

# SciTinyML

Scientific use of machine learning on low power devices  
Regional Workshop - Africa

## Unsupervised Learning and Anomaly Detection

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# Machine Learning

## Supervised learning

Task-driven

- Regression
- Classification
- Object detection

## Unsupervised learning

Data-driven

- Clustering
- Segmentation
- Anomaly detection

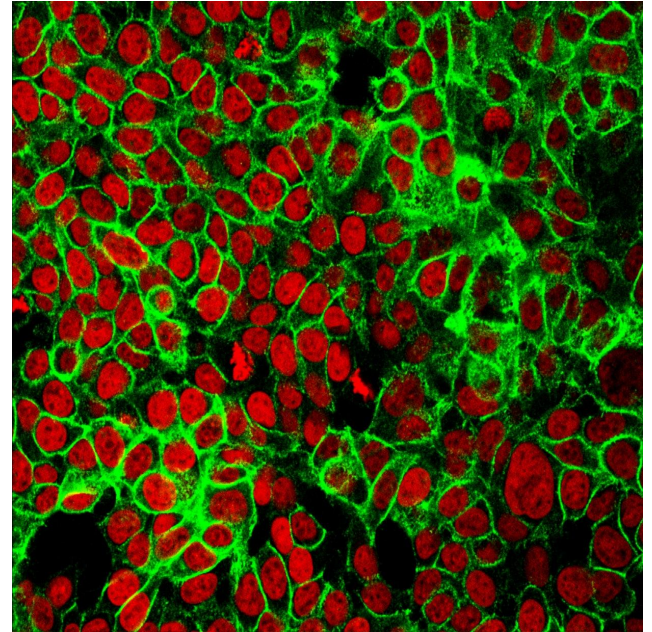
## Reinforcement learning

Learn from experience

- Robotics
- Games
- Recommender systems

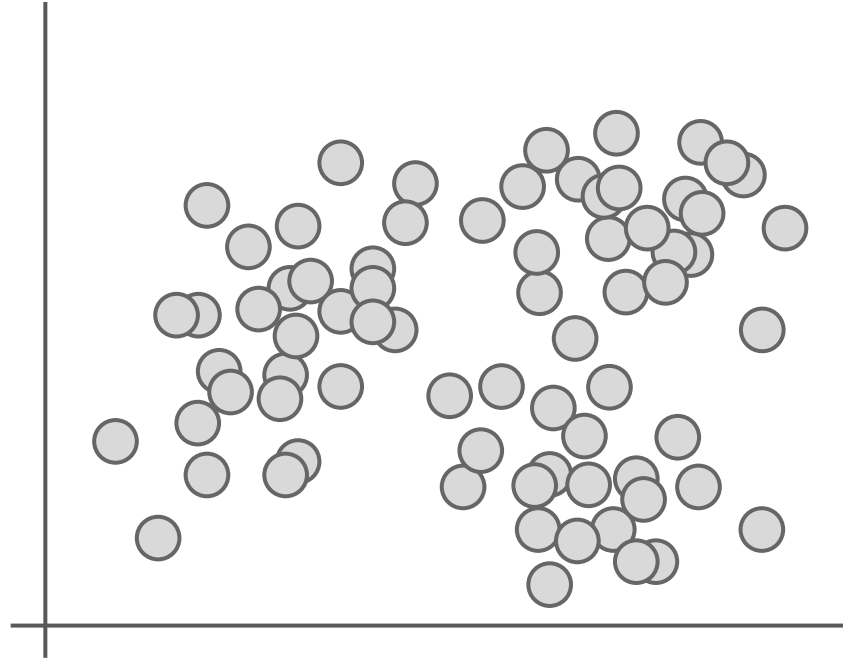
# Unsupervised Learning

- No labels!
- Model automatically discovers patterns in the data
- Uses
  - Segmentation
  - Clustering
  - Dimensionality reduction
  - Anomaly detection



