



[Home](#) [Installation](#)  
[Documentation](#)  
[Examples](#)

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# sklearn.linear\_model.LinearRegression

```
class sklearn.linear_model.LinearRegression(fit_intercept=True,  
normalize=False, copy_X=True, n_jobs=1) \[source\]
```

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, optional, default 1

The number of jobs to use for the computa-

tion. If -1 all CPUs are used. This will only provide speedup for `n_targets > 1` and sufficient large problems.

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**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.

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## Notes

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

## Methods

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**fit**(X, y[, sample\_weight]) Fit linear model.

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**get\_params**([deep]) Get parameters for this estimator.

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**predict**(X) Predict using the linear model

---

**score**(X, y[, sample\_weight]) Returns the coefficient of determination  $R^2$  of the prediction.

---

**set\_params**(\*\*params) Set the parameters of this estimator.

---

**\_\_init\_\_**(fit\_intercept=True, normalize=False, copy\_X=True, n\_jobs=1) [\[source\]](#)

**fit**(X, y, sample\_weight=None) [\[source\]](#)

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Fit linear model.

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**Parameters:** **X** : numpy array or sparse matrix of shape

`[n_samples, n_features]`

Training data

**y** : numpy array of 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.

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

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**get\_params**(*deep=True*)

[\[source\]](#)

Get parameters for this estimator.

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**Parameters:**   **deep** : boolean, optional

If True, will return the parameters for this estimator and contained subobjects that are estimators.

«

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**Returns:**     **params** : mapping of string to any

Parameter names mapped to their values.

---

**predict**(*X*)

[\[source\]](#)

Predict using the linear model

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**Parameters:**   **X** : {array-like, sparse matrix}, shape = (n\_samples, n\_features)

Samples.

---

**Returns:**     **C** : array, shape = (n\_samples,)

Returns predicted values.

---

**score**(*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  $((y_{\text{true}} - y_{\text{pred}})^2).sum()$  and  $v$  is the total sum of squares  $((y_{\text{true}} - y_{\text{true}.mean()})^2).sum()$ . 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.

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**Parameters:**   **X** : array-like, shape = (n\_samples, n\_features)

Test samples.

**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.  $y$ .

---

**set\_params**(\*\**params*)

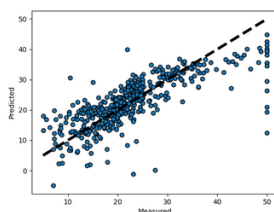
[\[source\]](#)

Set the parameters of this estimator.

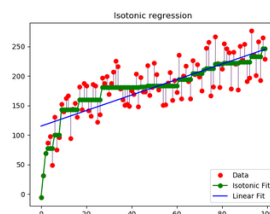
The method works on simple estimators as well as on nested objects (such as pipelines). The latter have parameters of the form `<component>__<parameter>` so that it's possible to update each component of a nested object.

**Returns:** `self` :

## Examples using `sklearn.linear_model.LinearRegression`



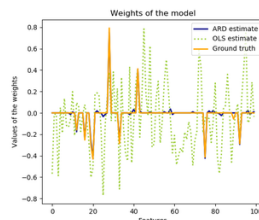
Plotting Cross-Validated Predictions



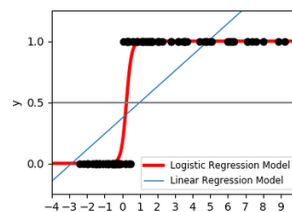
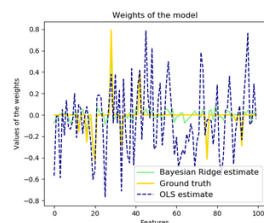
Isotonic Regression



Face completion with a multi-output estimators

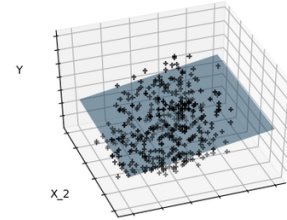
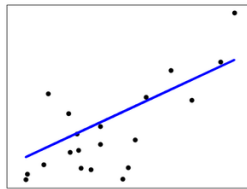


Automatic Relevance Determination Regression (ARD)



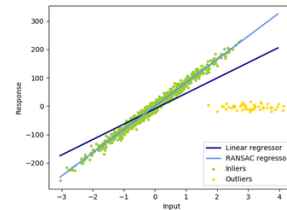
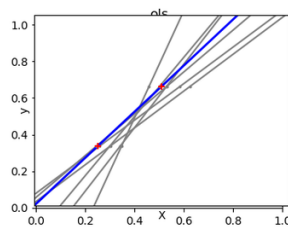
## Bayesian Ridge Regression

## Logistic function



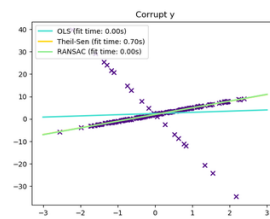
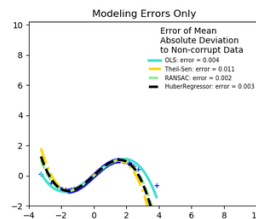
## Linear Regression Example

## Sparsity Example: Fitting only features 1 and 2



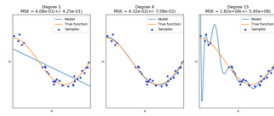
## Ordinary Least Squares and Ridge Regression Variance

## Robust linear model estimation using RANSAC



## Robust linear estimator fitting

## Theil-Sen Regression



## Underfitting vs. Overfitting