

# Rail Data Science

## AI Methods

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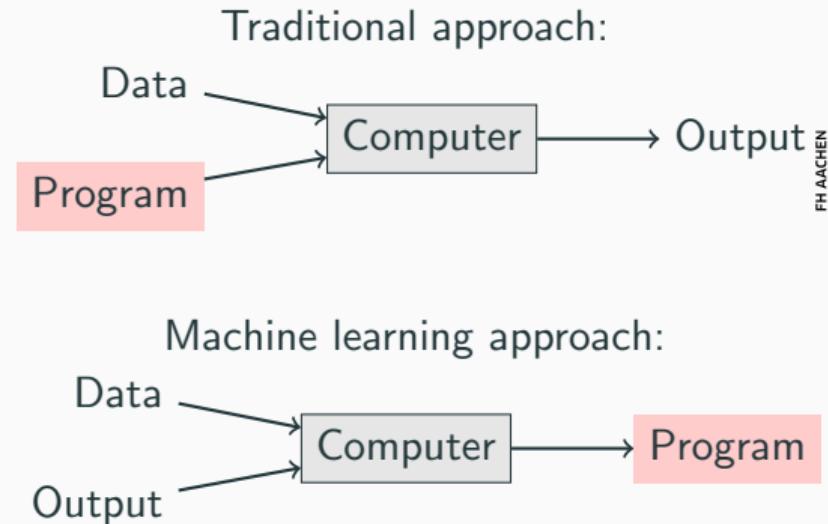
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13. Februar 2021

Fachhochschule Aachen

# What is machine learning?

- Different paradigm:
  - Derive rules from observations
- Typical procedure:
  - **Train:** Observe set of examples "training data"
  - **Fit:** Infer information of process behind data
  - **Test:** Make prediction on unseen data "Test data"
- Variations:
  - Supervised learning: provide labels with data
  - Unsupervised learning: cluster data based on patterns



