

Deep Learning Theory and Applications

Yale

CPSC/AMTH 663





Outline

1. Course logistics
2. What is Deep Learning?
3. Deep learning examples
 - CNNs
 - Word embeddings
 - RNNs
 - Autoencoders
 - Ultra deep learning (ResNet)
 - Generative models (e.g. GANs)
 - Deep reinforcement learning



Course Logistics

- Textbooks (available online)
 - Neural Networks and Deep Learning by Michael Nielsen
 - Deep Learning by Goodfellow, Bengio, and Courville
- Required background
 - Basic probability
 - Basic linear algebra & calculus
 - Programming experience
 - Python and Tensorflow will be used in this course
 - Look at the textbooks and HW 1 for an idea
- Canvas
 - Lectures posted after class
 - Announcements & HW



Course Logistics

- Office hours:
 - **Instructor Office Hours:** Tuesdays and Thursdays 2:00-3:30 pm AKW 104
 - **TA Office Hours:** Mondays and Wednesdays 12:00-1:30 pm AKW 407
- 5-6 HW assignments
 - Assigned about every 2 weeks, due on Thursdays
 - All/most will include some programming (Python & Tensorflow)
- Final project (details forthcoming)
 - In groups of 3-4



Goals of the Course

- A solid understanding of supervised feedforward neural networks
 - Stochastic gradient descent, backpropagation, etc.
 - Cost functions, regularizers, etc.
- The ability to design and train novel architectures
- An understanding of optimization strategies in training deep architectures
- Understanding of important deep architectures (e.g. CNN, RNN, autoencoders, GANs, deep reinforcement learning)



What is deep learning?

- Class of machine learning algorithms that use multiple levels of non-linear processing units in order to perform supervised or unsupervised analysis of data
 - Different levels contain different features of the data
 - Different levels contain different representations of the same data
- In this class we will learn only about the large class of deep artificial neural networks, loosely inspired by computation in the brain
 - Deep belief networks, logic circuits are also “deep learning”



Machine Learning

- Field of study that gives computers the ability to learn without being explicitly programmed
- Usually parameters of a selected models are fitted via optimization
- Model is selected to be not too complex and not too simple (overfit vs underfit)



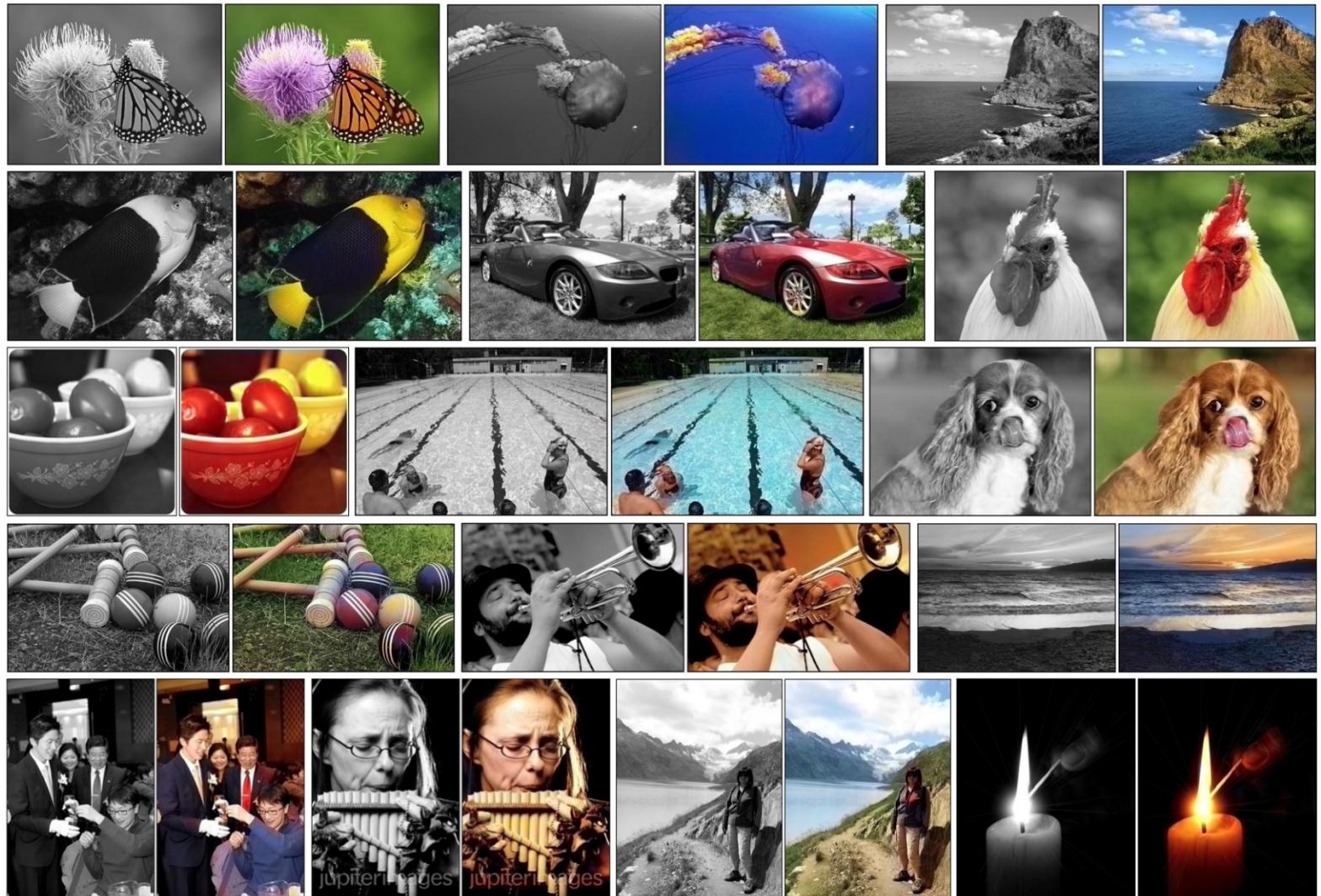
Artificial Neural Networks

- A computing system made up of simple, interconnected processing elements that process information by their dynamic state response to external inputs
- Loosely inspired by neural computation, hence processing elements are called “neurons”
- Trained with instead of programmed
- Capacity to encode vast array of functions and learn makes them capable of learning complicated functions of inputs amenable to various tasks



Image Colorization

(Zhang et al., 2016)



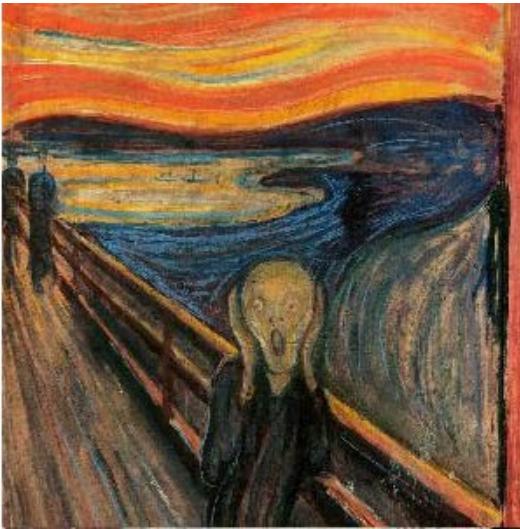


Style Transfer

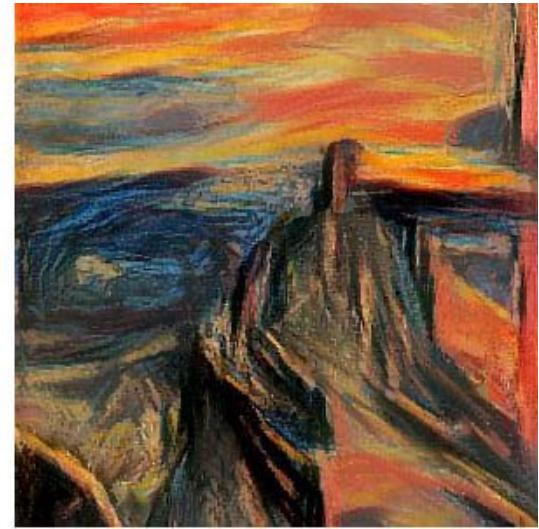
(Gatys et al., 2015)



+



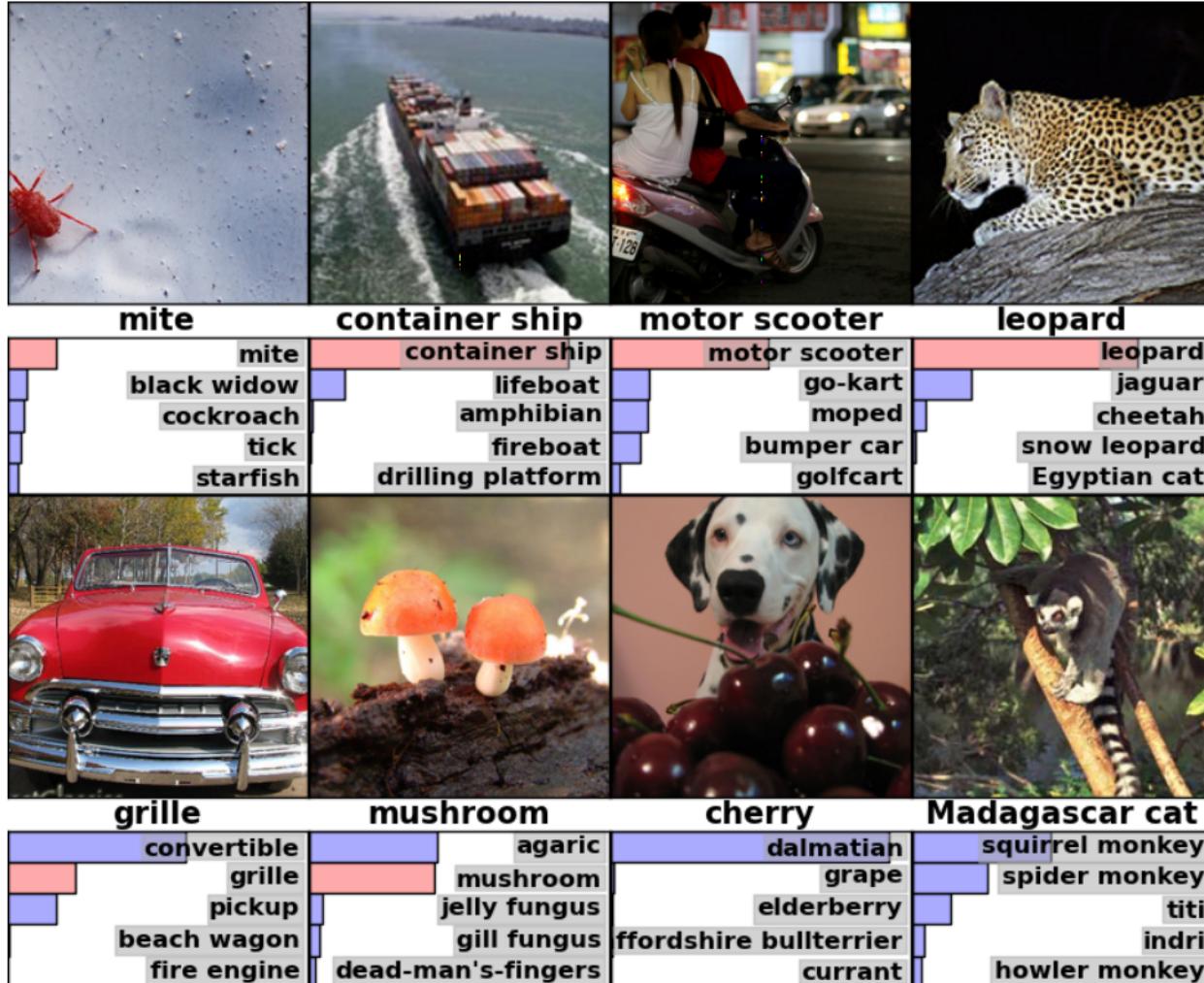
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Object Detection

(Krizhevsky et al., 2012)





Text Generation

(Andrej Karpathy blog, 2015)

PANDARUS:

Alas, I think he shall be come approached and the day
When little strain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:

They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:

Well, your wit is in the care of side and that.

