Recurrent Neural Networks and Encoder-Decoder Models

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ILLC

Unsupervised Language Learning 2016

Outline

Word Embeddings Recap

Recurrent Neural Networks

Encoder Decoder Approach

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- machine learning algorithms "understand" that `dog` is similar to `dogs`

but what about `cat` and `dog` ? or `good` and `amazing` ?

Distributed Word Representation

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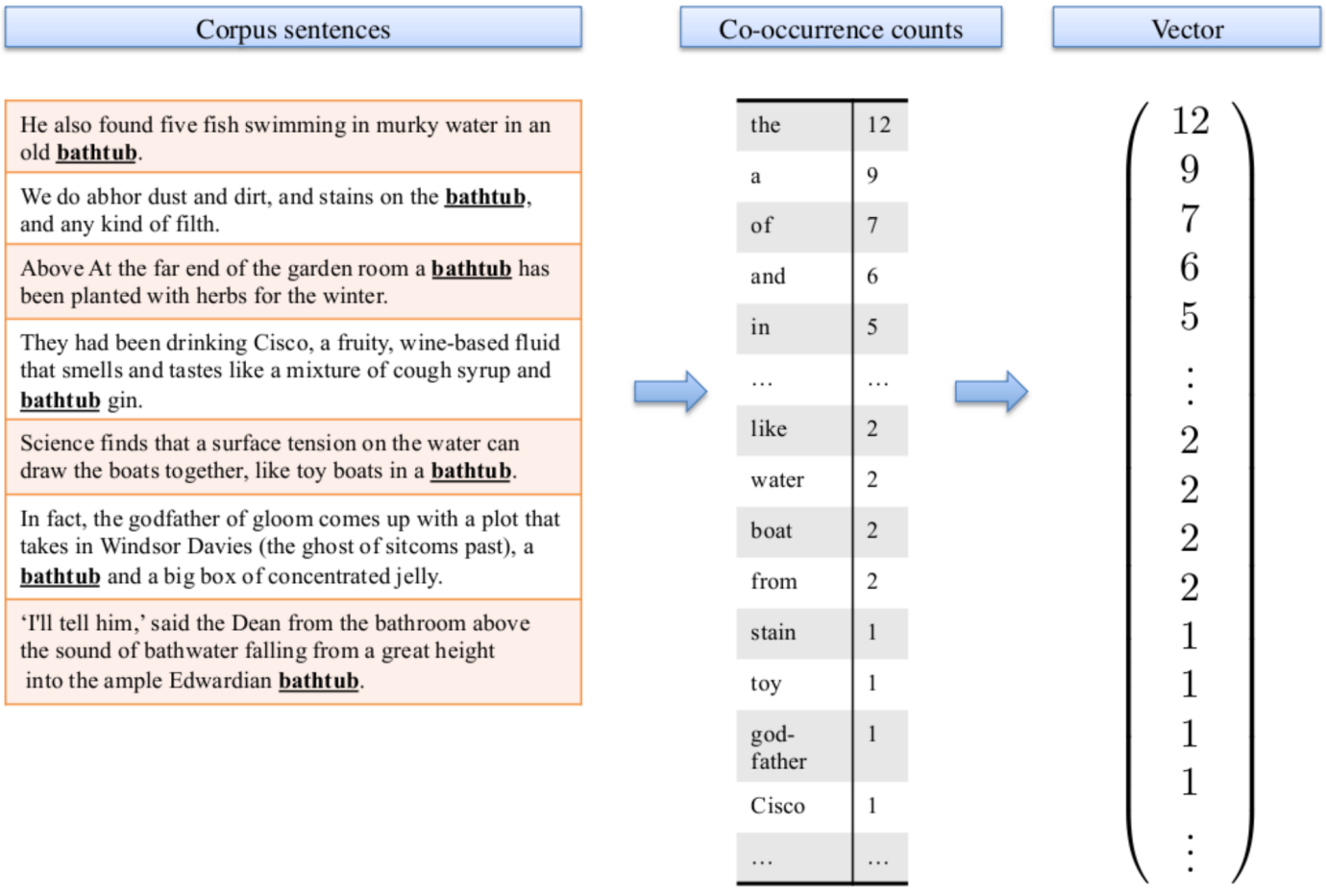
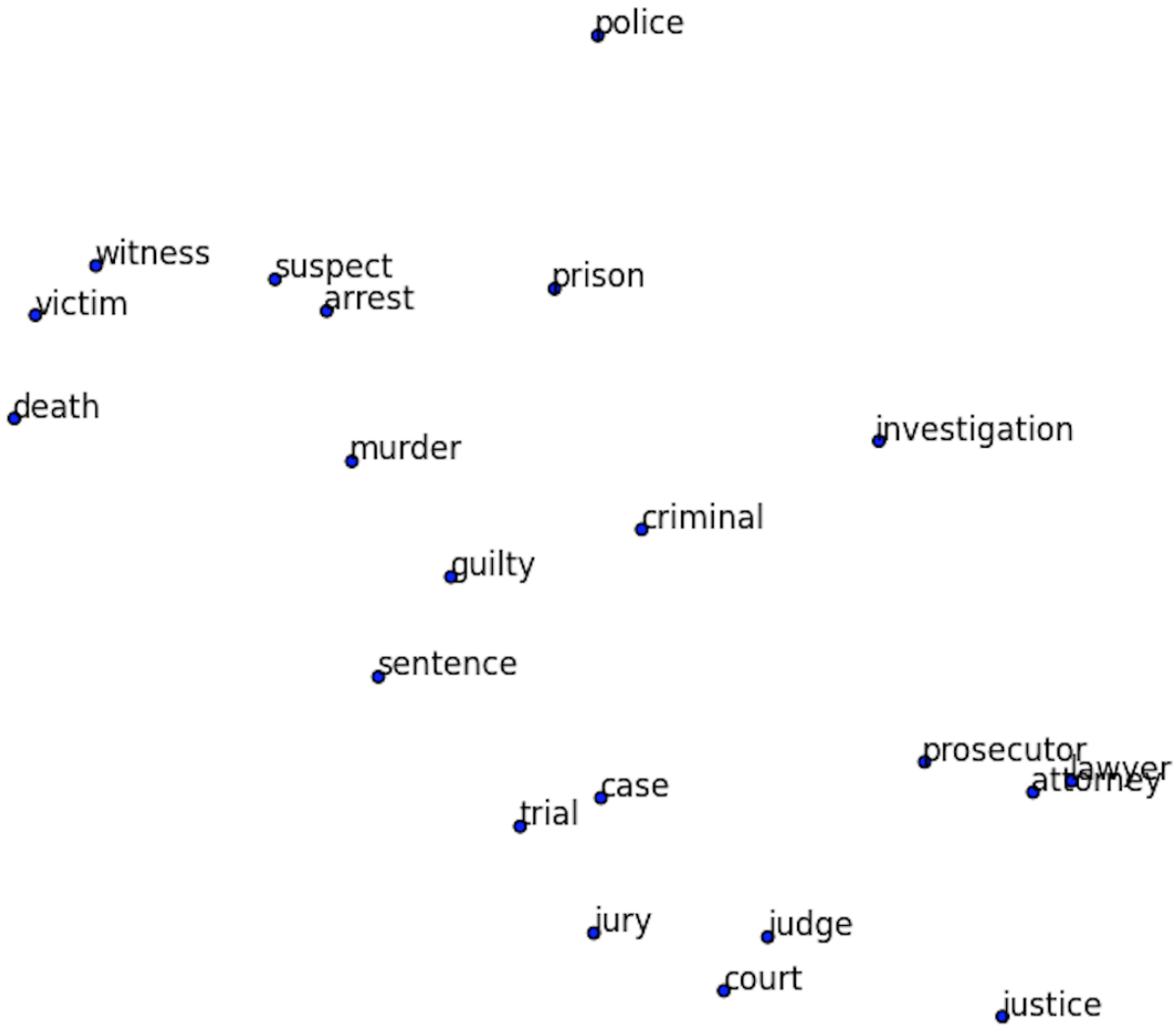
How can we formalize this intuition?

Co-occurence matrix



Word similarity



Learning word representations

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- Bengio et al. 2006 introduced a neural language model for learning word representations. expensive
- Most popular model nowadays is Google's skip-gram word2vec [Mikolov et al. 2013].
- The idea is to predict context words of a given word.

Skip-gram word2vec

- $W \in \mathbb{R}^{|V| \times d}$ is the word embedding matrix
- $C \in \mathbb{R}^{|V| \times d}$ is the context embedding matrix
- V is the words dictionary
- d is the vector size of the word representation
- the size of the context window is given as hyperparameter

For each context, word pair $(c, w) \in \mathcal{D}$, we want to maximize

$$p(c|w) = \frac{\exp(C(c) \cdot W(w))}{\sum_{c'} \exp(C(c') \cdot W(w))}, \tag{1}$$

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Cons

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Pros

- Log-linear, easy to train!

Word representations

Ok, well done! Now what?

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- word embeddings as input to neural networks
- since deep learning models seek to solve non-convex optimization problems, starting from a good point in the parameters space usually helps.