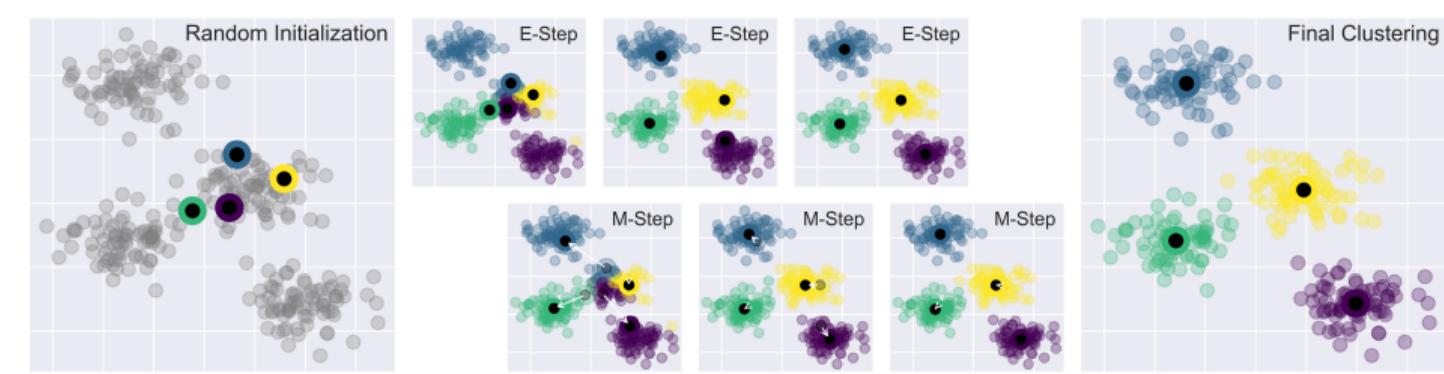
# Clustering

## Hierarchical clustering

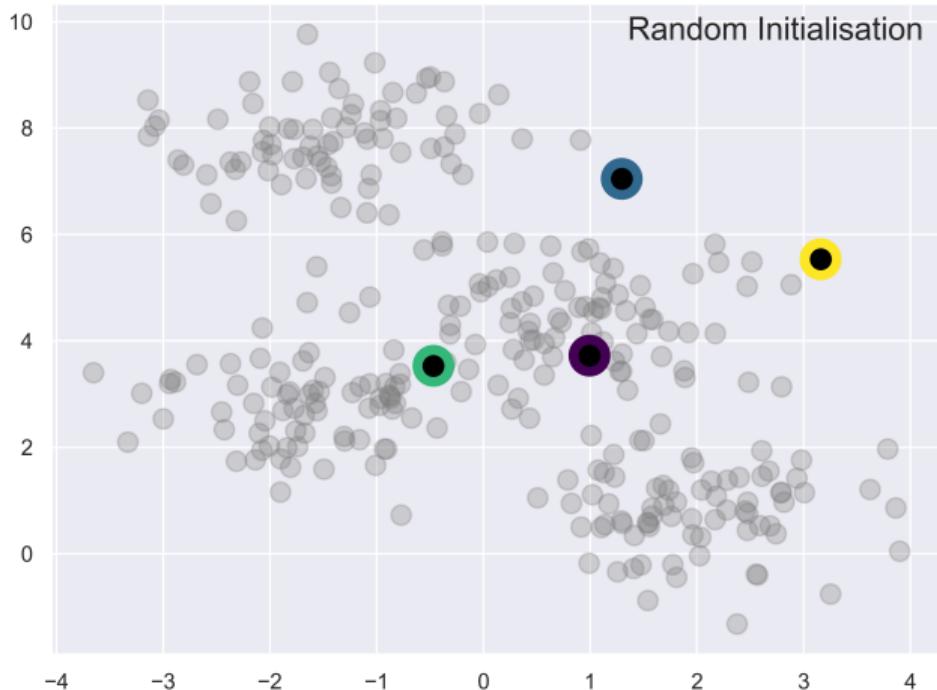
- 1 Assign each item to one cluster
- 2 Find closest (most similar cluster): merge them
- 3 Continue until desired number of clusters  $k$  is reached

## K-means clustering

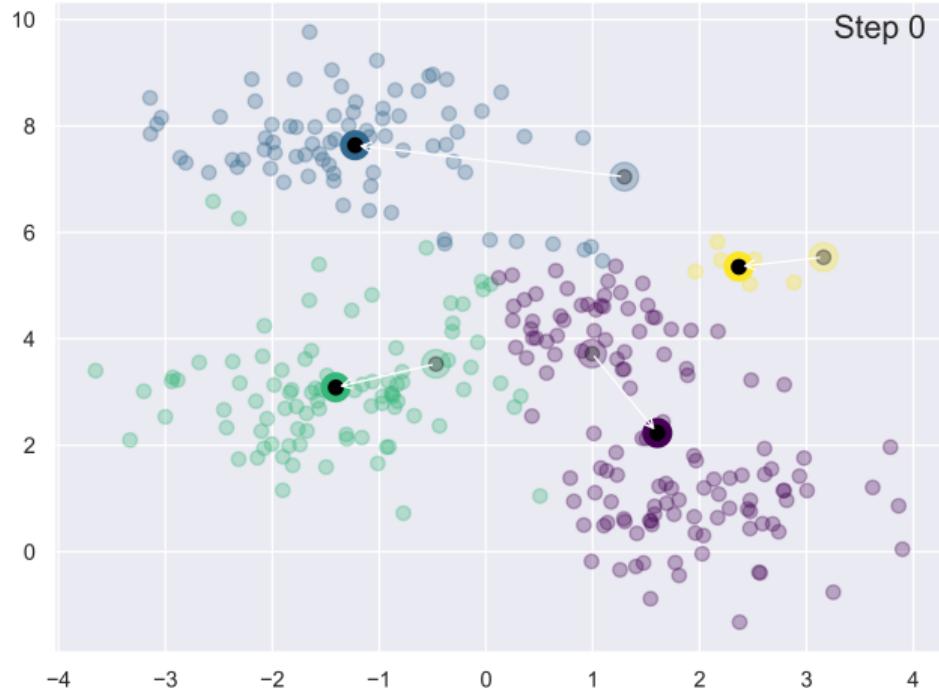
- 1 Randomly choose  $k$  initial centroids
- 2 While centroids don't change
  - E: Create  $k$  clusters by assigning each item to closest centroid
  - M: Compute  $k$  new centroids by averaging items in each cluster



