Lattice Recurrent Unit

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Motivation

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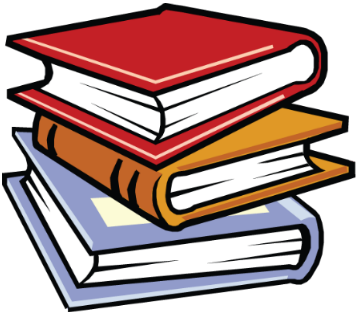

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We might lose information if the order is not preserved

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$$P\left(R \mid C\,H\,A \right)$$

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$$P\left(x_t \mid x_{1:t-1} \right)$$

Rise of **Neural Networks**

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  Are they **easy to train**?

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$$x_t = \mathsf{RNN}\left(x_{t-1}, c_{t-1}\right)$$

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$$
\begin{aligned}
x_t &= \mathsf{RNN}\left(x_{t-1}, c_{t-1}\right) \\
&= \mathsf{RNN}\left(x_{t-1}, x_{t-2} \ldots, x_1\right) \\
&= \mathsf{RNN}\left(x_{1:t-1}\right)
\end{aligned}
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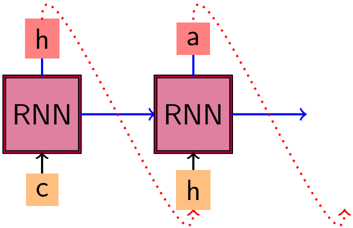
\Rightarrow \mathsf{RNN} &\sim \mathsf{P}\left(x_t \,\middle|\, x_{1:t-1}\right)
\end{aligned}
$$

Rise of **Recurrent** Neural Networks

Language Modeling



- Note: Blue Arrows correspond to **hidden states** (c_{t-1}).

Rise of **Recurrent** Neural Networks

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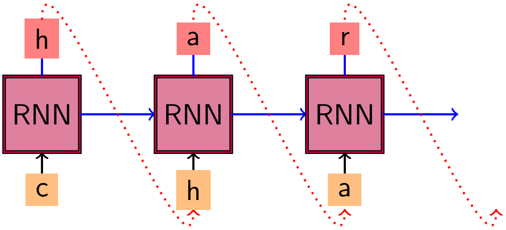

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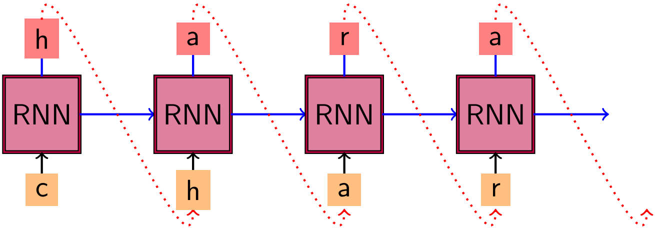

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- **Trainability:** Vanilla RNNs suffer from the **Vanishing Gradient** problem,

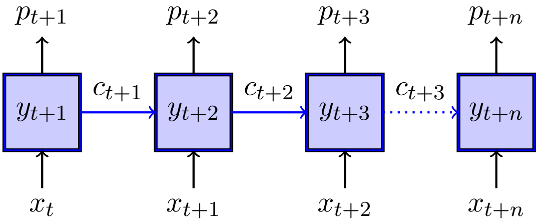

Figure 1: Forward Pass

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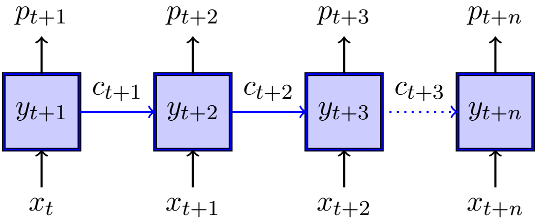

Figure 1: Forward Pass

$$y_{t+1} \quad = \quad \mathbf{X} x_t + \mathbf{C} c_t$$

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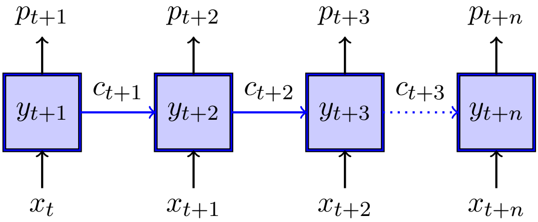

