

Unsupervised

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Schedule

- Clustering theory
- Clustering use case (k-means)
- Distance metrics theory
- Data analysis use case (HAC)
- Dimensionality reduction theory
- Feature selection use case

Usage

Python3	Programming language
NumPy	Apply calculations and linear algebra
Pandas	Store and view results
Matplotlib/sns	Plot (intermediate) results
Jupyter	For demonstration purpose
Pip3/conda	Installing required packages
Github	Share code

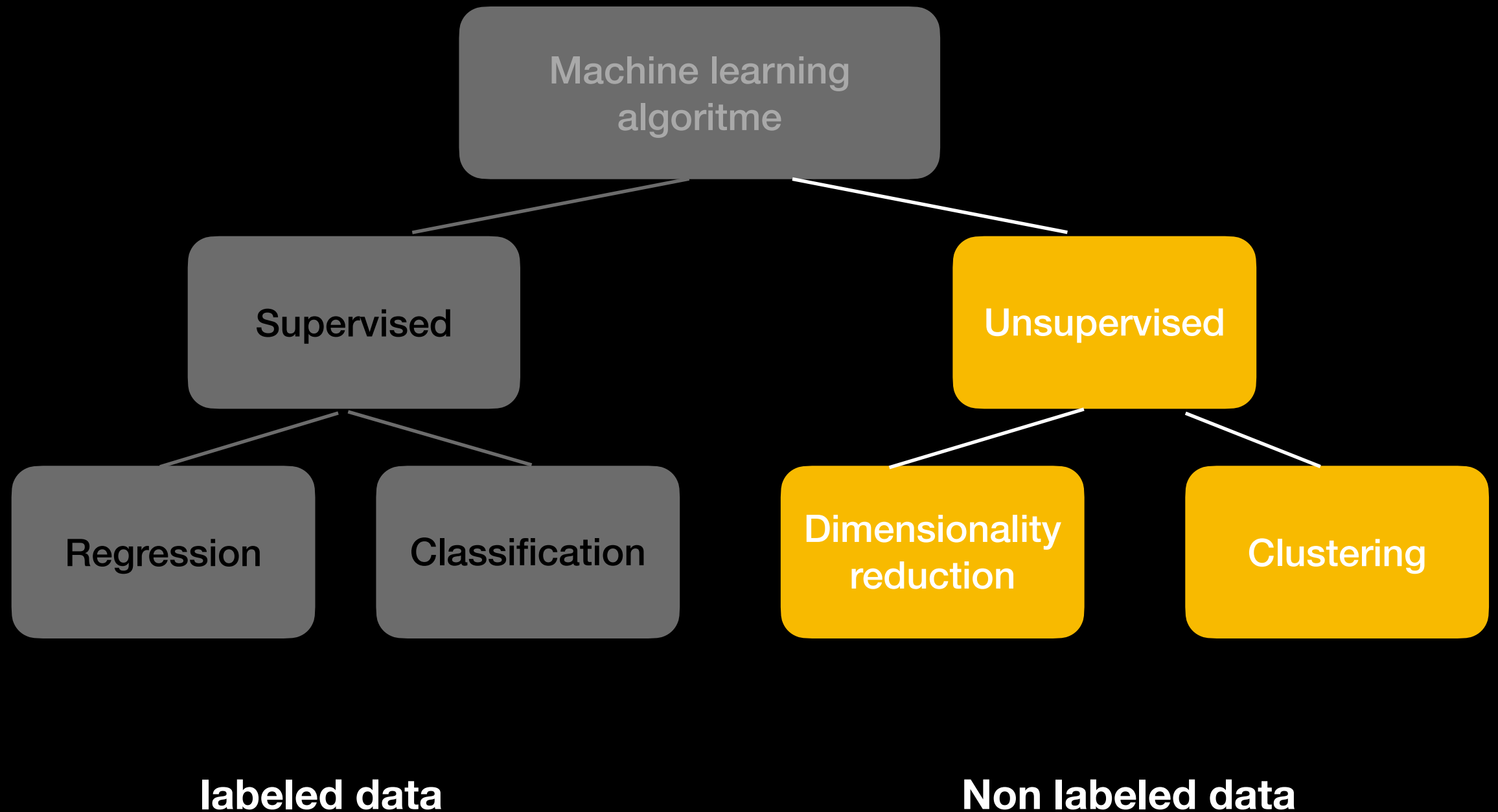
Material

Library	Docs	cheatsheet
python	https://www.python.org/doc/	https://perso.limsi.fr/pointal/media/python:cours:mementopython3-english.pdf
pandas	pandas.pydata.org/pandas-docs/stable/	https://pandas.pydata.org/Pandas_Cheat_Sheet.pdf
