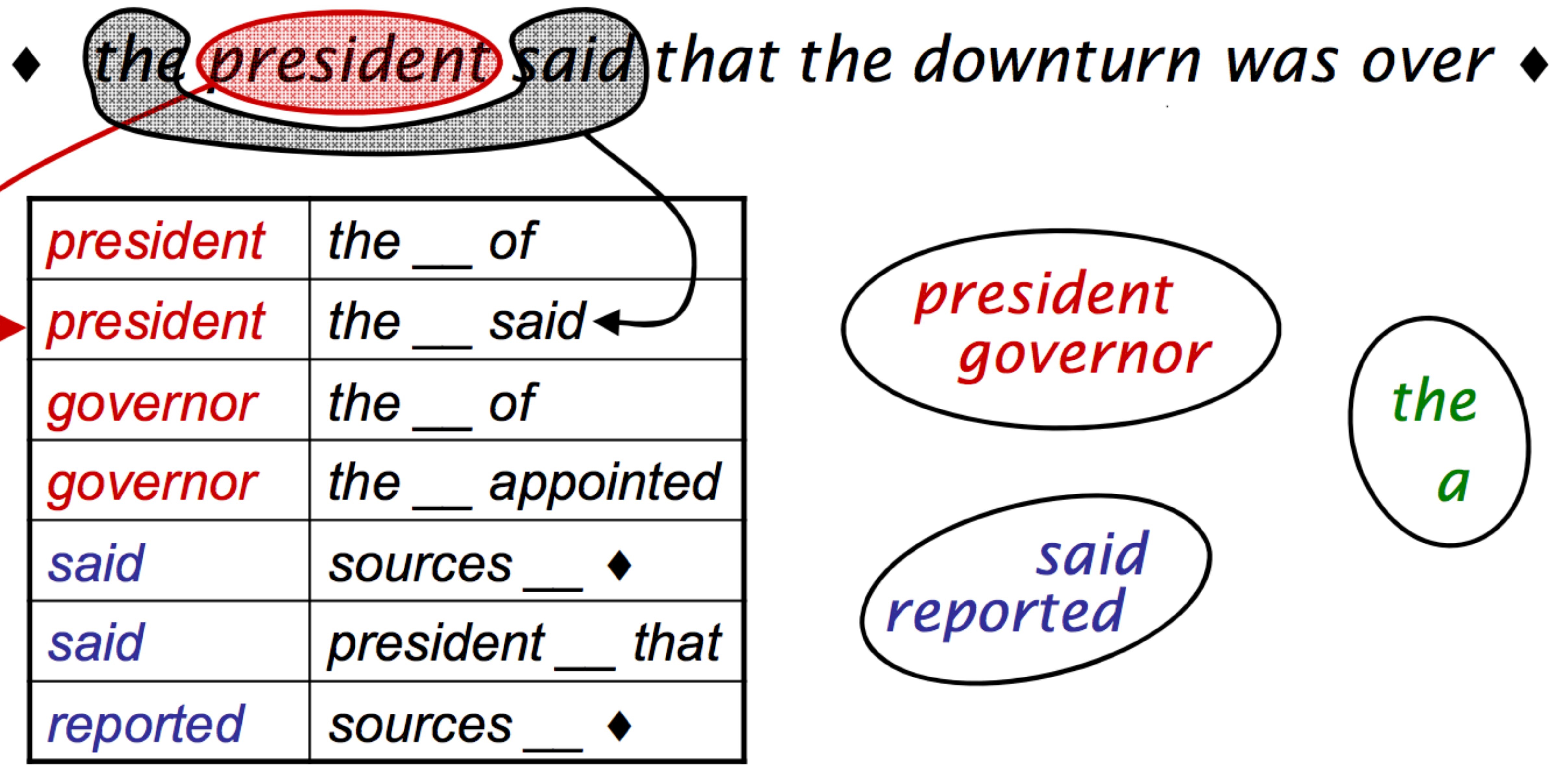
Recurrent Neural Networks

Wei Xu

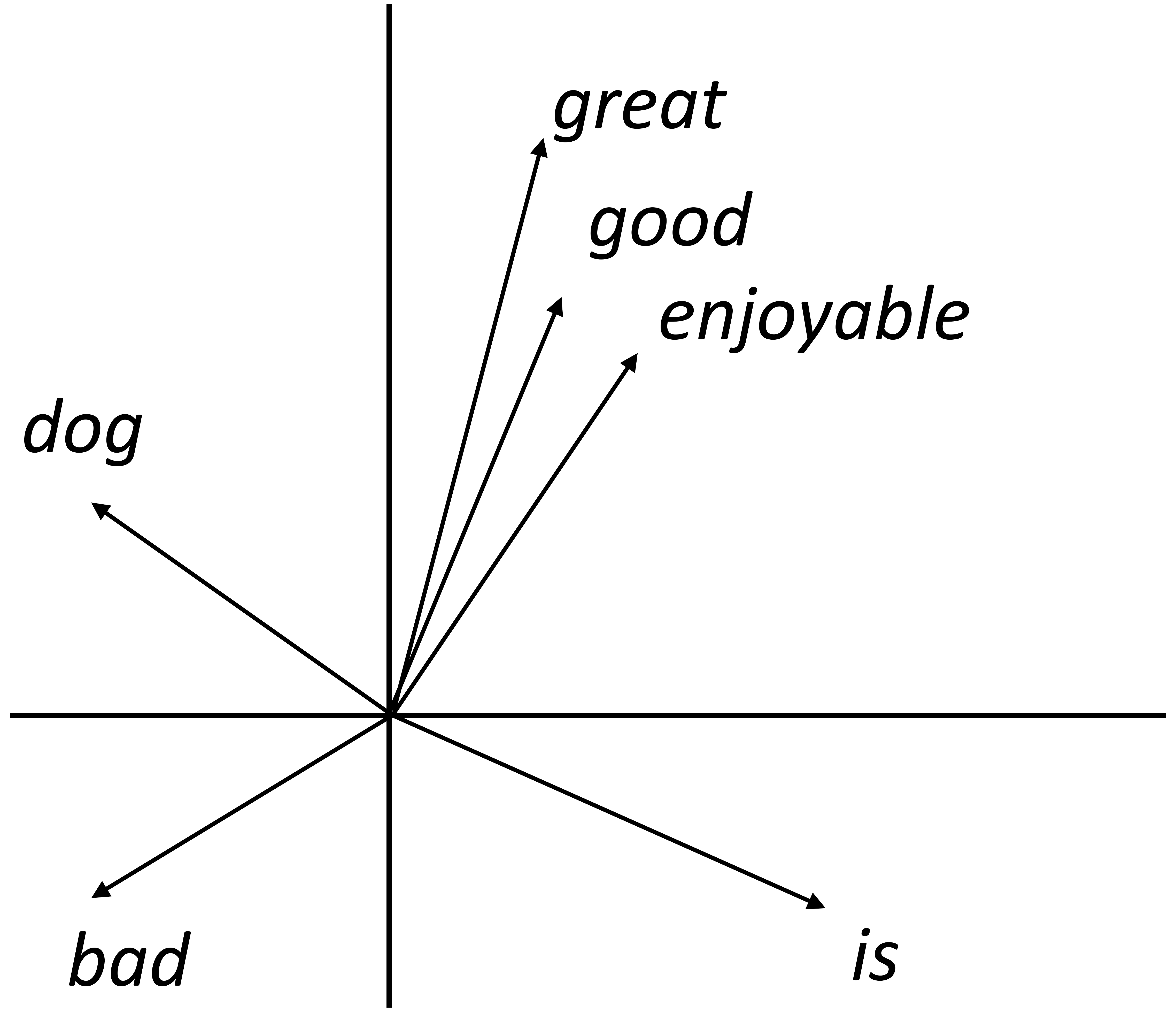
(many slides from Greg Durrett)

Recall: Word Vectors



president	the __ of
president	the __ said
governor	the __ of
governor	the __ appointed
said	sources __ ♦
said	president __ that
reported	sources __ ♦

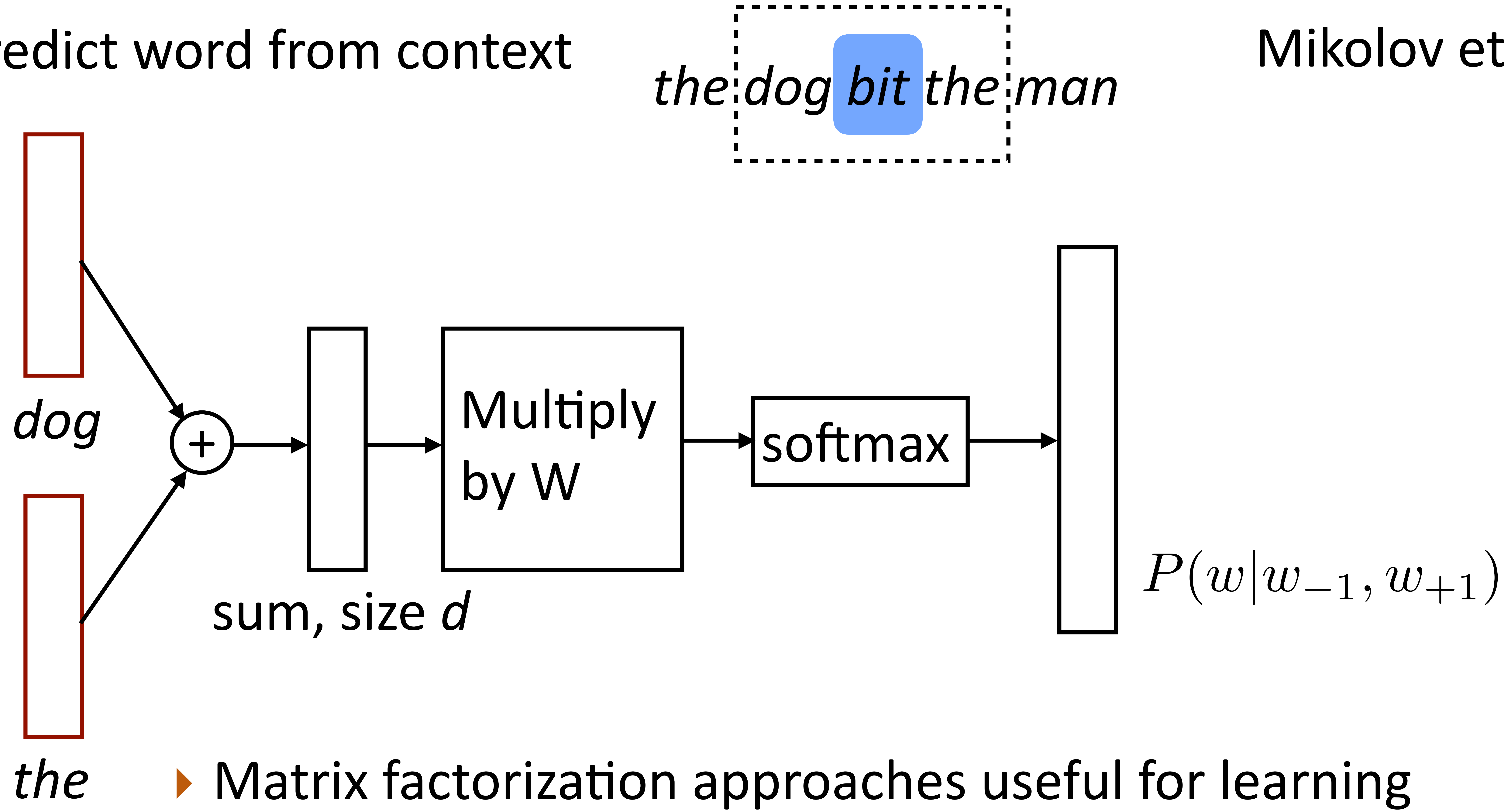
[Finch and Chater 92, Shuetze 93, many others]



Recall: Continuous Bag-of-Words

- Predict word from context

Mikolov et al. (2013)



- Matrix factorization approaches useful for learning vectors from really large data

Using Word Embeddings

- Approach 1: learn embeddings directly from data in your neural model, no pretraining
  - Often works pretty well
- Approach 2: pretrain using GloVe, keep fixed
  - Faster because no need to update these parameters
  - Need to make sure GloVe vocabulary contains all the words you need
- Approach 3: initialize using GloVe, fine-tune
  - Not as commonly used anymore

Compositional Semantics

- What if we want embedding representations for whole sentences?
- Is there a way we can compose vectors to make sentence representations? Summing? RNNs?

