Lecture Notes for

Machine Learning in Python

⟦👨‍🏫, 👨‍💻, 🐍, 👨‍🔬⟧

Professor Eric Larson

Sequential Networks Overview

Lecture Agenda

- Logistics
  - Grading Update
  - Sequential Networks due **on Canvas**
- Agenda
  - History of Sequential Networks
    - Recurrent Networks to Transformers
    - Word Embeddings

Class Overview, by topic

Table Data Visualization

Numpy, Pandas, Seaborn
Overviews with some in-depth discussion

Dimension Reduction and Image Processing

Scikit-learn, Scikit Image,
Intuition only, Some mathematics

Linear and Logistic Regression

Numpy, Recreate API for Scikit-learn
Detailed mathematics for simple optimization
intuition for advanced optimization

Neural Networks and Back Prop.

Numpy
Detailed mathematics for NN operations

Wide and Deep Networks

Convolutional Networks

Sequential Networks

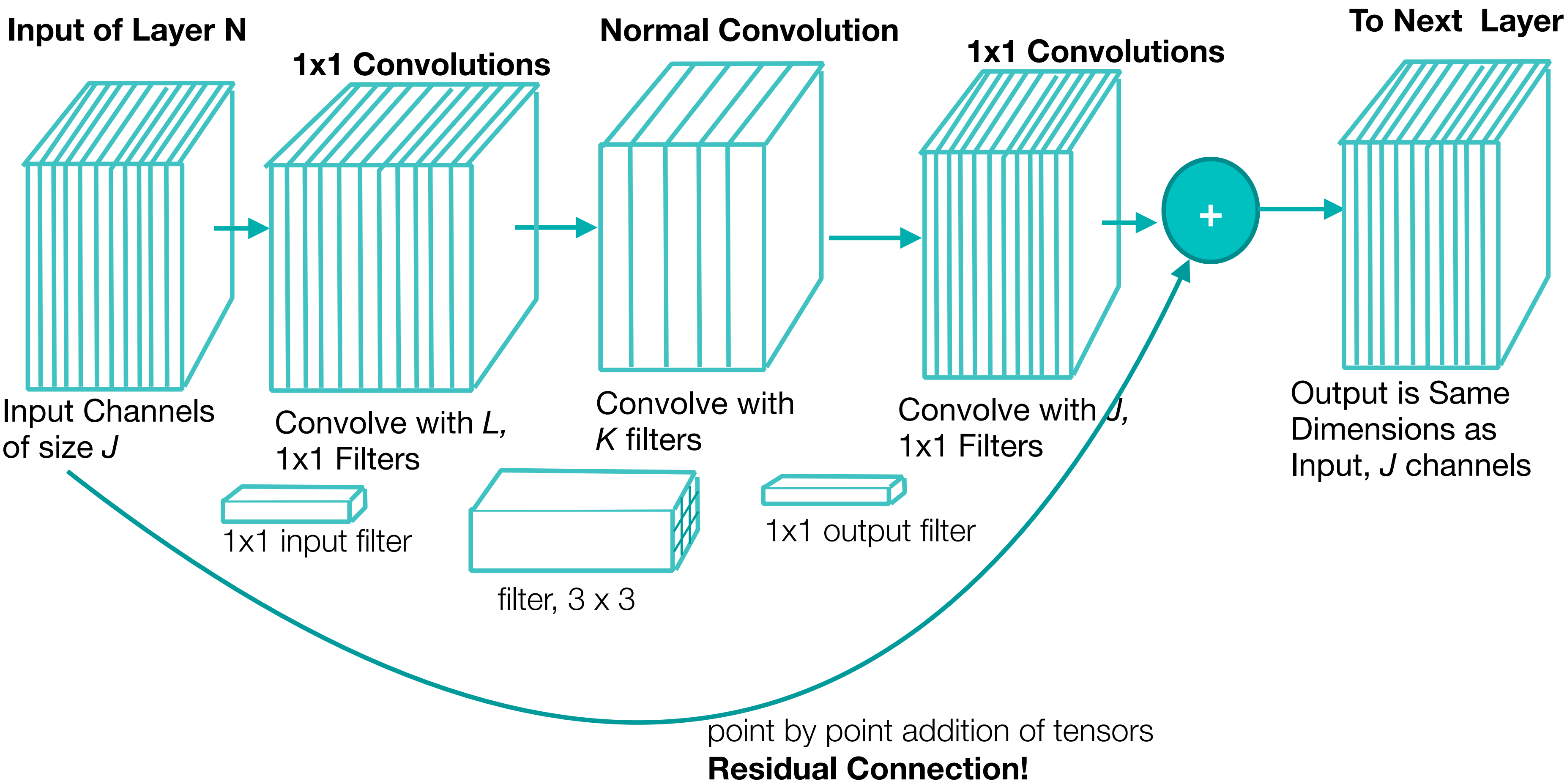
Keras, Tensorflow
Intuition, Detailed implement.

Ethics in Language Models

ConceptNet
Case studies

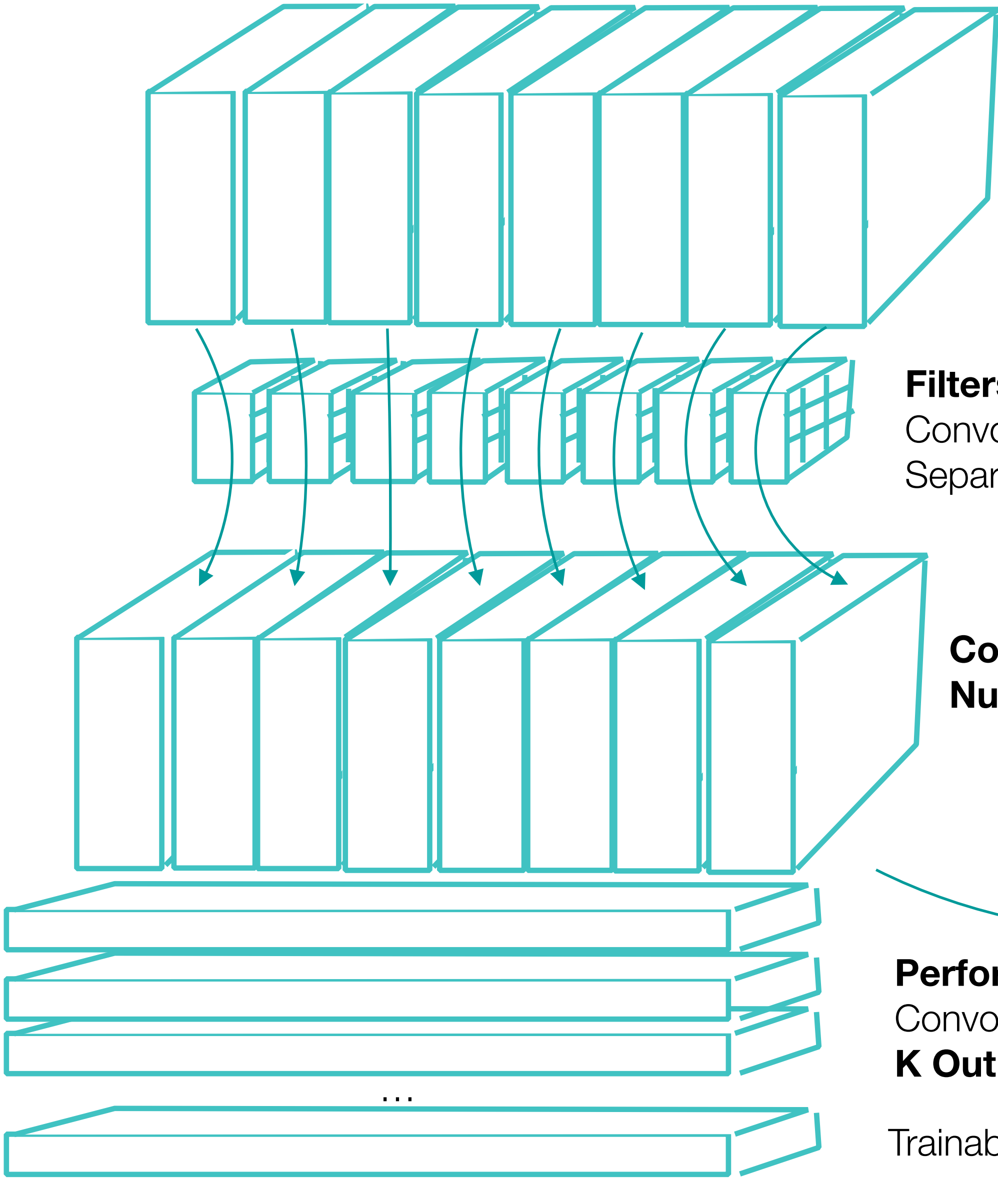
Advanced CNN Review Topics

Residual Connection Review



Back Propagation: Two paths, including one without ANY operations that cause the gradient to vanish…

Separable Convolution Review



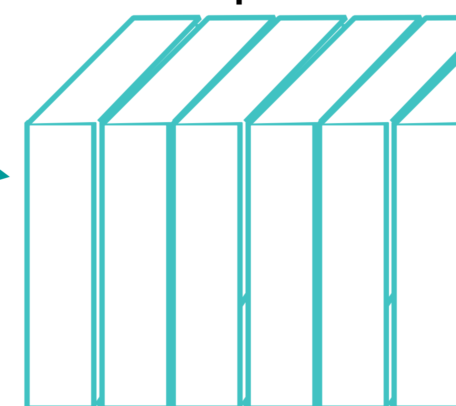
Inputs, From Layer N-1
Num Channels = J

Filters, Layer N
Convolve Each Channel Separately

Trainable params:
Same as one filter in traditional convolution!

Concat Outputs
Num Channels = J

K Outputs



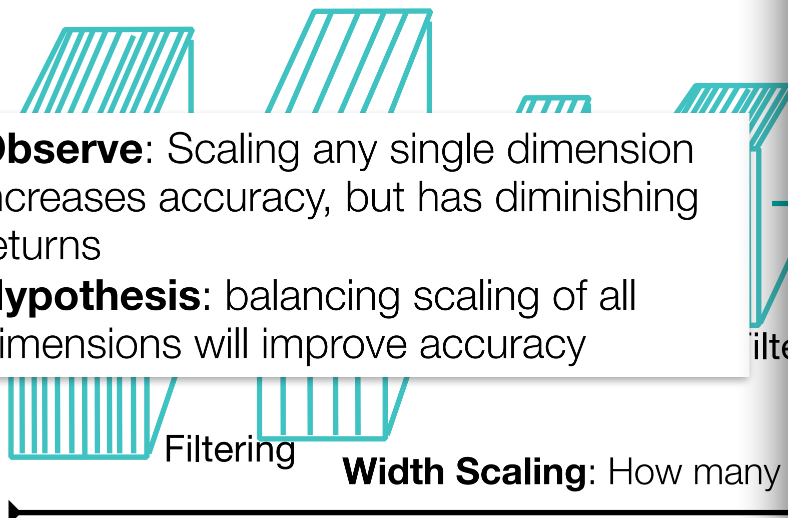
Perform K, 1x1 Traditional Convolutions
K Outputs

