USC Viterbi
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Department of Computer Science

CSCI 544
Applied Natural Language Processing

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Logistical Notes

- Potential Project Topics

https://docs.google.com/spreadsheets/d/1TQS5lM9VKsp4_lyyFl6rdqrba_WrRHQvSqWQCe-3S4c/edit?usp=sharing

- Check suitability during office hours
- Form teams (deadline Sep 14th + check incomplete teams)

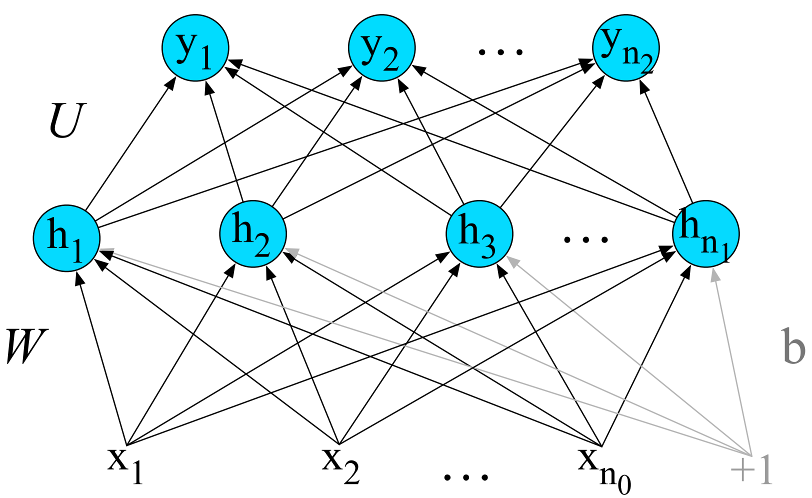
- PyTorch lecture

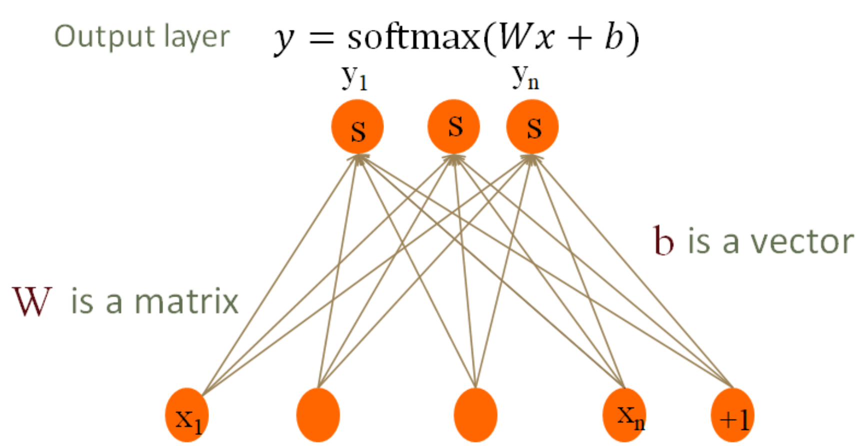
Feedforward Neural Networks

- Is a function approximator where the output depends on a single input

$$y = f(x)$$

- The inputs are assumed to be independent from each other





Figures adopted from slides by Jurafski and Martin

Feedforward Neural Networks

- Limitations of feedforward neural networks
  - Input size should be fixed
  - All the input instances should have the same length
- Language properties:
  - Contextual: “river bank” vs “bank branch”
  - Long-term Dependency: I was born in the US but grew up in Italy and moved back to the US when I was 18 for college, so I can speak __ and English.
  - Order of words is important: “this is a good book, but I do not like it” vs “this is not a good book, but I like it”

Figures adopted from slides by Jurafski and Martin

Recurrent Neural Networks

- We can consider NL data as sequential data points, where the current word depends on the previous words in the sequence:

  1 2 3 4 5 6 7 8 9 10 11

- Ex: Today, I want to play football and then watch a movie.

