Lecture Notes for

Machine Learning in Python

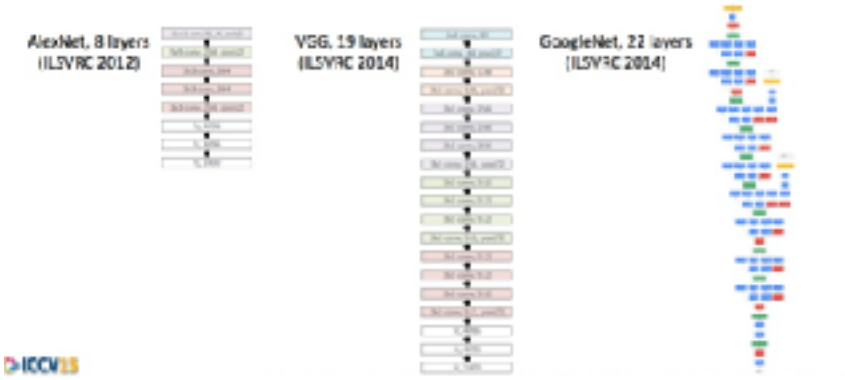
Professor Eric Larson

Demonstration of More Advanced Convolutional Neural Networks

Class logistics and Agenda

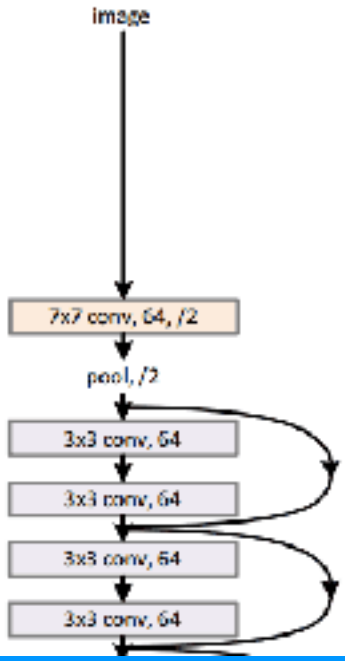
- CNNs due next week
- Agenda:
  - More Advanced CNN Demo
  - CNN Town Hall
  - Introduction to RNNs

Last Time:



ResNet, 152 layers
(ILSVRC 2015)

34-layer residual



Demo

Even more Convolutional
Neural Networks
…in TensorFlow
…with Keras

`12. More Advanced CNN Techniques.ipynb`

CNN Town Hall

Verification is getting out of hand…

- And then:
  - Intro to Recurrent Neural Network Architectures

Lecture Notes for

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History and Introduction to Recurrent Neural Networks

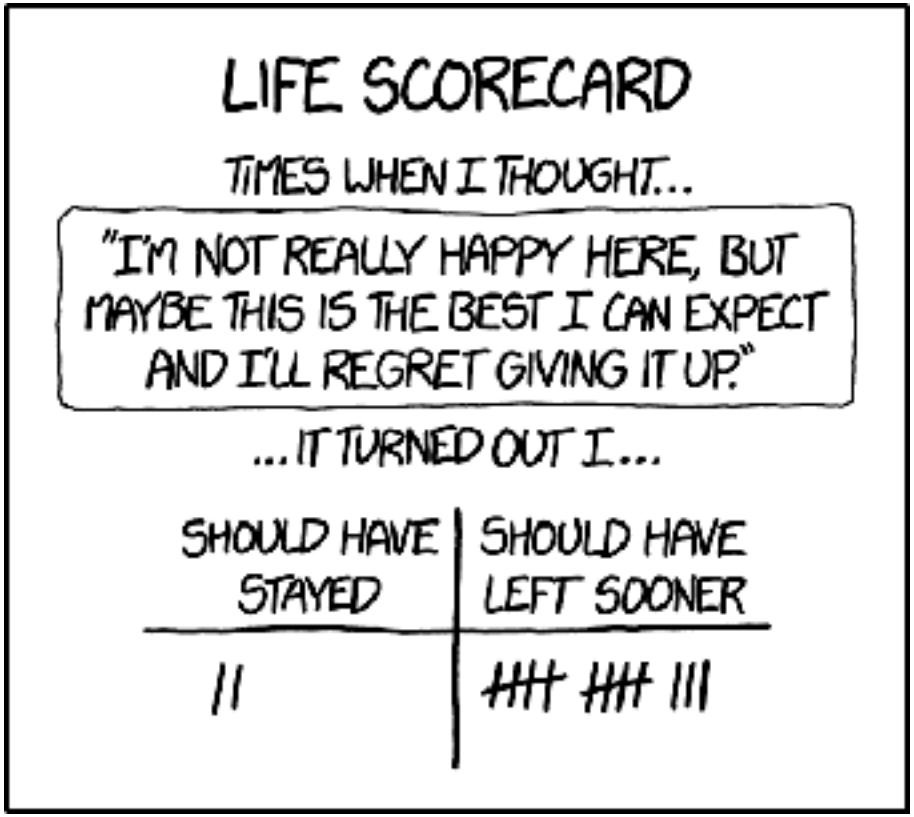
Agenda

- Intro to Recurrent Neural Network Architectures
  - RNNs, GRUs, LSTMs
  - Training for characters

Lecture Agenda

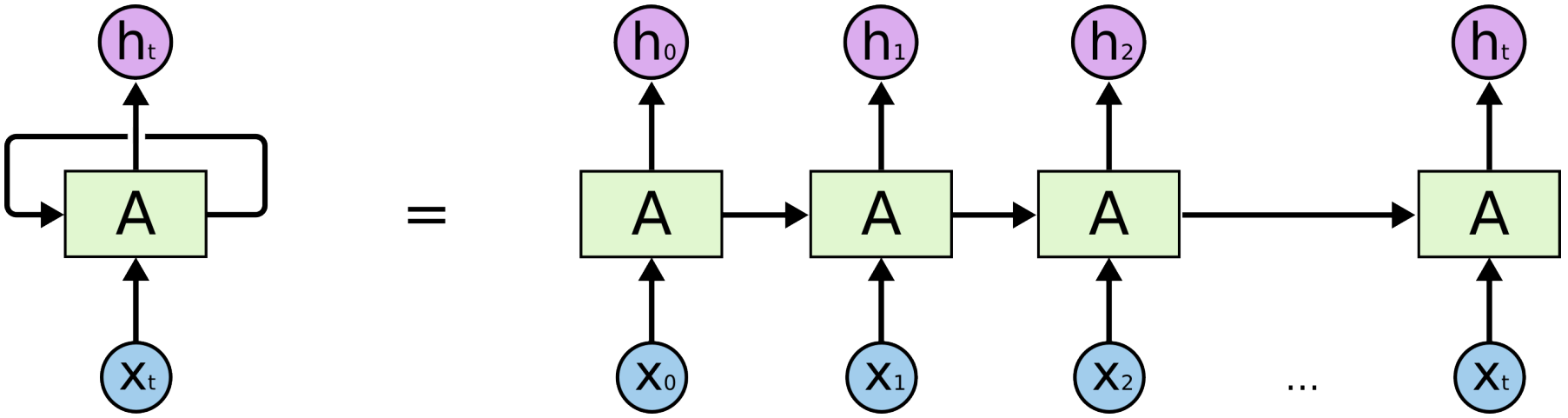
- Logistics
  - CNNs due!
  - RNNs due!
- Recurrent Networks (~three lecture agenda)
  - Overview
  - Problem Types
  - Embeddings
  - Types of RNNs
  - Demo A
  - CNNs and RNNs
  - Demo B
  - Modern RNN Architectures
  - Course Retrospective

History of Recurrent Neural Networks



Recurrent Networks: Main Idea

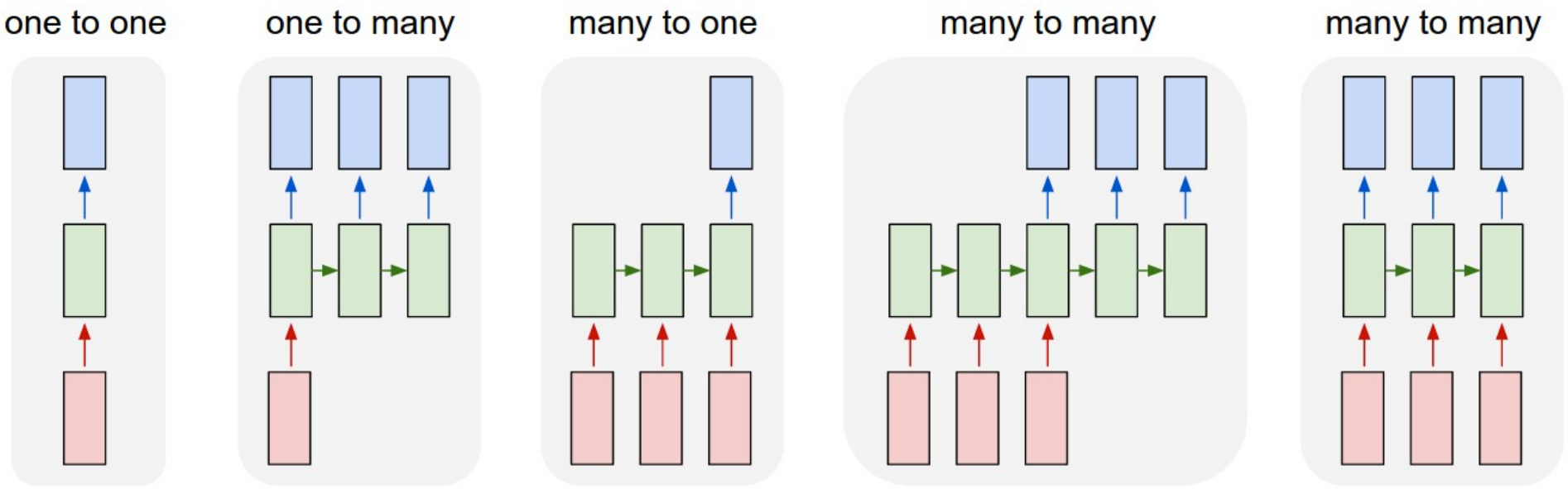
- equations for recurrent networks



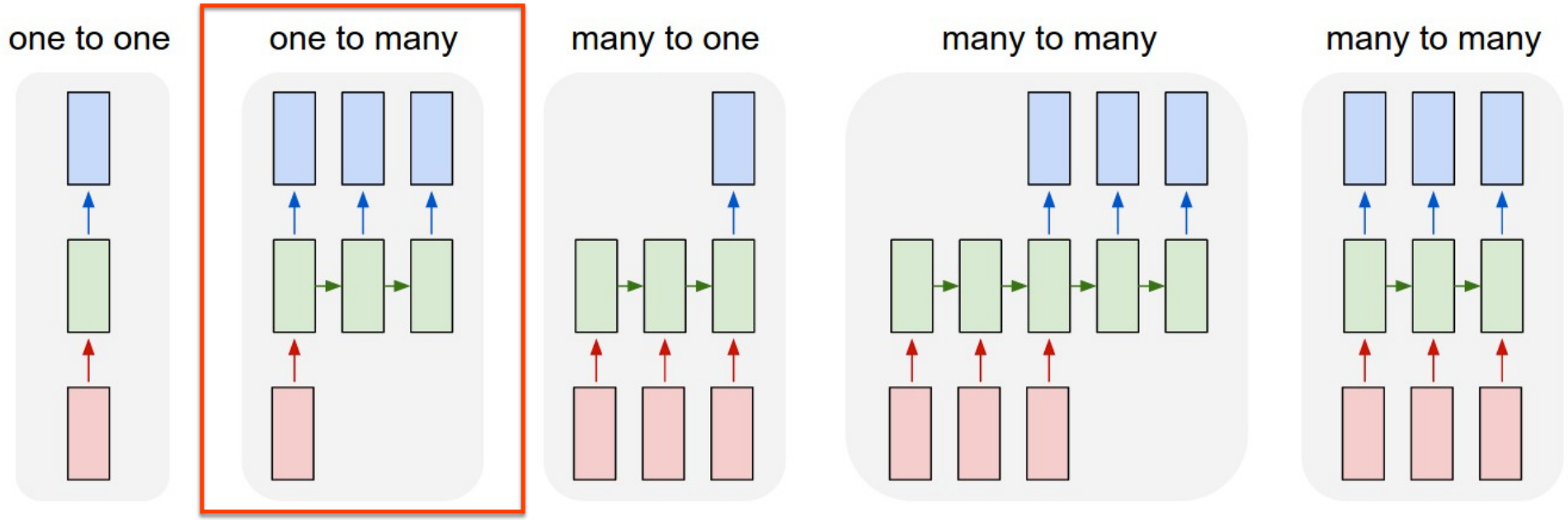
compact

unrolled

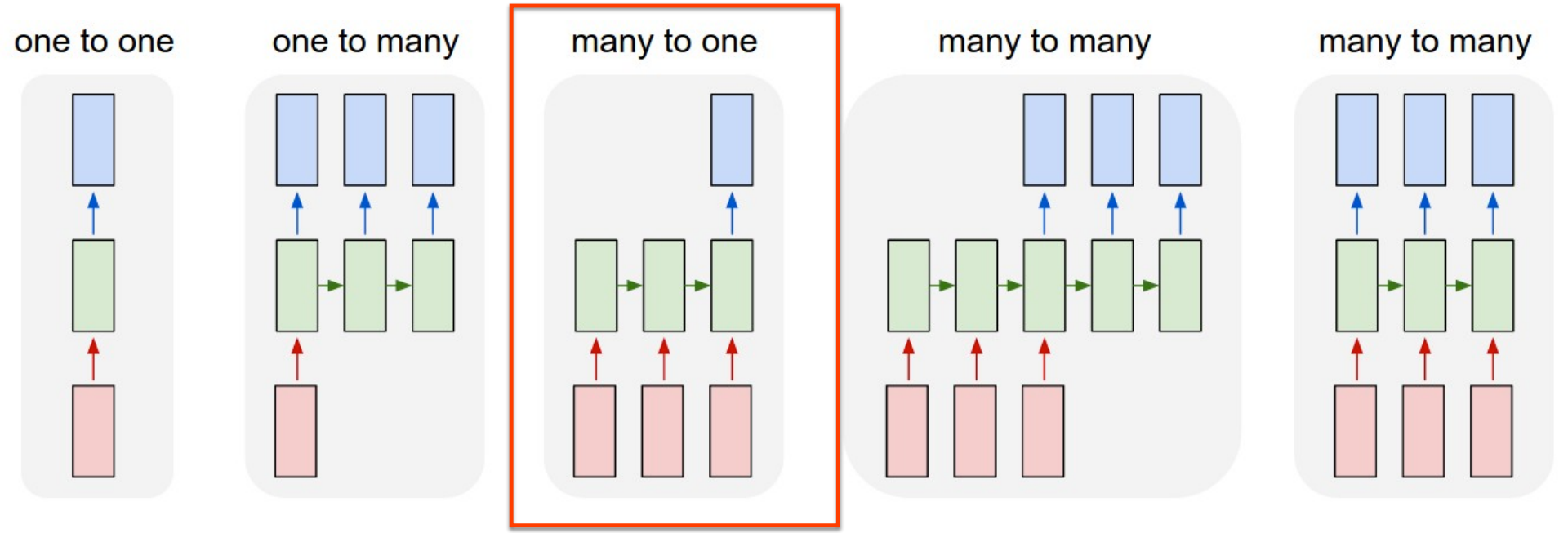
Recurrent Networks: Problem Types



Recurrent Networks: Problem Types



Recurrent Networks: Problem Types



The movie is great.

The movie stars Mr. X

The movie is horrible.

Recurrent Networks: Ontology

Eva Ingolf is a well known Icelandic violinist particularly recognized for her authoritative performances of solo works by J. S. Bach. She comes from a leading musical family and her father Ingólfur Guðbrandsson premiered many of the great choral works in Iceland and six of her sisters and brothers are professional musicians who have made an important contribution to the high quality of the musical life in the country.Eva Ingolf currently lives in New York City with her husband Kristinn Sv.

Artist

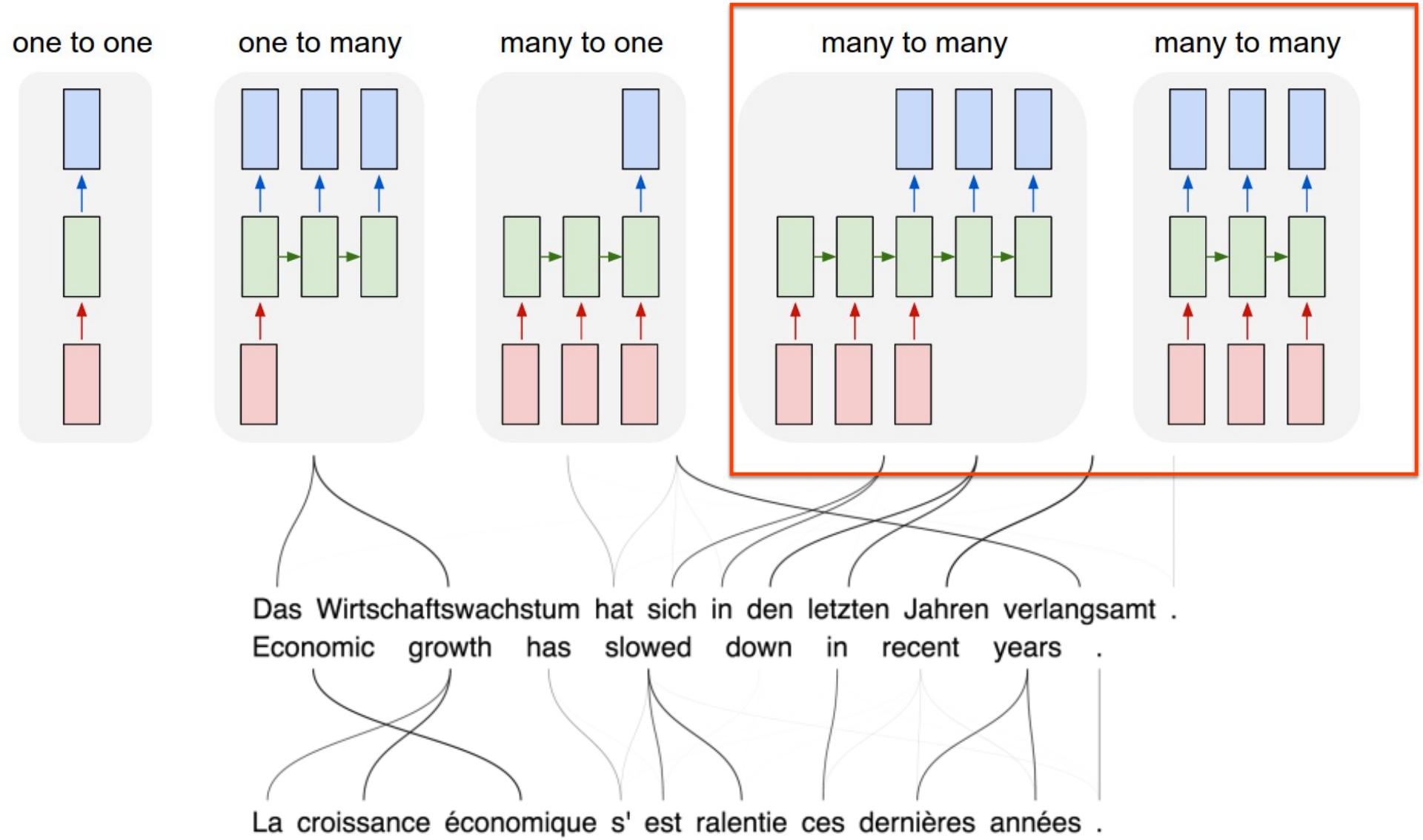
Shaun Norris (born 14 May 1982) is a South African professional golfer.Norris plays on the Sunshine Tour where he has won twice. He won the inaugural Africa Open in 2008 and the Nashua Masters in 2011. He also began playing on the European Tour in 2011 after graduating from qualifying school.

Athlete

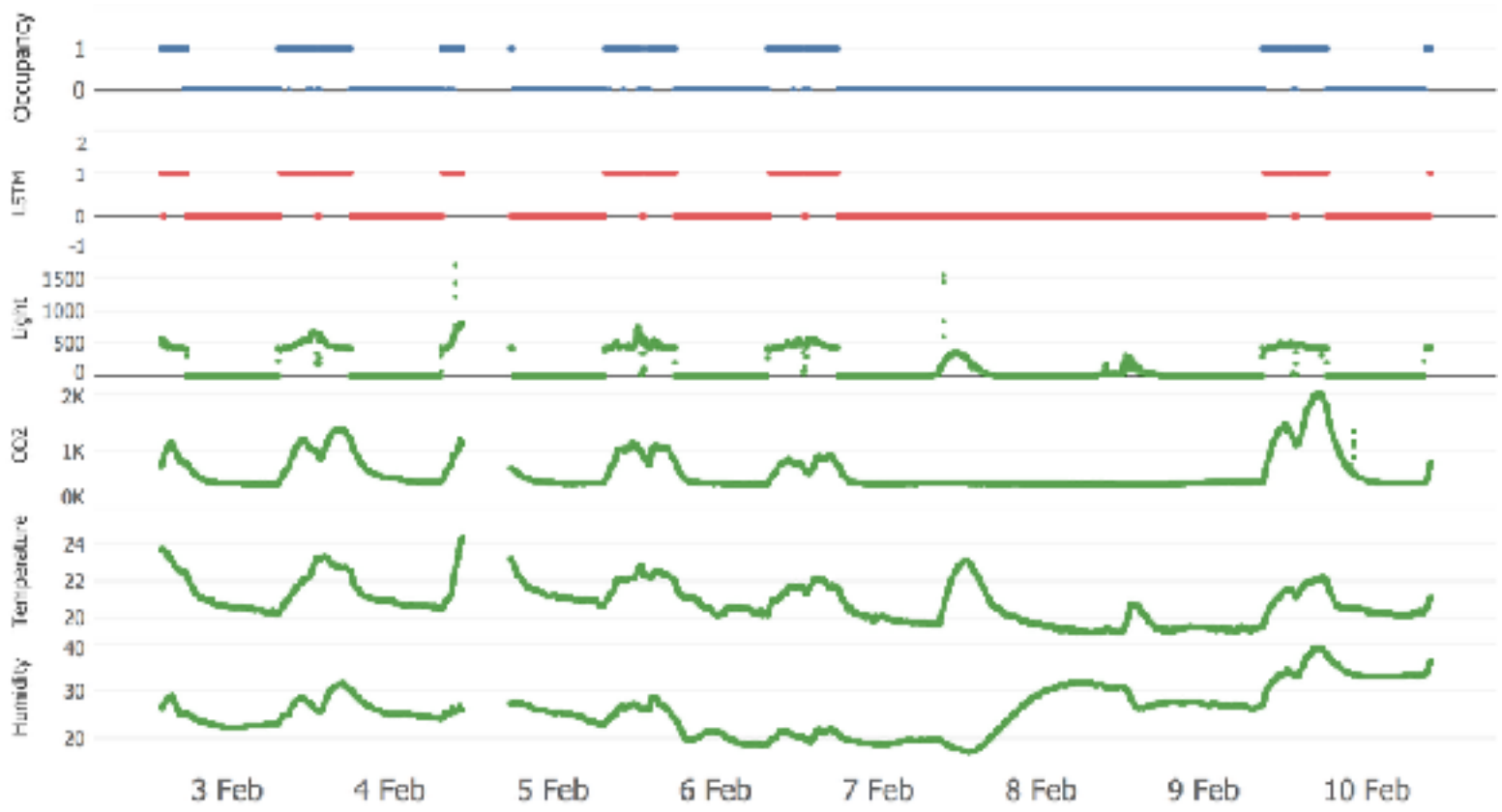
Palace Software was a British video game publisher and developer during the 1980s based in London England. It was notable for the Barbarian and Cauldron series of games for 8-bit home computer platforms in particular the ZX Spectrum Amstrad CPC and Commodore 64.

