Appendix C: TimeSeriesKMean on single sensor data

In [1]:

```
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
```

In [2]:

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

In [4]:

```
from tslearn.clustering import TimeSeriesKMeans
#tslearn requires numpy 1.22
#pip install --upgrade threadpoolctl --user
```

In [5]:

```
# Read the CSV data into a Pandas DataFrame, please update the path accord
df = pd.read_csv('D:\\Download\\Tool_Sensor_Data.csv')
print(df.shape)
df.head()
```

```
(14844, 90)
```

Out[5]:

	TimeStamp	ToolName	TOOL_ID	Run	RunStartTime	DATA_QUALITY	EQPType	HasComme
0	21/3/2023 19:14	A	A	62301	12:14:19 AM	63.49	A	
1	21/3/2023 19:14	A	A	62301	12:14:19 AM	63.49	A	
2	21/3/2023 19:14	A	A	62301	12:14:19 AM	63.49	A	
3	21/3/2023 19:14	A	A	62301	12:14:19 AM	63.49	A	
4	21/3/2023 19:14	A	A	62301	12:14:19 AM	63.49	A	

5 rows × 90 columns

In [6]:

```python
# All data cleaning in one Cell
# Remove Duplicated Rows, the timeline helps to ensure duplicated rows wou
print('Before = ', df.shape)
df = df.drop_duplicates()
print('After = ', df.shape)
# The TimeStamp indicates it is time series data, but since it is not a sa
# The more important info is the Run number for identifying which Wafer Ru
if 'TimeStamp' in df.columns:
    df = df.drop('TimeStamp', axis=1)
if 'RunStartTime' in df.columns:
    df = df.drop('RunStartTime', axis=1)
# Find/Check for any other non-integer columns
for column in df.columns:
    if df[column].dtypes == 'object':
        print('column name =',column, 'type =', df[column].dtypes, 'conter
# Verify manually if those columns are not useful (no value for ML), drop
for column in df.columns:
    if df[column].dtypes == 'object':
        print(column, df[column].dtypes, '= DROP')
        df = df.drop(column, axis=1)
# Calculate how many cells inside a row is filled with data
non_empty_columns_per_row = df.count(axis=1)
non_empty_columns_per_row
# Pick a cut off threshold, in this case, based on the chart above, we can
print('Total length = ', len(df.columns))
threshold = len(df.columns)/2
print('Threshold =', threshold)
# Remove empty rows below the threshold
print('Before remove=',df.shape)
df = df.dropna(thresh=threshold)
print('After remove=',df.shape)
# Fill in empty cells with Zero? Number zero allows calculation of standar
df = df.fillna(0)
df.head()
# Remove Useless Columns by using standard deviation check, likely those c
column_stddev = {}
for column in df.columns:
    std_deviation = df[column].std()
    if std_deviation == 0:
        print(column, std_deviation, "= DROP")
        df = df.drop(column, axis=1)
    else:
        column_stddev[column]=std_deviation
# Save a copy of the clean dataframe
df_clean=df.copy()
df.to_csv('d:\\download\\1.3_Cleaning.csv', index=False)
```

```
Before =  (14844, 90)
After =  (14113, 90)
column name = ToolName type = object content = A
column name = TOOL_ID type = object content = A
column name = EQPType type = object content = A
column name = LOT_ID type = object content = A
column name = LogicalRecipeID type = object content = A
column name = LotPurposeType type = object content = Process Lot
column name = LotType type = object content = Production
column name = MachineRecipeID type = object content = A
column name = PhysicalRecipeID type = object content = A
column name = PortID type = object content = A
column name = ProcessOpNum type = object content = A
column name = ProductGrpID type = object content = A
column name = ProductID type = object content = A
column name = RECIPE_ID type = object content = A
column name = RouteID type = object content = A
column name = Technology type = object content = A
column name = EventType type = object content = StartOfRun
column name = EventName type = object content = WaferStart
column name = EventId type = object content = WaferStart
ToolName object = DROP
TOOL_ID object = DROP
EQPType object = DROP
LOT_ID object = DROP
LogicalRecipeID object = DROP
LotPurposeType object = DROP
LotType object = DROP
MachineRecipeID object = DROP
PhysicalRecipeID object = DROP
PortID object = DROP
ProcessOpNum object = DROP
ProductGrpID object = DROP
ProductID object = DROP
RECIPE_ID object = DROP
RouteID object = DROP
Technology object = DROP
EventType object = DROP
EventName object = DROP
EventId object = DROP
Total length =  69
Threshold = 34.5
Before remove= (14113, 69)
After remove= (13657, 69)
HasComments 0.0 = DROP
ReticleID 0.0 = DROP
GPTmghByqMSY 0.0 = DROP
pZXcGFNpzPf 0.0 = DROP
EHVtYhnRGb 0.0 = DROP
XSOeMfJAB 0.0 = DROP
SYklrMAXe 0.0 = DROP
jQVGDTFl 0.0 = DROP
YDlkDLfFEEi 0.0 = DROP
CYiycrAoYbg 0.0 = DROP
oUWQRhjudAd 0.0 = DROP
WTcLPnkDtRwBuCou 0.0 = DROP
EventSource 0.0 = DROP
```

```
EventDescription 0.0 = DROP
AlarmCode 0.0 = DROP
AlarmStatus 0.0 = DROP
VcnDxeRWVfK 0.0 = DROP
HxXxxvS 0.0 = DROP
LqnSjZtcJs 0.0 = DROP
vmZiUljnYP 0.0 = DROP
yqScxEFPLde 0.0 = DROP
jrsnDLYHnMHD 0.0 = DROP
RunTag 0.0 = DROP
Unnamed: 85 0.0 = DROP
Unnamed: 86 0.0 = DROP
Unnamed: 87 0.0 = DROP
Unnamed: 88 0.0 = DROP
Unnamed: 89 0.0 = DROP
```

