sklearn.linear_model.LinearRegression

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class `sklearn.linear_model.`**`LinearRegression`**(*fit_intercept=True*, *normalize=False*, *copy_X=True*, *n_jobs=None*) [source]

Ordinary least squares Linear Regression.

Parameters:

fit_intercept : *boolean, optional, default True*

whether to calculate the intercept for this model. If set to False, no intercept will be used in calculations (e.g. data is expected to be already centered).

normalize : *boolean, optional, default False*

This parameter is ignored when `fit_intercept` is set to False. If True, the regressors X will be normalized before regression by subtracting the mean and dividing by the l2-norm. If you wish to standardize, please use `sklearn.preprocessing.StandardScaler` before calling `fit` on an estimator with `normalize=False`.

copy_X : *boolean, optional, default True*

If True, X will be copied; else, it may be overwritten.

n_jobs : *int or None, optional (default=None)*

The number of jobs to use for the computation. This will only provide speedup for n_targets > 1 and sufficient large problems. `None` means 1 unless in a `joblib.parallel_backend` context. `-1` means using all processors. See Glossary for more details.

Attributes:

coef_ : *array, shape (n_features,) or (n_targets, n_features)*

Estimated coefficients for the linear regression problem. If multiple targets are passed during the fit (y 2D), this is a 2D array of shape (n_targets, n_features), while if only one target is passed, this is a 1D array of length n_features.

intercept_ : *array*

Independent term in the linear model.

Notes

From the implementation point of view, this is just plain Ordinary Least Squares (scipy.linalg.lstsq) wrapped as a predictor object.

Examples

```
>>> import numpy as np
>>> from sklearn.linear_model import LinearRegression
>>> X = np.array([[1, 1], [1, 2], [2, 2], [2, 3]])
>>> # y = 1 * x_0 + 2 * x_1 + 3
>>> y = np.dot(X, np.array([1, 2])) + 3
>>> reg = LinearRegression().fit(X, y)
>>> reg.score(X, y)
1.0
>>> reg.coef_
array([1., 2.])
>>> reg.intercept_
3.0000...
>>> reg.predict(np.array([[3, 5]]))
array([16.])
```

Methods

`fit`(self, X, y[, sample_weight])	Fit linear model.
`get_params`(self[, deep])	Get parameters for this estimator.
`predict`(self, X)	Predict using the linear model
`score`(self, X, y[, sample_weight])	Returns the coefficient of determination R^2 of the prediction.
`set_params`(self, **params)	Set the parameters of this estimator.

`__init__`(*self, fit_intercept=True, normalize=False, copy_X=True, n_jobs=None*) [source]

`fit`(*self, X, y, sample_weight=None*) [source]

Fit linear model.

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

Training data

y : *array_like, shape (n_samples, n_targets)*

Target values. Will be cast to X's dtype if necessary

sample_weight : *numpy array of shape [n_samples]*

Individual weights for each sample

New in version 0.17: parameter *sample_weight* support to LinearRegression.

Returns: **self** : *returns an instance of self.*

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`get_params`(*self*, *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.

`predict`(*self*, *X*) [source]

Predict using the linear model

Parameters: **X** : *array_like or sparse matrix, shape (n_samples, n_features)*

Samples.

Returns: **C** : *array, shape (n_samples,)*

Returns predicted values.

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

Returns the coefficient of determination R^2 of the prediction.

The coefficient R^2 is defined as (1 - u/v), where u is the residual sum of squares ((y_true - y_pred) ** 2).sum() and v is the total sum of squares ((y_true - y_true.mean()) ** 2).sum(). The best possible score is 1.0 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

Parameters:

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

Test samples. For some estimators this may be a precomputed kernel matrix instead, shape = (n_samples, n_samples_fitted], where n_samples_fitted is the number of samples used in the fitting for the estimator.

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

True values for X.

sample_weight : *array-like, shape = [n_samples], optional*

Sample weights.

Returns:

score : *float*

R^2 of self.predict(X) wrt. y.

