

INTRODUCING UNSUPERVISED LEARNING

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REFERENCES

The material for this talk is primarily drawn from the notes, slides and lectures of the courses below:

Applied Machine Learning in Python

University of Michigan, Prof. Kevin Collins Thompson

<https://www.coursera.org/learn/python-machine-learning/home/welcome>

Machine Learning: Clustering & Retrieval

University of Washington, Profs. Emily Fox & Carlos Guestrin

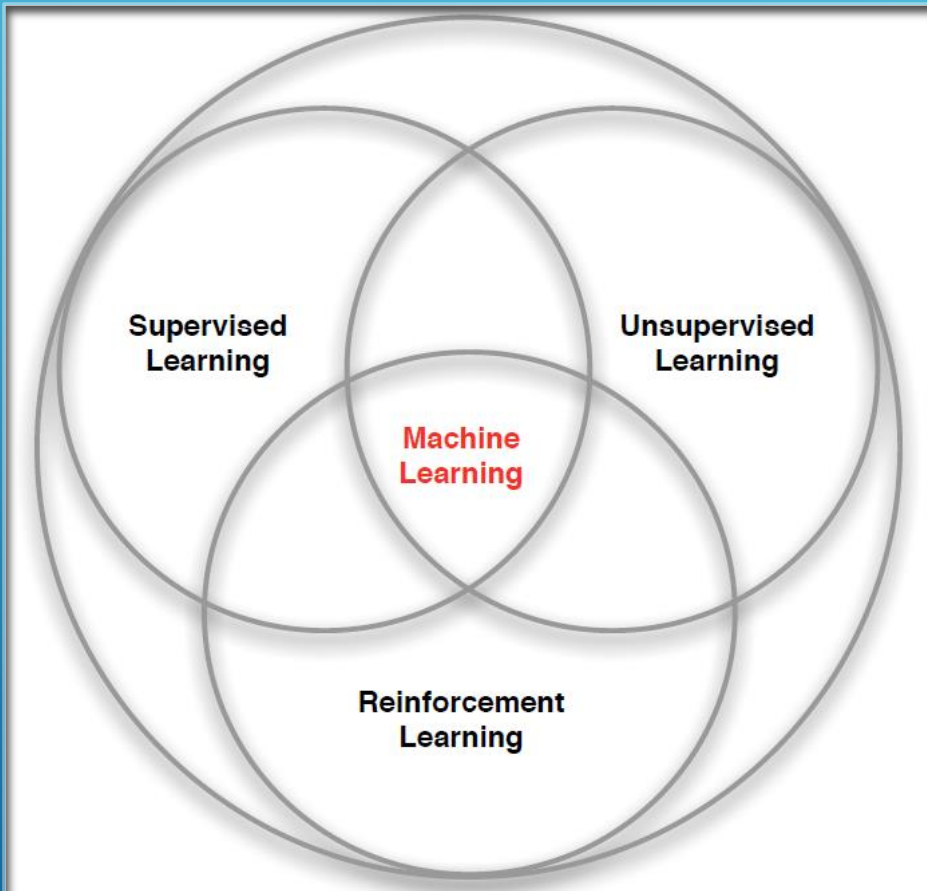
<https://www.coursera.org/learn/ml-regression/home/welcome>

The Hundred-Page Machine Learning Book (Ch. 9)

Andriy Burkov

<http://themlbook.com/>

3 TYPES OF MACHINE LEARNING



Supervised Learning – Learn a function from labeled data that maps input attributes to an output label e.g., linear regression, decision trees, SVMs.

Unsupervised Learning – Learn patterns in unlabeled data e.g., principle component analysis or clustering algorithms such as K-means, HAC, or Gaussian mixture models.

Reinforcement Learning – An agent learns to maximize rewards while acting in an uncertain environment.

WHAT IS UNSUPERVISED LEARNING?

- Unsupervised learning involves tasks that operate on datasets without labeled responses or target values.
- The goal is to discover interesting structure or information in the dataset.

APPLICATIONS OF UNSUPERVISED LEARNING

- Visualize structure of a complex dataset.
- Density estimation to predict probabilities of events.
- Compress and summarize the data.
- Extract features for supervised learning.
- Discover important clusters or outliers.

FOUR KINDS OF UNSUPERVISED LEARNING

References:

[The Hundred-Page Machine Learning Book](#). Andriy Burkov.

[Applied Machine Learning in Python](#). Coursera. University of Michigan, Prof. Kevin Collins Thompson

Cluster analysis,
https://en.wikipedia.org/w/index.php?title=Cluster_analysis&oldid=1002271612 (last visited Jan. 27, 2021).

Dimensionality reduction,
https://en.wikipedia.org/w/index.php?title=Dimensionality_reduction&oldid=1002754996 (last visited Jan. 27, 2021).

1. Density Estimation

- Model the probability density function of the unknown probability distribution from which the dataset has been drawn.

2. Dimensionality Reduction

- Finds an approximate version of a dataset using fewer features while retaining some meaningful properties of the original data.

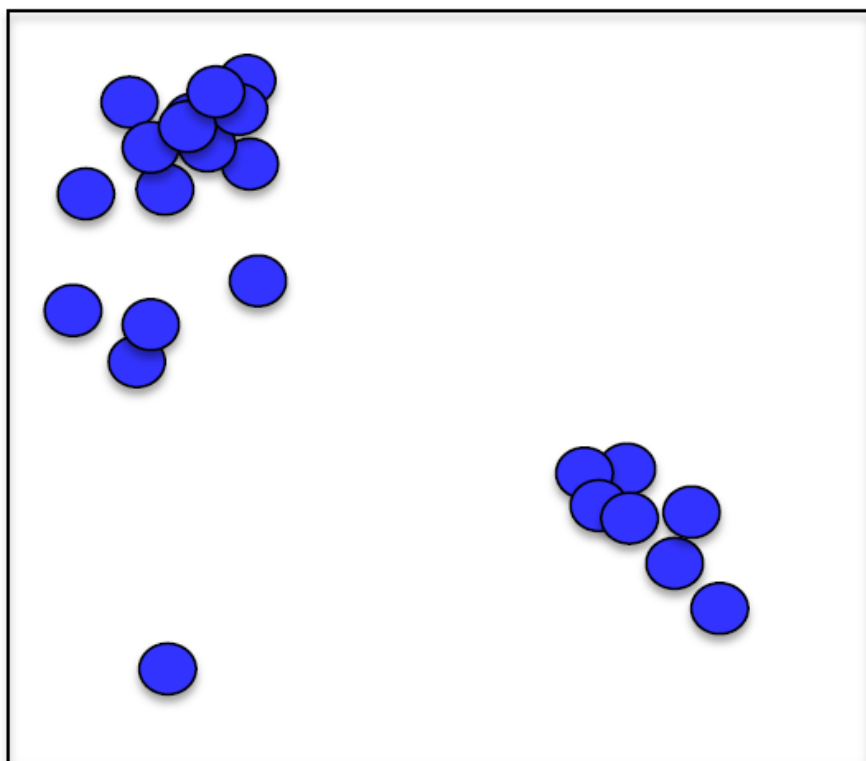
3. Outlier Detection

- Detect the examples in the dataset that are very different from what a typical example in the dataset looks like.

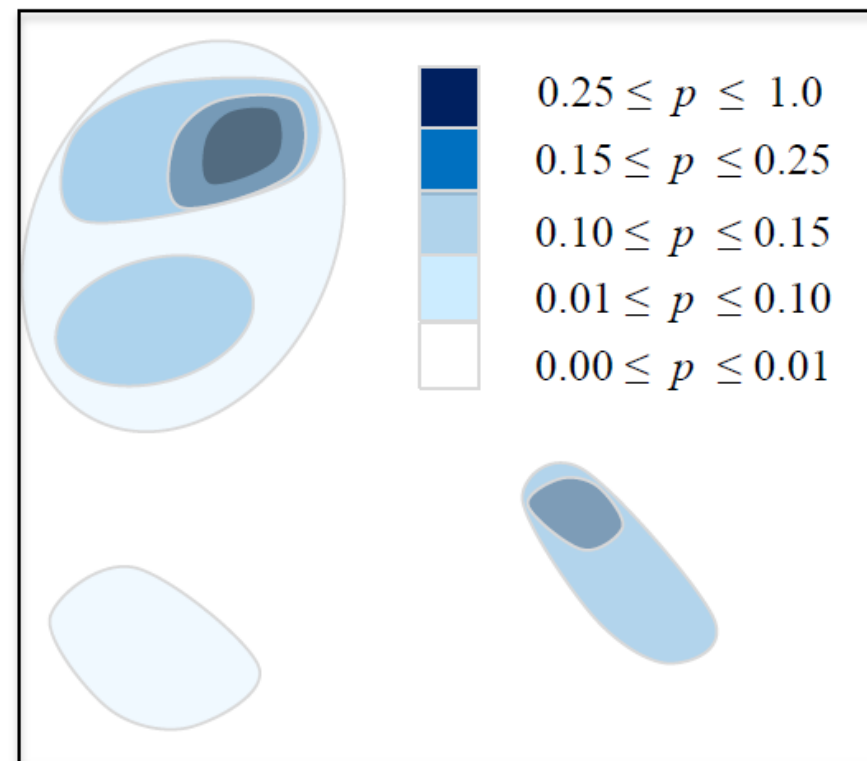
4. Clustering

- The task of grouping a set of objects in such a way that objects in the same group (called a **cluster**) are more like each other than to those in other groups (clusters).

DENSITY ESTIMATION

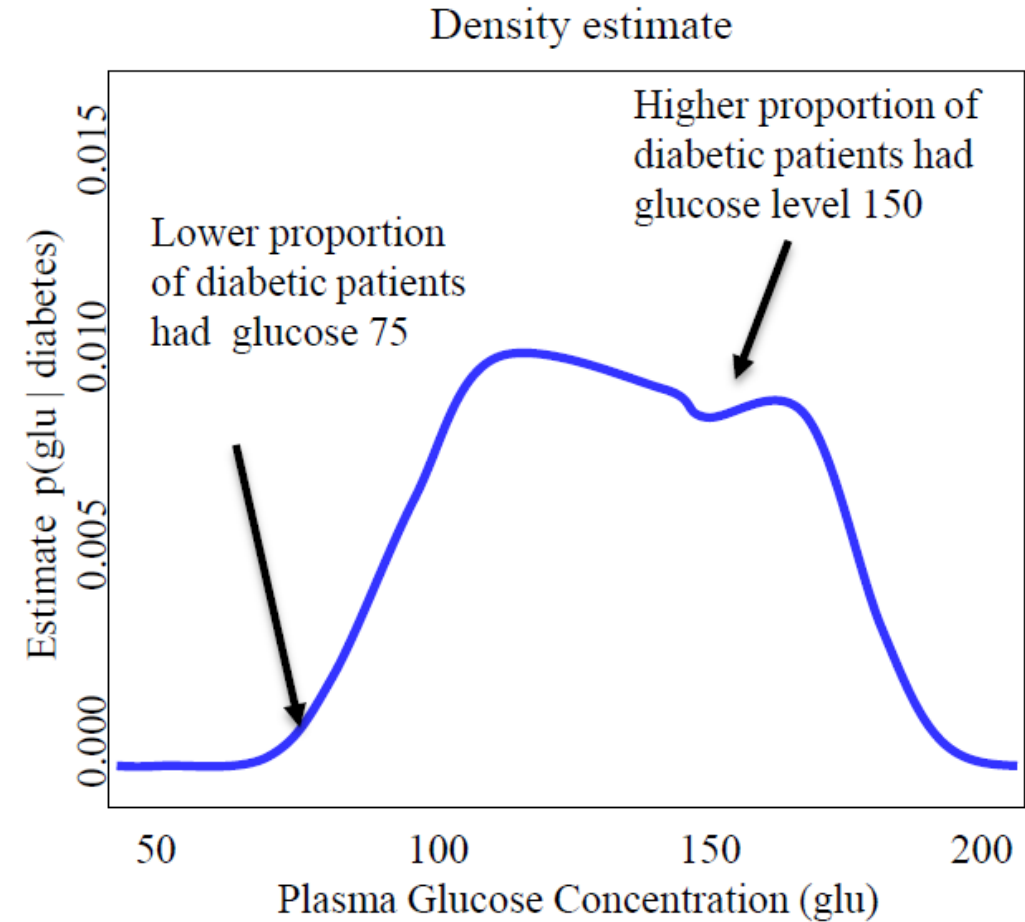
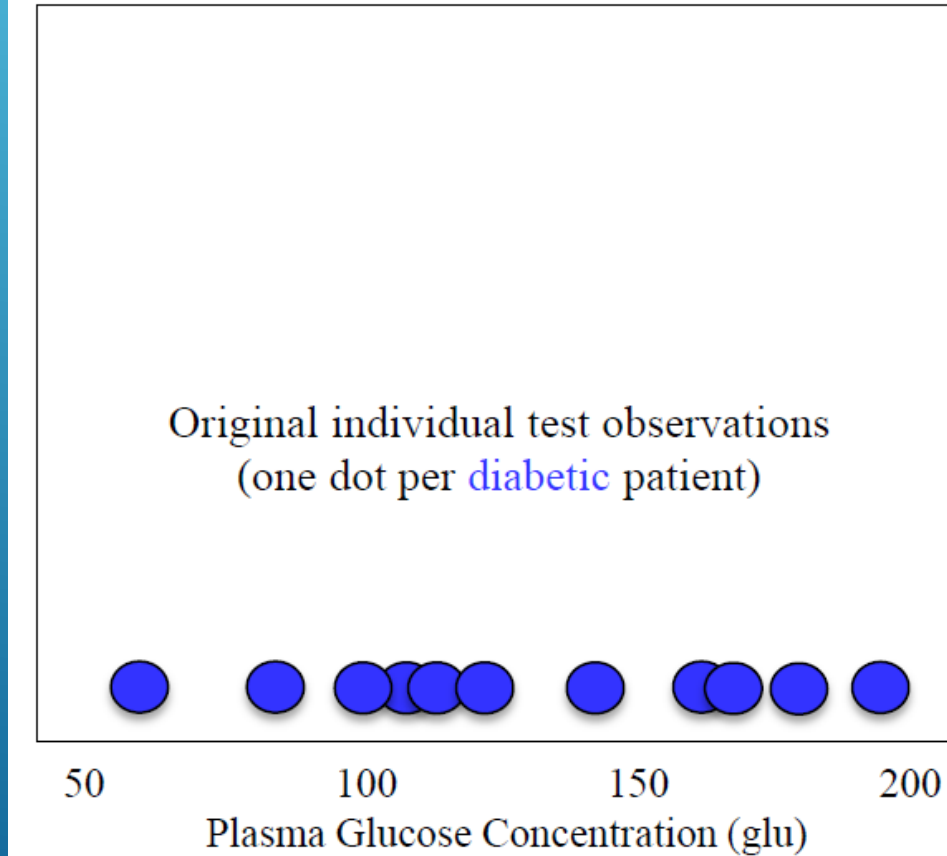


