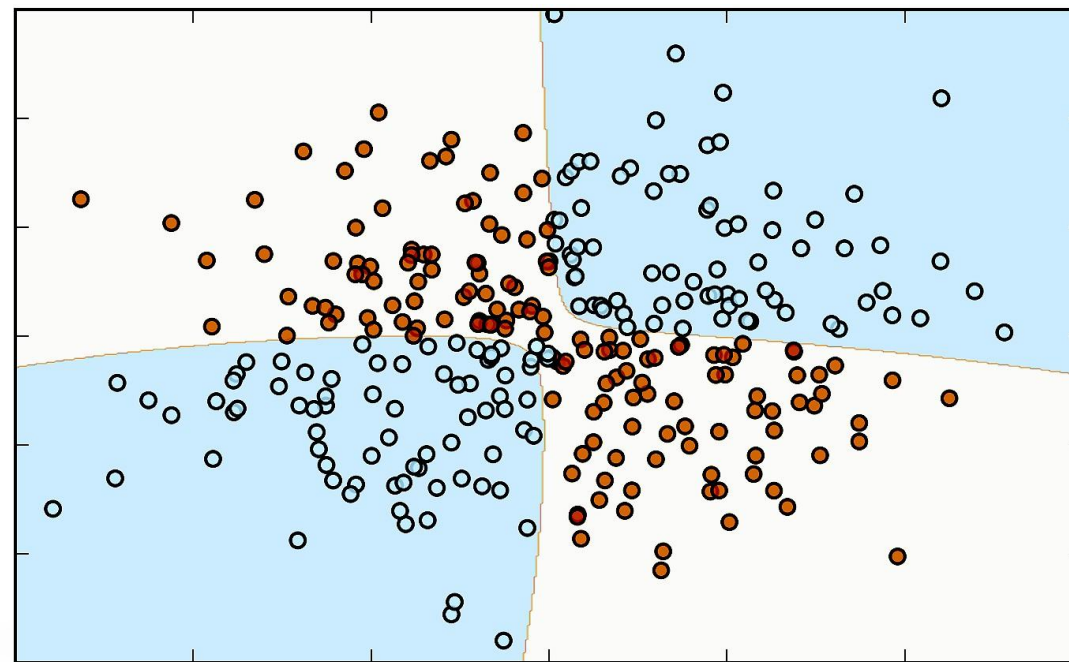


Teaching Demo

Introduction of Classification (Supervised Learning): Big Pictures and Practicum



Ludy Hasby Aulia

Our Agenda

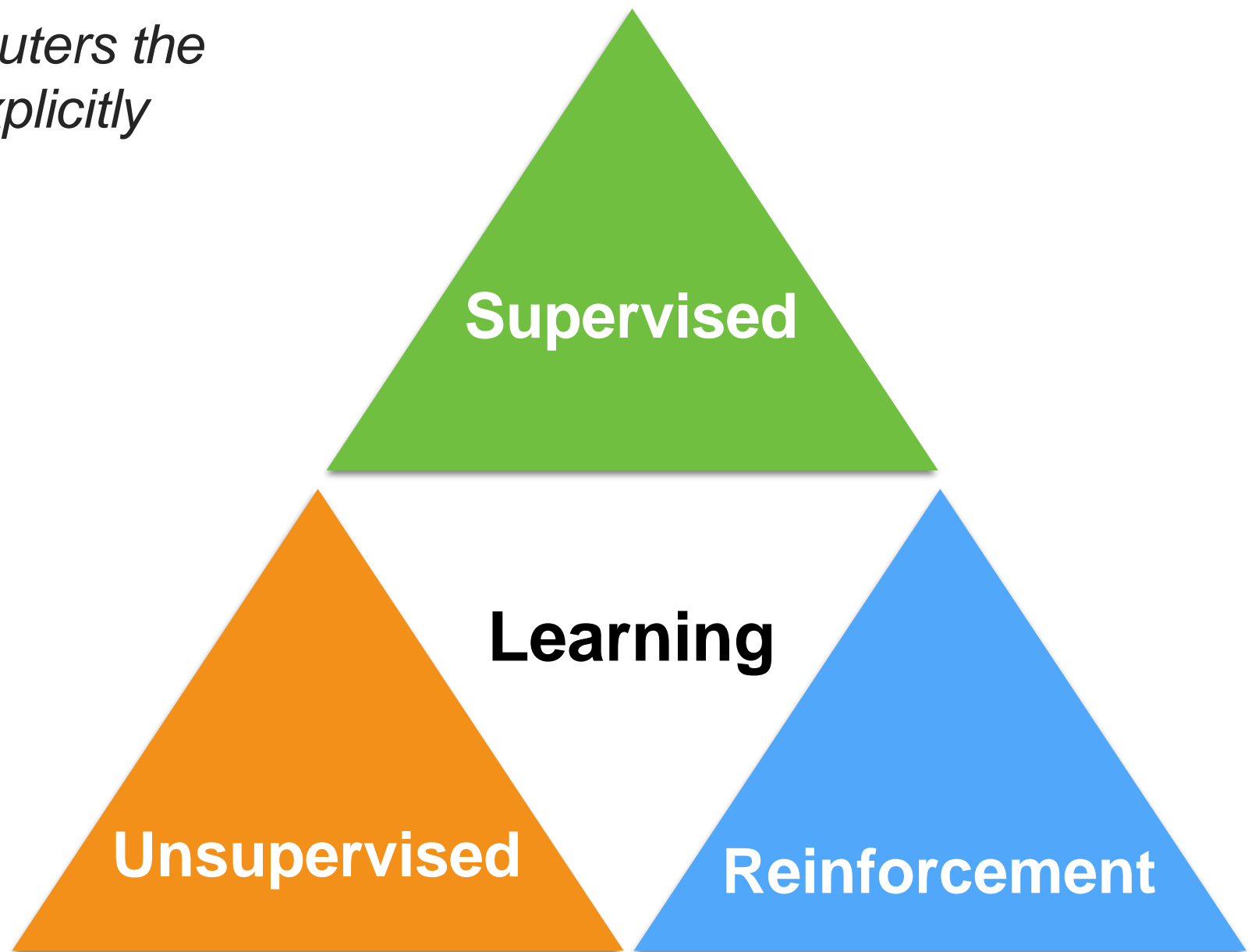
- **Algorithm in big picture**
- **Example Case**
- **Model Building Demo**

