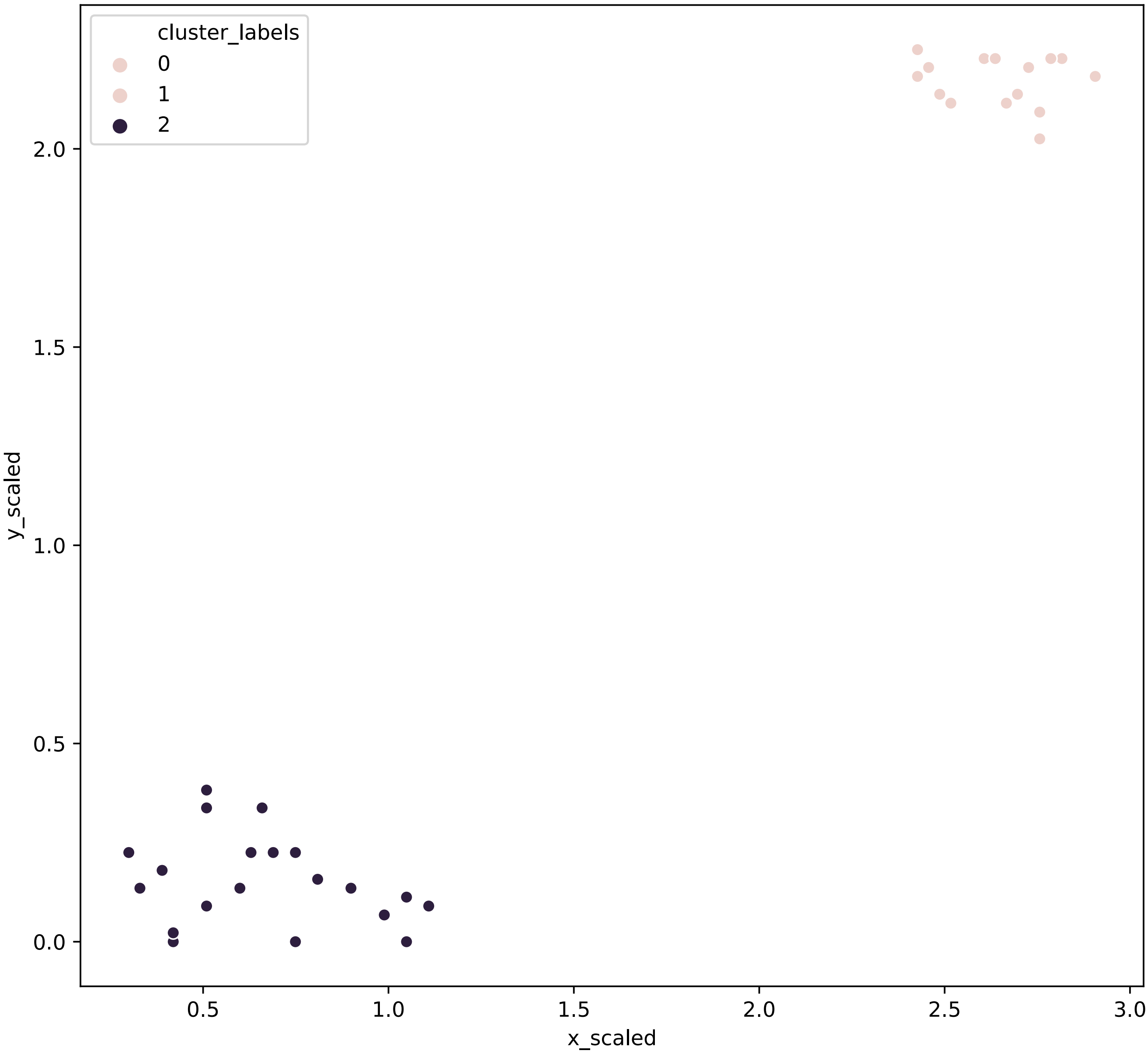
```
Hierarchical Clustering
```

Hierarchical clustering: ward

let's run clustering withu the 'ward' method and plot.

```
# Import the fcluster and linkage functions
from scipy.cluster.hierarchy import fcluster, linkage

# Use the linkage() function
distance_matrix = linkage(comic_con[['x_scaled', 'y_scaled']], method =
"ward", metric = 'euclidean')

# Assign cluster labels
comic_con['cluster_labels'] = fcluster(distance_matrix, 2,
criterion='maxclust')

# Plot clusters
sns.scatterplot(x='x_scaled', y='y_scaled',
                hue='cluster_labels', data = comic_con)
plt.show()
```



