Lecture 05

Data Preprocessing and Machine Learning with Scikit-Learn

(Computational Foundations Part 3/3)

STAT 479: Machine Learning, Fall 2018

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http://stat.wisc.edu/~sraschka/teaching/stat479-fs2018/

Part I: Introduction

- Lecture 1: What is Machine Learning? An Overview. [Lecture Material]
- Lecture 2: Intro to Supervised Learning: Nearest Neighbor Methods [Lecture Material]

Part II: Computational Foundations

- Lecture 3: Using Python, Anaconda, IPython, Jupyter Notebooks [Lecture Material]
- Lecture 4: Scientific Computing with NumPy, SciPy, and Matplotlib [Lecture Material]
- Data Preprocessing and Machine Learning with Scikit-Learn

Part III: Tree-Based Methods

- Decision Trees
- Ensemble Methods

Part IV: Evaluation

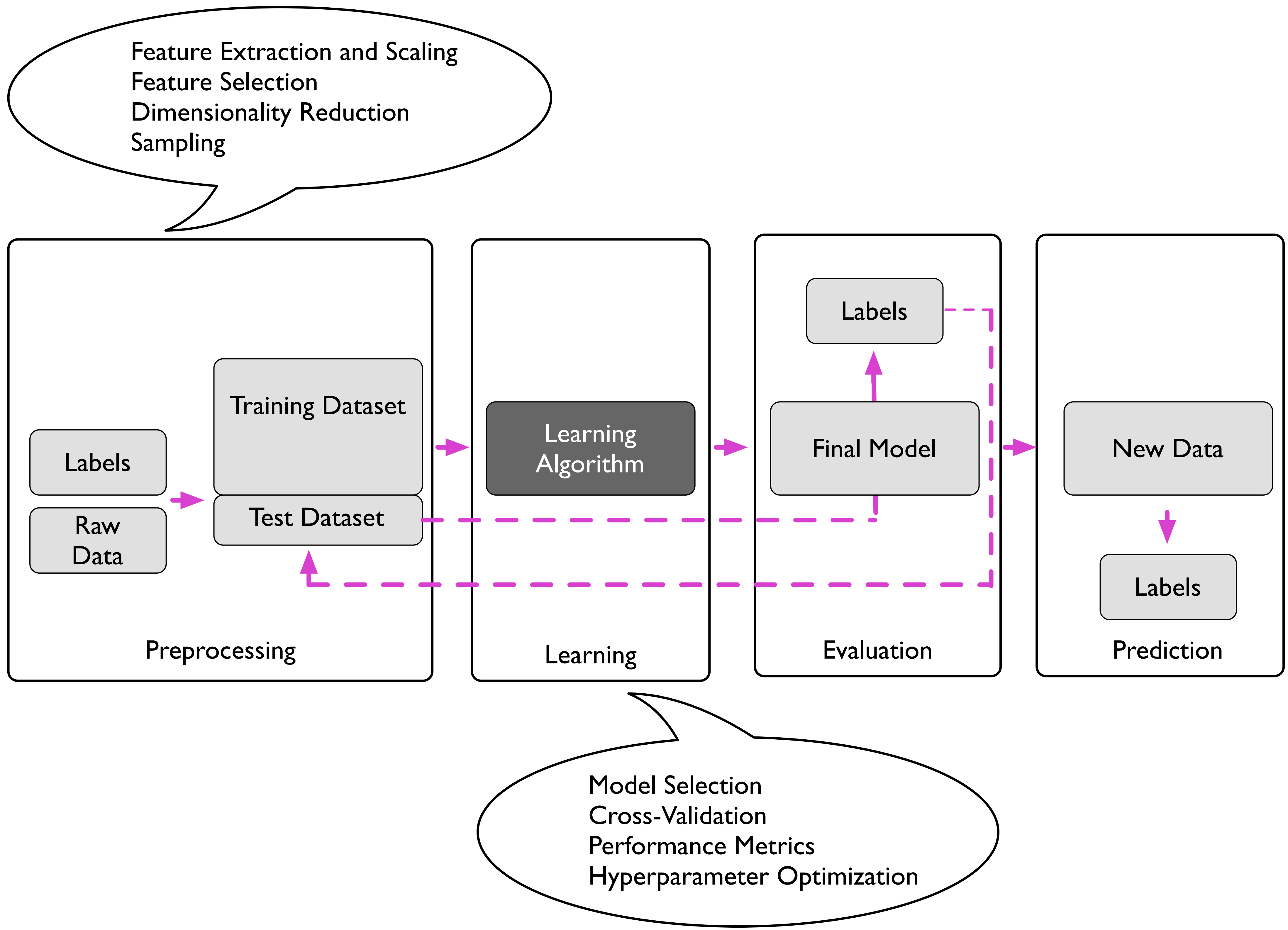
- Model Evaluation and Performance Metrics
- Model Selection and Cross-Validation

Part V: Dimensionality Reduction

- Feature Selection
- Feature Extraction

Part VI: Bayesian Learning

- Bayes Classifiers
- Text Data & Sentiment Analysis


Feature Extraction and Scaling
Feature Selection
Dimensionality Reduction
Sampling
Labels
Raw Data
Training Dataset
Test Dataset
Preprocessing
Learning Algorithm
Learning
Labels
Final Model
Evaluation
New Data
Labels
Prediction
Model Selection
Cross-Validation
Performance Metrics
Hyperparameter Optimization

Reading a Dataset from a Tabular Text File

Iris-Setosa **Iris-Versicolor** **Iris-Virginica**

Fisher, R.A. "The use of multiple measurements in taxonomic problems" Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to Mathematical Statistics" (John Wiley, NY, 1950).

```
!head iris.csv
```

```
Id,SepalLength[cm],SepalWidth[cm],PetalLength[cm],PetalWidth[cm],Species
1,5.1,3.5,1.4,0.2,Iris-setosa
2,4.9,3.0,1.4,0.2,Iris-setosa
3,4.7,3.2,1.3,0.2,Iris-setosa
4,4.6,3.1,1.5,0.2,Iris-setosa
5,5.0,3.6,1.4,0.2,Iris-setosa
6,5.4,3.9,1.7,0.4,Iris-setosa
7,4.6,3.4,1.4,0.3,Iris-setosa
8,5.0,3.4,1.5,0.2,Iris-setosa
9,4.4,2.9,1.4,0.2,Iris-setosa
```

https://pandas.pydata.org

McKinney, Wes. "Data structures for statistical computing in python." *Proceedings of the 9th Python in Science Conference*. Vol. 445. 2010.

pandas

$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

https://pandas.pydata.org

```
import pandas as pd


df = pd.read_csv('iris.csv')
df.head()
```

	Id	SepalLength[cm]	SepalWidth[cm]	PetalLength[cm]	PetalWidth[cm]	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

```
df.shape
```

```
(150, 6)
```

Basic Data Handling

Digression: Lambda Functions

```python
def some_func(x):
    return 'Hello World ' + str(x)

some_func(123)
```

```
'Hello World 123'
```

Digression: Lambda Functions

```
def some_func(x):
    return 'Hello World ' + str(x)

some_func(123)
```

```
'Hello World 123'
```

```
f = lambda x: 'Hello World ' + str(x)
f(123)
```

```
'Hello World 123'
```

Basic Data Handling

```
df['Species'] = df['Species'].apply(lambda x: 0 if x=='Iris-setosa' else x)
df.head()
```

	Id	SepalLength[cm]	SepalWidth[cm]	PetalLength[cm]	PetalWidth[cm]	Species
0	1	5.1	3.5	1.4	0.2	0
1	2	4.9	3.0	1.4	0.2	0
2	3	4.7	3.2	1.3	0.2	0
3	4	4.6	3.1	1.5	0.2	0
4	5	5.0	3.6	1.4	0.2	0

```
df.tail()
```

	Id	SepalLength[cm]	SepalWidth[cm]	PetalLength[cm]	PetalWidth[cm]	Species
145	146	6.7	3.0	5.2	2.3	2
146	147	6.3	2.5	5.0	1.9	2
147	148	6.5	3.0	5.2	2.0	2
148	149	6.2	3.4	5.4	2.3	2
149	150	5.9	3.0	5.1	1.8	2

