Lecture Notes for

Machine Learning in Python

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Professor Eric Larson

Sequential Networks Overview

Lecture Agenda

- Logistics
  - Grading Update
- Agenda
  - History of Sequential Networks
    - RNNs, CNNs, 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

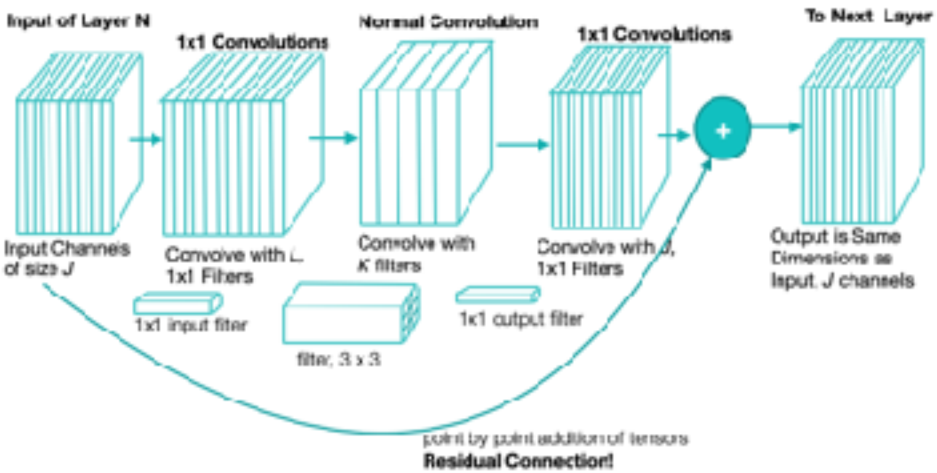
Sequential Networks

Keras, Tensorflow
Intuition, Detailed implement.

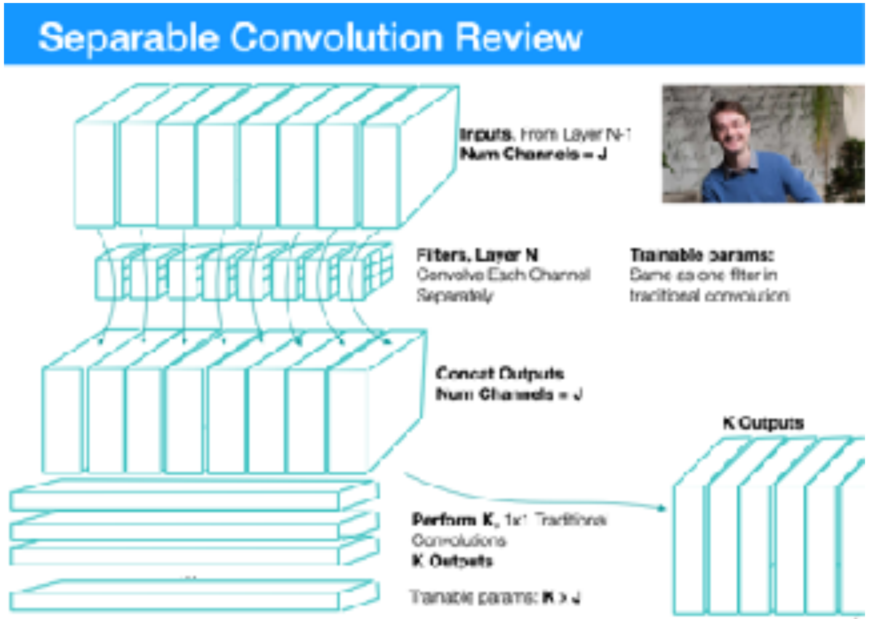
Ethics in Language Models

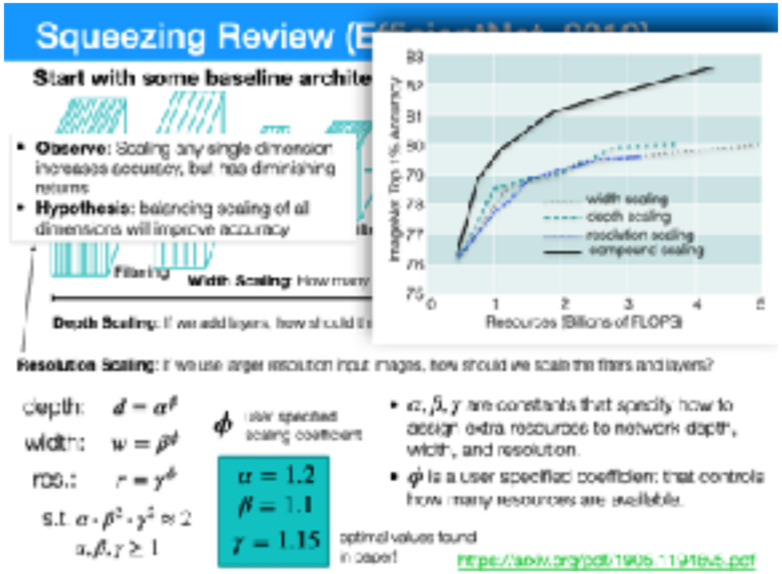
ConceptNet
Case studies

Last Time

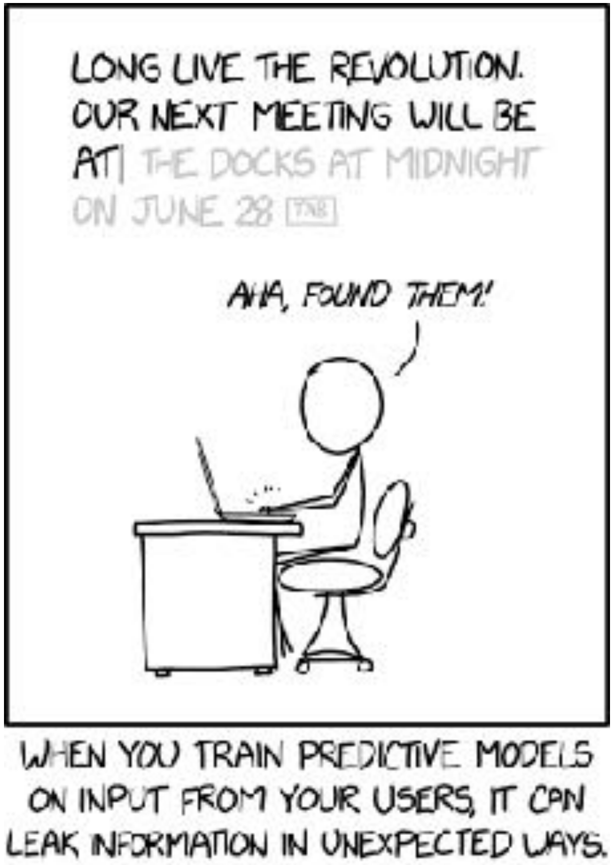


Back Propagation: Two paths, including one without ANY operations that cause the gradient to vanish…





