Foundations of Machine Learning

Module 1: Introduction

Part B: Different types of learning

Sudeshna Sarkar

IIT Kharagpur

Module 1

1. Introduction
   a) Introduction
   b) **Different types of learning**
   c) Hypothesis space, Inductive Bias
   d) Evaluation, Training and test set, cross-validation
2. Linear Regression and Decision Trees
3. Instance based learning
   Feature Selection
4. Probability and Bayes Learning
5. Neural Network
6. Support Vector Machines
7. Introduction to Computational Learning Theory
8. Clustering

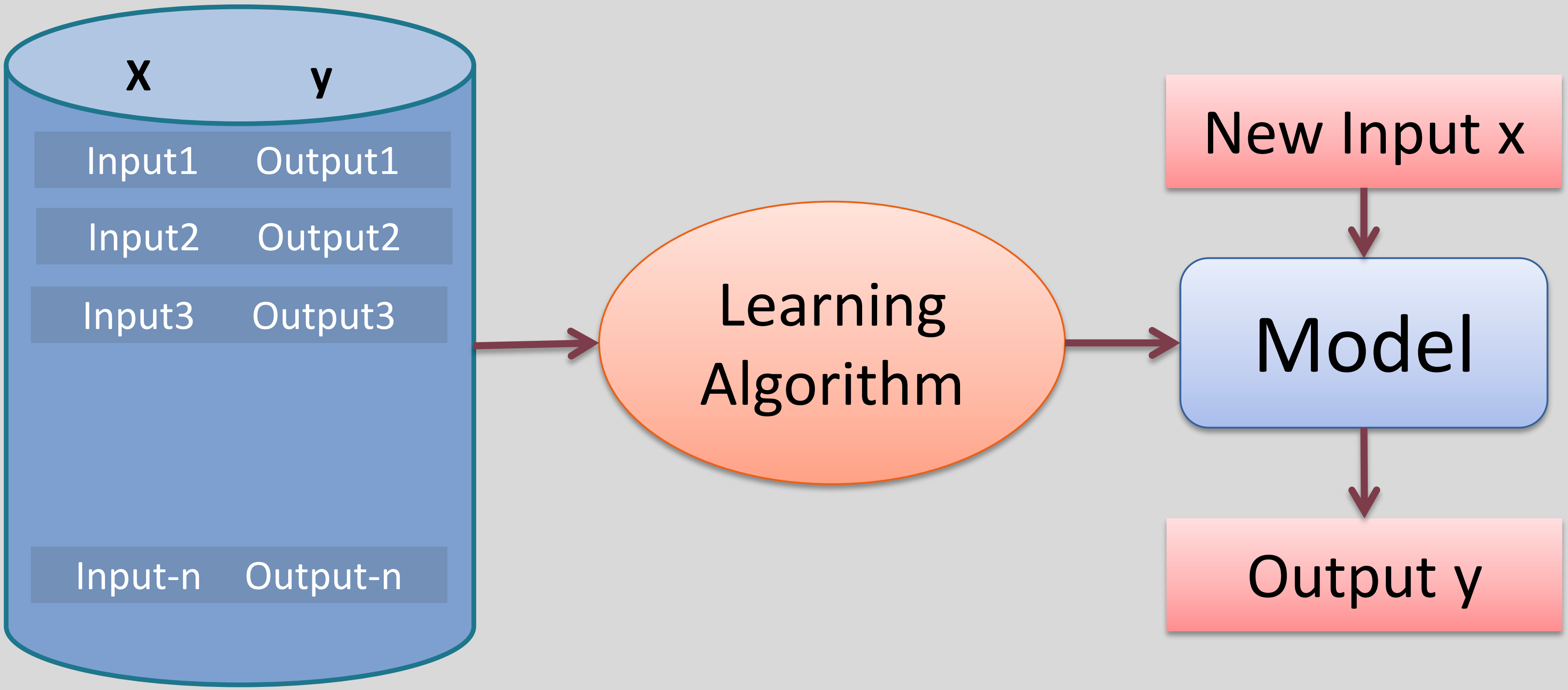
Broad types of machine learning

- Supervised Learning
  - X,y (pre-classified training examples)
  - Given an observation x, what is the best label for y?

