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.

`StandardScaler` is sensitive to outliers, and the features may scale differently from each other in the presence of outliers. For an example visualization, refer to Compare StandardScaler with other scalers.

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`.

> *Added 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` and `with_std=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_mean=False` and `with_std=False`.

n_features_in_ : ***int***

Number of features seen during fit.

> *Added 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.

> *Added 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.

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.]]
```

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.

> *Added 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_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.

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.

> *Added in version 0.24:* parameter *sample_weight* support to StandardScaler.

Returns:

self : *object*

Fitted scaler.

set_fit_request(*, *sample_weight: bool | None | str = '$UNCHANGED$'*) → StandardScaler [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.

Added 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_inverse_transform_request(*, *copy: bool | None | str = '$UNCHANGED$'*) → StandardScaler [source]

Request metadata passed to the `inverse_transform` 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 `inverse_transform` 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 `inverse_transform`.
- `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.

Added 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:

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

Metadata routing for `copy` parameter in `inverse_transform`.

Returns:

self : *object*

The updated object.

`set_output`(*, *transform=None*) [source]

Set output container.

See Introducing the set_output API for an example on how to use the API.

Parameters:

transform : *{"default", "pandas", "polars"}, default=None*

Configure output of `transform` and `fit_transform`.

- `"default"`: Default output format of a transformer
- `"pandas"`: DataFrame output
- `"polars"`: Polars output
- `None`: Transform configuration is unchanged

Added in version 1.4: `"polars"` option was added.

Returns:

self : *estimator instance*

Estimator instance.

`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_partial_fit_request(**, sample_weight: bool | None | str = '$UNCHANGED$'*) → StandardScaler [source]

Request metadata passed to the `partial_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 `partial_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 `partial_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.

> *Added 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 `partial_fit`.

Returns:

self : *object*

The updated object.

set_transform_request(*, *copy: bool | None | str = '$UNCHANGED$'*) → StandardScaler [source]

Request metadata passed to the `transform` 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 `transform` 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 `transform`.
- `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.

Added 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:

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

Metadata routing for `copy` parameter in `transform`.

Returns:

self : *object*

The updated object.

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***

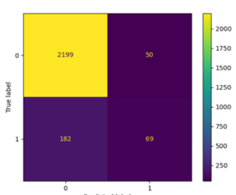
Copy the input X or not.

Returns:

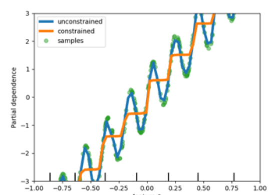
X_tr : ***{ndarray, sparse matrix} of shape (n_samples, n_features)***

