STree

Release 1.3.0

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Oct 21, 2022

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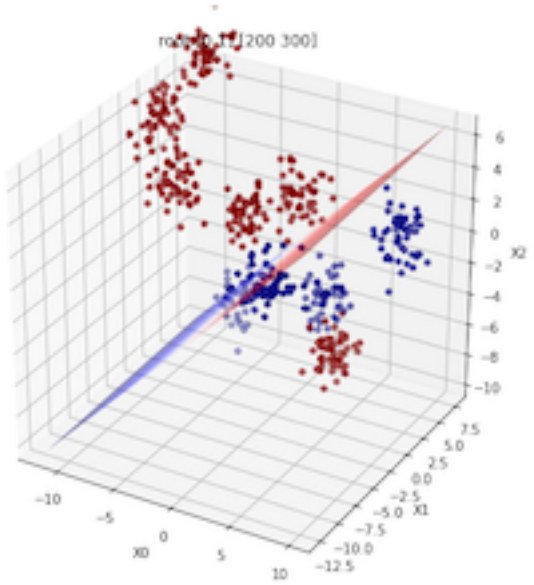
STREE

Oblique Tree classifier based on SVM nodes. The nodes are built and splitted with sklearn SVC models. Stree is a sklearn estimator and can be integrated in pipelines, grid searches, etc.



1.1 License

STree is MIT licensed

CHAPTER

TWO

INSTALL

The main stable release

```
pip install stree
```

or the last development branch

```
pip install git+https://github.com/doctorado-ml/stree
```

2.1 Tests

```
python -m unittest -v stree.tests
```

CHAPTER

THREE

HYPERPARAMETERS

	Hyperparameter	Type/Value	Default	Meaning
*	C	<float>	1.0	Regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive.
*	kernel	{"liblinear", "linear", "poly", "rbf", "sigmoid"}	linear	Specifies the kernel type to be used in the algorithm. It must be one of 'liblinear', 'linear', 'poly' or 'rbf'.liblinear uses liblinear library and the rest uses libsvm library through scikit-learn library
*	max_iter	<int>	1e5	Hard limit on iterations within solver, or -1 for no limit.
*	random_state	<int>	None	Controls the pseudo random number generation for shuffling the data for probability estimates. Ignored when probability is False.Pass an int for reproducible output across multiple function calls
	max_depth	<int>	None	Specifies the maximum depth of the tree
*	tol	<float>	1e-4	Tolerance for stopping criterion.
*	degree	<int>	3	Degree of the polynomial kernel function ('poly'). Ignored by all other kernels.
*	gamma	{"scale", "auto"} or <float>	scale	Kernel coefficient for 'rbf', 'poly' and 'sigmoid'.if gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma,if 'auto', uses 1 / n_features.
	split_criterion	{"impurity", "max_samples"}	impurity	Decides (just in case of a multi class classification) which column (class) use to split the dataset in a node**.max_samples is incompatible with 'ovo' multiclass_strategy
	criterion	{"gini", "entropy"}	entropy	The function to measure the quality of a split (only used if max_features != num_features).Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain.
	min_samples_split	<int>	0	The minimum number of samples required to split an internal node. 0 (default) for any
	max_features	<int>, <float> or {"auto", "sqrt", "log2"}	None	The number of features to consider when looking for the 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=sqrt(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.
	splitter	{"best", "random",	"random"	The strategy used to choose the feature set at each node (only used if max_features < num_features).Supported strategies are:**"best"**: sklearn SelectKBest algorithm is used in every node to choose the max_features best fea-

* Hyperparameter used by the support vector classifier of every node

** **Splitting in a STree node**

The decision function is applied to the dataset and distances from samples to hyperplanes are computed in a matrix. This matrix has as many columns as classes the samples belongs to (if more than two, i.e. multiclass classification) or 1 column if it's a binary class dataset. In binary classification only one hyperplane is computed and therefore only one column is needed to store the distances of the samples to it. If three or more classes are present in the dataset we need as many hyperplanes as classes are there, and therefore one column per hyperplane is needed.

In case of multiclass classification we have to decide which column take into account to make the split, that depends on hyperparameter *split_criteria*, if "impurity" is chosen then STree computes information gain of every split candidate using each column and chooses the one that maximize the information gain, otherwise STree choses the column with more samples with a predicted class (the column with more positive numbers in it).