Second Lord:

They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:

Come, sir, I will make did behold your worship.

VIOLA:

I'll drink it.



Image Captioning

(Karpathy & Fei-Fei, 2015)



"man in black shirt is playing guitar."



"construction worker in orange safety vest is working on road."



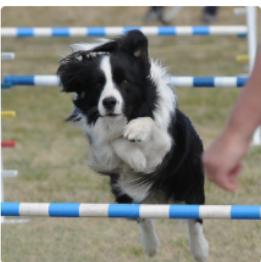
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"black and white dog jumps over bar."



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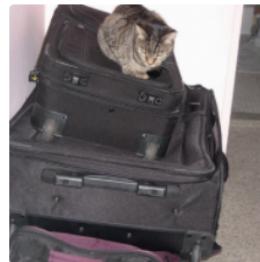
"little girl is eating piece of cake."



"baseball player is throwing ball in game."



"woman is holding bunch of bananas."



"black cat is sitting on top of suitcase."



Deep Reinforcement

Alpha Go Zero

nature
International journal of science

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Article

Mastering the game of Go without human knowledge

David Silver , Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, Yutian Chen, Timothy Lillicrap, Fan Hui, Laurent Sifre, George van den Driessche, Thore Graepel & Demis Hassabis

Nature 550, 354–359 (19 October 2017)
doi:10.1038/nature24270
[Download Citation](#)
[Computational science](#) [Computer science](#) [Reward](#)

Received: 07 April 2017
Accepted: 13 September 2017
Published online: 18 October 2017

Alpha Zero

[arXiv.org](#) > cs > arXiv:1712.01815

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Computer Science > Artificial Intelligence

Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm

David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, Timothy Lillicrap, Karen Simonyan, Demis Hassabis

(Submitted on 5 Dec 2017)

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Subjects: Artificial Intelligence (cs.AI); Learning (cs.LG)
Cite as: [arXiv:1712.01815 \[cs.AI\]](#)
(or [arXiv:1712.01815v1 \[cs.AI\]](#) for this version)

Submission history

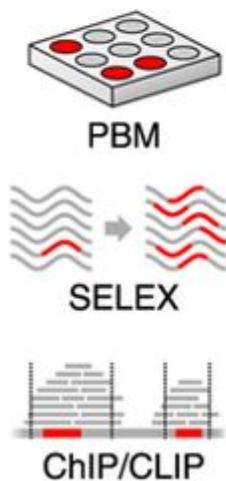
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[v1] Tue, 5 Dec 2017 18:45:38 GMT (272kb,D)



Genomics: Enhancer Binding

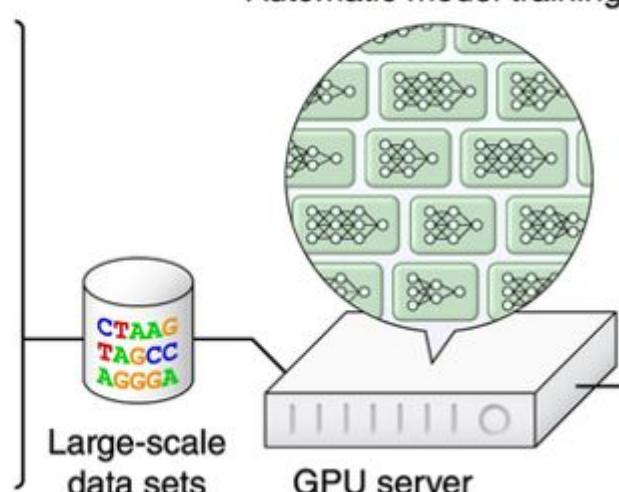
(Alipanahi et al. 2015)

1. High-throughput experiments

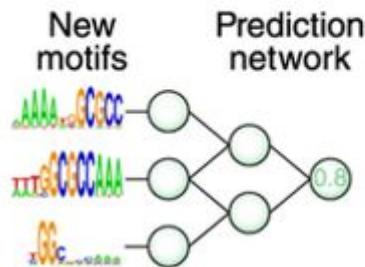


2. Massively parallel deep learning

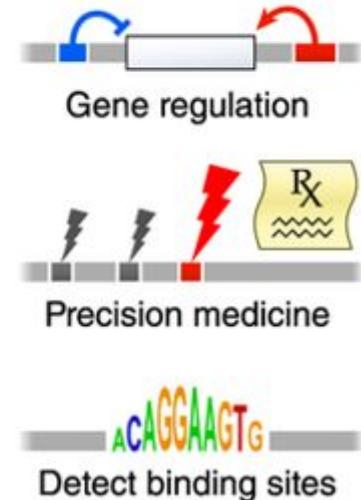
Automatic model training



Prediction network



3. Community needs

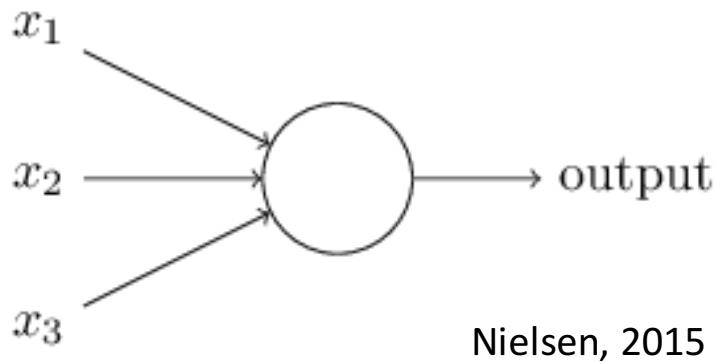


What is a neural
network?



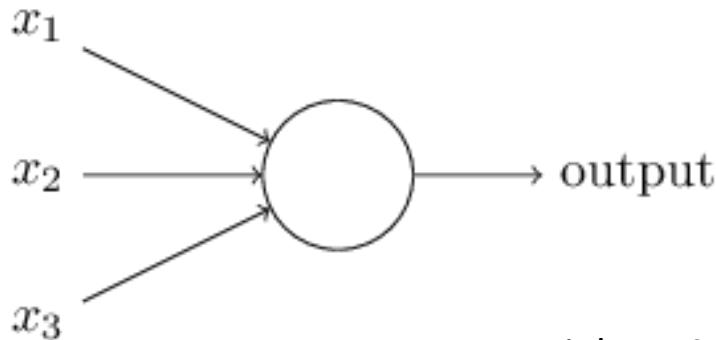
The perceptron

- Developed in 1950's and 1960's by Frank Rosenblatt
- Binary inputs
- Single binary output
- Example:





The perceptron



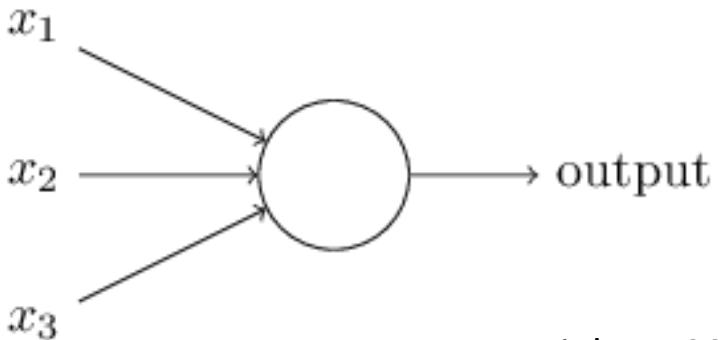
Nielsen, 2015

- Computing the output:
 - Assign weights to each input
 - Determine if weighted sum of inputs is greater than some threshold

$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{threshold} \end{cases}$$



The perceptron



Nielsen, 2015

- Example: Decide whether to attend a cheese festival
- Three factors:
 1. Is the weather good? x_1
 2. Does your friend want to accompany you? x_2
 3. Is the festival near public transit? (you don't own a car) x_3

$$x_j = \begin{cases} 0, & \text{if no} \\ 1, & \text{if yes} \end{cases}$$



The perceptron

- Example: Decide whether to attend a cheese festival
- Three factors:
 1. Is the weather good? x_1
 2. Does your friend want to accompany you? x_2
 3. Is the festival near public transit? (you don't own a car) x_3
- **Case 1:** Love cheese but hate bad weather
 - $w_1 = 6$
 - $w_2 = 2$
 - $w_3 = 2$
 - Threshold= 5
 - $\sum_j w_j x_j > \text{threshold}$ whenever weather is **good** ($x_1 = 1$)
 - $\sum_j w_j x_j < \text{threshold}$ whenever weather is **bad** ($x_1 = 0$)



