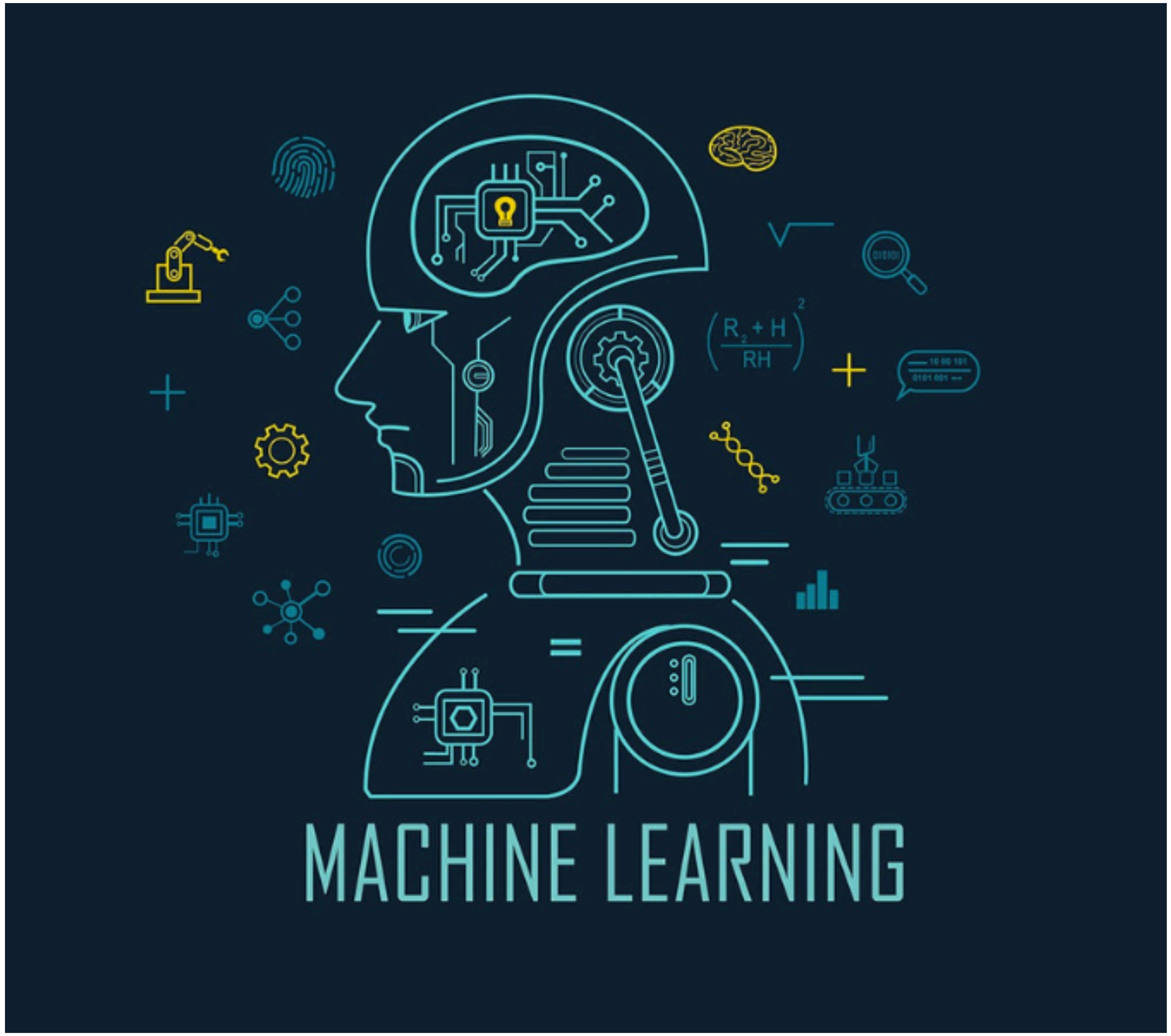
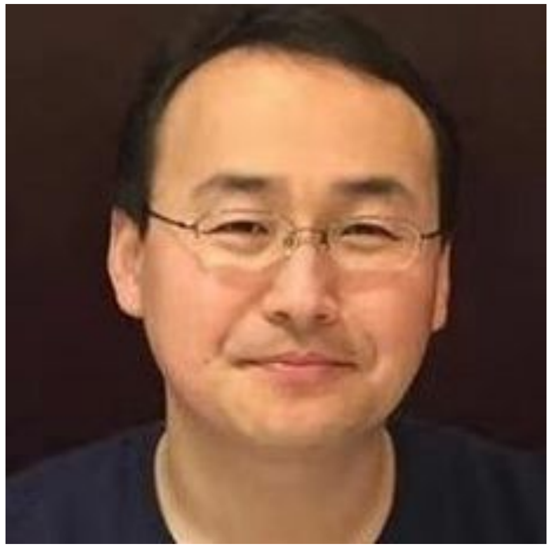


