HOCHSCHULE FÜR
TECHNIK UND WIRTSCHAFT
DRESDEN
UNIVERSITY OF APPLIED SCIENCES

Deep NLP 1: Recurrent Neural Networks

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Warm Up

How is the pace of this course?

(to slow, just right, to fast)

How do you feel about this course?

Do you have any questions?

(Do we talk about model x? etc.)

Okay - let’s play a game :)

Deep Learning for NLP

What will we learn?

Let’s ask ChatGPT

What will you learn

- What is NLP?
- Applications of NLP
- Introduction to Word Representations
  - One-hot Encoding
  - Word Embeddings
- Recurrent Neural Networks (RNNs)
  - Introduction to RNNs
  - Long Short-Term Memory (LSTM)
- Transformers and Attention Mechanisms
  - Introduction to Transformers
  - Self-Attention and Multi-head Attention
  - Pretrained Language Models (Transfer Learning and Fine-tuning)
  - Application: Offensive Language Classification
- Current Challenges and Future Directions in NLP
  - Interpretability and Explainability
  - Ethical Considerations

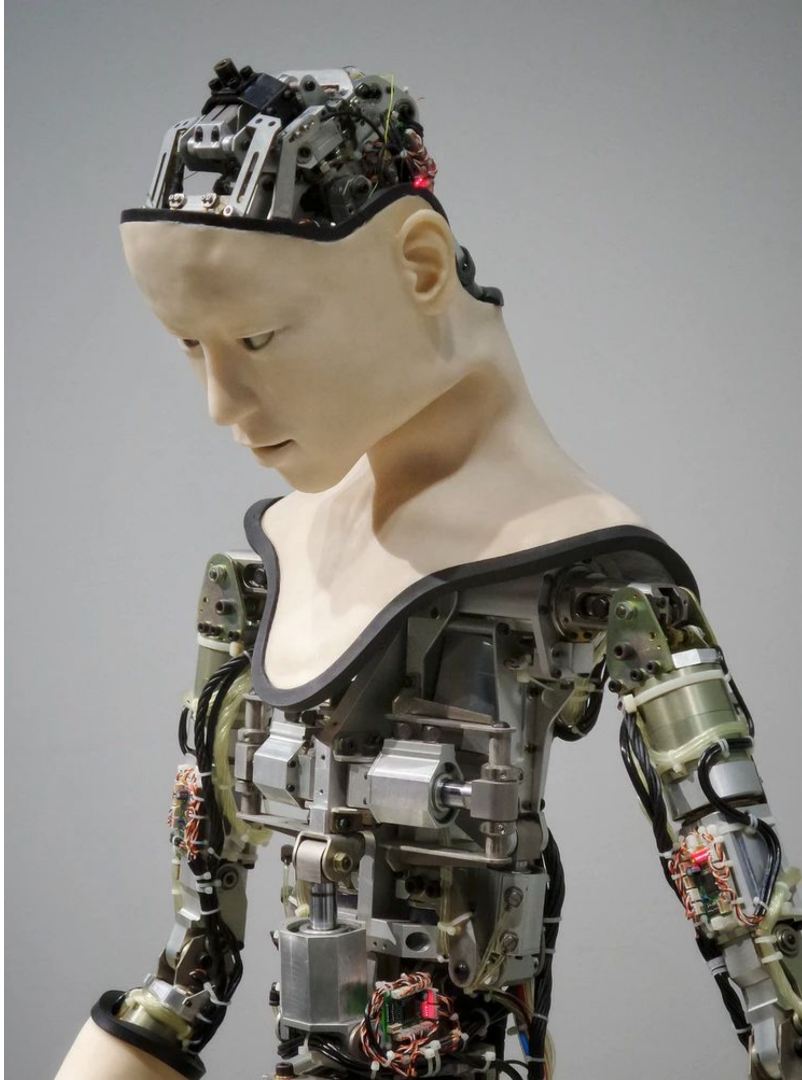
What would you like to learn?

What would you like to learn?

https://yopad.eu/p/htwdeepnlp-365days

Goal for today

- Warm Up
- First overview about NLP
- Learn about RNNS
- Train an RNN



Our Robots

Tesaro, August and Anna

AI Buzz: 2023 edition

Opinion Artificial intelligence (AI)

This article is more than **2 months old**

A robot wrote this entire article. Are you scared yet, human?

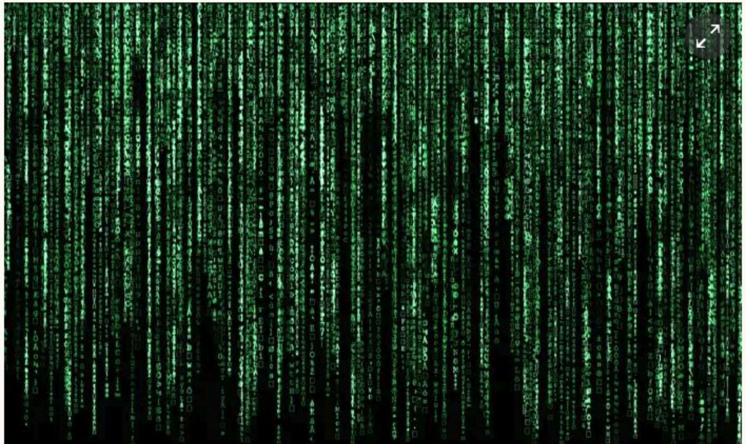
We asked GPT-3, OpenAI's powerful new language generator, to write an essay for us from scratch. The assignment? To convince us robots come in peace

- For more about GPT-3 and how this essay was written and edited, please read our editor's note below

GPT-3

Tue 8 Sep 2020 09.45 BST

69.630 1.188



15. Mai 2019, 19:00 Uhr **Fake-News-Generator**

Mit Lügen spielen

Enorme Datenmengen: Die Forscher beschreiben, dass sich der Bot mit Informationen von mehr als acht Millionen Webseiten nährt. (Foto: Franziska Gabbert/dpa)

Auf einer neuen Website können Nutzerinnen und Nutzer aus wenigen Stichworten Falschmeldungen generieren lassen. Eigentlich wollten die Entwickler das Werkzeug unter Verschluss halten, um Missbrauch auszuschließen.

Support The
Available for everyone, fund
Contribute →
Subscri
News
World UK Scier
Artificial in
(AI)
Alex Hern
@alexhern
Thu 14 Feb
AI
OpenAI let us try
generator
rt NLP text
OpenAI built a text generator so good, it's
considered too dangerous to release
Zack Whittaker @zackwhittaker / 3 months ago
Login
INDY/LIFE
AI TEXT GENERATOR TOO
DANGEROUS TO RELEASE, SAY
CREATORS
Developers cite concerns over fake news proliferation and risk of online impersonation
ially
endent,
o everyone
ferent approach –
rt it?
Guardian →
US-China trade war:
ng vows to retaliate as
fs raised - Business live
a Sorokin: fake German
ess sentenced to up to
ars in prison
die Starr: comedian

Künstliche Intelligenz

Wer hat Angst vor der bösen KI?

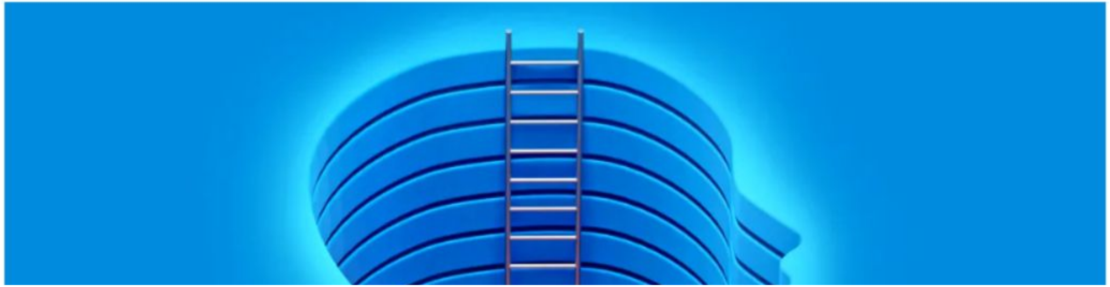
Die Debatte um künstliche Intelligenz ist zunehmend von Gruselszenarien bestimmt. Dabei sollten wir über deren soziale Auswirkungen reden – nur eben ganz anders.

Ein Essay von **Georg Diez**

Z+ EXKLUSIV FÜR ABONNENTEN

29. Mai 2023, 20:03 Uhr / 26 Kommentare /

Artikel hören



https://www.zeit.de/kultur/2023-05/kuenstliche-intelligenz-angst-zukunft-geoffrey-hinton-james-bridle

The New York Times

A.I. Poses 'Risk of Extinction,' Industry Leaders Warn

Leaders from OpenAI, Google DeepMind, Anthropic and other A.I. labs warn that future systems could be as deadly as pandemics and nuclear weapons.

Give this article | 1.4K

Executives from three of the leading A.I. companies, including Sam Altman, chief executive of OpenAI, have signed an open letter warning of the risks of artificial intelligence. Jim Lo Scalzo/EPA, via Shutterstock

https://www.nytimes.com/2023/05/30/technology/ai-threat-warning.html

Does AI pose a risk for humanity?

Artificial intelligence (AI)

New AI fake text generator may be too dangerous to release, say creators

The Elon Musk-backed nonprofit company OpenAI declines to release research publicly for fear of misuse

Alex Hern
@alexhern
Thu 14 Feb 2019 17.00 GMT

6.473 572

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Live US-China trade war: Beijing vows to retaliate as tariffs raised - Business live


Anna Sorokin: fake German heiress sentenced to up to 12 years in prison

Freddie Starr: comedian found dead at home in

Natural Language Processing

“processing of texts”

Natural Language Understanding

“extract information from texts”

Deep Natural Language Processing

"processing of texts with deep neural networks"

Language is hard.

Let’s eat grandpa.

Let’s eat grandpa.

Let’s eat, grandpa.

content.time.com

The Pope's Baby Step on Gays

3-4 Minuten

STEFANO SPAZIANI

First, the good news. Pope Francis is already showing himself to be a winsome, endearing and inspiring successor to St. Peter. His trip to Brazil catapulted him to rock-star status, with his care for the poor and the dispossessed, his willingness to engage the throngs with little regard for his security and even with his crowd-pleasing offer of a song on the guitar. This is no formal and aloof bishop but rather a man of and for the people. Justice is on his mind and his lips.

Source NY Time: http://ti.me/13XReHS

Language and AI

- Language processing problems are mostly optimization problems, mostly only approximate solutions exist.
- Different languages differ greatly from each other. Semantic structure, grammar, syntax, word order, text types, stylistics
- Language is ambiguous
- Language is creative
- Language is non-sequential (interactions between widely separated elements in a sentence)
- The context often determines the meaning.
- Further Information: Dagmar Gromann - Dialog or Dialogue?

Applications

Applications

- Standard Tasks
  - Named Entity Recognition
  - Text Classification
  - Text Summarization
  - Text Generation
  - Question Answering (Text and Multiple Choice)
  - Translation

- newer Tasks
  - Virtual Assistants / Voice Assistants
  - Playing Quiz
  - Dialogue Generation
  - Code Generation
  - HTML Layout Generator
  - Reasoning Questions
  - Fact Checking

Applications

- Standard Tasks
  - Named Entity Recognition
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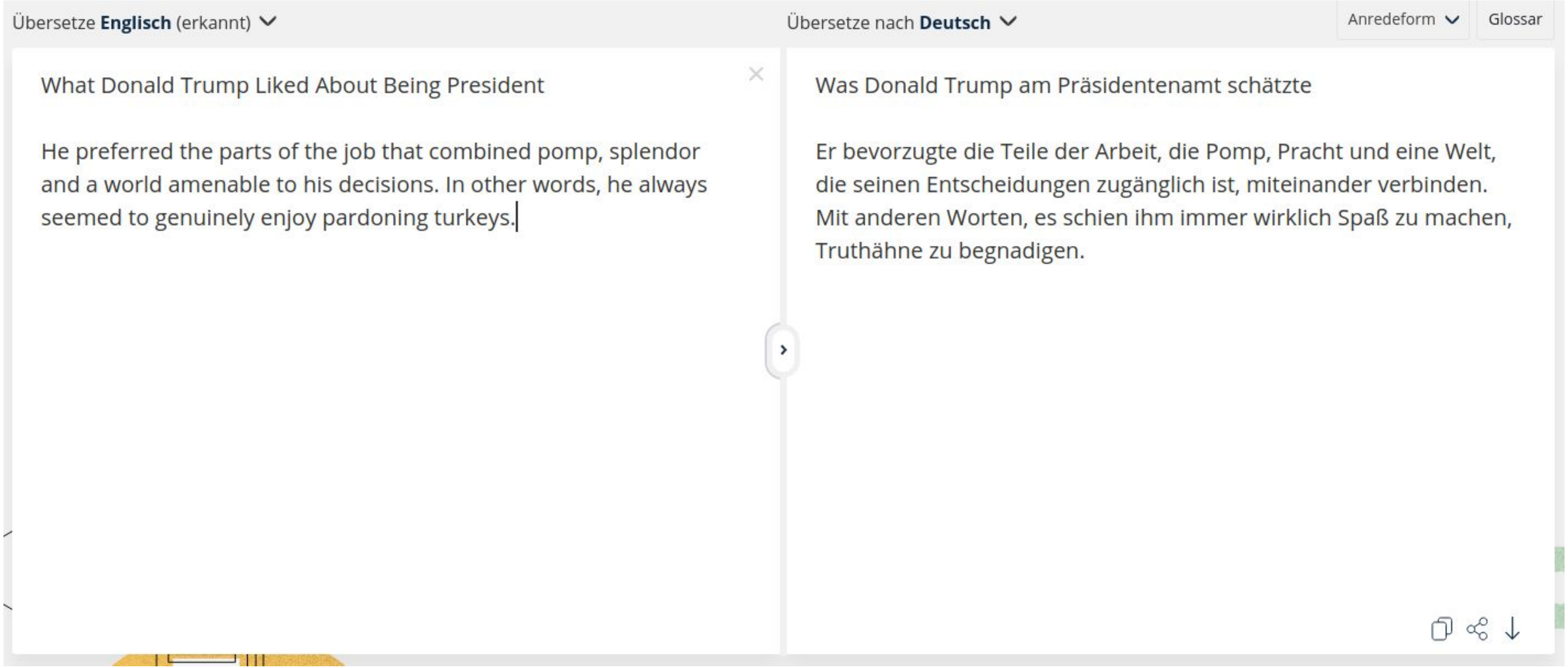
Today: Just use ChatGPT?

