COMPSCI 289A Homework 5 **Mitch Negus**
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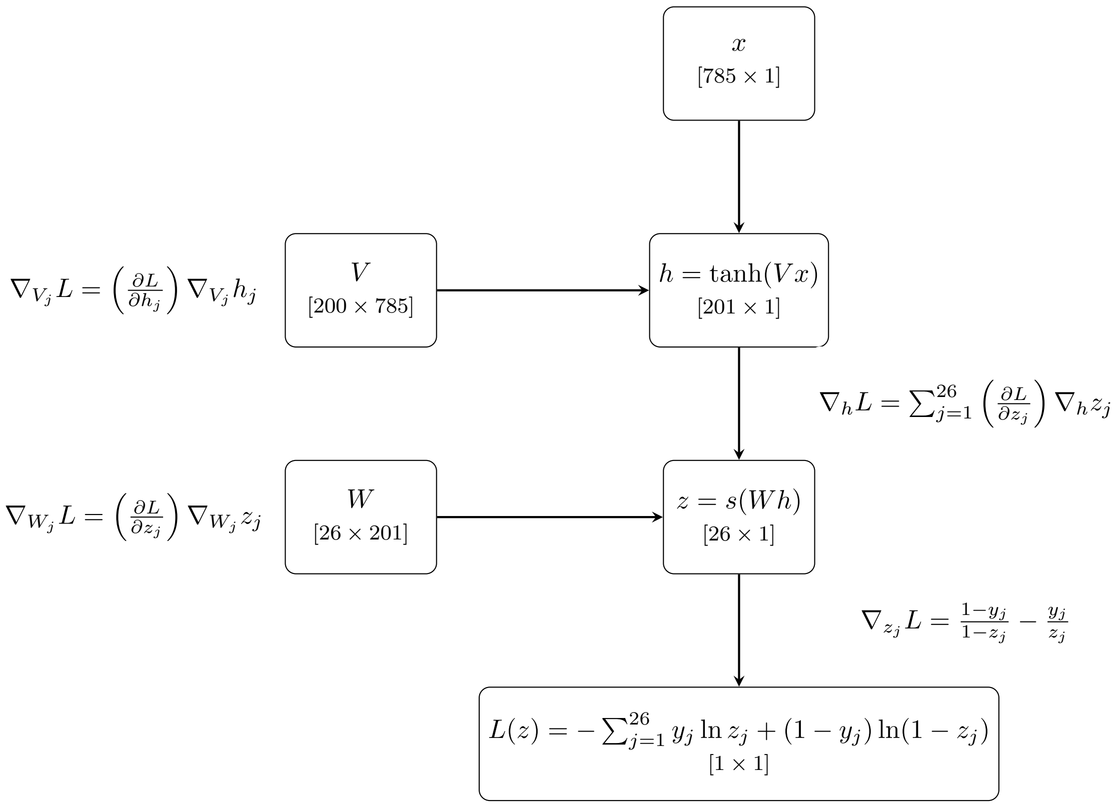
Problem 1

The constructed neural net follows the diagram below. $x \in \mathbb{R}^{785}$. For clarity, shapes of the solutions are given in brackets. Subscript j denotes a row index. A_j^T indicates the transpose of A_j.



We can substitute the following expressions:

$\nabla_{W_j} z_j = z_j(1-z_j)h^T \quad [1 \times 201]$

$\nabla_h z_j = z_j(1-z_j)W_j^T \quad [201 \times 1]$

$\nabla_{V_j} h_j = \text{sech}^2(V_j x)x^T \quad [1 \times 785]$

We can also use backpropagation to show:

$\nabla_{W_j} L = \left(\frac{1-y_j}{1-z_j} - \frac{y_j}{z_j}\right)\left(z_j(1-z_j)h^T\right) \quad [1 \times 201]$

$\nabla_h L = \sum_{j=1}^{26} \left(\frac{1-y_j}{1-z_j} - \frac{y_j}{z_j}\right)\left(z_j(1-z_j)W_j^T\right) \quad [201 \times 1]$

$\nabla_{V_j} L = (\nabla_h L)_j \, \text{sech}^2(V_j x)x^T \quad [1 \times 785]$

To enhance calculation efficiency, we can reduce some of these equations into matrices. First, let $\mathcal{Q}$ be the matrix

$$\mathcal{Q} = \begin{bmatrix} z_1(1-z_1)\left(\frac{1-y_1}{1-z_1} - \frac{y_1}{z_1}\right) \\ z_2(1-z_2)\left(\frac{1-y_2}{1-z_2} - \frac{y_2}{z_2}\right) \\ \vdots \\ z_{26}(1-z_{26})\left(\frac{1-y_{26}}{1-z_{26}} - \frac{y_{26}}{z_{26}}\right) \end{bmatrix} = \begin{bmatrix} z_1 - y_1 \\ z_2 - y_2 \\ \vdots \\ z_{26} - y_{26} \end{bmatrix}$$

