Lecture Notes for

Machine Learning in Python

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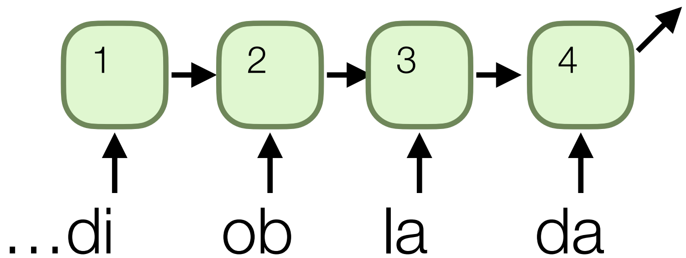
Lecture: RNN Demo

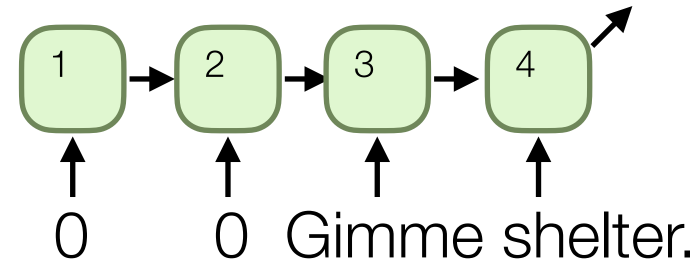
Lecture Agenda

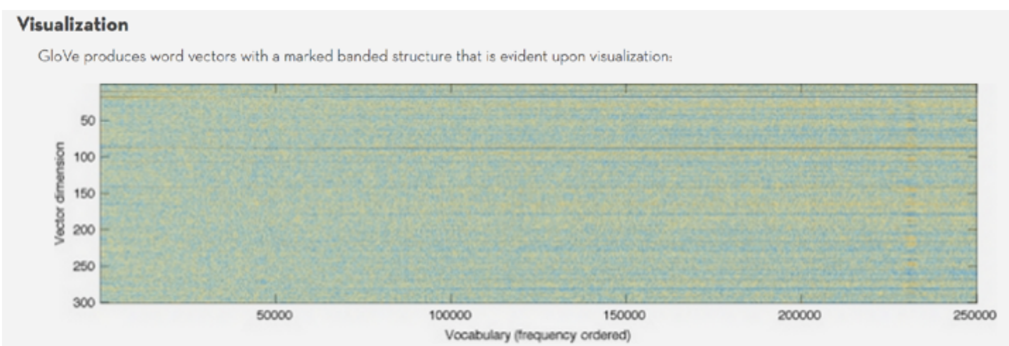
- Logistics
  - RNNs due **During Finals Time**
- Recurrent Networks
  - *Overview*
  - *Problem Types*
  - *Embeddings*
  - *Types of RNNs*
  - **Demo A**
  - **CNNs and RNNs**
  - **Demo B**
  - **Ethics Case Study**
  - **Course Retrospective**