In [7]:

```
# Get unique run numbers
runs = df['Run'].unique()
print('Total Unique Runs=',len(runs))
#runs

df_run = pd.DataFrame()
i=0
# Calculate each Run's lenght and record inside df_run
for run in runs:
    count = (df['Run'] == run).sum()
    df_run.loc[i, 'Run'] = run
    df_run.loc[i, 'Count'] = count
    i=i+1
df_run.head()
# SwpYipezsdueC - Remove all columns except SwpYipezsdueC and Run column
df_check=df
check_column = 'SwpYipezsdueC'
for column in df.columns:
    if column != check_column and column != 'Run':
        df_check=df_check.drop(column, axis=1)
print(df.shape)
# Split data into dicts by run number
data_by_run = {run: df[df['Run'] == run] for run in runs}
df.head()
# SwpYipezsdueC - Get the max lenght for resampling
i=0
mydict={}
for run, df1 in data_by_run.items():
    i = i + 1
    mylist = df1[check_column].tolist()
    mydict[run]=len(mylist)
max_key = max(mydict, key=lambda key: mydict[key])
max_value = mydict[max_key]
print('Maximum Run record lenght =', max_value)
# SwpYipezsdueC - Convert column to rows and Resample the time series and
new_df = pd.DataFrame()
i=0
for run, df1 in data_by_run.items():
    i = i + 1
    mylist = df1[check_column].tolist()
    # Resample mylist using linear interpolation to match the length of th
    if len(mylist) < max_value:
        x1 = np.arange(len(mylist))
        x2 = np.linspace(0, len(mylist) - 1, max_value)
        mylist = np.interp(x2, x1, mylist)
    mylist = np.insert(mylist, 0, run)
    new_row = pd.DataFrame([mylist])
    new_df = pd.concat([new_df, new_row], ignore_index=True)
new_df.set_index(0, inplace=True)
print(new_df.shape)
new_df.head()
```

```
Total Unique Runs= 228
(13657, 41)
Maximum Run record lenght = 87
(228, 87)
```

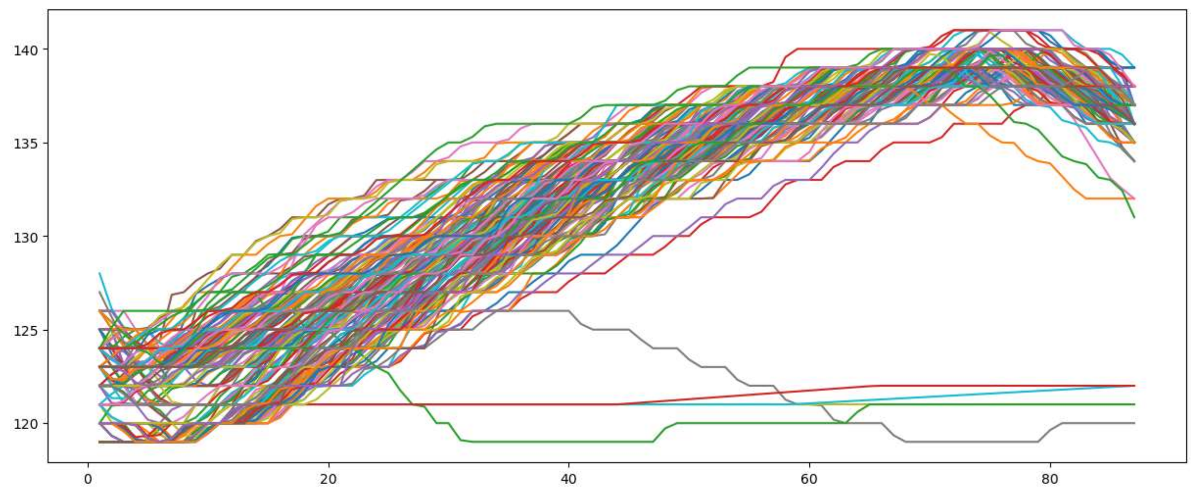
Out[7]:

0	1	2	3	4	5	6	7	8	
62301.0	125.0	123.697674	123.0	123.00000	123.000000	123.000000	123.000000	123.558140	12
62302.0	120.0	120.000000	120.0	120.00000	120.000000	119.395349	119.000000	119.046512	11
62303.0	121.0	121.000000	121.0	121.00000	121.000000	121.197674	121.837209	122.000000	12
62304.0	123.0	123.000000	123.0	123.00000	123.000000	123.000000	123.488372	124.000000	12
62305.0	120.0	120.000000	120.0	119.94186	119.255814	119.000000	119.116279	119.802326	12

5 rows × 87 columns

In [8]:

```python
plt.figure(figsize=(15, 6))
for index, row in new_df.iterrows():
    plt.plot(row, label=f'Line {index}')  # Plot each row with a label
plt.show()
```



Based on the pattern above, there are 4 lines which is out of normal pattern.

