sklearn.preprocessing.StandardScaler

class `sklearn.preprocessing.StandardScaler`(**, copy=True, with_mean=True, with_std=True*) [source]

Standardize features by removing the mean and scaling to unit variance.

The standard score of a sample `x` is calculated as:

```
z = (x - u) / s
```

where `u` is the mean of the training samples or zero if `with_mean=False`, and `s` is the standard deviation of the training samples or one if `with_std=False`.

Centering and scaling happen independently on each feature by computing the relevant statistics on the samples in the training set. Mean and standard deviation are then stored to be used on later data using `transform`.

Standardization of a dataset is a common requirement for many machine learning estimators: they might behave badly if the individual features do not more or less look like standard normally distributed data (e.g. Gaussian with 0 mean and unit variance).

For instance many elements used in the objective function of a learning algorithm (such as the RBF kernel of Support Vector Machines or the L1 and L2 regularizers of linear models) assume that all features are centered around 0 and have variance in the same order. If a feature has a variance that is orders of magnitude larger than others, it might dominate the objective function and make the estimator unable to learn from other features correctly as expected.

This scaler can also be applied to sparse CSR or CSC matrices by passing `with_mean=False` to avoid breaking the sparsity structure of the data.

Read more in the User Guide.

Parameters:

copy : ***bool, default=True***

If False, try to avoid a copy and do inplace scaling instead. This is not guaranteed to always work inplace; e.g. if the data is not a NumPy array or scipy.sparse CSR matrix, a copy may still be returned.

with_mean : ***bool, default=True***

If True, center the data before scaling. This does not work (and will raise an exception) when attempted on sparse matrices, because centering them entails building a dense matrix which in common use cases is likely to be too large to fit in memory.

with_std : ***bool, default=True***

If True, scale the data to unit variance (or equivalently, unit standard deviation).

Attributes:

scale_ : ***ndarray of shape (n_features,) or None***

Per feature relative scaling of the data to achieve zero mean and unit variance. Generally this is calculated using `np.sqrt(var_)`. If a variance is zero, we can't achieve unit variance, and the data is left as-is, giving a scaling factor of 1. `scale_` is equal to `None` when `with_std=False`.

*New in version 0.17: scale_*

mean_ : ***ndarray of shape (n_features,) or None***

The mean value for each feature in the training set. Equal to `None` when `with_mean=False`.

var_ : ***ndarray of shape (n_features,) or None***

The variance for each feature in the training set. Used to compute `scale_`. Equal to `None` when `with_std=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_samples_seen_ : ***int or ndarray of shape (n_features,)***

The number of samples processed by the estimator for each feature. If there are no missing samples, the `n_samples_seen` will be an integer, otherwise it will be an array of dtype int. If `sample_weights` are used it will be a float (if no missing data) or an array of dtype float that sums the weights seen so far. Will be reset on new calls to fit, but increments across `partial_fit` calls.

See also:

`scale`

Equivalent function without the estimator API.

`PCA`

Further removes the linear correlation across features with 'whiten=True'.

Notes

NaNs are treated as missing values: disregarded in fit, and maintained in transform.

We use a biased estimator for the standard deviation, equivalent to `numpy.std(x, ddof=0)`. Note that the choice of `ddof` is unlikely to affect model performance.

For a comparison of the different scalers, transformers, and normalizers, see examples/preprocessing/plot_all_scaling.py.

Examples

```
>>> from sklearn.preprocessing import StandardScaler
>>> data = [[0, 0], [0, 0], [1, 1], [1, 1]]
>>> scaler = StandardScaler()
>>> print(scaler.fit(data))
StandardScaler()
>>> print(scaler.mean_)
[0.5 0.5]
>>> print(scaler.transform(data))
[[-1. -1.]
 [-1. -1.]
 [ 1.  1.]
 [ 1.  1.]]
>>> print(scaler.transform([[2, 2]]))
[[3. 3.]]
```

Methods

`fit`(X[, y, sample_weight])	Compute the mean and std to be used for later scaling.
`fit_transform`(X[, y])	Fit to data, then transform it.
`get_feature_names_out`([input_features])	Get output feature names for transformation.
`get_params`([deep])	Get parameters for this estimator.
`inverse_transform`(X[, copy])	Scale back the data to the original representation.
`partial_fit`(X[, y, sample_weight])	Online computation of mean and std on X for later scaling.
`set_params`(**params)	Set the parameters of this estimator.
`transform`(X[, copy])	Perform standardization by centering and scaling.

