UCL ARTIFICIAL
INTELLIGENCE SOCIETY

TUTORIAL #4

Session 4

Introduction to unsupervised models and data pre-processing

UCL ARTIFICIAL
INTELLIGENCE SOCIETY

LECTURE OVERVIEW

01 | **Data Preprocessing**

What is it and how to use it

02 | **Model Training**

Overview of the most important terms in ML

03 | **Data visualisation**

04 | **Other Supervised Models**

Support Vector Machine
Decision Trees

Theory

SUPERVISED V. UNSUPERVISED LEARNING

Supervised L.

- It learns using data X and labels Y
- Learns X -> Y

Unspervised L.

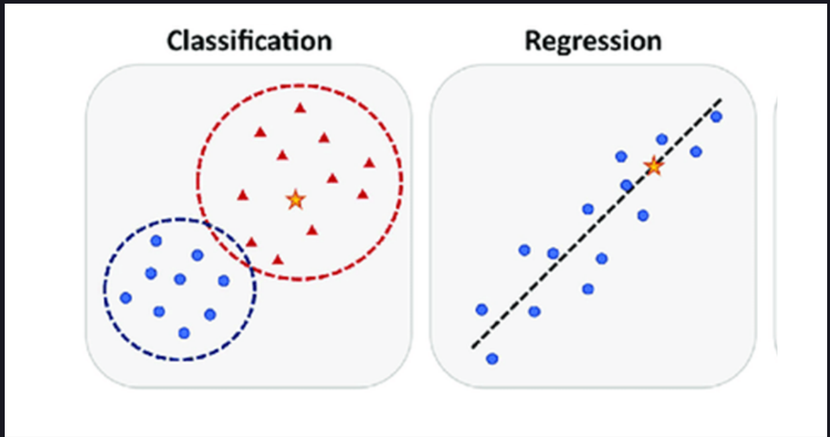
- It learns using just data X
- Observes underlying structures

Theory

SUPERVISED V. UNSUPERVISED LEARNING

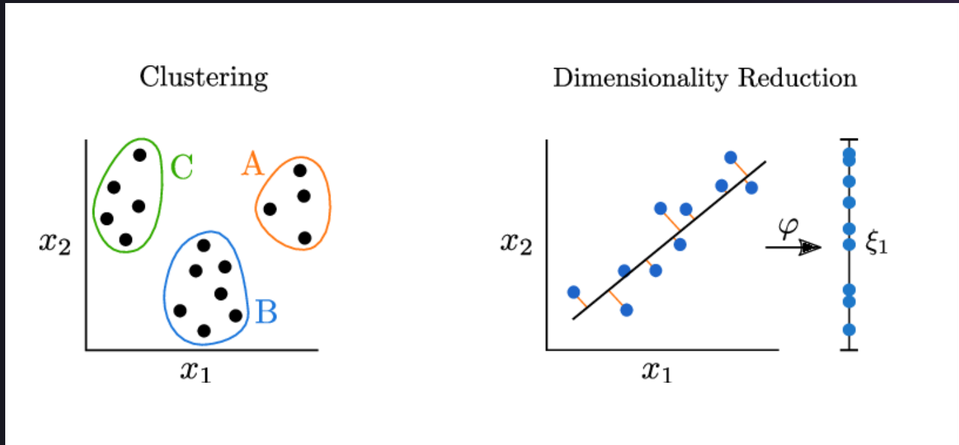
Supervised L.

- Fits some function
- Regression and Classification



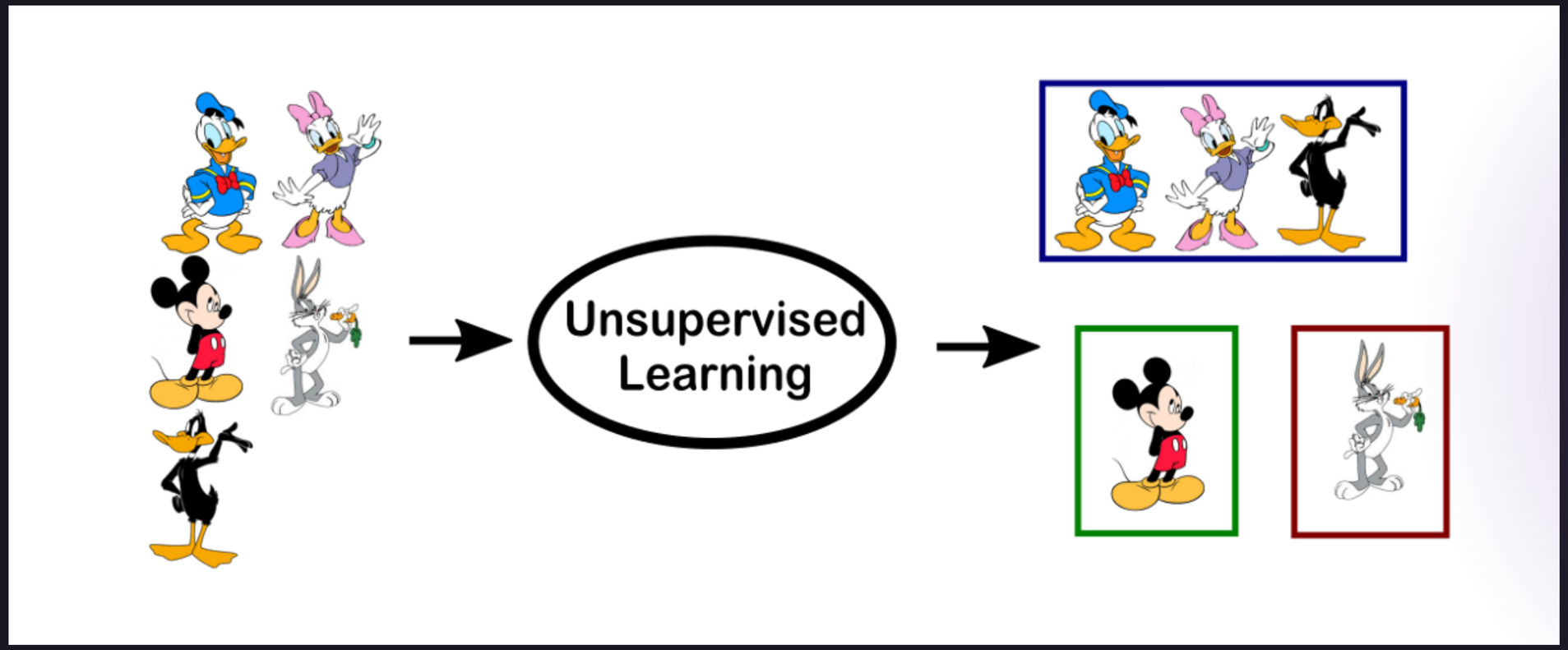
Unspervised L.

- Works with and transforms data
- Clustering and Dimensional Reduction



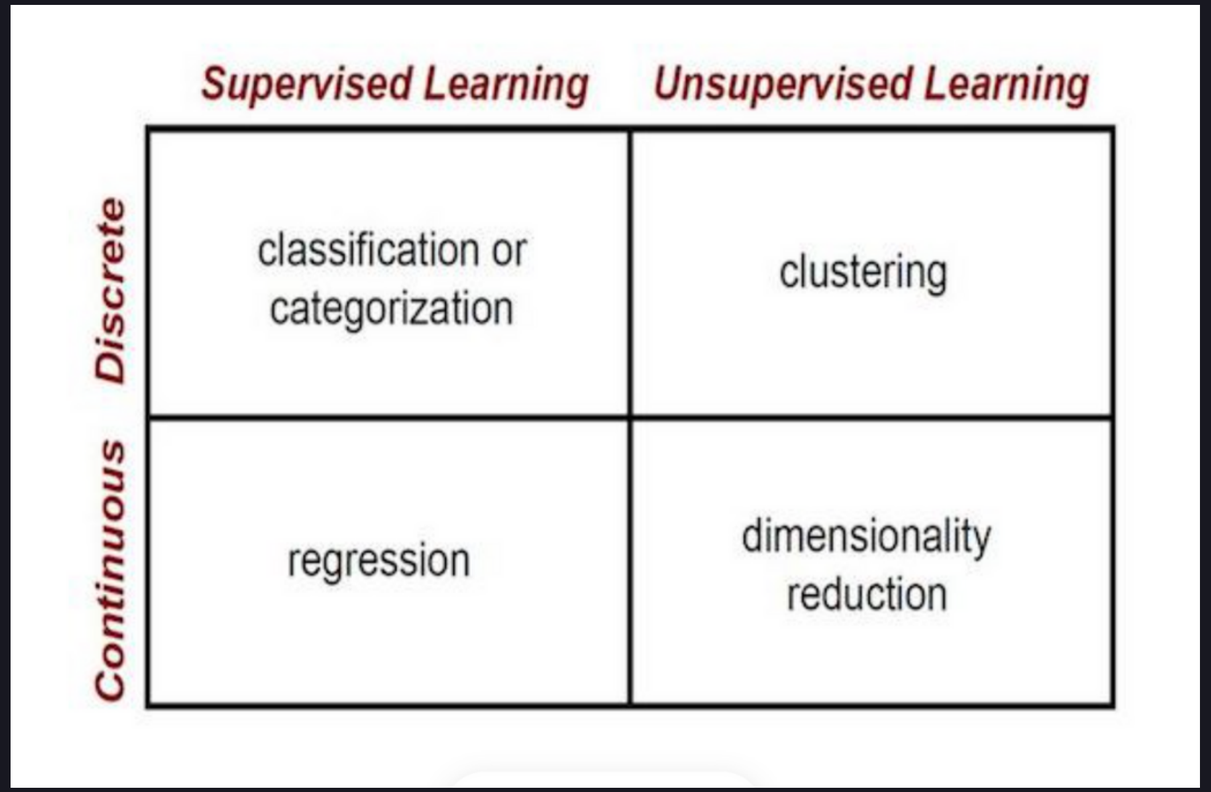
Theory

SUPERVISED V. UNSUPERVISED LEARNING



Theory

SUPERVISED V. UNSUPERVISED LEARNING



Theory

DATA PRE-PROCESSING

Raw Data:

Imagination:

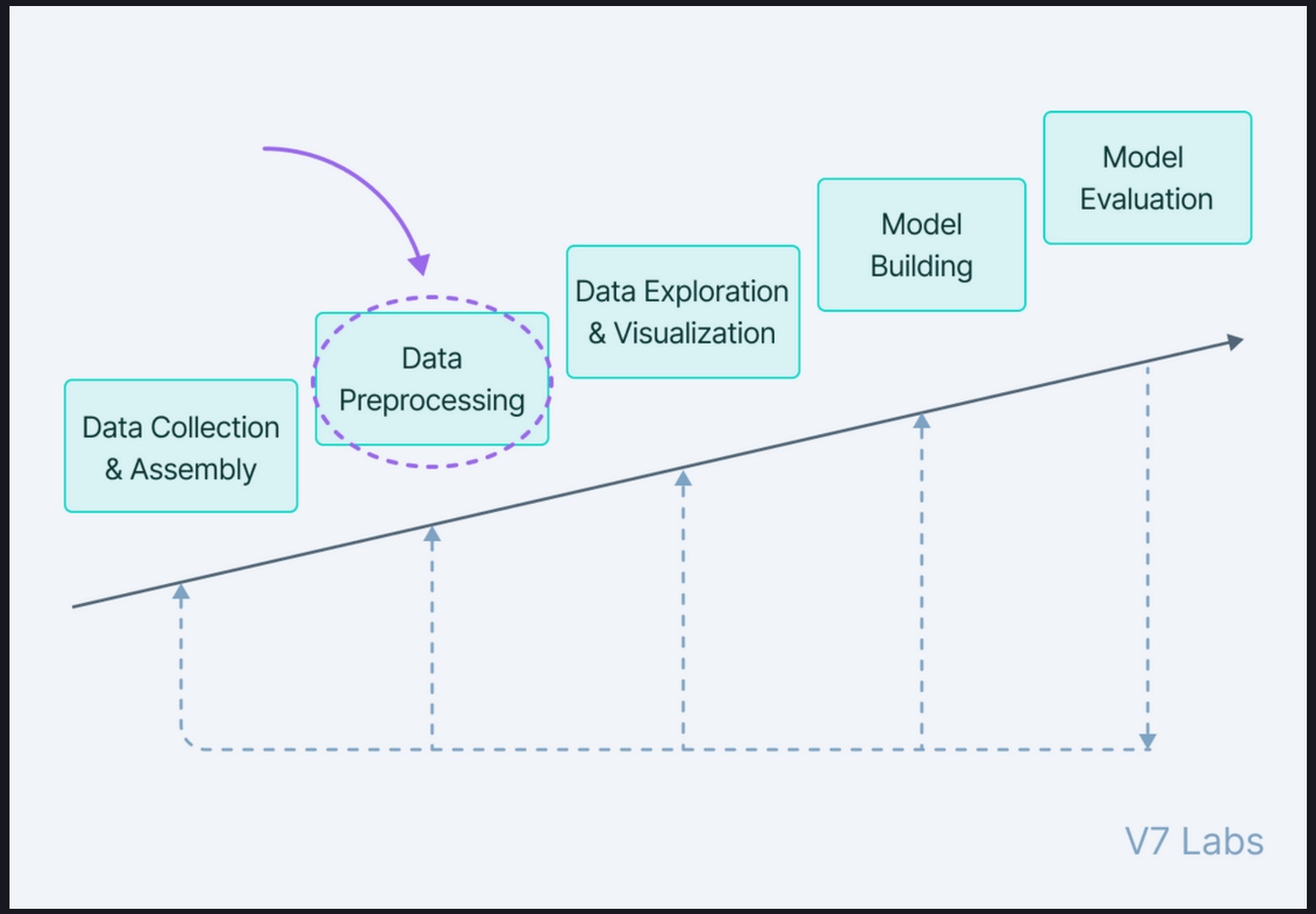
- No inconsistencies
- No noice
- Complete
- No missing values

