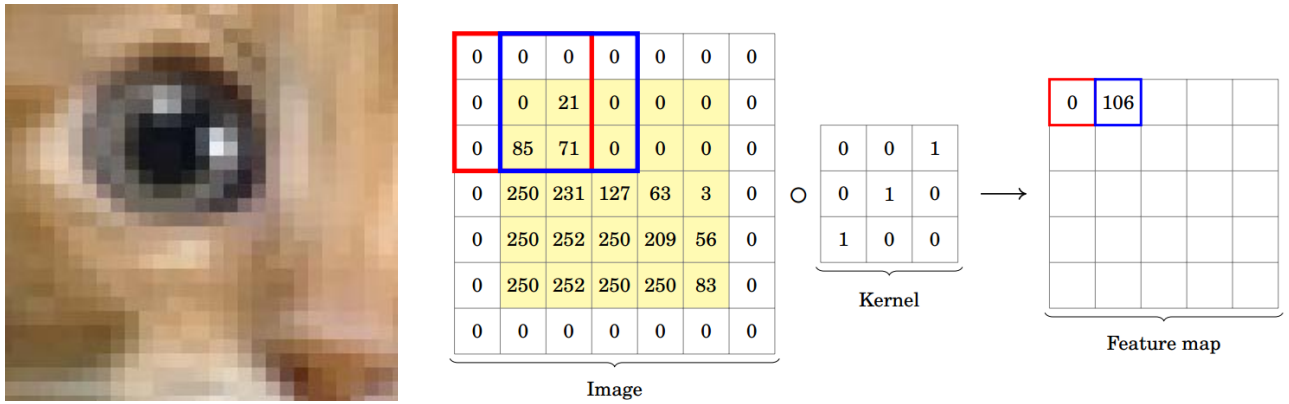
Recurrent Neural Networks

Fixed vs. Sequence

Image

- Fixed input size
- Related pixels are close together



Text

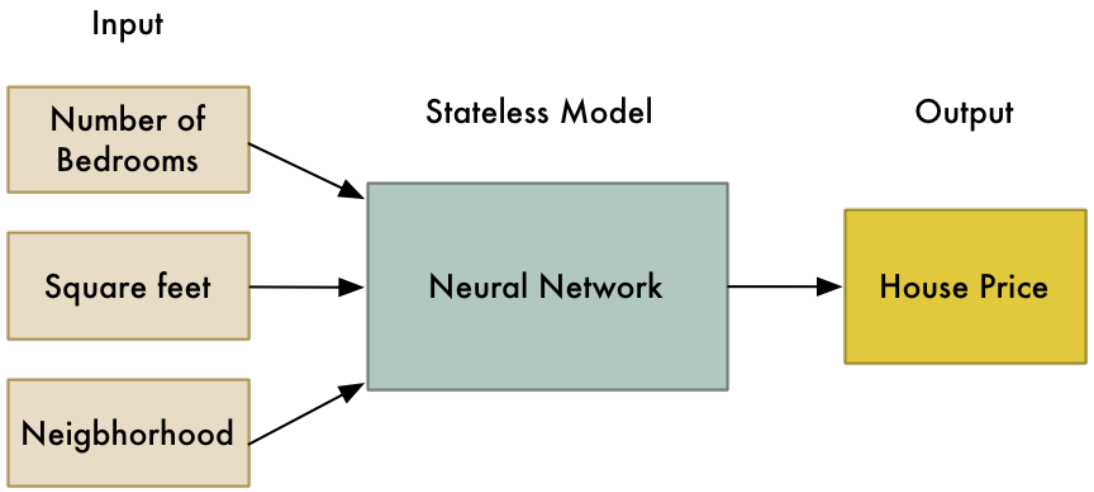
- Sequence, arbitrary input size
- Related words can be far, far away

```
This is one of Crichton's best books. The characters of Karen Ross, Peter Elliot,
Munro, and Amy are beautifully developed and their interactions are exciting,
complex, and fast-paced throughout this impressive novel. And about 99.8 percent of
that got lost in the film. Seriously, the screenplay AND the directing were
horrendous and clearly done by people who could not fathom what was good about the
novel. I can't fault the actors because frankly, they never had a chance to make this
turkey live up to Crichton's original work. I know good novels, especially those with
a science fiction edge, are hard to bring to the screen in a way that lives up to the
original. But this may be the absolute worst disparity in quality between novel and
screen adaptation ever. The book is really, really good. The movie is just dreadful.
```