With this, we can reexpress the above equations.
(1)
$\nabla_{W_j} L = \mathcal{Q}_j h^T \qquad [1 \times 201]$
or

$$\nabla_W L = \begin{bmatrix} \mathcal{Q}_1 h^T \\ \mathcal{Q}_2 h^T \\ \vdots \\ \mathcal{Q}_{26} h^T \end{bmatrix} = \mathcal{Q} h^T = \mathcal{Q} \otimes h \qquad [26 \times 201]$$

(2)
$\nabla_h L = \sum_{j=1}^{26} \mathcal{Q}_j W_j^T \qquad [201 \times 1]$
or

$$\nabla_h L = \left[\mathcal{Q}_1 W_1^T + \mathcal{Q}_2 W_2^T + ... + \mathcal{Q}_{26} W_{26}^T\right]$$
$$\nabla_h L = \left[W_1^T \mathcal{Q}_1 + W_2^T \mathcal{Q}_2 + ... + W_{26}^T \mathcal{Q}_{26}\right]$$
$$\nabla_h L = \begin{bmatrix} W_1^T & W_2^T & \dots & W_{26}^T \end{bmatrix} \begin{bmatrix} \mathcal{Q}_1 \\ \mathcal{Q}_2 \\ \vdots \\ \mathcal{Q}_{26} \end{bmatrix} = W^T \mathcal{Q} \qquad [201 \times 1]$$

(3)
Additionally, let

$$\mathcal{S} = \begin{bmatrix} \operatorname{sech}^2(V_1 x) \\ \operatorname{sech}^2(V_2 x) \\ \vdots \\ \operatorname{sech}^2(V_{200} x) \end{bmatrix} = \operatorname{sech}^2(Vx)$$

Then, $\nabla_{V_j} L = (W^T \mathcal{Q})_j \operatorname{sech}^2(V_j x) x^T \qquad [1 \times 785]$
or

$$\nabla_V L = \begin{bmatrix} (W^T \mathcal{Q})_1 \operatorname{sech}^2(V_1 x) x^T \\ (W^T \mathcal{Q})_2 \operatorname{sech}^2(V_2 x) x^T \\ \vdots \\ (W^T \mathcal{Q})_{200} \operatorname{sech}^2(V_{200} x) x^T \end{bmatrix} = \begin{bmatrix} (W^T \mathcal{Q})_1 \operatorname{sech}^2(V_1 x) \\ (W^T \mathcal{Q})_2 \operatorname{sech}^2(V_2 x) \\ \vdots \\ (W^T \mathcal{Q})_{200} \operatorname{sech}^2(V_{200} x) \end{bmatrix} x^T$$

$$\nabla_V L = \left(\begin{bmatrix} (W^T \mathcal{Q})_1 \\ (W^T \mathcal{Q})_2 \\ \vdots \\ (W^T \mathcal{Q})_{200} \end{bmatrix} \circ \begin{bmatrix} \operatorname{sech}^2(V_1 x) \\ \operatorname{sech}^2(V_2 x) \\ \vdots \\ \operatorname{sech}^2(V_{200} x) \end{bmatrix} \right) x^T = (W^T \mathcal{Q}) \circ \mathcal{S} x^T$$

Since we are updating our matrices V and W using stochastic gradient descent, we repeat the following process:

$V, W \leftarrow$ weight matrices initialized randomly from normal distribution with mean $\mu = 0$ and $\sigma^2 = (...)$
Forward calculation [$h = \tanh(Vx) \quad \rightarrow \quad z = s(Wh) \quad \rightarrow \quad L(z)$]
while (continue = True or $L(z) > 0$)
Backward calculation to return $\nabla_V L$ and $\nabla_W L$
$V \leftarrow V - \epsilon \nabla_V L)$
$W \leftarrow W - \epsilon \nabla_W L$
Forward calculation [$h = \tanh(Vx) \quad \rightarrow \quad z = s(Wh) \quad \rightarrow \quad L(z)$]
return V, W

where, using our derived equations from above, the update rules are more specifically
$V \leftarrow V - \epsilon(W^T \mathcal{Q}) \circ \mathcal{S} x^T$
$W \leftarrow W - \epsilon(\mathcal{Q} \otimes h)$.