sklearn.neural_network.MLPClassifier

» *class* `sklearn.neural_network.`**`MLPClassifier`**(*hidden_layer_sizes=(100,)*, *activation='relu'*, *solver='adam'*, *alpha=0.0001*, *batch_size='auto'*, *learning_rate='constant'*, *learning_rate_init=0.001*, *power_t=0.5*, *max_iter=200*, *shuffle=True*, *random_state=None*, *tol=0.0001*, *verbose=False*, *warm_start=False*, *momentum=0.9*, *nesterovs_momentum=True*, *early_stopping=False*, *validation_fraction=0.1*, *beta_1=0.9*, *beta_2=0.999*, *epsilon=1e-08*) [source]

Multi-layer Perceptron classifier.

This model optimizes the log-loss function using LBFGS or stochastic gradient descent.

New in version 0.18.

Parameters: **hidden_layer_sizes** : tuple, length = n_layers - 2, default (100,)

The ith element represents the number of neurons in the ith hidden layer.

activation : {'identity', 'logistic', 'tanh', 'relu'}, default 'relu'

Activation function for the hidden layer.

- 'identity', no-op activation, useful to implement linear bottleneck, returns f(x) = x
- 'logistic', the logistic sigmoid function, returns f(x) = 1 / (1 + exp(-x)).
- 'tanh', the hyperbolic tan function, returns f(x) = tanh(x).
- 'relu', the rectified linear unit function, returns f(x) = max(0, x)

solver : {'lbfgs', 'sgd', 'adam'}, default 'adam'

The solver for weight optimization.

- 'lbfgs' is an optimizer in the family of quasi-Newton methods.
- 'sgd' refers to stochastic gradient descent.
- 'adam' refers to a stochastic gradient-based optimizer proposed by Kingma, Diederik, and Jimmy Ba

Note: The default solver 'adam' works pretty well on relatively large datasets (with thousands of training samples or more) in terms of both training time and validation score. For small datasets, however, 'lbfgs' can converge faster and perform better.

alpha : float, optional, default 0.0001

L2 penalty (regularization term) parameter.

batch_size : int, optional, default 'auto'

Size of minibatches for stochastic optimizers. If the solver is ‘lbfgs’, the classifier will not use minibatch. When set to “auto”, *batch_size=min(200, n_samples)*

learning_rate : {‘constant’, ‘invscaling’, ‘adaptive’}, default ‘constant’

Learning rate schedule for weight updates.

- ‘constant’ is a constant learning rate given by ‘learning_rate_init’.
- ‘invscaling’ gradually decreases the learning rate `learning_rate_` at each time step ‘t’ using an inverse scaling exponent of ‘power_t’. effective_learning_rate = learning_rate_init / pow(t, power_t)
- ‘adaptive’ keeps the learning rate constant to ‘learning_rate_init’ as long as training loss keeps decreasing. Each time two consecutive epochs fail to decrease training loss by at least tol, or fail to increase validation score by at least tol if ‘early_stopping’ is on, the current learning rate is divided by 5.

Only used when `solver='sgd'`.

max_iter : int, optional, default 200

Maximum number of iterations. The solver iterates until convergence (determined by ‘tol’) or this number of iterations.

random_state : int or RandomState, optional, default None

State or seed for random number generator.

shuffle : bool, optional, default True

Whether to shuffle samples in each iteration. Only used when solver=’sgd’ or ‘adam’.

tol : float, optional, default 1e-4

Tolerance for the optimization. When the loss or score is not improving by at least tol for two consecutive iterations, unless *learning_rate* is set to ‘adaptive’, convergence is considered to be reached and training stops.

learning_rate_init : double, optional, default 0.001

The initial learning rate used. It controls the step-size in updating the weights. Only used when solver=’sgd’ or ‘adam’.

power_t : double, optional, default 0.5

The exponent for inverse scaling learning rate. It is used in updating effective learning rate when the learning_rate is set to ‘invscaling’. Only used when solver=’sgd’.

verbose : bool, optional, default False

Whether to print progress messages to stdout.

warm_start : bool, optional, default False

When set to True, reuse the solution of the previous call to fit as initialization, otherwise, just erase the previous solution.

momentum : float, default 0.9

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Momentum for gradient descent update. Should be between 0 and 1. Only used when solver='sgd'.

nesterovs_momentum : boolean, default True

Whether to use Nesterov's momentum. Only used when solver='sgd' and momentum > 0.

early_stopping : 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 10% of training data as validation and terminate training when validation score is not improving by at least tol for two consecutive epochs. Only effective when solver='sgd' or 'adam'

validation_fraction : float, optional, 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

beta_1 : float, optional, default 0.9

Exponential decay rate for estimates of first moment vector in adam, should be in [0, 1). Only used when solver='adam'

beta_2 : float, optional, default 0.999

Exponential decay rate for estimates of second moment vector in adam, should be in [0, 1). Only used when solver='adam'

epsilon : float, optional, default 1e-8

Value for numerical stability in adam. Only used when solver='adam'

Attributes:

`classes_` : array or list of array of shape (n_classes,)

Class labels for each output.

`loss_` : float

The current loss computed with the loss function.