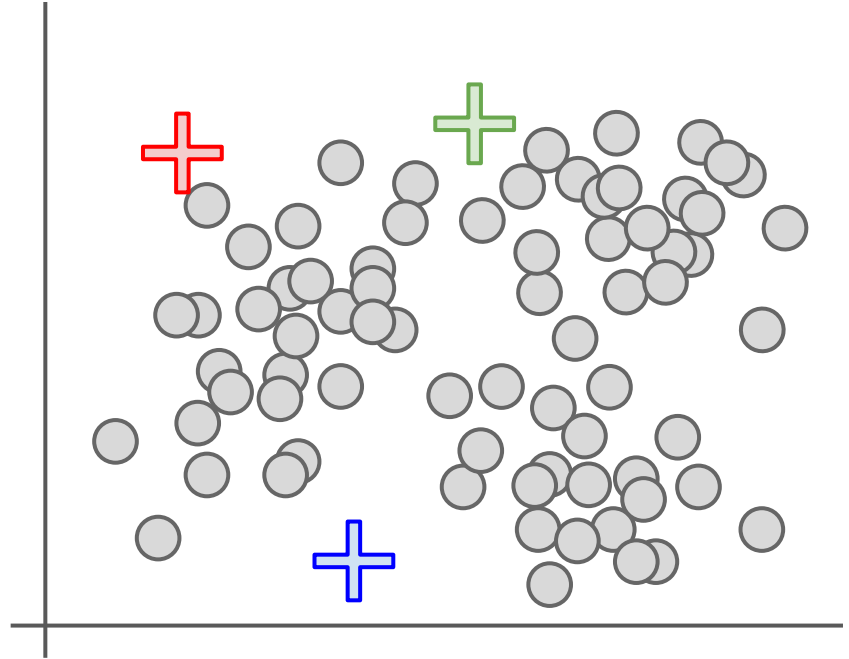
# K-means Clustering

1. Define  $k$  (e.g.  $k=3$ )



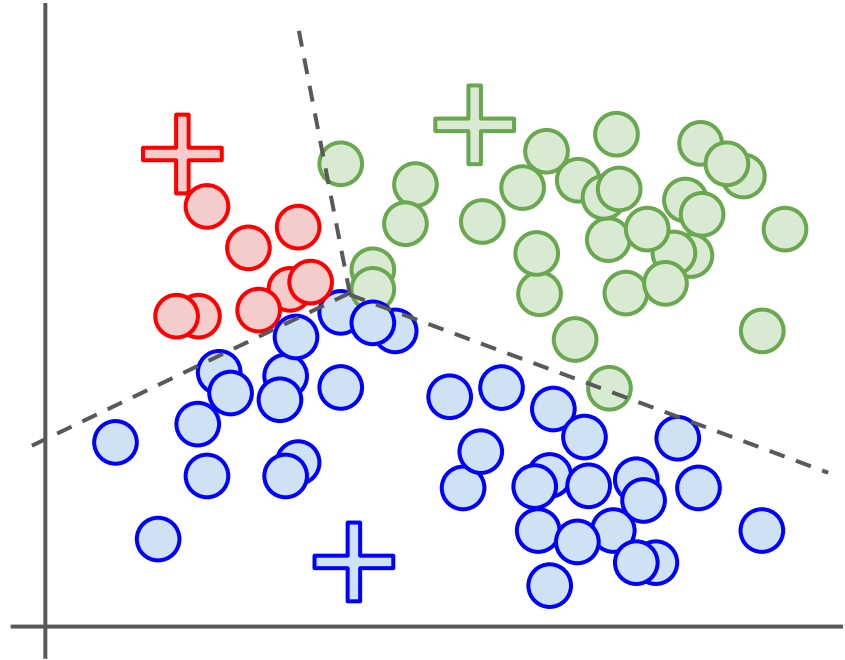
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1. Define  $k$  (e.g.  $k=3$ )
2. Randomly choose centroid for each cluster



