

On the Difficulty of Training RNNs

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1. Introduction & Background

2. The Problem

3. Solution & Experiments

1.1 Context

- **Importance of sequence modeling**
 - e.g., language, time-series in finance
- Identifying gradient problems (Bengio et al., 1994)
 - **Vanishing gradient problem**: impossible to learn long-term dependencies
 - **Exploding gradient problem**: numerical instabilities → unstable training
- → Why stable gradient flow is critical for learning temporal dependencies (paper's contribution)

1.2 Schematic & formal def. of RNN

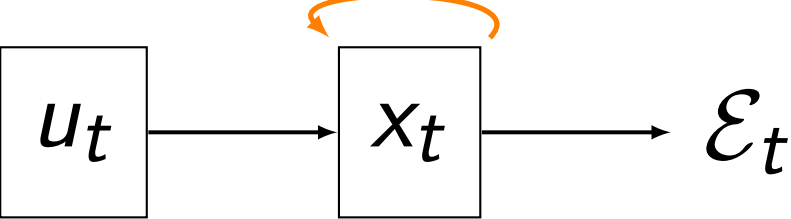


Fig. 1

$$\begin{aligned} x_t &= F(x_{t-1}, u_t, \theta) & (1) \text{ General} \\ x_t &= W_{\text{rec}} \sigma(x_{t-1}) + W_{\text{in}} u_t + \mathbf{b} & (2) \end{aligned}$$

where u_t : input, x_t : state, t : time step, \mathbf{b} : bias, $\mathcal{E}_t = \mathcal{L}(x_t)$ (error)

The recurrent connections in the hidden layer allow information to persist from one input to another.

