sklearn.linear_model.LogisticRegression

class `sklearn.linear_model.LogisticRegression`(*penalty='l2'*, ***, *dual=False*, *tol=0.0001*, *C=1.0*, *fit_intercept=True*, *intercept_scaling=1*, *class_weight=None*, *random_state=None*, *solver='lbfgs'*, *max_iter=100*, *multi_class='auto'*, *verbose=0*, *warm_start=False*, *n_jobs=None*, *l1_ratio=None*) [source]

Logistic Regression (aka logit, MaxEnt) classifier.

In the multiclass case, the training algorithm uses the one-vs-rest (OvR) scheme if the 'multi_class' option is set to 'ovr', and uses the cross-entropy loss if the 'multi_class' option is set to 'multinomial'. (Currently the 'multinomial' option is supported only by the 'lbfgs', 'sag', 'saga' and 'newton-cg' solvers.)

This class implements regularized logistic regression using the 'liblinear' library, 'newton-cg', 'sag', 'saga' and 'lbfgs' solvers. **Note that regularization is applied by default**. It can handle both dense and sparse input. Use C-ordered arrays or CSR matrices containing 64-bit floats for optimal performance; any other input format will be converted (and copied).

The 'newton-cg', 'sag', and 'lbfgs' solvers support only L2 regularization with primal formulation, or no regularization. The 'liblinear' solver supports both L1 and L2 regularization, with a dual formulation only for the L2 penalty. The Elastic-Net regularization is only supported by the 'saga' solver.

Read more in the User Guide.

Parameters:

penalty : *{'l1', 'l2', 'elasticnet', 'none'}, default='l2'*

Specify the norm of the penalty:

- `'none'`: no penalty is added;
- `'l2'`: add a L2 penalty term and it is the default choice;
- `'l1'`: add a L1 penalty term;
- `'elasticnet'`: both L1 and L2 penalty terms are added.

> **Warning:** Some penalties may not work with some solvers. See the parameter `solver` below, to know the compatibility between the penalty and solver.

New in version 0.19: l1 penalty with SAGA solver (allowing 'multinomial' + L1)

dual : *bool, default=False*

Dual or primal formulation. Dual formulation is only implemented for l2 penalty with liblinear solver. Prefer dual=False when n_samples > n_features.

tol : *float, default=1e-4*

Tolerance for stopping criteria.

C : *float, default=1.0*

Inverse of regularization strength; must be a positive float. Like in support vector machines, smaller values specify stronger regularization.

fit_intercept : *bool, default=True*

Specifies if a constant (a.k.a. bias or intercept) should be added to the decision function.

intercept_scaling : *float, default=1*

Useful only when the solver 'liblinear' is used and self.fit_intercept is set to True. In this case, x becomes [x, self.intercept_scaling], i.e. a "synthetic" feature with constant value equal to intercept_scaling is appended to the instance vector. The intercept becomes `intercept_scaling * synthetic_feature_weight`.

Note! the synthetic feature weight is subject to l1/l2 regularization as all other features. To lessen the effect of regularization on synthetic feature weight (and therefore on the intercept) intercept_scaling has to be increased.

class_weight : *dict or 'balanced', default=None*

Weights associated with classes in the form `{class_label: weight}`. 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))`.

Note that these weights will be multiplied with sample_weight (passed through the fit method) if sample_weight is specified.

New in version 0.17: class_weight='balanced'

random_state : *int, RandomState instance, default=None*

Used when `solver` == 'sag', 'saga' or 'liblinear' to shuffle the data. See Glossary for details.

solver : *{'newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'}, default='lbfgs'*

Algorithm to use in the optimization problem. Default is 'lbfgs'. To choose a solver, you might want to consider the following aspects:

- For small datasets, 'liblinear' is a good choice, whereas 'sag' and 'saga' are faster for large ones;
- For multiclass problems, only 'newton-cg', 'sag', 'saga' and 'lbfgs' handle multinomial loss;
- 'liblinear' is limited to one-versus-rest schemes.