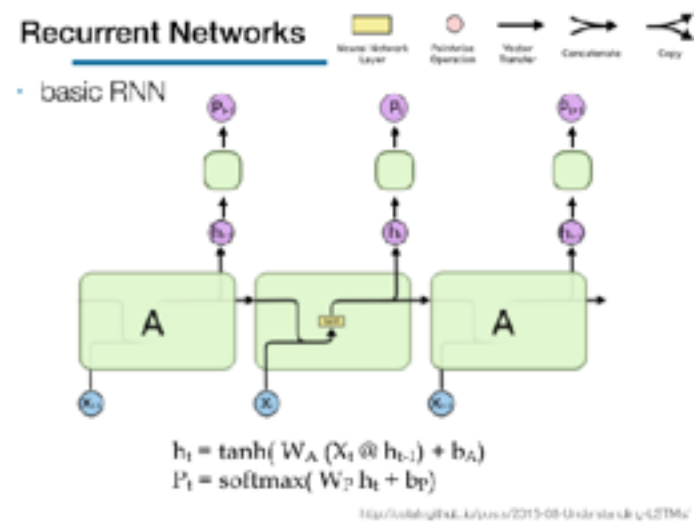
Last Time

- padding/clipping



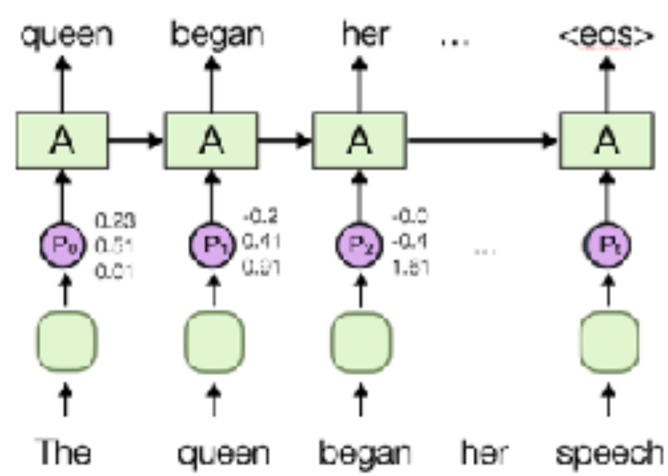






Self Test

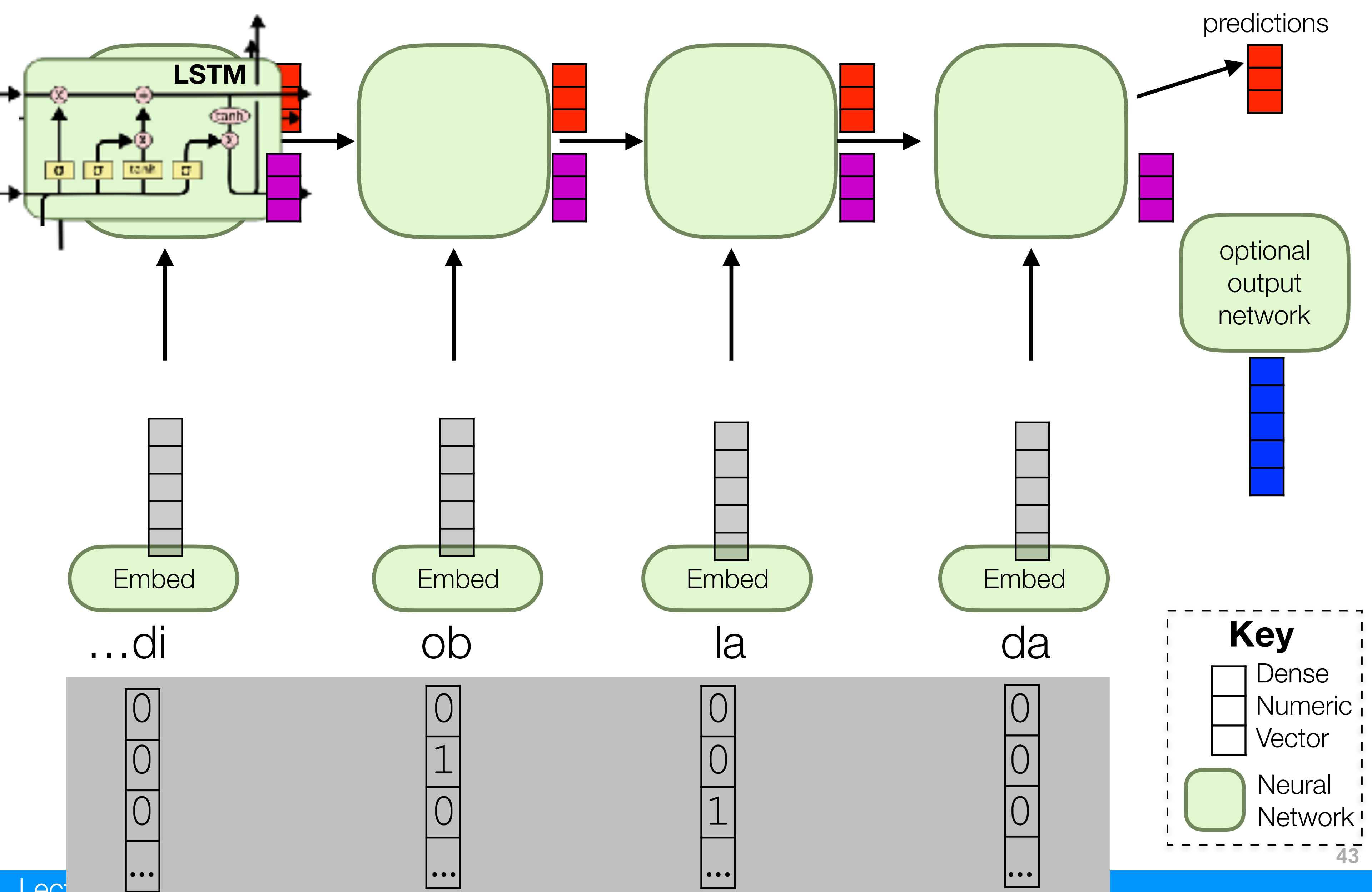
- T/F: In Recurrent Neural Networks that are “rolled out”, each RNN cell can be run in parallel.
  - A. **True**, state vectors can be added later
  - B. **True**, but parallelization must use forward backward (like Viterbi)
  - C. **False**, state vectors must be found sequentially
  - D. **False**, input changes due to sequential nature of X_t



Commonly Used RNN Nodes

I like this version better.

