9 Unsupervised Learning

Unsupervised learning works with ______ data (no ____), making evaluation more difficult.

Density Estimation

Density estimation models the probability _____ function of the (unknown) distribution from which data were drawn.¹

• Recall: We used a _____ model for density estimation in §7 to help with one-class classification: gm = mixture.GaussianMixture(n_components=1) estimates the parameters μ and Σ of the multivariate normal distribution $N_D(\mu_D, \Sigma_{D \times D})$, which has density function

$$f_{\boldsymbol{\mu},\boldsymbol{\Sigma}}(\mathbf{x}) = \frac{\exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right)}{\sqrt{(2\pi)^D|\boldsymbol{\Sigma}|}}\,.$$

For density estimation, use the same code to estimate $f_{\mu,\Sigma}(\mathbf{x})$ given $\{\mathbf{x}_i\}$. (Just omit the _____ used to decide whether a new \mathbf{x} is in the one class.)

• Recall: We used a *nonparameteric* model in _____ regression, a supervised learning method in §7. We used N Gaussians centered at $\{\mathbf{x}_i\}$ to make weighted averages of y's.

In kernel density estimation (KDE), use the _____ of the same N Gaussians to estimate the probability density function $f(\mathbf{x})$ which generated the unsupervised (no y) examples $\{\mathbf{x}_i\}$.

Consider the 1D case. Our kernel model is

$$\hat{f}_b(x) = \frac{1}{Nb} \sum_{i=1}^{N} k\left(\frac{x - x_i}{b}\right),$$

where b is a hyperparameter controlling the underfit-overfit tradeoff and $k(x) \ge 0$ is a kernel with $\int_{-\infty}^{\infty} k(x)dx = 1$.

As in §7, we use a Gaussian kernel, $k(z) = \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-z^2}{2}\right)$.

We can rewrite the model as

$$\hat{f}_b(x) = \underline{\hspace{1cm}}$$

which is the _____ of the N Gaussians $\{N(\mu = \underline{\hspace{1cm}}, \sigma = \underline{\hspace{1cm}})|i = 1, ..., N\}$.

¹These methods improve upon just using a (density) _____

²The notation of Burkov and Wikipedia conceals the essential point that the model is an ______ of N Gaussians centered at $\{x_i\}$. Possibly they emphasize we are passing $\frac{x-x_i}{b}$ to a parameterless kernel.

Python

- To estimate $N_D(\mu_D, \Sigma_{D \times D})$, use from sklearn import mixture and gm = mixture.GaussianMixture(n_components=1) as in §7. Then gm.fit(X), gm.means_, gm.covariances_, and np.exp(gm.score_samples(X)) work as before. To learn more:
 - User guide: https://scikit-learn.org/stable/modules/mixture.html
 - Reference manual: https://scikit-learn.org/stable/modules/generated/sklearn.mixture.GaussianMixture.html

• For KDE:

- from sklearn.neighbors import KernelDensity
- kde = KernelDensity(bandwidth=1.0, kernel='gaussian')
 - * b=bandwidth is the bandwidth
 - * kernel is one of 'gaussian' (the default), 'tophat', 'epanechnikov', 'exponential', 'linear', 'cosine'; see Example link below for their shapes and effects
- kde.fit(X) fits the model to the data.
- kde.score_samples(X) gives log-likelihood of each x in X, so np.exp(kde.score_samples(X)) gives $\hat{f}_b(x)$.

To learn more:

- User guide: https://scikit-learn.org/stable/modules/density.html
- Reference manual:

https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KernelDensity.html

- Example:

https://scikit-learn.org/stable/auto_examples/neighbors/plot_kde_1d.html3

 $^{^{3}}$ Click on "launch binder" to run it online. Change "N = 100" to "N = 10" to see kernels.

Clustering

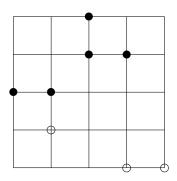
Clustering finds groups of _____ unlabeled examples and assigns a cluster ID to each example. It is used in, e.g., exploratory data analysis, market segmentation, social network analysis, recommender systems, and stock sector analysis.

