dtwhaclustering

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USAGE

CHAPTER

ONE

DYNAMIC TIME WARPING BASED HIERARCHICAL AGGLOMERATIVE CLUSTERING

Codes to perform Dynamic Time Warping Based Hierarchical Agglomerative Clustering of GPS data

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CHAPTER

TWO

INSTALLATION

2.1 Requirements

1. `dtaidistance`: For computing DTW distance
2. `pygmt`: For plotting high-resolution maps
3. `pandas`: Analyze tabular data
4. `numpy`: Computation
5. `matplotlib`: Plotting time series
6. `scipy`: Interpolating data
7. `xarray`: Multilayered data structure

2.2 Install from PyPI

This package is available on PyPI (requires Python 3):

```
pip install dtwhaclustering
```

CHAPTER

THREE

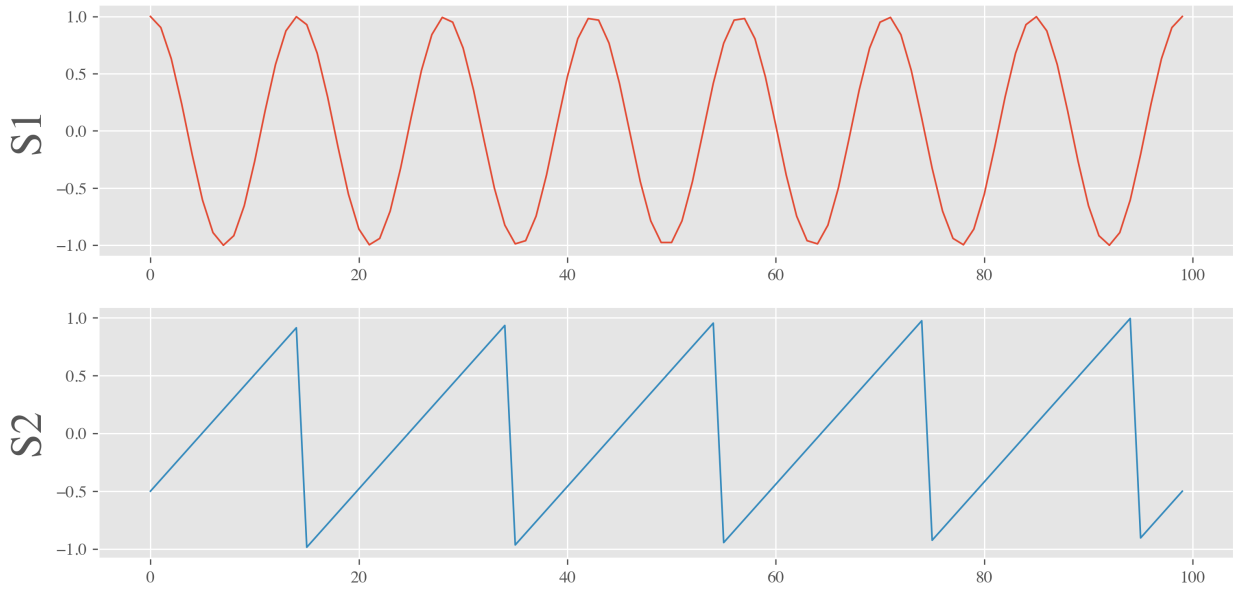
SIGNAL ANALYSIS

3.1 Create signals for analysis

```
np.random.seed(0)
# sampling parameters
fs = 100   # sampling rate, in Hz
T = 1      # duration, in seconds
N = T * fs  # duration, in samples

# time variable
t = np.linspace(0, T, N)

SNR = 0.2 #noise

XX0 = np.sin(2 * np.pi * t * 7+np.pi/2) #+ np.random.randn(1, N) * SNR
XX1 = signal.sawtooth(2 * np.pi * t * 5+np.pi/2) #+ np.random.randn(1, N) * SNR
s1, s2 = XX0, XX1
```

3.2 Inspect the DTW distance between two signals

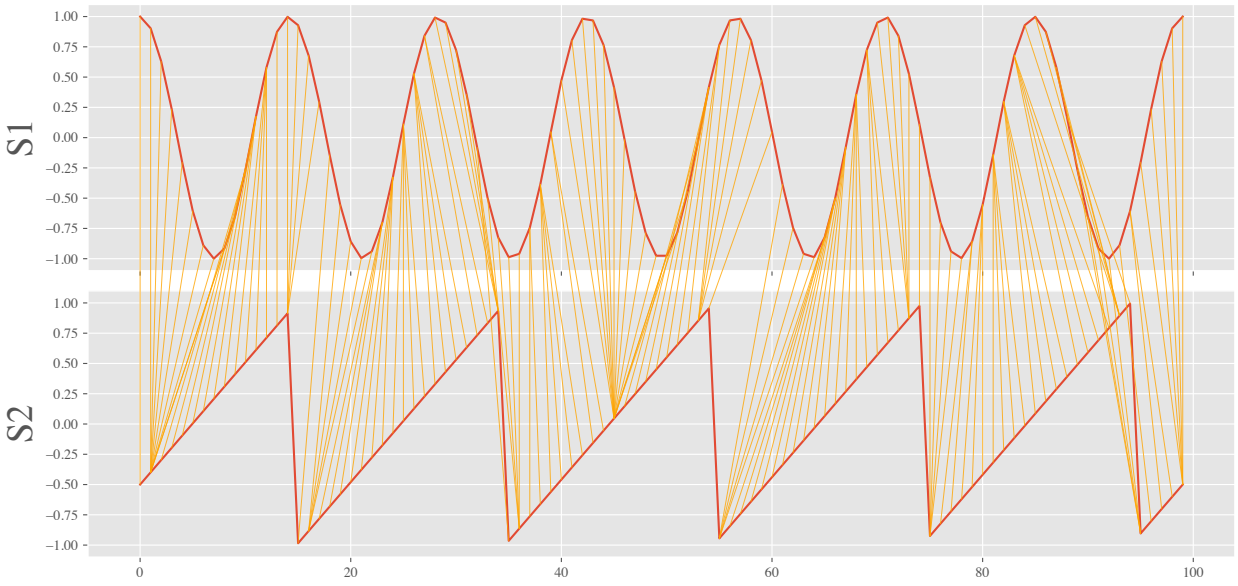
```
dtwsig = dtw_signal_pairs(s1, s2, labels=['S1', 'S2'])
dtwsig.plot_signals()
plt.show()
```



3.3 Plot warping path

```
matplotlib.rcParams['pdf.fonttype'] = 42
distance,_,_ = dtwsig.plot_warping_path()
print(f"DTW distance between signals: {distance:.4f}")

plt.savefig("warping_path_s1_s2.pdf", bbox_inches='tight')
```

DTW distance between signals: 5.2093




```
dtwsig.plot_matrix(windowfrac=0.6, psi=None) #Only allow for shifts up to 60% of the␣
↪minimum signal length away from the two diagonals.
```