- newer
  - Playing Quiz
  - Dialogue Generation
  - Code Generation
  - HTML Layout Generator
  - Reasoning Questions
  - Fact Checking

Some (of my) demos:

- Sentiment
  - https://huggingface.co/oliverguhr/german-sentiment-bert
- Punctuation Prediction
  - https://huggingface.co/oliverguhr/fullstop-punctuation-multilang-large
- Spelling Correction
  - https://huggingface.co/oliverguhr/spelling-correction-german-base
- Speech-to-Text (ASR)
  - https://huggingface.co/oliverguhr/wav2vec2-large-xlsr-53-german-cv9

Translations



Service: deepl.com

Question Answering

The 1973 oil crisis began in October 1973 when the members of the Organization of Arab Petroleum Exporting Countries (OAPEC, consisting of the Arab members of OPEC plus Egypt and Syria) proclaimed an oil embargo. By the end of the embargo in March 1974, the price of oil had risen from US$3 per barrel to nearly $12 globally; US prices were significantly higher. The embargo caused an oil crisis, or "shock", with many short- and long-term effects on global politics and the global economy. It was later called the "first oil shock", followed by the 1979 oil crisis, termed the "second oil shock."

When did the 1973 oil crisis begin?
Ground Truth Answers: October 1973 | October 1973 | October 1973 | October | 1973

What was the price of oil in March of 1974?
Ground Truth Answers: nearly $12 | $12 | $12 | $12 | $12

When was the second oil crisis?
Ground Truth Answers: 1979 | 1979 | 1979 | 1979 | 1979

What was another term used for the oil crisis?
Ground Truth Answers: first oil shock | shock | shock | first oil shock | shock

Who proclaimed the oil embargo?
Ground Truth Answers: members of the Organization of Arab Petroleum Exporting Countries | members of the Organization of Arab Petroleum Exporting Countries | Organization of Arab Petroleum Exporting Countries | members of the Organization of Arab Petroleum Exporting Countries | OAPEC

Question Answering

- Stanford Question Answering Dataset (SQuAD)
- Standard Datat set for QA
- consists of 150000 questions
- 44 MB of data
- https://rajpurkar.github.io/SQuAD-explorer/

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831	89.452

Question Answering

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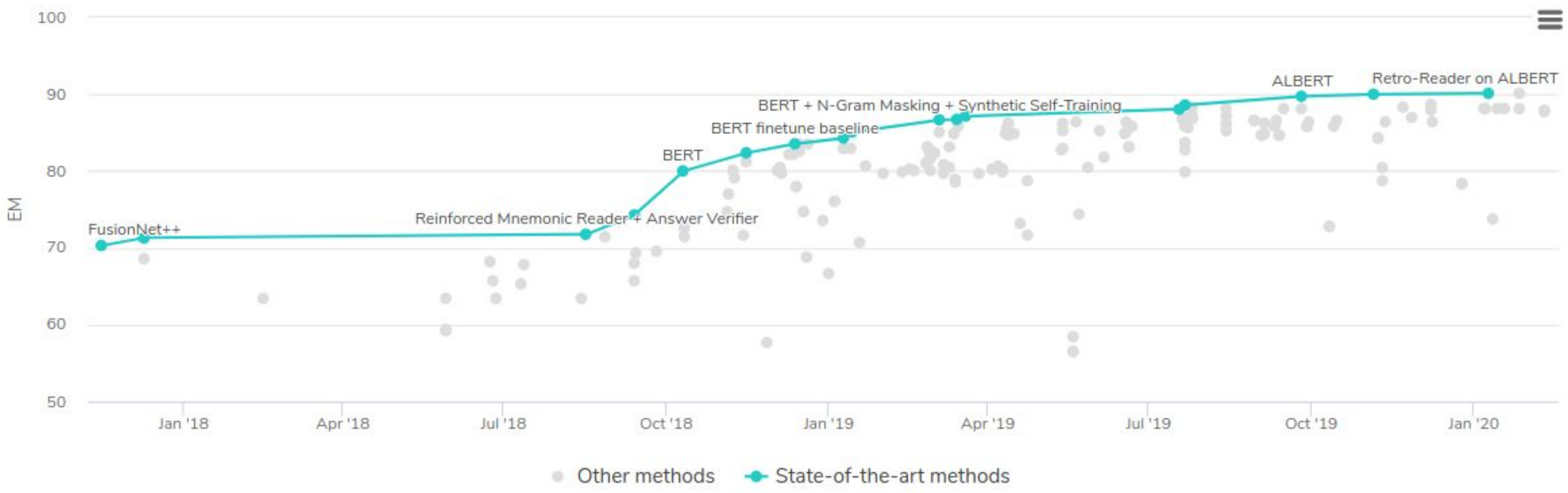
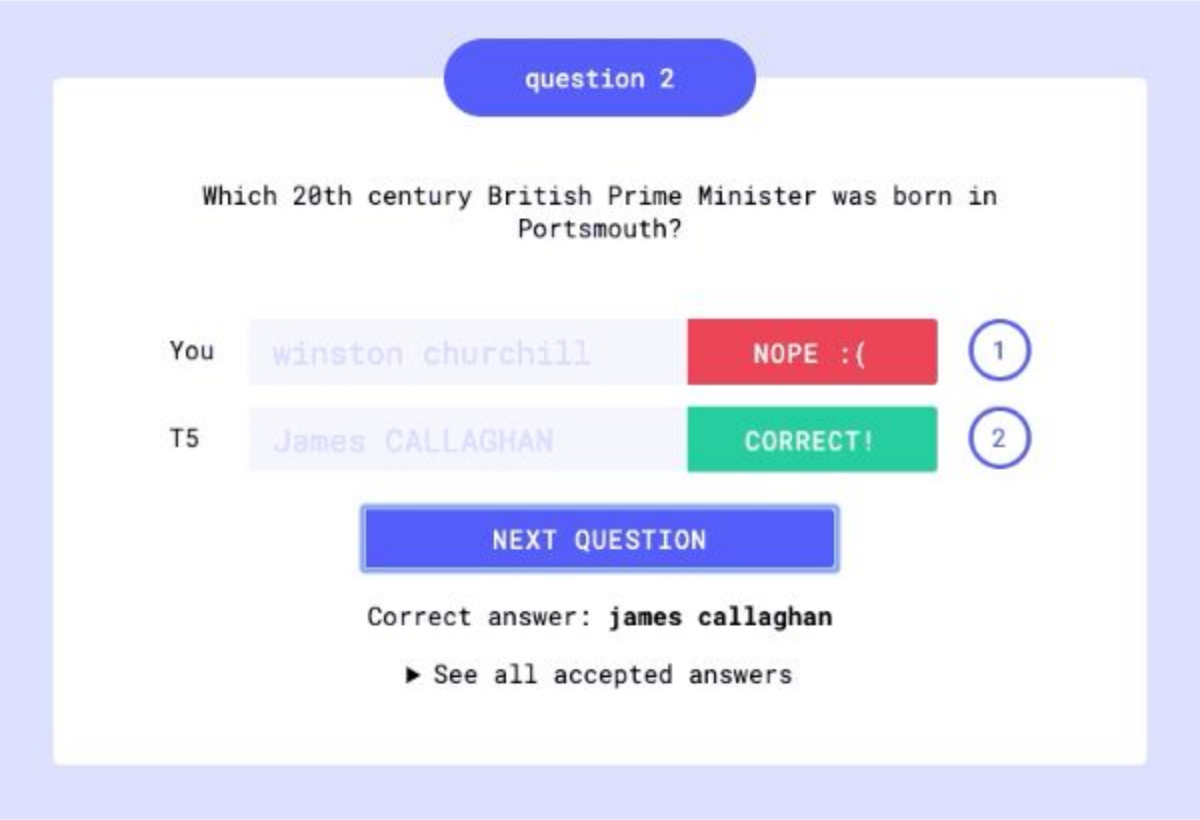
Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Apr 06, 2020	SA-Net on Albert (ensemble) *QIANXIN*	**90.724**	**93.011**
2 May 05, 2020	SA-Net-V2 (ensemble) *QIANXIN*	90.679	92.948
2 Apr 05, 2020	Retro-Reader (ensemble) *Shanghai Jiao Tong University* http://arxiv.org/abs/2001.09694	90.578	92.978
3 Jul 31, 2020	ATRLP+PV (ensemble) *Hithink RoyalFlush*	90.442	92.877
3 May 04, 2020	ELECTRA+ALBERT+EntitySpanFocus (ensemble) *SRCB_DML*	90.442	92.839
4 Jun 21, 2020	ELECTRA+ALBERT+EntitySpanFocus (ensemble) *SRCB_DML*	90.420	92.799

Question Answering on SQuAD 2.0



Transformer Quiz



Text Generation

Input

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

Text Generation

Model Output

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

[...]

GPT-4 Demo

Text to Shell

Playground

Text to command

Please provide a simple natural language description of the give shell command.

Q: cd ~
A: go to the home directory

Q: grep -r "pepsi" *
A: find occurrences of the string "pepsi" in every file in the current directly recursively

Q: python -m SimpleHTTPServer
A: start a simple web server with python

Q: lsof -i :8000
A: get information about the process using port 8000

Q: ps ax
A: show all processes

Q: npm install eslint --save-dev
A: install the eslint package as a development dependency

Q: git checkout feature-branch-3
A: switch to the branch feature-branch-3

Q: rm -rf *
A: remove all files in the current directory recursively

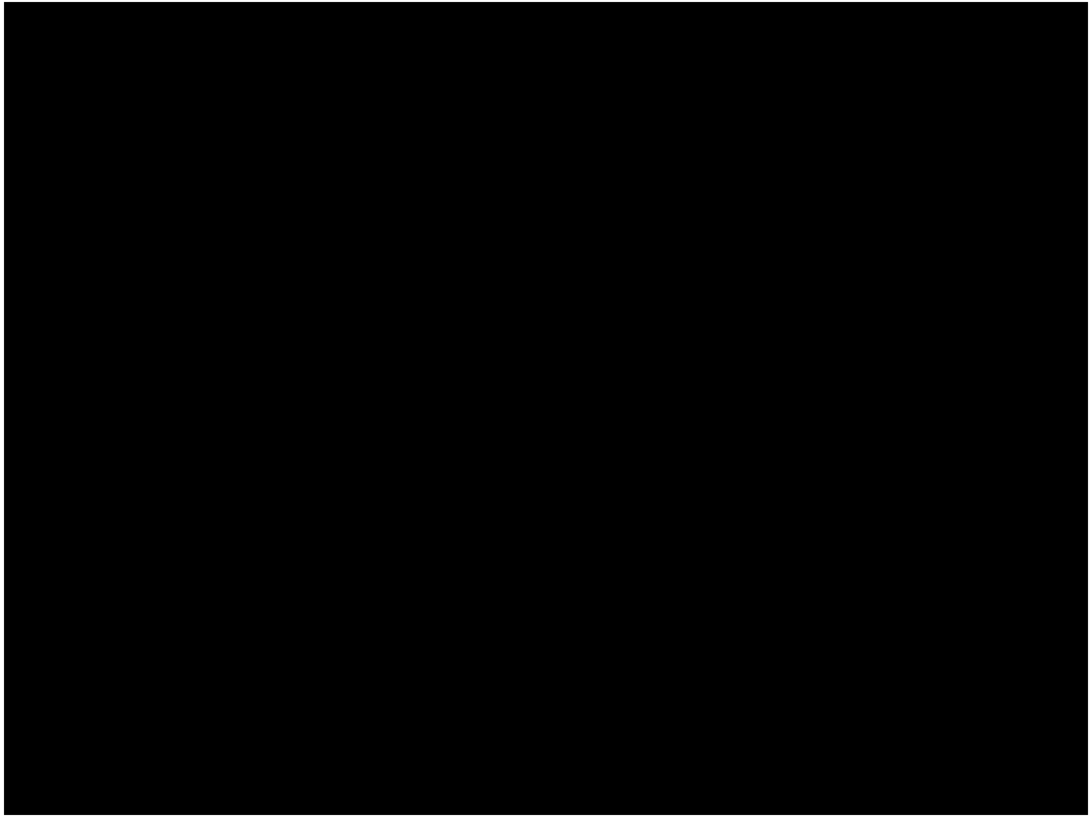
Q: head -n 3 testing.txt
A: print the first three lines of the file testing.txt

SUBMIT

Inject structural text (start sequence, reset sequence)

