Universidade Federal de Viçosa

Lecture 01 – Classifying images

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Agenda

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- Digital images
  - Colored images – RGB
- A classification problem
  - The nearest neighbor method
  - K-nearest neighbors – K-NN
- Classification pipelines
- Learning models
- Cross-validation
- Classification evaluation

Digital images

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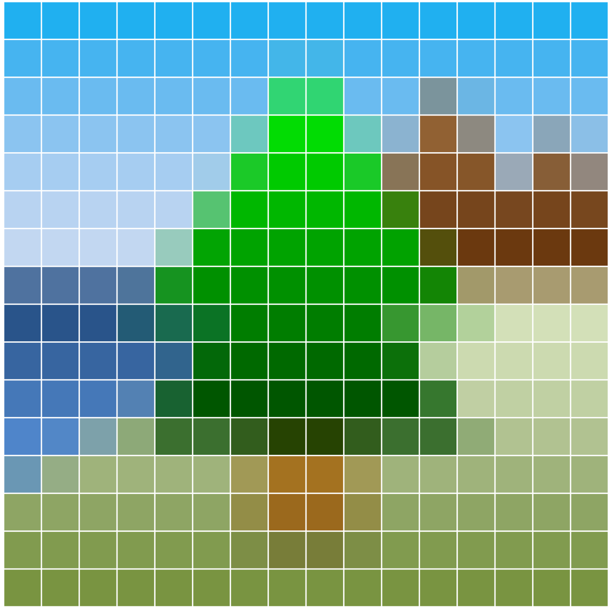
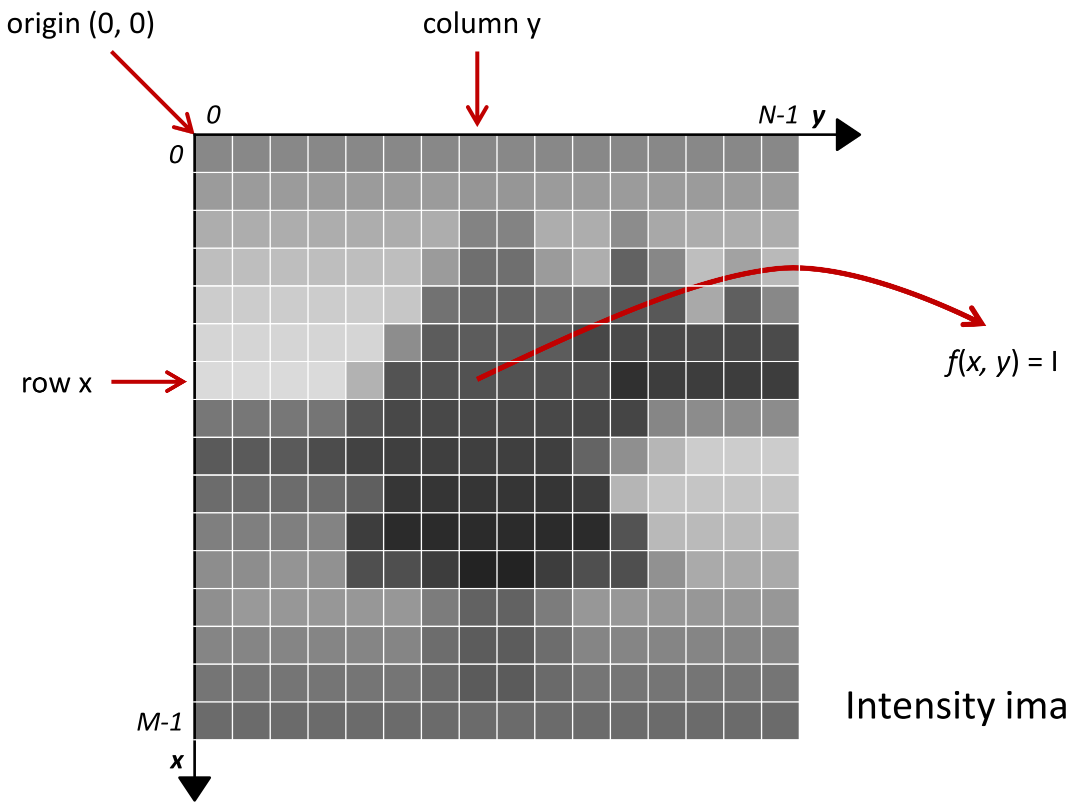


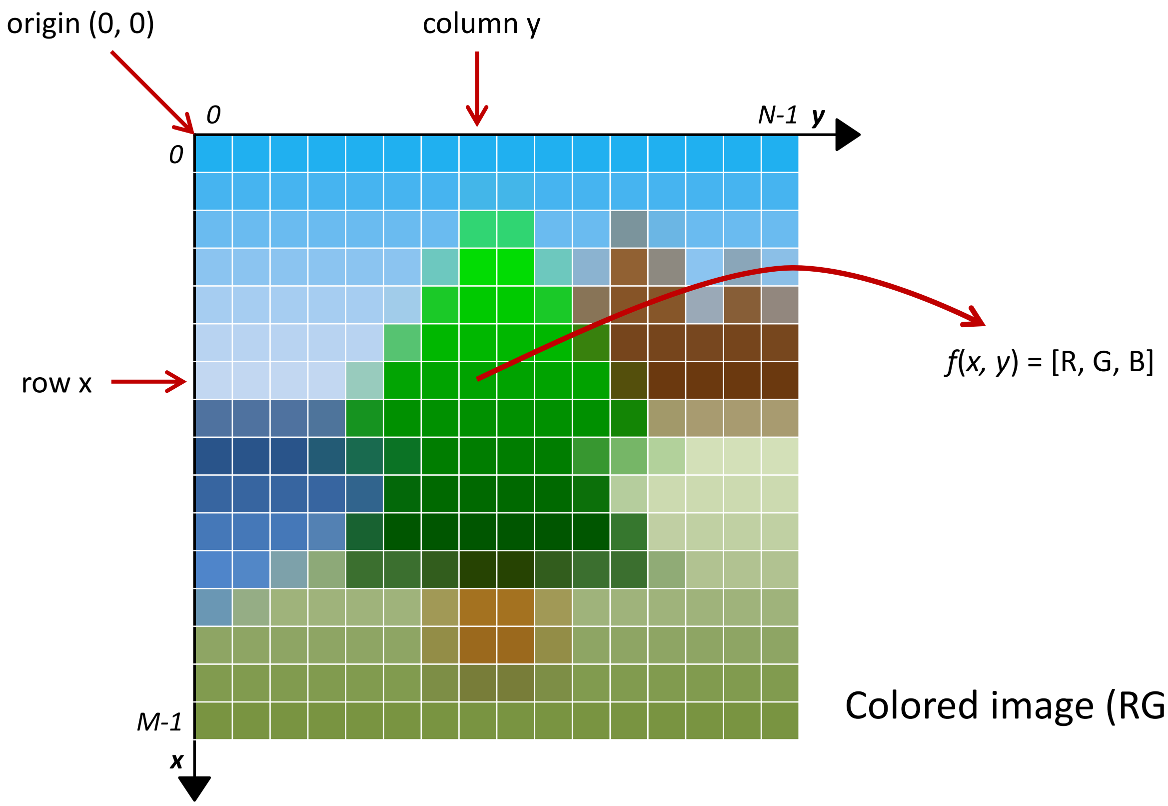
Digital images



Intensity image

M rows
N columns
M × N pixels

Digital images

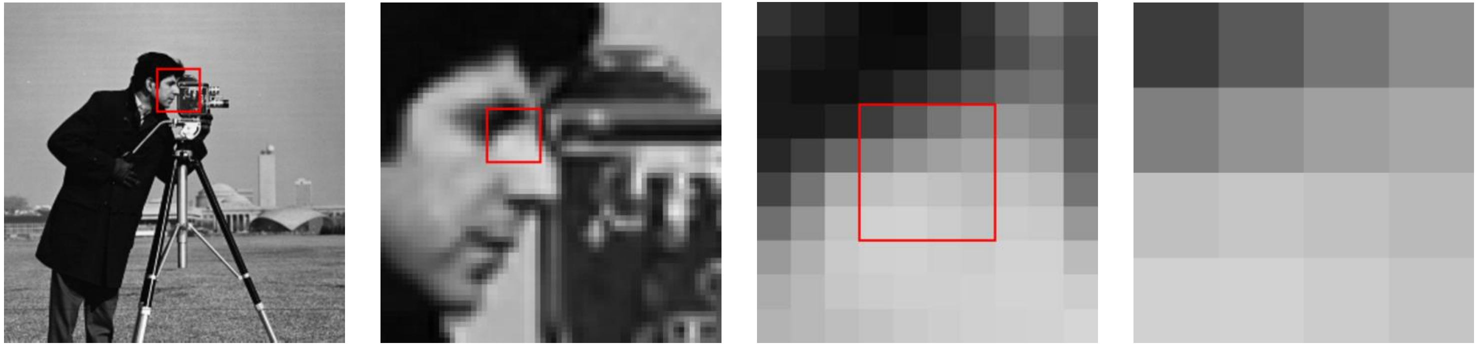


Colored image (RGB)

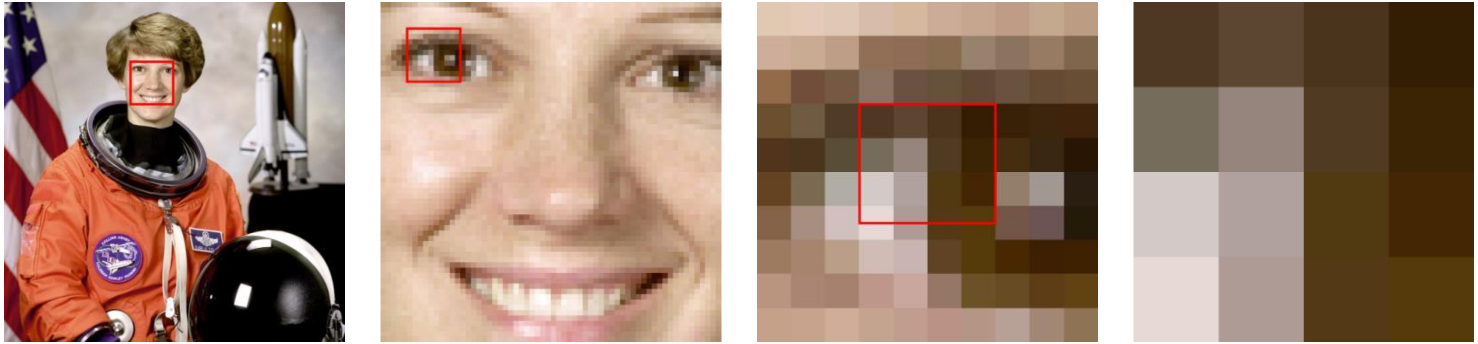
M rows
N columns
M × N pixels

Digital images

Intensity image (gray levels):

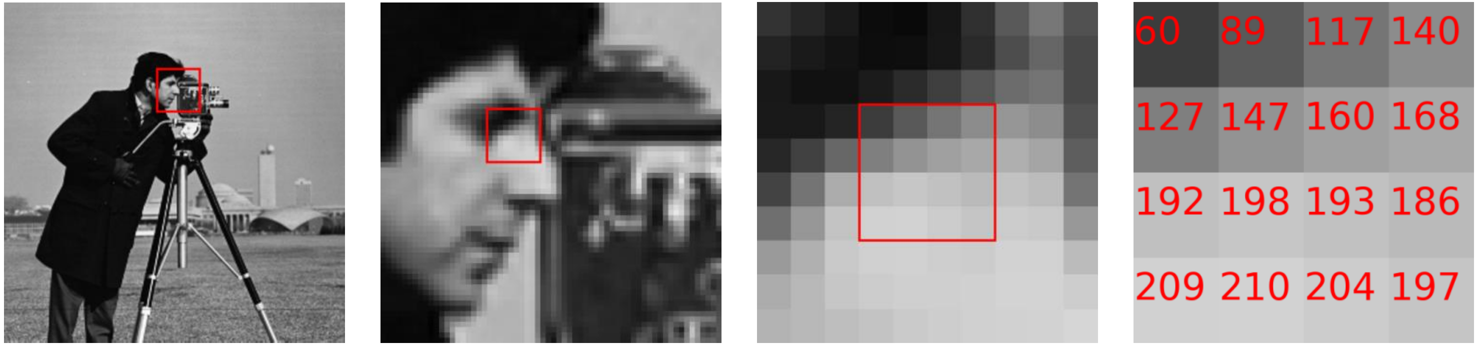


Colored image (RGB):

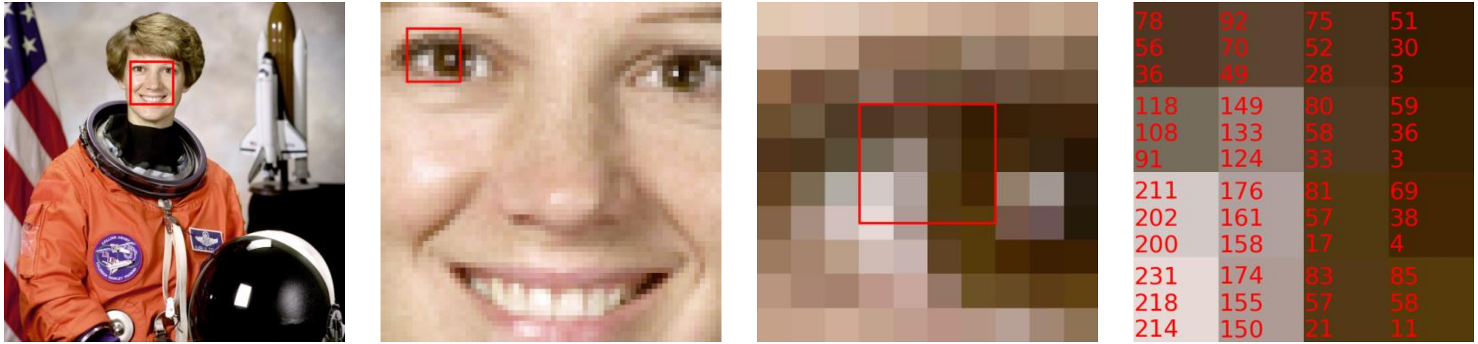


Digital images

Intensity image (gray levels):



Colored image (RGB):



Colored images – RGB

vermelho – R (red)

verde – G (green)

azul – B (blue)

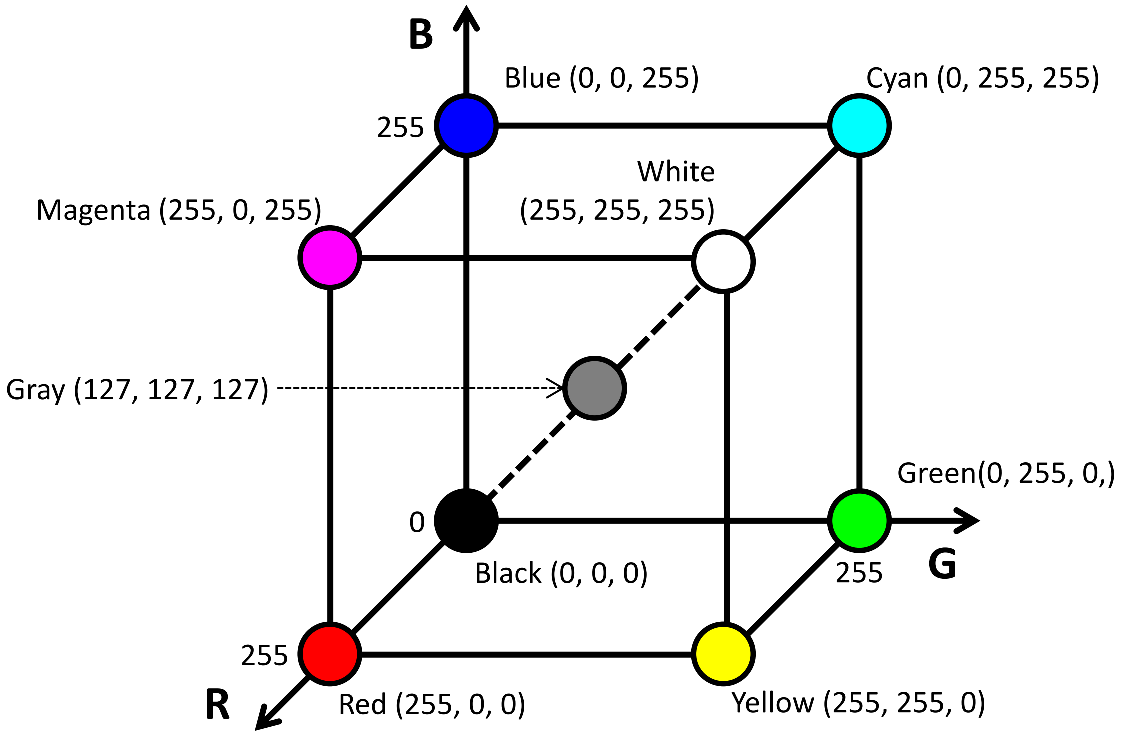
Colored images – RGB

red – R (red)

green – G (green)

blue – B (blue)

Colored images – RGB



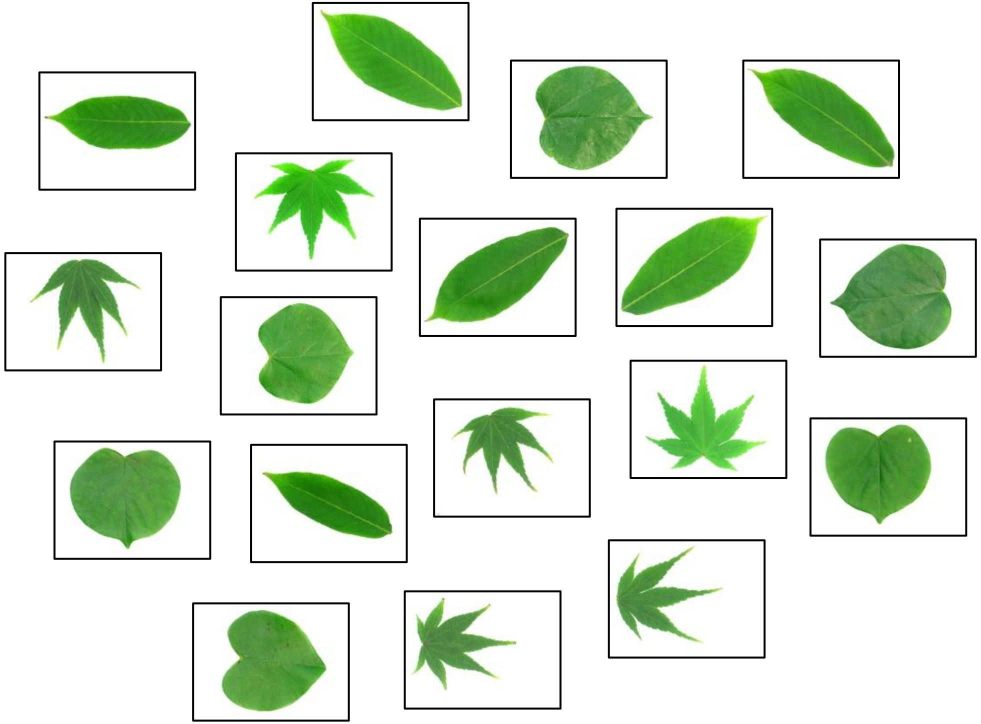
A CLASSIFICATION PROBLEM

A classification problem

- Learning to classify three types (classes) of leaves from images.

