DBSCAN Clustering — From Zero to Complete Understanding

This notebook implements **DBSCAN (Density-Based Spatial Clustering of Applications with Noise)** step by step.

We will:

- Generate data
- Scale it correctly
- Choose epsilon using k-distance graph
- Apply DBSCAN
- Analyze clusters, noise, core and border points
- Test parameter sensitivity

Step 1: Import Essential Libraries

Purpose of each import:

- **numpy** → numerical operations
- **matplotlib** → data visualization
- **DBSCAN** → clustering algorithm
- **make_blobs** → synthetic dataset creation
- **StandardScaler** → feature scaling (mandatory for DBSCAN)
- **NearestNeighbors** → epsilon (ε) selection using k-distance graph

In [11]:
```python
import numpy as np
import matplotlib.pyplot as plt

from sklearn.cluster import DBSCAN
from sklearn.datasets import make_blobs
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import NearestNeighbors
```

Step 2: Create a Synthetic Dataset

We generate a **2D dataset** so clustering can be visualized.

Parameters:

- `n_samples` → total number of points
- `centers` → number of true clusters (only for data generation)
- `cluster_std` → spread of clusters
- `_` → labels ignored (DBSCAN is unsupervised)

In [12]:
```
X, _ = make_blobs(
    n_samples=300,
    centers=3,
    cluster_std=0.6,
    random_state=42
)
```

Step 3: Feature Scaling (MANDATORY)

DBSCAN is **distance-based**.

If features are not scaled:

- epsilon (ε) becomes meaningless
- neighborhood calculation breaks

`StandardScaler`:

- mean → 0
- standard deviation → 1

In [13]:
```
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

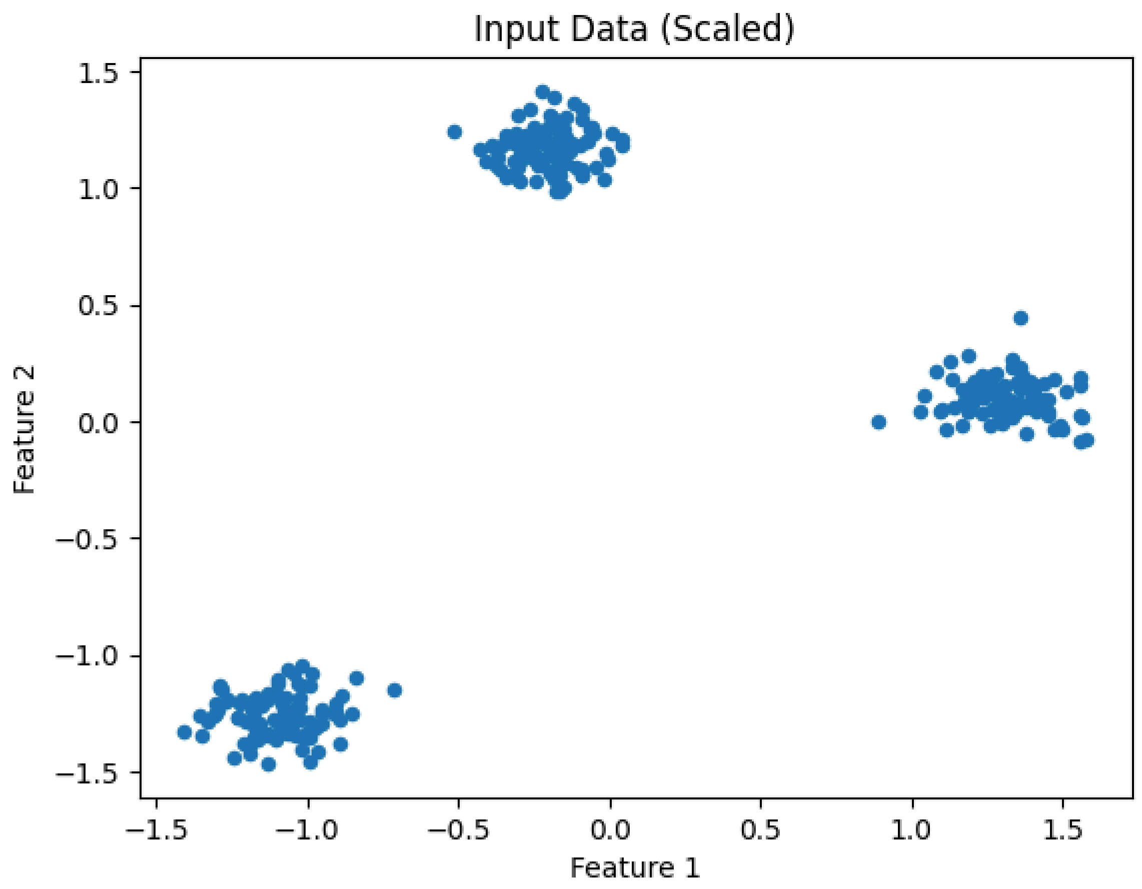
Step 4: Visualize Raw Data

Always visualize data **before clustering**.

This helps understand:

- shape
- density
- overlap

In [14]:
```
plt.scatter(X[:, 0], X[:, 1], s=20)
plt.title("Input Data (Scaled)")
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.show()
```



Step 5: Epsilon (ε) Selection using k-Distance Graph

Procedure:

1. Choose `k = min_samples`
2. Compute distance to the k-th nearest neighbor
3. Sort distances
4. Find the **elbow**

Interpretation:

- ε too small → most points become noise
- ε too large → clusters merge
- No elbow → DBSCAN is not suitable

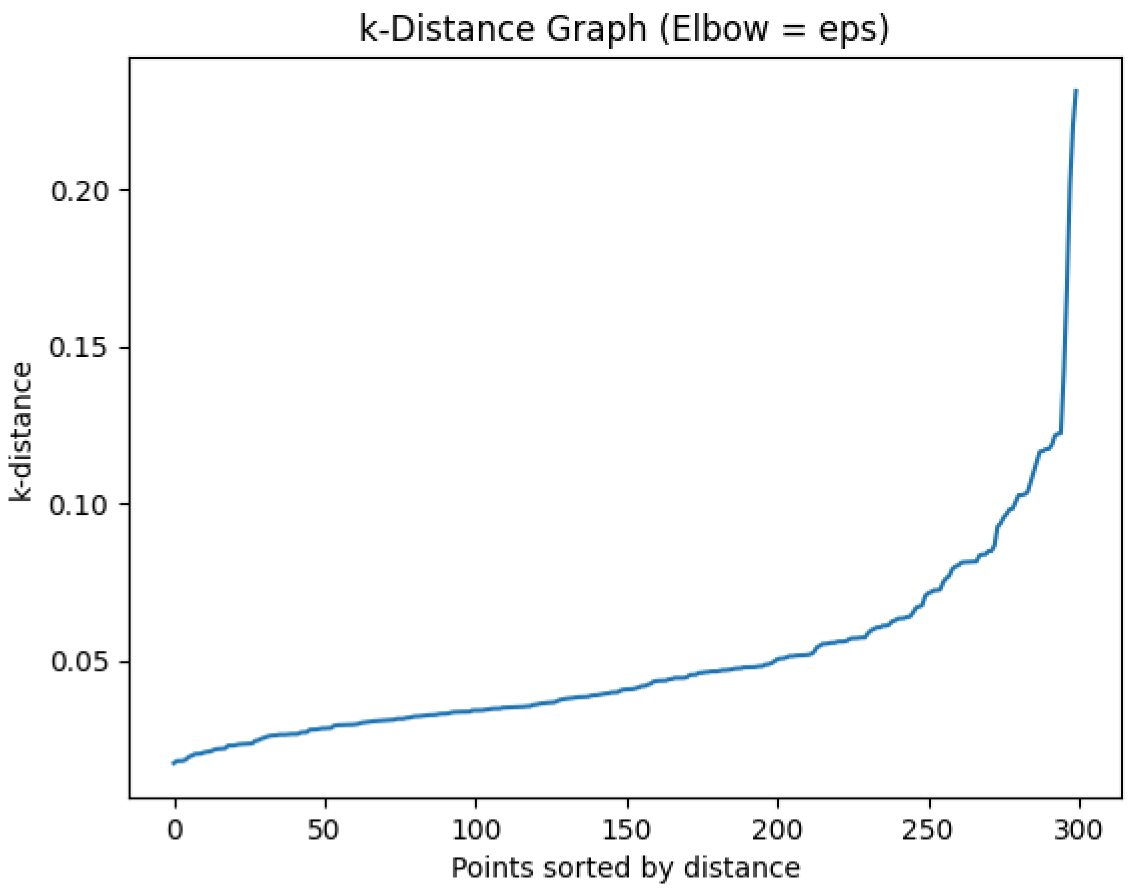
In [15]:
```
k = 5  # same as min_samples

nbrs = NearestNeighbors(n_neighbors=k)
nbrs.fit(X)

