Clustering techniques

```
from google.colab import drive
drive.mount('/content/drive')
```

```
     Mounted at /content/drive
```

Imports

```
import pandas as pd
from sklearn.cluster import KMeans, AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from datetime import datetime, date, time, timezone
from natsort import index_natsorted
```

Functions

```
def parseFilenameToDate(Filename):
  new_str = Filename.replace(".","/")
  dt = datetime.strptime(new_str, "%Y/%m/%d/%H/%M/%S")
  return dt
```

```
def getRealRUL(index, data):
  # Returns the time from the given point to the breakdown of the machine (last index)
  t1 = data.loc[index, "Filename"]
  t2 = data["Filename"].iloc[-1]
  diff = t2-t1
  return diff
```

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

    # 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)

    # Plot the corresponding dendrogram
    dendrogram(linkage_matrix, **kwargs)
```

Load Data

Choose desired filename in cell below

```
datafile = "/content/drive/MyDrive/nimbus-test3-CH3-fixed.csv"
```

Renaming

```
data = pd.read_csv(datafile, index_col=0)
data
```

	tsnePCA-2d-one	tsnePCA-2d-two	RMS	Filename
813	31.244444	69.245735	0.970453	2004.04.17.00.02.55
825	34.486343	65.962940	1.188294	2004.04.16.23.52.55
826	30.908306	68.715034	1.697124	2004.04.16.23.42.55
840	32.211372	69.867260	1.534403	2004.04.17.01.12.55
841	27.794624	73.280060	1.199807	2004.04.17.02.42.55
...	...	...	...	...
995	47.969376	59.155186	98.199024	2004.04.18.02.22.55
996	36.847652	67.585160	2.334934	2004.04.18.00.12.55
997	46.599865	59.537940	5.665934	2004.04.18.00.22.55

For convenience, renaming the columns

```
data = data.rename(columns={"tsnePCA-2d-one":"tsne-1", "tsnePCA-2d-two":"tsne-2"})
data
```

	tsne-1	tsne-2	RMS	Filename
813	31.244444	69.245735	0.970453	2004.04.17.00.02.55
825	34.486343	65.962940	1.188294	2004.04.16.23.52.55
826	30.908306	68.715034	1.697124	2004.04.16.23.42.55
840	32.211372	69.867260	1.534403	2004.04.17.01.12.55
841	27.794624	73.280060	1.199807	2004.04.17.02.42.55
...	...	...	...	...
995	47.969376	59.155186	98.199024	2004.04.18.02.22.55
996	36.847652	67.585160	2.334934	2004.04.18.00.12.55
997	46.599865	59.537940	5.665934	2004.04.18.00.22.55
998	47.822420	59.045563	89.106880	2004.04.18.02.32.55

Re-Order data by time

```
reordered_data = data.sort_values(
   by="Filename",
   key=lambda x: np.argsort(index_natsorted(data["Filename"]))
)
```

```
reordered_data
```

	tsne-1	tsne-2	RMS	Filename
826	30.908306	68.715034	1.697124	2004.04.16.23.42.55
825	34.486343	65.962940	1.188294	2004.04.16.23.52.55
813	31.244444	69.245735	0.970453	2004.04.17.00.02.55
860	31.777418	68.182550	1.552761	2004.04.17.00.12.55
858	33.993640	66.935420	1.749911	2004.04.17.00.22.55
...	...	...	...	...
995	47.969376	59.155186	98.199024	2004.04.18.02.22.55

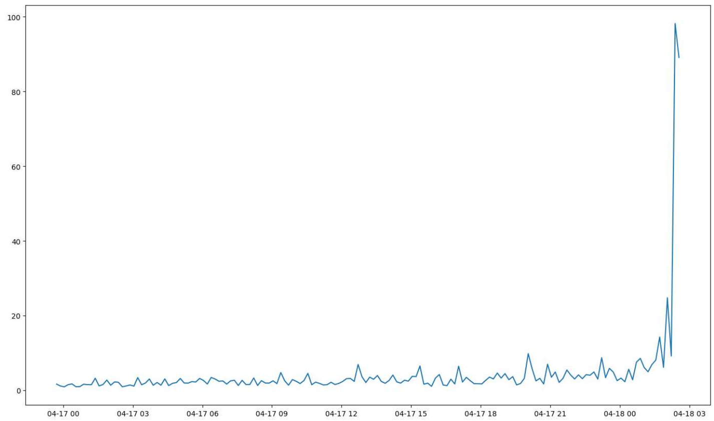
```
reordered_data.loc[:,"Filename"] = reordered_data.loc[:,"Filename"].apply(parseFilenameToDate)
```

