EFFECTIVE DENSITY BASED CLUSTERING

This paper provides a solution to perform density-based clustering on datasets that have incomplete data without loss of quality of clusters.

CI clustering with intermediate clustering based on the KD tree. LI clustering: Create a kD tree with the entire dataset and use the information of neighboring points to predict the missing values of a cluster. DBSCAN to achieve a result(cluster).

```
import numpy as np
import pandas as pd
from sklearn.impute import KNNImputer
from sklearn import datasets
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import DBSCAN
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

+ Code + Text

```
data=pd.read_csv("synb.csv")
print(data.head())
print(data.columns)
Before_imputation = pd.DataFrame(data)
print("Data Before performing imputation\n",Before_imputation.head())
```

```
       x      y  class
0  0.228  0.559      1
1  0.216  0.528      1
2  0.221  0.552      1
3  0.215  0.538      1
4  0.224  0.548      1
Index(['x', 'y', 'class'], dtype='object')
Data Before performing imputation
         x      y  class
0  0.228  0.559      1
1  0.216  0.528      1
2  0.221  0.552      1
3  0.215  0.538      1
4  0.224  0.548      1
```

```
from sklearn.impute import SimpleImputer
df=pd.DataFrame(data)
mean_imputer = SimpleImputer(missing_values=np.nan, strategy='mean')

# Fit the imputer on to the dataset
mean_imputer = mean_imputer.fit(df)


# Apply the imputation
results = mean_imputer.transform(df.values)
```

```
results
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid featu
  warnings.warn(
array([[0.228, 0.559, 1.   ],
       [0.216, 0.528, 1.   ],
       [0.221, 0.552, 1.   ],
       ...,
       [0.513, 0.233, 2.   ],
       [0.506, 0.221, 2.   ],
       [0.515, 0.26 , 2.   ]])
```

```

imputer = KNNImputer(n_neighbors=2)
After_imputation = imputer.fit_transform(Before_imputation)
ai=pd.DataFrame(After_imputation)
cdata = ai.to_csv("TrainingDataset.csv")
data1=pd.read_csv("TrainingDataset.csv",usecols=(1,2))
data1["class"]=Before_imputation["class"]
data1.head()
print(data1.shape)
data1.isnull().any().any()
x=data1.loc[:,['0','1']].values
print(x.shape)
data1
```

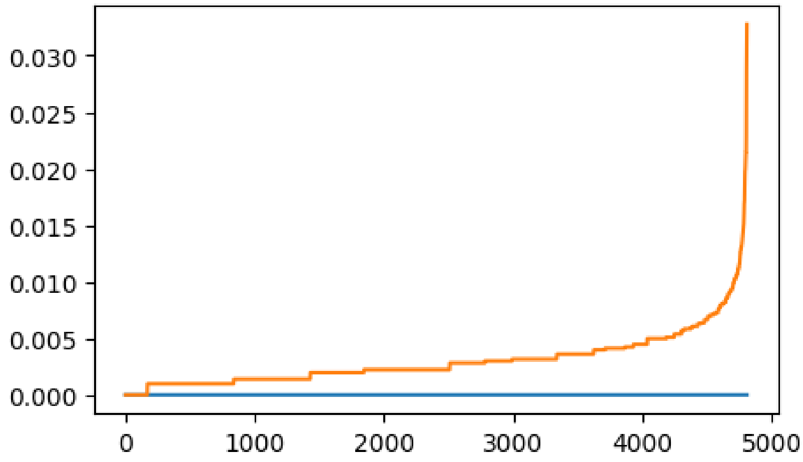
```
(4811, 3)
(4811, 2)
```

	0	1	class
0	0.228	0.559	1
1	0.216	0.528	1
2	0.221	0.552	1
3	0.215	0.538	1
4	0.224	0.548	1
...	...	...	...
4806	0.507	0.269	2
4807	0.526	0.237	2
4808	0.513	0.233	2
4809	0.506	0.221	2
4810	0.515	0.260	2

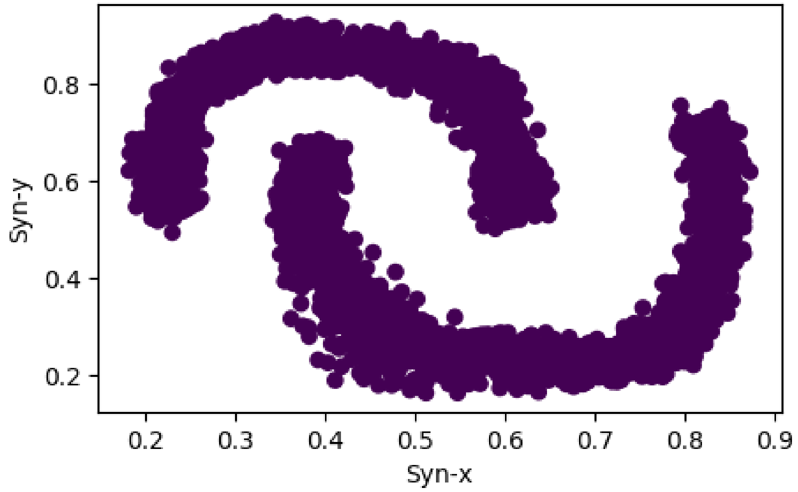
4811 rows × 3 columns

