Mean Shift Image Segmentation

A Non-parametric Clustering Technique for Image Analysis

by

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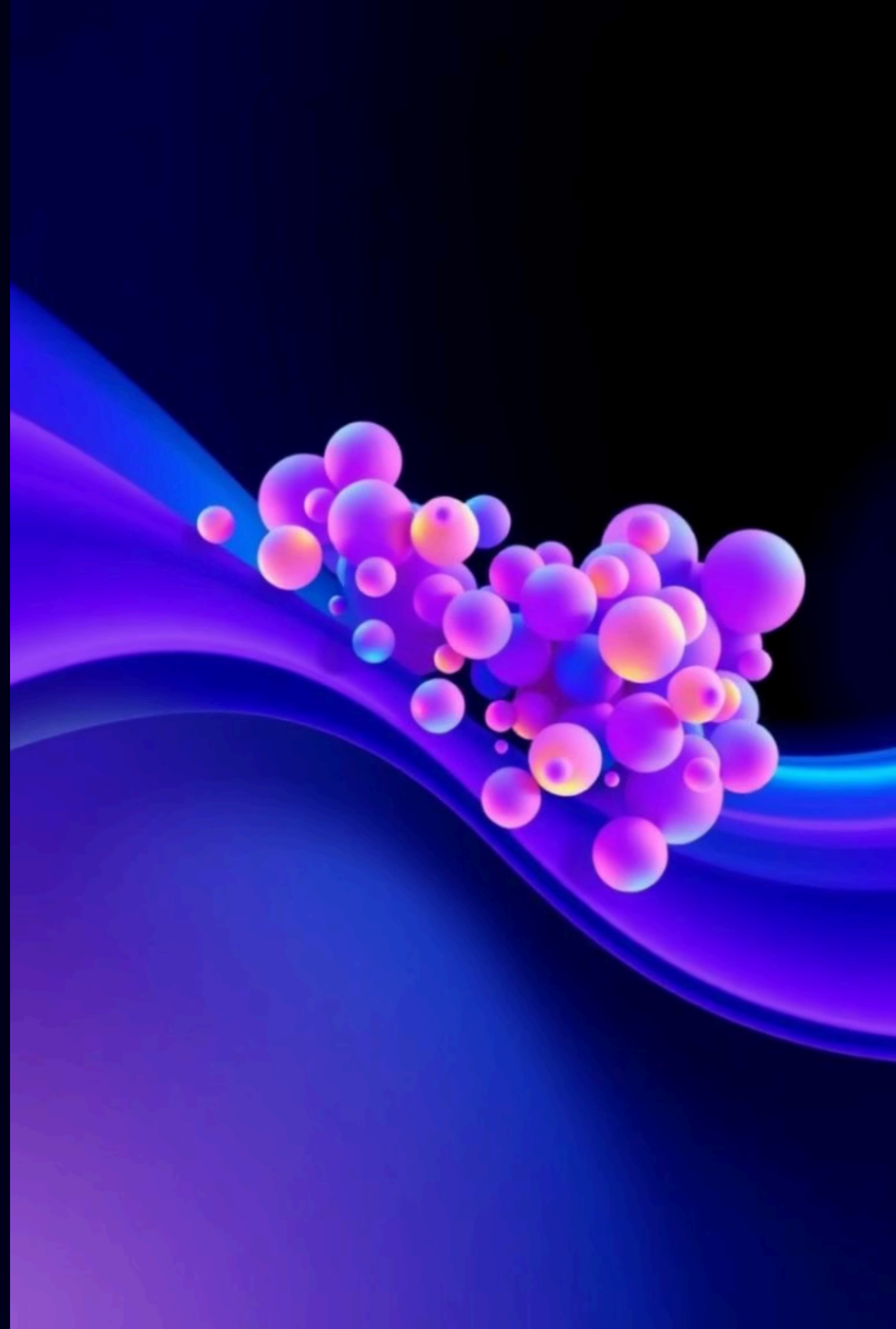
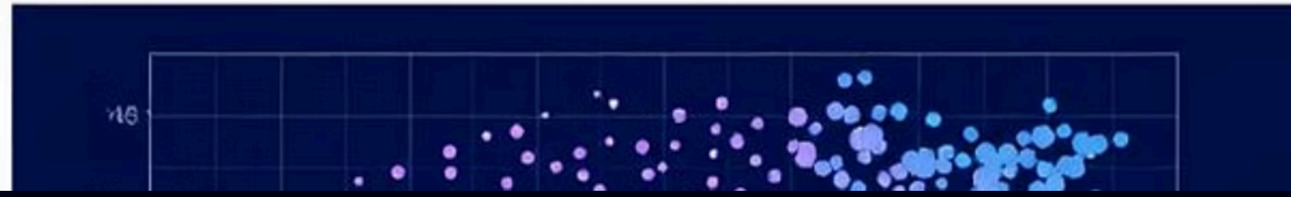
2023510017





Introduction to Image Segmentation

What is Image Segmentation?

Dividing an image into meaningful regions for analysis.

Importance

Critical for object recognition, medical imaging, and scene understanding.

Common Techniques

- Thresholding
- Edge-based
- Region-based
- Clustering-based

Mean Shift

Mean Shift is a non-parametric clustering technique used to locate dense regions in data.

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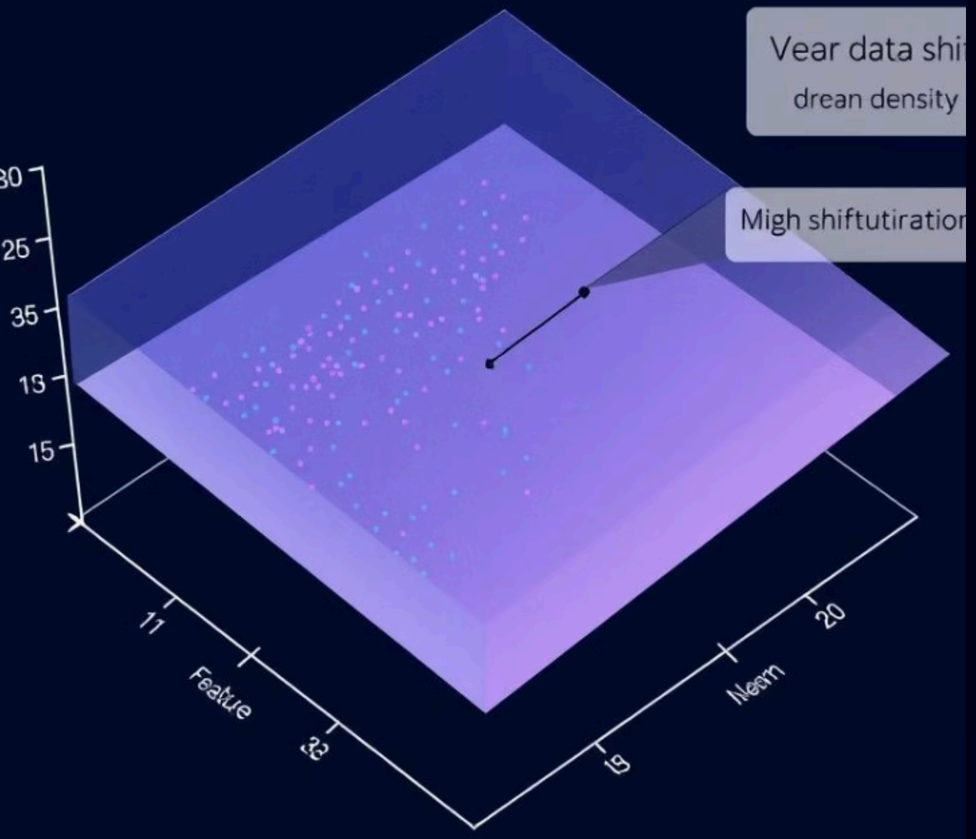