Trainable params: **K** x **J**

Squeezing Review (E

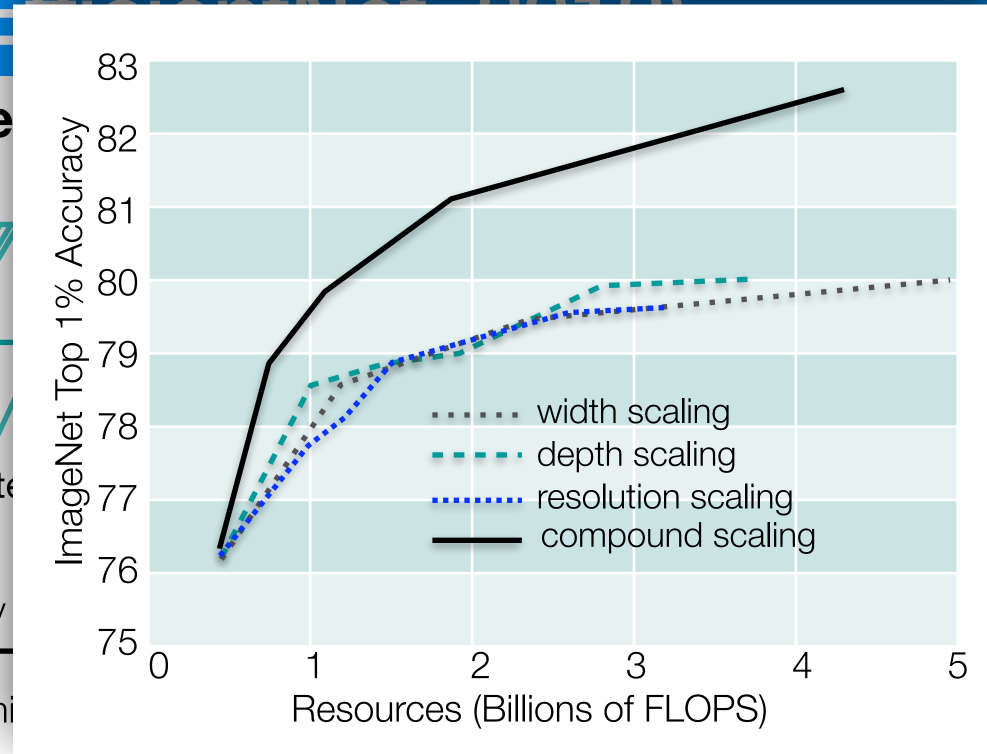
Start with some baseline archite

- **Observe**: Scaling any single dimension increases accuracy, but has diminishing returns
- **Hypothesis**: balancing scaling of all dimensions will improve accuracy



Width Scaling: How many

Depth Scaling: If we add layers, how should thi



Resolution Scaling: If we use larger resolution input images, how should we scale the filters and layers?

depth: $d = \alpha^\phi$

width: $w = \beta^\phi$

res.: $r = \gamma^\phi$

s.t. $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$

$\alpha, \beta, \gamma \geq 1$

ϕ user specified scaling coefficient

$$\boxed{\begin{array}{c}\alpha = 1.2 \\ \beta = 1.1 \\ \gamma = 1.15\end{array}}$$

optimal values found in paper!

- α, β, γ are constants that specify how to assign extra resources to network depth, width, and resolution.
- ϕ is a user specified coefficient that controls how many resources are available.

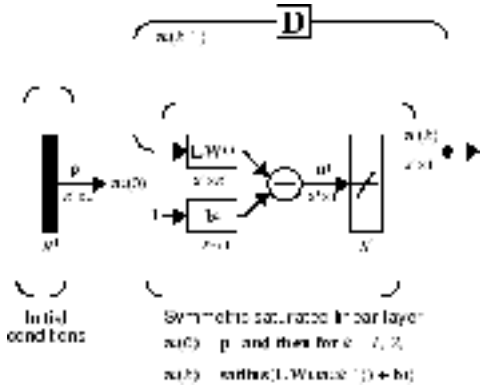
https://arxiv.org/pdf/1905.11946v5.pdf

History of Sequential Neural Networks

1980's Recurrent Networks

- Hopfield Network, 1982

John Hopfield, Princeton



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

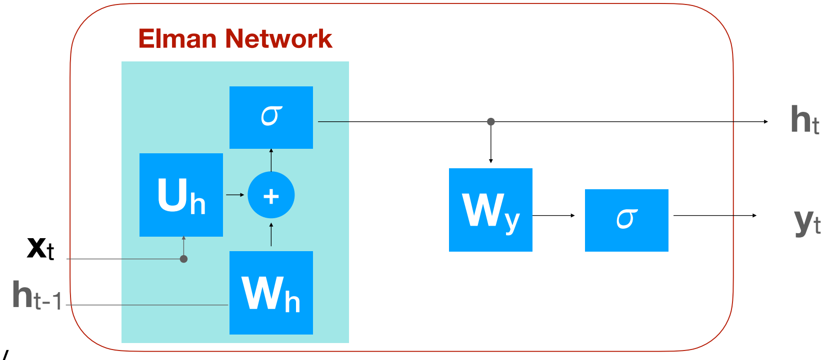
Contribution:
Training with Feedback

- Elman/Jordan Networks, ~1988

Contribution:
Time Steps for Unrolling
Separated output / state

Jeffrey Elman, UCSD

Michael Jordan, Berkeley

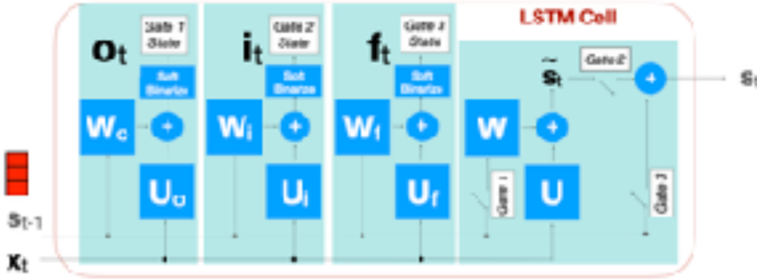


1990's-2000's Better Recurrent Networks

- Long Short Term Memory, ~1997 - 2010

Sepp Hochreiter, Many Universities

Jürgen Schmidhuber, Switzerland

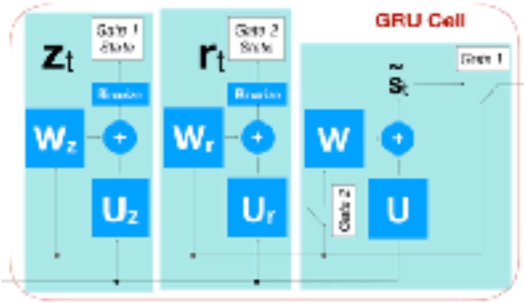


Contribution:
Long Duration Memory and State Vector Separate from Output

- Gated Recurrent Units, ~2014

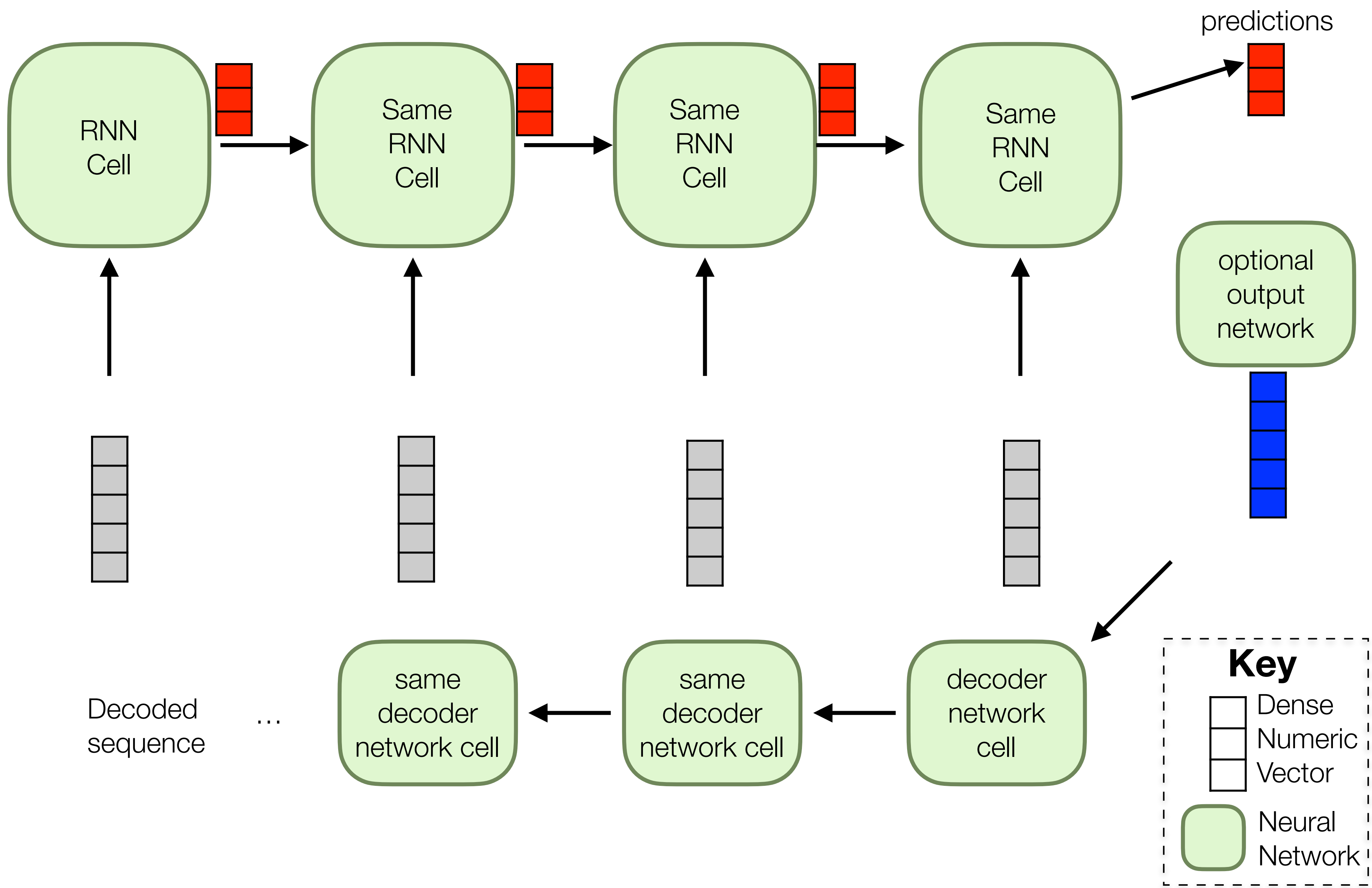
Yoshua Bengio

Kyunghyun Cho, Professor at NYU



Contribution:
Fewer parameters in RNN

General recurrent flow (many to one)



Attention (2016)