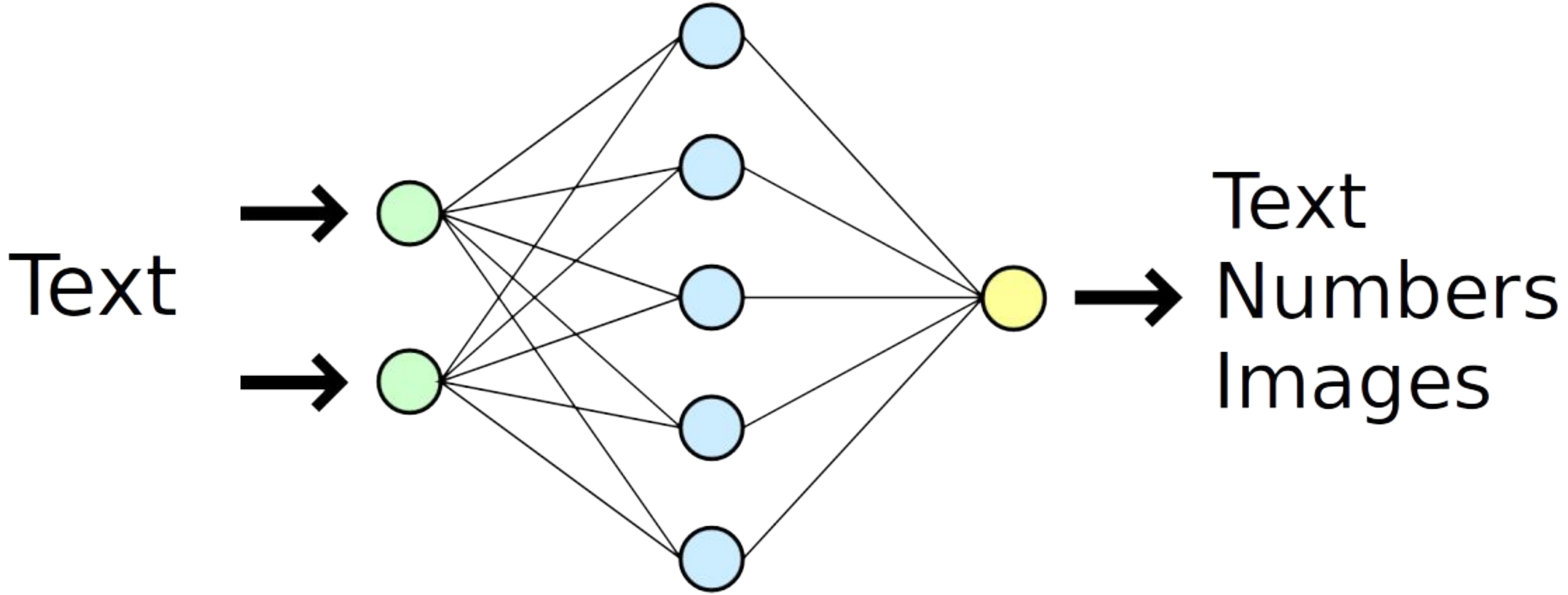
Quelle Harlan Duman

Text to HTML



Quelle / Produkt debuild.co

How do neural networks process texts?


Text
Text
Numbers
Images

How do we encode characters for a neural network?

One Hot Encoding

Lets encode the word „hello“

h	0	0	0	1
e	0	0	1	0
l	0	1	0	0
o	1	0	0	0

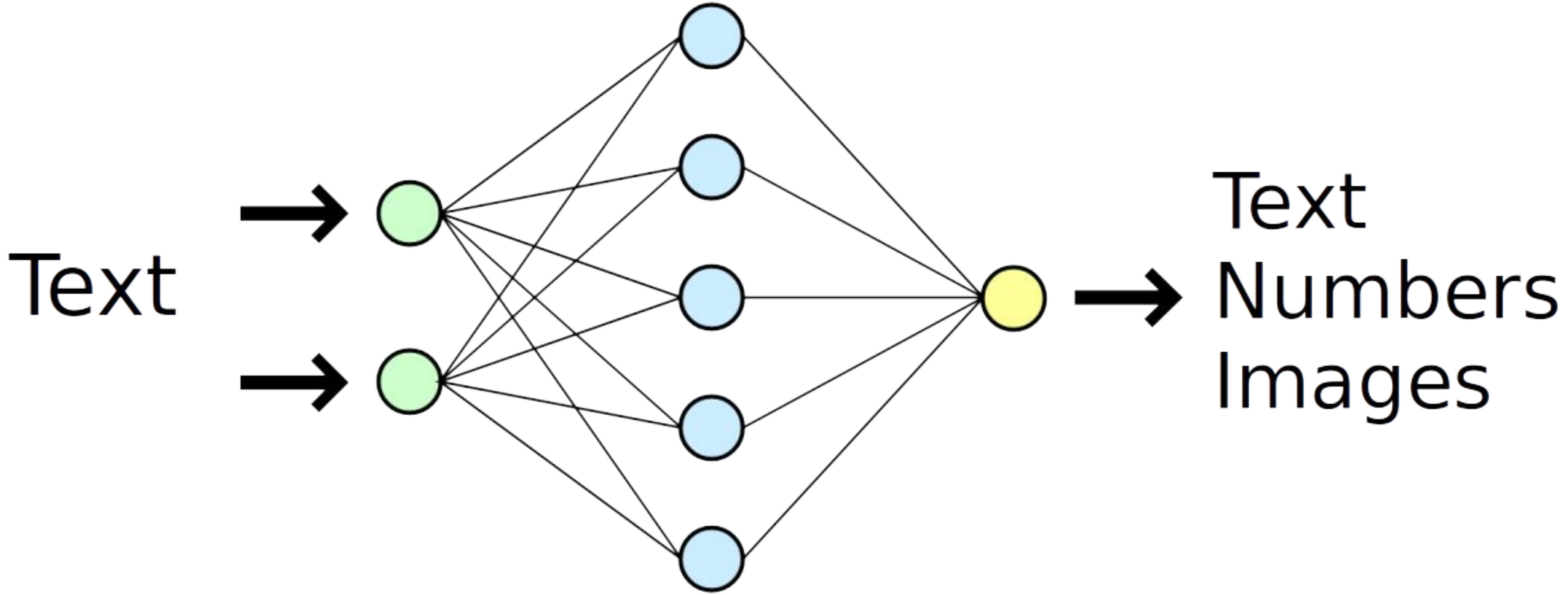
One Hot Encoding

Let’s encode the word „hello“

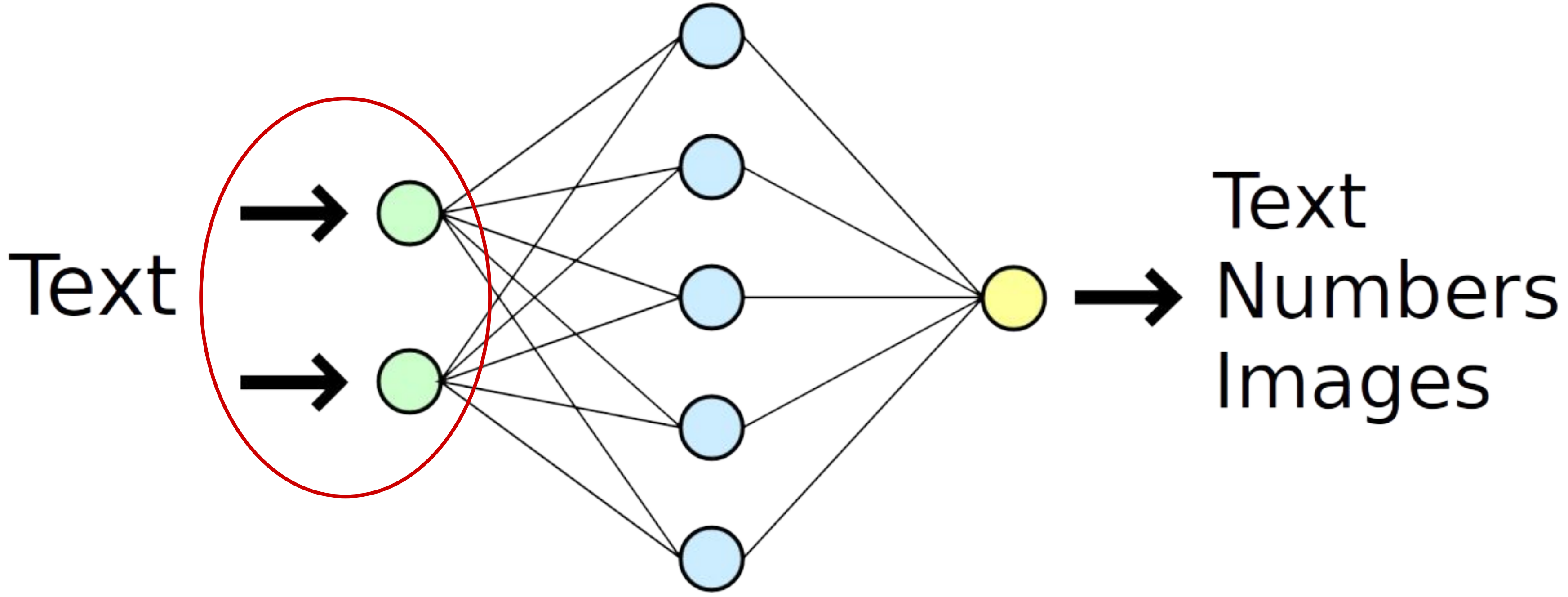
h	0	0	0	1
e	0	0	1	0
l	0	1	0	0
o	1	0	0	0

$$v^h = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \quad v^e = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad \ldots \longrightarrow \quad V^{hello} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Can you spot the issue?



Can you spot the issue?

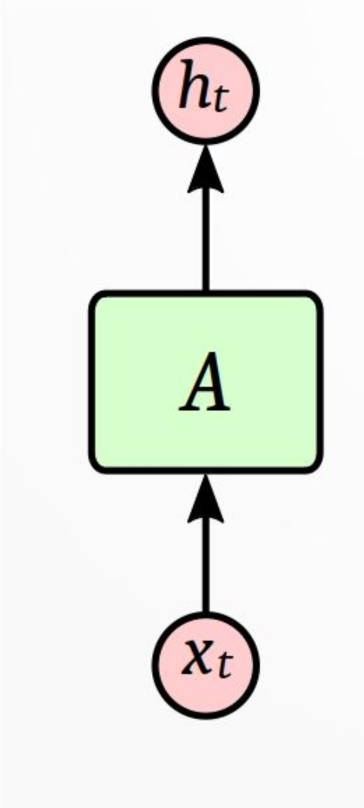


We need to handle inputs of arbitrary length.

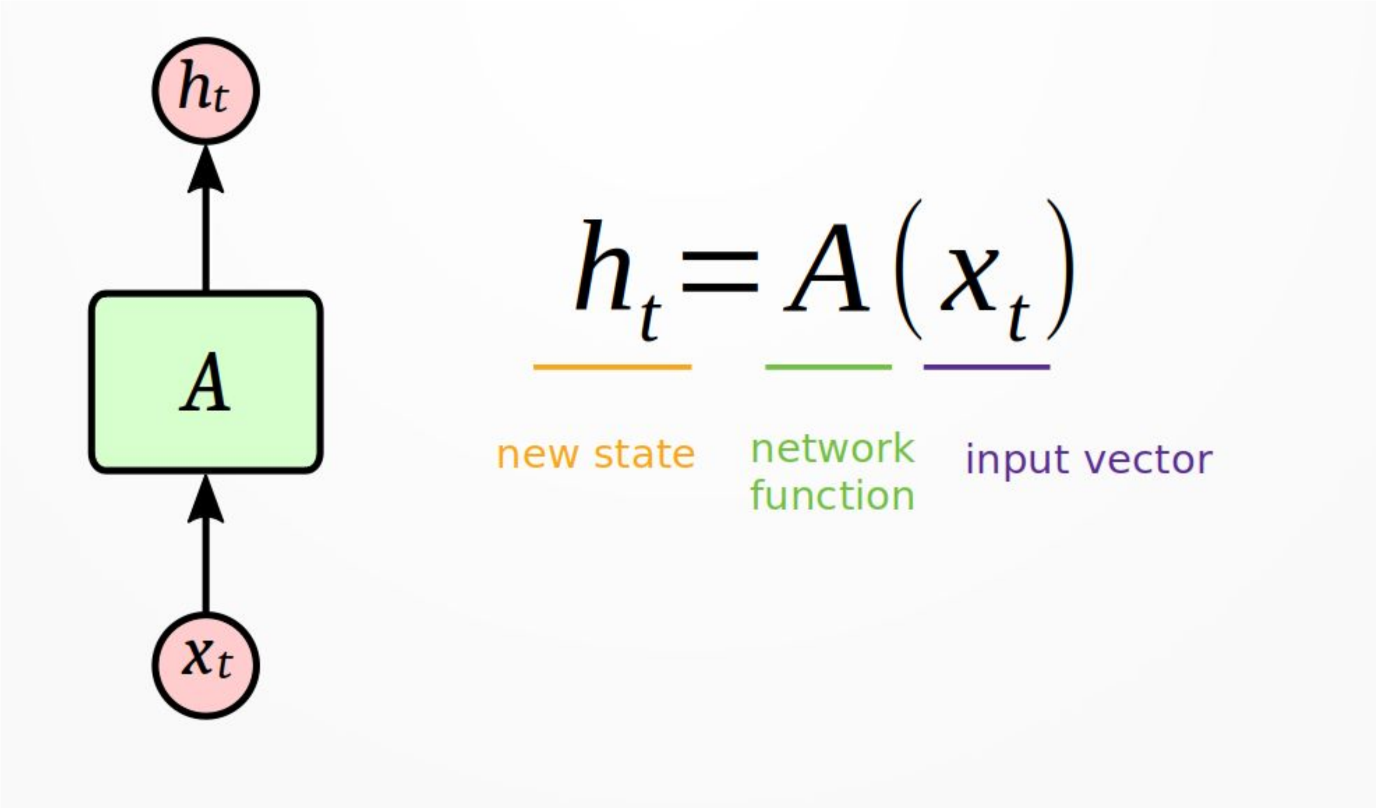
Recurrent Neural Networks

RNNs are networks with loops, allowing information to persist.
[Rummelhart et al. 1986]

