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1 The unreasonable effectiveness of the forget gate

1.1 Motivations

Whether all the gates of the LSTM network are necessary.

- Conflicting updates (gradients)
 - 1. having a single weight in the RNN creates conflicting updates.
 - 2. the long and short-range error act on the same weight at each step, and with sigmoid activated units, this results in the gradients vanishing faster thant the weights can grow.
- · The initialization of forget gates
 - Problems:
 - * most applications initialize the LSTM weights with small random weights
 - * the forget gate is set to 0.5
 - * introduces a vanishing gradient with a factor of 0.5 per timestep
 - Solution
 - * initialize all bias to zeros
 - * initialize the forget bias \mathbf{b}_f to a large value such as 1 or 2.

1.2 Just Another Network (JANET)

- 1. *Couple* the input and forget modulation
 - It seems sensible to have the accumulation and deletion of information to be related.
- 2. Remove the tanh activation of h_t
 - the tanh activation shrinks the gradients
 - weight matrix U_* can accommodate values beyond [-1, 1]

$$\begin{split} \mathbf{f}_t &= \sigma(\mathbf{U}_f \mathbf{h}_{t-1} + \mathbf{W}_f \mathbf{x}_t + \mathbf{x_f}) \\ \mathbf{c}_t &= \mathbf{f} \odot \mathbf{c}_{t-1} + (\mathbf{1} - \mathbf{f}_t) \odot \tanh(\mathbf{U_c} \mathbf{h}_{t-1} + \mathbf{W}_c \mathbf{x}_t + \mathbf{b}_c) \\ \mathbf{h}_t &= \mathbf{c}_t \end{split}$$

3. Allow slightly *more information to accumulate than the amount forgotten* would make sequence analysis easier.

$$\begin{split} \mathbf{s}_t &= \mathbf{U}_f \mathbf{h}_t + \mathbf{W}_f \mathbf{x}_t + \mathbf{b}_f \\ \mathbf{c}_t' &= \tanh(\mathbf{U}_c \mathbf{h}_{t-1} + \mathbf{W}_c \mathbf{x}_t + \mathbf{b}_c) \\ \mathbf{c}_t &= \sigma(\mathbf{s}_t) \odot \mathbf{c}_{t-1} + (\mathbf{1} - (\mathbf{s_t} -)) \odot \mathbf{c}_t' \\ \mathbf{h}_t &= \mathbf{c}_t \end{split}$$

4. chrono initializer

- If the value of both input and hidden layers are zero-centered over time, \mathbf{f}_t will be centered around $\sigma(1) = 0.7311$
- The memory values \mathbf{c}_t would not be retrained for more than a couple of time steps.

$$\begin{aligned} \mathbf{b}_f \sim \log(\mathcal{U}[1, T_{max} - 1]) \\ \mathbf{b}_i = -\mathbf{b}_f \end{aligned}$$

• an elegant implementation of skip-like connections between the memory cells over

1.3 References

1. An Empirical Exploration of Recurrent Network Architectures