```
<ipython-input-11-256ec5d2b8df>:1: DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will attempt to set t
  reordered_data.loc[:,"Filename"] = reordered_data.loc[:,"Filename"].apply(parseFilenameToDate)
```

```
getRealRUL(995,reordered_data)
```

```
Timedelta('0 days 00:10:00')
```

```
plt.figure(figsize=(17,10))
plt.plot(reordered_data.Filename, reordered_data["RMS"].values, label = "RMS")
plt.show()
```



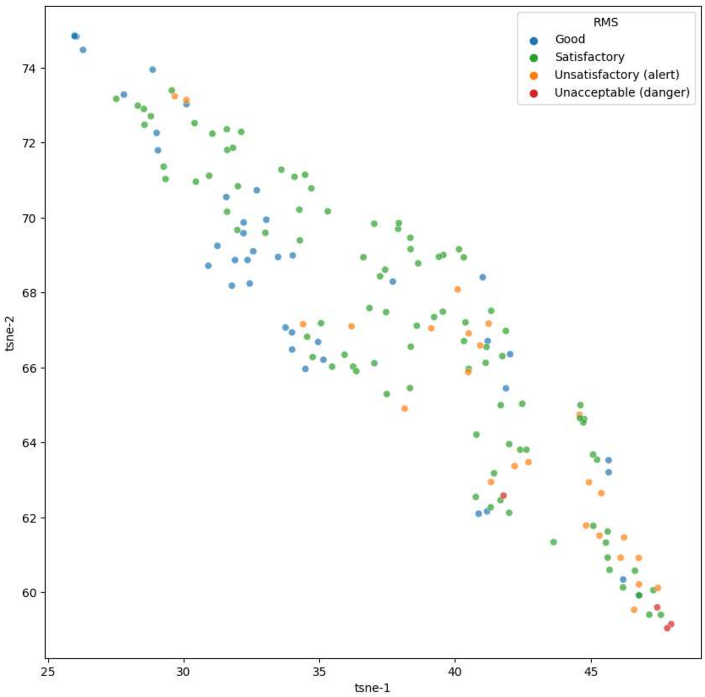

```
data = reordered_data
```

Plot with colours

```
def new_fromRMStoMedium(value):
  if (value < 1.80):
    return "Good"
  if (value < 4.50):
    return "Satisfactory"
  if (value < 11.20):
    return "Unsatisfactory (alert)"
  else:
    return "Unacceptable (danger)"
```

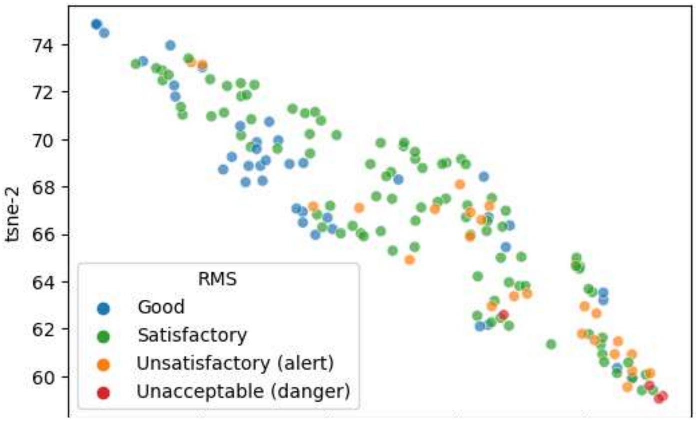
```
def new_tokenizeRMS(column):
  """
  Transforms a column of a df into a tokenized column
  according to ISO-10816, RMS mm/s
  """
  # For Medium Machine Class II
  result = column.apply(new_fromRMStoMedium)

