### Transformation pipelines

A transformation pipeline is a a sequence (sometimes called a *pipeline*) of independent transformations  $T_1, T_2, \ldots, T_l$ 

$$egin{aligned} ilde{\mathbf{x}}_{(1)} &= T_1(\mathbf{x}) \ ilde{\mathbf{x}}_{(2)} &= T_2( ilde{\mathbf{x}}_{(1)}) \ dots \ ilde{\mathbf{x}}_{(l)} &= T_l( ilde{\mathbf{x}}_{(l-1)}) \end{aligned}$$

The final transformed  $\tilde{\mathbf{x}}$  can be implemented as a function T that is the composition of each transformation function

$$\tilde{\mathbf{x}} = T(\mathbf{x}) = T_t(\ T_{t-1}(\dots T_1(\mathbf{x})\dots)\ )$$

# Pipelines in sklearn

sklearn has created a generic architecture called Pipeline to simplify this for you.

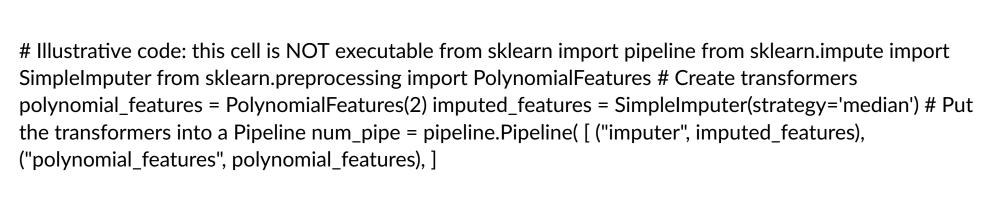
This module is **not meant to be a tutorial**, only to highlight a very convenient tool in sklearn.

<u>Here (https://scikit-learn.org/stable/modules/compose.html)</u> is a link to sklearn 's manual.

Let's illustrate with a two-step sequence of transformations on numeric features

- Missing data imputation
  - If feature j is missing for example i ( $\mathbf{x}_j^{(i)}$  not defined)
  - lacksquare Replace it with the median (over all m examples) of  $\mathbf{x}_j$
- Add a second order polynomial feature to each example

Here is some illustrative code



Each individual transformation has a fit and transform method, just like a model (e.g., LinearRegression)

- fit on the transformation SimpleImputer(strategy='median')
   computes the median value of each feature
  - ullet Computes  $\Theta_{transform}$ , the parameters of this transformation
- transform applies the transformation, after it has been fit
  - creates  $\tilde{\mathbf{x}}$  from  $\mathbf{x}$

The Pipeline num\_pipe defines a sequence of transformations

- Each element of the Pipeline is a tuple
  - name of the transformation (for your convenience in referencing it)
  - the transformer

The Pipeline also has methods fit and transform

- fit on a Pipeline applies fit to each component transformation in turn
- transform on a Pipeline applies transform to each component transformation in turn

The Pipeline is thus a composition of the individual transformations

$$\tilde{\mathbf{x}} = T(\mathbf{x}) = T_t(T_{t-1}(\dots T_1(\mathbf{x})\dots))$$

Observe that transformers and models both respond to the fit and transform methods. This means that you can include a model as the final element of a Pipeline!

# Illustrative code: this cell is NOT executable from sklearn import datasets, linear\_model linear\_regression = linear\_model.LinearRegression() full\_pipe = pipeline.Pipeline( [ ("imputer", imputed\_features), ("polynomial\_features", polynomial\_features), ("model", linear\_regression) ]

You can fit the transformations and the model in one step

full\_pipe.fit(X, y)

In addition to being a concise and convenient notation, pipelines with models as final elements

- Can be used in Cross Validation to avoid "cheating"
- The cross validation code passes in *only* the folds that are the training examples

# Example: Pipeline with model as final element

Let's apply a Pipeline to solve an example encountered in a previous module

- Linear Regression model
- With a second order feature added

Let's get the data again:



The PolynomialFeatures(2) transformer

- Replace each  $\boldsymbol{x}$
- With 3 features:  $\mathbf{x}^0, \mathbf{x}^1, \mathbf{x}^2$

That is: it creates an "intercept" dummy ( $\mathbf{x}^0 == 1$ ) plus first and second order features.

A pipeline successively applies transformations, with the result of transformation (i-1) fed as input to transformation i.

Let's look "inside" the pipeline at the stages, and apply them manually.

```
In [6]: # Examine the "stages" of the pipeline
    print("Input shape: {shp}".format(shp=X_test.reshape(-1,1).shape) )

# First stage: Create First and Second Order polynomial features
    (label_0, model_0) = poly_model.steps[0]
    transf_0 = model_0.transform(X_test.reshape(-1,1))
    print("{lab:s} returns shape: {shp}".format(lab=label_0, shp=transf_0.shape) )

# Second stage: Linear Regression
    (label_1, model_1) = poly_model.steps[1]
    transf_1 = model_1.predict( transf_0 )
    print("{lab:s} returns shape: {shp}".format(lab=label_1, shp=transf_1.shape) )

Input shape: (10, 1)
```

polynomialfeatures returns shape: (10, 3) linearregression returns shape: (10, 1)

```
In [7]: # Prediction based on test set
y_pred = poly_model.predict(X_test.reshape(-1,1))

# In and out of sample scores
print("Score (train): ", poly_model.score(X_train.reshape(-1,1), y_train))
print("Score (test): ", poly_model.score(X_test.reshape(-1,1), y_test))
```

