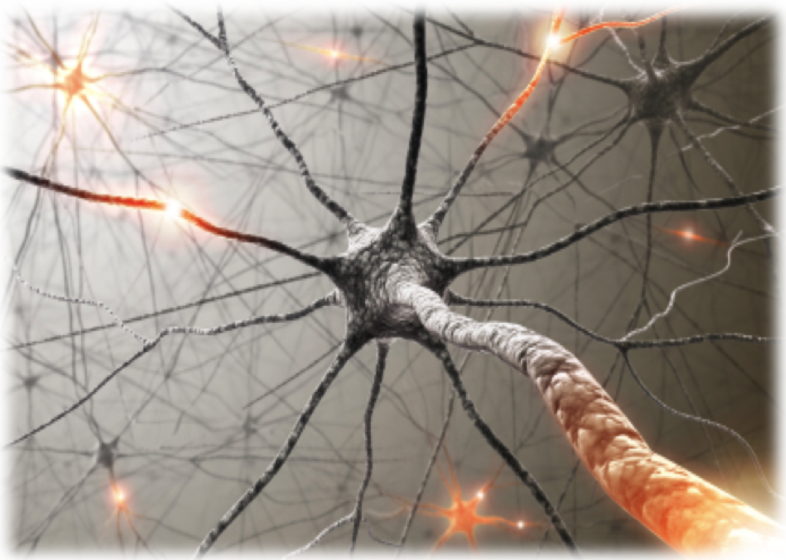
Lecture 18: Deep Learning



Reminders

- Projects due on Wednesday at noon PT (no late days allowed, to give time for grading).

- Exam regrade requests due Wednesday at midnight PT.

A brief history

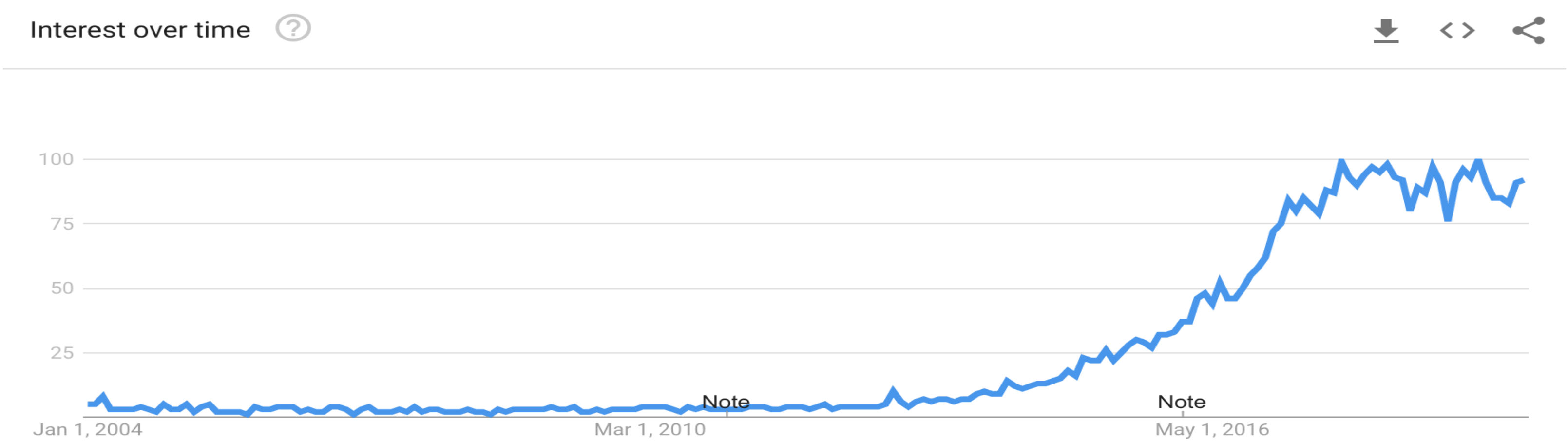
- 1943: neural networks $\Leftrightarrow$ logical circuits (McCulloch/Pitts)
- 1949: "cells that fire together wire together" learning rule (Hebb)
- 1969: theoretical limitations of neural networks (Minsky/Papert)
- 1974: backpropagation for training multi-layer networks (Werbos)
- 1986: popularization of backpropagation (Rumelhardt, Hinton, Williams)

A brief history

- 1980: Neocognitron, a.k.a. convolutional neural networks (Fukushima)
- 1989: backpropagation on convolutional neural networks (LeCun)
- 1990: recurrent neural networks (Elman)
- 1997: Long Short-Term Memory networks (Hochreiter/Schmidhuber)
- 2006: unsupervised layerwise training of deep networks (Hinton et al.)

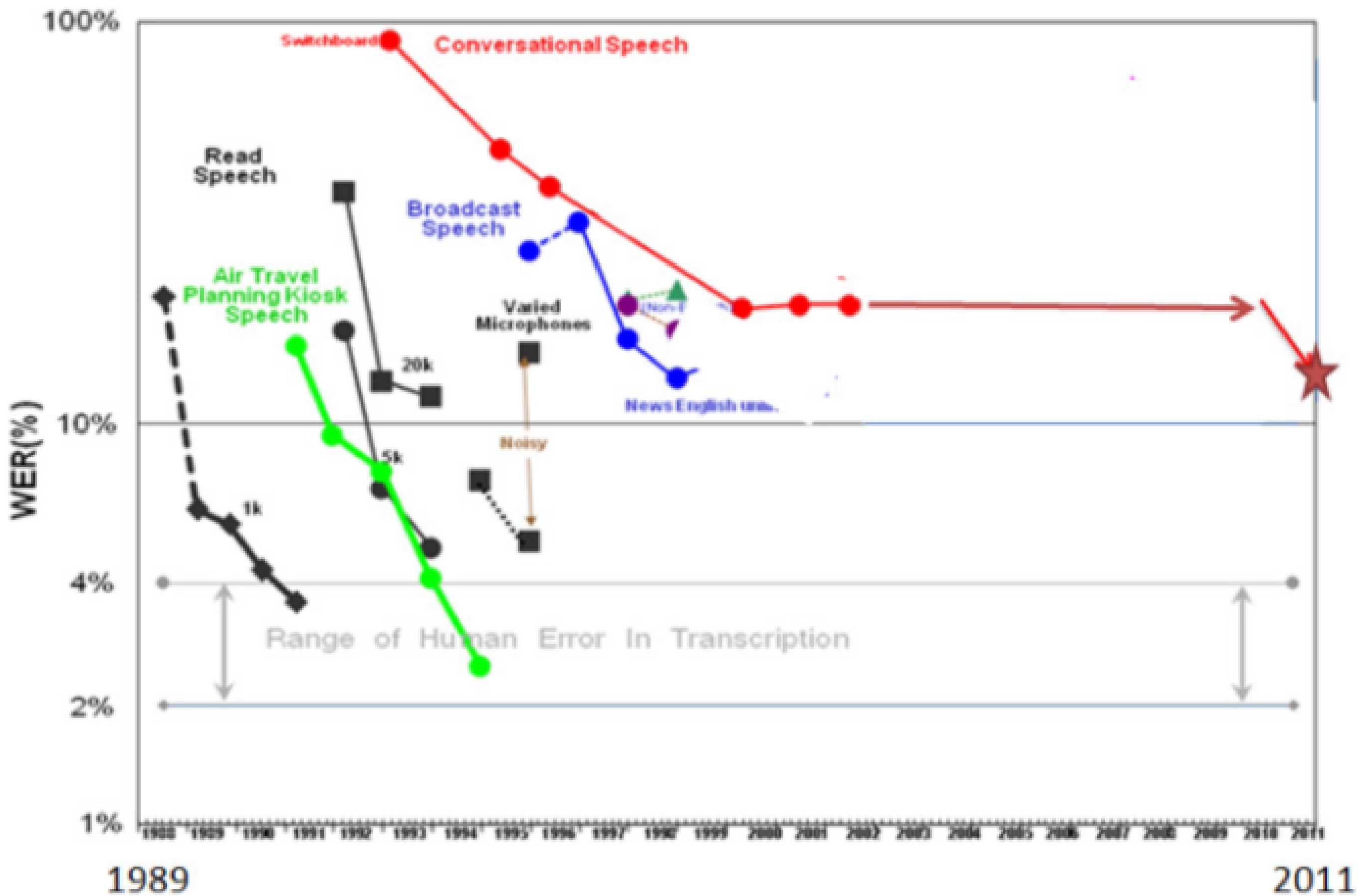
Google Trends

Query: deep learning



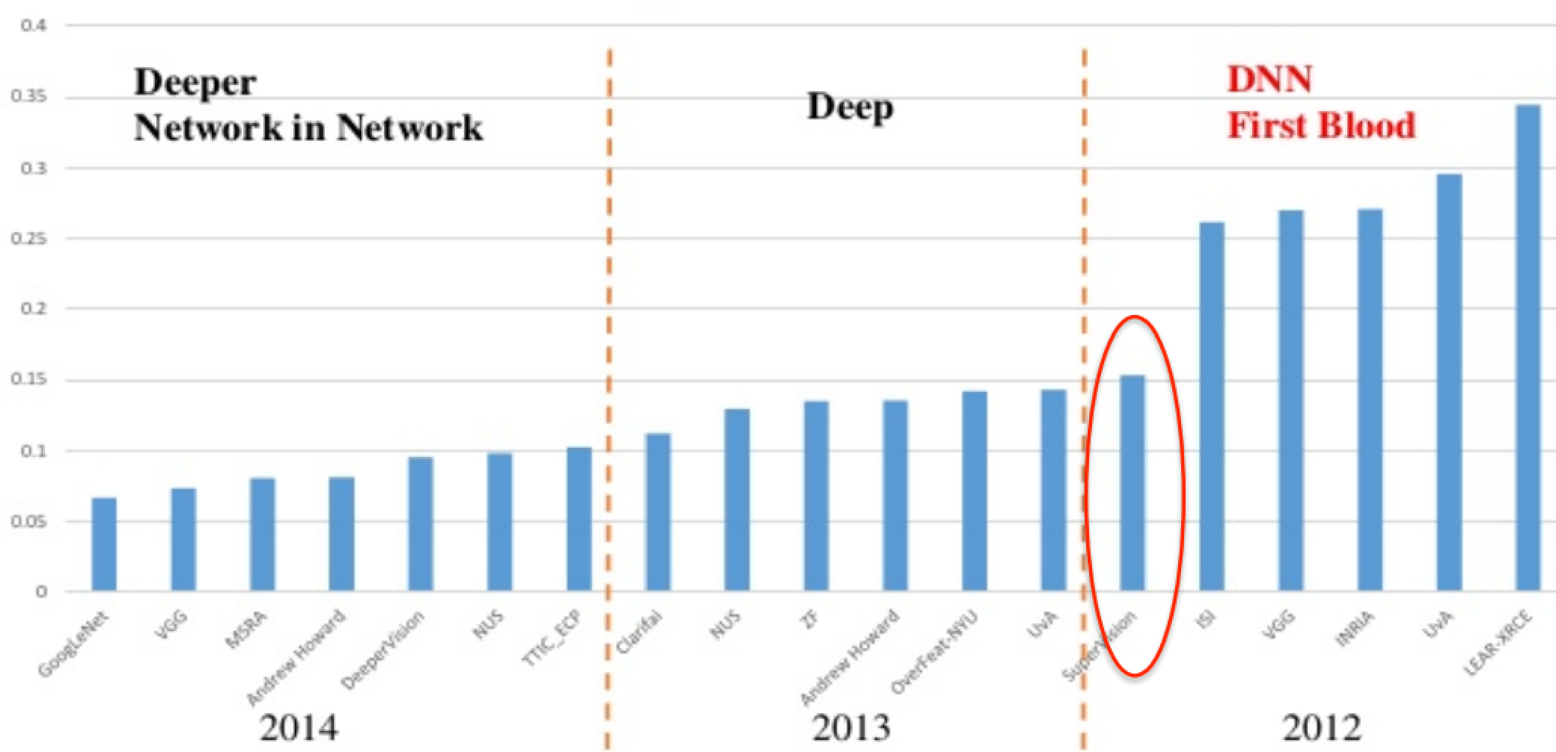
[figure from Li Deng]

Speech recognition (2009-2011)



- Steep drop in WER due to deep learning
- IBM, Google, Microsoft all switched over from GMM-HMM

Object recognition (2012)



- Landslide win in ILSVRC object recognition competition
- Computer vision community switched to CNNs
- Simpler than hand-engineered features (SIFT)

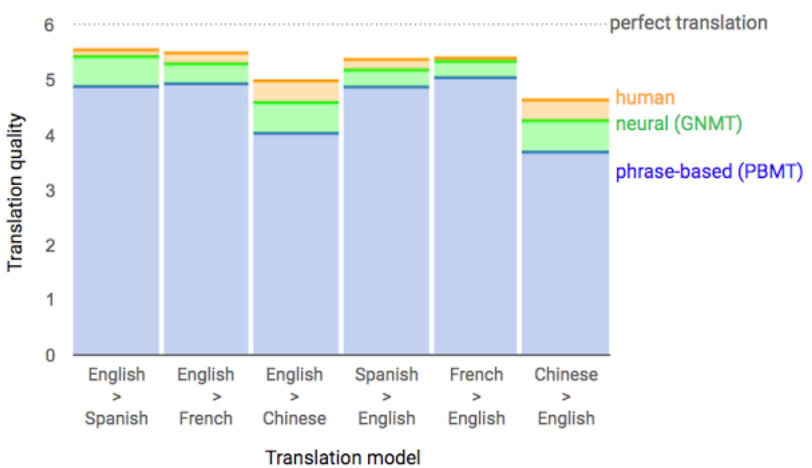
Machine translation (2016)

Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi
yonghui,schuster,zhifengc,qvl,mnorouzi@google.com

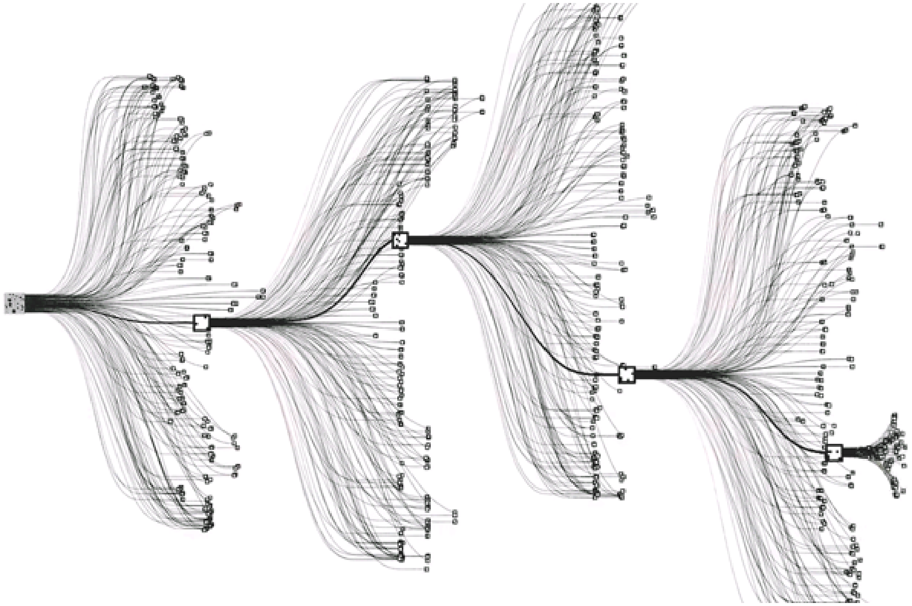
Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Łukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, Jeffrey Dean

Input sentence:	*Translation (PBMT):*	*Translation (GNMT):*	*Translation (human):*
李克強此行將啟動中加總理年度對話機制，與加拿大總理杜魯多舉行兩國總理首次年度對話。	Li Keqiang premier added this line to start the annual dialogue mechanism with the Canadian Prime Minister Trudeau two prime ministers held its first annual session.	Li Keqiang will start the annual dialogue mechanism with Prime Minister Trudeau of Canada and hold the first annual dialogue between the two premiers.	Li Keqiang will initiate the annual dialogue mechanism between premiers of China and Canada during this visit, and hold the first annual dialogue with Premier Trudeau of Canada.