  return result


tokenized = new_tokenizeRMS(data["RMS"])


seaborn_palette = sns.color_palette()
custom_palette = {
    "Good": seaborn_palette[0],
    "Satisfactory" : seaborn_palette[2],
    "Unsatisfactory (alert)" : seaborn_palette[1],
    "Unacceptable (danger)" : seaborn_palette[3]
}


plt.figure(figsize=(10,10))
sns.scatterplot(
    x="tsne-1", y="tsne-2",
    hue=tokenized,
    palette=custom_palette,
    data=data,
    legend="full",
    alpha=0.7
)
```

```
<Axes: xlabel='tsne-1', ylabel='tsne-2'>
```



```
plt.figure(figsize=(6,4))
sns.scatterplot(
    x="tsne-1", y="tsne-2",
    hue=tokenized,
    palette=custom_palette,
    data=data,
    legend="full",
    alpha=0.7
)
```

```
<Axes: xlabel='tsne-1', ylabel='tsne-2'>
```



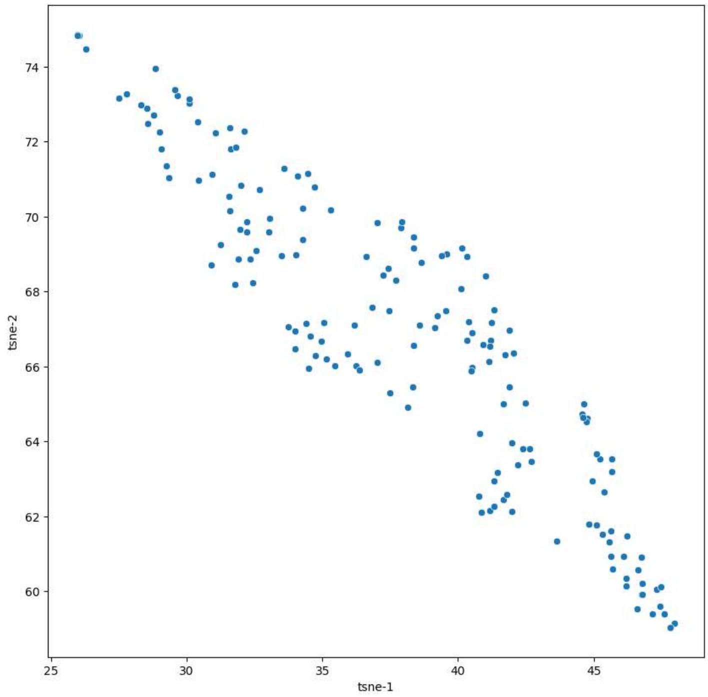
Split to only the necessary data for models

```
tsne_data = data.iloc[:, :2]
tsne_data
```

	tsne-1	tsne-2
826	30.908306	68.715034
825	34.486343	65.962940
813	31.244444	69.245735
860	31.777418	68.182550
858	33.993640	66.935420
...	...	...
991	46.104366	60.927776
993	47.453750	59.602410
983	38.144264	64.904370
995	47.969376	59.155186

```
plt.figure(figsize=(10,10))
sns.scatterplot(
    x="tsne-1", y="tsne-2",
    data=tsne_data
)
```

```
<Axes: xlabel='tsne-1', ylabel='tsne-2'>
```



Clustering

For the data that is more prone to fail, look for groups that may give more info about the state of the machine

Number of clusters known

K-Means

Applying the algorithm