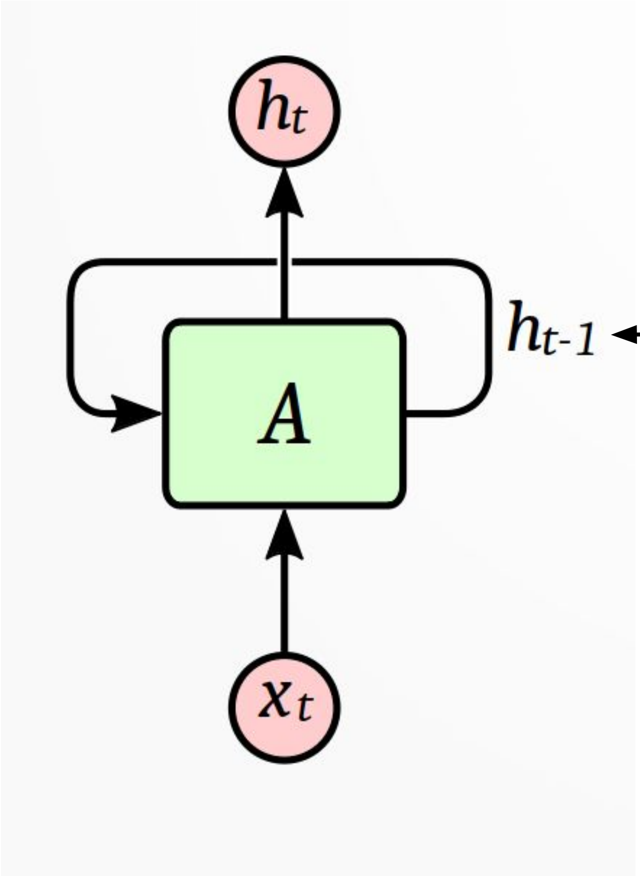
A simple neural network



A simple neural network

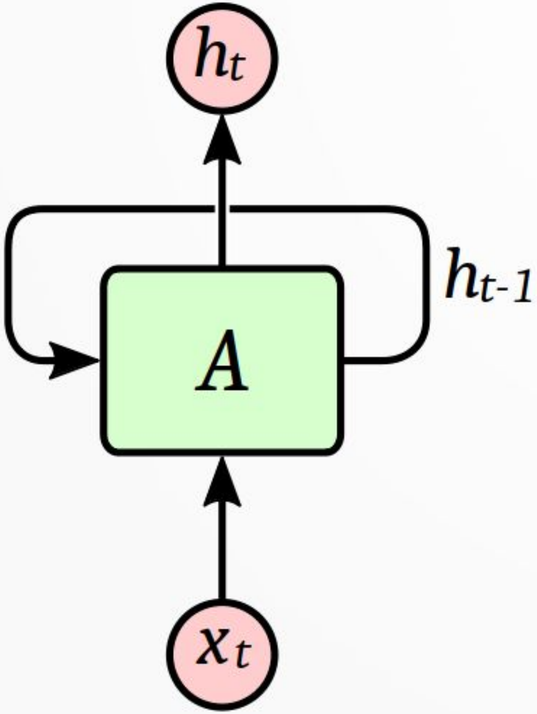


Recurrent Neural Networks



By passing the previous
hidden state, the network
can keep an „internal state“as the
input sequence is processed.

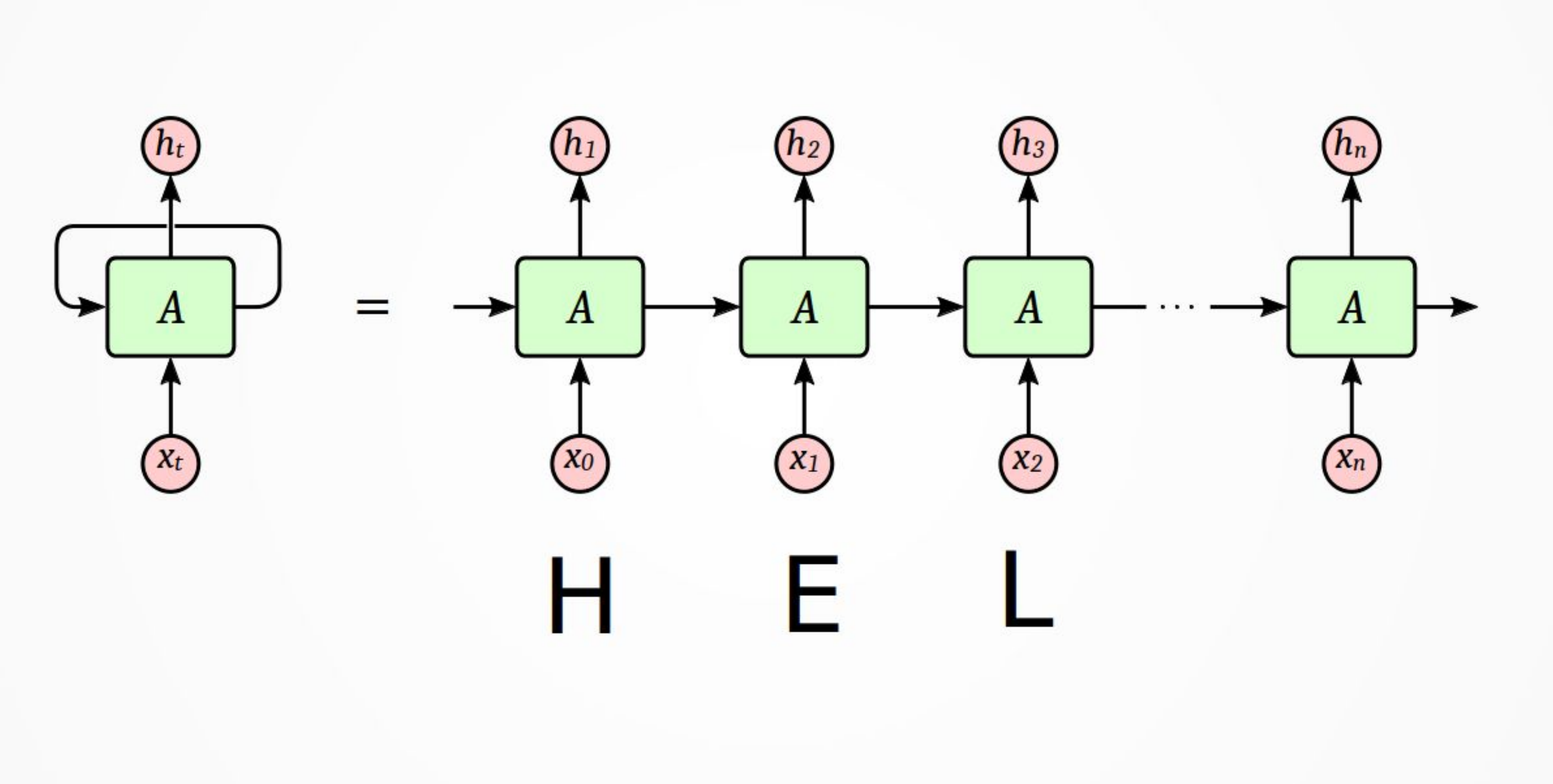
Recurrent Neural Networks



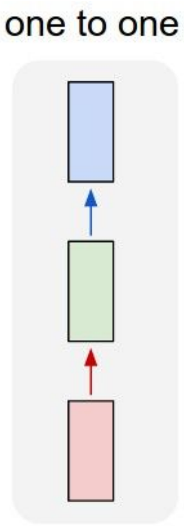
$$\underbrace{h_t}_{\text{new state}} = \underbrace{A}_{\text{network function}}\left(\underbrace{h_{t-1}}_{\text{previous state}}, \underbrace{x_t}_{\text{input vector}}\right)$$

How do we use this network to process text?

Unfolding in Time



Network Architectures



Simple Neural Network

Source: A. Karpathy http://karpathy.github.io/2015/05/21/rnn-effectiveness/

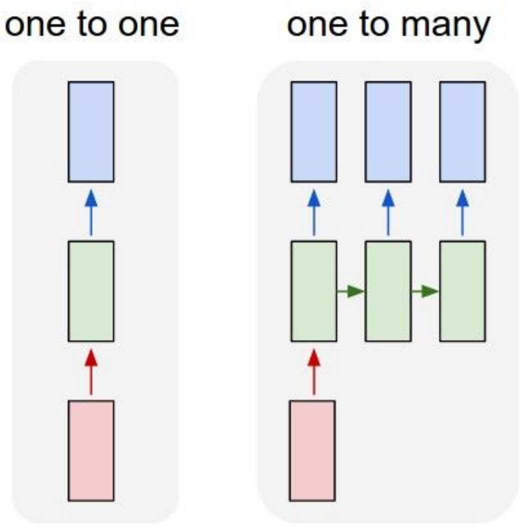
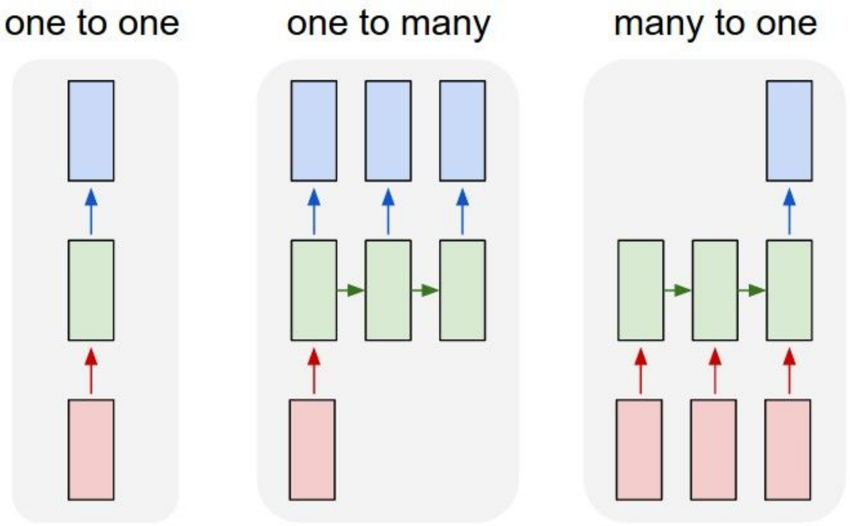


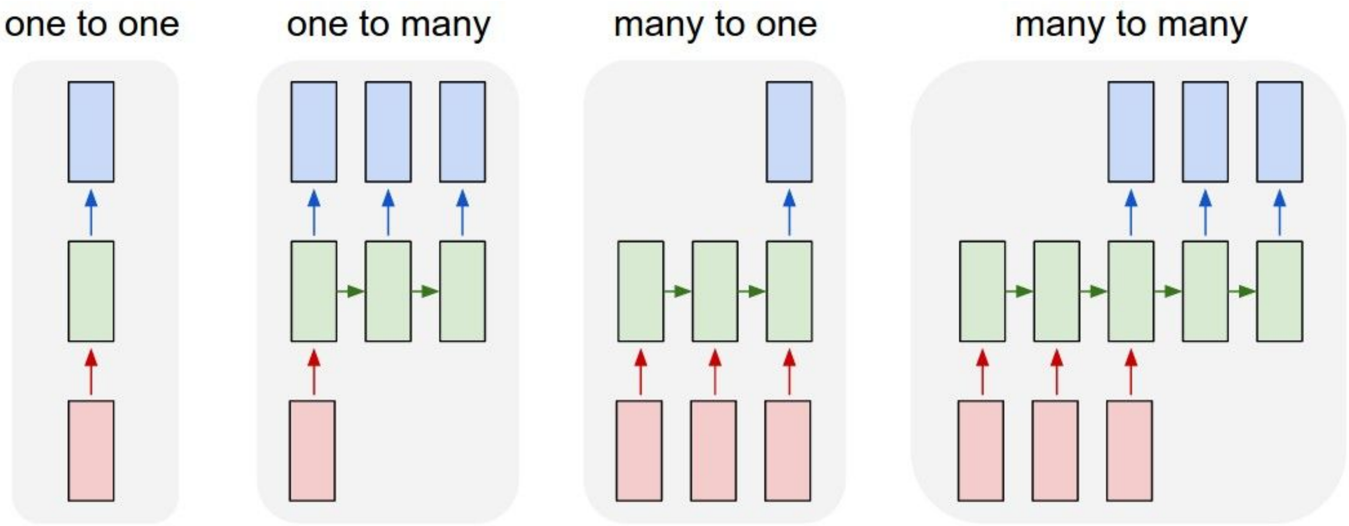
image captioning
Image to a sequence of words