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Notes

The R2 score used when calling `score` on a regressor will use `multioutput='uniform_average'` from version 0.23 to keep consistent with `metrics.r2_score`. This will influence the `score` method of all the multioutput regressors (except for `multioutput.MultiOutputRegressor`). To specify the default value manually and avoid the warning, please either call `metrics.r2_score` directly or make a custom scorer with `metrics.make_scorer` (the built-in scorer `'r2'` uses `multioutput='uniform_average'`).

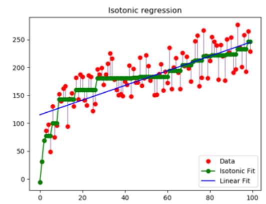
set_params(*self*, ***params*) [source]

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.

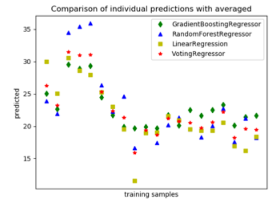
Returns: self

Examples using `sklearn.linear_model.LinearRegression`

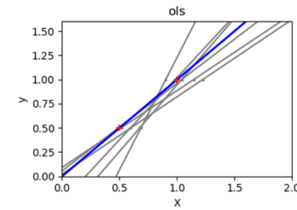


Isotonic Regression

Face completion with a multi-output estimators



Plot individual and voting regression predictions



Ordinary Least Squares and Ridge Regression Variance

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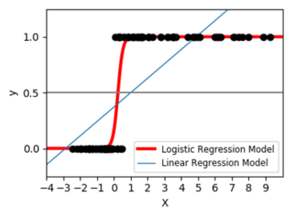
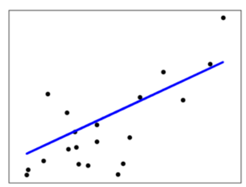
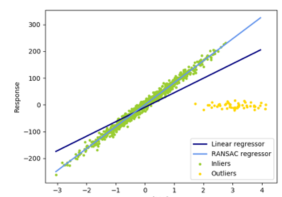


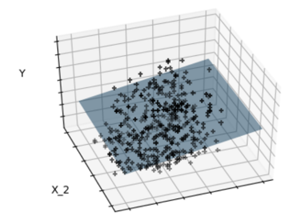
Logistic function



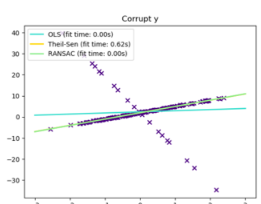
Linear Regression Example



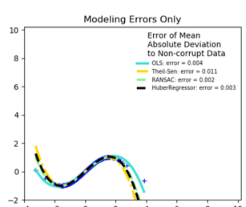
Robust linear model estimation using RANSAC



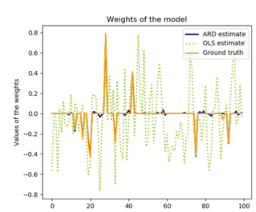
Sparsity Example: Fitting only features 1 and 2



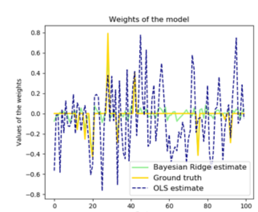
Theil-Sen Regression



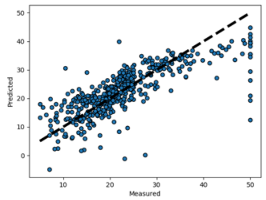
Robust linear estimator fitting

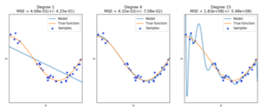


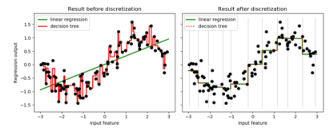
Automatic Relevance Determination Regression (ARD)



Bayesian Ridge Regression







» [Plotting Cross-Validated Predictions] [Underfitting vs. Overfitting] [Using KBinsDiscretizer to discretize continuous features]