KMean Clustering

In [9]:

```
import numpy
import matplotlib.pyplot as plt

from tslearn.clustering import KShape
from tslearn.datasets import CachedDatasets
from tslearn.preprocessing import TimeSeriesScalerMeanVariance

import pandas as pd
from sklearn.model_selection import train_test_split
```

In [10]:

```
# Load the dataset
#X_train, y_train, X_test, y_test = CachedDatasets().load_dataset("Trace")

# Split the data into features (X) and labels (y)
#X = df.drop('y_column_name', axis=1)  # Replace 'y_column_name' with the
#y = df['y_column_name']
#y = new_df.iloc[0]
#y = y.to_numpy().flatten()
#print(y)
#X = list(range(1, len(y) + 1))
#X = np.arange(1, len(y) + 1)
#X
# above wrong.
y = new_df.index
y = y.astype(int)
y

#X = np.arange(1, len(y) + 1)
index_variable = new_df.index
index_variable = index_variable.astype(int)
X_df = new_df.reset_index(drop=True)
X = X_df.values
y = np.arange(1, len(X) + 1)
#print(y)
#X
print(X.shape)
print(y.shape)
```

```
(228, 87)
(228,)
```

In [14]:

```
# Split the data into training and testing sets
#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
#print(X_train.shape)
#print(X_train)
#print(y_train.shape)
#print(y_train)
```

In [15]:

```
#X_train = X_train[y_train < 4]
#print(X_train.shape)
#X_train
```

In [16]:

```
#X_train = X_train[:50]
#X_train
```

In [18]:

```
#numpy.random.shuffle(X_train)
#print(X_train.shape)
#print(y_train.shape)
```

In [19]:

```
# For this method to operate properly, prior scaling is required
X_train = X
X_train = TimeSeriesScalerMeanVariance().fit_transform(X_train)
sz = X_train.shape[1]
```

KShape Clustering

In [21]:

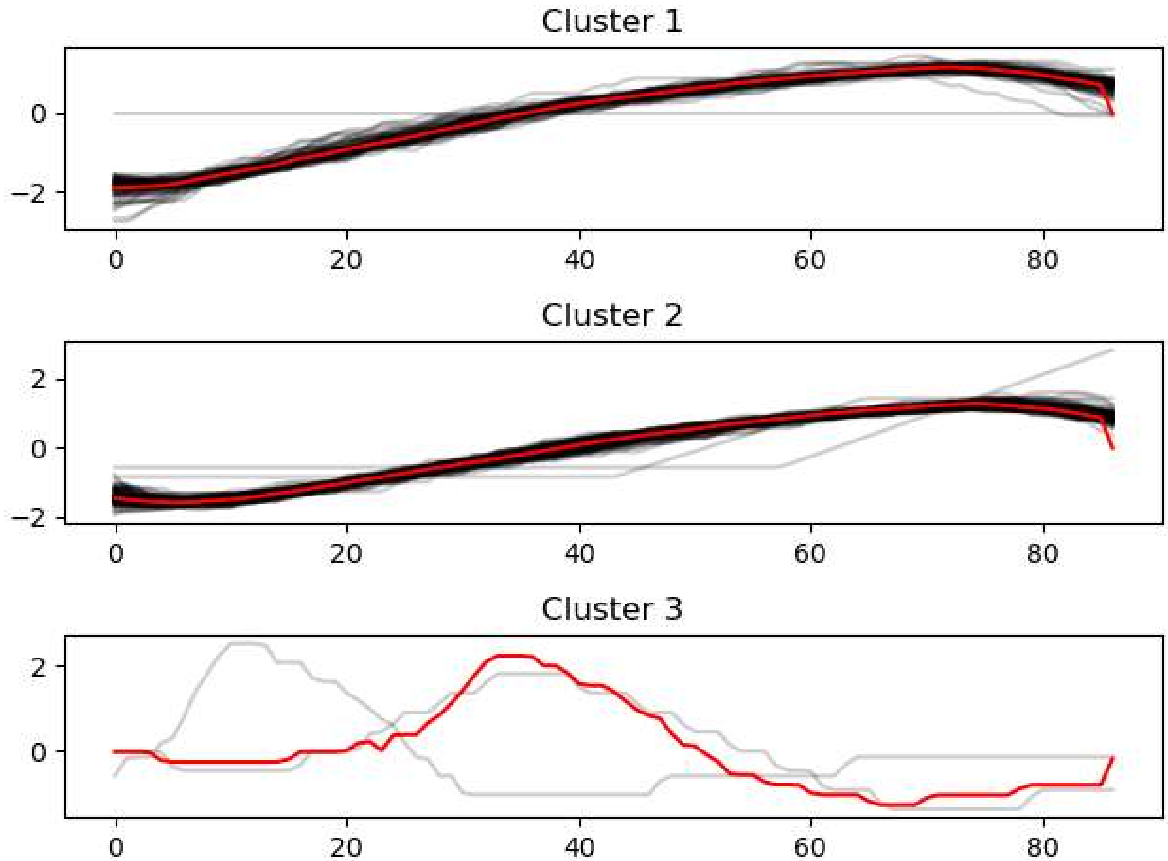
```python
#X_train = X_train[y_train < 4]
#X_train = X_train[:50]
#numpy.random.shuffle(X_train)
# For this method to operate properly, prior scaling is required
#X_train = TimeSeriesScalerMeanVariance().fit_transform(X_train)
#sz = X_train.shape[1]

# kShape clustering
seed = 0
numpy.random.seed(seed)
ks = KShape(n_clusters=3, verbose=True, random_state=seed)
y_pred = ks.fit_predict(X_train)
print(y_pred)

plt.figure()
for yi in range(3):
    plt.subplot(3, 1, 1 + yi)
    for xx in X_train[y_pred == yi]:
        plt.plot(xx.ravel(), "k-", alpha=.2)
    plt.plot(ks.cluster_centers_[yi].ravel(), "r-")
    #plt.xlim(0, sz)
    #plt.ylim(-4, 4)
    plt.title("Cluster %d" % (yi + 1))

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

