

# SIT720 Machine Learning

## 1.1

### Week 1

#### What is an Algorithm?

An algorithm is a well-defined sequence of instructions used to solve a specific problem or perform a task.

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#### Real-World Applications of Machine Learning

Machine learning uses computer algorithms that enable systems to learn from data and improve over time. Applications include:

- **Robotics** – Autonomous navigation and control
  - **Computer Vision** – Image and object recognition
  - **Board Games** – AI playing strategic games like Chess and Go
  - **Voice Recognition** – Speech-to-text and digital assistants
  - **Digit Recognition** – Reading handwritten numbers, such as postal codes
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#### Steps in a Machine Learning Workflow

1. **Data Manipulation** – Collecting, cleaning, and preparing data
  2. **Analytics** – Applying algorithms to analyze patterns or make predictions
  3. **Evaluation and Visualization** – Measuring model performance and interpreting results through visual tools
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#### Types of Machine Learning

##### 1. Supervised Learning

Involves training a model on labeled data. Two main types:

- **Regression** – Predicts continuous values (e.g., sales prediction)
- **Classification** – Predicts discrete categories (e.g., spam detection)

## 2. Unsupervised Learning

Used with unlabeled data to uncover hidden patterns. Key methods:

- **Clustering** – Grouping similar data points
- **Density Estimation** – Modeling the distribution of data
- **Factor Analysis** – Identifying underlying relationships in data

## 3. Reinforcement Learning

An agent learns optimal actions by interacting with an environment and receiving feedback (rewards or penalties). This approach mimics learning through trial and error.

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## Model Evaluation

Model evaluation is essential to determine how well a machine learning model performs on unseen (test) data. Common metrics include accuracy, precision, recall, and F1-score.

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## Model Selection

Model selection involves identifying the best-performing algorithm or hypothesis for a given problem. This includes testing different models and tuning parameters to achieve the best balance between bias and variance.

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## Python Programming Basics

- **Types of Variables:**

Python supports various data types such as integers ( `int` ), floating-point numbers ( `float` ), strings ( `str` ), and booleans ( `bool` ). Variables are dynamically typed.

- **Branching and Decisions:**

Use `if`, `elif`, and `else` statements to make decisions based on conditions.  
Example:

```
if age > 18:
    print("Adult")
else:
    print("Minor")
```

- **Iterations:**

Python supports loops to repeat actions:

- `for` loop – Iterates over sequences like lists or ranges
- `while` loop – Repeats as long as a condition is true

Example:

```
for i in range(5):  
    print(i)
```

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## Week 2

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### 1. Feature Vectors and Matrices

- In machine learning, **feature vectors** are ordered lists of numerical values representing an object's attributes.
- A **matrix** is a collection of multiple feature vectors, typically used as input data where rows represent instances and columns represent features.

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### 2. Probability Concepts

Understanding basic probability is essential for many machine learning algorithms and models.

#### Random Experiment & Event

- A **random experiment** is a process that leads to uncertain outcomes (e.g., flipping a coin).
- An **event** is a specific outcome or a set of outcomes from the experiment (e.g., getting heads).

#### Joint Probability

- The probability of two events occurring simultaneously.
- Example:  $P(A \text{ and } B)$

#### Conditional Probability

- The probability of event A occurring given that event B has already occurred.
- Written as:  $P(A | B)$

## Bayes' Rule

- A fundamental theorem that allows us to update probabilities based on new evidence.
- Formula:

$$P(A | B) = P(B | A) \cdot P(A) / P(B)$$

## Random Variable

- A variable that takes numerical values determined by the outcome of a random experiment.
- Can be **discrete** (e.g., number of students) or **continuous** (e.g., height, temperature).

## Distribution of Random Variables

- Describes the probabilities of different outcomes for a random variable.
  - Common types include **Uniform**, **Normal (Gaussian)**, and **Binomial** distributions.
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## 3. Data Wrangling

Data wrangling involves cleaning and transforming raw data into a usable format for analysis or machine learning.

### Missing Value Replacement

- Techniques include:
  - Mean/median/mode imputation
  - Forward/backward fill
  - Dropping rows/columns
  - Predictive models for imputation

### Scaling or Normalisation

- Converts features to a standard scale.
- Methods:
  - **Min-Max Scaling**: Scales values to a 0–1 range.
  - **Standardisation (Z-score Normalisation)**: Transforms data to have a mean of 0 and a standard deviation of 1.

## Non-Numeric Data Encoding

- Converts categorical data into numerical form for model processing.
- Common methods:
  - **Label Encoding** – Assigns a unique number to each category.
  - **One-Hot Encoding** – Creates binary columns for each category.

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## 1.2 Summary of Reading List

- <https://d2l.deakin.edu.au/d2l/le/content/1734011/viewContent/8095182/View>
- <https://d2l.deakin.edu.au/d2l/le/content/1734011/viewContent/8095321/View>
- <https://d2l.deakin.edu.au/d2l/le/content/1734011/viewContent/8095323/View>

## 1.3 Learning Reflection

This week deepened my understanding of the statistical foundations behind machine learning. I explored key probability concepts such as **random experiments**, **joint and conditional probability**, and **Bayes' Rule**, which helped me see how models handle uncertainty and update predictions with new data.


I also learned about **random variables** and their **distributions**, which are important when selecting or evaluating models. Understanding **feature vectors and matrices** gave me a better picture of how data is structured in machine learning workflows.

In the practical sessions, I worked on **data wrangling** techniques including handling **missing values**, **normalisation**, and **encoding categorical data**. Applying methods like **mean imputation**, **min-max scaling**, and **one-hot encoding** showed me how vital clean, well-prepared data is for model accuracy.

Overall, this week's content has strengthened my confidence in handling data and applying statistical thinking to machine learning problems.


# 1.4 Quiz Results

## Quiz Submissions - Week-1 quiz ▾

 Add to ePortfolio

Individual Attempts	Grade
<a href="#">Attempt 1</a>	<div><div></div> 10 / 10 - 100 %</div>
Overall Grade (highest attempt):	<div><div></div> 10 / 10 - 100 %</div>

## Quiz Submissions - Week 2 quiz ▾

 Add to ePortfolio

Individual Attempts	Grade
<a href="#">Attempt 1</a>	<div><div></div> 9 / 10 - 90 %</div>
Overall Grade (highest attempt):	<div><div></div> 9 / 10 - 90 %</div>