etc

Reality:

Theory

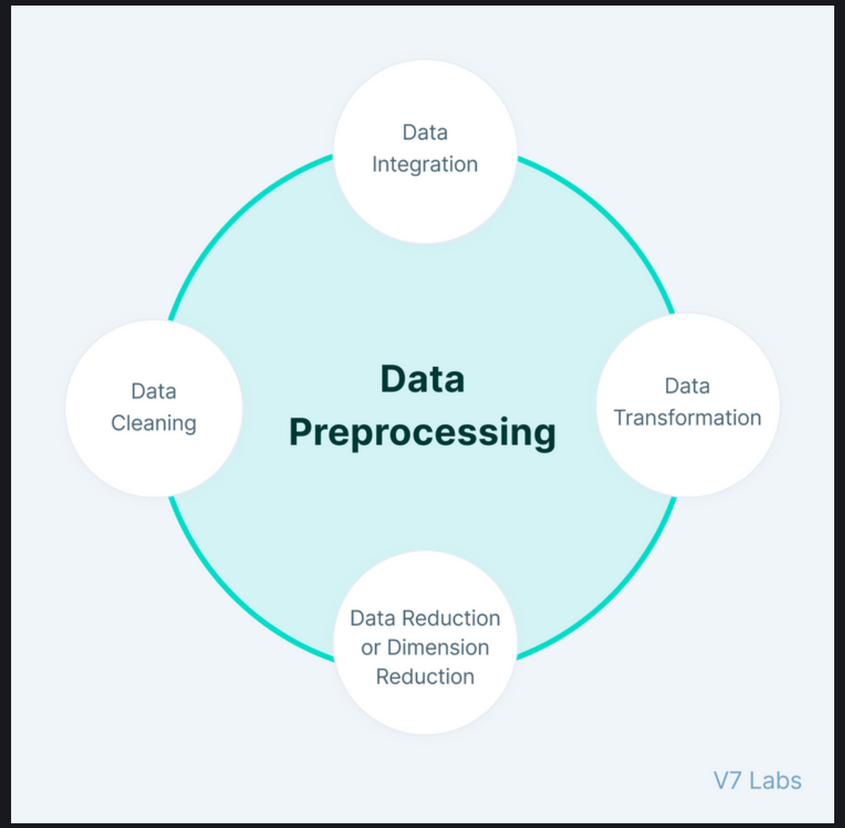
DATA PRE-PROCESSING



Theory

DATA PRE-PROCESSING

4 Steps in Data Preprocessing

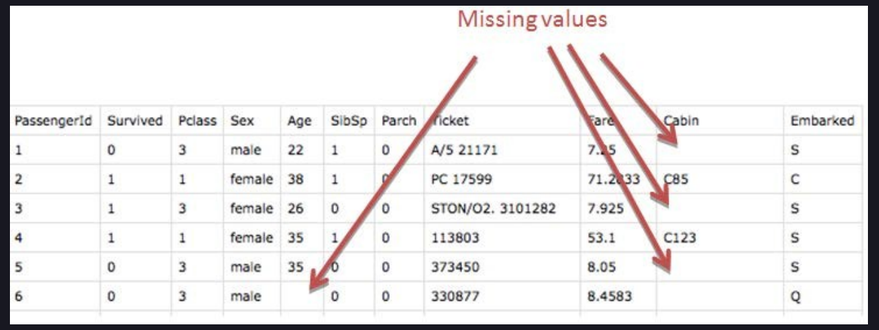


Theory

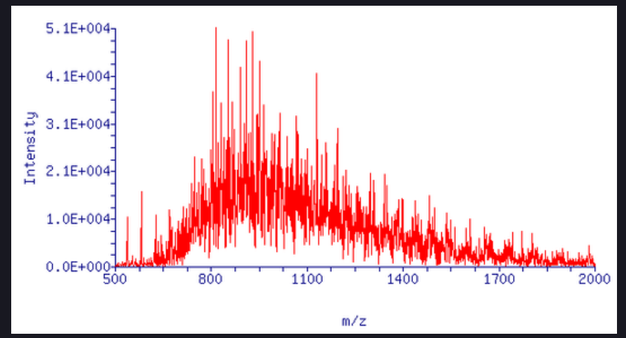
DATA PRE-PROCESSING

Data cleaning

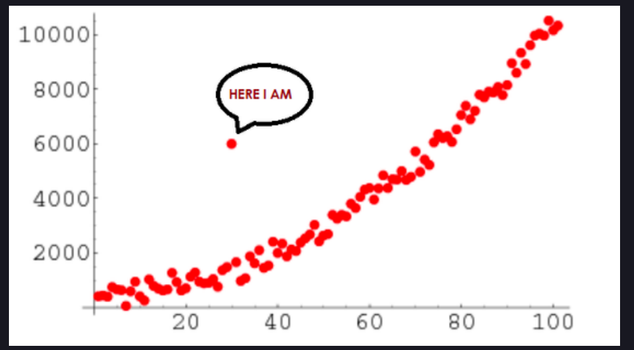
1) Missing values



2) Noisy data



3) Removing Outliers

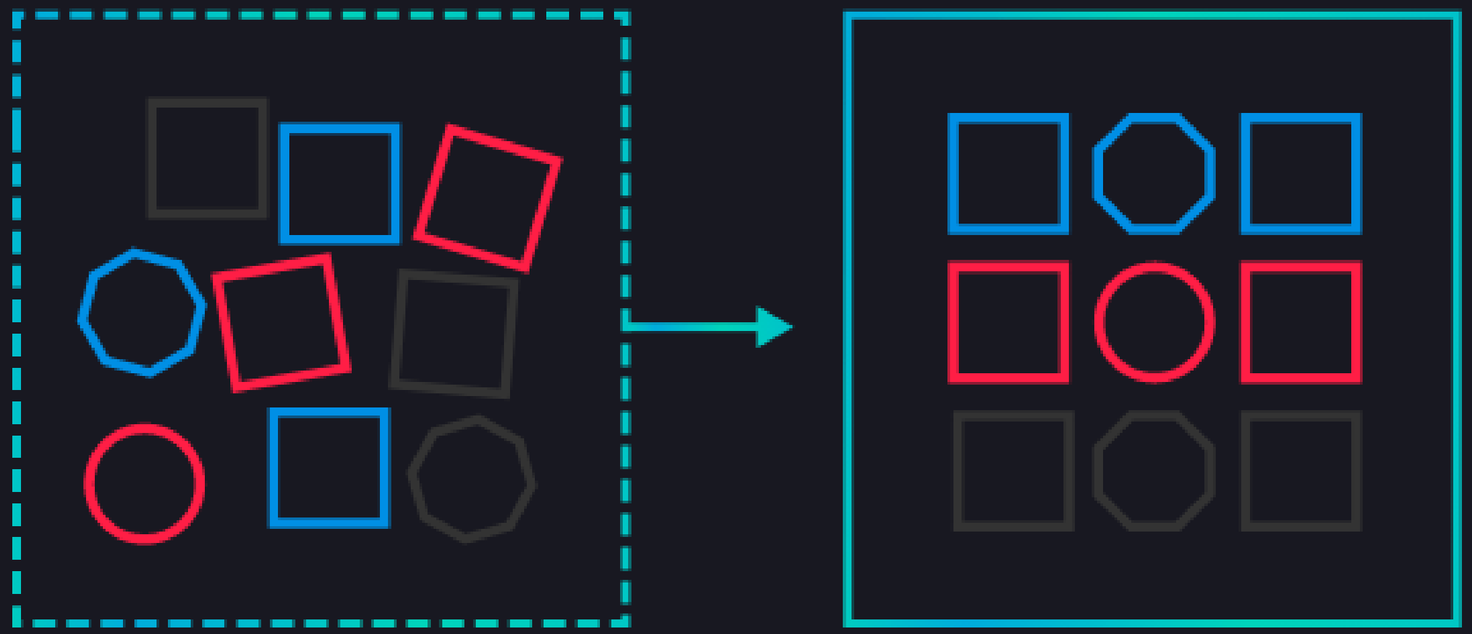


Theory

DATA INTEGRATION

Theory

DATA TRANSFORMATION



- Generalisation
- Normalisation
- Attribute Selection
- Aggregation

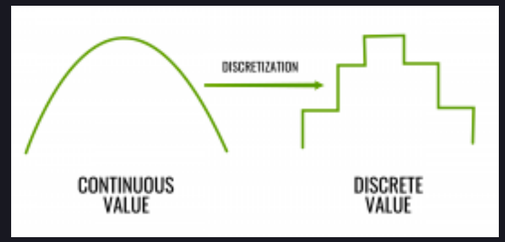
Basically, just making the data actually usable

Theory

DATA REDUCTION

How? Lot's of ways.
Perhaps even too many.
But here's a couple:

Discretisation



Numerosity Reduction

Honestly, couldn't find an image
But imagine an equation

Attribute Subset Selection

Theory

VISUALISATION

Why would we need to visualise data?

Theory

VISUALISATION

Why would we need to visualise data?

01 | **Identify patterns**

02 | **Identify corrupt data/outliers**

03 | **Feature selection**

04 | **Understanding high dimensional hata**

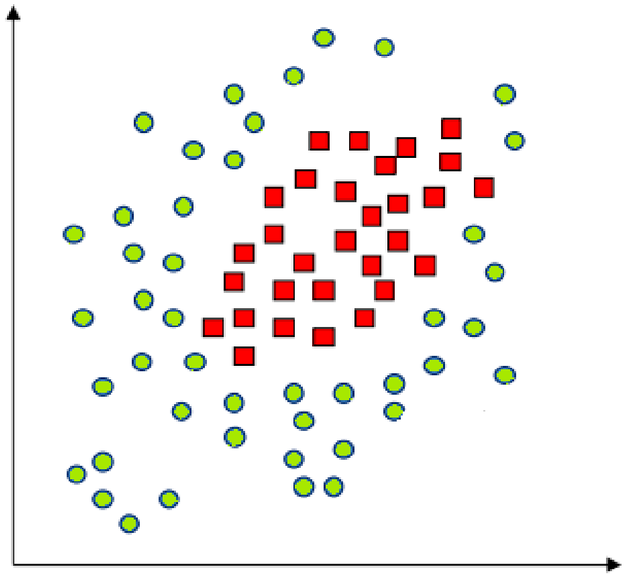
Theory

VISUALISATION

Why would we need to visualise data?

