IPTC Seminar
Introduction to Deep Learning and Keras

July 15, 16 and 17, 2019
ETSIT UPM, Madrid

Introduction to Deep Learning & Keras
Day 1

iptc

Information Processing and Telecommunications Center

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E.T.S. Ingenieros de Telecomunicación
Universidad Politécnica de Madrid

IPTC Information Processing and Telecommunications Center

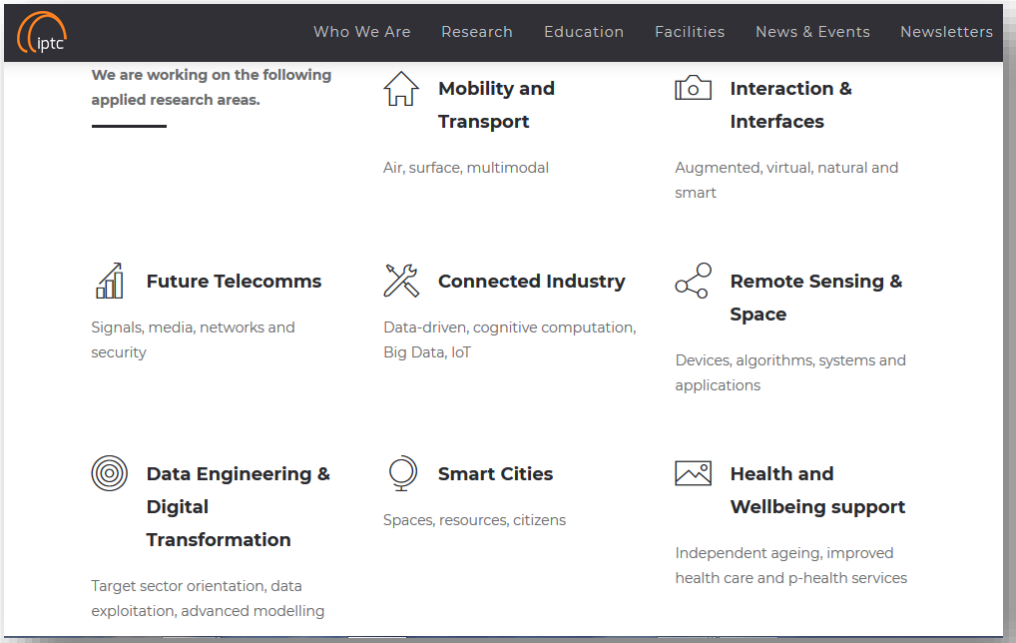
https://iptc.upm.es/

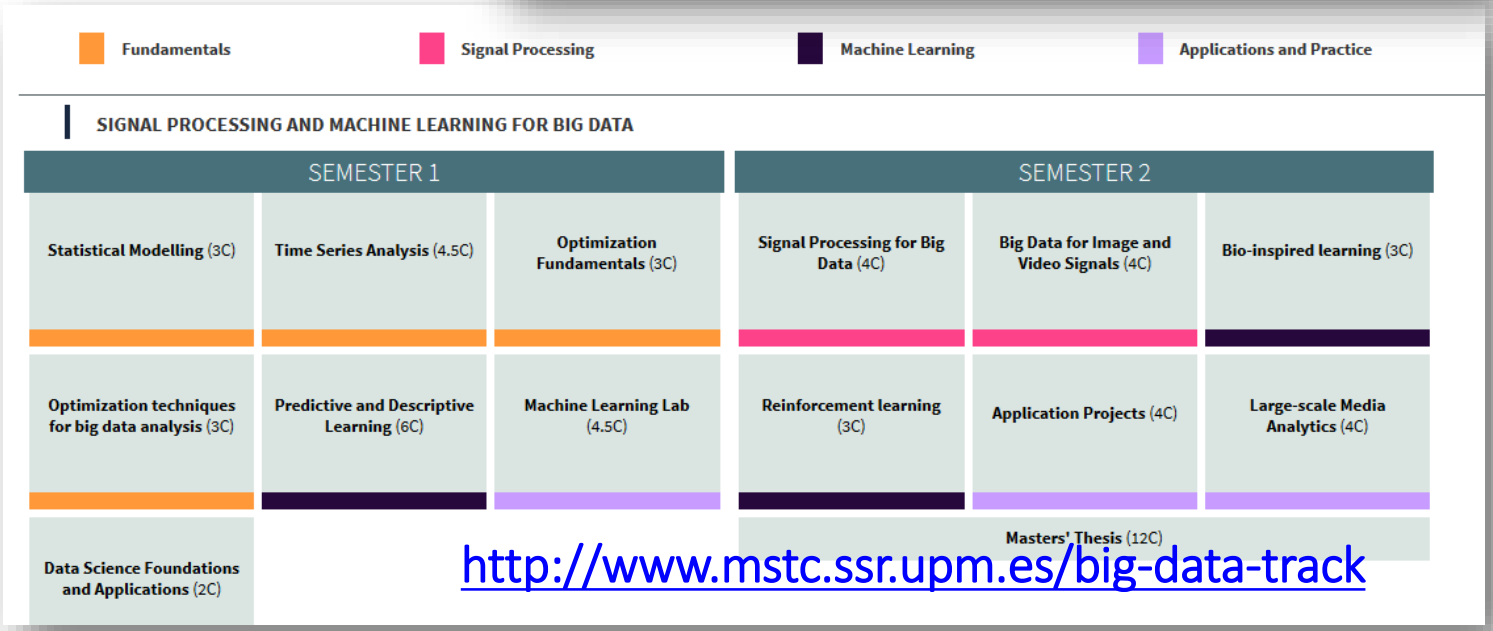
iptc
Information Processing and Telecommunications Center

ETSIT UPM

MSTC
SIGNAL PROCESSING & MACHINE LEARNING FOR BIG DATA

Master Program





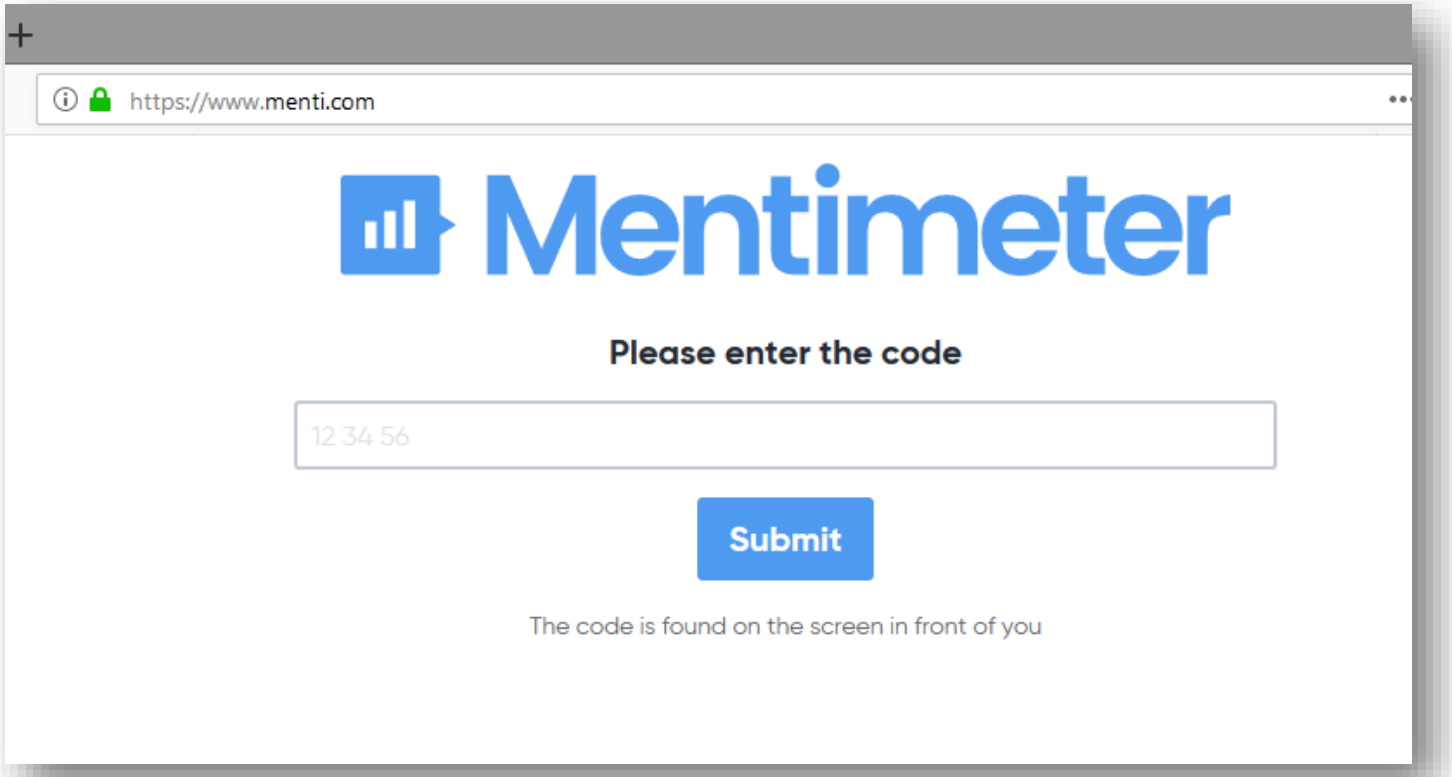
http://www.mstc.ssr.upm.es/big-data-track


POLITÉCNICA
iptc
Information Processing and Telecommunications Center
Day 1 (July 15) : Intro to Deep Learning & Keras.
Feed Forward models
Day 2 (July 16) : Backpropagation. Convolutional Networks
Transfer Learning. Data Augmentation.
Day 3 (July 17) : Recurrent Networks. Advanced Architectures.
GANs. Applications. Final discussion on AI
IPTC Seminar
Introduction to Deep Learning and Keras
July 15, 16 and 17, 2019
ETSIT UPM, Madrid

To have some feedback… we will use:

