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Gated recurrent unit

Gated recurrent units (**GRU**s) are a gating mechanism in recurrent neural networks, introduced in 2014 by Kyunghyun Cho et al.[1] The GRU is like a long short-term memory (LSTM) with a forget gate,[2] but has fewer parameters than LSTM, as it lacks an output gate.[3] GRU's performance on certain tasks of polyphonic music modeling, speech signal modeling and natural language processing was found to be similar to that of LSTM.[4][5] GRUs have been shown to exhibit better performance on certain smaller and less frequent datasets.[6][7]

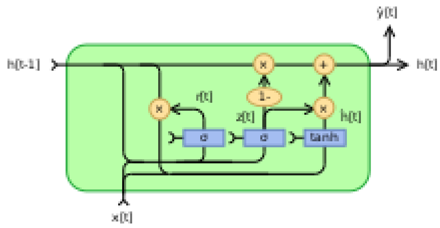
Contents

Architecture

There are several variations on the full gated unit, with gating done using the previous hidden state and the bias in various combinations, and a simplified form called minimal gated unit.[8]

The operator $\odot$ denotes the Hadamard product in the following.

Fully gated unit



Gated Recurrent Unit, fully gated version

Initially, for $t = 0$, the output vector is $h_0 = 0$.

$$\begin{aligned} z_t &= \sigma_g(W_z x_t + U_z h_{t-1} + b_z) \\ r_t &= \sigma_g(W_r x_t + U_r h_{t-1} + b_r) \\ \hat{h}_t &= \phi_h(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \\ h_t &= (1 - z_t) \odot h_{t-1} + z_t \odot \hat{h}_t \end{aligned}$$

Variables

- x_t: input vector
- h_t: output vector
- $\hat{h}_t$: candidate activation vector
- z_t: update gate vector
- r_t: reset gate vector
- W, U and b: parameter matrices and vector

Activation functions

- σ_g: The original is a sigmoid function.
- ϕ_h: The original is a hyperbolic tangent.

Alternative activation functions are possible, provided that $\sigma_g(x) \in [0, 1]$.

Alternate forms can be created by changing z_t and r_t[9]

- Type 1, each gate depends only on the previous hidden state and the bias.

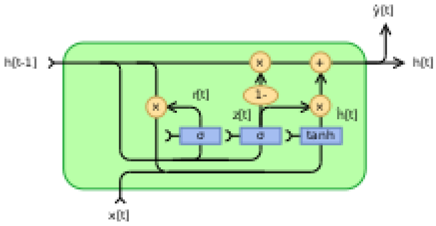
$$
\begin{aligned}
z_t &= \sigma_g(U_z h_{t-1} + b_z) \\
r_t &= \sigma_g(U_r h_{t-1} + b_r)
\end{aligned}
$$

- Type 2, each gate depends only on the previous hidden state.

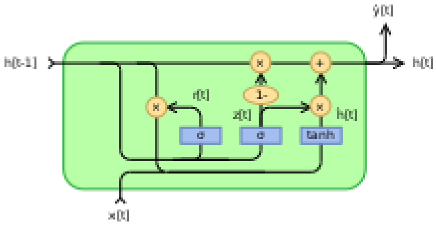
$$
\begin{aligned}
z_t &= \sigma_g(U_z h_{t-1}) \\
r_t &= \sigma_g(U_r h_{t-1})
\end{aligned}
$$

- Type 3, each gate is computed using only the bias.

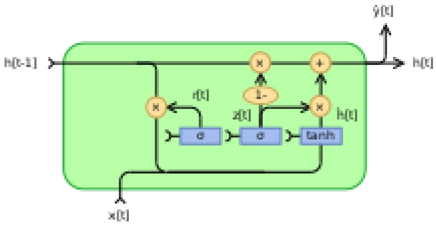
$$
\begin{aligned}
z_t &= \sigma_g(b_z) \\
r_t &= \sigma_g(b_r)
\end{aligned}
$$



Type 1



Type 2



Type 3

Minimal gated unit

The minimal gated unit is similar to the fully gated unit, except the update and reset gate vector is merged into a forget gate. This also implies that the equation for the output vector must be changed:[10]

$$
\begin{aligned}
f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\
\hat{h}_t &= \phi_h(W_h x_t + U_h(f_t \odot h_{t-1}) + b_h) \\
h_t &= (1 - f_t) \odot h_{t-1} + f_t \odot \hat{h}_t
\end{aligned}
$$

Variables

- x_t: input vector
- h_t: output vector
- $\hat{h}_t$: candidate activation vector
- f_t: forget vector
- W, U and b: parameter matrices and vector

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