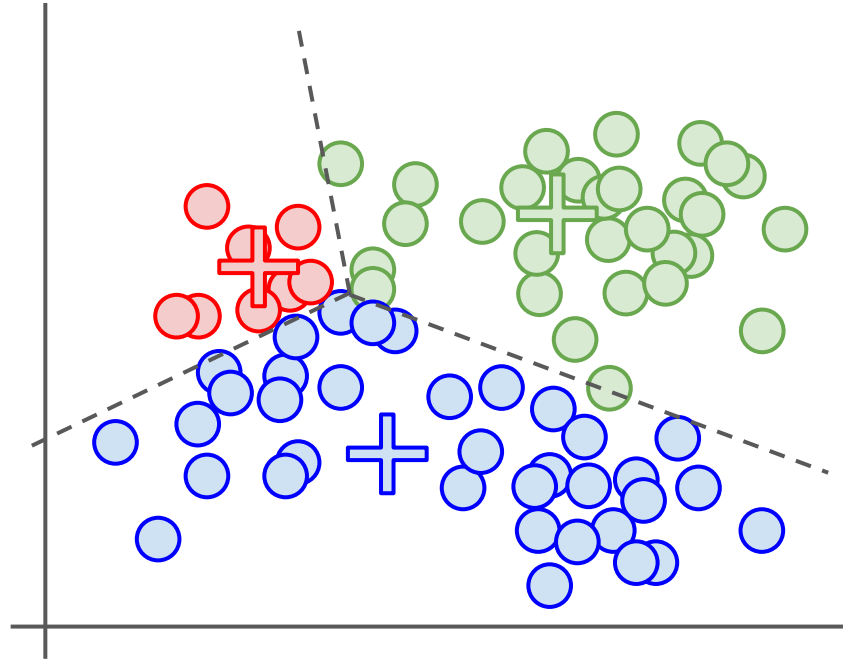
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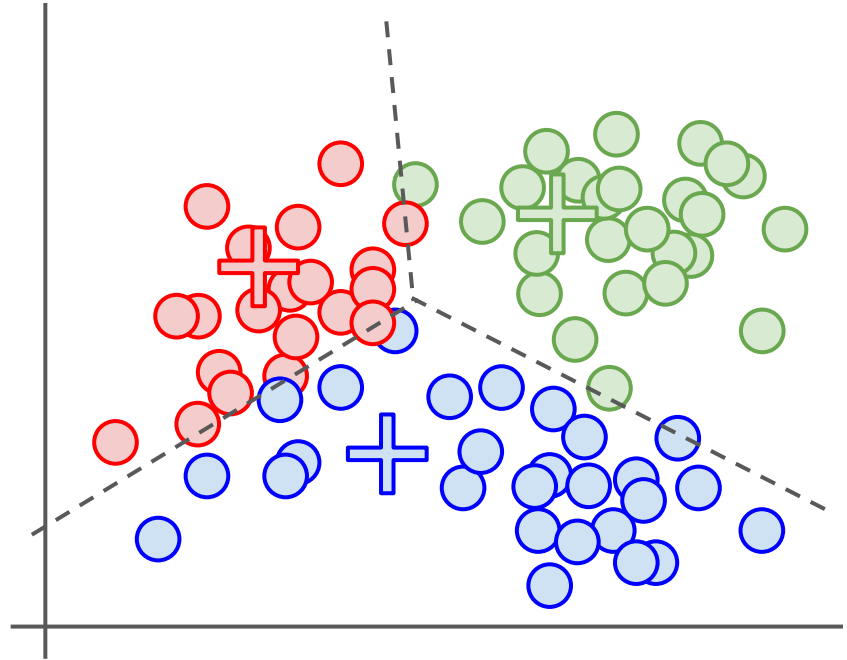
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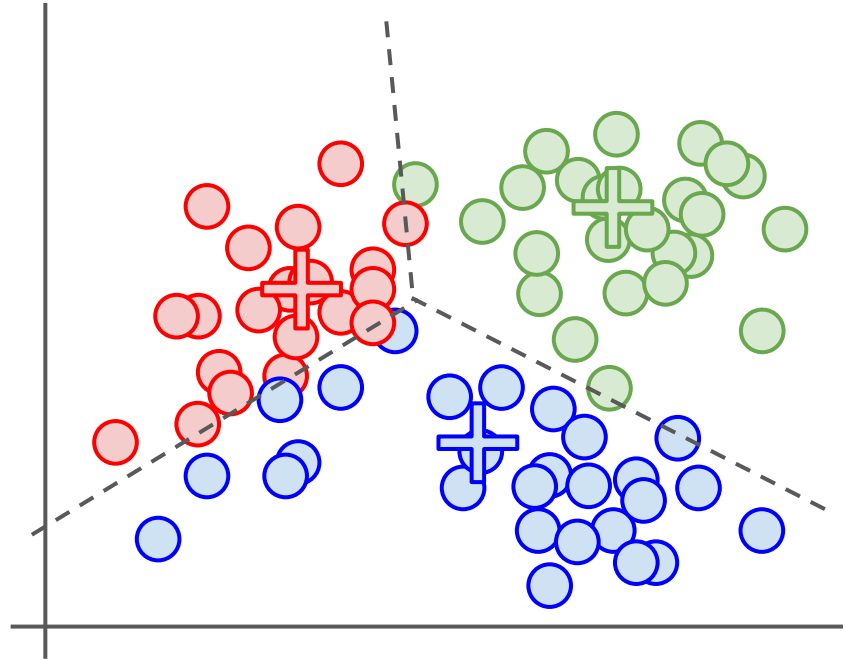
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5. Repeat steps 3-4





