Deep Learning 101

Cognitive Robotics

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About me

Present

- **PhD student** in Deep Learning and Computer Vision
- supervised by Prof. Matteo Matteucci
- ML engineer @ Horus

Background

Machine Learning, Signal Processing

- MSc at Politecnico di Milano, Como Campus
- BSc at Università degli studi di Firenze

Contacts

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Tentative Outline of the course

- Deep Learning introduction
- Optimization background
- Convolutional Neural Networks
- Recurrent Neural Networks
- Training Tricks
- Applications and very (very) brief TensorFlow tutorial [very optimistic]

Let’s start!

Deep Learning breakthrough

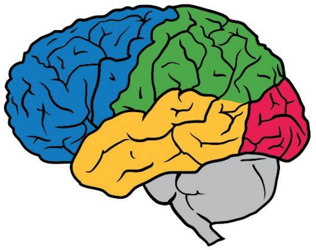
“With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart.”

https://www.technologyreview.com/s/513696/deep-learning/

“One of the 10 breakthrough technologies 2013”

MIT Technology Review

Companies



Big players in Academy

UNIVERSITY OF TORONTO

MILA

USI/SUPSI
Istituto
Dalle Molle
di studi
sull'intelligenza
artificiale
IDSIA

UNIVERSITY OF OXFORD

Carnegie Mellon University

Berkeley
UNIVERSITY OF CALIFORNIA

NYU

UNIVERSITY OF CAMBRIDGE

Deep Learning Stars

Many researchers sacrifices their life (and their GPUs) to the new and the old Deep Learning Gods

Joffrey Hinton (The Godfather, UToronto, Google)

Yoshua Bengio (MILA, Montreal)

Yann LeCun (ConvNets, NYU, Facebook)

Juergen Schmidhuber (IDSIA)

Kyunghyun Cho (NYU)

Ian Goodfellow (Google Brain)

Aaron Courville (MILA, Montreal)

Andrew Ng (Coursera, Stanford, Baidu)

Hugo Larochelle (Google Brain)

Marc'Aurelio Ranzato (Facebook)

Check the research groups here

Main conferences

NIPS

ICLR

ICML

Deep Learning is growing faster also in other conferences…

CVPR

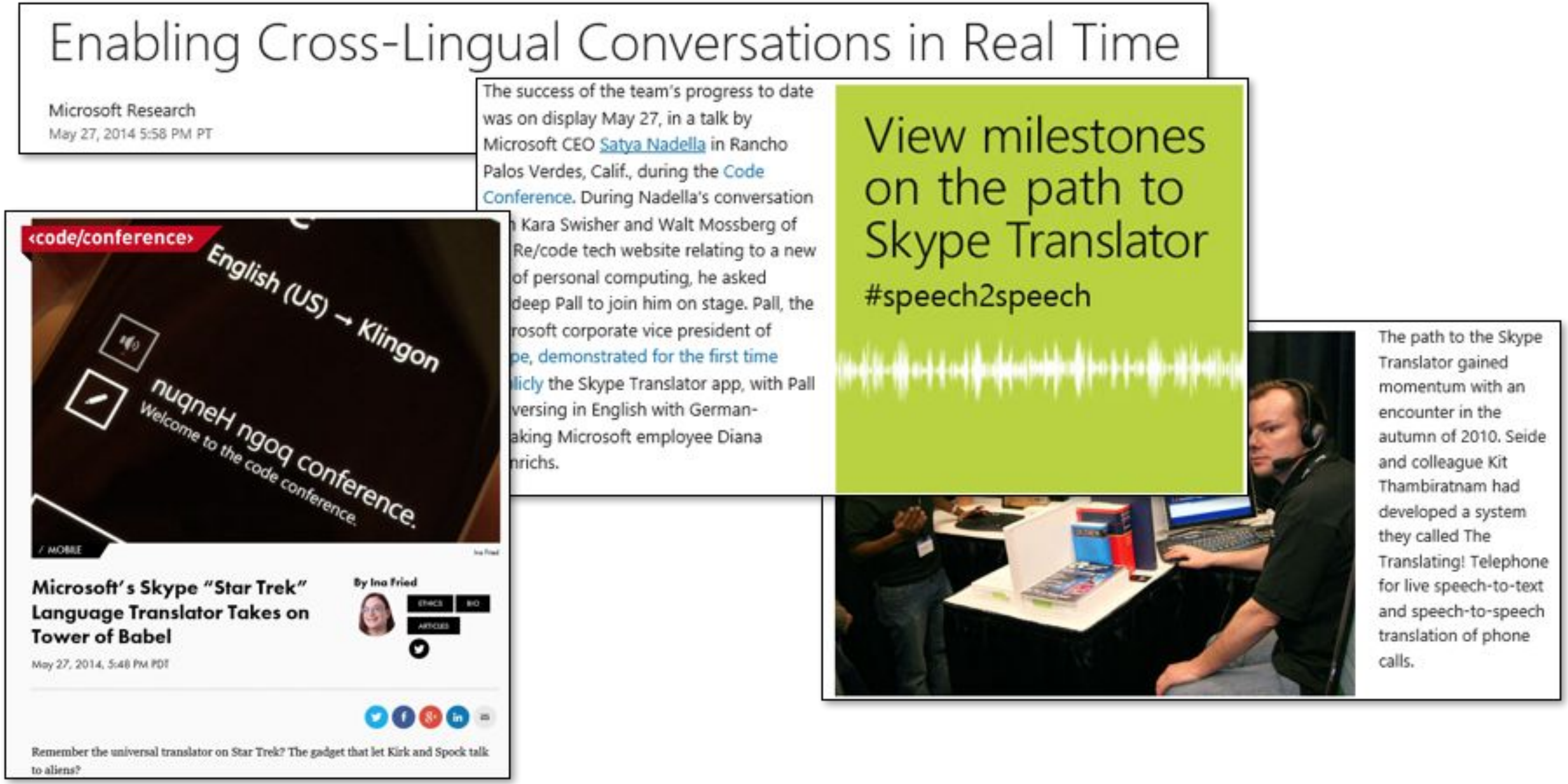
ICCV

ICASSP

ICRA

IROS

Natural Language Understanding



Enabling Cross-Lingual Conversations in Real Time

Microsoft Research
May 27, 2014 5:58 PM PT

The success of the team's progress to date was on display May 27, in a talk by Microsoft CEO Satya Nadella in Rancho Palos Verdes, Calif., during the Code Conference. During Nadella's conversation h Kara Swisher and Walt Mossberg of Re/code tech website relating to a new of personal computing, he asked deep Pall to join him on stage. Pall, the rosoft corporate vice president of pe, demonstrated for the first time licly the Skype Translator app, with Pall versing in English with German-aking Microsoft employee Diana nrichs.

