Lecture Notes for

Machine Learning in Python

Professor Eric Larson

History and Introduction to Recurrent Neural Networks

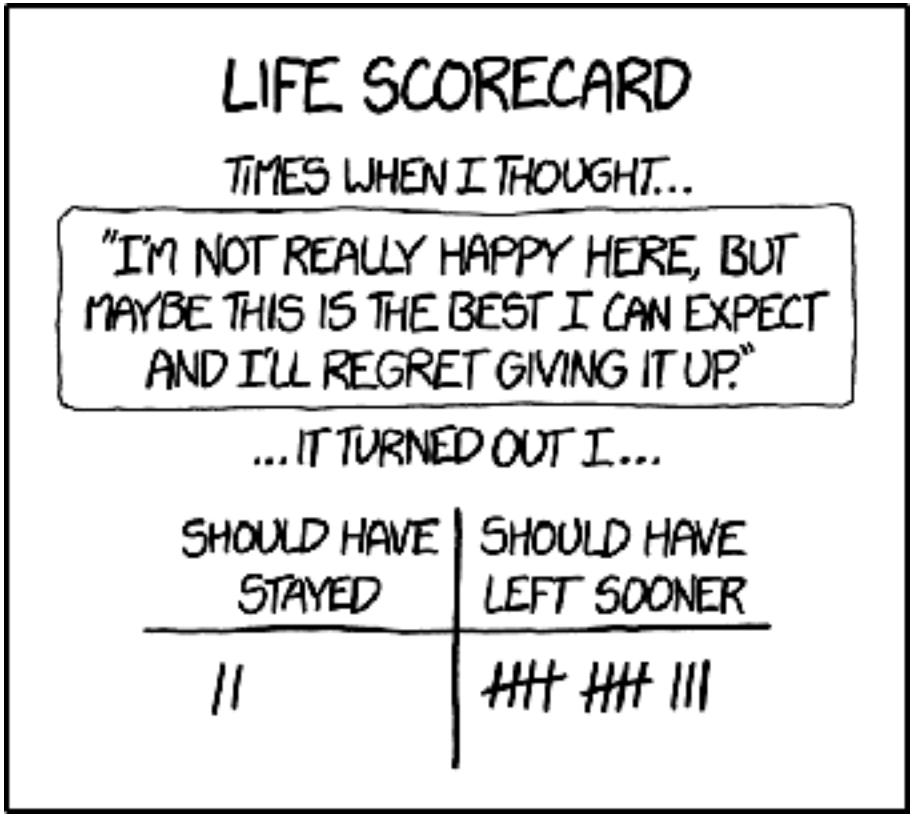
Lecture Agenda

- Logistics
  - RNNs due date Reminder
  - CNN Town Hall
- Recurrent Networks (~three lecture agenda)
  - Overview
  - Problem Types
  - Embeddings
  - Types of RNNs
  - Demo A
  - CNNs and RNNs
  - Demo B
  - Ethical Use Case for RNNs
  - Course Retrospective

