Projet Électif

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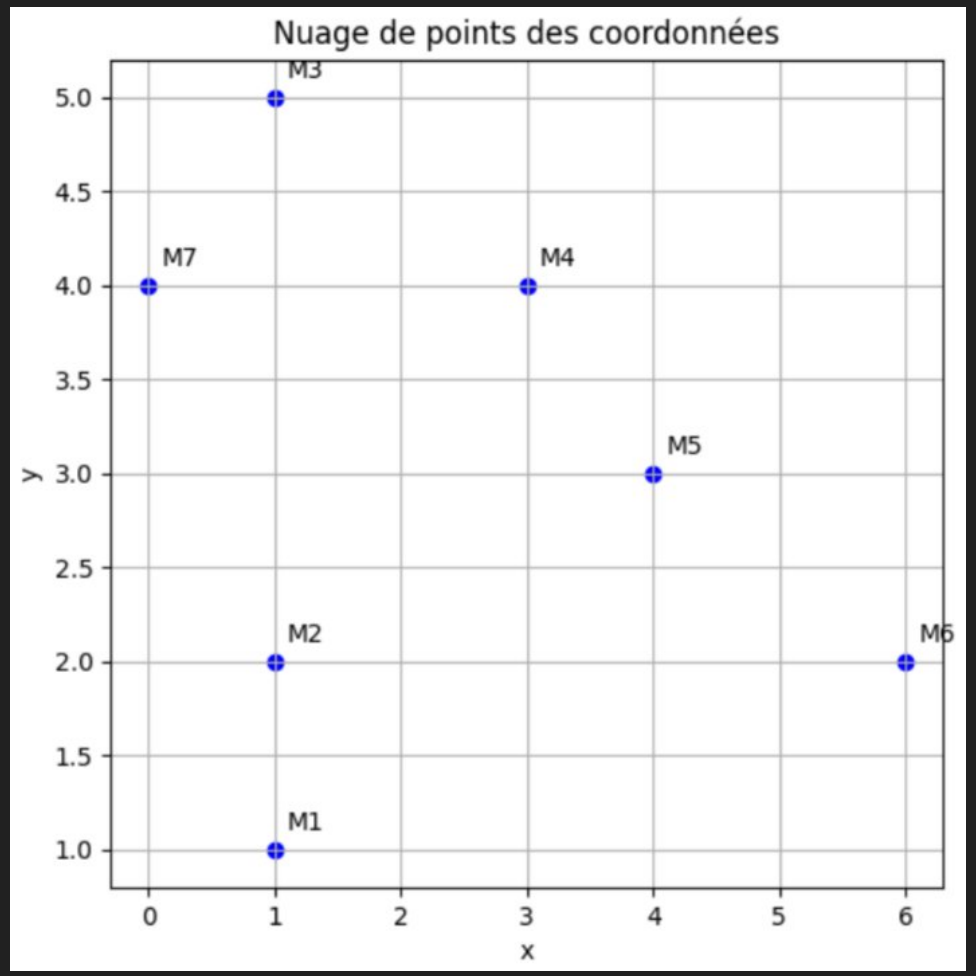
Statistiques Descriptives

	x	y
M1	1	1
M2	1	2
M3	1	5
M4	3	4
M5	4	3
M6	6	2
M7	0	4

	x	y
Moyenne	2.286	3.000
Médiane	1.000	3.000
Variance	4.571	2.000
Écart-type	2.138	1.414
Min	0.000	1.000
Max	6.000	5.000
Étendue	6.000	4.000

