JUNIA ISEN

Artificial Intelligence

Machine Learning (2)

Unsupervised Learning

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Junia ISEN / M1 / 2024-2025

Machine learning problems

	Supervised learning	Unsupervised learning
Discrete data	**Classification**	**Clustering**
Continuous data	**Regression**	**Dimensionality reduction**

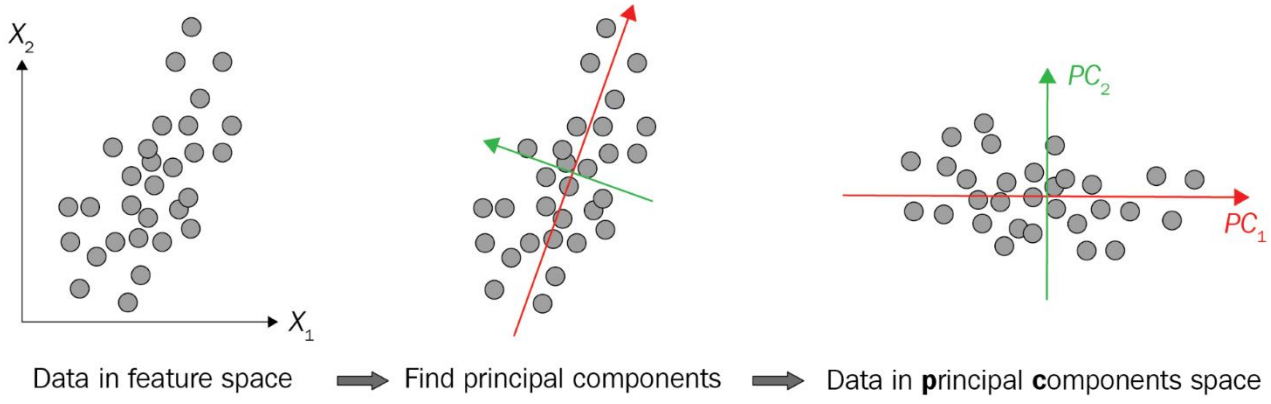
Dimensionality Reduction

- summarization of data (n examples) with many dimensions (m attributes) by a smaller set of (p) derived (synthetic, composite) dimension

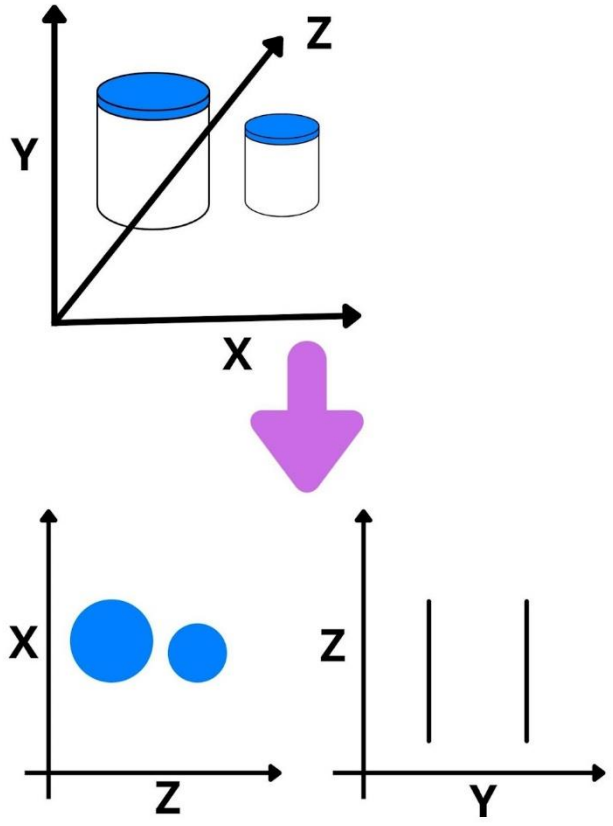
Why ?

- Data compression (with less loss of information)
- Structure Discovery
- Reducing training time and cost
- Effective visualization

Dimensionality Reduction



EXAMPLE 1



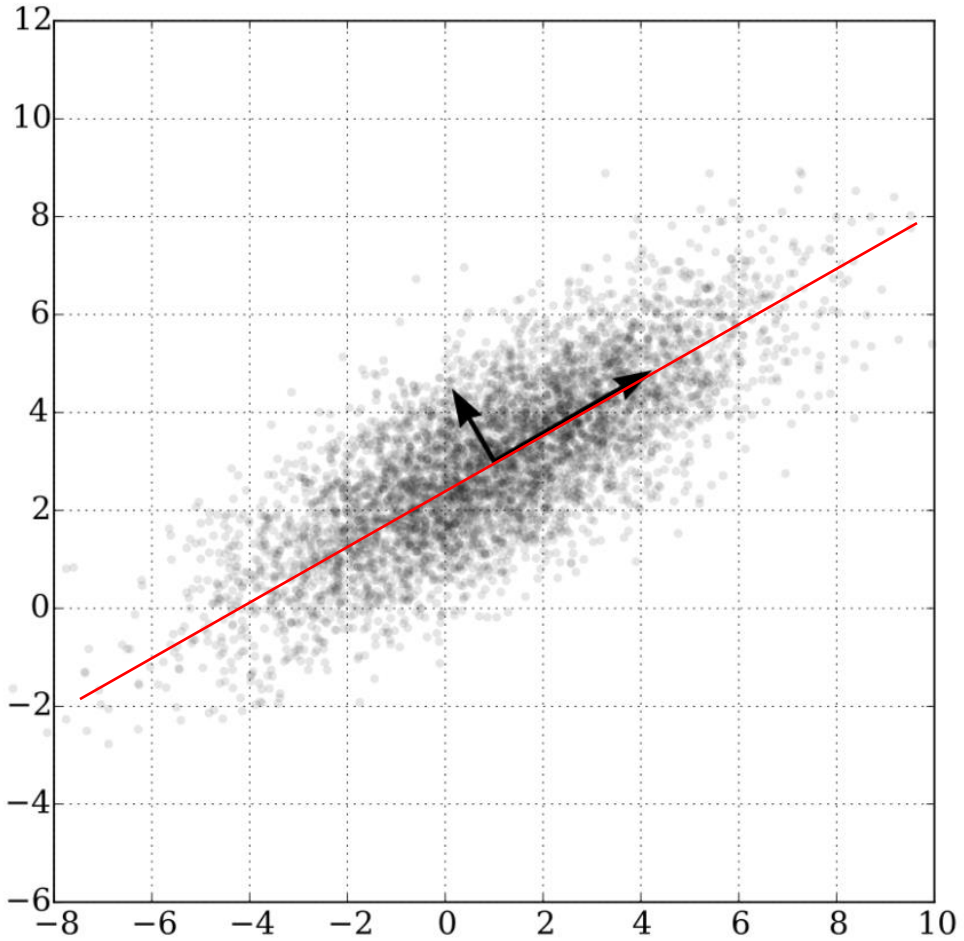
EXAMPLE 2

Dimensionality Reduction

- Multiple methods : **PCA,** ICA, LLE, Isomap, …
- Manifold Learning

Example :

https://scikit-learn.org/stable/auto_examples/manifold/plot_lle_digits.html



Tutorial

Apply PCA algorithm to IRIS dataset…

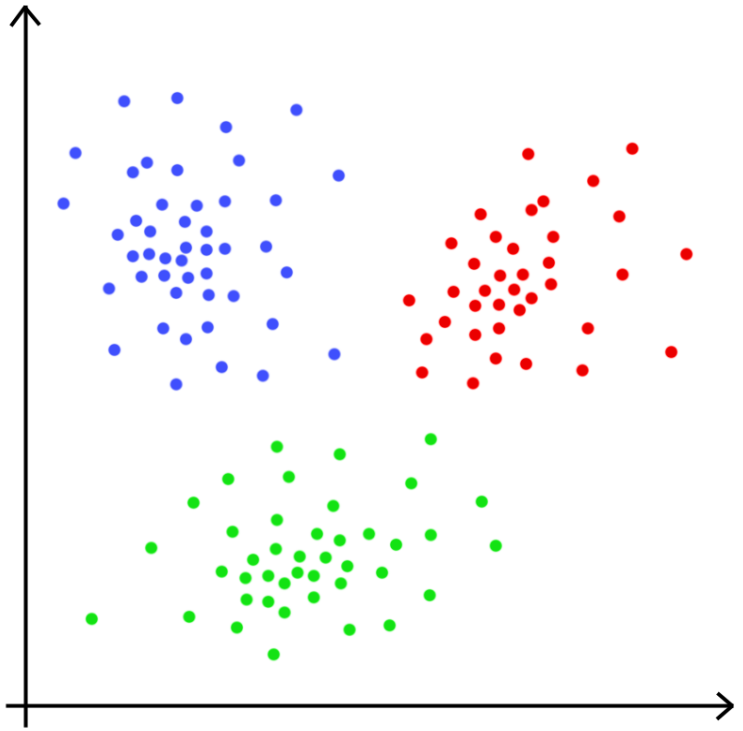
Machine learning problems

	Supervised learning	Unsupervised learning
Discrete data	**Classification**	**Clustering**
Continuous data	**Regression**	**Dimensionality reduction**

Intelligence is also the ability to recognize similar objects and group them!

The Problem of Clustering

Given a set of unlabeled items (in n-dimensions), with a notion of distance between items, group the points into some number of clusters, so that members of a cluster are in some sense as nearby as possible.



Data without labels

Labeled Data

Example : Clustering news

Winter storm moves north: Fast snowfall shocks forecasters as flights canceled, power outages continue

USA TODAY · 1 hour ago

- **Winter storm impacts much of East Coast, leaves 2 dead in North Carolina: LIVE UPDATES**
  Fox News · 1 hour ago
- **More than 50 million under winter weather alerts across the East Coast with snow and heavy winds on the way**
  CNN · 3 hours ago
- **PHOTOS: Snow continues to fall over the Pittsburgh area**
  WPXI Pittsburgh · 19 hours ago
- **Winter storm pounds Eastern US**
  CBS News · 4 hours ago

View Full Coverage

Winter Storm

The enormous Tonga volcano eruption was a once-in-a-millennium event

CNN · 2 hours ago · Opinion

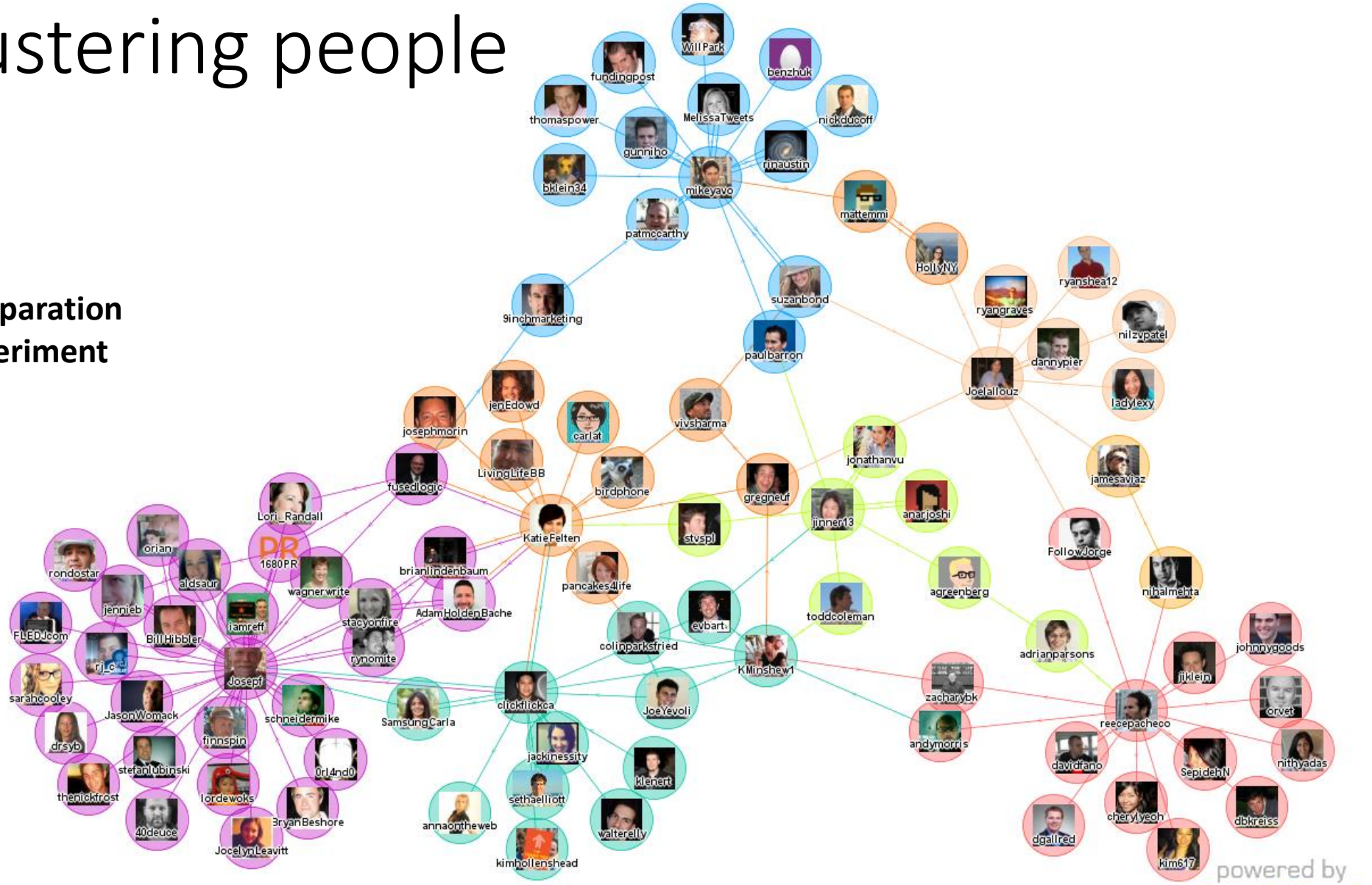
- **Tonga volcano: ash, smoke and lightning seen before eruption that caused tsunami**
  Guardian News · 9 hours ago
- **San Diego native overseeing Tsunami Advisory alerts**
  10News · 14 hours ago
- **Massive underwater volcano triggers tsunami, causing damage in Tonga**
  CBS News · 1 hour ago
- **Missionaries in Tonga Nuku'alofa Mission safe; no contact yet with Tonga Outer Island Mission**
  ksltv.com · 2 hours ago
- **A massive volcanic eruption and tsunami hit Tonga and the Pacific. Here's what we know**
  CNN · 14 minutes ago