```
from sklearn.neighbors import NearestNeighbors
neighb = NearestNeighbors(n_neighbors=2)
nbrs=neighb.fit(x)
```

```
distances,indices=nbrs.kneighbors(x)
distances = np.sort(distances, axis = 0)
distances = distances[:,]
plt.rcParams['figure.figsize'] = (5,3)
plt.plot(distances)
plt.show()
```



```
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps = 8, min_samples = 4).fit(x)
labels = dbscan.labels_
plt.scatter(x[:, 0], x[:,1], c = labels, cmap= "viridis")
plt.xlabel("Syn-x")
plt.ylabel("Syn-y")
plt.show()
```



```
Before_imputation = pd.DataFrame(data)
imputer = KNNImputer(n_neighbors=2)
After_imputation = imputer.fit_transform(Before_imputation)
ai=pd.DataFrame(After_imputation)
cdata = ai.to_csv("new.csv")
data1=pd.read_csv("new.csv",usecols=(1,2))
```

```
data1["class"]=Before_imputation["class"]
data1
```

```
          0      1  class
0     0.228  0.559      1
1     0.216  0.528      1
2     0.221  0.552      1
3     0.215  0.538      1
4     0.224  0.548      1
...     ...    ...    ...
4806  0.507  0.269      2
4807  0.526  0.237      2
4808  0.513  0.233      2
4809  0.506  0.221      2
4810  0.515  0.260      2

4811 rows × 3 columns
```

```
from sklearn.tree import DecisionTreeClassifier
data1.head()
X=data1.drop("class",axis=1)
Y=data1["class"]
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.30, random
dt=DecisionTreeClassifier()
dt.fit(X_train,y_train)
res=dt.score(X_test,y_test)
Xa=data1.drop("class",axis=1)
Ya=data1["class"]
X_1train, X_1test, y_1train, y_1test = train_test_split(Xa, Ya, test_size=0.30,
res
```