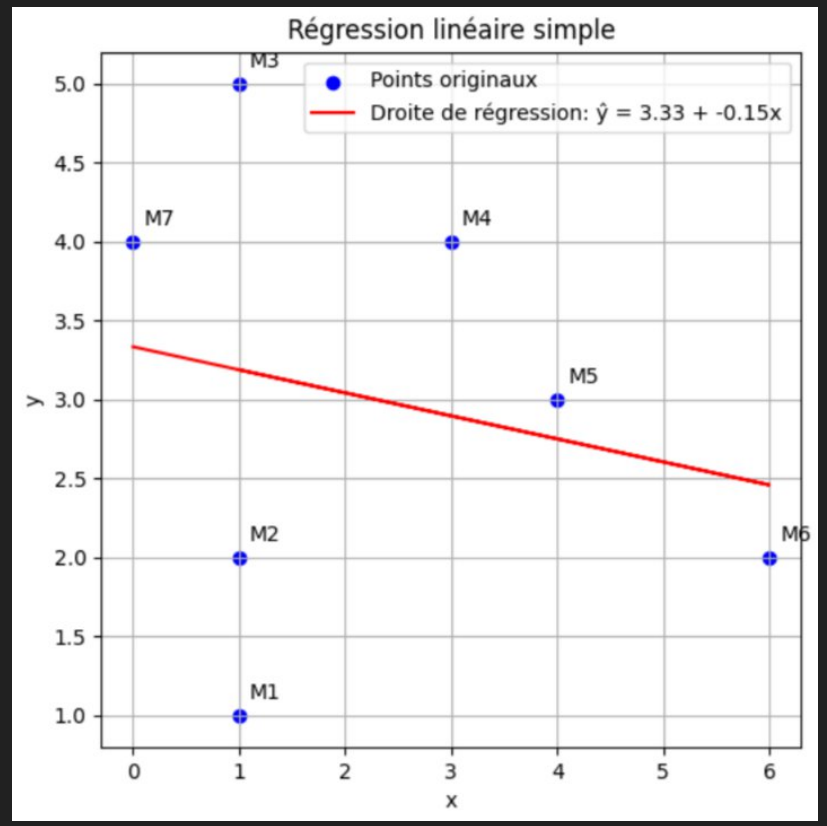


Régression Linéaire Simple

Coefficients de régression

$$b_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

$$b_0 = \bar{y} - b_1\bar{x}$$



Coefficient de détermination

$$R^2 = 1 - \frac{SCE}{SCT} = \frac{SCR}{SCT}$$

$$R^2 = 0.0486$$

Somme des carrés

$$SCE = \sum_{i=1}^{n}(y_i - \hat{y})^2$$
$$SCT = \sum_{i=1}^{n}(y_i - \bar{y})^2$$
$$SCR = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2$$

```
SCT = 12.0000
SCE = 11.4167
SCR = 0.5833
```

Estimation de l’erreur

Variance estimée des erreurs

$$\sigma^2 = MSE = \frac{SCE}{n-2}$$

Pourquoi $n-2$?

```
MSE : 2.2833
```

Écart-type des erreurs

$$\sigma = \sqrt{\sigma^2} = \sqrt{\frac{SCE}{n-2}}$$

```
Écart-type des erreurs : 1.5111
```

Tests statistiques

Erreur standard des coefficients

$$SE_{b_1} = \frac{\sigma}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}}$$

$$SE_{b_0} = \sigma \sqrt{\frac{1}{n} + \frac{\bar{x}^2}{\sum_{i=1}^{n}(x_i - \bar{x}^2)}}$$

```
Erreur standard de b1 : 0.2885
Erreur standard de b0 : 0.8724
```

Tests d'hypothèse

$$t = \frac{b_i - 0}{SE_{b_i}}$$

```
t statistique pour b1 : -0.5054
t statistique pour b0 : 3.8208
Valeur critique t (alpha=0.05, ddl=5) : 2.5706
```

Intervalles de confiance

$$\beta \pm t_{\alpha/2, n-2} \times SE_{\beta}$$

```
Intervalle de confiance à 95% pour b1 : [-0.8875, 0.5958]
Intervalle de confiance à 95% pour b0 : [1.0907, 5.576]
```

Classification Ascendante Hiérarchique

Explication de l'algorithme

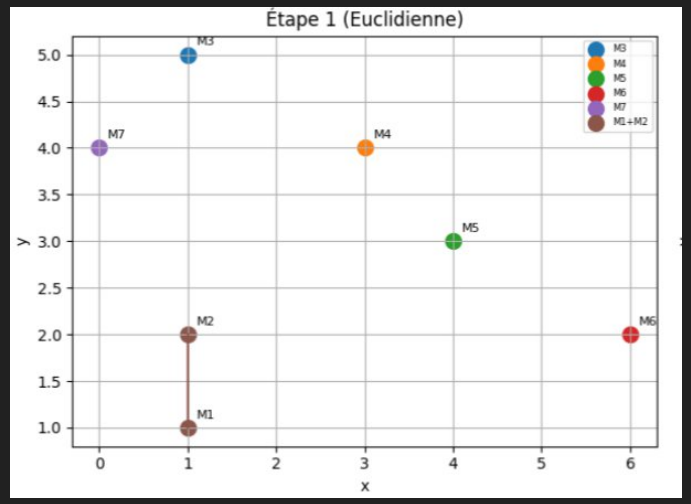
```python
def dist_euclidienne(p1: pd.Series, p2: pd.Series) -> float:
    '''Distance euclidienne entre 2 points'''

    return sqrt((p1['x'] - p2['x']) ** 2 + (p1['y'] - p2['y']) ** 2)
```

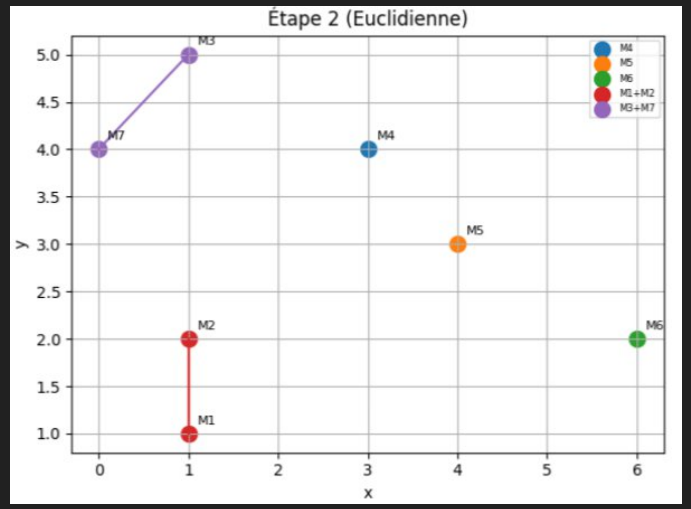
```python
def dist_group(g1: str, g2: str, clusters: dict, df: pd.DataFrame, dist_func: Callable) -> float:
    '''Distance minimale entre groupes'''

    return min(dist_func(df.loc[p1], df.loc[p2]) for p1 in clusters[g1] for p2 in clusters[g2])
```