Module Introduction

Leandro L. Minku

Module Lecturers

Leandro Minku



Jian Liu

Syed Fawad Hussain (Dubai)

Module Teaching Assistants

Rongqi Hong

Ziwei Yin

Outline

- Module Organisation
- Motivation to Machine Learning
- Machine Learning Definitions
- Supervised Learning
- What This Module Will Cover
- Other Types of Learning
- Relationships With Other Fields

Lectures and Tutorials

- Sessions:
  - Monday 11:00
  - Thursday 13:00 (usually a tutorial)
  - Friday 10:00
- Location of all sessions: Education - EDUC-Vaughan Jeffreys (135)
- Canvas page: information about topic of lectures, slides, reading materials, exercises, assignments, etc.
  - Informs which day of the week will be a tutorial.
- Notifications: please turn notifications on, as any important announcement about the module will be made via Canvas.

Recommended Study Pattern

- Attend the lecture.
- Do the essential reading.
- Each topic has a list of exercises.
  - You should attempt these exercises before the tutorial.
- Tutorial polls: I'll release polls to check what exercises or topics you would most like us to go through during the tutorials. The deadline to fill in these polls will usually be Tuesday 1pm.
- Do any recommended or optional reading.

Maths Requirements

- Machine learning is a discipline that heavily relies on maths, including calculus, linear algebra and probabilities.
- Refresher on basic concepts available on Canvas.

Assessment

- Graded quizzes (20% of marks):
    - Two Summative Canvas quizzes, worth 10% each.
    - Timed for 1h max.
        - Students with reasonable adjustment plans will have their time adjusted accordingly.
    - Can start at any time between the release and due (deadline) times.
    - Your assignment will be automatically submitted at the due time, even if you started less than 1h before.
    - Deadline is **strict** (mark of zero if not submitted by the deadline).
        - Please email welfare if your assignment is affected by welfare issues.
    - Marks and feedback released 10 working days after the deadline.
- Exam (80% of marks).
    - Main summer assessment period (May/June).
        - Exact date will be released centrally by the University.

Office Hours

- Room UG39
- Thursday 14:00-14:50
- Thursday 17:00-17:50

Microsoft Teams

- For Q&A throughout the week.
- MS Teams enables other students to gain from the answers.
- MS Teams enables peer support — students are also welcome to answer each other's questions!
- There is a channel for the content covered in each week, except for Week 6.
- We encourage you not to send questions by email unless you wish them to be confidential.

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Health / Medical Data

Financial Data

Fraud Data

Video Surveillance Data

Software Usage Data

Speech Data

Examples of Machine Learning Problems

Breast Cancer Prediction:

- Predict whether a person does or does not have breast cancer.
- Based on lump thickness, uniformity of cell size, cell thickness, etc.
- Designing a rule manually can be challenging.
- Machine learning can be used to automatically learn models based on data describing previous patients.

Examples of Machine Learning Problems

House Price Estimation:

- Estimation of the price of a house.
- Based on location, size, number of rooms, garage, etc.
- Designing a rule manually can be challenging and the rule may need to change over time.
- Machine learning can be used to automatically learn models based on data describing recently sold houses.

What is Machine Learning?

- Arthur Samuel (1959): Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed.
- Tom Mitchell (1998): A computer programme is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.
- Kevin Murphy (2012): The goal of machine learning is to develop methods that can automatically detect patterns in data, and then to use the uncovered patterns to predict future data or other outcomes of interest.
- Oxford Languages Dictionary: the use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyse and draw inferences from patterns in data.