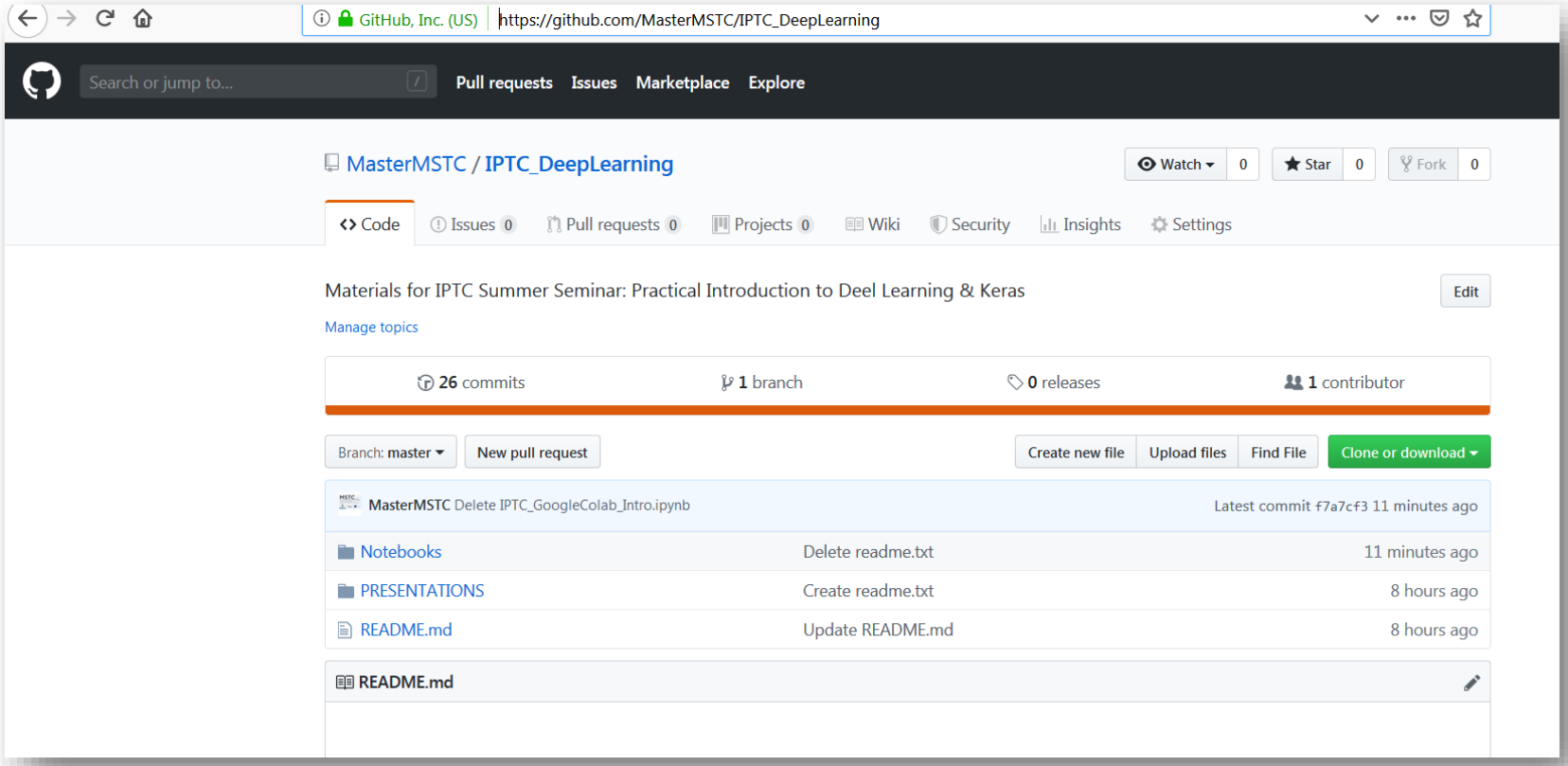
https://www.menti.com/

CODE: …..



IPTC Summer Seminar MATERIALS

Please go to our MSTC GitHub:
https://github.com/MasterMSTC/IPTC_DeepLearning



WiFi Connection

User: iptc

Password: n6gd44j8

The Artificial Intelligence Renaissance:

deep learning and the road to human-Level machine intelligence

https://www.cambridge.org/core/journals/apsipa-transactions-on-signal-and-information-processing/article/artificial-intelligence-renaissance-deep-learning-and-the-road-to-humanlevel-machine-intelligence/A82CA4909877C98B23755744A18EA64F

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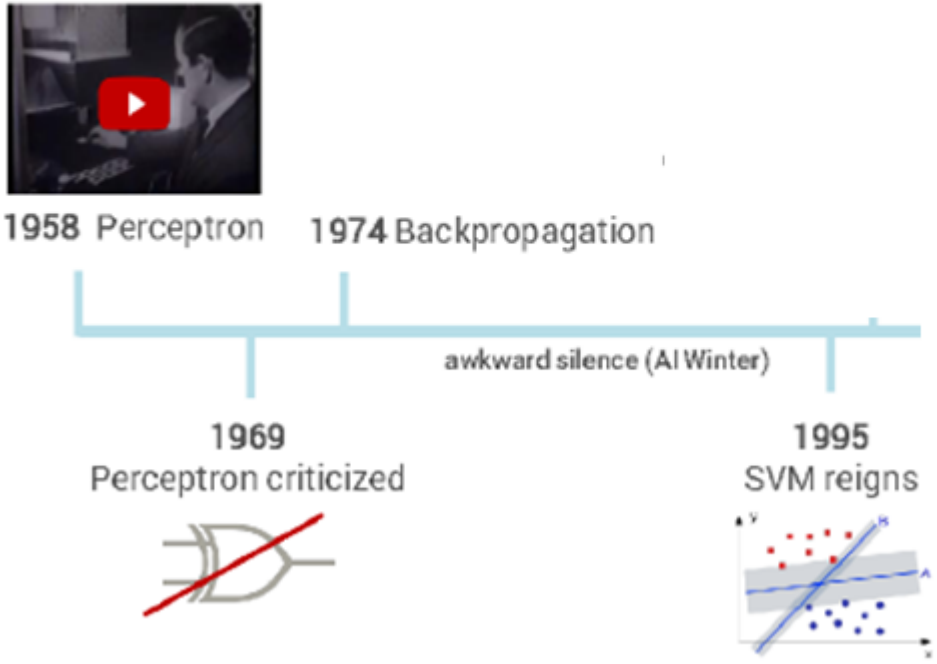
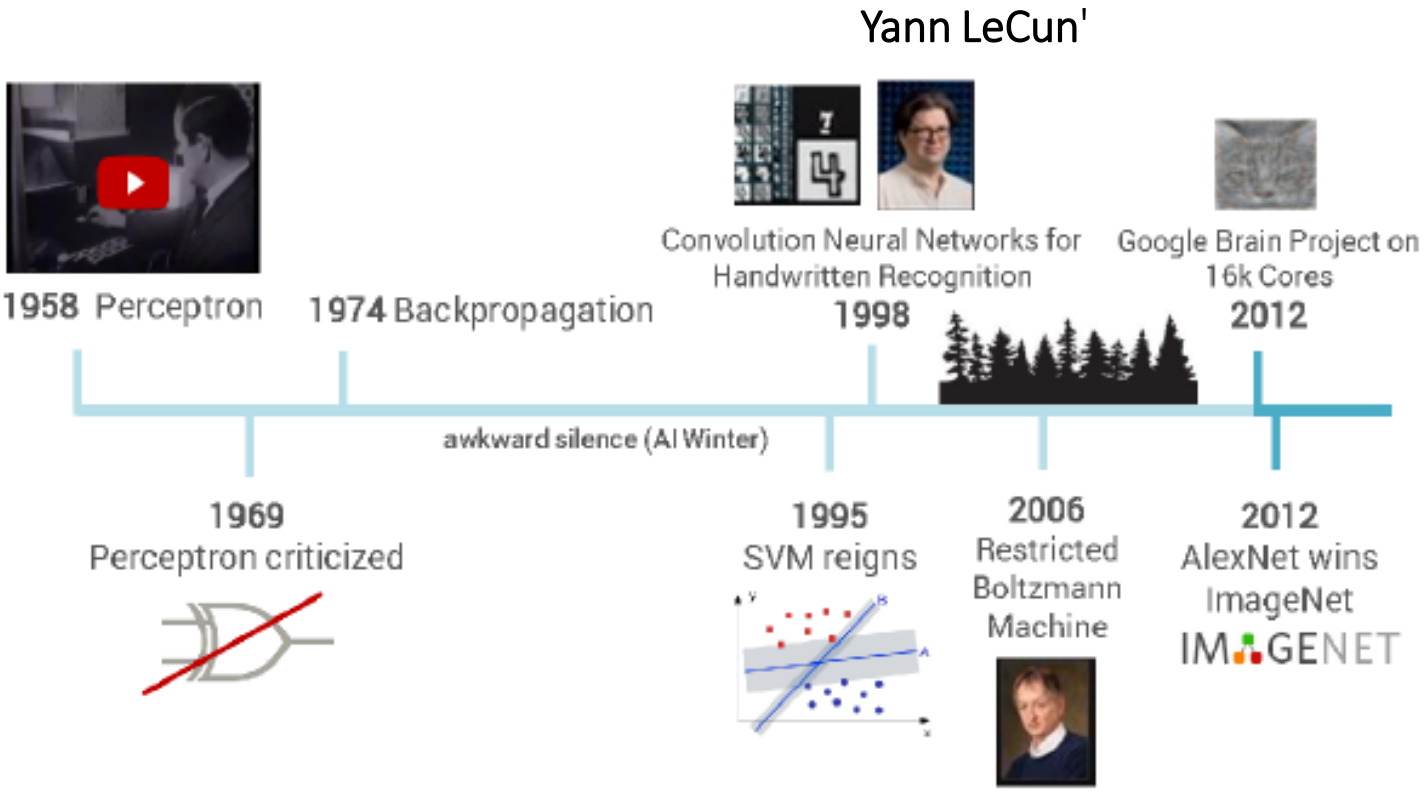
A Brief History



A Brief History



Deep Learning: Hype or Reality?