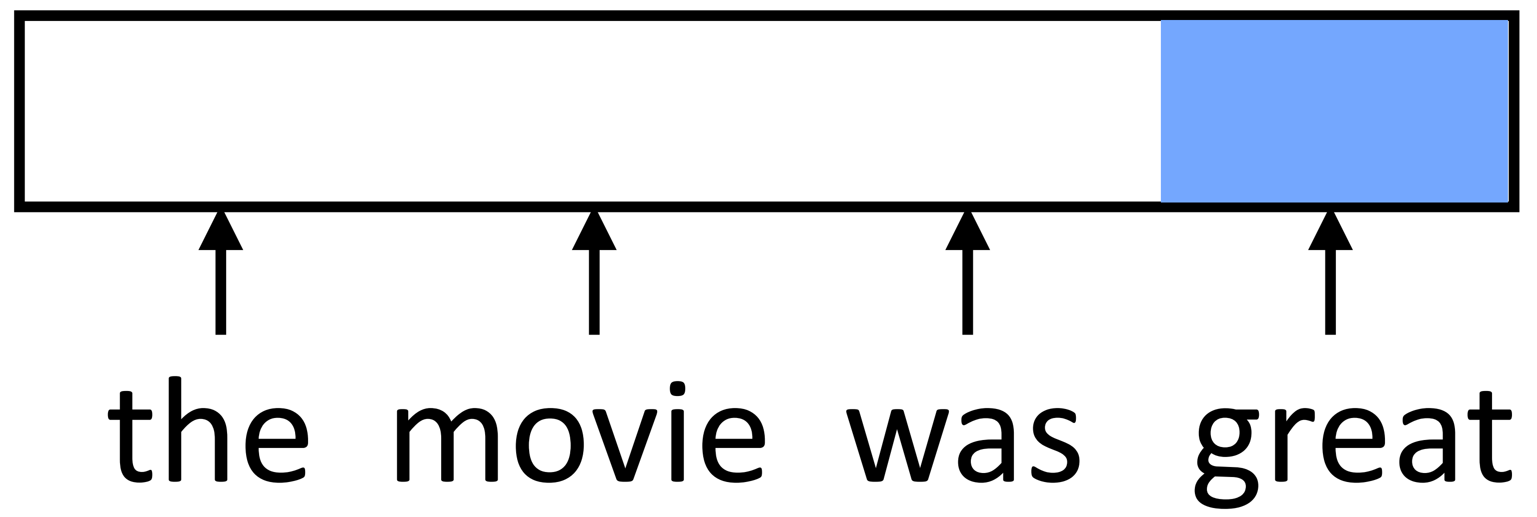
This Lecture

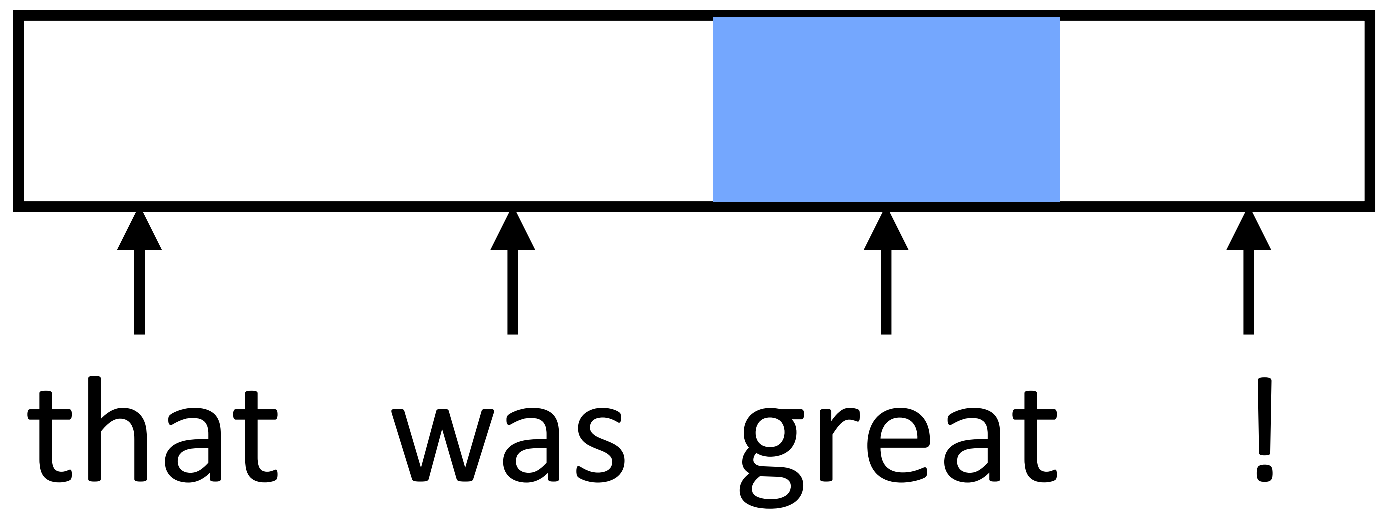
- Recurrent neural networks
- Vanishing gradient problem
- LSTMs / GRUs
- Applications / visualizations

RNN Basics

RNN Motivation

- Feedforward NNs can't handle variable length input: each position in the feature vector has fixed semantics





- These don't look related (*great* is in two different orthogonal subspaces)

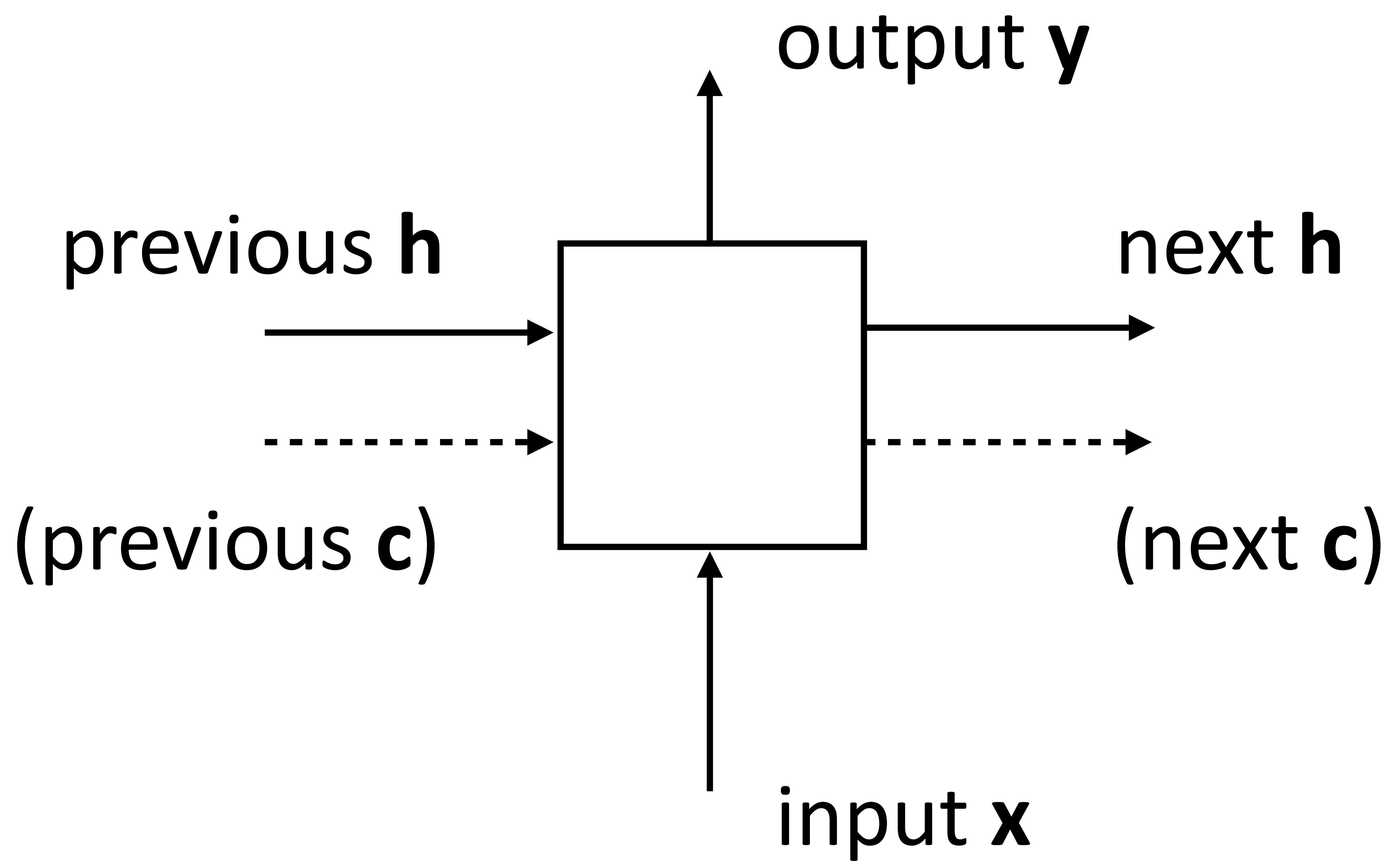
- Instead, we need to:

1) Process each word in a uniform way

2) …while still exploiting the context that that token occurs in

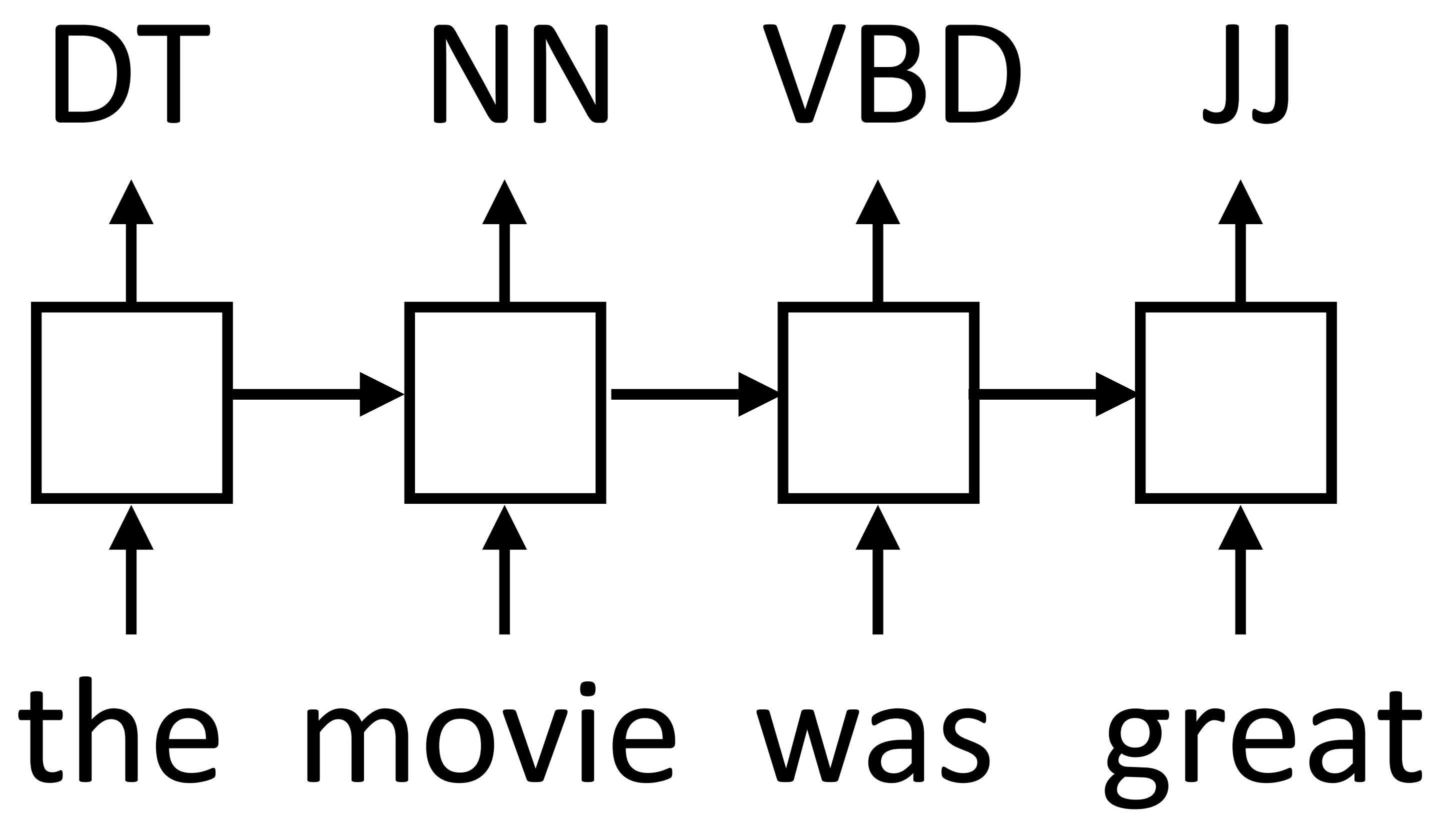
RNN Abstraction

- Cell that takes some input **x**, has some hidden state **h**, and updates that hidden state and produces output **y** (all vector-valued)