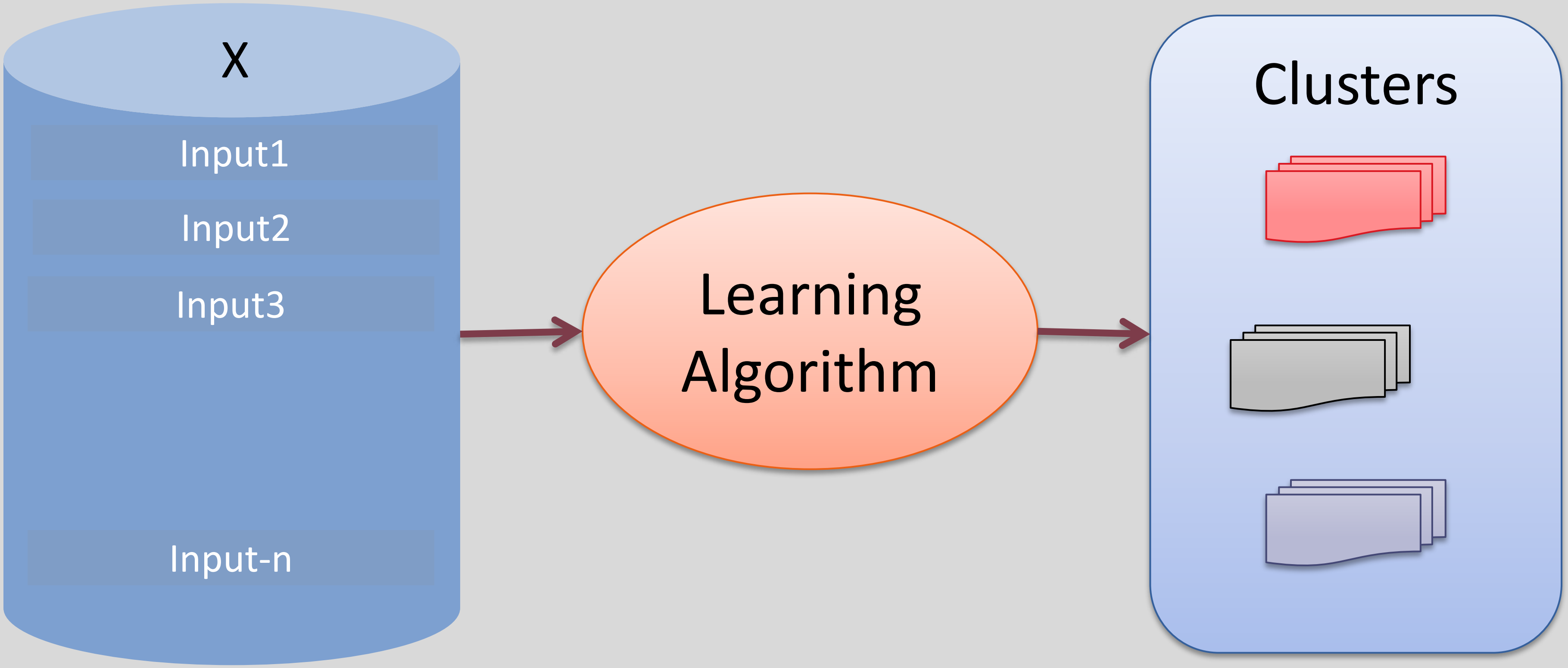
- Unsupervised learning
  - X
  - Given a set of x’s, cluster or summarize them

- Semi-supervised Learning
- Reinforcement Learning
  - Determine what to do based on rewards and punishments.