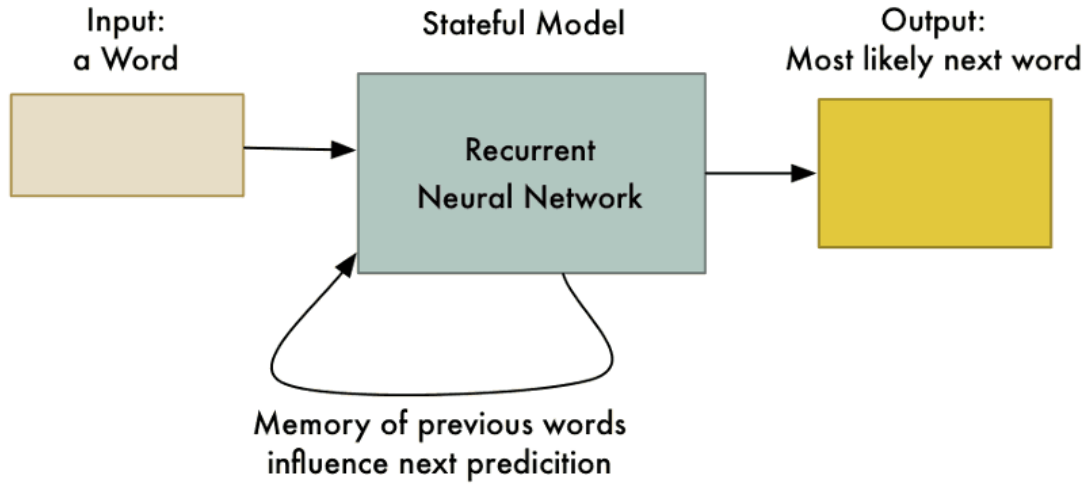
Source: [Tal Perry]

