# HW 4 Discussion

# Logistics

- HW4 Due May $9^{th}$. Late days applicable.
- Will upgrade the reading report grade soon
- HW3 Grade and solutions released next week

# HW4

- GAN
- Word2vec
- Some paper-related questions
  - Almost every paper has open-source code, you are welcome  to try them out

# GAN

- Python 3 + Tensorflow
- Find the right functions in tf
- Update the Generator to maximize the probability of the discriminator making the incorrect choice on generated data:

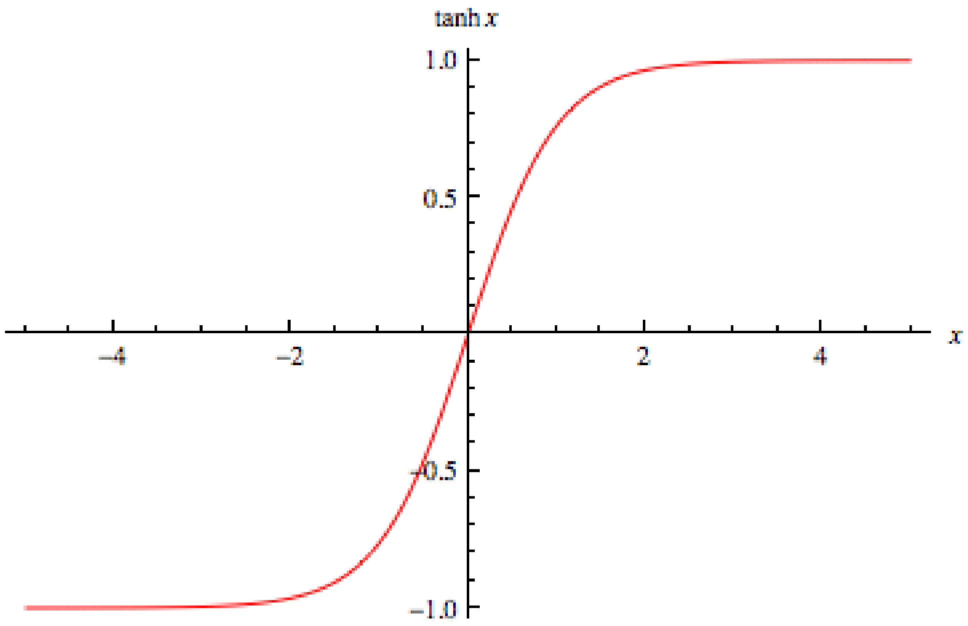
$$\underset{G}{\text{maximize}}\ \mathbb{E}_{z\sim p(z)}[\log D(G(z))]$$

- Update the Discriminator to maximize the probability of the discriminator making the correct choice on real and generated data:

$$\underset{D}{\text{maximize}}\ \mathbb{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbb{E}_{z\sim p(z)}[\log(1 - D(G(z)))]$$

# GAN Architectures

- Discriminator:
  - Same as CNN
- Generator:
  - Decovnet
  - Tanh as the activation for the final layer



# Variations of GAN

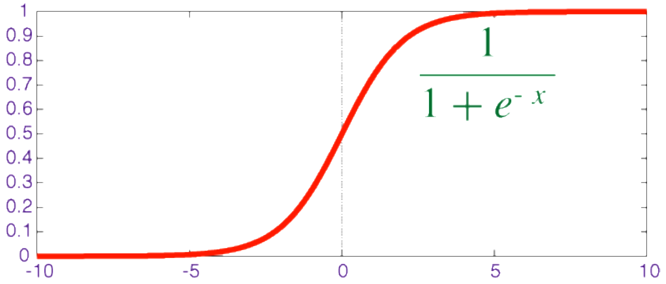
- A whole new research area
  - New paper coming out almost every day
- https://github.com/soumith/ganhacks
  - More stable variations for GAN
- https://github.com/tensorflow/cleverhans
  - Adversarial Example Library

# Word2vec

- Python 3
- Gradient Derivation
  - Similar to HW 1
- Implement the 2 different loss functions
  - Update all parameters
  - Negative Sampling

# Negative Sampling

Sigmoid Function:




Softmax

$$\boldsymbol{\hat{y}_o} = p(o|c) = \frac{exp(\boldsymbol{u_o^T v_c})}{\sum_{w \in V} exp(\boldsymbol{u_w^T v_c})} \tag{1}$$

Softmax Loss

$$J_{softmax-CE}(\boldsymbol{o}, \boldsymbol{v_c}, \boldsymbol{U}) = -\sum_{j=1}^{V} log(\boldsymbol{\hat{y}_j})\boldsymbol{y_j} \tag{2}$$

Negative Sampling Loss

$$J_{neg-sample}(\boldsymbol{o}, \boldsymbol{v_c}, \boldsymbol{U}) = -log(\sigma(\boldsymbol{u_o}^T \boldsymbol{v_c})) - \sum_{k=1}^{K} log(\sigma(\boldsymbol{-u_k}^T \boldsymbol{v_c})) \tag{3}$$

# Long Short Term Memory (LSTM) networks

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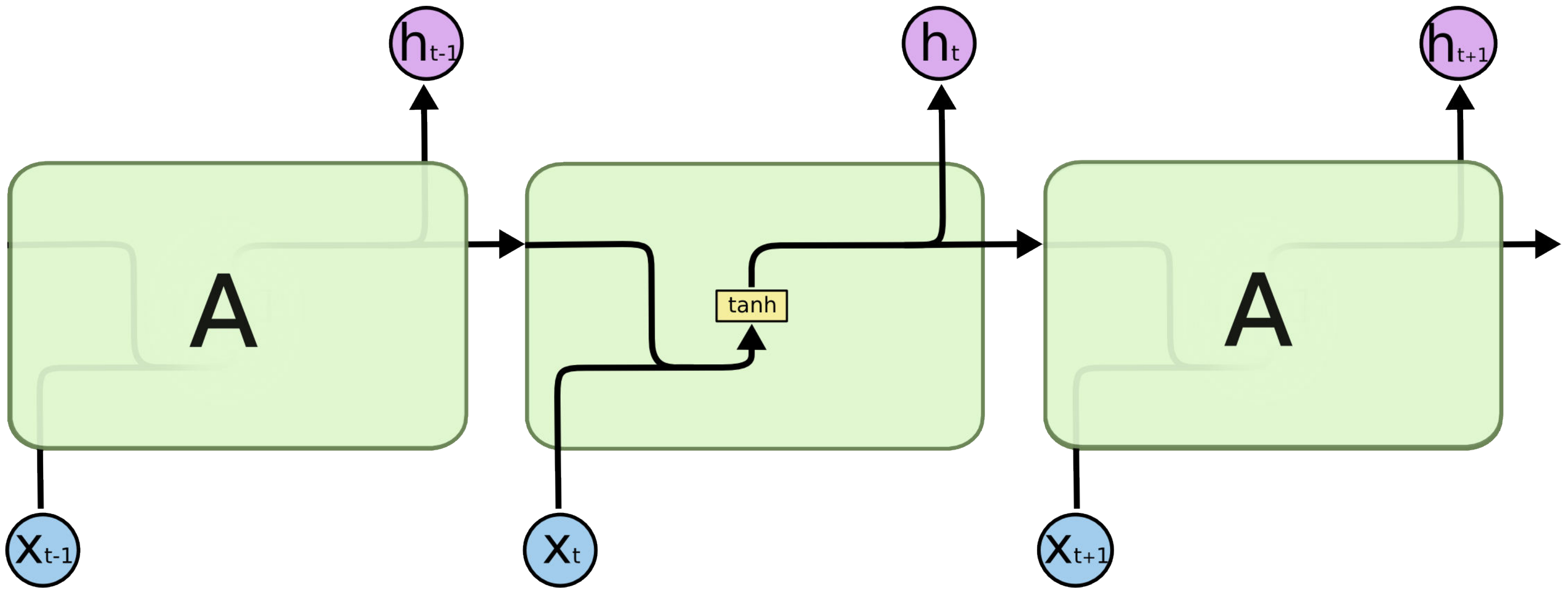
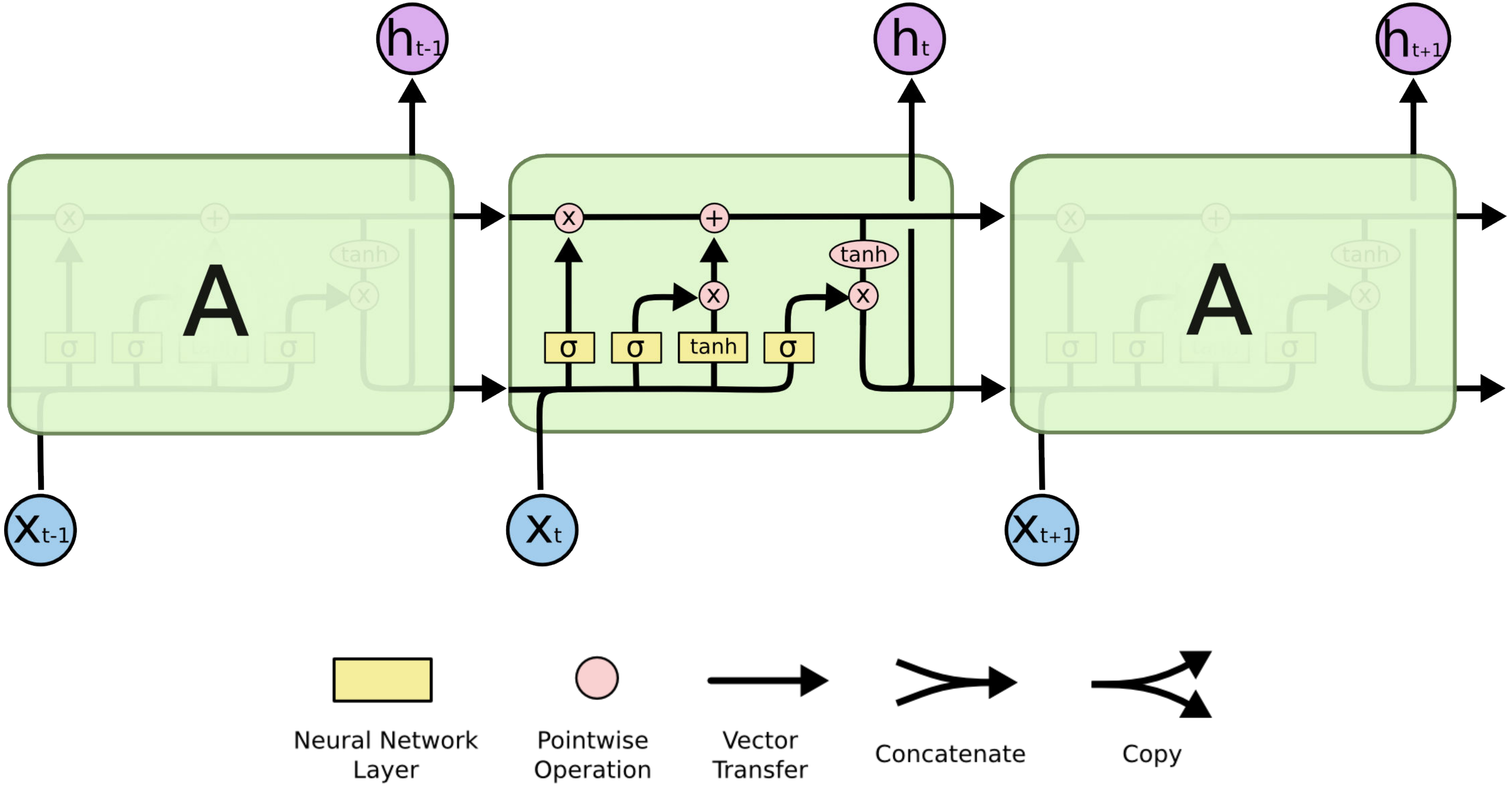
# Vanilla RNN