Machine Learning?

"Field of study that gives computers the ability to learn without being explicitly programmed."

(Arthur Samuel, 1959)

- Labeled data
- Direct feedback
- Predict outcome/future

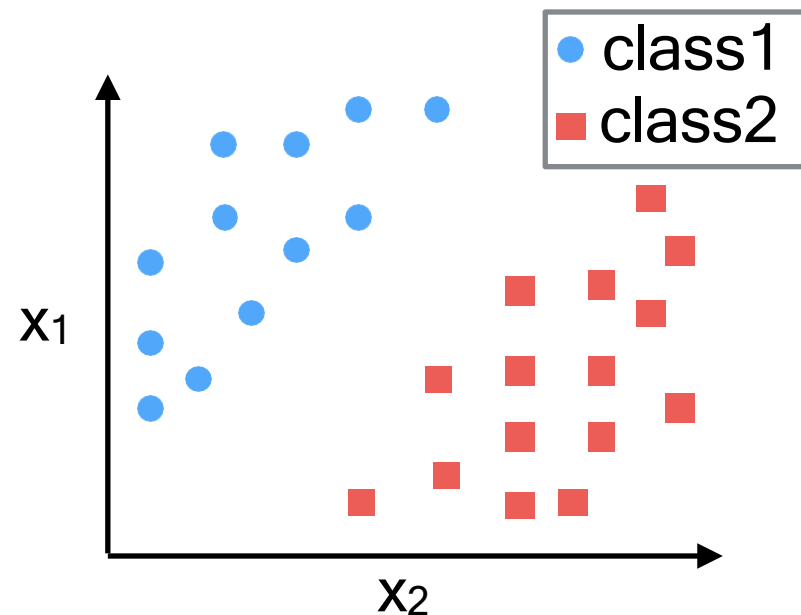


- No labels
- No feedback
- “Find hidden structure”

