

# Lecture 1 Jan 14 th

## What is Machine Learning?

It's an algorithm that has a specific goal; solving given task  
Not all tasks can be solved with an explicit algorithm.

Thus we use ML to solve these tasks by training models using data.

## 3 Main Ways of ML

### 1. Supervised Learning

- humans have annotated the data  
ie. the correct data has been provided
- Ex, classification

### 2. Unsupervised Learning

- no annotations, ex. grouping

### 3. Reinforced Learning

- provide incentive for completing task
- provide punishment for screwing up task

## Approaching ML Problems

1. What's the best technique to solve problem
2. Where can I get my data
3. Select an appropriate model
4. Training the model
5. Tuning the model

- see how it works on new data

## Problems in Data

- where to get the data
- no variation in data
- overfitting, model not generalized
  - to fix this problem, we split available data into 3 sets:
  - training, tuning process
  - validation, evaluating model
  - testing, final test using unbiased data.
- not enough data

## Regression

Regression is fitting model to given data, avoiding noise  
 It's useful for interpolation/extrapolation.

### 1D Input 1D Output

We solve:

$$y = w \cdot x + b$$

for input  $x$ , output  $y$  and tuning parameters  $w, b$ .

We evaluate this function using a Loss Function / Objective Function

For above  $y = w \cdot x + b$  one LF we can use is:

Least Square Error

The error for point  $(x_i, y_i)$  and model  $(w, b)$  is:

$$e_i = y_i - (w x_i - b)$$

The L.S.E. or objective function is:

$$E(w, b) = \sum_{i=1}^N e_i^2$$

To optimize, we minimize  $E$ , i.e. taking the derivatives relative to tuning params.

$$\text{Solve } \frac{dE}{db} = 0 \quad b^* = \bar{y} - w \bar{x} \quad , \bar{y}, \bar{x} \text{ are average of } y_i, x_i$$

$$\text{Solve } \frac{dE}{dw} \Big|_{b^*} = 0 \quad w^* = \frac{\sum_i (y_i - \bar{y})(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

Note: L.S.E. is very sensitive to outliers.

### Multidimensional Input 1D Outputs

Now there are more tuning parameters.

We solve:

$$y = w_1 x_1 + w_2 x_2 + \dots + w_n x_n$$

$$= [w_1 \ w_2 \ \dots \ w_n]^T \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \\ b \end{bmatrix}$$

For input  $\vec{x}$ , output  $y$  and parameters  $\vec{w}, b$

The objective function:

$$E(\vec{w}) = \sum_{i=1}^N (y_i - (\vec{w}^T \vec{x}_i))^2$$

$$= \|\vec{y} - \vec{x}^T \vec{w}\|^2$$

$\vec{x}$  is matrix of  $\vec{x}_i$ ,

$$= (\vec{y} - \vec{x}\vec{w})(\vec{y} - \vec{x}\vec{w})$$

$$\textcircled{1} \quad \vec{y}^T \vec{y} - 2\vec{y}^T \vec{x}\vec{w} + \vec{w}^T \vec{x}^T \vec{x}\vec{w}$$

$\vec{y}$  is vector of  $y_i$   
 $\vec{w}$  is vector of  $w_i$

By applying:  $\frac{d(a^T x)}{d x} = \frac{d(x^T a)}{d(x)} = a$

$$\frac{d(x^T A x)}{d x} = (A + A^T)x$$

to \textcircled{1}, we get optimal  $\vec{w}^* = (x^T x)^{-1} x^T \vec{y}$

### Multidimensional Input with Multidimensional Output

Thus solve:

$$\vec{y} = \vec{w}^T \vec{x}$$

$$= \begin{bmatrix} | & | & | \\ \vec{w}_1^T \vec{x}_1 & \vec{w}_2^T \vec{x}_2 & \dots \vec{w}_n^T \vec{x}_n \\ | & | & | \end{bmatrix}$$

where  $\vec{x}$  is output,  $\vec{y}$  is input and  $\vec{w}$  is matrix of tuning variables

The objective function:

$$\begin{aligned} E(\vec{w}) &= \sum_{:}^N \sum_j^K (y_{i,j} - (\vec{w}_j^T \vec{x}_i))^2 \\ &= \sum_j^K (\vec{y}_j - (\vec{x} \vec{w}_j))^2 \\ &= \|\vec{Y} - \vec{X}\vec{w}\|_F^2 \\ &= \sum_{i,j} (Y - XW)_{i,j}^2 \end{aligned}$$

Finally, the optimal solution is:

$$\vec{w}^* = (x^T x)^{-1} x^T Y$$