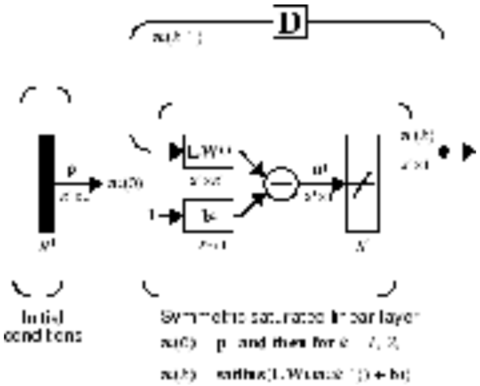
History of Sequential Neural Networks



1980's Recurrent Networks

- Hopfield Network, 1982

John Hopfield, Princeton
Winner of Nobel Prize in Physics, 2024



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

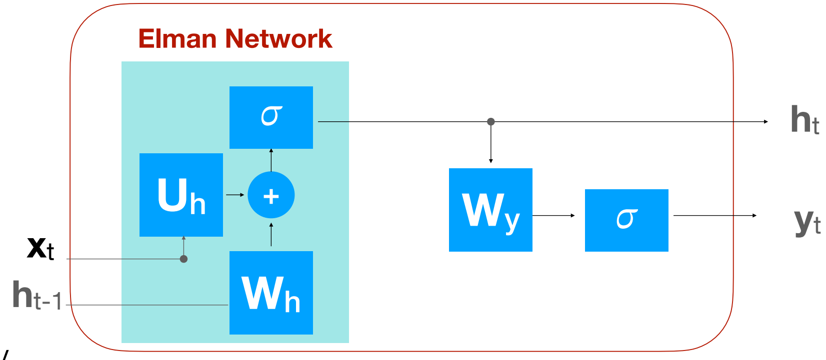
Contribution:
Training with Feedback

- Elman/Jordan Networks, ~1988

Contribution:
Time Steps for Unrolling
Separated output / state

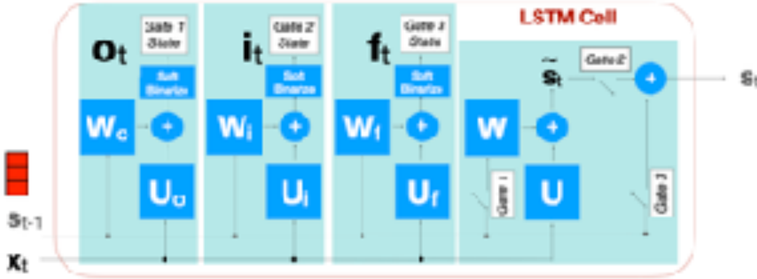
Jeffrey Elman, UCSD

Michael Jordan, Berkeley



1990's-2000's Better Recurrent Networks

- Long Short Term Memory, ~1997 - 2010

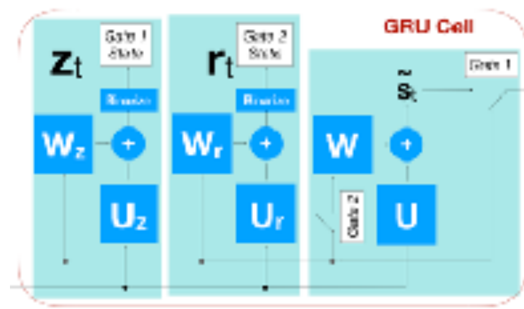


Sepp Hochreiter,
Many Universities

Jürgen Schmidhuber,
Switzerland

Contribution:
Long Duration Memory and State Vector Separate from Output

- Gated Recurrent Units, ~2014

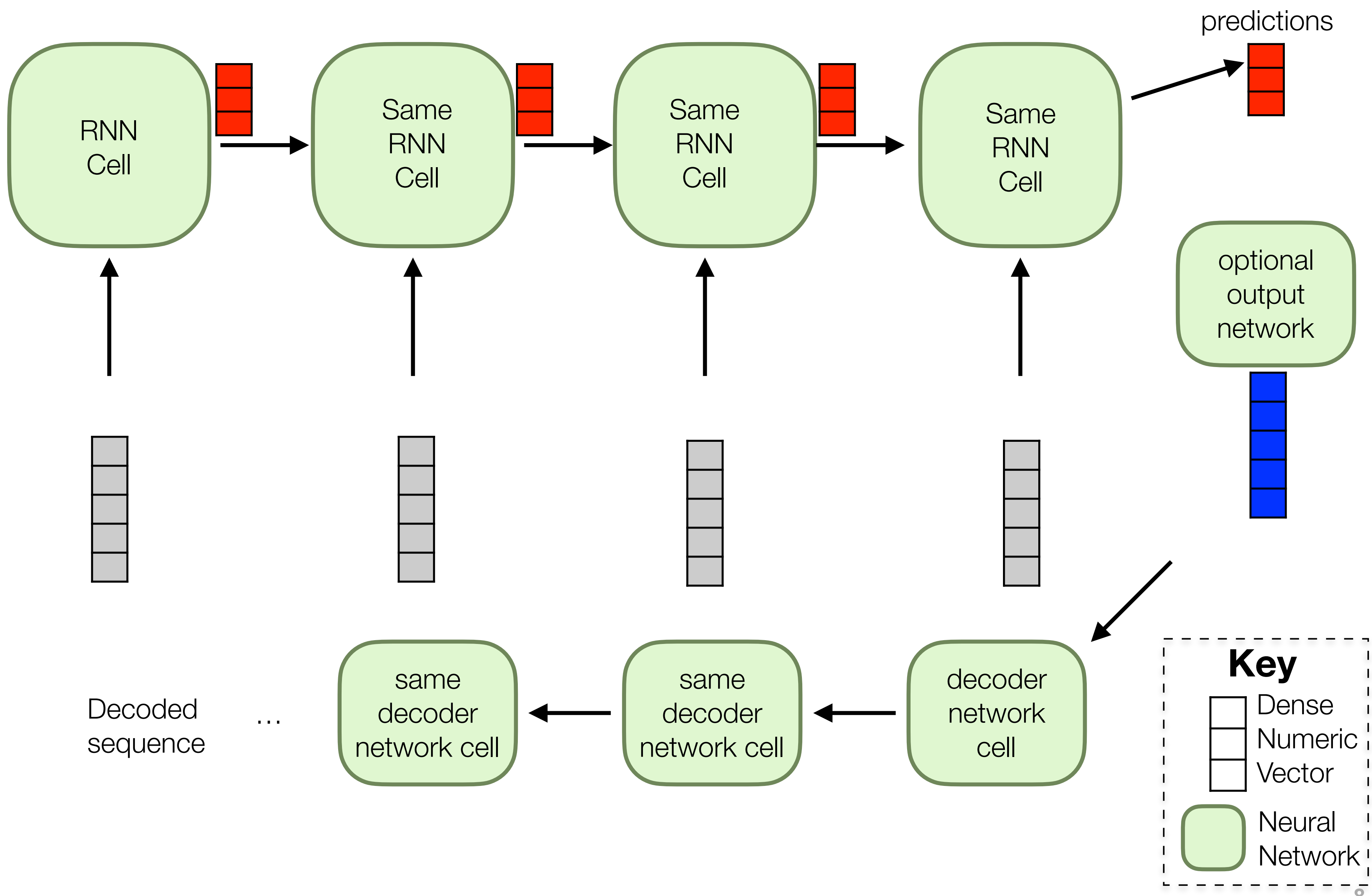


Contribution:
Fewer parameters in RNN

Yoshua Bengio

Kyunghyun Cho, Professor at NYU

General recurrent flow (many to one)



Attention (2016)

- Google

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

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

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

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

Other big advances

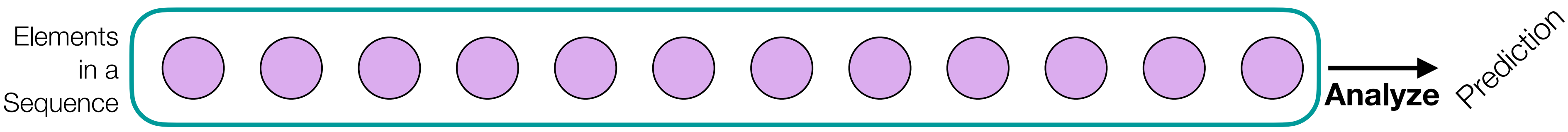
- **1D Convolution** to Replace RNN (2015-2018)
- **Attention is All You Need** (2017)
- **Self-attention** (2018)
- **Multi-headed** attention Transformer (2018)
- **BERT**, **GPT-#**, and other LLM etc. (2019-present)

