3.2.4.3.2. sklearn.ensemble.RandomForestRegressor

class sklearn.ensemble.**RandomForestRegressor**(*n_estimators=10*, *criterion='mse'*, *max_depth=None*, *min_samples_split=2*, *min_samples_leaf=1*, *min_weight_fraction_leaf=0.0*, *max_features='auto'*, *max_leaf_nodes=None*, *min_impurity_decrease=0.0*, *min_impurity_split=None*, *bootstrap=True*, *oob_score=False*, *n_jobs=1*, *random_state=None*, *verbose=0*, *warm_start=False*) [source]

A random forest regressor.

A random forest is a meta estimator that fits a number of classifying decision trees on various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement if *bootstrap=True* (default).

Read more in the User Guide.

Parameters:

n_estimators : integer, optional (default=10)

The number of trees in the forest.

criterion : string, optional (default="mse")

The function to measure the quality of a split. Supported criteria are "mse" for the mean squared error, which is equal to variance reduction as feature selection criterion, and "mae" for the mean absolute error.

New in version 0.18: Mean Absolute Error (MAE) criterion.

max_features : int, float, string or None, optional (default="auto")

The number of features to consider when looking for the best split:

- If int, then consider *max_features* features at each split.
- If float, then *max_features* is a percentage and *int(max_features * n_features)* features are considered at each split.
- If "auto", then *max_features=n_features*.
- If "sqrt", then *max_features=sqrt(n_features)*.

- If “log2”, then *max_features=log2(n_features)*.
- If None, then *max_features=n_features*.

Note: the search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than `max_features` features.

max_depth : integer or None, optional (default=None)

The maximum depth of the tree. If None, then nodes are expanded until all leaves are pure or until all leaves contain less than min_samples_split samples.

min_samples_split : int, float, optional (default=2)

The minimum number of samples required to split an internal node:

- If int, then consider *min_samples_split* as the minimum number.
- If float, then *min_samples_split* is a percentage and *ceil(min_samples_split * n_samples)* are the minimum number of samples for each split.

Changed in version 0.18: Added float values for percentages.

min_samples_leaf : int, float, optional (default=1)

The minimum number of samples required to be at a leaf node:

- If int, then consider *min_samples_leaf* as the minimum number.
- If float, then *min_samples_leaf* is a percentage and *ceil(min_samples_leaf * n_samples)* are the minimum number of samples for each node.

Changed in version 0.18: Added float values for percentages.

min_weight_fraction_leaf : float, optional (default=0.)

The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Samples have equal weight when sample_weight is not provided.

max_leaf_nodes : int or None, optional (default=None)

Grow trees with `max_leaf_nodes` in best-first fashion. Best nodes are defined as relative reduction in impurity. If None then unlimited number of leaf nodes.

min_impurity_split : float,

Threshold for early stopping in tree growth. A node will split if its impurity is above the threshold, otherwise it is a leaf.

Deprecated since version 0.19: `min_impurity_split` has been deprecated in favor of `min_impurity_decrease` in 0.19 and will be removed in 0.21. Use `min_impurity_decrease` instead.

«

min_impurity_decrease : float, optional (default=0.)

A node will be split if this split induces a decrease of the impurity greater than or equal to this value.

The weighted impurity decrease equation is the following:

```
N_t / N * (impurity - N_t_R / N_t * right_impurity
                    - N_t_L / N_t * left_impurity)
```

where `N` is the total number of samples, `N_t` is the number of samples at the current node, `N_t_L` is the number of samples in the left child, and `N_t_R` is the number of samples in the right child.

`N`, `N_t`, `N_t_R` and `N_t_L` all refer to the weighted sum, if `sample_weight` is passed.

New in version 0.19.

bootstrap : boolean, optional (default=True)

Whether bootstrap samples are used when building trees.

oob_score : bool, optional (default=False)

whether to use out-of-bag samples to estimate the R^2 on unseen data.

n_jobs : integer, optional (default=1)

The number of jobs to run in parallel for both *fit* and *predict*. If -1, then the number of jobs is set to the number of cores.

random_state : int, RandomState instance or None, optional (default=None)

If int, random_state is the seed used by the random number generator; If RandomState instance, random_state is the random number generator; If None, the random number genera-

tor is the RandomState instance used by *np.random*.

verbose : int, optional (default=0)

Controls the verbosity of the tree building process.

warm_start : bool, optional (default=False)

When set to `True`, reuse the solution of the previous call to fit and add more estimators to the ensemble, otherwise, just fit a whole new forest.

Attributes:

estimators_ : list of DecisionTreeRegressor

The collection of fitted sub-estimators.

feature_importances_ : array of shape = [n_features]

The feature importances (the higher, the more important the feature).

n_features_ : int

The number of features when `fit` is performed.

n_outputs_ : int

The number of outputs when `fit` is performed.

oob_score_ : float

Score of the training dataset obtained using an out-of-bag estimate.

oob_prediction_ : array of shape = [n_samples]

Prediction computed with out-of-bag estimate on the training set.

See also: `DecisionTreeRegressor`, `ExtraTreesRegressor`

Notes

The default values for the parameters controlling the size of the trees (e.g. `max_depth`, `min_samples_leaf`, etc.) lead to fully grown and unpruned trees which can potentially be very large on some data sets. To reduce memory consumption, the complexity and size of the trees should be controlled by setting those parameter values.

The features are always randomly permuted at each split. Therefore, the best found split

may vary, even with the same training data, `max_features=n_features` and `bootstrap=False`, if the improvement of the criterion is identical for several splits enumerated during the search of the best split. To obtain a deterministic behaviour during fitting, `random_state` has to be fixed.