Once we have the column to take into account for the split, the algorithm splits samples with positive distances to hyperplane from the rest.

CHAPTER

FOUR

EXAMPLES

4.1 Notebooks

- Benchmark
- Some features
- Gridsearch
- Ensembles

4.2 Sample Code

```
import time
from sklearn.model_selection import train_test_split
from sklearn.datasets import load_iris
from stree import Stree

random_state = 1
X, y = load_iris(return_X_y=True)
Xtrain, Xtest, ytrain, ytest = train_test_split(
    X, y, test_size=0.2, random_state=random_state
)
now = time.time()
print("Predicting with max_features=sqrt(n_features)")
clf = Stree(random_state=random_state, max_features="auto")
clf.fit(Xtrain, ytrain)
print(f"Took {time.time() - now:.2f} seconds to train")
print(clf)
print(f"Classifier's accuracy (train): {clf.score(Xtrain, ytrain):.4f}")
print(f"Classifier's accuracy (test) : {clf.score(Xtest, ytest):.4f}")
print("=" * 40)
print("Predicting with max_features=n_features")
clf = Stree(random_state=random_state)
clf.fit(Xtrain, ytrain)
print(f"Took {time.time() - now:.2f} seconds to train")
print(clf)
print(f"Classifier's accuracy (train): {clf.score(Xtrain, ytrain):.4f}")
print(f"Classifier's accuracy (test) : {clf.score(Xtest, ytest):.4f}")
```

CHAPTER

FIVE

API INDEX

5.1 Stree

class stree.**Stree**(*C: float = 1.0*, *kernel: str = 'linear'*, *max_iter: int = 100000.0*, *random_state: Optional[int] = None*, *max_depth: Optional[int] = None*, *tol: float = 0.0001*, *degree: int = 3*, *gamma='scale'*, *split_criteria: str = 'impurity'*, *criterion: str = 'entropy'*, *min_samples_split: int = 0*, *max_features=None*, *splitter: str = 'random'*, *multiclass_strategy: str = 'ovo'*, *normalize: bool = False*)

Bases: BaseEstimator, ClassifierMixin

Estimator that is based on binary trees of svm nodes can deal with sample_weights in predict, used in boosting sklearn methods inheriting from BaseEstimator implements get_params and set_params methods inheriting from ClassifierMixin implement the attribute _estimator_type with "classifier" as value

5.1.1 Parameters

C
: [float, optional] Regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive., by default 1.0

kernel
: [str, optional] Specifies the kernel type to be used in the algorithm. It must be one of 'liblinear', 'linear', 'poly' or 'rbf'. liblinear uses [liblinear](https://www.csie.ntu.edu.tw/~cjlin/liblinear/) library and the rest uses [libsvm](https://www.csie.ntu.edu.tw/~cjlin/libsvm/) library through scikit-learn library, by default "linear"

max_iter
: [int, optional] Hard limit on iterations within solver, or -1 for no limit., by default 1e5

random_state
: [int, optional] Controls the pseudo random number generation for shuffling the data for probability estimates. Ignored when probability is False.Pass an int for reproducible output across multiple function calls, by default None

max_depth
: [int, optional] Specifies the maximum depth of the tree, by default None

tol
: [float, optional] Tolerance for stopping, by default 1e-4

degree
: [int, optional] Degree of the polynomial kernel function ('poly'). Ignored by all other kernels., by default 3

gamma
[str, optional] Kernel coefficient for 'rbf', 'poly' and 'sigmoid'.if gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma,if 'auto', uses 1 / n_features., by default "scale"

split_criteria
[str, optional] Decides (just in case of a multi class classification) which column (class) use to split the dataset in a node. max_samples is incompatible with 'ovo' multiclass_strategy, by default "impurity"

criterion
[str, optional] The function to measure the quality of a split (only used if max_features != num_features). Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain., by default "entropy"

min_samples_split
[int, optional] The minimum number of samples required to split an internal node. 0 (default) for any, by default 0

max_features
[optional] The number of features to consider when looking for the 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= sqrt(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., by default None

splitter
[str, optional] The strategy used to choose the feature set at each node (only used if max_features < num_features). Supported strategies are: "best": sklearn SelectKBest algorithm is used in every node to choose the max_features best features. "random": The algorithm generates 5 candidates and choose the best (max. info. gain) of them. "trandom": The algorithm generates only one random combination. "mutual": Chooses the best features w.r.t. their mutual info with the label. "cfs": Apply Correlation-based Feature Selection. "fcbf": Apply Fast Correlation- Based , by default "random"

multiclass_strategy
[str, optional] Strategy to use with multiclass datasets, "ovo": one versus one. "ovr": one versus rest, by default "ovo"

normalize
[bool, optional] If standardization of features should be applied on each node with the samples that reach it , by default False

