Introduction to Deep learning: an historical perspective

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github.com/StephaneCanu/Deep_learning_lecture

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October 31

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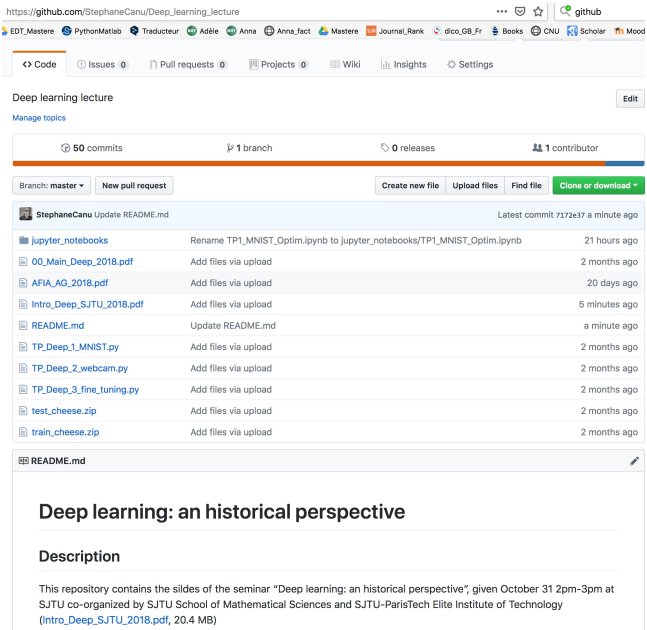
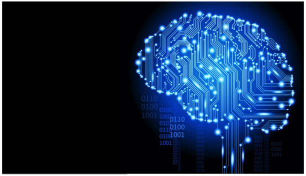
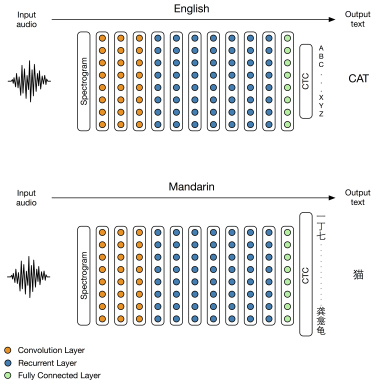


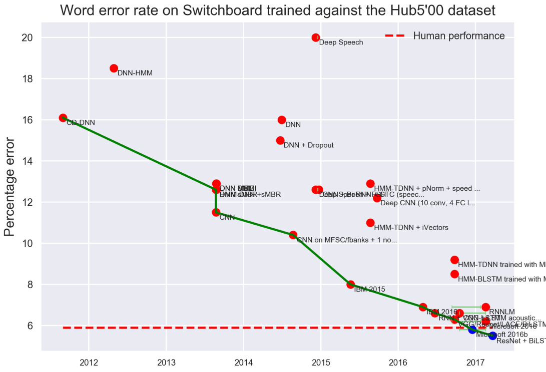
Road map

1. Why deep learning?
2. The first stage: 1890 - 1969
3. The second stage: 1985 - 1995
4. The third stage: 2006 - (2012) - 2018...
5. What's new in deep learning?
   - Big is beautiful
   - Two Hot topics: data and architecture
6. Conclusion



Deep learning for turning text into speech (and vice versa)



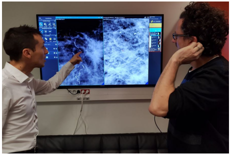


Baidu deep speech 2 (2015) and Deep voice (2017)

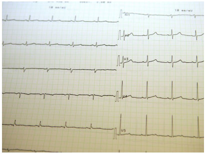
Trained on 9,400 hours of labeled audio with 11 million utterances.

Deep learning for healthcare

Skin cancer classification
130 000 training images
validation error rate : 28 % (human 34 %)



the Digital Mammography DREAM Challenge
640 000 mammographies (1209 participants)
5 % less false positive



heart rate analysis
500 000 ECG
precision 92.6 % (humain 80.0 %) sensitivity 97 %

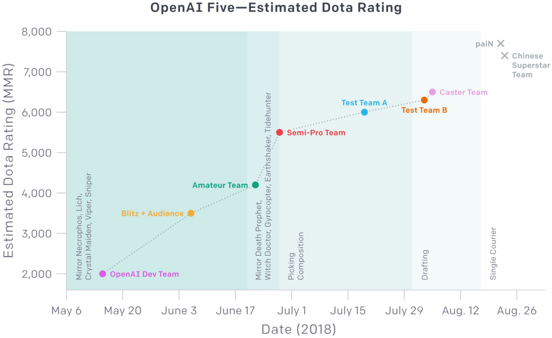
Statistical machine learning: retrieving correlations

with deep learning end-to-end architecture
"April showers bring May flowers"

Deep learning success in playing GO

Mastering the game of Go without human knowledge D. Silver et al. Nature, 550, 2017

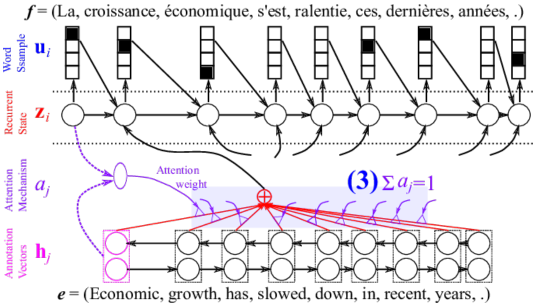
Deep learning progresses in playing Dota 2



- separate LSTM for each hero
- 180 years/days of games against itself
- Proximal Policy Optimization
- 256 GPUs and 128,000 CPU
- the OpenAI Five is very much still a work in progress project

`https://blog.openai.com/the-international-2018-results/`

Deep learning (limited) success in NLP

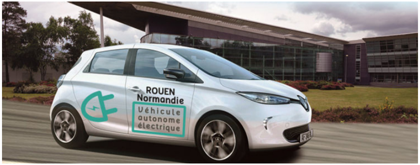


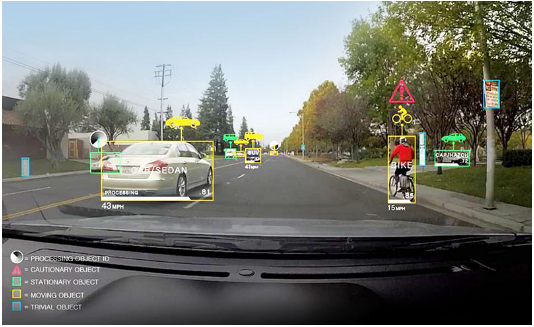
Learning to translate with 36 million sentences

