Derivation of (Deep) RNN

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Loss Function 1

$$J = \frac{1}{T} \sum_{t=1}^{T} J^{(t)}$$

$$= \frac{1}{T} \sum_{t=1}^{T} \sum_{j=1}^{|V|} -y_j^{(t)} \log \hat{y}_j^{(t)}$$

$$= \frac{1}{T} \sum_{t=1}^{T} -\log \hat{y}_k^{(t)}$$
(1)

$$J^{(t)} = -\log \hat{y}_k^{(t)} \tag{2}$$

$\mathbf{2}$ Forward Propagation

Assume that we have a n+1 layer Recurrent Neural Network,

$$\hat{y}^{(t)} = g(z^{(n)(t)}) \tag{3}$$

$$h^{(l)(t)} = \begin{cases} f(z^{(l-1)(t)}) & 0 < l < n \\ x^{(t)} & l = 0 \end{cases}$$
 (4)

$$z^{(l)(t)} = \begin{cases} W^{(l)}h^{(l-1)(t)} + b^{(l)} & l = n \\ H^{(l)}h^{(l)(t-1)} + W^{(l)}h^{(l-1)(t)} + b^{(l)} & 0 < l < n \end{cases}$$
 (5)

3 Backward Propagation

For the purpose of simplicity, all derivation in this chapter will be made with respect to the loss function of a single time step. Moreover, we will presume that g(x) here is the softmax function, which can be easily substituted with any other functions as needed.

3.1 Derivation of δs

3.1.1 The Output Layer

$$\frac{\partial J^{(t)}}{\partial z^{(n)(t)}} = \frac{\partial}{\partial z^{(n)(t)}} \left(-\log \hat{y}_k^{(t)} \right)
= \frac{\partial}{\partial z^{(n)(t)}} \left(-z_k^{(n)(t)} + \log \sum_{j=1}^{|V|} z_j^{(n)(t)} \right)
= (\hat{y}^{(t)} - y^{(t)})^T
\delta^{(n)(t)} = \nabla_{z^{(n)(t)}} J^{(t)}
= \hat{y}^{(t)} - y^{(t)}$$
(7)

3.1.2 Top Hidden Layer

$$\frac{\partial J^{(t)}}{\partial z^{(n-1)(t)}} = \frac{\partial J^{(t)}}{\partial z^{(n)(t)}} \frac{\partial z^{(n)(t)}}{\partial z^{(n-1)(t)}}
= (\delta^{(n)(t)})^T \frac{\partial}{\partial z^{(n-1)(t)}} (W^{(n)} f(z^{(n-1)(t)}) + b^{(n)})
= (\delta^{(n)(t)})^T W^{(n)} diag[f'(z^{(n-1)(t)})]$$
(8)

$$\delta^{(n-1)(t)} = \nabla_{z^{(n-1)(t)}} J^{(t)}$$

$$= diag[f'(z^{(n-1)(t)})](W^{(n)})^T \delta^{(n)(t)}$$
(9)

$$\begin{split} \frac{\partial J^{(t)}}{\partial z^{(n-1)(t-c)}} &= \frac{\partial J^{(t)}}{\partial z^{(n-1)(t-c+1)}} \frac{\partial z^{(n-1)(t-c+1)}}{\partial z^{(n-1)(t-c)}} \\ &= (\delta^{(n-1)(t-c+1)})^T \frac{\partial}{\partial z^{(n-1)(t-c)}} (H^{(n-1)}h^{(n-1)(t-c)} + W^{(n-1)}h^{(n-2)(t-c+1)} + b^{(n-1)}) \\ &= (\delta^{(n-1)(t-c+1)})^T \frac{\partial}{\partial z^{(n-1)(t-c)}} (H^{(n-1)}f(z^{(n-1)(t-c)})) \\ &= (\delta^{(n-1)(t-c+1)})^T H^{(n-1)} diag[f'(z^{(n-1)(t-c)})] \end{split}$$

$$(10)$$

$$\delta^{(n-1)(t-c)} = \nabla_{z^{(n-1)(t-c)}} J^{(t)}$$

$$= \operatorname{diag}[f'(z^{(n-1)(t-c)})] (H^{(n-1)})^T \delta^{(n-1)(t-c+1)}$$
(11)

