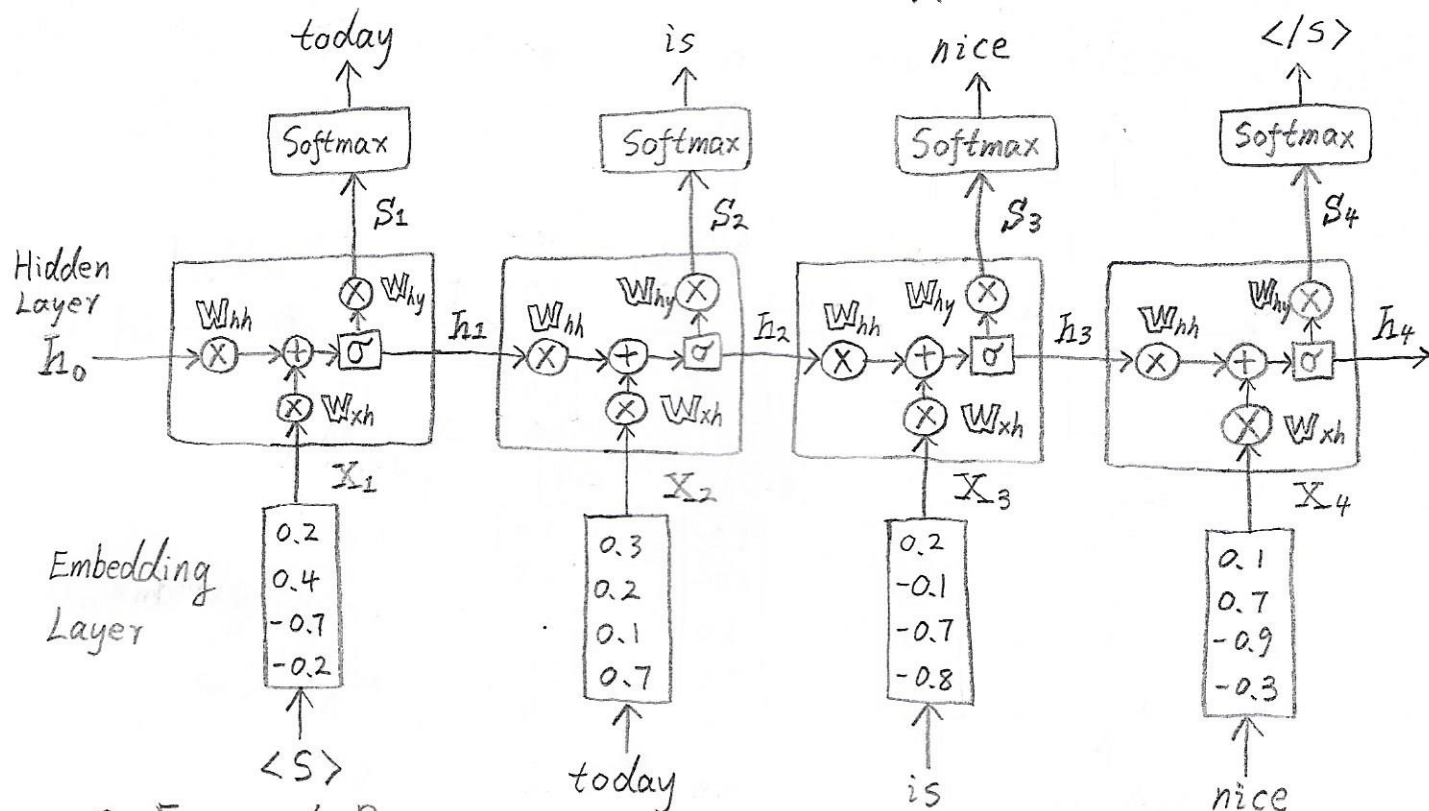


IX RECURRENT NEURAL NETWORK

1. Vanilla Recurrent Neural Network



2. Forward Pass

$$W_e = \{ \text{"hello"}: X_1, \text{"what"}: X_2, \dots, \text{"zaltan"}: X_{v\text{-size}} \}$$

