



SIGNAL PROCESSING &
MACHINE LEARNING FOR BIG DATA

DEPARTAMENTO DE SEÑALES, SISTEMAS Y RADIOCOMUNICACIONES



From Data Analysis to Artificial Intelligence

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Universidad Politécnica de Madrid

The Data Revolution: Big Data

May 5, 2016 | 931 views

Big Data At Sprint: Turning Mobile Network Data Into Business Value

Thanks to its huge network of users, Sprint has access to vast amounts of user data. Three years ago it established subsidiary Pinsight Media to investigate ways of capitalizing on that data. Since then it has gone from serving zero to six billion ad impressions per months, based on "authenticated [...]



Apr 19, 2016 | 20,645 views

How Big Data And Analytics Are Transforming The Construction Industry



Apr 22, 2016 | 14,793 views

How Big Data And Analytics Are Transforming Supply Chain Management

Apr 28, 2016 | 9,109 views

Big Data Overload: Why Most Companies Can't Deal With The Data Explosion

FEB 16, 2016 @ 02:54 AM 15,945 VIEWS

How Big Data Is Transforming Medicine



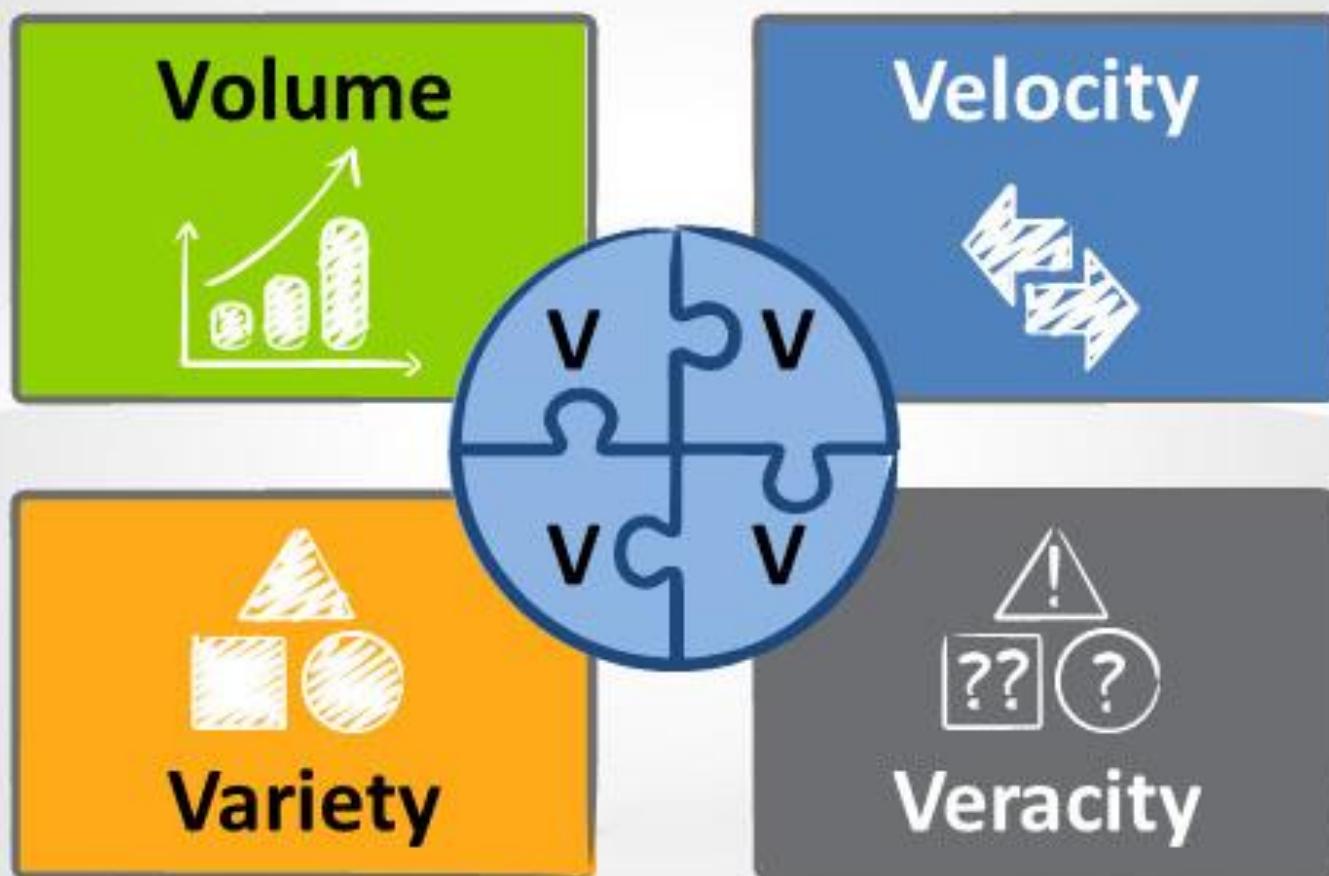
Forbes / Tech

SEP 8, 2015 @ 02:26 AM 131,676 VIEWS

4 Ways Big Data Will Change Every Business



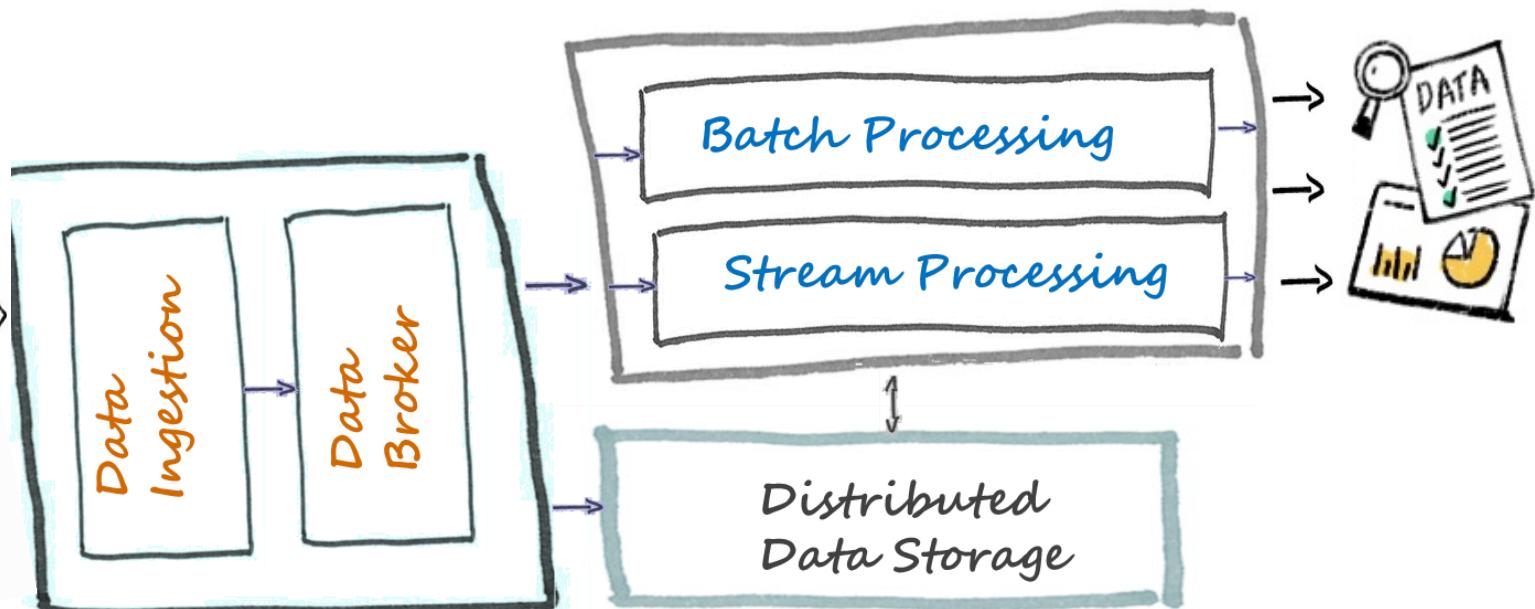
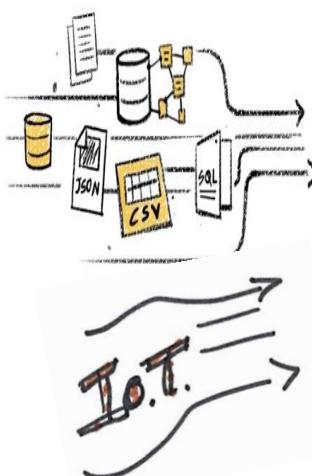
Big Data: 4V definition



Big Data Architecture

Data Customers

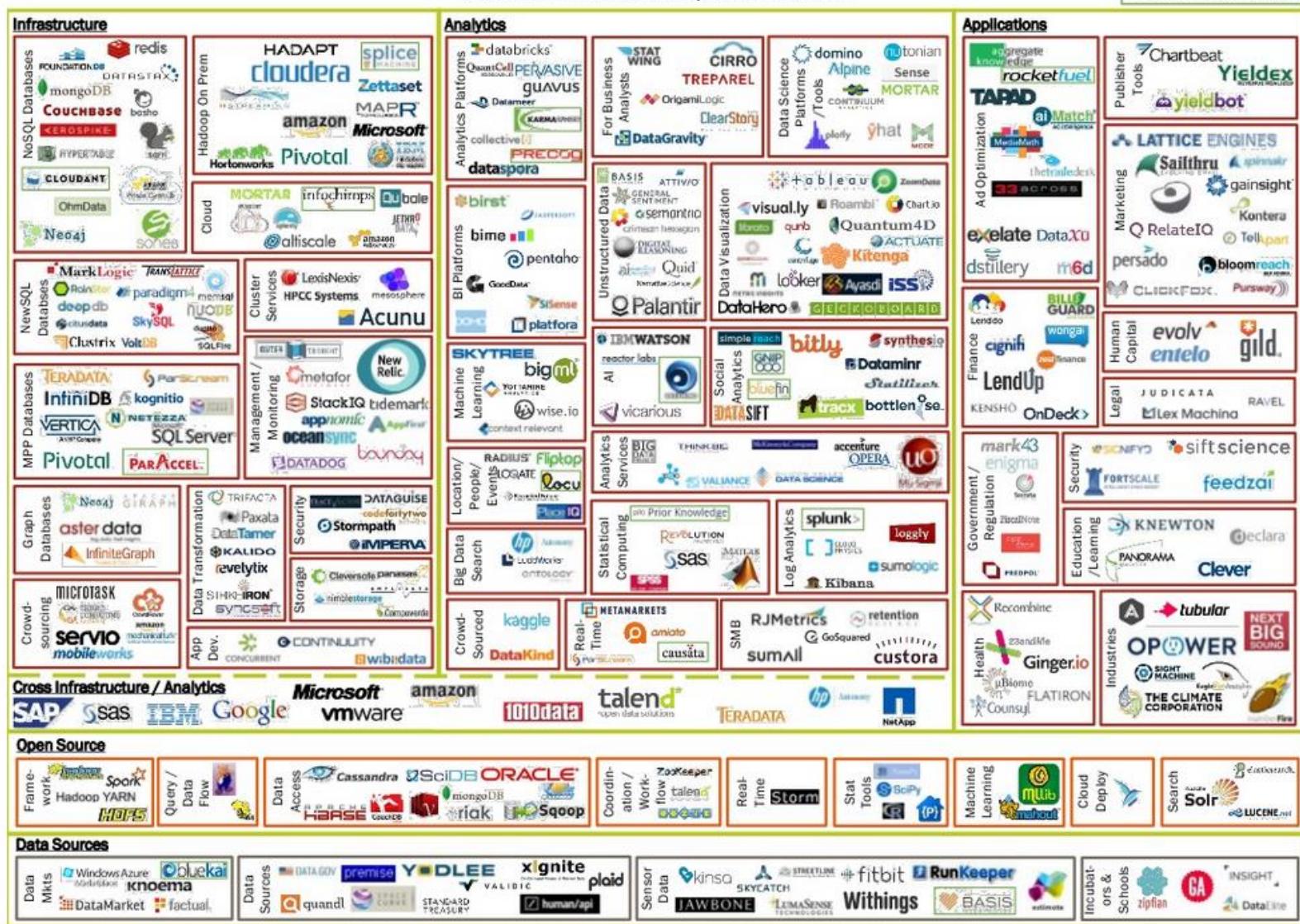
Data Sources



- Business Intelligence
- Visualization
- Analytics

BIG DATA LANDSCAPE, VERSION 3.0

Exited: Acquisition or IPO



© Matt Turck (@mattturck), Sutian Dong (@sutiantong) & FirstMark Capital (@firstmarkcap)



Intelligent Machines

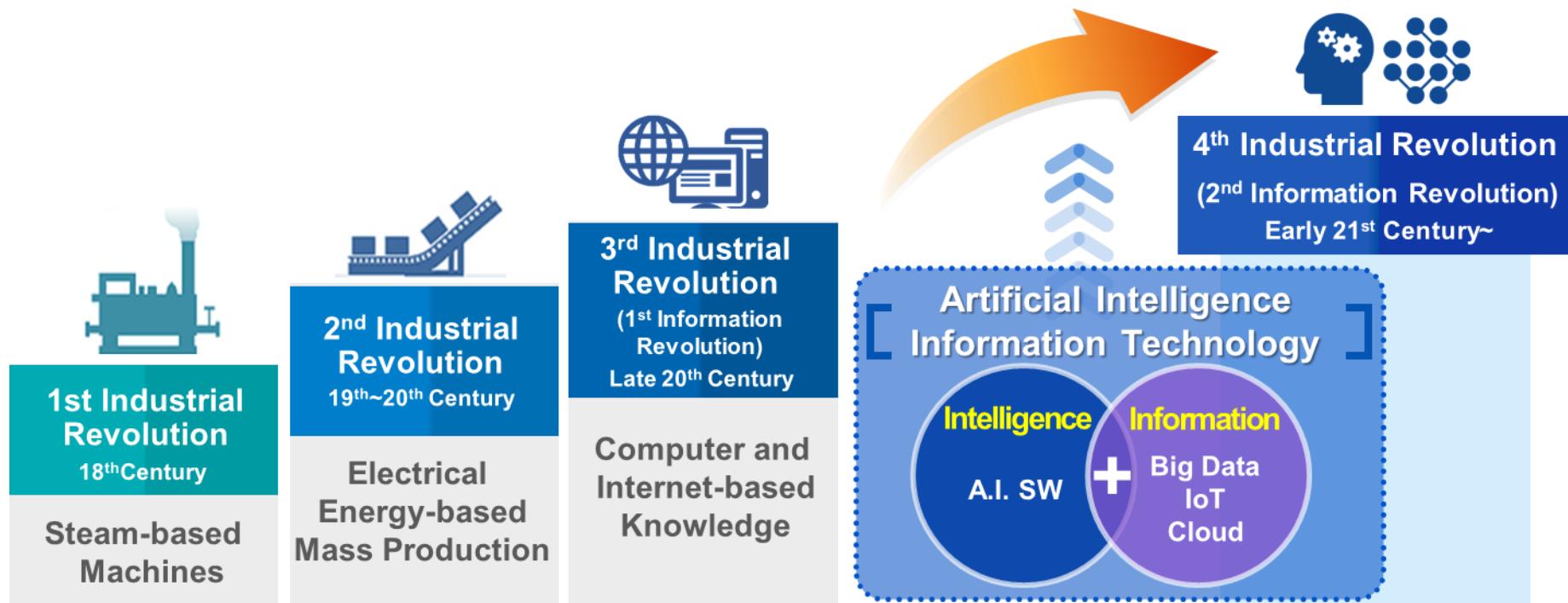
Nvidia CEO: Software Is Eating the World, but AI Is Going to Eat Software

Jensen Huang predicts that health care and autos are going to be transformed by artificial intelligence.

by Tom Simonite May 12, 2017

Nvidia CEO Jensen Huang at the company's developer conference in San Jose, California.





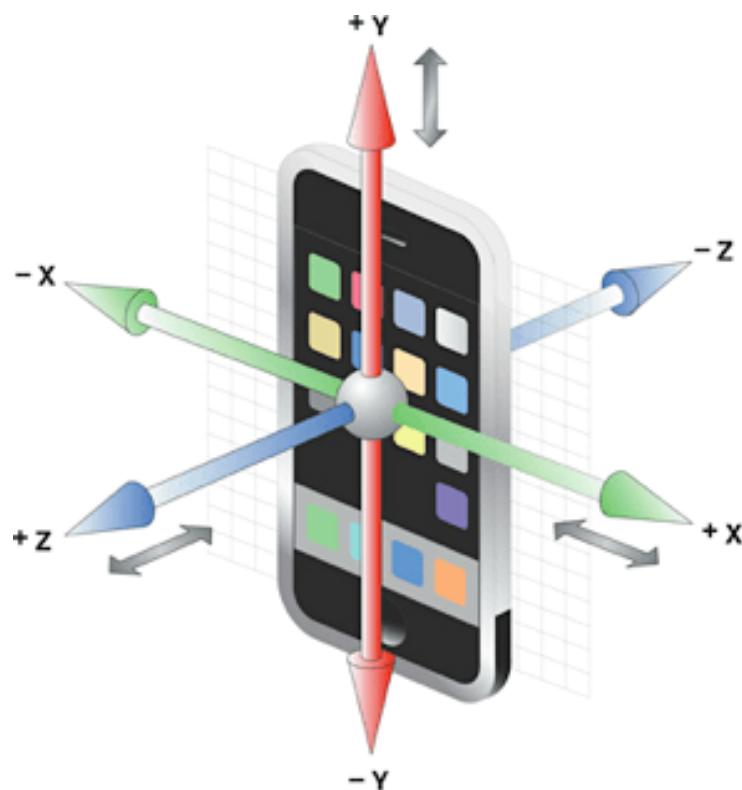
FROM : *humans*

- to *machines*
- to Artificial Intelligence (AI)

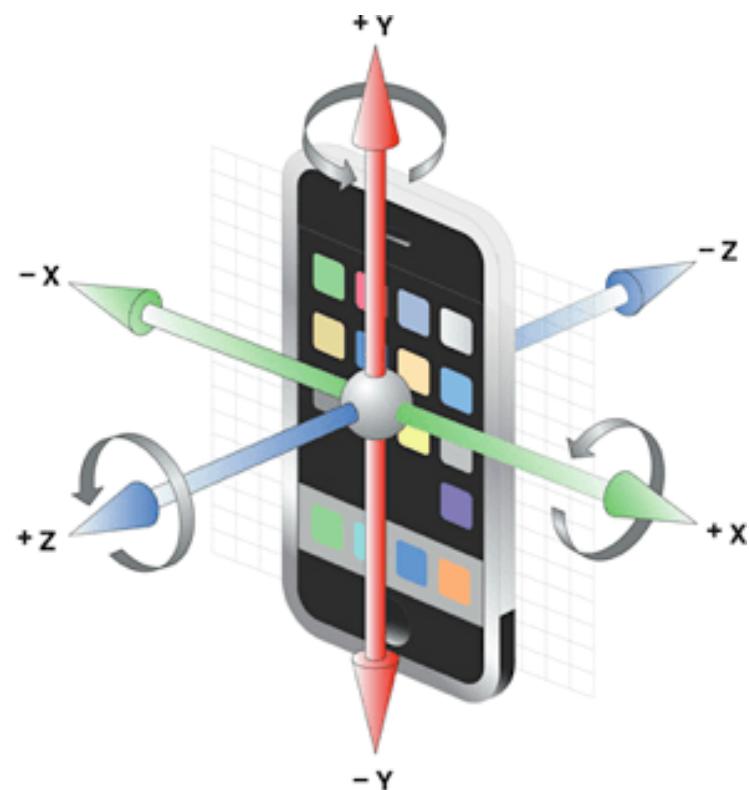
Drivies use case:

www.driviesapp.com



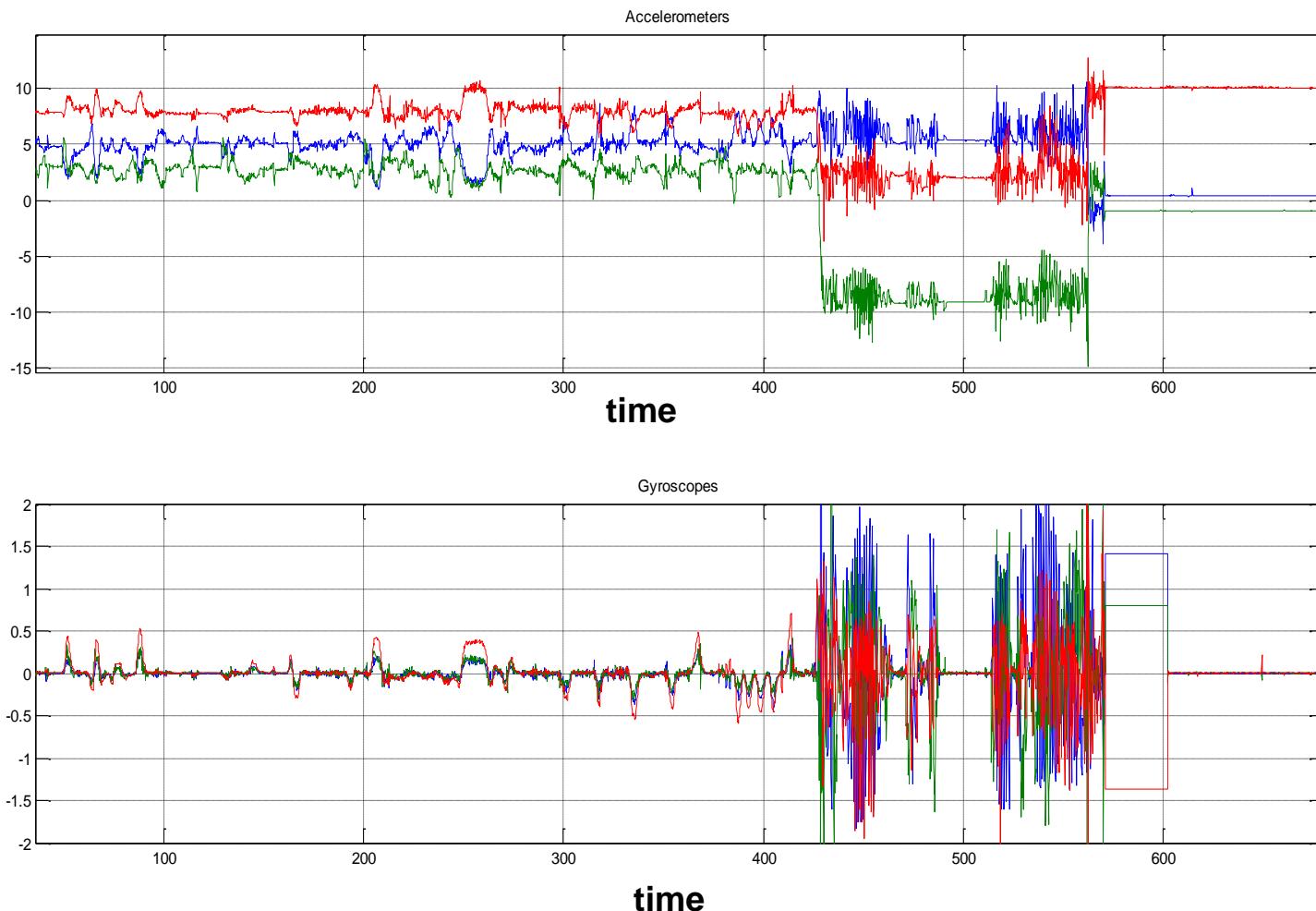


Accelerometer



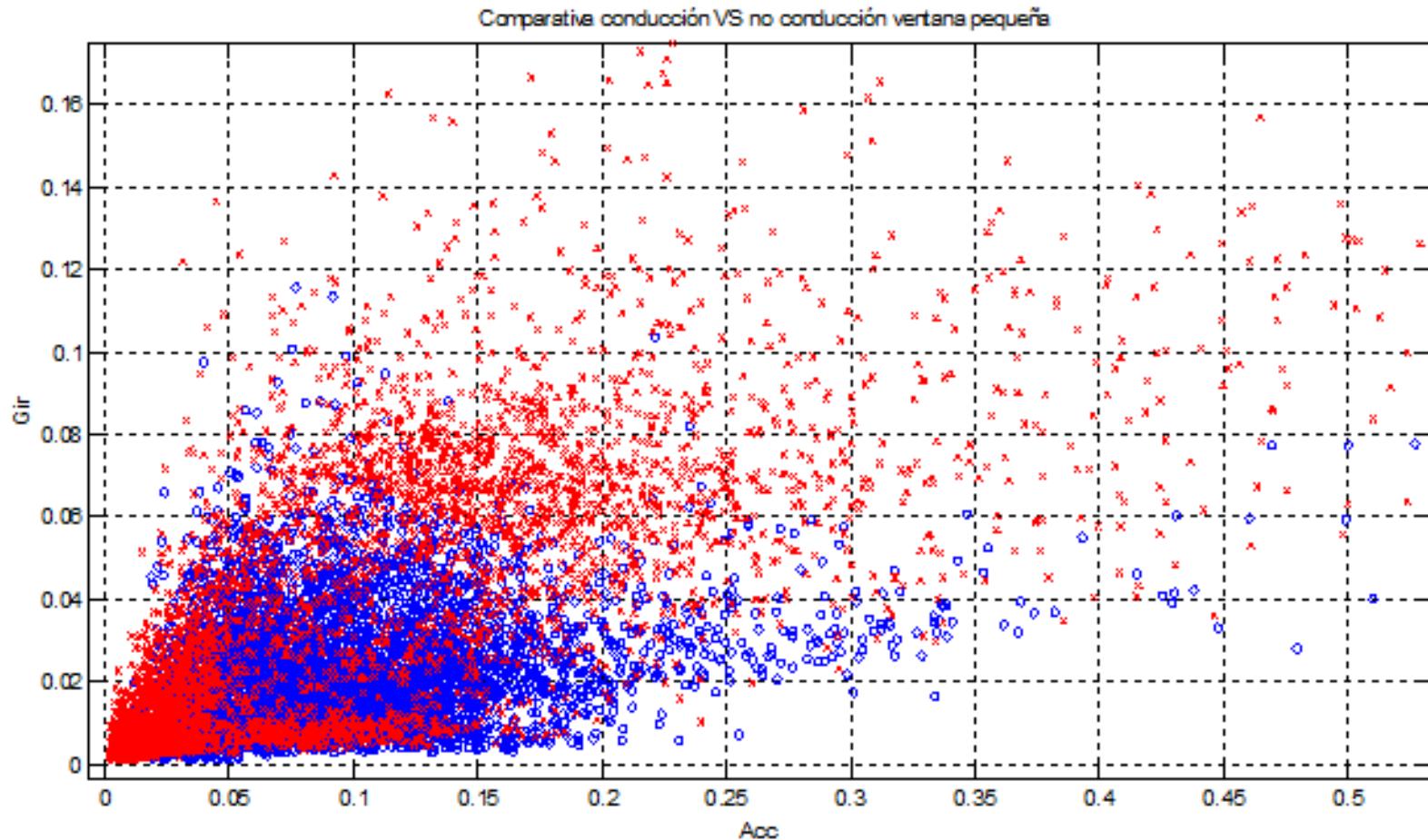
Gyroscope

SSR



From manual - linear classifiers TO Neural Networks

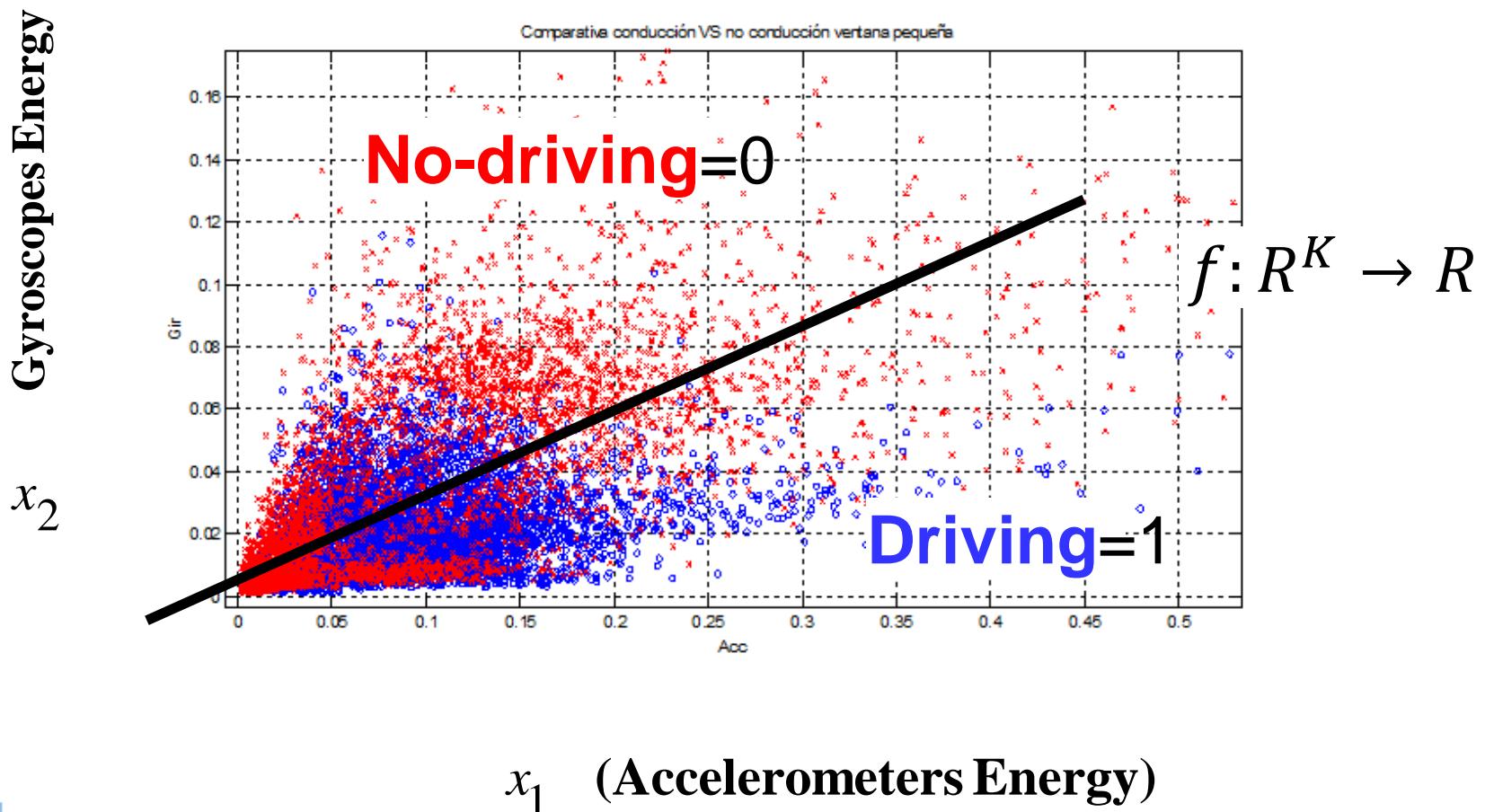
Gyroscopes Energy



x_1 : Accelerometers Energy

Driving detection (yes/no)