DNNs better than humans at image recognition

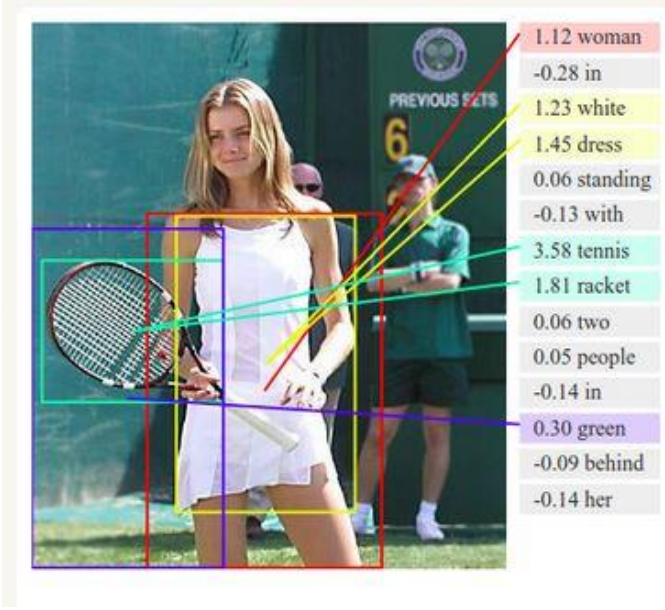
ImageNet

1000 categories

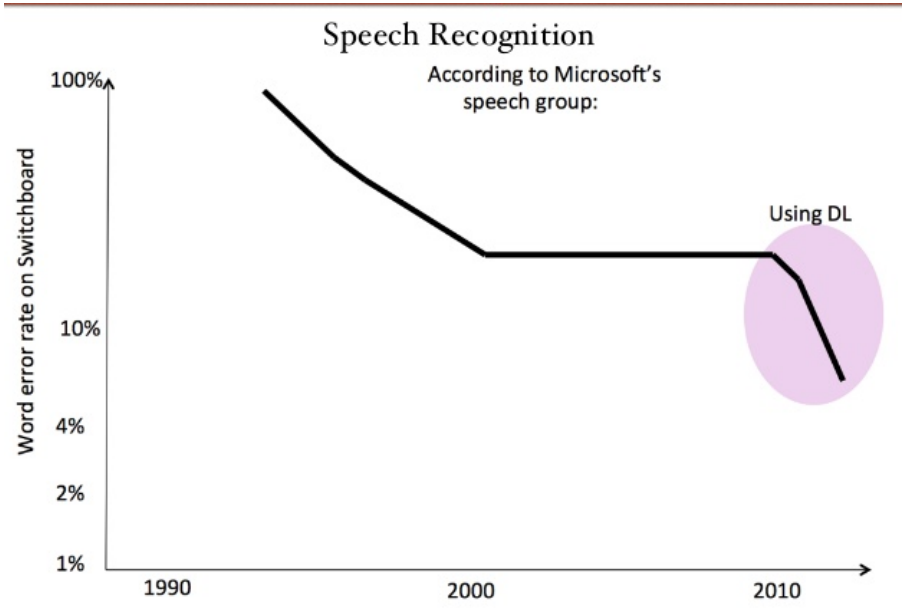
1.3M images

Human error: 5%

DNN: 3%



Deep Learning: Hype or Reality?



Pedro Moreno

Google Voice

Super-human speech recognition

Deep Learning: Hype or Reality?

Just with in Google

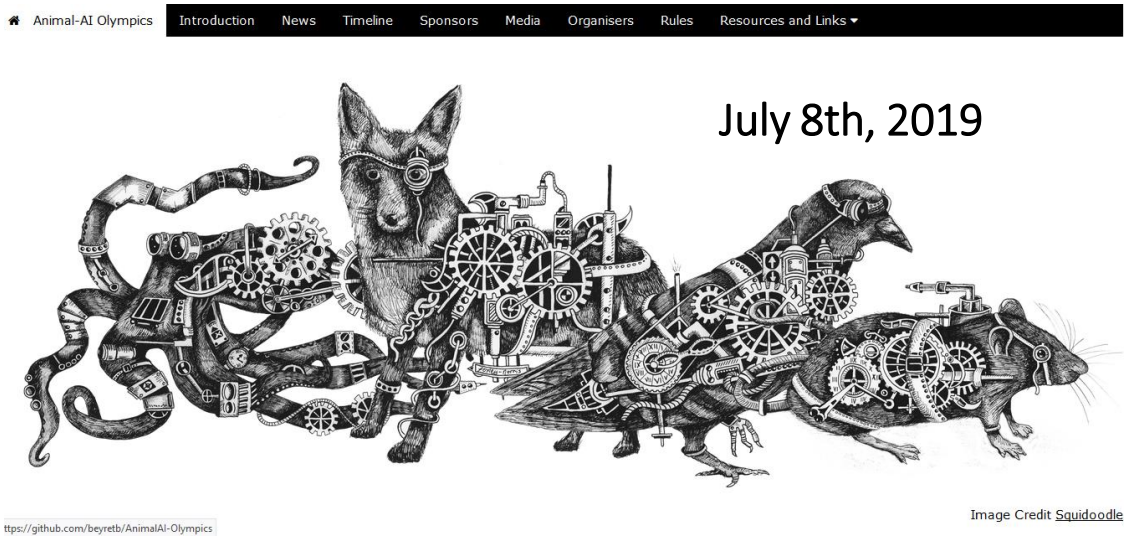
- Search
- Search by image
- Driveless cars
- Youtube recommendation
  - Videos
  - Thumbnails
- Maps
  - Reading street addresses

Deep Reinforcement Learning

AlphaGo

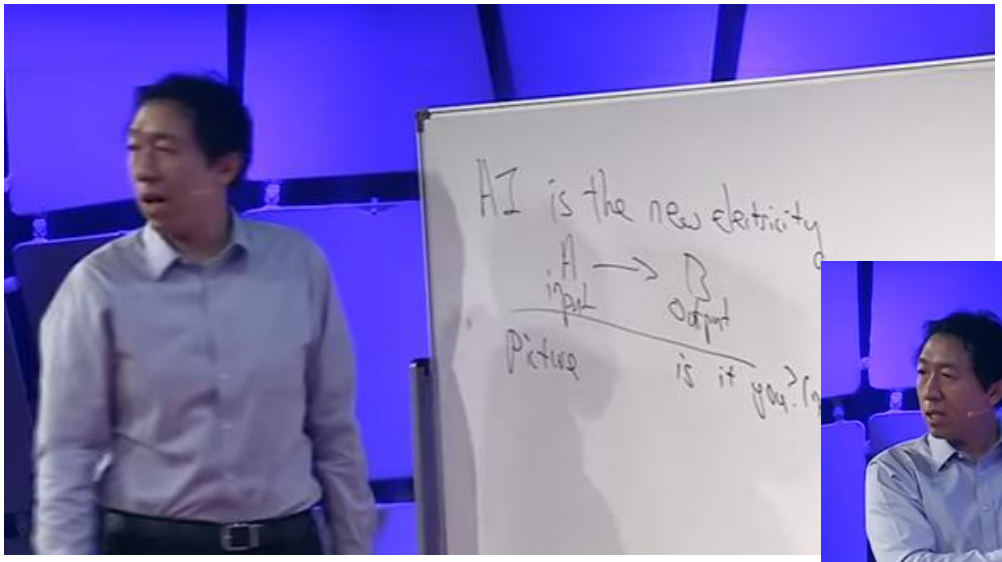
Humanoid Robots

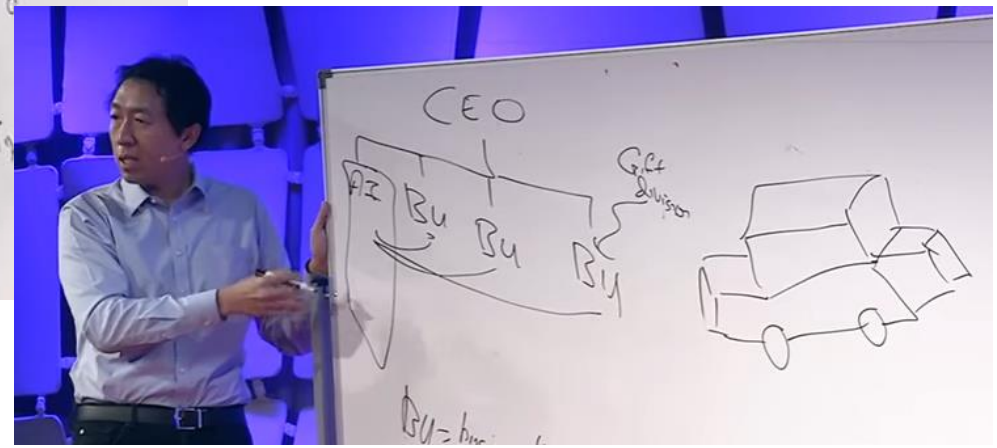
Conversational AI : Social Bots

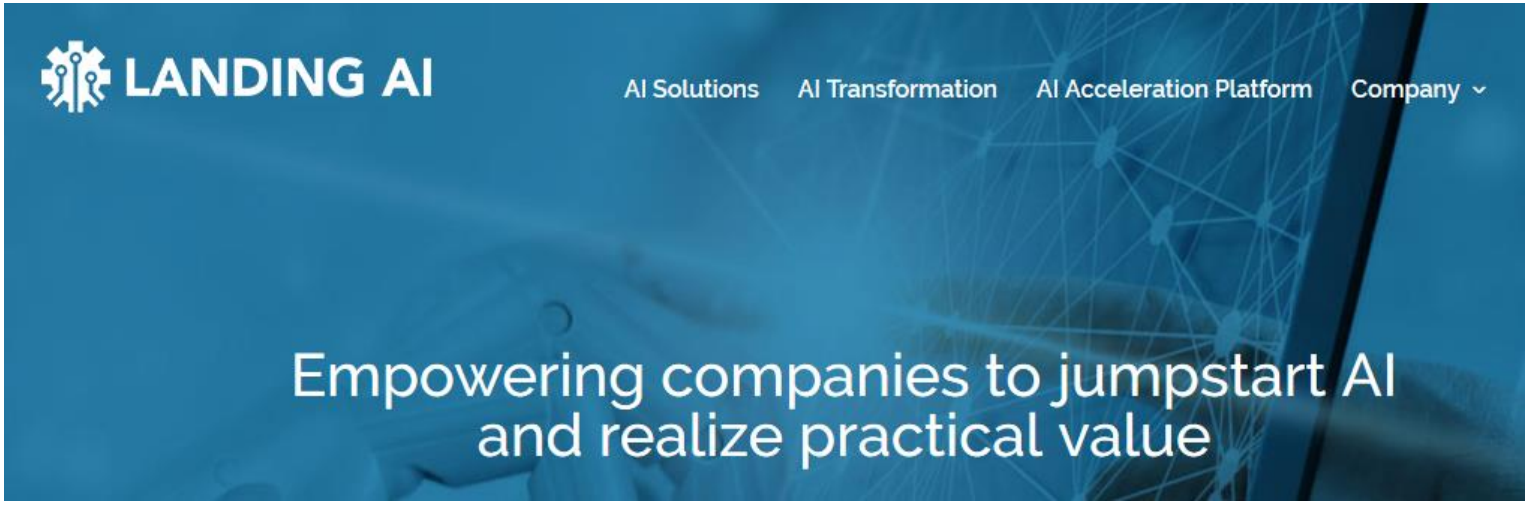



Inicio
Momentos
Buscar en Twitter
Andrew Ng
Andrew Ng
@AndrewYNg
Seguir
I'm glad DeepNude is dead. As a person and as a father, I thought this was one of the most disgusting applications of AI. To the AI Community: You have superpowers, and what you build matters. Please use your powers on worthy projects that move the world forward.
11:06 - 28 jun. 2019
1.984 Retweets 8.092 Me gusta
164 2,0K 8,1K
Muriz @MurgioMurmani · 28 jun.
En respuesta a @AndrewYNg
I feel like this is just the beginning of AI misuse
3 3 73

