# Towards Scalable and Stable Parallelization of Nonlinear RNNs

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# Motivation: Transformers vs RNNs



#### Transformers



RNNs

- Parallelizable Training (great for GPUs!) ✓
- Generation is expensive (KV cache grows with sequence length) X

- Sequential Training (hard to get GPU speed up over the sequence length) X
- Stateful generation

 $(s_2)$  ...  $(s_{T-1})$   $\xrightarrow{f}$   $(s_T)$  $(s_1)$  $s_0$ 

 $(s_2)$  ...  $(s_{T-1})$   $\xrightarrow{f}$   $(s_T)$ ( s<sub>1</sub>  $s_0$ 

 $s_2$  ...  $s_{T-1}$  f  $s_T$ ( s<sub>1</sub>  $s_0$ 

 $(s_2)$  ...  $(s_{T-1})$   $(s_T)$ ( s<sub>1</sub>  $s_0$ 

 $(s_2)$  ...  $(s_{T-1})$   $\xrightarrow{f}$   $(s_T)$ ( s<sub>1</sub>  $s_0$ 

 $(s_2)$  ...  $(s_{T-1})$   $\xrightarrow{f}$   $(s_T)$  $(s_1)$  $s_0$ 

Sequential Evaluation

 $\underbrace{s_0} \xrightarrow{f} \underbrace{s_1} \xrightarrow{f} \underbrace{s_2} \dots \underbrace{s_{T-1}} \xrightarrow{f} \underbrace{s_T}$ 

Parallel (Iterative) Evaluation



Sequential Evaluation

 $\underbrace{s_0} \xrightarrow{f} \underbrace{s_1} \xrightarrow{f} \underbrace{s_2} \dots \underbrace{s_{T-1}} \xrightarrow{f} \underbrace{s_T}$ 

Parallel (Iterative) Evaluation



Sequential Evaluation

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Parallel (Iterative) Evaluation



Sequential Evaluation

 $\underbrace{s_0} \xrightarrow{f} \underbrace{s_1} \xrightarrow{f} \underbrace{s_2} \dots \underbrace{s_{T-1}} \xrightarrow{f} \underbrace{s_T}$ 

#### Parallel (Iterative) Evaluation

#### DEER

Y.H. Lim, Q. Zhu, J. Selfridge, and M.F. Kasim. Parallelizing non-linear sequential models over the sequence length. *ICLR*, 2024.



 $\dots \xrightarrow{s_{T-1}} \xrightarrow{f} \xrightarrow{s_T}$  $\rightarrow (s_2)$  $\begin{pmatrix} s_0 \end{pmatrix}$  $\rightarrow (s_1)$ 



df df $\dots \xrightarrow{(s_{T-1})} \xrightarrow{df} \xrightarrow{(s_T)}$  $\rightarrow (s_2)$  $\begin{pmatrix} s_0 \end{pmatrix}$  $\rightarrow (s_1)$ 



 $\rightarrow (s_T)$  $\left(s_{T-1}\right)$  $s_0$  $s_1$  $s_2$ 

Use parallel associative scan



$$\Delta \mathbf{s}_t^{(i+1)} = \left[\frac{\partial f_t}{\partial \mathbf{s}}(\mathbf{s}_{t-1}^{(i)})\right] \Delta \mathbf{s}_{t-1}^{(i+1)} - \mathbf{r}_t(\mathbf{s}^{(i)})$$
$$-\mathbf{r}_t(\mathbf{s}^{(i)}) = f(\mathbf{s}_{t-1}^{(i)}) - \mathbf{s}_t^{(i)}$$



$$\Delta \mathbf{s}_{t}^{(i+1)} = \underbrace{\left[\frac{\partial f_{t}}{\partial \mathbf{s}}(\mathbf{s}_{t-1}^{(i)})\right]}_{\mathsf{D} \times \mathsf{D}} \Delta \mathbf{s}_{t-1}^{(i+1)} - \mathbf{r}_{t}(\mathbf{s}^{(i)})$$

- $\bullet$  Each matmul is  $\mathcal{O}(D^3)$
- $\bullet$  Memory is  $\mathcal{O}(TD^2)$



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$$\mathrm{Diag}\left[\frac{\partial f_t}{\partial \mathbf{s}}(\mathbf{s}_{t-1}^{(i)})\right]$$

Each matmul is O(D)
Memory is O(TD)



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 $\mathrm{Diag}\left[\frac{\partial f_t}{\partial \mathbf{s}}(\mathbf{s}_{t-1}^{(i)})\right]$ 

• Each matmul is  $\mathcal{O}(D)$ 

• Memory is  $\mathcal{O}(TD)$ 



- ELK: Evaluating Levenberg-Marquardt with Kalman
- Stability: Trust region restricts the size of  $\Delta s$
- Can be evaluated in parallel with Kalman filter

$$\Delta \mathbf{s}_{t}^{(i+1)} = \underbrace{\left[\frac{\partial f_{t}}{\partial \mathbf{s}}(\mathbf{s}_{t-1}^{(i)})\right]}_{\mathsf{D} \times \mathsf{D}} \Delta \mathbf{s}_{t-1}^{(i+1)} - \mathbf{r}_{t}(\mathbf{s}^{(i)})$$

- Each matmul is  $\mathcal{O}(D^3)$
- Memory is  $\mathcal{O}(TD^2)$

 $\mathrm{Diag}\left[\frac{\partial f_t}{\partial \mathbf{s}}(\mathbf{s}_{t-1}^{(i)})\right]$ 

- Each matmul is  $\mathcal{O}(D)$
- Memory is  $\mathcal{O}(TD)$



2000

4000

6000

Timestep, t

8000

10000

• Can be evaluated in parallel with Kalman filter

## Come by our poster to learn more!



- Paper: https://arxiv.org/abs/2407.19115
- Code: https://github.com/lindermanlab/elk