

MACHINE LEARNING AND PATTERN RECOGNITION

IMAGE AND VIDEO UNDERSTAND

K-means & Spectral Clustering

Image Segmentation

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Outline

1. K-means
2. Spectral Clustering
3. Elbow method
4. Apply to datasets
5. Image segmentation
6. F1 score & Conditional Entropy

K-means clustering

Step 1: Specify number of clusters K

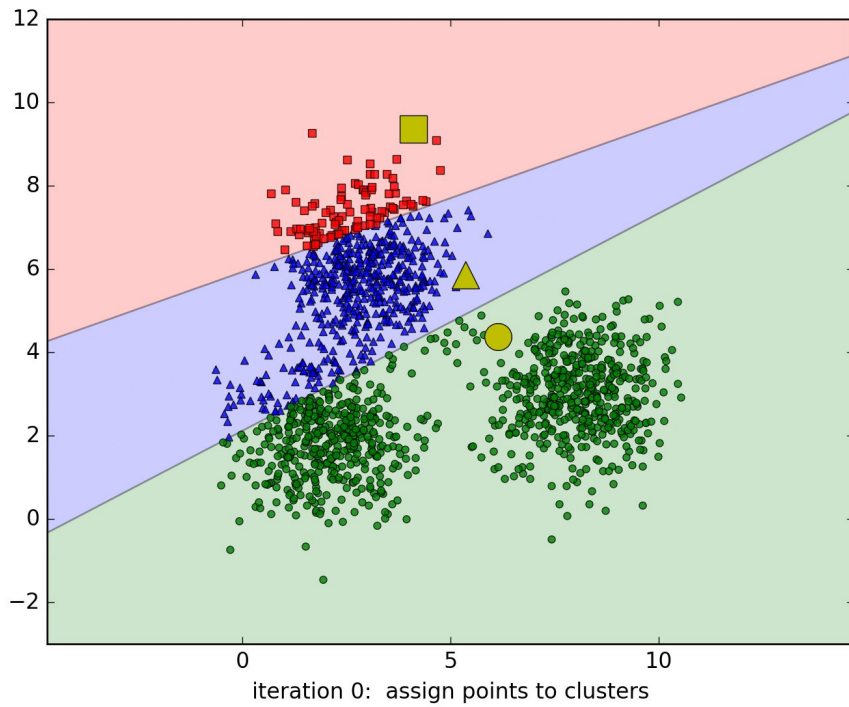
Step 2: Assign data points to the closest centroid

Step 3: Change the cluster centroid to the average of the assigned points

Step 4: Repeat step 2 and 3 until there is no change to the centroids

$$\mathbf{y}_i = \arg \min_{\mathbf{y}_i} \sum_{j=1}^K y_{ij} \|\mathbf{x}_i - \mathbf{m}_j\|_2^2$$

$$\text{subject to: } y_{ij} \in \{0, 1\} \quad \forall j; \quad \sum_{j=1}^K y_{ij} = 1$$