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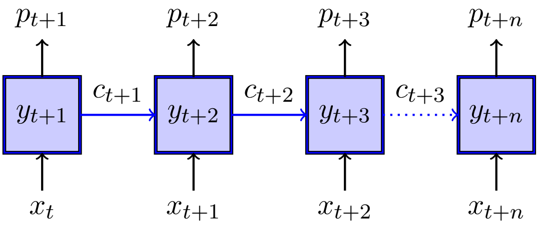

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y_{t+1} &= \mathbf{X} x_t + \mathbf{C} c_t \\
c_{t+1} &= \sigma\left(y_{t+1}\right) \\
p_{t+1} &= \text{softmax}\left(\mathbf{W} c_{t+1}\right)
\end{aligned}
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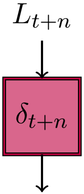

Figure 2: Gradients in Vanilla RNN

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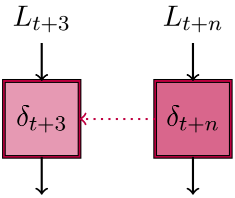

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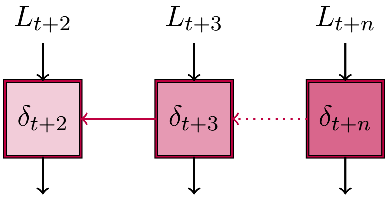

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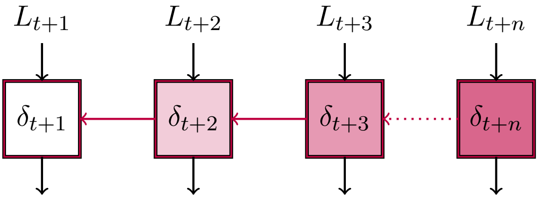

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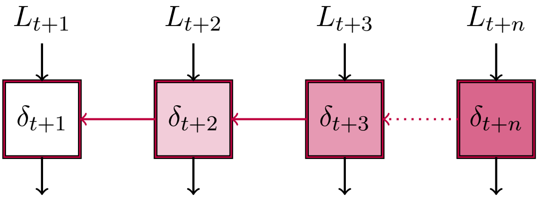

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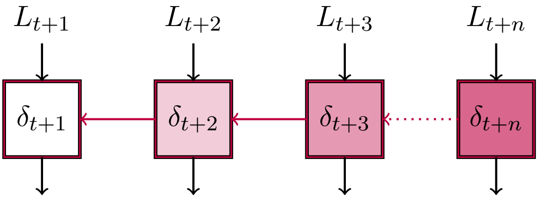
$$L_j = (p_j^{gt} - p_j)^2$$

Rise of **Recurrent** Neural Networks



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\frac{\partial L_{t+n}}{\partial y_{t+1}} &= \frac{\partial L_{t+n}}{\partial y_{t+n}} \cdot \frac{\partial y_{t+n}}{\partial y_{t+n-1}} \cdot \ldots \frac{\partial y_{t+2}}{\partial y_{t+1}}
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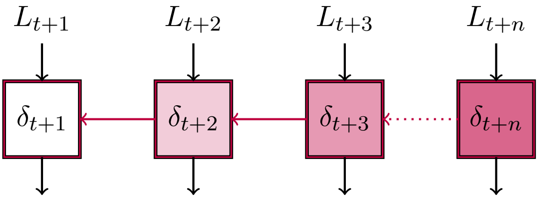

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&= \frac{\partial L_{t+n}}{\partial y_{t+n}} \cdot \prod_{\tau=t+2}^{t+n} \frac{\partial y_\tau}{\partial y_{\tau-1}}
\end{aligned}
$$

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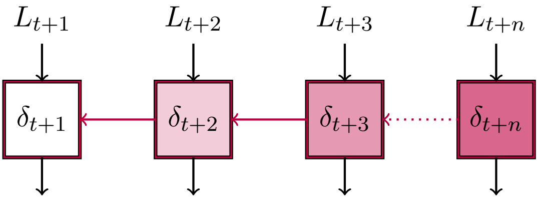

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$\prod_{\tau=t+2}^{t+n} \frac{\partial y_\tau}{\partial y_{\tau-1}}$

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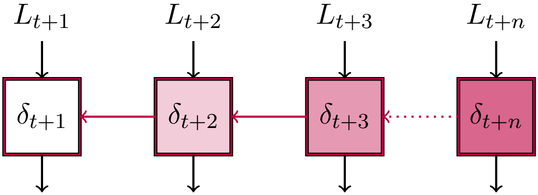