```
1.0
```

```
## KD TREE

class TreeNode(object):
    def __init__(self, v1,v2):
        self.x = v1
        self.y=v2
        self.left = None
        self.right = None

def create_tree(arr):
    if not arr:
        return None
    mid_num = len(arr)//2
    node = TreeNode(arr[mid_num][0],arr[mid_num][1])
    node.left = create_tree(arr[:mid_num])
    node.right = create_tree(arr[mid_num+1:])
    return node
def RangeSearch(elem,tree,temp,arr,num=0):
  if not tree or num>=len(elem):
    return None
  if not elem:
    return None
  # print(elem[num][0],tree.x,tree.y)
  if elem[num][0]==tree.x:
    # print("ahsh")
    if tree.left is None or tree.right is None:
      arr.append(tree)
    else:
      arr.append(tree.left)
      arr.append(tree.right)
    num+=1
    RangeSearch(elem,temp,temp,arr,num)
  else:
      RangeSearch(elem,tree.right,temp,arr,num)
      RangeSearch(elem,tree.left,temp,arr,num)

def Predict(elem,tree,arr):
  if not tree:
    return None
  if not elem:
    return None
  # print(elem[num][0],tree.x,tree.y)
  if elem[0]==tree.x:
    if tree.left is None or tree.right is None:
      arr.append(tree)
    else:
      arr.append(tree.left)
      arr.append(tree.right)
  else:
      Predict(elem,tree.right,arr)
      Predict(elem,tree.left,arr)

def insert(tree, x,y):
  if tree.x:
    if x < tree.x:
      if tree.left is None:
          tree.left = TreeNode(x,y)
      else:
          insert(tree.left,x,y)
    elif x > tree.x:
      if tree.right is None:
        tree.right = TreeNode(x,y)
      else:
        insert(tree.right,x,y)

def getlist(tree,f_list):
  if tree.left:
      getlist(tree.left,f_list)
  if tree.right:
      getlist(tree.right,f_list)
  f_list.append([tree.x,tree.y])
```

```
####################
"""
 CI-Clustering
Input: Xcomplete and Xincomplete
Output: Vector y denoting the clustering result
1: Normalize.Xcomplete/
2: Normalize.Xincomplete/
3: tree KD-TREE.Xcomplete/
4: neighborhoods RangeSearch.Xcomplete; tree/
5: clusters getClusters.Xcomplete; neighborhoods/
6: for x in Xincomplete do
7: x predict.x; tree; clusters/
8: insert.tree; x/
9: update neighborhoods.neighborhoods/
10: update clusters.clusters/
11: en
"""
from sklearn.metrics import f1_score
# from anytree import Node, RenderTree
from sklearn.cluster import DBSCAN
from sklearn import preprocessing
from sklearn.neighbors import KDTree
from sklearn.cluster import DBSCAN
complete=X_1train.values.tolist()
uncomplete=X_train.values.tolist()
complete_norm = preprocessing.normalize(X_1train)
uncomplete_norm=preprocessing.normalize(X_train)
# print(complete_norm.tolist())
# print(X_1train)
tree=create_tree(complete_norm.tolist())
# print(tree)
arr=[]
num=0
RangeSearch(complete_norm.tolist()[:20],tree,tree,arr,num)
```

```
weights=[]
for i in arr:
  weights.append(i.x)
  weights.append(i.y)
# print(arr)
dbscan = DBSCAN(eps = 8, min_samples = 4)
train=dbscan.fit(complete_norm)
clusters=train.labels_
# print(0 in clusters.tolist())
for x in uncomplete_norm:
  neigh=[]
  x=x.reshape(1,-1)
  # print(x)
  Predict(x.tolist()[0],tree,neigh)
  # print(neigh)
  miss_y=0
  miss_x=0
  for i in neigh:
    # print(i)
    miss_y+=i.y
    miss_x+=i.x
  insert(tree,miss_x,miss_y)
f_list=[]
getlist(tree,f_list)
  # print(f_list)
res=dt.predict(f_list)
print(res)
# check=X_1test.values.tolist().extend(X_test.values.tolist())
frames = [y_train, y_1train]
result = pd.concat(frames)
print(result.shape)
print(res.shape)
si=result.shape[0]-res.shape[0]
output=f1_score(res,result[si:],average='weighted')
output




