sklearn.feature_selection.RFE

class `sklearn.feature_selection.RFE`(*estimator*, *n_features_to_select=None*, *step=1*, *verbose=0*) [source]

Feature ranking with recursive feature elimination.

Given an external estimator that assigns weights to features (e.g., the coefficients of a linear model), the goal of recursive feature elimination (RFE) is to select features by recursively considering smaller and smaller sets of features. First, the estimator is trained on the initial set of features and the importance of each feature is obtained either through a `coef_` attribute or through a `feature_importances_` attribute. Then, the least important features are pruned from current set of features. That procedure is recursively repeated on the pruned set until the desired number of features to select is eventually reached.

Read more in the User Guide.

Parameters:

estimator : *object*
A supervised learning estimator with a `fit` method that provides information about feature importance either through a `coef_` attribute or through a `feature_importances_` attribute.

n_features_to_select : *int or None (default=None)*
The number of features to select. If `None`, half of the features are selected.

step : *int or float, optional (default=1)*
If greater than or equal to 1, then `step` corresponds to the (integer) number of features to remove at each iteration. If within (0.0, 1.0), then `step` corresponds to the percentage (rounded down) of features to remove at each iteration.

verbose : *int, (default=0)*
Controls verbosity of output.

Attributes:

n_features_ : *int*
The number of selected features.

support_ : *array of shape [n_features]*
The mask of selected features.

ranking_ : *array of shape [n_features]*
The feature ranking, such that `ranking_[i]` corresponds to the ranking position of the i-th feature. Selected (i.e., estimated best) features are assigned rank 1.

estimator_ : *object*
The external estimator fit on the reduced dataset.

See also:

RFECV
Recursive feature elimination with built-in cross-validated selection of the best number of features

Notes

Allows NaN/Inf in the input if the underlying estimator does as well.

References

Re310f679c81e-1 Guyon, I., Weston, J., Barnhill, S., & Vapnik, V., “Gene selection for cancer classification using support vector machines”, Mach. Learn., 46(1-3), 389–422, 2002.

Examples

The following example shows how to retrieve the 5 most informative features in the Friedman #1 dataset.

```
>>> from sklearn.datasets import make_friedman1
>>> from sklearn.feature_selection import RFE
>>> from sklearn.svm import SVR
>>> X, y = make_friedman1(n_samples=50, n_features=10, random_state=0)
>>> estimator = SVR(kernel="linear")
>>> selector = RFE(estimator, 5, step=1)
>>> selector = selector.fit(X, y)
>>> selector.support_
array([ True,  True,  True,  True,  True, False, False, False, False,
       False])
>>> selector.ranking_
array([1, 1, 1, 1, 1, 6, 4, 3, 2, 5])
```

Methods

`decision_function`(self, X)	Compute the decision function of x.
`fit`(self, X, y)	Fit the RFE model and then the underlying estimator on the selected
`fit_transform`(self, X[, y])	Fit to data, then transform it.
`get_params`(self[, deep])	Get parameters for this estimator.
`get_support`(self[, indices])	Get a mask, or integer index, of the features selected
`inverse_transform`(self, X)	Reverse the transformation operation
`predict`(self, X)	Reduce X to the selected features and then predict using the
`predict_log_proba`(self, X)	Predict class log-probabilities for X.
`predict_proba`(self, X)	Predict class probabilities for X.
`score`(self, X, y)	Reduce X to the selected features and then return the score of the
`set_params`(self, **params)	Set the parameters of this estimator.
`transform`(self, X)	Reduce X to the selected features.

`__init__`(*self, estimator, n_features_to_select=None, step=1, verbose=0*) [source]

Initialize self. See help(type(self)) for accurate signature.

`decision_function`(*self, X*) [source]

Compute the decision function of x.

Parameters:

X : *{array-like or sparse matrix} of shape (n_samples, n_features)*
The input samples. Internally, it will be converted to `dtype=np.float32` and if a sparse matrix is provided to a sparse `csr_matrix`.

Returns:

score : *array, shape = [n_samples, n_classes] or [n_samples]*
The decision function of the input samples. The order of the classes corresponds to that in the attribute classes . Regression and binary classification produce an array of shape [n_samples].

`fit`(*self, X, y*) [source]

Fit the RFE model and then the underlying estimator on the selected
features.

Parameters:

X : *{array-like, sparse matrix} of shape (n_samples, n_features)*
The training input samples.

y : *array-like of shape (n_samples,)*
The target values.

`fit_transform`(*self, X, y=None, **fit_params*) [source]

Fit to data, then transform it.

Fits transformer to X and y with optional parameters fit_params and returns a transformed version of X.

Parameters:

X : *numpy array of shape [n_samples, n_features]*
ng set.

Toggle Menu

y : *numpy array of shape [n_samples]*
Target values.

****fit_params : *dict***
Additional fit parameters.

Returns:

X_new : *numpy array of shape [n_samples, n_features_new]*
Transformed array.

`get_params`(*self*, *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 : *mapping of string to any*
Parameter names mapped to their values.

`get_support`(*self*, *indices=False*) [source]

Get a mask, or integer index, of the features selected

Parameters:

indices : *boolean (default False)*
If True, the return value will be an array of integers, rather than a boolean mask.

Returns:

support : *array*
An index that selects the retained features from a feature vector. If `indices` is False, this is a boolean array of shape [# input features], in which an element is True iff its corresponding feature is selected for retention. If `indices` is True, this is an integer array of shape [# output features] whose values are indices into the input feature vector.

`inverse_transform`(*self*, *X*) [source]

Reverse the transformation operation

Parameters:

X : *array of shape [n_samples, n_selected_features]*
The input samples.

Returns:

X_r : *array of shape [n_samples, n_original_features]*
X with columns of zeros inserted where features would have been removed by `transform`.

`predict`(*self*, *X*) [source]

Reduce X to the selected features and then predict using the
underlying estimator.

Parameters:

X : *array of shape [n_samples, n_features]*
The input samples.

Returns:

y : *array of shape [n_samples]*
The predicted target values.

`predict_log_proba`(*self*, *X*) [source]

Predict class log-probabilities for X.

Parameters:

X : *array of shape [n_samples, n_features]*
The input samples.

Returns:

p : *array of shape (n_samples, n_classes)*
The class log-probabilities of the input samples. The order of the classes corresponds to that in the attribute classes_.

`predict_proba`(*self*, *X*) [source]

Predict class probabilities for X.

Parameters:

X : *{array-like or sparse matrix} of shape (n_samples, n_features)*
The input samples. Internally, it will be converted to `dtype=np.float32` and if a sparse matrix is provided to a sparse `csr_matrix`.

Returns:

p : *array of shape (n_samples, n_classes)*
The class probabilities of the input samples. The order of the classes corresponds to that in the attribute classes_.

`score`(*self*, *X*, *y*) [source]

Reduce X to the selected features and then return the score of the
underlying estimator.

Parameters:

X : *array of shape [n_samples, n_features]*
The input samples.

y : *array of shape [n_samples]*
The target values.

`set_params`(*self*, ***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.

Parameters:

****params : *dict***
Estimator parameters.

Returns:

self : *object*
Estimator instance.

`transform`(*self*, *X*) [source]

Reduce X to the selected features.

Parameters:

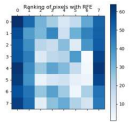
X : *array of shape [n_samples, n_features]*
The input samples.

Returns:

ray of shape [n_samples, n_selected_features]

The input samples with only the selected features.

Examples using `sklearn.feature_selection.RFE`



Recursive feature elimination