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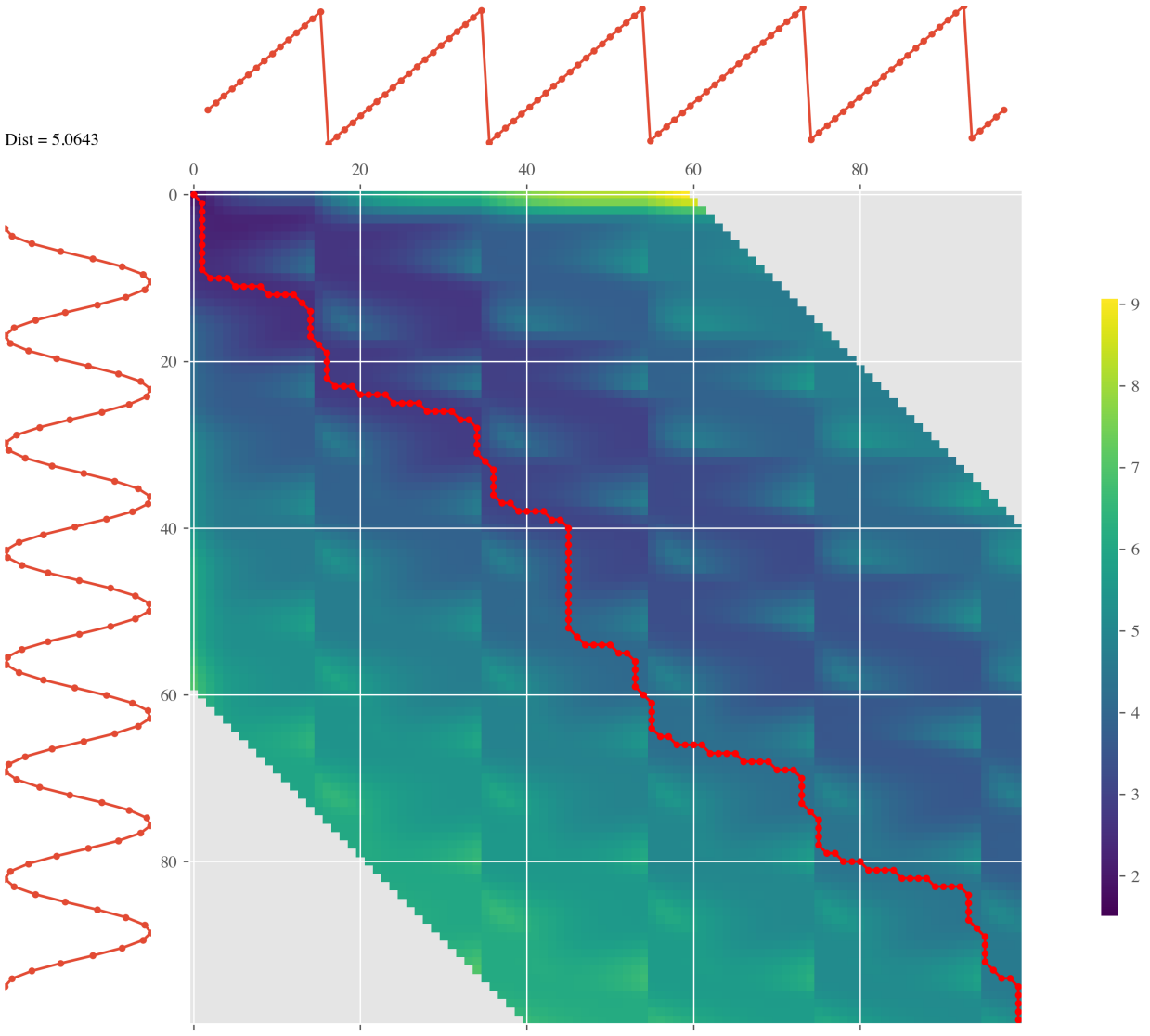
```
plt.show()
```



3.4 Create multiple signals

```
fs = 100   # sampling rate, in Hz
T  = 1     # duration, in seconds

N  = T * fs # duration, in samples
M  = 5      # number of sources
S1 = np.sin(2 * np.pi * t * 7)
S2 = signal.sawtooth(2 * np.pi * t * 5)
S3 = np.abs(np.cos(2 * np.pi * t * 3)) - 0.5
S4 = np.sign(np.sin(2 * np.pi * t * 8))
S5 = np.random.randn(N)
```

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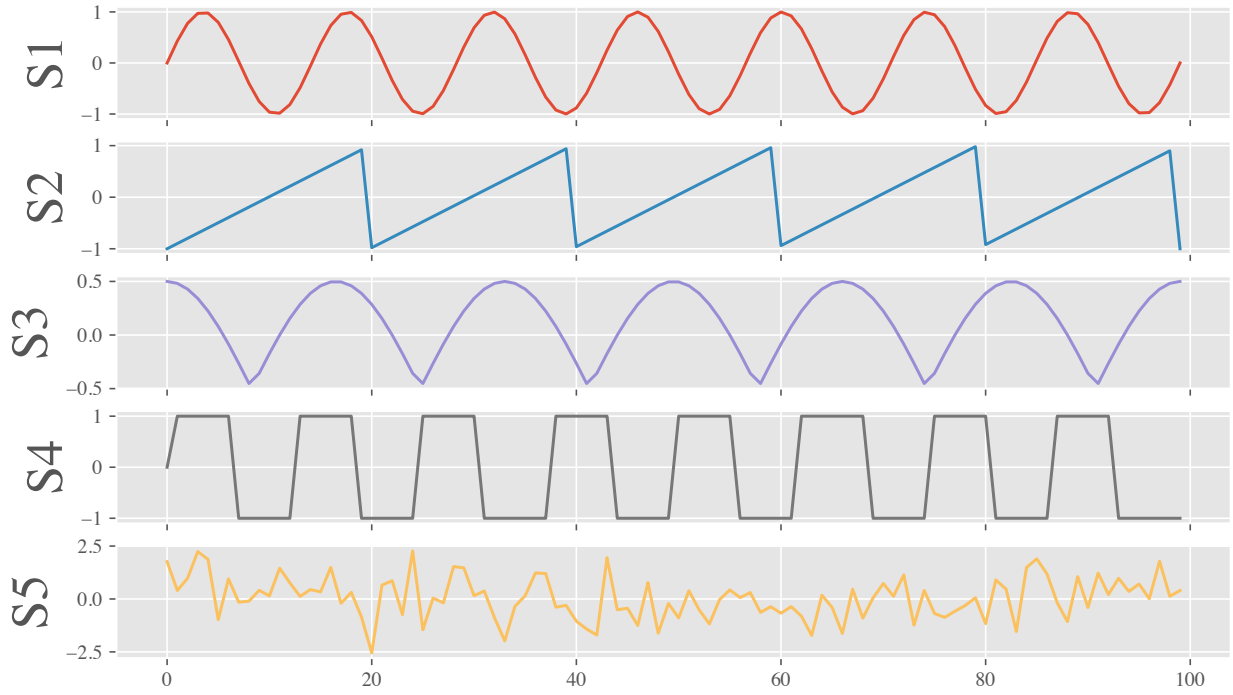
```
time_series = np.array([S1, S2, S3, S4, S5])

## instantiate the class
dtw_cluster = dtw_clustering(time_series,labels=['S1','S2','S3','S4','S5'])

matplotlib.rcParams['pdf.fonttype'] = 42
dtw_cluster.plot_signals()
# plt.show()
plt.savefig("base_functions.pdf", bbox_inches='tight')
```