Understanding Mean Shift

Non-parametric Method

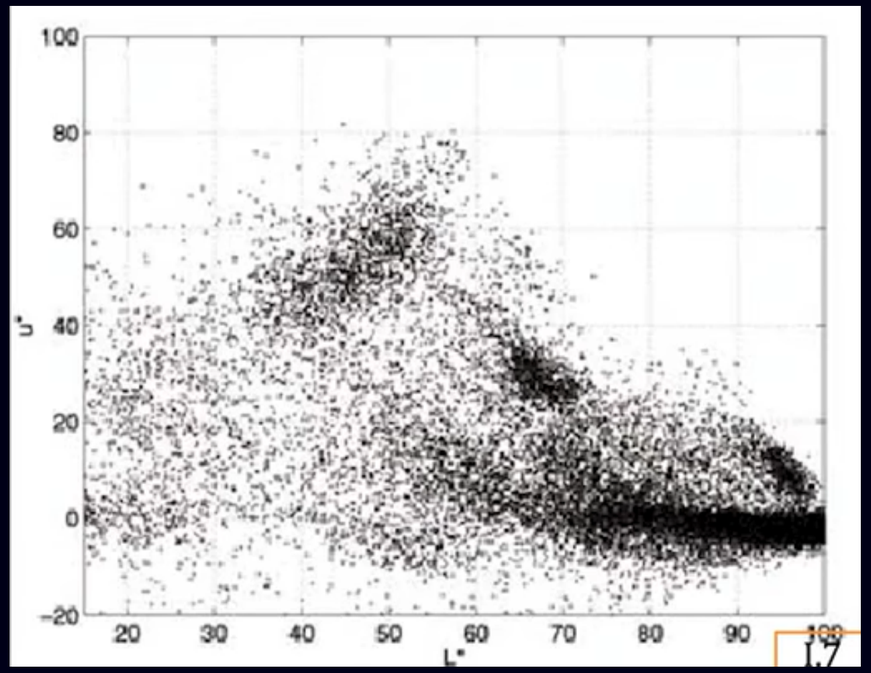
Does not assume a fixed distribution; uses kernel density estimation.

Iterative Process

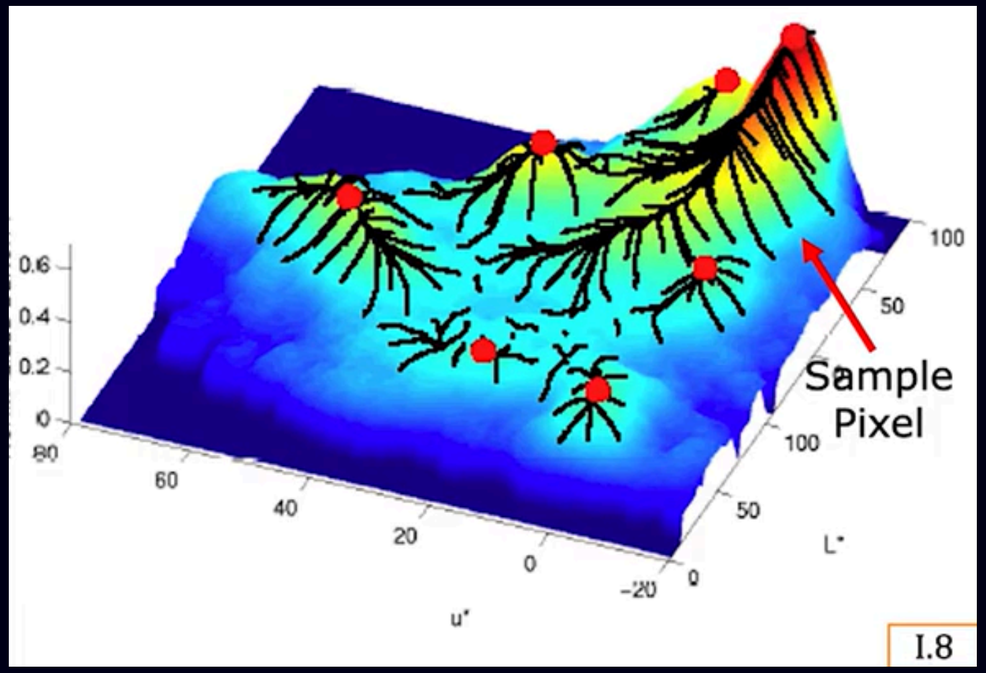
Shifts points toward local maxima of data density (modes).

Data-Driven

Automatically finds cluster centers without pre-specifying their number.