General recurrent flow (many to one)



Recurrent Networks: GRUs

- gated recurrent units

Selectivity controls, gates (**0 or 1**)

$$r_t = \sigma(W_r \boxed{s_{t-1}} + U_r \boxed{x_t} + b_r)$$

$$z_t = \sigma(W_z \boxed{s_{t-1}} + U_z \boxed{x_t} + b_z)$$

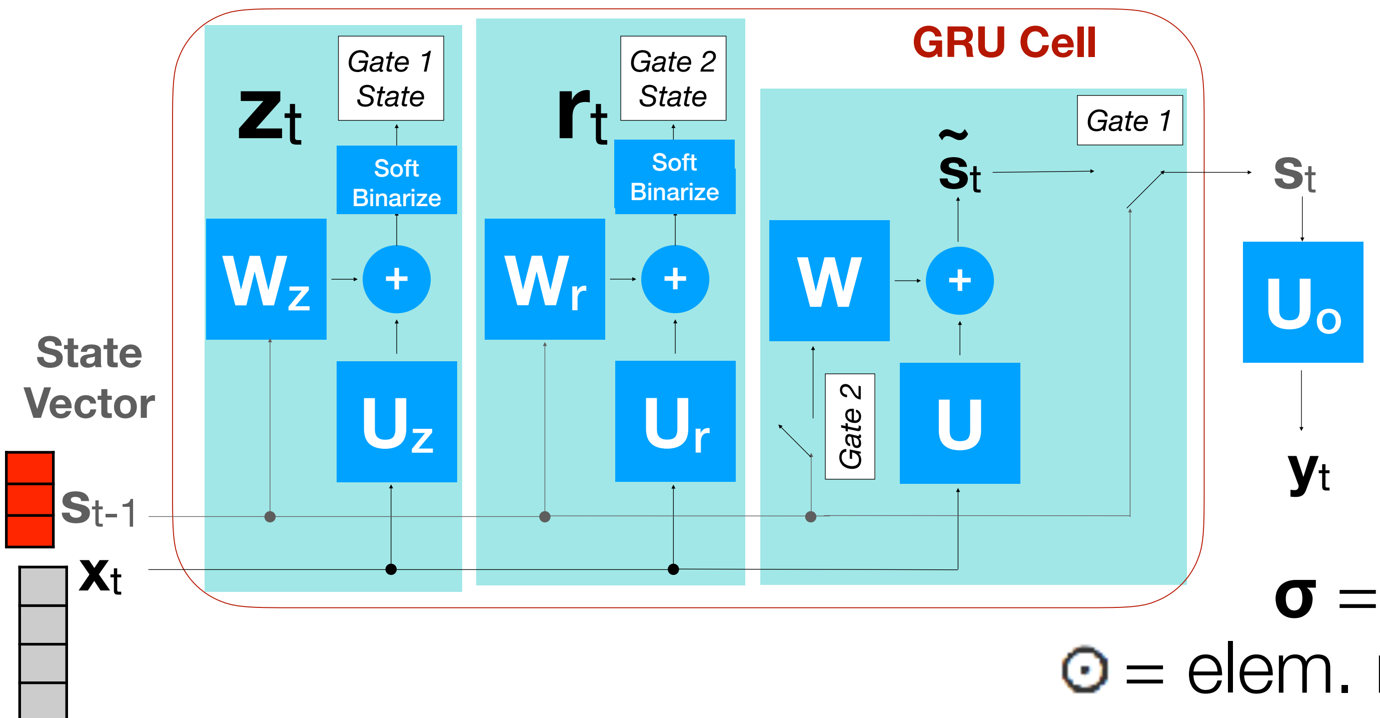
past state   current input

selectively remember   with influence

$$\tilde{s}_t = \phi(\boxed{W(r_t \odot s_{t-1})} + \boxed{Ux_t} + b)$$

$$s_t = \boxed{z_t \odot s_{t-1}} + \boxed{(1 - z_t) \odot \tilde{s}_t}$$

remember only past   OR remember with input



σ = sigmoid

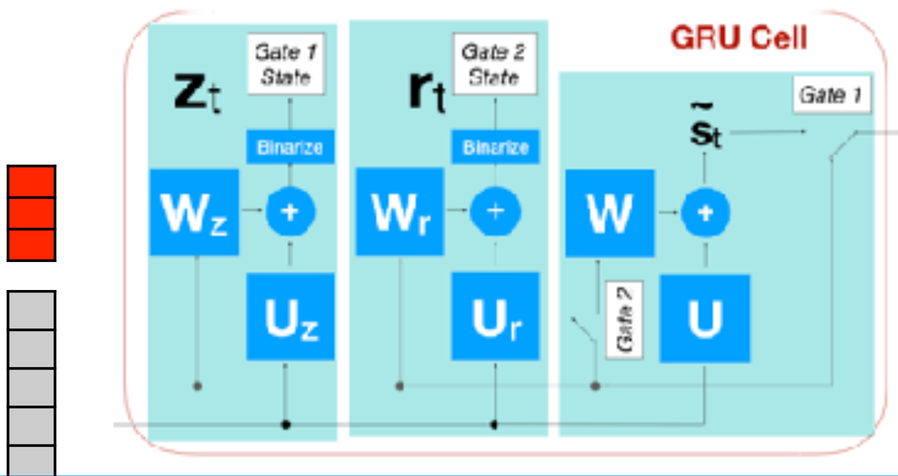
$\odot$ = elem. multiplication

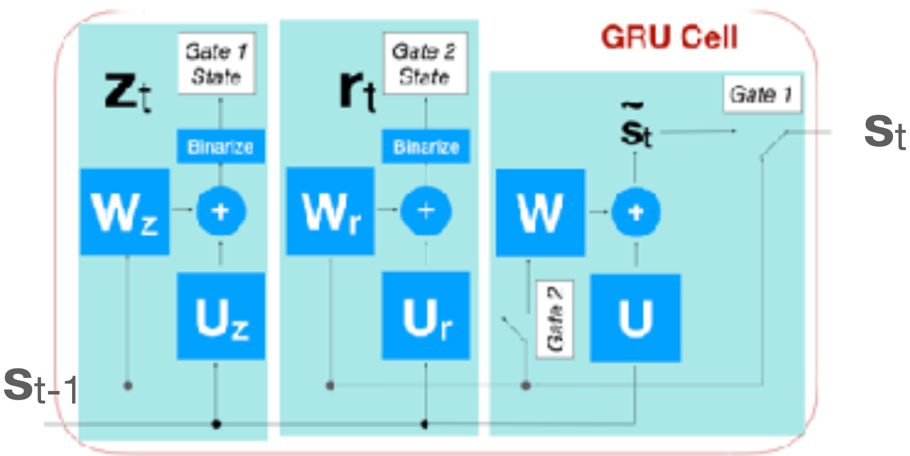
Self Test

- What element of the GRU helps with vanishing and exploding gradients?
- A. derivative of σ
- B. no activation function
- C. derivative of ϕ
- D. ϕ

$$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$$
$$z_t = \sigma(W_z s_{t-1} + U_z x_t + b_z)$$

$$\tilde{s}_t = \phi(W(r_t \odot s_{t-1}) + U x_t + b)$$
$$s_t = z_t \odot s_{t-1} + (1 - z_t) \odot \tilde{s}_t$$





$$r_t = \sigma(W_r s_{t-1} + U_r x_t + b_r)$$
$$z_t = \sigma(W_z s_{t-1} + U_z x_t + b_z)$$

$$\tilde{s}_t = \phi(W(r_t \odot s_{t-1}) + U x_t + b)$$
$$s_t = \boxed{z_t \odot s_{t-1}} + \boxed{(1 - z_t) \odot \tilde{s}_t}$$

Product Rule

Product Rule

To back propagate, we need sensitivity of state vector, w.r.t previous state

$$\partial s_t \,/\, \partial s_{t-1} = (\partial z_t \text{ x } s_{t-1}) + (\partial s_{t-1} \text{ x } z_t) + \partial \tilde{s}_t - (\partial z_t \text{ x } \tilde{s}_t) - (\partial \tilde{s}_t \text{ x } z_t)$$