View Full Coverage

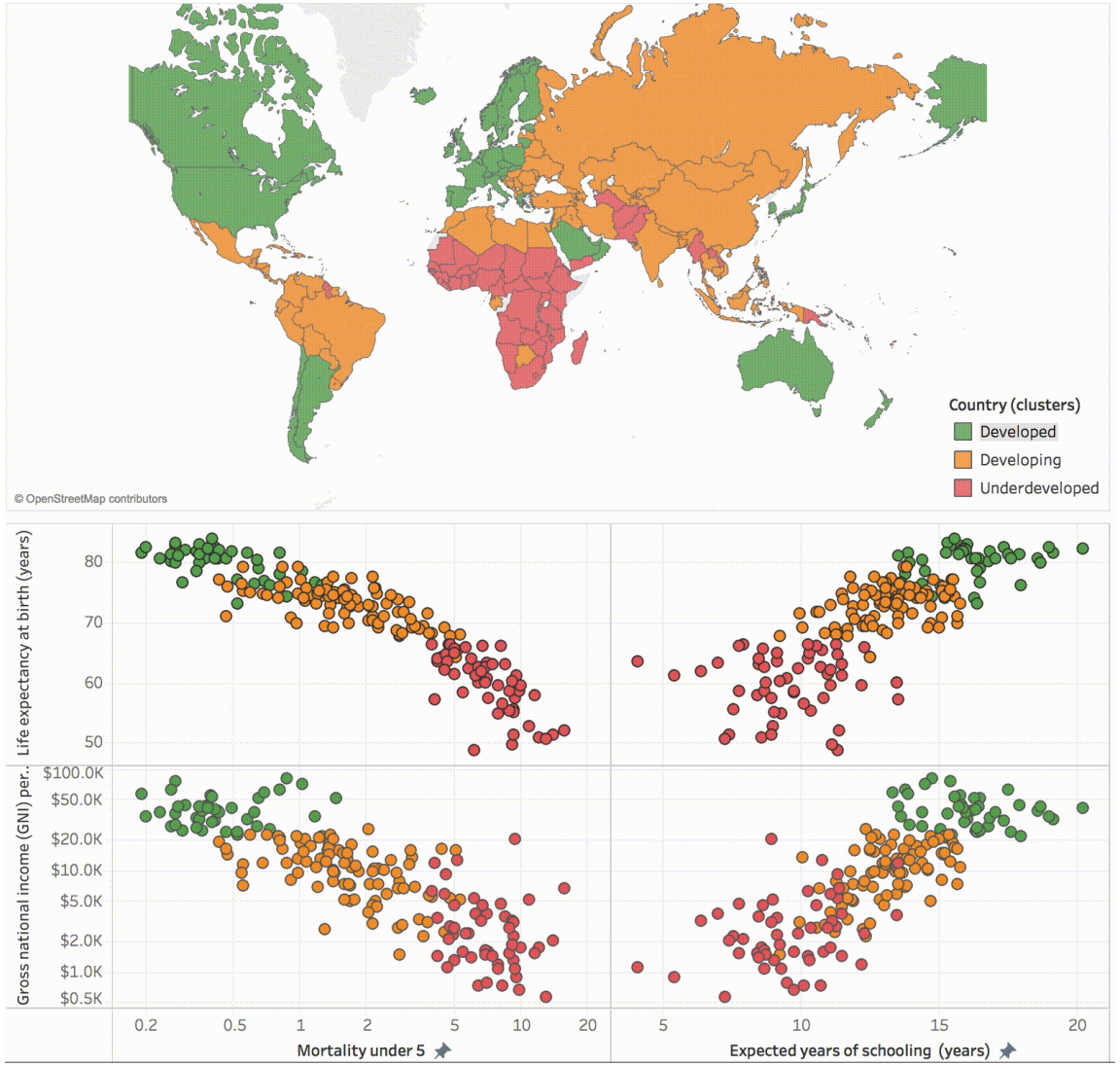
Tonga volcano Tsunami

Example : Clustering people

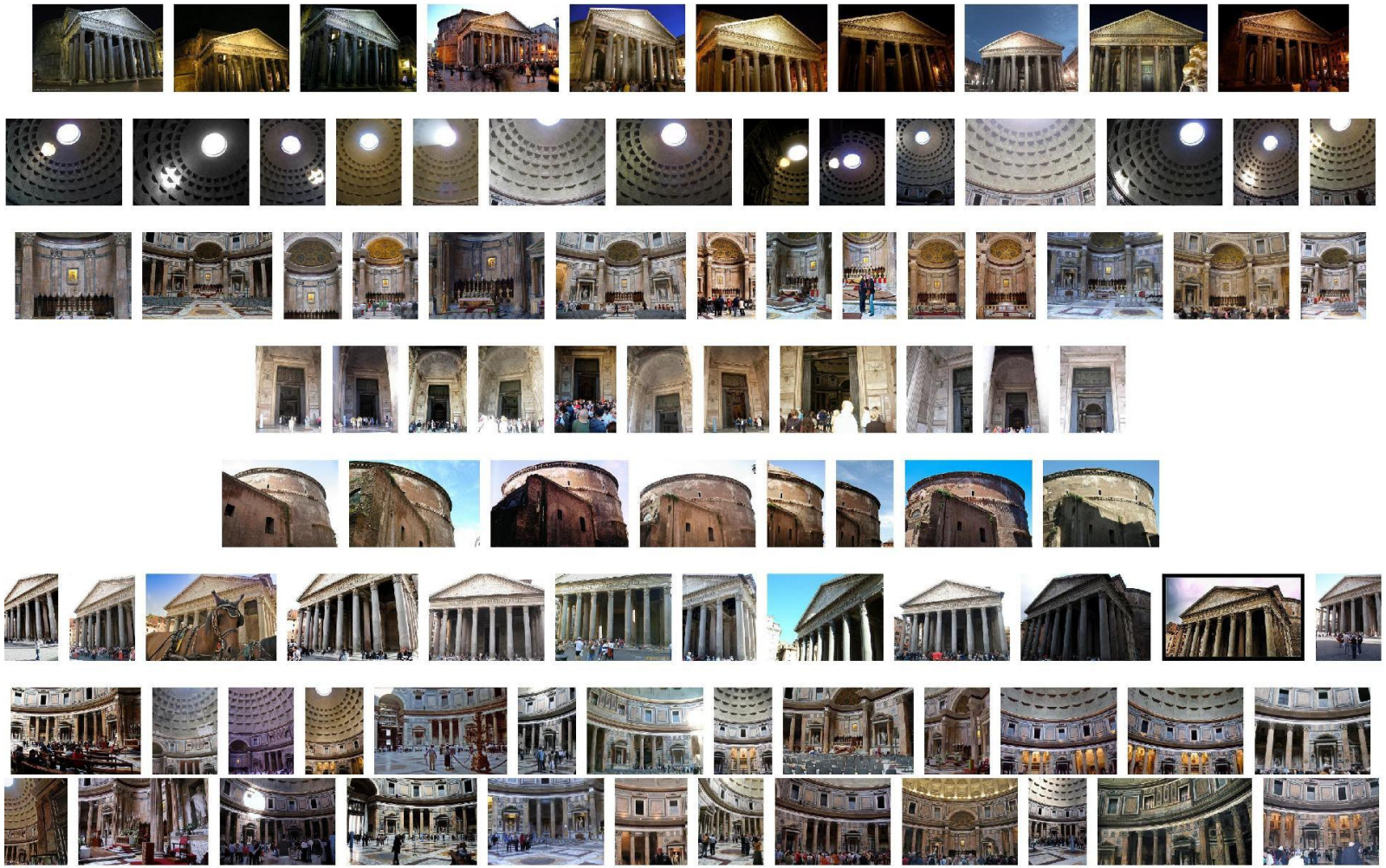
- **Six degrees of separation**
- **Small-world experiment**



