Projet de Data Mining (Iris clustering)

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```
import pandas as pd
import numpy as np

url =
"https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.d
ata"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width',
'class']
dataset = pd.read_csv(url, names=names)

print("Dimensions du dataset:", dataset.shape)
dataset.head()
```

```
Dimensions du dataset: (150, 5)
```

	sepal-length	sepal-width	petal-length	petal-width	class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

2. Prétraitement des Données

```
print("Valeurs manquantes par colonne:")
print(dataset.isnull().sum())

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
dataset['class'] = le.fit_transform(dataset['class'])

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = scaler.fit_transform(dataset.iloc[:, :-1])
y = dataset.iloc[:, -1]
```

```
Valeurs manquantes par colonne:
sepal-length    0
sepal-width     0
petal-length    0
petal-width     0
```

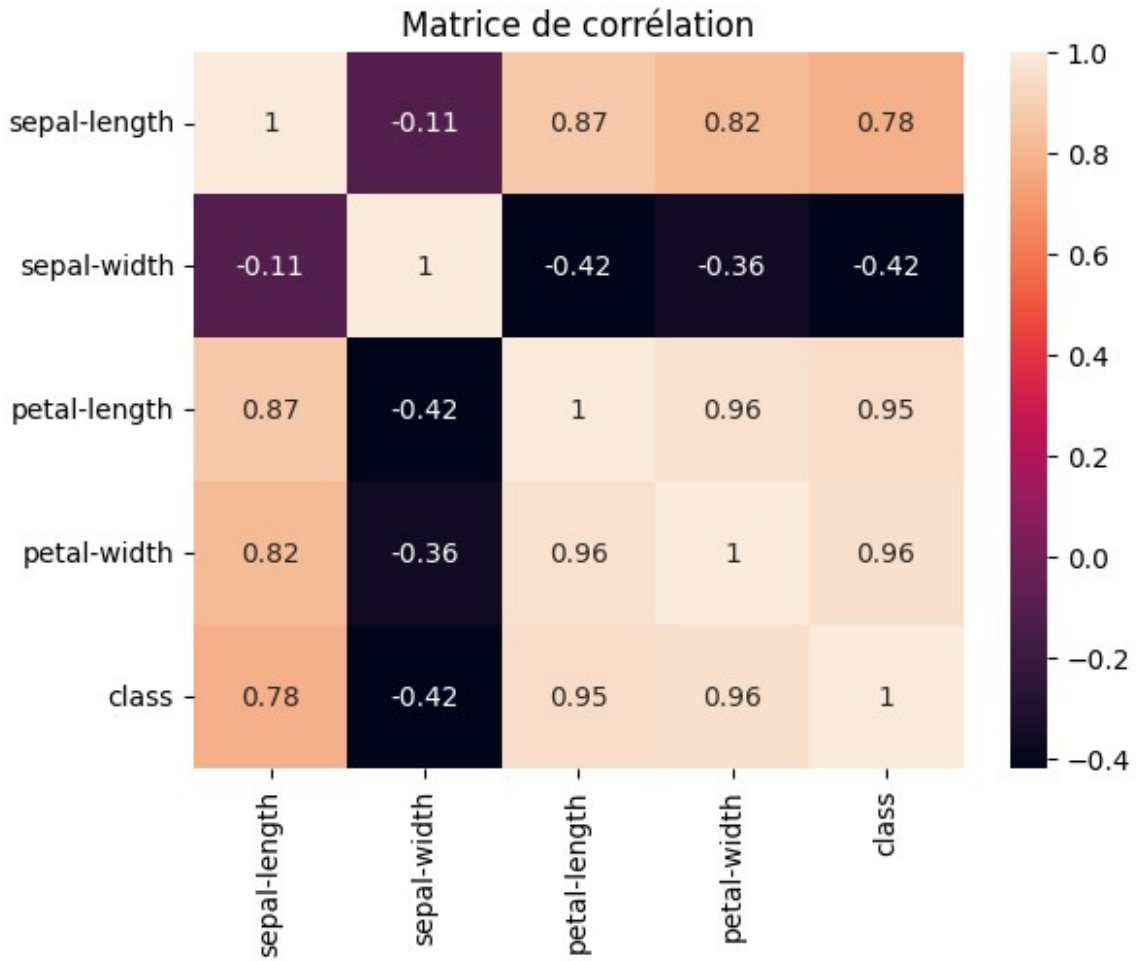
```
class            0
dtype: int64
```

3. Sélection de Features