3.5 Compute the relative DTW distance between the signals

```
ds = dtw_cluster.compute_distance_matrix(compact=False)
```

```
array([[0.        , 5.15998322, 4.19080907, 5.77875263, 7.95685039],
[5.15998322, 0.        , 4.74413601, 7.71110741, 9.31343712],
[4.19080907, 4.74413601, 0.        , 8.75201301, 8.51048008],
[5.77875263, 7.71110741, 8.75201301, 0.        , 9.18406086],
[7.95685039, 9.31343712, 8.51048008, 9.18406086, 0.        ]])
```

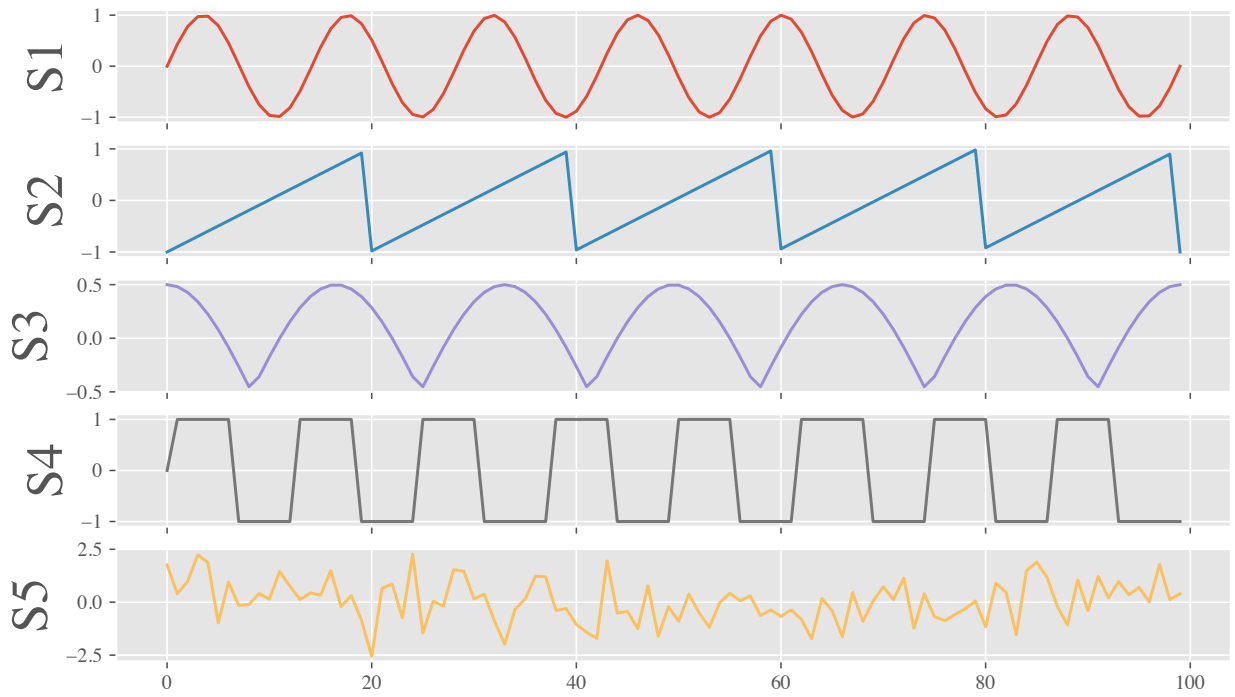
CHAPTER

FOUR

CLUSTERING ANALYSIS

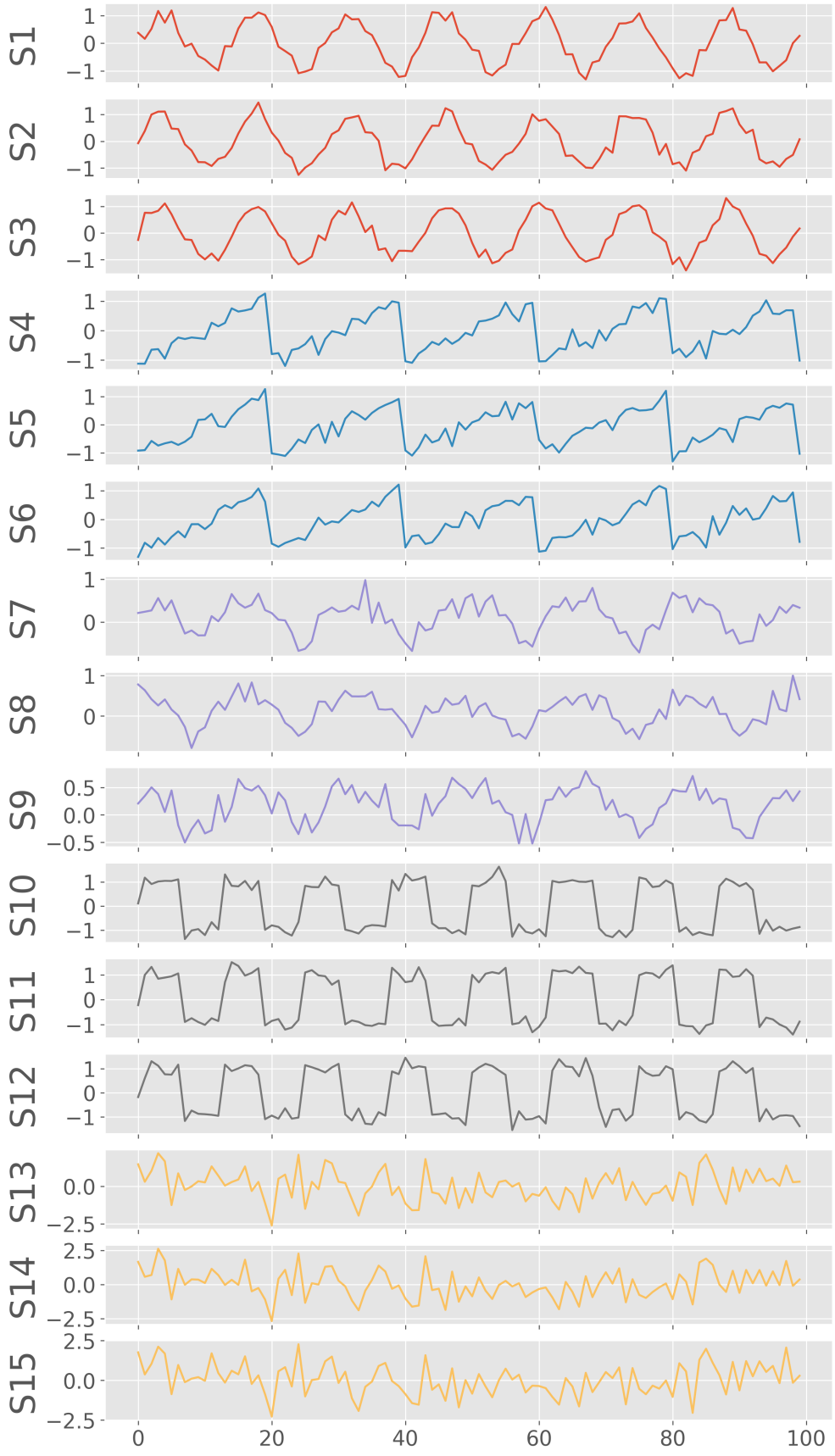
4.1 Create signals for analysis

```
from dtwhaclustering.dtw_analysis import dtw_signal_pairs, dtw_clustering, plot_signals,␣
↪shuffle_signals, plot_cluster
import numpy as np
from scipy import signal
import matplotlib.pyplot as plt
from dtaidistance import dtw
from scipy.cluster.hierarchy import fcluster

from scipy.cluster.hierarchy import dendrogram
from sklearn.cluster import AgglomerativeClustering

np.random.seed(0)
# sampling parameters
fs = 100   # sampling rate, in Hz
T  = 1      # duration, in seconds
N  = T * fs # duration, in samples
M  = 5      # number of sources
R  = 3      # number of copies
MR = M * R


# time variable
t = np.linspace(0, T, N)

S1 = np.sin(2 * np.pi * t * 7)
S2 = signal.sawtooth(2 * np.pi * t * 5)
S3 = np.abs(np.cos(2 * np.pi * t * 3)) - 0.5
S4 = np.sign(np.sin(2 * np.pi * t * 8))
S5 = np.random.randn(N)

time_series = np.array([S1, S2, S3, S4, S5])

fig, ax = plot_signals(time_series)
plt.show()
```