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$\prod_{\tau=t+2}^{t+n} \frac{\partial y_\tau}{\partial y_{\tau-1}}$

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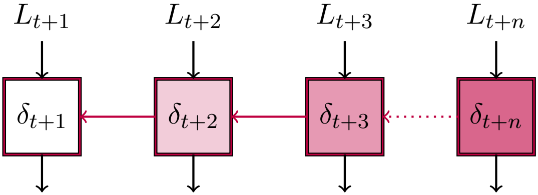

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$$\prod_{\tau=t+2}^{t+n} \frac{\partial y_\tau}{\partial y_{\tau-1}}$$

$$\begin{aligned} \frac{\partial y_\tau}{\partial y_{\tau-1}} &= \mathbf{C}^{\mathbf{T}} \sigma' \left(y_{\tau-1} \right) \\ \left\| \frac{\partial y_\tau}{\partial y_{\tau-1}} \right\| &\leq \|\mathbf{C}\| \frac{1}{4} \end{aligned}$$

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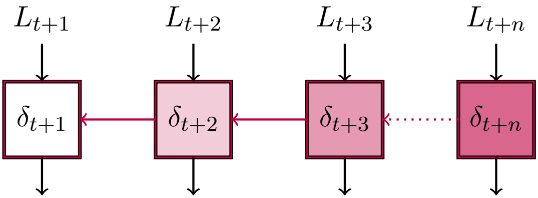

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\left\| \frac{\partial y_\tau}{\partial y_{\tau-1}} \right\| &\leq \|\mathbf{C}\| \frac{1}{4} \\
\prod_{\tau=t+2}^{t+n} \left\| \frac{\partial y_\tau}{\partial y_{\tau-1}} \right\| &\leq \left(\|\mathbf{C}\| \tfrac{1}{4}\right)^{n-1}
\end{aligned}$$

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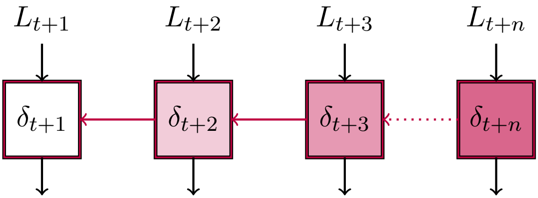

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$\prod_{\tau=t+2}^{t+n} \frac{\partial y_\tau}{\partial y_{\tau-1}}$

Exponentially Decaying Gradients

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$$\left\| \frac{\partial y_\tau}{\partial y_{\tau-1}} \right\| \leq \|\mathbf{C}\| \frac{1}{4}$$

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Rise of **Recurrent** Neural Networks

- GRUs/LSTMs alleviate this problem by using gates on inputs, outputs and hidden states [Hochreiter and Schmidhuber, 1997].

$$y_\tau = \mathbf{X} x_\tau + \mathbf{C} \sigma \left(y_{\tau - 1} \right) \tag{1}$$

Let $\mathbf{C} = \mathbf{I}$ and $\sigma(x) = x$. Then,

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$$y_\tau = \mathbf{X} x_\tau + y_{\tau-1} + \mathbf{z} \cdot \phi \left(y_{\tau-1} \right)$$

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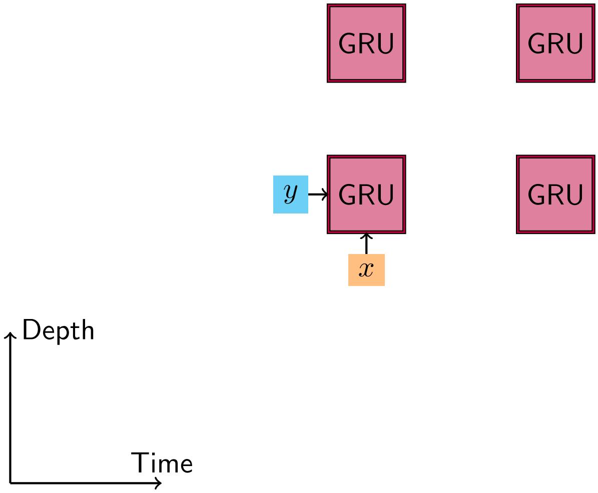
GRU Equations