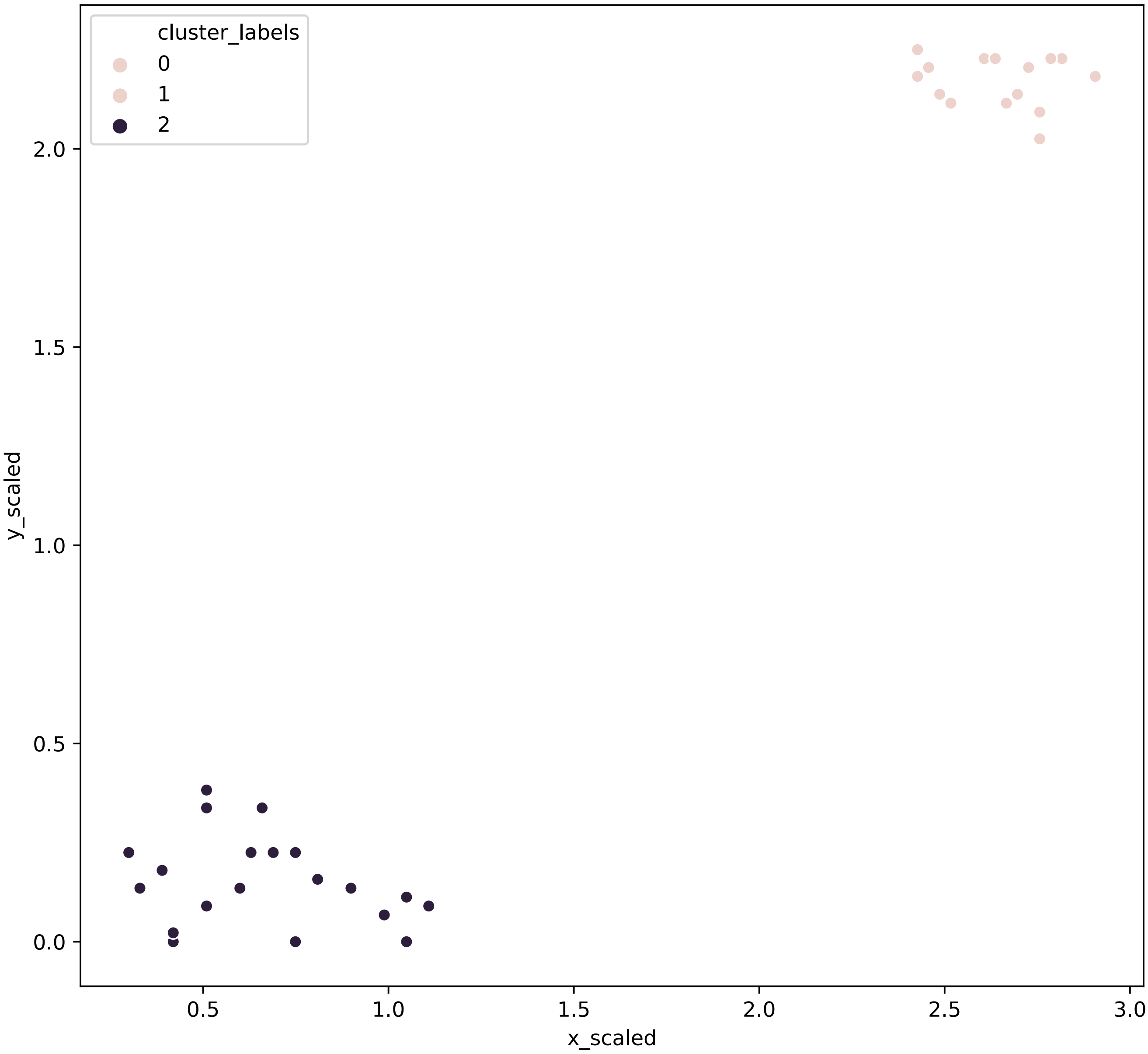
Basically:

- step 1: linkage (df,method: "ward", metric: "eucledian")
- step 2: fcluster(linkage, n_of_clusters, criterion: "maxclust")

Hierarchical CLustering: Single Method

we do the same thing. Only this time, our clustering method is `single` istead of `ward`.

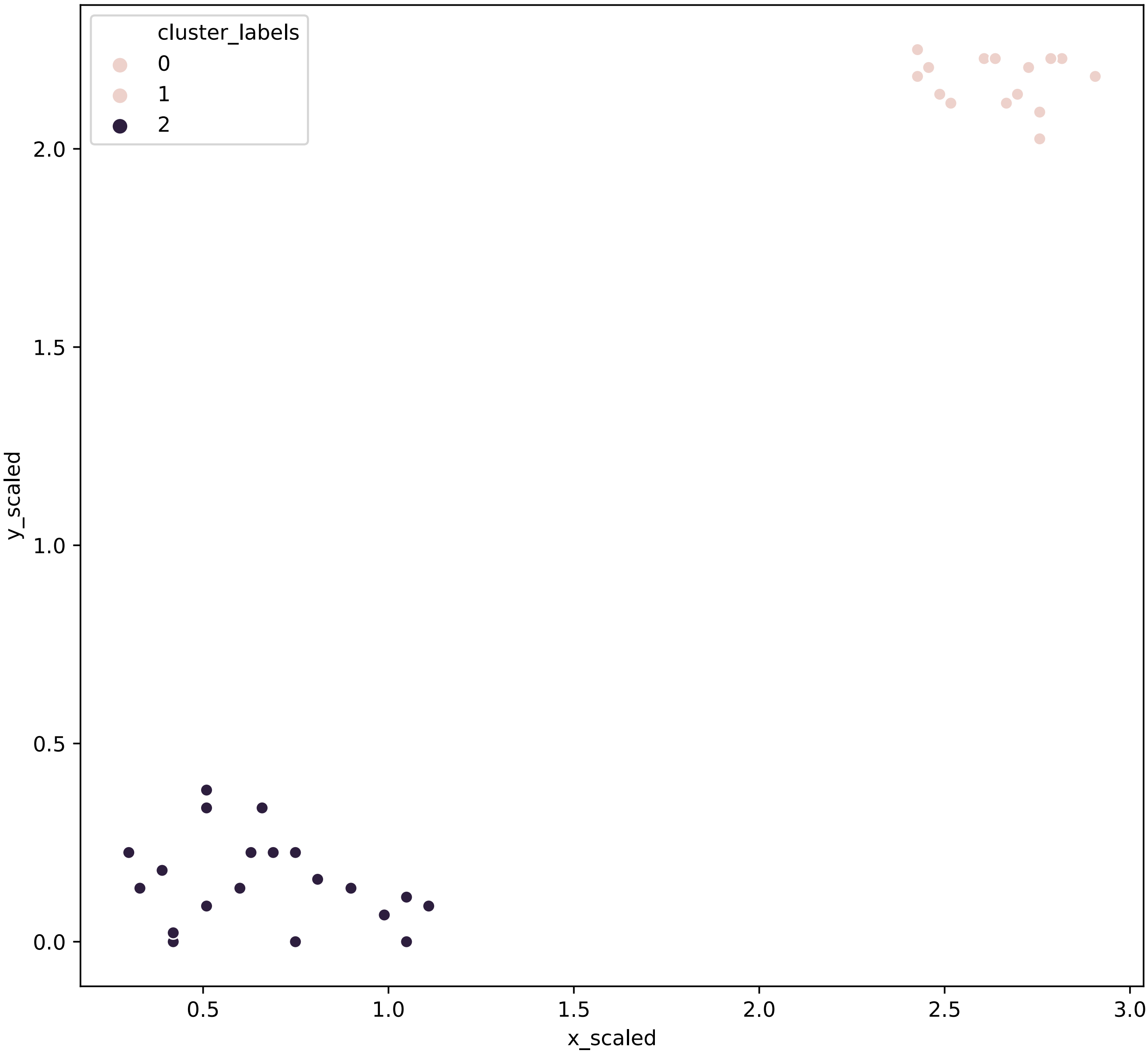
```
Result:
```



Single and ward are similar.