3.1.3 Other Hidden Layers

$$\begin{split} \frac{\partial J^{(t)}}{\partial z^{(l)(t)}} &= \frac{\partial J^{(t)}}{\partial z^{(l+1)(t)}} \frac{\partial z^{(l+1)(t)}}{\partial z^{(l)(t)}} \\ &= (\delta^{(l+1)(t)})^T \frac{\partial}{\partial z^{(l)(t)}} (H^{(l+1)}h^{(l+1)(t-1)} + W^{(l+1)}h^{(l)(t)} + b^{(l+1)}) \\ &= (\delta^{(l+1)(t)})^T \frac{\partial}{\partial z^{(l)(t)}} (W^{(l+1)}f(z^{(l)(t)})) \\ &= (\delta^{(l+1)(t)})^T W^{(l+1)} diag[f'(z^{(l)(t)})] \\ &\delta^{(l)(t)} &= \nabla_{z^{(l)(t)}} J^{(t)} \\ &= diag[f'(z^{(l)(t)})](W^{(l+1)})^T \delta^{(l+1)(t)} \end{split} \tag{13}$$

$$\delta^{(l)(t-c)} = \nabla_{z^{(l)(t-c)}} J^{(t)}$$

$$= diag[f'(z^{(l)(t-c)})]((H^{(l)})^T \delta^{(l)(t-c+1)} + W^{(l+1)}(\delta^{(l+1)(t-c)})^T)$$
(15)

 $= ((\delta^{(l)(t-c+1)})^T H^{(l)} + (\delta^{(l+1)(t-c)})^T W^{(l+1)}) diag[f'(z^{(l)(t-c)})]$

 $= (\delta^{(l)(t-c+1)})^T H^{(l)} diag[f'(z^{(l)(t-c)})] + (\delta^{(l+1)(t-c)})^T W^{(l+1)} diag[f'(z^{(l)(t-c)})]$

(14)

 $\left((\delta^{(l+1)(t-c)})^T \frac{\partial}{\partial z^{(l)(t-c)}} (W^{(l+1)} f(z^{(l)(t-c)})) \right)$

3.2 Gradients of Parameters

H – horizontally propagation matrix

$$\frac{\partial J^{(t)}}{\partial H^{(l)}} = \sum_{k=1}^{t} \frac{\partial J^{(t)}}{\partial H^{(l)}} \Big|_{(k)}$$

$$= \sum_{k=1}^{t} \frac{\partial J^{(t)}}{\partial z^{(l)(k)}} \frac{\partial z^{(l)(k)}}{\partial H^{(l)}} \Big|_{(k)}$$

$$= \sum_{k=1}^{t} (\delta^{(l)(k)})^{T} \left[\frac{\partial}{\partial H^{(l)}} (\epsilon_{i})^{T} (H^{(l)} h^{(l)(k-1)} + W^{(l)} h^{(l-1)(k)} + b^{(l)}) \right]$$

$$= \sum_{k=1}^{t} (\delta^{(l)(k)})^{T} \left[h^{(l)(k-1)} (\epsilon_{i})^{T} \right]$$

$$= \sum_{k=1}^{t} h^{(l)(k-1)} (\delta^{(l)(k)})^{T}$$
(16)

$$\nabla_{H^{(l)}} J^{(t)} = \sum_{k=1}^{t} \delta^{(1)(k)} (h^{(l)(k-1)})^{T}$$
(17)

