STree

Release 1.2.1

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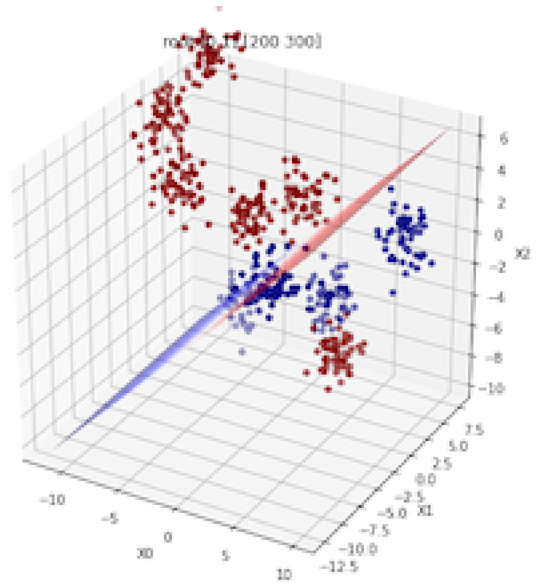
STREE

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/Values	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_criteria	{“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”, “ran-	“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

* 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
- Benchmark
- Some features
- Gridsearch
- Ensembles

4.2 Sample Code

```python
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: `sklearn.base.BaseEstimator`, `sklearn.base.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

_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

static _reorder_results(*y: numpy.array*, *indices: numpy.array*) → numpy.array

Reorder an array based on the array of indices passed

y [np.array] data untidy

indices [np.array] indices used to set order

np.array array y ordered

_train(*X: numpy.ndarray*, *y: numpy.ndarray*, *sample_weight: numpy.ndarray*, *depth: int*, *title: str*) → Optional[stree.Splitter.Snode]

Recursive function to split the original dataset into predictor nodes (leaves)

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

Optional[Snode] binary tree

fit(*X: numpy.ndarray*, *y: numpy.ndarray*, *sample_weight: Optional[numpy.array] = None*) → *stree.Strees.Stree*

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

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

ValueError if C < 0

ValueError if max_depth < 1

ValueError if all samples have 0 or negative weights

nodes_leaves() → tuple

Compute the number of nodes and leaves in the built tree

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

predict(*X: numpy.array*) → numpy.array

Predict labels for each sample in dataset passed

X [np.array] dataset of samples

np.array array of labels

ValueError if dataset with inconsistent number of features

NotFittedError if model is not fitted

5.2 Siterator

Oblique decision tree classifier based on SVM nodes Splitter class

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

Bases: `object`

Stree preorder iterator

_push(*node:* Splitter.Snode)

5.3 Snode

Oblique decision tree classifier based on SVM nodes Splitter class

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

Bases: `object`

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

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

get_classifier() → sklearn.svm._classes.SVC

get_down() → *Splitter.Snode*

get_features() → numpy.array

`get_impurity()` → float

`get_partition_column()` → int

`get_title()` → str

`get_up()` → *Splitter.Snode*

`is_leaf()` → bool

`make_predictor()`
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[sklearn.svm._classes.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`

`_distances`(*node:* Splitter.Snode, *data: numpy.ndarray*) → numpy.array
Compute distances of the samples to the hyperplane of the node

node [Snode] node containing the svm classifier

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

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: numpy.array*) → float
Compute entropy of a labels set

y [np.array] set of labels

float entropy

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

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)

tuple indices of the features selected

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

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)

tuple indices of the features selected

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

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)

tuple indices of the features selected

`static _fs_mutual`(*dataset: numpy.array*, *labels: numpy.array*, *max_features: int*) → tuple
Return the best features with mutual information with labels

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)

tuple indices of the features selected

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

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)

tuple indices of the features selected

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

features [int] number of features in each combination

max_features [int] number of features in dataset

list list with up to 5 combination of features randomly selected

`_get_subspaces_set`(*dataset: numpy.array*, *labels: numpy.array*, *max_features: int*) → tuple
Compute the indices of the features selected by splitter depending on the self._feature_select hyper parameter

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)

tuple indices of the features selected

`static _gini`(*y: numpy.array*) → float

`_impurity`(*data: numpy.array*, *y: numpy.array*) → numpy.array
return column of dataset to be taken into account to split dataset

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

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

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

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

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

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

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

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

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

labels [np.array] array of labels

features_sets [list] list of features sets to check

list best feature set

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

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

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

`information_gain`(*labels: numpy.array*, *labels_up: numpy.array*, *labels_dn: numpy.array*) → float
Compute information gain of a split candidate

labels [np.array] labels of the dataset

labels_up [np.array] labels of one side

labels_dn [np.array] labels on the other side

float information gain

`part`(*origin: numpy.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

origin [np.array] dataset to split

list list with two splits of the array

`partition`(*samples: numpy.array*, *node:* Splitter.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)

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: numpy.array*) → numpy.array

- genindex

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