

Coursera- Machine Learning

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Summary

Supervised learning

- linear regression, logistic regression, neural network, SVMs

Unsupervised learning

- k-means, PCA, Anomaly detection

Special applications/special topics

- Recommender systems, large scale machine learning

Advice for building a machine learning system

- bias/variance, regularization, deciding what to work next, evaluation of a learning algorithm, learning curves, error analysis, ceiling analysis

Week 1

Intro

Definition of ML

- A program learns from experience (E) w.r.t task(T) and performance measure (P) if its performance on T improves with more E.
- With supervised learning, we know what our answers are as a relation of input and output. But with unsupervised learning, we have little idea about the result.

Cost function

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$$h_{\theta}(x) = \theta_0 + \theta_1 x$$

our goal is to minimize the cost function, which is calculated as square error

$$\min_{\theta_0, \theta_1} J(\theta_0, \theta_1)$$

- where the error function is defined as

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

Linear regression

- Repeat until converge{ $\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$ for $j = 0, 1$ }
- Note that the update is simultaneous :

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$$\text{temp}_0 := \theta_0 - \alpha \frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1)$$

$$\text{temp}_1 := \theta_1 - \alpha \frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1)$$

$$\theta_0 := \text{temp}_0$$

$$\theta_1 := \text{temp}_1$$

- if we compute the derivative we get Repeat until converge{

$$\theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x_i) - y_i)$$

$$\theta_1 := \theta_1 - \alpha \frac{1}{m} \sum_{i=1}^m ((h_{\theta}(x_i) - y_i) x_i)$$

}

- α is the learning rate.
- we use linear regression algorithm to update the parameters until we arrive at the minimal cost.

Week 2

Multi-feature linear regression

- Hypothesis

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \dots \theta_n x_n$$

- convenience $\forall x, x_0 = 1$, so that $h_{\theta} = \sum_{i=0}^n \theta_i x_i$

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$$x = \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^{n+1} \text{ and that } \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_n \end{bmatrix}$$

- Hypothesis can be represented