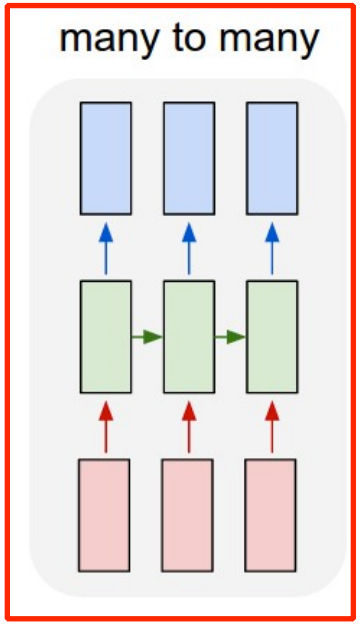
Company

Recurrent Networks: Problem Types



Recurrent Networks: Problem Types

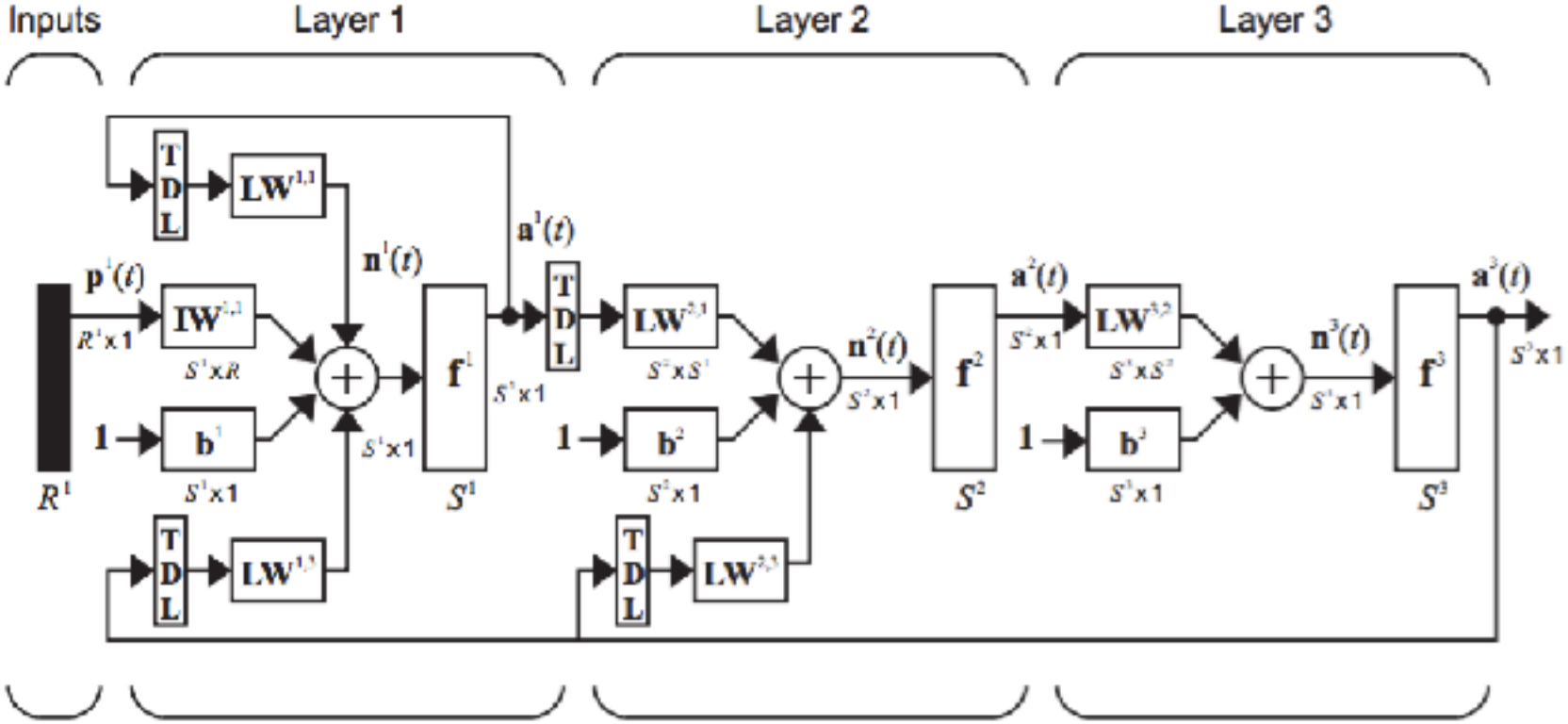




sequence to sequence

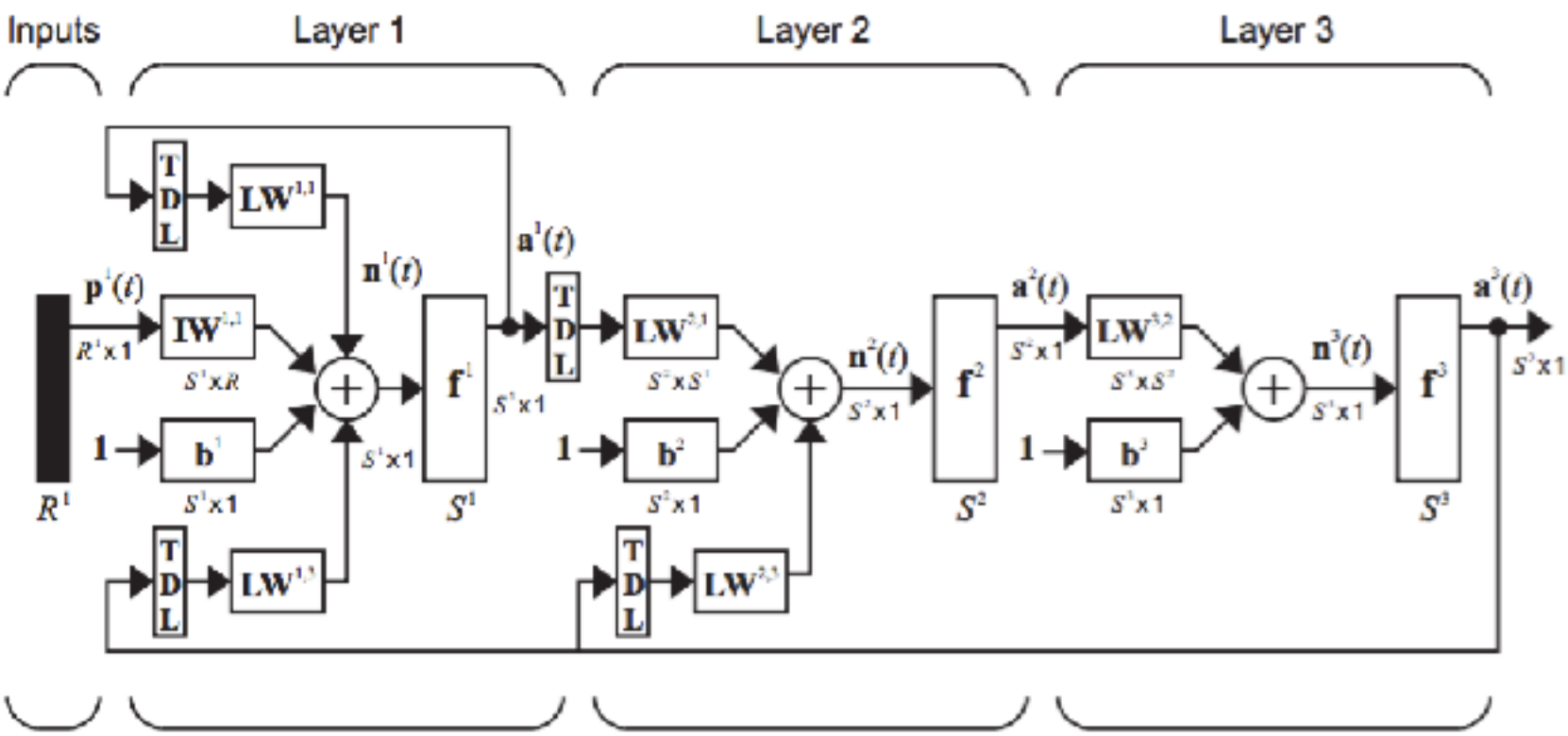
History of Recurrent Networks

- Dynamic Networks
  - can use current and previous inputs, in time
  - still popular, but simplified with discrete time steps
  - **been around for decades**



Neural Network Design, Hagan, Demuth, Beale, and De Jesus

An Exercise: Strategy for Back-prop?

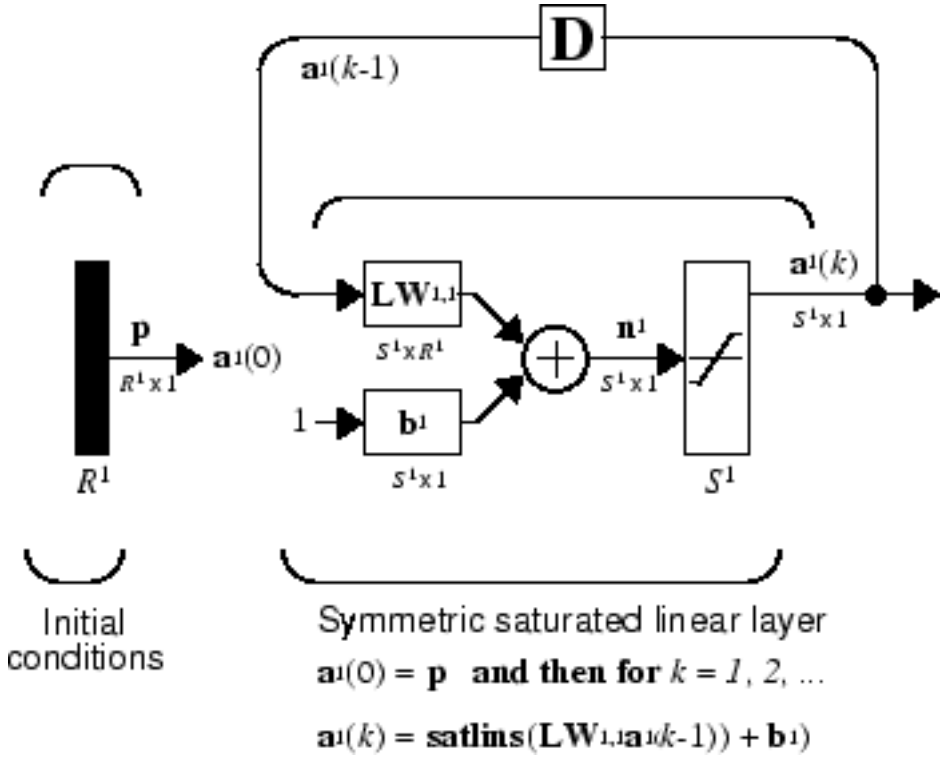


Neural Network Design, Hagan, Demuth, Beale, and De Jesus

History of Recurrent Networks

- Hopfield Network, 1982

John Hopfield, Princeton



Neural Network Design, Hagan, Demuth, Beale, and De Jesus

History of Recurrent Networks

- Elman/Jordan Networks, ~1988

Contribution:
Time Steps for Unrolling

Jeffrey Elman, UCSD

Michael Jordan, Berkeley

Elman network[10]

$$h_t = \sigma_h(W_h x_t + U_h h_{t-1} + b_h)$$
$$y_t = \sigma_y(W_y h_t + b_y)$$

Jordan network[11]

$$h_t = \sigma_h(W_h x_t + U_h y_{t-1} + b_h)$$
$$y_t = \sigma_y(W_y h_t + b_y)$$

Variables and functions

- x_t: input vector
- h_t: hidden layer vector
- y_t: output vector
- W, U and b: parameter matrices and vector
- σ_h and σ_y: Activation functions

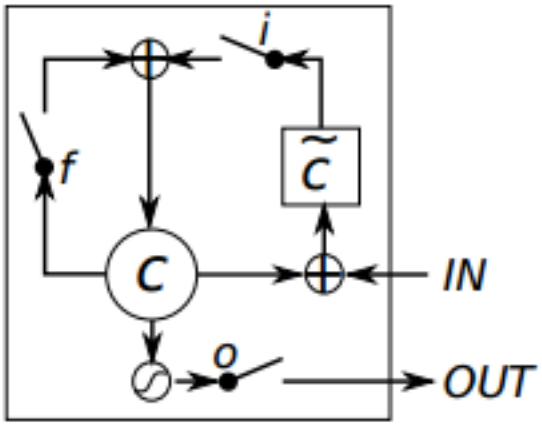
Wikipedia

History of Recurrent Networks

- Long Short Term Memory, ~1997 - 2010

Sepp Hochreiter, Many Universities

Jürgen Schmidhuber, Switzerland



More on these later

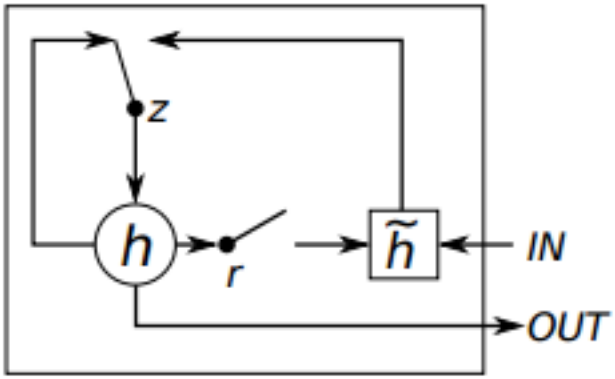
Contribution:
Long Duration Memory
State Vector separate from Output

History of Recurrent Networks

- Gated Recurrent Units, ~2014

Yoshua Bengio

Kyunghyun Cho, Professor at NYU



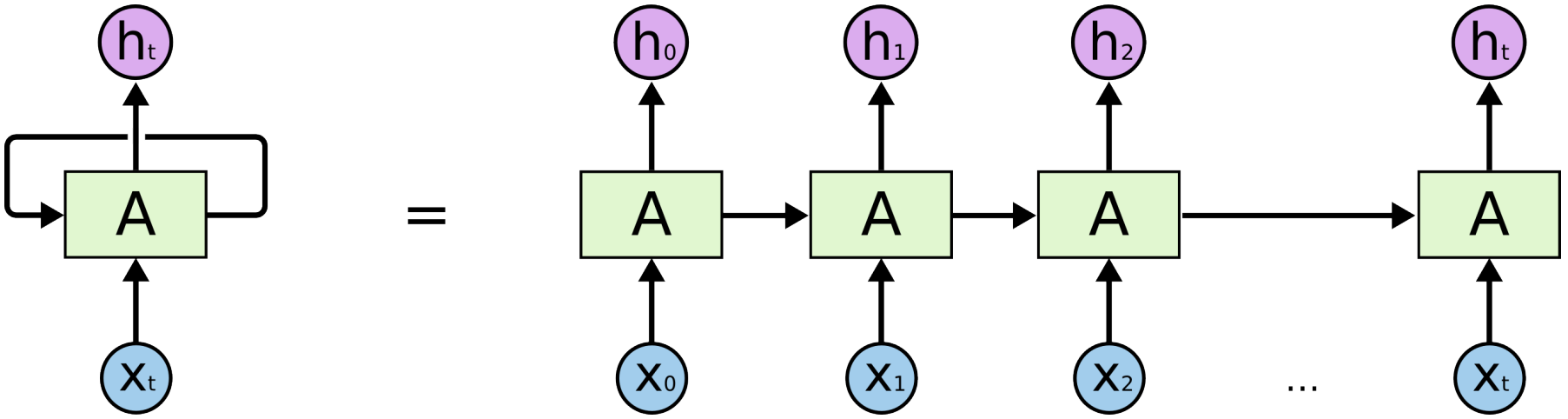
More on these later

Contribution:
Forced Decision on State Vector

Basics of Recurrent Neural Networks

For now, put those architectures in long term memory. 😂

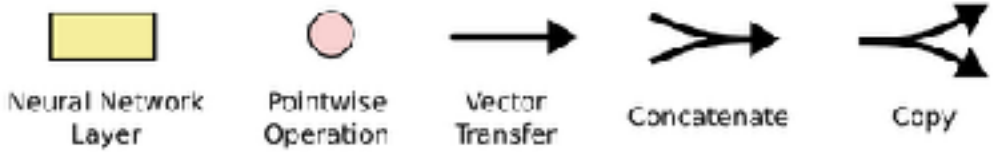
Recurrent Networks: Main Idea



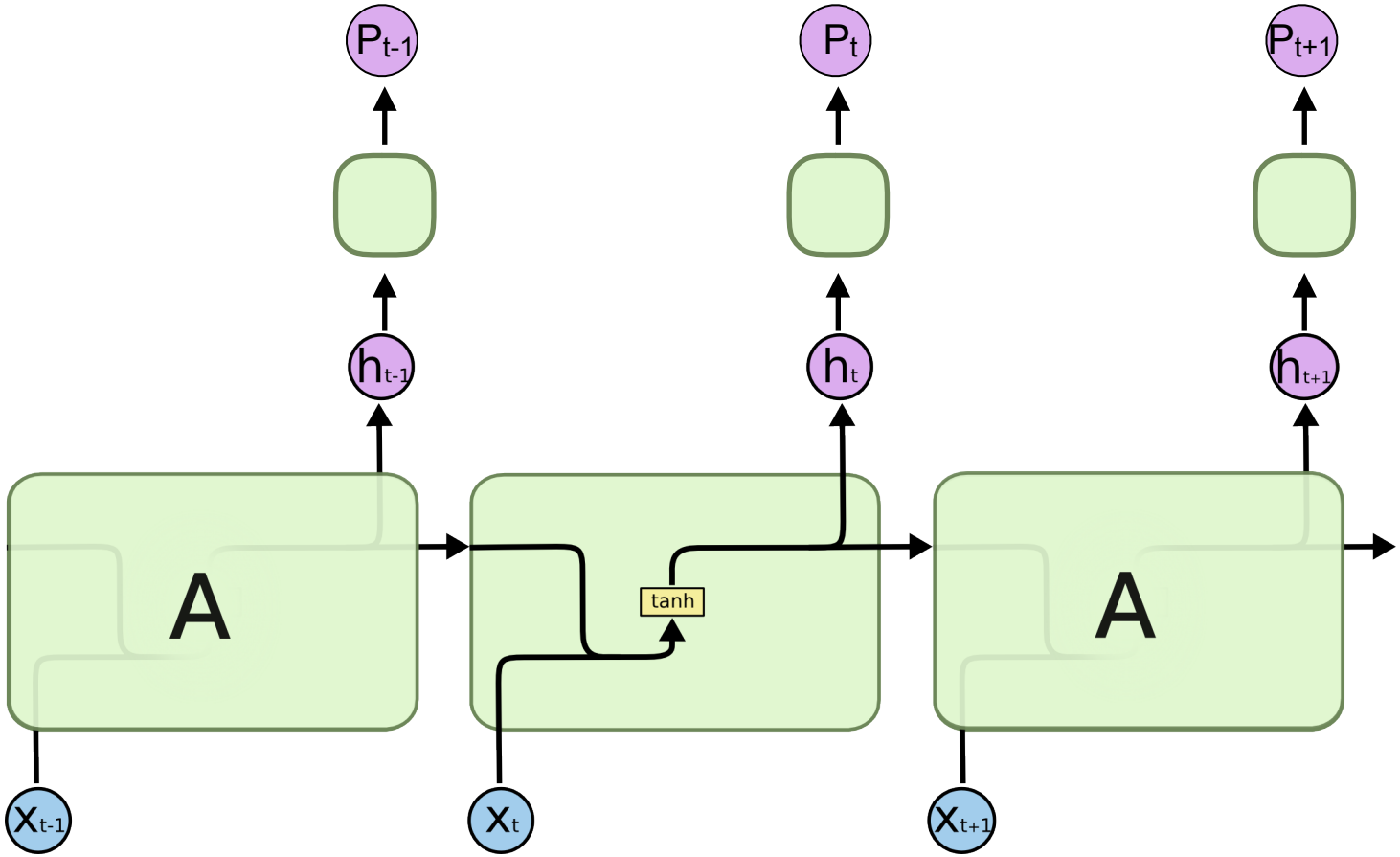
compact

unrolled

Starting Basic



- basic RNN



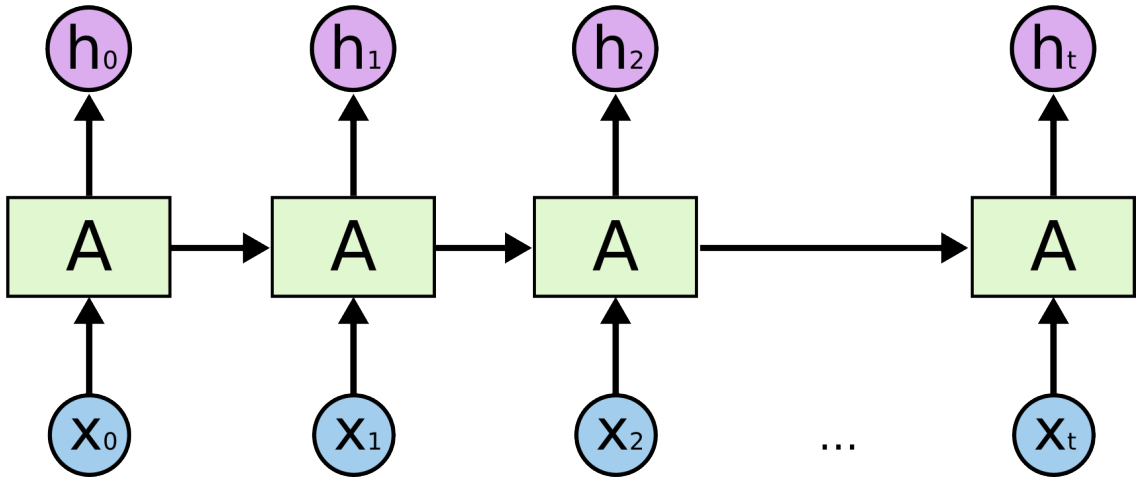
$$h_t = \tanh(W_A (X_t \oplus h_{t-1}) + b_A)$$

$$P_t = \text{softmax}(W_P h_t + b_P)$$

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

Recurrent Networks: Representation

- python:

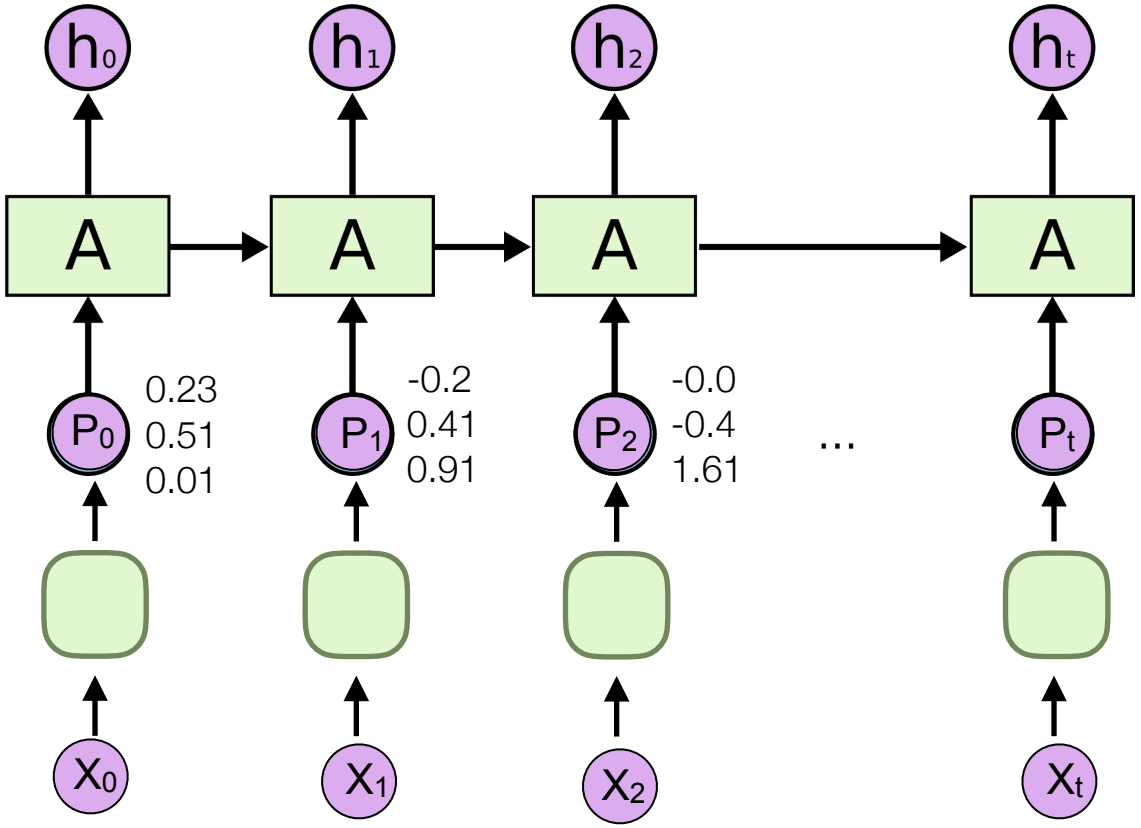


character:	T	quick	brown
int:	3	1	17
one hot:	0 0 1 0 0 0 0 ... 0 0	1 0 0 0 0 0 0 ... 0 0	0 0 0 0 0 0 0 ... 1 0

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

http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html

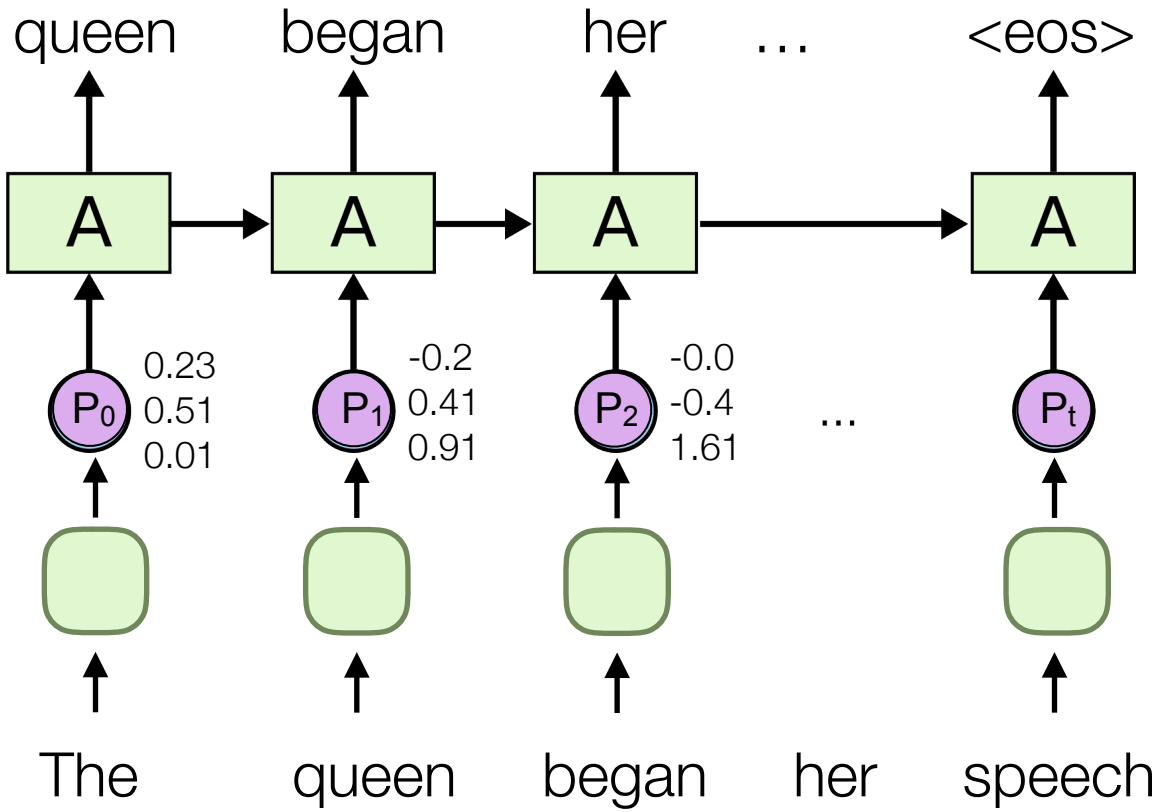
Word Embeddings (like Wide/Deep)



int:	3	1	17	
one hot:	0 0 1 0 0 0 0	1 0 0 0 0 0 0	0 0 0 0 0 0 0	

Word Embeddings: Training

- many training options exist
  - a popular option, next word prediction



Word Embeddings

- Many are pre-trained for you!!

GloVe

Global Vectors for Word Representation

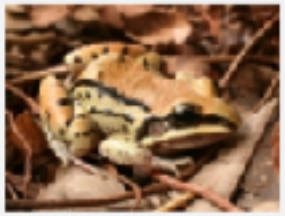
Highlights

1. **Nearest neighbors**

The Euclidean distance (or cosine similarity) between two word vectors provides an effective method for measuring the linguistic or semantic similarity of the corresponding words. Sometimes, the nearest neighbors according to this metric reveal rare but relevant words that lie outside an average human's vocabulary. For example, here are the closest words to the target word *frog*:

0. *frog*
1. frogs
2. toad
3. litoria
4. leptodactylidae
5. rana
6. lizard
7. eleutherodactylus

3. litoria

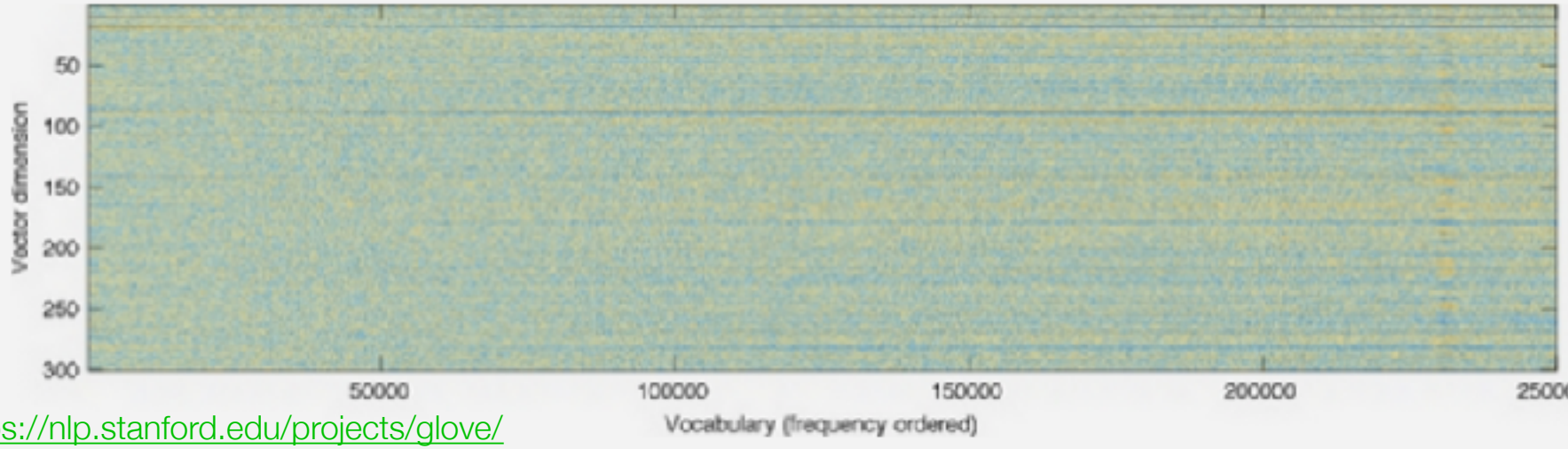


4. leptodactylidae

5. rana

7. eleutherodactylus

GloVe produces word vectors with a marked banded structure that is evident upon visualization:

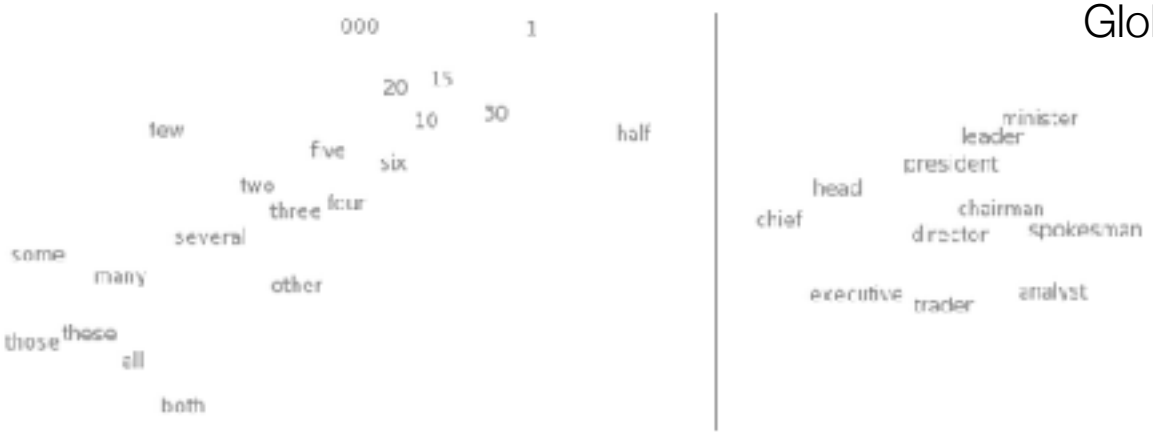


https://nlp.stanford.edu/projects/glove/

Word Embeddings: proximity

GloVe

Global Vectors for Word Representation



t-SNE visualizations of word embeddings. Left: Number Region; Right: Jobs Region. From Turian *et al.* (2010), see complete image.

FRANCE	JESUS	XBOX	REDDISH	SCRATCHED	MEGABITS
AUSTRIA	GOD	AMIGA	GREENISH	NAILED	OCTETS
BELGIUM	SATI	PLAYSTATION	BLUISH	SMASHED	MB/S
GERMANY	CHRIST	MSX	PINKISH	PUNCHED	BIT/S
ITALY	SATAN	IPOD	PURPLISH	POPPED	BAUD
GREECE	KALI	SEGA	BROWNISH	CRIMPED	CARATS
SWEDEN	INDRA	PSNUMBER	GREYISH	SCRAPED	KBIT/S
NORWAY	VISHNU	HD	GRAVISH	SCREWED	MEGAHERTZ
EUROPE	ANANDA	DREAMCAST	WHITISH	SECTIONED	MEGAPIXELS
HUNGARY	PARVATI	GEFORCE	SILVERY	SLASHED	GBIT/S
SWITZERLAND	GRACE	CAPCOM	YELLOWISH	RIPPED	AMPERES

What words have embeddings closest to a given word? From Collobert *et al.* (2011)

The **chairman** called the **meeting** to order.

The **director** called the **conference** to order.

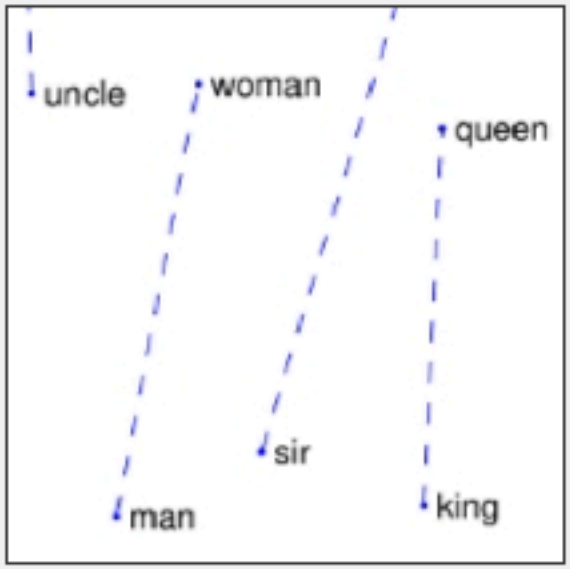
The **chief** called the **council** to order.

http://colah.github.io/posts/2014-07-NLP-RNNs-Representations/

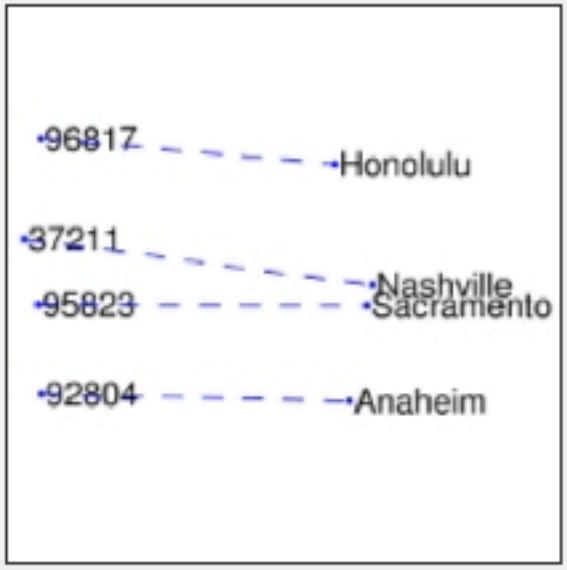
Word Embeddings: Analogy

GloVe

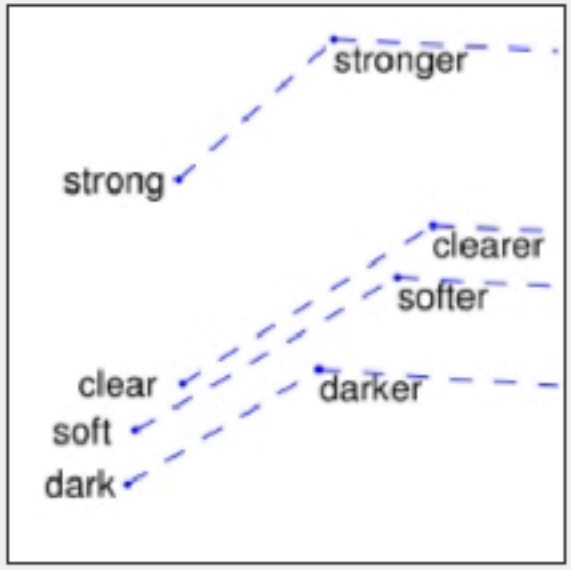
Global Vectors for Word Representation



man - woman



city - zip code

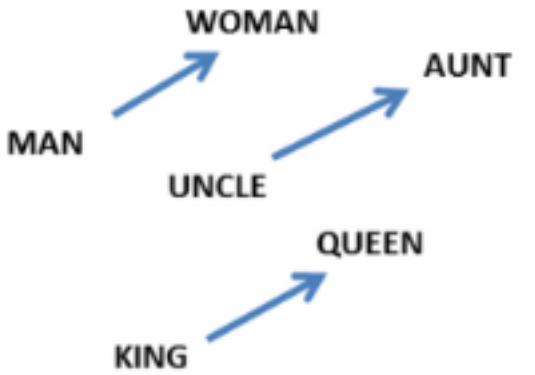


comparative - superlative

each axis **might** encode a different type of relationship

https://nlp.stanford.edu/projects/glove/ http://colah.github.io/posts/2014-07-NLP-RNNs-Representations/

Word Embeddings: Analogy



From Mikolov *et al.* (2013a)

GloVe

Global Vectors for Word Representation

$$W(\text{“woman”}) - W(\text{“man”}) \simeq W(\text{“aunt”}) - W(\text{“uncle”})$$

$$W(\text{“woman”}) - W(\text{“man”}) \simeq W(\text{“queen”}) - W(\text{“king”})$$

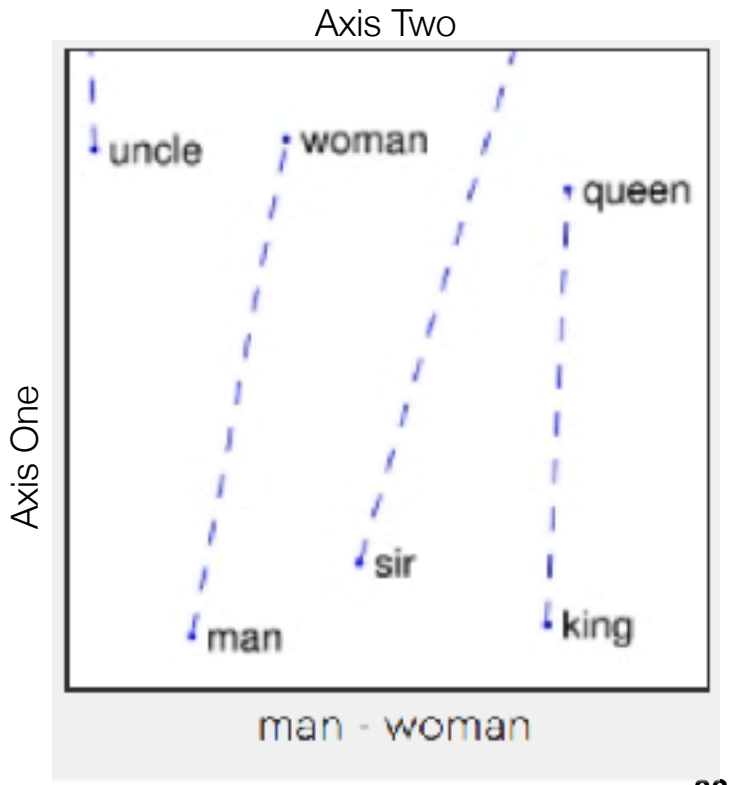
Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

Relationship pairs in a word embedding. From Mikolov *et al.* (2013b).

https://nlp.stanford.edu/projects/glove/ http://colah.github.io/posts/2014-07-NLP-RNNs-Representations/

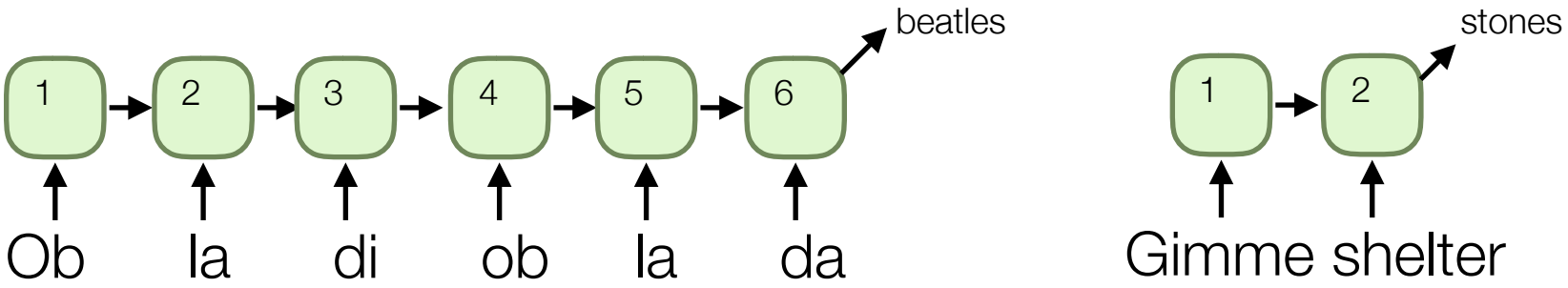
Self Test: Analogy

- Each axis on the embedding plot below corresponds to:
- A. a weight inside the embedding layer
- B. an average of weights inside the embedding layer
- C. the average of the one hot encoding for a word
- D. an output of the embedding layer



Practical Logistics: Sequence Length

- option A: dynamic length sequences



- option B: padding/clipping

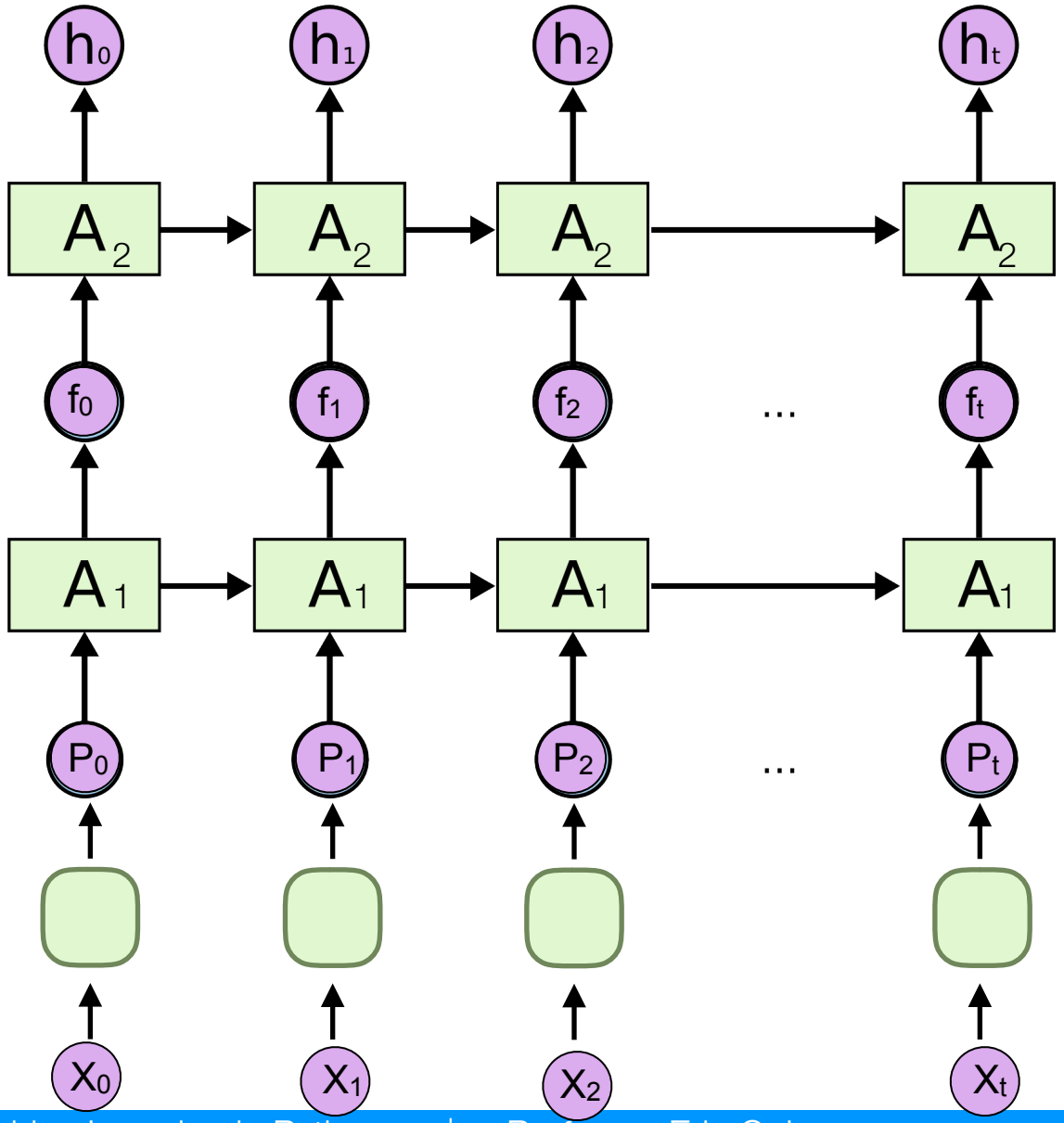
- main difference:

  speed based on computation graph design

Self Test

- The main reason dynamic length is slow is because:
  - A. the computation graph must be updated
  - B. weights must be tied together for each recurrent node
  - C. the weights must be multiplied until the output converges
  - D. the unrolling operation takes some time