likely vanish

could vanish, depending on ϕ

likely vanish

could vanish, depending on ϕ

hard to vanish unless $z_t = 0$

- LSTM prototype

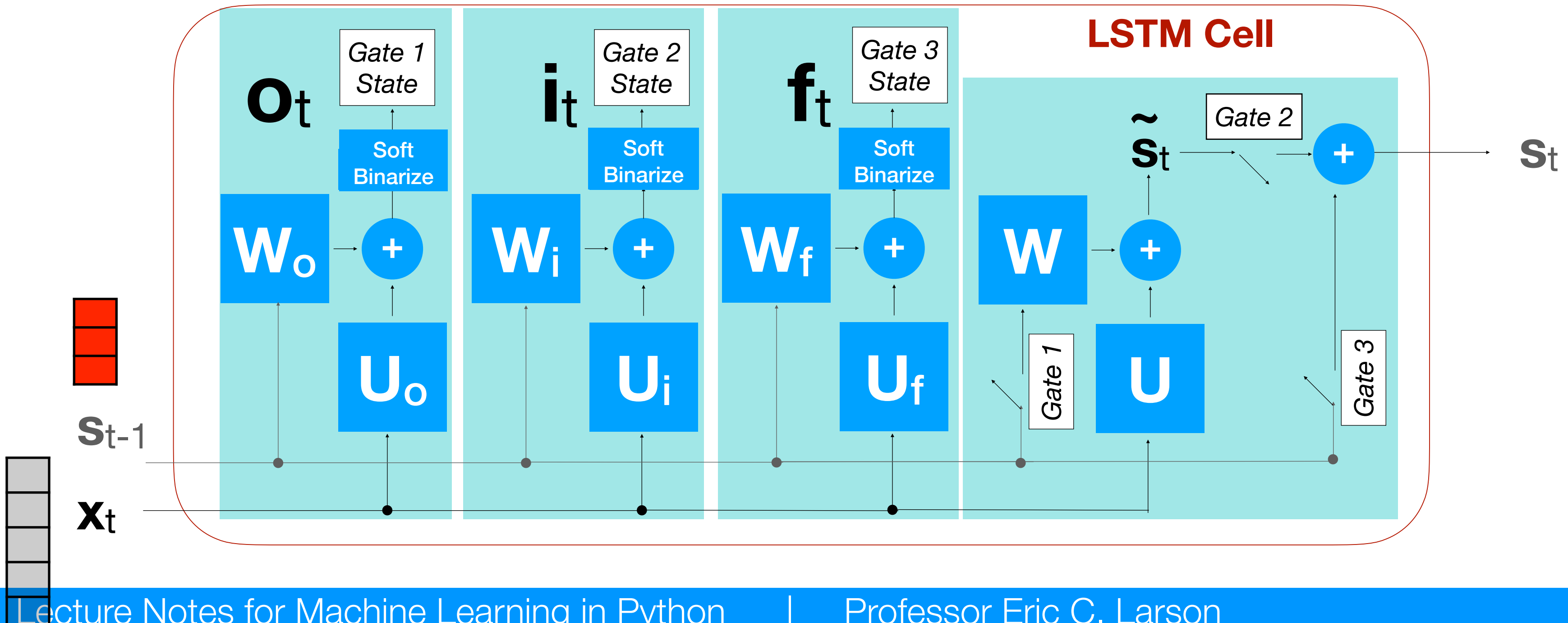
Selectivity controls (**gates, 0 or 1**)

$$o_t = \sigma(W_o s_{t-1} + U_o x_t + b_o)$$
$$i_t = \sigma(W_i s_{t-1} + U_i x_t + b_i)$$
$$f_t = \sigma(W_f s_{t-1} + U_f x_t + b_f)$$

selectively remember past — with influence

$$\tilde{s}_t = \phi(W\boxed{(o_t \odot s_{t-1})} + \boxed{U x_t + b})$$
$$s_t = \boxed{f_t \odot s_{t-1}} + \boxed{i_t \odot \tilde{s}_t}$$

selectively remember past — with past weighted influence



Recurrent Networks: Gen 2 LSTM

- LSTM in TensorFlow

Selectivity controls (**gates, 0 or 1**)

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i)$$
$$o_t = \sigma(W_o h_{t-1} + U_o x_t + b_o)$$
$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f)$$