Artificial Intelligence

- Russell and Norvig (2010) definition:
    - AI is the area of Computer Science which studies rational agents.
    - Rational agents are computer programs that perceive their environment and take actions that maximise their chances of achieving the best [expected] outcome.
- Machine learning can be seen as a field within AI.

Supervised Learning

Learns a mapping from inputs $\mathbf{x} = (x_1, \ldots, x_d)^T \in \mathcal{X}$

to outputs $y \in \mathcal{Y}$,

given a training set of input-output pairs
$\mathcal{T} = \{(\mathbf{x}^{(1)}, y^{(1)}), (\mathbf{x}^{(2)}, y^{(2)}), \cdots, (\mathbf{x}^{(N)}, y^{(N)})\}$.

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{pmatrix} \begin{array}{l} \longrightarrow \text{size} \\ \longrightarrow \text{\#rooms} \\ \\ \longrightarrow \text{location} \end{array}$$

$$y \longrightarrow \text{price}$$

Supervised Learning

Learns a mapping from inputs $\mathbf{x} = (x_1, \ldots, x_d)^T \in \mathcal{X}$

to outputs $y \in \mathcal{Y}$,

given a training set of input-output pairs

$$\mathcal{T} = \{(\mathbf{x}^{(1)}, y^{(1)}), (\mathbf{x}^{(2)}, y^{(2)}), \cdots, (\mathbf{x}^{(N)}, y^{(N)})\}.$$

$$\mathcal{T} = \{(\mathbf{x}^{(i)}, y^{(i)})\}_{i=1}^{N}$$

Design matrix: $\mathbf{X} = \begin{pmatrix} x_1^{(1)}, x_2^{(1)}, & \cdots, & x_d^{(1)} \\ x_1^{(2)}, x_2^{(2)}, & \cdots, & x_d^{(2)} \\ \vdots \quad \vdots & \ddots & \vdots \\ x_1^{(N)}, x_2^{(N)}, & \cdots, & x_d^{(N)} \end{pmatrix}$

Vector of independent variables: $\mathbf{y} = \begin{pmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(N)} \end{pmatrix}$