Example : Clustering countries

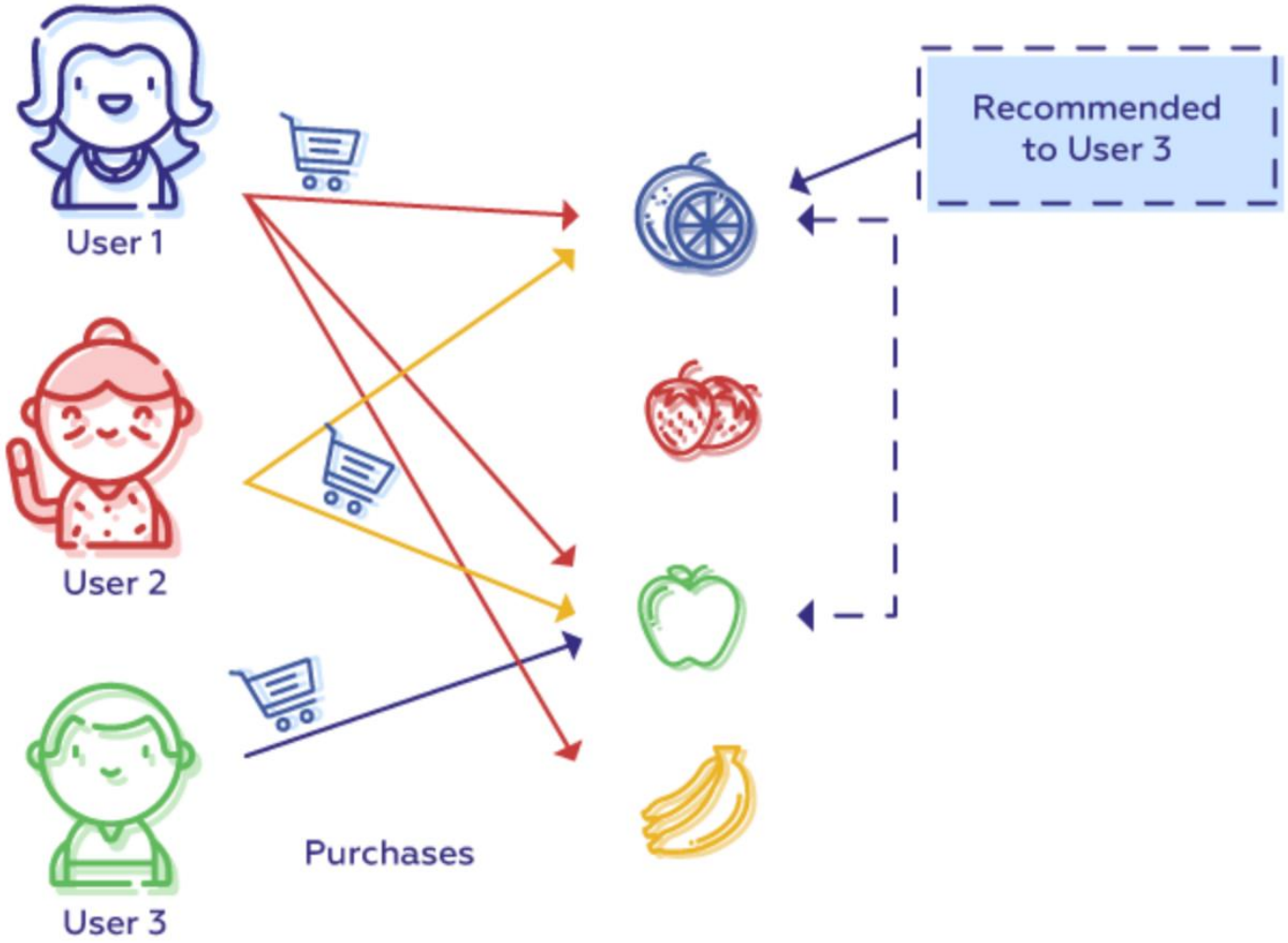


Example : Clustering images



Example : Clustering pixels

Example : Clustering items for recommendation

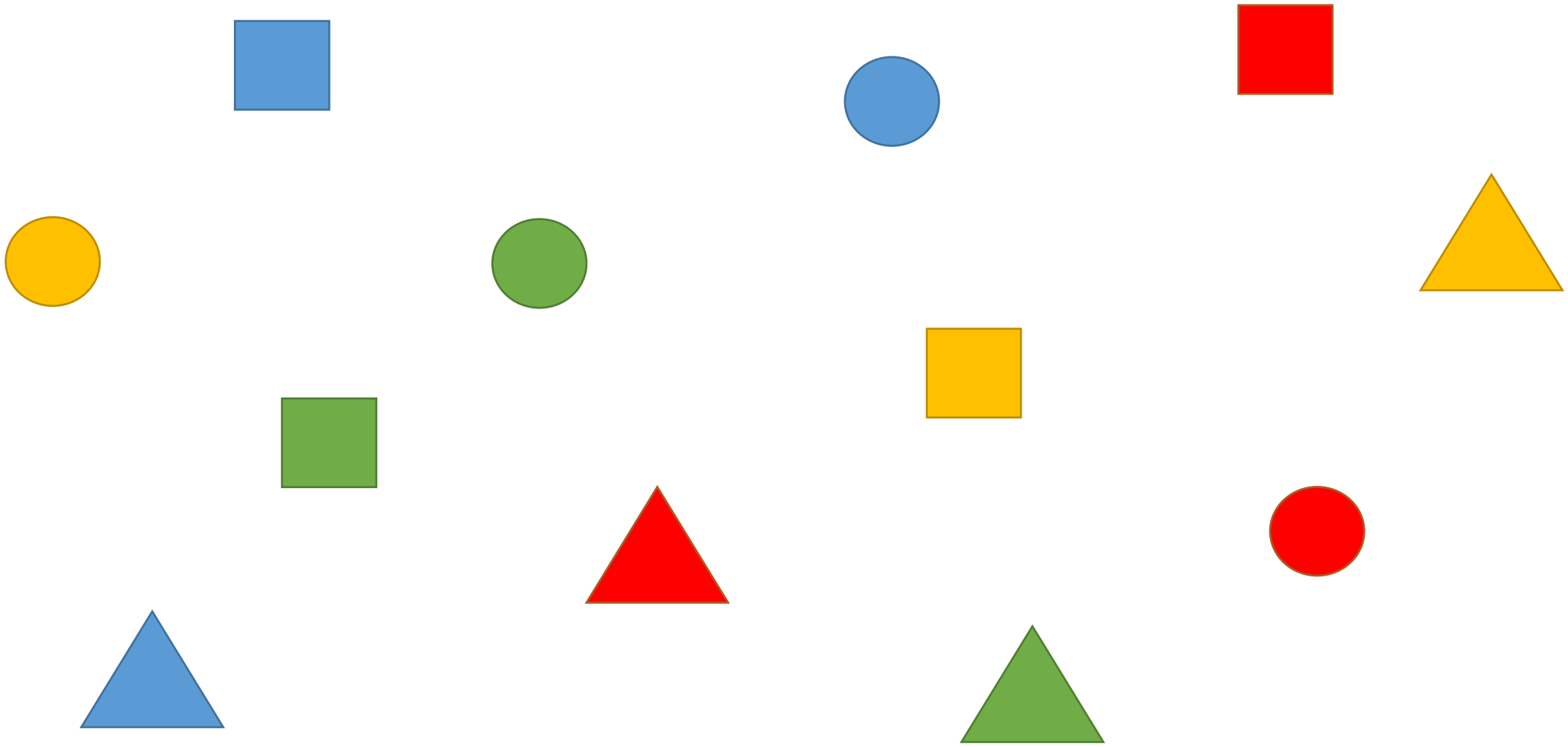


Examples

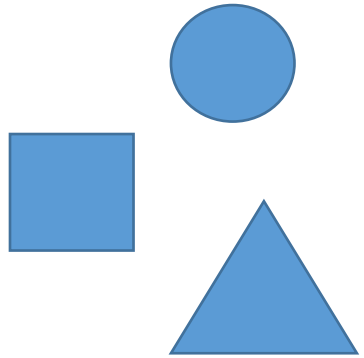
- What is the distance/similarity between :

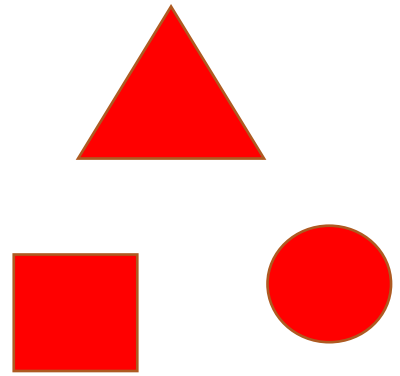
- Two articles in news feeds ?
- Two images in a gallery ?
- Two pixels in a photo ?
- Two shows in a VOD service ?
- Two products in an e-commerce website ?
- Two persons in a social network ?
- Two ADN sequences ?

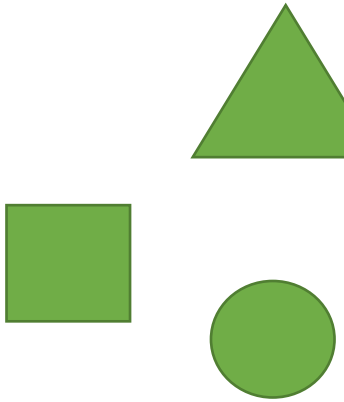
Grouping items with different colors and shapes

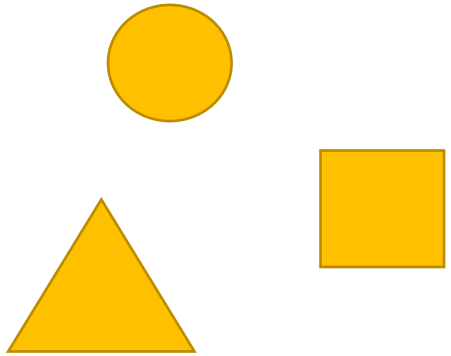


Based on color similarity → 4 groups

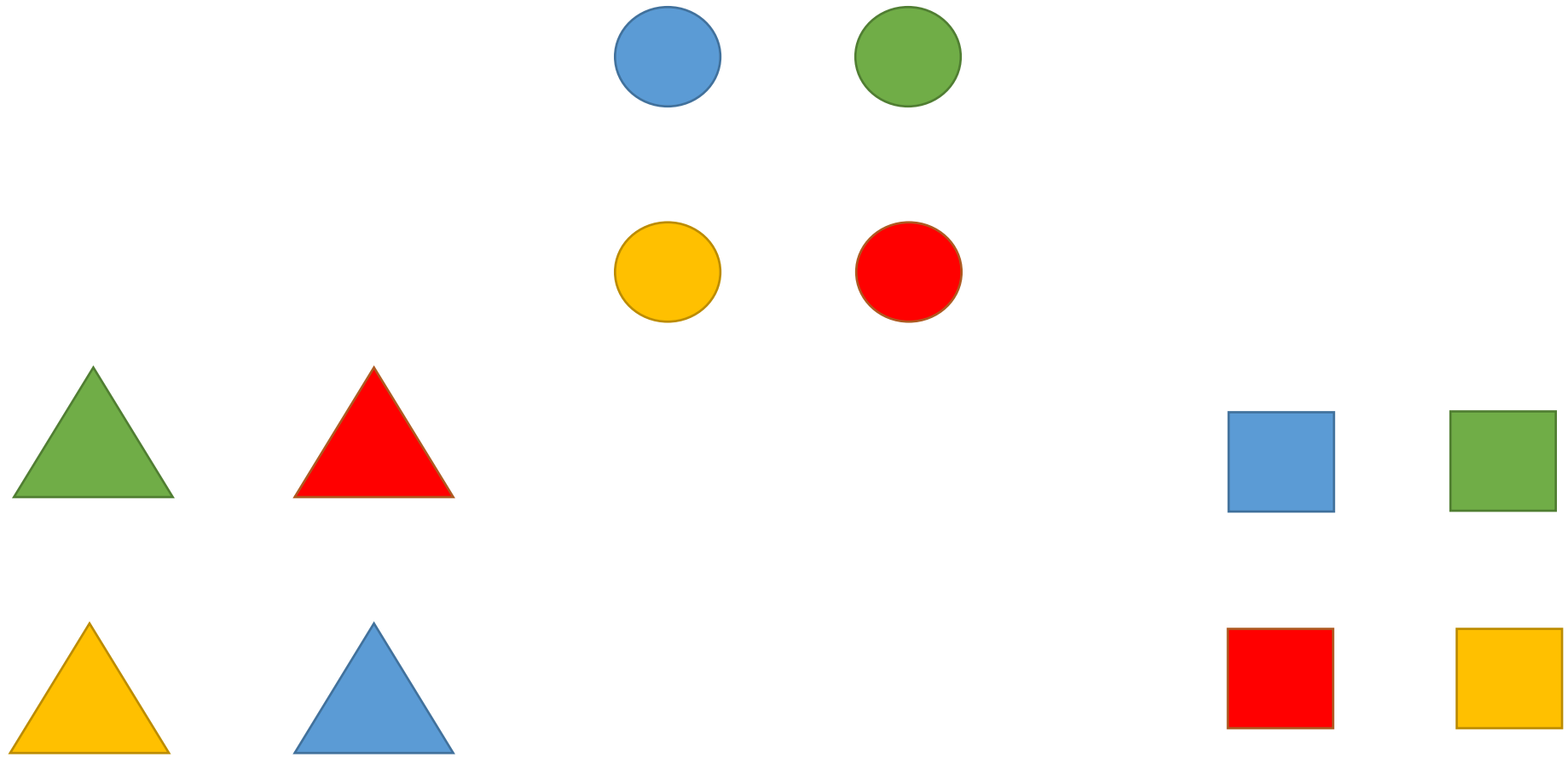








Based on shape similarity → 3 groups



The distance function

Distance axioms :

- The distance from a point to itself is null: d(x,x) = 0
- Positivity: d(x,y) >= 0
- Symmetry: d(x,y) = d(y,x)
- Triangle inequality: d(x,z) <= d(x,y) + d(y,z)

- Simplest case: one numeric attribute A

  Distance(X,Y) = A(X) – A(Y)