1.3 Training RNNs: Backprop Through Time (BPTT) on Unrolled RNN

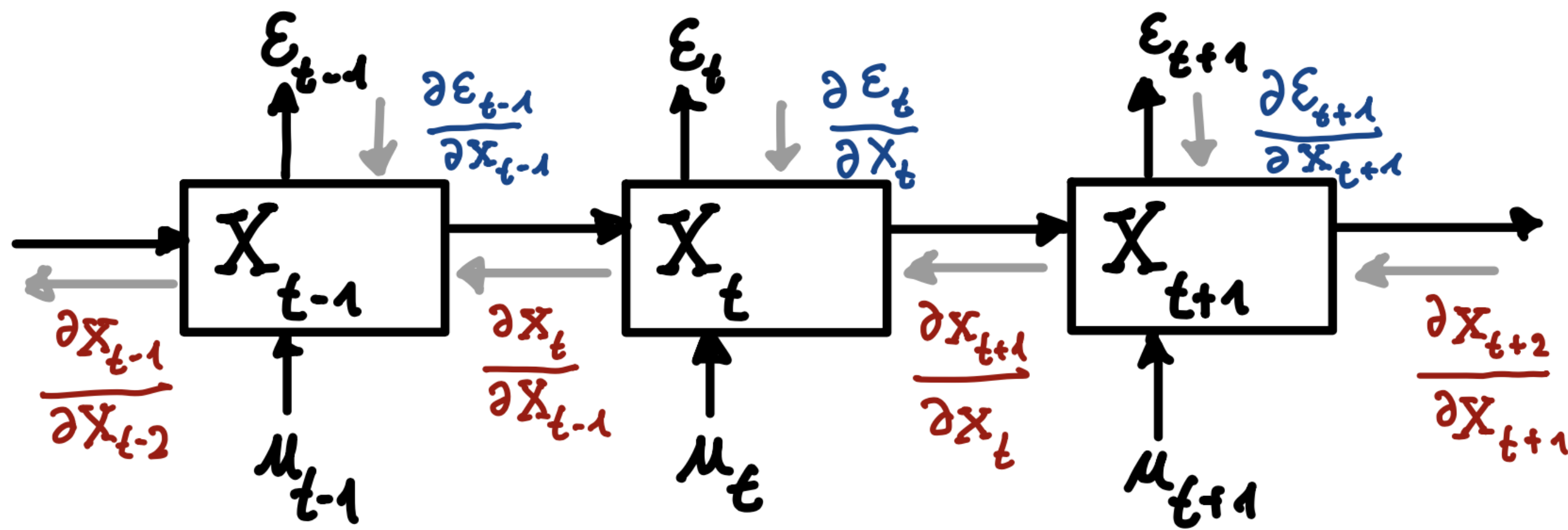


Fig. 2: Unrolled RNN

$$\begin{aligned} \frac{\partial \mathcal{E}}{\partial \theta} &= \sum_{t=1}^T \frac{\partial \mathcal{E}_t}{\partial \theta} & (3) \\ \frac{\partial \mathcal{E}_t}{\partial \theta} &= \sum_{k=1}^t \left(\frac{\partial \mathcal{E}_t}{\partial x_t} \frac{\partial x_t}{\partial x_k} \frac{\partial^+ x_k}{\partial \theta} \right) & (4) \\ \frac{\partial x_t}{\partial x_k} &= \prod_{i=k+1}^t W_{\text{rec}}^\top \cdot \text{diag}(\sigma'(x_{i-1})) & (5) \end{aligned}$$

where $\frac{\partial^+ x_k}{\partial \theta}$ denotes the “immediate” partial derivative (treating x_{k-1} as constant).

Blue: total gradient over time. Red: temporal error contribution.

2.1 Vanishing Gradient problem (VG)

Sufficient condition:

$$\lambda_1 < \frac{1}{\gamma}$$

where: λ_1 : largest singular value of W_{rec}

γ : bound on derivative of activation function

(proof: see eq. 6 & 7)

2.2 Exploding Gradient problem (EGs)

- gradients grow exponentially during backprop
- Necessary condition:

$$\lambda_1 > \frac{1}{\gamma}$$

2.2.1 Dynamical systems interpretation:

- EGs create steep wall-like structures that are perpendicular to exploding direction in error surface

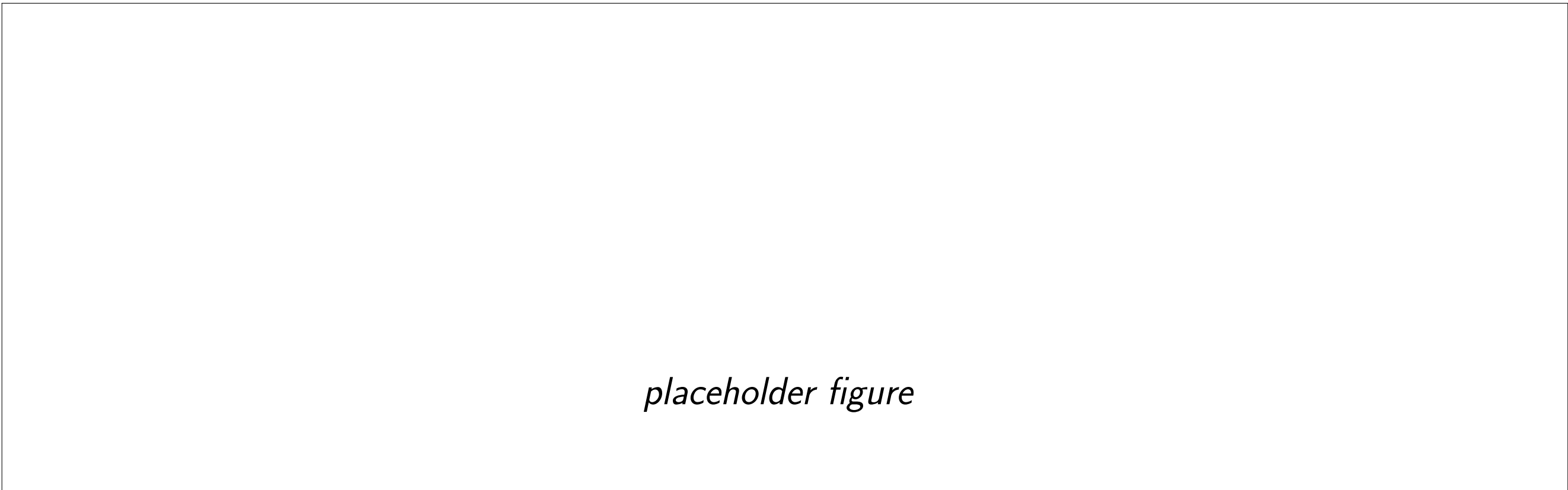


Fig. 3