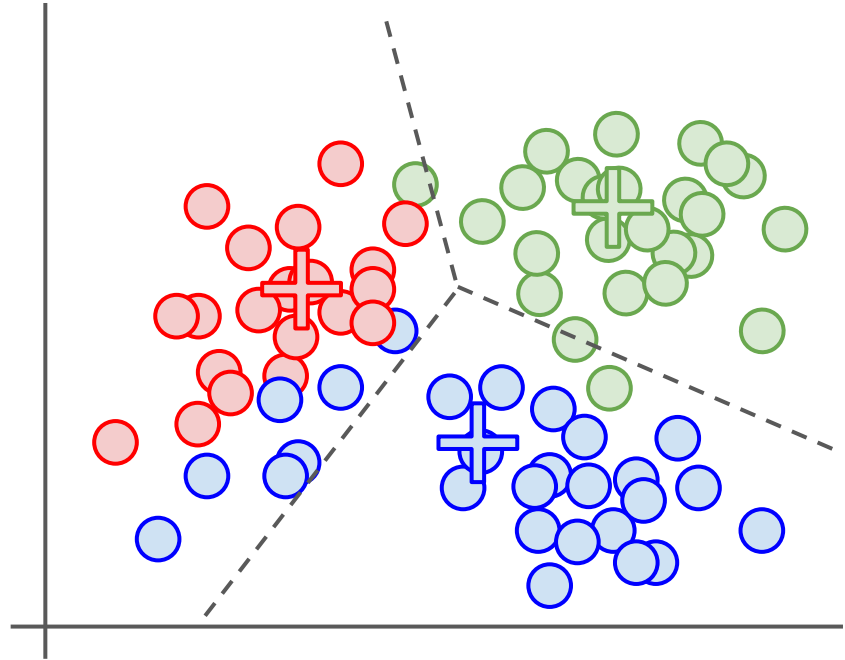
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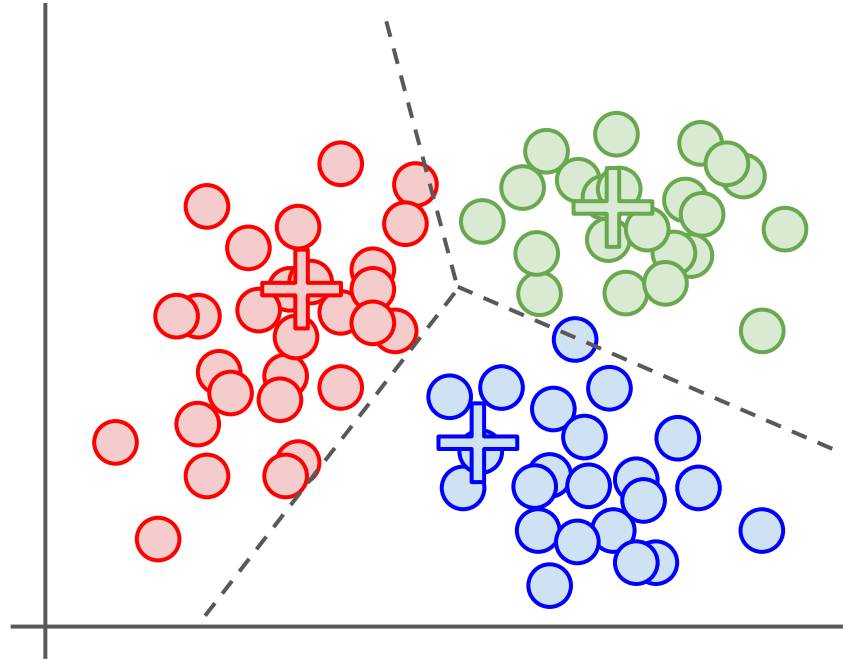
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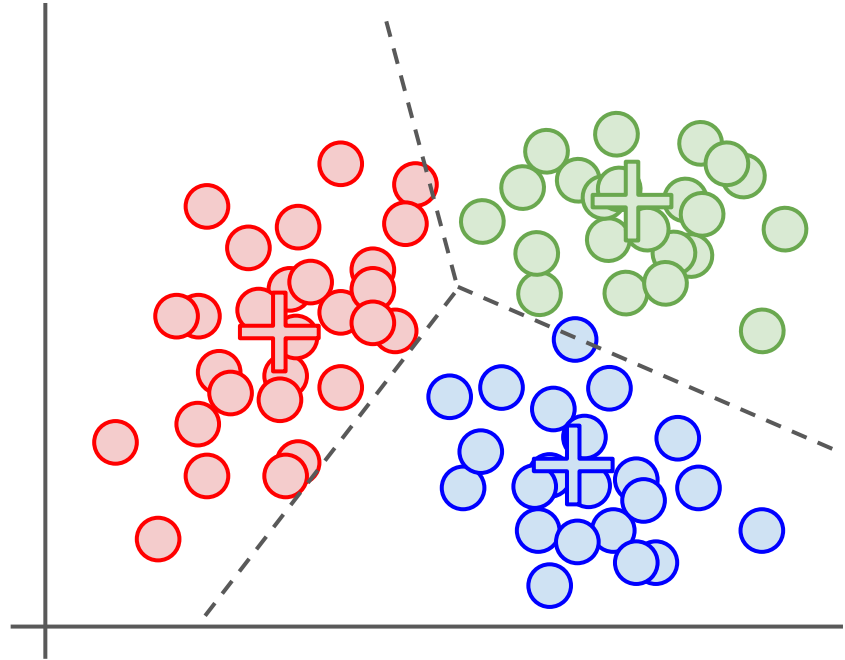