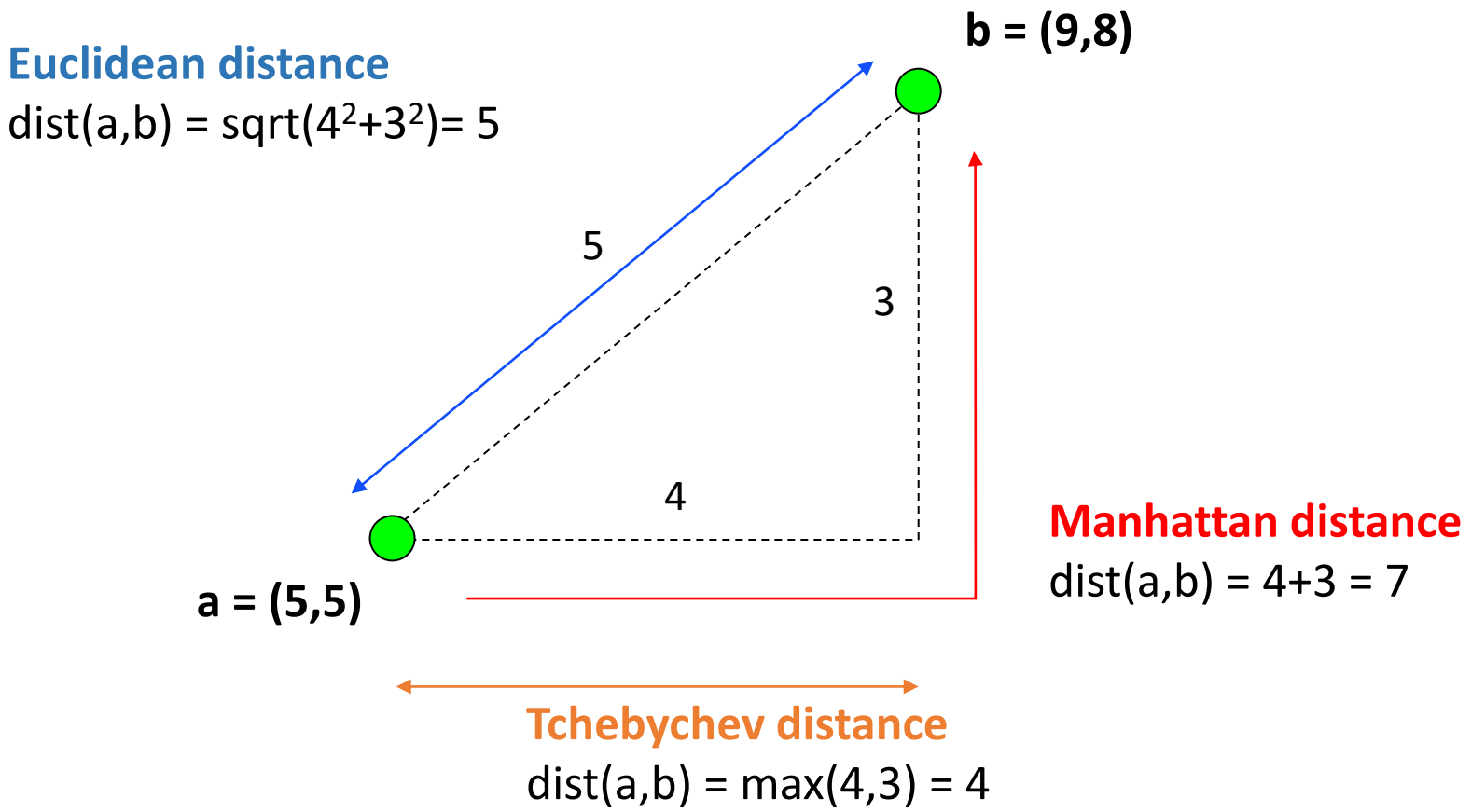
- Several numeric attributes:

  Distance(X,Y) = Euclidean distance between X,Y

- Nominal attributes:

  distance is set to 1 if values are different, 0 if they are equal

Examples of Euclidean Distances



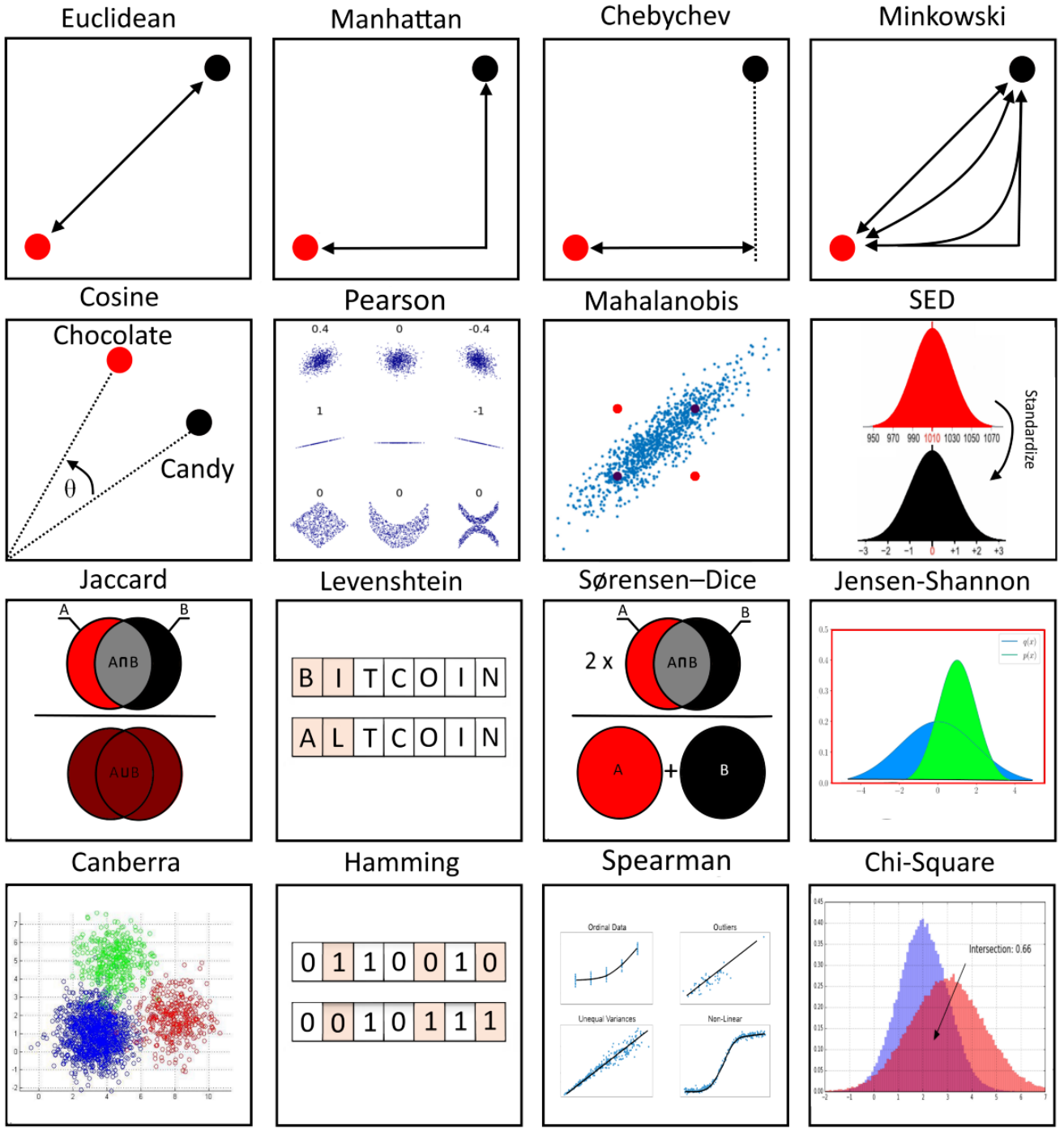
Distance / Similarity

How instances and samples
are related or close
to each other ?

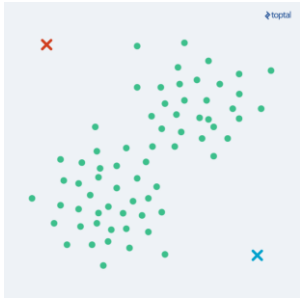
Different ways to measure
depending on the nature of data
and the problems

https://docs.scipy.org/doc/scipy/reference/spatial.distance.html

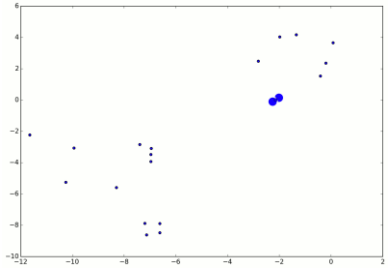
You can also define your own
distance for your specific problem



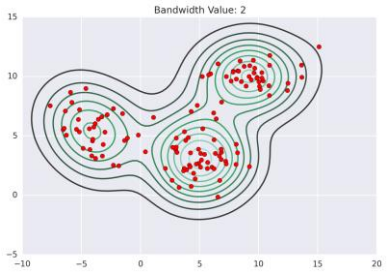
Some Clustering Algorithms



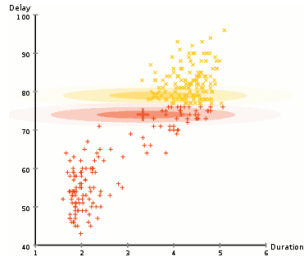
- K-means
  - Fix K. Iteratively re-assign points to the nearest cluster



- Agglomerative/Hierarchical clustering
  - Each point is a cluster. Iteratively merge the closest clusters



- Mean-shift clustering
  - Based on Kernel Density Estimation (KDE)



- EM Algorithm
  - Expectation of likelihood, Maximizing parameters

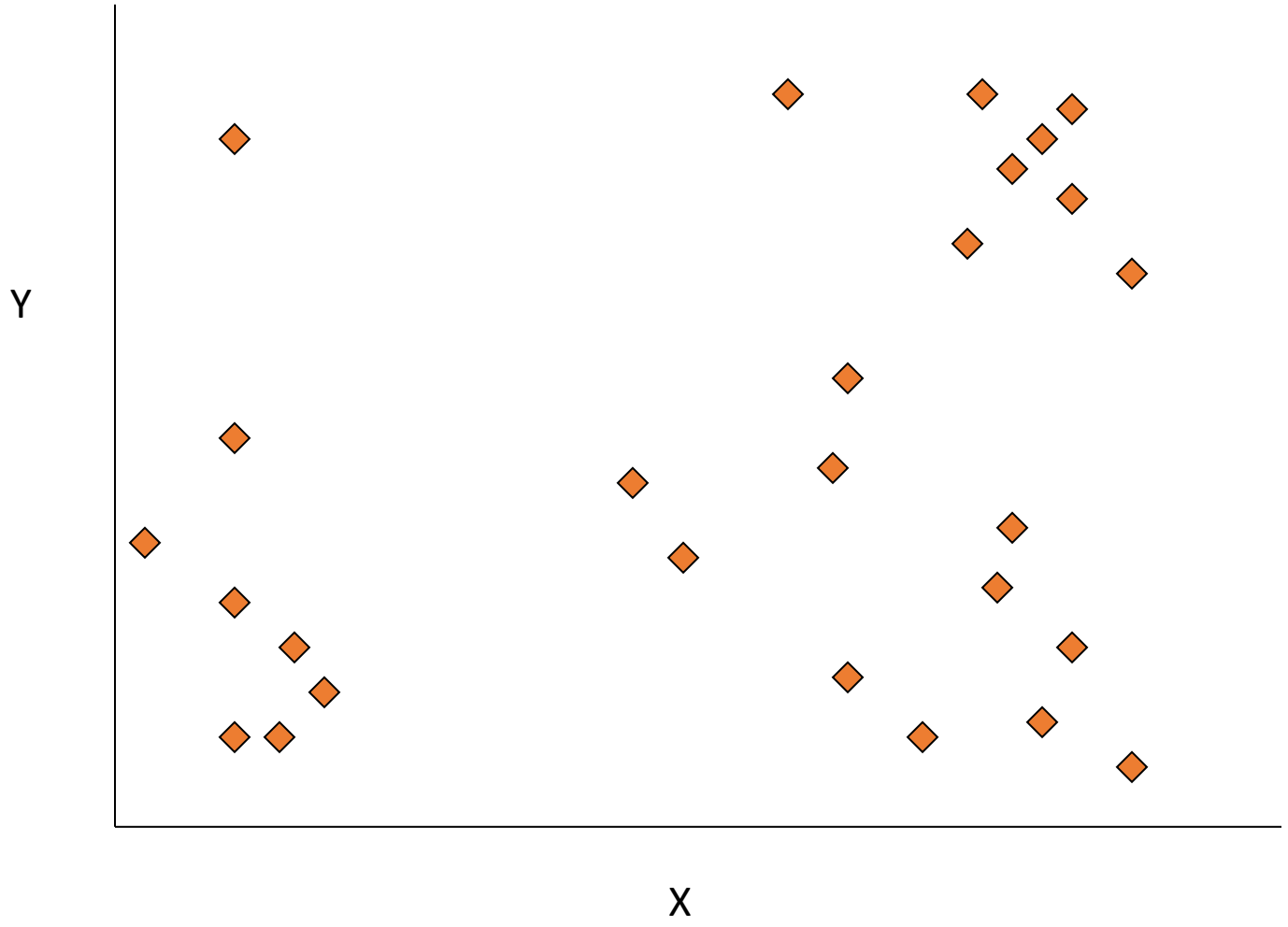
- And many others…

Simple Clustering: K-means

- Works with numeric data only
- Pick a number (K) of cluster centers (at random)
- Assign every item to its nearest cluster center (e.g. using Euclidean distance)
- Move each cluster center to the mean of its assigned items
- Repeat steps 2,3 until convergence (change in cluster assignments less than a threshold)