Stateless vs. Stateful

Predict current housing price



Predict the next most likely word

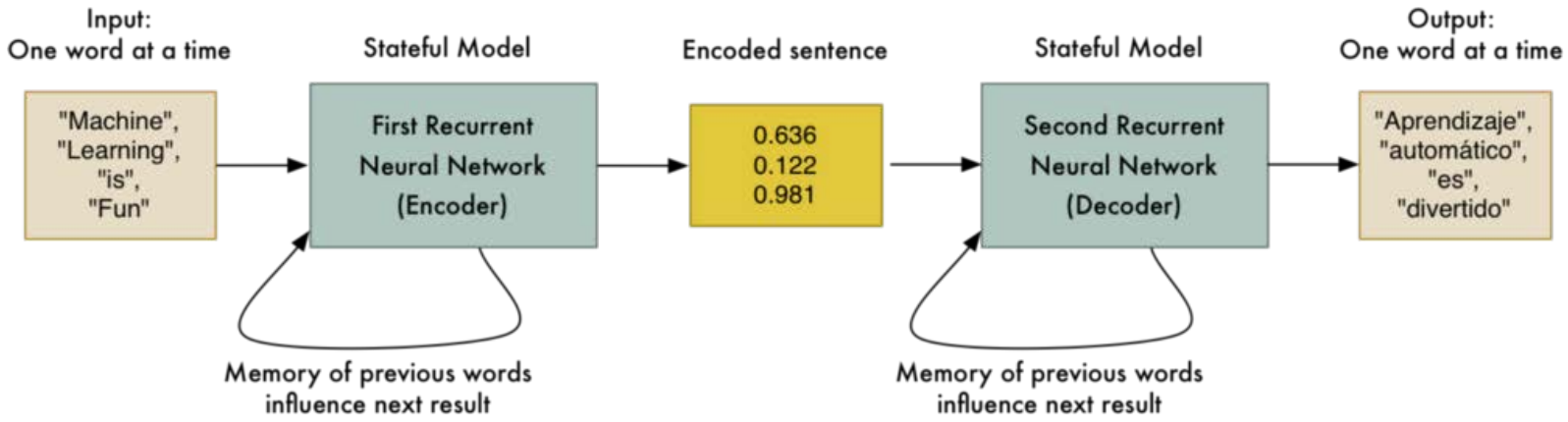


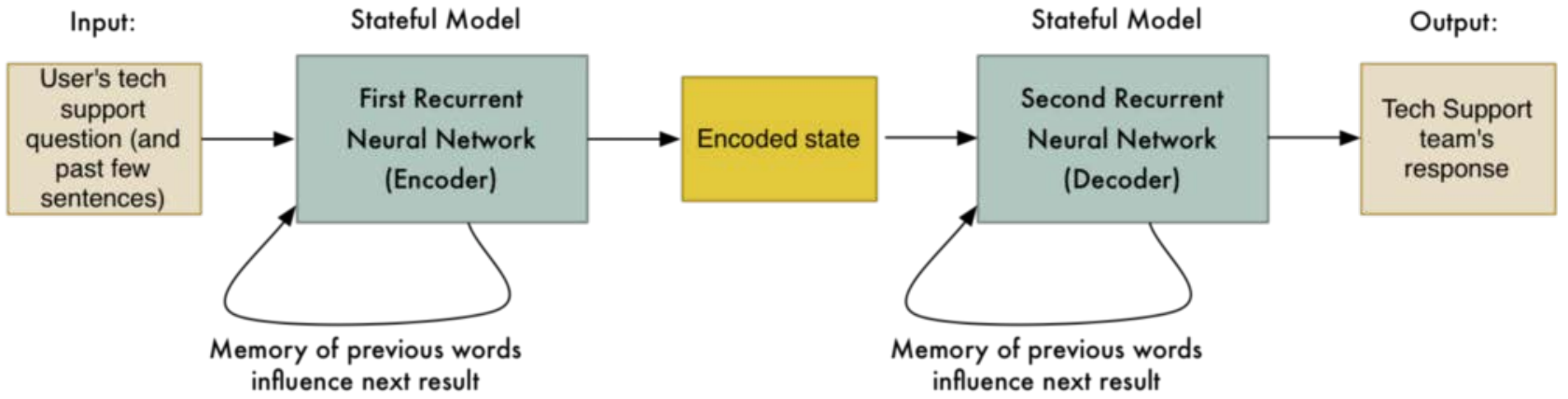
Output so far:

Machine

Source: Adam Geitgey

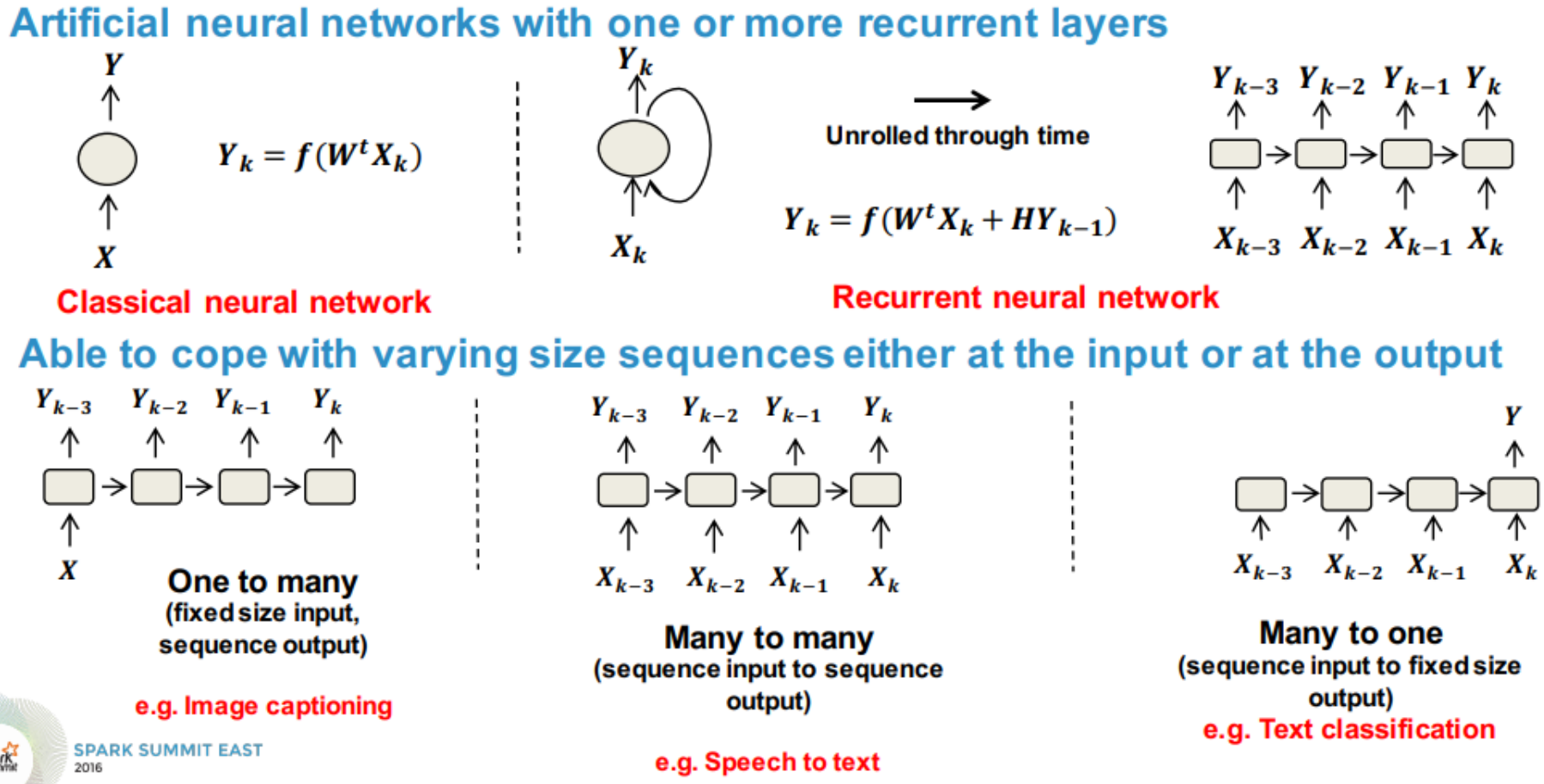
Sequence-to-Sequence





Source: [Adam Geitgey]

Fixed-to-Sequence, Sequence-to-fixed



Source: [Yves Mabiala]