/ MOBILE

Microsoft's Skype "Star Trek" Language Translator Takes on Tower of Babel

By Ina Fried

May 27, 2014, 5:48 PM PDT

Remember the universal translator on Star Trek? The gadget that let Kirk and Spock talk to aliens?

The path to the Skype Translator gained momentum with an encounter in the autumn of 2010. Seide and colleague Kit Thambiratnam had developed a system they called The Translating! Telephone for live speech-to-text and speech-to-speech translation of phone calls.

Speech and Music Generation

WaveNet (DeepMind)

https://deepmind.com/blog/wavenet-generative-model-raw-audio/

Magenta Team (Google Brain)

https://magenta.tensorflow.org/2016/12/16/nips-demo

https://magenta.tensorflow.org/

https://www.youtube.com/watch?v=vM5NaGoynjE

Neural Style Transfer

Code to have fun

https://github.com/jcjohnson/neural-style

https://github.com/jcjohnson/fast-neural-style

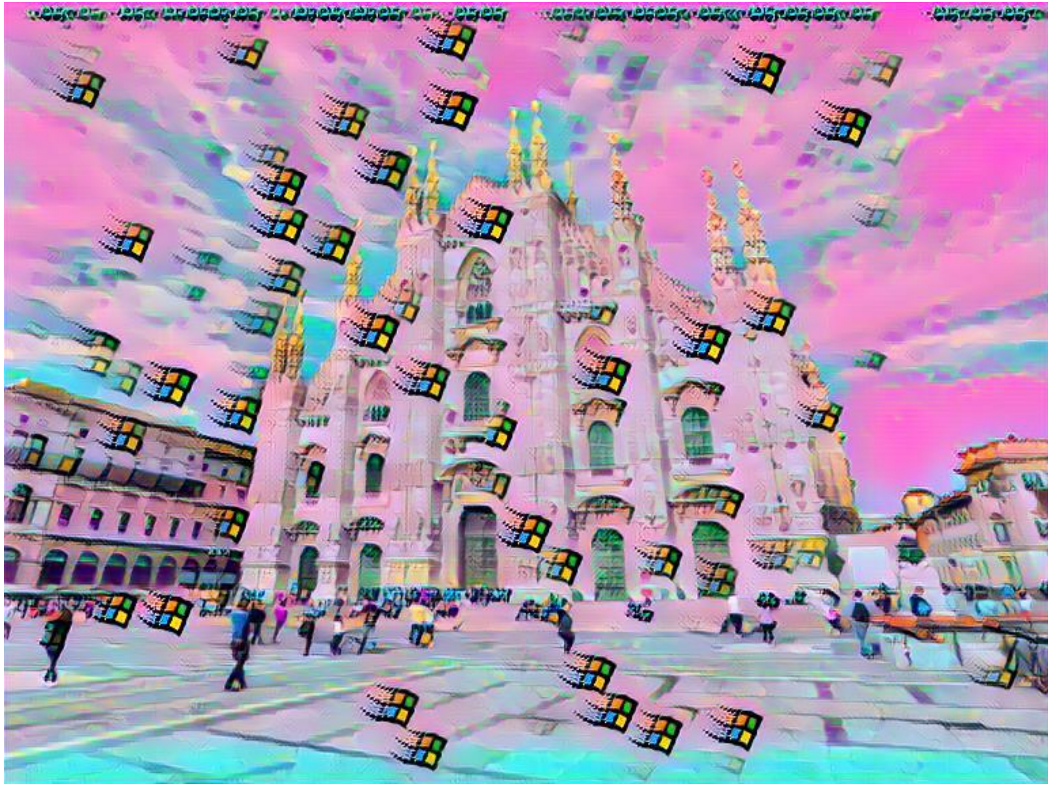
https://ml4a.github.io/ml4a/style_transfer/

Deep Photo Style Transfer

Input Style Output

https://github.com/luanfujun/deep-photo-styletransfer

Neural Vaporwave Style Transfer



Neural Vaporwave

provided by Spooky

Mask R-CNN on Image Instance Segmentation

[Mask R-CNN, He et Al](#)

