In the equations below,
$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} \\ \vdots & \vdots \\ x_{N1} & x_{N2} \end{pmatrix}$$
 is a matrix of data points. $\mathbf{U} = \begin{pmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \\ u_{31} & u_{32} \end{pmatrix} \in \mathbb{R}^{3 \times 2}, \mathbf{b} = \begin{pmatrix} b_1 \\ b_2 \\ b_3 \end{pmatrix} \in \mathbb{R}^3, \mathbf{W} = \begin{pmatrix} w_1 & w_2 & w_3 \end{pmatrix} \in \mathbb{R}^{1 \times 3}, c \in \mathbb{R}$ are neural network parameters.

Forward Equations (Vectorized form)

$$\mathbf{G} = \mathbf{X}\mathbf{U}^T + \mathbf{1}\mathbf{b}^T$$

$$\mathbf{H} = \tanh(\mathbf{G})$$

$$\mathbf{z} = \mathbf{H}\mathbf{W}^T + \mathbf{1}c$$

$$\mathbf{y} = \sigma(\mathbf{z})$$

Forward equations (Scalar form)

$$g_{ij} = u_{j1}x_{i1} + u_{j2}x_{i2} + b_{j}$$

$$h_{ij} = \tanh(g_{ij})$$

$$z_{i} = w_{1}h_{i1} + w_{2}h_{i2} + w_{3}h_{i3} + c$$

$$y_{i} = \sigma(z_{i})$$

Here, i indexes data points and j indexes hidden units, so $i \in \{1, ..., N\}$ and $j \in \{1, 2, 3\}$.

Cost function

$$\mathcal{E}(\mathbf{z}, \mathbf{t}) = \frac{1}{N} \left[\sum_{i=1}^{N} \mathcal{L}(z_i, t_i) \right]$$
$$\mathcal{L}(z, t) = t \log(1 + \exp(-z)) + (1 - t) \log(1 + \exp(z))$$

Backward Equations (Scalar form)

$$\overline{\mathcal{E}} = 1$$

$$\overline{z_i} = \overline{\mathcal{E}} \frac{\partial \mathcal{E}}{\partial z_i} = \frac{1}{N} (y_i - t_i) \text{ (see Lecture 4 notes)}$$

$$\overline{w_j} = \sum_{i=1}^N \overline{z_i} \frac{\partial z_i}{\partial w_j} = \sum_{i=1}^N \overline{z_i} h_{ij}$$

$$\overline{c} = \sum_{i=1}^N \overline{z_i} \frac{\partial z_i}{\partial c} = \sum_{i=1}^N \overline{z_i}$$

$$\overline{h_{ij}} = \overline{z_i} \frac{\partial z_i}{\partial h_{ij}} = \overline{z_i} w_j$$

$$\overline{g_{ij}} = \overline{h_{ij}} \frac{\partial h_{ij}}{\partial g_{ij}} = \overline{h_{ij}} (1 - \tanh^2(g_{ij})) \text{ (check derivative of tanh)}$$

$$\overline{u_{jk}} = \sum_{i=1}^N \overline{g_{ij}} \frac{\partial g_{ij}}{\partial u_{jk}} = \sum_{i=1}^N \overline{g_{ij}} x_{ik}$$

$$\overline{b_j} = \sum_{i=1}^N \overline{g_{ij}} \frac{\partial g_{ij}}{\partial b_j} = \sum_{i=1}^N \overline{g_{ij}}$$

As above, i indexes data points and j indexes hidden units, so $i \in \{1, ..., N\}$ and $j \in \{1, 2, 3\}$. In addition, k indexes the data dimension so $k \in \{1, 2, 3\}$.

Backward Equations (Vectorized form)

$$\begin{split} \overline{\mathcal{E}} &= 1 \\ \overline{\mathbf{z}} &= \frac{1}{N}(\mathbf{y} - \mathbf{t}) \\ \overline{\mathbf{W}} &= \mathbf{H}^T \overline{\mathbf{z}} \\ \overline{c} &= \mathbf{z}^T \mathbf{1} \quad \text{zer bar } ^{\Lambda} \mathbf{T} ^{\star} \mathbf{1} \\ \overline{\mathbf{H}} &= \overline{\mathbf{z}} \mathbf{W} \\ \overline{\mathbf{G}} &= \overline{\mathbf{H}} \odot (1 - \tanh^2(\mathbf{G})) \\ \overline{\mathbf{U}} &= \overline{\mathbf{G}}^T \mathbf{X} \\ \overline{\mathbf{b}} &= \overline{\mathbf{G}}^T \mathbf{1} \end{split}$$