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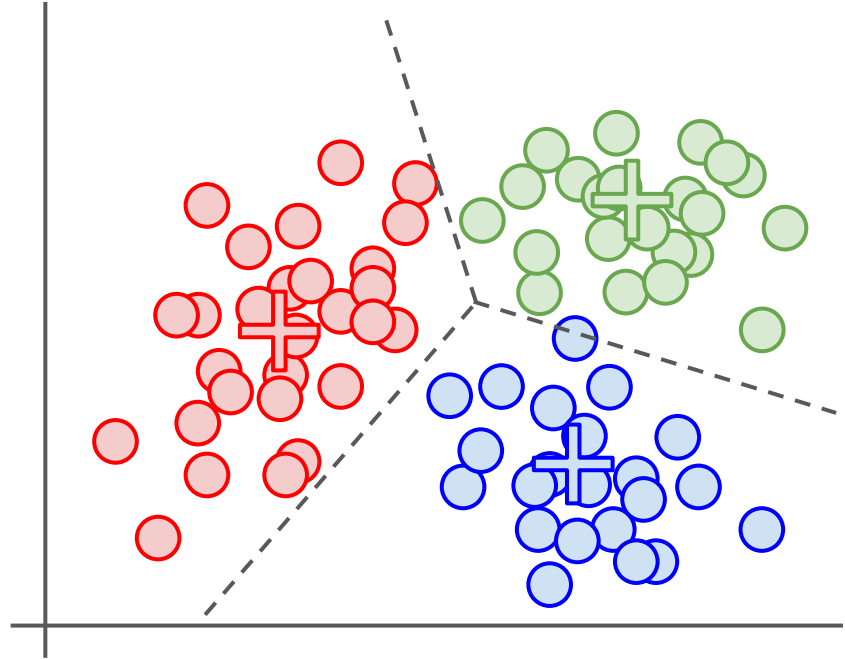
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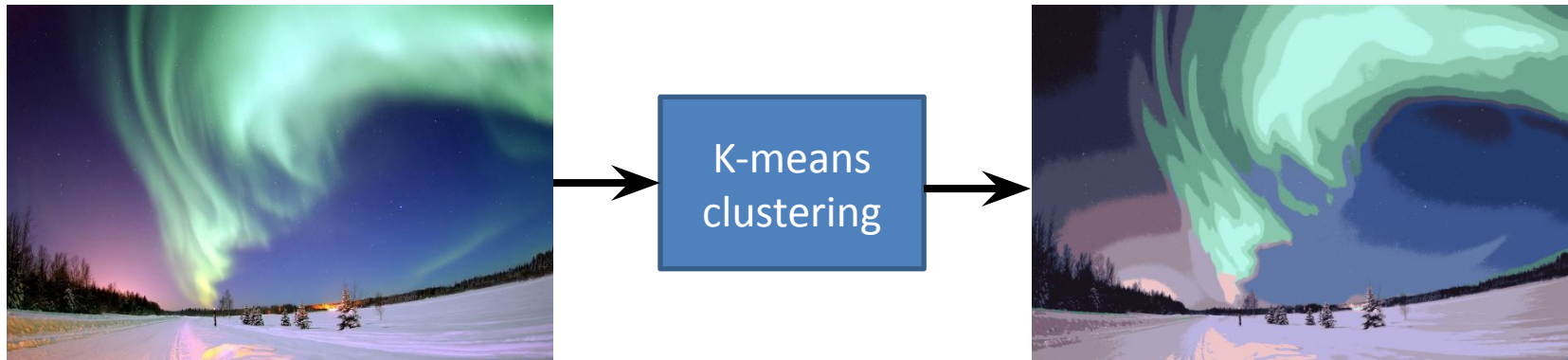