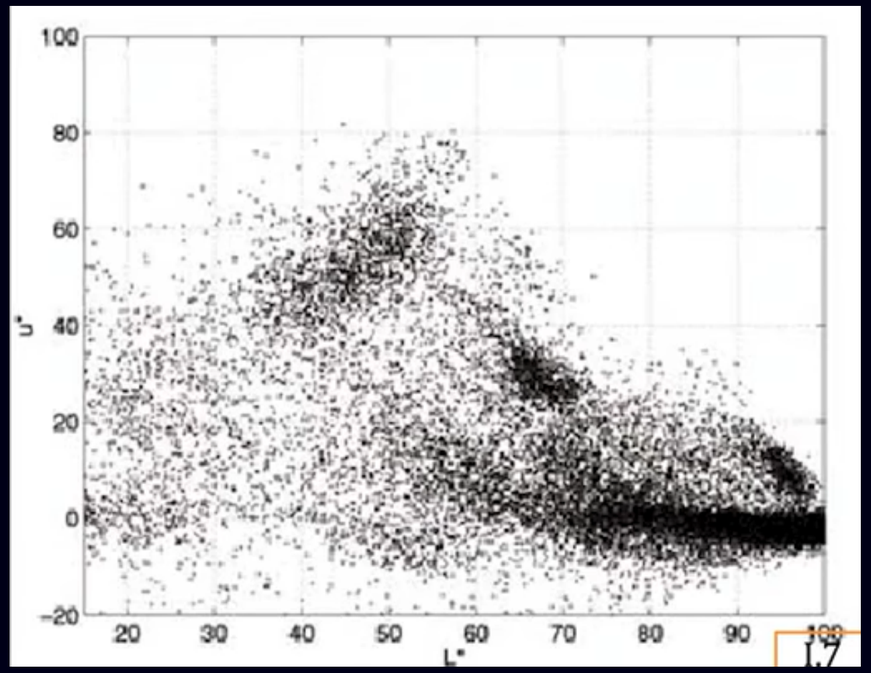


Pixel Feature Distribution

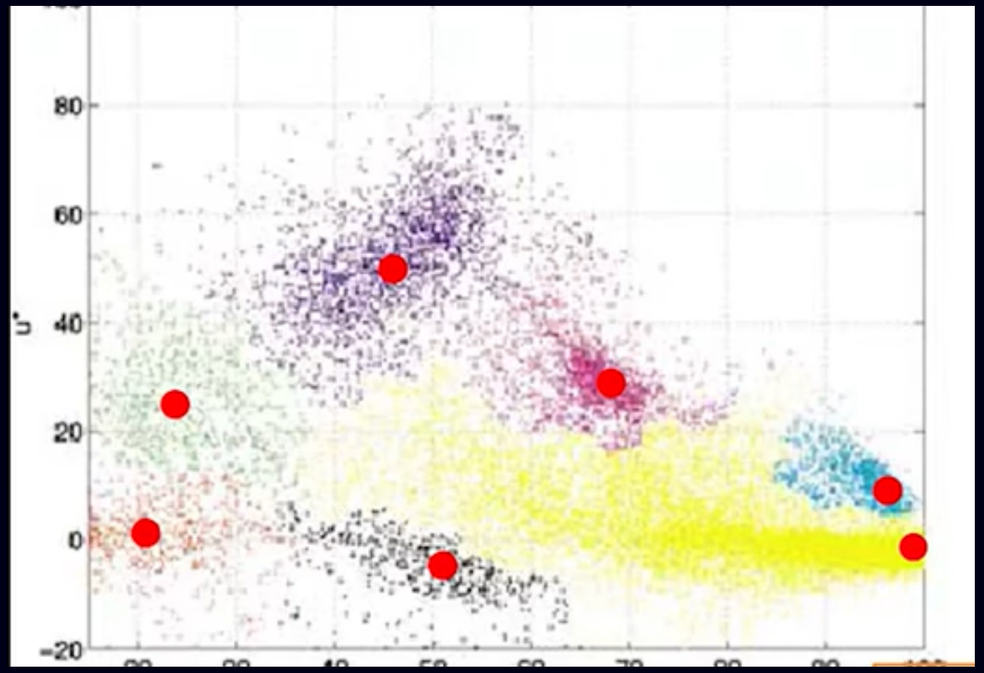


Normal Distribution

- Each hill represents a cluster.
- Peak (mode) of hill represents “center” of cluster.
- Each pixel climbs the steepest hill within its neighborhood.
- Pixel assigned to the hill (cluster) it climbs.



