

# Assignment 3

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# 1 Logistic Regression

## 1.1 CS 337: Logistic Regression

Given Soft-max expression and Categorical cross-entropy function of Multi-class Logistic Regression, we substitute  $K = 2$ .

$$\begin{aligned}
 P(Y = 1 | \mathbf{w}_1, \phi(\mathbf{x})) &= \frac{e^{\mathbf{w}_1^T \phi(\mathbf{x})}}{e^{\mathbf{w}_1^T \phi(\mathbf{x})} + e^{\mathbf{w}_2^T \phi(\mathbf{x})}} = \frac{1}{1 + e^{(\mathbf{w}_2^T - \mathbf{w}_1^T) \phi(\mathbf{x})}} \\
 P(Y = 2 | \mathbf{w}_2, \phi(\mathbf{x})) &= \frac{e^{\mathbf{w}_2^T \phi(\mathbf{x})}}{e^{\mathbf{w}_1^T \phi(\mathbf{x})} + e^{\mathbf{w}_2^T \phi(\mathbf{x})}} = \frac{e^{(\mathbf{w}_2^T - \mathbf{w}_1^T) \phi(\mathbf{x})}}{1 + e^{(\mathbf{w}_2^T - \mathbf{w}_1^T) \phi(\mathbf{x})}} \\
 E(\mathbf{w}_1, \mathbf{w}_2) &= -\frac{1}{N} \sum_{i=1}^N y_1^{(i)} \log(P(Y = 1 | \mathbf{w}_1, \phi(\mathbf{x}^{(i)}))) + y_2^{(i)} \log(P(Y = 2 | \mathbf{w}_2, \phi(\mathbf{x}^{(i)}))) \\
 &= -\frac{1}{N} \sum_{i=1}^N \frac{y_1^{(i)} + y_2^{(i)} e^{(\mathbf{w}_2^T - \mathbf{w}_1^T) \phi(\mathbf{x})}}{1 + e^{(\mathbf{w}_2^T - \mathbf{w}_1^T) \phi(\mathbf{x})}}
 \end{aligned}$$

Now, we substitute the one-hot vector  $[y_1^{(i)}, y_2^{(i)}]$  with  $[y^{(i)}, 1 - y^{(i)}]$  and  $\mathbf{w}_1 - \mathbf{w}_2$  with  $\mathbf{w}$ .

$$\begin{aligned}
 P(Y = 1 | \mathbf{w}, \phi(\mathbf{x})) &= \frac{1}{1 + e^{-\mathbf{w}^T \phi(\mathbf{x})}} = \sigma_{\mathbf{w}}(\mathbf{x}) \\
 P(Y = 2 | \mathbf{w}, \phi(\mathbf{x})) &= \frac{e^{-\mathbf{w}^T \phi(\mathbf{x})}}{1 + e^{-\mathbf{w}^T \phi(\mathbf{x})}} = 1 - \sigma_{\mathbf{w}}(\mathbf{x}) \\
 E(\mathbf{w}) &= -\frac{1}{N} \sum_{i=1}^N \frac{y^{(i)} + (1 - y^{(i)}) e^{-\mathbf{w}^T \phi(\mathbf{x})}}{1 + e^{-\mathbf{w}^T \phi(\mathbf{x})}} \\
 &= -\frac{1}{N} \sum_{i=1}^N \frac{y^{(i)}}{1 + e^{-\mathbf{w}^T \phi(\mathbf{x})}} + \frac{(1 - y^{(i)}) e^{-\mathbf{w}^T \phi(\mathbf{x})}}{1 + e^{-\mathbf{w}^T \phi(\mathbf{x})}} \\
 &= -\frac{1}{N} \sum_{i=1}^N y^{(i)} \sigma_{\mathbf{w}}(\mathbf{x}) + (1 - y^{(i)}) (1 - \sigma_{\mathbf{w}}(\mathbf{x}))
 \end{aligned}$$

Hence, cross entropy function used to train a binary logistic regression is a special case of the categorical cross entropy function given above.

## 1.2 CS 337: Logistic Regressions Decision surface

The model assigns a value of  $y = +1$  to a point  $\mathbf{x}$  if  $P(y = +1 | \mathbf{x}) = \frac{1}{1 + \exp(-\mathbf{w}^T \mathbf{x})} \geq \theta$  which is equivalent to  $\mathbf{w}^T \mathbf{x} \geq -\log\left(\frac{1 - \theta}{\theta}\right)$  and this forms the decision boundary.

When we say that a model is linear, we mean that its predictions are a linear function of its parameters.

Logistic regression is considered as a linear model because the **decision boundary used for classification purpose is linear** (i.e.  $f(\mathbf{x}) = \mathbf{w}^T \mathbf{x}$ ).