Unsupervised learning

Aprendizaje Automático para la Robótica Máster Universitario en Ingeniería Industrial

Departamento de Automática





Objectives

- 1. Define Machine Learning (ML)
- 2. Delimite ML scope
- 3. Introduce the main ML tasks4. Recognize problems as ML tasks

Bibliography

- Bishop, Christopher M. Pattern Recognition and Machine Learning. 2nd edition. Springer-Verlag. 2011
- Müller, Andreas C., Guido, Sarah. Introduction to Machine Learning with Python. O'Reilly. 2016

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 - PCA

K-means, DBSCAN and GMM

Clustering

Applications

Clustering is a set of unsupervised techniques that identify groups of data (named clusters)

- No universal definition of cluster
 - Centroid, meroid, dense regions, etc

Applications

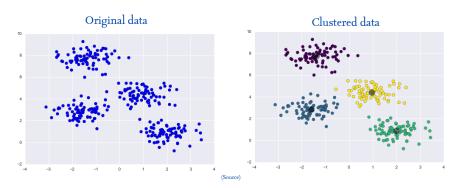
- Customer segmentation
- Data analysis
- Dimensionality reduction
- Anomaly detection
- Semi-supervised learning
- Search engines
- Image segmentation

Main algorithms

 K-means, DBScan, Gaussian Mixture Models (GMM), Expectation Maximization (EM), ...



K-means (I)



In k-means, clusters are identified by a centroid

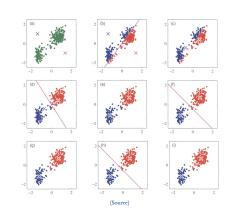
K-means (II)

K-means algorithm

- 1. Set k random centroids
- 2. Assign each data point to its closest centroid
- 3. Recompute centroids
- 4. Go to 2 until no point reassignment

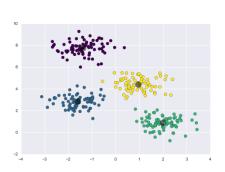
k is an hyperparameter

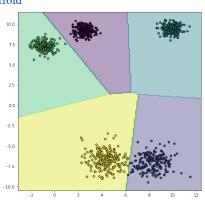
Number of clusters



K-means (III)

New data points are assigned to its closest centroid

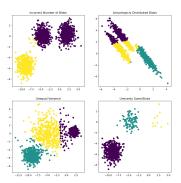




K-means (IV)

K-means can fail in several conditions

- 1. Incorrect number of clusters
- 2. Different clusters "diameter"
- 3. Non-spheric clusters



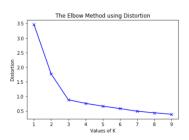
K-means (V)

K-means drawbacks

- Initial seed
- K election

Elbow method

- I. Select K = 1, ..., n
- 2. Visualize performance for each k
- 3. Choose K where metric stabilizes

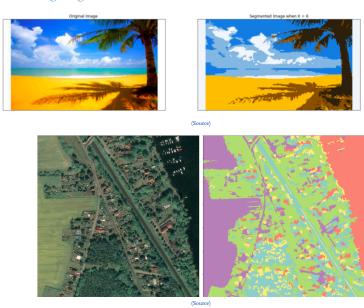


Performance measures

- Inertia: mean squared error between each instance and its closest centroid
- Silhouette: (b-a)/max(a,b), where a mean intra-cluster distance, and b is the mean nearest-cluster distance



K-means: Image segmentation



K-means: Clustering for semi-supervised learning

Semi-supervised learning: Only a subset of the dataset is labeled

- Supervised and unsupervised learning
- Quite common in real-world applications (labels use to be expensive)

f ₁	f_2		fn	Υ
$\mathfrak{a}_{1,1}$	$\mathfrak{a}_{2,1}$	• • •	$\mathfrak{a}_{\mathfrak{n},1}$	γ1
$\mathfrak{a}_{1,2}$	$\mathfrak{a}_{2,2}$	• • •	$\mathfrak{a}_{\mathfrak{n},2}$	
$\mathfrak{a}_{1,3}$	$\mathfrak{a}_{2,3}$	• • •	$\mathfrak{a}_{\mathfrak{n},3}$	
$\mathfrak{a}_{1,4}$	$\mathfrak{a}_{2,4}$	• • •	$\mathfrak{a}_{\mathfrak{n},4}$	γ4
$\mathfrak{a}_{1,5}$	$\mathfrak{a}_{2,5}$	• • •	$a_{n,5}$	

Label propagation

- 1. Obtain k clusters
- Get a representative instance of each cluster (medoid) measuring the distance to the centroid
- 3. Label the members of each cluster with its medoid's label

K-means: Summary

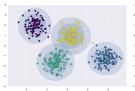
Hyperparameters	Advantages	Disadvantages
	Fast	Simple shapes
k	Few hyperparameters	Determine k
	Scalable	Random initialization

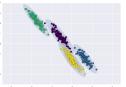
DBSCAN

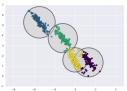
Algorithms

GMM builds a probabilic model of our data

- GMM is a generative clustering algorithm
- Assumes data coming from a set of multidimensional gaussian distributions
 - GMM fits a set $\{(\mu_i, \sigma_i)\}_{i=1,...,K}$
 - μ is a vector
 - σ is a covariance matrix





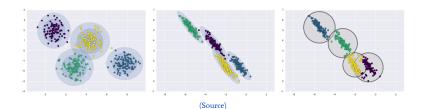


(Source)

Gaussian Mixure Model (GMM)

GMM builds a probabilic model of our data

- GMM is a generative clustering algorithm
- Assumes data coming from a set of multidimensional gaussian distributions
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PCA and manifold learning

Principal Components Analysis (I)

Dimensionality reduction transforms data into more convenient representations

- Reduce data dimensionality
- Visualize multidimensional data

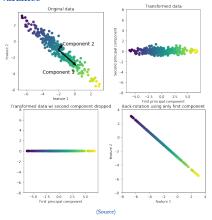
Main algorithms

- Isomap
- T-distributed Stochastic Neighbor Embedding (t-SNE)
- Principal Components Analysis (PCA)



Principal Components Analysis (II)

PCA maximizes data variance





Principal Components Analysis (III)

Example: Hand-written digits recognition

- Images of hand-written digits
- 8x8 images (64 dimensions)
- 10 digits
- Classification problem