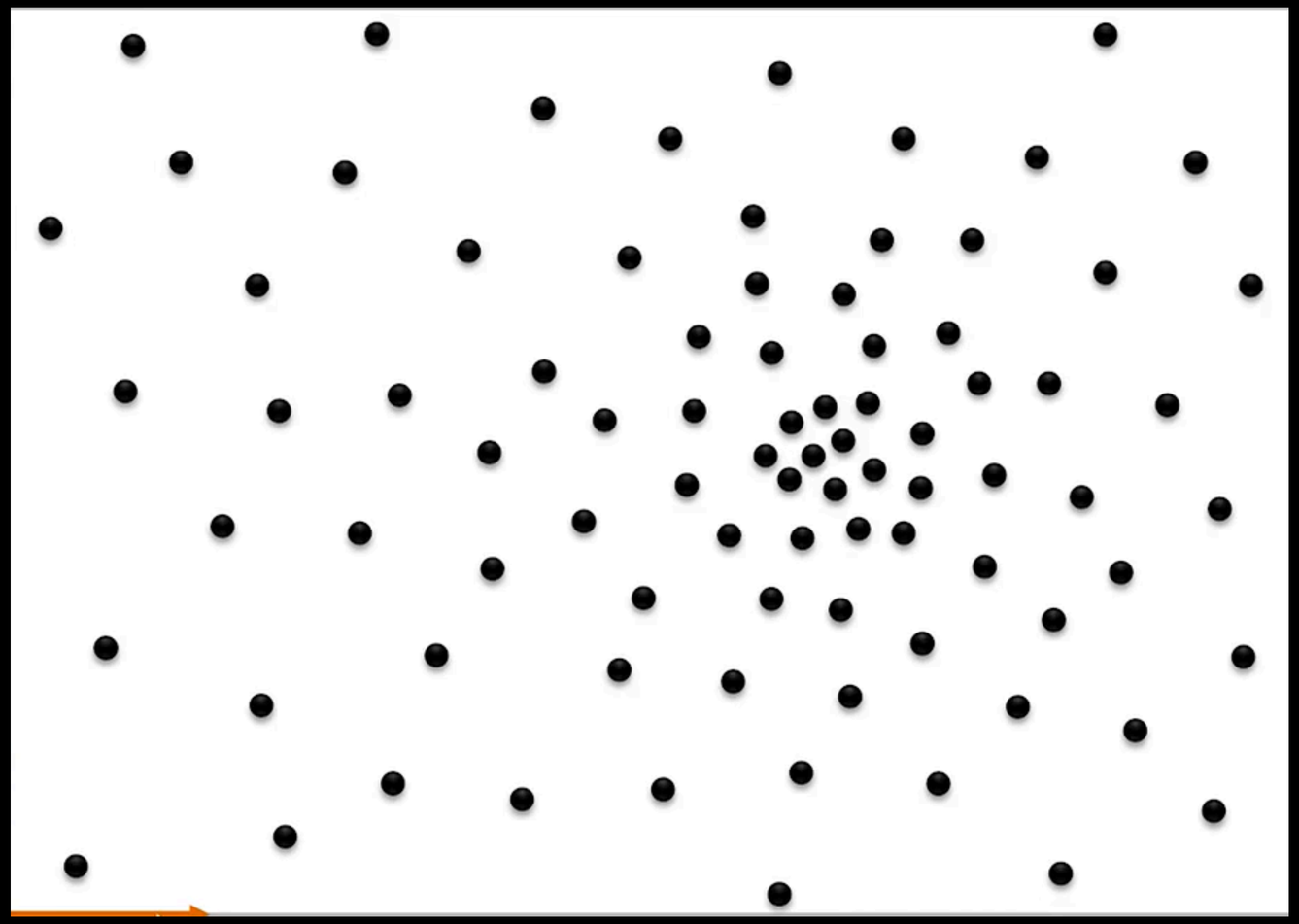
Pixel Feature Distribution



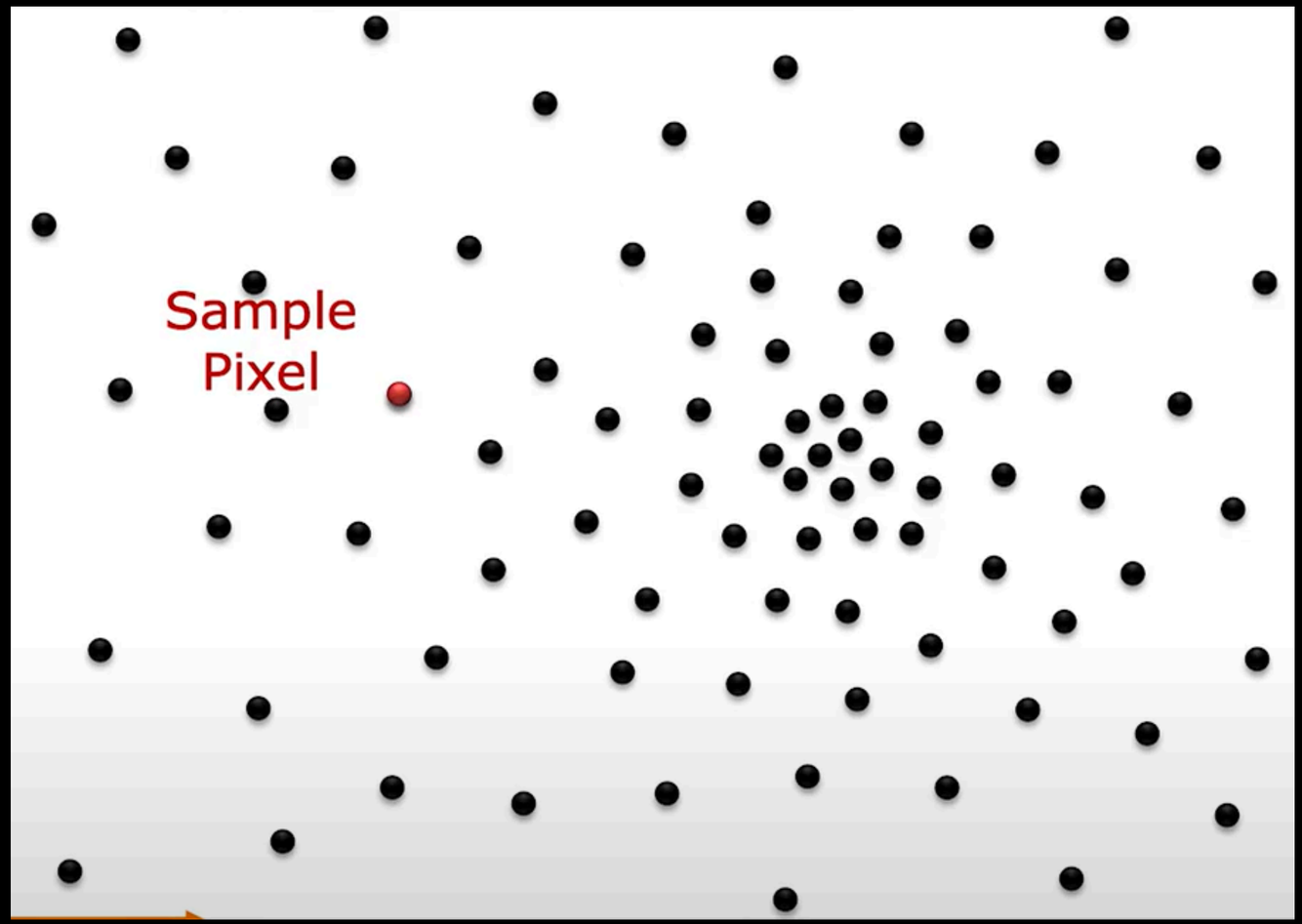
Colored Pixel Feature Distribution

- Each hill represents a cluster.
- Peak (mode) of hill represents “center” of cluster.
- Each pixel climbs the steepest hill within its neighborhood.
- Pixel assigned to the hill (cluster) it climbs.