- Decisive wins have taken longer to achieve in NLP (words are meaningful in a way that pixels are not)
- Current state-of-the-art in machine translation

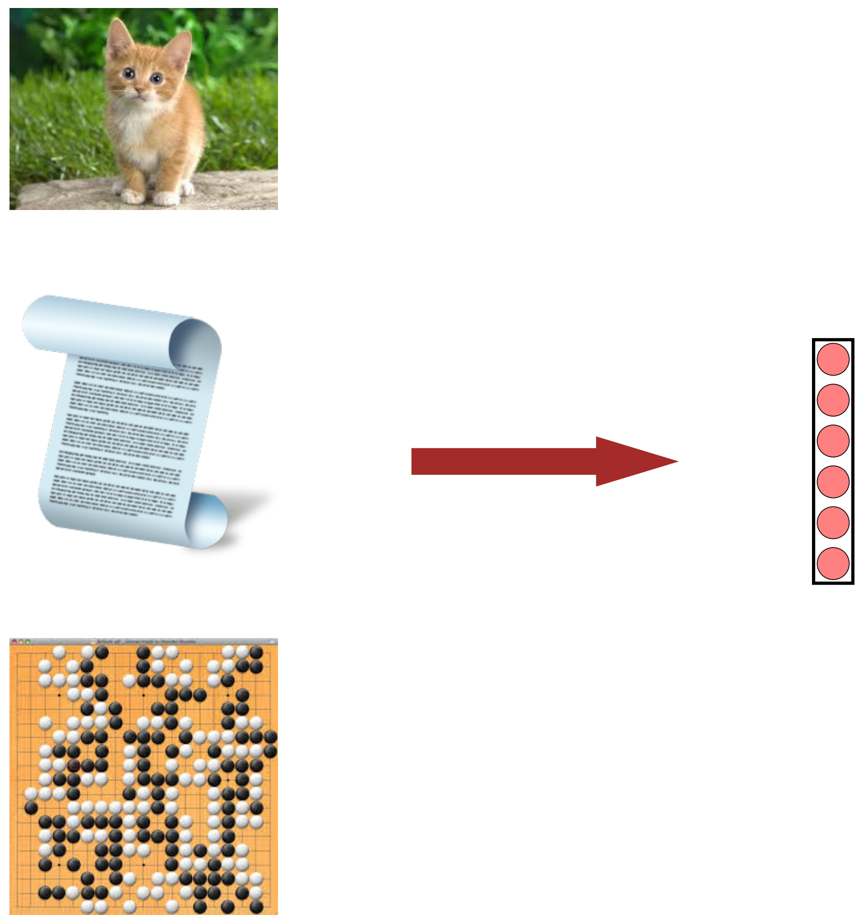
Go (2016)



- Defeated world champion Le Sedol 4-1
- Simple architecture (in contrast, DeepBlue was search + hand-crafted heuristics)
- 2017: AlphaGoZero does not require human expert games as supervision

What is deep learning?

A family of techniques for learning compositional vector representations of complex data.



Roadmap

Feedforward neural networks

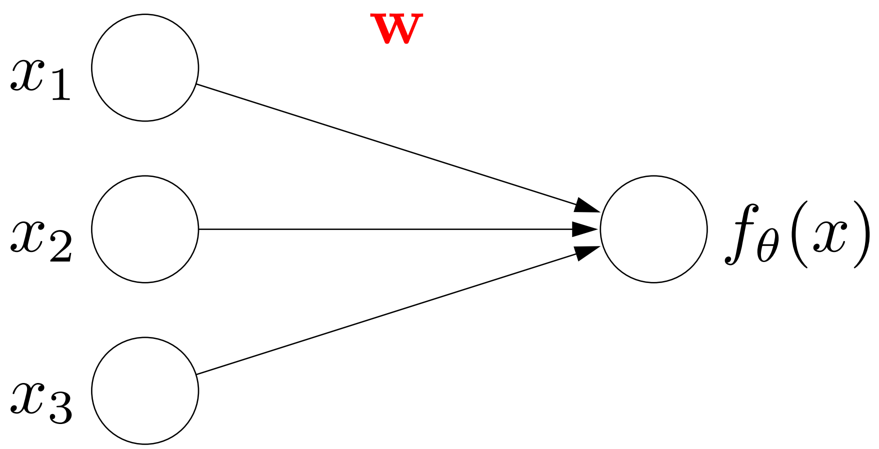
Convolutional networks

Sequence models

Unsupervised learning

Final remarks

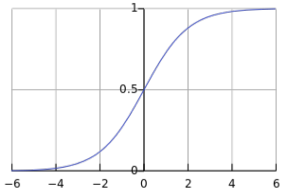
Review: linear predictors



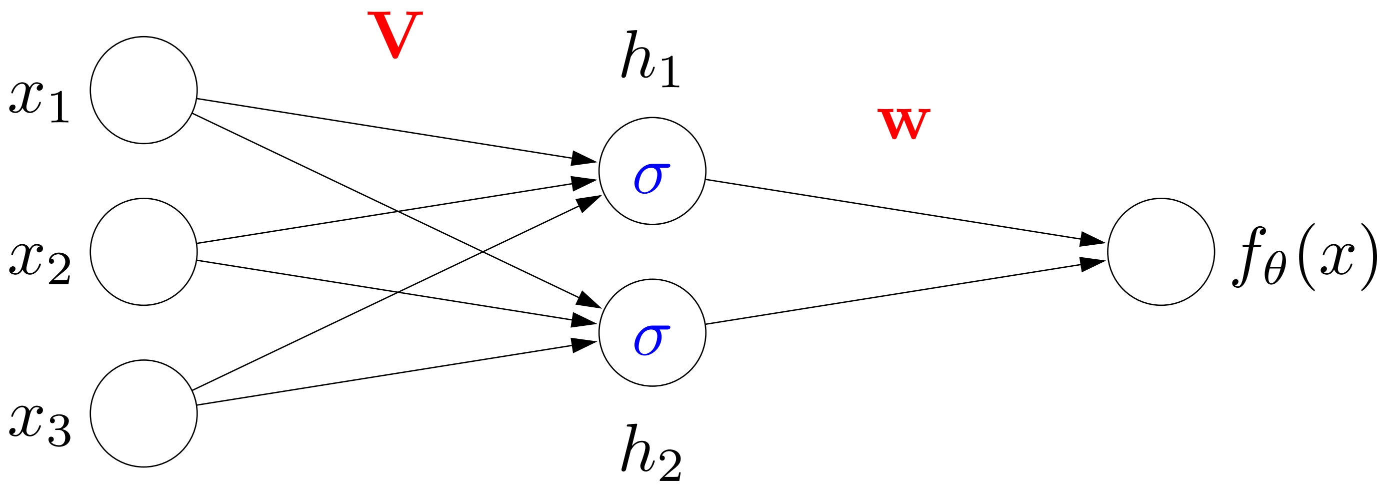
Output:

$$f_\theta(x) = \mathbf{w} \cdot x$$

Parameters: $\theta = \mathbf{w}$



Review: neural networks



Intermediate hidden units:

$$h_j(x) = \sigma(\mathbf{v}_j \cdot x) \quad \sigma(z) = (1 + e^{-z})^{-1}$$

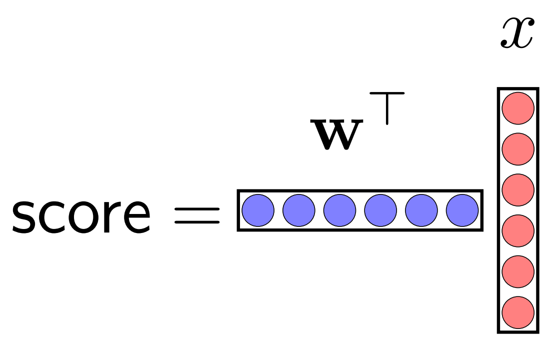
Output:

$$f_\theta(x) = \mathbf{w} \cdot \mathbf{h}(x)$$

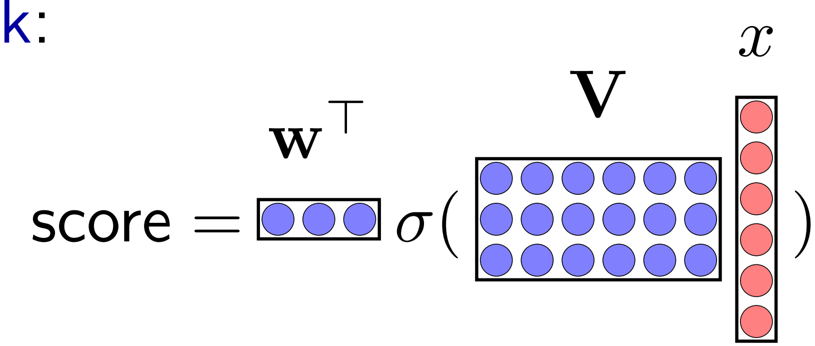
Parameters: $\theta = (\mathbf{V}, \mathbf{w})$

Deep neural networks

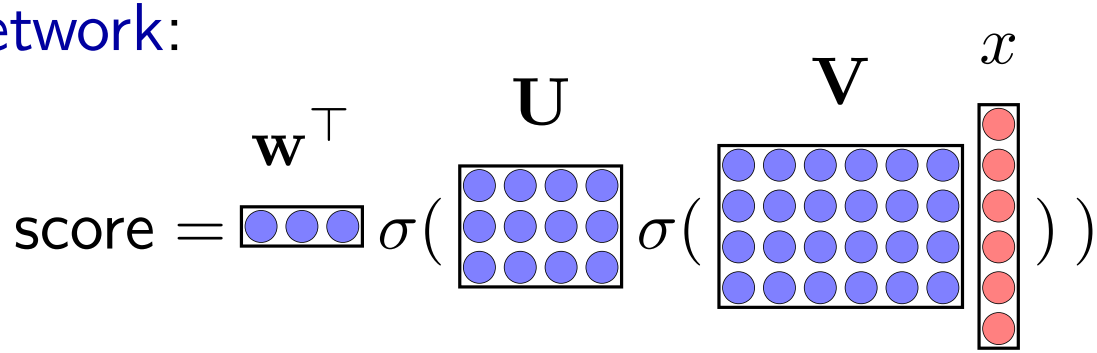
1-layer neural network:



2-layer neural network:

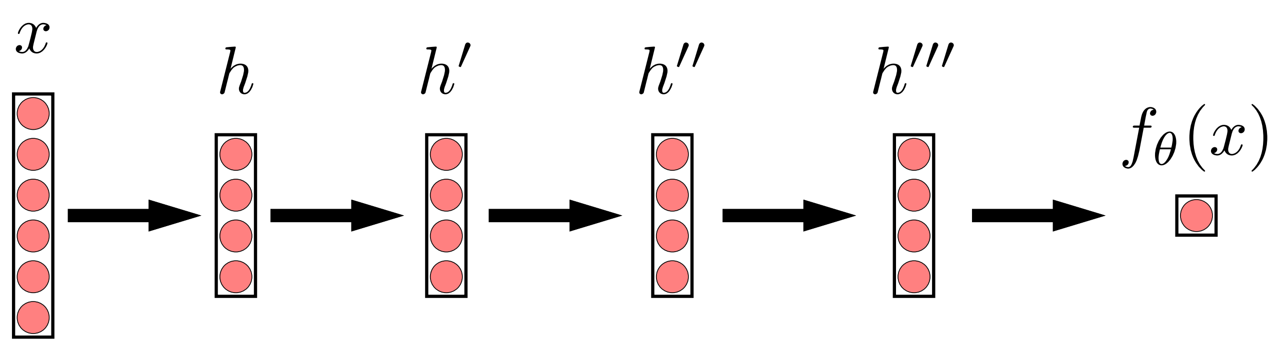


3-layer neural network:



...

Depth

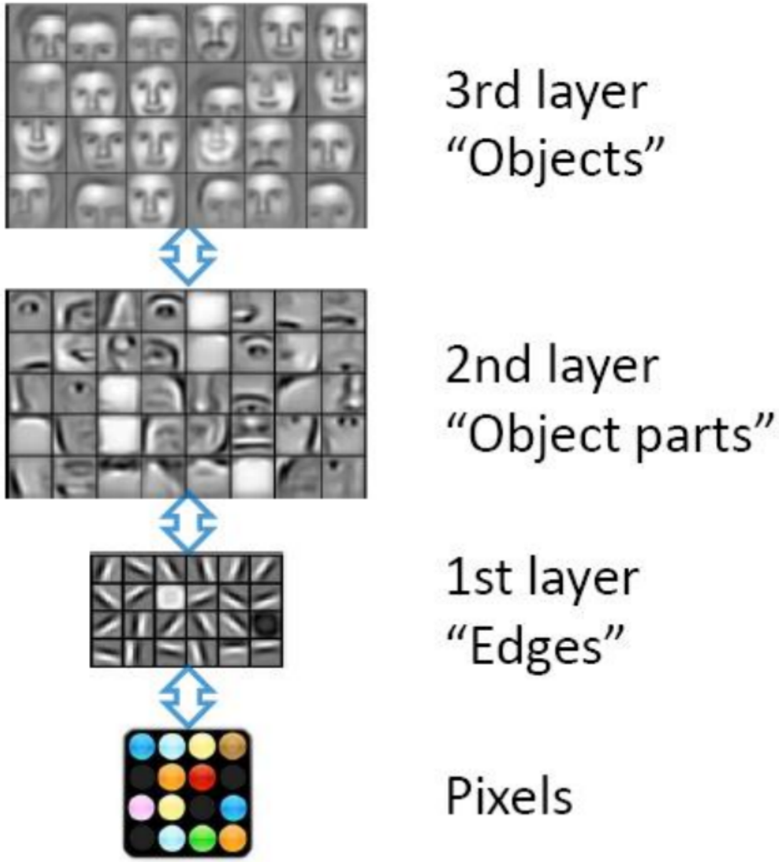


Intuitions:

- Hierarchical feature representations
- Can simulate a bounded computation logic circuit (original motivation from McCulloch/Pitts, 1943)
- Learn this computation (and potentially more because networks are real-valued)
- Formal theory/understanding is still incomplete
- Some hypotheses emerging: double descent, lottery ticket hypothesis

[figure from Honglak Lee]

What's learned?