`coefs_` : list, length n_layers - 1

The ith element in the list represents the weight matrix corresponding to layer i.

`intercepts_` : list, length n_layers - 1

The ith element in the list represents the bias vector corresponding to layer i + 1.

n_iter_ : int,

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The number of iterations the solver has ran.

n_layers_ : int

Number of layers.

`n_outputs_` : int

Number of outputs.

`out_activation_` : string

Name of the output activation function.

Notes

MLPClassifier trains iteratively since at each time step the partial derivatives of the loss function with respect to the model parameters are computed to update the parameters.

It can also have a regularization term added to the loss function that shrinks model parameters to prevent overfitting.

This implementation works with data represented as dense numpy arrays or sparse scipy arrays of floating point values.

References

Hinton, Geoffrey E.
“Connectionist learning procedures.” Artificial intelligence 40.1 (1989): 185-234.

Glorot, Xavier, and Yoshua Bengio. “Understanding the difficulty of
training deep feedforward neural networks.” International Conference on Artificial Intelligence and Statistics. 2010.

He, Kaiming, et al. “Delving deep into rectifiers: Surpassing human-level
performance on imagenet classification.” arXiv preprint arXiv:1502.01852 (2015).

Kingma, Diederik, and Jimmy Ba. “Adam: A method for stochastic
optimization.” arXiv preprint arXiv:1412.6980 (2014).

Methods

`fit`(X, y)	Fit the model to data matrix X and target y.

`get_params`([deep])	Get parameters for this estimator.
`predict`(X)	Predict using the multi-layer perceptron classifier
`predict_log_proba`(X)	Return the log of probability estimates.
`predict_proba`(X)	Probability estimates.
`score`(X, y[, sample_weight])	Returns the mean accuracy on the given test data and labels.
`set_params`(**params)	Set the parameters of this estimator.

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`__init__`(*hidden_layer_sizes=(100,)*, *activation='relu'*, *solver='adam'*, *alpha=0.0001*, *batch_size='auto'*, *learning_rate='constant'*, *learning_rate_init=0.001*, *power_t=0.5*, *max_iter=200*, *shuffle=True*, *random_state=None*, *tol=0.0001*, *verbose=False*, *warm_start=False*, *momentum=0.9*, *nesterovs_momentum=True*, *early_stopping=False*, *validation_fraction=0.1*, *beta_1=0.9*, *beta_2=0.999*, *epsilon=1e-08*) [source]

`fit`(*X*, *y*) [source]

Fit the model to data matrix X and target y.

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

The input data.

y : array-like, shape (n_samples,)

The target values.

Returns: **self** : returns a trained MLP model.

`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.

`partial_fit`

Fit the model to data matrix X and target y.

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

The input data.

y : array-like, shape (n_samples,)

The target values.

classes : array, shape (n_classes)

Classes across all calls to partial_fit. Can be obtained 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*.

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Returns: **self** : returns a trained MLP model.

predict(*X*) [source]

Predict using the multi-layer perceptron classifier

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

The input data.

Returns: **y** : array-like, shape (n_samples,) or (n_samples, n_classes)

The predicted classes.

predict_log_proba(*X*) [source]

Return the log of probability estimates.

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

The input data.

Returns: **log_y_prob** : array-like, shape (n_samples, n_classes)

The predicted log-probability of the sample for each class in the model, where classes are ordered as they are in *self.classes_*. Equivalent to log(predict_proba(X))

predict_proba(*X*) [source]

Probability estimates.

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

The input data.

Returns: **y_prob** : array-like, shape (n_samples, n_classes)

The predicted probability of the sample for each class in the model, where classes are ordered as they are in *self.classes_*.

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

Returns 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, shape = (n_samples, n_features) Test samples. **y** : array-like, shape = (n_samples) or (n_samples, n_outputs) True labels for X. **sample_weight** : array-like, shape = [n_samples], optional Sample weights.
Returns:	**score** : float Mean accuracy of self.predict(X) wrt. y.

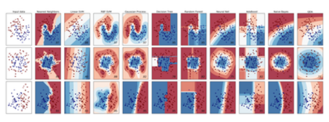
set_params(***params*) [source]

Set the parameters of this estimator.

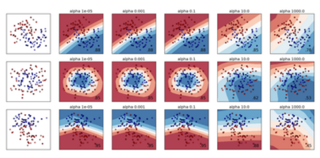
The method works on simple estimators as well as on nested objects (such as pipelines). The latter have parameters of the form `<component>__<parameter>` so that it's possible to update each component of a nested object.

Returns:	**self** :

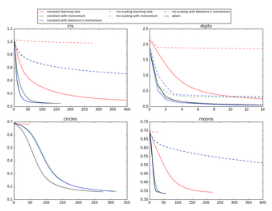
Examples using `sklearn.neural_network.MLPClassifier`



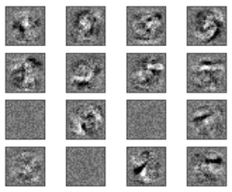
Classifier comparison



Varying regularization in Multi-layer Perceptron



Compare Stochastic learning strategies for MLPClassifier



» Visualization of MLP weights on MNIST