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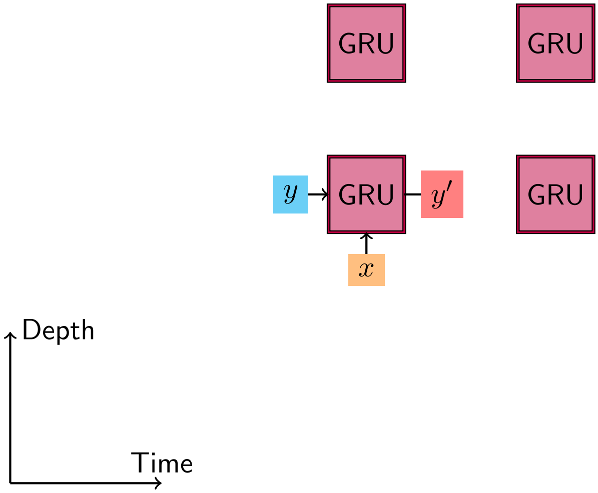

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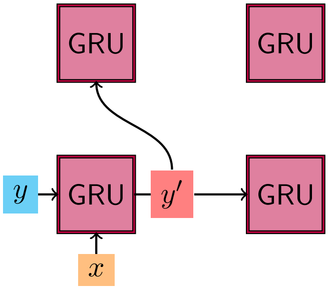

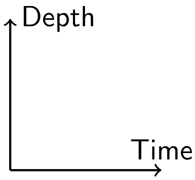

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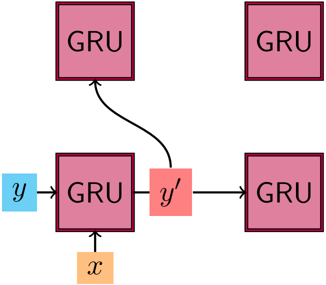
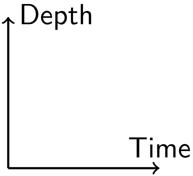


$$z = \sigma(\mathbf{X_z}\, x + \mathbf{Y_z}\, y)$$



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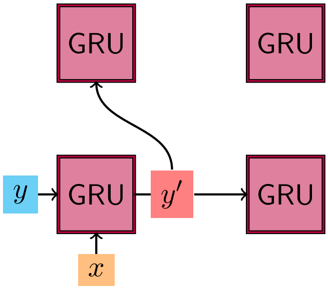
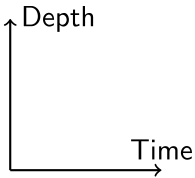
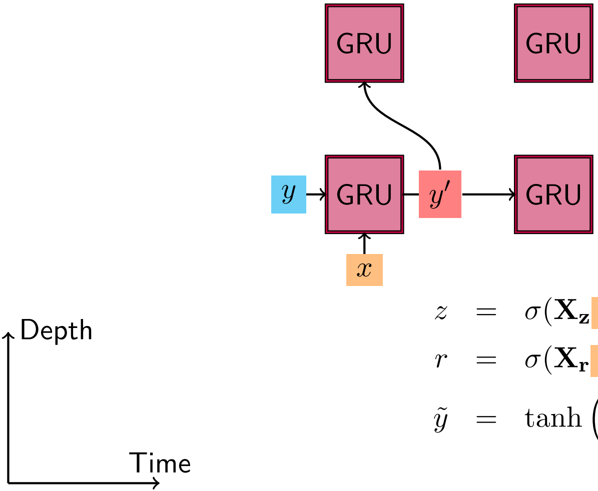


$$z = \sigma(\mathbf{X_z}\, x + \mathbf{Y_z}\, y)$$
$$r = \sigma(\mathbf{X_r}\, x + \mathbf{Y_r}\, y)$$

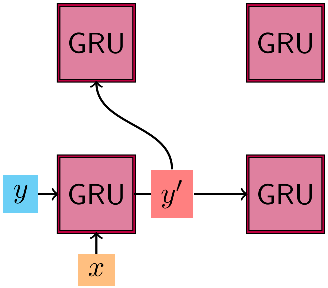


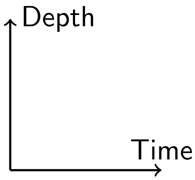
GRU Equations



$$
\begin{aligned}
z &= \sigma(\mathbf{X_z}\, x + \mathbf{Y_z}\, y) \\
r &= \sigma(\mathbf{X_r}\, x + \mathbf{Y_r}\, y) \\
\tilde{y} &= \tanh\left(\mathbf{X}\, x + \mathbf{Y}(r \cdot y)\right)
\end{aligned}
$$