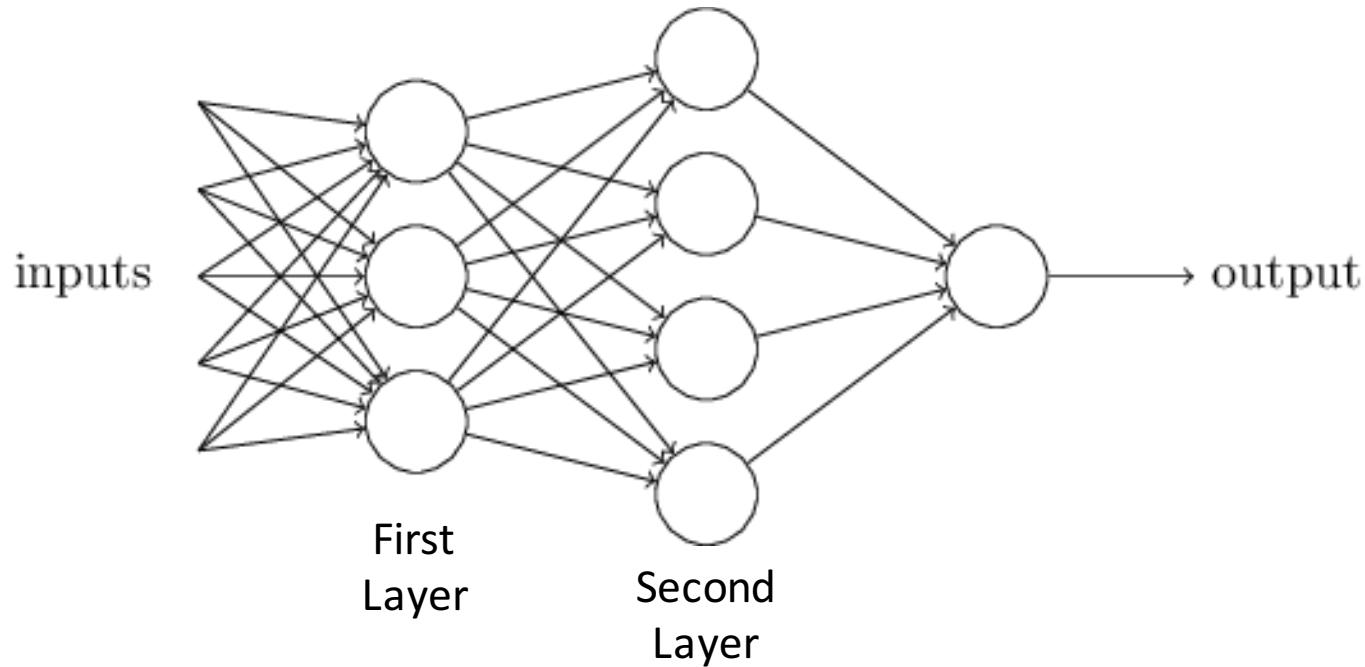
The perceptron

- Example: Decide whether to attend a cheese festival
- Three factors:
 1. Is the weather good? x_1
 2. Does your friend want to accompany you? x_2
 3. Is the festival near public transit? (you don't own a car) x_3
- **Case 2:** Love cheese but don't hate bad weather as much
 - $w_1 = 6$
 - $w_2 = 2$
 - $w_3 = 2$
 - Threshold= 3
 - $\sum_j w_j x_j > \text{threshold}$ whenever weather is **good** ($x_1 = 1$) *or* friend will go ($x_2 = 1$) *and* when the festival is near public transit ($x_3 = 1$)



The multilayer perceptron (MLP)

- A single perceptron is pretty simple
- A complex network of perceptrons can make subtle decisions





Notation Simplification

- $w \cdot x = \sum_j w_j x_j$
 - w and x are the weight and input vectors, respectively
- Replace the threshold with perceptron *bias*
 - Bias $b = -\text{threshold}$

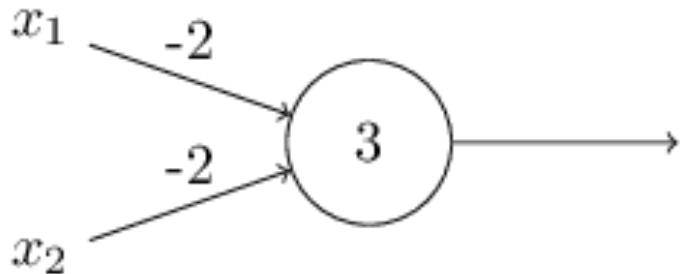
$$\text{output} = \begin{cases} 0 & \text{if } w \cdot x + b \leq 0 \\ 1 & \text{if } w \cdot x + b > 0 \end{cases}$$

- Bias is a measure of ease in *firing* the perceptron



Logic circuits with perceptrons

- $w_1, w_2 = -2, b = 3$



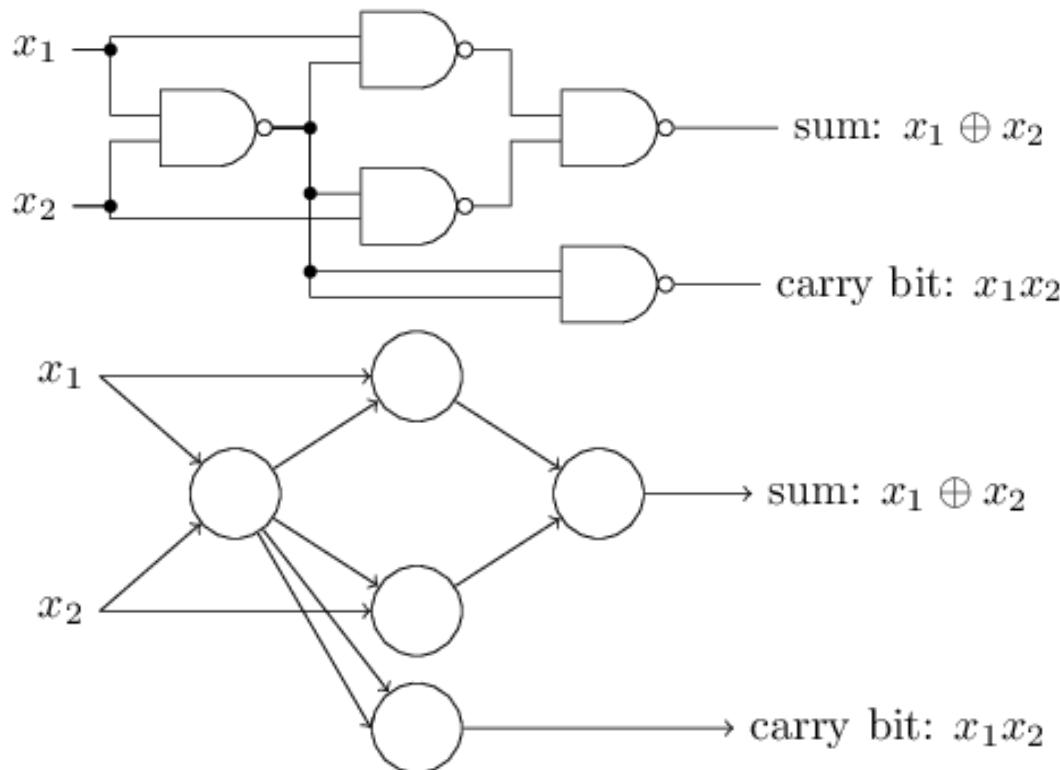
Nielsen, 2015

- What is the output of this perceptron for each possible input?
- What logic circuit is this?
- Input 00 produces 1
- Input 01 or 10 produce 1
- Input 11 produces 0
- This is a NAND gate!



Logic circuits with perceptrons

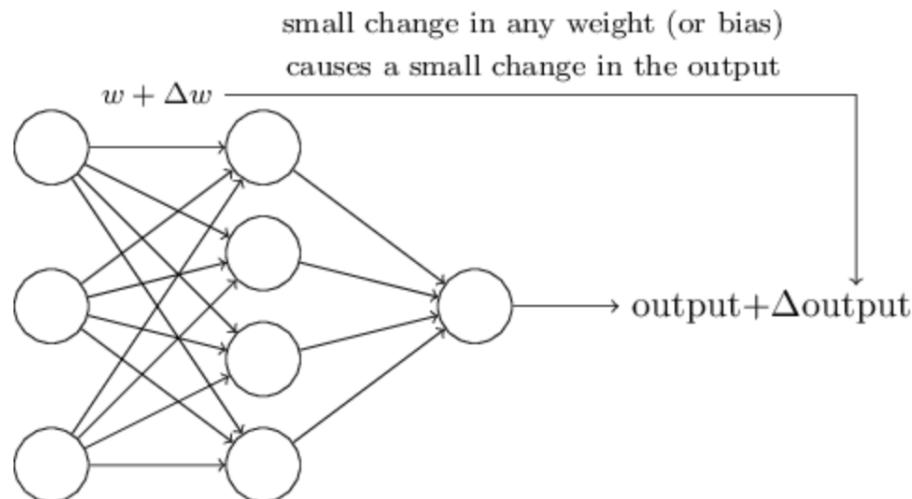
- NAND gates are universal for computation
 - Any computation can be built from NAND gates
 - Therefore, perceptrons are universal for computation
- Bitwise addition:





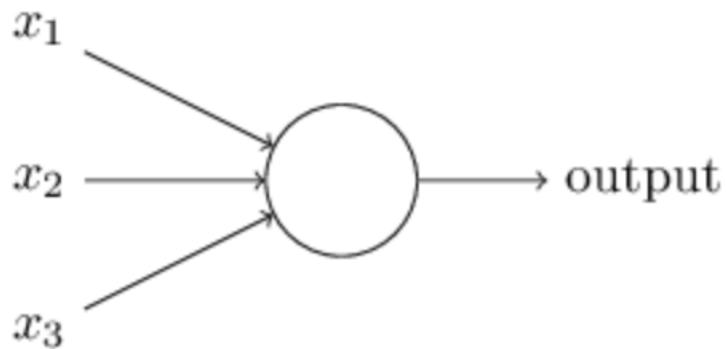
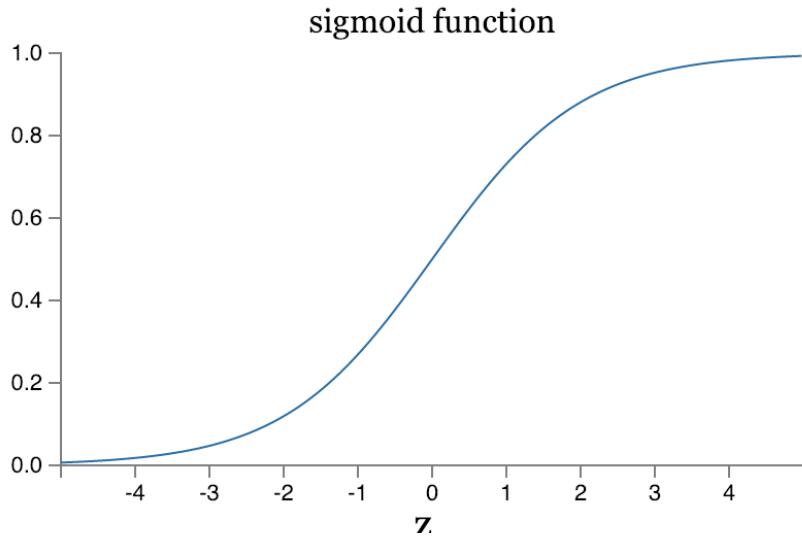
Problem with Logical Functions