References

[R167] L. Breiman, “Random Forests”, Machine Learning, 45(1), 5-32, 2001.

Examples

```
>>> from sklearn.ensemble import RandomForestRegressor
>>> from sklearn.datasets import make_regression
>>>
>>> X, y = make_regression(n_features=4, n_informative=2,
...                        random_state=0, shuffle=False)
>>> regr = RandomForestRegressor(max_depth=2, random_state=0)
>>> regr.fit(X, y)
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=2,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
           oob_score=False, random_state=0, verbose=0, warm_start=False)
>>> print(regr.feature_importances_)
[ 0.17339552  0.81594114  0.          0.01066333]
>>> print(regr.predict([[0, 0, 0, 0]]))
[-2.50699856]
```

Methods

apply(X)	Apply trees in the forest to X, return leaf indices.
decision_path(X)	Return the decision path in the forest
fit(X, y[, sample_weight])	Build a forest of trees from the training set (X, y).
get_params([deep])	Get parameters for this estimator.
predict(X)	Predict regression target for X.
score(X, y[, sample_weight])	Returns the coefficient of determination R^2 of the prediction.
set_params(**params)	Set the parameters of this estimator.

__init__(*n_estimators=10*, *criterion='mse'*, *max_depth=None*, *min_samples_split=2*, *min_samples_leaf=1*, *min_weight_fraction_leaf=0.0*, *max_features='auto'*, *max_leaf_nodes=None*, *min_impurity_decrease=0.0*, *min_impurity_split=None*, *bootstrap=True*, *oob_score=False*, *n_jobs=1*, *random_state=None*, *verbose=0*, *warm_start=False*) [source]

apply(*X*) [source]

Apply trees in the forest to X, return leaf indices.

Parameters: **X** : array-like or sparse matrix, shape = [n_samples, n_features]

The input samples. Internally, its dtype will be converted to `dtype=np.float32`. If a sparse matrix is provid-

ed, it will be converted into a sparse `csr_matrix`.

Returns: **X_leaves** : array_like, shape = [n_samples, n_estimators]

For each datapoint x in X and for each tree in the forest, return the index of the leaf x ends up in.

`decision_path`(*X*) [source]

Return the decision path in the forest

New in version 0.18.

Parameters: **X** : array-like or sparse matrix, shape = [n_samples, n_features]

The input samples. Internally, its dtype will be converted to `dtype=np.float32`. If a sparse matrix is provided, it will be converted into a sparse `csr_matrix`.

Returns: **indicator** : sparse csr array, shape = [n_samples, n_nodes]

Return a node indicator matrix where non zero elements indicates that the samples goes through the nodes.

n_nodes_ptr : array of size (n_estimators + 1,)

The columns from indicator[n_nodes_ptr[i]:n_nodes_ptr[i+1]] gives the indicator value for the i-th estimator.

`feature_importances_`

Return the feature importances (the higher, the more important the feature).

Returns: **feature_importances_** : array, shape = [n_features]

`fit`(*X*, *y*, *sample_weight=None*) [source]

Build a forest of trees from the training set (X, y).

Parameters: **X** : array-like or sparse matrix of shape = [n_samples, n_features]

The training input samples. Internally, its dtype will be converted to `dtype=np.float32`. If a sparse matrix is provided, it will be converted into a sparse

`csc_matrix`.

y : array-like, shape = [n_samples] or [n_samples, n_outputs]

The target values (class labels in classification, real numbers in regression).

sample_weight : array-like, shape = [n_samples] or None

Sample weights. If None, then samples are equally weighted. Splits that would create child nodes with net zero or negative weight are ignored while searching for a split in each node. In the case of classification, splits are also ignored if they would result in any single class carrying a negative weight in either child node.

Returns: **self** : object

Returns self.

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 regression target for X.

The predicted regression target of an input sample is computed as the mean predicted regression targets of the trees in the forest.

Parameters: **X** : array-like or sparse matrix of shape = [n_samples, n_features]

The input samples. Internally, its dtype will be converted to `dtype=np.float32`. If a sparse matrix is provided, it will be converted into a sparse `csr_matrix`.

Returns: **y** : array of shape = [n_samples] or [n_samples, n_outputs]

The predicted values.

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score(*X*, *y*, *sample_weight=None*) [source]

Returns the coefficient of determination R^2 of the prediction.

The coefficient R^2 is defined as (1 - u/v), where u is the residual sum of squares ((y_true - y_pred) ** 2).sum() and v is the total sum of squares ((y_true - y_true.mean()) ** 2).sum(). The best possible score is 1.0 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

Parameters: **X** : array-like, shape = (n_samples, n_features)

Test samples.

y : array-like, shape = (n_samples) or (n_samples, n_outputs)

True values for X.

sample_weight : array-like, shape = [n_samples], optional

Sample weights.

Returns: **score** : float

R^2 of self.predict(X) wrt. y.

---

set_params(***params*) [source]

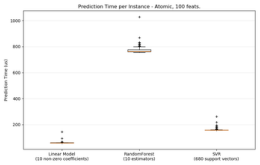
Set the parameters of this estimator.

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.

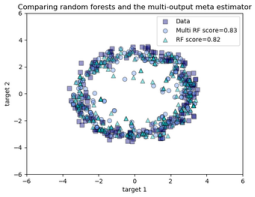
Returns: **self** :

3.2.4.3.2.1. Examples using `sklearn.ensemble.RandomForestRegressor`

Imputing missing values before building an estimator



Prediction Latency



Comparing random forests and the multi-output meta estimator