- Flavia leaf dataset:
  - http://flavia.sourceforge.net/
  - 1,907 images
  - 33 classes

- We selected 3 classes:
  - *aesculus chinensis*
  - *acer palmatum*
  - *cercis chinensis*



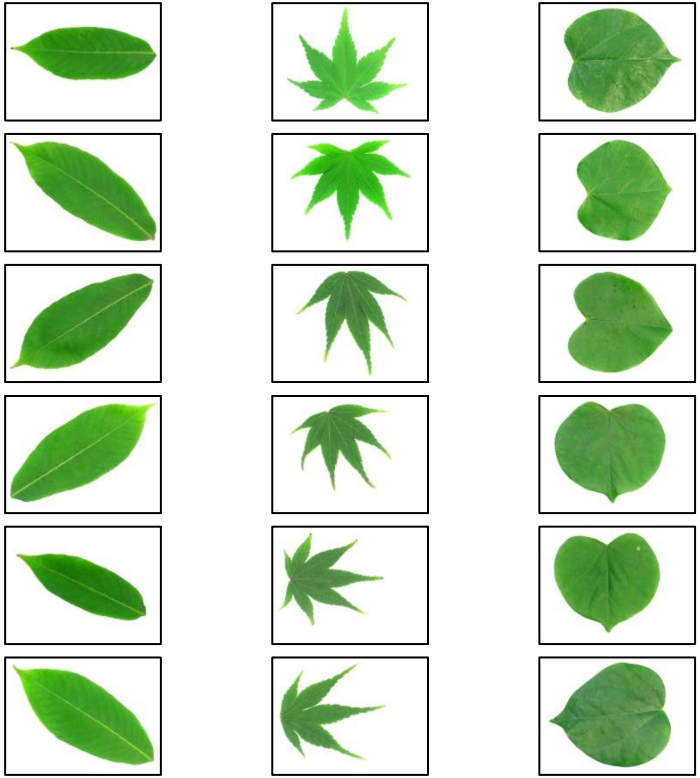
A classification problem

- Learning to classify three types (classes) of leaves from images.

- Feature extraction:
  - Select features from the images that can be used to distinguish between the classes.

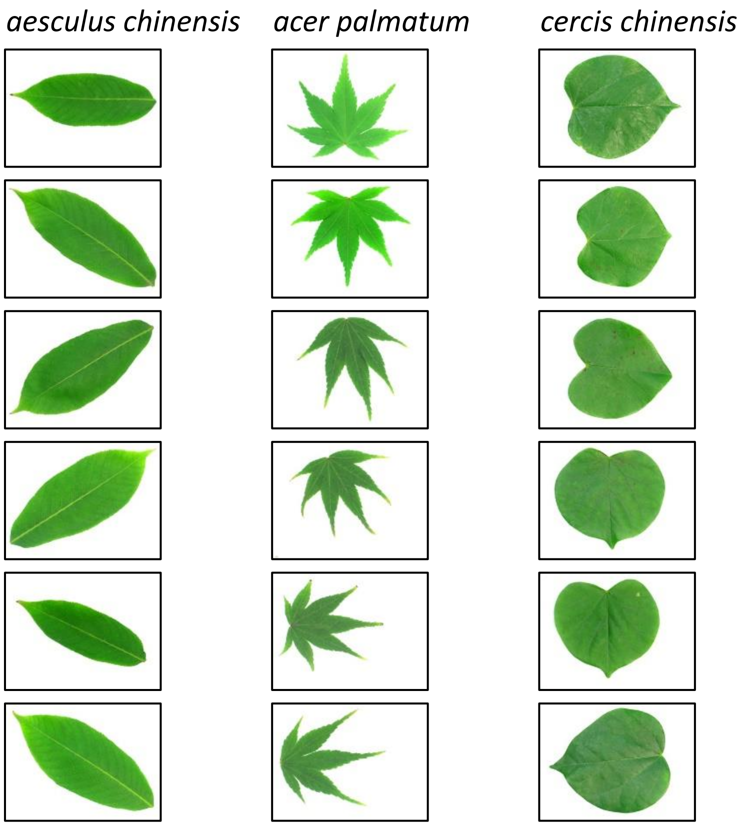
- Features can be:
  - Shapes
  - Colors
  - Textures
  - Histogram of gradients (HoG)
  - *Bag of Visual Words*
  - *Fisher Vectors*
  - ...

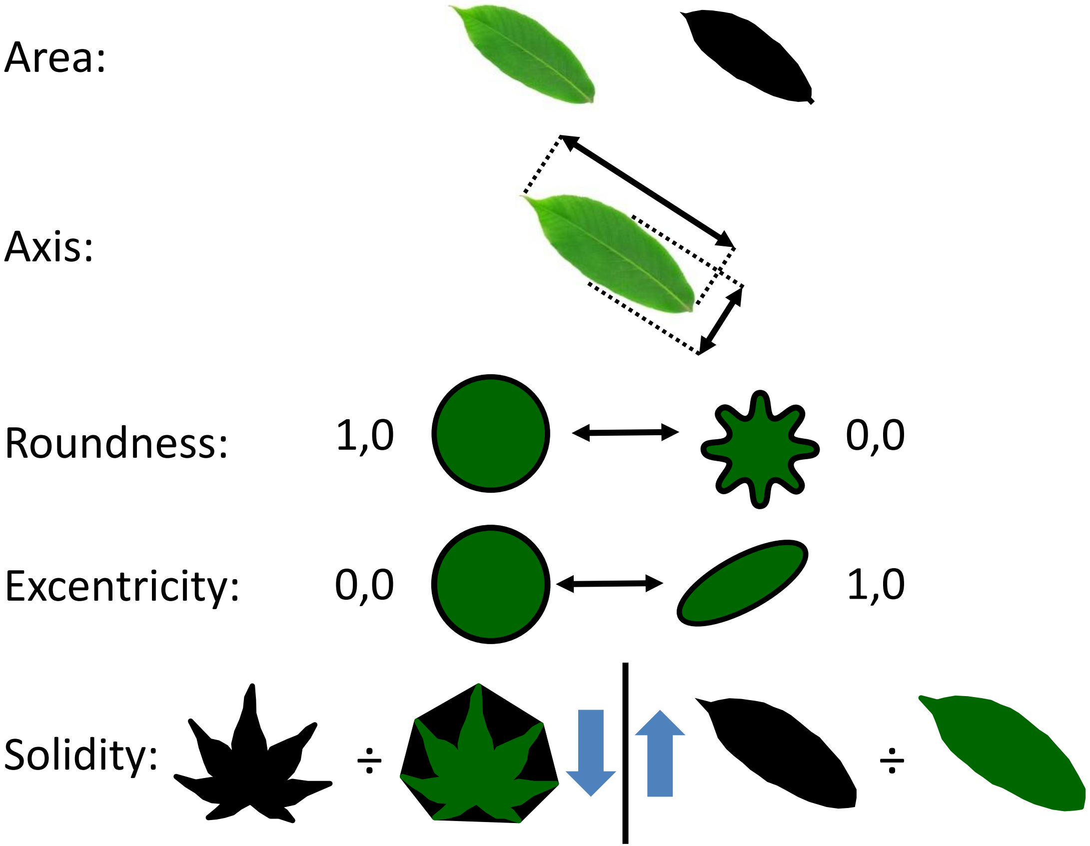
aesculus chinensis *acer palmatum* *cercis chinensis*



A classification problem

- Some feature shapes:



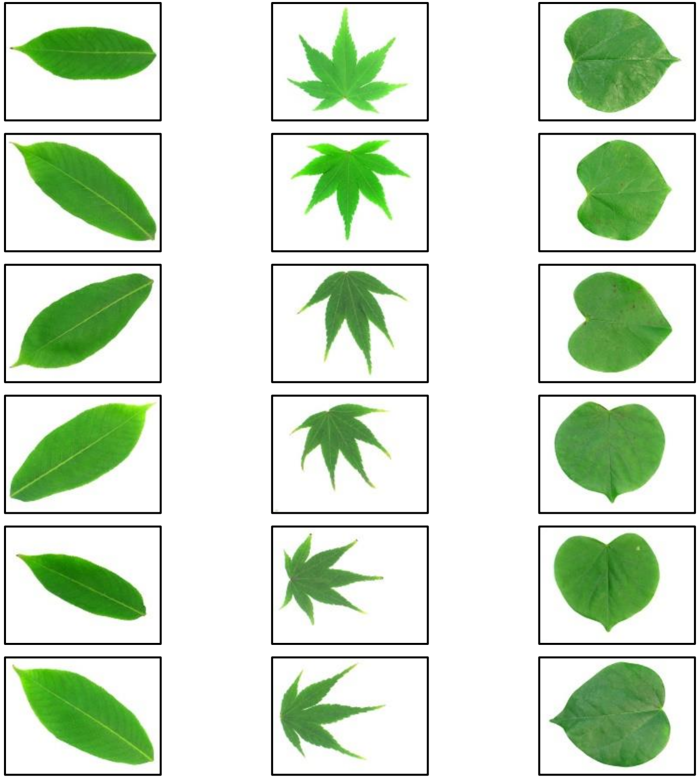


https://scikit-image.org/docs/stable/api/skimage.measure.html#skimage.measure.regionprops

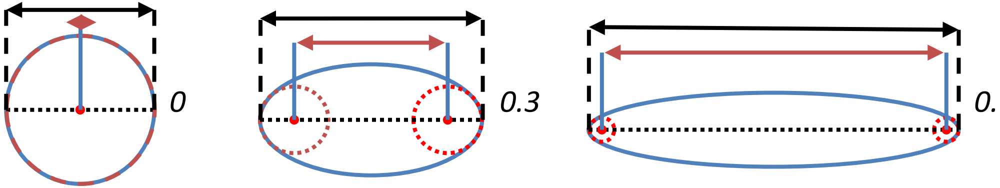
A classification problem

- Some feature shapes:

aesculus chinensis *acer palmatum* *cercis chinensis*



- **Area:** the number of pixels of the shape scaled by pixel-area.
- **Axis:** the length of the major and minor axis of the ellipse with the same normalized second central moments as the region.
- **Roundness:** a function of the perimeter and the area of the region
  - $roundness = \frac{4 \times \pi \times area}{perimeter^2}$
- **Eccentricity:** the ratio of the focal distance over the major axis length of the ellipse with the same second-moments.



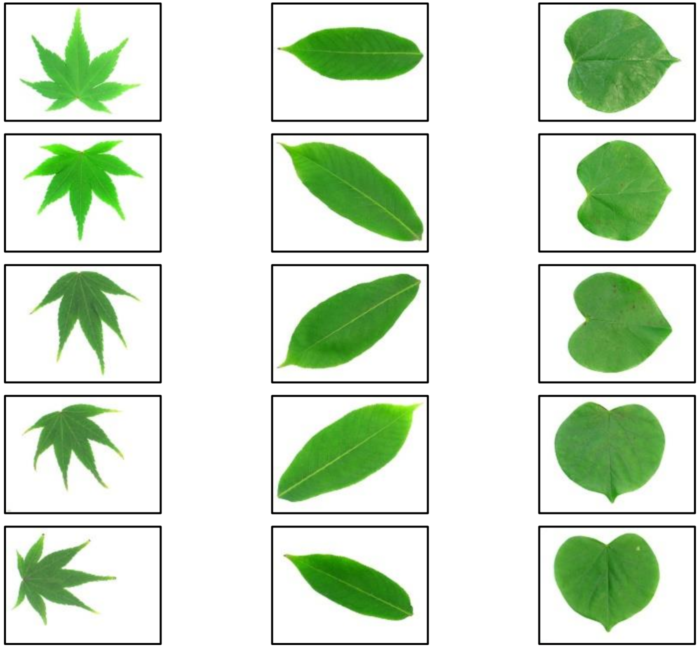
- **Solidity:** the ratio of pixels in the region to pixels of the convex hull image.
  - **Convex hull:** the smallest convex polygon that encloses the region.

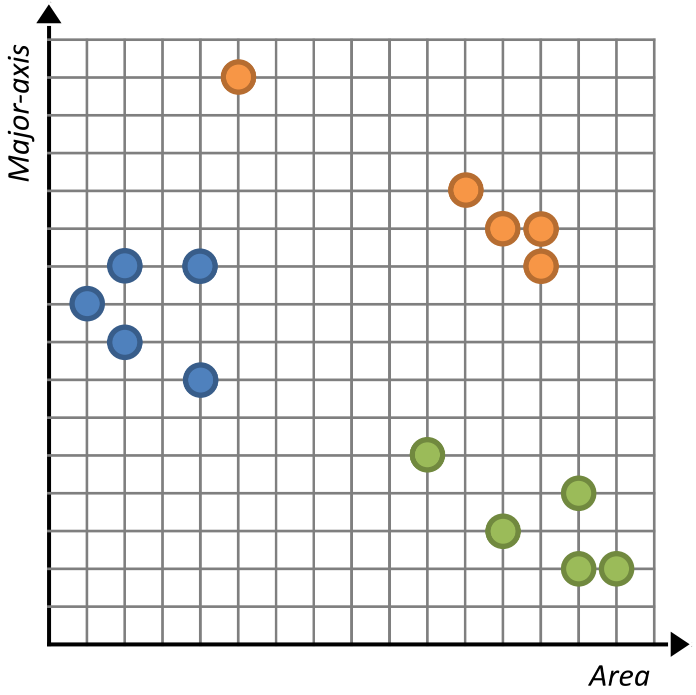
https://scikit-image.org/docs/stable/api/skimage.measure.html#skimage.measure.regionprops

A classification problem

- Learning to classify three types (classes) of leaves from images.

acer palmatum *aesculus chinensis* *cercis chinensis*





A classification problem

- Learning to classify three types (classes) of leaves from images.

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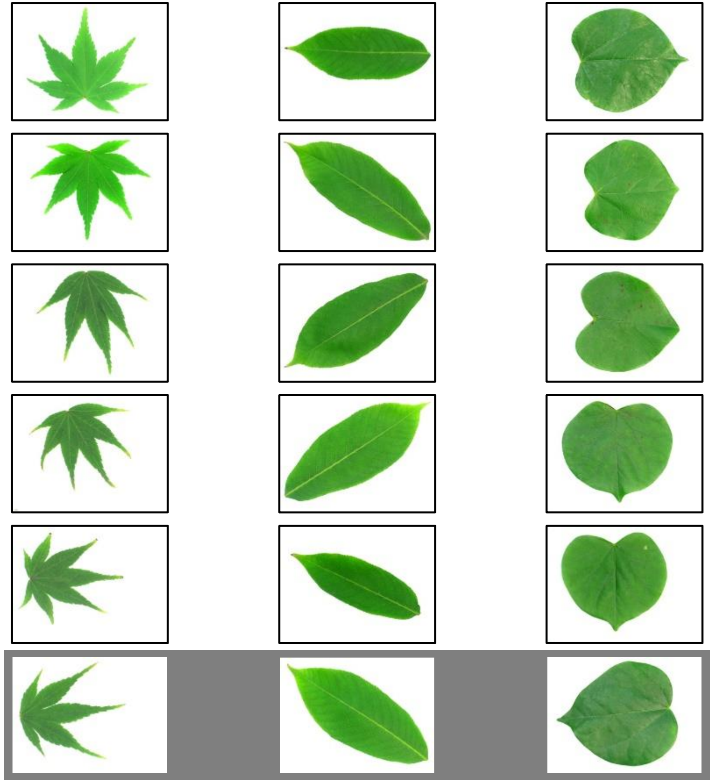
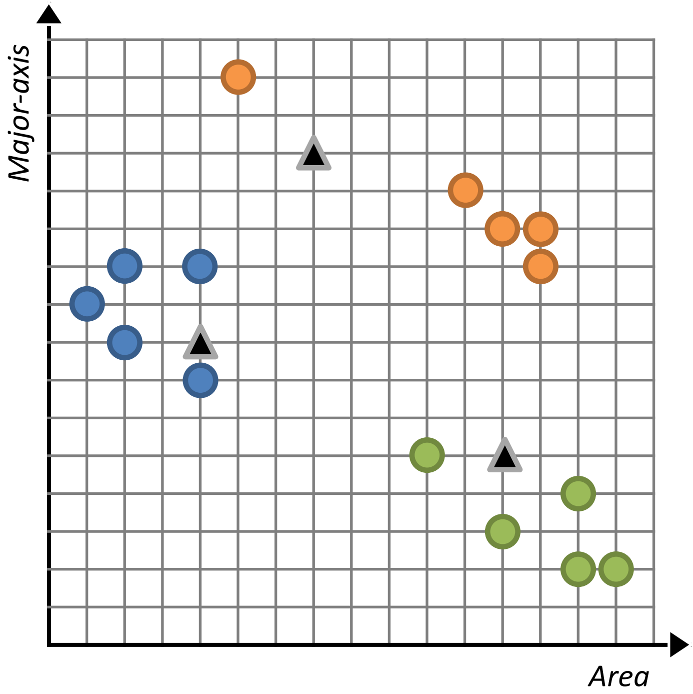
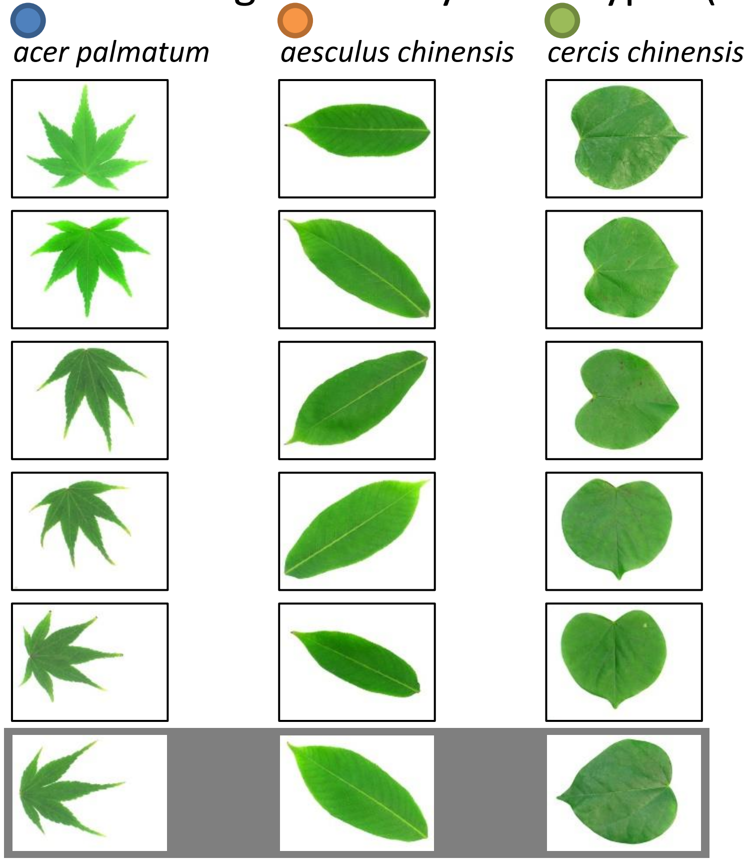


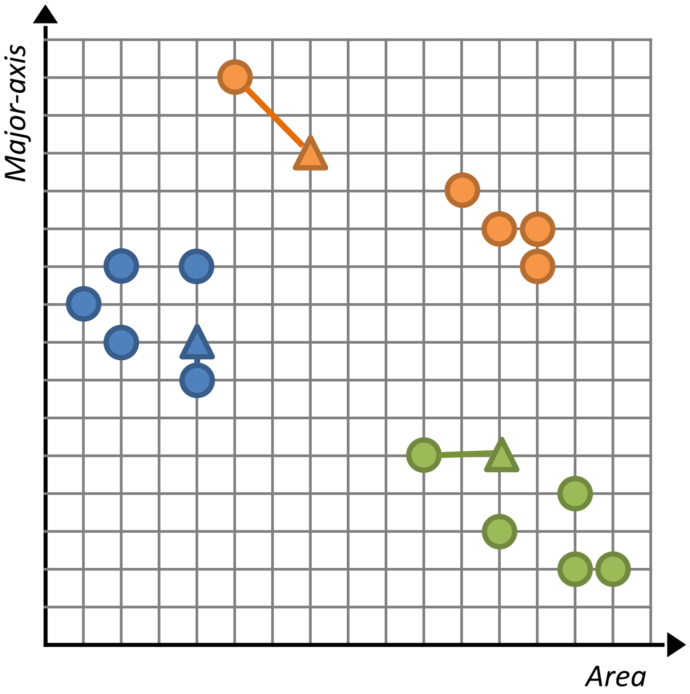


The nearest neighbor method

- Learning to classify three types (classes) of leaves from images.

acer palmatum *aesculus chinensis* *cercis chinensis*

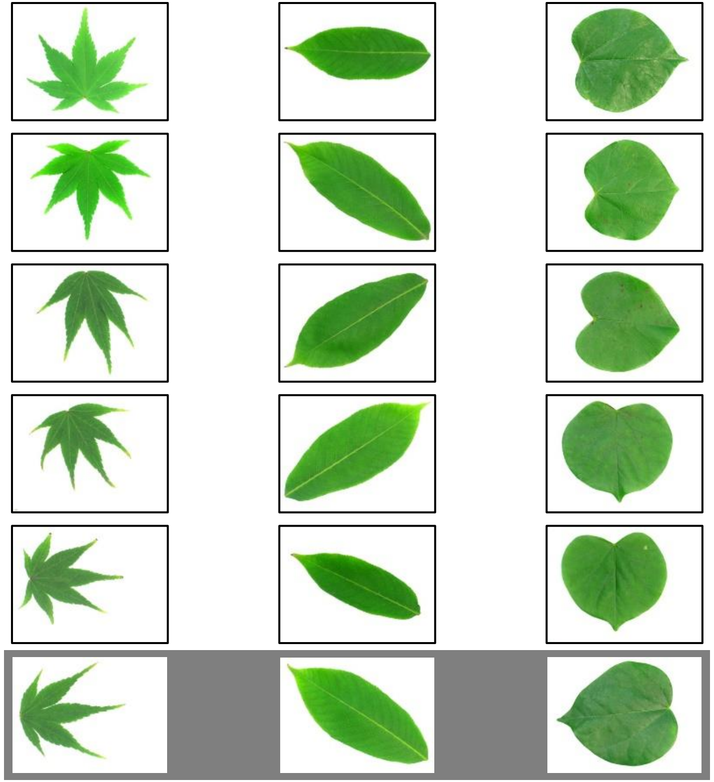




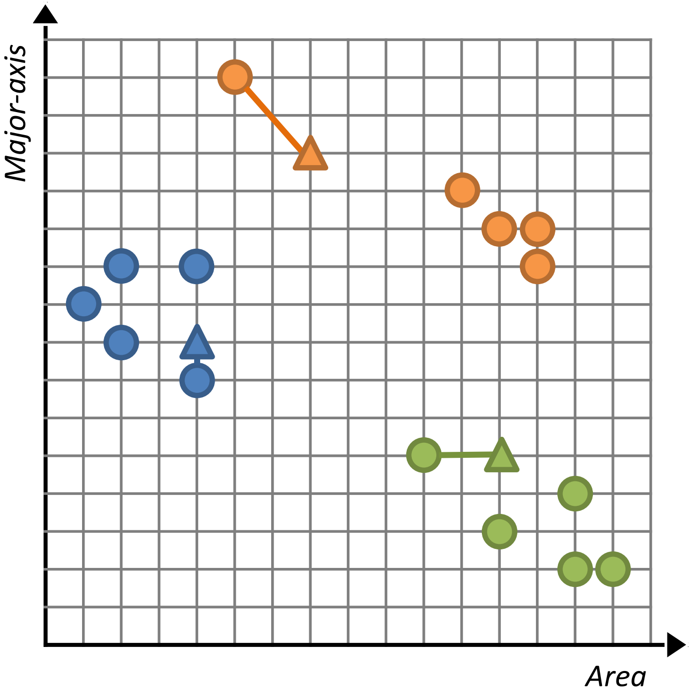
K-nearest neighbors – K-NN

- Learning to classify three types (classes) of leaves from images.

acer palmatum *aesculus chinensis* *cercis chinensis*



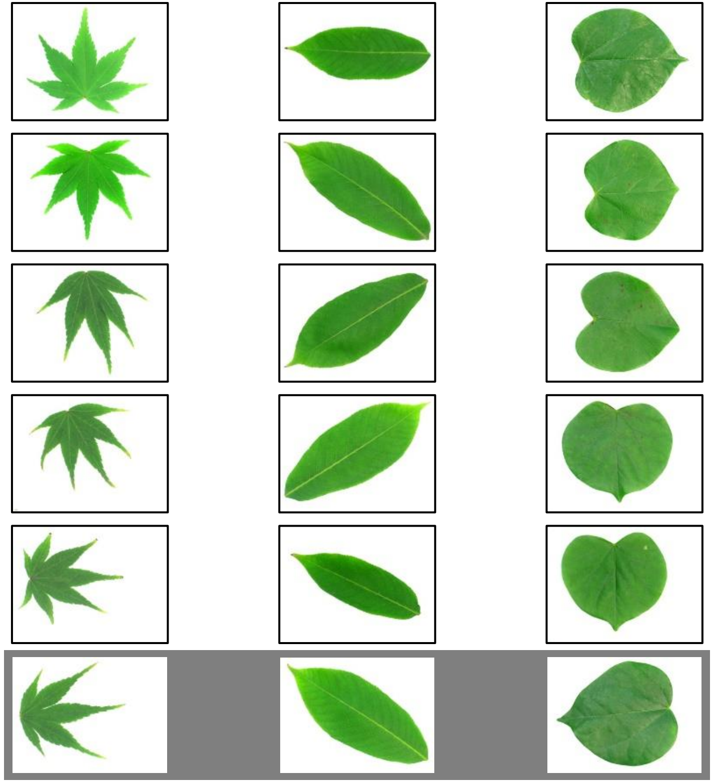
k = 1



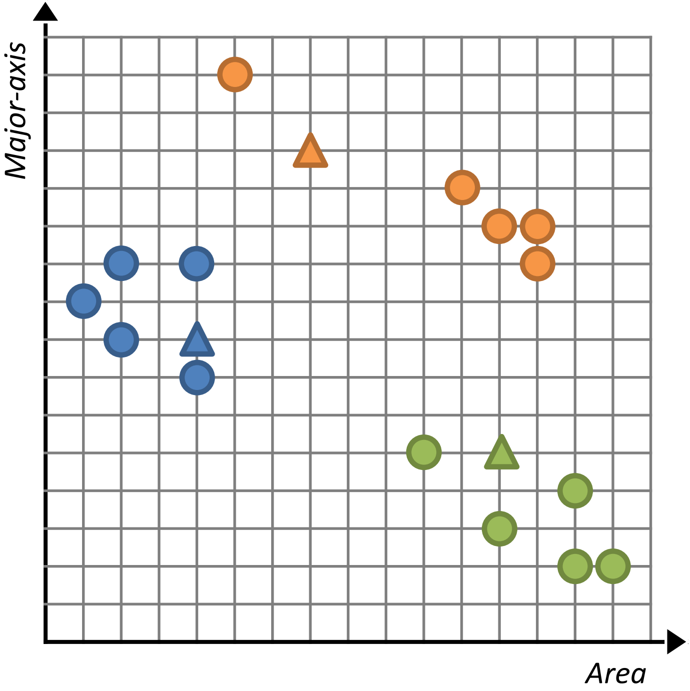
K-nearest neighbors – K-NN

- Learning to classify three types (classes) of leaves from images.

acer palmatum *aesculus chinensis* *cercis chinensis*



k = 3



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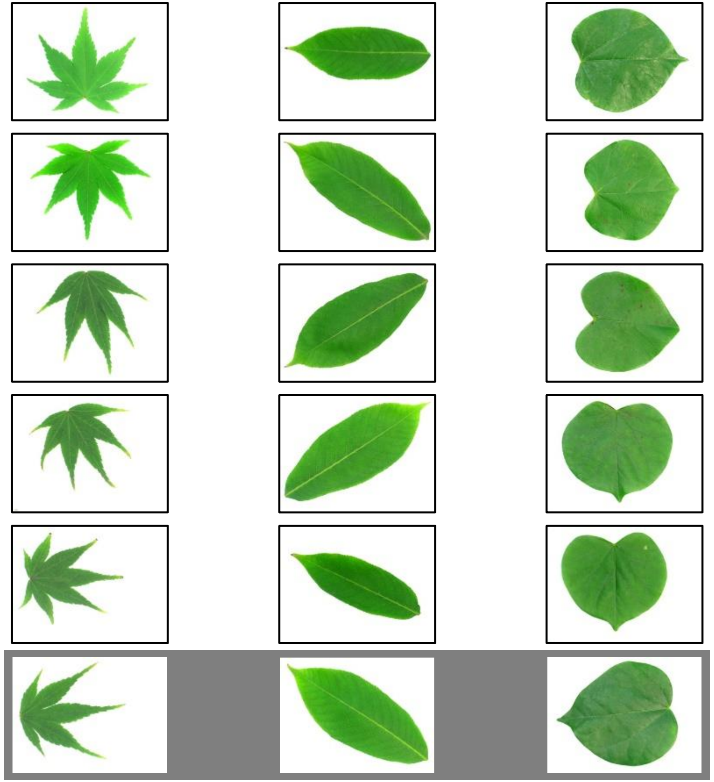
- Learning to classify three types (classes) of leaves from images.

acer palmatum *aesculus chinensis* *cercis chinensis*



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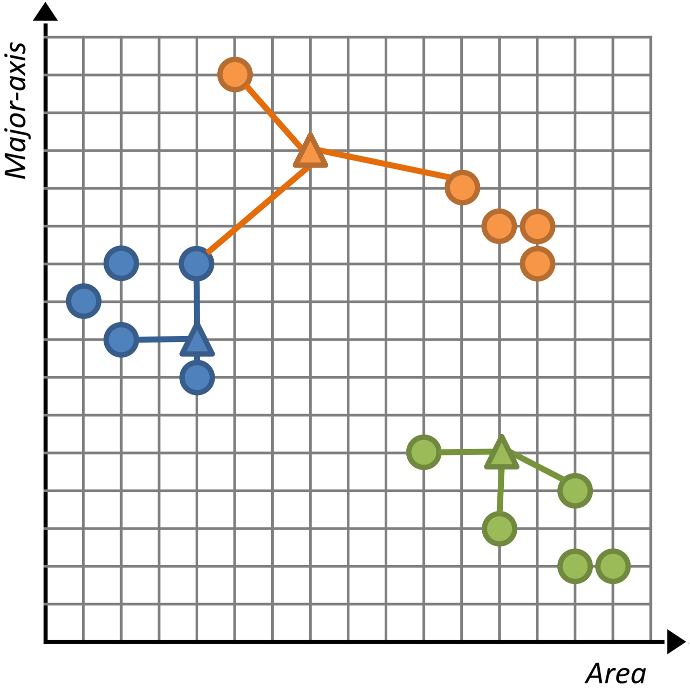
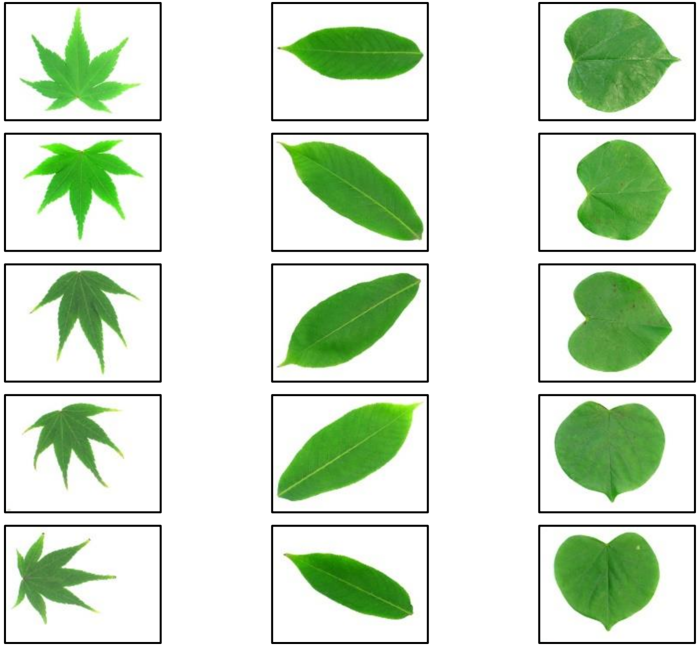
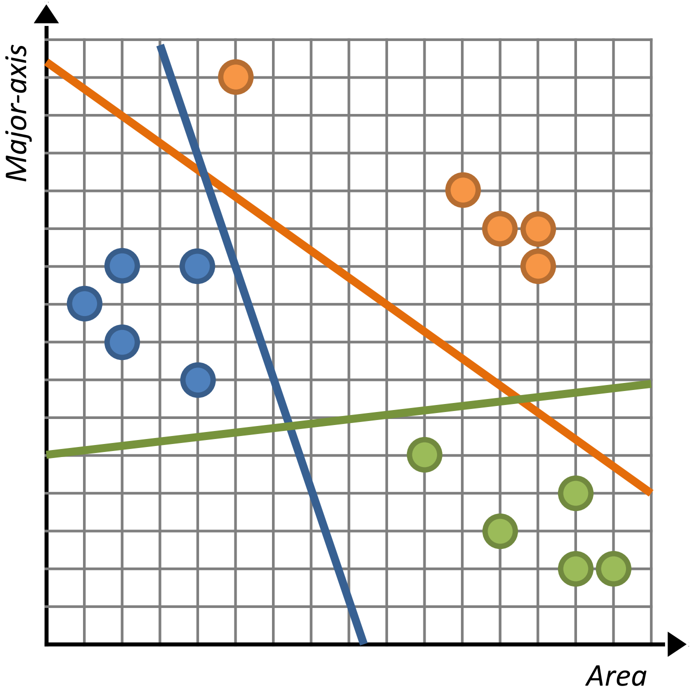


Linear functions (Perceptrons)

- Learning to classify three types (classes) of leaves from images.

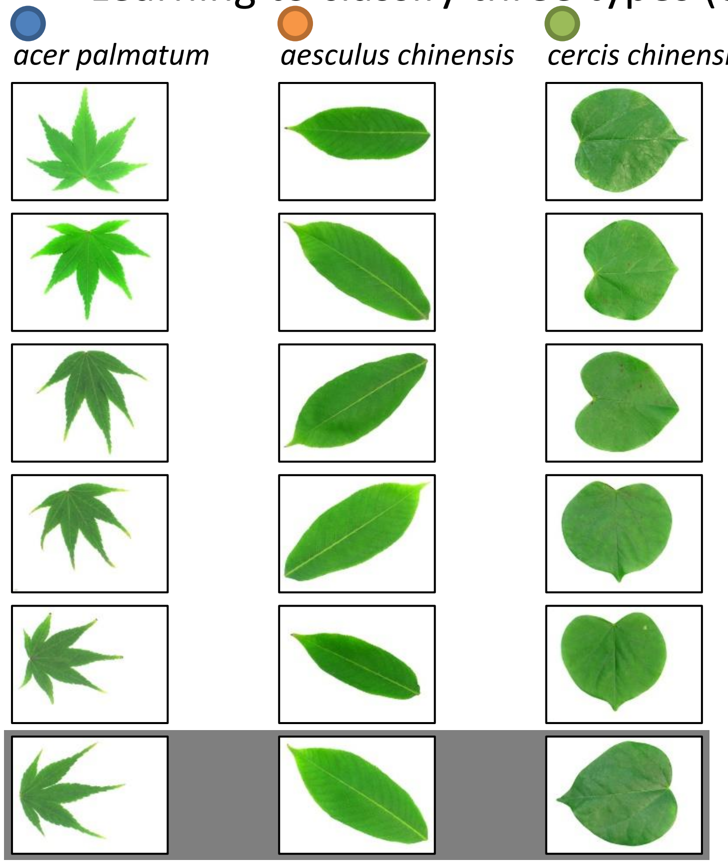
acer palmatum *aesculus chinensis* *cercis chinensis*

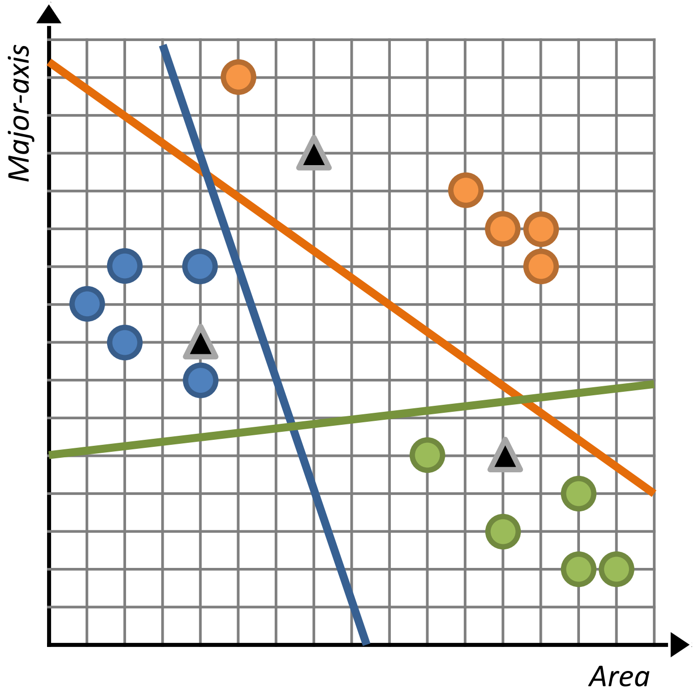




Linear functions (Perceptrons)

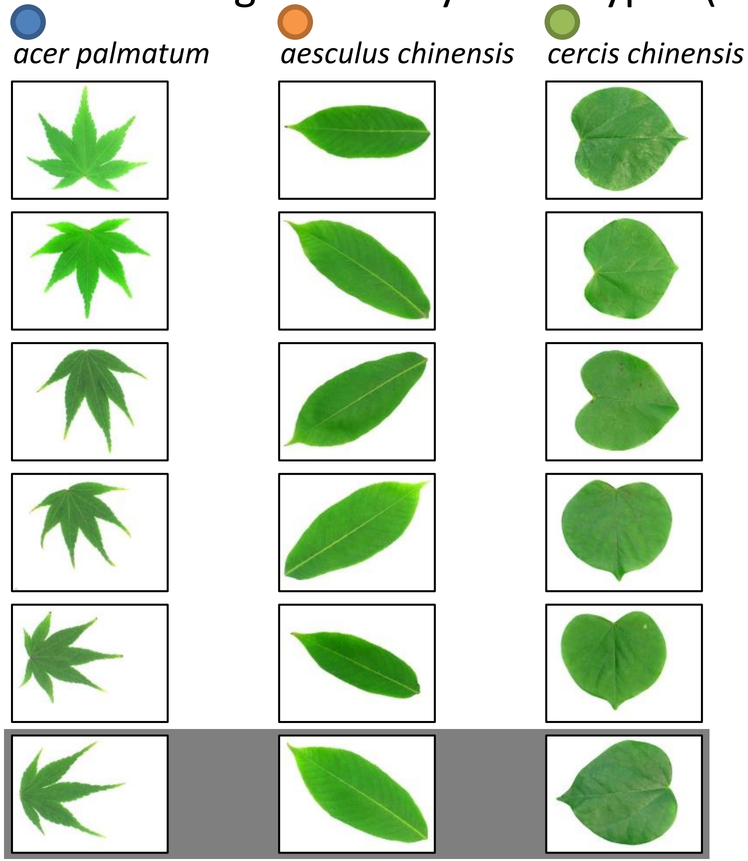
- Learning to classify three types (classes) of leaves from images.

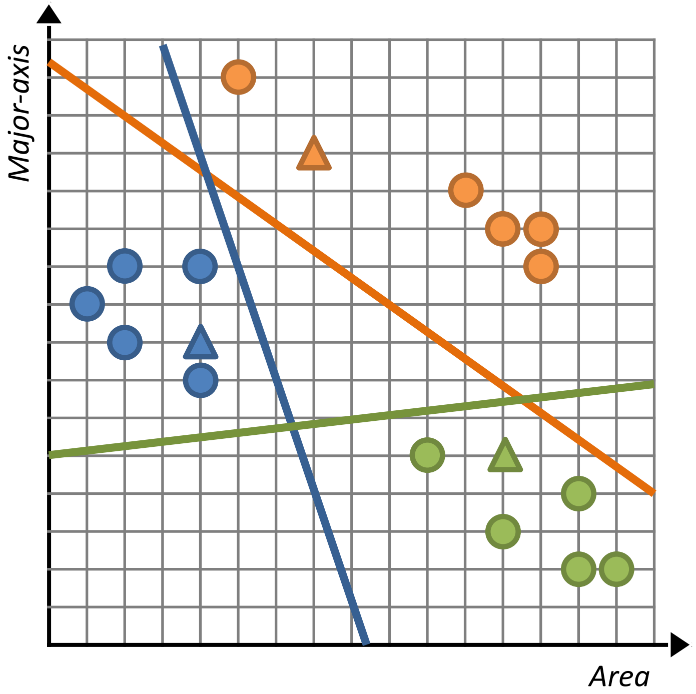




Linear functions (Perceptrons)

- Learning to classify three types (classes) of leaves from images.

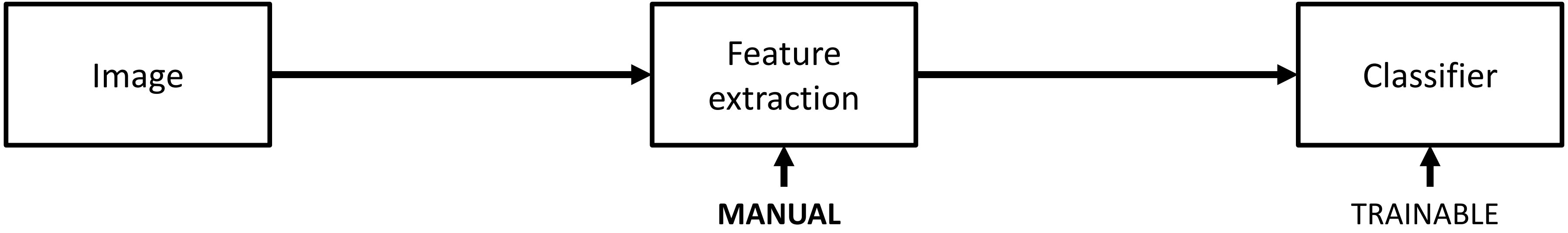




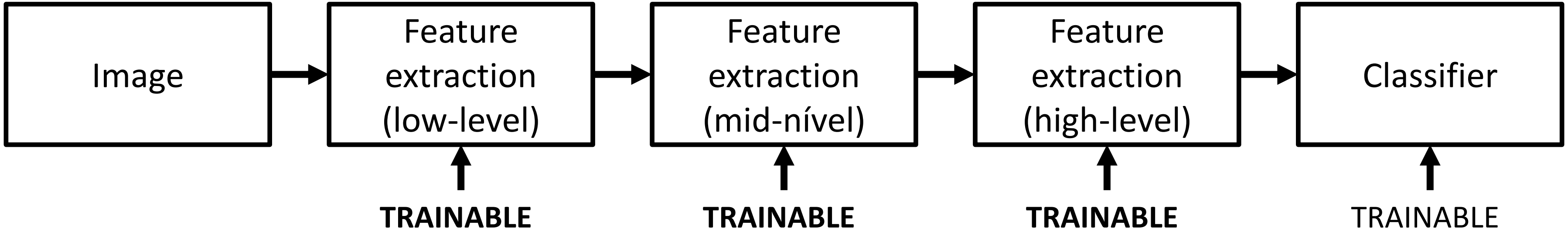
CLASSIFICATION PIPELINES

Classification pipelines

The classic image classification pipeline



Deep Learning



Yann LeCun's Deep Learning Course at CDS - SPRING 2021

LEARNING MODELS

Learning models

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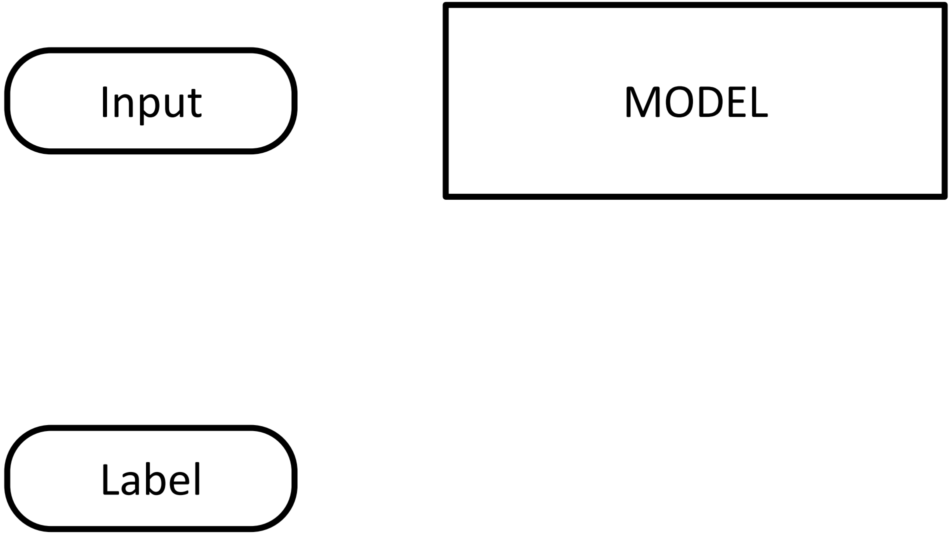
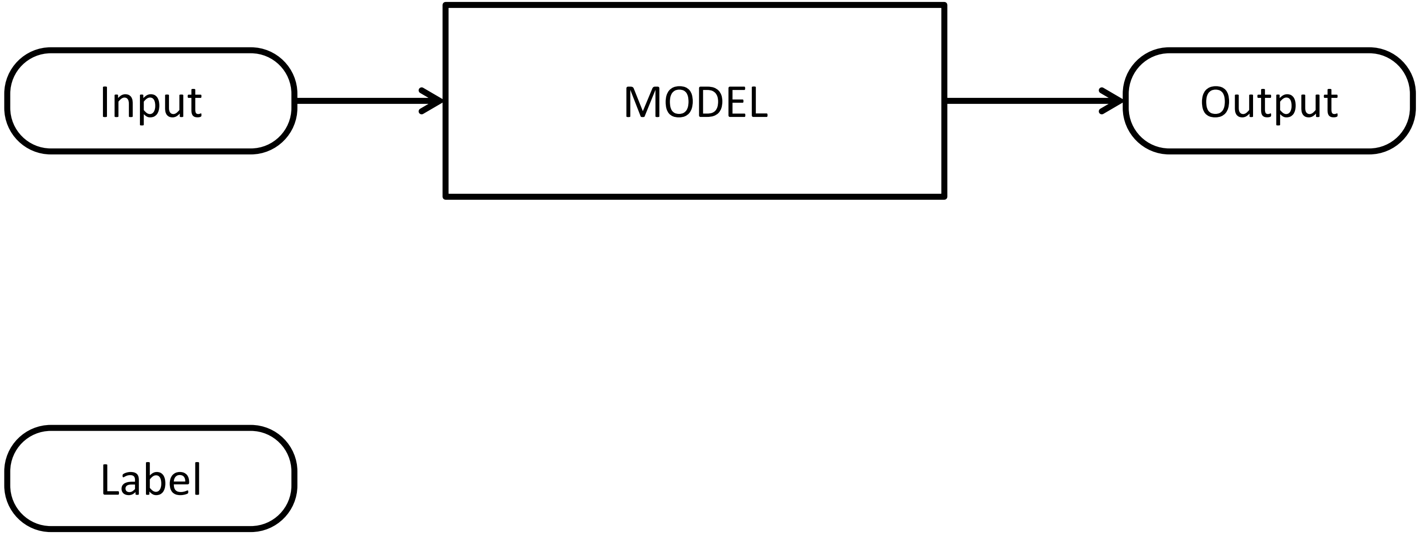
- Supervised learning
- Unsupervized learning
- Reinforcement learning
- Semi-supervised learning
- Self-supervised learning

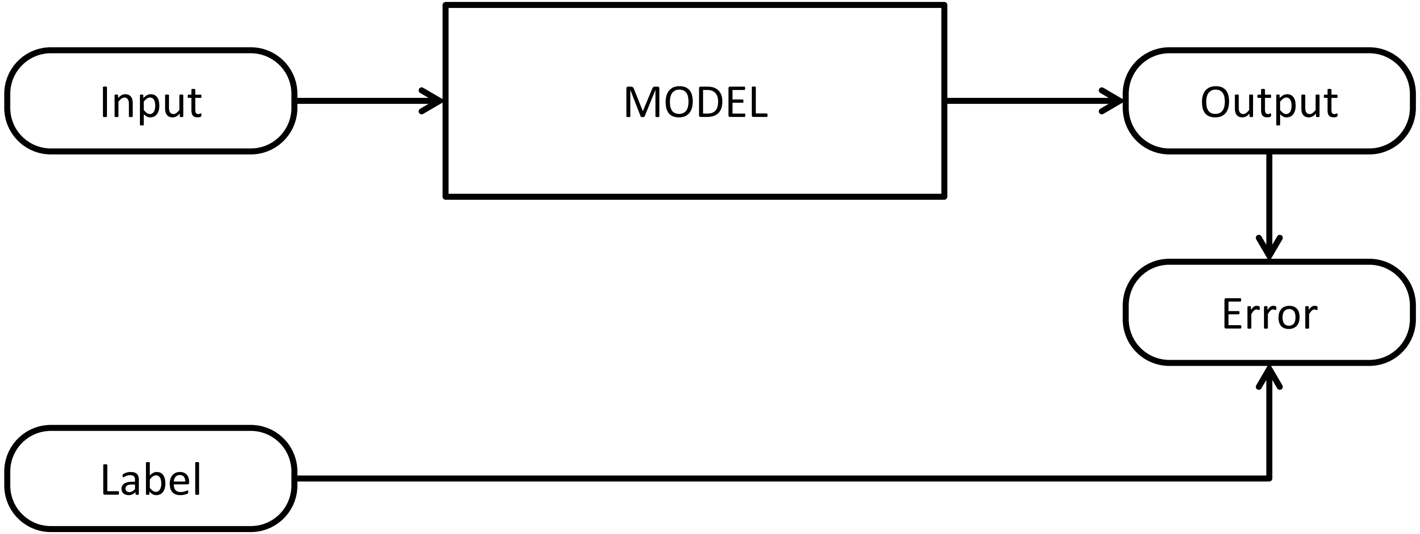
Supervised learning



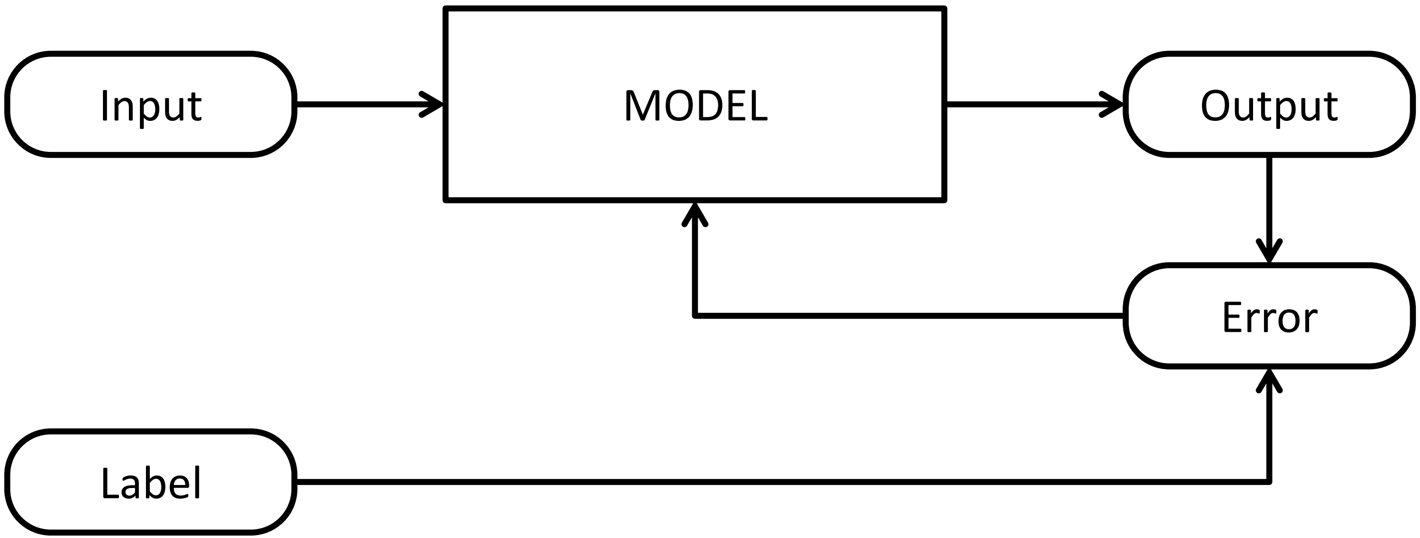
Supervised learning



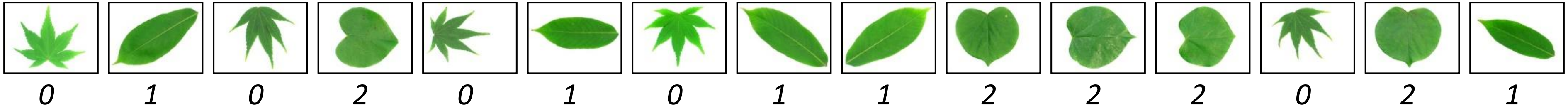
Supervised learning

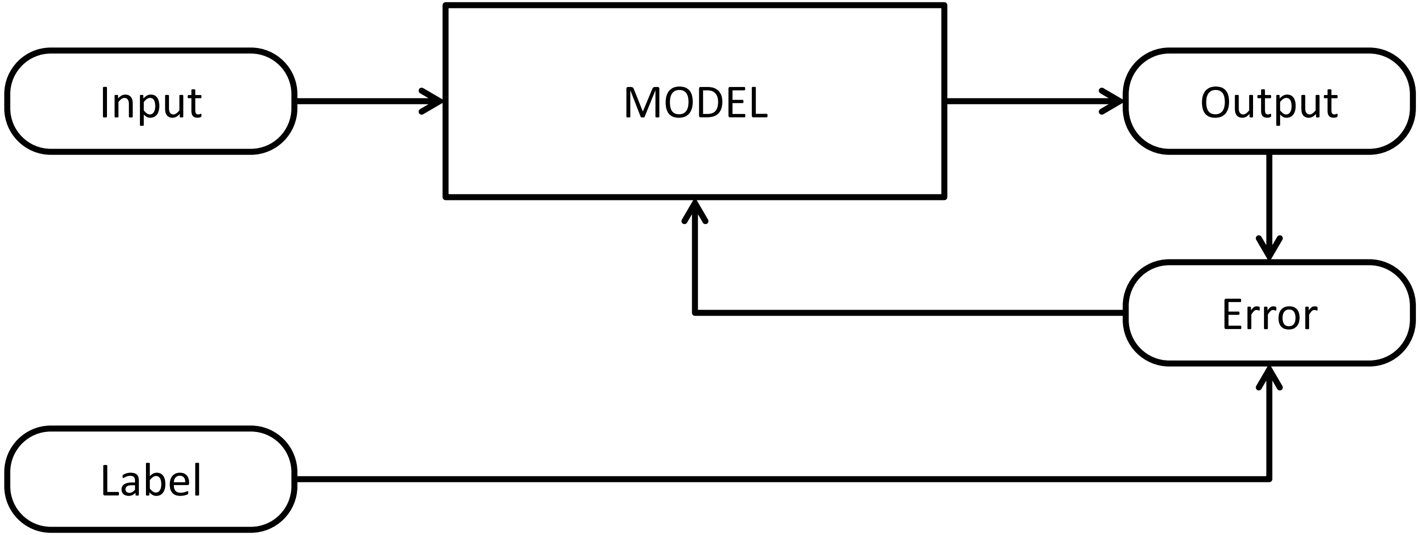


Supervised learning



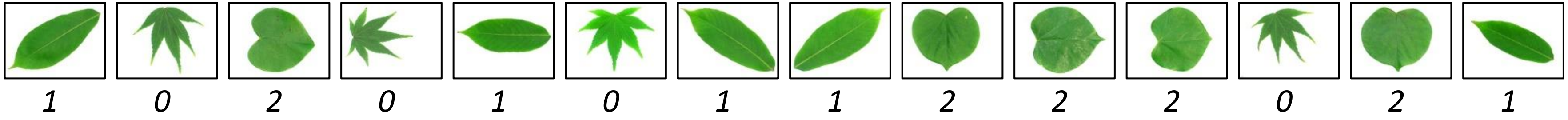
Example: Supervised learning

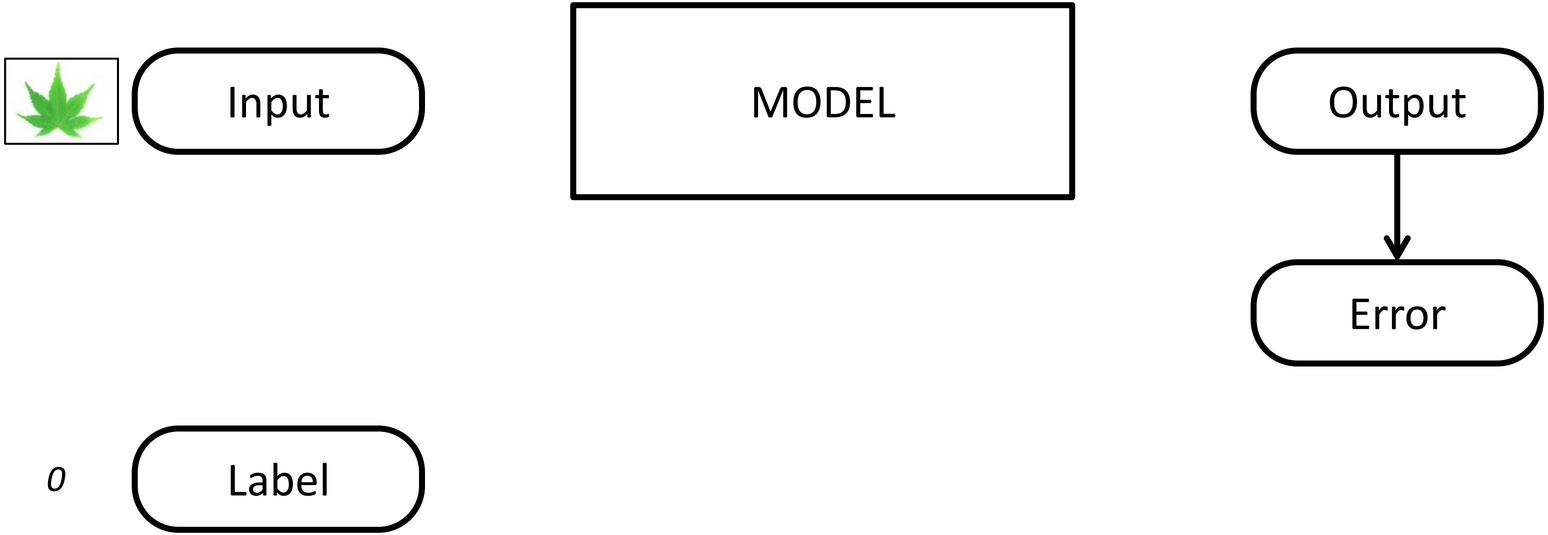




0: *acer palmatum*
1: *aesculus chinensis*
2: *cercis chinensis*

Example: Supervised learning





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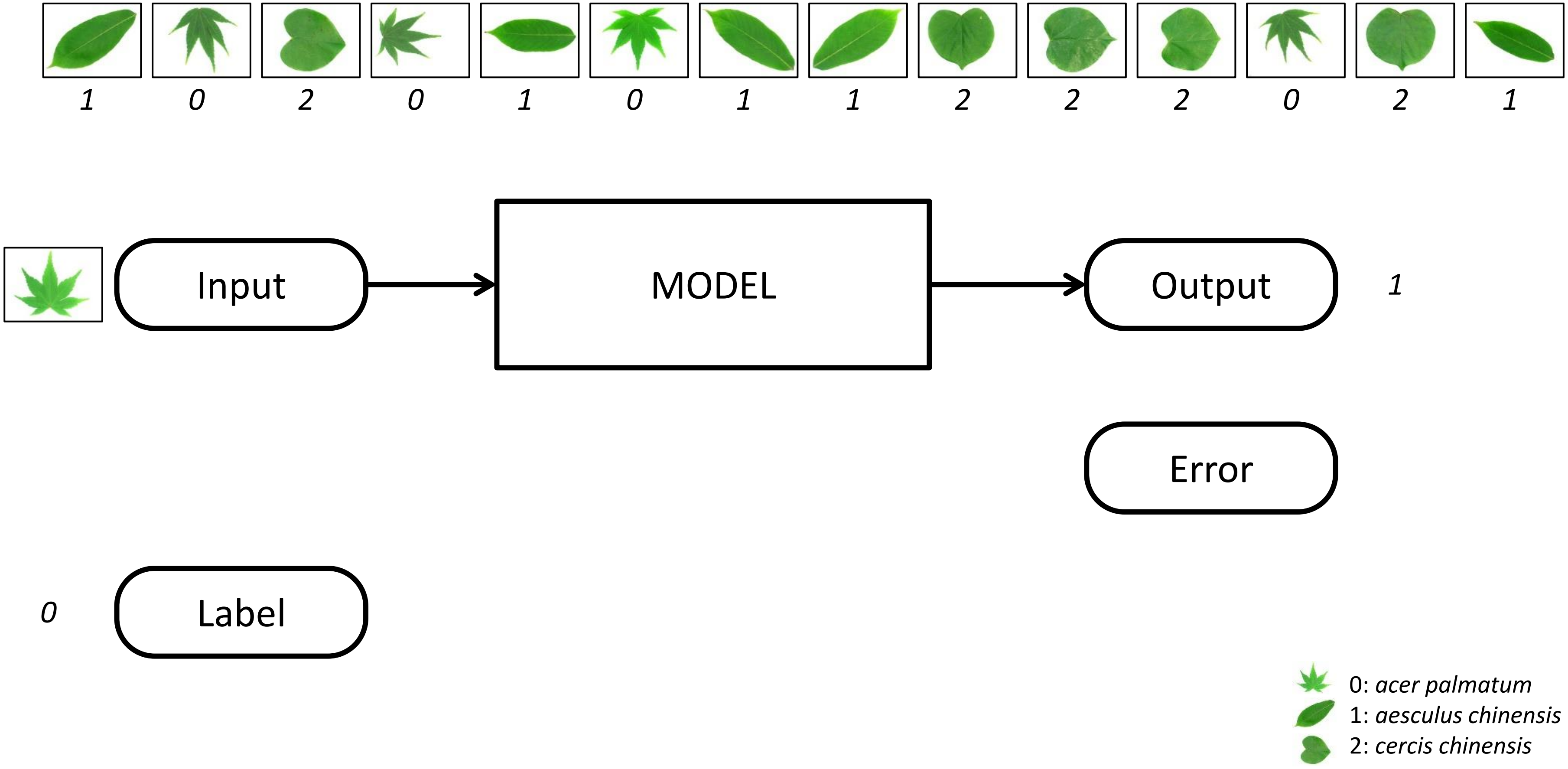
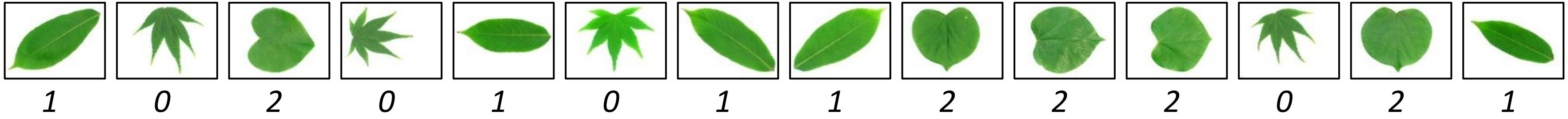
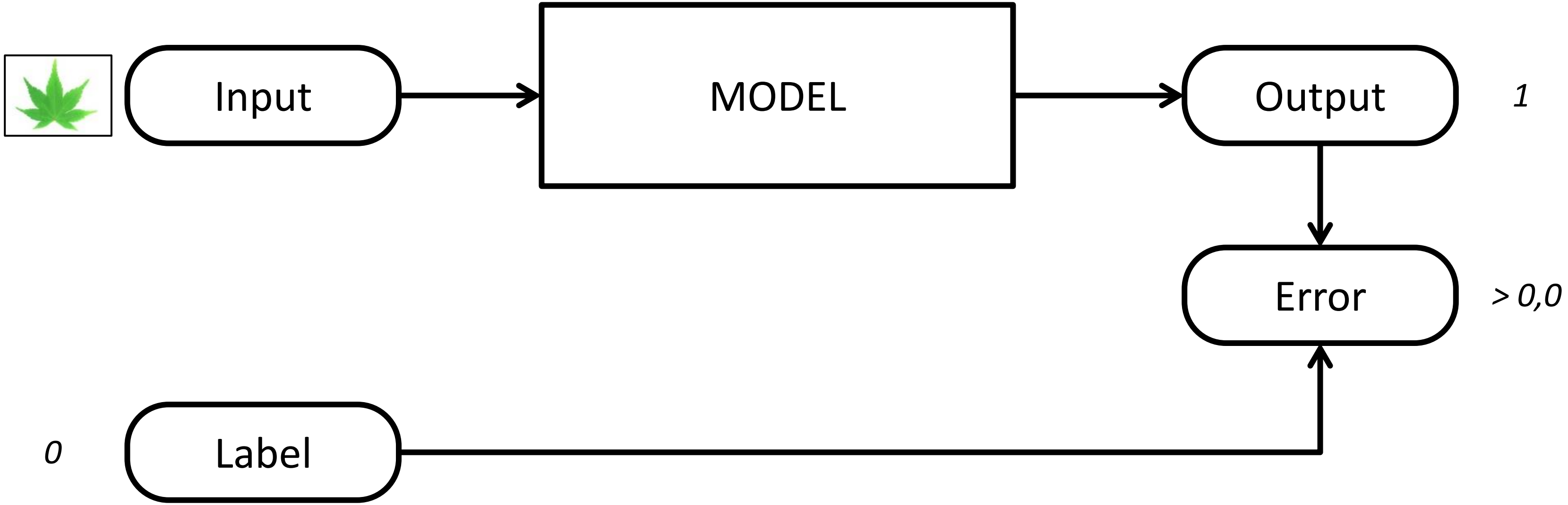
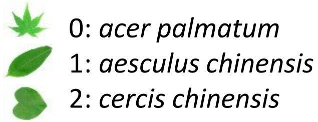
Example: Supervised learning




1 0 2 0 1 0 1 1 2 2 2 0 2 1


Input
MODEL
Output
1
Error
> 0,0
0
Label


0: *acer palmatum*
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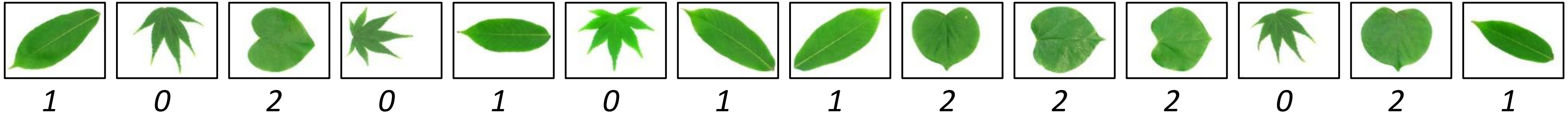
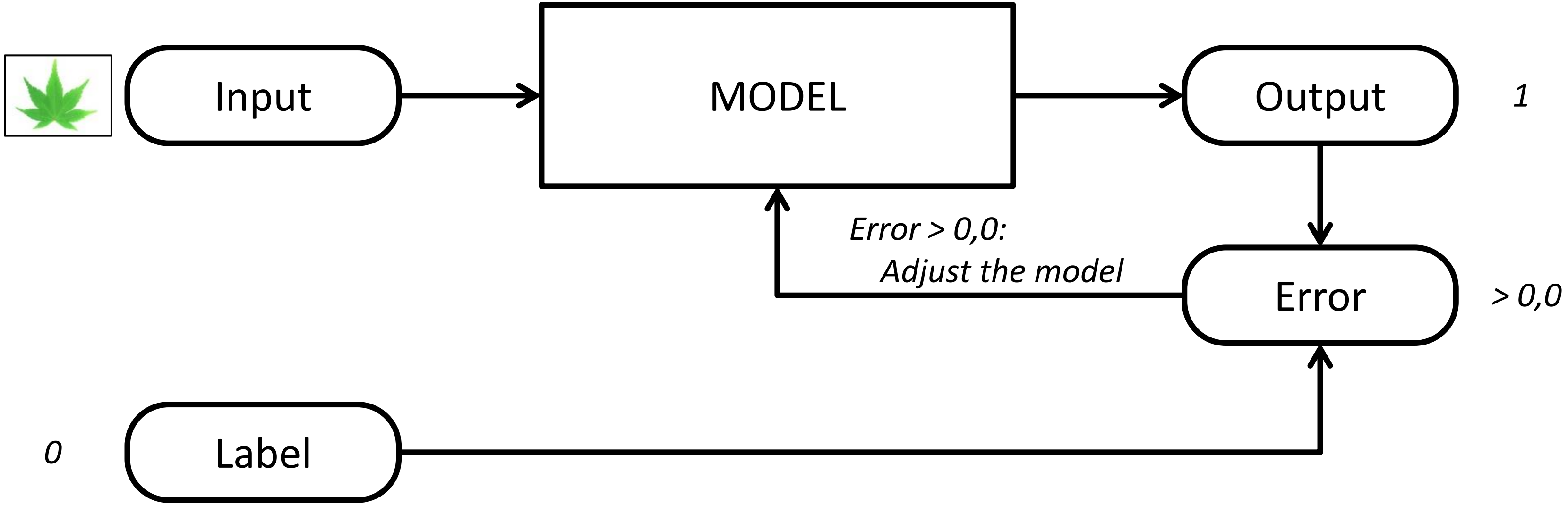
Example: Supervised learning





0: *acer palmatum*
1: *aesculus chinensis*
2: *cercis chinensis*

Example: Supervised learning

0 0 2 0 1 0 1 1 2 2 2 0 2 1

Input

MODEL

Output

Error

1

Label

0: *acer palmatum*
1: *aesculus chinensis*
2: *cercis chinensis*

Example: Supervised learning

~~0~~   0 2 0 1 0 1 1 2 2 2 0 2 1

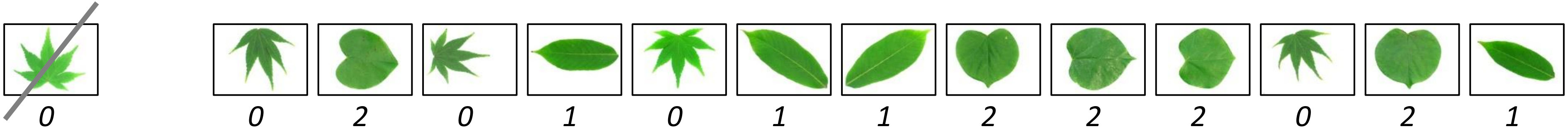
Input → MODEL → Output   *2*

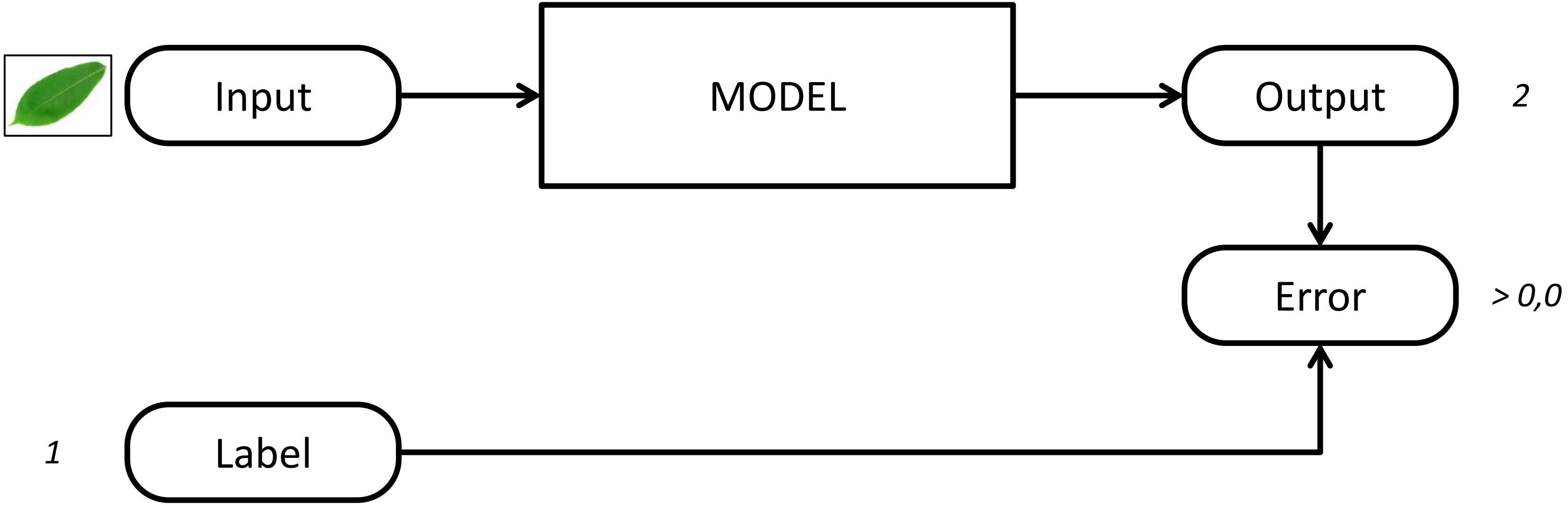
Error

1   Label

0: *acer palmatum*
1: *aesculus chinensis*
2: *cercis chinensis*

Example: Supervised learning





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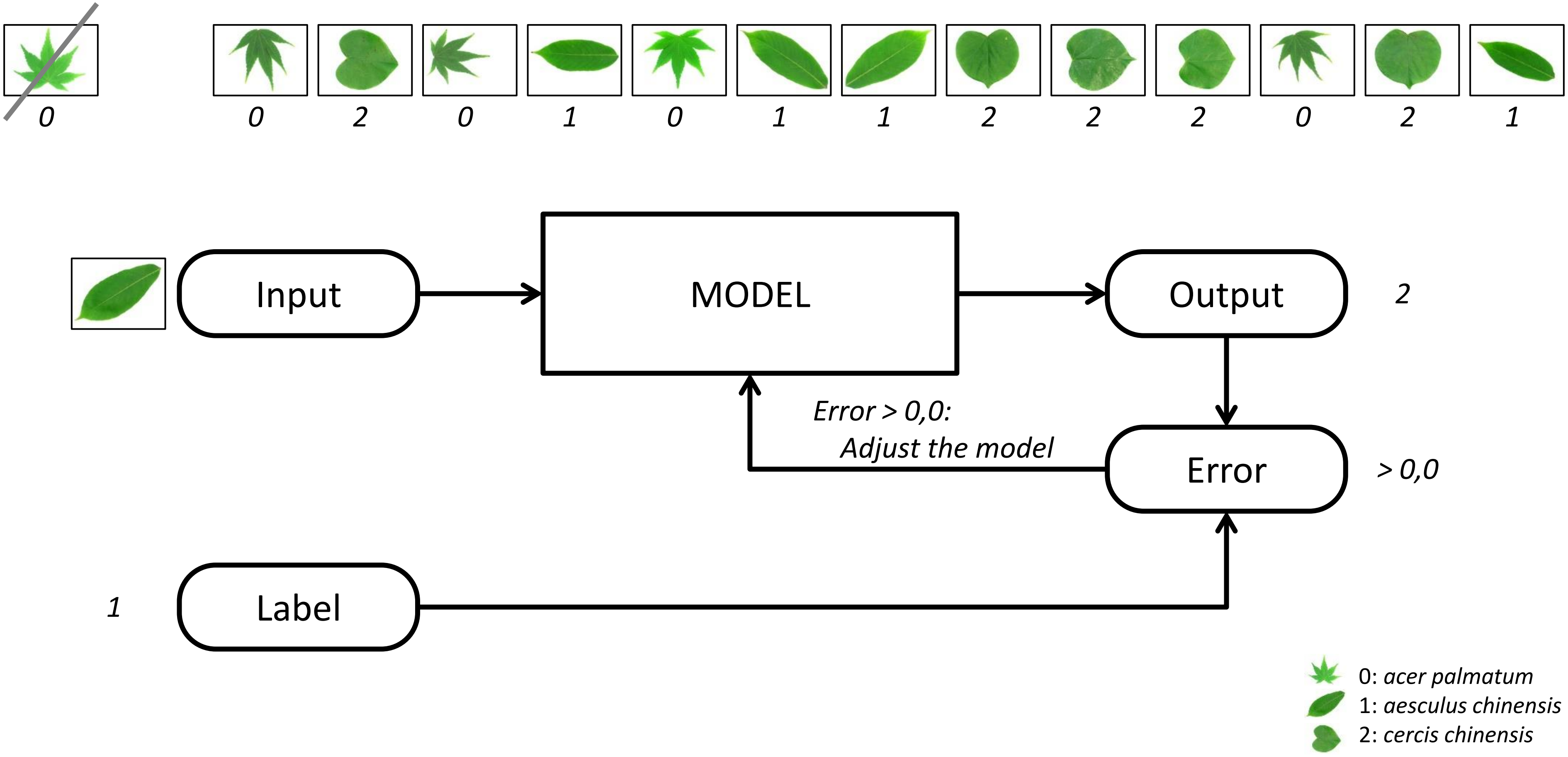
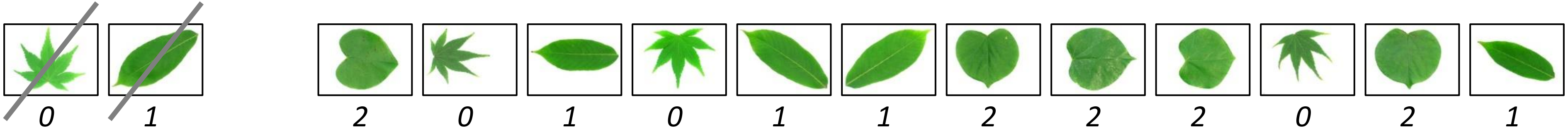
Example: Supervised learning



Example: Supervised learning



Input

MODEL

Output

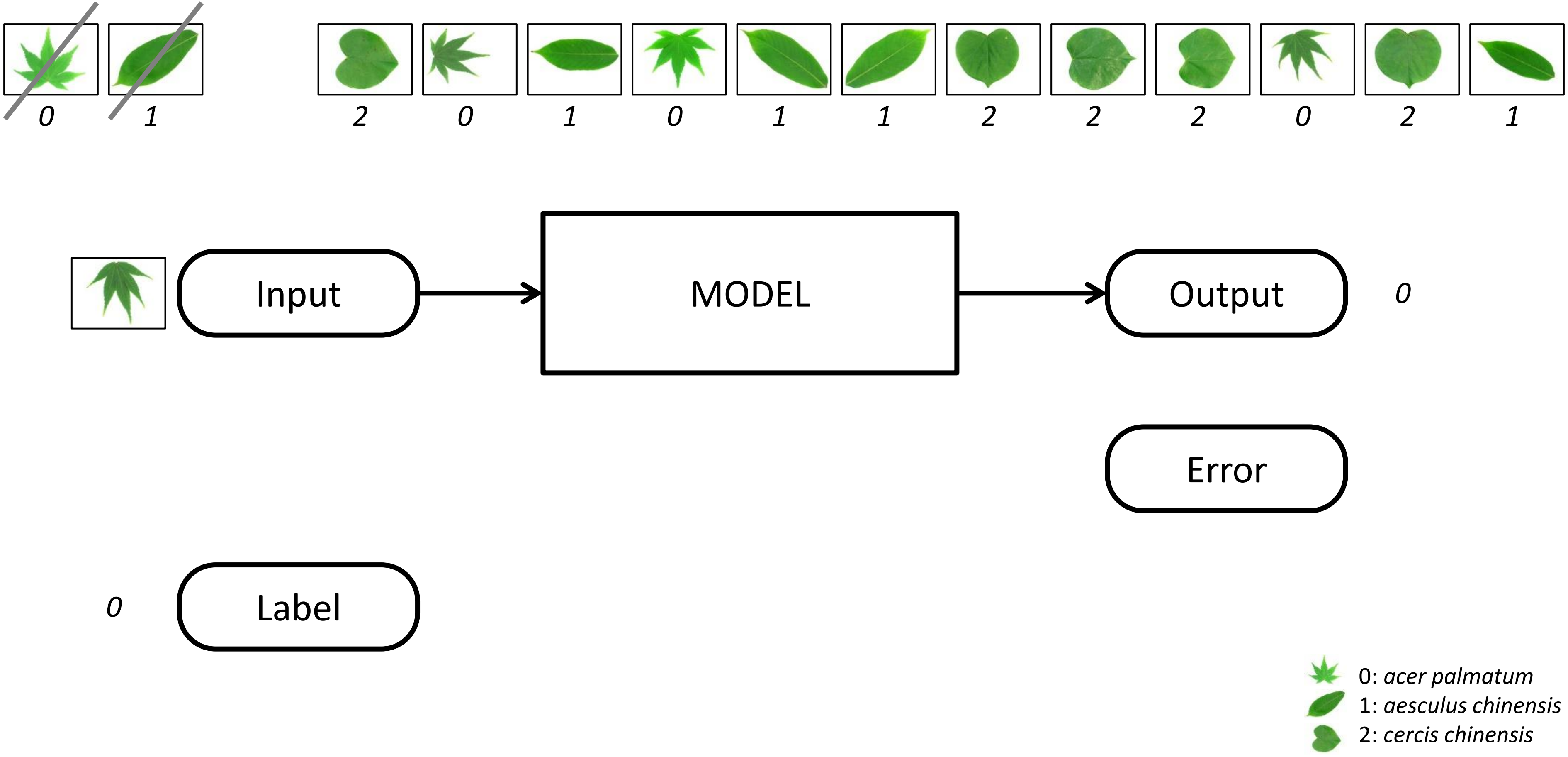
Error

0

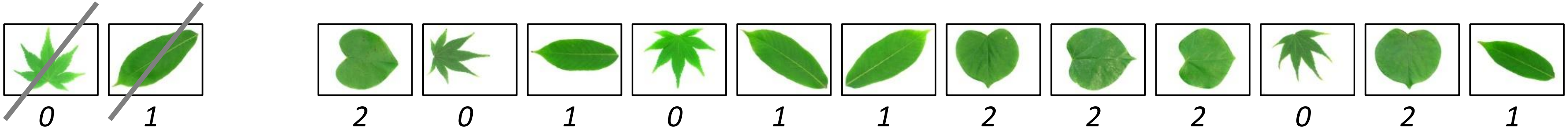
Label

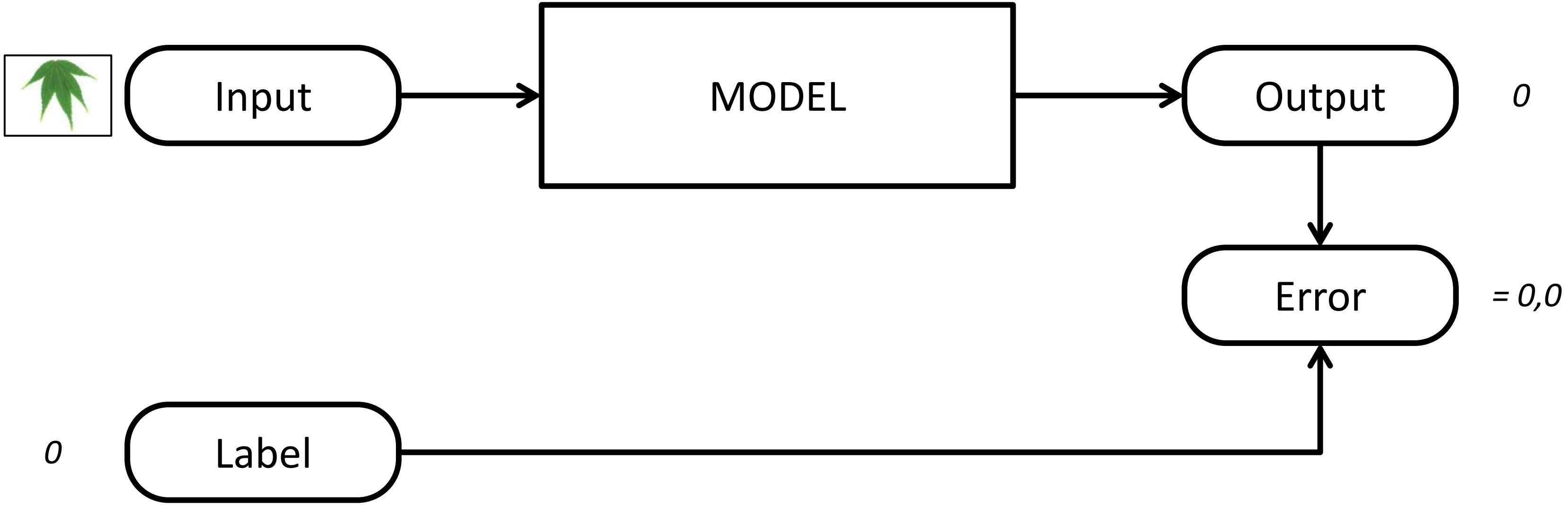
0: *acer palmatum*
1: *aesculus chinensis*
2: *cercis chinensis*

Example: Supervised learning



Example: Supervised learning





0: *acer palmatum*
1: *aesculus chinensis*
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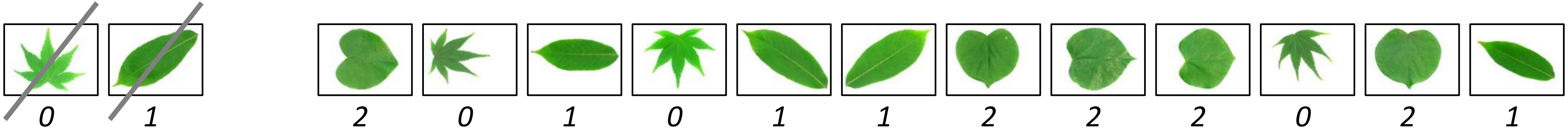
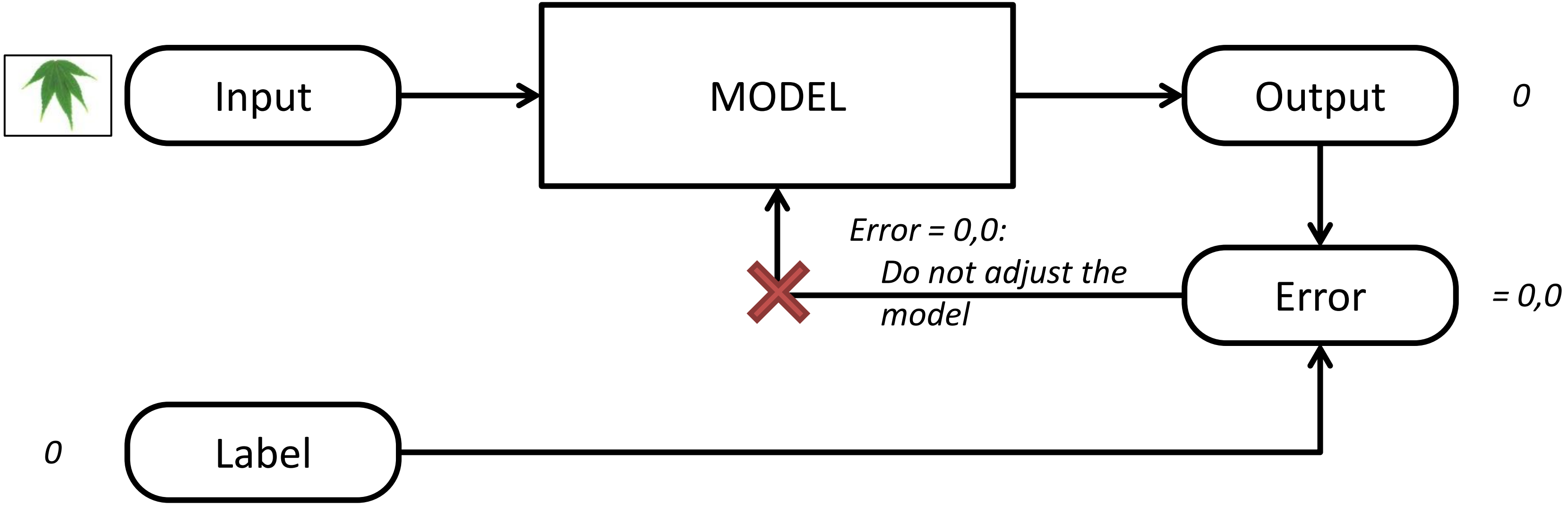
Example: Supervised learning





0: *acer palmatum*
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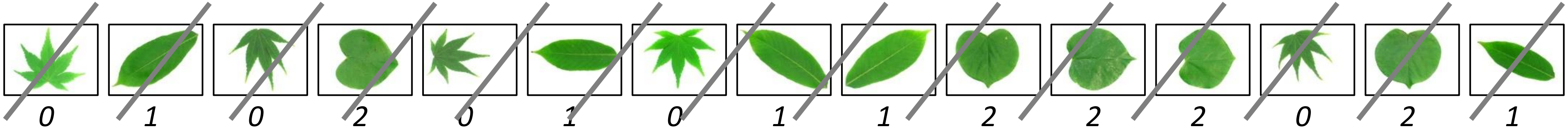
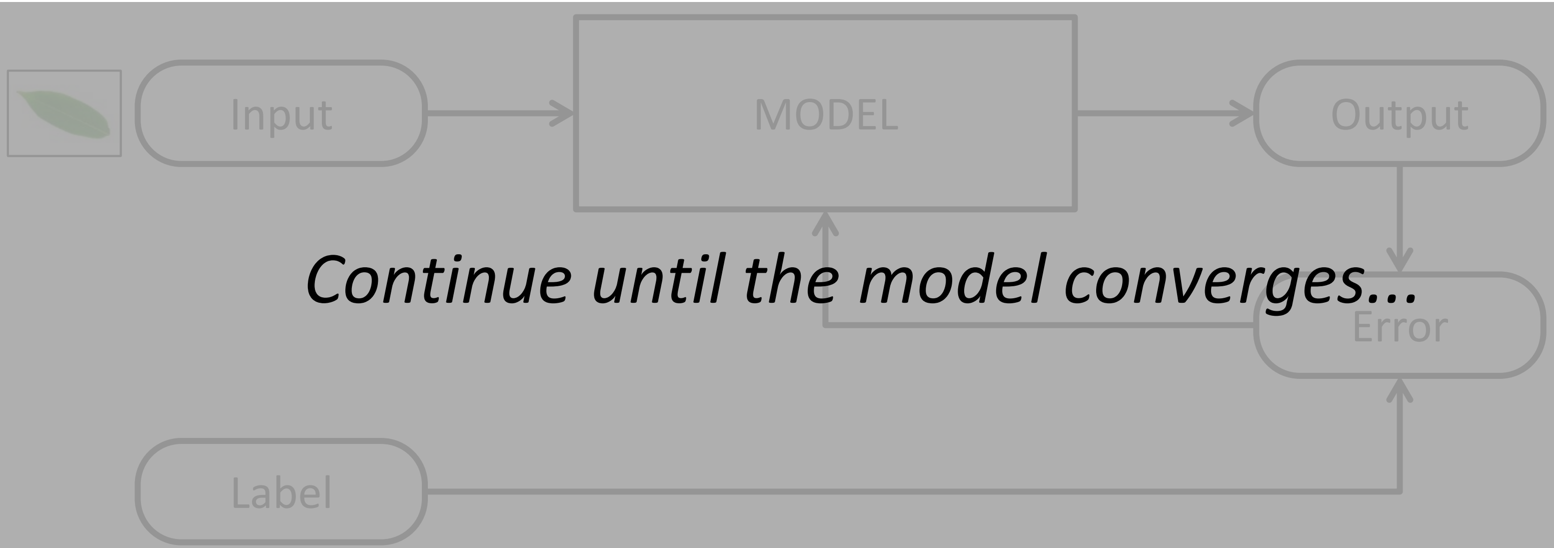
Example: Supervised learning

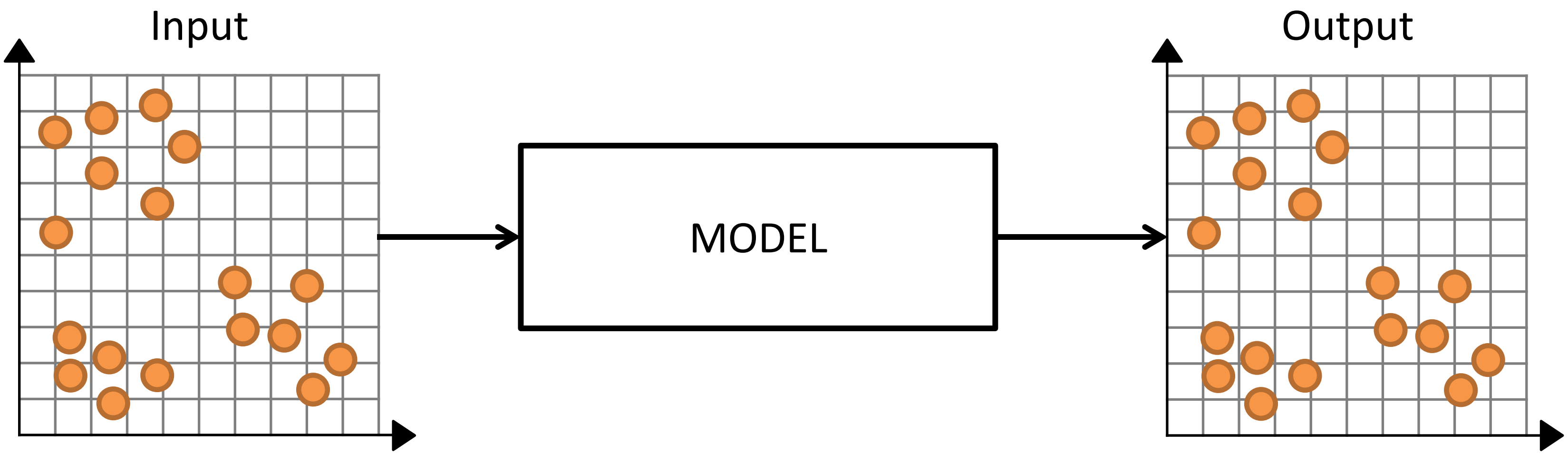




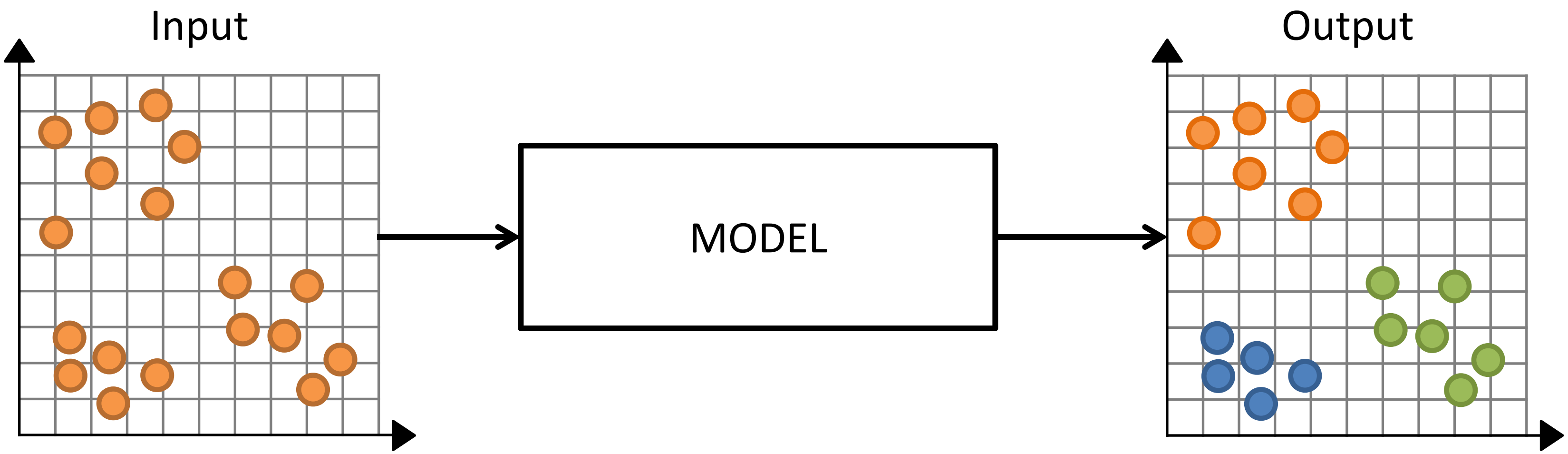
Continue until the model converges...

0: *acer palmatum*
1: *aesculus chinensis*
2: *cercis chinensis*

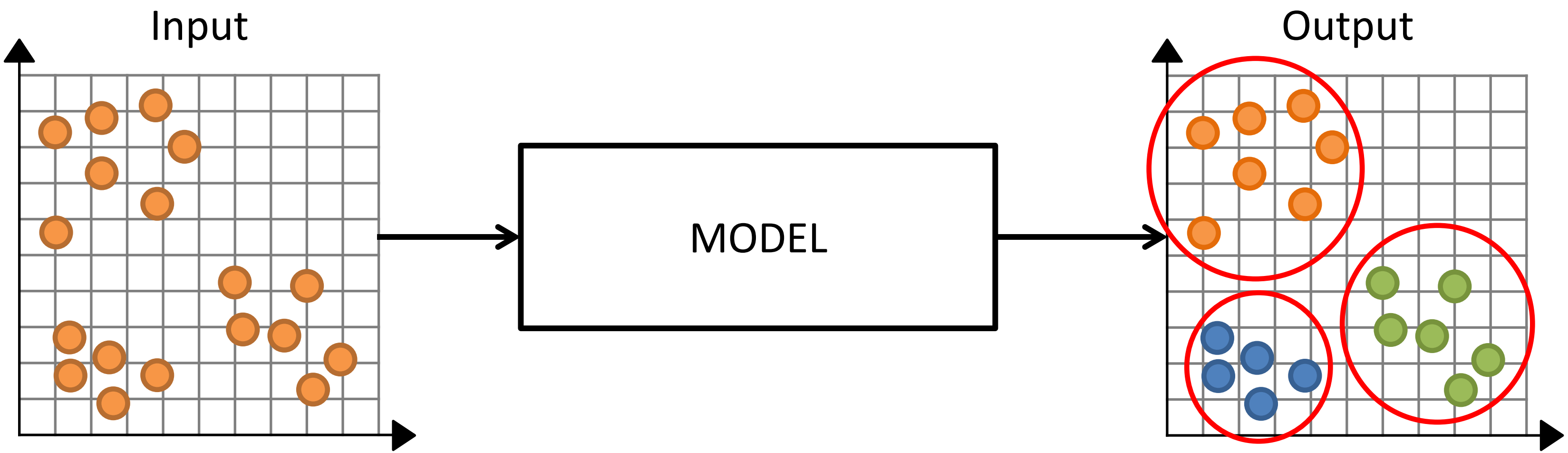
Unsupervized learning



Unsupervized learning

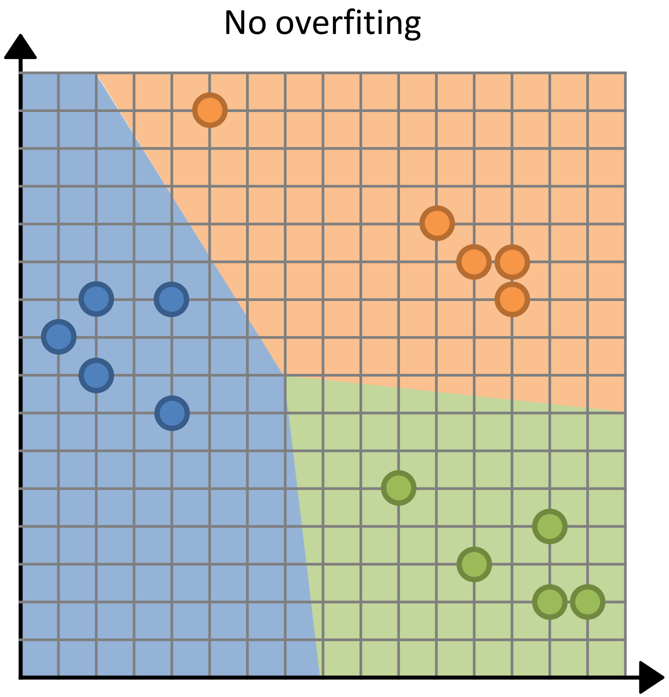


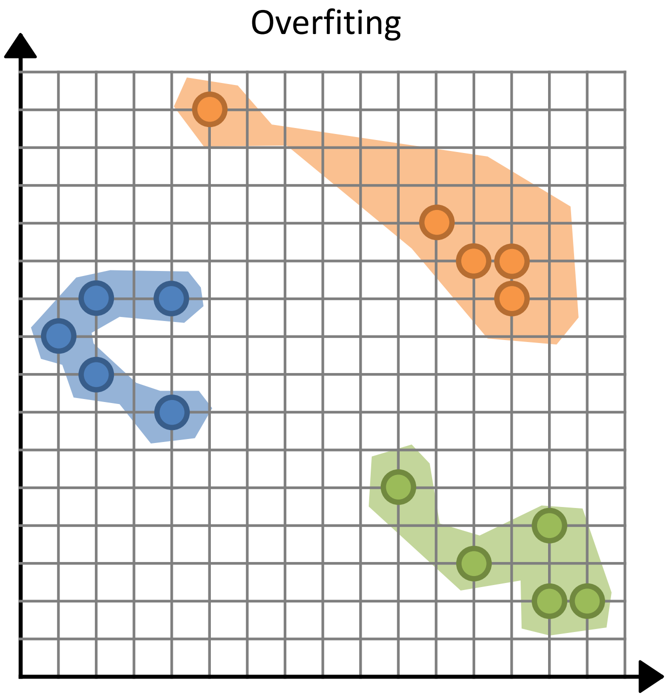
Unsupervized learning



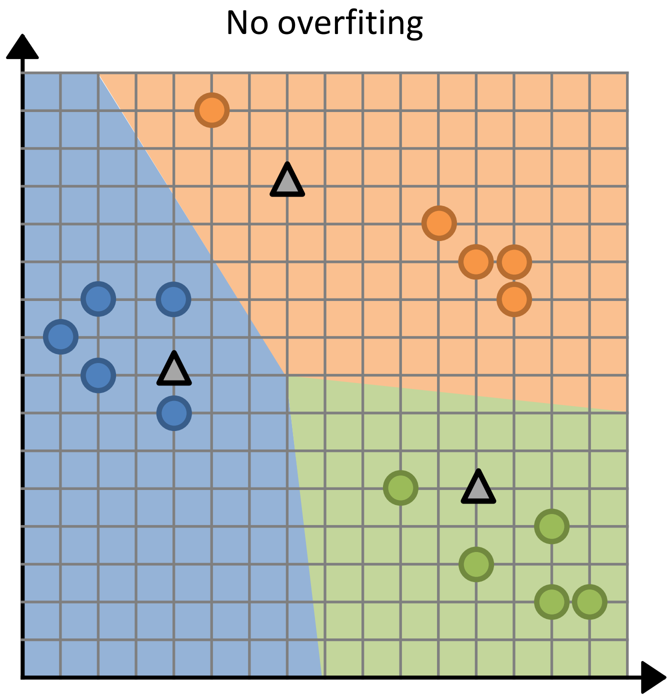
CROSS-VALIDATION

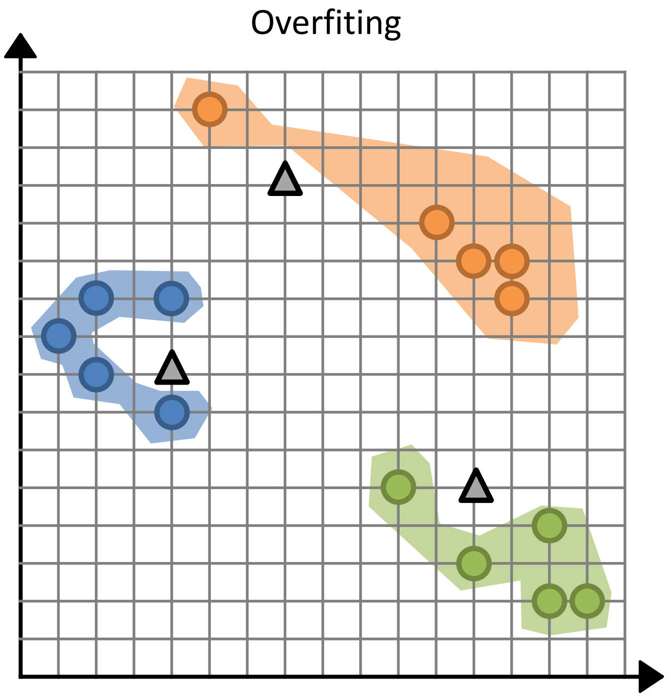
Overfiting



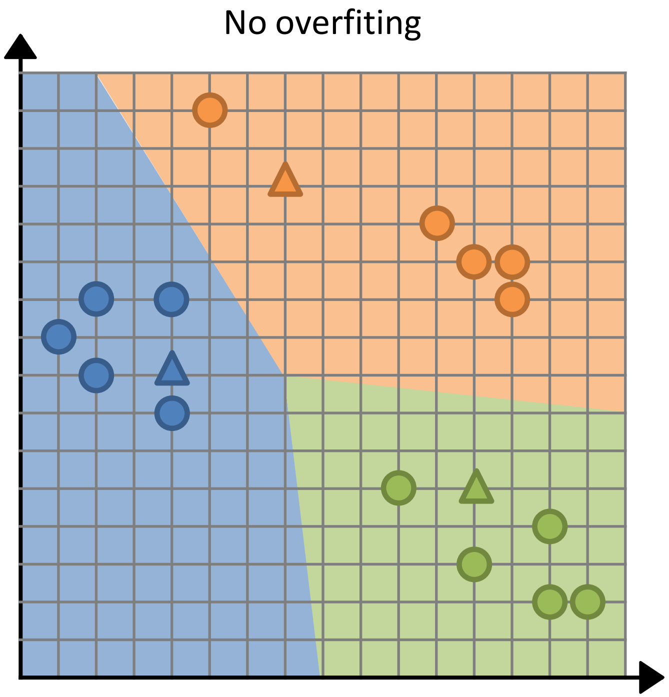


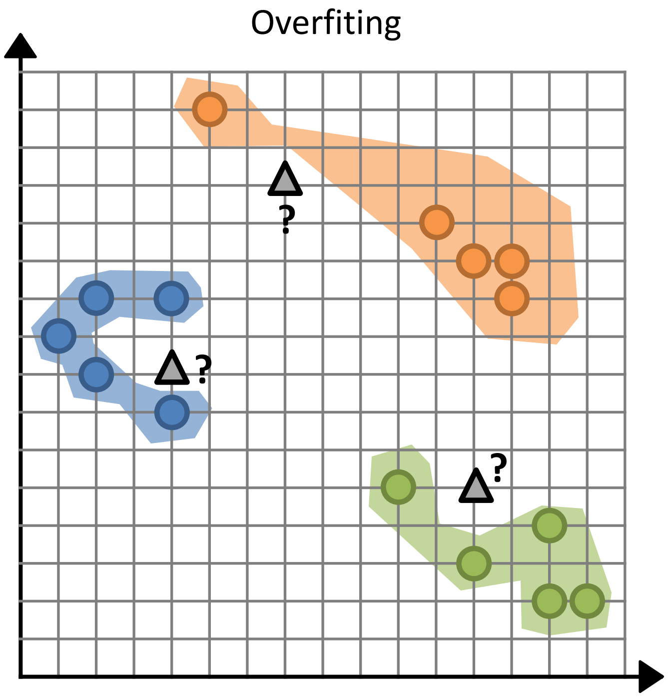
Overfiting



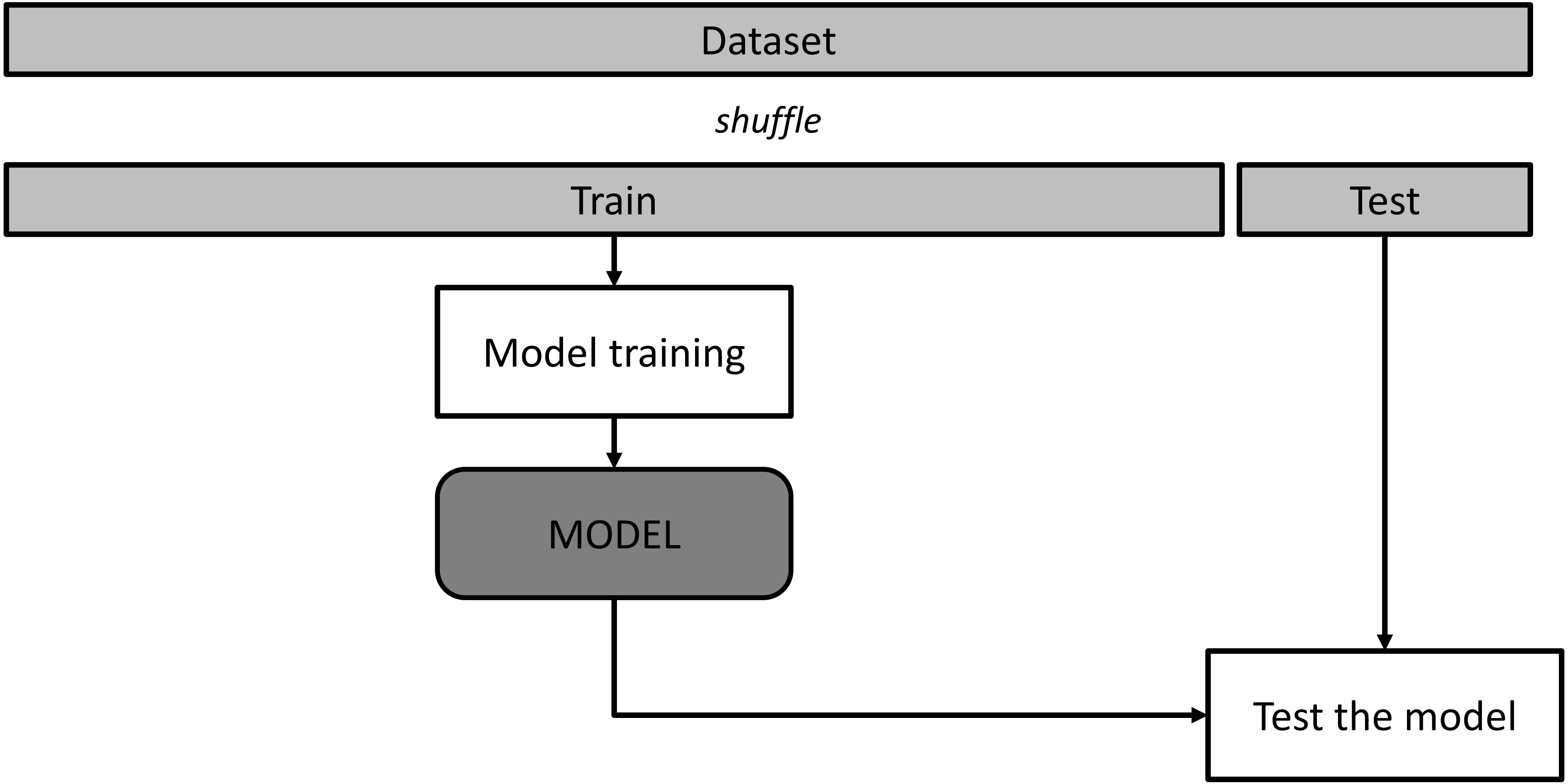


Overfiting

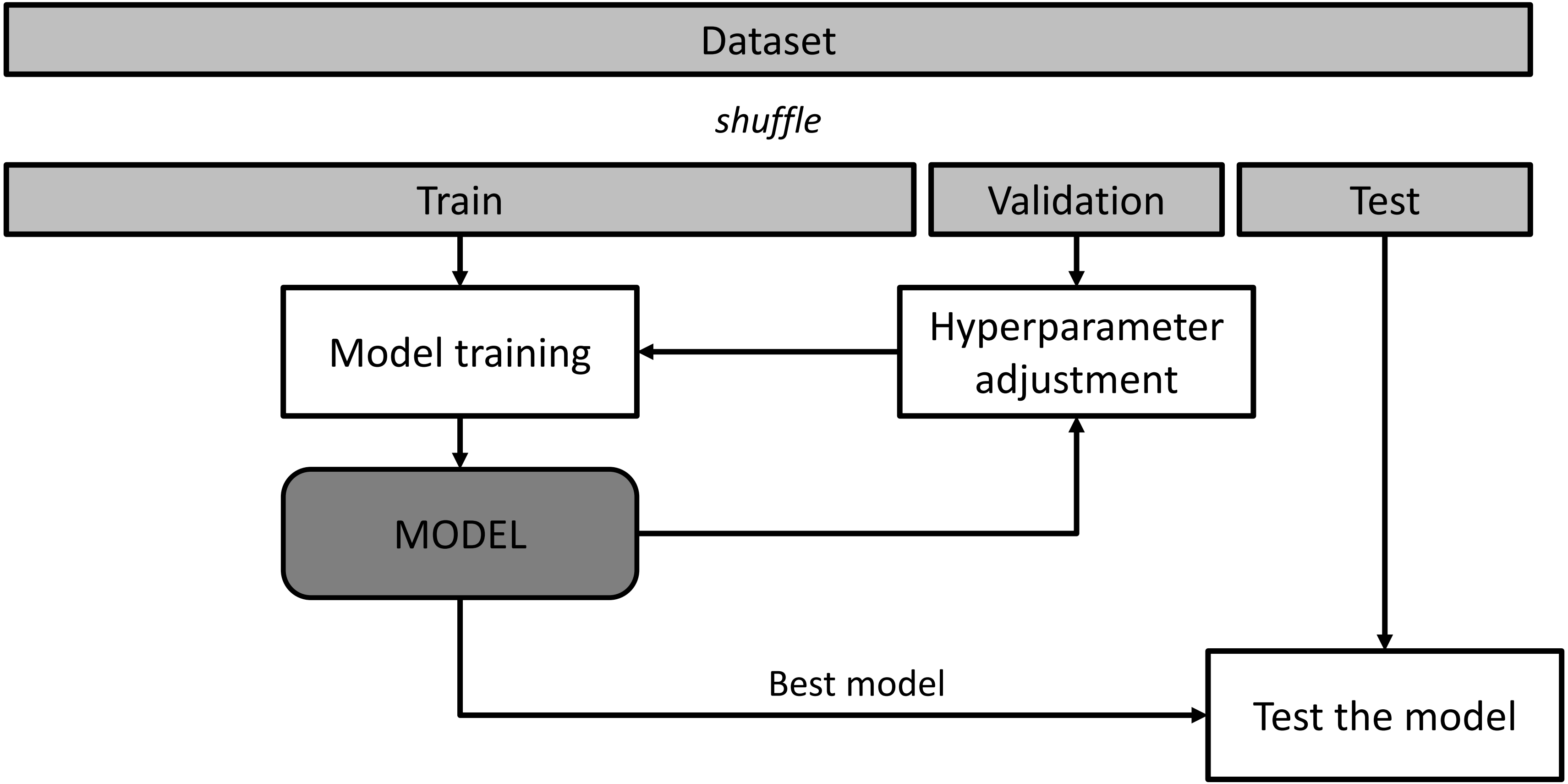




Hold-out cross-validation



Hold-out cross-validation



Hold-out cross-validation

Dataset

Image	excentricidade	área	classe
0	0,1	250	0
1	0,6	450	2
2	0,3	350	0
3	0,2	550	1
4	0,5	800	1
5	0,2	100	0
6	0,7	200	2
7	0,7	750	1
8	0,4	400	0
9	0,8	150	2
10	0,9	300	2
11	0,8	700	1
12	0,4	150	
13	0,4	300	
14	0,2	200	
15	0,7	250	

shuffle

Shuffled dataset

Image	excentricidade	área	classe
13	0,5	300	0
11	0,8	700	1
8	0,4	400	0
9	0,8	150	2
2	0,3	350	0
15	0,7	250	2
4	0.5	800	1
7	0,7	750	1
10	0,9	300	2
12	0,4	150	0
3	0,6	550	1
6	0,6	200	2
0	0,4	700	1
1	0,8	400	2
5	0,3	100	0
14	0,2	200	0

split

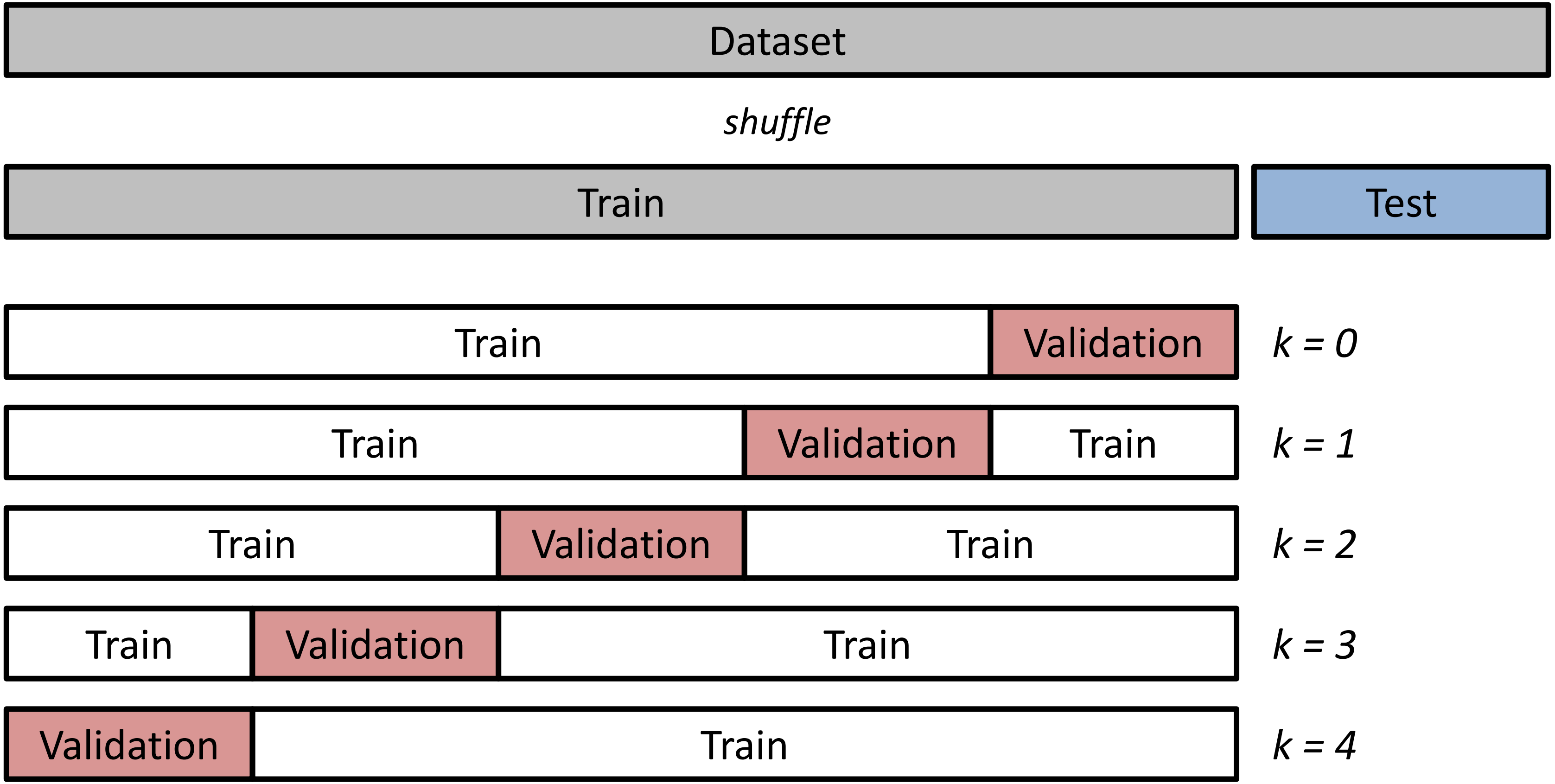
Train

Image	excentricidade	área	classe
13	0,5	300	0
11	0,8	700	1
8	0,4	400	0
9	0,8	150	2
2	0,3	350	0
15	0,7	250	2
4	0.5	800	1
7	0,7	750	1
10	0,9	300	2
12	0,4	150	0
3	0,6	550	1
6	0,6	200	2

Test

Image	excentricidade	área	classe
0	0,4	700	1
1	0,8	400	2
5	0,3	100	0
14	0,2	200	0

K-fold cross-validation



NORMALIZATION

Normalization

- Normal Feature Transform (Standard Scaler)

Training (X_{train})

Imagem	excentricidade	área
13	0,50	300
11	0,80	700
8	0,40	400
9	0,80	150
2	0,30	350
15	0,70	250
4	0.50	800
7	0,70	750
10	0,90	300
12	0,40	150
3	0,60	550
6	0,60	200
Mean:	*0.60*	*408.33*
Std. Dev.:	*0.1859*	*234.35*

Normalized Training (X'_{train})

Imagem	excentricidade	área
13		
11		
8		
9		
2		
15		
4		
7		
10		
12		
3		
6		
Mean:		
Std. Dev.:		

Test (X_{test})

Imagem	excentricidade	área
0	0,4	700
1	0,8	400
5	0,3	100
14	0,2	200

Normalized test (X'_{test})

Imagem	excentricidade	área
0		
1		
5		
14		
Mean:		
Std. Dev.:		

Normalization

- Normal Feature Transform (Standard Scaler)

Training (X_{train})

Imagem	excentricidade	área
13	0,50	300
11	0,80	700
8	0,40	400
9	0,80	150
2	0,30	350
15	0,70	250
4	0.50	800
7	0,70	750
10	0,90	300
12	0,40	150
3	0,60	550
6	0,60	200
Mean:	***0.60***	***408.33***
Std. Dev.:	***0.1859***	***234.35***

Normalized Training (X'_{train})

Imagem	excentricidade	área
13		
11		
8		
9		
2		
15		
4		
7		
10		
12		
3		
6		
Mean:		
Std. Dev.:		

Test (X_{test})

Imagem	excentricidade	área
0	0,4	700
1	0,8	400
5	0,3	100
14	0,2	200

Normalized test (X'_{test})

Imagem	excentricidade	área
0		
1		
5		
14		
Mean:		
Std. Dev.:		

$$X'_{train} = \frac{X_{train} - mean(X_{train})}{std(X_{train})} \qquad X'_{test} = \frac{X_{test} - mean(X_{train})}{std(X_{train})}$$

Normalization

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- Normal Feature Transform (Standard Scaler)

Training (X_{train})

Imagem	excentricidade	área
13	0,50	300
11	0,80	700
8	0,40	400
9	0,80	150
2	0,30	350
15	0,70	250
4	0.50	800
7	0,70	750
10	0,90	300
12	0,40	150
3	0,60	550
6	0,60	200
Mean:	***0.60***	***408.33***
Std. Dev.:	***0.1859***	***234.35***

Normalized Training (X'_{train})

Imagem	excentricidade	área
13	-0.5380	-0.4622
11	1.0760	1.2445
8	-1.0760	-0.0355
9	1.0760	-1.1022
2	-1.6140	-0.2489
15	0.5380	-0.6756
4	-0.5380	1.6712
7	0.5380	1.4578
10	1.6140	-0.4622
12	-1.0760	-1.1022
3	0.0000	0.6044
6	0.0000	-0.8889
Mean:	***0.00***	***1.00***
Std. Dev.:	***0.00***	***1.00***

Test (X_{test})

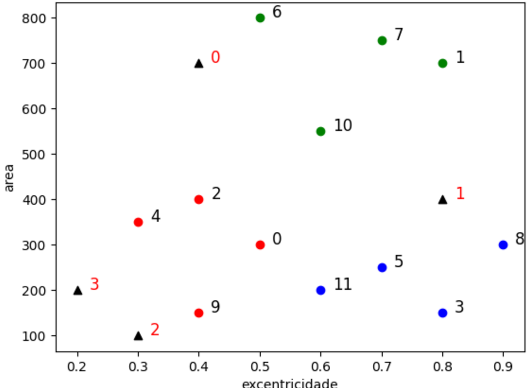
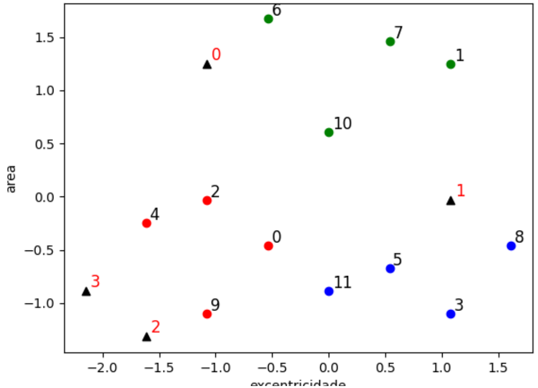
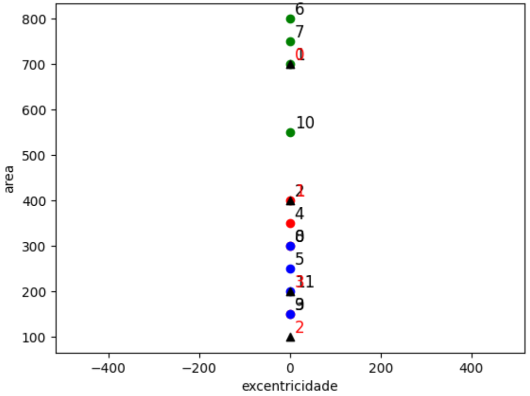
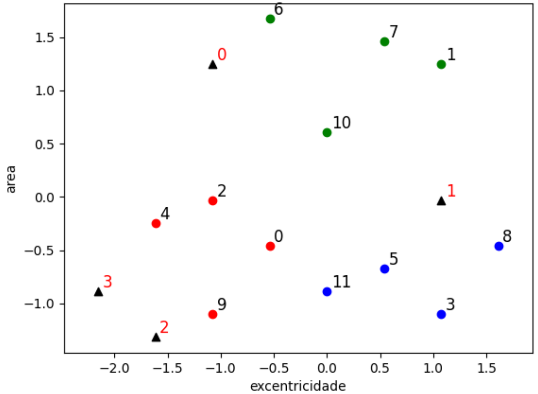
Imagem	excentricidade	área
0	0,4	700
1	0,8	400
5	0,3	100
14	0,2	200

Normalized test (X'_{test})

Imagem	excentricidade	área
0	-1.0760	1.244528
1	1.0760	-0.035558
5	-1.6140	-1.315644
14	-2.1521	-0.888949
Mean:	***-0.9415***	***-0.2489***
Std. Dev.:	***1.4150***	***1.1289***

$$X'_{train} = \frac{X_{train} - mean(X_{train})}{std(X_{train})} \qquad X'_{test} = \frac{X_{test} - mean(X_{train})}{std(X_{train})}$$

Normalization

	Non-normalized dataset	Normalized dataset
Adjusted aspect ratio		
Real aspect ratio		

CLASSIFICATION EVALUATION

Confusion matrix

- **True positive(TP):**
  - Objects of class C1 classified as C1.
- **True negative (TN):**
  - Objects of other classes (C2 and C3) classified as not being C1.
- **False positive (FP) (type I error):**
  - Objects classified as C1 but belonging to other classes (C2 or C3).
- **False negative (FN) (type II error):**
  - Objects of class C1 classified as other classes (C2 or C3).

		Classification			
		Class C1	Class C2	Class C3	Sum
Real class	Class C1	5	3	0	*8*
	Class C2	2	3	1	*6*
	Class C3	0	2	11	*13*
	Soma	*7*	*8*	*12*	

Confusion matrix

- **True positive(TP):**
  - Objects of class C1 classified as C1.
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  - Objects classified as C1 but belonging to other classes (C2 or C3).
- **False negative (FN) (type II error):**
  - Objects of class C1 classified as other classes (C2 or C3).

Class C1		Classification	
		Class C1	Others
Real class	Class C1	5 TP	3 FN
	Others	2 FP	17 TN

		Classification			
		Class C1	Class C2	Class C3	Sum
Real class	Class C1	5	3	0	*8*
	Class C2	2	3	1	*6*
	Class C3	0	2	11	*13*
	Soma	*7*	*8*	*12*	

Confusion matrix

- **True positive(TP):**
  - Objects of class C1 classified as C1.
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  - Objects of other classes (C2 and C3) classified as not being C1.
- **False positive (FP) (type I error):**
  - Objects classified as C1 but belonging to other classes (C2 or C3).
- **False negative (FN) (type II error):**
  - Objects of class C1 classified as other classes (C2 or C3).

Class C1		Classification	
		Class C1	Others
Real class	Class C1	5 TP	3 FN
	Others	2 FP	17 TN

		Classification			
		Class C1	Class C2	Class C3	Sum
Real class	Class C1	5	3	0	*8*
	Class C2	2	3	1	*6*
	Class C3	0	2	11	*13*
	Soma	*7*	*8*	*12*	

Confusion matrix

- **True positive(TP):**
  - Objects of class C1 classified as C1.
- **True negative (TN):**
  - Objects of other classes (C2 and C3) classified as not being C1.
- **False positive (FP) (type I error):**
  - Objects classified as C1 but belonging to other classes (C2 or C3).
- **False negative (FN) (type II error):**
  - Objects of class C1 classified as other classes (C2 or C3).

		Classification			
		Class C1	**Class C2**	**Class C3**	**Sum**
Real class	**Class C1**	5	3	0	*8*
	Class C2	2	3	1	*6*
	Class C3	0	2	11	*13*
	Soma	*7*	*8*	*12*	

Class C1		Classification	
		Class C1	Others
Real class	Class C1	5 TP	3 FN
	Others	2 FP	17 TN

Class C2		Classification	
		Class C2	Others
Real class	Class C2	3 TP	3 FN
	Others	5 FP	16 TN

Confusion matrix

- **True positive(TP):**
  - Objects of class C1 classified as C1.
- **True negative (TN):**
  - Objects of other classes (C2 and C3) classified as not being C1.
- **False positive (FP) (type I error):**
  - Objects classified as C1 but belonging to other classes (C2 or C3).
- **False negative (FN) (type II error):**
  - Objects of class C1 classified as other classes (C2 or C3).

		Classification			
		Class C1	**Class C2**	**Class C3**	**Sum**
Real class	**Class C1**	5	3	0	*8*
	Class C2	2	3	1	*6*
	Class C3	0	2	11	*13*
	Soma	*7*	*8*	*12*	

Class C1		Classification	
		Class C1	Others
Real class	Class C1	5 TP	3 FN
	Others	2 FP	17 TN

Class C2		Classification	
		Class C2	Others
Real class	Class C2	3 TP	3 FN
	Others	5 FP	16 TN

Class C3		Classification	
		Classe C3	Others
Real class	Class C3	11 TP	2 FN
	Others	1 FP	13 TN

Accuracy, precision, recall, and F1-score

- Accuracy:
  - $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
- Precision:
  - $Precision = \frac{TP}{TP+FP}$
- Recall:
  - $Recall = \frac{TP}{TP+FN}$
- F1-score:
  - $F1 - score = \frac{2 \times TP}{2 \times TP+FP+FN}$
- Support:
  - $Support = TP + FN$

Accuracy, precision, recall, and F1-score

- Accuracy:
  - $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
  - *How close the classification is to the true value.*
- Precision:
  - $Precision = \frac{TP}{TP+FP}$
  - *The ability of the classifier not to label a negative sample as positive.*
- Recall:
  - $Recall = \frac{TP}{TP+FN}$
  - *The ability of the classifier to find all the positive samples.*
- F1-score:
  - $F1 - score = \frac{2 \times TP}{2 \times TP+FP+FN}$
  - *The weighted harmonic mean of the precision and recall.*
- Support:
  - $Support = TP + FN$
  - The number of occurrences of each real (true) class.

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.precision_recall_fscore_support.html

Accuracy, precision, recall, and F1-score

- Accuracy:
  - $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
- Precision:
  - $Precision = \frac{TP}{TP+FP}$
- Recall:
  - $Recall = \frac{TP}{TP+FN}$
- F1-score:
  - $F1 - score = \frac{2 \times TP}{2 \times TP+FP+FN}$
- Support:
  - $Support = TP + FN$

Classes	TP	TN	FP	FN	Accuracy	Precision	Recall	F1-Score	Support
C1	5	17	2	3					
C2	3	16	5	3					
C3	11	13	1	2					
MEAN									
STD. DEV.									

Accuracy, precision, recall, and F1-score

- Accuracy:
  - $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
- Precision:
  - $Precision = \frac{TP}{TP+FP}$
- Recall:
  - $Recall = \frac{TP}{TP+FN}$
- F1-score:
  - $F1 - score = \frac{2 \times TP}{2 \times TP+FP+FN}$
- Support:
  - $Support = TP + FN$

Classes	TP	TN	FP	FN	Accuracy	Precision	Recall	F1-Score	Support
C1	5	17	2	3	0.8148	0.7143	0.6250	0.6667	8
C2	3	16	5	3	0.7037	0.3750	0.5000	0.4286	6
C3	11	13	1	2	0.8889	0.9167	0.8462	0.8800	13
MEAN									
STD. DEV.									

Accuracy, precision, recall, and F1-score

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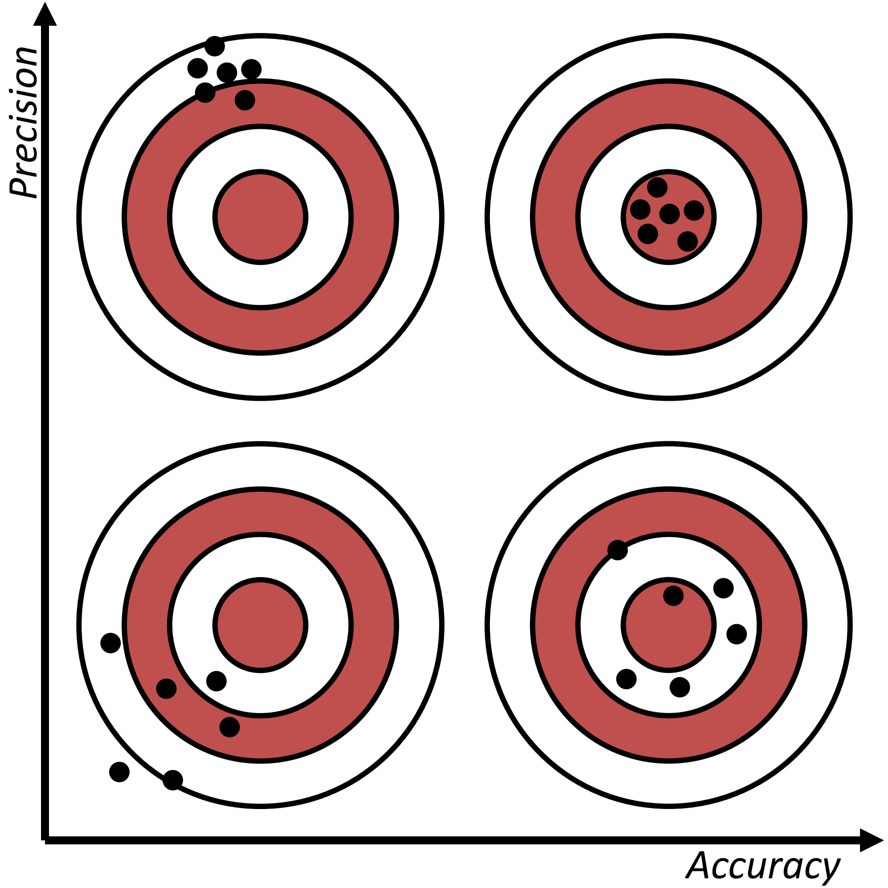
- Accuracy:
  - $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
- Precision:
  - $Precision = \frac{TP}{TP+FP}$
- Recall:
  - $Recall = \frac{TP}{TP+FN}$
- F1-score:
  - $F1 - score = \frac{2 \times TP}{2 \times TP+FP+FN}$
- Support:
  - $Support = TP + FN$

Classes	TP	TN	FP	FN	Accuracy	Precision	Recall	F1-Score	Support
C1	5	17	2	3	0.8148	0.7143	0.6250	0.6667	8
C2	3	16	5	3	0.7037	0.3750	0.5000	0.4286	6
C3	11	13	1	2	0.8889	0.9167	0.8462	0.8800	13
MEAN					0.8025	0.6687	0.6571	0.6584	
STD. DEV.					0.0761	0.2235	0.1431	0.1844	

Accuracy Vs. Precision

- *Accuracy*:
  - $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
    - *How close the classification is to the true value.*
- *Precision*:
  - $Precision = \frac{TP}{TP+FP}$
    - *The variation between different predictions.*



Bibliography

- GONZALEZ, R.C.; WOODS, R.E.; **Processamento Digital de Imagens.** 3ª edição. Editora Pearson, 2009.
- COSTA, L. DA F.; CESAR-JR., R. M. **Shape analysis and classification: theory and practice**. CRC Press, 2000. Chapter 8.
- Yann LeCun', Alfredo Canziani. **Yann LeCun's Deep Learning Course at CDS** - SPRING 2021
  - https://cds.nyu.edu/deep-learning/
- **scikit-learn – User Guide.**
  - https://scikit-learn.org/stable/user_guide.html

THE END