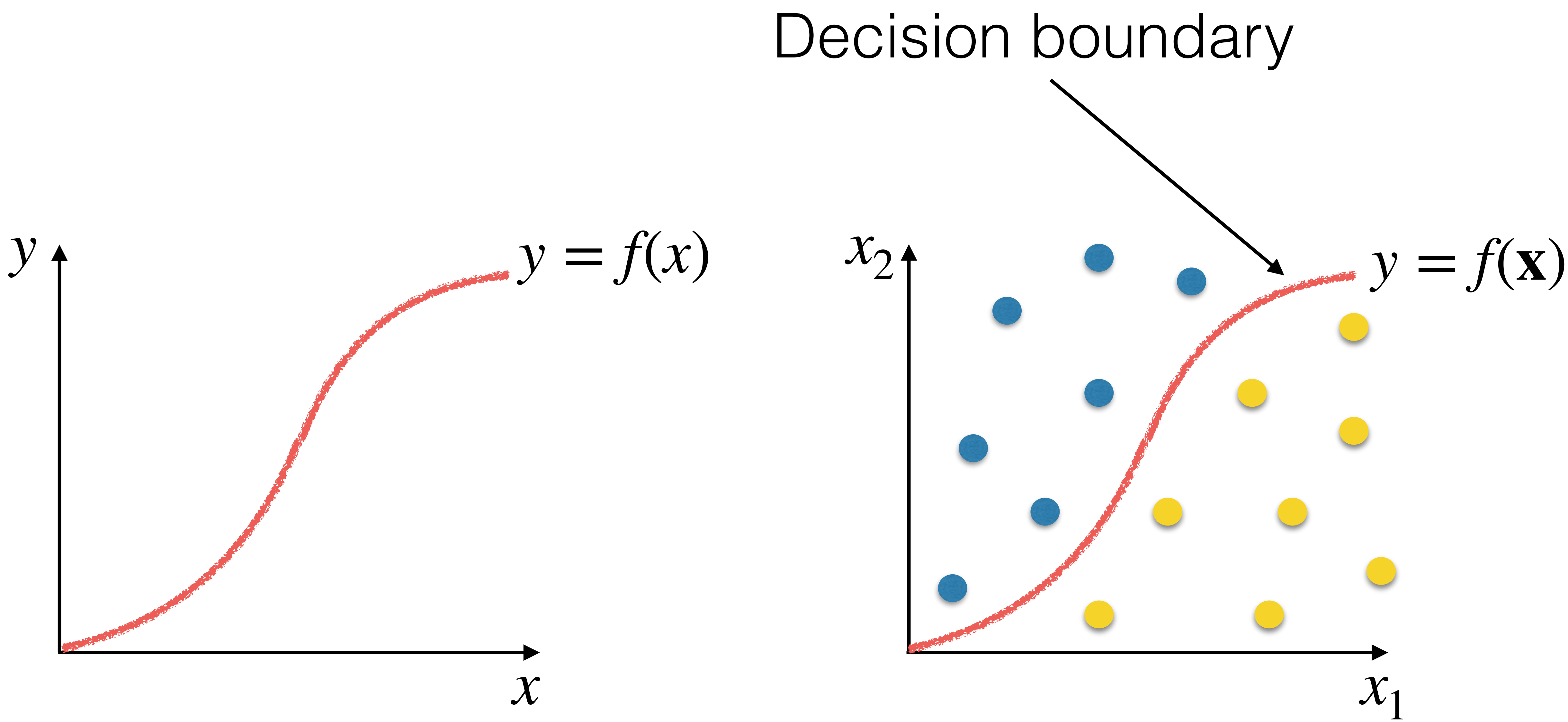
The Input Space $\mathcal{X}$

- d-dimensional space, where each dimension can usually be:
  - Numeric:
    - E.g., age, salary.
  - Ordinal:
    - E.g., expertise in {low, medium, high}.
  - Categorical:
    - E.g., car in {fiat, volkswagen, toyota}.
- Different dimensions may be of different types.
- Many machine learning approaches assume numeric inputs.
  - Relying on conversion from ordinal or categorical to numeric.
- Several machine learning approaches also accept vectorial inputs of ordinal or categorical types.
- Some machine learning approaches accept non-structured rather than vectorial inputs, e.g., trees, graphs, strings, etc.

