RNN

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Introduce 1

Formula 1 has to go to Appendix for RNN BPPT.

$$x_t = x_t^o E (1)$$

$$h_t = \Theta_h(W \ h_{t-1} + U \ x_t + b) \tag{2}$$

$$\Omega_t = V h_t + c \tag{3}$$

$$\hat{y}_t = \Theta_y(\Omega_t) \tag{4}$$

$$L_t = -y_t \ln(\hat{y}_t) \tag{5}$$

in (1), we use embedding layer. Θ 's represent all activation functions. In our example for analytics, Θ_h is tanh in (2), while Θ_y is softmax in (4), which is usually used.

Through Time for Recurrent Neural Network 2

2.1Softmax

Softmax $(x_t) = S_t = \frac{e^{x_t}}{\sum e^{x_k}}$ for t = 1, ..., kSince softmax is a $\mathbb{R}^k \to \mathbb{R}^k$ mapping function, most general Jacobian matrix for it:

$$\frac{\partial S}{\partial x} = \begin{bmatrix} \frac{\partial S_1}{\partial x_1} & \dots & \frac{\partial S_1}{\partial x_k} \\ \vdots & & & \\ \frac{\partial S_k}{\partial x_1} & \dots & \frac{\partial S_k}{\partial x_k} \end{bmatrix}$$

Let's compute $\frac{\partial S_i}{\partial x_j}$ for some arbitrary i and j :

$$\frac{\partial S_i}{\partial x_j} = \frac{\partial}{\partial x_j} \frac{e^{x_i}}{\sum_k e^{x_k}}$$

Let's examine the formula for division

$$f(x) = \frac{g(x)}{h(x)},$$

$$f'(x) = \frac{g'(x)h(x) - g(x)h'(x)}{h(x)^2}$$

In our case $g_i = e^{x_i}$ and $h_i = \sum e^{x_k}$. No matter which x_j , when we compute the derivative of h_i with respect to x_j , the answer will always be e^{x_j} .

$$\frac{\partial}{\partial x_j}h_i = \frac{\partial}{\partial x_j}\sum e^{x_k} = \sum \frac{\partial e^{x_k}}{\partial x_j} = e^{x_j}$$

because $\frac{\partial e^{x_k}}{\partial x_j} = 0$ for $k \neq j$. There are on the mean-fully derivatives for i = j in $\frac{\partial S}{\partial x}$ matrices for our problem.

$$\begin{split} &\frac{\partial \frac{e^{x_i}}{\sum e^{x_k}}}{\partial x_j} = \frac{e^{x_i} \sum e^{x_k} - e^{x_j} e^{x_i}}{\left(\sum e^{x_k}\right)^2} \\ &= \frac{e^{x_i} \left(\sum e^{x_k} - e^{x_j}\right)}{\left(\sum e^{x_k}\right)^2} \\ &= \frac{e^{x_i}}{\sum e^{x_k}} \cdot \left(\frac{\sum e^{x_k}}{\sum e^{x_k}} - \frac{e^{x_j}}{\sum e^{x_k}}\right) \end{split}$$

$$S_i \left(1 - S_j \right) \tag{6}$$

Now we found what derivative of softmax. Let's go back to the loss function.

2.2 Derivative of Loss Function and Ω_t

Let's examine the derivative formula for logarithm

$$f(x) = \log_y x$$
$$f'(x) = \frac{x'}{x} \cdot \log_e y$$

$$L(\hat{y}, y) = -\sum y_t \log \left(\operatorname{softmax} \left(\Omega_t \right) \right)$$

$$\frac{\partial L}{\partial \Omega_t} = -\frac{\partial}{\partial \Omega_t} \sum y_t \log \left(\operatorname{softmax} \left(\Omega_t \right) \right)$$

$$= -\sum y_t \frac{\partial \log \left(\operatorname{softmax} \left(\Omega_t \right) \right)}{\partial \Omega_t}$$

$$= -\sum \frac{\partial \hat{y}_t}{\partial \Omega_t} \cdot \frac{y_t}{\hat{y}_t}$$

$$= -\sum S_{t,i} \left(1 - S_{t,j} \right) \cdot \frac{y_t}{\hat{y}_t}$$

$$= -\sum \left(1 - S_{t,j} \right) y_t$$

$$= -\sum \left(y_t - S_{t,j} \hat{y}_t \right)$$

$$= \sum S_{t,i} \hat{y}_t - \sum y_t$$

$$= S_{t,j} \sum \hat{y}_t - \sum y_t$$

$$= \sum (\hat{y}_t - y_t)$$

$$\frac{\partial L_t}{\partial \hat{\Omega}_t} = (\hat{y}_t - y_t)$$
(7)