- Hard to “tune” in a traditional sense
- Small change in weight can lead to large changes in conditions (or no change at all)
 - Think the volume knob in your car behaving this way
- For this to happen we need neurons to perform a continuous *differentiable* function





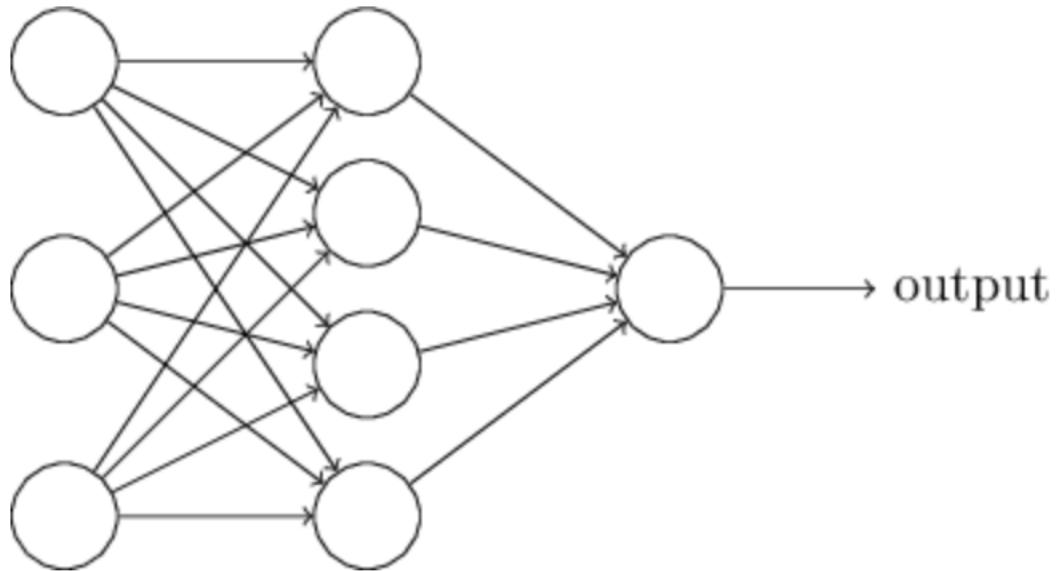
Sigmoidal Neuron



$$\frac{1}{1 + \exp(-\sum_j w_j x_j - b)}$$



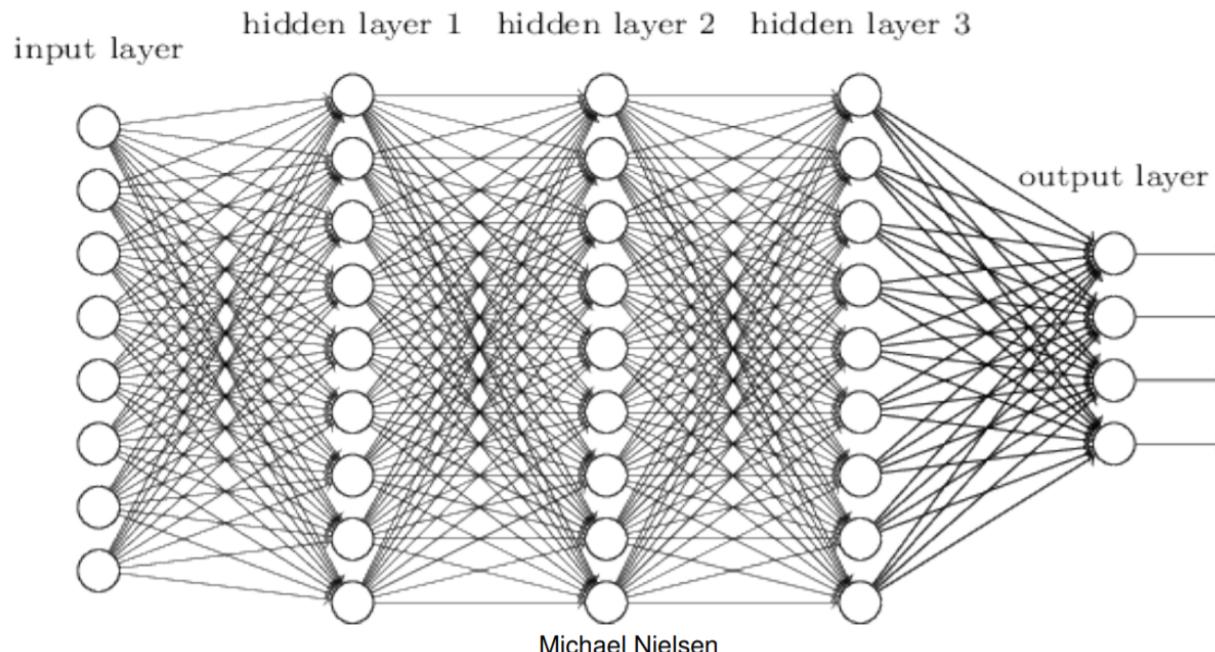
Multi-layers of Neurons





Differentiable Computing

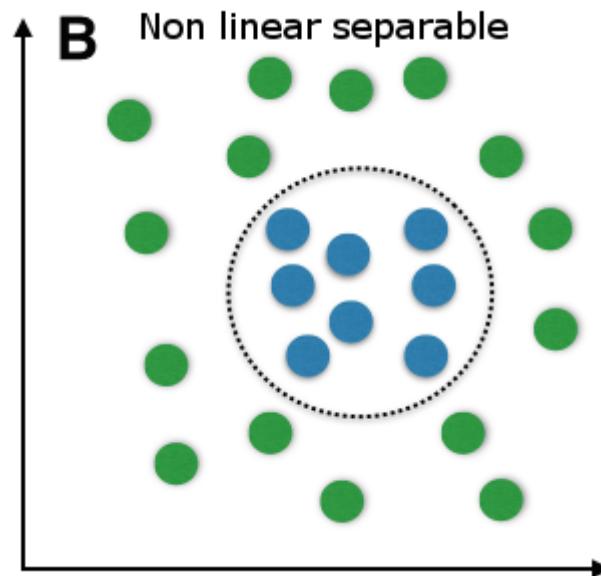
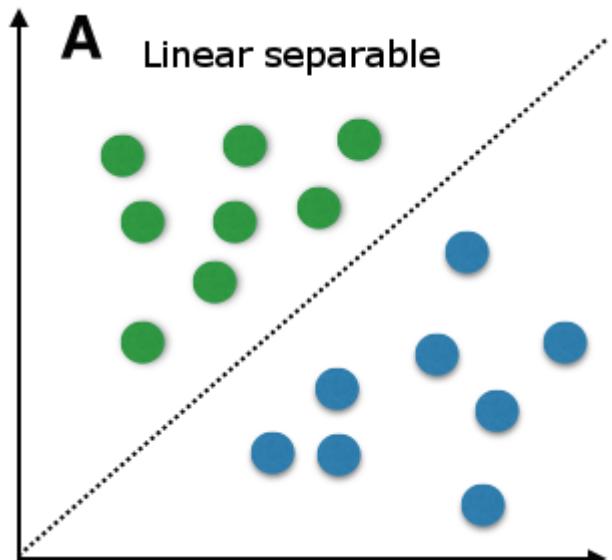
- We can create *learning algorithms* that automatically tune the weights and biases with *Gradient Descent*
 - Tuning occurs in response to external stimuli and w/o direct intervention
 - Creates a circuit designed for the problem at hand





Why go deep?

Depth = complexity

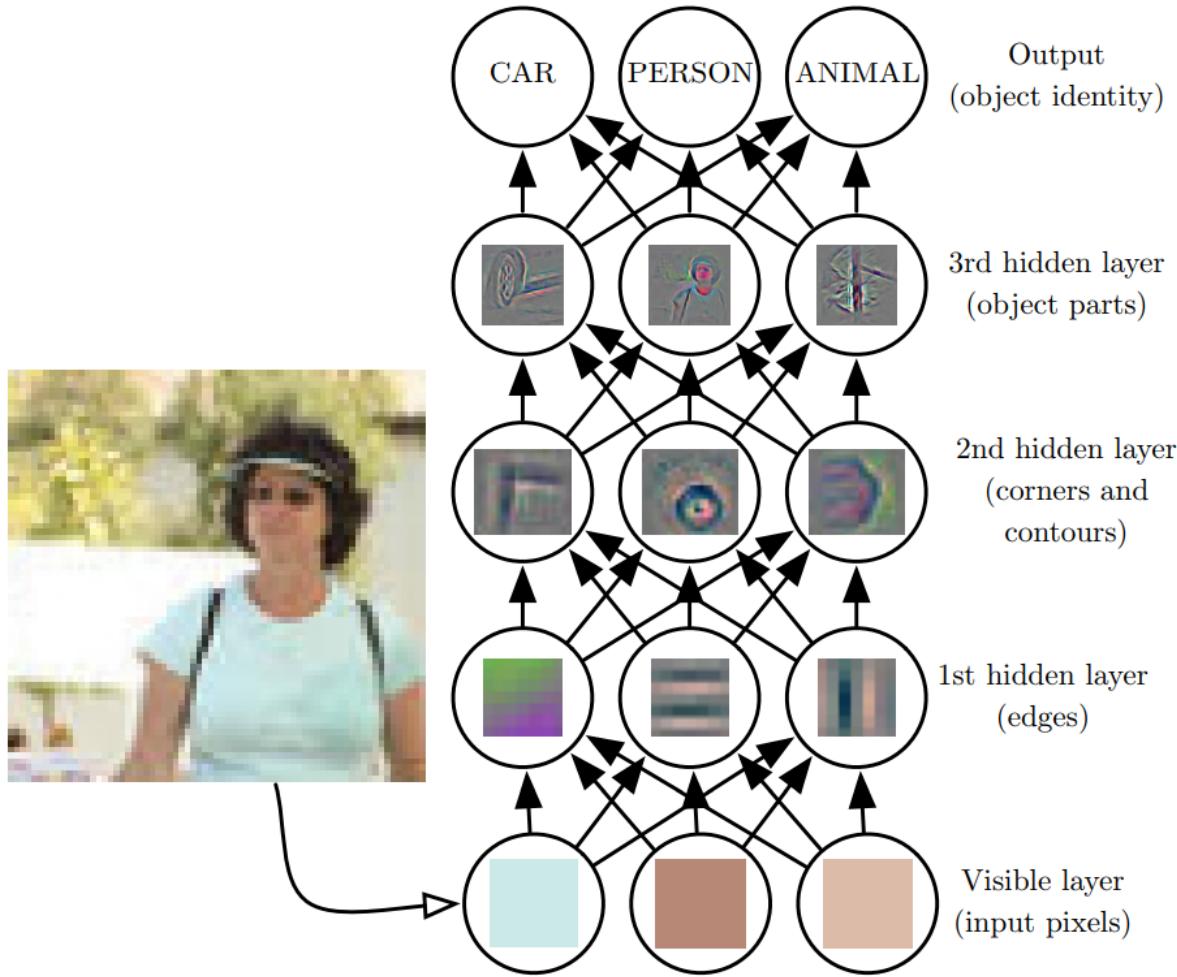


Single layer perceptrons can only handle linear separability



Why go deep?