numpy	https://docs.scipy.org/doc/numpy	https://s3.amazonaws.com/dq-blog-files/numpy-cheat-sheet.pdf
matplotlib	https://matplotlib.org/contents.html	https://s3.amazonaws.com/assets.datacamp.com/blog_assets/Scikit_Learn_Cheat_Sheet_Python.pdf
sklearn	scikit-learn.org	https://s3.amazonaws.com/assets.datacamp.com/blog_assets/Scikit_Learn_Cheat_Sheet_Python.pdf

Book



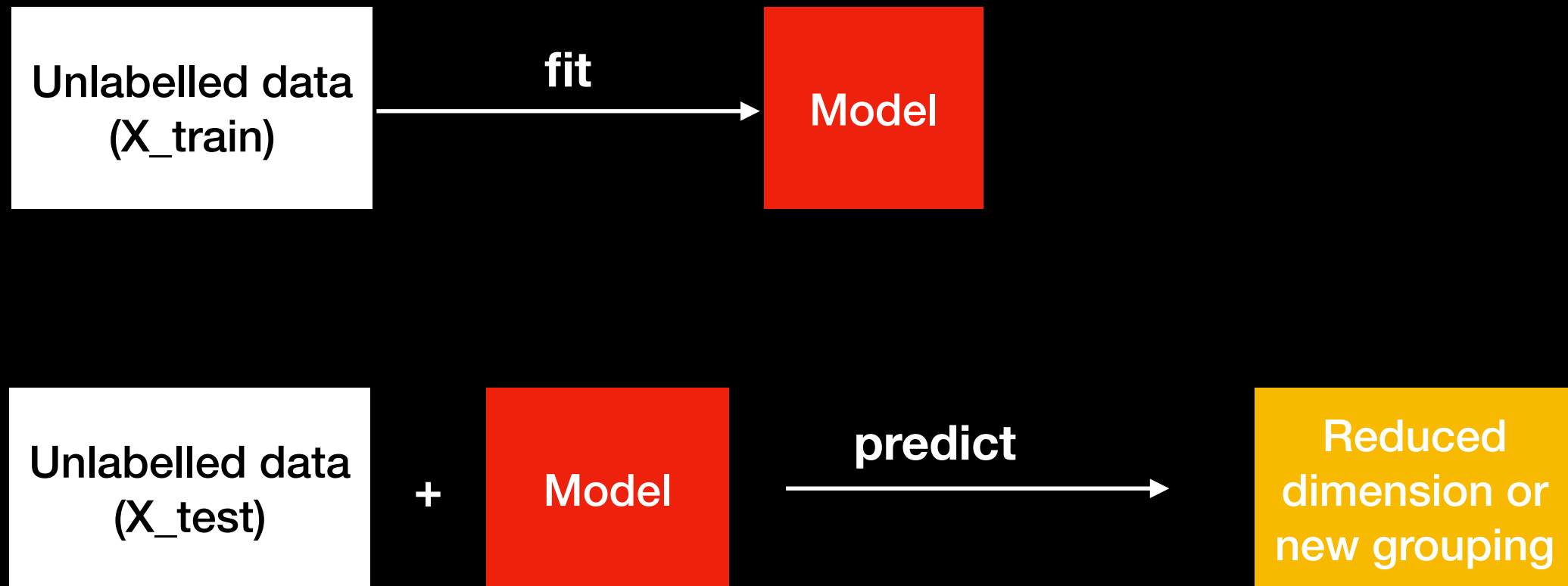
Machine learning



Use cases

- Try to find structures in our dataset
 - Clustering: identify unknown structures (group data, segmentation analysis, anomaly detection, classification, improve supervised learning by modelling per cluster)
 - Dimensionality reduction: use structural characteristics to simplify data (image compression, text analysing, feature selection, improve plotting)