Warning: The choice of the algorithm depends on the penalty chosen: Supported penalties by solver:

- 'newton-cg' - ['l2', 'none']
- 'lbfgs' - ['l2', 'none']
- 'liblinear' - ['l1', 'l2']
- 'sag' - ['l2', 'none']
- 'saga' - ['elasticnet', 'l1', 'l2', 'none']

Note: 'sag' and 'saga' fast convergence is only guaranteed on features with approximately the same scale. You can preprocess the data with a scaler from **`sklearn.preprocessing`**.

See also: Refer to the User Guide for more information regarding **`LogisticRegression`** and more specifically the Table summarazing solver/penalty supports. <!– # noqa: E501 –>

New in version 0.17: Stochastic Average Gradient descent solver.

New in version 0.19: SAGA solver.

Changed in version 0.22: The default solver changed from 'liblinear' to 'lbfgs' in 0.22.

max_iter : *int, default=100*

Maximum number of iterations taken for the solvers to converge.

multi_class : *{'auto', 'ovr', 'multinomial'}, default='auto'*

If the option chosen is 'ovr', then a binary problem is fit for each label. For 'multinomial' the loss minimised is the multinomial loss fit across the entire probability distribution, *even when the data is binary*. 'multinomial' is unavailable when solver='liblinear'. 'auto' selects 'ovr' if the data is binary, or if solver='liblinear', and otherwise selects 'multinomial'.

New in version 0.18: Stochastic Average Gradient descent solver for 'multinomial' case.

Changed in version 0.22: Default changed from 'ovr' to 'auto' in 0.22.

verbose : *int, default=0*

For the liblinear and lbfgs solvers set verbose to any positive number for verbosity.

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. Useless for liblinear solver. See [the Glossary](#).

New in version 0.17: warm_start to support *lbfgs*, *newton-cg*, *sag*, *saga* solvers.

n_jobs : *int, default=None*

Number of CPU cores used when parallelizing over classes if multi_class='ovr'". This parameter is ignored when the `solver` is set to 'liblinear' regardless of whether 'multi_class' is specified or not. `None` means 1 unless in a [`joblib.parallel_backend`](#) context. `-1` means using all processors. See [Glossary](#) for more details.

l1_ratio : *float, default=None*

The Elastic-Net mixing parameter, with `0 <= l1_ratio <= 1`. Only used if `penalty='elasticnet'`. Setting `l1_ratio=0` is equivalent to using `penalty='l2'`, while setting `l1_ratio=1` is equivalent to using `penalty='l1'`. For `0 < l1_ratio <1`, the penalty is a combination of L1 and L2.

Attributes:

classes_ : *ndarray of shape (n_classes,)*

A list of class labels known to the classifier.

coef_ : *ndarray of shape (1, n_features) or (n_classes, n_features)*

Coefficient of the features in the decision function.

`coef_` is of shape (1, n_features) when the given problem is binary. In particular, when `multi_class='multinomial'`, `coef_` corresponds to outcome 1 (True) and `-coef_` corresponds to outcome 0 (False).

intercept_ : *ndarray of shape (1,) or (n_classes,)*

Intercept (a.k.a. bias) added to the decision function.

If `fit_intercept` is set to False, the intercept is set to zero. `intercept_` is of shape (1,) when the given problem is binary. In particular, when `multi_class='multinomial'`, `intercept_` corresponds to outcome 1 (True) and `-intercept_` corresponds to outcome 0 (False).

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_ : *ndarray of shape (n_classes,) or (1,)*

Actual number of iterations for all classes. If binary or multinomial, it returns only 1 element. For liblinear solver, only the maximum number of iteration across all classes is given.

> *Changed in version 0.20:* In SciPy <= 1.0.0 the number of lbfgs iterations may exceed `max_iter`. `n_iter_` will now report at most `max_iter`.

See also:

[`SGDClassifier`](#)

Incrementally trained logistic regression (when given the parameter `loss="log"`).