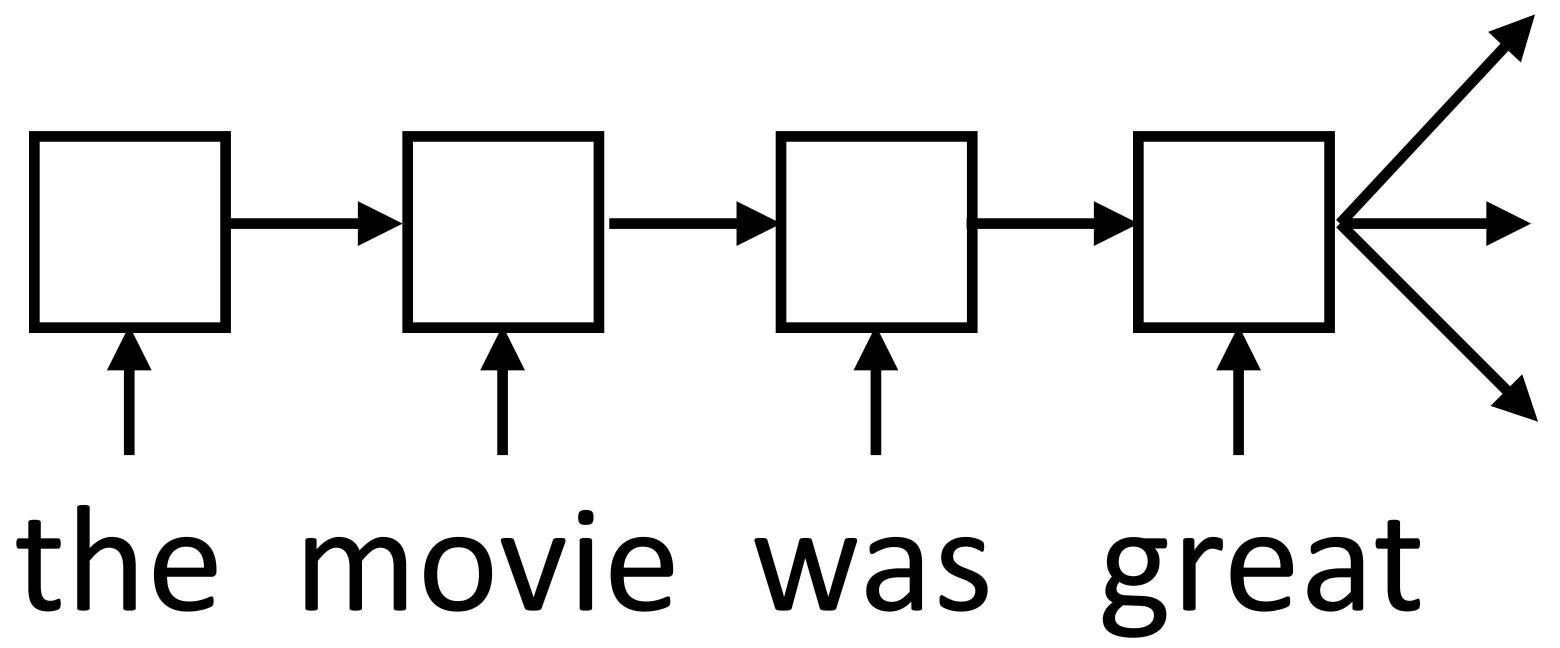
RNN Uses

- Transducer: make some prediction for each element in a sequence



output **y** = score for each tag, then softmax

- Acceptor/encoder: encode a sequence into a fixed-sized vector and use that for some purpose

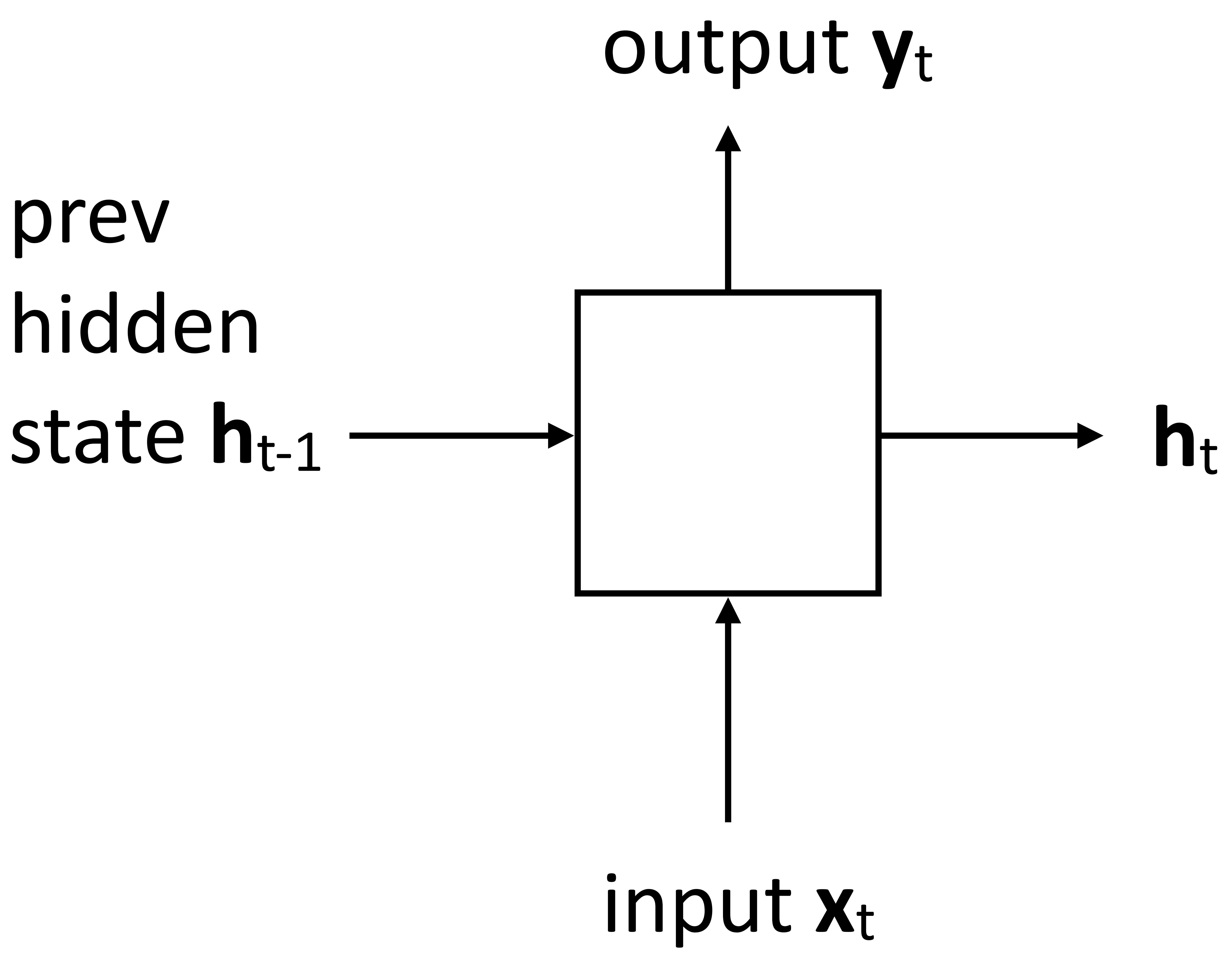


predict sentiment (matmul + softmax)

translate

paraphrase/compress

Elman Networks



$$\mathbf{h}_t = \tanh(W\mathbf{x}_t + V\mathbf{h}_{t-1} + \mathbf{b}_h)$$

- Updates hidden state based on input and current hidden state

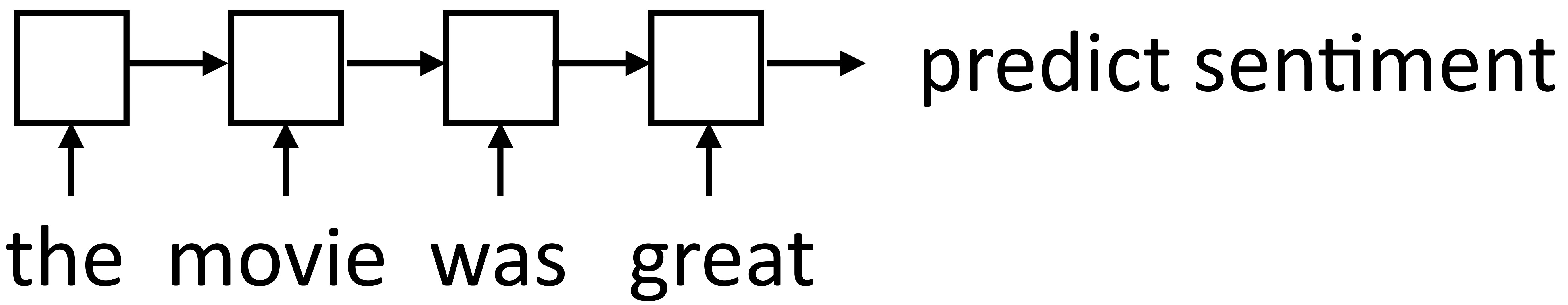
$$\mathbf{y}_t = \tanh(U\mathbf{h_t} + \mathbf{b}_y)$$

- Computes output from hidden state

- Long history! (invented in the late 1980s)

Elman (1990)