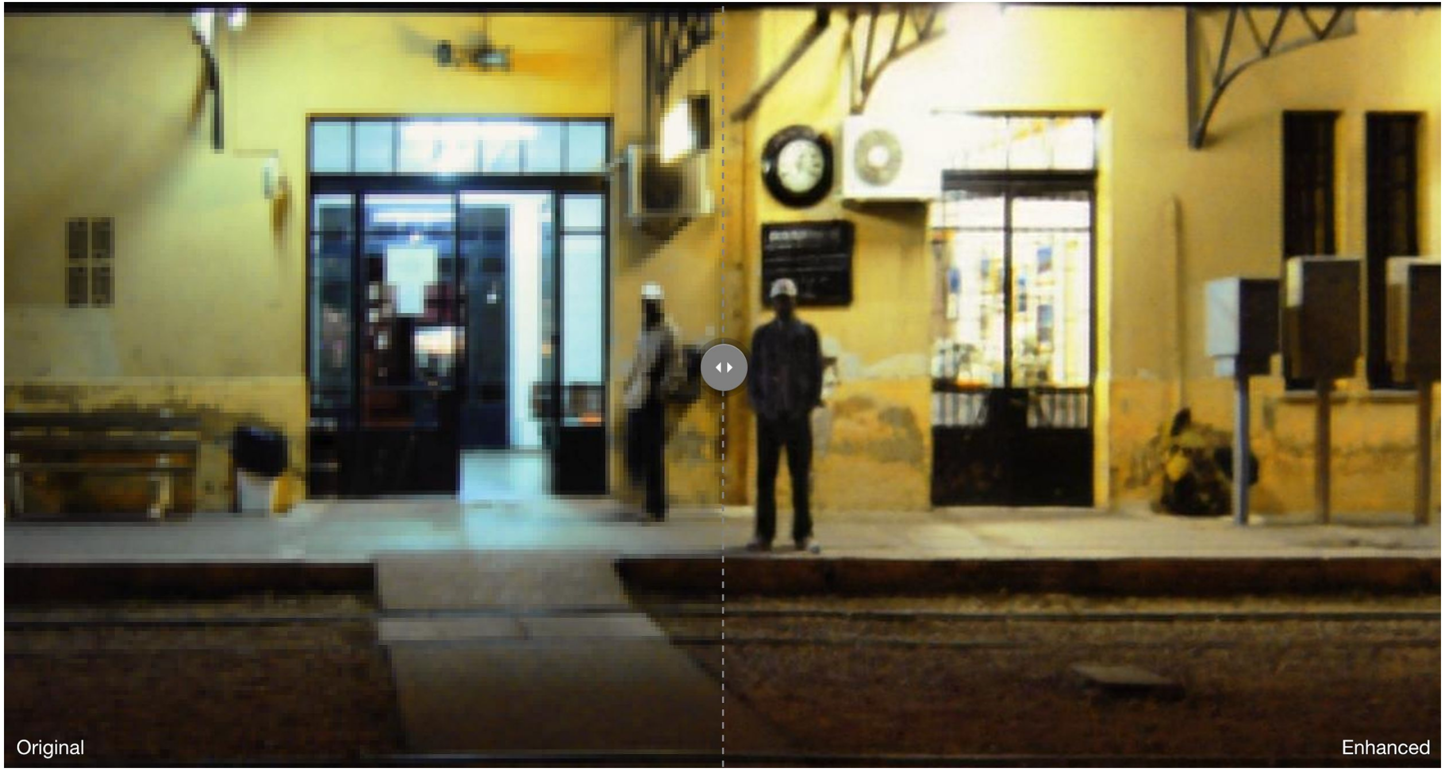
Facebook Research

Mask R-CNN on Detection and Segmentation

Mask R-CNN on Keypoint detection

Super Resolution

[Live Demo]



https://github.com/alexjc/neural-enhance

Generative Adversarial Network (GAN)

Text-to-Photo Realistic Image Synthesis

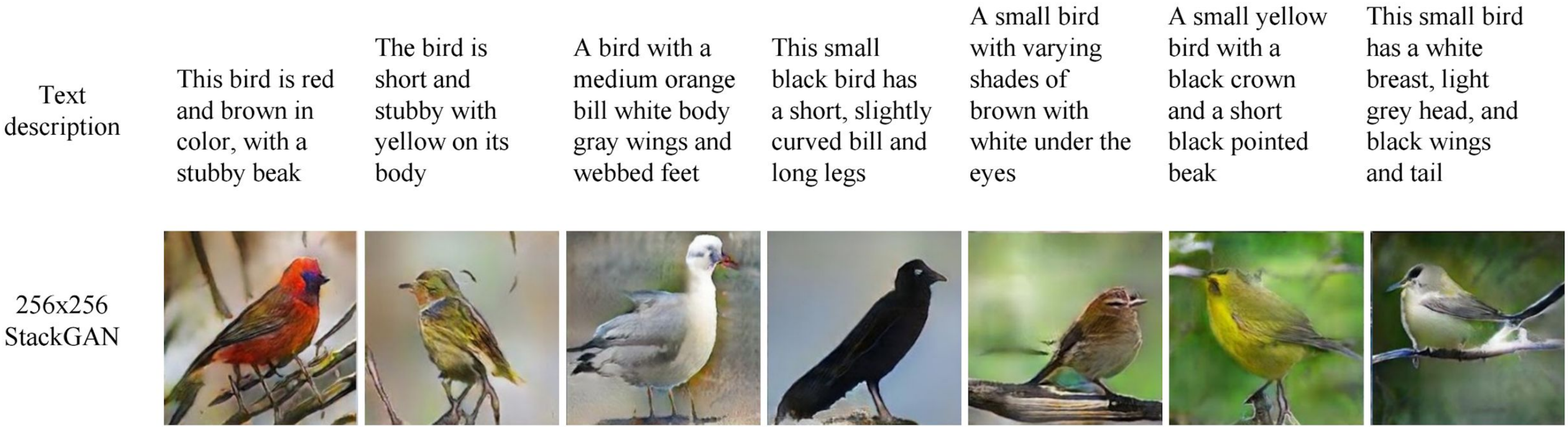
Text description	This flower has petals that are white and has pink shading	This flower has a lot of small purple petals in a dome-like configuration	This flower has long thin yellow petals and a lot of yellow anthers in the center	This flower is pink, white, and yellow in color, and has petals that are striped	This flower is white and yellow in color, with petals that are wavy and smooth	This flower has upturned petals which are thin and orange with rounded edges	This flower has petals that are dark pink with white edges and pink stamen

256x256 StackGAN

https://github.com/hanzhanggit/StackGAN

Generative Adversarial Network (GAN)

Text-to-Photo Realistic Image Synthesis



Recommender Systems

https://research.google.com/pubs/pub45530.html

http://benanne.github.io/2014/08/05/spotify-cnns.html

Deep Reinforcement Learning

'Go is implicit. It's all pattern matching. But that's what deep learning does very well.'