```
n_clusters = 2
seed = 0
```

```
model = KMeans(n_clusters=n_clusters, random_state=seed, n_init="auto")
```

```
kmeans = model.fit_predict(tsne_data)
kmeans
```

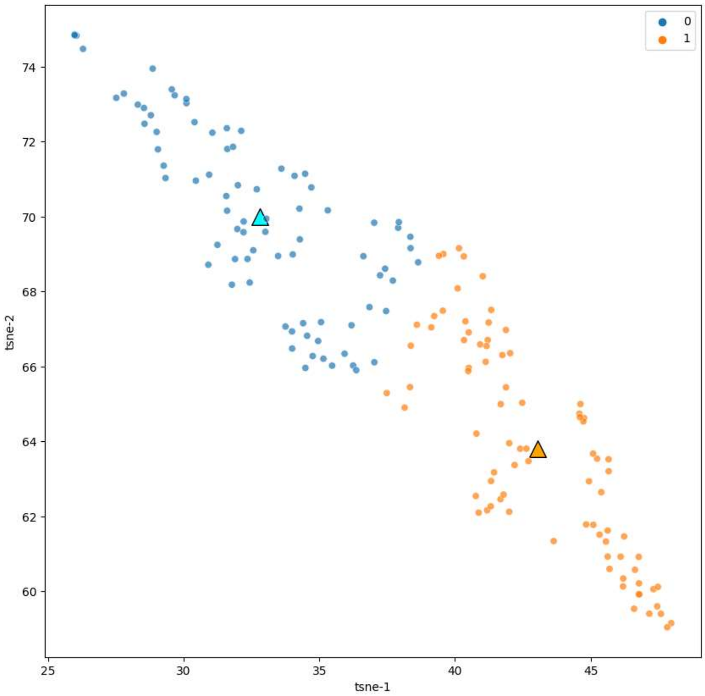
```
array([0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0,
       0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1,
       0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1,
       1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0,
       1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1,
       1, 1, 1, 1, 1, 1, 1, 1], dtype=int32)
```

```
c1 = model.cluster_centers_[0]
c2 = model.cluster_centers_[1]
```

```
plt.figure(figsize=(10,10))
plt.scatter(x=c1[0], y=c1[1], color="cyan", edgecolors="black", marker="^", s=200)
plt.scatter(x=c2[0], y=c2[1], color="orange", edgecolors="black", marker="^", s=200)
```

```
sns.scatterplot(
    x="tsne-1", y="tsne-2",
    data=tsne_data,
    hue=kmeans,
    palette=sns.color_palette(),
    legend="full",
    alpha=0.7
)
```

```
<ipython-input-59-5e60b7af5bcf>:4: UserWarning: The palette list h
  sns.scatterplot(
<Axes: xlabel='tsne-1', ylabel='tsne-2'>
```



Analyse results with RUL

Thresholds:

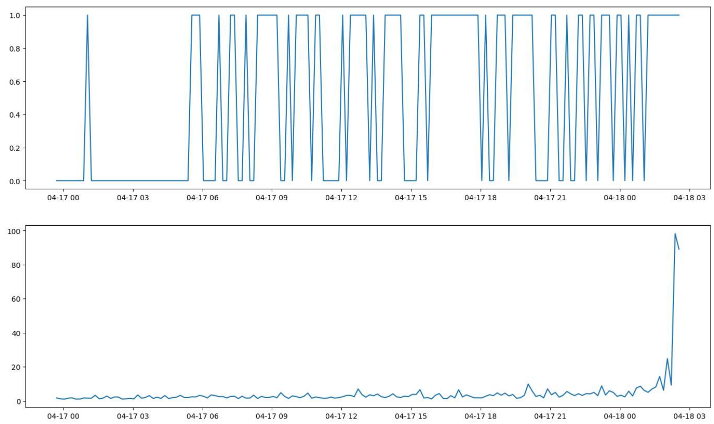
- Good: <1.80
- Satisfactory: <4.50
- Unsatisfactory (Alert): <11.20
- Unnaceptable (Danger): >=11.20