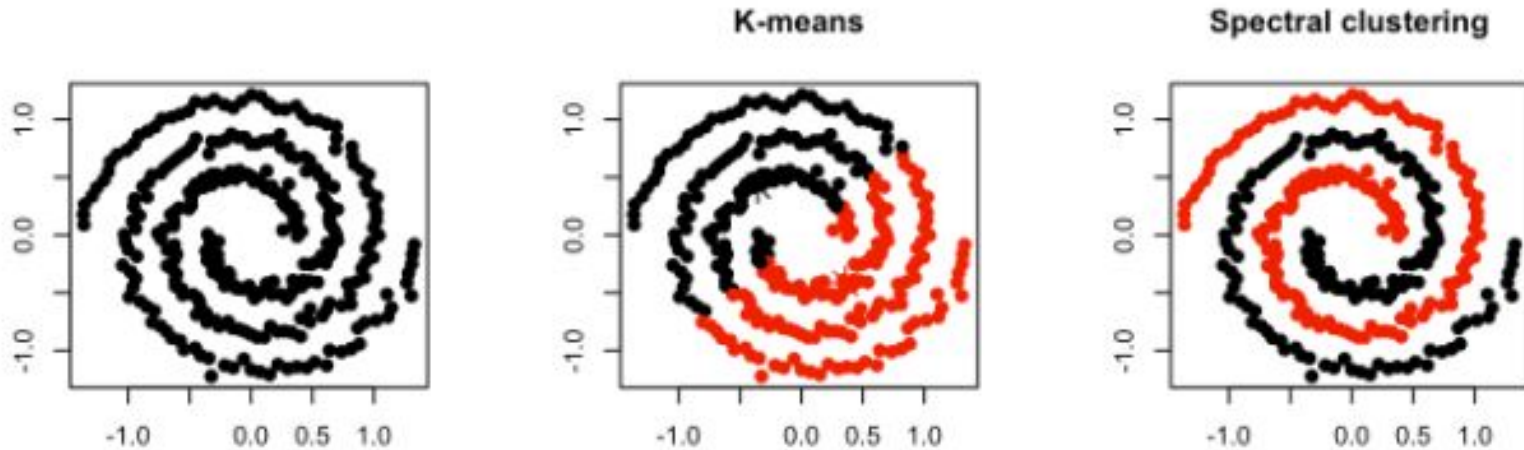
Spectral clustering

Step 1: Construct a similarity graph (KNN graph)

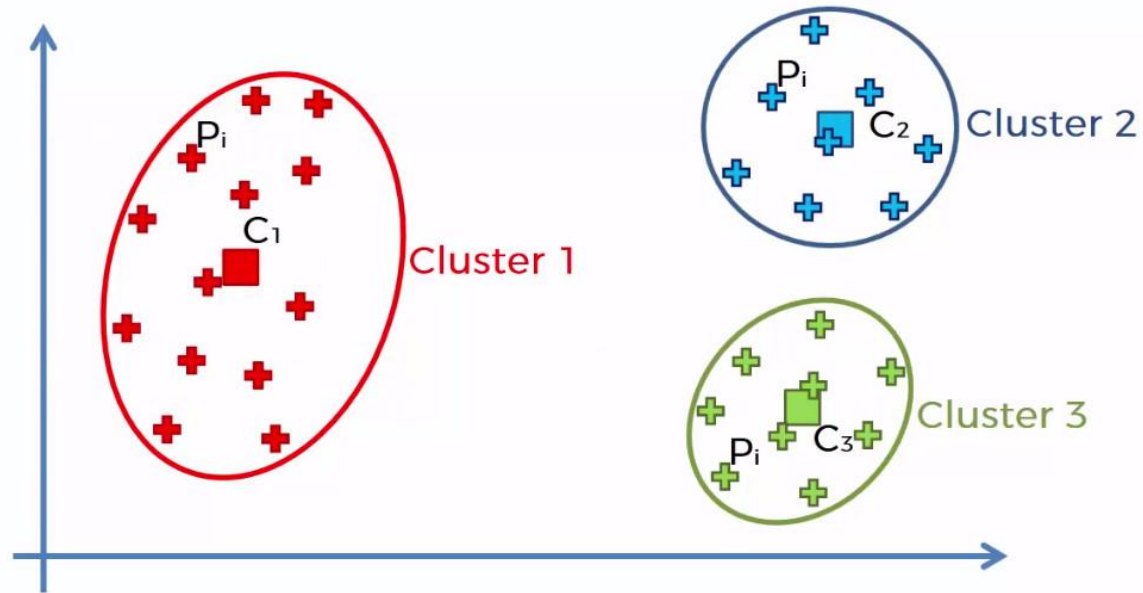
Step 2: Embed the data points in low dimensional space in which the clusters are

Step 3: Use the lowest eigenvalue in order to choose the eigenvector for clusters

The difference between the 2 can easily be shown by this illustration:

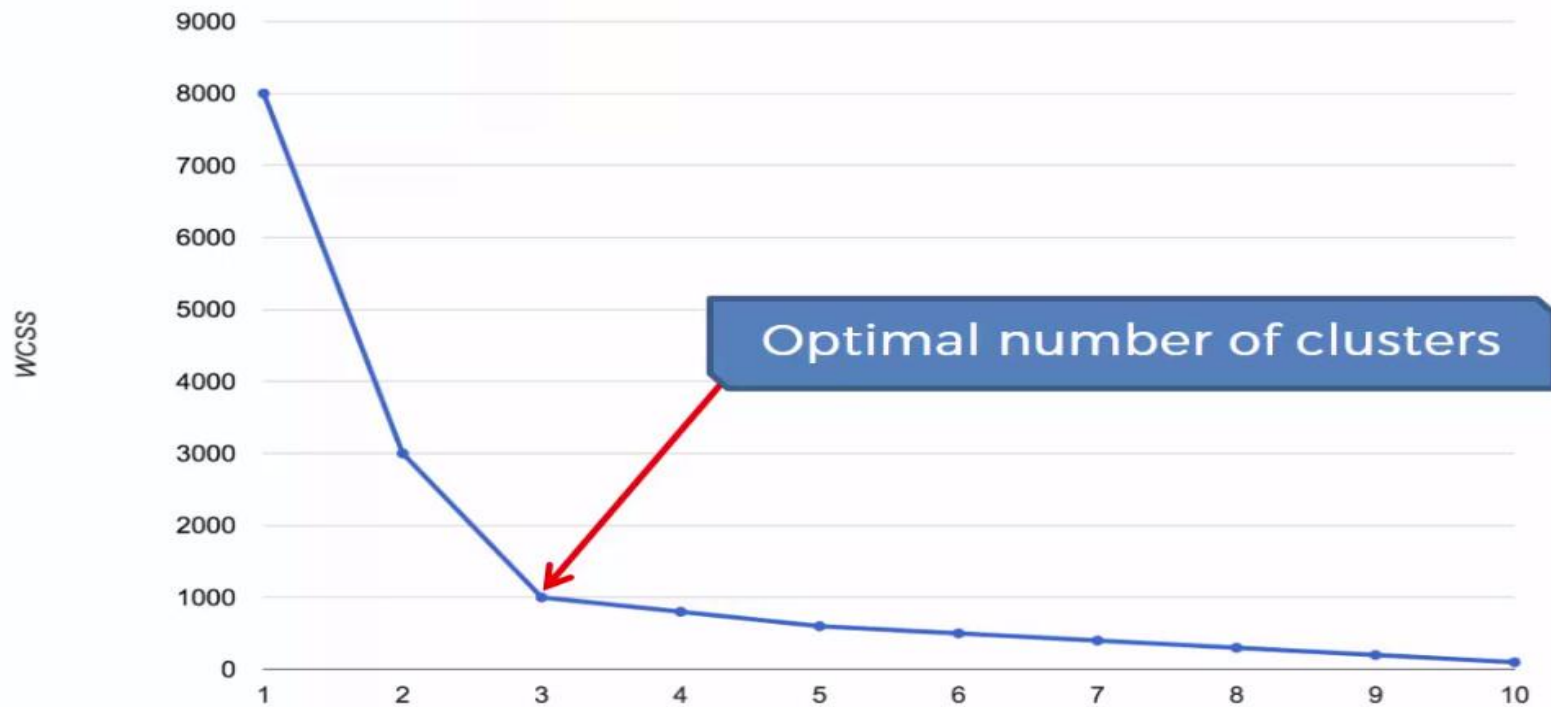


Elbow method



$$WCSS = \sum_{P_i \text{ in Cluster 1}} \text{distance}(P_i, C_1)^2 + \sum_{P_i \text{ in Cluster 2}} \text{distance}(P_i, C_2)^2 + \sum_{P_i \text{ in Cluster 3}} \text{distance}(P_i, C_3)^2$$

