COMP2261 ARTIFICIAL INTELLIGENCE / MACHINE LEARNING

Multivariate Linear Regression

-- Cost Function & Gradient Descent

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Supervised Learning

• To build a model represented as a hypothesis function $h_{\theta}(x)$.







Supervised Learning

income (input x, dependent variable)



model (hypothesis function, mapping $x \rightarrow y$)



happiness (output y, independent variable)







Hypothesis Function

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

Independent Variable

 χ

Parameters

$$\theta_0, \theta_1$$

Cost Function

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





Multivariate Linear Regression

Hypothesis Function

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

$$h_{\theta}(\mathbf{x}) = \theta_0 + \theta_1 \cdot x_1 + \theta_2 \cdot x_2 + \dots + \theta_n \cdot x_n$$

Independent Variable

$$\chi$$

Model Parameters

$$\theta_0, \theta_1$$

$$m{ heta} = \begin{bmatrix} \theta_1 \\ \theta_1 \\ \dots \\ \theta_n \end{bmatrix} \in \mathbb{R}^{n+1} \qquad h_{m{\theta}}(\mathbf{x}) = \mathbf{\theta}^T \mathbf{x}$$
 vectors

Cost Function

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

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} (h_{\theta}(x)^{(i)} - y^{(i)})^{2}$$

(n = 1)

Cost Function

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

Multivariate Linear Regression

$$J(\boldsymbol{\theta}) = \frac{1}{2m} \sum_{i=1}^{m} (h_{\boldsymbol{\theta}}(\boldsymbol{x})^{(i)} - y^{(i)})^2$$

Partial derivative of / with respect to parameters

$$\frac{\partial J}{\partial \theta_0}(\theta_0, \theta_1) = \frac{1}{m} \sum_{i=1}^m (h_\theta(x)^{(i)} - y^{(i)}) x_0^{(i)} \Big|_{x_0^{(i)} = 1} \frac{\partial J}{\partial \theta_0}(\boldsymbol{\theta}) = \frac{1}{m} \sum_{i=1}^m (h_\theta(x)^{(i)} - y^{(i)}) x_0^{(i)} \Big|_{x_0^{(i)} = 1}$$

$$\frac{\partial J}{\partial \theta_1}(\theta_0, \theta_1) = \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x)^{(i)} - y^{(i)}) x_1^{(i)} \qquad \frac{\partial J}{\partial \theta_1}(\theta) = \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x)^{(i)} - y^{(i)}) x_1^{(i)}$$

$$\frac{\partial J}{\partial \theta_1}(\boldsymbol{\theta}) = \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x)^{(i)} - y^{(i)}) x_1^{(i)}$$

$$\frac{\partial J}{\partial \theta_n}(\boldsymbol{\theta}) = \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x)^{(i)} - y^{(i)}) x_n^{(i)}$$





Gradient Descent

Repeat until convergence {

$$\frac{\partial J}{\partial \theta_0}(\theta_0, \theta_1)$$

$$\theta_0 := \theta_0 - \alpha \cdot \frac{1}{m} \sum_{i=1}^m (h_\theta(x)^{(i)} - y^{(i)})$$
learning rate

$$\theta_1 := \theta_1 - \alpha$$
learning rate
$$\frac{1}{m} \sum_{i=1}^m (h_{\theta}(x)^{(i)} - y^{(i)}) x^{(i)}$$

 $\}$ simultaneously update $heta_0$, $heta_1$

$$\frac{\partial J}{\partial \theta_1}(\theta_0, \theta_1)$$

Multivariate Linear Regression

Repeat until convergence {

$$\frac{\partial J}{\partial \theta_0}(\boldsymbol{\theta})$$

$$\theta_0 := \theta_0 - \alpha$$
learning rate
$$\frac{1}{m} \sum_{i=1}^m (h_\theta(x)^{(i)} - y^{(i)}) x_0^{(i)}$$

$$\theta_1 := \theta_1 - \alpha$$
learning rate
$$\frac{1}{m} \sum_{i=1}^m (h_\theta(x)^{(i)} - y^{(i)}) x_1^{(i)}$$

..

$$\frac{\partial J}{\partial \theta_1}(\boldsymbol{\theta})$$

$$\theta_n := \theta_1 - \alpha$$
learning rate
$$\frac{1}{m} \sum_{i=1}^m (h_{\theta}(x)^{(i)} - y^{(i)}) x_n^{(i)}$$

 $\}$ simultaneously update $\theta_0, \dots, \theta_n$

 $\frac{\partial J}{\partial \theta_n}(\boldsymbol{\theta})$







✓ Takeaway Points

- Univariate linear regression is a special case of multivariate linear regression when the number of features n=1.
- n+1 dimensional column vectors to denote features and model parameters.
- Feature vectors and parameters vectors to express hypothesis function and cost function.
- Each iteration in gradient descent, all the n parameters (θ s) need to be updated simultaneously.