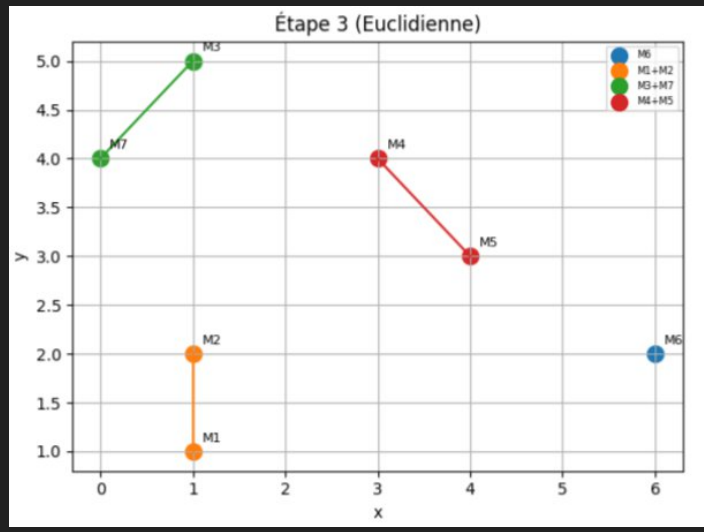
```python
def dist_min(t: pd.DataFrame, clusters: dict, dist_func: Callable) -> tuple:
    '''Retourne la paire de clusters les plus proches selon une fonction de distance donnée.'''

    # Liste des clés (identifiants des clusters)
    keys = list(clusters.keys())

    # Génère toutes les combinaisons uniques (i < j) d'indices de clusters
    combi = np.dstack(np.triu_indices(len(keys), k=1))[0]

    # Calcule les distances entre chaque paire de clusters avec la fonction fournie
    combi_dist = [
        dist_group(keys[i], keys[j], clusters, t, dist_func)
        for i, j in combi
    ]

    # Trouve l'indice de la paire avec la plus petite distance
    i, j = combi[np.argmin(combi_dist)]
    closest_pair = (keys[i], keys[j])
    return closest_pair
```