```
0.005 --> 0.005 -->
[1 0 1 1 1 1 1 1 1 0 0 1 1 0 1 0 1 1 1 0 1 1 0 1 0 0 1 1 1 1 1 1 1 1 1 1 1
 1 1 0 1 1 0 1 1 0 1 1 0 1 1 0 1 1 0 1 1 0 1 1 0 1 1 0 1 1 1 1 1 0 1 1 0 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 1 0 1 0 1 1 1 0 0 0 0 1 1 1 1 1 0
 1 1 1 1 0 0 2 0 1 0 1 0 0 0 0 0 0 0 0 0 0 2 1 0 0 0 0 1 1 1 0 1 1 0 0 1 0
 0 1 0 0 1 1 1 1 1 1 0 1 1 1 1 1 0 1 0 1 1 0 0 1 0 1 1 0 0 1 0 0 1 1 0 1 0
 0 1 0 0 1 1 0 0 1 0 0 1 1 1 1 1 1 0 1 0 1 1 1 0 1 1 0 0 1 1 0 0 0 1 1 0 1
 0 0 1 1 1 1]
```



Cluster 1
0
−2
0
20
40
60
80
Cluster 2
2
0
−2
0
20
40
60
80
Cluster 3
2
0
0
20
40
60
80

In [22]:

```python
print('X_train')
print(X_train)
print('y_pred')
print(y_pred)
```

```
X_train
[[[-1.34464998]
  [-1.58249252]
  [-1.70990816]
  ...
  [ 0.90211251]
  [ 0.84689907]
  [ 0.84689907]]

 [[-1.61992522]
  [-1.61992522]
  [-1.61992522]
  ...
  [ 0.89738317]
  [ 0.8193271 ]
  [ 0.61768224]]

 [[-1.79545174]
  [-1.79545174]
  [-1.79545174]
  ...
  [ 0.89863921]
  [ 0.80782715]
  [ 0.80782715]]

 ...

 [[-1.55746254]
  [-1.55746254]
  [-1.55746254]
  ...
  [ 0.98059225]
  [ 0.91102763]
  [ 0.79930262]]

 [[-1.59519967]
  [-1.59519967]
  [-1.59519967]
  ...
  [ 1.02032427]
  [ 0.90306542]
  [ 0.78580656]]

 [[-1.38152918]
  [-1.38152918]
  [-1.452847  ]
  ...
  [ 1.20092642]
  [ 1.15588359]
  [ 1.03952294]]]
y_pred
[1 0 1 1 1 1 1 1 1 0 0 1 1 0 1 0 1 1 1 0 1 1 0 1 0 0 1 1 1 1 1 1 1 1 1 1 1
 1 1 0 1 1 0 1 1 0 1 1 0 1 1 0 1 1 0 1 1 0 1 1 0 1 1 0 1 1 1 1 1 0 1 1 0 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 1 0 1 0 1 1 1 0 0 0 0 1 1 1 1 1 0
 1 1 1 1 0 0 2 0 1 0 1 0 0 0 0 0 0 0 0 0 0 2 1 0 0 0 0 1 1 1 0 1 1 0 0 1 0
 0 1 0 0 1 1 1 1 1 1 0 1 1 1 1 1 0 1 0 1 1 0 0 1 0 1 1 0 0 1 0 0 1 1 0 1 0
```

```
0 1 0 0 1 1 0 0 1 0 0 1 1 1 1 1 1 0 1 0 1 1 1 0 1 1 0 0 1 1 0 0 0 1 1 0 1
0 0 1 1 1 1]
```

In [23]:

```python
X_train_df = pd.DataFrame(X_train[:, 0, 0])  # Assuming X_train is a 3D ar
y_pred_df = pd.DataFrame(y_pred, columns=['y_pred'])
#merged_df = pd.concat([X_train_df, y_pred_df], axis=1)
merged_df = pd.concat([X_df, y_pred_df], axis=1)
merged_df = merged_df.set_index(index_variable)
merged_df
```

Out[23]:

	1	2	3	4	5	6	7	8
0								
62301	125.0	123.697674	123.00000	123.000000	123.000000	123.000000	123.000000	123.558140
62302	120.0	120.000000	120.00000	120.000000	120.000000	119.395349	119.000000	119.046512
62303	121.0	121.000000	121.00000	121.000000	121.000000	121.197674	121.837209	122.000000
62304	123.0	123.000000	123.00000	123.000000	123.000000	123.000000	123.488372	124.000000
62305	120.0	120.000000	120.00000	119.941860	119.255814	119.000000	119.116279	119.802326
...	...	...	...	...	...	...	...	...
62596	124.0	124.000000	124.00000	124.000000	124.232558	124.790698	125.000000	125.000000
62597	120.0	120.000000	120.00000	119.906977	119.209302	119.000000	119.186047	119.883721
62598	123.0	123.000000	123.00000	123.000000	123.000000	123.000000	123.000000	123.000000
62599	121.0	121.000000	121.00000	121.000000	121.000000	121.000000	121.000000	121.000000
62600	122.0	122.000000	121.55814	121.000000	121.000000	121.000000	121.000000	121.000000

228 rows × 88 columns

In [24]:

```python
df=merged_df
print('0',(df['y_pred'] == 0).sum())
print('1',(df['y_pred'] == 1).sum())
print('2',(df['y_pred'] == 2).sum())
print('3',(df['y_pred'] == 3).sum())
```

```
0 84
1 142
2 2
3 0
```

In [25]:

```python
df.to_csv('d:\\download\\timeserieskmean.csv', index=False)
```

Conclusion: KMean KShape clustering does provide some accurate clustering but missed out a few abnormal patterns. Increasing the number of cluster up to 6 can help improve the accuracy.

TimeSeriesKMeans - DTW

In [26]:
```
index_variable = new_df.index
index_variable = index_variable.astype(int)
X_df = new_df.reset_index(drop=True)
X = X_df.values
y = np.arange(1, len(X) + 1)
print(X.shape)
```

```
(228, 87)
```

In [27]:

```
# For this method to operate properly, prior scaling is required
X_train = X
print(X_train.shape)

from tslearn.preprocessing import TimeSeriesResampler
# Don't scale it because the size of the pattern is important
#X_train = TimeSeriesScalerMeanVariance().fit_transform(X_train)
#X_train = TimeSeriesResampler().fit_transform(X_train)
X_train_scale = X_train.copy()
sz = X_train.shape[1]
print(sz)
X_train = TimeSeriesResampler(sz=sz).fit_transform(X_train)
print(X_train.shape)
X_train
```

```
(228, 87)
87
(228, 87, 1)
```

```
Out[27]: array([[[125.        ],
          [123.69767442],
          [123.        ],
          ...,
          [137.30232558],
          [137.        ],
          [137.        ]],

         [[120.        ],
          [120.        ],
          [120.        ],
          ...,
          [138.        ],
          [137.44186047],
          [136.        ]],

         [[121.        ],
          [121.        ],
          [121.        ],
          ...,
          [137.55813953],
          [137.        ],
          [137.        ]],

         ...,

         [[123.        ],
          [123.        ],
          [123.        ],
          ...,
          [137.        ],
          [136.61627907],
          [136.        ]],

         [[121.        ],
          [121.        ],
          [121.        ],
          ...,
          [139.6744186 ],
          [138.8372093 ],
          [138.        ]],

         [[122.        ],
          [122.        ],
          [121.55813953],
          ...,
          [138.        ],
          [137.72093023],
          [137.        ]]])
```

In [28]:

```
n_cluster=6
model = TimeSeriesKMeans(n_clusters=n_cluster, metric="dtw", max_iter=10,
model.fit(X_train)
y_pred = model.predict(X_train)
print(y_pred)
```

```
[4 2 0 4 2 0 0 2 0 0 4 2 0 0 2 0 4 2 0 4 0 0 0 0 0 0 0 3 3 0 3 3 0 3 0 0 3
 4 0 2 3 3 2 3 3 2 0 3 2 0 4 0 0 3 2 0 4 2 0 3 2 3 4 2 3 0 0 3 3 2 3 3 2 0
 3 2 0 0 2 0 4 2 0 0 2 0 3 2 0 0 2 0 0 2 0 4 2 0 0 2 0 0 2 0 4 2 0 4 2 0 4
 0 4 4 0 3 0 5 1 1 0 0 4 0 3 0 0 0 4 0 0 4 5 1 2 0 3 2 0 4 2 3 4 2 0 4 2 0
 4 2 0 4 2 0 4 2 0 4 2 2 2 4 2 0 4 2 3 3 2 0 4 2 0 2 2 0 4 2 4 4 2 4 4 2 0
 0 2 0 0 2 0 4 2 0 3 2 0 4 2 0 0 2 4 4 2 0 4 2 0 0 2 0 4 2 0 2 0 0 2 0 0 2
 3 4 2 0 2 0]
```

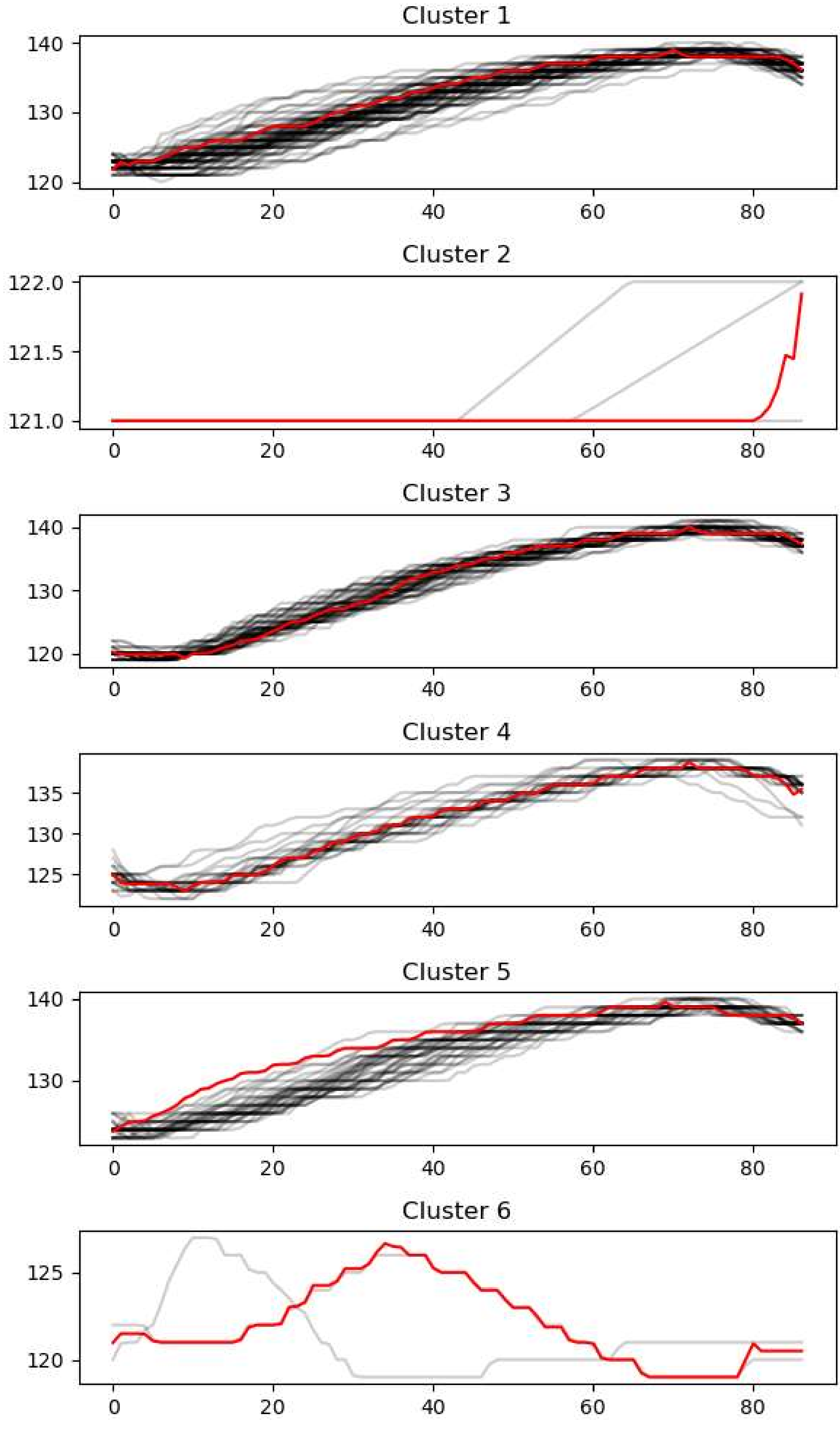
In [29]:

```
#model.cluster_centers_[0]
```

In [30]:

```
#plt.figure()
plt.figure(figsize=(6, 10))
for yi in range(n_cluster):
    plt.subplot(n_cluster, 1, 1 + yi)
    for xx in X_train[y_pred == yi]:
        plt.plot(xx.ravel(), "k-", alpha=.2)
    plt.plot(model.cluster_centers_[yi].ravel(), "r-")
    #plt.xlim(0, sz)
    #plt.ylim(-4, 4)
    plt.title("Cluster %d" % (yi + 1))

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



Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Cluster 6

Cluster 2 and Cluster 6 seems to identified all the abnormal patterns.

In [31]:

```
#X_train_df = pd.DataFrame(X_train[:, 0, 0])  # Assuming X_train is a 3D a
y_pred_df = pd.DataFrame(y_pred, columns=['y_pred'])
#merged_df = pd.concat([X_train_df, y_pred_df], axis=1)
merged_df = pd.concat([X_df, y_pred_df], axis=1)
merged_df = merged_df.set_index(index_variable)
#merged_df
```

In [32]:

```
df=merged_df
print('0',(df['y_pred'] == 0).sum())
print('1',(df['y_pred'] == 1).sum())
print('2',(df['y_pred'] == 2).sum())
print('3',(df['y_pred'] == 3).sum())
print('4',(df['y_pred'] == 4).sum())
print('5',(df['y_pred'] == 5).sum())
```

```
0 90
1 3
2 63
3 29
4 41
5 2
```

In [33]:

```
print(X_train_scale.shape)
#X_train_scale
#X_train_scale[0]
X_train_scale
```

```
(228, 87)
```

Out[33]:

```
array([[125.        , 123.69767442, 123.        , ..., 137.30232558,
        137.        , 137.        ],
       [120.        , 120.        , 120.        , ..., 138.        ,
        137.44186047, 136.        ],
       [121.        , 121.        , 121.        , ..., 137.55813953,
        137.        , 137.        ],
       ...,
       [123.        , 123.        , 123.        , ..., 137.        ,
        136.61627907, 136.        ],
       [121.        , 121.        , 121.        , ..., 139.6744186 ,
        138.8372093 , 138.        ],
       [122.        , 122.        , 121.55813953, ..., 138.        ,
        137.72093023, 137.        ]])
```

In [34]:
```
X_train_scale2 = X_train_scale.reshape(X_train_scale.shape[0], X_train_sca
X_train_scale2
```

Out[34]:
```
array([[125.        , 123.69767442, 123.        , ..., 137.30232558,
        137.        , 137.        ],
       [120.        , 120.        , 120.        , ..., 138.        ,
        137.44186047, 136.        ],
       [121.        , 121.        , 121.        , ..., 137.55813953,
        137.        , 137.        ],
       ...,
       [123.        , 123.        , 123.        , ..., 137.        ,
        136.61627907, 136.        ],
       [121.        , 121.        , 121.        , ..., 139.6744186 ,
        138.8372093 , 138.        ],
       [122.        , 122.        , 121.55813953, ..., 138.        ,
        137.72093023, 137.        ]])
```

In [35]:
```
#X_train_chart = pd.DataFrame(X_train)
X_train_chart = pd.DataFrame(X_train_scale2)
X_train_chart
```

Out[35]:

	0	1	2	3	4	5	6	7
0	125.0	123.697674	123.00000	123.000000	123.000000	123.000000	123.000000	123.558140
1	120.0	120.000000	120.00000	120.000000	120.000000	119.395349	119.000000	119.046512
2	121.0	121.000000	121.00000	121.000000	121.000000	121.197674	121.837209	122.000000
3	123.0	123.000000	123.00000	123.000000	123.000000	123.000000	123.488372	124.000000
4	120.0	120.000000	120.00000	119.941860	119.255814	119.000000	119.116279	119.802326
...	...	...	...	...	...	...	...	...
223	124.0	124.000000	124.00000	124.000000	124.232558	124.790698	125.000000	125.000000
224	120.0	120.000000	120.00000	119.906977	119.209302	119.000000	119.186047	119.883721
225	123.0	123.000000	123.00000	123.000000	123.000000	123.000000	123.000000	123.000000
226	121.0	121.000000	121.00000	121.000000	121.000000	121.000000	121.000000	121.000000
227	122.0	122.000000	121.55814	121.000000	121.000000	121.000000	121.000000	121.000000

228 rows × 87 columns

In [36]:
```
merged_df_chart = X_train_chart.set_index(index_variable)
X_train_chart
```