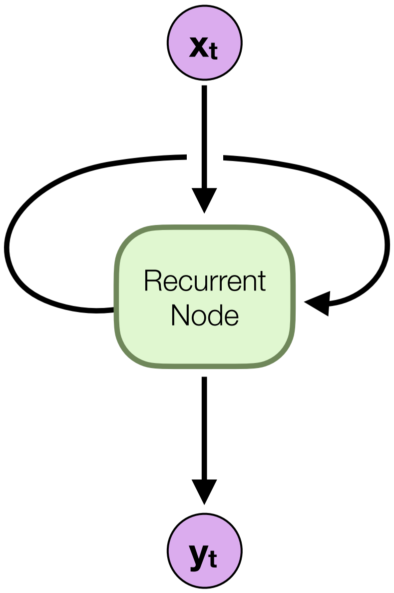
This Course

MLII Course

Overview of Sequential Networks

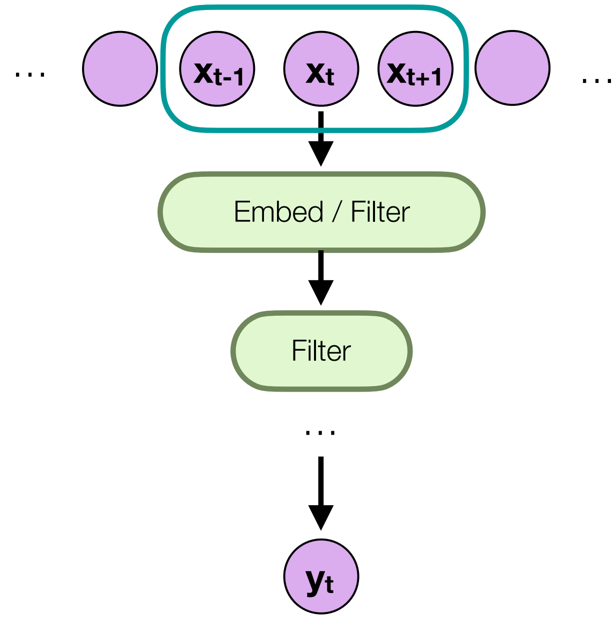
Sequential Networks Types





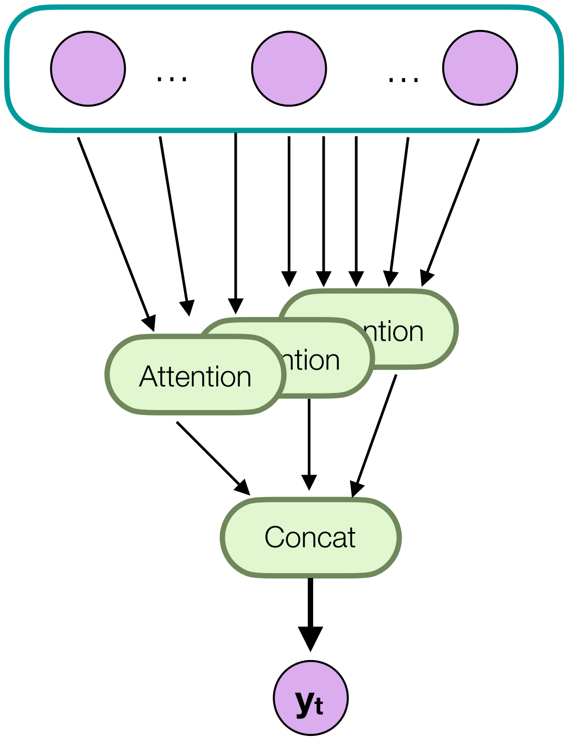
recurrent

Update Sequence State
one element at a time



convolutional

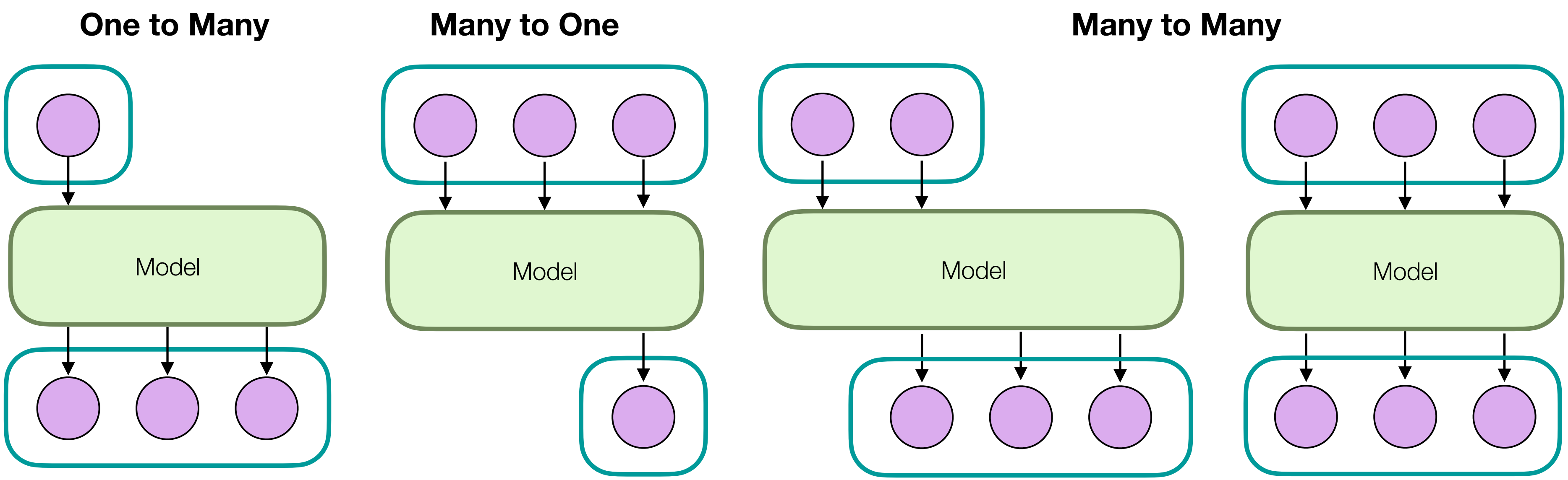
Look at groups of Elements
in Parallel



transformer

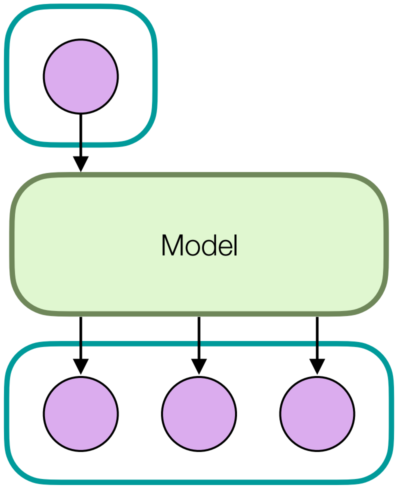
Everything Everywhere All at Once

Sequential Networks: Problem Types

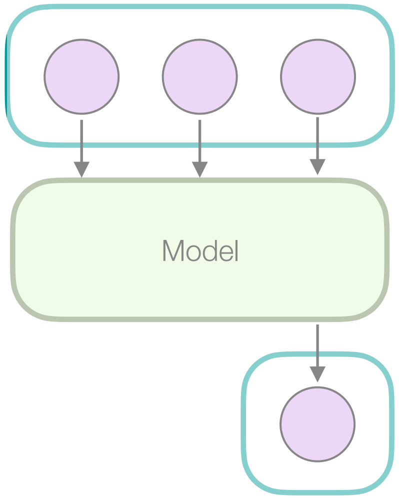


Sequential Networks: Problem Types

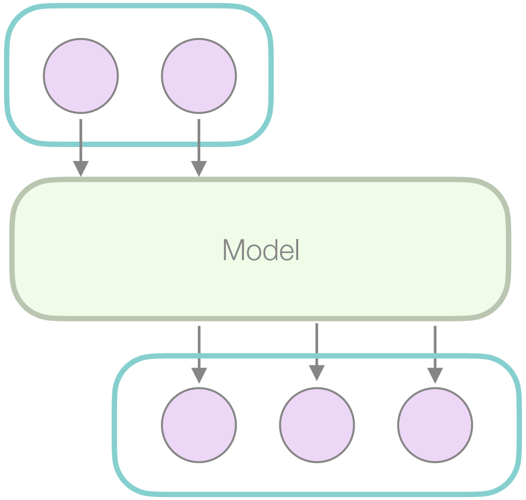
One to Many

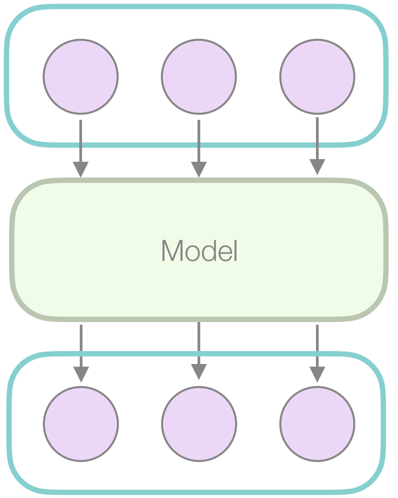


Many to One

