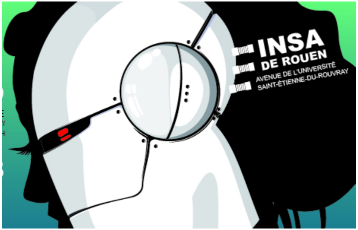
L’IA à l’ère de la programmation par l’exemple

Stéphane Canu

http://asi.insa-rouen.fr/enseignants/~scanu/

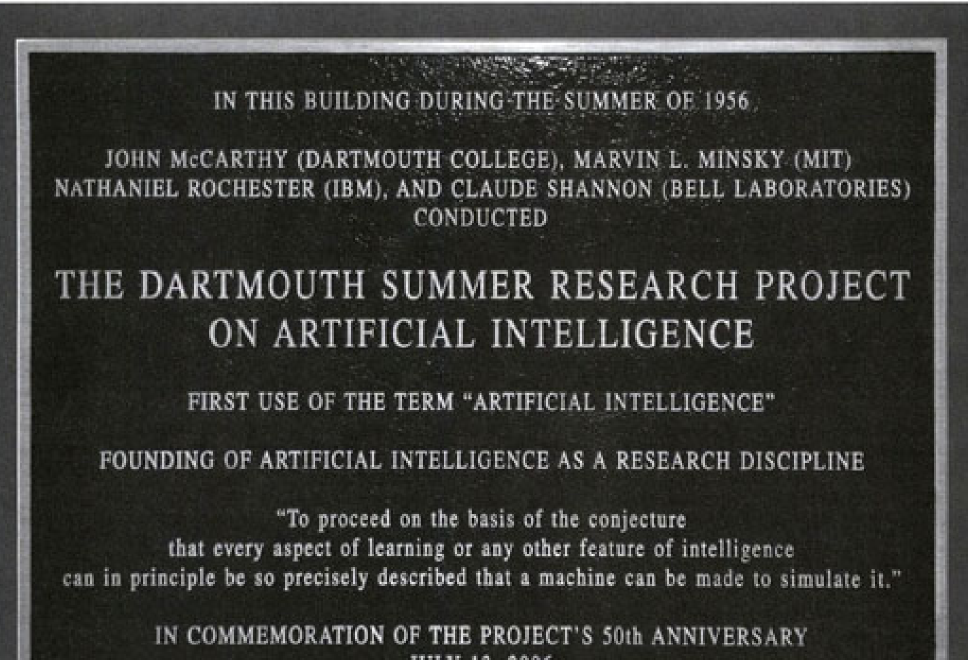


AGO 2018 de l’AFIA, 10 octobre 2018


HAPPY
NEW YEAR
1927

1927 : Année de naissance de John McCarthy, LE (grand) père de l'IA

1956: the Dartmouth Summer Research Project

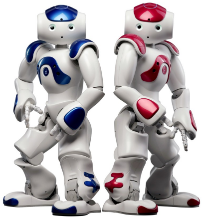


To do's list # 1 : définir l'IA

Cette recherche se basera sur le fait que chaque aspect de l'apprentissage ou caractéristique de l'intelligence peut, en principe, être décrit avec une telle précision que vous pouvez créer une machine qui les simule.

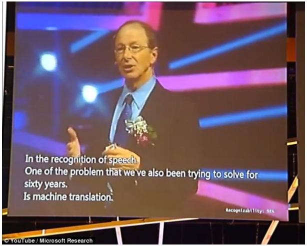
Apprendre !

Apprentissage : humain vs. machine

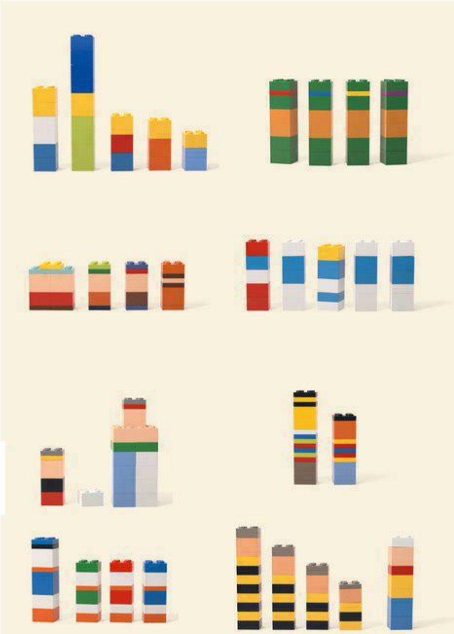


Les apprentissages d'un enfant

- marcher : un an
- parler : deux ans
- raisonner : le reste



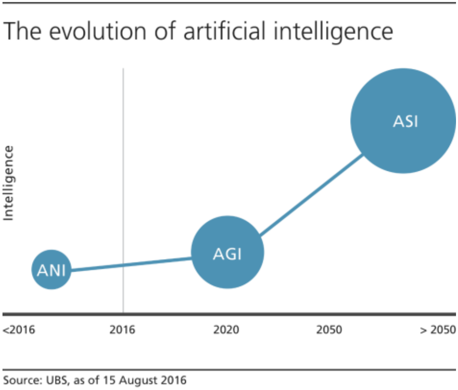
Apprendre à raisonner



Les 3 niveaux de l'IA

Qu'y a-t-il sur cette image ? (Est-ce un chat ?)	l'intelligence spécifique
Pourquoi est-ce un chat ?	l'intelligence générale
Est-ce qu'il monte ou il descend ?	la super intelligence