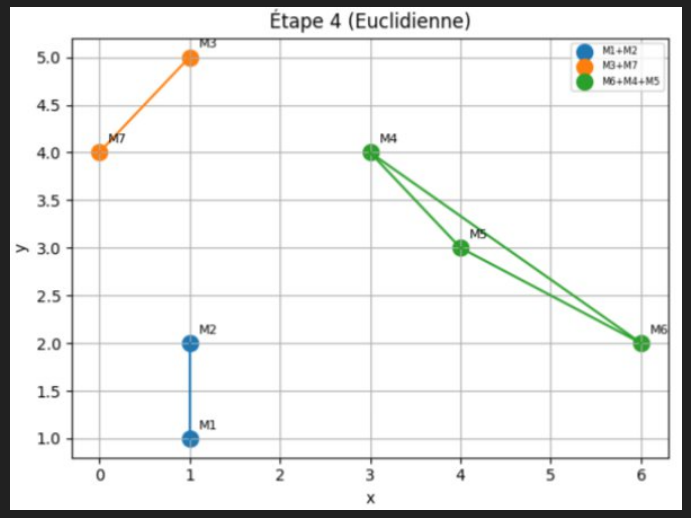
Classification Ascendante Hiérarchique

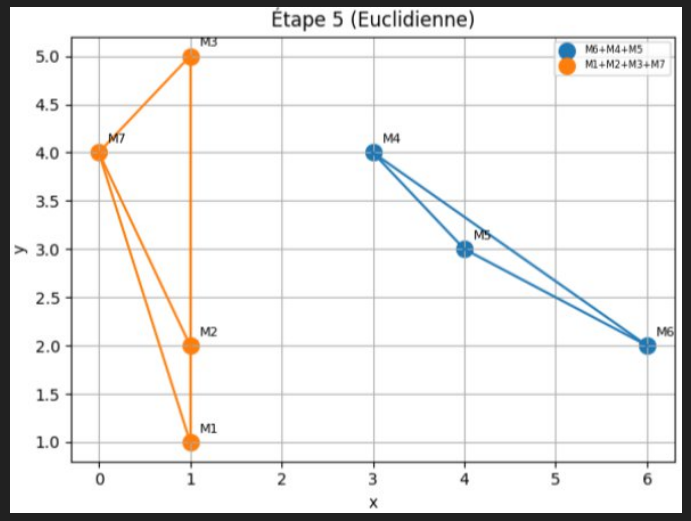
Application et résultats

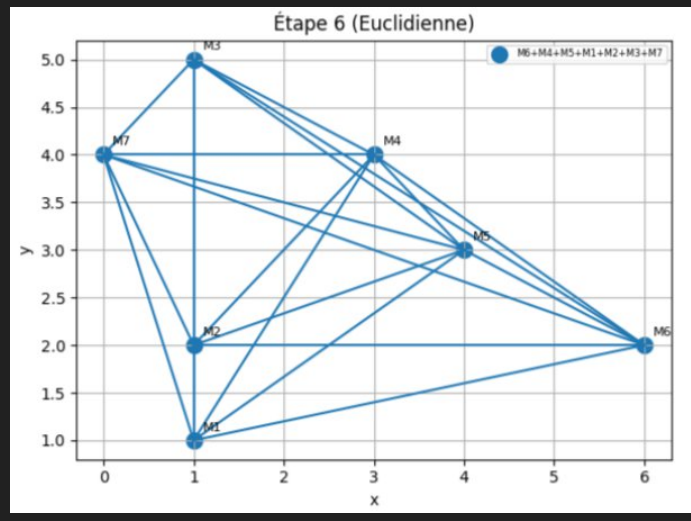






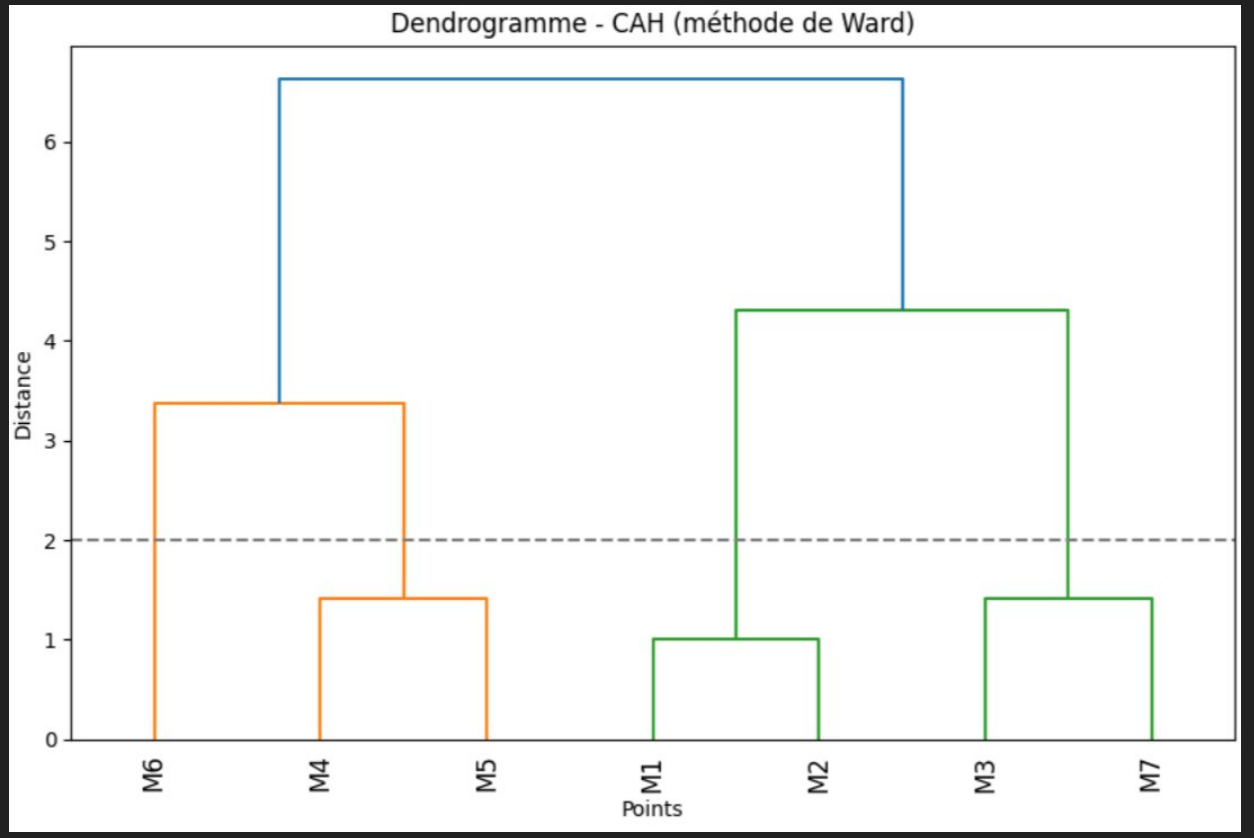






Classification Ascendante Hiérarchique

Application et résultats



Évaluation et validation du clustering

Indices d’évaluation

```
Silhouette Score (29, 9) : 0.4006
```

