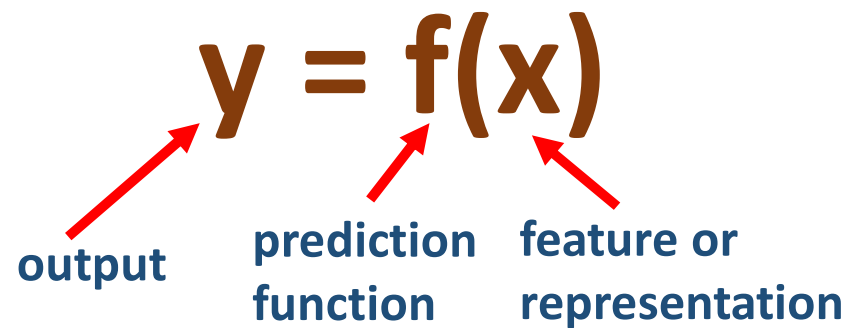


Supervised Machine Learning

Classification, Regression, Time Series

Recap – Machine Learning Framework



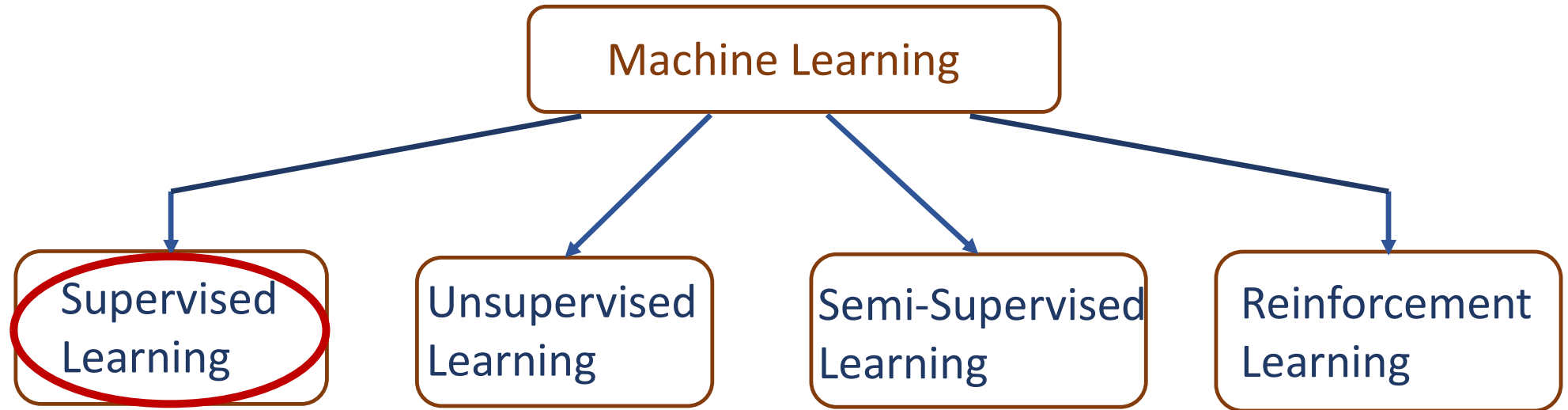
The diagram shows the equation $y = f(x)$ in large brown font. Three red arrows point from labels below to the equation: one from 'output' to y , one from 'prediction function' to f , and one from 'feature or representation' to x . The labels are in blue text.

$$y = f(x)$$

output prediction function feature or representation

- The input is converted to a vector x
- The output is a value indicated by y
- Depending on the nature of x and y , we define different types of learning