- Core Idea: the function approximator can receive the input word by word such that its output depend on the history, i.e., relying on a notion of memory

FNN $$y = f(x)$$

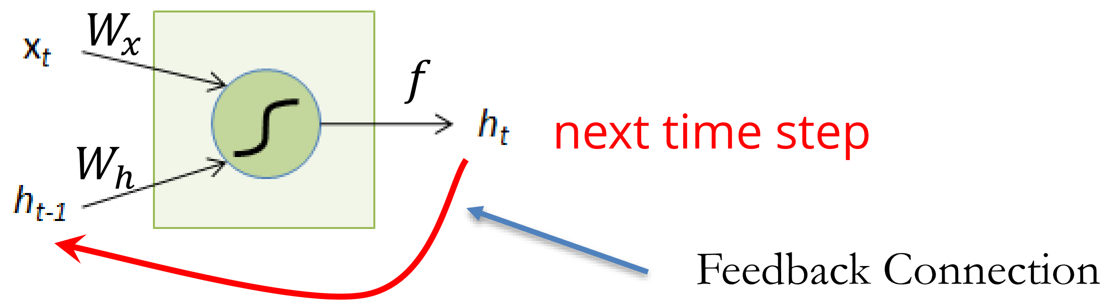
RNN $$y_t = f(x_t, h_{t-1})$$

output input memory

Recurrent Neural Networks

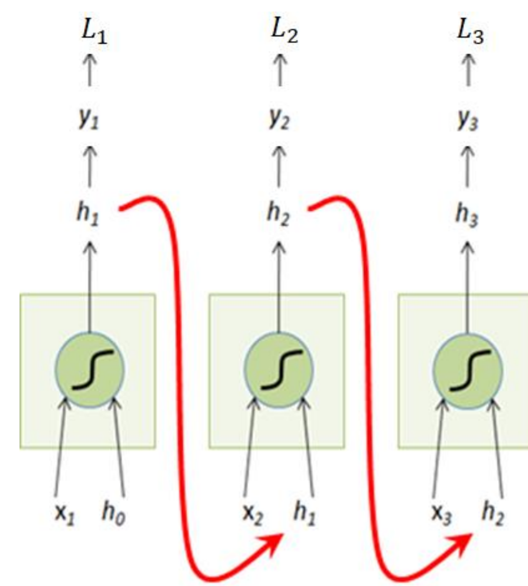
- Equipping perceptron with memory

- x_t: Input at time t
- h_{t-1}: State at time t-1



$$h_t = f(W_x x_t + W_h h_{t-1}), W_x \in \mathbb{R}^{M*N}, W_h \in \mathbb{R}^{H*H}$$