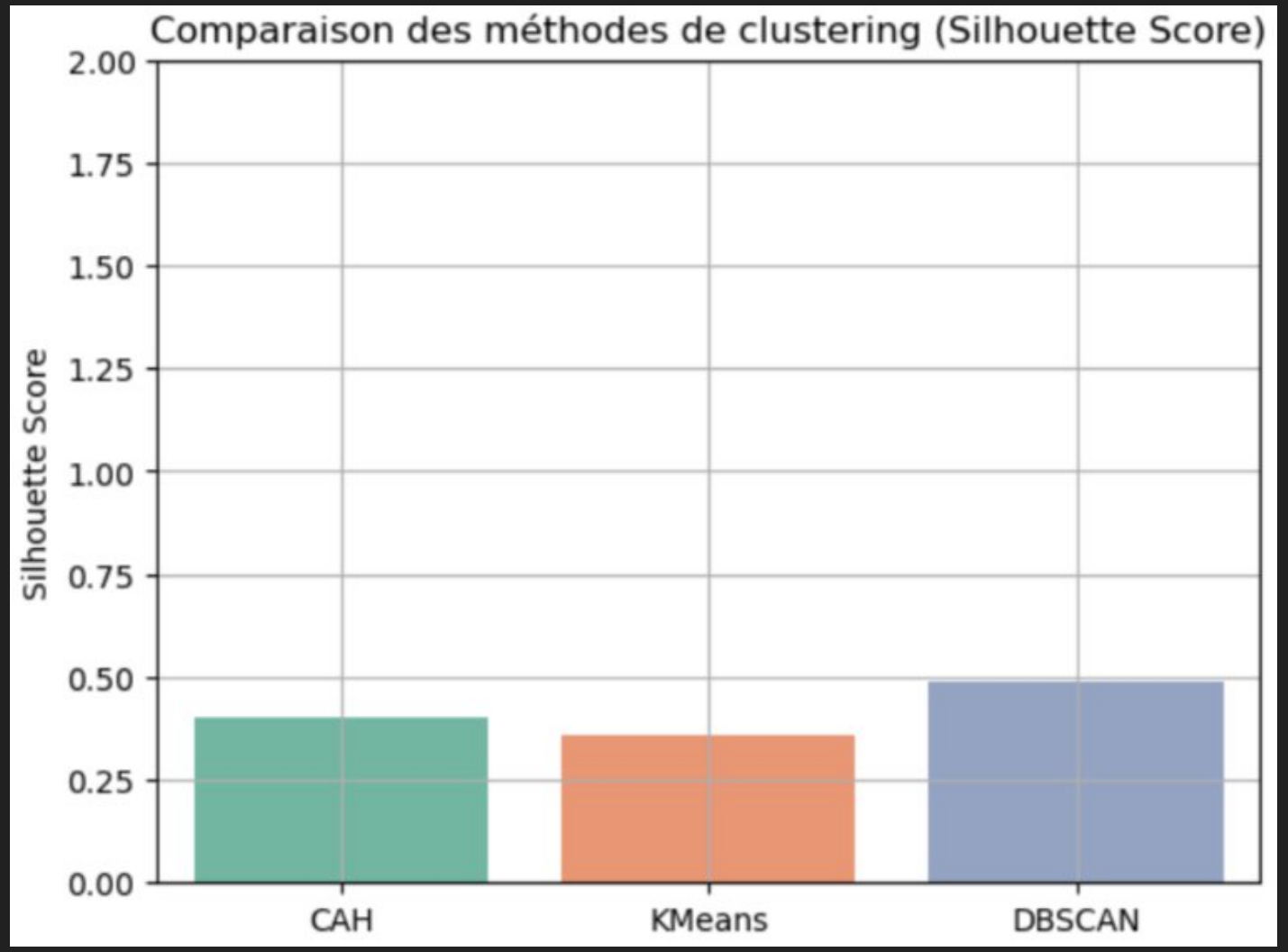
```
Indice de Dunn : 0.4756
```

```
Cohésion intra-cluster : 51.2785
Séparation inter-cluster : 14.6867
```

Évaluation et validation du clustering

Validation croisée

```
Silhouette Score CAH      : 0.4006
Silhouette Score KMeans   : 0.3603
Silhouette Score DBSCAN   : 0.4907
ARI CAH - KMeans     : 0.5924
ARI CAH - DBSCAN     : 0.5656
ARI DBSCAN - Kmeans  : 0.3811
```



