Lab 3-Suyash Srivastava-22MCS108

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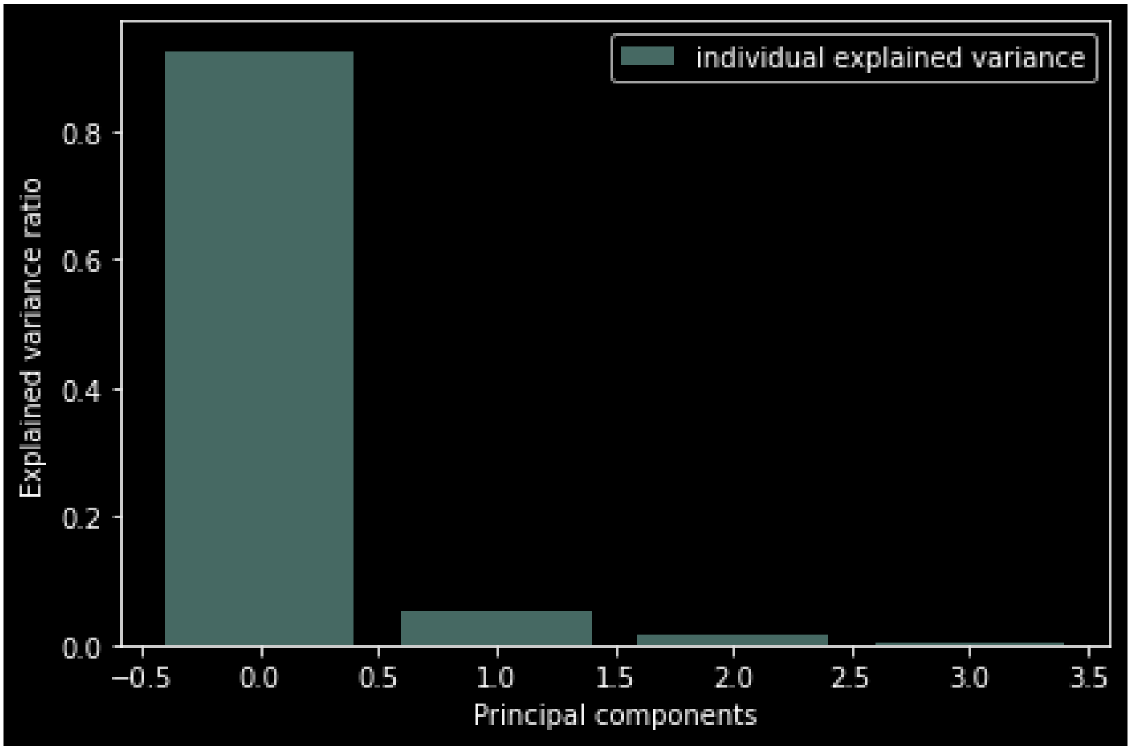
0.1 Lab 3 : Suyash Srivastava (22MCS108)

[1]:

```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.decomposition import PCA
iris = datasets.load_iris()
X = iris.data[:, :]
pca = PCA()
X_new = pca.fit_transform(X)
explained_variance=pca.explained_variance_ratio_
explained_variance
with plt.style.context('dark_background'):
    plt.figure(figsize=(6, 4))
    plt.bar(range(4), explained_variance, alpha=0.5, align='center',
            label='individual explained variance')
    plt.ylabel('Explained variance ratio')
    plt.xlabel('Principal components')
    plt.legend(loc='best')
    plt.tight_layout()
```



0.1.1 Apply PCA using iris dataset.

[2]:
```
import matplotlib.pyplot as plt

from sklearn import datasets
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

iris = datasets.load_iris()

X = iris.data
y = iris.target
target_names = iris.target_names

pca = PCA(n_components=2)
X_r = pca.fit(X).transform(X)



# Percentage of variance explained for each components
print(
    "explained variance ratio (first two components): %s"
    % str(pca.explained_variance_ratio_)
```