01

Identify patterns

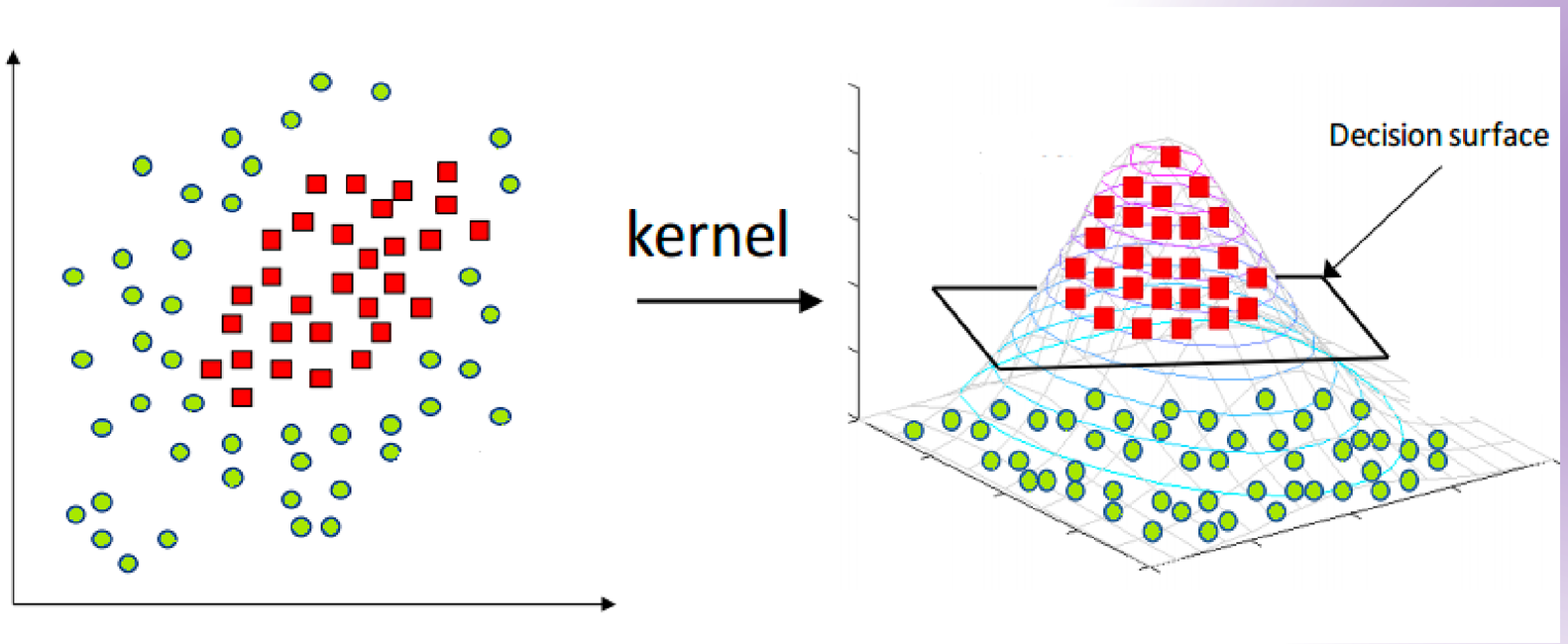


Theory

VISUALISATION

Why would we need to visualise data?

01 Identify patterns



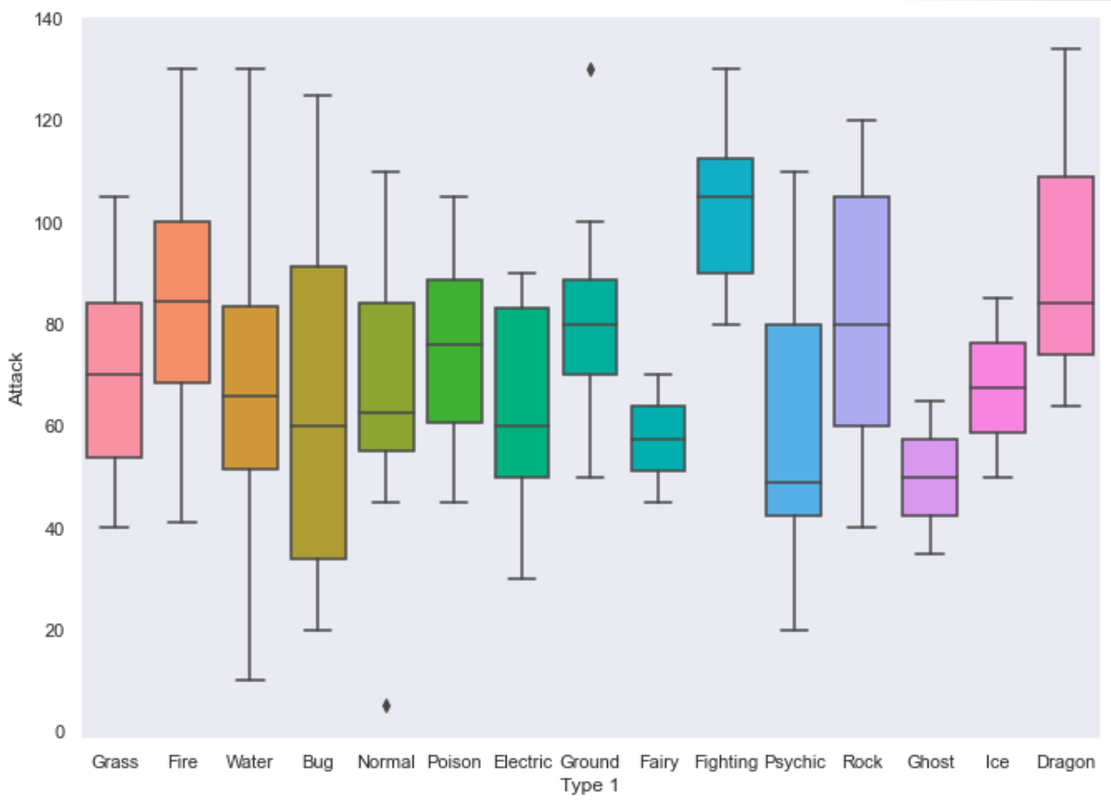
Theory

VISUALISATION

Why would we need to visualise data?

02

Identify outliers

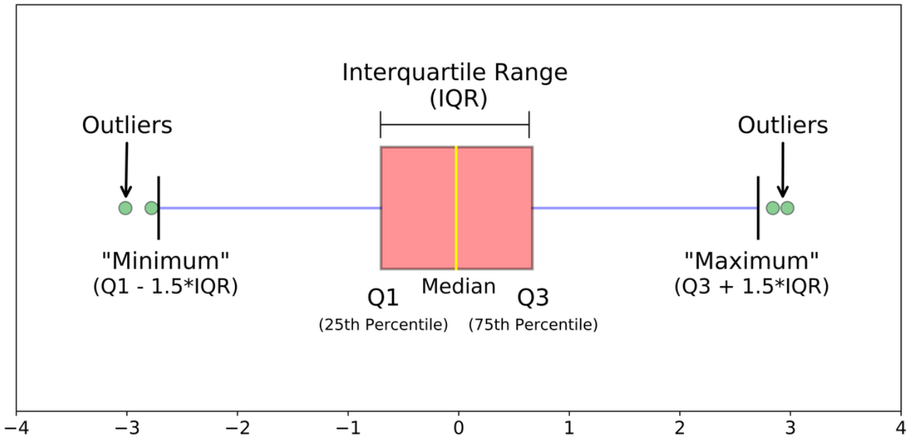


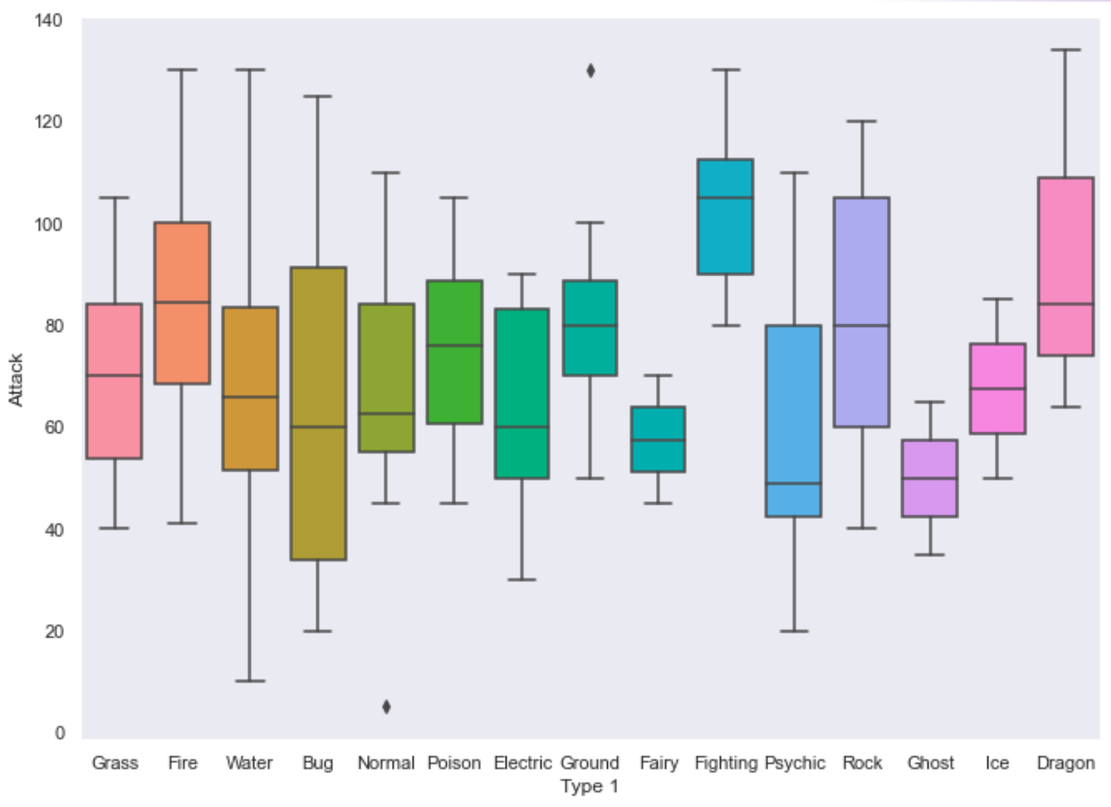
Theory

VISUALISATION

Why would we need to visualise data?

02 Identify outliers



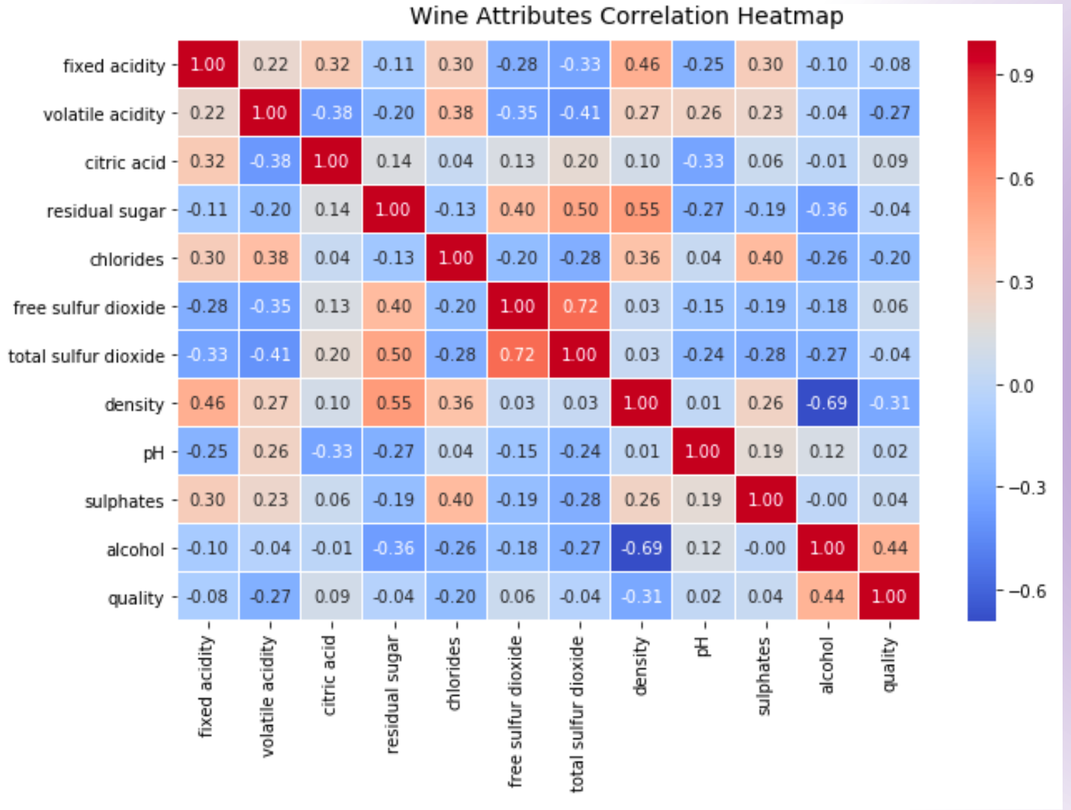


Theory

VISUALISATION

Why would we need to visualise data?