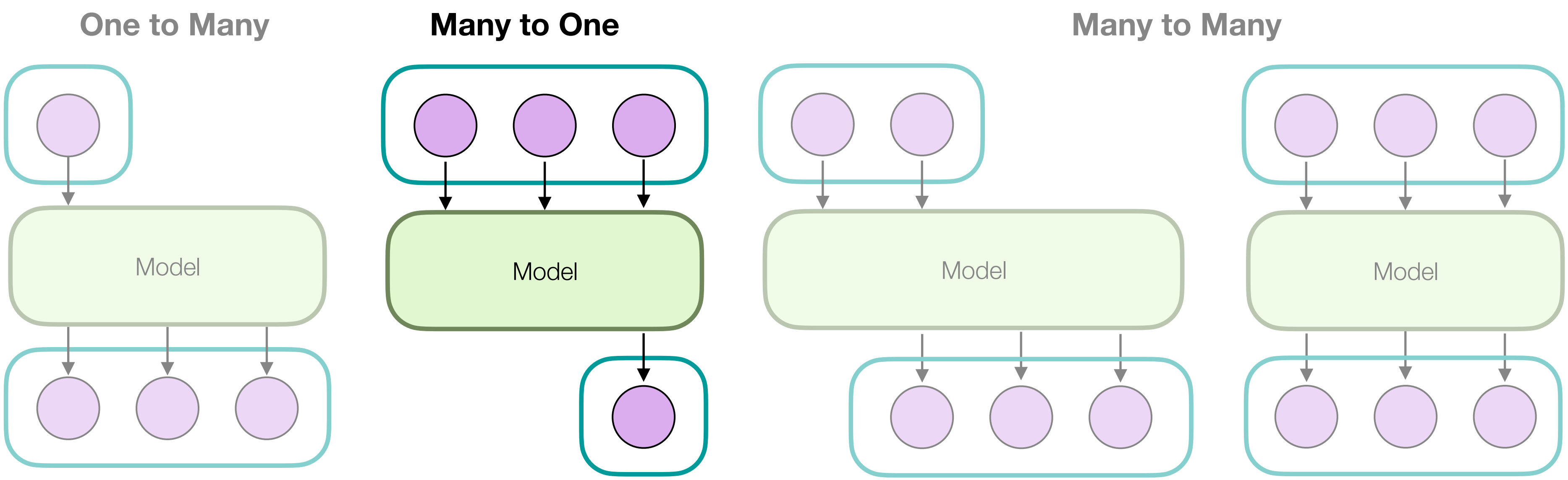


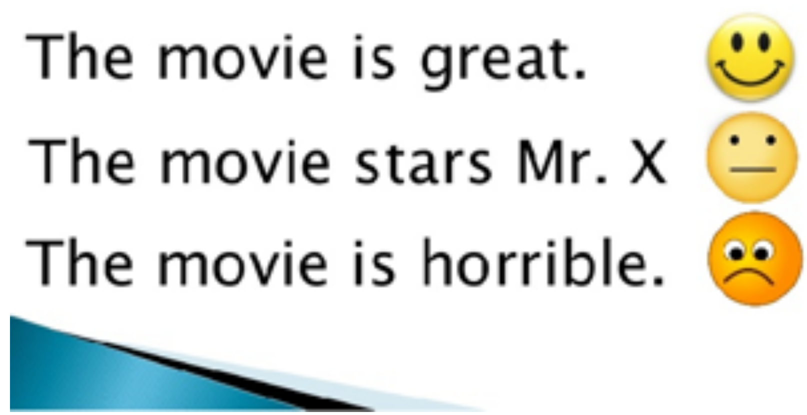
Many to Many





Sequential Networks: Problem Types

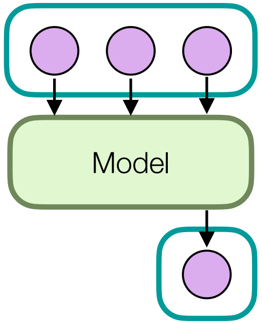




Sequential Networks: Ontology Classification

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

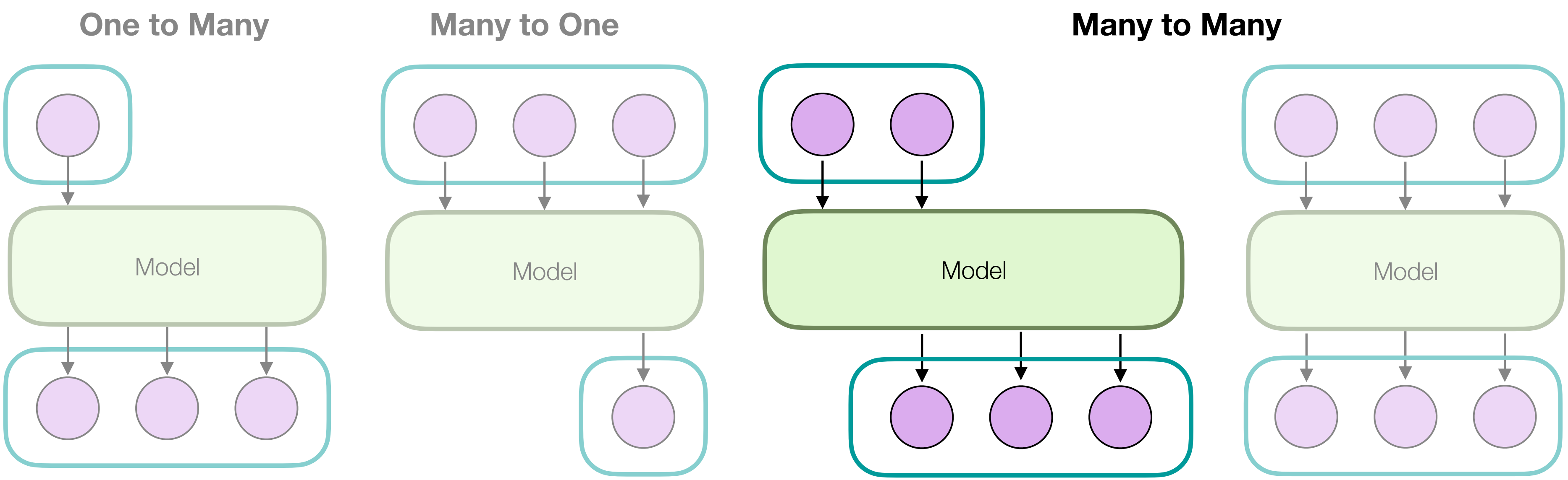
Shaun Norris (born 14 May 1982) is a South African professional golfer.Norris plays on the Sunshine Tour where he has won twice. He won the inaugural Africa Open in 2008 and the Nashua Masters in 2011. He also began playing on the European Tour in 2011 after graduating from qualifying school.

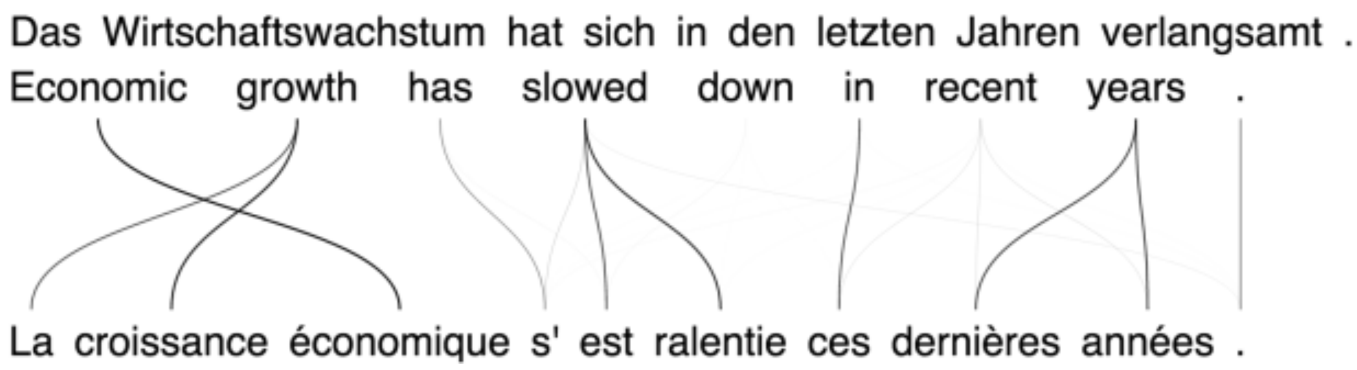
Athlete

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.