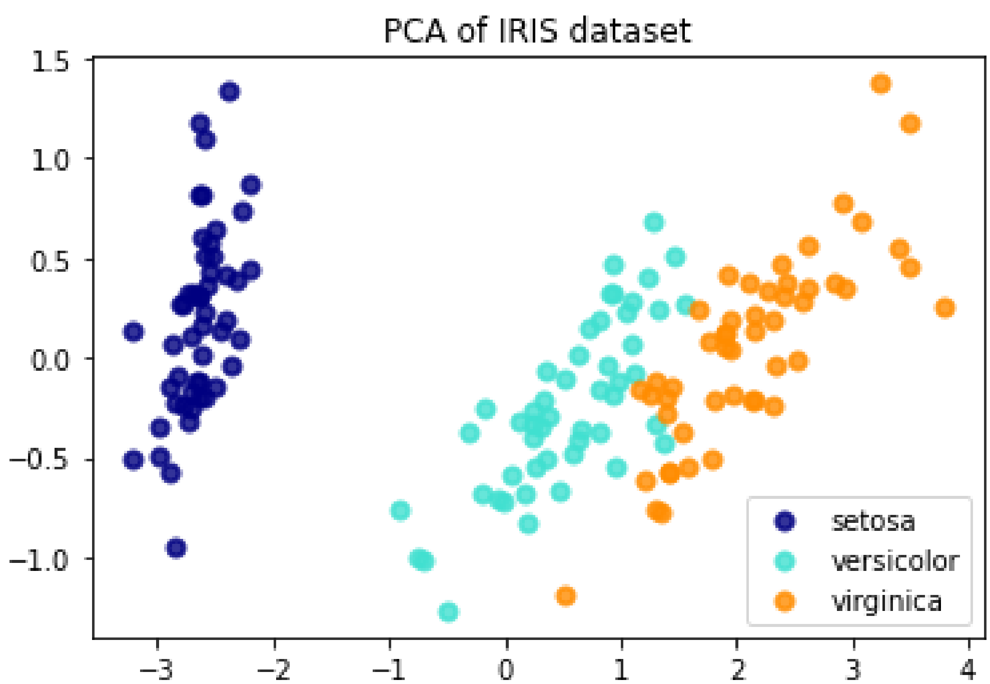
```
)

plt.figure()
colors = ["navy", "turquoise", "darkorange"]
lw = 2

for color, i, target_name in zip(colors, [0, 1, 2], target_names):
    plt.scatter(
        X_r[y == i, 0], X_r[y == i, 1], color=color, alpha=0.8, lw=lw,␣
 ↪label=target_name
    )
plt.legend(loc="best", shadow=False, scatterpoints=1)
plt.title("PCA of IRIS dataset")

plt.show()
```

```
explained variance ratio (first two components): [0.92461872 0.05306648]
```



0.1.2 Plot a histogram using above list and draw bins in it.

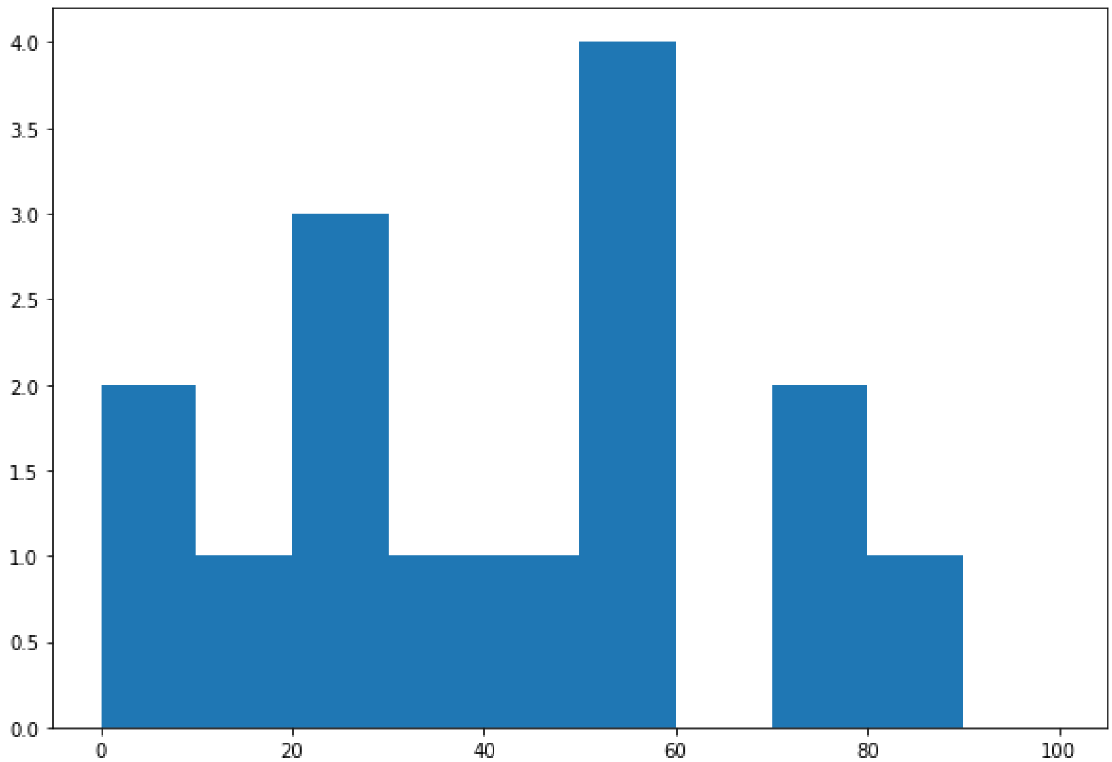
[22, 87, 5, 43, 56,73, 55, 54, 11,20, 51, 5, 79, 31,27]