4.2 Add noise and make 3 copies of each signal

```
SNR = 0.2
X0 = np.tile(S1, (R, 1)) + np.random.randn(R, N) * SNR
X1 = np.tile(S2, (R, 1)) + np.random.randn(R, N) * SNR
X2 = np.tile(S3, (R, 1)) + np.random.randn(R, N) * SNR
X3 = np.tile(S4, (R, 1)) + np.random.randn(R, N) * SNR
X4 = np.tile(S5, (R, 1)) + np.random.randn(R, N) * SNR
X = np.concatenate((X0, X1, X2, X3, X4))

color = ['C0']*3+['C1']*3+['C2']*3+['C3']*3+['C4']*3
fig, ax = plot_signals(X,figsize=(10,20), color=color)
plt.show()
```

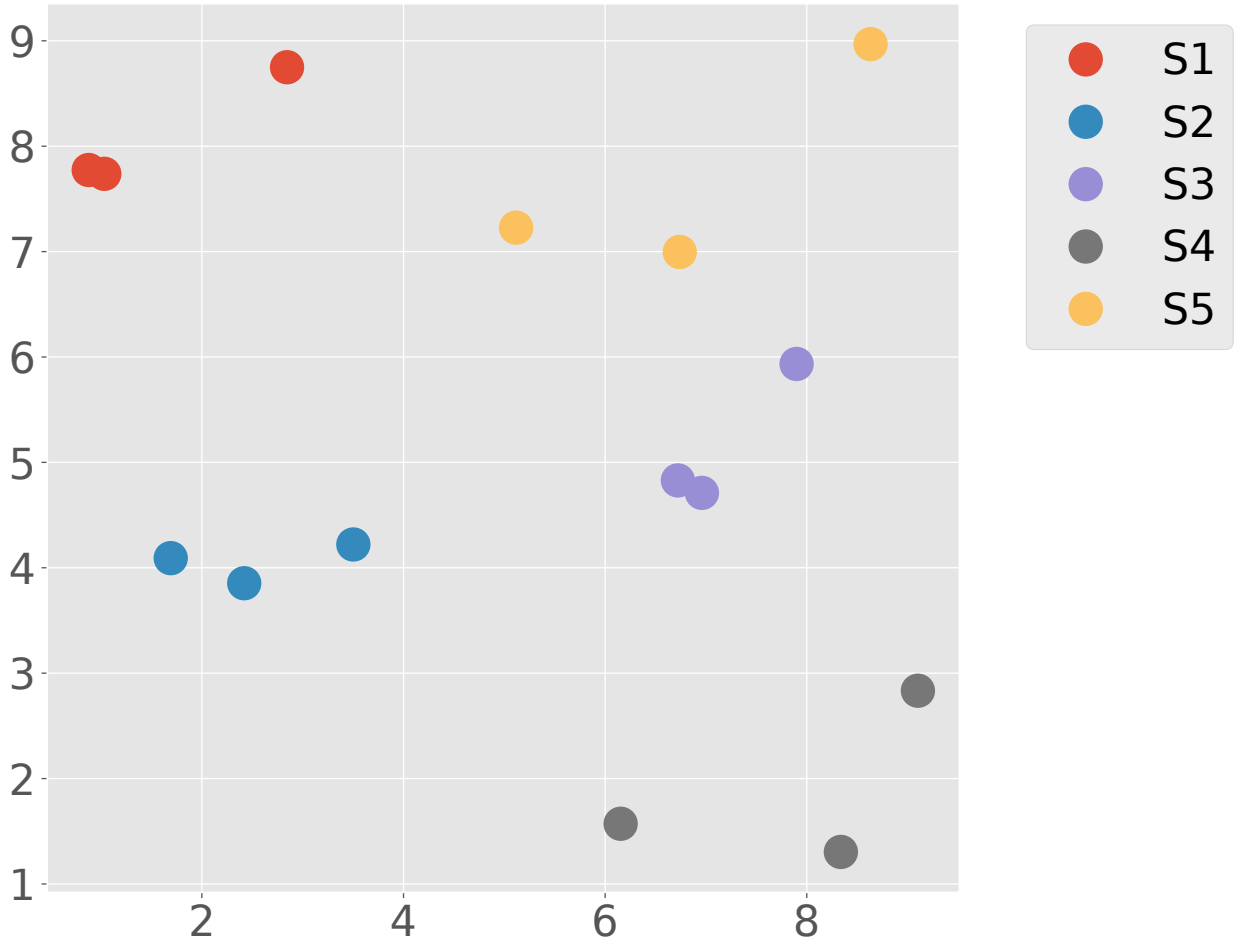

S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
S13
S14
S15
0
20
40
60
80
100

4.3 Geographically distribute the signals

Now, we have 15 signals in total. Let us also randomly make these signals distributed in geographical space by assigning them longitudes and latitudes. We assume that the signals with similar waveforms are geographically co-located.

