sklearn.tree.DecisionTreeRegressor

class sklearn.tree.DecisionTreeRegressor(*, *criterion='squared_error'*, *splitter='best'*, *max_depth=None*, *min_samples_split=2*, *min_samples_leaf=1*, *min_weight_fraction_leaf=0.0*, *max_features=None*, *random_state=None*, *max_leaf_nodes=None*, *min_impurity_decrease=0.0*, *ccp_alpha=0.0*) [source]

A decision tree regressor.

Read more in the User Guide.

Parameters:

criterion : *{"squared_error", "friedman_mse", "absolute_error", "poisson"}, default="squared_error"*

The function to measure the quality of a split. Supported criteria are "squared_error" for the mean squared error, which is equal to variance reduction as feature selection criterion and minimizes the L2 loss using the mean of each terminal node, "friedman_mse", which uses mean squared error with Friedman's improvement score for potential splits, "absolute_error" for the mean absolute error, which minimizes the L1 loss using the median of each terminal node, and "poisson" which uses reduction in Poisson deviance to find splits.

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

New in version 0.24: Poisson deviance criterion.

Deprecated since version 1.0: Criterion "mse" was deprecated in v1.0 and will be removed in version 1.2. Use `criterion="squared_error"` which is equivalent.

Deprecated since version 1.0: Criterion "mae" was deprecated in v1.0 and will be removed in version 1.2. Use `criterion="absolute_error"` which is equivalent.

splitter : *{"best", "random"}, default="best"*

The strategy used to choose the split at each node. Supported strategies are "best" to choose the best split and "random" to choose the best random split.

max_depth : *int, 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 or float, 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 fraction 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 fractions.

min_samples_leaf : *int or float, default=1*

The minimum number of samples required to be at a leaf node. A split point at any depth will only be considered if it leaves at least `min_samples_leaf` training samples in each of the left and right branches. This may have the effect of smoothing the model, especially in regression.

- If int, then consider `min_samples_leaf` as the minimum number.
- If float, then `min_samples_leaf` is a fraction 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 fractions.

min_weight_fraction_leaf : *float, default=0.0*
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_features : *int, float or {"auto", "sqrt", "log2"}, default=None*
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 fraction 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.

random_state : *int, RandomState instance or None, default=None*
Controls the randomness of the estimator. The features are always randomly permuted at each split, even if `splitter` is set to `"best"`. When `max_features < n_features`, the algorithm will select `max_features` at random at each split before finding the best split among them. But the best found split may vary across different runs, even if `max_features=n_features`. That is the case, if the improvement of the criterion is identical for several splits and one split has to be selected at random. To obtain a deterministic behaviour during fitting, `random_state` has to be fixed to an integer. See Glossary for details.

max_leaf_nodes : *int, default=None*
Grow a tree 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_decrease : *float, default=0.0*
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.

ccp_alpha : *non-negative float, default=0.0*
Complexity parameter used for Minimal Cost-Complexity Pruning. The subtree with the largest cost complexity that is smaller than `ccp_alpha` will be chosen. By default, no pruning is performed. See Minimal Cost-Complexity Pruning for details.

New in version 0.22.

Attributes:

`feature_importances_` **: *ndarray of shape (n_features,)***
Return the feature importances.

max_features_ : *int*
The inferred value of max_features.

n_features_ : *int*
DEPRECATED: The attribute `n_features_` is deprecated in 1.0 and will be removed in 1.2.

n_features_in_ : *int*
Number of features seen during fit.

New in version 0.24.

feature_names_in_ : *ndarray of shape (`n_features_in_`,)*
Names of features seen during fit. Defined only when `X` has feature names that are all strings.

New in version 1.0.

n_outputs_ : *int*
The number of outputs when `fit` is performed.

tree_ : *Tree instance*
The underlying Tree object. Please refer to `help(sklearn.tree._tree.Tree)` for attributes of Tree object and Understanding the decision tree structure for basic usage of these attributes.

See also:

`DecisionTreeClassifier`
A decision tree classifier.

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.