2.3 Derivative of V

The weight V is consistent across the entire time sequence, allowing us to perform differentiation at each time step and then aggregate the results.

$$\frac{\partial L}{\partial V} = \sum_{t=1}^{S} \frac{\partial L_t}{\partial V}$$

$$= \sum_{t=1}^{S} \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial \Omega_t} \frac{\partial \Omega_t}{\partial V}$$

$$= \sum_{t=1}^{S} \frac{\partial L}{\partial \Omega_t} \frac{\partial \Omega_t}{\partial V}$$

We know that this formula $\frac{\partial \hat{y}_t}{\partial \Omega_t}$ from (7) and no other function exists between Omega and V, so simply taking the derivative coefficient of V yields h, thus the answer is h.

$$= \sum_{t=1}^{S} (\hat{y}_t - y_t) \cdot h_t^{\top} \tag{8}$$

2.4 Derivative of c

Similar to V, but its derivative is easier to calculate since it stands alone in the function.

$$\frac{\partial L}{\partial c} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial c}$$

$$= \sum_{t=1}^{T} \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial \Omega_t} \frac{\partial \Omega_t}{\partial c}$$

$$= \sum_{t=1}^{T} \frac{\partial L}{\partial \Omega_t} \frac{\partial \Omega_t}{\partial c}$$

In this case, The Analytical Derivatives of c becomes:

$$= \sum_{t=1}^{T} (\hat{y}_t - y_t) \tag{9}$$

2.5 Derivative of W

This function employs recursion, therefore, computing its derivative may take some time.

$$h_{t} = tanh(W \ h_{t-1} + U \ x_{t} + b)$$

$$h_{1} = tanh(W \ h_{0} + U \ x_{1} + b) \quad h_{2} = tanh(W \ h_{1} + U \ x_{2} + b)$$

$$h_{3} = tanh(W \ h_{2} + U \ x_{3} + b) \quad h_{4} = tanh(W \ h_{3} + U \ x_{4} + b)$$

By placing h_t into the last term, we get:

$$h_4 = \\ tanh(W \ ta$$

We start from the first step go to the last step:

Simplifying:

Since the calculation process needs to be simplified, let's expand $\frac{h_t}{h_h}$

Let us group them under a $\sum \prod$ for step t:

$$\frac{\partial L_t}{\partial W} = \sum_{k=1}^t \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \prod_{j=k}^{t-1} \left(\frac{\partial h_{j+1}}{\partial h_j} \right) \frac{\partial h_k}{\partial W}$$

Let us now present the formula for S steps:

$$\frac{\partial L}{\partial W} = \sum_{t=1}^{S} \left(\sum_{k=1}^{t} \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \prod_{j=k}^{t-1} \left(\frac{\partial h_{j+1}}{\partial h_j} \right) \frac{\partial h_k}{\partial W} \right)$$
(10)

Finally, we insert the individual partial derivatives to calculate our final gradients of L with respect to W, where:

$$\begin{split} \frac{\partial L_t}{\partial \hat{y}_t} &= (y_t - \hat{y}_t) \\ \frac{\partial \hat{y}_t}{\partial h_t} &= V^\top \\ \frac{\partial h_{j+1}}{\partial h_j} &= W^\top \left(1 - h_{j+1}^2\right) \\ \frac{\partial h_k}{\partial W} &= (1 - h_k^2) \ h_{k-1} \end{split}$$

In this case, The Analytical Derivatives of Eq. (10) becomes:

$$\frac{\partial L}{\partial W} = \sum_{t=1}^{\mathcal{S}} \left(\sum_{k=1}^{t} (y_t - \hat{y}_t) V^{\top} \prod_{j=k}^{t-1} \left(W^{\top} (1 - h_{j+1}^2) \right) (1 - h_k^2) h_{k-1} \right)$$
(11)

2.6 Derivative of U

Now, let's derive the gradient with respect to U. Similarly, we calculate the gradient with respect to U like Eq. (10) as follows:

$$\frac{\partial L}{\partial U} = \sum_{t=1}^{\mathcal{S}} \left(\sum_{k=1}^{t} \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \prod_{j=k}^{t-1} \left(\frac{\partial h_{j+1}}{\partial h_j} \right) \frac{\partial h_k}{\partial U} \right)$$
(12)

we insert the individual partial derivatives to calculate our final gradients of L with respect to W, where:

$$\frac{\partial L_t}{\partial \hat{y}_t} = (y_t - \hat{y}_t)$$
$$\frac{\partial \hat{y}_t}{\partial h_t} = V^{\top}$$
$$\frac{\partial h_{j+1}}{\partial h_j} = W^{\top} (1 - h_{j+1}^2)$$
$$\frac{\partial h_k}{\partial U} = (1 - h_k^2) x_k$$