.map vs. .apply

```python
d = {'Iris-setosa': 0,
     'Iris-versicolor': 1,
     'Iris-virginica': 2}

df = pd.read_csv('iris.csv')
df['Species'] = df['Species'].map(d)
df.head()
```

	Id	SepalLength[cm]	SepalWidth[cm]	PetalLength[cm]	PetalWidth[cm]	Species
0	1	5.1	3.5	1.4	0.2	0
1	2	4.9	3.0	1.4	0.2	0
2	3	4.7	3.2	1.3	0.2	0
3	4	4.6	3.1	1.5	0.2	0
4	5	5.0	3.6	1.4	0.2	0

NumPy Arrays

```
y = df['Species'].values
y
```

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

NumPy Arrays

```
y = df['Species'].values
y
```

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

```
X = df.iloc[:, 1:5].values
X[:5]
```

```
array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3. , 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2]])
```

MLXTEND http://rasbt.github.io/mlxtend/

Raschka, Sebastian. "MLxtend: Providing machine learning and data science utilities and extensions to Python’s scientific computing stack." *The Journal of Open Source Software* 3.24 (2018).

Exploratory Data Analysis

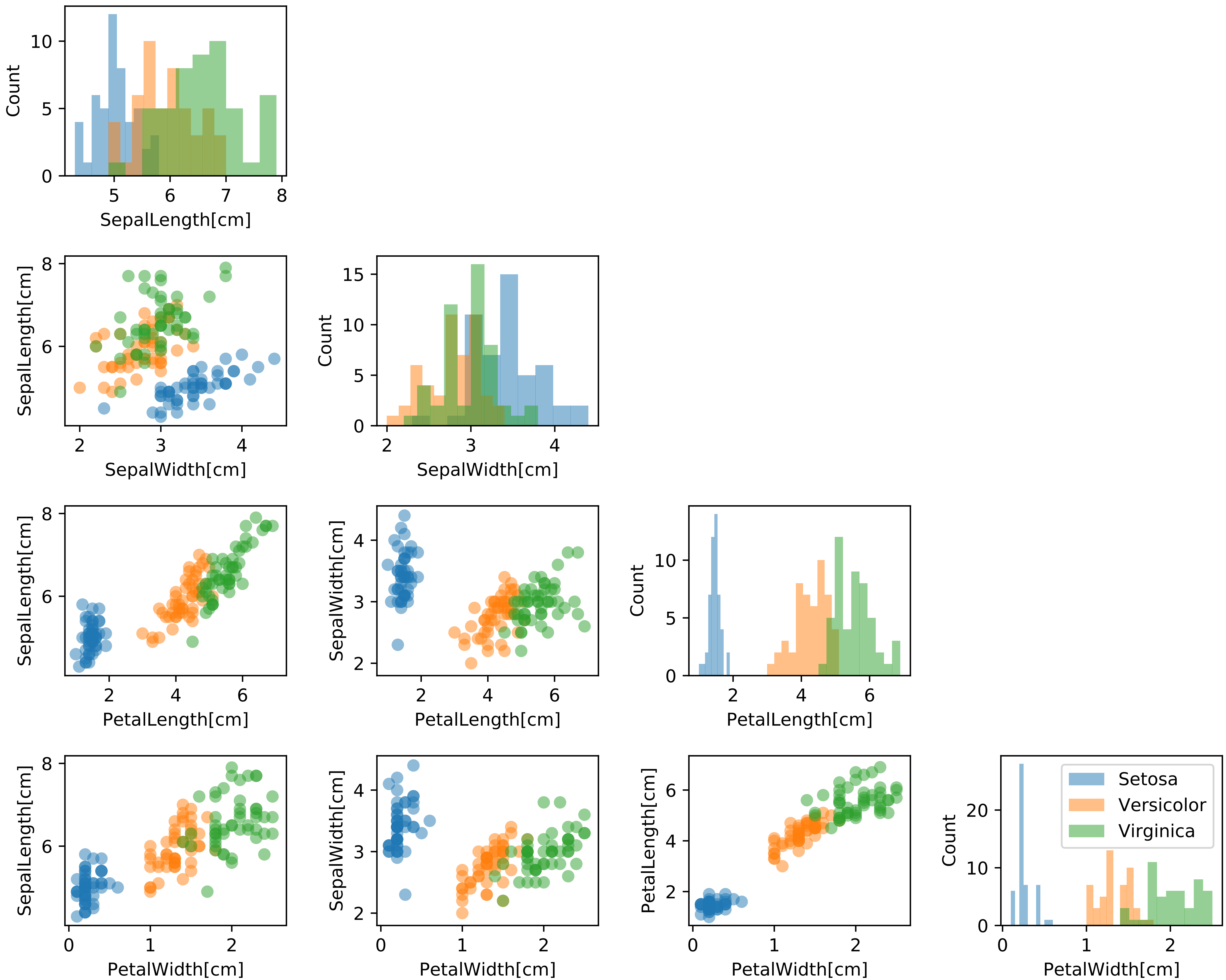
```
#!pip install git+git://github.com/rasbt/mlxtend.git
```

```
%matplotlib inline
import matplotlib.pyplot as plt
from mlxtend.data import iris_data
from mlxtend.plotting import scatterplotmatrix


names = df.columns[1:5]

fig, axes = scatterplotmatrix(X[y==0], figsize=(10, 8), alpha=0.5)
fig, axes = scatterplotmatrix(X[y==1], fig_axes=(fig, axes), alpha=0.5)
fig, axes = scatterplotmatrix(X[y==2], fig_axes=(fig, axes), alpha=0.5, names=names)

plt.tight_layout()
plt.legend(labels=['Setosa', 'Versicolor', 'Virginica'])
plt.show()
```


Count
SepalLength[cm]
SepalWidth[cm]
PetalLength[cm]
PetalWidth[cm]
Setosa
Versicolor
Virginica

Splitting a Dataset into Train, Validation, and Test Subsets

```
import numpy as np

indices = np.arange(X.shape[0])
rng = np.random.RandomState(123)
permuted_indices = rng.permutation(indices)
permuted_indices
```

Splitting a Dataset into Train, Validation, and Test Subsets

```python
import numpy as np

indices = np.arange(X.shape[0])
rng = np.random.RandomState(123)
permuted_indices = rng.permutation(indices)
permuted_indices
```

```
array([ 72, 112, 132,  88,  37, 138,  87,  42,   8,  90, 141,  33,  59,
       116, 135, 104,  36,  13,  63,  45,  28, 133,  24, 127,  46,  20,
        31, 121, 117,   4, 130, 119,  29,   0,  62,  93, 131,   5,  16,
        82,  60,  35, 143, 145, 142, 114, 136,  53,  19,  38, 110,  23,
         9,  86,  91,  89,  79, 101,  65, 115,  41, 124,  95,  21,  11,
       103,  74, 122, 118,  44,  51,  81, 149,  12, 129,  56,  50,  25,
       128, 146,  43,   1,  71,  54, 100,  14,   6,  80,  26,  70, 139,
        30, 108,  15,  18,  77,  22,  10,  58, 107,  75,  64,  69,   3,
        40,  76, 134,  34,  27,  94,  85,  97, 102,  52,  92,  99, 105,
         7,  48,  61, 120, 137, 125, 147,  39,  84,   2,  67,  55,  49,
        68, 140,  78, 144, 111,  32,  73,  47, 148, 113,  96,  57, 123,
       106,  83,  17,  98,  66, 126, 109])
```