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

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

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

- Google

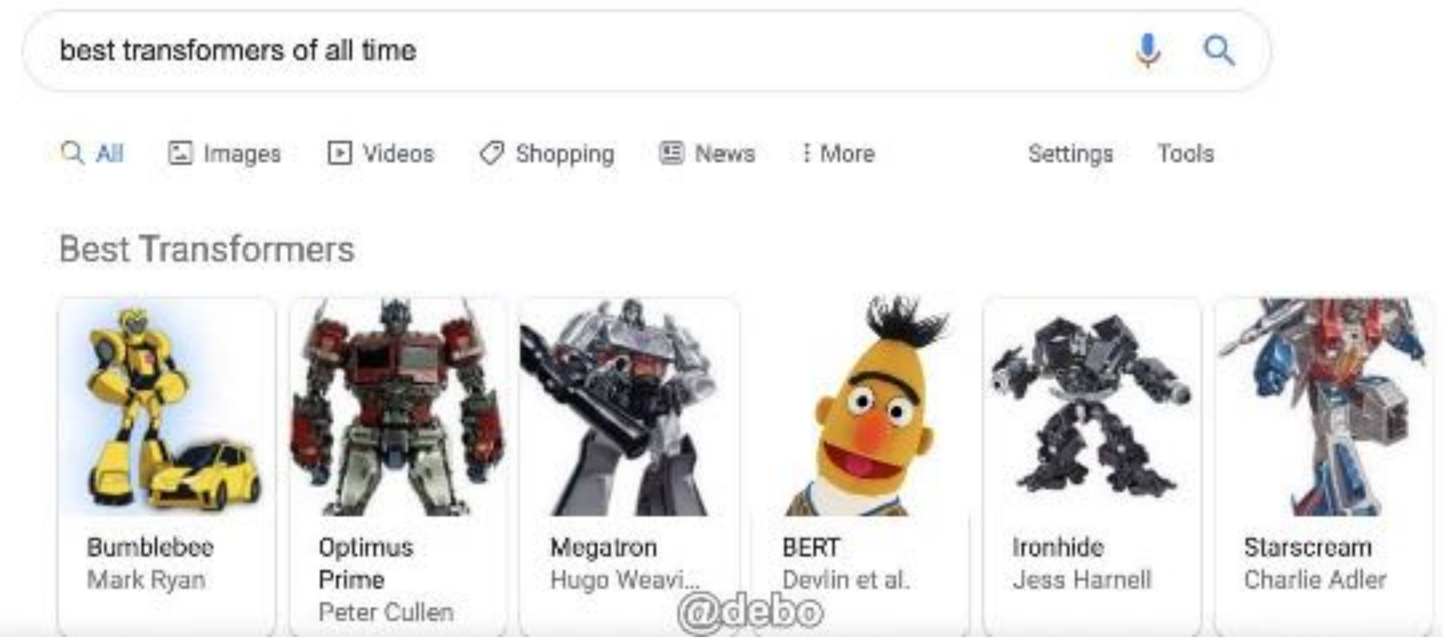
Google Neural Machine Translation:
https://arxiv.org/pdf/1609.08144.pdf
https://medium.com/@Synced/history-and-frontier-of-the-neural-machine-translation-dc981d25422d

Other big advances

- **1D Convolution** to Replace RNN (2015-2018)
- **Attention is All You Need** (2017)
- **Self-attention** (2018)
- **Multi-headed** attention Modern Transformer (2018)
- **BERT**, **GPT-#**, and other LLM etc. (2019-present)