In this case, The Analytical Derivatives of Eq. (12) becomes:

$$\frac{\partial L}{\partial W} = \sum_{t=1}^{\mathcal{S}} \left(\sum_{k=1}^{t} (y_t - \hat{y}_t) V^{\top} \prod_{j=k}^{t-1} \left(W^{\top} (1 - h_{j+1}^2) \right) (1 - h_k^2) h_{k-1} \right)$$
(13)

2.7 Derivative of b

Now, let's derive the gradient with respect to b. Similarly, we calculate the gradient with respect to b like Eq. (12) as follows:

$$\frac{\partial L}{\partial b} = \sum_{t=1}^{\mathcal{S}} \left(\sum_{k=1}^{t} \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \prod_{j=k}^{t-1} \left(\frac{\partial h_{j+1}}{\partial h_j} \right) \frac{\partial h_k}{\partial b} \right)$$
(14)

we insert the individual partial derivatives to calculate our final gradients of L with respect to W, where:

$$\frac{\partial L_t}{\partial \hat{y}_t} = (y_t - \hat{y}_t)$$
$$\frac{\partial \hat{y}_t}{\partial h_t} = V^{\top}$$
$$\frac{\partial h_{j+1}}{\partial h_j} = W^{\top} (1 - h_{j+1}^2)$$
$$\frac{\partial h_k}{\partial b} = (1 - h_k^2)$$

In this case, The Analytical Derivatives of Eq. (14) becomes:

$$\frac{\partial L}{\partial W} = \sum_{t=1}^{\mathcal{S}} \left(\sum_{k=1}^{t} (y_t - \hat{y}_t) V^{\top} \prod_{j=k}^{t-1} \left(W^{\top} (1 - h_{j+1}^2) \right) (1 - h_k^2) \right)$$
(15)

2.8 Derivative of E

ADD THIS ONE TO THE APPENDIX AS TH DIFFERENCE WHEN EMBEDDING LAYERS ARE USED

This function employs recursion, therefore, computing its derivative may take some time.

$$\begin{split} x_t &= x_t^o \ E \\ h_t &= tanh(W \ h_{t-1} \ + \ U \ x_t \ + \ b) \\ h_1 &= tanh(W \ h_0 \ + \ U \ x_1 \ + \ b) \quad h_2 = tanh(W \ h_1 \ + \ U \ x_2 \ + \ b) \\ h_3 &= tanh(W \ h_2 \ + \ U \ x_3 \ + \ b) \quad h_4 = tanh(W \ h_3 \ + \ U \ x_4 \ + \ b) \end{split}$$

By placing h_t into the last term, we get:

$$h_4 = tanh(W \ tanh$$

We start from the first step go to the last step:

$$\frac{\partial L_1}{\partial E} = \frac{\partial L_1}{\partial \hat{y}_1} \frac{\partial \hat{y}_1}{\partial h_1} \frac{\partial h_1}{\partial h_1} \frac{\partial h_1}{\partial x_1} \frac{\partial x_1}{\partial E}$$

$$\frac{\partial L_2}{\partial E} = \frac{\partial L_2}{\partial \hat{y}_2} \frac{\partial \hat{y}_2}{\partial h_2} \frac{\partial h_2}{\partial h_1} \frac{\partial h_1}{\partial x_1} \frac{\partial x_1}{\partial E} + \frac{\partial L_2}{\partial \hat{y}_2} \frac{\partial \hat{y}_2}{\partial h_2} \frac{\partial h_2}{\partial h_2} \frac{\partial h_2}{\partial x_2} \frac{\partial x_2}{\partial E}$$

$$\frac{\partial L_3}{\partial E} = \frac{\partial L_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial h_3} \frac{\partial h_3}{\partial h_1} \frac{\partial h_1}{\partial x_1} \frac{\partial x_1}{\partial E} + \frac{\partial L_3}{\partial E} \frac{\partial \hat{y}_3}{\partial h_3} \frac{\partial h_3}{\partial h_3} \frac{\partial h_3}{\partial h_2} \frac{\partial h_3}{\partial h_3} \frac{\partial h_3}{\partial h_3$$

