Actual: no	false positive: 0.1%	true negative: 0.9%

In [39]:

```
# All sets (Total)
# Plot the training error
plt.plot(range(1, len(loss_array1) + 1), loss_array1, color='red', label='set1', linewidth=3.0)
plt.plot(range(1, len(loss_array2) + 1), loss_array2, color='green', label='set2', linewidth=3.0)
plt.plot(range(1, len(loss_array3) + 1), loss_array3, color='blue', label='set3', linewidth=3.0)
plt.plot(range(1, len(loss_array3) + 1), 1 / 3 * (loss_array1 + loss_array2 + loss_array3),
color='black', label='avg')
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error)')
plt.legend(loc='best')
plt.show()


end_total = time.time()


print(f"Code execution total time: {round(end_total - start_total, 2)} seconds")


# Loss == t - y_in
df3_total = pd.DataFrame({'Loss (Sum-squared-error) of all sets (total)' : 1 / 3 * (loss_array1 + l
oss_array2 + loss_array3), 'Epoch' : range(1, len(loss_array3) + 1)})
df3_total
```




```
Code execution total time: 24.36 seconds
```

Out[39]:

	Loss (Sum-squared-error) of all sets (total)	Epoch
0	64.000000	1
1	62.868154	2
2	61.850526	3
3	60.926306	4
4	60.078992	5
...	...	...
9995	27.020701	9996

	Loss (Sum-squared-error) of all sets (total)	Epoch
9996	27.020600	9997
9997	27.020500	9998
9998	27.020399	9999
9999	27.020298	10000

10000 rows × 2 columns

In [40]:

```
param1 = 1/3 * ( (true_pos1 / actual_recurred1) + (true_pos2 / actual_recurred2) + (true_pos3 /
actual_recurred3) )
param2 = 1/3 * ( (false_pos1 / actual_not_recurred1) + (false_pos2 / actual_not_recurred2) +
(false_pos3 / actual_not_recurred3) )
param3 = 1/3 * ( (false_neg1 / actual_recurred1) + (false_neg2 / actual_recurred2) + (false_neg3 / a
ctual_recurred3) )
param4 = 1/3 * ( (true_neg1 / actual_not_recurred1) + (true_neg2 / actual_not_recurred2) +
(true_neg3 / actual_not_recurred3) )

df2_total = pd.DataFrame({'First method: 66%-33%': ['',''] ,
                    ' ':    [ "Actual: yes  ",  "Actual: no  "],
                    'Predicted: yes': [f"true positive: {round(param1, 2)}%",
                                       f"false positive: {round(param2, 2)}%"],
                    'Predicted: no': [f"false negative: {round(param3, 2)}%",
                                       f"true negative: {round(param4, 2)}%"]})

df2_total.head()
```

Out[40]:

	First method: 66%-33%		Predicted: yes	Predicted: no
0		Actual: yes	true positive: 0.44%	false negative: 0.56%
1		Actual: no	false positive: 0.11%	true negative: 0.89%