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5. Repeat steps 3-4
6. ...until one of:
  - a. Sum of distances between data points and corresponding centroid is minimized
  - b. No change in centroids
  - c. Maximum iterations reached



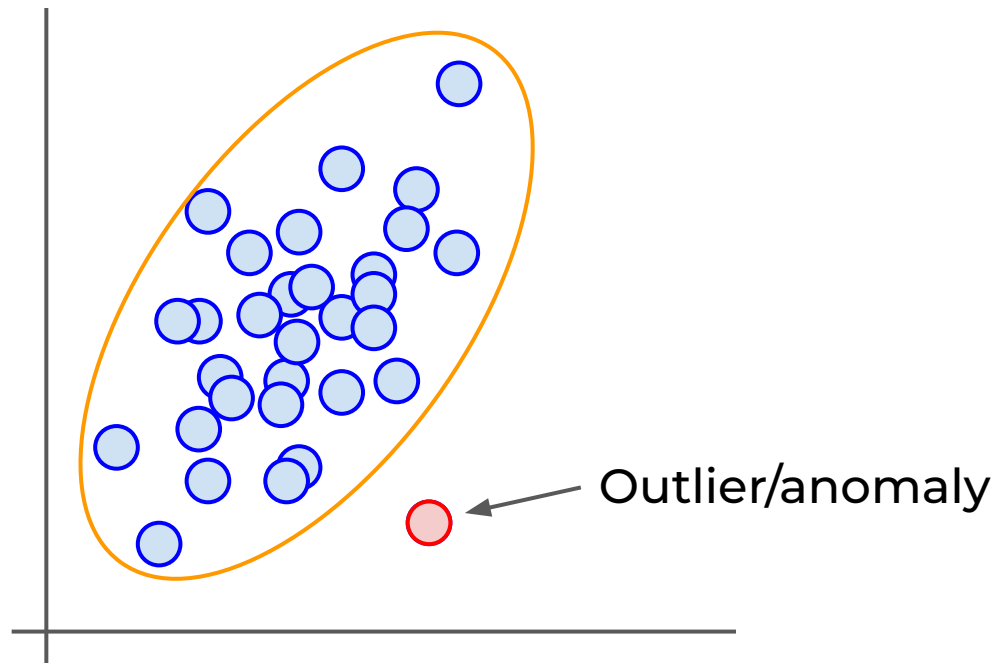