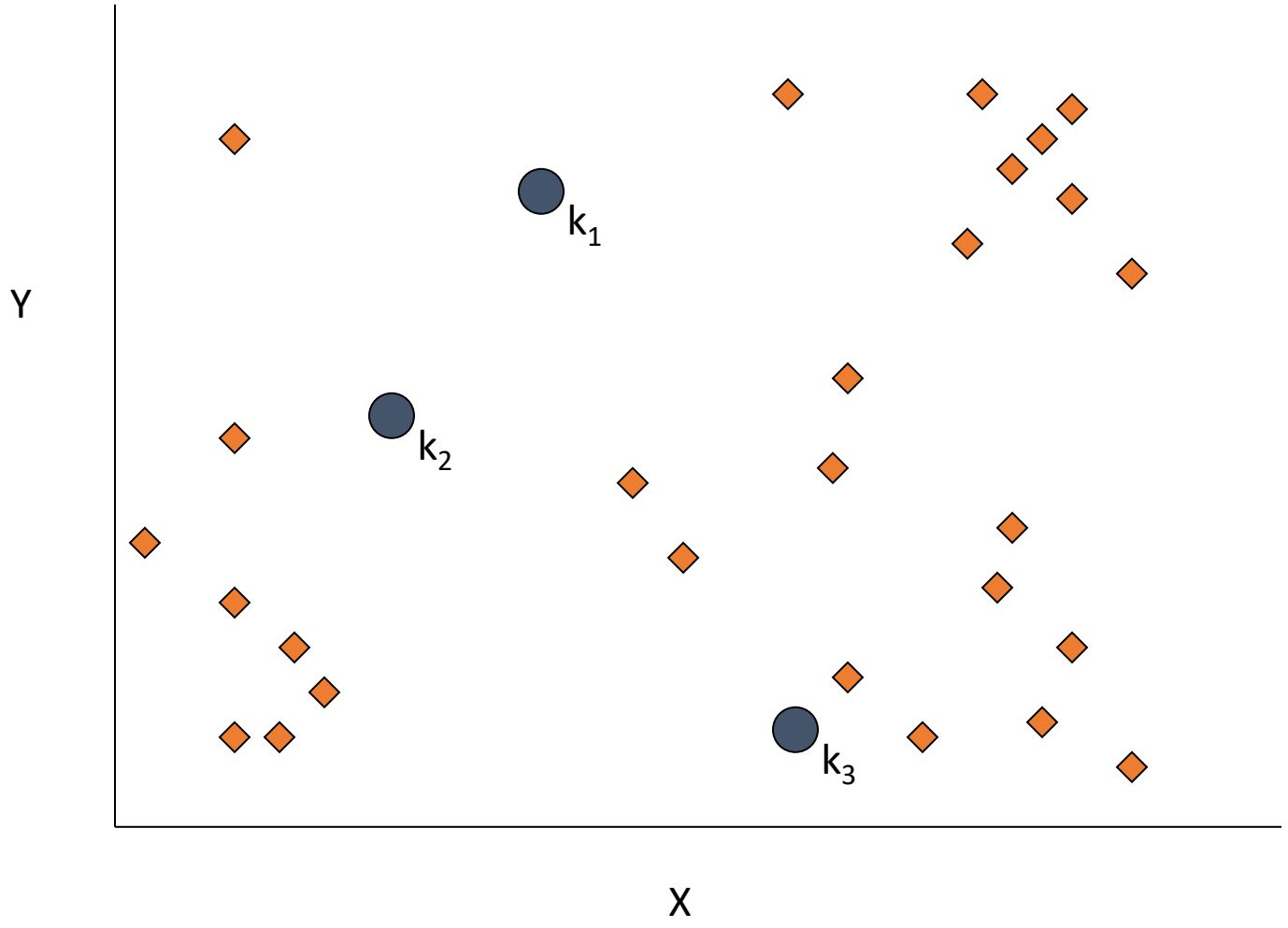
K-means example

Data
without labels



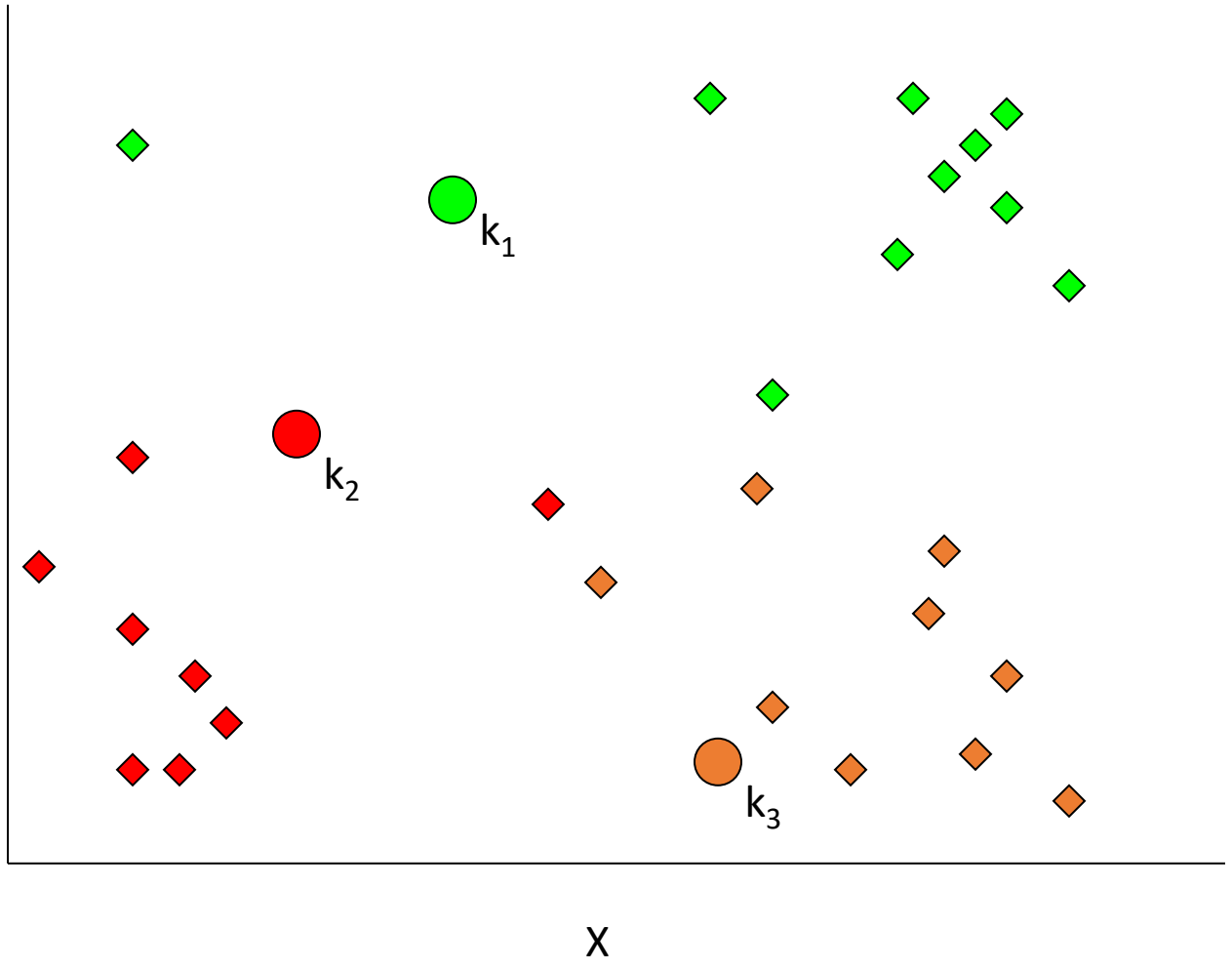
K-means example, step 1

Pick 3 initial cluster centers (randomly)