In [230]:

```
# Backpropogation (with tensorflow) Part:

import tensorflow.compat.v1 as tf
tf.disable_v2_behavior()


# train features (data) with one hidden layer
# f == features, t == targets f_len == features length, out == output
def train_one_hidden_layer(f, t):
    f_len = len(f[0])
    out = 1

    # "tf.placeholder()": Inserts a placeholder for a tensor that will be always fed
    # Source "tf.placeholder()" (TensorFlow):
    # https://www.tensorflow.org/api_docs/python/tf/keras/backend/placeholder
    # Placing holder of features length => Our output: x= Tensor("Placeholder_91:0", shape=(?, 33)
, dtype=float32)
    x = tf.placeholder(tf.float32, [None, f_len])


    # Placing holder of output => Our output: y_= Tensor("Placeholder_92:0", shape=(?, 1), dtype=f
loat32)
    y_ = tf.placeholder(tf.float32, [None, out])


    # hidden layer length == 7
    # The recommended formula to choose number of hidden layer
    # Source to formula:
    # https://stats.stackexchange.com/questions/181/how-to-choose-the-number-of-hidden-layers-and-
nodes-in-a-feedforward-neural-netw
    hidden_len = 7


    # Placing holder of First hidden layer weights => Our output:
    # w1= <tf.Variable 'Variable_174:0' shape=(33, 10) dtype=float32_ref>
```

```
    # w1 = <tf.Variable 'Variable_174:0' shape=(33, 10) dtype=float32_ref>
    # tf.truncated_normal(): Outputs random values from a truncated normal distribution
    # "tf.truncated_normal()"
    # Source "tf.truncated_normal()" (TensorFlow):
    # https://www.tensorflow.org/api_docs/python/tf/random/truncated_normal
    # tf.truncated_normal() => Our output: Tensor("truncated_normal_94:0", shape=(33, 10), dtype=f
loat32)
    # Source "tf.Variable()" (TensorFlow): https://www.tensorflow.org/api_docs/python/tf/Variable
    w1 = tf.Variable(tf.truncated_normal([f_len, hidden_len], stddev=0.1))


    # Placing holder of first hidden layer bias =>
    # Our output: b1= <tf.Variable 'Variable_175:0' shape=(10,) dtype=float32_ref>
    b1 = tf.Variable(tf.constant(0.1, shape=[hidden_len]))


    # Placing holder of first hidden layer sigmoid => x*w1 + b1 => x*w1(i) + bias1 =>
    # Our output: z1= Tensor("Sigmoid_84:0", shape=(?, 10), dtype=float32)
    # tf.nn: Wrappers for primitive Neural Net (NN) Operations
    # Source "tf.nn" (TensorFlow): https://www.tensorflow.org/api_docs/python/tf/nn
    # tf.math.sigmoid(): Computes sigmoid of x element-wise
    # Formula for calculating sigmoid(x): y = 1 / (1 + exp(-x))
    # Source "tf.nn.sigmoid()" (TensorFlow):
https://www.tensorflow.org/api_docs/python/tf/math/sigmoid
    z1 = tf.nn.sigmoid(tf.matmul(x, w1) + b1)


    # Placing holder of second hidden layer weights =>
    # Our output: w2= <tf.Variable 'Variable_176:0' shape=(10, 1) dtype=float32_ref>
    #
    # "stddev()" function to calculate standard deviation.
    # *Standard deviation is a measure of the spread of a data value system
    # And gives a degree of divergence.
    # **A low measure of Standard Deviation indicates that the data are less spread out.
    # **High value of Standard Deviation shows that the data in a set are spread apart from
    # their mean average values.
    # A useful property of the standard deviation is that, unlike the variance, it is expressed in

    # the same units as the data.
    # Source "stddev()" (GeeksforGeeks) : https://www.geeksforgeeks.org/python-statistics-stdev/
    w2 = tf.Variable(tf.truncated_normal([hidden_len, out], stddev=0.1))


    # Placing holder of second (hidden) layer bias =>
    # Our output: b2= <tf.Variable 'Variable_177:0' shape=() dtype=float32_ref>
    b2 = tf.Variable(0.1, [out], dtype=tf.float32)


    # y = (z1 * w2) + b2
    # Source "tf.matmul()" (TensorFlow):
https://www.tensorflow.org/api_docs/python/tf/linalg/matmul
    # tf.matmul => multiply matrixes => tf.matmul(z1, w2) => z1 * w2
    y = tf.matmul(z1,w2) + b2


    # Loss: Sum of squared error
    # "tf.square(y - y_)" => (y - y_)^2
    # tf.square(y - y_) => Tensor("Square_42:0", shape=(?, 1), dtype=float32)
    # Source "tf.square(y_ - y)" (TensorFlow):
https://www.tensorflow.org/api_docs/python/tf/math/square
    # tf.reduce_mean(): Computes the mean of elements across dimensions of a tensor
    # Source "tf.reduce_mean()" (TensorFlow):
https://www.tensorflow.org/api_docs/python/tf/math/reduce_mean
    loss = tf.reduce_mean(tf.square(y - y_))


    # tf.train.GradientDescentOptimizer(): Optimizer that implements the gradient descent
algorithm
    # Source "tf.train.GradientDescentOptimizer()" (TensorFlow):
    # https://www.tensorflow.org/api_docs/python/tf/compat/v1/train/GradientDescentOptimizer
    # tfp.math.minimize: Minimize a loss function using a provided optimizer
    # Source "tfp.math.minimize" (TensorFlow):
    # https://www.tensorflow.org/probability/api_docs/python/tfp/math/minimize
    # update => Our output:
    # update= name: "GradientDescent_48"
    # op: "NoOp"
    # input: "^GradientDescent_48/update_Variable_202/ApplyGradientDescent"
    # input: "^GradientDescent_48/update_Variable_203/ApplyGradientDescent"
```

```
    # input: "^GradientDescent_48/update_Variable_203/ApplyGradientDescent"
    # input: "^GradientDescent_48/update_Variable_204/ApplyGradientDescent"
    # input: "^GradientDescent_48/update_Variable_205/ApplyGradientDescent"
    update = tf.train.GradientDescentOptimizer(0.01).minimize(loss)


    loss_array = np.array([])


    # tf.Session(): A class for running TensorFlow operations
    # Source "tf.Session()" (TensorFlow):
https://www.tensorflow.org/api_docs/python/tf/compat/v1/Session
    # sess => Our output: <tensorflow.python.client.session.Session object at 0x000001B8C05B2D88>
    sess = tf.Session()

    # Our output: sess.run(tf.global_variables_initializer()) None
    sess.run(tf.global_variables_initializer())
    for i in range(0, 10000):
        sess.run(update, feed_dict={x: f, y_: t})
        if i % 1000 == 0:
            # "feed_dict" argument allows the caller to override the value of tensors in the graph
            loss_array = np.append(loss_array, [loss.eval(session=sess, feed_dict={x: f, y_: t})])

    return x, y, sess, loss_array



# train features (data) with two hidden layers
# f == features, t == targets f_len == features length, out == output
def train_two_hidden_layer(f, t):
    f_len = len(f[0])
    out = 1


    # "tf.placeholder()": Inserts a placeholder for a tensor that will be always fed
    # Source "tf.placeholder()" (TensorFlow):
    # https://www.tensorflow.org/api_docs/python/tf/keras/backend/placeholder
    # Placing holder of features length => Our output: x= Tensor("Placeholder_91:0", shape=(?, 33)
, dtype=float32)
    x = tf.placeholder(tf.float32, [None, f_len])


    # Placing holder of output => Our output: y_= Tensor("Placeholder_92:0", shape=(?, 1), dtype=f
loat32)
    y_ = tf.placeholder(tf.float32, [None, out])


    # First hidden layer length == 7, Second hidden layer length == 4
    # The recommended formula to choose number of hidden layer
    # Source to formula:
    # https://stats.stackexchange.com/questions/181/how-to-choose-the-number-of-hidden-layers-and-
nodes-in-a-feedforward-neural-netw
    (hidden_len, hidden2_len) = (12, 3)


    # Placing holder of First hidden layer weights => Our output:
    # w1= <tf.Variable 'Variable_174:0' shape=(33, 10) dtype=float32_ref>
    # tf.truncated_normal(): Outputs random values from a truncated normal distribution
    # "tf.truncated_normal()"
    # Source "tf.truncated_normal()" (TensorFlow):
    # https://www.tensorflow.org/api_docs/python/tf/random/truncated_normal
    # tf.truncated_normal() => Our output: Tensor("truncated_normal_94:0", shape=(33, 10), dtype=f
loat32)
    # Source "tf.Variable()" (TensorFlow): https://www.tensorflow.org/api_docs/python/tf/Variable
    w1 = tf.Variable(tf.truncated_normal([f_len, hidden_len], stddev=0.1))


    # Placing holder of first hidden layer bias =>
    # Our output: b1= <tf.Variable 'Variable_175:0' shape=(10,) dtype=float32_ref>
    b1 = tf.Variable(tf.constant(0.1, shape=[hidden_len]))


    # z1 = x*w1 + b1
    # tf.nn.relu(): Computes rectified linear: max(features, 0)
    # Source "tf.nn.relu()" (TensorFlow): https://www.tensorflow.org/api_docs/python/tf/nn/relu
    z1 = tf.nn.relu(tf.matmul(x, w1) + b1)
```