The Elbow Method

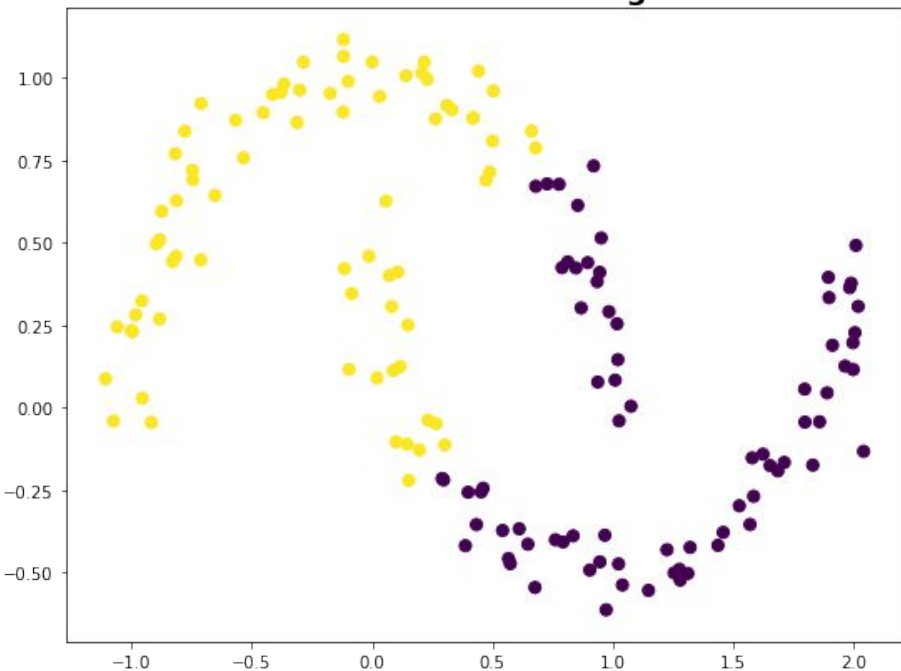


Datasets

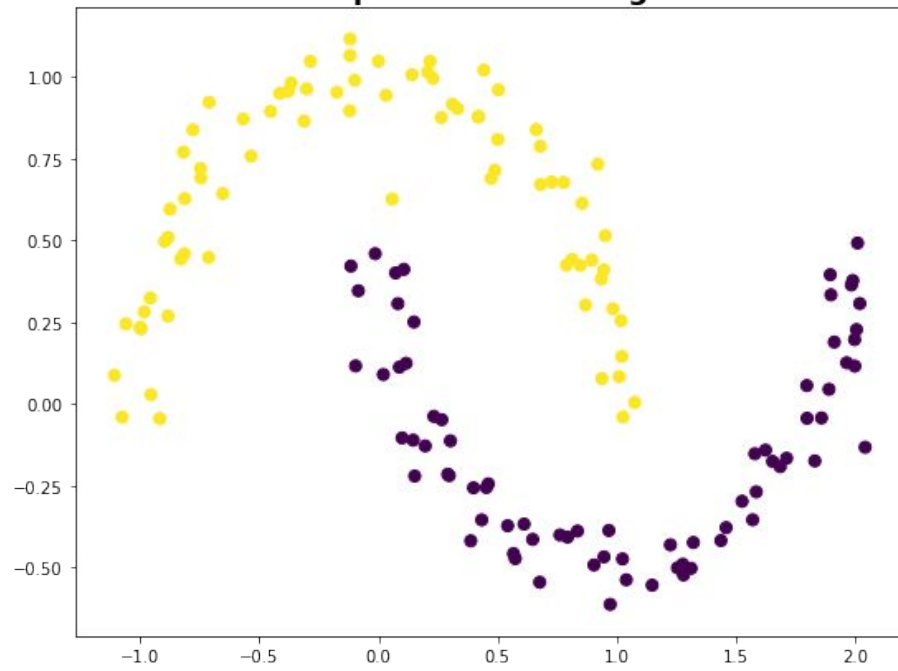
Dataset	Num of instances	Num of attributes	Num of clusters
Moons	150	2	2
Iris	150	4	3
Seeds	210	7	3