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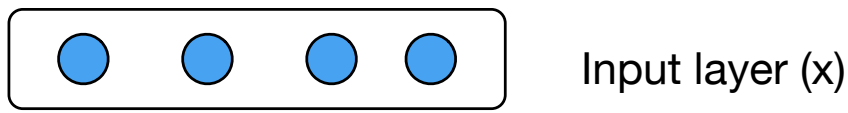
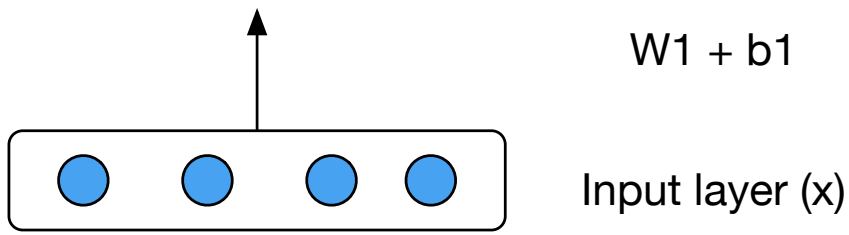
Neural networks recap



Neural networks recap



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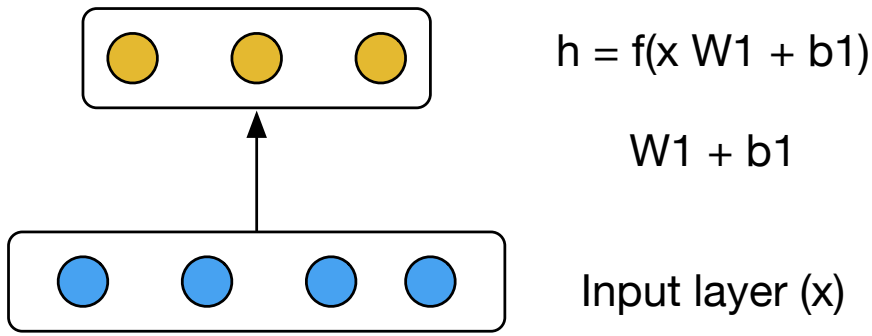

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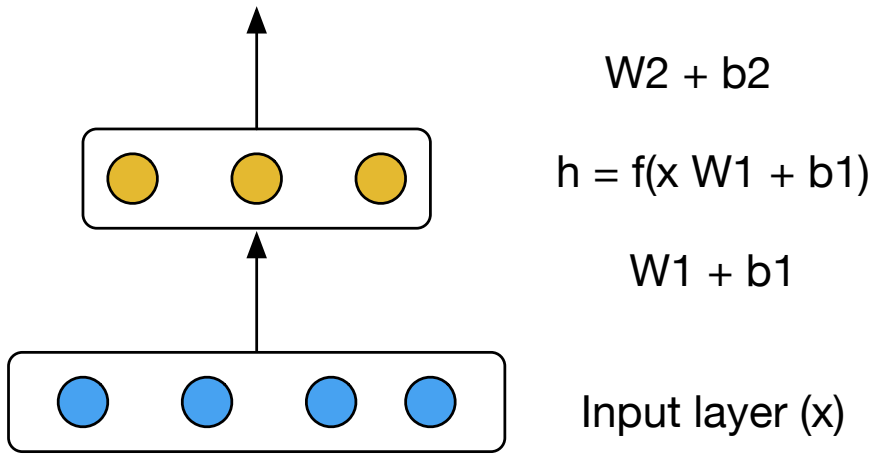

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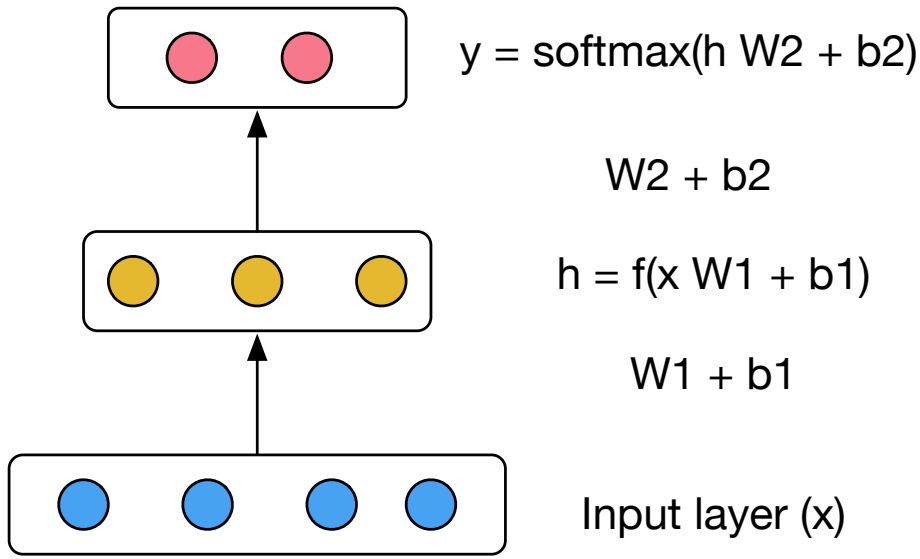
- W_2, b_2 more parameters

Multi-layer perceptron



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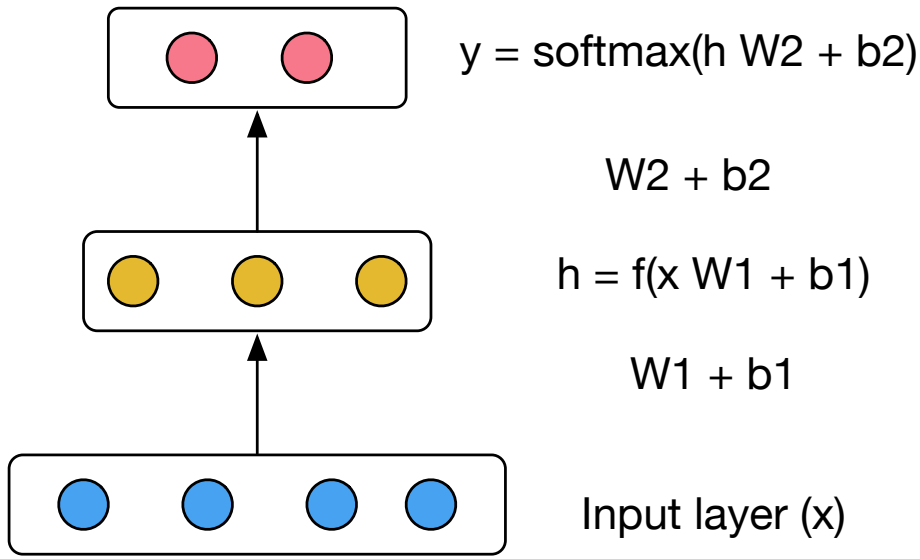

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We can add as many hidden layers as we like transforming it in a deep neural network.

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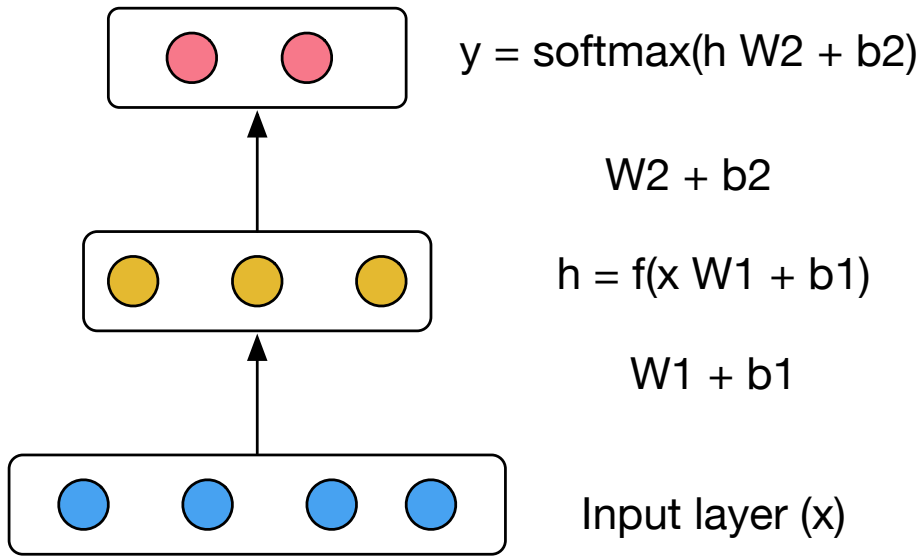
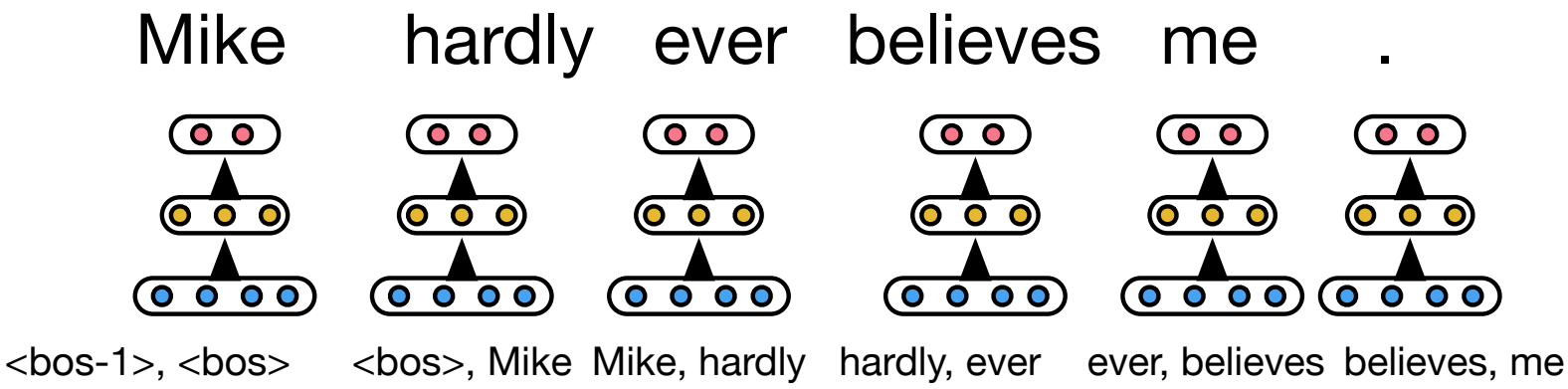


Standard feedforward neural networks cannot deal with variable length input.

Language modeling

Compute the probability of a sentence, or
given a sequence of words predicting the word that comes next.

- trigram language model $p(x_t|x_{t-1}, x_{t-2})$



- cannot "see" the subject so cannot predict the right verb
- increase the size of the model.