Individual measurements

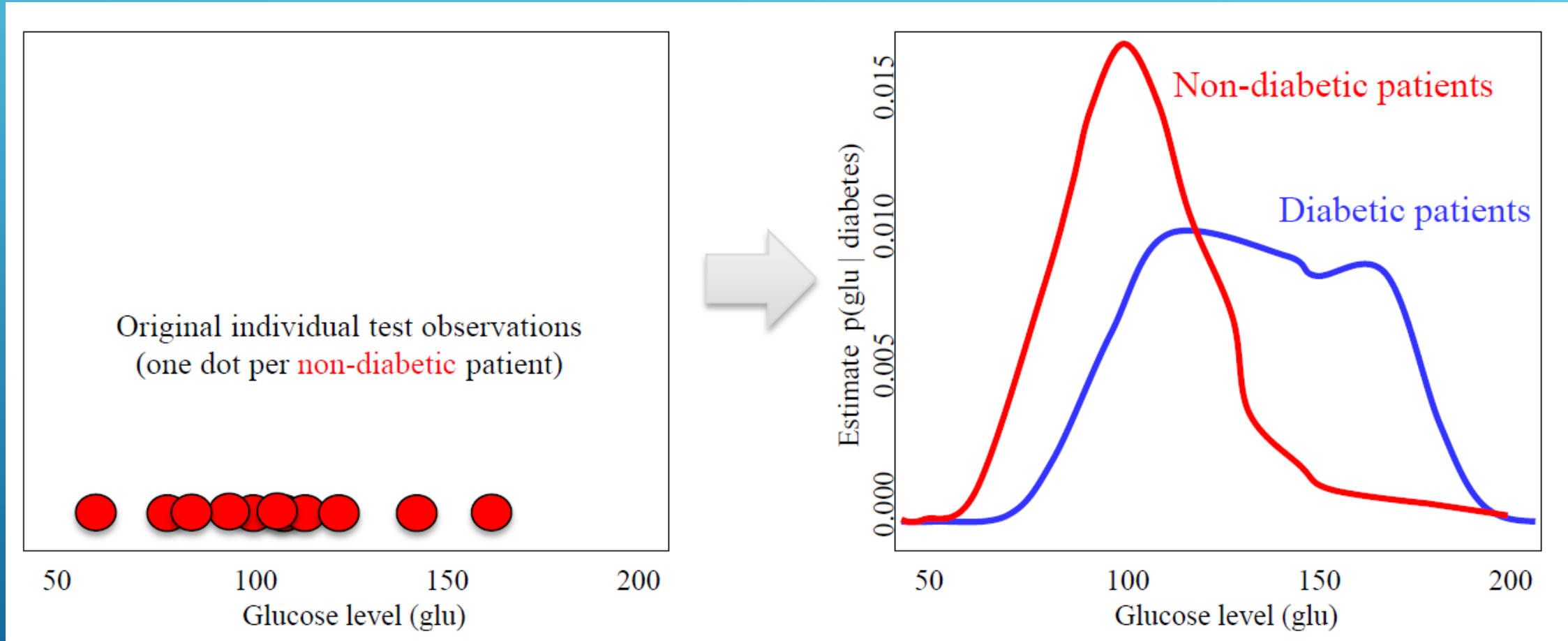


Density estimate
(Estimated probability p of observing a measurement at a given location)

DENSITY ESTIMATION EXAMPLE



DENSITY ESTIMATION EXAMPLE

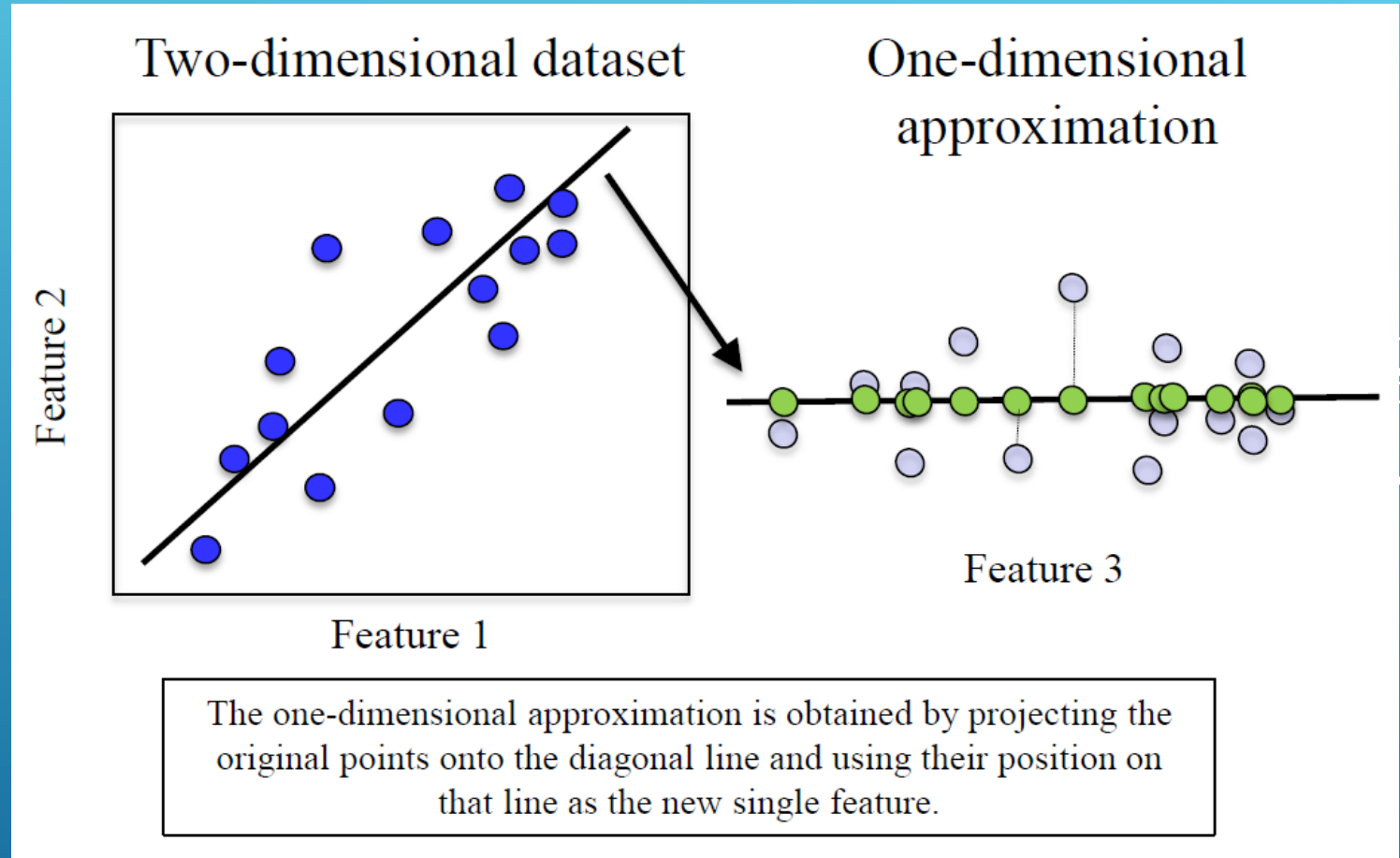


DENSITY ESTIMATION TECHNIQUES

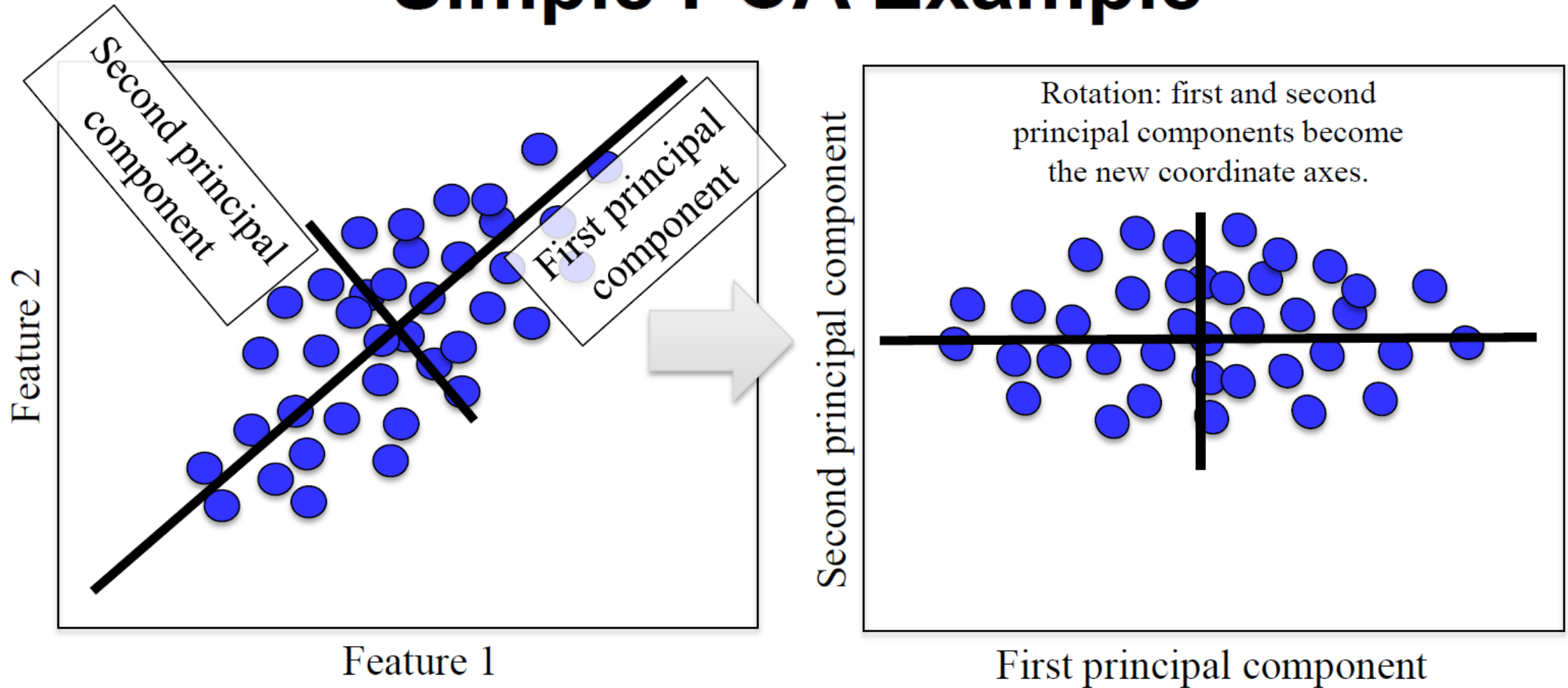
- Histograms
- Kernel Density Estimation
- etc.