Representations matter

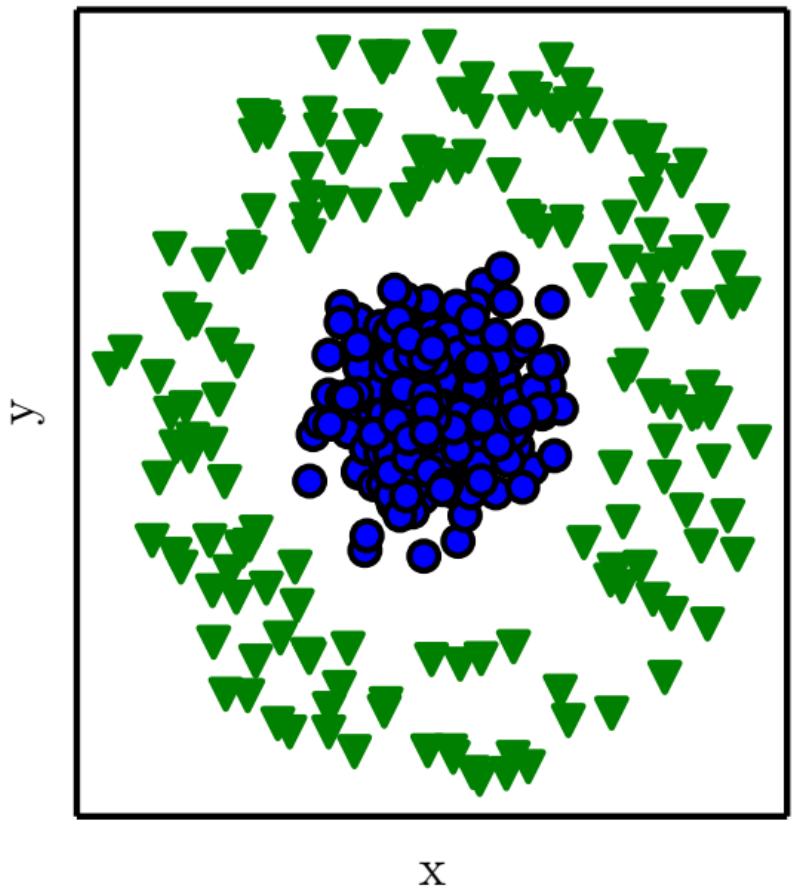


Goodfellow et al., 2016

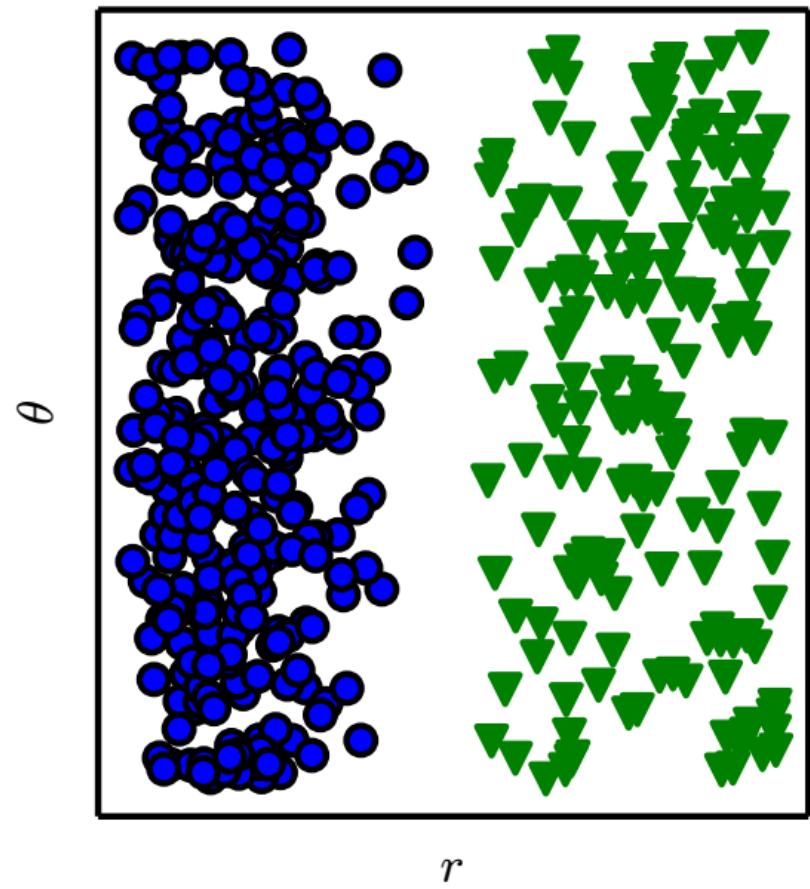


Representations matter

Cartesian coordinates



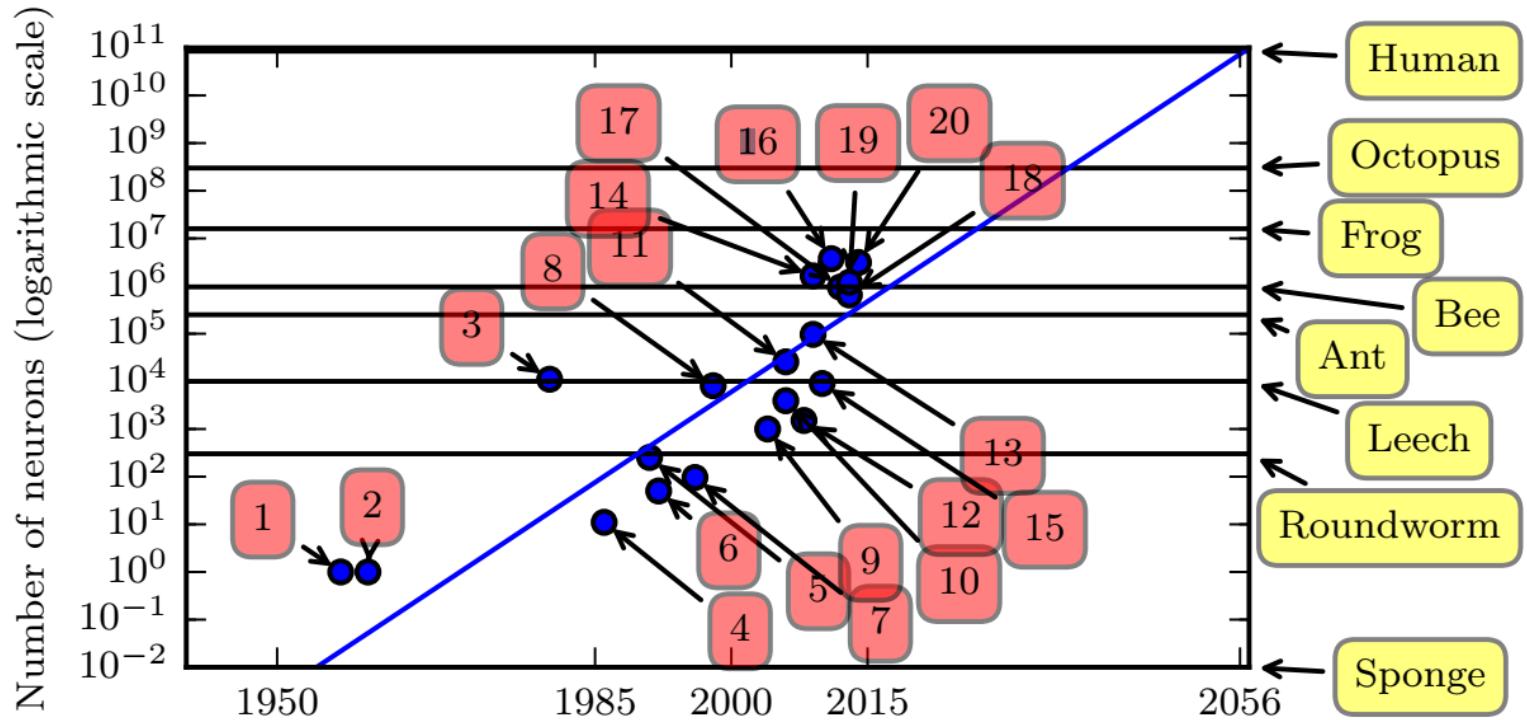
Polar coordinates



Goodfellow et al., 2016



Increasing # of neurons



1. Perceptron (Rosenblatt, 1958)

Goodfellow et al., 2016

4. Early backpropagation network

6. MLP for speech recognition (Bengio et al, 1991)

11. GPU-accelerated convolutional network (Challeapilla et al., 2006)

20. GoogLeNet (Szegedy et al., 2014a)



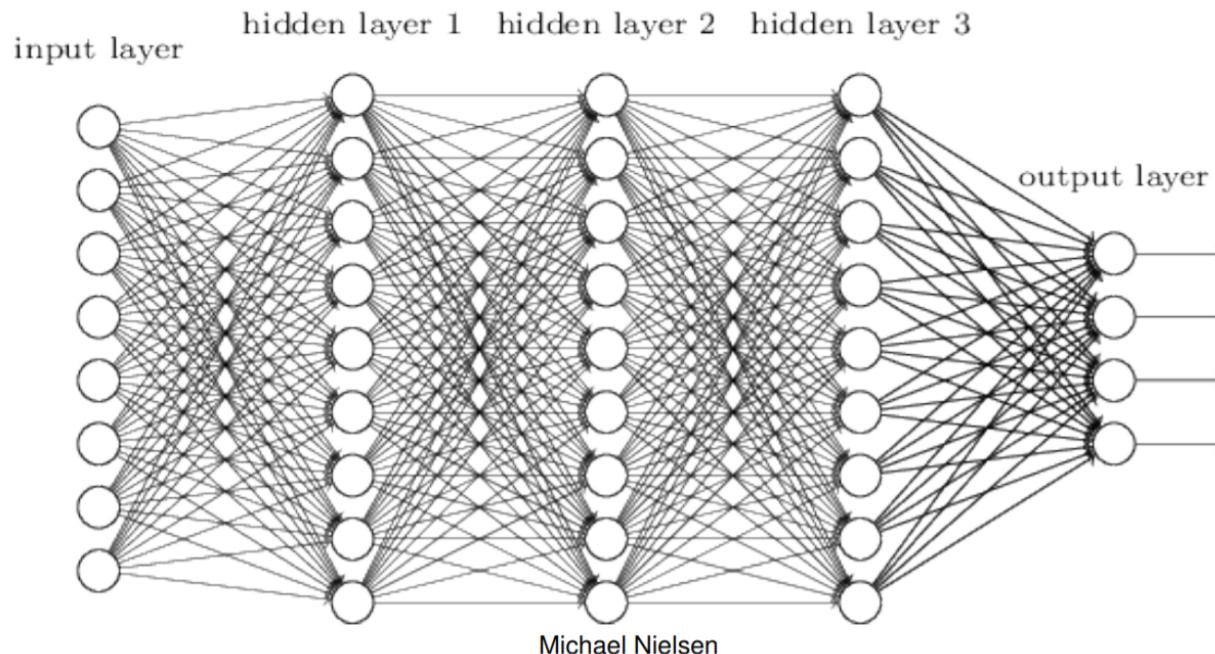
Design choices for an ANN

- Learning algorithms
 - Backpropagation
 - Stochastic gradient descent (SGD)
- Activation function (e.g. threshold)
- Cost functions
- Number and dimension of layers
- Connections between layers
- Regularizations
 - Layers
 - Batches
- More...



