

Lecture 8: Unsupervised learning

Introduction to Machine Learning

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Question

Can anyone remind me what is the definition of **unsupervised learning** ?

Definition: unsupervised learning

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Question

Can anyone remind me what is the definition of **unsupervised learning** ?

Unsupervised learning

Unsupervised learning* is a type of algorithm that **learns patterns from untagged data**: through likeliness, algorithms build a concise representation of the data to generate imaginative content.

Definition: unsupervised learning

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While the goal of supervised learning is to **predict actions for unseen data**, the goal of unsupervised learning is to help us understand better **existing data**.

Definition: unsupervised learning

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While the goal of supervised learning is to **predict actions for unseen data**, the goal of unsupervised learning is to help us understand better **existing data**.

Several types of unsupervised learning exist in the literature:

- **Clustering methods**
- Latent models
- Anomaly detection

Definition: unsupervised learning

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While the goal of supervised learning is to **predict actions for unseen data**, the goal of unsupervised learning is to help us understand better **existing data**.

Several types of unsupervised learning exist in the literature:

- **Clustering methods**
- Latent models
- Anomaly detection

In this course, we'll focus on **clustering methods**.

Definition: clustering

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Clustering

Clustering consists in **grouping a set of objects** so that objects in the same group (called a **cluster**) are more "similar" to each other than to those in other groups.

There is no class to be predicted but **the instances are to be divided into natural groups.**

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Clustering

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There is no class to be predicted but **the instances are to be divided into natural groups.**

Given a set of j individuals described by their features $(x_{j,1}, \dots, x_{j,n})$, assign each individual into a cluster i ($1 \leq i \leq m$).

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Clustering consists in finding **groups** where:

- Individuals **within** the group are similar
- Individuals **across** groups are dissimilar

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Clustering consists in finding **groups** where:

- Individuals **within** the group are similar
- Individuals **across** groups are dissimilar

There are many different clustering algorithms, that have a different interpretation of "similar" and "cluster".

Definition: clustering

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Interpretation of clusters

Clustering consists in finding **groups** where:

- Individuals **within** the group are similar
- Individuals **across** groups are dissimilar

There are many different clustering algorithms, that have a different interpretation of "similar" and "cluster".

Similar to supervised learning, **there is no single best method for all datasets.**

Example: clustering

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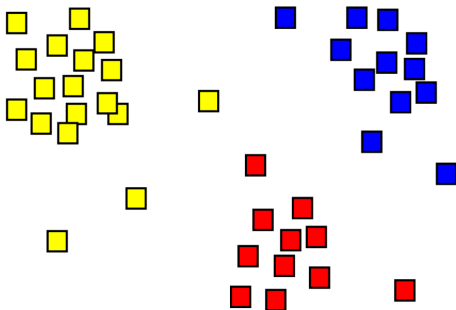
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of clusters

Height	Weight	Cluster
10	5	?
8	3	?
20	15	?
17	16	?



Example use-cases

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Possible use-cases for clustering:

- Finding groups within the data: streaming behavior, shopping behavior (market segmentation ...) ...
- Finding outlier individuals in the dataset (individuals too far apart need to be investigated further)
- Semi-supervised learning: mapping samples to a set of class and using it for training.

Definition: clustering

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Selecting the right number of clusters can be done:

- Natively by the selected algorithm
- Iteratively by testing different values, evaluating different number of clusters and selecting the best

Clustering is also sensitive to overfitting: the variance-bias trade-off also applies here.

Definition: clustering

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of clusters

Clustering can be:

- **Hard* clustering**: each individual belongs to a **single cluster**.
- **Soft* clustering** (*fuzzy*): an individual can belong to several clusters at the same time.

Clustering algorithms

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Any algorithms grouping a set of individuals into **groups of data** is a **clustering algorithms**.

Clustering algorithms

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Interpretation
of clusters

Any algorithms grouping a set of individuals into **groups of data** is a **clustering algorithms**.

There are diverse algorithms:

- Centroid model based (k-means ...)
- Connectivity models (hierarchical clustering ...)
- Distribution-based clustering (latent models and gaussian mixtures ...)
- Density based (DBSCAN ...)

Evaluation of clustering algorithms

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Question

Do you think we can apply supervised learning metrics to the case of unsupervised learning ?

Evaluation of clustering algorithms

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Question

Do you think we can apply supervised learning metrics to the case of unsupervised learning ?

As we have no **ground truth**, we cannot directly use supervised learning metrics.

Evaluation of clustering algorithms

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Question

Do you think we can apply supervised learning metrics to the case of unsupervised learning ?

As we have no **ground truth**, we cannot directly use supervised learning metrics.

We need some metrics specific to the **unsupervised learning task**.

Evaluation metrics

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Question

What could be some good metrics to assess the performance of an algorithm for a clustering task ?

Different possible approaches:

- Internal evaluation (**find a score describing the performance of the algorithm**)

Evaluation metrics

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Question

What could be some good metrics to assess the performance of an algorithm for a clustering task ?

Different possible approaches:

- Internal evaluation (**find a score describing the performance of the algorithm**)
- Manual evaluation (**use a human expert to validate clusters meaning and see if they are consistent**)

Evaluation metrics

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Question

What could be some good metrics to assess the performance of an algorithm for a clustering task ?