DIMENSIONALITY REDUCTION

- Finds an approximate version of your dataset using fewer features.
- Used for exploring and visualizing a dataset to understand grouping or relationships
- Often visualized using a 2-dimensional scatterplot
- Also used for compression, finding features for supervised learning

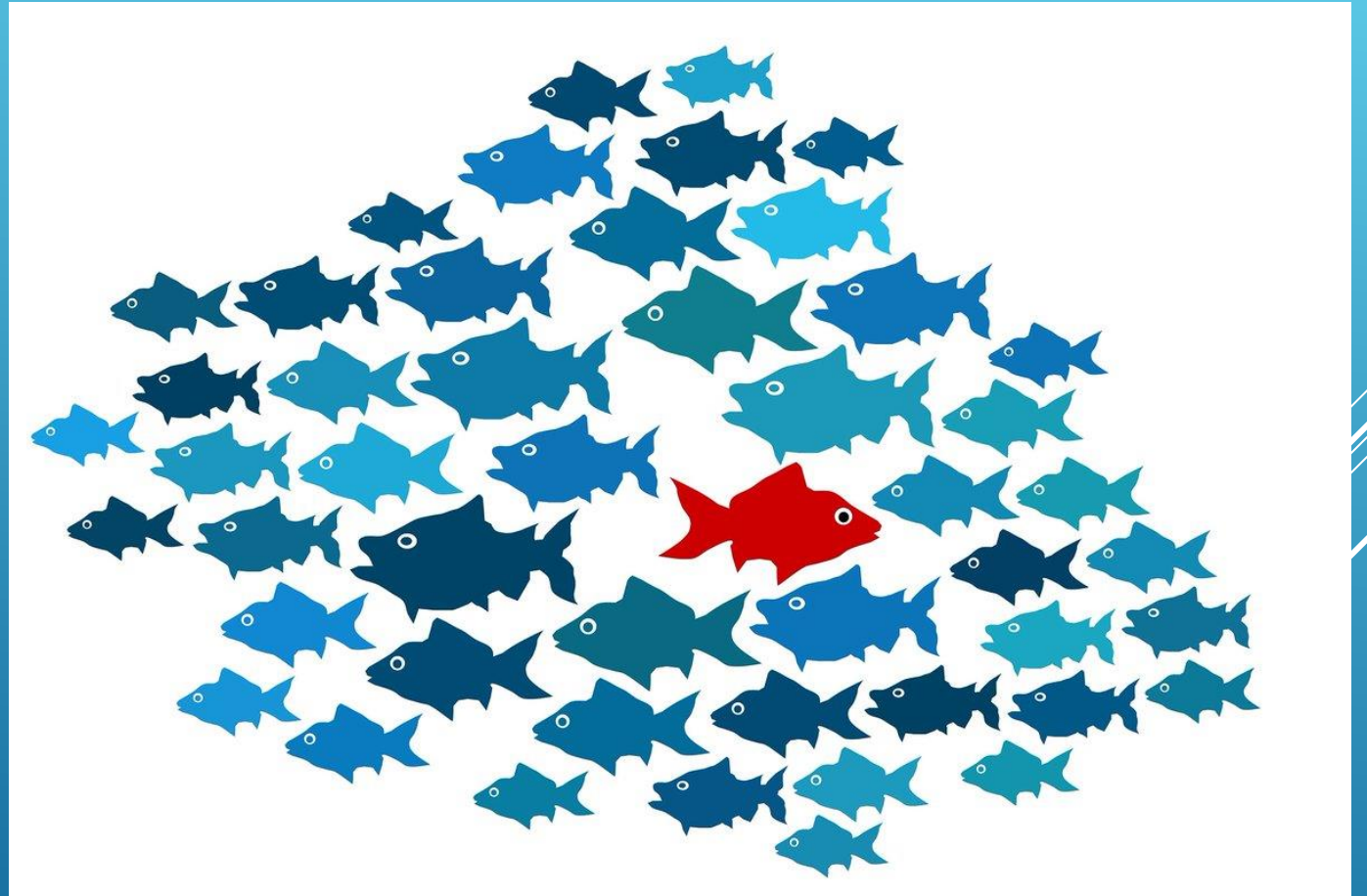


Simple PCA Example



OUTLIER DETECTION

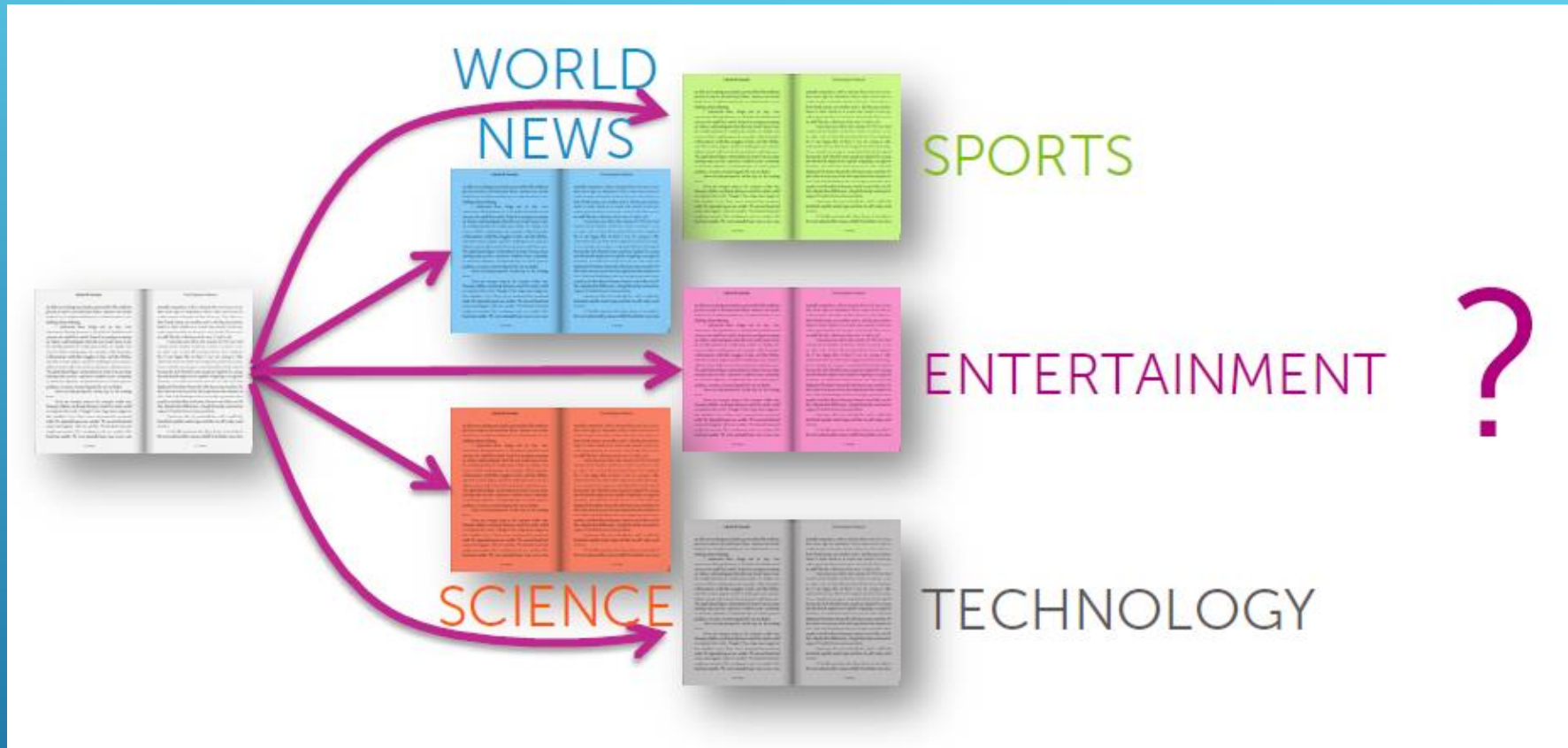
Outlier detection is the problem of detecting the examples in the dataset that are very different from what a typical example in the dataset looks like.



OUTLIER DETECTION ALGORITHMS

- Many outlier detection algorithms are adapted from more general clustering algorithms.
- One-Class Algorithms:
 - One-class gaussian
 - One-class mixture of gaussians.
 - One-class K-means
 - One-class KNN
 - One-class SVM
- Autoencoder

A SUPERVISED LEARNING TASK



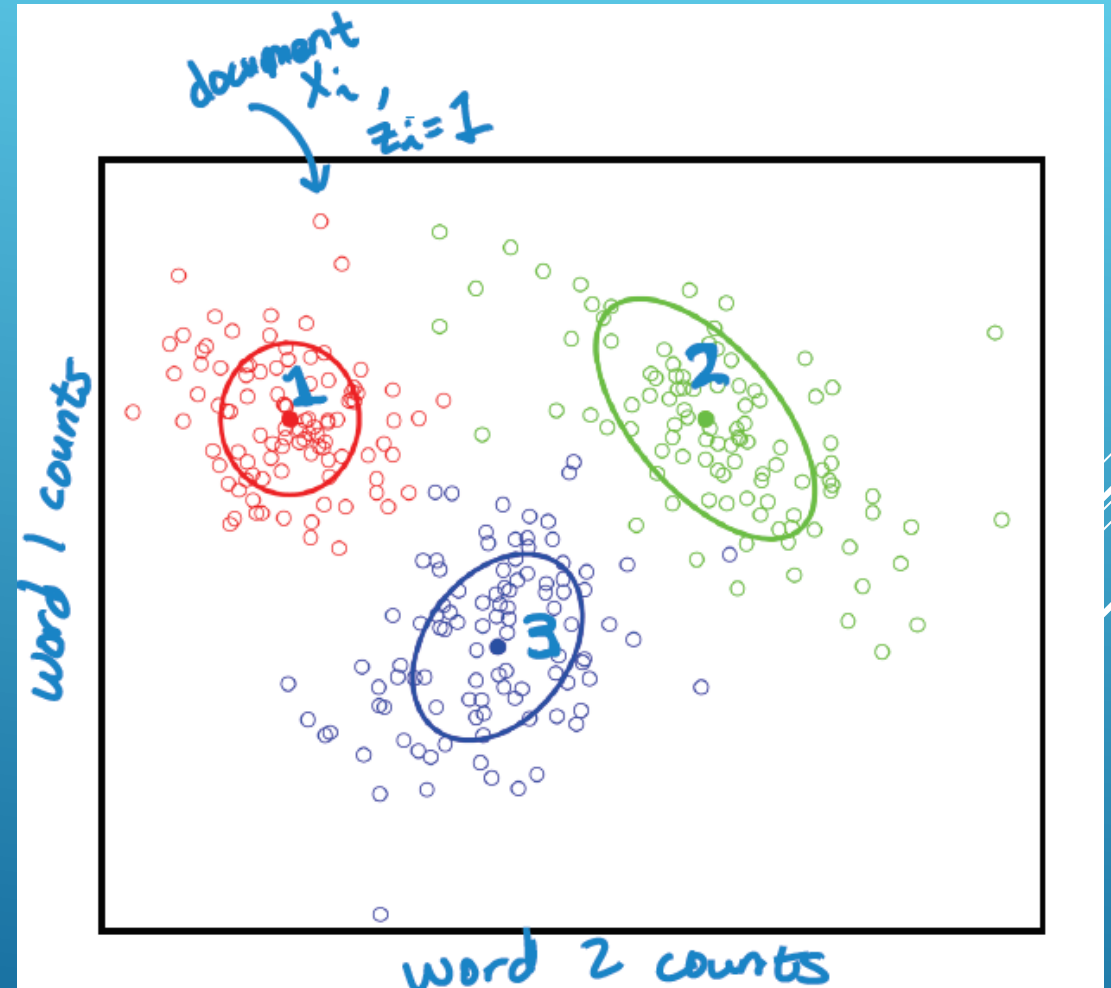
But what if you don't have labels?