03 | **Feature selection**

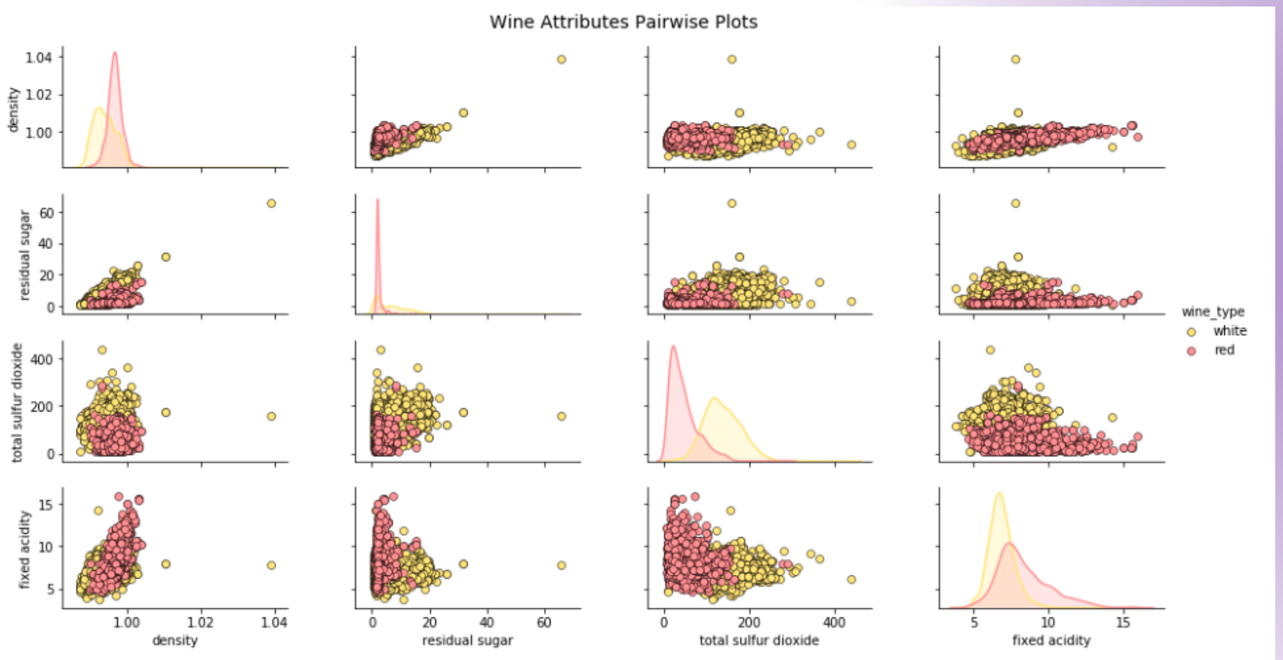


Theory

VISUALISATION

Why would we need to visualise data?

04 Understanding high dimensional data



Theory

PCA

Dimensionality reduction

- Curse of dimensionality
  - Sparse and dissimilar data

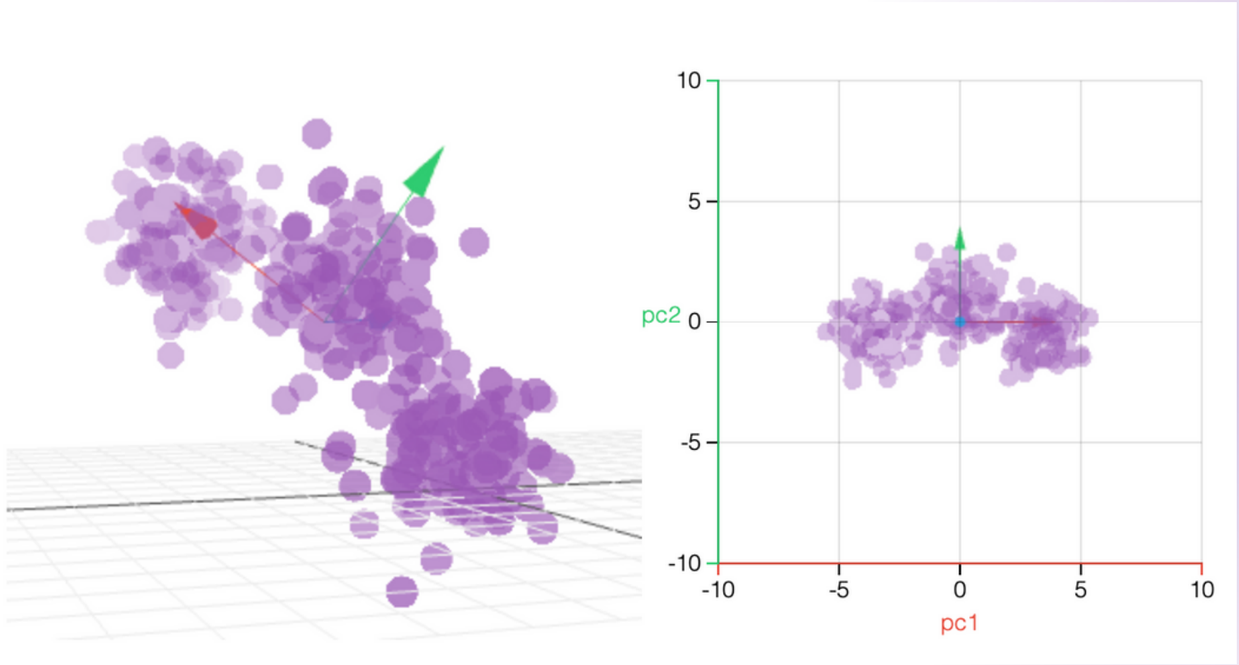
2D

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

3D

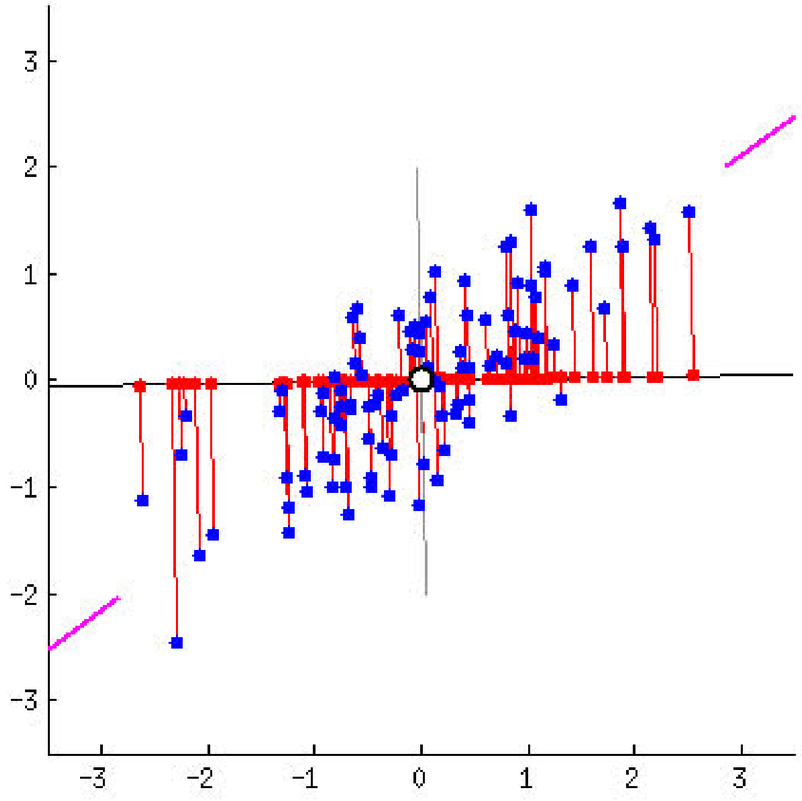
$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2}$$