# labels = dbscan.labels_
# n_clusters = len(set(labels)) - (1 if -1 in labels else 0)
# ans=tree.query_radius(X_train[:1], r=0.3)
# appender=np.array(normalized)
# dbscan = DBSCAN(eps = 8, min_samples = 4)
# # ans
# for x in nomr2:
#   x=x.reshape(1,-1)
#   val=dbscan.fit_predict(x)
#   np.insert(appender,obj=len(appender),values=val)
#   # tree=array_to_bst(appender)
#   labels = dbscan.labels_
#   # n_clusters = len(set(labels)) - (1 if -1 in labels else 0)
# appender

```

```
[1 1 1 ... 1 2 2]
(6734,)
(6669,)
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid featu
  warnings.warn(
0.5032554188832492
```

```
#LI Clustering
from sklearn.metrics import f1_score
# from anytree import Node, RenderTree
from sklearn.cluster import DBSCAN
from sklearn import preprocessing
from sklearn.neighbors import KDTree
complete=X_1train.values.tolist()
uncomplete=X_train.values.tolist()
complete_norm = preprocessing.normalize(X_1train)
uncomplete_norm=preprocessing.normalize(X_train)
# print(complete_norm.tolist())
# print(X_1train)
tree=create_tree(complete_norm.tolist())
dbscan = DBSCAN(eps = 8, min_samples = 4)
train=dbscan.fit(complete_norm)
clusters=train.labels_
# print(0 in clusters.tolist())
for x in uncomplete_norm:
  neigh=[]
  x=x.reshape(1,-1)
  # print(x)
  Predict(x.tolist()[0],tree,neigh)
  # print(neigh)
  miss_y=0
  miss_x=0
  for i in neigh:
    # print(i)
    miss_y+=i.y
    miss_x+=i.x
  insert(tree,miss_x,miss_y)
f_list=[]
getlist(tree,f_list)
train=dbscan.fit(f_list)
clusters=train.labels_
```

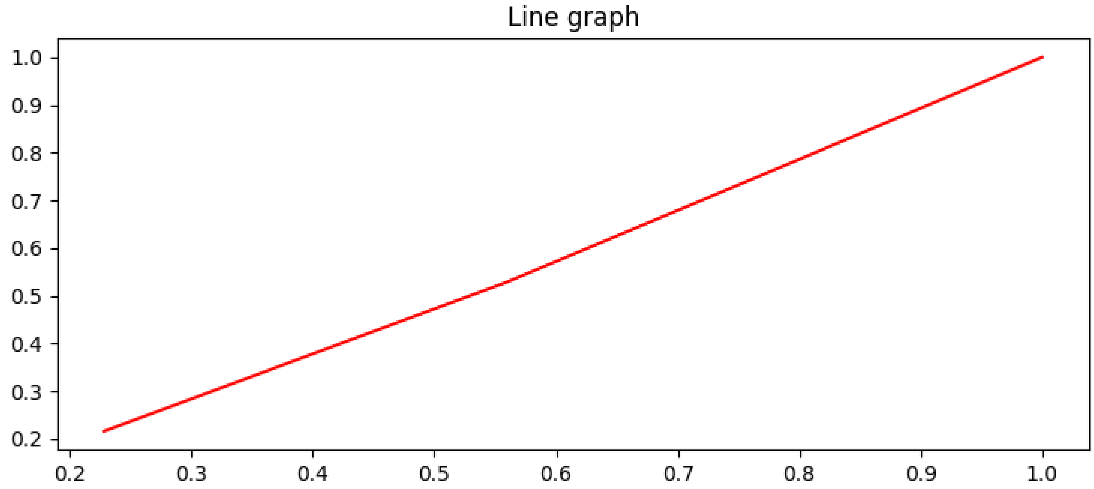
```
res=dt.predict(f_list)
print(res)

```