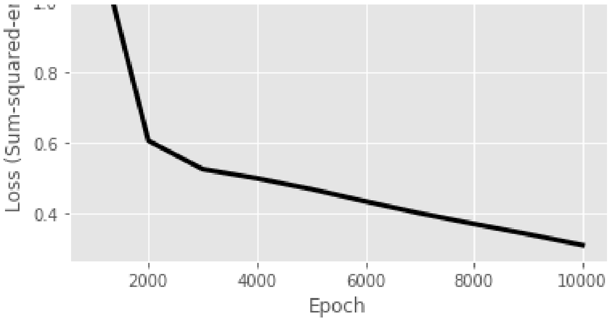
```
    # Placing holder of first hidden layer weights =>
    # Our output: w2= <tf.Variable 'Variable_176:0' shape=(10, 1) dtype=float32_ref>
    #
    # "stddev()" function to calculate standard deviation.
    # *Standard deviation is a measure of the spread of a data value system
    # And gives a degree of divergence.
    # **A low measure of Standard Deviation indicates that the data are less spread out.
    # **High value of Standard Deviation shows that the data in a set are spread apart from
    # their mean average values.
    # A useful property of the standard deviation is that, unlike the variance, it is expressed in

    # the same units as the data.
    # Source "stddev()" (GeeksforGeeks) : https://www.geeksforgeeks.org/python-statistics-stdev/
    w2 = tf.Variable(tf.truncated_normal([hidden_len, hidden2_len], stddev=0.1))


    # Placing holder of second (hidden) layer bias =>
    # Our output: b2= <tf.Variable 'Variable_177:0' shape=() dtype=float32_ref>
    b2 = tf.Variable(tf.constant(0.1, shape=[hidden2_len]))


    # z2 = z1*w2 + b2
    # tf.nn.relu(): Computes rectified linear: max(features, 0)
    # Source "tf.nn.relu()" (TensorFlow): https://www.tensorflow.org/api_docs/python/tf/nn/relu
    z2 = tf.nn.relu(tf.matmul(z1, w2) + b2)


    # Placing holder of second hidden layer weights =>
    # Our output: w2= <tf.Variable 'Variable_176:0' shape=(10, 1) dtype=float32_ref>
    #
    # "stddev()" function to calculate standard deviation.
    # *Standard deviation is a measure of the spread of a data value system
    # And gives a degree of divergence.
    # **A low measure of Standard Deviation indicates that the data are less spread out.
    # **High value of Standard Deviation shows that the data in a set are spread apart from
    # their mean average values.
    # A useful property of the standard deviation is that, unlike the variance, it is expressed in

    # the same units as the data.
    # Source "stddev()" (GeeksforGeeks) : https://www.geeksforgeeks.org/python-statistics-stdev/
    w3 = tf.Variable(tf.truncated_normal([hidden2_len, out], stddev=0.1))


    # Placing holder of second hidden layer bias
    b3 = tf.Variable(0.1, [out], dtype=tf.float32)


    # y = (z2 * w3) + b3
    # Source "tf.matmul()" (TensorFlow):
https://www.tensorflow.org/api_docs/python/tf/linalg/matmul
    # tf.matmul => multiply matrixes => tf.matmul(z2, w3) => z2 * w3
    y = tf.matmul(z2, w3) + b3


    # Loss: Sum of squared error
    # "tf.square(y - y_)" => (y - y_)^2
    # tf.square(y - y_) => Tensor("Square_42:0", shape=(?, 1), dtype=float32)
    # Source "tf.square(y_ - y)" (TensorFlow):
https://www.tensorflow.org/api_docs/python/tf/math/square
    # tf.reduce_mean(): Computes the mean of elements across dimensions of a tensor
    # Source "tf.reduce_mean()" (TensorFlow):
https://www.tensorflow.org/api_docs/python/tf/math/reduce_mean
    loss = tf.reduce_mean(tf.square(y - y_))


    # tf.train.GradientDescentOptimizer(): Optimizer that implements the gradient descent
algorithm
    # Source "tf.train.GradientDescentOptimizer()" (TensorFlow):
    # https://www.tensorflow.org/api_docs/python/tf/compat/v1/train/GradientDescentOptimizer
    # tfp.math.minimize: Minimize a loss function using a provided optimizer
    # Source "tfp.math.minimize" (TensorFlow):
    # https://www.tensorflow.org/probability/api_docs/python/tfp/math/minimize
    # update => Our output:
    # update= name: "GradientDescent_48"
    # op: "NoOp"
    # input: "^GradientDescent_48/update_Variable_202/ApplyGradientDescent"
    # input: "^GradientDescent_48/update_Variable_203/ApplyGradientDescent"
```

```
    # input: "^GradientDescent_48/update_Variable_203/ApplyGradientDescent"
    # input: "^GradientDescent_48/update_Variable_204/ApplyGradientDescent"
    # input: "^GradientDescent_48/update_Variable_205/ApplyGradientDescent"
    update = tf.train.GradientDescentOptimizer(0.01).minimize(loss)


    loss_array = np.array([])


    # tf.Session(): A class for running TensorFlow operations
    # Source "tf.Session()" (TensorFlow):
https://www.tensorflow.org/api_docs/python/tf/compat/v1/Session
    # sess => Our output: <tensorflow.python.client.session.Session object at 0x000001B8C05B2D88>
    sess = tf.Session()

    # Our output: sess.run(tf.global_variables_initializer()) None
    sess.run(tf.global_variables_initializer())
    for i in range(0, 10000):
        sess.run(update, feed_dict={x: f, y_: t})
        if i % 1000 == 0:
            # "feed_dict" argument allows the caller to override the value of tensors in the graph
            loss_array = np.append(loss_array, [loss.eval(session=sess, feed_dict={x: f, y_: t})])

    return x, y, sess, loss_array



# Get predictions (backpropogation)
# If [num>= 0.5] => return [1.], Otherwise, returns [-1.]
# f_test == features test
# The eval() method returns the result evaluated from the expression
# Source eval(): https://www.programiz.com/python-programming/methods/built-in/eval
# In our example val its array of small numbers array that should be around to 0.5
# predict_back_prop() method returns array of value (1 or -1) arrays
def predict_back_prop(x, y, sess, f_test):
    val = y.eval(session=sess, feed_dict={x: f_test})
    return np.where(val >= 0.5, 1, -1)
```