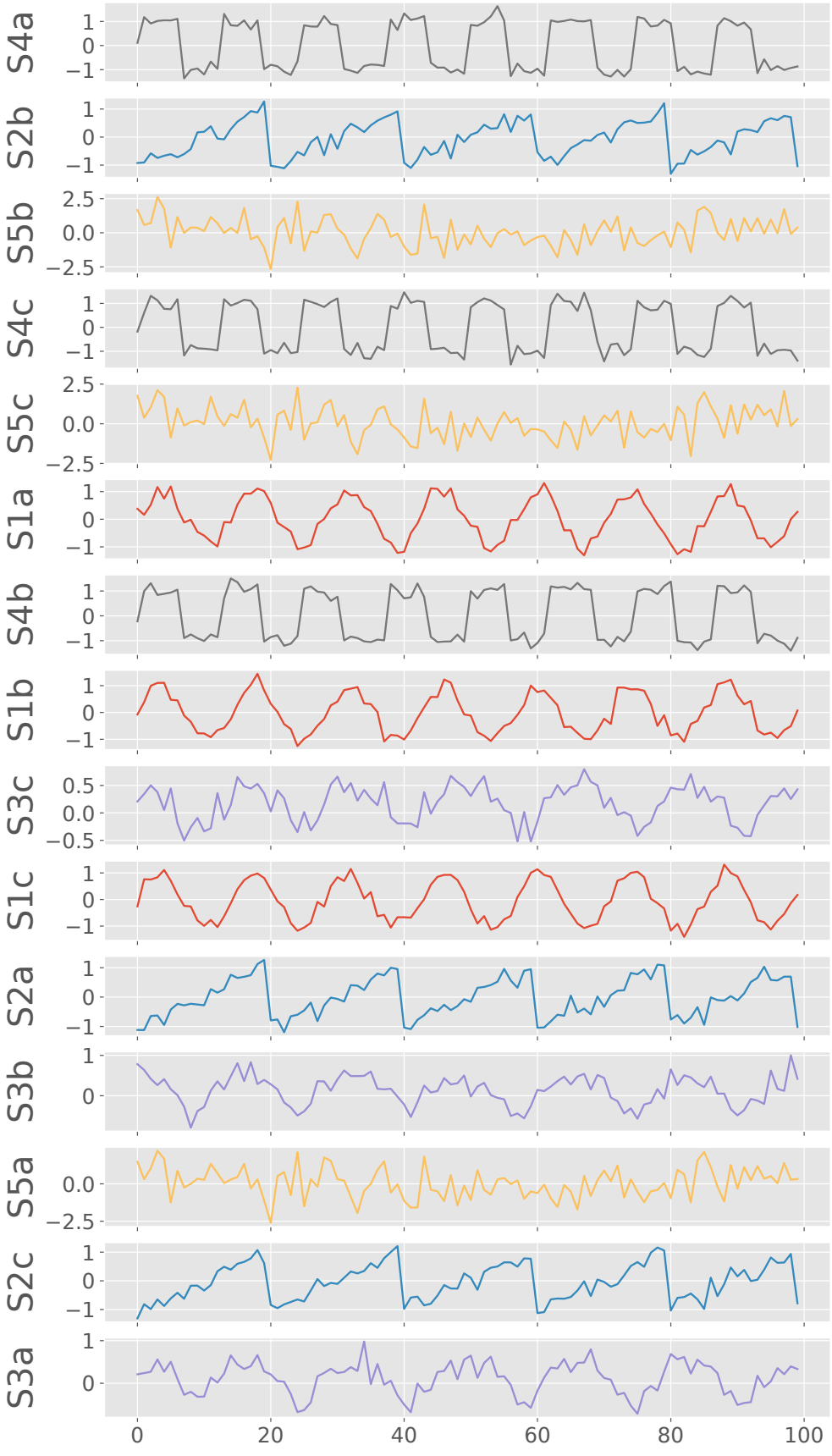
```
S0 variants (S0, S1, S2) -> xrange(0-3) yrange(7-10)
S1 variants (S3, S4, S5) -> xrange(1-4) yrange(3-5)
S2 variants (S6, S7, S8) -> xrange(4-8) yrange(4-6)
S3 variants (S9, S10, S11) -> xrange(5-10) yrange(0-4)
S4 variants (S12, S13, S14) -> xrange(5-9) yrange(6-9)
```

```
S0_lons = np.random.uniform(0, 3, 3)
S0_lats = np.random.uniform(7, 10, 3)

S1_lons = np.random.uniform(1, 4, 3)
S1_lats = np.random.uniform(3, 5, 3)

S2_lons = np.random.uniform(4, 8, 3)
S2_lats = np.random.uniform(4, 6, 3)

S3_lons = np.random.uniform(5, 10, 3)
S3_lats = np.random.uniform(0, 4, 3)

S3_lons = np.random.uniform(5, 10, 3)
S3_lats = np.random.uniform(0, 4, 3)

S4_lons = np.random.uniform(5, 9, 3)
S4_lats = np.random.uniform(6, 9, 3)

lons = np.concatenate((S0_lons, S1_lons, S2_lons, S3_lons, S4_lons))
lats = np.concatenate((S0_lats, S1_lats, S2_lats, S3_lats, S4_lats))

plot_cluster(lons,lats)
# plt.show()
plt.savefig("signals_locations.pdf", bbox_inches='tight')
```



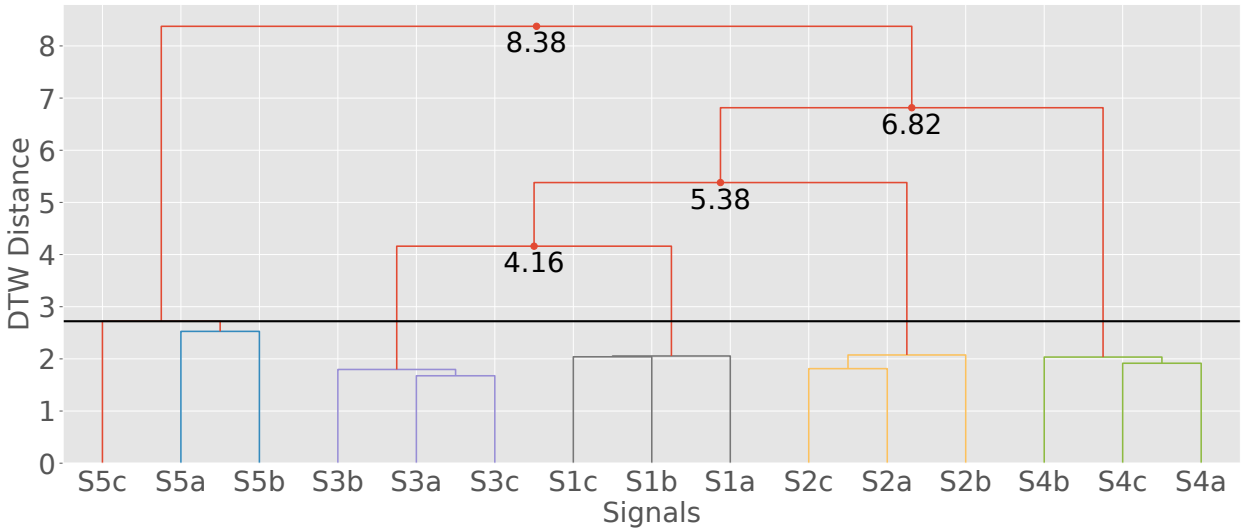
4.4 Reshuffle the noisy signals

```
shuffled_idx, shuffled_matrix = shuffle_signals(X, labels=[], plot_signals=False,␣
↪figsize=(10, 20))
shuffled_lons = lons[shuffled_idx]
shuffled_lats = lats[shuffled_idx]

labels = np.array(['S1a', 'S1b', 'S1c','S2a', 'S2b', 'S2c','S3a', 'S3b', 'S3c','S4a',
↪'S4b', 'S4c','S5a', 'S5b', 'S5c'])
newlabels = labels[shuffled_idx]

color = np.array(color)
color = color[shuffled_idx]
fig, ax = plot_signals(shuffled_matrix,figsize=(10,20), color=color, labels=newlabels)
plt.savefig("shuffled_signals.pdf", bbox_inches='tight')
```