Splitting a Dataset into Train, Validation, and Test Subsets

```
import numpy as np

indices = np.arange(X.shape[0])
rng = np.random.RandomState(123)
permuted_indices = rng.permutation(indices)
permuted_indices
```

```
       106,  83,  17,  98,  66, 126, 109])
```

```
train_size, valid_size = int(0.65*X.shape[0]), int(0.15*X.shape[0])
test_size = X.shape[0] - (train_size + valid_size)
print(train_size, valid_size, test_size)
```

```
97 22 31
```

```
train_ind = permuted_indices[:train_size]
valid_ind = permuted_indices[train_size:(train_size + valid_size)]
test_ind = permuted_indices[(train_size + valid_size):]
```

```
X_train, y_train = X[train_ind], y[train_ind]
X_valid, y_valid = X[valid_ind], y[valid_ind]
X_test, y_test = X[test_ind], y[test_ind]
```

```
(97, 4)
```

Python Classes

Python Classes

```python
class VehicleClass():

    def __init__(self, horsepower):
        "This is the 'init' method"
        # this is a class attribute:
        self.horsepower = horsepower

    def horsepower_to_torque(self, rpm):
        "This is a regular method"
        numerator = self.horsepower * 33000
        denominator = 2* np.pi * 5000
        return numerator/denominator

    def tune_motor(self):
        self.horsepower *= 2

    def _private_method(self):
        print('this is private')

    def __very_private_method(self):
        print('this is very private')
```

Python Classes

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    def _private_method(self):
        print('this is private')

    def __very_private_method(self):
        print('this is very private')
```

```python
# instantiate an object:
car1 = VehicleClass(horsepower=123)
print(car1.horsepower)
```

```
123
```

Python Classes

```python
class VehicleClass():

    def __init__(self, horsepower):
        "This is the 'init' method"
        # this is a class attribute:
        self.horsepower = horsepower

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    def _private_method(self):
        print('this is private')

    def __very_private_method(self):
        print('this is very private')
```

```python
# instantiate an object:
car1 = VehicleClass(horsepower=123)
print(car1.horsepower)
```

```
123
```

```python
car1.horsepower_to_torque(rpm=5000)
```

```
129.20198280200063
```

```python
car1.tune_motor()
car1.horsepower_to_torque(rpm=5000)
```

```
258.40396560400126
```

```python
class VehicleClass():

    def __init__(self, horsepower):
        "This is the 'init' method"
        # this is a class attribute:
        self.horsepower = horsepower

    def horsepower_to_torque(self, rpm):
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        numerator = self.horsepower * 33000
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    def tune_motor(self):
        self.horsepower *= 2

    def _private_method(self):
        print('this is private')

    def __very_private_method(self):
        print('this is very private')
```

```python
car1._private_method()
```

```
this is private
```

```python
car1.__very_private_method()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-23-818c47ec0aa2> in <module>()
----> 1 car1.__very_private_method()

AttributeError: 'VehicleClass' object has no attribute '__very_private_method'
```

Python Classes

```python
class VehicleClass():

    def __init__(self, horsepower):
        "This is the 'init' method"
        # this is a class attribute:
        self.horsepower = horsepower

    def horsepower_to_torque(self, rpm):
        "This is a regular method"
        numerator = self.horsepower * 33000
        denominator = 2* np.pi * 5000
        return numerator/denominator

    def tune_motor(self):
        self.horsepower *= 2

    def _private_method(self):
        print('this is private')

    def __very_private_method(self):
        print('this is very private')
```

```python
car1._private_method()
```

```
this is private
```

```python
car1.__very_private_method()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-23-818c47ec0aa2> in <module>()
----> 1 car1.__very_private_method()

AttributeError: 'VehicleClass' object has no attribute '__very_private_method'
```

```python
car1._VehicleClass__very_private_method()
```

```
this is very private
```

Python Classes

```
class CarClass(VehicleClass):

    def __init__(self, horsepower):
        super(CarClass, self).__init__(horsepower)
        self.num_wheels = 4

new_car = CarClass(horsepower=123)
print('Number of wheels:', new_car.num_wheels)
print('Horsepower:', new_car.horsepower)
new_car.tune_motor()
print('Horsepower:', new_car.horsepower)
```

```
Number of wheels: 4
Horsepower: 123
Horsepower: 246
```

K-Nearest Neighbors Implementation

```
class KNNClassifier(object):
    def __init__(self, k, dist_fn=None):
        self.k = k
        if dist_fn is None:
            self.dist_fn = self._euclidean_dist

    def _euclidean_dist(self, a, b):
        dist = 0.
        for ele_i, ele_j in zip(a, b):
            dist += ((ele_i - ele_j)**2)
        dist = dist**0.5
        return dist

    def _find_nearest(self, x):
        dist_idx_pairs = []
        for j in range(self.dataset_.shape[0]):
            d = self.dist_fn(x, self.dataset_[j])
            dist_idx_pairs.append((d, j))

        sorted_dist_idx_pairs = sorted(dist_idx_pairs)

        return sorted_dist_idx_pairs

    def fit(self, X, y):
        self.dataset_ = X.copy()
        self.labels_ = y.copy()
        self.possible_labels_ = np.unique(y)

    def predict(self, X):
        predictions = np.zeros(X.shape[0], dtype=int)
        for i in range(X.shape[0]):
            k_nearest = self._find_nearest(X[i])[:self.k]
            indices = [entry[1] for entry in k_nearest]
            k_labels = self.labels_[indices]
            counts = np.bincount(k_labels,
                                 minlength=self.possible_labels_.shape[0])
            pred_label = np.argmax(counts)
            predictions[i] = pred_label
        return predictions
```

K-Nearest Neighbors Implementation

```python
class KNNClassifier(object):
    def __init__(self, k, dist_fn=None):
        self.k = k
        if dist_fn is None:
            self.dist_fn = self._euclidean_dist

    def _euclidean_dist(self, a, b):
        dist = 0.
        for ele_i, ele_j in zip(a, b):
            dist += ((ele_i - ele_j)**2)
        dist = dist**0.5
        return dist

    def _find_nearest(self, x):
        dist_idx_pairs = []
        for j in range(self.dataset_.shape[0]):
            d = self.dist_fn(x, self.dataset_[j])
            dist_idx_pairs.append((d, j))

        sorted

        return

    def fit(se
        self.d
        self.l
        self.p

    def predic
        predic
        for i
            k_nearest = self._find_nearest(X[i])[:self.k]
            indices = [entry[1] for entry in k_nearest]
            k_labels = self.labels_[indices]
            counts = np.bincount(k_labels,
                                 minlength=self.possible_labels_.shape[0])
            pred_label = np.argmax(counts)
            predictions[i] = pred_label
        return predictions
```