Review: optimization

Regression:

$$\text{Loss}(x, y, \theta) = (f_\theta(x) - y)^2$$

Key idea: minimize training loss

$$\text{TrainLoss}(\theta) = \frac{1}{|\mathcal{D}_{\text{train}}|} \sum_{(x,y) \in \mathcal{D}_{\text{train}}} \text{Loss}(x, y, \theta)$$

$$\min_{\theta \in \mathbb{R}^d} \text{TrainLoss}(\theta)$$

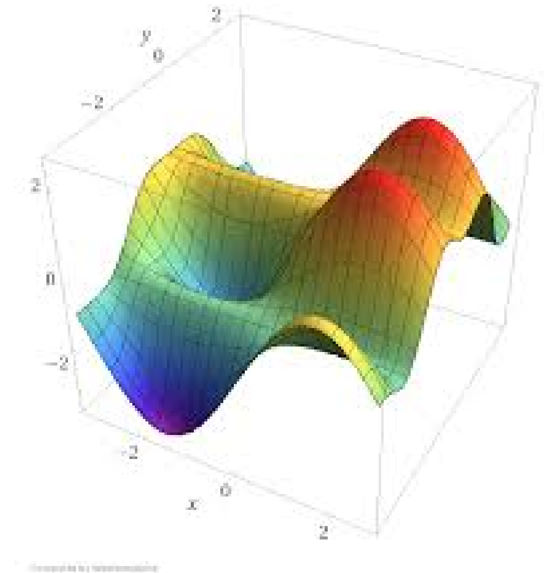
Algorithm: stochastic gradient descent

For $t = 1, \ldots, T$:

For $(x, y) \in \mathcal{D}_{\text{train}}$:

$$\theta \leftarrow \theta - \eta_t \nabla_\theta \text{Loss}(x, y, \theta)$$

Training



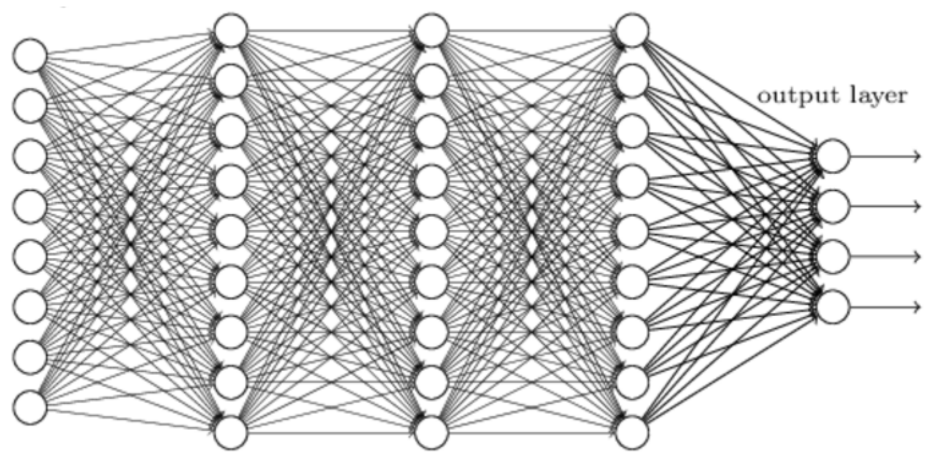
- Non-convex optimization
- No theoretical guarantees that it works
- Before 2000s, empirically very difficult to get working

What's different today

Computation (time/memory)

Information (data)

How to make it work



- More hidden units (over-parameterization)
- Adaptive step sizes (AdaGrad, Adam)
- Dropout to guard against overfitting
- Careful initialization (pre-training)
- Batch normalization

Model and optimization are tightly coupled

Summary

- Deep networks learn hierarchical representations of data

- Train via SGD, use backpropagation to compute gradients

- Non-convex optimization, but works empirically given enough compute and data

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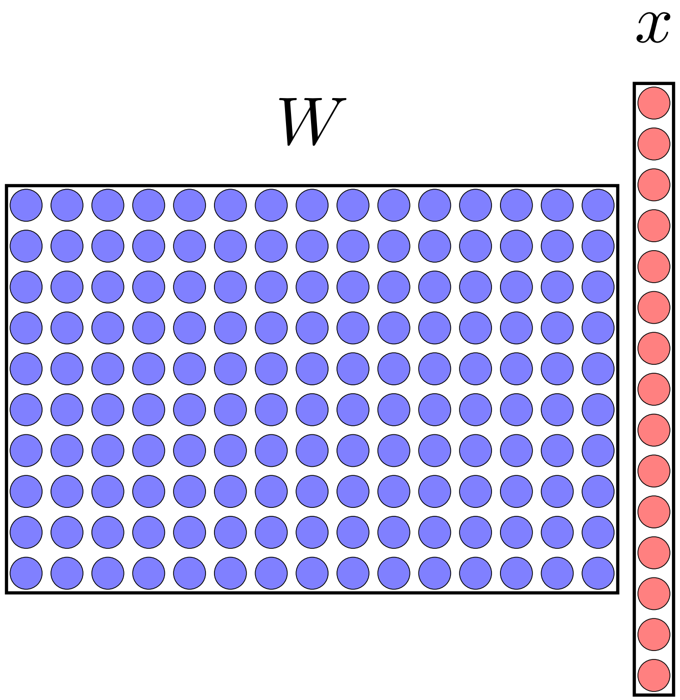
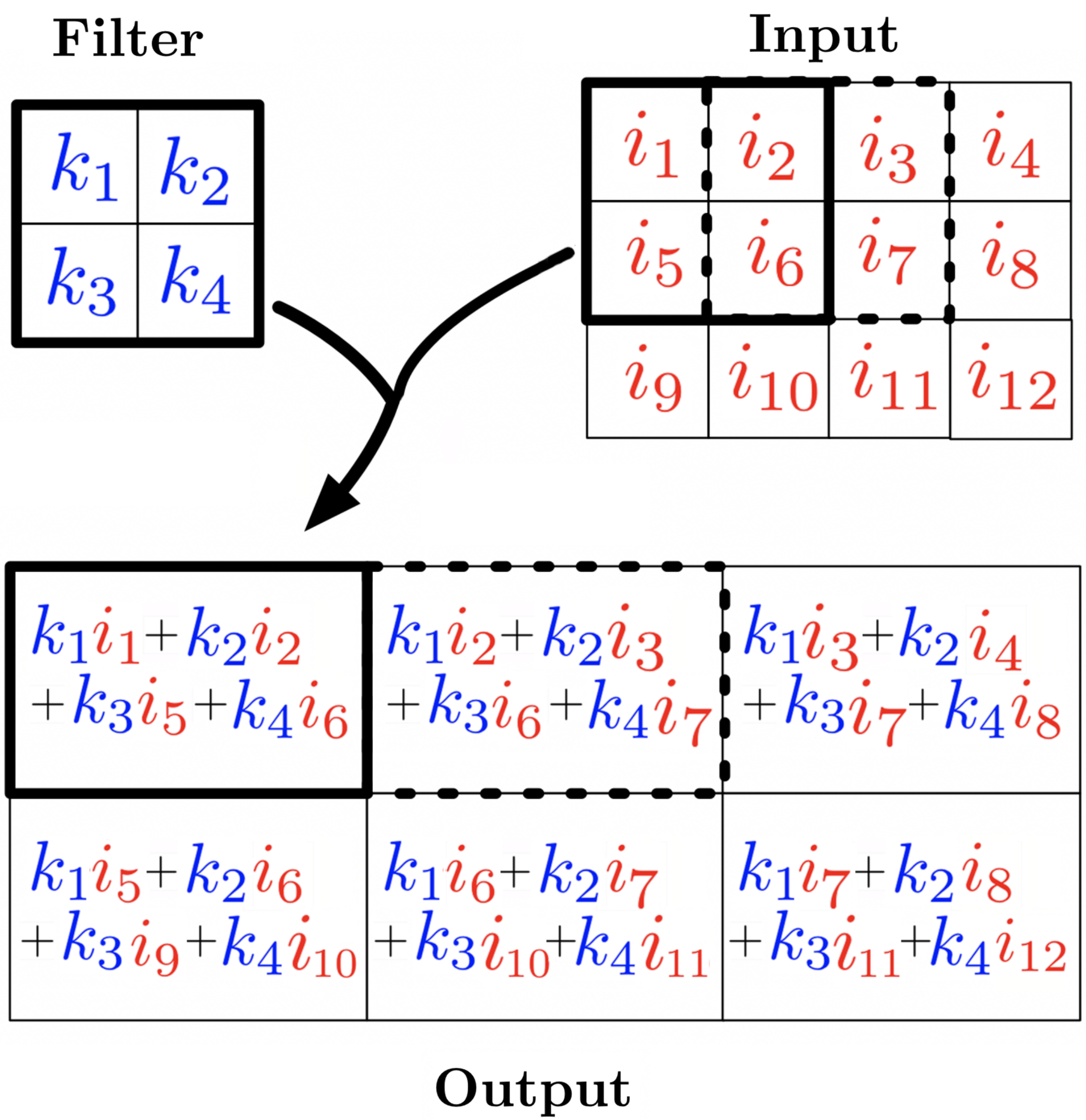
Motivation

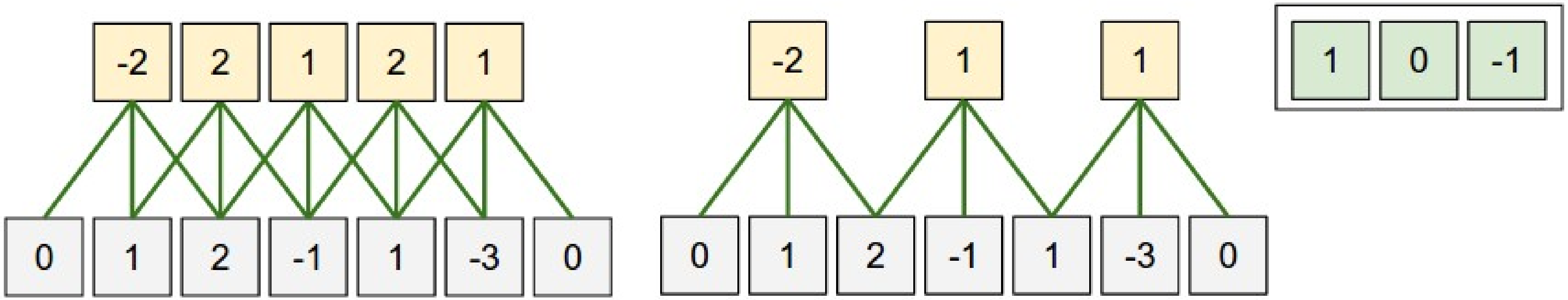


- Observation: images are not arbitrary vectors
- Goal: leverage spatial structure of images (translation equivariance)

Idea: Convolutions



Prior knowledge

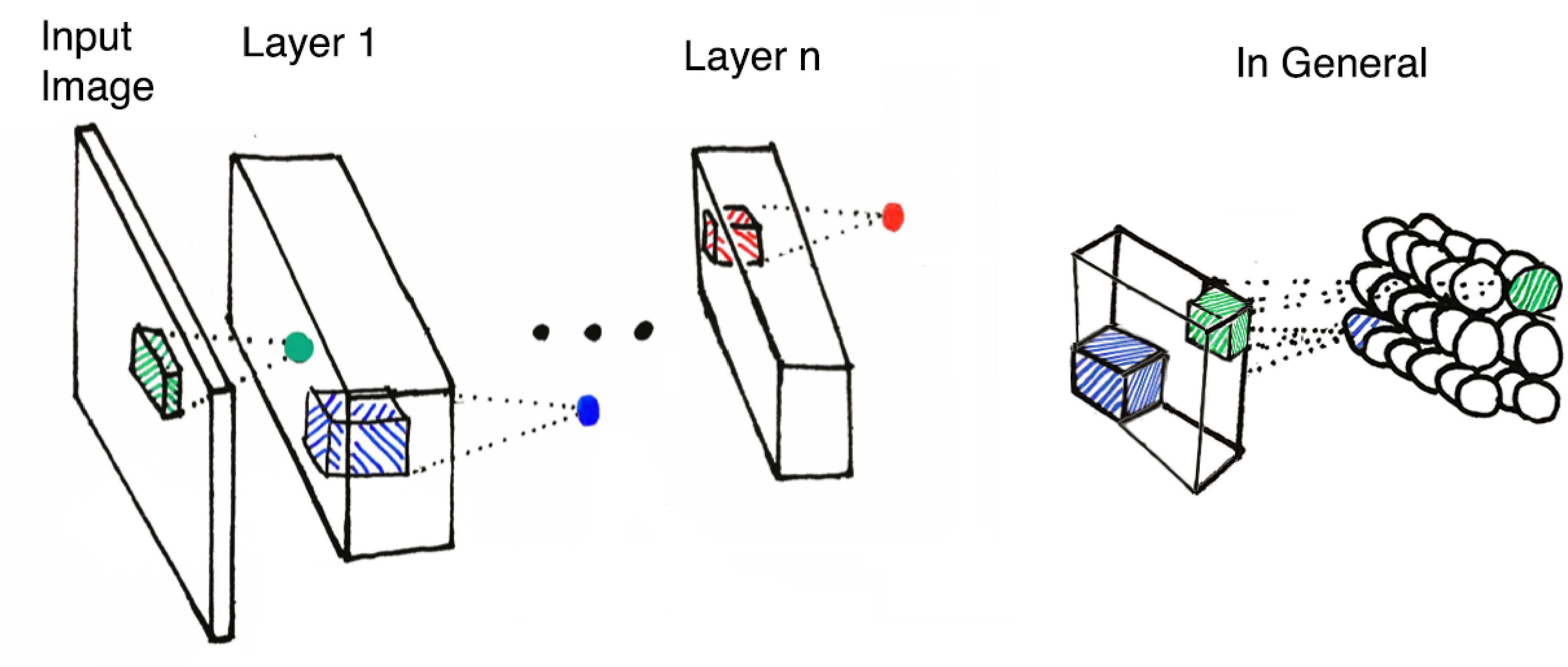


- Local connectivity: each hidden unit operates on a local image patch (3 instead of 7 connections per hidden unit)

- Parameter sharing: processing of each image patch is same (3 parameters instead of $3 \cdot 5$)