5.1.2 Attributes

classes_
[ndarray of shape (n_classes,)] The classes labels.

n_classes_
[int] The number of classes

n_iter_
[int] Max number of iterations in classifier

depth_
[int] Max depht of the tree

n_features_
[int] The number of features when `fit` is performed.

n_features_in_
[int] Number of features seen during fit.

max_features_
[int] Number of features to use in hyperplane computation

tree_
[Node] root of the tree

X_
[ndarray] points to the input dataset

y_
[ndarray] points to the input labels

5.1.3 References

R. Montañana, J. A. Gámez, J. M. Puerta, "STree: a single multi-class oblique decision tree based on support vector machines.", 2021 LNAI 12882

__predict_class(*X: array*) → array
Compute the predicted class for the samples in X. Returns the number of samples of each class in the corresponding leaf node.

Parameters

X
[np.array] Array of samples

Returns

np.array
Array of shape (n_samples, n_classes) with the number of samples of each class in the corresponding leaf node

_build_clf()
Build the right classifier for the node

_initialize_max_features() → int

_more_tags() → dict
Required by sklearn to supply features of the classifier make mandatory the labels array

Returns
the tag required

Return type
dict

_train(*X: ndarray*, *y: ndarray*, *sample_weight: ndarray*, *depth: int*, *title: str*) → Optional[Snode]
Recursive function to split the original dataset into predictor nodes (leaves)

Parameters

X
: [np.ndarray] samples dataset

y
: [np.ndarray] samples labels

sample_weight
: [np.ndarray] weight of samples. Rescale C per sample.

depth
: [int] actual depth in the tree

title
: [str] description of the node

Returns

Optional[Snode]
: binary tree

`check_predict`(*X*) → array

Checks predict and predict_proba preconditions. If input X is not an np.array convert it to one.

Parameters

X
: [np.ndarray] Array of samples

Returns

np.array
: Array of samples

Raises

ValueError
: If number of features of X is different of the number of features in training data

`fit`(*X: ndarray*, *y: ndarray*, *sample_weight: Optional[array] = None*) → *Stree*

Build the tree based on the dataset of samples and its labels

Returns

Stree
itself to be able to chain actions: fit().predict() ...

Raises

ValueError
if C < 0

ValueError
if max_depth < 1

ValueError
if all samples have 0 or negative weights

`graph`(*title=''*) → str

Graphviz code representing the tree

Returns

str
graphviz code

`nodes_leaves`() → tuple

Compute the number of nodes and leaves in the built tree

Returns

[tuple]
tuple with the number of nodes and the number of leaves

`predict`(*X: array*) → array

Predict labels for each sample in dataset passed

Parameters

X
[np.array] dataset of samples

Returns

np.array
array of labels

Raises

ValueError
if dataset with inconsistent number of features

NotFittedError
if model is not fitted

predict_proba(*X: array*) → array

Predict class probabilities of the input samples X.

The predicted class probability is the fraction of samples of the same class in a leaf.

Parameters

X : dataset of samples.

Returns

proba
[array of shape (n_samples, n_classes)] The class probabilities of the input samples.

Raises

ValueError
if dataset with inconsistent number of features

NotFittedError
if model is not fitted

static version() → str

Return the version of the package.