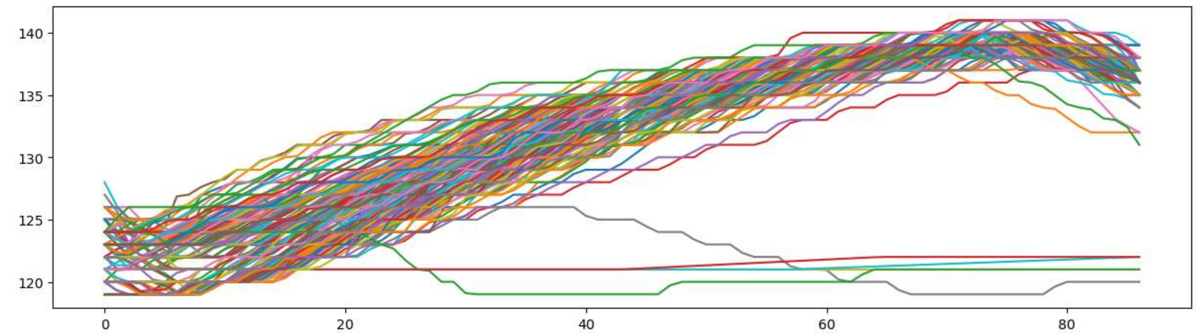
Out[36]:

	0	1	2	3	4	5	6	7
0	125.0	123.697674	123.00000	123.000000	123.000000	123.000000	123.000000	123.558140
1	120.0	120.000000	120.00000	120.000000	120.000000	119.395349	119.000000	119.046512
2	121.0	121.000000	121.00000	121.000000	121.000000	121.197674	121.837209	122.000000
3	123.0	123.000000	123.00000	123.000000	123.000000	123.000000	123.488372	124.000000
4	120.0	120.000000	120.00000	119.941860	119.255814	119.000000	119.116279	119.802326
...	...	...	...	...	...	...	...	...
223	124.0	124.000000	124.00000	124.000000	124.232558	124.790698	125.000000	125.000000
224	120.0	120.000000	120.00000	119.906977	119.209302	119.000000	119.186047	119.883721
225	123.0	123.000000	123.00000	123.000000	123.000000	123.000000	123.000000	123.000000
226	121.0	121.000000	121.00000	121.000000	121.000000	121.000000	121.000000	121.000000
227	122.0	122.000000	121.55814	121.000000	121.000000	121.000000	121.000000	121.000000

228 rows × 87 columns

In [38]:

```python
plt.figure(figsize=(15, 4))
for index, row in merged_df_chart.iterrows():
    plt.plot(row, label=f'Line {index}')  # Plot each row with a label
plt.show()
merged_df_chart
```



Out[38]:

0	0	1	2	3	4	5	6	7
62301	125.0	123.697674	123.00000	123.000000	123.000000	123.000000	123.000000	123.558140
62302	120.0	120.000000	120.00000	120.000000	120.000000	119.395349	119.000000	119.046512
62303	121.0	121.000000	121.00000	121.000000	121.000000	121.197674	121.837209	122.000000
62304	123.0	123.000000	123.00000	123.000000	123.000000	123.000000	123.488372	124.000000
62305	120.0	120.000000	120.00000	119.941860	119.255814	119.000000	119.116279	119.802326
...	...	...	...	...	...	...	...	...
62596	124.0	124.000000	124.00000	124.000000	124.232558	124.790698	125.000000	125.000000
62597	120.0	120.000000	120.00000	119.906977	119.209302	119.000000	119.186047	119.883721
62598	123.0	123.000000	123.00000	123.000000	123.000000	123.000000	123.000000	123.000000
62599	121.0	121.000000	121.00000	121.000000	121.000000	121.000000	121.000000	121.000000
62600	122.0	122.000000	121.55814	121.000000	121.000000	121.000000	121.000000	121.000000

228 rows × 87 columns

In [39]:

```
# Optimization/Hyperparameter Tuning
import numpy as np
from tslearn.clustering import TimeSeriesKMeans
from sklearn.metrics import silhouette_score
X_train2 = X_train.reshape(X_train.shape[0], X_train.shape[1])
print(X_train2.shape)

max_clusters = 10  # Adjust the maximum number of clusters as needed
silhouette_scores = []

for n_clusters in range(2, max_clusters + 1):
    # Create a TimeSeriesKMeans model with the current number of clusters
    model = TimeSeriesKMeans(n_clusters=n_clusters, verbose=False, random_

    # Fit the model to your time series data
    model.fit(X_train2)

    # Predict cluster labels for your data
    cluster_labels = model.predict(X_train2)

    # Calculate the silhouette score for the current number of clusters
    silhouette = silhouette_score(X_train2, cluster_labels)

    silhouette_scores.append(silhouette)
silhouette_scores
```

```
(228, 87)

d:\Users\tklim\anaconda3\lib\site-packages\tslearn\utils\utils.py:90: User
Warning: 2-Dimensional data passed. Assuming these are 228 1-dimensional t
imeseries
  warnings.warn(
d:\Users\tklim\anaconda3\lib\site-packages\tslearn\utils\utils.py:90: User
Warning: 2-Dimensional data passed. Assuming these are 228 1-dimensional t
imeseries
  warnings.warn(
d:\Users\tklim\anaconda3\lib\site-packages\tslearn\utils\utils.py:90: User
Warning: 2-Dimensional data passed. Assuming these are 228 1-dimensional t
imeseries
  warnings.warn(
d:\Users\tklim\anaconda3\lib\site-packages\tslearn\utils\utils.py:90: User
Warning: 2-Dimensional data passed. Assuming these are 228 1-dimensional t
imeseries
  warnings.warn(
d:\Users\tklim\anaconda3\lib\site-packages\tslearn\utils\utils.py:90: User
Warning: 2-Dimensional data passed. Assuming these are 228 1-dimensional t
```