= define a **decision function**





24
HOURS

7
DAYS A WEEK

365
DAYS A YEAR

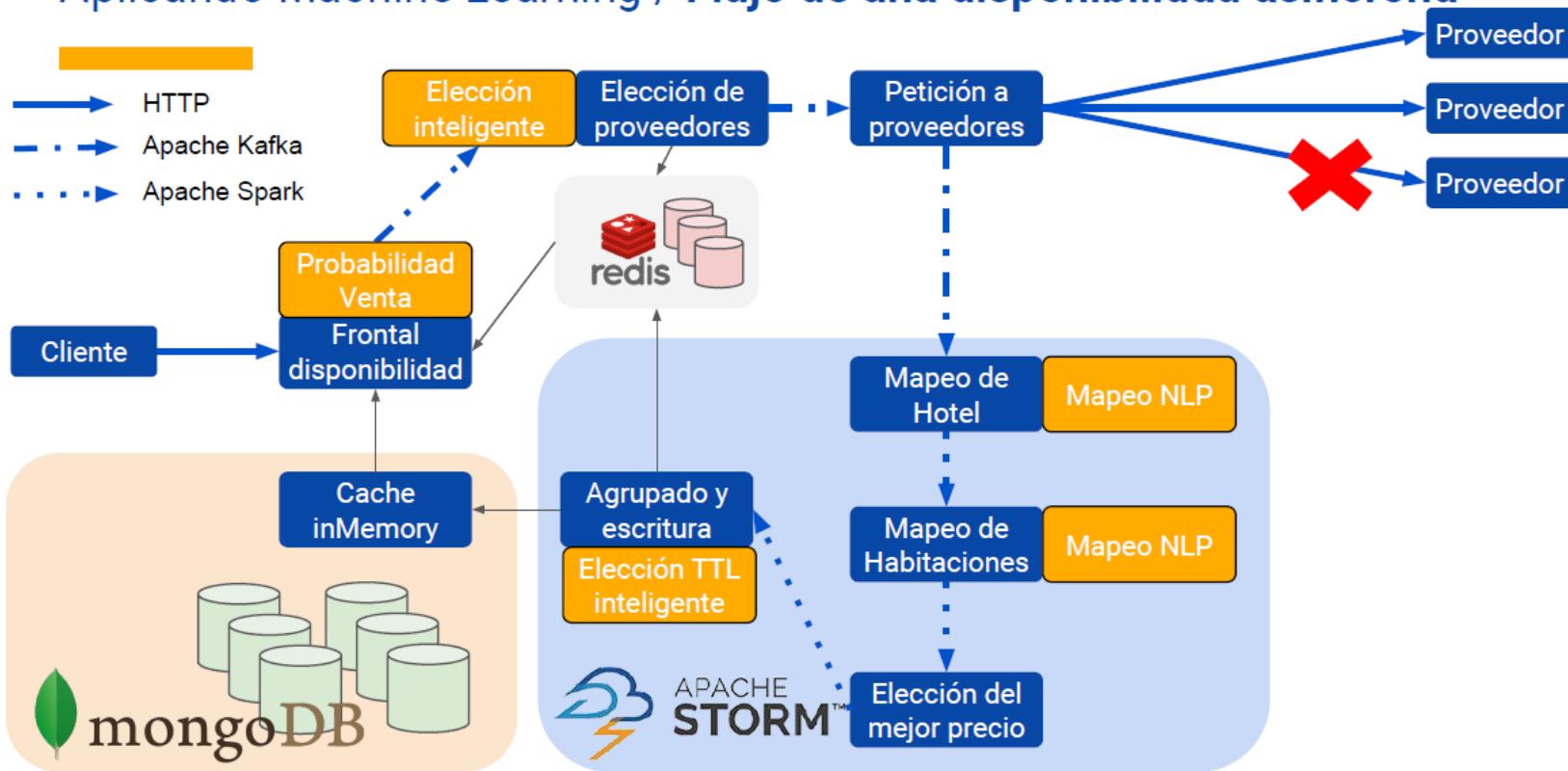


@sukiweb





Aplicando Machine Learning / Flujo de una disponibilidad asincrónica

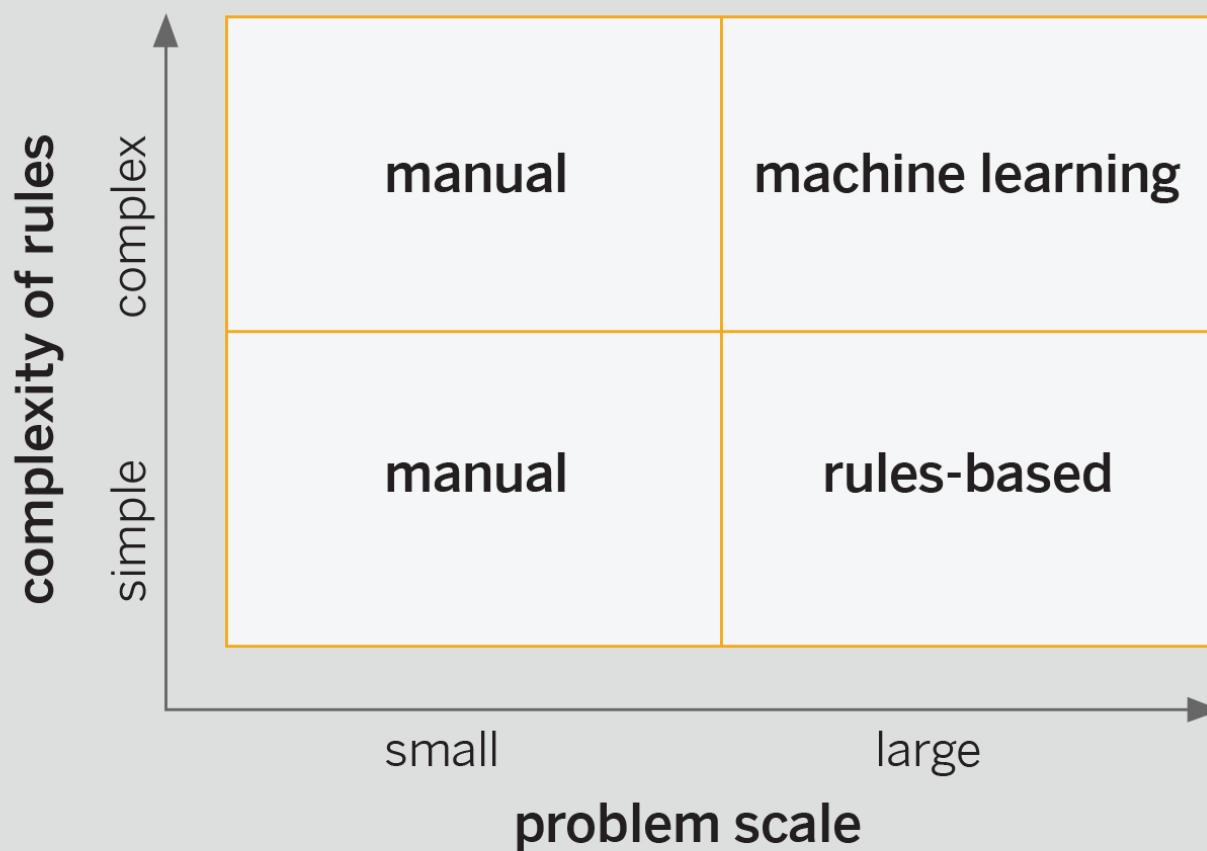


Logitravel Group

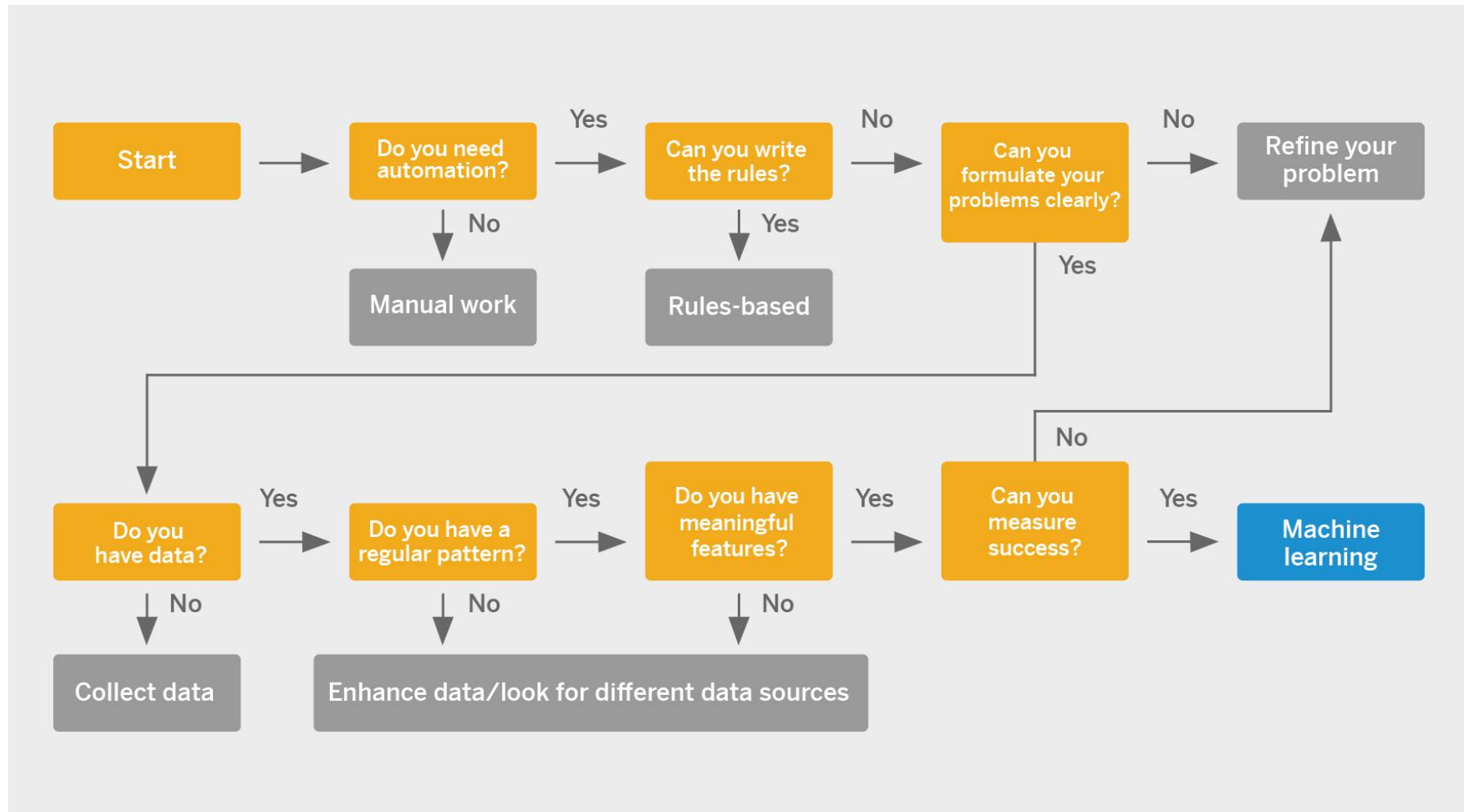


24 horas
7 días
365 días a la semana





Why Machine Learning and Why Now?



Process optimization

Don't fire people. Rent their avatars

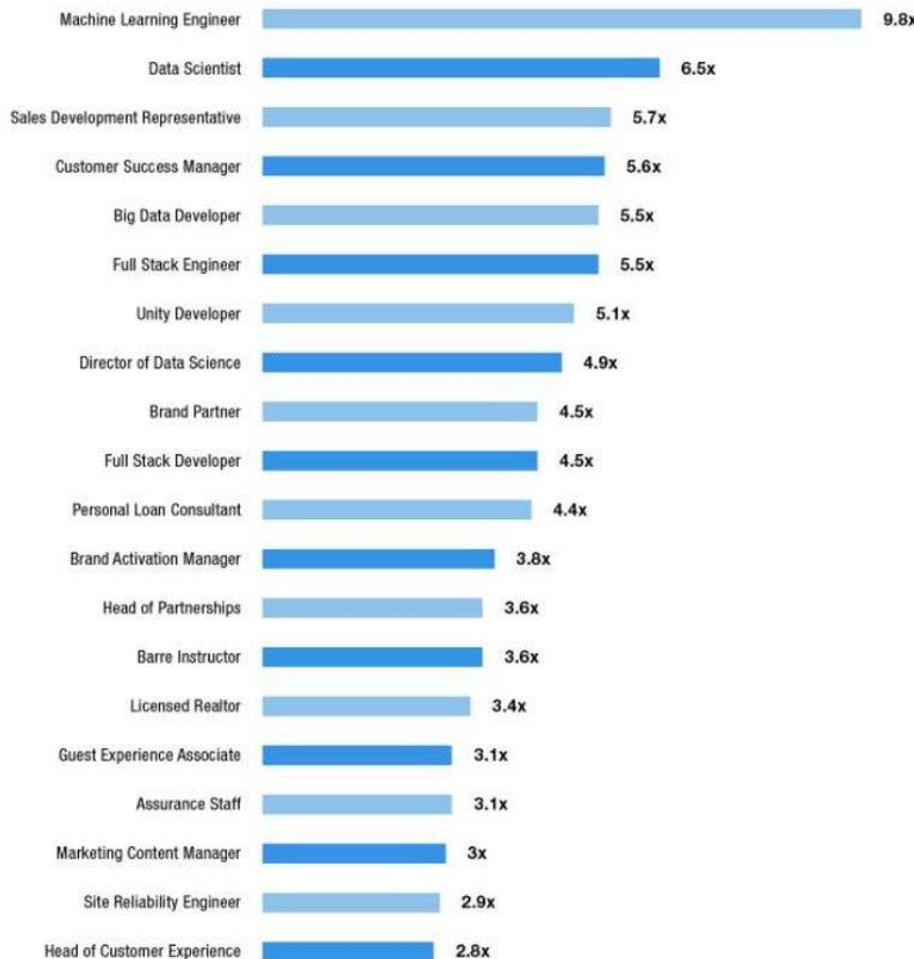


Sergio Álvarez-Teleña

LinkedIn's Fastest-Growing Jobs Today Are In Data Science And Machine Learning

Top 20 Emerging Jobs

LinkedIn Economic Graph



DATA Engineer

Develops, constructs, tests,
and maintains architectures.
Such as databases
and large-scale
processing systems.



DataCamp
Learn Data Science By Doing

DATA Scientist

Cleans, massages
and organizes (big) data.
Performs descriptive statistics
and analysis to develop
insights, build models and
solve a business need.



MODERN DATA SCIENTIST

Data Scientist, the sexiest job of 21th century requires a mixture of multidisciplinary skills ranging from an intersection of mathematics, statistics, computer science, communication and business. Finding a data scientist is hard. Finding people who understand who a data scientist is, is equally hard. So here is a little cheat sheet on who the modern data scientist really is.

MATH & STATISTICS

- ★ Machine learning
- ★ Statistical modeling
- ★ Experiment design
- ★ Bayesian inference
- ★ Supervised learning: decision trees, random forests, logistic regression
- ★ Unsupervised learning: clustering, dimensionality reduction
- ★ Optimization: gradient descent and variants



DOMAIN KNOWLEDGE & SOFT SKILLS

- ★ Passionate about the business
- ★ Curious about data
- ★ Influence without authority
- ★ Hacker mindset
- ★ Problem solver
- ★ Strategic, proactive, creative, innovative and collaborative

PROGRAMMING & DATABASE

- ★ Computer science fundamentals
- ★ Scripting language e.g. Python
- ★ Statistical computing package e.g. R
- ★ Databases SQL and NoSQL
- ★ Relational algebra
- ★ Parallel databases and parallel query processing
- ★ MapReduce concepts
- ★ Hadoop and Hive/Pig
- ★ Custom reducers
- ★ Experience with xaaS like AWS

COMMUNICATION & VISUALIZATION

- ★ Able to engage with senior management
- ★ Story telling skills
- ★ Translate data-driven insights into decisions and actions
- ★ Visual art design
- ★ R packages like ggplot or lattice
- ★ Knowledge of any of visualization tools e.g. Flare, D3.js, Tableau

Data Science Workflow





Machine Learning:

automatic methods of data analysis

- What is the best prediction about the future given some past data?
- What is the best model to explain some data?
- What action should be performed next?

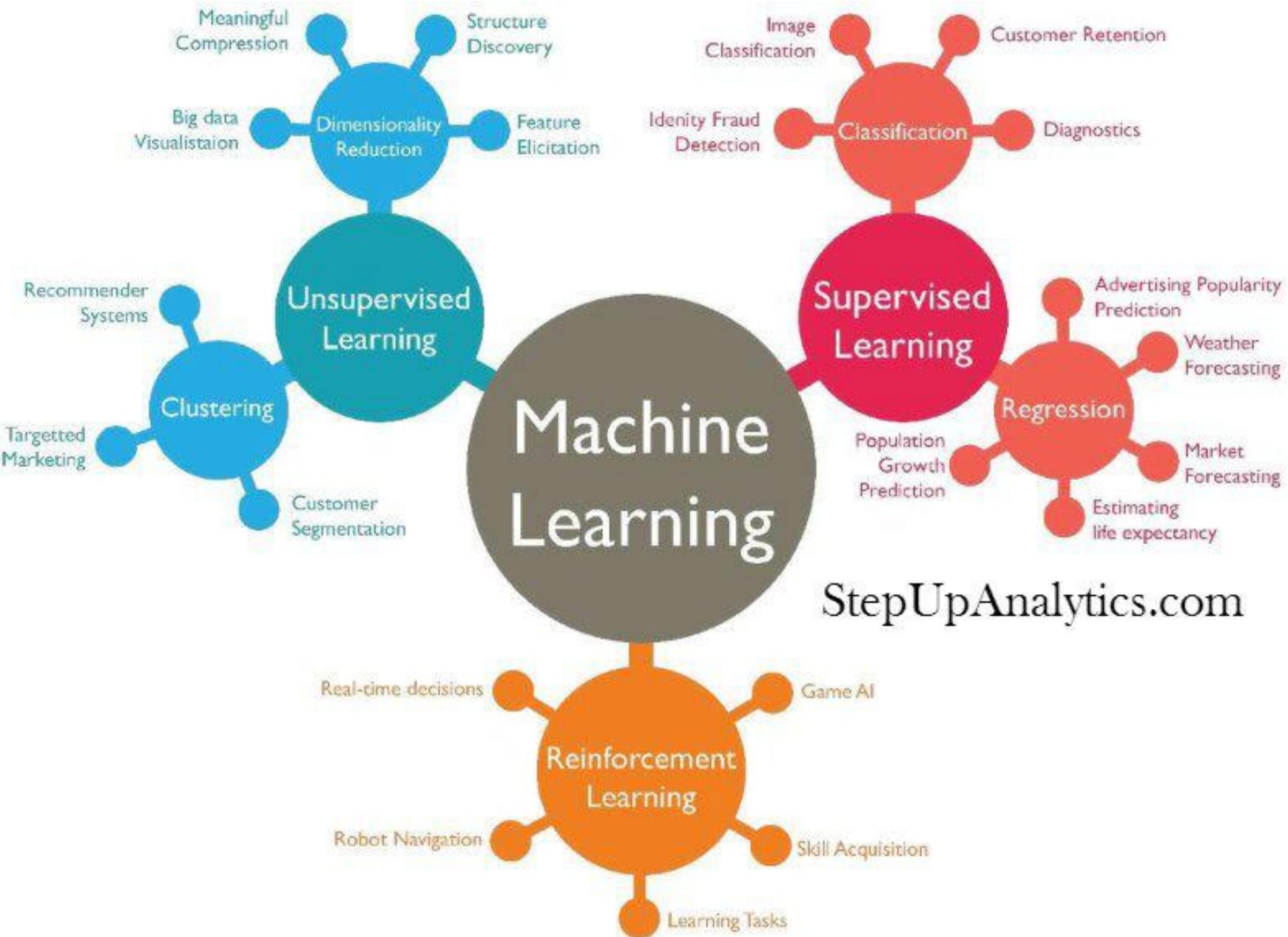
MANY DIFFERENT FIELDS & APPLICATION DOMAINS

Music Recommendation systems

- Is this song similar to that one?
- When can this song become a hit?
- Should I recommend this song?

Predictive Maintenance of machinery

- Is that behavior normal?
- When the machine is going to fail?
- Should I add this machine to the review list?

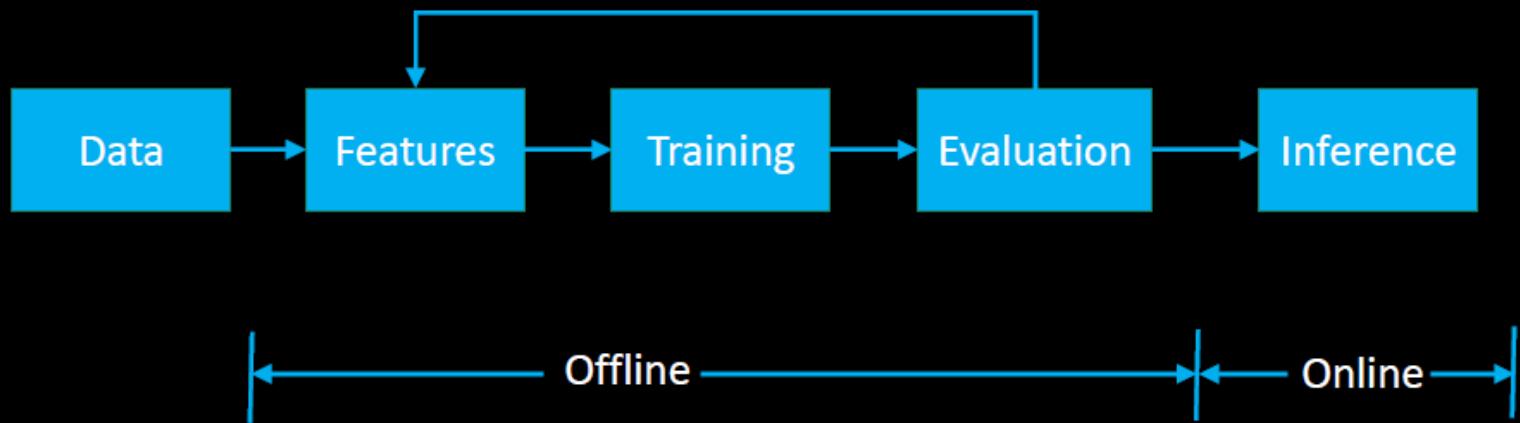




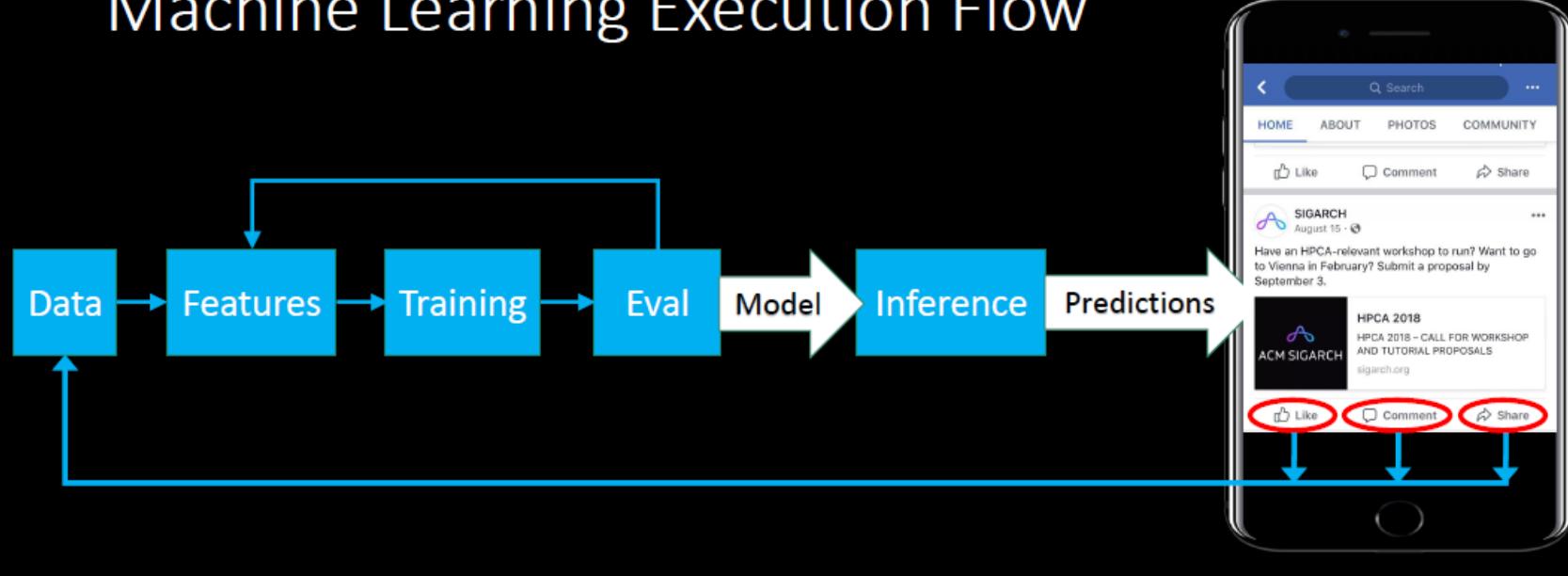
ML at Facebook: An Infrastructure View

Yangqing Jia
Director, Facebook AI Infra

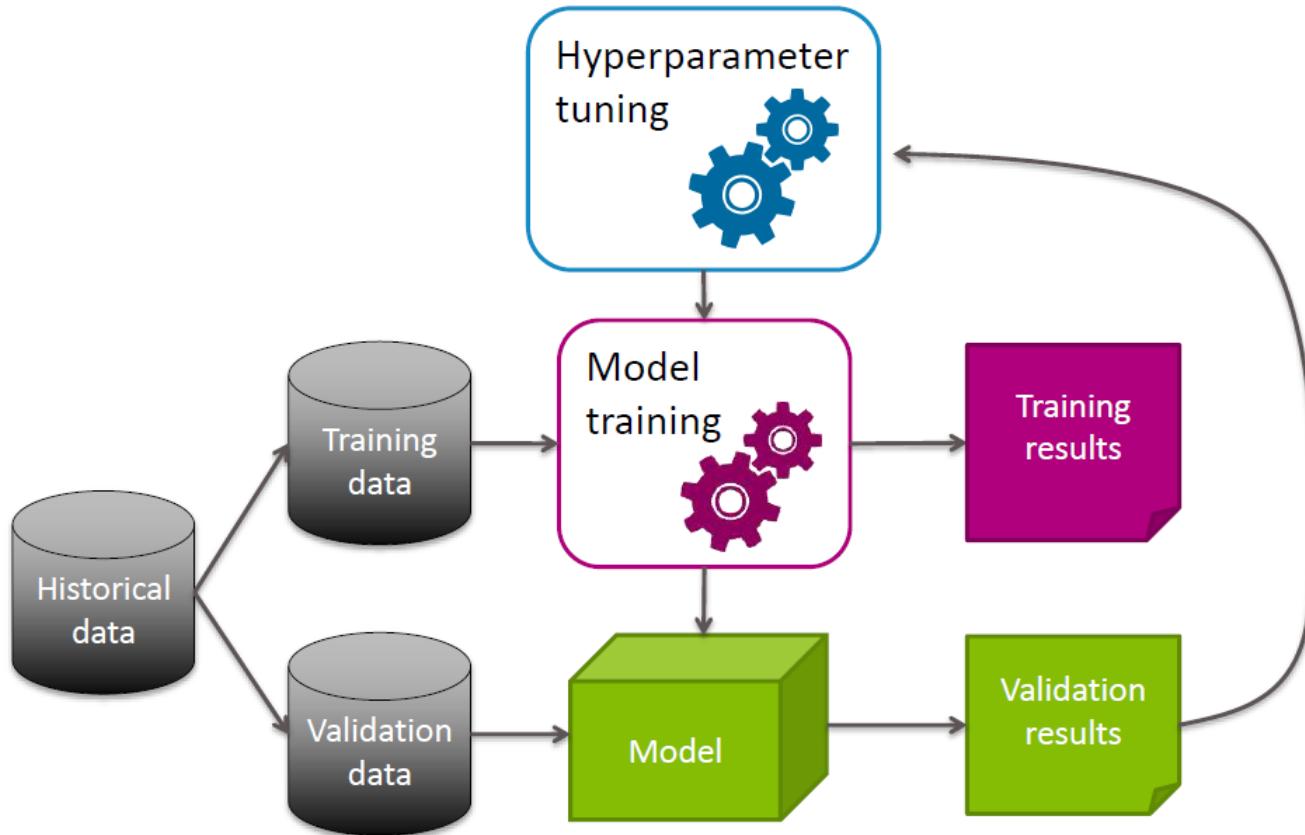
Machine Learning Execution Flow



Machine Learning Execution Flow



Model Selection and Tuning





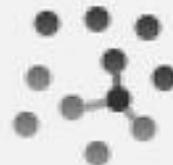
Classify



Regression



Mean
Learner



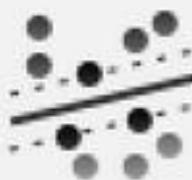
Nearest
Neighbors



Regress...
Tree



Random
Forest ...