5.2 Siterator

Oblique decision tree classifier based on SVM nodes Splitter class

class Splitter.**Siterator**(*tree:* Snode)

Bases: object

Stree preorder iterator

_push(*node:* Snode)

5.3 Snode

Oblique decision tree classifier based on SVM nodes Splitter class

class Splitter.**Snode**(*clf: SVC*, *X: ndarray*, *y: ndarray*, *features: array*, *impurity: float*, *title: str*, *weight: Optional[ndarray] = None*, *scaler: Optional[StandardScaler] = None*)

Bases: `object`

Nodes of the tree that keeps the svm classifier and if testing the dataset assigned to it

5.3.1 Parameters

clf
: [SVC] Classifier used

X
: [np.ndarray] input dataset in train time (only in testing)

y
: [np.ndarray] input labes in train time

features
: [np.array] features used to compute hyperplane

impurity
: [float] impurity of the node

title
: [str] label describing the route to the node

weight
: [np.ndarray, optional] weights applied to input dataset in train time, by default None

scaler
: [StandardScaler, optional] scaler used if any, by default None

classmethod copy(*node:* Snode) → *Snode*

get_classifier() → SVC

get_down() → *Snode*

get_features() → array

get_impurity() → float

get_partition_column() → int

get_title() → str

get_up() → *Snode*

graph()
: Return a string representing the node in graphviz format

is_leaf() → bool

make_predictor(*num_classes: int*) → None

Compute the class of the predictor and its belief based on the subdataset of the node only if it is a leaf

set_classifier(*clf*)

set_down(*son*)

set_features(*features*)

set_impurity(*impurity*)

set_partition_column(*col: int*)

set_title(*title*)

set_up(*son*)

5.4 Splitter

Oblique decision tree classifier based on SVM nodes Splitter class

class Splitter.**Splitter**(*clf: Optional[SVC] = None*, *criterion: Optional[str] = None*, *feature_select: Optional[str] = None*, *criteria: Optional[str] = None*, *min_samples_split: Optional[int] = None*, *random_state=None*, *normalize=False*)

Bases: `object`

Splits a dataset in two based on different criteria

5.4.1 Parameters

clf

[SVC, optional] classifier, by default None

criterion

[str, optional] The function to measure the quality of a split (only used if max_features != num_features). Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain., by default "entropy", by default None

feature_select

[str, optional] The strategy used to choose the feature set at each node (only used if max_features < num_features). Supported strategies are: "best": sklearn SelectKBest algorithm is used in every node to choose the max_features best features. "random": The algorithm generates 5 candidates and choose the best (max. info. gain) of them. "trandom": The algorithm generates only one random combination. "mutual": Chooses the best features w.r.t. their mutual info with the label. "cfs": Apply Correlation-based Feature Selection. "fcbf": Apply Fast Correlation- Based, by default None

criteria

[str, optional] ecides (just in case of a multi class classification) which column (class) use to split the dataset in a node. max_samples is incompatible with 'ovo' multiclass_strategy, by default None

min_samples_split

[int, optional] The minimum number of samples required to split an internal node. 0 (default) for any, by default None

random_state
[optional] Controls the pseudo random number generation for shuffling the data for probability estimates. Ignored when probability is False.Pass an int for reproducible output across multiple function calls, by default None

normalize
[bool, optional] If standardization of features should be applied on each node with the samples that reach it , by default False

5.4.2 Raises

ValueError
clf has to be a sklearn estimator

ValueError
criterion must be gini or entropy

ValueError
criteria has to be max_samples or impurity

ValueError
splitter must be in {random, best, mutual, cfs, fcbf}

`_distances`(*node:* Snode, *data: ndarray*) → array

Compute distances of the samples to the hyperplane of the node

Parameters

node
[Snode] node containing the svm classifier

data
[np.ndarray] samples to compute distance to hyperplane

Returns

np.array
array of shape (m, nc) with the distances of every sample to the hyperplane of every class. nc = # of classes

`static _entropy`(*y: array*) → float

Compute entropy of a labels set

Parameters

y
[np.array] set of labels

Returns

float
entropy

`static _fs_best`(*dataset: array*, *labels: array*, *max_features: int*) → tuple
Return the variabes with higher f-score

Parameters

dataset
[np.array] array of samples

labels
[np.array] labels of the dataset

max_features
[int] number of features of the subspace (< number of features in dataset)

Returns

tuple
indices of the features selected

`static _fs_cfs`(*dataset: array*, *labels: array*, *max_features: int*) → tuple
Correlattion-based feature selection with max_features limit

Parameters

dataset
[np.array] array of samples

labels
[np.array] labels of the dataset

max_features
[int] number of features of the subspace (< number of features in dataset)

Returns

tuple
indices of the features selected

`static _fs_fcbf`(*dataset: array*, *labels: array*, *max_features: int*) → tuple
Fast Correlation-based Filter algorithm with max_features limit