- Near Human-Level Performance in Grammatical Error Correction
- Achieving Human Parity on Automatic News Translation

https://devblogs.nvidia.com/author/kcho/

Deep learning to drive: the Rouen autonomous lab





Driving Video Database = 100.000 videos – 120 million images

- When It Comes to Safety, Autonomous Cars Are Still "Teen Drivers"
- companies are developing many different levels of automation

https://www.rouennormandyautonomouslab.com/?lang=en
http://bdd-data.berkeley.edu

So far, so good

- Deep learning allow real progress
  - low level perception tasks: image, audio, NLP, playing
- It requires
  - Big data (training vs learning)
  - big computers
  - specific tasks

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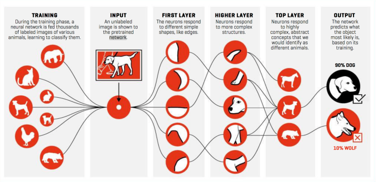


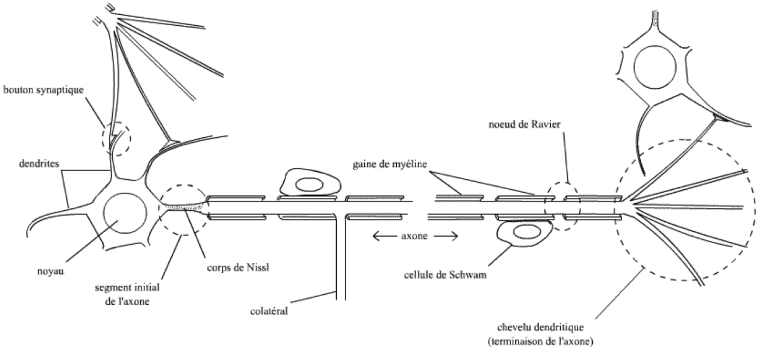
The neural networks time line

- The first stage: 1890 - 1969

$\sim$1890 Ramón y Cajal: the biological neuron
1943 McCulloch & Pitts formal neuron
1949 Hebb's rule
1958 Rosenblatt's Perceptron: learning with stochastic gradient
1969 Minsky & Papert: stop – the 1st NN winter

- The second stage: 1985 - 1995
- The third stage: 2006 - (2012) - 2018...

The biological neuron



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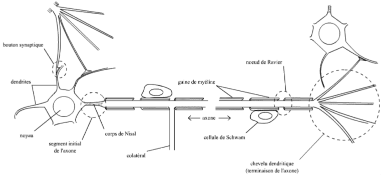
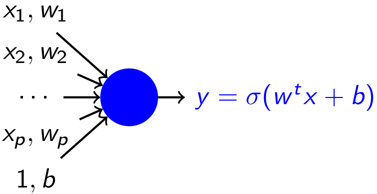
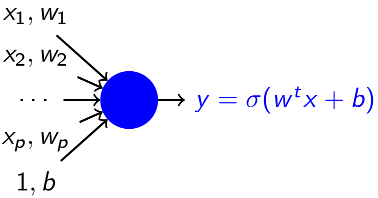
McCulloch & Pitts formal neuron 1943

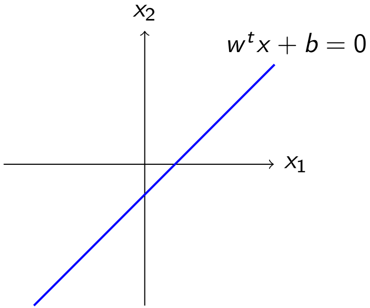




- x input $\in \mathbb{R}^p$
- w weight, b bias
- σ activation function
- y output $\in \mathbb{R}$

The artificial neuron as a linear threshold unit





- x input $\in \mathbb{R}^p$
- w weight, b bias
- a activation, $a = w^t x + b$
- σ activation function
- Φ transfer function
- y output $\in \mathbb{R}$

σ activation function (non linear)

$$\begin{array}{ccc} \mathbb{R} & \mapsto & \mathbb{R} \\ a & \rightarrow & y = \sigma(a) \end{array}$$

Φ transfer function

$$\begin{array}{ccc} \mathbb{R}^p & \mapsto & \mathbb{R} \\ \mathbf{x} & \rightarrow & y = \Phi(\mathbf{x}) = \sigma(w^t x + b) \end{array}$$

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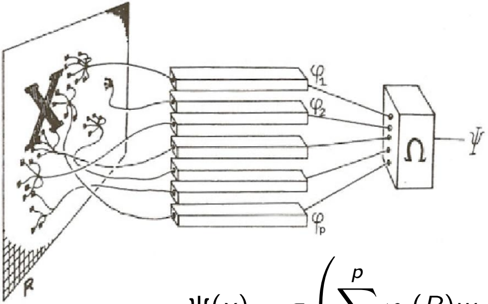
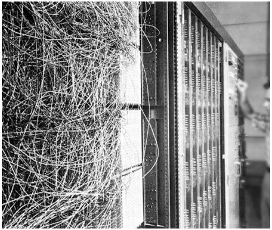
The formal neuron as a learning machine: fit the w





$$\Psi(x) = \sigma\left(\sum_{j=1}^{p} \varphi_j(R) w_j + b\right)$$

Rosenblatt's Perceptron, 1958 (Widrow & Hoff's Adaline, 1960)

given n pairs of input–output data $\mathbf{x}_i = \varphi_j(R_i), t_i, i = 1, n$

find w such that $\underbrace{\sigma(\mathrm{w}^t \mathbf{x}_i)}_{\text{prediction of the model}} = \underbrace{t_i}_{\text{ground truth}}$

Cost minimization (energy-based model)

Minimize a loss $\quad \min_{\mathrm{w} \in \mathbb{R}^{p+1}} \sum_{i=1}^{n} \textit{loss}(\mathrm{w}) \quad \textit{loss}(\mathrm{w}) = \big(\sigma(\mathrm{w}^t \mathbf{x}_i) - t_i\big)^2$

Gradient descent $\quad \mathrm{w} \leftarrow \mathrm{w} - \rho \mathbf{d} \quad \mathbf{d} = \sum_{i=1}^{n} \nabla_{\mathrm{w}} \textit{loss}(\mathrm{w})$

Stochastic gradient $\quad \mathbf{d} = \nabla_{\mathrm{w}} \textit{loss}(\mathrm{w})$

Algorithm 1 Gradient epoch

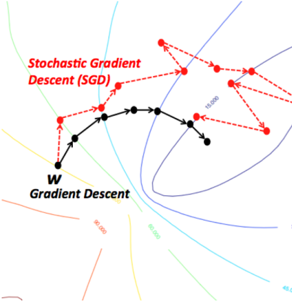
Data: w initialization, ρ stepsize
Result: w
for *i=1,n* **do**
  $\mathbf{x}_i, t_i \leftarrow$ pick a point i
  $\mathbf{d} \leftarrow d + \nabla_{\mathrm{w}} \textit{loss}(\mathrm{w}, x_i, t_i)$
end
$\mathrm{w} \leftarrow \mathrm{w} - \rho \mathbf{d}$