—DEMIS HASSABIS, DEEPMIND

The win is more than a novelty. Online services like Google, Facebook, and Microsoft, already use deep learning to identify images, recognize spoken words, and understand natural

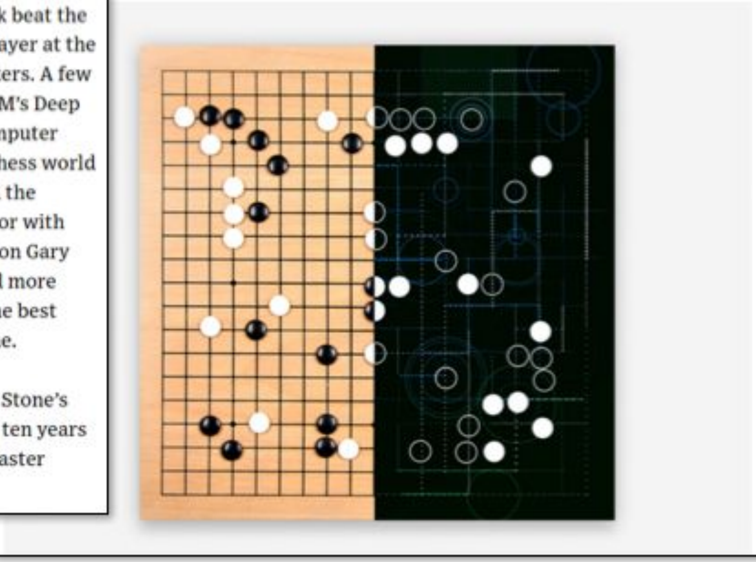
with a technology called reinfor
methods, point the way to a futu
can learn to perform physical ta
environment. "It's a natural fit f

It's incredibly difficult to build a machine that duplicates the kind of intuition that makes the top human players so good at

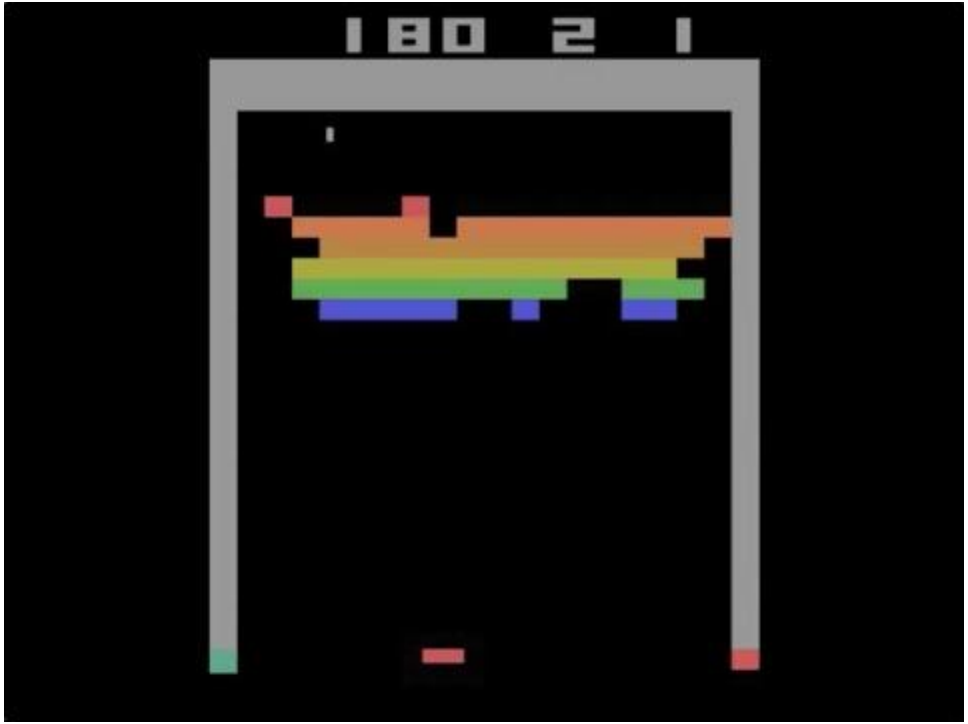
In the mid-'90s, a computer program called Chinook beat the world's top player at the game of checkers. A few years later, IBM's Deep Blue supercomputer shocked the chess world when it wiped the proverbial floor with world champion Gary Kasparov. And more
BM machine, Watson, topped the best
dy!, the venerable TV trivia game.
mastered Othello, Scrabble,
poker. But in the wake of Crazy Stone's
Coulom predicted that another ten years
a machine could beat a grandmaster
rt.

IN A HUGE BREAKTHROUGH, GOOGLE'S AI BEATS A TOP PLAYER AT THE GAME OF GO

WIRED



Playing Atari with Deep Reinforcement Learning



AlphaGo

Nice article:

https://medium.com/@karpathy/alphago-in-context-c47718cb95a5

Autonomous Driving

NVIDIA

UBER

Baidu 百度

Check other NVIDIA automotive partners

NVIDIA self-driving car demo

HORUS

Wearable device for blind people

Text Reading

Face Recognition

Object Recognition

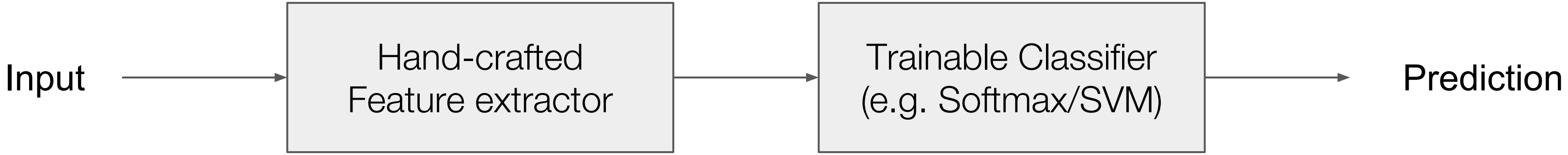
HORUS

eyra

Ok, many funny applications but how does this black magic work?

It’s all about extracting good features!

In the beginning were the hand engineered features



Descriptors are based on fixed heuristics

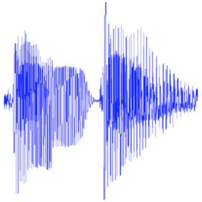
- SIFT, HoG, BRIEF (...) for visual tasks
- MCCF for speech recognition

Bad:

- They need to be carefully designed depending on the task
- Time consuming
- Fixed and cannot deal with data variability

Traditional Pattern Recognition pipelines

Speech Recognition (early 90s - 2011)



MFCC
Low Level Features → Mixture of Gaussian
Mid Level Features → Classifier →

MFCC (Low Level Features)	Mixture of Gaussian (Mid Level Features)	Classifier
Fixed	Unsupervised	Supervised

Object Recognition (2006 - 2012)

SIFT/HoG (Low Level Features)	K-means / Sparse Coding (Mid Level Features)	Classifier
Fixed	Unsupervised	Supervised

