Supervised Learning

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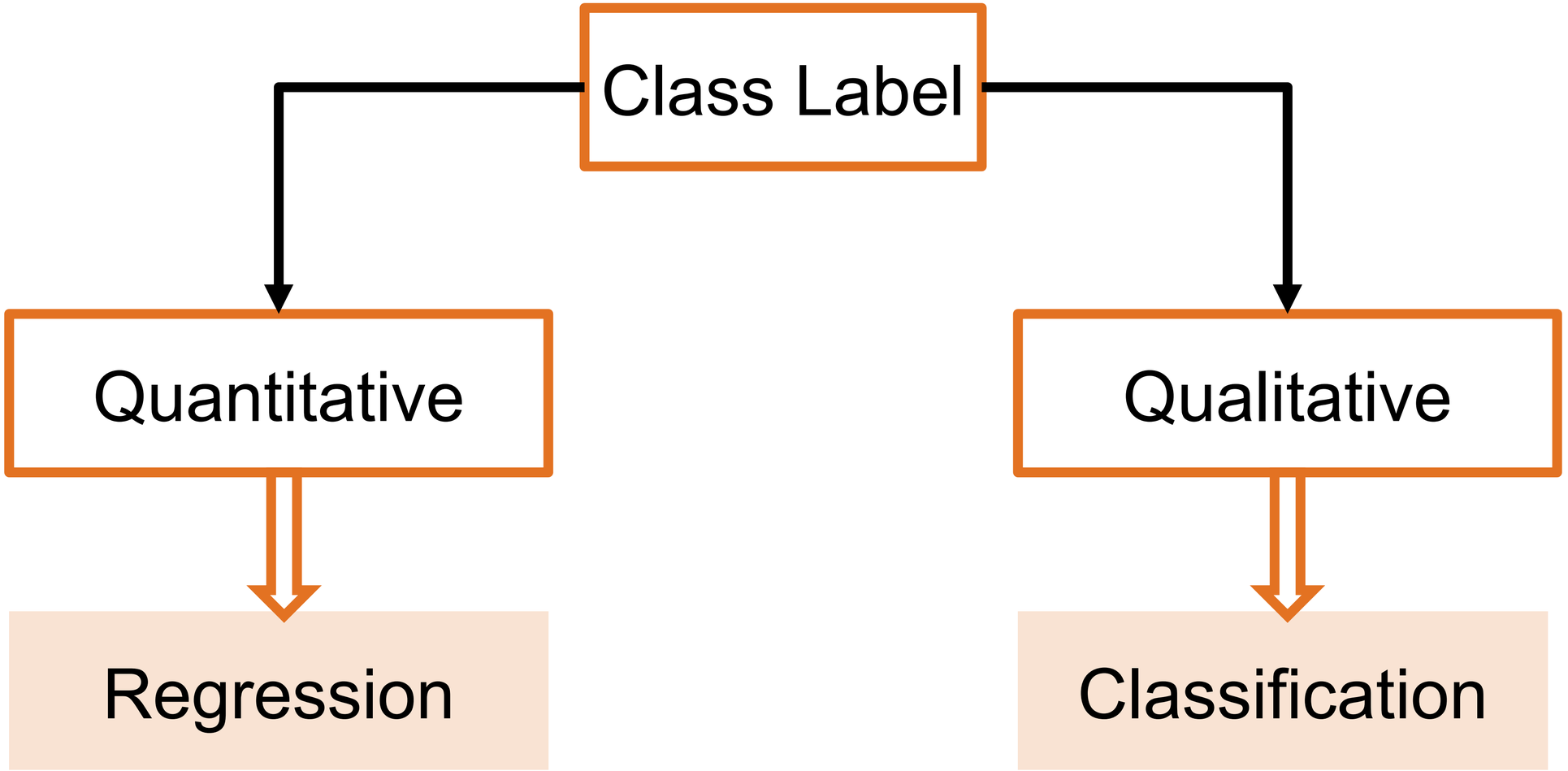
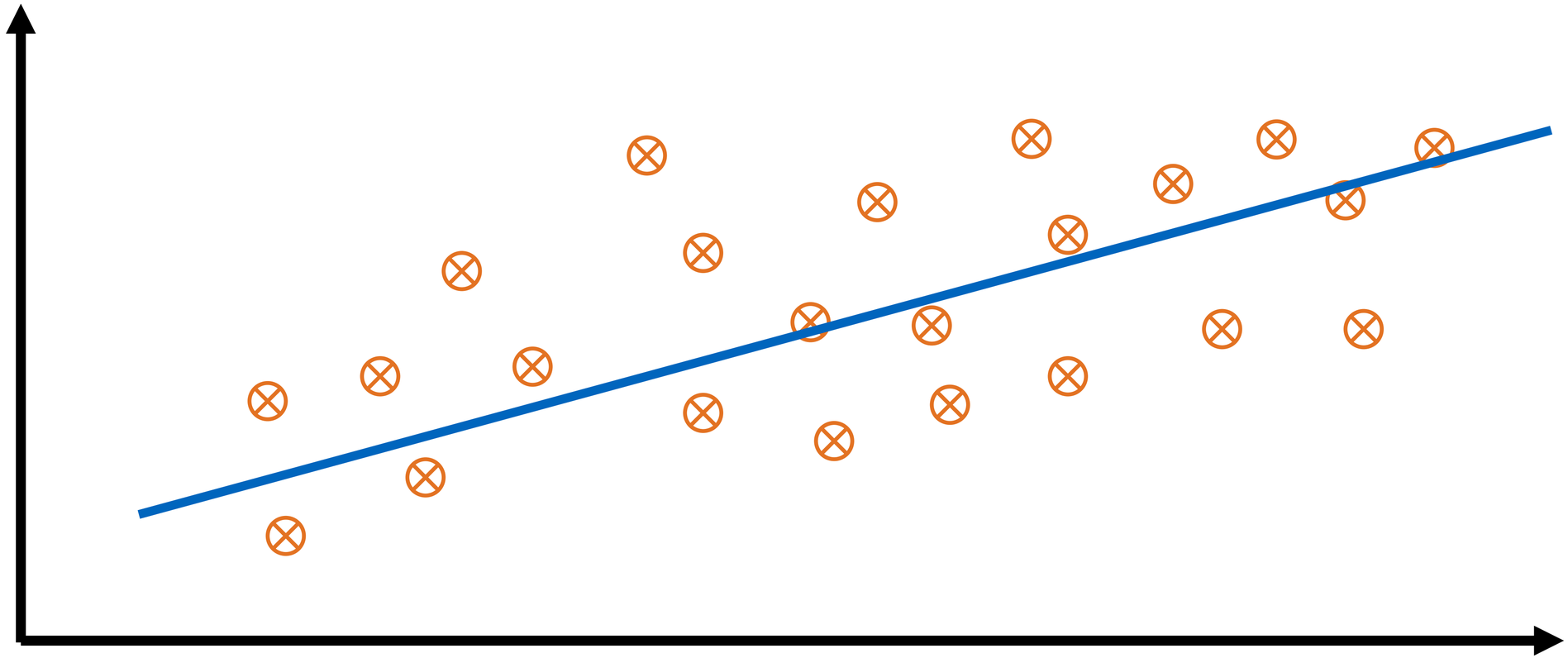
Supervised Machine Learning

https://exeter-data-analytics.github.io/MachineLearning/supervised-learning-1.html

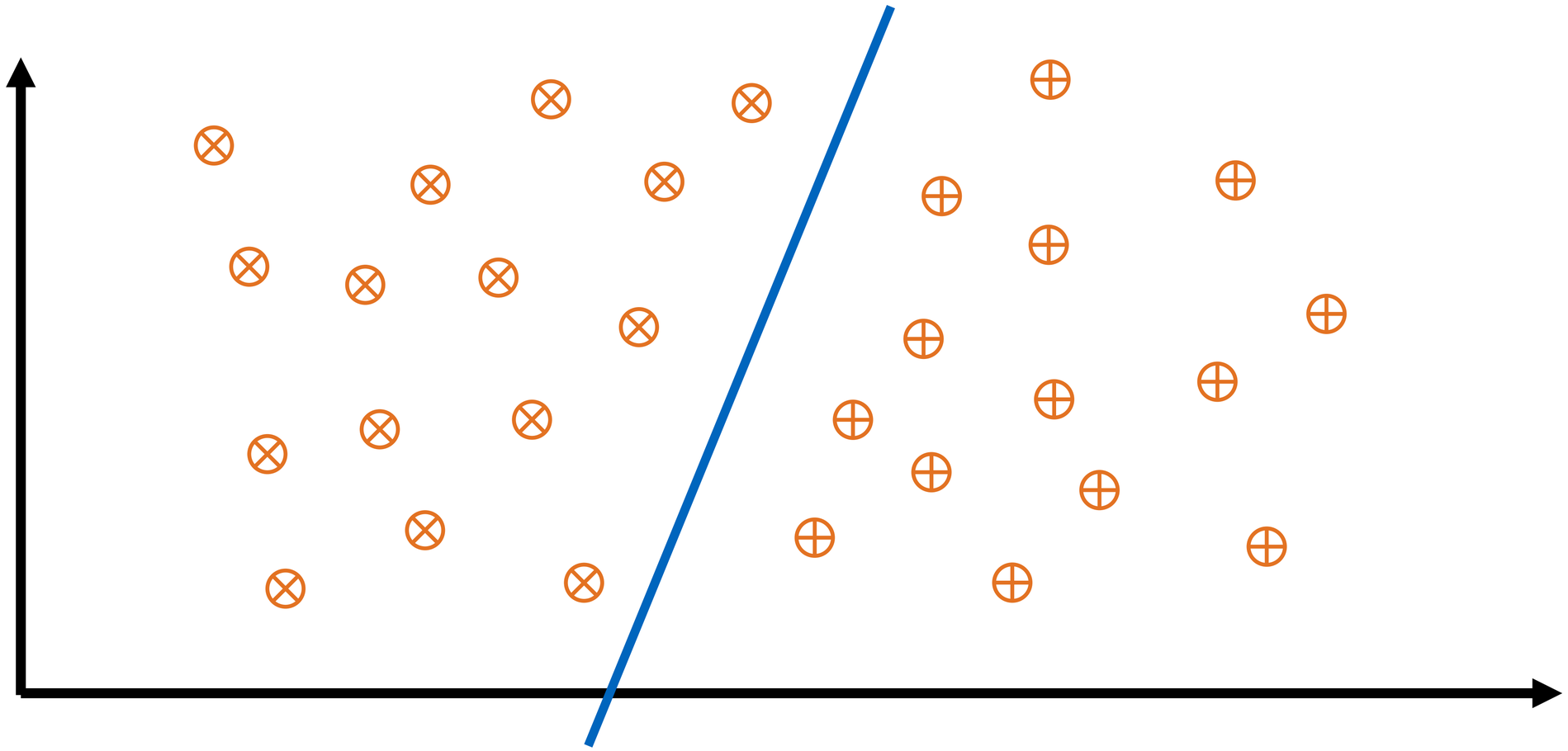
Nature of the Class Label



Regression



Classification



Supervised Learning

X_1	X_2	X_3	X_p	Y

Target

Un-Supervised Learning

X_1	X_2	X_3	X_p	Y

No Target

https://www.sharpsightlabs.com/blog/supervised-vs-unsupervised-learning/

Supervised Machine Learning…in (other) words

Supervised Machine Learning aims at forecasting class labels for measured data

Correct class labels are known for training data

Training means to search for a good function mapping
measured artifacts to known class labels

What you need:

- Classificator
- Measured data
- Class labels

Supervised Machine Learning… do you speak math?

Objective:

learn the *class label* y for each value of x, the *feature vector* consisting of multiple *features* (categorical or numerical)

Result:

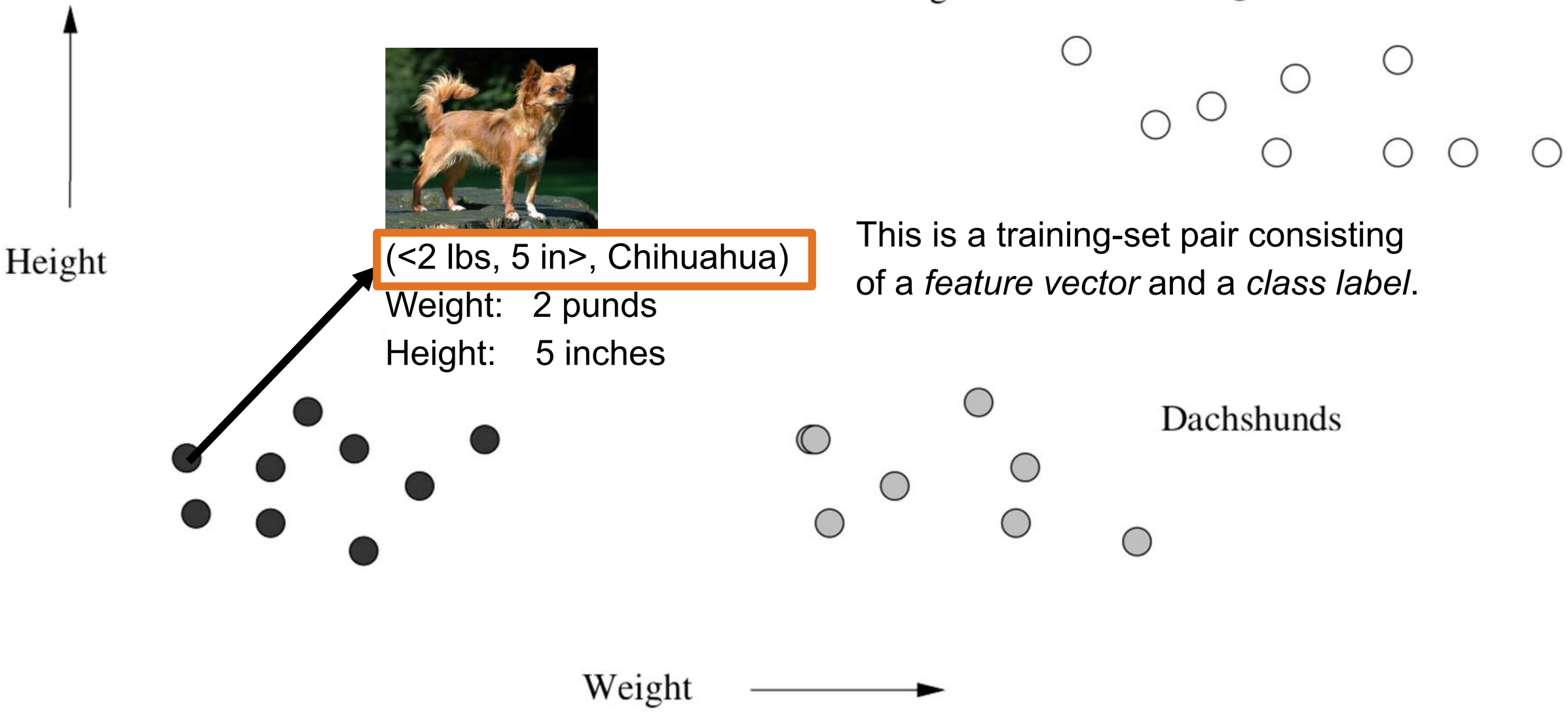
A function $f(x) = y$ that best predicts y for each value of x

If y is

- a real number, a regression model is learned
- a Boolean value (true/false, +1/-1), we speak of *binary classification*
- a nominal value of some finite set, it is a *multiclass classification*

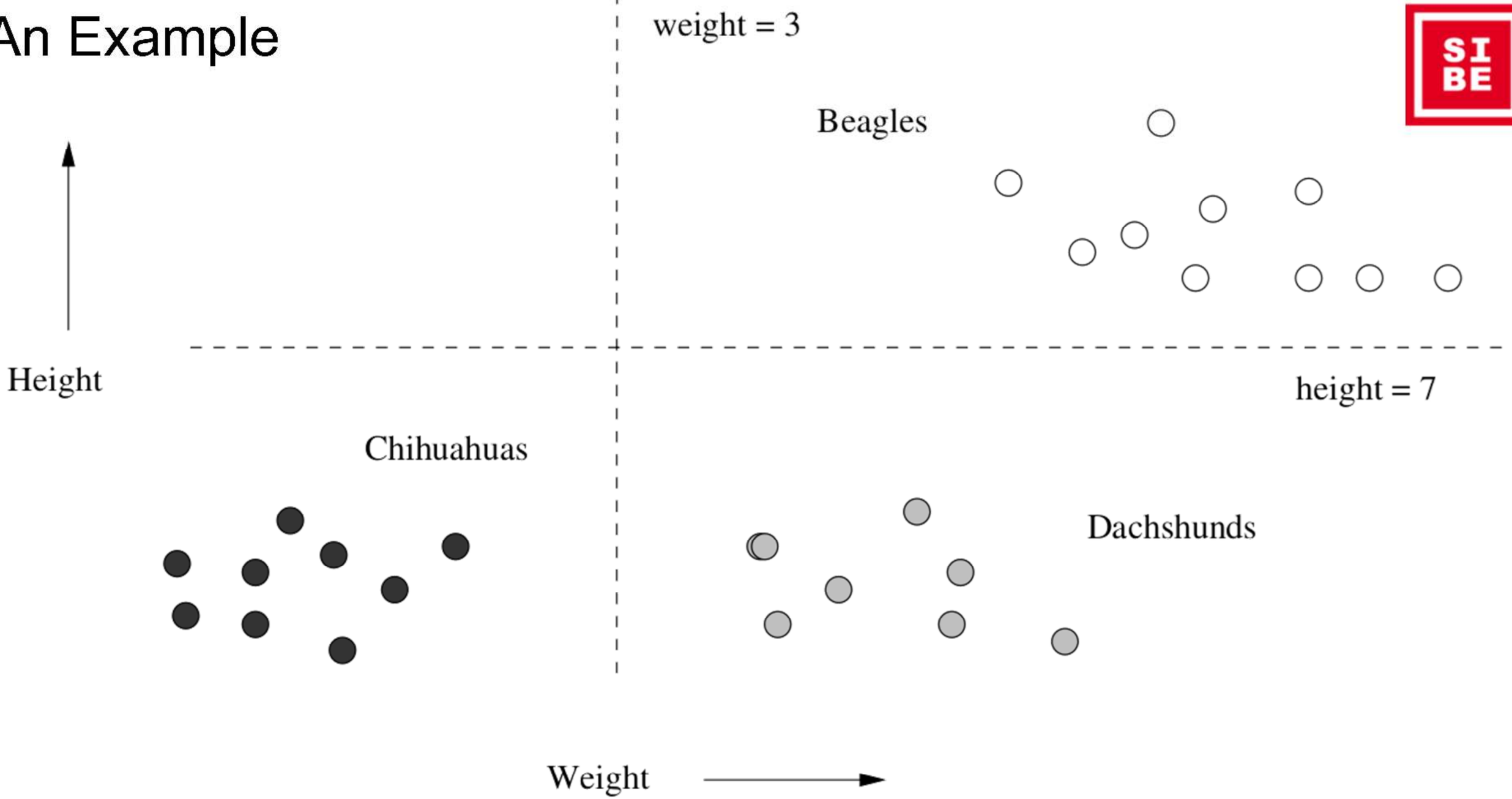
An Example

An Example

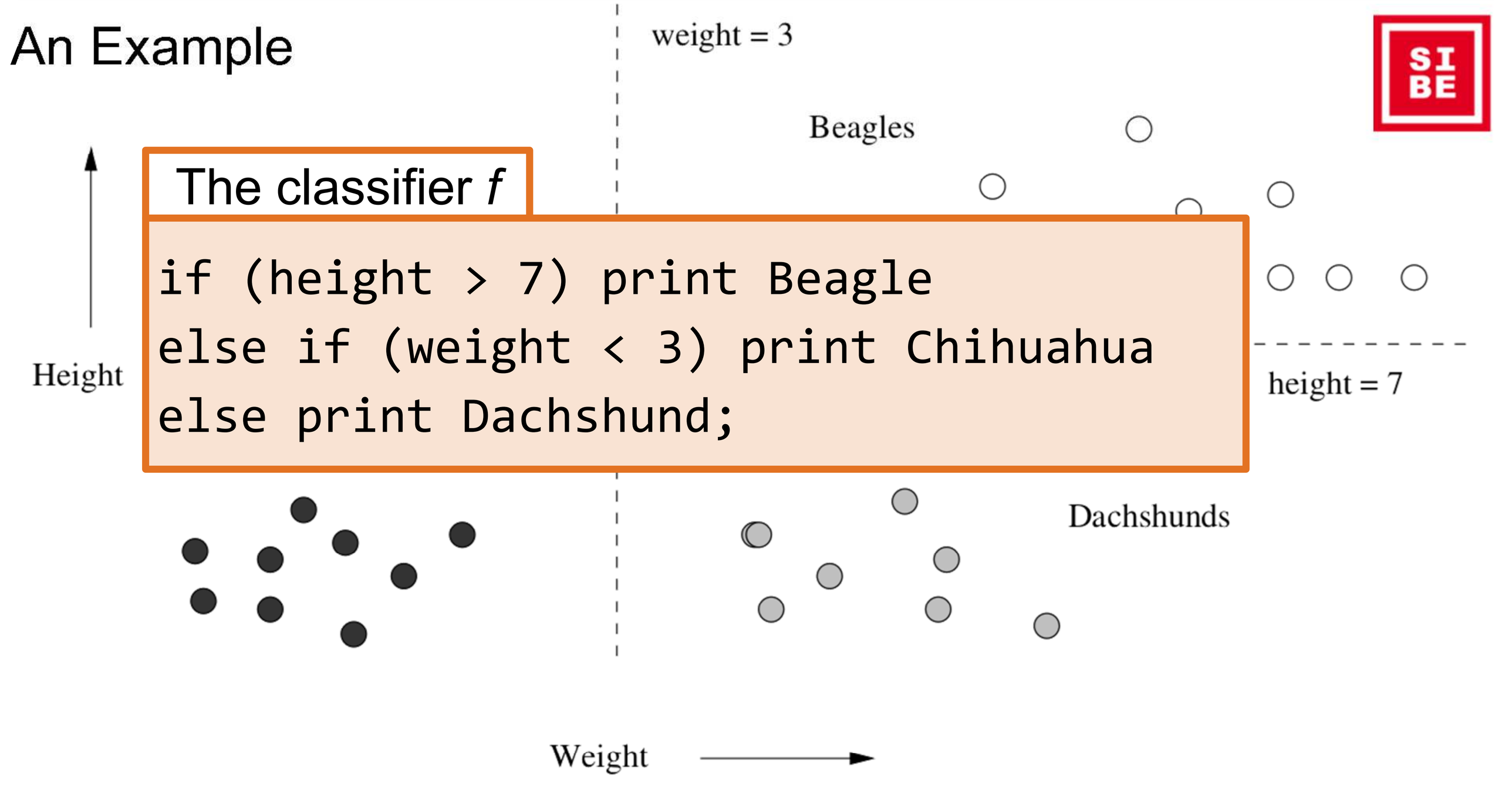


This is a training-set pair consisting of a *feature vector* and a *class label*.

An Example


weight = 3
Beagles
Height
height = 7
Chihuahuas
Dachshunds
Weight

An Example



The classifier *f*

```
if (height > 7) print Beagle
else if (weight < 3) print Chihuahua
else print Dachshund;
```

Relation to Clustering

Classification:

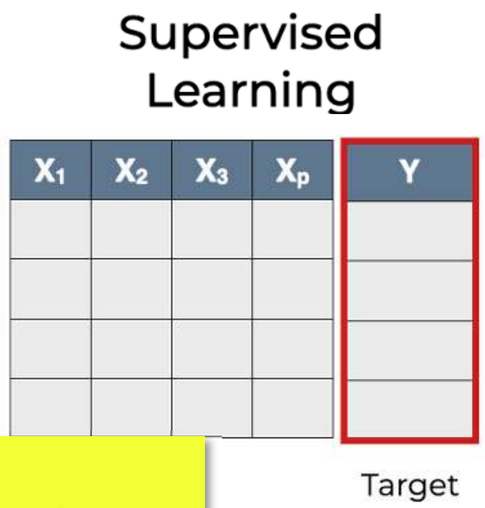
- Class label is discrete
- Enough training data for *each class*

Regression:

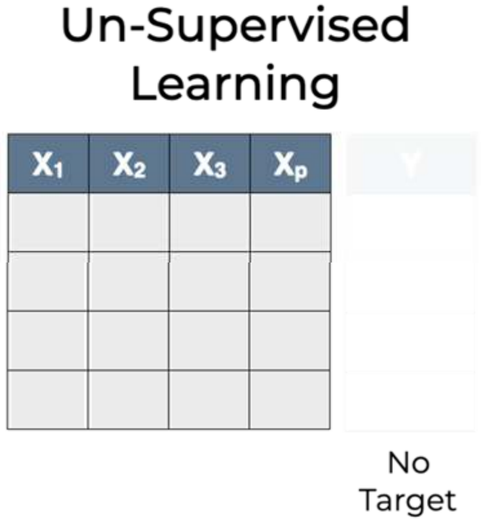
- Target variable is numeric

Clustering:

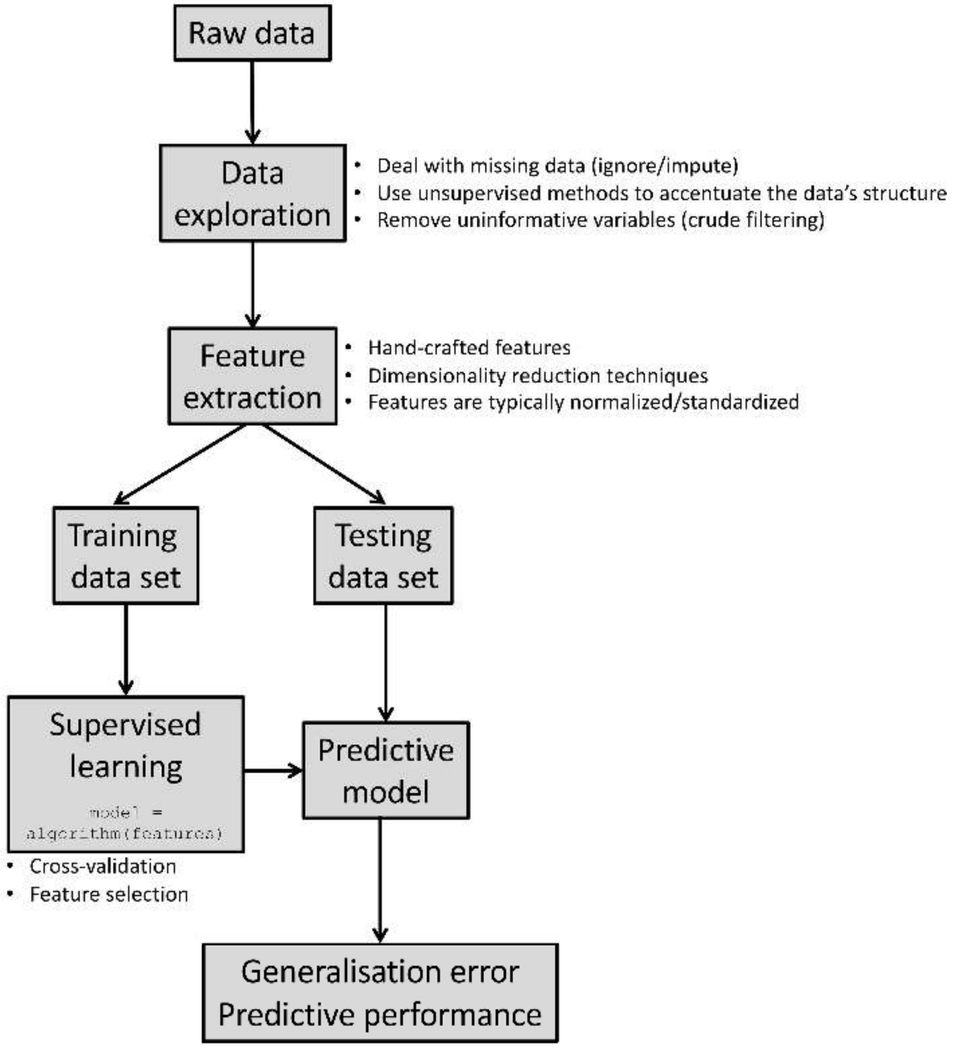
- no class label / target variable
- no training – input data without pre-defined classes
- produces partitioning of data



Clusters could be used to identify new classes

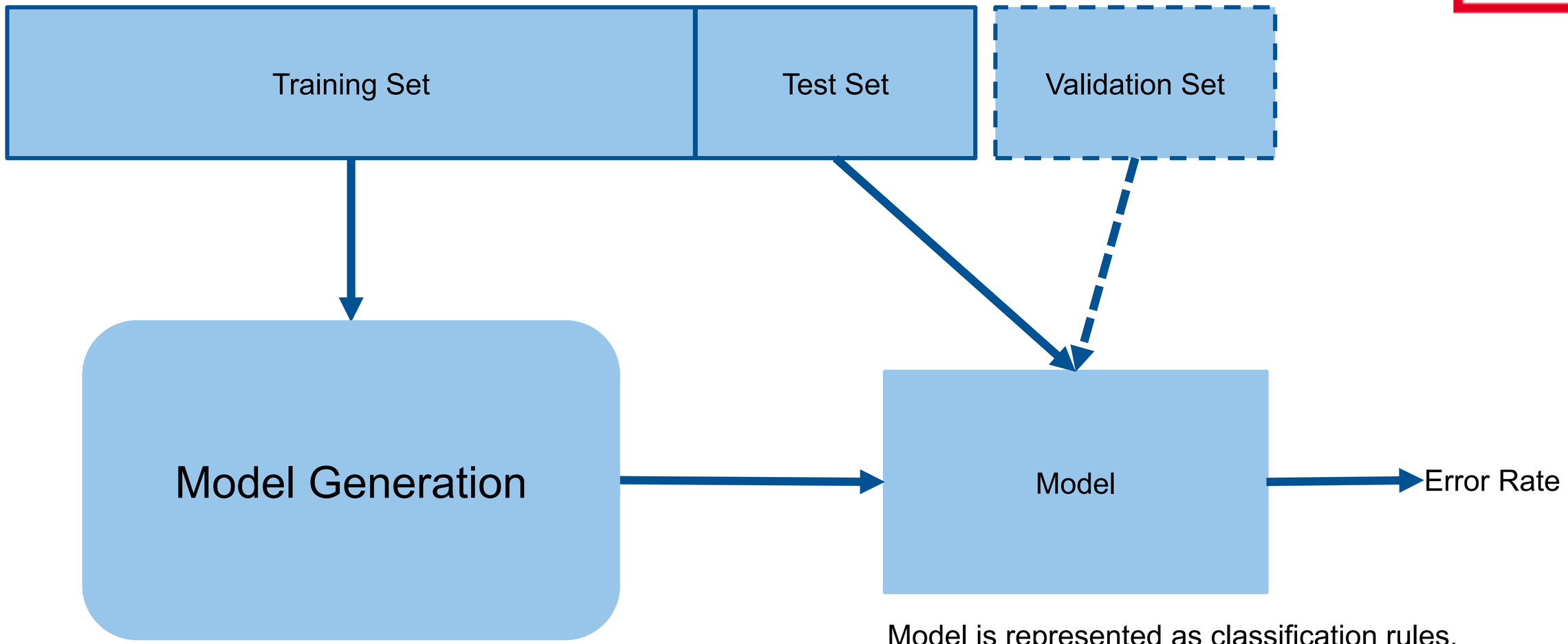


Supervised Machine Learning: Bird View



https://exeter-data-analytics.github.io/MachineLearning/supervised-learning-1.html

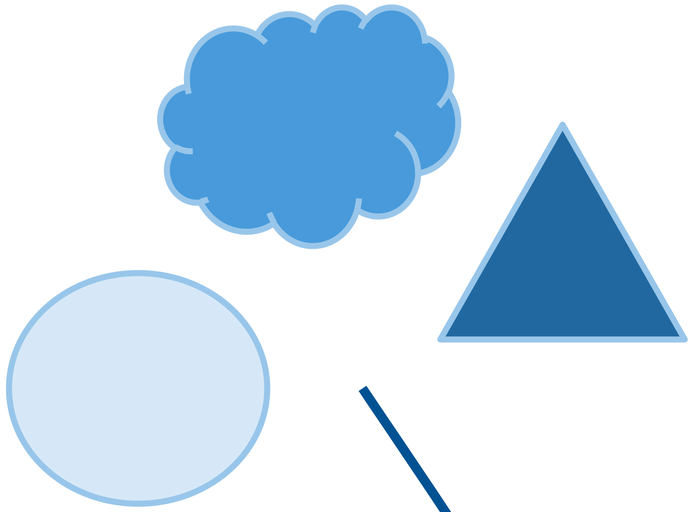
Supervised Learning: Training and Testing

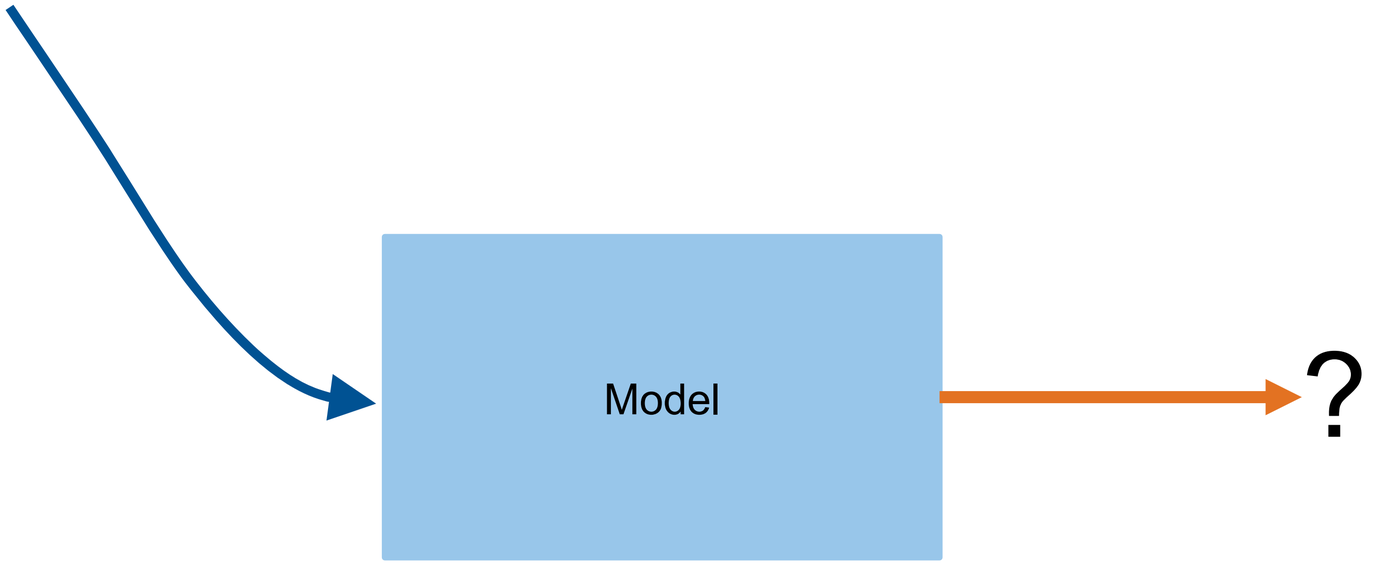


Model is represented as classification rules, decision trees, or mathemical formulas

Leskovec, J., Rajaraman, A. and Ullman, J.D., 2020. *Mining of massive data sets*. Cambridge university press.

What the Model is for

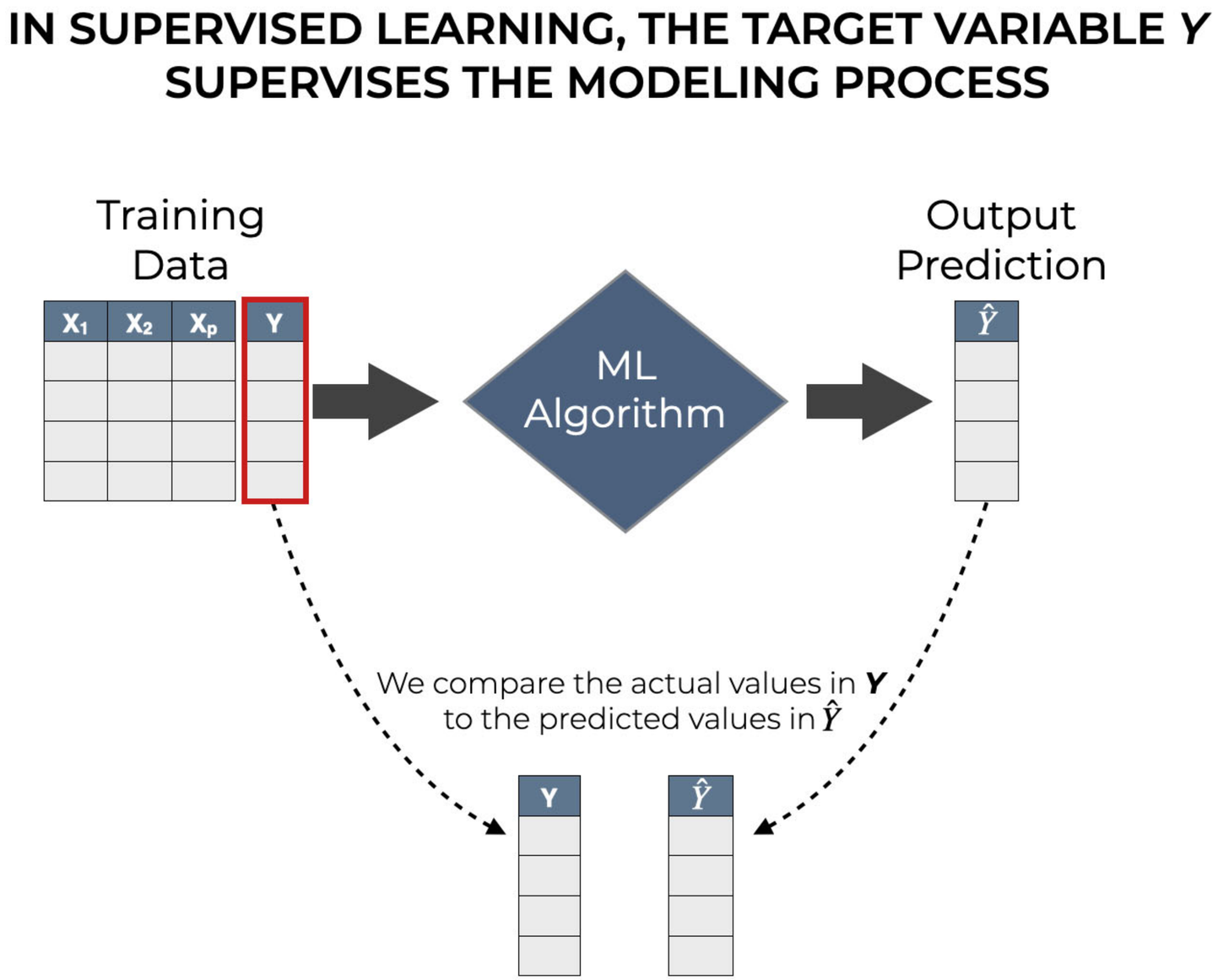




The model is used to classify the data whose class is *unknown*!

Its purpose is *generalization*!

Models make mistakes…

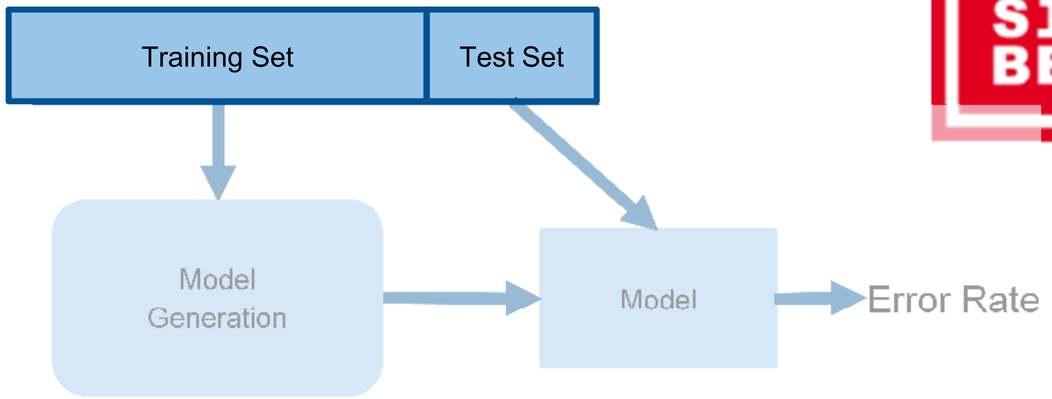


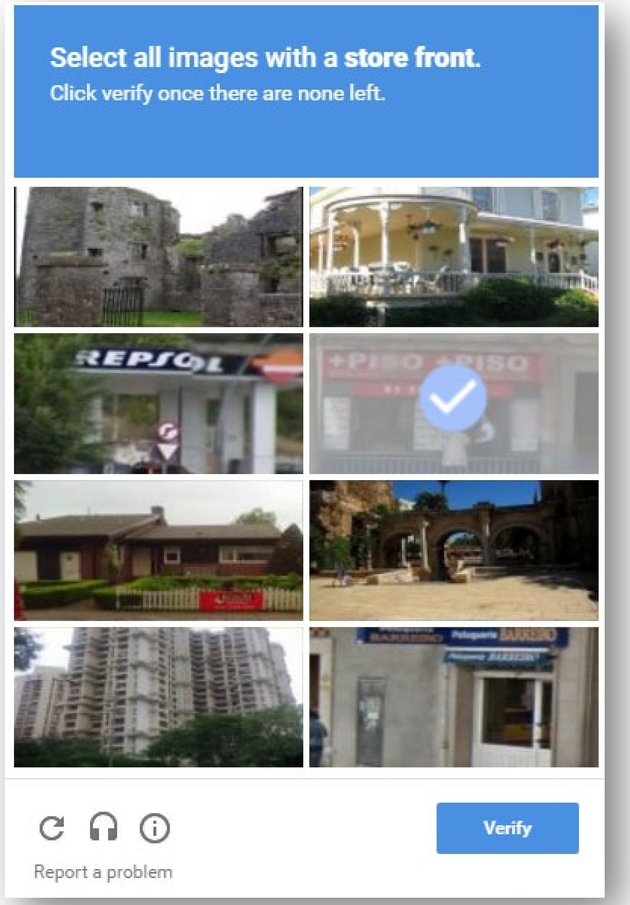
https://www.sharpsightlabs.com/blog/supervised-vs-unsupervised-learning/

/kæp.tʃə/ or Creating a Training Set

Label Data Manually?

Often time consuming and costly process for large training sets





Active learning:

kick start a classifier only with some training examples, but leave it primarily with unclassified data, which it must classify. If the classifier is unsure of the classification (e.g., the newly arrived example is very close to the boundary), then the classifier can ask for ground truth at some significant cost

Major Classes of Classifiers

- Decision trees

  Suitable for binary and multiclass classification with a limited number of features
- Perceptrons

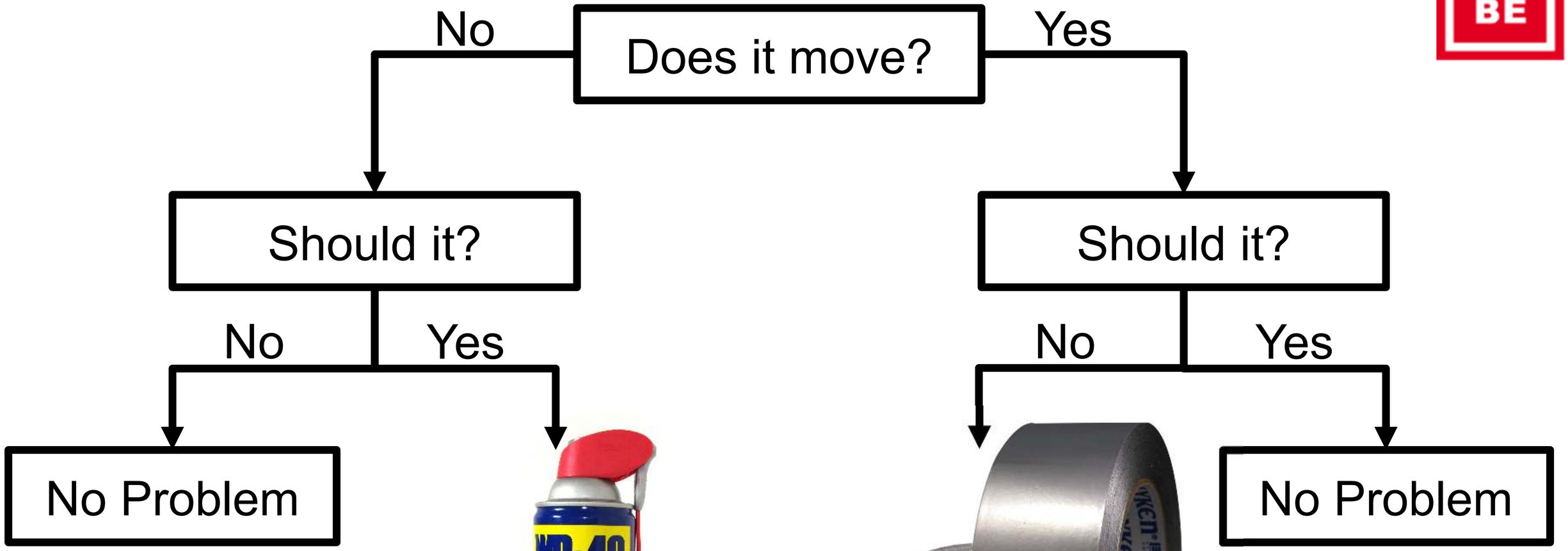
  Applies weights to components of vectors. Output +1 if sum exceeds a threshold, otherwise -1.
- Neural networks

  Acyclic networks of perceptrons
- Instance-based learning

  Compares instances of data to the entire training set. Example: k-nearest neighbor.
- Support-vector machines

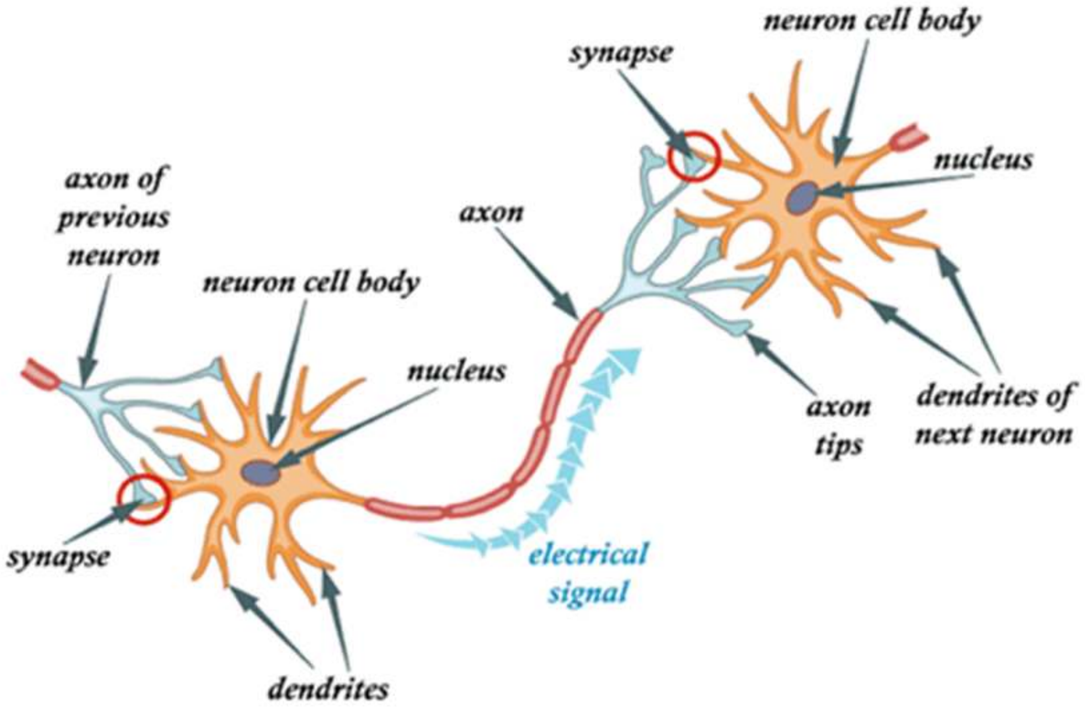
  Maps training examples to points in space so as to maximise the gap between categories

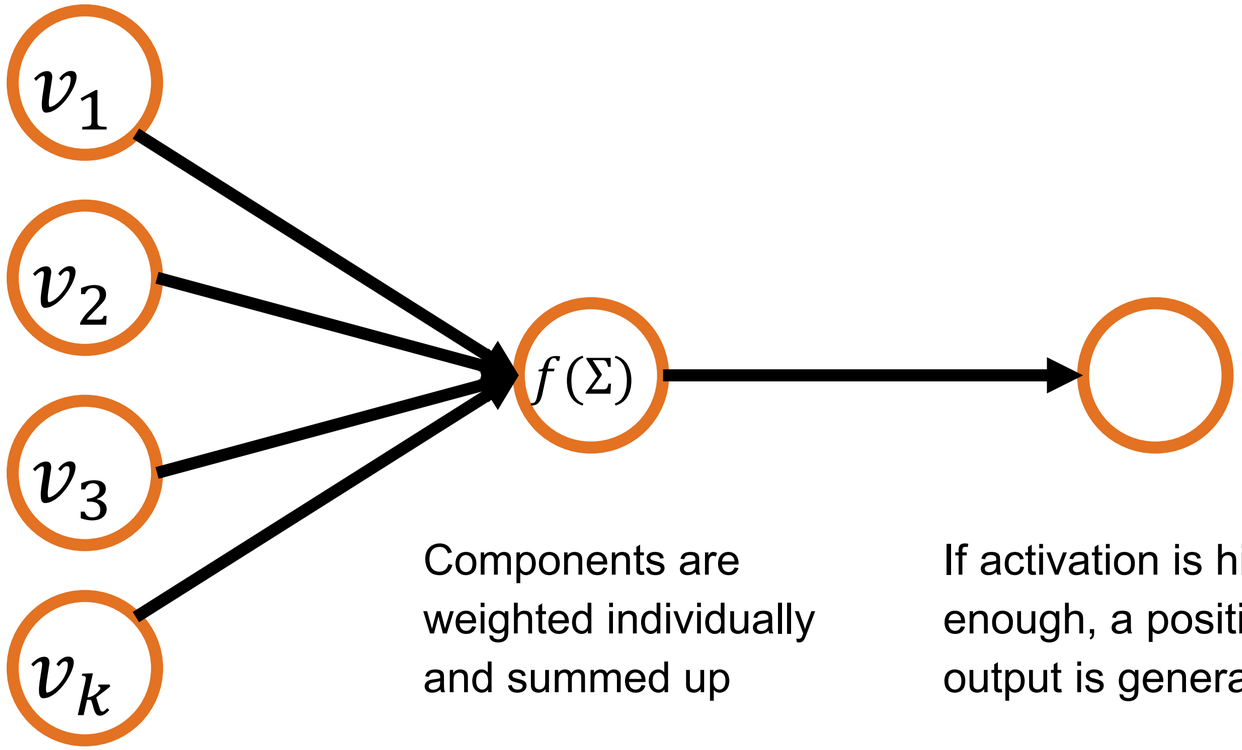
Decision Trees



https://commons.wikimedia.org/wiki/File:WD-40_Smart_Straw.JPG
https://commons.wikimedia.org/wiki/File:Duct-tape.jpg
https://commons.wikimedia.org/wiki/File:Polyken_Duct_Tape.jpg

Perceptrons





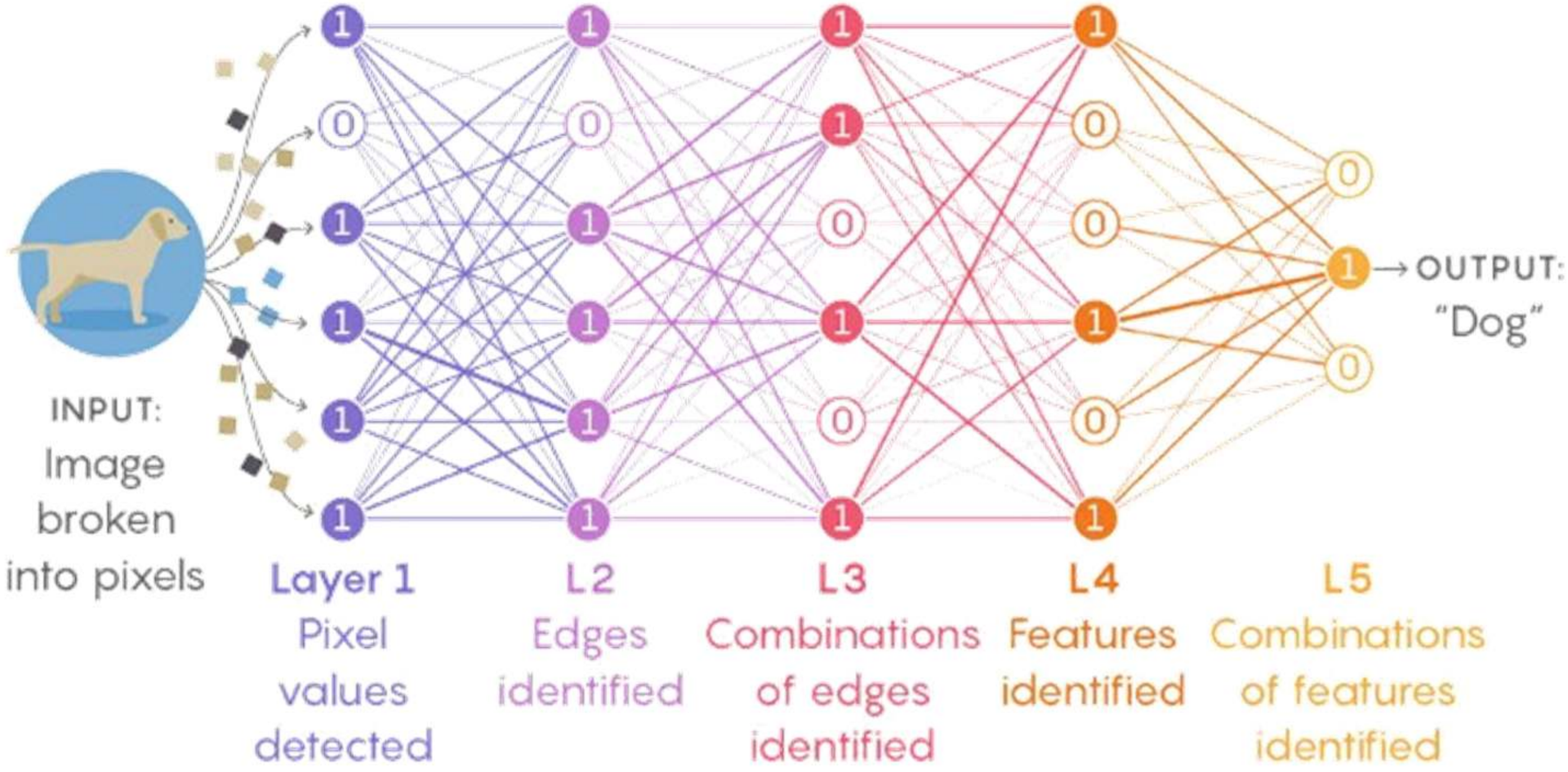
Components are weighted individually and summed up

If activation is high enough, a positive output is generated

Components of instances

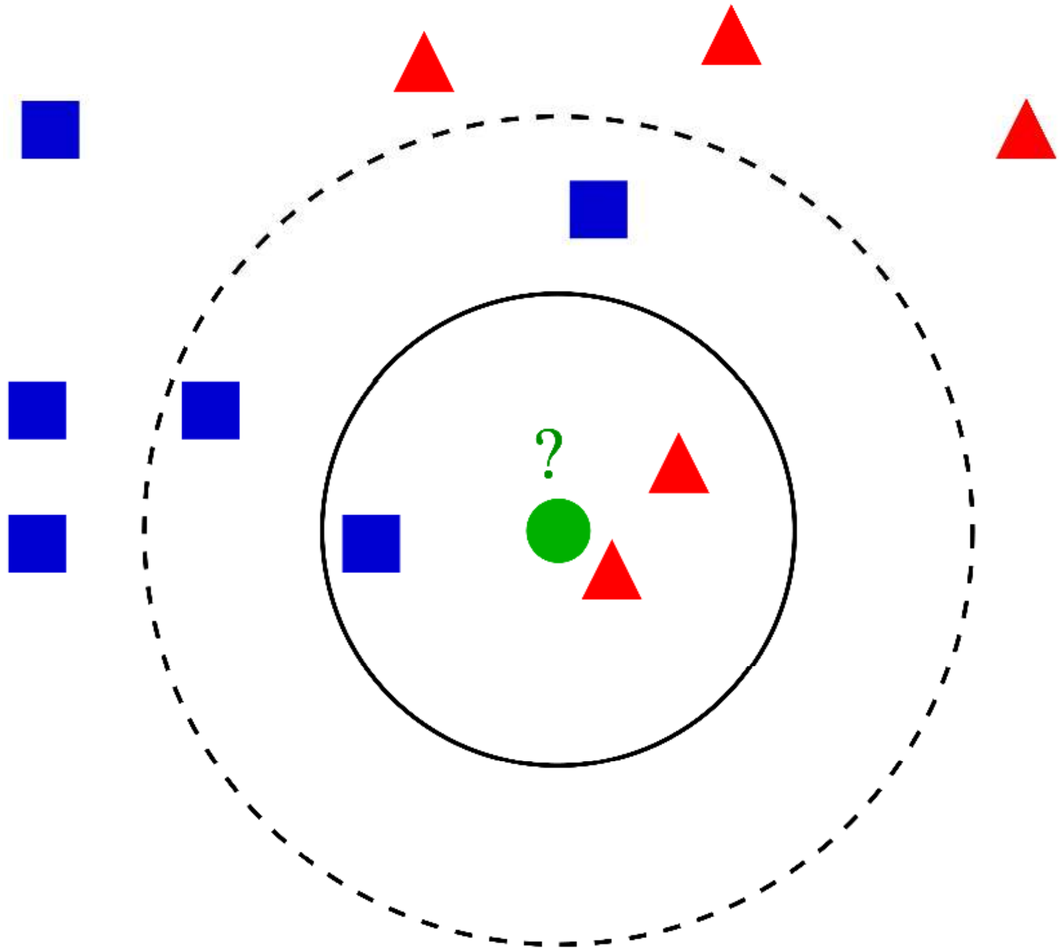
https://www.deeplearningtrack.com/single-post/2017/07/09/Introduction-to-NEURAL-NETWORKS-Advantages-and-Applications

Neural Networks



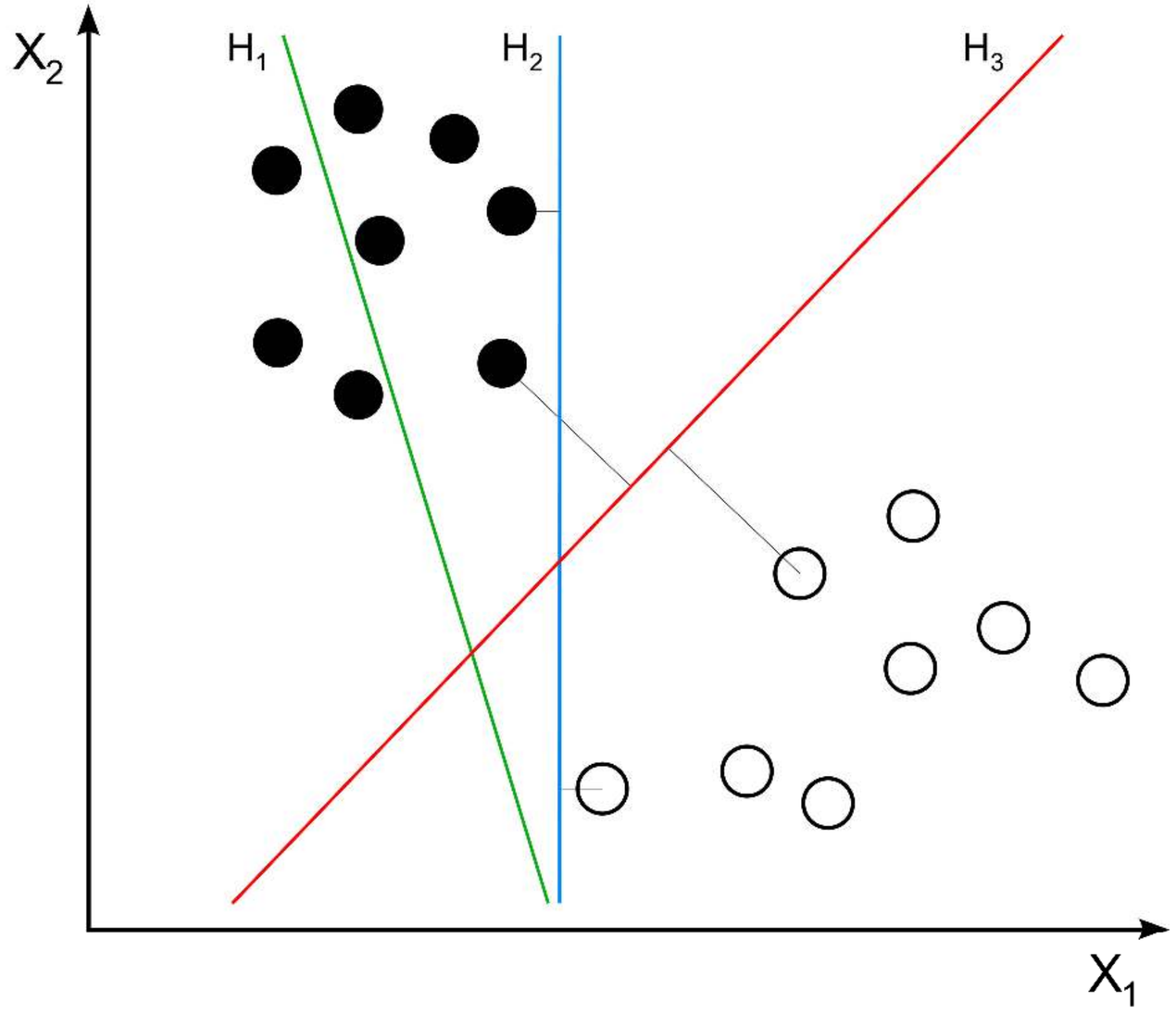
https://towardsdatascience.com/designing-your-neural-networks-a5e4617027ed

k-Nearest Neighbors



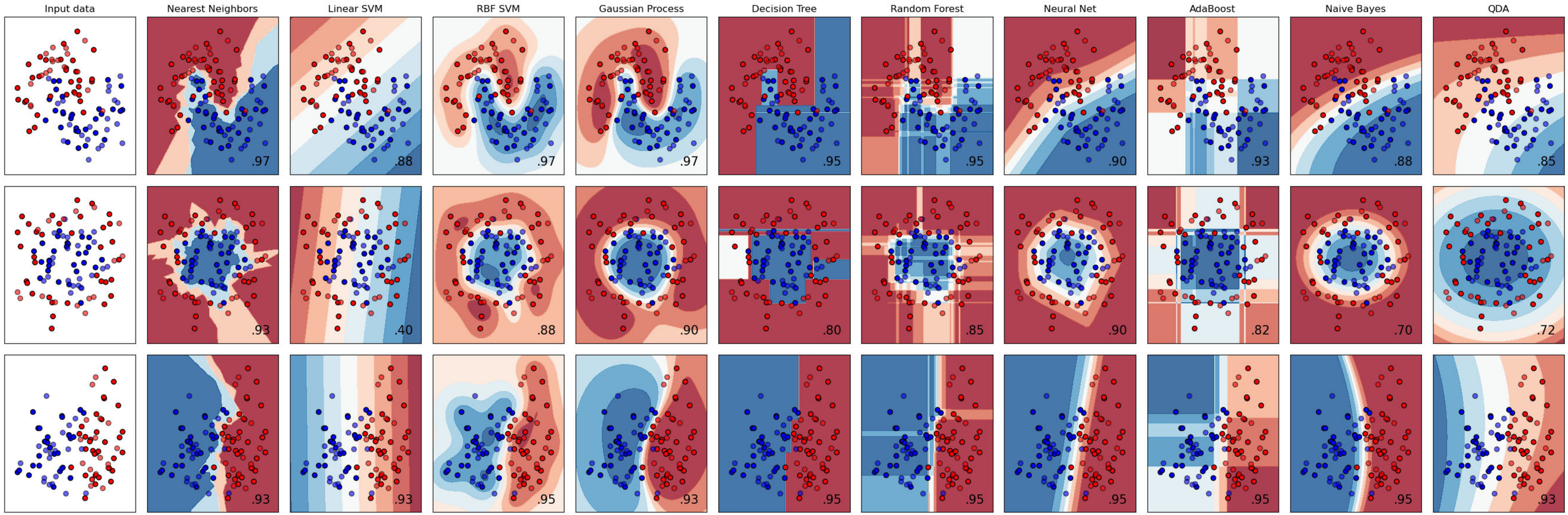
https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

Support Vector Machines



https://en.wikipedia.org/wiki/Support-vector_machine

Some Classification Algorithms Compared



https://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html

Ensemble Models

Inspectable models ease debugging problems in
data collection, feature engineering, etc

Ensemble models provide ways to restrict features to separate models that otherwise would interact in unintended ways

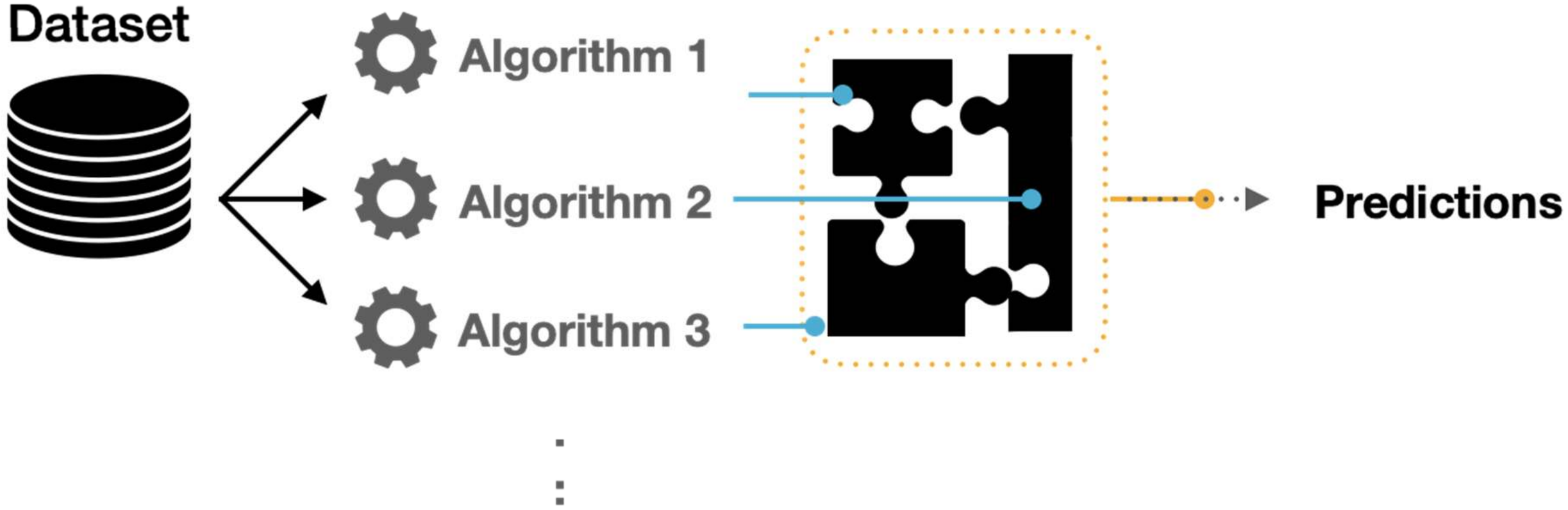
Helps overcoming

- high variance: single estimators are very sensitive to inputs to the learned features
- low accuracy: single models/algorithms might not be good enough
- features noise and bias: single estimators might rely heavily on one or few features

Various ways to combine models

Ensemble Models

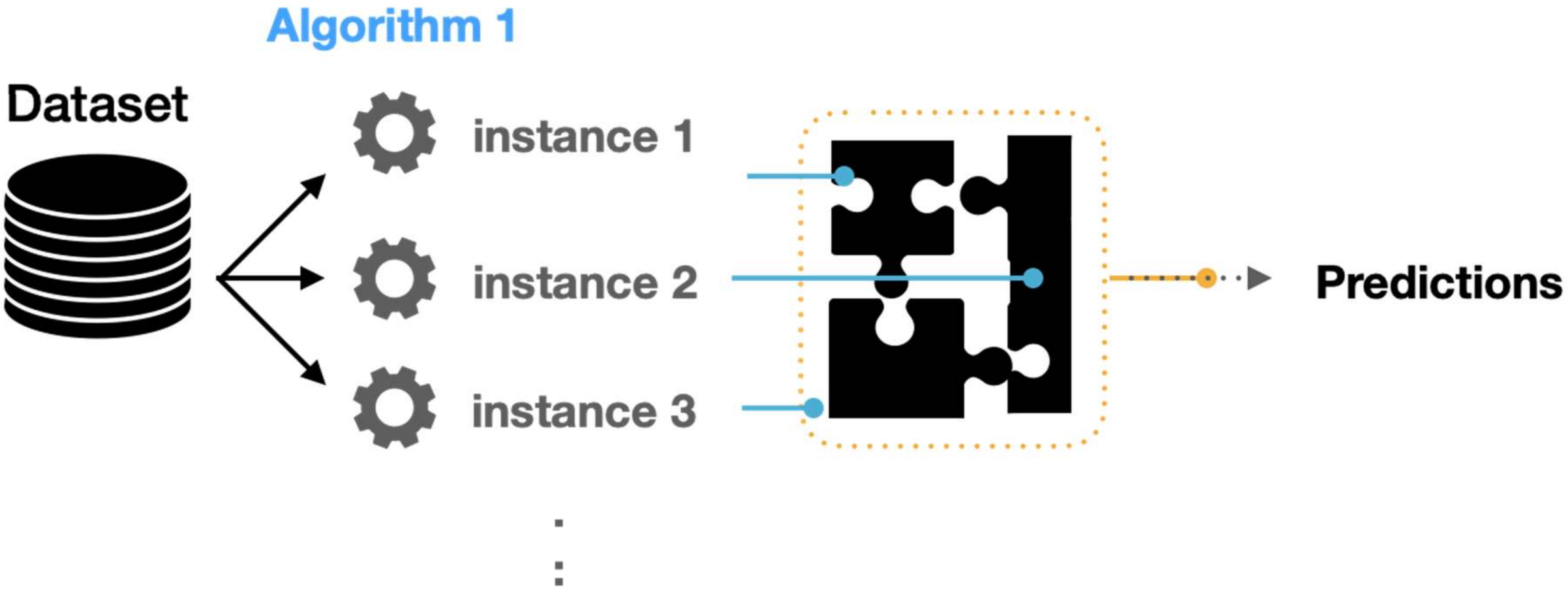
Using multiple algorithms to diversify model predictions



https://towardsdatascience.com/ensemble-models-5a62d4f4cb0c

Ensemble Models

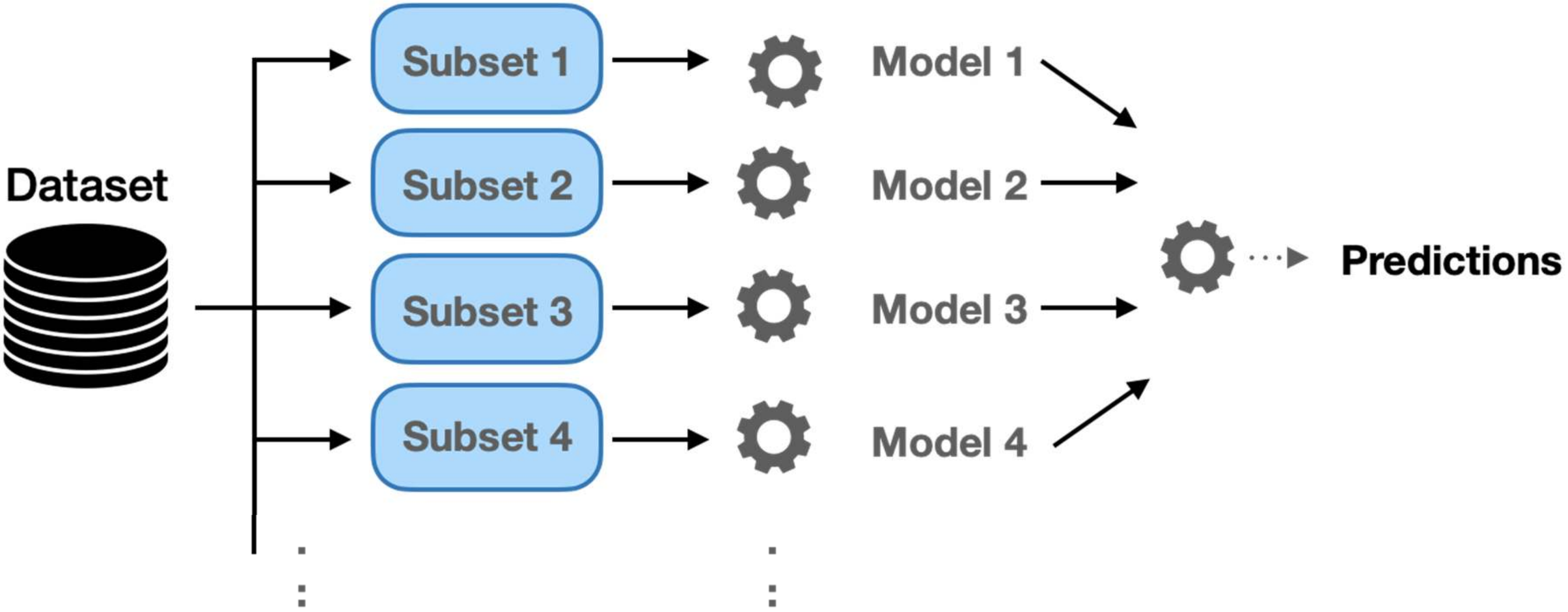
Using multiple weak instances of the same algorithm



https://towardsdatascience.com/ensemble-models-5a62d4f4cb0c

Ensemble Models: Bagging & Bootstrapping

Combine predictions from multiple models

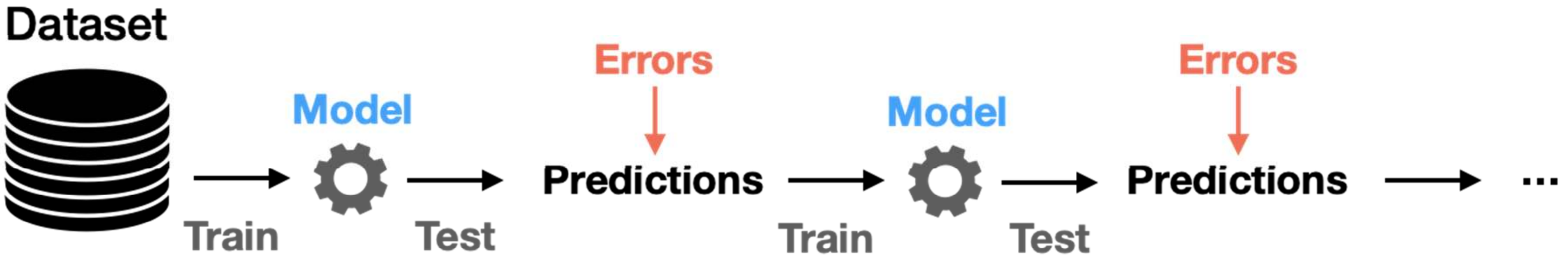


https://towardsdatascience.com/ensemble-models-5a62d4f4cb0c

Ensemble Models: Boosting

Ensemble of algorithms that builds models on top of several weak learners

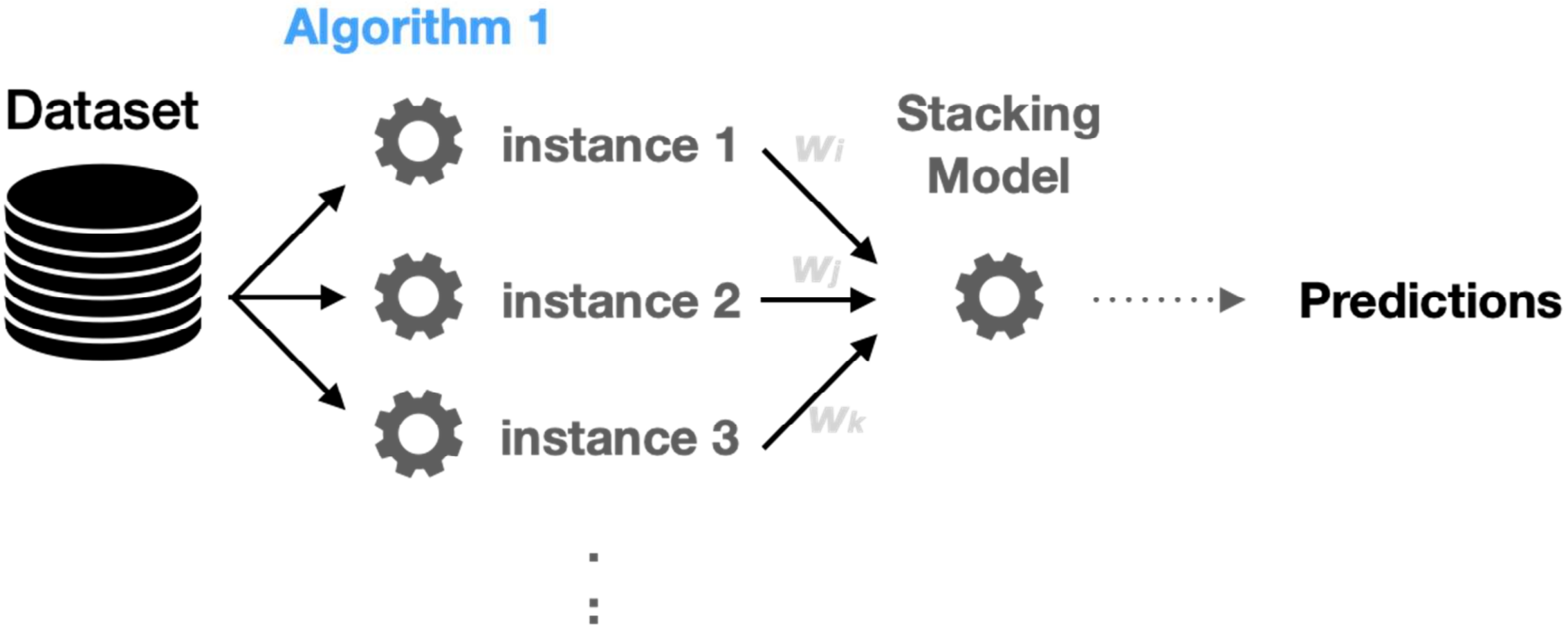
Here: Sequental Adaptive Boosting (AdaBoost)



https://towardsdatascience.com/ensemble-models-5a62d4f4cb0c

Ensemble Models: Stacking

Stacking intermediate predictions to make a final prediction



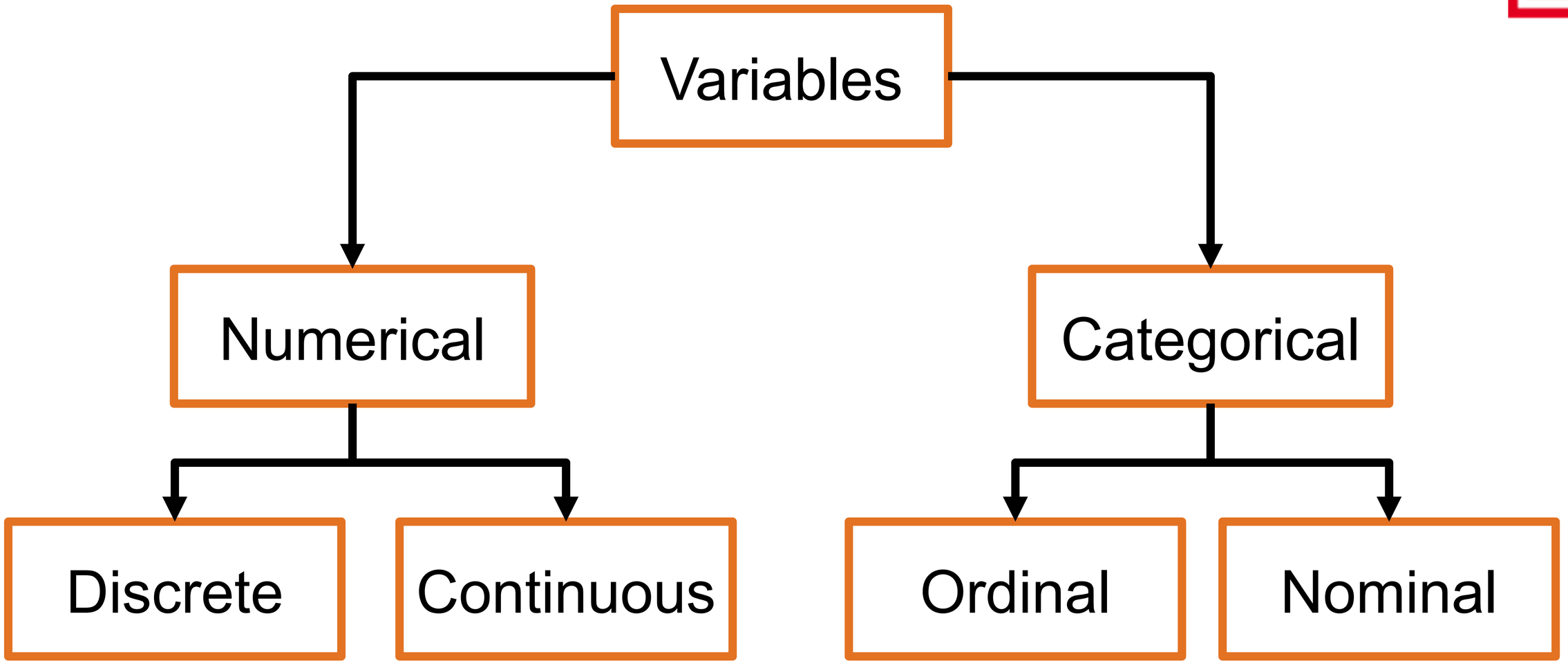
https://towardsdatascience.com/ensemble-models-5a62d4f4cb0c

How to select a model?

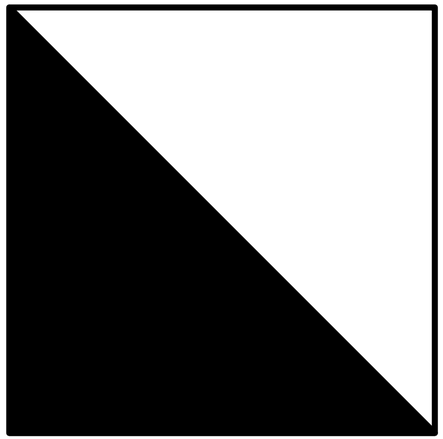
- Quality of predictions
  i.e. performance in terms of a quality metric
- Speed
  i.e. training time, prediction time
- Robustness
  i.e. handling noise or missing values and still classify correctly
- Scalability
  i.e. computational efficiency
- Interpretability
  subjective means
- Other

Different Types of Data

Hello Data


Variables
Numerical
Categorical
Discrete
Continuous
Ordinal
Nominal

Discrete vs. Continuous



Dichotomous data:

Data points can only take up 2 values

Discrete data:

Data points can only take up values from a set of possible values.

Either finite or infinite but countable

Continuous data:

Data points can be measured to an arbitrary level of exactness

Scales

Nominal

Values divide space of possible values into different segments

No order between segments

Example: gender, nationality

Ordinal

Allows for rank order – data can be sorted

No relative degree or relative difference between groups

Example: school grades

Interval

Order and difference between groups is defined

No natural „zero“ & ratio between points is undefined

Example: temperature in Celsius

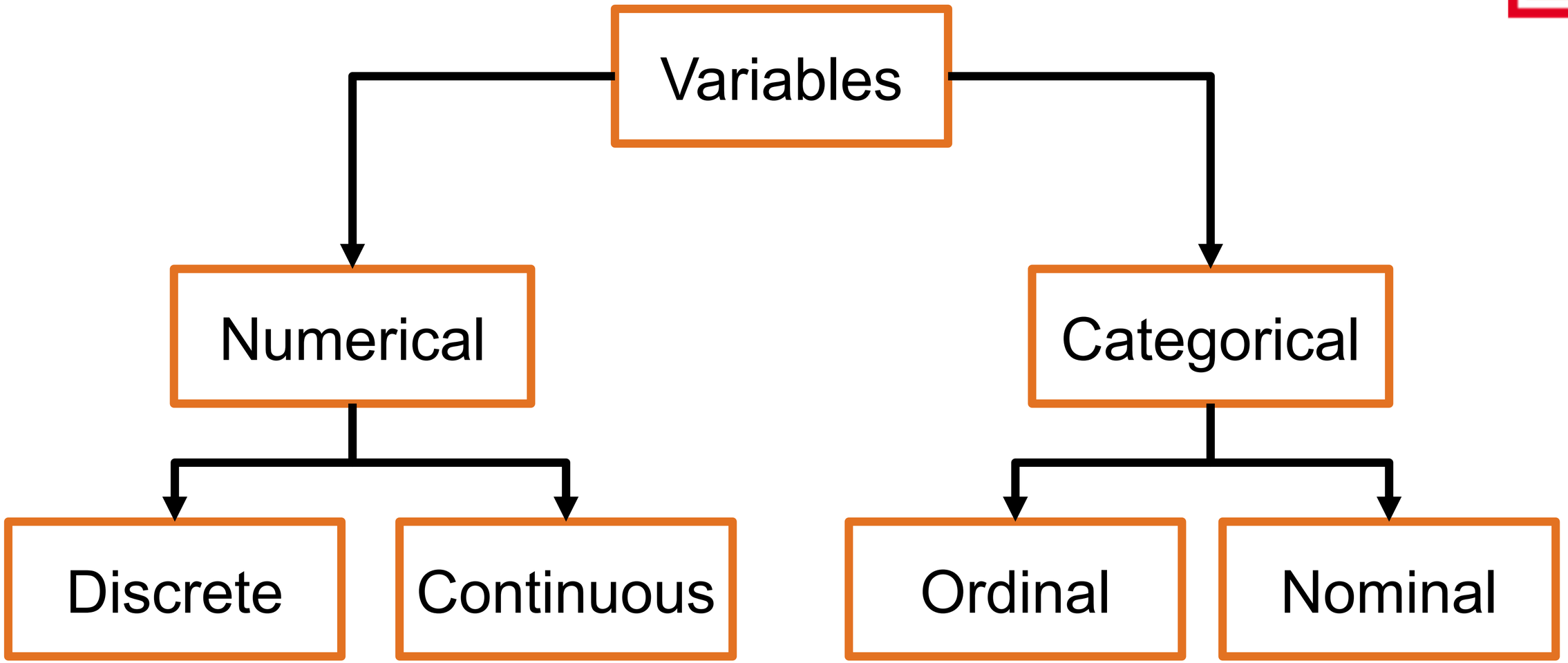
Ratio

Meaningful zero, i.e. unique and non-arbitrary

Example: temperature in Kelvin, age, weight, height

S. S. Stevens: On the Theory of Scales of Measurement. In: Science. 1946, 103, S. 677–680.

Hello Data


Variables
Numerical
Categorical
Discrete
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Ordinal
Nominal

https://xkcd.com/1838/

Thanks.

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