Training Elman Networks

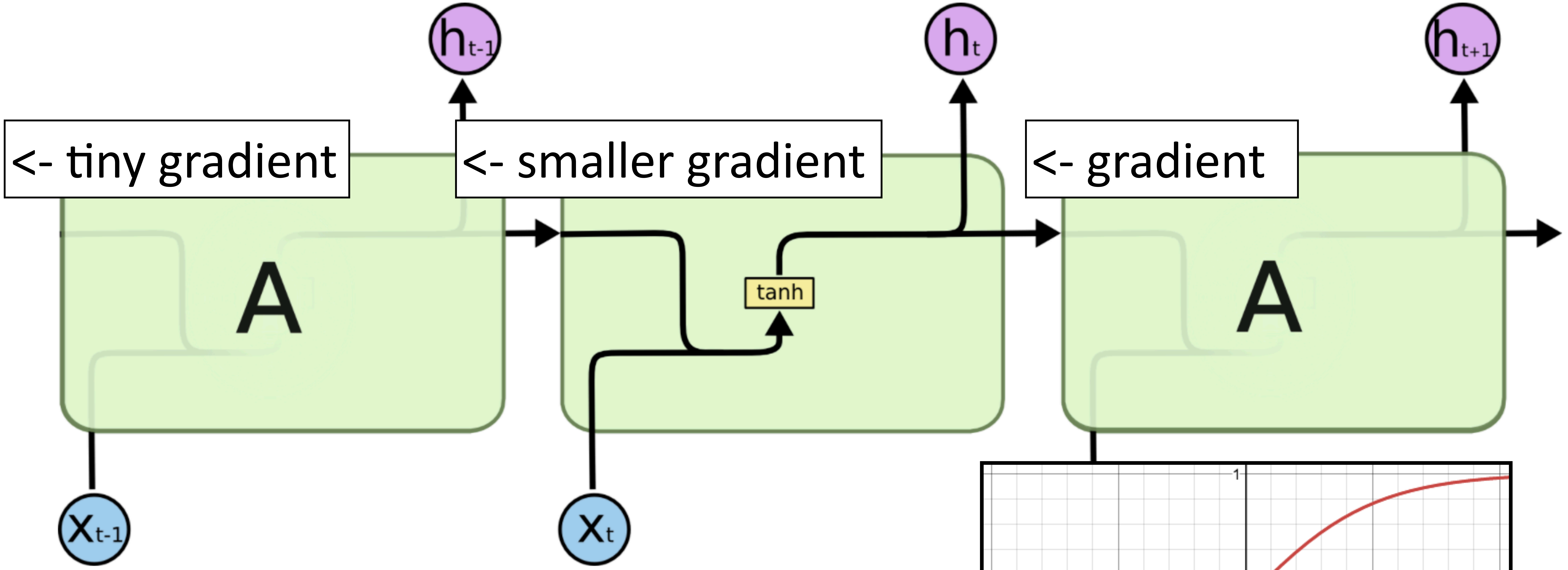


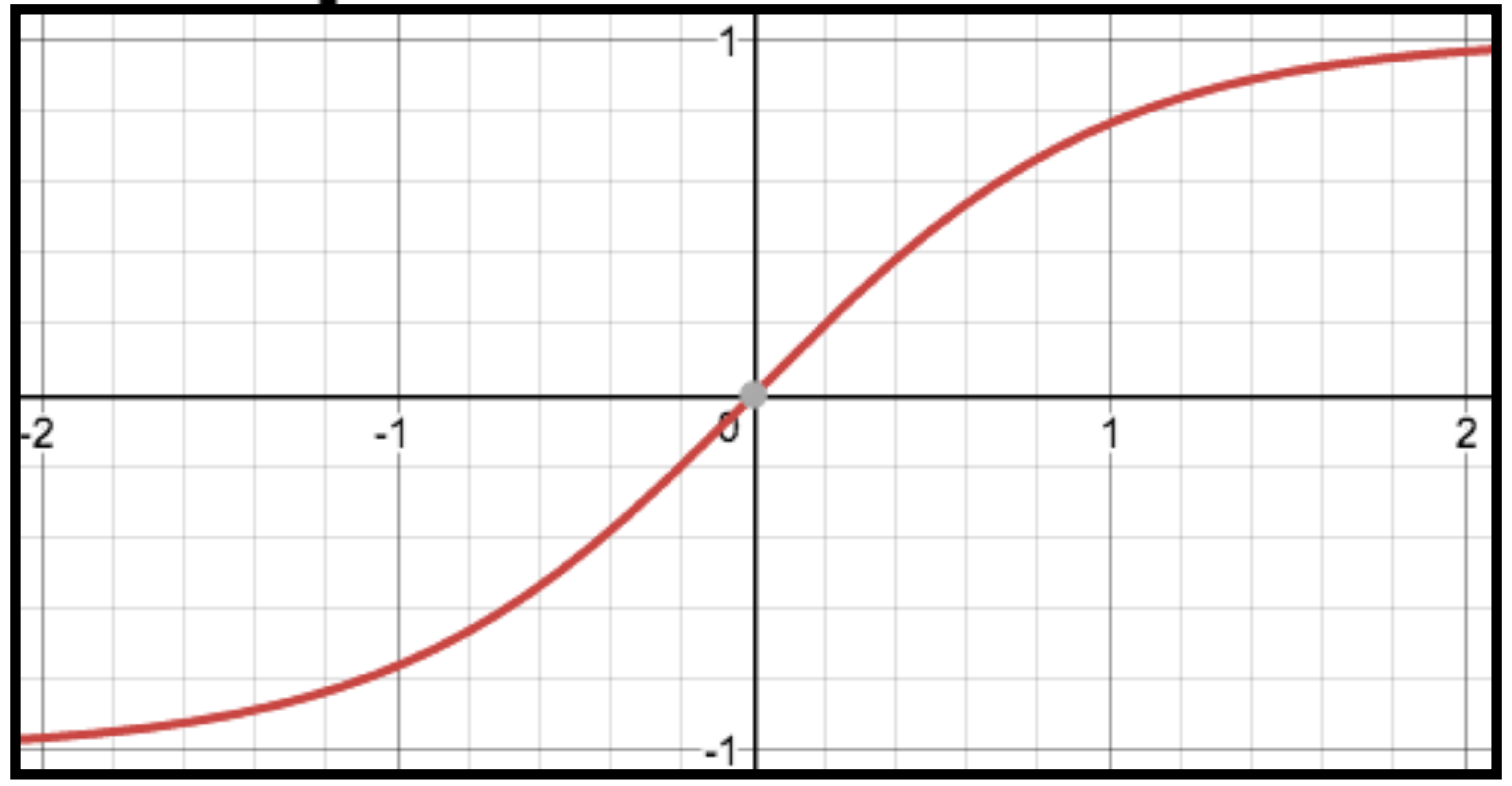
- "Backpropagation through time": build the network as one big computation graph, some parameters are shared
- RNN potentially needs to learn how to "remember" information for a long time!

it was my favorite movie of 2016, though it wasn't without problems -> **+**

- "Correct" parameter update is to do a better job of remembering the sentiment of *favorite*

Vanishing Gradient





- Gradient diminishes going through tanh; if not in [-2, 2], gradient is almost 0

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTMs/GRUs

Gated Connections

- Designed to fix "vanishing gradient" problem using *gates*

$$\mathbf{h}_t = \mathbf{h}_{t-1} \odot \mathbf{f} + \mathrm{func}(\mathbf{x}_t)$$

gated

$$\mathbf{h}_t = \tanh(W\mathbf{x}_t + V\mathbf{h}_{t-1} + \mathbf{b}_h)$$

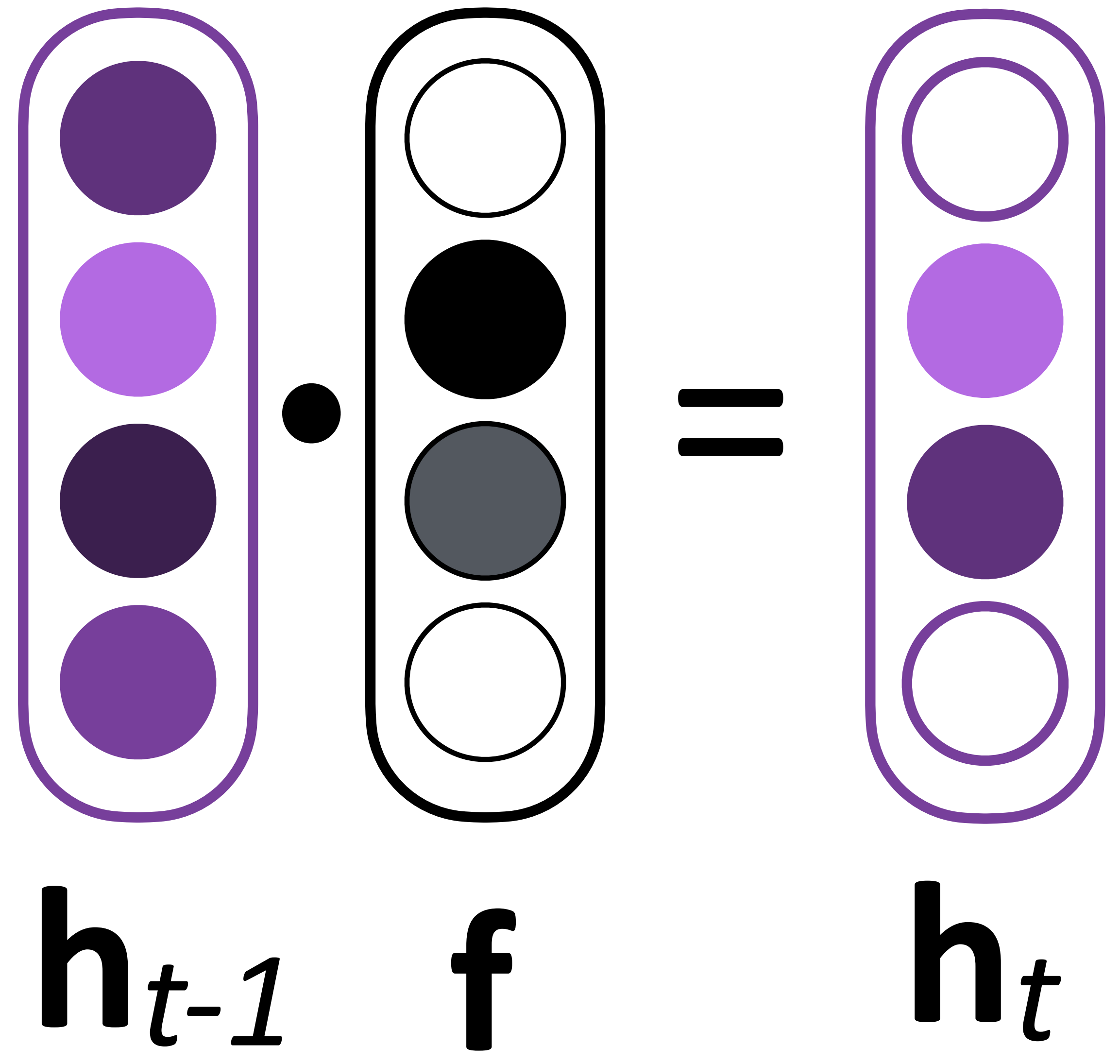
Elman

- Vector-valued "forget gate" **f** computed based on input and previous hidden state

$$\mathbf{f} = \sigma(W^{xf}\mathbf{x}_t + W^{hf}\mathbf{h}_{t-1})$$

- Sigmoid: elements of **f** are in (0, 1)

- If **f** ≈ **1**, we simply sum up a function of all inputs — gradient doesn't vanish!



LSTMs

- "Cell" **c** in addition to hidden state **h**

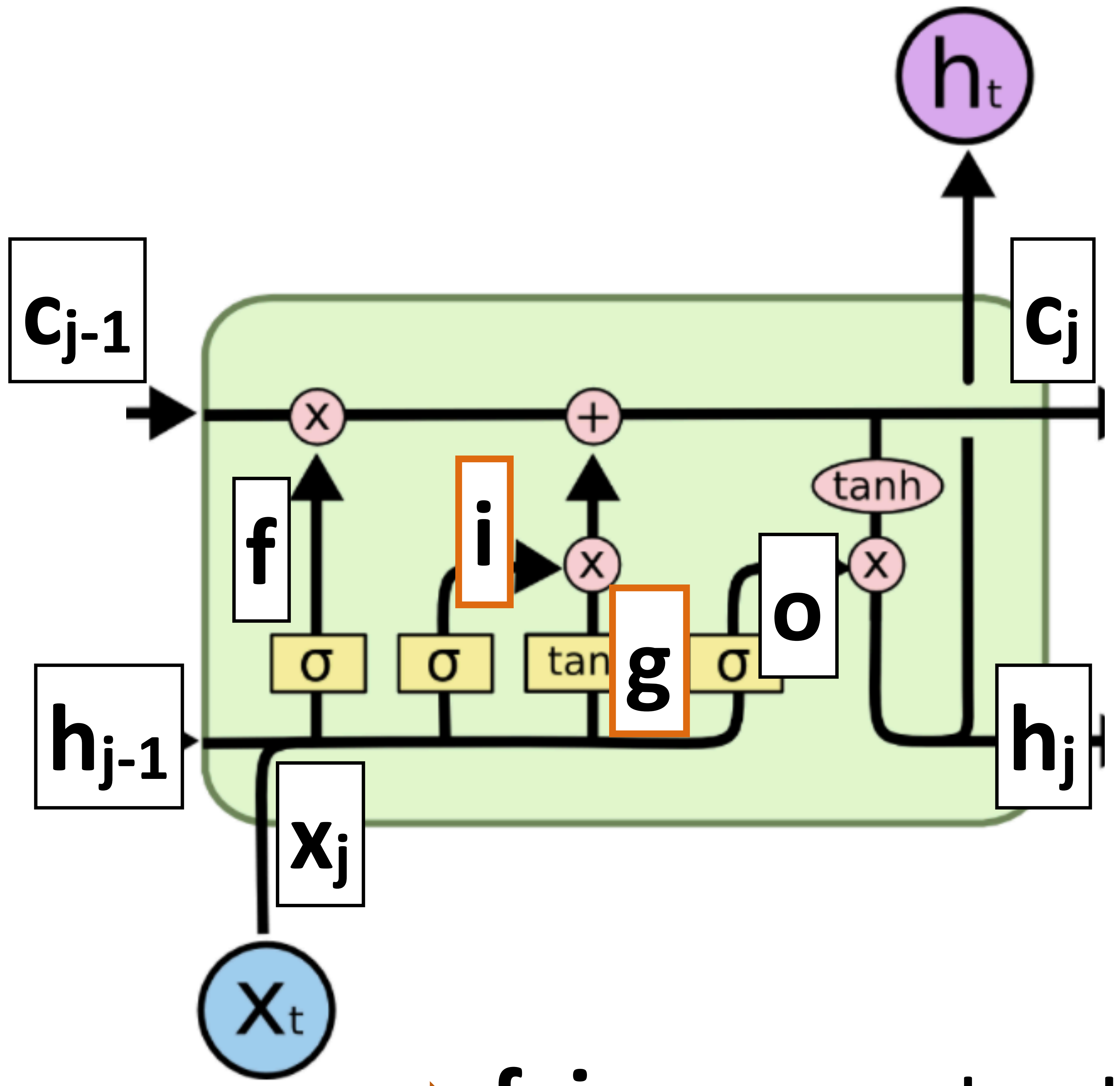
$$\mathbf{c}_t = \mathbf{c}_{t-1} \odot \mathbf{f} + \boxed{\text{func}(\mathbf{x}_t, \mathbf{h}_{t-1})}$$

- Vector-valued forget gate **f** depends on the **h** hidden state

$$\mathbf{f} = \sigma(W^{xf}\mathbf{x}_t + W^{hf}\mathbf{h}_{t-1})$$

- Basic communication flow: **x** -> **c** -> **h** **->** output**,** each step of this process is gated in addition to gates from previous timesteps