```
alert_threshold = 4.5
```

```
kmeans_data = data
kmeans_data["Class"] = model.labels_
kmeans_data
```

	tsne-1	tsne-2	RMS	Filename	Class
826	30.908306	68.715034	1.697124	2004-04-16 23:42:55	0
825	34.486343	65.962940	1.188294	2004-04-16 23:52:55	0
813	31.244444	69.245735	0.970453	2004-04-17 00:02:55	0
860	31.777418	68.182550	1.552761	2004-04-17 00:12:55	0
858	33.993640	66.935420	1.749911	2004-04-17 00:22:55	0
...	...	...	...	...	...
991	46.104366	60.927776	6.183291	2004-04-18 01:52:55	1
993	47.453750	59.602410	24.815157	2004-04-18 02:02:55	1
983	38.144264	64.904370	9.229391	2004-04-18 02:12:55	1
995	47.969376	59.155186	98.199024	2004-04-18 02:22:55	1

```
plt.figure(figsize=(17,10))
plt.subplot(211)
plt.plot(kmeans_data["Filename"], kmeans_data["Class"])
plt.subplot(212)
plt.plot(kmeans_data["Filename"], kmeans_data["RMS"])
plt.show()
```




```
plt.figure(figsize=(17,5))
plt.scatter(kmeans_data["Filename"], kmeans_data["Class"])
```

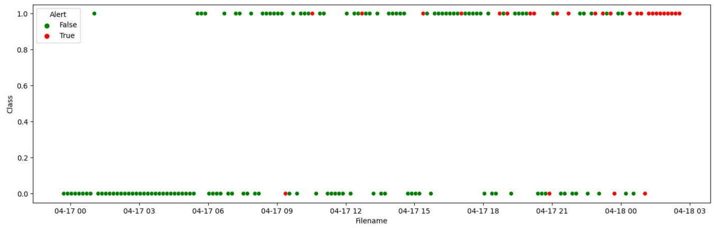
```
<matplotlib.collections.PathCollection at 0x7fa74246b700>
```


```
kmeans_data["Alert"] = kmeans_data["RMS"] >= alert_threshold
kmeans_data
```

	tsne-1	tsne-2	RMS	Filename	Class	Alert
826	30.908306	68.715034	1.697124	2004-04-16 23:42:55	0	False
825	34.486343	65.962940	1.188294	2004-04-16 23:52:55	0	False
813	31.244444	69.245735	0.970453	2004-04-17 00:02:55	0	False
860	31.777418	68.182550	1.552761	2004-04-17 00:12:55	0	False
858	33.993640	66.935420	1.749911	2004-04-17 00:22:55	0	False
...	...	...	...	...	...	...
991	46.104366	60.927776	6.183291	2004-04-18	1	True

```
plt.figure(figsize=(17,5))
sns.scatterplot(x=kmeans_data["Filename"], y=kmeans_data["Class"], hue=kmeans_data["Alert"], palette=["green","red"])
```

```
<Axes: xlabel='Filename', ylabel='Class'>
```



Explicación puntos intercalados

```
plt.figure(figsize=(17,5))
plt.plot(kmeans_data["Filename"], kmeans_data["RMS"])
plt.axhline(y=alert_threshold, color='r', linestyle='-')
plt.show()
```

Same for more clusters

