FACULTAD DE MEDICINA
UNIVERSIDAD DE CHILE

INSTITUTO DE CIENCIAS BIOMÉDICAS

Laboratory for SCIAN Scientific Image Analysis

CIMT CENTRO DE INFORMATICA MEDICA Y TELEMEDICINA

Applications of AI in image processing

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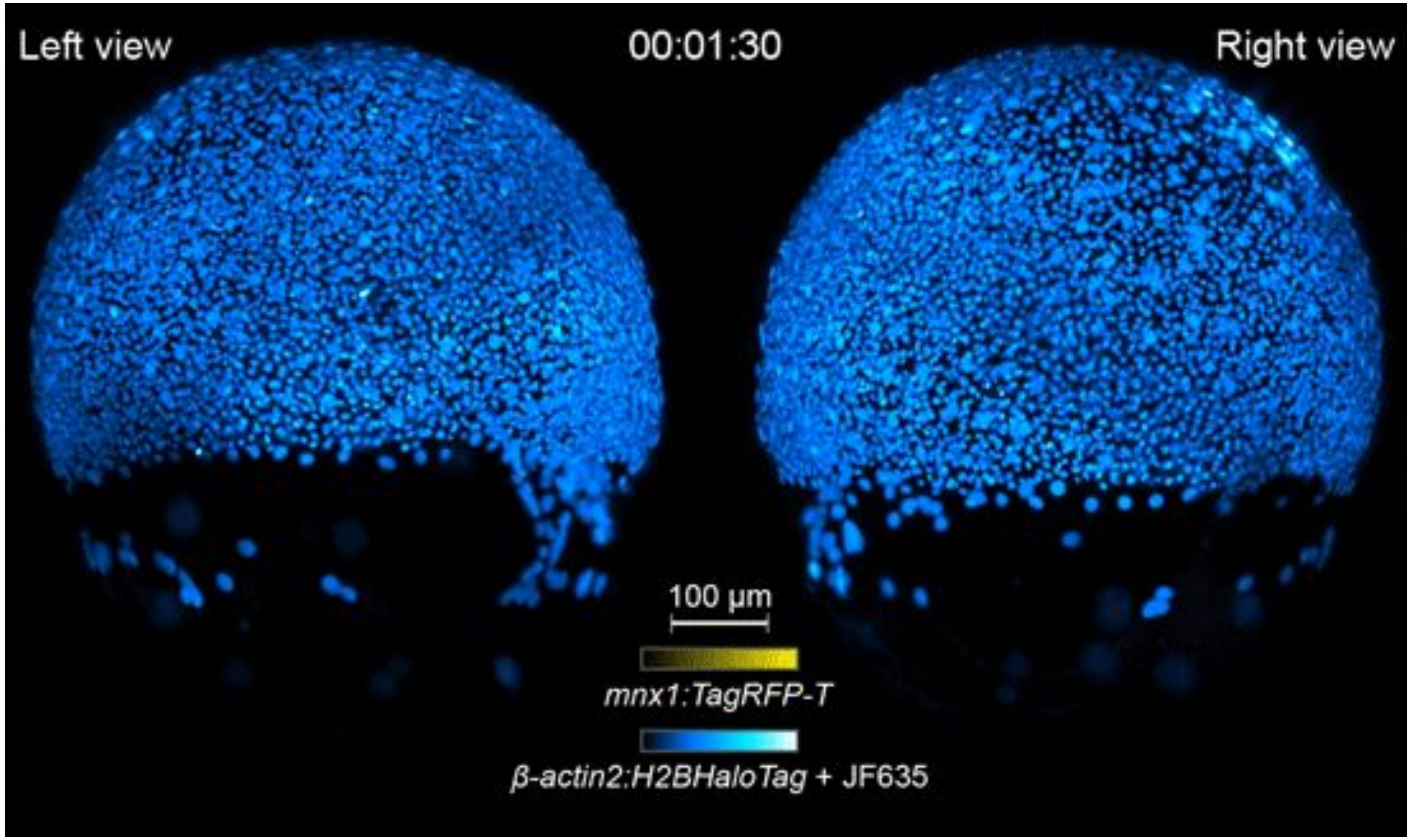
- Santiago 2026 -

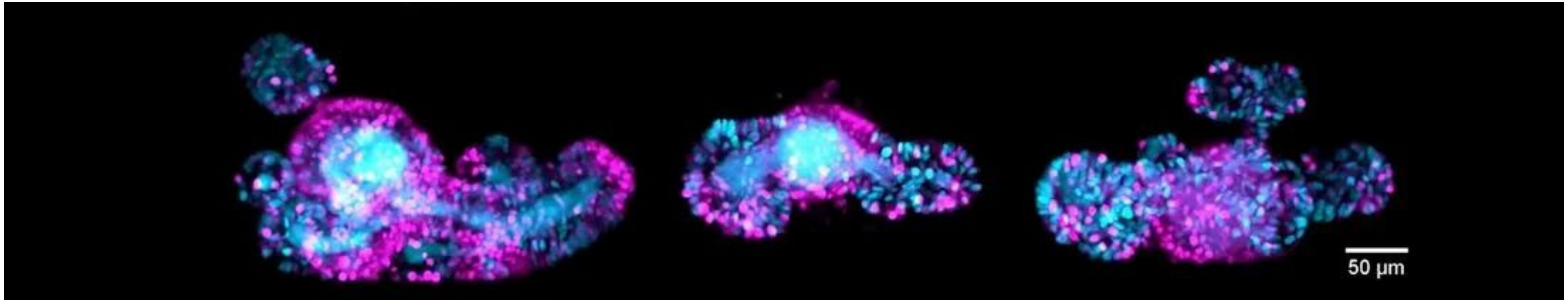
A picture is worth a thousand words …



…but only when we can extract meaningful information from it.

Wan, Y., Wei, Z., Looger, L. L., Koyama, M., Druckmann, S., & Keller, P. J. (2019). Single-cell reconstruction of emerging population activity in an entire developing circuit. *Cell*, *179*(2), 355-372.

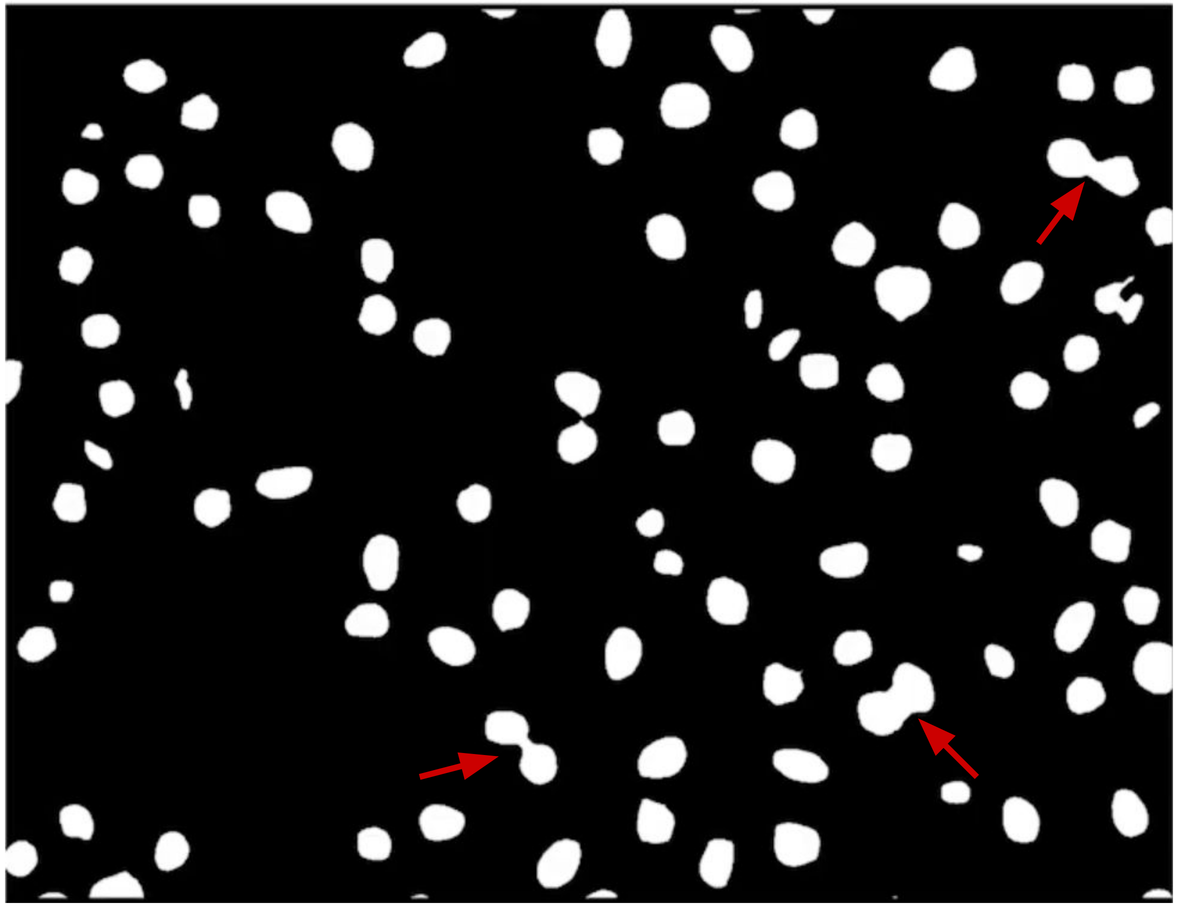
Microscopy image analysis

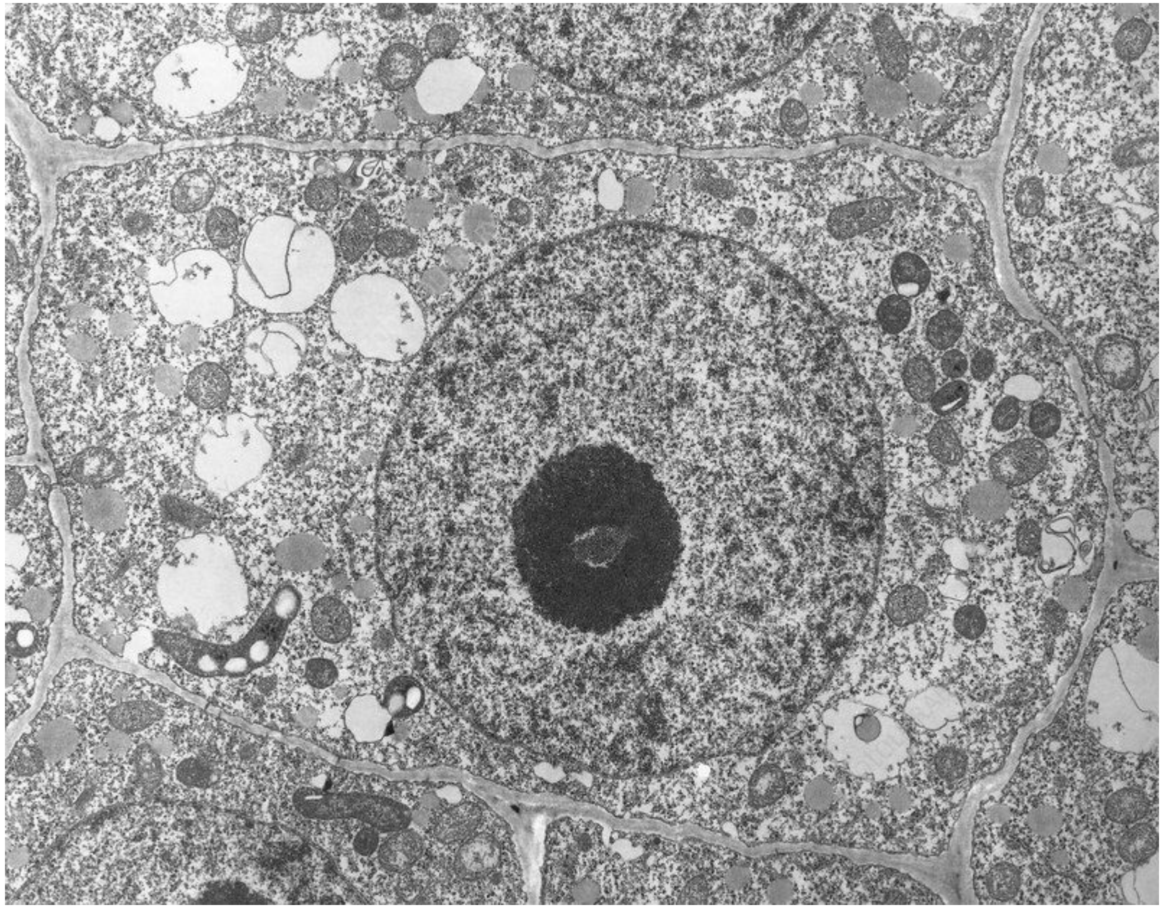


- Highly dimensional and complex datasets
- Manual analysis can be time-consuming and tedious
- Manual analysis is prone to human error and bias

Moos, F., *et al.* Open-top multisample dual-view light-sheet microscope for live imaging of large multicellular systems. *Nat Methods* 21, 798–803 (2024).

Limits of classical image analysis





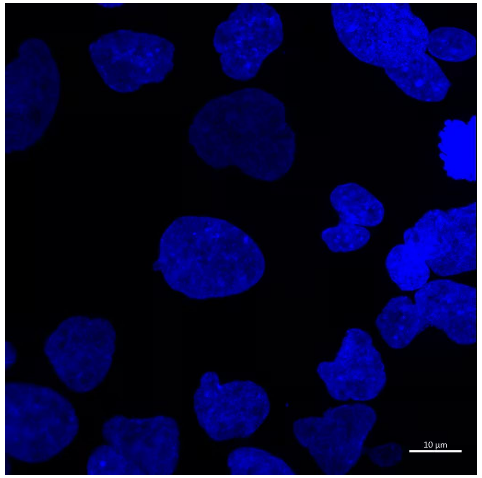
Learn from features

What is a feature?

An individual, measurable characteristic of a data sample

- ✔ Color: red
- ✔ Texture: soft
- ✔ Firmness: hard
- ✔ Shape: round

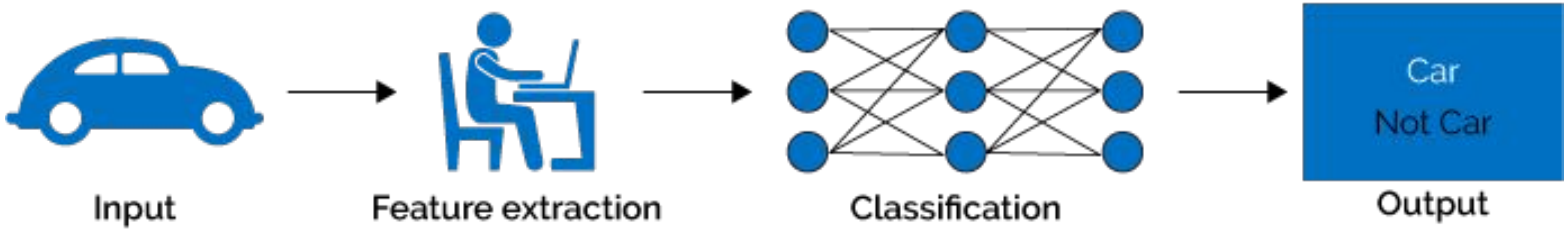
- ✔ Number of legs: 4
- ✔ Material: wood
- ✔ Backrest: high
- ✔ Seat height: 45 cm



- ✔ Mean intensity
- ✔ Local texture
- ✔ Edge gradient
- ✔ Shape descriptors

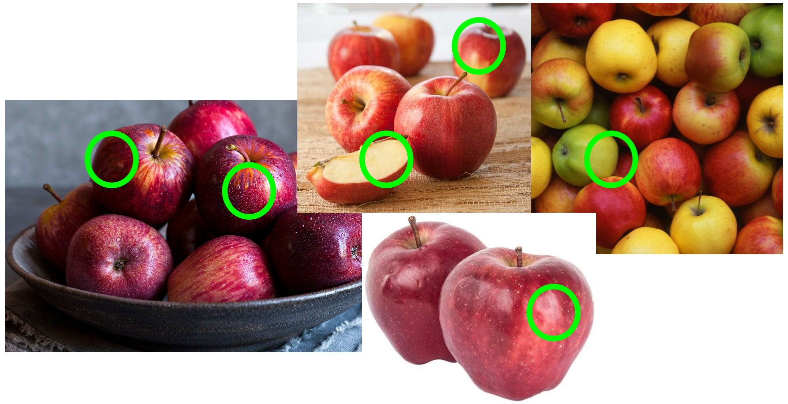
Machine Learning

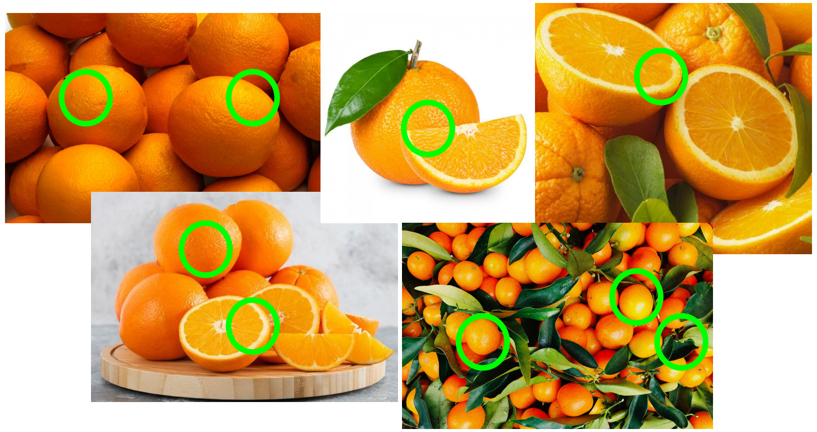
Systems that automatically learn from data



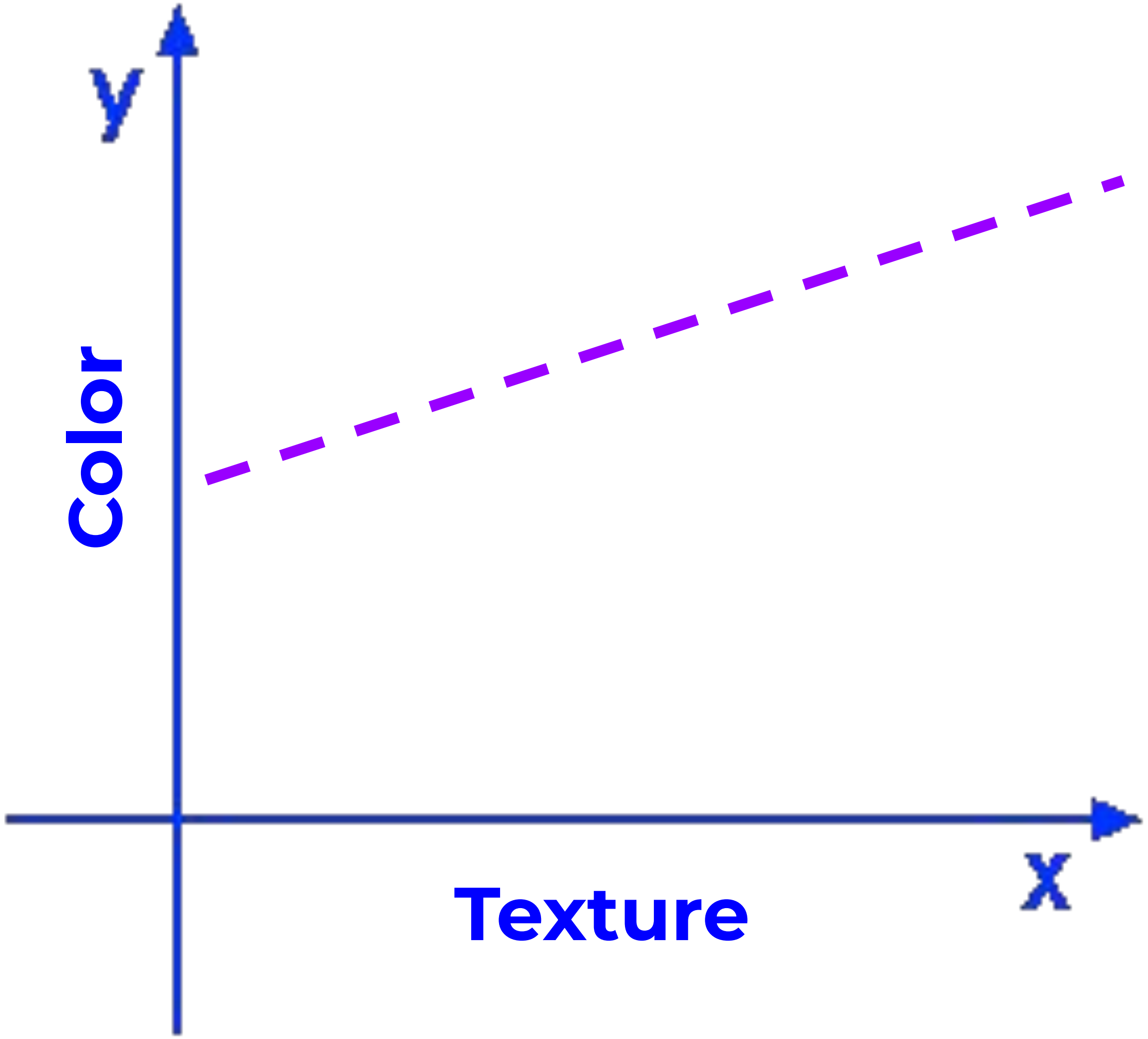
Source: https://viso.ai/deep-learning/deep-learning-vs-machine-learning/