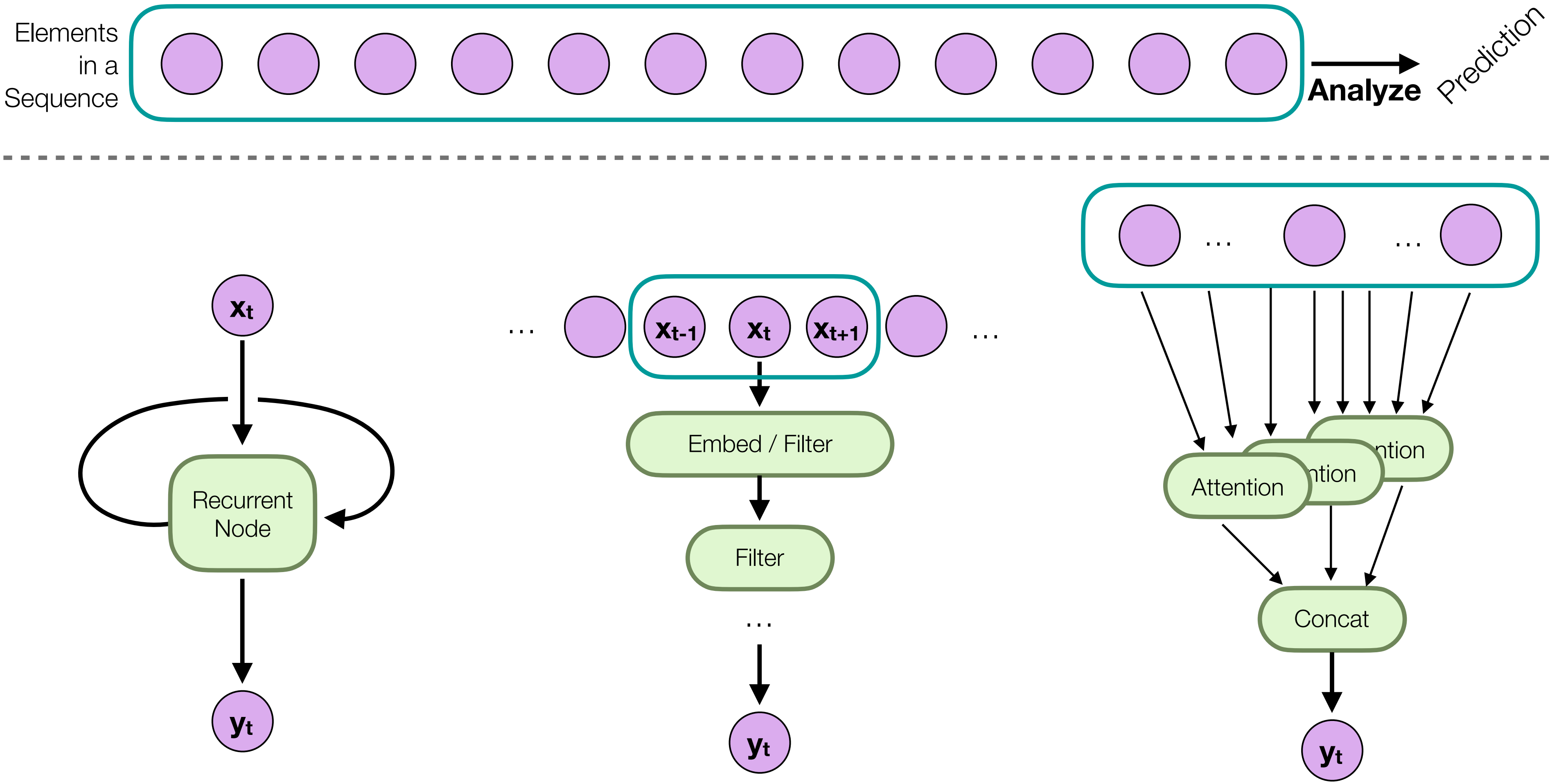
This Course

MLII Course



Overview of Sequential Networks

Sequential Networks Types



recurrent

Update Sequence State
one element at a time

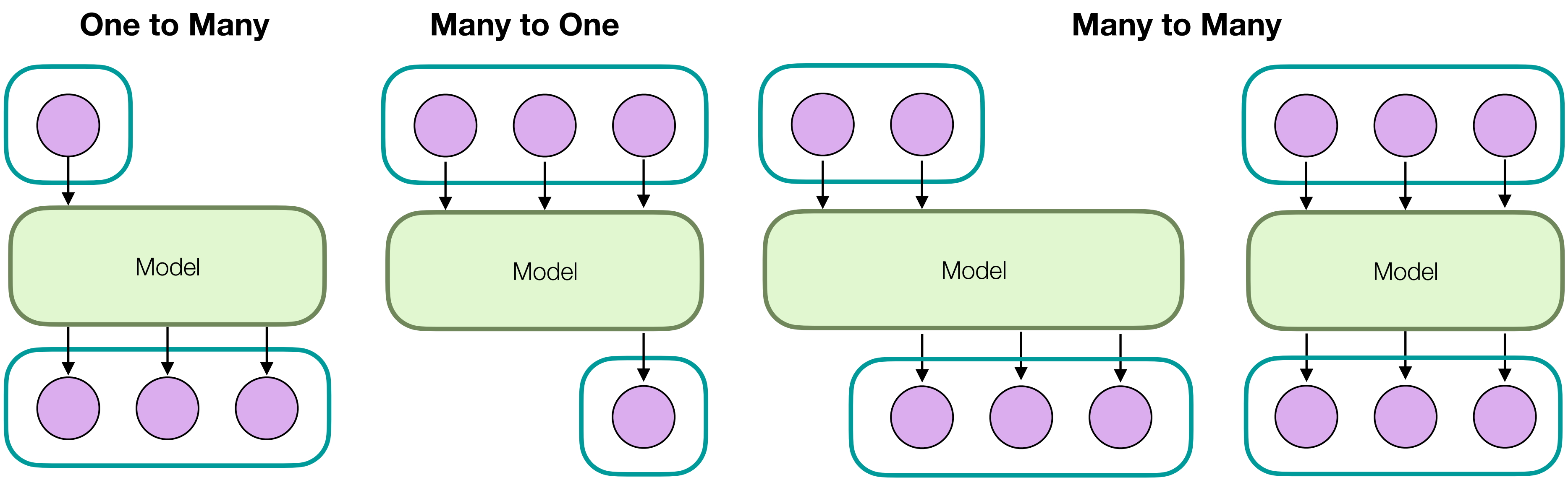
convolutional

Look at groups of Elements
in Parallel

transformer

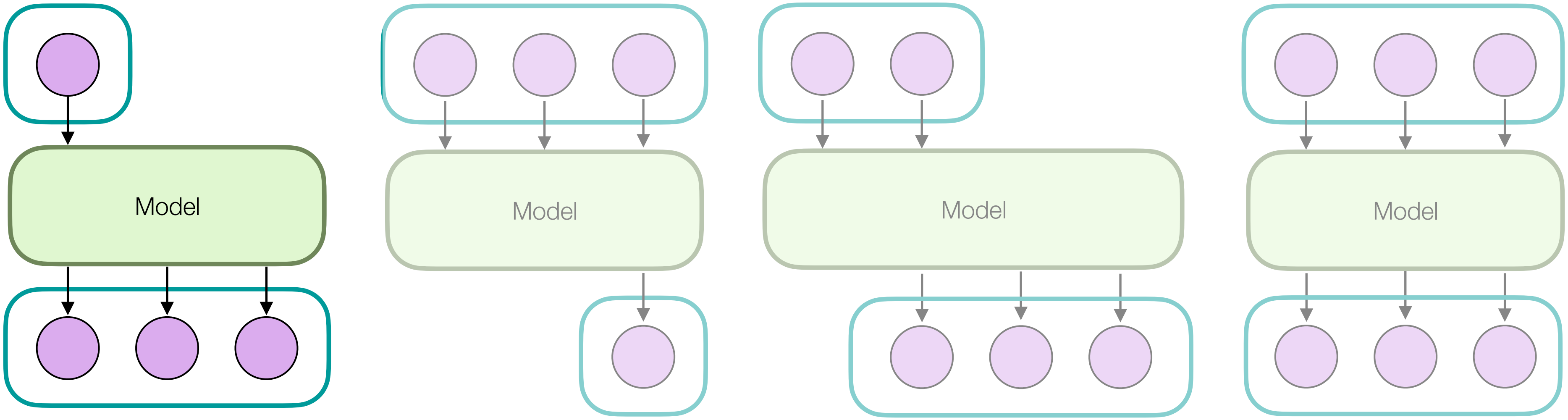
Everything Everywhere All at Once

Sequential Networks: Problem Types

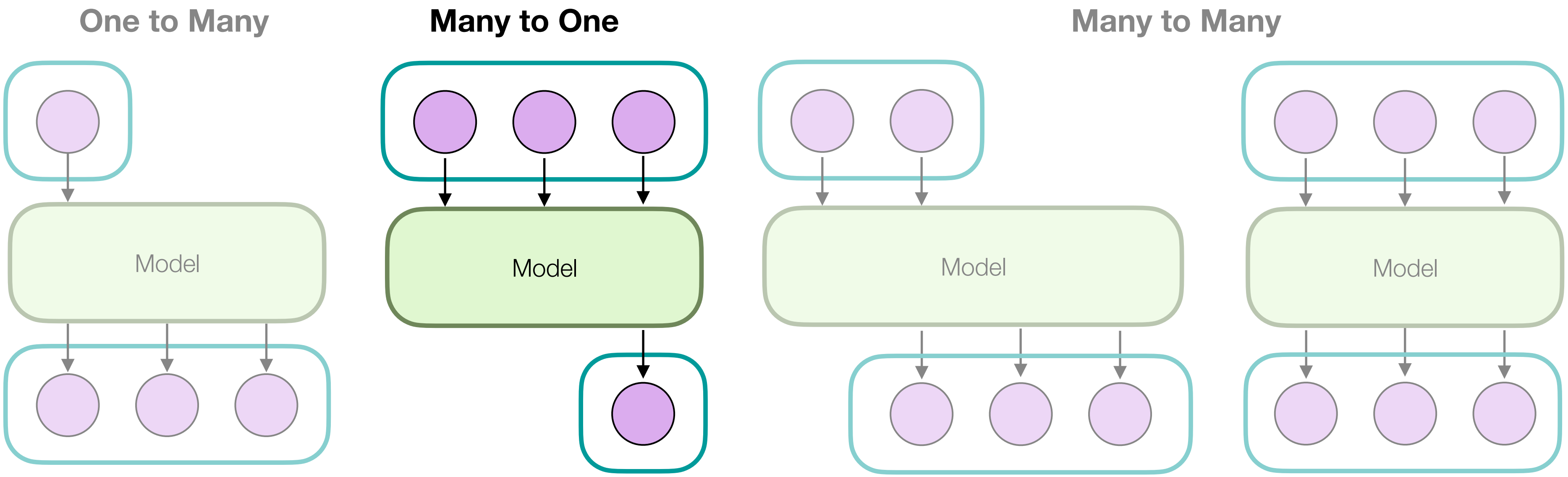


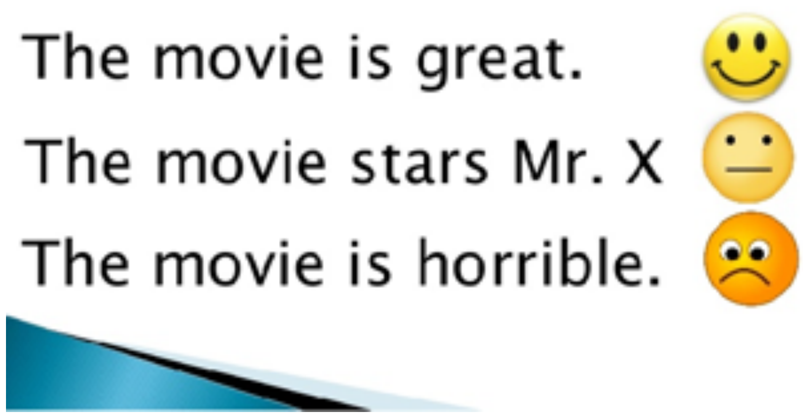
Sequential Networks: Problem Types

One to Many Many to One Many to Many



Sequential Networks: Problem Types

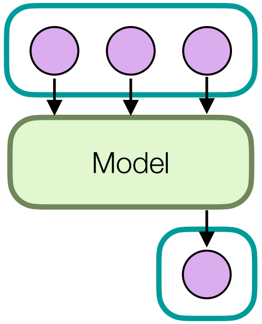




Sequential Networks: Ontology Classification

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.

Many to One



Artist

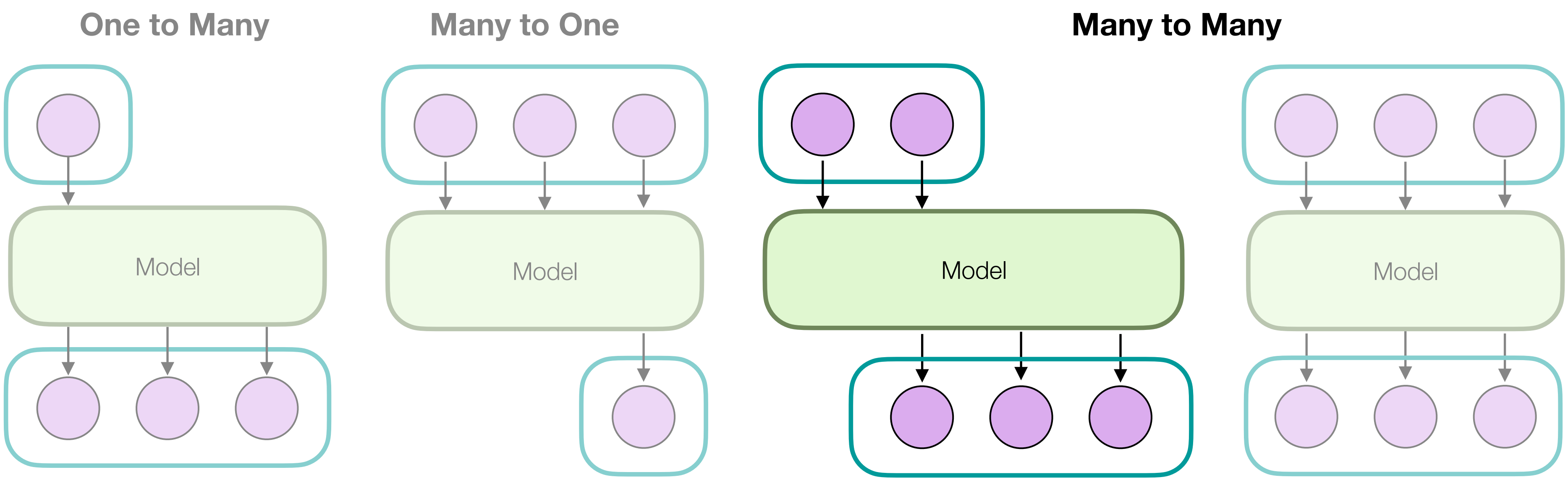
Shaun Norris (born 14 May 1982) is a South African professional golfer.Norris plays on the Sunshine Tour where he has won twice. He won the inaugural Africa Open in 2008 and the Nashua Masters in 2011. He also began playing on the European Tour in 2011 after graduating from qualifying school.

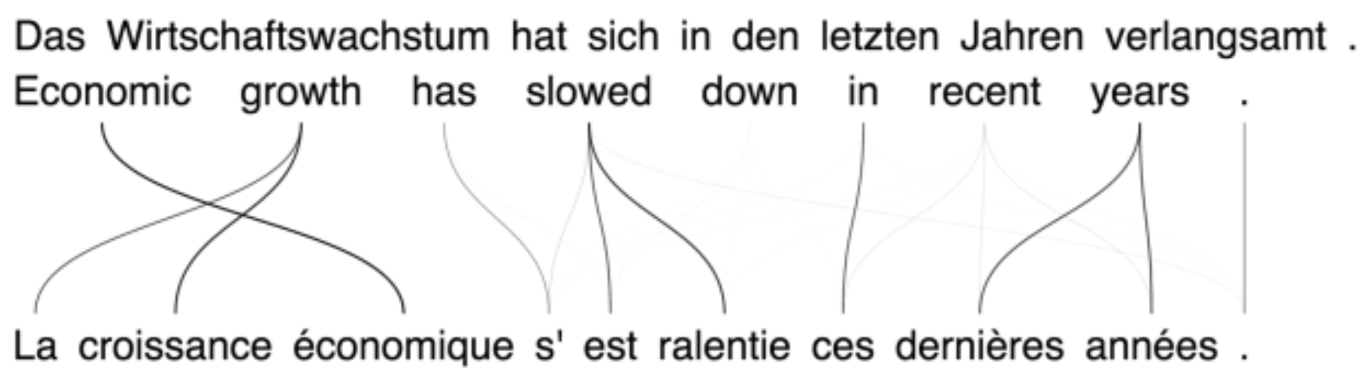
Athlete

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.