Intelligence spécifique, générale et supérieure

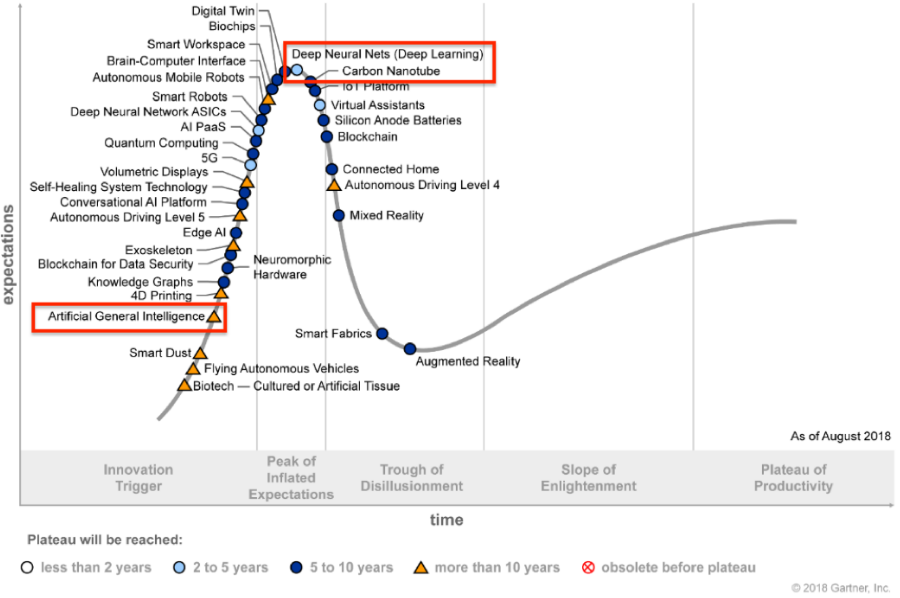


Qu'y a-t-il sur cette image ? (Est-ce un chat ?)
Pourquoi est-ce un chat ?
Est-ce qu'il monte ou il descend ?

l'intelligence spécifique
l'intelligence générale
la super intelligence

La super intelligence, c'est pour quand ?

C'est pas pour demain...



AI et machine learning (deep learning)

Yann LeCun

9 décembre 2013 ·

Big news today!

Facebook has created a new research laboratory with the ambitious, long-term goal of bringing about major advances in Artificial Intelligence.

Facebook AI Research is machine learning

facebook research

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- Machine Learning
- Natural Language Processing & Speech
- Security & Privacy
- Systems & Networking

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Adversarial Image Defenses

bAbI

Business Insights Panel

Caffe2

CLEVR Dataset Generator

Colorless green RNNs

CommAI

DensePose

Detectron

DrQA

ELF

End-to-End Negotiator

Facebook AI Research Sequence-to-Sequence Toolkit

Faiss

FastText

Global Climate Statistical Analysis Library (GCSAL)

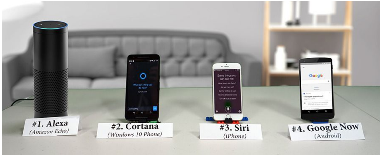
Google research: AI Fundamentals & Applications

Research areas

- Graph-based learning
- Supervised machine learning
- Large-scale machine learning
- Online clustering
- Coauthor
- Modeling and data science
- Structured data
- Scalable matching
- Speech and language algorithms
- Sensitive content detection
- ML for personalization and assistance
- Semi-supervised and unsupervised machine learning
- ML model compression for mobile devices
- Media understanding in conversations
- Combinatorial machine learning
- Glassbox

Les enjeux de l'IA pour eux

- les assistants vocaux



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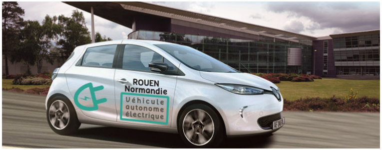
- les véhicules autonomes



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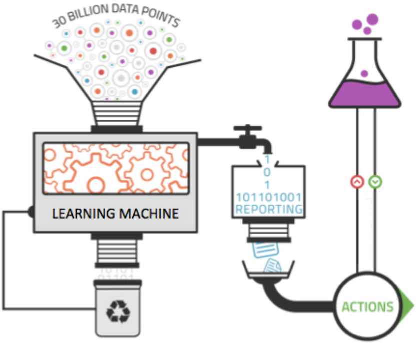
- la santé
- la sécurité
- ...

Qu'est-ce l'IA aujourd'hui pour eux ?



La programmation basée sur les exemples

Les 3 principales familles d’apprentissage stat.

Apprendre à prédire : apprentissage supervisé

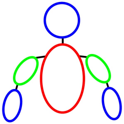
Entrée x sorties y

- $y \in \{0, 1\}$ classification binaire ou multiple



- $y \in \mathbf{R}$ régression

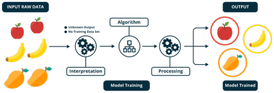

- $y \in \{\textit{faible}, \textit{moyen}, \textit{fort}\}$ ordonnancement
- y structuré

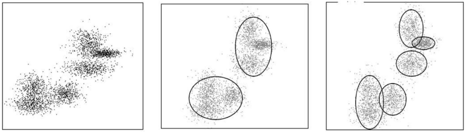



Apprendre à résumer : apprentis. non supervisé

Entrée x seul (pas de y)

- Catégoriser (clustering) : qui se ressemble s'assemble   k-means, CHA

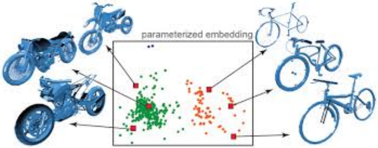




(a) Input data   (b) GMM (K=2)   (c) GMM (K=5)

.