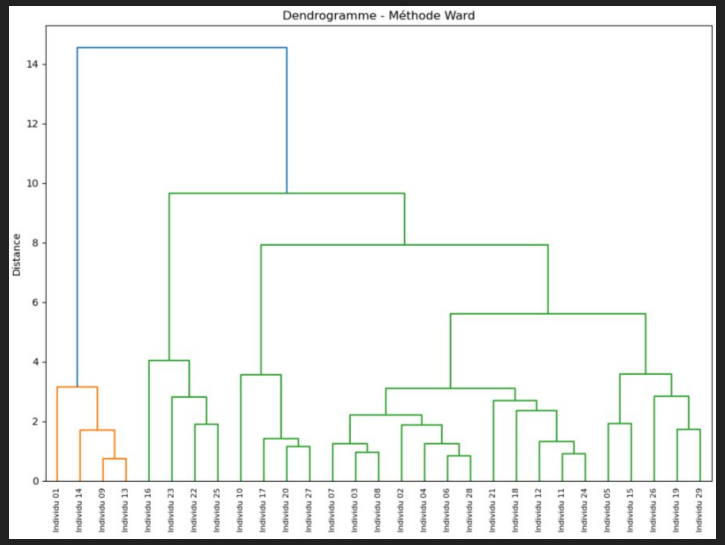
Évaluation et validation du clustering

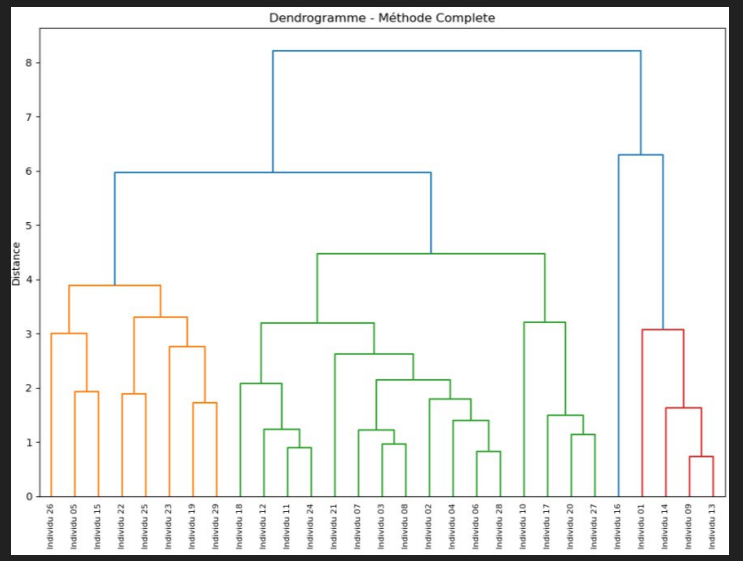
Interprétation des résultats

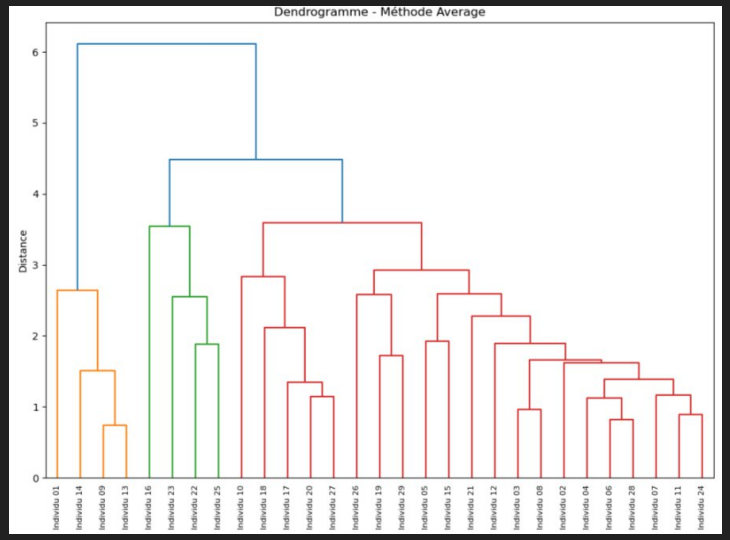
	Données 1	Données 2	Données 3	Données 4	Données 5	Données 6	Données 7	Données 8	Données 9
1 - mean	101.750	44.750	133.750	6.275	55.150	16.475	7.200	18.250	11.250
1 - median	97.500	33.000	120.550	5.650	56.700	20.200	7.650	16.500	10.500
1 - std	33.049	31.941	61.850	3.431	10.462	9.122	2.288	8.884	1.893
2 - mean	276.500	235.500	127.200	22.825	115.000	34.050	17.950	65.000	24.250
2 - median	278.000	234.000	110.050	22.450	109.700	34.400	18.650	65.000	22.500
2 - std	57.512	71.636	64.445	4.551	25.989	2.726	5.133	12.910	8.655
3 - mean	342.286	236.738	206.786	27.819	60.890	8.343	23.062	87.143	30.476
3 - median	338.000	238.000	211.100	28.000	57.600	5.700	22.400	80.000	28.000
3 - std	36.318	96.284	66.909	3.044	13.117	8.063	4.435	16.169	10.186