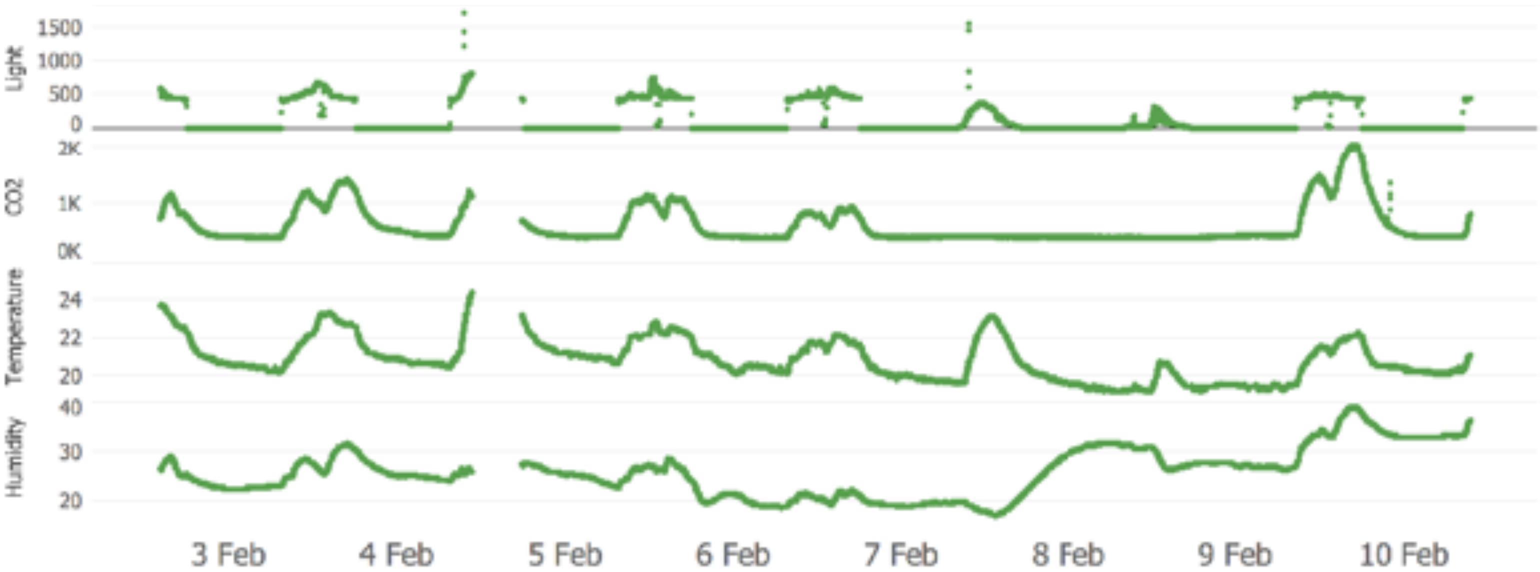
Company

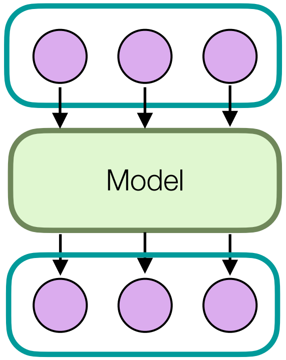
Sequential Networks: Problem Types





Sequential Networks: Problem Types



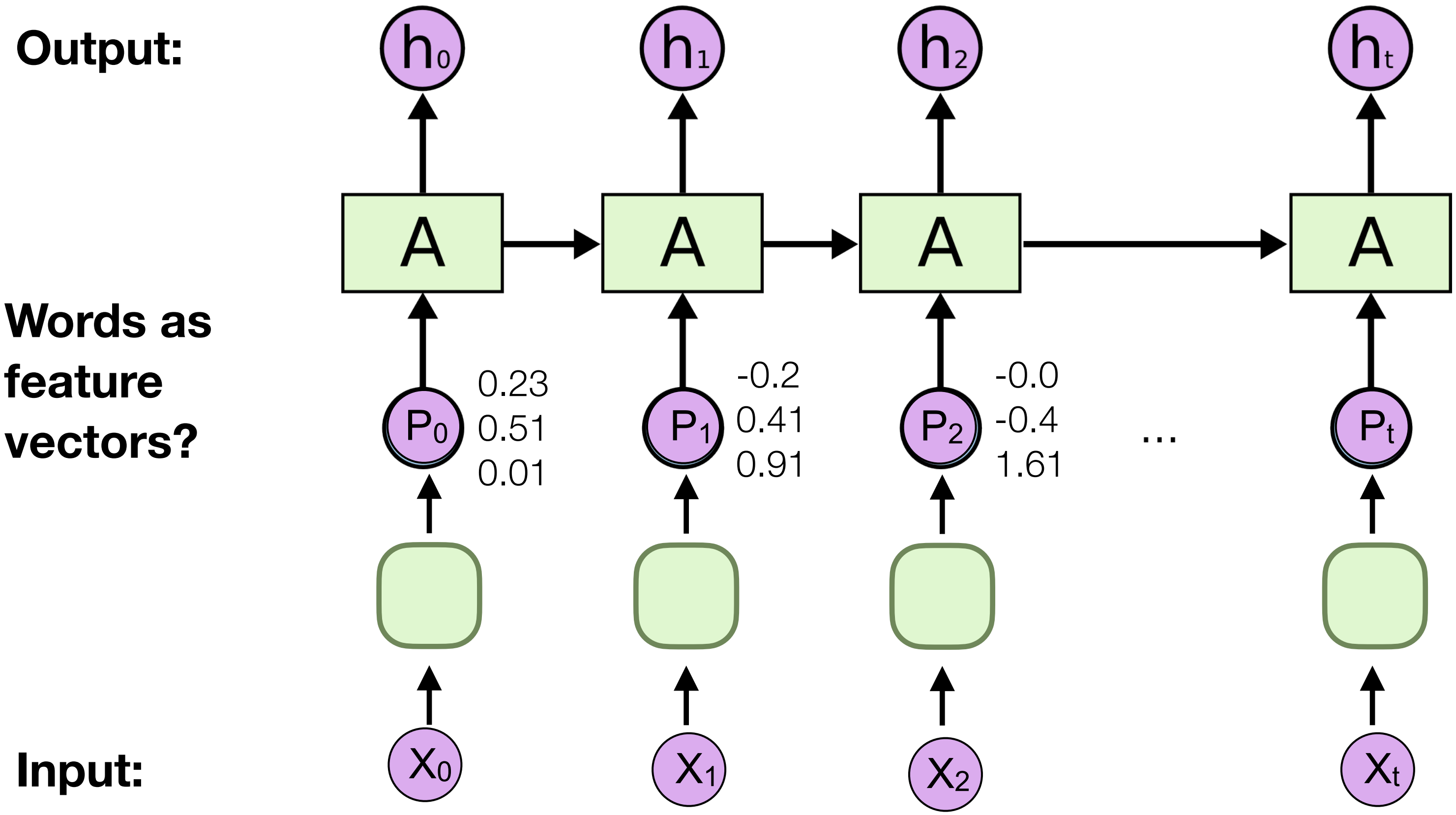


Many to Many

sequence to sequence

Word Embeddings

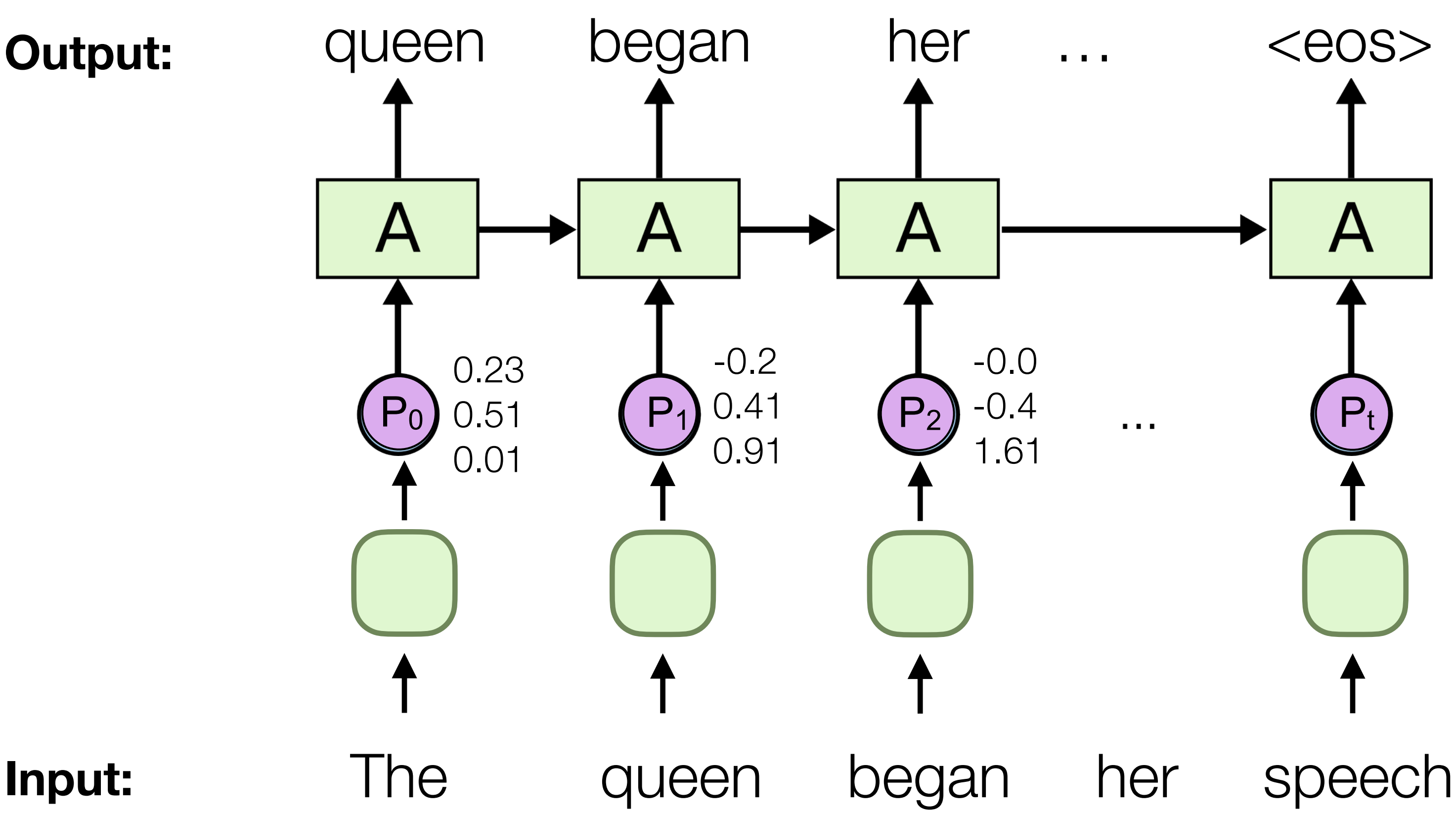
Word Embeddings (like Wide/Deep)



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

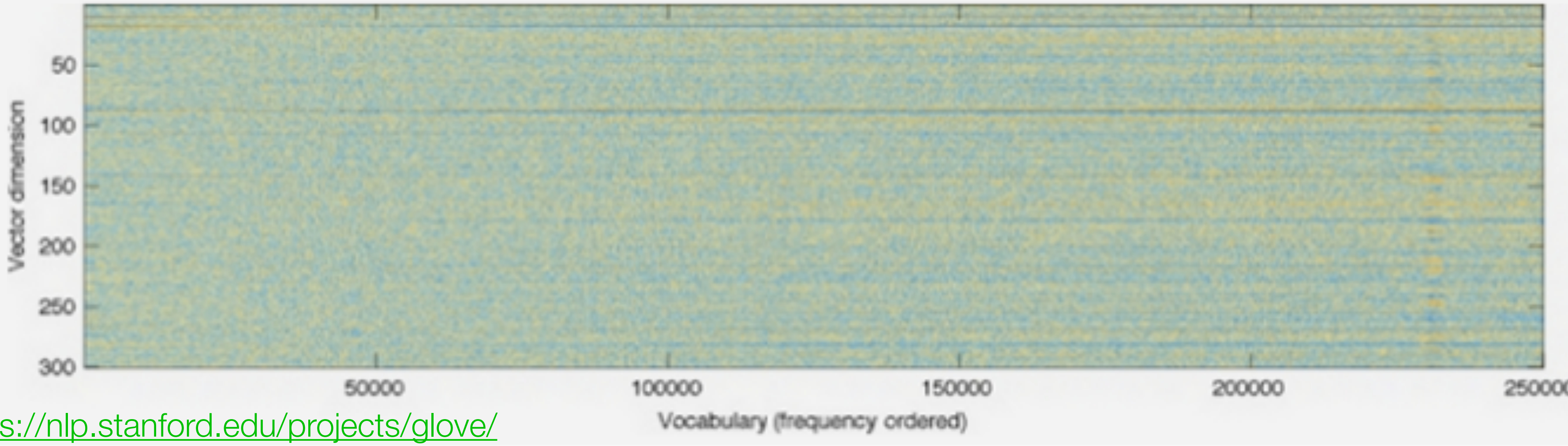
3. litoria

4. leptodactylidae

5. rana

7. eleutherodactylus

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



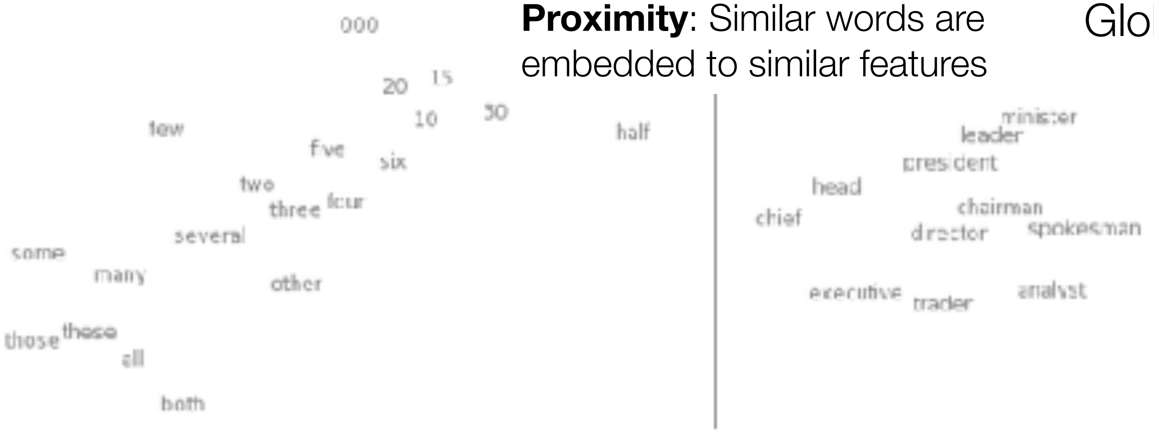
https://nlp.stanford.edu/projects/glove/

Word Embeddings: proximity

GloVe

Global Vectors for Word Representation

Proximity: Similar words are embedded to similar features



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.