Hierarchical Clustering: Complete method

We do the same thing. Only this time our clustering method is `complete` instead of `single`



Coincidently, war, single and complete are the same in this example.

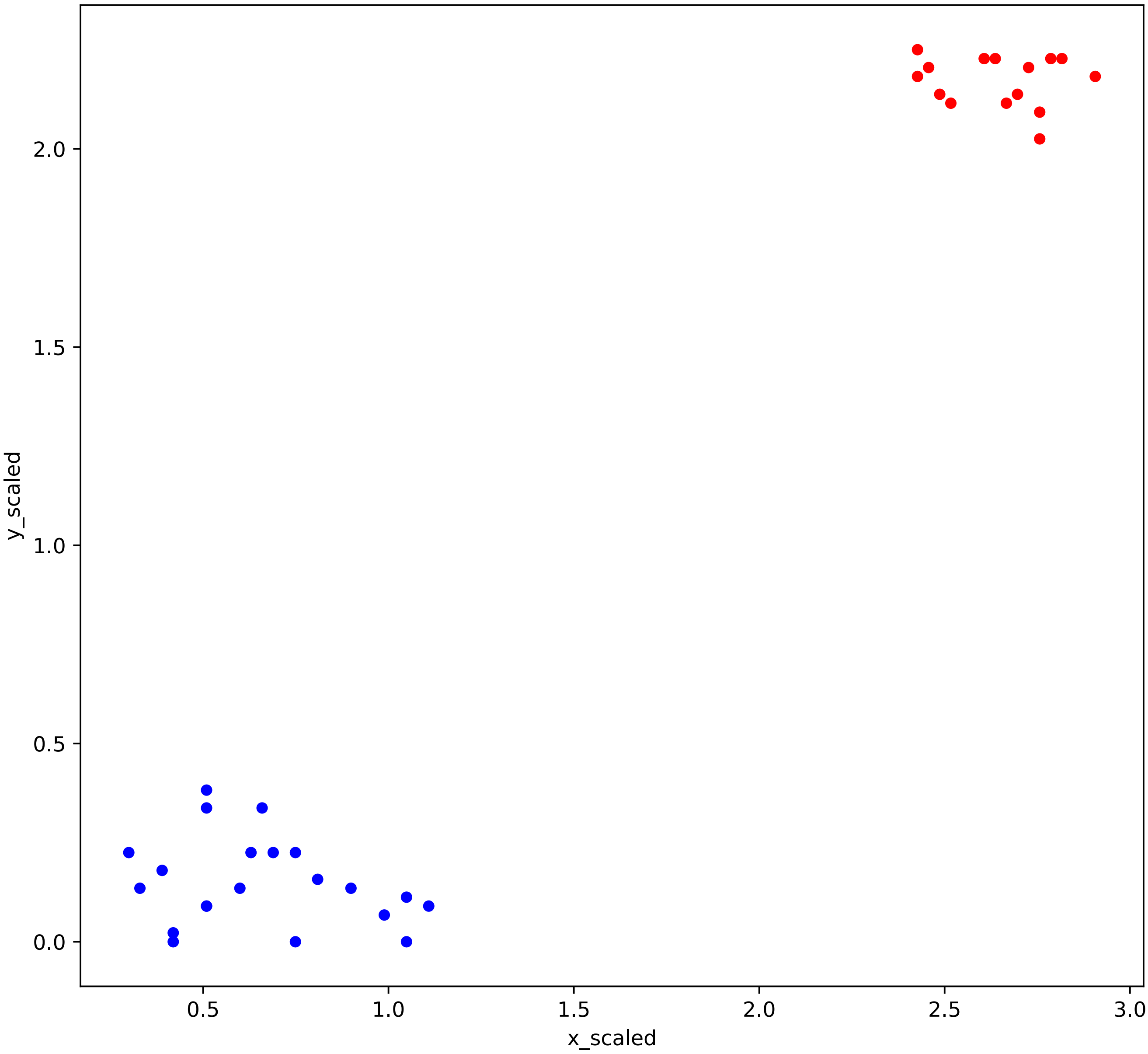
Visualize clusters: matplotlib

we do a scatter plot with the XY coordinates in question.

The colors are sstored in a dictionary that isi accessed yhrouigh the lambda function `lambda x: dict[x]`