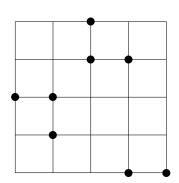
- k-means clustering maps each unlabeled example \mathbf{x} to a cluster ID.
 - Choose the number of clusters _____.
 - Randomly choose one example to start each cluster as its _____ ${f c}$.
 - Label each example **x** with the centroid to which it is _____.
 - Recompute each centroid as the _____ of the examples labeled with it.
 - Repeat the last two steps until centroids .

k is a hyperparameter typically decided by an educated guess.

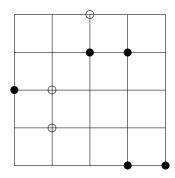
k-means seeks to minimize ______, the sum of squared distances of examples to their respective centroids. Avoid poor results by running it ______ times.

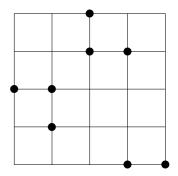
e.g. Run k-means with k=3, starting with the three unfilled points as cluster centers.

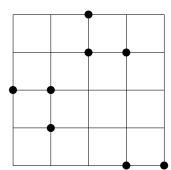




e.g. Run k-means with k=3, starting with the three unfilled points as cluster centers.







⁴Clustering labeled examples is not classification, as it y_i .

Python

- from sklearn.cluster import KMeans
<pre>- kmeans = KMeans(n_clusters=8, n_init=10, random_state=0):</pre>
* n_clusters is the number of clusters to be found
* n_{init} is the number of times k -means is run, each with different centroid seeds
* random_state=0 determines centroid initialization
<pre>- kmeans.fit(X) computes the clusters</pre>
- kmeans.labels_ gives the labels (cluster IDs) of each ${\bf x}$ in the training ${\bf X}$
- kmeans.cluster_centers_ gives coordinates of the cluster centers
- kmeans.predict(X) gives the closest cluster for each ${\bf x}$ in X
To learn more:
$- \ {\rm User \ guide: \ https://scikit-learn.org/stable/modules/clustering.html\#k-means}$
- Reference manual:
https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html
- Examples:
$2D: \verb https://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_plusplus.html and the stable of the sta$
$3D$: https://scikit-learn.org/stable/auto_examples/cluster/plot_cluster_iris.html
$ullet$ DBSCAN 5 is abased clustering algorithm that puts ${f x}$ in a cluster if it is
to many points in that cluster.
Hyperparameters:
$-\epsilon$ is a distance threshold ().
-n is the number of examples in a cluster.
Definitions:
$-\mathbf{x}'$ is a of \mathbf{x} if its distance to \mathbf{x} is $\leq \epsilon$.
$-\mathbf{x}$ is a example if its neighborhood size is at least n .
- An (or <i>noisy</i> example) has no neighbors.
Algorithm:
- For each unexamined core example:
* Make its neighborhood a
* add core-example neighbors of this cluster's examples.
* Add non-core example neighbors (recursively) of cluster examples.
- Call remaining examples

 $^{^5\,\}mathrm{"DBSCAN"}$ refers to "Density-based spatial clustering of applications with noise."