- Représenter: $x \in \mathbb{R}^p \longrightarrow z \in \mathbb{R}^d, d \ll p$ ACP, t-SNE, UMAP



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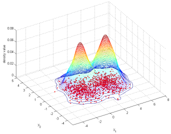
- Estimer une densitée $\mathbb{P}(x)$ Parzen,



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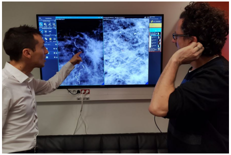
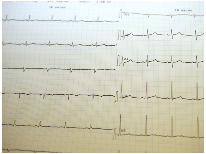
L'IA en santé

détection de mélanome de la peau
130 000 images
taux d'erreur 28 % (humain 34 %)



the Digital Mammography DREAM Challenge
640 000 mammographies (1209 participants)
5 % de faux positif en moins

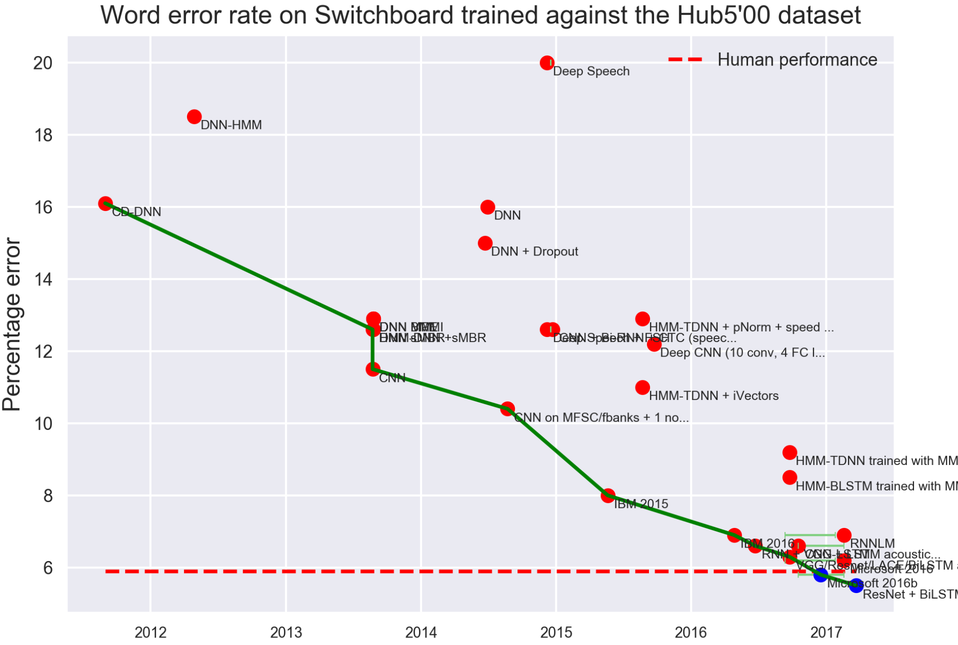


analyse du rythme cardiaque
500 000 ECG
précision 92.6 % (humain 80.0 %) sensibilité de 97 %

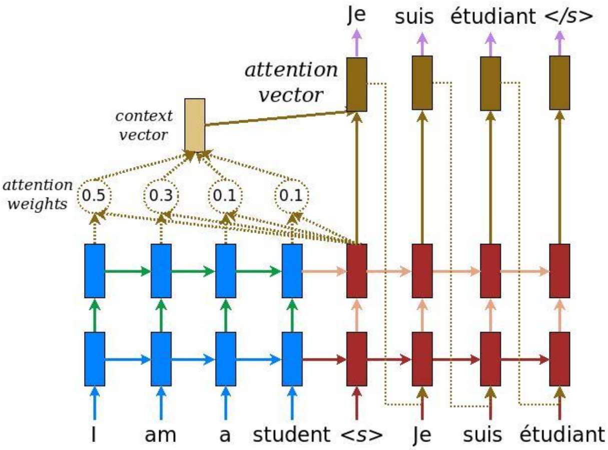
Apprentissage statistique supervisé

Entrainer des réseaux de neurones profonds à assimiler des données

L'IA pour la parole (entrainée sur 2000 heures)



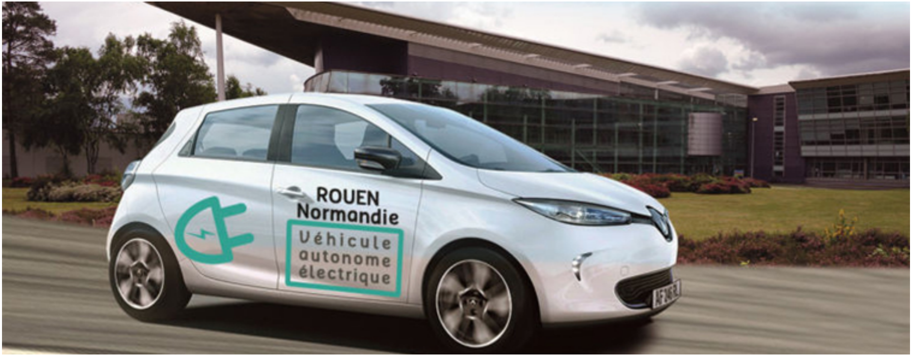
L'IA pour le texte



Apprendre à traduire

avec 36 millions de phrases

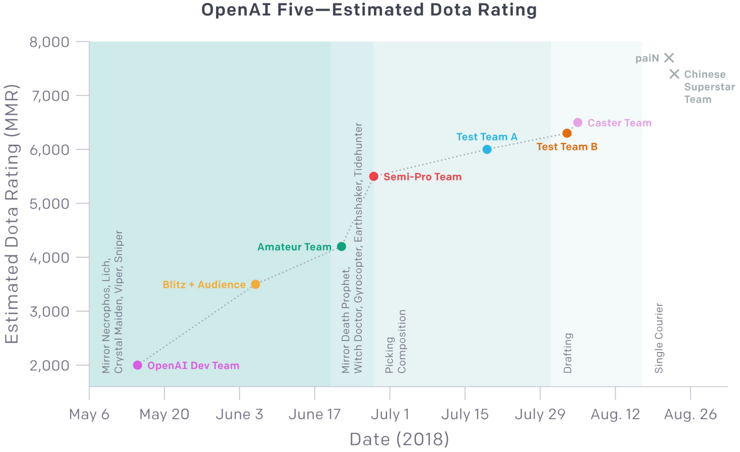
L'IA pour la voiture



Apprendre à conduire (on ne sait pas très bien encore)