explicit remembering state

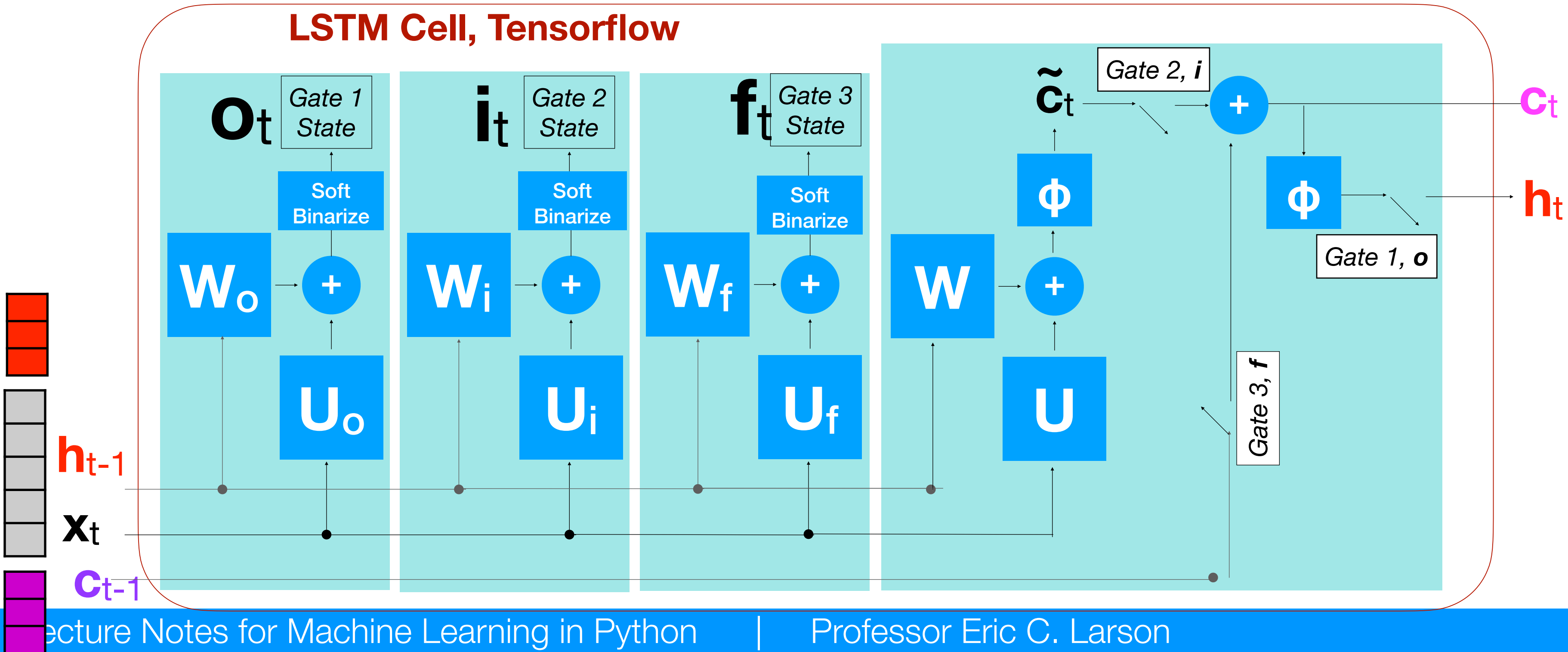
$$\tilde{c}_t = \phi(W h_{t-1} + U x_t + b)$$
$$c_t = \boxed{f_t \odot c_{t-1}} + \boxed{i_t \odot \tilde{c}_t}$$

remember previous state

update with output, h_t

$$h_t = \boxed{o_t \odot \phi(c_t)}$$

get next ht for selecting gates



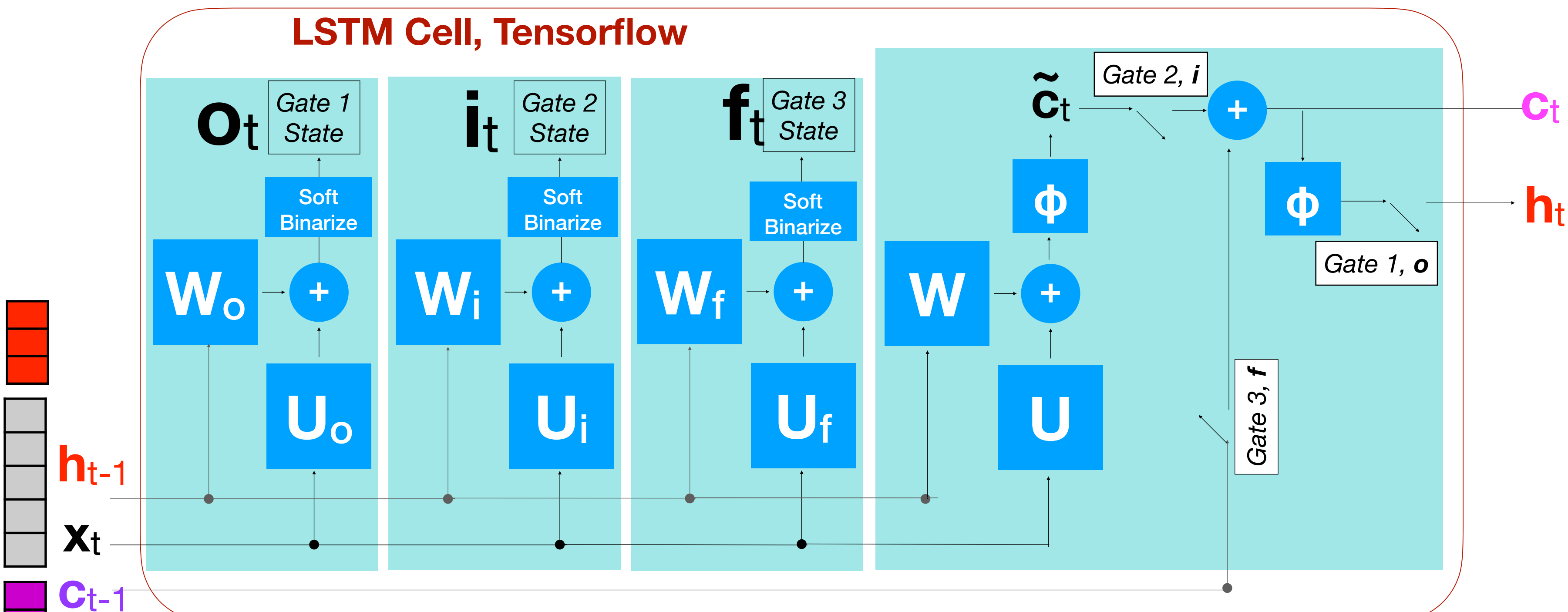
LSTM Dropout

$$
\begin{aligned}
i_t &= \sigma(W_i h_{t-1} + U_i x_t + b_i) \\
o_t &= \sigma(W_o h_{t-1} + U_o x_t + b_o) \\
f_t &= \sigma(W_f h_{t-1} + U_f x_t + b_f)
\end{aligned}
$$