Aside: Sequence Stacking?



keras:
return sequences

Recurrent Generation

Generating More Outputs

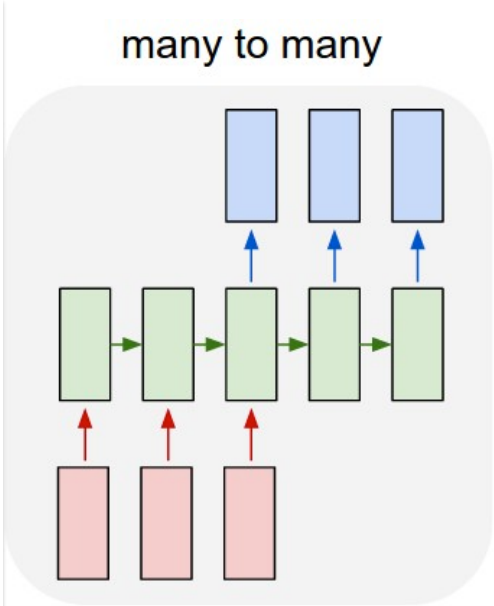
- Highly sophisticated steps:
  - train an RNN to generate the **next** word/character from the **current** word/character
  - train on a corpus of text
    - Shakespeare
    - Movie Scripts
    - Whatever!
  - seed with random word, feed output words as input to next node
  - rinse, repeat

Training Data: Plays by Shakespeare

```
First Citizen:
Before we proceed any further, hear me speak.

All:
Speak, speak.

First Citizen:
You are all resolved rather to die than to famish?

All:
Resolved. resolved.

First Citizen:
First, you know Caius Marcius is chief enemy to the people.

All:
We know't, we know't.

First Citizen:
Let us kill him, and we'll have corn at our own price.
Is't a verdict?

All:
No more talking on't; let it be done: away, away!

Second Citizen:
One word, good citizens.

ervices he has done for his country?

First Citizen:
Very well; and could be content to give him good
report fort, but that he pays himself with being proud.

Second Citizen:
Nay, but speak not maliciously.
```

```
First Citizen:
We are accounted poor citizens, the patricians g
What authority surfeits on would relieve us: if
would yield us but the superfluity, while it wer
wholesome, we might guess they relieved us human
but they think we are too dear: the leanness tha
afflicts us, the object of our misery, is as an
inventory to particularise their abundance; our
sufferance is a gain to them Let us revenge this
our pikes, ere we become rakes: for the gods kno
speak this in hunger for bread, not in thirst fo

Second Citizen:
Would you proceed especially against Caius Marci

All:
Against him first: he's a very dog to the common

Second Citizen:
Consider you what s
```

Generating Shakespeare




```
ATOOOS

UIEAOUYOUZZZZZZUZAAAYAYf n fsflflrurctuateot t ta's  a  wtut
Whith then, a do makes and them and to sees,
I wark on this ance may string take thou honon
To sorriccorn of the bairer, whither, all
I'd see if yiust the would a peid.

LARYNGLe:
To would she troust they fould.

PENMES:
Thou she so the havin to my shald woust of
As tale we they all my forder have
As to say heant thy wansing thag and
Whis it thee shath his breact, I be and might, she
Tirs you desarvishensed and see thee: shall,
What he hath with that is all time,
And sen the have would be sectiens, way thee,
They are there to man shall with me to the mon,
And mere fear would be the balte, as time an at
And the say oun touth, thy way womers thee.
```

Generating Movies

more data: star wars + star trek + tarantino + the matrix

```
DENT'SUEENCK

Bartholomew of the TIE FIGHTERS are stunned. There is a crowd and armored
switcheroos.

PICARD
(continuing)
Couns two dim is tired. In order to the sentence...

The sub    bottle appears on the screen into a small shuttle shift of the
ceiling. The DAMBA FETT splash fires and matches them into the top, transmit to stable high above
upon their statels,
falling from an alien shaft.

ANAKIN and OBI-WAN stand next to OBI-WAN down the control plate of smoke at the TIE fighter. They
stare at the centre of the station loose into a comlink cover -- comes up to the General, the
GENERAL HUNTAN AND FINNFURMBARD from the PICADOR to a beautiful Podracisly.

ENGINEER
Naboo from an army seventy medical
security team area re-weilergular.

EXT.
```

THE MULTIVERSE —

Movie written by algorithm turns out to be hilarious and intense

For *Sunspring*'s exclusive debut on Ars, we talked to the filmmakers about collaborating with an AI.

ANNALEE NEWITZ - 6/9/2016, 5:30 AM

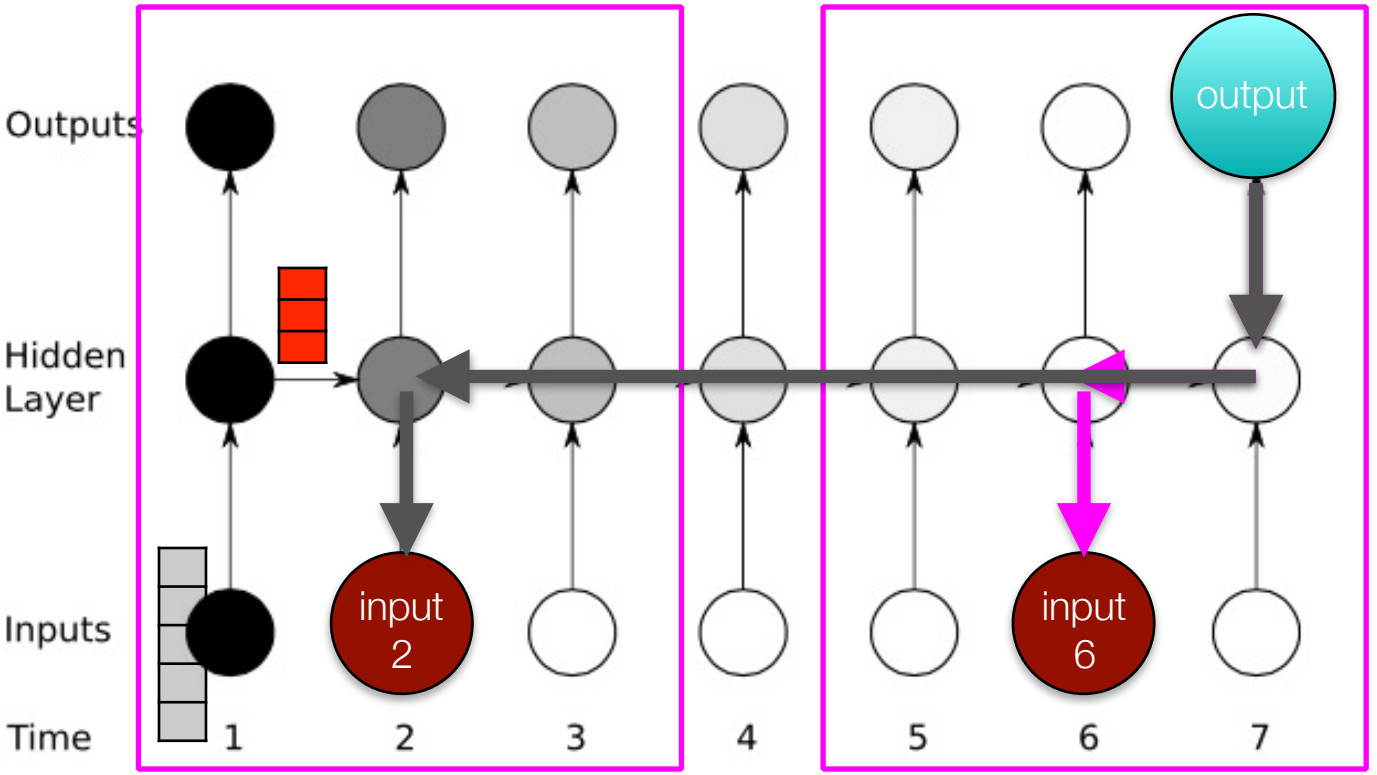
Back to Reality: Types of RNNs

People with no idea about AI saying it will take over the world:

My Neural Network:

Recurrent Networks, the Age Old Problem

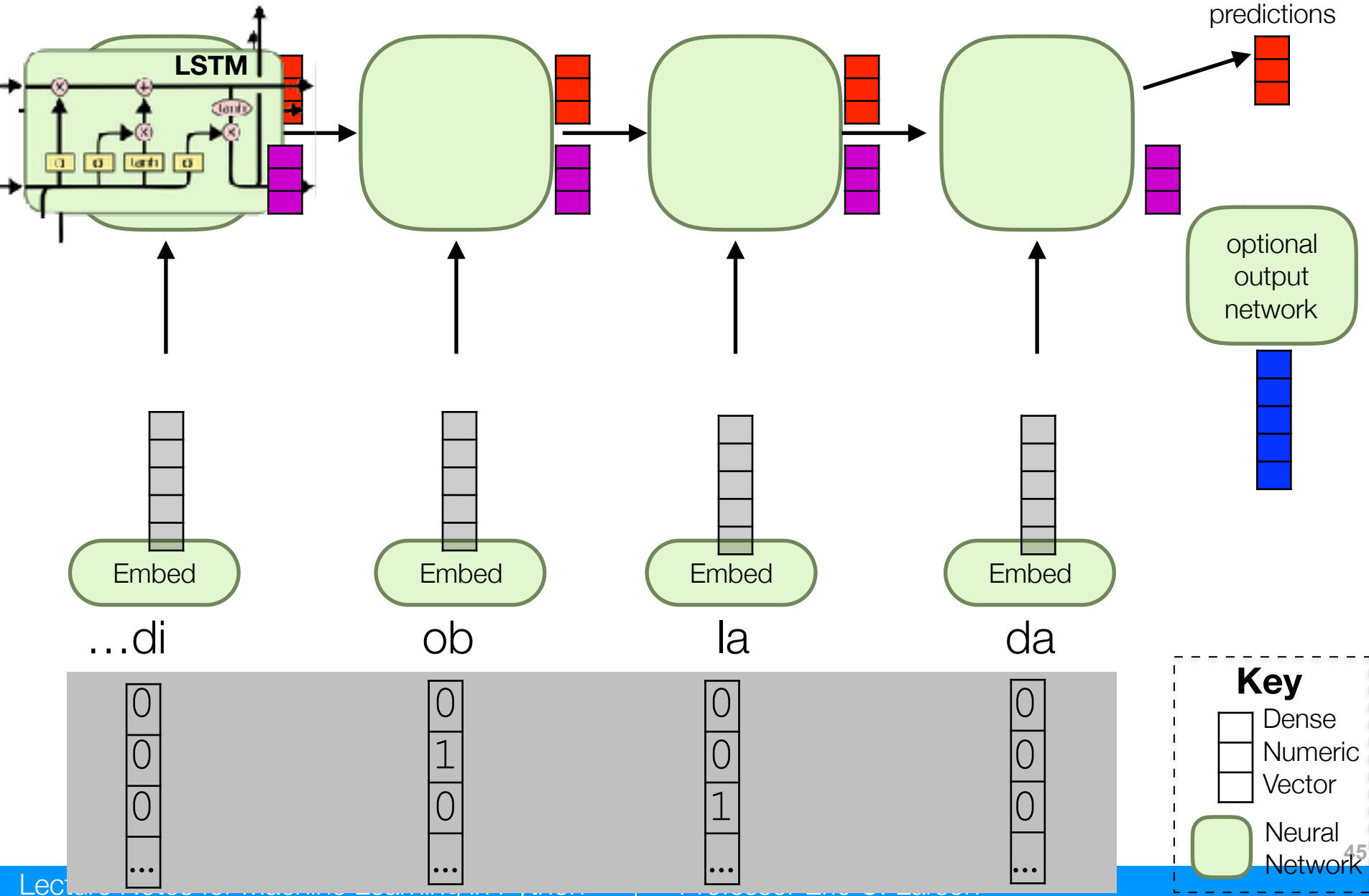
- vanishing gradients: why are these a problem?



$$\frac{\partial E_i}{\partial S_{i-k}} = \frac{\partial E_i}{\partial S_t}\frac{\partial S_t}{\partial S_{t-k}} = \frac{\partial E_t}{\partial S_t}\left(\frac{\partial S_t}{\partial S_{t-1}}\frac{\partial S_{t-1}}{\partial S_{t-2}}\cdots\frac{\partial S_{t-k+1}}{\partial S_{t-k}}\right) = \frac{\partial E_t}{\partial S_t}\prod_{i-1}^{k}\frac{\partial S_{t-i+1}}{\partial S_{t-i}}$$

http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html

General recurrent flow (many to one)



Recurrent Networks: GRUs

- gated recurrent units

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

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

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

past state

current input

selectively remember

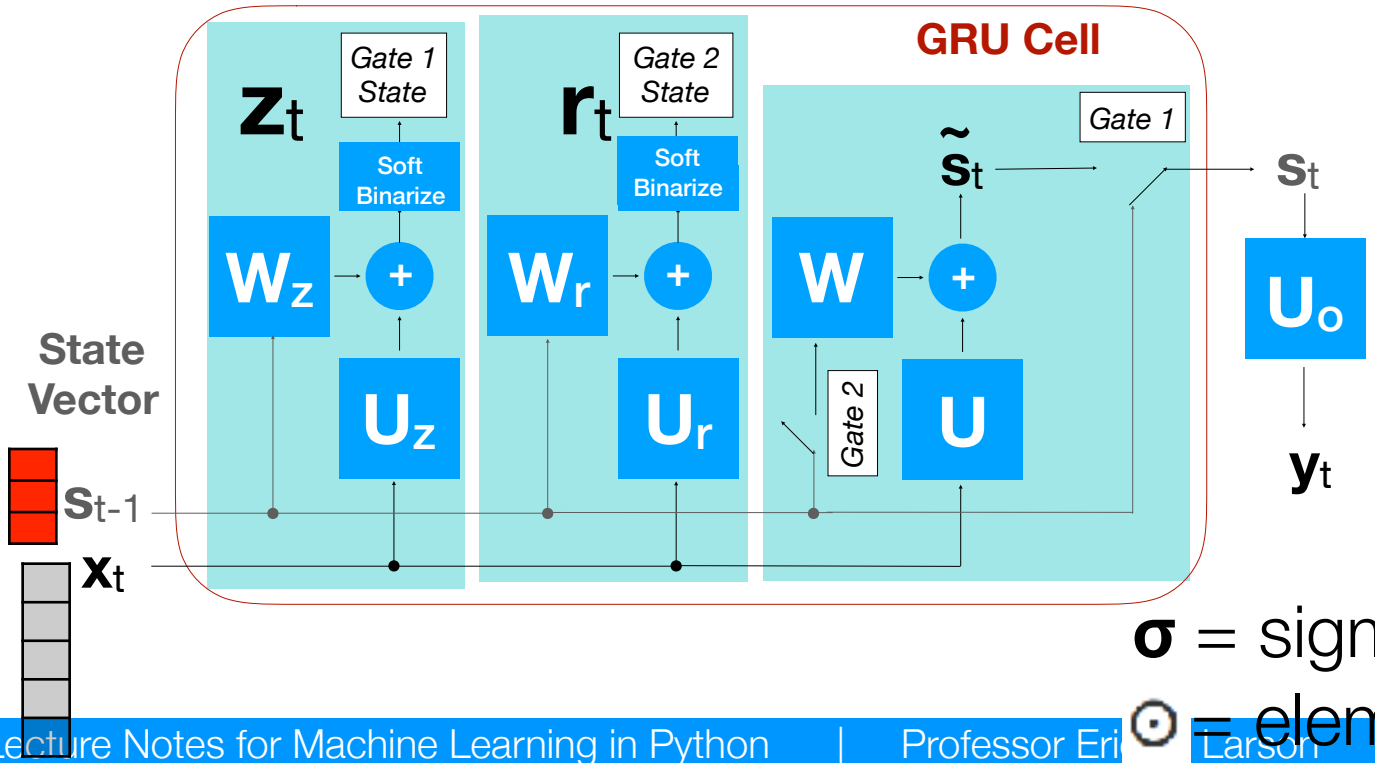
with influence

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

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

remember only past

OR remember with input



σ = sigmoid

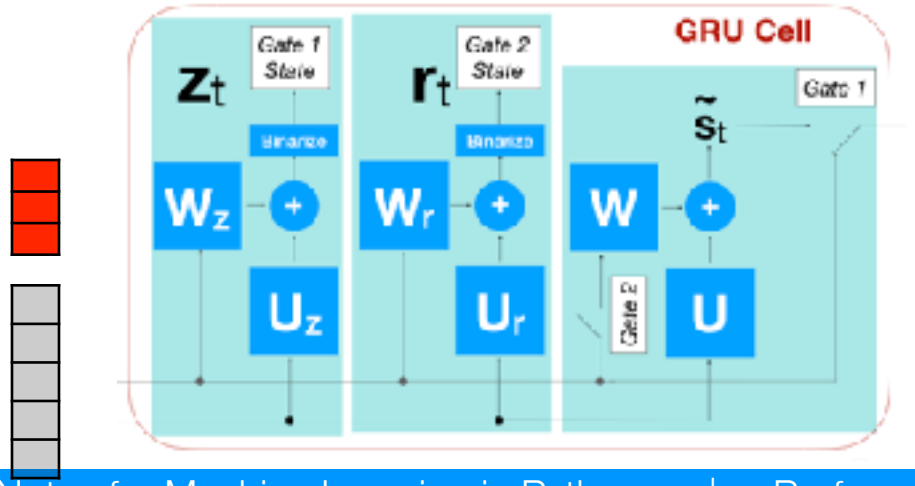
⊙ = elem. multiplication

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

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

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



Derivative of GRU

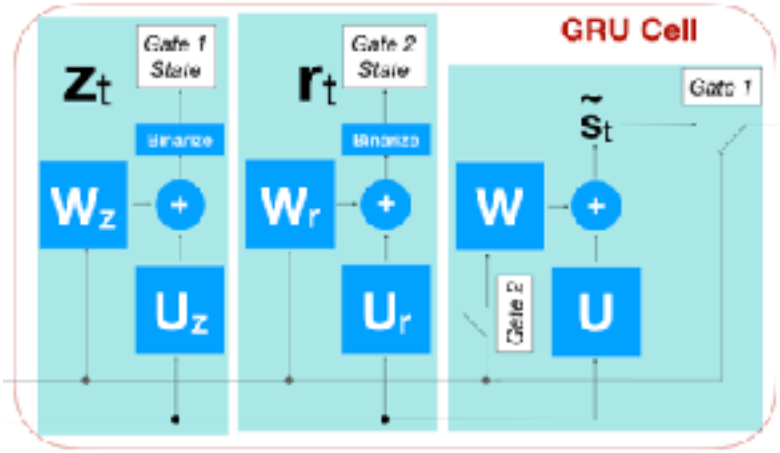
hard to vanish unless $z_t = 0$

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

could vanish

could vanish, depending on ϕ

could vanish



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

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

derivative of multiplication

Recurrent Networks: Gen 1 LSTM

- LSTM prototype

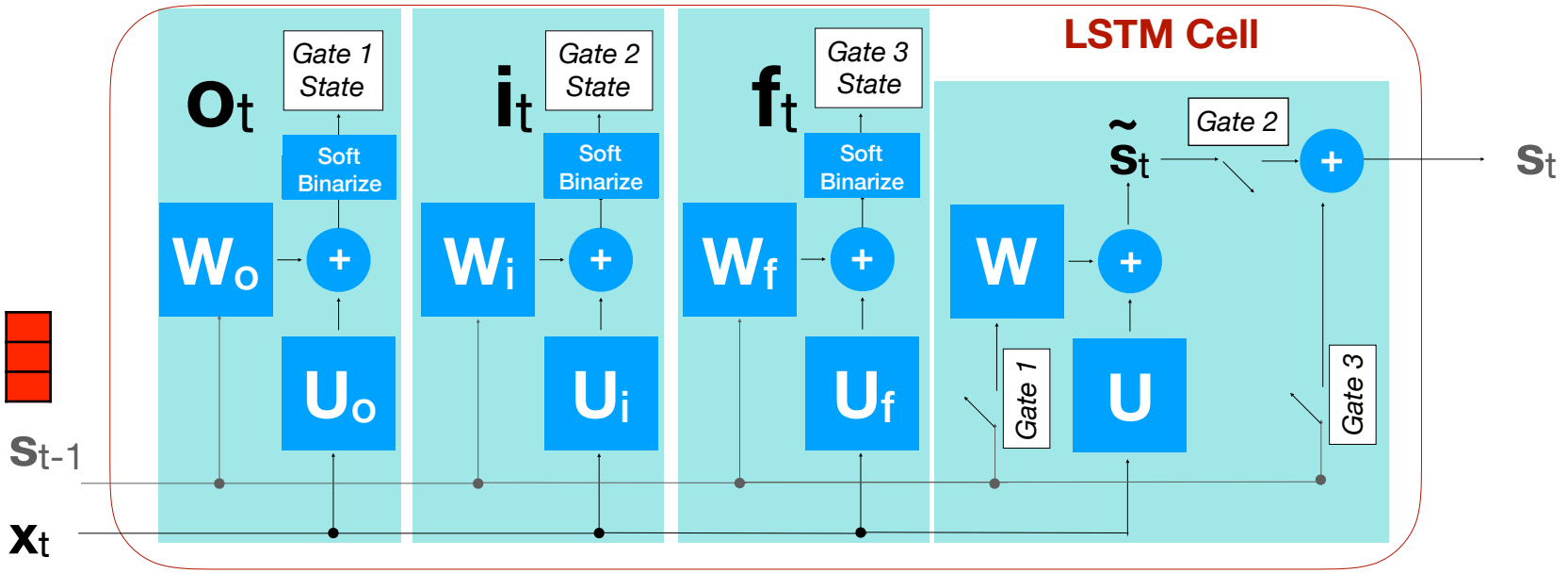
Selectivity controls (**gates, 0 or 1**)