GRU Equations





$$z = \sigma(\mathbf{X_z}\, x + \mathbf{Y_z}\, y)$$

$$r = \sigma(\mathbf{X_r}\, x + \mathbf{Y_r}\, y)$$

$$\tilde{y} = \tanh\left(\mathbf{X}\, x + \mathbf{Y}(r \cdot y)\right)$$

$$y_{t+1} = y' = (1 - z) \cdot y + z \cdot \tilde{y}$$

Rise of **Deep** Recurrent Neural Networks

- Even though the gating mechanisms (i.e. CEC) resolve vanishing gradient issues along time,

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- Gradients have been shown to vanish along depth.

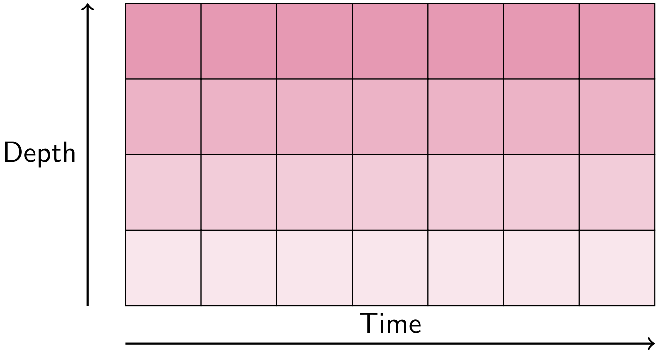


Figure 3: Gradients along Depth in a GRU

Rise of **Deep** Recurrent Neural Networks

- We observe the gradients while training a Deep GRU network on Character-Level Language Model.

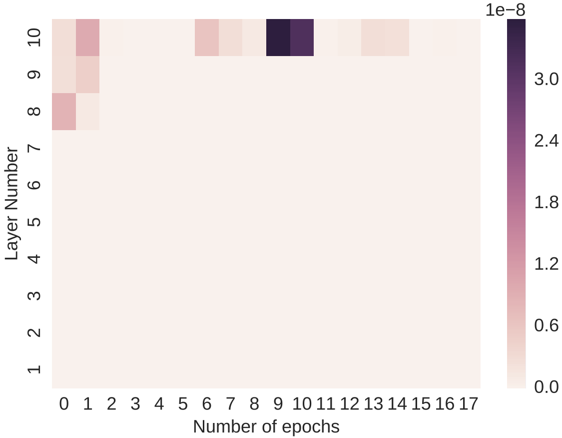
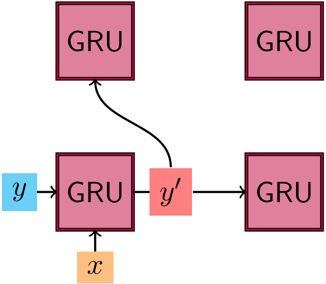


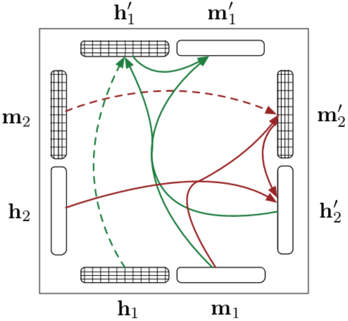
Figure 4: Gradient-Norms across depth in a 10-layered GRU

Rise of **Deep** Recurrent Neural Networks



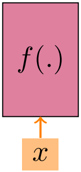
Same hidden state y' passed along time and depth

- Grid-LSTMs [Kalchbrenner et al., 2015] is to have **different hidden states along time and depth**.



Related Work

- Recurrent Highway Networks [Zilly et al., 2016] use gating in the depth to enforce **Constant Error Carrousel**.



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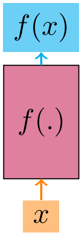

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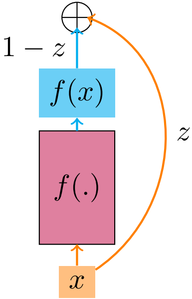

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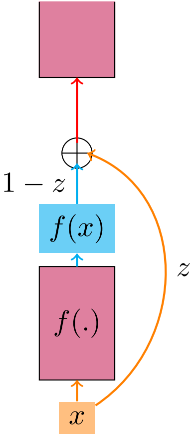

Research Question

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YES!!!

