Lecture 1: Introductory remarks

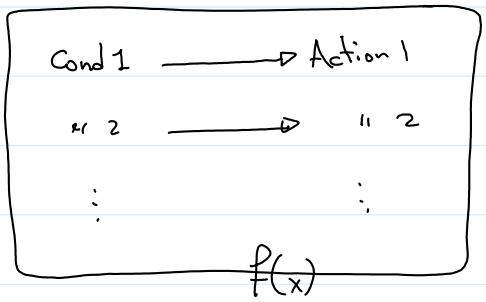
February 11, 2020 12:18 PM

- [ ] Goals of this course
- [ ] Machine learning
  - [ ] Descriptive ML
  - [ ] Predictive ML
  - [ ] Generative ML
  - [ ] Learning
- [ ] Notation

Goals

- Learn to use basic ML techniques
- Improve ML → New algorithms
  New models
  New metrics
- New paradigms → Quantum ML

Typically



f(x) : X is checked for {cond i} and the proper action is implemented.

But how do we learn?

We see / observe

(A) and try to fit with some known outcome

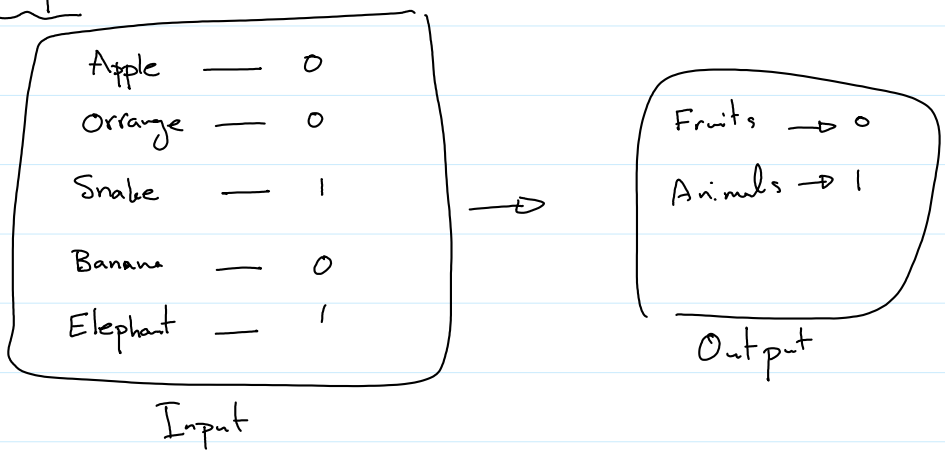
→ Prediction

Instance 1 ⟷ Output 1 Output i ∈ Set of outputs

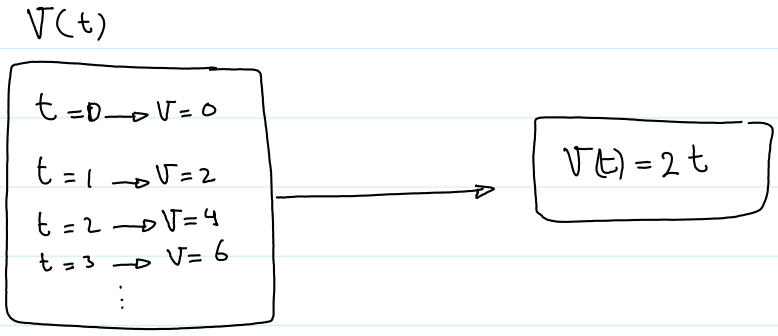
" 2 ⟷ Output 2 * It is smaller than {instance i}.

We infer the relation.

Example



This is known as "classification".



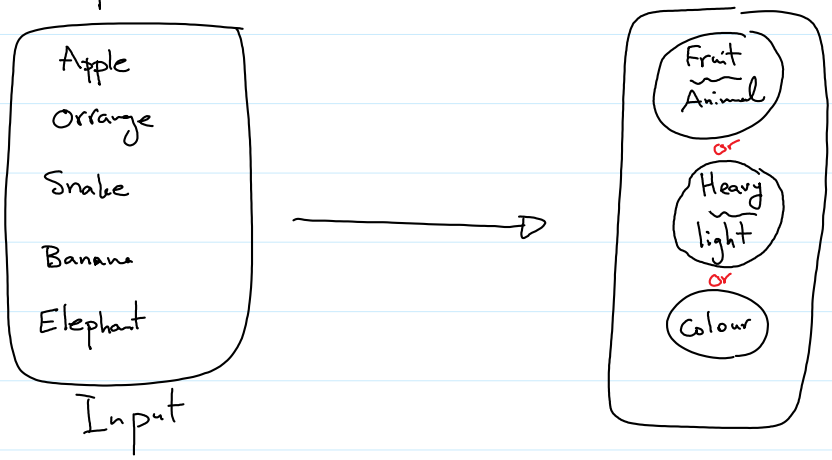
Regression

Both classification & regression come with some target values and the goal is to estimate / predict the outcome for some unseen instance.

(B) try to recognize some pattern in the data.

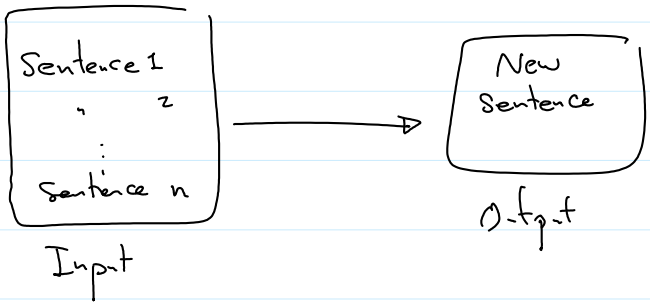
Sometimes only the instances are given and the task is to draw some conclusion / describe the data.