CNN Town Hall

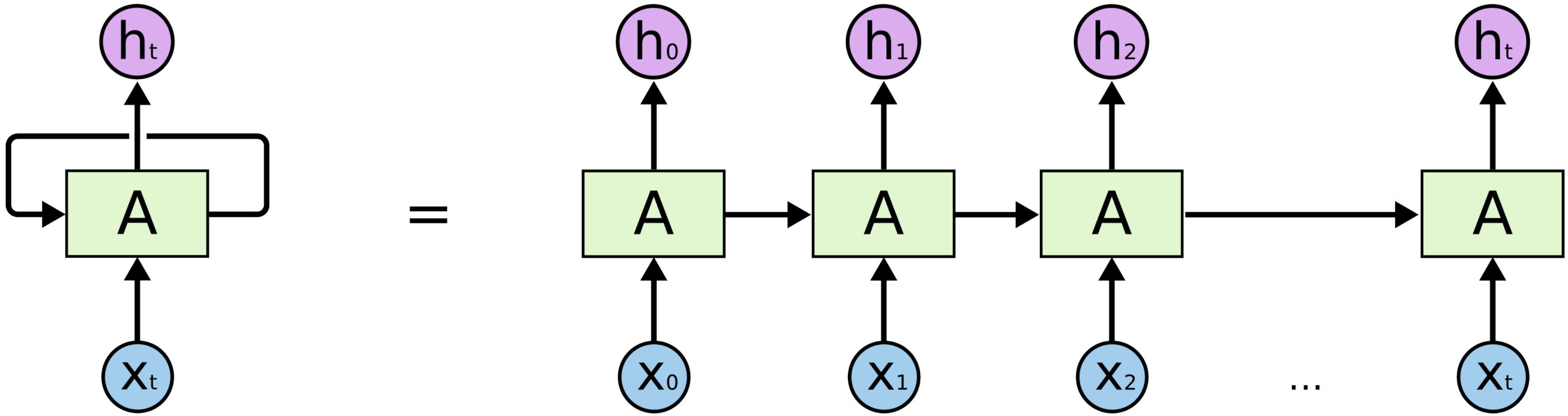
Machine Learning 101

History of Recurrent Neural Networks



Recurrent Networks: Main Idea

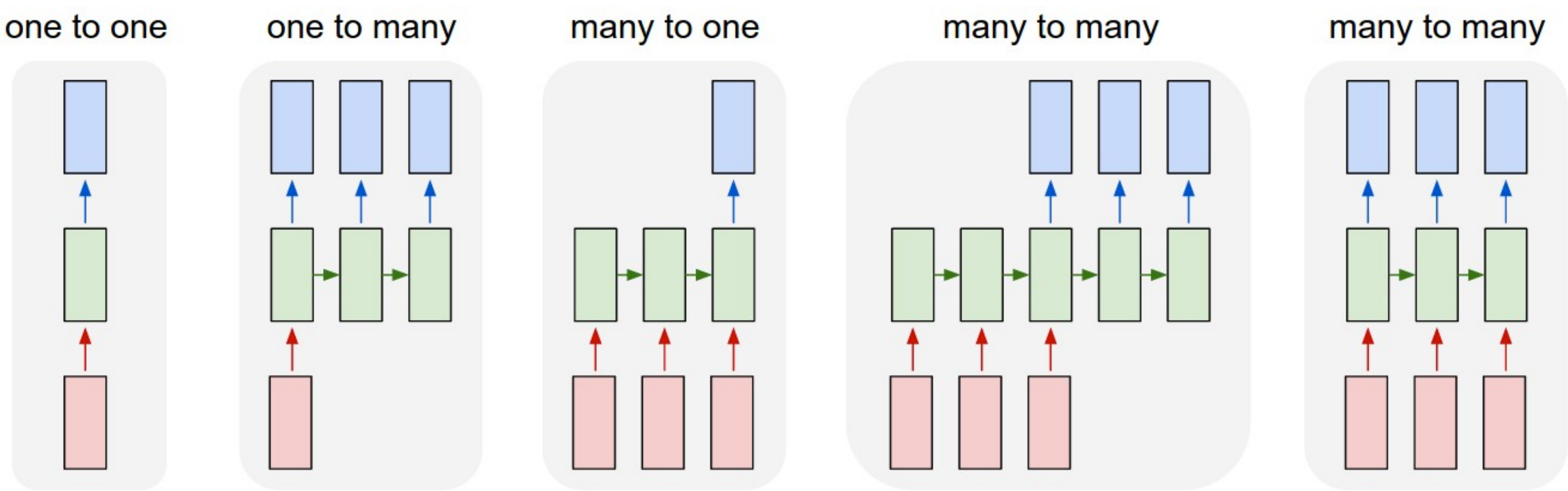
- equations for recurrent networks



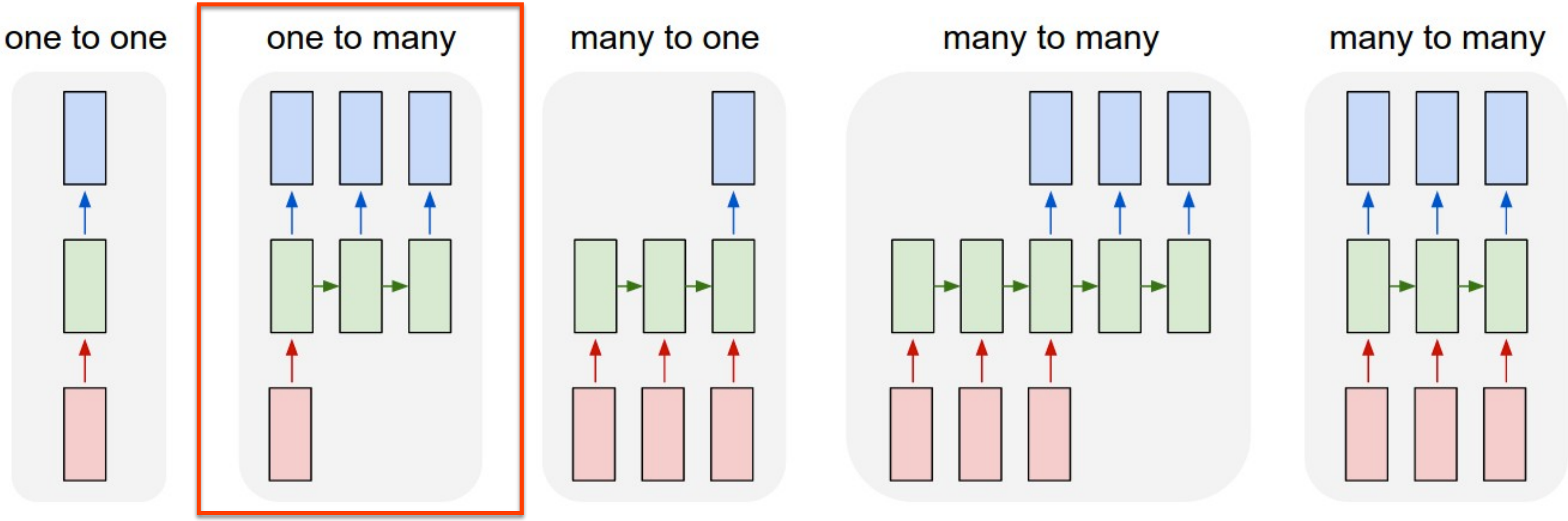
compact

unrolled

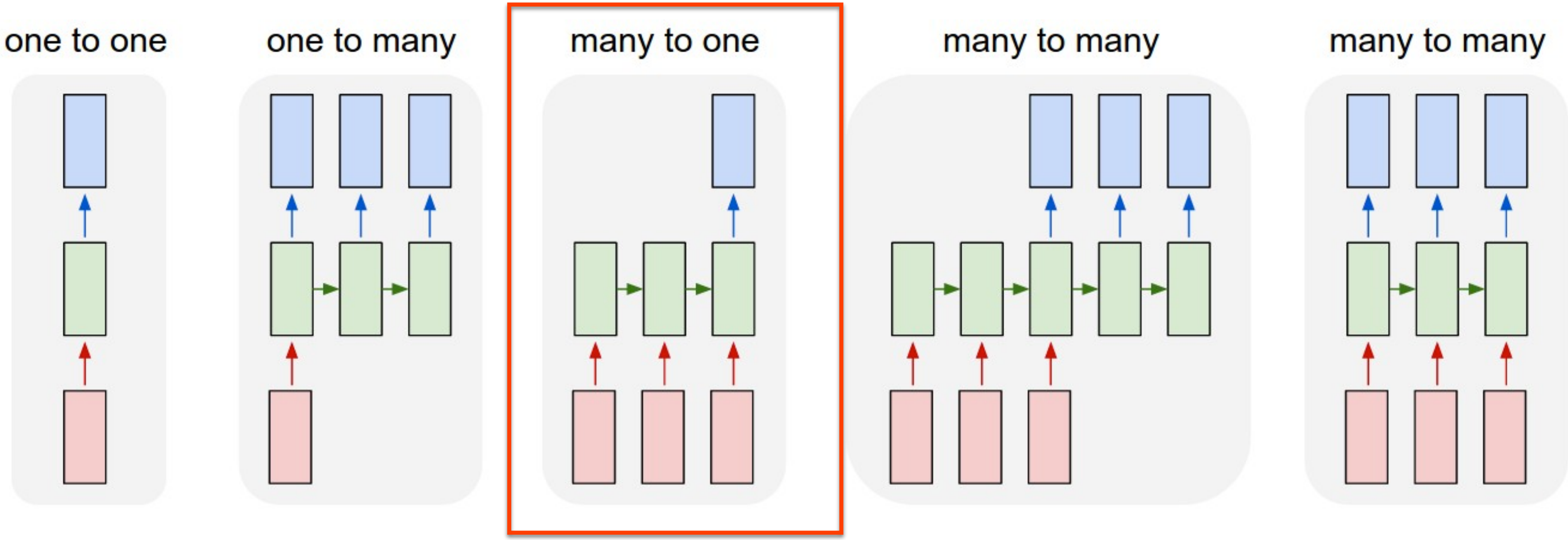
Recurrent Networks: Problem Types

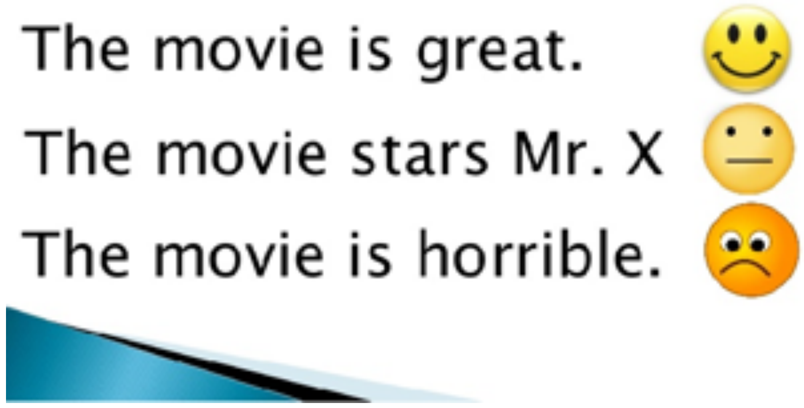


Recurrent Networks: Problem Types



Recurrent Networks: Problem Types





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

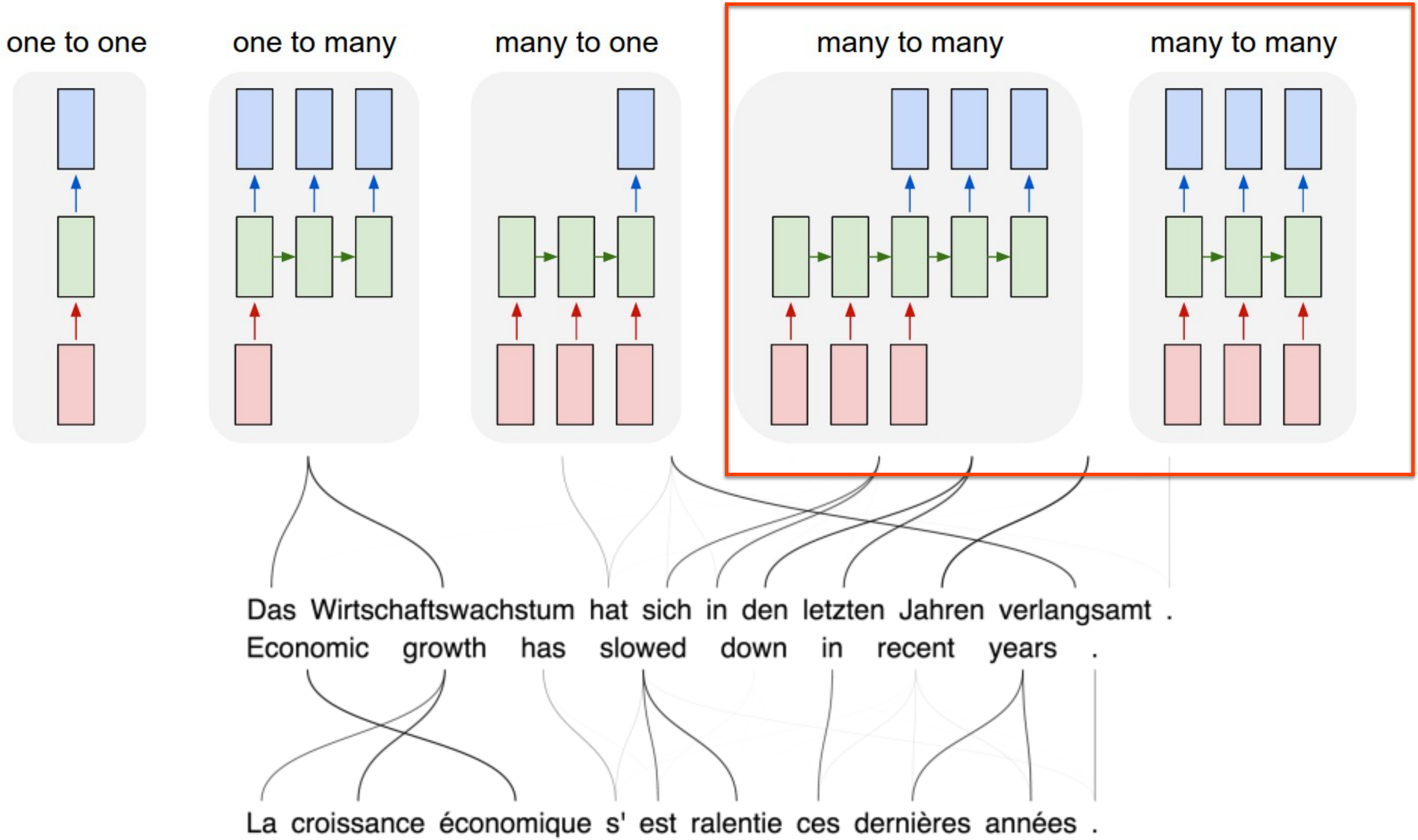
Shaun Norris (born 14 May 1982) is a South African professional golfer.Norris plays on the Sunshine Tour where he has won twice. He won the inaugural Africa Open in 2008 and the Nashua Masters in 2011. He also began playing on the European Tour in 2011 after graduating from qualifying school.

