

sklearn.cluster.KMeans

```
class sklearn.cluster.KMeans(n_clusters=8, *, init='k-means++', n_init=10, max_iter=300, tol=0.0001, verbose=0, random_state=None,
copy_x=True, algorithm='auto')
```

[\[source\]](#)

K-Means clustering.

Read more in the [User Guide](#).

Parameters:

n_clusters : *int*, **default=8**

The number of clusters to form as well as the number of centroids to generate.

init : {'k-means++', 'random'}, callable or array-like of shape (n_clusters, n_features), **default='k-means++'**

Method for initialization:

'k-means++': selects initial cluster centers for k-mean clustering in a smart way to speed up convergence. See section Notes in `k_init` for more details.

'random': choose n_clusters observations (rows) at random from data for the initial centroids.

If an array is passed, it should be of shape (n_clusters, n_features) and gives the initial centers.

If a callable is passed, it should take arguments X, n_clusters and a random state and return an initialization.

n_init : *int*, **default=10**

Number of time the k-means algorithm will be run with different centroid seeds. The final results will be the best output of n_init consecutive runs in terms of inertia.

max_iter : *int*, **default=300**

Maximum number of iterations of the k-means algorithm for a single run.

tol : *float*, **default=1e-4**

Relative tolerance with regards to Frobenius norm of the difference in the cluster centers of two consecutive iterations to declare convergence.

verbose : *int*, **default=0**

Verbosity mode.

random_state : *int*, *RandomState* instance or *None*, **default=None**

Determines random number generation for centroid initialization. Use an int to make the randomness deterministic. See [Glossary](#).

copy_x : *bool*, **default=True**

When pre-computing distances it is more numerically accurate to center the data first. If copy_x is True (default), then the original data is not modified. If False, the original data is modified, and put back before the function returns, but small numerical differences may be introduced by subtracting and then adding the data mean. Note that if the original data is not C-contiguous, a copy will be made even if copy_x is False. If the original data is sparse, but not in CSR format, a copy will be made even if copy_x is False.

algorithm : {'auto', 'full', 'elkan'}, **default='auto'**

K-means algorithm to use. The classical EM-style algorithm is "full". The "elkan" variation is more efficient on data with well-defined clusters, by using the triangle inequality. However it's more memory intensive due to the allocation of an extra array of shape (n_samples, n_clusters).

For now "auto" (kept for backward compatibility) chooses "elkan" but it might change in the future for a better heuristic.

Changed in version 0.18: Added Elkan algorithm

Attributes:

cluster_centers_ : *ndarray of shape (n_clusters, n_features)*

Coordinates of cluster centers. If the algorithm stops before fully converging (see `tol` and `max_iter`), these will not be consistent with `labels_`.

labels_ : *ndarray of shape (n_samples,)*

Labels of each point

inertia_ : *float*

Sum of squared distances of samples to their closest cluster center, weighted by the sample weights if provided.

n_iter_ : *int*

Number of iterations run.

n_features_in_ : *int*

Number of features seen during [fit](#).

New in version 0.24.

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n_features_in_ : *ndarray of shape (n_features_in_,)*

See also:[MiniBatchKMeans](#)

Alternative online implementation that does incremental updates of the centers positions using mini-batches. For large scale learning (say `n_samples > 10k`) `MiniBatchKMeans` is probably much faster than the default batch implementation.

Notes

The k-means problem is solved using either Lloyd's or Elkan's algorithm.

The average complexity is given by $O(k n T)$, where n is the number of samples and T is the number of iteration.

The worst case complexity is given by $O(n^{(k+2/p)})$ with $n = n_samples$, $p = n_features$. (D. Arthur and S. Vassilvitskii, 'How slow is the k-means method?' SoCG2006)

In practice, the k-means algorithm is very fast (one of the fastest clustering algorithms available), but it falls in local minima. That's why it can be useful to restart it several times.

If the algorithm stops before fully converging (because of `tol` or `max_iter`), `labels_` and `cluster_centers_` will not be consistent, i.e. the `cluster_centers_` will not be the means of the points in each cluster. Also, the estimator will reassign `labels_` after the last iteration to make `labels_` consistent with `predict` on the training set.

Examples

```
>>> from sklearn.cluster import KMeans
>>> import numpy as np
>>> X = np.array([[1, 2], [1, 4], [1, 0],
...              [10, 2], [10, 4], [10, 0]])
>>> kmeans = KMeans(n_clusters=2, random_state=0).fit(X)
>>> kmeans.labels_
array([1, 1, 1, 0, 0, 0], dtype=int32)
>>> kmeans.predict([[0, 0], [12, 3]])
array([1, 0], dtype=int32)
>>> kmeans.cluster_centers_
array([[10.,  2.],
       [ 1.,  2.]])
```

Methods

<code>fit</code> (<code>X</code> [, <code>y</code> , <code>sample_weight</code>])	Compute k-means clustering.
<code>fit_predict</code> (<code>X</code> [, <code>y</code> , <code>sample_weight</code>])	Compute cluster centers and predict cluster index for each sample.
<code>fit_transform</code> (<code>X</code> [, <code>y</code> , <code>sample_weight</code>])	Compute clustering and transform <code>X</code> to cluster-distance space.
<code>get_params</code> ([<code>deep</code>])	Get parameters for this estimator.
<code>predict</code> (<code>X</code> [, <code>sample_weight</code>])	Predict the closest cluster each sample in <code>X</code> belongs to.
<code>score</code> (<code>X</code> [, <code>y</code> , <code>sample_weight</code>])	Opposite of the value of <code>X</code> on the K-means objective.
<code>set_params</code> (** <code>params</code>)	Set the parameters of this estimator.
<code>transform</code> (<code>X</code>)	Transform <code>X</code> to a cluster-distance space.