# Recall problem

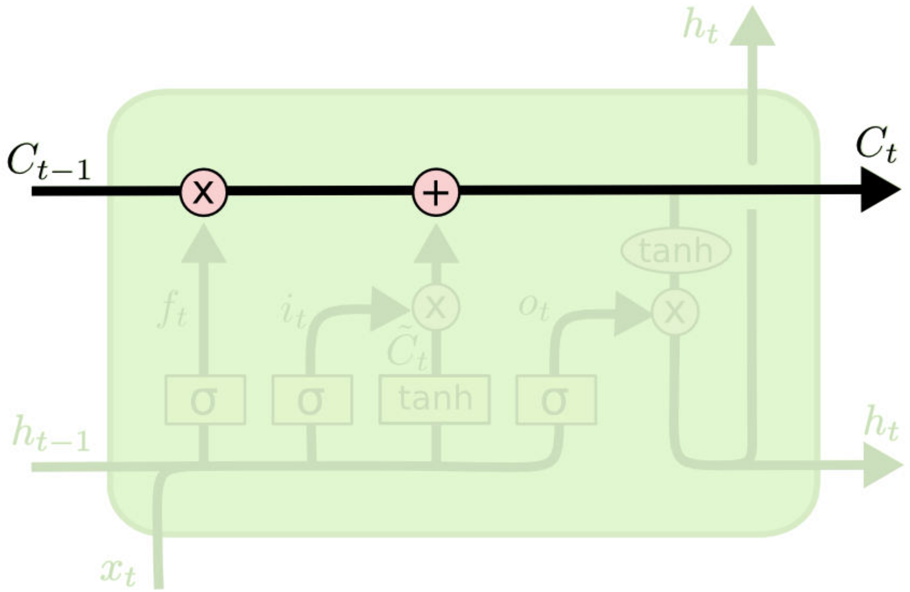
- Vanishing or exploding gradients
    - difficult to learn long term dependencies

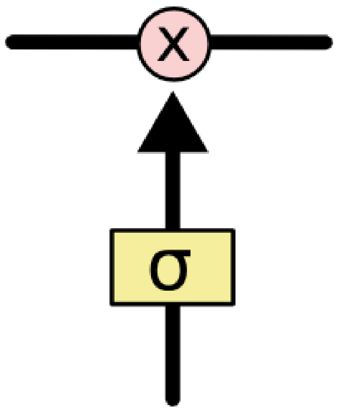
# LSTM


h t-1
h t
h t+1
A
A
σ
σ
tanh
σ
tanh
X t-1
X t
X t+1
Neural Network Layer
Pointwise Operation
Vector Transfer
Concatenate
Copy