Athlete

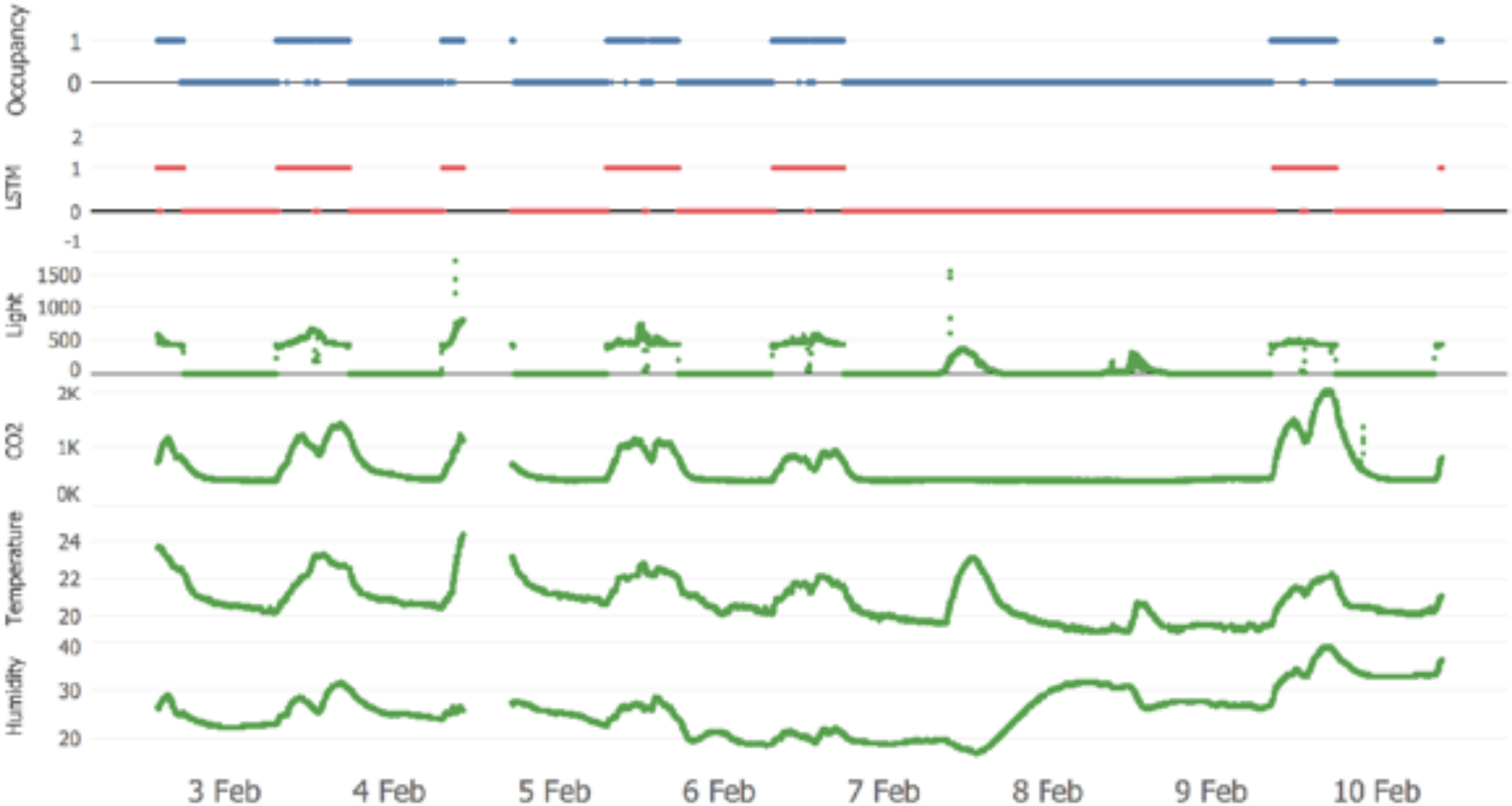
Palace Software was a British video game publisher and developer during the 1980s based in London England. It was notable for the Barbarian and Cauldron series of games for 8-bit home computer platforms in particular the ZX Spectrum Amstrad CPC and Commodore 64.

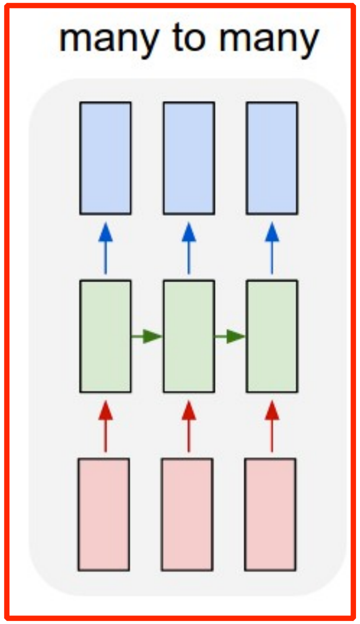
Company

Recurrent Networks: Problem Types



Recurrent Networks: Problem Types

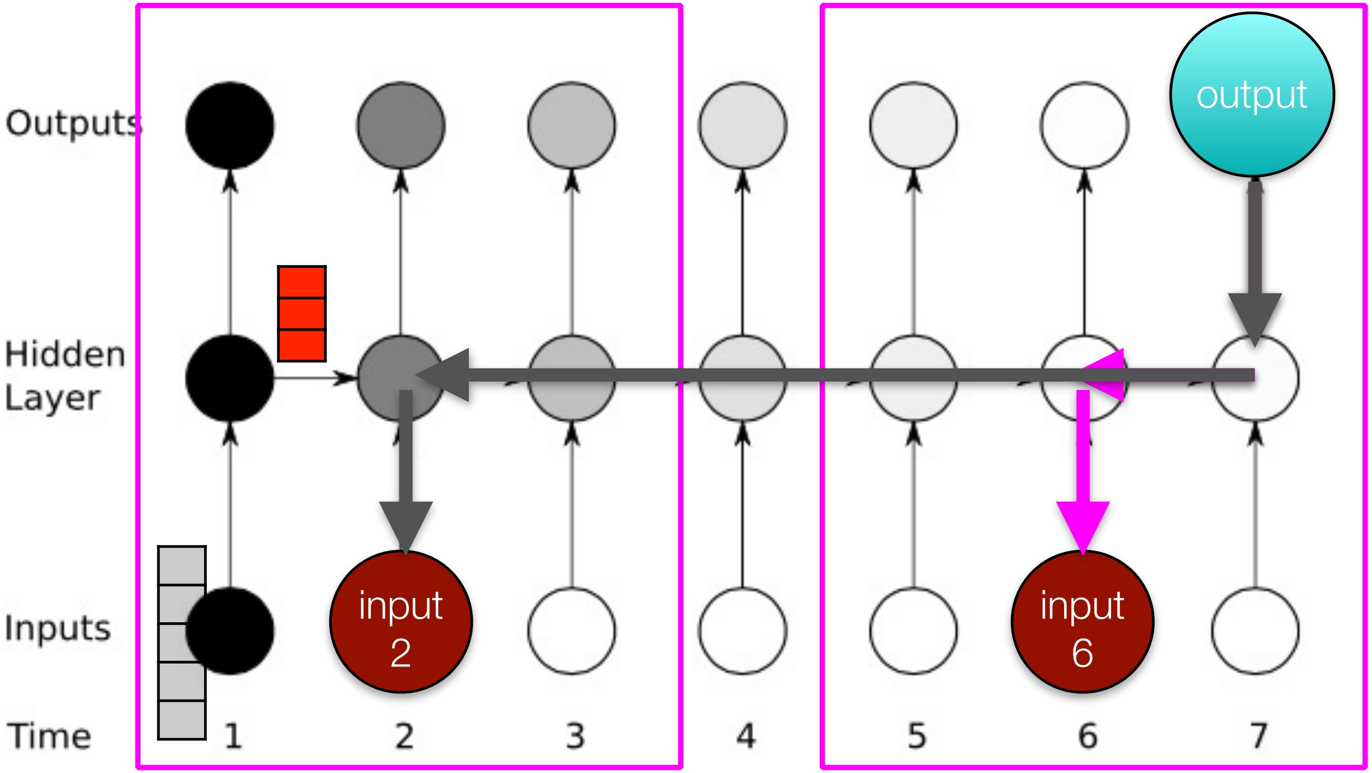




sequence to sequence

Recurrent Networks, the Age Old Problem

- vanishing gradients: why are these a problem?