Algorithm 2 Stochastic gradient

Data: w initialization, ρ stepsize
Result: w
for *i=1,n* **do**
  $\mathbf{x}_i, t_i \leftarrow$ pick a point i
  $\mathbf{d} \leftarrow \nabla_{\mathrm{w}} \textit{loss}(\mathrm{w}, x_i, t_i)$
  $\mathrm{w} \leftarrow \mathrm{w} - \rho \mathbf{d}$
end

Accelerating the stochastic gradient

- stochastic average (mini batch)
  - parameters (Polyak and Juditsky, 1992)
  - gradients SAG-A, (Le Roux et al 2012)
  - variance reduction (Johnson, Zhang, 2013)
- convergence acceleration
  - Nesterov's method (1983)
  - momentum (heuristic)
- acceleration and averaging
  - (Dieuleveut, Flammarion & Bach, 2016)
- stepsize adaptation
  - RMSprop (Tieleman & Hinton, 2012)
  - Adaptive Moment Estimation – ADAM (Kingma & Ba, 2015)
  - AMSGRAD (Reddi et al, BPA ICRL 2018)



http://ruder.io/optimizing-gradient-descent/ https://wikidocs.net/3413

Optimization methods for large-scale machine learning L Bottou, FE Curtis, J Nocedal - stat, 2017 -

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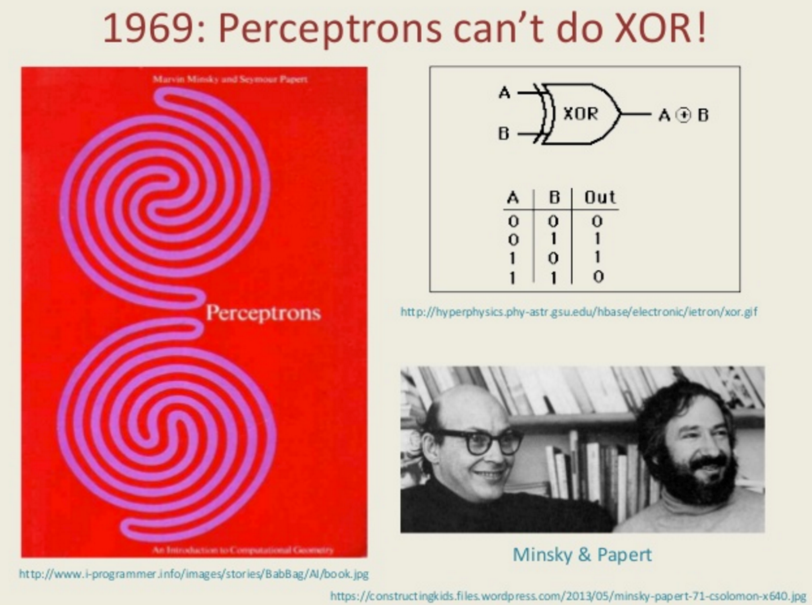
However, linear neurons ar linear



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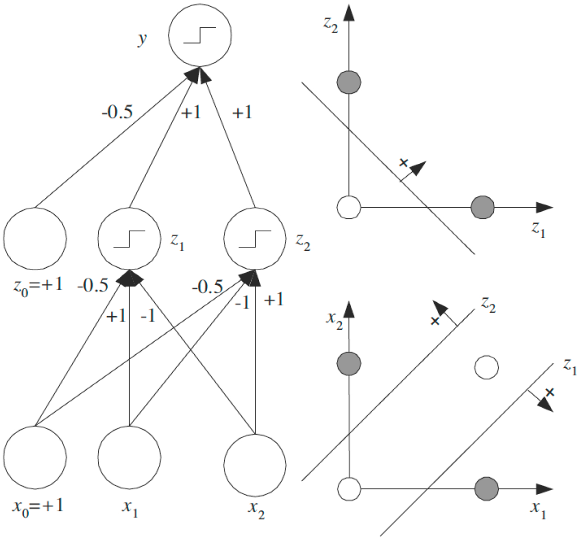
Non linearity combining linear neurons: the Xor case



Alpaydın, Introduction to Machine Learning, 2010

Neural networks

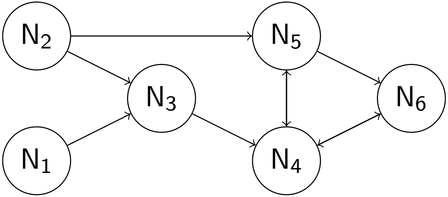
Definition: Neural network

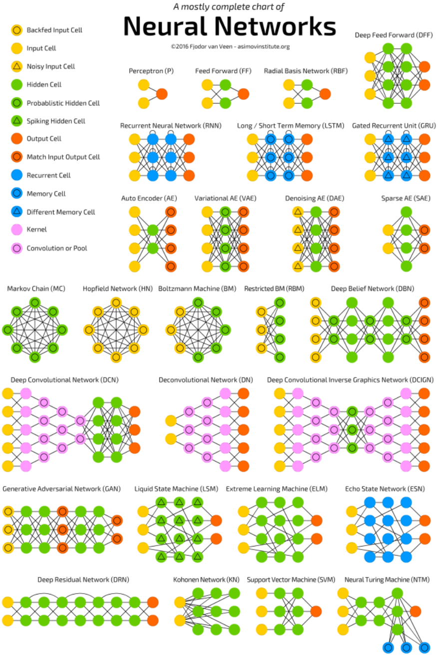
A neural network is an oriented graph of formal neurons

When two neurons are connected (linked by an oriented edge of the graph), the output of the head neuron is used as an input by the tail neuron. It can be seen as a weighted directed graph

3 different neurons are considered:

- input neurons (connected with the input)
- output neurons
- hidden neurons





The Asimov Institute: `http://www.asimovinstitute.org/neural-network-zoo/`

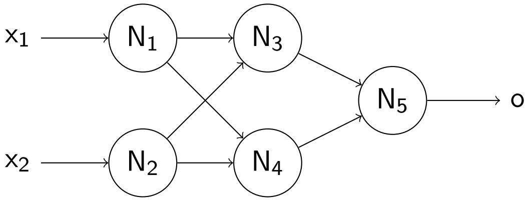
The Multiplayred peceptron (MLP)

Definition: Multiplayred peceptron

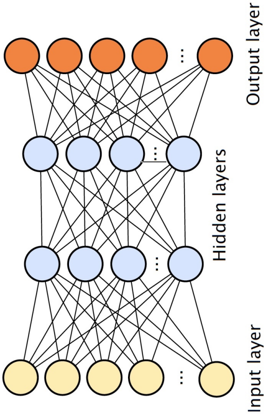
A Multiplayred peceptron is an acyclic neural network,

where the neurons are structued in successive layers, begining by an input layer and finishing with an output layer.

