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## sklearn.preprocessing.OrdinalEncoder

class sklearn.preprocessing.OrdinalEncoder(categories='auto', dtype=<class
'numpy.float64'>) ¶

[source]

Encode categorical features as an integer array.

The input to this transformer should be an array-like of integers or strings, denoting the values taken on by categorical (discrete) features. The features are converted to ordinal integers. This results in a single column of integers (0 to n\_categories - 1) per feature.

Read more in the User Guide.

Parameters: categories: 'auto' or a list of lists/arrays of values.

Categories (unique values) per feature:

- 'auto': Determine categories automatically from the training data.
- list: categories[i] holds the categories expected in the ith column. The
  passed categories should not mix strings and numeric values, and should be
  sorted in case of numeric values.

The used categories can be found in the categories\_ attribute.

dtype: number type, default np.float64

Desired dtype of output.

**Attributes:** categories\_: list of arrays

The categories of each feature determined during fitting (in order of the features in X and corresponding with the output of transform).

## See also:

sklearn.preprocessing.OneHotEncoder

performs a one-hot encoding of categorical features.

sklearn.preprocessing.LabelEncoder

encodes target labels with values between 0 and n\_classes-1.

## **Examples**

Given a dataset with two features, we let the encoder find the unique values per feature and transform

the data to an ordinal encoding.

## **Methods**

<pre>transform(self, X)</pre>	Transform X to ordinal codes.
<pre>set_params(self, \*\*params)</pre>	Set the parameters of this estimator.
<pre>inverse_transform(self, X)</pre>	Convert the data back to the original representation.
<pre>get_params(self[, deep])</pre>	Get parameters for this estimator.
${\tt fit\_transform}({\tt Self},X[,y])$	Fit to data, then transform it.
<pre>fit(self, X[, y])</pre>	Fit the OrdinalEncoder to X.

```
__init__(self, categories='auto', dtype=<class 'numpy.float64'>) [source]
```

```
fit(self, X, y=None)
```

Fit the OrdinalEncoder to X.

**Parameters: X**: array-like, shape [n\_samples, n\_features]

The data to determine the categories of each feature.

Returns: self

```
fit_transform(self, 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 : numpy array of shape [n\_samples, n\_features] Training set.

y : numpy array of shape [n\_samples] Target values. **Returns:** X\_new: numpy array of shape [n\_samples, n\_features\_new] Transformed array.

get\_params(self, deep=True)

[source]

Get parameters for this estimator.

Parameters: deep: boolean, optional

If True, will return the parameters for this estimator and contained subob-

jects that are estimators.

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

Parameter names mapped to their values.

inverse\_transform(self, X)

[source]

Convert the data back to the original representation.

**Parameters:** X: array-like or sparse matrix, shape [n\_samples, n\_encoded\_features]

The transformed data.

**Returns: X\_tr**: array-like, shape [n\_samples, n\_features]

Inverse transformed array.

set\_params(self, \*\*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

transform(self, X)

[source]

Transform X to ordinal codes.

**Parameters:** X : array-like, shape [n\_samples, n\_features]

The data to encode.

Transformed input.

**X\_out** : sparse matrix or a 2-d array

Returns:

Previous