In [161]:

```
# Backpropogation (with tensorflow) Part: With one hidden layer:

#start_time = time.time()


# Calculating 66% of dataset length to train and other (34%) to test
# train_len = 194 * 0.66 = 128.04 => 128
# test_len = 194 - 128 = 66
train_len, test_len = get_train_n_test_len(myLst, 0.66)


# Creating sets for train and test features (data) (by spliting data according to the percent sepa
rated by
# date_split method) and the output of their expected results called "train_diagnoses" and
# "test_diagnoses", respectively.
# train_f == train features, test_f == test features
train_f, train_diagnoses, test_f, test_diagnoses \
    = data_split(myLst, train_len, test_len, False)


# standardization set of train features (data) from bits-type to float type
# print(f"train_f {train_f} ")
train_f = standardization(train_f)


# standardization set of test features (data) from bits-type to float type
# print(f"test_f {test_f} ")
# **Note: The values in the diagnoses datasets are not required to be converted
(standardizationed) because
# they were initially saved as an integer type.
test_f = standardization(test_f)


# For self tests:
#print(f"train_len {train_len} ")
#print(f"test_len {test_len} ")
#print(f"train_f {train_f} ")
```

```
#print(f"train_f {train_f} ")
#print(f"train_diagnoses {train_diagnoses} ")
#print(f"test_f {test_f} ")
#print(f"test_diagnoses {test_diagnoses} ")


# Source "np.reshape()" (NumPy):
https://numpy.org/doc/stable/reference/generated/numpy.reshape.html
# "np.reshape()" example: np.reshape(3,-1) == np.reshape([-1. 1. -1.]) => [ [-1.] /n [1.] /n [-1.]
]
# train_diagnoses.shape[0] = 128, if [128,] -> [128,1]
train_diagnoses = train_diagnoses.reshape(train_diagnoses.shape[0], -1)

# Training the features set:
x, y, sess, loss_array_back = train_one_hidden_layer(train_f, train_diagnoses)


# Plot the training error
#plt.plot(range(1, len(loss_array1) + 1), loss_array1, color='red', label='set1', linewidth=3.0)
#print(loss_array_back)
plt.plot(range(1 * 1000, (len(loss_array_back) + 1) * 1000, 1000), loss_array_back, color='black',
linewidth=3.0)
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error)')
plt.show()


# Our final results set: (true positive, false negative, false positive, true negative) =
(a,b,c,b)
print(f"Features set:")
#print(f"check_predictions {check_predictions(test_diagnoses, predict_back_prop(x, y, sess, test_f
))} ")
tmp_res = check_predictions(test_diagnoses, predict_back_prop(x, y, sess, test_f))
check_score(tmp_res[0], tmp_res[1], tmp_res[2], tmp_res[3])

#end_time = time.time()


#print(f"Code execution time: {round(end_time - start_time, 2)} seconds")
# Loss == t - y_in
df3 = pd.DataFrame({'Loss (Sum-squared-error)' : loss_array_back, 'Epoch' :range(1 * 1000, (len(los
s_array_back) + 1) * 1000, 1000)})
df3


# Our results and conclusions (with one hidden layer):
# First case: n_epochs = 10000, lr = 0.00001, stddev() = 0.1 => Min Loss = 0.9170, (0,14,0,52)
# Second case: n_epochs = 10000, lr = 0.0001, stddev() = 0.1 => Min Loss = 0.7283, (0,14,0,52)
# Third case: n_epochs = 10000, lr = 0.001, stddev() = 0.1 => Min Loss = 0.6170, (0,14,0,52)
# Fourth case: n_epochs = 10000, lr = 0.01, stddev() = 0.1 => Min Loss = 0.3514, (4,10,1,51), acc=
0.83
# Fifth case: n_epochs = 10000, lr = 0.01, stddev() = 0.1 => Min Loss = 0.2980, (4,10,0,52), acc=
0.85
## We can see that the standard deviation value, choosing number to hidden layer and choosing a le
arning rate
## plays a significant role in finding the convergence point and getting the maximum result accura
cy.
## (4,10,0,52) => It can be seen that this is the better solution because our algorithm matched it
s prediction
## accurately to the target results of cancer recurrence prediction and cancer recurrence predicti
on.
## In other results such as (0,14,0,52) and (4,10,1,51), for example, we can see that our algorith
m has made
## some predictions different from the target results.
## This is the reason we cited the factors (number of epochs, learning rate, standard deviation, e
tc.) that, if
## we do not precisely target them as accurately as possible, that may affect non-convergence to t
he minimum
## point and reach the most accurate result.
## **Note: It is important to note that in the beginning, we trained our training data well
##         (66 percent of the data) to train the algorithm and predict the test data as the target
results.
```




```
Features set:
true positive: 4
false negative: 10
false positive: 0
true negative: 52

accuracy: 0.85
precision: 1.0
recall: 0.29
f_score: 0.44
```