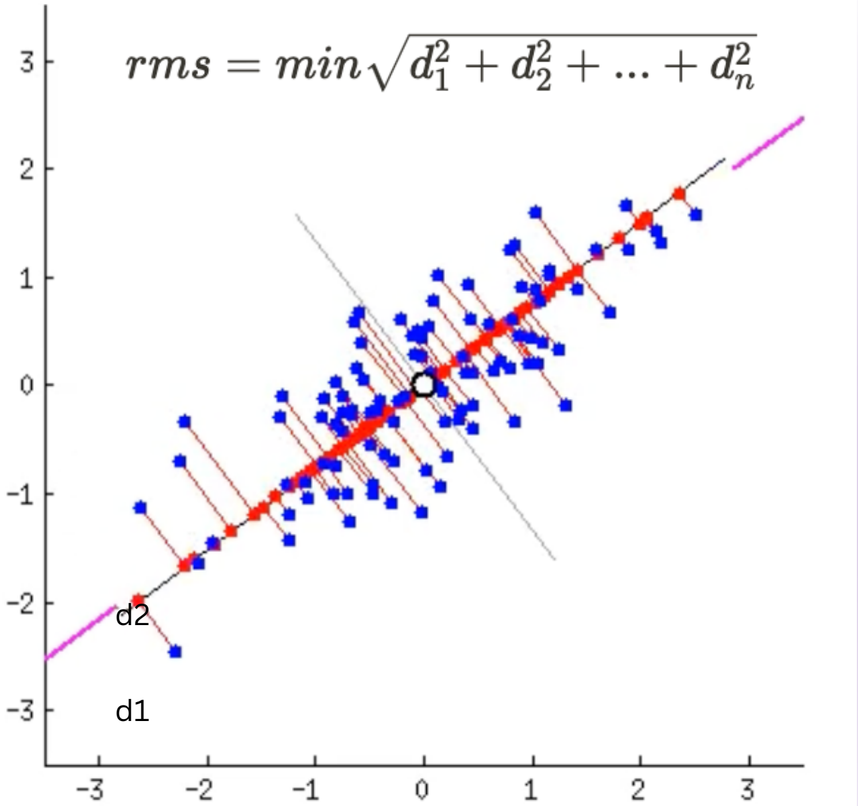
- Reduces multicollinearity



Theory

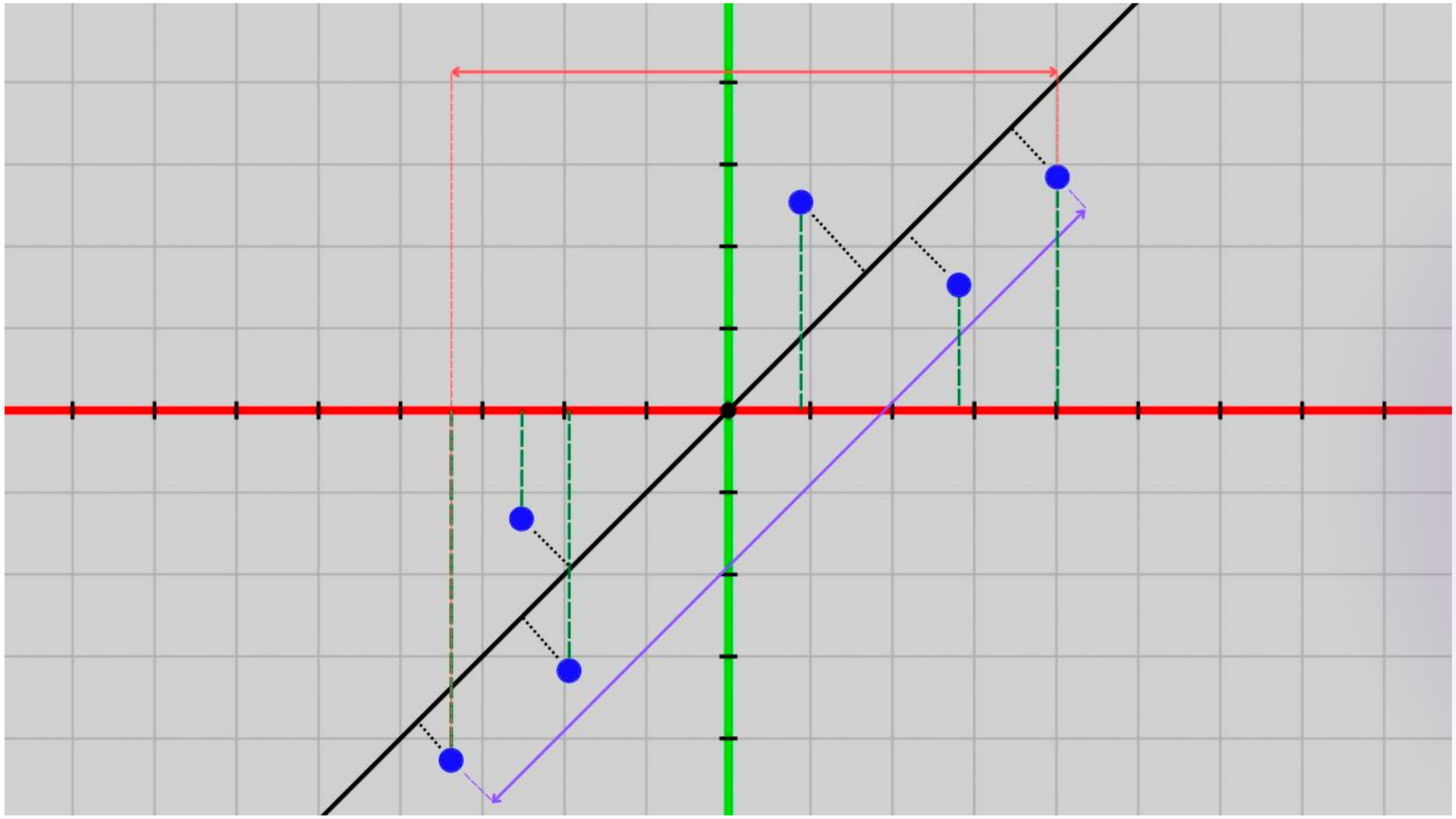
PCA


3
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2
3


$rms = min\sqrt{d_1^2 + d_2^2 + ... + d_n^2}$
d2
d1
3
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2
3

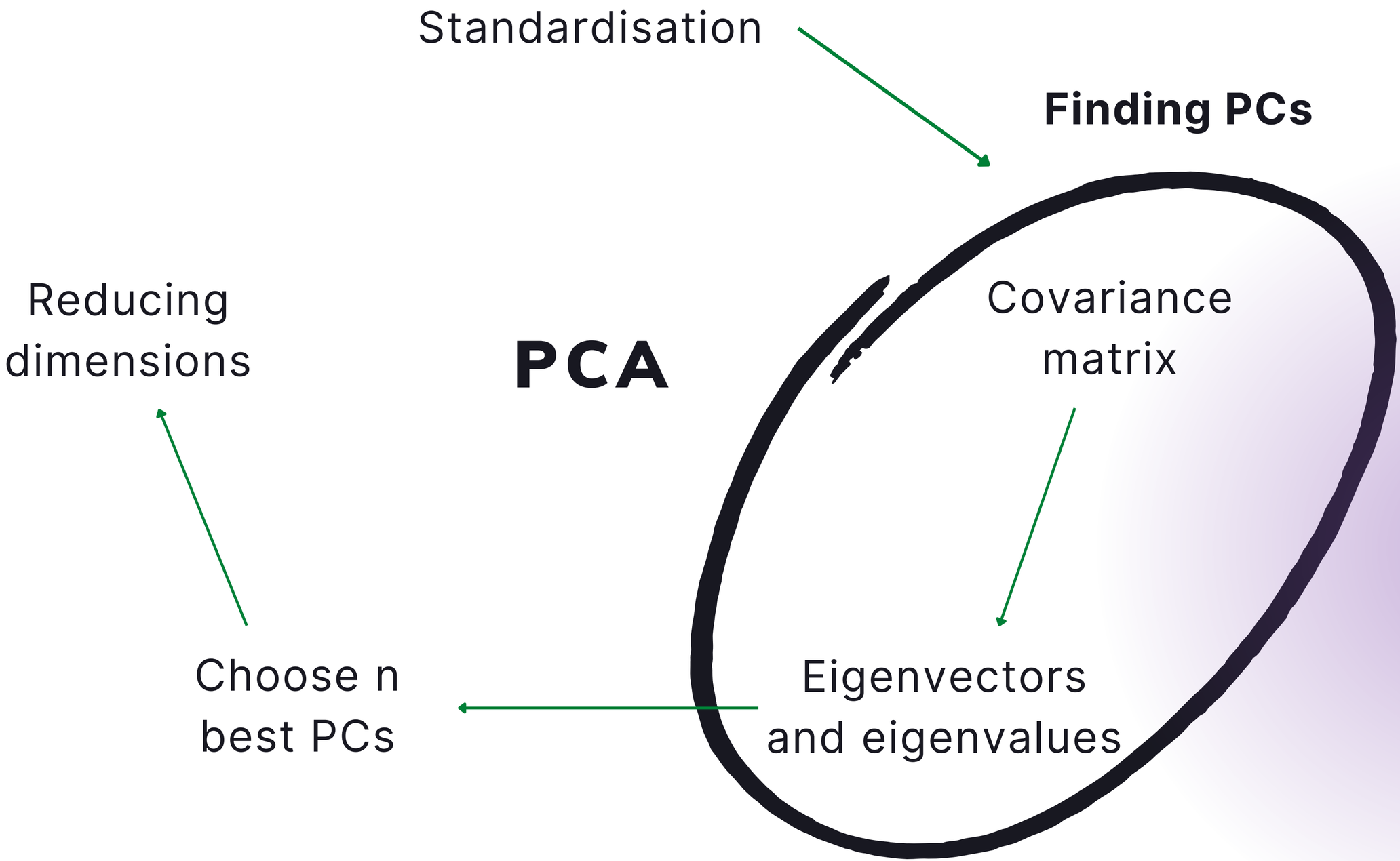
Theory

PCA



Theory

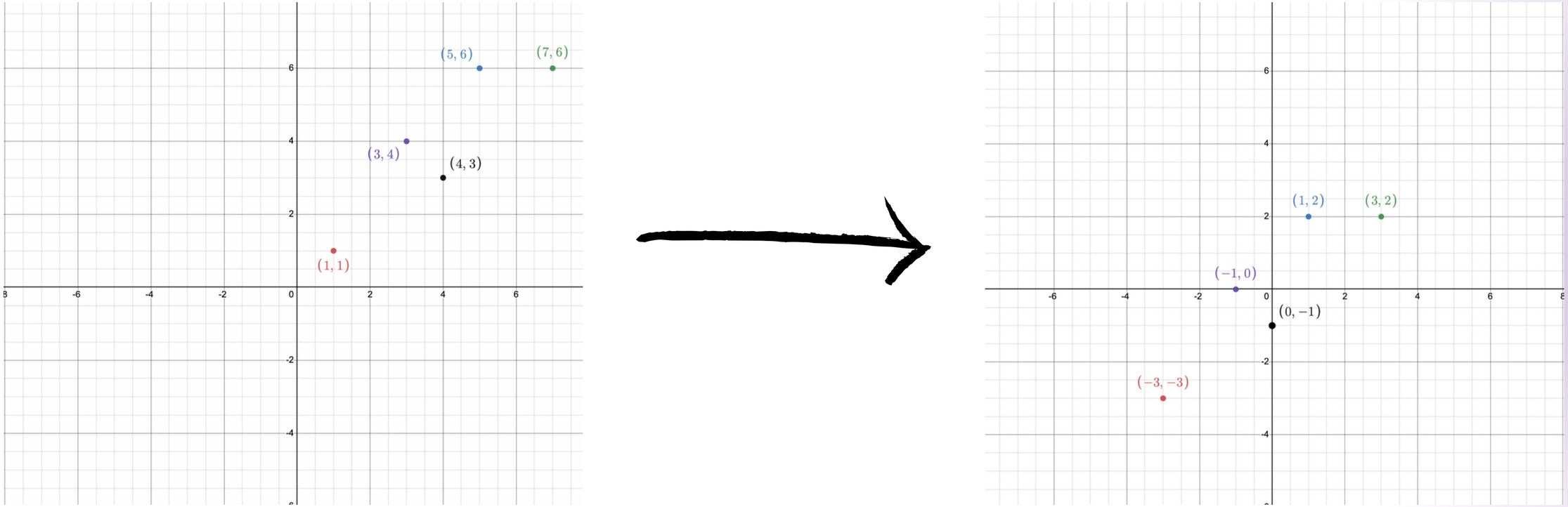
PCA


Standardisation
Finding PCs
Covariance matrix
Eigenvectors and eigenvalues
Choose n best PCs
Reducing dimensions
PCA

Theory

PCA

Standardisation



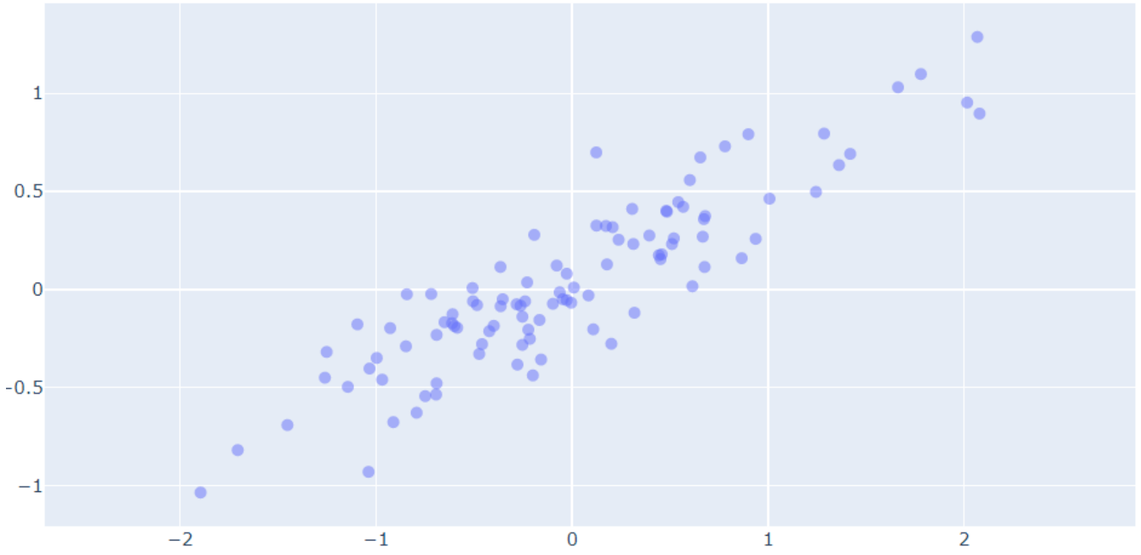
Theory

PCA

Covariance matrix

- Measuring the levels by which each pair of variables/attributes vary

$$\mathrm{Cov}(x, y) = \frac{1}{N-1} \sum_{j=1}^{N} (x_j - \mu_x)(y_j - \mu_j)$$



$$\begin{pmatrix} 2.5 & 3.0 \\ 3.0 & 10.0 \end{pmatrix}$$

Theory

PCA

Eigenvalues and eigenvectors

$$\mathbf{A}\vec{v}_i = \lambda_i \vec{v}_i$$

$$\mathbf{A} = \begin{bmatrix} -2 & 2 & 1 \\ -5 & 5 & 1 \\ -4 & 2 & 3 \end{bmatrix} \longrightarrow det(\mathbf{A} - \lambda \mathbf{I}) = \begin{vmatrix} -2-\lambda & 2 & 1 \\ -5 & 5-\lambda & 1 \\ -4 & 2 & 3-\lambda \end{vmatrix} = \mathbf{0}$$