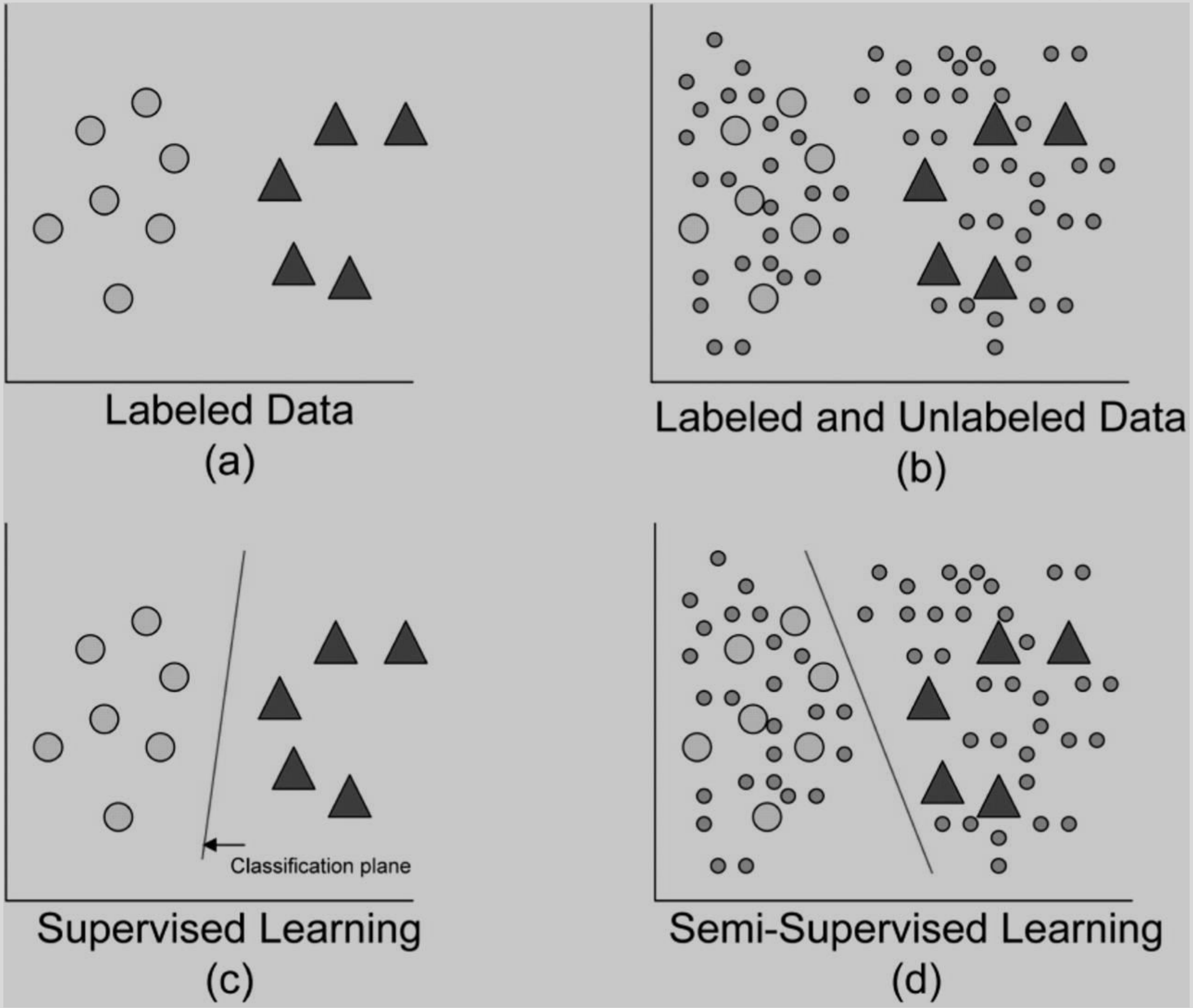
Supervised Learning



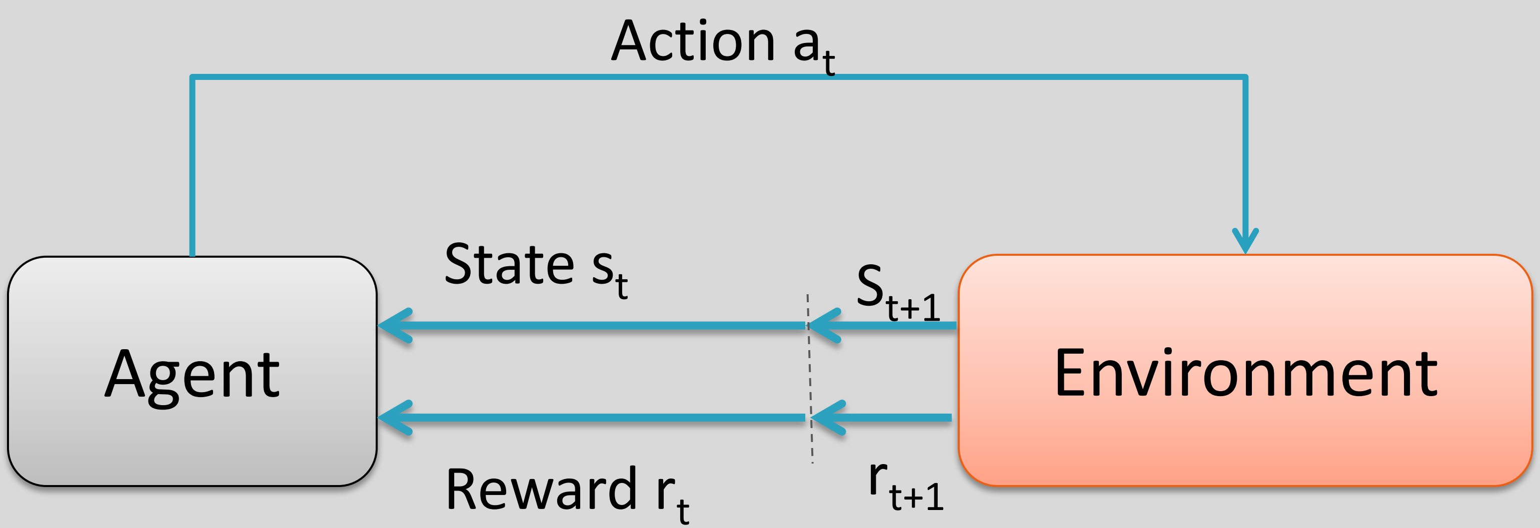
Unsupervised Learning



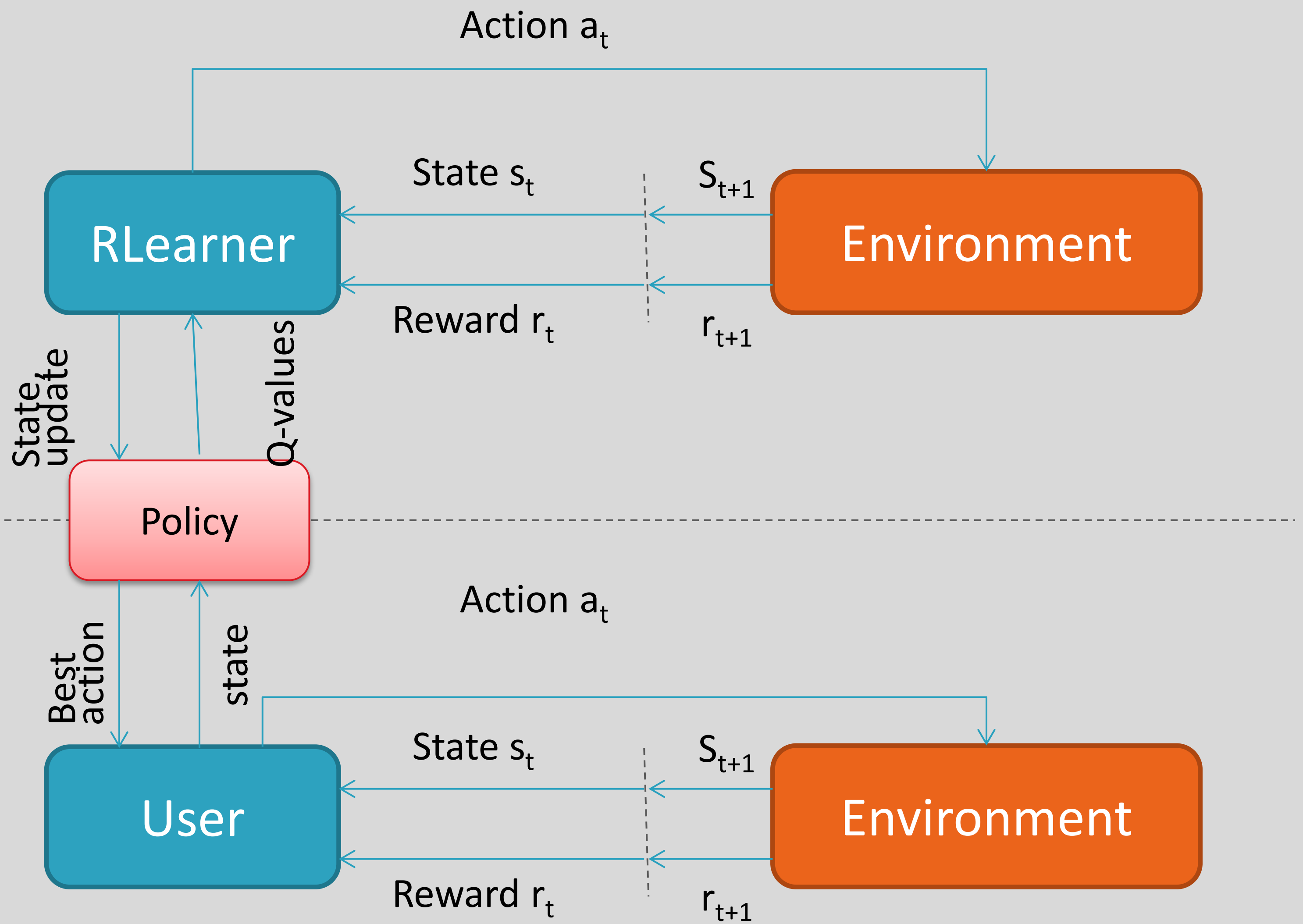
Semi-supervised learning



Reinforcement Learning



Reinforcement Learning



Supervised Learning

Given:

- a set of input features $X_1, \ldots, X_n$
