sklearn.linear_model.LinearRegression

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

Ordinary least squares Linear Regression.

LinearRegression fits a linear model with coefficients w = (w1, …, wp) to minimize the residual sum of squares between the observed targets in the dataset, and the targets predicted by the linear approximation.

Parameters:

fit_intercept : *bool, default=True*
Whether to calculate the intercept for this model. If set to False, no intercept will be used in calculations (i.e. data is expected to be centered).

copy_X : *bool, default=True*
If True, X will be copied; else, it may be overwritten.

n_jobs : *int, default=None*
The number of jobs to use for the computation. This will only provide speedup in case of sufficiently large problems, that is if firstly `n_targets > 1` and secondly `X` is sparse or if `positive` is set to `True`. `None` means 1 unless in a `joblib.parallel_backend` context. `-1` means using all processors. See Glossary for more details.

positive : *bool, default=False*
When set to `True`, forces the coefficients to be positive. This option is only supported for dense arrays.

New in version 0.24.

Attributes:

coef_ : *array of 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.

rank_ : *int*
Rank of matrix `X`. Only available when `X` is dense.

singular_ : *array of shape (min(X, y),)*
Singular values of `X`. Only available when `X` is dense.

intercept_ : *float or array of shape (n_targets,)*
Independent term in the linear model. Set to 0.0 if `fit_intercept = 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.

See also:

`Ridge`

Ridge regression addresses some of the problems of Ordinary Least Squares by imposing a penalty on the size of the coefficients with l2 regularization.

Lasso

The Lasso is a linear model that estimates sparse coefficients with l1 regularization.

ElasticNet

Elastic-Net is a linear regression model trained with both l1 and l2 -norm regularization of the coefficients.

Notes

From the implementation point of view, this is just plain Ordinary Least Squares (scipy.linalg.lstsq) or Non Negative Least Squares (scipy.optimize.nnls) 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_
3.0...
>>> reg.predict(np.array([[3, 5]]))
array([16.])
```

Methods

`fit`(X, y[, sample_weight])	Fit linear model.
`get_metadata_routing`()	Get metadata routing of this object.
`get_params`([deep])	Get parameters for this estimator.
`predict`(X)	Predict using the linear model.
`score`(X, y[, sample_weight])	Return the coefficient of determination of the prediction.
`set_fit_request`(*[, sample_weight])	Request metadata passed to the `fit` method.
`set_params`(**params)	Set the parameters of this estimator.
`set_score_request`(*[, sample_weight])	Request metadata passed to the `score` method.

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

Fit linear model.

Parameters:

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

y : *array-like of shape (n_samples,) or (n_samples, n_targets)*
Target values. Will be cast to X's dtype if necessary.

sample_weight : *array-like of shape (n_samples,), default=None*
Individual weights for each sample.

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

Returns:

self : *object*
Fitted Estimator.

`get_metadata_routing`() [source]

Get metadata routing of this object.

Please check User Guide on how the routing mechanism works.

Returns:

routing : *MetadataRequest*
A `MetadataRequest` encapsulating routing information.

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

Return the coefficient of determination of the prediction.

The coefficient of determination R^2 is defined as $(1 - \frac{u}{v})$, 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 of shape (n_samples, n_features)*
Test samples. For some estimators this may be a precomputed kernel matrix or a list of generic objects instead with 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 of shape (n_samples,) or (n_samples, n_outputs)*
True values for `X`.

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

Returns:

score : *float*
R^2 of `self.predict(X)` w.r.t. `y`.

Notes

The R^2 score used when calling `score` on a regressor uses `multioutput='uniform_average'` from version 0.23 to keep consistent with default value of `r2_score`. This influences the `score` method of all the multioutput regressors (except for `MultiOutputRegressor`).

`set_fit_request`(**, sample_weight: Union[bool, None, str] = '$UNCHANGED$'*) → LinearRegression [source]

Request metadata passed to the `fit` method.

Note that this method is only relevant if `enable_metadata_routing=True` (see `sklearn.set_config`). Please see User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `fit` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `fit`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

New in version 1.3.

Note: This method is only relevant if this estimator is used as a sub-estimator of a meta-estimator, e.g. used inside a `Pipeline`. Otherwise it has no effect.

Parameters:

sample_weight : *str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*
Metadata routing for `sample_weight` parameter in `fit`.

Returns:

self : *object*
The updated object.

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.

set_score_request(**, sample_weight: Union[bool, None, str] = '$UNCHANGED$'*) → LinearRegression [source]

Request metadata passed to the `score` method.

Note that this method is only relevant if `enable_metadata_routing=True` (see **sklearn.set_config**). Please see User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `score` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `score`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

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Note: This method is only relevant if this estimator is used as a sub-estimator of a meta-estimator, e.g. used inside a **Pipeline**. Otherwise it has no effect.

Parameters:

sample_weight : *str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*

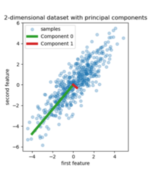
Metadata routing for `sample_weight` parameter in `score`.

Returns:

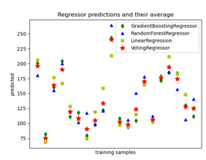
self : *object*

The updated object.

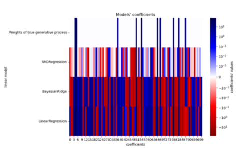
Examples using `sklearn.linear_model.LinearRegression`



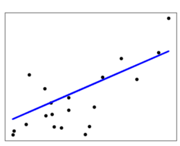
Principal Component



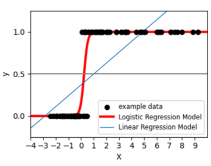
Plot individual and



Comparing Linear



Linear Regression



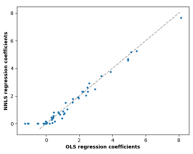
Logistic function

Regression vs Partial Least Squares Regression

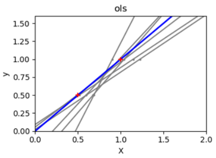
voting regression predictions

Bayesian Regressors

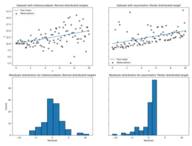
Example



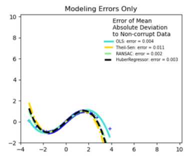
Non-negative least squares



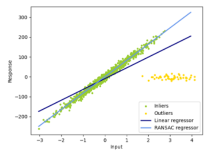
Ordinary Least Squares and Ridge Regression Variance



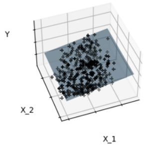
Quantile regression



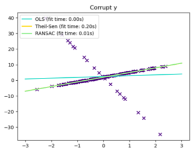
Robust linear estimator fitting



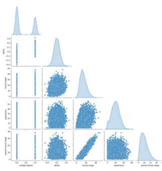
Robust linear model estimation using RANSAC



Sparsity Example: Fitting only features 1 and 2

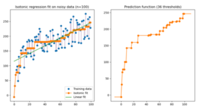


Theil-Sen Regression



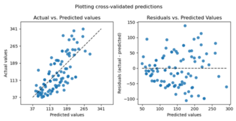
Failure of Machine Learning to infer causal effects

Face completion with a multi-output estimators

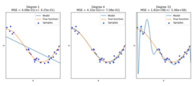


Isotonic Regression

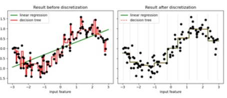
Metadata Routing



Plotting Cross-Validated Predictions



Underfitting vs. Overfitting



Using KBinsDiscretizer to discretize continuous features

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