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

selectively remember past — with influence

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

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

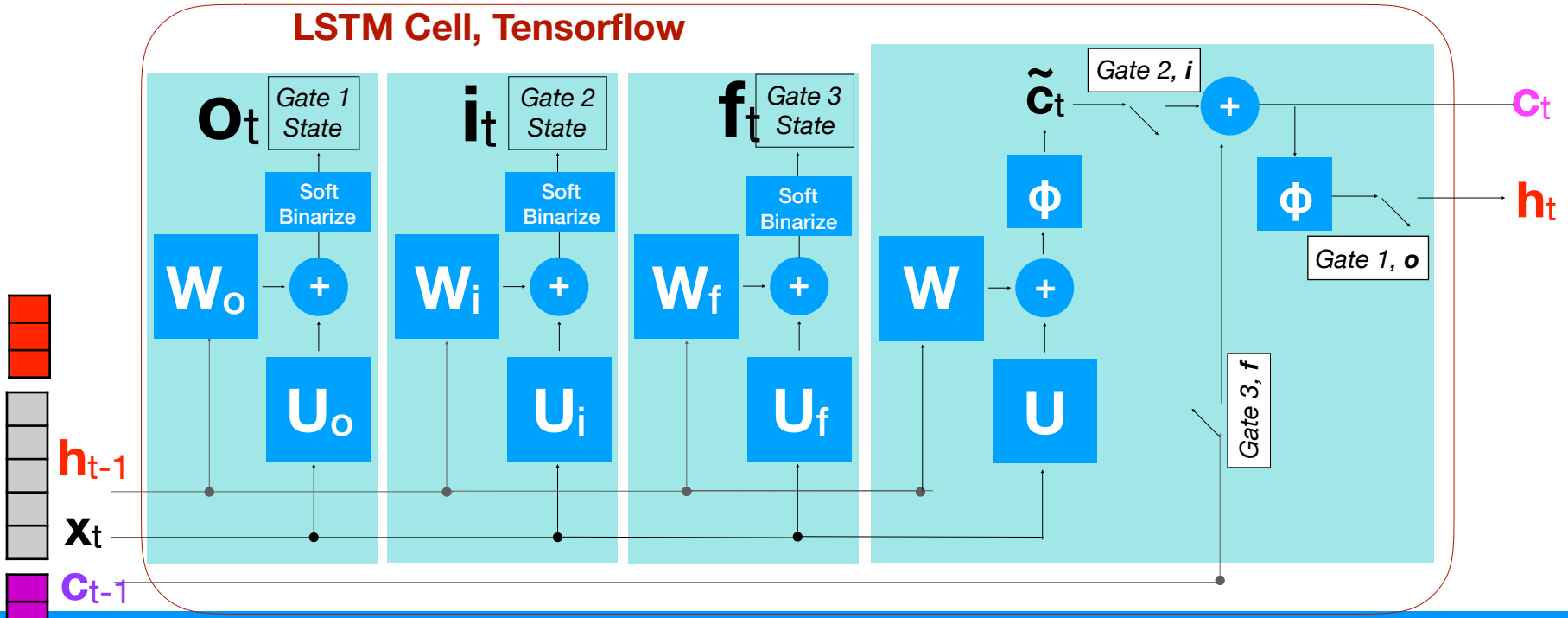
$$\tilde{c}_t = \phi(W h_{t-1} + U x_t + b)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

remember previous state

update with output, h_t

$$h_t = o_t \odot \phi(c_t)$$

get next ht for selecting gates



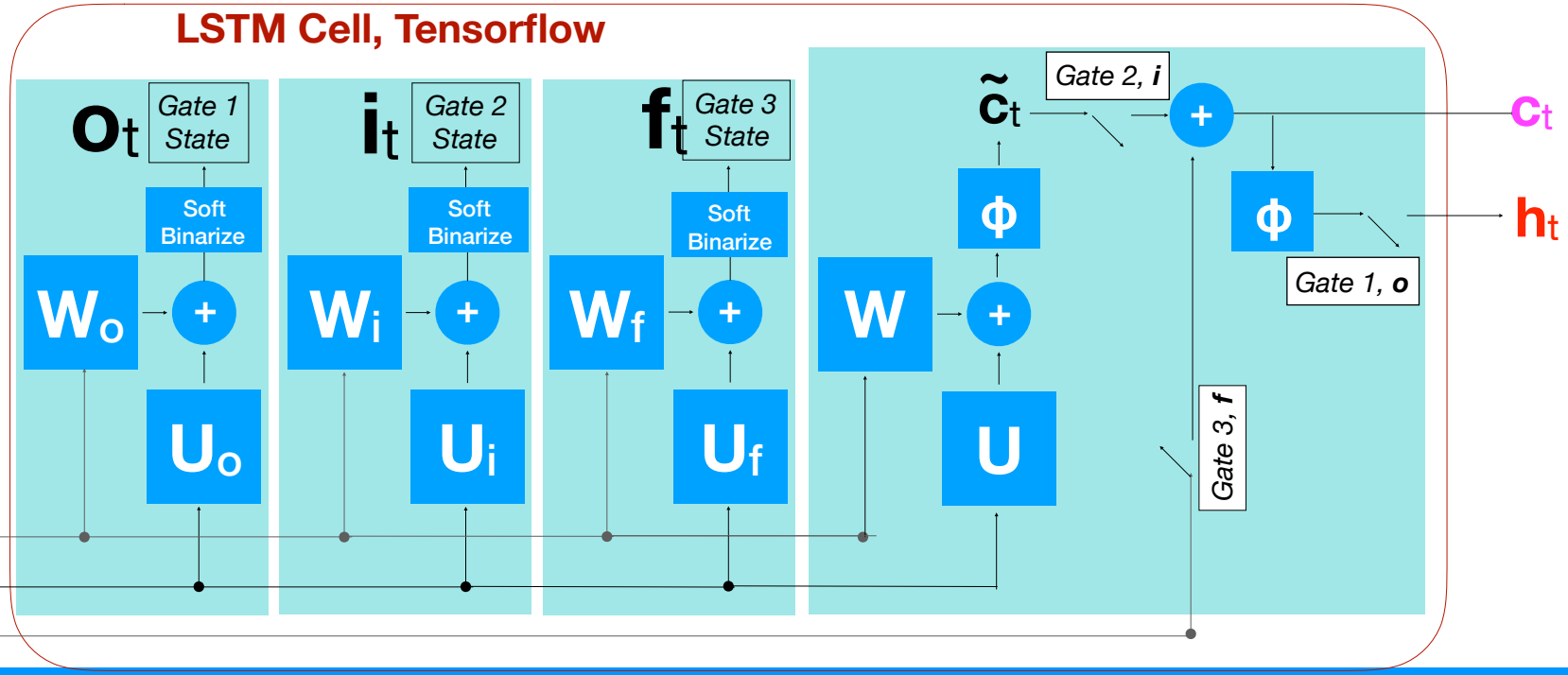
LSTM Dropout

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

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…

Next time

- Recurrent Networks (two lecture agenda)
  - *Overview*
  - *Problem Types*
  - *Embeddings*
  - *Types of RNNs*
  - **Demo A**
  - **CNNs and RNNs**
  - **Demo B**
  - **Modern RNNs**
  - **Course Retrospective**

Lecture Notes for

Machine Learning in Python

Professor Eric Larson

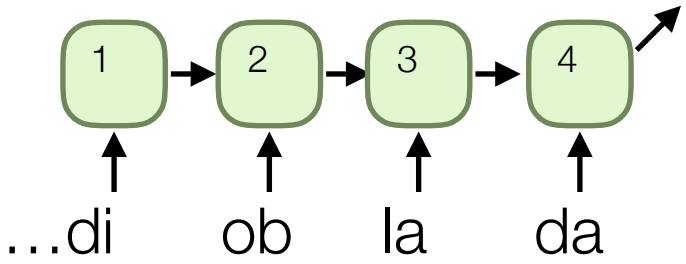
Lecture: RNN Demo

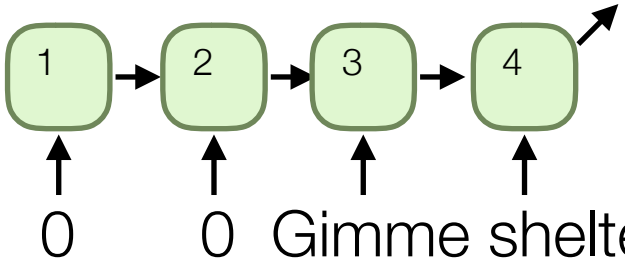
Lecture Agenda

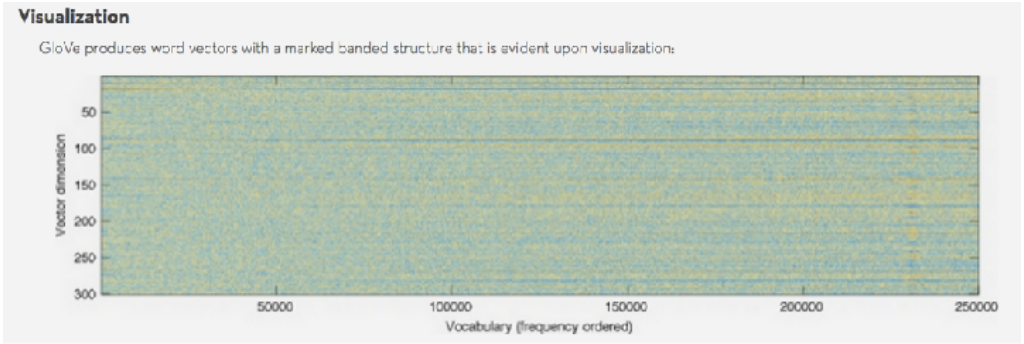
- Logistics
  - RNNs due **During Finals Time**
- Recurrent Networks (two lecture agenda)
  - *Overview*
  - *Problem Types*
  - *Embeddings*
  - *Types of RNNs*
  - Demo A
  - CNNs and RNNs
  - Demo B
  - Modern RNNs
  - Course Retrospective

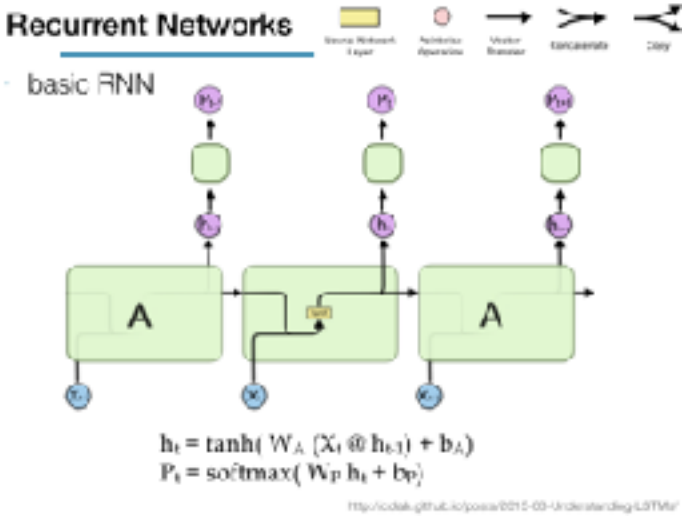
Last Time

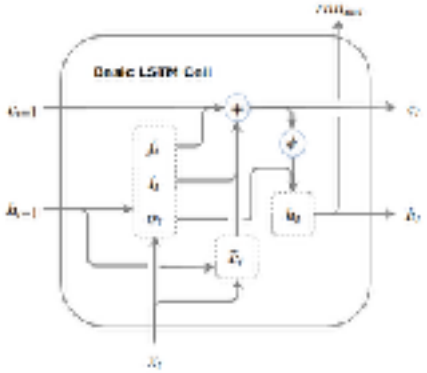
- padding/clipping

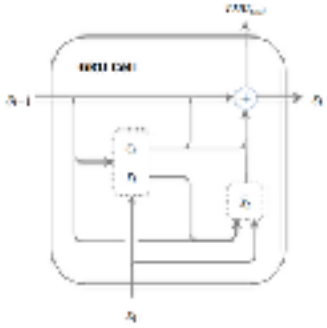






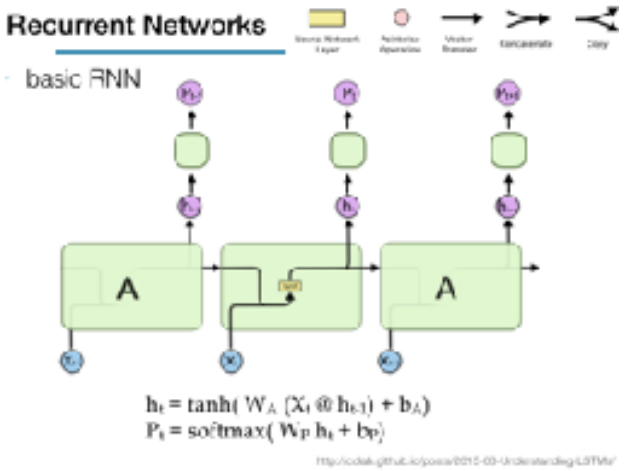




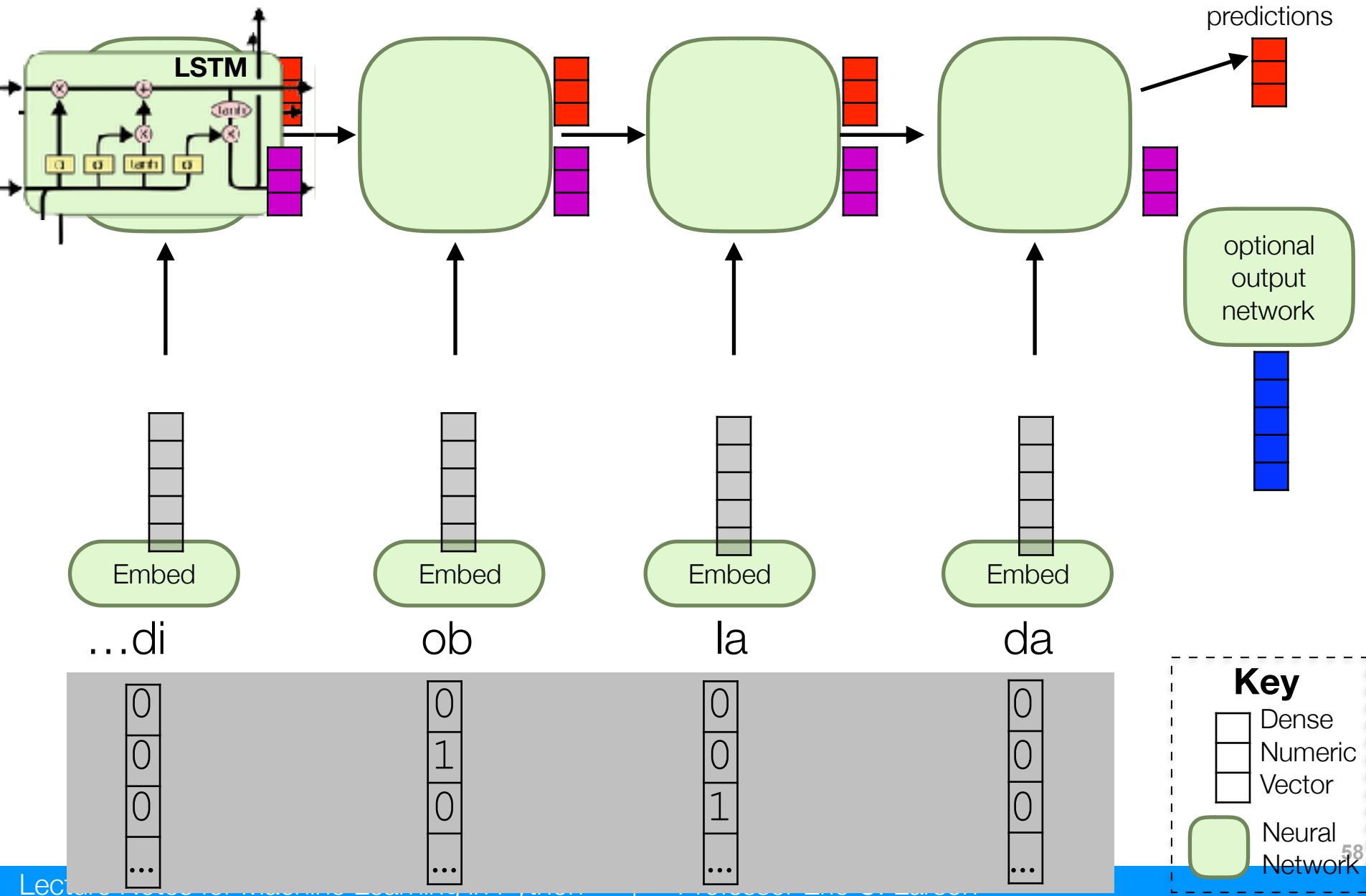


Self Test

- 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



General recurrent flow (many to one)



Recurrent Networks: GRUs

- gated recurrent units

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

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

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

past state

current input

selectively remember

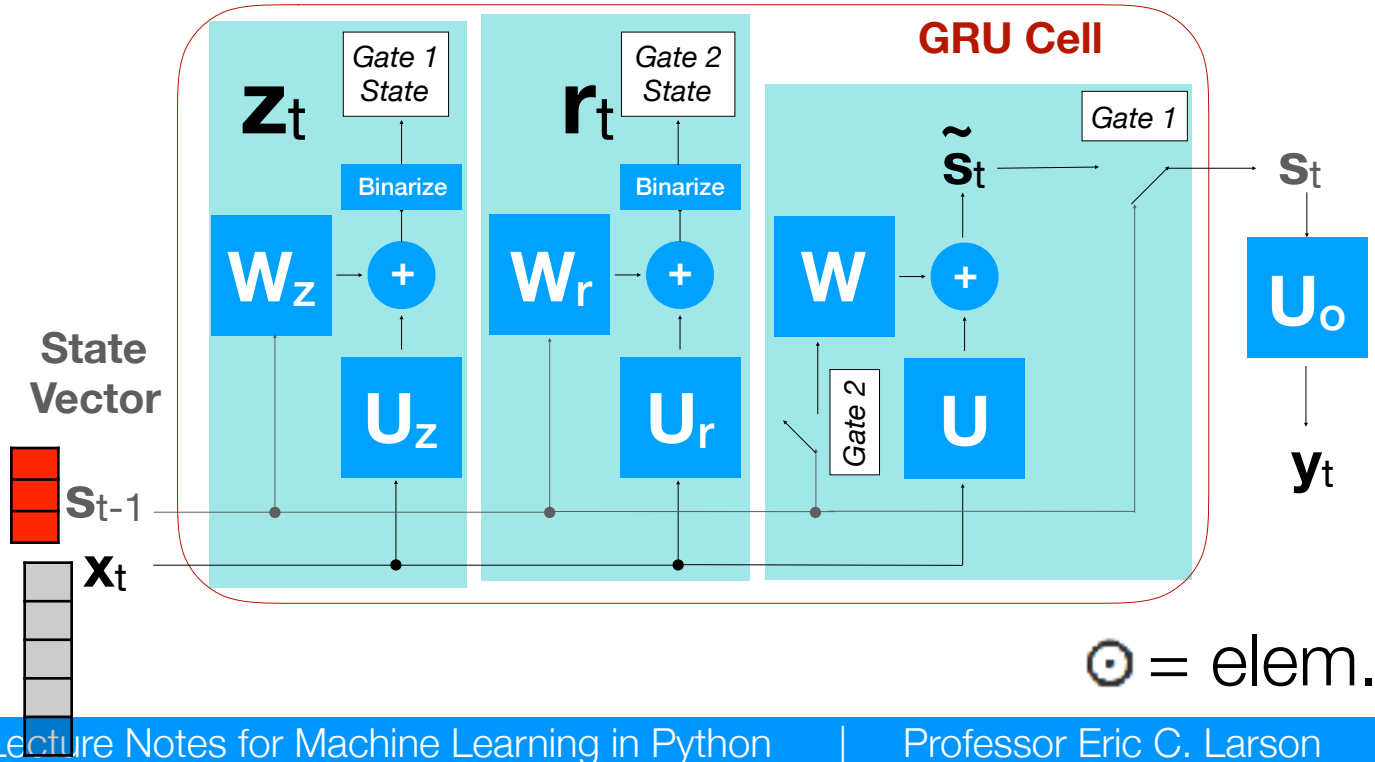
with influence

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

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

remember only past

OR remember with input



σ = hard limit

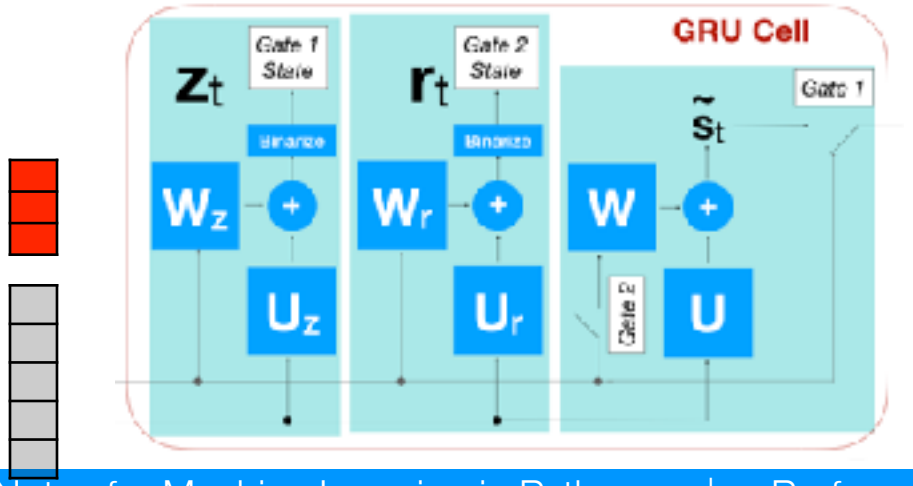
⊙ = elem. multiplication

Self Test

- What element of the GRU helps with vanishing and exploding gradients?
- A. derivative of ϕ
- B. derivative of σ
- C. σ
- D. ϕ

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

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



Recurrent Networks: Gen 1 LSTM

- LSTM prototype

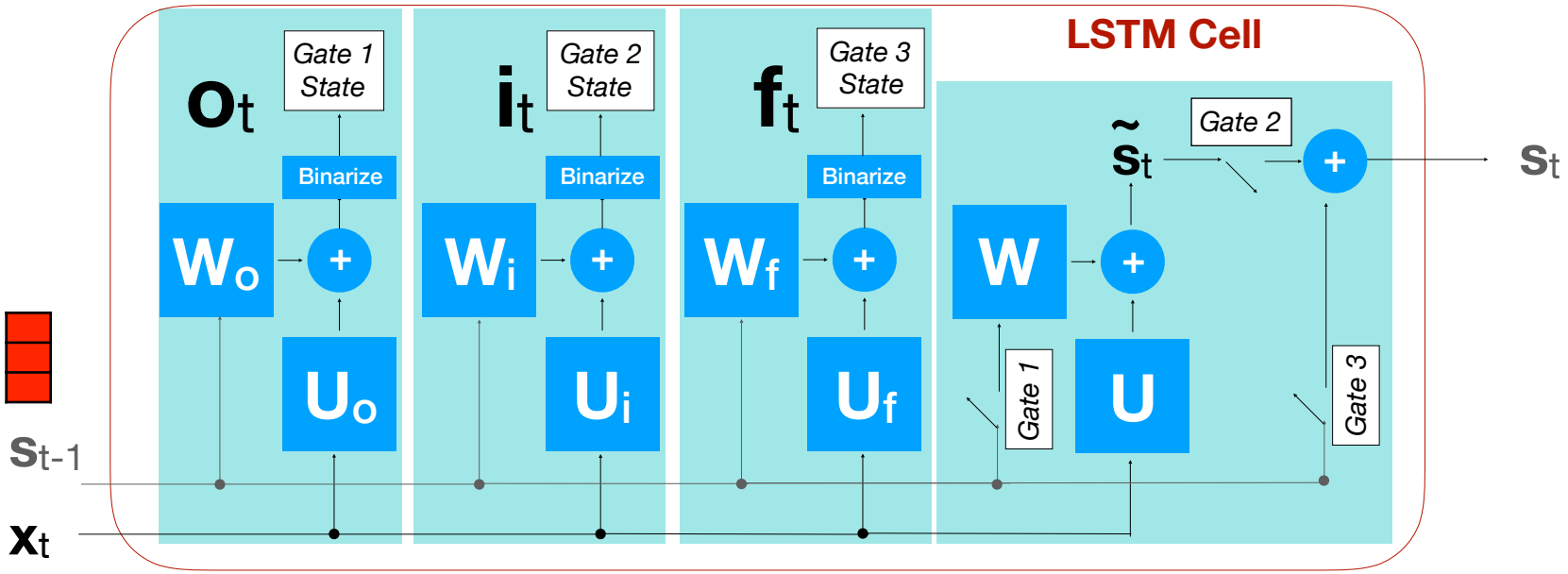
Selectivity controls (**gates, 0 or 1**)