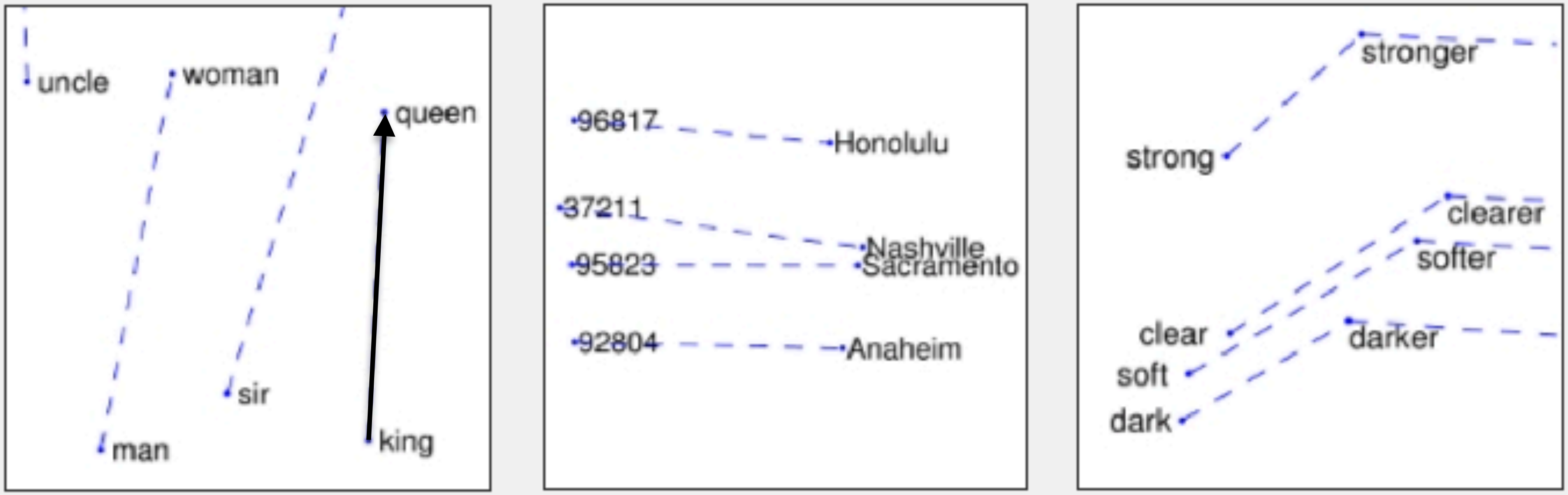
The **chief** called the **council** to order.

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

Word Embeddings: Analogy

GloVe

Global Vectors for Word Representation

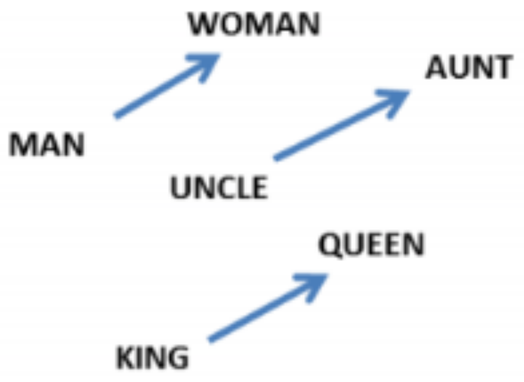


man - woman | city - zip code | comparative - superlative

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

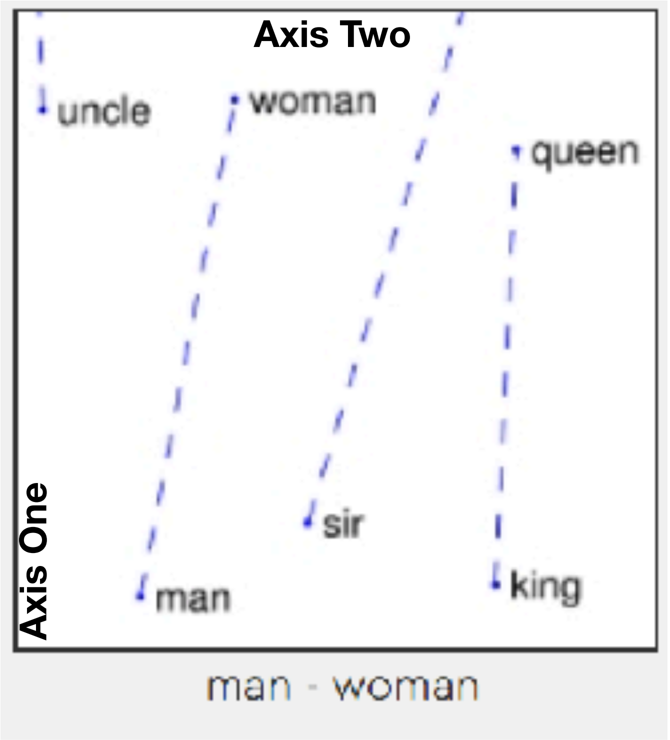
Relationship pairs in a word embedding. From Mikolov *et al.* (2013b).

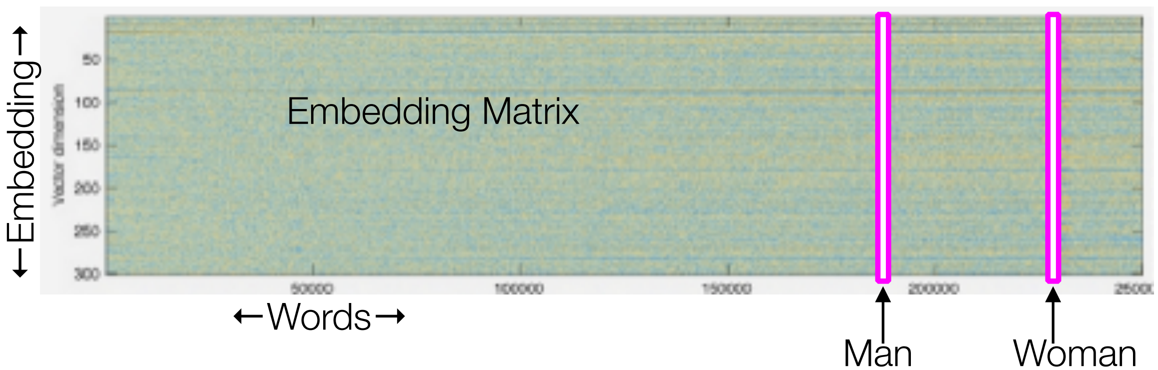
https://nlp.stanford.edu/projects/glove/

