Hierarchical Multiscale Recurrent Neural Networks

Problem proposed in this paper

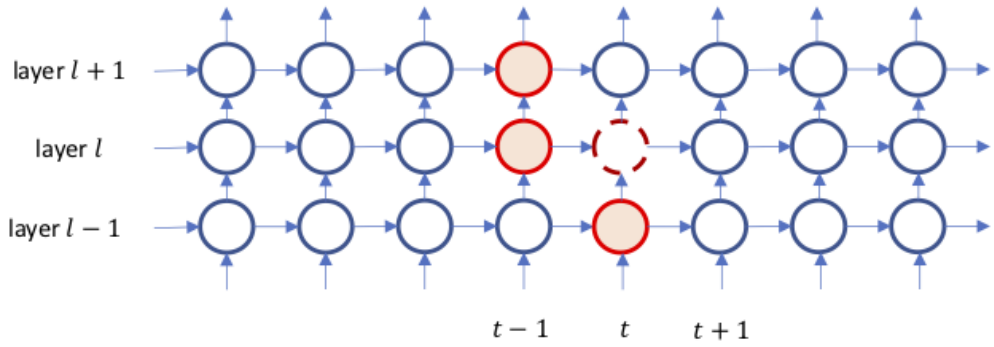
Learn the hierarchical multiscale structure from temporal data ***without explicit boundary information***.

Key ideas

1. Introduce ***a parametrized binary boundary detector*** at each layer.

- turned on only at the time steps where a segment of the corresponding abstraction level is completely processed.
- **avoids "soft" gating which leads to "curse of updating every timestep".**

2. select one of the three operations below according to boundary state z_t^{l-1} and z_{t-1}^{l} depicted in the below picture.



- UPDATE: similar to update rule of the LSTM.
- COPY: ***simply copies*** cell and hidden states of the previous time step which is unlike the ***leaky integration*** in LSTM/GRU.
- FLUSH: executed when a boundary is detected, where it first ejects the summarized representation of the current segment to the upper layer and then reinitializes the states to start processing the next segment.

z_{t-1}^{l} left	z_{t}^{l-1} buttom	The Selected Operation	
0	0	COPY	buttom and left states both do not reach to a boundary.

z_{t-1}^{l} left	z_{t}^{l-1} buttom	The Selected Operation	
0	1	UPDATE	left state does not reaches to a boundary but buttom does. UPDATE is executed sparsely
1	0	FLUSH	left state reaches to a boundary.

z_{t-1}^{l} left	z_{t}^{l-1} buttom	The Selected Operation	
1	1	FLUSH	left state reaches to a boundary.

3. boundary state is a discrete variable.***straight-through estimator*** is used to calculate its gradient.
    - the straight-through estimator is a very easy-to-implement solution to incorporate ***a binary stochastic variable*** into the neural network. It seems that some research work generalizes this method into a binary vector to quantize NN.

HM-LSTM: computation details

0. Recap LSTM's equation first:

$$\begin{bmatrix} \mathbf{i}_t \\ \mathbf{f}_t \\ \mathbf{u}_t \\ \mathbf{o}_t \end{bmatrix} = W\mathbf{x}_t + U\mathbf{h}_{t-1} + \mathbf{b} \qquad \text{(gates and candidate)}$$

$$\mathbf{c}_t = \mathbf{c}_{t-1} \odot \sigma(\mathbf{f}_t) + \tanh(\mathbf{u}_t) \odot \sigma(\mathbf{i}_t) \qquad \text{(cell state)}$$

$$\mathbf{h}_t = \sigma(\mathbf{o}_t) \odot \tanh(\mathbf{c}_t) \qquad \text{(hidden state)}$$

HM-RNN is based on LSTM cell.

1. compute pre-activation

$$\begin{pmatrix} \mathbf{f}_t^\ell \\ \mathbf{i}_t^\ell \\ \mathbf{o}_t^\ell \\ \mathbf{g}_t^\ell \\ \tilde{z}_t^\ell \end{pmatrix} = \begin{pmatrix} \texttt{sigm} \\ \texttt{sigm} \\ \texttt{sigm} \\ \texttt{tanh} \\ \texttt{hard sigm} \end{pmatrix} f_{\texttt{slice}} \left(\mathbf{s}_t^{\text{recurrent}(\ell)} + \mathbf{s}_t^{\text{top-down}(\ell)} + \mathbf{s}_t^{\text{bottom-up}(\ell)} + \mathbf{b}^{(\ell)} \right),$$

where

$$\begin{aligned} \mathbf{s}_t^{\text{recurrent}(\ell)} &= U_\ell^\ell \mathbf{h}_{t-1}^\ell, \\ \mathbf{s}_t^{\text{top-down}(\ell)} &= z_{t-1}^\ell U_{\ell+1}^\ell \mathbf{h}_{t-1}^{\ell+1}, \\ \mathbf{s}_t^{\text{bottom-up}(\ell)} &= z_t^{\ell-1} W_{\ell-1}^\ell \mathbf{h}_t^{\ell-1}. \end{aligned}$$

2. cell update

$$\mathbf{c}_t^l = \begin{cases} f_t^l \odot \mathbf{c}_{t-1}^l + \mathbf{i}_t^l \odot \mathbf{g}_t^l, & \text{if UPDATE} \\ \mathbf{c_{t-1}^l}, & \text{if COPY} \\ \mathbf{i}_t^i \odot \mathbf{g}_t^l, & \text{if FLUSH} \end{cases}$$

3. hidden update

$$\mathbf{h}_t^l = \begin{cases} h_{t-1}^l, & \text{if COPY} \\ \mathbf{o}_t^l \odot \tanh(\mathbf{c}_t^l), & \text{otherwise} \end{cases}$$

- $\mathbf{g}$ is a cell proposal vector.
- $\mathbf{i}$, $\mathbf{f}$, $\mathbf{o}$ are the input/forget/output gate.

Calculate the gradient for boundary detector

1. Straight–through estimator
    - forward pass uses the step function to activate z_t^l
    - backward pass uses hardsigmoid function as the biased estimator of the outgoing gradient.

$$\sigma(x) = \max(0, \min(1, (\alpha x + 1)/2))$$

2. Slope annealing
    - start from slope $\alpha = 1$.
    - slowly increase the slope until it reaches a threshold. In the paper, the annealing function task–specific.

Some claims made (and learned) from this paper

1. However, because ***non–stationarity is prevalent in temporal data***, and that many entities of abstraction such as words and sentences are in variable length, we claim that ***it is important for an RNN to dynamically adapt its timescales*** to the particulars of the input entities of various length.
2. It has been a challenge for an RNN to discover the latent hierarchical structure in temporal data without explicit boundary information.
3. Although the LSTM has a ***self–loop for the gradients that helps to capture the long–term dependencies*** by mitigating the vanishing gradient problem, in practice, it is still limited to a few hundred–time steps due to the leaky

integration by which the contents to memorize for a long–term is gradually diluted at every time step.

References

1. Hierarchical Multiscale Recurrent Neural Networks
    - its slides
2. Revisiting the Hierarchical Multiscale LSTM
3. This paper uses the [***straight–through estimator***] to train neural networks with discrete variables. This paper points to two references using this methods:
    - Binarized neural networks: Training deep neural networks with weights and activations constrained to+ 1 or–1
    - Strategic attentive writer for learning macro–actions
    - Estimating or Propagating Gradients Through Stochastic Neurons for Conditional Computation
4. Notes on Hierarchical Multiscale Recurrent Neural Networks