SVM
Regressor...



Linear
Regressor...



AdaBoost



Stochas...
Gradien...



Univariate
Polyno...

A Brief History



1958 Perceptron

1974 Backpropagation



Convolution Neural Networks for
Handwritten Recognition

1998



Google Brain Project on
16k Cores
2012

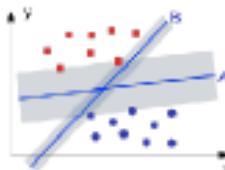


1969
Perceptron criticized



awkward silence (AI Winter)

1995
SVM reigns



2006
Restricted
Boltzmann
Machine



2012
AlexNet wins
ImageNet
IMagenet

Deep Learning: Hype or Reality?

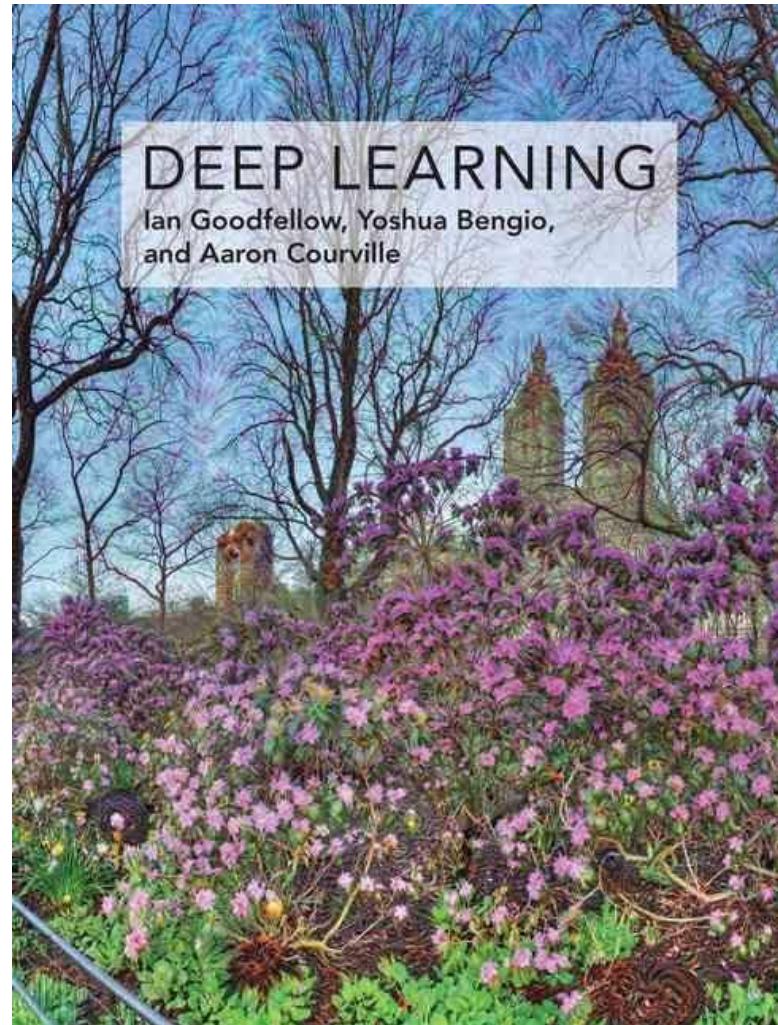


Introduction to Deep Learning

...the Machine Learning background...

Learn the whole
Machine Learning
context

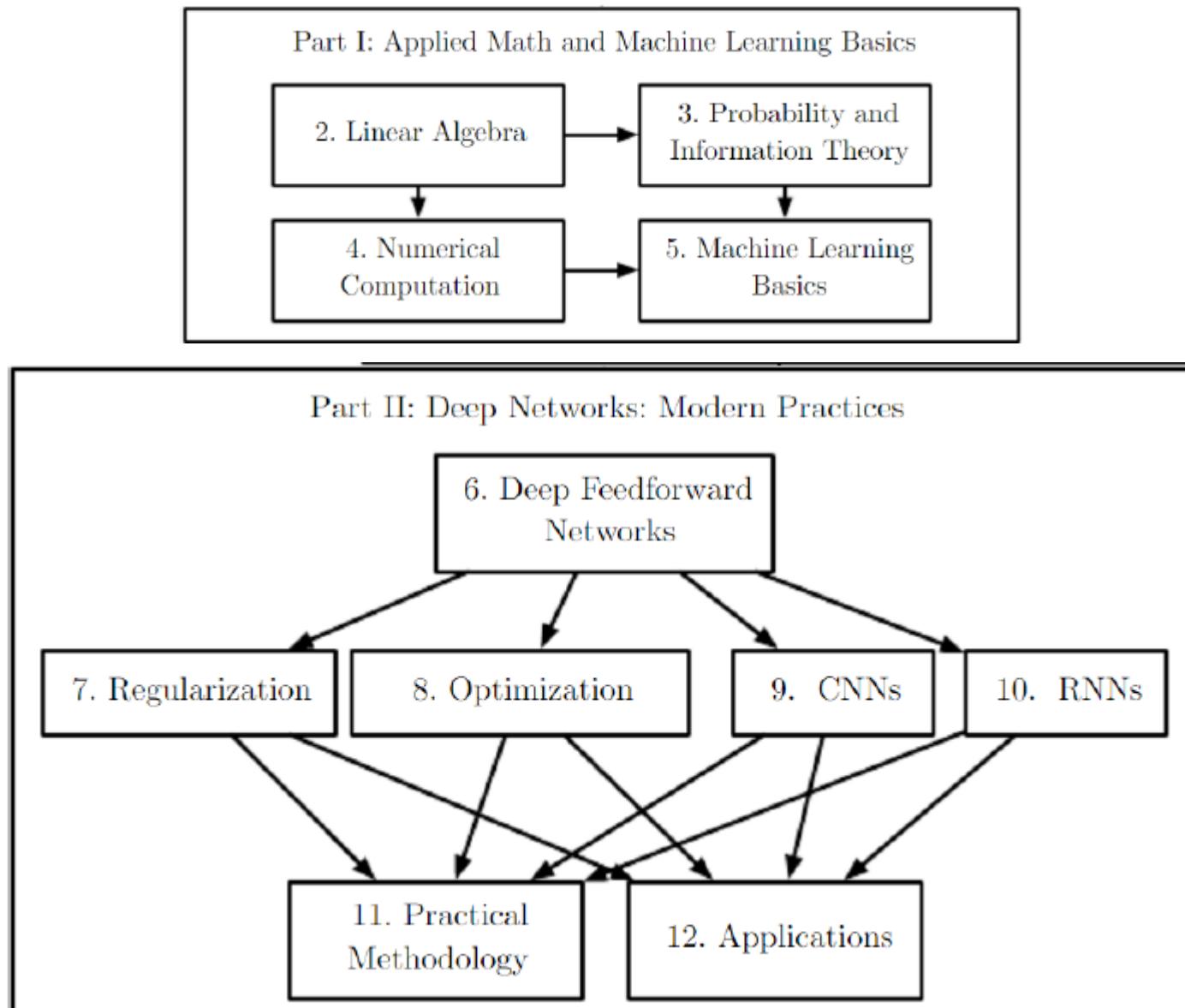
On line:
www.deeplearningbook.org



Deep Learning courses
Prof. Hung-yi Lee National Taiwan University (NTU)
Taipei

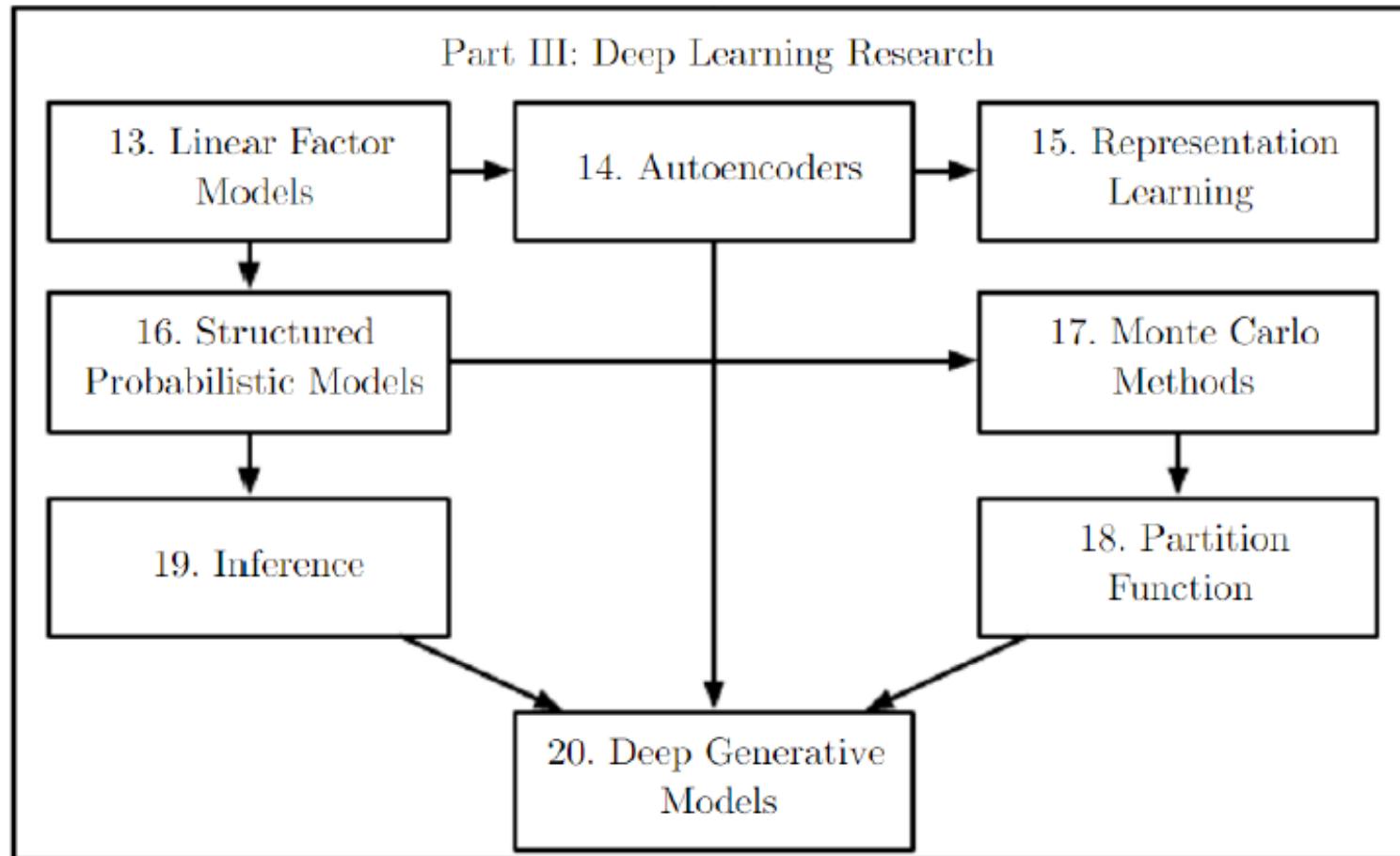
Introduction to Deep Learning

...the Machine Learning background...



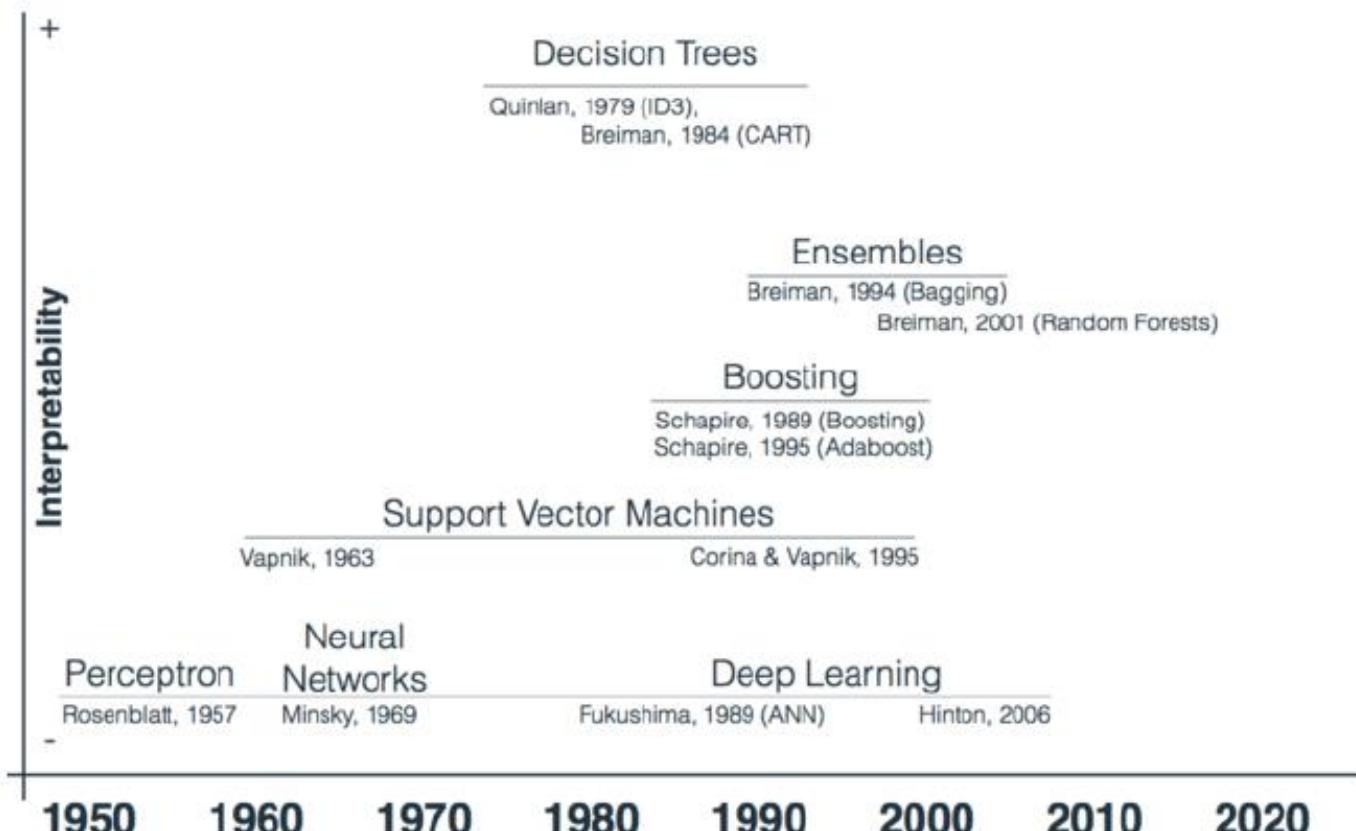
Introduction to Deep Learning

...the Machine Learning background...

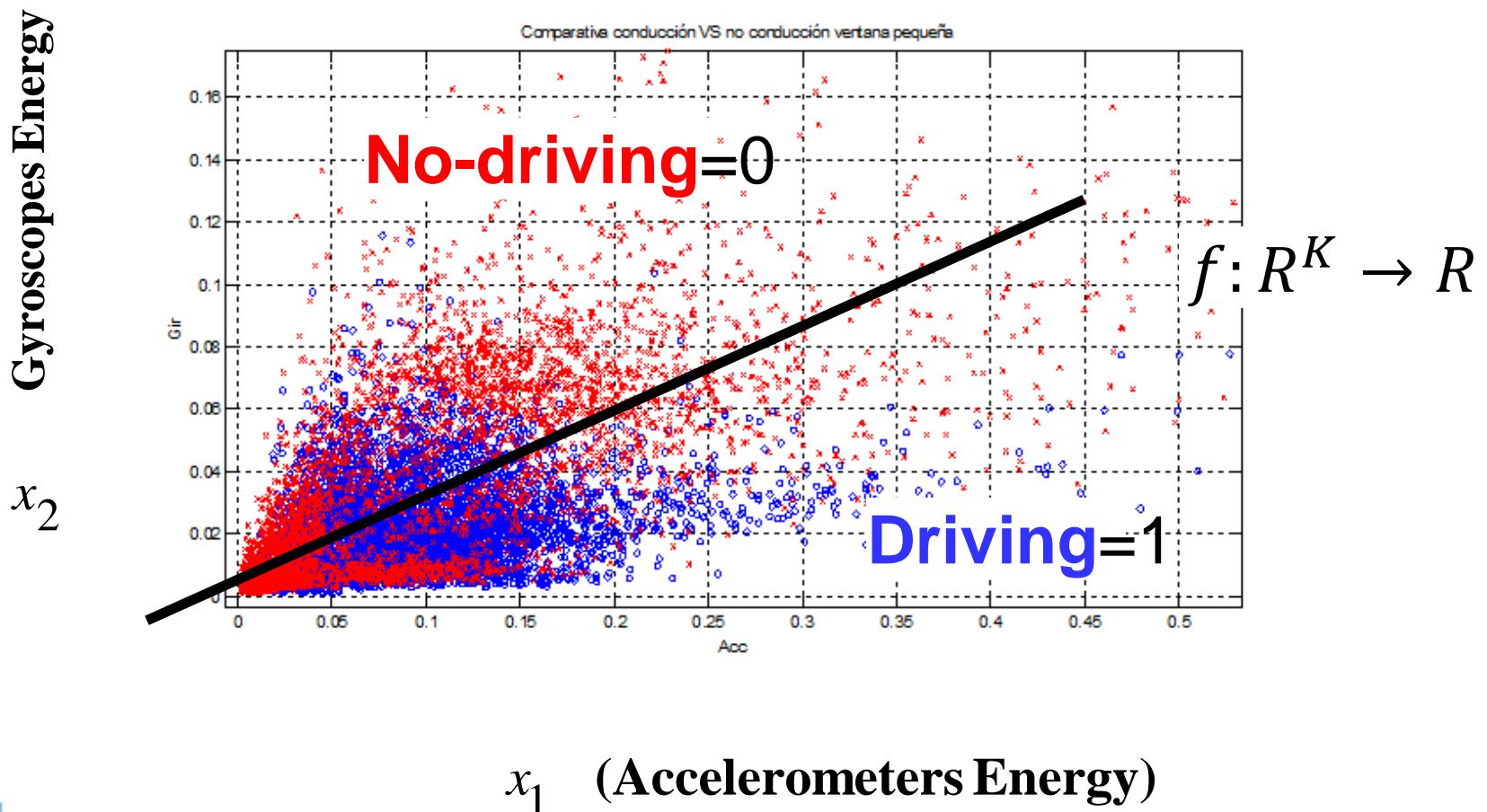


Model interpretability?

CETINSOY MARTIN ORTEGA PETERSEN

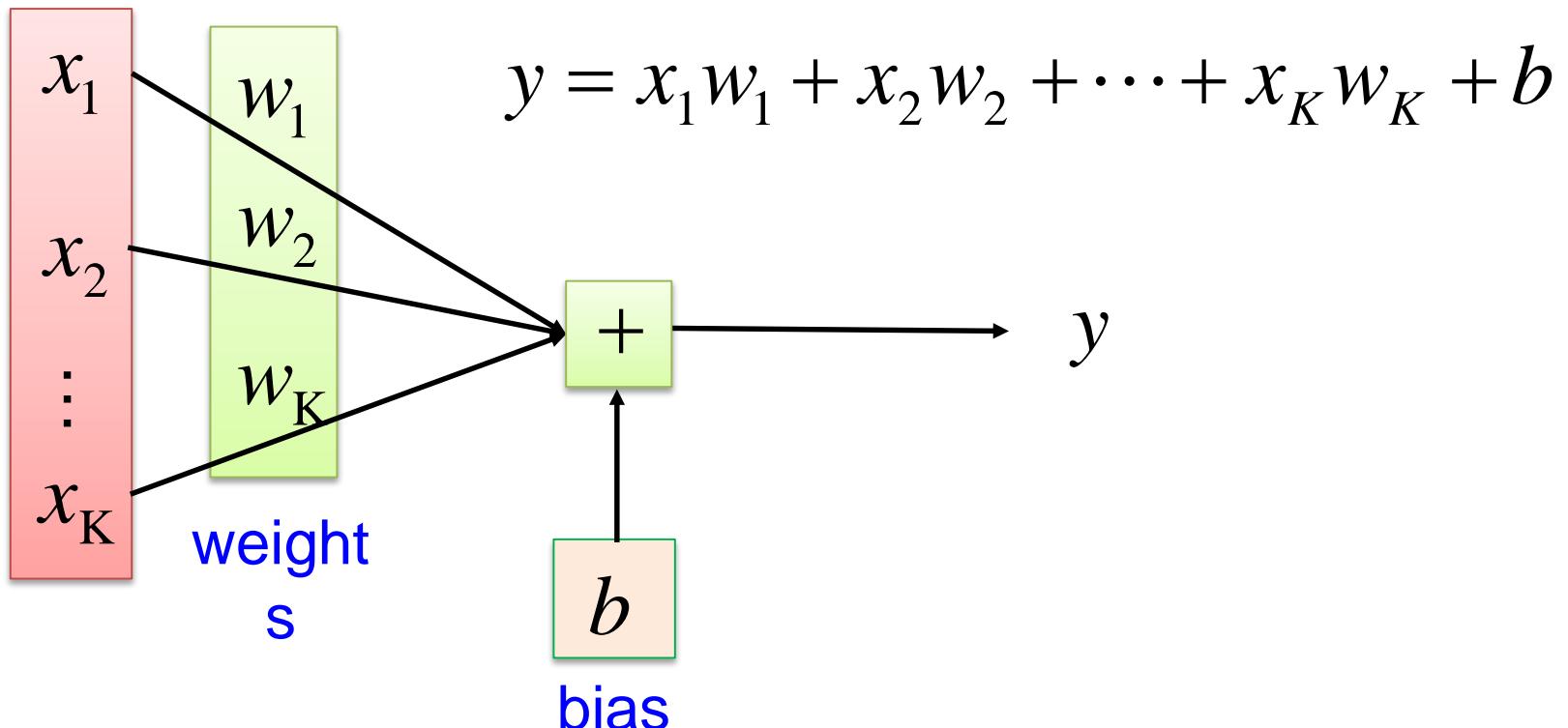


Driving detection (yes/no) = define a decision function



From linear classifiers TO Neural Networks

A Linear decision function



From linear classifiers TO Neural Networks

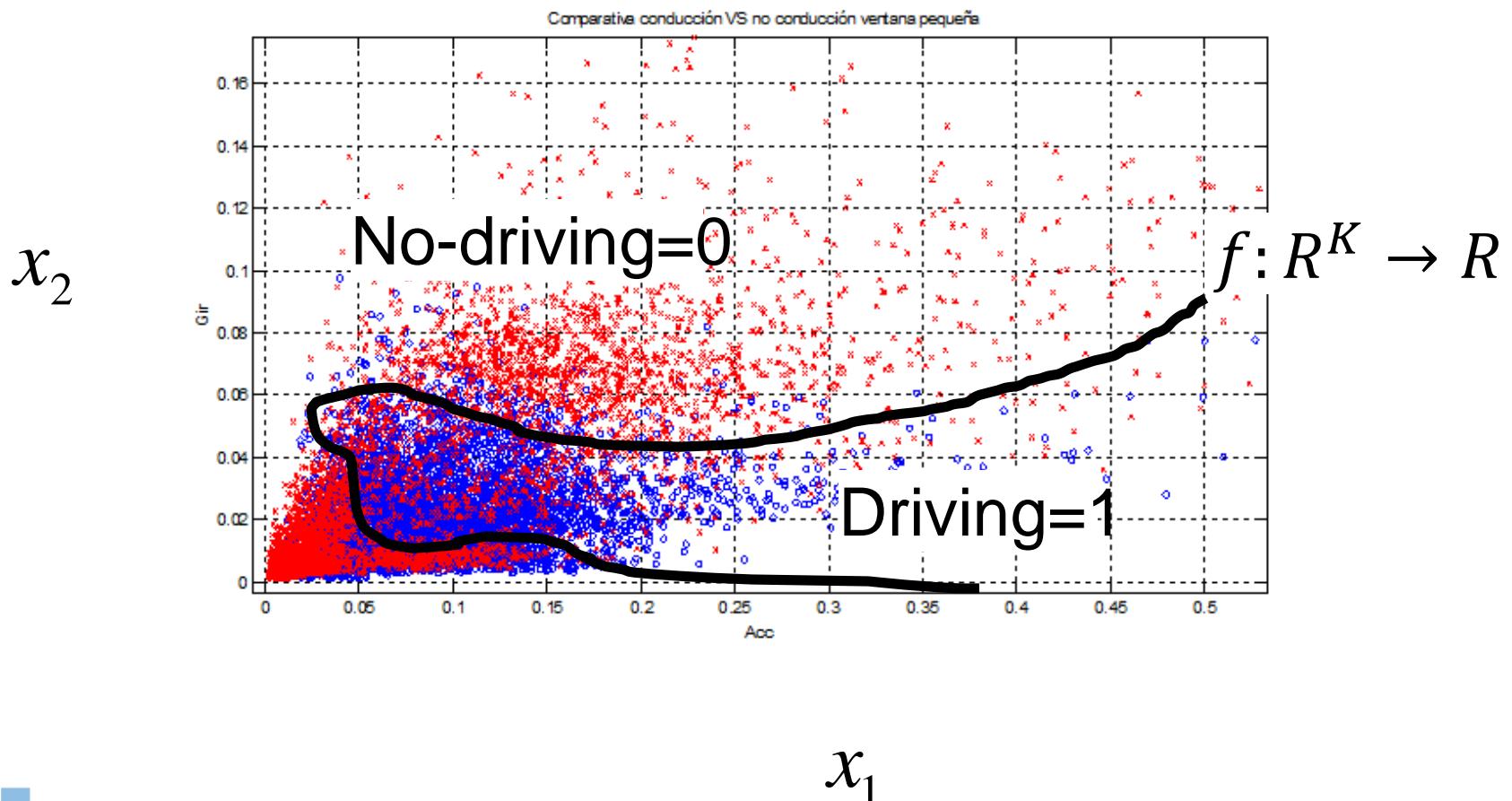
A Linear **decision function**

$$y = x_1 w_1 + x_2 w_2 + \cdots + x_K w_K + b$$

$$y = \mathbf{x}^T \mathbf{w}$$

From linear classifiers TO Neural Networks

Nonlinear decision function?