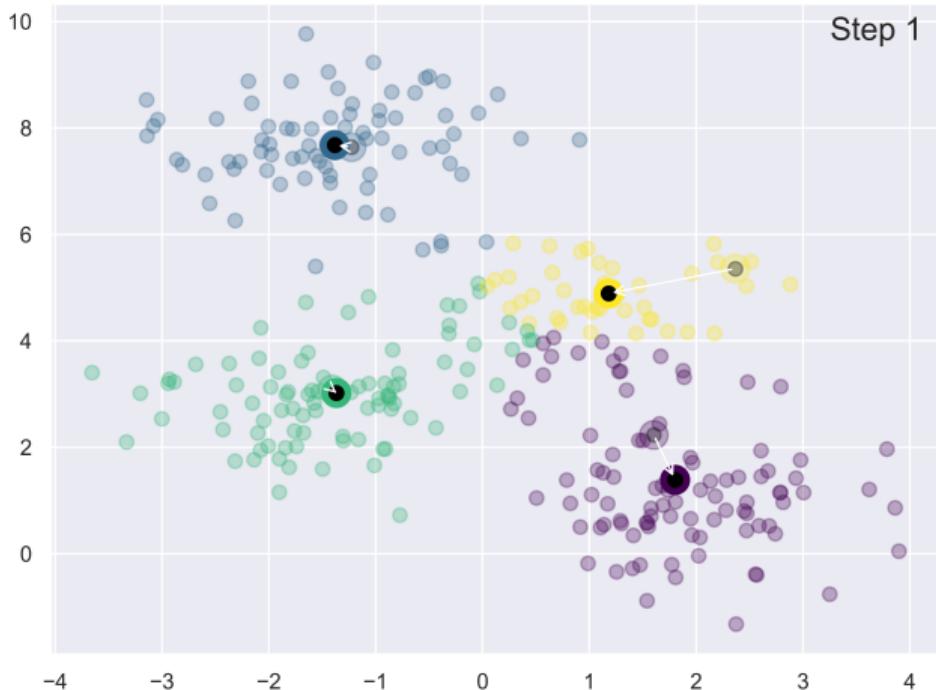
# K-means clustering procedure



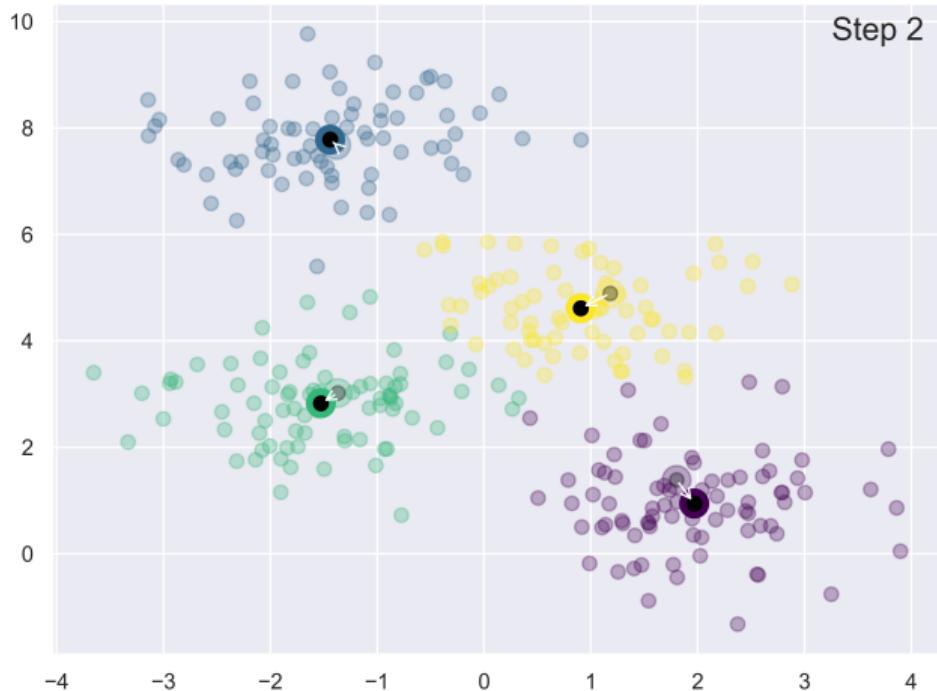
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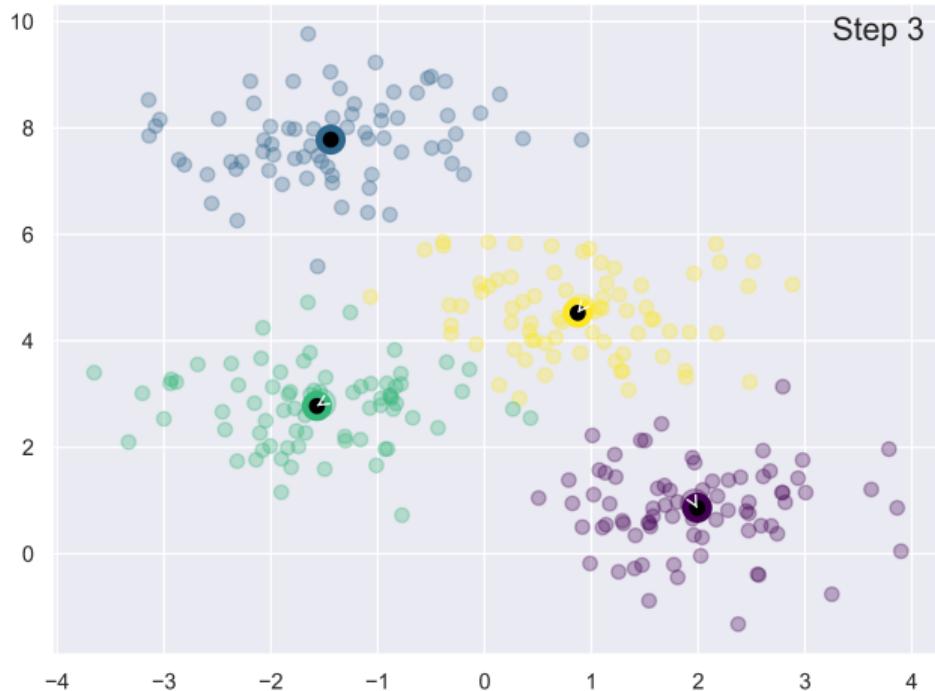