distances, _ = nbrs.kneighbors(X)

k_distances = np.sort(distances[:, k - 1])

plt.plot(k_distances)
plt.xlabel("Points sorted by distance")
plt.ylabel("k-distance")
plt.title("k-Distance Graph (Elbow = eps)")
plt.show()
```



Step 6: Apply DBSCAN

Parameters:

- `eps` → chosen from k-distance graph
- `min_samples` → density threshold

`fit_predict()` :

- fits the model
- assigns cluster labels

- noise points get label `-1`

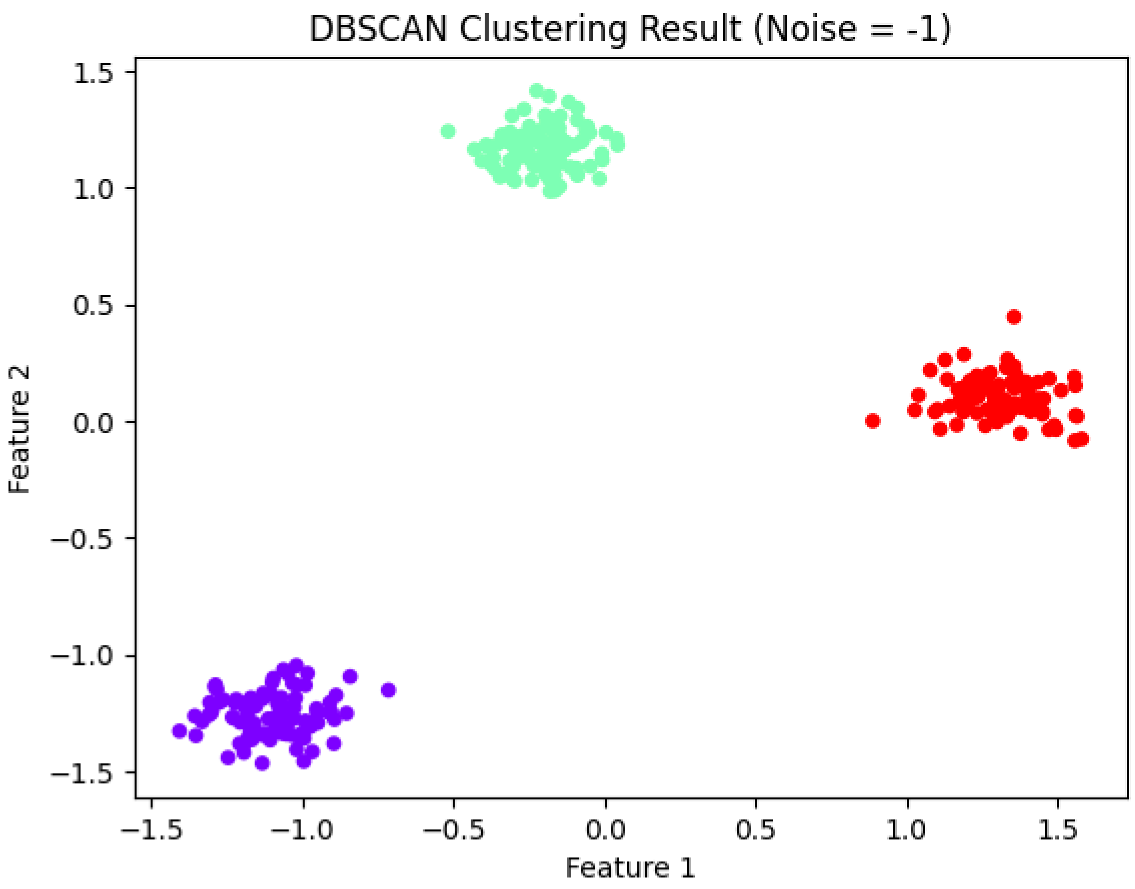
In [16]:
```
dbscan = DBSCAN(eps=0.3, min_samples=5)
labels = dbscan.fit_predict(X)
```

Step 7: Visualize DBSCAN Clusters

Color meaning:

- Same color → density-connected points
- `-1` → noise (outliers)

In [17]:
```
plt.scatter(
    X[:, 0],
    X[:, 1],
    c=labels,
    cmap="rainbow",
    s=20
)
plt.title("DBSCAN Clustering Result (Noise = -1)")
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.show()
```



Step 8: Count Clusters and Noise Points

DBSCAN automatically decides:

- number of clusters
- number of noise points

Logic:

- unique labels except `-1` → clusters
- count of `-1` → noise

In [18]:
```
unique_labels = set(labels)

n_clusters = len(unique_labels) - (1 if -1 in unique_labels else 0)
n_noise = list(labels).count(-1)

print("Number of clusters:", n_clusters)
print("Number of noise points:", n_noise)
```

