Cortical microcircuits as gated-recurrent neural networks

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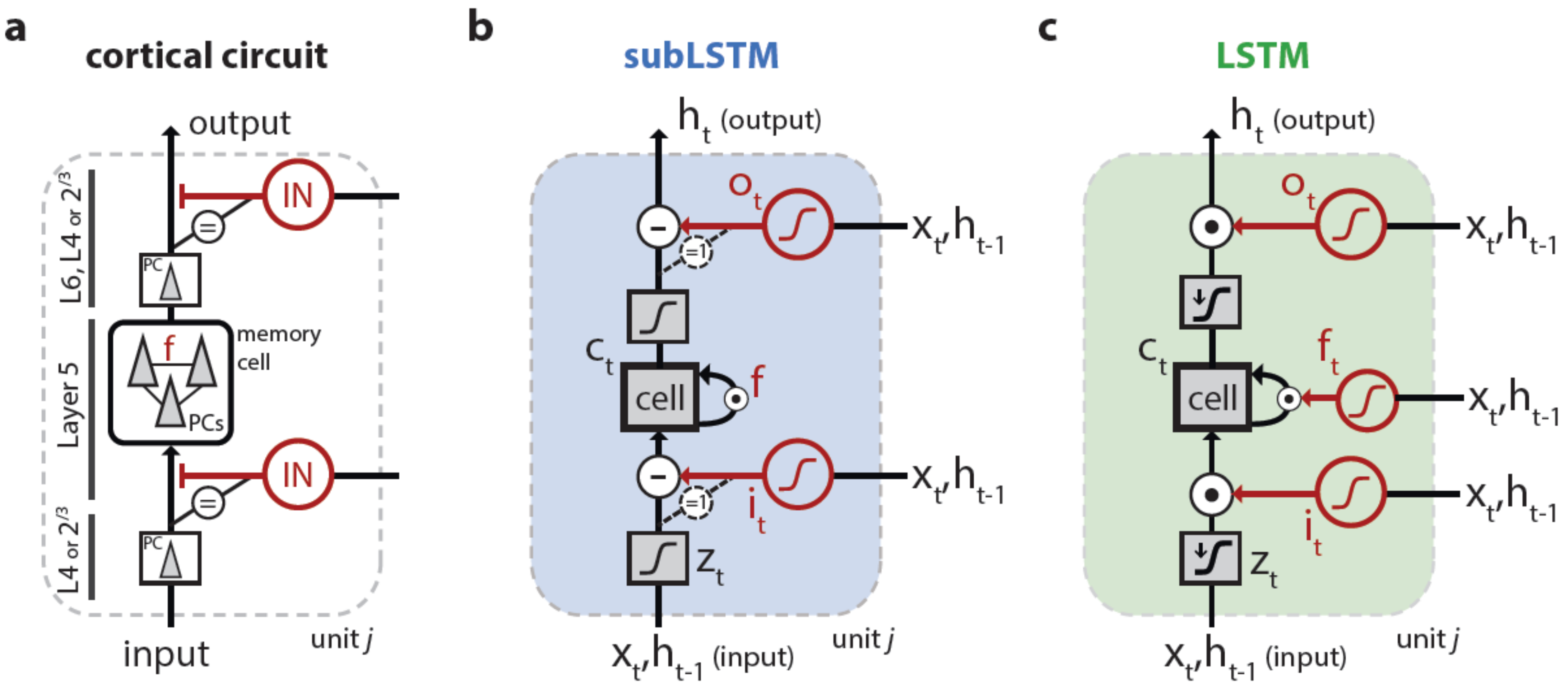
Motivation



- Cortical circuit(외피 회로)의 입출력 메커니즘을 모방한 새로운 gated-recurrent NN 구조.

Subtractive–gated long short–term memory

	LSTM	subLSTM
$[\mathbf{f}_t, \mathbf{o}_t, \mathbf{i}_t]^T =$	$\sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$	$\sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$
$\mathbf{z}_t =$	$\tanh(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$	$\sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$
$\mathbf{c}_t =$	$\mathbf{c}_{t-1} \odot \mathbf{f}_t + \mathbf{z}_t \odot \mathbf{i}_t,$	$\mathbf{c}_{t-1} \odot \mathbf{f}_t + \mathbf{z}_t - \mathbf{i}_t,$
$\mathbf{h}_t =$	$\tanh(\mathbf{c}_t) \odot \mathbf{o}_t.$	$\sigma(\mathbf{c}_t) - \mathbf{o}_t.$

- Input, output gate에서 원소 별 곱셈이 아닌 뺄셈을 사용하였다는 것이 가장 큰 차이점.

Gradients analysis (subLSTM vs LSTM)

$$\Delta_t \stackrel{\text{def}}{=} \frac{d\text{loss}}{d\mathbf{h}_t}$$

$$
\begin{aligned}
\delta\mathbf{h}_t &= \Delta_t \\
\delta\overline{\mathbf{o}}_t &= -\delta\mathbf{h}_t \odot \sigma'(\overline{\mathbf{o}}_t) \\
\delta\mathbf{c}_t &= \delta\mathbf{h}_t \odot \sigma'(\mathbf{c}_t) + \delta\mathbf{c}_{t+1} \odot \mathbf{f}_{t+1} \\
\delta\overline{\mathbf{f}}_t &= \delta\mathbf{c}_t \odot \mathbf{c}_{t-1} \odot \sigma'(\overline{\mathbf{f}}_t) \\
\delta\overline{\mathbf{i}}_t &= -\delta\mathbf{c}_t \odot \sigma'(\overline{\mathbf{i}}_t) \\
\delta\overline{\mathbf{z}}_t &= \delta\mathbf{c}_t \odot \sigma'(\overline{\mathbf{z}}_t)
\end{aligned}
$$