```
import seaborn as sns
import matplotlib.pyplot as plt

corr_matrix = dataset.corr()
sns.heatmap(corr_matrix, annot=True)
plt.title("Matrice de corrélation")
plt.show()

from sklearn.feature_selection import SelectKBest, f_classif
selector = SelectKBest(score_func=f_classif, k=2)
X_new = selector.fit_transform(X, y)
print("Features sélectionnées:", np.array(names[:-1])
[selector.get_support()])
```



```
Features sélectionnées: ['petal-length' 'petal-width']
```

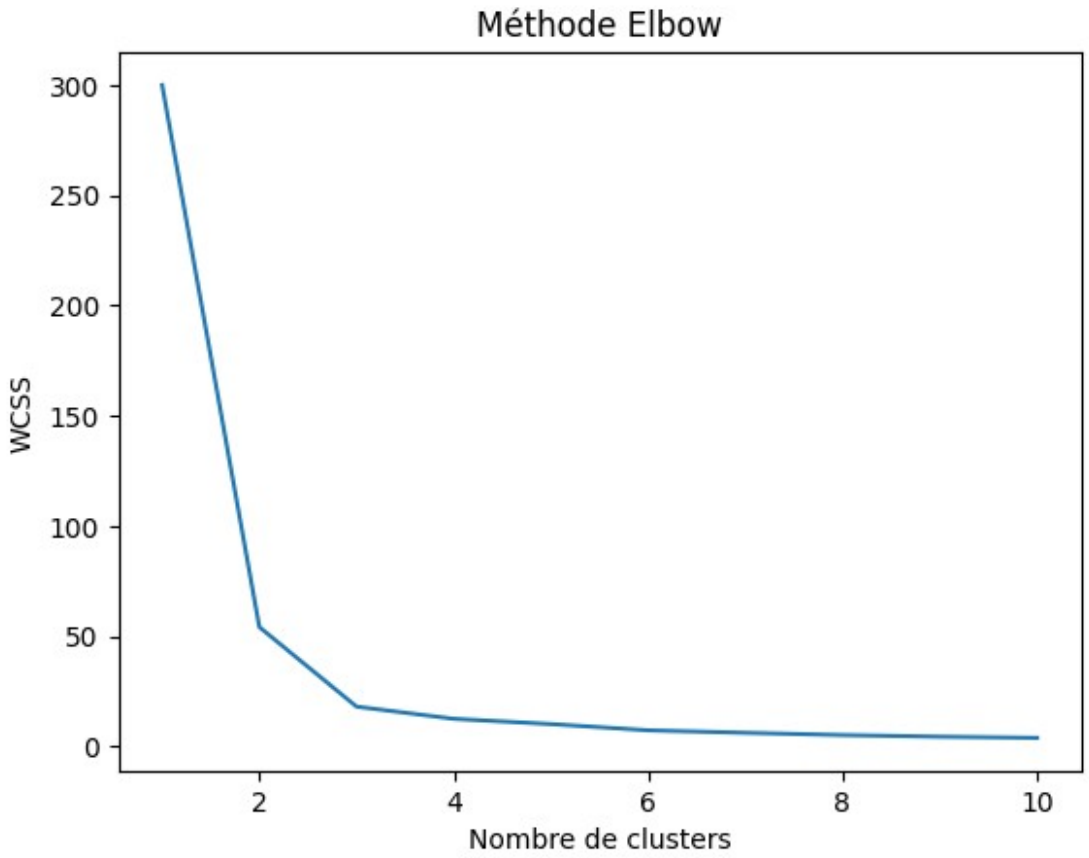
4. Data Mining (K-Means)