Example: The X-or neural network is a MLP with a single hidden unit with 2 hidden neurons.



MLP training with back propagation (and SGD)



$$y = \sigma(W_3 h^{(2)}) \qquad \nabla_{W_3} J = (y - y_a)\sigma'(W_3 h^{(2)}) h^{(2)\top}$$

$$\uparrow \qquad\qquad\qquad \downarrow$$

$$h^{(2)} = \sigma(W_2 h^{(1)}) \qquad \nabla_{W_2} J = \nabla_{h^{(2)}} J \sigma'(W_2 h^{(1)}) h^{(1)\top}$$

$$\uparrow \qquad\qquad\qquad \downarrow$$

$$h^{(1)} = \sigma(W_1 \mathbf{x}) \qquad \nabla_{W_1} J = \nabla_{h^{(1)}} J \sigma'(W_1 x) x^\top$$

$$\uparrow$$

$$\mathbf{x}$$

$$y = \sigma\Big(W_3 \sigma\big(W_2 \sigma(W_1 \mathbf{x})\big)\Big)$$

backpropagation = chain rule (autodiff)

Used to learn internal representation W_1, W_2, W_3

Back propagation is differential learning

Yann LeCun

5 janvier ·

OK, Deep Learning has outlived its usefulness as a buzz-phrase.
Deep Learning est mort. Vive Differentiable Programming!