Non-linear decision functions

$$y = x_1 w_1 + x_1^2 w_2 + x_1^3 w_3 + x_1 x_2 w_4 + \dots + b$$

A linear model of transformed inputs:

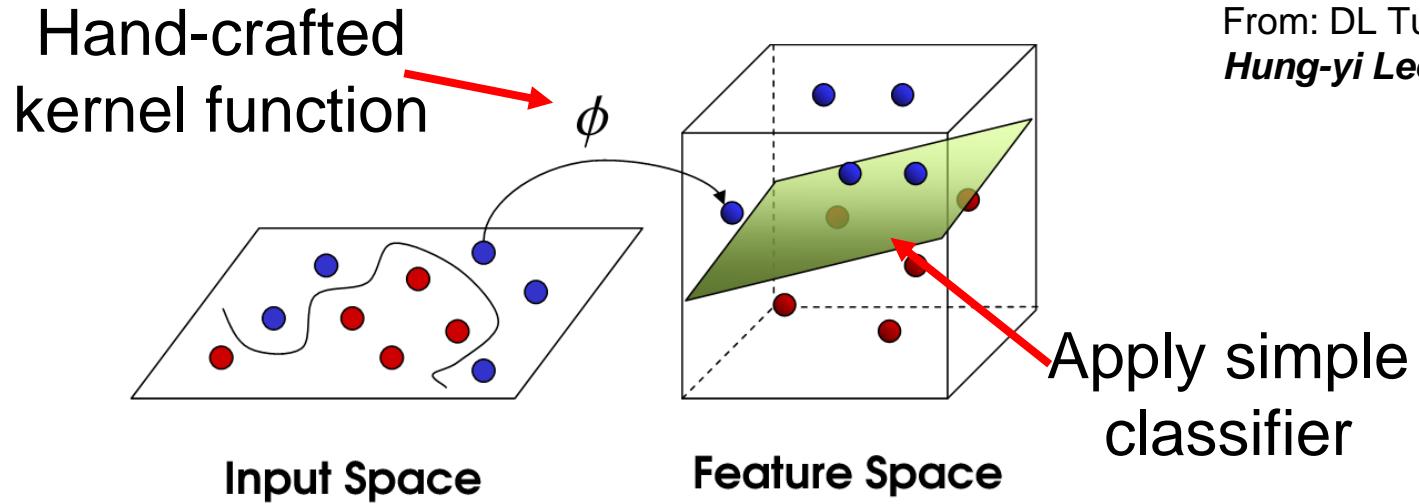
$$y = \phi(\mathbf{x})^T \mathbf{w}$$

$\phi(\mathbf{x})$ where ϕ is a non linear transformation

How choosing the mapping $\phi(.)$?

1. To feature engineer $\phi(.)$
2. Use a very generic $\phi(.)$ as kernel machines (e.g. SVM, RBF kernel)
3. The strategy of **deep learning** : to learn $\phi(.)$

SVM



Source of image: http://www.gipsa-lab.grenoble-inp.fr/transfert/seminaire/455_Kadri2013Gipsa-lab.pdf

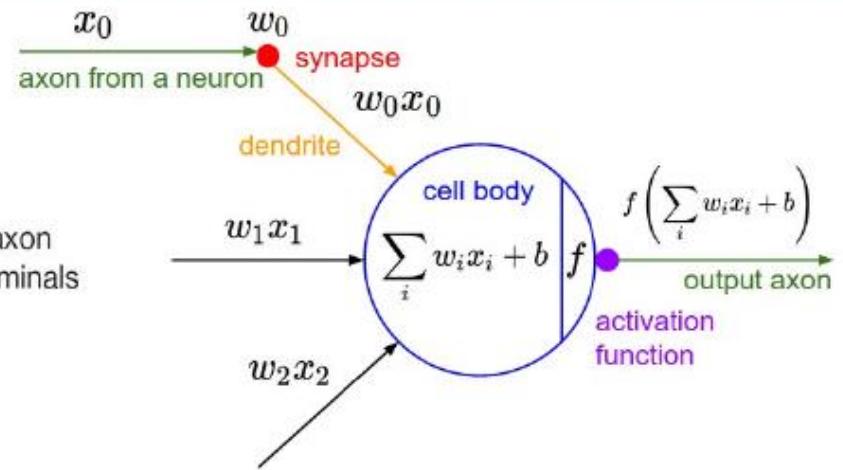
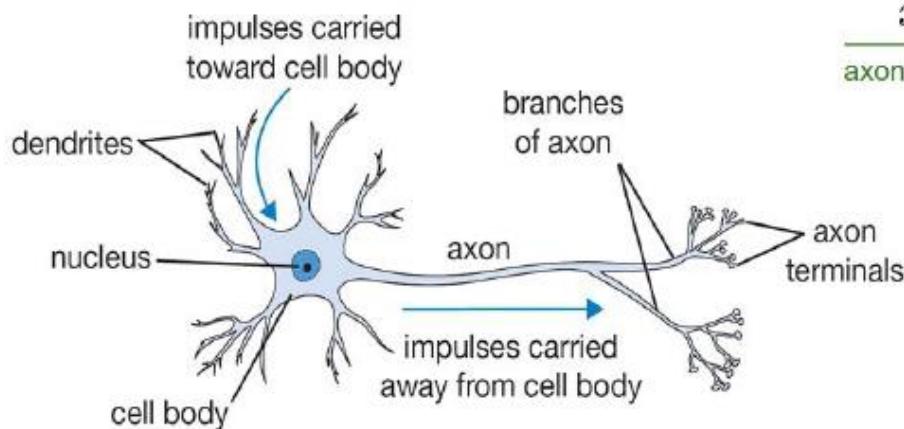
The DL approach: learn $\phi(\cdot)$

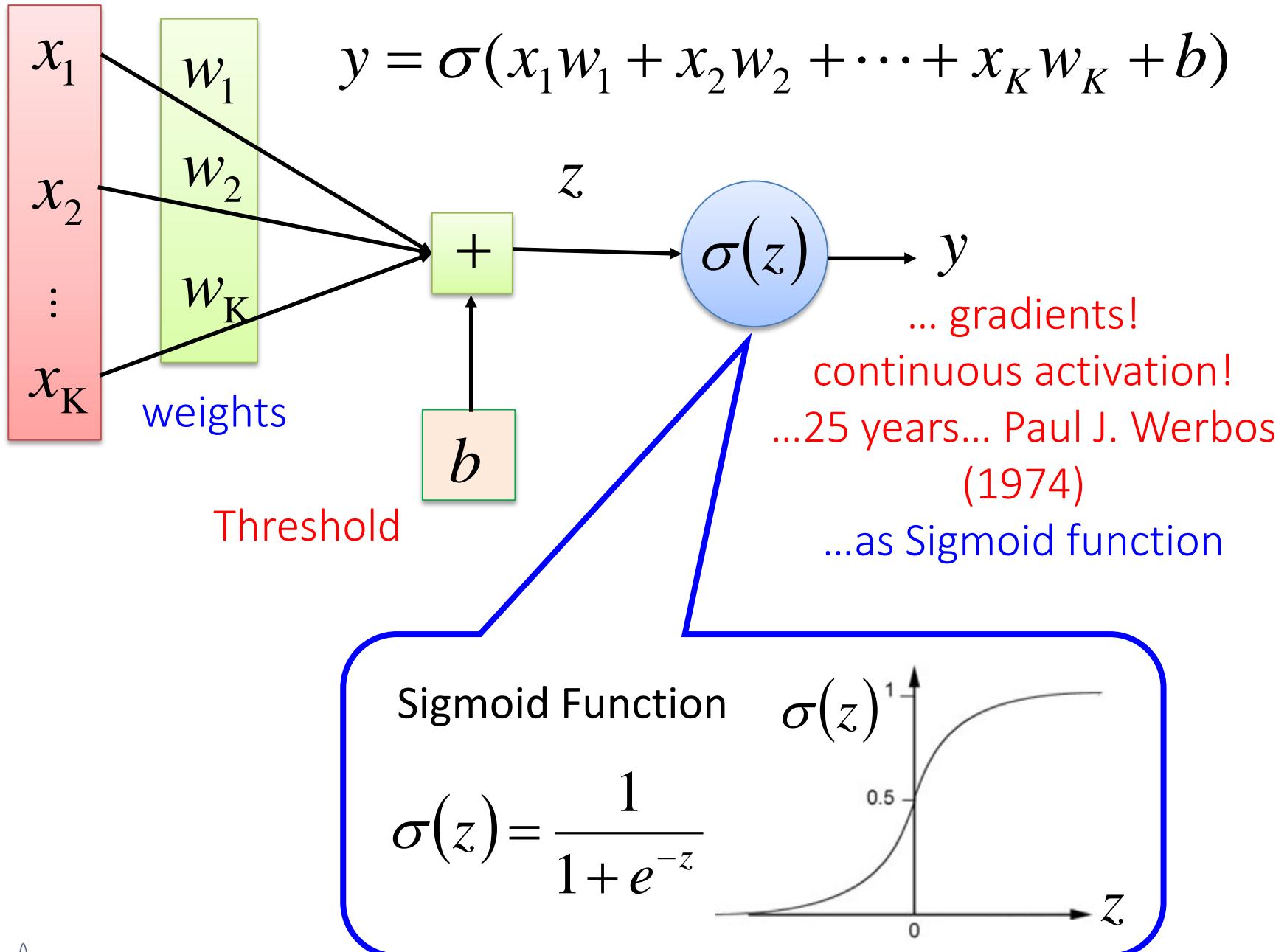
Now we have:

- Parameters θ that we use to learn $\phi(\cdot)$ from a broad class of functions
- Parameters w that map $\phi(x)$ to the desired output

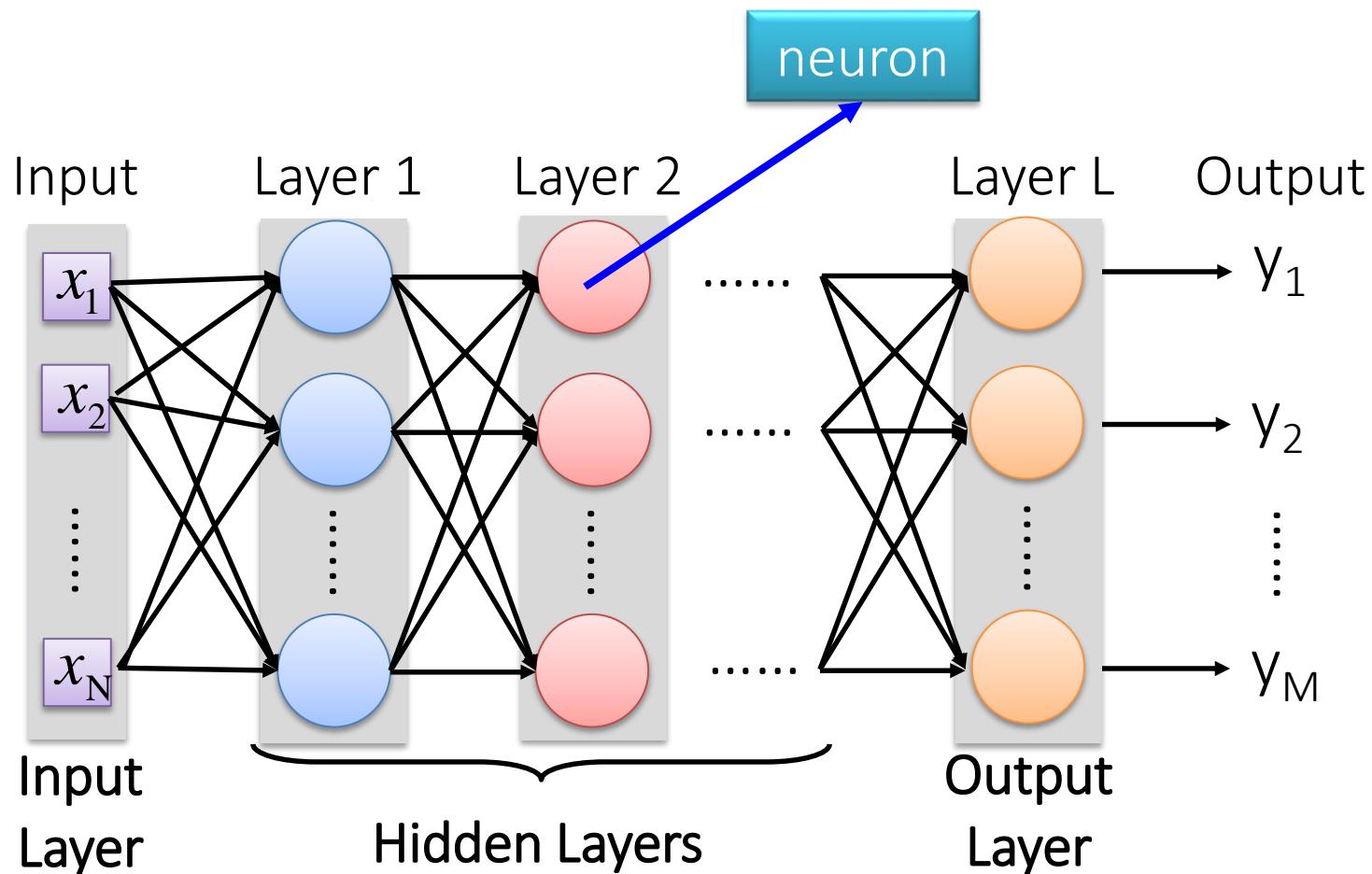
$$y = f(\mathbf{x}; \theta, w) = \phi(\mathbf{x})^T w$$

Deep Learning





Neural Network (from Hung-yi Lee “Deep Learning Tutorial”)

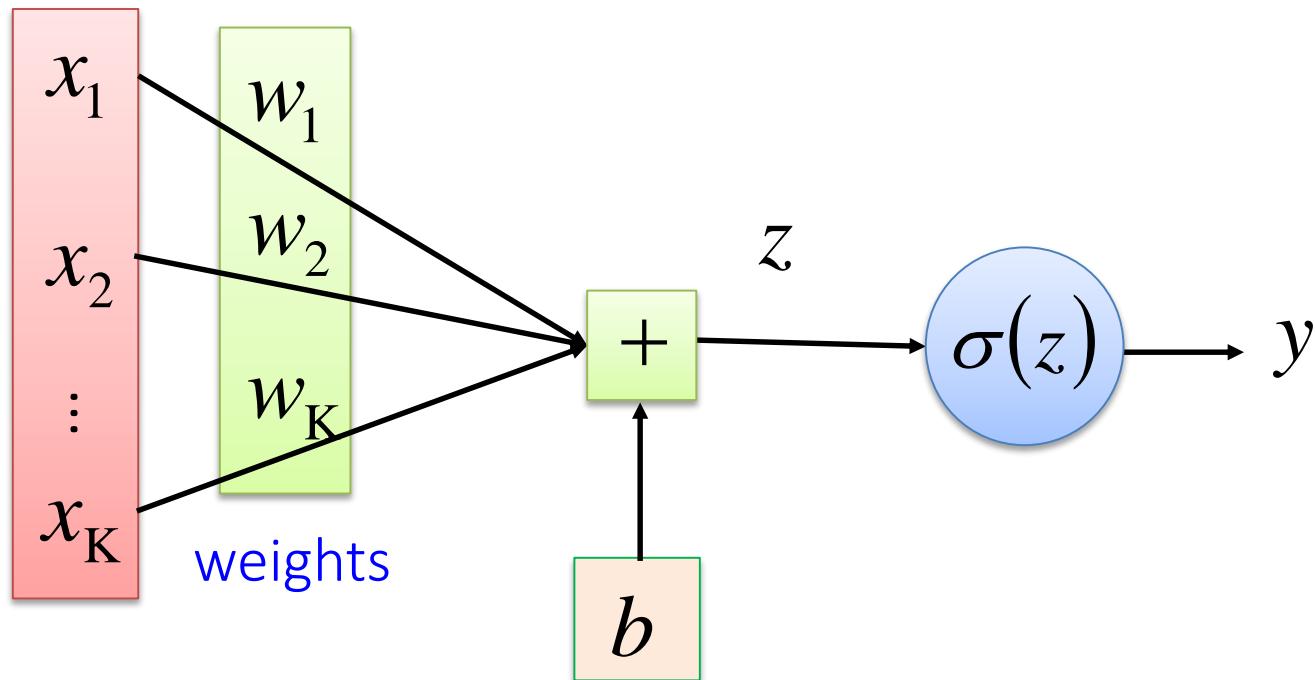


Deep means many hidden layers

From linear classifiers TO Neural Networks

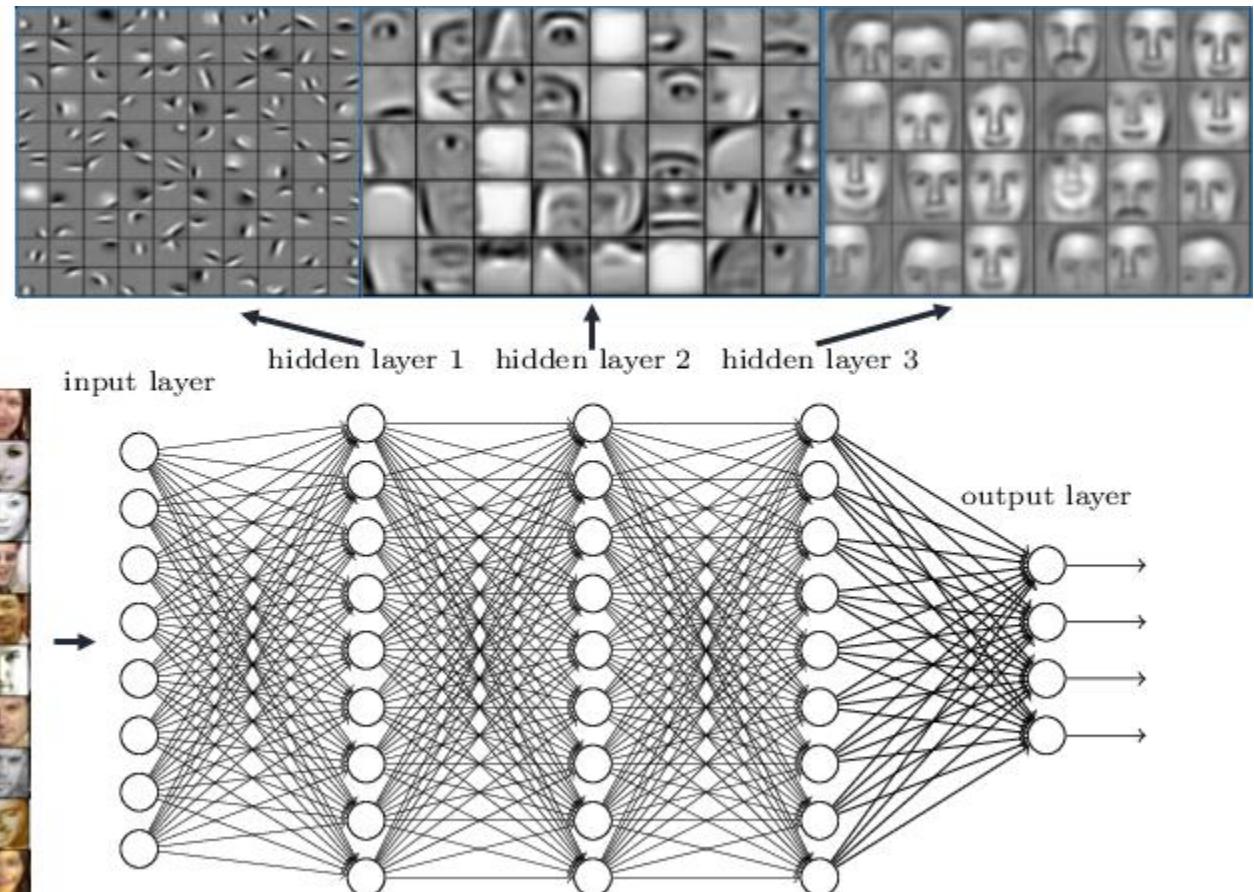
- Parameters Θ that we use to learn $\phi(\cdot)$ from a broad class of functions
- **Weights** and **thresholds** are estimated from training examples:
 - to minimize a **loss function** (i.e. similarity between NN outputs y and desired outputs \hat{y})

- But recall that this is also logistic regression!

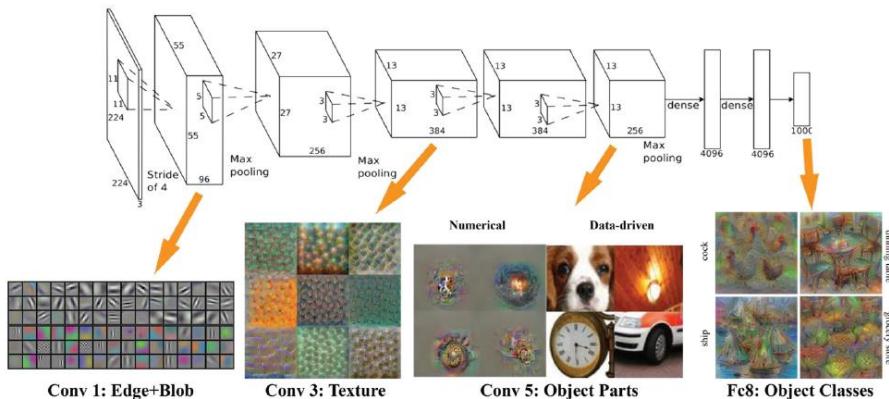


Deep Learning

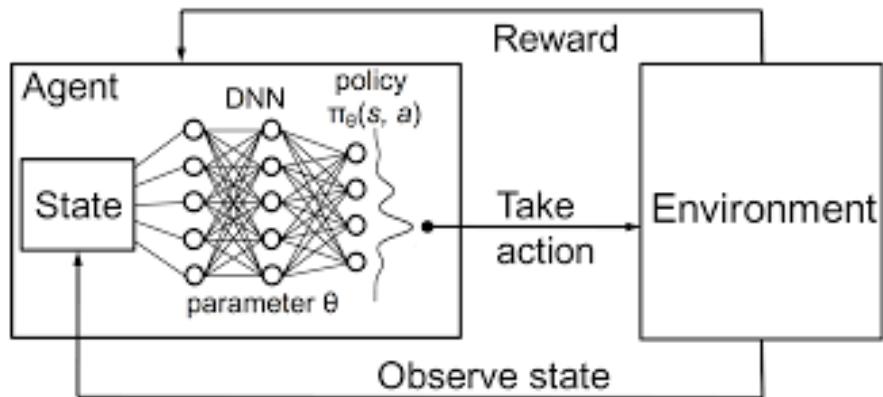
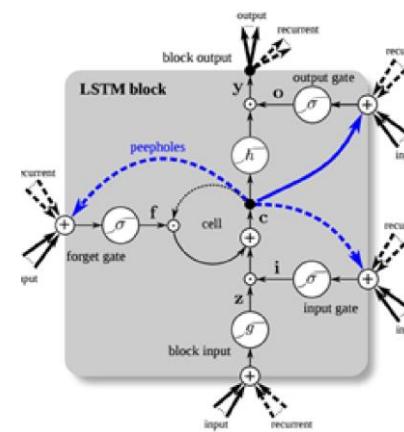
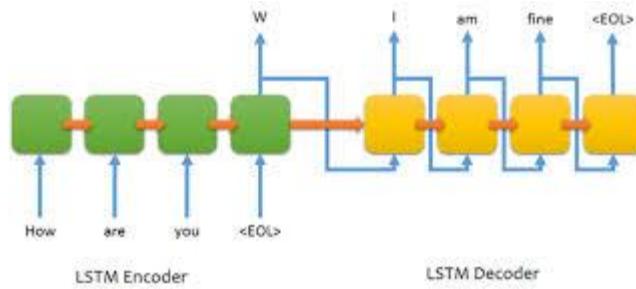
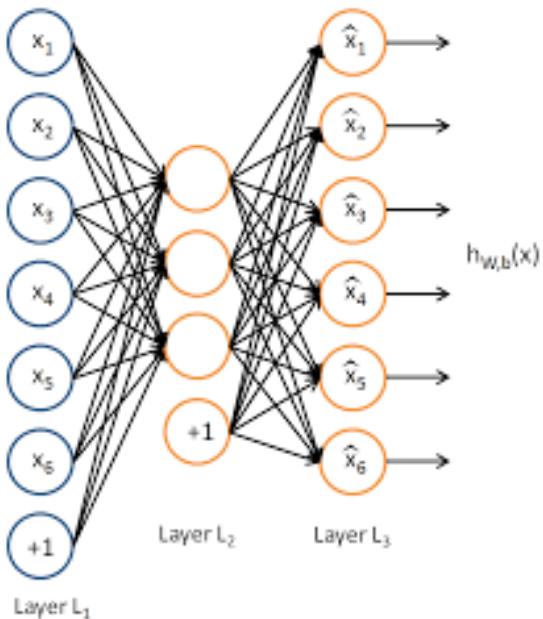
Deep neural networks learn hierarchical feature representations



DL: architectures

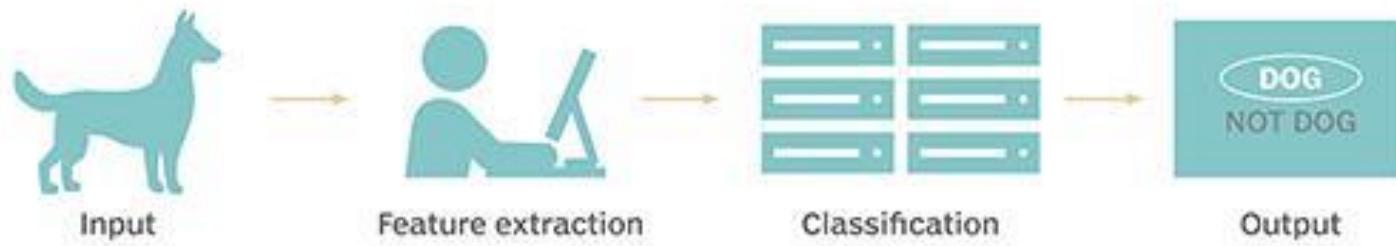


http://vision03.csail.mit.edu/cnn_art/data/single_layer.png

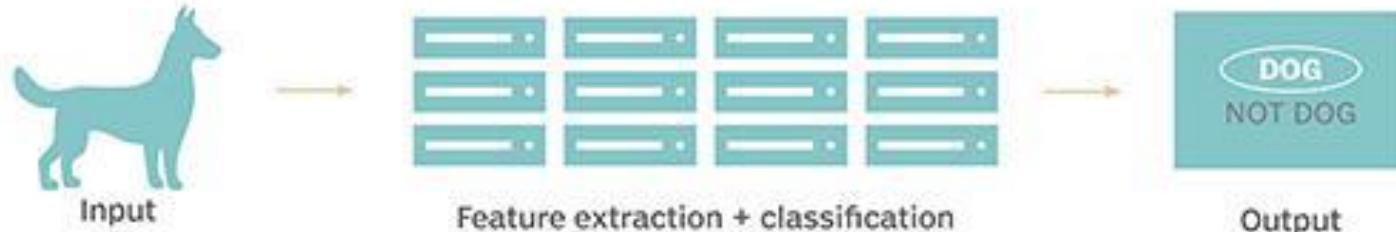


DL: no more feature engineering

TRADITIONAL MACHINE LEARNING



DEEP LEARNING



What Changed?