# Core idea behind LSTMs

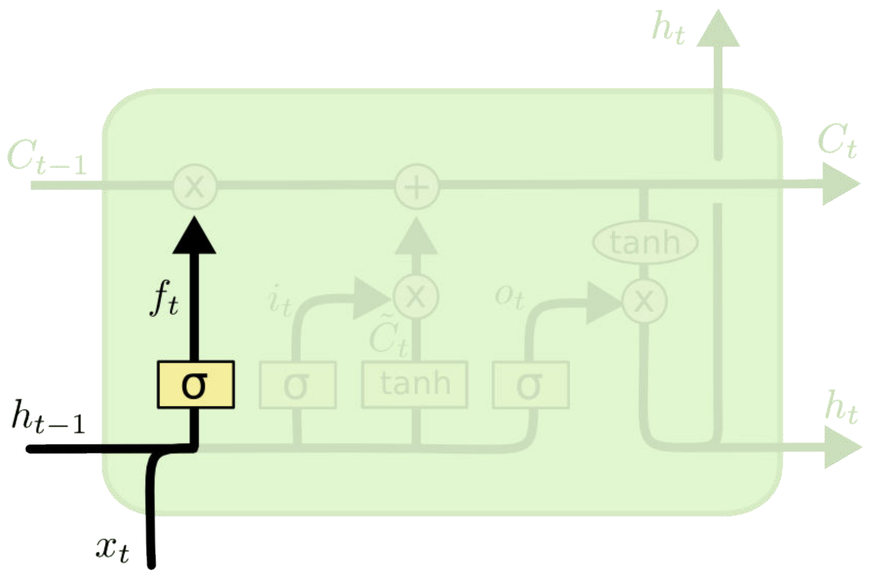
- Cell state and gates



# LSTM walk-through

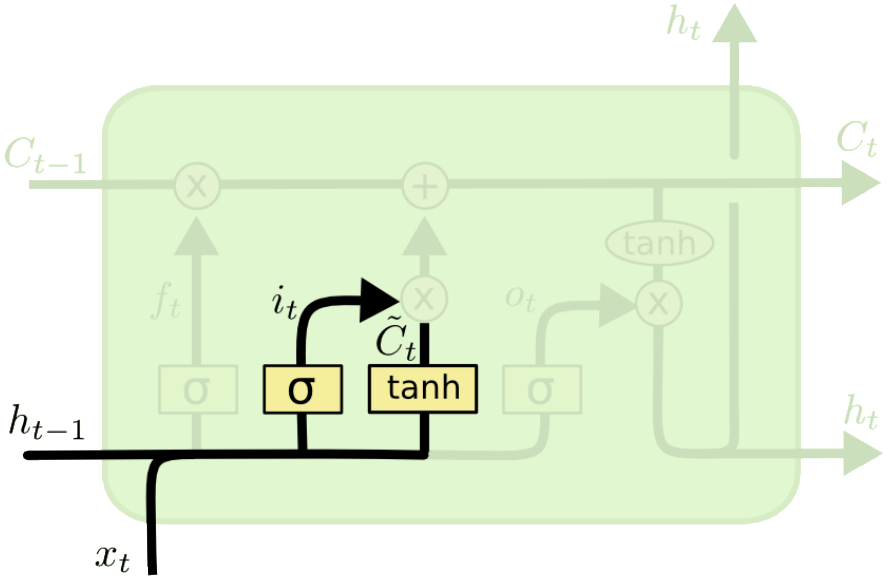
# Forget information




$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

- What information are we going to forget from the cell state?
- sigmoid output in [0,1]; if output 0, then forget completely
- Language model example: Forget gender of old subject when model sees new subject

# Create new information

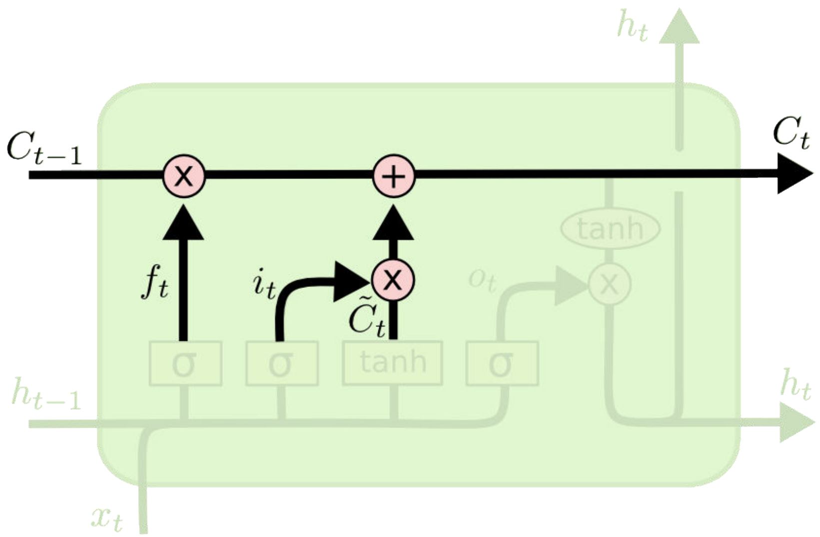



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

- input gate layer decides which values we'll update
- tanh layer creates a vector of new candidate values that could be added to the state
- Language model example: the gender of the new subject

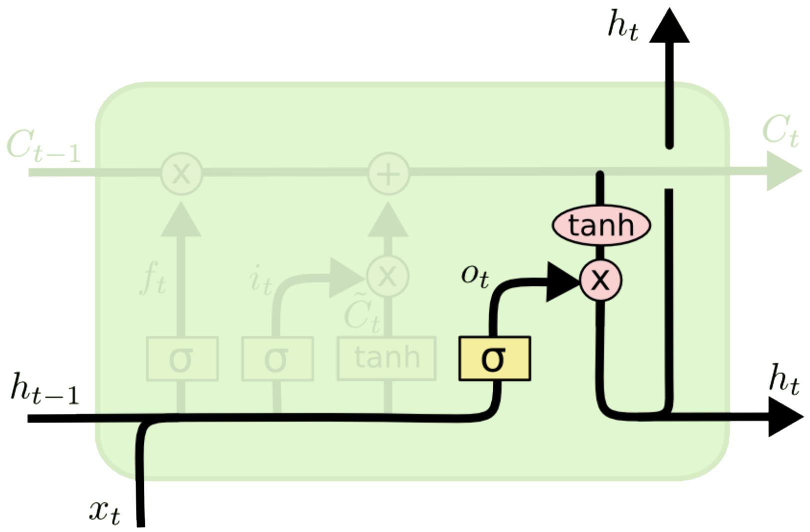
# Store new information




$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

- Update state by forgetting some info and adding new info
- Language model example: drop the information about the old subject’s gender and add information about new subject’s gender