```
[1 1 1 ... 1 2 2]
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid featu
  warnings.warn(
```

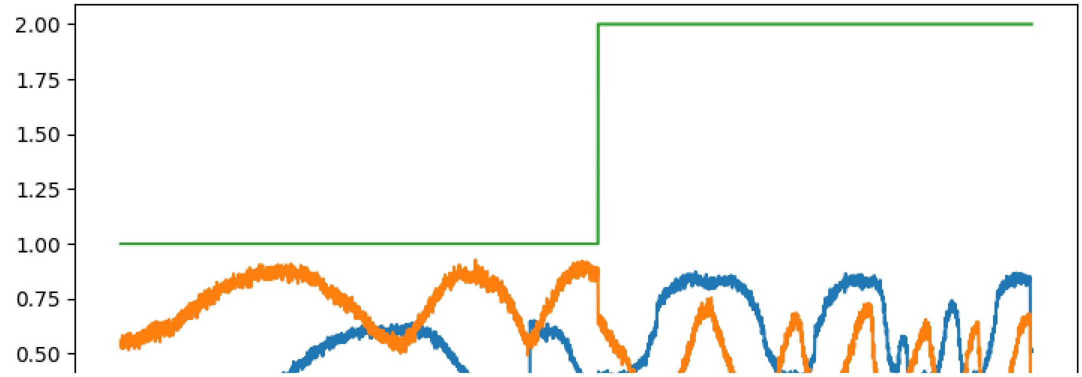
```

f_list
```

```
[[0.27078309672430856, 0.962640386919432],
 [0.2683244075628877, 0.9633286107585642],
 [0.27335843910850066, 0.9619122432780259],
 [0.2714601650218062, 0.9624496759864037],
 [0.2755596101787932, 0.9612839857389238],
 [0.27506063191739133, 0.961426881655181],
 [0.27999999999999997, 0.96],
 [0.2791280434473638, 0.960253891094041],
 [0.2809958715857758, 0.9597089768006498],
 [0.2778914668170219, 0.9606124778860017],
 [0.2823263743670628, 0.9593184134252554],
 [0.28229584288523907, 0.959327398279499],
 [0.28202020961790236, 0.9594084642982228],
 [0.28129180444881063, 0.9596222802488134],
 [0.28309107310433124, 0.959093032155191],
 [0.2844470071718319, 0.9586917649124705],
 [0.2843842936854435, 0.9587103699788749],
 [0.2839187315269263, 0.9588483477005846],
 [0.2848216774098792, 0.9585805193500557],
 [0.28490737963640583, 0.9585550505989299],
 [0.2828468469575132, 0.9591650854603669],
 [0.27424240625163093, 0.9616605963713577],
 [0.2633256370467511, 0.9647070067507143],
 [0.2858699884915783, 0.958268412126699],
 [0.2855359490356974, 0.9583679991570482],
 [0.2869073234121886, 0.9579583434432073],
 [0.28713457785972973, 0.9578902516454141],
 [0.29024666225192924, 0.9569518666325985],