- A target feature Y
- a set of training examples where the values for the input features and the target features are given for each example
- a new example, where only the values for the input features are given

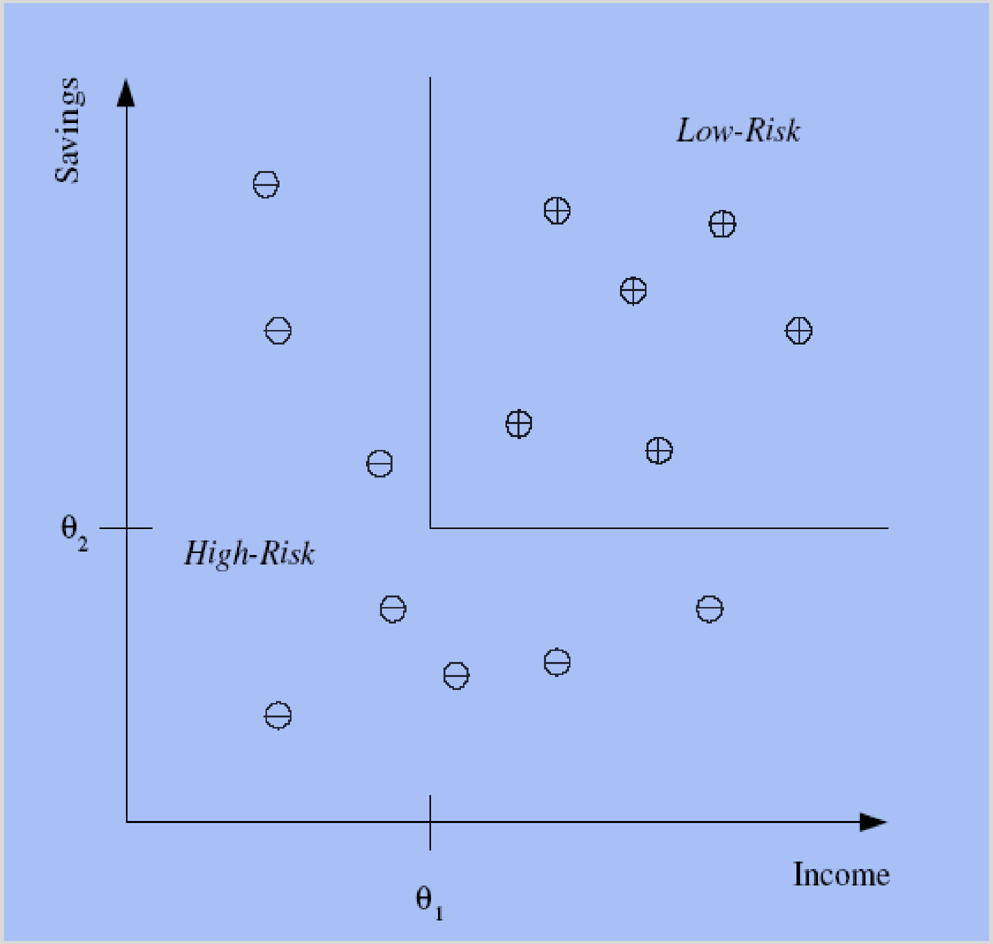
Predict the values for the target features for the new example.