- Unfolding RNN
- We can make the unit multi-layer



Figures adopted from slides by Arun Mallya

Recurrent Neural Networks

- The weight matrices are shared across time

- multi-output

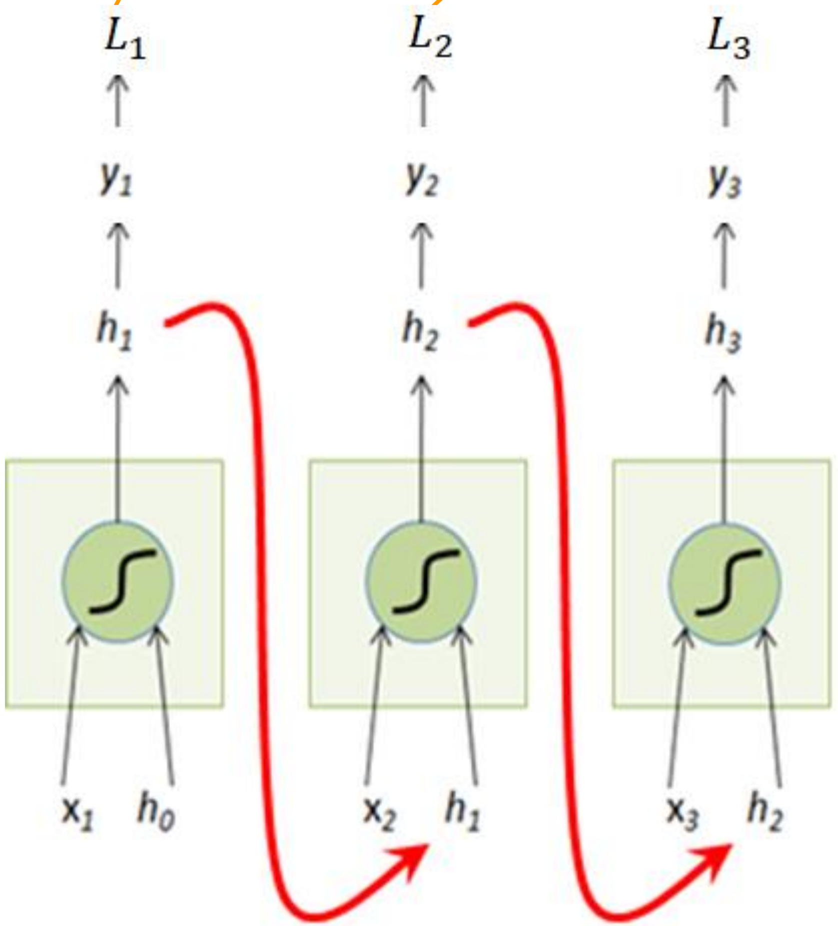
$$L = L_1 + L_2 + L_3$$

$$L = \sum_{t=1}^{T} L_t$$

$$y_t = f(x_t, h_{t-1})$$
$$L_t = l(y, \hat{y}_t)$$

- Single Output

$$L = L_3$$



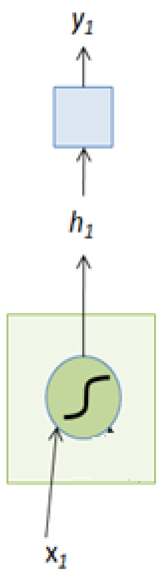
Figures adopted from slides by Arun Mallya

Training Feedforward Networks

- For every training data point (x, y)
  - Run *forward* computation to find model estimate $\hat{y}$
  - Run *backward* computation to update weights:
    - For every output node
      - Compute loss L between true y and the estimated $\hat{y}$
      - For every weight w from hidden layer to the output layer

        Update the weight using gradient descent $\frac{d}{dw} L(f(x; w), y)$
    - For all other nodes
      - Assess how much blame it deserves for the current answer

$$\frac{\partial L}{\partial W} = \frac{\partial L}{\partial y} \frac{\partial y}{\partial h} \frac{\partial h}{\partial W} \quad , \quad L = L(\mathrm{y}(\mathrm{h}(\mathrm{W})))$$



Figures adopted from slides by Arun Mallya

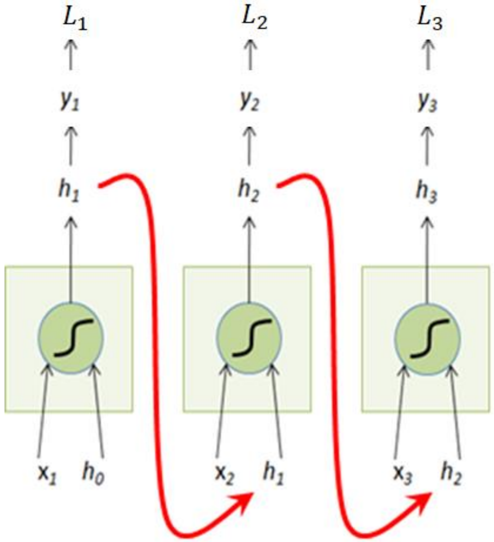
Training RNNs

- For every training data point (x, y)
  - Run *forward* computation to find model estimates $\hat{y}_t$
  - Run *backward* computation to update weights:
    - For every output node
    - Compute loss L between true y and the estimated $\hat{y}_t$
    - For every weight w from hidden layer to the output layer