[3]:
```
import matplotlib.pyplot as plt
import numpy as np
```

```python
# Creating dataset
a = np.array([22, 87, 5, 43, 56,73, 55, 54, 11,20, 51, 5, 79, 31,27])

# Creating histogram
fig, ax = plt.subplots(figsize =(10, 7))
ax.hist(a, bins = [0,10,20,30,40,50,60,70,80,90,100])

# Show plot
plt.show()
```



0.1.3 Do min max scaling in below data and form a data frame

```
z-score normalization and decimal scaling.

(You can also use your own data.)

 [[180000, 110, 18.9, 1400],
 [360000, 905, 23.4, 1800],
 [230000, 230, 14.0, 1300],
 [60000, 450, 13.5, 1500]]
```

0.1.4 Z-score normalization:

[4]:
```
import numpy as np
import pandas as pd
df_z_scaled = pd.DataFrame([[180000, 110, 18.9, 1400],
 [360000, 905, 23.4, 1800],
 [230000, 230, 14.0, 1300],
 [60000, 450, 13.5, 1500]]
)
mean_Value=np.mean(a,axis=0)
std_deviation=np.std(a,axis=0)

# apply normalization techniques Z score
for column in df_z_scaled.columns:
    df_z_scaled[column] = (df_z_scaled[column] -df_z_scaled[column].mean()) /
 ↪df_z_scaled[column].std()

# view normalized data
display(df_z_scaled)
```

	0	1	2	3
0	-0.221422	-0.895492	0.311486	-0.46291
1	1.227884	1.373564	1.278167	1.38873
2	0.181163	-0.552993	-0.741122	-0.92582
3	-1.187625	0.074922	-0.848531	0.00000

0.1.5 Decimal Scaling Method For Normalization

[5]:
```
a = np.array([[180000, 110, 18.9, 1400], [360000, 905, 23.4, 1800], [230000,
 ↪230, 14.0, 1300], [60000, 450, 13.5, 1500]])
max_Value=np.max(a)
num=0;
while max_Value>1:
    max_Value=max_Value/10
    num=num+1
# print(max_Value)
# print(a)
# print(num)
a=a/pow(10,num)
# print(a)
output=pd.DataFrame(a)
output
```

[5]:

	0	1	2	3
0	0.18	0.000110	0.000019	0.0014
1	0.36	0.000905	0.000023	0.0018
2	0.23	0.000230	0.000014	0.0013
3	0.06	0.000450	0.000013	0.0015

0.1.6 Min-Max Normalization

[6]:
```
df_min_max_scaled = pd.DataFrame([[180000, 110, 18.9, 1400],
 [360000, 905, 23.4, 1800],
 [230000, 230, 14.0, 1300],
 [60000, 450, 13.5, 1500]]
)

# apply normalization techniques
for column in df_min_max_scaled.columns:
    df_min_max_scaled[column] = (df_min_max_scaled[column] -
 ↪df_min_max_scaled[column].min()) / (df_min_max_scaled[column].max() -
 ↪df_min_max_scaled[column].min())

# view normalized data
print(df_min_max_scaled)
```

```
          0         1         2    3
0  0.400000  0.000000  0.545455  0.2
1  1.000000  1.000000  1.000000  1.0
2  0.566667  0.150943  0.050505  0.0
3  0.000000  0.427673  0.000000  0.4
```