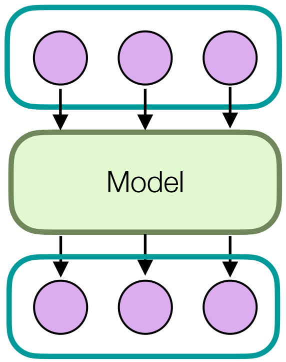
Company

Sequential Networks: Problem Types





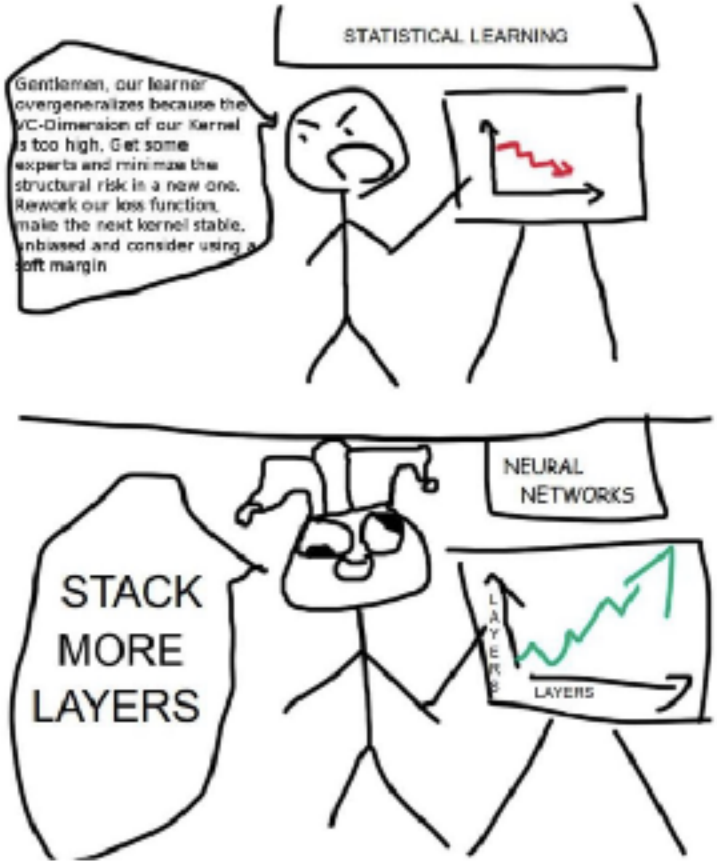
Sequential Networks: Problem Types



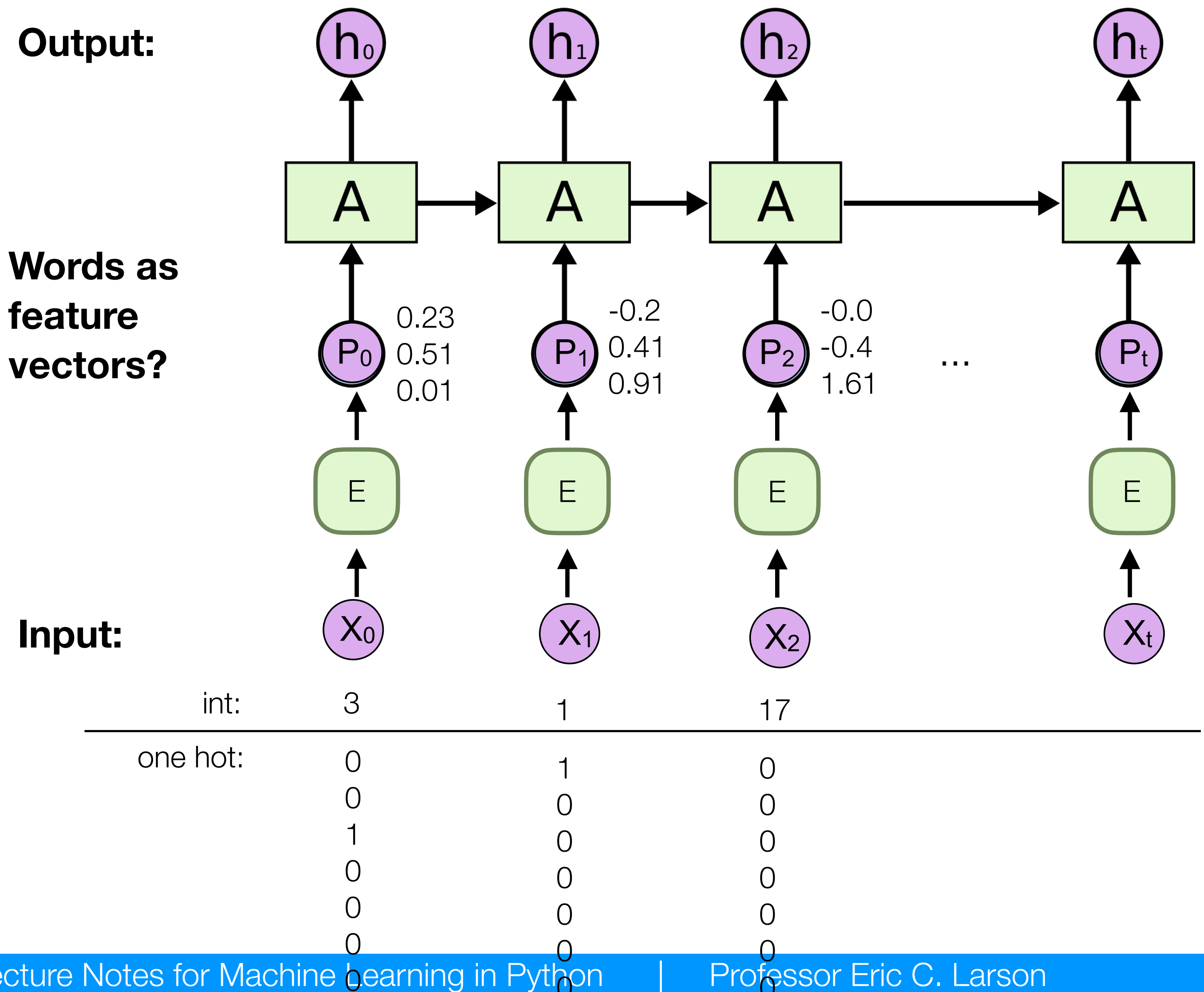
Many to Many

sequence to sequence

Word Embeddings

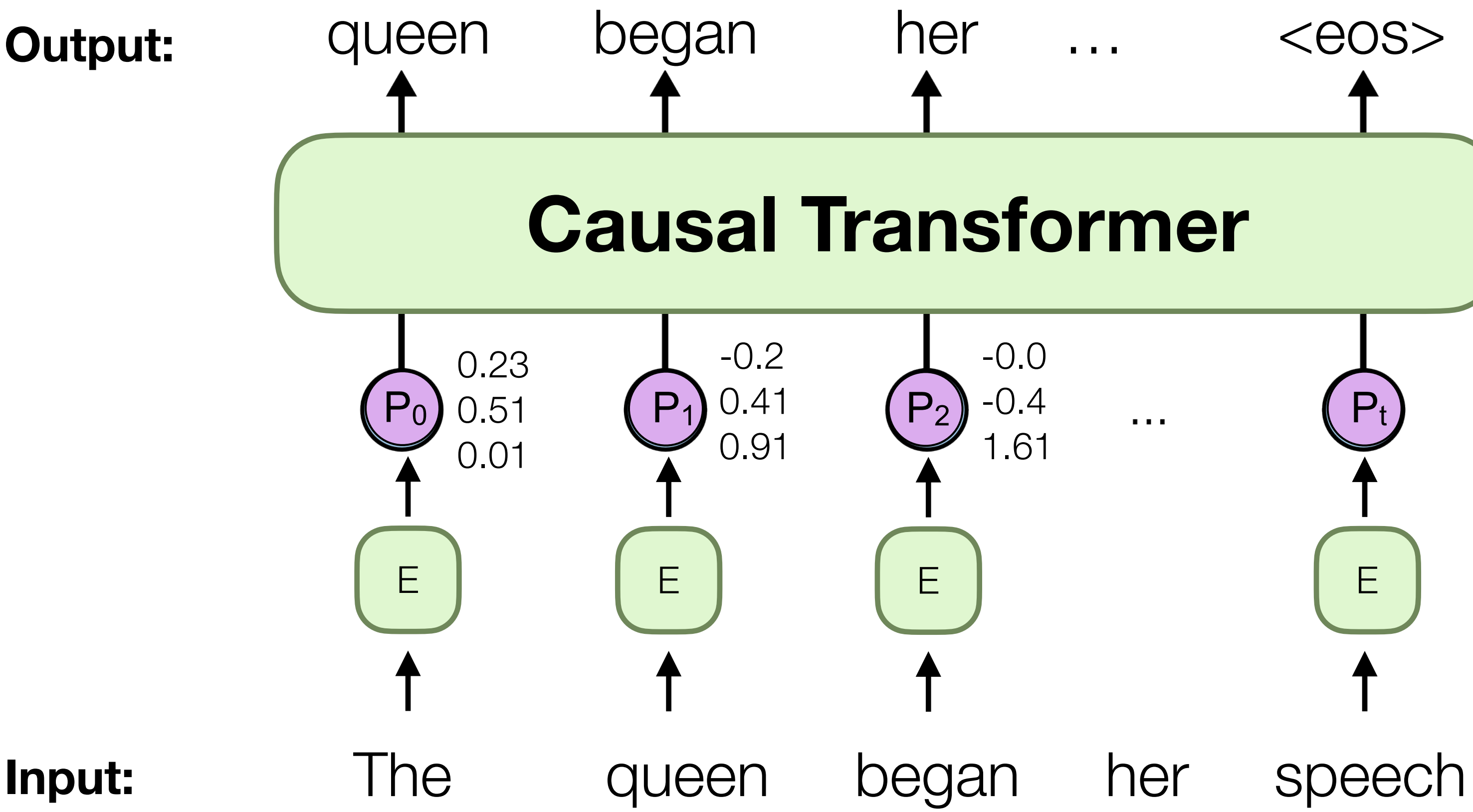


Word Embeddings (like Wide/Deep)



Word Embeddings: Training

- many training options exist
  - popular option: next word/sentence prediction (NSP)



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

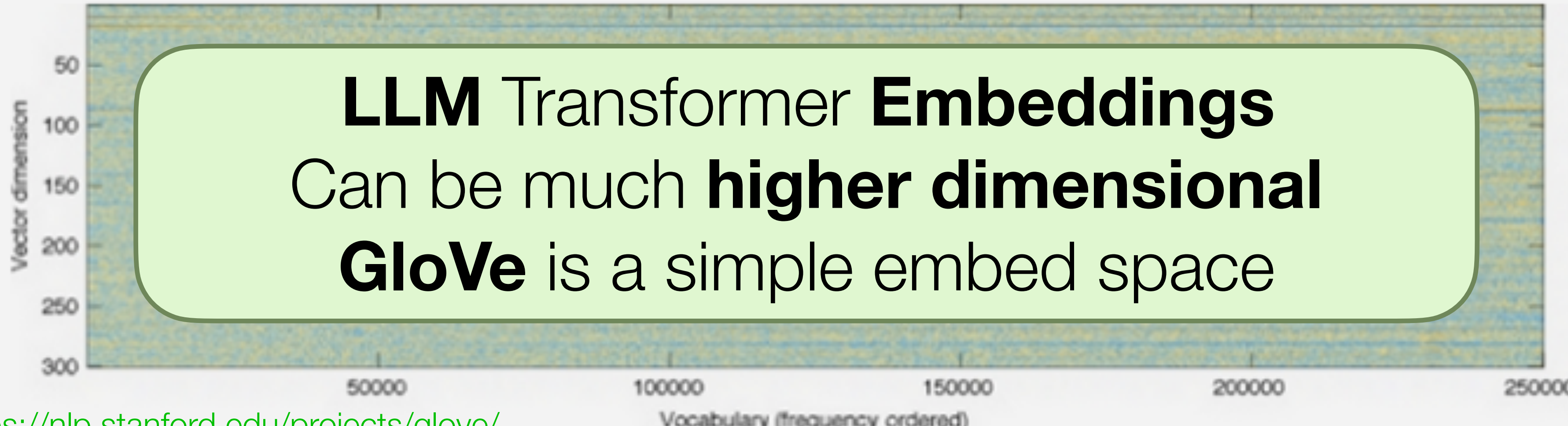

3. litoria


4. leptodactylidae


5. rana


7. eleutherodactylus

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



LLM Transformer **Embeddings**
Can be much **higher dimensional**
GloVe is a simple embed space