Update the weight using gradient descent $\frac{d}{dw}\sum_{t=1}^{T} L_t$

$$\frac{\partial L_t}{\partial W} = \frac{\partial L}{\partial y_t}\frac{\partial y_t}{\partial h_t}\frac{\partial h_t}{\partial W} \quad ???$$

$$L_2 = L_2(y_2(h_2(W, h_1(W))))$$



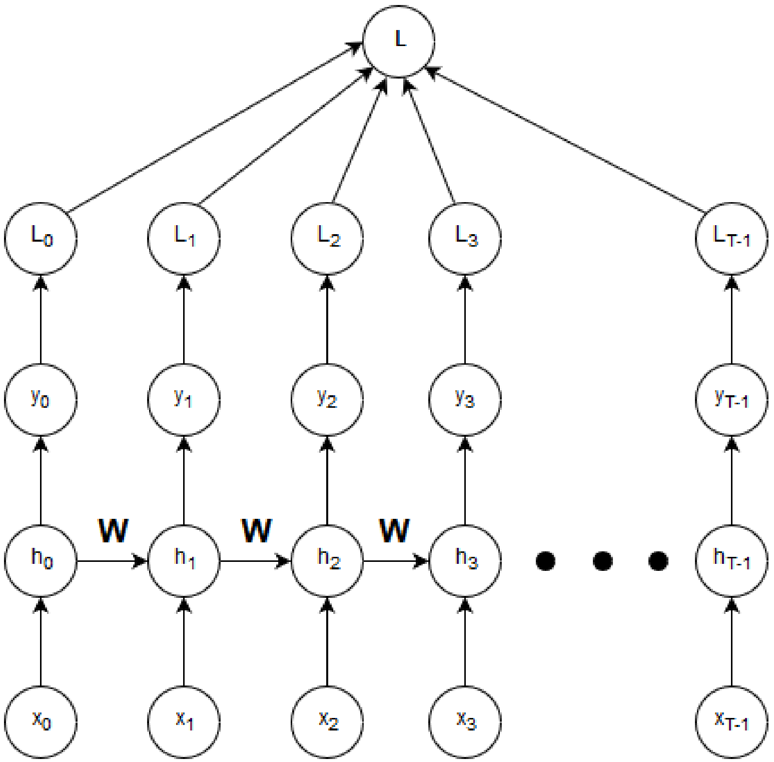
Figures adopted from slides by Arun Mallya

Backpropagation Through Time

- Gradient descent step to update the weights:

$$\mathbf{W} \rightarrow \mathbf{W} - \alpha \frac{\partial L}{\partial \mathbf{W}}$$

- Issue: **W** occurs each timestep
- **Every** path from **W** to L is one dependency for differentiation
- We need to find all paths from **W** to L
- There is one depenency through L_1
- There are two depenencies through L_2