Moons dataset

K-means clustering



Spectral clustering



Iris dataset

1. sepal length in cm

2. sepal width in cm

3. petal length in cm

4. petal width in cm

5. Class:

-- Iris Setosa

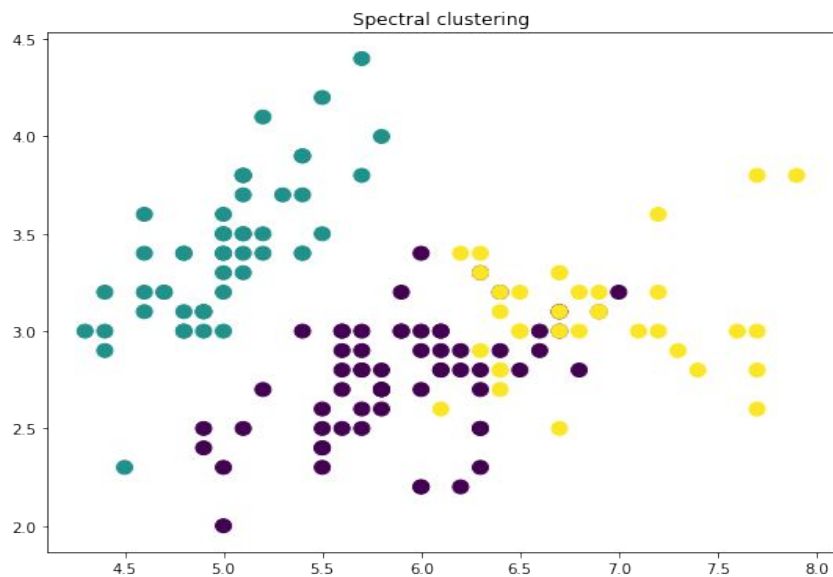
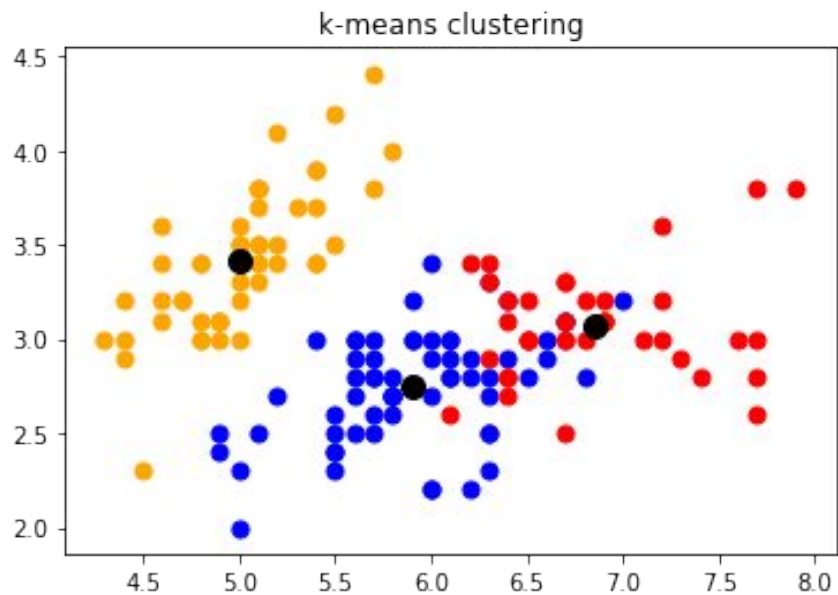
-- Iris Versicolour