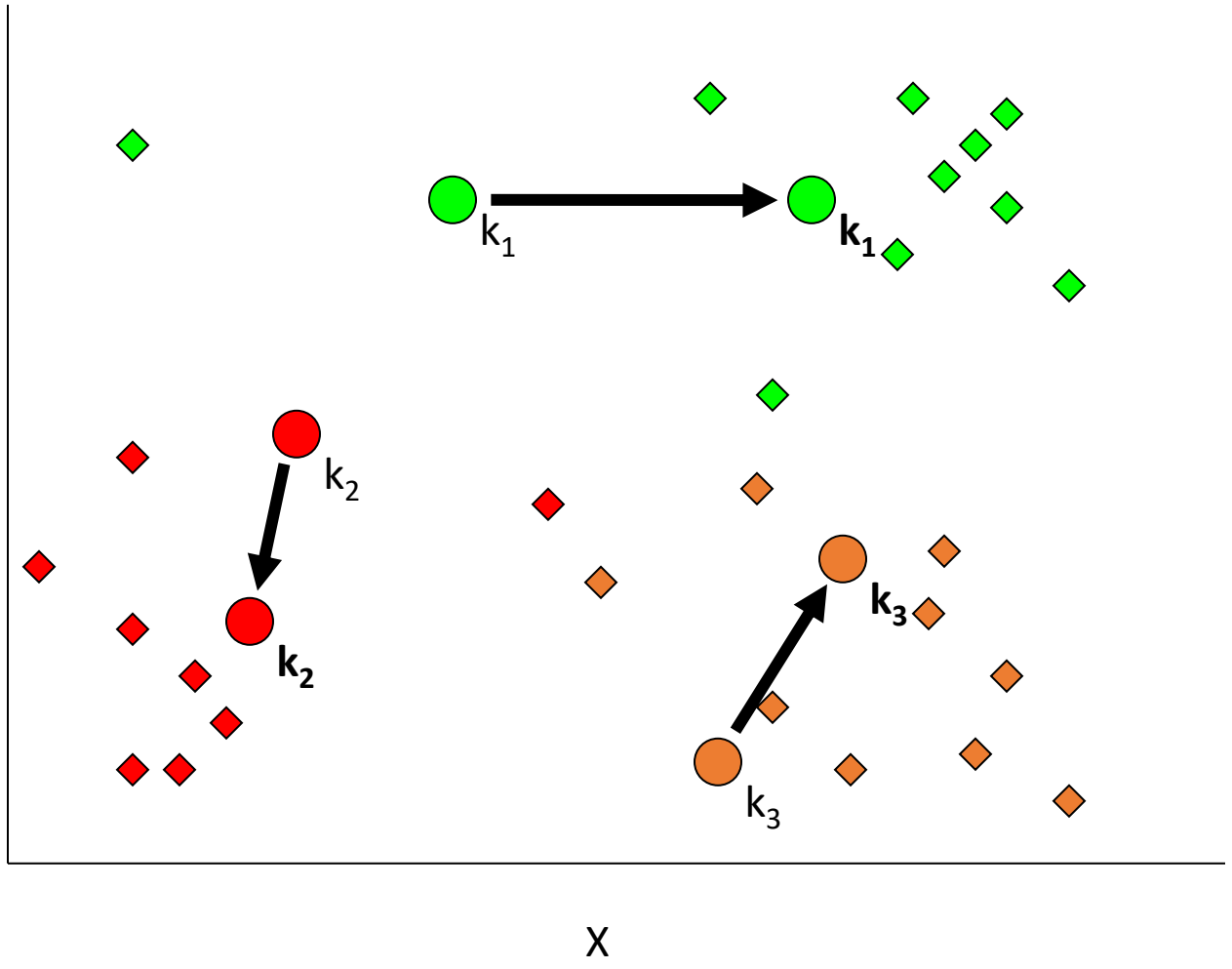
K-means example, step 2

Assign each point to the closest cluster center



K-means example, step 3

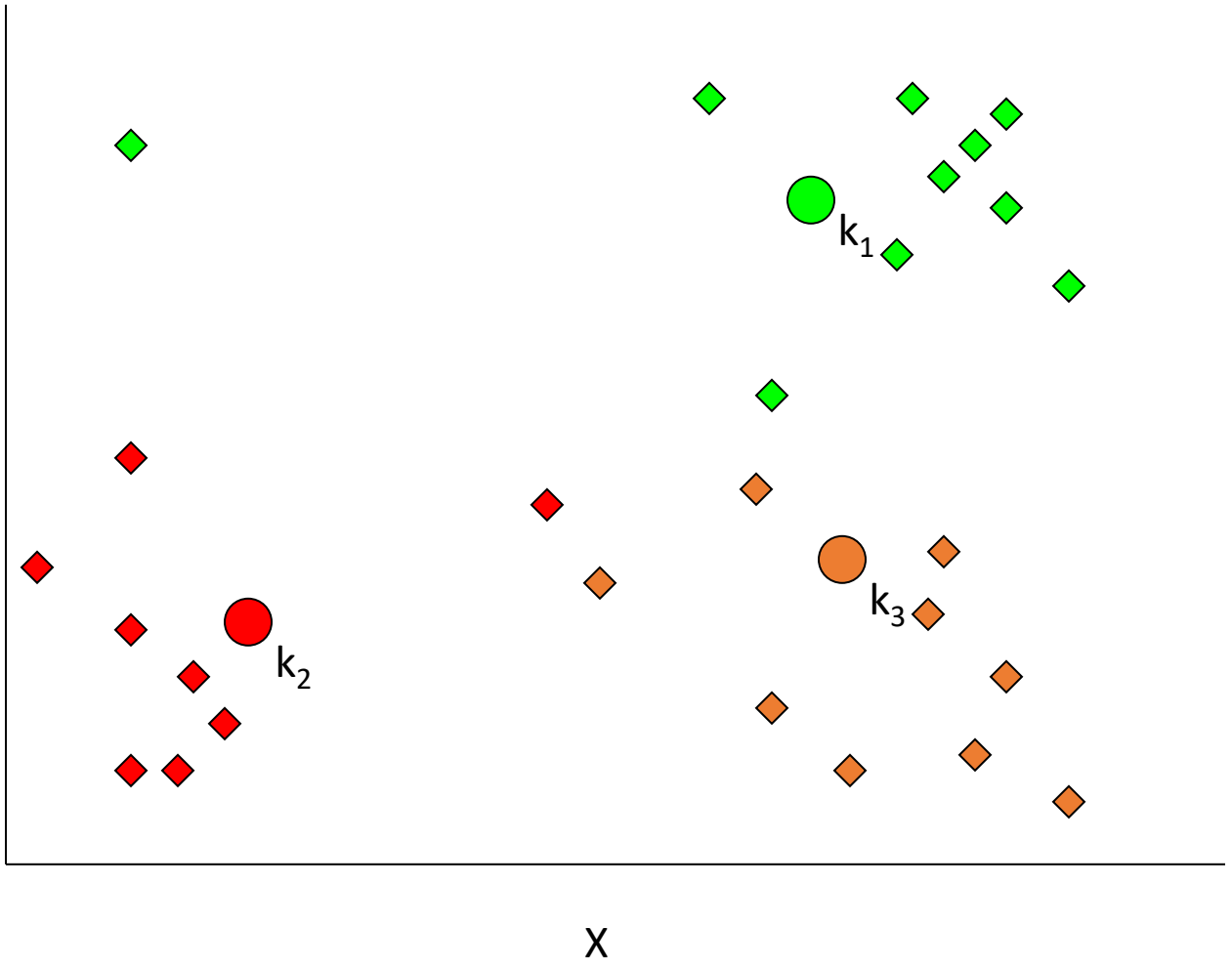
Move each cluster center to the mean of each cluster



K-means example, step 4

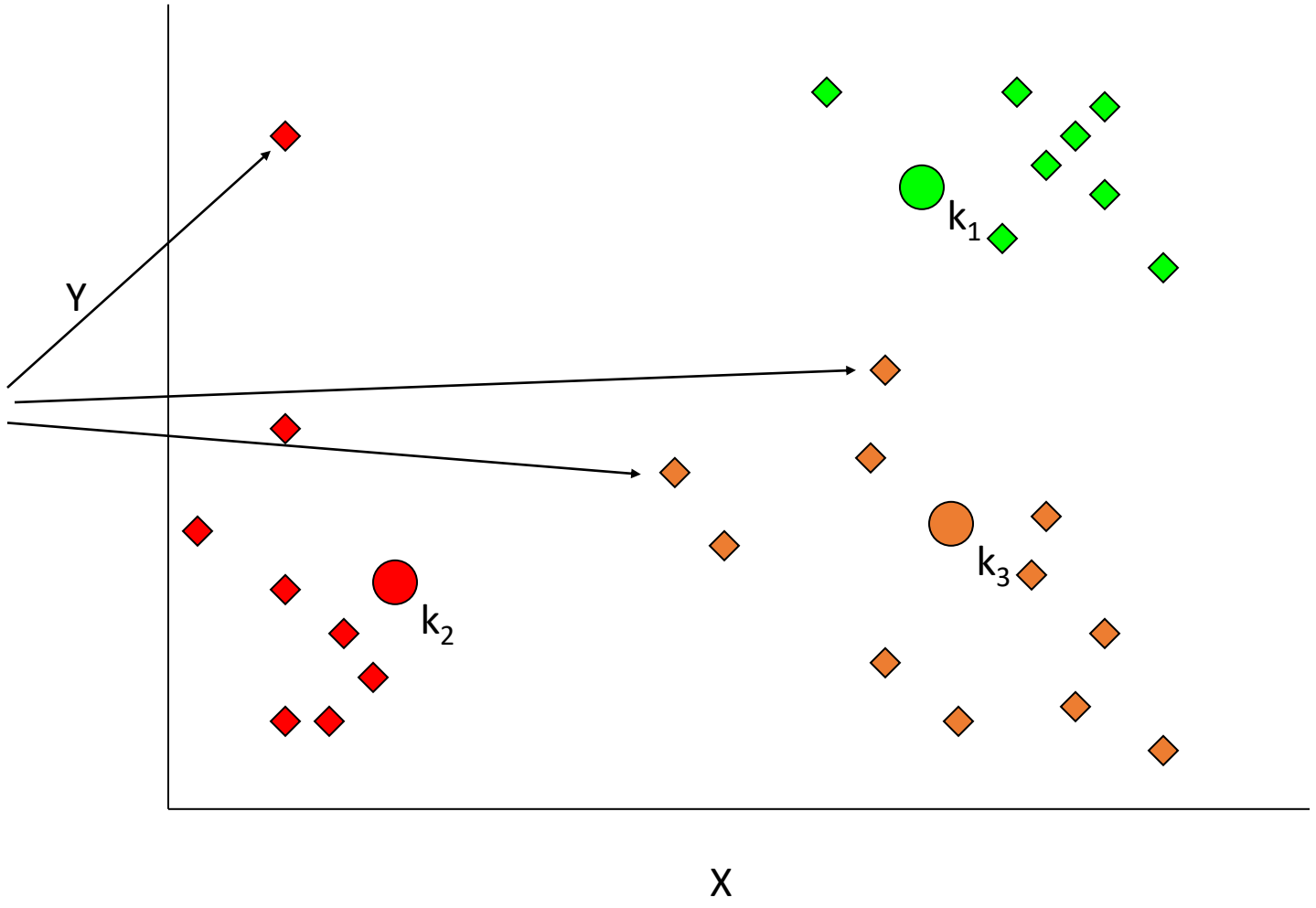
Reassign
points
closest to a different
new cluster center

Q: Which points are reassigned?



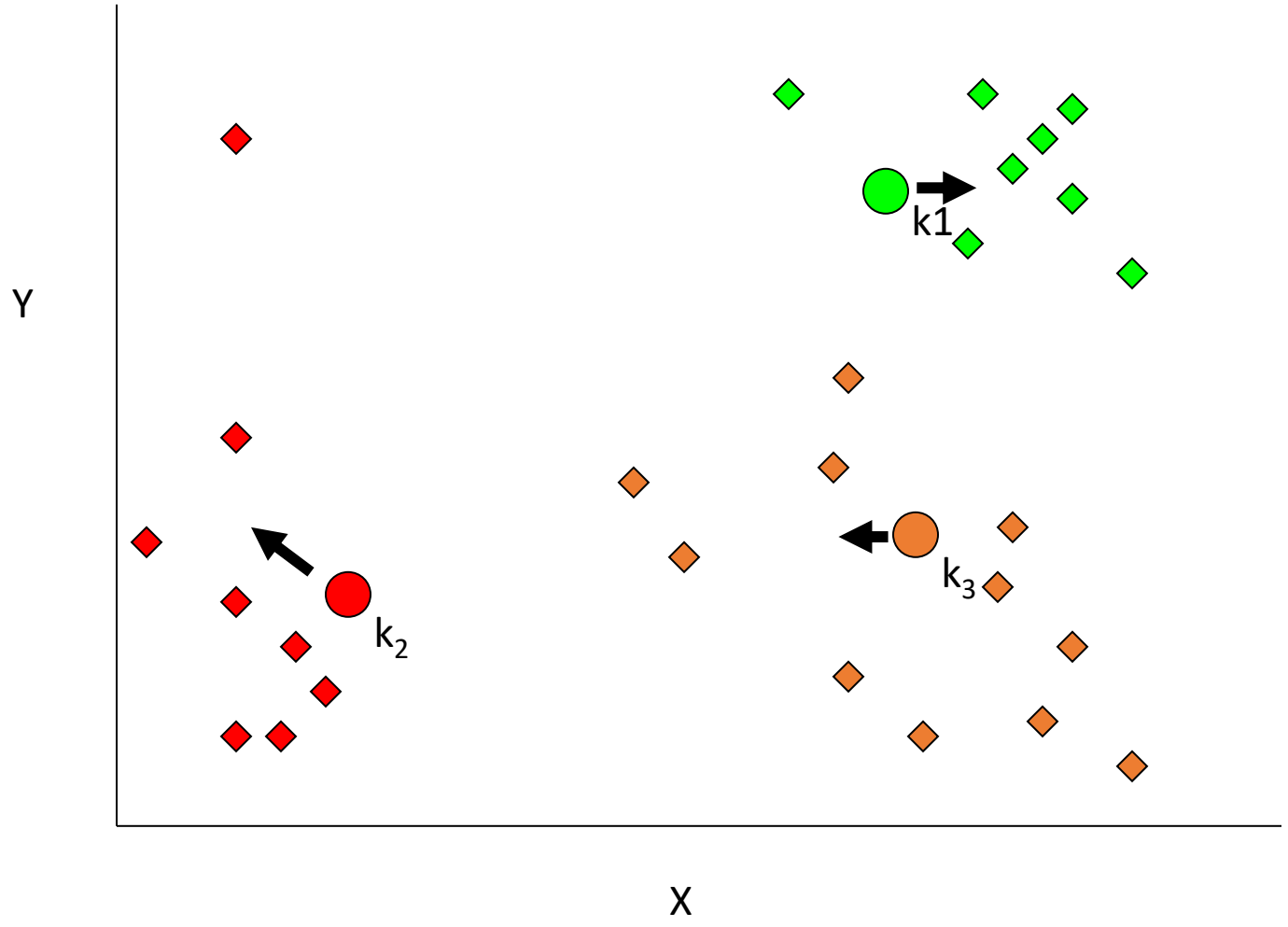
K-means example, step 4 …

for these three points ?