- Intuition: try to match a pattern in image

Convolutional layers

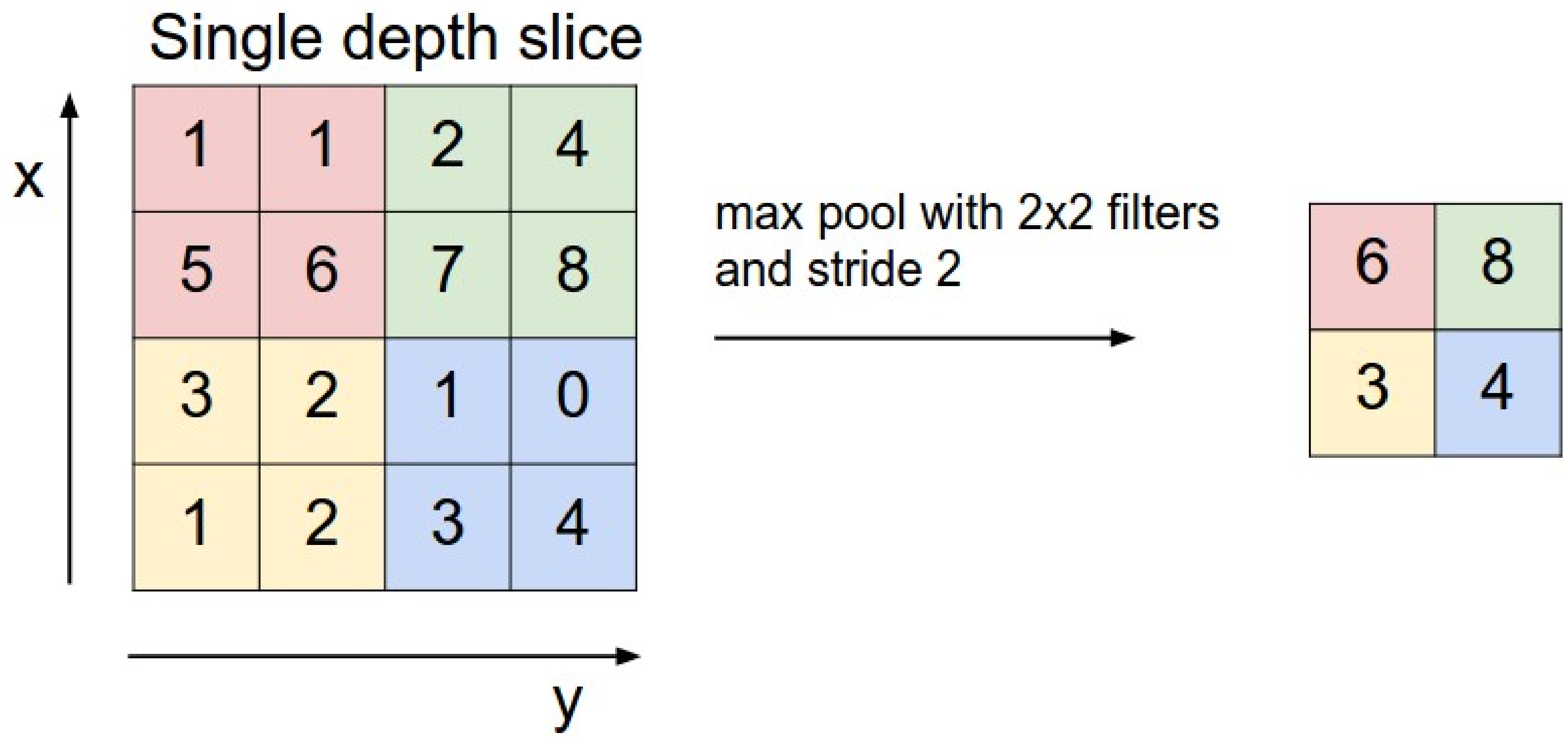


- Instead of vector to vector, we do volume to volume

[Andrej Karpathy's demo]

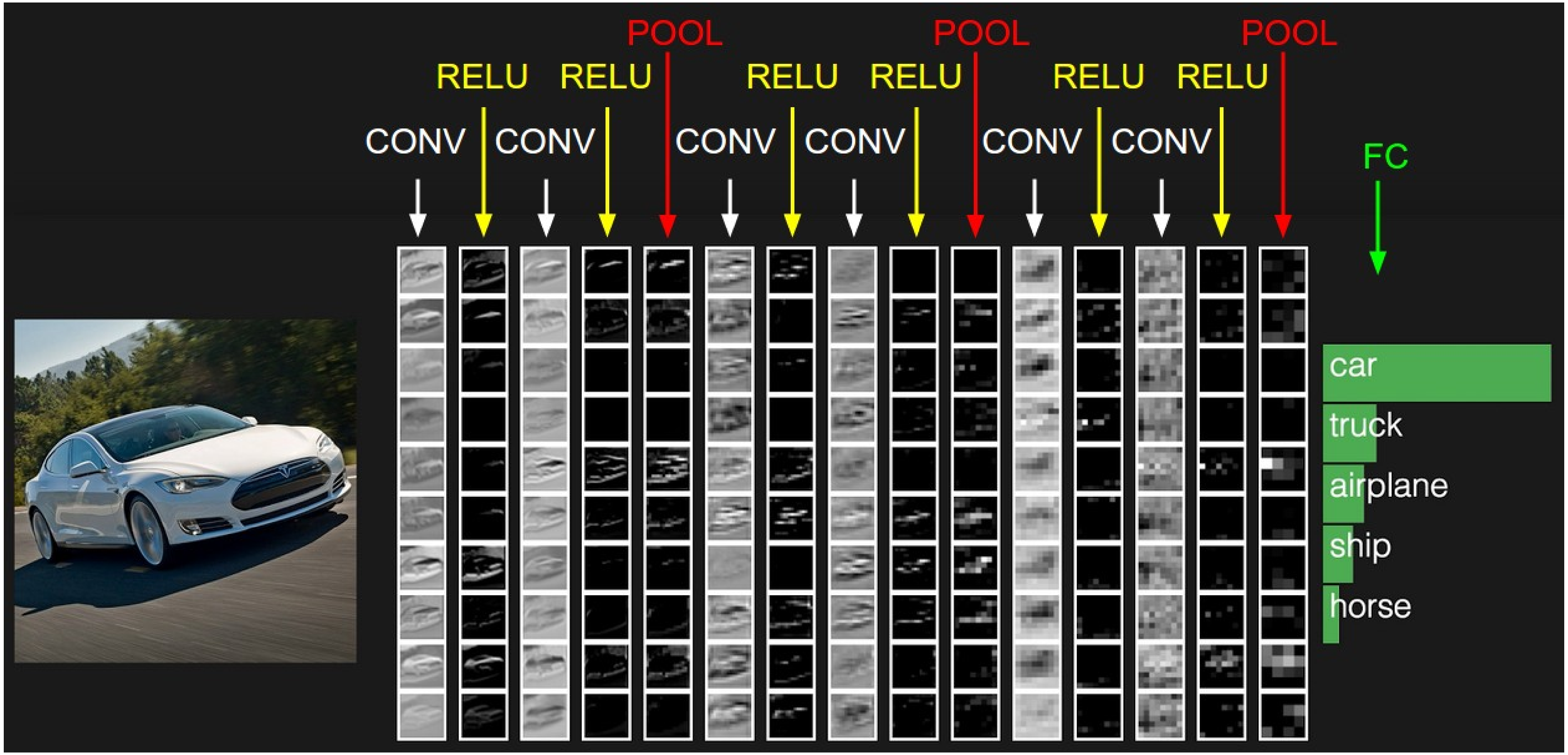
[figure from Andrej Karpathy]

Max-pooling



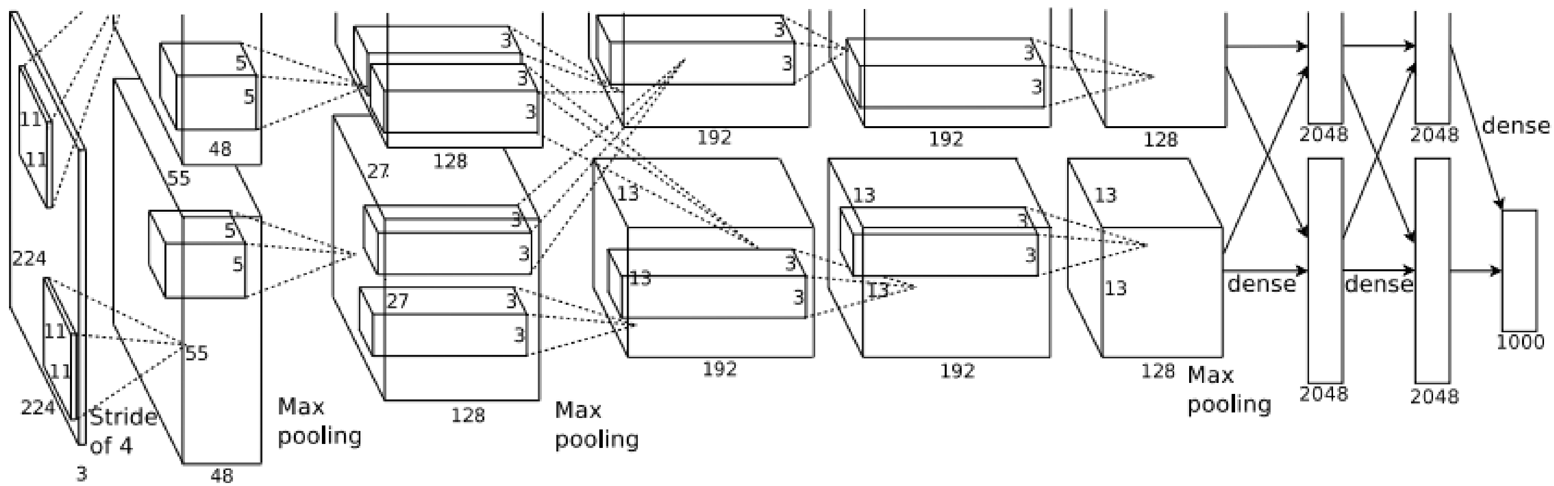
- Intuition: test if there exists a pattern in neighborhood
- Reduce computation, prevent overfitting

Example of function evaluation



[Andrej Karpathy's demo]

AlexNet

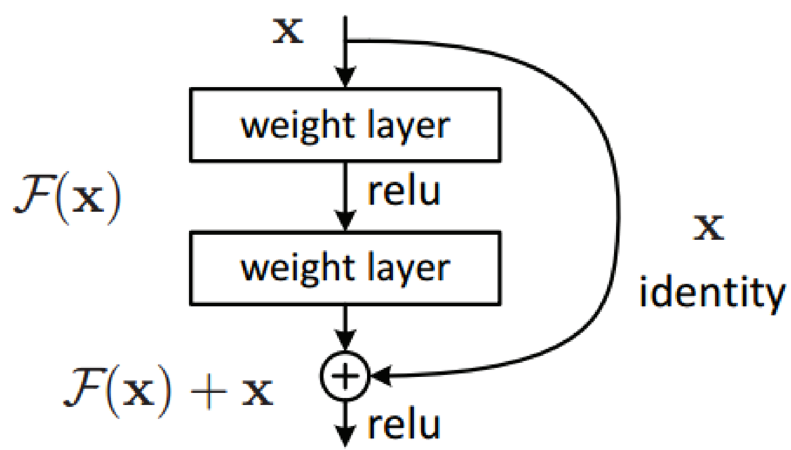


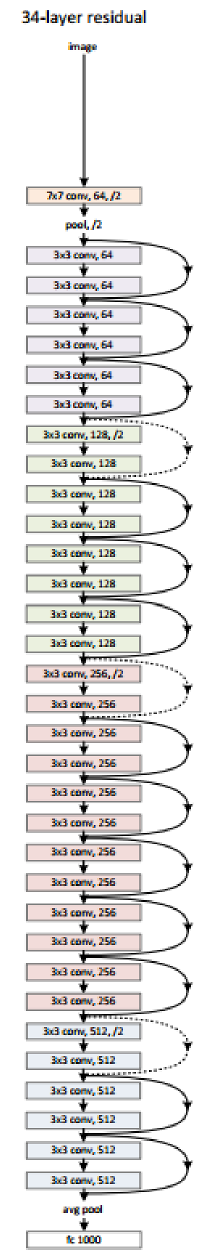
- Non-linearity: use ReIU $(\max(z, 0))$ instead of logistic
- Data augmentation: translate, horizontal reflection, vary intensity, dropout (guard against overfitting)
- Computation: parallelize across two GPUs (6 days)
- Results on ImageNet: 16.4% error (next best was 25.8%)

[He et al. 2015]

Residual networks

$$x \mapsto \sigma(Wx) + x$$





- Key idea: make it easy to learn the identity (good inductive bias)
- Enables training 152 layer networks
- Results on ImageNet: 3.6% error

Summary

- Key idea 1: locality of connections, capture spatial structure

- Key idea 2: Filters share parameters, capture translational equivariance

- Depth matters

- Applications to images, text, Go, drug design, etc.

Roadmap

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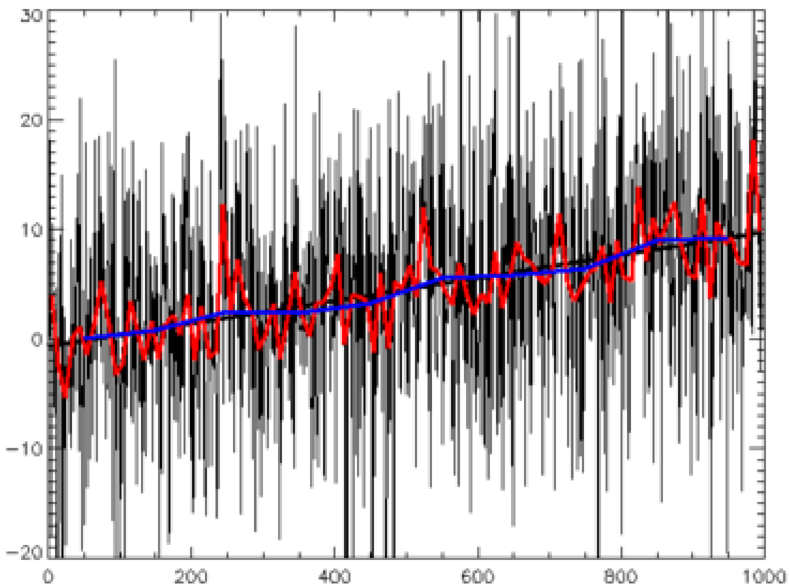
Final remarks

Motivation: modeling sequences

Sentences:

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
Paris	*Talks*	*Set*	*Stage*	*for*	*Action*	*as*	*Risks*	*to*	*the*	*Climate*	*Rise*

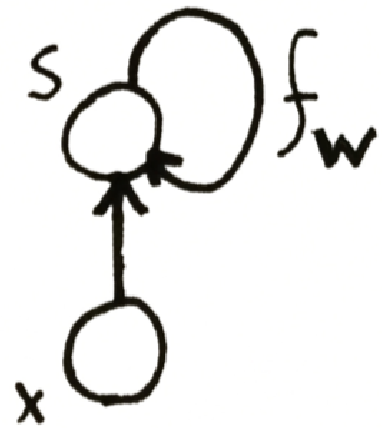
Time series:



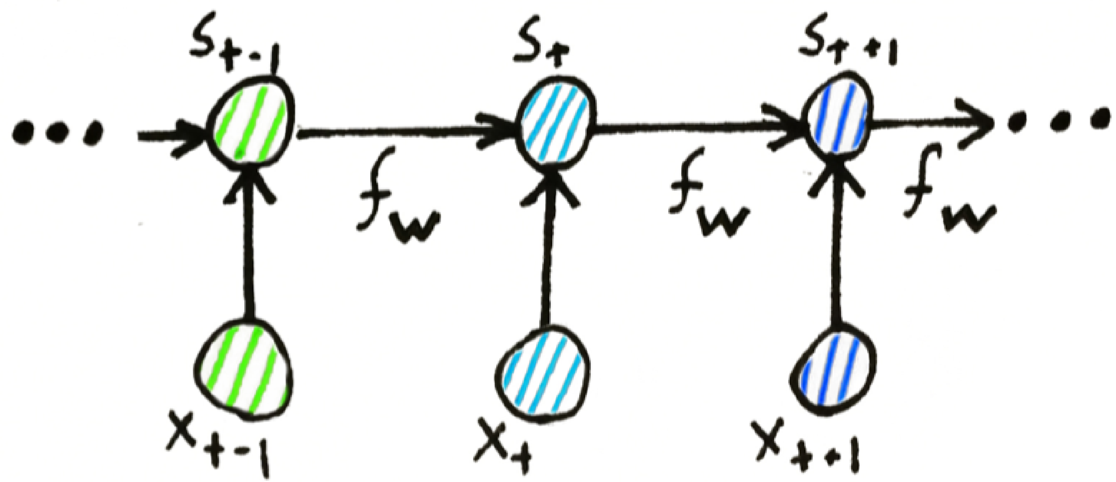
Sequence models

Formula $$\boldsymbol{s}_t = f_{\boldsymbol{W}}(\boldsymbol{s}_{t-1}, \boldsymbol{x}_t)$$

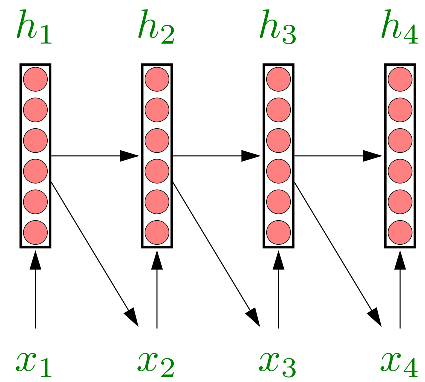
Network



Computation Graph



Language models with RNNs



$$h_1 = \text{Encode}(x_1)$$
$$x_2 \sim \text{Decode}(h_1)$$
$$h_2 = \text{Encode}(h_1, x_2)$$
$$x_3 \sim \text{Decode}(h_2)$$
$$h_3 = \text{Encode}(h_2, x_3)$$
$$x_4 \sim \text{Decode}(h_3)$$
$$h_4 = \text{Encode}(h_3, x_4)$$

Update context vector:

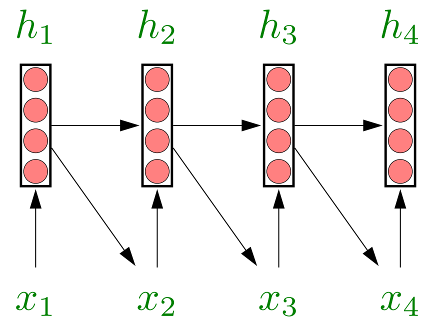
$$h_t = \text{Encode}(h_{t-1}, x_t)$$

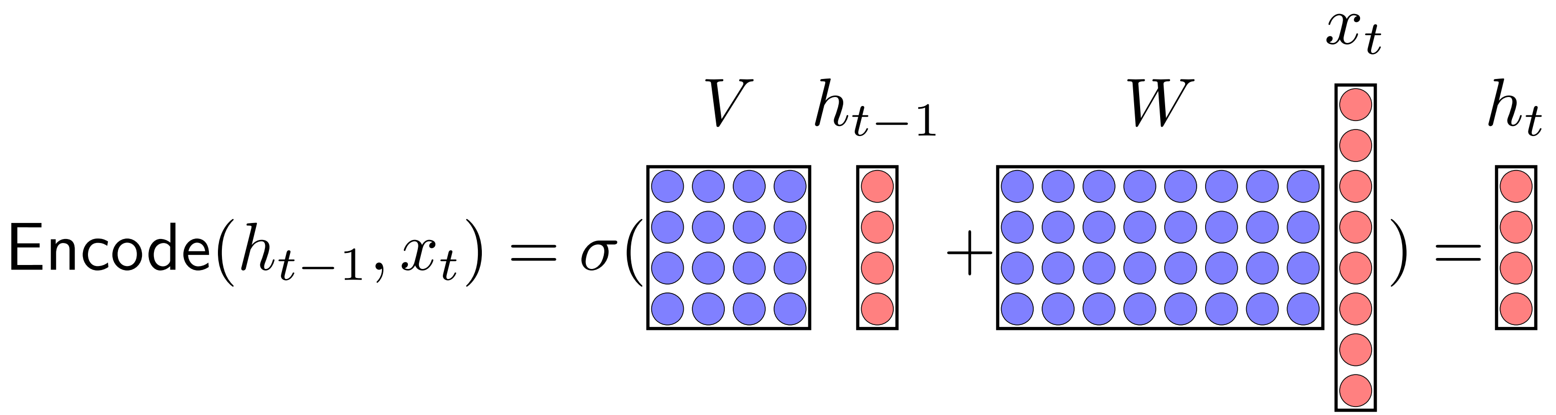
Predict next character:

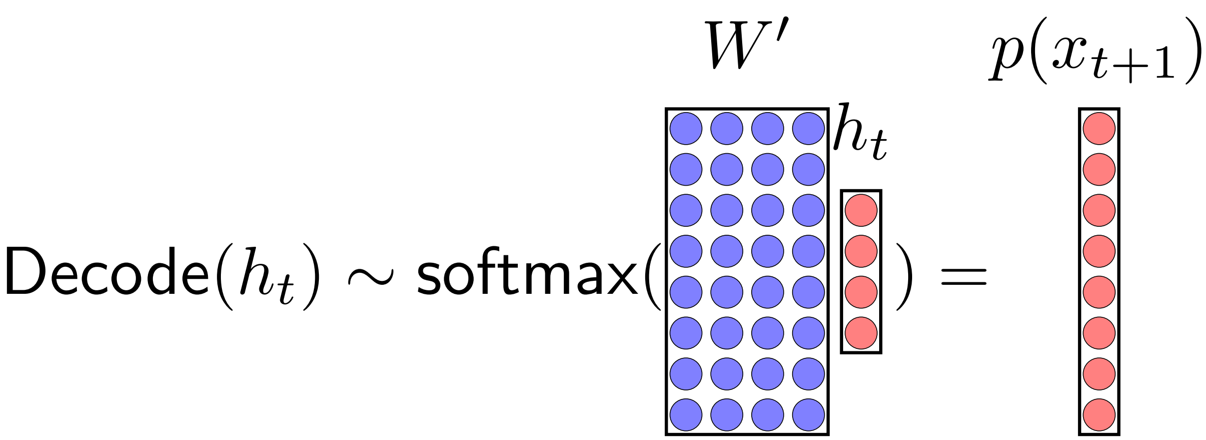
$$x_{t+1} = \text{Decode}(h_t)$$

$\boxed{\text{context } h_t \text{ compresses } x_1, \ldots x_t}$

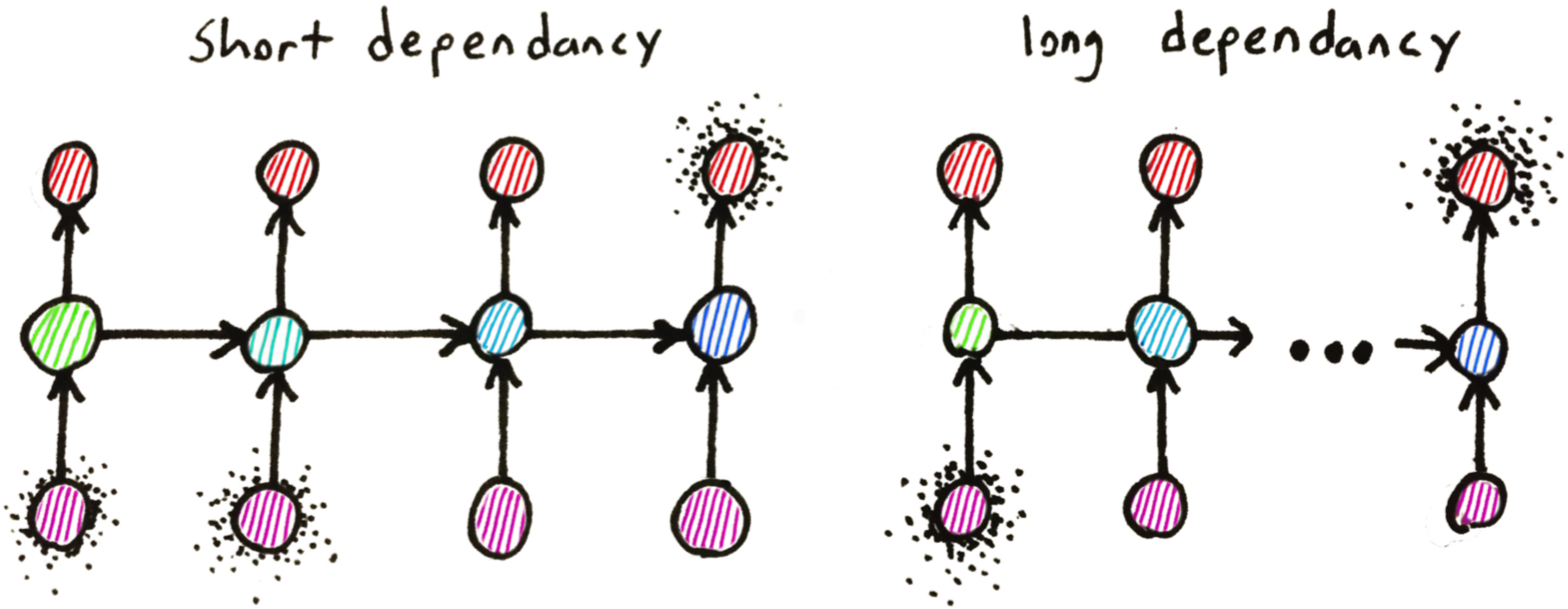
Simple recurrent network





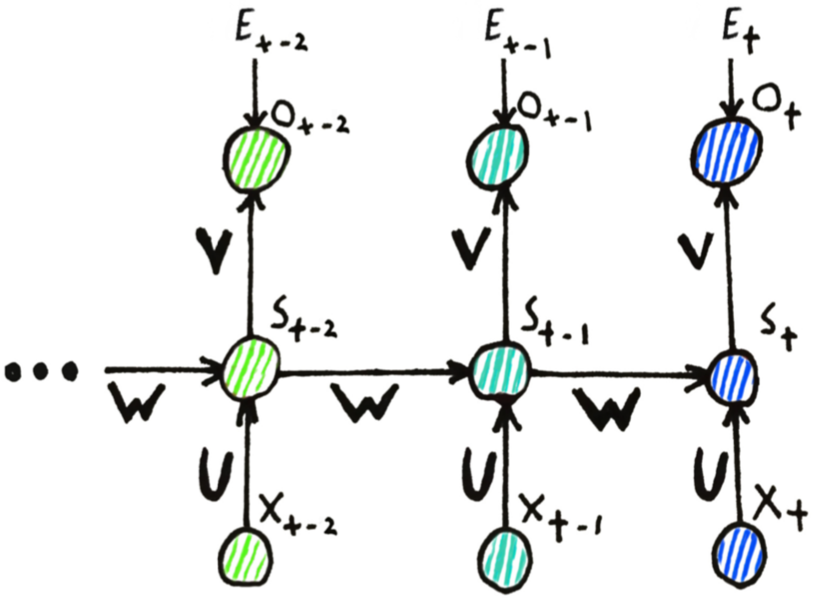


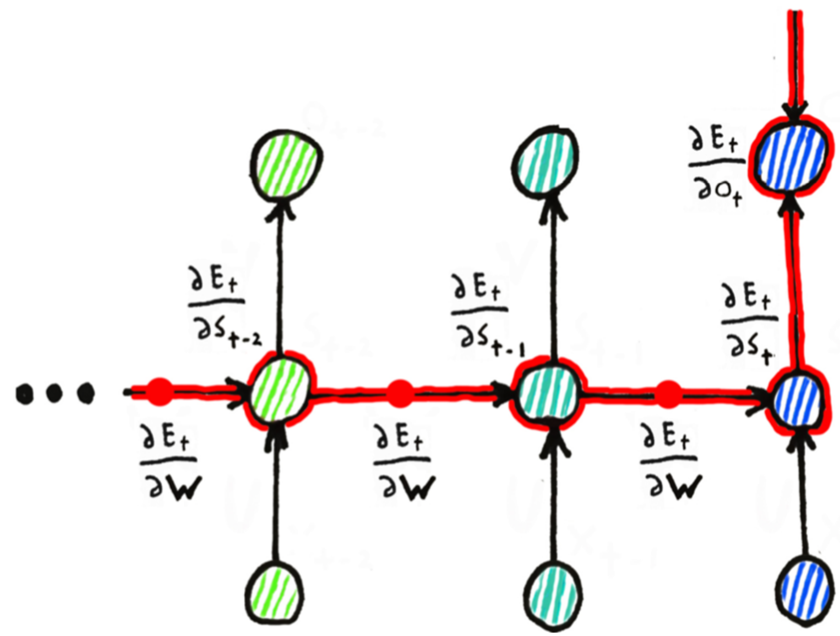
Vanishing/exploding gradient problem



- RNNs can have long or short dependencies
- When there are long dependencies, gradients have trouble back-propagating through

Vanishing/exploding gradient problem





Chain rule => multiplications

Can explode or shrink!

$$\frac{\partial E_t}{\partial \boldsymbol{W}} = \sum_{k=0}^{t} \frac{\partial E_t}{\partial \boldsymbol{o}_t} \frac{\partial \boldsymbol{o}_t}{\partial \boldsymbol{s}_t} \frac{\partial \boldsymbol{s}_t}{\partial \boldsymbol{s}_k} \frac{\partial \boldsymbol{s}_k}{\partial \boldsymbol{W}}$$

$$\frac{\partial \boldsymbol{s}_t}{\partial \boldsymbol{s}_k} = \prod_{j=k+1}^{t} \frac{\partial \boldsymbol{s}_j}{\partial \boldsymbol{s}_{j-1}}$$

[Schmidhuber & Hochreiter, 1997]

Long Short Term Memory (LSTM)

API:

$$(h_t, c_t) = \mathsf{LSTM}(h_{t-1}, c_{t-1}, x_t)$$

Input gate:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + V_i c_{t-1} + b_i)$$

Forget gate (initialize with b_f large, so f_t close to 1):

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + V_f c_{t-1} + b_f)$$

Cell: additive combination of RNN update with previous cell

$$c_t = i_t \odot \tanh(W_c x_t + U_c h_{t-1} + b_c) + f_t \odot c_{t-1}$$

Output gate:

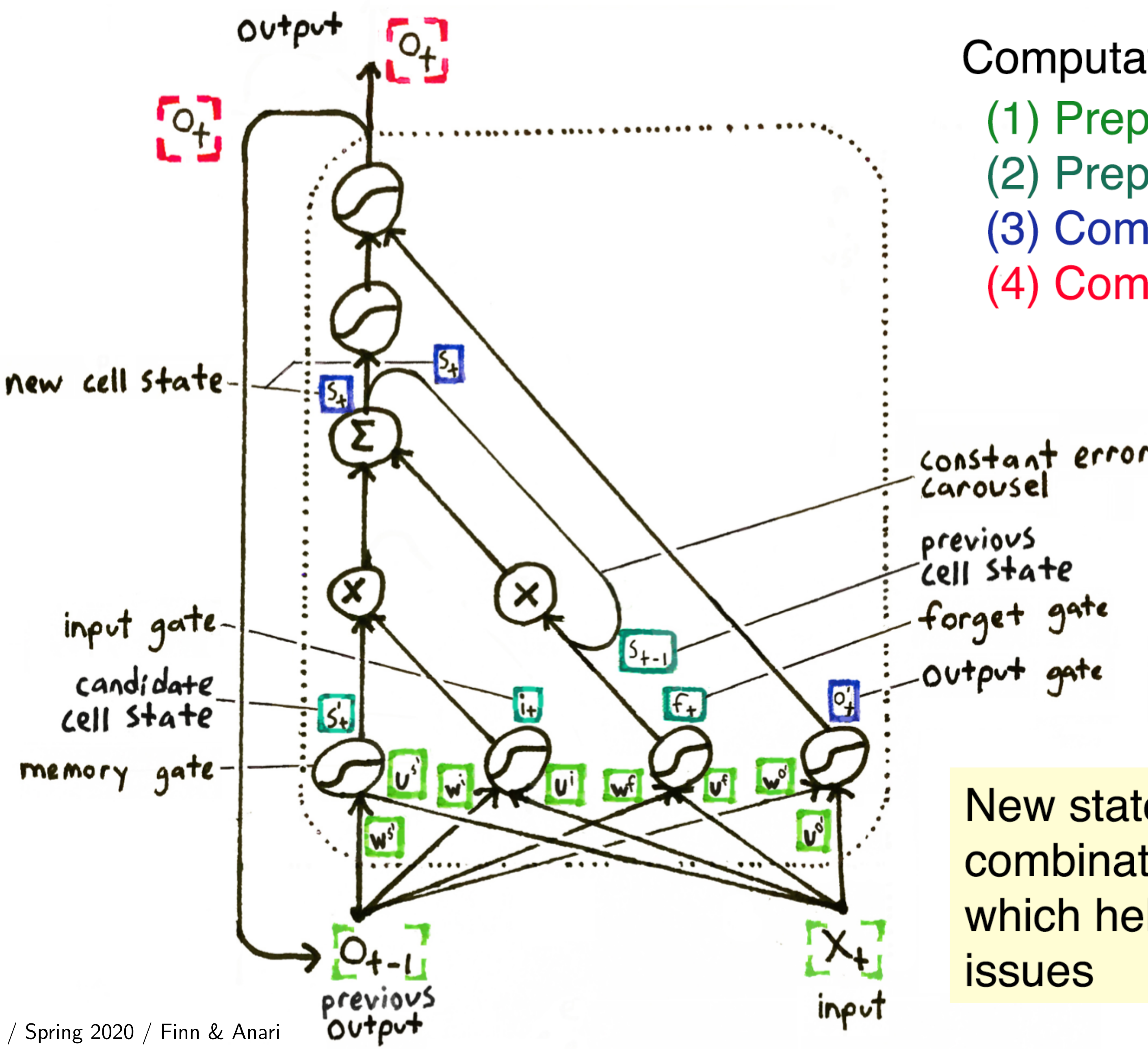
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + V_o c_t + b_o)$$

Hidden state:

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

[Schmidhuber & Hochreiter, 1997]

Long Short Term Memory (LSTM)



Computation:

(1) Prepare cell inputs
(2) Prepare new state inputs
(3) Compute new state
(4) Compute output

New state is additive combination with old state, which helps avoid gradient issues

Character-level language modeling

Sampled output:

Naturalism and decision for the majority of Arab countries' capitalide was grounded by the Irish language by [[John Clair]], [[An Imperial Japanese Revolt]], associated with Guangzham's sovereignty. His generals were the powerful ruler of the Portugal in the [[Protestant Immineners]], which could be said to be directly in Cantonese Communication, which followed a ceremony and set inspired prison, training. The emperor travelled back to [[Antioch, Perth, October 25—21]] to note, the Kingdom of Costa Rica, unsuccessful fashioned the [[Thrales]], [[Cynth's Dajoard]], known in western [[Scotland]], near Italy to the conquest of India with the conflict.

[from Andrej Karpathy's blog]

Cell sensitive to position in line:

The sole importance of the crossing of the Berezina lies in the fact that it plainly and indubitably proved the fallacy of all the plans for cutting off the enemy's retreat and the soundness of the only possible line of action--the one Kutuzov and the general mass of the army demanded--namely, simply to follow the enemy up. The French crowd fled at a continually increasing speed and all its energy was directed to reaching its goal. It fled like a wounded animal and it was impossible to block its path. This was shown not so much by the arrangements it made for crossing as by what took place at the bridges. When the bridges broke down, unarmed soldiers, people from Moscow and women with children who were with the French transport, all--carried on by vis inertiae--pressed forward into boats and into the ice-covered water and did not, surrender.

Cell that turns on inside quotes:

"You mean to imply that I have nothing to eat out of.... On the contrary, I can supply you with everything even if you want to give dinner parties," warmly replied Chichagov, who tried by every word he spoke to prove his own rectitude and therefore imagined Kutuzov to be animated by the same desire.

Kutuzov, shrugging his shoulders, replied with his subtle penetrating smile: "I meant merely to say what I said."

Cell that robustly activates inside if statements:

```
static int __dequeue_signal(struct sigpending *pending, sigset_t *mask,
    siginfo_t *info)
{
  int sig = next_signal(pending, mask);
  if (sig) {
    if (current->notifier) {
      if (sigismember(current->notifier_mask, sig)) {
        if (!(current->notifier)(current->notifier_data)) {
          clear_thread_flag(TIF_SIGPENDING);
          return 0;
        }
      }
    }
    collect_signal(sig, pending, info);
  }
  return sig;
}
```

A large portion of cells are not easily interpretable. Here is a typical example:

```
/* Unpack a filter field's string representation from user-space
 * buffer. */
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)
{
  char *str;
  if (!*bufp || (len == 0) || (len > *remain))
    return ERR_PTR(-EINVAL);
  /* Of the currently implemented string fields, PATH_MAX
   * defines the longest valid length.
   */
```

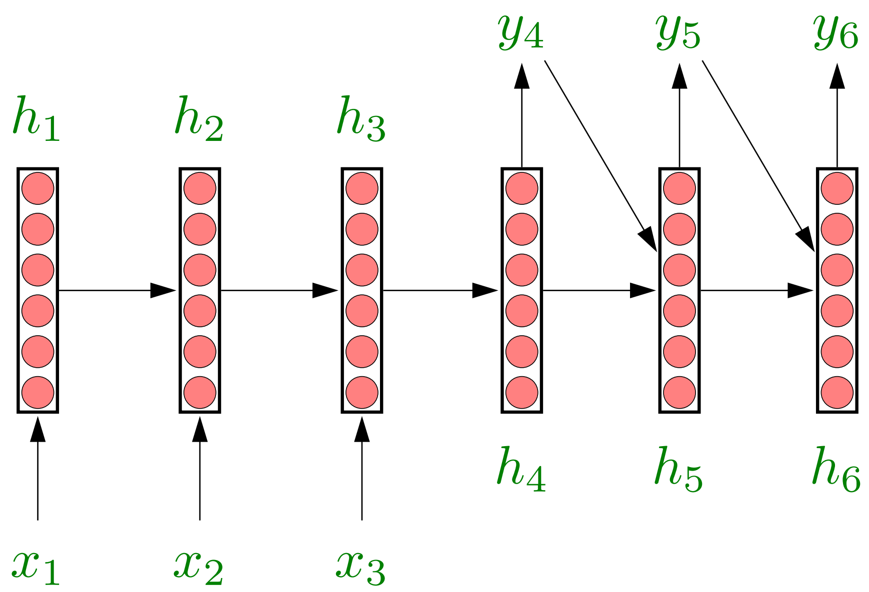
[Sutskever et al., 2014]

Sequence-to-sequence model

Motivation: machine translation

x: *Je crains l'homme de un seul livre.*

y: *Fear the man of one book.*



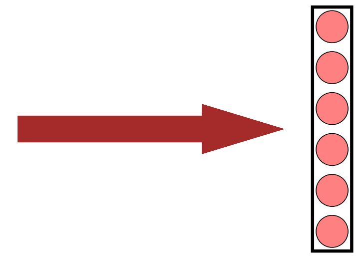
Read in a sentence first, output according to RNN:

$$h_t = \textcolor{red}{\text{Encode}}(h_{t-1}, x_t \text{ or } y_{t-1}), \quad y_t = \textcolor{red}{\text{Decode}}(h_t)$$

Attention-based models

Motivation: long sentences — compress to finite dimensional vector?

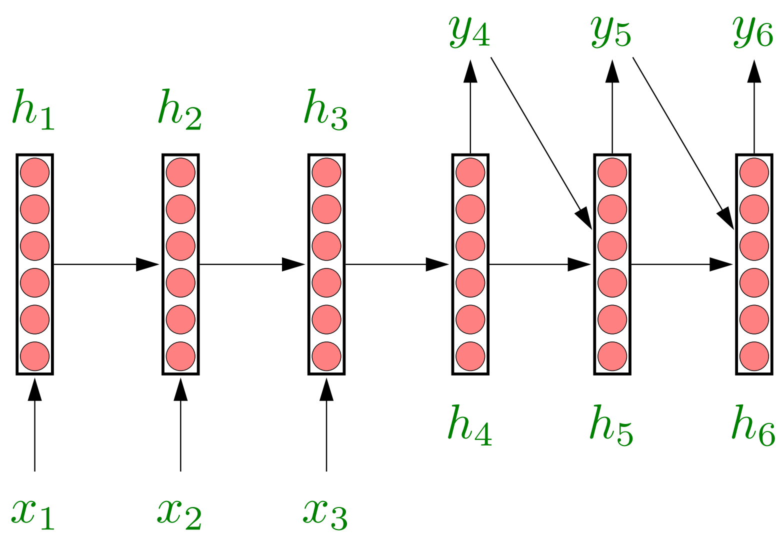
Eine Folge von Ereignissen bewirkte, dass aus Beethovens Studienreise nach Wien ein dauerhafter und endgültiger Aufenthalt wurde. Kurz nach Beethovens Ankunft, am 18. Dezember 1792, starb sein Vater. 1794 besetzten französische Truppen das Rheinland, und der kurfürstliche Hof musste fliehen.



Key idea: attention

Learn to look back at your notes.

Attention-based models



Distribution over input positions:

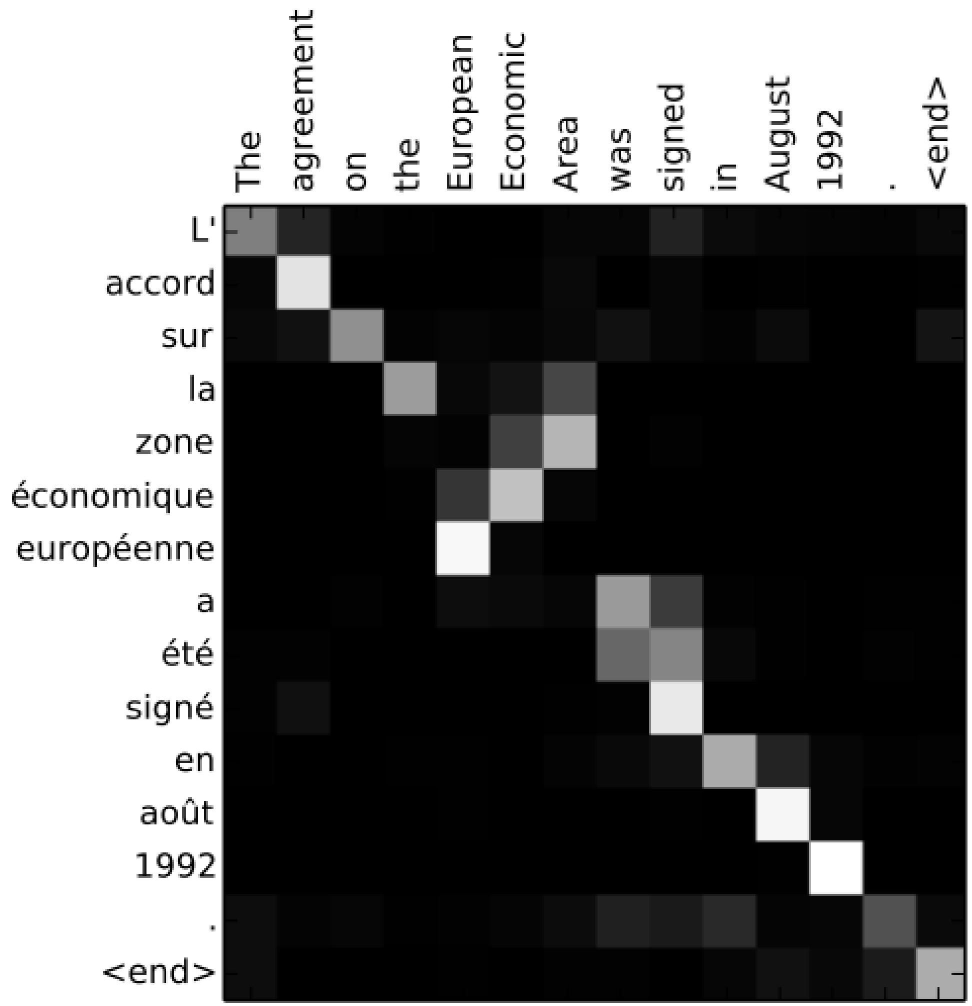
$$\alpha_t = \text{softmax}([\text{Attend}(h_1, h_{t-1}), \ldots, \text{Attend}(h_L, h_{t-1})])$$

Generate with attended input:

$$h_t = \text{Encode}(h_{t-1}, y_{t-1}, \textstyle\sum_{j=1}^{L} \alpha_t h_j)$$

Transformer models: attention only – no RNN!