Figures adopted from slides by Arun Mallya

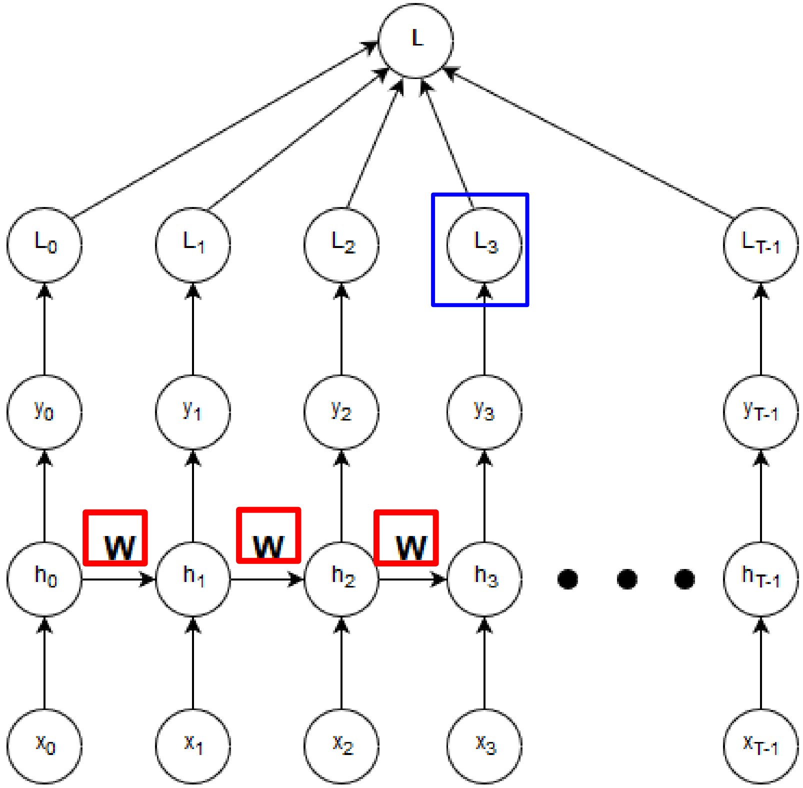
Backpropagation Through Time

$$L = \sum_{t=1}^{T} L_t$$

$$\frac{\partial L_t}{\partial W} = \sum_{k=1}^{t} \boxed{\frac{\partial L_t}{\partial h_k}} \frac{\partial h_k}{\partial W}$$

$$\frac{\partial L_t}{\partial y_t} \frac{\partial y_t}{\partial h_t} \frac{\partial h_t}{\partial h_k}$$

$$\frac{\partial L_t}{\partial W} = \sum_{k=1}^{t} \frac{\partial L_t}{\partial y_t} \frac{\partial y_t}{\partial h_t} \frac{\partial h_t}{\partial h_k} \frac{\partial h_k}{\partial W}$$



$$\frac{\partial L_t}{\partial W} = \sum_{k=1}^{t} \frac{\partial L_t}{\partial y_t} \frac{\partial y_t}{\partial h_t} \prod_{m=k+1}^{t} \frac{\partial h_m}{\partial h_{m-1}} \frac{\partial h_k}{\partial W}$$

Backpropagation Through Time

$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \sum_{k=1}^{t} \frac{\partial L_t}{\partial y_t} \frac{\partial y_t}{\partial h_t} \prod_{m=k+1}^{t} \frac{\partial h_m}{\partial h_{m-1}} \frac{\partial h_k}{\partial W}$$

- Computationally expensive
- Vanishing/Exploding gradients challenge

- Short memory challenge Truncated Backpropgation

- Tutorial

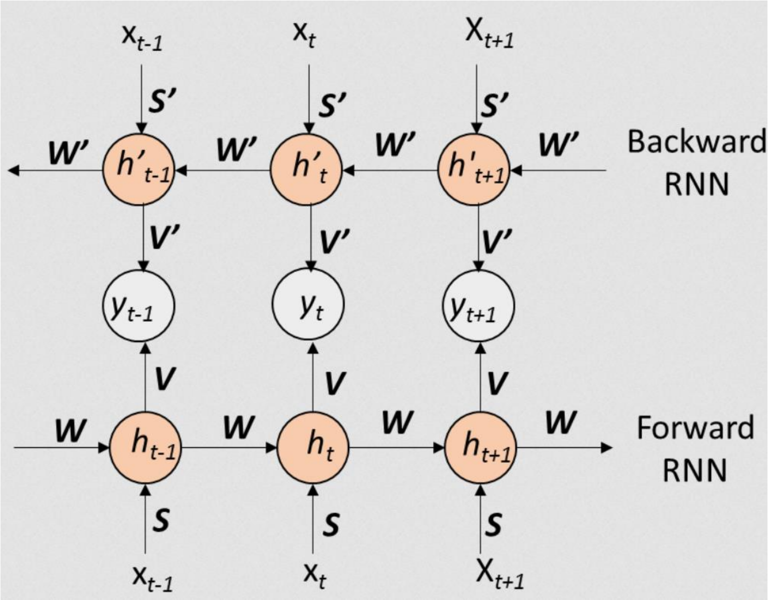
https://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