Hill-Climb using Mean-shift

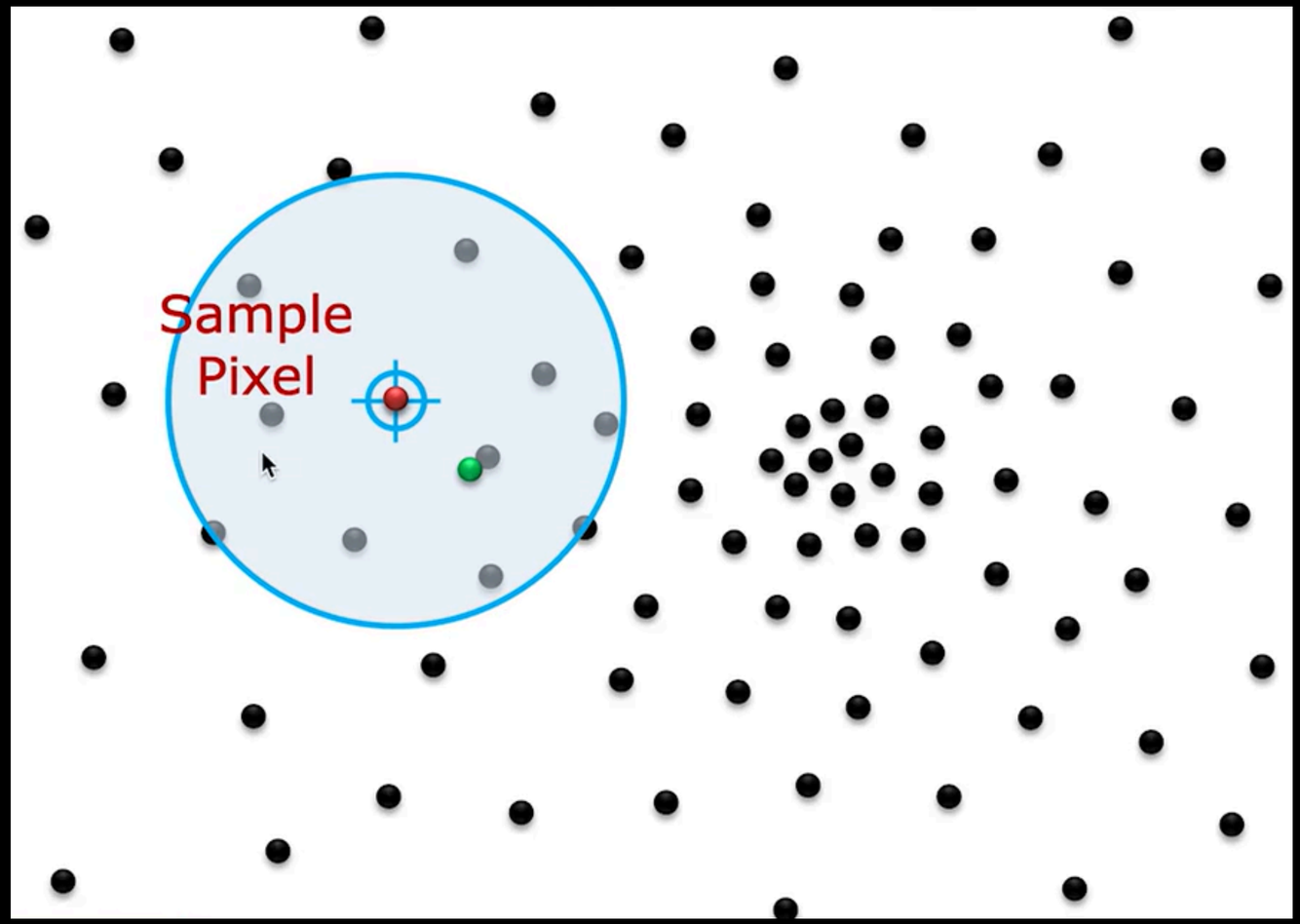


Hill-Climb using Mean-shift



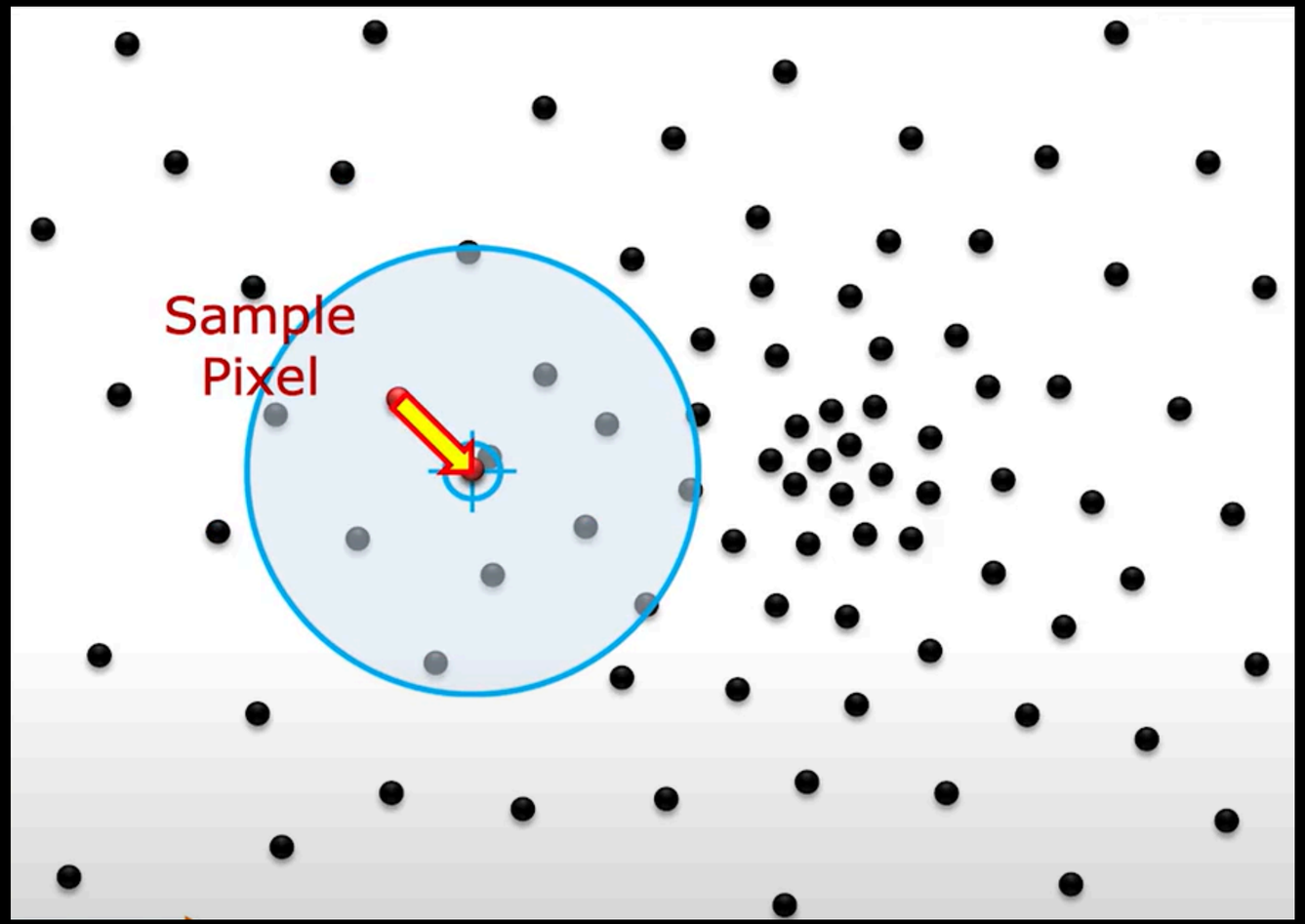
- Select a random pixel to initiate

Hill-Climb using Mean-shift



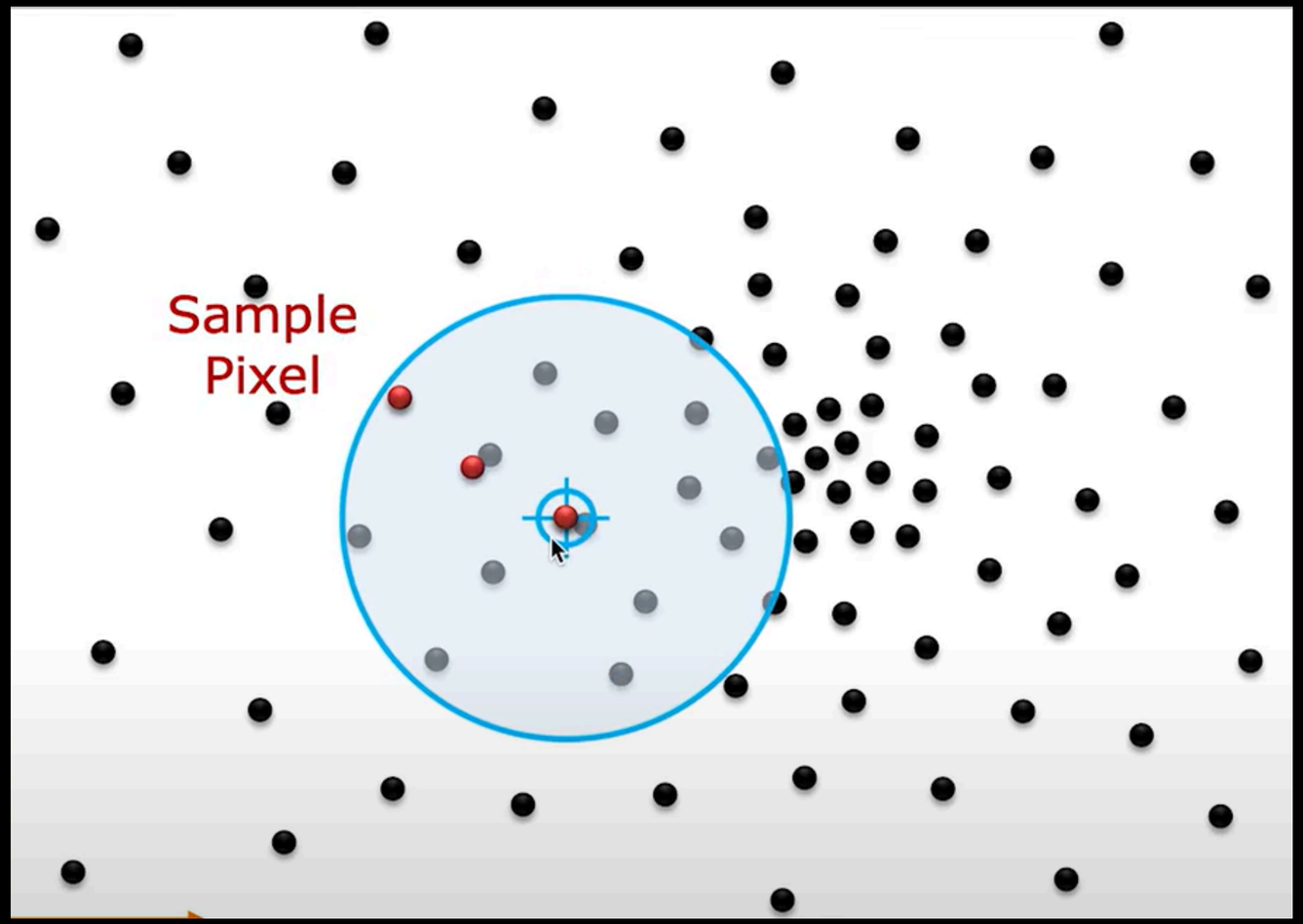
- Compute a (.) centroid within the window W