Error Calculation, ***E***

low influence on gradient **high influence on gradient**

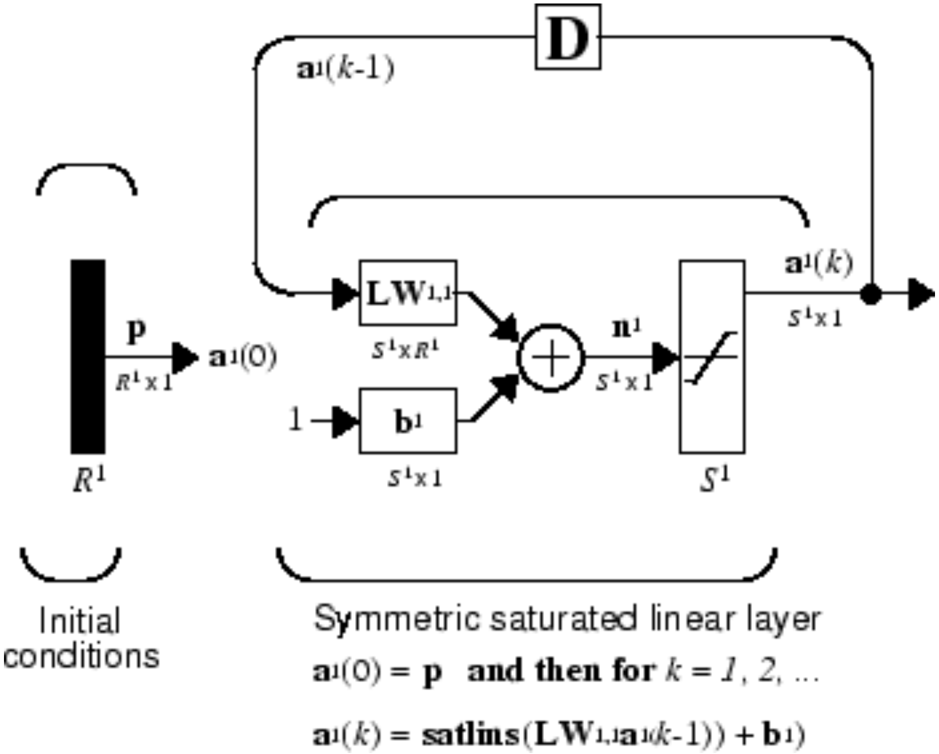
$$\frac{\partial E_t}{\partial s_{t-k}} = \frac{\partial E_t}{\partial s_t}\frac{\partial s_t}{\partial s_{t-k}} = \frac{\partial E_t}{\partial s_t}\left(\frac{\partial s_t}{\partial s_{t-1}}\frac{\partial s_{t-1}}{\partial s_{t-2}}\cdots\frac{\partial s_{t-k+1}}{\partial s_{t-k}}\right) = \frac{\partial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

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

History of Recurrent Networks

- Hopfield Network, 1982

John Hopfield, Princeton



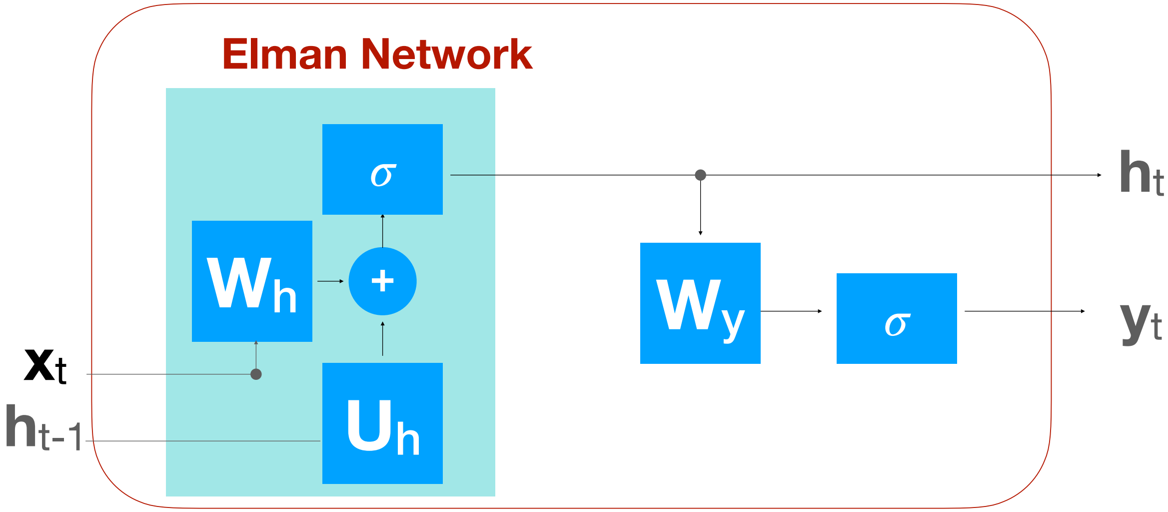
Neural Network Design, Hagan, Demuth, Beale, and De Jesus