Formulation of Lattice Recurrent Unit

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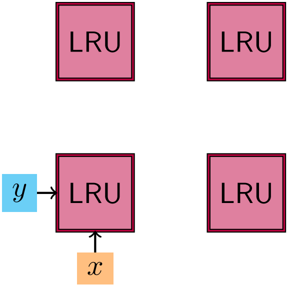

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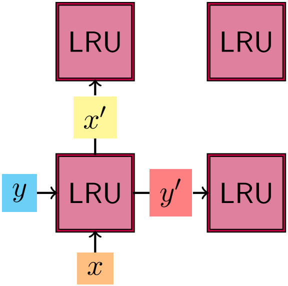

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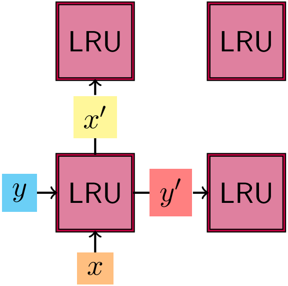

$$z = \sigma(\mathbf{X_z}\, x + \mathbf{Y_z}\, y)$$

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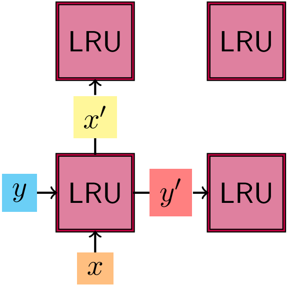

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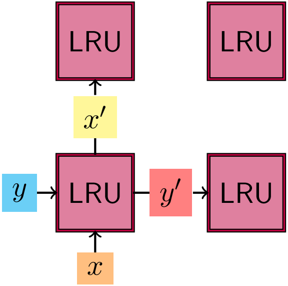

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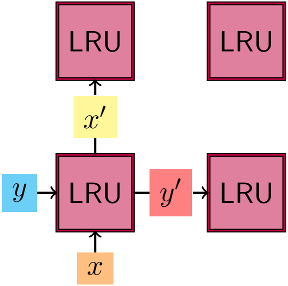

$$\tilde{x} = \tanh\left(\mathbf{X_x}\, x + \mathbf{Y_x}\left(r \cdot y\right)\right)$$

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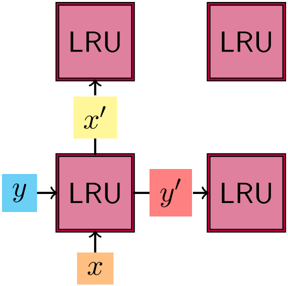

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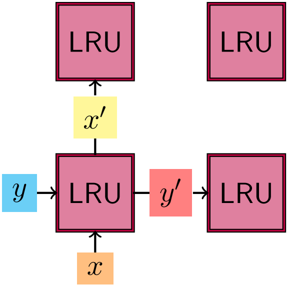

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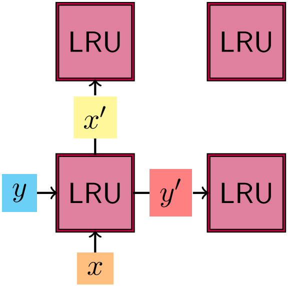

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x_{t+1} = x' &= z \cdot \tilde{y} + (1 - z) \cdot x \\
y_{t+1} = y' &= z \cdot \tilde{x} + (1 - z) \cdot y
\end{aligned}$$

Task: **Character Level** Language Modeling

- Out of Vocabulary Words can potentially be modeled.

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- Speech Synthesis [Wang et al., 2017]

Datasets

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Datasets

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- Each of them has around **5 million** characters.

War and Peace (WP)

Well, Prince, so Genoa and Lucca are now just family estates of the Bonapartes. But I warn you, if you don't tell me that this means war, if you still try to defend the infamies and horrors perpetrated by that Antichrist–I really believe he is Antichrist–I will have nothing more to do with you and you are no longer my friend, no longer my 'faithful slave,' as you call yourself!

Penn Tree Bank (PTB)

the asbestos fiber <unk> is unusually <unk> once it enters the <unk> with even brief exposures to it causing symptoms that show up decades later researchers said, <unk> inc. the unit of new york-based <unk> corp. that makes kent cigarettes stopped using <unk> in its <unk> cigarette filters in N.

Experimental Setup

- Multi-Class Classification Problem

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- Categorical Cross-Entropy Loss
  - loss $= \sum_{\forall i \in \mathcal{C}} p_i \log(\hat{p}_i)$
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- RNN unrolled 50 time-steps in time.