Source: A. Karpathy http://karpathy.github.io/2015/05/21/rnn-effectiveness/



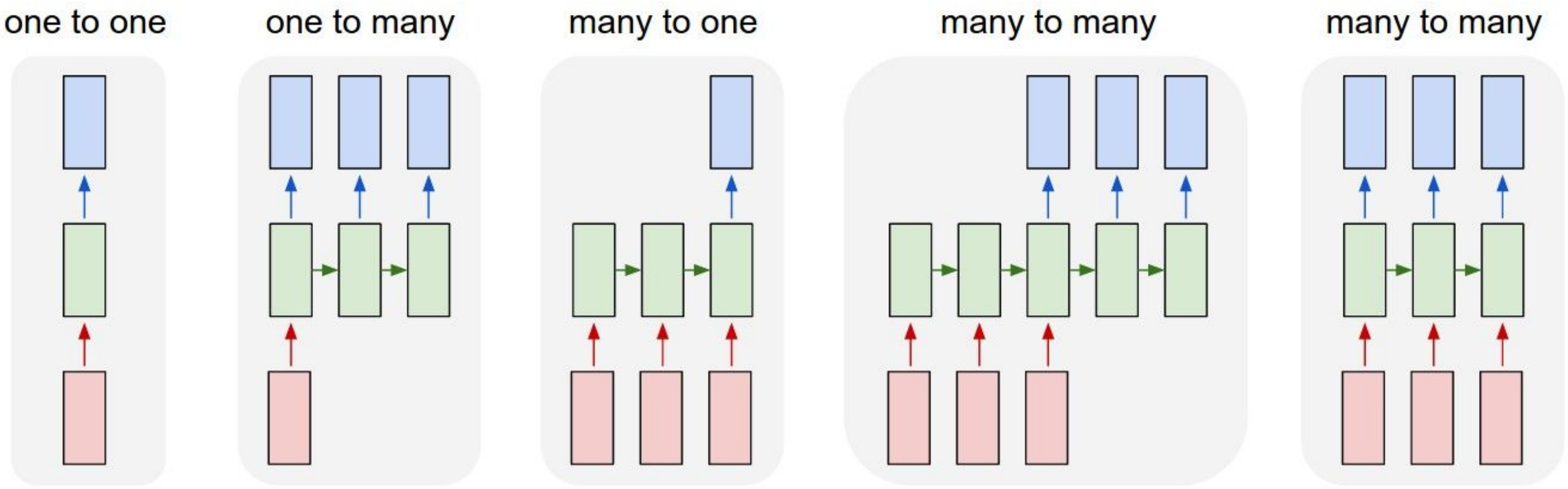
classification
sequence of words to a class

Source: A. Karpathy http://karpathy.github.io/2015/05/21/rnn-effectiveness/



machine translation
sequence of words to sequence of words

Source: A. Karpathy http://karpathy.github.io/2015/05/21/rnn-effectiveness/

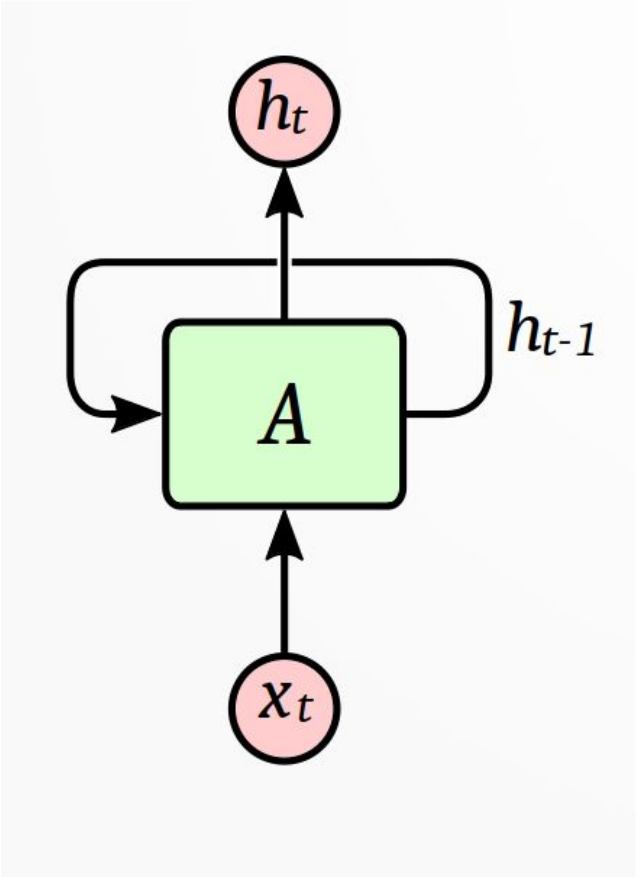


Video classification
A list of frames to a list of classes

Source: A. Karpathy http://karpathy.github.io/2015/05/21/rnn-effectiveness/

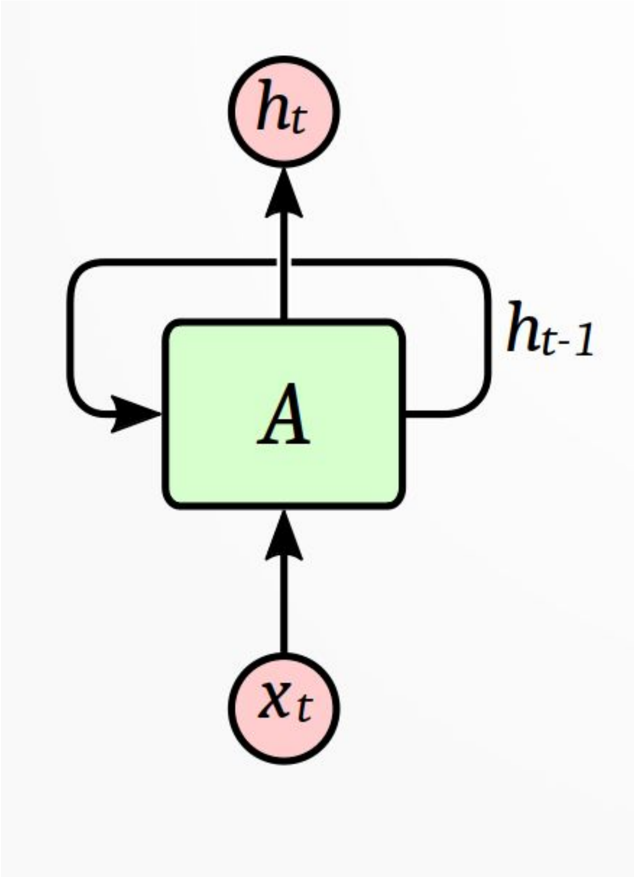
Training RNNs

Training RNNs



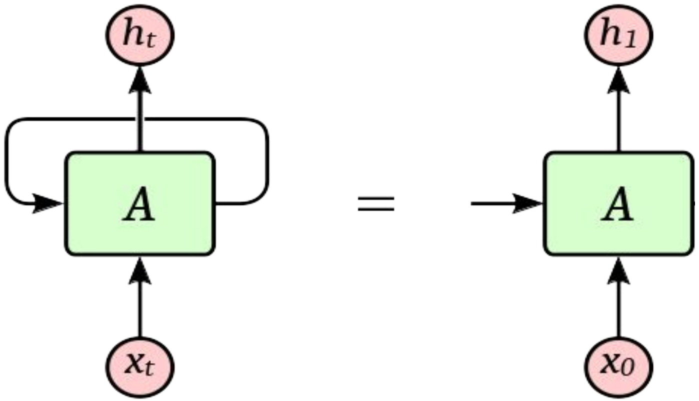
How can we apply backpropagation to nets with loops?

Training RNNs

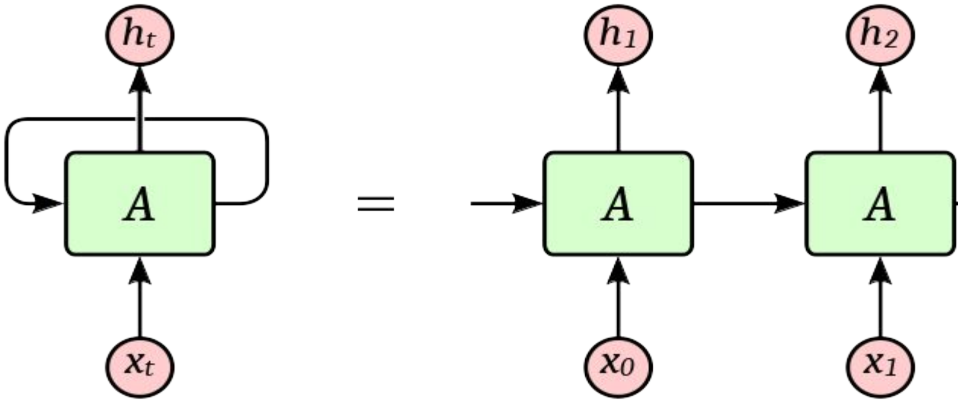


with backpropagation through time (BPTT)

Training RNNs

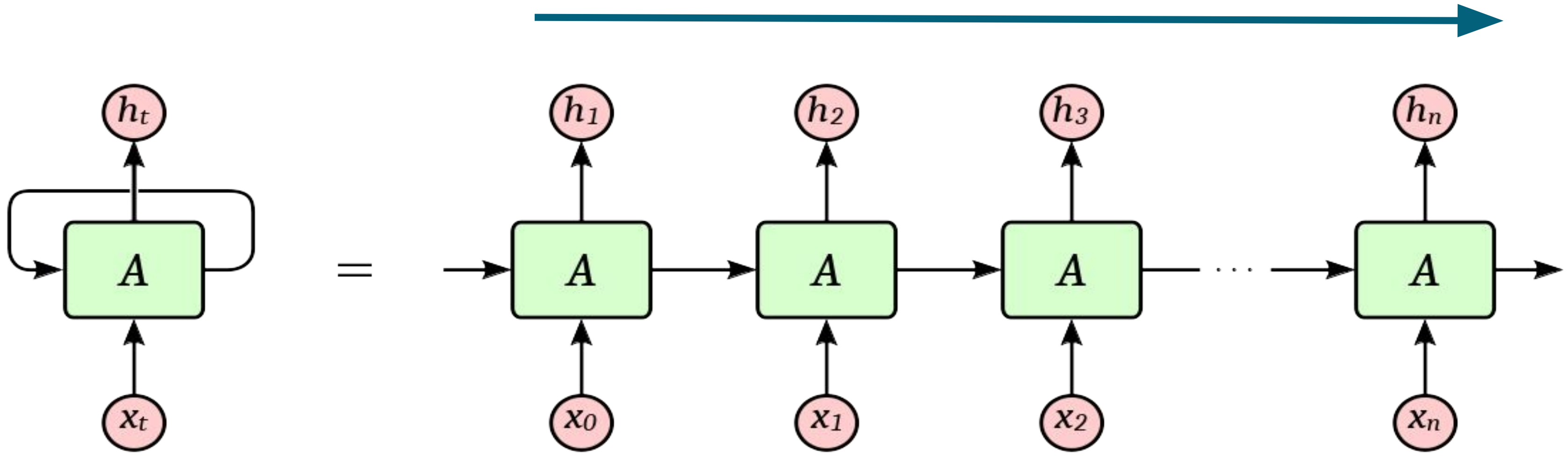


Training RNNs



Training RNNs

1. forward-propagate the inputs over the unfolded network



Training RNNs

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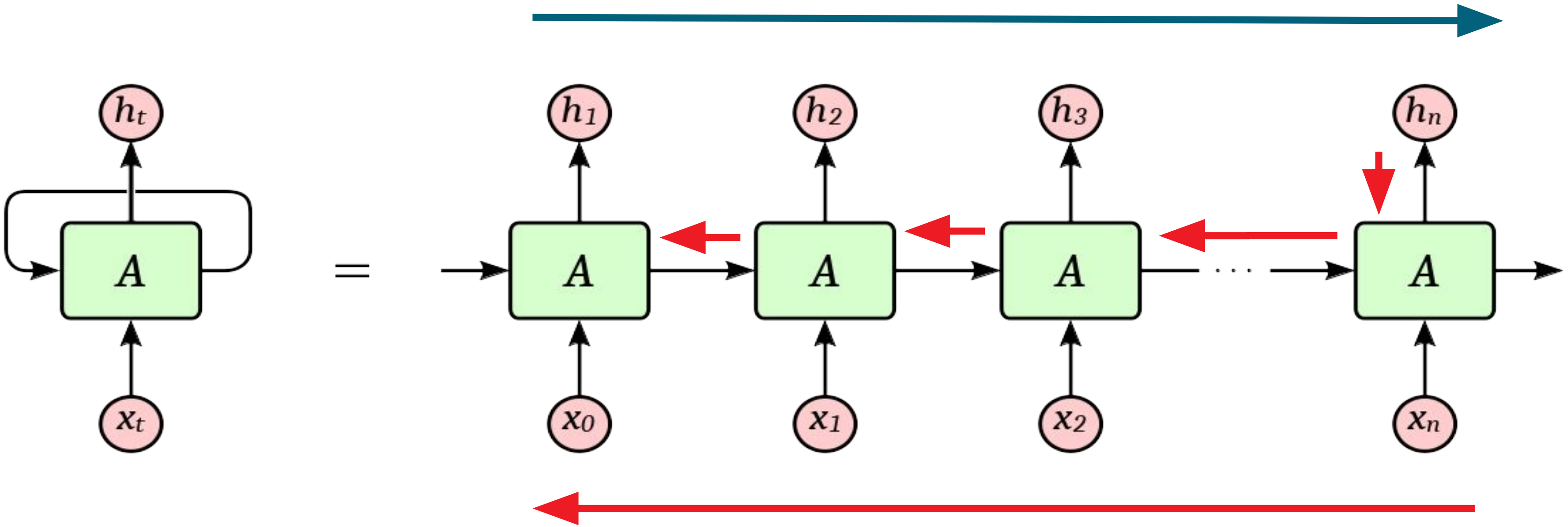
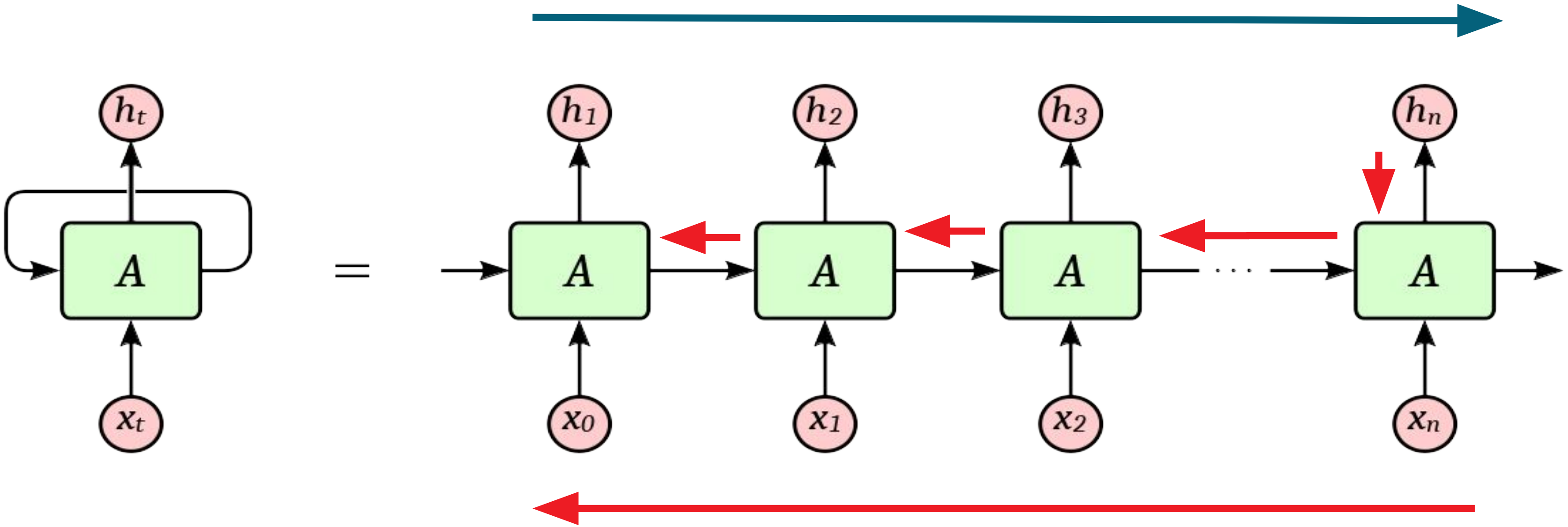