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



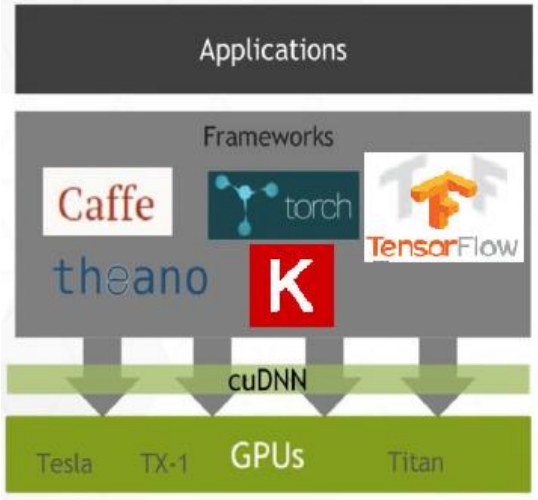




Introduction to Deep Learning
but what is new?

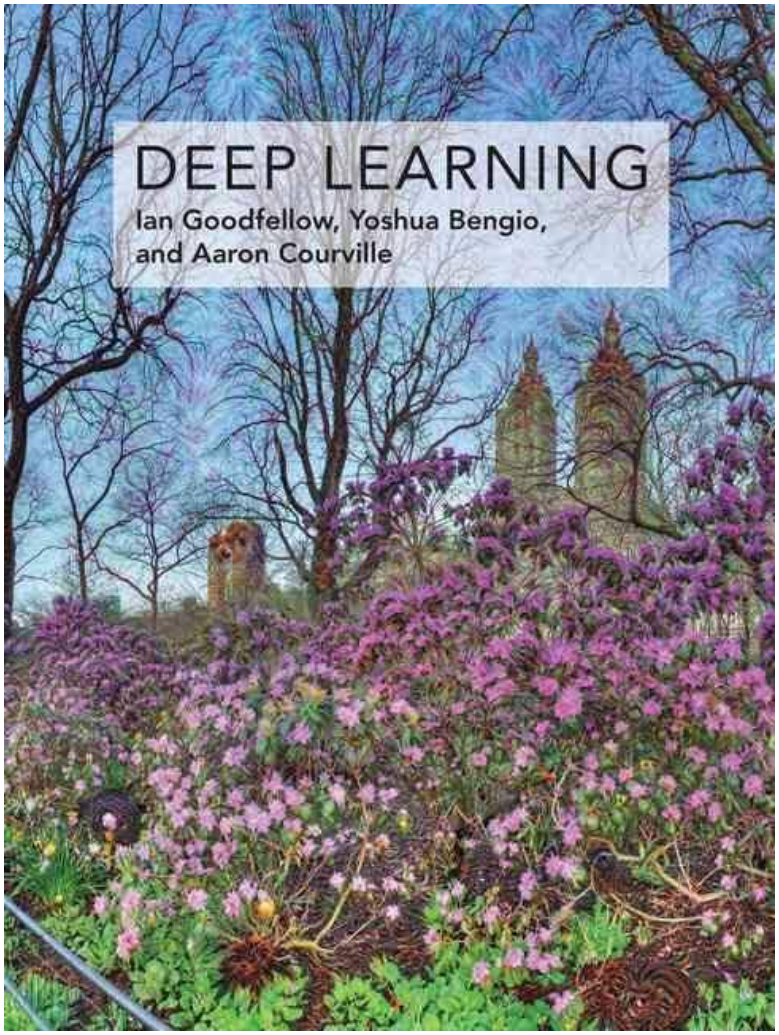
What Changed?
Old wine in new bottles

UDACITY
FREE COURSE
Deep Learning
by Google



Introduction to Deep Learning
…the Machine Learning background…

You should Learn the **whole** Machine Learning context !