S4a
S2b
S5b
S4c
S5c
S1a
S4b
S1b
S3c
S1c
S2a
S3b
S5a
S2c
S3a
0
20
40
60
80
100

4.5 Cluster reshuffled signals

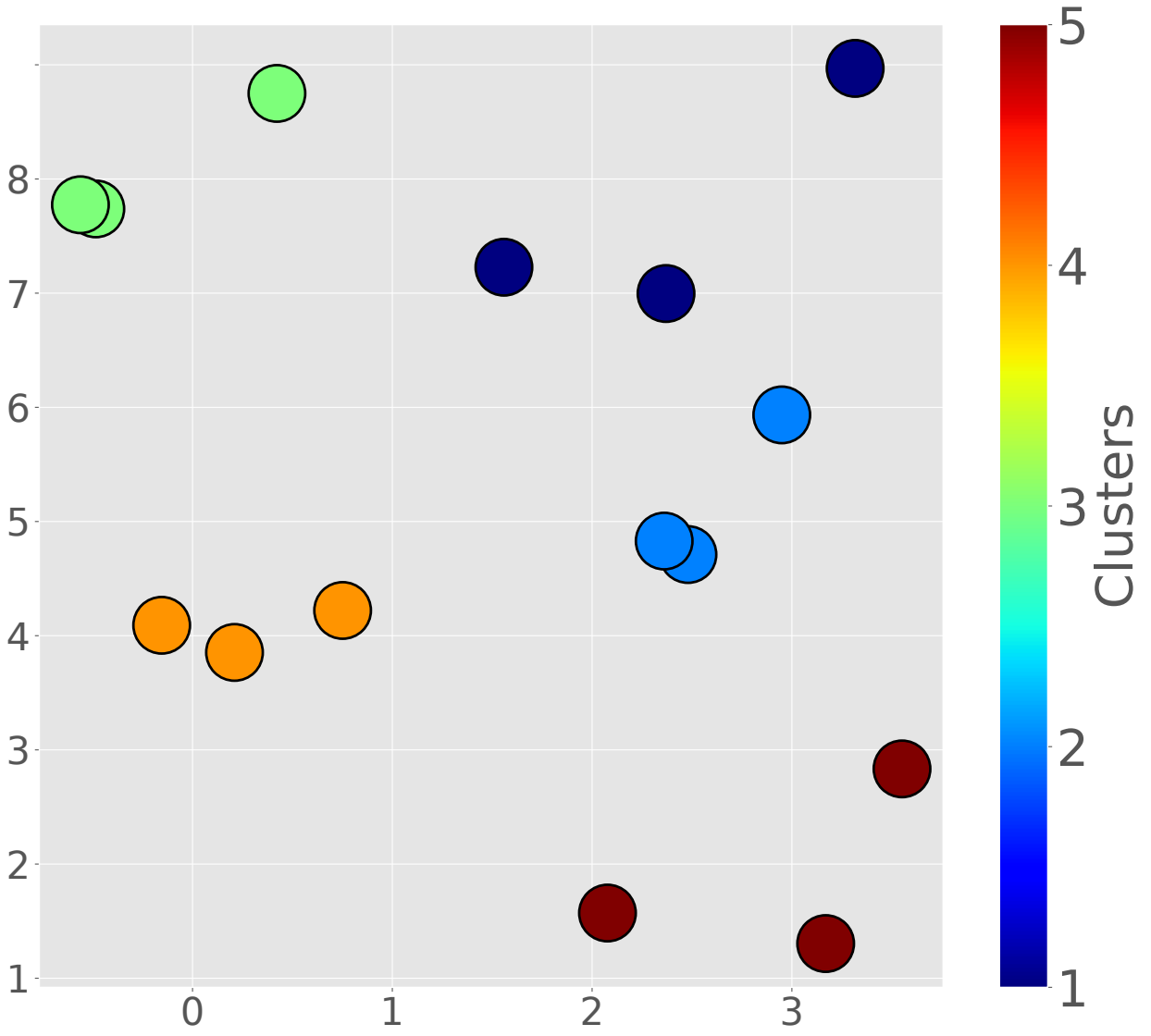
```
dtw_cluster2 = dtw_clustering(shuffled_matrix, labels=newlabels, longitudes=shuffled_
↪lons, latitudes=shuffled_lats)
dtw_cluster2.plot_dendrogram(annotate_above=3,xlabel="Signals", figname="example_dtw_
↪cluster.png",distance_threshold="optimal")
```



In the above dendrogram, we manually selected the threshold distance to be 3 to find the best clusters

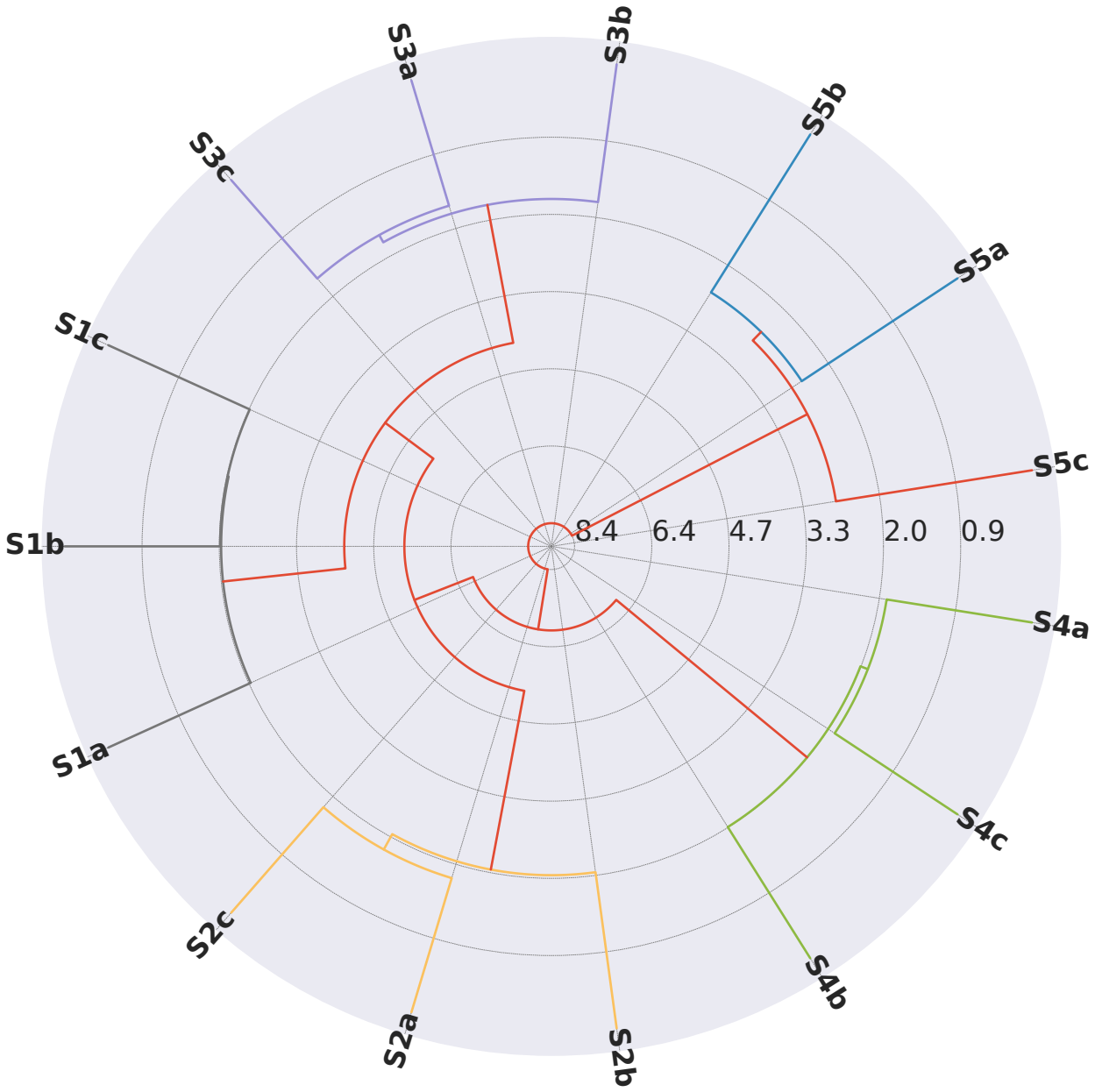
4.6 Plot the geographical locations of the clusters

```
dtw_cluster2.plot_cluster_xymap(dtw_distance=3, figname=None, xlabel='', ylabel='',␣
↪fontsize=40, markersize=200, tickfontsize=30, cbarsize=40)
plt.savefig("signals_cluster_xy_map.pdf", bbox_inches='tight', edgecolors='black',␣
↪linewidths=5)
```



