sklearn.linear_model.Perceptron

class sklearn.linear_model.Perceptron(**, penalty=None, alpha=0.0001, l1_ratio=0.15, fit_intercept=True, max_iter=1000, tol=0.001, shuffle=True, verbose=0, eta0=1.0, n_jobs=None, random_state=0, early_stopping=False, validation_fraction=0.1, n_iter_no_change=5, class_weight=None, warm_start=False*) ¶ [source]

Linear perceptron classifier.

Read more in the User Guide.

Parameters:

penalty : *{'l2','l1','elasticnet'}, default=None*
The penalty (aka regularization term) to be used.

alpha : *float, default=0.0001*
Constant that multiplies the regularization term if regularization is used.

l1_ratio : *float, default=0.15*
The Elastic Net mixing parameter, with `0 <= l1_ratio <= 1`. `l1_ratio=0` corresponds to L2 penalty, `l1_ratio=1` to L1. Only used if `penalty='elasticnet'`.

New in version 0.24.

fit_intercept : *bool, default=True*
Whether the intercept should be estimated or not. If False, the data is assumed to be already centered.

max_iter : *int, default=1000*
The maximum number of passes over the training data (aka epochs). It only impacts the behavior in the `fit` method, and not the `partial_fit` method.

New in version 0.19.

tol : *float, default=1e-3*
The stopping criterion. If it is not None, the iterations will stop when (loss > previous_loss - tol).

New in version 0.19.

shuffle : *bool, default=True*
Whether or not the training data should be shuffled after each epoch.

verbose : *int, default=0*
The verbosity level.

eta0 : *float, default=1*
Constant by which the updates are multiplied.

n_jobs : *int, default=None*
The number of CPUs to use to do the OVA (One Versus All, for multi-class problems) computation. `None` means 1 unless in a `joblib.parallel_backend` context. `-1` means using all processors. See Glossary for more details.

random_state : *int, RandomState instance, default=None*
Used to shuffle the training data, when `shuffle` is set to `True`. Pass an int for reproducible output across multiple function calls. See Glossary.

Toggle Menu **ing : *bool, default=False***

Whether to use early stopping to terminate training when validation. score is not improving. If set to True, it will automatically set aside a stratified fraction of training data as validation and terminate training when validation score is not improving by at least tol for n_iter_no_change consecutive epochs.

New in version 0.20.

validation_fraction : *float, default=0.1*
The proportion of training data to set aside as validation set for early stopping. Must be between 0 and 1. Only used if early_stopping is True.

New in version 0.20.

n_iter_no_change : *int, default=5*
Number of iterations with no improvement to wait before early stopping.

New in version 0.20.

class_weight : *dict, {class_label: weight} or "balanced", default=None*
Preset for the class_weight fit parameter.

Weights associated with classes. If not given, all classes are supposed to have weight one.

The "balanced" mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as `n_samples / (n_classes * np.bincount(y))`.

warm_start : *bool, default=False*
When set to True, reuse the solution of the previous call to fit as initialization, otherwise, just erase the previous solution. See the Glossary.

Attributes:

classes_ : *ndarray of shape (n_classes,)*
The unique classes labels.

coef_ : *ndarray of shape (1, n_features) if n_classes == 2 else (n_classes, n_features)*
Weights assigned to the features.

intercept_ : *ndarray of shape (1,) if n_classes == 2 else (n_classes,)*
Constants in decision function.

loss_function_ : *concrete LossFunction*
The function that determines the loss, or difference between the output of the algorithm and the target values.

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_iter_ : *int*
The actual number of iterations to reach the stopping criterion. For multiclass fits, it is the maximum over every binary fit.

t_ : *int*
Number of weight updates performed during training. Same as `(n_iter_ * n_samples)`.

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See also:

`sklearn.linear_model.SGDClassifier`
Linear classifiers (SVM, logistic regression, etc.) with SGD training.

Notes

`Perceptron` is a classification algorithm which shares the same underlying implementation with `SGDClassifier`. In fact, `Perceptron()` is equivalent to `SGDClassifier(loss="perceptron", eta0=1, learning_rate="constant", penalty=None)`.

References

https://en.wikipedia.org/wiki/Perceptron and references therein.

Examples

```
>>> from sklearn.datasets import load_digits
>>> from sklearn.linear_model import Perceptron
>>> X, y = load_digits(return_X_y=True)
>>> clf = Perceptron(tol=1e-3, random_state=0)
>>> clf.fit(X, y)
Perceptron()
>>> clf.score(X, y)
0.939...
```

Methods

`decision_function`(X)	Predict confidence scores for samples.
`densify`()	Convert coefficient matrix to dense array format.
`fit`(X, y[, coef_init, intercept_init, ...])	Fit linear model with Stochastic Gradient Descent.
`get_params`([deep])	Get parameters for this estimator.
`partial_fit`(X, y[, classes, sample_weight])	Perform one epoch of stochastic gradient descent on given samples.
`predict`(X)	Predict class labels for samples in X.
`score`(X, y[, sample_weight])	Return the mean accuracy on the given test data and labels.
`set_params`(**params)	Set the parameters of this estimator.
`sparsify`()	Convert coefficient matrix to sparse format.

decision_function(*X*) [source]

Predict confidence scores for samples.