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

selectively remember past — with influence

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

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

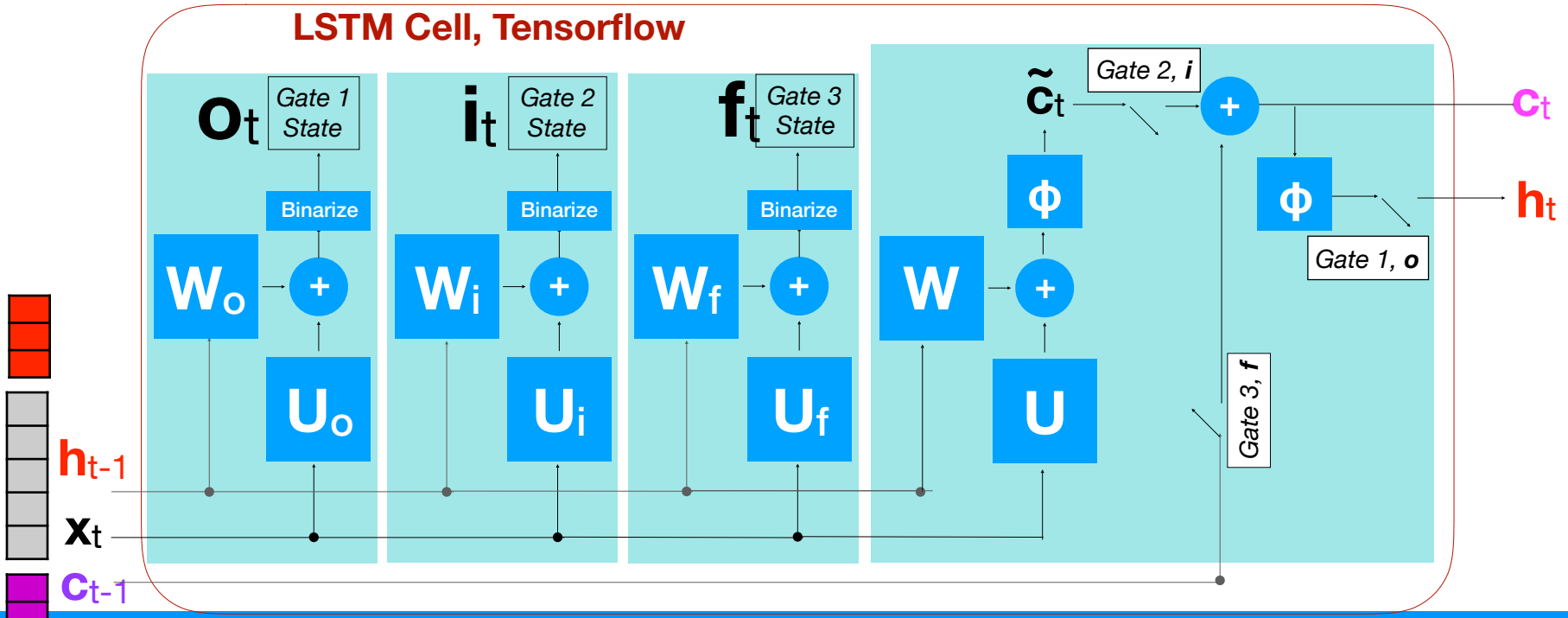
$$\tilde{c}_t = \phi(W h_{t-1} + U x_t + b)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

remember previous state

update with output, h_t

$$h_t = o_t \odot \phi(c_t)$$

get next ht for selecting gates



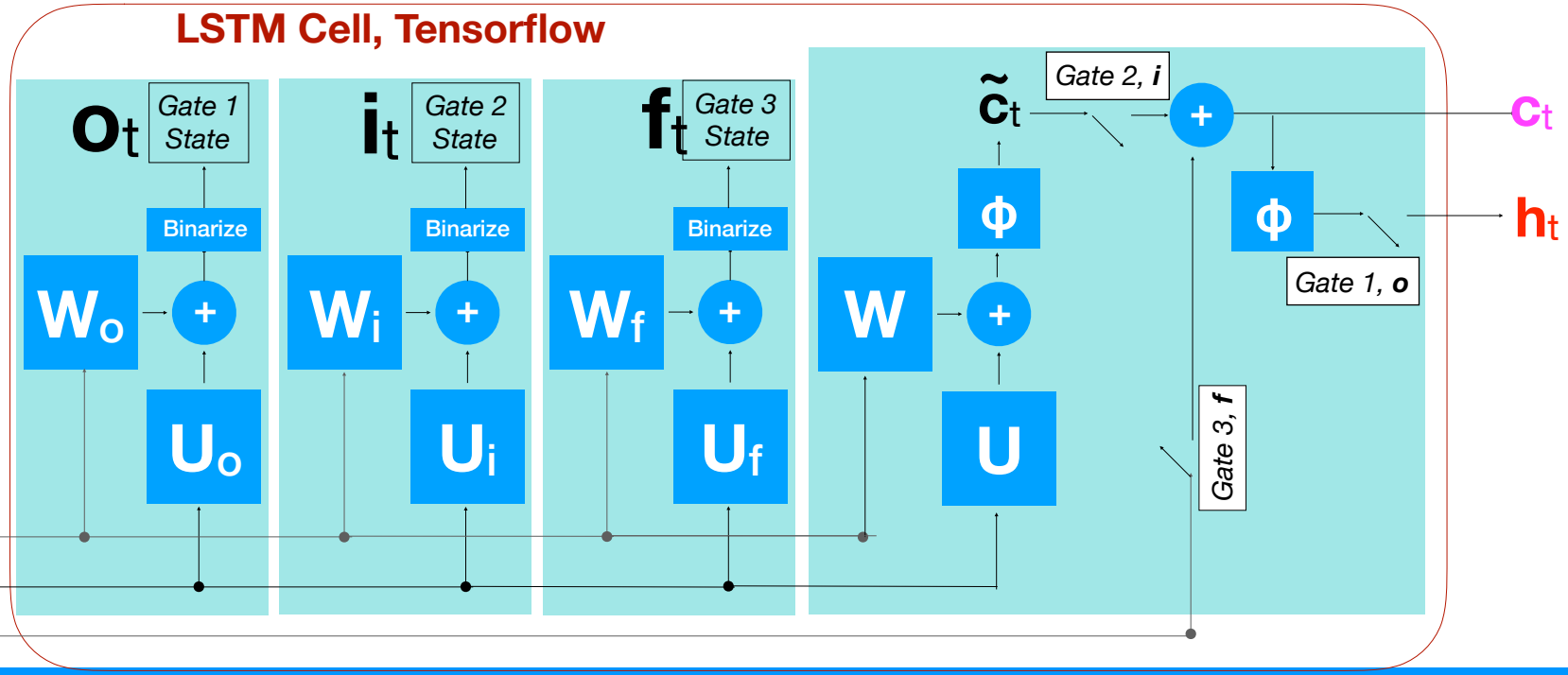
LSTM Dropout

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

Recurrent Dropout

Input Dropout

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



Final Demo - Part A

Many to one:

- Simple RNNs
- GRUs
- LSTMs

More examples:

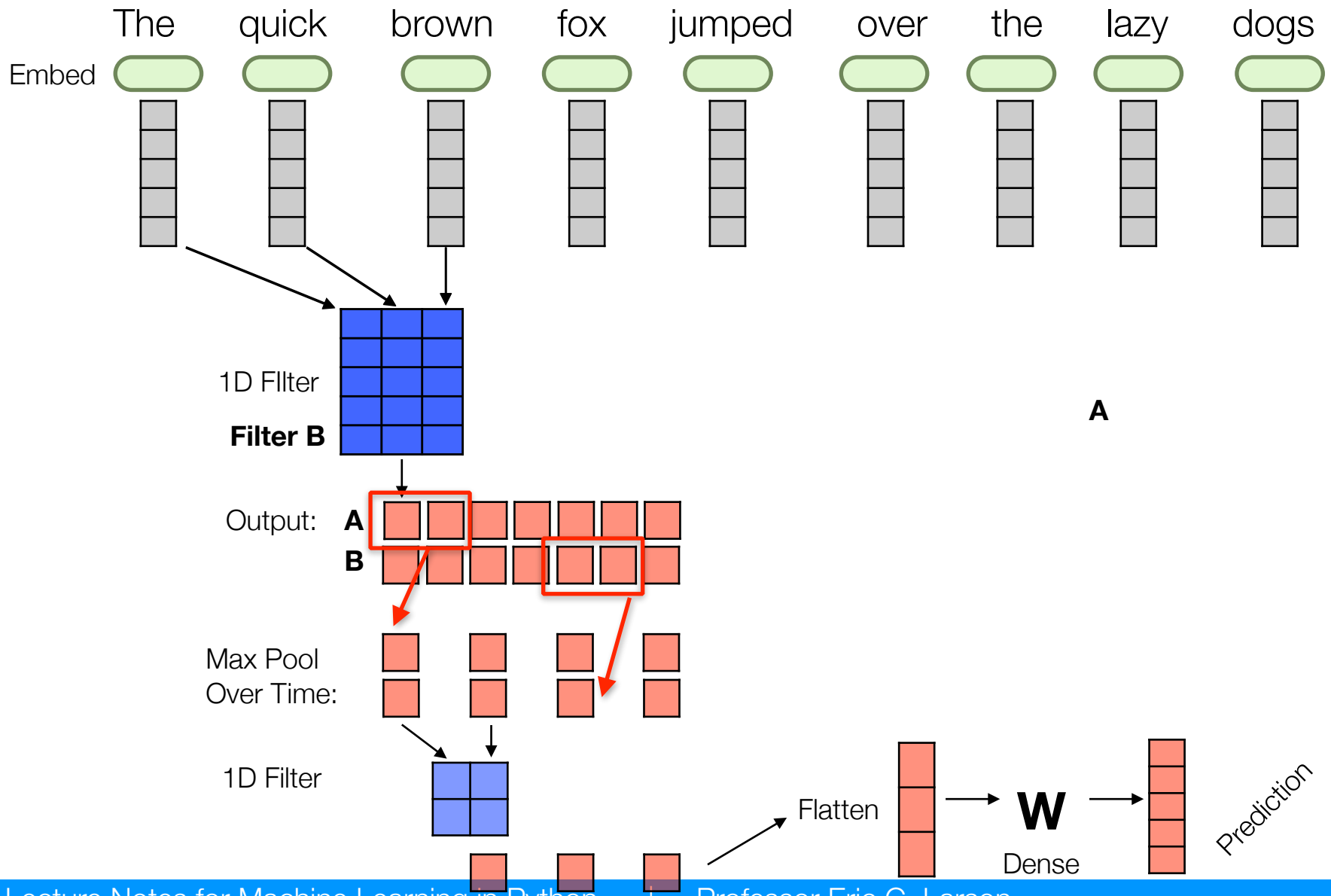
https://github.com/tensorflow/tensorflow/tree/r0.11/tensorflow/examples/skflow
http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html
http://machinelearningmastery.com/sequence-classification-lstm-recurrent-neural-networks-python-keras/

Seq2Seq:

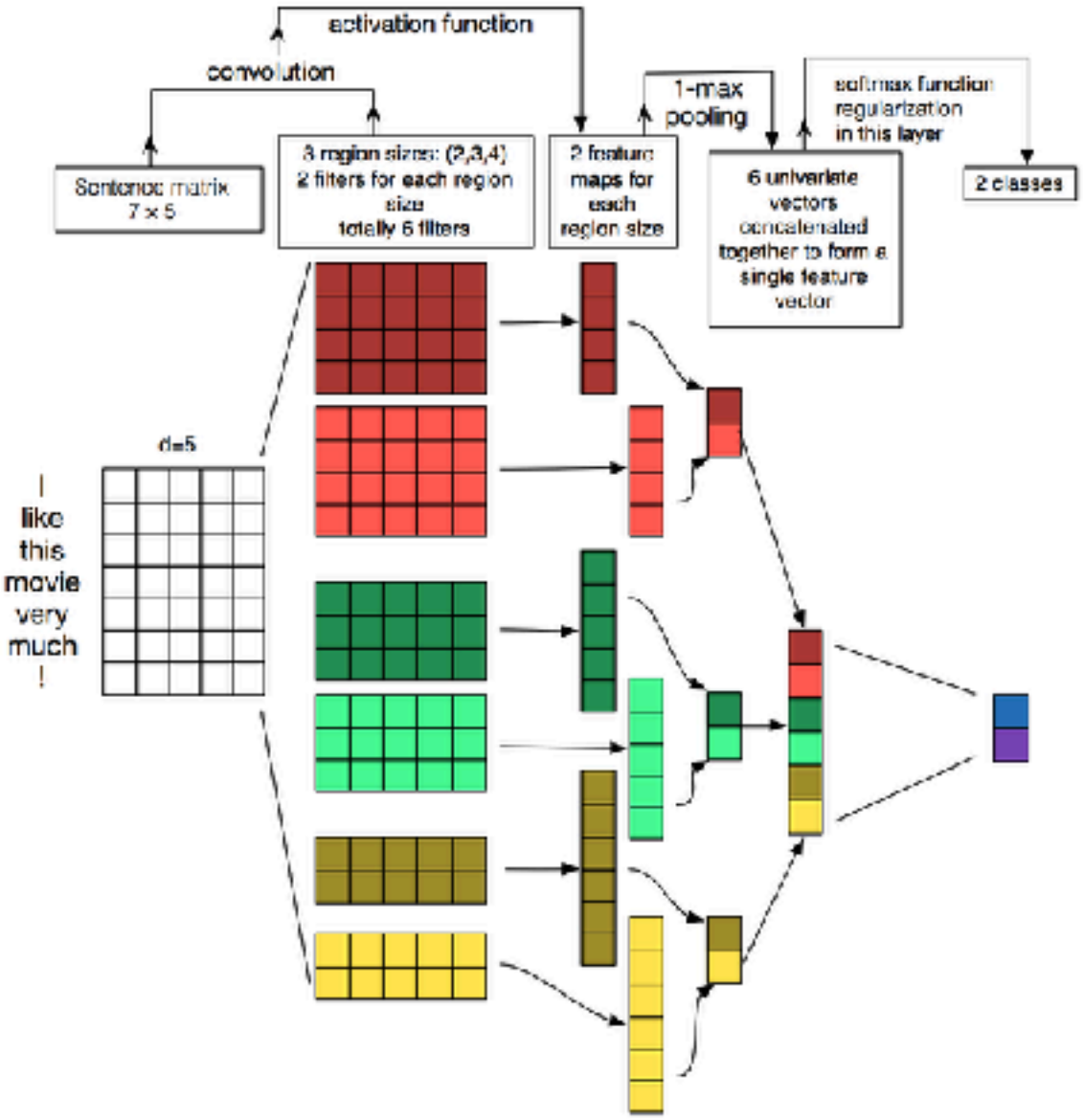
https://github.com/tensorflow/tensorflow/blob/r0.11/tensorflow/examples/skflow/neural_translation_word.py

CNNs and RNNs

is an RNN similar to a CNN?



CNNs and RNNs



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

Demo - Part B

Back to the CNN

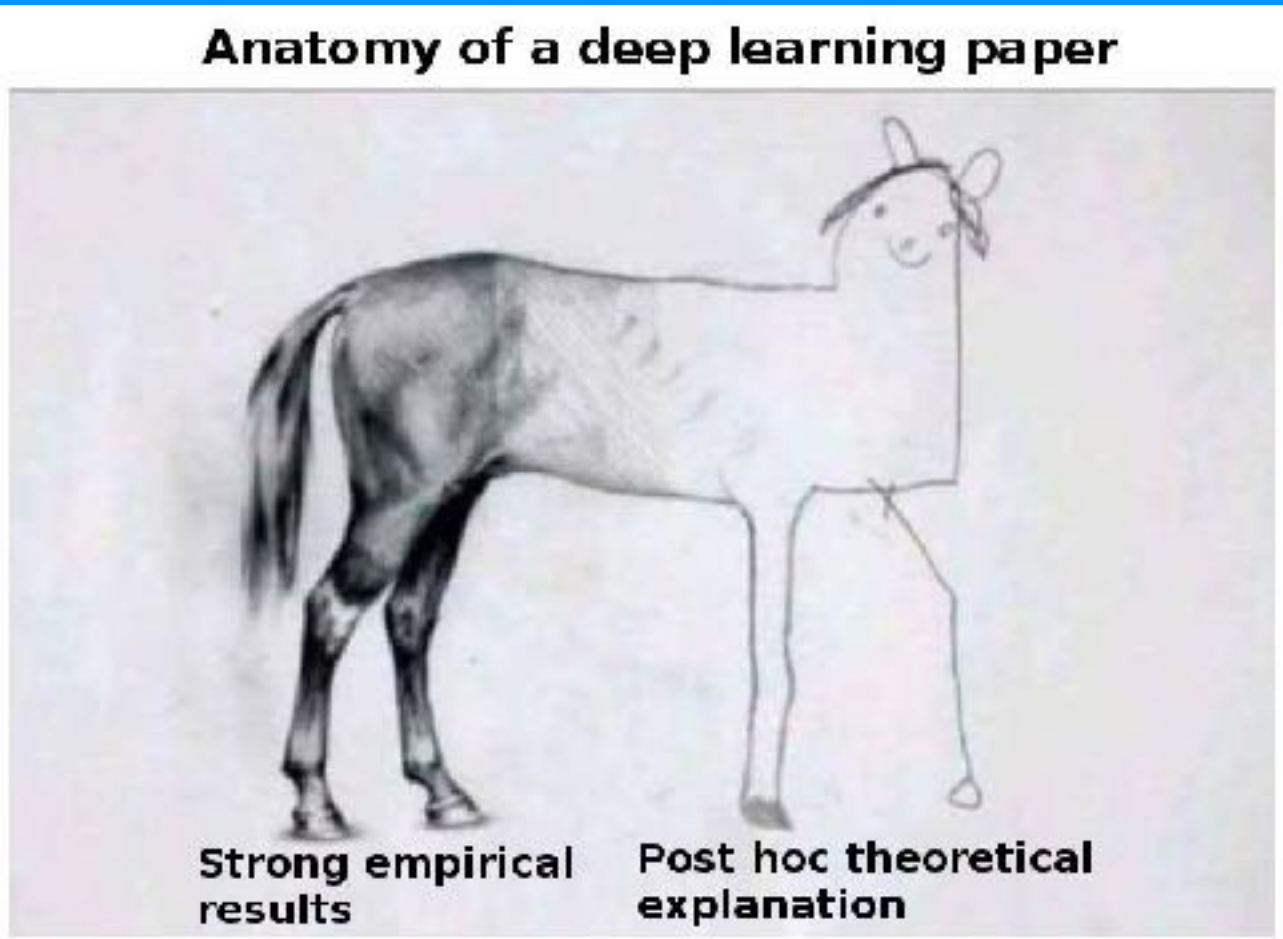
More examples:

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

Seq2Seq:

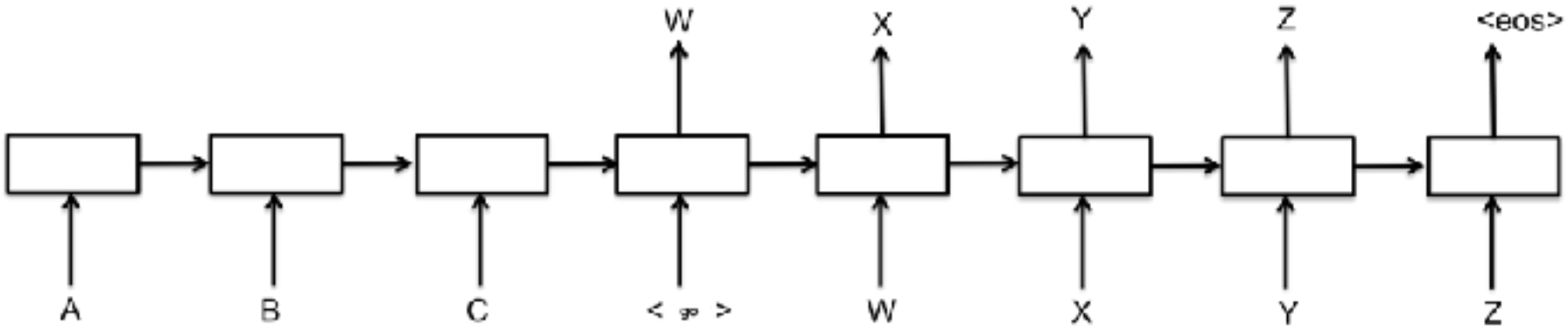
https://github.com/tensorflow/tensorflow/blob/r0.11/tensorflow/examples/skflow/neural_translation_word.py

Sequence to Sequence



Modeling Sequence to Sequence

Need to translate outputs of unknown size.



- Additional Vocabulary Special Casing:
  - <UNKNOWN>, for unknown input or characters not included in vocabulary
  - <EOS>, end of sentence
  - <GO>, start output sequence
  - <DONTCARE>, outputs before <GO> command

Sutskever et al. Sequence to Sequence Learning with Neural Networks, arXiv. 2014
https://arxiv.org/pdf/1409.3215.pdf

Modeling Sequence to Sequence

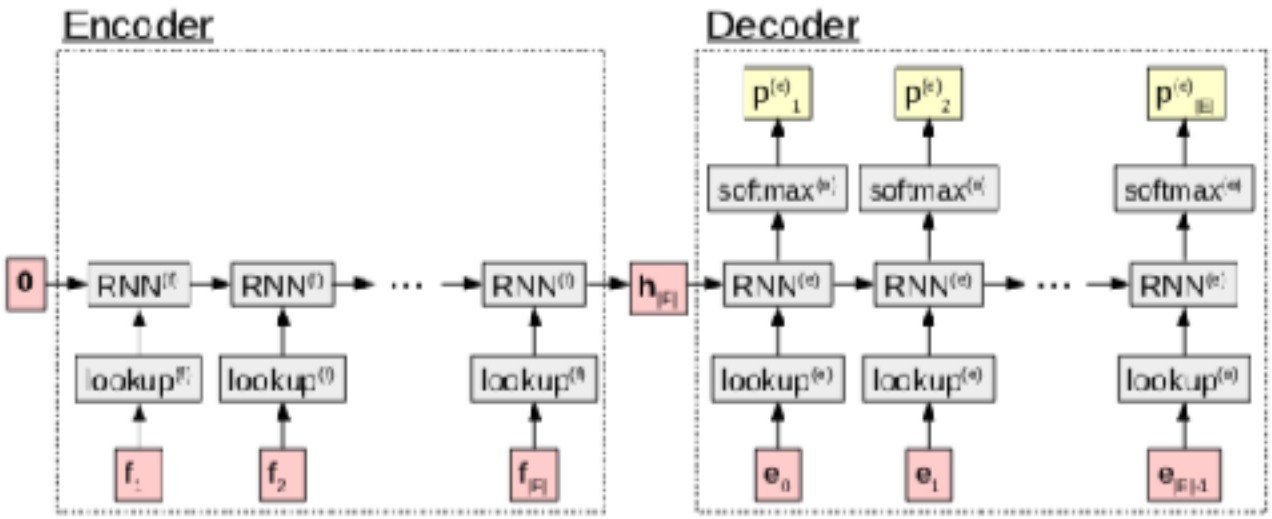


Figure 21: A computation graph of the encoder-decoder model.