Image + Text: Dense Captioning

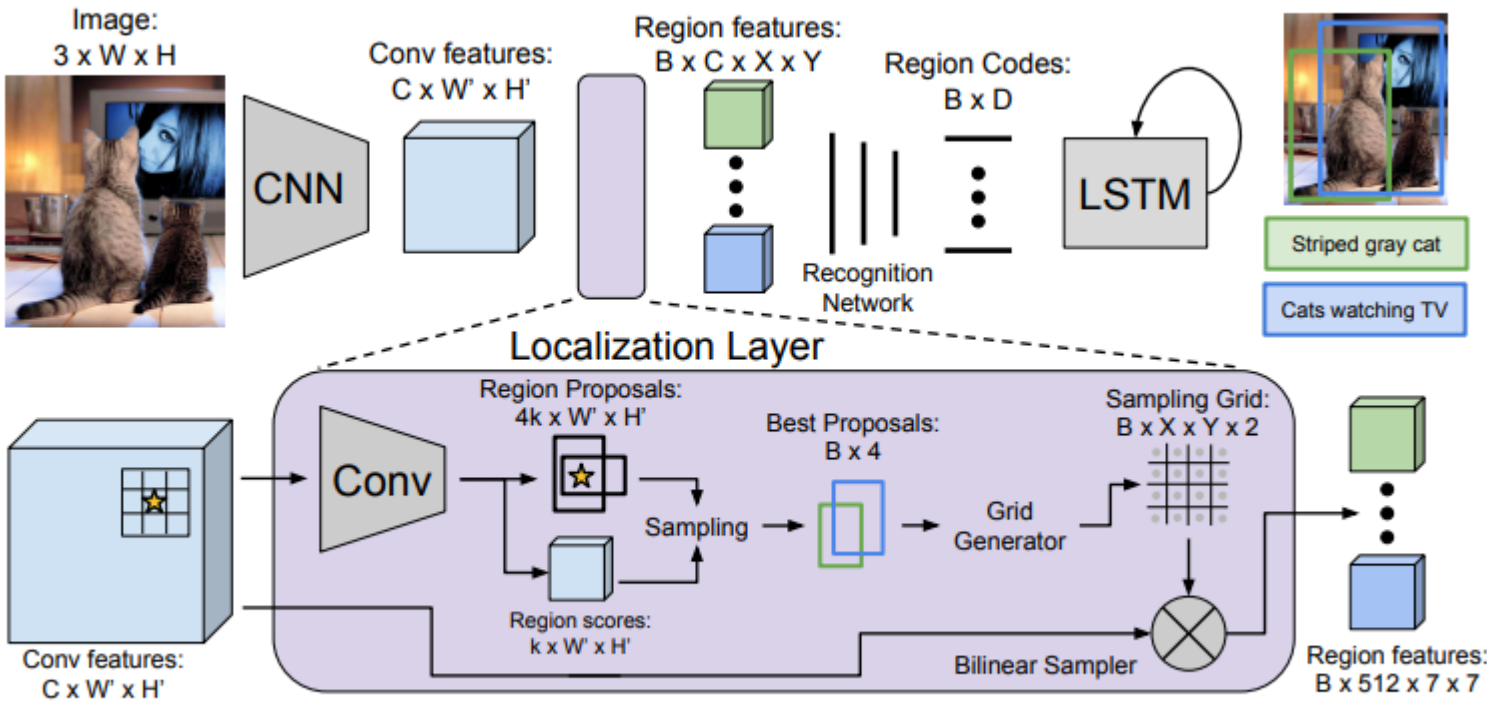


Figure 2. Model overview. An input image is first processed a CNN. The Localization Layer proposes regions and smoothly extracts a batch of corresponding activations using bilinear interpolation. These regions are processed with a fully-connected recognition network and described with an RNN language model. The model is trained end-to-end with gradient descent.

Source: https://arxiv.org/pdf/1511.07571.pdf

Recurrent Unit (Cell)

Stores state

Information from previous step(s)

In practice

Long **S**hort **T**erm **M**emory,

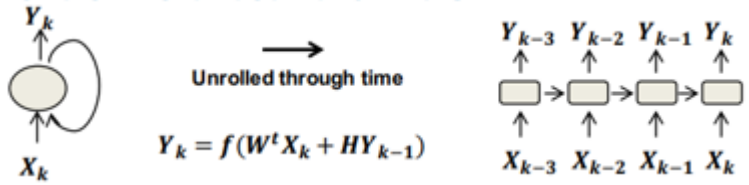
Gated **R**ecurrent **U**nit

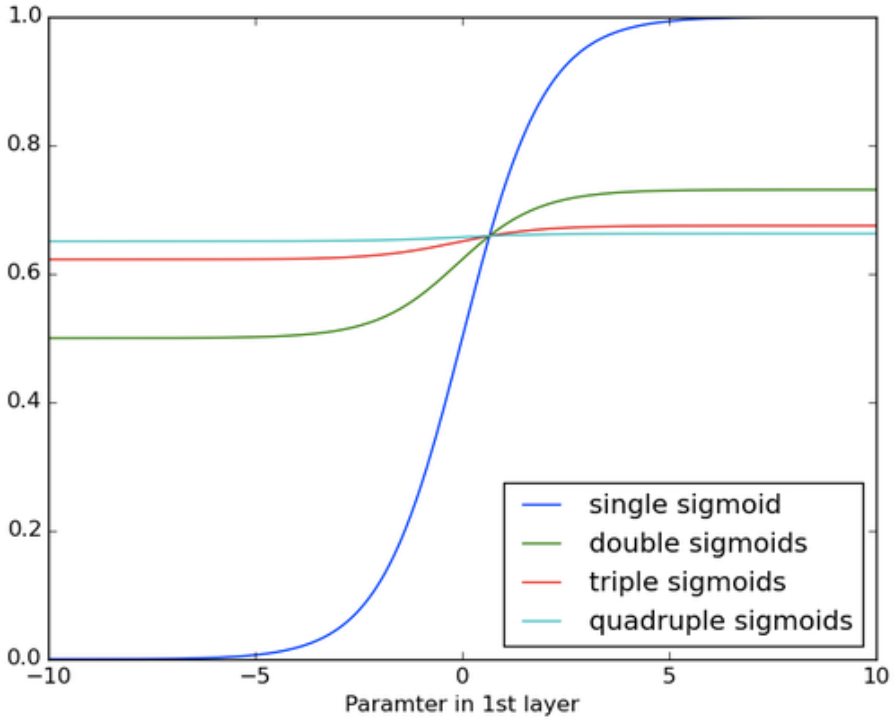
```
rnn = RNN()
y = rnn.step(x) # x: input, y: output
```

```
class RNN:
  def step(self, x):
    # update h, the hidden state
    self.h = np.tanh(np.dot(self.W_hh,
                            self.h) + np.dot(self.W_xh, x))
    # compute the output vector
    y = np.dot(self.W_hy, self.h)
    return y
```

