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Long Short-Term Memory

- Long Short-Term Memory

  Sepp Hochreiter and Jürgen Schmidhuber. Neural Computation, 1997

- Learning to Forget: Continual Prediction with LSTM

  Felix A. Gers, Jürgen Schmidhuber, Fred Cummins. Neural Computation, 2000

David R. Morrison

The Goal

- Implementing memory in a neural network
  - Long term: weight changes
  - Short term: recent input events
- Why?

Solutions?

- Recurrent Networks
  - Back-Propagation Through Time
  - Real-Time Recurrent Learning

Problems

- No clear advantages over feed-forward backprop
- What to put in short-term memory?
- Error Signals
  - Vanish (hard to bridge long time lags)
  - Explode (oscillating weights)

Long Short-Term Memory

- Enforces constant error flow
- Stores information in memory cells
  - What information to store
  - When to release information

Network Architecture

Experiments

- Embedded Reber Grammar
- Noise-Free/Noisy Sequence
- Noise and Signal on Same Channel
- Adding Problem
- Multiplication Problem
- Temporal Order

Fixing LSTM

- Forget Gates
  - Learns when stored information is no longer necessary
- Experimental results

How it learns

Cell block c_j's truncated derivatives are:

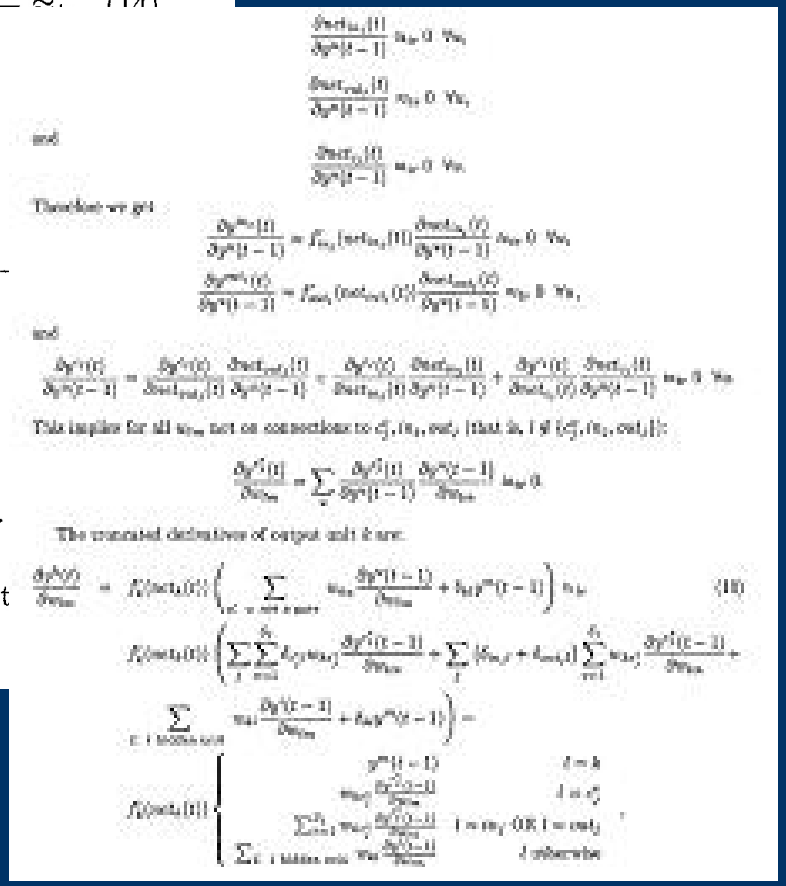
$$\frac{\partial y^{in_j}(t)}{\partial w_{lm}} = f'_{in_j}(net_{in_j}(t))\frac{\partial net_{in_j}(t)}{\partial w_{lm}} \approx_{tr} \delta_{in_j l} f'_{in_j}(net_{in_j}(t)) y^m(t-1) \ . \tag{12}$$

$$\frac{\partial y^{out_j}(t)}{\partial w_{lm}} = f'_{out_j}(net_{out_j}(t))\frac{\partial net_{out_j}(t)}{\partial w_{lm}} \approx_{tr} \delta_{out_j l} f'_{out_j}(net_{out_j}(t)) y^m(t-1) \ . \tag{13}$$

$$\begin{aligned}\frac{\partial s_{c_j^v}(t)}{\partial w_{lm}} &= \frac{\partial s_{c_j^v}(t-1)}{\partial w_{lm}} + \frac{\partial y^{in_j}(t)}{\partial w_{lm}} g\left(net_{c_j^v}(t)\right) + y^{in_j}(t) g'\left(net_{c_j^v}(t)\right)\frac{\partial net_{c_j^v}(t)}{\partial w_{lm}} \sim \\ &\left(\delta_{in_j l} + \delta_{c_j^v l}\right)\frac{\partial s_{c_j^v}(t-1)}{\partial w_{lm}} + \delta_{in_j l}\frac{\partial y^{in_j}(t)}{\partial w_{lm}} g\left(net_{c_j^v}(t)\right) + \\ &\delta_{c_j^v l} y^{in_j}(t) g'\left(net_{c_j^v}(t)\right)\frac{\partial net_{c_j^v}(t)}{\partial w_{lm}} = \\ &\left(\delta_{in_j l} + \delta_{c_j^v l}\right)\frac{\partial s_{c_j^v}(t-1)}{\partial w_{lm}} + \delta_{in_j l} f'_{in_j}(net_{in_j}(t))\ g\left(net_{c_j^v}(t)\right) y^m(t- \\ &\delta_{c_j^v l}\ y^{in_j}(t)\ g'\left(net_{c_j^v}(t)\right) y^m(t-1) \ .\end{aligned}$$

$$\begin{aligned}\frac{\partial y^{c_j^v}(t)}{\partial w_{lm}} &= \frac{\partial y^{out_j}(t)}{\partial w_{lm}} h(s_{c_j^v}(t)) + h'(s_{c_j^v}(t))\frac{\partial s_{c_j^v}(t)}{\partial w_{lm}} y^{out_j}(t) \approx_{tr} \\ &\delta_{out_j l}\frac{\partial y^{out_j}(t)}{\partial w_{lm}} h(s_{c_j^v}(t)) + \left(\delta_{in_j l} + \delta_{c_j^v l}\right) h'(s_{c_j^v}(t))\frac{\partial s_{c_j^v}(t)}{\partial w_{lm}} y^{out_j}(t) \ .\end{aligned}$$

To efficiently update the system at time t, the only (truncated) derivatives that need t
at time $t-1$ are $\frac{\partial s_{c_j^v}(t-1)}{\partial w_{lm}}$, where $l = c_j^v$ or $l = in_j$.



Learning Rules

- Forward Pass
- Backward Pass and Weight Update
  - Output learning, neuron learning, output gate learning
  - Cell learning, forget gate learning, input gate learning

What does it all mean?

- LSTM is a unique network architechture that shows a lot of promise for learning how to remember things.
- It is quickly growing in popularity, used successfully in areas of music composition, speech recognition, protein structure analysis, and others