Numpy

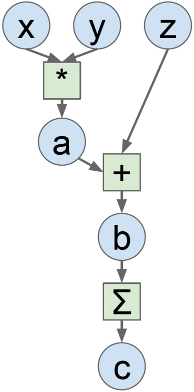
```
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)

grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```



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MLP with one hidden layer as universal approximator

Universal approximation theorem for MLP

- given any $\varepsilon > 0$
- for any continuous function f on compact subsets of $\mathbb{R}^p$
- for any admissible activation function σ (not a polynomial)
- there exists h, $W_1 \in \mathbb{R}^{p \times h}$, $b \in \mathbb{R}^h$, $c \in \mathbb{R}$ and $w_2 \in \mathbb{R}^h$ such that

$$\|f(x) - w_2\sigma(W_1 x + b) + c\|_\infty \leq \varepsilon$$

SVM, Boosting and Random Forest also

Approximation theory of the MLP model in neural networks, A Pinkus - Acta Numerica, 1999
The power of depth for feedforward neural networks, R. Eldan and O. Shamir, 2015.

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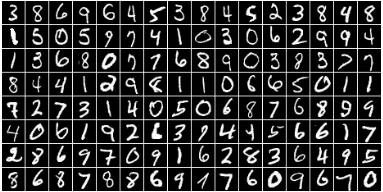
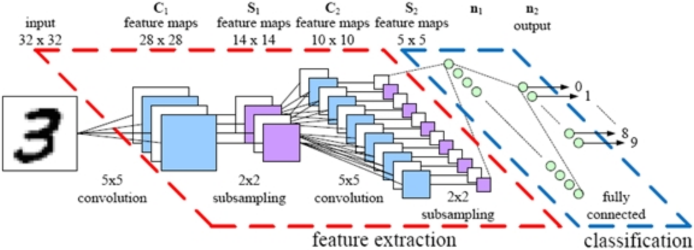
OCR: MNIST database (LeCun, 1989)





use convolution layers

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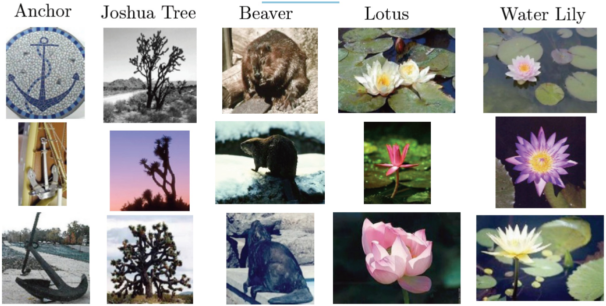
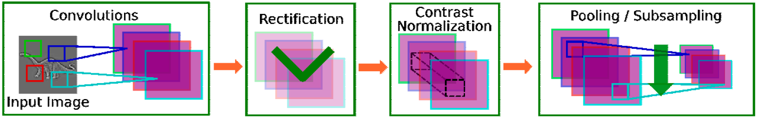
The caltech 101 database (2004)



- 101 classes,
- 30 training images per category
- ...and the winner is NOT a deep network
  - dataset is too small



use convolution + Recitification + Normalization + Pooling

in What is the Best Multi-Stage Architecture for Object Recognition? Jarrett et al, 2009

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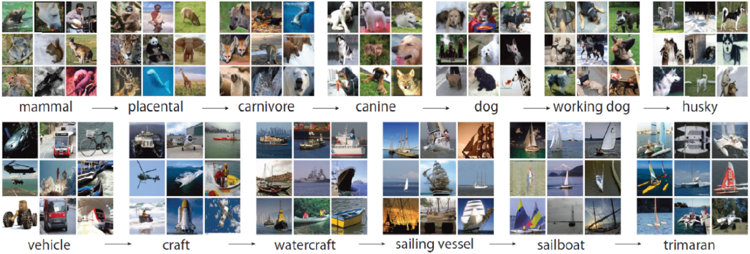
2004 CIFAR Research Program: Learning in Machines & Brains
2006 Deep learning: Bengio's, Hinton's RBM, Y LeCun's proposals
2010 Andrw Ng's GPU for Deep GPU
2011 Deep frameworks, tools (theano, torch, cuda-convnet...)
2012 ImageNet – AlexNet
2013 M. Zuckerberg at NIPS the deep fashion
2014 Representation learning fine tuning
2015 Deep learning in the industry: speech, traduction, image...
2016 Goodfellow's generative adversarial networks (GAN)
2017 Reinforcement learning: Deep win's GO
2018 Automatic design, adversarial defense, green learning, theory...

The image net database (Deng et al., 2012)



ImageNet = 15 million high-resolution images of 22,000 categories.
Large-Scale Visual Recognition Challenge (a subset of ImageNet)

- 1000 categories.
- 1.2 million training images,
- 50,000 validation images,
- 150,000 testing images.

www.image-net.org/challenges/LSVRC/2012/

A new fashion in image processing

2012 Teams	%error
Supervision (Toronto)	15.3
ISI (Tokyo)	26.1
VGG (Oxford)	26.9
XRCE/INRIA	27.0
UvA (Amsterdam)	29.6
INRIA/LEAR	33.4

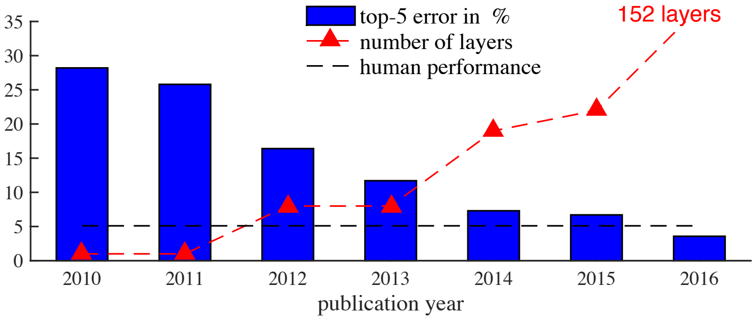
2013 Teams	%error
Clarifai (NYU spinoff)	11.7
NUS (singapore)	12.9
Zeiler-Fergus (NYU)	13.5
A. Howard	13.5
OverFeat (NYU)	14.1
UvA (Amsterdam)	14.2
Adobe	15.2
VGG (Oxford)	15.2
VGG (Oxford)	23.0

2014 Teams	%error
GoogLeNet	6.6
VGG (Oxford)	7.3
MSRA	8.0
A. Howard	8.1
DeeperVision	9.5
NUS-BST	9.7
TTIC-ECP	10.2
XYZ	11.2
UvA	12.1

shallow approaches

deep learning

ImageNet results



2012 Alex Net

2013 ZFNet

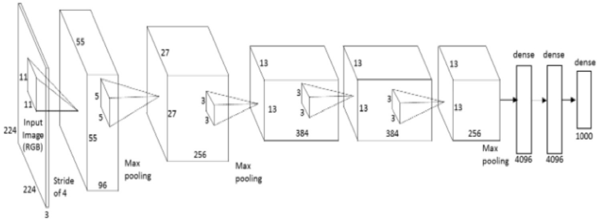
2014 VGG

2015 GoogLeNet / Inception