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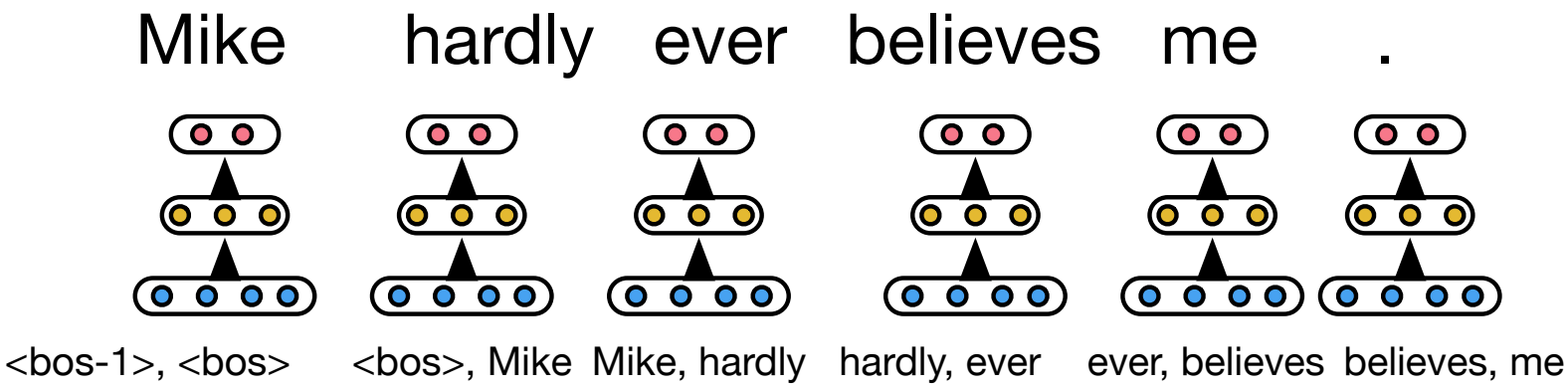
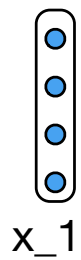


- cannot "see" the subject so cannot predict the right verb
- increase the size of the model.
- what about longer dependencies ?

Recurrent Neural Networks



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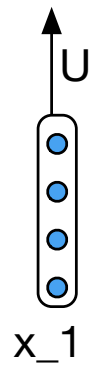

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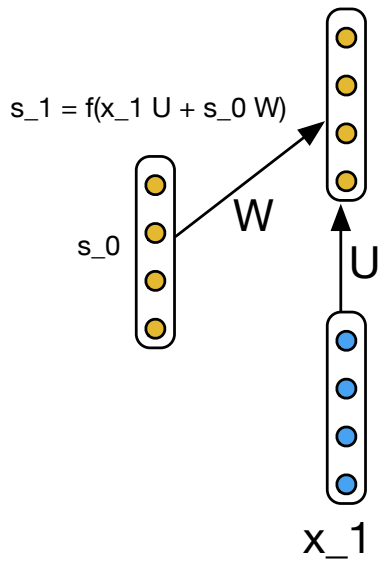

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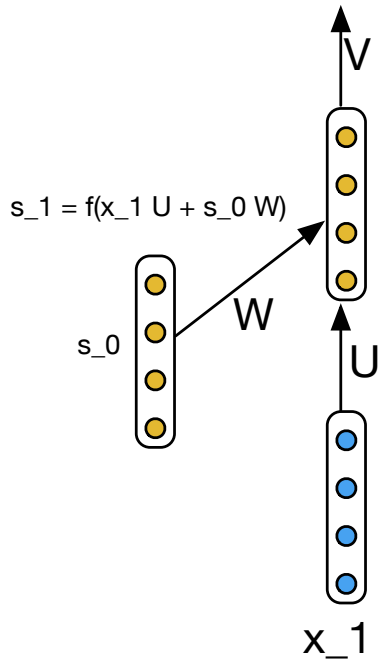

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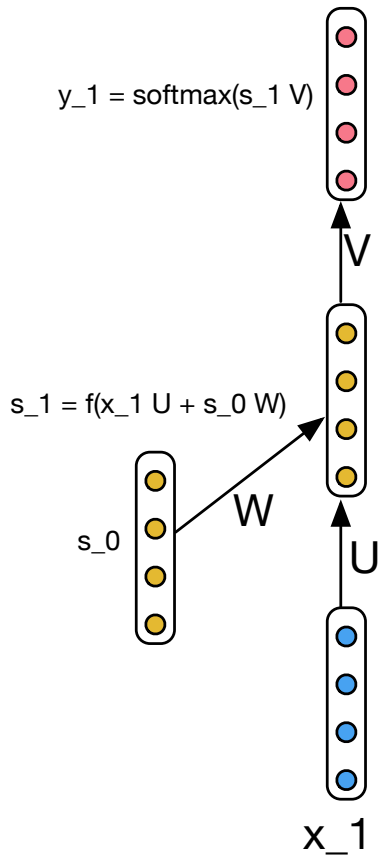
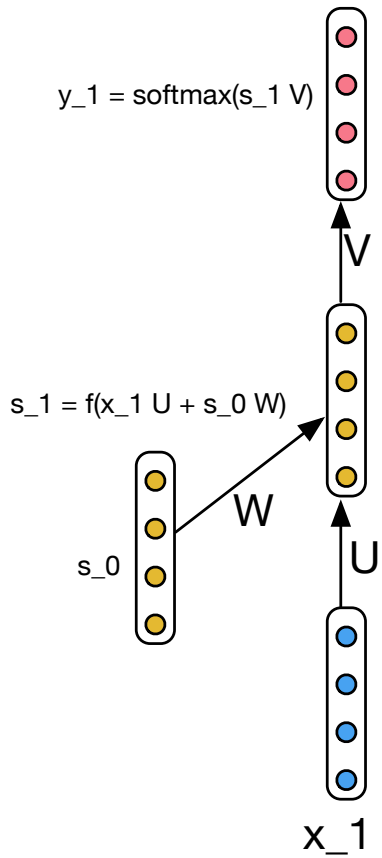
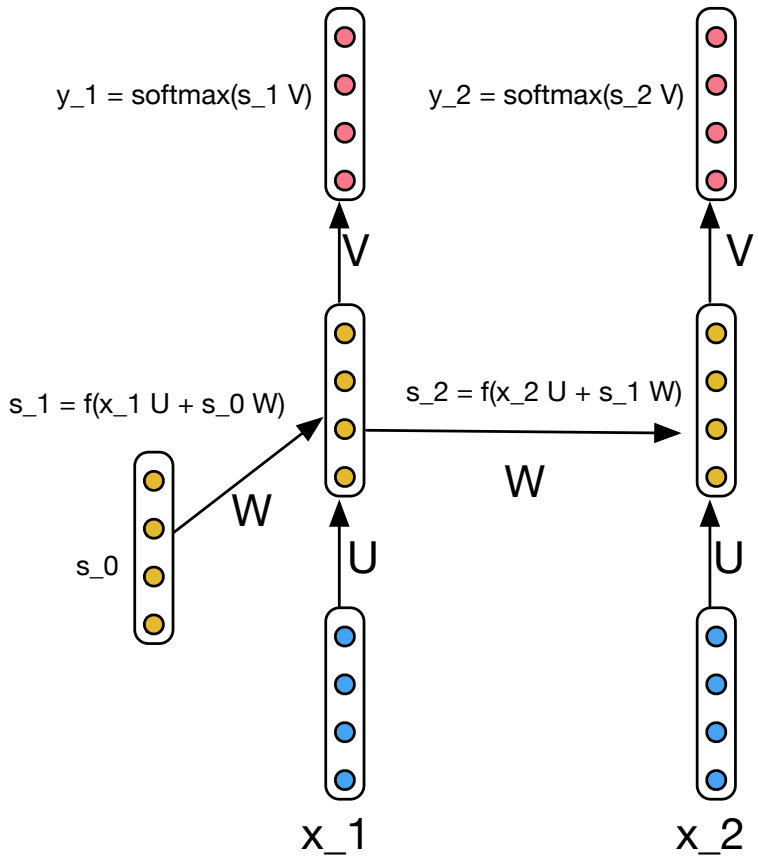