```
Number of clusters: 3
Number of noise points: 0
```

Step 9: Identify Core, Border, and Noise Points

Definitions:

- **Core** → has ≥ min_samples neighbors within ε
- **Border** → inside ε of a core point
- **Noise** → not reachable from any core point

Only **core points** can expand clusters.

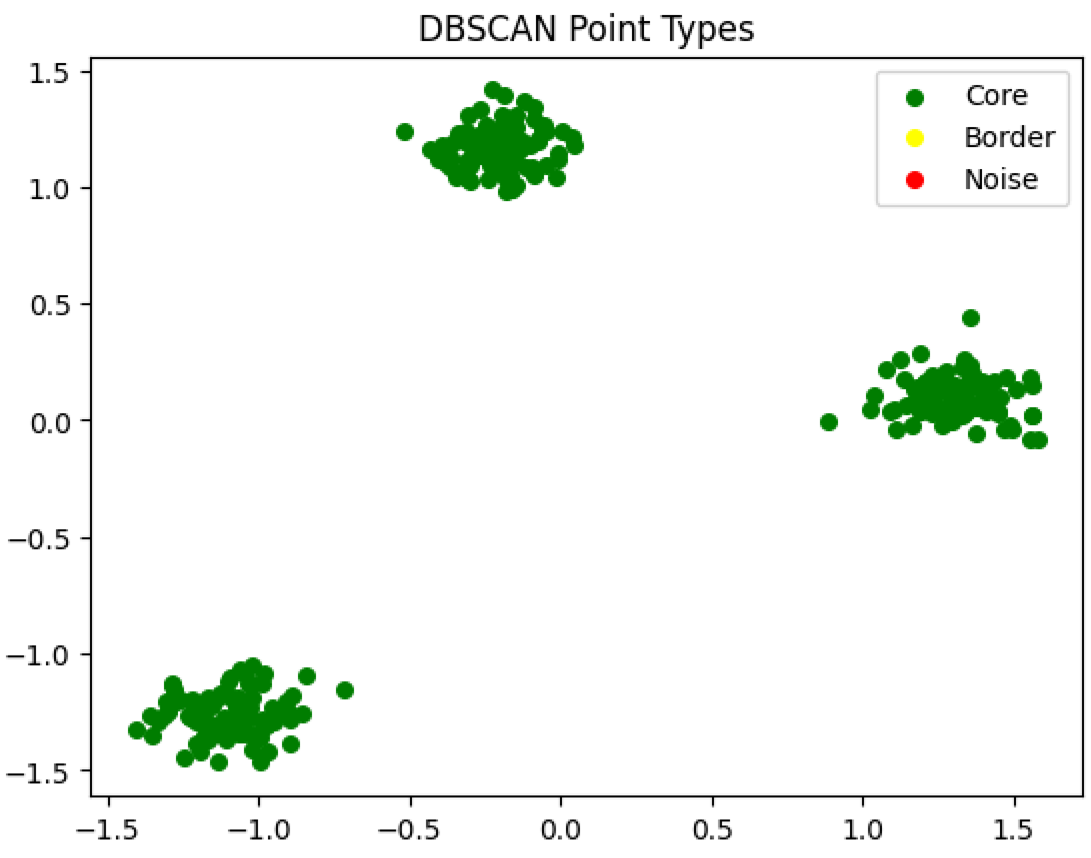
In [19]:
```
core_mask = np.zeros_like(labels, dtype=bool)
core_mask[dbscan.core_sample_indices_] = True

plt.scatter(X[core_mask, 0], X[core_mask, 1],
            c="green", s=30, label="Core")

plt.scatter(X[~core_mask & (labels != -1), 0],
            X[~core_mask & (labels != -1), 1],
            c="yellow", s=30, label="Border")

plt.scatter(X[labels == -1, 0],
            X[labels == -1, 1],
            c="red", s=30, label="Noise")