Bidirectional RNN

- RNN is developed for temporal data (unidirectional)
- Effects in NL are bidirectional:

- Ex: I lived in __ for ten years so I can speak French

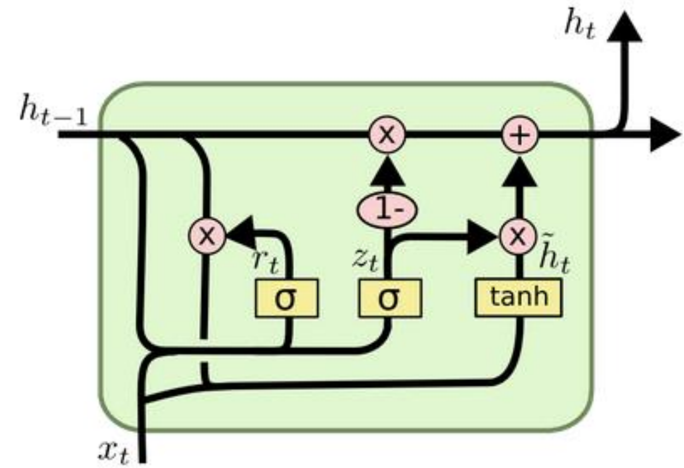
- Solution: we can use two RNNs that process the input in opposite directions

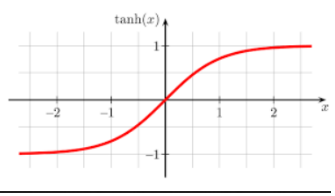


$$h_t = f(W_x x_t + W_h h_{t-1})$$
$$h'_{t'} = f(W'_x x_{t'} + W'_h h'_{t'-1})$$
$$t' = T - t$$
$$y_t = g(h_t, h'_{t'})$$

Gated RNN

- Gated recurrent unit: can learn long-range dependencies
- Control mechanism on information flow
- Gates control information flow
- Resent and Update gates are often close to either 0 or 1 due to using sigmoid
- New gate is used as a preliminary candidate to update the state variable





Reset Gate $$r_t = \sigma(W_{ir}x_t + W_{hr}h_{(t-1)})$$

Update Gate $$z_t = \sigma(W_{iz}x_t + W_{hz}h_{(t-1)})$$

New Gate $$\tilde{h}_t = \tanh(W_{in}x_t + r_t \odot (W_{hn}h_{(t-1)}))$$

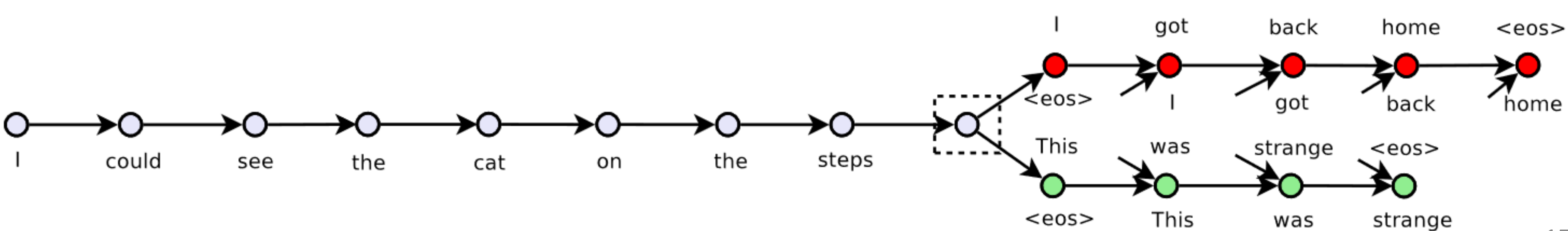
$$h_t = (1 - z_t) \odot \tilde{h}_t + z_t \odot h_{(t-1)}$$