```
n_clusters = 3
seed = 0


model = KMeans(n_clusters=n_clusters, random_state=seed, n_init="auto")


kmeans = model.fit_predict(tsne_data)
kmeans
```

```
     array([0, 2, 0, 0, 2, 2, 2, 0, 1, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
            0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 1, 2, 2, 0, 2, 2, 1, 0,
            0, 1, 1, 0, 0, 1, 2, 2, 1, 1, 1, 1, 1, 1, 2, 2, 1, 2, 1, 1, 1, 1,
            0, 2, 1, 0, 0, 0, 2, 2, 2, 0, 1, 1, 1, 1, 1, 0, 2, 0, 2, 1, 2, 2,
            2, 2, 0, 0, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1, 1, 2, 1, 2, 1, 2, 1, 1,
            2, 1, 2, 2, 1, 2, 2, 0, 2, 1, 1, 2, 2, 2, 0, 0, 0, 0, 2, 1, 0, 2,
            2, 0, 2, 2, 2, 0, 2, 2, 0, 2, 1, 1, 0, 1, 1, 2, 1, 2, 1, 1, 2, 1,
            1, 1, 1, 1, 1, 2, 1, 1], dtype=int32)
```

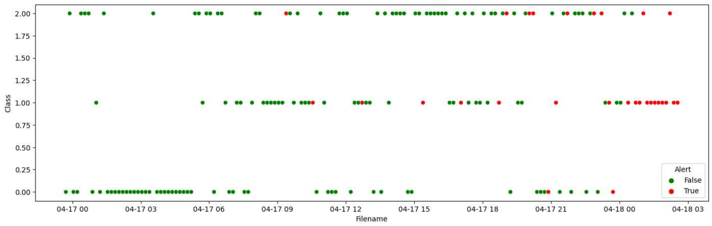
```
cc = model.cluster_centers_


plt.figure(figsize=(10,10))
plt.scatter(x=cc[0][0], y=cc[0][1], color="cyan", edgecolors="black", marker="^", s=200)
plt.scatter(x=cc[1][0], y=cc[1][1], color="orange", edgecolors="black", marker="^", s=200)
plt.scatter(x=cc[2][0], y=cc[2][1], color="green", edgecolors="black", marker="^", s=200)
sns.scatterplot(
    x="tsne-1", y="tsne-2",
    data=tsne_data,
    hue=kmeans,
    palette=sns.color_palette(),
    legend="full",
    alpha=0.7
)
```

```
<ipython-input-71-9eef67d06d3d>:5: UserWarning: The palette list h
  sns.scatterplot(
<Axes: xlabel='tsne-1', ylabel='tsne-2'>
```


```
kmeans_data = data
kmeans_data["Class"] = model.labels_
kmeans_data["Alert"] = kmeans_data["RMS"] >= alert_threshold
```

```
plt.figure(figsize=(17,5))
sns.scatterplot(x=kmeans_data["Filename"], y=kmeans_data["Class"], hue=kmeans_data["Alert"], palette=["green","red"])
```

```
<Axes: xlabel='Filename', ylabel='Class'>
```



Unknown number of Clusters

Hierarchical Clustering: [AgglomerativeClustering]()

Depending on the linkage, different results can be obtained:

- 'ward' minimizes the variance of the clusters being merged.
- 'average' uses the average of the distances of each observation of the two sets.
- 'complete' or 'maximum' linkage uses the maximum distances between all observations of the two sets.
- 'single' uses the minimum of the distances between all observations of the two sets.

Compute_distances for dendogram representations

```
linkage = "ward"
```

Dendogram

[Plot dendogram]()

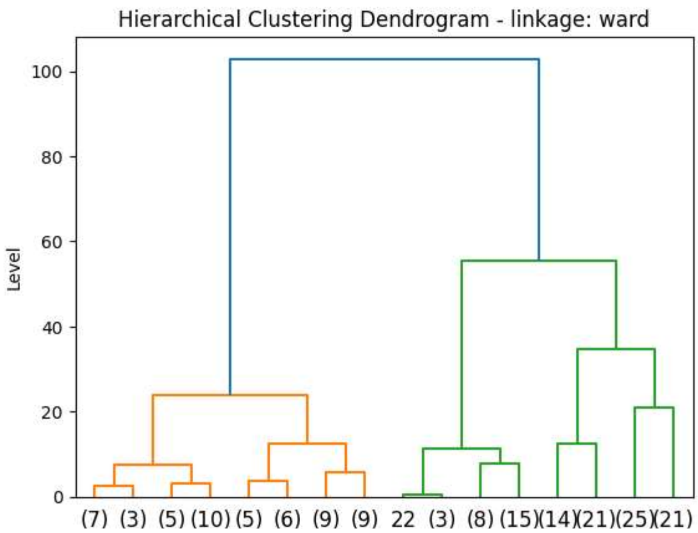
No more than p levels of the dendrogram tree are displayed. A "level" includes all nodes with p merges from the final merge.