LSTMs



$$\mathbf{c_j} = \mathbf{c_{j-1}} \odot \mathbf{f} + \boxed{\mathbf{g} \odot \mathbf{i}}$$

$$\mathbf{f} = \sigma(\mathbf{x_j W^{xf}} + \mathbf{h_{j-1} W^{hf}})$$

$$\boxed{\begin{aligned} \mathbf{g} &= \tanh(\mathbf{x_j W^{xg}} + \mathbf{h_{j-1} W^{hg}}) \\ \mathbf{i} &= \sigma(\mathbf{x_j W^{xi}} + \mathbf{h_{j-1} W^{hi}}) \end{aligned}}$$

$$\mathbf{h_j} = \tanh(\mathbf{c_j}) \odot \mathbf{o}$$

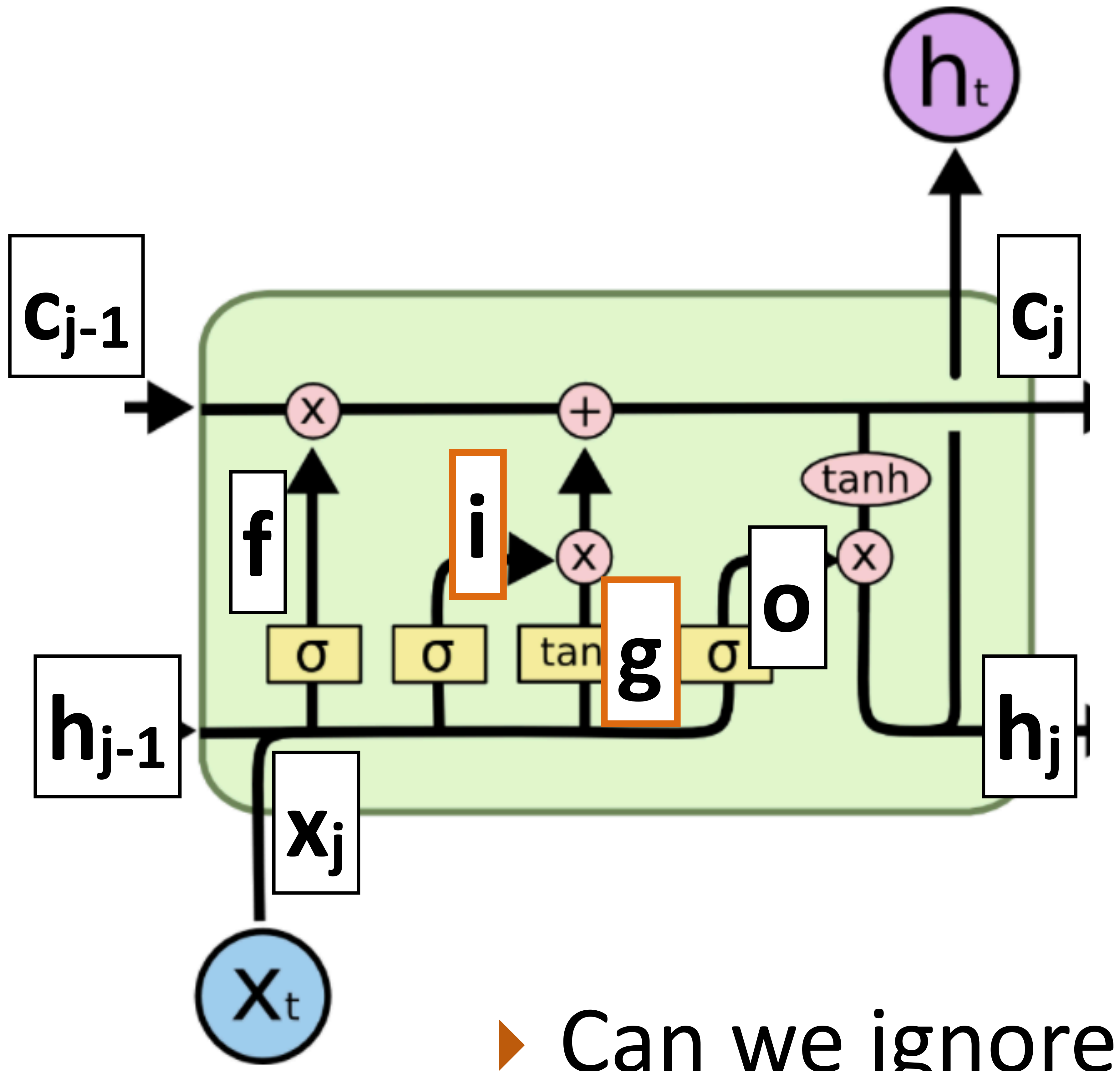
$$\mathbf{o} = \sigma(\mathbf{x_j W^{xo}} + \mathbf{h_{j-1} W^{ho}})$$

- **f**, **i**, **o** are gates that control information flow
- **g** reflects the main computation of the cell

Goldberg lecture notes

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTMs



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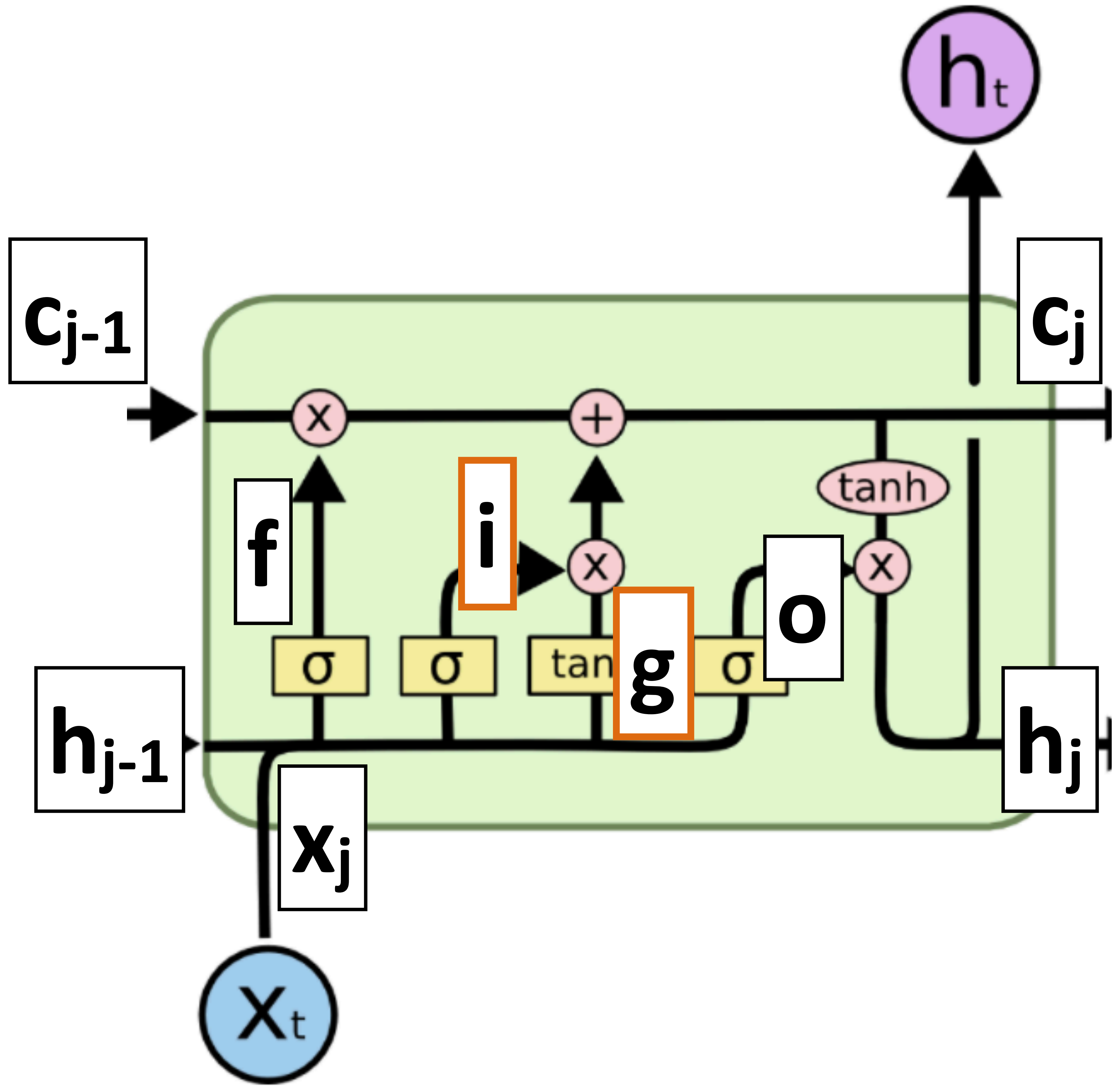
$$\mathbf{h_j} = \tanh(\mathbf{c_j}) \odot \mathbf{o}$$

$$\mathbf{o} = \sigma(\mathbf{x_j W^{xo}} + \mathbf{h_{j-1} W^{ho}})$$

- Can we ignore the old value of **c** for this timestep?
- Can an LSTM sum up its inputs **x**?
- Can we ignore a particular input **x**?
- Can we output something without changing **c**?

LSTMs

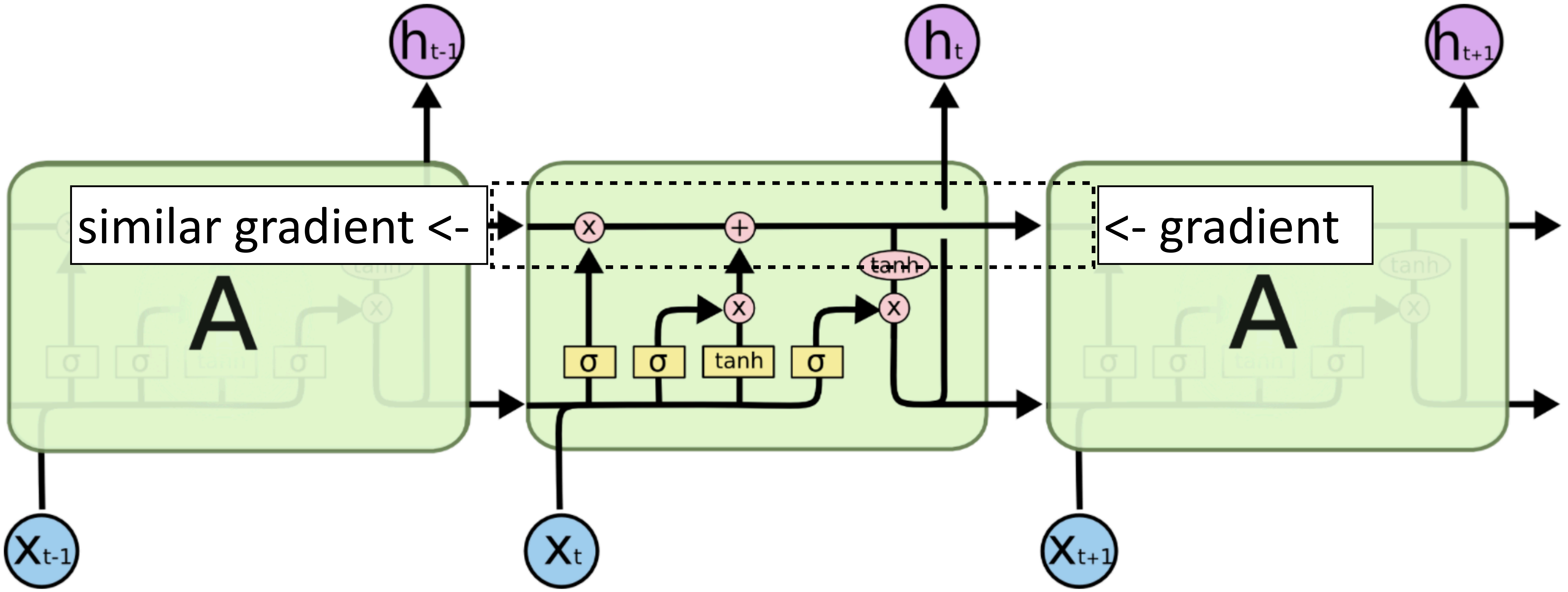


- Ignoring recurrent state entirely:
  - Lets us get feedforward layer over token
- Ignoring input:
  - Lets us discard stopwords
- Summing inputs:
  - Lets us compute a bag-of-words representation