2016 Residual Network

karpathy's blog: `karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/`

Deep architecture for image net (15%)

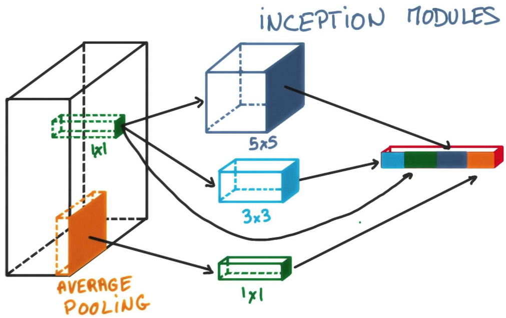


The *Alex Net* architecture [Krizhevsky, Sutskever, Hinton, 2012]

Convolution + Recitification (ReLU) + Normalization + Pooling

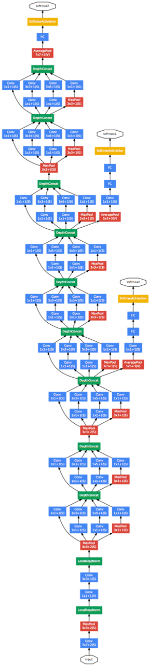
- 60 million parameters
- using 2 GPU – 6 days
- regularization
  - data augmentation
  - dropout
  - weight decay

From 15% to 7%: Inceptionism

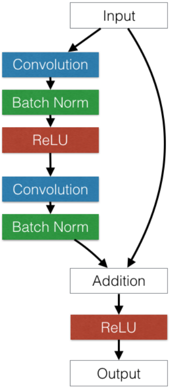


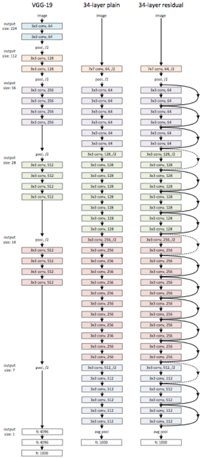
Network in a network (deep learning lecture at Udacity)

Christian Szegedy et. al. Going deeper with convolutions. CVPR 2015.



From 7% to 3%: Residual Nets





Beating the gradient vanishing effect

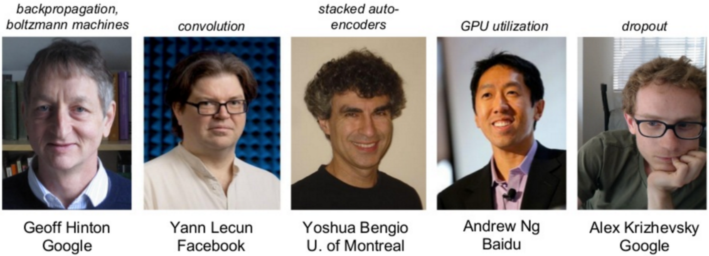
K. He *et al*, 2016

The neural networks time line

- The first stage: 1890 - 1969
- The second stage: 1985 - 1995
- The third stage: 2006 - (2012) - 2018...

2004	CIFAR Research Program: Learning in Machines & Brains
2006	Deep learning: Bengio's, Hinton's RBM, Y LeCun's proposals
2010	Andrw Ng's GPU for Deep GPU
2011	Deep frameworks, tools (theano, torch...)
2012	ImageNet – AlexNet
2013	M. Zuckerberg at NIPS: the deep fashion
2014	Representation learning fine tuning
2015	Deep learning in the industry: speech, traduction, image...
2016	Goodfellow's generative adversarial networks (GAN)
2017	Reinforcement learning: Deep win's GO
2018	Automatic design, adversarial defense, green learning, theory...

Deep learning, AI and the industry



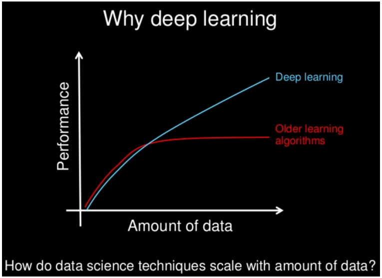
- data science, artificial intelligence and deep learning
- the BATX - GAFAM vision
  - they got the infrastructure (hard+software)
  - they got the data
  - deep learning bridges the gap between applications and ML

In 2016, Google Chief Executive Officer (CEO) Sundar Pichai said,

Machine learning [a subfield of AI] is a core, transformative way by which we're rethinking how we're doing everything.

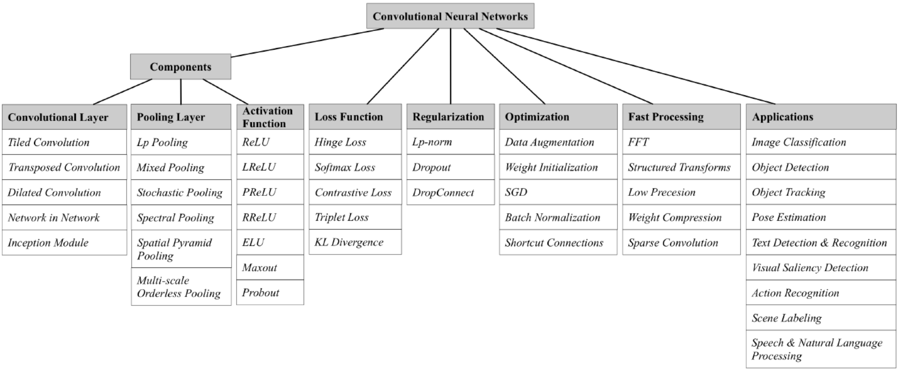
Road map

1. Why deep learning?
2. The first stage: 1890 - 1969
3. The second stage: 1985 - 1995
4. The third stage: 2006 - (2012) - 2018...
5. What's new in deep learning?
    - Big is beautiful
    - Two Hot topics: data and architecture
6. Conclusion



What's new with deep learning

- a lot of data (big data)
- big computing resources (hardware & software),
- big model (deep vs. shalow)
  - → new architectures
  - → new learning tricks

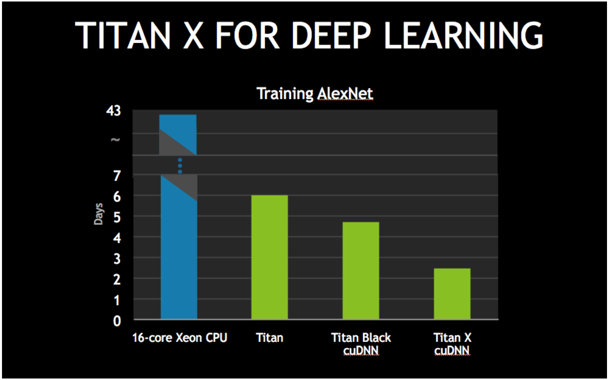


from Recent advances in convolutional neural networks Gu et al. Pattern Recognition, 2017

Big data: a lot of available training data

- ImageNet: 1,200,000x256x256x3 (about 200GB) block of pixels
- MS COCO for supervised learning
  - Multiple objects per image
  - More than 300,000 images
  - More than 2 Million instances
  - 80 object categories
  - 5 captions per image
- YFCC100M for unsupervised learning
- Google Open Images, 9 million URLs to images annotated over 6000 categories
- Visual genome: data + knowledge `http://visualgenome.org/`

Big computers: GPU needed



Now 2 hours with Nvidia DGX-1, and enough Memory

Yann LeCun:

learning a relevant model takes 3 weeks