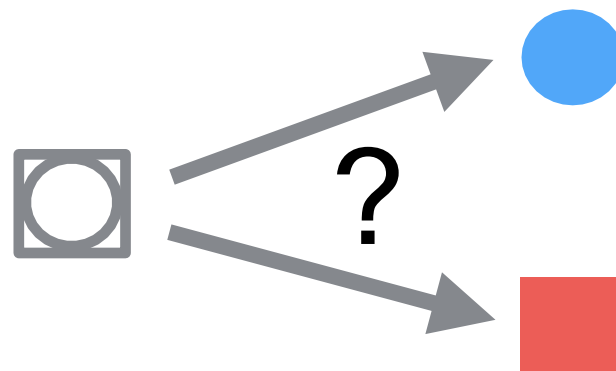
- Decision process
- Reward system
- Learn series of actions

Classification

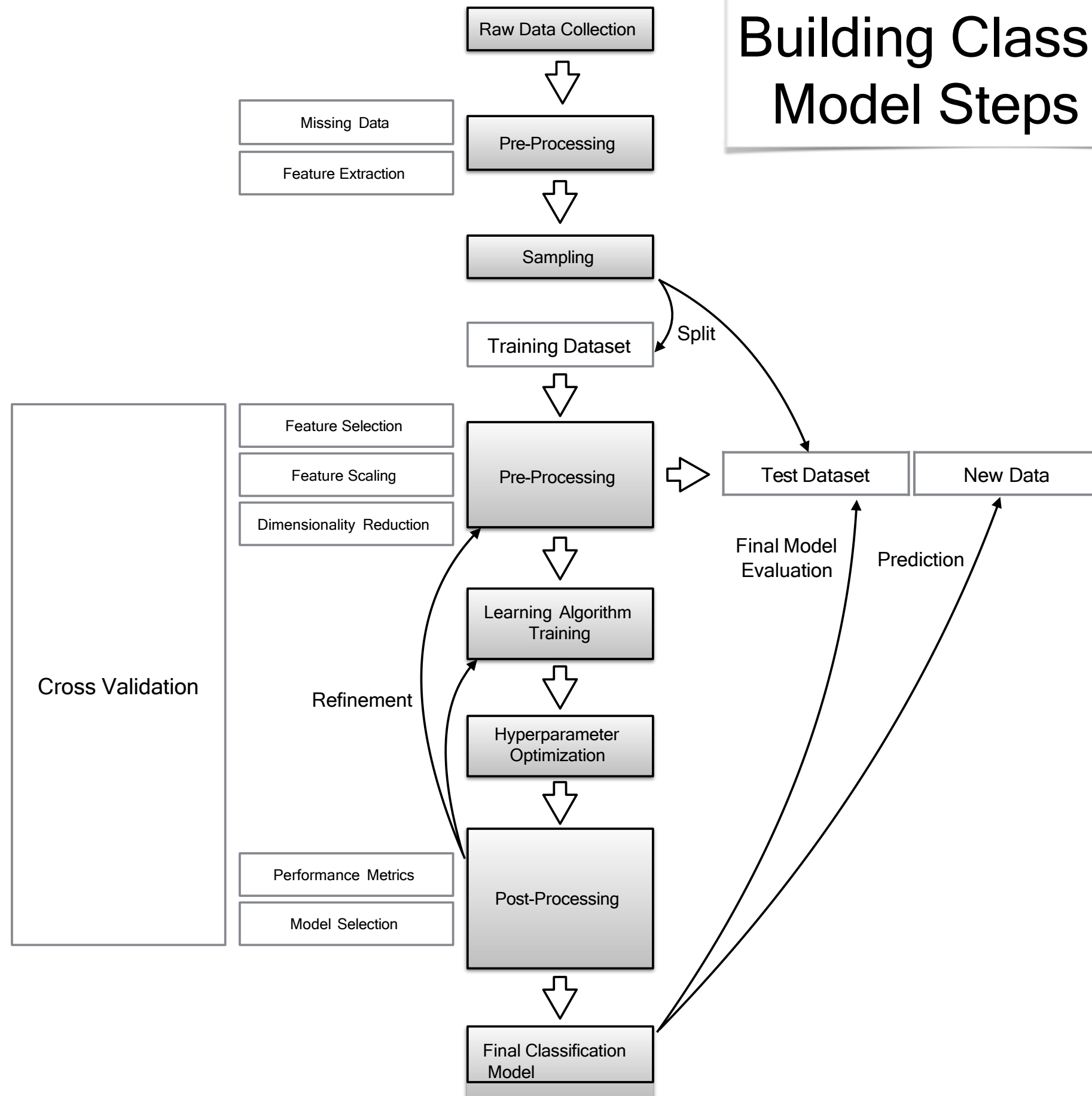
1) Learn from training data

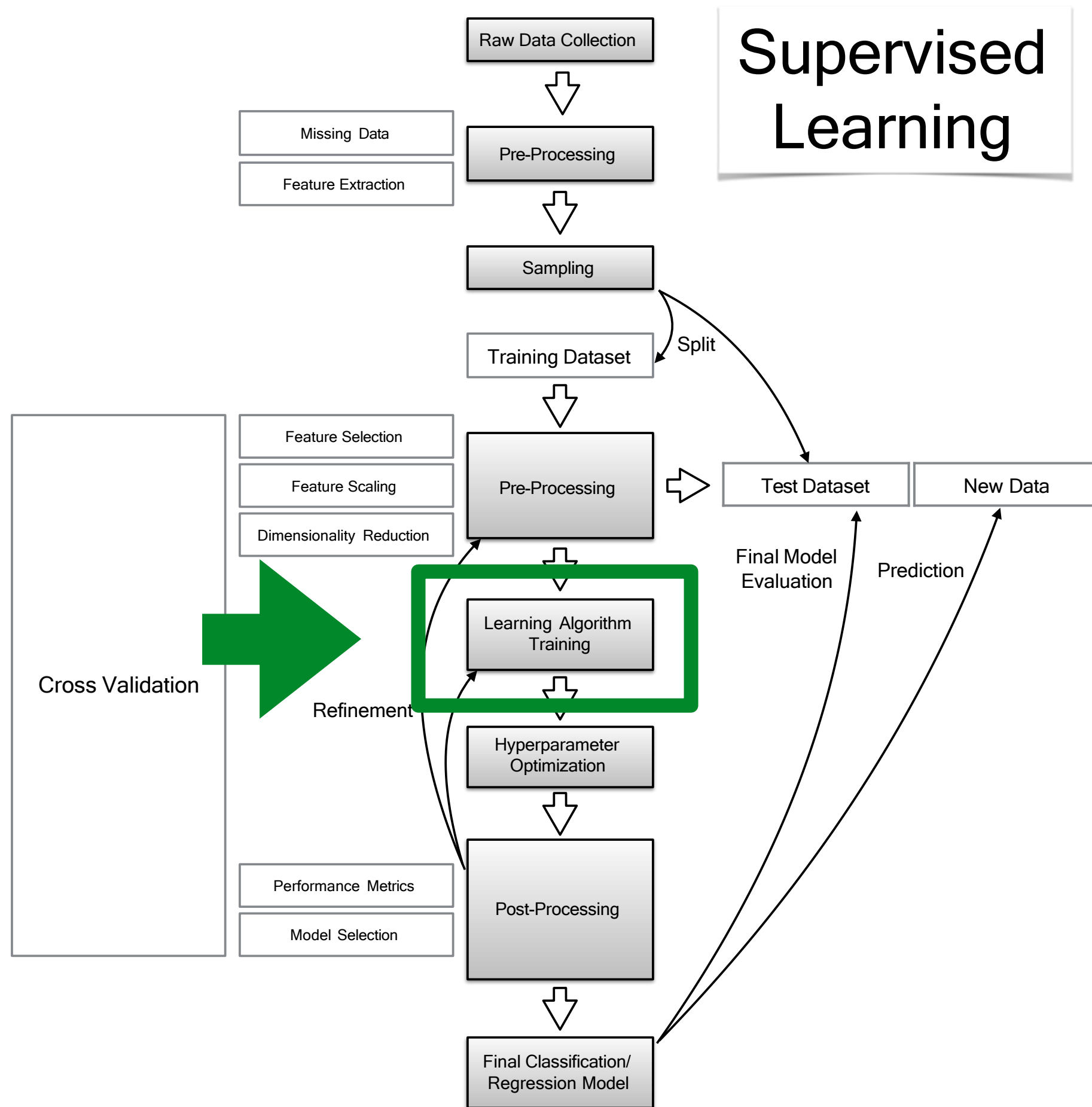


2) Map unseen (new) data



Building Classification Model Steps





A Few Common Classifiers