```
from sklearn.cluster import KMeans

wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(X_new)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss)
plt.title('Méthode Elbow')
plt.xlabel('Nombre de clusters')
plt.ylabel('WCSS')
plt.show()

kmeans = KMeans(n_clusters=3, init='k-means++', random_state=42)
clusters = kmeans.fit_predict(X_new)
```



5. Évaluation des Résultats

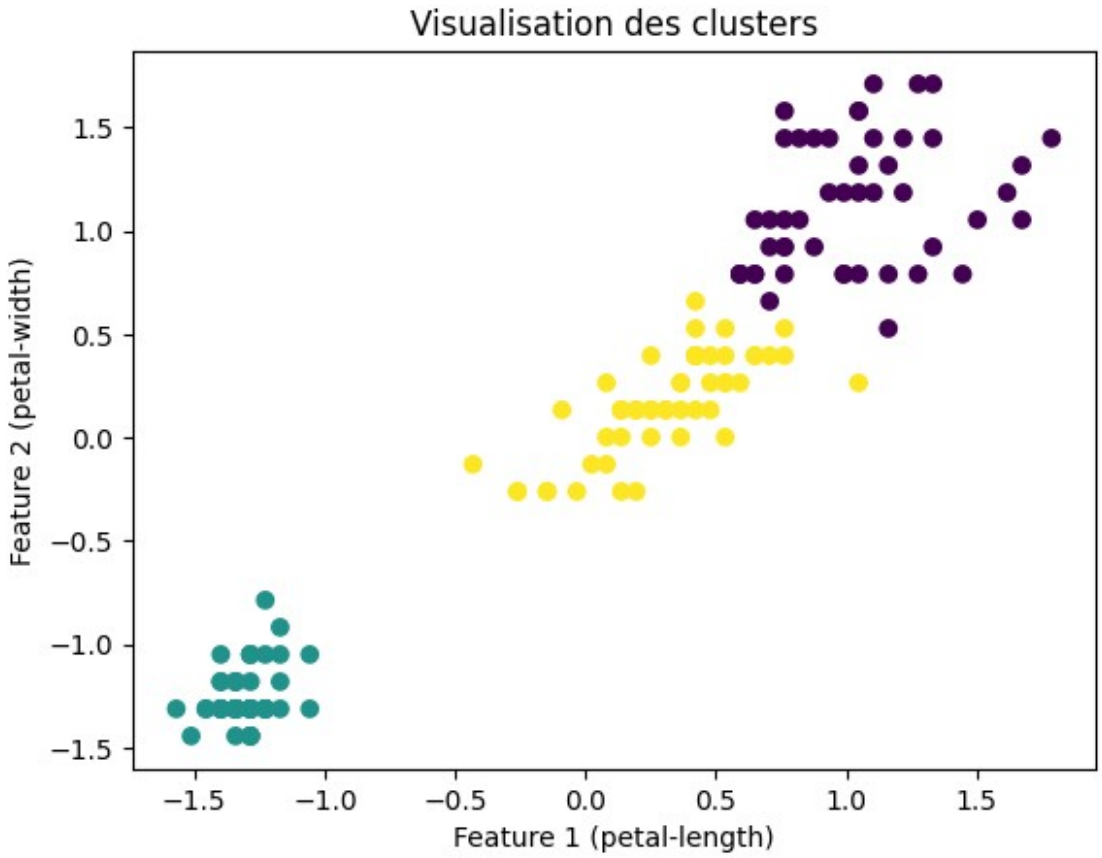
```
from sklearn.metrics import silhouette_score, adjusted_rand_score

silhouette = silhouette_score(X_new, clusters)
print(f"Score de silhouette: {silhouette:.2f}")

ari = adjusted_rand_score(y, clusters)
print(f"Adjusted Rand Index: {ari:.2f}")

plt.scatter(X_new[:,0], X_new[:,1], c=clusters, cmap='viridis')
plt.title('Visualisation des clusters')
plt.xlabel('Feature 1 (petal-length)')
plt.ylabel('Feature 2 (petal-width)')
plt.show()
```

```
Score de silhouette: 0.67
Adjusted Rand Index: 0.89
```



6. Conclusion

- **Score de silhouette:** 0.67 (indique une bonne séparation des clusters).
- **Adjusted Rand Index:** 0.89 (indique une forte correspondance avec les vraies classes).

- Les features sélectionnées (`petal-length` et `petal-width`) sont les plus pertinentes pour le clustering.
- Le nombre optimal de clusters est **3**, comme déterminé par la méthode Elbow.