Categorization of ML Based on Learning

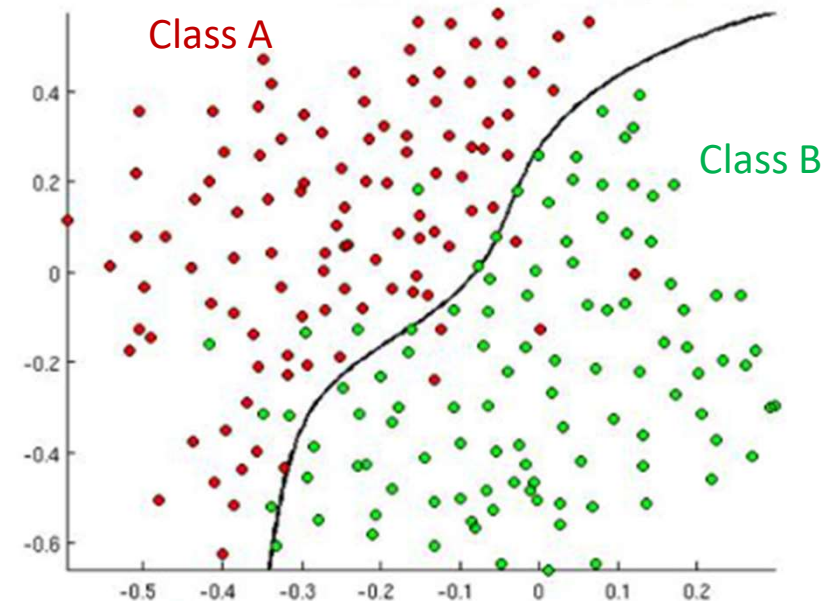


Supervised Learning

- Machine learning that are designed to learn by examples
- It is trained with labelled data
 - Feature vectors: x_{ij} , $i = 1..N$, $j = 1..M$
 - Output values: y_i , $i = 1..N$
- It maps the input to an output based on previous input-output pairs, through a mapping function, $Y = f(X)$
- Depending on the nature of y , we define:
 1. Classification
 2. Regression

Classification

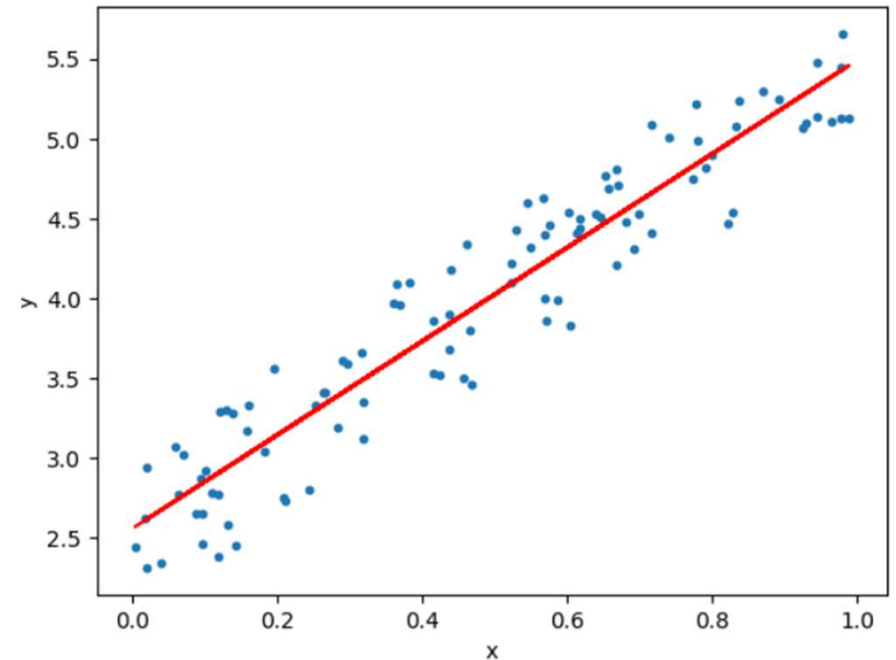
- Classification predicts a discrete value/class label
- Some common classification algorithms include:
 - Decision Trees
 - Support Vector Machines
 - Naïve Bayes Classifier
- Classification is often used for tasks such as:
 - Spam filtering
 - Image classification
 - Text classification



Regression

- Regression is a type of machine learning that predicts a continuous value.
- Some common regression algorithms include:
 - Linear regression
 - Polynomial regression
- Regression is often used for tasks such as:
 - Predicting the price of a house
 - Predicting the number of sales
 - Predicting the risk of a disease

e.g., a house's [Area, Age] (x) vs.
its Price(y)



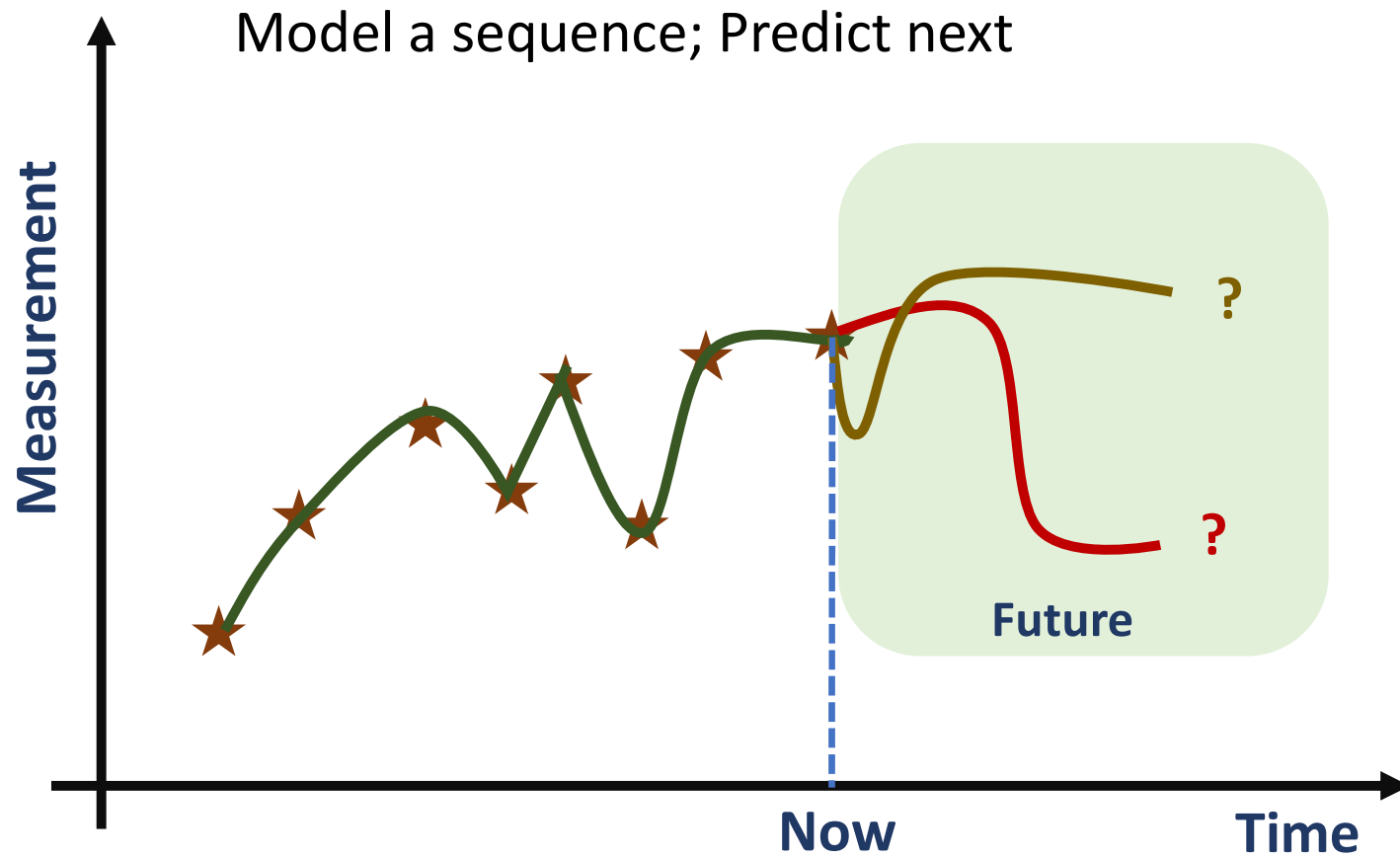
$y = f(x)$, interpolating (approximating) a function from examples

Time Series Model

- Time series is a sequence of observations often ordered in time
- Popular Problem: Given a sequence, predict future samples
- Applications:
 - Meteorology,
 - Finance,
 - Marketing, etc
- We want a machine learning model to understand sequences, not samples
- Assume we have a sequence of measurements, and we want to take N sequential measurements and predict the next one

Year	Sales (in Million)
1921	251
1931	279
1941	319
1951	261
1961	439
1971	348
1981	585

Time Series Prediction



Nearest Neighbour Classifier

Classification with Association by Similarity

Nearest Neighbour Classifier

X_{test} : [42.5, 39]

→ *Is the person diabetic or not?*

- How do we compare a test sample to a classification?
- We find distance to feature vectors of known classes - Association by Similarity
- We assign label of that sample which is nearest to the test sample

BMI	Age	Diabetic
32.6	49	1
34.2	23	1
22.4	31	0
25.7	43	0
29.8	15	0
31	58	1
43.2	65	0
37.6	52	1

Nearest Neighbour Classifier

BMI	Age	Diabetic
32.6	49	1
34.2	23	1
22.4	31	0
25.7	43	0
29.8	15	0
31	58	1
43.2	65	0
37.6	52	1



Feature Vector	Label
X_1 [32.6, 49]	1
X_2 [34.2, 23]	1
X_3 [22.4, 31]	0
X_4 [25.7, 43]	0
X_5 [29.8, 15]	0
X_6 [31.0, 58]	1
X_7 [43.2, 65]	0
X_8 [37.6, 52]	1

Nearest Neighbour Classifier

Feature Vector	Label
X_1 [32.6, 49]	1
X_2 [34.2, 23]	1
X_3 [22.4, 31]	0
X_4 [25.7, 43]	0
X_5 [29.8, 15]	0
X_6 [31.0, 58]	1
X_7 [43.2, 65]	0
X_8 [37.6, 52]	1

Distance
14.07
18.02
21.63
17.27
27.15
22.21
26.01
13.89

X_{test} : [42.5, 39]

$$\sqrt{(42.5 - 32.6)^2 + (39 - 49)^2} = 14.07$$

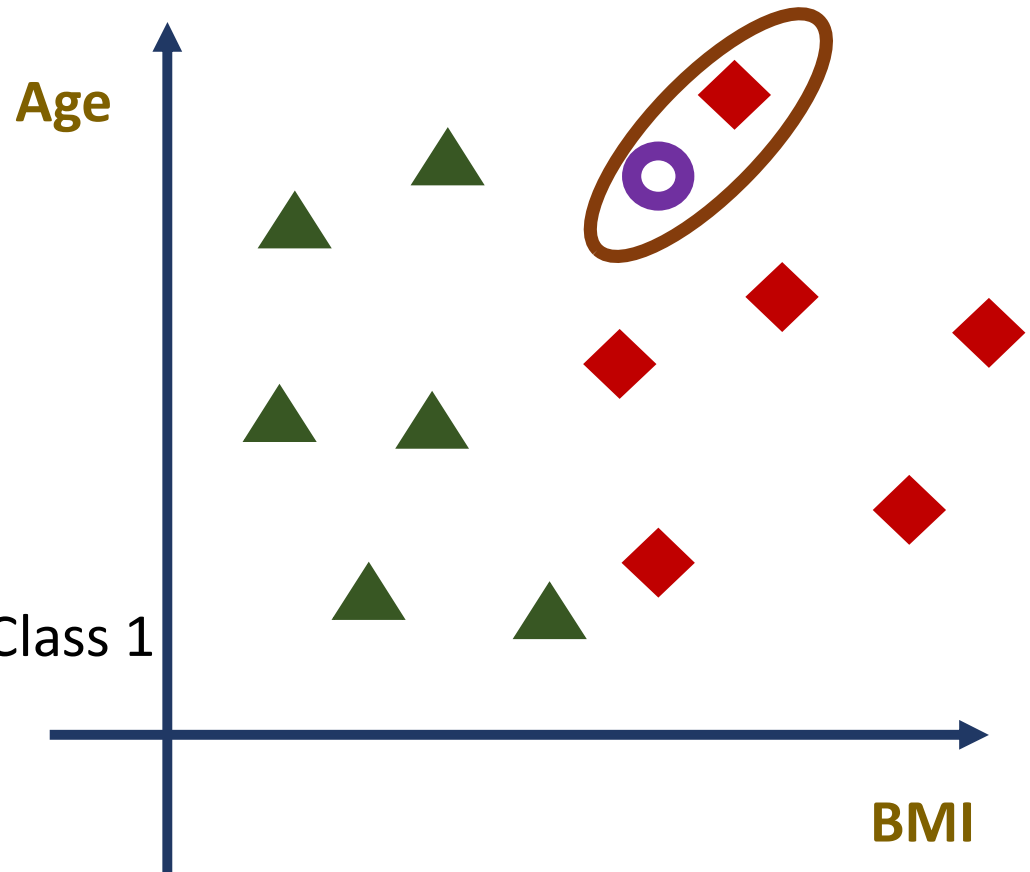
✓ *The test sample has diabetes*

Visualization in Feature Space

◆ Class 1

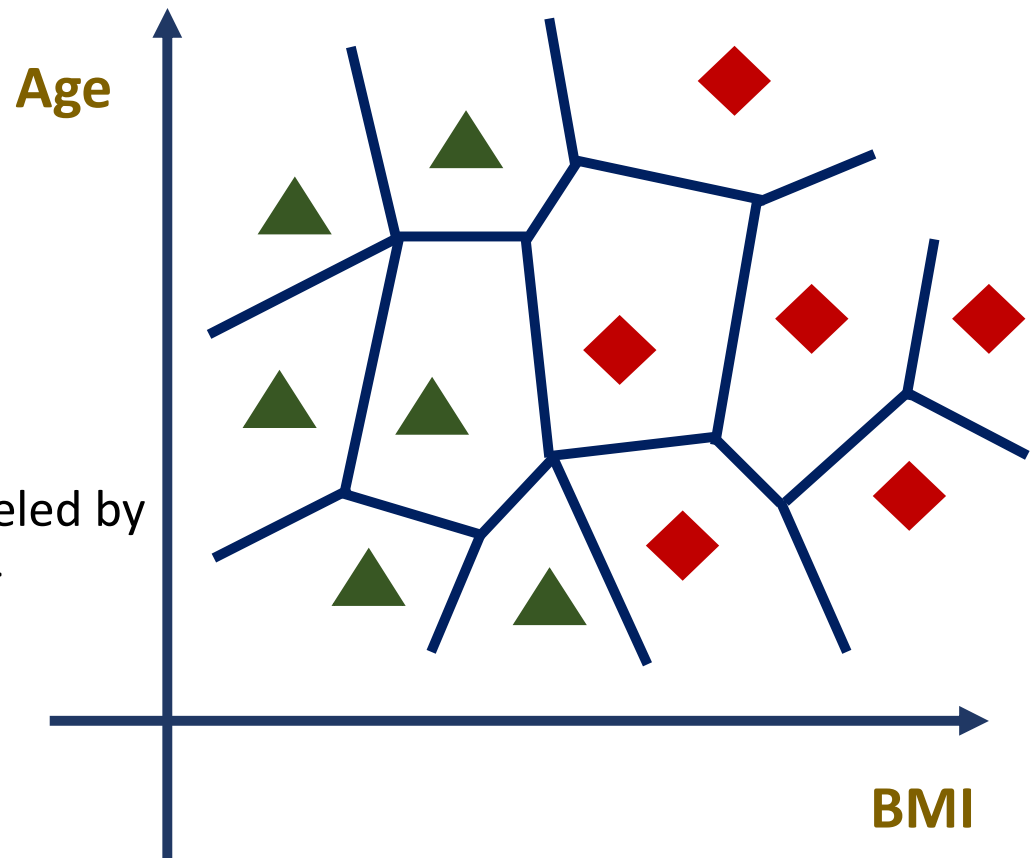
▲ Class 0

- The nearest sample is a ◆
- We assign the test sample to Class 1



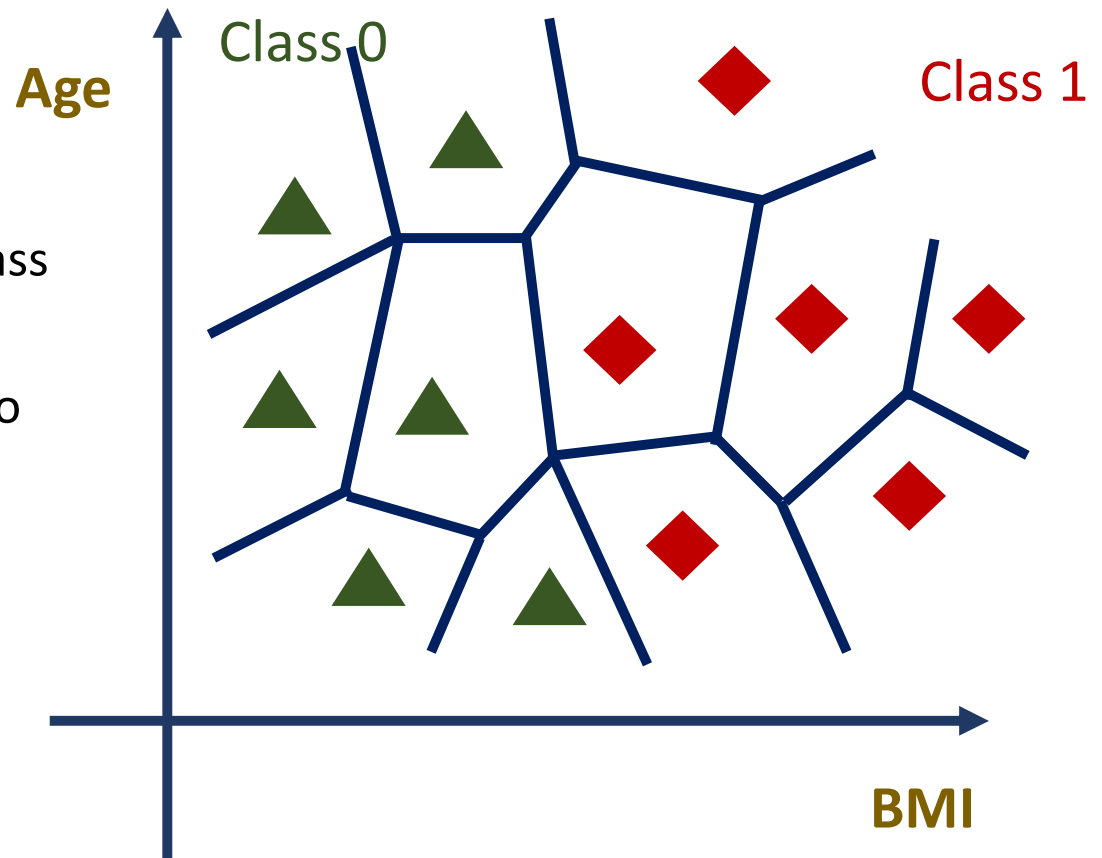
Class Boundaries

- The classifier effectively partitions the feature space into cells consisting of all points closer to a given training point (x_1, x_2) than to any other training points.
- All points in such a cell are thus labeled by the category of the training point – **Voronoi tessellation** of the space



Class Boundaries – Partition of Feature Space

- We now ignore boundaries between samples of the same class
- The decision boundary is found to be piece-wise linear



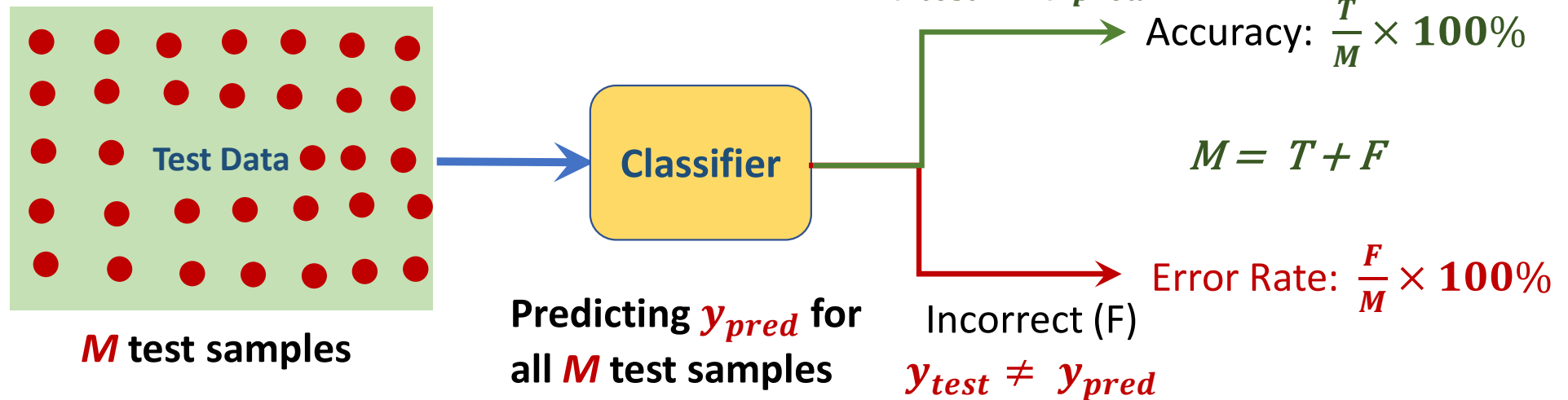
The Classification Algorithm

Problem

- Given:
 - A set of training n training samples: (x_i, y_i)
 - A set of m test samples: (x_{test}, y_{test}) , $m \ll n$
- Find:
 - Label (x_{test}) using Similarity Measure and return y_{pred}
- Find accuracy of the prediction
 - Evaluation of a classifier

Evaluating a Classifier

- Several Metrics used to evaluate a classifier



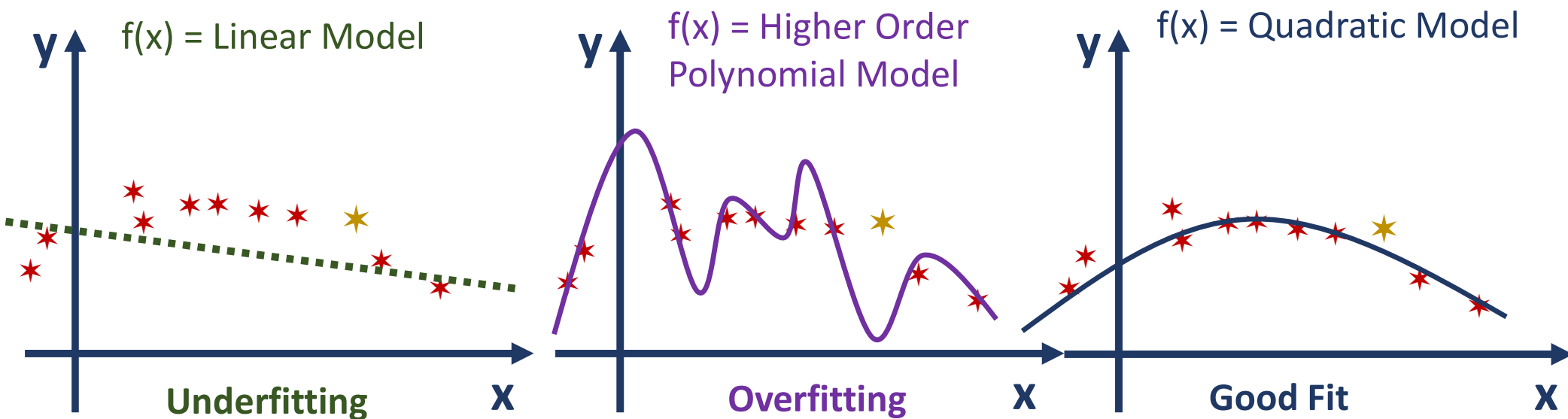
- In a 2-class classifier, what does an accuracy of 65% tell us about the classifier?

Supervised Machine Learning - Methodology

- **Step 1:** A set of training n training samples: $(x_i, y_i), i = 1, \dots, n$
- **Step 2:** We need to correctly predict labels of unseen m test sample: $(x_{test}, y_{test}), test = 1, \dots, m$. Predicted value = y_{pred}
- **Step 3:** We need to maximize the accuracy on unseen m test sample: $(x_{test}, y_{test}), test = 1, \dots, m$. $y_{pred} = y_{test}$
- **Assumption:** Test samples come from the same distribution as training samples
- Can we have situations where we do well on training samples but perform badly on test samples? **Rote Learning / Memorization**

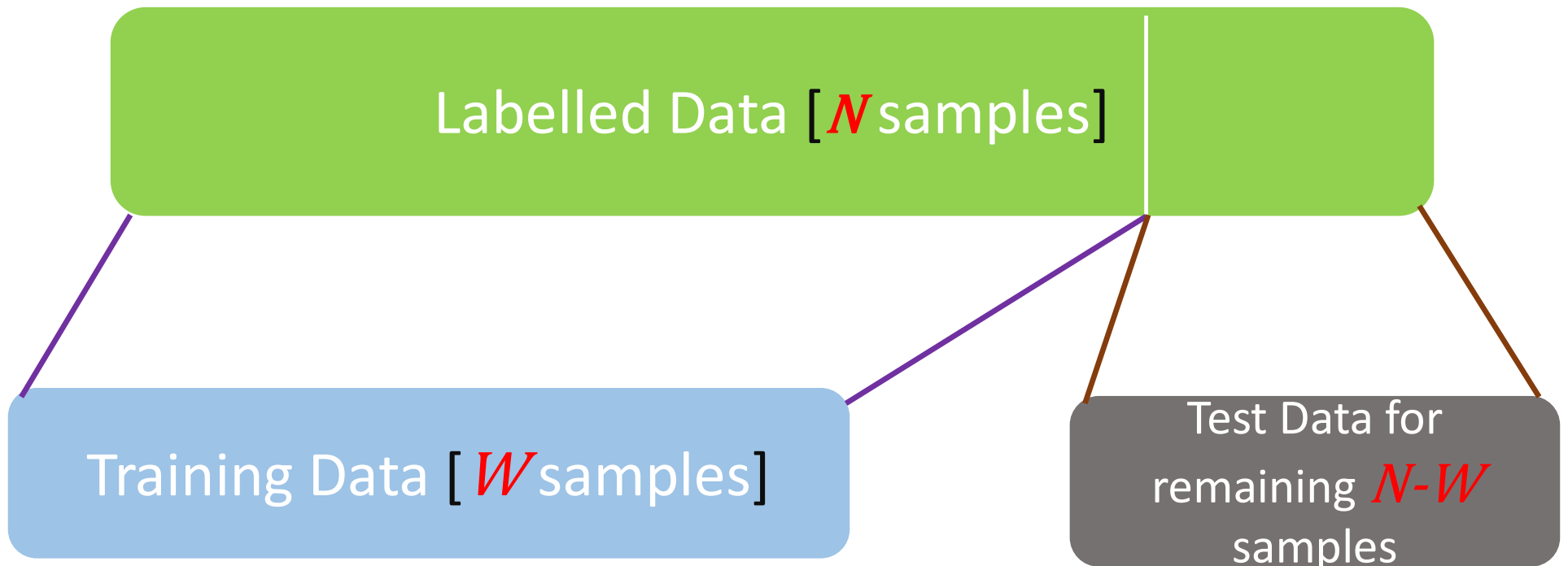
Overfitting vs Generalization

- We try to fit the data with different models in various orders of complexity



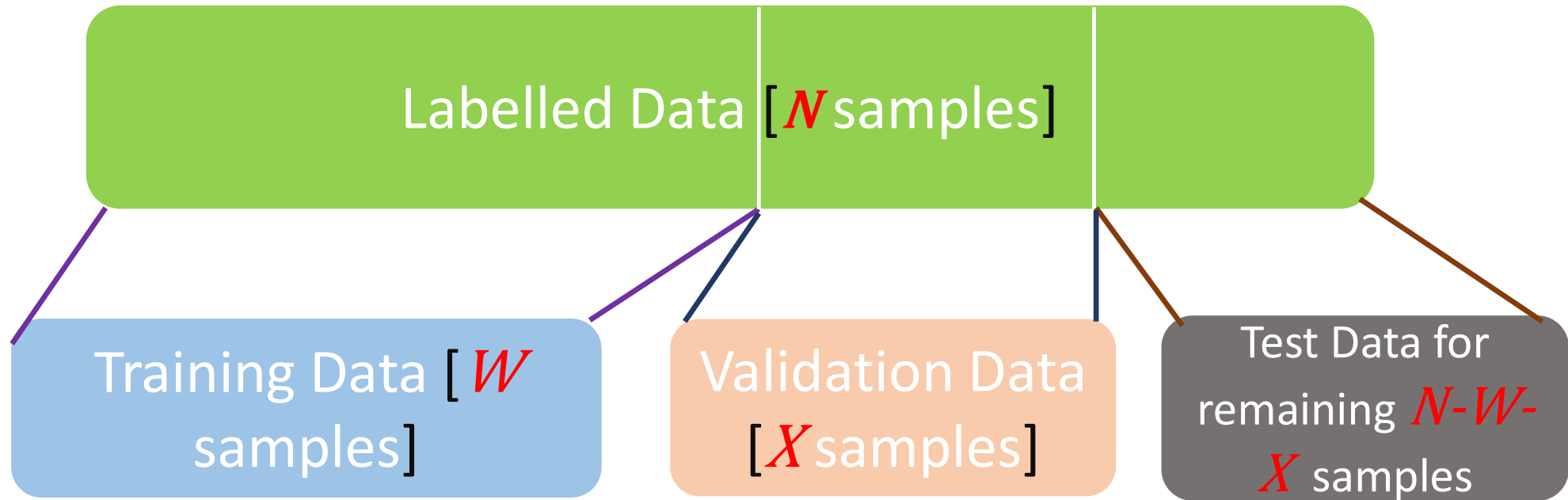
- Which of the above model will perform best on the unseen test data?

ML Based on Training-Testing Data



- Take care to not leak information from Test Data into the Model with repeated testing

ML Based on Training - Validation - Testing Data



- The validation model is repeatedly used during development
- The test data is used once for the final prediction