$$X_t = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{256} \end{bmatrix}, \text{ hidden_size} = 256$$

$$h_t = \sigma(W_{xh} \cdot X_t + W_{hh} \cdot h_{t-1})$$

$256 \times 1 \quad \quad 256 \times 256 \quad 256 \times 1 \quad 256 \times 256 \quad 256 \times 1$

$$= \frac{1}{1 + e^{-(W_{xh} \cdot X_t + W_{hh} \cdot h_{t-1})}}$$

$$S_t = W_{hy} \cdot h_t = \begin{bmatrix} S_t(y_1) \\ S_t(y_2) \\ \vdots \\ S_t(y_m) \end{bmatrix}, Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$$

$|Y| \times 1 \quad |Y| \times 256 \quad 256 \times 1$

$$P_t = \text{softmax}(S_t)$$

$$= \text{Softmax} \left(\begin{bmatrix} S_t(y_1) \\ S_t(y_2) \\ \vdots \\ S_t(y_m) \end{bmatrix} \right)$$

$$= \begin{bmatrix} \frac{e^{S_t(y_1)}}{\sum_{y' \in Y} e^{S_t(y')}} \\ \vdots \\ \frac{e^{S_t(y_m)}}{\sum_{y' \in Y} e^{S_t(y')}} \end{bmatrix} = \begin{bmatrix} p_t(y_1) \\ \vdots \\ p_t(y_m) \end{bmatrix} = \begin{bmatrix} p_t(y_1) \\ \vdots \\ p_t(y_t) \\ \vdots \\ p_t(y_m) \end{bmatrix}$$

$$\text{loss}_t = - \sum_{i=1}^m y'_i \cdot \log(p_t(y_i)) = - y'_t \cdot \log(p_t(y_t)) \quad (\text{If } y'_i = y'_t)$$

\nearrow True output at index i \nearrow Estimated output at index i .

$$= - \log \left(\frac{e^{S_t(y_t)}}{\sum_{y' \in Y} e^{S_t(y')}} \right)$$

$y'_i = 1$;
 if $y'_i \neq y'_t$,
 $y'_i = 0$.

(Cross Entropy Loss)

$$= \log \sum_{y' \in Y} e^{S_t(y')} - \log e^{S_t(y_t)}$$

$$= \log \sum_{y' \in Y} e^{S_t(y')} - S_t(y_t)$$

3. Backward Pass

$$dS_t(y) = \frac{\partial \text{loss}_t}{\partial S_t(y)} = \frac{\partial}{\partial S_t(y)} \left(\log \sum_{y' \in Y} e^{S_t(y')} - S_t(y_t) \right)$$

$$= \frac{\partial}{\partial S_t(y)} \left(\log \sum_{y' \in Y} e^{S_t(y')} \right) - \frac{\partial}{\partial S_t(y)} (S_t(y_t))$$

$$= \frac{1}{\sum_{y' \in Y} e^{S_t(y')}} \cdot \frac{\partial}{\partial S_t(y)} \left(\sum_{y' \in Y} e^{S_t(y')} \right) - \frac{\partial}{\partial S_t(y)} (S_t(y_t))$$

(chain rule)

When $y = y_t$

$$dS_t(y_t) = \frac{e^{S_t(y_t)}}{\sum_{y' \in Y} e^{S_t(y')}} - 1$$
$$= p_t(y_t) - 1$$

When $y \neq y_t$

$$dS_t(y) = \frac{e^{S_t(y)}}{\sum_{y' \in Y} e^{S_t(y')}} = p_t(y)$$

$$dS_t = \frac{\partial \text{loss}_t}{\partial S_t} = \begin{bmatrix} dS_t(y_1) \\ \vdots \\ dS_t(y_t) \\ \vdots \\ dS_t(y_m) \end{bmatrix} = \begin{bmatrix} p_t(y_1) \\ \vdots \\ p_t(y_t) - 1 \\ \vdots \\ p_t(y_m) \end{bmatrix}$$

$$= \begin{bmatrix} p_t(y_1) \\ \vdots \\ p_t(y_t) \\ \vdots \\ p_t(y_m) \end{bmatrix} - \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} = P_t - 1_{y=y_t} \quad \textcircled{O}$$

