RobustScaler

class sklearn.preprocessing.**RobustScaler**(**, with_centering=True, with_scaling=True, quantile_range=(25.0, 75.0), copy=True, unit_variance=False*) [source]

Scale features using statistics that are robust to outliers.

This Scaler removes the median and scales the data according to the quantile range (defaults to IQR: Interquartile Range). The IQR is the range between the 1st quartile (25th quantile) and the 3rd quartile (75th quantile).

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

Standardization of a dataset is a common preprocessing for many machine learning estimators. Typically this is done by removing the mean and scaling to unit variance. However, outliers can often influence the sample mean / variance in a negative way. In such cases, using the median and the interquartile range often give better results. For an example visualization and comparison to other scalers, refer to Compare RobustScaler with other scalers.

Added in version 0.17.

Read more in the User Guide.

Parameters:

with_centering : *bool, default=True*

If `True`, center the data before scaling. This will cause `transform` to 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_scaling : *bool, default=True*

If `True`, scale the data to interquartile range.

quantile_range : *tuple (q_min, q_max), 0.0 < q_min < q_max < 100.0, default=(25.0, 75.0)*

Quantile range used to calculate `scale_`. By default this is equal to the IQR, i.e., `q_min` is the first quantile and `q_max` is the third quantile.

> **Added in version 0.18.**

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.

unit_variance : *bool, default=False*

If `True`, scale data so that normally distributed features have a variance of 1. In general, if the difference between the x-values of `q_max` and `q_min` for a standard normal distribution is greater than 1, the dataset will be scaled down. If less than 1, the dataset will be scaled up.

> **Added in version 0.24.**

Attributes:

center_ : *array of floats*

The median value for each feature in the training set.

scale_ : *array of floats*

The (scaled) interquartile range for each feature in the training set.

> **Added in version 0.17:** *scale_* attribute.

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.**

See also

`robust_scale`
Equivalent function without the estimator API.

`sklearn.decomposition.PCA`
Further removes the linear correlation across features with 'whiten=True'.

Notes

https://en.wikipedia.org/wiki/Median https://en.wikipedia.org/wiki/Interquartile_range

Examples

```
>>> from sklearn.preprocessing import RobustScaler
>>> X = [[ 1., -2.,  2.],
...      [ -2.,  1.,  3.],
...      [ 4.,  1., -2.]]
>>> transformer = RobustScaler().fit(X)
>>> transformer
RobustScaler()
>>> transformer.transform(X)
array([[ 0. , -2. ,  0. ],
       [-1. ,  0. ,  0.4],
       [ 1. ,  0. , -1.6]])
```

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

Compute the median and quantiles to be used for scaling.

Parameters:

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

y : *Ignored*
Not used, present here for API consistency by convention.

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*) [source]

Scale back the data to the original representation.

Parameters:

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

The rescaled data to be transformed back.

Returns:

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

Transformed array.

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.

`transform(X)` [source]

Center and scale the data.

Parameters:

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

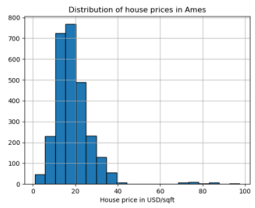
The data used to scale along the specified axis.

Returns:

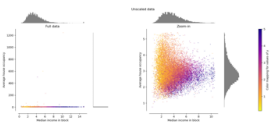
X_tr : *{ndarray, sparse matrix} of shape (n_samples, n_features)*

Transformed array.

Gallery examples



Evaluation of outlier detection estimators



Compare the effect of different scalers on data with