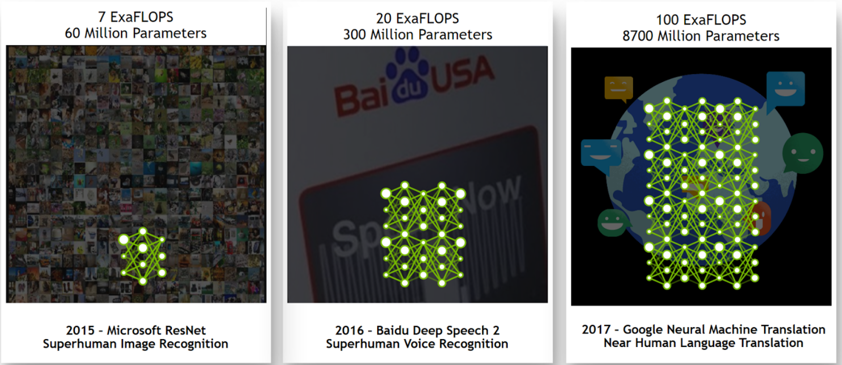
big software: deep learning frameworks

	Languages	Tutorials and training materials	CNN modeling capability	RNN modeling capability	Architecture: easy-to-use and modular front end	Speed	Multiple GPU support	Keras compatible
Theano	Python, C++	++	++	++	+	++	+	+
Tensor-Flow	Python	+++	+++	++	+++	++	++	+
Torch	Lua, Python (new)	+	+++	++	++	+++	++	
Caffe	C++	+	++		+	+	+	
MXNet	R, Python, Julia, Scala	++	++	+	++	++	+++	
Neon	Python	+	++	+	+	++	+	
CNTK	C++	+	+	+++	+	++	+	

Tensoflow (Google) is the most popular with Keras. Pytorch is a chalenger.

http://www.kdnuggets.com/2017/03/getting-started-deep-learning.html

Big architectures



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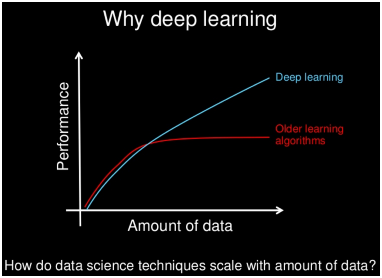
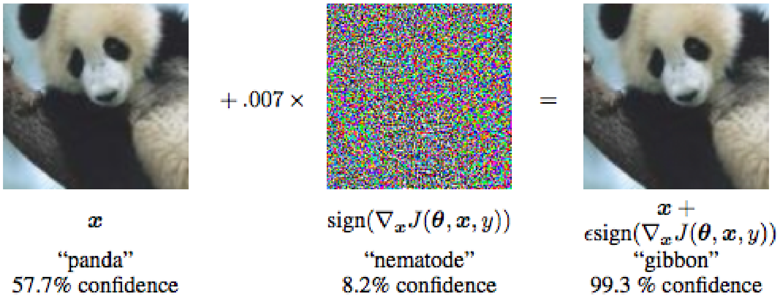


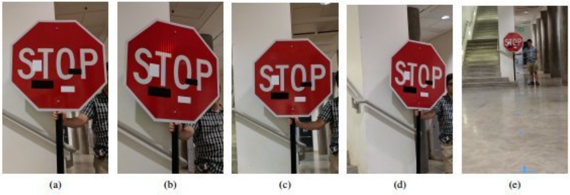
Deep neural networks are easily fooled (1/2)



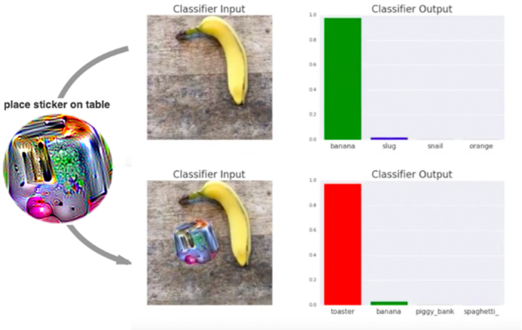
Explaining and Harnessing Adversarial Examples, Ian J. Goodfellow, Jonathon Shlens, Christian Szegedy, 2015

https://arxiv.org/abs/1412.6572

Adversarial examples (2/2)

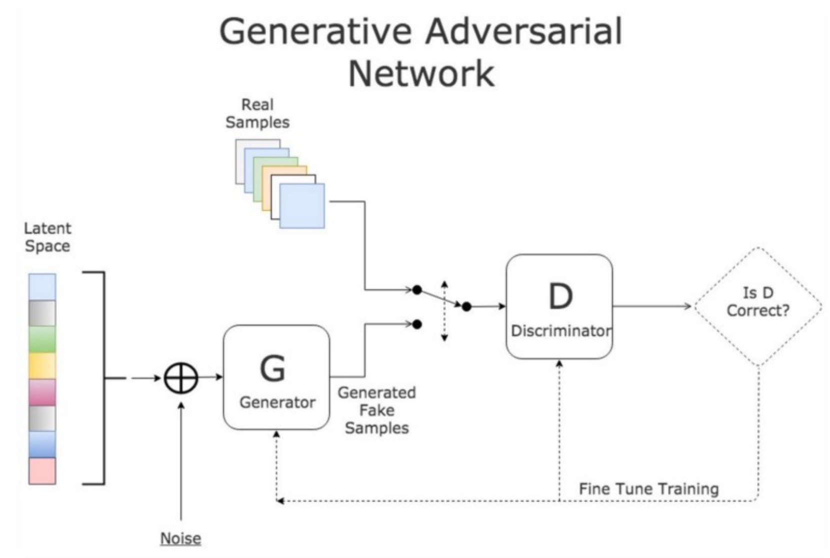


Adversarial Examples for Evaluating Reading Comprehension Systems, Robin Jia, Percy Liang, 2017



Adversarial Patch Tom B. Brown, Dandelion Mané, Aurko Roy, Martin Abadi, Justin Gilmer, 2017

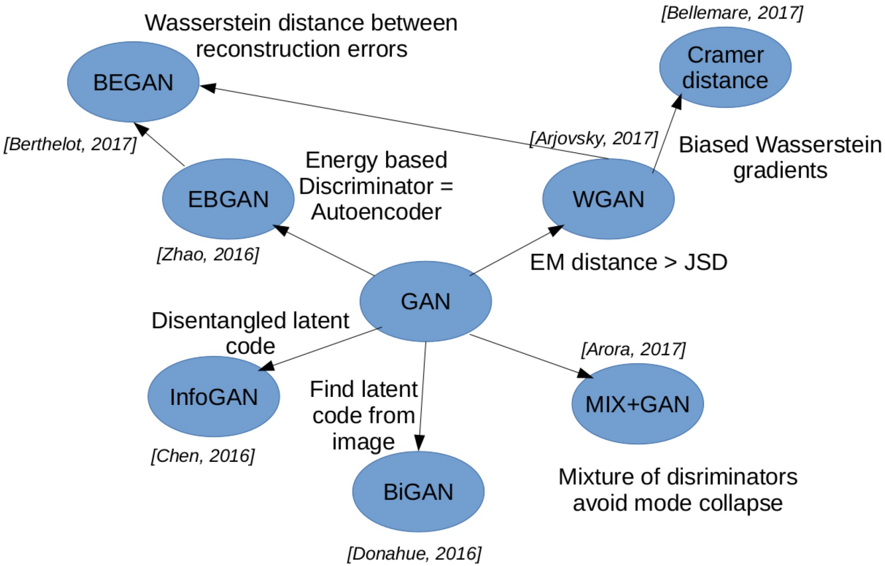
Generative models



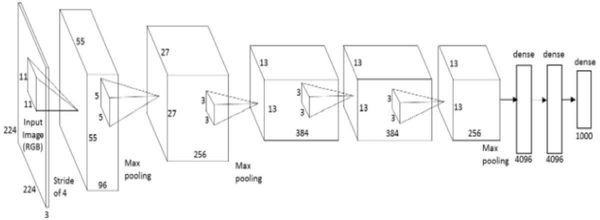
https://www.datasciencecentral.com/profiles/blogs/generative-adversarial-networks-gans-engine-and-applications

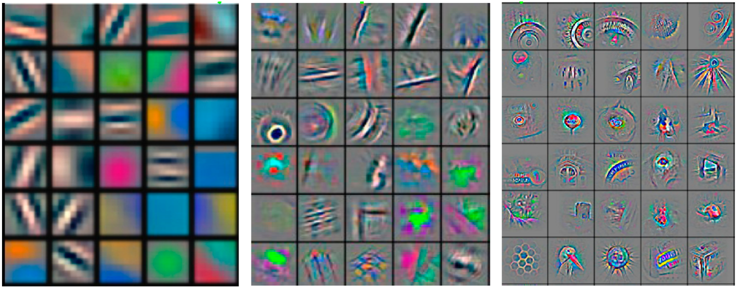
Defense-GAN: Protecting classifiers against adversarial attacks using generative models, 2018

Other Generative architectures



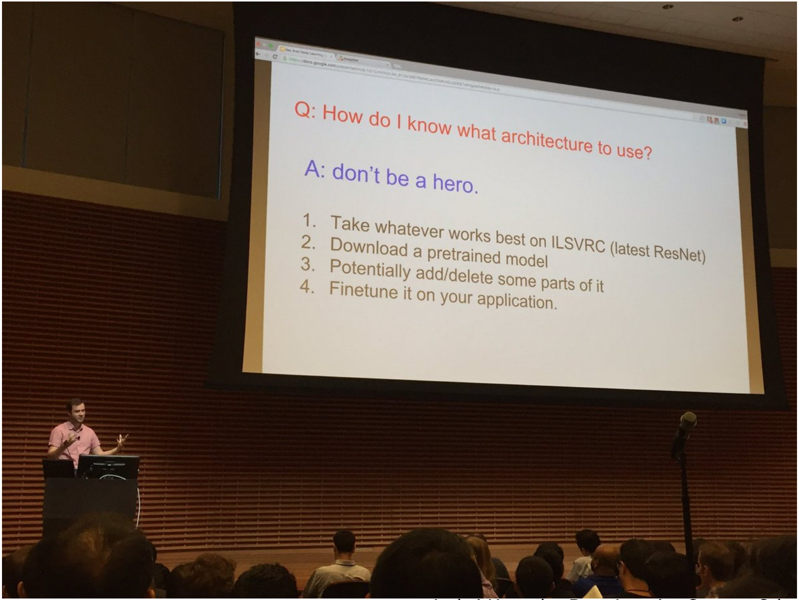
AlexNet works because of learning internal representation





Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

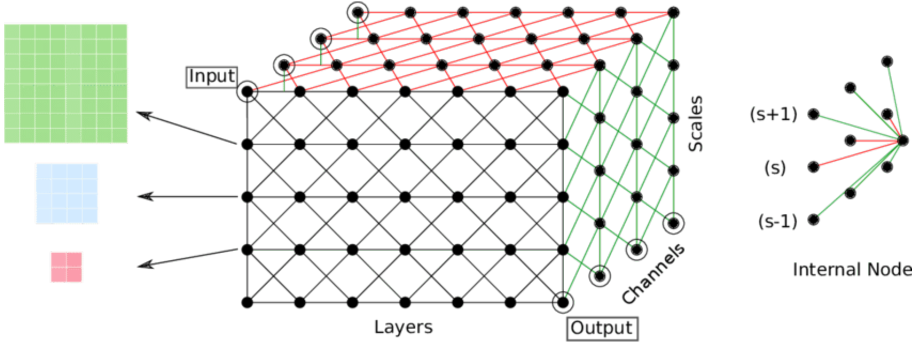
How to start with deep learning?



Andrej Karpathy, Deep Learning Summer School 2016

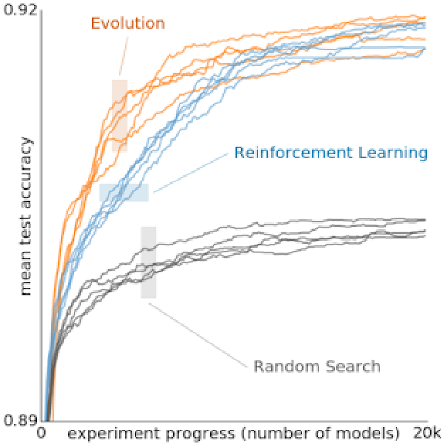
Convolutional Neural Fabrics

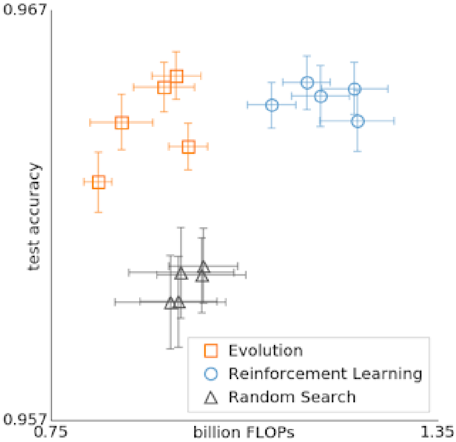
- problem: how to find the most relevant architecture
- todays solution: try and test
- A new solution: learn the architecture



Convolutional Neural Fabrics, Saxena and Verbeek, NIPS 2016

Neural Architecture Search





Regularized Evolution for Image Classifier Architecture Search, E. Real et al, 2018
https://chinagdg.org/2018/03/using-evolutionary-automl-to-discover-neural-network-architectures/

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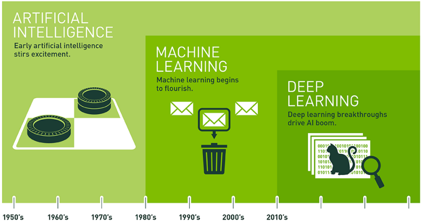

Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

The deep learning time line

- The first stage: 1890 - 1969
  - learning is optimization with stochastic gradient (to scale)
- The second stage: 1985 - 1995
  - NN are universal approximator differentiable graphs (that scales)
- The third stage: 2006 - (2012) - 2018...
  - scale with big data+computers+architecture (deep)
- Open issues
  - Many...

Open issues in *Deep learning : A critical apaisal*

arXiv.org > cs > arXiv:1801.00631

Search or Art
(Help | Advanced

Computer Science > Artificial Intelligence