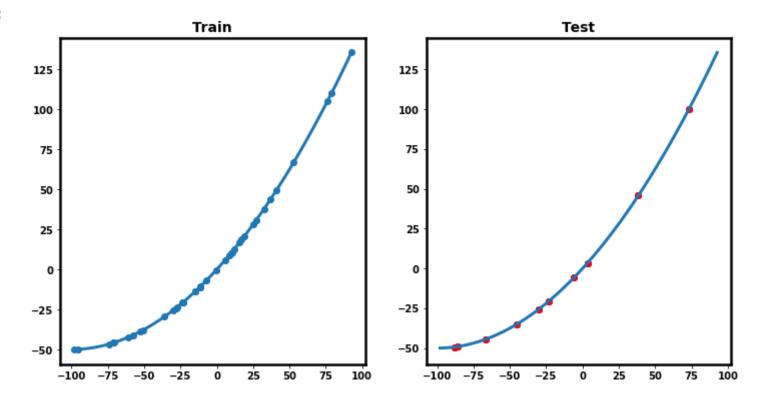
Score (train): 1.0 Score (test): 1.0

```
In [8]: # Plot the results
        # Create a figure
        fig, axs = plt.subplots(1,2, figsize=(12,6))
        = axs[0].scatter(X train,y train)
        xfit = np.linspace(X train[:,0].min(), X train[:,0].max()).reshape(-1,1)
        yfit = poly model.predict(xfit)
        = axs[0].plot(xfit, yfit);
        = axs[0].set title("Train")
        = axs[1].scatter(X test, y test, color="blue")
        = axs[1].scatter(X test, y pred, color="red")
        = axs[1].plot(xfit, yfit)
        _= axs[1].set_title("Test")
        print("R-squared score (test): {:.2f}".format(r2 score(y test, y pred)) )
        # Hide the figure for now, will show it in the next slide
        plt.close(fig)
```

R-squared score (test): 1.00

In [9]: | fig

Out[9]:



<u>Here's (external/PythonDataScienceHandbook/notebooks/05.04-Feature-Engineering.ipynb#Feature-Pipelines)</u> a slightly longer pipeline from VanderPlas.

- Imputer to deal with misssing values
- PolynomialFeatures(degree=2)
- LinearRegression()

### **Nested Pipelines**

A Pipeline responds to the same methods (fit, transform) as its elements.

This means that a Pipeline can also be used as a *nested* element of an outer Pipeline.

This is very convenient: we will illustrate this in our detailed example for Classification.

### **Advanced Pipelines**

An issue with Pipelines is that each transformation is applied to *all* the features in an example.

But some transformations need to be applied to *selected* features

- Can't apply numeric transformations to non-numeric data, and vice-versa
- May want to apply a particular transformation to only a subset of features

#### sklearn facilitates this by

- Allowing you to create "filters" that restrict features to a subset
- Applying one pipeline per subset
- Creating a union of transformed features at the end

### **FeatureUnion**

sklearn allows you to create complex Pipelines with the FeatureUnion Pipeline

- "glue together" the features of separate Pipelines. For example
  - Create one pipeline to be applied only to numeric features
  - Create one pipeline to be applied only to non-numeric features

Here is some illustrative code:

num\_pipeline = Pipeline([ ("select\_numeric", DataFrameSelector(["Age", "SibSp", "Parch", "Fare"])), ("imputer", SimpleImputer(strategy="median")), ]) cat\_pipeline = Pipeline([ ("select\_cat", DataFrameSelector(["Pclass", "Sex", "Embarked"])), ("imputer", MostFrequentImputer()), ("cat\_encoder", OneHotEncoder(sparse=False)), ]) from sklearn.pipeline import FeatureUnion preprocess\_pipeline = FeatureUnion(transformer\_list=[ ("num\_pipeline", num\_pipeline), ("cat\_pipeline", cat\_pipeline), ])

The first element in each pipeline (DataFrameSelector)

• restricts each example to a selected subset of features

So the numeric and categorical pipelines above transform disjoint groups of features.

The FeatureUnion concatenates (along the horizontal axis) the result of the separate transformations.

### ColumnTransformer

There is an experimental Pipeline object in sklearn called Column Transformers, that is a simplification of the FeatureUnion paradigm

- No need to filter the features with DataFrameSelector
  - just provide a list of feature names
- No need to use `FeatureUnion'

This object *only works* for collections of examples in which we can access features *by name* 

Panda DataFrames!

Here is some illustrative code

```
cat_features = ["Sex", "Pclass" ] cat_transformers= Pipeline(steps=[ ('imputer', MostFrequentImputer()),
  ('sex_encoder', SexToInt()) ] ) cat_pipeline = ColumnTransformer( transformers=[ ("categorical",
  cat_transformers, cat_features) ] )
```

### Creating your own transformations

In addition to supplying a number of built-in transformers, sklearn let's use build your own.

- Create an object that is subclass of the types used by built-in transformer
- Provide your own implementation of fit and transform

Here's a transformation for imputation of missing values using the most frequent value as the substitute.

Similar in function to the built-in
 SimpleImputer(strategy="most\_frequent")

# **Example**

We will use Pipelines in our Classification task.

```
In [11]: print("Done")
```

Done