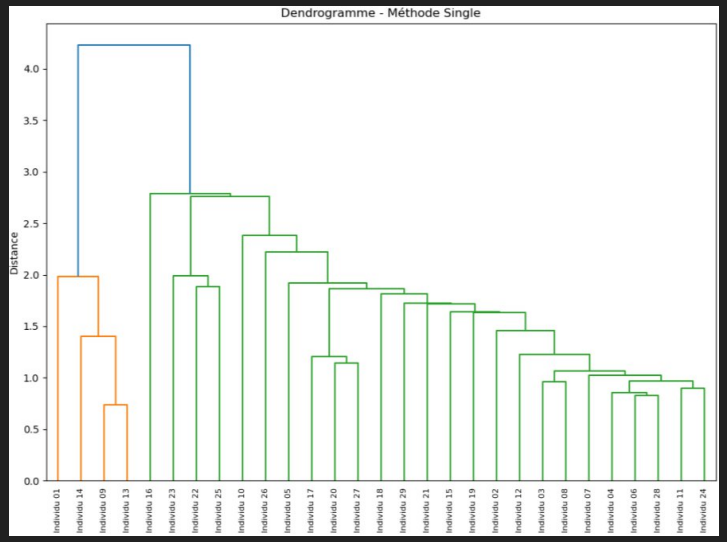
Évaluation et validation du clustering

Analyse critique de la méthode



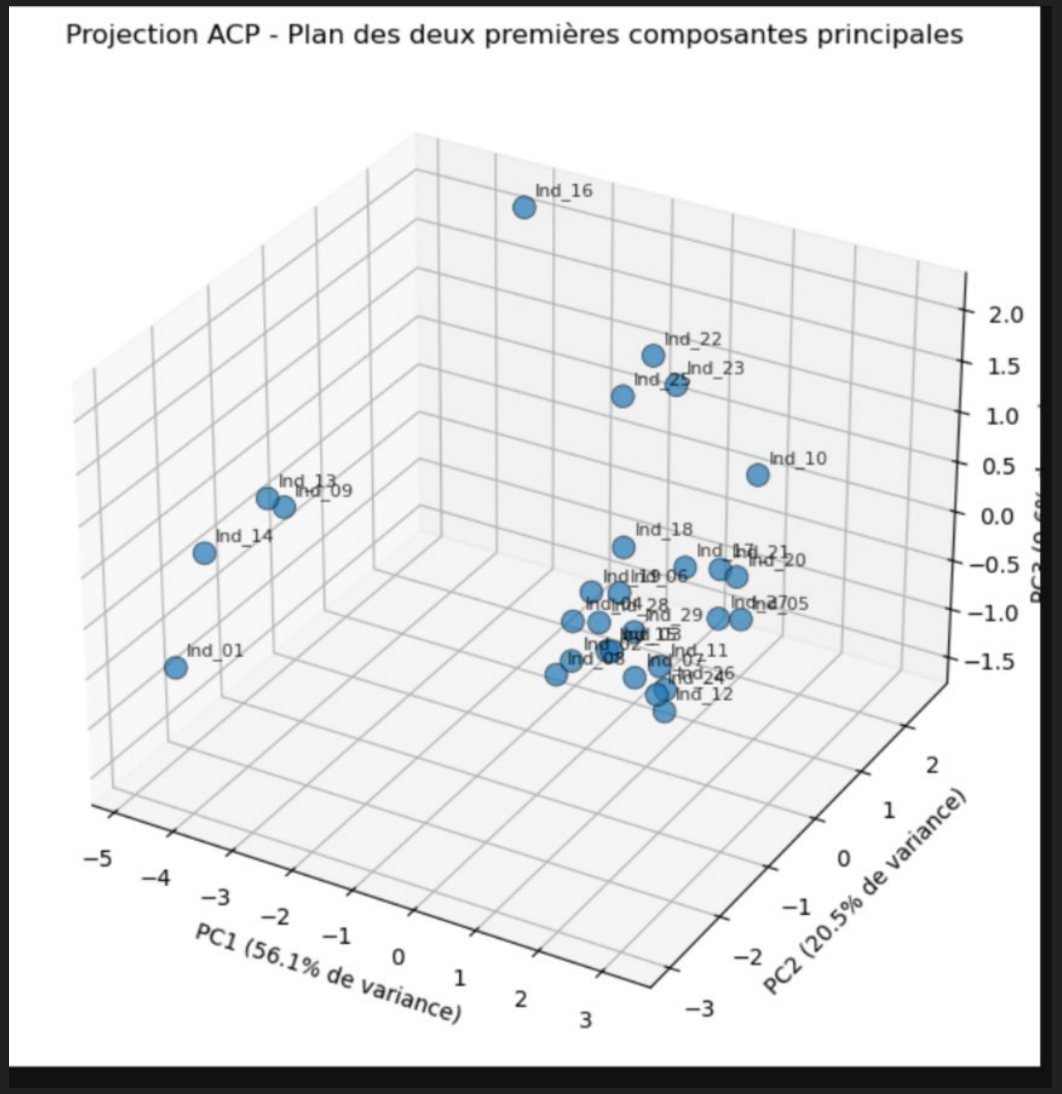


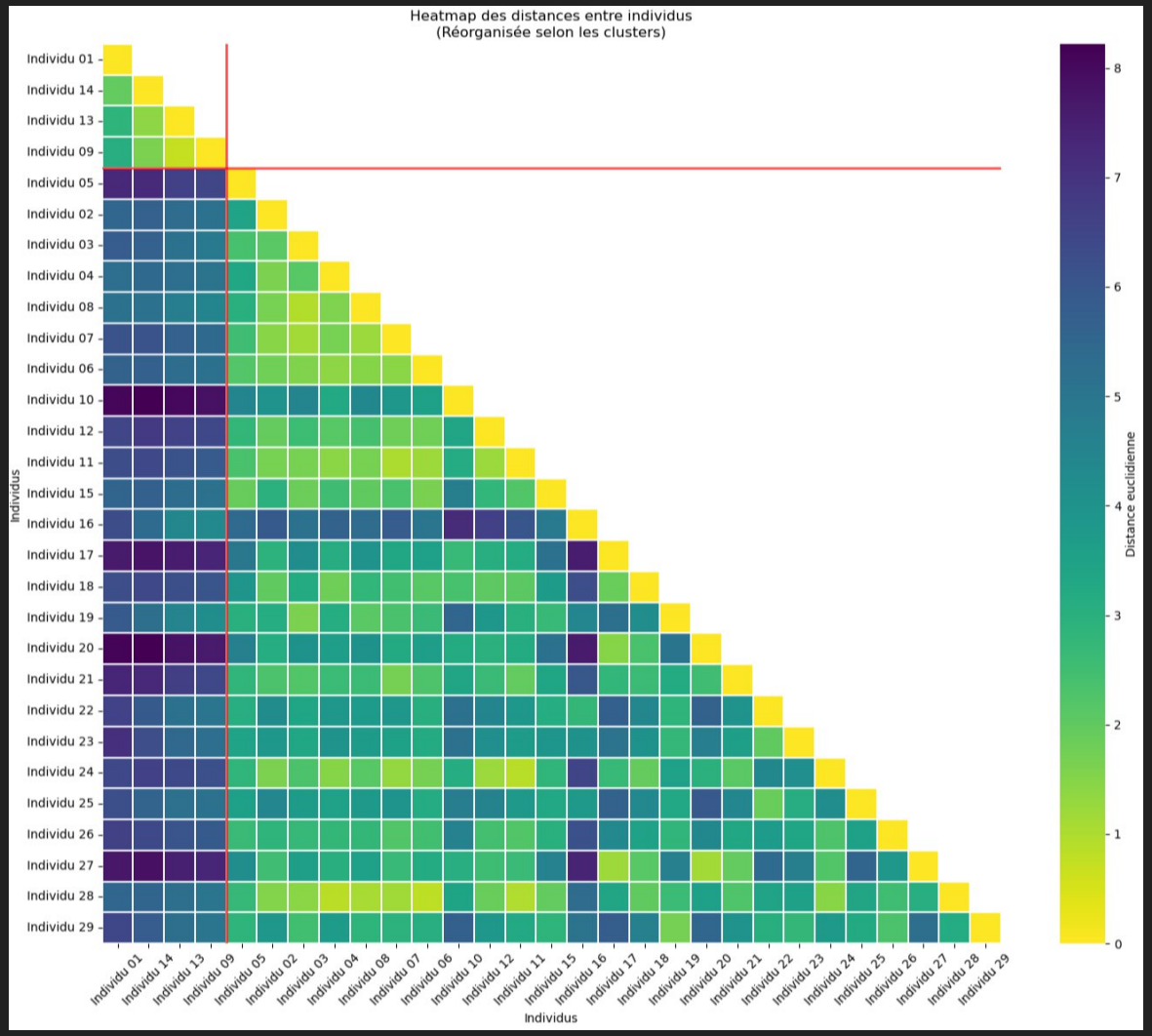




Évaluation et validation du clustering

Visualisation avancée





Merci de votre écoute

h1 title

h2 title

h3 title

p text

p value

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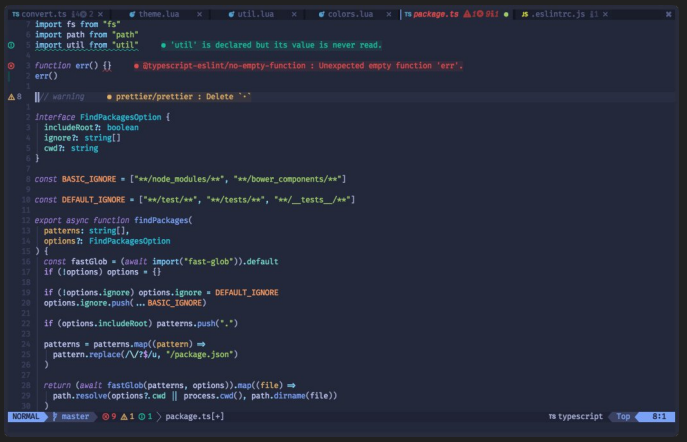

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main.py

```python
if __name__ == '__main__':
  httpd = HTTPServer((DOMAIN, PORT), Handler)
  httpd.serve_forever()
```