

Multiple Linear Regression

- Algorithm implemented in Octave
- Simple data were applied with the algorithm

- Same data were analyzed in R
- Same data were analyzed in Python

Algorithm:

Hypothesis: $h_{\theta}(x) = \theta^T x = \theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$

Parameters: $\theta_0, \theta_1, \dots, \theta_n$ \rightarrow $n+1$ -dimensional vector

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

Repeat {
 $\rightarrow \theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$
(simultaneously update θ_j for $j = 0, \dots, n$)
}

Gradient descent in
practice I: Feature Scaling
Idea: Make sure features are on a similar scale.

Gradient descent in
practice II: Learning rate
- If α is too small: slow convergence.
- If α is too large: $J(\theta)$ may not decrease on every iteration; may not converge. (Slow)

To choose α , try

$\dots, 0.001, 0.003, 0.01, 0.03, 0.1, 0.3, 1, \dots$

Implemented in Octave

multiple_linear_regression.m

Feature Normalization

Gradient Descent

Predict Testing Data

prediction.txt

training.txt
 $x' = \frac{x - \min(x)}{\max(x) - \min(x)}$

featureNormalize.m

computeCostMulti.m

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

gradientDescentMulti.m

testing.txt

predictTesting.m

Data Analyzed in R

File Name:
multiple_linear_regression.R

Usage:
/usr/bin/Rscript multiple_linear_regression.R
training.txt testing.txt prediction.txt

Core Functions{Packages} Used:
build model
lm{stats}
make prediction on testing data

Data Analyzed in Python

File Name:
multiple_linear_regression.py

Usage:
python multiple_linear_regression.py training.txt
testing.txt prediction.txt

Core Functions{Modules} Used:
build model
linear_model.LinearRegression().fit(){sklearn}
make prediction on testing data