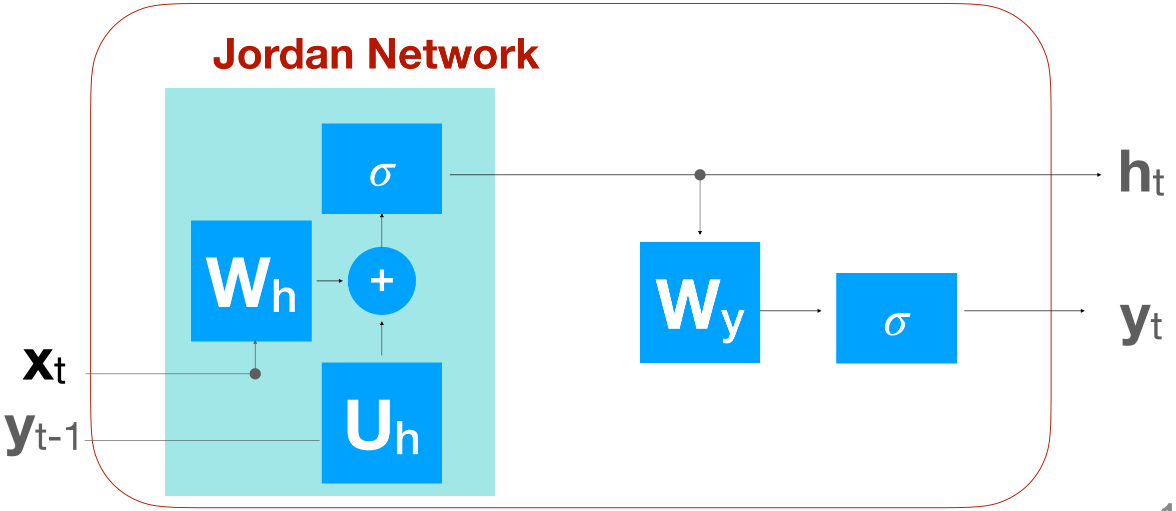
- Elman/Jordan Networks, ~1988

Contribution:
Time Steps for Unrolling

Jeffrey Elman, UCSD

Michael Jordan, Berkeley

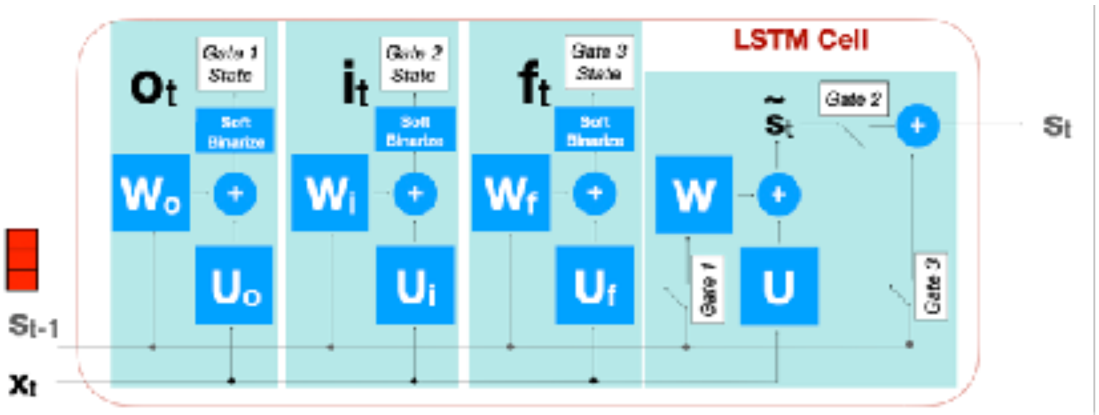




- Long Short Term Memory, ~1997 - 2010

Sepp Hochreiter, Many Universities

Jürgen Schmidhuber, Switzerland



More on these later

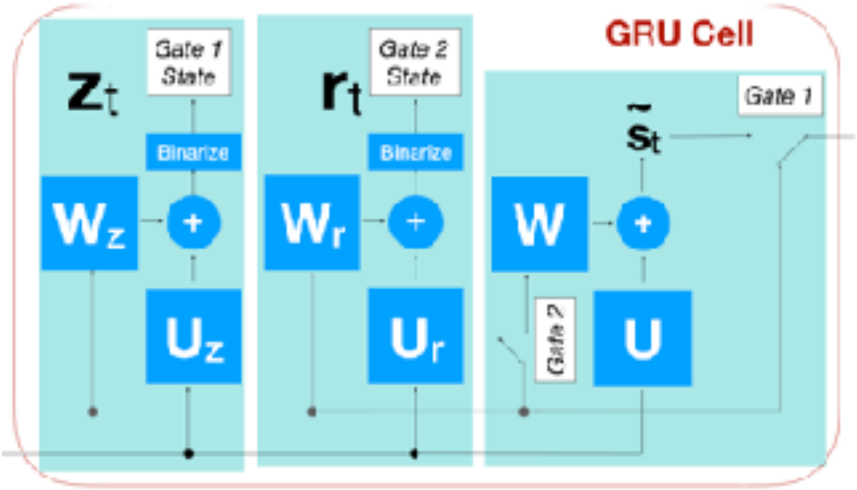
Contribution:
Long Duration Memory
State Vector separate from Output

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

Other big advances

- **Attention** (early 2017)
- 1D **Convolution** to Replace RNN (late 2017)
- Marriage of CNN and RNN
  - The **transformer** architecture (early 2018)
  - Self-attention (late 2018)
- **Multi-headed** attention in transformers (2018)
- **BERT**, **GPT-#**, etc. (2019-present)

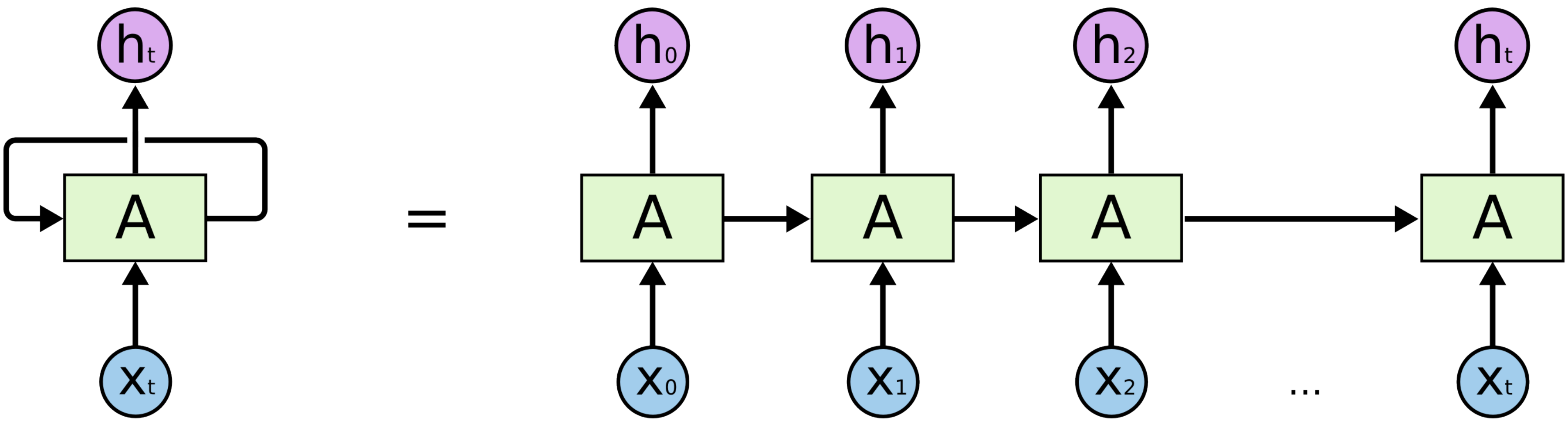
This Course

NLP Course

Basics of Recurrent Neural Networks

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

Recurrent Networks: Main Idea



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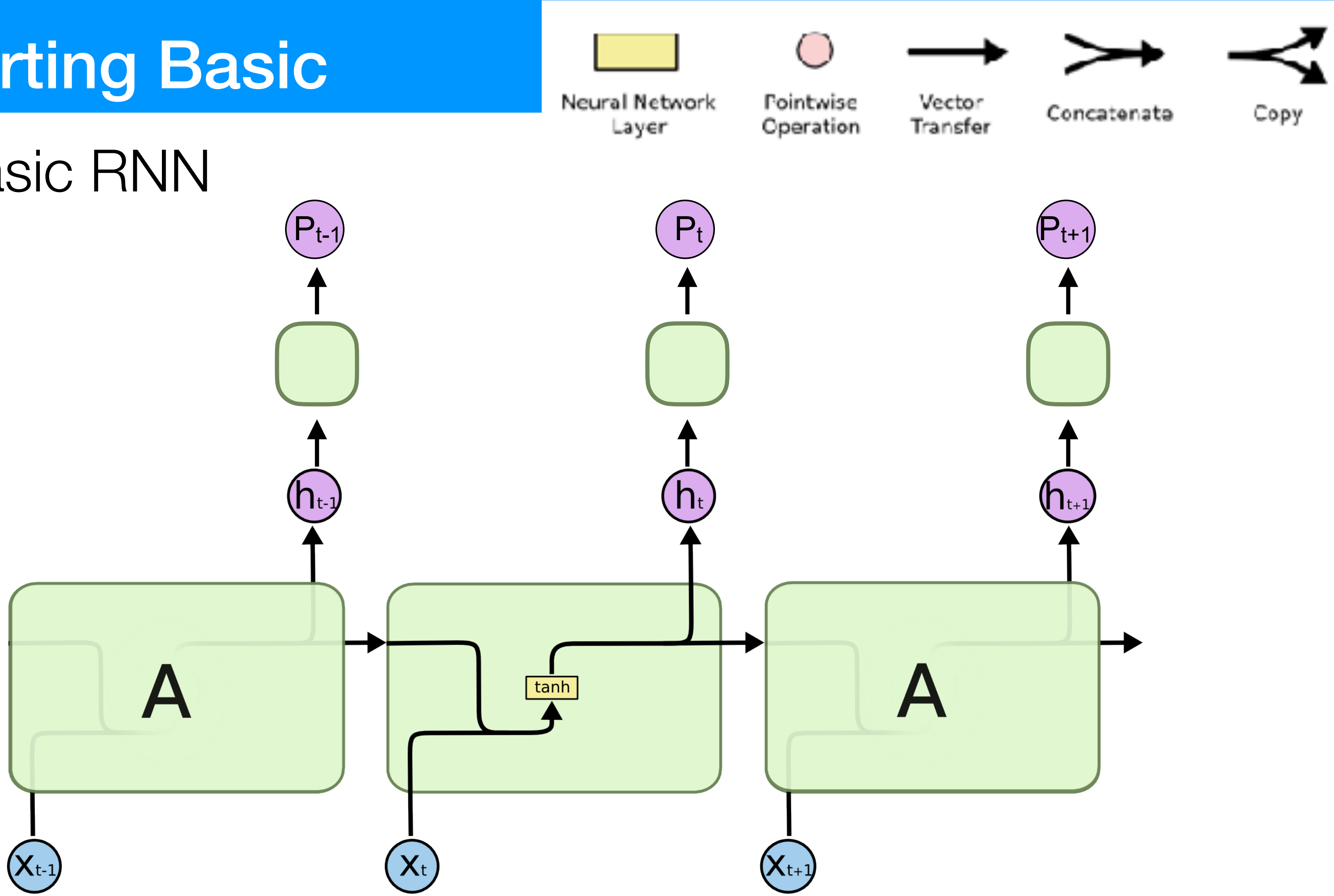
Starting Basic