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

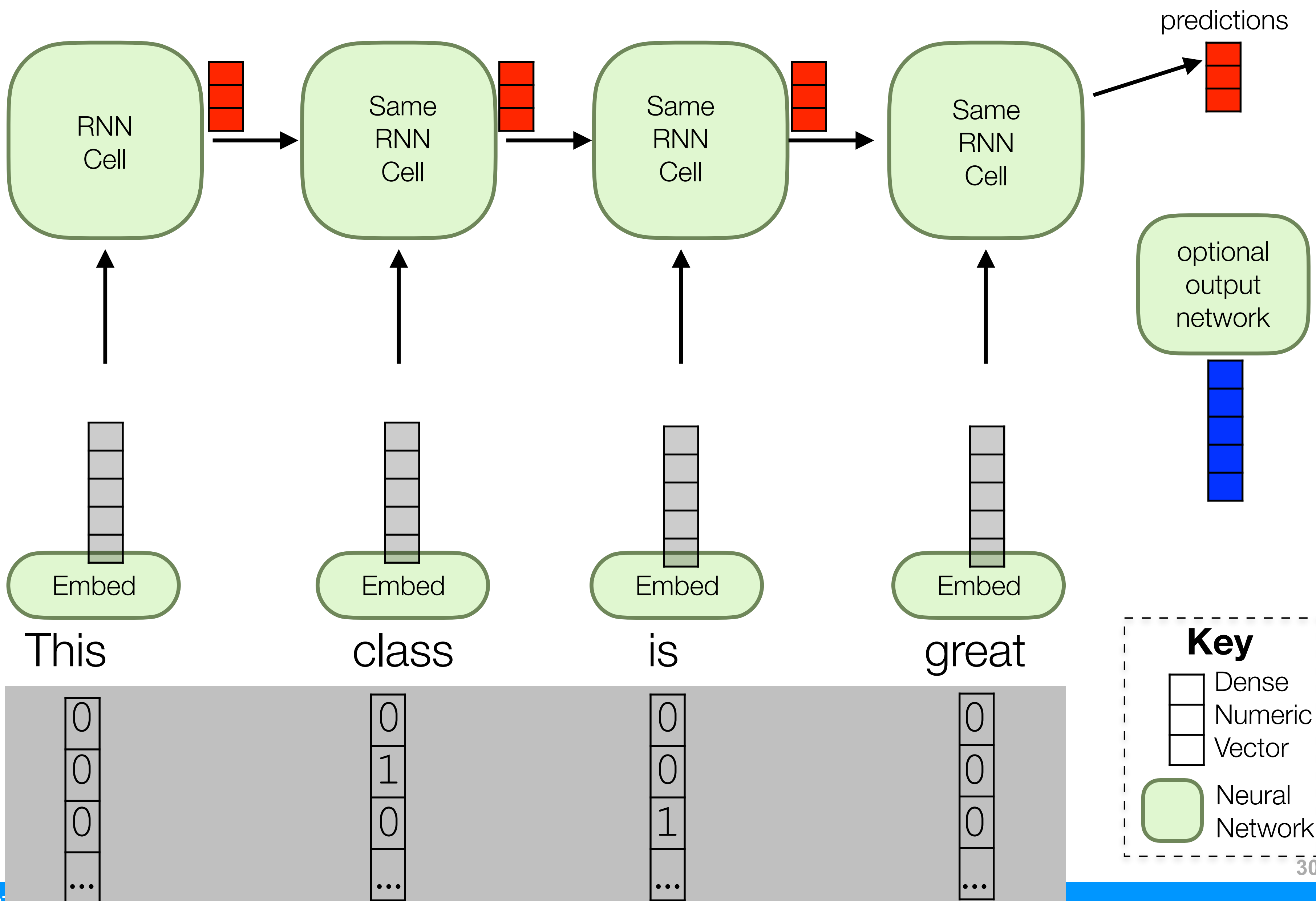
Self Test: Analogy

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



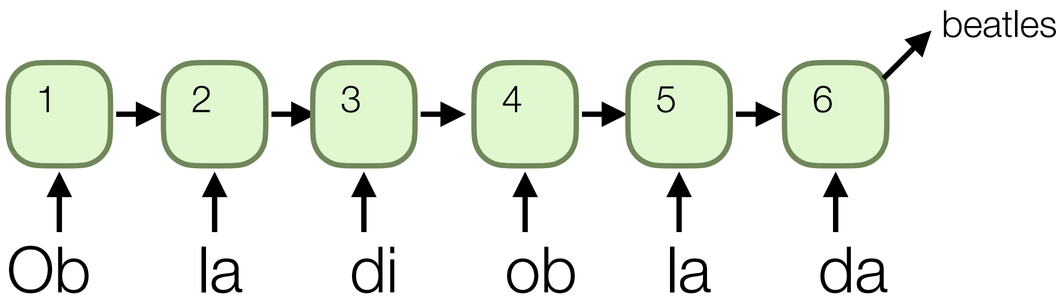


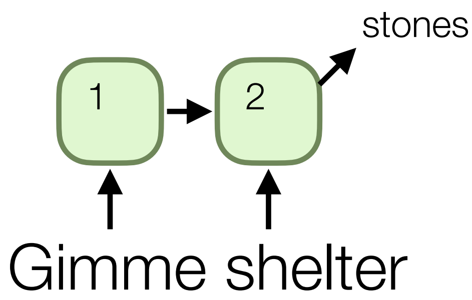
Recurrent flow with embeddings



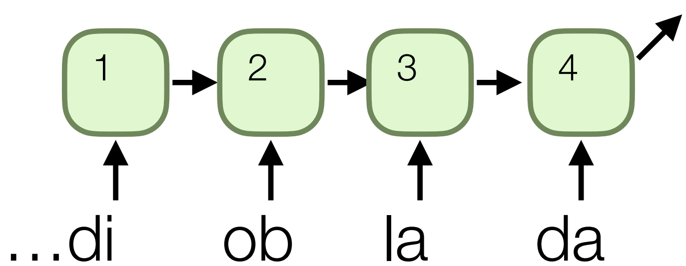
Different length input documents?