- classification when Y is discrete
- regression when **Y** is continuous

Classification

Example: Credit scoring

Differentiating between low-risk and high-risk customers from their *income* and *savings*



Regression

Example: Price of a used car

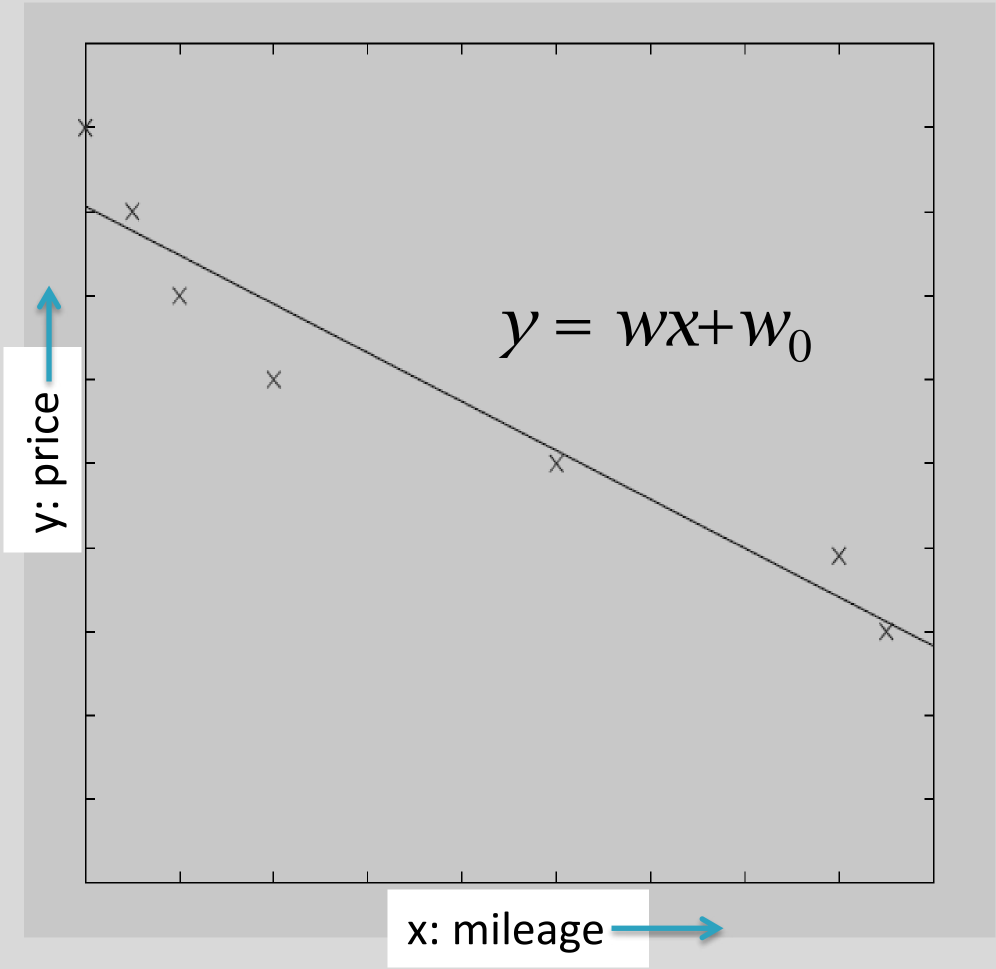
x : car attributes

y : price

$$y = g(x, \theta)$$

$g(\,)$ model,

θ parameters



Features

- Often, the individual observations are analyzed into a set of quantifiable properties which are called features. May be
  - categorical (e.g. "A", "B", "AB" or "O", for blood type)
  - ordinal (e.g. "large", "medium" or "small")
  - integer-valued (e.g. the number of words in a text)
  - real-valued (e.g. height)