Perceptron

Naive Bayes

Decision Tree

K-Nearest Neighbor

Logistic Regression

Artificial Neural Network / Deep Learning

Support Vector Machine

Ensemble Methods: Random Forest, Bagging, AdaBoost

A Few Common Classifiers

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Logistic Regression

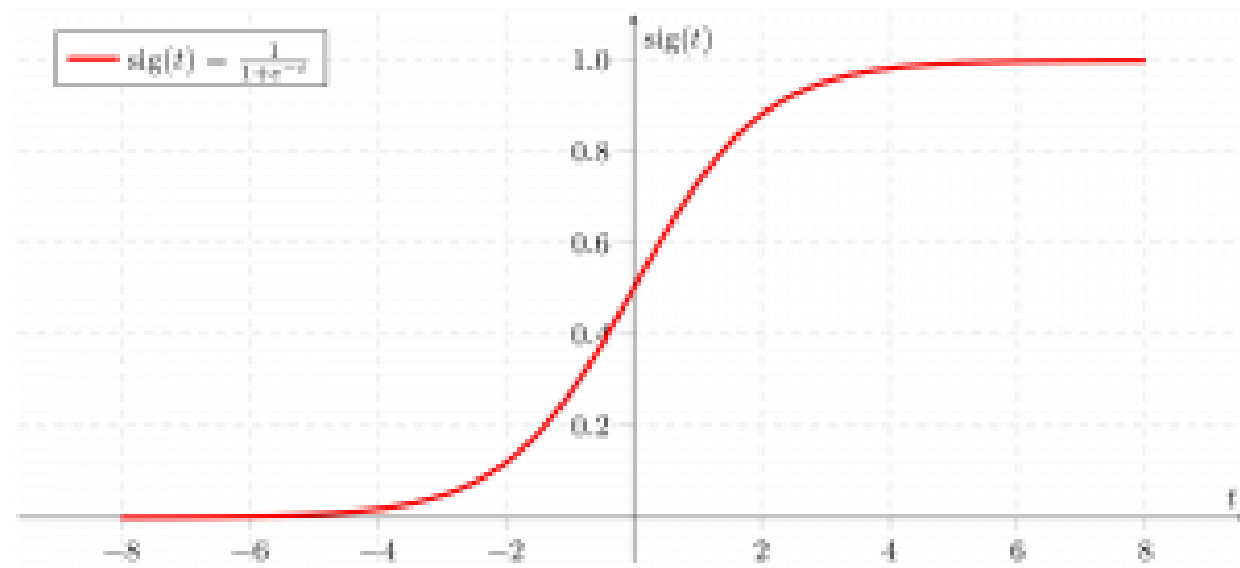
Binomial

Step 1. Calculate and Predict MLR

$$\mathbf{z} = \mathbf{b} + \mathbf{w} \cdot \mathbf{X}$$

Step 2. Convert to Sigmoid Function

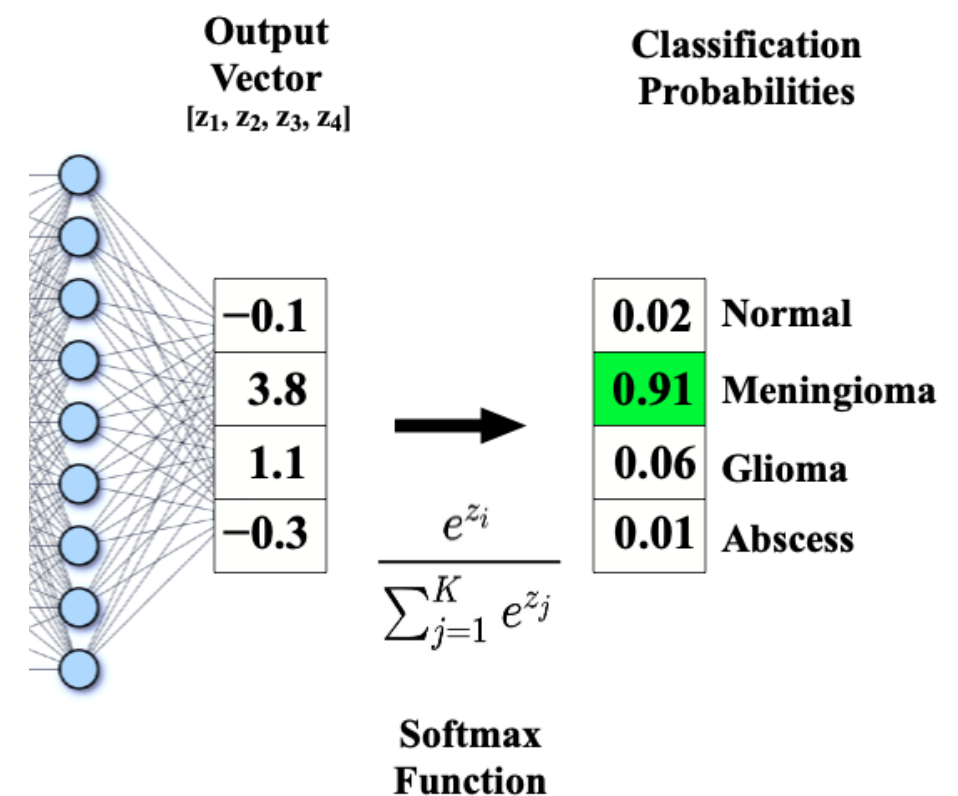
$$\sigma(z) = \frac{1}{1 + e^{-z}}$$



Multinomial

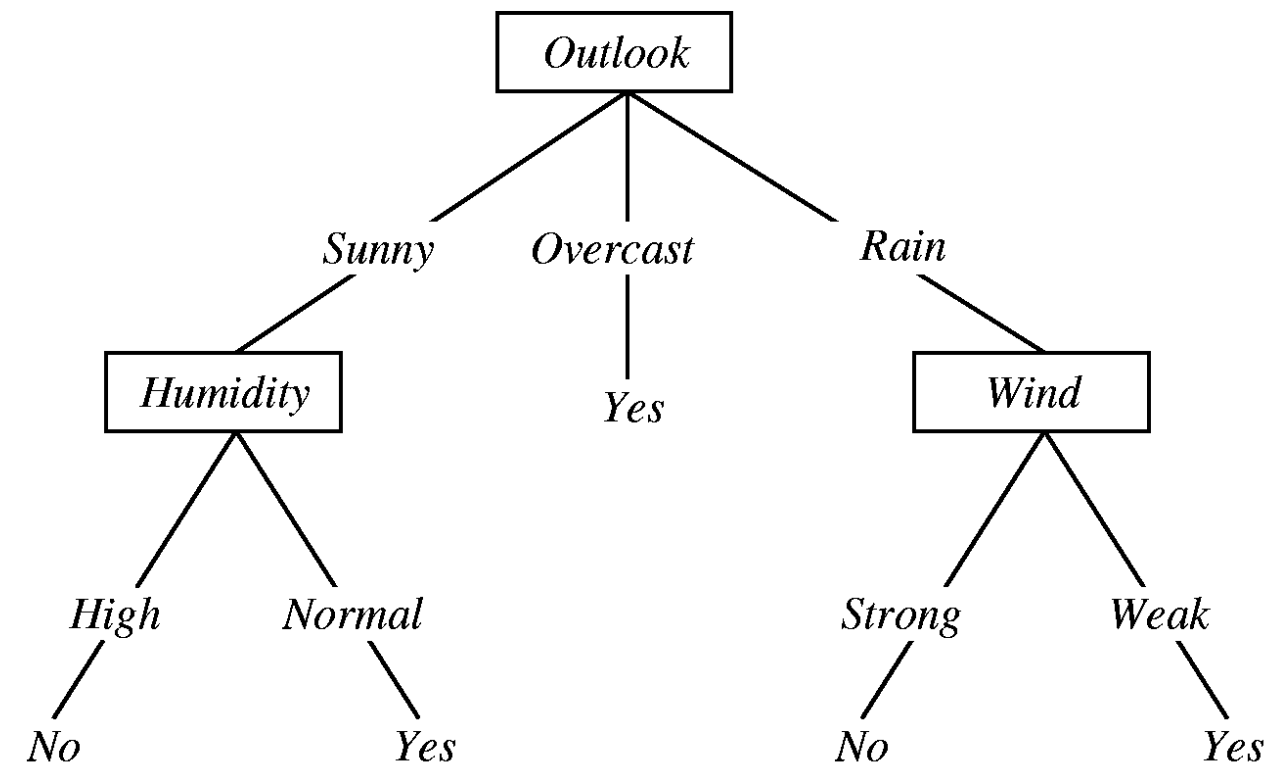
Use Softmax Function