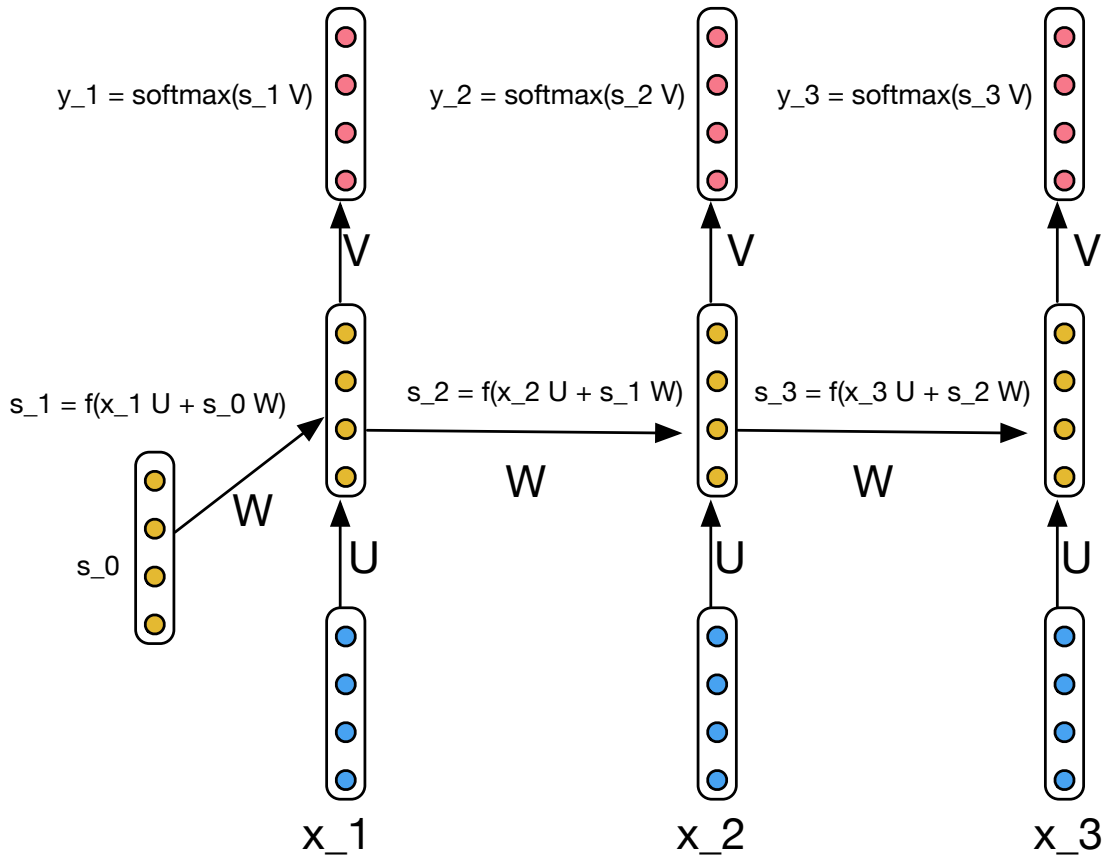
RNN step 1



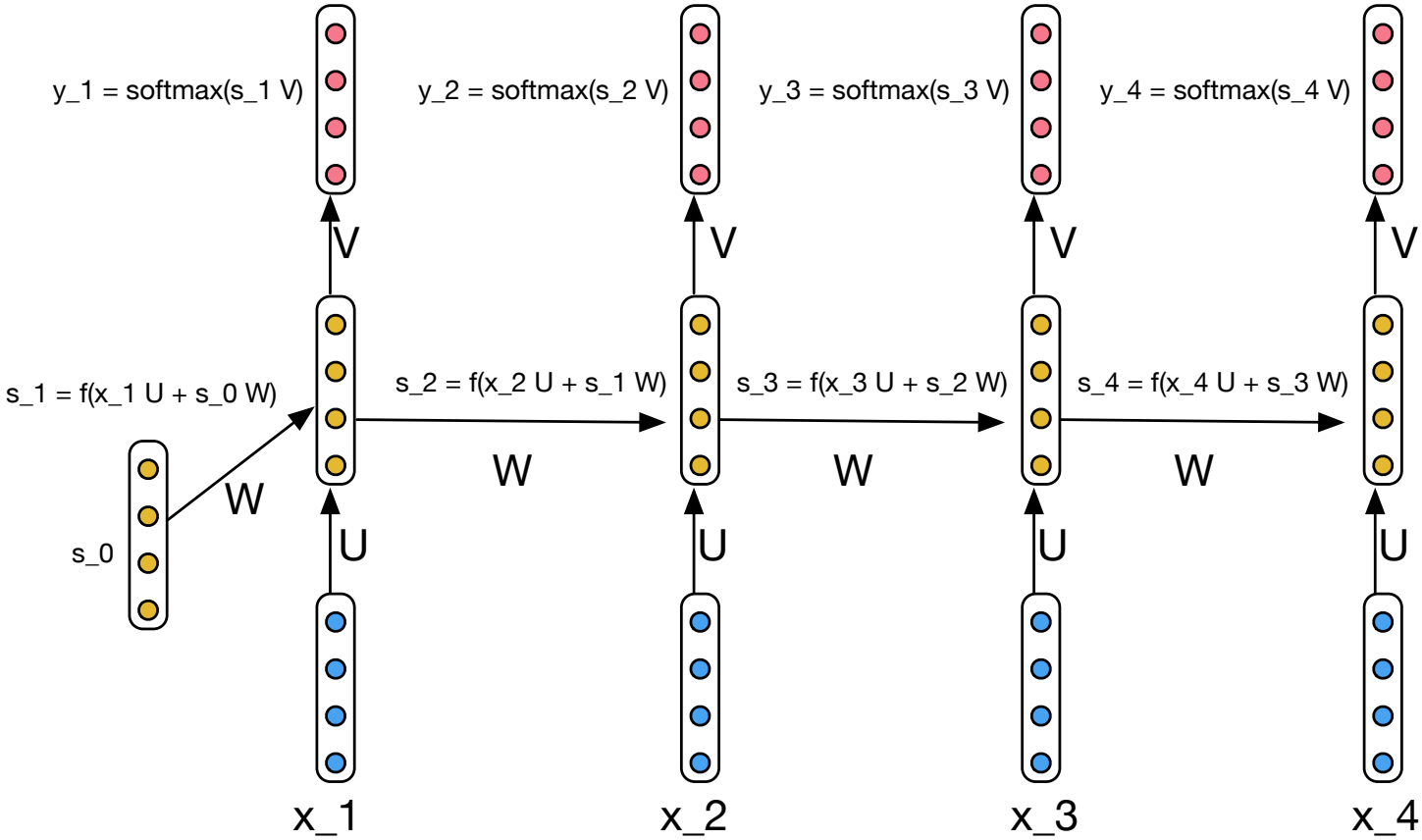
RNN step 2


y_1 = softmax(s_1 V)
y_2 = softmax(s_2 V)
V
V
s_1 = f(x_1 U + s_0 W)
s_2 = f(x_2 U + s_1 W)
W
W
s_0
U
U
x_1
x_2

RNN step 3

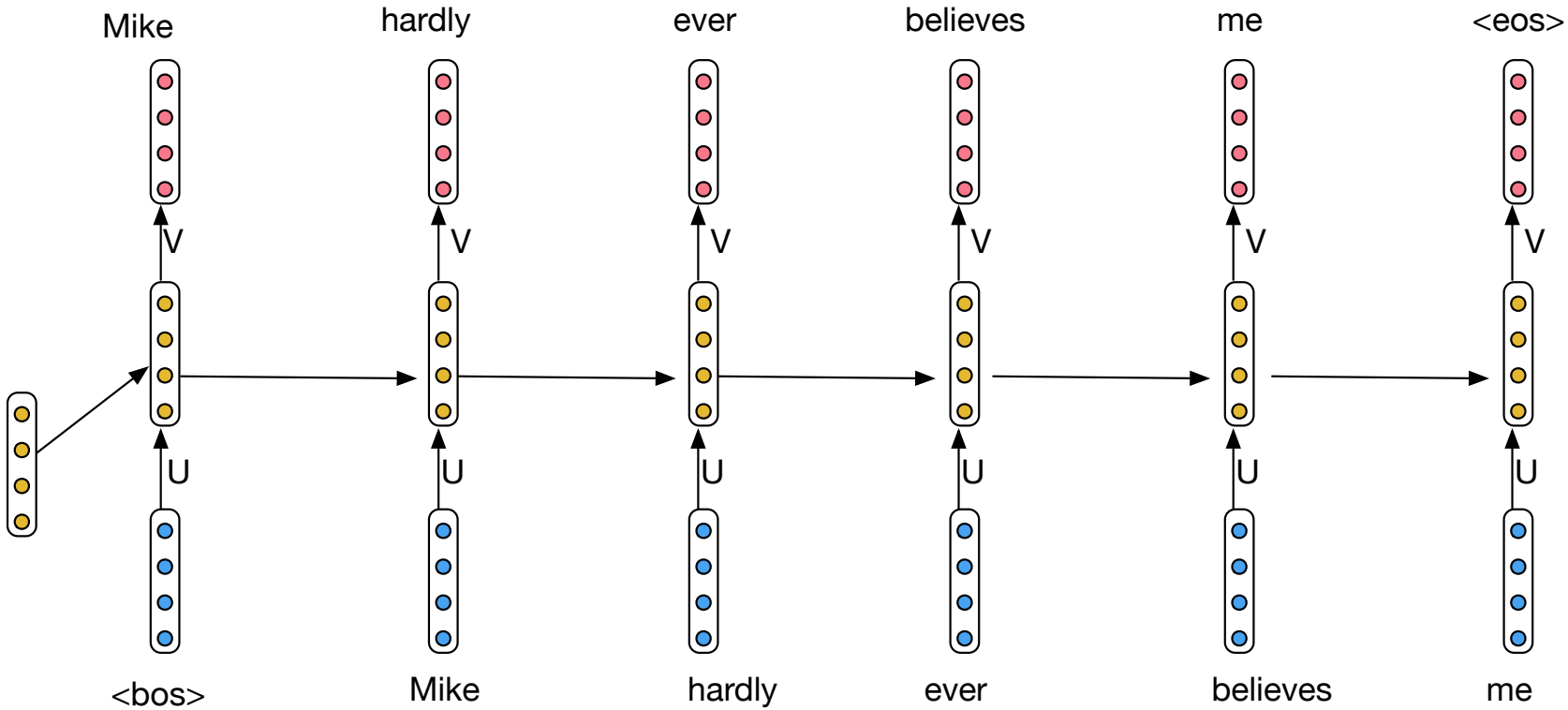

y_1 = softmax(s_1 V)
y_2 = softmax(s_2 V)
y_3 = softmax(s_3 V)
V
V
V
s_1 = f(x_1 U + s_0 W)
s_2 = f(x_2 U + s_1 W)
s_3 = f(x_3 U + s_2 W)
W
W
W
s_0
U
U
U
x_1
x_2
x_3

RNN step 4



In each step we use information coming from all the previous steps.