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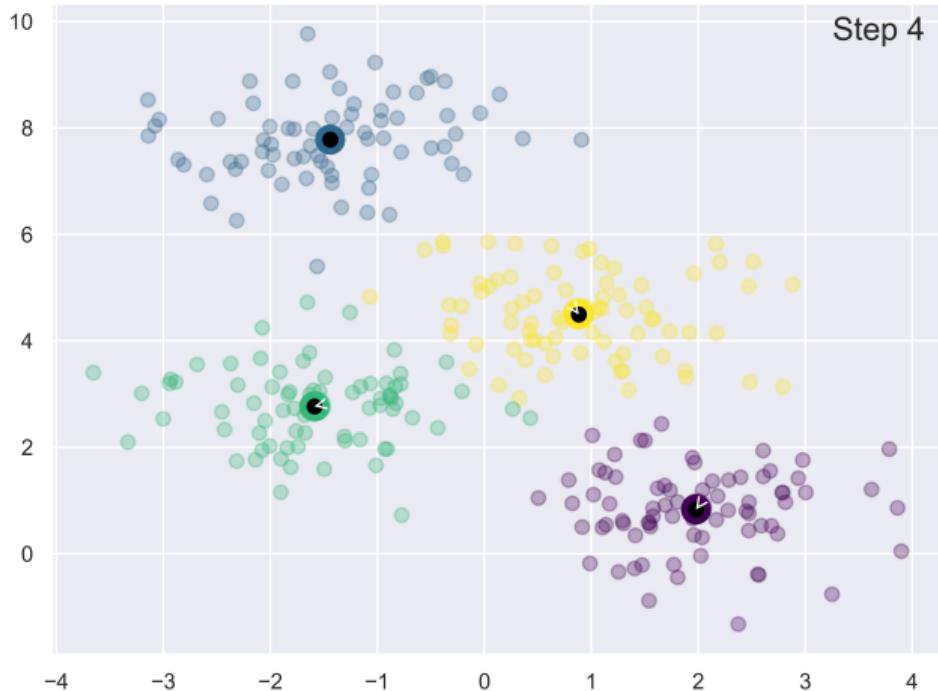
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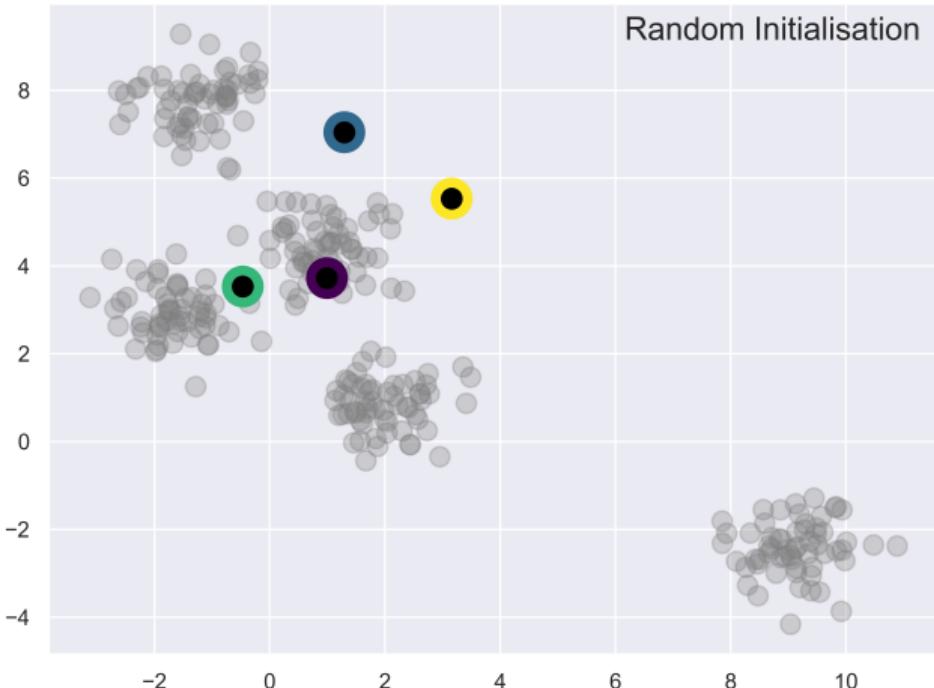