DBSCAN builds clusters with an ______ shape. (k-means builds hyper-_ clusters.) Choosing ϵ and n is not easy. Increasing n or decreasing ϵ requires higher density to make a cluster. DBSCAN cannot effectively handle clusters of density. e.g. Run DBSCAN with $\epsilon = 1$ and n = 2: Python - from sklearn.cluster import DBSCAN - db = DBSCAN(eps=0.5, min_samples=5, metric='euclidean') eps is ϵ , min_samples is n, and metric options include those we used in k-NN - db.fit(X) computes the clusters - db.labels_ gives labels (cluster IDs) of each x in the training X; noisy examples get -1 - db.core_sample_indices_ gives indices of core samples - For each $k \neq -1$ in db.labels, we can find neighbors in cluster k: is_in_cluster_k = (db.labels_ == k) is_core_sample = np.zeros(shape=db.labels_.shape) is_core_sample[db.core_sample_indices_] = True is_neighbor_of_cluster_k = (is_in_cluster_k & ~is_core_sample) To learn more: - User guide: https://scikit-learn.org/stable/modules/clustering.html#dbscan - Reference manual: https://scikit-learn.org/stable/modules/generated/sklearn.cluster.DBSCAN.html - Example: https://scikit-learn.org/stable/auto_examples/cluster/plot_dbscan.html • HDBSCAN improves upon DBSCAN and can handle clusters of ______ density. (It drops ϵ . Details are omitted.) Try it _____ To learn more: - User guide: https://scikit-learn.org/stable/modules/clustering.html#hdbscan - Reference manual: https://scikit-learn.org/stable/modules/generated/sklearn.cluster.HDBSCAN.html

There is a _____ comparison of many clustering methods at https://scikit-learn.org/stable/modules/clustering.html.

Dimensionality Reduction

Dimensionality reduction maps \mathbf{x} into a vector with fractures, reduce noise, visualize data (we see only 2D or 3D), a	_
• Principal component analysis (PCA) fits a new coordination is called a principal component (PC):	ate system to $\{\mathbf{x}_i\}$ where each new
- Each PC is a vector (length 1).	
- The first PC is the direction of the axis of a "minimal" ellipsoid encl	of the data $\{\mathbf{x}_i\}$. (It osing the data.)
- For $i > 1$, the <i>i</i> th PC is orthogonal ⁶ to the first i - greatest variance in the data.	- 1 PCs and in the direction of the
A helpful picture is Figure 7 on p. 15 of	
https://www.dropbox.com/s/y9a7b0hzmuksqar/Chapte	er9.pdf?dl=0.
To do dimensionality reduction, we choose some number each \mathbf{x}_i onto the first p PCs, transforming	
p-dimensional example. Burkov omits details.	
Benefits of PCA:	
- PCA does while retain memory, disk space, and computation time.	ning most of the information, saving
 PCA can mitigate the of dimensionality of the feature space increases faster than the available Many elementary models/algorithms/insights are no 	${\rm data,whichbecome\underline{\qquad}}.$
e.g. The number of D -digit binary numbers in $\{0, D$ -digit decimal numbers in $\{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}^{L}$	$\{1\}^D$ is The number of is
e.g. We need $N = 10^D$ points to sample each unit int $[0, 10]^D$ Draw $[0, 10]^D$ and unit hypercubes for ϵ	
 PCA does feature (It creates seve combinations of original features. This is not feature 	eral important new features as linear ee)
- The first PCs often account even high-dimensional data can be visualized in 2D	for most of the data variability, so or 3D.

⁶Two vectors **a** and **b** are *orthogonal* if $\mathbf{a} \cdot \mathbf{b} = 0$. In 2D, orthogonal means

Python

from sklearn.decomposition import PCA

- pca = PCA(n_components=None, random_state=0) keeps n_components PCs; using None keeps all D components
- pca.fit(X) learns n_components PCs from $\{x_i\}$ in X
- pca.components_ gives PCs (axes/directions of maximum variance in the data)
- pca.explained_variance_ratio_ gives % of variance explained by each PC
- pca.transform(X) applies dimensionality reduction to each x in X

To learn more:

- User guide: https://scikit-learn.org/stable/modules/decomposition.html
- Reference manual: https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html

Perspective

"Burkov has undertaken a very useful but impossibly hard task in reducing all of machine learning
to 100 pages. He succeeds well in choosing the topics—both theory and practice—that will be useful
to practitioners, and for the reader who understands that this is the 100 (or actually
150) pages you will read, not the, provides a solid introduction to the field."
—Peter Norvig, Research Director at Google and author of Artificial Intelligence: A Modern Approach