plt.legend()
plt.title("DBSCAN Point Types")
plt.show()
```



Step 10: Epsilon Sensitivity Analysis

Purpose:

- Check robustness of clustering
- Stable clusters across ε → good DBSCAN fit
- Large changes → DBSCAN unsuitable

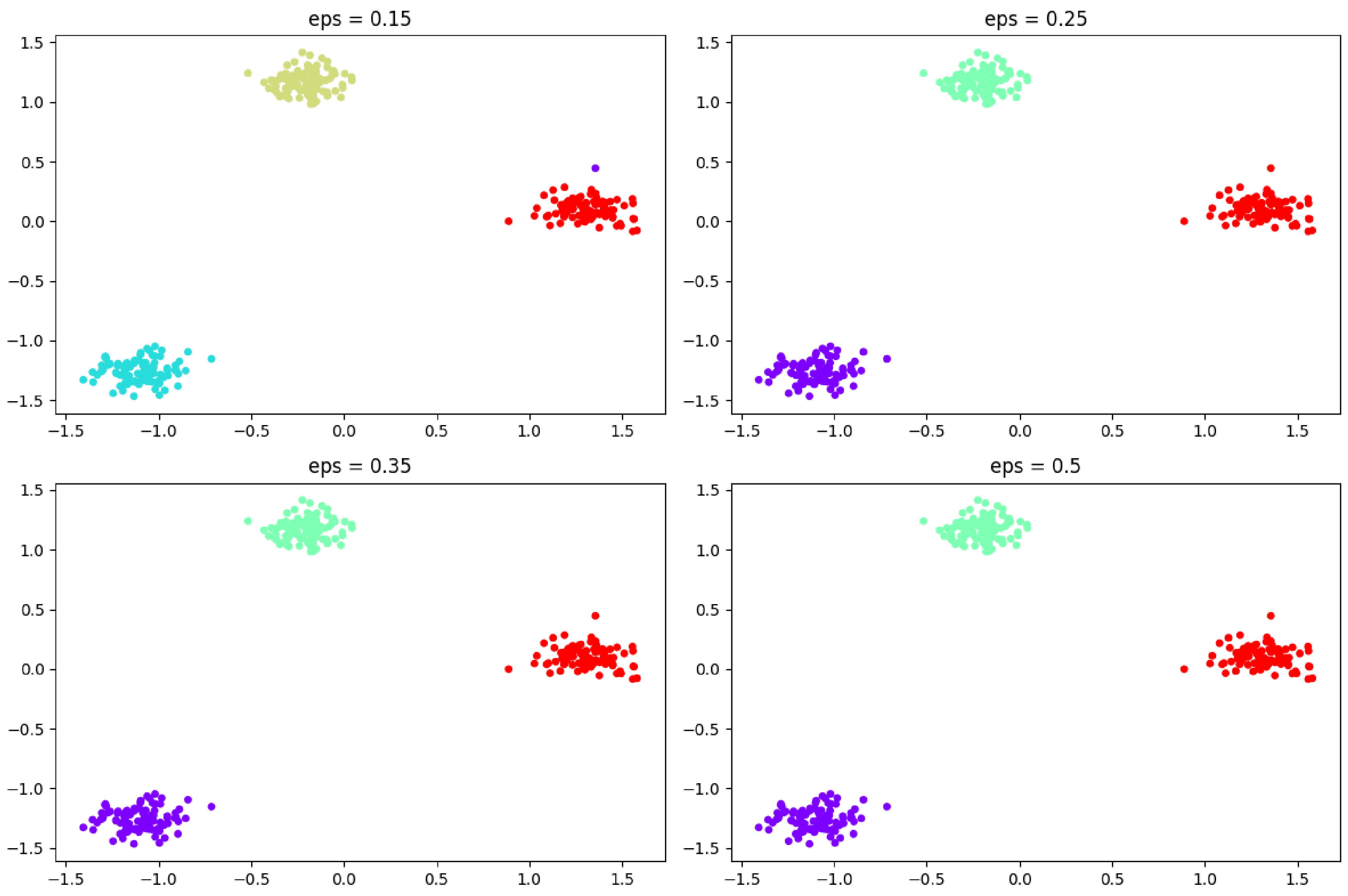
In [20]:
```
eps_values = [0.15, 0.25, 0.35, 0.5]

plt.figure(figsize=(12, 8))

for i, eps in enumerate(eps_values, 1):
    db = DBSCAN(eps=eps, min_samples=5)
    lbls = db.fit_predict(X)

    plt.subplot(2, 2, i)
    plt.scatter(X[:, 0], X[:, 1], c=lbls, cmap="rainbow", s=15)
    plt.title(f"eps = {eps}")

plt.tight_layout()
plt.show()
```


eps = 0.15
eps = 0.25
eps = 0.35
eps = 0.5
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

```
In [ ]:
```