$$\downarrow$$

$$\lambda = 3, 2, 1$$

$$\downarrow$$

$$\mathbf{A}\vec{v}_i = \lambda_i \vec{v}_i$$

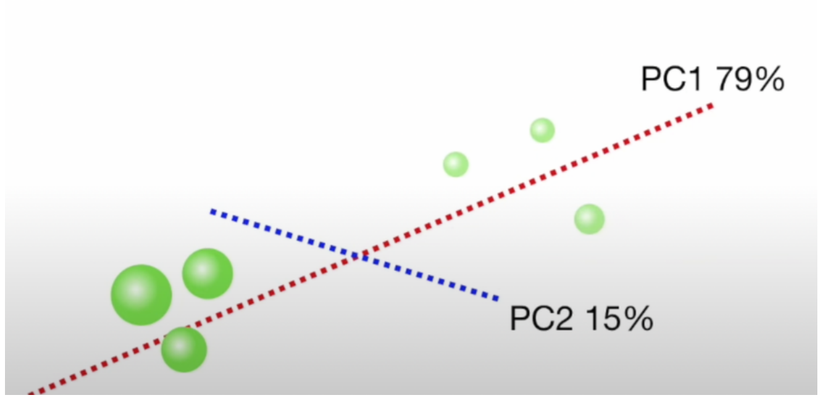
$$\lambda_1 = 3: \quad \hat{v}_1 = (1/\sqrt{6}, 2/\sqrt{6}, 1/\sqrt{6})^T$$

$$\lambda_2 = 2: \quad \hat{v}_2 = (1/\sqrt{6}, 1/\sqrt{6}, 2/\sqrt{6})^T$$

$$\lambda_3 = 1: \quad \hat{v}_3 = (1, 1, 1)^T/\sqrt{3}$$

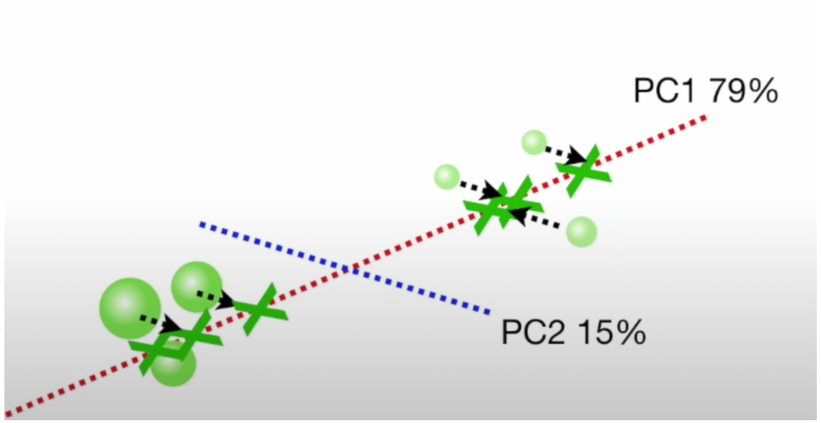
Theory

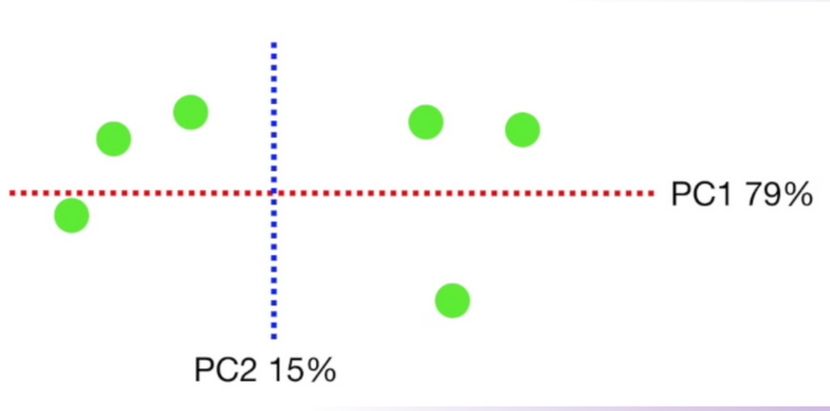
PCA



Find principal components

Project all the datapoints to the new PCs



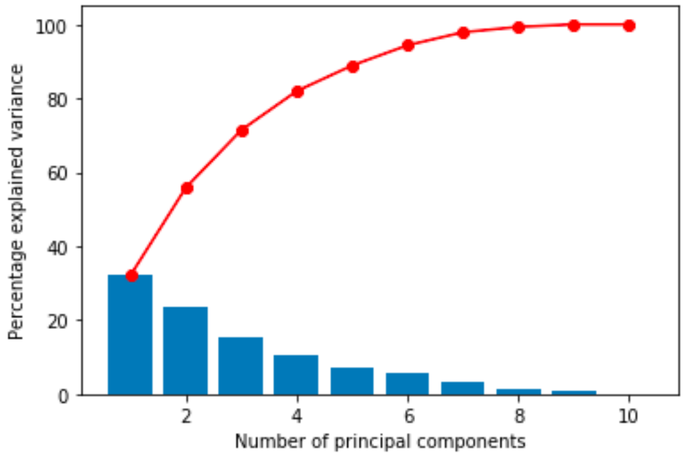


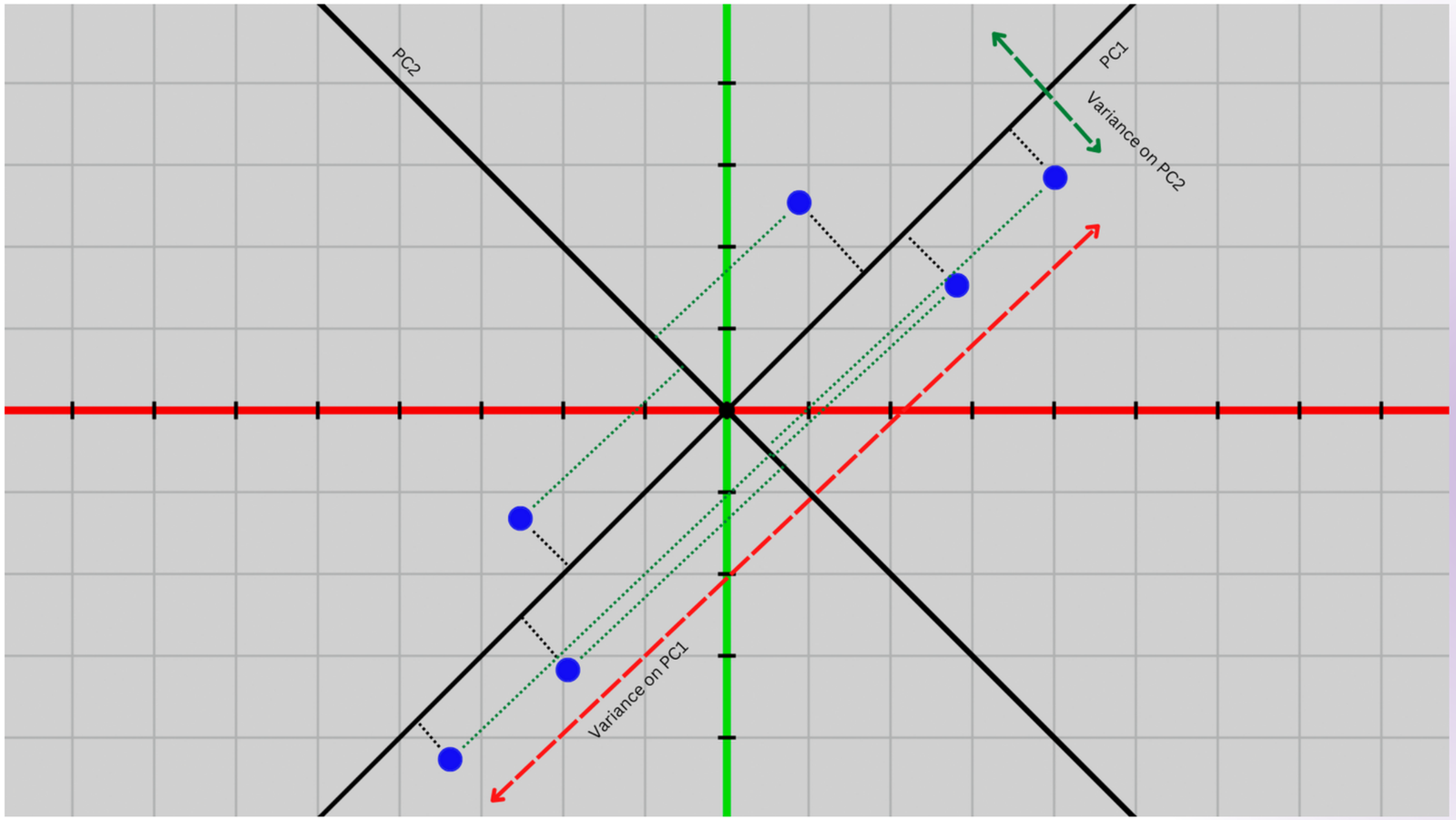
Final dataset

Theory

PCA

Explained variance!





Theory

PCA

PCA from scratch

```
import numpy as np

# Step 1: Standardisation
X_meaned = X - np.mean(X, axis=0)

# Step 2: Computing covariance matrix
cov_mat = np.cov(X_meaned, rowvar=False)

# Step 3: Finding eigenvalues and eigenvectors
eigenvalues, eigenvectors = np.linalg.eigh(cov_mat)
```

Theory

PCA

PCA from scratch

```
import numpy as np

# Step 4: Sorting the eigenvectors based on highest eigenvalues
sorted_index = np.argsort(eigenvalues)[::-1]
sorted_eigenvectors = eigenvectors[:, sorted_index]

# Step 5: Choosing n best eigenvectors
eigenvector_subset = sorted_eigenvectors[:, 0:num_components]

# Step 6: Creating the new dataset with n features
X_reduced = np.dot(eigenvector_subset.transpose(), X_meaned.transpose()).transpose()
```