0.1.7 Reduction

0.1.8 4. Perform binning in iris dataset (mean, boundaries, median)

[7]:
```
import numpy as np
import math
from sklearn.datasets import load_iris
from sklearn import datasets, linear_model, metrics

# load iris data set
dataset = load_iris()
a = dataset.data
b = np.zeros(150)

# take 1st column among 4 column of data set
for i in range (150):
    b[i]=a[i,1]

b=np.sort(b) #sort the array

# create bins
bin1=np.zeros((30,5))
bin2=np.zeros((30,5))
bin3=np.zeros((30,5))
```

```python
# Bin mean
for i in range (0,150,5):
    k=int(i/5)
    mean=(b[i] + b[i+1] + b[i+2] + b[i+3] + b[i+4])/5
    for j in range(5):
        bin1[k,j]=mean
print("Bin Mean: \n",bin1)

# Bin boundaries
for i in range (0,150,5):
    k=int(i/5)
    for j in range (5):
        if (b[i+j]-b[i]) < (b[i+4]-b[i+j]):
            bin2[k,j]=b[i]
        else:
            bin2[k,j]=b[i+4]
print("Bin Boundaries: \n",bin2)

# Bin median
for i in range (0,150,5):
    k=int(i/5)
    for j in range (5):
        bin3[k,j]=b[i+2]
print("Bin Median: \n",bin3)
```

```
Bin Mean:
 [[2.18 2.18 2.18 2.18 2.18]
 [2.34 2.34 2.34 2.34 2.34]
 [2.48 2.48 2.48 2.48 2.48]
 [2.52 2.52 2.52 2.52 2.52]
 [2.62 2.62 2.62 2.62 2.62]
 [2.7  2.7  2.7  2.7  2.7 ]
 [2.74 2.74 2.74 2.74 2.74]
 [2.8  2.8  2.8  2.8  2.8 ]
 [2.8  2.8  2.8  2.8  2.8 ]
 [2.86 2.86 2.86 2.86 2.86]
 [2.9  2.9  2.9  2.9  2.9 ]
 [2.96 2.96 2.96 2.96 2.96]
 [3.   3.   3.   3.   3.  ]
 [3.   3.   3.   3.   3.  ]
 [3.   3.   3.   3.   3.  ]
 [3.   3.   3.   3.   3.  ]
 [3.04 3.04 3.04 3.04 3.04]
 [3.1  3.1  3.1  3.1  3.1 ]
 [3.12 3.12 3.12 3.12 3.12]
 [3.2  3.2  3.2  3.2  3.2 ]
 [3.2  3.2  3.2  3.2  3.2 ]
```

```