References

1 https://en.wikipedia.org/wiki/Decision_tree_learning

2 L. Breiman, J. Friedman, R. Olshen, and C. Stone, "Classification and Regression Trees", Wadsworth, Belmont, CA, 1984.

3 T. Hastie, R. Tibshirani and J. Friedman. "Elements of Statistical Learning", Springer, 2009.

4 L. Breiman, and A. Cutler, "Random Forests", https://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm

Examples

```
>>> from sklearn.datasets import load_diabetes
>>> from sklearn.model_selection import cross_val_score
>>> from sklearn.tree import DecisionTreeRegressor
>>> X, y = load_diabetes(return_X_y=True)
>>> regressor = DecisionTreeRegressor(random_state=0)
>>> cross_val_score(regressor, X, y, cv=10)
...
...
array([-0.39..., -0.46...,  0.02...,  0.06..., -0.50...,
       0.16...,  0.11..., -0.73..., -0.30..., -0.00...])
```

Methods

`apply`(X[, check_input])	Return the index of the leaf that each sample is predicted as.
`cost_complexity_pruning_path`(X, y[, ...])	Compute the pruning path during Minimal Cost-Complexity Pruning.
`decision_path`(X[, check_input])	Return the decision path in the tree.
`ble_weight, check_input, ...])	Build a decision tree regressor from the training set (X, y).

get_depth()	Return the depth of the decision tree.
get_n_leaves()	Return the number of leaves of the decision tree.
get_params([deep])	Get parameters for this estimator.
predict(X[, check_input])	Predict class or regression value for X.
score(X, y[, sample_weight])	Return the coefficient of determination of the prediction.
set_params(**params)	Set the parameters of this estimator.

apply(*X*, *check_input=True*) [source]

Return the index of the leaf that each sample is predicted as.

New in version 0.17.

Parameters:

X : *{array-like, 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`.

check_input : *bool, default=True*
Allow to bypass several input checking. Don't use this parameter unless you know what you do.

Returns:

X_leaves : *array-like of shape (n_samples,)*

For each datapoint x in X, return the index of the leaf x ends up in. Leaves are numbered within `[0; self.tree_.node_count)`, possibly with gaps in the numbering.

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

Compute the pruning path during Minimal Cost-Complexity Pruning.

See Minimal Cost-Complexity Pruning for details on the pruning process.

Parameters:

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

y : *array-like of shape (n_samples,) or (n_samples, n_outputs)*
The target values (class labels) as integers or strings.

sample_weight : *array-like of shape (n_samples,), default=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. Splits are also ignored if they would result in any single class carrying a negative weight in either child node.

Returns:

ccp_path : *Bunch*
Dictionary-like object, with the following attributes.

ccp_alphas : *ndarray*
Effective alphas of subtree during pruning.

ities : *ndarray*
of the impurities of the subtree leaves for the corresponding alpha value in `ccp_alphas`.

decision_path(*X*, *check_input=True*) [source]

Return the decision path in the tree.

New in version 0.18.

Parameters:

X : *{array-like, 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`.

check_input : *bool, default=True*
Allow to bypass several input checking. Don't use this parameter unless you know what you do.

Returns:

indicator : *sparse matrix of shape (n_samples, n_nodes)*
Return a node indicator CSR matrix where non zero elements indicates that the samples goes through the nodes.

***property* feature_importances_**
Return the feature importances.

The importance of a feature is computed as the (normalized) total reduction of the criterion brought by that feature. It is also known as the Gini importance.

Warning: impurity-based feature importances can be misleading for high cardinality features (many unique values). See `sklearn.inspection.permutation_importance` as an alternative.

Returns:

feature_importances_ : *ndarray of shape (n_features,)*
Normalized total reduction of criteria by feature (Gini importance).

fit(*X*, *y*, *sample_weight=None*, *check_input=True*, *X_idx_sorted='deprecated'*) [source]

Build a decision tree regressor from the training set (X, y).

