

## **Cheat Sheet: Building Unsupervised Learning Models**

## **Unsupervised learning models**

Model Name	Brief Description	Code Syntax
UMAP	UMAP (Uniform Manifold Approximation and Projection) is used for dimensionality reduction.  Pros: High performance, preserves global structure.  Cons: Sensitive to parameters.  Applications: Data visualization, feature extraction.  Key hyperparameters:  • n_neighbors: Controls the local neighborhood size (default = 15).  • min_dist: Controls the minimum distance between points in the embedded space (default = 0.1).  • n_components: The dimensionality of the embedding (default = 2).	1 from umap.umap_ import UMAP 2 umap = UMAP(n_neighbors=15, min_dist=0.1, n_components=2)
t-SNE	t-SNE (t-Distributed Stochastic Neighbor Embedding) is a nonlinear dimensionality reduction technique.  Pros: Good for visualizing high-dimensional data.  Cons: Computationally expensive, prone to overfitting.  Applications: Data visualization, anomaly detection.  Key hyperparameters:  • n_components: The number of dimensions for the output (default = 2).  • perplexity: Balances attention between local and global aspects of the data (default = 30).  • learning_rate: Controls the step size during optimization (default = 200).	1 from sklearn.manifold import TSNE 2 tsne = TSNE(n_components=2, perplexity=30, learning_rate=200)
PCA	PCA (principal component analysis) is used for linear dimensionality reduction.  Pros: Easy to interpret, reduces noise.  Cons: Linear, may lose information in nonlinear data.  Applications: Feature extraction, compression.  Key hyperparameters:  • n_components: Number of principal components to retain (default = 2).  • whiten: Whether to scale the components (default = False).  • svd_solver: The algorithm to compute the components (default = 'auto').	1 from sklearn.decomposition import PCA 2 pca = PCA(n_components=2)  □ □ □
DBSCAN	DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a density-based clustering algorithm.  Pros: Identifies outliers, does not require the number of clusters.  Cons: Difficult with varying density clusters.  Applications: Anomaly detection, spatial data clustering.  Key hyperparameters:  • eps: The maximum distance between two points to be considered neighbors (default = 0.5).  • min_samples: Minimum number of samples in a neighborhood to form a cluster (default = 5).	1 from sklearn.cluster import DBSCAN 2 dbscan = DBSCAN(eps=0.5, min_samples=5)  2 dbscan = DBSCAN(eps=0.5, min_samples=5)
HDBSCAN	HDBSCAN (Hierarchical DBSCAN) improves on DBSCAN by handling varying density clusters.  Pros: Better handling of varying densities.  Cons: Can be slower than DBSCAN.  Applications: Large datasets, complex clustering problems.  Key hyperparameters:  • min_cluster_size: The minimum size of clusters (default = 5).  • min_samples: Minimum number of samples to form a cluster (default = 10).	1 import hdbscan 2 clusterer = hdbscan.HDBSCAN(min_cluster_size=5)
K-Means clustering	K-Means is a centroid-based clustering algorithm that groups data into k clusters.  Pros: Efficient, simple to implement.  Cons: Sensitive to initial cluster centroids.  Applications: Customer segmentation, pattern recognition.  Key hyperparameters:  • n_clusters: Number of clusters (default = 8).  • init: Method for initializing the centroids ('k-means++' or 'random', default = 'k-means++').  • n_init: Number of times the algorithm will run with different centroid	1 from sklearn.cluster import KMeans 2 kmeans = KMeans(n_clusters=3)

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## Associated fuctions used

Method	Brief Description	Code Syntax
make_blobs	Generates isotropic Gaussian blobs for clustering.	<pre>from sklearn.datasets import make_blobs X, y = make_blobs(n_samples=100, centers=2, random_state=42)</pre>
multivariate_normal	Generates samples from a multivariate normal distribution.	from numpy.random import multivariate_normal  samples = multivariate_normal(mean=[0, 0], cov=[[1, 0], [0, 1]], size=100)
plotly.express.scatter_3d	Creates a 3D scatter plot using Plotly Express.	<pre>import plotly.express as px fig = px.scatter_3d(df, x='x', y='y', z='z') fig.show()</pre>
geopandas.GeoDataFrame	Creates a GeoDataFrame from a Pandas DataFrame.	1 import geopandas as gpd 2 gdf = gpd.GeoDataFrame(df, geometry='geometry')  2 gdf = gpd.GeoDataFrame(df, geometry='geometry')
geopandas.to_crs	Transforms the coordinate reference system of a GeoDataFrame.	1 gdf = gdf.to_crs(epsg=3857) ② ■
contextily.add_basemap	Adds a basemap to a GeoDataFrame plot for context.	<pre>import contextily as ctx ax = gdf.plot(figsize=(10, 10)) ctx.add_basemap(ax)</pre>
pca.explained_variance_ratio_	Returns the proportion of variance explained by each principal component.	<pre>1  from sklearn.decomposition import PCA 2  pca = PCA(n_components=2) 3  pca.fit(X) 4  variance_ratio = pca.explained_variance_ratio_</pre>

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