Machine translation



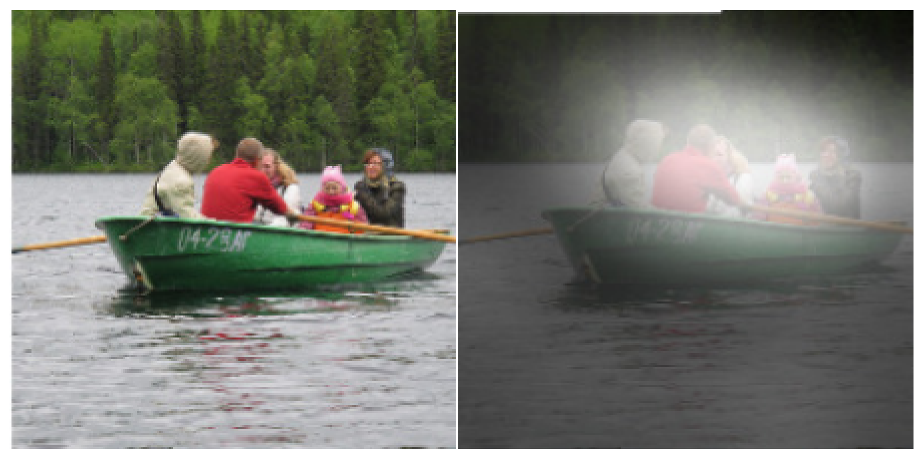
[Xu et al., 2015]

Image captioning

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A little girl sitting on a bed with a teddy bear.



A group of people sitting on a boat in the water.

Summary

- Recurrent neural networks: model sequences (non-linear version of Kalman filter or HMM)

- Logic intuition: learning a program with a for loop (reduce)

- LSTMs mitigate the vanishing gradient problem

- Attention-based models: when only part of input is relevant at a time

- Newer models with "external memory": memory networks, neural Turing machines

Roadmap

Feedforward neural networks

Convolutional networks

Sequence models

Unsupervised learning

Final remarks

Motivation

- Deep neural networks require lot of data
- Sometimes not very much labeled data, but plenty of unlabeled data (text, images, videos)
- Humans rarely get direct supervision; can learn from raw sensory information?

Autoencoders

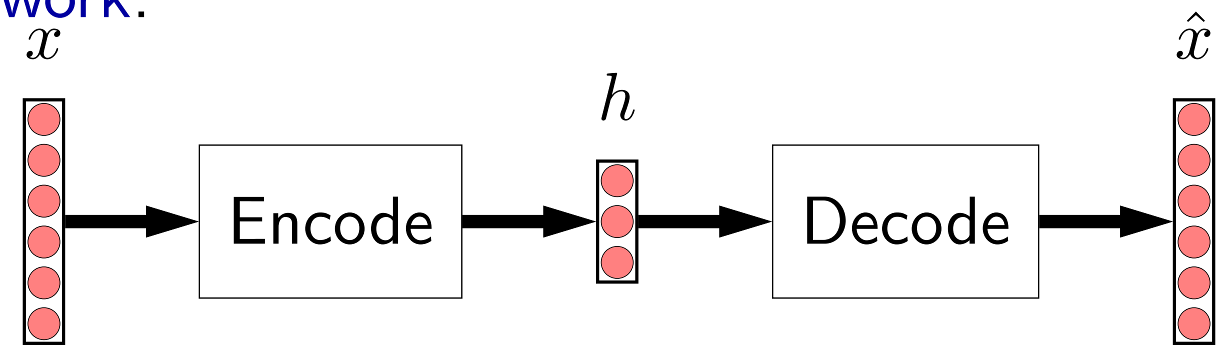
Analogy:

A A A A B B B B B $\longrightarrow$ 4 A's, 5 B's $\longrightarrow$ A A A A B B B B B

Key idea: autoencoders

If we can compress a data point and still reconstruct it, then we have learned something generally useful.

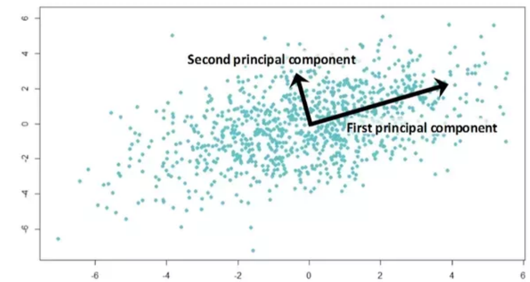
General framework:

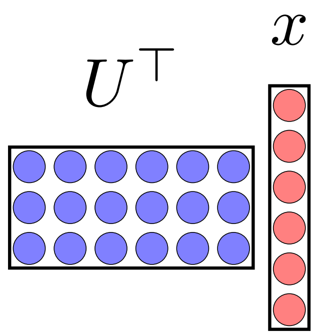


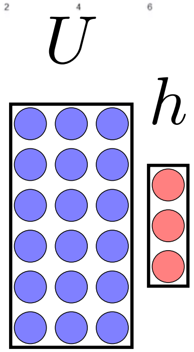
minimize $\|x - \hat{x}\|^2$

Principal component analysis

Input: points $x_1, \dots, x_n$



Encode$(x) =$ 

Decode$(h) =$ 

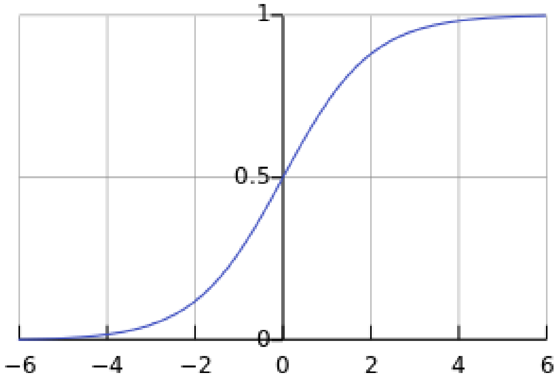
(assume x_i's are mean zero and U is orthogonal)

PCA objective:

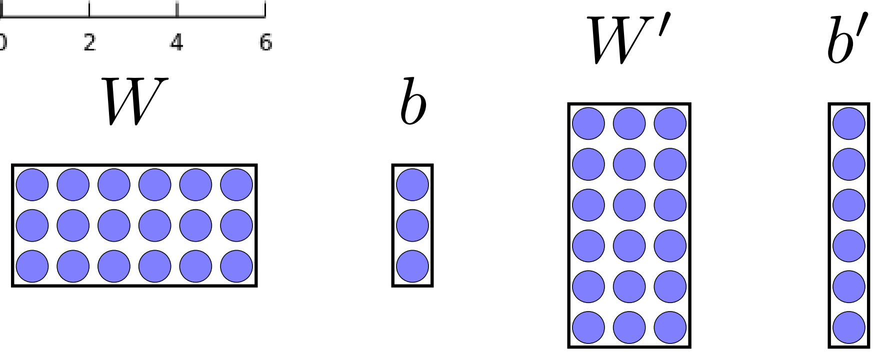
$$\text{minimize} \sum_{i=1}^{n} \|x_i - \text{Decode}(\text{Encode}(x_i))\|^2$$

Non-linear autoencoders

Non-linear transformation (e.g., logistic function):



$$\text{Encode}(x) = \sigma(Wx + b)$$
$$\text{Decode}(h) = \sigma(W'h + b')$$

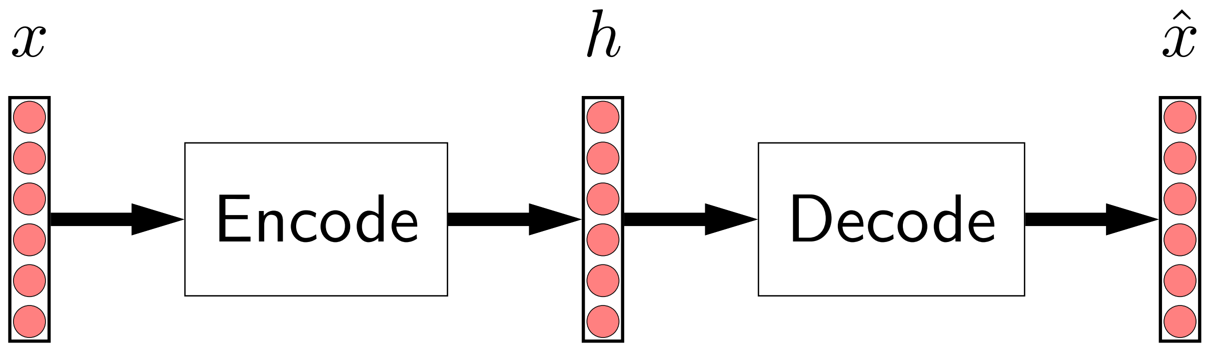


Loss function:

$$\text{minimize } \|x - \text{Decode}(\text{Encode}(x))\|^2$$

Autoencoders

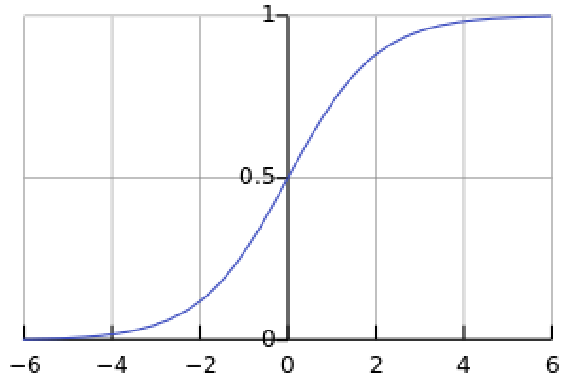
Increase dimensionality of hidden dimension:



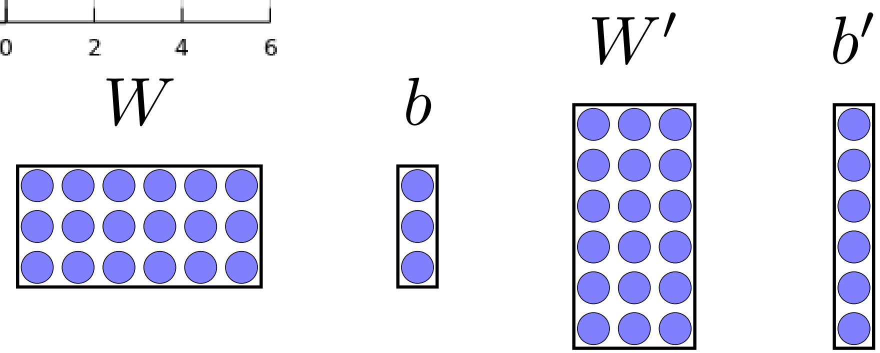
- Problem: learning nothing — just set Encode, Decode to identity function!

Non-linear autoencoders

Non-linear transformation (e.g., logistic function):



$$\text{Encode}(x) = \sigma(Wx + b)$$
$$\text{Decode}(h) = \sigma(W'h + b')$$

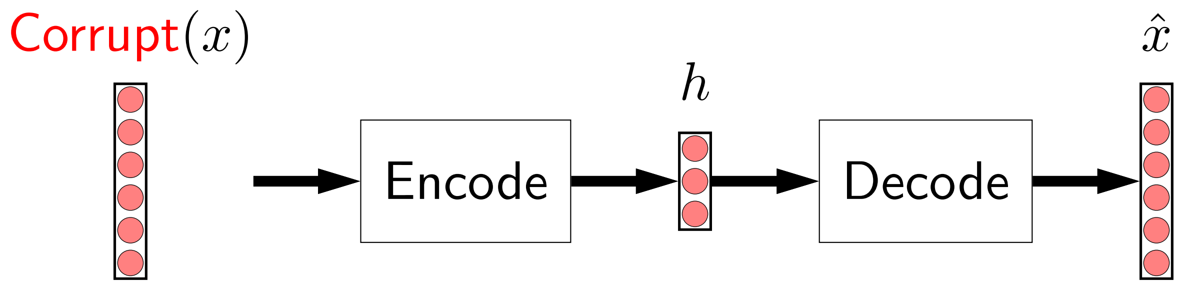


Loss function:

$$\text{minimize } \|x - \text{Decode}(\text{Encode}(x))\|^2$$

Key: Compressing h (e.g. low-dim, sparse) prevents identity

Denoising autoencoders



Types of noise:

- Blankout: Corrupt$([1,2,3,4]) = [0,2,3,0]$
- Gaussian: Corrupt$([1,2,3,4]) = [1.1, 1.9, 3.3, 4.2]$

Objective:

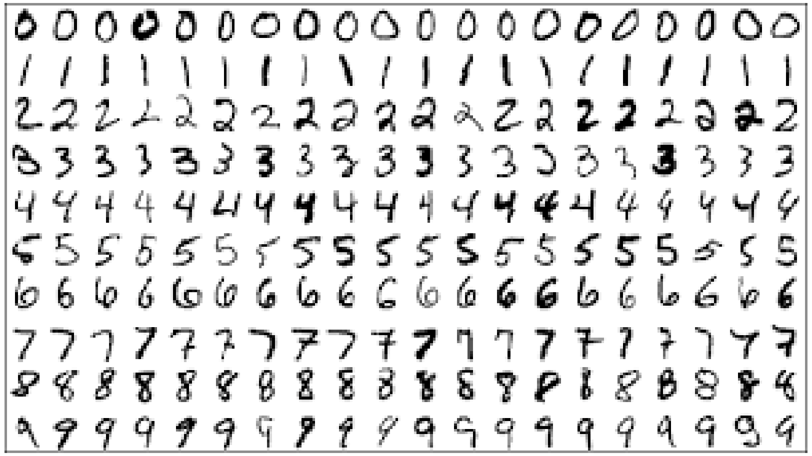
$$\text{minimize } \|x - \text{Decode}(\text{Encode}(\text{Corrupt}(x)))\|^2$$

Algorithm: pick example, add fresh noise, SGD update

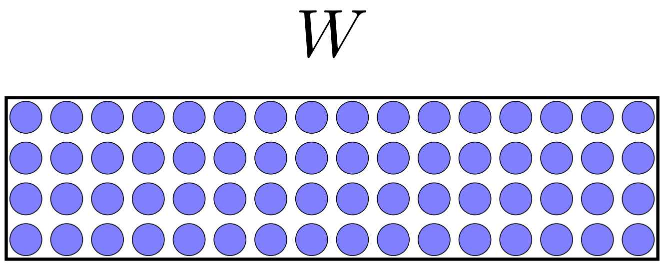
Key: noise makes life harder, identity function no longer good

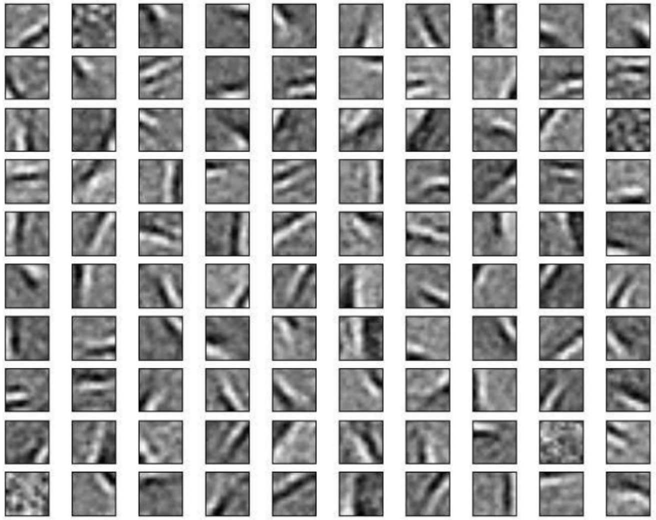
Denoising autoencoders

MNIST: 60,000 images of digits (784 dimensions)



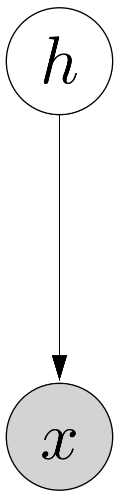
200 learned filters (rows of W):





Variational autoencoders

Motivation: learn a latent-variable model

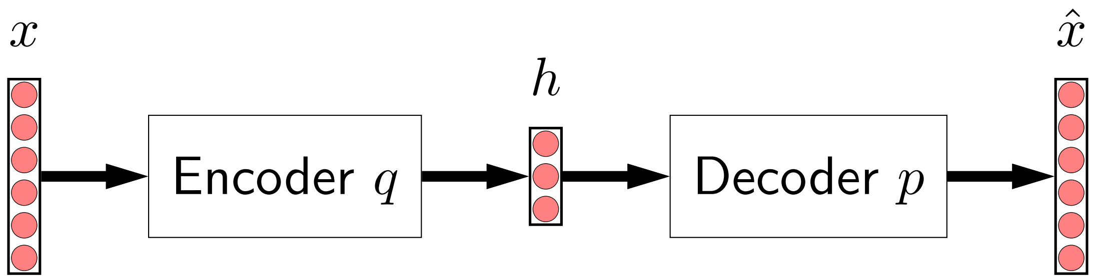


$$p(h, x) = p(h)p(x \mid h)$$

E-step in EM: computing $p(h \mid x)$ is intractable

Solution: approximate using a neural network $q(h \mid x)$

Variational autoencoders



Objective: maximize

$$\log p(x) \geq \mathbb{E}_{q(h|x)}[\log p(x \mid h)] - \mathsf{KL}(q(h \mid x)||p(h))$$

Algorithm:

- Sample h from encoder q, gradient update on q and p
- Reparametrization trick [Kingma/Welling, 2014]

Reading comprehension (SQuAD)

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called "showers".