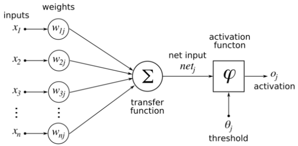
avec 100.000 vidéos – 120 millions d'images
(nous en 20 heures)

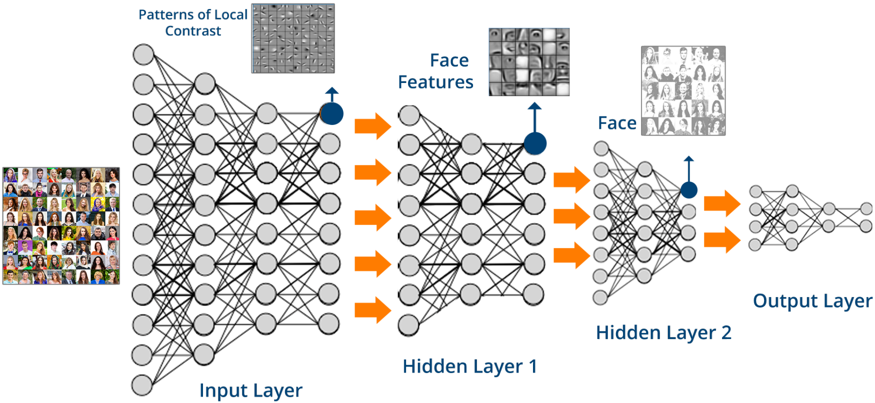
L'IA pour le jeu : E. Musk OpenAI



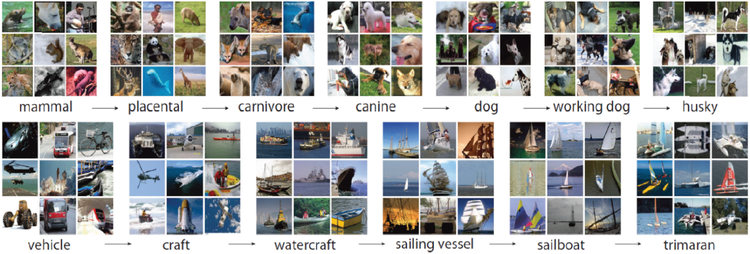
- separate LSTM for each hero
- 180 years/days of games against itself
- Proximal Policy Optimization running
- 256 GPUs and 128,000 CPU cores

Entrainer quoi : un réseau de neurones profond





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

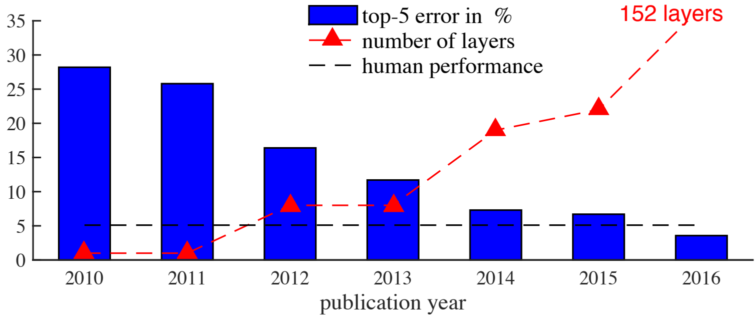
2013 Teams	%error
Clarifai (NYU spinoff)	11.7
NUS (singapore)	12.9
Zeiler-Fergus (NYU)	13.5
A. Howard	13.5
OverFeat (NYU)	14.1
UvA (Amsterdam)	14.2
Adobe	15.2
VGG (Oxford)	15.2
VGG (Oxford)	23.0

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/`

Neural Network for Identifying Exoplanets

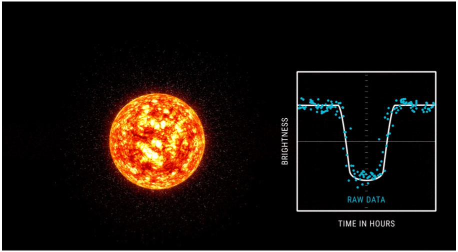
THE ASTRONOMICAL JOURNAL, 155:94 (21pp), 2018 February https://doi.org/10.3847/1538-3881/aa9e09

Identifying Exoplanets with Deep Learning: A Five-planet Resonant Chain around Kepler-80 and an Eighth Planet around Kepler-90

Christopher J. Shallue[1] and Andrew Vanderburg[2,3,4]
[1] Google Brain, 1600 Amphitheatre Parkway, Mountain View, CA 94043, USA; shallue@google.com
[2] Department of Astronomy, The University of Texas at Austin, 2515 Speedway, Stop C1400, Austin, TX 78712, USA
[3] Harvard–Smithsonian Center for Astrophysics, 60 Garden Street, Cambridge, MA 02138, USA
Received 2017 September 19; revised 2017 November 13; accepted 2017 November 20; published 2018 January 30

Abstract

NASA's *Kepler Space Telescope* was designed to determine the frequency of Earth-sized planets orbiting Sun-like stars, but these planets are on the very edge of the mission's detection sensitivity. Accurately determining the occurrence rate of these planets will require automatically and accurately assessing the likelihood that individual candidates are indeed planets, even at low signal-to-noise ratios. We present a method for classifying potential planet signals using deep learning, a class of machine learning algorithms that have recently become state-of-the-