$$\text{softmax}(z) = \frac{e^z}{\sum_{j=1}^K e^{z_j}} = P(Y = c | X)$$



[Read More](#)

Decision Tree



Read More

<https://www.geeksforgeeks.org/machine-learning/decision-tree-algorithms/>

Algorithm ID3

Step 1. Select an attribute as the root (Highest Gains)

$$Entropy(S) = \sum_{i=1}^n -p_i * \log_2 p_i$$

$$Gain(S, A)$$

$$= Entropy(S) - \sum_{i=1}^n \frac{|S_i|}{|S|} * Entropy(S_i)$$

Step 2. Create Branch Each Value

Step 3. Repeat the process until each branch has the same class

Random Forest

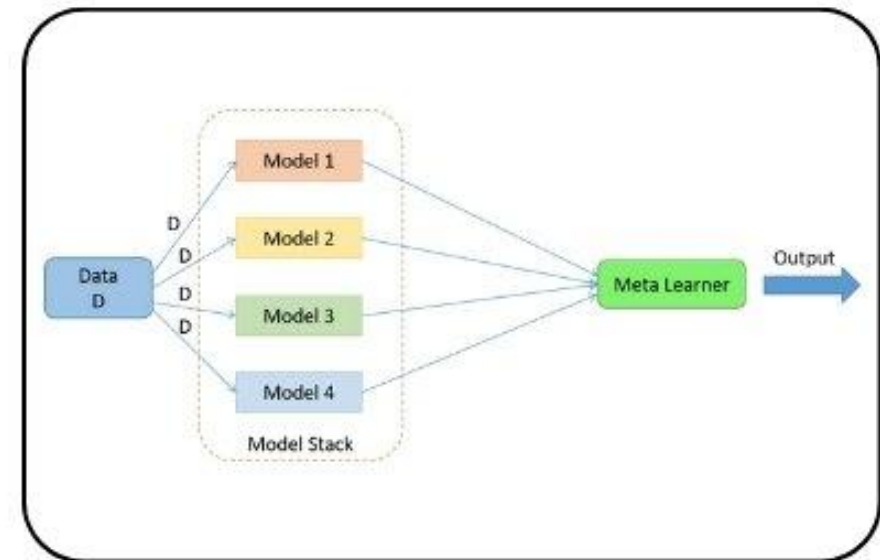
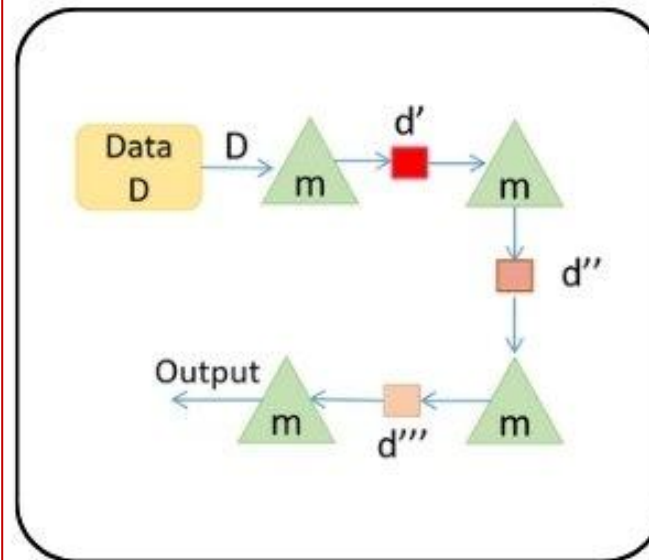
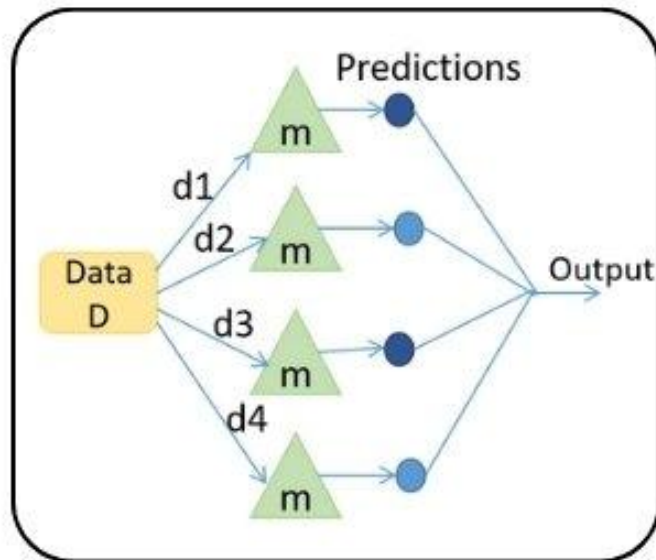
viso.ai