Source: Andrej Karpathy

Vanishing / Exploding Gradient Problem





Source: [deeplearning4j]

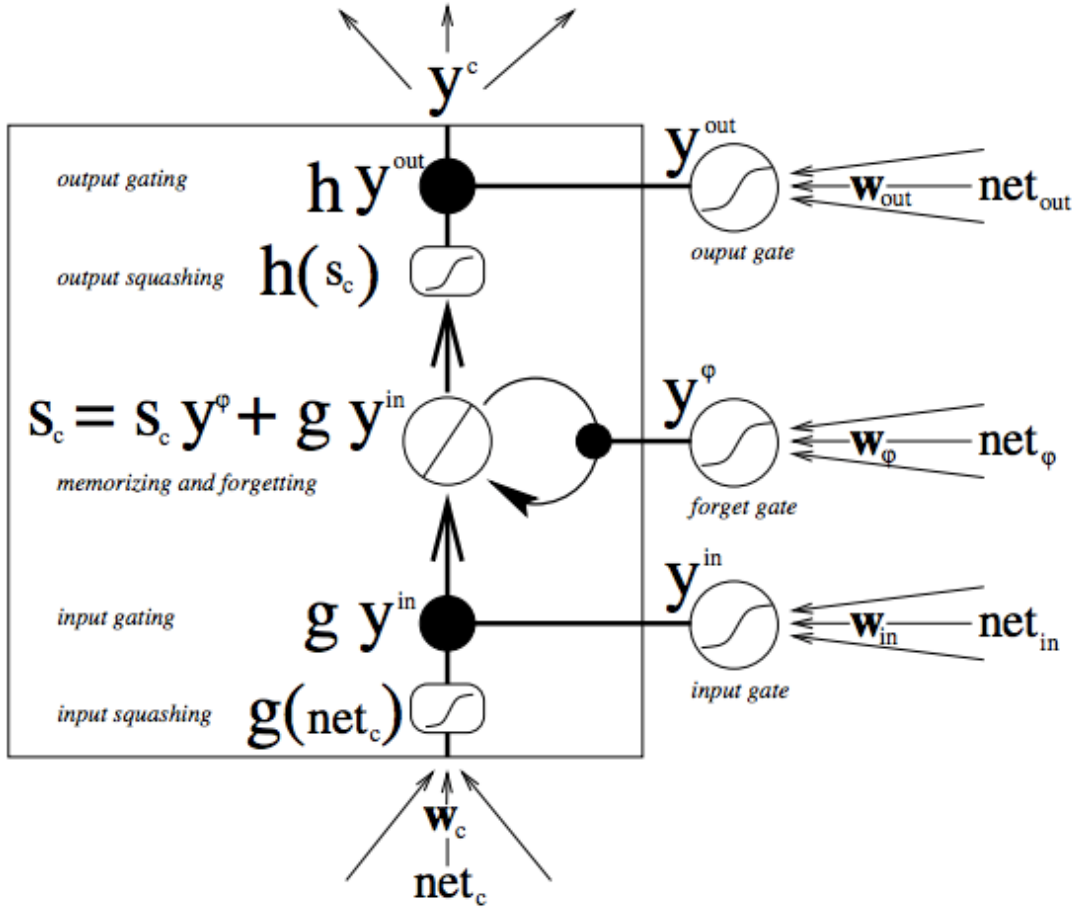
Long Short Term Memory

3 sigmoid “logic gates”