4. Mathematical Helpers

1). Definition 1

If U and V are vectors, then

$$\begin{aligned} & \text{diag}(U) \cdot V \\ &= \text{diag}\left(\begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix}\right) \cdot \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} = \begin{bmatrix} u_1 & 0 & \dots & 0 \\ 0 & u_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & u_n \end{bmatrix} \cdot \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} = \begin{bmatrix} u_1 v_1 \\ u_2 v_2 \\ \vdots \\ u_n v_n \end{bmatrix} = U \circ V \end{aligned}$$

2). Lemma 1

V and h are vectors. W is a matrix. $dV = \frac{\partial \ell}{\partial V}$ is known.

$V = f(W \cdot h)$, where f is an element-wise function. Then

$$dh = \frac{\partial \ell}{\partial h} = W^T \cdot (f'(W \cdot h) \circ dV), \quad \textcircled{1} \text{ and}$$

$$dW = \frac{\partial \ell}{\partial W} = (f'(W \cdot h) \circ dV) \cdot h^T \quad \textcircled{2}$$

Proof:

$\ell = g(f(W \cdot h))$, where $V = f(W \cdot h)$, $z = W \cdot h$

$$\frac{\partial \ell}{\partial h} = \frac{\partial f}{\partial h} \cdot \frac{\partial \ell}{\partial f} \quad (\text{Chain rule, D.L., P104, Denominator-Layout})$$

$$= \left(\frac{\partial z}{\partial h} \cdot \frac{\partial f}{\partial z} \right) \cdot \frac{\partial \ell}{\partial f} \quad (\text{Chain rule, again})$$

$$= \frac{\partial W h}{\partial h} \cdot \frac{\partial f(z)}{\partial z} \cdot \frac{\partial \ell}{\partial V}$$

$$= \frac{\partial W h}{\partial h} \cdot \text{diag}(f'(z)) \cdot dV$$

$$= \frac{\partial W \cdot h}{\partial h} \cdot (f'(Wh) \circ dv) \quad (\text{Definition 1})$$

$$W = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \dots & w_{mn} \end{bmatrix}, \quad h = \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{bmatrix}, \quad \text{then}$$

$$Wh = \begin{bmatrix} w_{11}h_1 + w_{12}h_2 + \dots + w_{1n}h_n \\ w_{21}h_1 + w_{22}h_2 + \dots + w_{2n}h_n \\ \vdots \\ w_{m1}h_1 + w_{m2}h_2 + \dots + w_{mn}h_n \end{bmatrix} = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix}$$

$$\frac{\partial Wh}{\partial h} = \begin{bmatrix} \frac{\partial z_1}{\partial h_1} & \frac{\partial z_2}{\partial h_1} & \dots & \frac{\partial z_m}{\partial h_1} \\ \frac{\partial z_1}{\partial h_2} & \frac{\partial z_2}{\partial h_2} & \dots & \frac{\partial z_m}{\partial h_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial z_1}{\partial h_n} & \frac{\partial z_2}{\partial h_n} & \dots & \frac{\partial z_m}{\partial h_n} \end{bmatrix} = \begin{bmatrix} w_{11} & w_{21} & \dots & w_{m1} \\ w_{12} & w_{22} & \dots & w_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ w_{1n} & w_{2n} & \dots & w_{mn} \end{bmatrix} = W^T$$

(Denominator-Layout)

$$dh = \frac{\partial \ell}{\partial h} = W^T \cdot (f'(Wh) \circ dv)$$

$$\text{Let } w_1 = \begin{bmatrix} w_{11} \\ w_{12} \\ \vdots \\ w_{1n} \end{bmatrix}, \quad w_2 = \begin{bmatrix} w_{21} \\ w_{22} \\ \vdots \\ w_{2n} \end{bmatrix}, \quad \dots, \quad w_m = \begin{bmatrix} w_{m1} \\ w_{m2} \\ \vdots \\ w_{mn} \end{bmatrix}, \quad \text{then}$$