```
n_clusters = None
distance_threshold = 0
compute_distances = True

model = AgglomerativeClustering(linkage=linkage, n_clusters=n_clusters,
                                distance_threshold=distance_threshold, compute_distances=compute_distances)

clustering = model.fit_predict(tsne_data)

clustering
```

```
array([ 82, 110, 141, 161, 133, 139, 114, 104, 150, 126,  94, 103, 143,
        99, 159, 121, 140,  80, 128, 125, 108,  62,  93, 115, 119, 111,
```

```
       101, 160, 134,  69, 142, 116,  89, 144, 127, 102, 137,  90, 151,
        85, 138, 123, 129, 153,  57, 120,  46, 117, 112, 107, 100, 152,
        71,  87, 145,  70, 130,  79,  81,  88,  39,  40,  63, 109, 124,
       118, 155, 131,  75, 147, 154,  59,  86,  53, 135,  84, 148,  61,
        66,  34,  43, 122,  92, 136,  60,  68,  95,  30,  58, 105, 113,
        96,  64,  76,  97, 106, 157,  37,  91, 149, 132,  29, 158,  14,
       156,  74,  52,  65, 146,  28,  50,  55,  42,  19,  56,  47,  83,
        27,  98,  49,  45,  51,  41,  31,  20,  48,  77,  72,  32,  73,
        13,  78,  44,  25,  15,  54,  36,  21,  38,  22,   6,  18,  67,
        35,  24,  33,  16,  10,   9,   7,  23,  17,  26,  12,   8,  11,
         5,   2,   3,   4,   1,   0])
```

```
plt.title(f"Hierarchical Clustering Dendrogram - linkage: {linkage}")
plot_dendrogram(model, truncate_mode="level", p=3)
plt.xlabel("Number of points in node (or index of point if no parenthesis).")
plt.ylabel("Level")
plt.show()
```



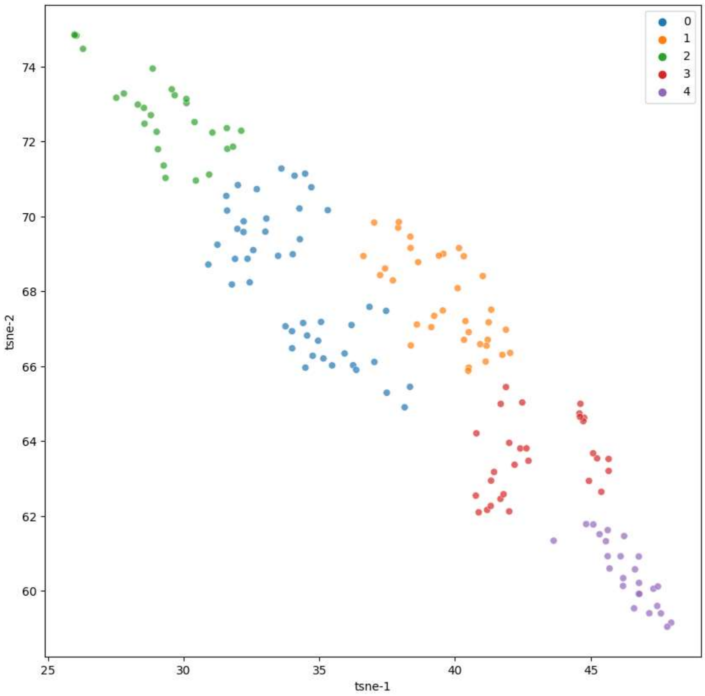
5 clusters, different linkages