On line:
www.deeplearningbook.org

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

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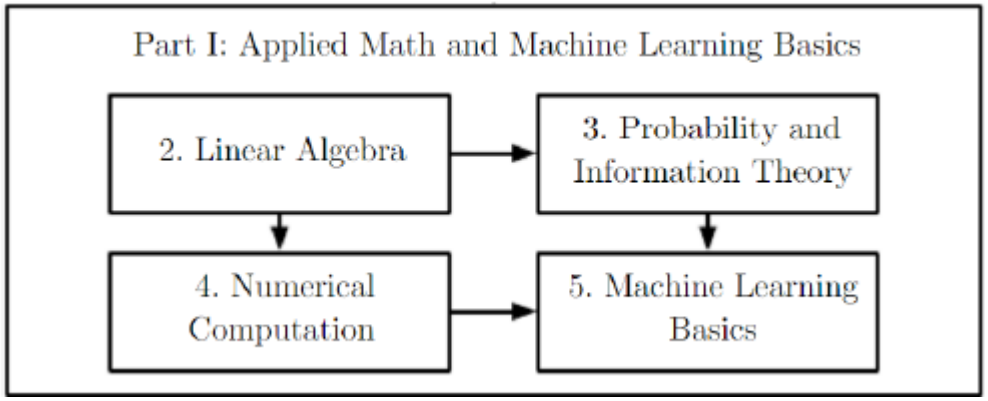
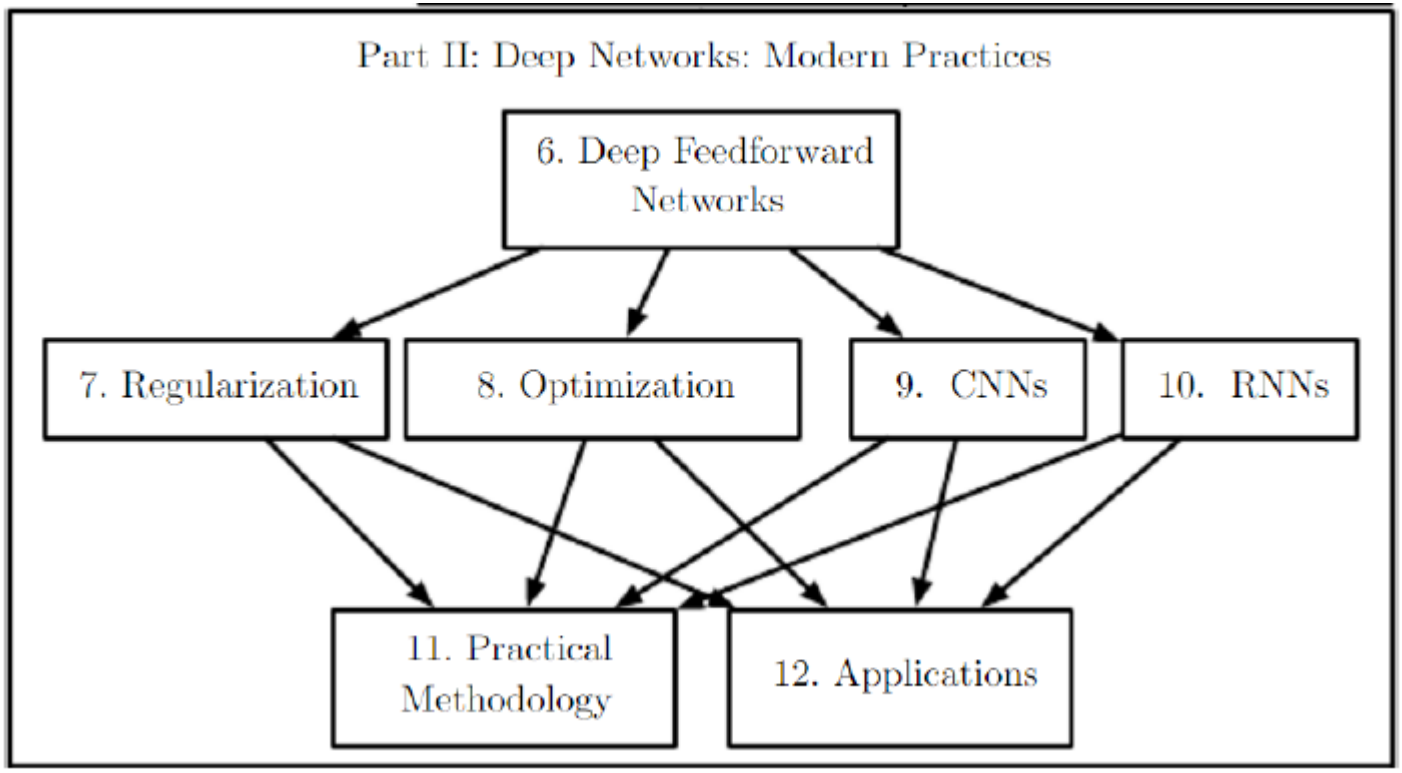
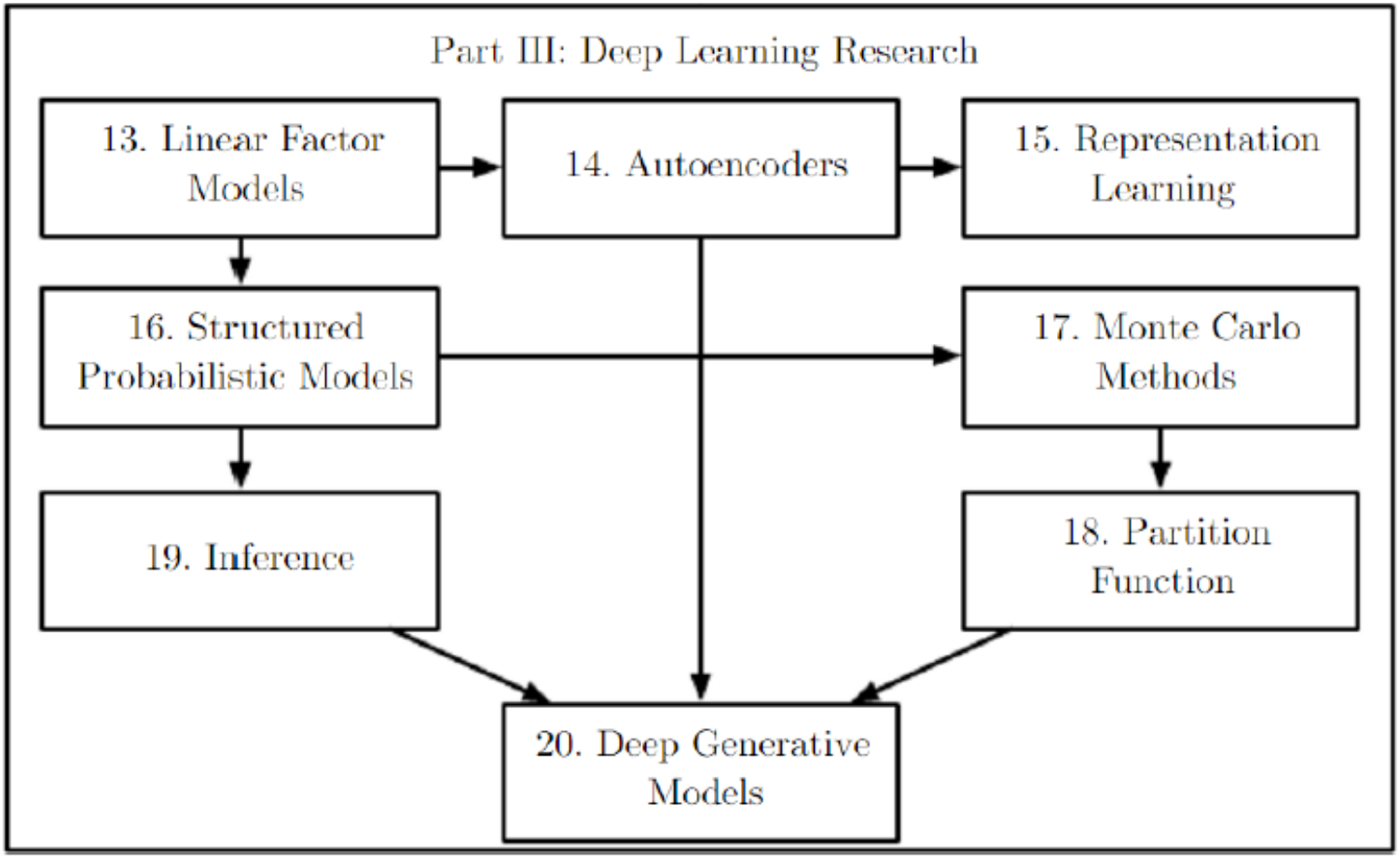
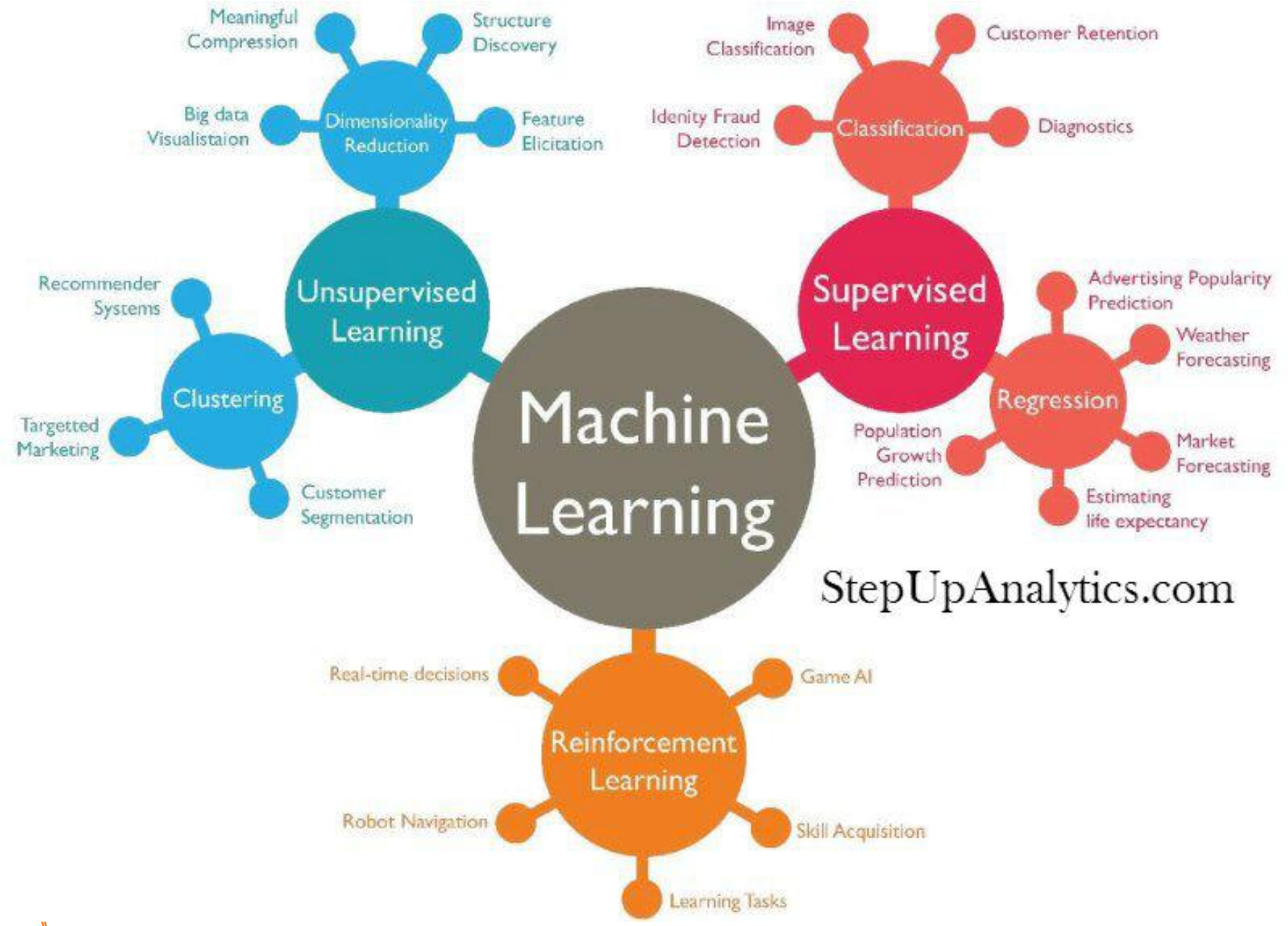
Introduction to Deep Learning
…the Machine Learning background…





Introduction to Deep Learning
…the Machine Learning background…



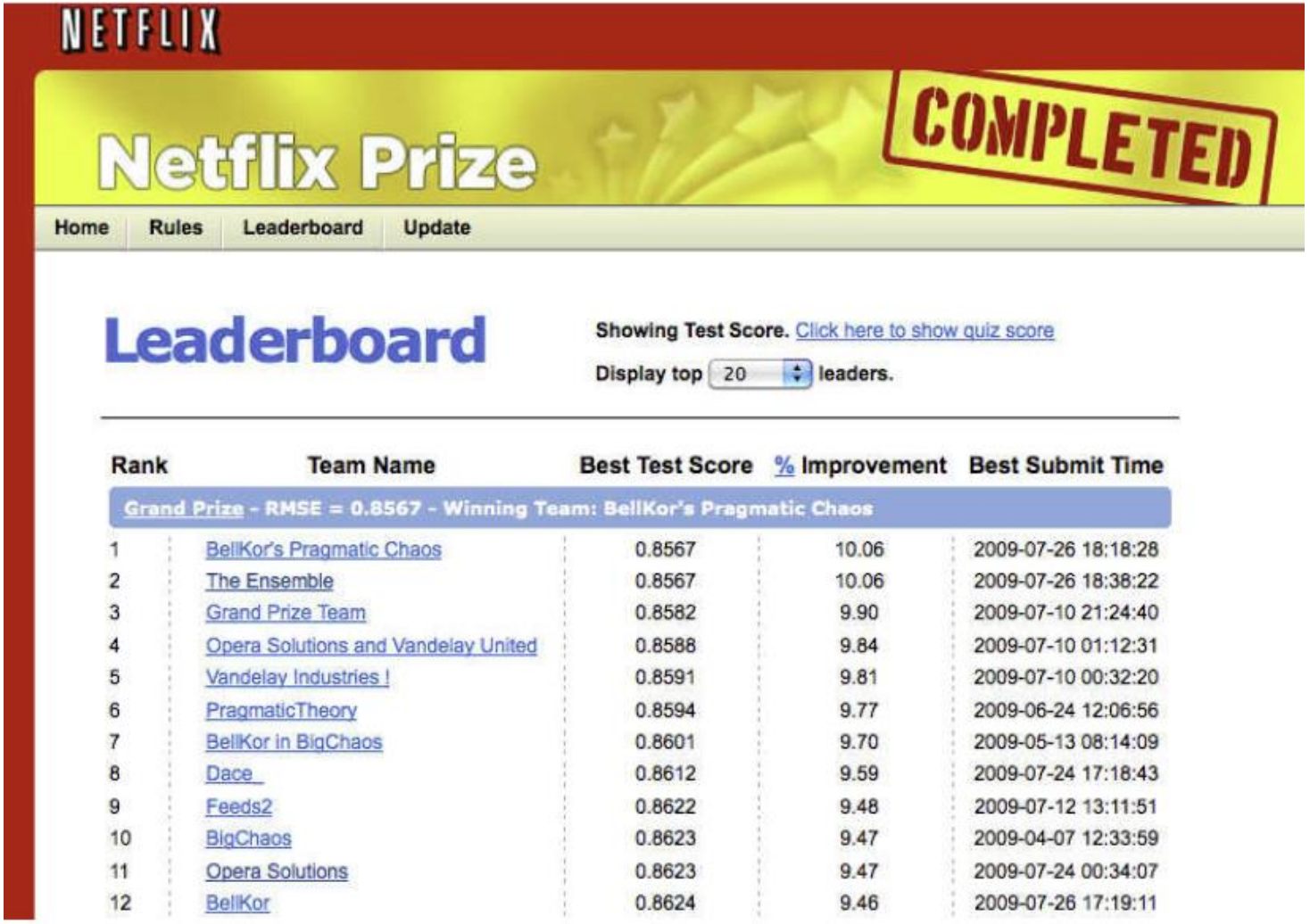

Machine Learning
Unsupervised Learning
Supervised Learning
Reinforcement Learning
Dimensionality Reduction
Clustering
Classification
Regression
Meaningful Compression
Structure Discovery
Big data Visualistaion
Feature Elicitation
Recommender Systems
Targetted Marketing
Customer Segmentation
Image Classification
Customer Retention
Idenity Fraud Detection
Diagnostics
Advertising Popularity Prediction
Weather Forecasting
Population Growth Prediction
Market Forecasting
Estimating life expectancy
Real-time decisions
Game AI
Robot Navigation
Skill Acquisition
Learning Tasks
StepUpAnalytics.com

Supervised or unsupervised?
Recommendation systems (I)

The Netflix prize

- Competition started in October 2006. Training data is ratings for 18.000 movies by 400.000 Netflix customers, each rating between 1 and 5.
- Training data is very sparse – about 98% missing.
- Objective is to predict the rating for a set of 1 million customer-movie pairs that are missing in the training data.
- Netflix's original algorithm achieved a root MSE of 0.953.
- The first team to achieve a 10% improvement **wins one million dollars**.
- Is this a supervised or unsupervised problem?