AN UNSUPERVISED LEARNING TASK

No labels provided
...uncover cluster structure
from input alone

Input: docs as vectors \mathbf{x}_i

Output: cluster labels z_i

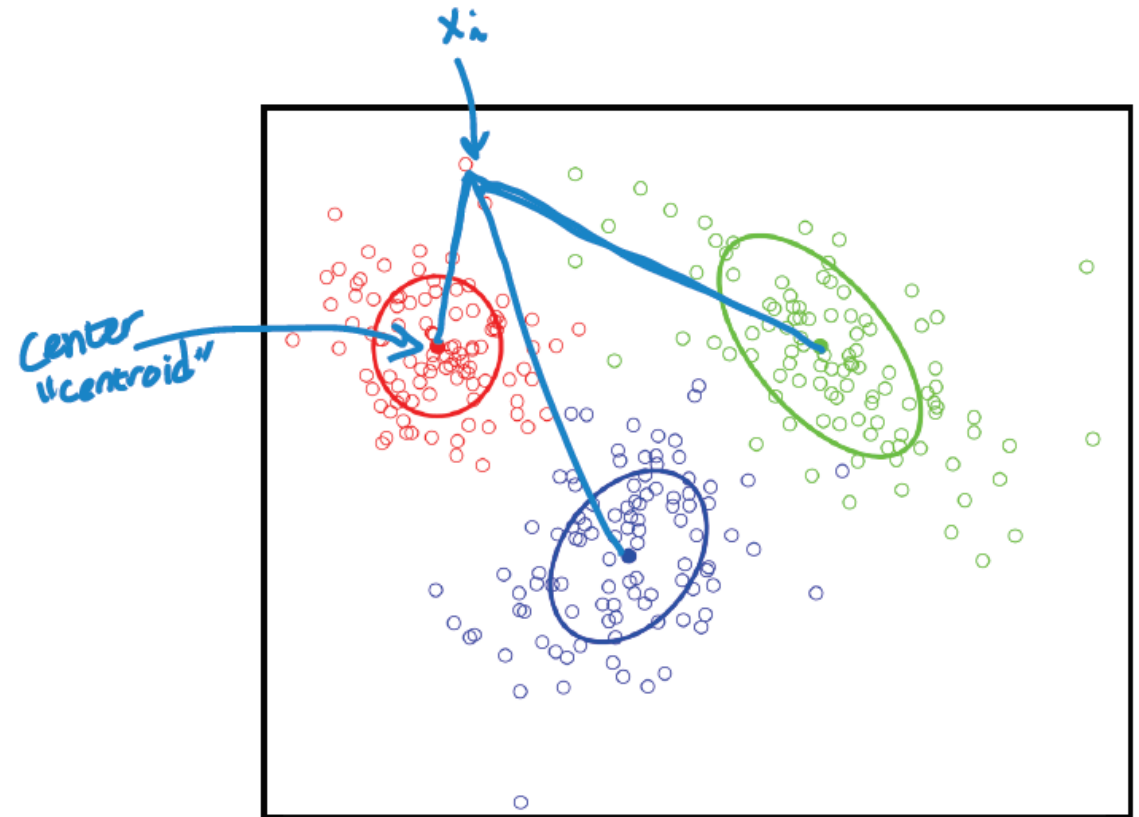


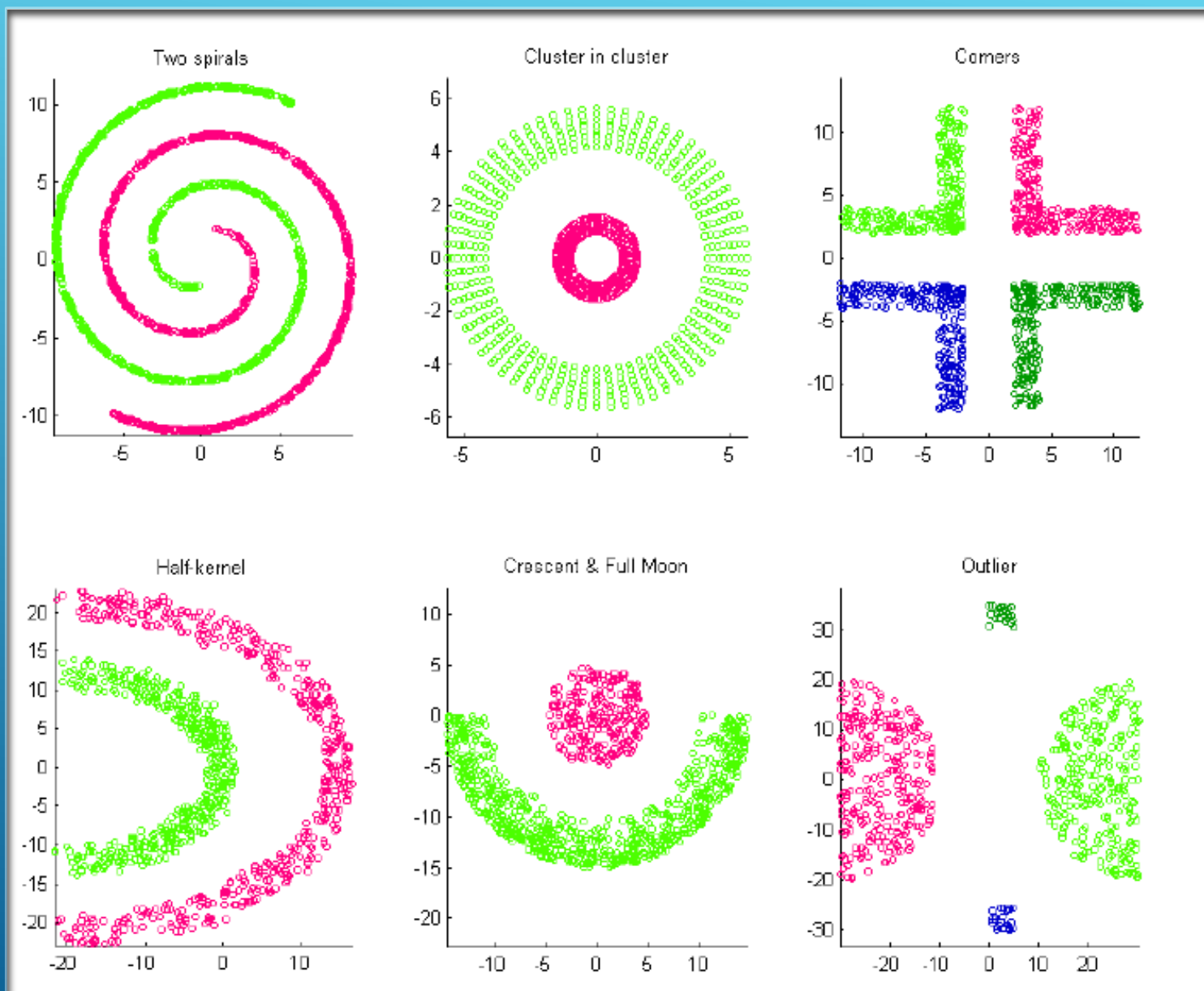
What defines a cluster?

Cluster defined by
center & shape/spread

Assign observation \mathbf{x}_i (doc)
to cluster k (topic label) if

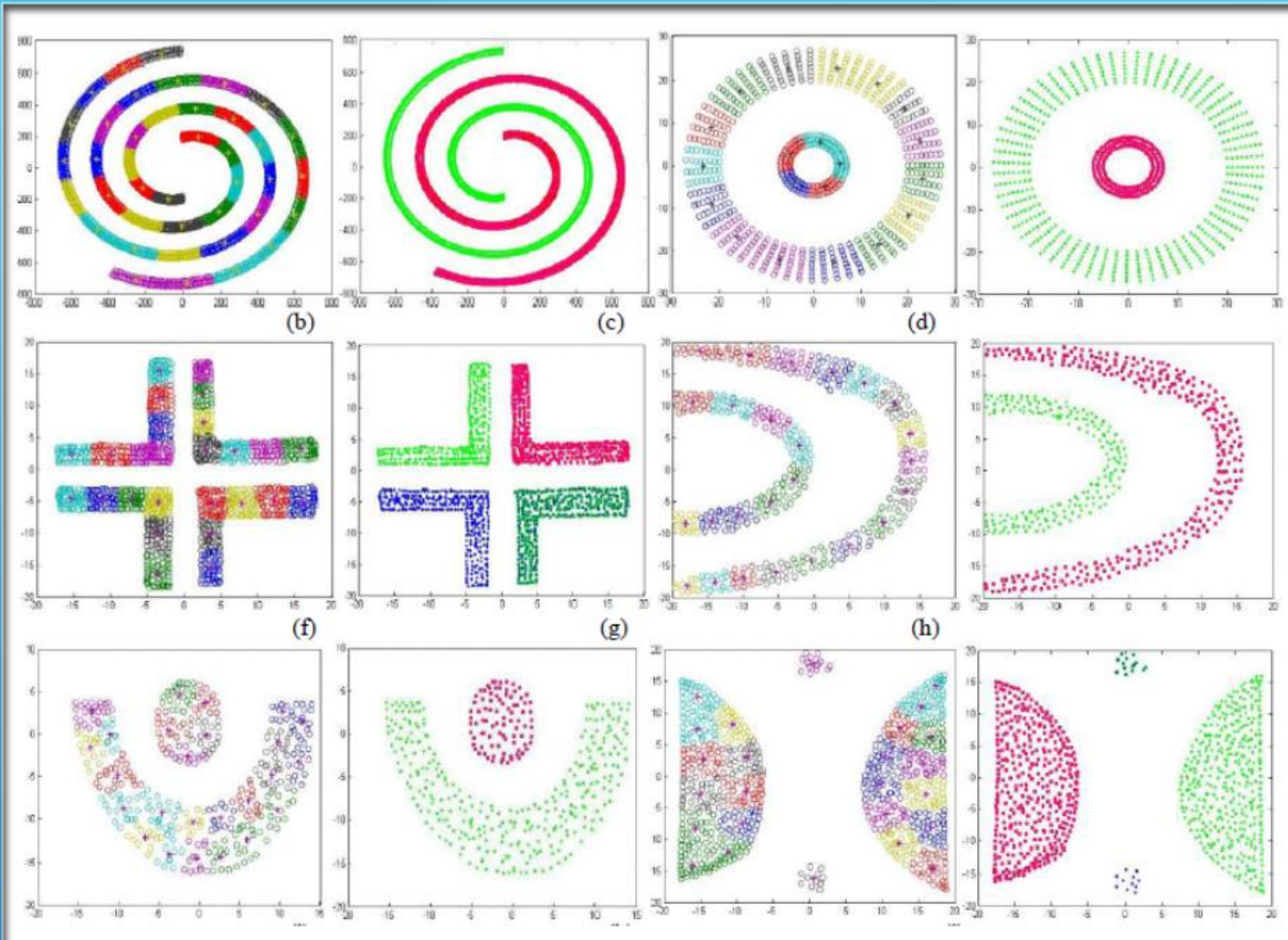
- Score under cluster k is higher than under others
- For simplicity, often define score as distance to cluster center (ignoring shape)





CHALLENGING CLUSTERS

MORE CHALLENGING CLUSTERS



K-means Clustering

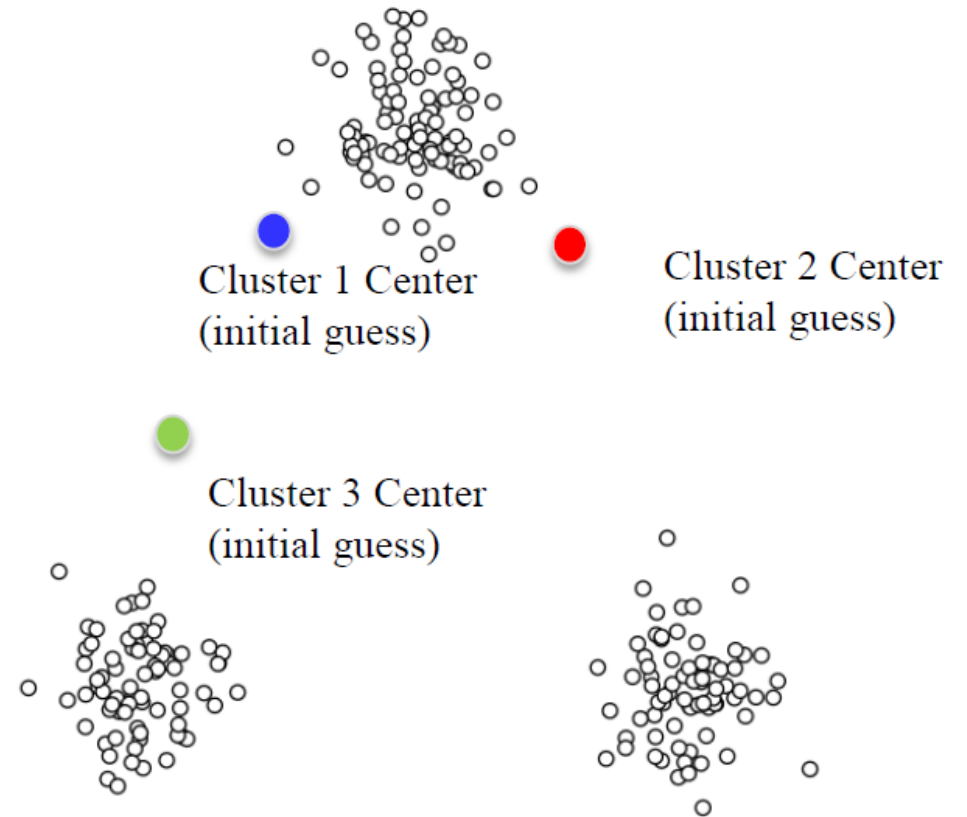
The k-means algorithm

Initialization Pick the number of clusters k you want to find. Then pick k *random* points to serve as an initial guess for the cluster centers.