-- Iris Virginica

```
dataset.head()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

Iris dataset



Seeds dataset

0. area A,
1. perimeter P,
2. compactness $C = 4 \cdot \pi \cdot A / P^2$,
3. length of kernel,
4. width of kernel,
5. asymmetry coefficient
6. Length of kernel groove.
7. Labels

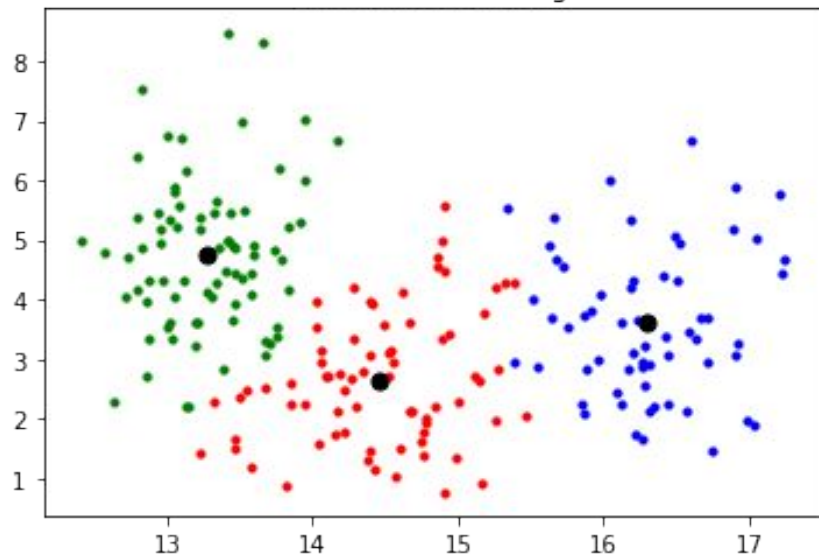
```
data.head()
```

	0	1	2	3	4	5	6	7
0	15.26	14.84	0.8710	5.763	3.312	2.221	5.220	1
1	14.88	14.57	0.8811	5.554	3.333	1.018	4.956	1
2	14.29	14.09	0.9050	5.291	3.337	2.699	4.825	1
3	13.84	13.94	0.8955	5.324	3.379	2.259	4.805	1
4	16.14	14.99	0.9034	5.658	3.562	1.355	5.175	1