What causes precipitation to fall?
gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
graupel

Where do water droplets collide with ice crystals to form precipitation?
within a cloud

100K examples

Raw text

Stanford University (officially **Leland Stanford Junior University**,[10] colloquially "the Farm") is a private research university in Stanford, California. Stanford is known for its academic strength, wealth, proximity to Silicon Valley, and ranking as one of the world's top universities.[11][12][13][14][15]

The university was founded in 1885 by Leland and Jane Stanford in memory of their only child, Leland Stanford Jr., who had died of typhoid fever at age 15 the previous year. Stanford was a U.S. Senator and former Governor of California who made his fortune as a railroad tycoon. The school admitted its first students on October 1, 1891,[2][3] as a coeducational and non-denominational institution.

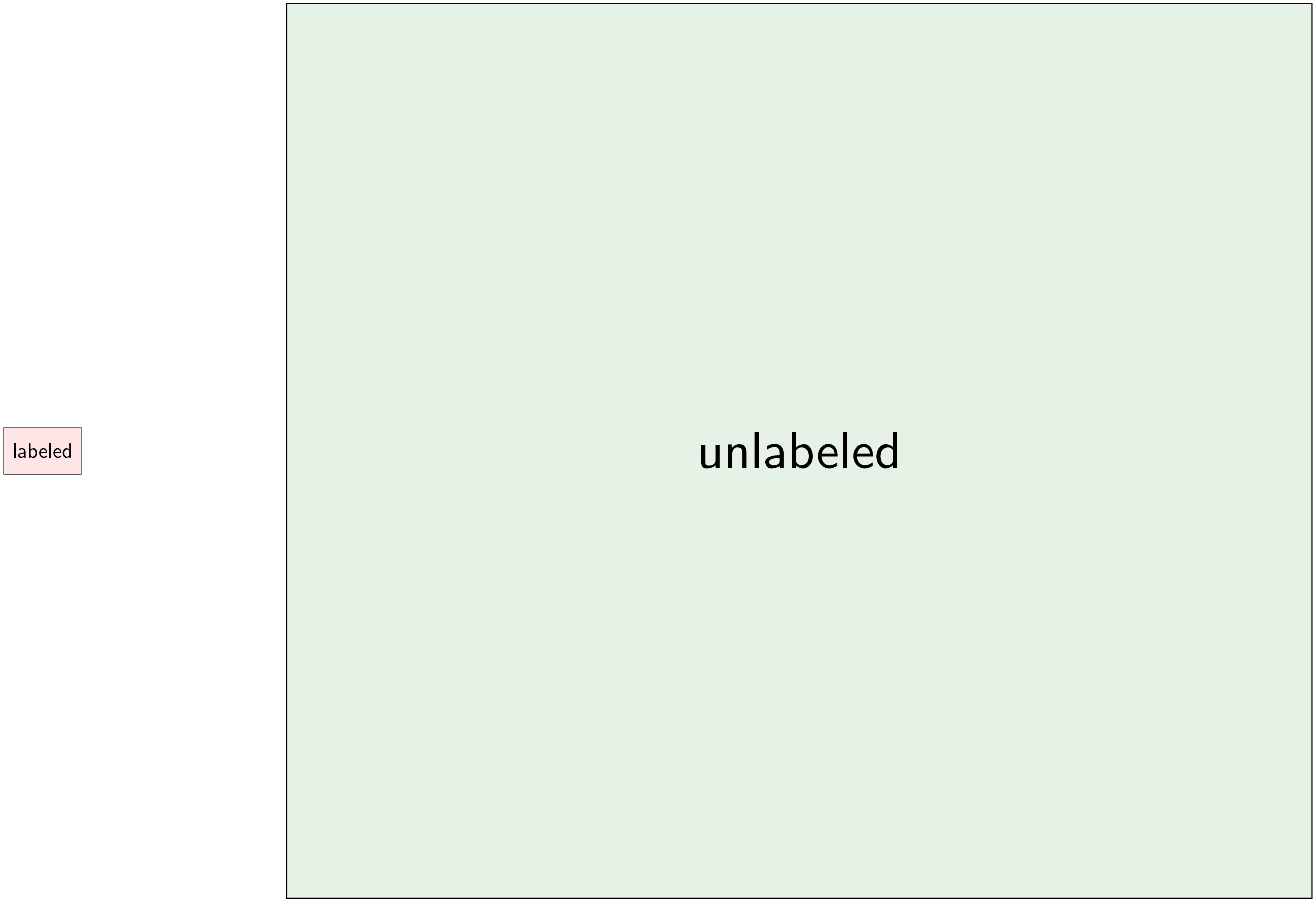
Stanford University struggled financially after the death of Leland Stanford in 1893 and again after much of the campus was damaged by the 1906 San Francisco earthquake.[16] Following World War II, Provost Frederick Terman supported faculty and graduates' entrepreneurialism to build self-sufficient local industry in what would later be known as Silicon Valley.[17] The university is also one of the top fundraising institutions in the country, becoming the first school to raise more than a billion dollars in a year.[18]

The university is organized around three traditional schools consisting of 40 academic departments at the undergraduate and graduate level and four professional schools that focus on graduate programs in Law, Medicine, Education and Business. Stanford's undergraduate program is one of the top three most selective in the United States by acceptance rate.[19][20][21][22][23] Students compete in 36 varsity sports, and the university is one of two private institutions in the Division I FBS Pac-12 Conference. It has gained 117 NCAA team championships,[24] the most for a university. Stanford athletes have won 512 individual championships,[25] and Stanford has won the NACDA Directors' Cup for 23 consecutive years, beginning in 1994–1995.[26] In addition, Stanford students and alumni have won 270 Olympic medals including 139 gold medals.[27]

...

3.3 billion words

Unsupervised pre-training



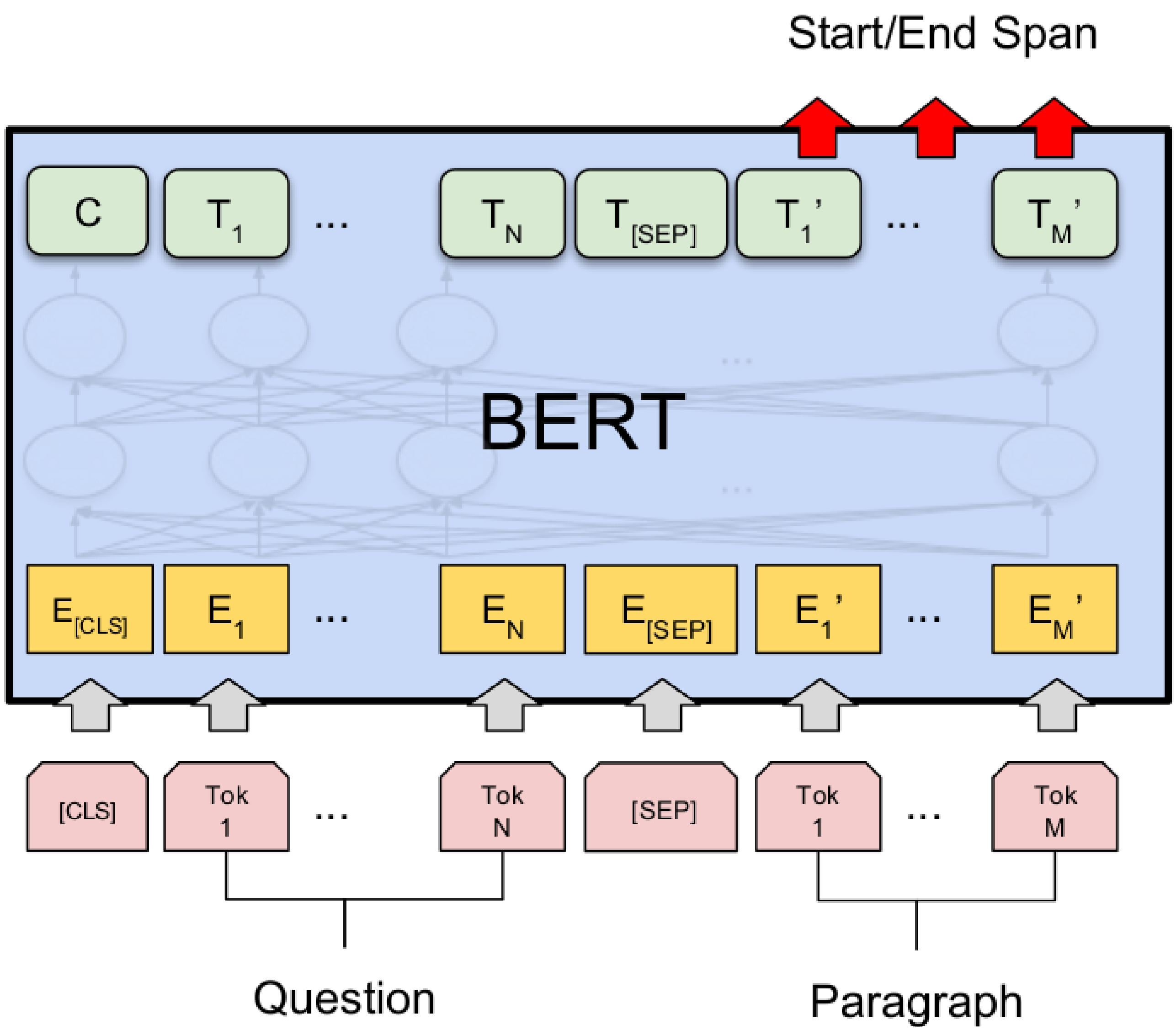
BERT

Paris Talks ___ Stage for _____ as Risks to ___ Climate Rise

Paris Talks Set Stage for Action as Risks to the Climate Rise

- Tasks: fill in words, predict whether is next sentence
- Trained on 3.3B words, 4 days on 64 TPUs

BERT


Start/End Span
C
T1
...
TN
T[SEP]
T1'
TM'
BERT
E[CLS]
E1
EN
E[SEP]
E1'
EM'
[CLS]
Tok 1
Tok N
[SEP]
Tok 1
Tok M
Question
Paragraph

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar et al. '16)	82.304	91.221
1 Oct 05, 2018	BERT (ensemble) *Google A.I.*	**87.433**	**93.160**
2 Oct 05, 2018	BERT (single model) *Google A.I.*	85.083	91.835
2 Sep 09, 2018	nlnet (ensemble) *Microsoft Research Asia*	85.356	91.202
2 Sep 26, 2018	nlnet (ensemble) *Microsoft Research Asia*	85.954	91.677
3 Jul 11, 2018	QANet (ensemble) *Google Brain & CMU*	84.454	90.490
4 Jul 08, 2018	r-net (ensemble) *Microsoft Research Asia*	84.003	90.147
5 Mar 19, 2018	QANet (ensemble) *Google Brain & CMU*	83.877	89.737
5 Sep 09, 2018	nlnet (single model) *Microsoft Research Asia*	83.468	90.133
5 Jun 20, 2018	MARS (ensemble) *YUANFUDAO research NLP*	83.982	89.796
6 Sep 01, 2018	MARS (single model) *YUANFUDAO research NLP*	83.185	89.547

Unsupervised learning

- Principle: make up prediction tasks (e.g., x given x or context)
- Hard task $\rightarrow$ pressure to learn something
- Loss minimzation using SGD
- Discriminatively fine tune: initialize feedforward neural network and backpropagate to optimize task accuracy
- How far can one push this?

Roadmap

Feedforward neural networks

Convolutional networks

Sequence models

Unsupervised learning

Final remarks

Getting things to work

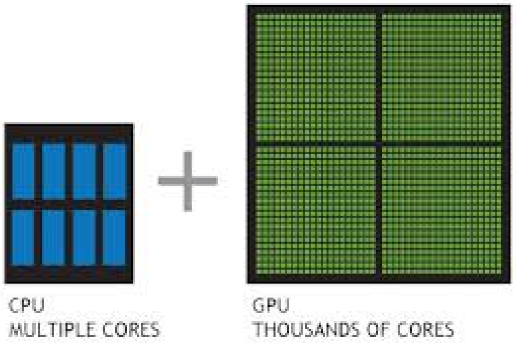
Better optimization algorithms: SGD, SGD+momentum, AdaGrad, AdaDelta, momentum, Nesterov, Adam

Tricks: initialization, gradient clipping, batch normalization, dropout

More hyperparameter tuning: step sizes, architectures

More data: larger, broader datasets

Better hardware: GPUs, TPUs



...wait for a long time...

Theory: why does it work?

Two questions:

- Approximation: why are neural networks good hypothesis classes?
- Optimization: why can SGD optimize a high-dimensional non-convex problem?

Partial answers:

- 1-layer neural networks can approximate any continuous function on compact set [Cybenko, 1989; Barron, 1993]
- Generate random features works too [Rahimi/Recht, 2009; Andoni et. al, 2014]
- Use statistical physics to analyze loss surfaces [Choromanska et al., 2014]

Summary

Phenomena	Ideas
Fixed vectors	Feedforward NNs
Spatial structure	convolutional NNs
Sequence	recurrent NNs LSTMs
Sequence-to-sequence	encoder-decoder attention-based models
Unsupervised	autoencoders variational autoencoders any auxiliary task

Outlook

Extensibility: able to compose modules

LSTM | Attend | Encode

Learning programs: think about analogy with a computer

$$x \rightarrow \boxed{f_\theta} \rightarrow y$$