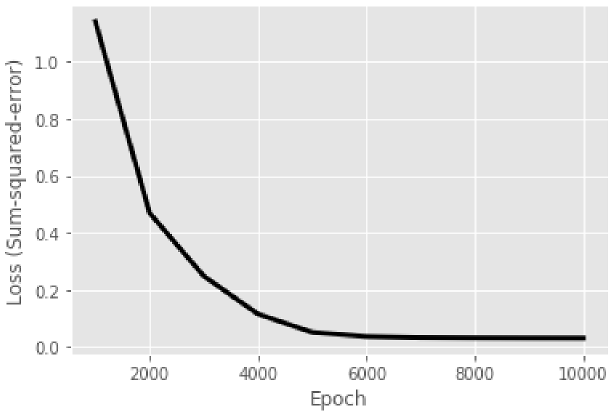
Out[161]:

	Loss (Sum-squared-error)	Epoch
0	1.208034	1000
1	0.605328	2000
2	0.524645	3000
3	0.498712	4000
4	0.468158	5000
5	0.433380	6000
6	0.399969	7000
7	0.369706	8000
8	0.340557	9000
9	0.309753	10000

In [236]:

```
# Backpropogation (with tensorflow) Part: With two hidden layers:

#start_time = time.time()


# Calculating 66% of dataset length to train and other (34%) to test
# train_len = 194 * 0.66 = 128.04 => 128
# test_len = 194 - 128 = 66
train_len, test_len = get_train_n_test_len(myLst, 0.66)


# Creating sets for train and test features (data) (by spliting data according to the percent sepa
rated by
# date_split method) and the output of their expected results called "train_diagnoses" and
# "test_diagnoses", respectively.
# train_f == train features, test_f == test features
train_f, train_diagnoses, test_f, test_diagnoses \
    = data_split(myLst, train_len, test_len, False)


# standardization set of train features (data) from bits-type to float type
# print(f"train_f {train_f} ")
train_f = standardization(train_f)


# standardization set of test features (data) from bits-type to float type
# print(f"test_f {test_f} ")
# **Note: The values in the diagnoses datasets are not required to be converted
```

```
(standardizationed) because
# they were initially saved as an integer type.
test_f = standardization(test_f)


# For self tests:
#print(f"train_len {train_len} ")
#print(f"test_len {test_len} ")
#print(f"train_f  {train_f} ")
#print(f"train_diagnoses {train_diagnoses} ")
#print(f"test_f {test_f} ")
#print(f"test_diagnoses {test_diagnoses} ")


# Source "np.reshape()" (NumPy):
https://numpy.org/doc/stable/reference/generated/numpy.reshape.html
# "np.reshape()" example: np.reshape(3,-1) == np.reshape([-1. 1. -1.]) => [ [-1.] /n [1.] /n [-1.]
]
# train_diagnoses.shape[0] = 128, if [128,] -> [128,1]
train_diagnoses = train_diagnoses.reshape(train_diagnoses.shape[0], -1)

# Training the features set:
x, y, sess, loss_array_back = train_two_hidden_layer(train_f, train_diagnoses)


# Plot the training error
#plt.plot(range(1, len(loss_array1) + 1), loss_array1, color='red', label='set1', linewidth=3.0)
#print(loss_array_back)
plt.plot(range(1 * 1000, (len(loss_array_back) + 1) * 1000, 1000), loss_array_back, color='black',
linewidth=3.0)
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error)')
plt.show()


# Our final results set: (true positive, false negative, false positive, true negative) =
(a,b,c,b)
print(f"Features set:")
#print(f"check_predictions {check_predictions(test_diagnoses, predict_back_prop(x, y, sess, test_f
))} ")
tmp_res = check_predictions(test_diagnoses, predict_back_prop(x, y, sess, test_f))
check_score(tmp_res[0], tmp_res[1], tmp_res[2], tmp_res[3])

#end_time = time.time()


#print(f"Code execution time: {round(end_time - start_time, 2)} seconds")
# Loss == t - y_in
df3 = pd.DataFrame({'Loss (Sum-squared-error)' : loss_array_back, 'Epoch' :range(1 * 1000, (len(los
s_array_back) + 1) * 1000, 1000)})
df3
```




```
Features set:
true positive: 7
false negative: 7
false positive: 1
true negative: 51

accuracy: 0.88
```

```
precision: 0.88
recall: 0.5
f_score: 0.64
```