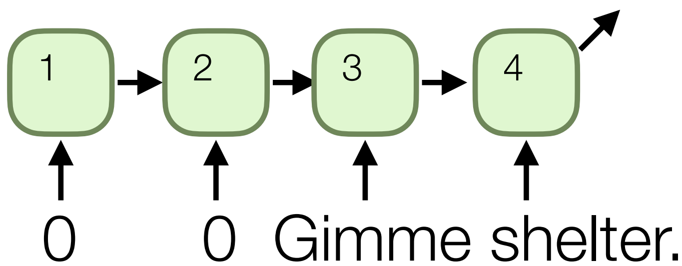
- option A: dynamic length sequences





- option B: padding/clipping

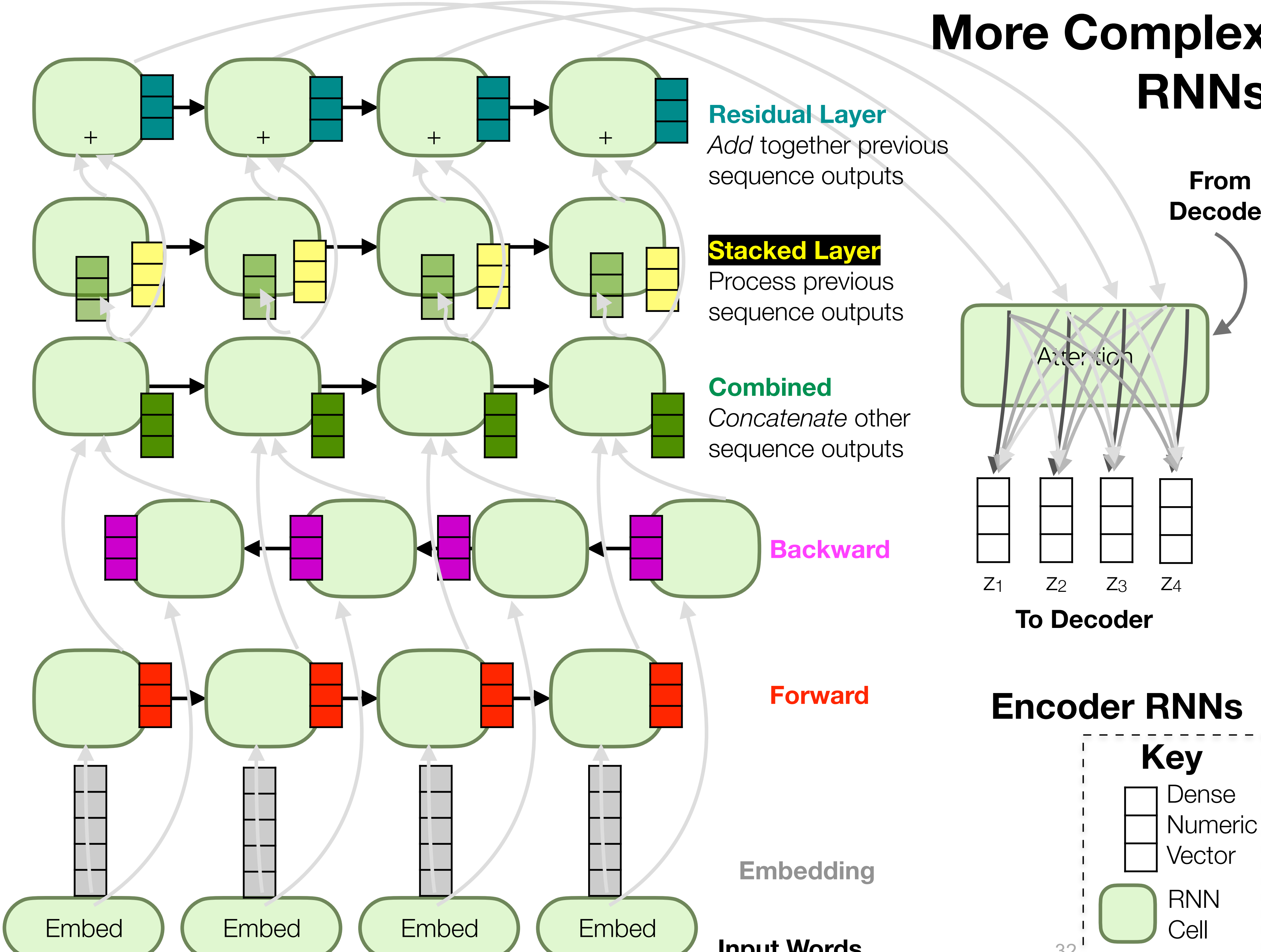




- main difference:
  speed based on computation graph design

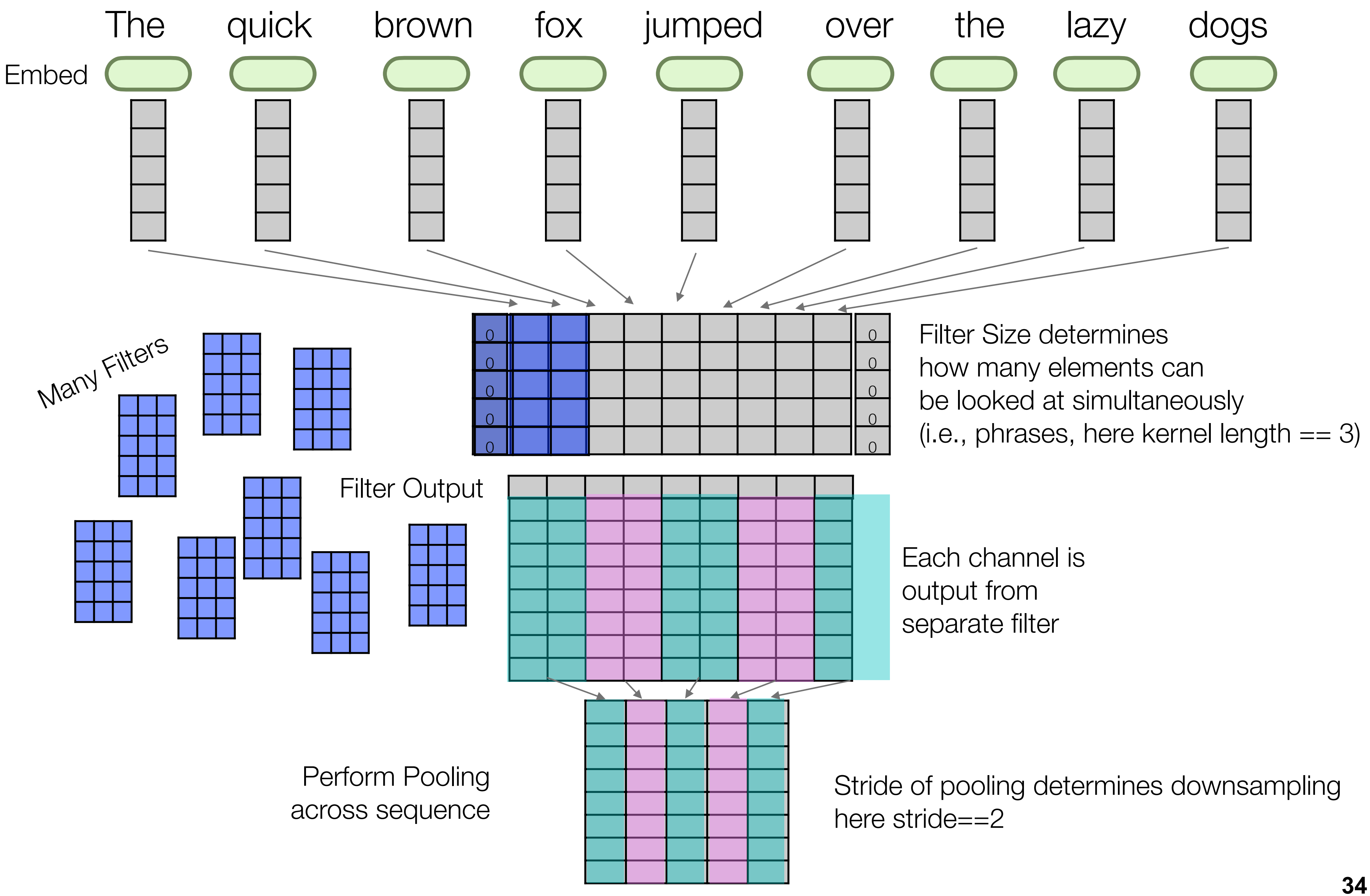
More Complex RNNs

Encoder RNNs



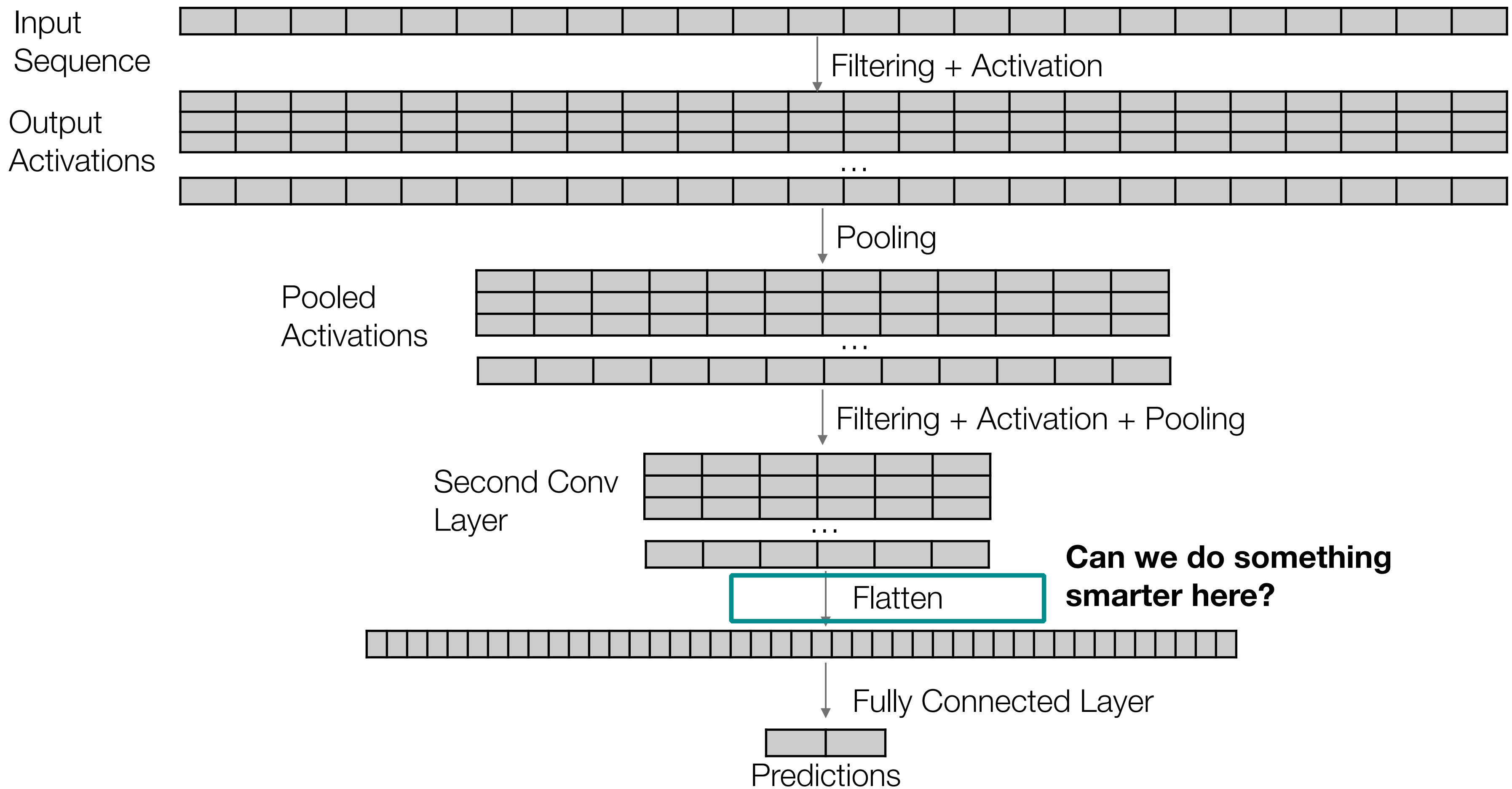
CNNs for Sequences

CNNs for Sequences



CNNs for Sequences

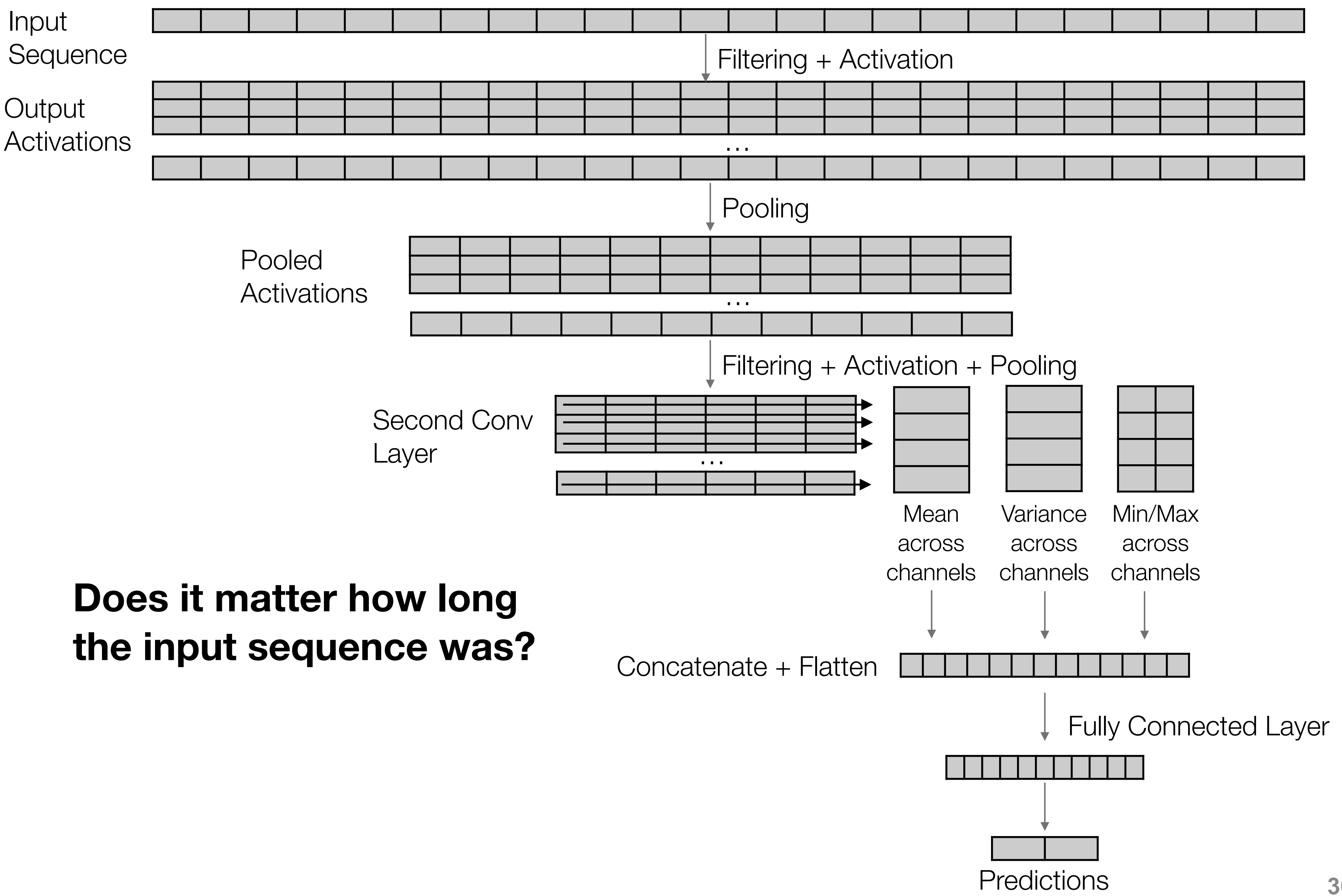
- RNNs are not inherently parallelized or efficient at remembering based on state vector, but CNNs can be run in parallel groups



Can we do something smarter here?

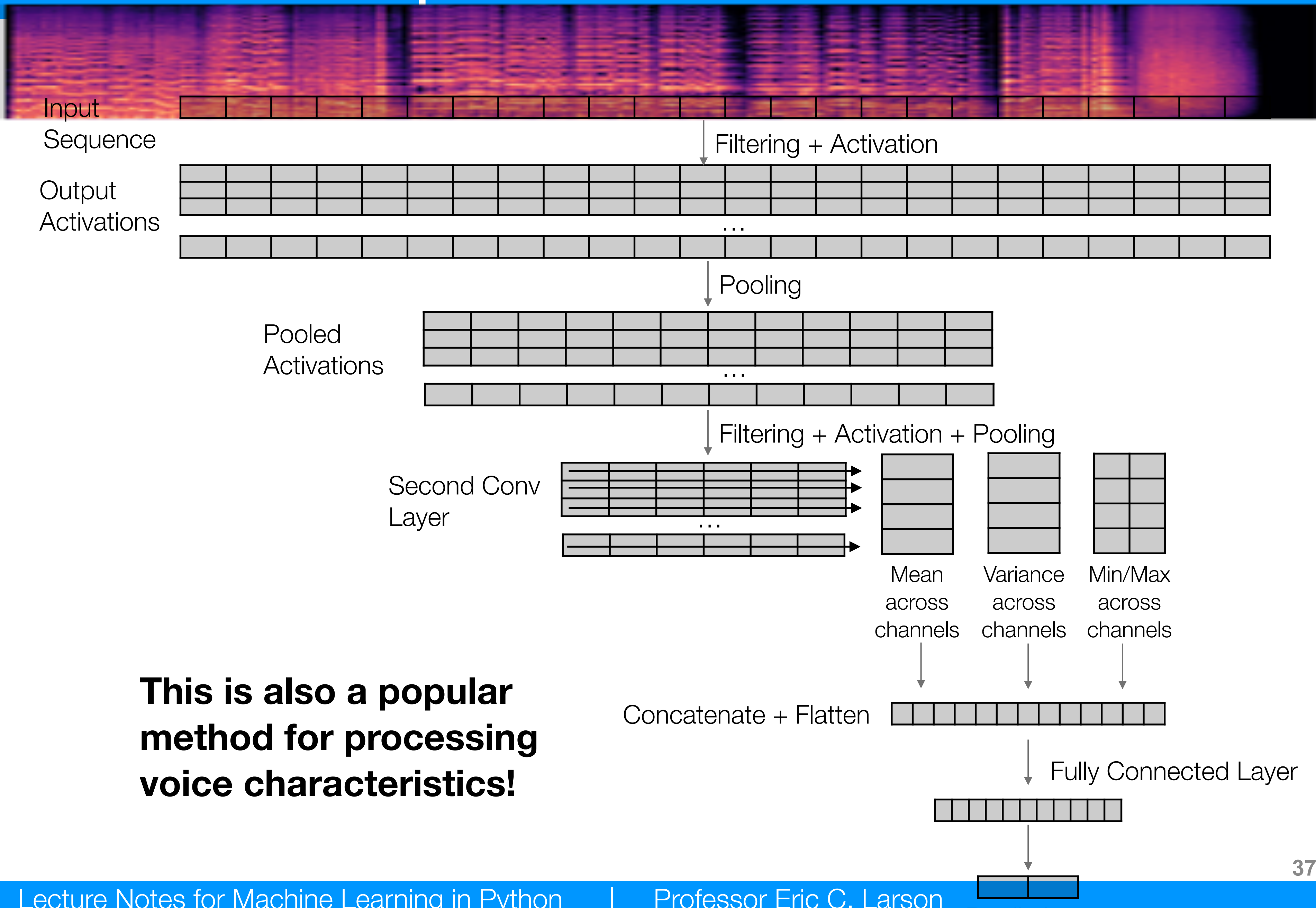
- Everything we learned in 2D CNNs can be applied to 1D CNNs…
- Residuals, separable convolution, squeezing, everything

CNNs for Sequences



Does it matter how long the input sequence was?

CNNs for Sequences



This is also a popular method for processing voice characteristics!

Demo

The Sequential CNN
IMdB sentiment analysis

`13a. Sequence Basics [Experimental].ipynb`

Lecture Notes for

Machine Learning in Python

[👨‍🏫, 👨‍💻, 🐍, 👨‍🔬]

Professor Eric Larson

Sequential Networks Overview