```python
knn_model = KNNClassifier(k=3)
knn_model.fit(X_train, y_train)
```

```python
print(knn_model.predict(X_valid))
```

```
[0 1 2 1 1 1 0 0 1 2 0 0 1 1 1 2 1 1 1 2 0 0]
```

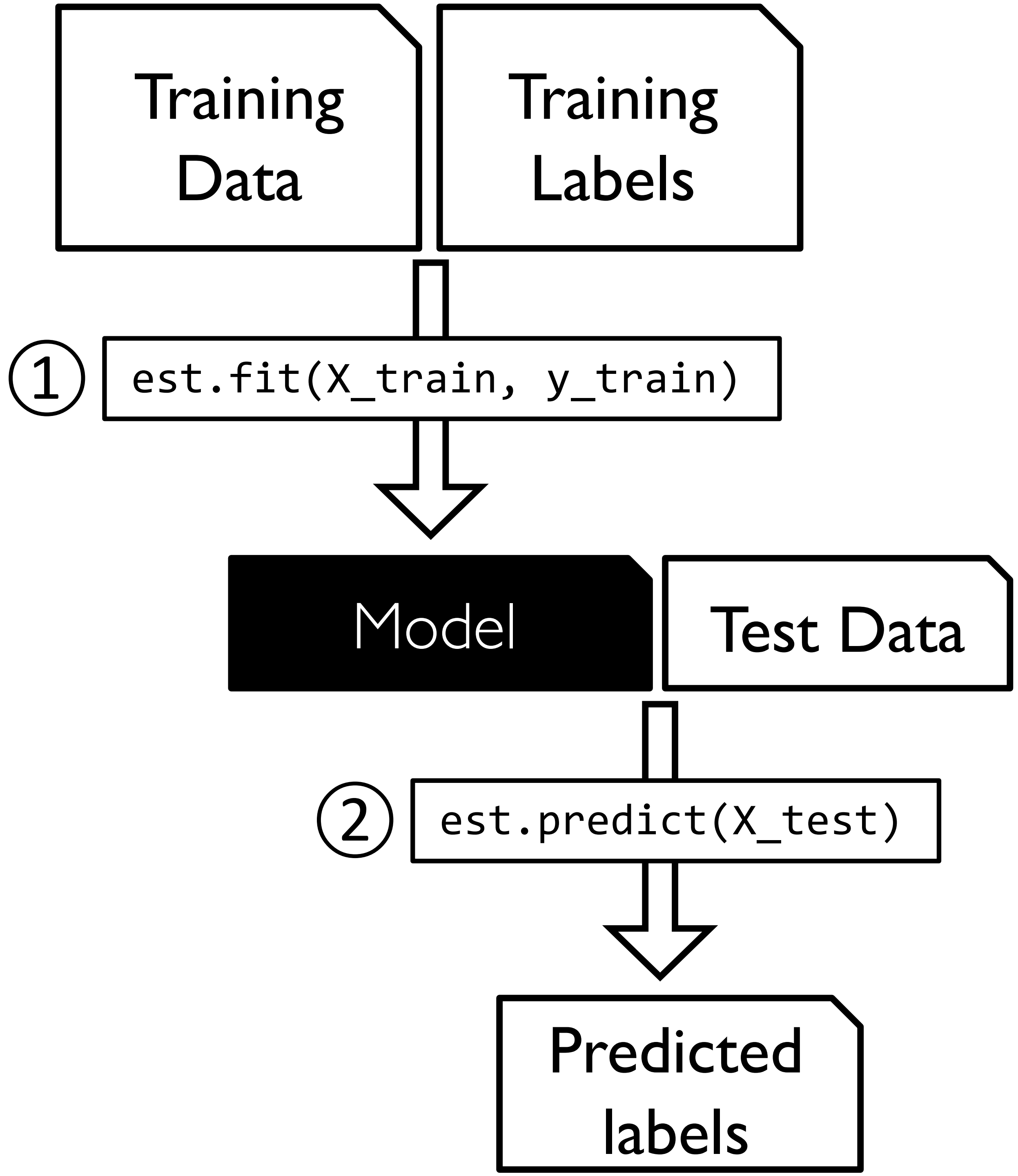
http://scikit-learn.org

Pedregosa, Fabian, et al. "Scikit-learn: Machine learning in Python." *Journal of machine learning research* 12.Oct (2011): 2825-2830.

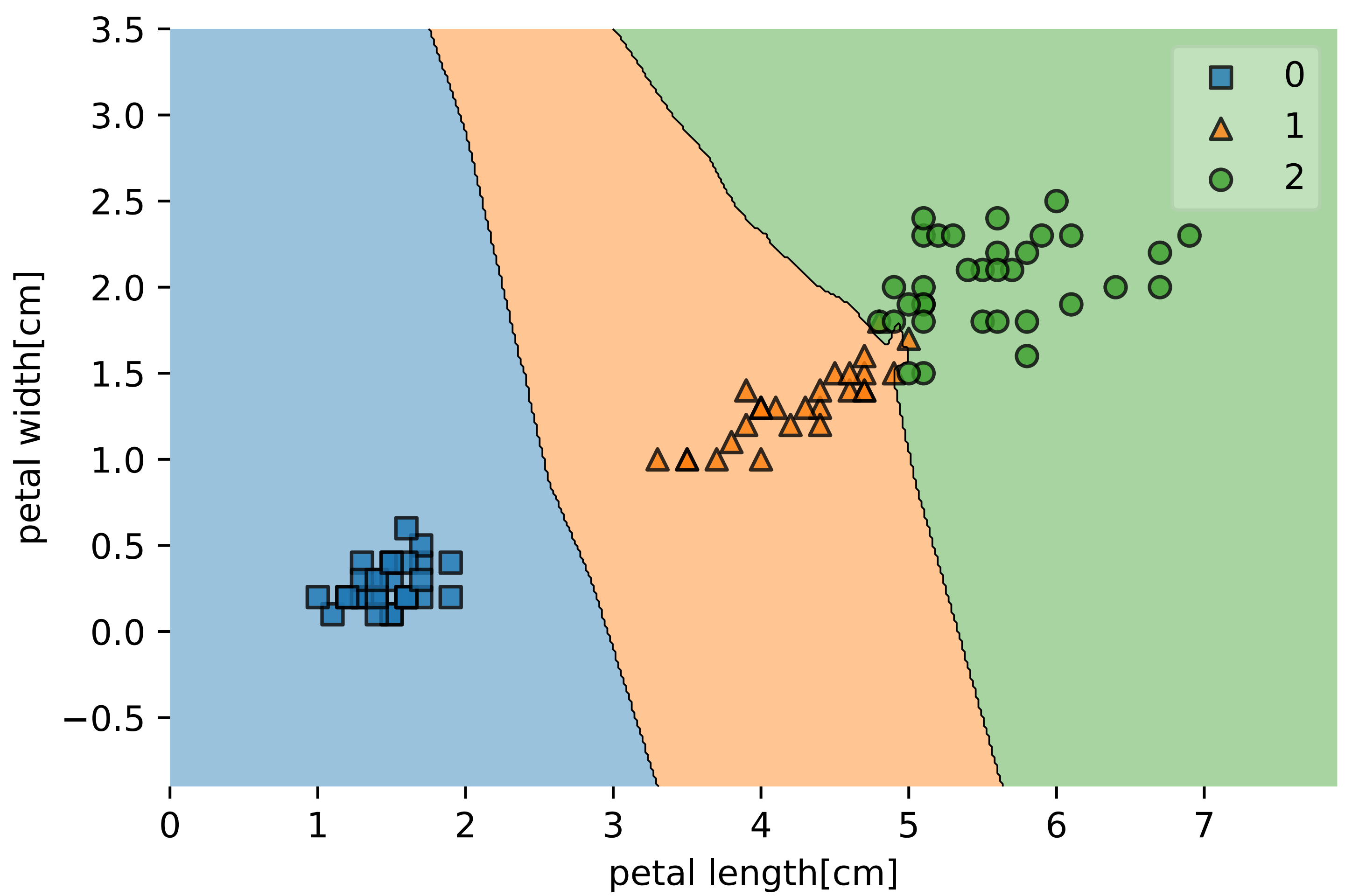
The Scikit-Learn Estimator API

```
class SupervisedEstimator(...):

    def __init__(self, hyperparam_1, ...):
        self.hyperparm_1
        ...