Recurrent Dropout

Input Dropout

The days of training **without** using **dropout** are **over**.



What to choose?

- There is no hard and fast rule
  - try both
  - basic LSTM has had great success
  - GRU also sometimes is easier to train
  - you will see many variations
    - peephole LSTM
    - hierarchical LSTM
    - and many more…

Final Demo - Part A

Many to one:

- Simple RNNs
- GRUs
- LSTMs

More examples:

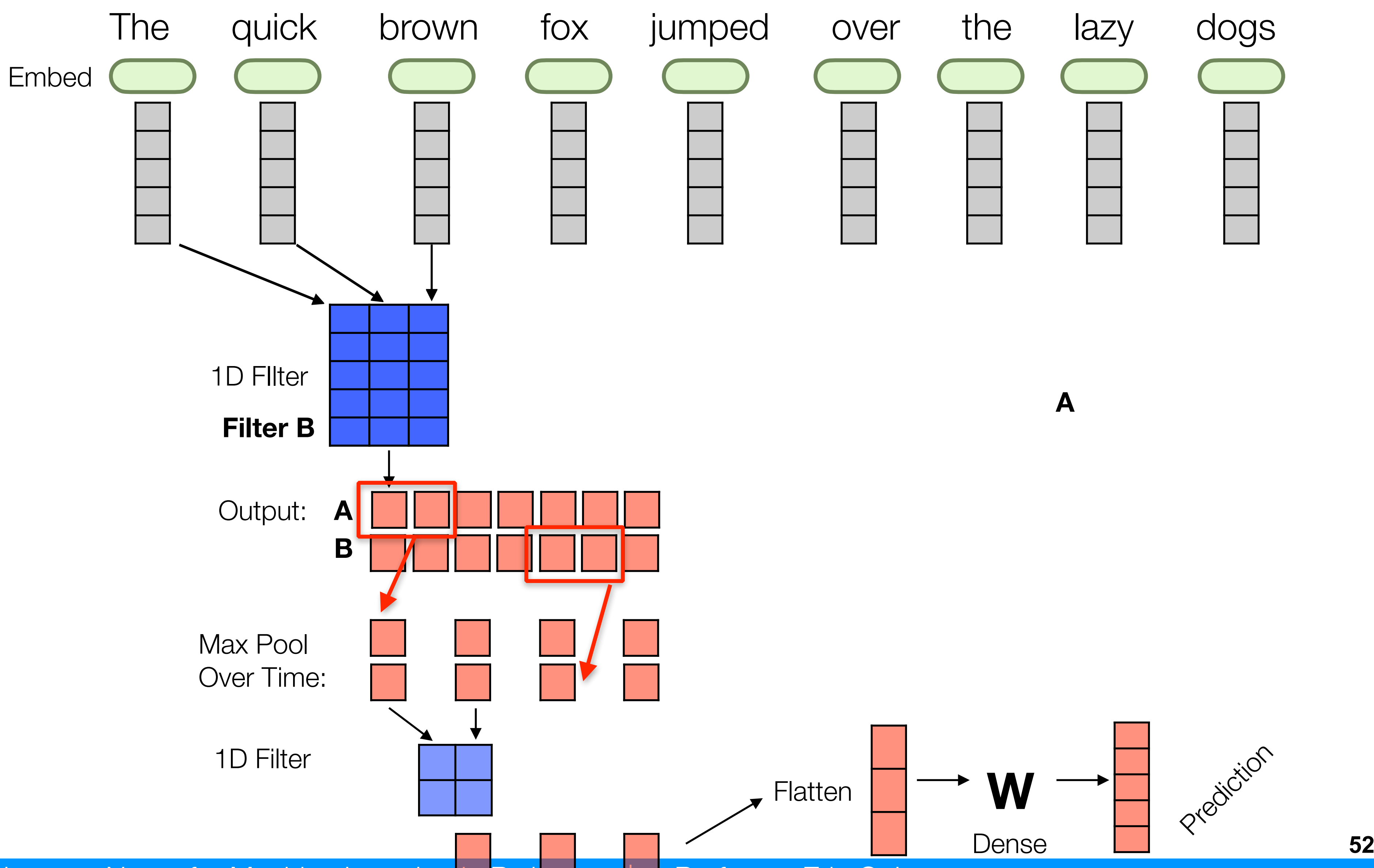
https://github.com/tensorflow/tensorflow/tree/r0.11/tensorflow/examples/skflow
http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html
http://machinelearningmastery.com/sequence-classification-lstm-recurrent-neural-networks-python-keras/