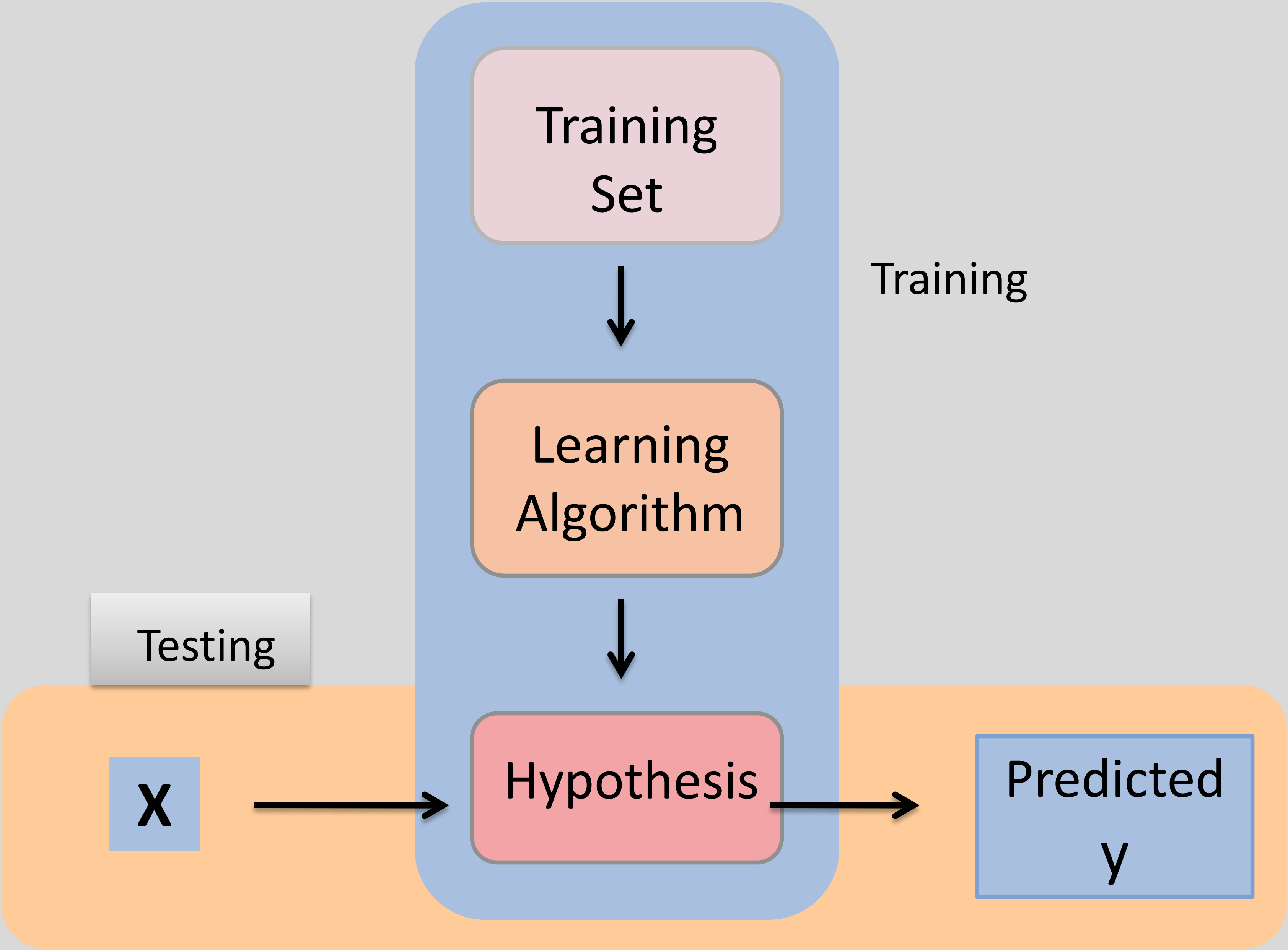
Example Data

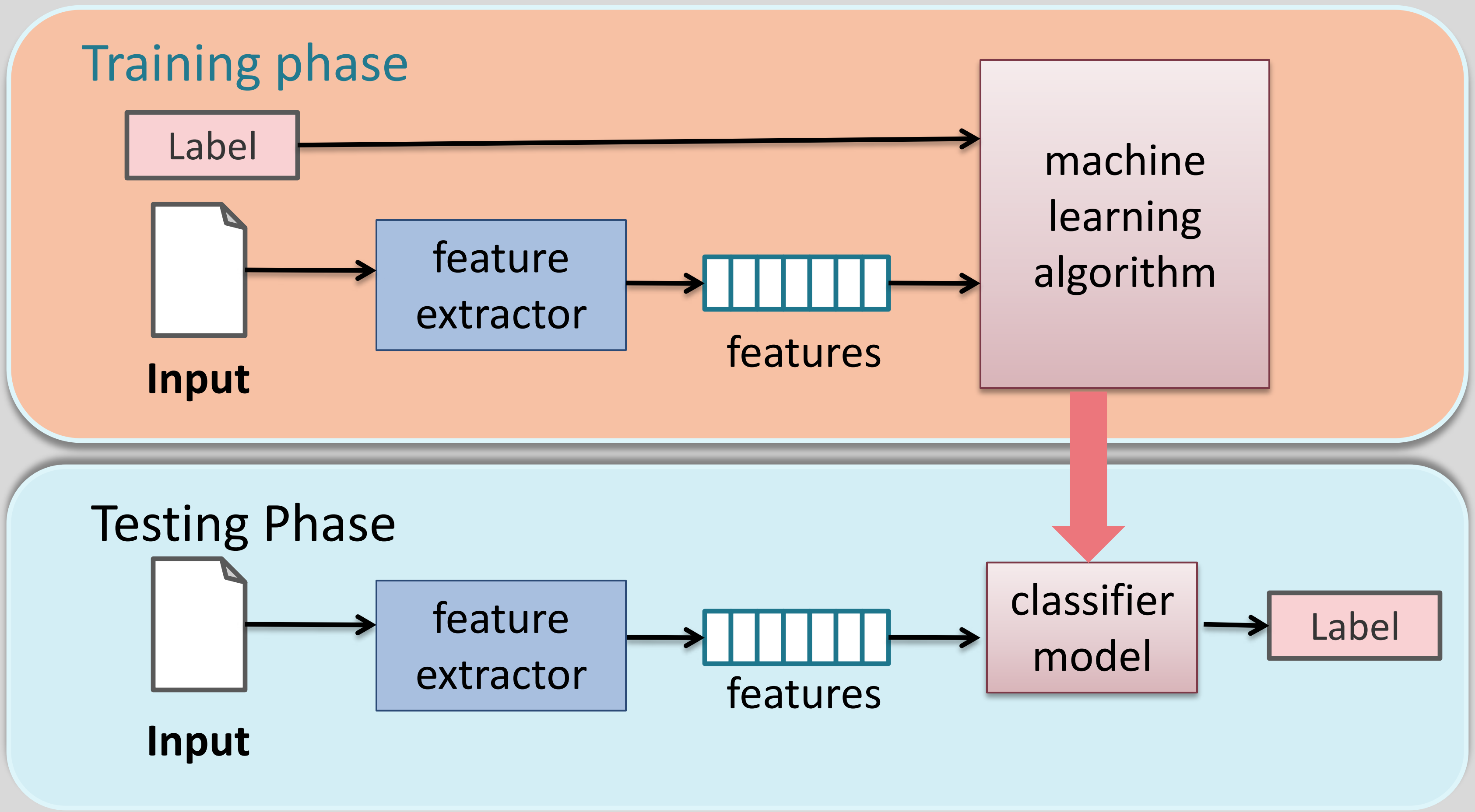
Training Examples:

	Action	Author	Thread	Length	Where
e1	skips	known	new	long	Home
e2	reads	unknown	new	short	Work
e3	skips	unknown	old	long	Work
e4	skips	known	old	long	home
e5	reads	known	new	short	home
e6	skips	known	old	long	work

New Examples:

e7	???	known	new	short	work
e8	???	unknown	new	short	work


Training
Set
Training
Learning
Algorithm
Testing
X
Hypothesis
Predicted
y



Training phase
Label
machine learning algorithm
feature extractor
features
Input
Testing Phase
feature extractor
features
classifier model
Label
Input

Classification learning

- Task *T:*
  - input:
  - output:
- Performance metric *P:*
- Experience *E:*

Classification learning

- Task *T*:
  - input: a set of *instances* $d_1,\ldots,d_n$
    - an instance has a set of *features*
    - we can represent an instance as a vector $\mathbf{d}=<x_1,\ldots,x_n>$
  - output: a set of *predictions* $\hat{y}_1,\ldots,\hat{y}_n$
    - one of a fixed set of constant values:
      - *{+1,-1}* or *{cancer, healthy}*, or *{rose, hibiscus, jasmine, …}*, or …
- Performance metric *P:*
- Experience *E:*

Classification Learning

Task	Instance	Labels
medical diagnosis	**patient record:** blood pressure diastolic, blood pressure systolic, age, sex (0 or 1), BMI, cholesterol	{-1,+1} = low, high risk of heart disease
finding entity names in text	**a word in context:** capitalized (0,1), word-after-this-equals-Inc, bigram-before-this-equals-acquired-by, …	{first,later,outside} = first word in name, second or later word in name, not in a name
image recognition	**image:** 1920*1080 pixels, each with a code for color	{0,1} = no house, house

Classification learning

we care about performance on the *distribution*, not the *training data*

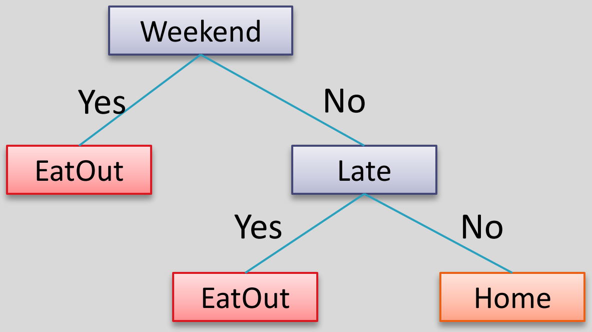
- Task *T:*
  - input: a set of *instances* $d_1,\ldots,d_n$
  - output: a set of *predictions* $\hat{y}_1,\ldots,\hat{y}_n$
- Performance metric *P:*
  - Prob (wrong prediction) on examples from *D*
- Experience *E:*
  - a set of *labeled examples (x,y)* where *y* is the true label for *x*
  - ideally, examples should be *sampled* from some fixed distribution *D*

Classification Learning

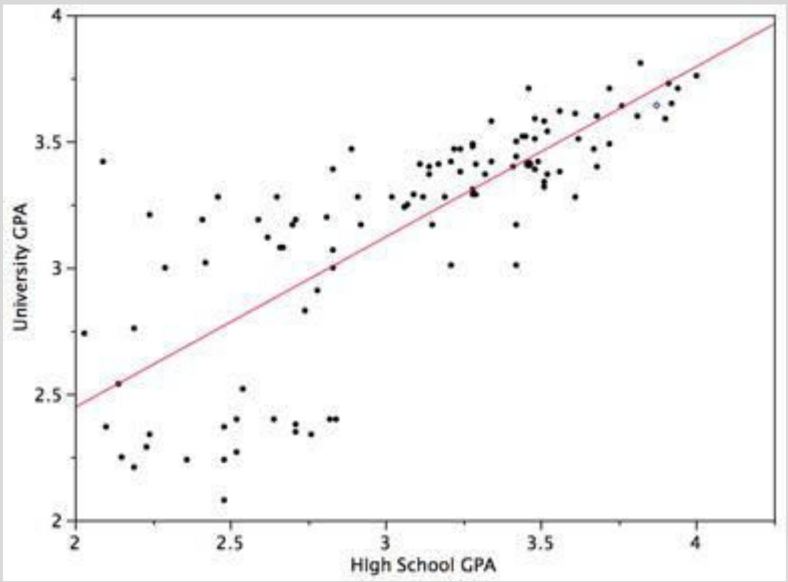
Task	Instance	Labels	Getting data
medical diagnosis	**patient record:** lab readings	risk of heart disease	wait and look for heart disease
finding entity names in text	**a word in context:** capitalized, nearby words, ...	{first,later,outside}	text with manually annotated entities
image recognition	**image:** pixels	no house, house	hand-labeled images