Transformed array.

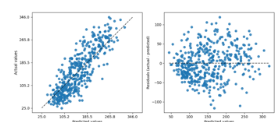
Gallery examples



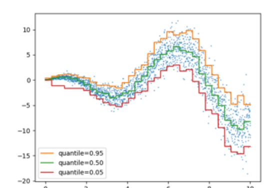
Release Highlights for scikit-learn 1.5



Release Highlights for scikit-learn 1.4

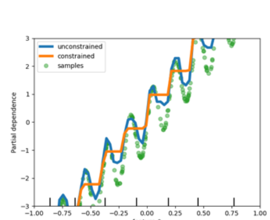


Release Highlights for scikit-learn 1.2

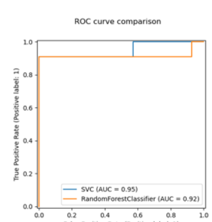


Release Highlights for scikit-learn 1.1

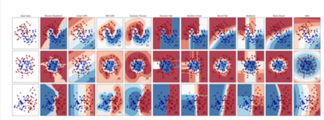
Release Highlights for scikit-learn 1.0



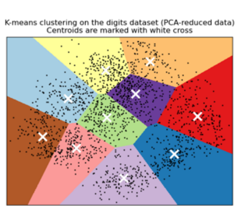
Release Highlights for scikit-learn 0.23

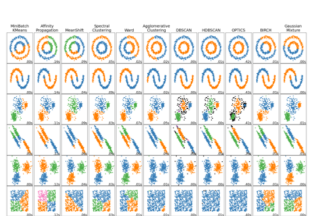


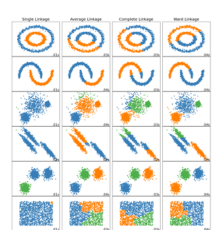
Release Highlights for scikit-learn 0.22

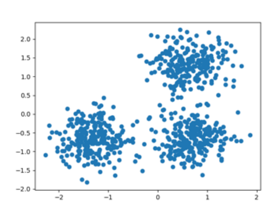


Classifier comparison







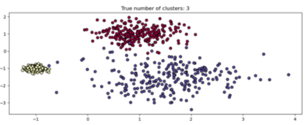


A demo of K-Means clustering on the handwritten digits data

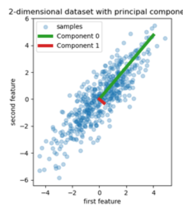
Comparing different clustering algorithms on toy datasets

Comparing different hierarchical linkage methods on toy datasets

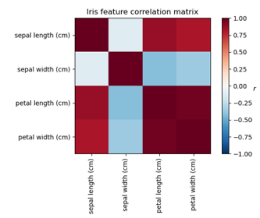
Demo of DBSCAN clustering algorithm



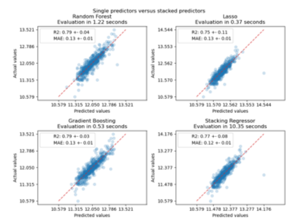
Demo of HDBSCAN clustering algorithm



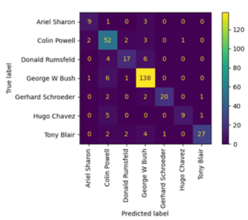
Principal Component Regression vs Partial Least Squares Regression



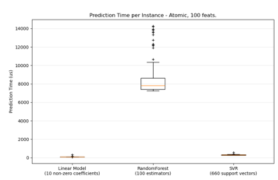
Factor Analysis (with rotation) to visualize patterns



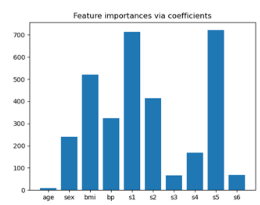
Combine predictors using stacking



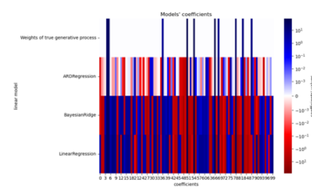
Faces recognition example using eigenfaces and SVMs



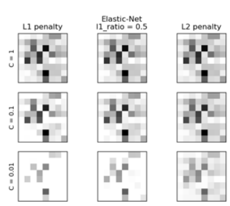
Prediction Latency



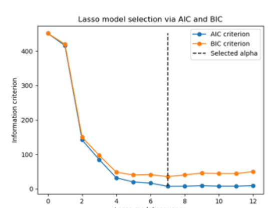
Model-based and sequential feature selection



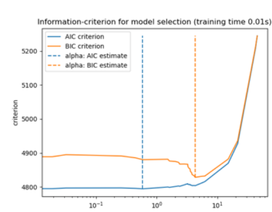
Comparing Linear Bayesian Regressors



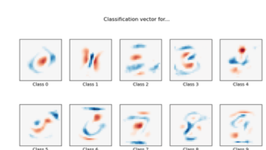
L1 Penalty and Sparsity in Logistic Regression



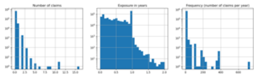
Lasso model selection via information criteria



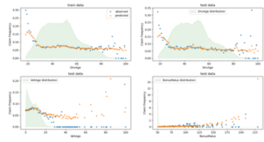
Lasso model selection: AIC-BIC / cross-validation



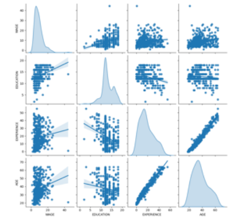
MNIST classification using multinomial logistic + L1



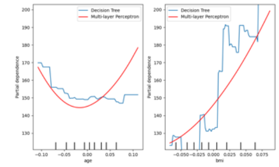
Poisson regression and non-normal loss



Tweedie regression on insurance claims



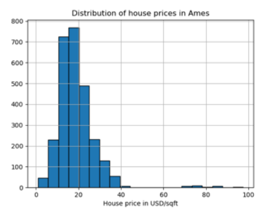
Common pitfalls in the interpretation of coefficients of linear models



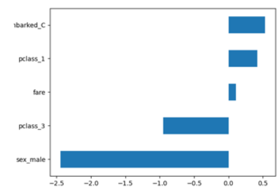
Advanced Plotting With Partial Dependence

Displaying Pipelines

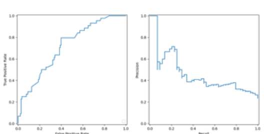
Displaying estimators and complex pipelines



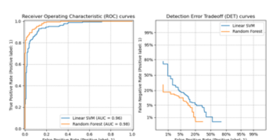
Evaluation of outlier detection estimators



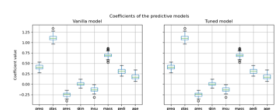
Introducing the set_output API



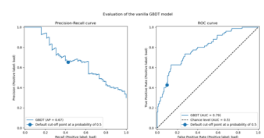
Visualizations with Display Objects



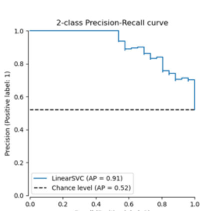
Detection error tradeoff (DET) curve



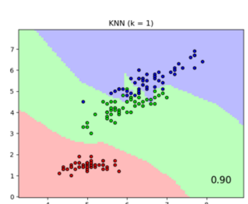
Post-hoc tuning the cut-off point of decision function



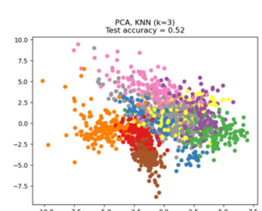
Post-tuning the decision threshold for cost-sensitive learning



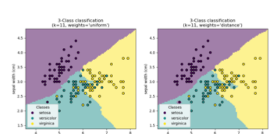
Precision-Recall



Comparing Nearest Neighbors with and without



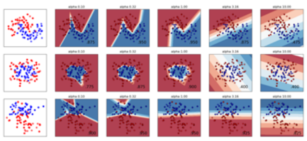
Dimensionality Reduction with Neighborhood



Nearest Neighbors Classification

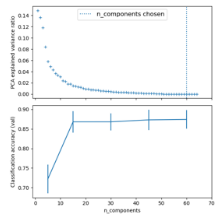
Neighborhood Components Analysis

Components Analysis

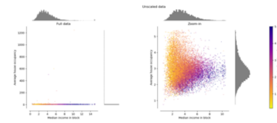


Varying regularization in Multi-layer Perceptron

Column Transformer with Mixed Types



Pipelining: chaining a PCA and a logistic regression



Compare the effect of different scalers on data with outliers