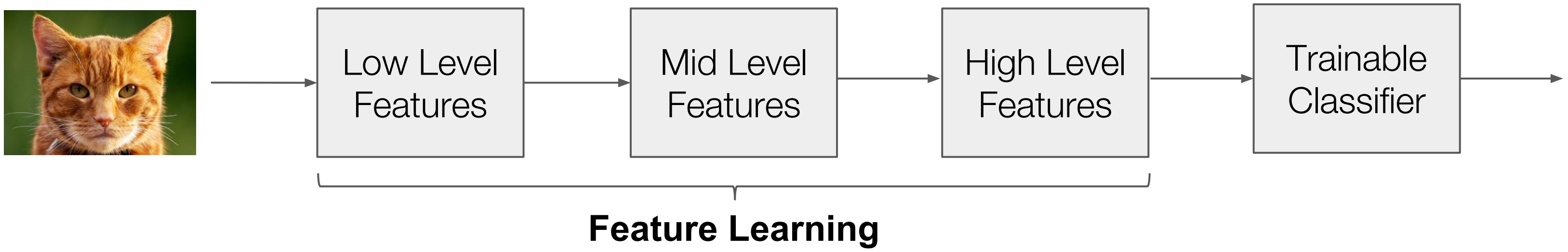
Hand-engineered features still work very well for task that involves feature matching!

But Deep Learning is coming…

LIFT: DL-based descriptor

https://arxiv.org/abs/1603.09114

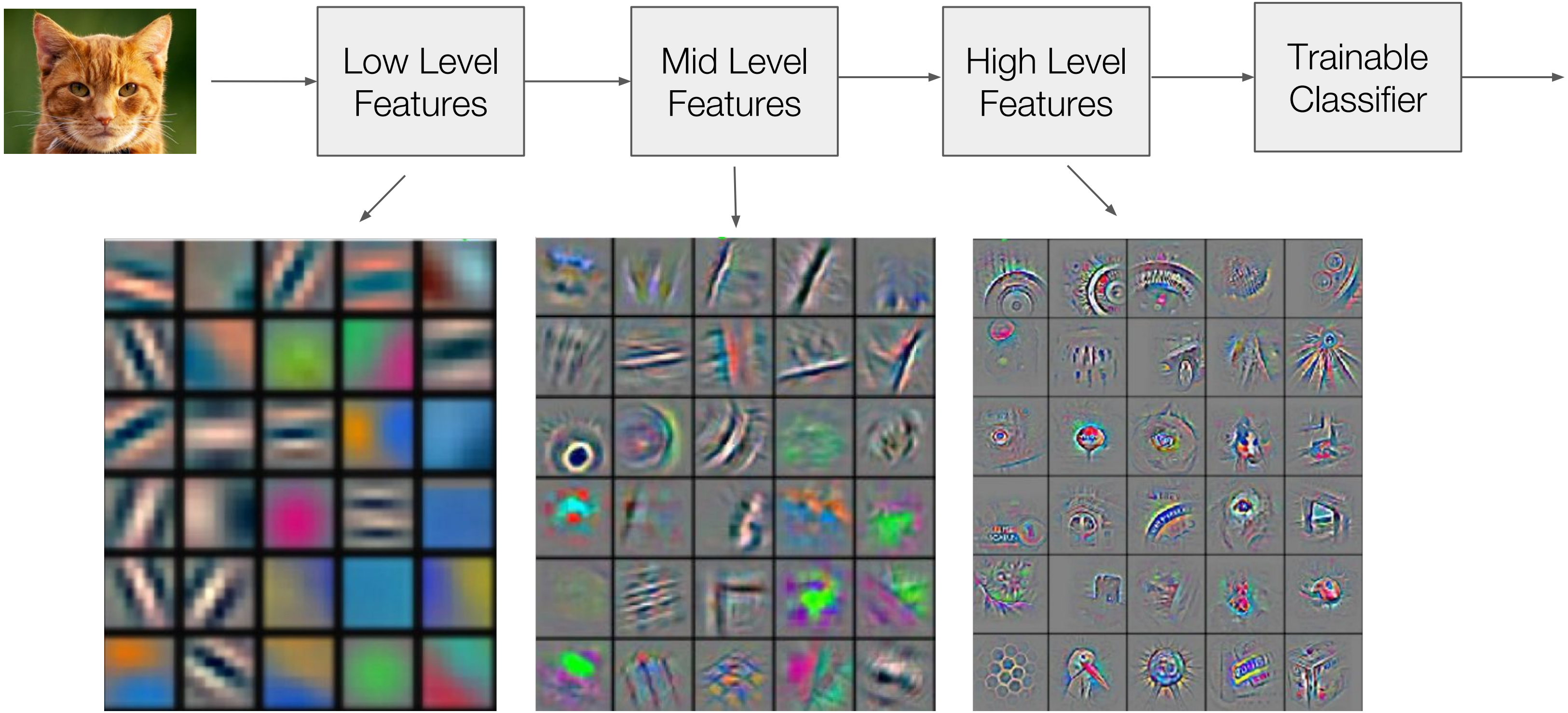
Deep Learning pipeline



Representation Learning address the problem of learning a general and hierarchical feature representation that can be exploited for different tasks.

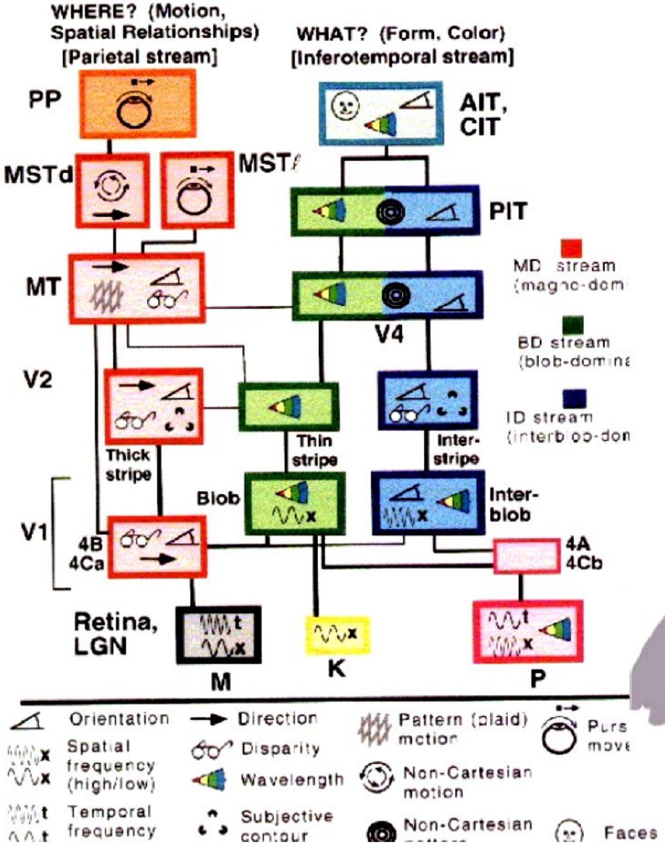
Deep Learning puts together **Representation Learning + Trainable Classifier** in a single *end-to-end training* procedure stacking multiple layers of nonlinear transformation.