Representations

1. Decision Tree

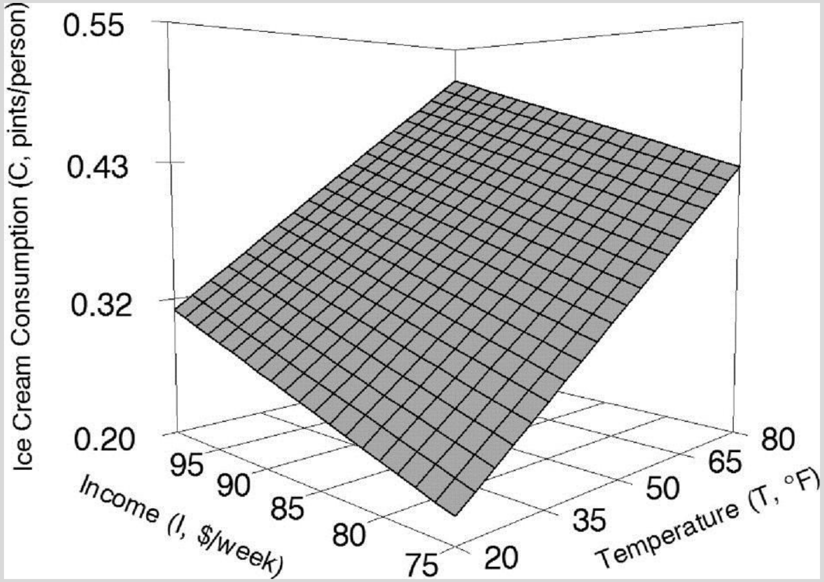


2. Linear function

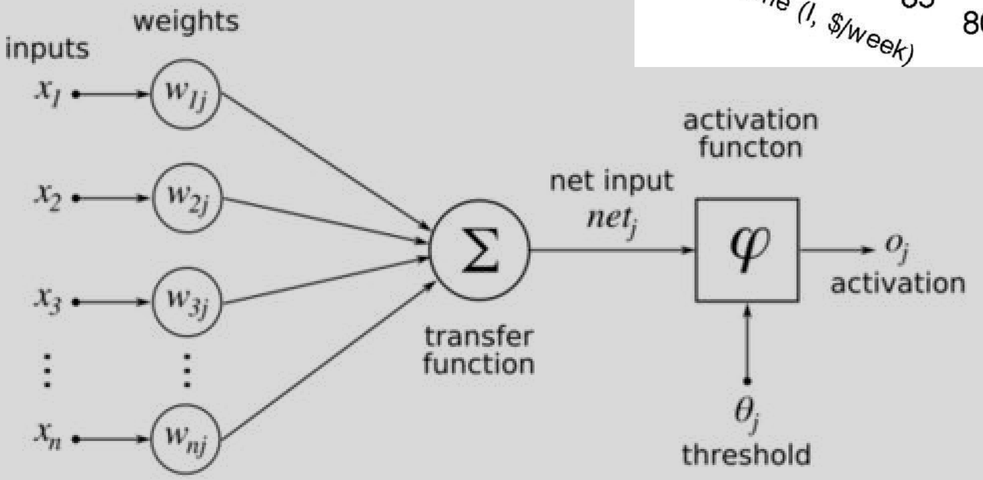


Representations

3. Multivariate linear function

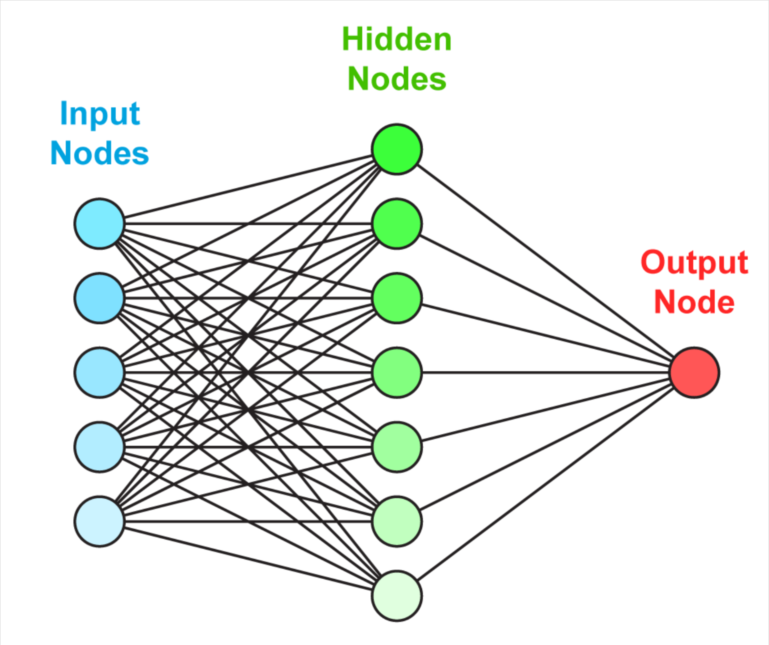


4. Single layer perceptron



Representations

5. Multi-layer neural network



Hypothesis Space

- One way to think about a supervised learning machine is as a device that explores a "hypothesis space".
  - Each setting of the parameters in the machine is a different hypothesis about the function that maps input vectors to output vectors.

Terminology

- **Features:** The number of features or distinct traits that can be used to describe each item in a quantitative manner.
- **Feature vector**: n-dimensional vector of numerical features that represent some object
- **Instance Space X**: Set of all possible objects describable by features.
- **Example (x,y)**: Instance x with label y=f(x).

Terminology

- **Concept c:** Subset of objects from X (c is unknown).
- **Target Function f:** Maps each instance x ∈ X to target label y ∈ Y
- **Example (x,y):** Instance x with label y=f(x).
- **Training Data S:** Collection of examples observed by learning algorithm.

  Used to discover potentially predictive relationships