Theory

PCA

PCA using libraries

```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Theory

PCA

Drawbacks

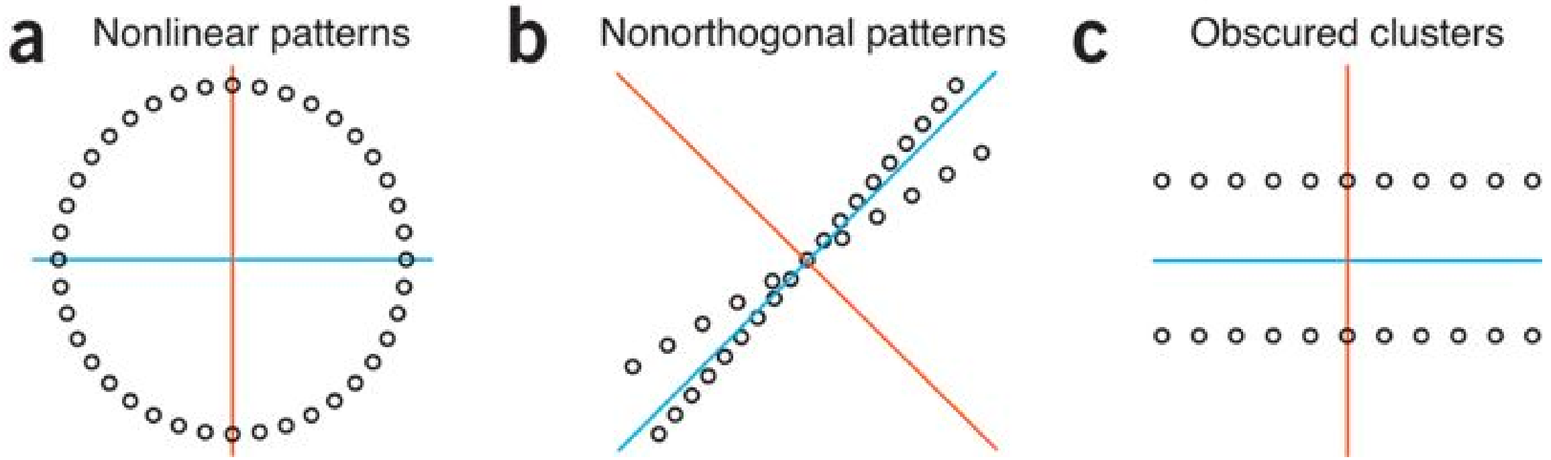
1. Doesn't work on certain data patterns

Theory

PCA

Drawbacks

1. Doesn't work on certain data patterns



2. Scaling matters
3. Interpretation of the PCs can be hard!

Theory

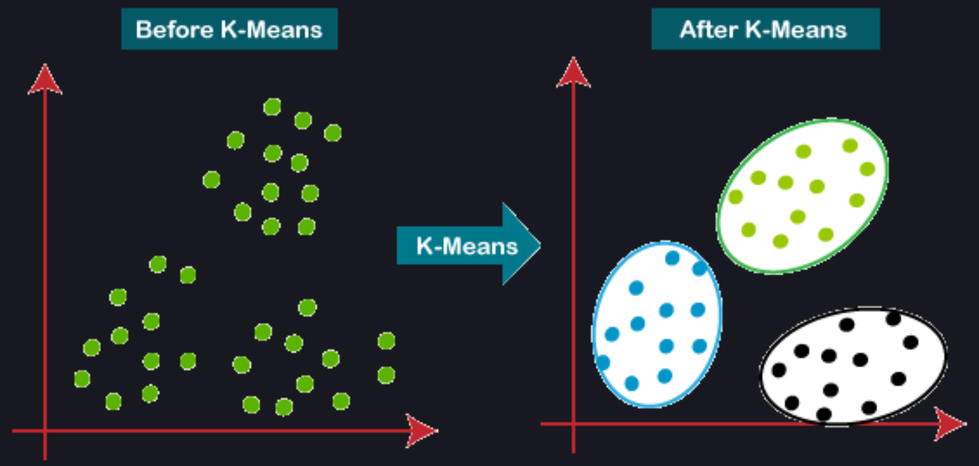
K-MEANS CLUSTERING

- Vector Quantization (Dividing vectors into groups)
- Can be used for classification
- Not to be confused with KNN!

Theory

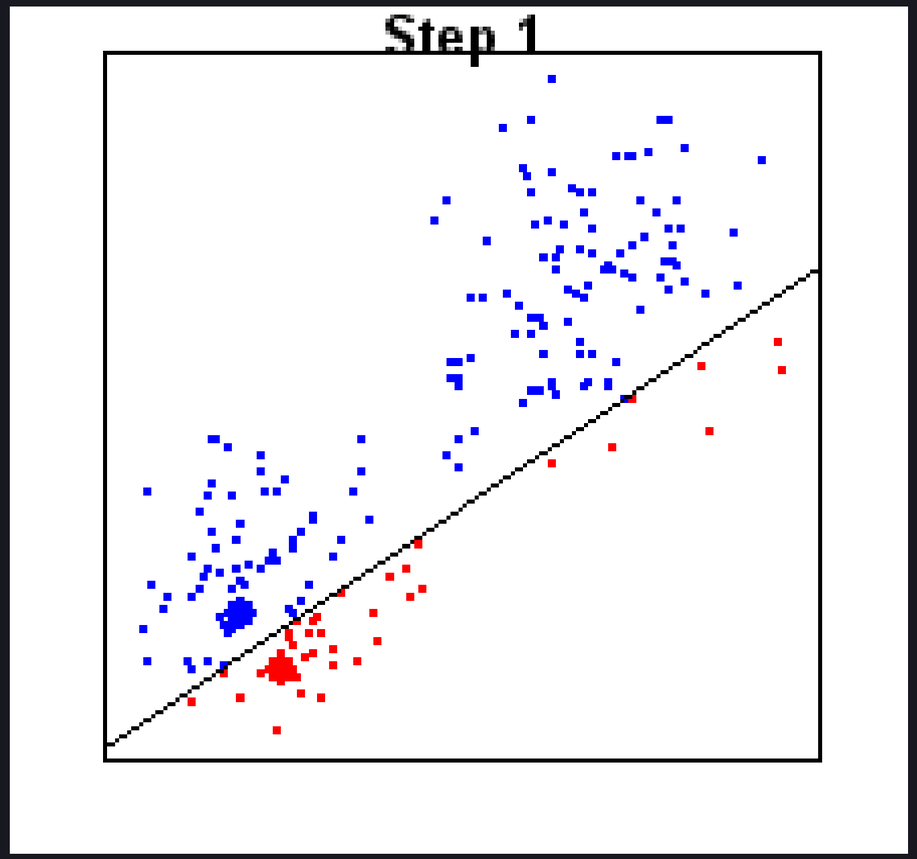
K-MEANS CLUSTERING

- Iterative process
- Partition points to their nearest mean
- Relatively simple algorithm



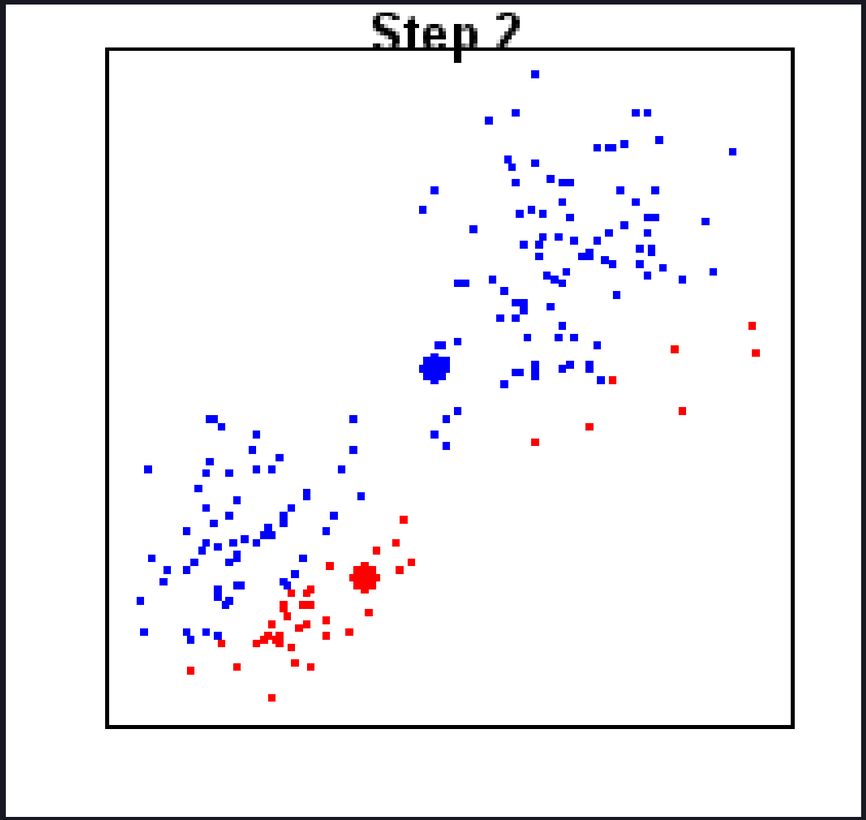
Theory

K-MEANS CLUSTERING



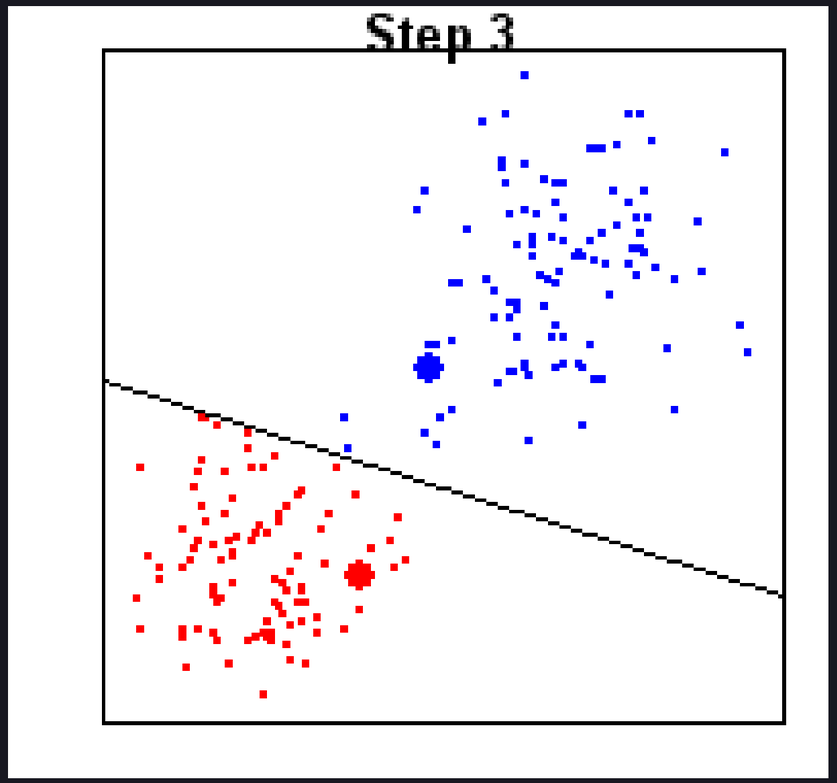
Theory

K-MEANS CLUSTERING