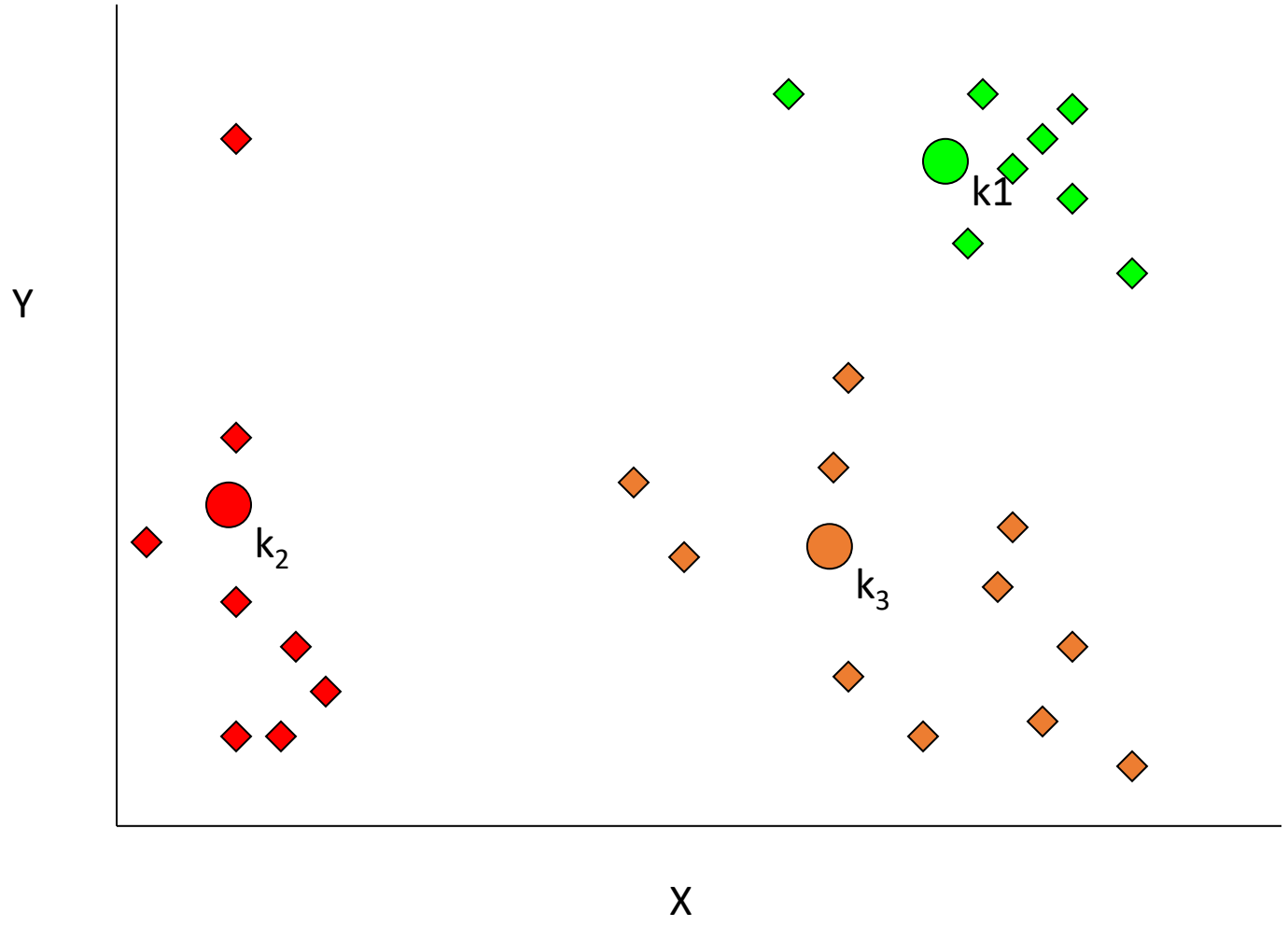
K-means example, step 4b

re-compute
cluster means

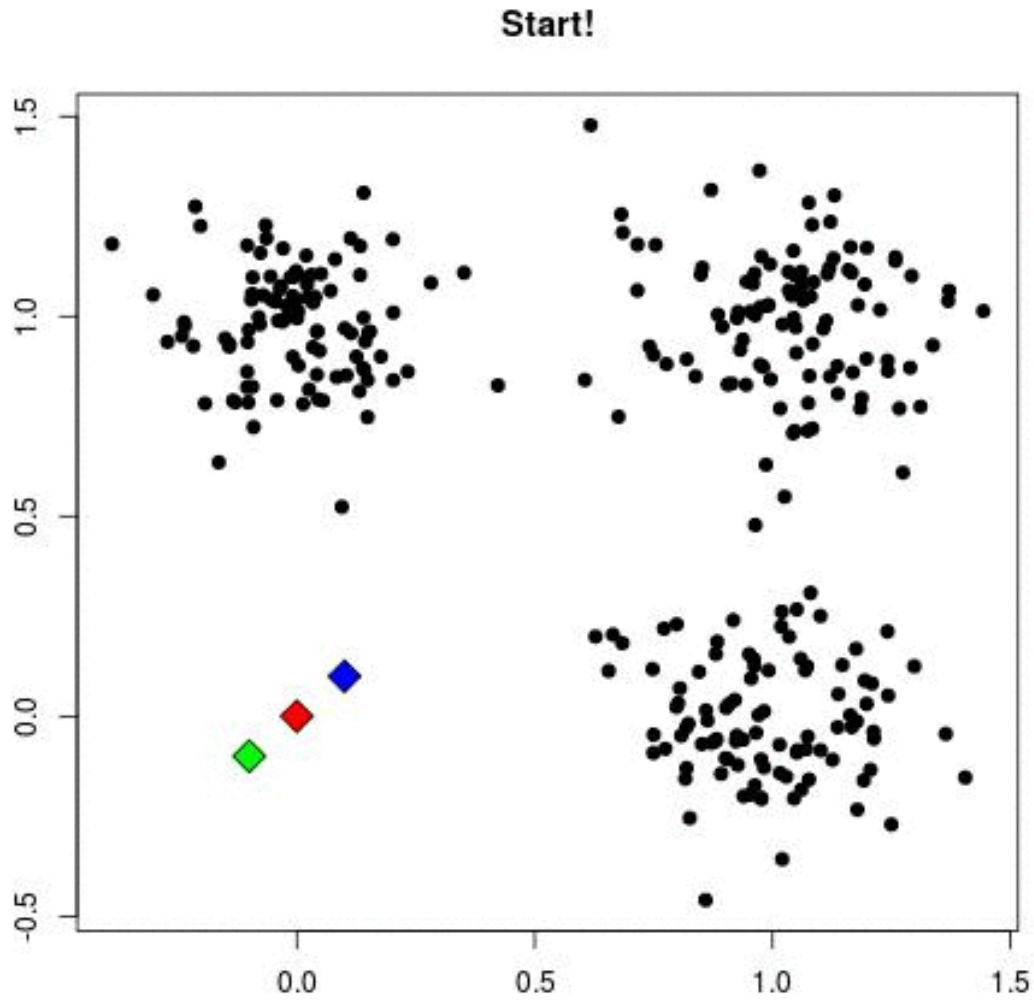


K-means example, step 5

move cluster centers to cluster means



K-means example, iterate…



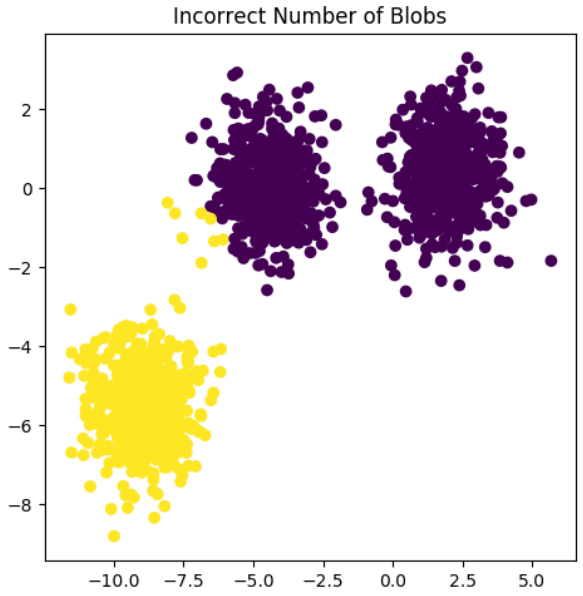
K-Means pros and cons

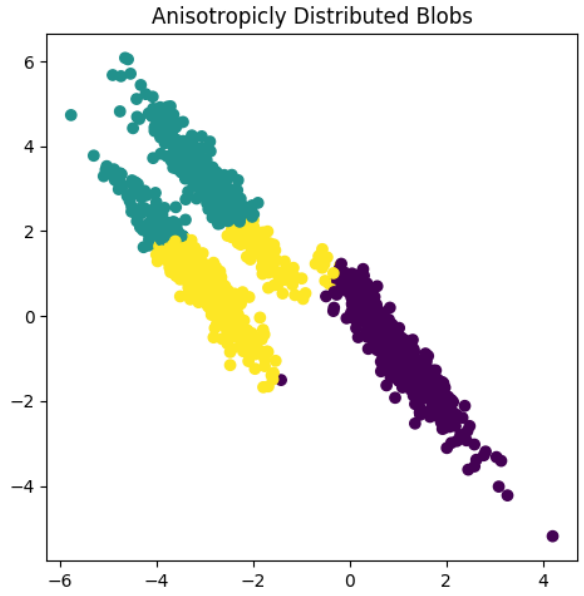
- **Pros**
  - Finds cluster centers that minimize conditional variance
  - Simple and fast
  - Easy to implement
  - …
- **Cons**
  - Need to choose K
  - Sensitive to outliers
  - All clusters have the same parameters
  - …

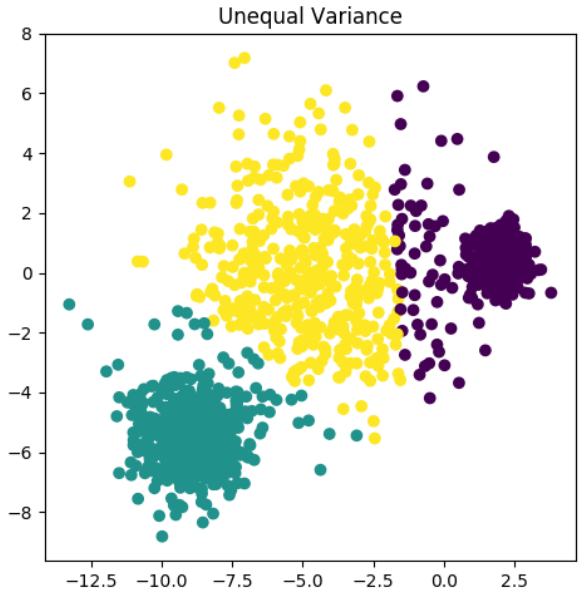
k-means assumptions

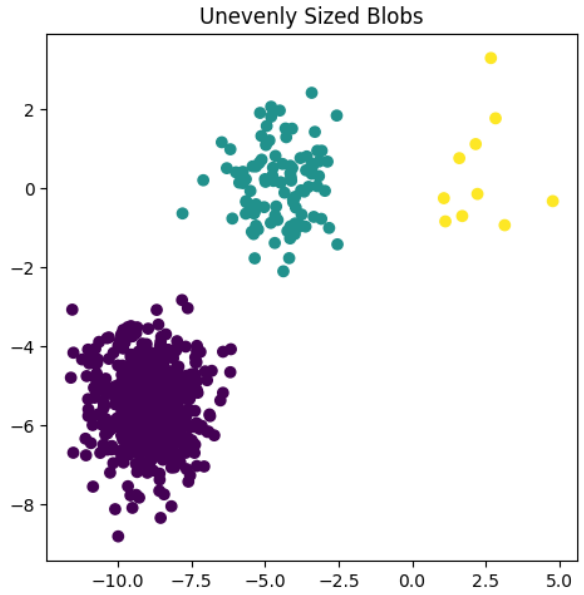
Situations where
k-means will produce
unintuitive and possibly
unexpected clusters