Example:



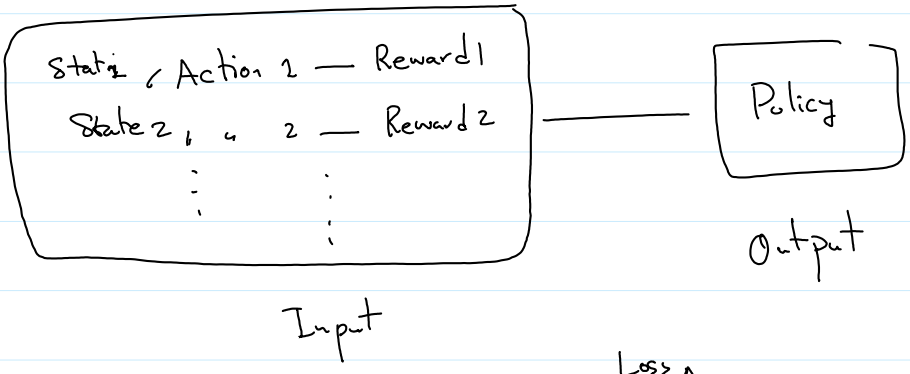
(C) try to mimic the data we get: learning to speak
draw
sing
play music

Generative



© try to learn a procedure : how to play a game, ...

* Learning ?!!

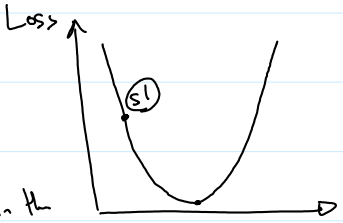


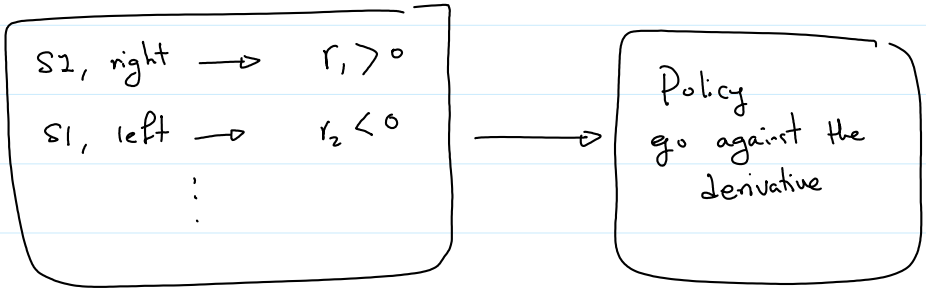
Example

Minimize

Reward ~ $-\Delta$ loss

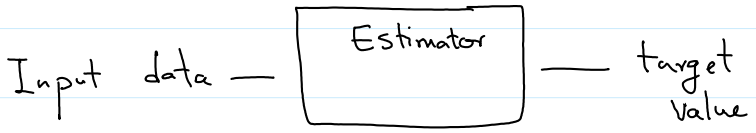
change in the loss



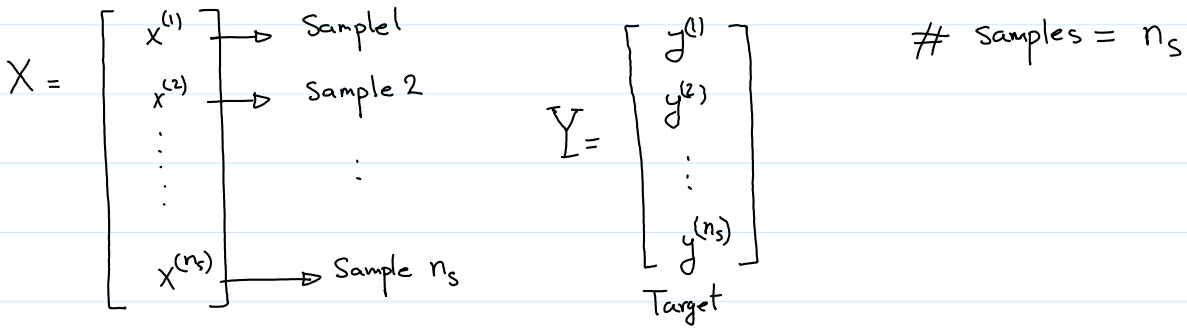


* Reinforcement learning

Notation



X $\qquad$ Y



Sample i $X^{(i)}$: $\left(x_1^{(i)}, x_2^{(i)}, \ldots x_{n_f}^{(i)}\right) \rightarrow$ Properteas of each sample.

We refer to each property (column) as a "feature".

example:

Complet gas: $(P, V, n) \rightarrow T$

Measurement 1: $\left(p^{(1)}, V^{(1)}, n^{(1)}\right) \longrightarrow T^{(1)}$

" 2: $\left(p^{(2)}, V^{(2)}, n^{(2)}\right) \longrightarrow T^{(2)}$

$\left(p^{(100)}, V^{(100)}, n^{(100)}\right) \longrightarrow T^{(100)}$

What's X & Y?

What's n_f & n_s?