Deep Learning pipeline

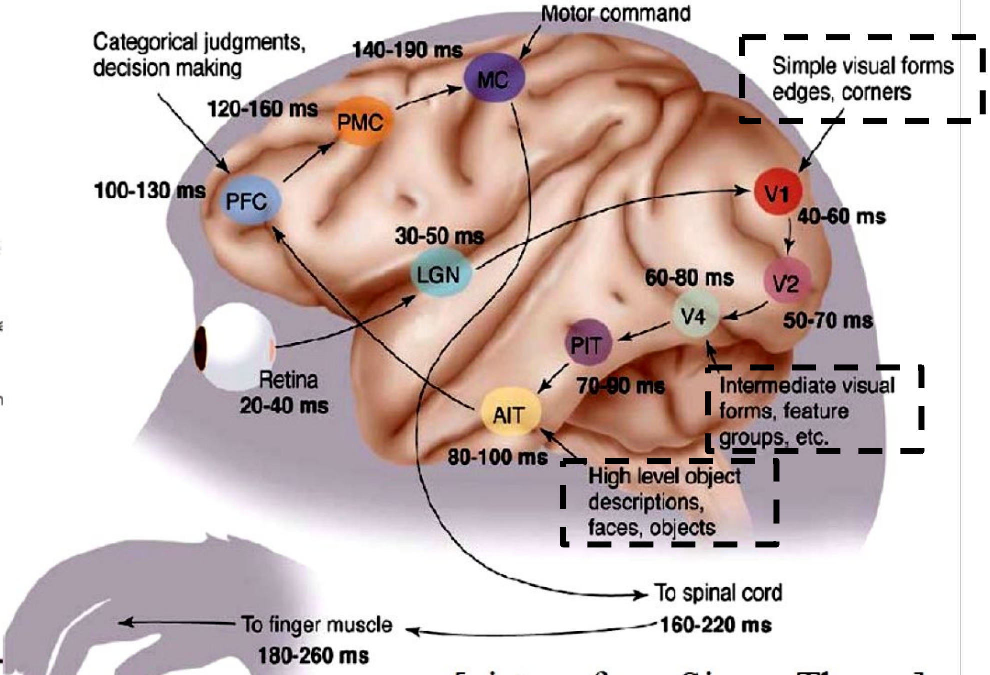


[Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]]()

Mammalian visual cortex is hierarchical



[Gallant & Van Essen]



[picture from Simon Thorpe]

Hierarchical Feature Learning

In Deep learning layers are ***nonlinear trainable*** *feature transforms* that learn a hierarchy of descriptors with increasing abstraction, i.e.,

Image recognition

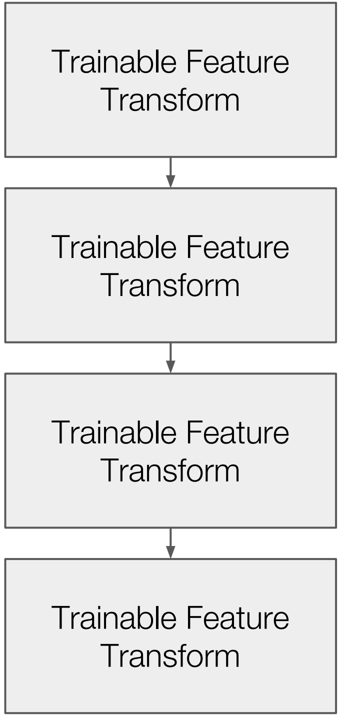
Pixel → edge → texton → motif → part → object

Text analysis

Character → word → word group → clause → sentence → story

Speech recognition

Sample → spectral band → sound → phone → phoneme → word



Representation Learning

Learning the representation is a challenging problem that can have several interpretations

Cognitive perspective

- How can a perceptual system build itself by looking at the external world?
- How much prior structure is necessary?

Neuroscience

- Does the cortex «run» a single, general learning algorithm? Or multiple simpler ones?

ML/AI Perspective

- What is the fundamental principle?
- What is the learning algorithm?
- What is the architecture?

DL addresses the problem of learning hierarchical representations with a single algorithm

It all started from Image Classification

IMAGENET

Large Scale Visual Recognition Challenge (ILSVRC)

[2010] NEC-UIUC

↓

Dense descriptor grid: HOG, LBP

↓

Coding: local coordinate, super-vector

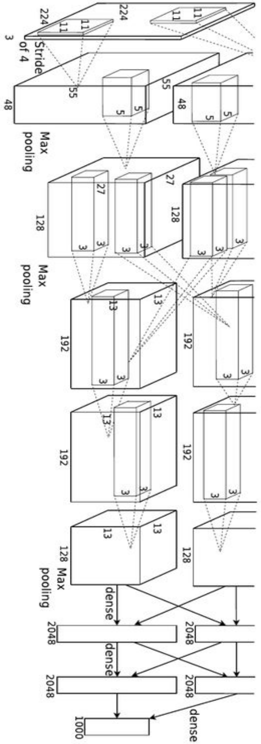
↓

Pooling, SPM

↓

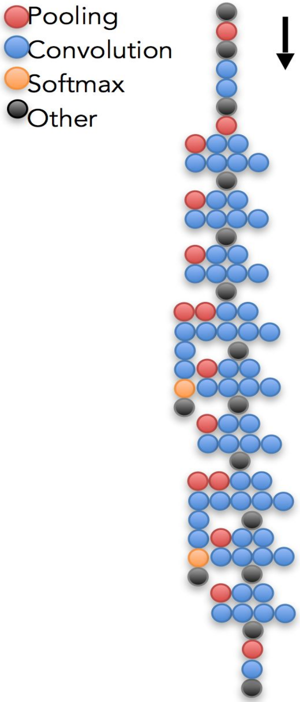
Linear SVM

[2012] AlexNet



Krizhevsky et Al.