[`LogisticRegressionCV`](#)

Logistic regression with built-in cross validation.

Notes

The underlying C implementation uses a random number generator to select features when fitting the model. It is thus not uncommon, to have slightly different results for the same input data. If that happens, try with a smaller tol parameter.

Predict output may not match that of standalone liblinear in certain cases. See differences from liblinear in the narrative documentation.

References

L-BFGS-B – Software for Large-scale Bound-constrained Optimization
Ciyou Zhu, Richard Byrd, Jorge Nocedal and Jose Luis Morales. http://users.iems.northwestern.edu/~nocedal/lbfgsb.html

LIBLINEAR – A Library for Large Linear Classification
https://www.csie.ntu.edu.tw/~cjlin/liblinear/

SAG – Mark Schmidt, Nicolas Le Roux, and Francis Bach
Minimizing Finite Sums with the Stochastic Average Gradient https://hal.inria.fr/hal-00860051/document

SAGA – Defazio, A., Bach F. & Lacoste-Julien S. (2014).
"SAGA: A Fast Incremental Gradient Method With Support for Non-Strongly Convex Composite Objectives"

Hsiang-Fu Yu, Fang-Lan Huang, Chih-Jen Lin (2011). Dual coordinate descent
methods for logistic regression and maximum entropy models. Machine Learning 85(1-2):41-75.
https://www.csie.ntu.edu.tw/~cjlin/papers/maxent_dual.pdf

Examples

```
>>> from sklearn.datasets import load_iris
>>> from sklearn.linear_model import LogisticRegression
>>> X, y = load_iris(return_X_y=True)
>>> clf = LogisticRegression(random_state=0).fit(X, y)
>>> clf.predict(X[:2, :])
array([0, 0])
>>> clf.predict_proba(X[:2, :])
array([[9.8...e-01, 1.8...e-02, 1.4...e-08],
       [9.7...e-01, 2.8...e-02, ...e-08]])
>>> clf.score(X, y)
0.97...
```

Methods

`decision_function`(X)	Predict confidence scores for samples.
`densify`()	Convert coefficient matrix to dense array format.
`fit`(X, y[, sample_weight])	Fit the model according to the given training data.
`get_params`([deep])	Get parameters for this estimator.
`predict`(X)	Predict class labels for samples in X.
`predict_log_proba`(X)	Predict logarithm of probability estimates.
`predict_proba`(X)	Probability estimates.
`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]

Convert coefficient 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*, *sample_weight=None*) [source]

Fit the model according to the given training data.

Parameters:

X : *{array-like, sparse matrix} of shape (n_samples, n_features)*
Training vector, where `n_samples` is the number of samples and `n_features` is the number of features.

y : *array-like of shape (n_samples,)*
Target vector relative to X.

sample_weight : *array-like of shape (n_samples,) default=None*
Array of weights that are assigned to individual samples. If not provided, then each sample is given unit weight.

New in version 0.17: sample_weight support to LogisticRegression.

Returns:

self
Fitted estimator.

Notes

The SAGA solver supports both float64 and float32 bit arrays.

`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.

`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.

`predict_log_proba`(*X*) [source]

Predict logarithm of probability estimates.

The returned estimates for all classes are ordered by the label of classes.

Parameters:

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

Vector to be scored, where `n_samples` is the number of samples and `n_features` is the number of features.

Returns:

T : *array-like of shape (n_samples, n_classes)*

Returns the log-probability of the sample for each class in the model, where classes are ordered as they are in `self.classes_`.

`predict_proba`(*X*) [source]

Probability estimates.

The returned estimates for all classes are ordered by the label of classes.

For a multi_class problem, if multi_class is set to be “multinomial” the softmax function is used to find the predicted probability of each class. Else use a one-vs-rest approach, i.e calculate the probability of each class assuming it to be positive using the logistic function. and normalize these values across all the classes.

Parameters:

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

Vector to be scored, where `n_samples` is the number of samples and `n_features` is the number of features.