In [40]:
```python
print(type(silhouette_scores))
silhouette_scores
```

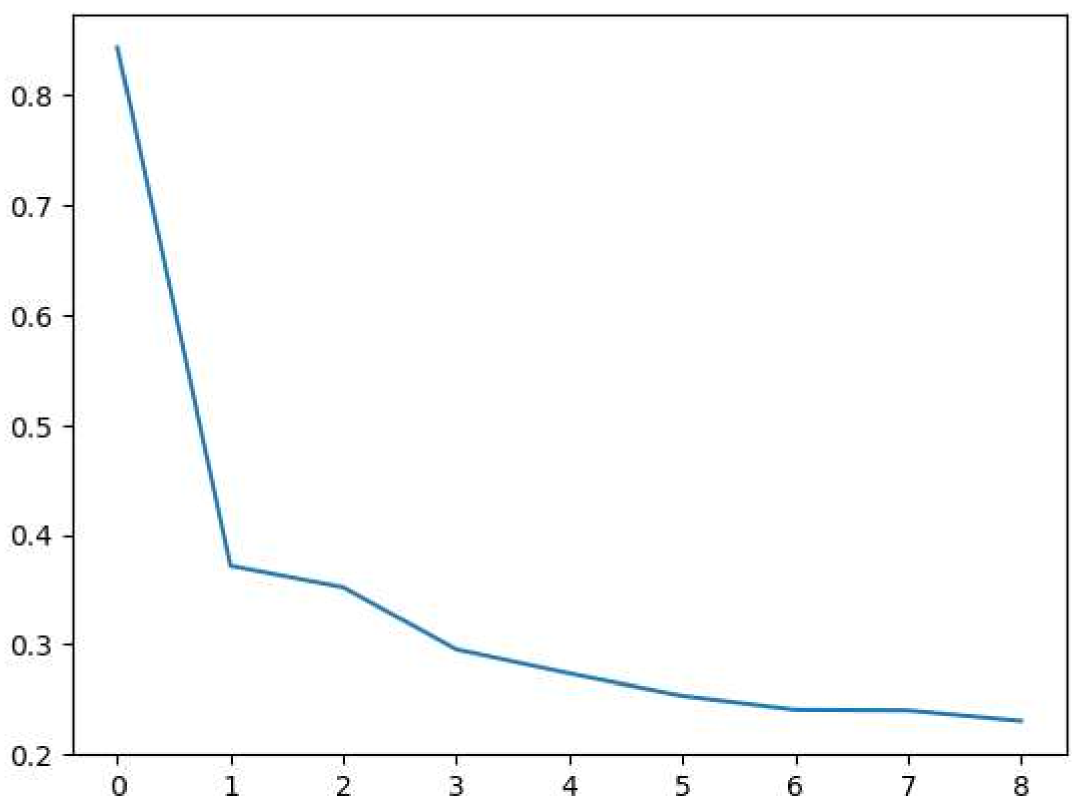
```
<class 'list'>
```

Out[40]:
```
[0.8435585406819868,
 0.37147139080283603,
 0.3518400762253112,
 0.2951402633521269,
 0.27339617881284395,
 0.2530568447035266,
 0.24049922433566023,
 0.23991270989282823,
 0.23030860525031174]
```

In [41]:
```python
plt.plot(silhouette_scores)

   # plt.plot(row, label=f'Line {index}')  # Plot each row with a label
#plt.show()
```

Out[41]:
```
[<matplotlib.lines.Line2D at 0x1f2b45e5e20>]
```



Conlusion: The Elbow analysis shows the clustering is at 1 cluster but 3 and 6 is the more accurate clusting number.

In [ ]:

```
# Reference
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhoue
#sklearn.metrics.silhouette_score(X, labels, *, metric='euclidean', sample
```

In [ ]:

```
# Example:
from sklearn.datasets import make_blobs
X, y = make_blobs(
    n_samples=500,
    n_features=2,
    centers=4,
    cluster_std=1,
    center_box=(-10.0, 10.0),
    shuffle=True,
    random_state=1,
)  # For reproducibility
print(X.shape)
X
```

Reference sample code

In [ ]:

```
import numpy as np
from tslearn.clustering import TimeSeriesKMeans
from tslearn.datasets import CachedDatasets
from tslearn.preprocessing import TimeSeriesScalerMeanVariance
```

In [ ]:

```
mylist = CachedDatasets().list_datasets()
mylist
```

In [ ]:

```
data_loader = CachedDatasets()
X_train, y_train, X_test, y_test = data_loader.load_dataset("Trace")
#https://tslearn.readthedocs.io/en/stable/gen_modules/datasets/tslearn.dat
```

In [ ]:

```
X_train
```

In [ ]:

```python
# Author: Romain Tavenard
# License: BSD 3 clause
#https://tslearn.readthedocs.io/en/stable/auto_examples/clustering/plot_ks
import numpy
import matplotlib.pyplot as plt

from tslearn.clustering import KShape
from tslearn.datasets import CachedDatasets
from tslearn.preprocessing import TimeSeriesScalerMeanVariance

seed = 0
numpy.random.seed(seed)
X_train, y_train, X_test, y_test = CachedDatasets().load_dataset("Trace")
# Keep first 3 classes and 50 first time series
X_train = X_train[y_train < 4]
X_train = X_train[:50]
numpy.random.shuffle(X_train)
# For this method to operate properly, prior scaling is required
X_train = TimeSeriesScalerMeanVariance().fit_transform(X_train)
sz = X_train.shape[1]

# kShape clustering
ks = KShape(n_clusters=3, verbose=True, random_state=seed)
y_pred = ks.fit_predict(X_train)

plt.figure()
for yi in range(3):
    plt.subplot(3, 1, 1 + yi)
    for xx in X_train[y_pred == yi]:
        plt.plot(xx.ravel(), "k-", alpha=.2)
    plt.plot(ks.cluster_centers_[yi].ravel(), "r-")
    plt.xlim(0, sz)
    plt.ylim(-4, 4)
    plt.title("Cluster %d" % (yi + 1))

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

In [ ]:

```python

```