Fully connected network

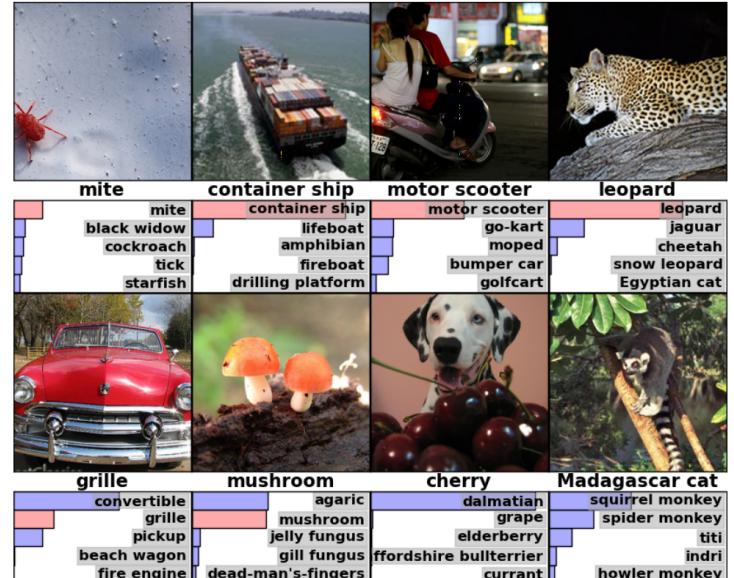
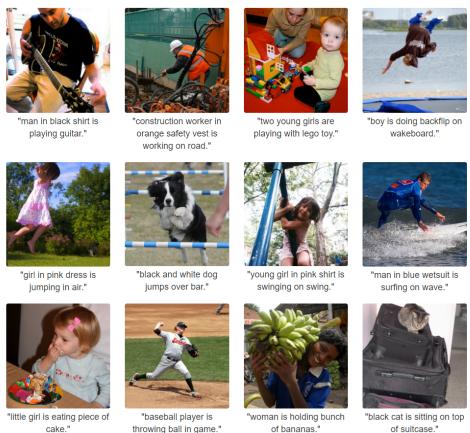
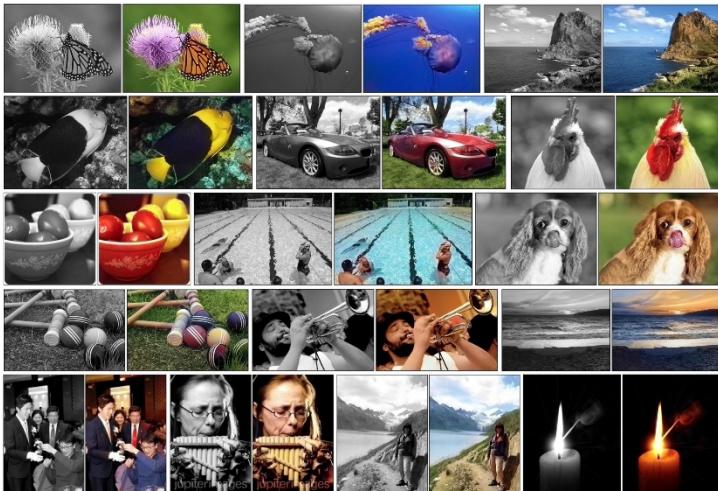
- Every feature interacts with every other feature
- Weight matrix at every level allowed to be dense





Convolutional Neural Networks (CNNs)

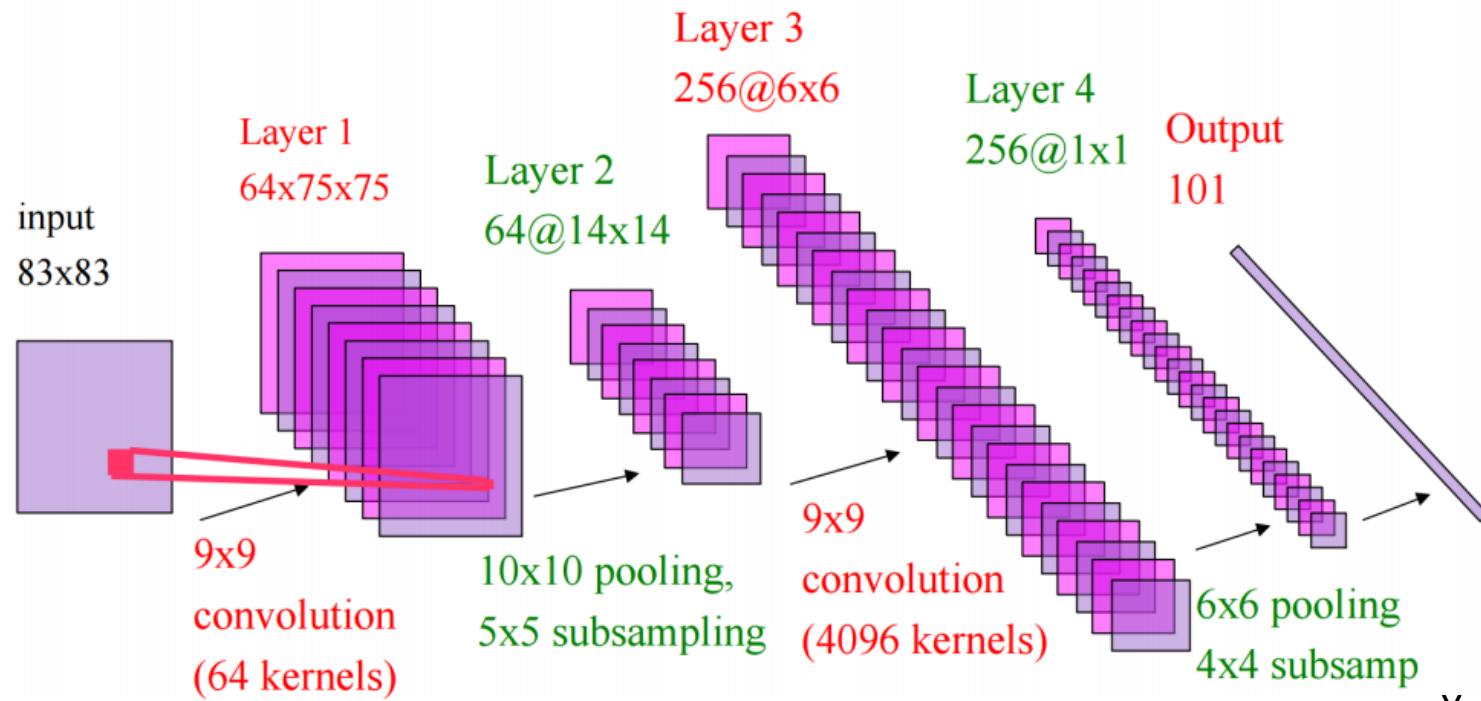
- Very successful in images





Convolutional Neural Networks (CNNs)

- Only pixels that are close to each other in the image interact with each other (convolution layer)
- Weight matrices are highly structured
- “Pooling” helps to simplify output of convolution layer

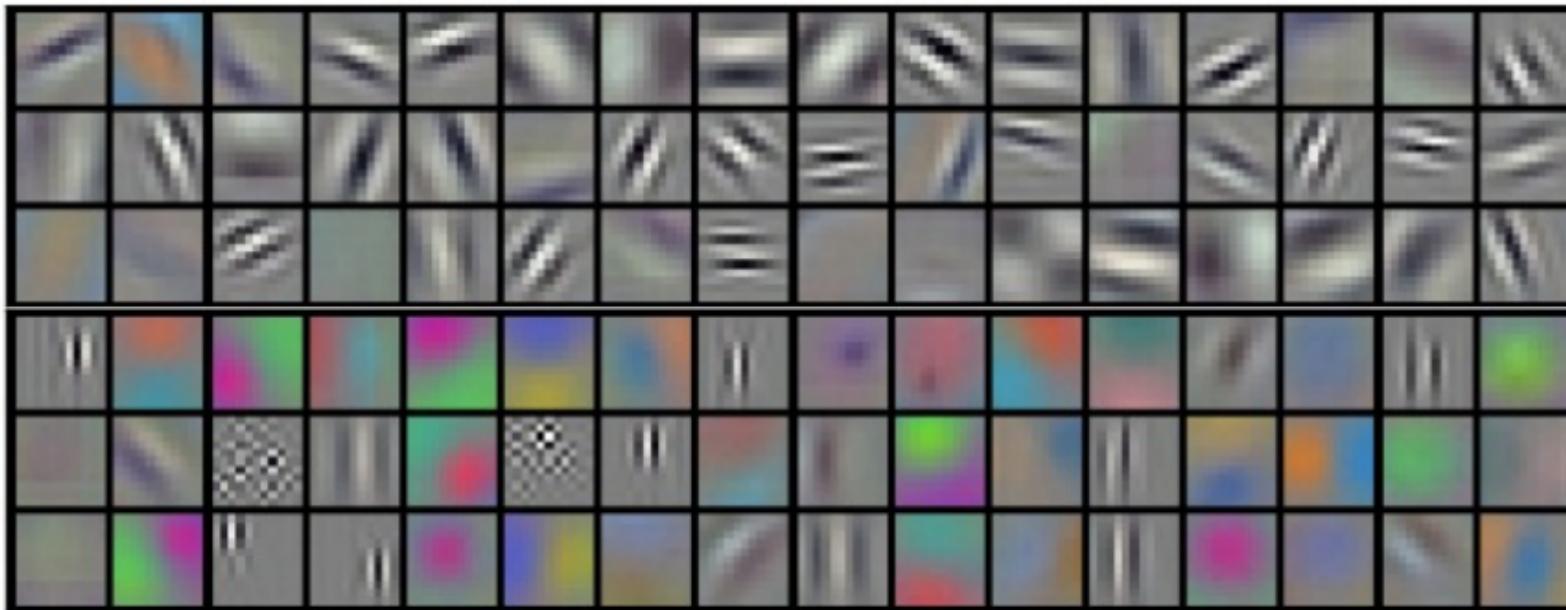


Yann LeCun



Convolutional Neural Networks (CNNs)