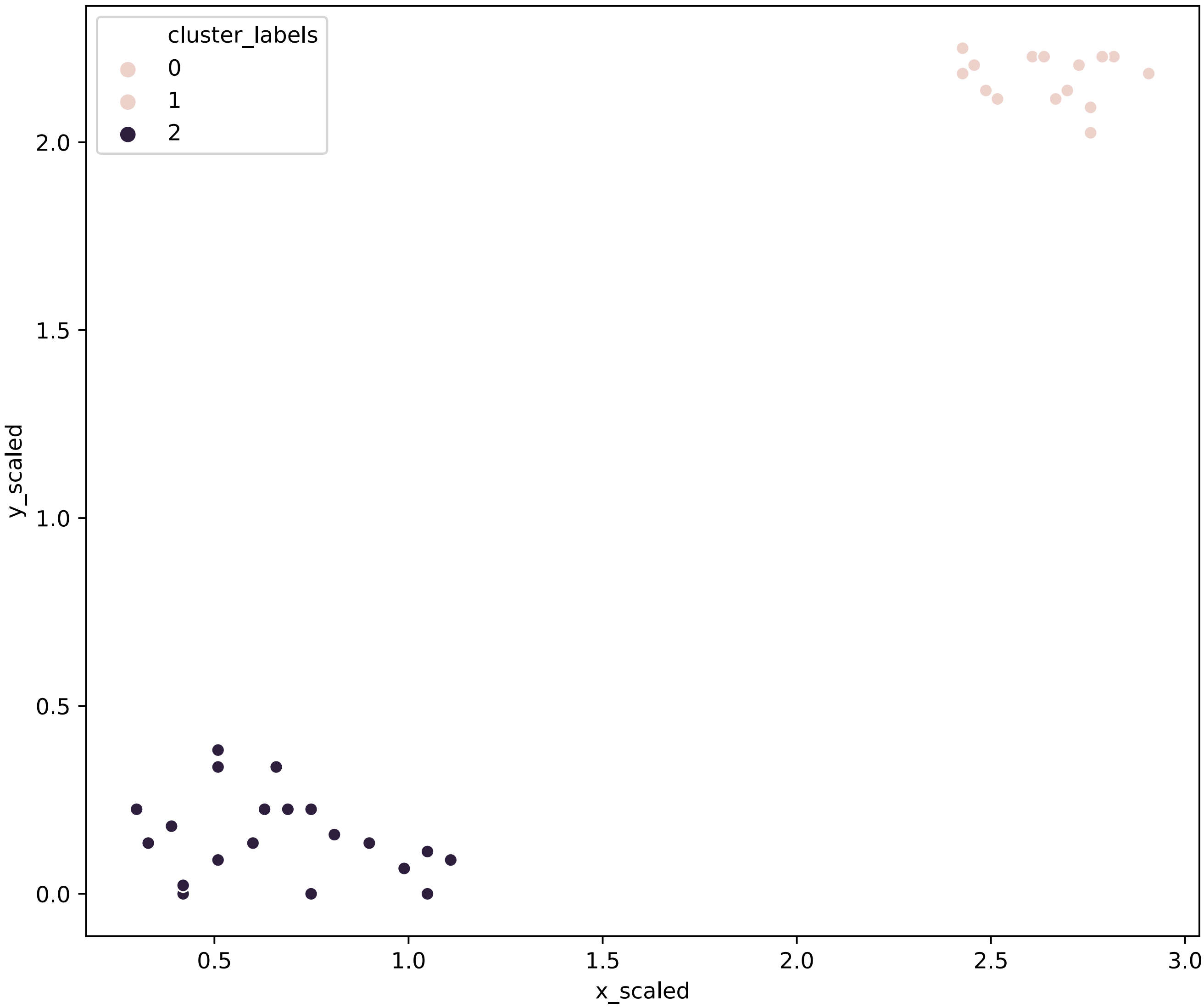
```
# Import the pyplot class
import matplotlib.pyplot as plt

# Define a colors dictionary for clusters
colors = {1:'red', 2:'blue'}

# Plot a scatter plot
```

```
comic_con.plot.scatter(x='x_scaled',
                       y='y_scaled',
                       c=comic_con['cluster_labels'].apply(lambda x:
colors[x])) #we defined the color names ina dictionary, then put it in a
lambda funcction
plt.show()
```