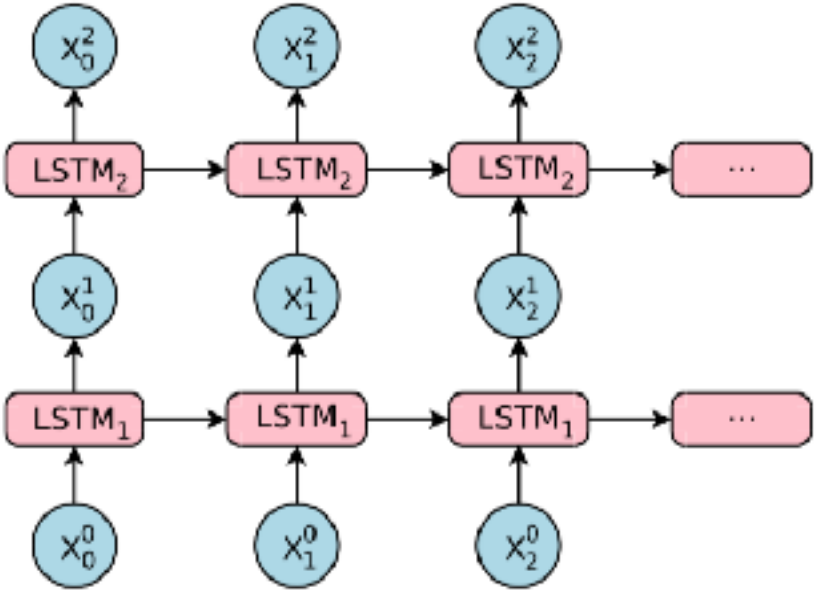
- **Training Process**: Give actual decoded letters for predicting next token
- **Decoding Process** can alter reliability of results:
  - Greedy Search, always choose most likely "next" symbol, seed
  - Keep list of "best" predictions for seeding (i.e., Beam Search)

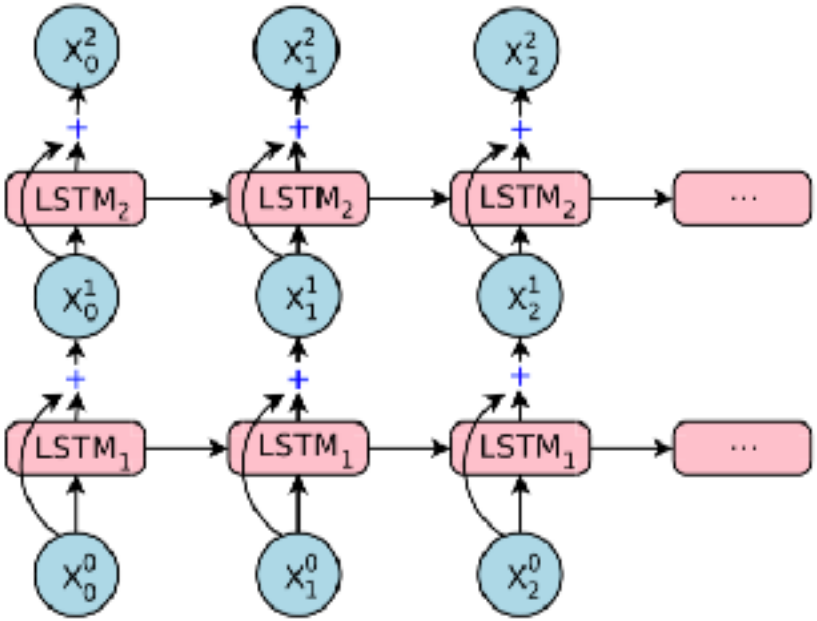
Graham Neubig. 2017
Neural Machine Translation and
Sequence-to-sequence Models: A Tutorial
https://arxiv.org/pdf/1703.01619.pdf

https://github.com/m2dsupsdlclass/lectures-labs/blob/master/labs/07_seq2seq/Translation_of_Numeric_Phrases_with_Seq2Seq_rendered.ipynb

GNMT: Residuals

- Google, 2016

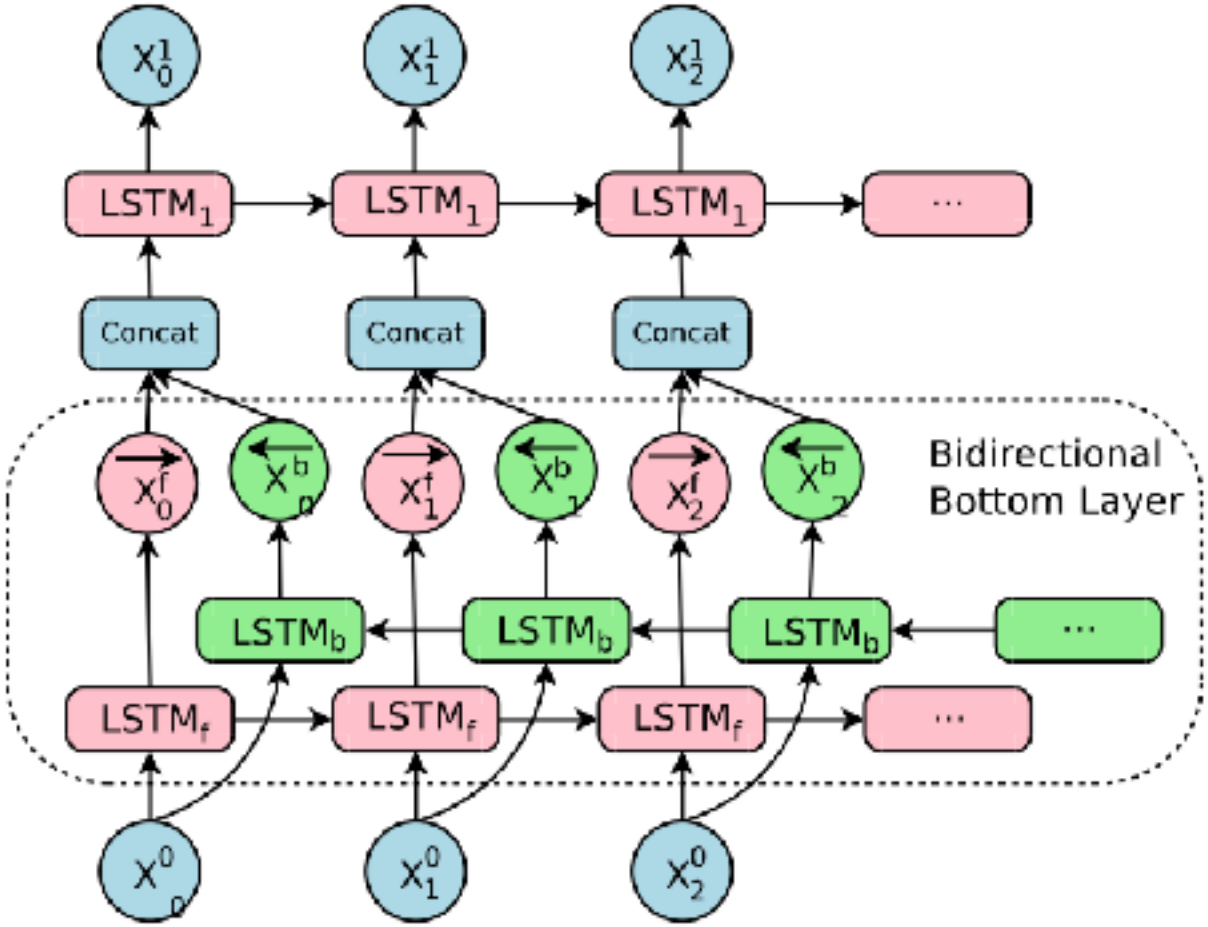




Google's Neural Machine Translation: https://arxiv.org/pdf/1609.08144.pdf

GNMT: Bidirectionality

- Google, 2016



Google Neural Machine Translation:
https://arxiv.org/pdf/1609.08144.pdf

GNMT: Attention

- Google, 2016

$$s_t = AttentionFunction(\mathbf{y}_{i-1}, \mathbf{x}_t) \quad \forall t, \quad 1 \leq t \leq M$$

$$p_t = \exp(s_t) / \sum_{t=1}^{M} \exp(s_t) \quad \forall t, \quad 1 \leq t \leq M$$

$$\mathbf{a}_i = \sum_{t=1}^{M} p_t . \mathbf{x}_t$$

where $\mathbf{x}_t$ is output of the t^{th} encoder
$\mathbf{y}_{i-1}$ is the output of the previous decoder
and $\mathbf{a}_i$ is the input for the i^{th} decoder

Google Neural Machine Translation:
https://arxiv.org/pdf/1609.08144.pdf

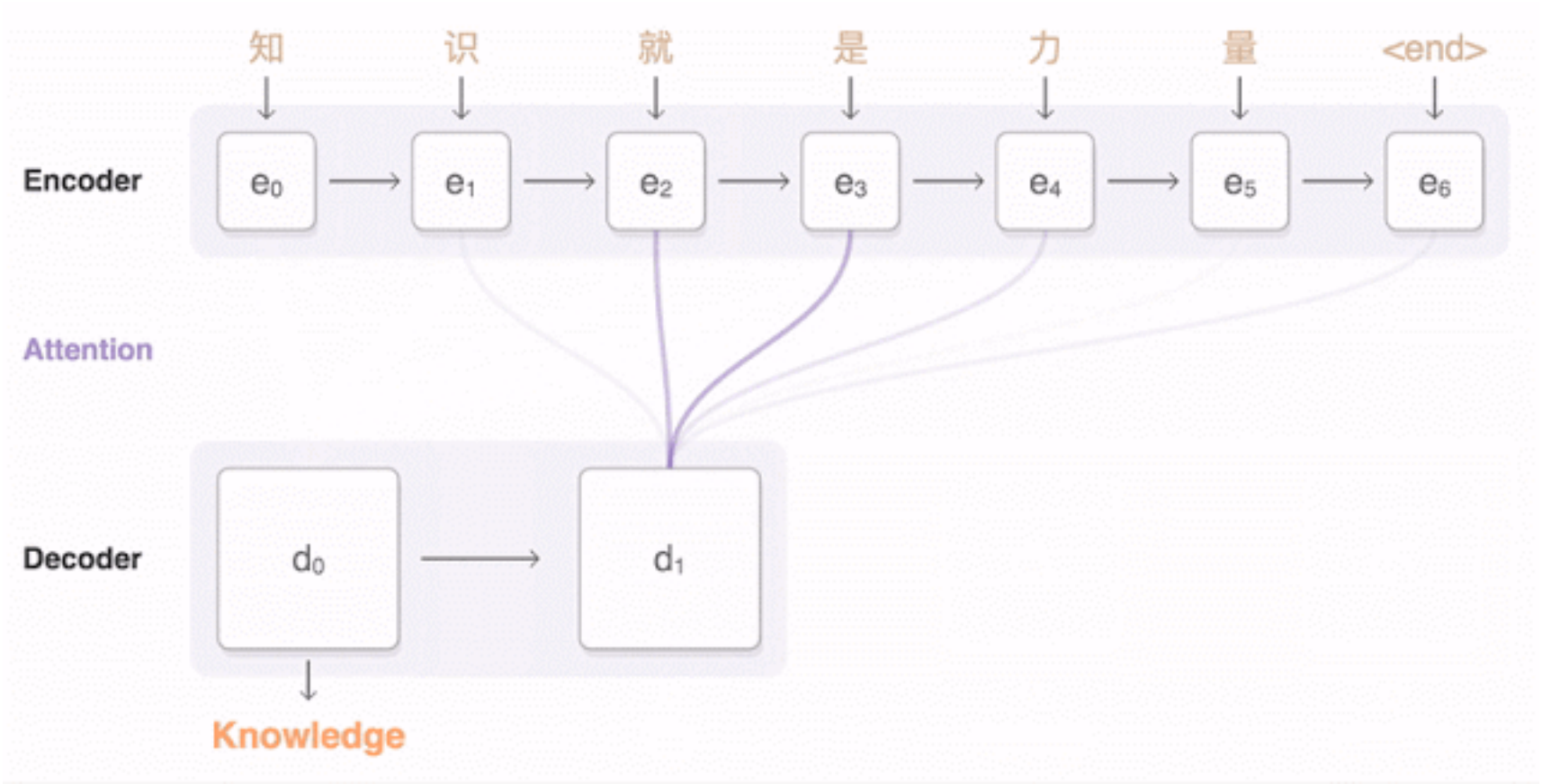
GNMT: Attention

- Google, 2016

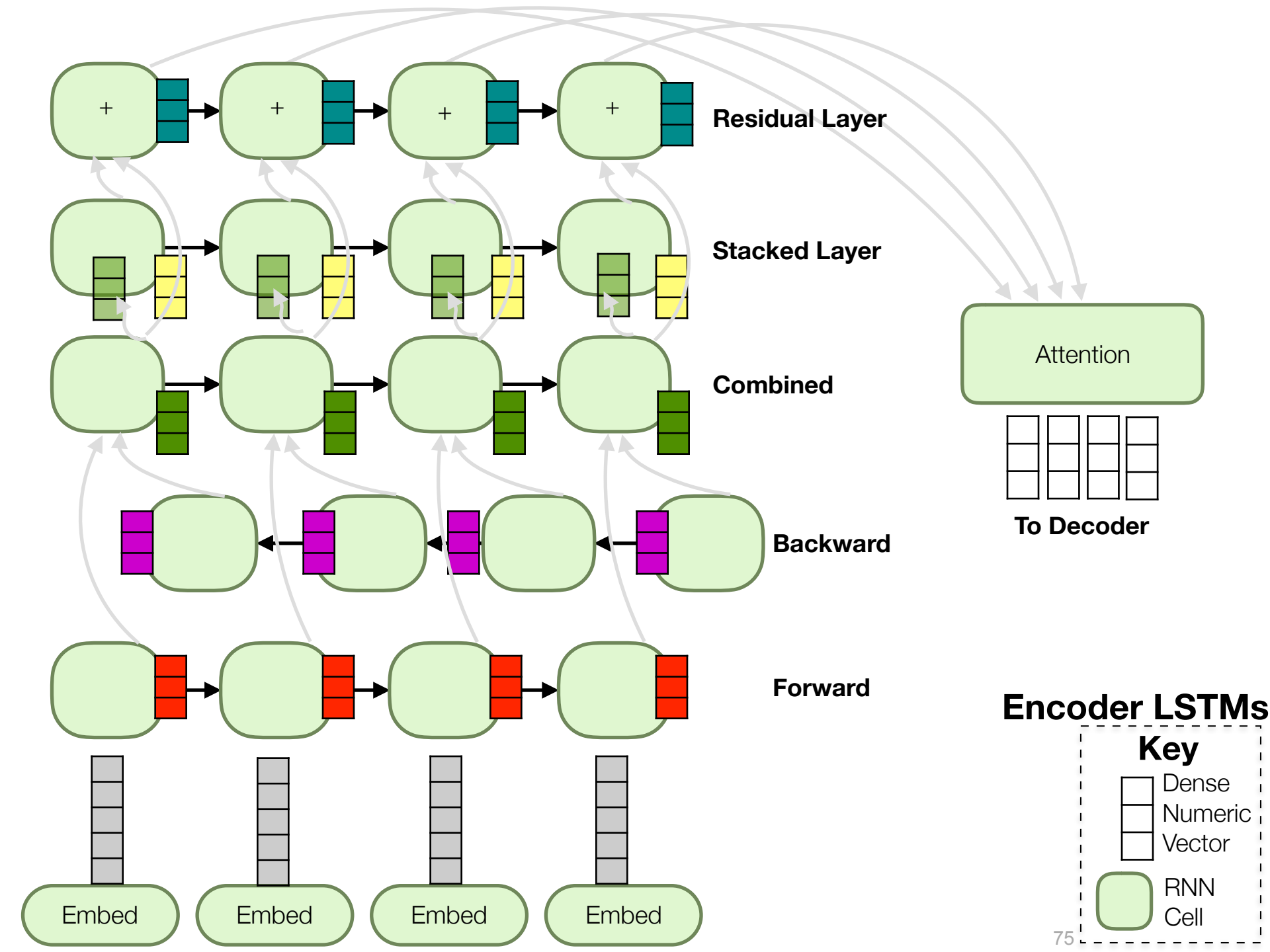
$$s_t = AttentionFunction(\mathbf{y}_{i-1}, \mathbf{x}_t) \quad \forall t, \quad 1 \le t \le M$$

$$p_t = \exp(s_t) / \sum_{t=1}^{M} \exp(s_t) \quad \forall t, \quad 1 \le t \le M$$

$$\mathbf{a}_i = \sum_{t=1}^{M} p_t . \mathbf{x}_t$$

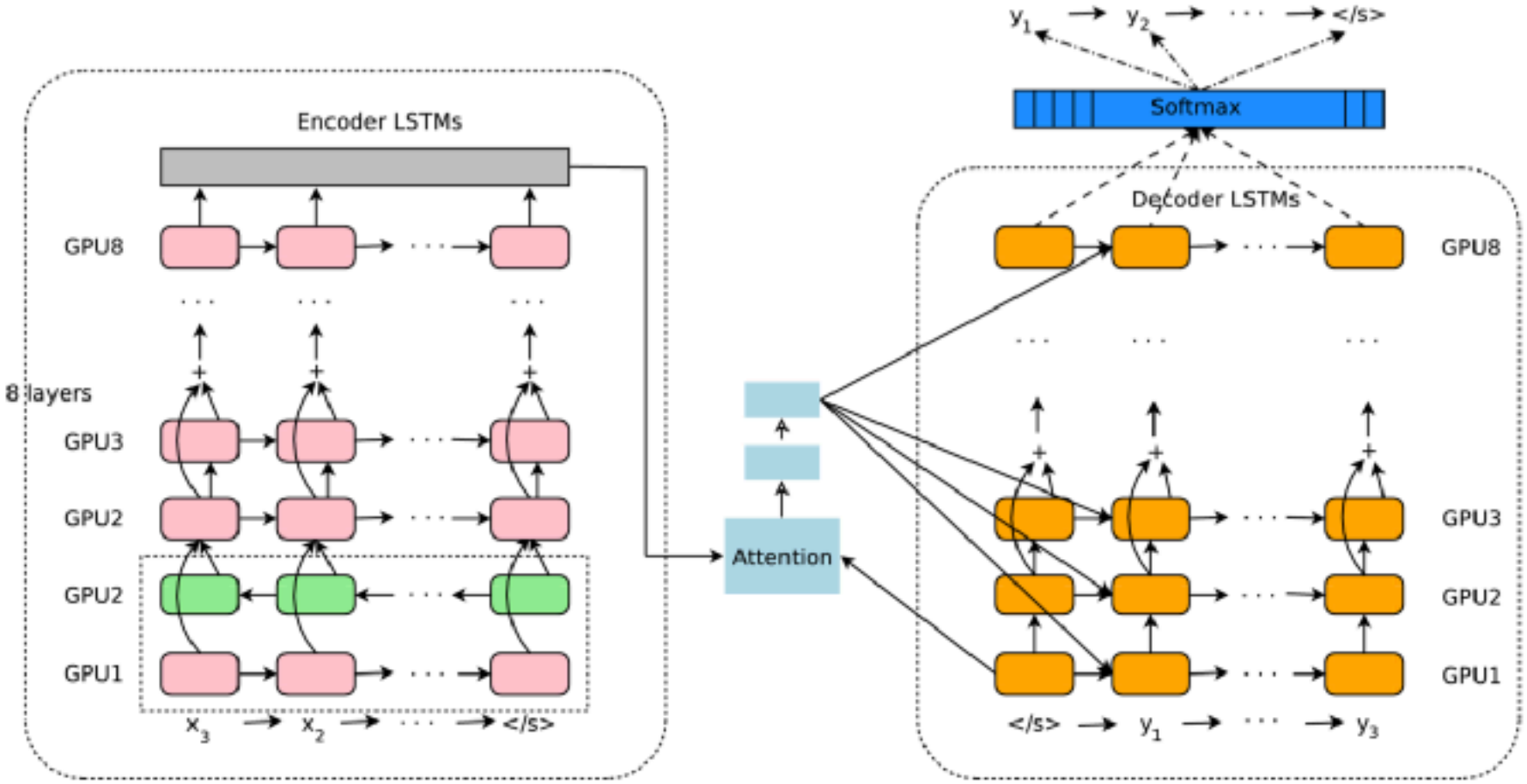


Google Neural Machine Translation:
https://arxiv.org/pdf/1609.08144.pdf
https://medium.com/@Synced/history-and-frontier-of-the-neural-machine-translation-dc981d25422d


Residual Layer
Stacked Layer
Combined
Backward
Forward
Attention
To Decoder
Embed
Embed
Embed
Embed
Encoder LSTMs
Key
Dense
Numeric
Vector
RNN
Cell

GNMT: Putting it All together

- Google, 2016



Google Neural Machine Translation:
https://arxiv.org/pdf/1609.08144.pdf

Demo, if time

… from Olivier Grisel

https://github.com/m2dsupsdlclass/lectures-labs/blob/master/labs/07_seq2seq/Translation_of_Numeric_Phrases_with_Seq2Seq_rendered.ipynb

Next time

- Class Retrospective and Town Hall

Lecture Notes for

Machine Learning in Python

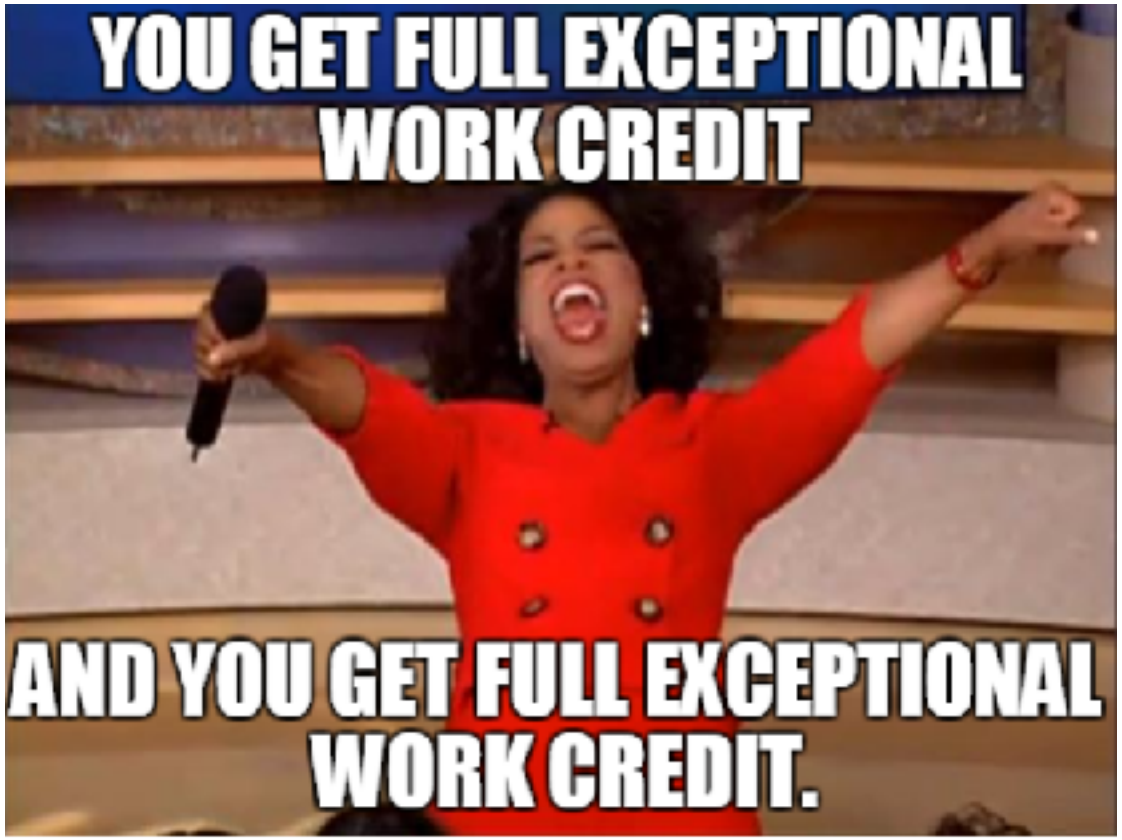
Professor Eric Larson

Final Lecture: Retrospective

Lecture Agenda

- Logistics
  - RNNs due **During Finals Time**
- Agenda
  - Town Hall
  - Retrospective

Town Hall



Courtesy of Daniel F.P. Garcia and Oprah

Course Retrospective

- AI winters exi
  machine learn
  repeat)
- Formal metho
- At the end of
- **Open sourc**
  advancemen
  - http://ww

Leading ML researchers issue statement of support for JMLR

From: Michael Jordan [mailto:jordan@CS.Berkeley.EDU]
Sent: Monday, October 08, 2001 5:33 PM
Subject: letter of resignation from Machine Learning journal

Dear colleagues in machine learning,

The forty people whose names appear below have resigned from the Editorial Board of the Machine Learning Journal (MLJ). We would like to make our resignations public, to explain the rationale for our action, and to indicate some of the implications that we see for members of the machine learning community worldwide.