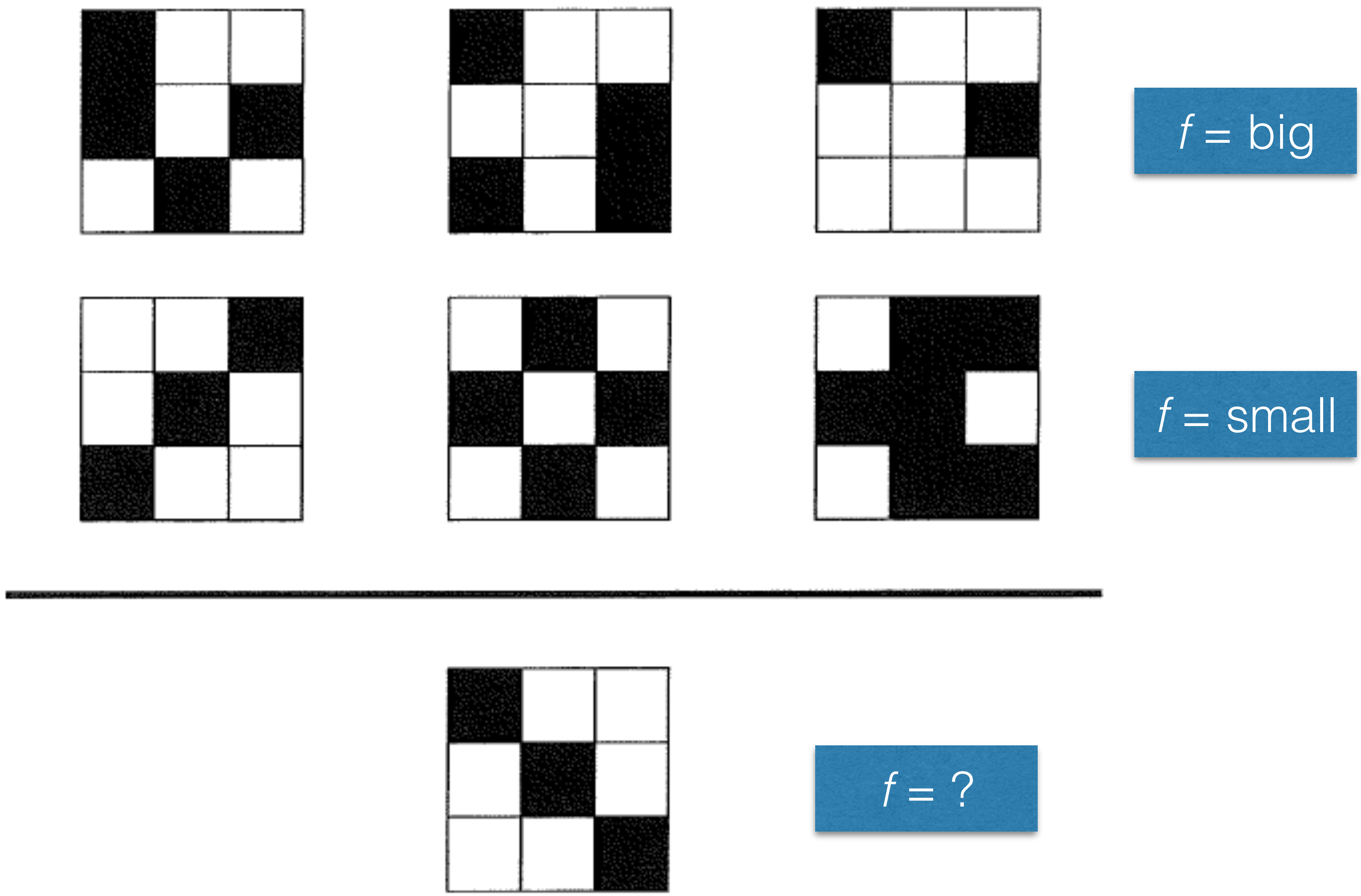
The Output Space $\mathscr{Y}$

- Regression: $\mathscr{Y} = R$.
- Classification: $\mathscr{Y}$ is a set of categories.
  - 2 categories: binary classification
  - >2 categories: multi-class classification

Regression vs Classification



Exercise



Learning faces a challenge: its goal is to find a mapping that generalises well to unseen examples, based on a limited set of training examples.

Is learning feasible?

Why? Under what conditions?

How to learn?

In This Module…

- You will learn supervised learning approaches.
- You'll gain an in depth understanding of how these approaches work.
- You'll obtain a solid theoretical foundation on when and why machine learning works.
- How theory informs practice, enabling you to apply machine learning in a more informed way.

Emphasis on depth and not breadth. Why?

Topics to Be Covered (Subject To Changes)