# Image Segmentation



# Anomaly Detection

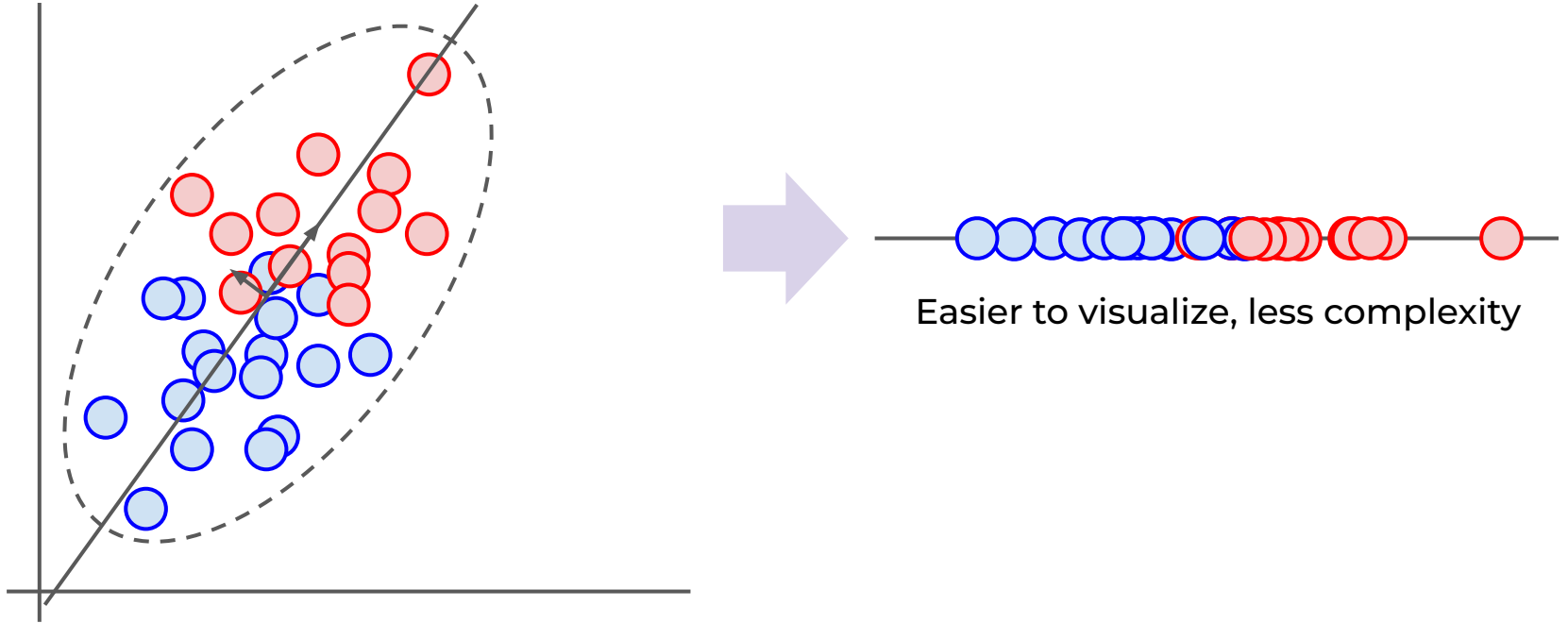
## Examples:

- Email spam
- Credit card fraud
- Motion alarm
- Fault detection



# Dimensionality Reduction

Example: principal component analysis (PCA)







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