Goldberg lecture notes

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

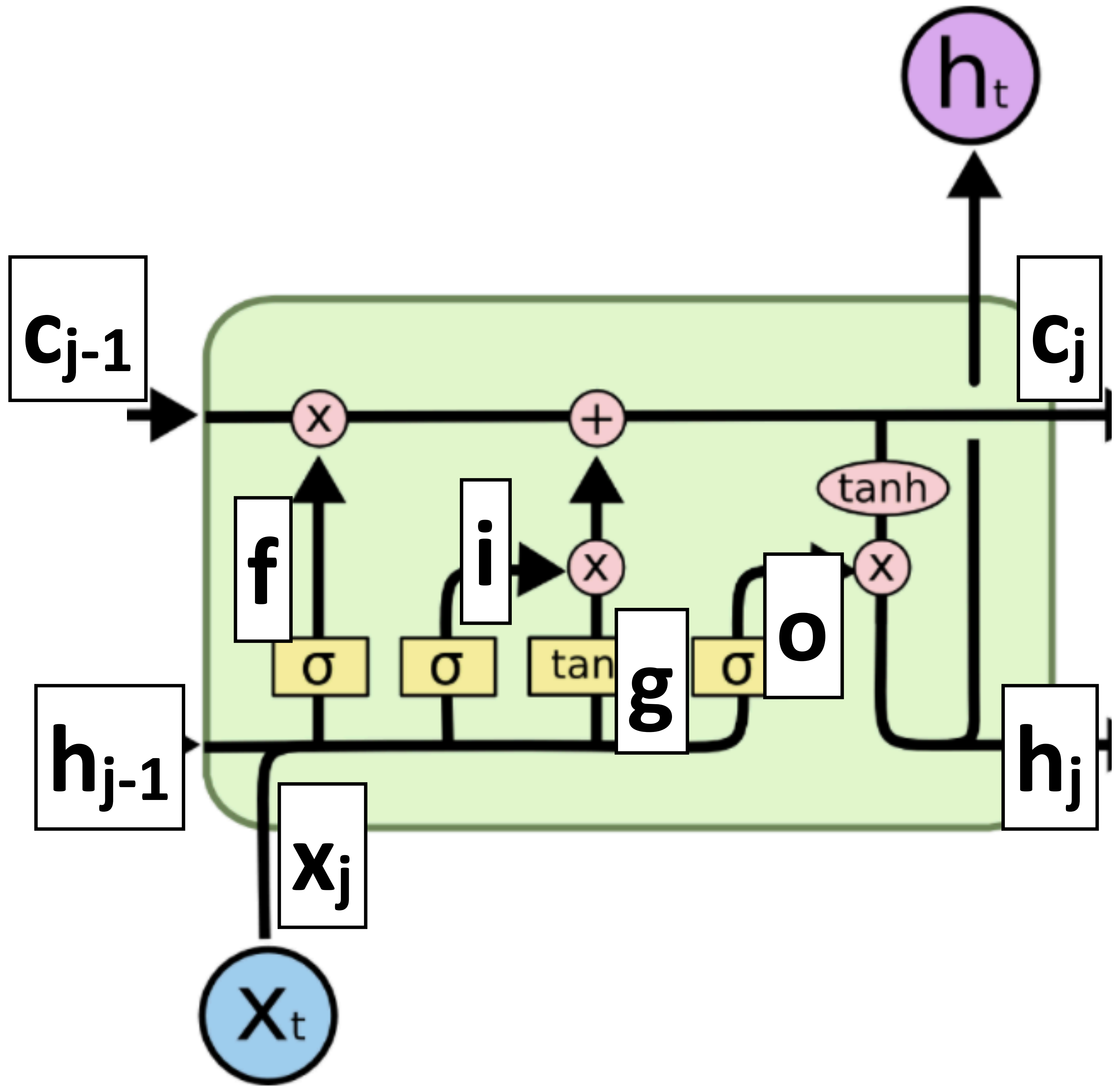
LSTMs

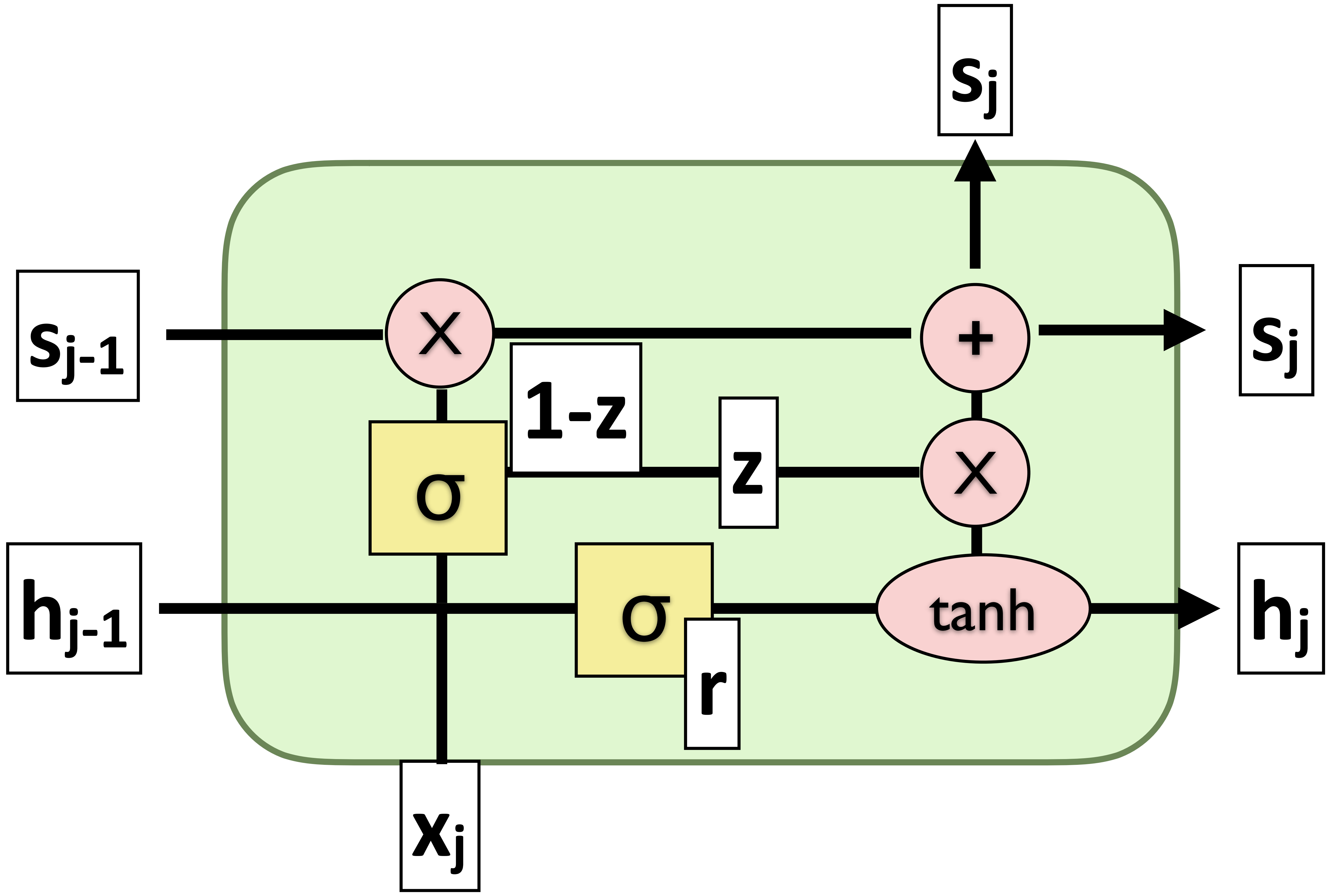


- Gradient still diminishes, but in a controlled way and generally by less — usually initialize forget gate = 1 to remember everything to start

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

GRUs

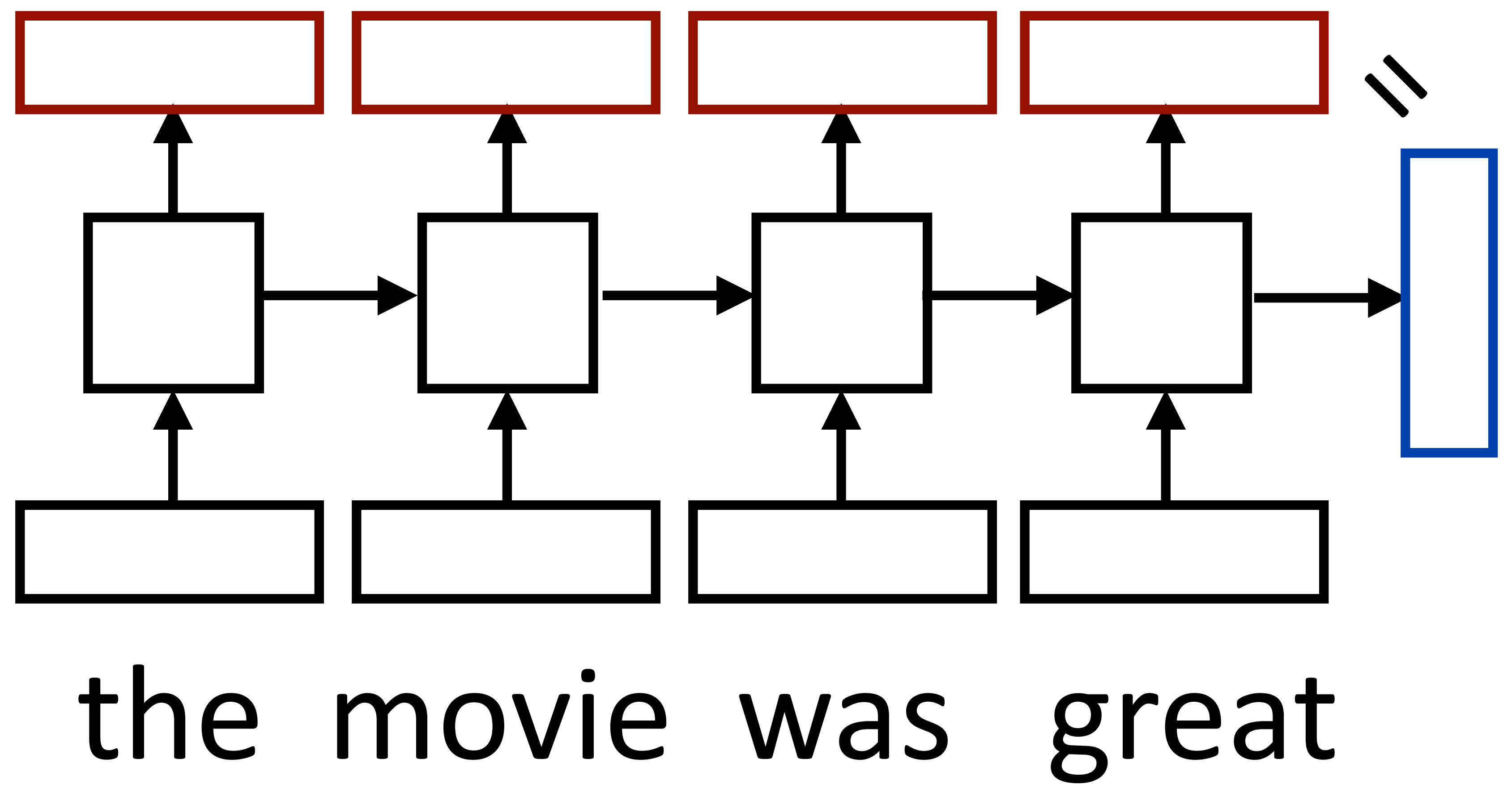




- LSTM: more complex and slower, may work a bit better

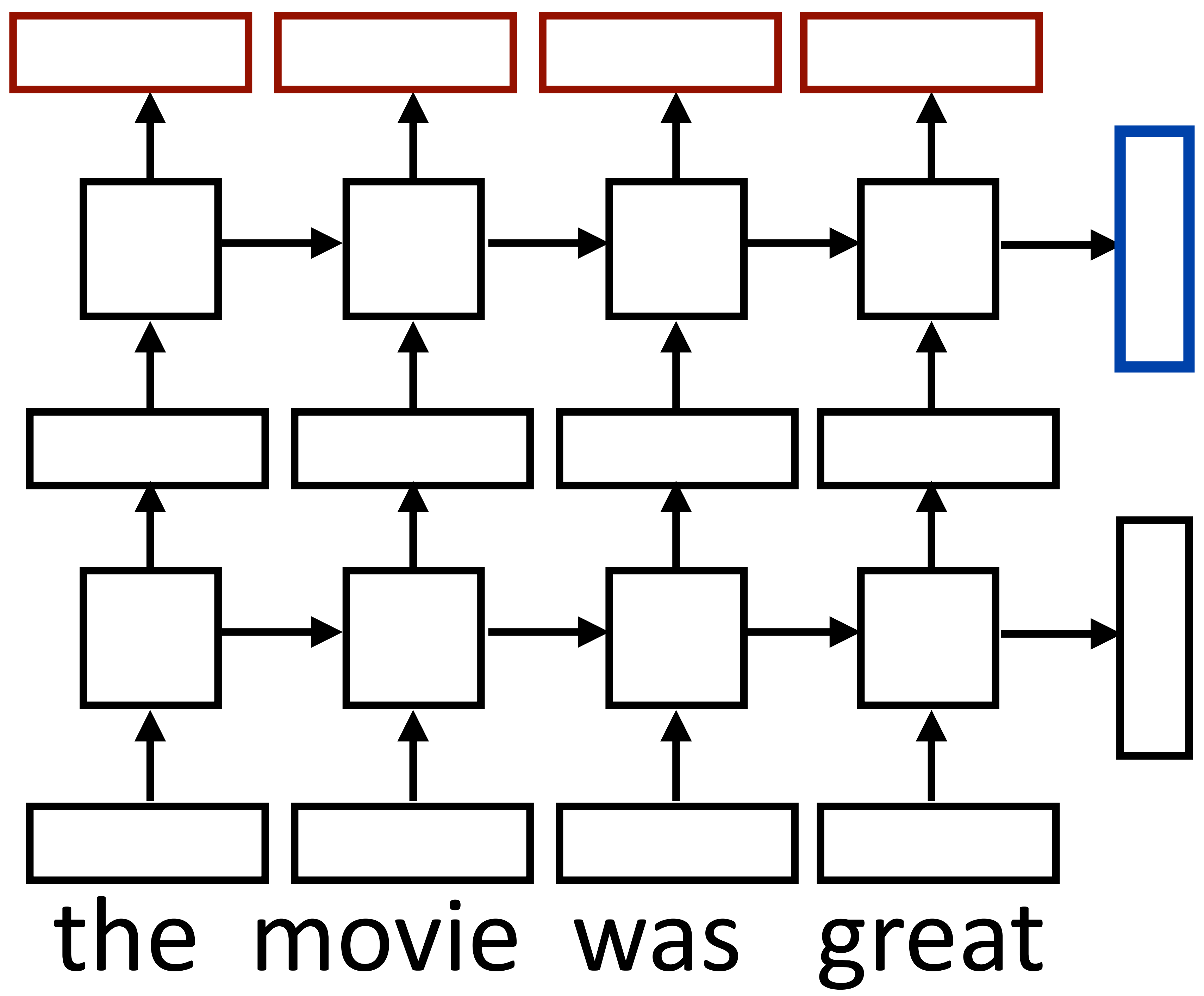
- GRU: faster, a bit simpler
- Two gates: **z** (forget, mixes **s** and **h**) and **r** (mixes **h** and **x**)