Visualizing in seaborn

Seaborn is similar to pyplot. but the author prefers seaborn for two reasons: simplicity and the templates of seaborn.



How many clusters?

We draw a dendrogram to see the distances between our datapoints.

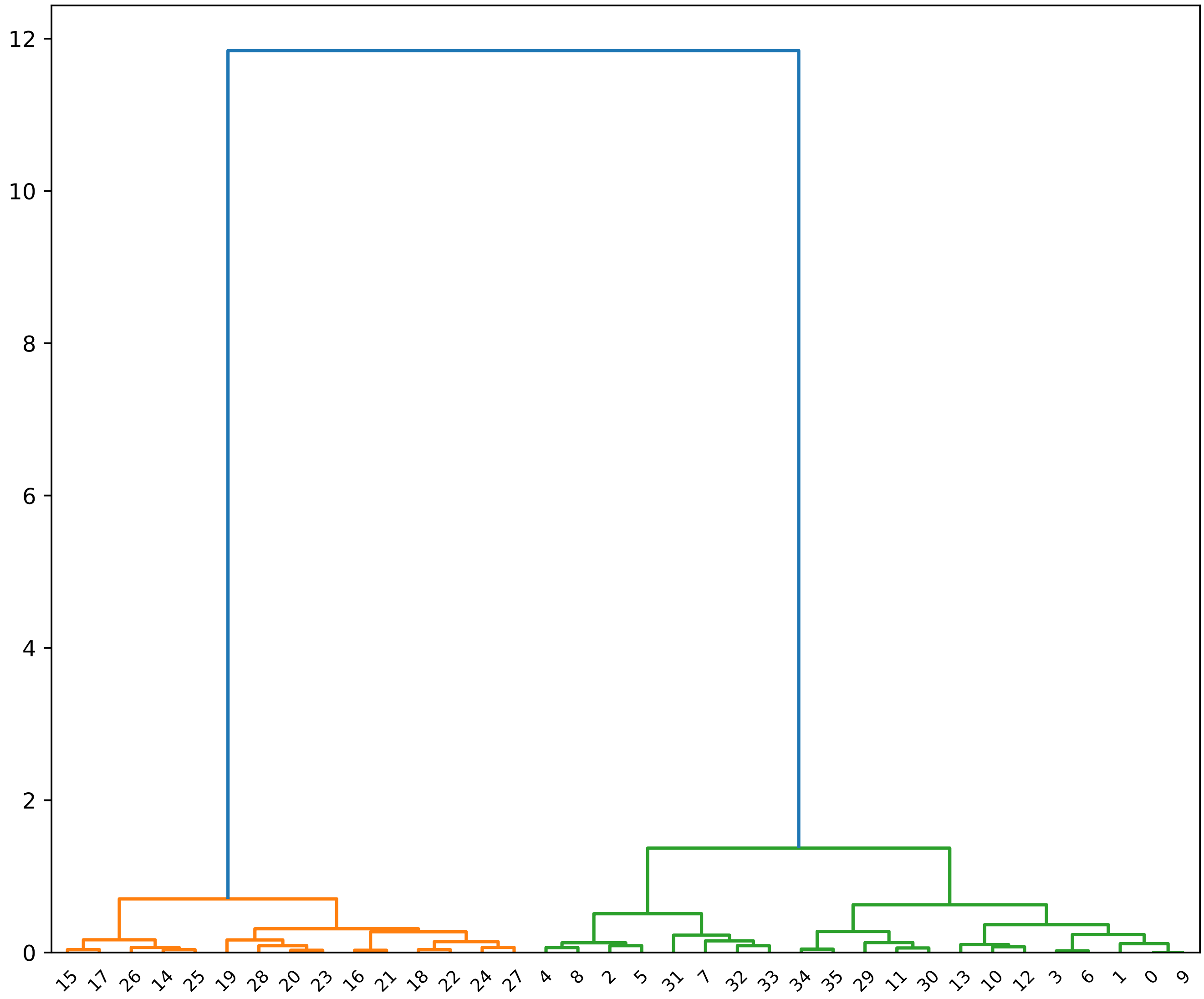
Choosing the number of cluster is more of an art than a science. *With the help of dendrograms*