The machine learning community has come of age during a period of enormous change in the way that research publications are circulated. Fifteen years ago research papers did not circulate easily, and as with other research communities we were fortunate that a viable commercial publishing model was in place so that the fledgling MLJ could begin to circulate. The needs of the community, principally those of seeing our published papers circulate as widely and rapidly as possible, and the business model of commercial publishers were in harmony.

Times have changed. Articles now circulate easily via the Internet, but unfortunately MLJ publications are under restricted access. Universities and research centers can pay a yearly fee of $1050 US to obtain unrestricted access to MLJ articles (and individuals can pay $120 US). While these fees provide access for institutions and individuals who can afford them, we feel that they also have the effect of limiting contact between the current machine learning community and the potentially much larger community of researchers worldwide whose participation in our field should be the fruit of the modern Internet.

None of the revenue stream from the journal makes its way back to authors, and in this context authors should expect a particularly favorable return on their intellectual contribution---they should expect a service that maximizes the distribution of their work. We see little benefit accruing to our community from a mechanism that ensures revenue for a third party by restricting the communication channel between authors and readers.

Sincerely yours,

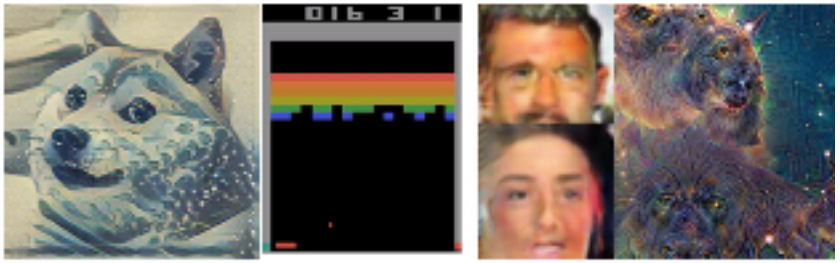
Chris Atkeson
Peter Bartlett
Andrew Barto
Jonathan Baxter
Yoshua Bengio
Kristin Bennett
Chris Bishop
Justin Boyan
Carla Brodley
Claire Cardie
William Cohen
Peter Dayan
Tom Dietterich
Jerome Friedman
Nir Friedman
Zoubin Ghahramani
David Heckerman
Geoffrey Hinton
Haym Hirsh
Tommi Jaakkola
Michael Jordan
Leslie Kaelbling
Daphne Koller
John Lafferty
Sridhar Mahadevan
Marina Meila
Andrew McCallum
Tom Mitchell
Stuart Russell
Lawrence Saul
Bernhard Schoelkopf
John Shawe-Taylor
Yoram Singer
Satinder Singh
Padhraic Smyth
Richard Sutton
Sebastian Thrun
Manfred Warmuth
Chris Williams
Robert Williamson

Topics review

- Data **munging** in pandas and numpy
- Data **visualization** in jupyter with matplotlib, pandas, seaborn, and plotly
- Data preprocessing: **dim reduction**, images, text, categorical features, **embeddings**
- **Linear models**: linear regression, logistic regression, support vector machines
- **Optimization** strategies: Gradient ascent, Quasi-Newton
- **Back propagation** in MLP (from scratch)
- Tensorflow/Keras for **wide and deep networks**
- **Convolutional** neural networks
- **Recurrent** neural networks

Topics Not Covered

- Visualizing Deep Convolutional Networks
- Fully Convolutional Networks
- Transfer/Multi-Task Learning
- Style Transfer
- Generative Adversarial Networks
- Reinforcement Learning



Syllabus for CSE8321: Machine Learning and Neural Networks

Course Schedule

Syllabus for CSE8321: Machine Learning and Neural Networks

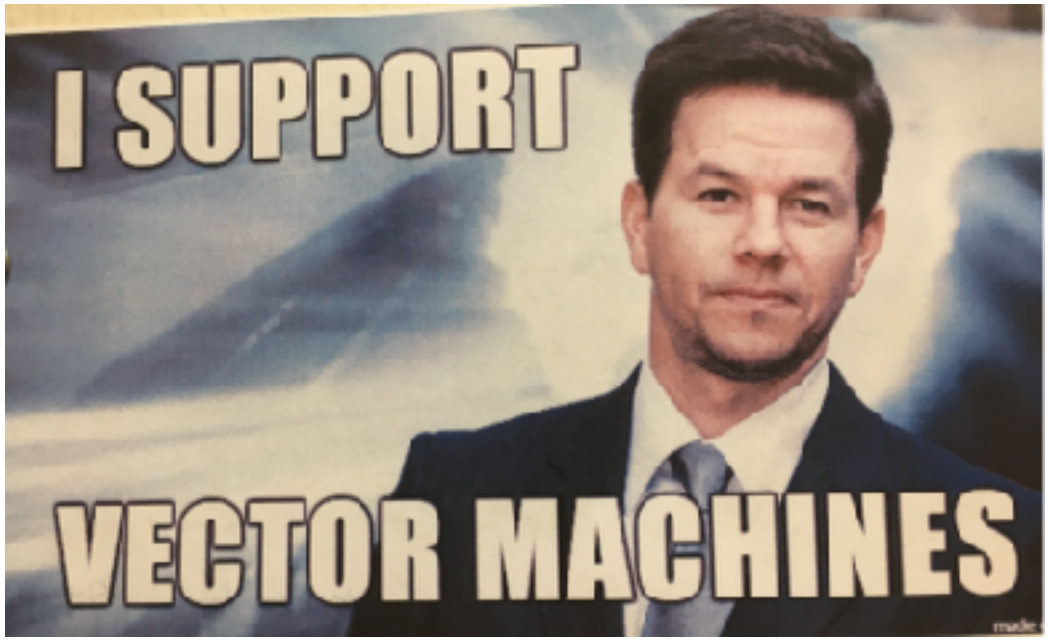
Overview

This course extends basic knowledge of the use of Neural Networks in machine learning beyond simple prediction, especially targeted outputs that are generation or alteration of images, text, and audio. This course emphasizes topics of neural networks in the "deep learning" subdomain. This course will survey of important topics and current areas of research, including transfer learning, multi-task and multi modal learning, image style transfer, neural network visualization, deep convolutional generative adversarial networks, and deep reinforcement learning. For grading, students are expected to complete smaller team-based projects throughout the semester, present one research paper in a 15-20 minute group presentation (covering topics in the course), and complete a comprehensive final project that involves a number of different deep learning architectures.

Thank you for a great semester!

- but it could **have been better** somehow, right?
  - how could you learn better?
  - what should **not be cut** or **changed**?
  - SVMs?
  - RNNs?
  - More convolutional approaches/depth?
  - More APIs? Turi / Pytorch?

Thank You for an Excellent Semester!



Courtesy of Omar Roa

Backup slides

TensorFlow

http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html

```
with tf.variable_scope('rnn_cell'):
    W = tf.get_variable('W', [num_classes + state_size, state_size])
    b = tf.get_variable('b', [state_size], initializer=tf.constant_initializer(0.0))

def rnn_cell(rnn_input, state):
    with tf.variable_scope('rnn_cell', reuse=True):
        W = tf.get_variable('W', [num_classes + state_size, state_size])
        b = tf.get_variable('b', [state_size], initializer=tf.constant_initializer(0.0))
    return tf.tanh(tf.matmul(tf.concat(1, [rnn_input, state]), W) + b)

state = init_state
rnn_outputs = []
for rnn_input in rnn_inputs:
    state = rnn_cell(rnn_input, state)
    rnn_outputs.append(state)
final_state = rnn_outputs[-1]

#logits and predictions
with tf.variable_scope('softmax'):
    W = tf.get_variable('W', [state_size, num_classes])
    b = tf.get_variable('b', [num_classes], initializer=tf.constant_initializer(0.0))
logits = [tf.matmul(rnn_output, W) + b for rnn_output in rnn_outputs]
predictions = [tf.nn.softmax(logit) for logit in logits]

# Turn our y placeholder into a list labels
y_as_list = [tf.squeeze(i, squeeze_dims=[1]) for i in tf.split(1, num_steps, y)]

#losses and train_step
losses = [tf.nn.sparse_softmax_cross_entropy_with_logits(logit,label) for \
          logit, label in zip(logits, y_as_list)]
total_loss = tf.reduce_mean(losses)
train_step = tf.train.AdagradOptimizer(learning_rate).minimize(total_loss)
```

recurrent networks

http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html

```
def train_network(num_epochs, num_steps, state_size=4, verbose=True):
    with tf.Session() as sess:
        sess.run(tf.initialize_all_variables())
        training_losses = []
        for idx, epoch in enumerate(gen_epochs(num_epochs, num_steps)):
            training_loss = 0
            training_state = np.zeros((batch_size, state_size))
            if verbose:
                print("\nEPOCH", idx)
            for step, (X, Y) in enumerate(epoch):
                tr_losses, training_loss_, training_state, _ = \
                    sess.run([losses,
                              total_loss,
                              final_state,
                              train_step],
                                  feed_dict={x:X, y:Y, init_state:training_state})
                training_loss += training_loss_
                if step % 100 == 0 and step > 0:
                    if verbose:
                        print("Average loss at step", step,
                              "for last 250 steps:", training_loss/100)
                    training_losses.append(training_loss/100)
                    training_loss = 0

    return training_losses
```

TensorFlow

http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html

```
def train_network(num_epochs, num_steps, state_size=4, verbose=True):
    with tf.Session() as sess:
        sess.run(tf.initialize_all_variables())
        for idx, epoch in enumerate(gen_epochs(num_epochs, num_steps)):
            training_state = np.zeros((batch_size, state_size))
            for X, Y in epoch:
                tr_losses, training_loss_, training_state, _ = \
                    sess.run([losses,
                              total_loss,
                              final_state,
                              train_step],
                             feed_dict={x:X, y:Y, init_state:training_state})
```

TensorFlow (simplified)

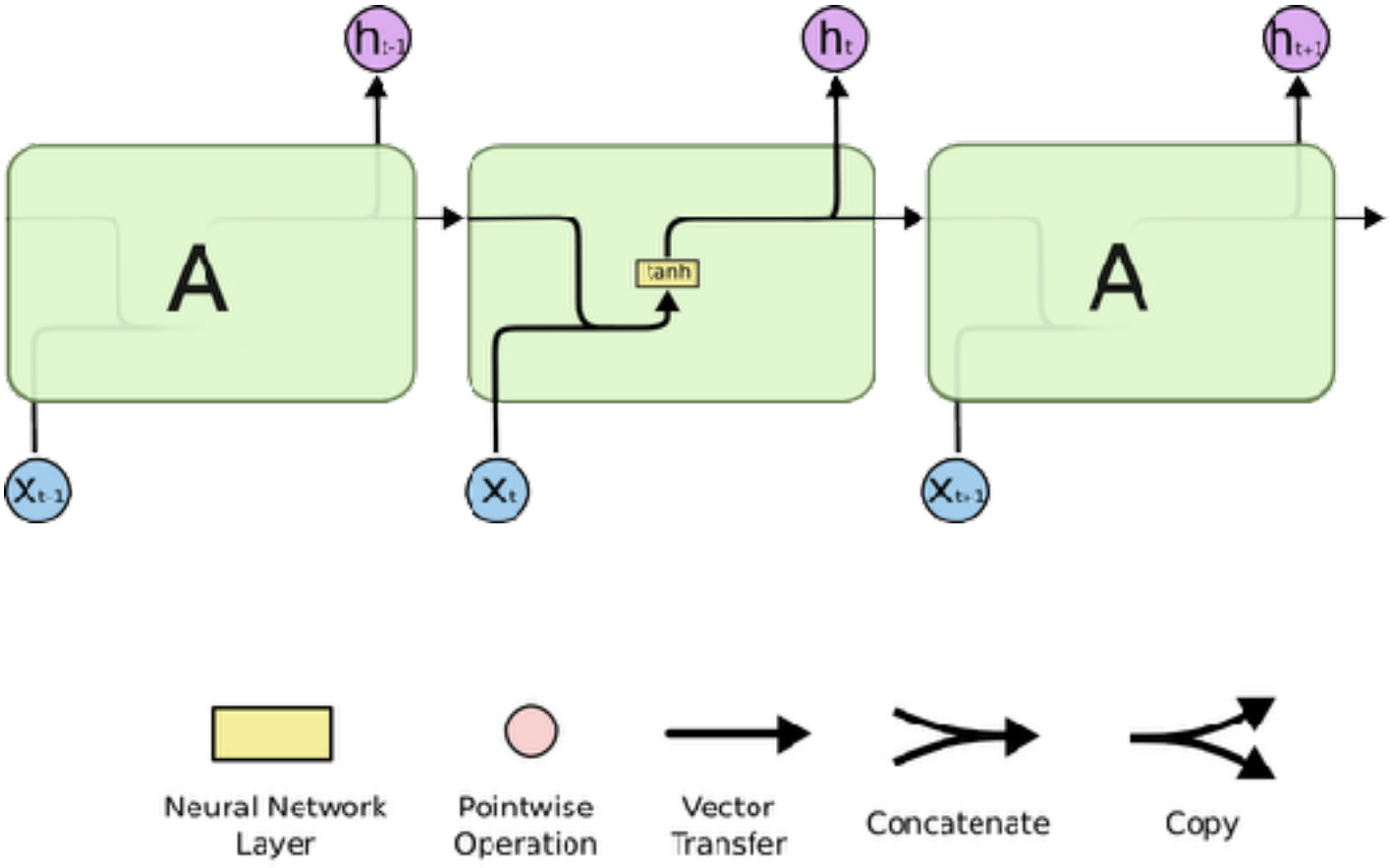
http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html

```
cell = tf.nn.rnn_cell.BasicRNNCell(state_size)
rnn_outputs, final_state = tf.nn.rnn(cell, rnn_inputs, initial_state=init_state)


loss_weights = [tf.ones([batch_size]) for i in range(num_steps)]
losses = tf.nn.seq2seq.sequence_loss_by_example(logits, y_as_list, loss_weights)
```

```
x = tf.placeholder(tf.int32, [batch_size, num_steps], name='input_placeholder')
y = tf.placeholder(tf.int32, [batch_size, num_steps], name='labels_placeholder')
init_state = tf.zeros([batch_size, state_size])

x_one_hot = tf.one_hot(x, num_classes)
rnn_inputs = tf.unpack(x_one_hot, axis=1)

cell = tf.nn.rnn_cell.BasicRNNCell(state_size)
rnn_outputs, final_state = tf.nn.rnn(cell, rnn_inputs, initial_state=init_state)


with tf.variable_scope('softmax'):
    W = tf.get_variable('W', [state_size, num_classes])
    b = tf.get_variable('b', [num_classes], initializer=tf.constant_initializer(0.0))
logits = [tf.matmul(rnn_output, W) + b for rnn_output in rnn_outputs]
predictions = [tf.nn.softmax(logit) for logit in logits]

y_as_list = [tf.squeeze(i, squeeze_dims=[1]) for i in tf.split(1, num_steps, y)]

loss_weights = [tf.ones([batch_size]) for i in range(num_steps)]
losses = tf.nn.seq2seq.sequence_loss_by_example(logits, y_as_list, loss_weights)
total_loss = tf.reduce_mean(losses)
train_step = tf.train.AdagradOptimizer(learning_rate).minimize(total_loss)
```

More Advanced Architectures

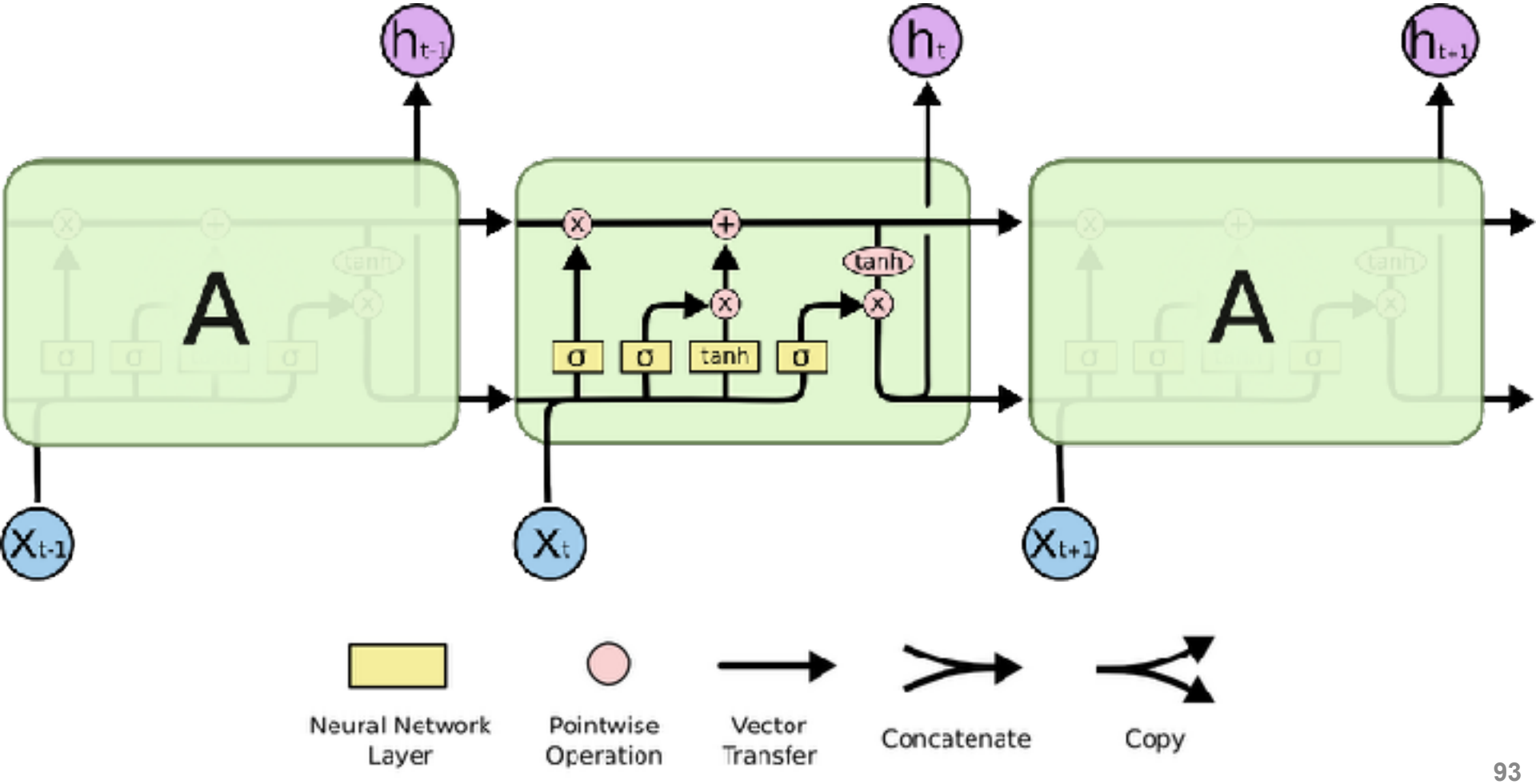
- **LSTM key idea**: limit how past data can affect output



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

More Advanced Architectures

- **LSTM key idea**: limit how past data can affect output



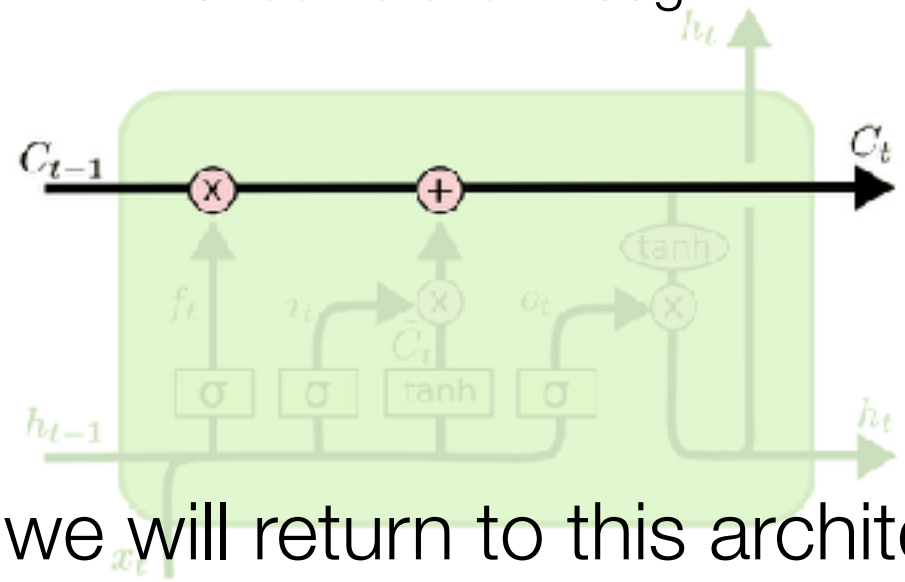
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

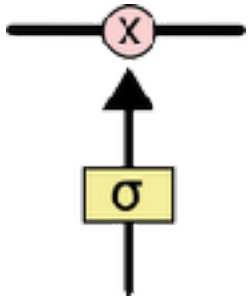
More Advanced Architectures

- **LSTM key idea**: limit how past data can affect output

let **cell state** through

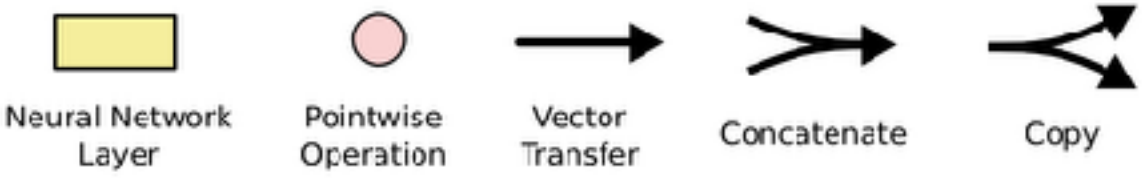
potentially **forget past** inputs via "gate" σ





we will return to this architecture later, for now:

put it in long term memory 😂



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