Parallelizing Linear Recurrent Neural Nets Over Sequence Length

Eric Martin and Chris Cundy

Fill in institutes

Abstract

RNN training and inference generally takes time linear in the sequence length because of non-linear sequential dependencies. We show the training and inference of RNNs with only linear sequential dependencies can be parallelized over the sequence length using the parallel scan algorithm, leading to rapid training on long sequences even with small minibatch size. We use this insight and a parallel linear recurrence CUDA kernel to accelerate several state of the art RNN architectures by up to 9x and to solve a synthetic sequence classification task with a one million timestep dependency.

Background

Large minibatches are necessary for computational performance but create large memory requirements and may damage model generalization ability.

Linear RNNs and convolutional models such as strongly typed RNNs, Wavenet, Bytenet, quasi-RNNs, and simple recurrent units have achieved state of the art results on many sequential tasks with rapid training times.

Given x_t, λ_t can compute $h_t = \lambda_t h_{t-1} + x_t$ for $t = 1 \ldots T$ on p processors in $O(T/p + \log(p))$ with the classic parallel scan algorithm.

Gated Impulse Linear Recurrence

We designed a recurrent layer that can take maximium advantage of parallel linear recurrence??

$$\begin{aligned} g_t &= \sigma(U x_t + b_g) \\ i_t &= \tau(V x_t + b_z) \\ h_t &= g_t \odot h_{t-1} + (1 - g_t) \odot i_t \end{aligned}$$

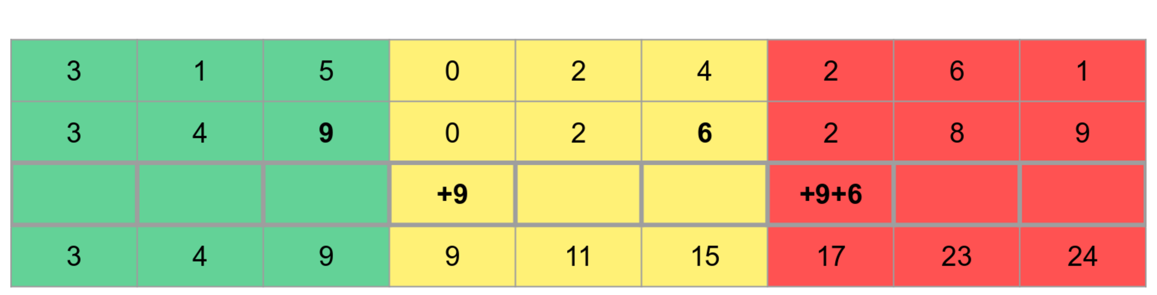

Figure 1: Parallel cumulative sum example

Linear Surrogate RNNs

RNNs have a transition function $s_t = f(s_{t-1}, x_t)$. s_t serves dual roles as a summary of the past as well as the output of the unit. Non-linear f in units such as vanilla RNN and LSTM prevents parallelization over sequence length.

Replacing the summary of the past s_{t-1} with a linear surrogate $\tilde{s}_{t-1}$ allows the easy adaption of any existing RNN architecture for parallel computation.

The state of an LSTM consists of (c_t, h_t). c_t is already computed by linear recurrence, so a linear surrogate LSTM must only compute a linear $\tilde{h}_t$. We let $h = \mathrm{GILR}(x)$ and call it a GILR-LSTM.

Scan diagram and complexity??

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Important Result (???)

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Mathematical Section

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$$E = mc^2 \tag{1}$$

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$$\cos^3\theta = \frac{1}{4}\cos\theta + \frac{3}{4}\cos 3\theta \tag{2}$$

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$$\kappa = \frac{\xi}{E_{\text{max}}} \tag{3}$$

Results

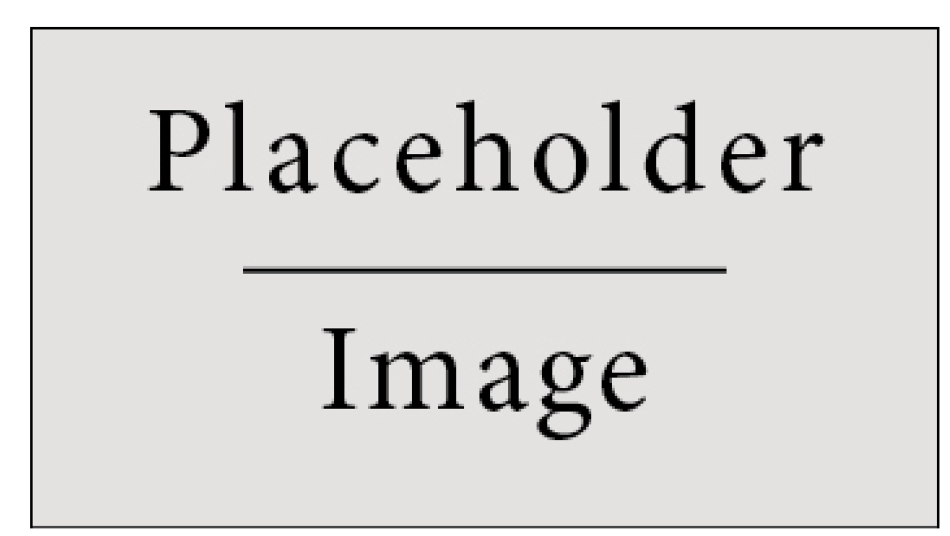

Figure 2: Figure caption

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Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296

Table 1: Table caption

Conclusion

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Additional Information

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References

Acknowledgements

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Contact Information

- Web: http://www.university.edu/smithlab
- Email: john@smith.com
- Phone: +1 (000) 111 1111