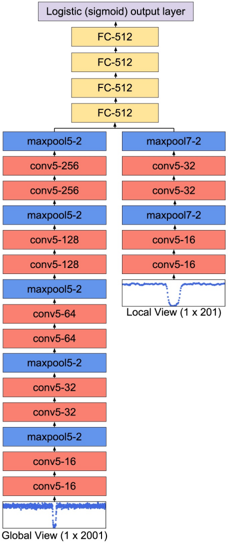
Astronet: brute force CNN

- Data
  - 3600 planet candidates
  - 9596 astrophysical false positive
  - 2541 nontransiting phenomenon

- model
  - inputs: both global and local input
  - convolutional deep network

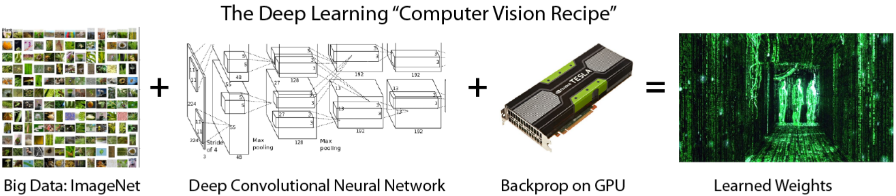
- training
  - Google vizier for hyper parameters tuning
  - 100 CPUs in parallel

- prediction: 10 copies model averaging



Golovin, Daniel, et al. "Google vizier: A service for black-box optimization." Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, 2017 `github.com/tobegit3hub/advisor`

L’équation de l’IA d’aujourd’hui



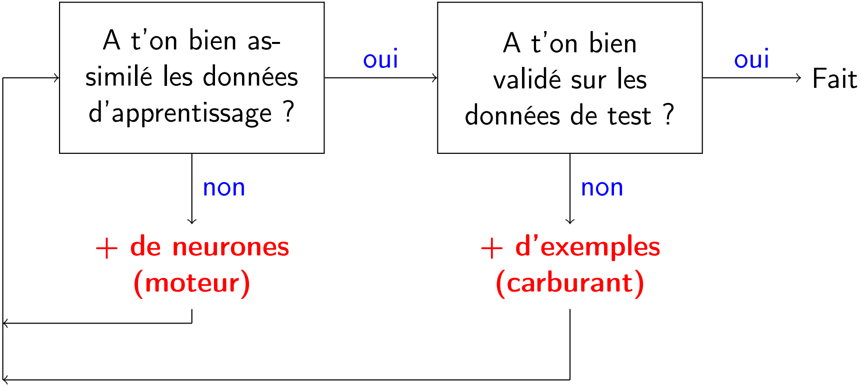
Entrainer plutôt qu'apprendre

Apprentissage statistique selon Andrew Ng

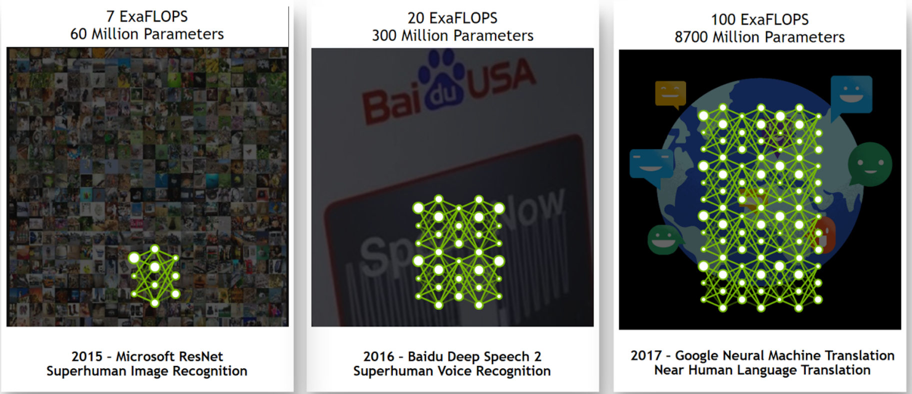
moteur le réseaux de neurones profond

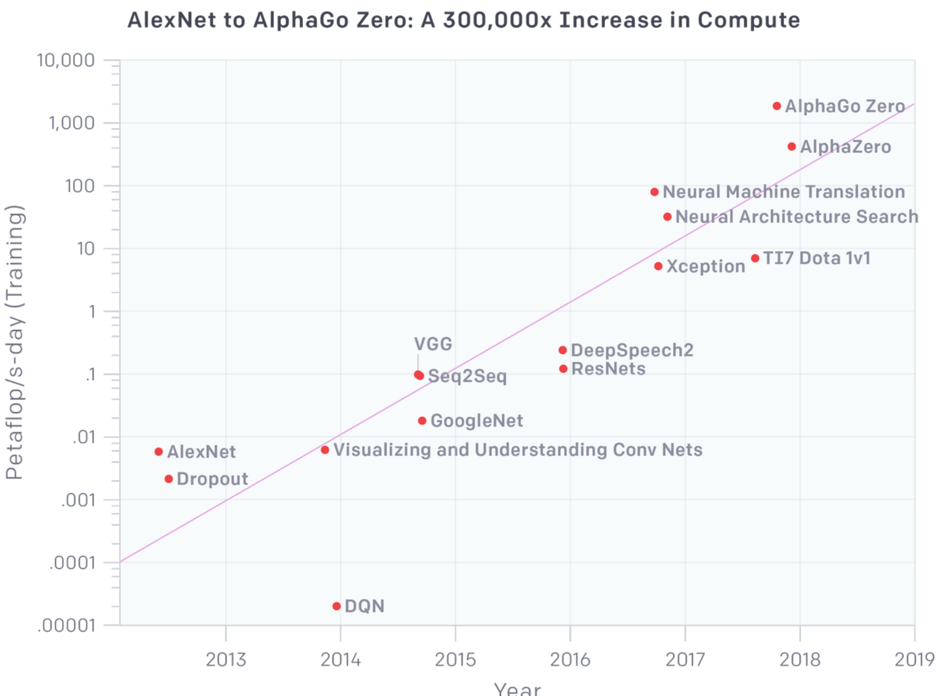
carburant les données

Pour apprendre : la recette d'Andrew Ng



Quelle est la taille des réseaux ?