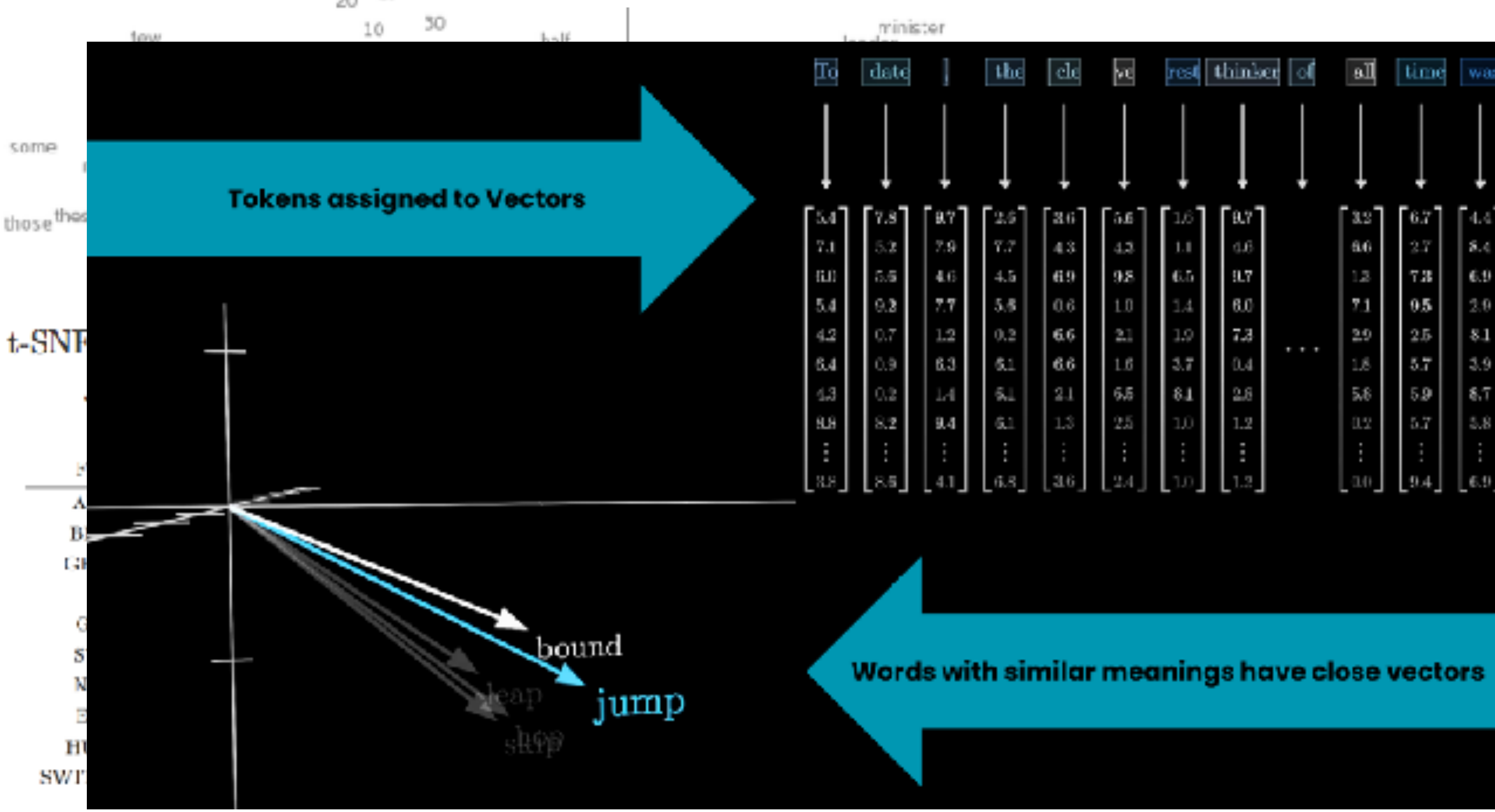
https://nlp.stanford.edu/projects/glove/

Word Embeddings: proximity

GloVe

Proximity: Similar words are embedded to similar features

Global Vectors for Word Representation



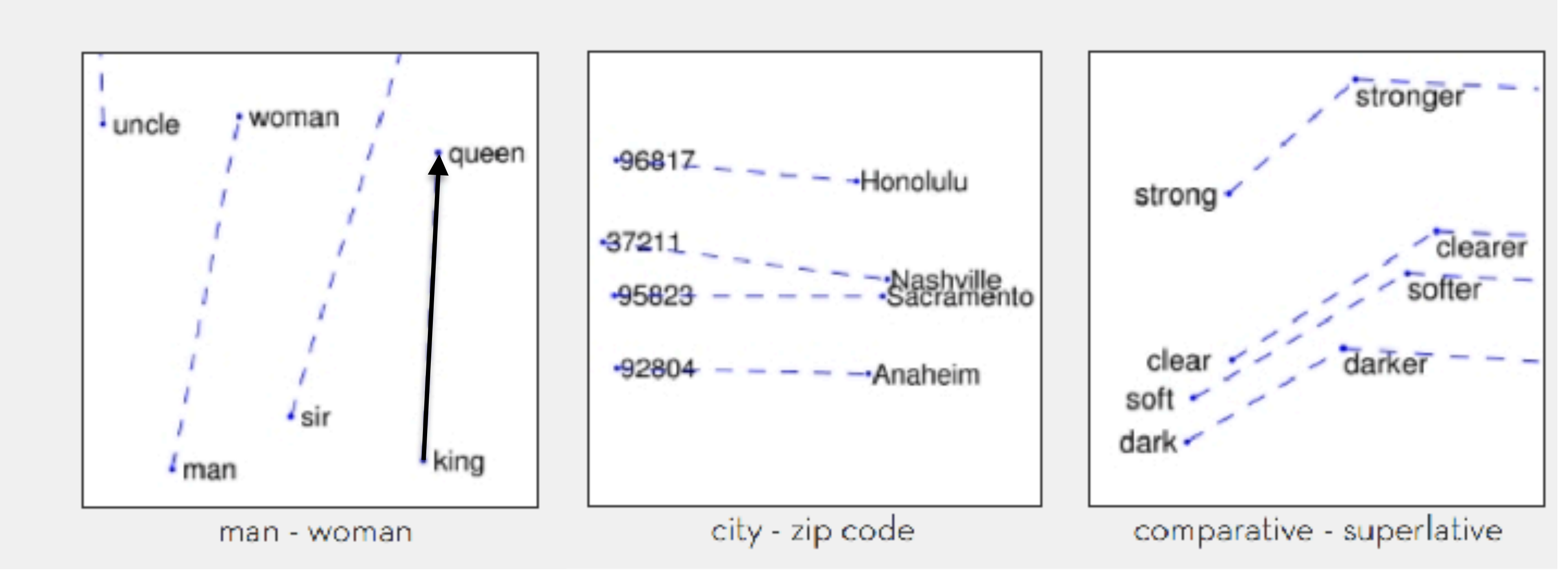
What words have embeddings closest to a given word? From Collobert *et al.* (2011)

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

Word Embeddings: Analogy

GloVe

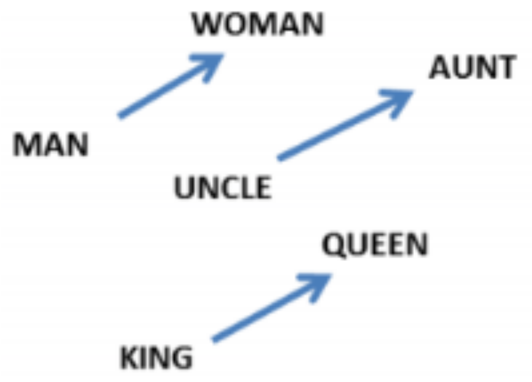
Global Vectors for Word Representation



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

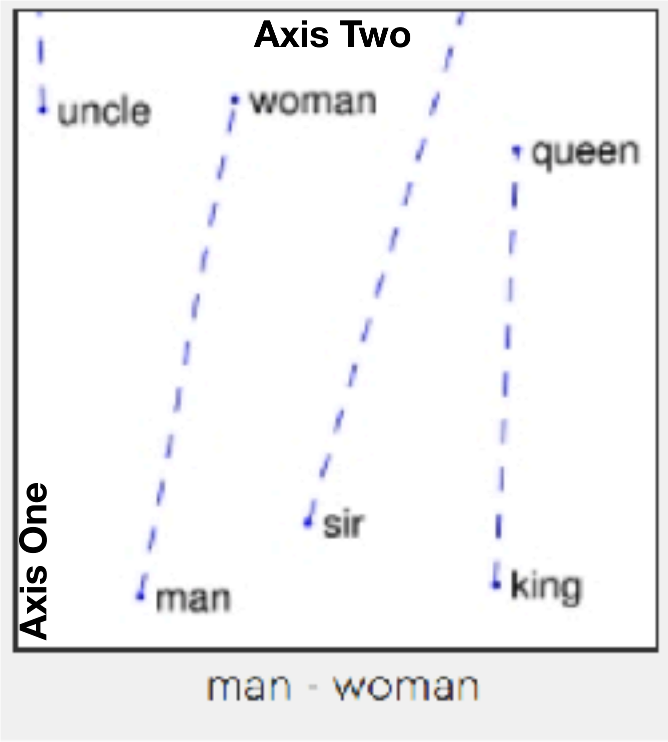
Relationship pairs in a word embedding. From Mikolov *et al.* (2013b).