Language modeling (reprise)



Long dependencies are captured

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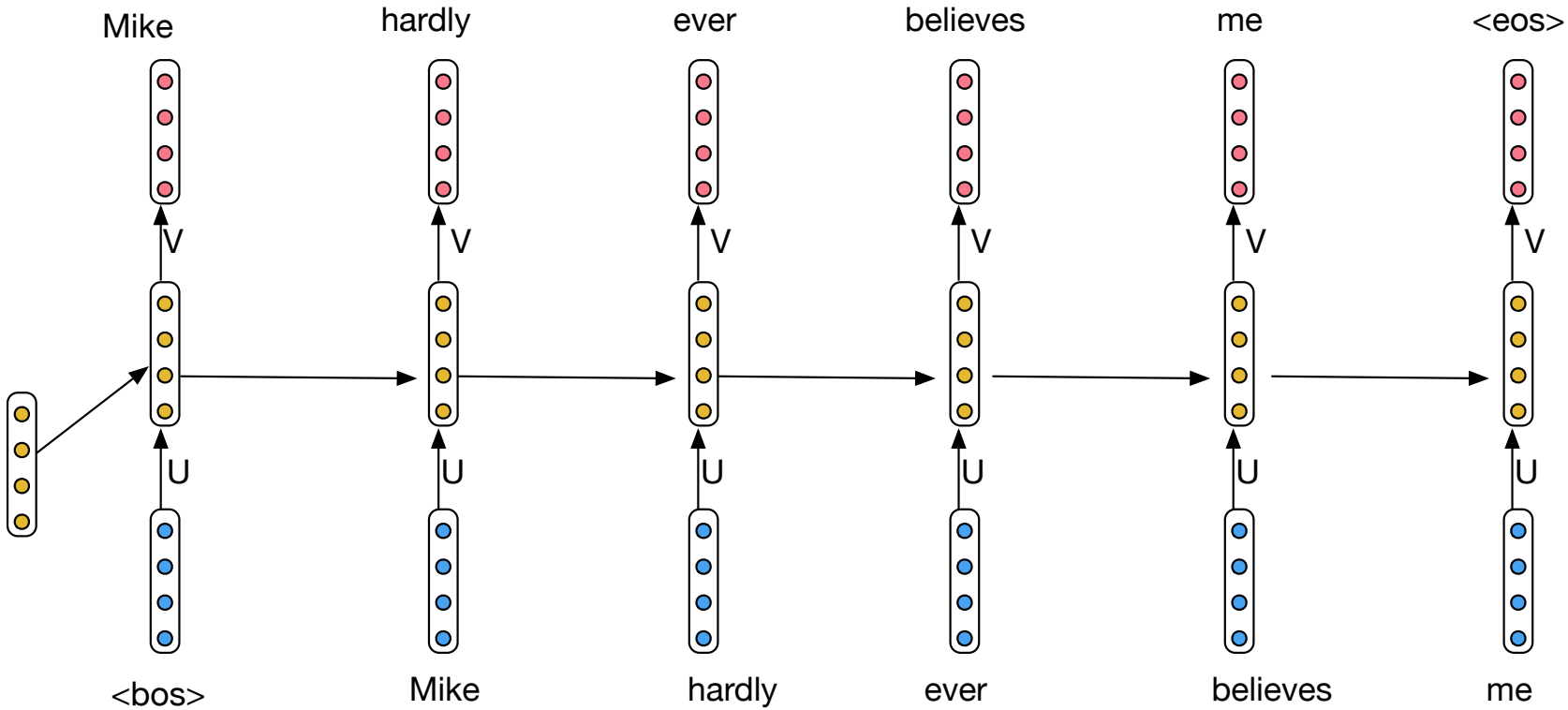
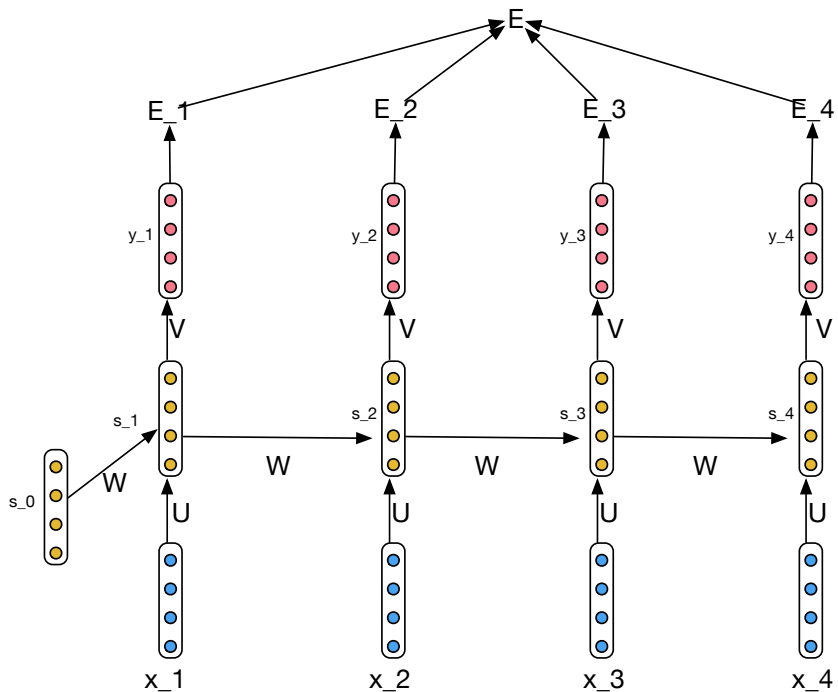


Long dependencies are captured (at least in theory)

Training RNNs

- Total error is the sum of errors at each time step $\sum_t E(y_t^*, y_t)$
- Error is calculated as cross entropy loss $E(y_t^*, y_t) = -y_t^* \log y_t$
- Calculating the gradients for V depends only on the current time step t.
- For the recurrent parameters W is a bit different.



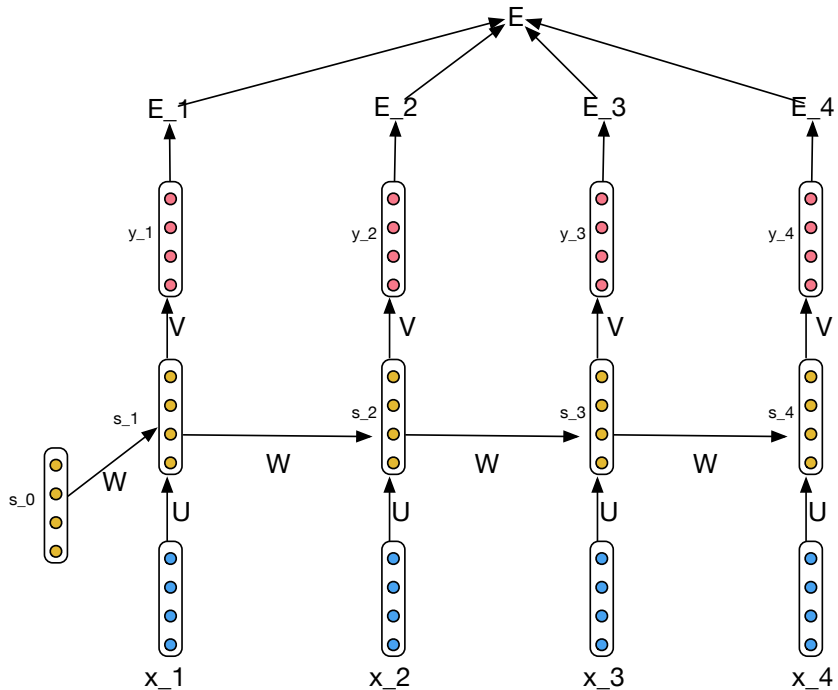
Backpropagation through time

Since we sum errors, we also sum gradients at each time step.

$$\frac{\partial E}{\partial W} = \sum_t \frac{\partial E_t}{\partial W}$$

Following standard backprop derivation, for each time step t we end-up having:

$$\frac{\partial E_t}{\partial W} = \sum_{k=1}^{t-1} \frac{\partial E_t}{\partial y_t} \frac{\partial y_t}{\partial s_t} \frac{\partial s_t}{\partial s_k} \frac{\partial s_k}{\partial W}$$



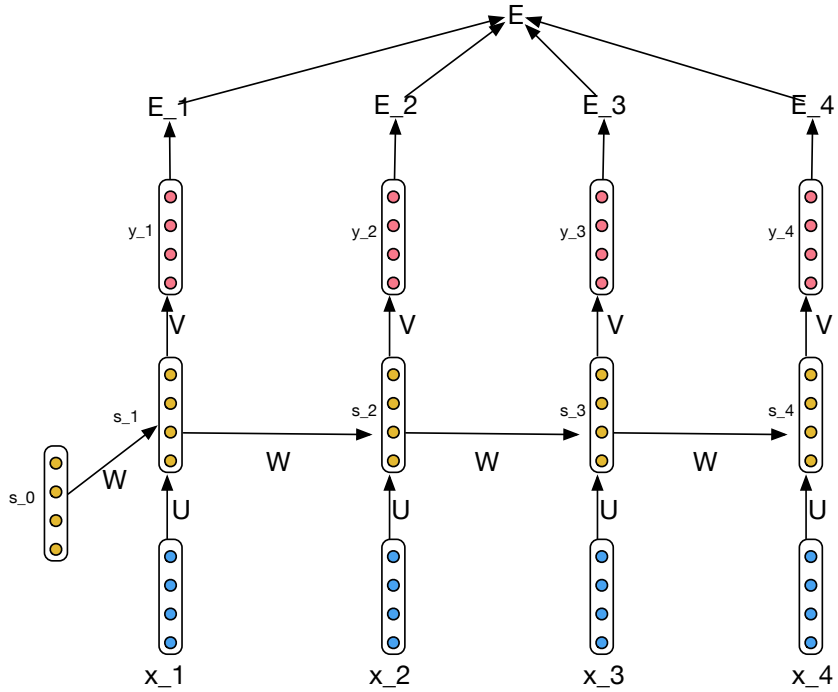
Backpropagation through time

For t = 3 we have:

$$\frac{\partial E_3}{\partial W} = \sum_{k=1}^{2} \frac{\partial E_3}{\partial y_3} \frac{\partial y_3}{\partial s_3} \frac{\partial s_3}{\partial s_k} \frac{\partial s_k}{\partial W}$$

that is unfolded as:

$$\frac{\partial E_3}{\partial W} = \frac{\partial E_3}{\partial y_3} \frac{\partial y_3}{\partial s_3} \frac{\partial s_3}{\partial s_2} \frac{\partial s_2}{\partial s_1} \frac{\partial s_1}{\partial W} + \frac{\partial E_3}{\partial y_3} \frac{\partial y_3}{\partial s_3} \frac{\partial s_3}{\partial s_2} \frac{\partial s_2}{\partial W}$$