AlexNet to AlphaGo Zero: A 300,000x Increase in Compute
Petaflop/s-day (Training)
10,000
1,000
100
10
1
.1
.01
.001
.0001
.00001
2013
2014
2015
2016
2017
2018
2019
Year
AlphaGo Zero
AlphaZero
Neural Machine Translation
Neural Architecture Search
TI7 Dota 1v1
Xception
VGG
Seq2Seq
DeepSpeech2
ResNets
GoogleNet
AlexNet
Dropout
Visualizing and Understanding Conv Nets
DQN


WINTER
IS COMING

Deep learning : une évaluation critique

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

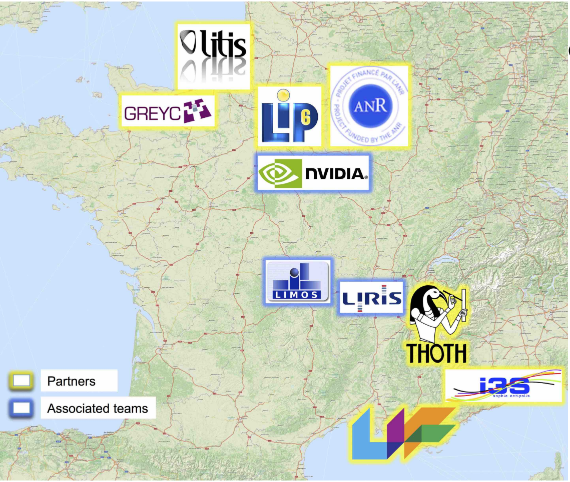
10 limites de l'apprentissage profond

- nécessite trop de données
- trop spécialisés
- ne gère pas les structures complexes (NLP)
- pas facile d'intégrer des connaissances a priori
- on n'y comprend rien : pas de théorie explicative
- n'intègre que des corrélations
- ne permet pas de distinguer la causalité
- gère mal les évolutions
- ne garanti pas la qualité des décisions
- l'ingénierie est compliquée

10 limites de l'apprentissage en profondeur

- nécessite trop de données
- trop spécialisés
- ne gère pas les structures complexes (NLP)
- pas facile d'intégrer des connaissances a priori
- on n'y comprend rien : pas de théorie explicative
- n'intègre que des corrélations
- ne permet pas de distinguer la causalité
- gère mal les évolutions
- ne garanti pas la qualité des décisions
- l'ingénierie est compliquée

Deep in France basic research projet



Expanding the frontier of green deep learning

- ANR labelized
- Network: 6 partners
- 42 months
- 4 Tasks
  1. green deep architectures
  2. optimization algorithms
  3. scalable embedded deep learning
  4. pilot applications

LITIS	Audio scene recog.
I3S	Vision for robotics
LIF	Video forecasting

Deep in France

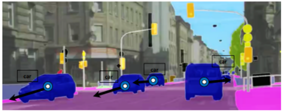
- Publications

Predicting Deeper into the Future of Semantic Segmentation

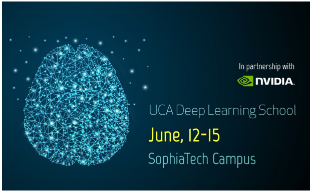
Pauline Luc[1,2*] Natalia Neverova[1*] Camille Couprie[1] Jakob Verbeek[2] Yann LeCun[1,3]
[1] Facebook AI Research
[2] Inria Grenoble, Laboratoire Jean Kuntzmann, Université Grenoble Alpes
[3] New York University
{paulineluc,nneverova,coupriec,yann}@fb.com jakob.verbeek@inria.fr

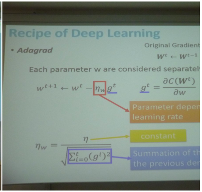
Abstract

The ability to predict and therefore to anticipate the future is an important attribute of intelligence. It is also of utmost importance in real-time systems, e.g. in robotics or autonomous driving, which depend on visual scene understanding for decision making. While prediction of the raw RGB pixel values in future video frames has been studied



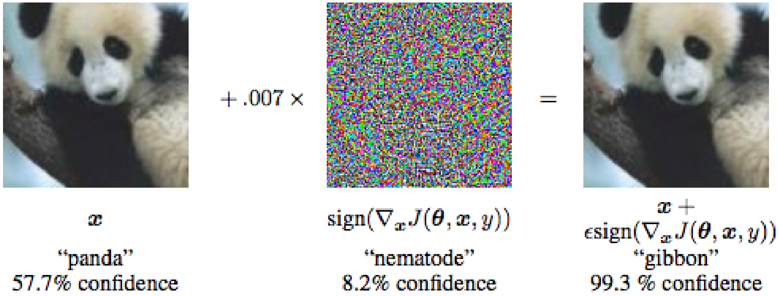
- Deep learning schools





- Conferences
  - CAP 2018 (Rouen 20, 21 et 22 juin 2018) `cap2018.litislab.fr`
  - RFIAP 2018 (Marne-la-Vallée les 26, 27 et 28 juin 2018)

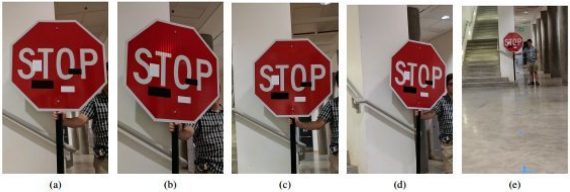
Deep neural networks are easily fooled (1/2)