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

Compute the mean and std to be used for later scaling.

Parameters:

X : *{array-like, sparse matrix} of shape (n_samples, n_features)*
The data used to compute the mean and standard deviation used for later scaling along the features axis.

y : *None*
Ignored.

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

New in version 0.24: parameter *sample_weight* support to StandardScaler.

Returns:

self : *object*
Fitted scaler.

fit_transform(*X*, *y=None*, ***fit_params*) [source]

Fit to data, then transform it.

Fits transformer to `X` and `y` with optional parameters `fit_params` and returns a transformed version of `X`.

Parameters:

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

y : ***array-like of shape (n_samples,) or (n_samples, n_outputs), default=None***
Target values (None for unsupervised transformations).

****fit_params** : ***dict***
Additional fit parameters.

Returns:

X_new : ***ndarray array of shape (n_samples, n_features_new)***
Transformed array.

`get_feature_names_out`(*input_features=None*) [source]

Get output feature names for transformation.

Parameters:

input_features : ***array-like of str or None, default=None***
Input features.

- If `input_features` is `None`, then `feature_names_in_` is used as feature names in. If `feature_names_in_` is not defined, then the following input feature names are generated: `["x0", "x1", ..., "x(n_features_in_ - 1)"]`.
- If `input_features` is an array-like, then `input_features` must match `feature_names_in_` if `feature_names_in_` is defined.

Returns:

feature_names_out : ***ndarray of str objects***
Same as input features.

`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.

`inverse_transform`(*X*, *copy=None*) [source]

Scale back the data to the original representation.

Parameters:

X : *{array-like, sparse matrix} of shape (n_samples, n_features)*
The data used to scale along the features axis.

copy : *bool, default=None*
Copy the input X or not.

Returns:

X_tr : *{ndarray, sparse matrix} of shape (n_samples, n_features)*
Transformed array.

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

Online computation of mean and std on X for later scaling.

All of X is processed as a single batch. This is intended for cases when **`fit`** is not feasible due to very large number of `n_samples` or because X is read from a continuous stream.

The algorithm for incremental mean and std is given in Equation 1.5a,b in Chan, Tony F., Gene H. Golub, and Randall J. LeVeque. "Algorithms for computing the sample variance: Analysis and recommendations." The American Statistician 37.3 (1983): 242-247:

Parameters:

X : *{array-like, sparse matrix} of shape (n_samples, n_features)*
The data used to compute the mean and standard deviation used for later scaling along the features axis.

y : *None*
Ignored.

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

New in version 0.24: parameter *sample_weight* support to StandardScaler.

Returns:

self : *object*
Fitted scaler.

`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.

`transform`(*X*, *copy=None*) [source]

Perform standardization by centering and scaling.

Parameters:

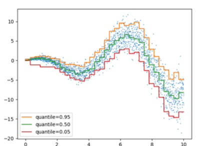
X : *{array-like, sparse matrix of shape (n_samples, n_features)}*
The data used to scale along the features axis.

copy : *bool, default=None*
Copy the input X or not.

Returns:

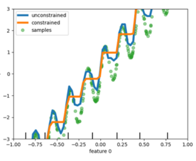
X_tr : *{ndarray, sparse matrix} of shape (n_samples, n_features)*
Transformed array.

Examples using `sklearn.preprocessing.StandardScaler`

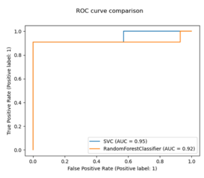


Release Highlights for scikit-learn 1.1

Release Highlights for scikit-learn 1.0



Release Highlights for scikit-learn 0.23



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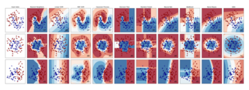
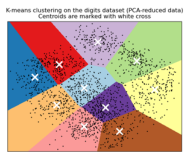
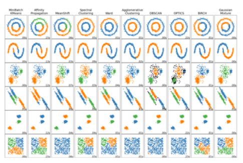


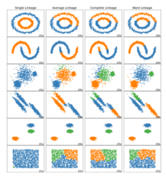
Classifier comparison



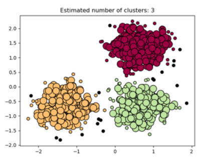
A demo of K-Means clustering on the handwritten digits data



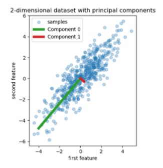
Comparing different clustering algorithms on toy datasets