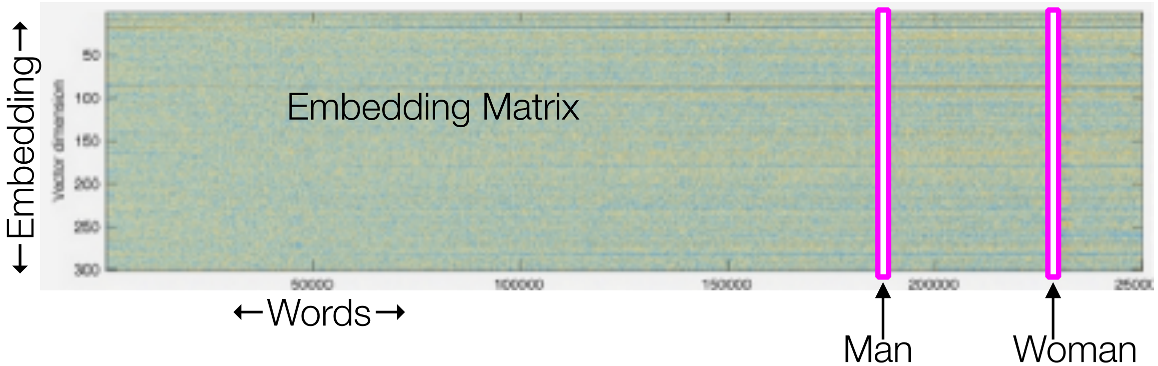
https://nlp.stanford.edu/projects/glove/

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

Self Test: Analogy

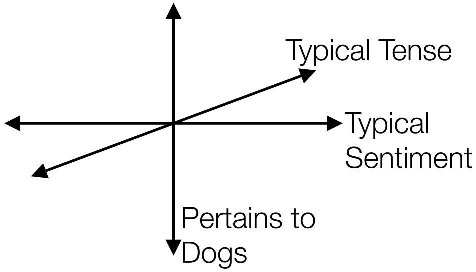
- Each axis on the **embedding plot** below is:
  - A. a weight inside the embedding matrix
  - B. a weighted average of weights inside the embedding layer
  - C. the average of the one hot encoding for a word
  - D. an output of the embedding matrix





Dimensionality of Embeddings

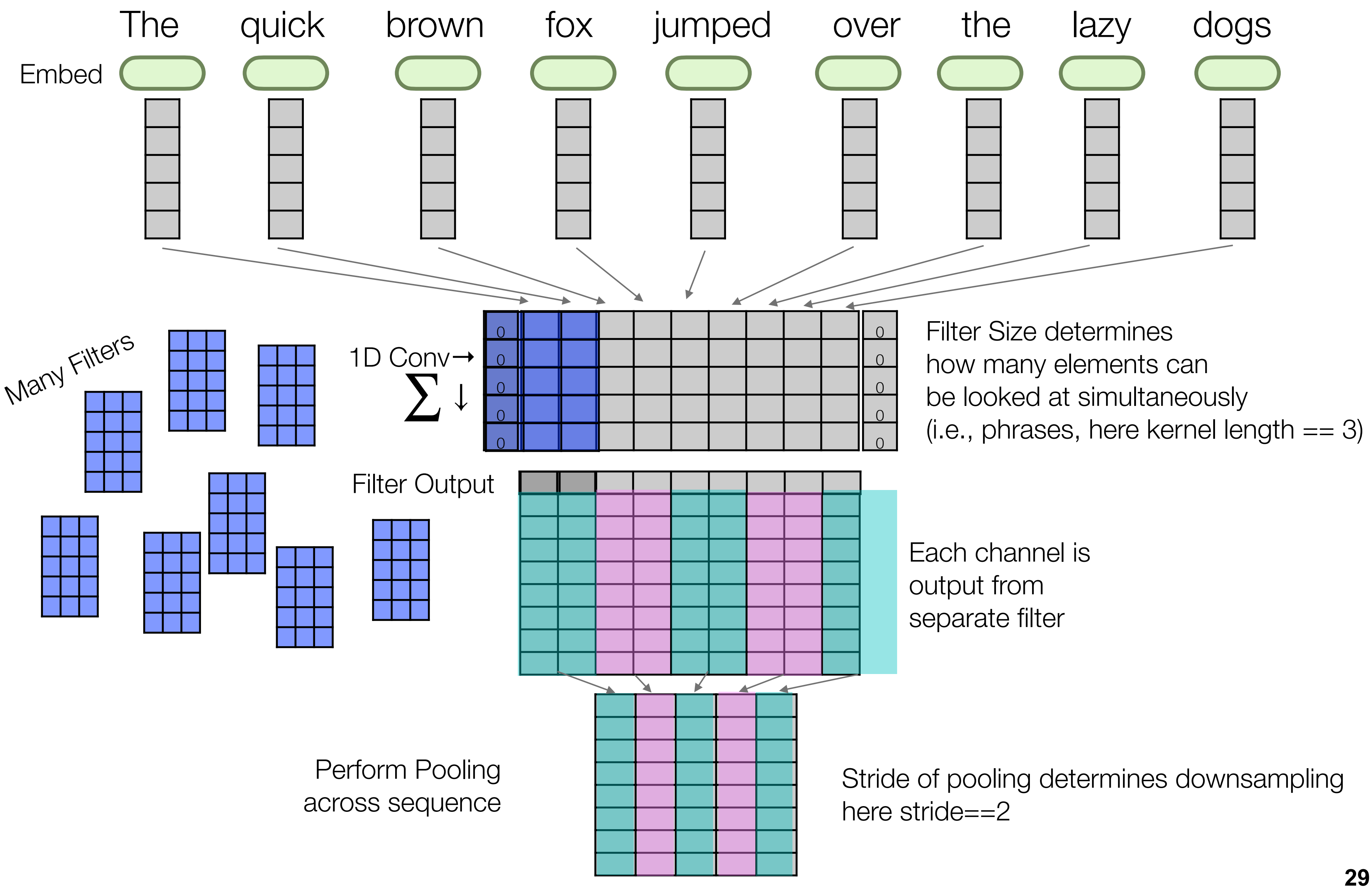
- Each dimension can add a unique aspect of language
    - Orthogonality ensures that aspects are independent in embedding space



- Johnson-Lindenstrauss Lemma:
    - Instead of enforcing strict orthogonality, *what if the dimensions are almost orthogonal, 89-91 degrees apart?* $\epsilon = \pm 5^\circ / 90^\circ$
    - With this relaxation, the total number of almost orthogonal vectors becomes: $N_{eff} \approx \exp(\epsilon \cdot N)$ using N dimensions
    - Glove and $\epsilon = \pm 5^\circ / 90^\circ$:
        - N=300 → 17.3M mostly independent dimensions