    def fit(self, X, y):
        ...
        self.fit_attribute_
        return self

    def predict(self, X):
        ...
        return y_pred

    def score(self, X, y):
        ...
        return score

    def _private_method(self):
        ...
    ...
```

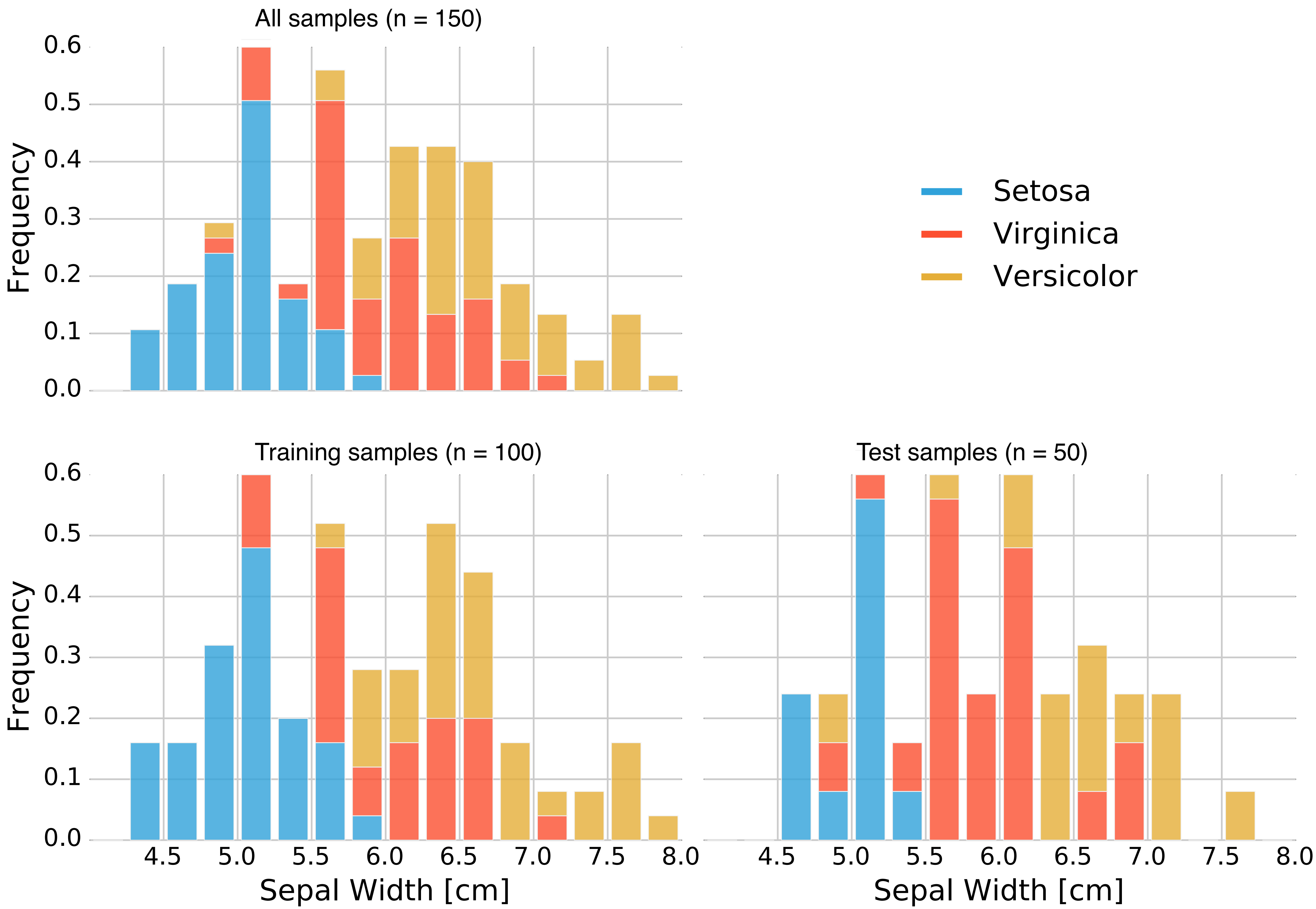
Scikit-learn Estimator API



```python
from sklearn.neighbors import KNeighborsClassifier
from mlxtend.plotting import plot_decision_regions

knn_model = KNeighborsClassifier(n_neighbors=3)
knn_model.fit(X_train[:, 2:], y_train)
plot_decision_regions(X_train[:, 2:], y_train, knn_model)
plt.xlabel('petal length[cm]')
plt.ylabel('petal width[cm]')
plt.savefig('images/decisionreg.pdf')
plt.show()
```



Issues with Subsampling



Stratified Split

```
from sklearn.model_selection import train_test_split

X_temp, X_test, y_temp, y_test = \
        train_test_split(X, y, test_size=0.2,
                         shuffle=True, random_state=123, stratify=y)
np.bincount(y_temp)
```

```
array([40, 40, 40])
```

```
X_train, X_valid, y_train, y_valid = \
        train_test_split(X_temp, y_temp, test_size=0.2,
                         shuffle=True, random_state=123, stratify=y_temp)
X_train.shape
```

```
(96, 4)
```

Normalization: Min-Max Scaling

$$x_{norm}^{[i]} = \frac{x^{[i]} - x_{min}}{x_{max} - x_{min}}$$

Normalization: Min-Max Scaling

$$x_{norm}^{[i]} = \frac{x^{[i]} - x_{min}}{x_{max} - x_{min}}$$

```
x = np.arange(6).astype(float)
x
```

```
array([0., 1., 2., 3., 4., 5.])
```

```
x_norm = (x - x.min()) / (x.max() - x.min())
x_norm
```

```
array([0. , 0.2, 0.4, 0.6, 0.8, 1. ])
```

Normalization: Standardization

$$x_{std}^{[i]} = \frac{x^{[i]} - \mu_x}{\sigma_x}$$

Normalization: Standardization

$$x_{std}^{[i]} = \frac{x^{[i]} - \mu_x}{\sigma_x}$$

```
x = np.arange(6).astype(float)
x
```

```
array([0., 1., 2., 3., 4., 5.])
```

```
x_std = (x - x.mean()) / x.std()
x_std
```

```
array([-1.46385011, -0.87831007, -0.29277002,  0.29277002,  0.87831007,
        1.46385011])
```

Normalization: Standardization

```
df = pd.DataFrame([1, 2, 1, 2, 3, 4])
df[0].std()
```

```
1.1690451944500122
```

```
df[0].values.std()
```

```
1.0671873729054748
```

Sample vs Population Standard Deviation

$$s_x = \sqrt{\frac{1}{n-1} \sum_{n}^{i=1} (x^{[i]} - \bar{x})^2}$$

$$\sigma_x = \sqrt{\frac{1}{n} \sum_{n}^{i=1} (x^{[i]} - \mu_x)^2}$$

Sample vs Population Standard Deviation

```
df = pd.DataFrame([1, 2, 1, 2, 3, 4])
df[0].std()
```

1.1690451944500122

```
df[0].values.std()
```

1.0671873729054748

```
df[0].values.std(ddof=1)
```

1.1690451944500122

$$s_x = \sqrt{\frac{1}{n-1} \sum_{n}^{i=1} (x^{[i]} - \bar{x})^2}$$

$$\sigma_x = \sqrt{\frac{1}{n} \sum_{n}^{i=1} (x^{[i]} - \mu_x)^2}$$

Scaling Validation and Test Sets

```
mu, sigma = X_train.mean(axis=0), X_train.std(axis=0)

