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## sklearn.cluster.MeanShift

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```
class sklearn.cluster.MeanShift(bandwidth=None,  
seeds=None, bin_seeding=False, min_bin_freq=1,  
cluster_all=True, n_jobs=1)
```

[\[source\]](#)

Mean shift clustering using a flat kernel.

Mean shift clustering aims to discover “blobs” in a smooth density of samples. It is a centroid-based algorithm, which works by updating candidates for centroids to be the mean of the points within a given region. These candidates are then filtered in a post-processing stage to eliminate near-duplicates to form the final set of centroids.

Seeding is performed using a binning technique for scalability.

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

**Parameters:** **bandwidth** : float, optional

Bandwidth used in the RBF kernel.

If not given, the bandwidth is estimated using `sklearn.cluster.estimate_bandwidth`; see the documentation for that function for hints on scalability (see also the Notes, below).

**seeds** : array, shape=[*n\_samples*, *n\_features*], optional

Seeds used to initialize kernels. If not set, the seeds are calculated by `clustering.get_bin_seeds` with `bandwidth` as the grid size and default values for other parameters.

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**bin\_seeding** : boolean, optional

If true, initial kernel locations are not locations of all points, but rather the location of the discretized version of points, where points are binned onto a grid whose coarseness corresponds to the bandwidth. Setting this option to True will speed up the algorithm because fewer seeds will be initialized. default value: False Ignored if seeds argument is not None.

**min\_bin\_freq** : int, optional

To speed up the algorithm, accept only those bins with at least min\_bin\_freq points as seeds. If not defined, set to 1.

**cluster\_all** : boolean, default True

If true, then all points are clustered, even those orphans that are not within any kernel. Orphans are assigned to the nearest kernel. If false, then orphans are given cluster label -1.

**n\_jobs** : int

The number of jobs to use for the computation. This works by computing each of the n\_init runs in parallel.

If -1 all CPUs are used. If 1 is given, no parallel computing code is used at all, which is useful for debugging. For n\_jobs below -1, (n\_cpus + 1 + n\_jobs) are used. Thus for n\_jobs = -2, all CPUs but one are used.

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**Attributes:** **cluster\_centers\_** : array, [n\_clusters, n\_features]

Coordinates of cluster centers.

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**labels\_** :

Labels of each point.

## Notes

Scalability:

Because this implementation uses a flat kernel and a Ball Tree to look up members of each kernel, the complexity will tend towards  $O(T \cdot n \cdot \log(n))$  in lower dimensions, with  $n$  the number of samples and  $T$  the number of points. In higher dimensions the complexity will tend towards  $O(T \cdot n^2)$ .

Scalability can be boosted by using fewer seeds, for example by using a higher value of `min_bin_freq` in the `get_bin_seeds` function.

Note that the `estimate_bandwidth` function is much less scalable than the mean shift algorithm and will be the bottleneck if it is used.

## References

Dorin Comaniciu and Peter Meer, “Mean Shift: A robust approach toward feature space analysis”. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2002. pp. 603-619.

## Methods

<code>fit(X[, y])</code>	Perform clustering.
<code>fit_predict(X[, y])</code>	Performs clustering on X and returns cluster labels.
<code>get_params([deep])</code>	Get parameters for this estimator.
<code>predict(X)</code>	Predict the closest cluster each sample in X belongs to.
<code>set_params(**params)</code>	Set the parameters of this estimator.

`__init__(bandwidth=None, seeds=None, bin_seeding=False, min_bin_freq=1, cluster_all=True, n_jobs=1)` [\[source\]](#)

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**fit**(*X*, *y=None*)[\[source\]](#)

Perform clustering.

**Parameters:** **X** : array-like, shape=(*n\_samples*,  
*n\_features*)

Samples to cluster.

**y** : Ignored

**fit\_predict**(*X*, *y=None*)[\[source\]](#)

Performs clustering on *X* and returns cluster labels.

**Parameters:** **X** : ndarray, shape (*n\_samples*,  
*n\_features*)

Input data.

**Returns:** **y** : ndarray, shape (*n\_samples*,)

cluster labels

**get\_params**(*deep=True*)[\[source\]](#)

Get parameters for this estimator.

**Parameters:** **deep** : boolean, optional

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

**Returns:** **params** : mapping of string to any

Parameter names mapped to  
their values.

**predict**(*X*)[\[source\]](#)

Predict the closest cluster each sample in *X* belongs to.

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**Parameters:** **X** : {array-like, sparse matrix}, shape=[n\_samples, n\_features]

New data to predict.

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**Returns:** **labels** : array, shape [n\_samples,]

Index of the cluster each sample belongs to.

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```
set_params(**params)
```

[\[source\]](#)

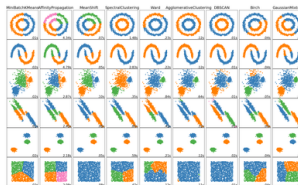
Set the parameters of this estimator.

The method works on simple estimators as well as on nested objects (such as pipelines). The latter have parameters of the form <component>\_\_<parameter> so that it's possible to update each component of a nested object.

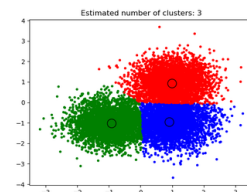
**Returns:** **self** :

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## Examples using sklearn.cluster.MeanShift



Comparing different clustering algorithms on toy datasets



A demo of the mean-shift clustering algorithm

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