Returns:

T : *array-like of shape (n_samples, n_classes)*

Returns the 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]

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`.

`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

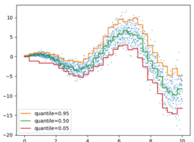
Fitted estimator.

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.

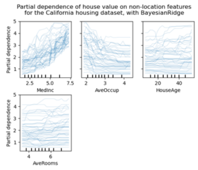
After calling this method, further fitting with the partial_fit method (if any) will not work until you call densify.

Examples using `sklearn.linear_model.LogisticRegression`

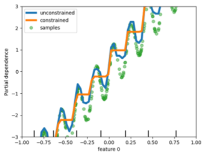


Release Highlights for scikit-learn 1.1

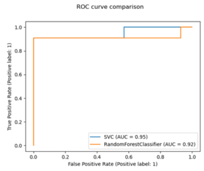
Release Highlights for scikit-learn 1.0



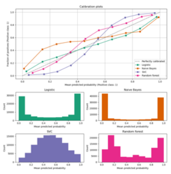
Release Highlights for scikit-learn 0.24



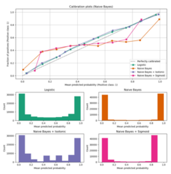
Release Highlights for scikit-learn 0.23



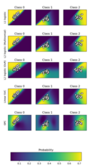
Release Highlights for scikit-learn 0.22



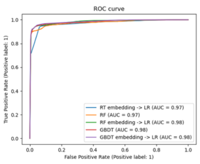
Comparison of Calibration of Classifiers



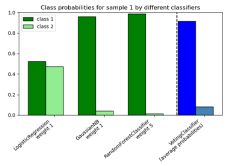
Probability Calibration curves



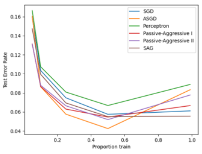
Plot classification probability



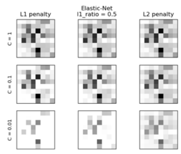
Feature transformations with ensembles of trees



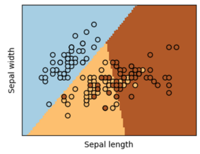
Plot class probabilities calculated by the VotingClassifier



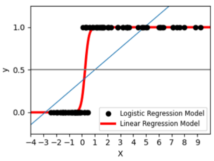
Comparing various online solvers



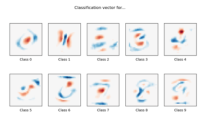
L1 Penalty and Sparsity in Logistic Regression



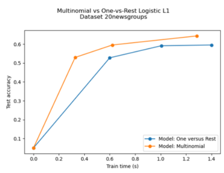
Logistic Regression 3-class Classifier

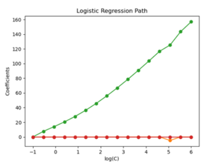


Logistic function



MNIST classification using multinomial logistic + L1





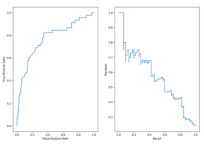
Multiclass sparse logistic regression on 20newgroups

Plot multinomial and One-vs-Rest Logistic Regression

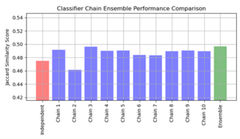
Regularization path of L1- Logistic Regression

Compact estimator representations

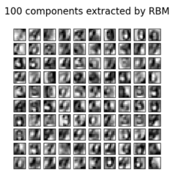
Displaying Pipelines



Visualizations with Display Objects

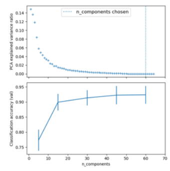


Classifier Chain

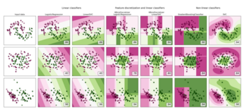


Restricted Boltzmann Machine features for digit classification

Column Transformer with Mixed Types



Pipelining: chaining a PCA and a logistic regression



Feature discretization

Digits Classification Exercise

Toggle Menu

 Show this page source