 [3.26 3.26 3.26 3.26 3.26]
 [3.34 3.34 3.34 3.34 3.34]
 [3.4  3.4  3.4  3.4  3.4 ]
 [3.4  3.4  3.4  3.4  3.4 ]
 [3.5  3.5  3.5  3.5  3.5 ]
 [3.58 3.58 3.58 3.58 3.58]
 [3.74 3.74 3.74 3.74 3.74]
 [3.82 3.82 3.82 3.82 3.82]
 [4.12 4.12 4.12 4.12 4.12]]
Bin Boundaries:
 [[2.  2.3 2.3 2.3 2.3]
 [2.3 2.3 2.3 2.4 2.4]
 [2.4 2.5 2.5 2.5 2.5]
 [2.5 2.5 2.5 2.5 2.6]
 [2.6 2.6 2.6 2.6 2.7]
 [2.7 2.7 2.7 2.7 2.7]
 [2.7 2.7 2.7 2.8 2.8]
 [2.8 2.8 2.8 2.8 2.8]
 [2.8 2.8 2.8 2.8 2.8]
 [2.8 2.8 2.9 2.9 2.9]
 [2.9 2.9 2.9 2.9 2.9]
 [2.9 2.9 3.  3.  3. ]
 [3.  3.  3.  3.  3. ]
 [3.  3.  3.  3.  3. ]
 [3.  3.  3.  3.  3. ]
 [3.  3.  3.  3.  3. ]
 [3.  3.  3.  3.1 3.1]
 [3.1 3.1 3.1 3.1 3.1]
 [3.1 3.1 3.1 3.1 3.2]
 [3.2 3.2 3.2 3.2 3.2]
 [3.2 3.2 3.2 3.2 3.2]
 [3.2 3.2 3.3 3.3 3.3]
 [3.3 3.3 3.3 3.4 3.4]
 [3.4 3.4 3.4 3.4 3.4]
 [3.4 3.4 3.4 3.4 3.4]
 [3.5 3.5 3.5 3.5 3.5]
 [3.5 3.6 3.6 3.6 3.6]
 [3.7 3.7 3.7 3.8 3.8]
 [3.8 3.8 3.8 3.8 3.9]
 [3.9 3.9 3.9 4.4 4.4]]
Bin Median:
 [[2.2 2.2 2.2 2.2 2.2]
 [2.3 2.3 2.3 2.3 2.3]
 [2.5 2.5 2.5 2.5 2.5]
 [2.5 2.5 2.5 2.5 2.5]
 [2.6 2.6 2.6 2.6 2.6]
 [2.7 2.7 2.7 2.7 2.7]
 [2.7 2.7 2.7 2.7 2.7]
```

```
 [2.8 2.8 2.8 2.8 2.8]
 [2.8 2.8 2.8 2.8 2.8]
 [2.9 2.9 2.9 2.9 2.9]
 [2.9 2.9 2.9 2.9 2.9]
 [3.  3.  3.  3.  3. ]
 [3.  3.  3.  3.  3. ]
 [3.  3.  3.  3.  3. ]
 [3.  3.  3.  3.  3. ]
 [3.  3.  3.  3.  3. ]
 [3.  3.  3.  3.  3. ]
 [3.1 3.1 3.1 3.1 3.1]
 [3.1 3.1 3.1 3.1 3.1]
 [3.2 3.2 3.2 3.2 3.2]
 [3.2 3.2 3.2 3.2 3.2]
 [3.3 3.3 3.3 3.3 3.3]
 [3.3 3.3 3.3 3.3 3.3]
 [3.4 3.4 3.4 3.4 3.4]
 [3.4 3.4 3.4 3.4 3.4]
 [3.5 3.5 3.5 3.5 3.5]
 [3.6 3.6 3.6 3.6 3.6]
 [3.7 3.7 3.7 3.7 3.7]
 [3.8 3.8 3.8 3.8 3.8]
 [4.1 4.1 4.1 4.1 4.1]]
```