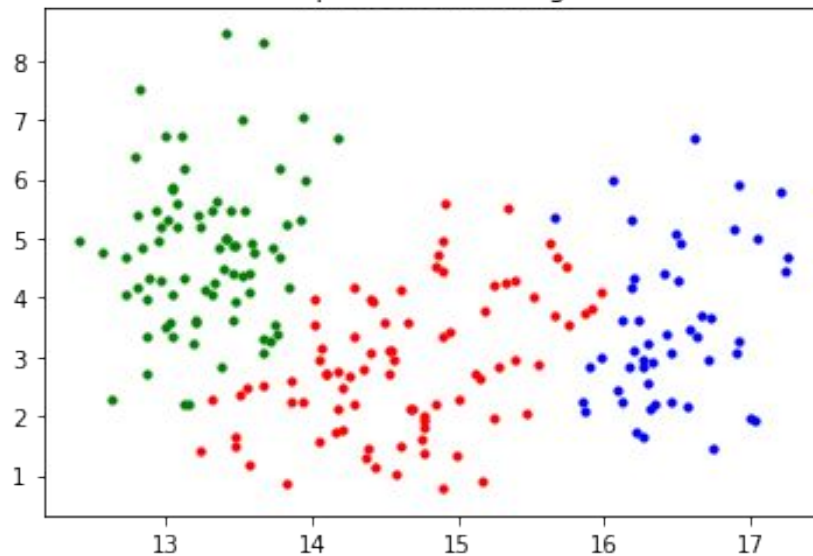
All of these parameters were real-valued continuous.

Seeds dataset

K-means clustering



Spectral Clustering



K-means vs Spectral Clustering

K-Means:

- Efficient
- Fast and simple
- Need to pick K
- Sensitive to outliers
- Only finds “spherical” clusters

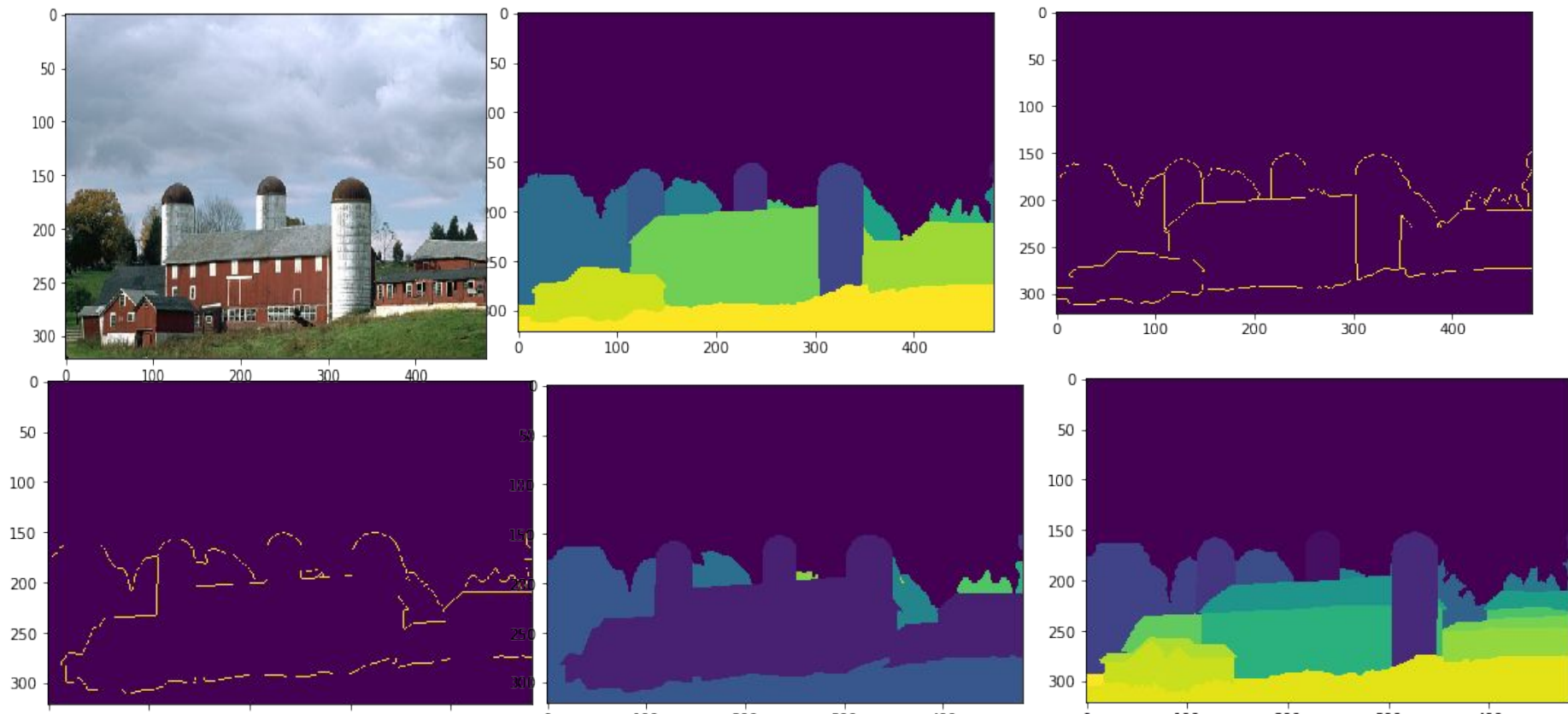
Spectral clustering:

- Excellent quality under many different data forms
- Much slower than KMeans

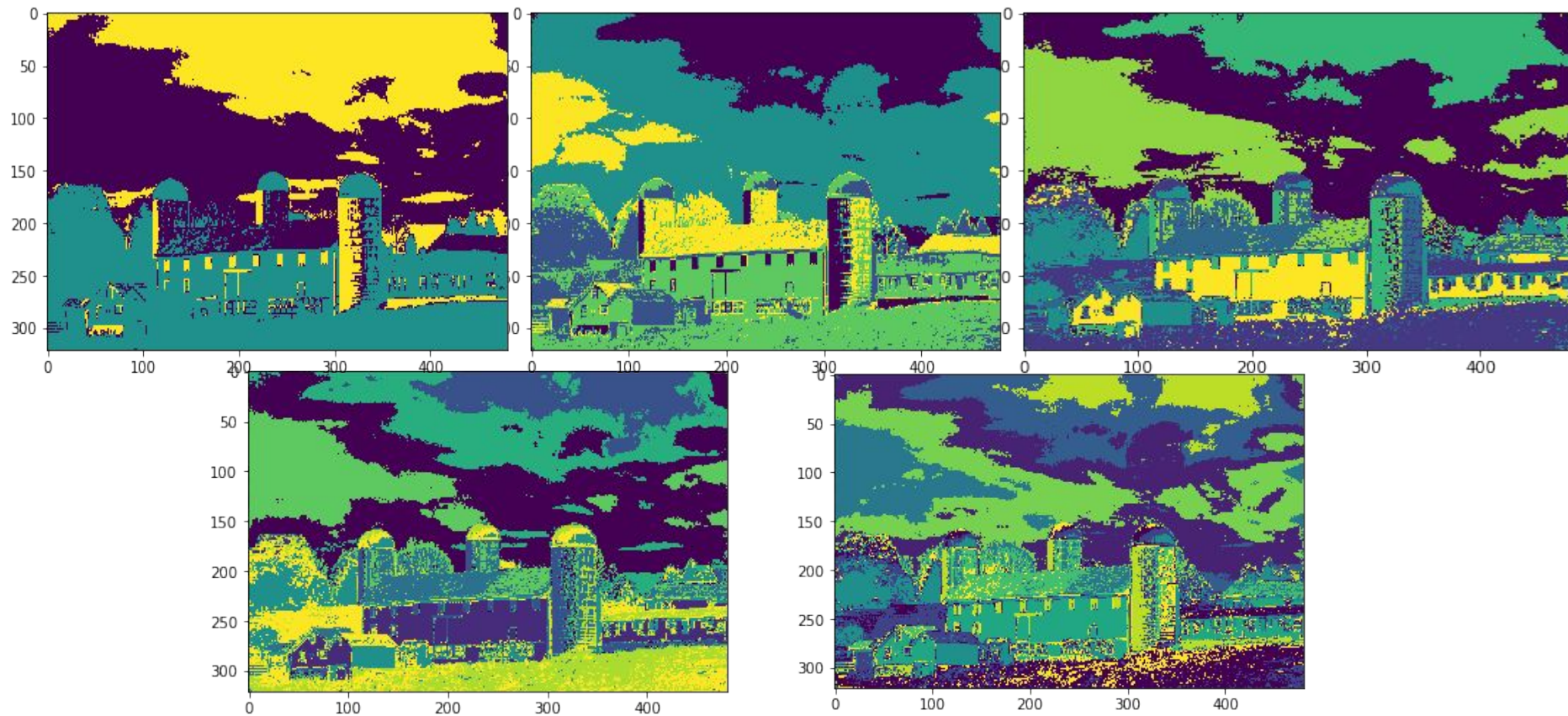
Image Segmentation

- We will use Berkeley Segmentation Benchmark:
 - Original images (.jpg) and ground truth (.mat)