Hadamard Product

Skip-Thought Vectors

- An encoder-decoder model:
- Encoder: maps a sentence into a vector
- Decoder: conditions on this vector to generate surrounding sentences

- Architecture: RNN encoder with GRU activations, RNN decoder with conditioned GRU
- Benefit: Skip-thoughts sentence representations lead to robust performance across important NLP tasks



Skip-Thought Vectors

- Encoder Structure:

- Let w_i^j be the word j in sentence I, where N is the number of words in that sentence
- At each time step, the encoder produces a hidden state h_i^t as the representation of the sequence $w_i^1, \ldots, w_i^t$
- The hidden state h_i^N represents the full sentence

$$
\begin{aligned}
\mathbf{r}^t &= \sigma(\mathbf{W}_r\mathbf{x}^t + \mathbf{U}_r\mathbf{h}^{t-1}) \\
\mathbf{z}^t &= \sigma(\mathbf{W}_z\mathbf{x}^t + \mathbf{U}_z\mathbf{h}^{t-1}) \\
\bar{\mathbf{h}}^t &= \tanh(\mathbf{W}\mathbf{x}^t + \mathbf{U}(\mathbf{r}^t \odot \mathbf{h}^{t-1})) \\
\mathbf{h}^t &= (1 - \mathbf{z}^t) \odot \mathbf{h}^{t-1} + \mathbf{z}^t \odot \bar{\mathbf{h}}^t
\end{aligned}
$$

Skip-Thought Vectors

- Decoder Structure:
  - The matrices C_z, C_r, and C that are used to bias the update gate, reset gate and hidden state computation by the sentence vector
  - Separate decoders are used for previous and next sentences
  - Parameters for each decoder are separated

$$
\begin{aligned}
\mathbf{r}^t &= \sigma(\mathbf{W}_r^d \mathbf{x}^{t-1} + \mathbf{U}_r^d \mathbf{h}^{t-1} + \mathbf{C}_r \mathbf{h}_i) \\
\mathbf{z}^t &= \sigma(\mathbf{W}_z^d \mathbf{x}^{t-1} + \mathbf{U}_z^d \mathbf{h}^{t-1} + \mathbf{C}_z \mathbf{h}_i) \\
\bar{\mathbf{h}}^t &= \tanh(\mathbf{W}^d \mathbf{x}^{t-1} + \mathbf{U}^d (\mathbf{r}^t \odot \mathbf{h}^{t-1}) + \mathbf{C}\mathbf{h}_i) \\
\mathbf{h}_{i+1}^t &= (1 - \mathbf{z}^t) \odot \mathbf{h}^{t-1} + \mathbf{z}^t \odot \bar{\mathbf{h}}^t
\end{aligned}
$$

Given $\mathbf{h}_{i+1}^t$, the probability of word w_{i+1}^t given the previous $t-1$ words and the encoder vector is

$$P(w_{i+1}^t | w_{i+1}^{<t}, \mathbf{h}_i) \propto \exp(\mathbf{v}_{w_{i+1}^t} \mathbf{h}_{i+1}^t)$$

Skip-Thought Vectors

- Objective function: Given the sentence tuple (s_{i-1}, s_i, s_{i+1}) the objective function is the sum of the log-probabilities for the forward and backward sentences conditioned on the encoder representation:

$$\sum_t \log P(w_{i+1}^t | w_{i+1}^{<t}, \mathbf{h}_i) + \sum_t \log P(w_{i-1}^t | w_{i-1}^{<t}, \mathbf{h}_i)$$