Old wine in new bottles



Big Data
(Digitalization)



Computation
(Moore's Law, GPUs)

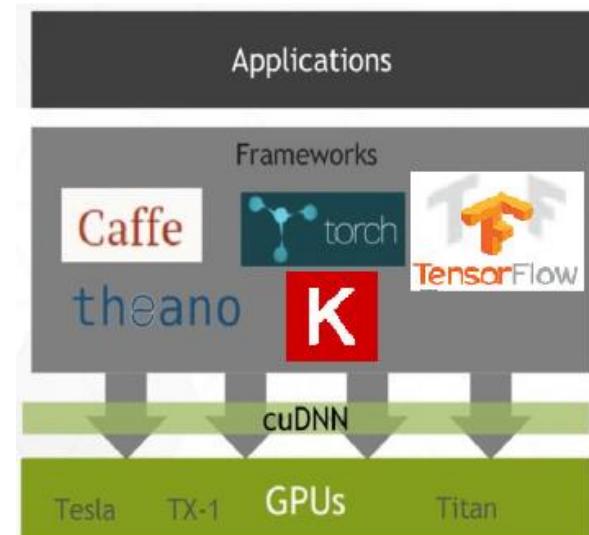


Algorithmic
Progress

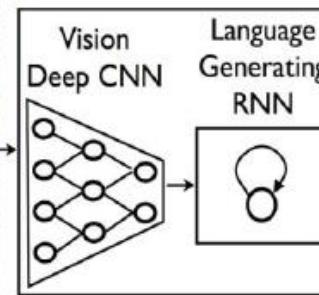
UDACITY

FREE COURSE

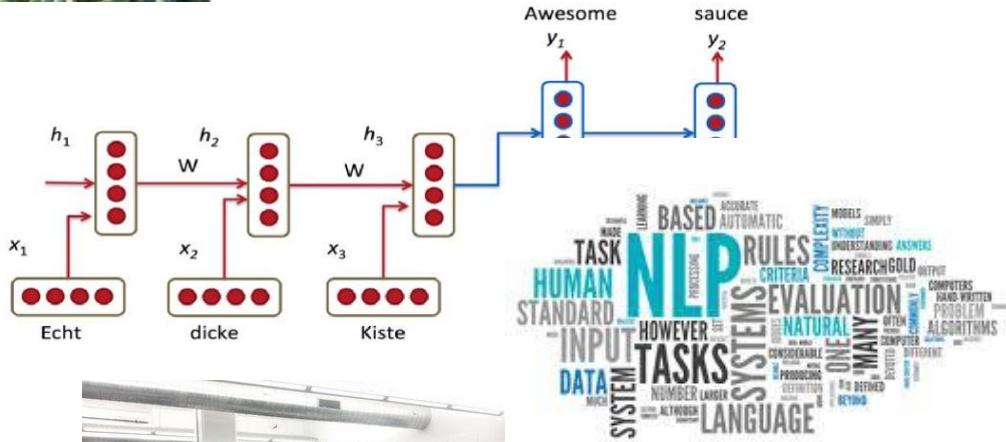
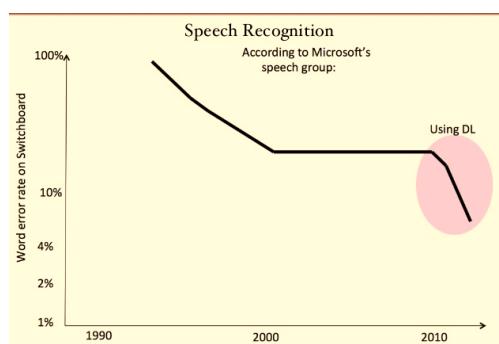
Deep Learning
by Google



DL: super-human performance



A group of people shopping at an outdoor market.
There are many vegetables at the fruit stand.



From linear classifiers TO Neural Networks

- So let's stop here and start playing with



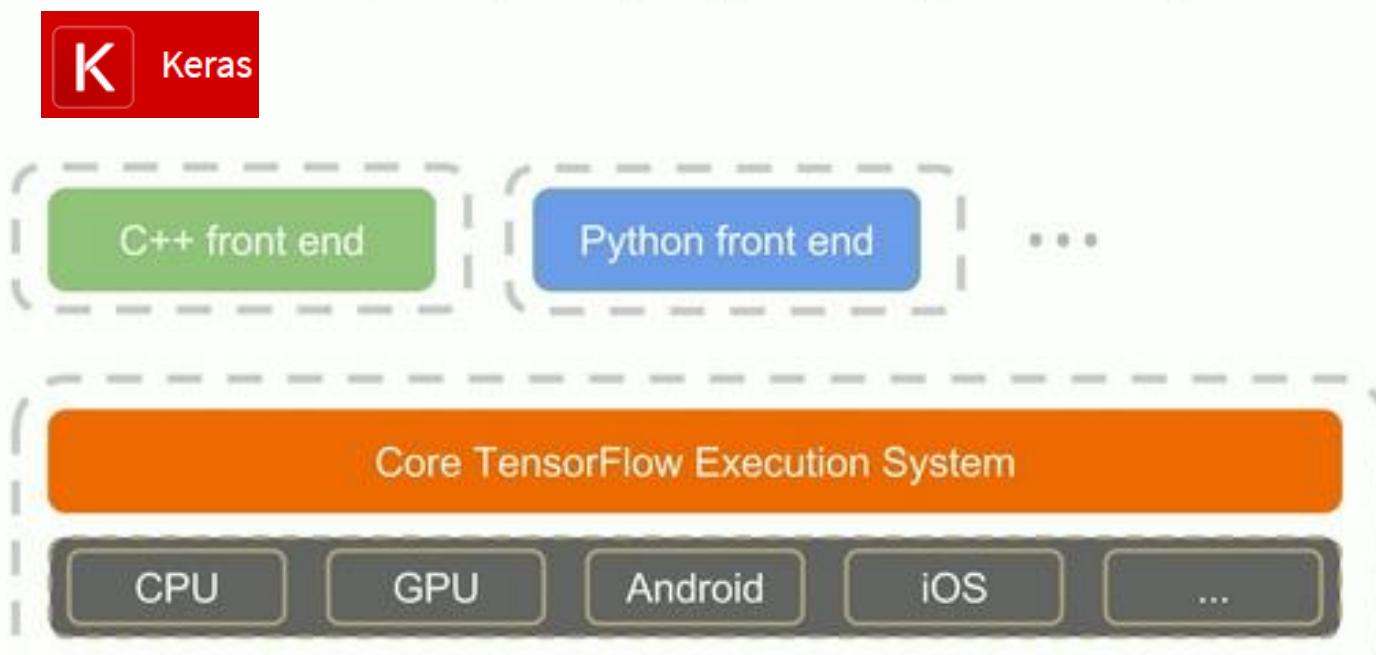


Google TensorFlow

- Library for writing “machine intelligence” algorithms
- Very popular for deep learning and neural networks
- Can also be used for general purpose numerical computations
- Interface in C++ and Python

TensorFlow: Expressing High-Level ML Computations

- Core in C++
- Different front ends for specifying/driving the computation



A word of caution: the APIs in languages other than Python are not yet covered by the [API stability promises](#).

- Python
- C++
- Java
- Go

A multidimensional array.



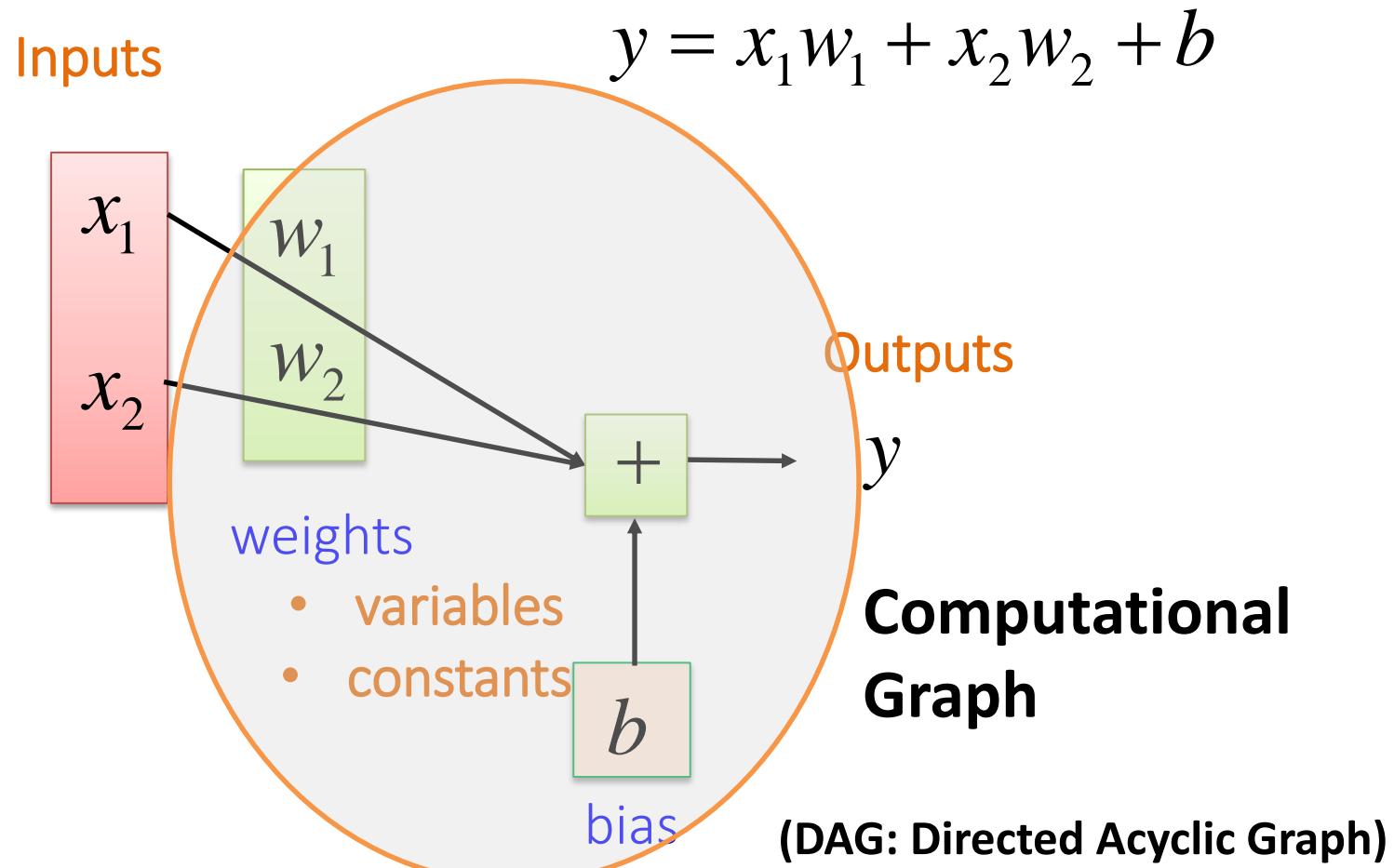
A graph of operations.

From Mihaela Rosca Talk (Deep Mind)



Generates a computational graph like Theano
Everything about TensorFlow is here:

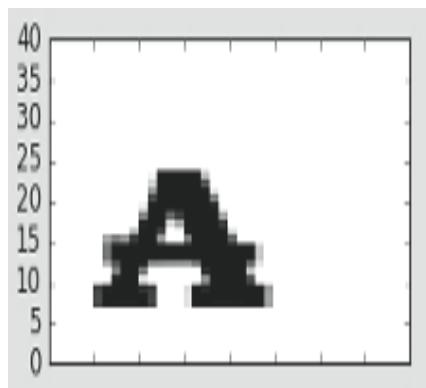
<https://www.tensorflow.org>





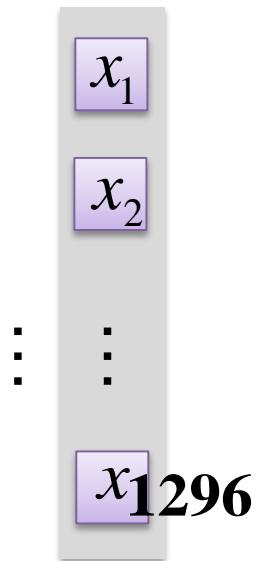
Font type Recognition

Input

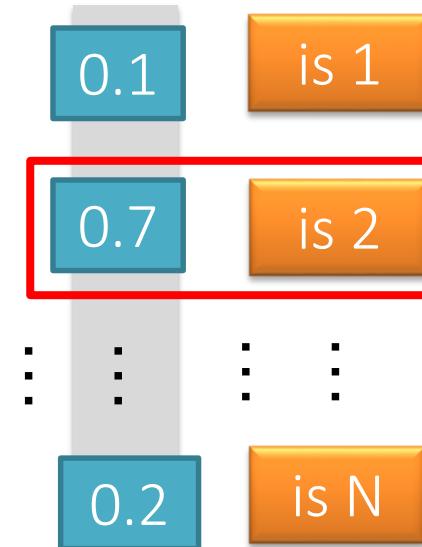


$36 \times 36 = 1296$

reShape



Output



Font type
is “2”

0
1
⋮
0

Elements [0:255]

White pixel → 0

Black pixel → 255

OHE
One-Hot-Encoding

We recommend you try: **Colaboratory**

It's a Jupyter notebook environment
that requires no setup to use and
runs entirely in the cloud.

Colaboratory is free to use.

Welcome to Colaboratory!

- Colaboratory is a Google research project created to help disseminate machine learning education and research.
- Colaboratory notebooks are stored in [Google Drive](#) and can

GPU Support (NEW!)

Colab now supports running TensorFlow computations on a

Eurielec_FontReco_LogisticRegression_2018.ipynb

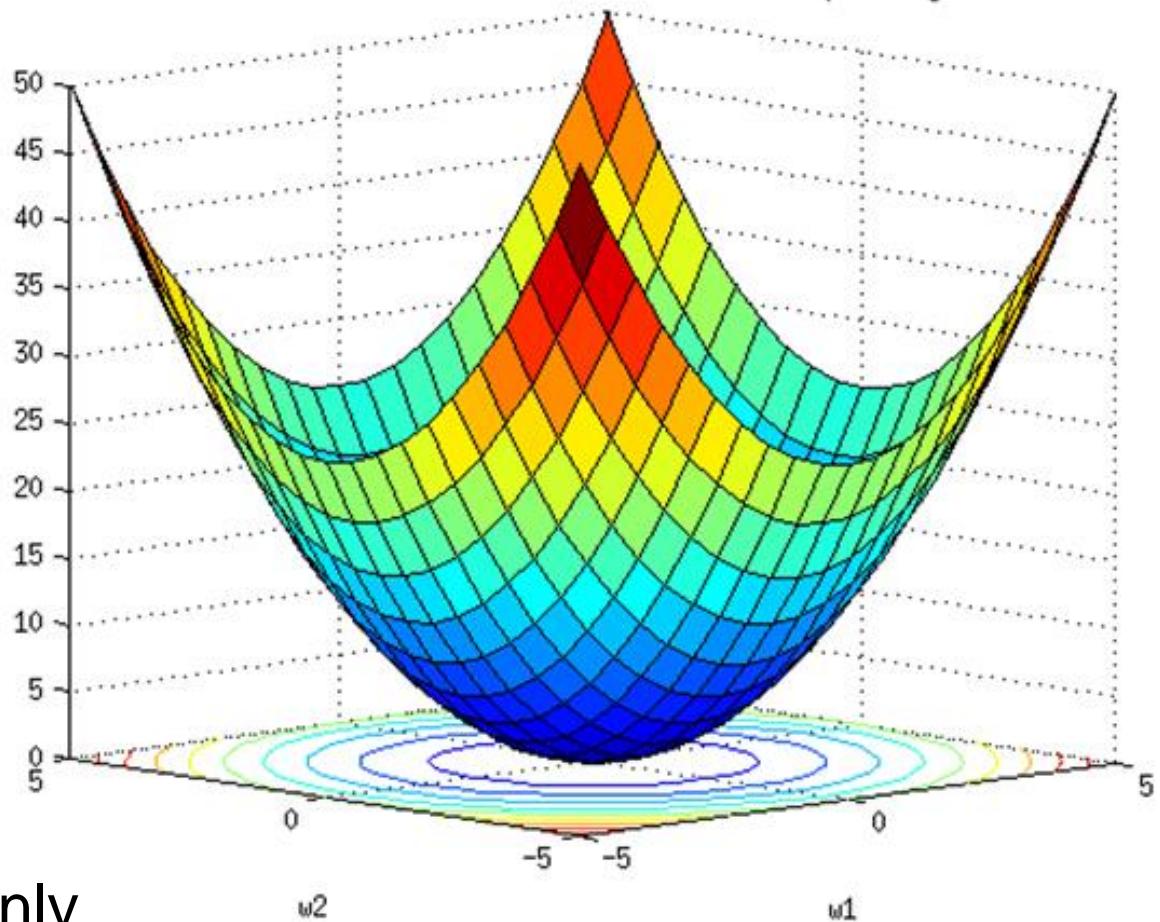
Eurielec_ColaboratoryInfo_2018.ipynb

OPTIMIZATION

Gradient Descent

Cost
Or
Loss function

$C(\theta)$



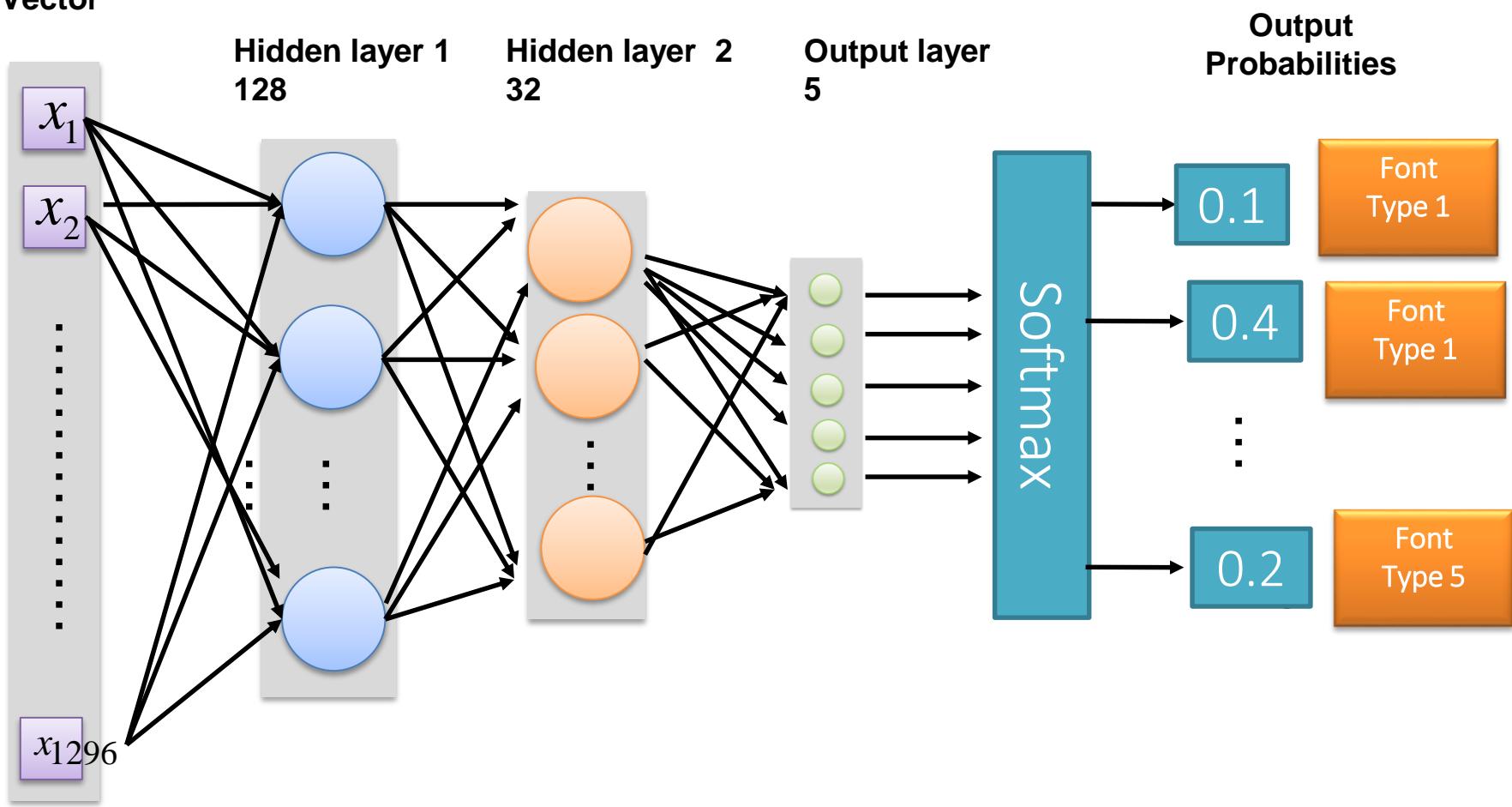
Assume there are only two parameters w_1 and w_2 in a network.

$$\theta = \{w_1, w_2\}$$

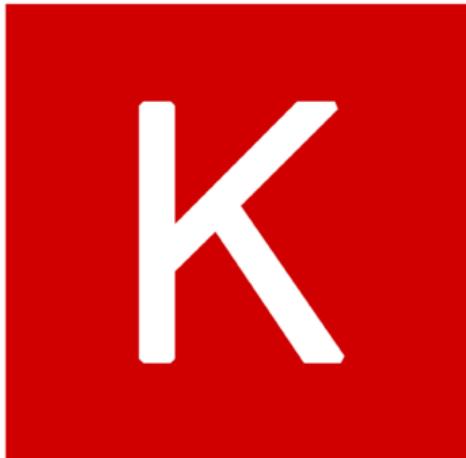


Eurielec_FontReco_LogisticRegression_2018.ipynb

Input
Image
Vector



Keras: The Python Deep Learning library



Keras

Guiding principles

- User friendliness
- Modularity
- Easy extensibility
- Work with Python

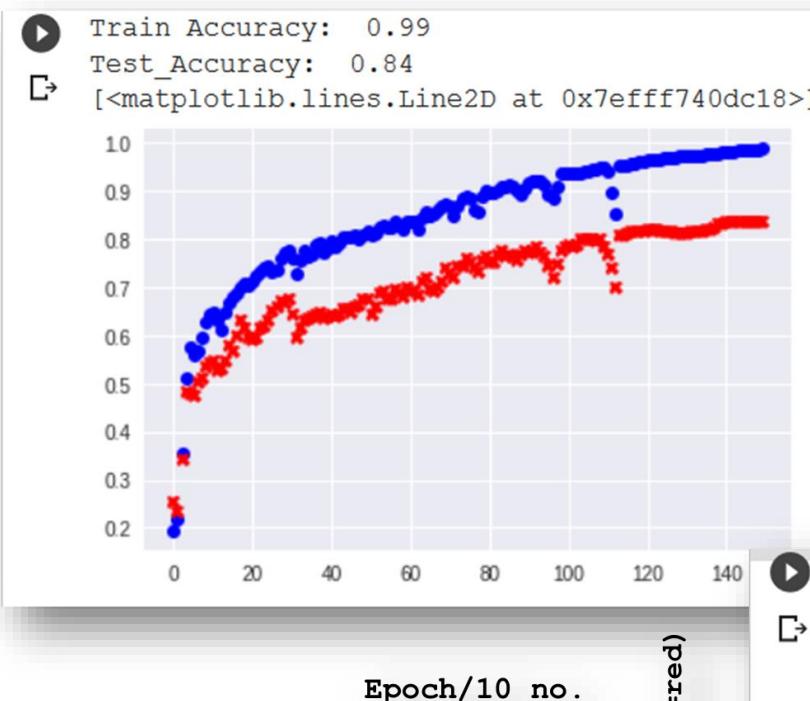


Activities:

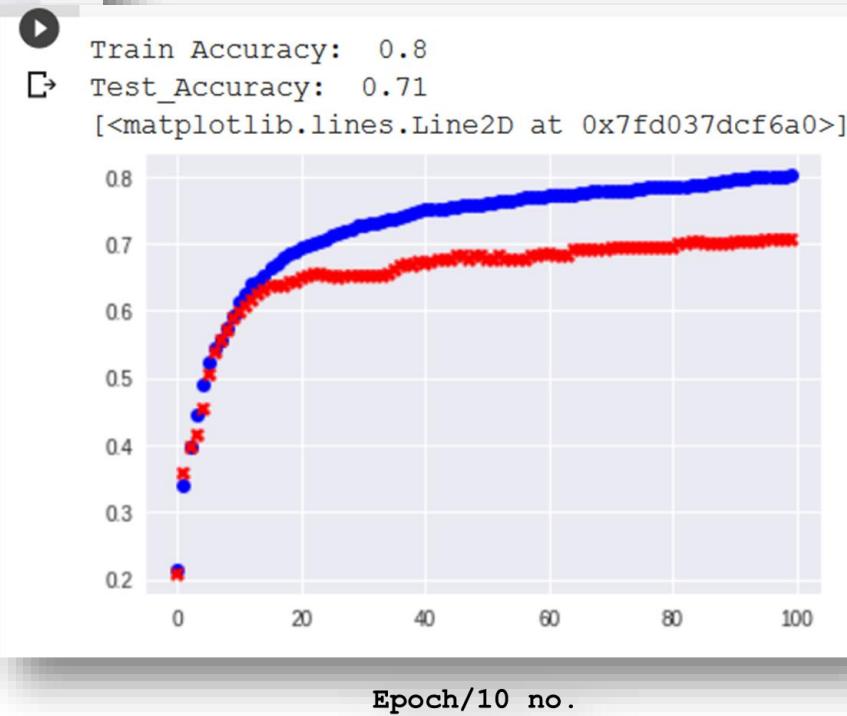
**Introduction to Keras: Font Recognition using:
Eurielec_Keras_FontReco_FeedForward.ipynb**

Feed Forward

Acc (Train=blue; test=red)

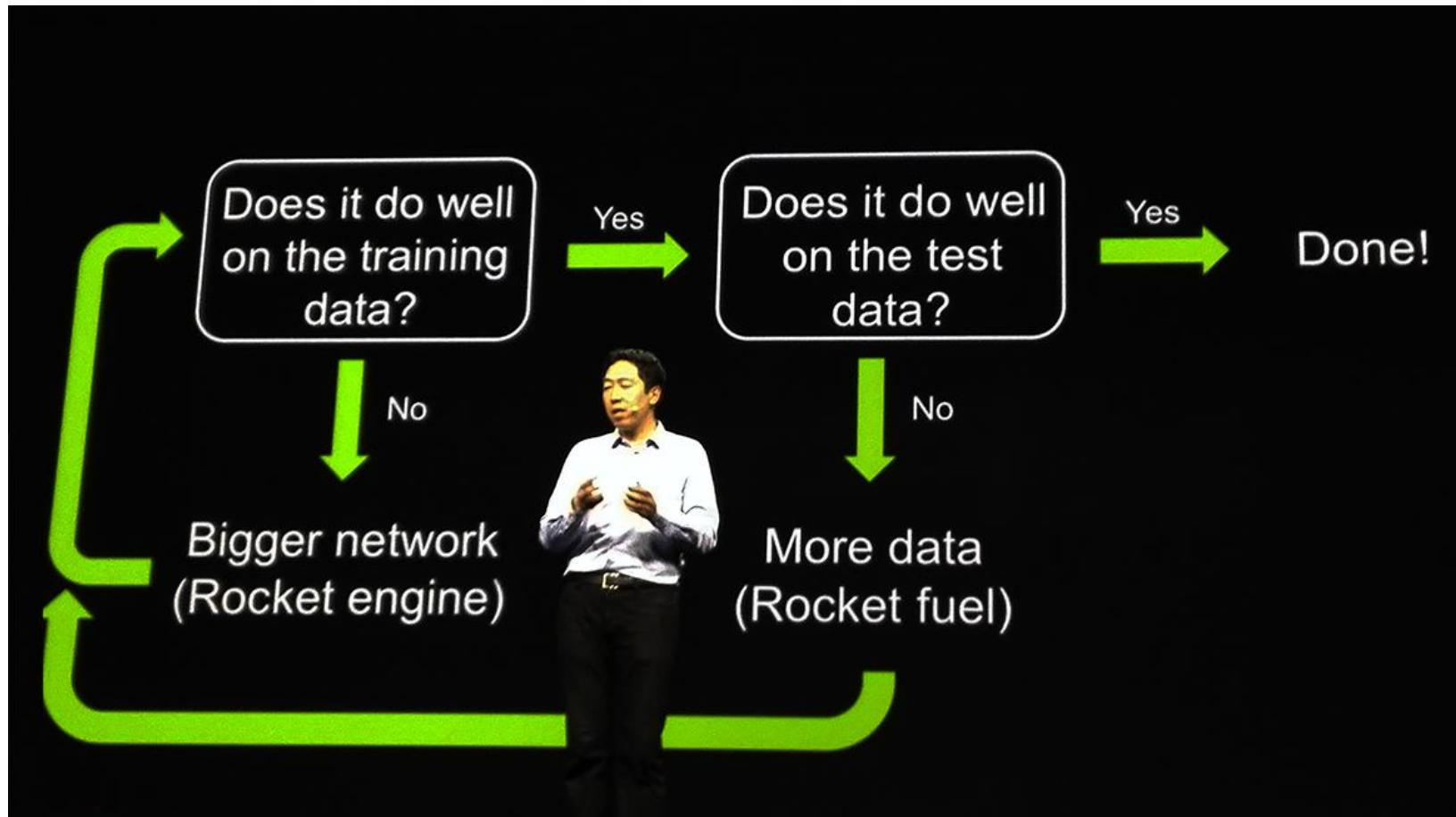


Acc (Train=blue; test=red)