X_train_std = (X_train - mu) / sigma
X_valid_std = (X_valid - mu) / sigma
X_test_std = (X_test - mu) / sigma
```

Scaling Validation and Test Sets

Given 3 training examples:

- example1: 10 cm -> class 2
- example2: 20 cm -> class 2
- example3: 30 cm -> class 1

Estimate:

mean: 20 cm
standard deviation: 8.2 cm

Scaling Validation and Test Sets

Given 3 training examples:

- example1: 10 cm -> class 2
- example2: 20 cm -> class 2
- example3: 30 cm -> class 1

Estimate:

mean: 20 cm
standard deviation: 8.2 cm

Standardize:

- example1: -1.21 -> class 2
- example2: 0.00 -> class 2
- example3: 1.21 -> class 1

Scaling Validation and Test Sets

Given 3 training examples:

- example1: 10 cm -> class 2
- example2: 20 cm -> class 2
- example3: 30 cm -> class 1

Estimate:

mean: 20 cm
standard deviation: 8.2 cm

Standardize (z scores):

- example1: -1.21 -> class 2
- example2: 0.00 -> class 2
- example3: 1.21 -> class 1

$$h(z) = \begin{cases} 1 & z \leq 0.6 \\ 2 & otherwise \end{cases}$$

Scaling Validation and Test Sets

Given 3 training examples:

- example1: 10 cm -> class 2
- example2: 20 cm -> class 2
- example3: 30 cm -> class 1

Estimate:

mean: 20 cm
standard deviation: 8.2 cm

Standardize (z scores):

- example1: -1.21 -> class 2
- example2: 0.00 -> class 2
- example3: 1.21 -> class 1

$$h(z) = \begin{cases} 1 & z \leq 0.6 \\ 2 & otherwise \end{cases}$$

*Given 3 **NEW** examples:*

- example4: 5 cm -> class ?
- example5: 6 cm -> class ?
- example6: 7 cm -> class ?

Estimate "new" mean and std.:

- *example5: -1.21 -> class 2*
- *example6: 0.00 -> class 2*
- *example7: 1.21 -> class 1*

Scaling Validation and Test Sets

Given 3 training examples:

- example1: 10 cm -> class 2
- example2: 20 cm -> class 2
- example3: 30 cm -> class 1

Estimate:

mean: 20 cm
standard deviation: 8.2 cm

Standardize (z scores):

- example1: -1.21 -> class 2
- example2: 0.00 -> class 2
- example3: 1.21 -> class 1

$$h(z) = \begin{cases} 1 & z \leq 0.6 \\ 2 & otherwise \end{cases}$$

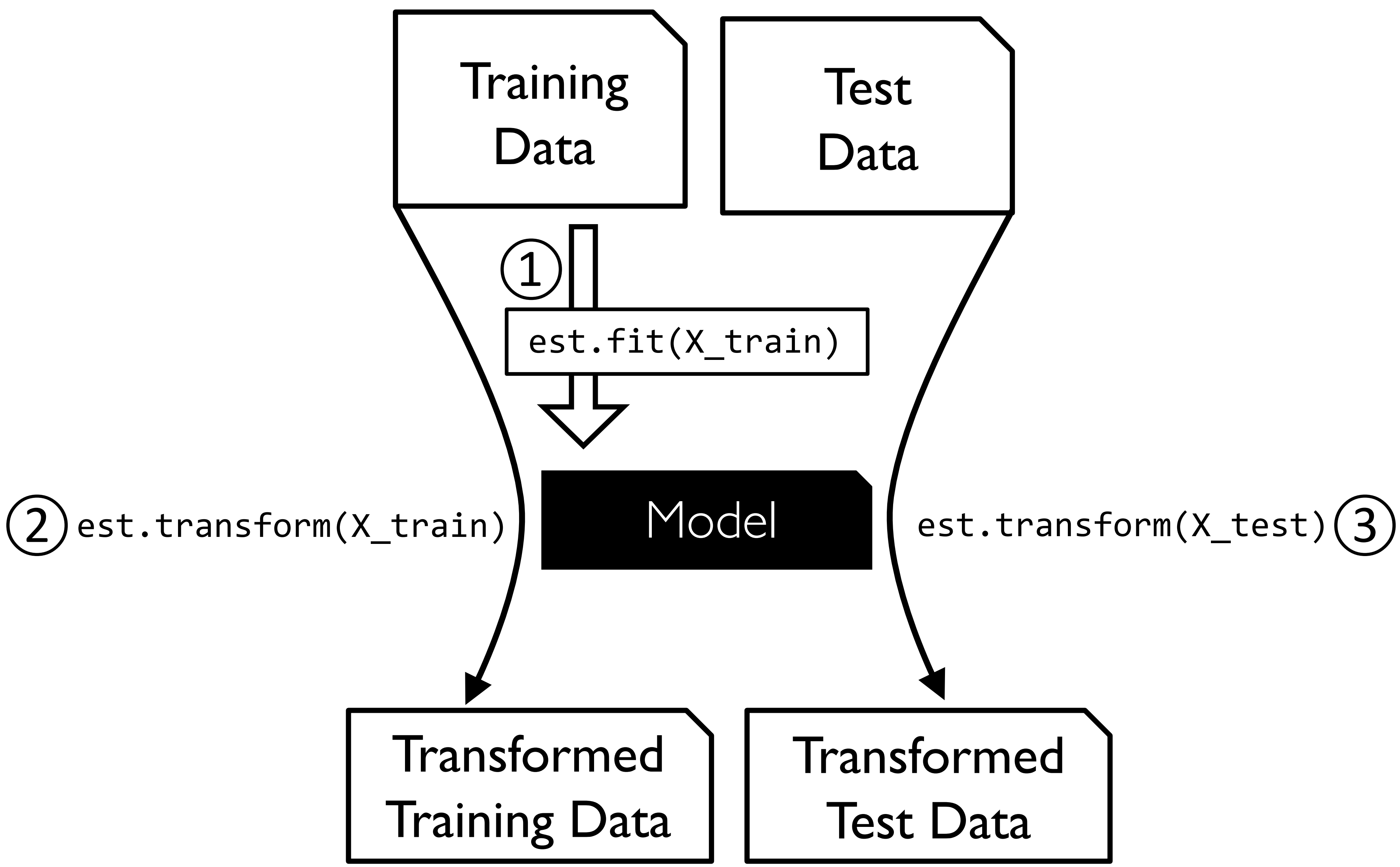
- example4: 5 cm -> class ?
- example5: 6 cm -> class ?
- example6: 7 cm -> class ?

~~*Estimate "new" mean and std.:*~~

- ~~*example5: -1.21 -> class 2*~~
- ~~*example6: 0.00 -> class 2*~~
- ~~*example7: 1.21 -> class 1*~~

- example5: -18.37
- example6: -17.15
- example7: -15.92

Scikit-Learn Transformer API



Scikit-Learn Transformer API

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler


scaler = StandardScaler()
scaler.fit(X_train)
X_train_std = scaler.transform(X_train)
X_valid_std = scaler.transform(X_valid)
X_test_std = scaler.transform(X_test)
```

Categorical Data

```
df = pd.read_csv('categoricaldata.csv')
df
```

	color	size	price	classlabel
0	green	M	10.1	class1
1	red	L	13.5	class2
2	blue	XXL	15.3	class1

Categorical: Ordinal

```
mapping_dict = {'M': 2,
                'L': 3,
                'XXL': 5}

df['size'] = df['size'].map(mapping_dict)
df
```

	color	size	price	classlabel
0	green	2	10.1	class1
1	red	3	13.5	class2
2	blue	5	15.3	class1

Categorical: Ordinal

Categorical: Nominal

	color	size	price	classlabel
0	green	2	10.1	class1
1	red	3	13.5	class2
2	blue	5	15.3	class1

```
from sklearn.preprocessing import LabelEncoder


le = LabelEncoder()
df['classlabel'] = le.fit_transform(df['classlabel'])
df
```

	color	size	price	classlabel
0	green	2	10.1	0
1	red	3	13.5	1
2	blue	5	15.3	0

One-hot Encoding

	color	size	price	classlabel
0	green	2	10.1	0
1	red	3	13.5	1
2	blue	5	15.3	0

```
pd.get_dummies(df)
```

	size	price	classlabel	color_blue	color_green	color_red
0	2	10.1	0	0	1	0
1	3	13.5	1	0	0	1
2	5	15.3	0	1	0	0

One-hot Encoding

```
pd.get_dummies(df)
```

	size	price	classlabel	color_blue	color_green	color_red
0	2	10.1	0	0	1	0
1	3	13.5	1	0	0	1
2	5	15.3	0	1	0	0

```
pd.get_dummies(df, drop_first=True)
```

	size	price	classlabel	color_green	color_red
0	2	10.1	0	1	0
1	3	13.5	1	0	1
2	5	15.3	0	0	0

Missing Data

```
df = pd.read_csv('missingdata.csv')
df
```

	A	B	C	D
0	1.0	2.0	3.0	4.0
1	5.0	6.0	NaN	8.0
2	10.0	11.0	12.0	NaN

Missing Data

```
df = pd.read_csv('missingdata.csv')
df
```

	A	B	C	D
0	1.0	2.0	3.0	4.0
1	5.0	6.0	NaN	8.0
2	10.0	11.0	12.0	NaN

```
# drop rows with missing values:

df.dropna(axis=0)
```

	A	B	C	D
0	1.0	2.0	3.0	4.0

```
# drop columns with missing values:

df.dropna(axis=1)
```