0.1.9 5. Apply wavelet-based data reduction.

[8]:
```
import pywt
import matplotlib.pyplot as plt
print(pywt.families(short=False))
```

```
['Haar', 'Daubechies', 'Symlets', 'Coiflets', 'Biorthogonal', 'Reverse
biorthogonal', 'Discrete Meyer (FIR Approximation)', 'Gaussian', 'Mexican hat
wavelet', 'Morlet wavelet', 'Complex Gaussian wavelets', 'Shannon wavelets',
'Frequency B-Spline wavelets', 'Complex Morlet wavelets']
```

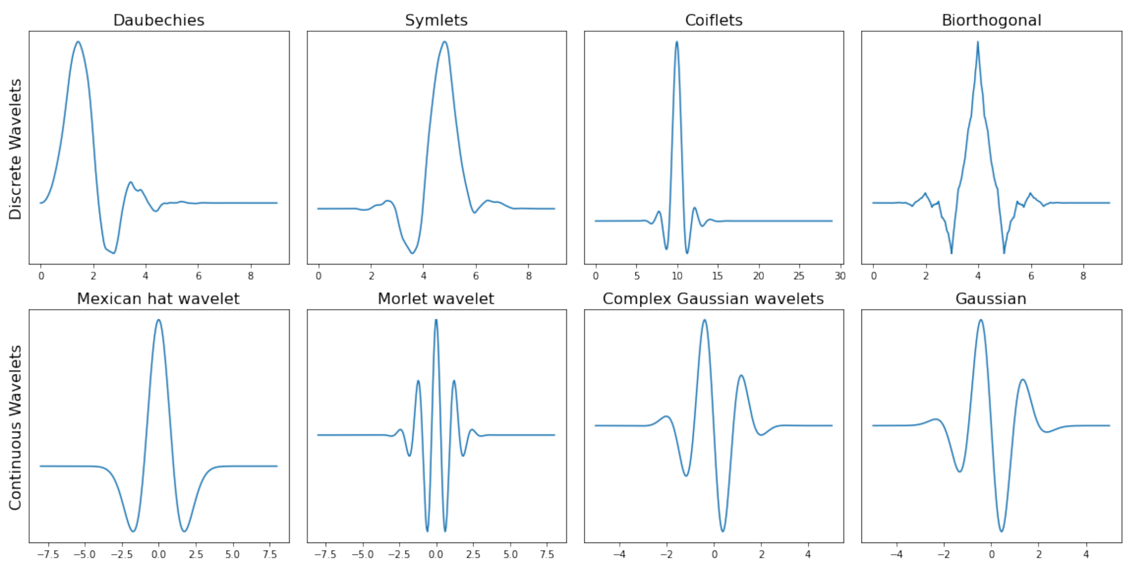
[9]:
```
import warnings
warnings.filterwarnings('ignore')
discrete_wavelets = ['db5', 'sym5', 'coif5', 'bior2.4']
continuous_wavelets = ['mexh', 'morl', 'cgau5', 'gaus5']

list_list_wavelets = [discrete_wavelets, continuous_wavelets]
list_funcs = [pywt.Wavelet, pywt.ContinuousWavelet]

fig, axarr = plt.subplots(nrows=2, ncols=4, figsize=(16,8))
for ii, list_wavelets in enumerate(list_list_wavelets):
    func = list_funcs[ii]
    row_no = ii
```

```
    for col_no, waveletname in enumerate(list_wavelets):
        wavelet = func(waveletname)
        family_name = wavelet.family_name
        biorthogonal = wavelet.biorthogonal
        orthogonal = wavelet.orthogonal
        symmetry = wavelet.symmetry
        if ii == 0:
            _ = wavelet.wavefun()
            wavelet_function = _[0]
            x_values = _[-1]
        else:
            wavelet_function, x_values = wavelet.wavefun()
        if col_no == 0 and ii == 0:
            axarr[row_no, col_no].set_ylabel("Discrete Wavelets", fontsize=16)
        if col_no == 0 and ii == 1:
            axarr[row_no, col_no].set_ylabel("Continuous Wavelets", fontsize=16)
        axarr[row_no, col_no].set_title("{}".format(family_name), fontsize=16)
        axarr[row_no, col_no].plot(x_values, wavelet_function)
        axarr[row_no, col_no].set_yticks([])
        axarr[row_no, col_no].set_yticklabels([])

plt.tight_layout()
plt.show()
```



0.1.10 6. Apply sampling based data reduction.

[10]:
```
from sklearn.datasets import load_iris
import pandas as pd

data = load_iris()
df = pd.DataFrame(data.data, columns=data.feature_names)
df.head(5)
```

[10]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

[11]:
```
df.shape
```

[11]:
```
(150, 4)
```

[12]:
```
## random sampling

subset = df.sample(n=100)
subset.shape
```

[12]:
```
(100, 4)
```

[13]:
```
## Knowning the percentage of samples to return
subset = df.sample(frac=0.5)
subset.shape
```

[13]:
```
(75, 4)
```

[14]:
```
##Sampling with condition
##Return 10 random sample where sepal width (cm) < 3
##Firstly count the number of records which satisfy the condition

condition = df['sepal width (cm)'] < 3
condition
```

[14]:
```
0      False
1      False
2      False
3      False
4      False
       …
145    False
```

```
146     True
147    False
148    False
149    False
Name: sepal width (cm), Length: 150, dtype: bool
```

[15]:
```python
true_index = condition[condition == True].index
len(true_index)
```

[15]:
```
57
```

[16]:
```python
subset = df[condition].sample(n = 10)
subset.shape
```

[16]:
```
(10, 4)
```

[17]:
```python
##Sampling at a Constant Rate
rate = 10
subset = df[::rate]
subset.shape
```

[17]:
```
(15, 4)
```

[18]:
```python
subset.head()
```

[18]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
10	5.4	3.7	1.5	0.2
20	5.4	3.4	1.7	0.2
30	4.8	3.1	1.6	0.2
40	5.0	3.5	1.3	0.3

[19]:
```python
##Getting the remaining part of the dataset

remaining = df.drop(labels=subset.index)
remaining.shape
```

[19]:
```
(135, 4)
```

[20]:
```python
remaining.head()
```

[20]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
5	5.4	3.9	1.7	0.4