- basic RNN



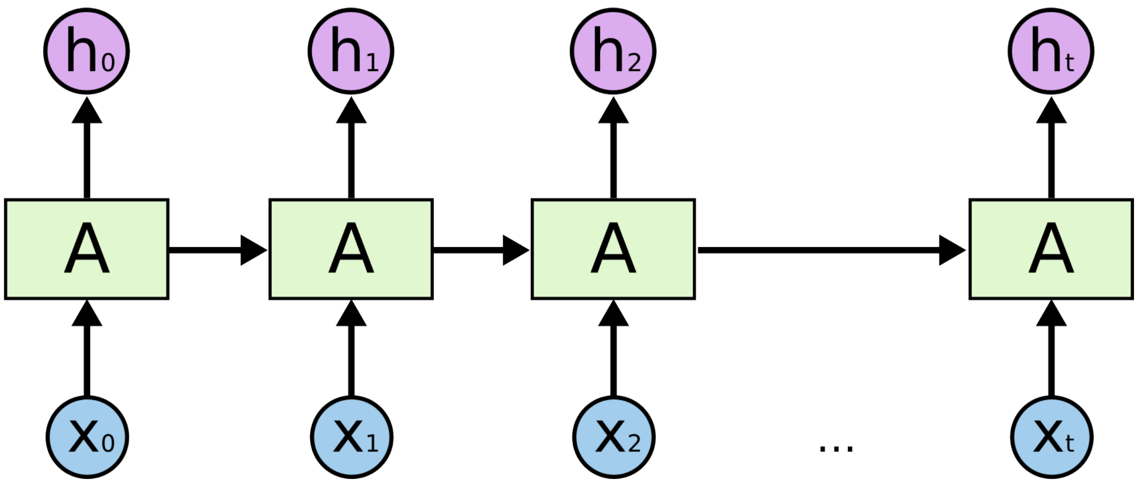
$$h_t = \tanh(W_A (X_t \oplus h_{t-1}) + b_A)$$

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

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

Recurrent Networks: Representation

- python:

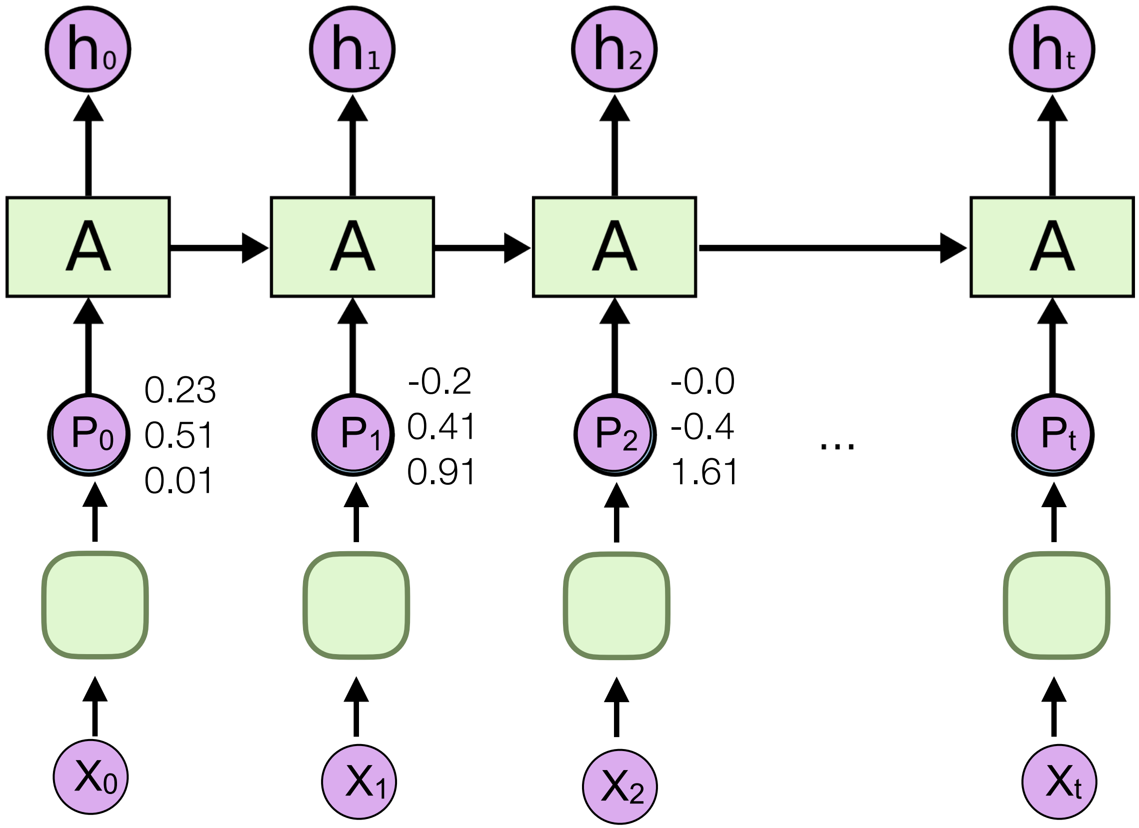


character: / word:	C / The	A / quick	T / brown
int:	3	1	17
one hot:	0 0 1 0 0 0 0 … 0 0	1 0 0 0 0 0 0 … 0 0	0 0 0 0 0 0 0 … 1 0

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

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

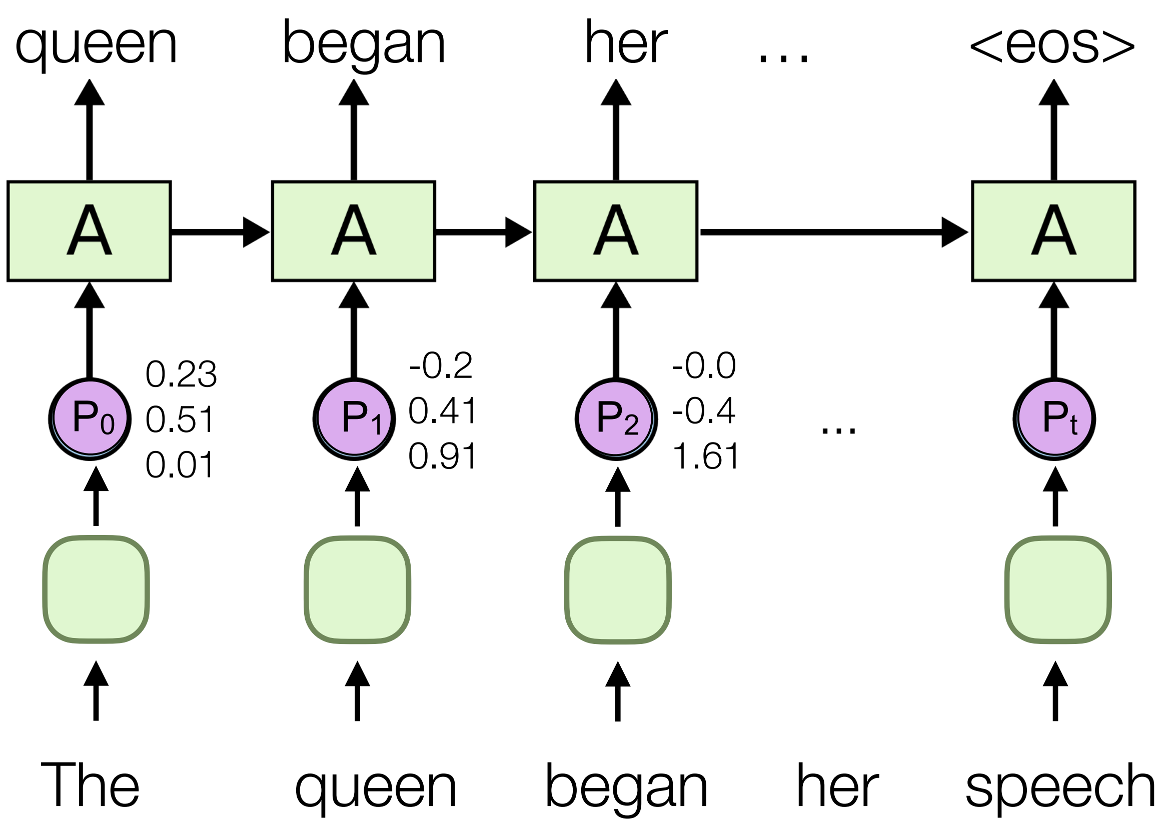
Word Embeddings (like Wide/Deep)