`fit`(`X`, `y=None`, `sample_weight=None`)

[\[source\]](#)

Compute k-means clustering.

Parameters:

X : {array-like, sparse matrix} of shape (n_samples, n_features)

Training instances to cluster. It must be noted that the data will be converted to C ordering, which will cause a memory copy if the given data is not C-contiguous. If a sparse matrix is passed, a copy will be made if it's not in CSR format.

y : Ignored

Not used, present here for API consistency by convention.

sample_weight : array-like of shape (n_samples,), default=None

The weights for each observation in X. If None, all observations are assigned equal weight.

New in version 0.20.

Returns:

self : object

Fitted estimator.

```
fit_predict(X, y=None, sample_weight=None)
```

[\[source\]](#)

Compute cluster centers and predict cluster index for each sample.

Convenience method; equivalent to calling fit(X) followed by predict(X).

Parameters:

X : {array-like, sparse matrix} of shape (n_samples, n_features)

New data to transform.

y : Ignored

Not used, present here for API consistency by convention.

sample_weight : array-like of shape (n_samples,), default=None

The weights for each observation in X. If None, all observations are assigned equal weight.

Returns:

labels : ndarray of shape (n_samples,)

Index of the cluster each sample belongs to.

```
fit_transform(X, y=None, sample_weight=None)
```

[\[source\]](#)

Compute clustering and transform X to cluster-distance space.

Equivalent to fit(X).transform(X), but more efficiently implemented.

Parameters:

X : {array-like, sparse matrix} of shape (n_samples, n_features)

New data to transform.

y : Ignored

Not used, present here for API consistency by convention.

sample_weight : array-like of shape (n_samples,), default=None

The weights for each observation in X. If None, all observations are assigned equal weight.

Returns:

X_new : ndarray of shape (n_samples, n_clusters)

X transformed in the new space.

```
get_params(deep=True)
```

[\[source\]](#)

Get parameters for this estimator.

Parameters:**deep** : *bool, default=True*

If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns:**params** : *dict*

Parameter names mapped to their values.

`predict(X, sample_weight=None)`[\[source\]](#)

Predict the closest cluster each sample in X belongs to.

In the vector quantization literature, `cluster_centers_` is called the code book and each value returned by `predict` is the index of the closest code in the code book.**Parameters:****X** : *{array-like, sparse matrix} of shape (n_samples, n_features)*

New data to predict.

sample_weight : *array-like of shape (n_samples,), default=None*

The weights for each observation in X. If None, all observations are assigned equal weight.

Returns:**labels** : *ndarray of shape (n_samples,)*

Index of the cluster each sample belongs to.

`score(X, y=None, sample_weight=None)`[\[source\]](#)

Opposite of the value of X on the K-means objective.

Parameters:**X** : *{array-like, sparse matrix} of shape (n_samples, n_features)*

New data.

y : *Ignored*

Not used, present here for API consistency by convention.

sample_weight : *array-like of shape (n_samples,), default=None*

The weights for each observation in X. If None, all observations are assigned equal weight.

Returns:**score** : *float*

Opposite of the value of X on the K-means objective.

`set_params(**params)`[\[source\]](#)

Set the parameters of this estimator.

The method works on simple estimators as well as on nested objects (such as [Pipeline](#)). The latter have parameters of the form `<component>__<parameter>` so that it's possible to update each component of a nested object.**Parameters:******params** : *dict*

Estimator parameters.

Returns:**self** : *estimator instance*

Estimator instance.

`transform(X)`[\[source\]](#)

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to a cluster-distance space.

In the new space, each dimension is the distance to the cluster centers. Note that even if X is sparse, the array returned by `transform` will typically be dense.

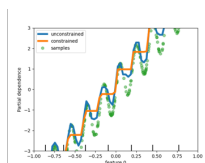
Parameters:

X : {array-like, sparse matrix} of shape $(n_samples, n_features)$
New data to transform.

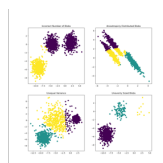
Returns:

X_new : ndarray of shape $(n_samples, n_clusters)$
 X transformed in the new space.

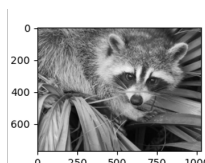
Examples using `sklearn.cluster.KMeans`



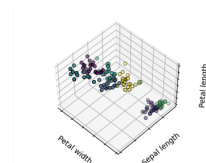
[Release Highlights for scikit-learn 0.23](#)



[Demonstration of k-means assumptions](#)



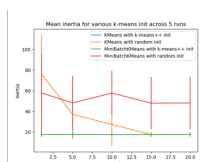
[Vector Quantization Example](#)



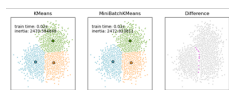
[K-means Clustering](#)



[Color Quantization using K-Means](#)



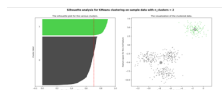
[Empirical evaluation of the impact of k-means initialization](#)



[Comparison of the K-Means and MiniBatchKMeans clustering algorithms](#)



[A demo of K-Means clustering on the handwritten digits data](#)



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