 [0.29034787420366054, 0.9569211628684023],
 [0.2906651705296417, 0.9568248317434985],
 [0.28800838692634273, 0.9576278865300896],
 [0.2916117358986437, 0.9565367716330511],
 [0.29116161578269606, 0.9566738804288585],
 [0.29212614799498027, 0.956379795718006],
 [0.2920730352508251, 0.9563960173899567],
 [0.2931899571800256, 0.9560542081957355],
 [0.29565517699940536, 0.9552947274603008],
 [0.2942486550630724, 0.9557288993190344],
 [0.2956837280711308, 0.9552858906913456],
 [0.296185537019156, 0.9551304244241591],
 [0.2961898556879876, 0.9551290851960949],
 [0.295711663547997, 0.9552772435485294],
 [0.29631921181100485, 0.9550889616740971],
 [0.2962812500611317, 0.9551007385936905],
 [0.2940858488375231, 0.9557790087219501],
 [0.2922552926885215, 0.9563403389461026],
 [0.2974553528859832, 0.9547357294243655],
 [0.2975019851605442, 0.9547211995266133],
 [0.297928771152136, 0.9545881034874562],
 [0.2982749931359468, 0.9544799780350297],
 [0.2971421220725826, 0.9548332625595961],
 [0.29847650945703846, 0.9544169808329808],
 [0.2984726016411747, 0.9544182029223608],
 [0.296753085796801, 0.9549542429195634],
 [0.2916566072042332, 0.9565230909257316],
 [0.28633736098090873, 0.95812886174381],
 [0.2995681609197765, 0.9540749011283878],
 [0.2998554748750533, 0.9539846404358177],
```

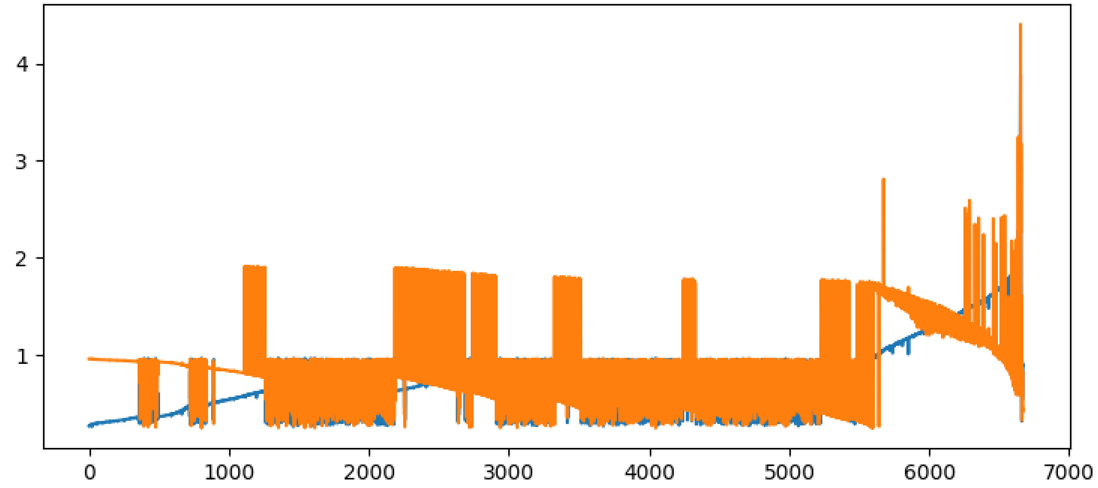
```python