2. back-propagate the error, back across the unfolded network

Training RNNs

1. forward-propagate the inputs over the unfolded network



2. back-propagate the error, back across the unfolded network

3. sum the weight changes and update all weights

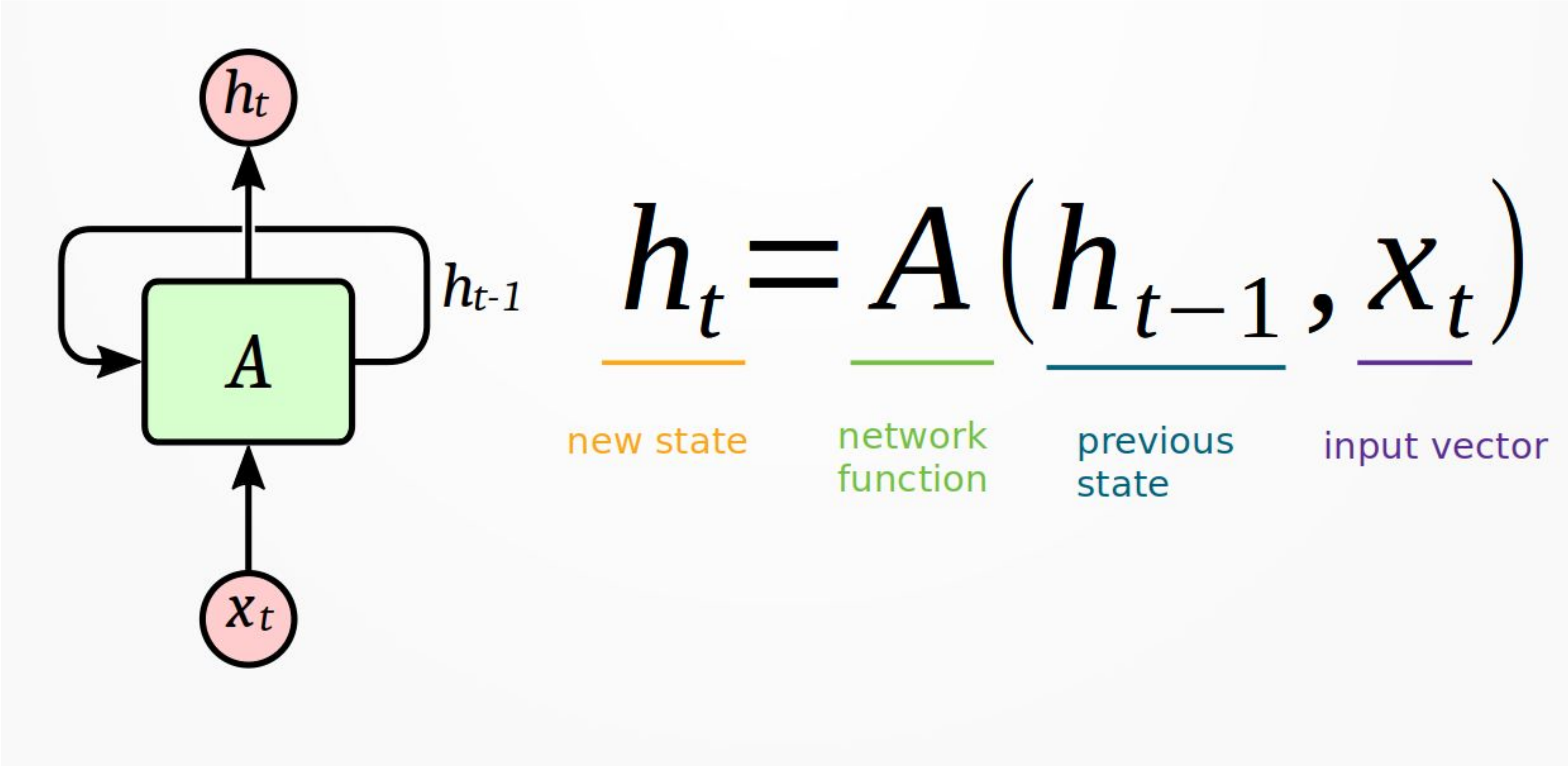
Further Information

- A well explained implementation of BPTT an be found here
- Andrew Ng explaining BPTT

Learning long-term dependencies with gradient descent is difficult

Y. Bengio, P. Simard and P. Frasconi in IEEE Transactions on Neural Networks, vol. 5, no. 2, pp. 157-166, March 1994.

Recurrent Neural Networks



Recurrent Neural Networks

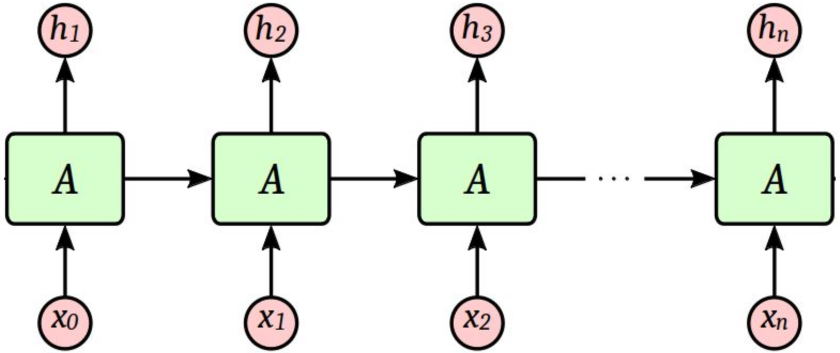
$$\underbrace{h_t}_{\text{new state}} = \underbrace{A}_{\text{network function}} \big(\underbrace{h_{t-1},}_{\text{previous state}} \underbrace{x_t}_{\text{input vector}} \big)$$

A simple example of a Elman-network

$$h_t = \tanh\left(W_{hh} h_{t-1} + W_{xh} x_t\right)$$

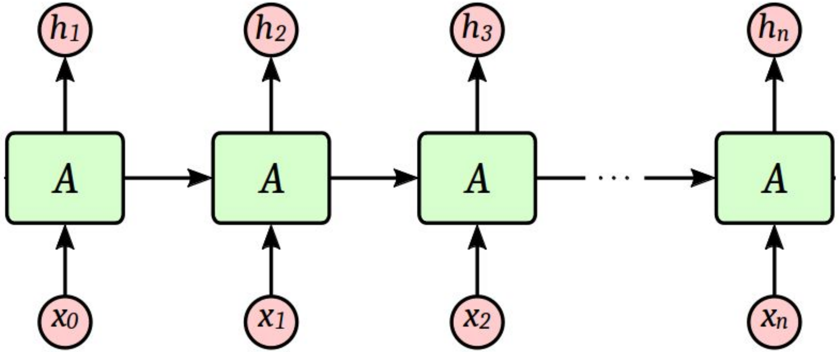
$$y_t = W_{yh} h_t$$

The vanishing gradient problem



$$h_1 = \tanh\left(W_{hh} h_0 + W_{xh} x_1\right)$$

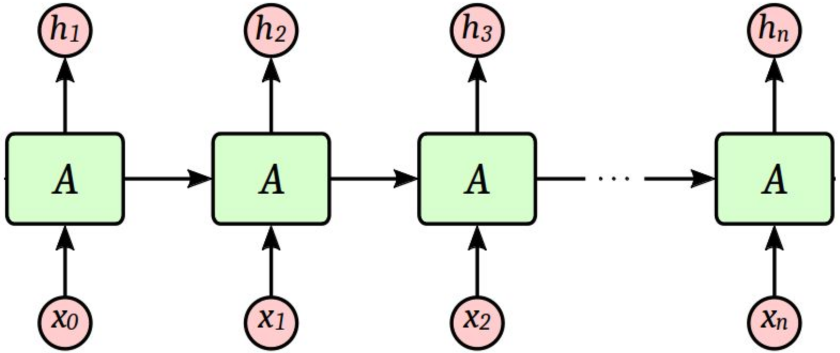
The vanishing gradient problem



$$h_1 = \tanh\left(W_{hh} h_0 + W_{xh} x_1\right)$$

$$h_2 = \tanh\left(W_{hh}\left(\tanh\left(W_{hh} h_0 + W_{xh} x_1\right)\right) + W_{xh} x_2\right)$$

The vanishing gradient problem

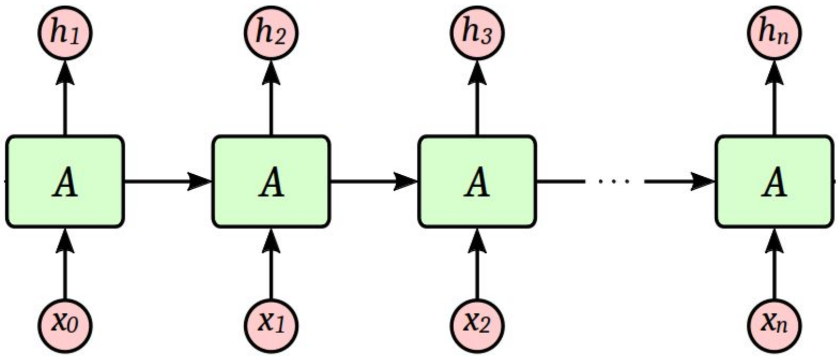


$$h_1 = \tanh\left(W_{hh} h_0 + W_{xh} x_1\right)$$

$$h_2 = \tanh\left(W_{hh}\left(\tanh\left(W_{hh} h_0 + W_{xh} x_1\right)\right) + W_{xh} x_2\right)$$

$$h_3 = \tanh\left(W_{hh}\left(\tanh\left(W_{hh}\left(\tanh\left(W_{hh} h_0 + W_{xh} x_1\right)\right) + W_{xh} x_2\right)\right) + W_{xh} x_3\right)$$

The vanishing gradient problem



$$h_1 = \tanh(W_{hh} h_0 + W_{xh} x_1)$$

$$h_2 = \tanh(W_{hh}(\tanh(W_{hh} h_0 + W_{xh} x_1)) + W_{xh} x_2)$$

$$h_3 = \tanh(W_{hh}(\tanh(W_{hh}(\tanh(W_{hh} h_0 + W_{xh} x_1)) + W_{xh} x_2)) + W_{xh} x_3)$$

$$h_4 = \underline{\tanh(W_{hh}(\tanh(W_{hh}(\tanh(W_{hh}(\tanh(W_{hh}}\, h_0 + W_{xh} x_1)) + W_{xh} x_2)) + W_{xh} x_3))$$

Backpropagating this recursive function leads to exploding or vanishing gradients.