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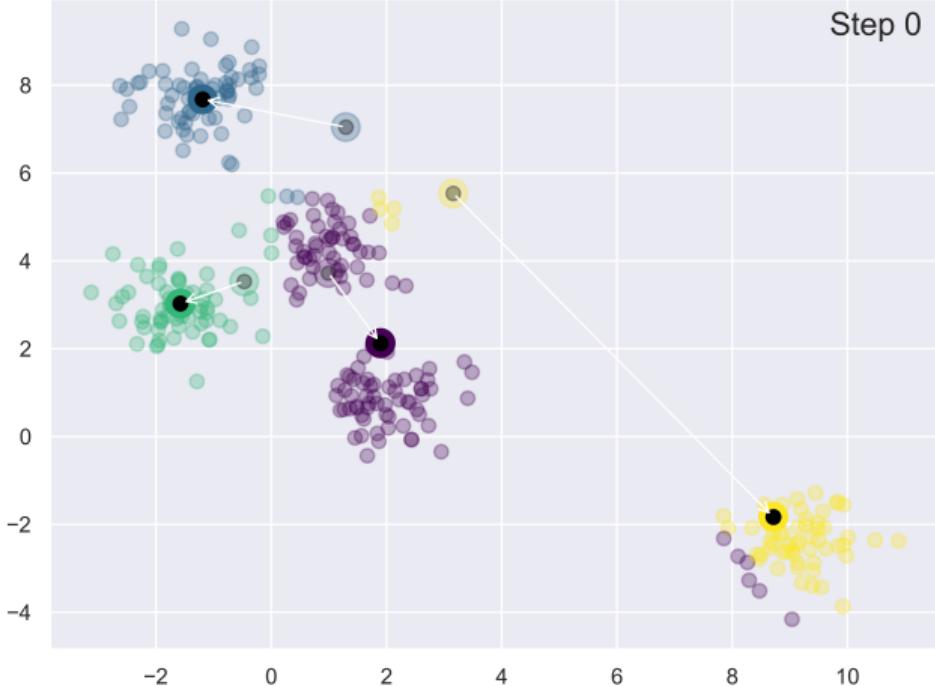
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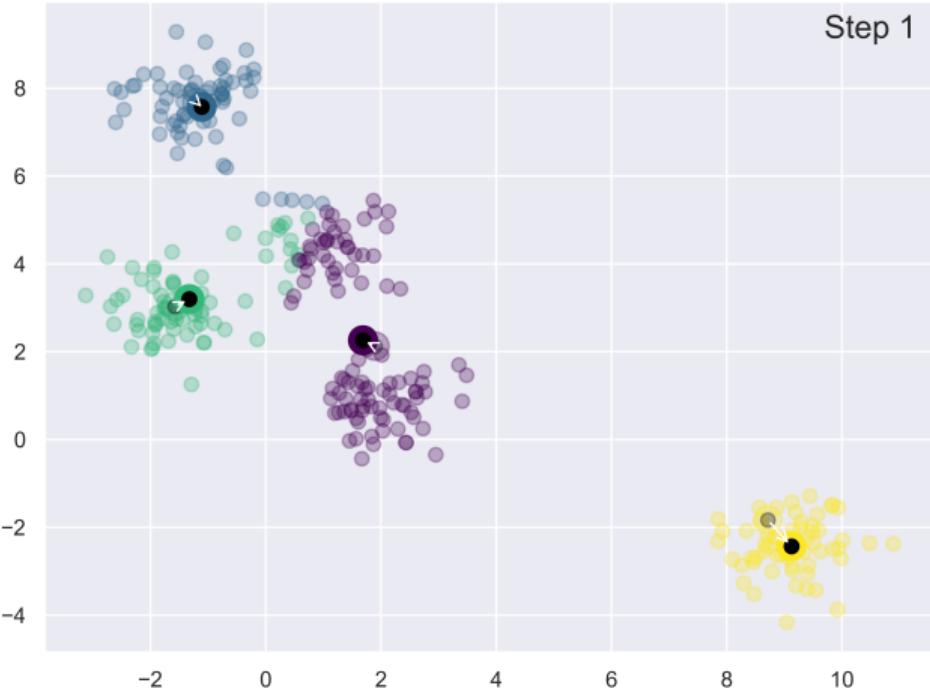
# K-means inappropriate cluster number