# Output new hidden state



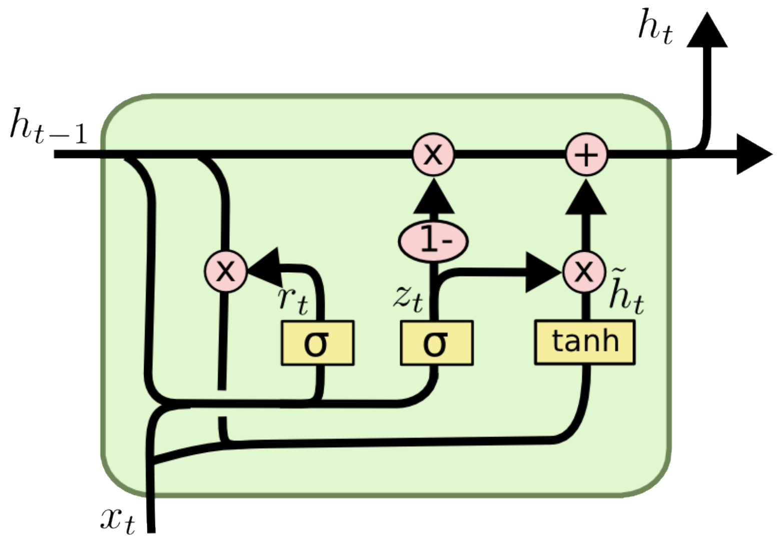

$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

- Language model example: Since it just saw a subject, it might want to output information relevant to a verb, in case that's what is coming next. For example, it might output whether the subject is singular or plural, so that we know what form a verb should be conjugated into if that's what follows next.

# LSTM variant: Gated Recurrent Unit (GRU)

# GRU




$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

- Combines the forget and input gates into a single “update gate”
- Merges the cell state and hidden state
- …

# GRU intuition

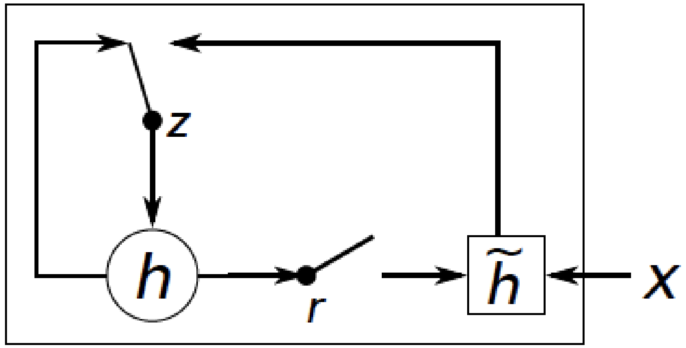
- If reset is close to 0,
ignore previous hidden state
→ Allows model to drop information that is irrelevant in the future

$$z_t = \sigma\left(W^{(z)}x_t + U^{(z)}h_{t-1}\right)$$
$$r_t = \sigma\left(W^{(r)}x_t + U^{(r)}h_{t-1}\right)$$
$$\tilde{h}_t = \tanh\left(Wx_t + r_t \circ Uh_{t-1}\right)$$
$$h_t = z_t \circ h_{t-1} + (1 - z_t) \circ \tilde{h}_t$$

- Update gate z controls how much of past state should matter now.
    - If z close to 1, then we can copy information in that unit through many time steps! **Less vanishing gradient**!
- Units with short-term dependencies often have reset gates very active

# GRU intuition

- Units with long term dependencies have active update gates z
- Illustration:



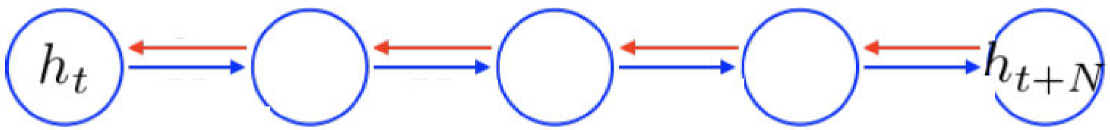

$$z_t = \sigma\left(W^{(z)}x_t + U^{(z)}h_{t-1}\right)$$
$$r_t = \sigma\left(W^{(r)}x_t + U^{(r)}h_{t-1}\right)$$
$$\tilde{h}_t = \tanh\left(Wx_t + r_t \circ Uh_{t-1}\right)$$
$$h_t = z_t \circ h_{t-1} + (1 - z_t) \circ \tilde{h}_t$$

# How GRUs fix vanishing gradients problem

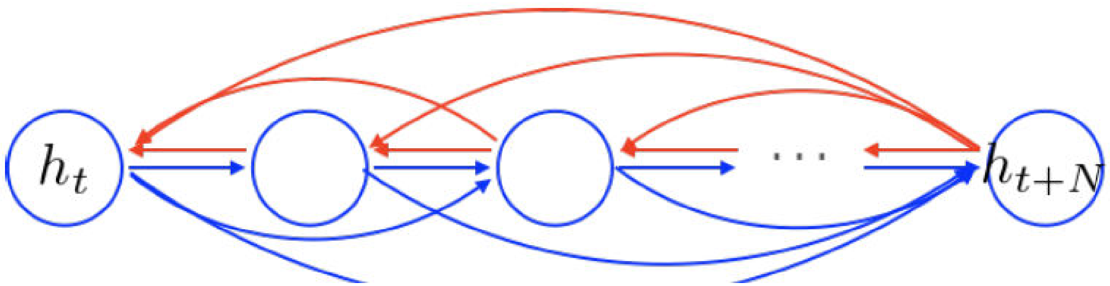
- Is the problem with standard RNNs the naïve transition function?

$$h_t = f\left(W^{(hh)}h_{t-1} + W^{(hx)}x_t\right)$$

- It implies that the error must backpropagate through all the intermediate nodes:

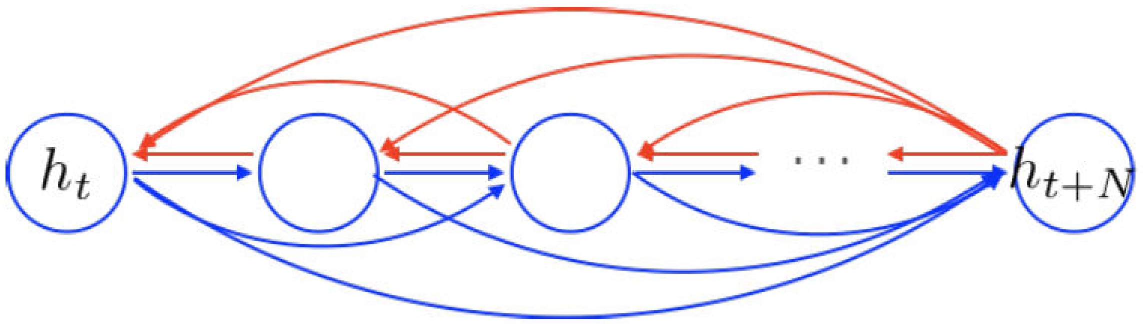



- Perhaps we can create shortcut connections.



# How GRUs fix vanishing gradients problem

- Perhaps we can create *adaptive* shortcut connections.
- Let the net prune unnecessary connections *adaptively*.




- That's what the gates do.

$$z_t = \sigma\left(W^{(z)}x_t + U^{(z)}h_{t-1}\right)$$

$$r_t = \sigma\left(W^{(r)}x_t + U^{(r)}h_{t-1}\right)$$

$$\tilde{h}_t = \tanh\left(Wx_t + r_t \circ Uh_{t-1}\right)$$

$$h_t = z_t \circ h_{t-1} + (1 - z_t) \circ \tilde{h}_t$$

# Acknowledgments

- C. Olah, Understanding LSTM Networks
- Stanford cs244n, Vanishing gradients and fancy RNNs