W – vertically propagation matrix

$$\frac{\partial J^{(t)}}{\partial W^{(n)}} = \frac{\partial J^{(t)}}{\partial z^{(n)(t)}} \frac{\partial z^{(n)(t)}}{\partial W^{(n)}}
= (\delta^{(n)(t)})^T \left[\frac{\partial z_i^{(n)(t)}}{\partial W^{(n)}} \right]
= (\delta^{(n)(t)})^T \left[\frac{\partial}{\partial W^{(n)}} ((\epsilon_i)^T W^{(n)} h^{(n-1)(t)} + b_i^{(n)}) \right]
= (\delta^{(n)(t)})^T \left[h^{(n-1)(t)} (\epsilon_i)^T \right]
= h^{(n-1)(t)} (\delta^{(n)(t)})^T$$
(18)

$$\nabla_{W^{(n)}} J^{(t)} = \delta^{(n)(t)} (h^{(n-1)(t)})^T \tag{19}$$

$$\frac{\partial J^{(t)}}{\partial W^{(l)}} = \sum_{k=1}^{t} \frac{\partial J^{(t)}}{\partial W^{(l)}} \Big|_{(k)}$$

$$= \sum_{k=1}^{t} \frac{\partial J^{(t)}}{\partial z^{(l)(k)}} \frac{\partial z^{(l)(k)}}{\partial W^{(l)}} \Big|_{(k)}$$

$$= \sum_{k=1}^{t} (\delta^{(l)(k)})^{T} \left[\frac{\partial}{\partial W^{(l)}} (\epsilon_{i})^{T} (H^{(l)} h^{(l)(k-1)} + W^{(l)} h^{(l-1)(k)} + b^{(l)}) \right] (20)$$

$$= \sum_{k=1}^{t} (\delta^{(l)(k)})^{T} \left[h^{(l-1)(k)} (\epsilon_{i})^{T} \right]$$

$$= \sum_{k=1}^{t} h^{(l-1)(k)} (\delta^{(l)(k)})^{T}$$

$$\nabla_{W^{(l)}} J^{(t)} = \sum_{k=1}^{t} \delta^{(l)(k)} (h^{(l-1)(k)})^{T}$$
(21)

b - bias term

$$\frac{\partial J^{(t)}}{\partial b^{(n)}} = \frac{\partial J^{(t)}}{\partial z^{(n)(t)}} \frac{\partial z^{(n)(t)}}{\partial b^{(n)}}
= (\delta^{(n)(t)})^T I
= (\delta^{(n)(t)})^T$$
(22)

$$\nabla_{b^{(n)}} J^{(t)} = \delta^{(n)(t)} \tag{23}$$

$$\frac{\partial J^{(t)}}{\partial b^{(l)}} = \sum_{k=1}^{t} \frac{\partial J^{(t)}}{\partial b^{(l)}} \Big|_{(k)}$$

$$= \sum_{k=1}^{t} \frac{\partial J^{(t)}}{\partial z^{(l)(k)}} \frac{\partial z^{(l)(k)}}{\partial b^{(l)}} \Big|_{(k)}$$

$$= \sum_{k=1}^{t} (\delta^{(l)(k)})^{T} I$$

$$= \sum_{k=1}^{t} (\delta^{(l)(k)})^{T}$$
(24)

$$\nabla_{b^{(l)}} J^{(t)} = \sum_{k=1}^{t} \delta^{(l)(k)}$$
 (25)

3.3 Conclusion

$$\delta^{(n)(t)} = \hat{y}^{(t)} - y^{(t)} \tag{26}$$

$$\delta^{(n-1)(t)} = diag[f'(z^{(n-1)(t)})](W^{(n)})^T \delta^{(n)(t)}$$
(27)

$$\delta^{(n-1)(t-c)} = diag[f'(z^{(n-1)(t-c)})](H^{(n-1)})^T \delta^{(n-1)(t-c+1)}$$
(28)

$$\delta^{(l)(t)} = diag[f'(z^{(l)(t)})](W^{(l+1)})^T \delta^{(l+1)(t)}$$
(29)

$$\delta^{(l)(t-c)} = diag[f'(z^{(l)(t-c)})]((H^{(l)})^T \delta^{(l)(t-c+1)} + (W^{(l+1)})^T \delta^{(l+1)(t-c)})$$
(30)

$$\nabla_{H^{(l)}} J^{(t)} = \sum_{k=1}^{t} \delta^{(l)(t)} (h^{(l)(k-1)})^{T}$$
(31)

$$\nabla_{W^{(n)}} J^{(t)} = \delta^{(n)(t)} (h^{(n-1)(t)})^T$$
(32)

$$\nabla_{W^{(l)}} J^{(t)} = \sum_{k=1}^{t} \delta^{(l)(k)} (h^{(l-1)(k)})^{T}$$

$$\nabla_{b^{(n)}} J^{(t)} = \delta^{(n)(t)}$$
(33)

$$\nabla_{b^{(n)}} J^{(t)} = \delta^{(n)(t)} \tag{34}$$

$$\nabla_{b^{(l)}} J^{(t)} = \sum_{k=1}^{t} \delta^{(l)(k)}$$
(35)