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

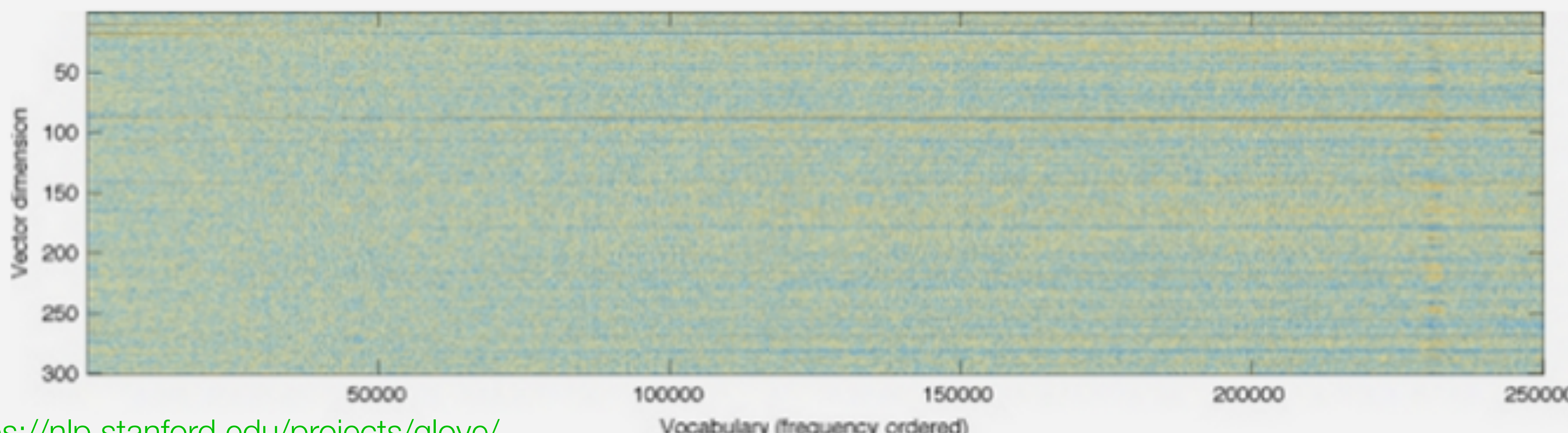
3. litoria

4. leptodactylidae

5. rana

7. eleutherodactylus

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

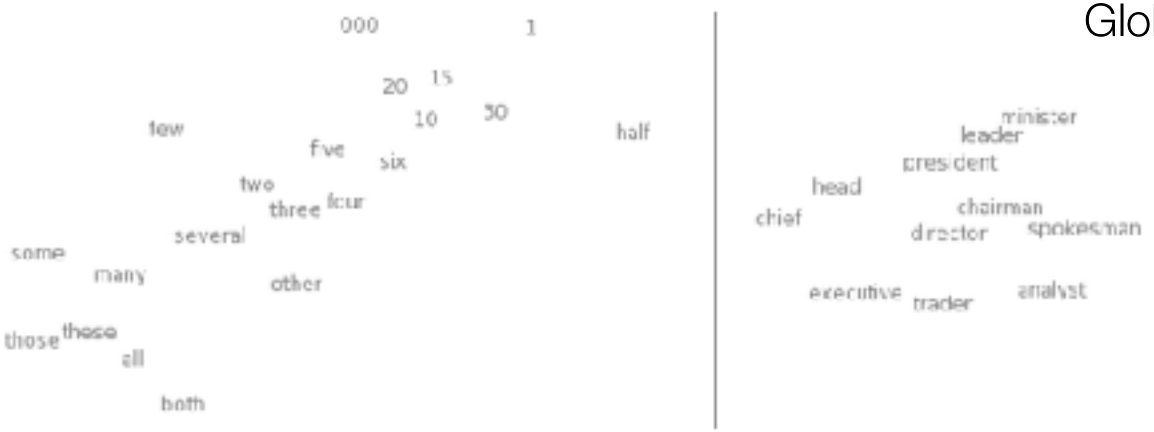


https://nlp.stanford.edu/projects/glove/

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	GRAYISH	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.

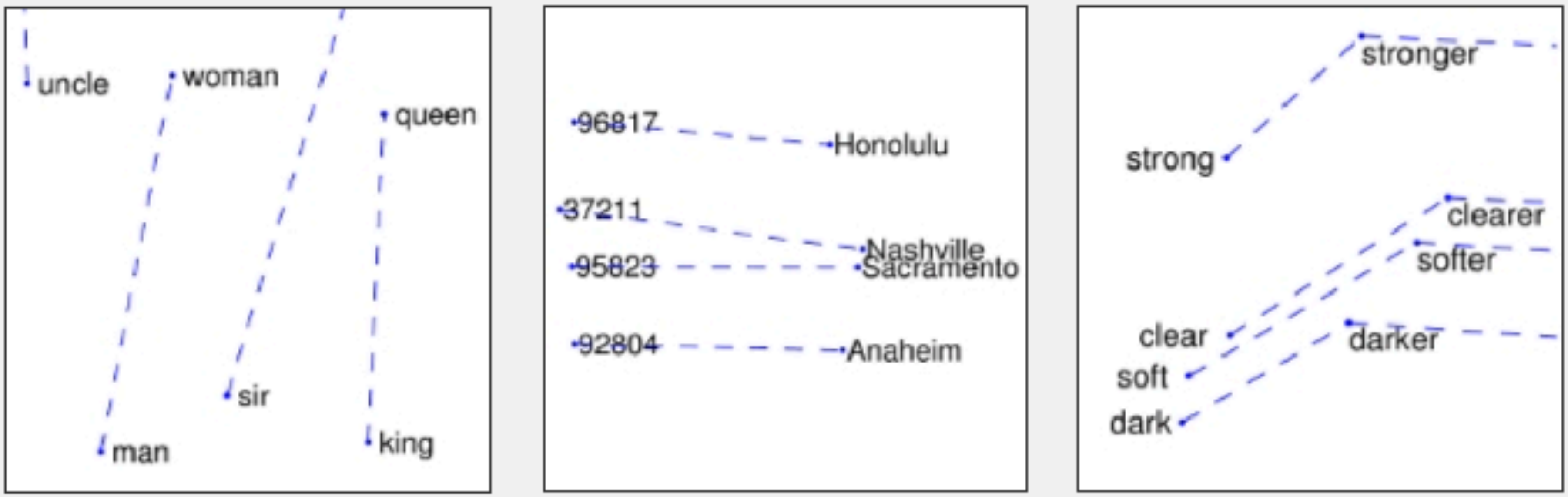
The **chief** called the **council** to order.