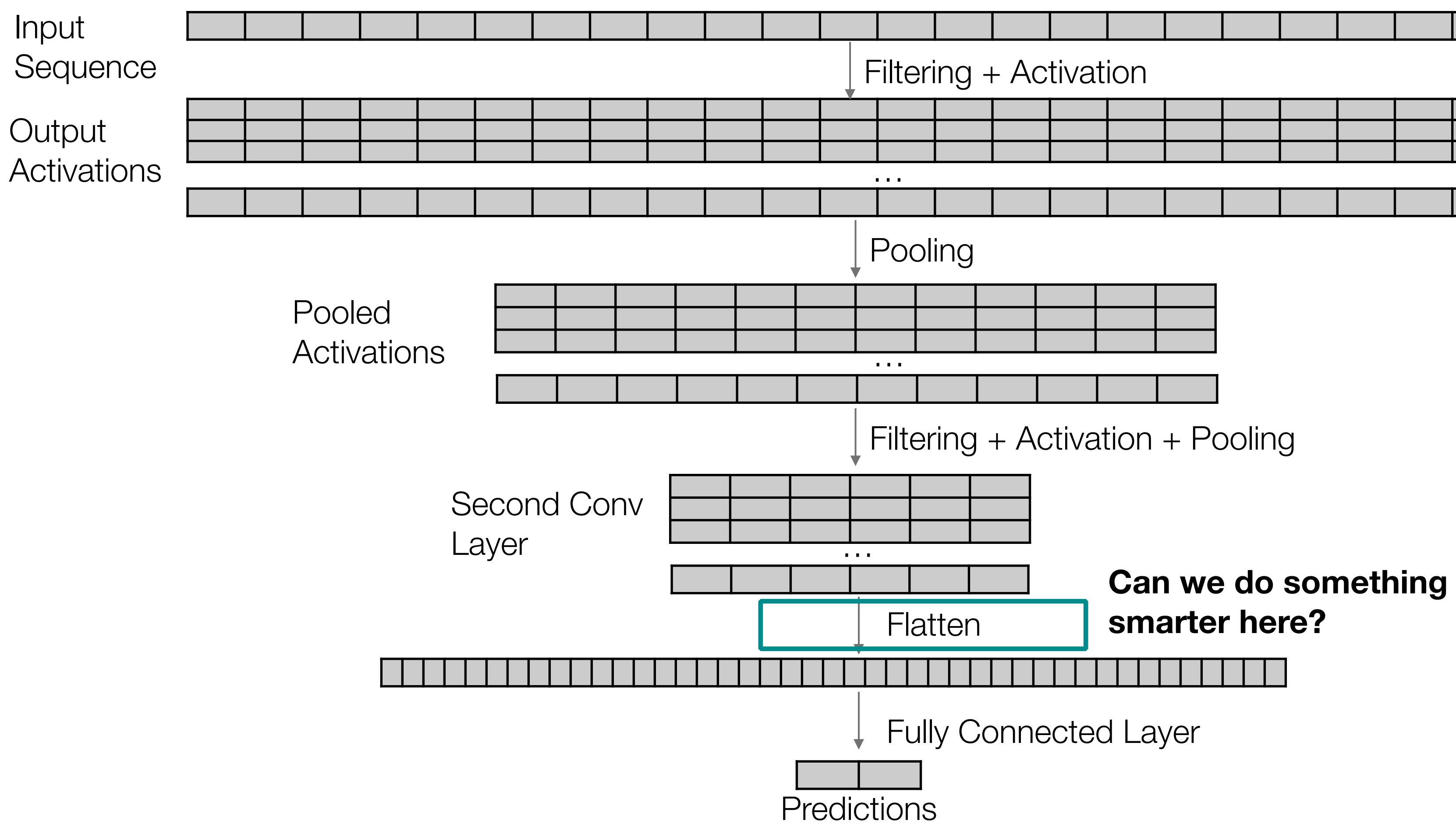
CNNs for Sequences

CNNs for Sequences



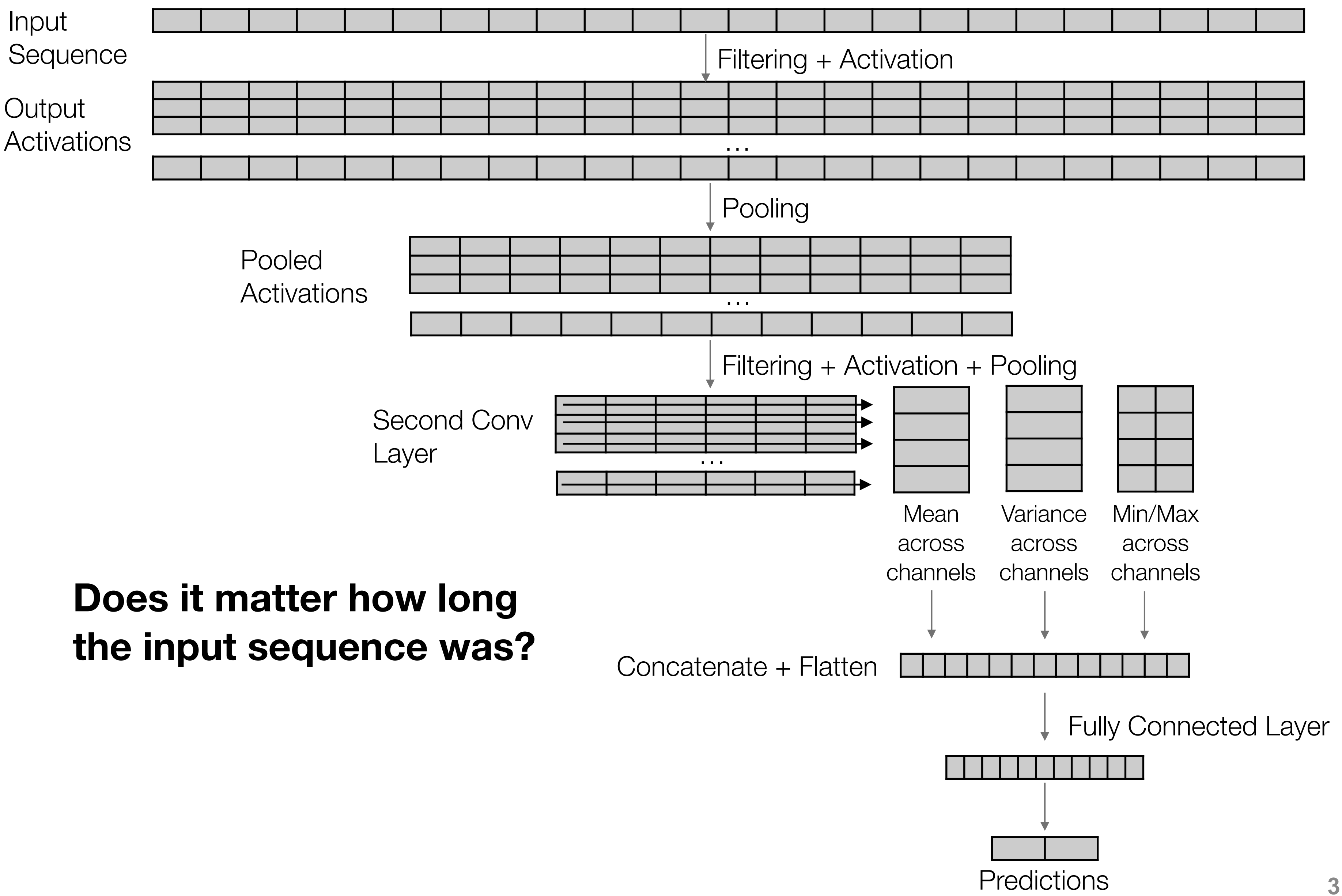
CNNs for Sequences

- RNNs are not inherently parallelized, but CNNs can be run in parallel groups



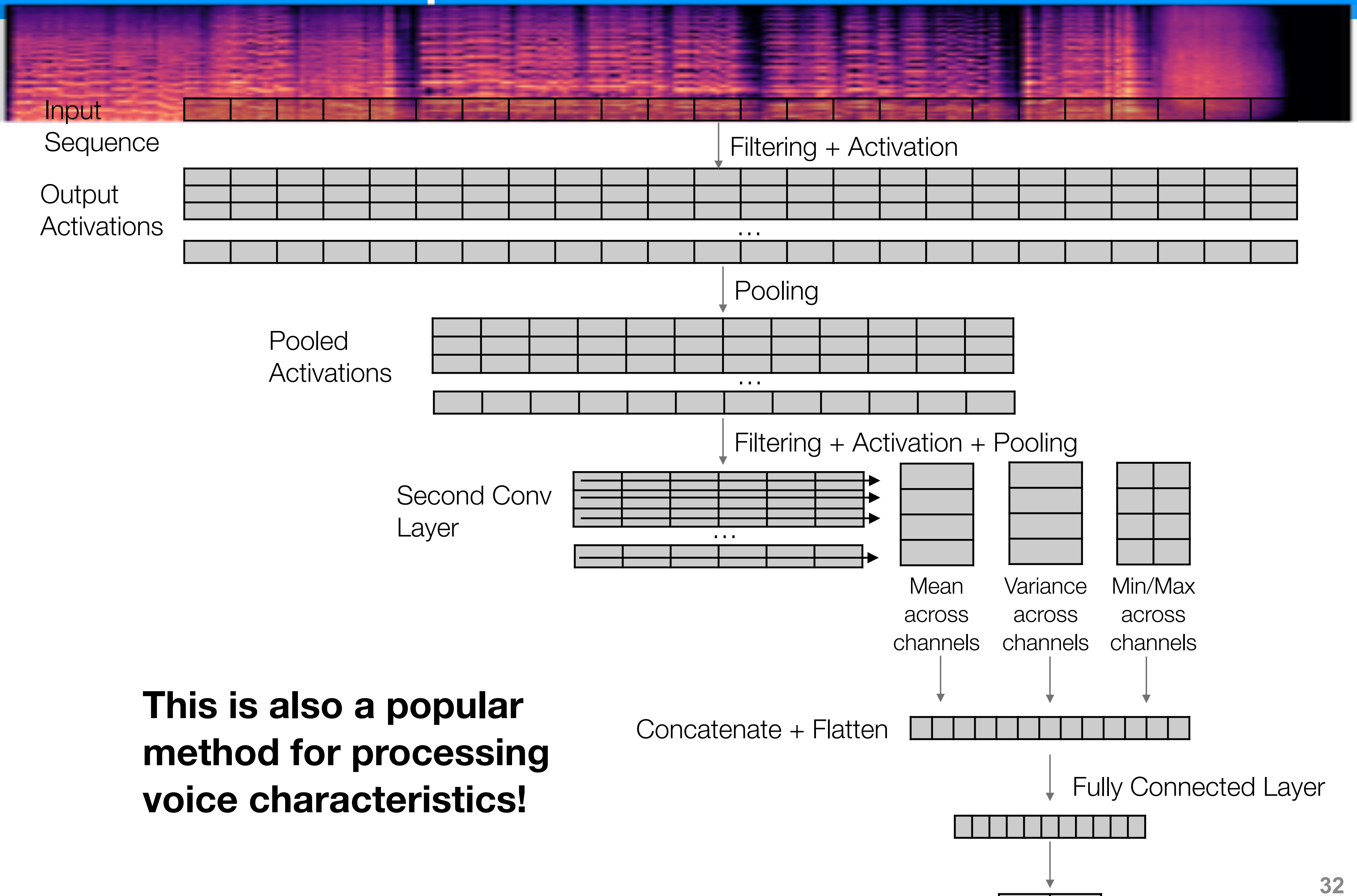
- Everything we learned in 2D CNNs can be applied to 1D CNNs…
- Residuals, separable convolution, squeezing, everything

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

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Professor Eric Larson

Sequential Networks Overview