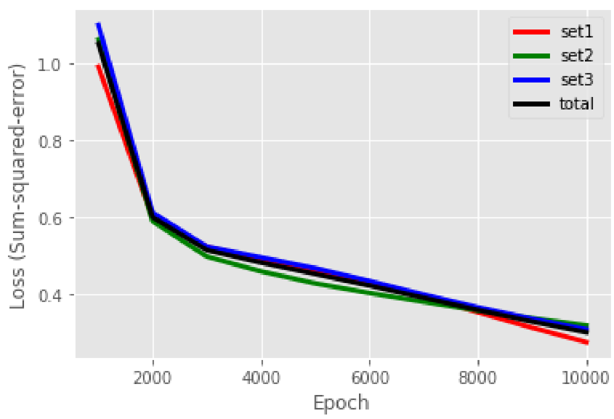
Out[236]:

	Loss (Sum-squared-error)	Epoch
0	1.141000	1000
1	0.469765	2000
2	0.248087	3000
3	0.115115	4000
4	0.050980	5000
5	0.036435	6000
6	0.032273	7000
7	0.031162	8000
8	0.030662	9000
9	0.030334	10000

In [239]:

```
# Backpropogation (with tensorflow) "Cross-validation" Part: With one hidden layer

# Calculating 66% of dataset length to train and other (34%) to test
# train_len = 194 * 0.66 = 128.04 => 128
# test_len = 194 - 128 = 66
train_len, test_len = get_train_n_test_len(myLst, 0.66)


# Creating 3 sets for train and test features (data) (by spliting data according to the percent se
parated by
# date_split method) and the output of their expected results called "train_diagnoses" and
# "test_diagnoses", respectively.
# train_f == train features, test_f == test features

# First set:
train_f1, train_diagnoses1, test_f1, test_diagnoses1 \
    = data_split(myLst, train_len, test_len, False)

# Second set:
train_f2, train_diagnoses2, test_f2, test_diagnoses2 \
    = data_split(myLst, train_len, test_len, True)

# Third set:
train_f3, train_diagnoses3, test_f3, test_diagnoses3 \
    = data_split(myLst, train_len, test_len, False)


# standardization set of train features (data) from bits-type to float type
# print(f"train_f {train_f} ")
#
# standardization set of test features (data) from bits-type to float type
# print(f"test_f {test_f} ")
# **Note: The values in the diagnoses datasets are not required to be converted
(standardizationed) because
# they were initially saved as an integer type.
train_f1 = standardization(train_f1)
test_f1 = standardization(test_f1)

train_f2 = standardization(train_f2)
test_f2 = standardization(test_f2)

train_f3 = standardization(train_f3)
test_f3 = standardization(test_f3)


# Source "np.reshape()" (NumPy):
https://numpy.org/doc/stable/reference/generated/numpy.reshape.html
# "np.reshape()" example: np.reshape(3,-1) == np.reshape([-1. 1. -1.]) => [ [-1.] /n [1.] /n [-1.]
```

```python
]
# train_diagnoses.shape[0] = 128, if [128,] -> [128,1]
train_diagnoses1 = train_diagnoses1.reshape(train_diagnoses1.shape[0], -1)
train_diagnoses2 = train_diagnoses2.reshape(train_diagnoses2.shape[0], -1)
train_diagnoses3 = train_diagnoses3.reshape(train_diagnoses3.shape[0], -1)


# Training the features set:
x1, y1, sess1, loss_array_back1 = train_one_hidden_layer(train_f1, train_diagnoses1)
x2, y2, sess2, loss_array_back2 = train_one_hidden_layer(train_f2, train_diagnoses2)
x3, y3, sess3, loss_array_back3 = train_one_hidden_layer(train_f3, train_diagnoses3)


# Plot the training error
# loss_total == average of all 3 sets
loss_total = 1/3 * (loss_array_back1 + loss_array_back2 + loss_array_back3)
plt.plot(range(1 * 1000, (len(loss_array_back1) + 1) * 1000, 1000), loss_array_back1, color='red',
label='set1', linewidth=3.0)
plt.plot(range(1 * 1000, (len(loss_array_back2) + 1) * 1000, 1000), loss_array_back2, color='green'
, label='set2', linewidth=3.0)
plt.plot(range(1 * 1000, (len(loss_array_back3) + 1) * 1000, 1000), loss_array_back3, color='blue',
label='set3', linewidth=3.0)
plt.plot(range(1 * 1000, (len(loss_total) + 1) * 1000, 1000), loss_total, color='black', label='tot
al', linewidth=3.0)
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error)')
plt.legend(loc='best')
plt.show()


# Our final results sets: (true positive, false negative, false positive, true negative) =
(a,b,c,b)

print(f"Feature set1:")
tmp_res1 = check_predictions(test_diagnoses1, predict_back_prop(x1, y1, sess1, test_f1))
check_score(tmp_res1[0], tmp_res1[1], tmp_res1[2], tmp_res1[3])


print(f"Feature set2:")
tmp_res2 = check_predictions(test_diagnoses2, predict_back_prop(x2, y2, sess2, test_f2))
check_score(tmp_res2[0], tmp_res2[1], tmp_res2[2], tmp_res2[3])


print(f"Feature set3:")
tmp_res3 = check_predictions(test_diagnoses3, predict_back_prop(x3, y3, sess3, test_f3))
check_score(tmp_res3[0], tmp_res3[1], tmp_res3[2], tmp_res3[3])
```




```
Feature set1:
true positive: 2
false negative: 12
false positive: 0
true negative: 52

accuracy: 0.82
precision: 1.0
recall: 0.14
f_score: 0.25

Feature set2:
true positive: 4
```

```
true positive: 4
false negative: 11
false positive: 3
true negative: 48

accuracy: 0.79
precision: 0.57
recall: 0.27
f_score: 0.36

Feature set3:
true positive: 1
false negative: 13
false positive: 0
true negative: 52

accuracy: 0.8
precision: 1.0
recall: 0.07
f_score: 0.13
```

