Introduction to Support Vector Machines & Random Forest

Supervised learning

Cédric Hassen-Khodja, Volker Baecker, Jean-Bernard Fiche, Francesco Pedaci

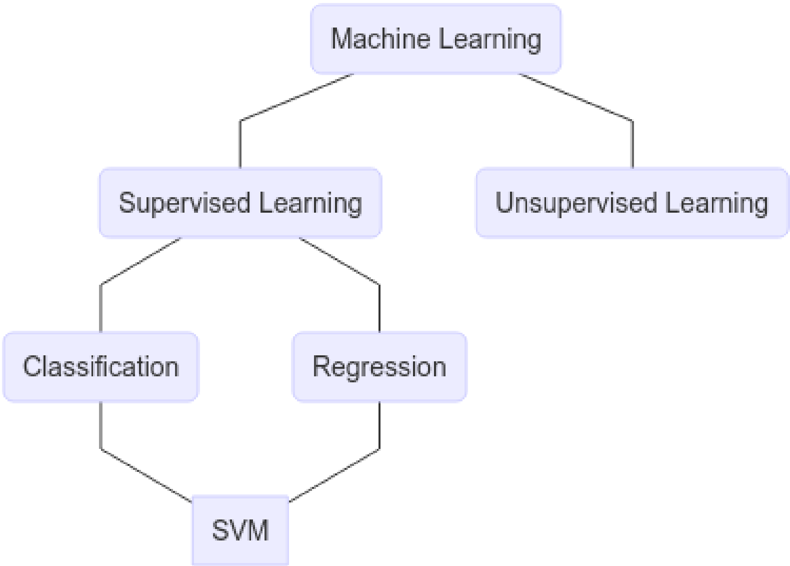
Summary

1. **History of SVM**
2. Types Of Machine Learning
3. Why support vector machine ?
4. What is support vector machine ?
5. How does it work ?
   a. Hard Margin
   b. Soft Margin c. Kernel trick
6. SVM in practice - Implementing biological application with Python
   a. Use Case - Problem Statement
   b. Use Case - Translocation Activity

History of SVM

1. 1963: Linear classifier - Maximal Margin Classifier by Vapnik and Chervonenkis.
2. 1992: Nonlinear classification – Kernel trick by Bernhard E. Boser.
3. 1995: The Soft Margin Classifier by Corinna Cortes and Vapnik.

Types of Machine Learning

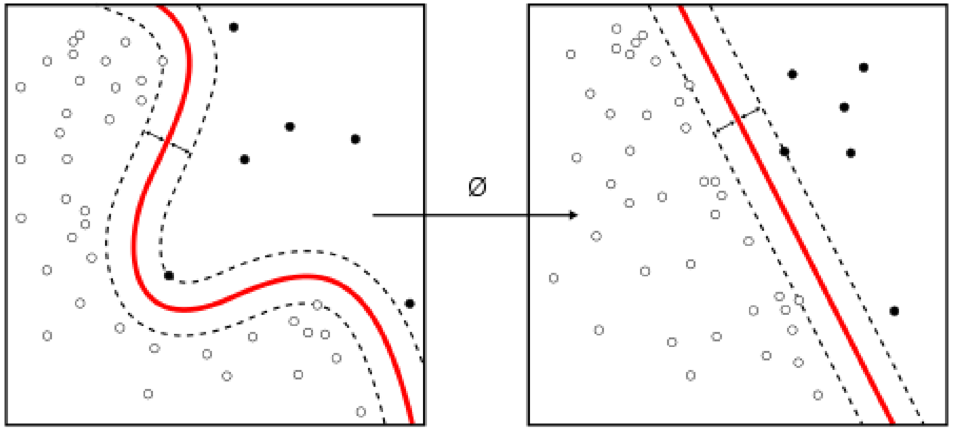


Why support vector machine ?

- It works really well with clear margin of separation.
- It is effective in high dimensional spaces.
- Robust against the outliers (controlled with the parameter C).

What is support vector machine ?

Support vector machines (SVMs) aim to find a decision hyperplane that separates data points of different classes with a maximal margin.

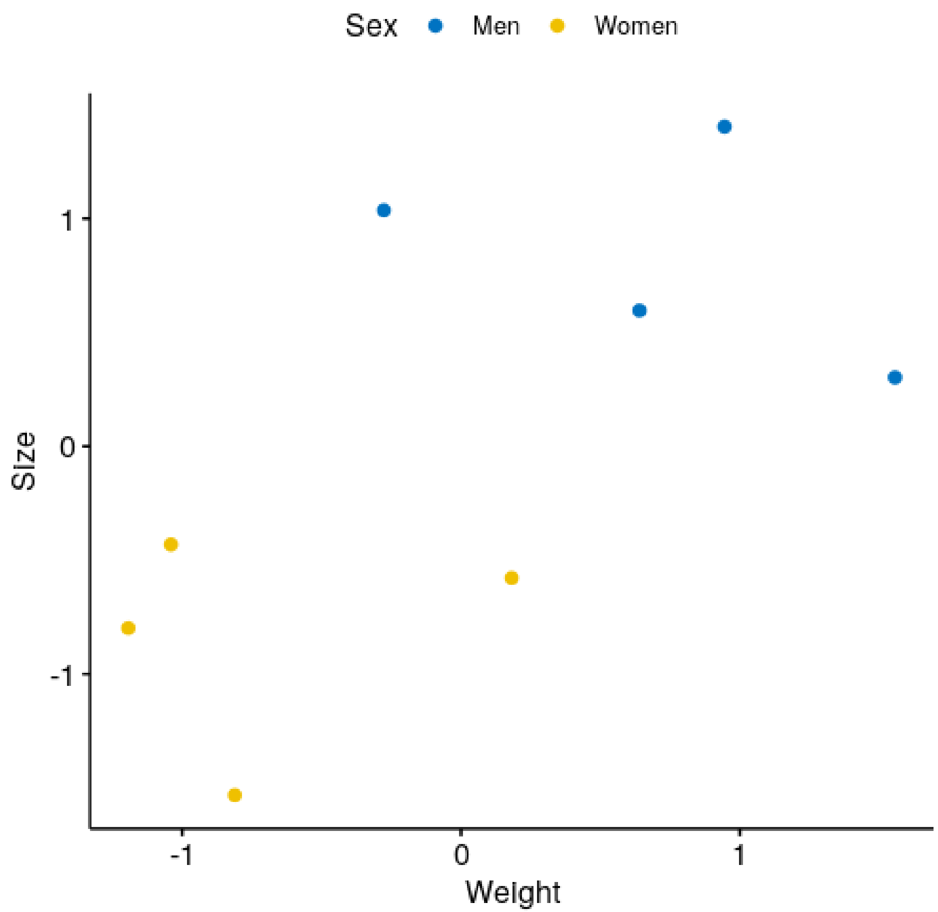


How does it work ?

We are given a set of people with different:

HEIGHT	WEIGHT	SEX
145	55	Woman
155	50	Woman
160	52	Woman
158	68	Woman
174	74	Man
170	86	Man
180	62	Man
185	78	Man

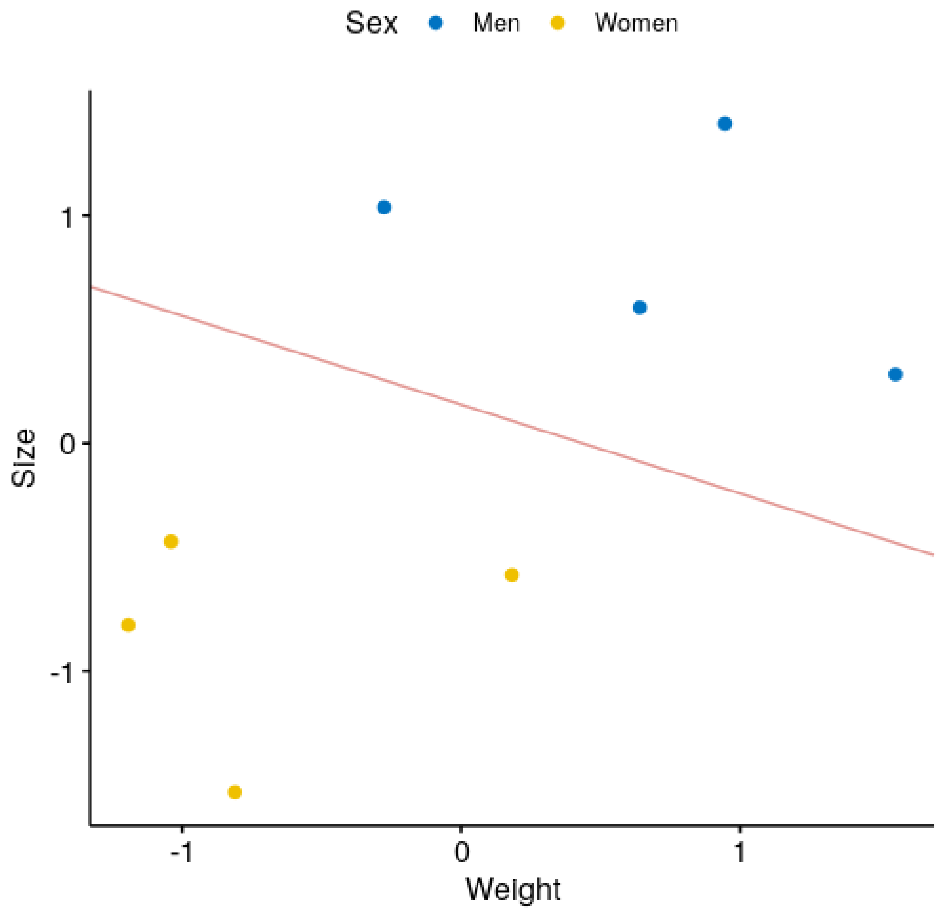
How does it work ?



How does it work ?

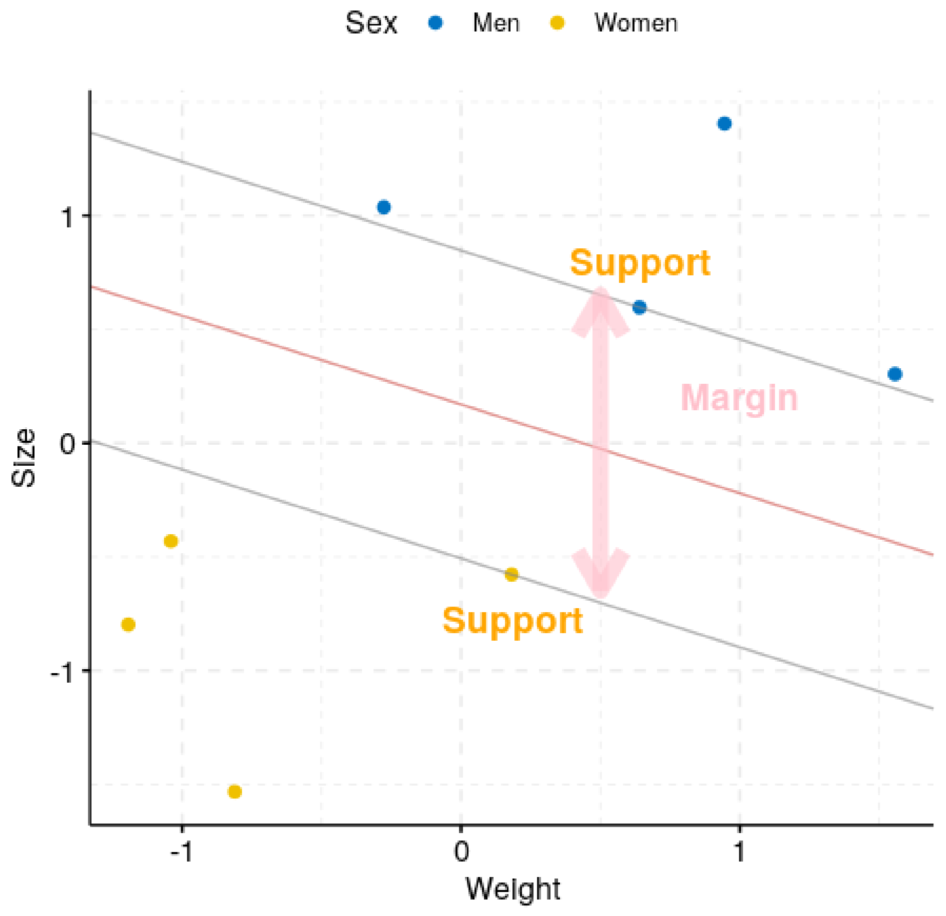
Hard Margin

To separate the two classes we should split the data in the best possible way.



How does it work ?

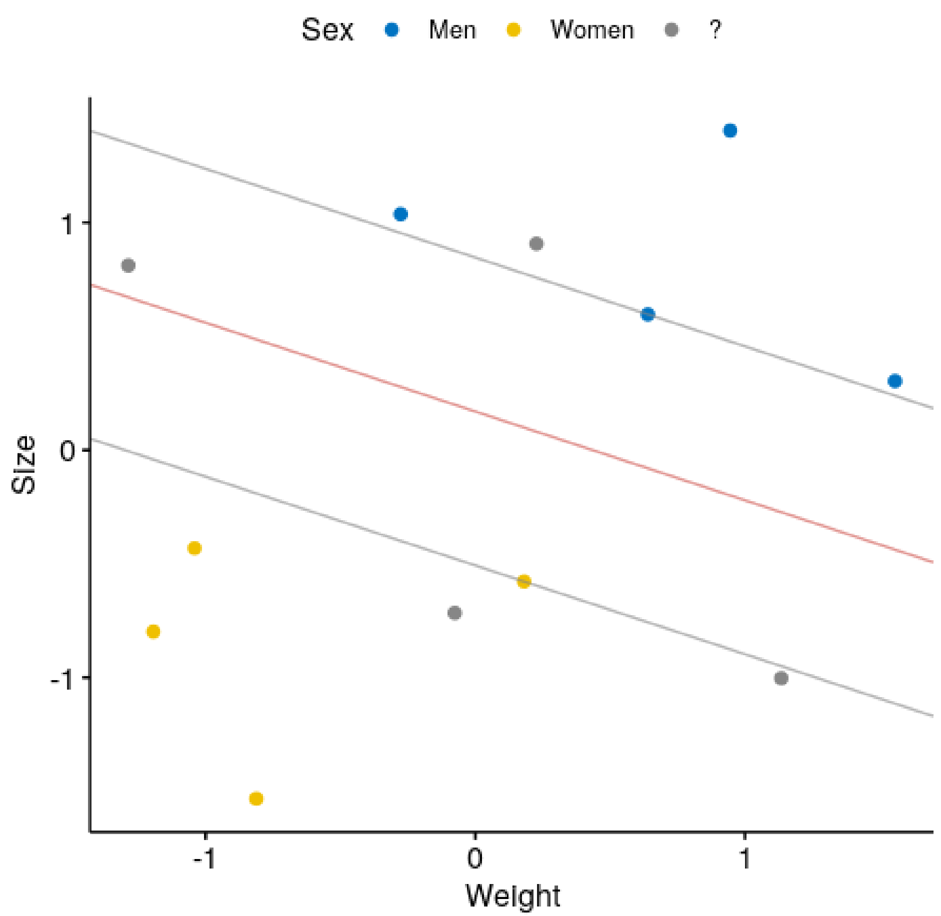
Hard Margin

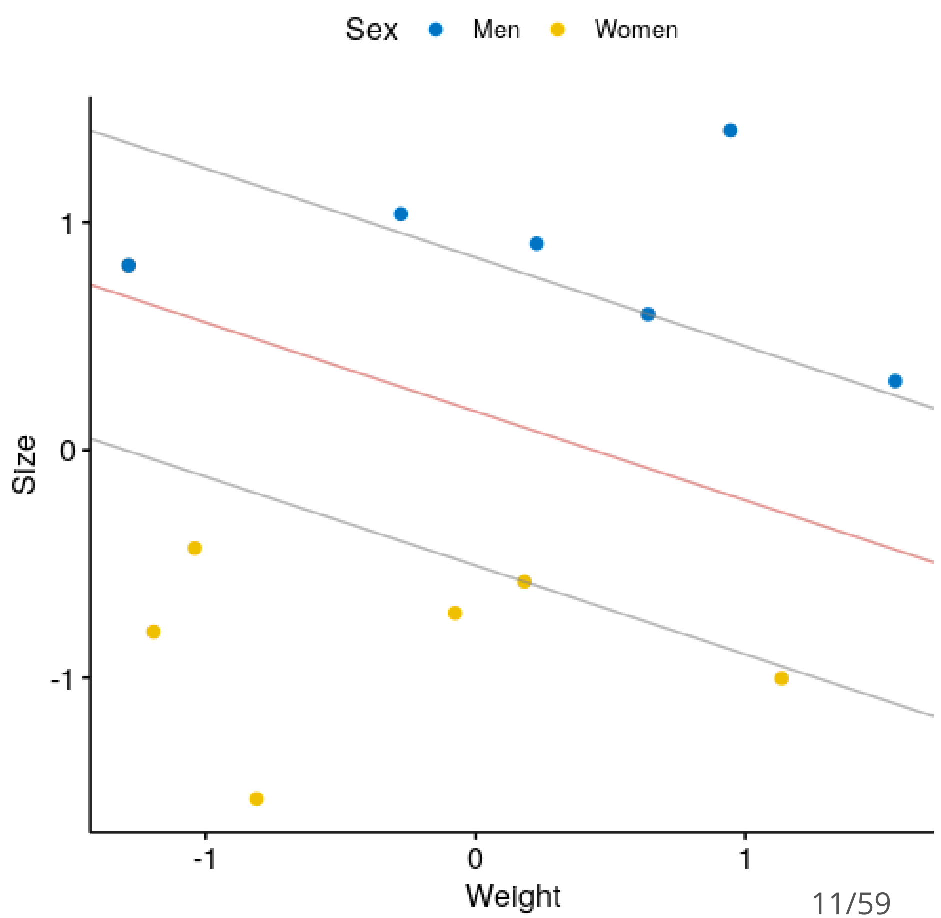


How does it work ?

Hard Margin

Prediction





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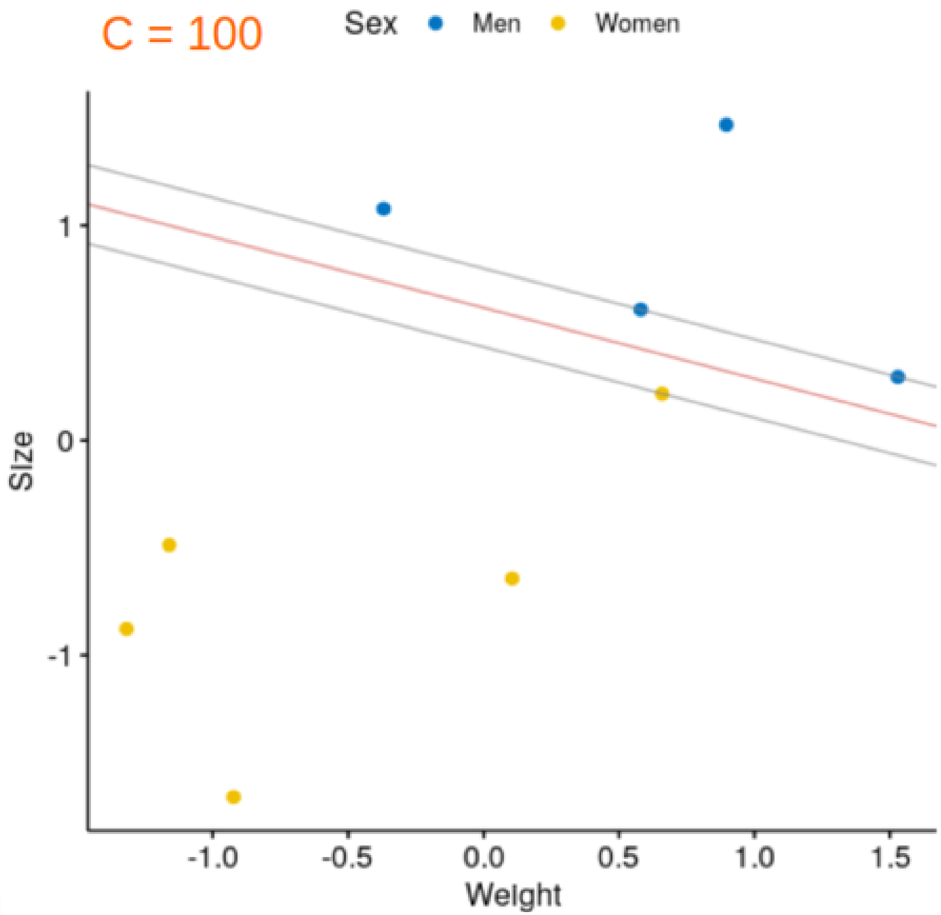
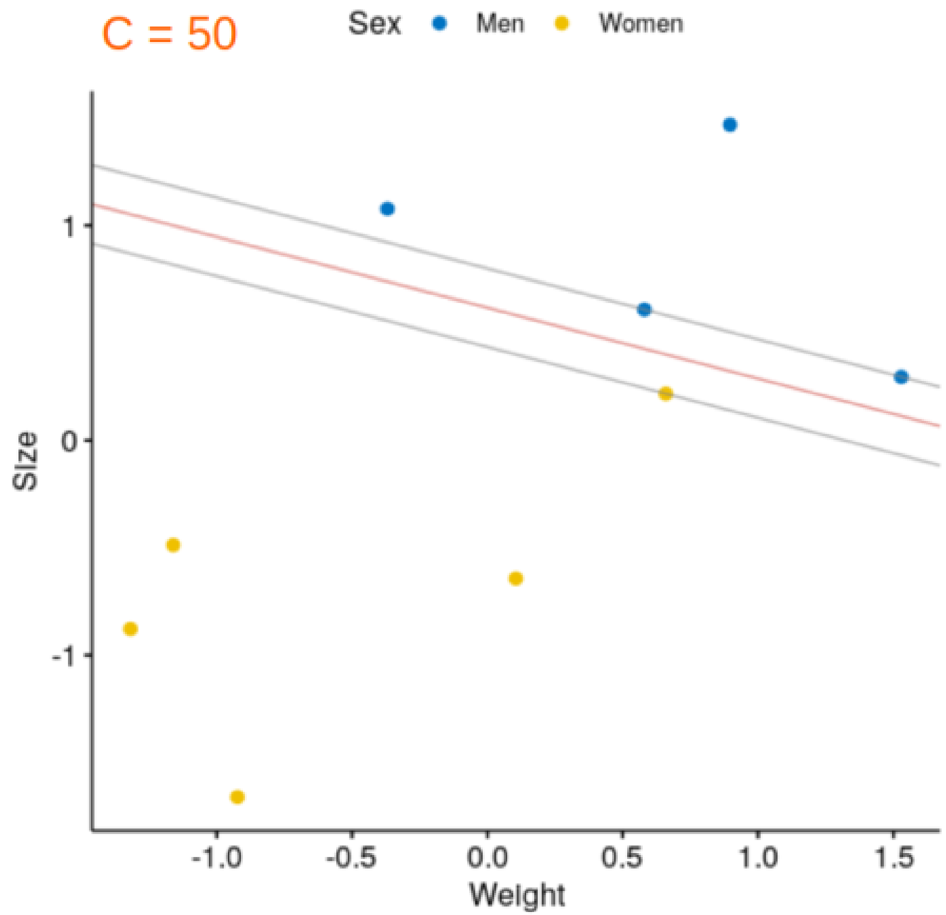
How does it work ?

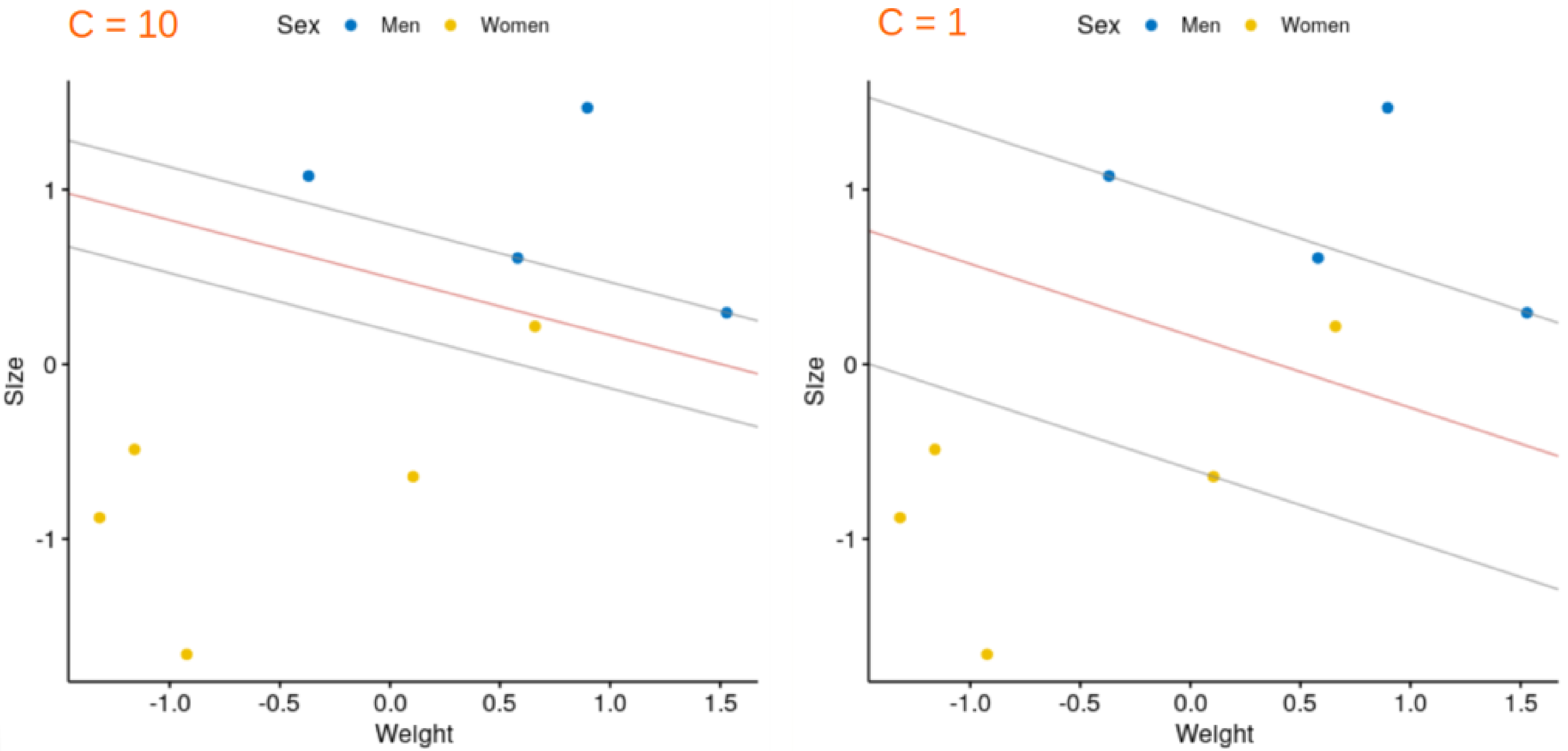
Soft Margin





How does it work ?

Soft Margin



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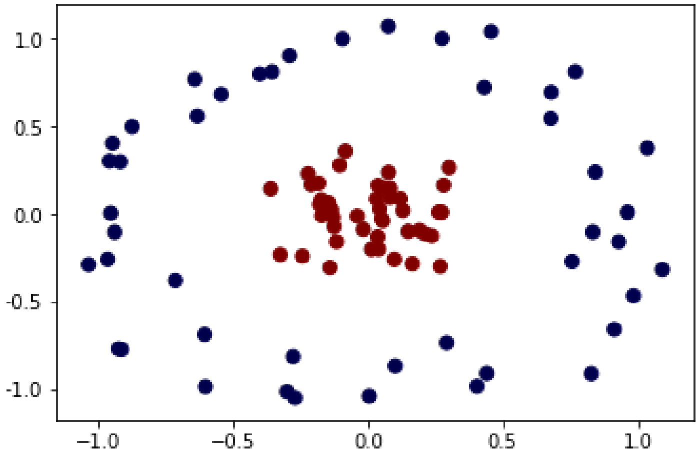
How does it work ?

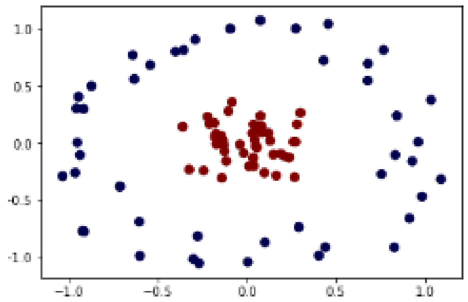
Kernel trick

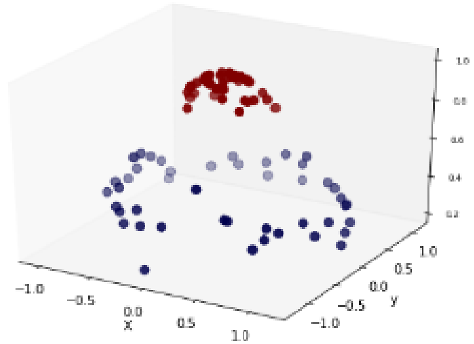
How to perform SVM for this type of dataset ?

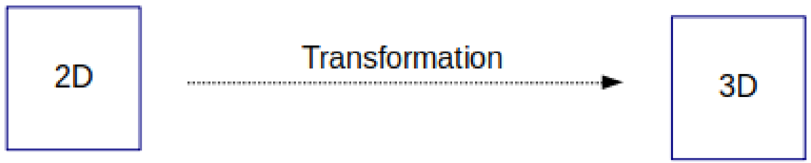


How does it work ?

Kernel trick







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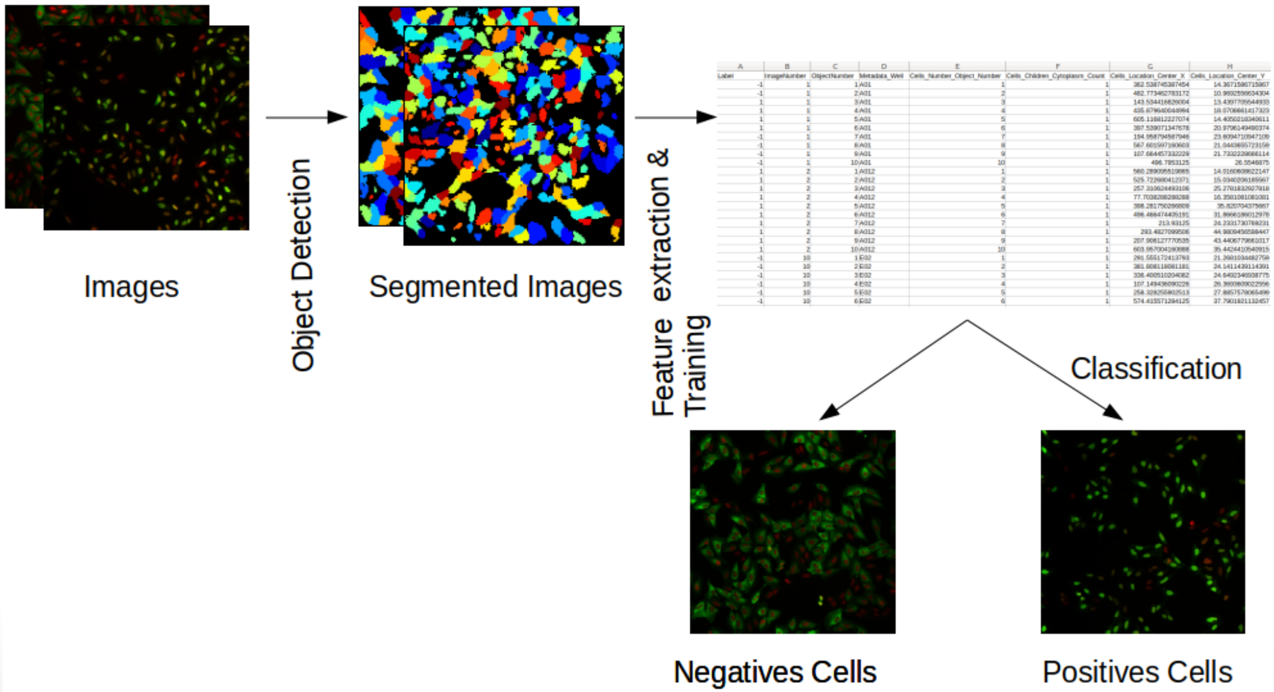
SVM in practice - Implementing biological application with Python

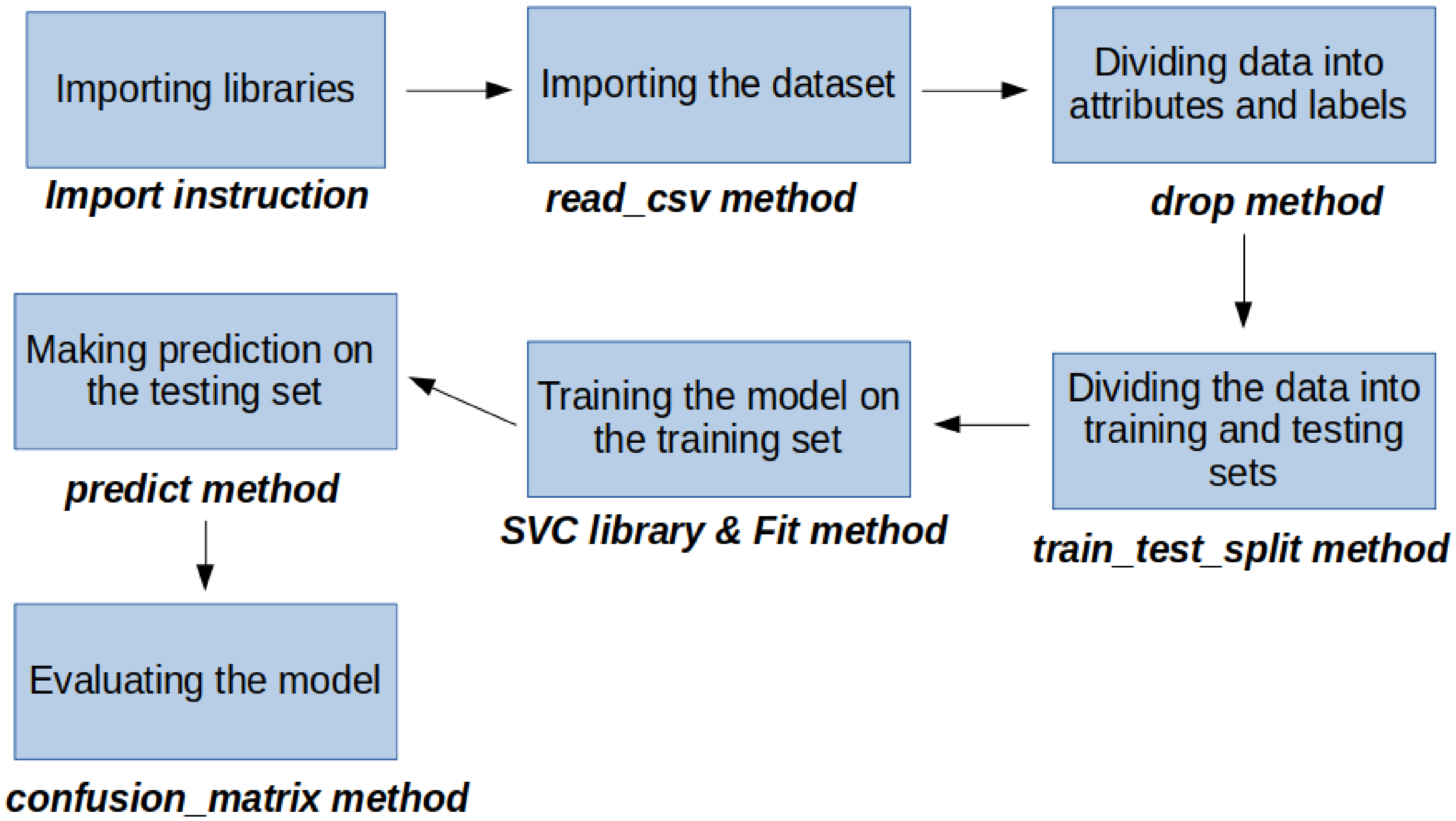
Use Case - Problem Statement

Estimate the lowest dose necessary to induce the cytoplasm to nucleus translocation of the FKHR-EGFP in U2OS (osteosarcoma cell line). Channel 1 = FKHR-GFP; Channel 2 = DNA



SVM in practice - Implementing biological application with Python

Use Case - Translocation Activity



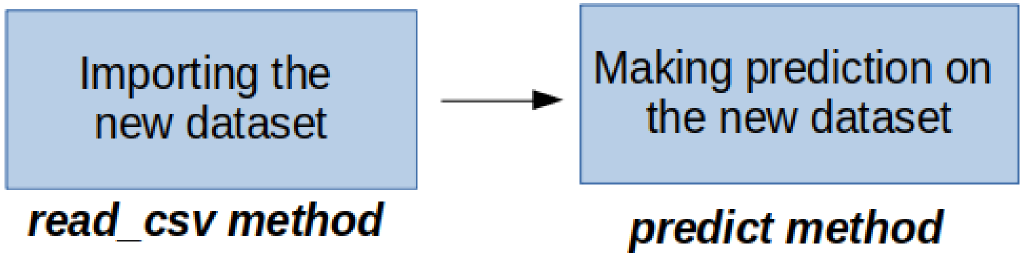
Use Case - Translocation Activity

$$Accuracy = (\frac{CountTrue}{CountTotal}) * 100$$

$$ErrorRate = (\frac{CountFalse}{CountTotal}) * 100$$

$$ErrorRate = 1 - Accuracy$$

Use Case - Translocation Activity



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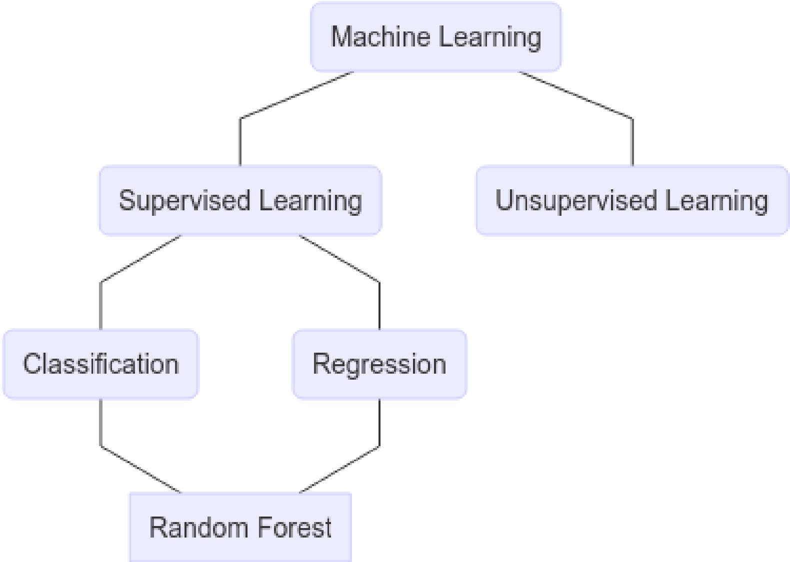
History of Random Forest

1. 1997: In an important paper on written character recognition, Amit and Geman define a large number of geometric features and search over a random selection of these for the best split at each node.
2. 1998: Ho has written a number of papers on "the random subspace" method which does a random selection of a subset of features to use to grow each tree.
3. 2001: The introduction of random forests proper was first made in a paper by Leo Breiman. This paper describes a method of building a forest of uncorrelated trees using a CART like procedure, combined with randomized node optimization and bagging.

Types of Machine Learning



Why Random Forest ?

No Overfitting:

- Number of trees increase
- Training time is less

High Accuracy:

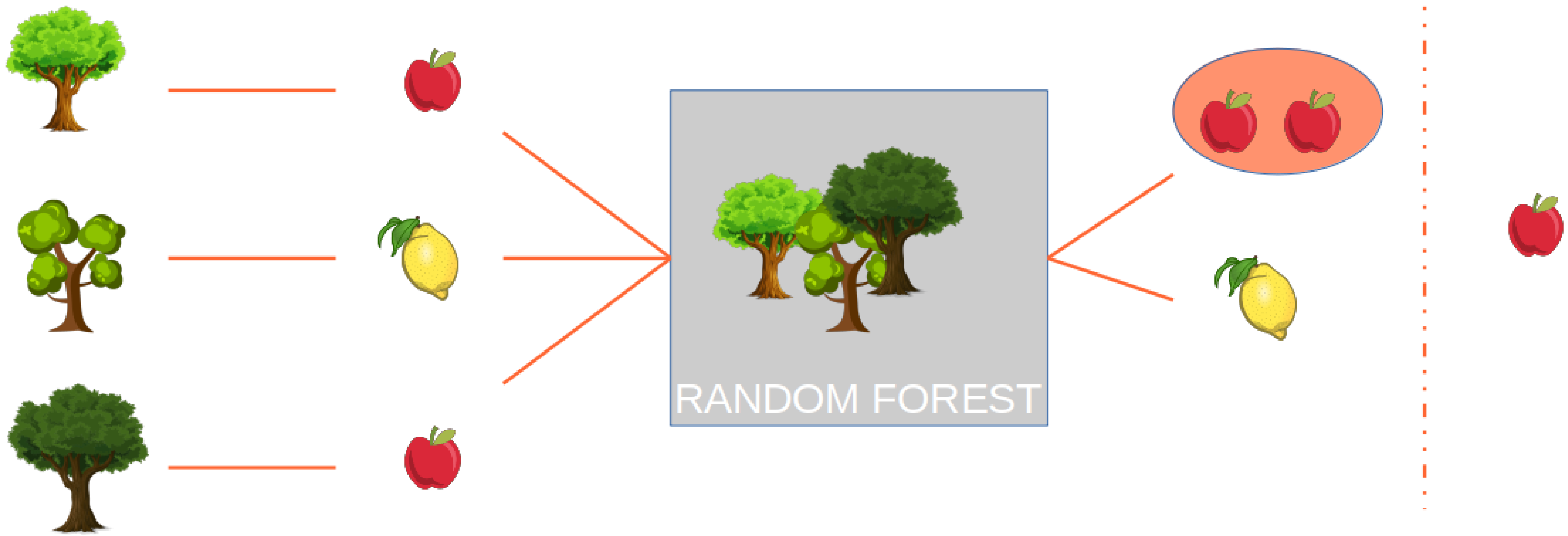
- Run efficiently on large database

Missing data:

- Accuracy when large proportion of data is missing

What is Random Forest ?

Random Forest creates multiple Decision Trees during training phase. The Decision of the majority of the trees is chosen by the random forest as the final decision.



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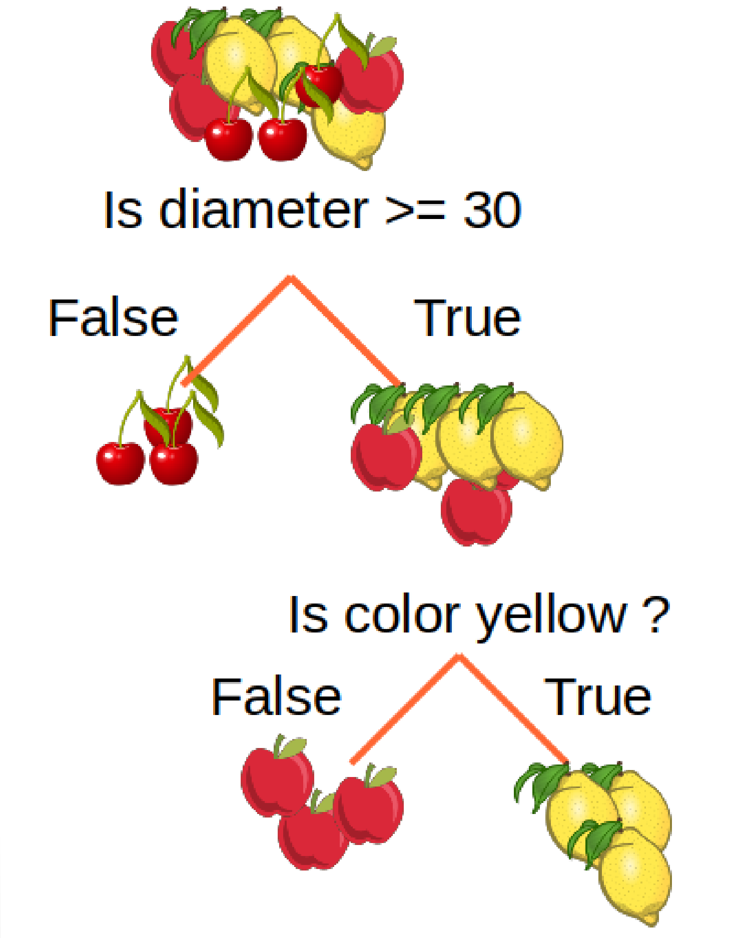
Decision Tree

Decision Tree is a tree shaped diagram. Each branch of the tree is an action and each node as a result of the decision taken.



Decision Tree

Entropy

Entropy is a measure of disorder,
of uncertainty
In a dataset.

Information gain

Leaf node

Decision node

Root node

Decision Tree

Entropy

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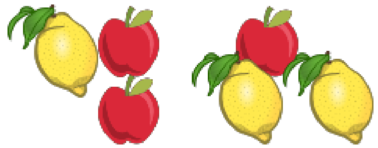

E1

High Entropy

Decision Tree

Entropy

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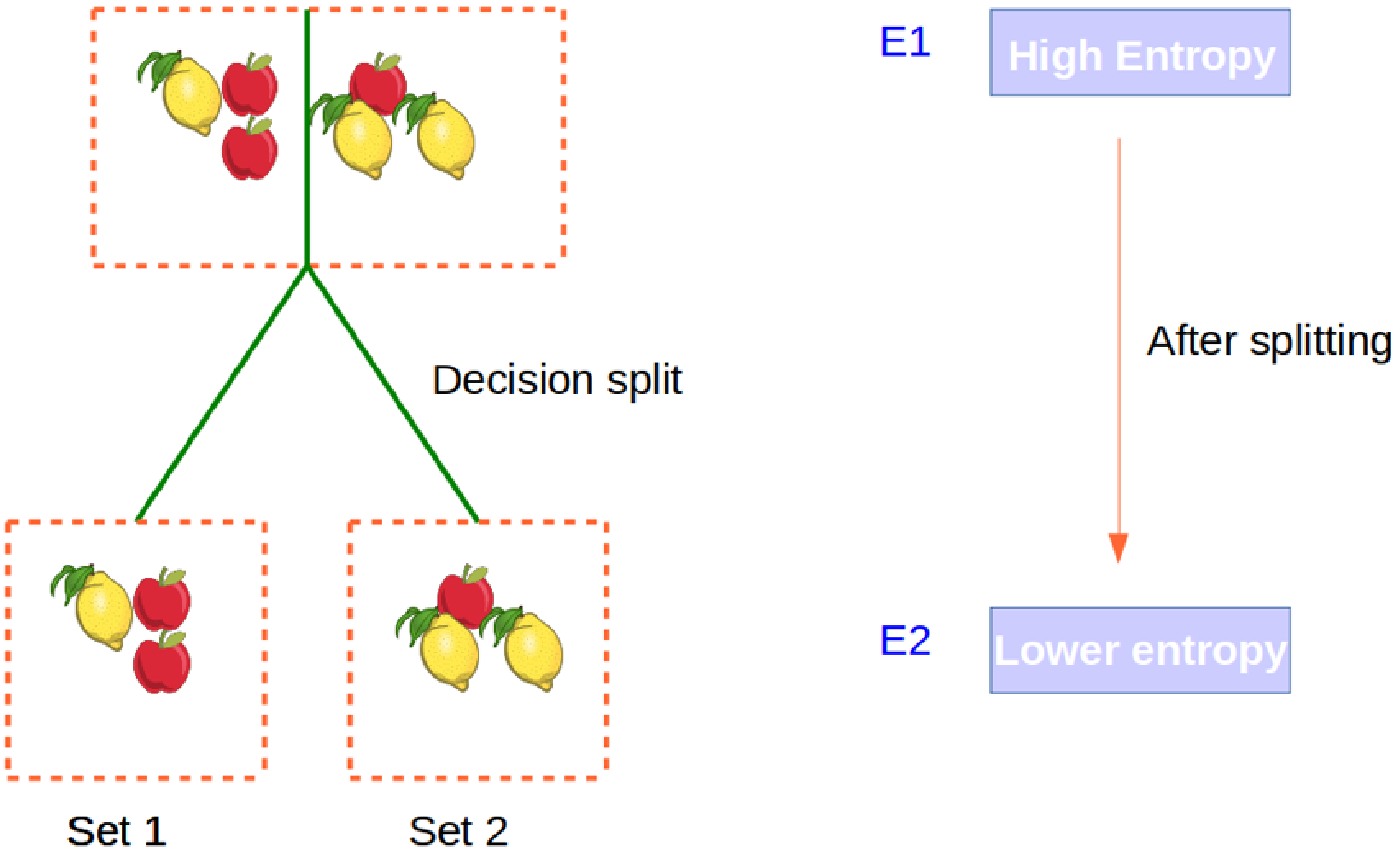

Decision Tree

Calculate entropy

$$Entropy = -\sum P(X) logp(X)$$

where p(x) is a fraction of a given class

$$P_{lemon} = \frac{3}{6} = 0.5$$

$$P_{apple} = \frac{3}{6} = 0.5$$

$$E_1 = -\sum P_{lemon} log_2(P_{lemon}) + P_{apple} log_2(P_{apple})$$

$$E_1 = -(-0.5 + (-0.5)) = 1$$

Decision Tree

Calculate entropy

$$P_{lemon} = \frac{1}{3} = 0.334$$

$$P_{apple} = \frac{2}{3} = 0.667$$

$$E_{left} = -(0.334 log_2(0.334) + 0.667 log_2(0.667)) = -(-0.52 + (-0.38)) = 0.9$$

$$E_{right} = -(0.334 log_2(0.334) + 0.667 log_2(0.667)) = -(-0.52 + (-0.38)) = 0.9$$

$$E_2 = \frac{nclassesinleftchildnode}{ntotalclassesinparentnode} * E_{left} + \frac{nclassesinrightchildnode}{ntotalclassesinparentnode} * E_{right}$$

$$E_2 = \frac{3}{6} * 0.9 + \frac{3}{6} * 0.9 = 0.9$$

Decision Tree

Entropy

Information Gain

It is the measure of decrease in entropy after dataset is split

Leaf node

Decision node

Root node

Decision Tree

Information Gain

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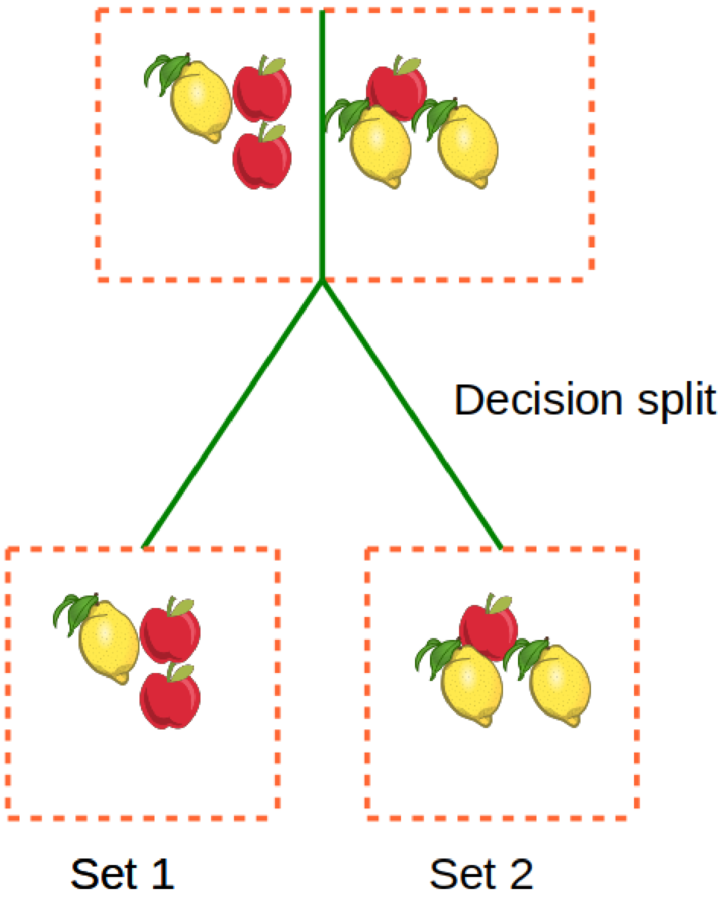
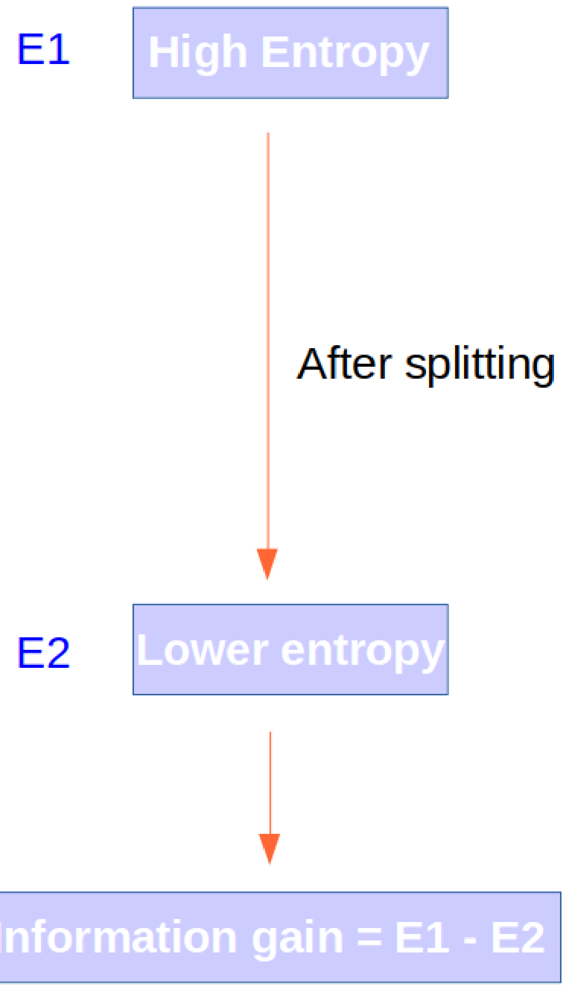




Decision Tree

Information Gain

$$Information gain = E_{parent} - [weightes average] * E_{children}$$

$$Information gain = E_1 - E_2 = 1 - 0.9 = 0.10$$

Decision Tree

Entropy

Information Gain

Leaf node

caries the classification of the decision

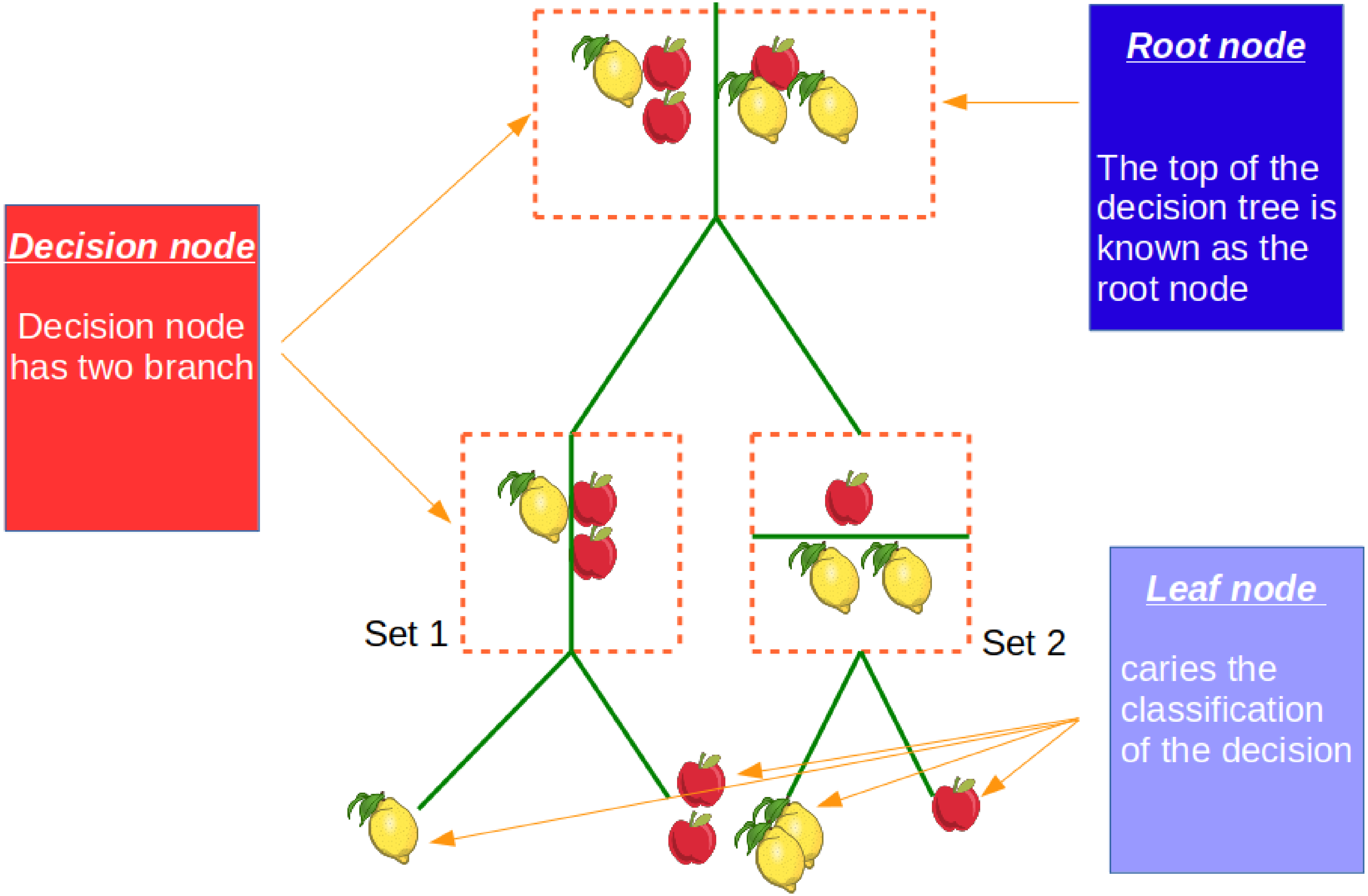
Decision node

Decision node has two branch

Root node

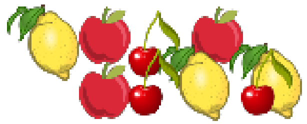
The top of the decision tree is known as the root node

Decision Tree



How Does a decision tree work ?

Use case :
To classify the
Different types of
Fruits based on features



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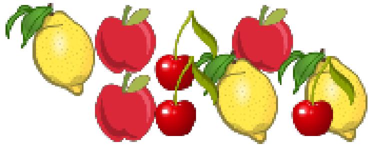

The dataset is looking messy and the entropy is high in this case

How Does a decision tree work ?

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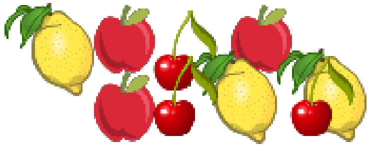

The dataset is looking
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How to split the data

We looking for a high information gain to split the dataset

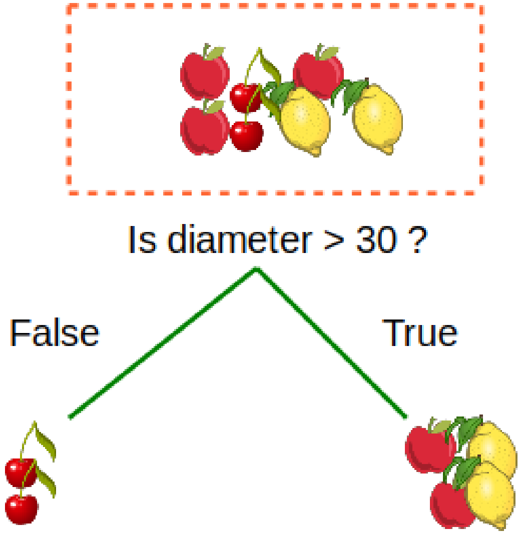
Training dataset

Color	***Diameter***	***Label***
Red	30	Cherry
Yellow	80	Lemon
Red	90	Apple
Red	30	Cherry
Yellow	80	Lemon
Red	90	Apple

How Does a decision tree work ?

We split the data

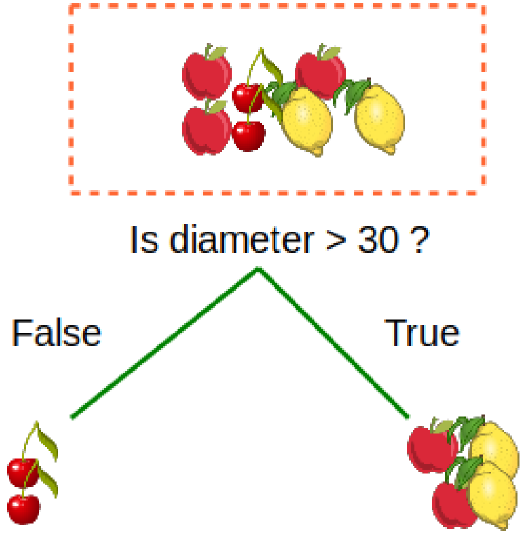
After the split, entropy has decreases considerably.



This node has an entropy equals to zero. No split is required.

How Does a decision tree work ?

We split the data



After the split, entropy has decreases considerably.

This node has an entropy equals to zero. No split is required.

This node require a split to decrease the entropy.

How Does a decision tree work ?

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After the split,
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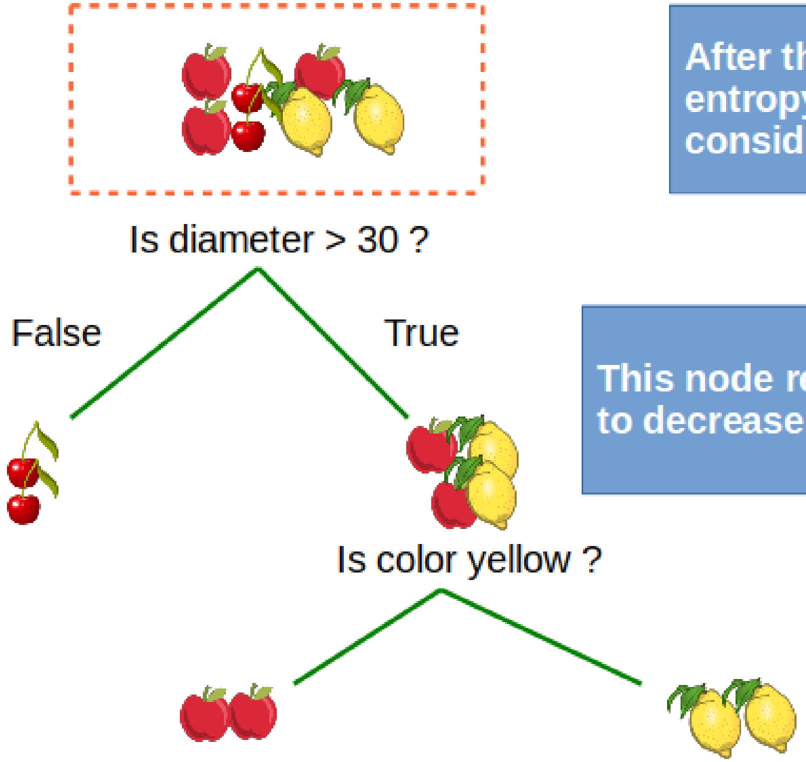

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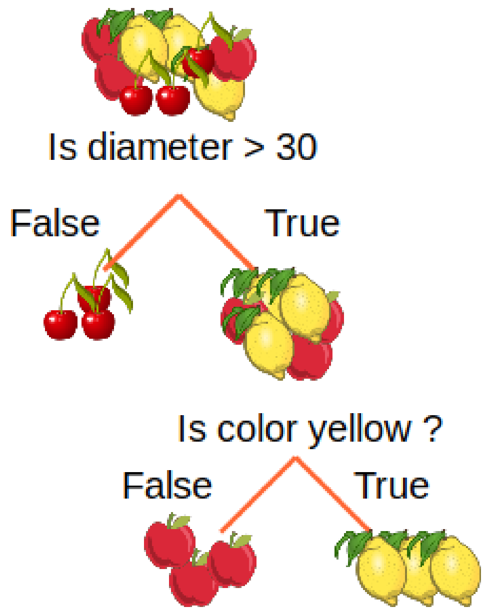
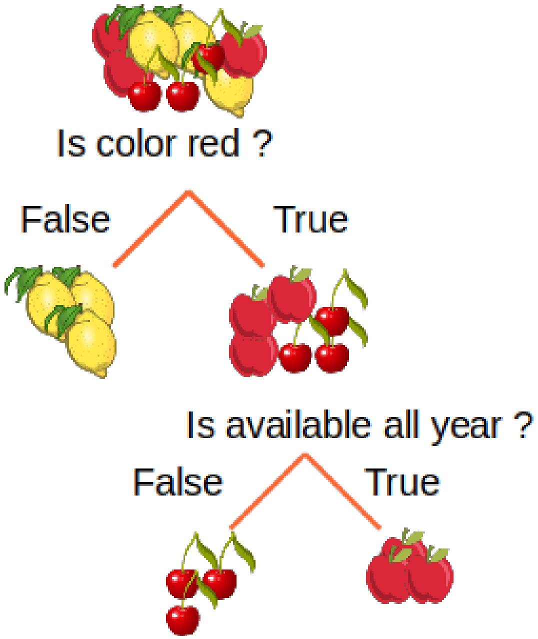
How Does a random forest work ?

Let this be tree 1



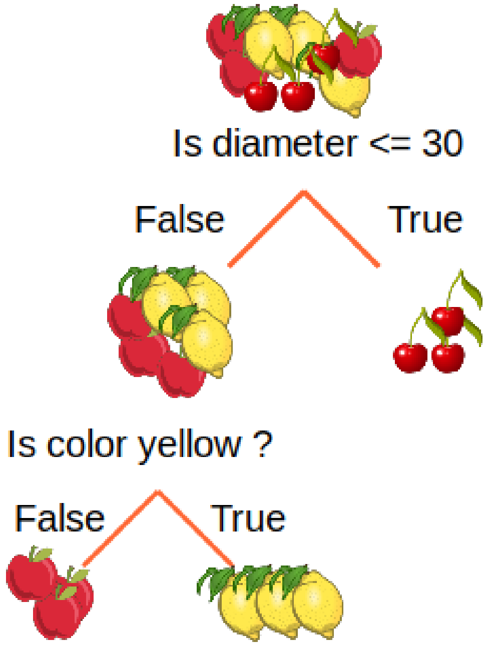
How Does a random forest work ?

Let this be tree 2



How Does a random forest work ?

Let this be tree 3



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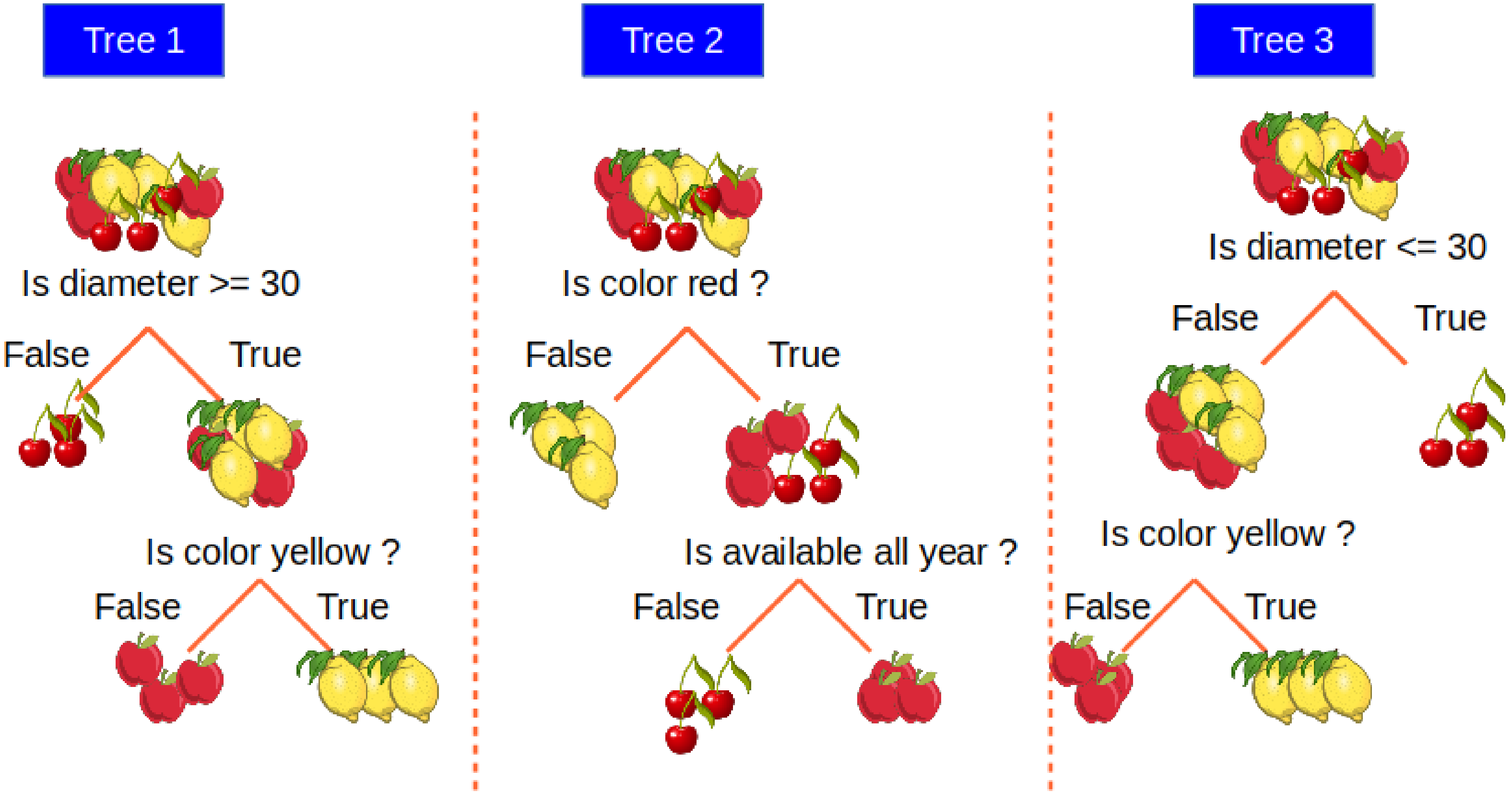
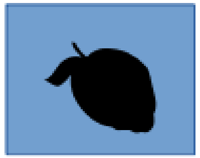
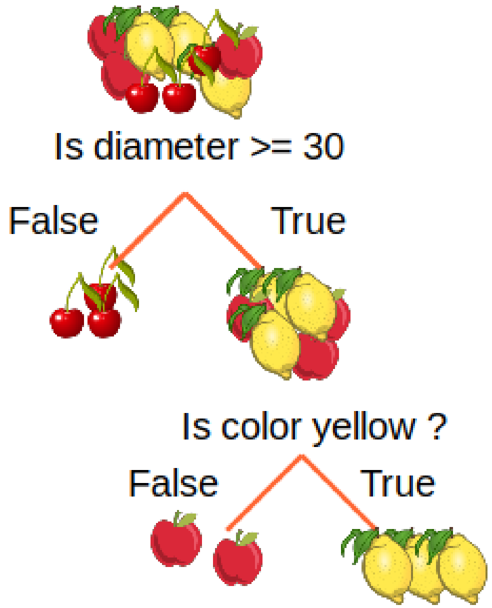


How Does a random forest work ?

Now lets try to classify this fruit



Tree 1 classify this fruit as a lemon



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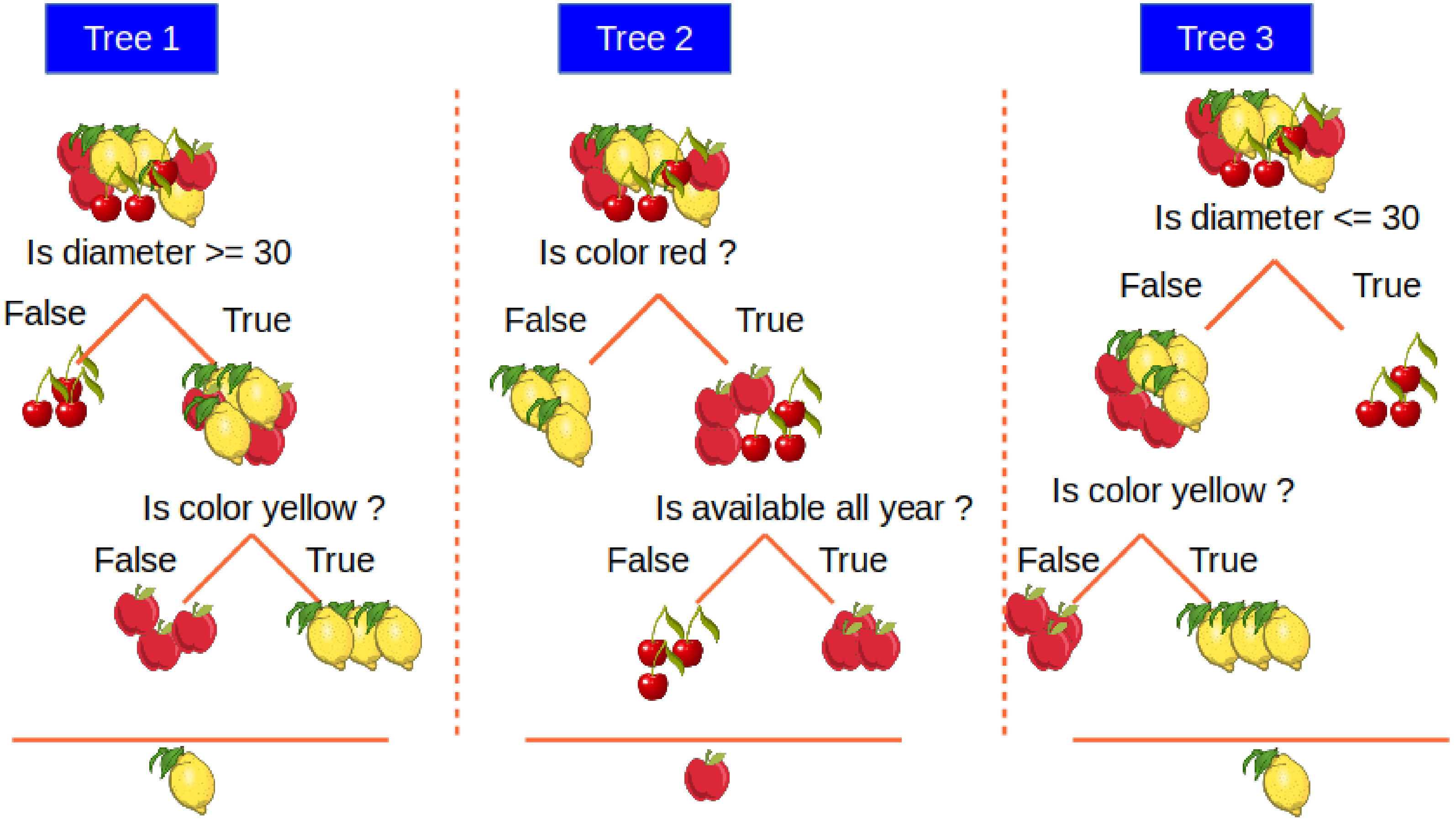

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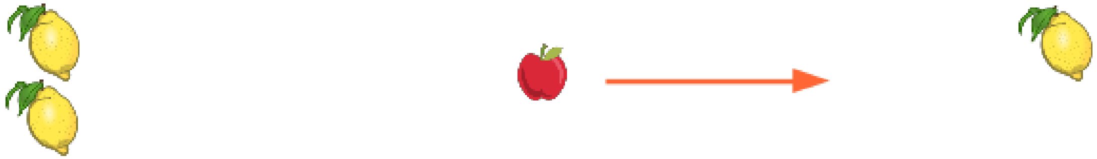

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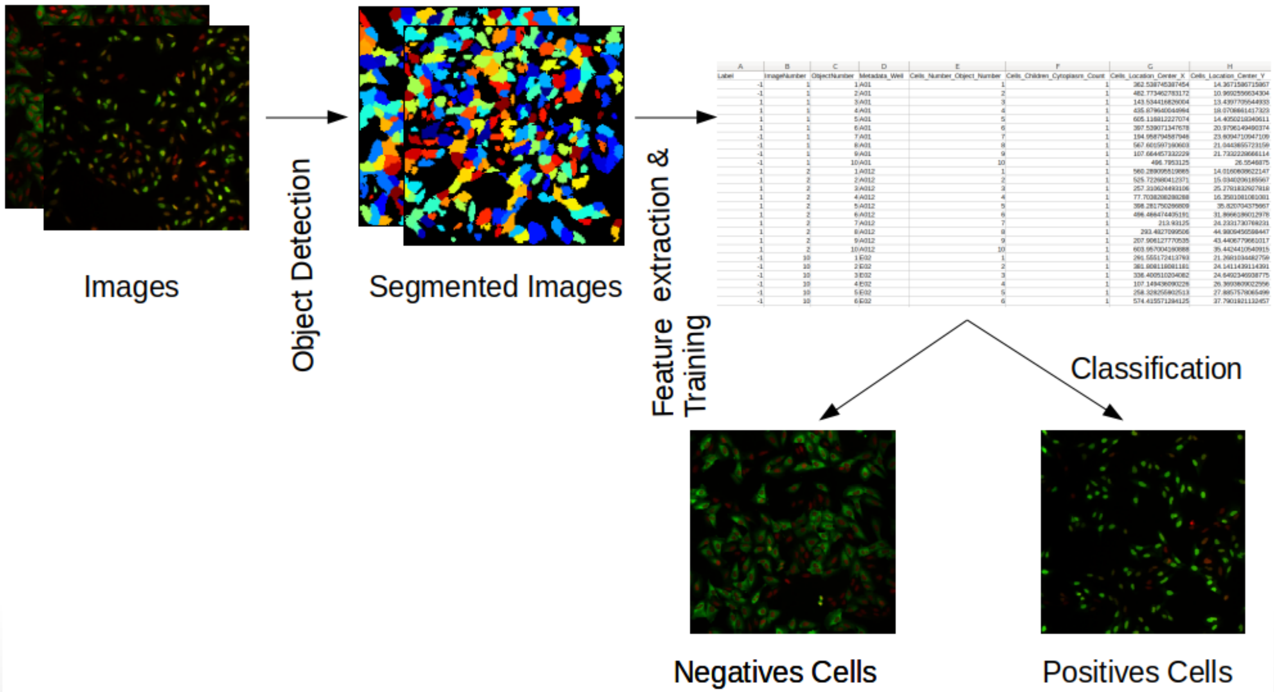

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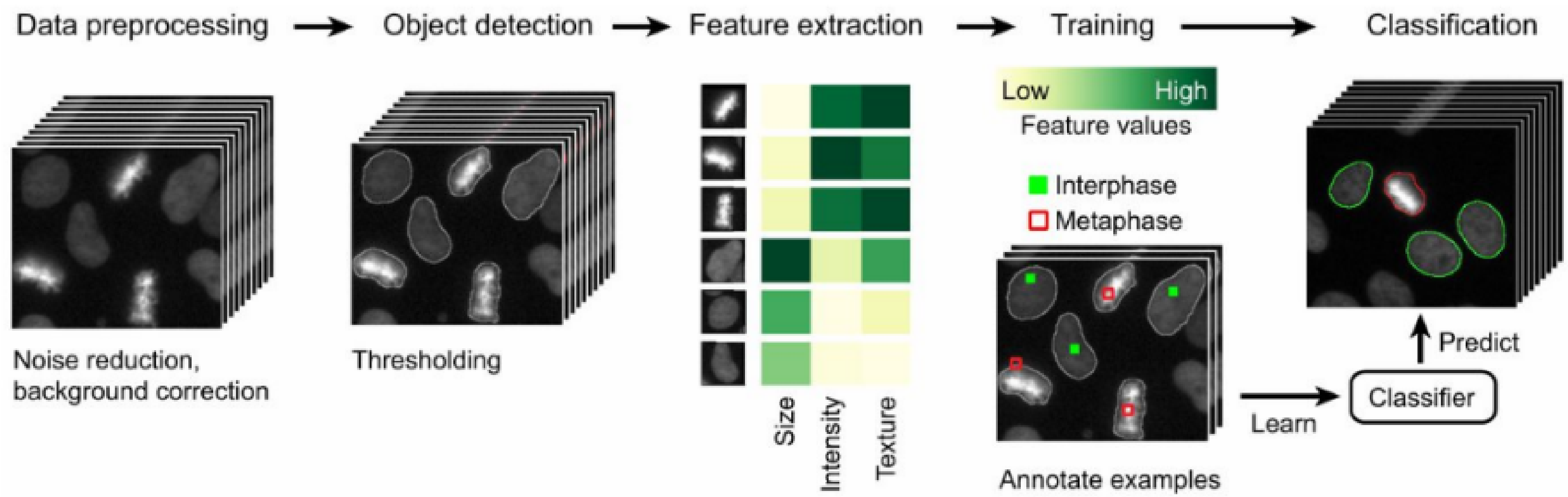

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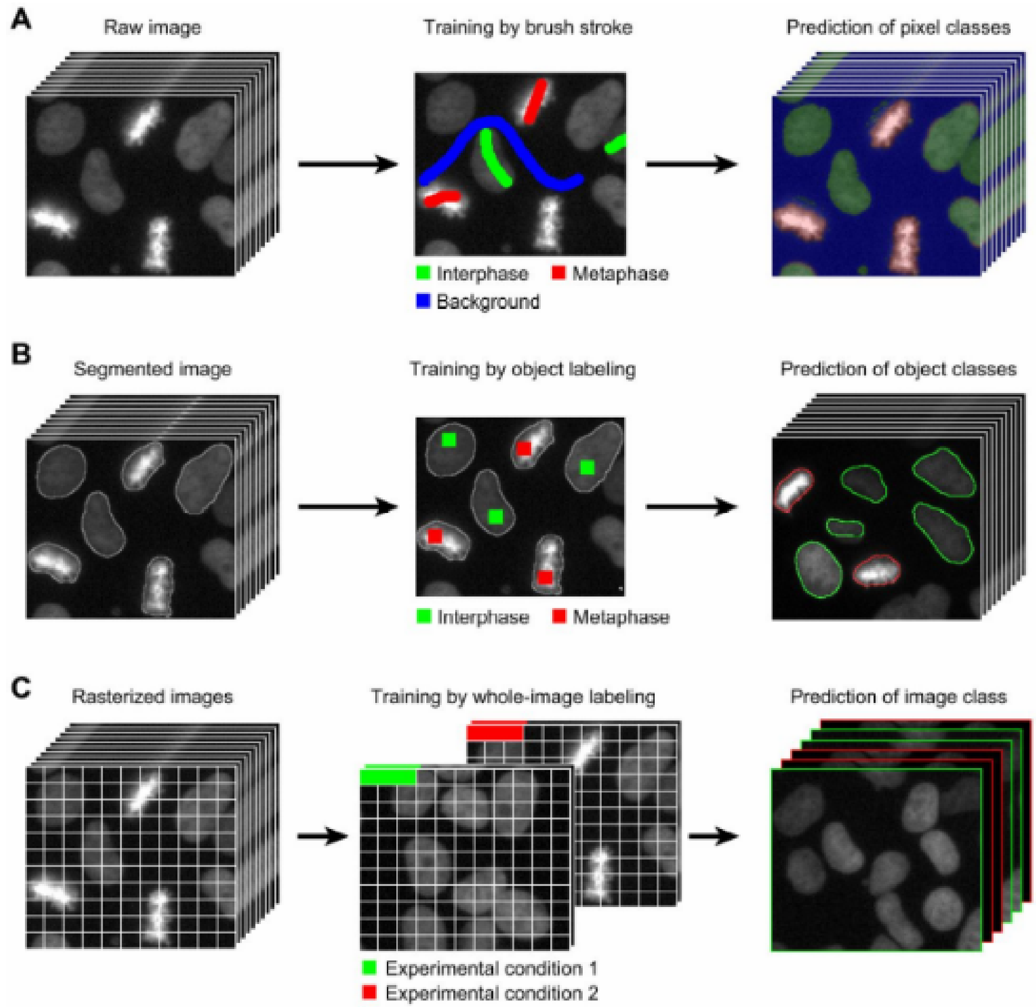
Machine Learning in Bioimage analysis



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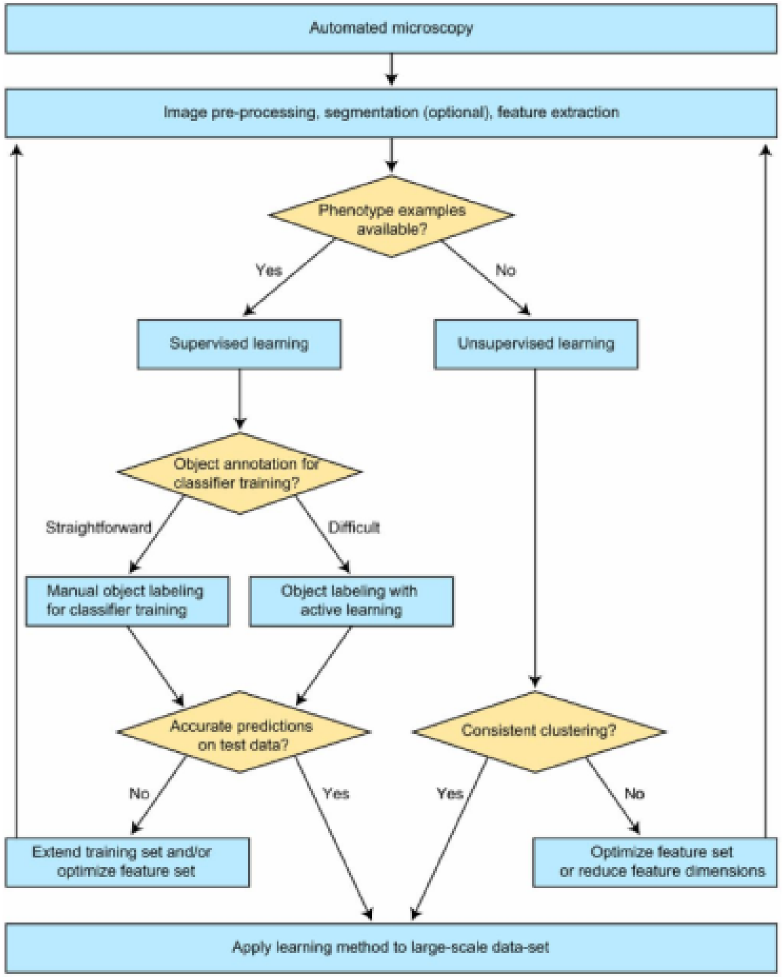

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