$$\ell = g(f(Wh))$$

$$= g\left(f\left(\begin{bmatrix} w_1^T \\ w_2^T \\ \vdots \\ w_m^T \end{bmatrix} \cdot h\right)\right)$$

$$= g\left(f\left(\begin{bmatrix} w_1^T \cdot h \\ w_2^T \cdot h \\ \vdots \\ w_m^T \cdot h \end{bmatrix}\right)\right) = g\left(f\left(\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix}\right)\right)$$

$$= g\left(\begin{bmatrix} f(z_1) \\ f(z_2) \\ \vdots \\ f(z_m) \end{bmatrix}\right) = g\left(\begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix}\right)$$

$$\frac{\partial \ell}{\partial w_i} = \frac{\partial v_i}{\partial w_i} \cdot \frac{\partial \ell}{\partial v_i} \quad (\text{Chain Rule})$$

$$= \left(\frac{\partial z_i}{\partial w_i} \cdot \frac{\partial v_i}{\partial z_i}\right) \cdot \frac{\partial \ell}{\partial v_i} \quad (\text{Chain Rule})$$

$$= \frac{\partial w_i^T h}{\partial w_i} \cdot f'(z_i) \cdot dv_i$$

$$= \begin{bmatrix} \frac{\partial (w_{i1}h_1 + w_{i2}h_2 + \dots + w_{in}h_n)}{\partial w_{i1}} \\ \vdots \\ \frac{\partial (w_{i1}h_1 + w_{i2}h_2 + \dots + w_{in}h_n)}{\partial w_{in}} \end{bmatrix} \cdot f'(z_i) \cdot dv_i$$

$$= \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{bmatrix} \cdot f'(z_i) \cdot dv_i$$

$$= h \cdot f'(z_i) \cdot dv_i$$

$$dw_i^T = \frac{\partial \ell}{\partial w_i^T} = f'(z_i) \cdot dv_i \cdot h^T$$

$$dW = \frac{\partial \ell}{\partial W} = \begin{bmatrix} \frac{\partial \ell}{\partial w_1^T} \\ \frac{\partial \ell}{\partial w_2^T} \\ \vdots \\ \frac{\partial \ell}{\partial w_m^T} \end{bmatrix} = \begin{bmatrix} f'(z_1) \cdot dv_1 \\ f'(z_2) \cdot dv_2 \\ \vdots \\ f'(z_m) \cdot dv_m \end{bmatrix} \cdot h^T$$

$$= (f'(W \cdot h) \circ dv) \cdot h^T \quad \square$$

3) Corollary 1

If $v = f(W \cdot h) = W \cdot h$, then

$$dh = W^T \cdot dv \quad (3)$$

$$dW = dv \cdot h^T \quad (4)$$

Proof :

$$f(W \cdot h) = f\left(\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix}\right) = \begin{bmatrix} f(z_1) \\ f(z_2) \\ \vdots \\ f(z_m) \end{bmatrix} = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix}$$

$$f'(W \cdot h) = f'\left(\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix}\right) = \begin{bmatrix} f'(z_1) \\ f'(z_2) \\ \vdots \\ f'(z_m) \end{bmatrix} = \begin{bmatrix} \frac{dz_1}{dz_1} \\ \frac{dz_2}{dz_2} \\ \vdots \\ \frac{dz_m}{dz_m} \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$

$$\therefore dh = W^T \cdot dv, \quad dW = dv \cdot h^T \quad (\text{From (1) and (2)}) \quad \square$$

4) Lemma 2

u, v and S are vectors. $S = u \circ f(v)$.

