# Types of Learning

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### Introduction

This article is the study notes of the course: The foundation of Machine Learning. In today's speech, Professor Lin introduces different types of machine learning problems. In general, we can classify different machine learning problems from the perspective of **the output space Y**, **the data label**, **the protocol and the input space**.

## 1 Learning with different output space Y

### 1.1 Structured Learning: Sequence Tagging Problem

 $\begin{array}{cccc} I & love & ML \\ \\ pronoun & verb & noun \\ \end{array}$ 

- multiclass classification: word ⇒ word class
- structured learning: sentence ⇒ (class of each word)
- $Y = \{PVN, PVP, NVN, PV, ...\}$ , not including VVVVV
- huge muticlass classification problem (structure = hyperclass) without 'explicit' class definition

### 1.2 Mini Summary

- binary classification: $Y = \{-1, +1\}$
- multiclass classification:  $Y = \{1, 2, ..., K\}$
- regression: Y = R
- structured learning: Y =structures
- · and a lot more

## 2 Learning with different Data Label

#### 2.1 Supervised learning

Every  $x_n$  comes with corresponding  $y_n$ 

## 2.2 Unsupervised Learning

'Learning without  $y_n$ '

- clustering: {x<sub>n</sub>} ⇒ cluster(x)
  (≈ 'unsupervised multiclass classification')
  i.e. articles ⇒ topics
- density estimation :  $\{x_n\} \Rightarrow density(x)$ ( $\approx$  'unsupervised bounded regression') i.e. traffic reports with location  $\Rightarrow$  dangerous areas
- outlier detection {x<sub>n</sub>} ⇒ unusual(x)
  (≈ extreme 'unsupervised binary classification')
  i.e. Internet logs ⇒ intrusion alert
- · and a lot more

#### 2.3 Semi-supervised learning

Leverage unlabeled data to avoid 'expensive' labeling.

- face images with a few labeled ⇒ face identifier (Face book)
- medicine data with a few labeled ⇒ medicine effect predictor

### 2.4 Reinforcement Learning

Learn with 'partial/implicit information' (often sequentially)

Other Reinforcement Learning Problems Using  $(x, \sim y, goodness)$ 

- (customer, ad choice, ad click earning) ⇒ ad system
- (cards, strategy, winning amount) ⇒ black jack agent

#### 2.5 Mini Summary

- supervised: all  $y_n$
- unsupervised: no  $y_n$
- semi-supervised: some  $y_n$
- reinforcement: implicit  $y_n$  by goodness  $\sim y_n$
- and more

## 3 Learning with Different Protocol

#### 3.1 Batch learning

Learn from all known data.

#### 3.2 Online: Spam Filter that 'Improves'

Hypothesis "improves" through receiving data instances sequentially.

- batch spam filter: learning with known (email, spam?) pairs, and predict with fixed g
- online spam filter, which sequentially:
  - observe an email  $x_t$
  - predict spam status with current  $g_t(x_t)$
  - receive 'desired label'  $y_t$  from user, and then update  $g_t$  with  $(x_t, y_t)$

#### 3.2.1 Connection to What We Have Learned

- PLA can be easily adapted to online Protocol
- Reforcement learning is often done online

## 3.3 Learning Philosophy

• batch: 'duck feeding'

• online: 'passive sequential'

· active: strategically-observed data

· and more

active: improve hypothesis with fewer labels(hopefully) by asking questions strategically.

## 4 Learning with Different Input Space

#### 4.1 Concrete features

Each dimension of  $X \subset \mathbb{R}^d$  represents 'sophisticated physical meaning'.

#### 4.2 Raw features

• image pixels, speech signal, etc

Often need human or machines to convert to concrete ones.

#### 4.3 Abstract features

Need 'feature conversion/extraction/construction'

- given previous (userid, itemid, rating) tuples, predict the rating that some userid would give to itemid?
- a regression problem with  $Y \subset R$  as rating and  $X \subset N \times N$  as (userid, itemid)
- 'no physical meaning'; thus even more difficult for ML

#### Other Problems with Abstract Features

- student ID in online tutoring system
- · advertisement ID in online ad system

## 4.4 Mini Summary

• concrete: sophisticated (and related) physical meaning

• raw: simple physical meaning

• abstract: no (or little) phyical meaning

• and more