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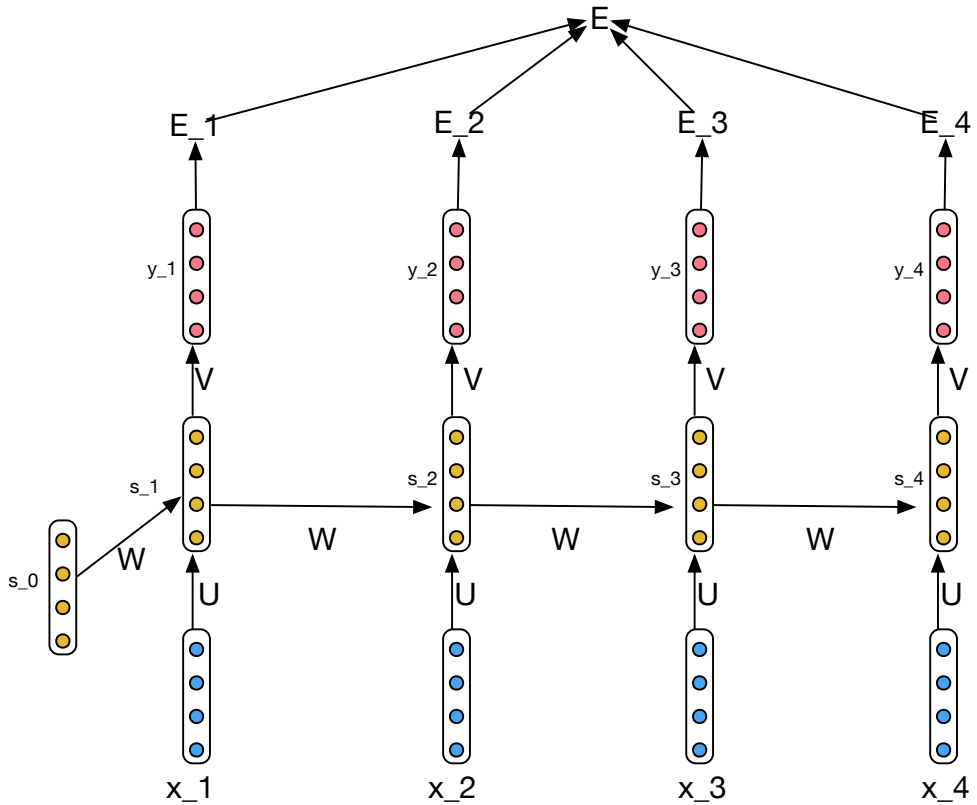

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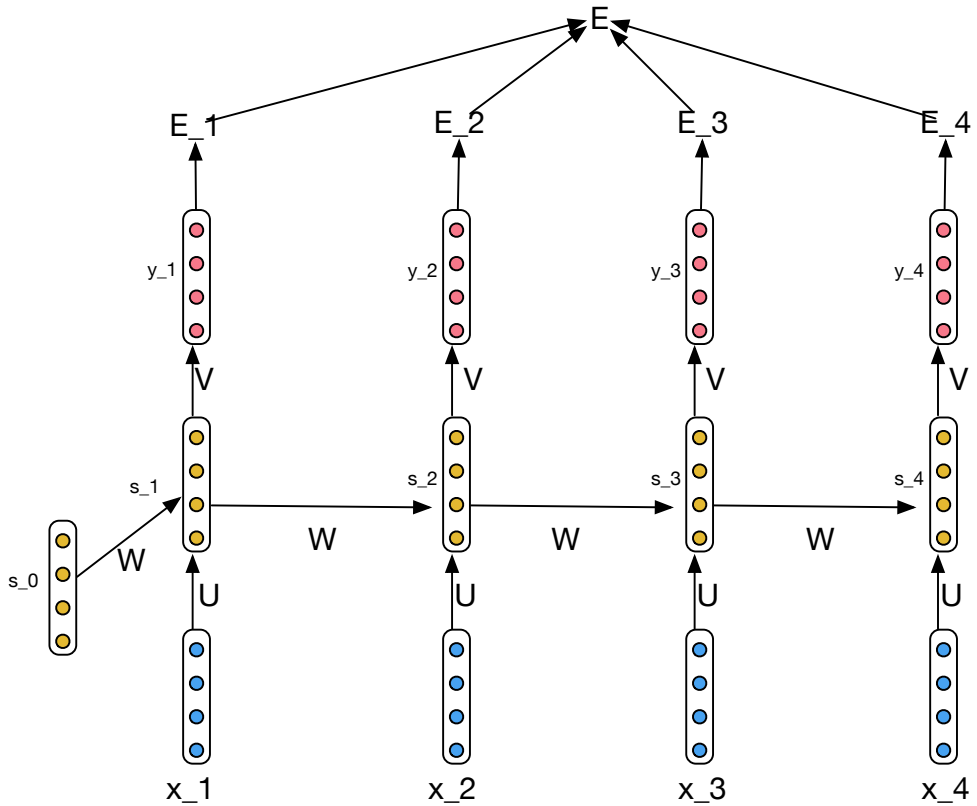

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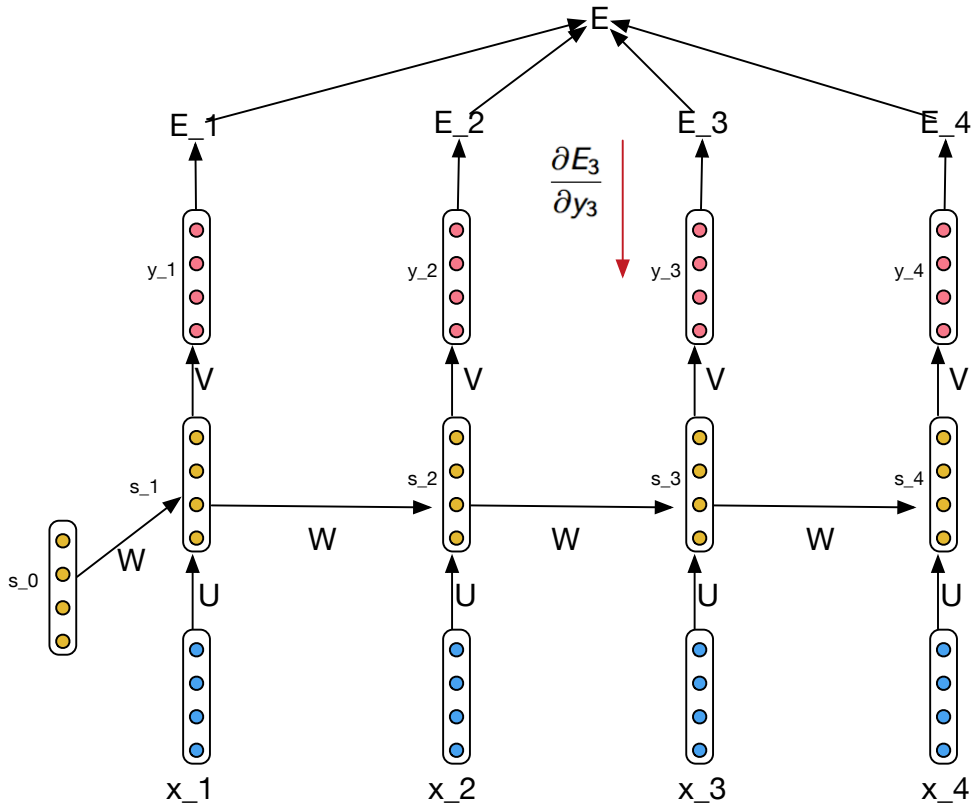

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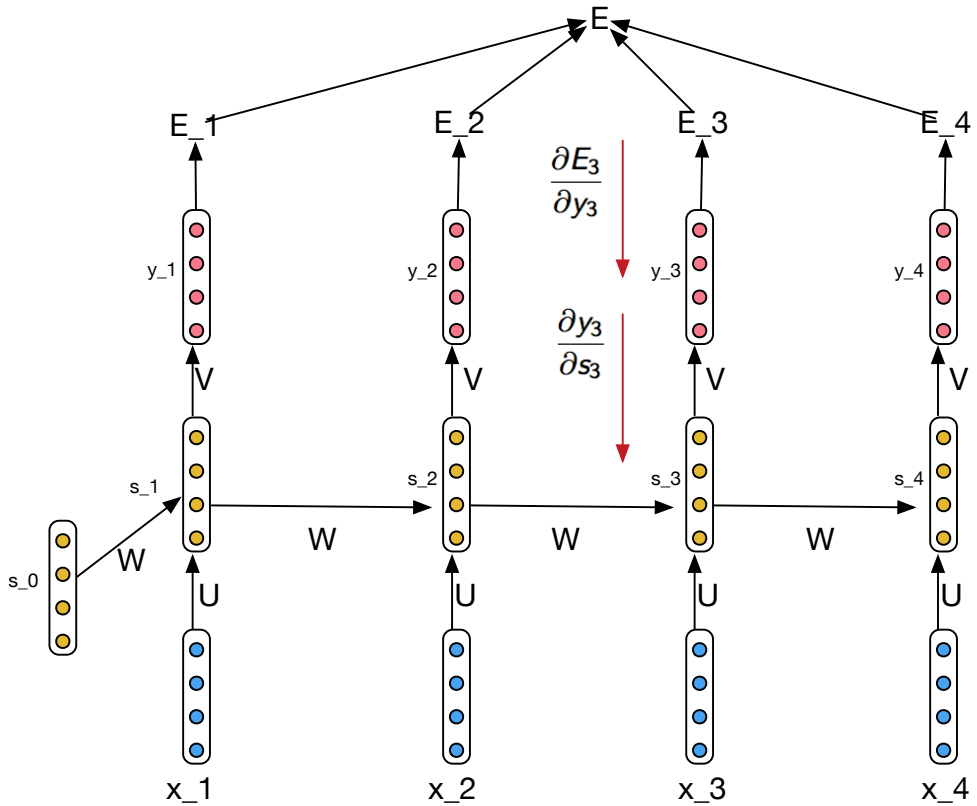