General method



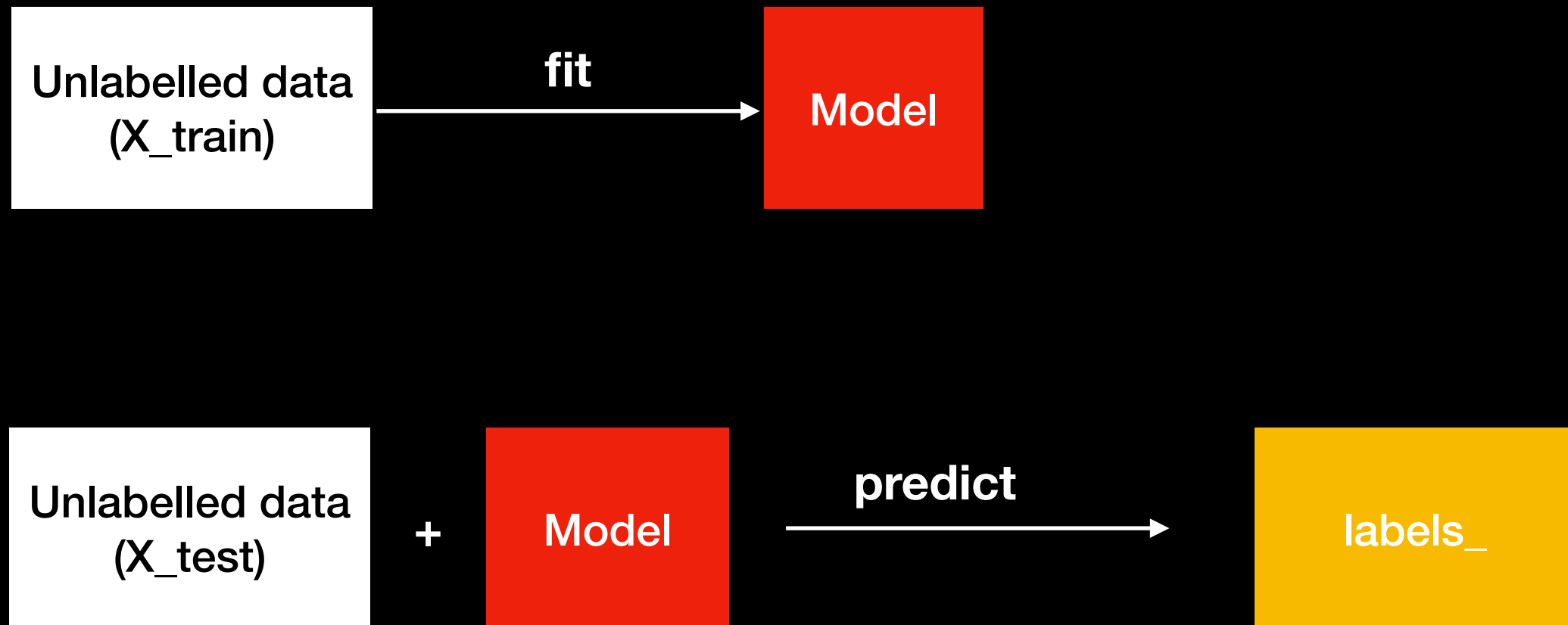
Clustering

- Group data points based on certain similarities. Data does not have labels, best algorithm depends on use case.

Most common:

- K-means
- Meanshift
- HAC
- DBSCAN

Cluster method



Examples

- Group documents by topic
- Group organism by genetic information
- Group colours into cluster-IDs to compress image