Hill-Climb using Mean-shift



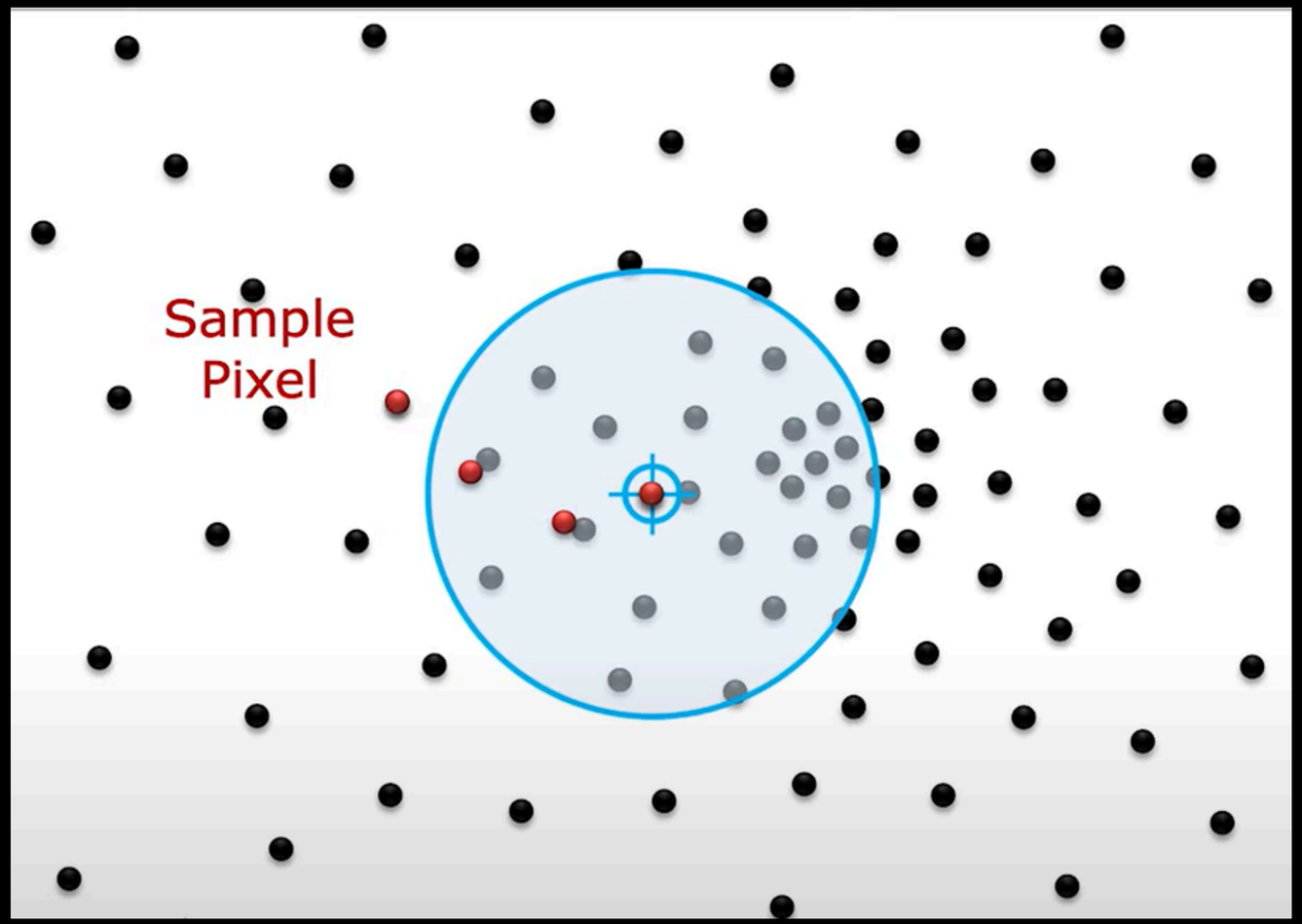
- Shift the mean to the centroid

Hill-Climb using Mean-shift



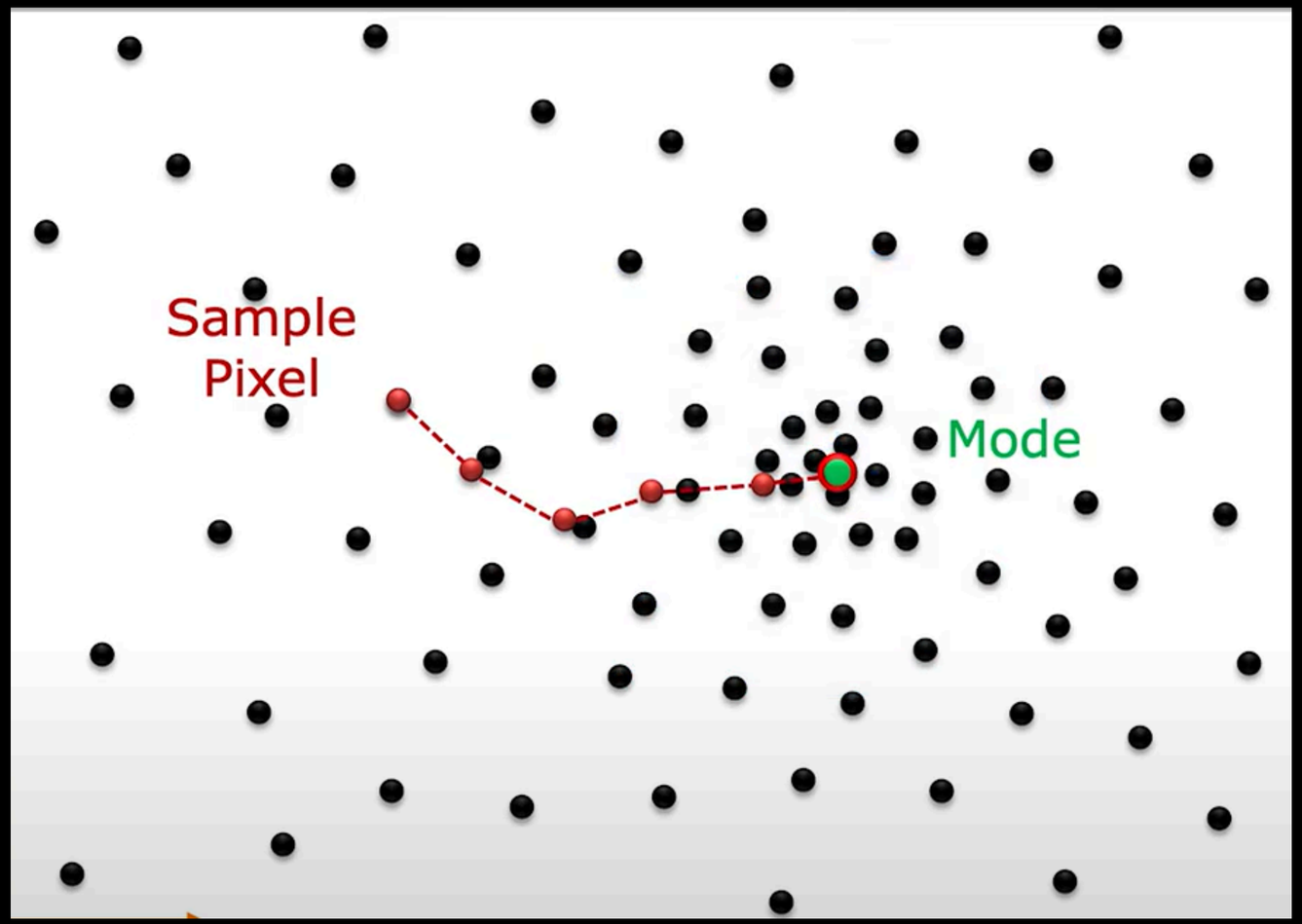
- Repeat untill it converge

Hill-Climb using Mean-shift



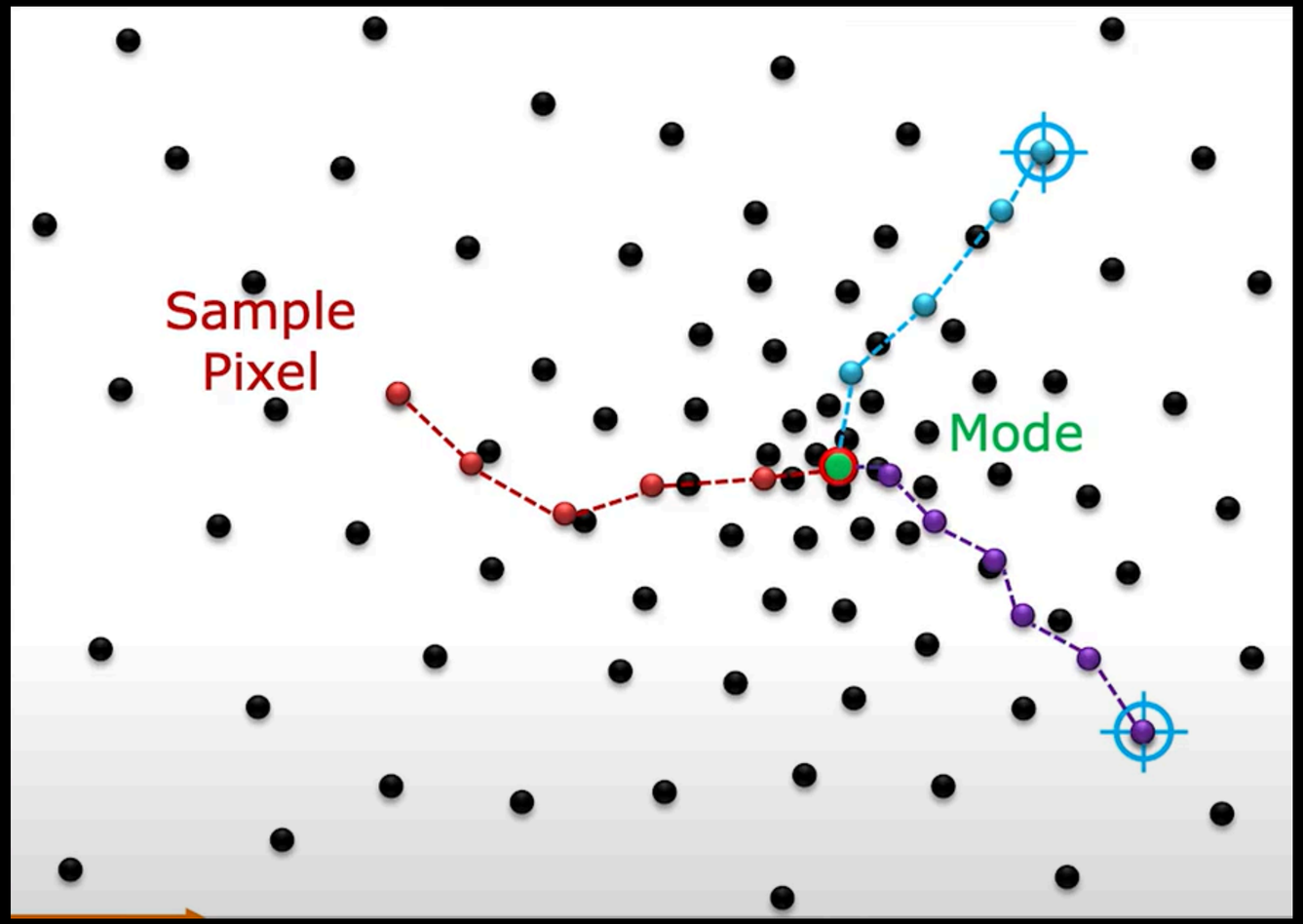
- Repeat untill it converge

Hill-Climb using Mean-shift



- Declare mode and assign it as cluster label

Hill-Climb using Mean-shift



- Repeat for all pixels

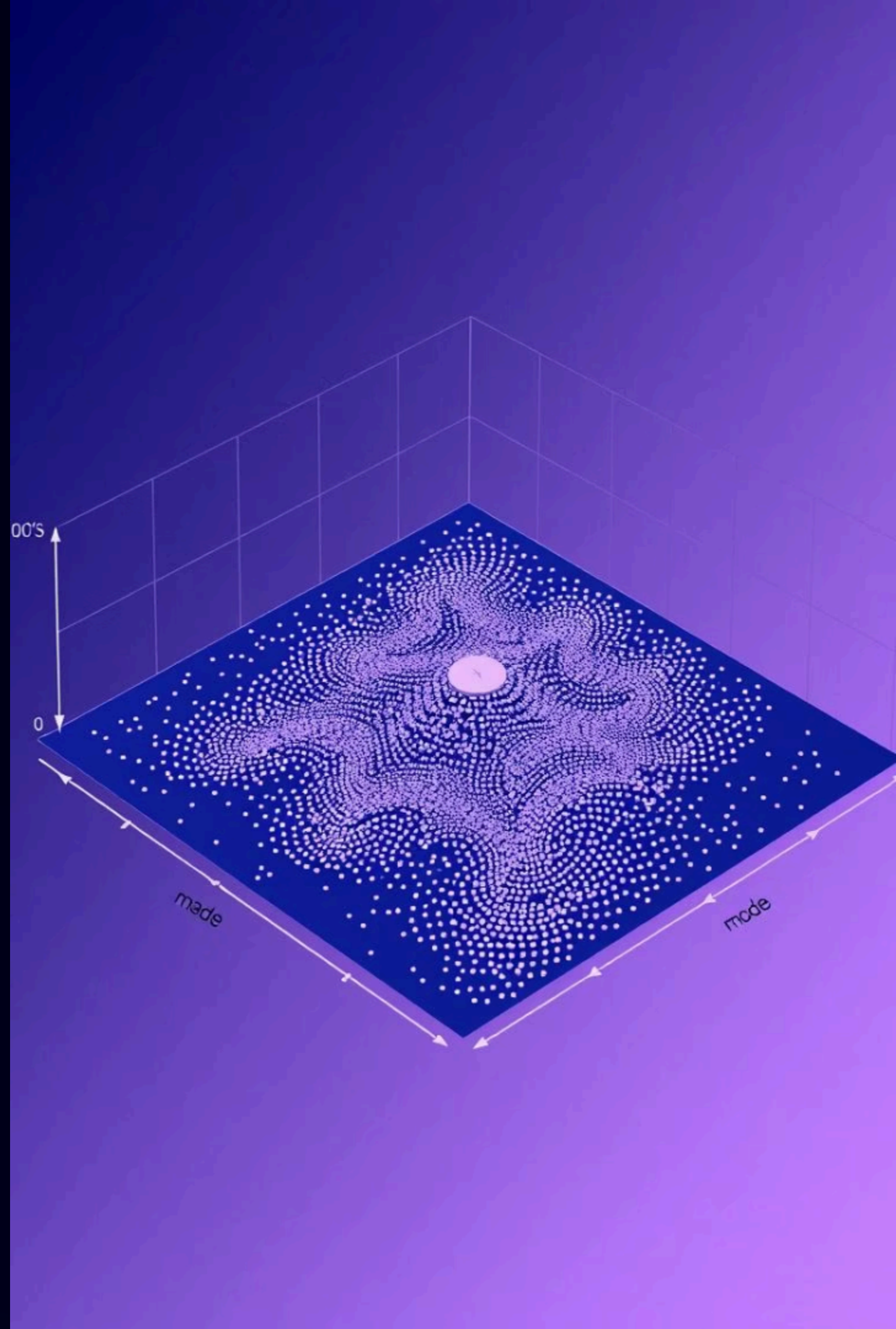
Mean-shift Algorithm

Given: Distribution of N pixels in feature space.

Task: Find modes (clusters) of the distribution.

Clustering Steps:

1. Set $m_i = f_i$ as the initial mean for each pixel i.
2. Repeat the following for each mean m_i:
   a. Place a window of size W around m_i.
   b. Compute the centroid m within the window. Set $m_i = m$.
   c. Stop if the shift in mean m_i is less than a threshold ε.
3. Then m_i is the mode.
4. Label all pixels that have the same mode as belonging to the same cluster.



Visual Comparison of Segmentation Methods

Original Image

Raw input with complex structures and colors.

Mean Shift Output

Smoothly segmented with clear boundaries and fewer artifacts.