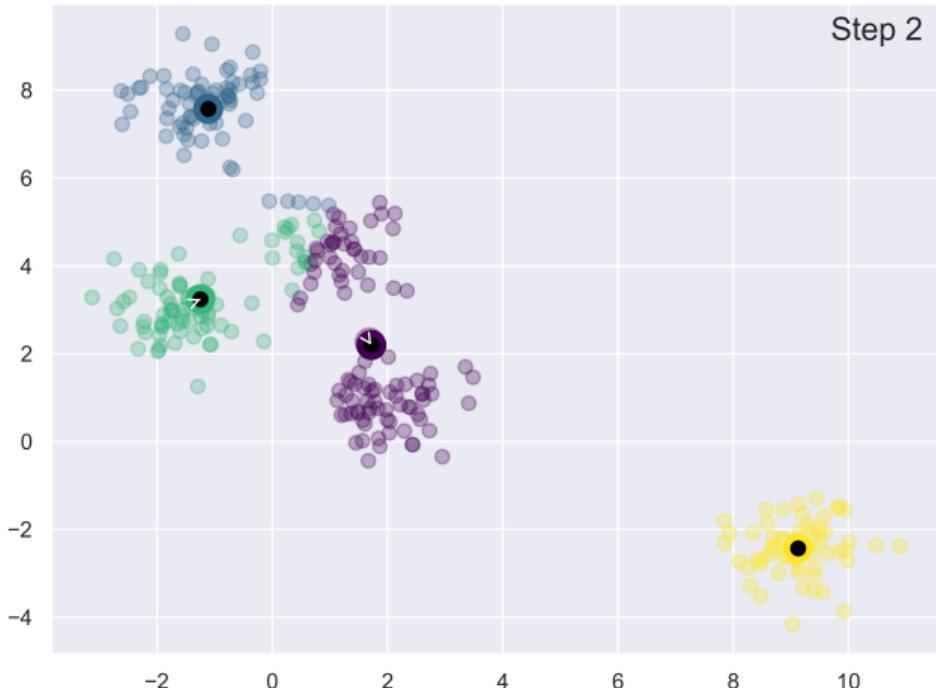
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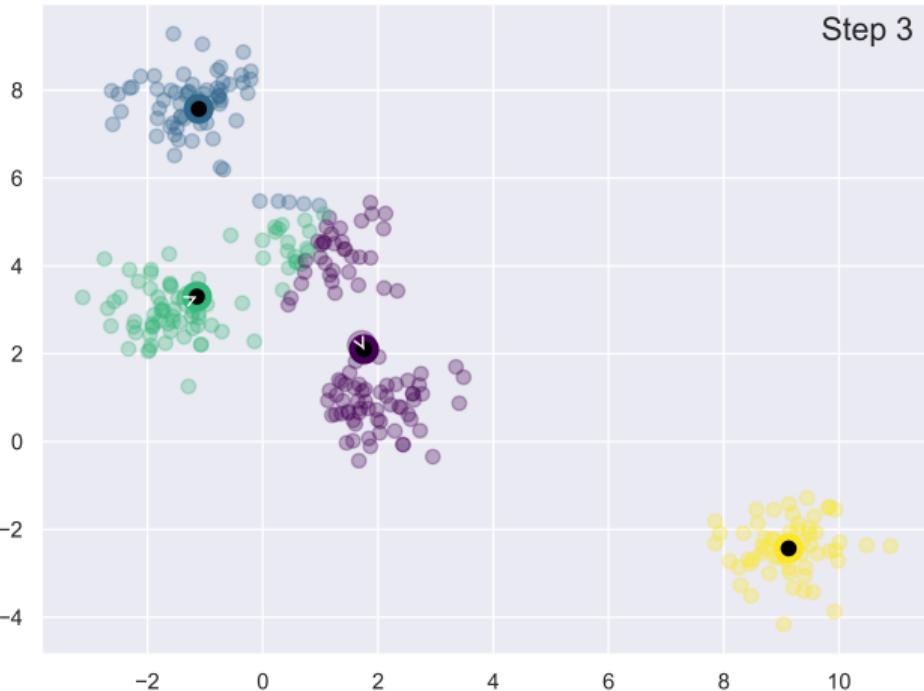
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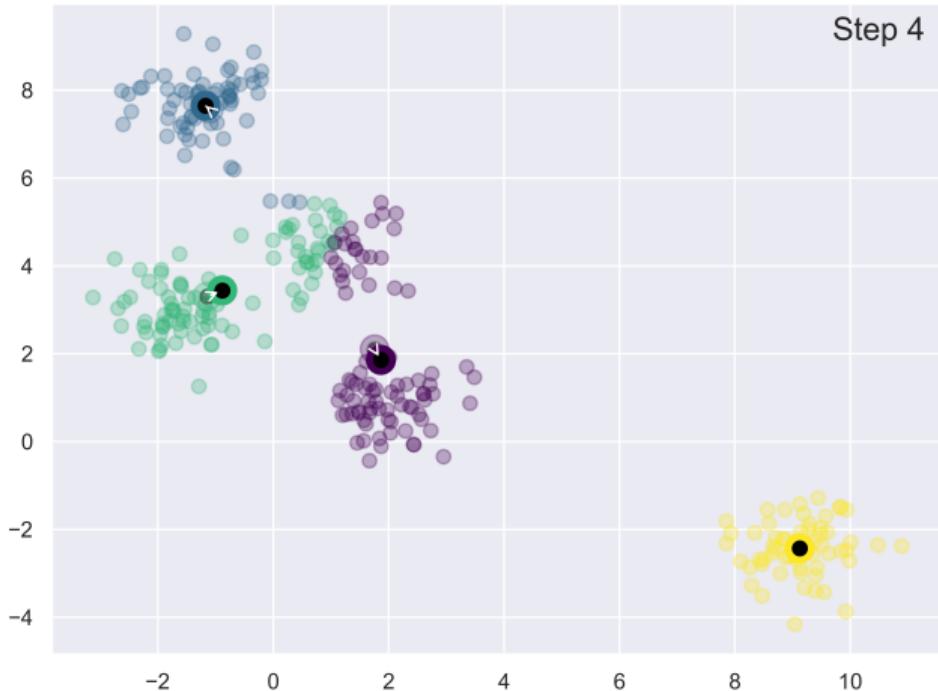
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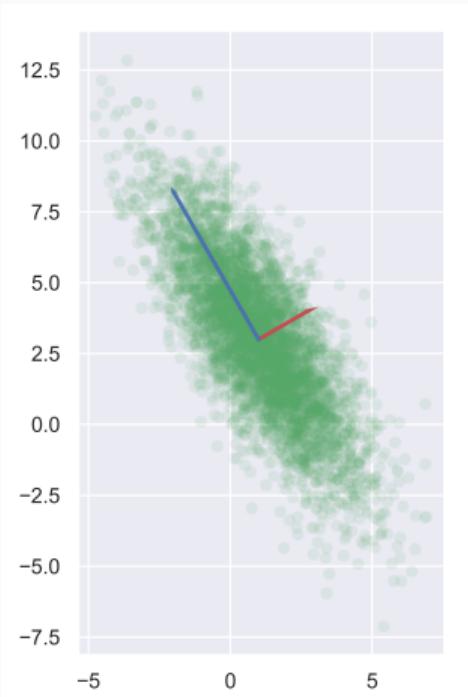