Parameters

dataset
[np.array] array of samples

labels
[np.array] labels of the dataset

max_features
[int] number of features of the subspace (< number of features in dataset)

Returns

tuple
indices of the features selected

`static _fs_iwss`(*dataset: array*, *labels: array*, *max_features: int*) → tuple

Correlattion-based feature selection based on iwss with max_features limit

Parameters

dataset
[np.array] array of samples

labels
[np.array] labels of the dataset

max_features
[int] number of features of the subspace (< number of features in dataset)

Returns

tuple
indices of the features selected

`_fs_mutual`(*dataset: array*, *labels: array*, *max_features: int*) → tuple

Return the best features with mutual information with labels

Parameters

dataset
[np.array] array of samples

labels
[np.array] labels of the dataset

max_features
[int] number of features of the subspace (< number of features in dataset)

Returns

tuple
indices of the features selected

_fs_random(*dataset: array*, *labels: array*, *max_features: int*) → tuple
Return the best of five random feature set combinations

Parameters

dataset
[np.array] array of samples

labels
[np.array] labels of the dataset

max_features
[int] number of features of the subspace (< number of features in dataset)

Returns

tuple
indices of the features selected

static _fs_trandom(*dataset: array*, *labels: array*, *max_features: int*) → tuple
Return the a random feature set combination

Parameters

dataset
[np.array] array of samples

labels
[np.array] labels of the dataset

max_features
[int] number of features of the subspace (< number of features in dataset)

Returns

tuple
indices of the features selected

static _generate_spaces(*features: int*, *max_features: int*) → list
Generate at most 5 feature random combinations

Parameters

features
[int] number of features in each combination

max_features
[int] number of features in dataset

Returns

list
list with up to 5 combination of features randomly selected

_get_subspaces_set(*dataset: array*, *labels: array*, *max_features: int*) → tuple

Compute the indices of the features selected by splitter depending on the self._feature_select hyper parameter

Parameters

dataset
[np.array] array of samples

labels
[np.array] labels of the dataset

max_features
[int] number of features of the subspace (<= number of features in dataset)

Returns

tuple
indices of the features selected

static _gini(*y: array*) → float

_impurity(*data: array*, *y: array*) → array

return column of dataset to be taken into account to split dataset

Parameters

data
[np.array] distances to hyper plane of every class

y
[np.array] vector of labels (classes)

Returns

np.array
column of dataset to be taken into account to split dataset

static _max_samples(*data: array*, *y: array*) → array
return column of dataset to be taken into account to split dataset

Parameters

data
[np.array] distances to hyper plane of every class

y
[np.array] column of dataset to be taken into account to split dataset

Returns

np.array
column of dataset to be taken into account to split dataset

_select_best_set(*dataset: array*, *labels: array*, *features_sets: list*) → list
Return the best set of features among feature_sets, the criterion is the information gain

Parameters

dataset
[np.array] array of samples (# samples, # features)

labels
[np.array] array of labels

features_sets
[list] list of features sets to check

Returns

list
best feature set

get_subspace(*dataset: array*, *labels: array*, *max_features: int*) → tuple
Re3turn a subspace of the selected dataset of max_features length. Depending on hyperparameter

Parameters

dataset
[np.array] array of samples (# samples, # features)

labels
[np.array] labels of the dataset

max_features
[int] number of features to form the subspace

Returns

tuple
tuple with the dataset with only the features selected and the indices of the features selected

`information_gain`(*labels: array*, *labels_up: array*, *labels_dn: array*) → float

Compute information gain of a split candidate

Parameters

labels
[np.array] labels of the dataset

labels_up
[np.array] labels of one side

labels_dn
[np.array] labels on the other side

Returns

float
information gain

`part`(*origin: array*) → list

Split an array in two based on indices (self._up) and its complement partition has to be called first to establish up indices

Parameters

origin
[np.array] dataset to split

Returns

list
list with two splits of the array

partition(*samples: array*, *node:* Snode, *train: bool*)

Set the criteria to split arrays. Compute the indices of the samples that should go to one side of the tree (up)

Parameters

samples
[np.array] array of samples (# samples, # features)

node
[Snode] Node of the tree where partition is going to be made

train
[bool] Train time - True / Test time - False

partition_impurity(*y: array*) → array

- genindex

PYTHON MODULE INDEX

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