Papers

On the difficulty of training recurrent neural networks
Pascanu, Mikolov and Bengio, 2013
http://proceedings.mlr.press/v28/pascanu13.pdf

Learning long-term dependencies with gradient descent is difficult
Bengio, Simard and Frasconi, 1994
https://ieeexplore.ieee.org/document/279181

Untersuchungen zu dynamischen neuronalen Netzen
Hochreiter, 1991
http://people.idsia.ch/~juergen/SeppHochreiter1991ThesisAdvisorSchmidhuber.pdf

Solutions for this problem:

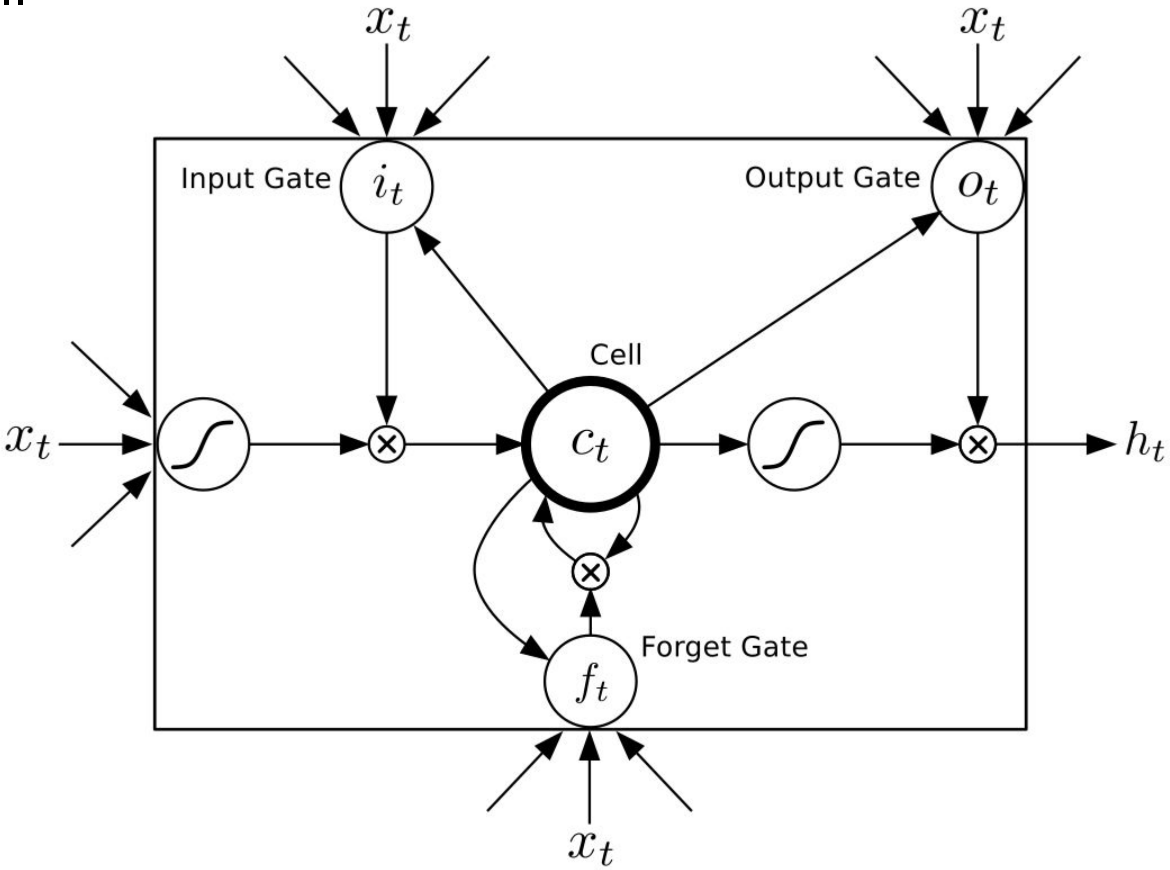
- Limiting the number of past time steps (Hochreiter, 1991)
- Exploding gradient can be fixed with gradient clipping
- Vanishing gradients can be controlled different architectures (LSTM)
- New: Not using recursions :)

LSTM

Long short-term memory

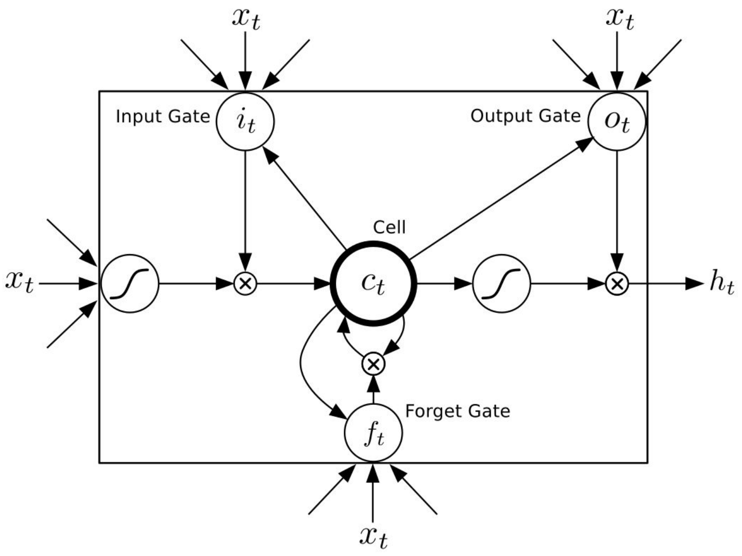
[Hochreiter et al., 1997]

A LSTM Cell



Graves et al. 2013, Speech Recognition with Deep Recurrent Neural Networks

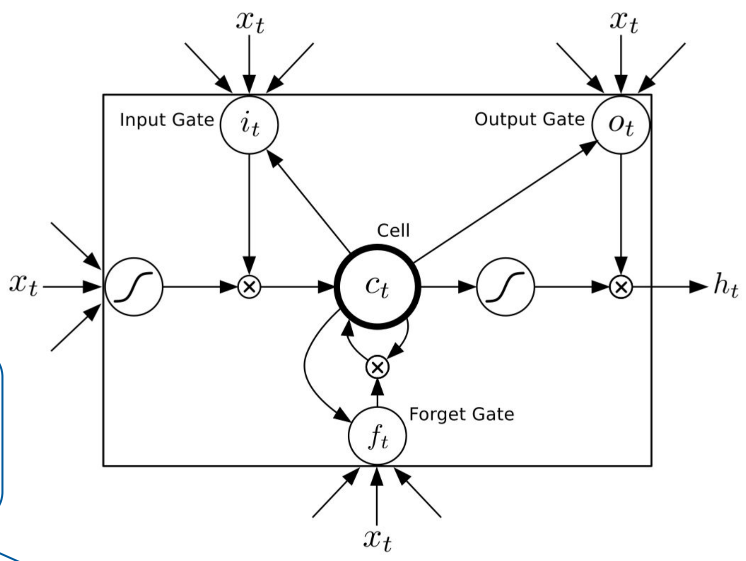
A LSTM Cell



$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i\right)$$
$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right)$$
$$c_t = f_t c_{t-1} + i_t \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right)$$
$$o_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o\right)$$
$$h_t = o_t \tanh(c_t)$$

Graves et al. 2013, Speech Recognition with Deep Recurrent Neural Networks

A LSTM Cell



The sigmoid function outputs a number between 0 and 1

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i\right)$$
$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right)$$
$$c_t = f_t c_{t-1} + i_t \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right)$$
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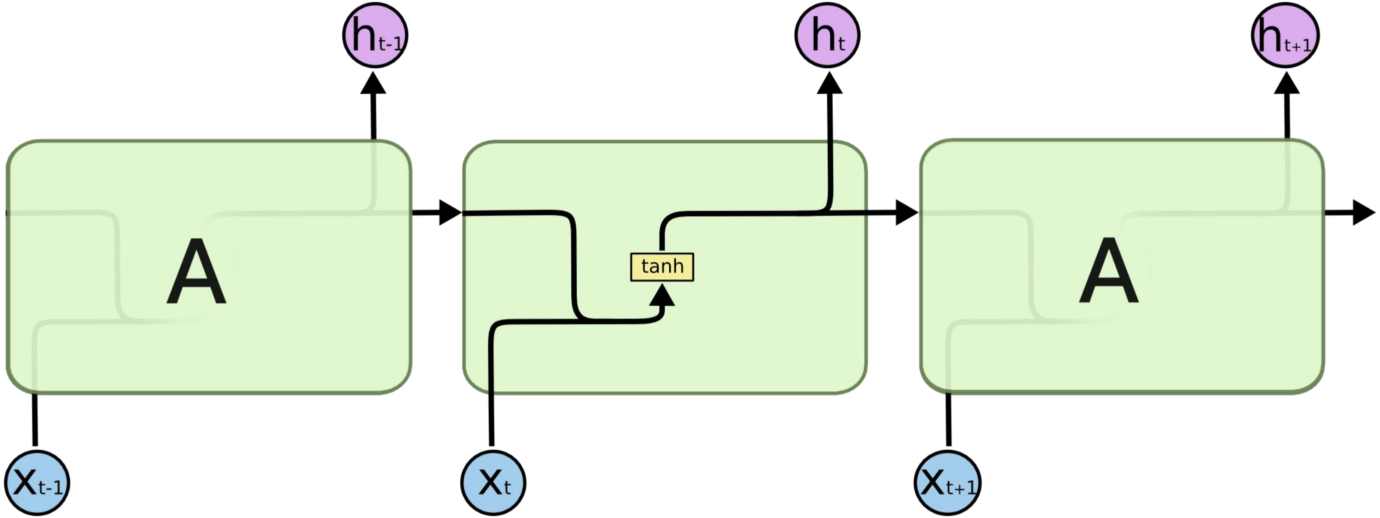
$$h_t = o_t \tanh(c_t)$$

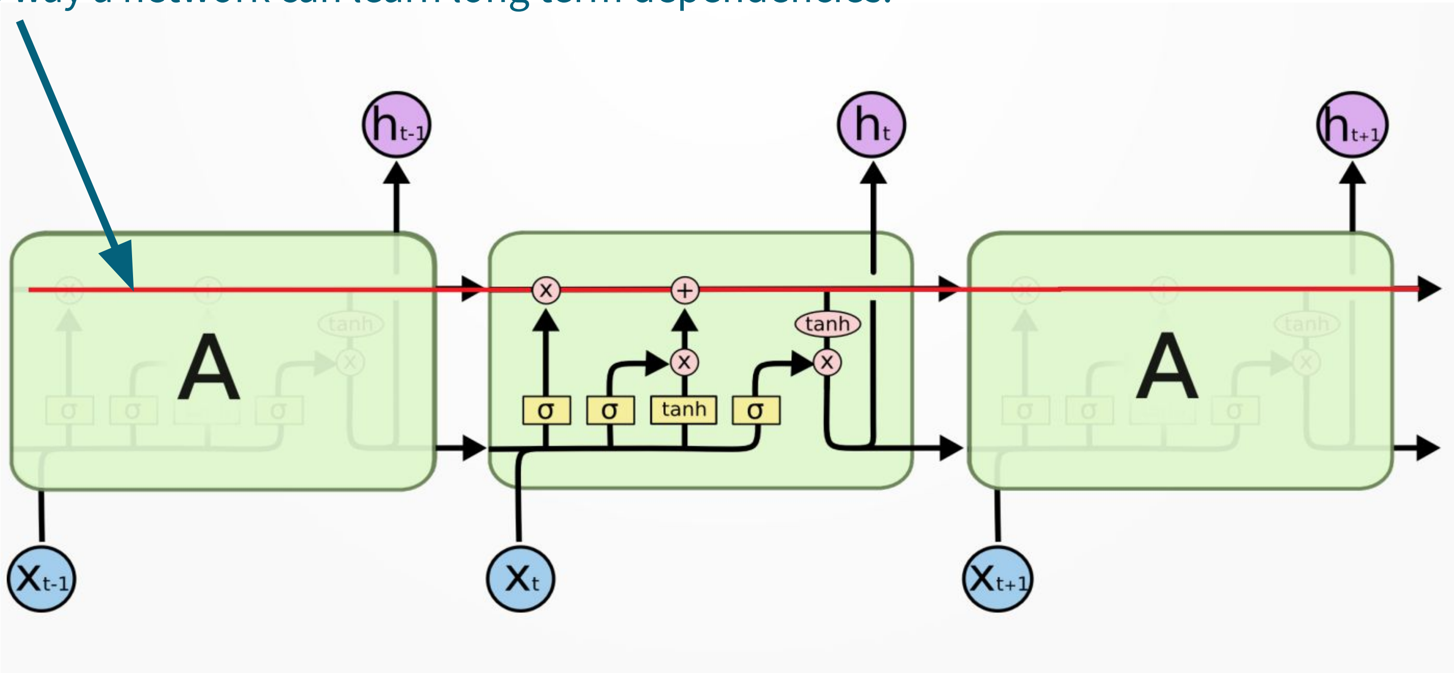
Graves et al. 2013, Speech Recognition with Deep Recurrent Neural Networks

Standard RNN



LSTM

A LSTM cell can keep its internal state unchanged over many timesteps.
This way a network can learn long term dependencies.