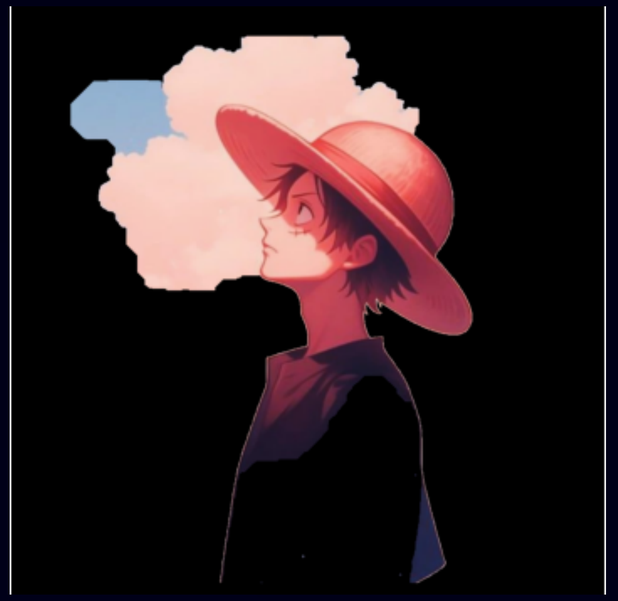
Other Methods

K-means and graph cut show varying boundary sharpness and cluster shapes.

Original Image

Mean-shift

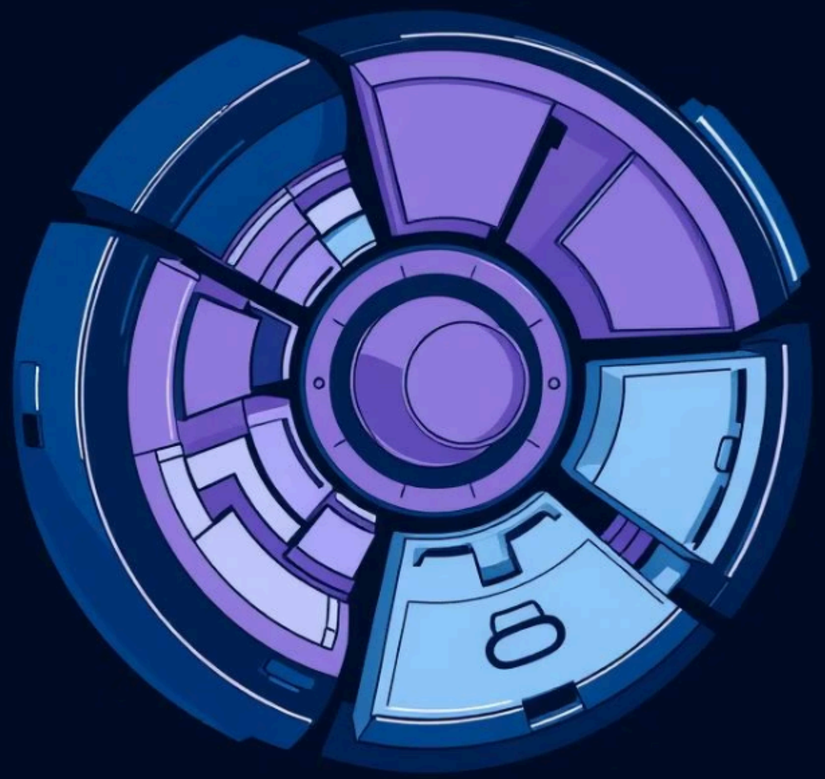
K-means



Graph cut

Mean-shift Outputs

Mean-shift Outputs



Advantages of Mean Shift Segmentation

No Predefined Clusters

Dynamic detection of cluster count from data.

Arbitrary Shape

Clusters of any shape can be detected accurately.

Smooth Boundaries

Produces visually coherent segment borders.

Noise Robust

Less sensitive to noise compared to other clustering methods.

Limitations and Challenges

Computational Cost

Iterative shifting is computationally intensive on large images.

Bandwidth Selection

Bandwidth parameter heavily influences segmentation quality.

Scalability

Scaling to high-dimensional features or large datasets is challenging.

Applications of Mean Shift

Object Tracking

Tracks object contours by following modes in feature space.

Image Segmentation

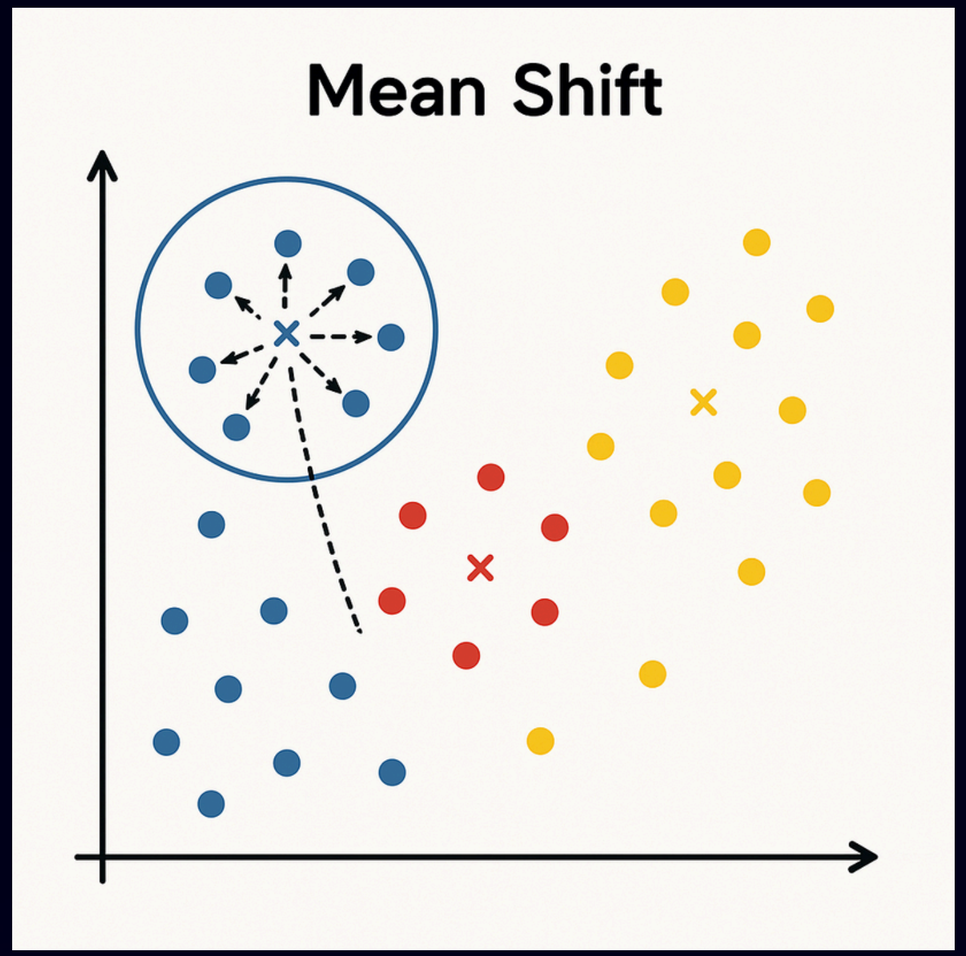
Separates objects/regions for recognition and analysis.

Mode Detection

Detects dense regions for data analysis in many contexts.

Scene Understanding

Aids in comprehending complex environments and structures visually.



Mean Shift comments

1. Simple but computationally expensive
2. Finds arbitrary number of clusters
3. No initialization required
4. Robust to outliers


TO BE
CONTINUED