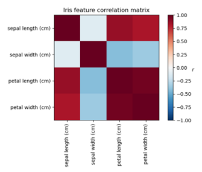
Comparing different hierarchical linkage methods on toy datasets



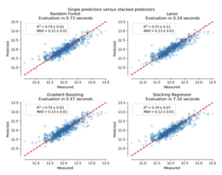
Demo of DBSCAN clustering algorithm



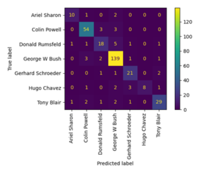
Principal Component Regression vs Partial Least Squares Regression



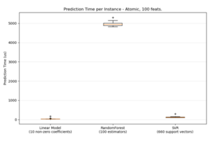
Factor Analysis (with rotation) to visualize patterns



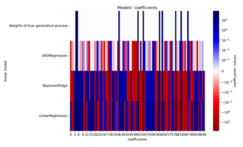
Combine predictors using stacking



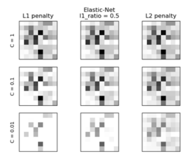
Faces recognition example using eigenfaces and SVMs

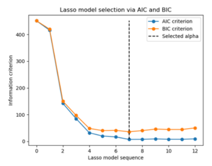


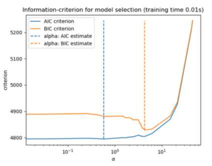
Prediction Latency

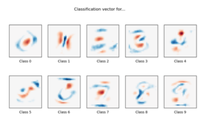


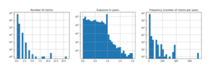
Comparing Linear Bayesian Regressors











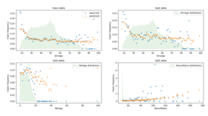
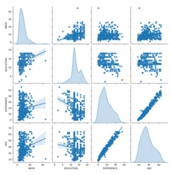
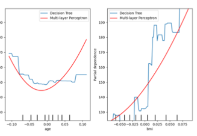
L1 Penalty and Sparsity in Logistic Regression

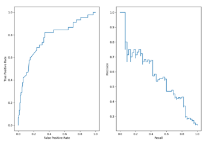
Lasso model selection via information criteria

Lasso model selection: AIC-BIC / cross-validation

MNIST classification using multinomial logistic + L1

Poisson regression and non-normal loss



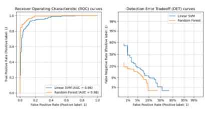
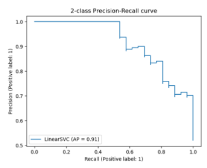
Tweedie regression on insurance claims

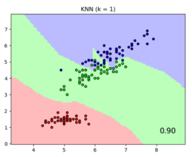
Common pitfalls in the interpretation of coefficients of linear models

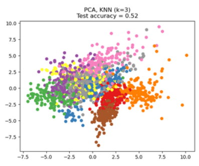
Advanced Plotting With Partial Dependence

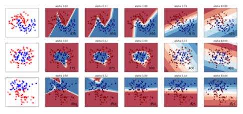
Displaying Pipelines

Visualizations with Display Objects







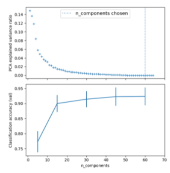
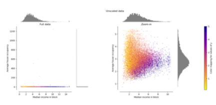
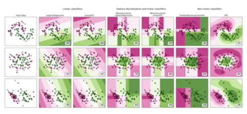
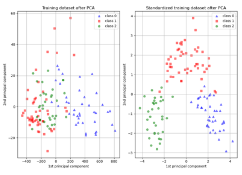
Detection error tradeoff (DET) curve

Precision-Recall

Comparing Nearest Neighbors with and without Neighborhood Components Analysis

Dimensionality Reduction with Neighborhood Components Analysis

Varying regularization in Multi-layer Perceptron

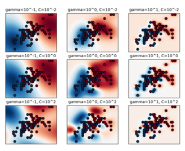
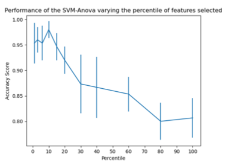
Column Transformer with Mixed Types

Pipelining: chaining a PCA and a logistic regression

Compare the effect of different scalers on data with outliers

Feature discretization

Importance of Feature Scaling

RBF SVM parameters

SVM-Anova: SVM with univariate feature selection

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