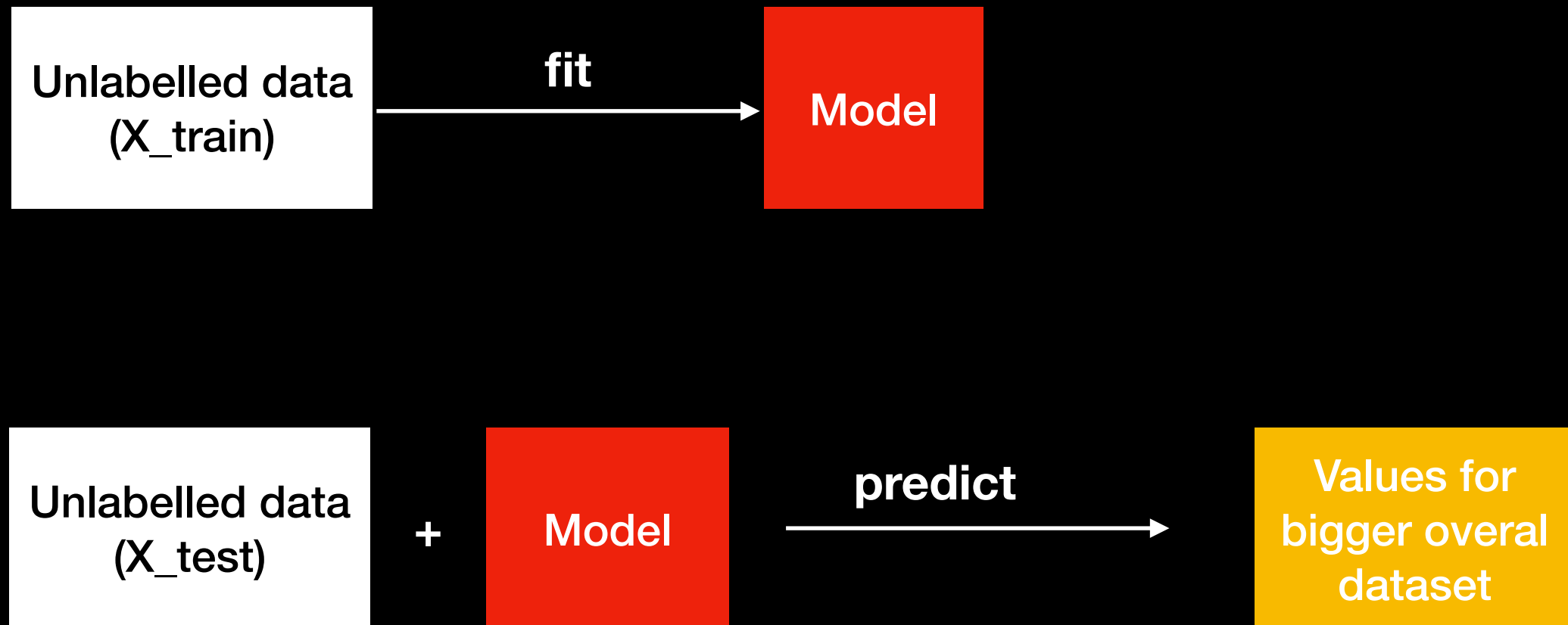
Clustering methods

Method	K-means	Mean Shift	HAC	DBSCAN
Class	KMeans	<u>MeanShift</u>	Agglomerative Clustering	DBSCAN
Essential Parameters	n_clusters	bandwidth	n_clusters, linkage, affinity	epsilon, min_samples, metric
Distance methods	Euclidean	Euclidean	euclidean/l1/L2/Manhattan/cosine/precomputed	<u>About 23 different metrics</u>
Use case	find a few clusters of ~ same size	determine the (large) amount of clusters	get a full tree (informative)	tons of data and weird shapes
Remark	Fast, but bad on non spherical clusters	Slow, bad on weird shapes	Slow, good on weird shapes or uneven cluster sizes	Highly configurable, good performance

Dimensionality reduction

- Coming up with a **lower dimensional representation** of our original data that maintains the majority of the information important for us in the original dataset (create **new features as combination** of original features). Most common:
 - PCA (linear principal component analysis)
 - KernelPCA (non linear principal component analysis)
 - MDS (Multidimensional Scaling)
 - t-SNE (t-distributed Stochastic Neighbor Embedding)
 - NMF (non negative matrix factorisation)

dimensionality reduction



Dimensions reduction example



fit

Compression
Model



+

Compression
Model

predict
(reconstruct
picture)