The confidence score for a sample is proportional to the signed distance of that sample to the hyperplane.

Parameters:

X : *{array-like, sparse matrix} of shape (n_samples, n_features)*
The data matrix for which we want to get the confidence scores.

Returns:

scores : *ndarray of shape (n_samples,) or (n_samples, n_classes)*
Confidence scores per `(n_samples, n_classes)` combination. In the binary case, confidence score for `self.classes_[1]` where >0 means this class would be predicted.

densify() [source]

Toggle Menu fficient matrix to dense array format.

Converts the `coef_` member (back) to a numpy.ndarray. This is the default format of `coef_` and is required for fitting, so calling this method is only required on models that have previously been sparsified; otherwise, it is a no-op.

Returns:

self
Fitted estimator.

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

Fit linear model with Stochastic Gradient Descent.

Parameters:

X : *{array-like, sparse matrix}, shape (n_samples, n_features)*
Training data.

y : *ndarray of shape (n_samples,)*
Target values.

coef_init : *ndarray of shape (n_classes, n_features), default=None*
The initial coefficients to warm-start the optimization.

intercept_init : *ndarray of shape (n_classes,), default=None*
The initial intercept to warm-start the optimization.

sample_weight : *array-like, shape (n_samples,), default=None*
Weights applied to individual samples. If not provided, uniform weights are assumed. These weights will be multiplied with class_weight (passed through the constructor) if class_weight is specified.

Returns:

self : *object*
Returns an instance of self.

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.

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

Perform one epoch of stochastic gradient descent on given samples.

Internally, this method uses `max_iter = 1`. Therefore, it is not guaranteed that a minimum of the cost function is reached after calling it once. Matters such as objective convergence, early stopping, and learning rate adjustments should be handled by the user.

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Parameters:

X : *{array-like, sparse matrix}, shape (n_samples, n_features)*

Subset of the training data.

y : *ndarray of shape (n_samples,)*

Subset of the target values.

classes : *ndarray of shape (n_classes,), default=None*

Classes across all calls to partial_fit. Can be obtained by via `np.unique(y_all)`, where y_all is the target vector of the entire dataset. This argument is required for the first call to partial_fit and can be omitted in the subsequent calls. Note that y doesn't need to contain all labels in `classes`.

sample_weight : *array-like, shape (n_samples,), default=None*

Weights applied to individual samples. If not provided, uniform weights are assumed.

Returns:

self : *object*

Returns an instance of self.

predict(*X*) [source]

Predict class labels for samples in X.

Parameters:

X : *{array-like, sparse matrix} of shape (n_samples, n_features)*

The data matrix for which we want to get the predictions.

Returns:

y_pred : *ndarray of shape (n_samples,)*

Vector containing the class labels for each sample.

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

Return the mean accuracy on the given test data and labels.

In multi-label classification, this is the subset accuracy which is a harsh metric since you require for each sample that each label set be correctly predicted.

Parameters:

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

Test samples.

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

True labels for `X`.

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

Sample weights.

Returns:

score : *float*

Mean accuracy of `self.predict(X)` wrt. `y`.

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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.

sparsify() [source]

Convert coefficient matrix to sparse format.

Converts the `coef_` member to a scipy.sparse matrix, which for L1-regularized models can be much more memory- and storage-efficient than the usual numpy.ndarray representation.

The `intercept_` member is not converted.

Returns:

self

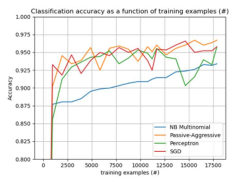
Fitted estimator.

Notes

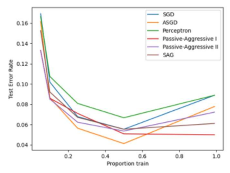
For non-sparse models, i.e. when there are not many zeros in `coef_`, this may actually *increase* memory usage, so use this method with care. A rule of thumb is that the number of zero elements, which can be computed with `(coef_ == 0).sum()`, must be more than 50% for this to provide significant benefits.

After calling this method, further fitting with the partial_fit method (if any) will not work until you call densify.

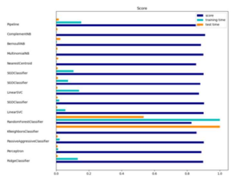
Examples using `sklearn.linear_model.Perceptron`



Out-of-core classification of text documents



Comparing various online solvers



Classification of text documents using sparse features

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