Source Chris Olah: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

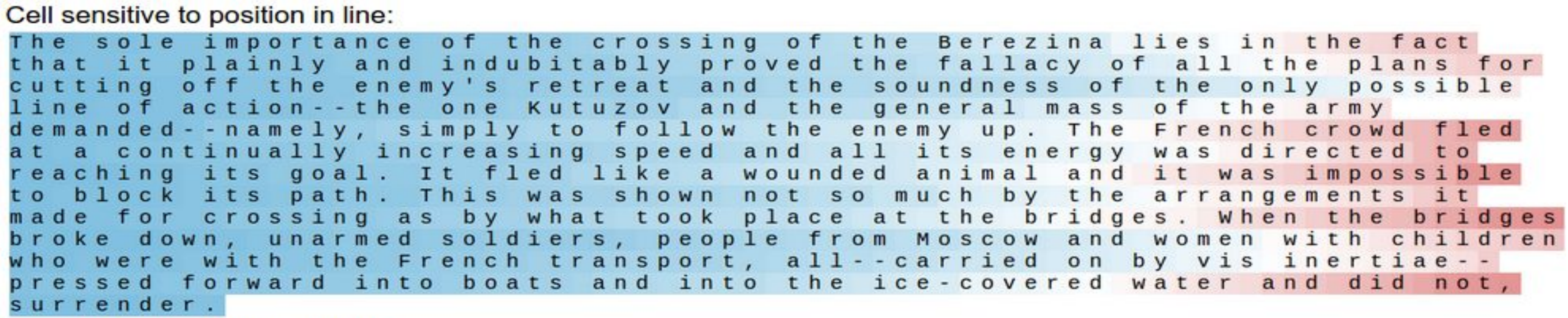
Further Information

- Chris Olah: Understanding LSTM Networks
- Jürgen Schmidhuber: Tutorial on LSTM Recurrent Networks

- **LSTM: A Search Space Odyssey**
  Klaus Greff, Rupesh K. Srivastava, Jan Koutník, Bas R. Steunebrink, Jürgen Schmidhuber 2015
- **Speech Recognition with Deep Recurrent Neural Networks**
  Graves et al. 2013
- **Long Short-term Memory**
  Sepp Hochreiter, Jürgen Schmidhuber

What does the network learn?

Visualizing the cell activations

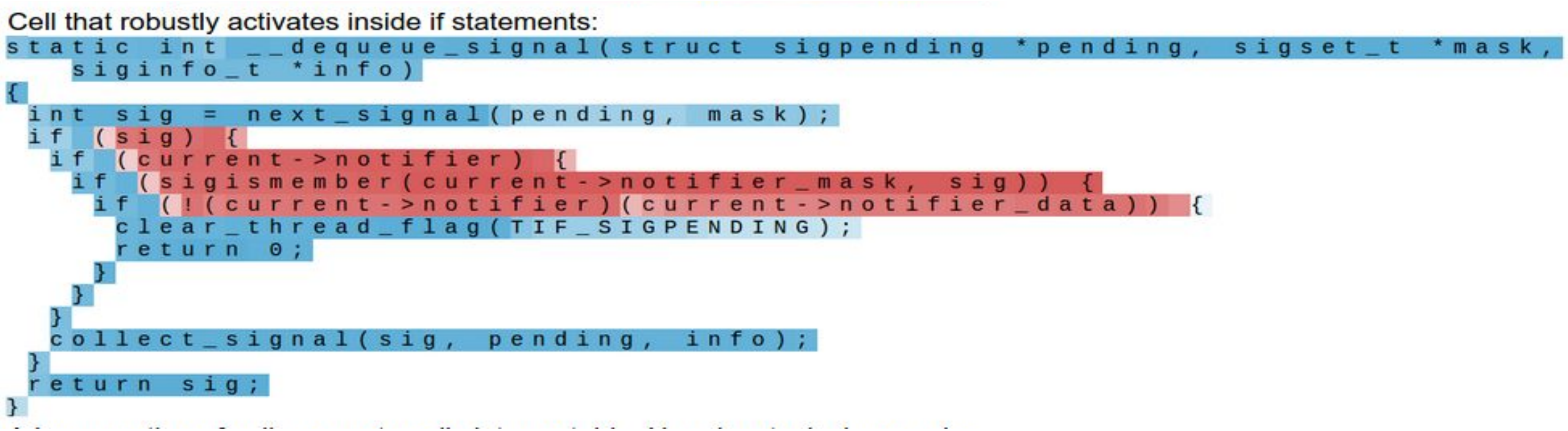


Andrej Karpathy http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Visualizing the cell activations

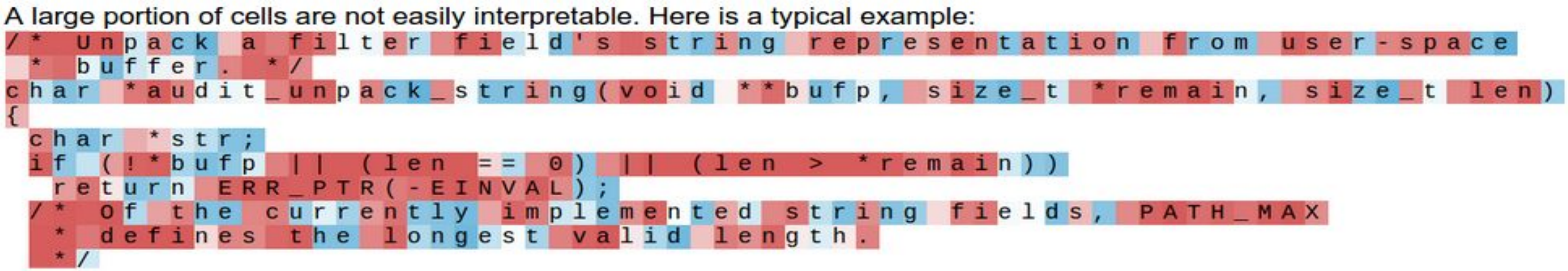
Andrej Karpathy http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Visualizing the cell activations



Andrej Karpathy http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Visualizing the cell activations



Andrej Karpathy http://karpathy.github.io/2015/05/21/rnn-effectiveness/

What does the network learn?

- Visualizing the predictions and the “neuron” firings in the RNN
- Set the background color based on the neurons activation
- Literature:
    - http://karpathy.github.io/2015/05/21/rnn-effectiveness
- Paper:
    - Karpathy, Johnson, and Fei-Fei: Visualizing and Understanding Recurrent Networks, ICLR Workshop 2016

Other applications for RNNs

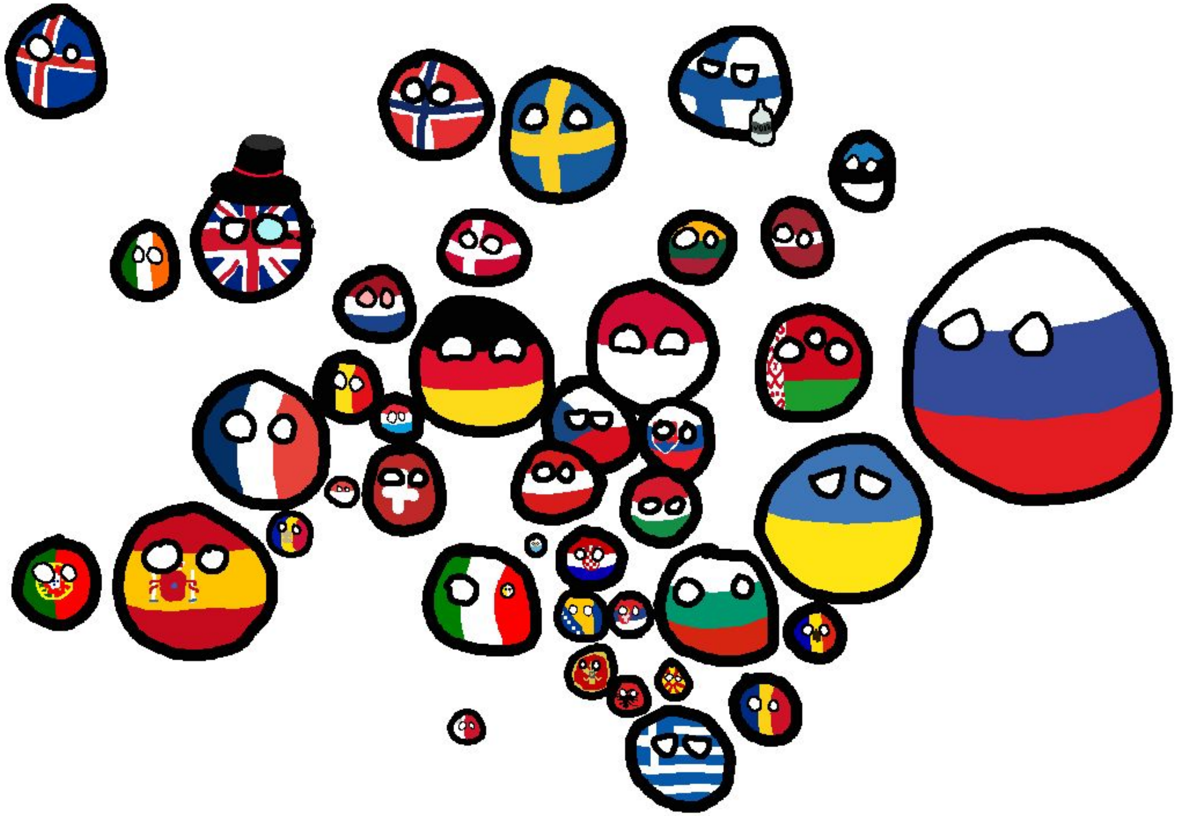
- Time Series Prediction
- Speech Recognition
  - Speech Recognition with Deep Recurrent Neural Networks Graves et al. 2013
- Drawing (Pictures, handwriting)
  - Generating Sequences With Recurrent Neural Networks Graves 2013
- Music Generation
  - Song From PI: A Musically Plausible Network for Pop Music Generation

Summary

- RNNs are used to process sequential data
- They have applications in many other domains:
  - Speech Recognition
  - Time Series Prediction
  - Drawing (Pictures, Handwriting)
- During Backpropagation gradients can explode or vanish
- Processing sequential information is a hot topic of research (GTP-4)

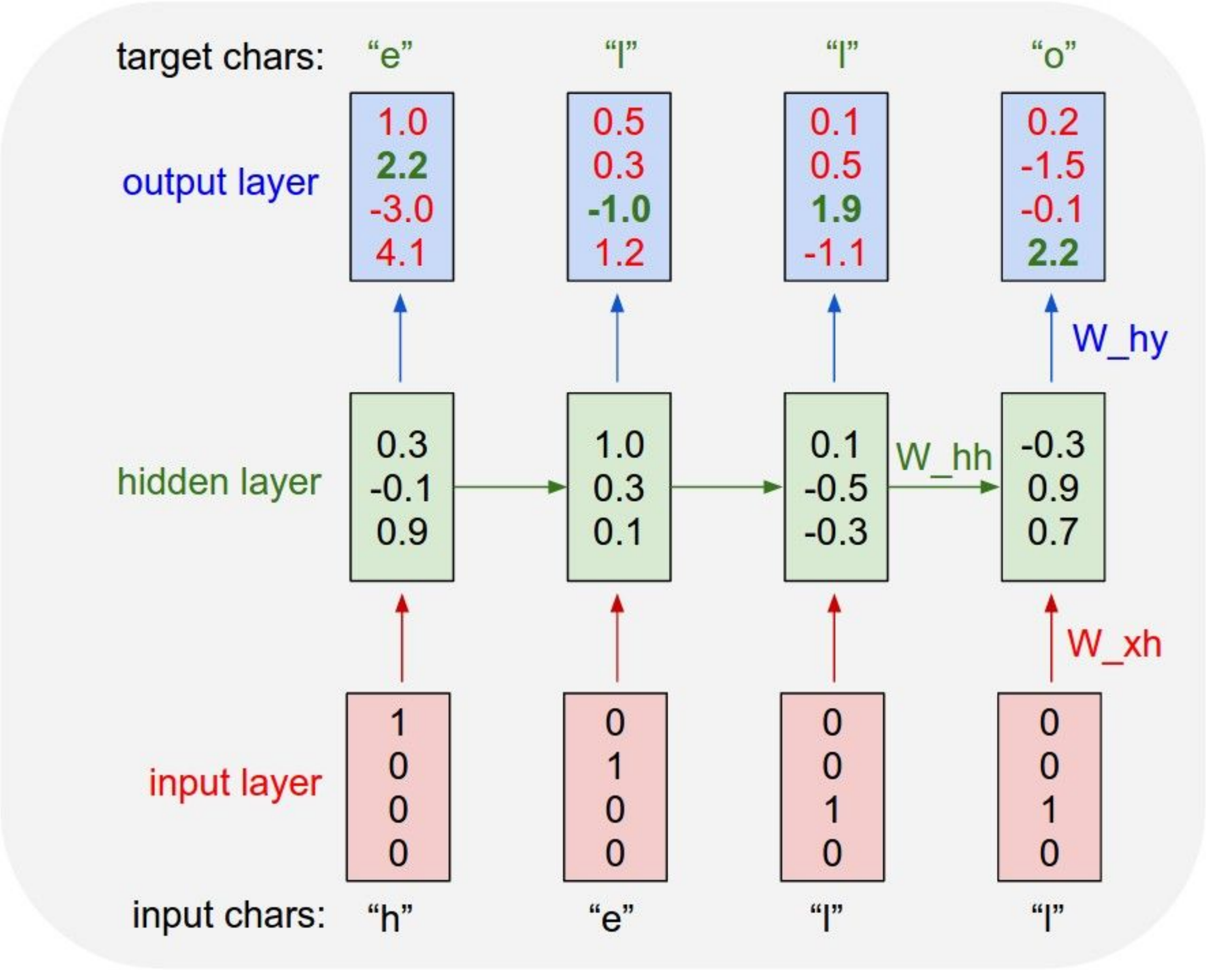
Tutorial

Guess where is my name from?



Tutorial

- You will classify names using a character-level RNN
- Take a look at the notebook for your tasks
- What you will learn:
    - One Hot Encoding
    - Character level RNNs
    - How to use LSTM and GRUs



Andrej Karpathy http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Recurrent Neural Networks

$$\underbrace{h_t}_{\text{new state}} = \underbrace{A}_{\text{network function}} \left(\underbrace{h_{t-1}}_{\text{previous state}} , \underbrace{x_t}_{\text{input vector}} \right)$$

A simple example of a Elman-network

$$h_t = \tanh\left(W_{hh} h_{t-1} + W_{xh} x_t \right)$$

$$y_t = W_{yh} h_t$$