Machine Learning



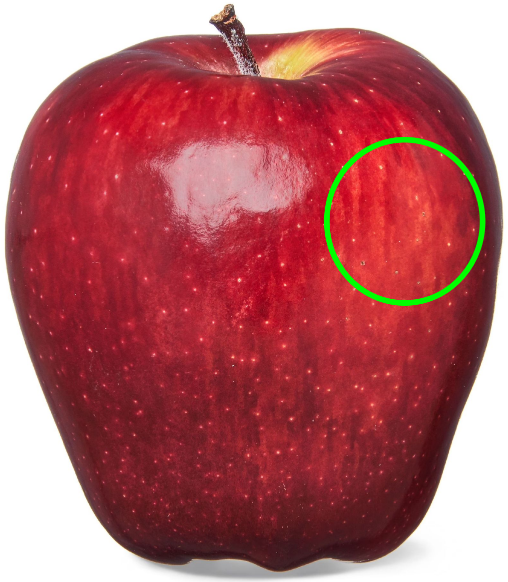


Handcrafted features

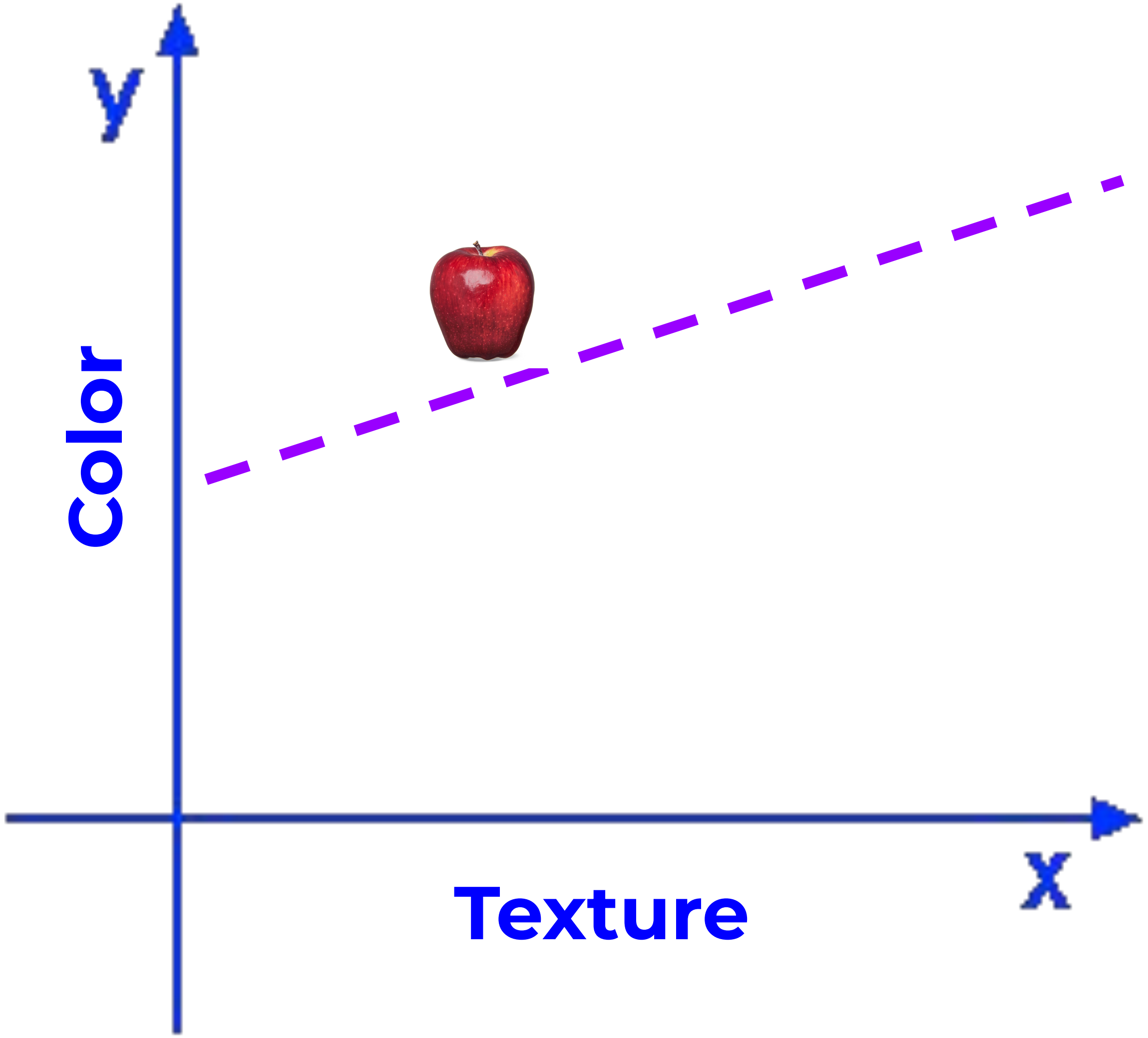


Feature space representation

Machine Learning

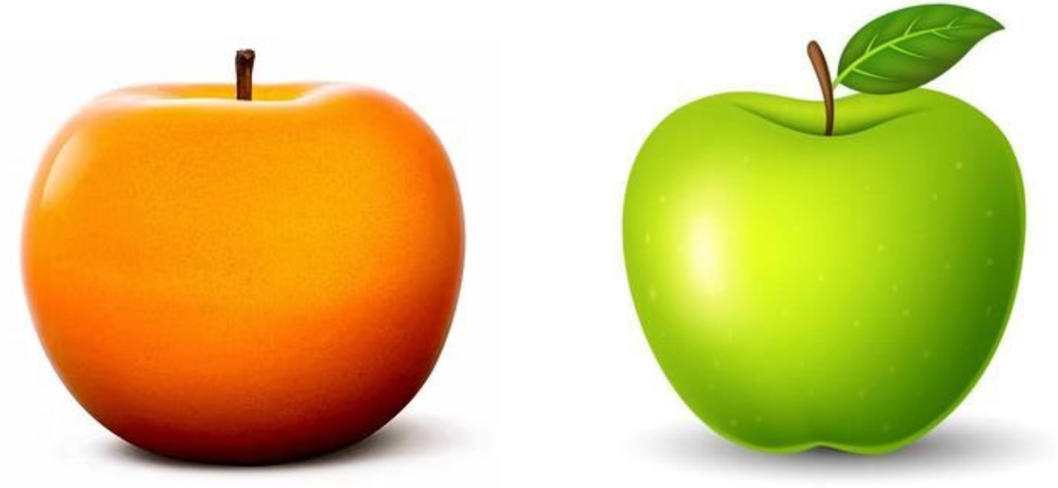


Handcrafted features

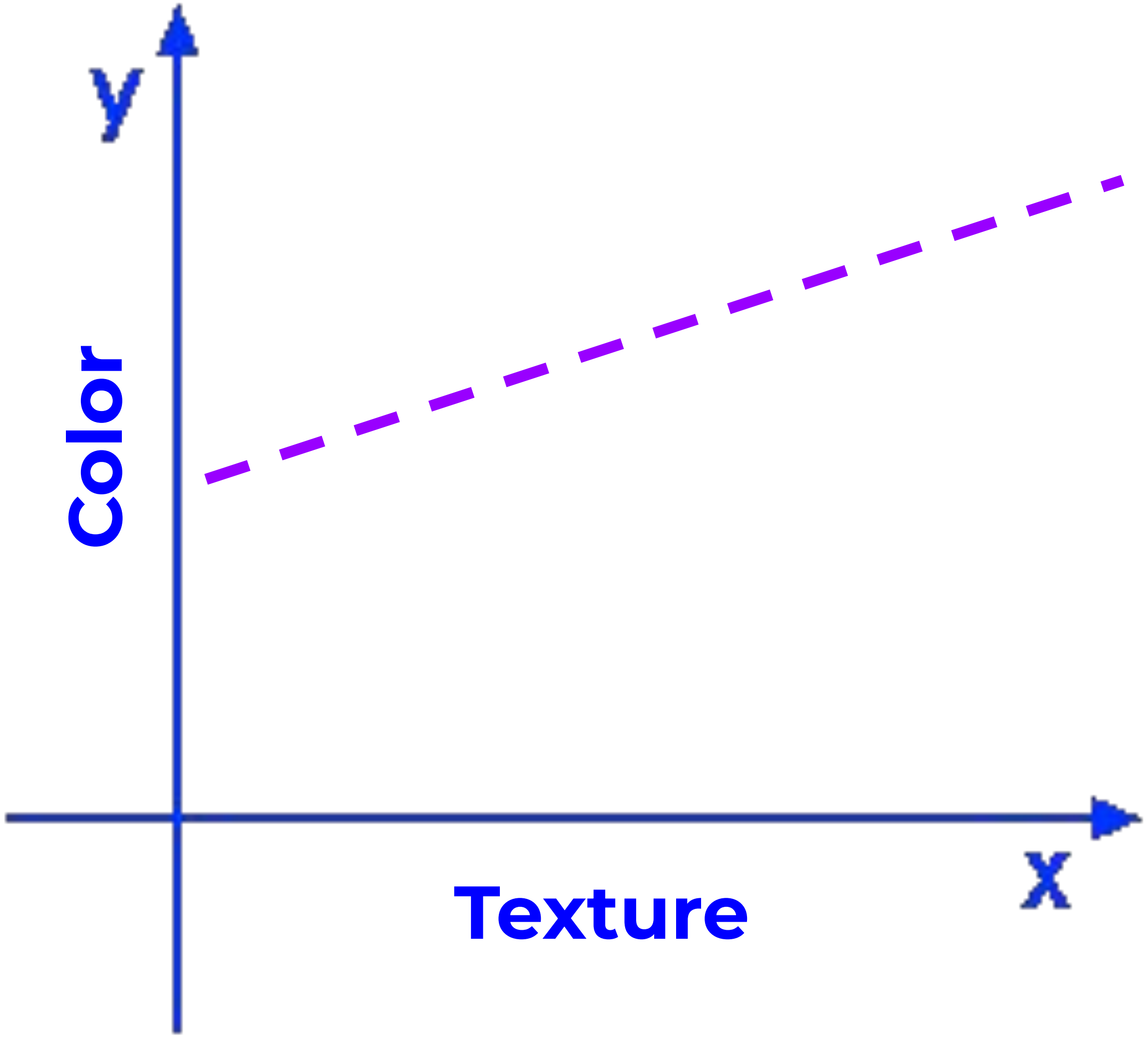


Feature space representation

Machine Learning

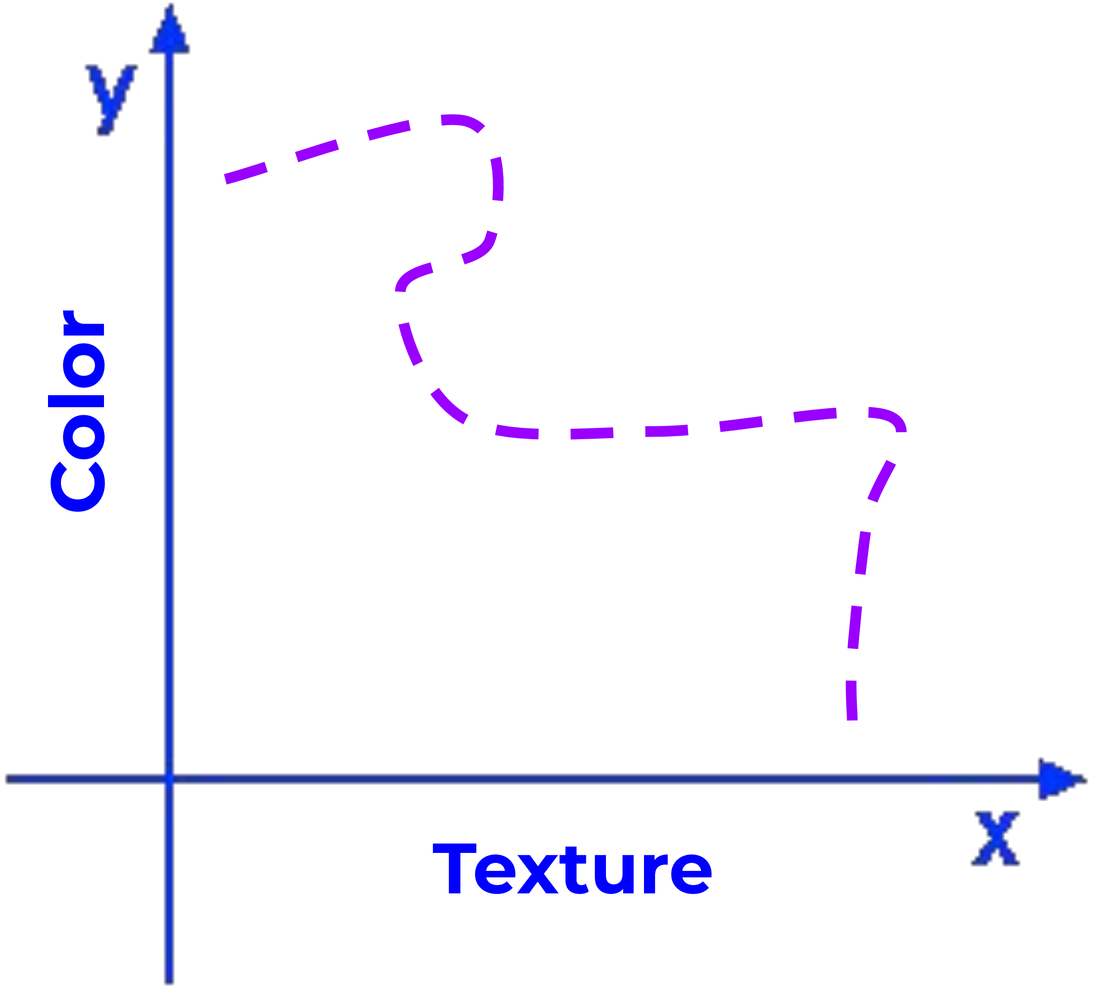


Handcrafted features



Feature space representation

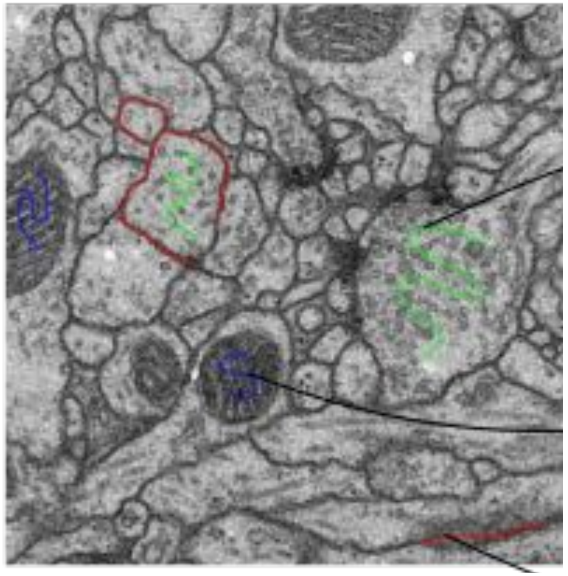
Machine Learning



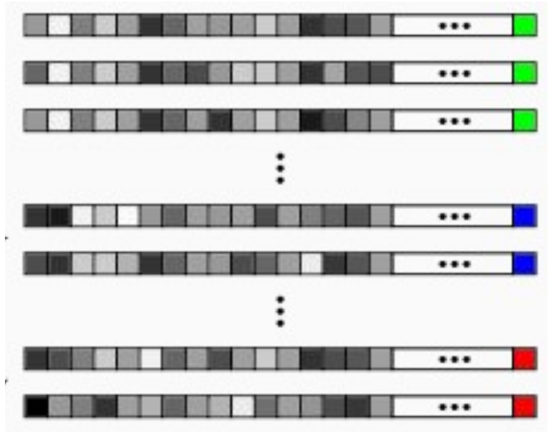
Feature space representation

Machine Learning Segmentation

Segmentation with ML is simply classifying every pixel in an image

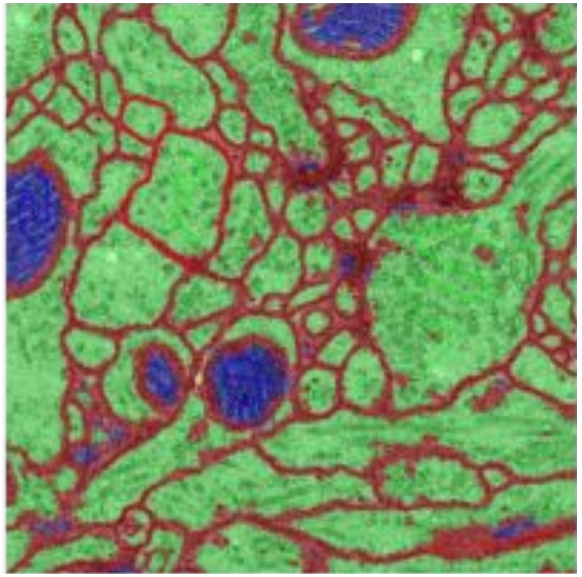


Input Image



Pixel-level Features

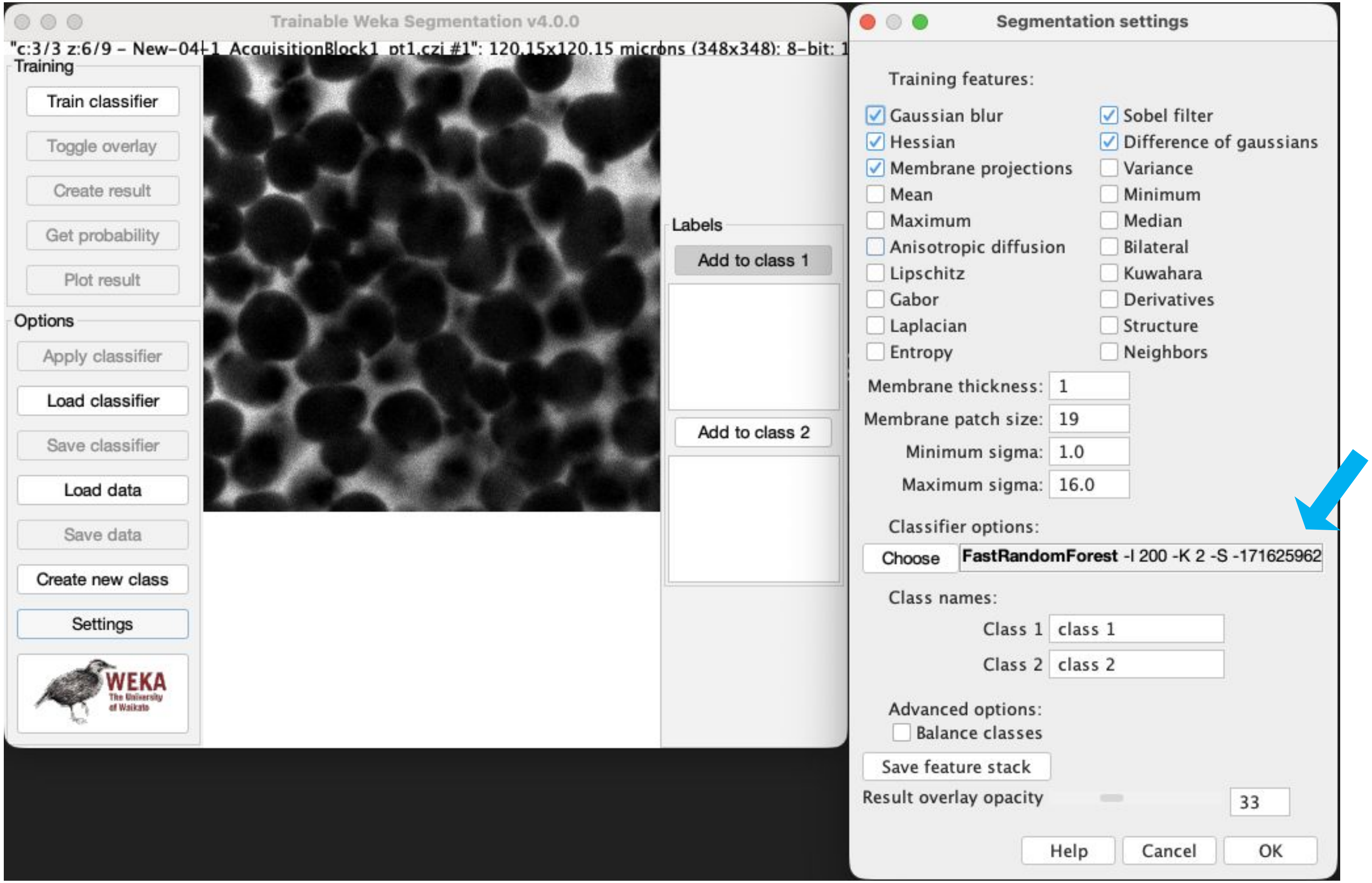
ML Classifier



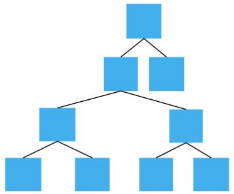
Segmented Image

Source: https://imagej.net/plugins/tws/

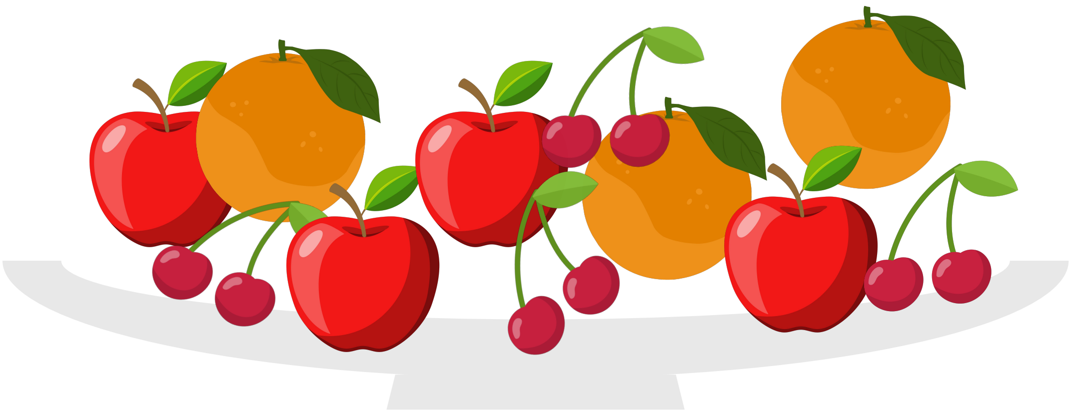
Random Forest



Decision Trees



Is a model which aims to solve a complex problem through smaller steps



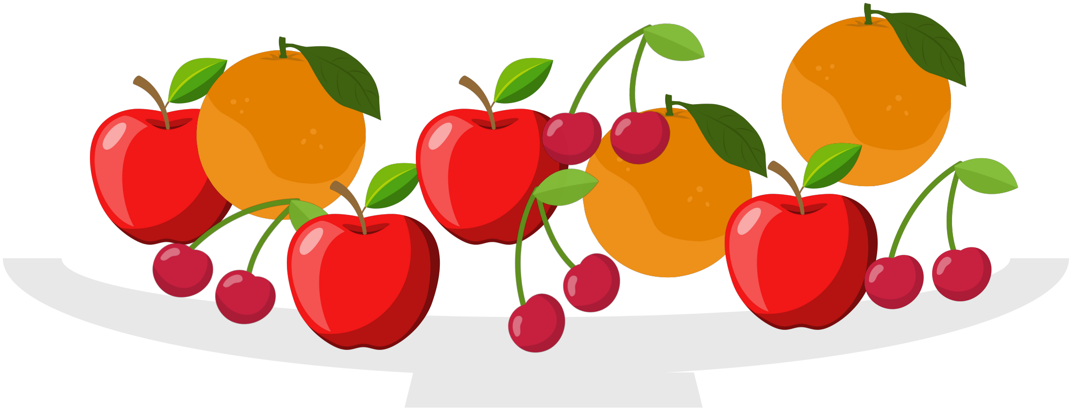
Color	Diameter	Label
Red	3	Apple
Orange	3	Orange
Red	1	Cherry
Red	3	Apple
Orange	3	Orange
Red	1	Cherry
Red	1	Cherry
Orange	3	Orange
Red	3	Apple
Red	3	Apple
Red	1	Cherry

Decision Trees ~ Entropy and Information Gain

- Entropy measures the disorder or impurity of the class labels in a node *high entropy = labels are mixed, low entropy = labels are homogeneous*

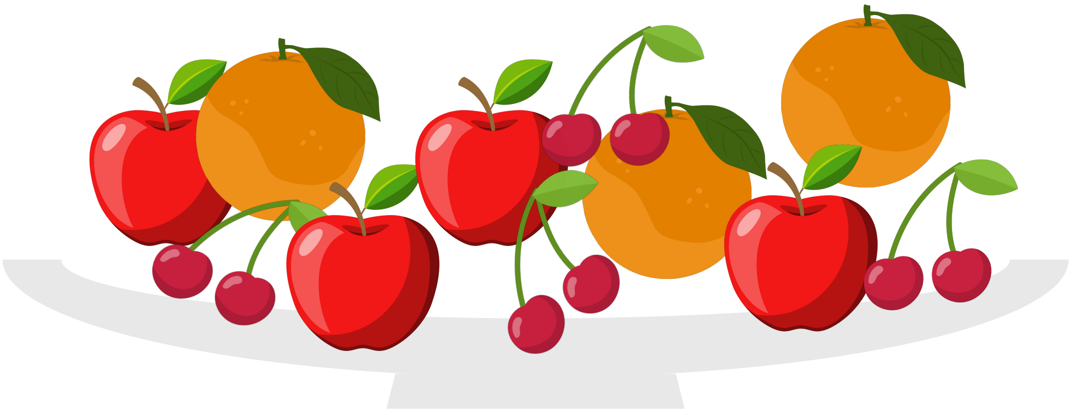
- Information Gain is the reduction in entropy after a split.

- A Decision Tree tests different feature splits and evaluates how much each split reduces entropy



Decision Trees ~ Entropy and Information Gain

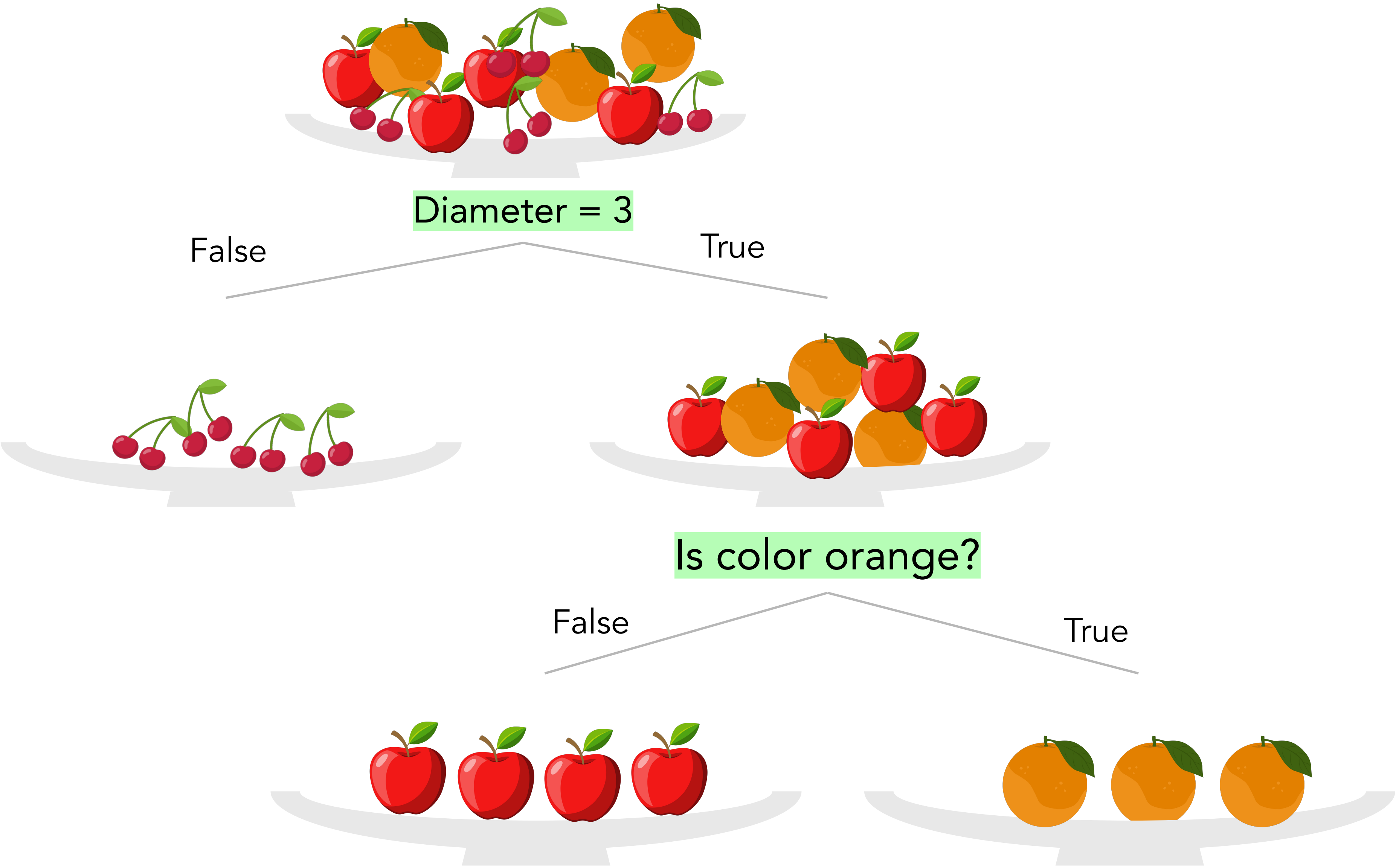
We have to select the condition that splits the data in a way that increases the information gain



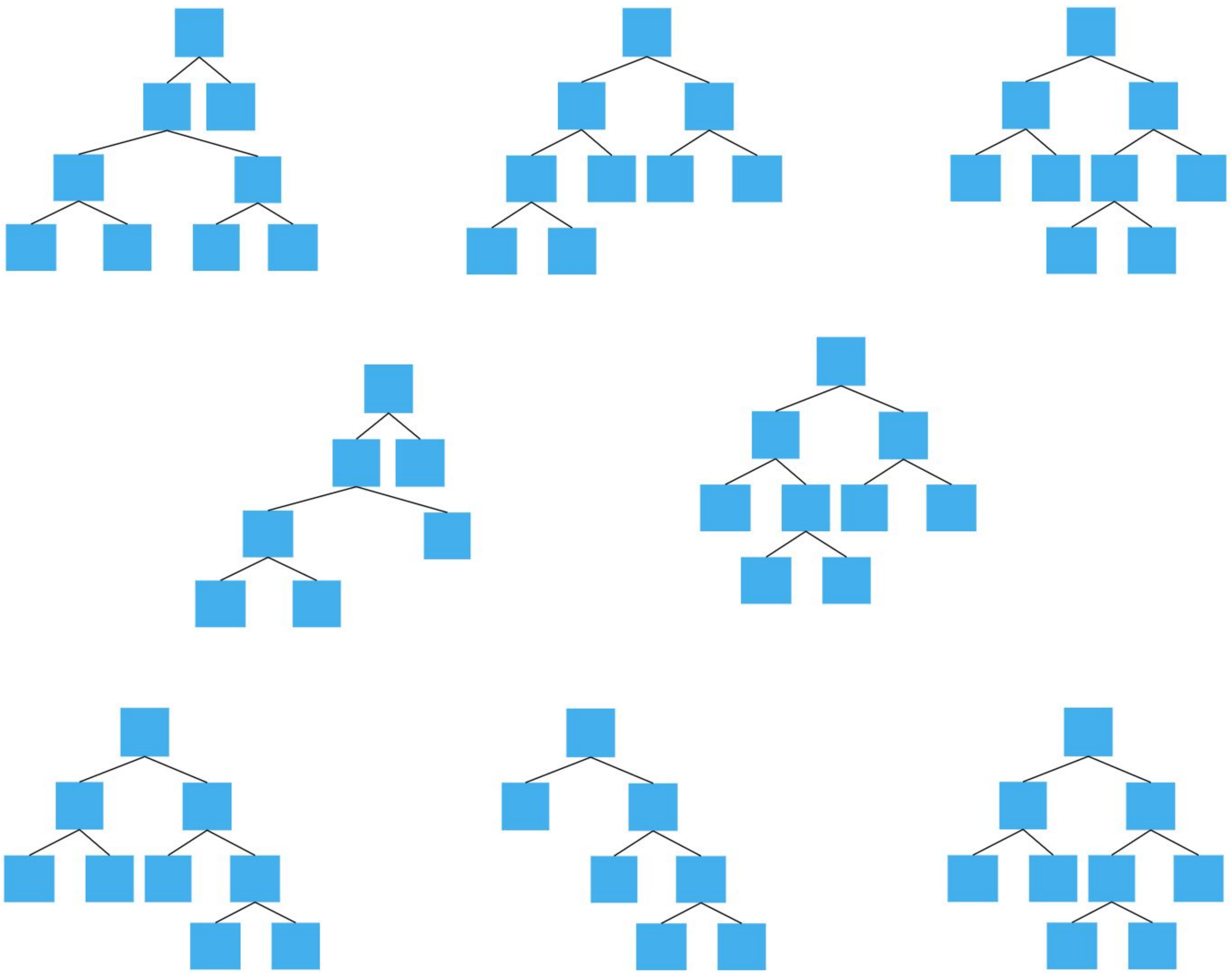
Diameter = 3

Color	Diameter	Label
Red	3	Apple
Orange	3	Orange
Red	1	Cherry
Red	3	Apple
Orange	3	Orange
Red	1	Cherry
Red	1	Cherry
Orange	3	Orange
Red	3	Apple
Red	3	Apple
Red	1	Cherry

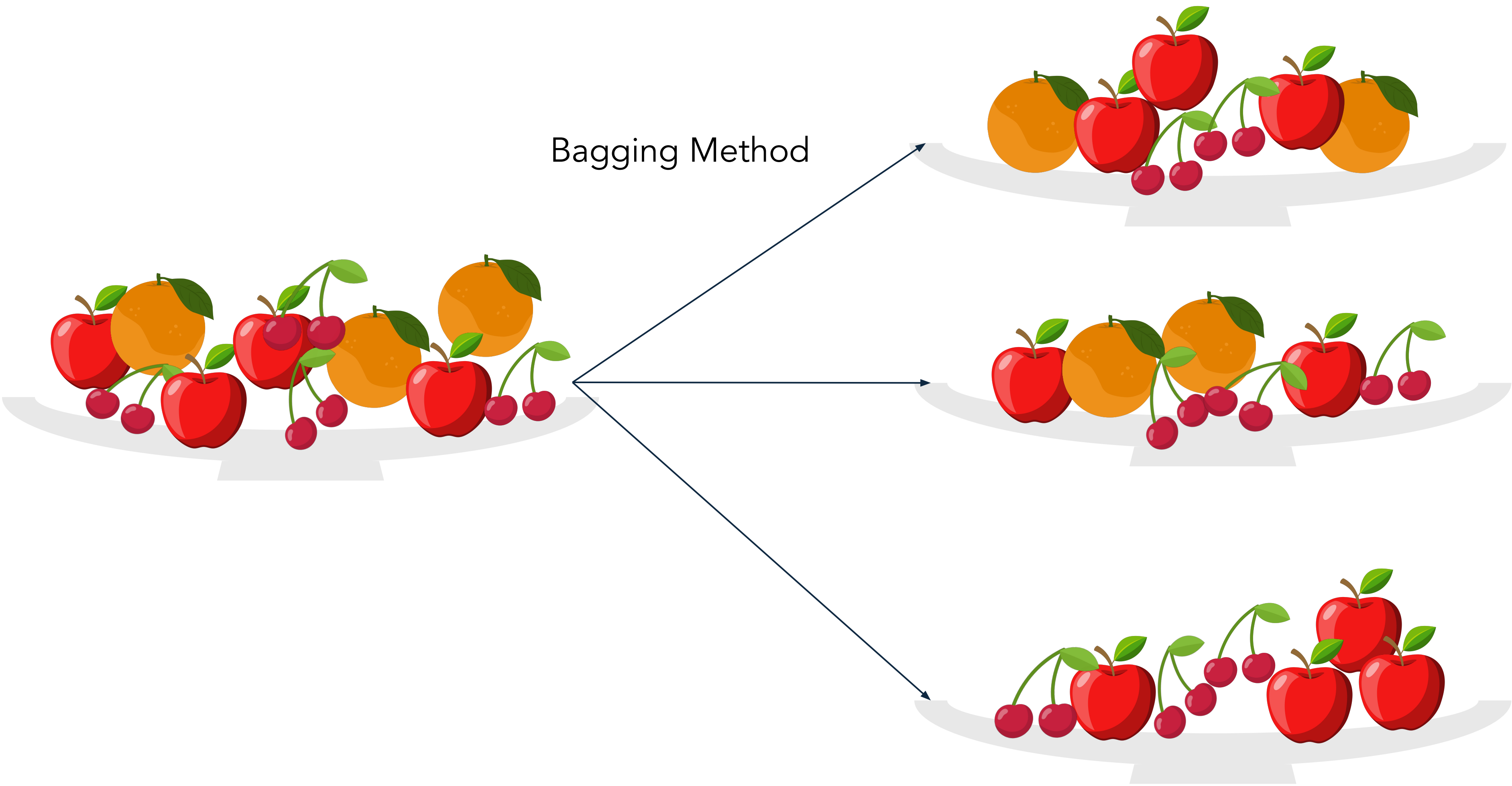
Decision Trees ~ Entropy and Information Gain



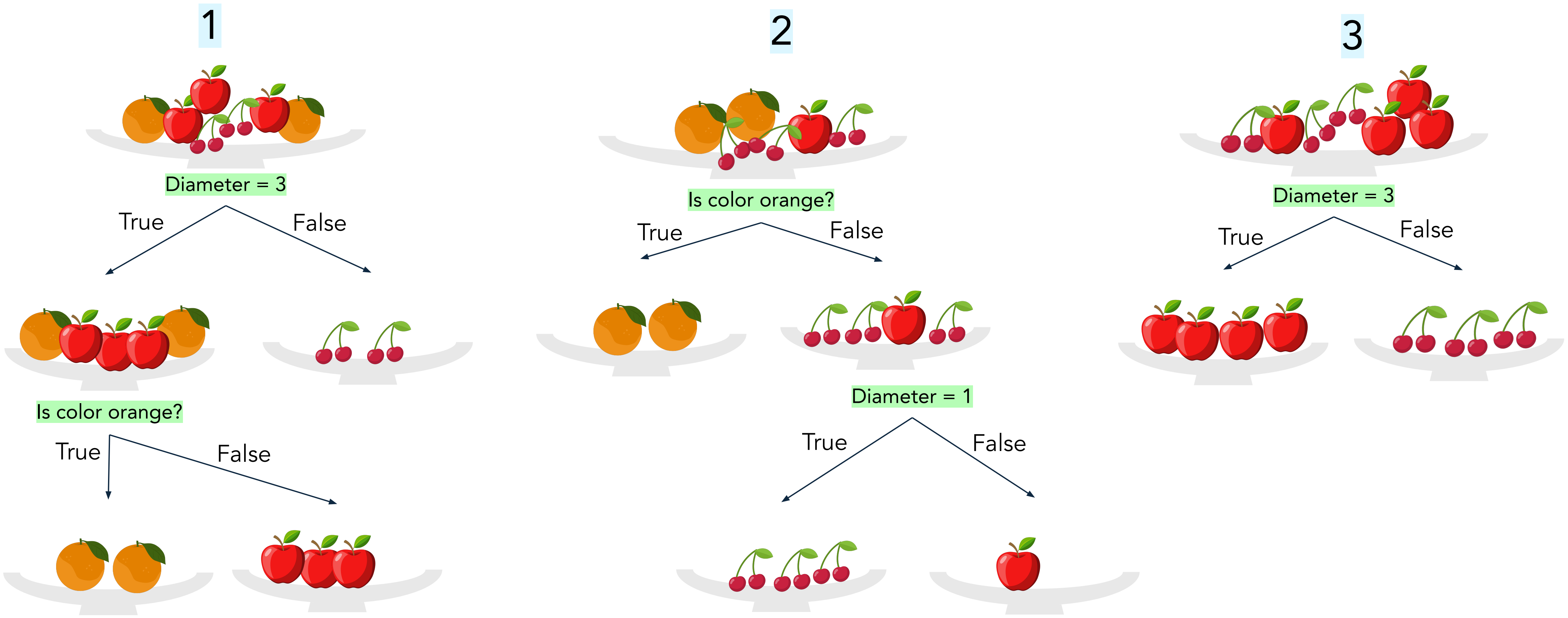
Random Forest



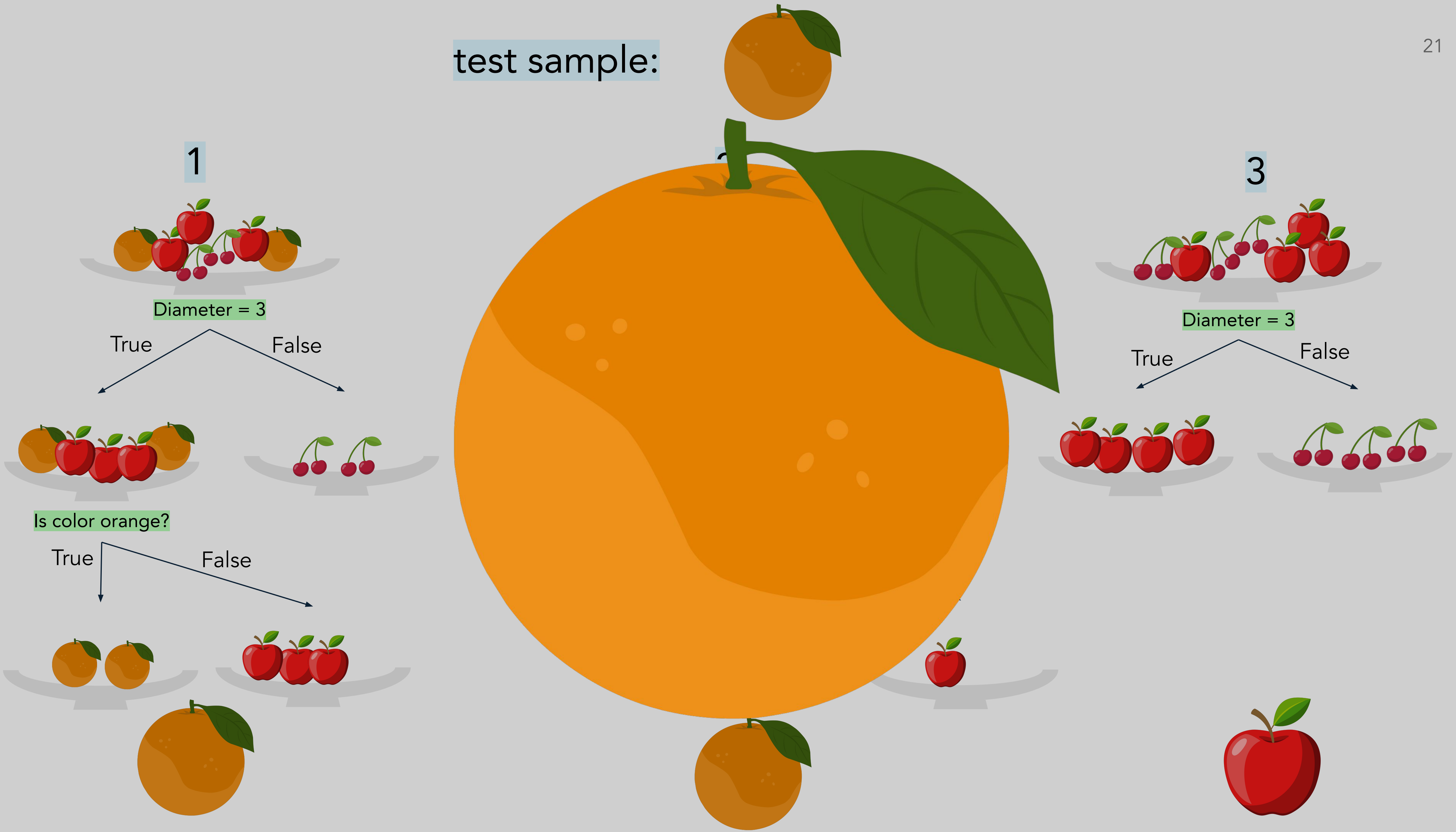
Random Forest



Random Forest



test sample:


1
Diameter = 3
True
False
Is color orange?
True
False
3
Diameter = 3
True
False

Traditional ML in Microscopy: Pros & Cons

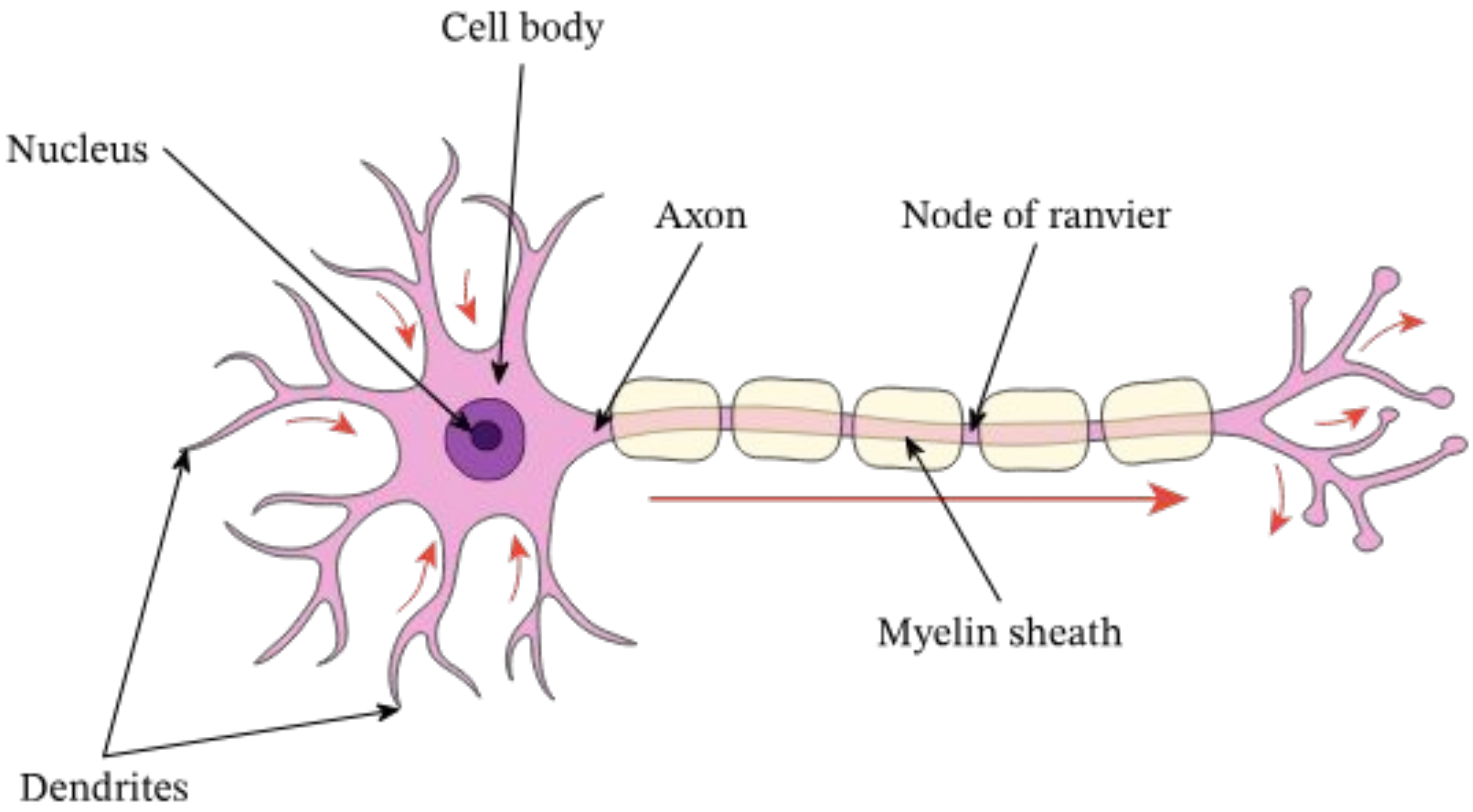
Pros

- Works with small datasets
- Fast training
- Interpretable decisions
- Easy to tune manually
- Useful for prototyping

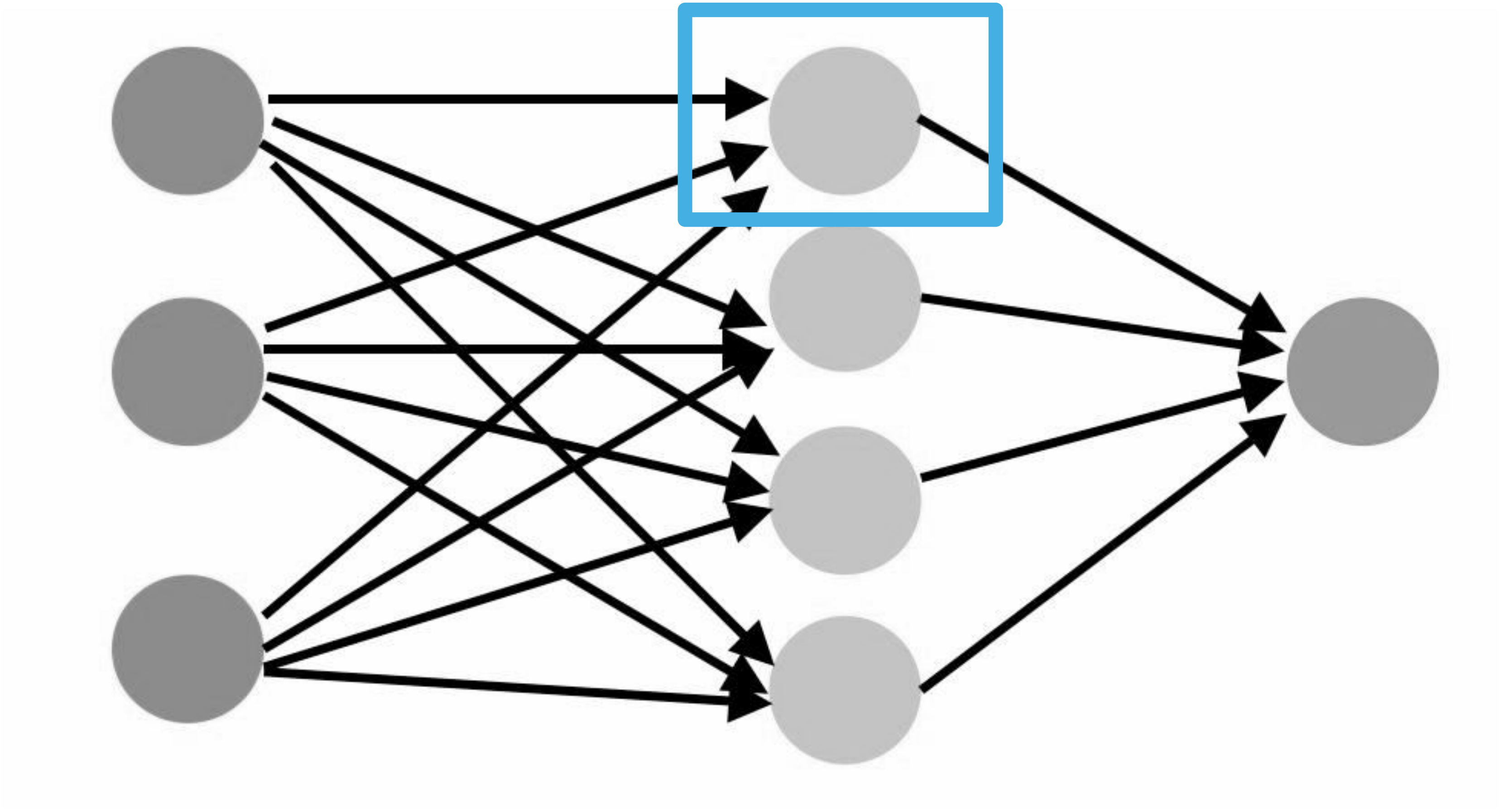
Cons

- Limited ability to capture hierarchical and global context
- Limited spatial understanding
- Sensitive to imaging variability
- Hard to scale to 3D
- Limited generalization

Artificial Neural Networks

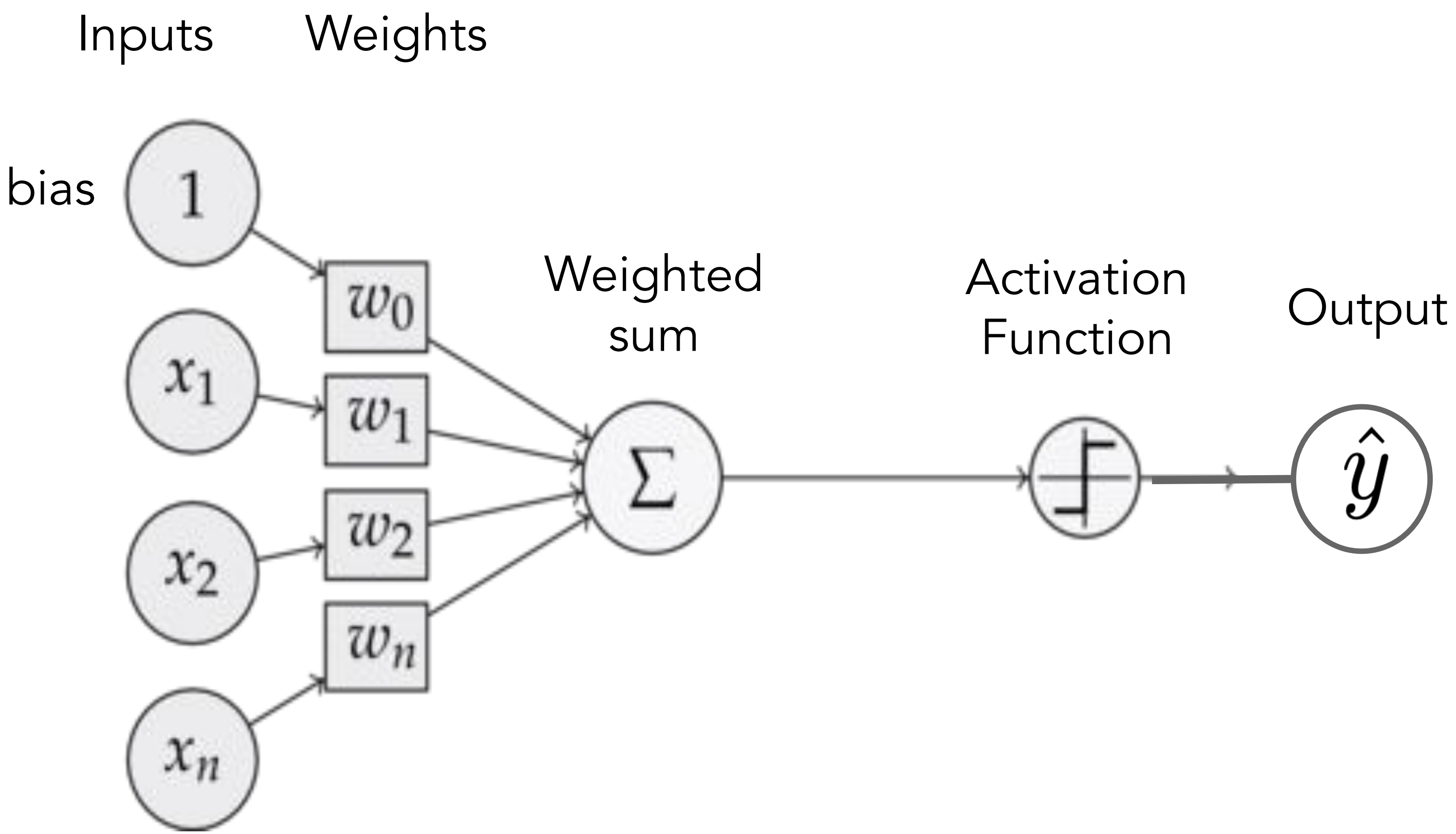


Artificial Neural Networks

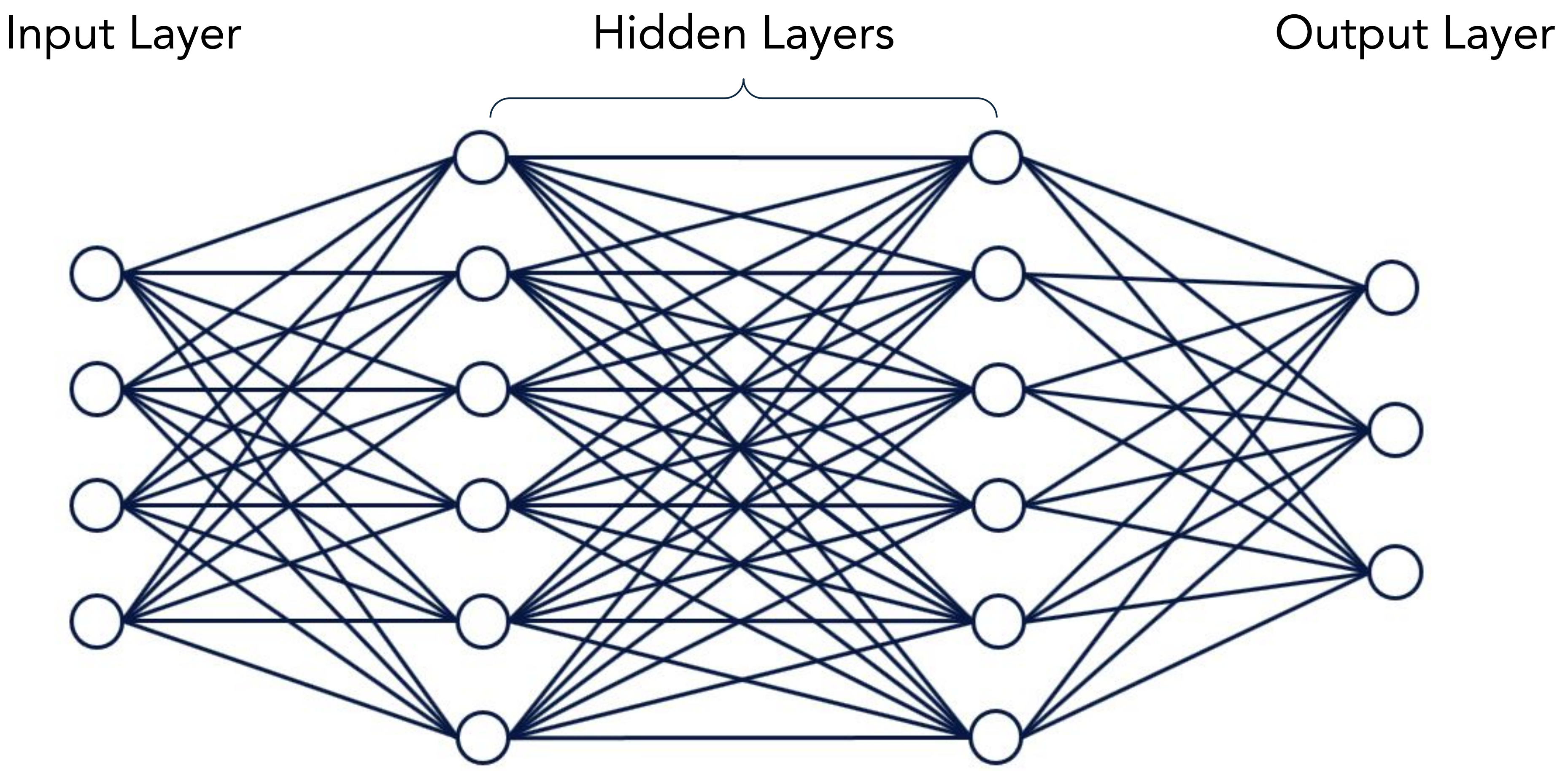


Artificial Neural Networks

A perceptron is the fundamental building block of artificial neural networks

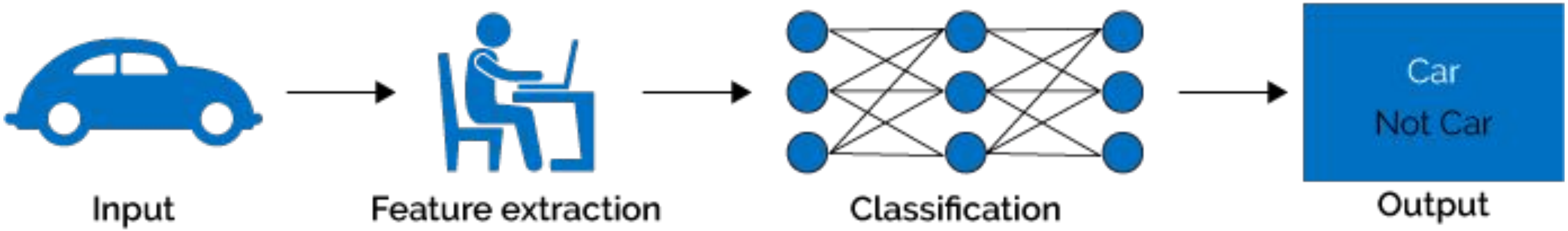


Multilayer Perceptron

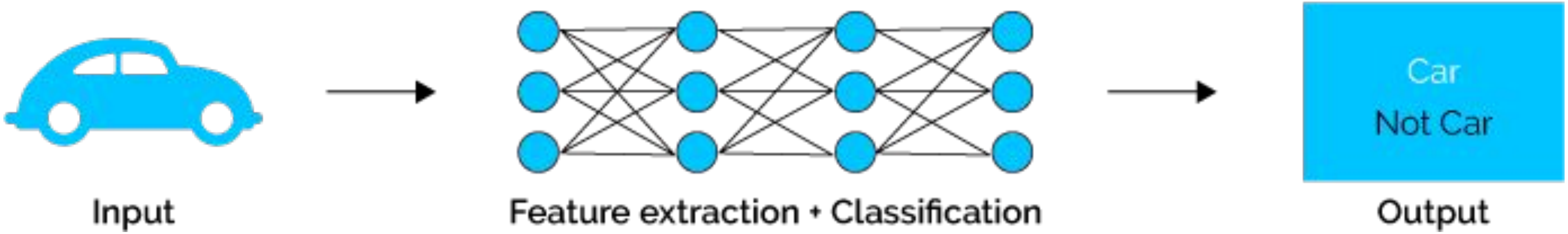


Traditional Machine Learning vs Deep Learning

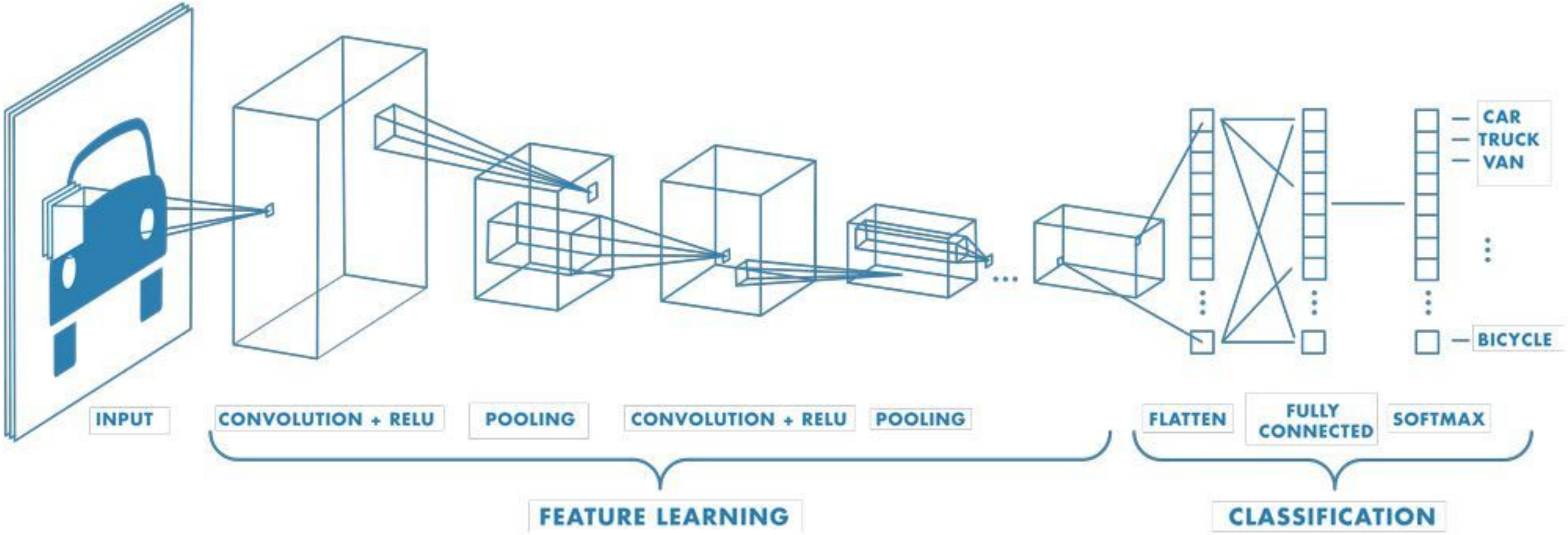
Traditional Machine Learning



Deep Learning

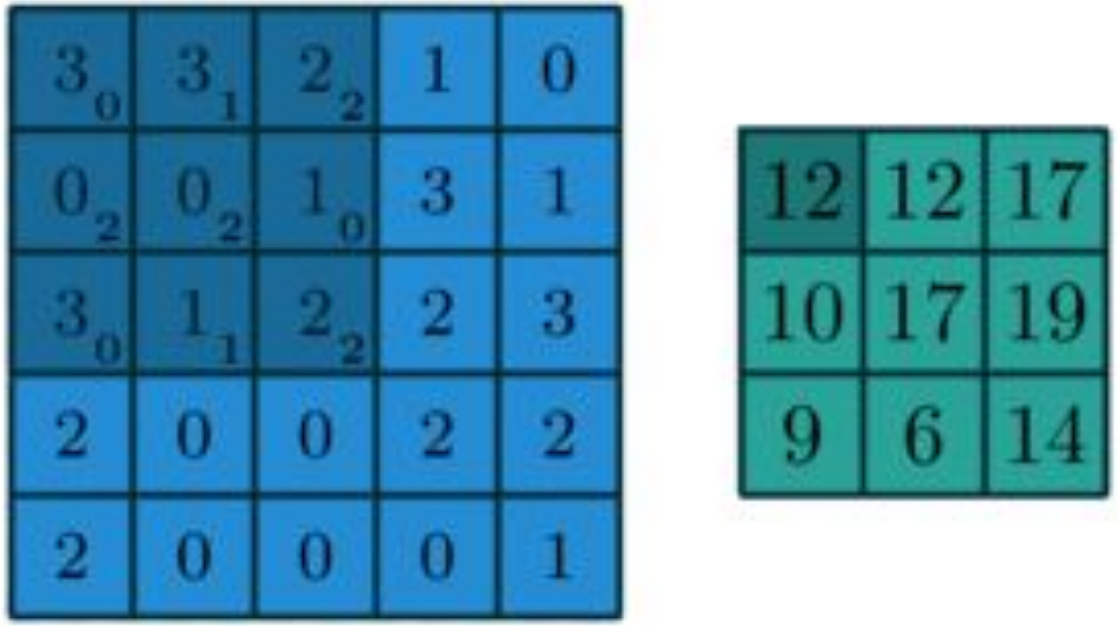


How Deep Learning works for images?



Source: https://la.mathworks.com/discovery/convolutional-neural-network.html

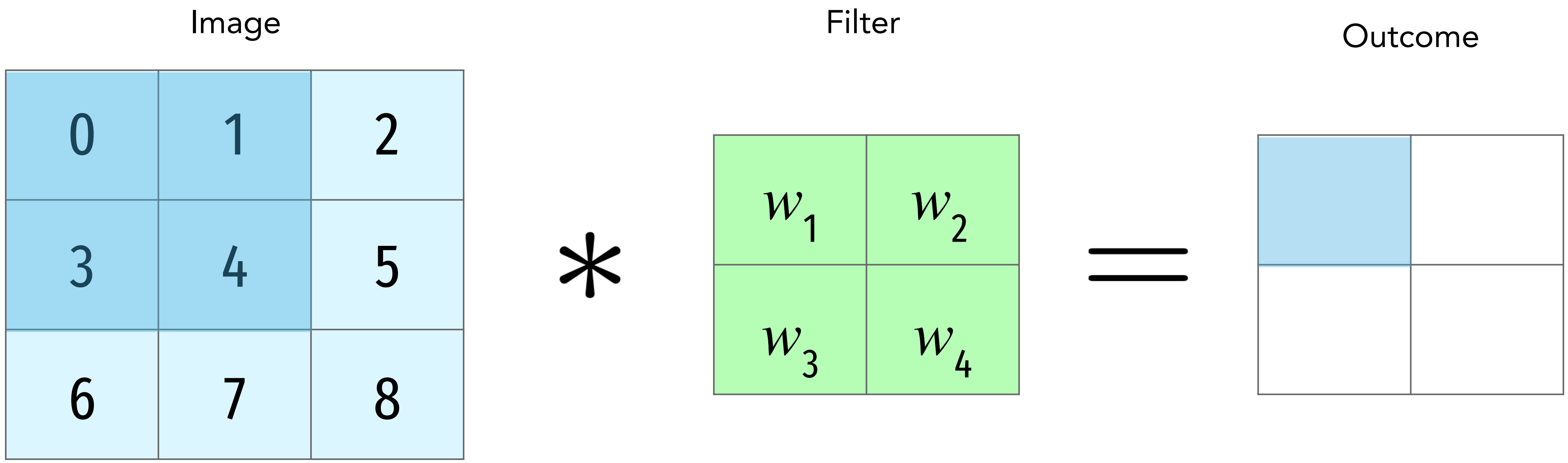
Convolution Operation



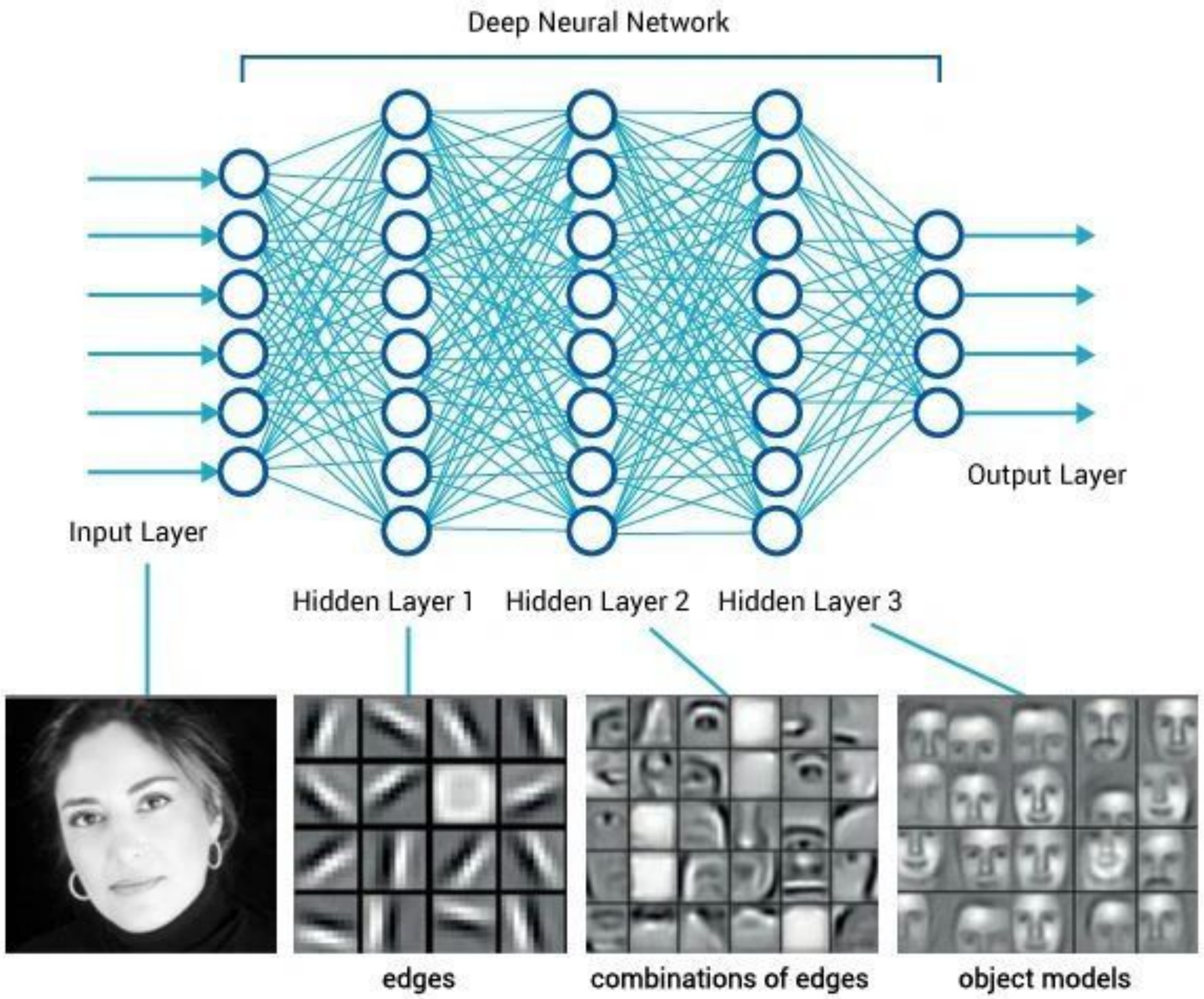
- Blue grid: Image (I).
- Shaded area: Filter (K).
- Green grid: S(i, j)

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n).$$

Convolution Operation in Deep Learning

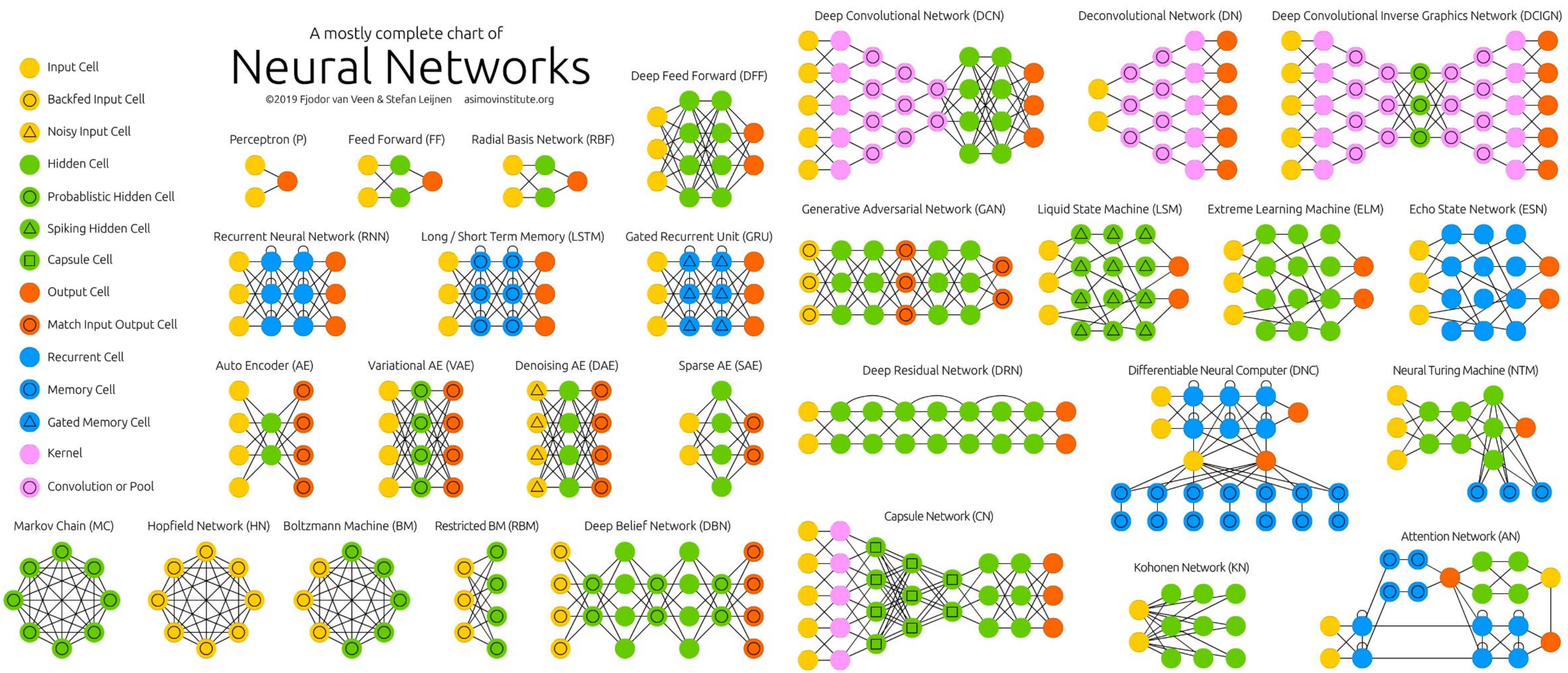


What do CNN filters learn?



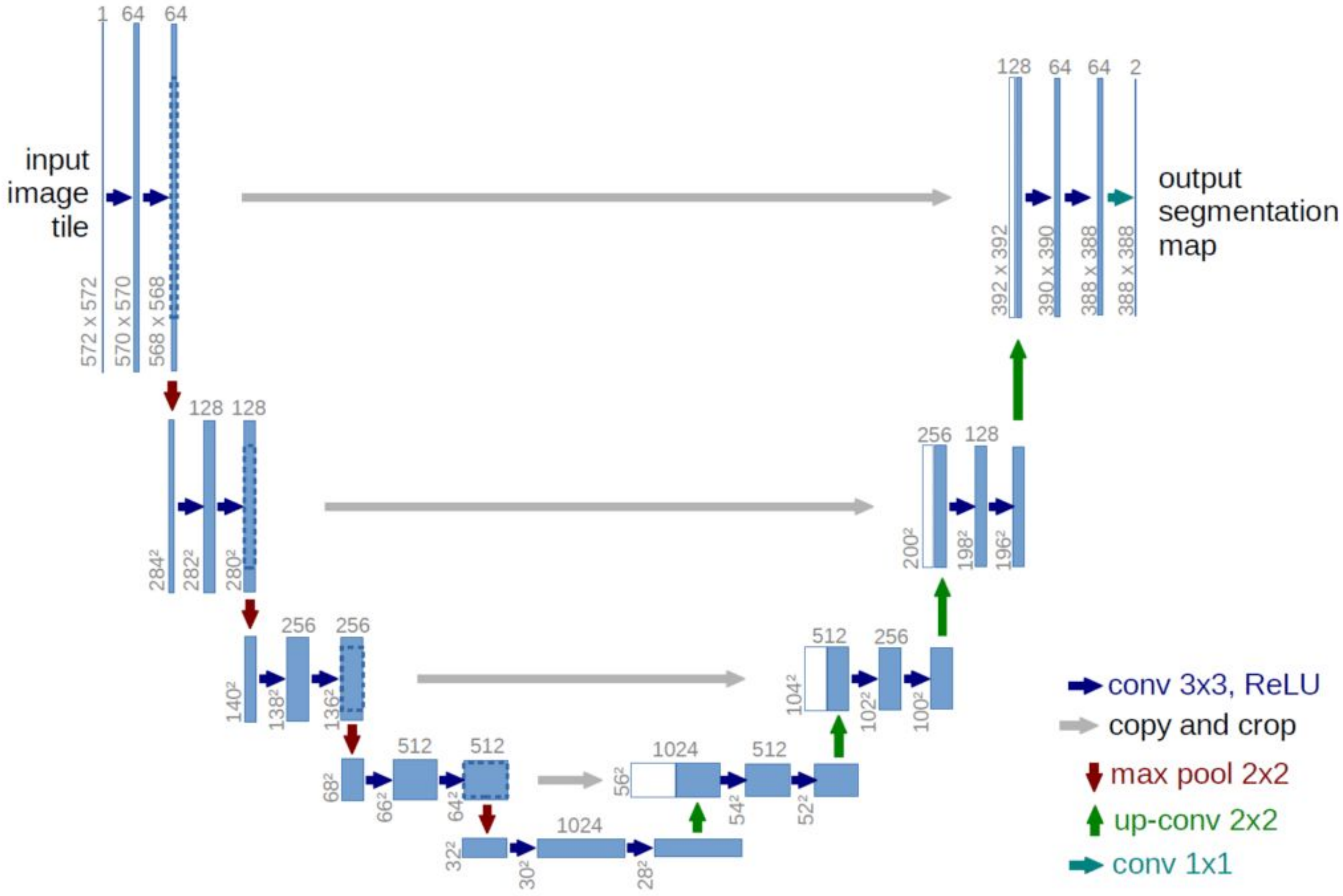
Source: https://arunaddagatla.medium.com/the-deep-learning-bc4db7959cbd

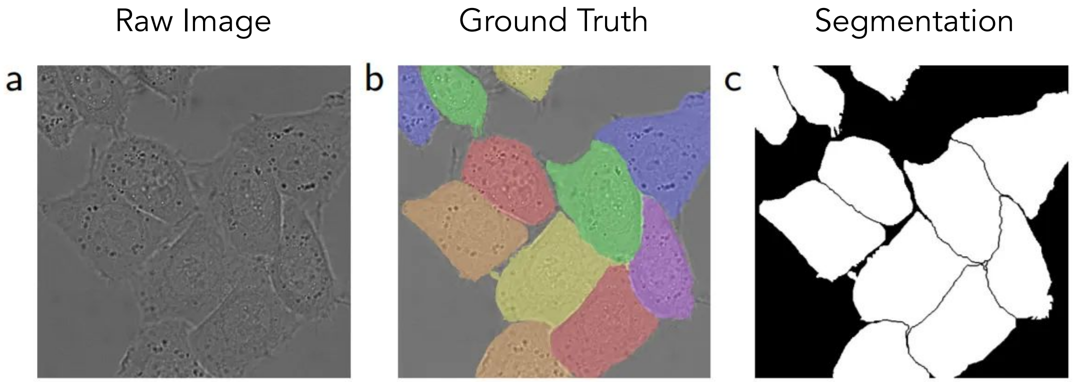
How do we solve different problems with CNNs?



Source: https://www.asimovinstitute.org/neural-network-zoo/

CNNs for Segmentation



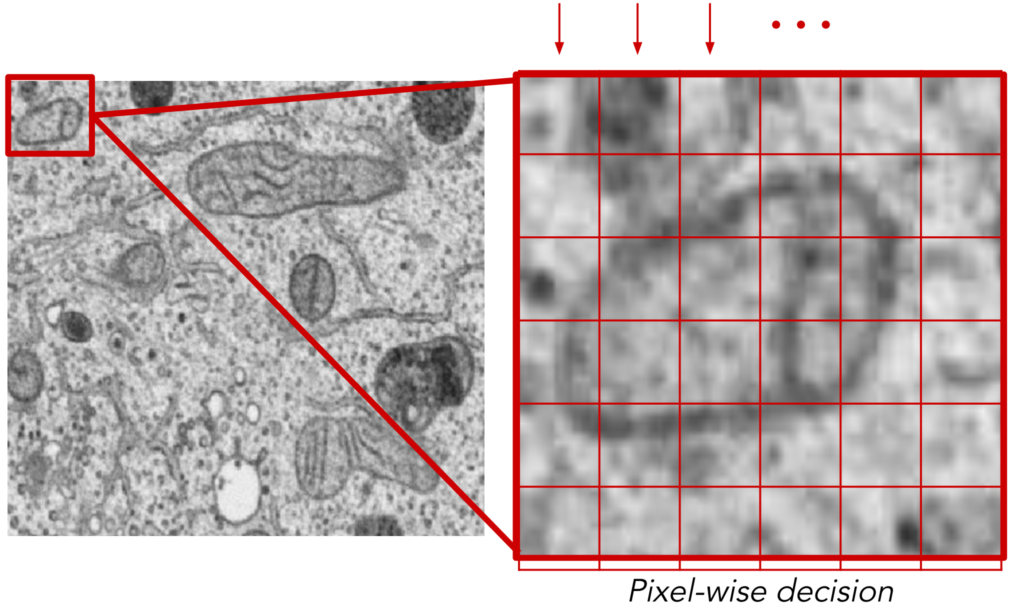


HeLa cells on glass recorded with differential interference contrast microscopy

Ronneberger, O., et al. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention* (pp. 234-241). Cham: Springer international publishing.

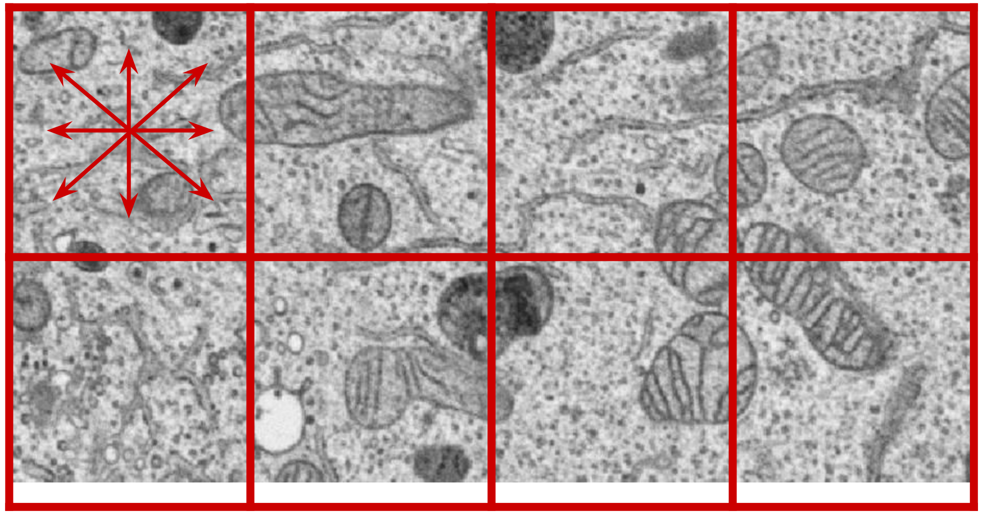
Why Convolution Helps

Traditional Machine Learning



- Classifies each pixel independently
- Relies on handcrafted features
- Fails when noise, illumination, or morphology changes
- No understanding of shapes or spatial relationships

CNNs



- Analyze local patches, not isolated pixels
- Learn features automatically
- Are translation-invariant (pattern recognized anywhere)
- Capture neighborhood, context, and object structure

Convolutional Neural Networks (CNNs): Pros & Cons

Pros

- Automatic Feature Learning
- Spatial context awareness
- Hierarchical representations
- Robust to noise and variability
- State-of-the-art performance

Cons

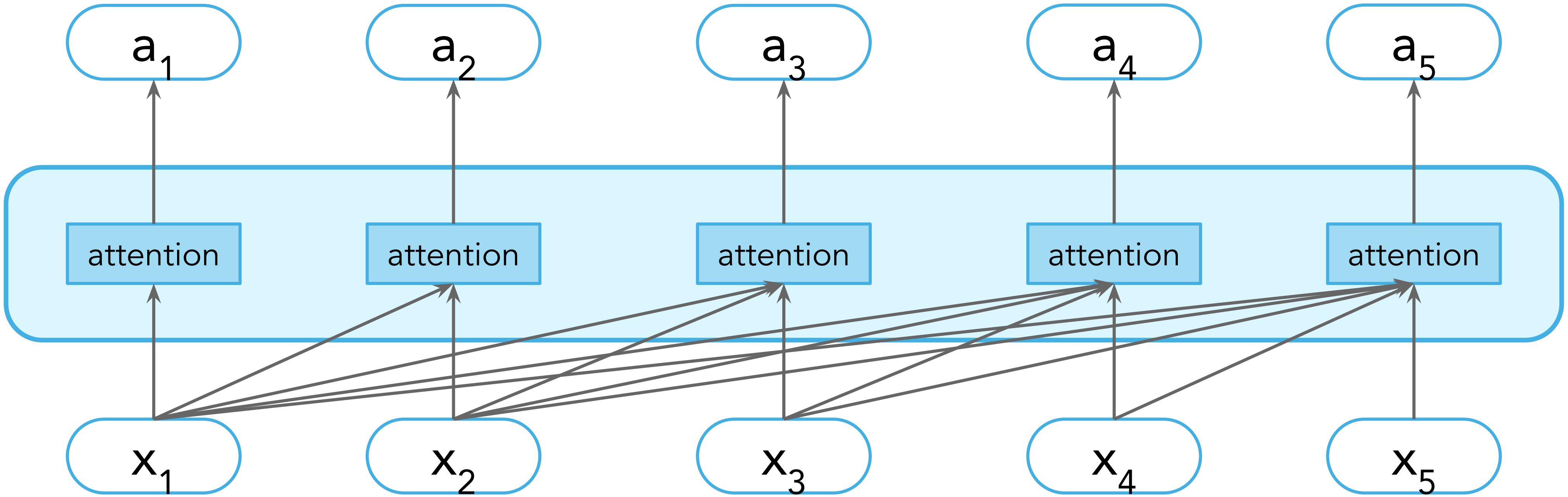
- Limited global context
- Fixed receptive field
- Frame-by-frame processing
- Scaling is expensive
- Hard to model long-range interactions

Vision Transformers

Dosovitskiy, A. (2020). An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*.

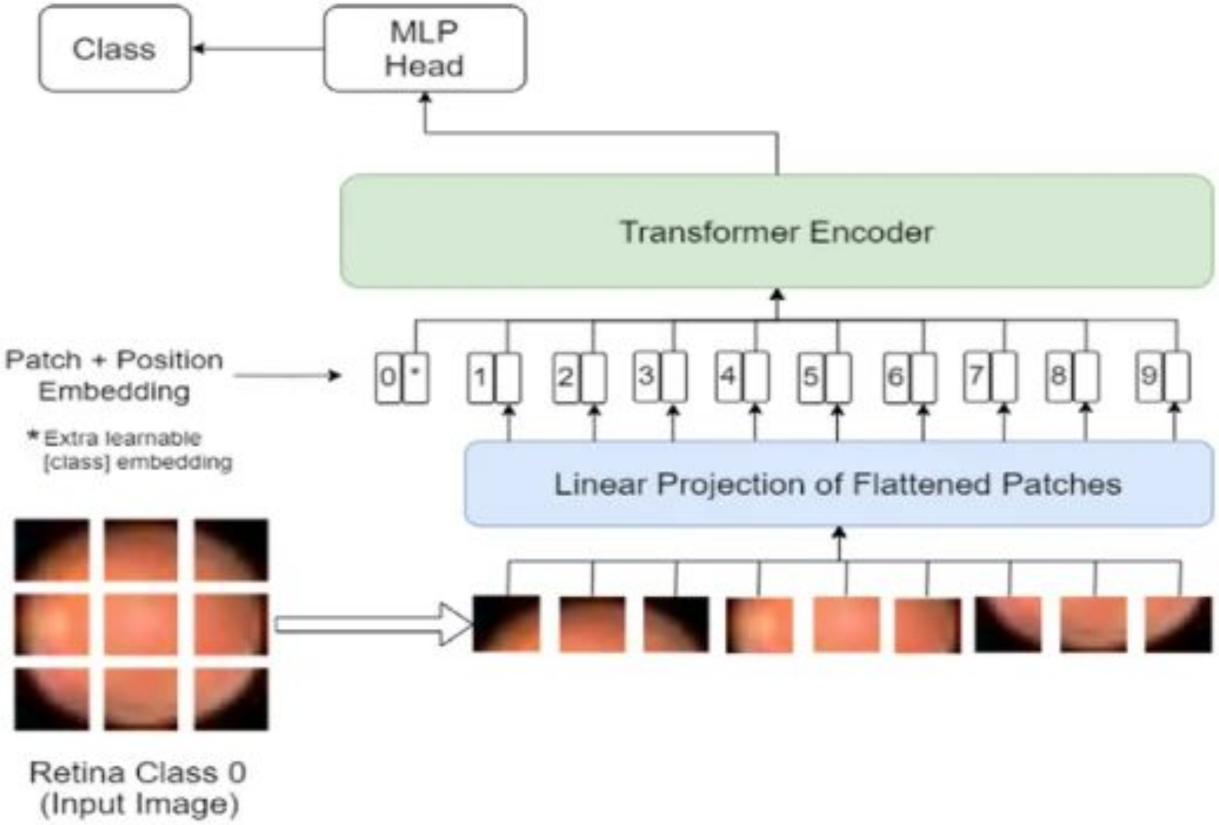
Self-attention in Transformers

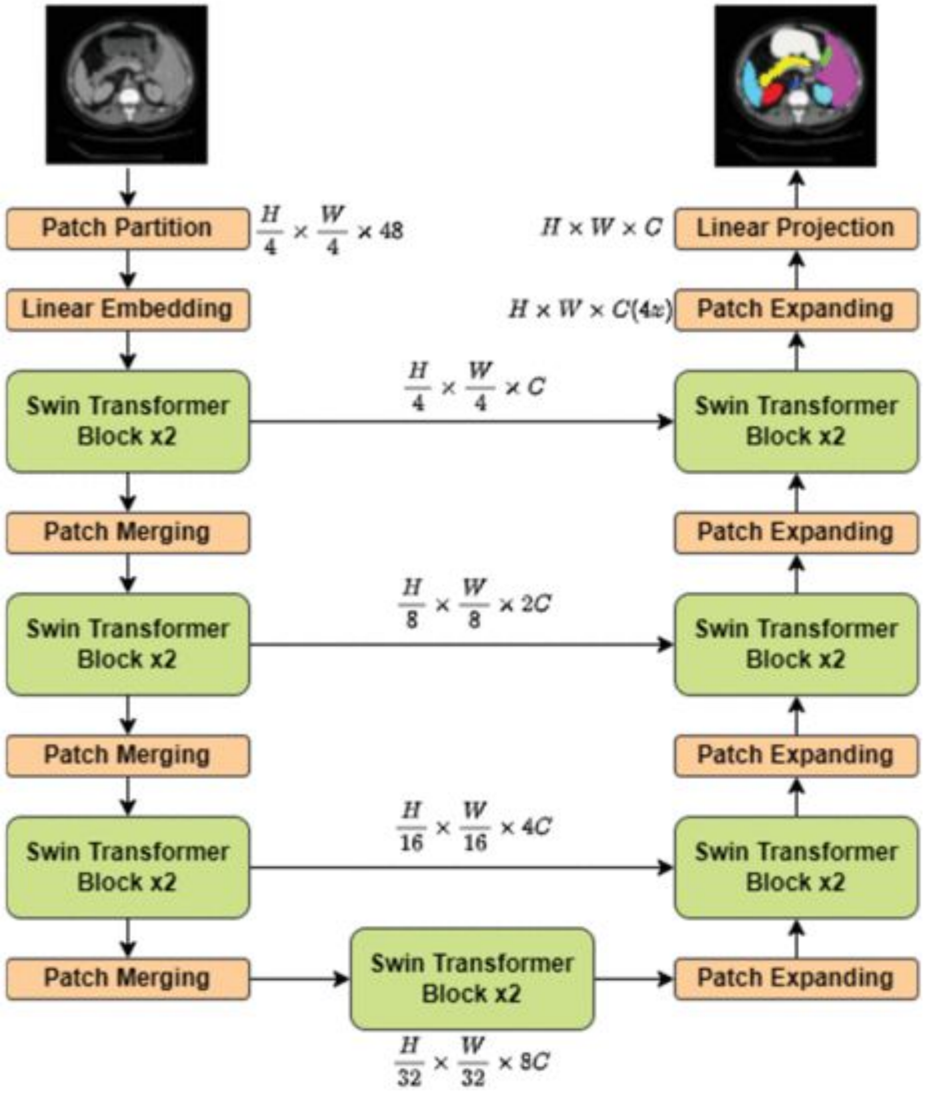
Transformers are neural networks that use self-attention to understand global relationships within images or sequences.



When processing each input x_i, the model attends to all the inputs up to, and including x_n.

Applications of Vision Transformers

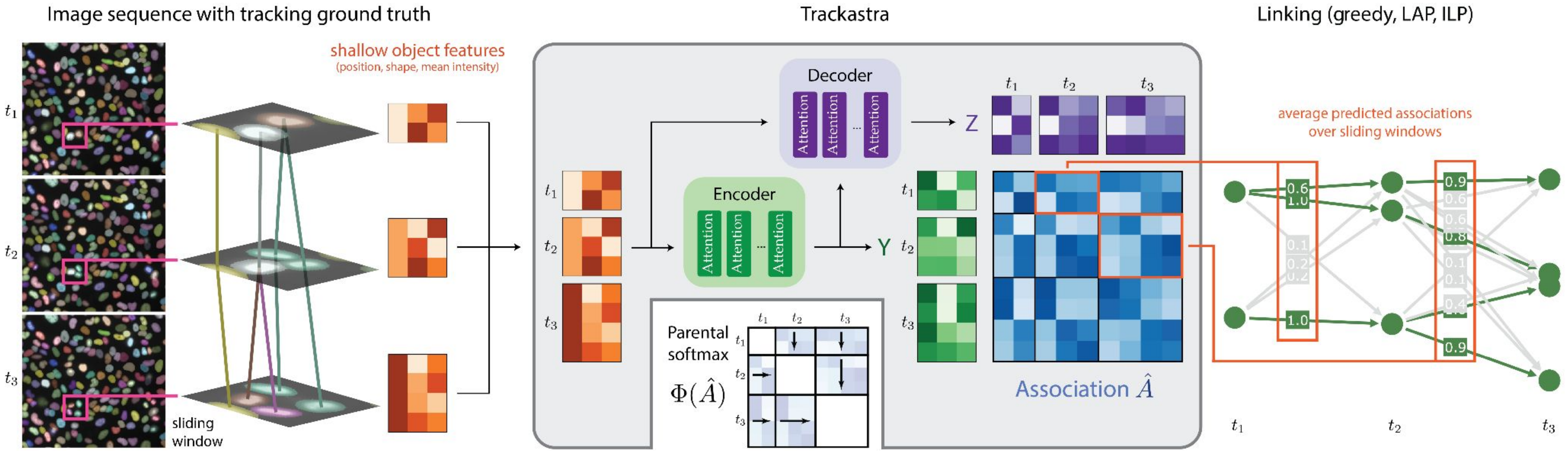




Halder, A., Gharami, S., Sadhu, P. *et al.* Implementing vision transformer for classifying 2D biomedical images. *Sci Rep* 14, 12567 (2024). https://doi.org/10.1038/s41598-024-63094-9

H. Cao, Y. Wang, J. Chen, D. Jiang, X. Zhang, Q. Tian, and M. Wang, "Swin-UNet: UNet-like pure transformer for medical image segmentation," in *Proc. Eur. Conf. Comput. Vis.-ECCV*, 2023, pp. 205–218, doi: 10.1007/978-3-031-25066-8_9.

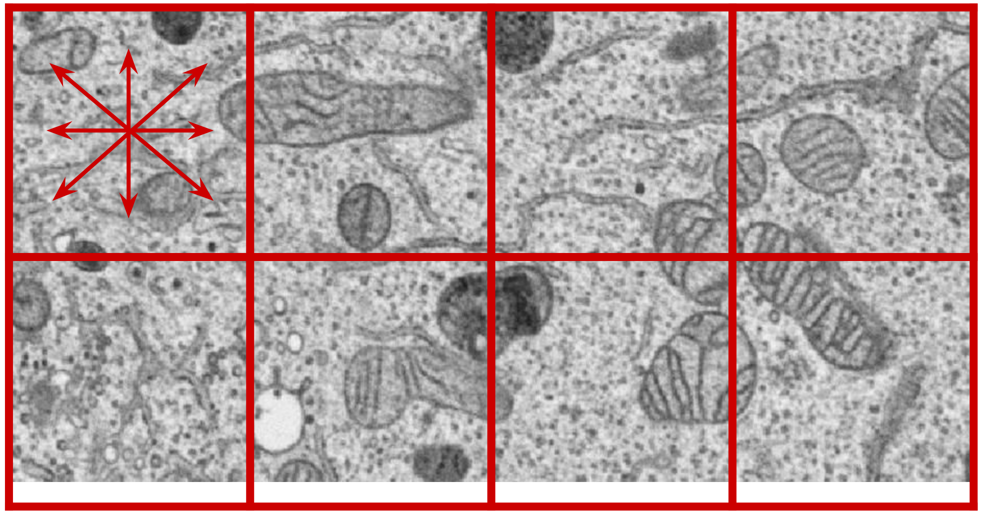
Transformers for Tracking



Gallusser, B., & Weigert, M. (2024, September). Trackastra: Transformer-based cell tracking for live-cell microscopy. In *European conference on computer vision* (pp. 467-484). Cham: Springer Nature Switzerland.

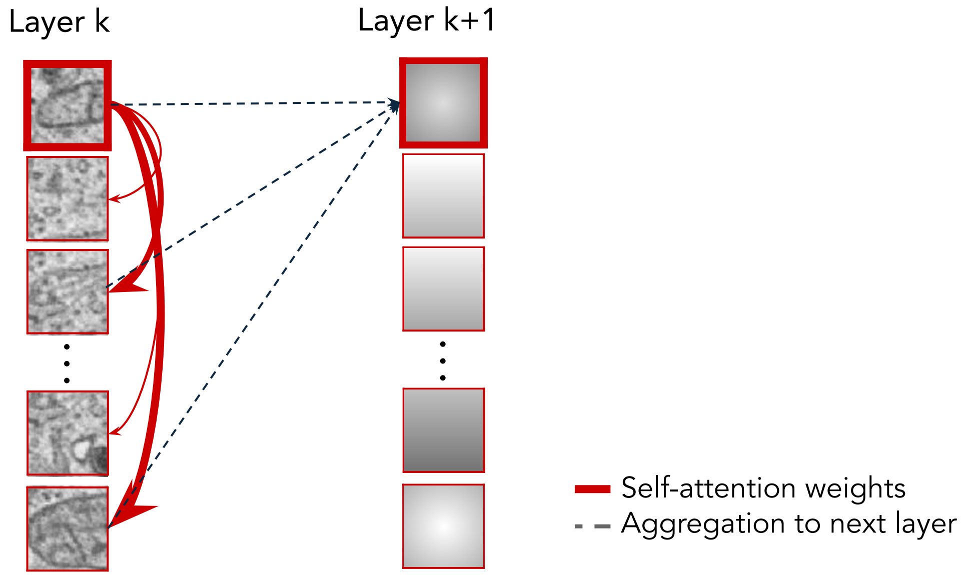
Why Transformers Help

CNNs



- Aggregate local context hierarchically
- Learn features automatically
- Are translation-invariant (pattern recognized anywhere)
- Capture neighborhood, context, and object structure

Transformer - self-attention across patches



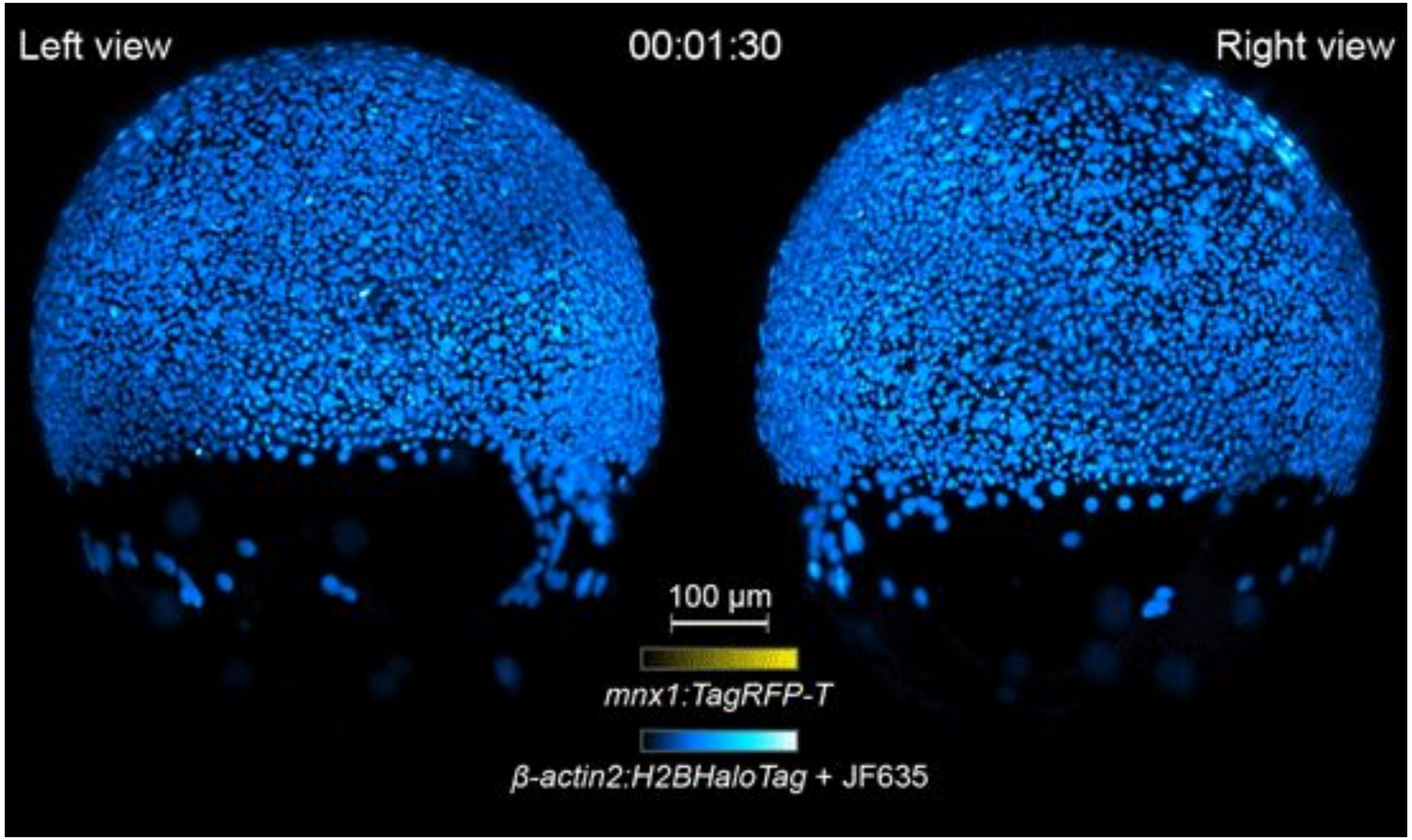
Updated representation

- Model global context via self-attention
- Capture long-range dependencies
- Relate distant regions of the image directly
- Provide a global view of object structure

Wrapping up: When to use each image analysis approach

Approach	Typical use cases	Strengths	Limitations
Traditional image processing	Simple images, high contrast, well-controlled acquisition	Fast, interpretable, no training data required	Fragile to noise, illumination changes, complex morphology
Machine learning (classical)	Moderate variability, limited data, need for interpretability	Uses handcrafted features, works with small datasets	Feature design is manual, limited spatial context
CNN	Complex shapes, crowded scenes, low contrast	Learns features automatically, captures spatial context	Requires more data and compute, limited global context
Transformers	Long-range dependencies, large structures, temporal consistency	Models global context directly, flexible representations	Computationally expensive, data-hungry

A picture is worth a thousand words …



…but only when we can extract meaningful information from it.

Wan, Y., Wei, Z., Looger, L. L., Koyama, M., Druckmann, S., & Keller, P. J. (2019). Single-cell reconstruction of emerging population activity in an entire developing circuit. *Cell*, *179*(2), 355-372.

Applications of AI in image processing

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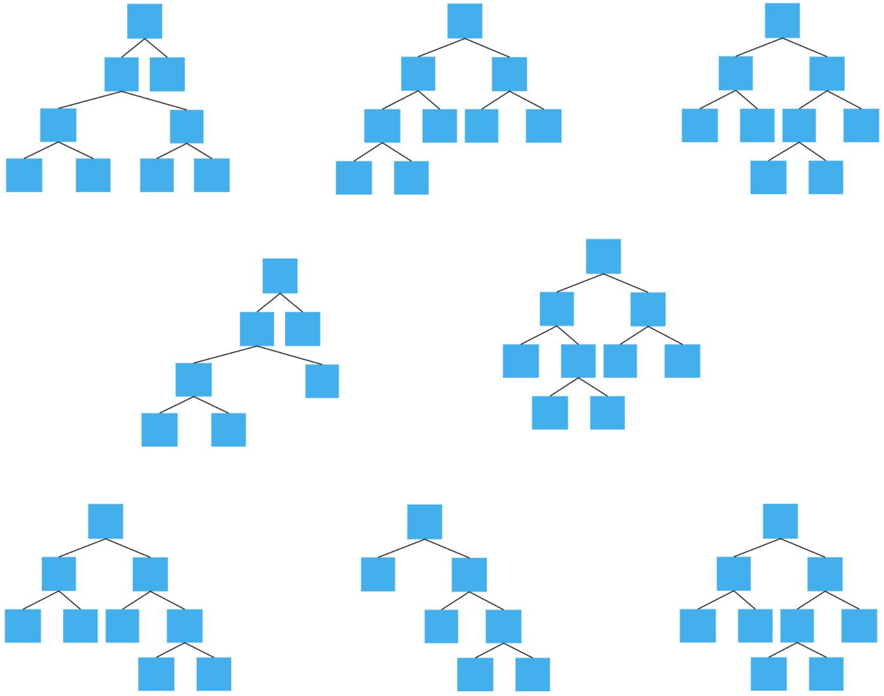
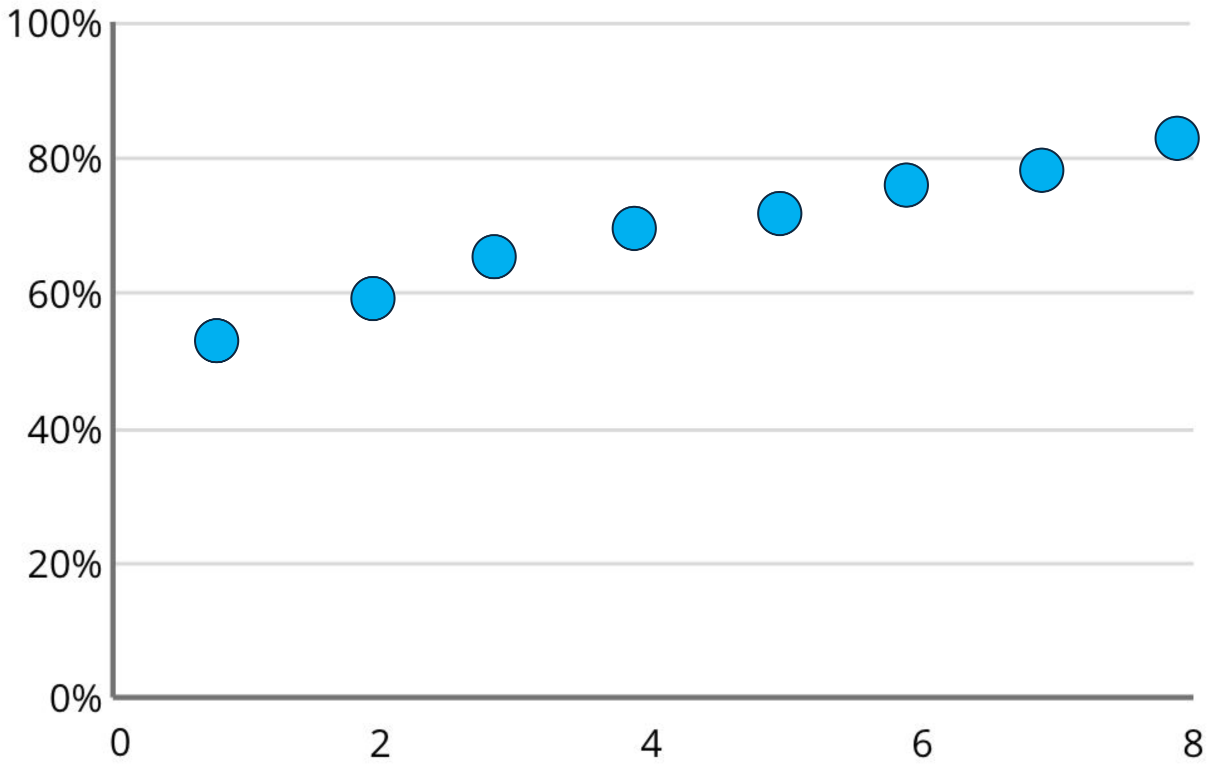
- Santiago 2026 -

Decision Trees

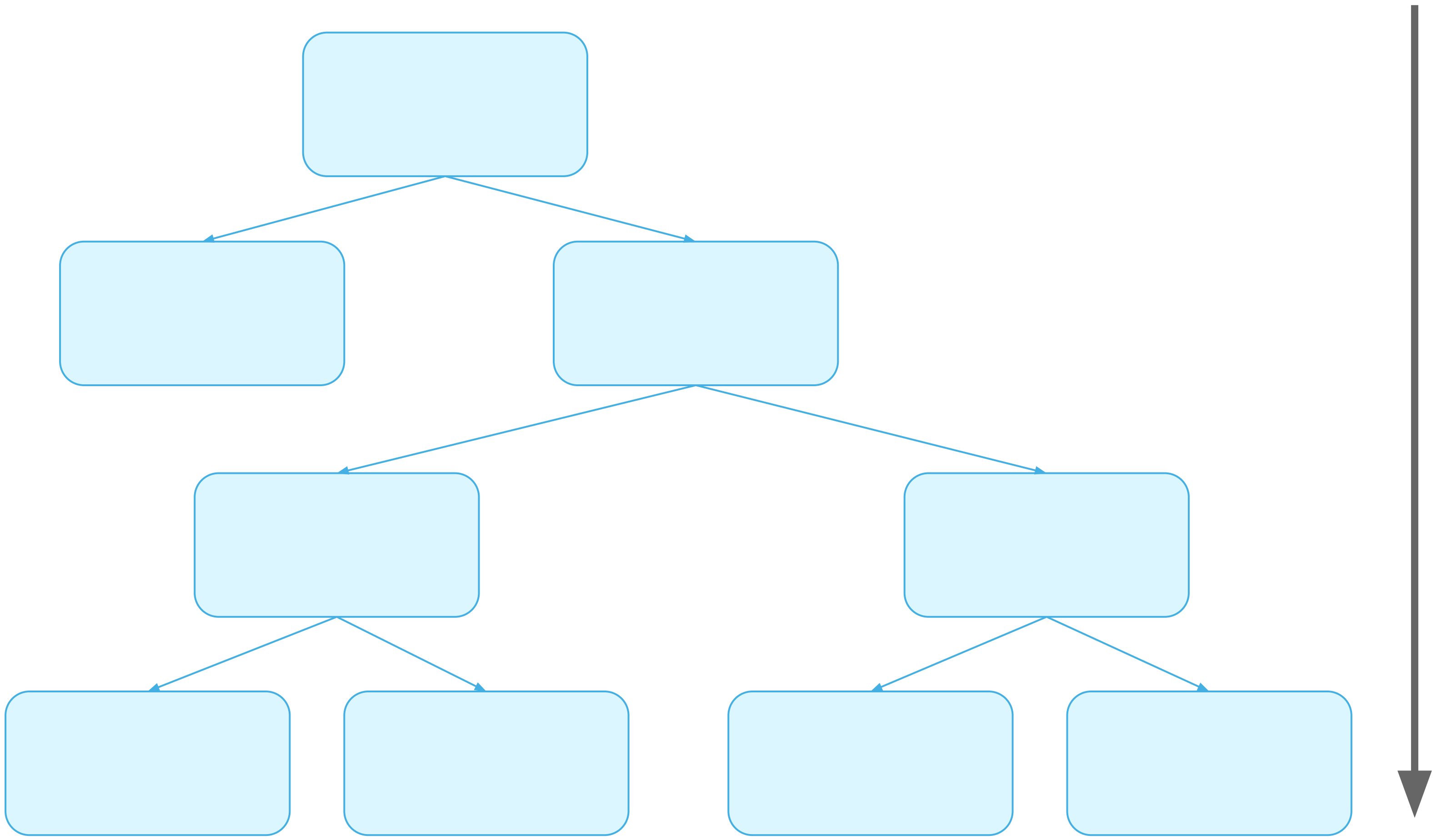
Probability of the majority vote being correct can go up as we add more models





Ensemble learning creates a stronger model by aggregating the predictions of multiple weak models

How to find the optimum split of the features?



- In decision trees, we aim to reduce the impurity (or disorder) of the labels.
- The goal of a split is to separate the samples so that child nodes are more “pure”, meaning they contain mostly a single class.

How to find the optimum split of the features?

Entropy and Information Gain

- Entropy measures the disorder or impurity of the class labels in a node *high entropy = labels are mixed, low entropy = labels are homogeneous*

  Entropy = 0 → node contains only one class

- Information Gain is the reduction in entropy after a split. It measures how informative a feature is for predicting the class

- A Decision Tree tests different feature splits and evaluates how much each split reduces entropy

Gini Index

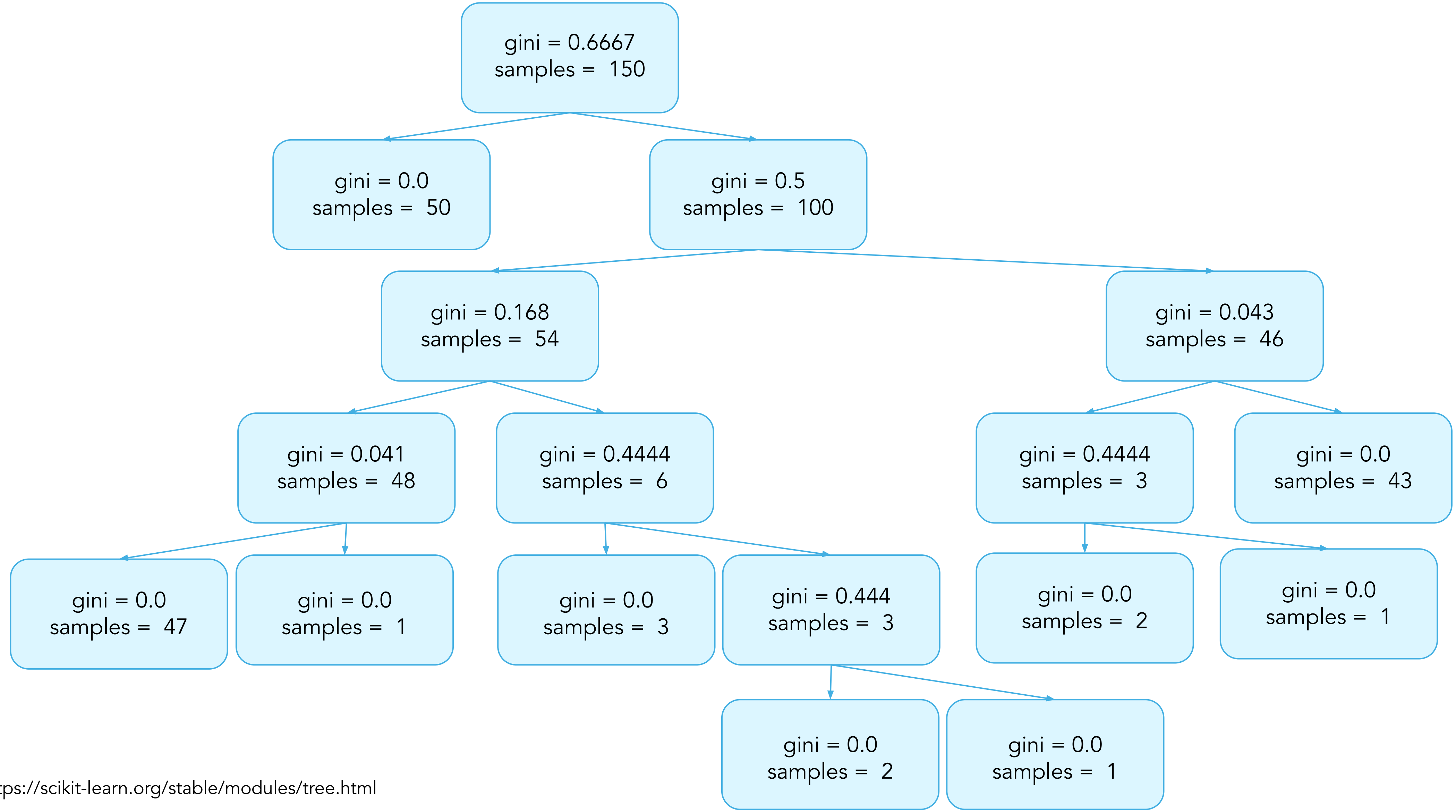
- The Gini index measures how heterogeneous the labels inside the node are. It estimates how often a randomly chosen sample would be misclassified.

- Gini = 0 → all samples are from the same class. *No mixture, no uncertainty, no misclassification, perfect purity*

  Gini increases as classes become more evenly mixed. *More mixture, more uncertainty, higher chance of misclassification*

- Decision Trees test candidate splits and choose the one that minimizes the Gini index in the resulting child nodes

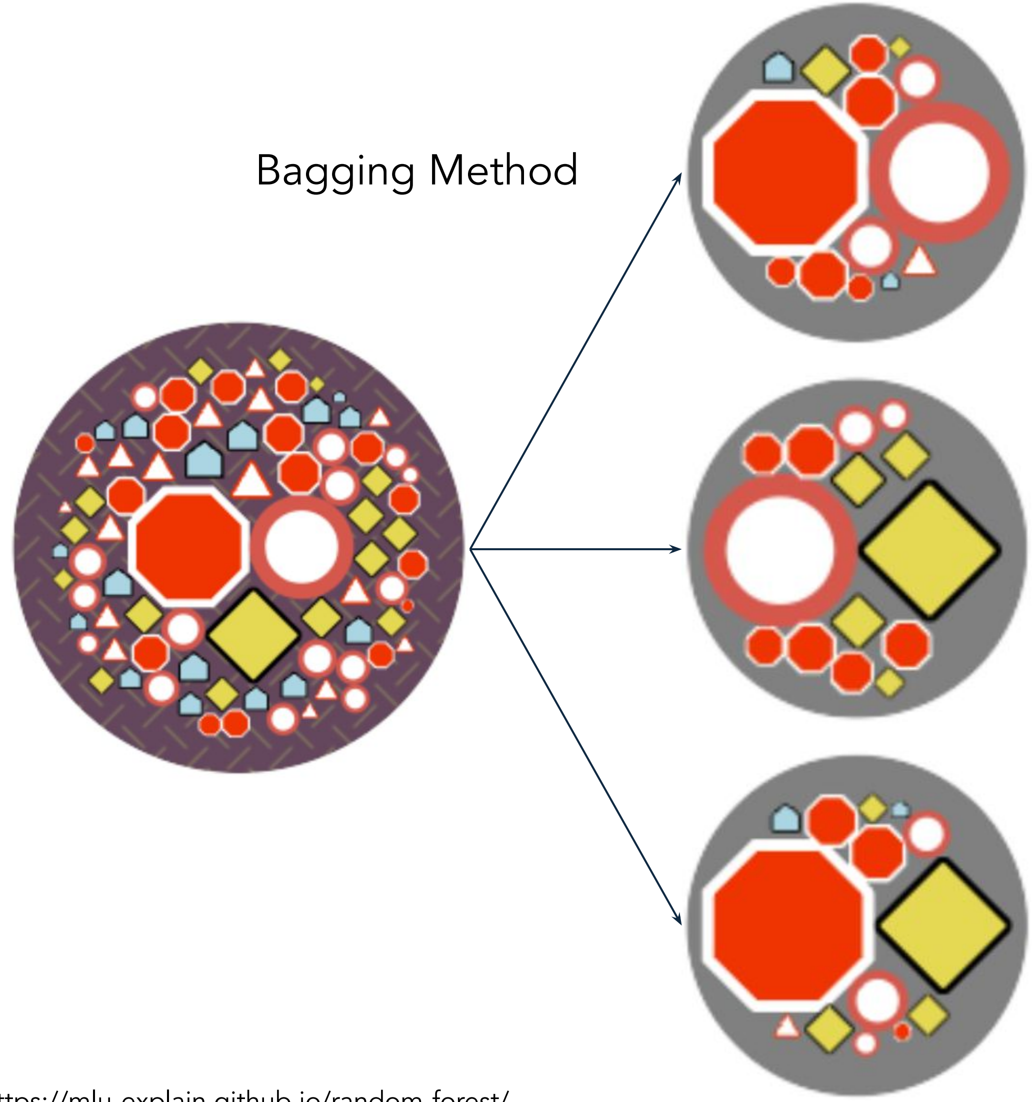
How to find the optimum split of the features?



Source: https://scikit-learn.org/stable/modules/tree.html

Random Forest

Bagging Method



Feature Selection

Size

Sides

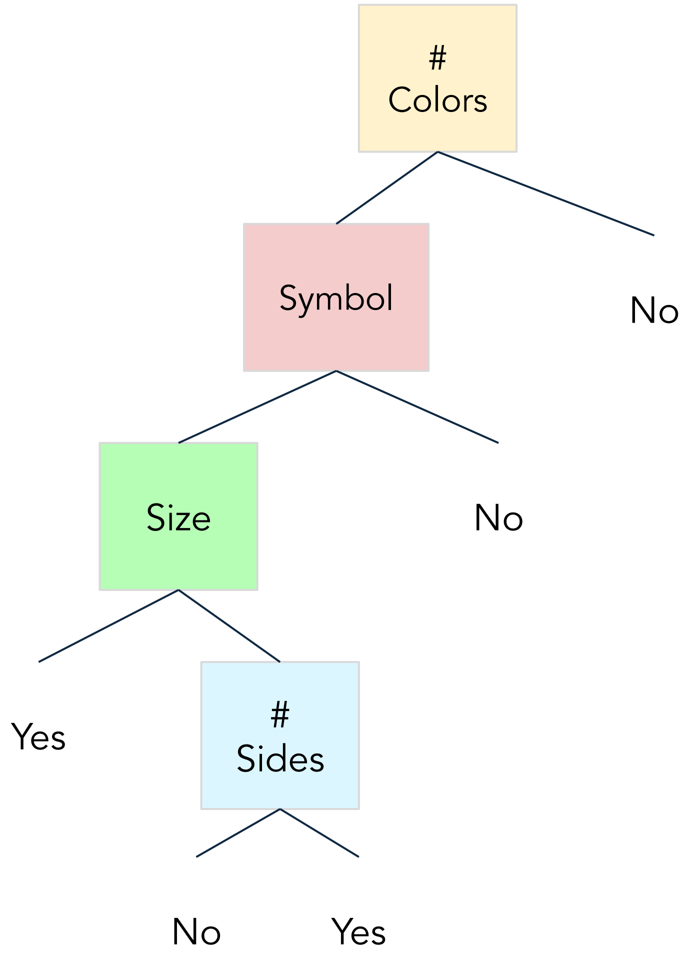
Colors

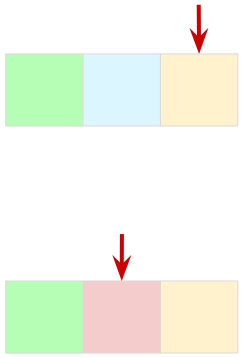
Symbol

Source: https://mlu-explain.github.io/random-forest/

Random Forest

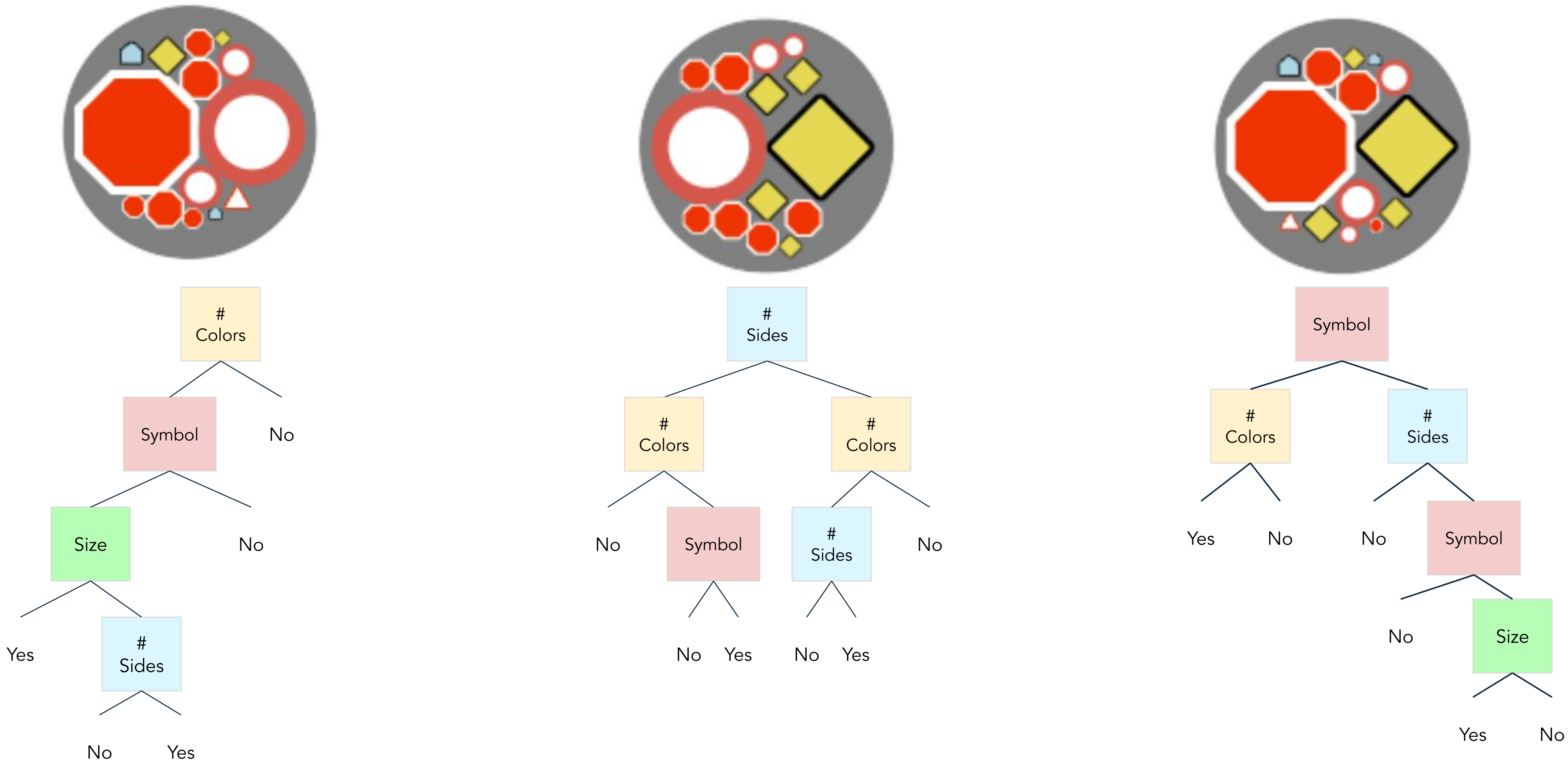
In each split of the tree, the feature for splitting is randomly selected from a subset of features.





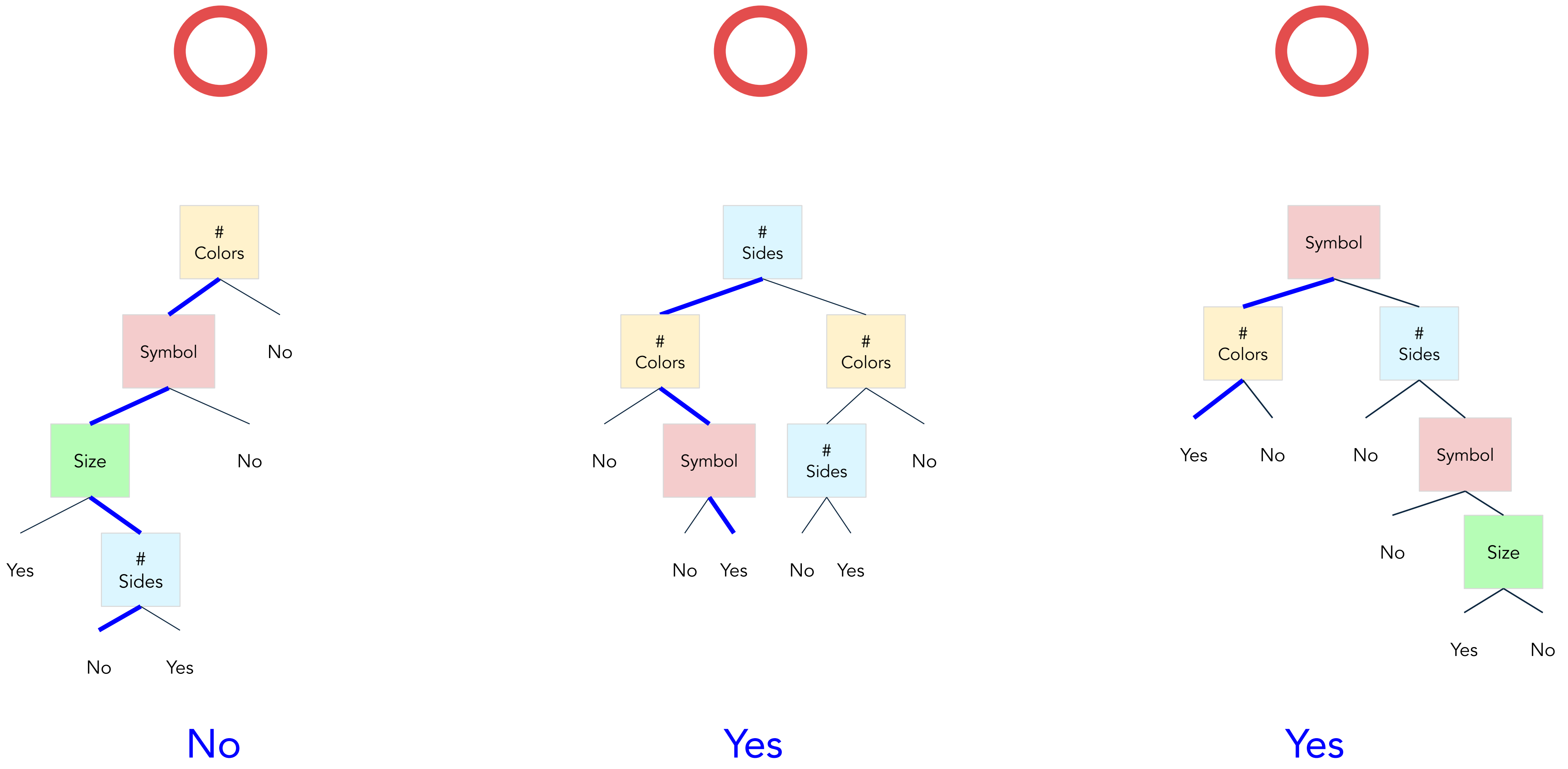
Source: https://mlu-explain.github.io/random-forest/

Random Forest



Source: https://mlu-explain.github.io/random-forest/

Random Forest



Source: https://mlu-explain.github.io/random-forest/