	A	B
0	1.0	2.0
1	5.0	6.0
2	10.0	11.0

Missing Data

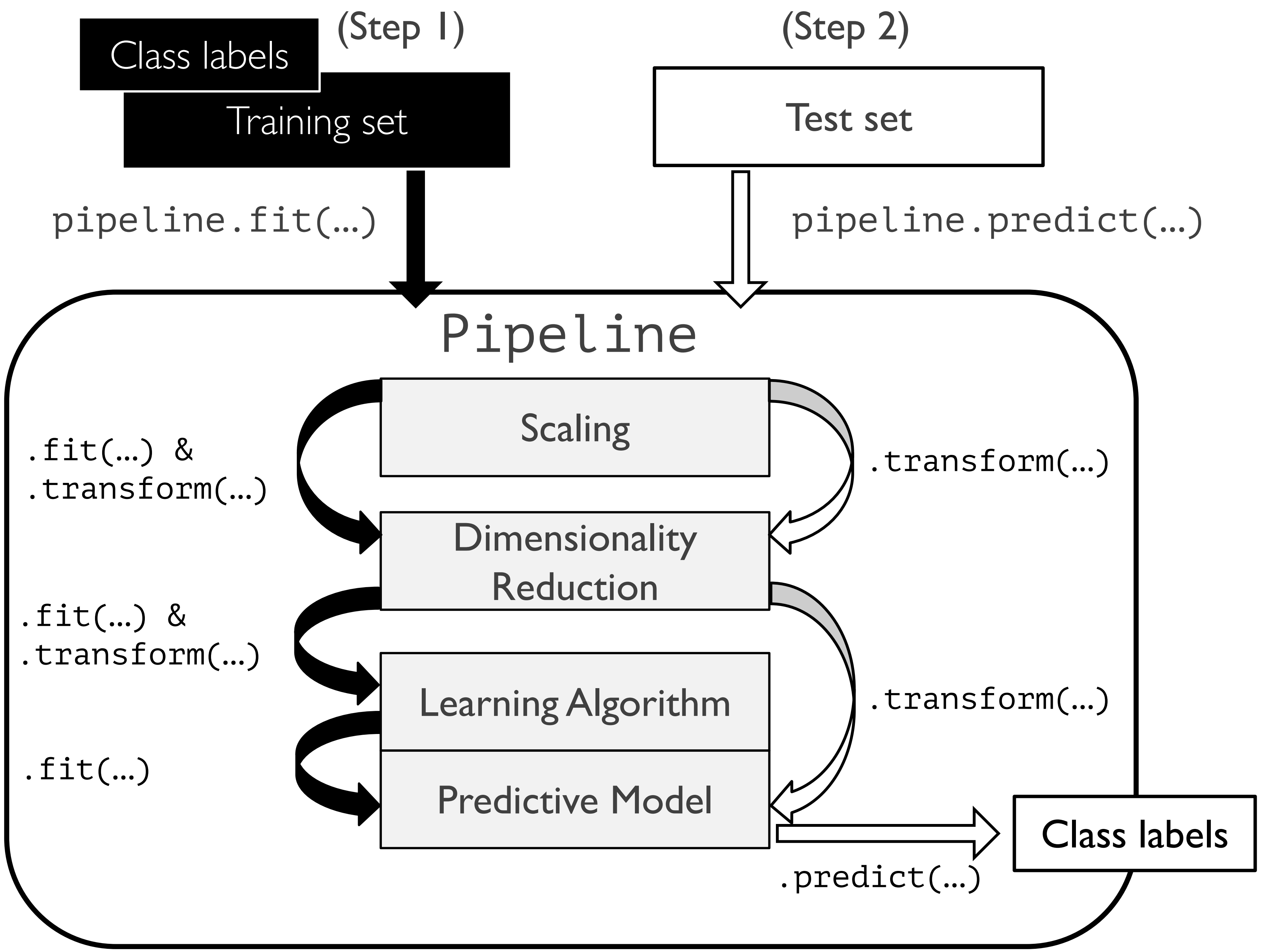
```
df = pd.read_csv('missingdata.csv')
df
```

	A	B	C	D
0	1.0	2.0	3.0	4.0
1	5.0	6.0	NaN	8.0
2	10.0	11.0	12.0	NaN

```
from sklearn.preprocessing import Imputer


imputer = Imputer(missing_values='NaN', strategy='mean', axis=0)
X = df.values
X = imputer.fit_transform(df.values)
X
```

```
array([[ 1. ,  2. ,  3. ,  4. ],
       [ 5. ,  6. ,  7.5,  8. ],
       [10. , 11. , 12. ,  6. ]])
```

Scikit-Learn Pipelines



Scikit-Learn Pipelines

```
from sklearn.pipeline import make_pipeline


pipe = make_pipeline(StandardScaler(),
                     KNeighborsClassifier(n_neighbors=3))
```

```
pipe
```

```
Pipeline(memory=None,
     steps=[('standardscaler', StandardScaler(copy=True, with_mean=Tr
ue, with_std=True)), ('kneighborsclassifier', KNeighborsClassifier(al
gorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=3, p=2,
           weights='uniform'))])
```

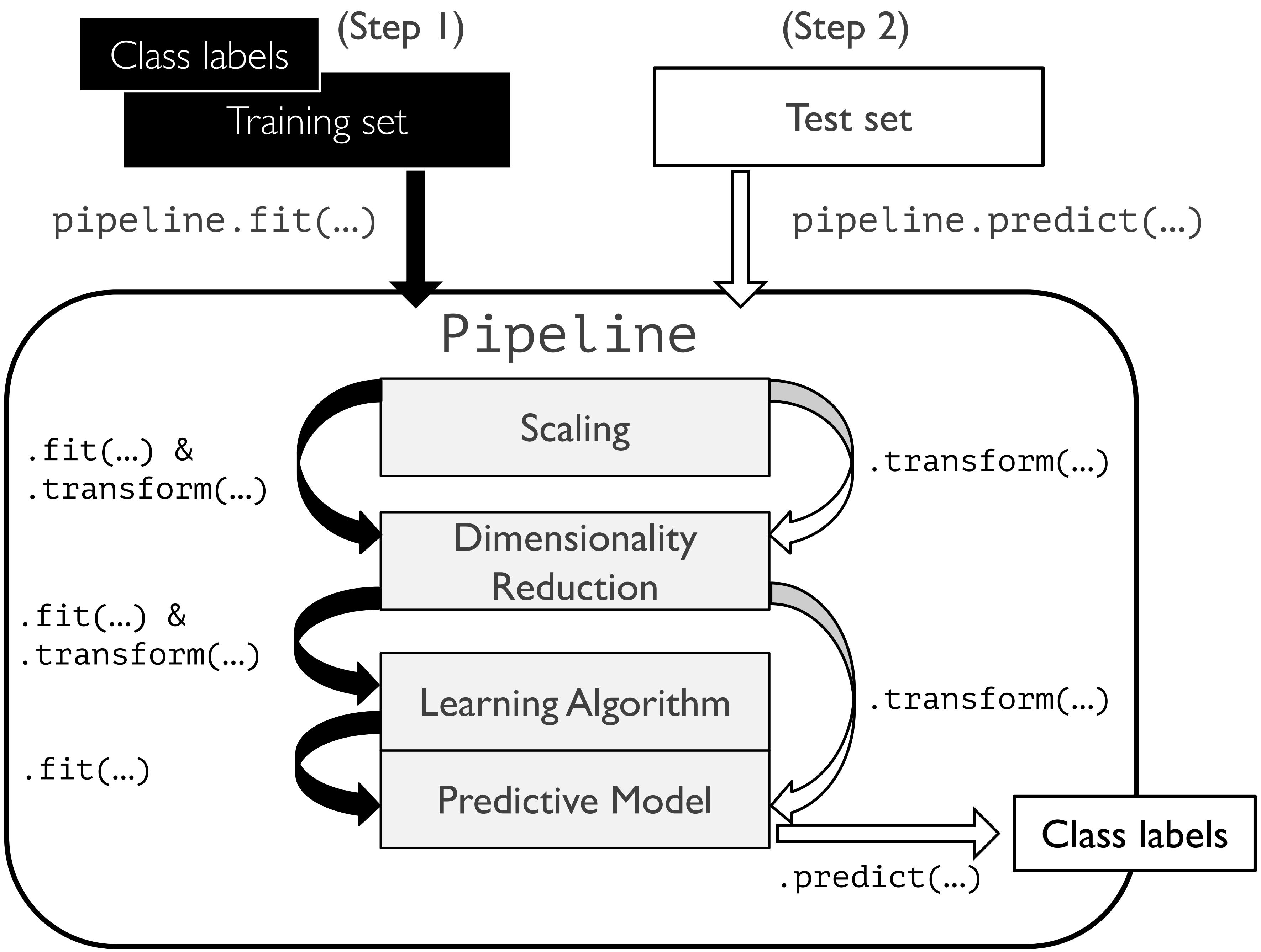
Scikit-Learn Pipelines

```
from sklearn.pipeline import make_pipeline


pipe = make_pipeline(StandardScaler(),
                     KNeighborsClassifier(n_neighbors=3))
```