4 Trick for Implementation

Derivation above is made with respect to the loss function of a single time step, (i.e. $\nabla J^{(t)}$). When taking derivative of the final loss function ∇J with respect to $H^{(l)},\,W^{(l)}$, and $b^{(l)}$ for l < n, instead of calculate $\nabla J^{(t)}$ for every time step and sum them up at last, which is correct but inefficient, we backprop only once by keeping record of $\gamma^{(l)(t)}$, which is the accumulating sum of $\delta^{(l)(t)(i)}$ over range t to T.

It is easy to find that, when t = T - 1:

$$\gamma^{(l)(t)} = \delta^{(l)(t)(t)} \tag{36}$$

when 1 < t < T - 1:

$$\begin{split} \gamma^{(n-1)(t)} &= \sum_{i=t}^{T} \delta^{(n-1)(t)(i)} \\ &= \delta^{(n-1)(t)(t)} + \sum_{i=t+1}^{T} \delta^{(n-1)(t)(i)} \\ &= \delta^{(n-1)(t)(t)} + \sum_{i=t+1}^{T} diag[f'(z^{(n-1)(t)})](H^{(n-1)})^{T} \delta^{(n-1)(t+1)(i)} \\ &= \delta^{(n-1)(t)(t)} + diag[f'(z^{(n-1)(t)})](H^{(n-1)})^{T} \sum_{i=t+1}^{T} \delta^{(n-1)(t+1)(i)} \\ &= \delta^{(n-1)(t)(t)} + diag[f'(z^{(n-1)(t)})](H^{(n-1)})^{T} \gamma^{(n-1)(t+1)} \\ &= \delta^{(n-1)(t)(t)} + f'(z^{(n-1)(t)}) \circ ((H^{(n-1)})^{T} \gamma^{(n-1)(t+1)}) \end{split}$$

 $^{^1\}text{We}$ will slightly change our notation here by adding one more superscript to δ so as to differentiate δ from different $J^{(t)},$ now $\delta^{(l)(t)(i)} = \nabla_{z^{(l)(t)}} J^{(i)}.$

when $1 \le t \le T-1$ and $1 \le l \le n-2$:

$$\begin{split} \gamma^{(l)(t)} &= \sum_{i=t}^{T} \delta^{(l)(t)(i)} \\ &= \sum_{i=t}^{T} diag[f'(z^{(l)(t)})]((H^{(l)})^{T} \delta^{(l)(t+1)(i)} + (W^{(l+1)})^{T} \delta^{(l+1)(t)(i)}) \\ &= \delta^{(l)(t)(t)} + \sum_{i=t+1}^{T} \delta^{(l)(t)(i)} \\ &= \delta^{(l)(t)(t)} + \sum_{i=t+1}^{T} diag[f'(z^{(l)(t)})]((H^{(l)})^{T} \delta^{(l)(t+1)(i)} + (W^{(l+1)})^{T} \delta^{(l+1)(t)(i)}) \\ &= \delta^{(l)(t)(t)} + diag[f'(z^{(l)(t)})] \\ &\left((H^{(l)})^{T} \left(\sum_{i=t+1}^{T} \delta^{(l)(t+1)(i)} \right) + (W^{(l+1)})^{T} \left(\sum_{i=t+1}^{T} \delta^{(l+1)(t)(i)} \right) \right) \\ &= \delta^{(l)(t)(t)} + f'(z^{(l)(t)}) \circ ((H^{(l)})^{T} \gamma^{(l)(t+1)} + (W^{(l+1)})^{T} (\gamma^{(l+1)(t)} - \delta^{(l+1)(t)(t)})) \\ &= f'(z^{(l)(t)}) \circ ((H^{(l)})^{T} \gamma^{(l)(t+1)} + (W^{(l+1)})^{T} \gamma^{(l+1)(t)}) \end{split}$$