Importance of dataviz



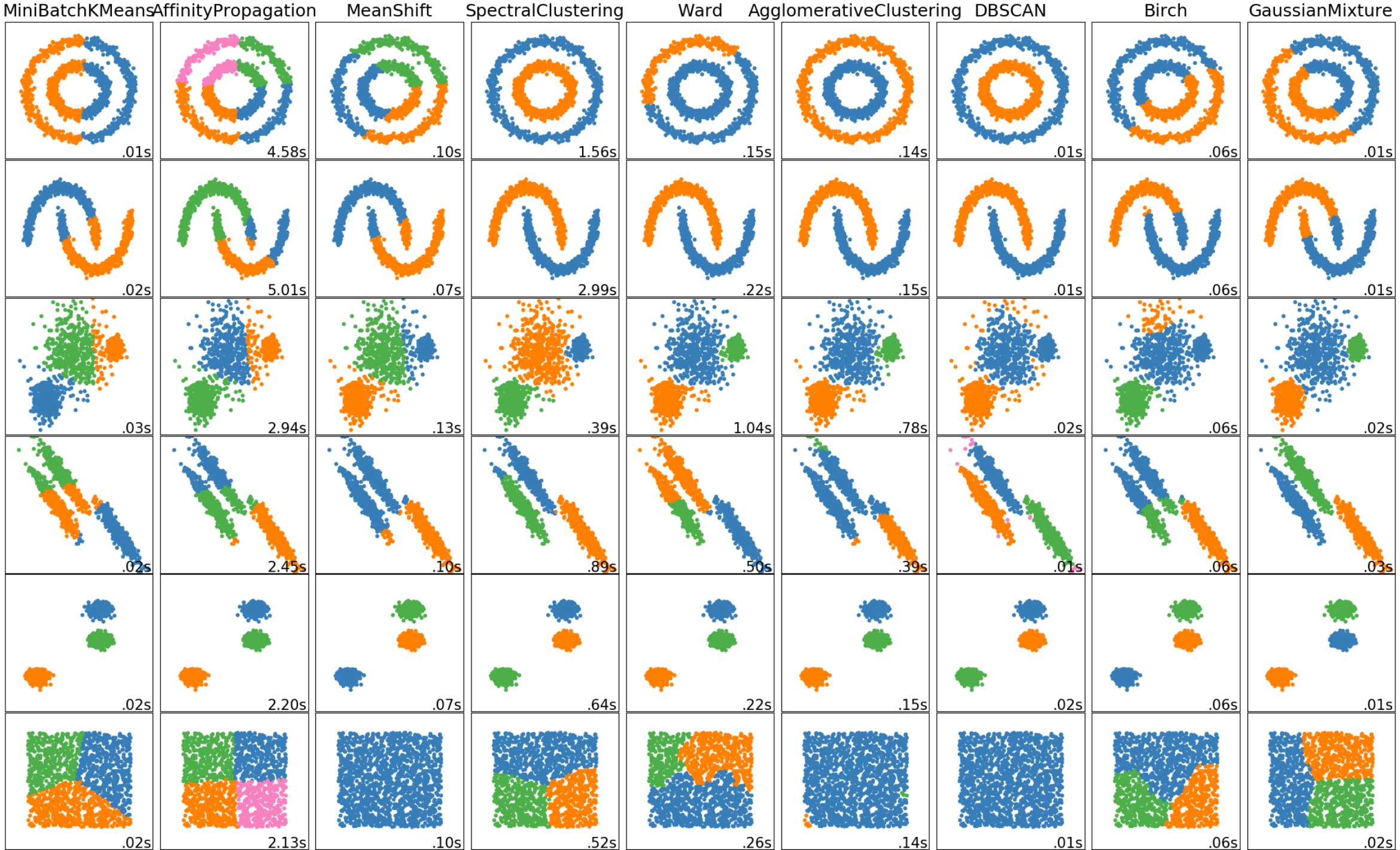






- Clustering in 2D looks easy
- Clustering small amounts of data look easy too

- Many applications involve more than 2D (Ex. > 10000 dimensions) with huge amounts of data


MiniBatchKMeans
AffinityPropagation
MeanShift
SpectralClustering
Ward
AgglomerativeClustering
DBSCAN
Birch
GaussianMixture
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4.58s
.10s
1.56s
.15s
.14s
.01s
.06s
.01s
.02s
5.01s
.07s
2.99s
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1.04s
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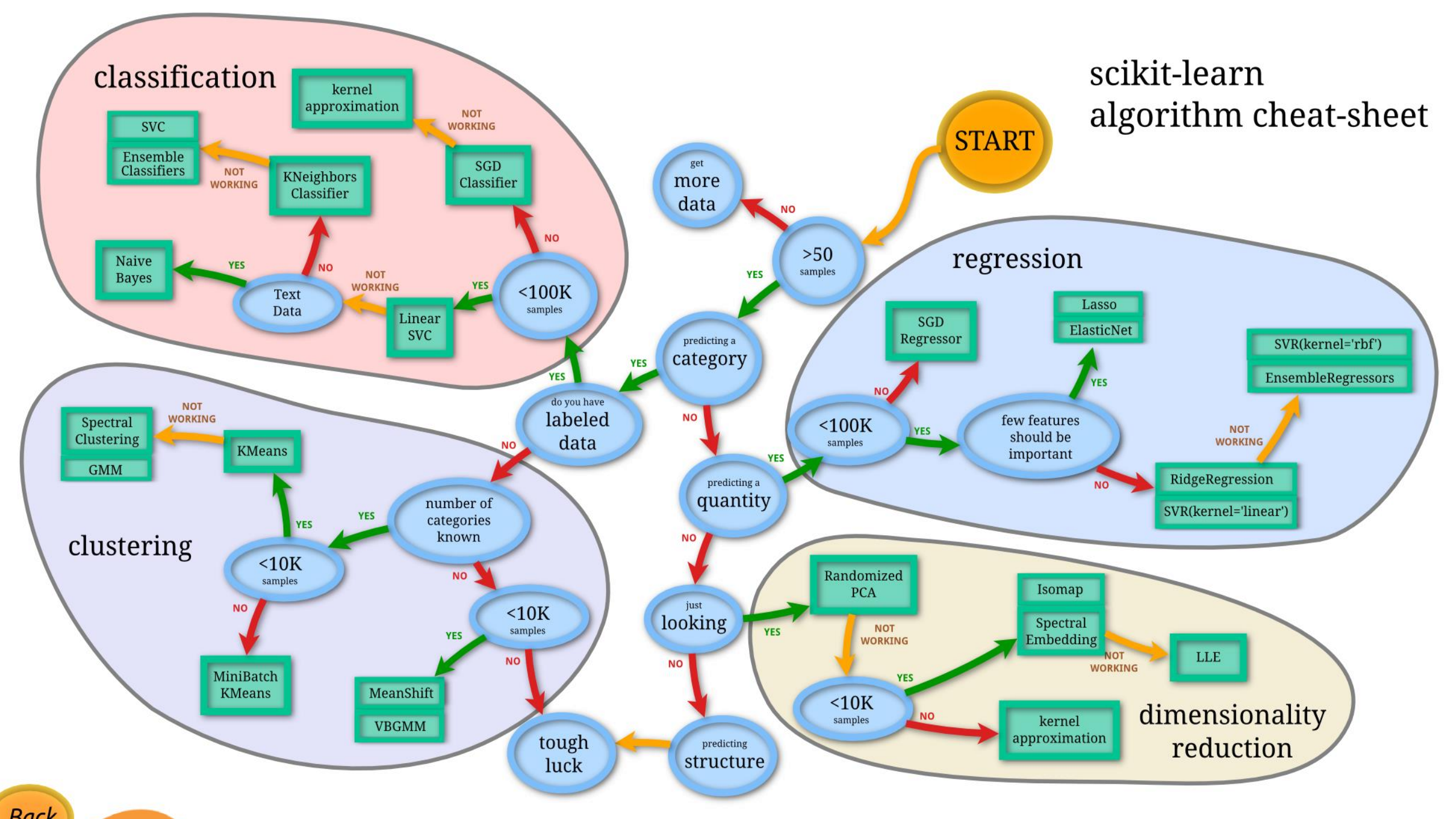
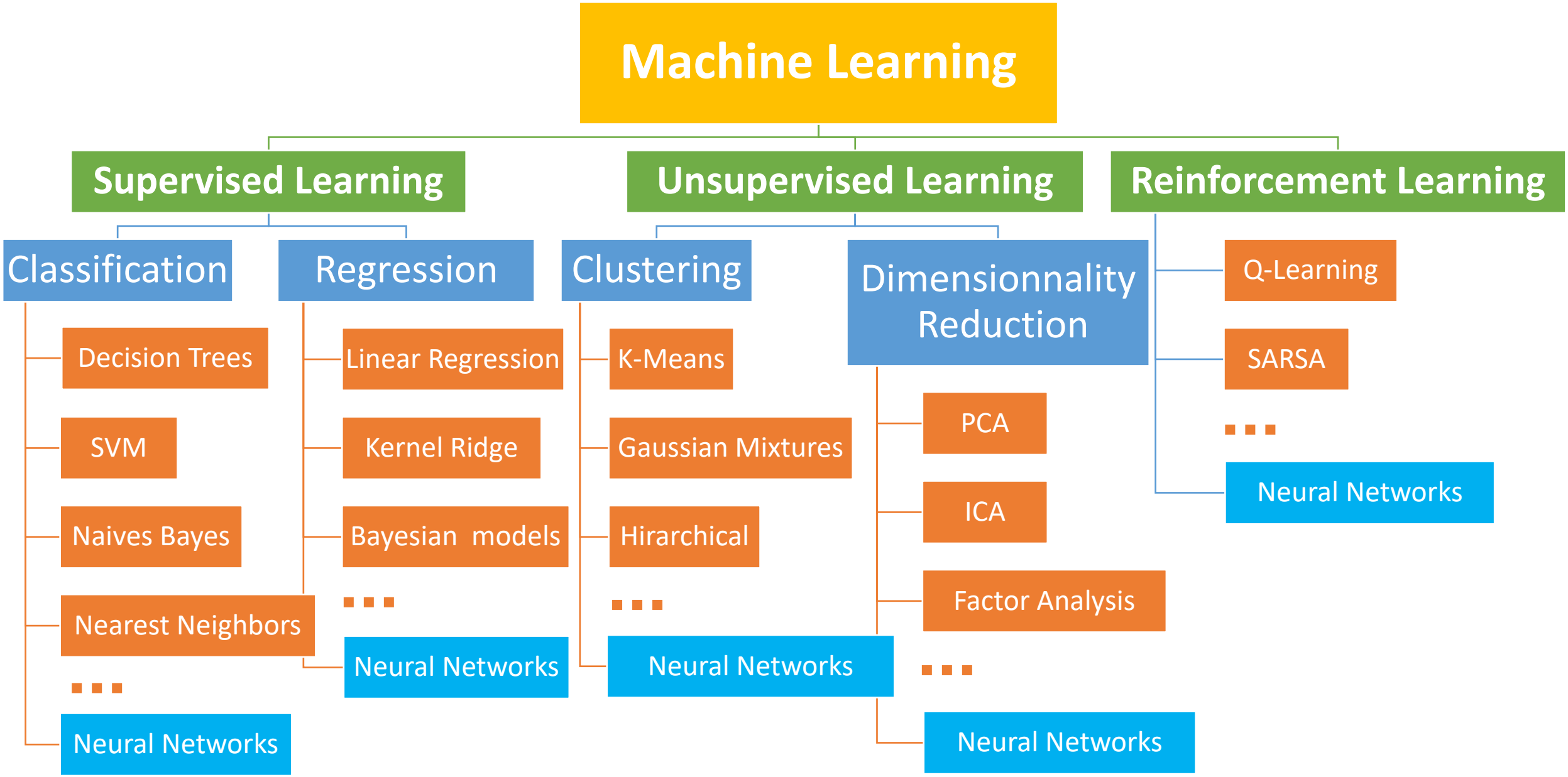

scikit-learn
algorithm cheat-sheet
START
>50 samples
NO
get more data
YES
predicting a category
YES
do you have labeled data
YES
<100K samples
NO
SGD Classifier
NOT WORKING
kernel approximation
NOT WORKING
KNeighbors Classifier
NOT WORKING
SVC
Ensemble Classifiers
YES
Naive Bayes
NO
Text Data
NOT WORKING
Linear SVC
classification
NO
predicting a quantity
YES
<100K samples
NO
SGD Regressor
YES
few features should be important
YES
Lasso
ElasticNet
NO
RidgeRegression
NOT WORKING
SVR(kernel='rbf')
EnsembleRegressors
SVR(kernel='linear')
regression
NO
number of categories known
YES
<10K samples
NO
KMeans
NOT WORKING
Spectral Clustering
GMM
MiniBatch KMeans
NO
<10K samples
YES
MeanShift
VBGMM
NO
clustering
NO
just looking
YES
Randomized PCA
NOT WORKING
<10K samples
YES
Isomap
Spectral Embedding
NOT WORKING
LLE
NO
kernel approximation
dimensionality reduction
NO
predicting structure
tough luck
Back

https://www.knime.com/


Machine Learning
Supervised Learning
Unsupervised Learning
Reinforcement Learning
Classification
Regression
Clustering
Dimensionnality Reduction
Q-Learning
Decision Trees
Linear Regression
K-Means
PCA
SARSA
SVM
Kernel Ridge
Gaussian Mixtures
ICA
Naives Bayes
Bayesian models
Hirarchical
Factor Analysis
Nearest Neighbors
Neural Networks
Neural Networks
Neural Networks
Neural Networks
Neural Networks