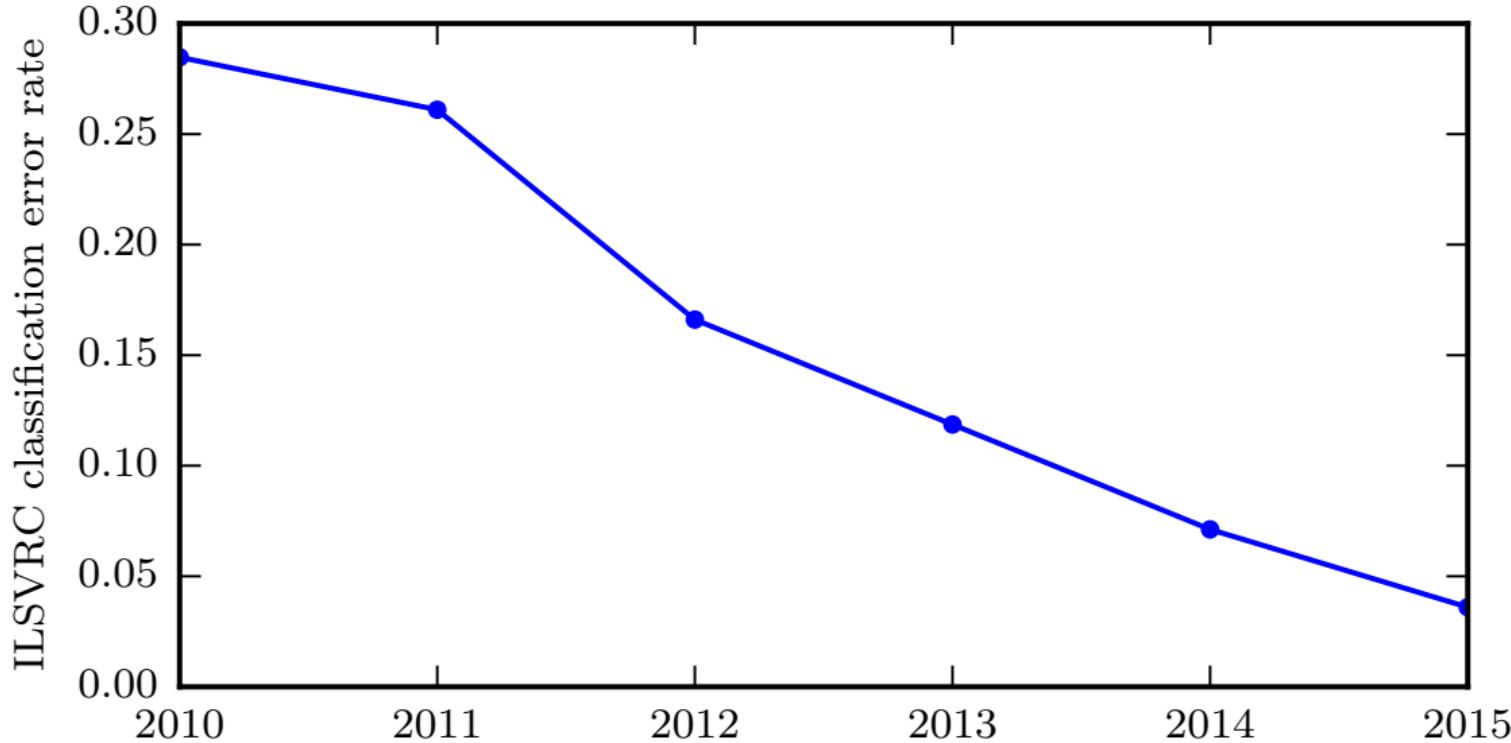
- Weights from the first layer tend to look like directional filters after training
 - Detects edges, color change, etc.



CS 231n, Karpathy



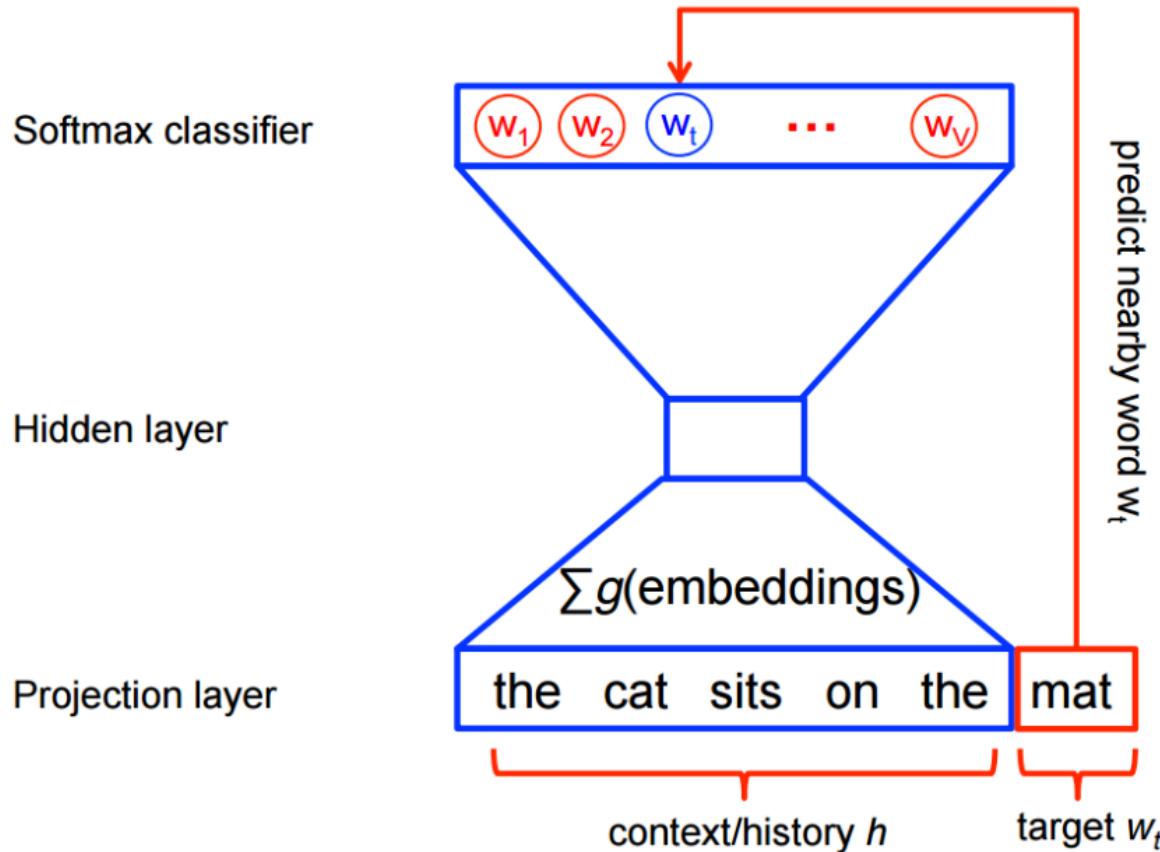
Convolutional Neural Networks (CNNs)





Word2Vec

- Organization of words via neural networks
- Next word in a sentence can be predicted based on organization





Recurrent Neural Networks (RNNs)

- Useful when time is important



"man in black shirt is playing guitar."



"construction worker in orange safety vest is working on road."



"two young girls are playing with lego toy."



"boy is doing backflip on wakeboard."



"girl in pink dress is jumping in air."



"black and white dog jumps over bar."



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VIOLA:

I'll drink it.

Mörk

Mörk → Dark

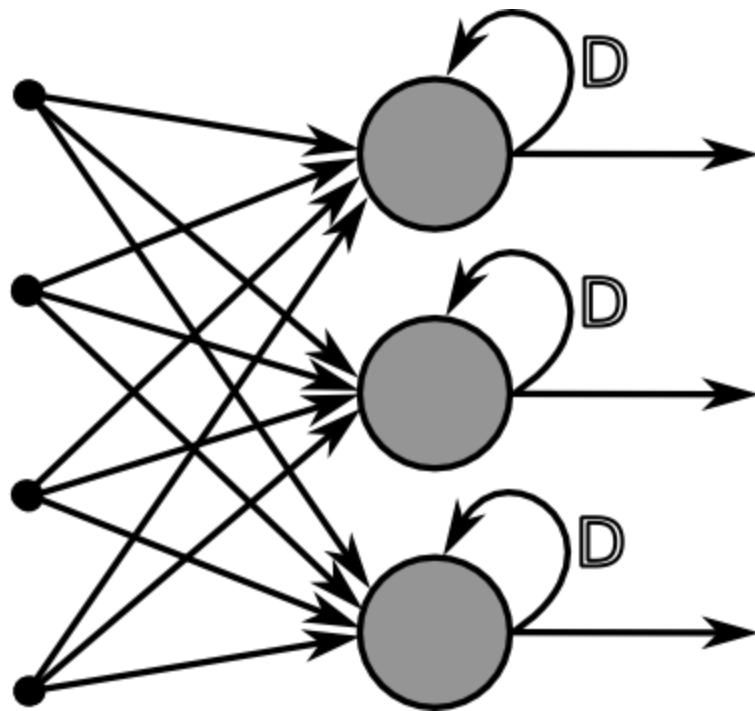


Recurrent Neural Networks (RNNs)

- In feedforward nets (everything we've considered so far), activations of later layers are completely determined by the input
- RNNs allow the hidden layers to be affected by activations at earlier times (i.e. feedback)
 - E.g. a neuron's activation may include as input its activation at an earlier time
 - Cycles are now included in the network
- This time-varying behavior make RNNs useful for analyzing data that change over time (e.g. speech)
- Training can be difficult for long-term dependencies



