"Install a pip package in the current Jupyter kernel\n", "Memo to self: Install modules with 'sys.executable' and then restart kernel"

In [1]:
```
import sys
#!{sys.executable} -m pip install --upgrade statsmodels
```

In [17]:
```
#************** Start importing python modules
import time
import os # For
import pandas as pd
import numpy as np
from functools import partial # For partial functions
from scipy.interpolate import CubicSpline
import statsmodels.api as sm
import scipy.cluster.hierarchy as spc
from matplotlib import pyplot as plt
from math import sqrt
#************ Start GUI modules
import io
import traitlets
import ipywidgets as widgets
from IPython.display import display
from tkinter import Tk, filedialog
#************ End GUI modules
#************** End importing python modules
# Start
```

Start importing data First ask the user to select the json file containing

In [3]:
```
btn_upload = widgets.FileUpload(
    accept = '*.json',
    multiple = False
)
display(btn_upload)
```

```
FileUpload(value=(), accept='*.json', description='Upload')
```

Extract the content of the json-file and convert the json to a data frame

In [4]:
```
stringContent = btn_upload.value[0]['content'].tobytes().decode("utf-8")
df =  pd.read_json(io.StringIO(stringContent),orient = 'index')
print(f'top part is {df.head()}')
print(f'bottom part is {df.tail()}')
```

```
top part is                          series_0  series_1  series_2  series_3  series_4
2022-06-01 00:00:00       0.0 -0.012866       0.0  0.009272 -0.943774  \
2022-06-01 00:01:00       0.1  0.106740       0.1 -0.004306 -0.734072
2022-06-01 00:02:00       0.2  0.209939       0.2  0.005588  3.272961
2022-06-01 00:03:00       0.3  0.293082       0.3 -0.005641  0.832609
2022-06-01 00:04:00       0.4  0.391814       0.4 -0.006649 -2.225293

                     series_5  series_6
2022-06-01 00:00:00       NaN       NaN
2022-06-01 00:01:00       NaN       NaN
2022-06-01 00:02:00       NaN       NaN
2022-06-01 00:03:00     228.0       1.0
2022-06-01 00:04:00       NaN       1.0
bottom part is                          series_0    series_1    series_2  series_3  s
eries_4
2022-06-02 23:55:00     287.5  287.498961  287.323143 -0.165455  2.017107  \
2022-06-02 23:56:00     287.6  287.599466  287.600000 -0.010588 -1.490229
2022-06-02 23:57:00     287.7  287.719646  287.700000 -0.005317 -0.667750
2022-06-02 23:58:00     287.8  287.790522  287.800000  0.005404 -3.185175
2022-06-02 23:59:00     287.9  287.910746  287.900000 -0.006259 -0.760504

                     series_5  series_6
2022-06-02 23:55:00    2375.0       3.0
2022-06-02 23:56:00       NaN       3.0
2022-06-02 23:57:00       NaN       3.0
2022-06-02 23:58:00       NaN       3.0
2022-06-02 23:59:00       NaN       3.0
```

End importing dataWe start by imputing missing values using cubic splines

In [18]:
```
# v needs to be a single column/vector
def find_index_missing(v,include_nonmissing = True):
    index_missing_values = [index for index in range(len(v)) if np.isnan(v[index
    returnValue = index_missing_values
    if(include_nonmissing):
        index_nonmissing = [index for index in range(len(v)) if index not in inc
        returnValue = index_missing_values,index_nonmissing
    #
    return returnValue
#
# By default 'extrapolate' is set to False since the behavior of cubic splines c
# and last spline can sometimes be erratic
def imputeCubicSpline(x,y,extrapolate = False):
    index_missing_values,index_nonmissing = find_index_missing(
        y,include_nonmissing=True)
    #
    if len(index_missing_values) > 0 :
        cs = CubicSpline(x[index_nonmissing],y[index_nonmissing],extrapolate = e
        y = cs(x)
    #
    return y
#
# If 'timeCol' is  None, then the index is assumed to be a timestamp. Oth
# This function imputes missing values by fitting a cubic spline to the non-miss
# If "imputationCols" is a string (single column),then it is converted to a list
# I 'imputationCols" is None,then every column in the dataframe is imputed
def df_impute_cubic(df,imputationCols=None,timeCols = None,crop = False,**kwargs
    if type(imputationCols) is str:
        imputationCols = [imputationCols]
    elif imputationCols is None:
        imputationCols = list(df.columns)
```

```
    #Datetimes need to be converted to unix time
    listOfTimes = None
    if type(timeCols) is str:
        listOfTimes = df[timeCol].tolist()
    elif timeCols is None:
        listOfTimes = list(df.index)
    #
    timeValues =  np.asarray([ts.timestamp() for ts in listOfTimes])
    #
    imputer = partial(imputeCubicSpline,timeValues,**kwargs)
    df[imputationCols] = df[imputationCols].apply(imputer)
    #
    if crop:
        df = df.dropna()
    return df
#
```

Do the imputation

In [19]:
```
df = df_impute_cubic(df,crop=True)
```

For single numerical columns x and y (of equal length) we choose aboluste value of the correlation og x and y as our distance metrix i,e,

$$dist(x,y) = 1 - |corr(x,y)|.$$

(1)

When either x or y have missing values we choose to calculate the correlation as the