- input gate, forget gate, output gate
- weights (*w*) filter what to forget or remember

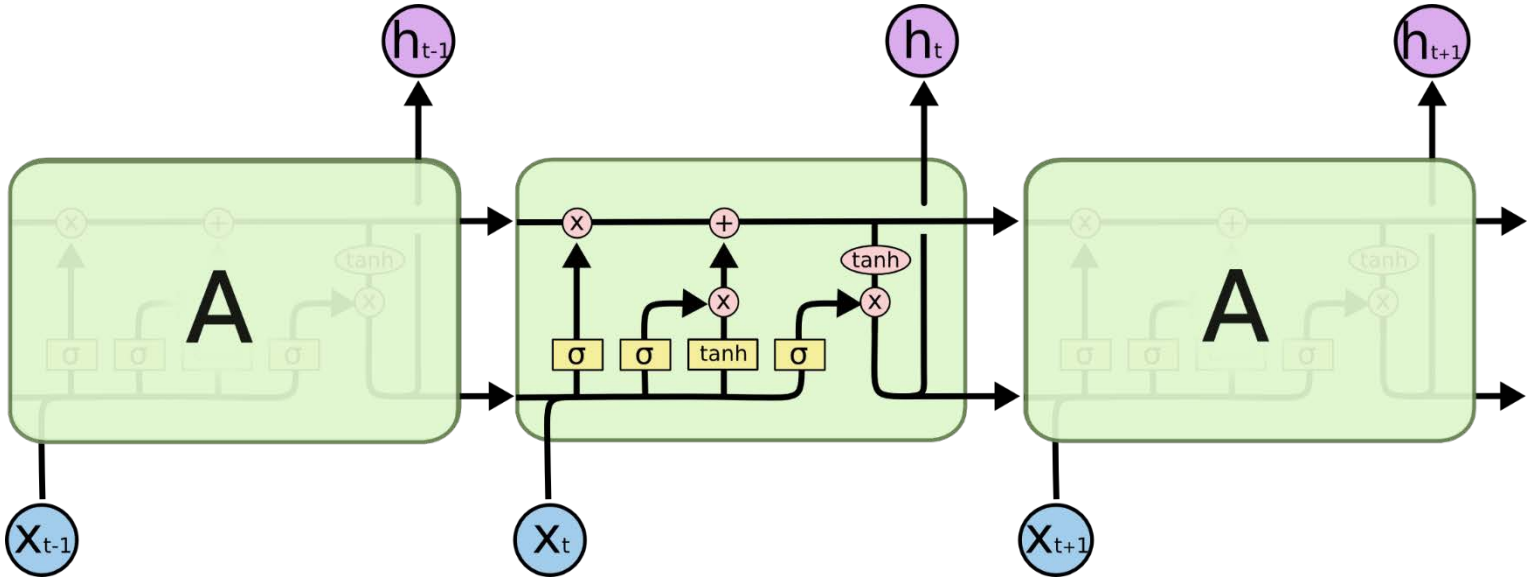
Memory unit

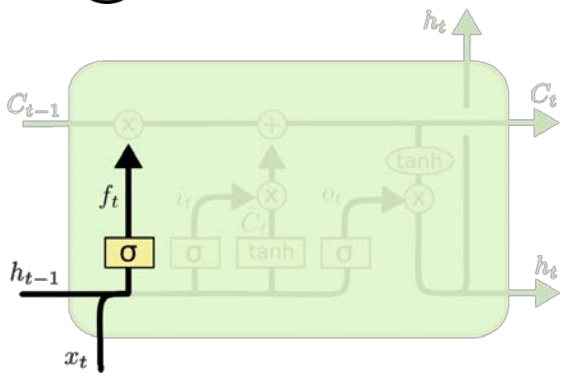
- Partially forgets existing memory, adds new memory
- No vanishing gradient