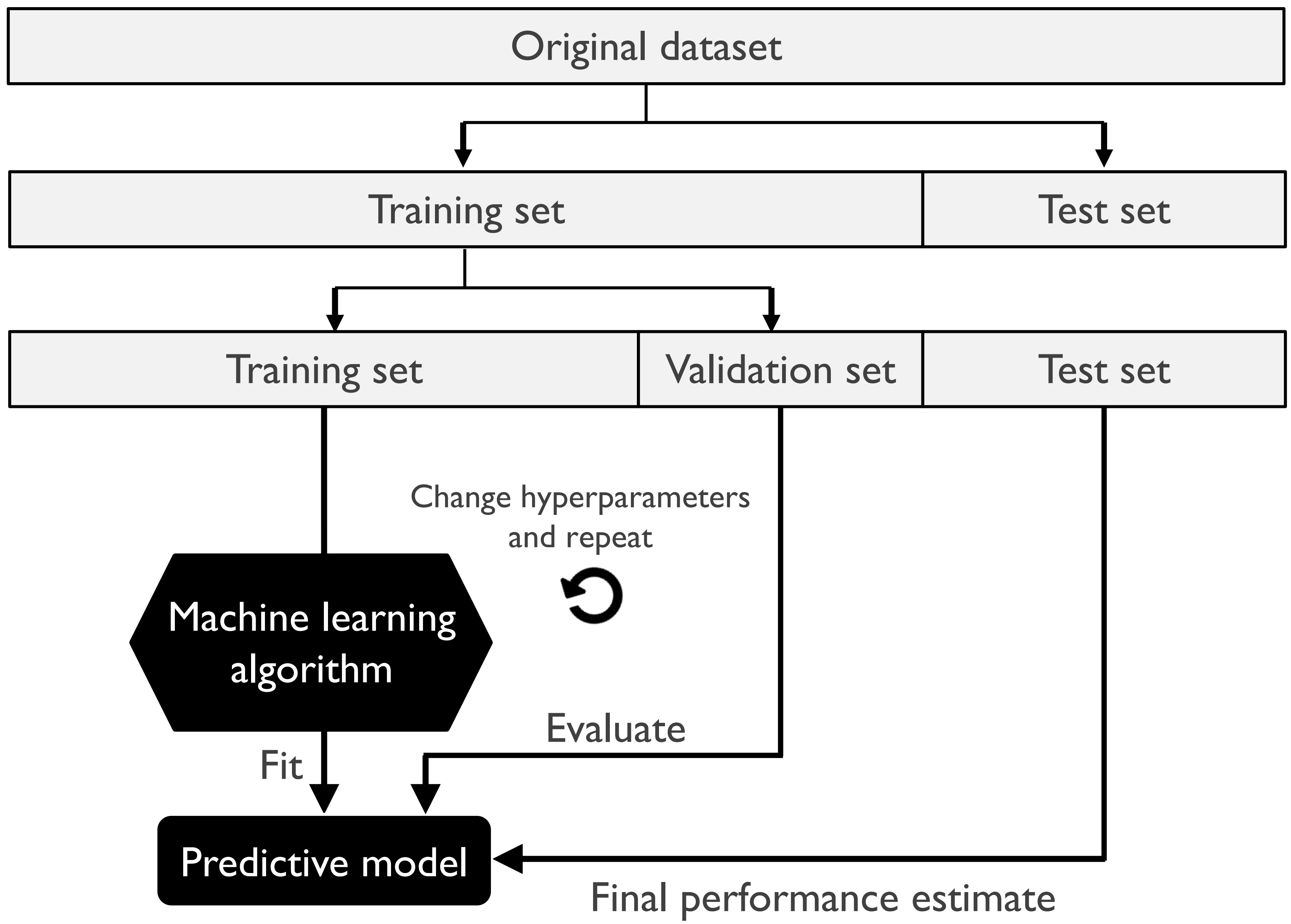
```
pipe.fit(X_train, y_train)
pipe.predict(X_test)
```

```
array([1, 0, 2, 2, 0, 0, 2, 1, 2, 0, 0, 2, 2, 1, 2, 1, 0, 0, 0, 0, 0, 2,
       2, 1, 2, 2, 1, 1, 1, 1])
```

Scikit-Learn Pipelines



Model Selection: Simple Holdout Method



Model Selection: Simple Holdout Method

```
from sklearn.model_selection import GridSearchCV
from mlxtend.evaluate import PredefinedHoldoutSplit
from sklearn.pipeline import make_pipeline
from sklearn.datasets import load_iris

iris = load_iris()
X, y = iris.data, iris.target

train_ind, valid_ind = train_test_split(np.arange(X.shape[0]),
                                        test_size=0.2, shuffle=True,
                                        random_state=123, stratify=y)
```

Model Selection:
Simple Holdout Method

```
from sklearn.model_selection import GridSearchCV
from mlxtend.evaluate import PredefinedHoldoutSplit
from sklearn.pipeline import make_pipeline
from sklearn.datasets import load_iris

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                                        test_size=0.2, shuffle=True,
                                        random_state=123, stratify=y)
```

```
pipe = make_pipeline(StandardScaler(),
                     KNeighborsClassifier())

params = {'kneighborsclassifier__n_neighbors': [1, 3, 5],
          'kneighborsclassifier__p': [1, 2]}

split = PredefinedHoldoutSplit(valid_indices=valid_ind)

grid = GridSearchCV(pipe,
                    param_grid=params,
                    cv=split)
```

Model Selection:
Simple Holdout Method

```python
from sklearn.model_selection import GridSearchCV
from mlxtend.evaluate import PredefinedHoldoutSplit
from sklearn.pipeline import make_pipeline
from sklearn.datasets import load_iris

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split = PredefinedHoldoutSplit(valid_indices=valid_ind)

grid = GridSearchCV(pipe,
                    param_grid=params,
                    cv=split)
```

```python
grid.fit(X, y)
grid.grid_scores_
```

```
[mean: 0.90000, std: 0.00000, params: {'kneighborsclassifier__n_neighbors': 1, 'kneighborsclassifier__p': 1},
 mean: 0.96667, std: 0.00000, params: {'kneighborsclassifier__n_neighbors': 1, 'kneighborsclassifier__p': 2},
 mean: 0.96667, std: 0.00000, params: {'kneighborsclassifier__n_neighbors': 3, 'kneighborsclassifier__p': 1},
 mean: 0.93333, std: 0.00000, params: {'kneighborsclassifier__n_neighbors': 3, 'kneighborsclassifier__p': 2},
 mean: 0.90000, std: 0.00000, params: {'kneighborsclassifier__n_neighbors': 5, 'kneighborsclassifier__p': 1},
 mean: 0.90000, std: 0.00000, params: {'kneighborsclassifier__n_neighbors': 5, 'kneighborsclassifier__p': 2}]
```

Reading Assignments

- *Python Machine Learning, 2nd ed.*:
  Ch04 up to "Selecting Meaningful Features"
  (pg 107-123)

- *Python Machine Learning, 2nd ed.*:
  Ch06 up to "Debugging Algorithms with Learning and Validation Curves"
  (pg 185-194)