Parameters:

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

y : *array-like of shape (n_samples,) or (n_samples, n_outputs)*
The target values (real numbers). Use `dtype=np.float64` and `order='C'` for maximum efficiency.

sample_weight : *array-like of shape (n_samples,), default=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.

check_input : *bool, default=True*
Allow to bypass several input checking. Don't use this parameter unless you know what you do.

X_idx_sorted : *deprecated, default="deprecated"*
ameter is deprecated and has no effect. It will be removed in 1.1 (renaming of 0.26).

Deprecated since version 0.24.

Returns:

self : *DecisionTreeRegressor*
Fitted estimator.

get_depth() [source]

Return the depth of the decision tree.

The depth of a tree is the maximum distance between the root and any leaf.

Returns:

self.tree_.max_depth : *int*
The maximum depth of the tree.

get_n_leaves() [source]

Return the number of leaves of the decision tree.

Returns:

self.tree_.n_leaves : *int*
Number of leaves.

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.

***property* n_features_**
DEPRECATED: The attribute `n_features_` is deprecated in 1.0 and will be removed in 1.2. Use `n_features_in_` instead.

predict(*X*, *check_input=True*) [source]

Predict class or regression value for X.

For a classification model, the predicted class for each sample in X is returned. For a regression model, the predicted value based on X is returned.

Parameters:

-like, 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`.

check_input : *bool, default=True*
Allow to bypass several input checking. Don't use this parameter unless you know what you do.

Returns:

y : *array-like of shape (n_samples,) or (n_samples, n_outputs)*
The predicted classes, or the predict values.

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

Return the coefficient of determination of the prediction.

The coefficient of determination R^2 is defined as $(1 - \frac{u}{v})$, 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 of shape (n_samples, n_features)*
Test samples. For some estimators this may be a precomputed kernel matrix or a list of generic objects instead with shape `(n_samples, n_samples_fitted)`, where `n_samples_fitted` is the number of samples used in the fitting for the estimator.

y : *array-like of shape (n_samples,) or (n_samples, n_outputs)*
True values for `X`.

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

Returns:

score : *float*
R^2 of `self.predict(X)` wrt. `y`.

Notes

The R^2 score used when calling `score` on a regressor uses `multioutput='uniform_average'` from version 0.23 to keep consistent with default value of `r2_score`. This influences the `score` method of all the multioutput regressors (except for `MultiOutputRegressor`).

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.

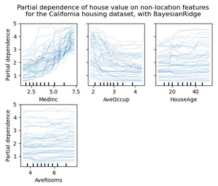
Parameters:

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

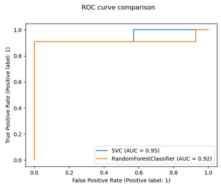
Returns:

self : *estimator instance*
Estimator instance.

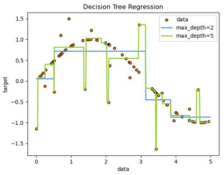
Examples using `sklearn.tree.DecisionTreeRegressor`



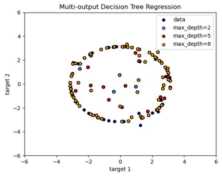
Release Highlights for scikit-learn 0.24



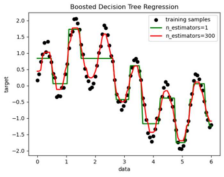
Release Highlights for scikit-learn 0.22



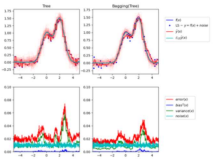
Decision Tree Regression



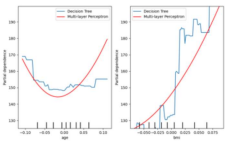
Multi-output Decision Tree Regression



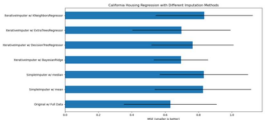
Decision Tree Regression with AdaBoost



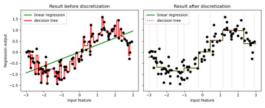
Single estimator versus bagging: bias-variance decomposition



Advanced Plotting With Partial Dependence



Imputing missing values with variants of IterativeImputer



Using KBinsDiscretizer to discretize continuous features