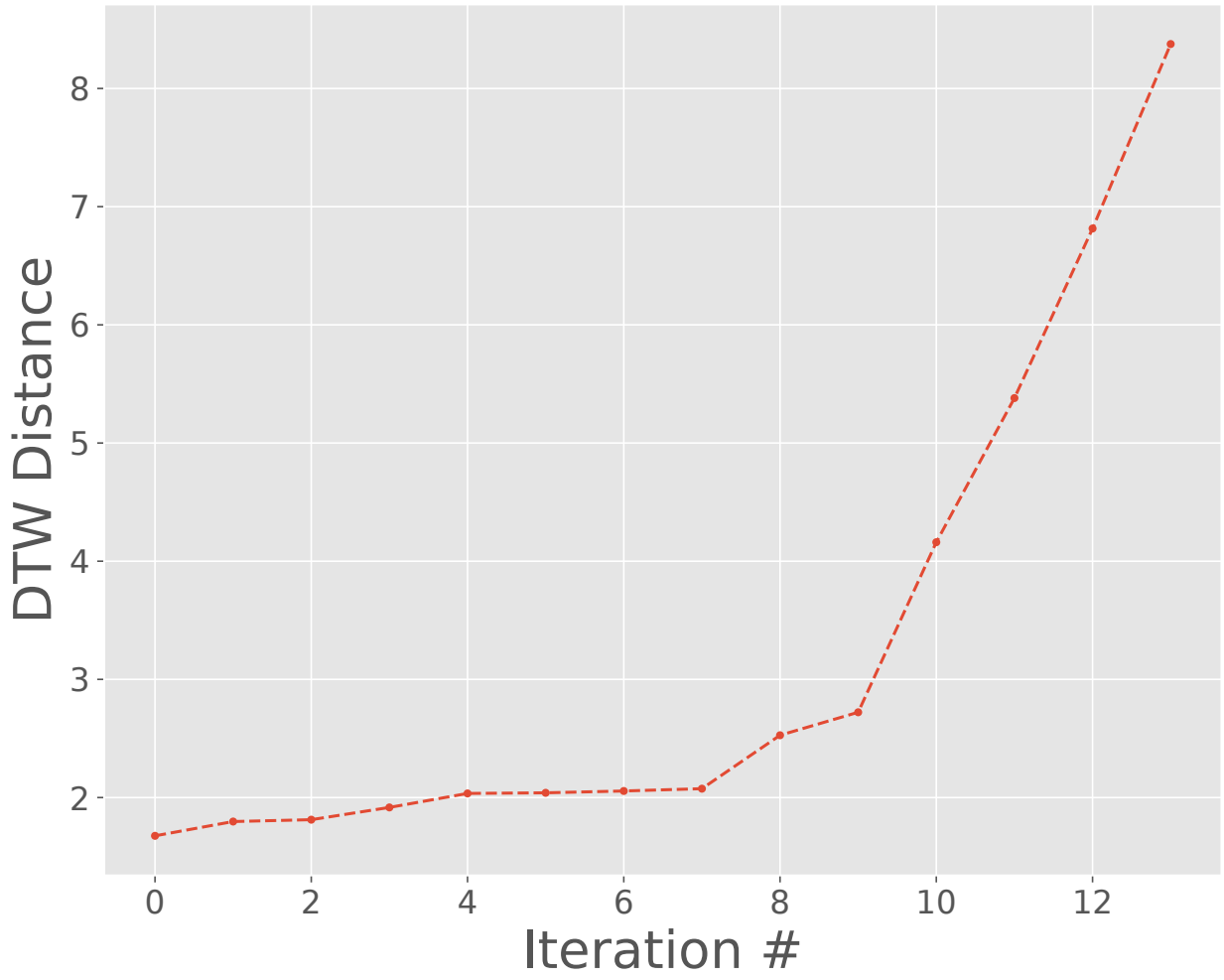
4.7 Polar dendrogram

```
kwargs_dendro={
"plotstyle":'seaborn',
"linewidth":5,
"gridwidth":0.8,
"gridcolor":'gray',
'xtickfontsize':60,
'ytickfontsize':60,
"figsize":(40,40),
"distance_threshold":"optimal" #use optimal number of clusters estimated by elbow method
}

dtw_cluster2.plot_polar_dendrogram(**kwargs_dendro)
plt.savefig("example_polar_dendro.pdf", bbox_inches='tight')
```