[2014] GoogleNet



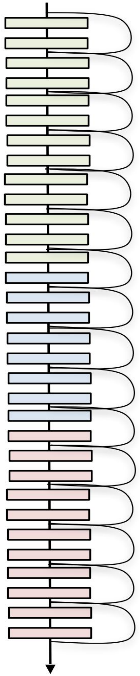
Szegedy et Al.

VGG

Image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
fc-4096
fc-4096
fc-1000
softmax

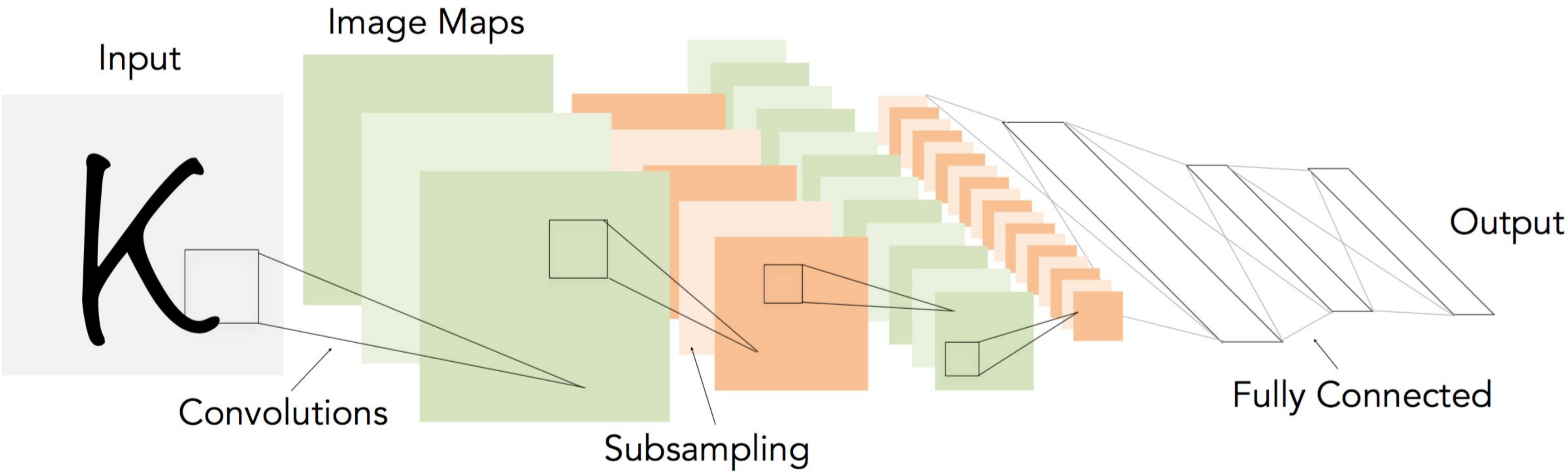
Symonian & Zisserman

[2015] ResNet



He et Al.

CNNs are not a new idea!



[1998] LeNet-5

[LeCun et al., 1998]
Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner.
Gradient-based learning applied to document recognition.

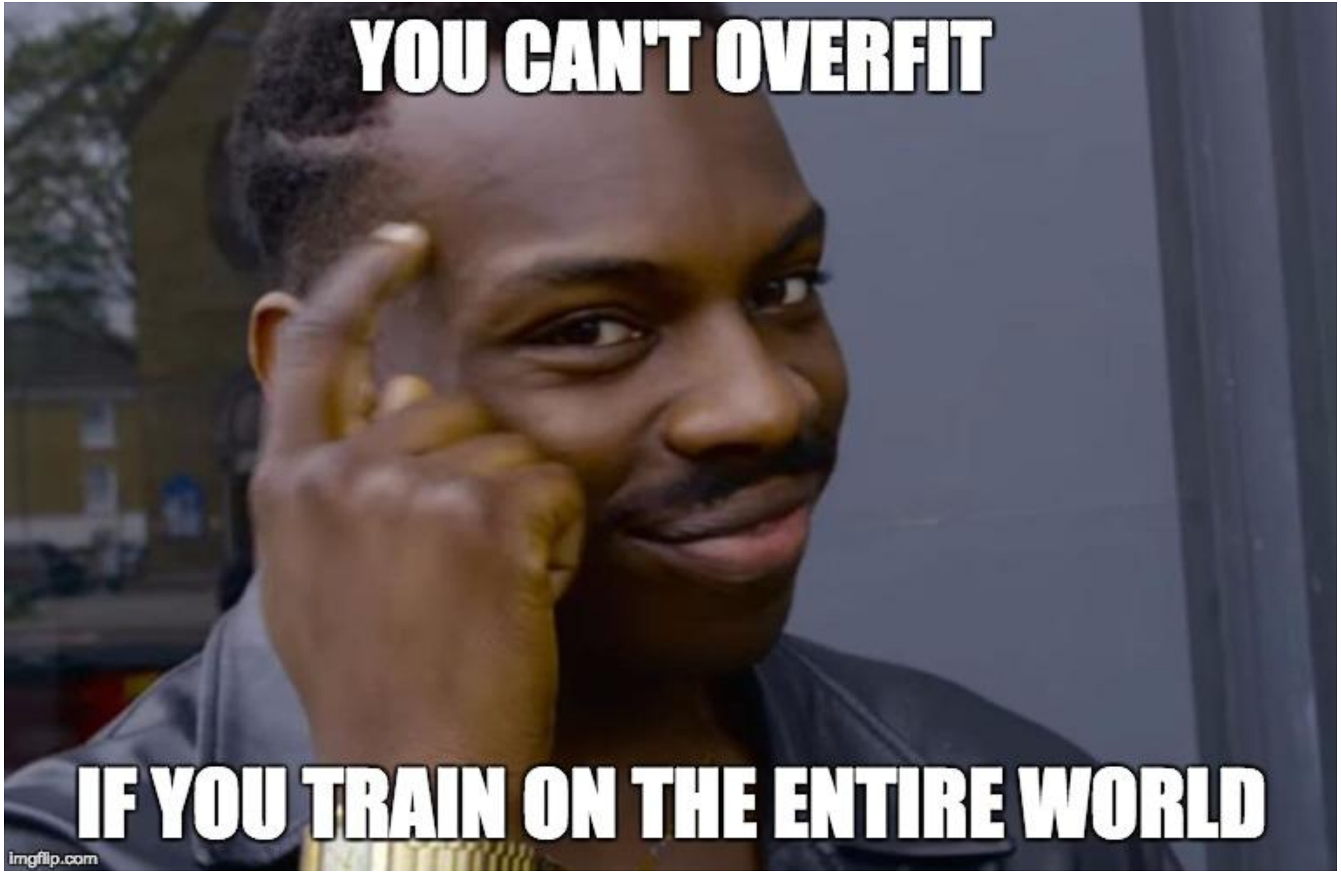
But, why Deep Learning didn’t work until now?