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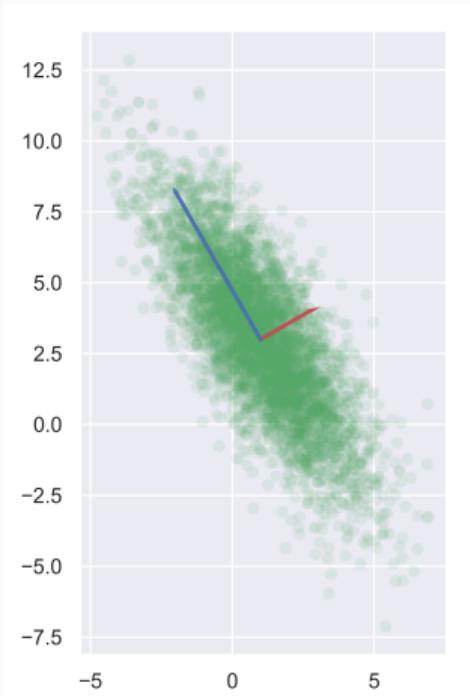
# Principal Component Analysis (PCA)

- Sample  $X_1, \dots, X_n$  is a cloud of points in  $\mathbb{R}^d$
- Typically,  $d$  is large
- **Question:** can we project the point cloud onto a linear subspace of dimension  $d' < d$  while keeping as much of the information as possible?