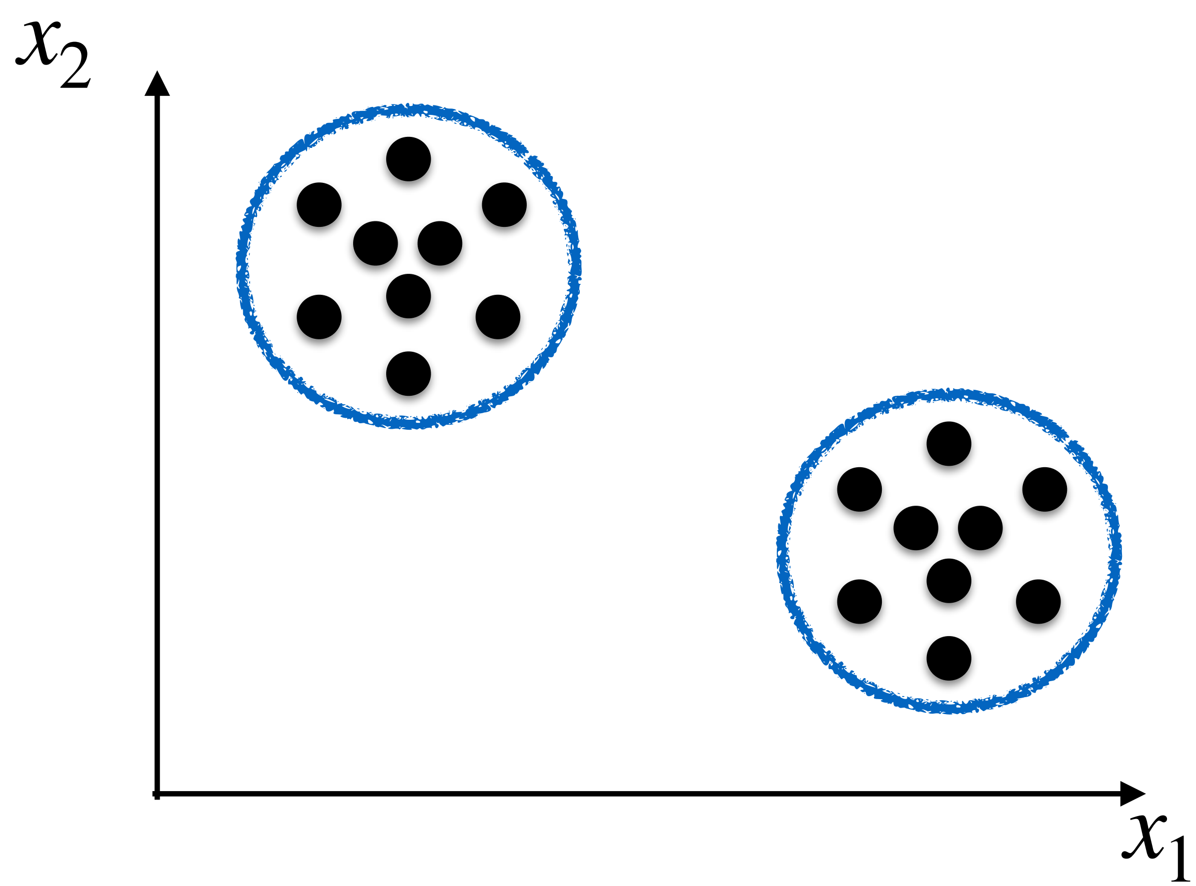
- Introduction / definition of learning
- Learning approaches for classification:
  - Logistic Regression
  - Nonlinear Transformations
  - Support Vector Machines
- Learning approaches for regression:
  - Linear Regression and its closed form solution
  - Support Vector Regression
- Kernels as similarity functions
  - Other kernel-based methods

Class Plan (Subject To Changes)

- Optimisation algorithms:
  - Gradient Descent and its weaknesses
  - Newton Raphson and Iterative Reweighted Least Squares
  - Sequential Minimal Optimisation
- Fundamentals:
  - Is learning feasible? Learning theory
  - Bias and variance
  - Generalisation, overfitting and regularisation
  - Validation and model selection

Other Types of Machine Learning

Unsupervised learning: given a data set containing examples of inputs $\mathscr{D} = \{\mathbf{x}^{(i)}\}_{i=1}^{N}$, find "interesting patterns" in the data.



Other Types of Machine Learning

Reinforcement learning: learn what actions in $\mathscr{A}$ are best to take given a certain state in $\mathscr{S}$ by trying them out and observing the corresponding rewards from the environment.

Relationship With Other Fields

Data Mining: practical field that focuses on finding patterns, correlations or anomalies in large datasets.

- Same as learning, but more focused on the application.

Statistics: uses a set of observations to uncover an underlying process.

- Same basic premise of learning from data.
- Typically focuses on approaches with more restrictive assumptions, which lend themselves to rigorous mathematical proofs.

Summary

- We’ve discussed what machine learning is and positioned it within AI and in relation to statistics and data mining.

- We’ve covered different types of learning and established the focus on supervised learning.

- We’ve seen that learning can be challenging given the limited amount of data and the goal of generalisation.

- We’ve gone through an overview of what the module will cover.

Equivalent Terms

- $\mathbf{x}$: input attribute, input feature, independent variable, input variable.
- y: output attribute, output variable, dependent variable, label (for classification).
- mapping: learned function, predictive model, classifier (for classification).
- Learning a model, training a model, building a model.
- $\mathcal{T}$: set of training examples, training data.
- $(\mathbf{x}, y)$: example, observation, data point, instance (more frequently used for examples with unknown outputs).
- Different people and books will use different notations!

Further Reading

The reading materials can be found at the module's resource list and elsewhere on the web.

Essential reading: Abu-Mostafa et al.'s Learning from Data: A Short Course. Sections 1.1 (Problem Setup), 1.2 (Types of Learning).

Recommended reading: Bishop's Pattern Recognition and Machine Learning. Pages 1—4 (Introduction).

Optional reading: you may read the whole Chapter 1 of Abu-Mostafa's book if you are curious, though parts of this chapter will be covered only later on in the course.