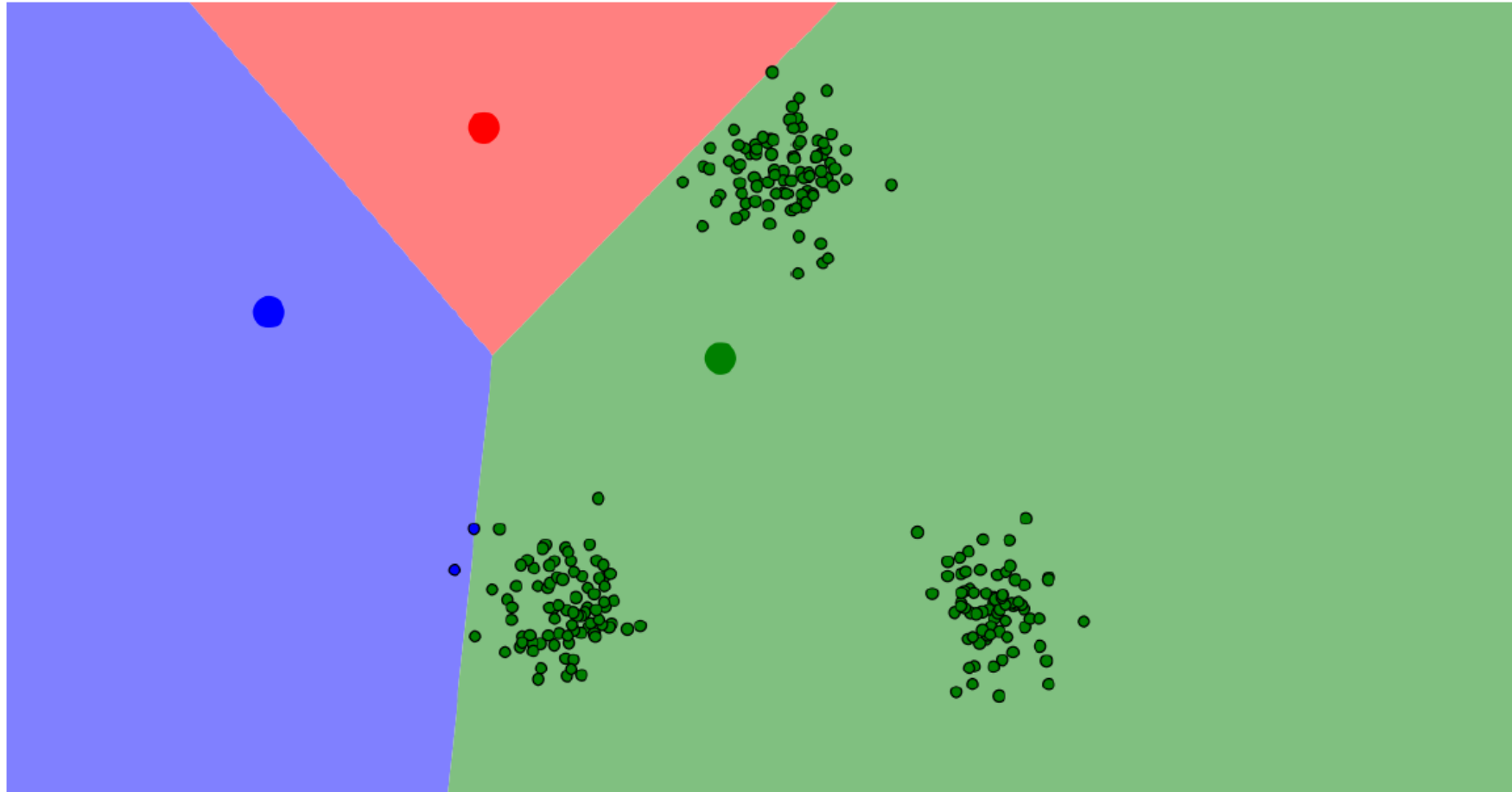
Step A Assign each data point to the nearest cluster center.

Step B Update each cluster center by replacing it with the mean of all points assigned to that cluster (in step A).

Repeat steps A and B until the centers converge to a stable solution.



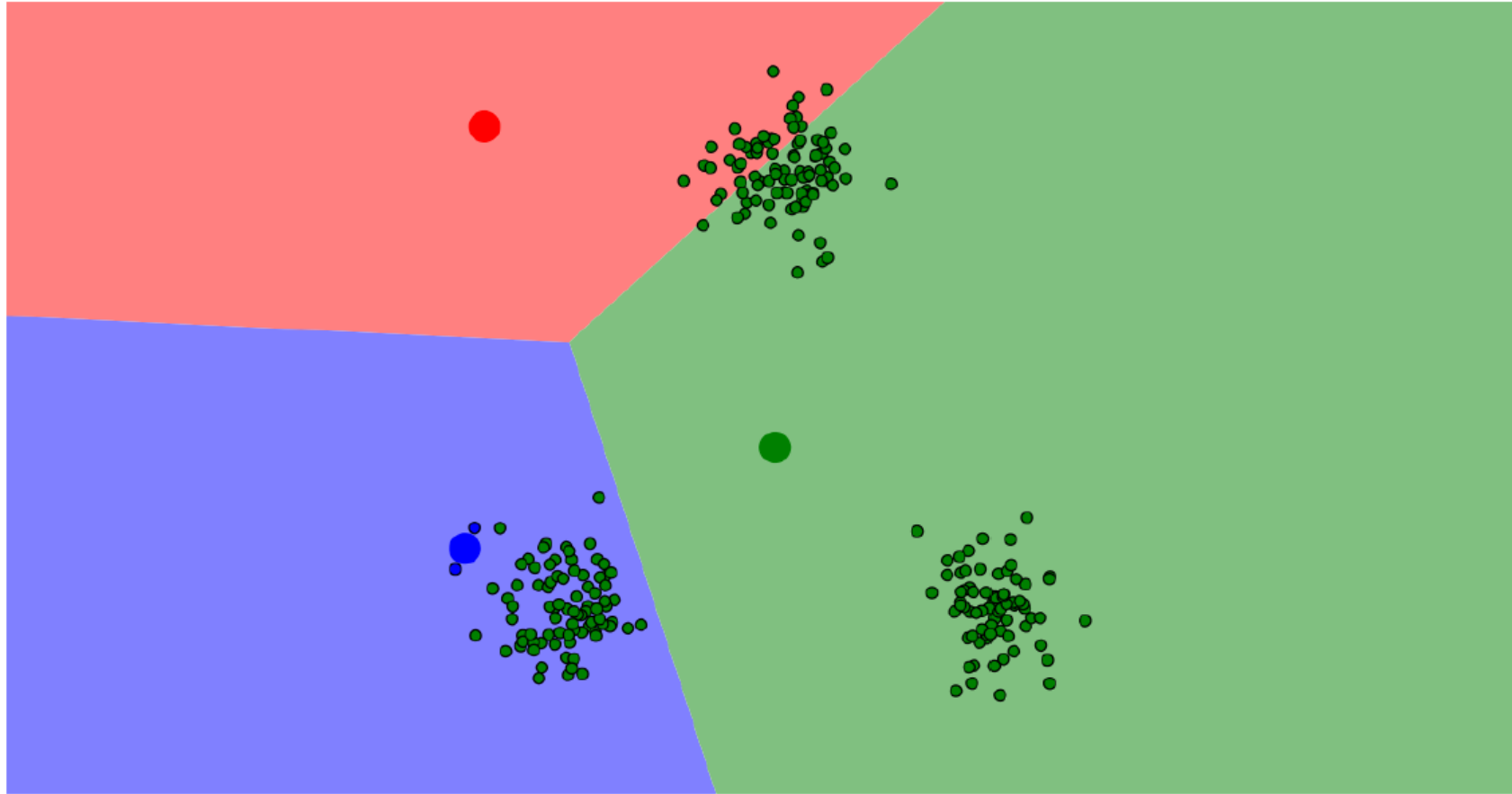
K-means Example: Step 1A



We want three clusters, so three centers are chosen randomly.

Data points are colored according to the closest center.

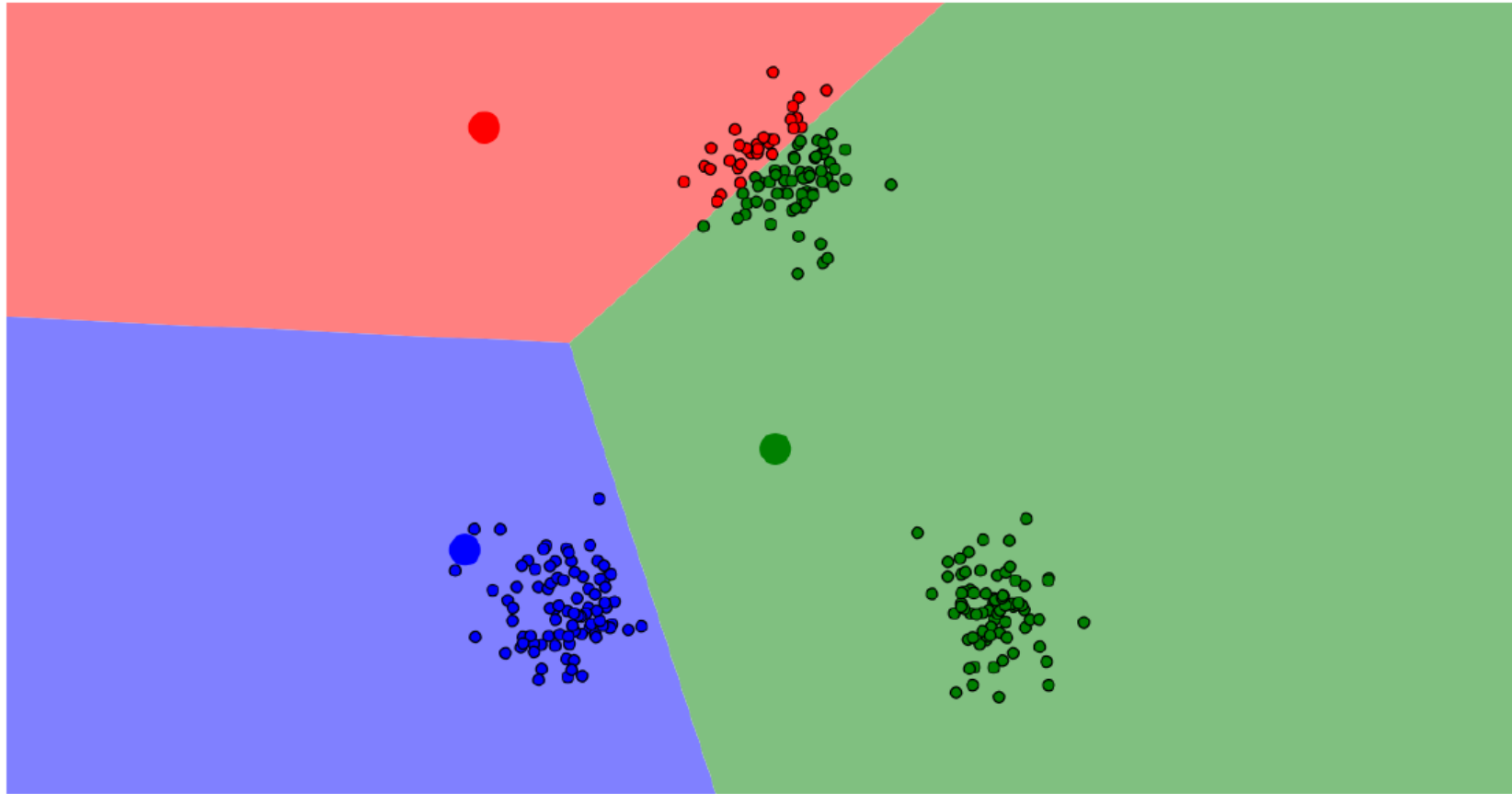
K-means Example: Step 1B



Each center is then updated...