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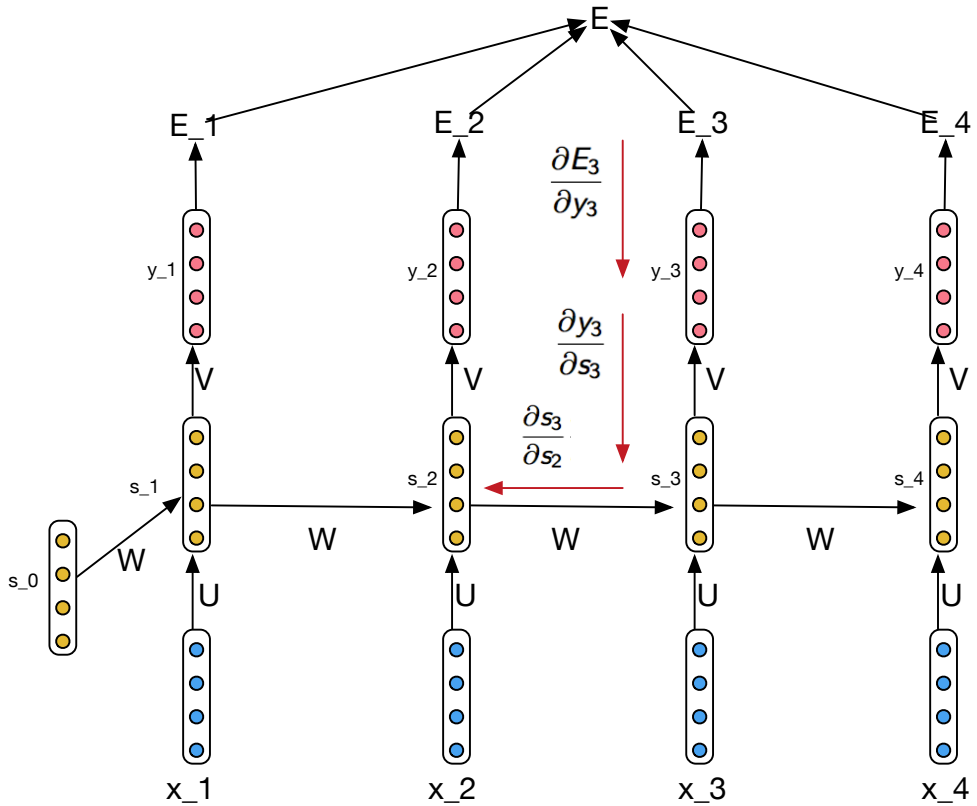

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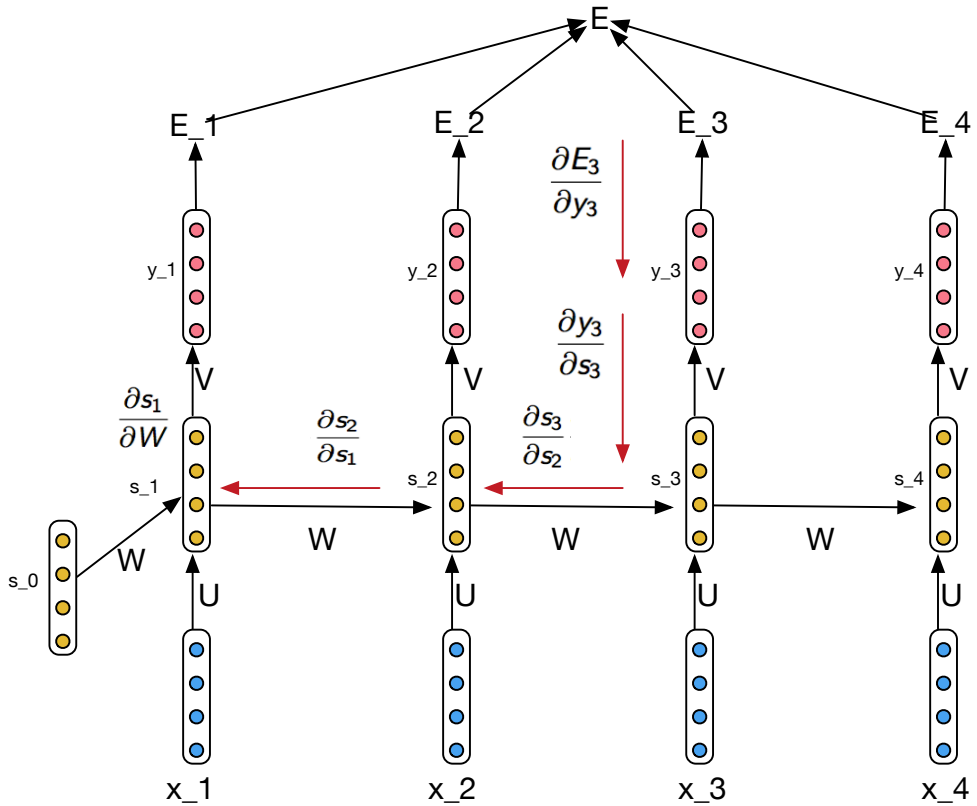

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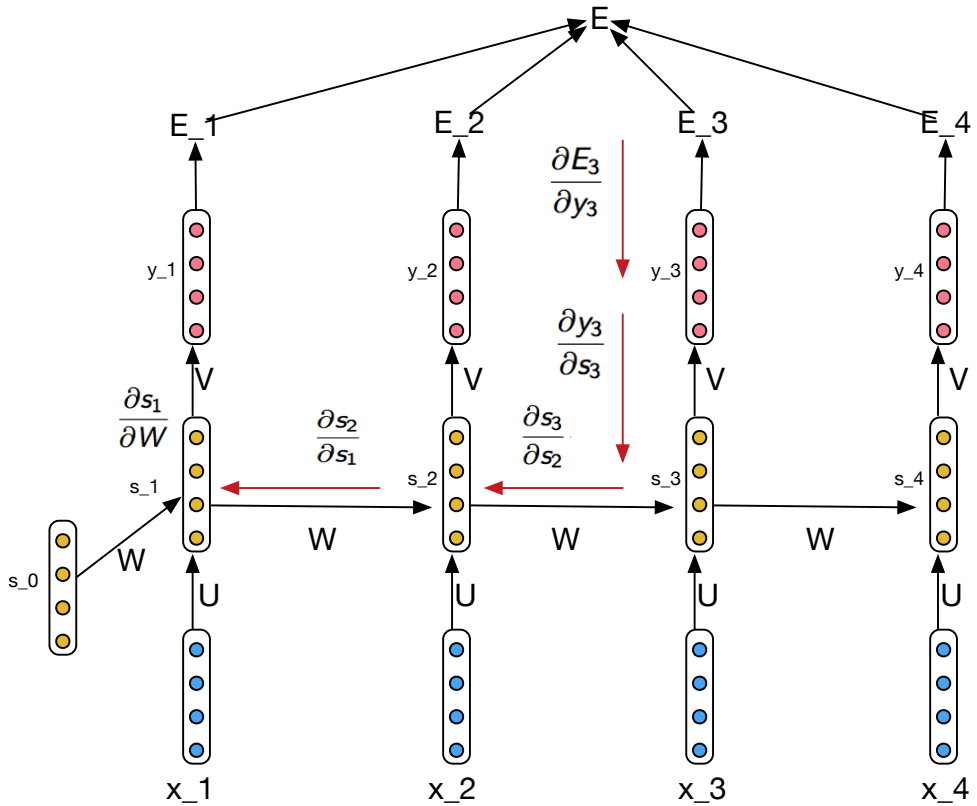
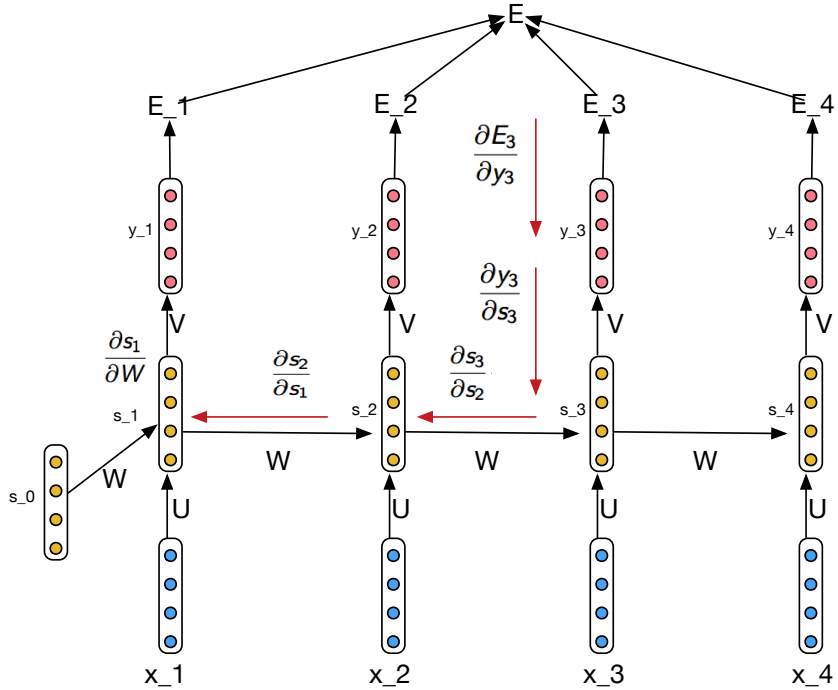


RNN learning issues

Vanishing (exploding) gradient for long dependencies.