$du = \frac{\partial \ell}{\partial u}$, $dv = \frac{\partial \ell}{\partial v}$, $dS = \frac{\partial \ell}{\partial S}$, then

$$du = f(v) \circ dS \quad (5)$$

$$dv = f'(v) \circ u \circ dS \quad (6)$$

Proof:

$$\ell = g(S) = g(u \circ f(v))$$

$$du = \frac{\partial S}{\partial u} \cdot \frac{\partial \ell}{\partial S} = f(v) \circ dS$$

$$dv = \frac{\partial S}{\partial v} \cdot \frac{\partial \ell}{\partial S} = \frac{\partial f}{\partial v} \cdot \frac{\partial S}{\partial f} \cdot \frac{\partial \ell}{\partial S} = f'(v) \circ u \circ dS \quad \square$$

5) Corollary 2

If $f(v) = v$, then

$$du = v \circ dS \quad (7)$$

$$dv = u \circ dS \quad (8)$$

5. Backward Pass - Continue

Since $S_t = W_{hy} \cdot h_t$,

$$dh_t = W_{hy}^T \cdot dS_t \quad (\text{by } \textcircled{3}) \quad \textcircled{9}$$

$$dW_{hy} = dS_t \cdot h_t^T \quad (\text{by } \textcircled{4}) \quad \textcircled{10}$$

$$W_{xh} \cdot X_t + W_{hh} \cdot h_{t-1}$$

$$= \begin{bmatrix} w_{xh11} & w_{xh12} & \dots & w_{xh1n} \\ w_{xh21} & w_{xh22} & \dots & w_{xh2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{xhm1} & w_{xhm2} & \dots & w_{xhmn} \end{bmatrix} \cdot \begin{bmatrix} x_{t1} \\ x_{t2} \\ \vdots \\ x_{tn} \end{bmatrix} + \begin{bmatrix} w_{hh11} & w_{hh12} & \dots & w_{hh1n} \\ w_{hh21} & w_{hh22} & \dots & w_{hh2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{hhm1} & w_{hhm2} & \dots & w_{hhmn} \end{bmatrix} \cdot \begin{bmatrix} h_{t-11} \\ h_{t-12} \\ \vdots \\ h_{t-1n} \end{bmatrix}$$

$$= \begin{bmatrix} w_{xh11} & w_{xh12} & \dots & w_{xh1n} & w_{hh11} & w_{hh12} & \dots & w_{hh1n} \\ w_{xh21} & w_{xh22} & \dots & w_{xh2n} & w_{hh21} & w_{hh22} & \dots & w_{hh2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{xhm1} & w_{xhm2} & \dots & w_{xhmn} & w_{hhm1} & w_{hhm2} & \dots & w_{hhmn} \end{bmatrix} \cdot \begin{bmatrix} x_{t1} \\ x_{t2} \\ \vdots \\ x_{tn} \\ h_{t-11} \\ h_{t-12} \\ \vdots \\ h_{t-1n} \end{bmatrix}$$

$$= \begin{bmatrix} W_{xh} & W_{hh} \end{bmatrix} \cdot \begin{bmatrix} X_t \\ h_{t-1} \end{bmatrix}$$

$$= \begin{bmatrix} W_{xh} & W_{hh} \end{bmatrix} \cdot \begin{bmatrix} X_t; h_{t-1} \end{bmatrix}$$

$$= T_{rnn} \cdot Z_t$$

$$\therefore \mathbf{h}_t = \sigma(\mathbf{T}_{rnn} \cdot \mathbf{Z}_t)$$

$$d\mathbf{Z}_t = \mathbf{T}_{rnn}^T \cdot (\sigma'(\mathbf{T}_{rnn} \mathbf{Z}_t) \circ d\mathbf{h}_t) \quad (\text{by } ①) \quad ⑪$$

$$\begin{bmatrix} d\mathbf{X}_t \\ d\mathbf{h}_{t-1} \end{bmatrix} = \begin{bmatrix} \mathbf{W}_{xh}^T \\ \mathbf{W}_{hh}^T \end{bmatrix} \cdot (\sigma'(\mathbf{T}_{rnn} \mathbf{Z}_t) \circ d\mathbf{h}_t)$$

$$d\mathbf{X}_t = \mathbf{W}_{xh}^T \cdot (\sigma'(\mathbf{T}_{rnn} \mathbf{Z}_t) \circ d\mathbf{h}_t) \quad ⑫$$

$$d\mathbf{h}_{t-1} = \mathbf{W}_{hh}^T \cdot (\sigma'(\mathbf{T}_{rnn} \mathbf{Z}_t) \circ d\mathbf{h}_t) \quad ⑬$$