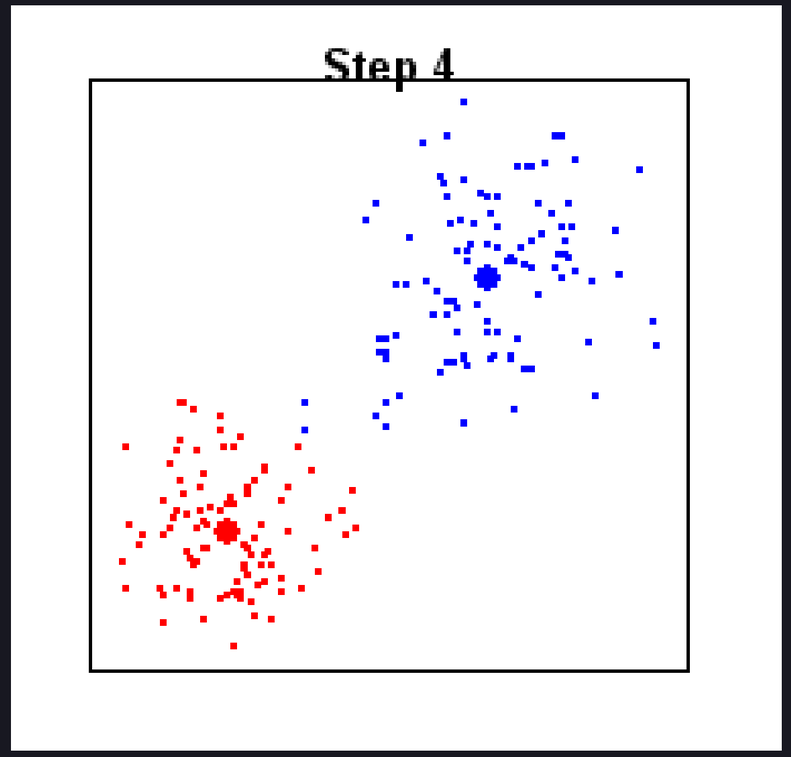
Theory

K-MEANS CLUSTERING



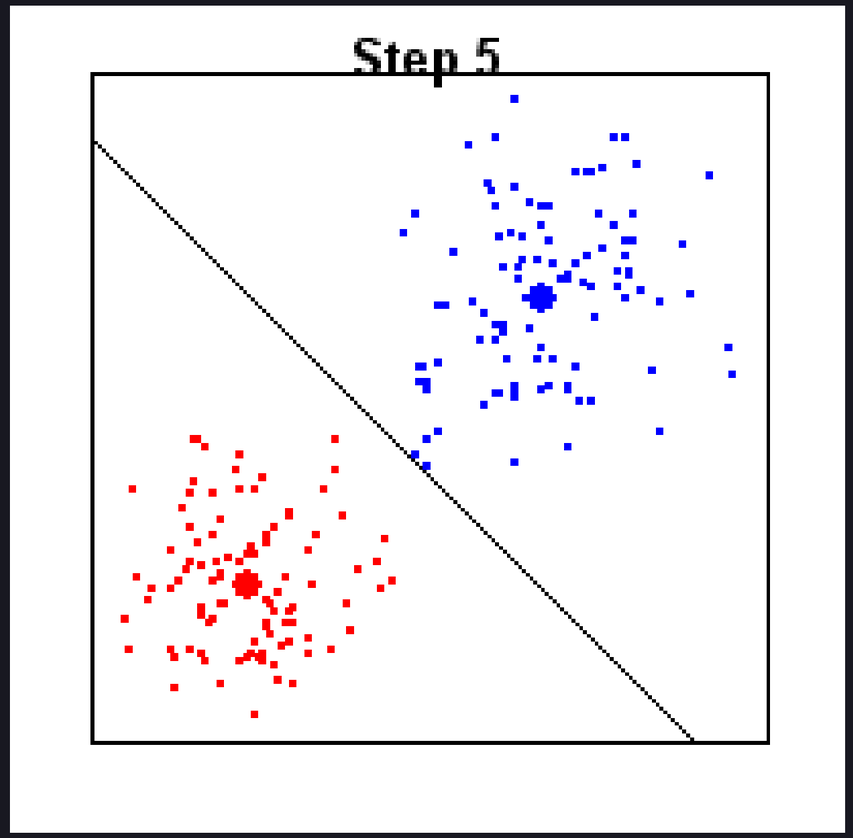
Theory

K-MEANS CLUSTERING



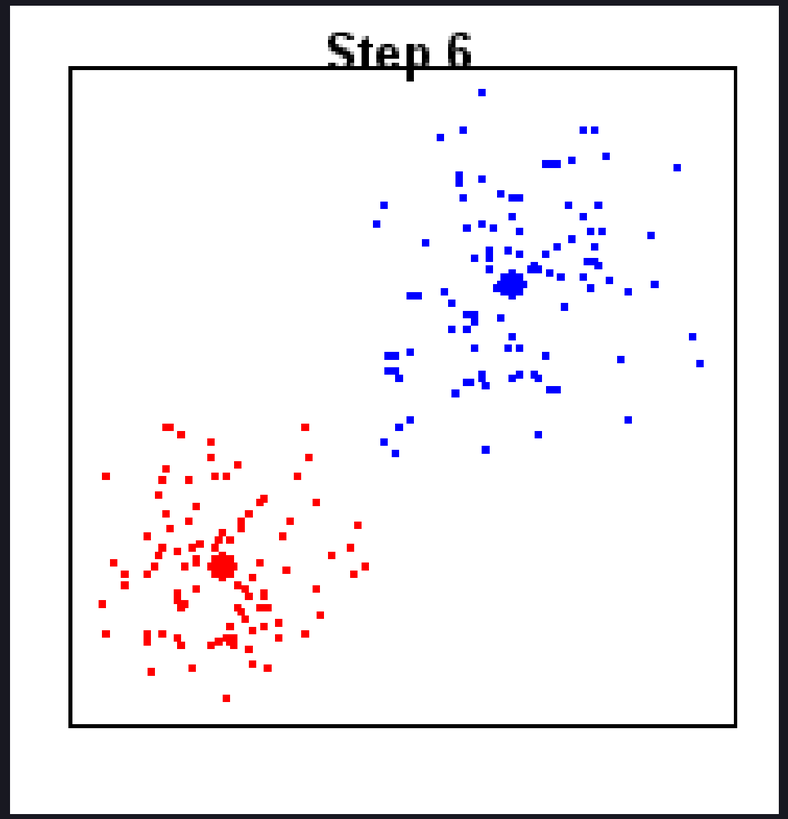
Theory

K-MEANS CLUSTERING



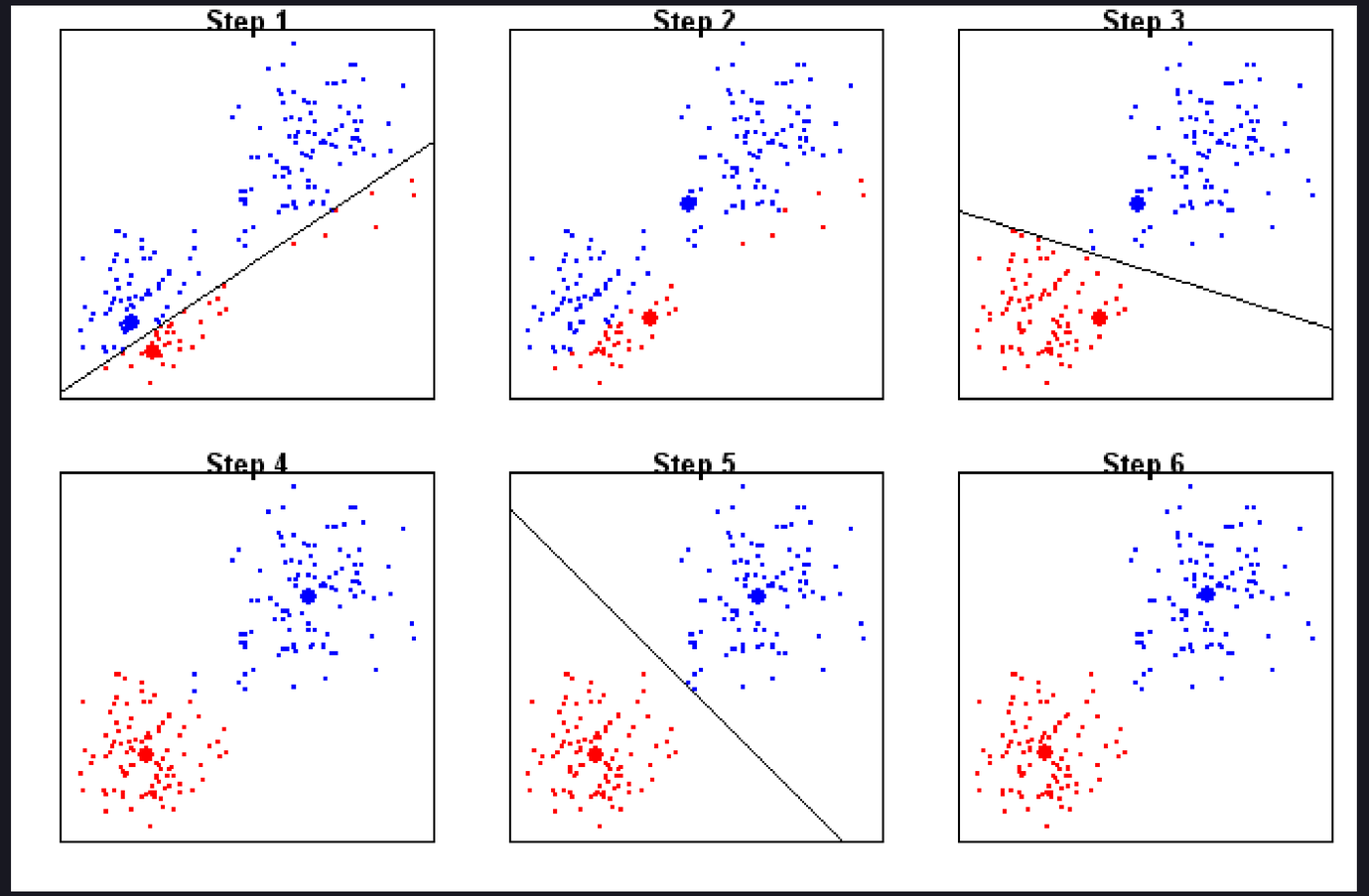
Theory

K-MEANS CLUSTERING



Theory

K-MEANS CLUSTERING



Theory

K-MEANS CLUSTERING

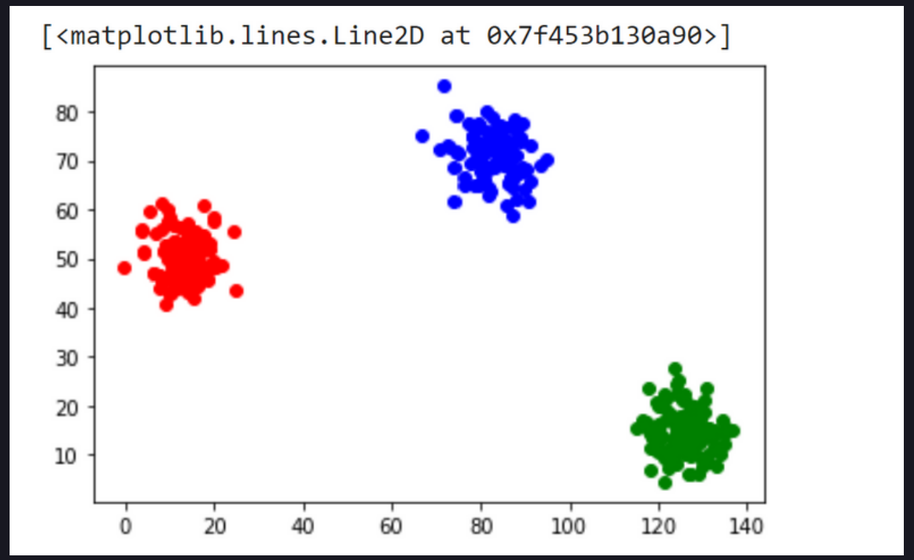
Drawbacks:

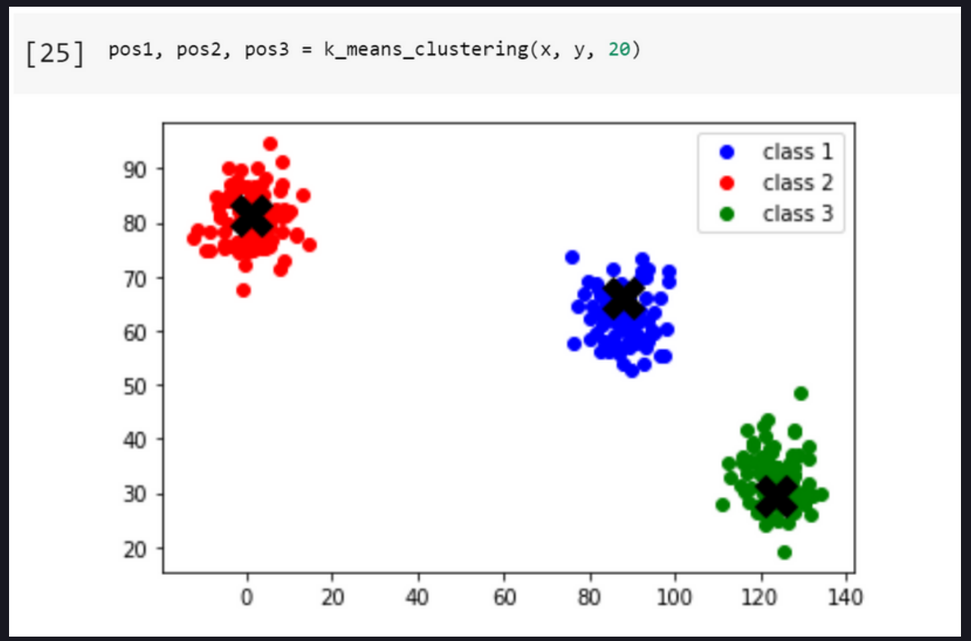
- The solution is NP-Hard, so we use heuristic algorithms to converge to local minima
- Does not guarantee global maximum
- The solution highly dependent on initialization and position of clusters
- Very difficult to choose k when number of classes unknown/data hard to visualize

Theory

K-MEANS CLUSTERING

Implement your own algorithm!





QUESTIONS?

SEE YOU NEXT TIME