Simplifying:

$$\frac{\partial L_1}{\partial E} = \frac{\partial L_1}{\partial \hat{y}_1} \frac{\partial \hat{y}_1}{\partial h_1} \frac{\partial h_1}{\partial x_1} \frac{\partial x_1}{\partial E}$$

$$\frac{\partial L_2}{\partial E} = \frac{\partial L_2}{\partial \hat{y}_2} \frac{\partial \hat{y}_2}{\partial h_2} \frac{\partial h_2}{\partial h_1} \frac{\partial h_1}{\partial x_1} \frac{\partial x_1}{\partial E} + \frac{\partial L_2}{\partial \hat{y}_2} \frac{\partial \hat{y}_2}{\partial h_2} \frac{\partial h_2}{\partial x_2} \frac{\partial x_2}{\partial E}$$

$$\frac{\partial L_3}{\partial E} = \frac{\partial L_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial h_3} \frac{\partial h_3}{\partial h_1} \frac{\partial h_1}{\partial x_1} \frac{\partial x_1}{\partial E} + \frac{\partial L_3}{\partial E} \frac{\partial \hat{y}_3}{\partial h_3} \frac{\partial h_3}{\partial h_3} \frac{\partial h_2}{\partial h_4} \frac{\partial h_2}{\partial h_4} \frac{\partial h_3}{\partial h_5} \frac{\partial h_5}{\partial h_5$$

Since the calculation process needs to be simplified, let's expand $\frac{h_t}{h_k}$

$$\frac{\partial L_1}{\partial E} = \frac{\partial L_1}{\partial \hat{y}_1} \frac{\partial \hat{y}_1}{\partial h_1} \frac{\partial h_1}{\partial x_1} \frac{\partial x_1}{\partial E}$$

$$\frac{\partial L_2}{\partial E} = \frac{\partial L_2}{\partial \hat{y}_2} \frac{\partial \hat{y}_2}{\partial h_2} \frac{\partial h_2}{\partial h_1} \frac{\partial h_1}{\partial x_1} \frac{\partial x_1}{\partial E} + \frac{\partial L_2}{\partial \hat{y}_2} \frac{\partial \hat{y}_2}{\partial h_2} \frac{\partial h_2}{\partial h_2} \frac{\partial h_2}{\partial E}$$

$$\frac{\partial L_3}{\partial E} = \frac{\partial L_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial h_3} \frac{\partial h_3}{\partial h_2} \frac{\partial h_2}{\partial h_1} \frac{\partial h_1}{\partial x_1} \frac{\partial x_1}{\partial E} + \frac{\partial L_3}{\partial E} \frac{\partial \hat{y}_3}{\partial h_3} \frac{\partial h_3}{\partial h_3} \frac{\partial h_2}{\partial h_2} \frac{\partial h_2}{\partial h_2} \frac{\partial h_1}{\partial h_2} \frac{\partial x_1}{\partial h_2} + \frac{\partial L_3}{\partial E} \frac{\partial \hat{y}_3}{\partial h_3} \frac{\partial h_3}{\partial h_2} \frac{\partial h_2}{\partial h_2} \frac{\partial h_3}{\partial h_3} \frac{\partial h_3}{\partial h_2} \frac{\partial h_3}{\partial h_3} \frac{\partial h_3}{\partial$$

Let us group them under a $\sum \prod$ for step t:

$$\frac{\partial L_t}{\partial E} = \sum_{k=1}^t \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \prod_{j=k}^{t-1} \left(\frac{\partial h_{j+1}}{\partial h_j} \right) \frac{\partial h_k}{\partial x_k} \frac{\partial x_k}{\partial E}$$

Let us now present the formula for $\mathcal S$ steps:

$$\frac{\partial L}{\partial E} = \sum_{t=1}^{\mathcal{S}} \left(\sum_{k=1}^{t} \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \prod_{j=k}^{t-1} \left(\frac{\partial h_{j+1}}{\partial h_j} \right) \frac{\partial h_k}{\partial x_k} \frac{\partial x_k}{\partial E} \right)$$
(16)

Finally, we insert the individual partial derivatives to calculate our final gradients of L with respect to W, where:

$$\begin{split} \frac{\partial L_t}{\partial \hat{y}_t} &= (y_t - \hat{y}_t) \\ \frac{\partial \hat{y}_t}{\partial h_t} &= V^\top \\ \frac{\partial h_{j+1}}{\partial h_j} &= W^\top \ (1 - h_{j+1}^2) \\ \frac{\partial h_k}{\partial x_k} &= (1 - h_k^2) \ U \\ \frac{\partial x_k}{\partial E} &= x_k^o \end{split}$$

In this case, The Analytical Derivatives of Eq. (16) becomes:

$$\frac{\partial L}{\partial E} = \sum_{t=1}^{\mathcal{S}} \left(\sum_{k=1}^{t} (y_t - \hat{y}_t) V^{\top} \prod_{j=k}^{t-1} \left(W^{\top} (1 - h_{j+1}^2) \right) (1 - h_k^2) U x_k^o \right)$$
(17)