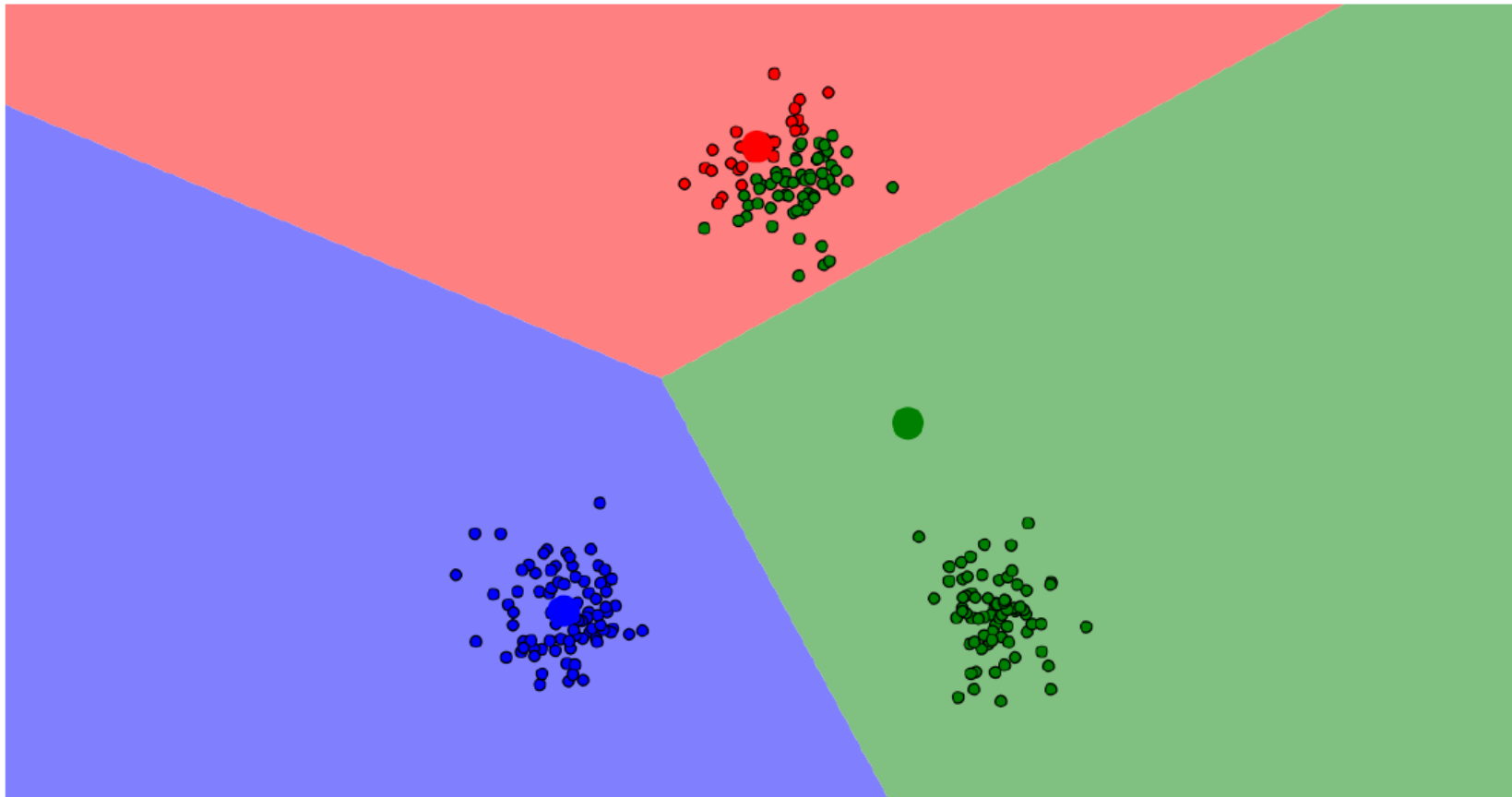
... using the mean of all points assigned to that cluster.

K-means Example: Step 2A



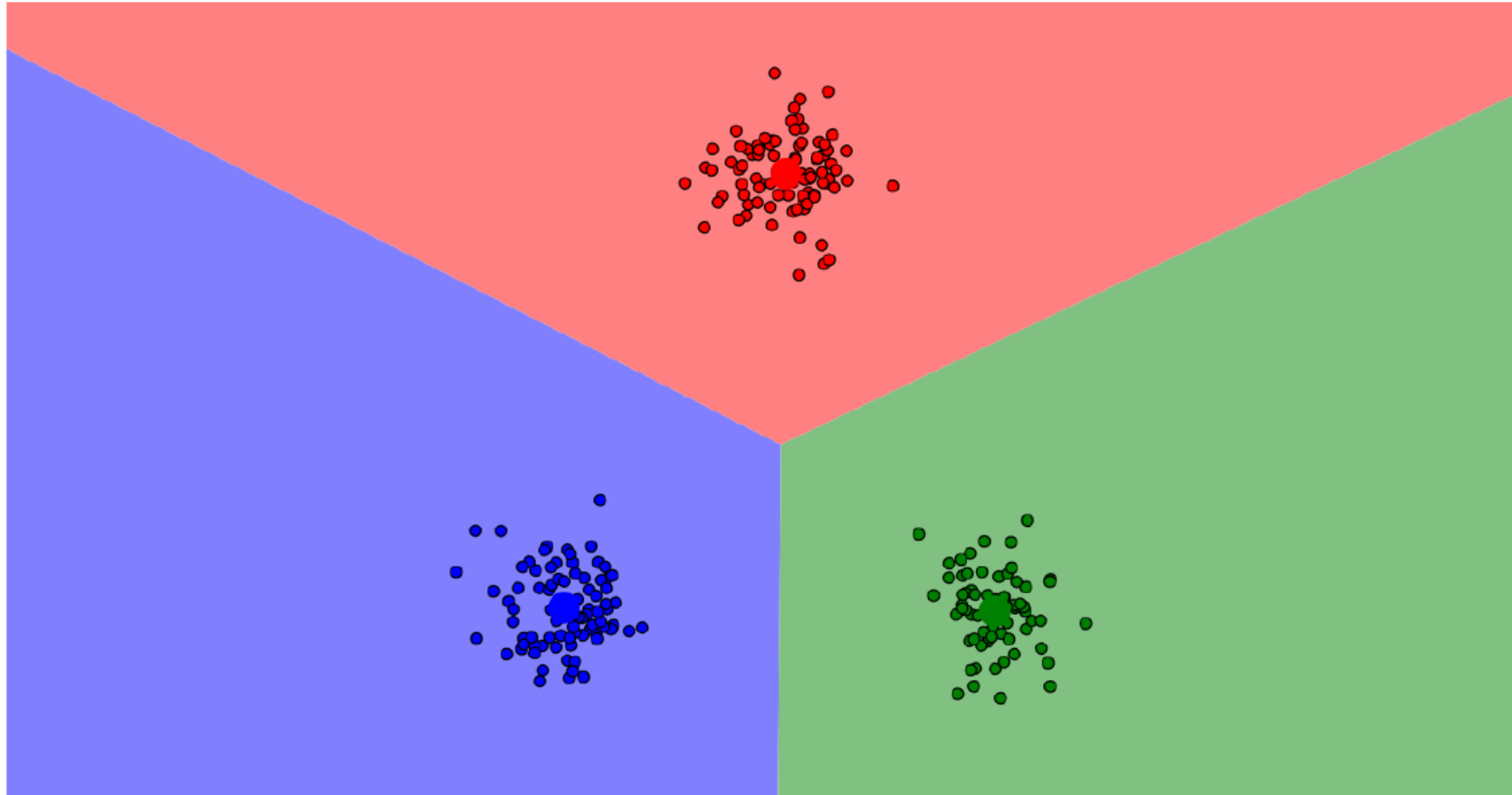
Data points are colored (again) according to the closest center.

K-means Example: Step 2B



Re-calculate all
cluster centers.

K-means Example: Converged



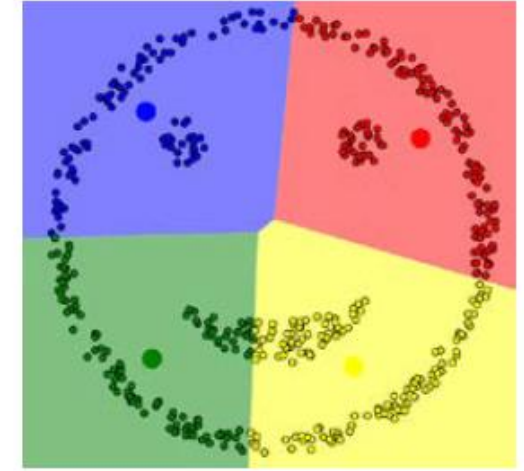
After repeating these steps for several more iterations...

The centers converge to a stable solution!

These centers define the final clusters.

LIMITATIONS OF K-MEANS

- **Works well for simple clusters that are same size, well-separated, globular shapes.**
- **Does not do well with irregular, complex clusters.**



K-means typically performs poorly with data having complex, irregular clusters.

Converges to:

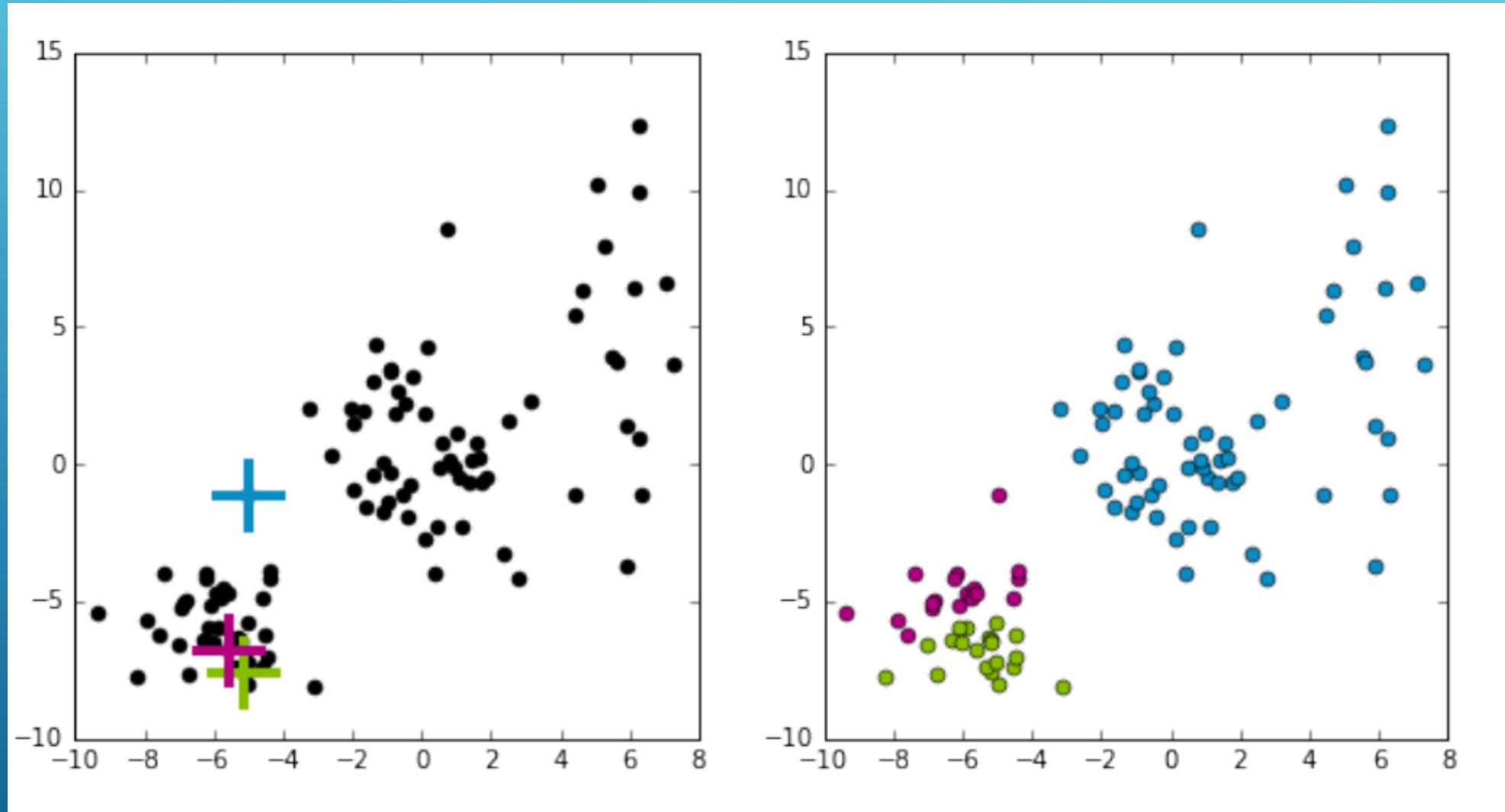
~~- Global optimum~~

- Local optimum

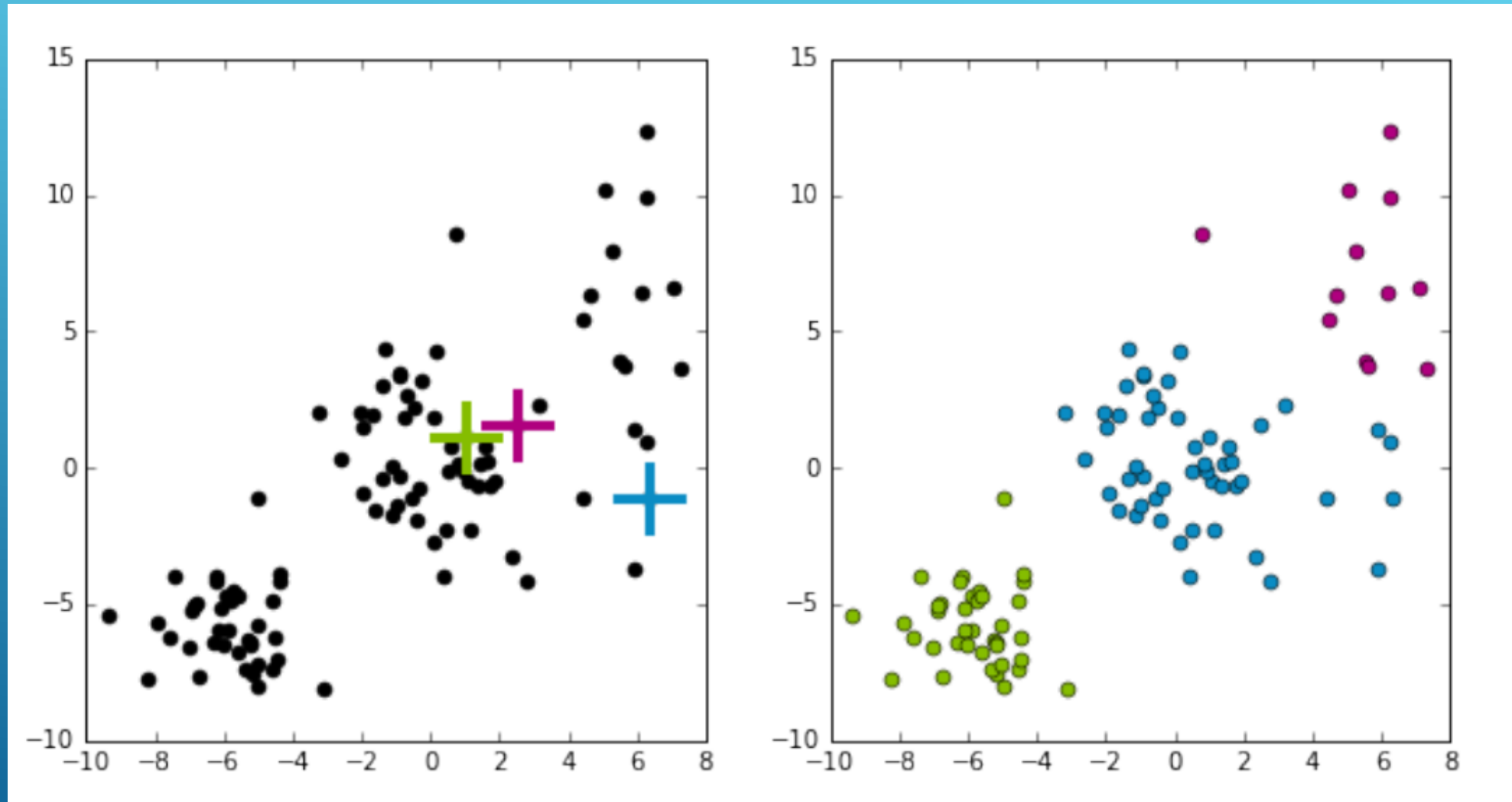
~~- neither~~

CONVERGENCE OF K-MEANS

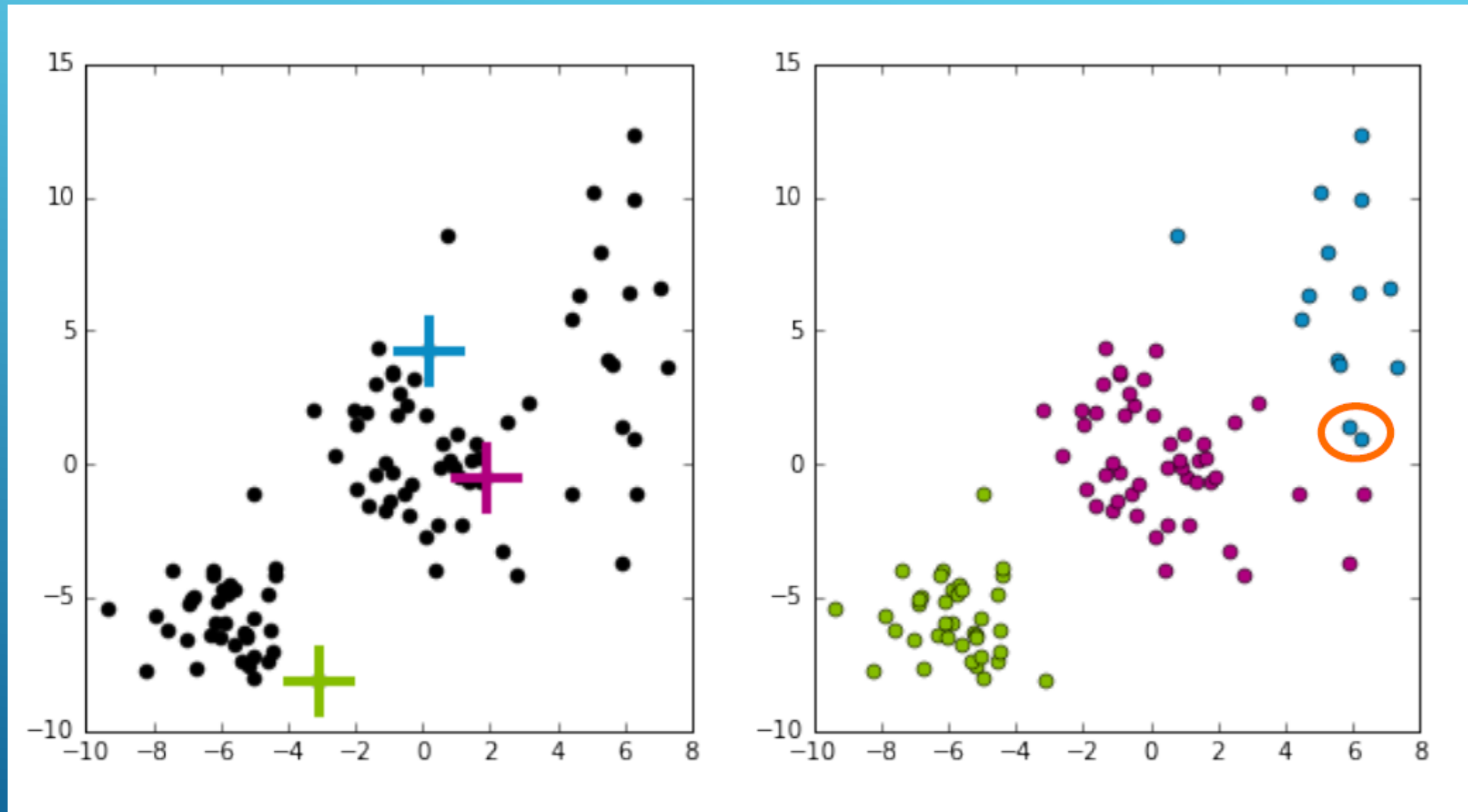
CONVERGENCE OF K-MEANS TO LOCAL OPTIMUM



CONVERGENCE OF K-MEANS TO LOCAL OPTIMUM



CONVERGENCE OF K-MEANS TO LOCAL OPTIMUM



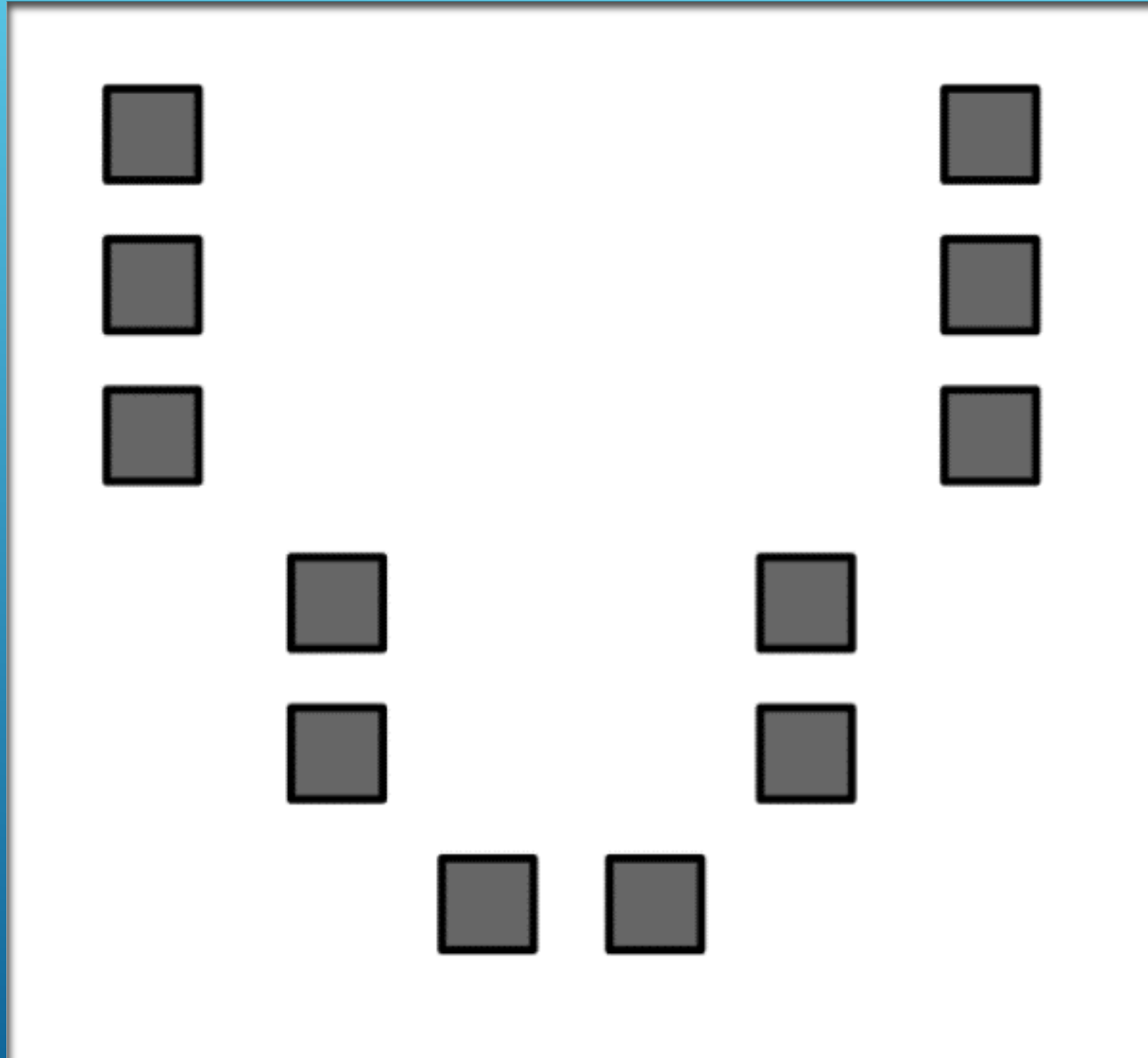
k-means++ overview

Initialization of k-means algorithm is critical to quality of local optima found

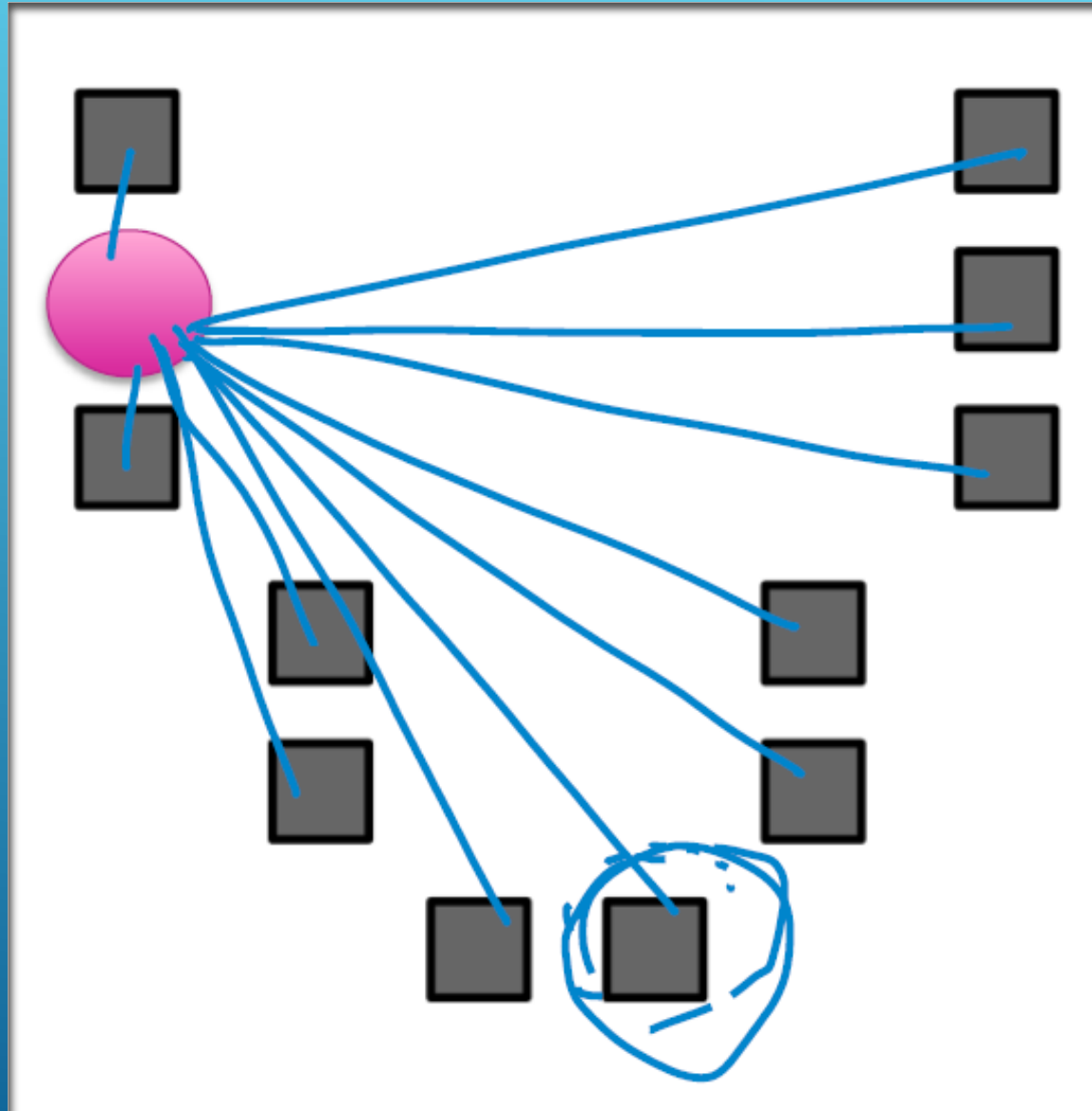
Smart initialization:

1. Choose first cluster center uniformly at random from data points
2. For each obs \mathbf{x} , compute distance $d(\mathbf{x})$ to nearest cluster center
3. Choose new cluster center from amongst data points, with probability of \mathbf{x} being chosen proportional to $d(\mathbf{x})^2$
4. Repeat Steps 2 and 3 until k centers have been chosen

SMART
INITIALIZATION
WITH
K-MEANS++

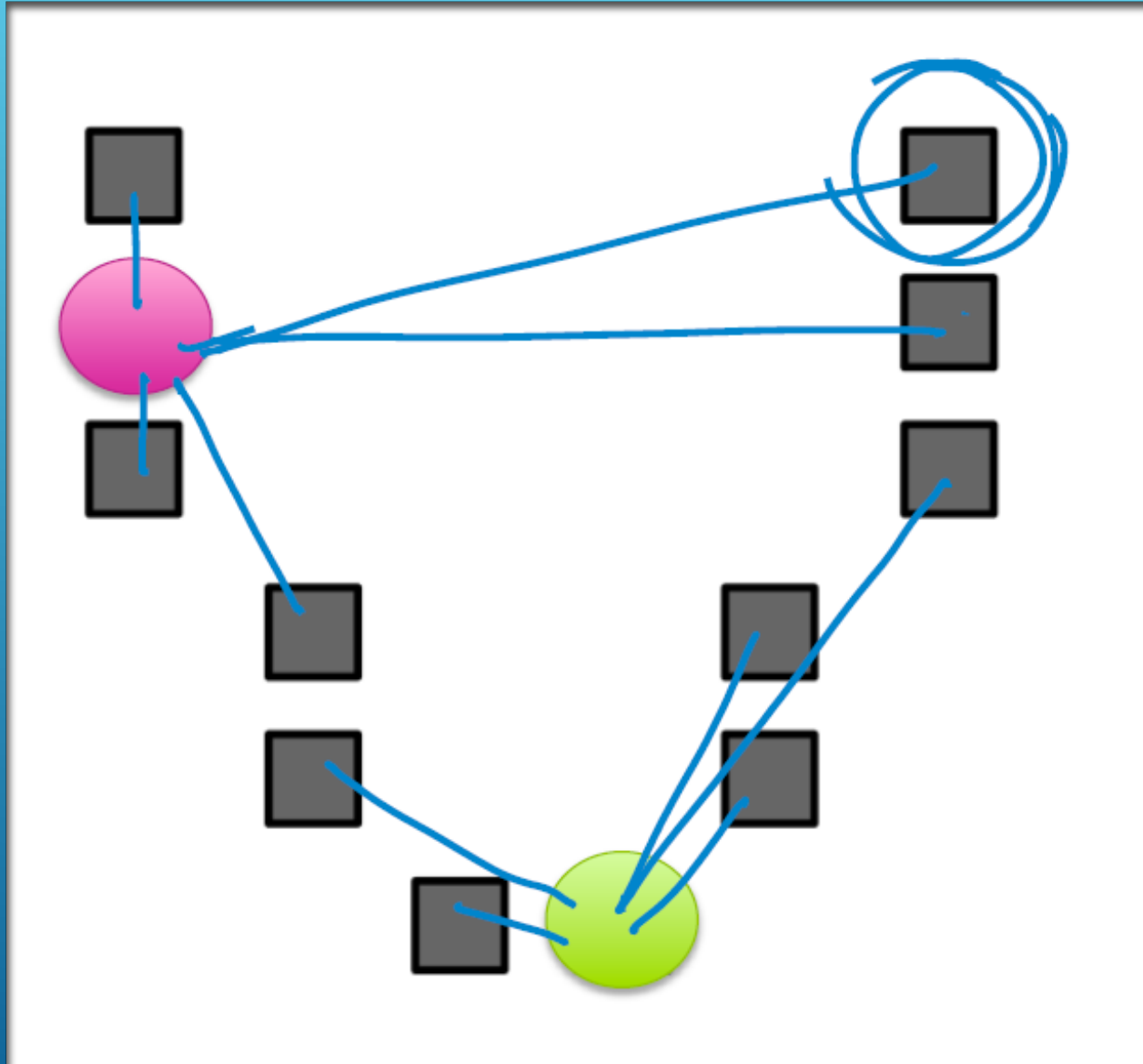


K-MEANS++ VISUALIZED

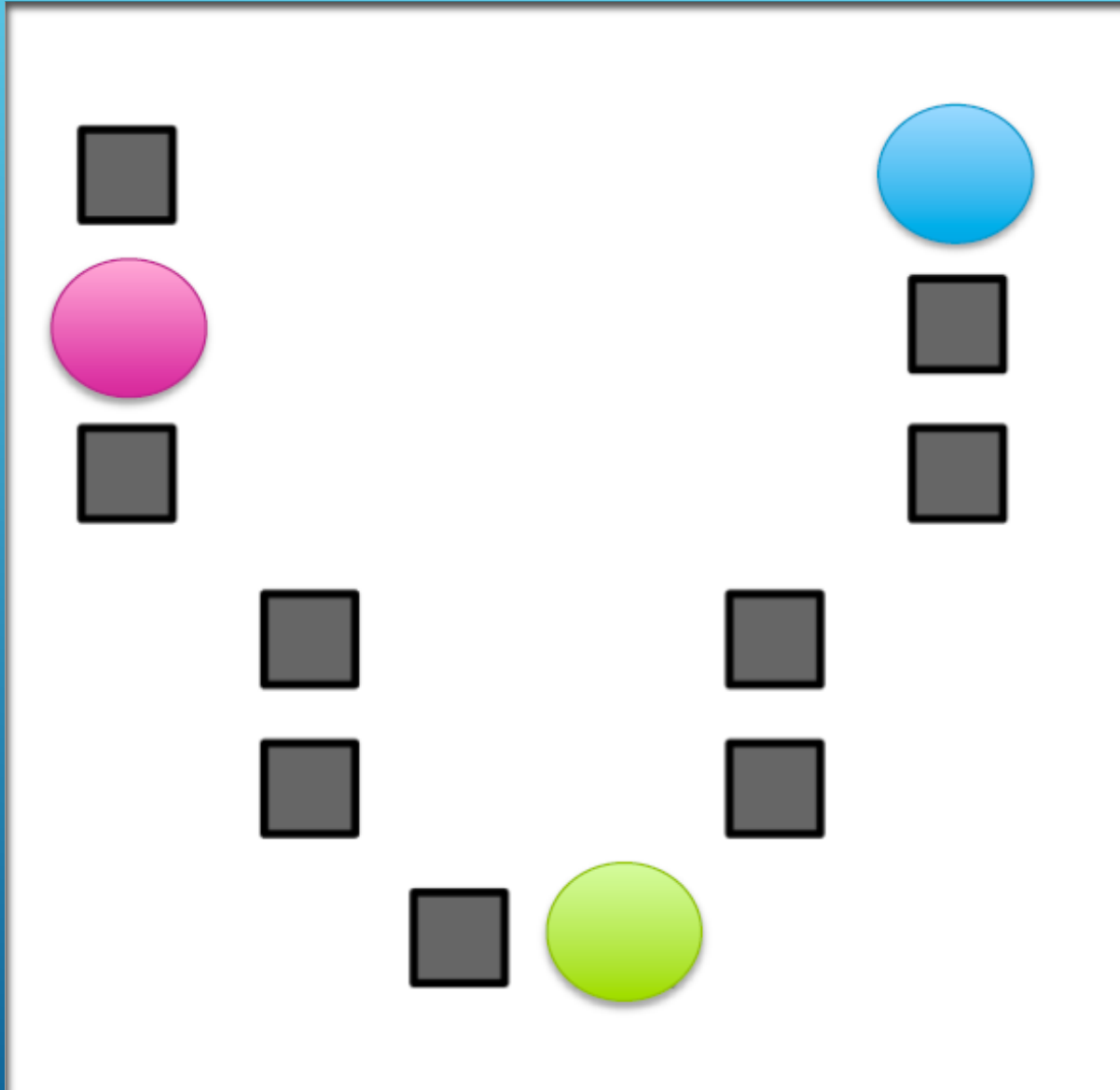


K-MEANS++ VISUALIZED

more likely to
select a datapoint
as a cluster center
if that datapoint is
far away
(dist^2 increases
this effect)



K-MEANS++ VISUALIZED



K-MEANS++ VISUALIZED

FUTURE TOPICS

References:

The Hundred-Page Machine Learning Book. Andriy Burkov.

Applied Machine Learning in Python. Coursera. University of Michigan, Prof. Kevin Collins Thompson

Cluster analysis,
https://en.wikipedia.org/w/index.php?title=Cluster_analysis&oldid=1002271612 (last visited Jan. 27, 2021).

Dimensionality reduction,
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1. Density Estimation Topics

- Histograms
- Kernel Density Estimation

2. Dimensionality Reduction

- Principal Component Analysis (PCA)
- t-SNE
- UMAP
- Autoencoders

3. Outlier Detection Topics

- One-Class Classifier Learning
- Autoencoders

4. Clustering Topics

- Hierarchical Agglomerative Clustering
- Gaussian Mixture Model
- DBSCAN
- HDBSCAN*
- Cross-validation

5. Deep Neural Network Approaches

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NEW TALK

Reference: Machine Learning: Clustering & Retrieval
University of Washington, Profs. Emily Fox & Carlos Guestrin

Reference: The Hundred-Page Machine Learning Book. Andriy Burkov.

Reference: Applied Machine Learning in Python. Coursera.
University of Michigan, Prof. Kevin Collins Thompson