Deep Learning: A Critical Appraisal

Gary Marcus

(Submitted on 2 Jan 2018)

Although deep learning has historical roots going back decades, neither the term "deep learning" nor the approach was popular just over five years ago, when the field was reignited by papers such as Krizhevsky, Sutskever and Hinton's now classic (2012) deep network model of Imagenet. What has the field discovered in the five subsequent years? Against a background of considerable progress in areas such as speech recognition, image recognition, and game playing, and considerable enthusiasm in the popular press, I present ten concerns for deep learning, and suggest that deep learning must be supplemented by other techniques if we are to reach artificial general intelligence.

Comments: 1 figure
Subjects: **Artificial Intelligence (cs.AI)**; Machine Learning (cs.LG); Machine Learning (stat.ML)
MSC classes: 97R40
ACM classes: I.2.0; I.2.6
Cite as: arXiv:1801.00631 **[cs.AI]**
(or **arXiv:1801.00631v1 [cs.AI]** for this version)

Bibliographic data

[Enable Bibex (What is Bibex?)]

Submission history

From: Gary Marcus [view email]
[v1] Tue, 2 Jan 2018 12:49:35 GMT (258kb)

For most problems where deep learning has enabled transformationally better solutions (vision, speech), we've entered diminishing returns territory in 2016-2017.

Francois Chollet, Google, author of Keras neural network library Dec. 2017

10 Limits on the scope of deep learning

- It is data hungry
- specialized training (no learning)
- it has no natural way to deal with hierarchical structure
- it has struggled with open-ended inference
- it is not sufficiently transparent
- not well integrated with prior knowledge (NLP)
- cannot distinguish causation from correlation
- assume stationarity
- can be fooled (it is not robust)
- is difficult to engineer with

10 Limits on the scope of deep learning

GREEN LEARNNING

- It is data hungry
- specialized training (no learning)
- it has no natural way to deal with hierarchical structure
- it has struggled with open-ended inference

THEORY NEEDED

- it is not sufficiently transparent

Texte

- not well integrated with prior knowledge (NLP)
- cannot distinguish causation from correlation
- assume stationarity

ADVERSARIAL TRANING

- can be fooled (it is not robust)
- is difficult to engineer with

AUTO ML

To go further

- books
  - I. Goodfellow, Y. Bengio & A. Courville, *Deep Learning*, MIT Press book, 2016 http://www.deeplearningbook.org/
  - Gitbook leonardoaraujosantos.gitbooks.io/artificial-inteligence/
- conferences
  - NIPS, ICLR, xCML, AIStats,
- Journals
  - JMLR, Machine Learning, Foundations and Trends in Machine Learning, machine learning survey http://www.mlsurveys.com/
- lectures
  - Deep Learning: Course by Yann LeCun at Collège de France in 2016 college-de-france.fr/site/en-yann-lecun/inaugural-lecture-2016-02-04-18h00.htm
  - Convolutional Neural Networks for Visual Recognition (Stanford)
  - deep mind (https://deepmind.com/blog/)
  - CS 229: Machine Learning at stanford Andrew Ng
- Blogs
  - Andrej Karpathy blog (http://karpathy.github.io/)
  - http://deeplearning.net/blog/
  - https://computervisionblog.wordpress.com/category/computer-vision/