Fully Recurrent Network

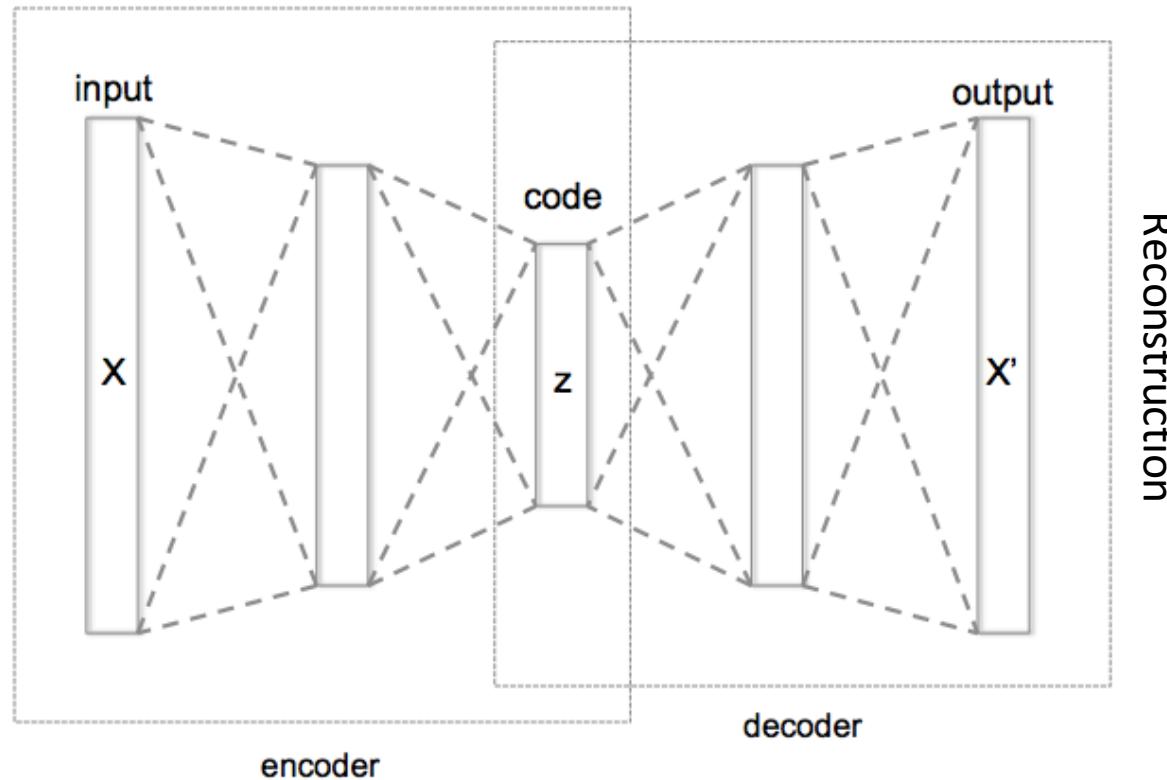




Autoencoders

- Attempts to compress the data and then reconstruct the input

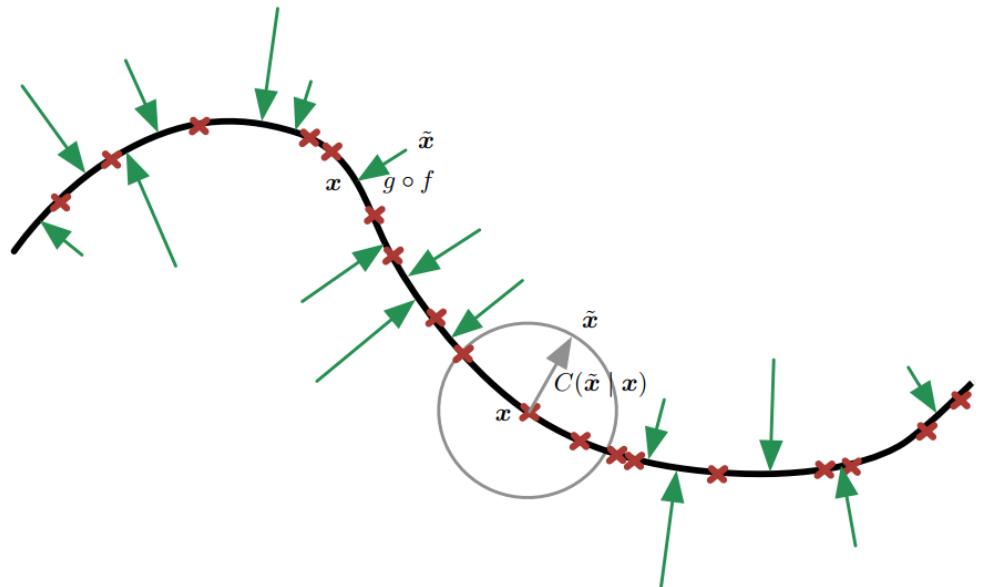
“Bottleneck” layer





Autoencoder Applications

- Pretraining
- Dimensionality reduction
 - Information retrieval
 - Denoising
 - Data compression
- Generative modeling
- Batch correction

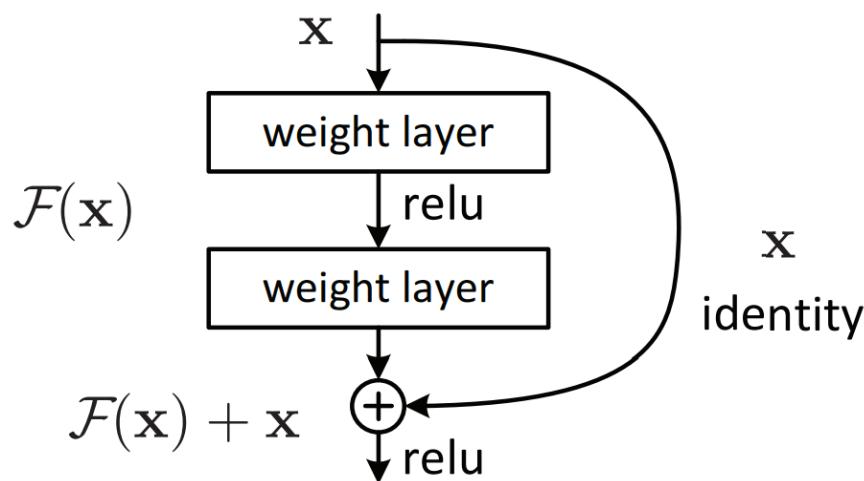


Goodfellow et al., 2016



Ultra Deep Learning (e.g. ResNet)

- Very deep neural nets are difficult to train
 - Accuracy can degrade with deeper networks
- ResNet developed a framework to address this degradation
 - Successfully trained a 152 layer network
 - Won the ILSVRC 2015 image classification task





Generative Models

- Create a map from random noise into distribution of training data to generate samples
- Generative Adversarial Net (GAN)
 - Generative model is pitted against an discriminative model that determines whether a sample is from the model or the data
 - Improves both generation and discrimination



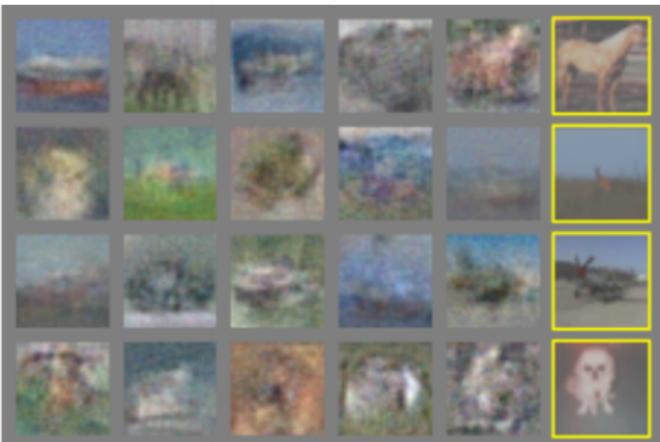
Generative Models



a)



b)



c)



d)

Goodfellow



Deep Reinforcement Learning

Alpha Go Zero

nature
International Journal of science

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Article

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Alpha Zero

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Computer Science > Artificial Intelligence

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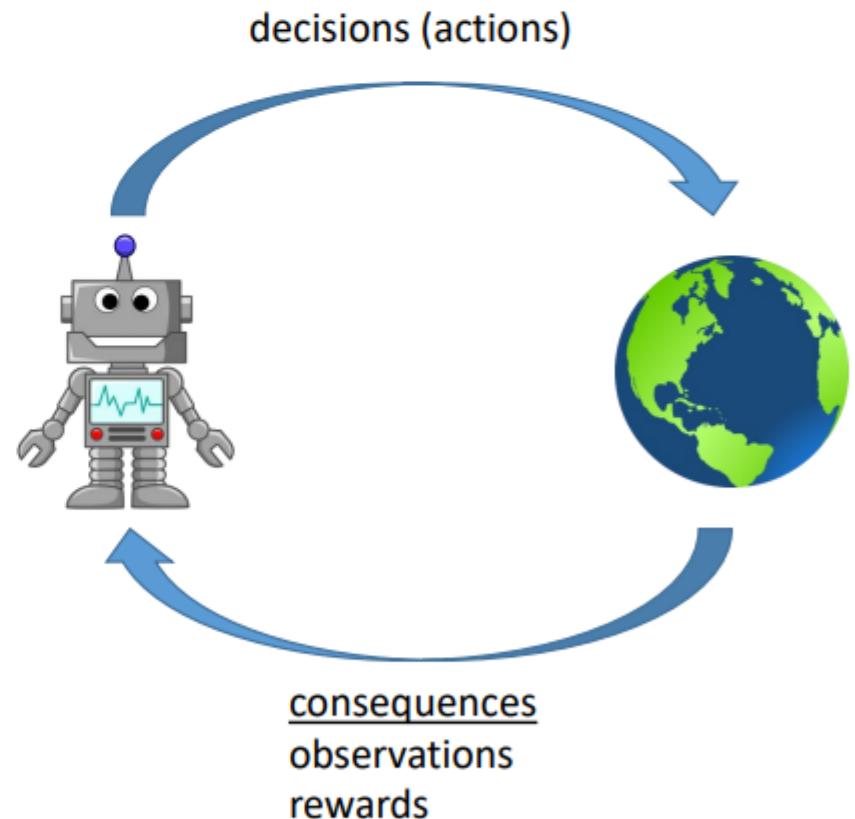
Submission history

From: David Silver [[view email](#)]
[v1] Tue, 5 Dec 2017 18:45:38 GMT (272kb,D)



Deep Reinforcement Learning

- What is reinforcement learning?





Deep Reinforcement Learning

- Examples



Actions: muscle contractions
Observations: sight, smell
Rewards: food



Actions: motor current or torque
Observations: camera images
Rewards: task success measure
(e.g., running speed)



Actions: what to purchase
Observations: inventory levels
Rewards: profit



Further reading

- Nielsen, Chapter 1
- Goodfellow et al., Chapter 1