```
n_clusters = 5
distance_threshold = None
compute_distances = True


model = AgglomerativeClustering(linkage=linkage, n_clusters=n_clusters,
                                distance_threshold=distance_threshold, compute_distances=compute_distances)

clustering = model.fit_predict(tsne_data)

clustering
```

```
    array([0, 0, 0, 0, 0, 0, 0, 2, 3, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 0, 2, 2,
           2, 0, 2, 0, 2, 0, 2, 0, 0, 0, 2, 2, 1, 3, 3, 1, 0, 2, 1, 1, 4, 2,
           0, 4, 3, 0, 0, 3, 0, 0, 4, 3, 4, 4, 3, 4, 0, 0, 4, 0, 4, 4, 4, 4,
           0, 3, 3, 0, 0, 2, 0, 0, 0, 0, 4, 4, 4, 3, 3, 0, 0, 2, 0, 3, 1, 1,
           1, 1, 0, 2, 1, 1, 3, 3, 1, 1, 1, 1, 1, 3, 3, 1, 3, 1, 3, 1, 3, 3,
           1, 3, 0, 1, 4, 1, 1, 0, 1, 3, 3, 1, 1, 1, 0, 2, 2, 2, 1, 3, 2, 1,
           1, 0, 1, 1, 1, 2, 1, 1, 0, 1, 4, 4, 2, 3, 4, 0, 4, 0, 4, 3, 0, 3,
           3, 4, 3, 4, 4, 0, 4, 4])
```

```
plt.figure(figsize=(10,10))
sns.scatterplot(
    x="tsne-1", y="tsne-2",
    data=tsne_data,
    hue=clustering,
    palette=sns.color_palette(),
    legend="full",
    alpha=0.7
)
```

```
<ipython-input-98-65eb2b0fc0e0>:2: UserWarning: The palette list h
  sns.scatterplot(
<Axes: xlabel='tsne-1', ylabel='tsne-2'>
```

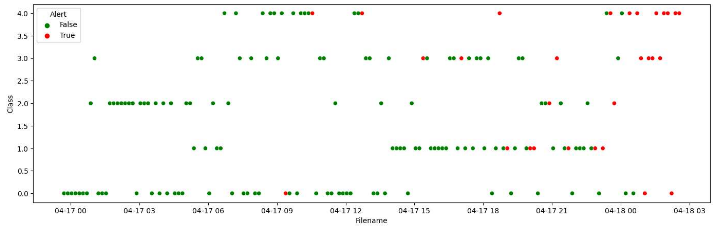



```
cluster_data = data
cluster_data["Class"] = model.labels_
cluster_data["Alert"] = cluster_data["RMS"] >= alert_threshold
cluster_data
```

	tsne-1	tsne-2	RMS	Filename	Class	Alert
826	30.908306	68.715034	1.697124	2004-04-16 23:42:55	0	False
825	34.486343	65.962940	1.188294	2004-04-16 23:52:55	0	False
813	31.244444	69.245735	0.970453	2004-04-17 00:02:55	0	False
860	31.777418	68.182550	1.552761	2004-04-17 00:12:55	0	False
858	33.993640	66.935420	1.749911	2004-04-17 00:22:55	0	False
...	...	...	...	...	...	...
991	46.104366	60.927776	6.183291	2004-04-18	4	True

```
plt.figure(figsize=(17,5))
sns.scatterplot(x=cluster_data["Filename"], y=cluster_data["Class"], hue=cluster_data["Alert"], palette=["green","red"])
```

```
<Axes: xlabel='Filename', ylabel='Class'>
```



0 s completado a las 11:39