Seq2Seq:

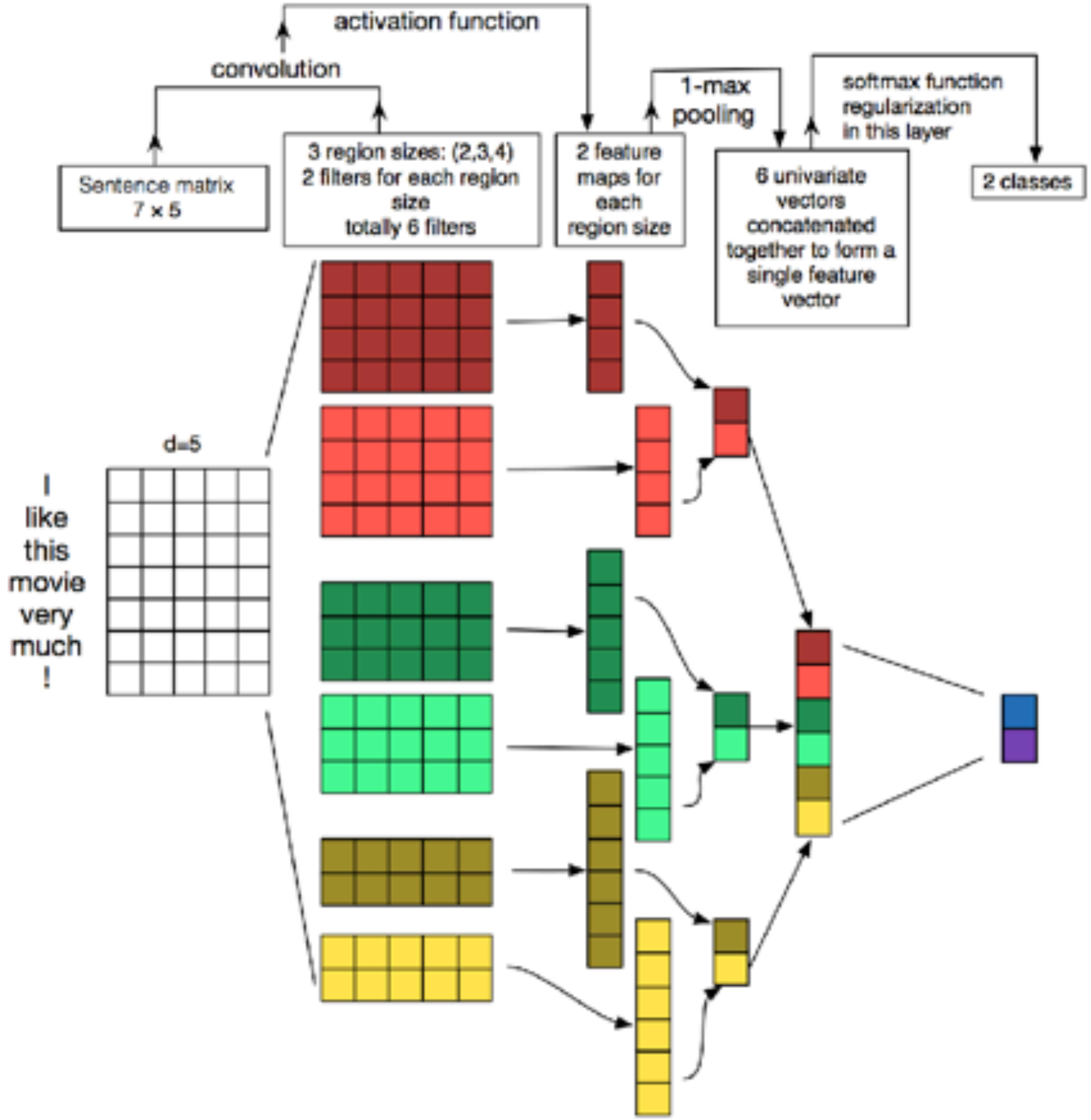
https://github.com/tensorflow/tensorflow/blob/r0.11/tensorflow/examples/skflow/neural_translation_word.py

CNNs and RNNs

is an RNN similar to a CNN?



CNNs with Multiple Region Sizes



http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/

Demo - Part B

Back to the CNN

More examples:

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Seq2Seq:

https://github.com/tensorflow/tensorflow/blob/r0.11/tensorflow/examples/skflow/neural_translation_word.py