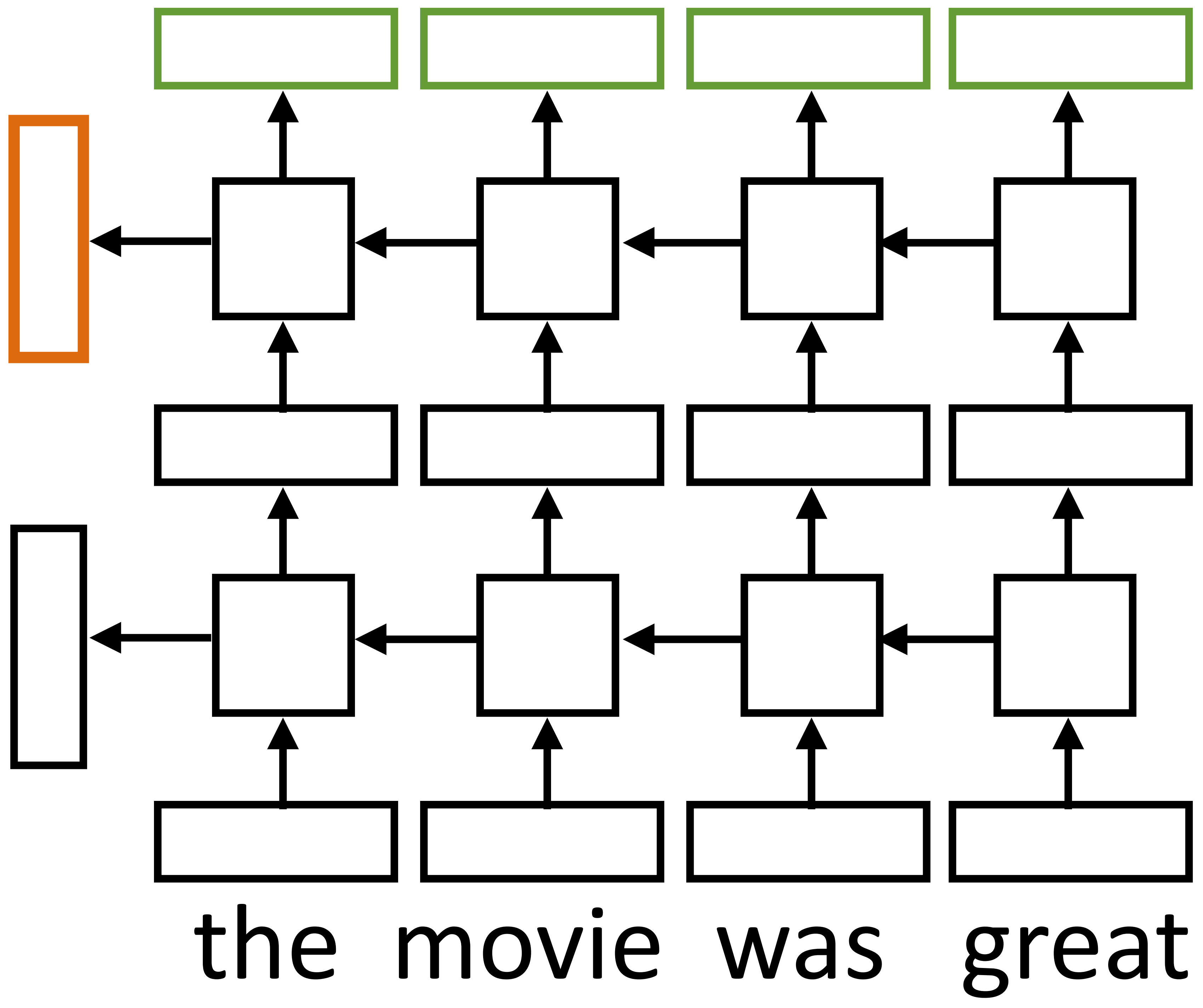
What do RNNs produce?



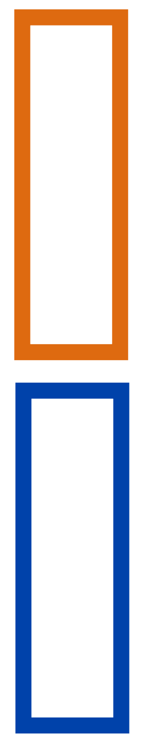
- Encoding of the sentence — can pass this a decoder or make a classification decision about the sentence
- Encoding of each word — can pass this to another layer to make a prediction (can also pool these to get a different sentence encoding)
- RNN can be viewed as a transformation of a sequence of vectors into a sequence of context-dependent vectors

Multilayer Bidirectional RNN

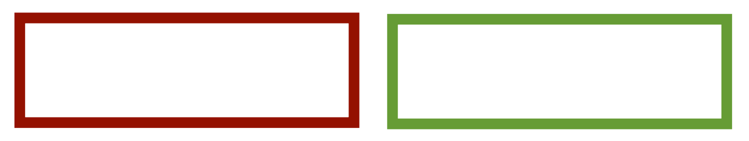




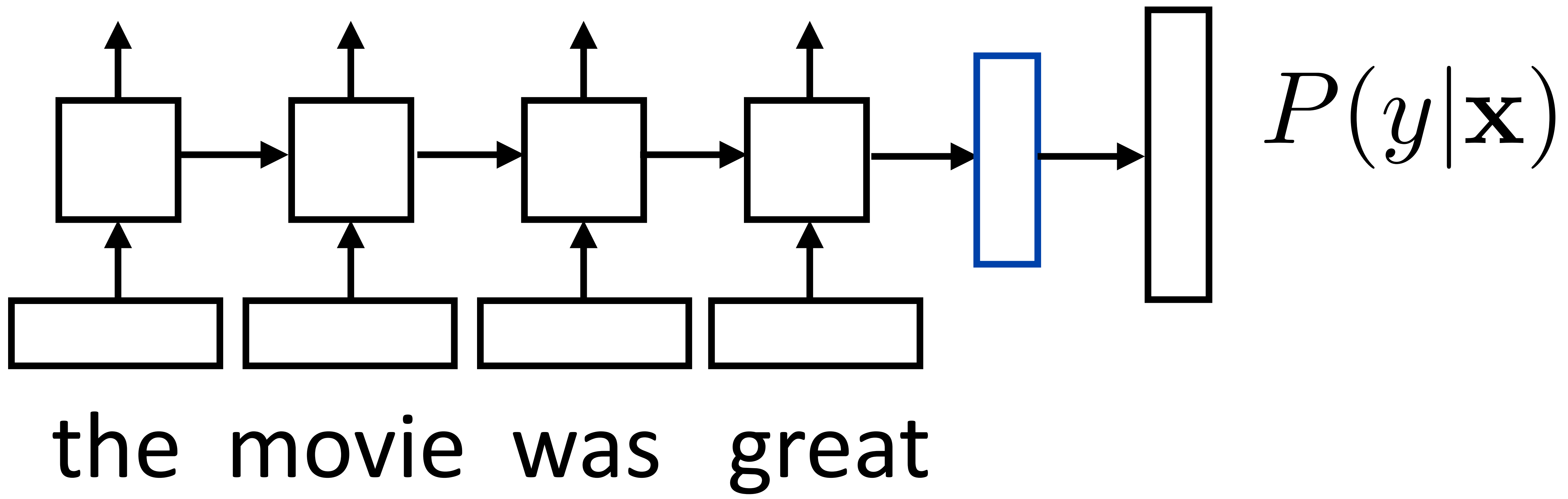
- Sentence classification based on concatenation of both final outputs



- Token classification based on concatenation of both directions' token representations

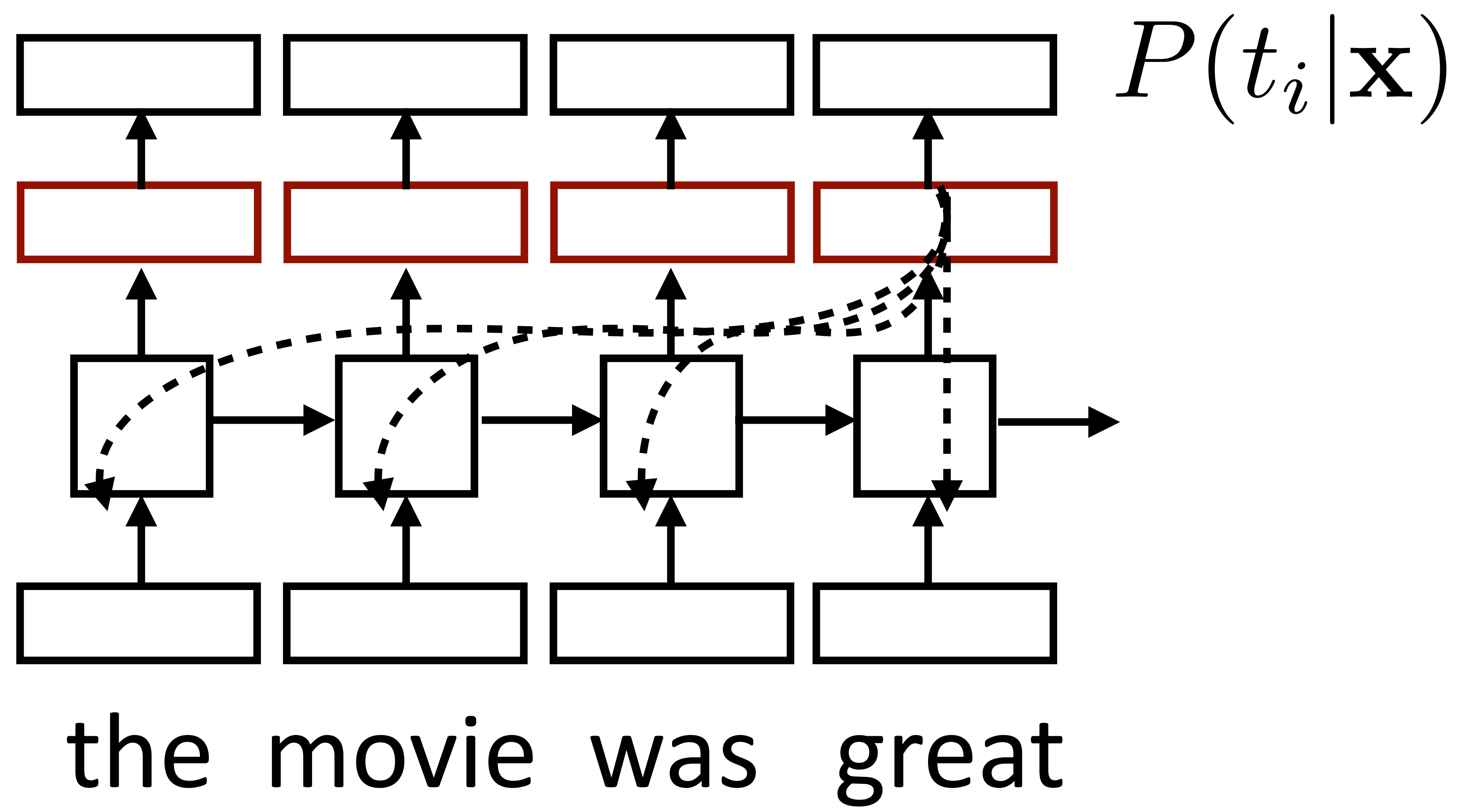


Training RNNs



- Loss = negative log likelihood of probability of gold label (or use SVM or other loss)
- Backpropagate through entire network
- Example: sentiment analysis

Training RNNs



- Loss = negative log likelihood of probability of gold predictions, summed over the tags
- Loss terms filter back through network
- Example: language modeling (predict next word given context)

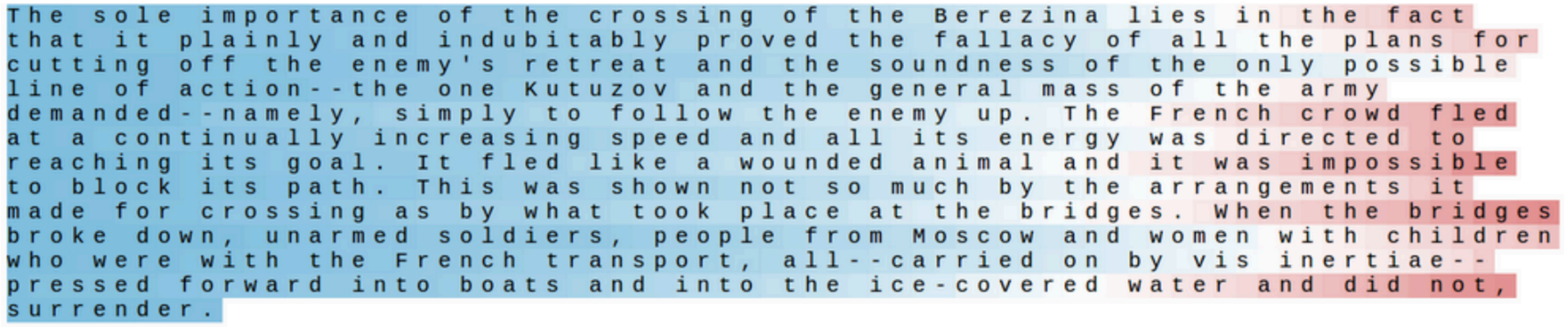
Applications

What can LSTMs model?