$$d\mathbf{T}_{rnn} = (\sigma'(\mathbf{T}_{rnn} \mathbf{Z}_t) \circ d\mathbf{h}_t) \cdot \mathbf{Z}_t^T \quad (\text{by } ②) \quad ⑭$$

$$\begin{bmatrix} d\mathbf{W}_{xh} & d\mathbf{W}_{hh} \end{bmatrix} = (\sigma'(\mathbf{T}_{rnn} \mathbf{Z}_t) \circ d\mathbf{h}_t) \cdot \begin{bmatrix} \mathbf{X}_t^T & \mathbf{h}_{t-1}^T \end{bmatrix}$$

$$d\mathbf{W}_{xh} = (\sigma'(\mathbf{T}_{rnn} \mathbf{Z}_t) \circ d\mathbf{h}_t) \cdot \mathbf{X}_t^T \quad ⑮$$

$$d\mathbf{W}_{hh} = (\sigma'(\mathbf{T}_{rnn} \mathbf{Z}_t) \circ d\mathbf{h}_t) \cdot \mathbf{h}_{t-1}^T \quad ⑯$$

Backpropagation-Through-Time-Vanilla-RNN():

for t from T to 1 :

$$\frac{\partial \ell_t}{\partial s_t} = p_t - 1 y = y_t \quad (8)$$

$$\frac{\partial \ell_t}{\partial w_{hy}} = \frac{\partial \ell_{t+1}}{\partial w_{hy}} + \frac{\partial \ell_t}{\partial s_t} \cdot h^T \quad (9)$$

$$\frac{\partial \ell_t}{\partial h_t} = \frac{\partial \ell_{t+1}}{\partial h_t} + w_{hy}^T \cdot \frac{\partial \ell_t}{\partial s_t} \quad (10)$$

$$\frac{\partial \ell_t}{\partial w_{xh}} = \frac{\partial \ell_{t+1}}{\partial w_{xh}} + \left(\sigma'(T_{rnn} Z_t) \circ \frac{\partial \ell_t}{\partial h_t} \right) \cdot x_t^T \quad (11)$$

$$\frac{\partial \ell_t}{\partial w_{hh}} = \frac{\partial \ell_{t+1}}{\partial w_{hh}} + \left(\sigma'(T_{rnn} Z_t) \circ \frac{\partial \ell_t}{\partial h_t} \right) \cdot h_{t-1}^T \quad (12)$$

$$\frac{\partial \ell_t}{\partial x_t} = w_{xh}^T \cdot \left(\sigma'(T_{rnn} Z_t) \circ \frac{\partial \ell_t}{\partial h_t} \right) \quad (13)$$

$$\frac{\partial \ell_t}{\partial h_{t-1}} = w_{hh}^T \cdot \left(\sigma'(T_{rnn} Z_t) \circ \frac{\partial \ell_t}{\partial h_t} \right) \quad (14)$$

Comments:

1) $\frac{\partial \ell_t}{\partial w_{hy}}, \frac{\partial \ell_t}{\partial w_{xh}}, \frac{\partial \ell_t}{\partial w_{hh}}, \frac{\partial \ell_t}{\partial h_t}$ are aggregated through time since

$$\frac{\partial \ell_{total}}{\partial w} = \frac{\partial \ell_{t=T} + \ell_{t=T-1} + \dots + \ell_{t=1}}{\partial w} = \frac{\partial \ell_{t=T}}{\partial w} + \frac{\partial \ell_{t=T-1}}{\partial w} + \dots + \frac{\partial \ell_{t=1}}{\partial w}$$

$$2) \sigma'(T_{rnn} Z_t) = \sigma(T_{rnn} Z_t) - \sigma^2(T_{rnn} Z_t) = \sigma\left([w_{xh} w_{hh}] \cdot \begin{bmatrix} x_t \\ h_{t-1} \end{bmatrix}\right) - \sigma^2\left([w_{xh} w_{hh}] \cdot \begin{bmatrix} x_t \\ h_{t-1} \end{bmatrix}\right)$$