In [241]:

```
# First set table loss:
# Loss == t - y_in
df3_1 = pd.DataFrame({'Loss (Sum-squared-error) of set1' : loss_array_back1, 'Epoch' :range(1 * 100
, (len(loss_array_back1)
                                                                                                  + 1)
0, 100)})
df3_1
```

Out[241]:

	Loss (Sum-squared-error) of set1	Epoch
0	0.992339	100
1	0.599473	200
2	0.524425	300
3	0.493046	400
4	0.463547	500
5	0.431598	600
6	0.394834	700
7	0.354942	800
8	0.314818	900
9	0.277323	1000

In [242]:

```
# Second set table loss:
# Loss == t - y_in
df3_2 = pd.DataFrame({'Loss (Sum-squared-error) of set2' : loss_array_back2, 'Epoch' :range(1 * 100
, (len(loss_array_back2)
                                                                                                  + 1)
0, 100)})
df3_2
```

Out[242]:

	Loss (Sum-squared-error) of set2	Epoch
0	1.063079	100
1	0.591129	200
2	0.499403	300
3	0.460791	400

	Loss (Sum-squared-error) of set2	Epoch
4	0.429716	500
5	0.404697	600
6	0.381797	700
7	0.359320	800
8	0.339391	900
9	0.320823	1000

In [243]:

```
# Third set table loss:
# Loss == t - y_in
df3_3 = pd.DataFrame({'Loss (Sum-squared-error) of set3' : loss_array_back3, 'Epoch' :range(1 * 100
, (len(loss_array_back3)
                                                                                              + 1)
0, 100)})
df3_3
```

Out[243]:

	Loss (Sum-squared-error) of set3	Epoch
0	1.100323	100
1	0.613377	200
2	0.525099	300
3	0.497178	400
4	0.469012	500
5	0.435799	600
6	0.400620	700
7	0.367525	800
8	0.337877	900
9	0.310650	1000

In [244]:

```
# Second set table loss:
# Loss == t - y_in
df3_total = pd.DataFrame({'Loss (Sum-squared-error) of total' : loss_total, 'Epoch' :range(1 * 100,
(len(loss_total)
                                                                                              + 1)
0, 100)})
df3_total
```

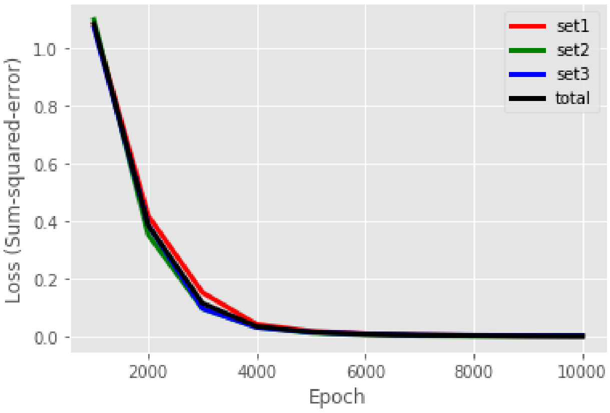
Out[244]:

	Loss (Sum-squared-error) of total	Epoch
0	1.051914	100
1	0.601326	200
2	0.516309	300
3	0.483672	400
4	0.454092	500
5	0.424031	600
6	0.392417	700
7	0.360596	800
8	0.330695	900
9	0.302932	1000