- Exploding gradient solution:
  - Gradient clipping – clipping the norm of the gradient if exceeds a certain threshold.
- Vanishing gradient solution:
  - Long short-term memory networks (LSTM) [Hochreiter and Schmidhuber 1997]
  - Gated recurrent unit networks (GRU) [Cho et al. 2014]



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- question answering: `Tim is playing in his room.||Where is Tim? ->`

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- What if we want an output of variable length with respect to the input?
- Can we use RNN for tasks where we have a sequence as input and we want another sequence as output?
- machine translation: `Mary eats apples.` -> `Marie mange des pommes.`
- question answering: `Tim is playing in his room.||Where is Tim?` -> `Tim is in his room.`

Encoder decoder a.k.a. sequence to(2) sequence learning.
[Sutskever et al. 2014]

Sequence to sequence learning - Encoding

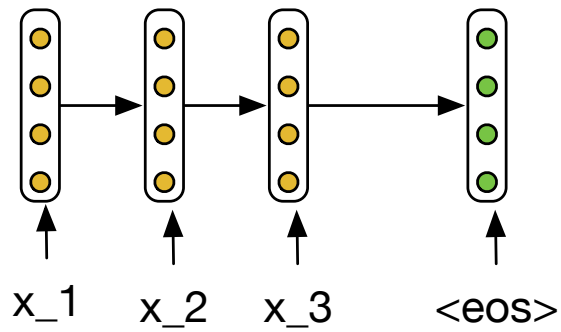
$$p(z_1, ..., z_{T'} | x_1, ..., x_T)$$

Sequence to sequence learning - Encoding

$$p(z_1, ..., z_{T'} | x_1, ..., x_T)$$

- Encode the entire input sequence in a single vector

$$s_t = f(U \cdot x_t + W \cdot s_{t-1})$$

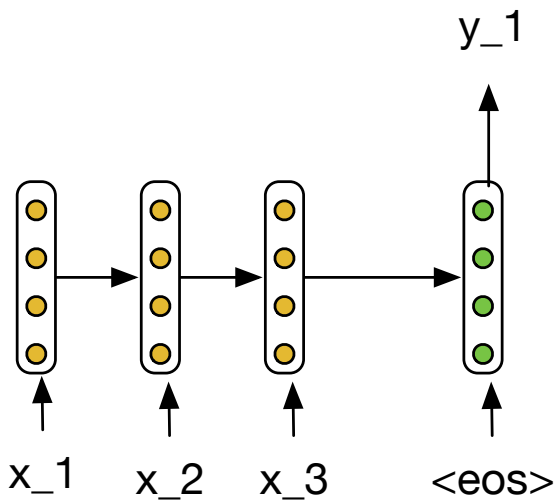


Sequence to sequence learning - Decoding

$$p(z_1, ..., z_{T'} | x_1, ..., x_T)$$

- proceed like in a standard RNN starting from the encoding vector

$$y_1 = softmax(V \cdot s_{T_e})$$



Sequence to sequence learning - Decoding

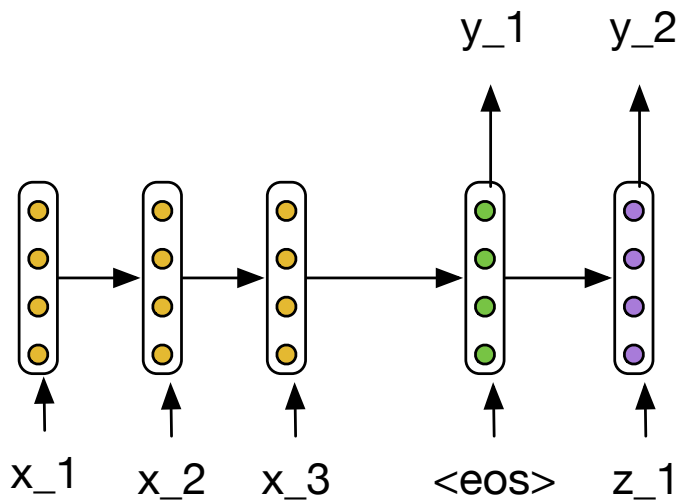
$$p(z_1, ..., z_{T'} | x_1, ..., x_T)$$

- proceed like in a standard RNN starting from the encoding vector

$$y_1 = softmax(V \cdot s_{T_e})$$

- and then continue decoding the second word in the sequence with

$$s_1^d = f(U \cdot z_1 + W \cdot s_{T_e}), \quad y_2 = softmax(V \cdot s_1^s)$$



Sequence to sequence learning - Decoding

$$p(z_1, ..., z_{T'} | x_1, ..., x_T)$$

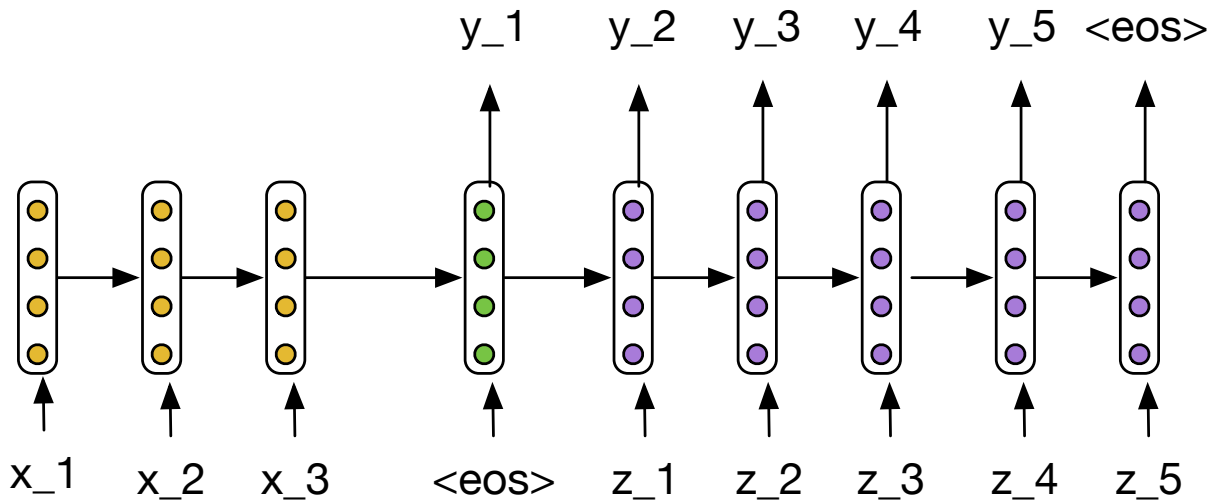
- Begin to decode the output sequence conditioning on this vector

$$y_1 = softmax(V \cdot s_{T_e})$$

- continue decoding the second word in the sequence with

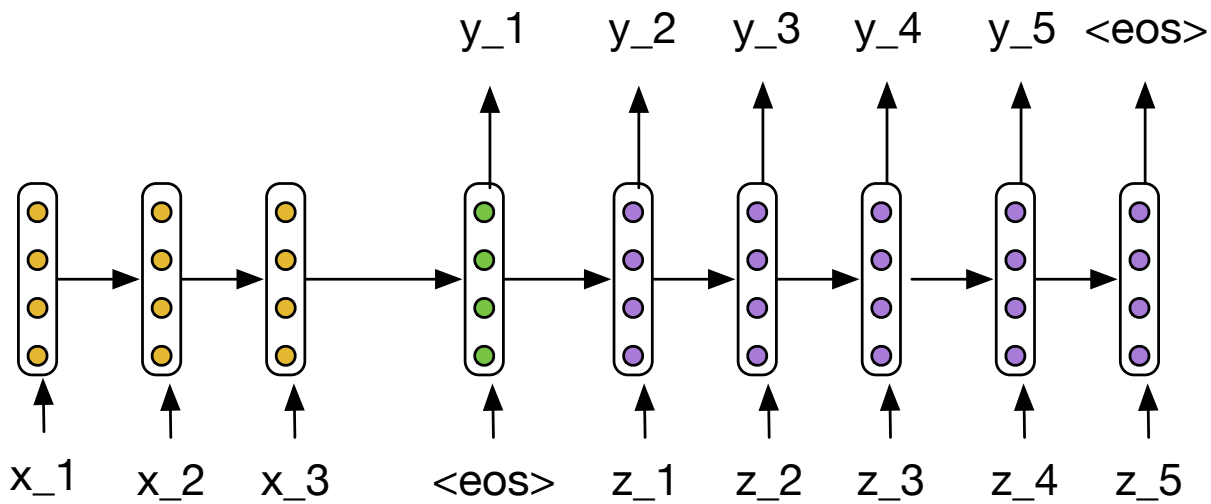
$$s_1^d = f(U \cdot z_1 + W \cdot s_{T_e}), \quad y_2 = softmax(V \cdot s_1^d)$$

- keep decoding until an <eos> token is predicted.



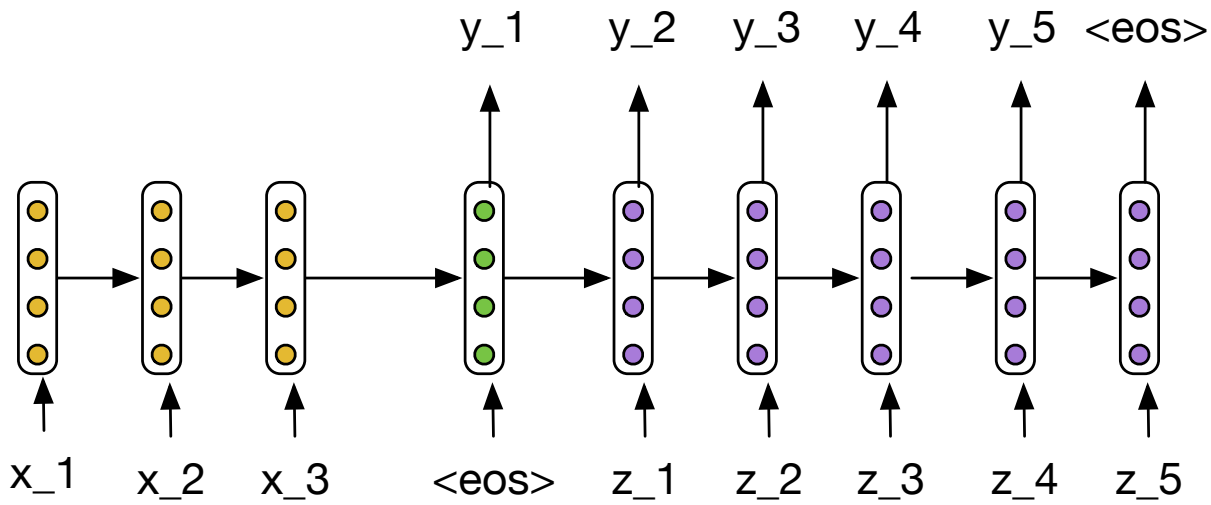
Encoder decoder

$$p(z_1, \ldots, z_{T'} | x_1, \ldots, x_T) = \prod_{t=1}^{T'} p(z_t | s_{T_e}, z_1, \ldots, z_{t-1})$$



Conclusions

- Vanishing gradient is even more problematic in this setting.
- LSTMs or GRUs are crucial to capture long term dependencies.
- Very appealing in task like machine translation.



Lecture recap

- Word embeddings recap
- Neural networks recap
- Recurrent neural networks
- Sequence to sequence learning with neural networks

That's it!

Thanks for your attention!
Questions?