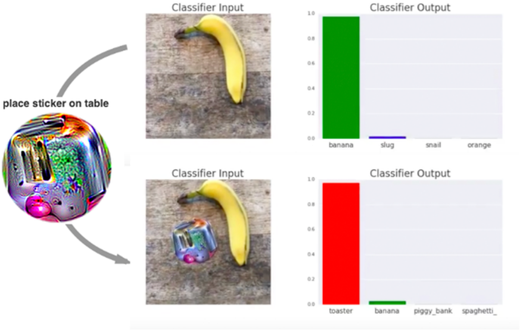
Explaining and Harnessing Adversarial Examples, Ian J. Goodfellow, Jonathon Shlens, Christian Szegedy, 2015

https://arxiv.org/abs/1412.6572

Adversarial examples (2/2)

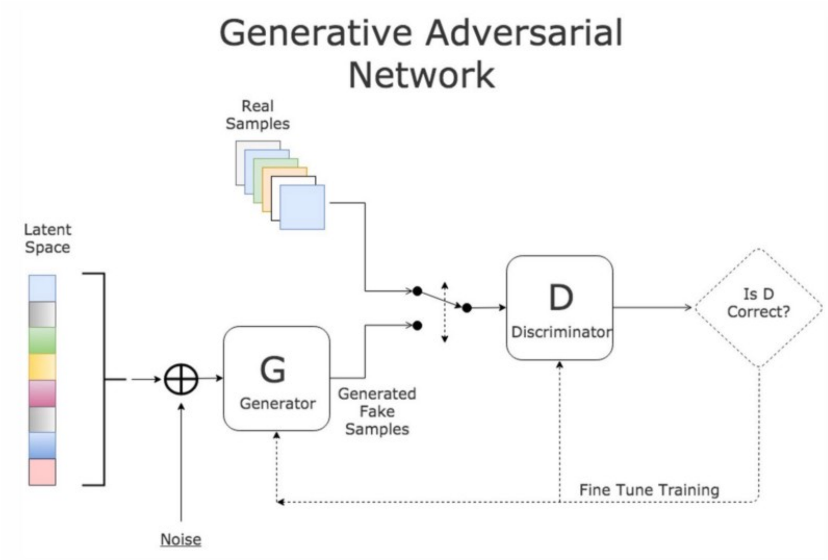


Adversarial Examples for Evaluating Reading Comprehension Systems, Robin Jia, Percy Liang, 2017



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

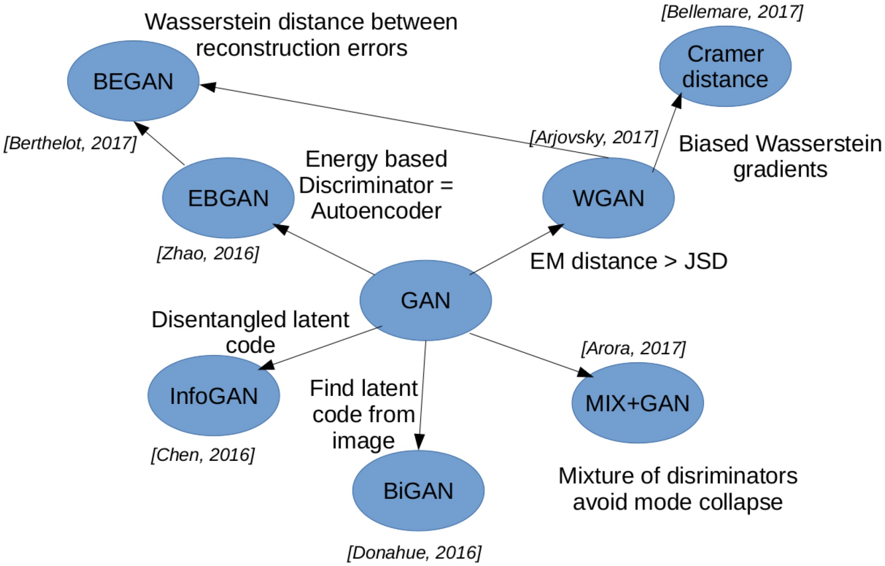
Generative models



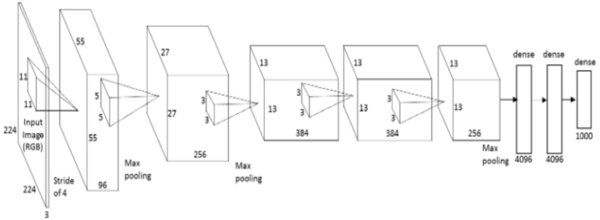
https://www.datasciencecentral.com/profiles/blogs/generative-adversarial-networks-gans-engine-and-applications

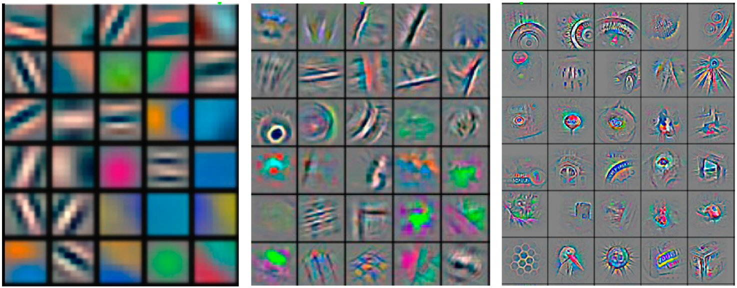
Defense-GAN: Protecting classifiers against adversarial attacks using generative models, 2018