Source: deeplearning4j.org

Repeating over time





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

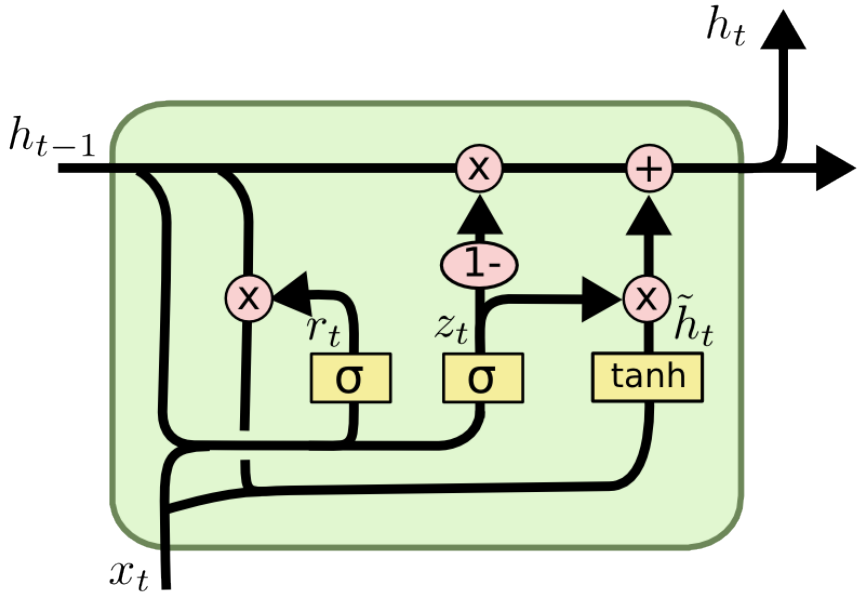
Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit

2 sigmoid “logic gates”

- reset gate (r), update gate (z)

No memory unit



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

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

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

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

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

GRU vs. LSTM

When to use GRU vs. LSTM

- GRU: simpler, faster to train, needs less data
- GRU: is newer research
- LSTM should work better with longer sequences

- First try GRU
- If lots of data, use LSTM too

			performance	lr	hidden	batch	sentLen	filter_size	margin
TextC	SentiC (acc)	CNN	82.38	0.2	20	5	60	3	–
		GRU	**86.32**	0.1	30	50	60	–	–
		LSTM	84.51	0.2	20	40	60	–	–
	RC (F1)	CNN	68.02	0.12	70	10	20	3	–
		GRU	**68.56**	0.12	80	100	20	–	–
		LSTM	66.45	0.1	80	20	20	–	–
SemMatch	TE (acc)	CNN	77.13	0.1	70	50	50	3	–
		GRU	**78.78**	0.1	50	80	65	–	–
		LSTM	77.85	0.1	80	50	50	–	–
	AS (MAP & MRR)	CNN	**(63.69,65.01)**	0.01	30	60	40	3	0.3
		GRU	(62.58,63.59)	0.1	80	150	40	–	0.3
		LSTM	(62.00,63.26)	0.1	60	150	45	–	0.1
	QRM (acc)	CNN	**71.50**	0.125	400	50	17	5	0.01
		GRU	69.80	1.0	400	50	17	-	0.01
		LSTM	71.44	1.0	200	50	17	-	0.01
SeqOrder	PQA (hit@10)	CNN	54.42	0.01	250	50	5	3	0.4
		GRU	**55.67**	0.1	250	50	5	–	0.3
		LSTM	55.39	0.1	300	50	5	–	0.3
ContextDep	POS tagging (acc)	CNN	94.18	0.1	100	10	60	5	–
		GRU	93.15	0.1	50	50	60	–	–
		LSTM	93.18	0.1	200	70	60	–	–
		Bi-GRU	94.26	0.1	50	50	60	–	–
		Bi-LSTM	**94.35**	0.1	150	5	60	–	–

Table 1: Best results or CNN, GRU and LSTM in NLP tasks

Source: Wenpeng Yin et al.

Hyperparameters: tuning

General: https://cs231n.github.io/neural-networks-3

- RNNs have higher risk of overfitting

RNNs for text: https://arxiv.org/abs/1707.06799

- Choice of word embeddings
- Optimizers: Adam, Nadam, RMSProp
- Dropout: on both output and recurrent units
- Gradient normalization: better performance, avoid exploding gradient