import numpy as np
import matplotlib.pyplot as plt

plt.rcParams["figure.figsize"] = [7.50, 3.50]
plt.rcParams["figure.autolayout"] = True

x = results[0]
y = results[1]

plt.title("Line graph")
plt.plot(x, y, color="red")

plt.show()
```



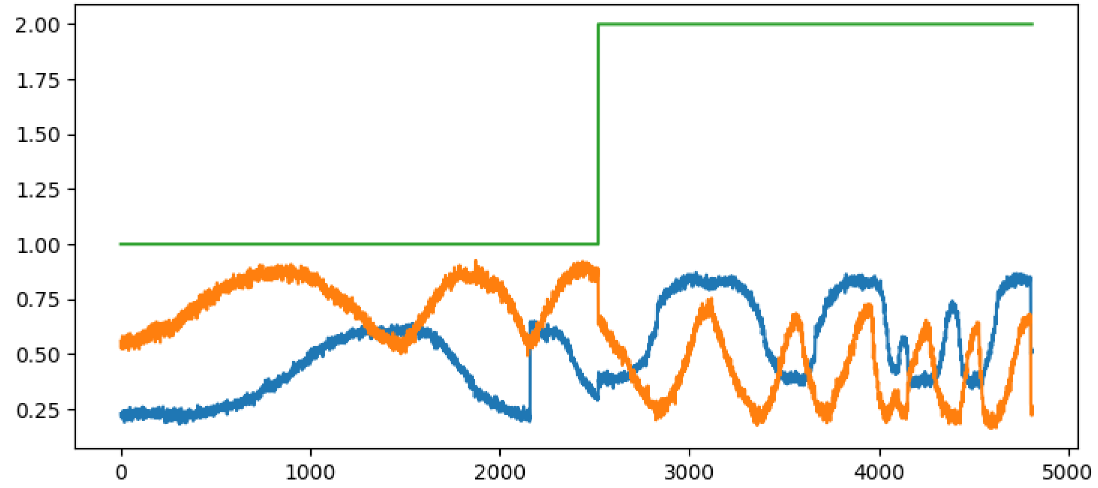
```python
plt.plot(results)
plt.show()

```



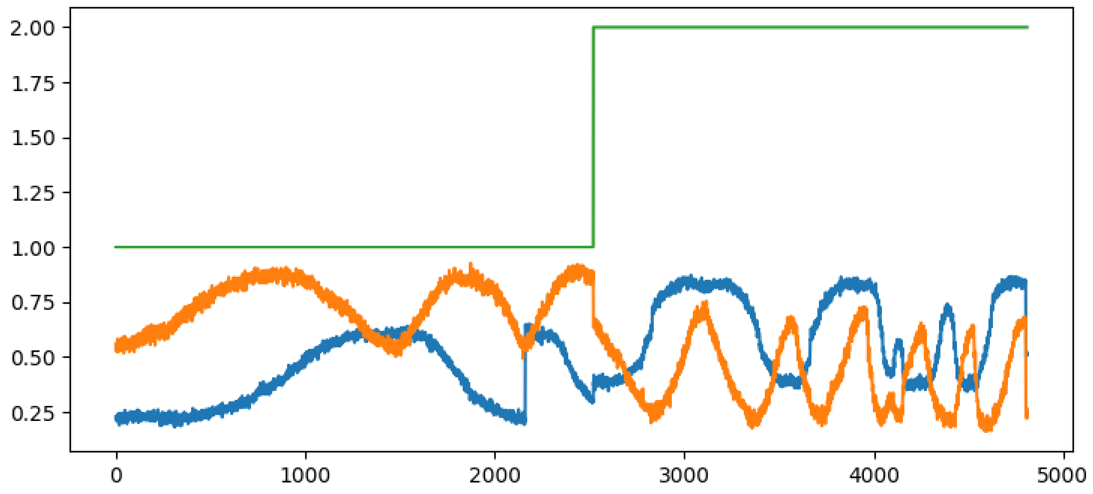
```
plt.plot(f_list)
plt.show()
```



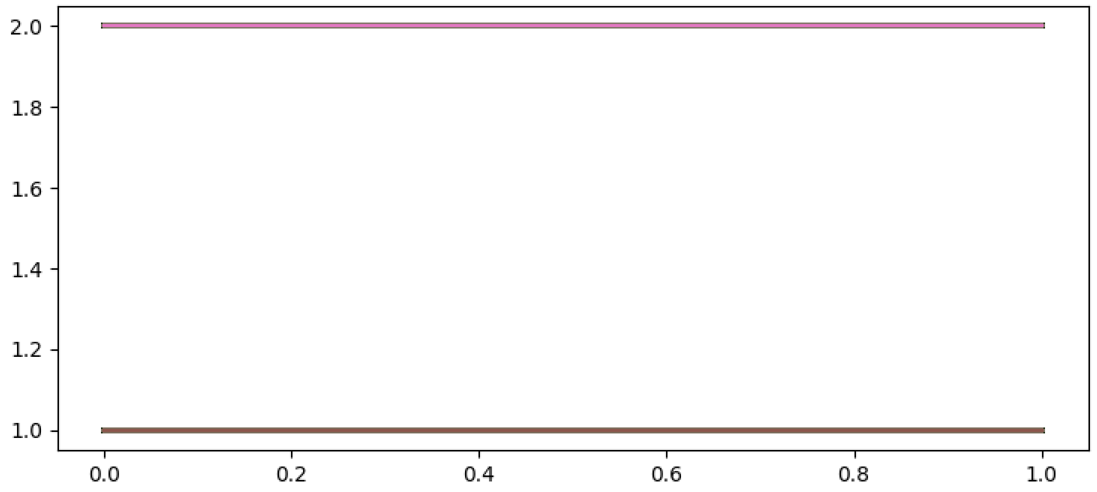
```
plt.plot(data)
plt.show()
```



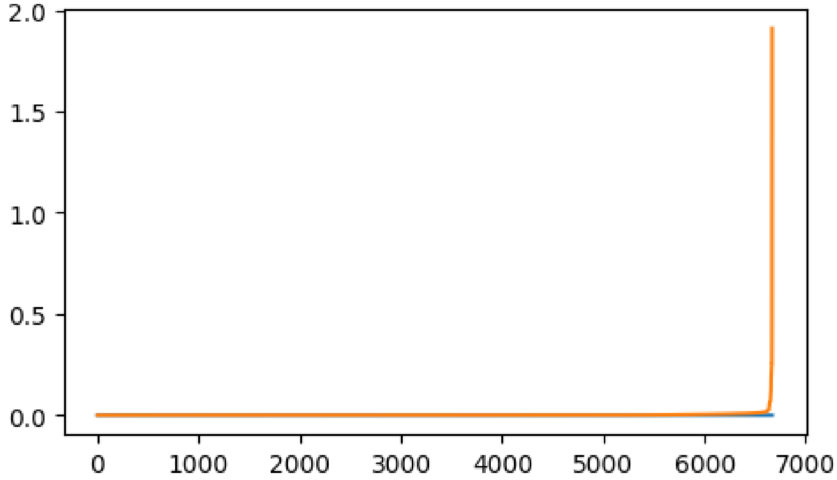