Other Generative architectures



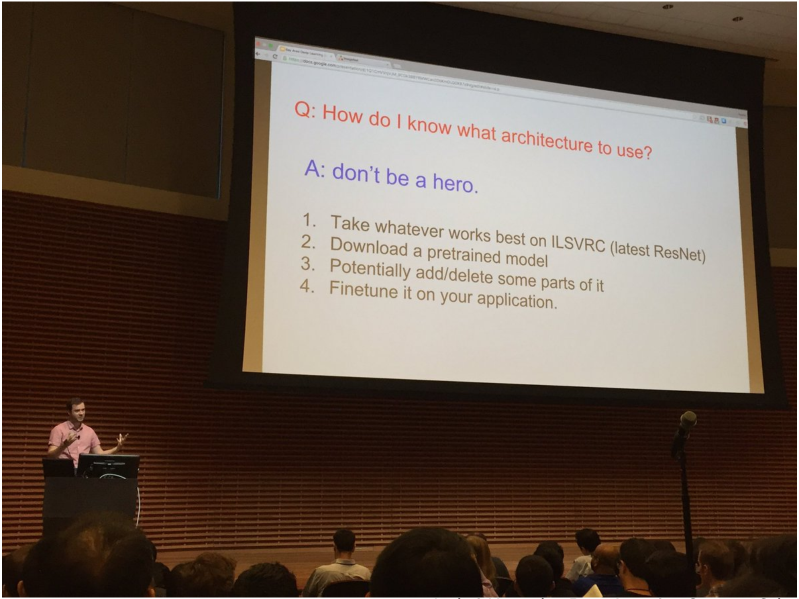
AlexNet works because of learning internal representation





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

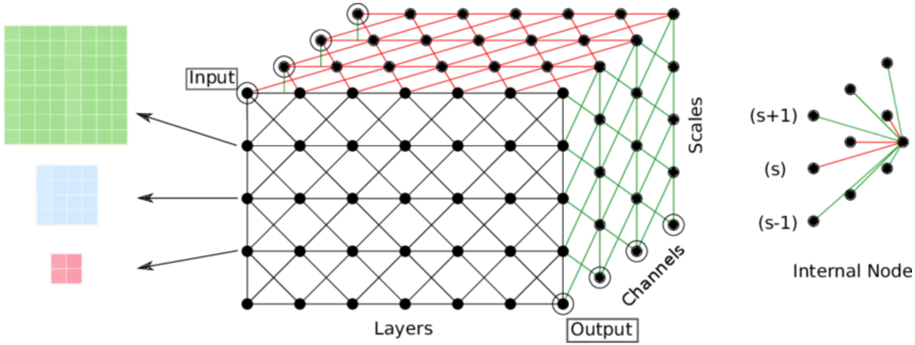
How to start with deep learning?



Andrej Karpathy, Deep Learning Summer School 2016

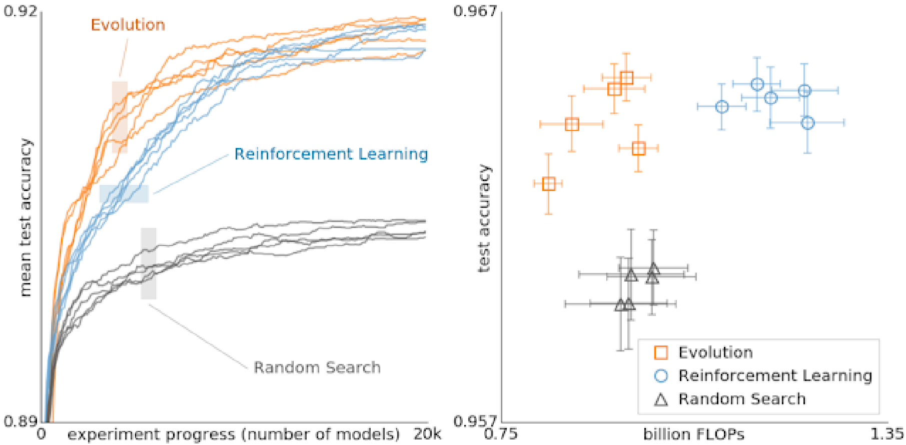
Convolutional Neural Fabrics

- 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



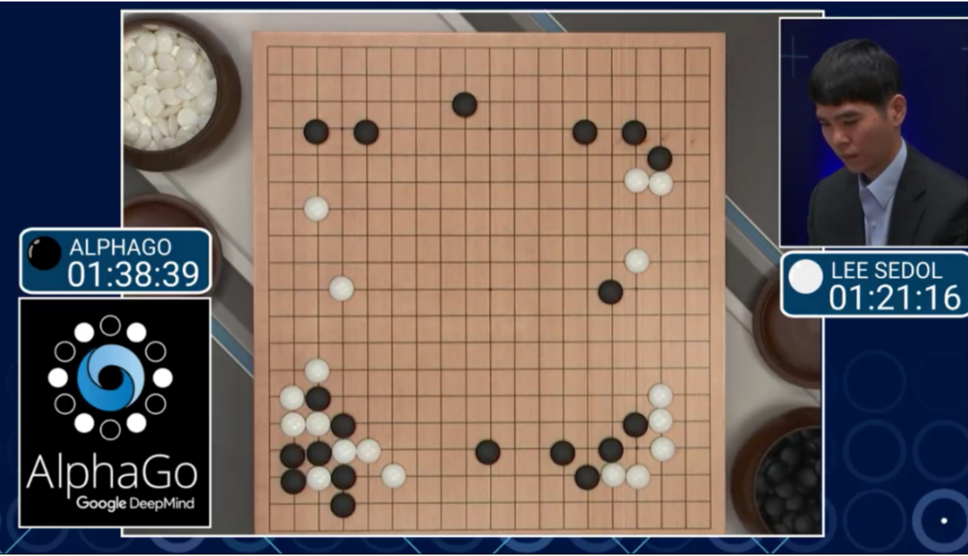
Regularized Evolution for Image Classifier Architecture Search, E. Real et al, 2018

https://chinagdg.org/2018/03/using-evolutionary-automl-to-discover-neural-network-architectures/

Je sais entrainer des machines,

mais je cherche toujours à comprendre ce qu'est l'apprentissage

le Deep learning joue et gagne



Les amateurs en profitent