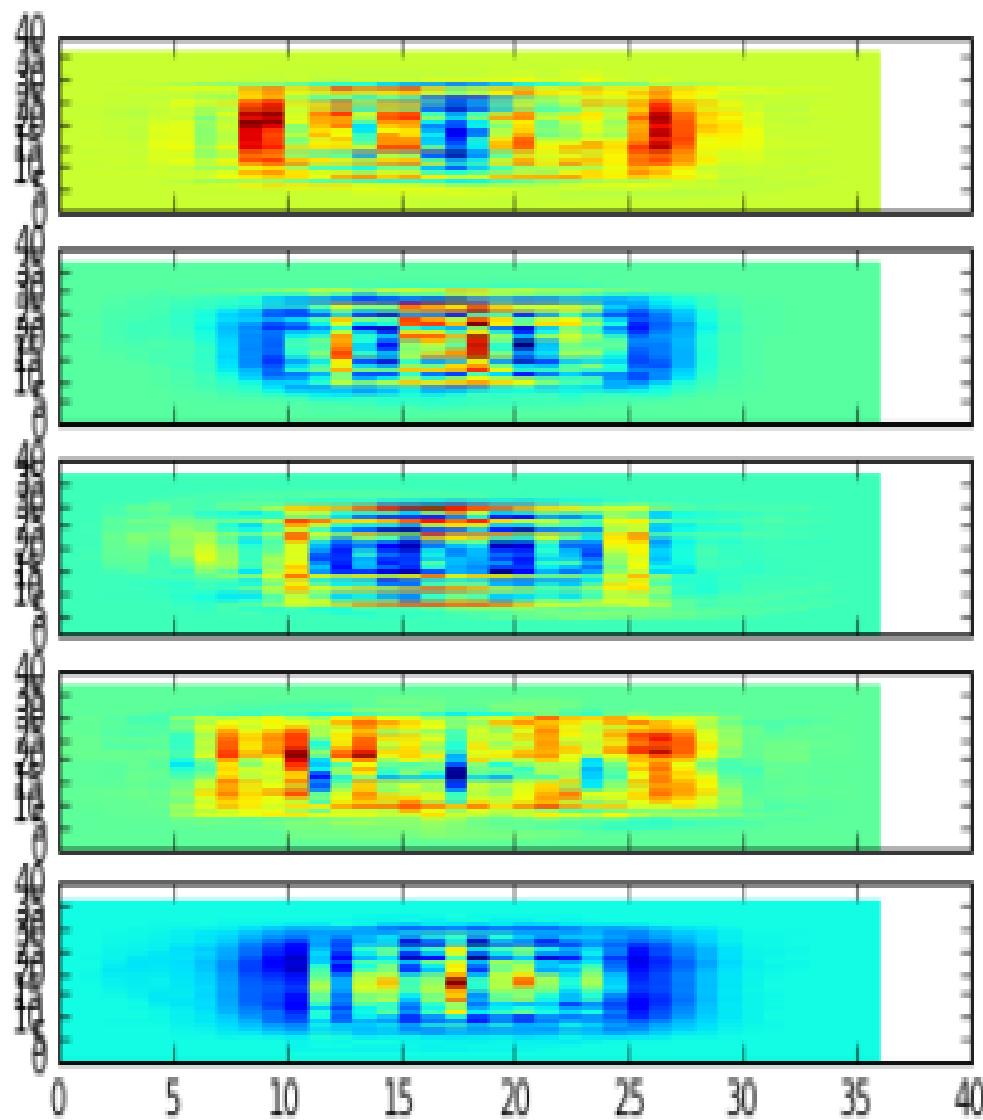
Logistic Regression

Recipe for Learning



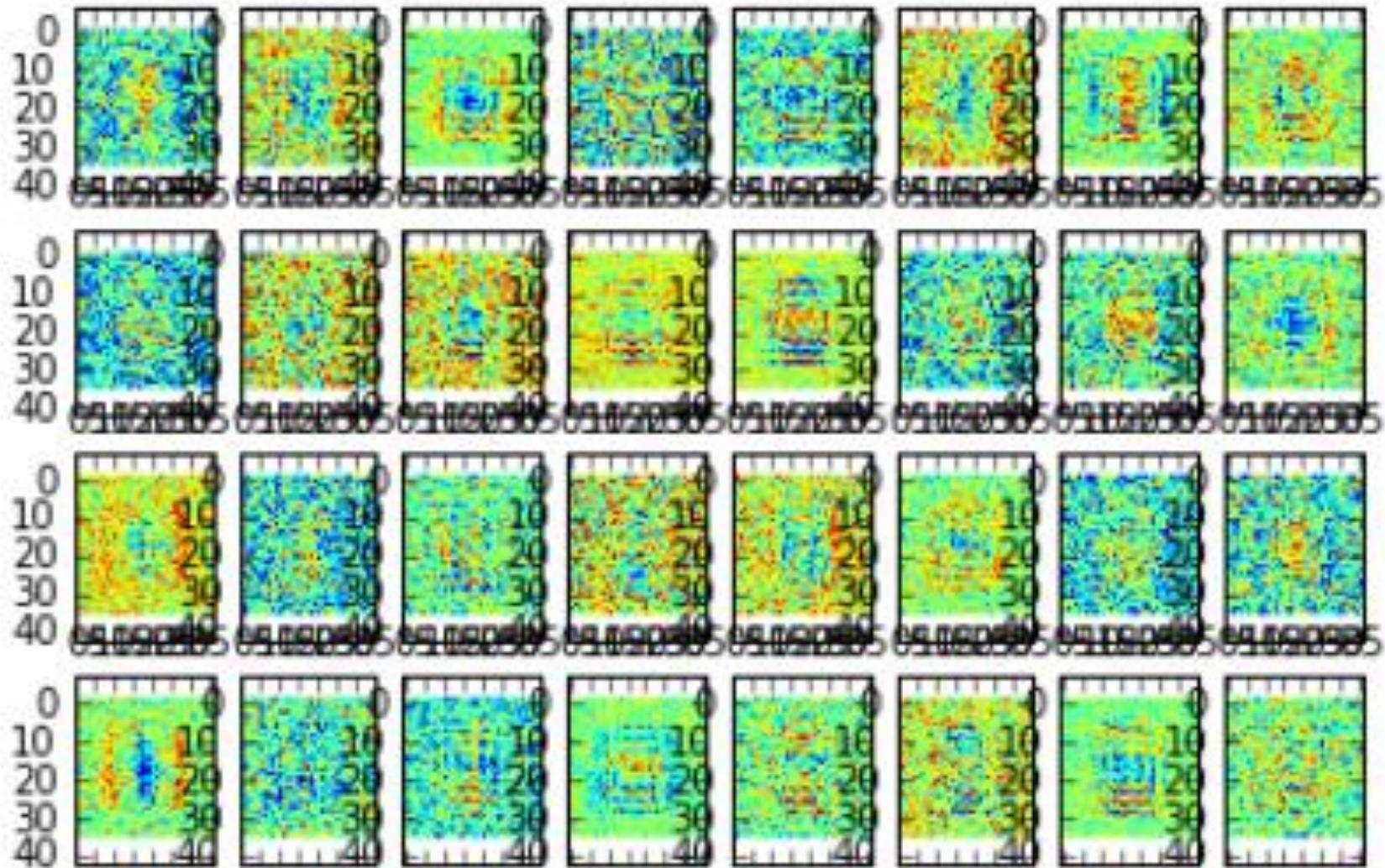
<http://www.gizmodo.com.au/2015/04/the-basic-recipe-for-machine-learning-explained-in-a-single-powerpoint-slide/>

Logistic Regression



Feed Forward

05.08.08.85 05.08.08.85 05.08.08.85 05.08.08.85 05.08.08.85 05.08.08.85 05.08.08.85 05.08.08.85



The Building Blocks of Interpretability

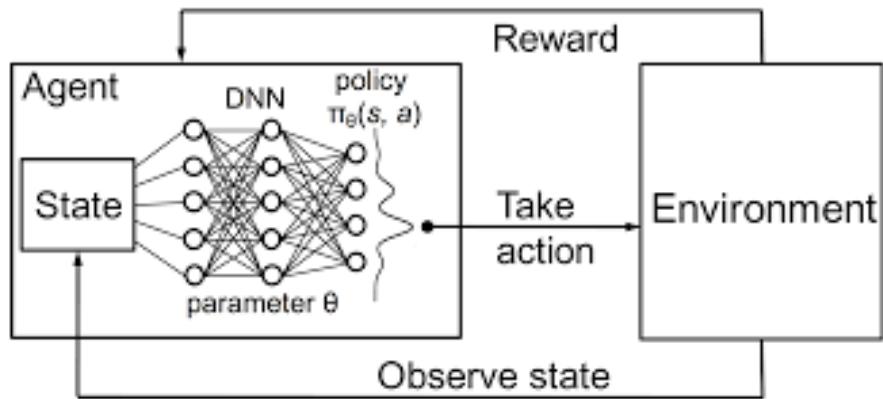
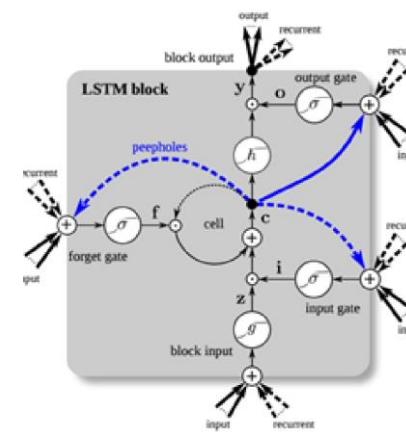
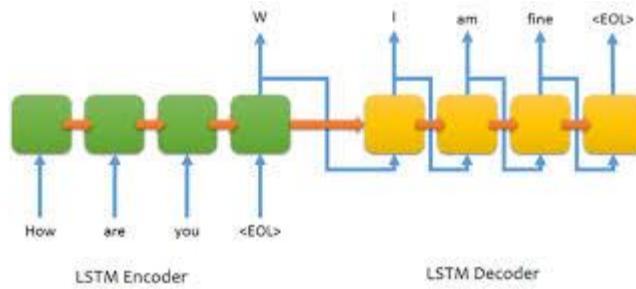
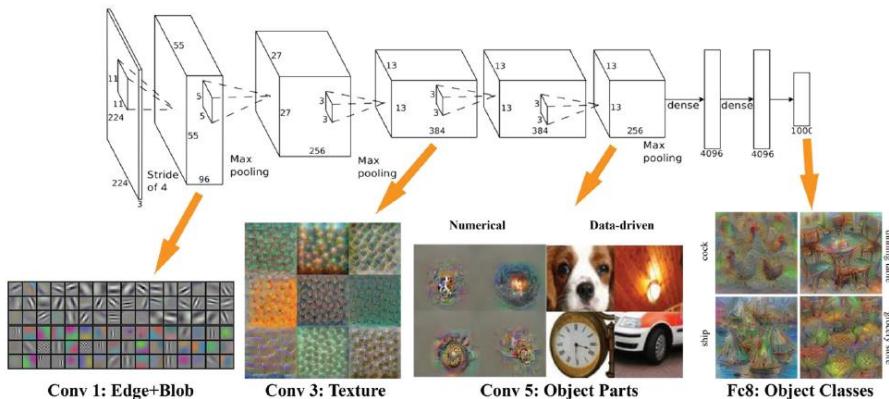
<https://distill.pub/2018/building-blocks/>

Interpretability techniques are normally studied in isolation.

We explore the powerful interfaces that arise when you combine them — and the rich structure of this combinatorial space



DL: architectures



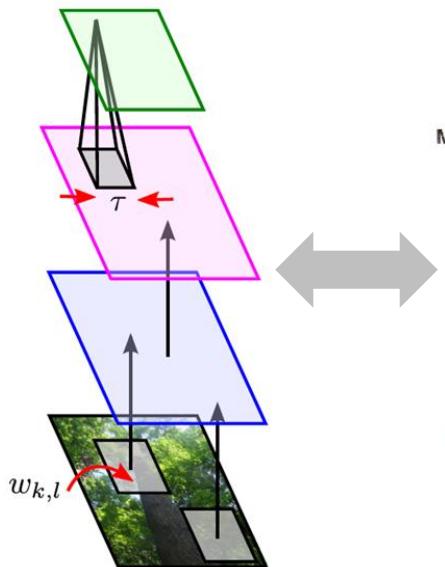
CNN / ConvNets: Convolutional Neural Network

organizes neurons based on animal's visual cortex system, which allows for learning patterns at both local level and global level.

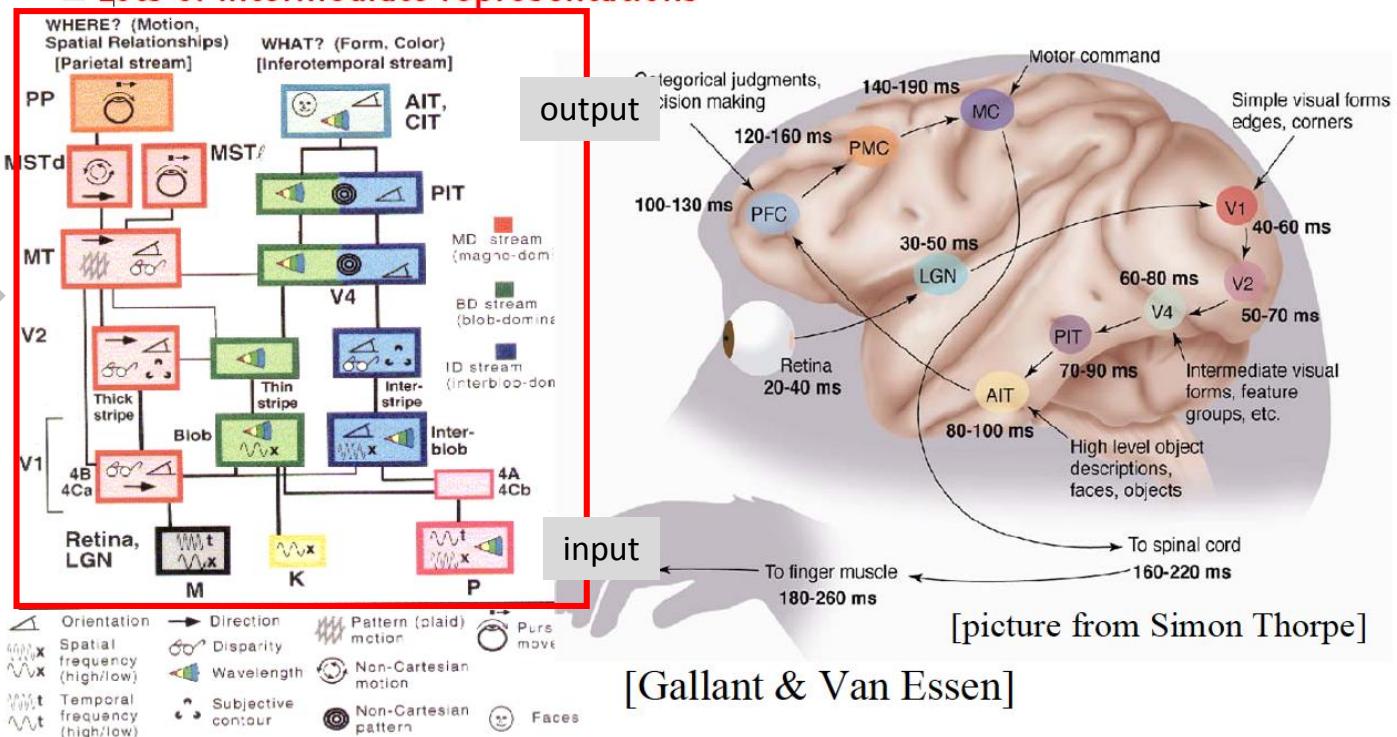
- Y. LeCun, L. Bottou, Y. Bengio and P. Haffner: Gradient-Based Learning Applied to Document Recognition, Proceedings of the IEEE, 86(11):2278-2324, November 1998

The Mammalian Visual Cortex Inspires CNN

Convolutional Neural Net



- The ventral (recognition) pathway in the visual cortex has multiple stages
- Retina - LGN - V1 - V2 - V4 - PIT - AIT
- Lots of intermediate representations

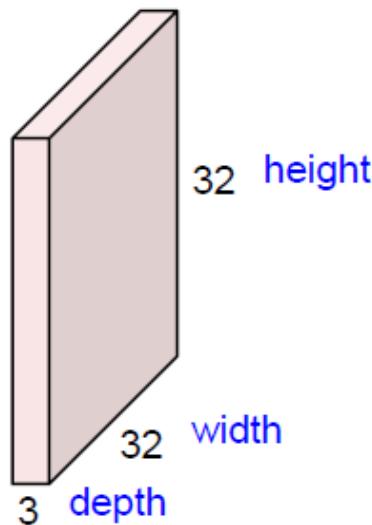


Convolutional Neural Networks

(First without the brain stuff)

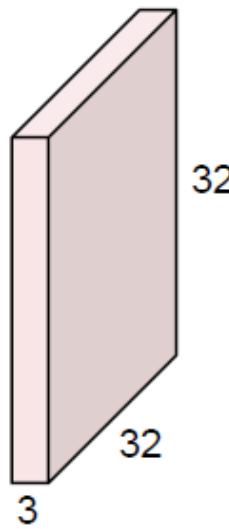
Convolution Layer

32x32x3 image



Convolution Layer

32x32x3 image

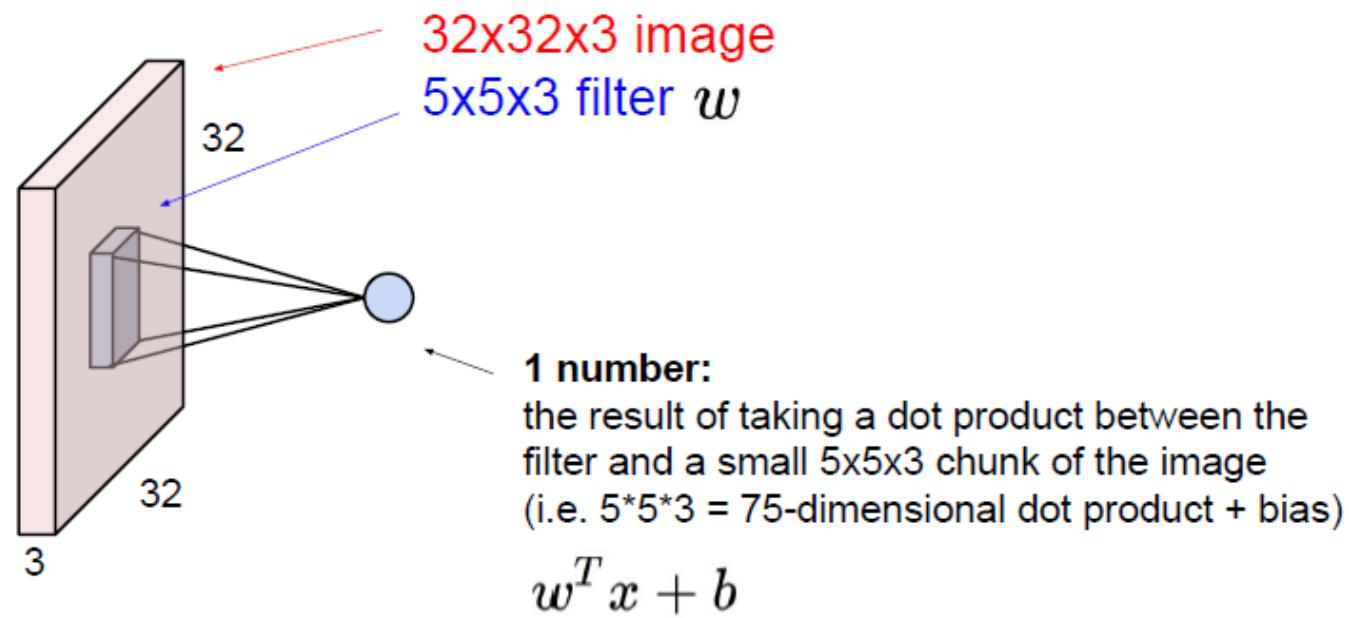


5x5x3 filter

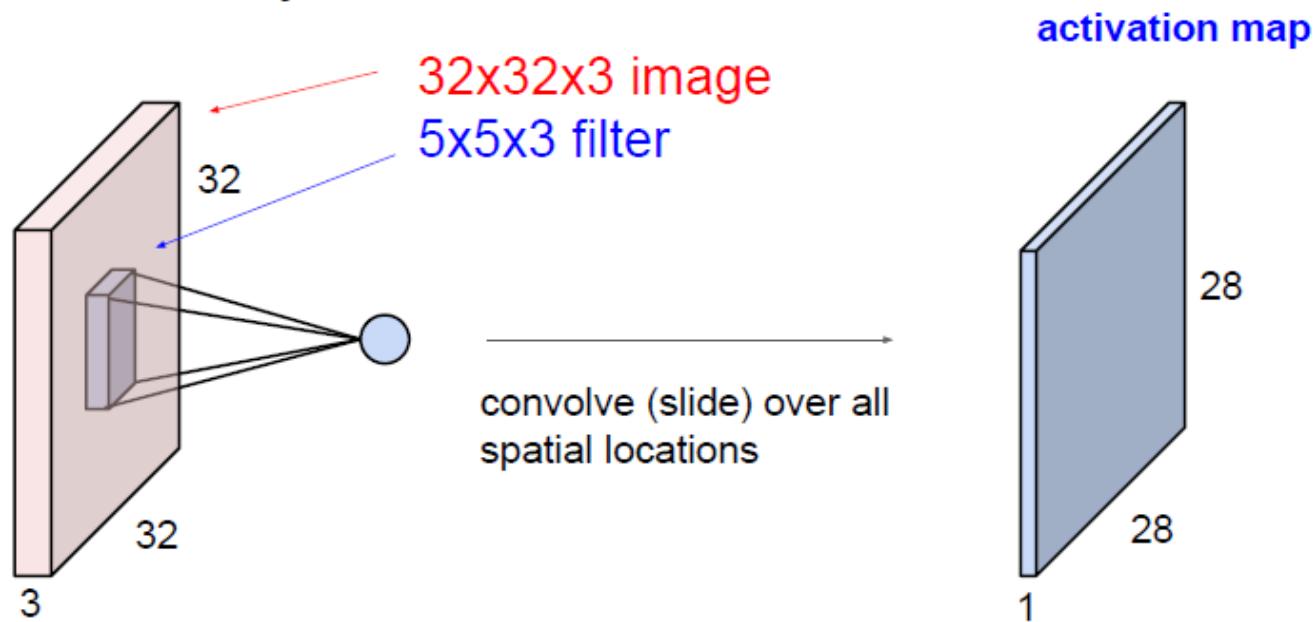


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Convolution Layer

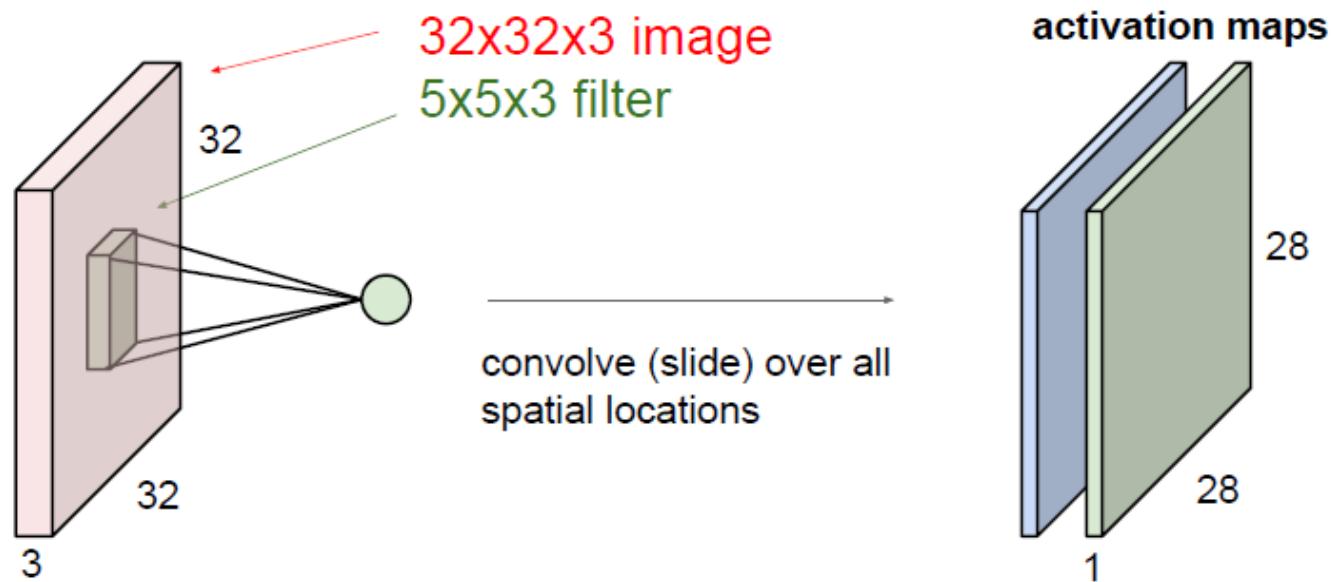


Convolution Layer

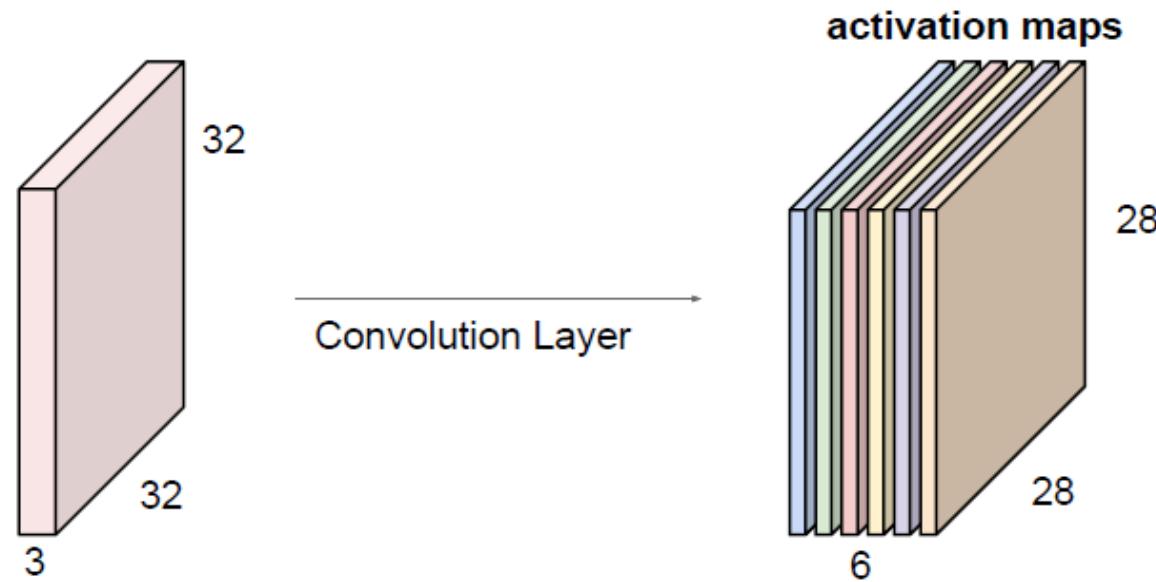


Convolution Layer

consider a second, green filter



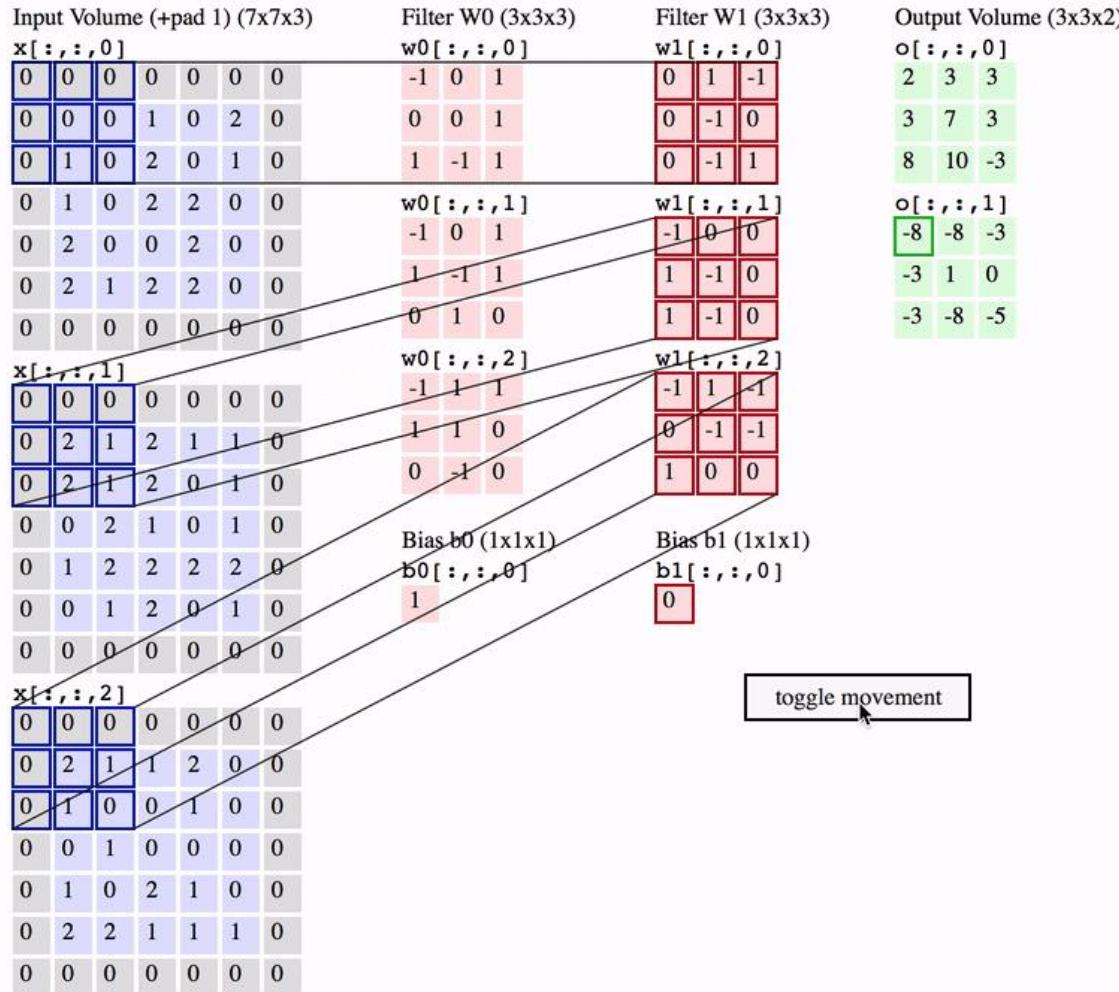
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