We can now simplify our gradients by reorganizing terms and using γs instead of δs ,

$$\nabla_{H^{(l)}} J = \frac{1}{T} \sum_{i=1}^{T} \sum_{j=1}^{i} \delta^{(l)(j)(i)} (h^{(j-1)})^{T}$$

$$= \frac{1}{T} \sum_{i=1}^{T} \sum_{j=i}^{T} \delta^{(l)(i)(j)} (h^{(l)(i-1)})^{T}$$

$$= \frac{1}{T} \sum_{i=1}^{T} \gamma^{(l)(i)} (h^{(l)(i-1)})^{T}$$
(39)

$$\nabla_{W^{(l)}} J = \frac{1}{T} \sum_{i=1}^{T} \sum_{j=1}^{i} \delta^{(l)(j)(i)} (h^{(l-1)(j)})^{T}$$

$$= \frac{1}{T} \sum_{i=1}^{T} \sum_{j=i}^{T} \delta^{(l)(i)(j)} (h^{(l-1)(i)})^{T}$$

$$= \frac{1}{T} \sum_{i=1}^{T} \gamma^{(l)(i)} (h^{(l-1)(i)})^{T}$$
(40)

$$\nabla_{b^{(l)}} J = \frac{1}{T} \sum_{i=1}^{T} \sum_{j=1}^{i} \delta^{(l)(j)(i)}$$

$$= \frac{1}{T} \sum_{i=1}^{T} \sum_{j=i}^{T} \delta^{(l)(i)(j)}$$

$$= \frac{1}{T} \sum_{i=1}^{T} \gamma^{(l)(i)}$$
(41)

Hmm, now we can put every thing together,

$$\delta^{(l)(t)(t)} = \begin{cases} \hat{y}^{(t)} - y^{(t)} & l = n \\ f'(z^{(l)(t)}) \circ ((W^{(l+1)})^T \delta^{(l+1)(t)(t)}) & l < n \end{cases}$$
(42)

$$\delta^{(l)(t)(t)} = \begin{cases}
\hat{y}^{(t)} - y^{(t)} & l = n \\
f'(z^{(l)(t)}) \circ ((W^{(l+1)})^T \delta^{(l+1)(t)(t)}) & l < n
\end{cases}$$

$$\gamma^{(l)(t)} = \begin{cases}
\delta^{(l)(t)(t)} & t = T \\
\delta^{(l)(t)(t)} + f'(z^{(l)(t)}) \circ ((H^{(l)})^T \gamma^{(l)(t+1)}) & l = n - 1 \\
f'(z^{(l)(t)}) \circ ((H^{(l)})^T \gamma^{(l)(t+1)} + \\
(W^{(l+1)})^T \gamma^{(l+1)(t)}) & l < n - 1
\end{cases}$$
(42)

$$\nabla_{H^{(l)}} J = \frac{1}{T} \sum_{t=1}^{T} \gamma^{(l)(t)} (h^{(l)(t-1)})^{T}$$
(44)

$$\nabla_{W^{(l)}} J = \begin{cases} \frac{1}{T} \sum_{t=1}^{T} \delta^{(n)(t)(t)} (h^{(n-1)(t)})^{T} & l = n \\ \frac{1}{T} \sum_{t=1}^{T} \gamma^{(l)(t)} (h^{(l-1)(t)})^{T} & l < n \end{cases}$$

$$\nabla_{b^{(l)}} J = \begin{cases} \frac{1}{T} \sum_{t=1}^{T} \delta^{(n)(t)(t)} & l = n \\ \frac{1}{T} \sum_{t=1}^{T} \gamma^{(l)(t)} & l < n \end{cases}$$

$$(45)$$

$$\nabla_{b^{(l)}} J = \begin{cases} \frac{1}{T} \sum_{t=1}^{T} \delta^{(n)(t)(t)} & l = n\\ \frac{1}{T} \sum_{t=1}^{T} \gamma^{(l)(t)} & l < n \end{cases}$$
 (46)