Why DL didn’t work until now?

- **Our labeled datasets were thousands of times too small.**
- Our computers were millions of times too slow.
- We initialized the weights in a stupid way.
- We didn’t know the Loss surface we were optimizing.
- We used the wrong type of nonlinearity.

Huge datasets

22K categories and 14M images


YOU CAN'T OVERFIT
IF YOU TRAIN ON THE ENTIRE WORLD
imgflip.com

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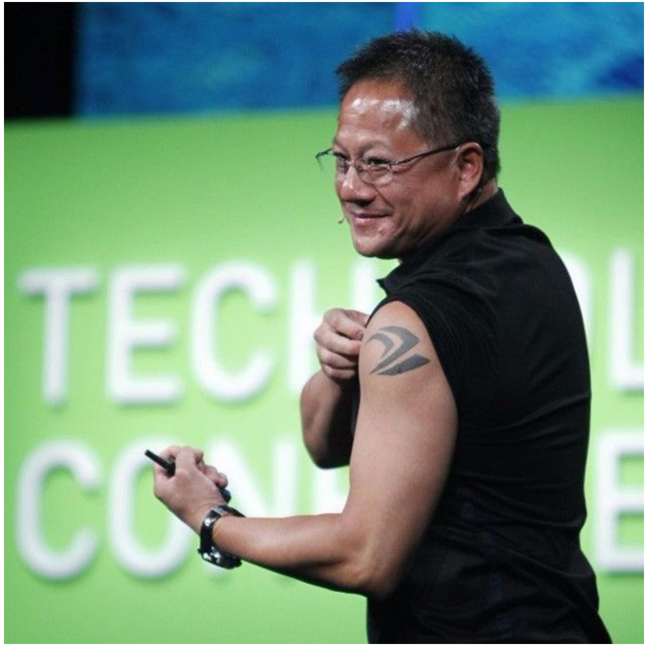
GPU acceleration and scalable algorithms



Approved by Jensen (Gianni)

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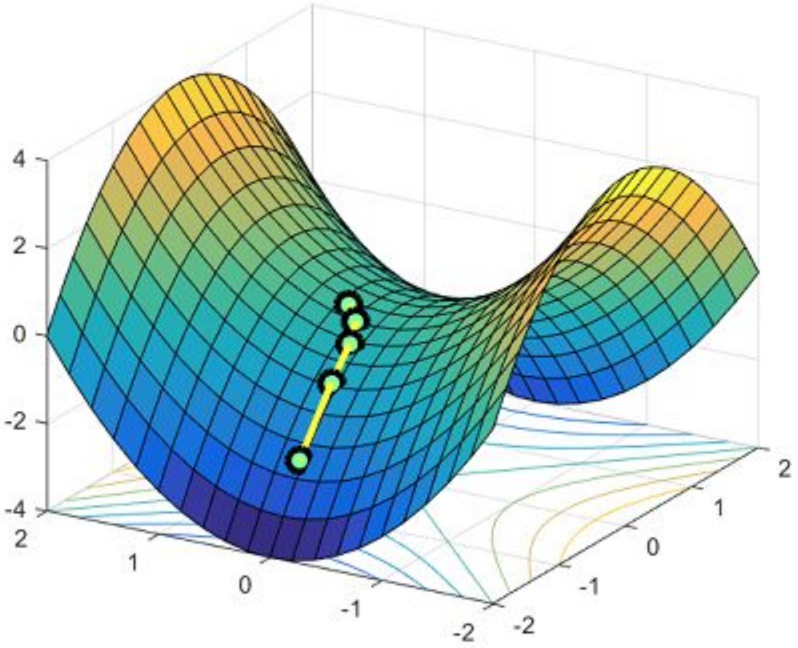

References

- On the saddle point problem for non-convex optimization, Pascanu, Dauphin, Ganguli, Bengio, 2014
- Identifying and attacking the saddle point problem in high-dimensional non-convex optimization, YN Dauphin, R Pascanu, C Gulcehre, K Cho, S Ganguli, Y Bengio, NIPS 2014
- **Escaping from Saddle Points** (13-minutes read)

Why DL didn’t work until now?

- Our labeled datasets were thousands of times too small.
- Our computers were millions of times too slow.
- We initialized the weights in a stupid way.
- We didn’t know the Loss surface we were optimizing.
- **We used the wrong type of nonlinearity (we’ll see).**

What should I know before starting?

Pre-requisites

We will be formulating *cost functions*, taking derivatives and performing optimization with gradient descent so...

It’s strictly recommended to have a strong background of:

- Calculus
- Linear Algebra, Matrix Calculus
- Probability Theory
- Machine Learning basic concepts (e.g. Supervised Training, Overfitting…)

I will give you a brief overview on *Optimization theory* and techniques.

Resources

- **Slides provided by me,** mainly based on other brilliant material such as:

  Hugo Larochelle, slides and videos

  Andrej Karpathy, Stanford CS231n Course Notes

  Laurent Dinh, Introduction to DL with Theano

- **The Deep Learning Book** by Ian Goodfellow, Yoshua Bengio, Aaron Courville

  Available online for free: http://www.deeplearningbook.org/