Different possible approaches:

- Internal evaluation (**find a score describing the performance of the algorithm**)
- Manual evaluation (**use a human expert to validate clusters meaning and see if they are consistent**)
- Empirical/indirect evaluation (**see if in practice the results of this clustering yields efficient information**)

Clustering scores

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Interpretation of clusters

Clustering scores assign the best score to the algorithm that produces clusters with **high similarity within a cluster** and **low similarity between clusters**.

Possible scores include:

- Silhouette scores

Clustering scores

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Interpretation
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Clustering scores assign the best score to the algorithm that produces clusters with **high similarity within a cluster** and **low similarity between clusters**.

Possible scores include:

- Silhouette scores
- Davies-Boulin index

Silhouette scores

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Silhouette

The silhouette score* measures **how similar an object is to its own cluster** compared to other clusters:

With a the mean intra-cluster distance and b the mean nearest-cluster distance, the silhouette score for an instance is:

$$\frac{b - a}{\max(a, b)}$$

Silhouette scores

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Silhouette

The silhouette score* measures **how similar an object is to its own cluster** compared to other clusters:

With a the mean intra-cluster distance and b the mean nearest-cluster distance, the silhouette score for an instance is:

$$\frac{b - a}{\max(a, b)}$$

It ranges from -1 to 1: a high value indicates that the objects is **well matched to its own cluster** and **poorly matched to neighboring clusters**.

Silhouette scores

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If most objects have a high value, then the clustering configuration is appropriate. If many points have a low or negative value (= individuals might have been clustered in the wrong cluster), then:

Silhouette scores

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If most objects have a high value, then the clustering configuration is appropriate. If many points have a low or negative value (= individuals might have been clustered in the wrong cluster), then:

- Dataset may not be adequate for clustering

Silhouette scores

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Interpretation
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If most objects have a high value, then the clustering configuration is appropriate. If many points have a low or negative value (= individuals might have been clustered in the wrong cluster), then:

- Dataset may not be adequate for clustering
- Number of clusters may be poorly chosen (we will see for the different algorithms how to select the optimal number of clusters)

Silhouette scores

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Evaluation of clustering algorithms

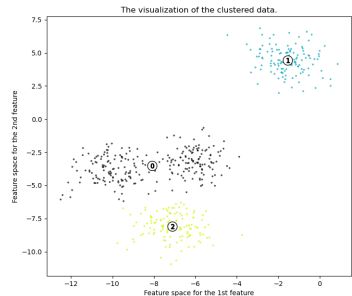
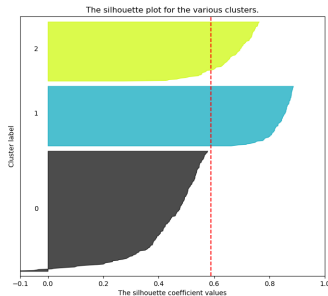
Silhouette scores

Davies-Bouldin index

Interpretation of clusters

Silhouette scores are usually visually represented as a *silhouette* plot to visually see how well the algorithm behaves.

Silhouette analysis for KMeans clustering on sample data with $n_{\text{clusters}} = 3$



Silhouette scores: example

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Interpretation
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Question

Given the following clustering result, compute silhouette scores (Manhattan distance) and plot the graph.

ID	Height	Weight	Cluster
1	10	16	1
2	12	14	1
3	14	15	1
4	14	30	2
5	30	30	2

Davies-Bouldin index

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Davies-Bouldin index

The **Davies-Boulin index*** measures the average similarity of each cluster with its most similar cluster, where similarity is **the ratio of within-cluster distances to between-cluster distances**.

Davies-Bouldin index

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We define similarity between cluster i and j as:

$$R_{i,j} = \frac{s_i + s_j}{d_{i,j}}$$

with s_i the average distance between each point of cluster i and the centroid of that cluster and $d_{i,j}$ the distance between cluster centroids i and j .

$$DB = \frac{1}{k} \times \sum_{i=1}^k \max_{i \neq j} R_{i,j}$$

Davies-Bouldin score: example

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Interpretation
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Question

Given the following clustering result, compute Davies-Bouldin index (Euclidean distance) and plot the graph.

ID	Height	Weight	Cluster
1	10	16	1
2	12	14	1
3	14	15	1
4	14	30	2
5	30	30	2

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Interpretation
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Usually as hard as the clustering task itself !

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Interpretation
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Usually as hard as the clustering task itself !
Possible interpretations of clusters can be done:

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Interpretation
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Usually as hard as the clustering task itself !

Possible interpretations of clusters can be done:

- By looking at the different scores to see how relevant clustering is

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Interpretation
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Usually as hard as the clustering task itself !

Possible interpretations of clusters can be done:

- By looking at the different scores to see how relevant clustering is
- By looking at estimator values of the different features within each cluster

Intepretation of clusters

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Interpretation
of clusters

Usually as hard as the clustering task itself !

Possible interpretations of clusters can be done:

- By looking at the different scores to see how relevant clustering is
- By looking at estimator values of the different features within each cluster
- By plotting the different clusters against the features and understanding why they were clustered together.

Questions

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Question ?