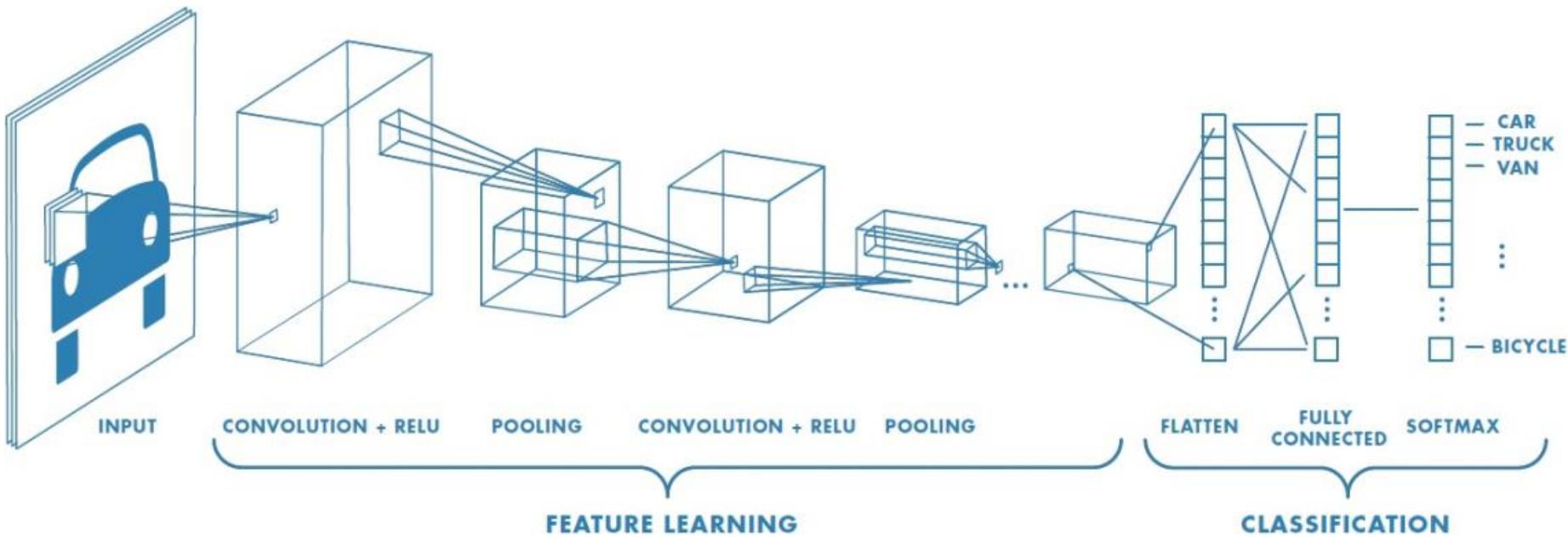
We stack these up to get a “new image” of size 28x28x6!

CNN nice visualization

<http://cs231n.github.io/convolutional-networks/>



CNN / ConvNet Architecture:





Keras

Play with:

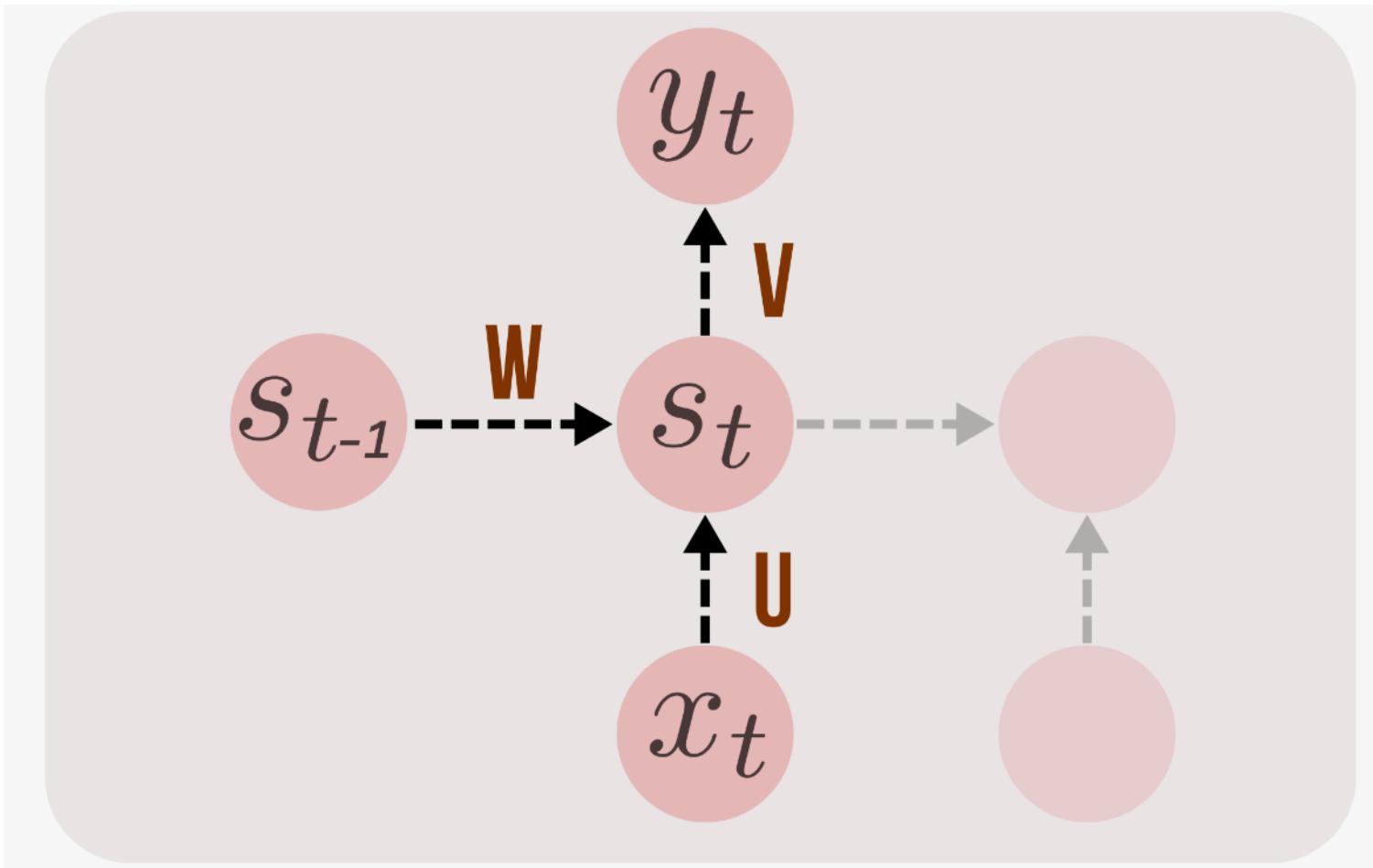
Eurielec_Keras_FontReco_CNN_2018.ipynb

... and much more to learn!!!

OUTPUT y_t

$\text{logits} = \text{tf.matmul}(\text{state}, V) + b$

$\text{predictions} = \text{tf.nn.softmax}(\text{logits})$



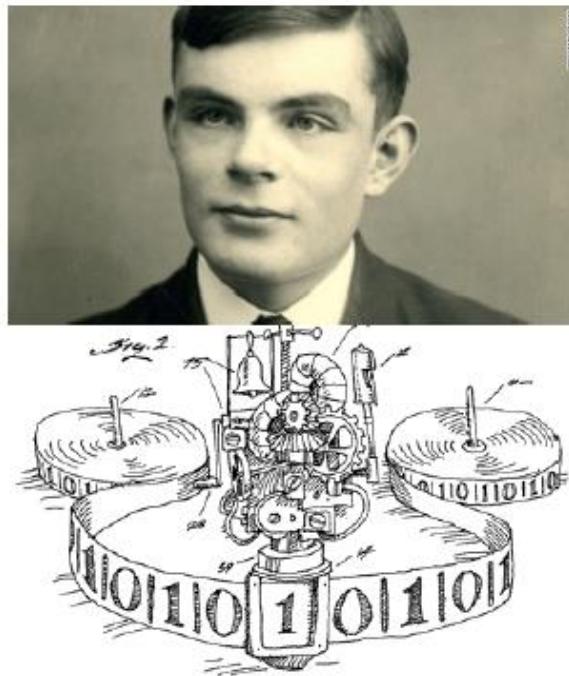
RNN essentially describe programs:

inputs + some internal variables.

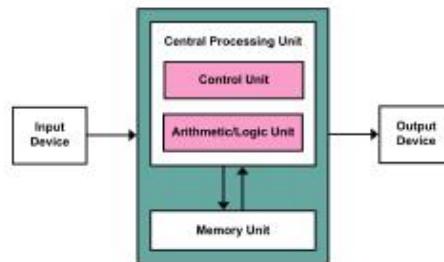
In fact, it is known that RNNs are Turing-Complete in the sense that they can simulate arbitrary programs (with proper weights).

Neural Turing Machines

Can neural nets learn programs?



Alex Graves
Greg Wayne
Ivo Danihelka



...path to AI??

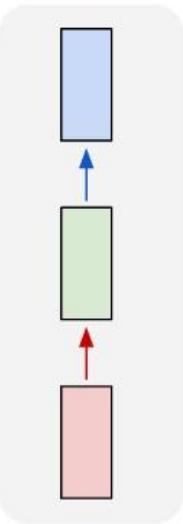
.... *But “forget I said anything.”*

Andrej Karpathy

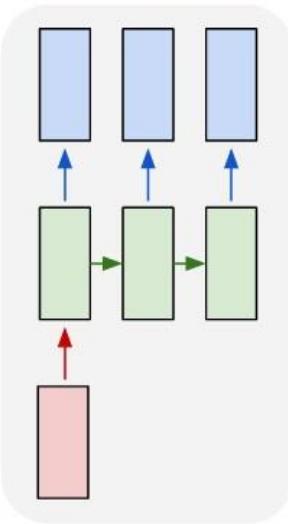
<http://karpathy.github.io/2015/05/21/rnn-effectiveness>

Recurrent Neural Networks Applications

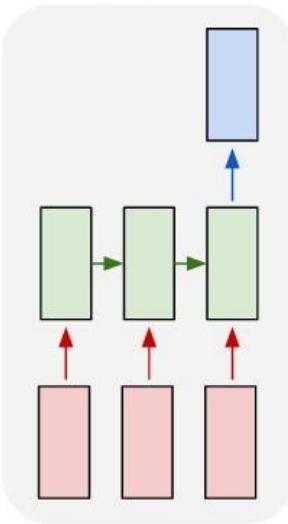
one to one



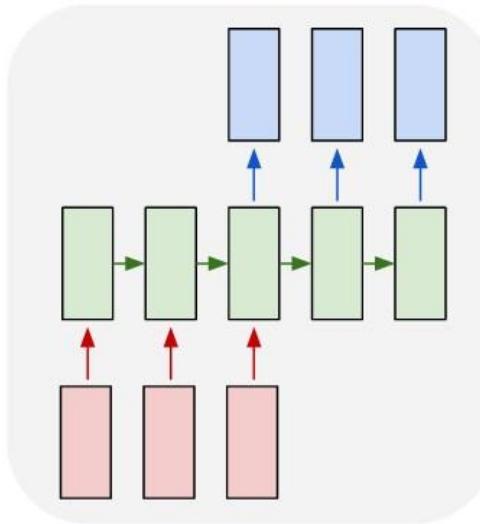
one to many



many to one



many to many



many to many

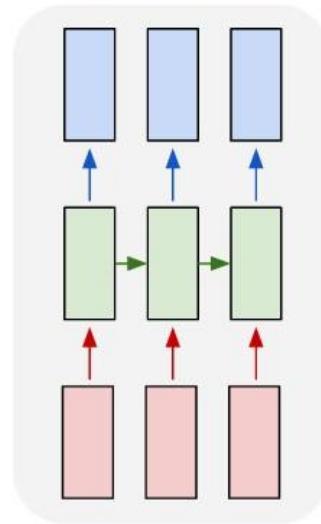


Image
description
using text

Emotion
Recognition

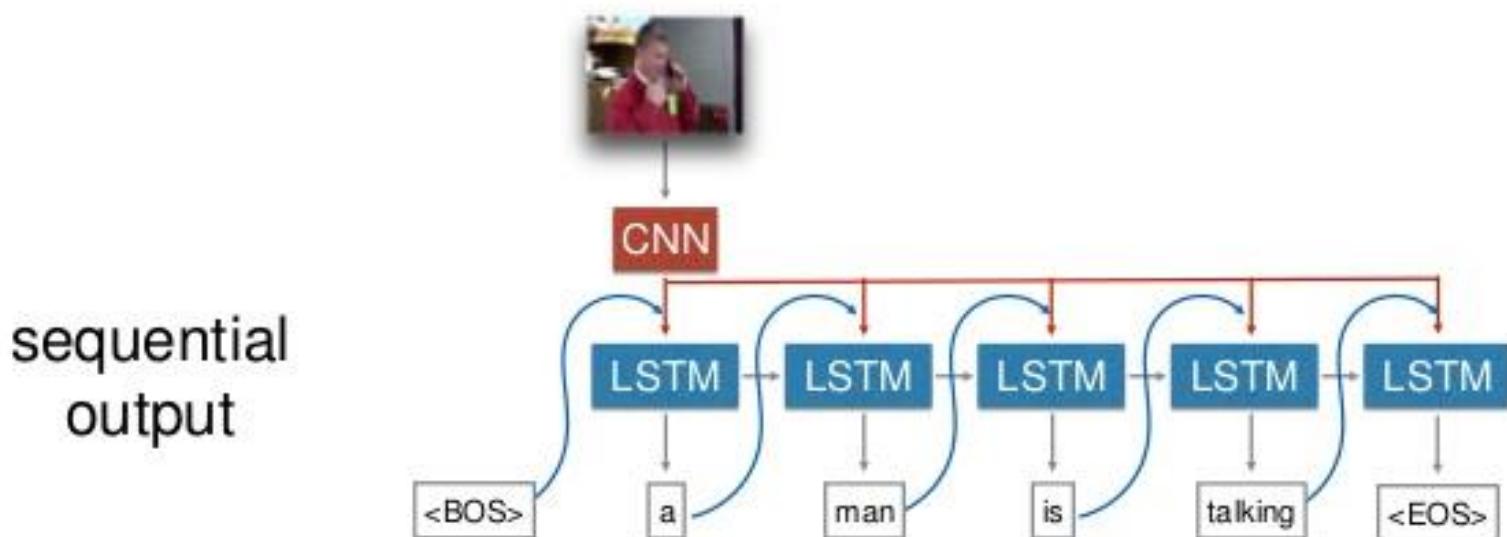
Language
Model

Machine
Translation

Video frame
labelling

Phoneme
Recognition

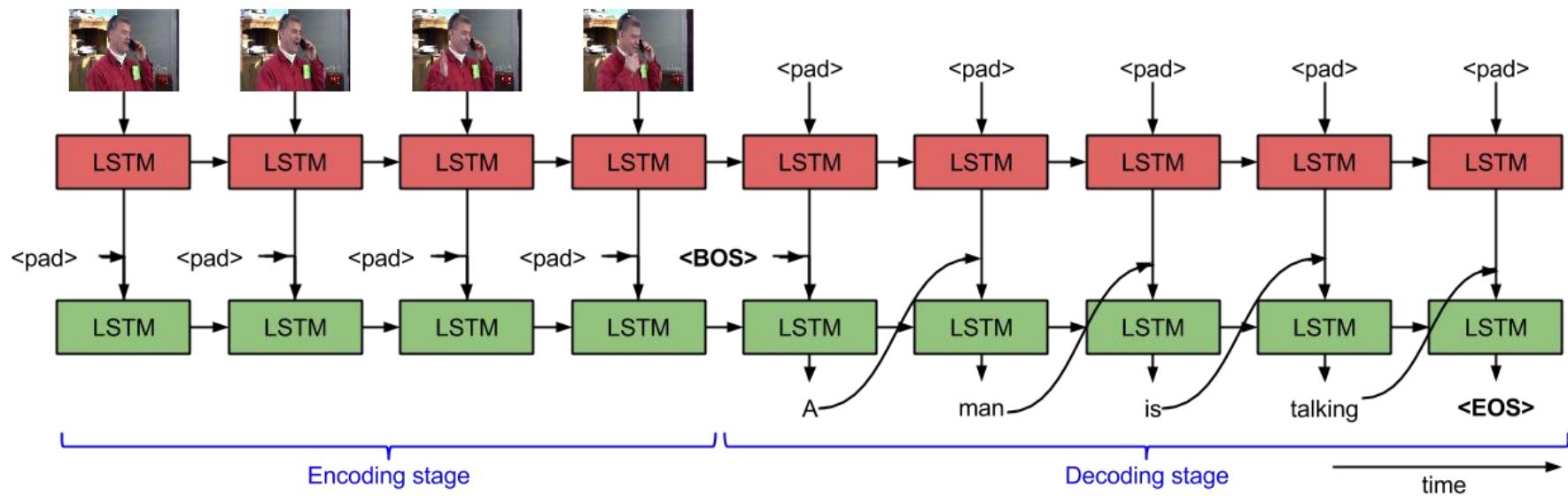
Image Description



- Jeff Donahue, CVPR Caffe Tutorial, June 6, 2015

Sequence to Sequence - Video to Text

Subhashini Venugopalan, et al.



Text prediction & generation using RNN



Text Prediction/Generation with Keras using **LSTM: Long Short Term Memory networks**

In this example we will work with the book: Alice's Adventures in Wonderland by Lewis Carroll.

We are going to learn the dependencies between characters and the conditional probabilities of characters in sequences so that we can in turn generate wholly new and original sequences of characters.



Adapted from:

[Text Generation With LSTM Recurrent Neural Networks in Python with Keras](#)

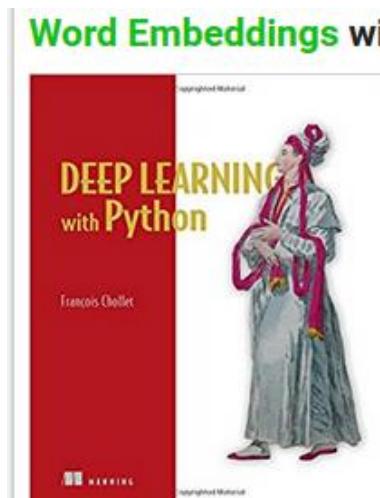
By Jason Brownlee

Embedding:

Indices by themselves, carry no **semantic** meaning

https://github.com/MasterMSTC/DeepLearning_TF_Keras

MSTC_Keras_RNN_3_Word_EMBEDDINGS_2018.ipynb

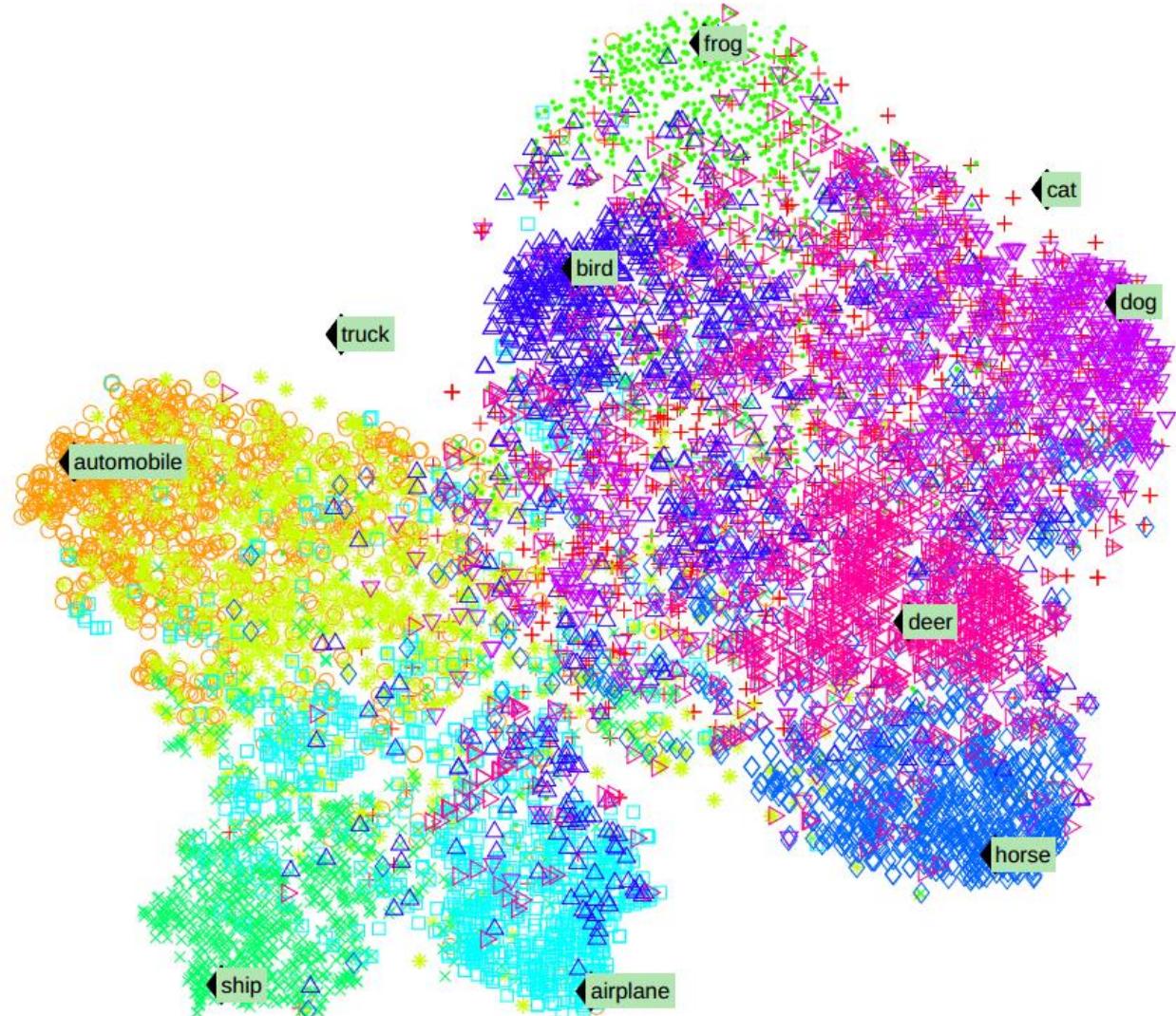
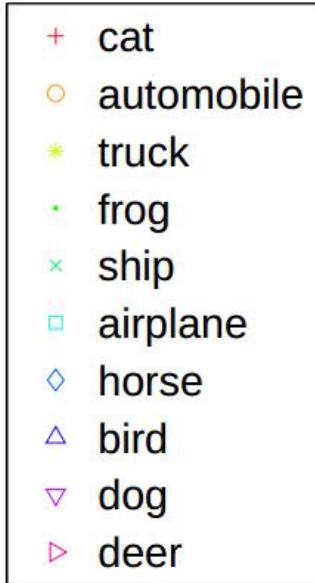


Adapted from:

[6.1-using-word-embeddings](#)

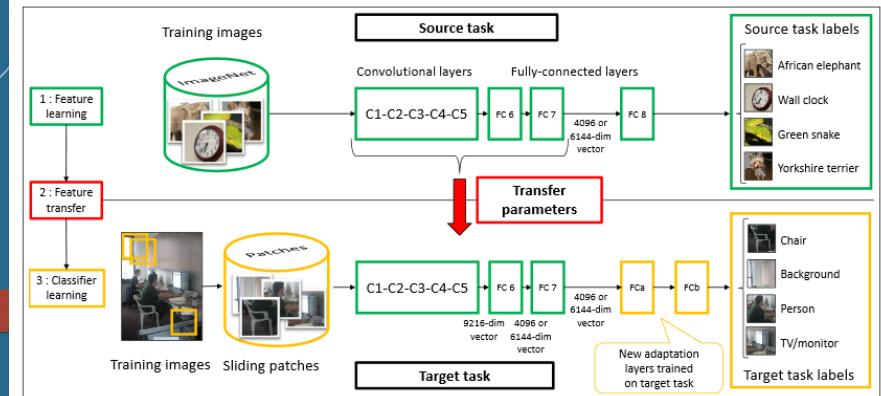
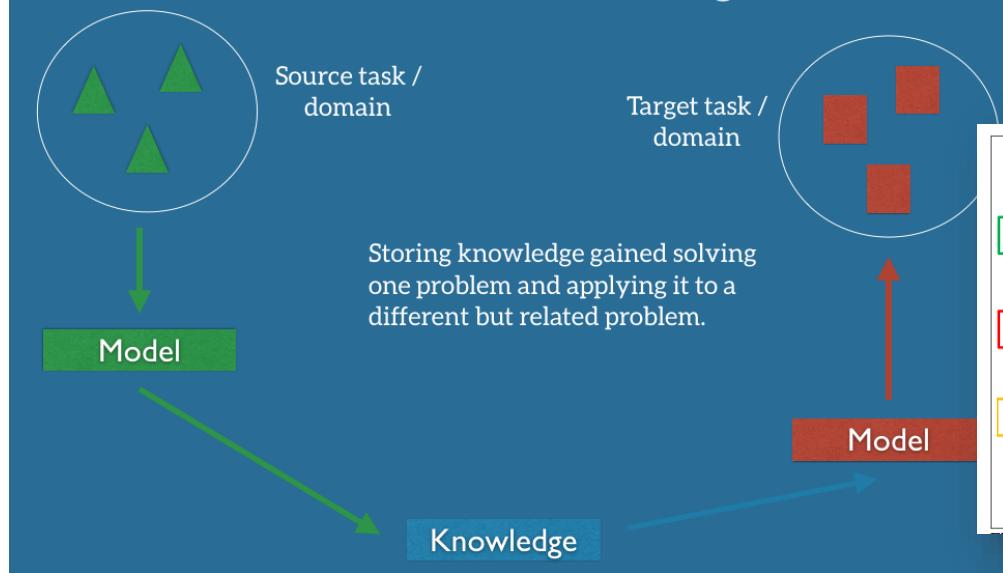
By François Chollet