The reason why we are using the absolute value of the ccrrelation is h For gorups of colums we choose method = 'complete' as our distance metric From documentation: method='complete' assigns

$$d(u,v) = \max(dist(u[i], v[j])).$$

(2)

for all points (in our case columns) `i` in cluster u and `j` in cluster `v`., This is also known by the Farthest Point Algorithm or Voor Hees Algorithm.Description algorithm: 1. Calculate (1) defined above for each pair of columns in the data frame ("condensed values") 2. Do Agglomerative Hiearchical Clustering based We don't want to calculate the correlation of the same two vectors more than once. To avoid that we first calculate (1) defined above for each pair of columns in the data frame ("condensed" and the used that to and pass the "condensed values" (each distance

In [47]:
```
def CCorDistance(u,v,max_lag = None):
    # Use default value suggested in documentation of sm.tsa.stattools.acf
    centered_u = u - np.mean(u) # Demean
    centered_v = v - np.mean(v)  # Demean
    cc_full  = np.correlate(a=centered_u, v=centered_v,mode = 'full')
    cc_full = cc_full/ (len(u) * np.std(u) * np.std(v)) # Normalization
    # Only negative lags are used
    cc_non_positive_lags = cc_full[range(len(v)),]
    squared_cc = [cc_non_positive_lags[ind,]**2 for ind in range(cc_non_positive
    #
    D = sqrt((1.0-squared_cc[-1]) /sum(squared_cc[:-1]))
    return D
#
def condensedSet(df):
    listDists = []
```

```
    # col1 ie every column except for the last one
    # col2 ie every column except for the first
    for i in range(df.shape[1]-1):
        for j in range(i+1,df.shape[1]):
            listDists.append(CCorDistance(df.iloc[:,i].to_numpy(),df.iloc[:,j].t
    #
    listDists = np.asarray(listDists)
    return listDists
#
def clusterByCrossCorr(df,max_intra_dist = None):
    print('Er nå inne i clusterByCrossCorr')
    pdist_condensed = condensedSet(df)
    # if max_intra_dist is not provided then st the max distance within the same
    if max_intra_dist is None:
        max_intra_dist = np.quantile(pdist_condensed,0.2)
    #
    print(f'type(pdist_condensed) er {type(pdist_condensed)} og pdist_condensed.
    print(f'max_intra_dist er {max_intra_dist}')
    print('pdist_condensed er')
    print(pdist_condensed)
    linkage = spc.linkage(pdist_condensed, method='complete')
    idx = spc.fcluster(linkage, max_intra_dist, 'distance')
    # Put the cluster information into a data frame. The first column is the nam
    # The second columns is an indicator that says which cluster group each colu
    groupingFrame = pd.DataFrame(list(df.columns),columns=['Series'])
    groupingFrame['Group'] = list(idx)
    #
    clusterDict = {}
    #
    for group in list(set(list(idx))):
        clusterDict['_'.join(['group',str(group)])] = [
            list(df.columns)[col] for col in list(groupingFrame[groupingFrame['G
            ]
        #
    #
    return linkage,clusterDict
#
```

In [48]:
```
linkage,clusterGroups = clusterByCrossCorr(df)
```

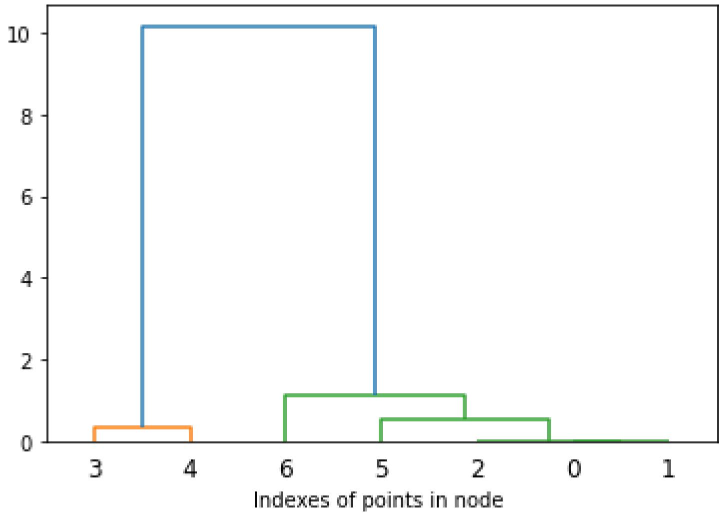
```
Er nå inne i clusterByCrossCorr
type(pdist_condensed) er <class 'numpy.ndarray'> og pdist_condensed.shape er (2
1,)
max_intra_dist er 0.5522145670160576
pdist_condensed er
[5.51152745e-06 3.43892418e-04 1.01662004e+01 2.64099058e+00
 5.52214567e-01 1.12485465e+00 3.43907633e-04 1.01657290e+01
 2.64099706e+00 5.52215090e-01 1.12486036e+00 9.36371247e+00
 2.64029720e+00 5.52227870e-01 1.12490892e+00 3.45256371e-01
 1.74282065e+00 1.68013211e+00 1.46002755e+00 1.36709347e+00
 6.57015666e-01]
```

In [49]:
```
print(f' The cluster groups outputted from the algorithm are \n{clusterGroups}')
```

```
 The cluster groups outputted from the algorithm are
{'group_1': ['series_3', 'series_4'], 'group_2': ['series_0', 'series_1', 'series
_2'], 'group_3': ['series_5'], 'group_4': ['series_6']}
```

In [50]:
```
spc.dendrogram(linkage)
plt.xlabel("Indexes of points in node ")
```

```
plt.show()
```



Thee first grouping is of "series_0','series_1' and 'series_2'. The distances between these 3 are so small that it is not visible in the dendrogram above.