Creating a dendrogram

we feed the distance matrix to the dendrogram() function.

```
# Import the dendrogram function
from scipy.cluster.hierarchy import dendrogram

# Create a dendrogram
dn = dendrogram(distance_matrix)

# Display the dendogram
plt.show()
```

now we have a plot to see



We might say that we need two clusters.

```
I would go about it with a LOD way, Tableau style
```

Limitation of hierarchical clustering

linkage is slow as datasets get bigger.

FIFA 18: exploring defenders

Before doing the work, I need to prepare my dataset.

Imports

```
Best practice: put the imports on top
```

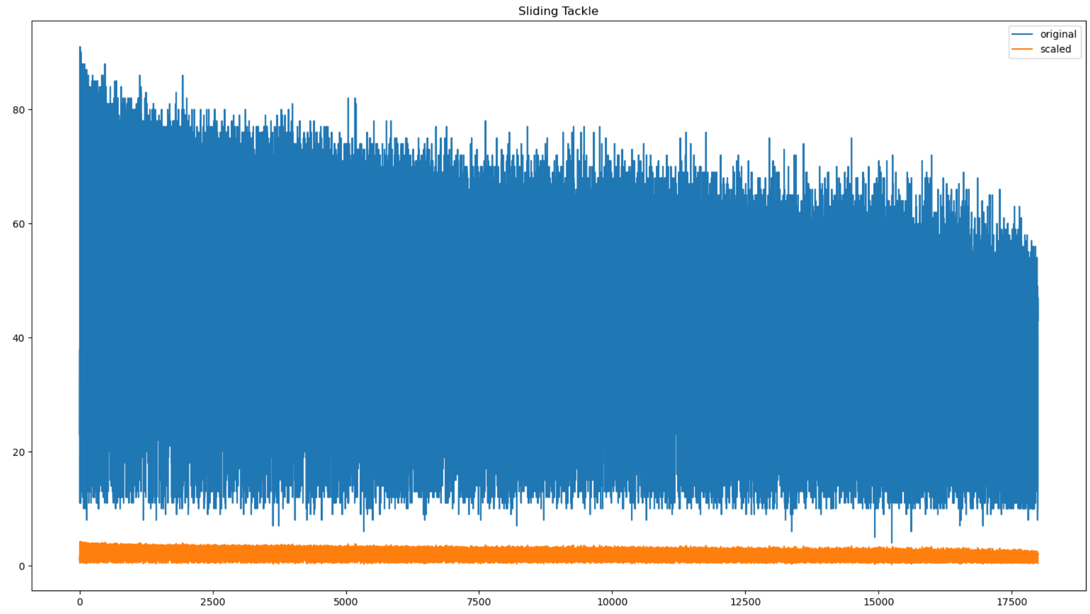
This doesn't necessarily mean that we should remember **ALL** of them at the beginning.