```
plt.plot(data1)
plt.show()
```



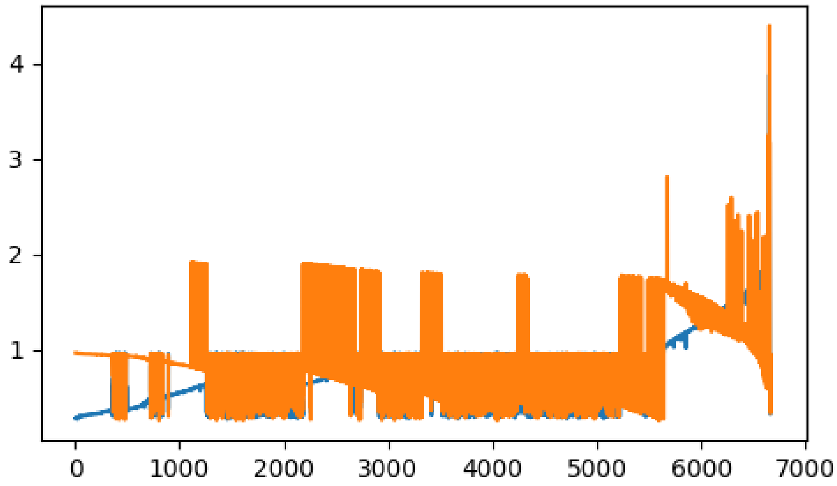
```
plt.plot(frames)
plt.show()
```



```
from sklearn.neighbors import NearestNeighbors
neighb = NearestNeighbors(n_neighbors=2)
nbrs=neighb.fit(f_list)
distances,indices=nbrs.kneighbors(f_list)
distances = np.sort(distances, axis = 0)
distances = distances[:,]
plt.rcParams['figure.figsize'] = (5,3)
plt.plot(distances)
plt.show()
```



```
df = pd.DataFrame(f_list, columns = ['x','y'])
plt.plot(df)
plt.show()
```



● ✕