In [245]:

```
# Backpropogation (with tensorflow) "Cross-validation" Part: With two hidden layer

# Calculating 66% of dataset length to train and other (34%) to test
# train_len = 194 * 0.66 = 128.04 => 128
# test_len = 194 - 128 = 66
train_len, test_len = get_train_n_test_len(myLst, 0.66)


# Creating 3 sets for train and test features (data) (by spliting data according to the percent se
parated by
# date_split method) and the output of their expected results called "train_diagnoses" and
# "test_diagnoses", respectively.
# train_f == train features, test_f == test features

# First set:
train_f1, train_diagnoses1, test_f1, test_diagnoses1 \
    = data_split(myLst, train_len, test_len, False)

# Second set:
train_f2, train_diagnoses2, test_f2, test_diagnoses2 \
    = data_split(myLst, train_len, test_len, True)

# Third set:
train_f3, train_diagnoses3, test_f3, test_diagnoses3 \
    = data_split(myLst, train_len, test_len, False)


# standardization set of train features (data) from bits-type to float type
# print(f"train_f {train_f} ")
#
# standardization set of test features (data) from bits-type to float type
# print(f"test_f {test_f} ")
# **Note: The values in the diagnoses datasets are not required to be converted
(standardizationed) because
# they were initially saved as an integer type.
train_f1 = standardization(train_f1)
test_f1 = standardization(test_f1)

train_f2 = standardization(train_f2)
test_f2 = standardization(test_f2)

train_f3 = standardization(train_f3)
test_f3 = standardization(test_f3)


# Source "np.reshape()" (NumPy):
https://numpy.org/doc/stable/reference/generated/numpy.reshape.html
# "np.reshape()" example: np.reshape(3,-1) == np.reshape([-1. 1. -1.]) => [ [-1.] /n [1.] /n [-1.]
]
# train_diagnoses.shape[0] = 128, if [128,] -> [128,1]
train_diagnoses1 = train_diagnoses1.reshape(train_diagnoses1.shape[0], -1)
train_diagnoses2 = train_diagnoses2.reshape(train_diagnoses2.shape[0], -1)
train_diagnoses3 = train_diagnoses3.reshape(train_diagnoses3.shape[0], -1)


# Training the features set:
x1, y1, sess1, loss_array_back1 = train_two_hidden_layer(train_f1, train_diagnoses1)
x2, y2, sess2, loss_array_back2 = train_two_hidden_layer(train_f2, train_diagnoses2)
x3, y3, sess3, loss_array_back3 = train_two_hidden_layer(train_f3, train_diagnoses3)


# Plot the training error
# loss_total == average of all 3 sets
loss_total = 1/3 * (loss_array_back1 + loss_array_back2 + loss_array_back3)
plt.plot(range(1 * 1000, (len(loss_array_back1) + 1) * 1000, 1000), loss_array_back1, color='red',
label='set1', linewidth=3.0)
plt.plot(range(1 * 1000, (len(loss_array_back2) + 1) * 1000, 1000), loss_array_back2, color='green'
, label='set2', linewidth=3.0)
plt.plot(range(1 * 1000, (len(loss_array_back3) + 1) * 1000, 1000), loss_array_back3, color='blue',
label='set3', linewidth=3.0)
plt.plot(range(1 * 1000, (len(loss_total) + 1) * 1000, 1000), loss_total, color='black', label='tot
al', linewidth=3.0)
plt.xlabel('Epoch')
plt.ylabel('Loss (Sum-squared-error)')
plt.legend(loc='best')
plt.show()
```

```
# Our final results sets: (true positive, false negative, false positive, true negative) =
(a,b,c,b)

print(f"Feature set1:")
tmp_res1 = check_predictions(test_diagnoses1, predict_back_prop(x1, y1, sess1, test_f1))
check_score(tmp_res1[0], tmp_res1[1], tmp_res1[2], tmp_res1[3])


print(f"Feature set2:")
tmp_res2 = check_predictions(test_diagnoses2, predict_back_prop(x2, y2, sess2, test_f2))
check_score(tmp_res2[0], tmp_res2[1], tmp_res2[2], tmp_res2[3])


print(f"Feature set3:")
tmp_res3 = check_predictions(test_diagnoses3, predict_back_prop(x3, y3, sess3, test_f3))
check_score(tmp_res3[0], tmp_res3[1], tmp_res3[2], tmp_res3[3])
```




```
Feature set1:
true positive: 7
false negative: 7
false positive: 4
true negative: 48

accuracy: 0.83
precision: 0.64
recall: 0.5
f_score: 0.56

Feature set2:
true positive: 9
false negative: 6
false positive: 5
true negative: 46

accuracy: 0.83
precision: 0.64
recall: 0.6
f_score: 0.62

Feature set3:
true positive: 4
false negative: 10
false positive: 7
true negative: 45

accuracy: 0.74
precision: 0.36
recall: 0.29
f_score: 0.32
```

In [246]:

```
# First set table loss:
# Loss == t - y_in
df3_1 = pd.DataFrame({'Loss (Sum-squared-error) of set1' : loss_array_back1, 'Epoch' :range(1 * 100
```

```
, (len(loss_array_back1)
                                                                                            + 1)
0, 100)})
df3_1
```

Out[246]:

	Loss (Sum-squared-error) of set1	Epoch
0	1.080022	100
1	0.417427	200
2	0.151810	300
3	0.041449	400
4	0.017573	500
5	0.008670	600
6	0.004633	700
7	0.002723	800
8	0.001427	900
9	0.000764	1000

In [247]:

```
# Second set table loss:
# Loss == t - y_in
df3_2 = pd.DataFrame({'Loss (Sum-squared-error) of set2' : loss_array_back2, 'Epoch' :range(1 * 100
, (len(loss_array_back2)
                                                                                            + 1)
0, 100)})
df3_2
```

Out[247]:

	Loss (Sum-squared-error) of set2	Epoch
0	1.096982	100
1	0.351485	200
2	0.095389	300
3	0.031188	400
4	0.012289	500
5	0.005323	600
6	0.002362	700
7	0.001096	800
8	0.000590	900
9	0.000358	1000

In [248]:

```
# Third set table loss:
# Loss == t - y_in
df3_3 = pd.DataFrame({'Loss (Sum-squared-error) of set3' : loss_array_back3, 'Epoch' :range(1 * 100
, (len(loss_array_back3)
                                                                                            + 1)
0, 100)})
df3_3
```

Out[248]:

	Loss (Sum-squared-error) of set3	Epoch
0	1.069589	100

	Loss (Sum-squared-error) of set3	Epoch
1	0.385348	200
2	0.096773	300
3	0.030616	400
4	0.014426	500
5	0.008299	600
6	0.004862	700
7	0.003046	800
8	0.002075	900
9	0.001493	1000

In [249]:

```
# Second set table loss:
# Loss == t - y_in
df3_total = pd.DataFrame({'Loss (Sum-squared-error) of total' : loss_total, 'Epoch' :range(1 * 100,
(len(loss_total)
                                                                                                    + 1)
0, 100)})
df3_total
```

Out[249]:

	Loss (Sum-squared-error) of total	Epoch
0	1.082198	100
1	0.384753	200
2	0.114657	300
3	0.034417	400
4	0.014763	500
5	0.007430	600
6	0.003952	700
7	0.002288	800
8	0.001364	900
9	0.000872	1000

In [ ]: