MONASH
INFORMATION
TECHNOLOGY

Introduction to Machine Learning

This unit is about

1. **Volume** ➔ Topics 1, 2, 3, 4
   - How to process Big Data Volume?

2. **Complexity** ➔ Topics 5, 6, 7, 8
   - How to apply machine learning algorithms to every aspect of Big Data?

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1. **Volume** ➔ Topics 1, 2, 3, 4
   – How to process Big Data Volume?

2. **Complexity** ➔ Topics 5, 6, 7, 8
   – How to apply machine learning algorithms to every aspect of Big Data?

This week

- What is Machine Learning?
- Machine Learning Basics
- Types of Machine Learning
- Featurization

What is Machine Learning?

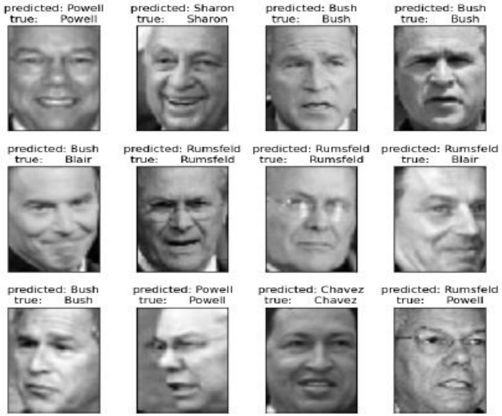
A primary school example: Predict the next number
1,2,3,4,?
1,2,3,4,1,2,3,4,?

1. Learn a model/pattern from data
2. The quality of your model is based on your data quality

What is Machine Learning?

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E", (Tom Mitchell, 1997)

Face recognition



Experience E	Task T	Performance P
databases of thousands of known faces	given a new photo, recognise the name of the face	how accurate the recognition is

Examples

Watson, Ken Jennings, and Brad Rutter in their *Jeopardy!* exhibition match.

Detecting Spam Emails

Detect credit card fraud

Experience E	Task T	Performance P
databases of millions of question-answer pairs	given an question, find the best answer	how accurate the answer is
Examples of spam emails and not-spam email	To assign a label “spam” or “not-spam” to an email	how accurate spam email can be detected
Data collected for credit-card transactions deemed as fraud and not-fraud	To assign a label ‘fraud’ or “not fraud” to a given credit-card transaction	how accurate a credit-card fraud transaction can be detected.

Elements of machine learning

① Data

feature $x \in \mathbb{R}^d$
label $y \in Y$

Dataset $\mathcal{D} = \{x_i, y_i\}_{i=1}^{n}$

Data processing

feature extraction,
feature selection,
feature transformation,
feature reduction,
feature scaling, feature normalization

② Model

Supervised: $f_\theta : X \to Y$
X is data space
Y is label space
θ: model parameter

Predictive Model $Y = f_\theta(X)$

e.g. Linear regression, decision tree

Model Learning (Training/Estimation)

- Find an optimal model f_θ (by estimating model parameters θ) using training data
- Based on loss/objective function (e.g., minimize error between true and predicted labels)

③ Assessment

How well is f_θ doing w.r.t data $\mathcal{D}$?

Model Testing $\hat{y} = f_\theta(x_{test})$

- Test the learned model in predicting unseen test data
- Performance metrics to assess model accuracy

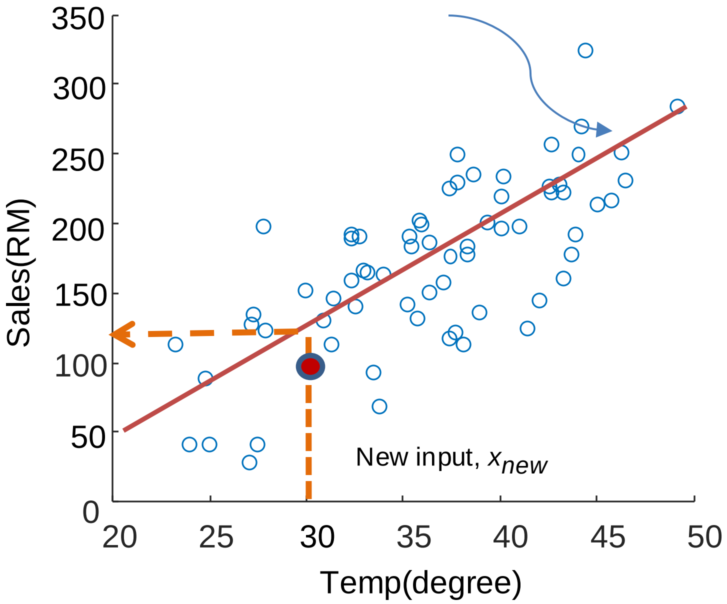
Illustration: Linear Regression model

Problem: Predict ice cream sales given temperature

Data

Day	Temp	Sales
i	x_i	y_i
1	36	200
2	31	100
3	24	50
⋮	⋮	
100	38	250

$f(x) = 50 + 2.5x$



Predictive Model:

- What is good model *f*(.) to maps *x* to *y*?

$$f(x) = \theta_o + \theta_1 x$$

Model Learning/Estimation:

- How to choose parameters θ_o, θ_1 ?
  - ❑ Define loss function
  - ❑ Estimate using learning algorithm

Estimated parameters: $\theta_o = 50, \ \theta_1 = 2.5$

Prediction:

- Given new input, predict *y* with learned model $\hat{y} = f(x_{new}) = \theta_o + \theta_1 x_{new}$

Predicted output $\hat{y} = 50 + 2.5(30) = 125$

Assessment: $\text{error}(\hat{y}, y) = (\hat{y} - y)^2$

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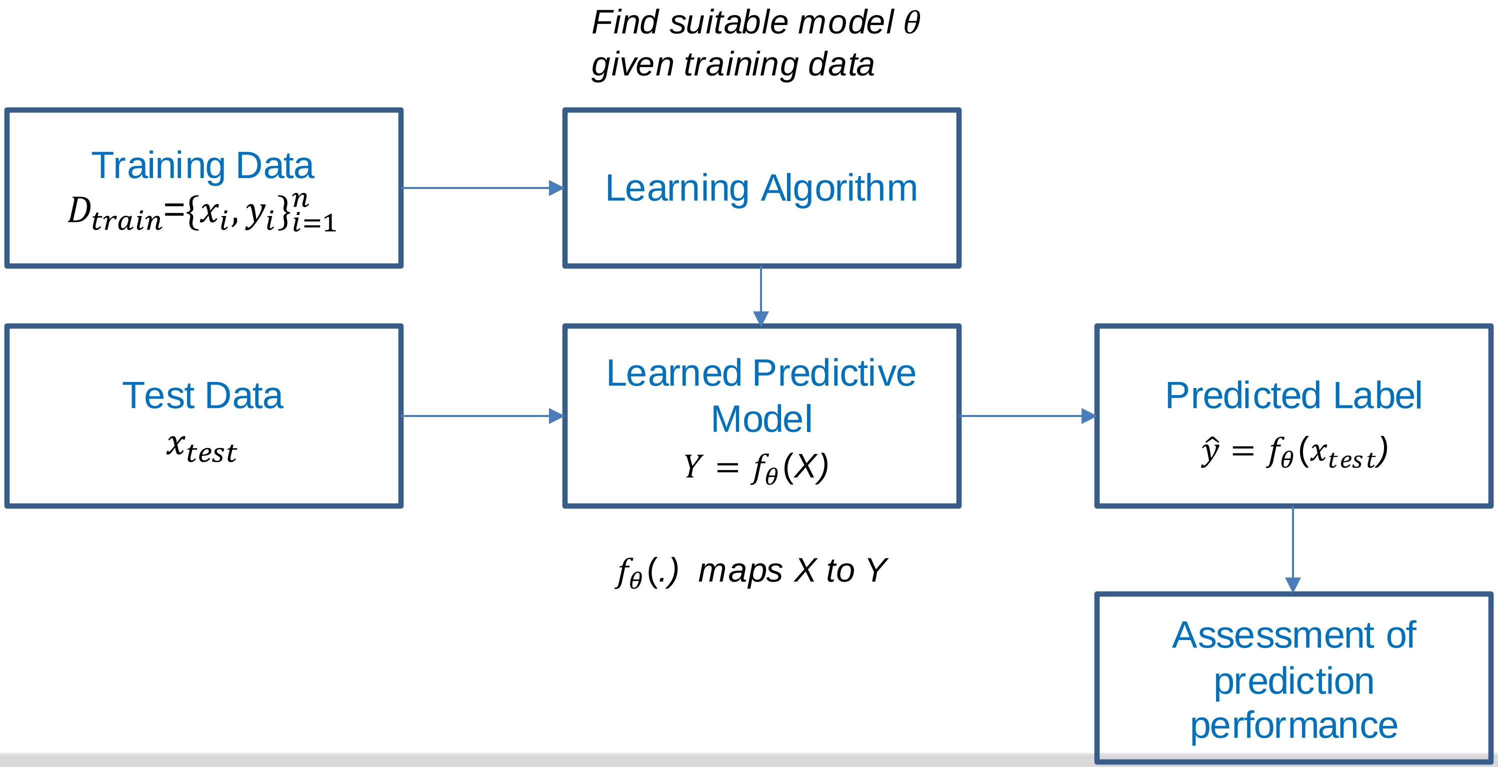
Overview of machine learning



Data

Features: x_i

- a set of attributes, each is usually in form of a vector or matrix.
- E.g., represent each email (data point) into a bag-of-word vector (feature); or a face photo into a real-valued matrix.

Labels: y_i

- values, categories, classes, assigned to data points.
- E.g., 0 = non-spam, 1 = spam,

Data points (aka instances, samples) $\{x_i\}$ or $\{x_i, y_i\}$

- these are items or instances of data used for training and evaluating ML models.
- E.g., labelled emails in spam detection; transaction data in credit card fraud detection; a photo in face recognition.

data points ... $\{x_i\}$

data points with labels ... $\{x_i, y_i\}$

$$\begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots. & 0 \\ & & \dots & \\ 0 & 0 & \dots & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 2 & \dots. & 0 \\ & & \dots & \\ 0 & 0 & \dots & 1 \end{bmatrix}$$

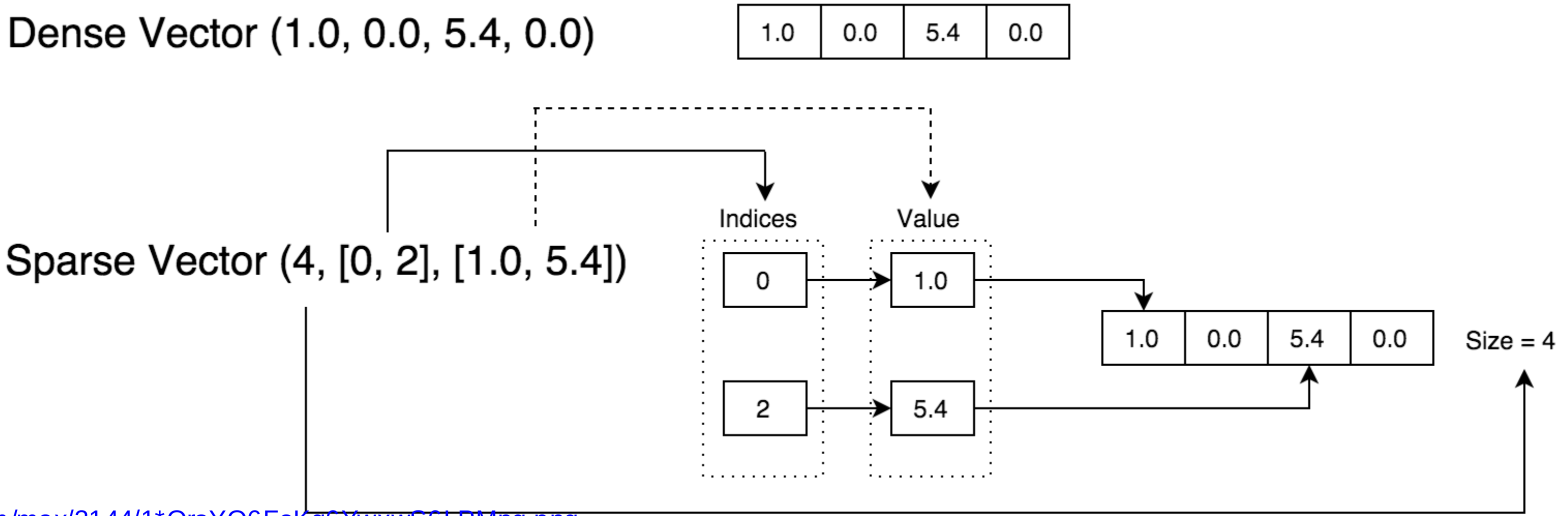
x_i features

y_i 0 = Jack, 1 = John, etc ...

Dataset with n samples: $\mathcal{D} = \{x_i, y_i\}_{i=1}^{n}$

Machine Learning: Data Types

- **Vector**
  - A mathematical vector.
  - *dense vectors*, where every entry is stored, and
  - *sparse vectors*, where only the nonzero entries are stored to save space.



https://miro.medium.com/max/3144/1*OrsYQ6FoKq6YwxwS6LPMpg.png

Modelling

What is a model?

A specification of a mathematical (or probabilistic) relationship that exist between multiple different variables

Cost of fuel *(y)* = demand of oil *(X_1)* / supply of oil *(X_2)*

Machine Learning Basics

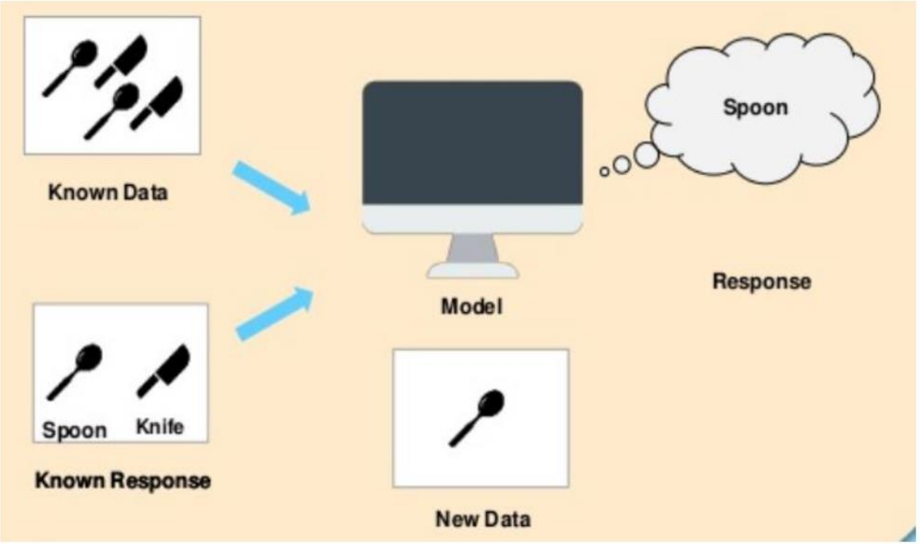
- All learning algorithms require defining a set of *features* for each item, which will be fed into the learning function.
  - *For example, for an email, some features might include the server it comes from, or the number of mentions of the word free, or the color of the text.*
- In many cases, defining the right features is the most challenging part of using machine learning.
  - *For example, in a product recommendation task, simply adding another feature (e.g., realizing that which book you should recommend to a user might also depend on which movies she's watched) could give a large improvement in results.*

Machine Learning Fundamentals

- Supervised and Unsupervised Models
- Bias and Variance
- Underfitting and Overfitting

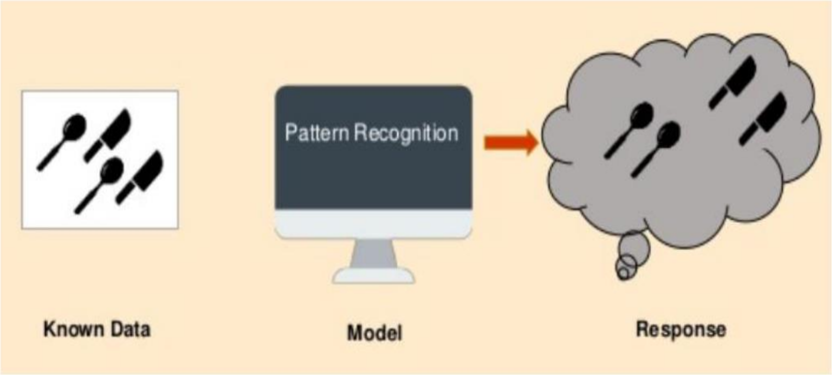
Model: Types of Model Learning

Supervised



Learn a model from labelled training data

Unsupervised



Explore the underlying structure of unlabeled data

https://www.simplilearn.com/tutorials/machine-learning-tutorial/supervised-and-unsupervised-learning

Types of Model Learning: Supervised

- Goal: Learn a function from labelled training data to predict the output label(s) given a new unlabelled input.

- Training data consists of input features and output information (labels)

- Two types of supervised learning:
  - ❑ Classification
  - ❑ Regression

Data: $(x_1, y_1), \ldots, (x_n, y_n)$

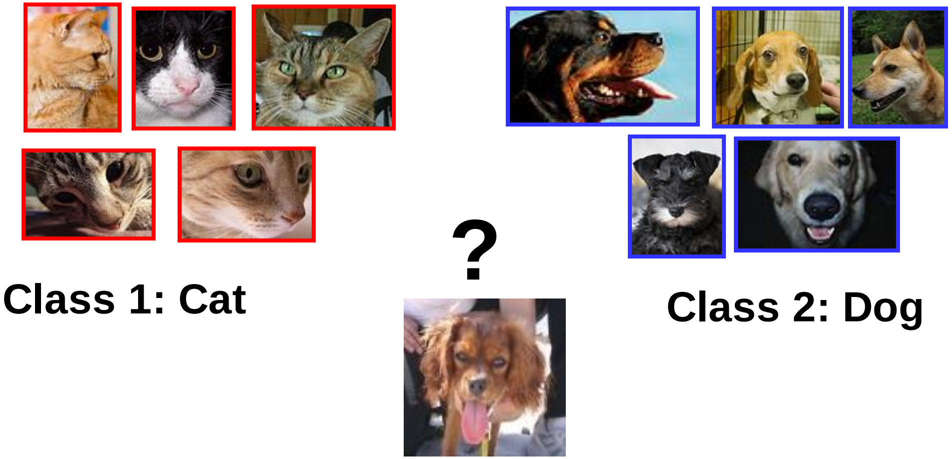
Function: $f: X \rightarrow Y$

x = feature
y = a discrete label (classification),
y = a continuous value (regression)

Supervised Machine Learning: Classification

Classification problem: To separate inputs into a discrete set of classes or labels.

- ❑ Binary classification
- ❑ Multinomial (Multi-class) classification



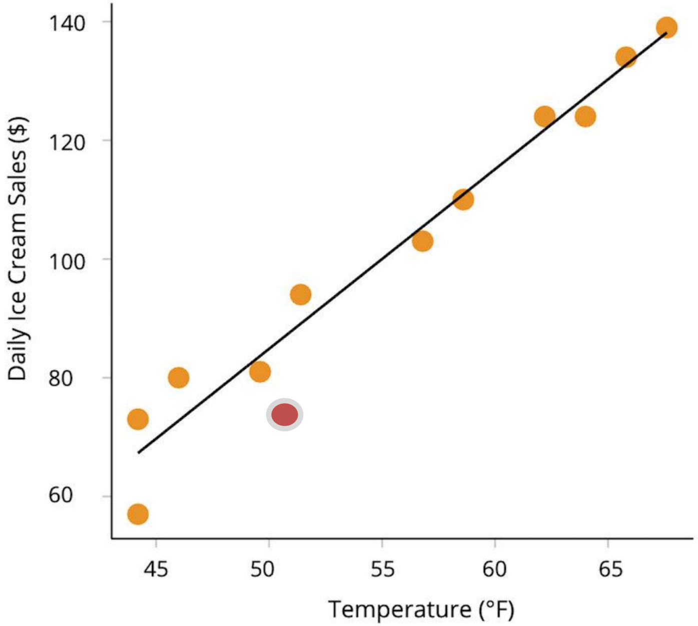
Binary classification example: dog or not dog

Supervised Machine Learning: Classification

Multinomial classification example: Australian shepherd, golden retriever, or poodle

Supervised Machine Learning: Regression

- A regression problem is when the output variable is a real value, such as “dollars” or “weight”.



Regression example: predicting ice cream sales based on temperature

Supervised Machine Learning in Apache Spark

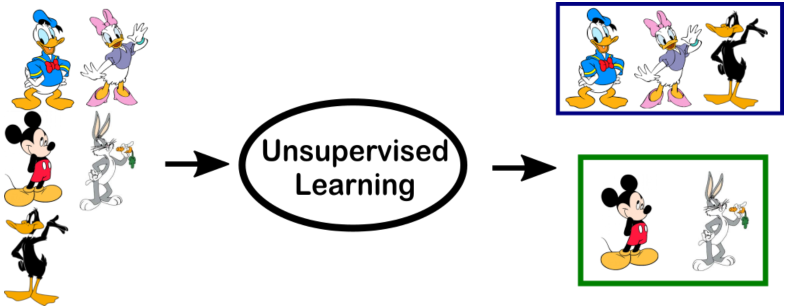
Algorithm	Typical usage
Linear regression	Regression
Logistic regression	Classification (we know, it has regression in the name!)
Decision trees	Both
Gradient boosted trees	Both
Random forests	Both
Naive Bayes	Classification
Support vector machines (SVMs)	Classification

Types of Model Learning: Unsupervised

- Goal: Explore the underlying structure of the data to extract meaningful information. without guidance of known output info.

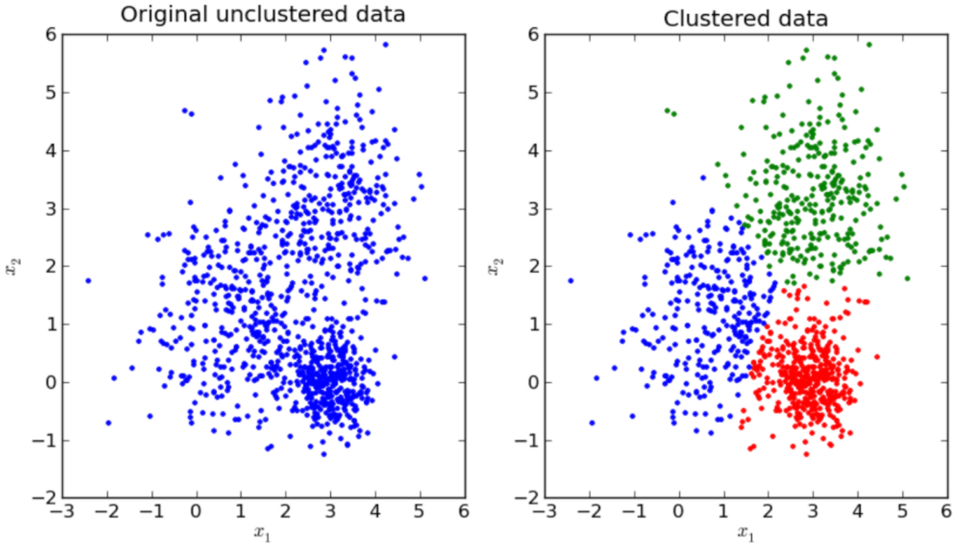
- Deals with unlabelled data (no output labels)

- Two types of unsupervised learning:
  - ❑ Clustering
  - ❑ Association



Unsupervised Machine Learning: Clustering

- Clustering problem: Divide data into clusters which are similar between them and are dissimilar to the data belonging to another cluster.
- Where you want to discover the inherent groupings in the data, eg. grouping customers by purchasing behaviour

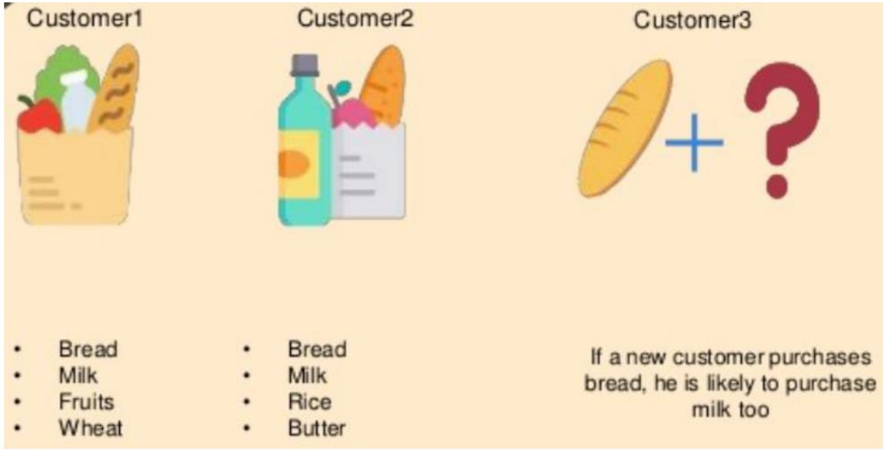


x1: number of items purchased
x2: averaged prices of items purchased

Clustering example

Unsupervised Machine Learning: Association

- Association rule learning problem: Discover the probability of the co-occurrence (association) between items in a large dataset
- Where you want to discover rules that describe large portions of your data, e.g., people who buy X also tend to buy Y.



Unsupervised Machine Learning: Association

According to a McKinsey study, 35% of what consumers purchase on Amazon and 75% of what they watch on Netflix is driven by machine learning–based product recommendations.

Unsupervised Machine Learning in Apache Spark

- *k*-means clustering,
- Latent Dirichlet Allocation (LDA), and
- Gaussian mixture models.

Machine Learning: Assessment

How to prepare the data?

- Train-Test split
- K-fold cross-validation

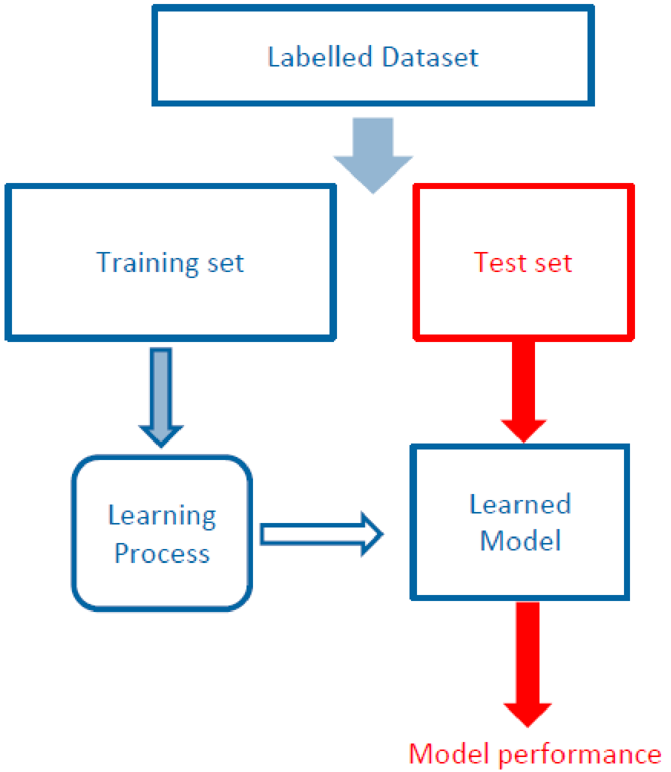
How to measure performance?

- TP, FP, TN, FN, confusion matrix
- Accuracy, Recall, Precision, F1-score

Day	Temp	Sales
i	x_i	y_i
1	36	200
2	31	100
3	24	50
⋮	⋮	
100	38	250

80% - Train set

20% - Test set



Machine Learning: Performance Metrics

Example: Email Spam Detection (binary)

In test set: 10 spam, 20 non-spam

Positive = spam, Negative: non-spam

True labels

Predicted labels

	SPAM (1)	NON-SPAM (0)
SPAM (1)	7	5
NON-SPAM (0)	3	15

$$\text{Accuracy} = \frac{\#\, correctly\ classified\ samples}{\#\, test\ samples} \text{ x } 100\%$$

$$= \frac{7+15}{10+20} \text{ x } 100\% = 70\%$$

Confusion matrix

		actual class: positive	actual class: negative
predicted class	positive	true positives (TP)	false positives (FP)
	negative	false negatives (FN)	true negatives (TN)

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

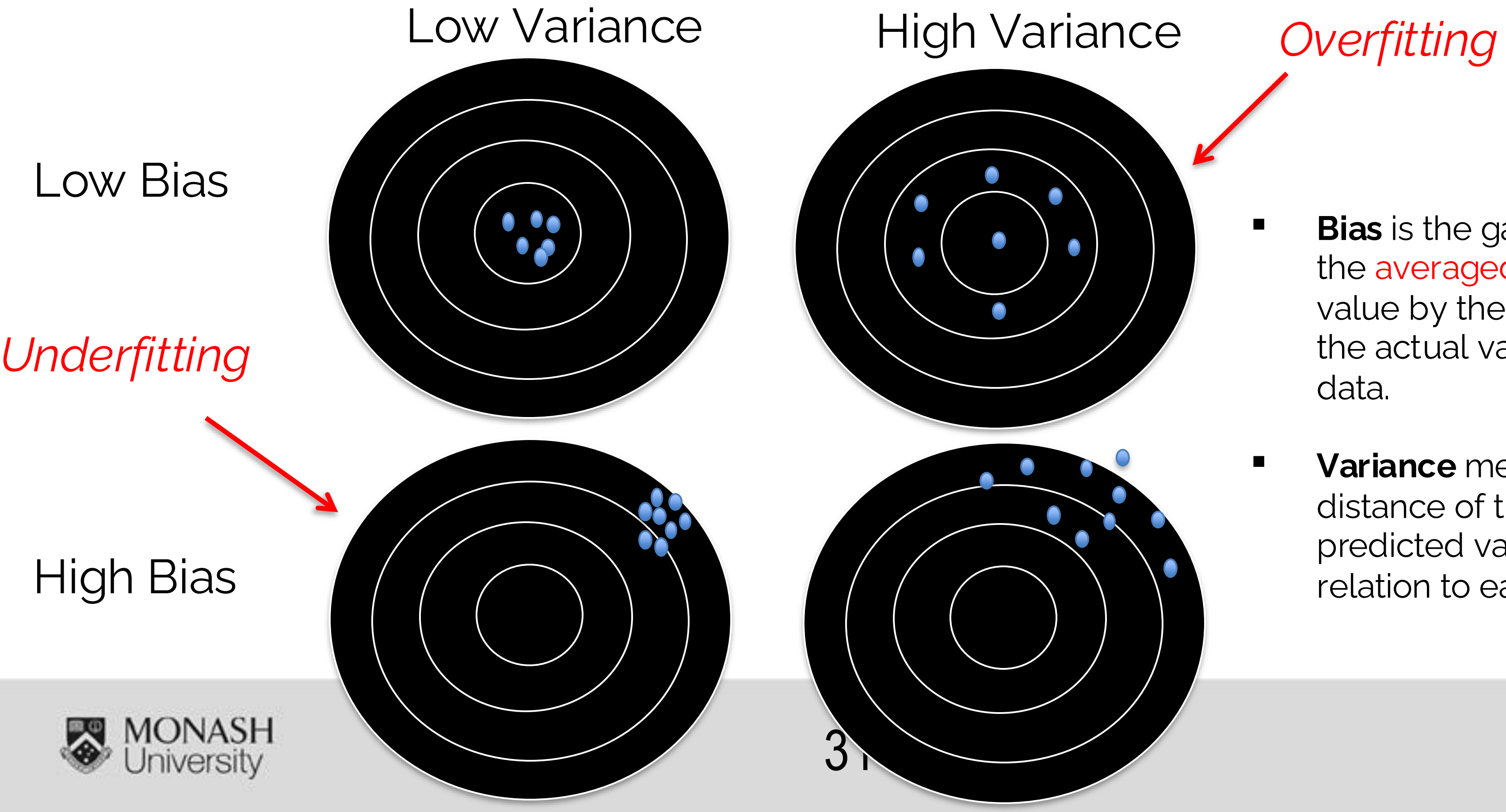
$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

Precision - number of positive class predictions that actually belong to the positive class.
Recall (sensitivity) - number of positive class predictions made out of all positive testing examples.

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Machine Learning: Bias and Variance



- **Bias** is the gap between the averaged predicted value by the model and the actual value of the data.
- **Variance** measures the distance of the predicted values in relation to each other.

Machine Learning: Overfitting and Underfitting

- **Overfitting** (high variance, low bias) is a model that performs well on the training data but generalizes poorly to any new data.

- **Underfitting** (low variance, high bias) is an overly simple model that does not perform well even on the training data.

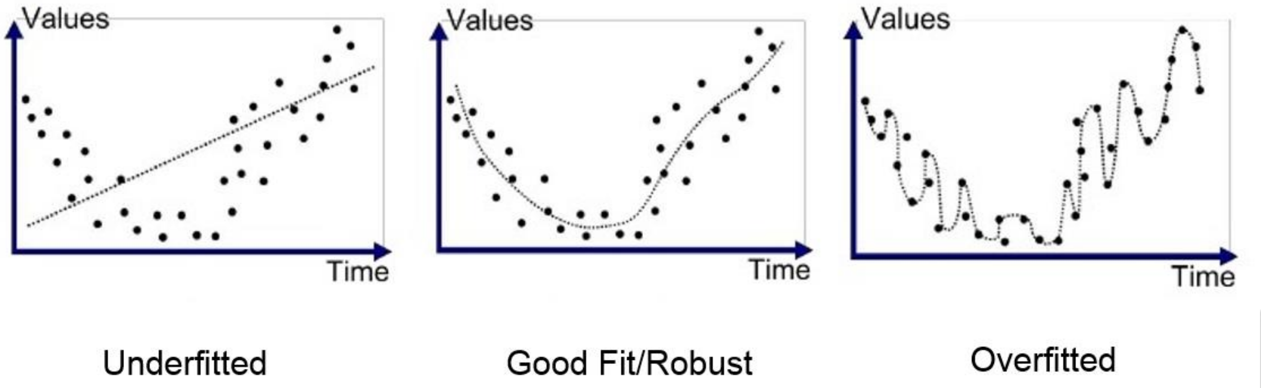


Figure from https://medium.com/greyatom/what-is-underfitting-and-overfitting-in-machine-learning-and-how-to-deal-with-it-6803a989c76

Question from student:

How to prevent overfitting?

- Preventing Overfitting
  - Train with more data

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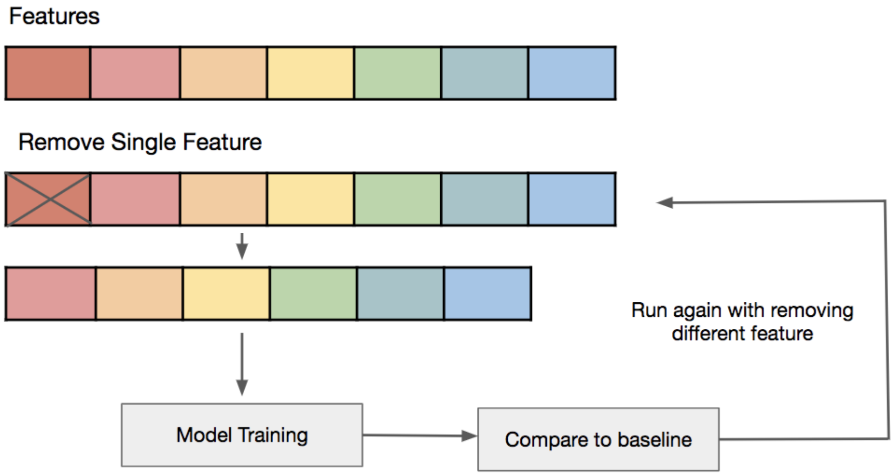
How to prevent overfitting?

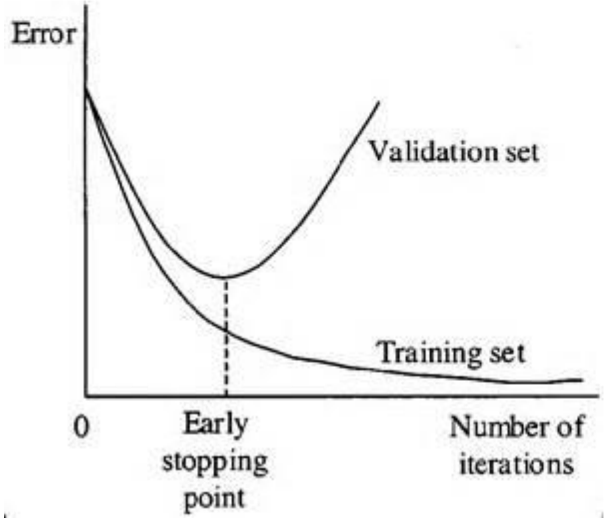
- Preventing Overfitting
  - Train with more data
  - Remove features



Question from student:

How to prevent overfitting?

- **Preventing Overfitting**
  - Train with more data
  - Remove features
  - Early stopping



Question from student:

How to prevent overfitting?

- **Preventing Overfitting**
  - Train with more data
  - Remove features
  - Early stopping
  - Cross validation

K-Fold Cross-Validation