

## Multinomial Logistic Regression

The Multinomial Logistic Regression is a generalization of the logistic regression to multivariate classification problems. The theoretical background of multinomial logistic regression algorithm is as follows:

Assume the training dataset consist of  $m$   $(x_i, y_i)$  pairs and  $k$  is the number of all possible classes. The probability of given  $x$  to be classified as  $y$  is:

$$p(y^{(i)} = j | x^{(i)}; \theta) = \frac{\exp(\theta_j^T x^{(i)})}{\sum_{i=1}^k \exp(\theta_i^T x^{(i)})}$$

Thus the hypothesis function will return a  $k$  dimensional vector with the estimated probabilities, as follows:

$$h_{\theta}(x^{(i)}) = [p_1, p_2, \dots, p_k]^T = \frac{1}{\sum_{i=1}^k \exp(\theta_i^T x^{(i)})} [\exp(\theta_1^T x^{(i)}), \exp(\theta_2^T x^{(i)}), \dots, \exp(\theta_k^T x^{(i)})]^T$$

The category with the highest probability will be chosen as the classification for the entry  $x$ . The parameter  $\theta$  is calculated by minimizing the cost function  $J$  using gradient descent. Thus, the Multinomial Logistic Regression algorithm requires significantly more time to be trained comparing to Naive Bayes,

$$J(\theta) = -\frac{1}{m} \left[ \sum_{i=1}^m \sum_{j=1}^k \{y^{(i)} = j\} \log \frac{\exp(\theta_j^T x^{(i)})}{\sum_{i=1}^k \exp(\theta_i^T x^{(i)})} \right]$$

Here  $\{y^{(i)} = j\}$  is the proportion of  $y(i)$  over sum of all  $y(i)$  values.

Reference:

<http://blog.datumbox.com/machine-learning-tutorial-the-multinomial-logistic-regression-softmax-regression/>