- Sentiment
  - Encode one sentence, predict
- Language models
  - Move left-to-right, per-token prediction
- Translation
  - Encode sentence + then decode, use token predictions for attention weights (later in the course)

Visualizing LSTMs

- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells (components of **c**) to understand them
- Counter: know when to generate \n

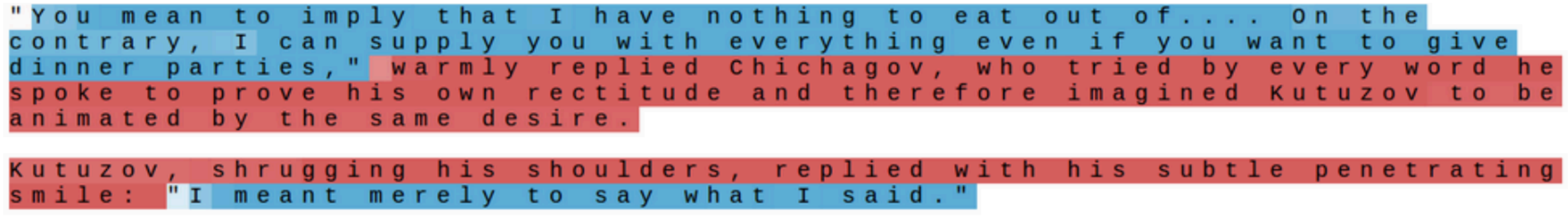


```
The sole importance of the crossing of the Berezina lies in the fact
that it plainly and indubitably proved the fallacy of all the plans for
cutting off the enemy's retreat and the soundness of the only possible
line of action--the one Kutuzov and the general mass of the army
demanded--namely, simply to follow the enemy up. The French crowd fled
at a continually increasing speed and all its energy was directed to
reaching its goal. It fled like a wounded animal and it was impossible
to block its path. This was shown not so much by the arrangements it
made for crossing as by what took place at the bridges. When the bridges
broke down, unarmed soldiers, people from Moscow and women with children
who were with the French transport, all--carried on by vis inertiae--
pressed forward into boats and into the ice-covered water and did not,
surrender.
```

Karpathy et al. (2015)

Visualizing LSTMs

- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells to see what they track
- Binary switch: tells us if we're in a quote or not



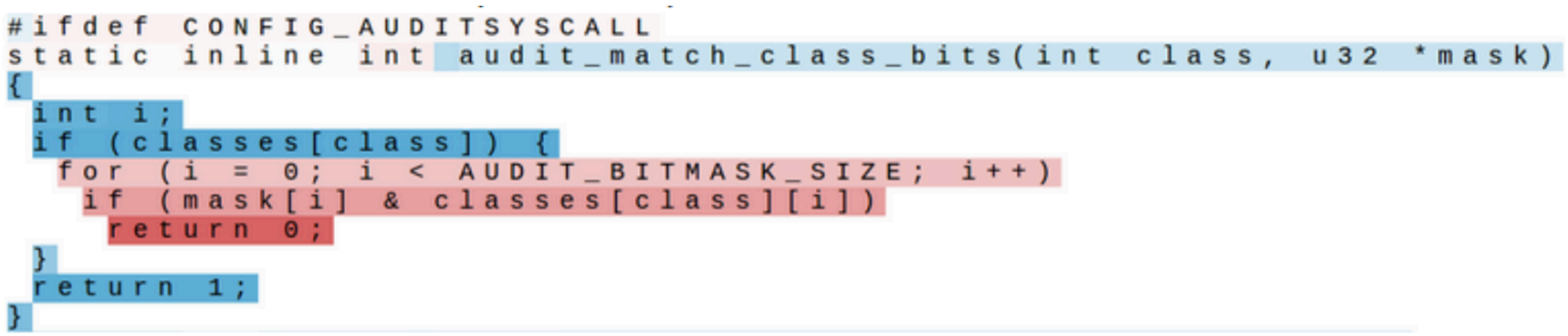
"You mean to imply that I have nothing to eat out of.... On the contrary, I can supply you with everything even if you want to give dinner parties," warmly replied Chichagov, who tried by every word he spoke to prove his own rectitude and therefore imagined Kutuzov to be animated by the same desire.

Kutuzov, shrugging his shoulders, replied with his subtle penetrating smile: "I meant merely to say what I said."

Karpathy et al. (2015)

Visualizing LSTMs

- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells to see what they track
- Stack: activation based on indentation

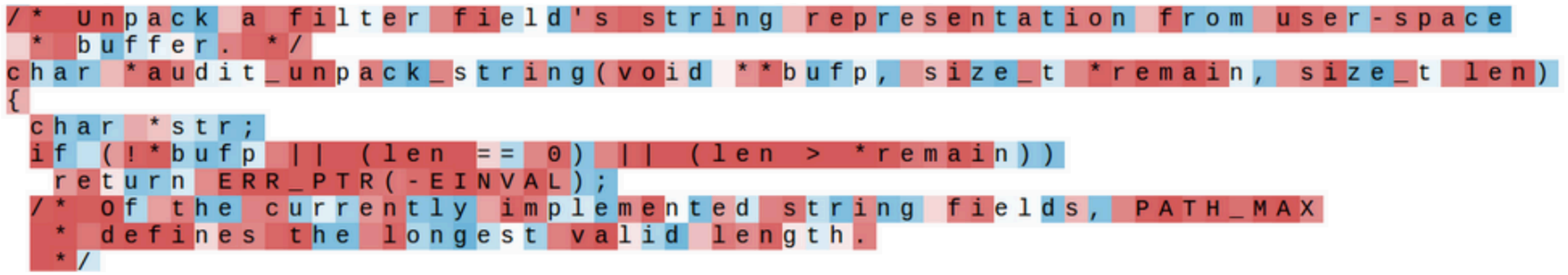


```
#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
{
 int i;
 if (classes[class]) {
  for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
   if (mask[i] & classes[class][i])
    return 0;
 }
 return 1;
}
```

Karpathy et al. (2015)

Visualizing LSTMs

- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells to see what they track
- Uninterpretable: probably doing double-duty, or only makes sense in the context of another activation



```
/* Unpack a filter field's string representation from user-space
 * buffer. */
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)
{
 char *str;
 if (!*bufp || (len == 0) || (len > *remain))
  return ERR_PTR(-EINVAL);
 /* Of the currently implemented string fields, PATH_MAX
  * defines the longest valid length.
  */
```

Karpathy et al. (2015)

What can LSTMs model?

- Sentiment
  - Encode one sentence, predict
- Language models
  - Move left-to-right, per-token prediction
- Translation
  - Encode sentence + then decode, use token predictions for attention weights (next lecture)
- Textual entailment
  - Encode two sentences, predict

Natural Language Inference

Premise		Hypothesis
A boy plays in the snow	*entails*	A boy is outside
A man inspects the uniform of a figure	*contradicts*	The man is sleeping
An older and younger man smiling	*neutral*	Two men are smiling and laughing at cats playing

- Long history of this task: “Recognizing Textual Entailment” challenge in 2006 (Dagan, Glickman, Magnini)
- Early datasets: small (hundreds of pairs), very ambitious (lots of world knowledge, temporal reasoning, etc.)

SNLI Dataset

- Show people captions for (unseen) images and solicit entailed / neural / contradictory statements
- >500,000 sentence pairs
- Encode each sentence and process

100D LSTM: 78% accuracy

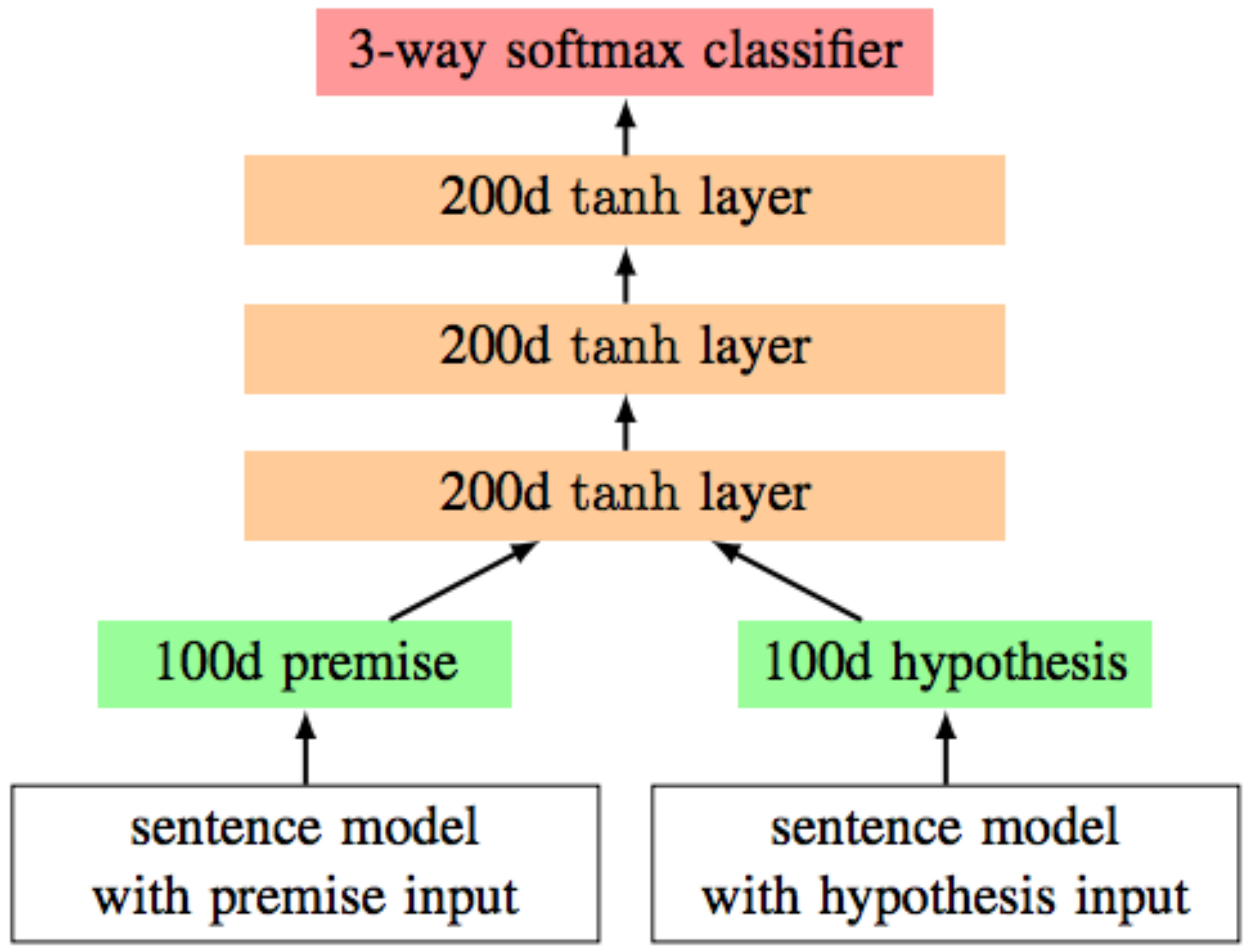
300D LSTM: 80% accuracy

(Bowman et al., 2016)

300D BiLSTM: 83% accuracy

(Liu et al., 2016)

- Later: better models for this



Bowman et al. (2015)

Takeaways

- RNNs can transduce inputs (produce one output for each input) or compress the whole input into a vector

- Useful for a range of tasks with sequential input: sentiment analysis, language modeling, natural language inference, machine translation

- Next time: CNNs and neural CRFs