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

Word Embeddings: Analogy

GloVe

Global Vectors for Word Representation

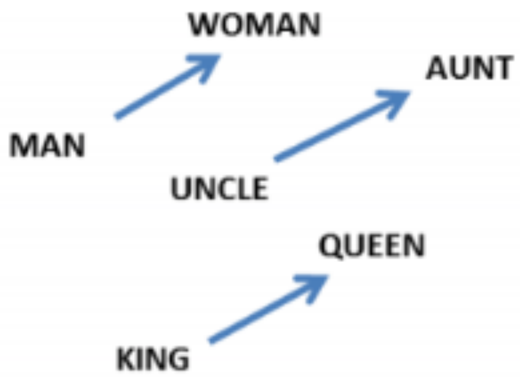


man - woman city - zip code comparative - superlative

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

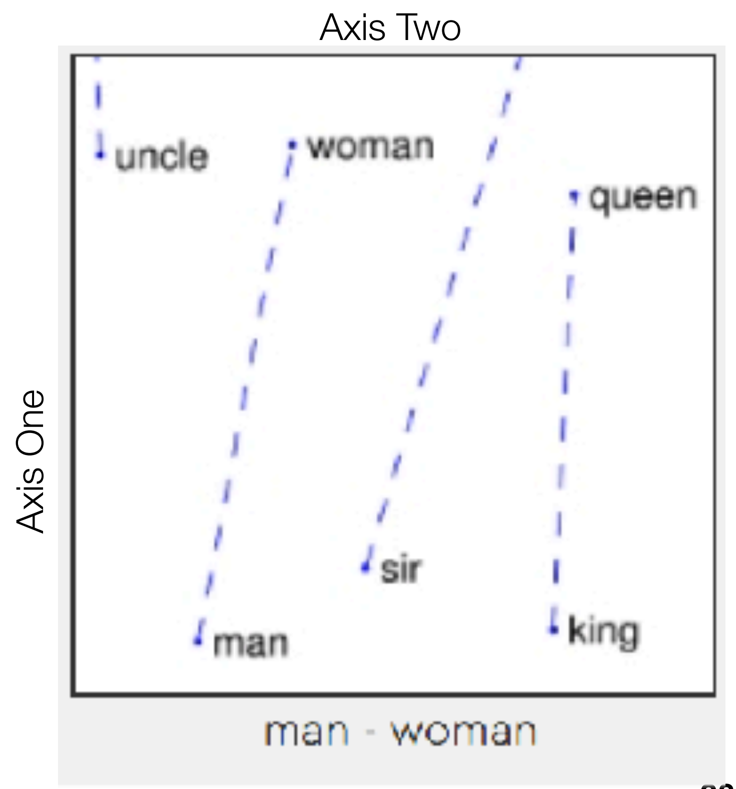
Relationship pairs in a word embedding. From Mikolov *et al.* (2013b).

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

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

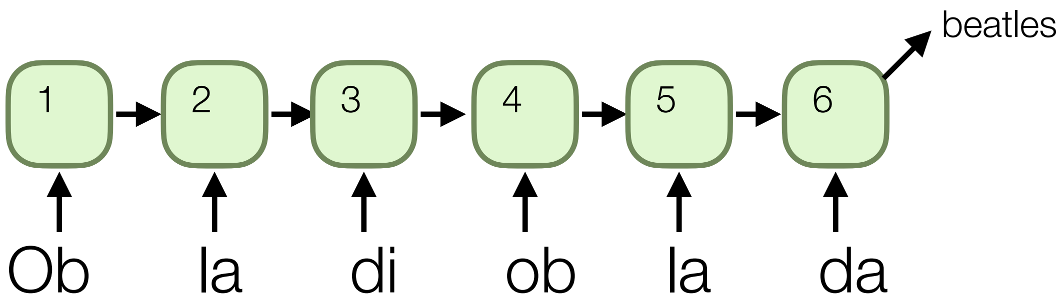
Self Test: Analogy

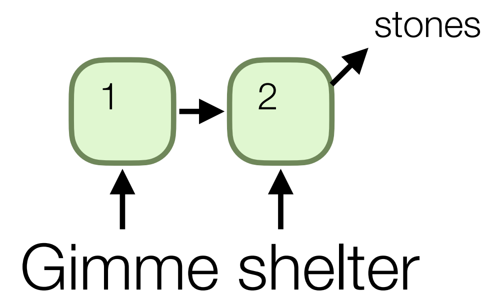
- Each axis on the embedding plot below corresponds to:
- A. a weight inside the embedding layer
- B. an average of weights inside the embedding layer
- C. the average of the one hot encoding for a word
- D. an output of the embedding layer



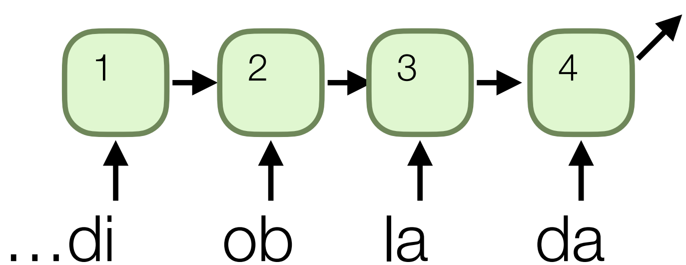
Practical Logistics: Sequence Length

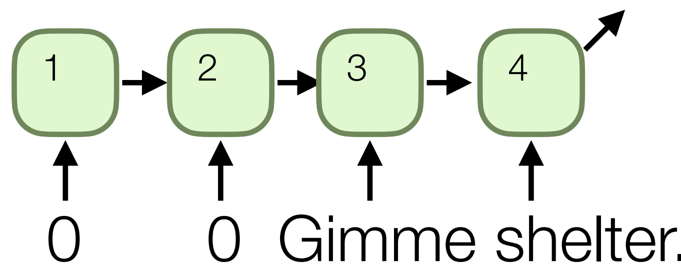
- option A: dynamic length sequences





- option B: padding/clipping



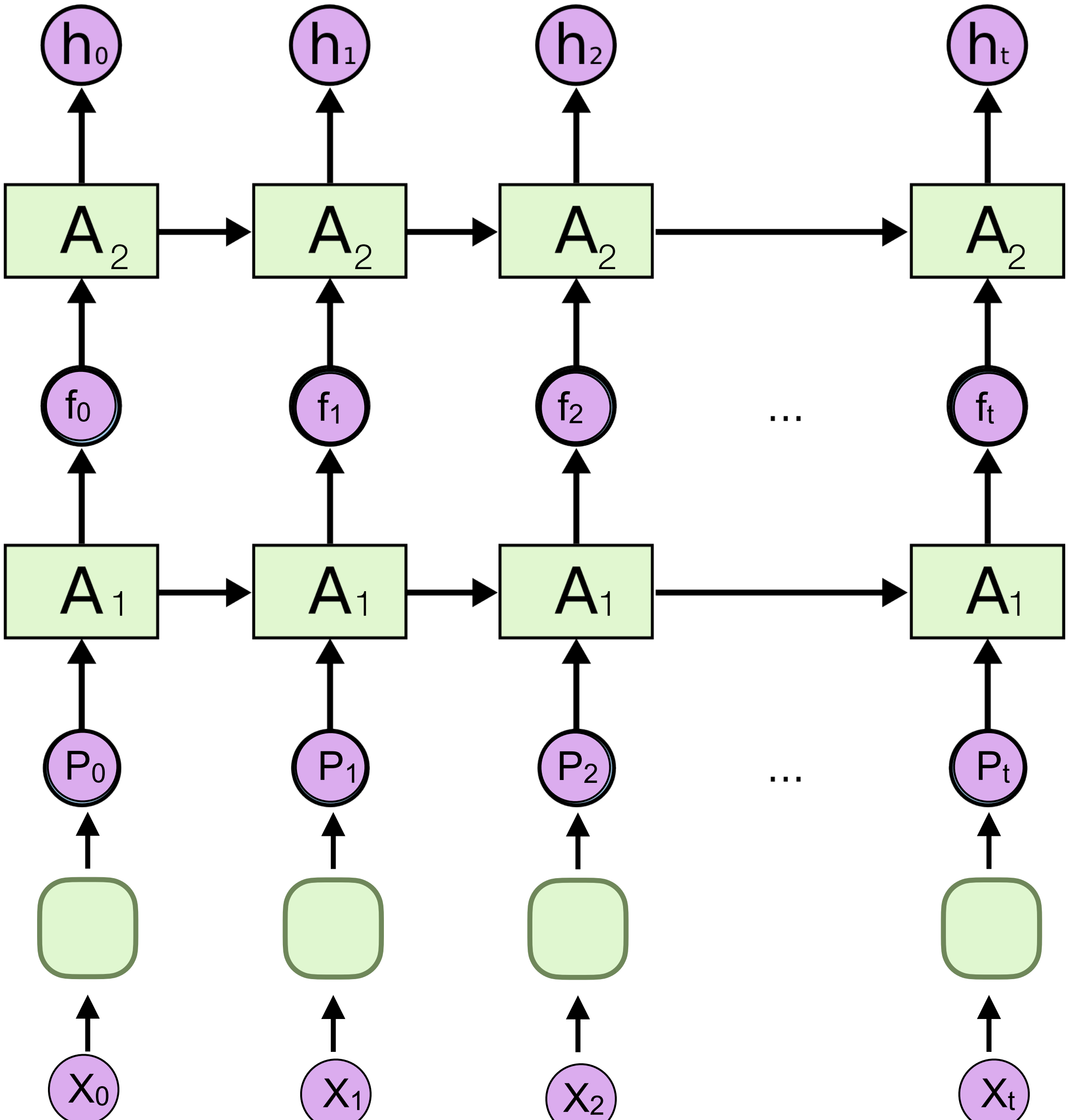


- main difference:

speed based on computation graph design

Sequence Stacking

keras:
return sequences



keras default:
return last
element only