Curse of dimensionality

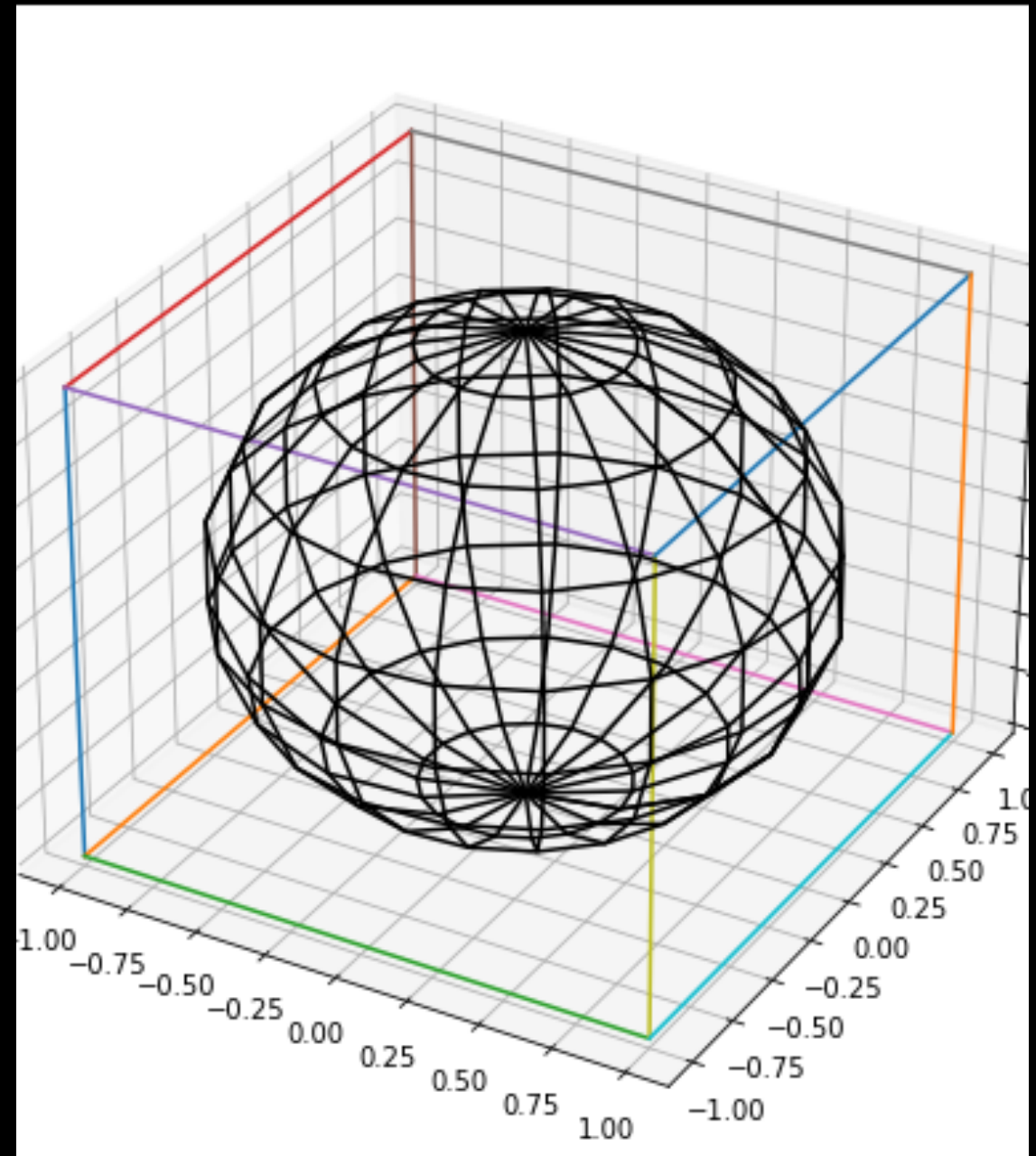
Curse of Dimensionality describes the explosive nature of increasing data dimensions and its resulting exponential increase in computational efforts required for its processing and/or analysis

2 dim -> 79% inside sphere

3 dim -> 52% inside sphere

10 dim -> 0.25% inside sphere

high-dimensional space leads to sparse data; clustering is difficult when points are far away from each other



unsupervised+ supervised

Use dimensionality reduction to lower number of features

- PCA
- Matrix factorisation
- t-SNE
- MDS

<https://machinelearningmastery.com/dimensionality-reduction-for-machine-learning/>

methods

Method	PCA	KernelPCA	MDS	NMF
Class	PCA	KernelPCA	MDS	NMF
Essential Parameters	n_components	n_components, kernel, gamma	n_components	n_components, init
Use case	In case of linear combination of features	Non linear relationships	Non linear relationships	Only for positive values (words, images)
Remark	Preserves variance as much as possible	Requires more computation	Preserving distance between points rather than variance	