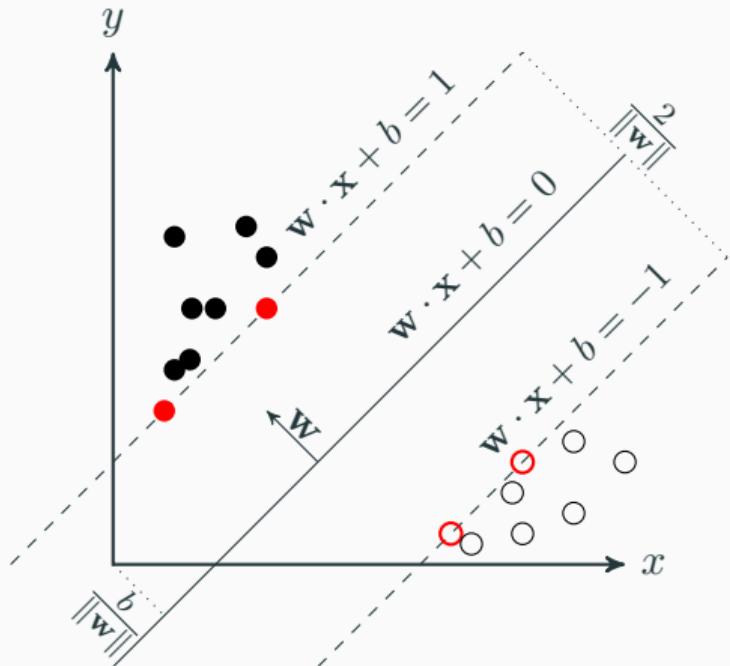
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- **Answer:** PCA achieves this by keeping important aspects of the covariance structure in orthogonal directions.



# Support Vector Machine

- Idea:
  - Find separating hyperplane maximising the distance between borderline instances
  - For data mixed in feature space, slack parameter (and penalty  $C$ ) is used
  - If no separating hyperplane can be found in feature space, dimension is increased “Kernel trick”
- Robust:
  - High dimensionality
  - Small datasets
- Simple to complex models



# Support Vector Machine

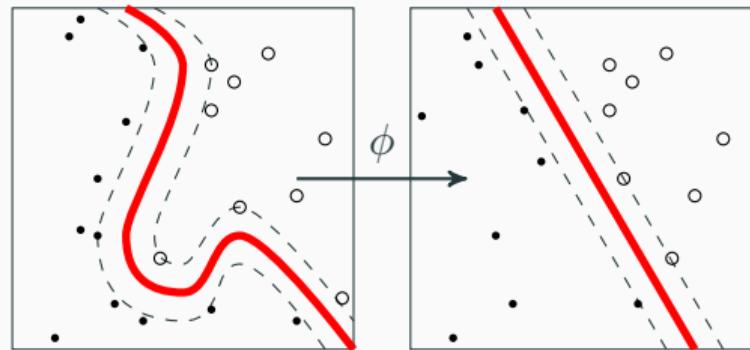
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## ■ Robust:

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## ■ Simple to complex models



# Practical hints for application of data science methods

- Get to know your data
- Use training and validation sets
- For clustering and ML:
  - Regularise
  - Remove outliers, NaN
- When building models:
  - Don't expect perfect fit
  - Inspect confusion matrix

		Prediction outcome	
		p	n
actual value	p'	True Positive	False Negative
	n'	False Positive	True Negative
	total	P	N

Get to work!