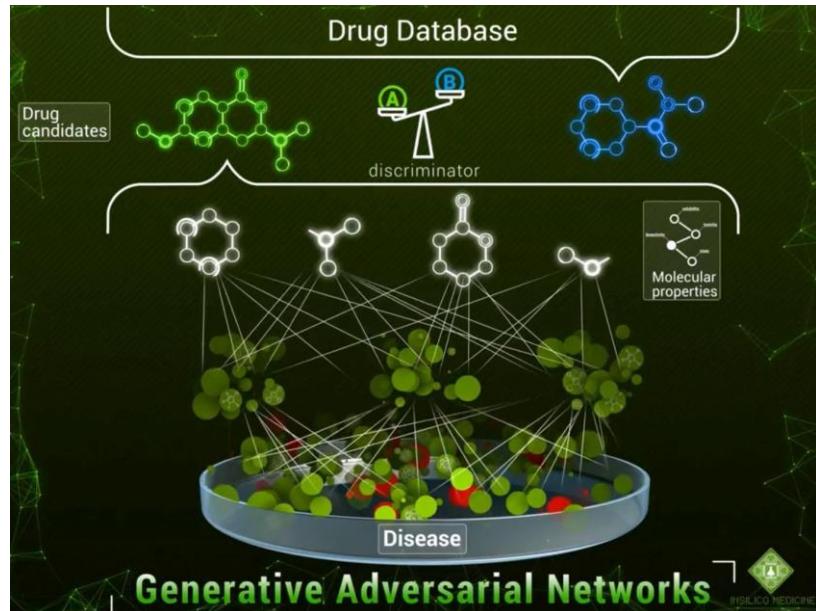
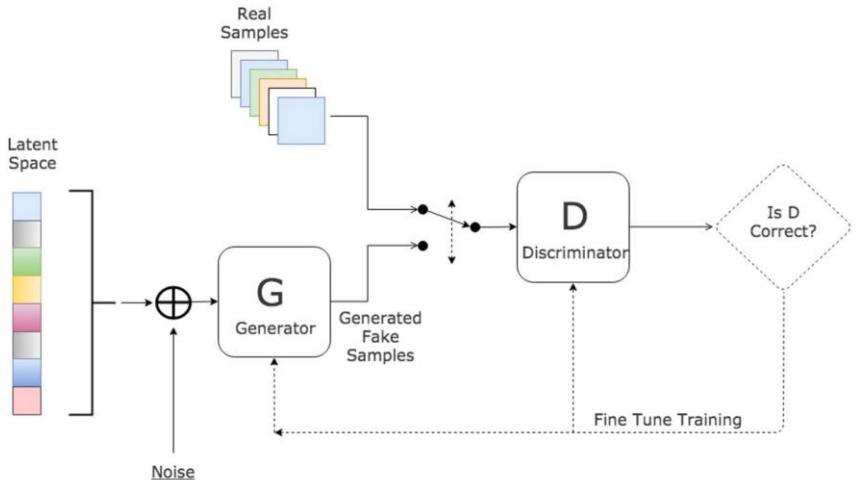


<http://colah.github.io/posts/2014-07-NLP-RNNs-Representations/>

Transfer learning



Generative Adversarial Network

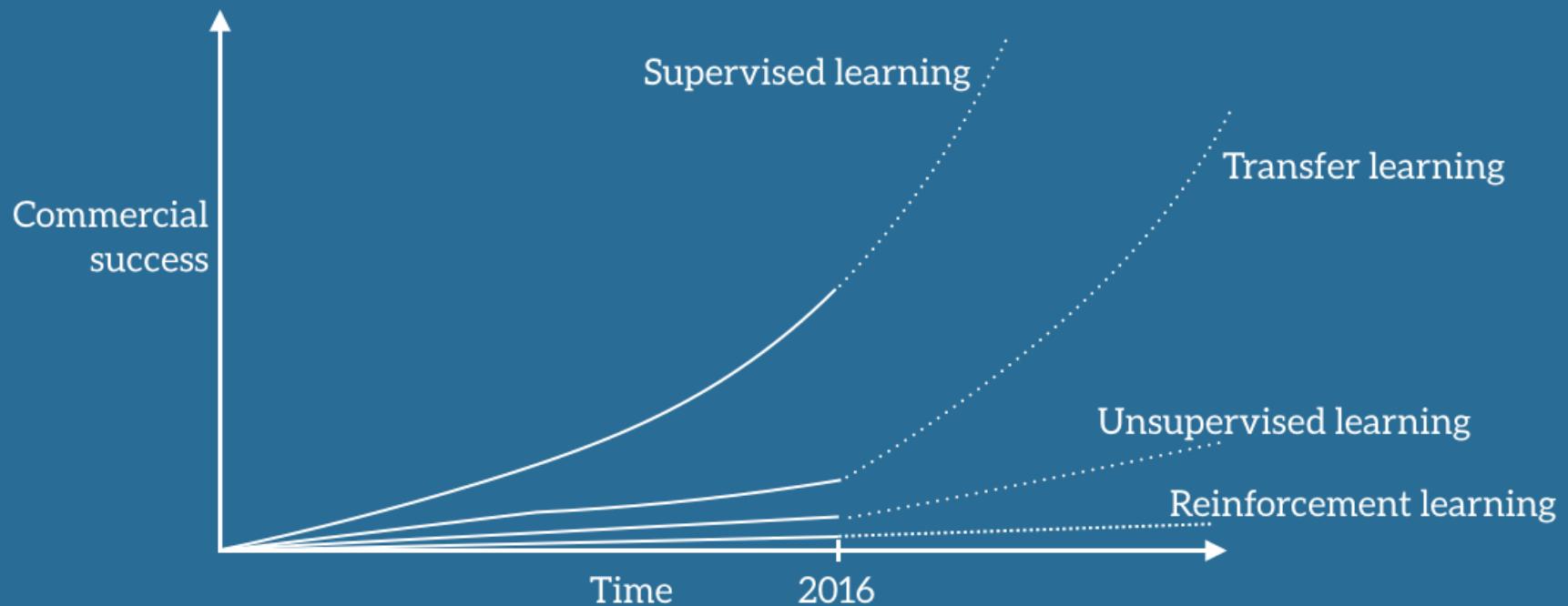


DL Applications



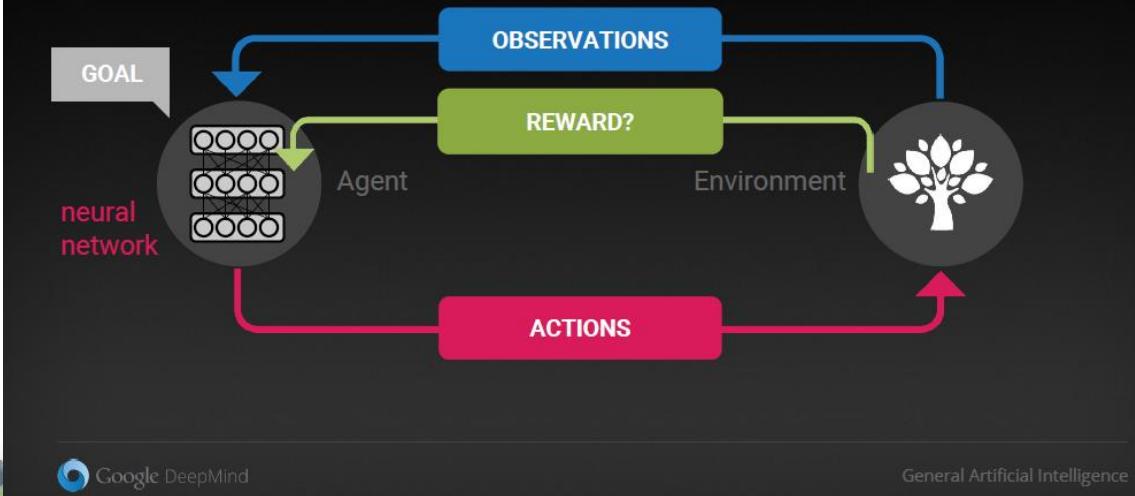
Progressive Growing of GANs, Karras2018. [\[link\]](#)

Drivers of ML success in industry



Unsupervised learning is a next frontier in artificial intelligence and we are moving towards it.

Deep Reinforcement Learning



Self-Driving Car Engineer
by UBER ATG NVIDIA





Human-level control through deep reinforcement learning

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves, Martin Riedmiller, Andreas K. Fidjeland, Georg Ostrovski, Stig Petersen, Charles Beattie, Amir Sadik, Ioannis Antonoglou, Helen King, Dharshan Kumaran, Daan Wierstra, Shane Legg & Demis Hassabis

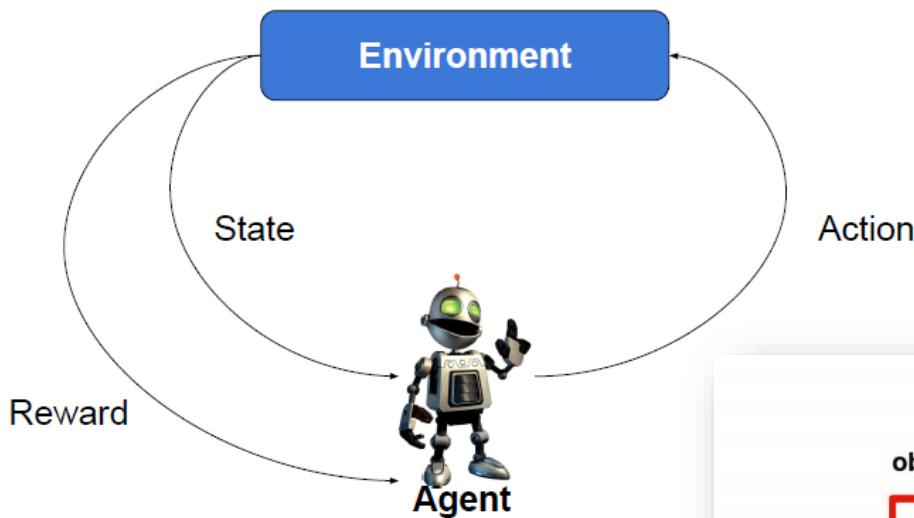
Nature volume 518, pages 529–533 (26 February 2015)

By combining:

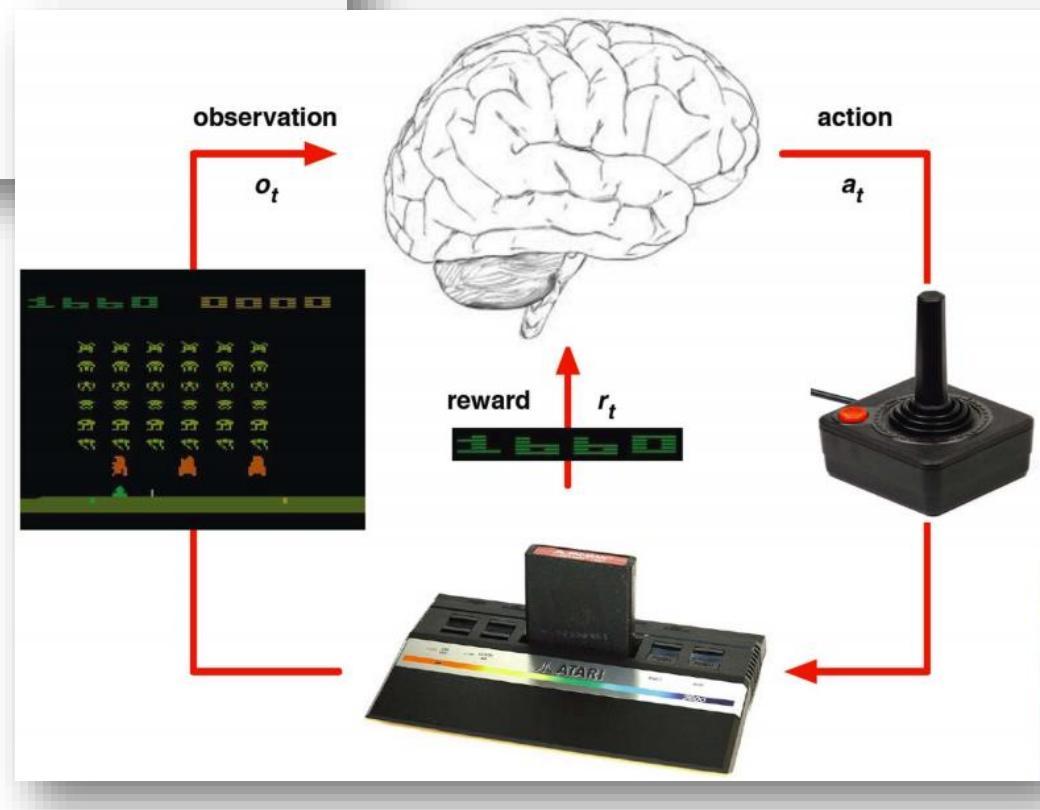
- ***Reinforcement Learning***: selecting actions that maximize reward in this case the game score
- with ***Deep Learning***: multilayered feature extraction from high-dimensional data in this case the pixels

the game-playing agent **takes artificial intelligence a step nearer** the goal of systems capable of learning a diversity of challenging tasks from scratch.

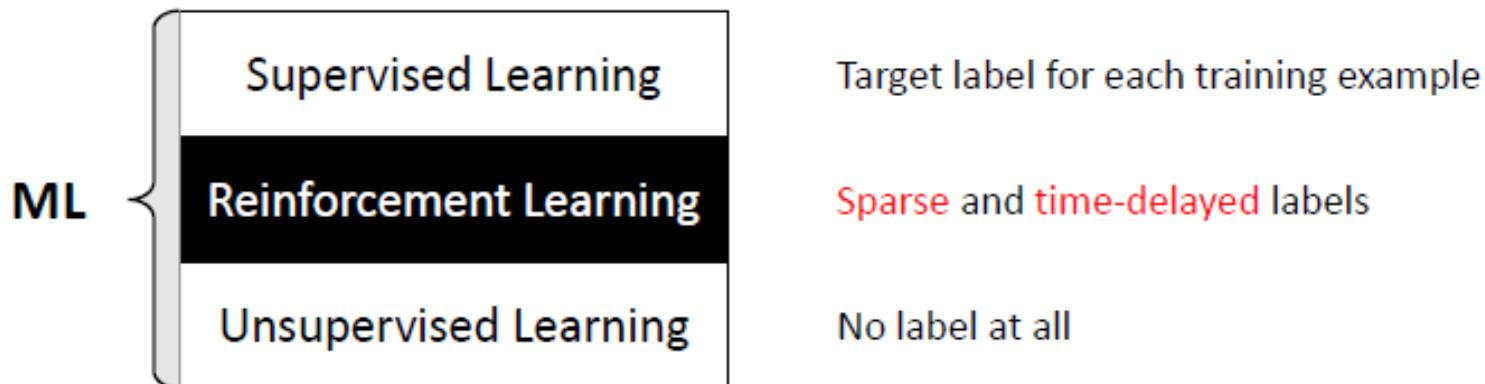
What's Reinforcement Learning?



- Agent interacts with an environment and learns by maximizing a reward.
- No labels or any other supervision is given.



Reinforcement Learning



- ▶ **Play** games: Atari, poker, Go, ...
- ▶ **Navigate** worlds: 3D worlds, Labyrinth, ...
- ▶ **Control** physical systems: manipulate, walk, swim, ...
- ▶ **Interact** with users: recommend, optimise, personalise, ...

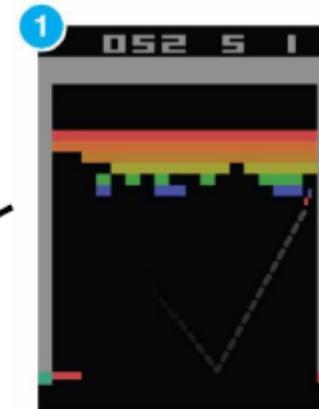
Universal approach!

State Representation

Think about the **Breakout** game

- How to define a state?

- Location of the paddle
- Location/direction of the ball
- Presence/absence of each individual brick

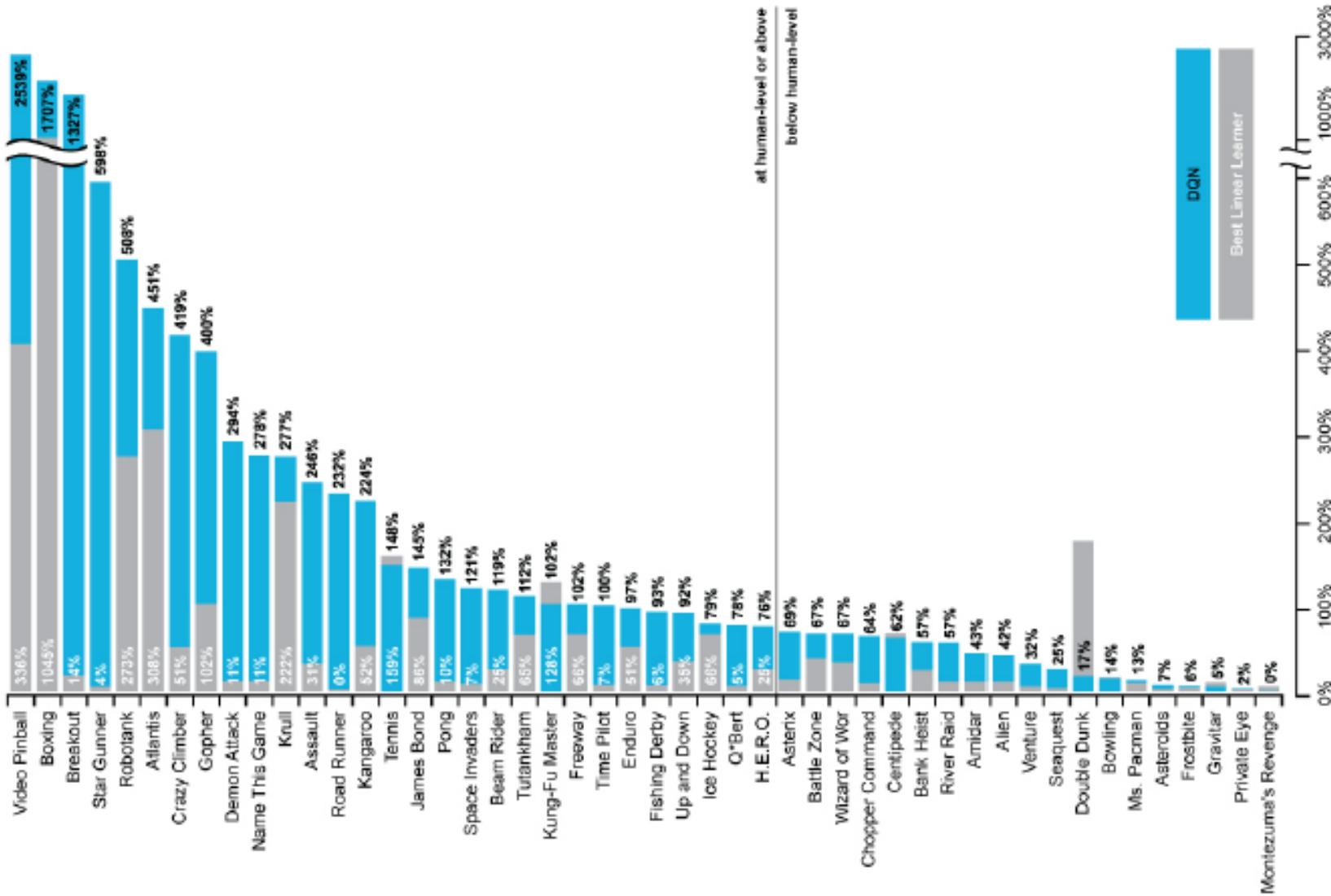


Let's make it more universal!

Screen pixels



DQN Results in Atari

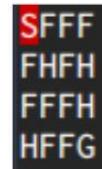


Hands-on practice!

There is a large number of environments

OpenAI Gym

- ▶ A standard Python API for RL environments
- ▶ A set of tools to measure agent performance
- ▶ An online scoreboard for comparing and benchmarking approaches
- ▶ <https://gym.openai.com/>



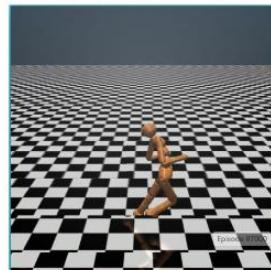
(a) Toy Text



(b) Atari



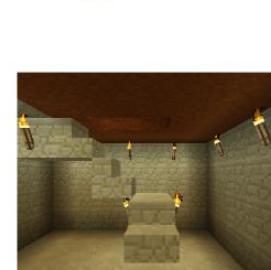
(c) Controls



(d) MuJoCo



(e) Doom

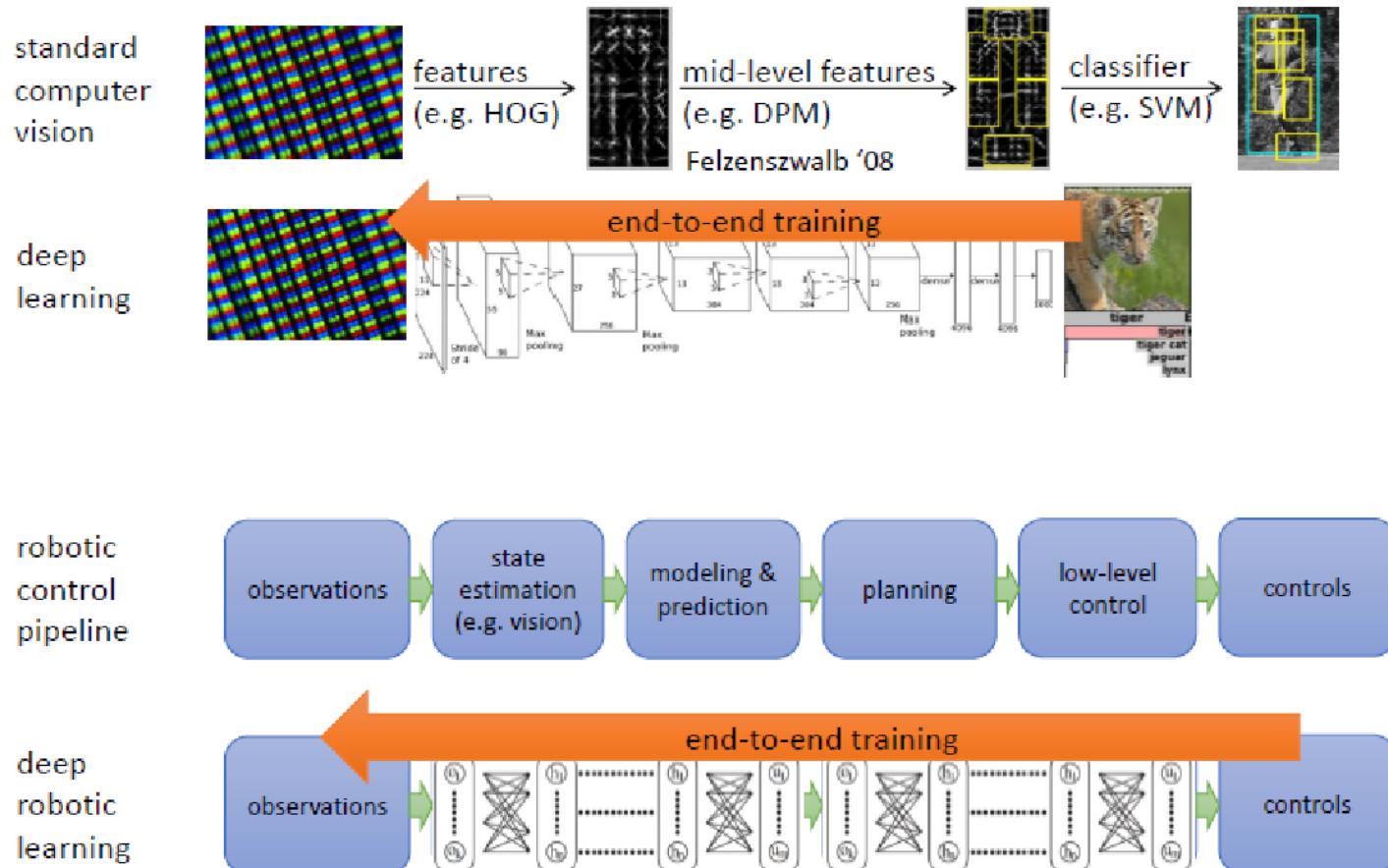


(f) Minecraft

Environment libraries

- OpenAI [Roboschool](#): Robot simulation
- OpenAI [Universe](#): gym on VNC servers inside docker containers
- Intel Nervana [Coach](#): Environments + DLR algorithms
- Deepmind [Lab](#):
- Deepmind [Pysc2](#): Star Craft 2 - like environments





Wide range of applications!



... but there are some
“buts”!!!



... there are “some” important issues to consider!

and not “only” those related to data privacy,



**.... and not only
some particular
cases....**

United Airlines Passenger Is Dragged From an Overbooked Flight



.... each airline sets its own system and procedures for deciding whom to bump

Faceapp uses facial recognition technology to alter selfies.

Many took to Twitter to brand the app racist, as they watched their skin turn lighter before their eyes.



<http://metro.co.uk/2017/04/26/face-changing-app-branded-racist-for-lightening-skin-on-selfies-6599159/>

Yaroslav Goncharov, founder and chief executive of FaceApp said:

- ‘We are deeply sorry for this unquestionably serious issue.
- ‘It is an unfortunate side-effect of the underlying **neural network** caused by the training set bias, not intended behaviour.

**.... but more serious
issues when we can
exclude some
segments of
population....**

WEAPONS OF MATH DESTRUCTION



HOW BIG DATA INCREASES INEQUALITY
AND THREATENS DEMOCRACY

CATHY O'NEIL

So focus your future big professional potential in improving our world!!!



[HOME](#) [FIND DATA](#) [PREPARE DATA](#) [BUILD ANALYTICS](#) [RESOURCES](#) [STATUS](#) [LOGIN](#) [SIGN UP](#)



We often hear that the world is drowning in data. Yet, when you want to learn and experiment, finding open, easily-accessible data sets remains a major challenge. Open data is data that can be freely used, intermixed with other datasets, and distributed to others without restrictions. We have compiled a small selection of publicly accessible data sources that should give an aspiring data scientist a quick start. We will be constantly adding new data sources to this page:

- Medical research
- Air Traffic Controllers
- To detect diseases in Cassava plants to improving yield for farmers in Africa



<https://medium.com/tensorflow/highlights-from-tensorflow-developer-summit-2018-cd86615714b2>



DEPARTAMENTO DE SEÑALES, SISTEMAS Y RADIOCOMUNICACIONES

Master of Science in Signal Theory and Communications

mstc.ssr.upm.es
[@mstc_upm](https://twitter.com/mstc_upm)



Signal Processing and Machine Learning for Big Data

<http://mstc.ssr.upm.es/>

 Fundamentals

 Signal Processing

 Machine Learning

 Applications and Practice

SIGNAL PROCESSING AND MACHINE LEARNING FOR BIG DATA

SEMESTER 1			SEMESTER 2		
Statistical Modelling (3C)	Time Series Analysis (4.5C)	Optimization Fundamentals (3C)	Signal Processing for Big Data (4C)	Big Data for Image and Video Signals (4C)	Bio-inspired learning (3C)
Optimization techniques for big data analysis (3C)	Predictive and Descriptive Learning (6C)	Machine Learning Lab (4.5C)	Reinforcement learning (3C)	Application Projects (4C)	Large-scale Media Analytics (4C)
Data Science Foundations and Applications (2C)				Masters' Thesis (12C)	