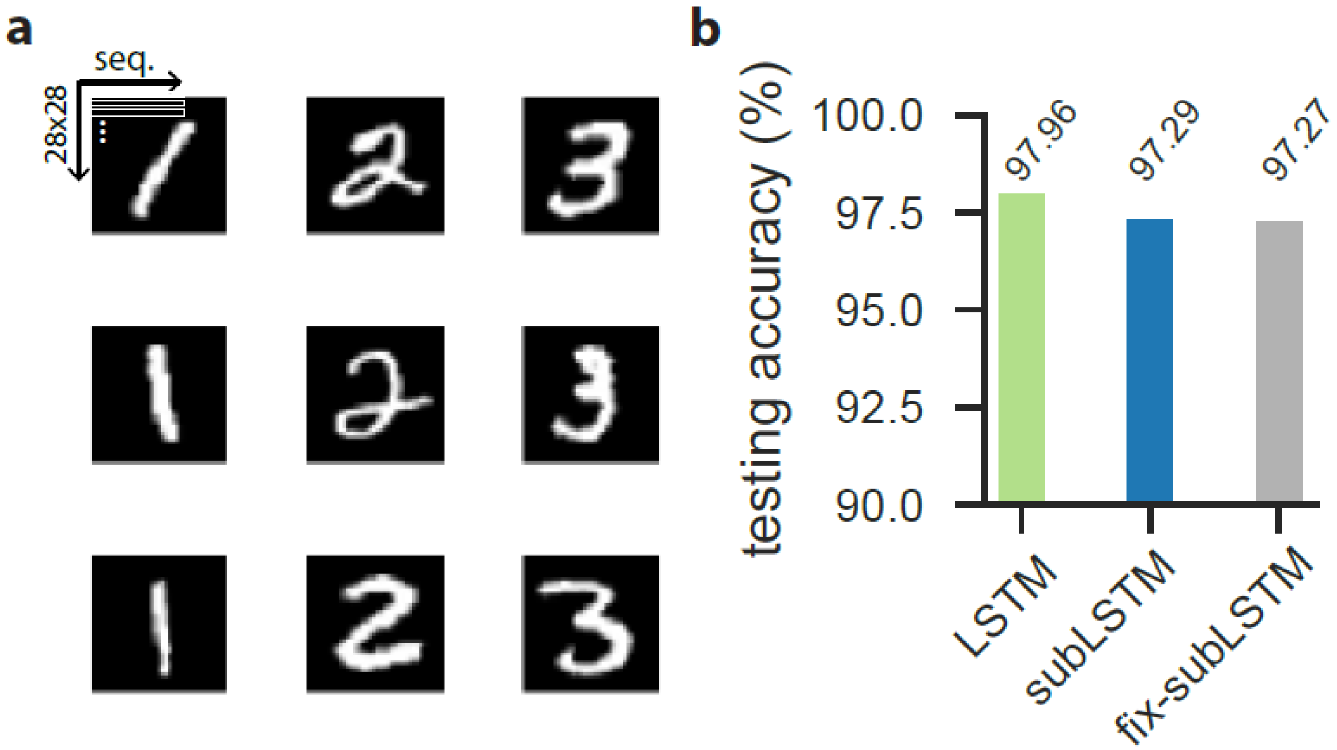
subLSTM

$$
\begin{aligned}
\delta\mathbf{h}_t &= \Delta_t \\
\delta\overline{\mathbf{o}}_t &= \mathbf{h}_t \odot \tanh(\mathbf{c}_t) \odot \sigma'(\overline{\mathbf{o}}_t) \\
\delta\mathbf{c}_t &= \mathbf{h}_t \odot \mathbf{o}_t \odot \tanh'(\mathbf{c}_t) + \delta\mathbf{c}_{t+1} \odot \mathbf{f}_{t+1} \\
\delta\overline{\mathbf{f}}_t &= \delta\mathbf{c}_t \odot \mathbf{c}_{t-1} \odot \sigma'(\overline{\mathbf{f}}_t) \\
\delta\overline{\mathbf{i}}_t &= \delta\mathbf{c}_t \odot \mathbf{z}_t \odot \sigma'(\overline{\mathbf{i}}_t) \\
\delta\overline{\mathbf{z}}_t &= \delta\mathbf{c}_t \odot \mathbf{i}_t \odot \tanh'(\overline{\mathbf{z}}_t)
\end{aligned}
$$

LSTM

Experiments

- MNIST classification



Experiments

- Language modelling
  - 주어진 단어로부터 그 다음 단어를 예측.
  - Penn Treebank dataset과 Wikitext-2 dataset을 이용
  - Test measure : Perplexity

$$\text{perplexity} = P(w_1, \ldots, w_n)^{-1/n}$$

(a) Penn Treebank (PTB) test perplexity

size	subLSTM	fix-subLSTM	LSTM
10	222.80	213.86	215.93
100	91.46	91.84	88.39
200	79.59	81.97	74.60
650	76.17	70.58	64.34

(b) Wikitext-2 test perplexity

size	subLSTM	fix-subLSTM	LSTM
10	268.33	259.89	271.44
100	103.36	105.06	102.77
200	89.00	94.33	86.15
650	78.92	79.49	74.27