Ensemble Methods

Bagging

Boosting

Stacking



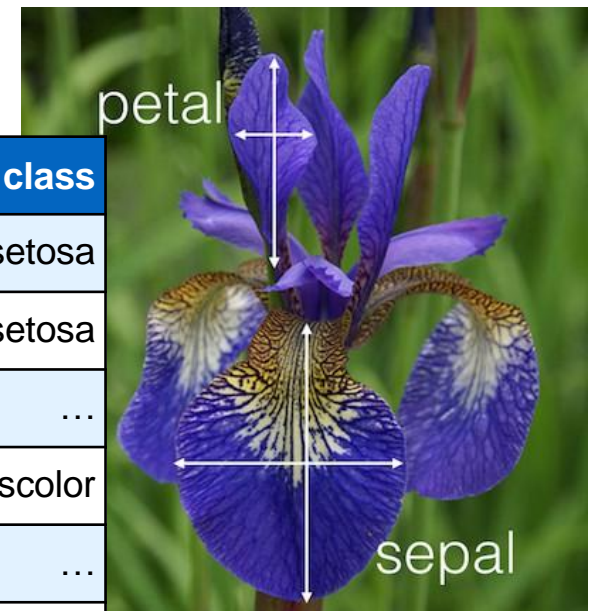
Classification Case

IRIS

<https://archive.ics.uci.edu/ml/datasets/Iris>

Instances (samples, observations)

	sepal_length	sepal_width	petal_length	petal_width	class
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
...
50	6.4	3.2	4.5	1.5	vericolor
...
150	5.9	3.0	5.1	1.8	virginica



Features (attributes, dimensions)

Classes (targets)

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1D} \\ x_{21} & x_{22} & \cdots & x_{2D} \\ x_{31} & x_{32} & \cdots & x_{3D} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{ND} \end{bmatrix}$$

$$\mathbf{y} = [y_1, y_2, y_3, \cdots y_N]$$

Missing Values:

- Remove features (columns)
- Remove samples (rows)
- Imputation (mean, nearest neighbor, ...)

Feature Scaling:

e.g., *standardization*: $z = \frac{x_{ik} - \mu_k}{\sigma_k}$ (use same parameters for the test/new data!)

- Faster convergence (gradient descent)
- Distances on same scale (k-NN with Euclidean distance)
- Mean centering for free
- Normal distributed data
- Numerical stability by avoiding small weights

Sampling:

- Random split into training and validation sets
- Typically 60/40, 70/30, 80/20
- Don't use validation set until the very end! (overfitting)

Error Metrics

here: “setosa” = “positive”

actual class	setosa	versicolor	
	setosa	versicolor	
predicted class	setosa	versicolor	
	setosa	versicolor	
TP 47	FN 3	FP 2	TN 48

setosa versicolor
predicted class

[Linear SVM on sepal/petal lengths]

“micro” and “macro”
averaging for multi-class

$$\text{Accuracy} = \frac{TP + TN}{FP + FN + TP + TN} \\ = 1 - \text{Error}$$

$$\text{False Positive Rate} = \frac{FP}{N}$$

$$\text{True Positive Rate} = \frac{TP}{P} \\ (\text{Recall})$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

Demo Time