scaling the points

I scale both datapoints with the `whiten` function:

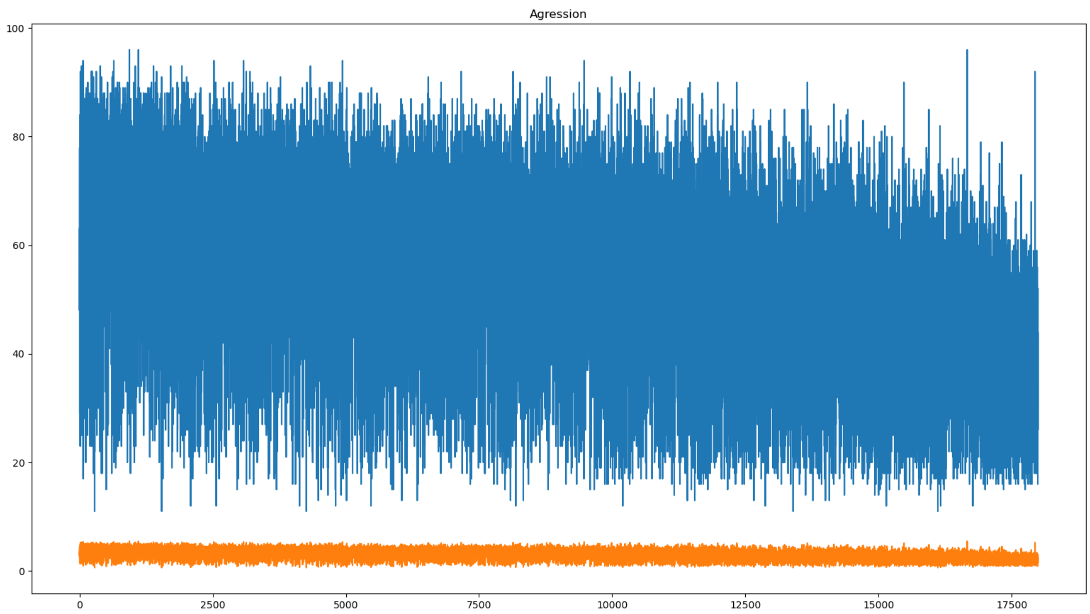
```
import matplotlib.pyplot as plt
from scipy.cluster.vq import whiten
import pandas as pd

fifa=pd.read_csv("data/fifa_18_dataset.csv")
sliding_tackle= fifa['sliding_tackle']
agression= fifa['aggression']

#scaling
sliding_tackle_scaled=whiten(sliding_tackle)
agression_scaled=whiten(agression)

# Plot original data
plt.plot(sliding_tackle, label='original')

# Plot scaled data
plt.plot(sliding_tackle_scaled, label='scaled')

# Show the legend in the plot
plt.legend()
plt.title("Sliding Tackle")
# Display the plot
plt.show()
```

This gives me:



Agression:

```
plt.plot(agression, label='original')
plt.plot(agression_scaled, label='scaled')
plt.title("Agression")
plt.show()
```



Fitting the data with `linkage()`

Now, I input both scaled

```
distance_matrix=linkage(fifa[['sliding_tackle_scaled','agression_scaled']]
,"ward")
```

Cluster data with `fcluster`

To get the clusters, we create a new column using the two columns and the distancematrix

```
# Assign cluster labels to each row of data
fifa['cluster_labels'] = fcluster(distance_matrix, 3,
criterion='maxclust')
```

Display cluster centers of each cluster

```
print(fifa[['scaled_sliding_tackle', 'scaled_aggression',
'cluster_labels']].groupby('cluster_labels').mean())
```

cluster_labels

Centroid	x	y
Cluster 1	0.987373	1.849142
Cluster 2	3.013487	4.063492
Cluster 3	1.934455	3.210802

Create a scatter plot through seaborn

```
sns.scatterplot(x='scaled_sliding_tackle', y='scaled_aggression',
hue='cluster_labels', data=fifa)
plt.show()
```

The scatter plot with seaborn is elegantly beautiful.