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- **Convergence Rate:** How many epochs does it take for the model to converge?
- **Trainability:** How are the **gradient norms** distributed across layers?

Results - Accuracy

Table 1: Penn Treebank Dataset and losses are in bits per character (BPC). Lower is better. l is the number of layers.

	Tess Loss (BPC)				**Hidden**
Model	$l=2$	$l=4$	$l=6$	$l=8$	**Units**
GRU	1.107	**1.092**	1.125	2.99	387

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GLSTM	1.119	1.106	1.111	1.105	237
Highway	1.110	1.102	1.107	-	-
LRU	**1.097**	1.102	**1.101**	**1.103**	300

Results - Accuracy

Table 2: War and Peace Dataset and losses are in bits per character (BPC). Lower is better. l is the number of layers.

	Tess Loss (BPC)				**Hidden**
Model	$l = 2$	$l = 4$	$l = 6$	$l = 8$	**Units**
GRU	1.285	1.293	1.344	3.104	387

Results - Accuracy

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Model	$l = 2$	$l = 4$	$l = 6$	$l = 8$	**Units**
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LSTM	1.297	1.353	1.530	3.100	335

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LSTM	1.297	1.353	1.530	3.100	335
GLSTM	1.319	1.317	1.312	1.31	237
Highway	1.294	1.298	1.306	1.305	-

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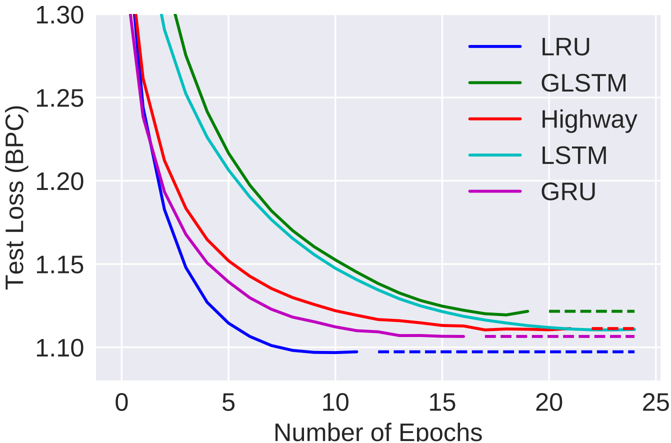
LRU	**1.279**	**1.280**	**1.281**	**1.287**	300

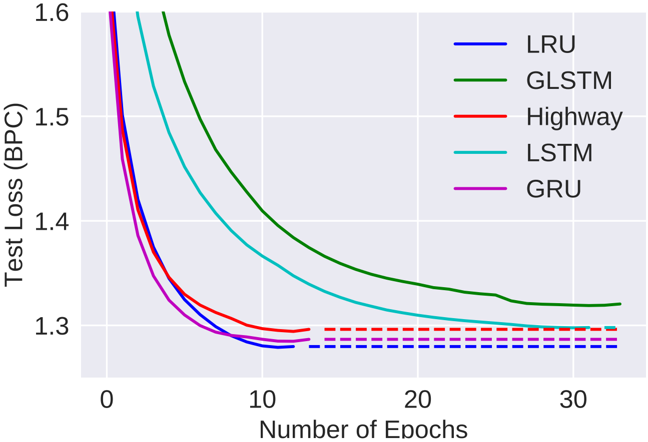
Results - Convergence Rates



(a) PTB dataset

Figure 5: Convergence rates of various models on PTB and WP datasets.