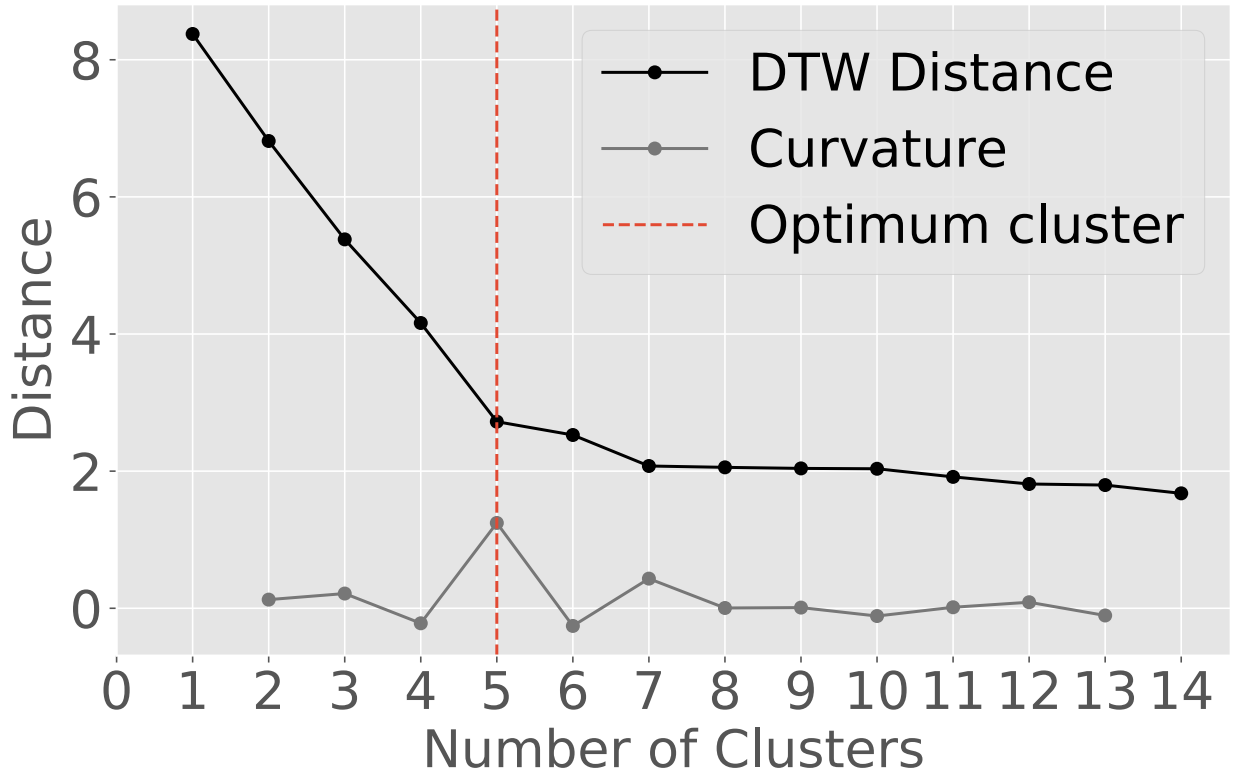


4.8 How the DTW distance changes with iterations to obtain the dendrogram?

```
dtw_cluster2.plot_hac_iteration()
plt.show()
```




```
dtw_cluster2.plot_optimum_cluster(legend_outside=False)
plt.savefig("optimum_clusters.pdf", bbox_inches='tight')
```



4.9 Euclidean distance-based cluster

```
def compute_linkage(model):
    # create the counts of samples under each node
    counts = np.zeros(model.children_.shape[0])
    n_samples = len(model.labels_)
    for i, merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1  # leaf node
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count

    linkage_matrix = np.column_stack([model.children_, model.distances_,
                                      counts]).astype(float)
    return linkage_matrix

def plot_dendrogram(model, **kwargs):
    # Create linkage matrix and then plot the dendrogram

    linkage_matrix = compute_linkage(model)

    # Plot the corresponding dendrogram
```

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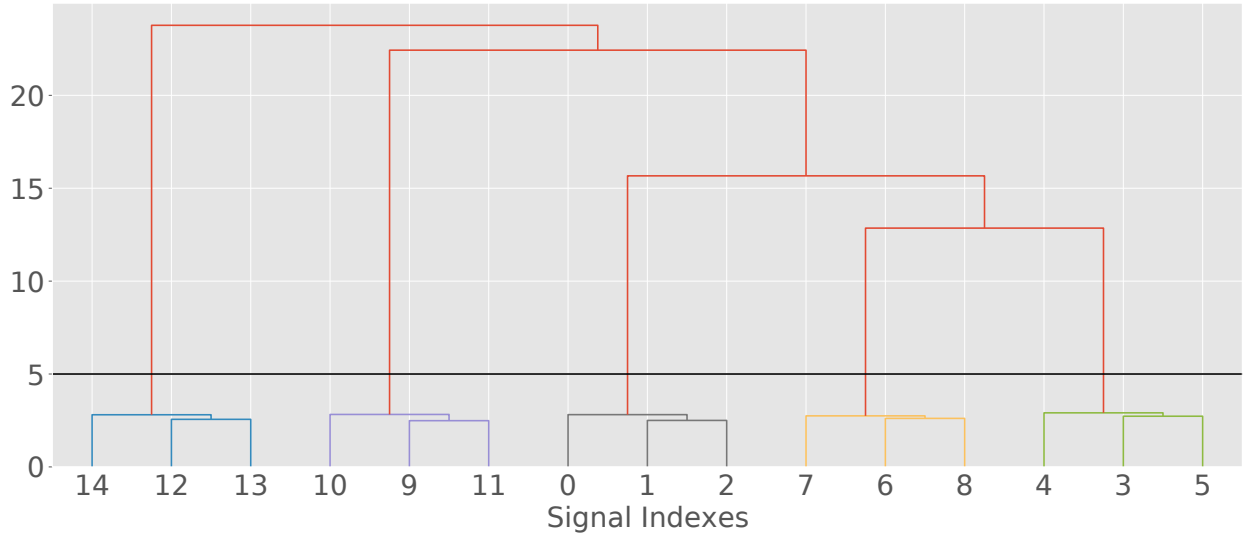
```
    dendrogram(linkage_matrix, **kwargs)


#'ward' minimizes the variance of the clusters being merged
model = AgglomerativeClustering(distance_threshold=0, n_clusters=None, affinity=
↪'euclidean',linkage='ward')

model = model.fit(X)

plt.figure(figsize=(20, 8))
# plot the top three levels of the dendrogram
plot_dendrogram(model, p=5, color_threshold=5)
plt.xticks(fontsize=26)
plt.yticks(fontsize=26)
plt.axhline(y=5, c='k')


plt.xlabel("Signal Indexes")
plt.savefig('example_euclidean_cluster.pdf',bbox_inches='tight')
plt.close()
```



Both Euclidean and DTW based clustering results are similar. However, we can see some obvious differences. Let us list some of the similarity and differences for the above example.

- Both the results found 5 significant clusters.
- Both Euclidean and DTW based HAC found that the random function based time series (12, 13, 14) are most dissimilar
- The two closest clusters with DTW is sawtooth (6,7,8) and sine func(0,1,2). While that with the Euclidean, it is abs_cosine (6,7,8) and sawtooth fn (3,4,5)

The two results are similar because the signals considered for this example are stationary in nature.

CHAPTER

FIVE

DTWHACLUSTERING.ANALYSIS_SUPPORT

DTW HAC analysis support functions (*analysis_support*)

author Utpal Kumar, Institute of Earth Sciences, Academia Sinica

dtwhaclustering.analysis_support.**dec2dt**(*start*)
Convert the decimal type time array to the date-time type array

Parameters **start** (*list*) – list or numpy array of decimal year values e.g., [2020.001]

Returns date-time type array

Return type list

dtwhaclustering.analysis_support.**dec2dt_scalar**(*st*)
Convert the decimal type time value to the date-time type

Parameters **st** – scalar decimal year value e.g., 2020.001

Returns time as datetime type

Return type str

dtwhaclustering.analysis_support.**toYearFraction**(*date*)
Convert the date-time type object to decimal year

Parameters **date** – the date-time type object

Returns decimal year

Return type float

CHAPTER

SIX

DTWHACLUSTERING.PLOT_LINEAR_TREND

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SEVEN

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EIGHT

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