 - Each image have 5 ground truth segmentations
- Apply k-means and spectral clustering algorithms
- The evaluation using F-measures and Conditional Entropy

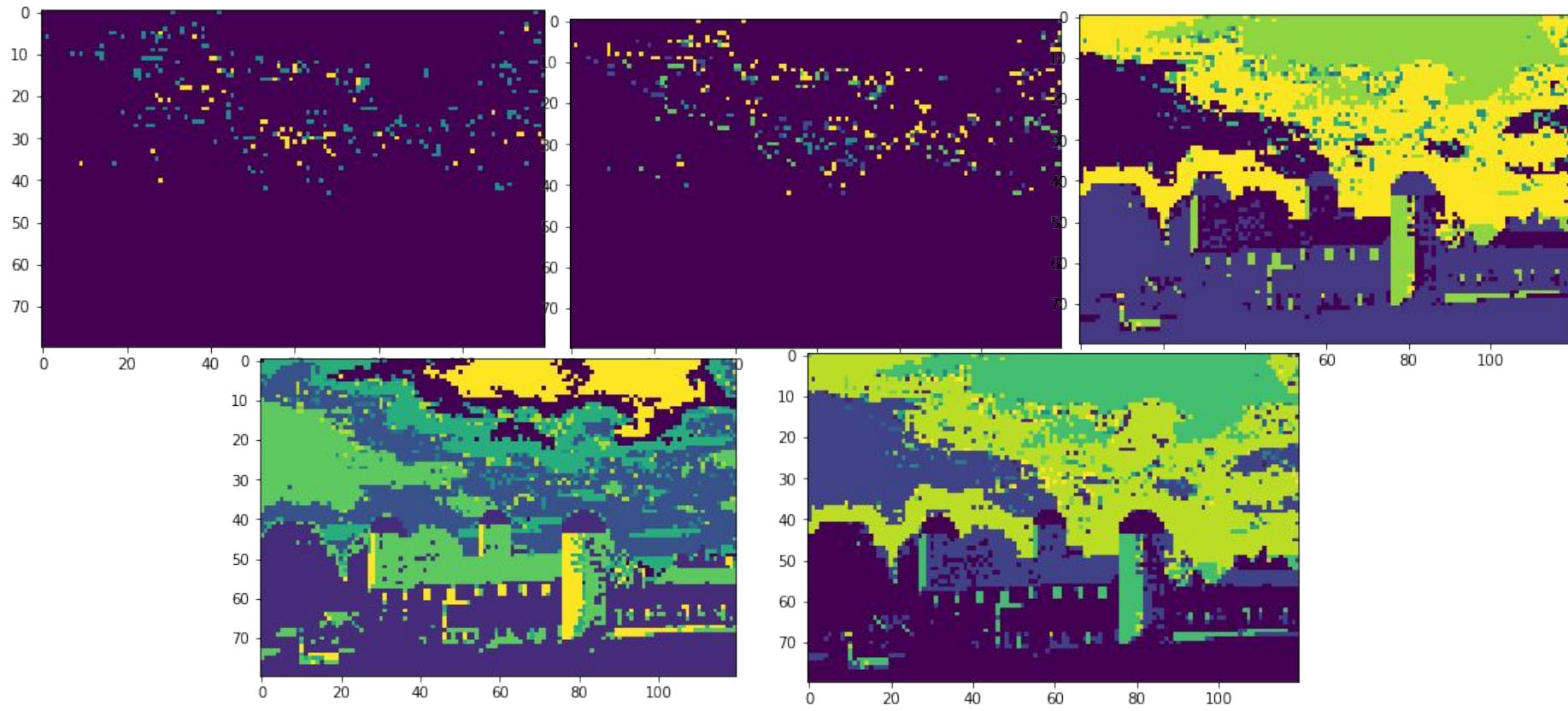
Original image and GroundTruth



K-means: k=3,5,7,9,11



Spectral clustering: $k=3,5,7,9,11$



F1 score & Conditional Entropy

k	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10	k=11
F1 score	0.00045	0.02893	0.23084	0.04445	0.03253	0.28533	0.28359	0.26506	0.02397	0.02072
Condition Entropy	0.20140	0.23542	0.24351	0.26916	0.53136	0.41086	0.46782	0.64620	0.44827	0.69523

Thank you!