Results - Convergence Rates



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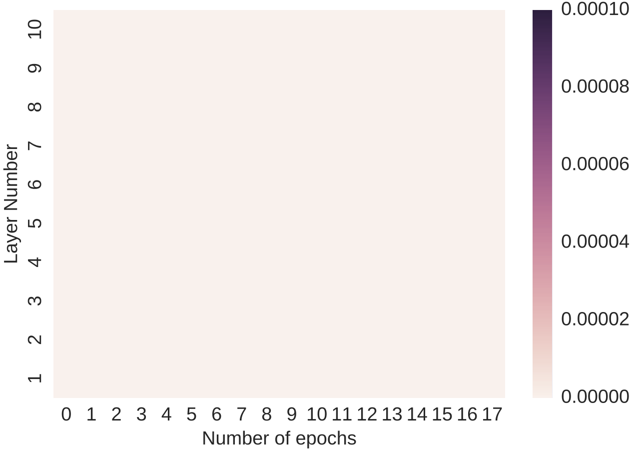
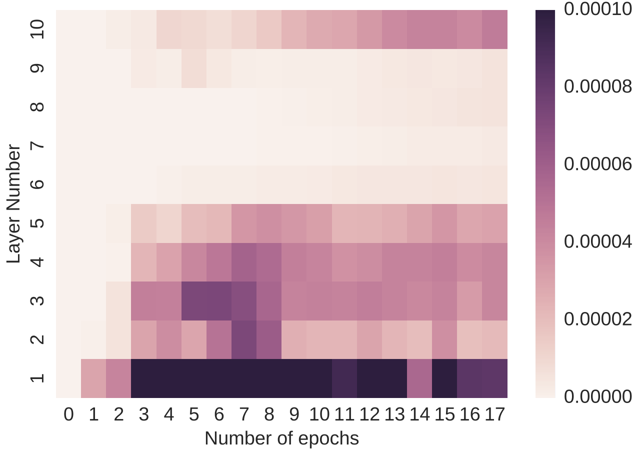
Results - Trainability



(a) GRU

Figure 6: Gradient Norms across layers and number of epochs as a heatmap. Darker values are bigger.

Results - Trainability



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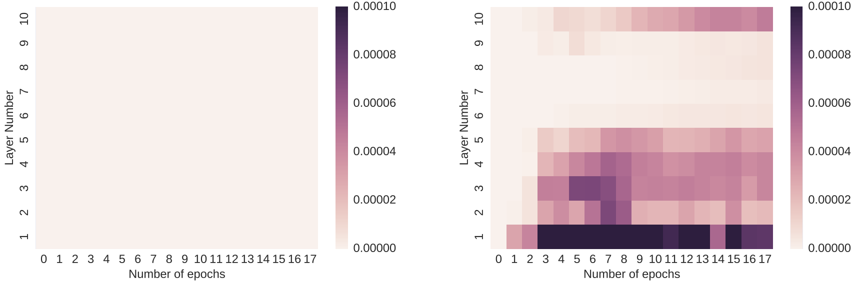

(a) GRU

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- While **not aggravating** the performance.

References I

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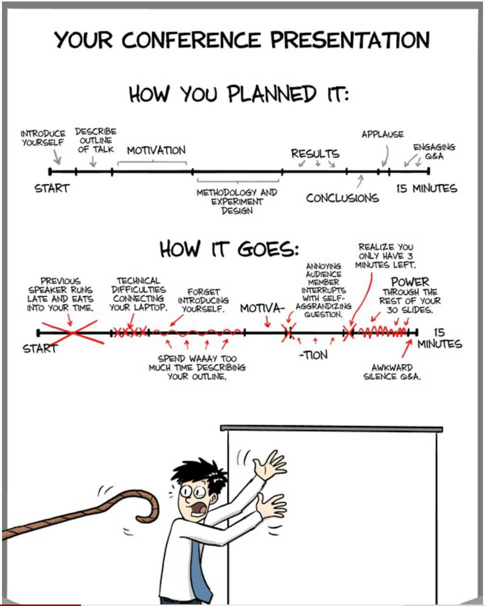
Thank You


YOUR CONFERENCE PRESENTATION
HOW YOU PLANNED IT:
INTRODUCE YOURSELF
DESCRIBE OUTLINE OF TALK
MOTIVATION
RESULTS
APPLAUSE
ENGAGING Q&A
START
METHODOLOGY AND EXPERIMENT DESIGN
CONCLUSIONS
15 MINUTES
HOW IT GOES:
PREVIOUS SPEAKER RUNS LATE AND EATS INTO YOUR TIME.
TECHNICAL DIFFICULTIES CONNECTING YOUR LAPTOP.
FORGET INTRODUCING YOURSELF.
MOTIVA-
ANNOYING AUDIENCE MEMBER INTERRUPTS WITH SELF-AGGRANDIZING QUESTION.
REALIZE YOU ONLY HAVE 3 MINUTES LEFT.
POWER THROUGH THE REST OF YOUR 30 SLIDES.
START
15 MINUTES
SPEND WAAAY TOO MUCH TIME DESCRIBING YOUR OUTLINE.
-TION
AWKWARD SILENCE Q&A.