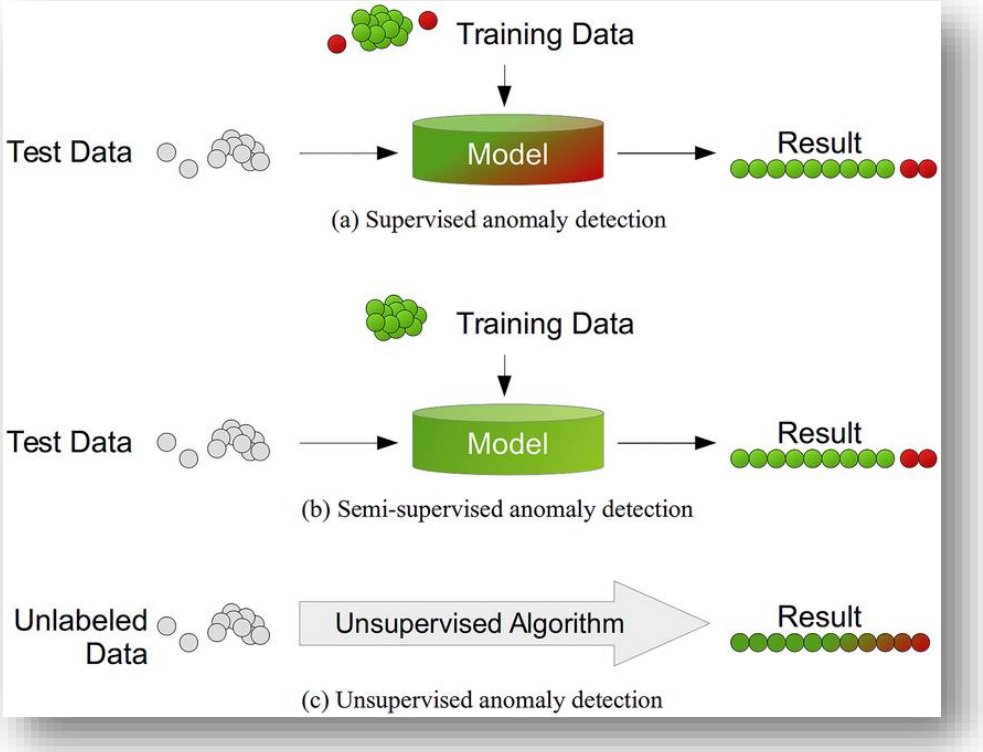
Supervised or unsupervised?
Recommendation systems (II)



BellKor's Pragmatic Chaos wins, beating The Ensemble by a narrow margin.

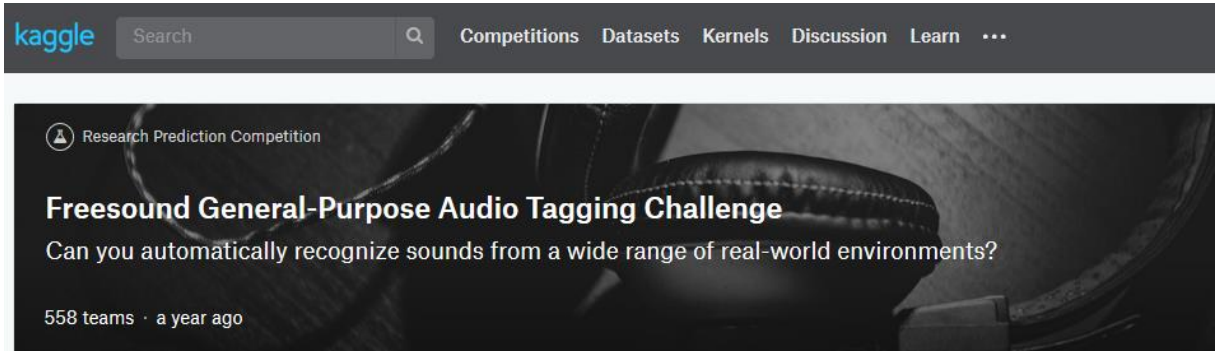
Supervised or unsupervised?

- Fraud detection?
- Anomaly detection?



- Sound classification (FreeSound Challenge)

Noisy labels



https://www.kaggle.com

kaggle Search Competitions Datasets Kernels Discussion Courses ...

Kaggle is the place to do data science projects

See how it works

Register with just one click:

We won't share anything without your permission

Sign up with Google

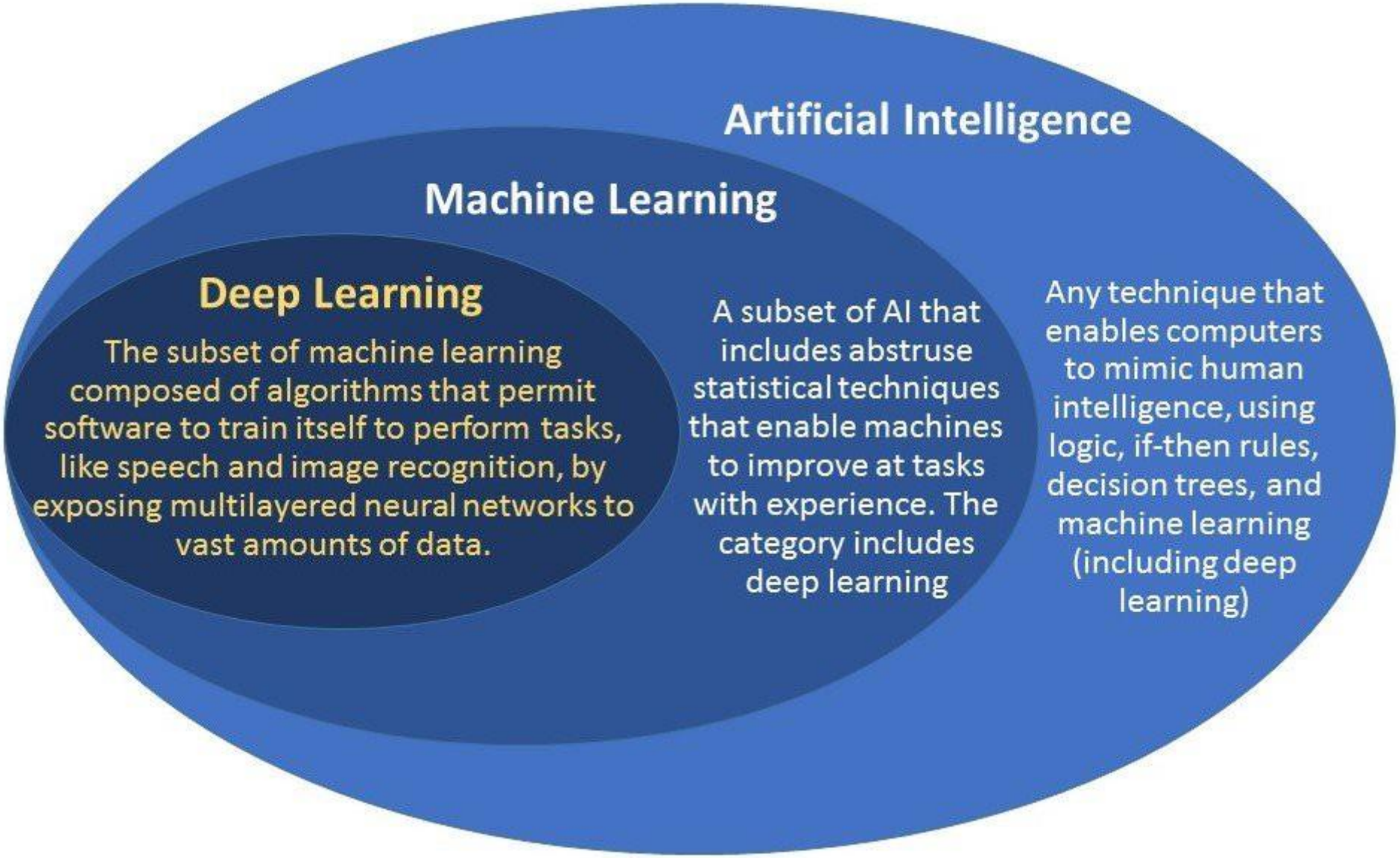
Sign up with Facebook

Manually create an account:

Email

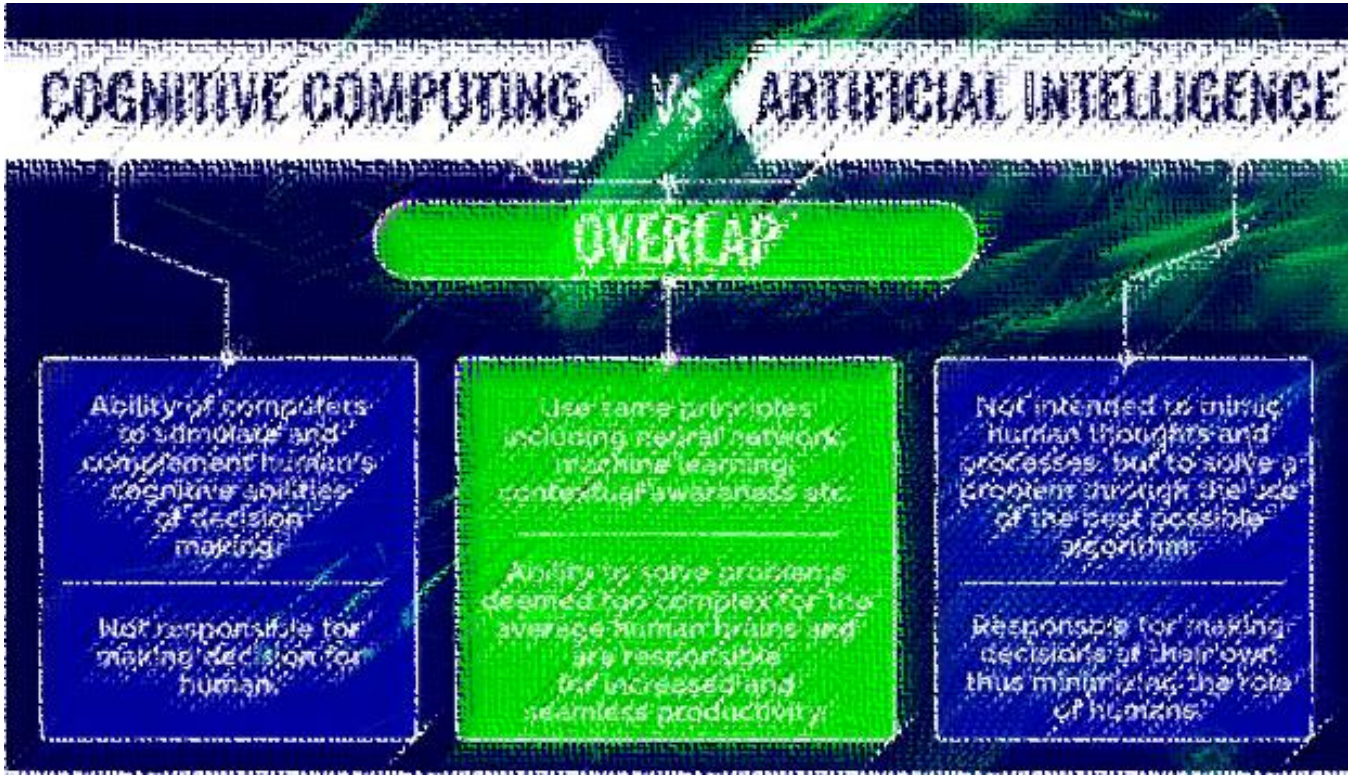
Password

Register


Artificial Intelligence
Any technique that enables computers to mimic human intelligence, using logic, if-then rules, decision trees, and machine learning (including deep learning)
Machine Learning
A subset of AI that includes abstruse statistical techniques that enable machines to improve at tasks with experience. The category includes deep learning
Deep Learning
The subset of machine learning composed of algorithms that permit software to train itself to perform tasks, like speech and image recognition, by exposing multilayered neural networks to vast amounts of data.

Research by your own on:
...we will discuss it by the end of Seminar (day-3)

- Cognitive Computing
- Artificial General Intelligence (AGI)



Deep Learning est mort. Vive Differentiable Programming!

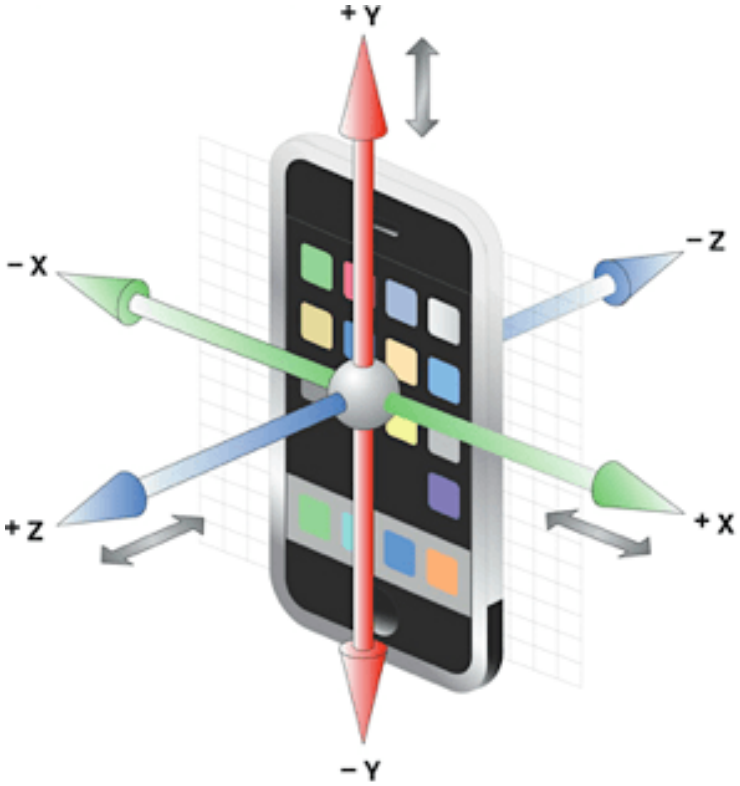
Yann LeCun, Director of Facebook AI Research and the inventor of convolutional neural networks, took it.

FROM : *humans* …

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

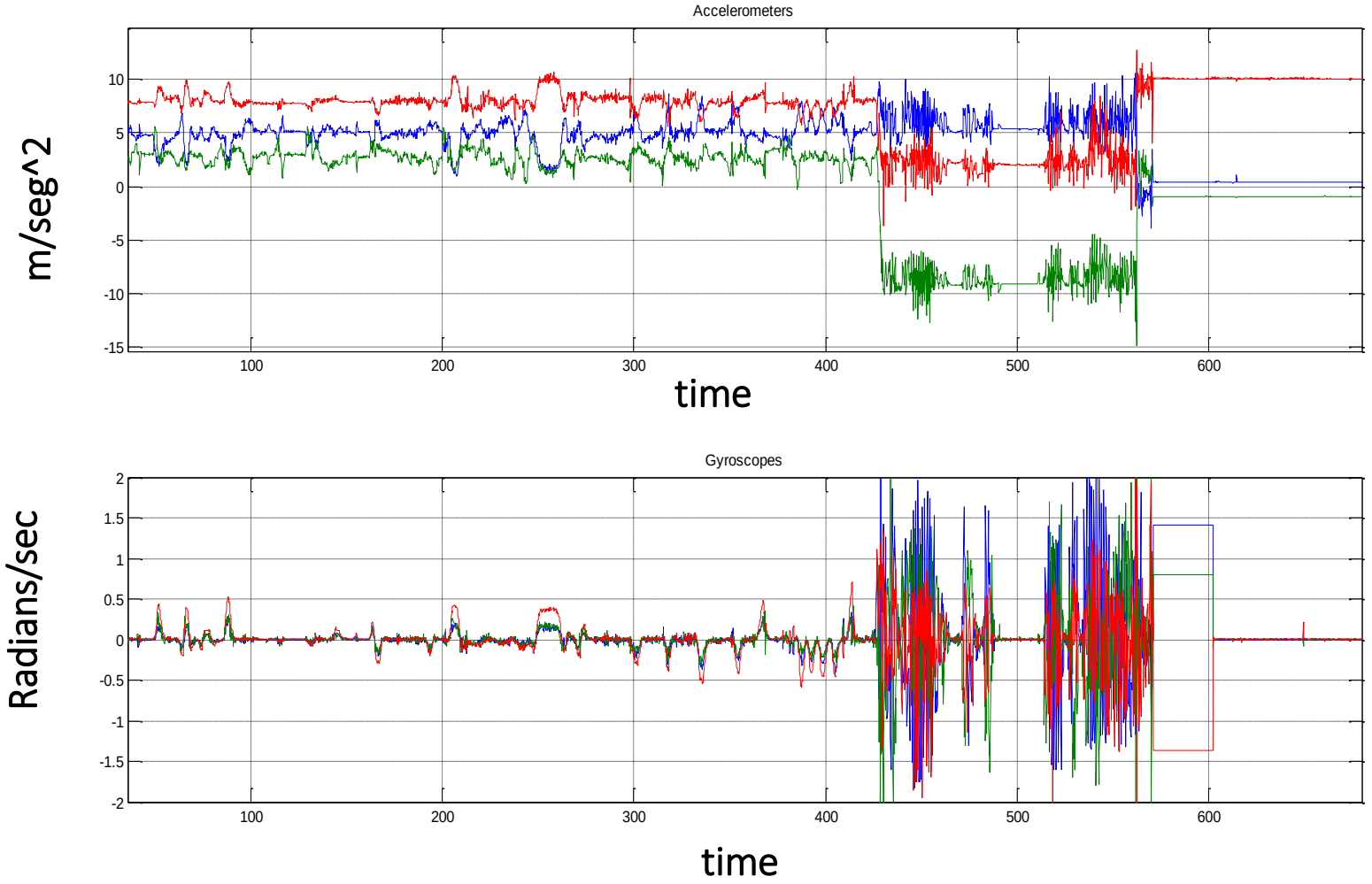
Drivies use case:

www.driviesapp.com



Accelerometer

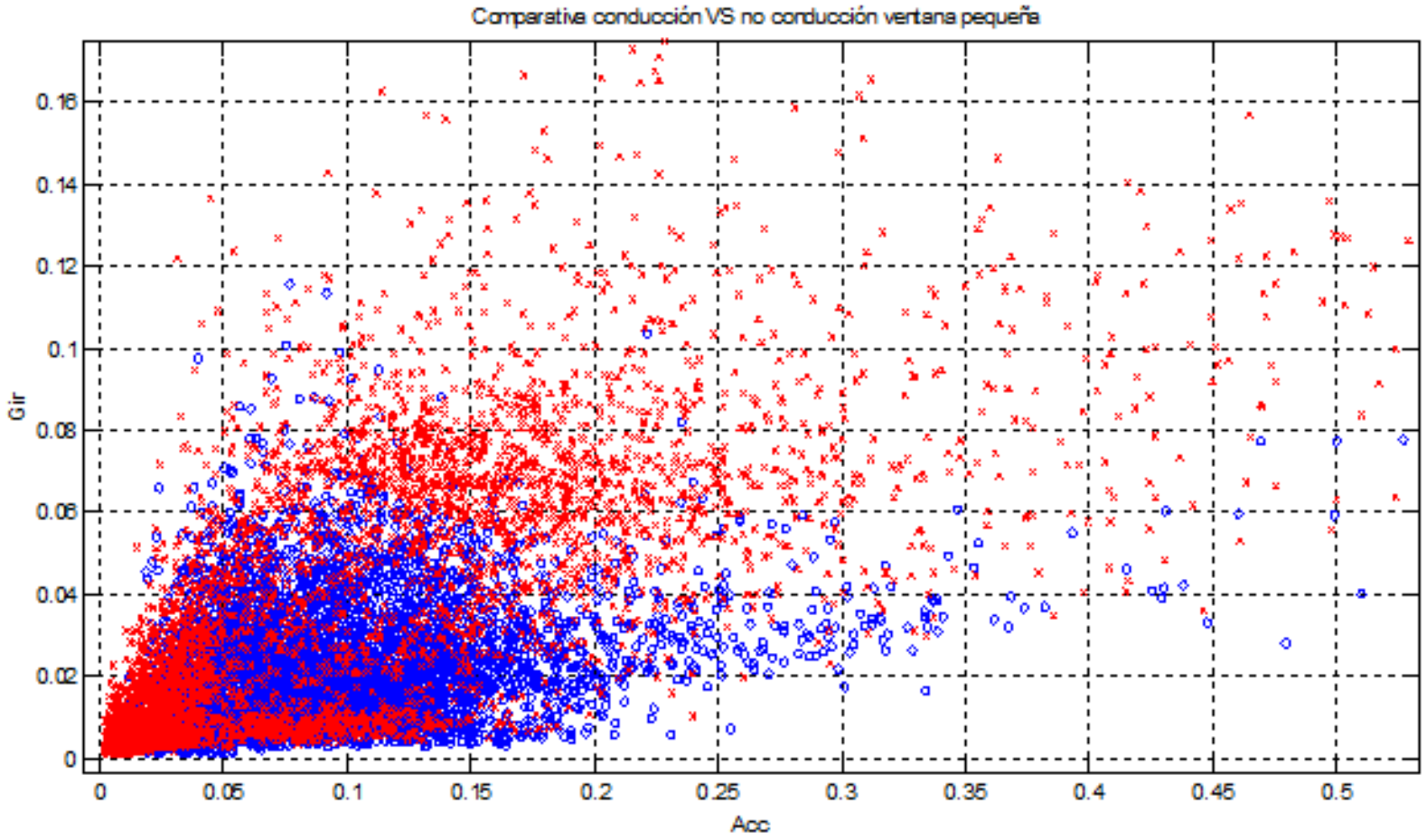
Gyroscope


Accelerometers
m/seg^2
10
5
0
-5
-10
-15
100
200
300
400
500
600
time
Gyroscopes
Radians/sec
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
100
200
300
400
500
600
time

From manual - linear classifiers TO Neural Networks

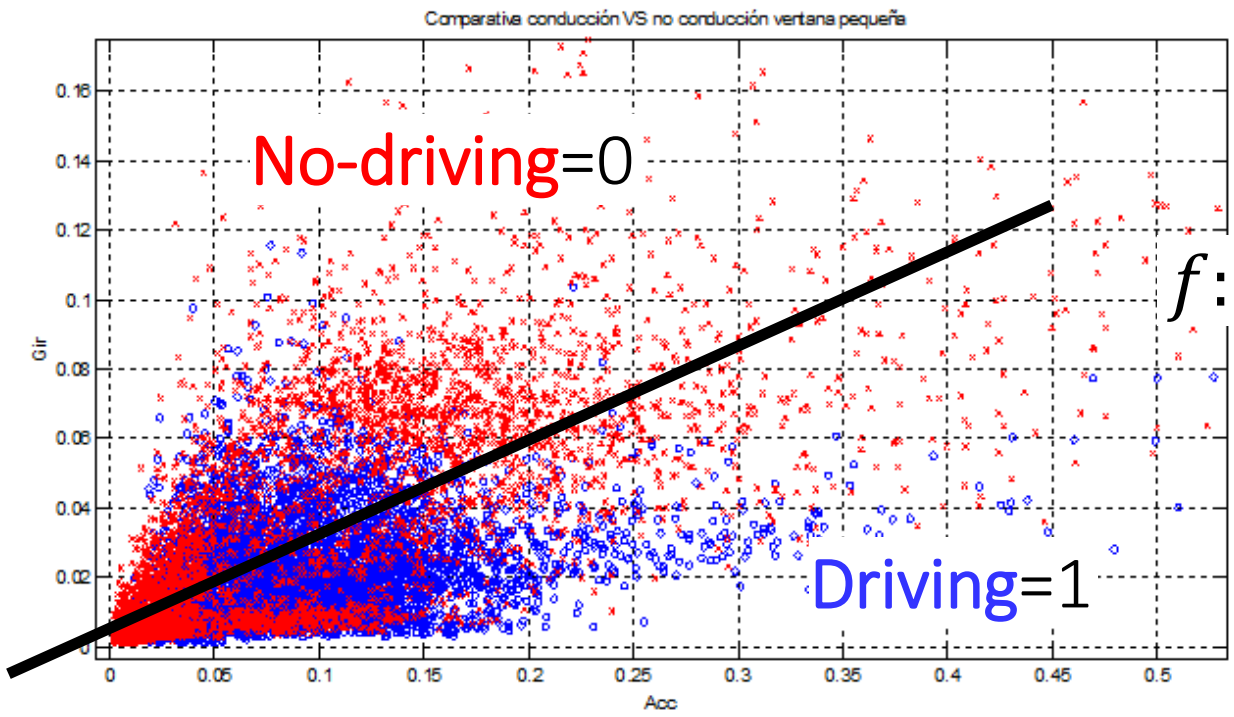
Gyroscopes Energy

x_2



x_1 : **Accelerometers Energy**

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



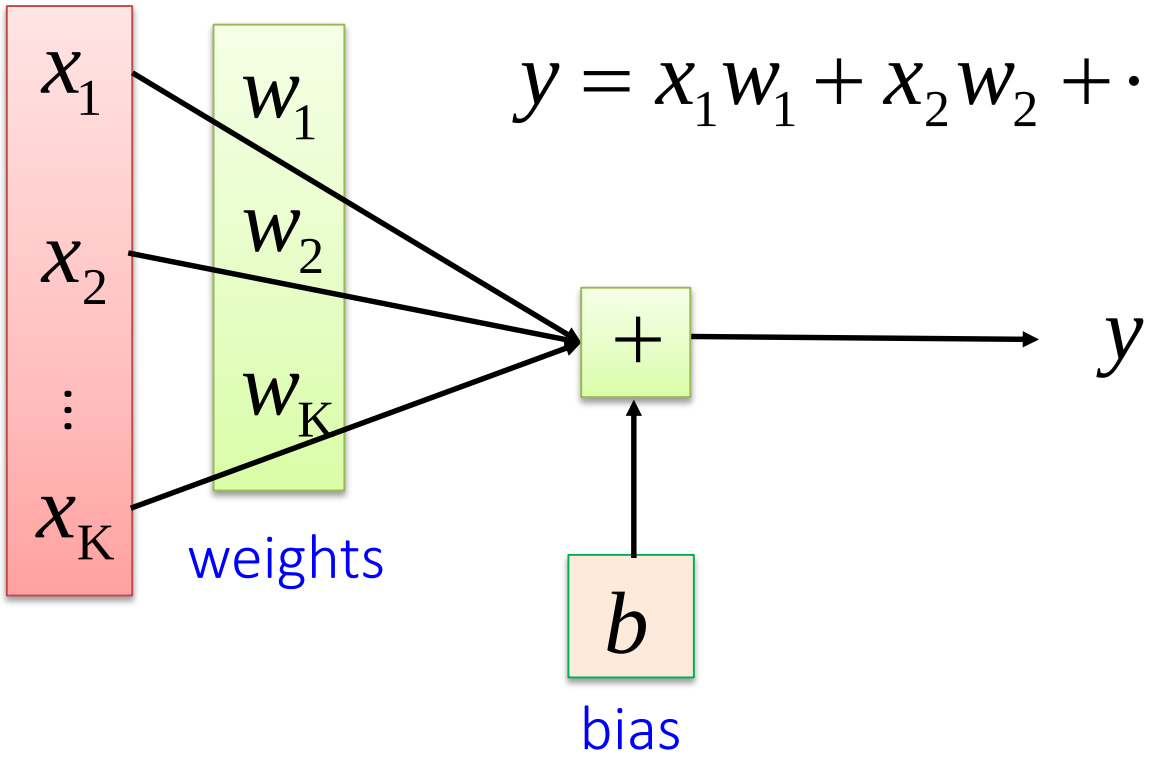
$f: R^K \rightarrow R$

Gyroscopes Energy x_2

x_1 **(Accelerometers Energy)**

From linear classifiers TO Neural Networks

A Linear **decision function**



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

From linear classifiers TO Neural Networks

A Linear **decision function**

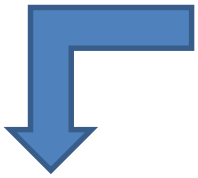
$$y = x_1 w_1 + x_2 w_2 + \cdots + x_K w_K + b$$

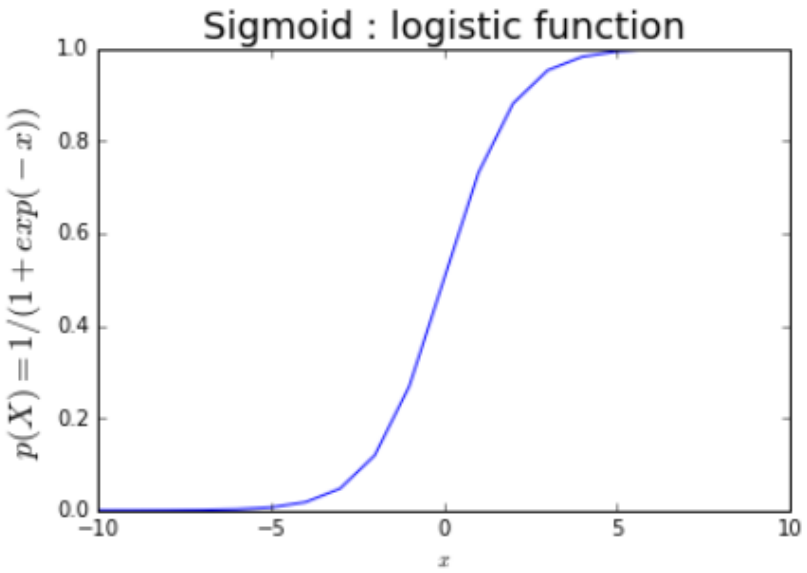
$$y = \mathbf{x}^{\mathrm{T}} \mathbf{w}$$

From linear classifiers TO Neural Networks

We typically use a **Sigmod** Function

$$\sigma(z) = \frac{1}{1+e^{-z}}$$





To approach *posterior* probabilities:

- $\mathrm{P}(\mathrm{Driving}\,|\boldsymbol{X})$
- $\mathrm{P}(\mathrm{No\ Driving}|\boldsymbol{X})$

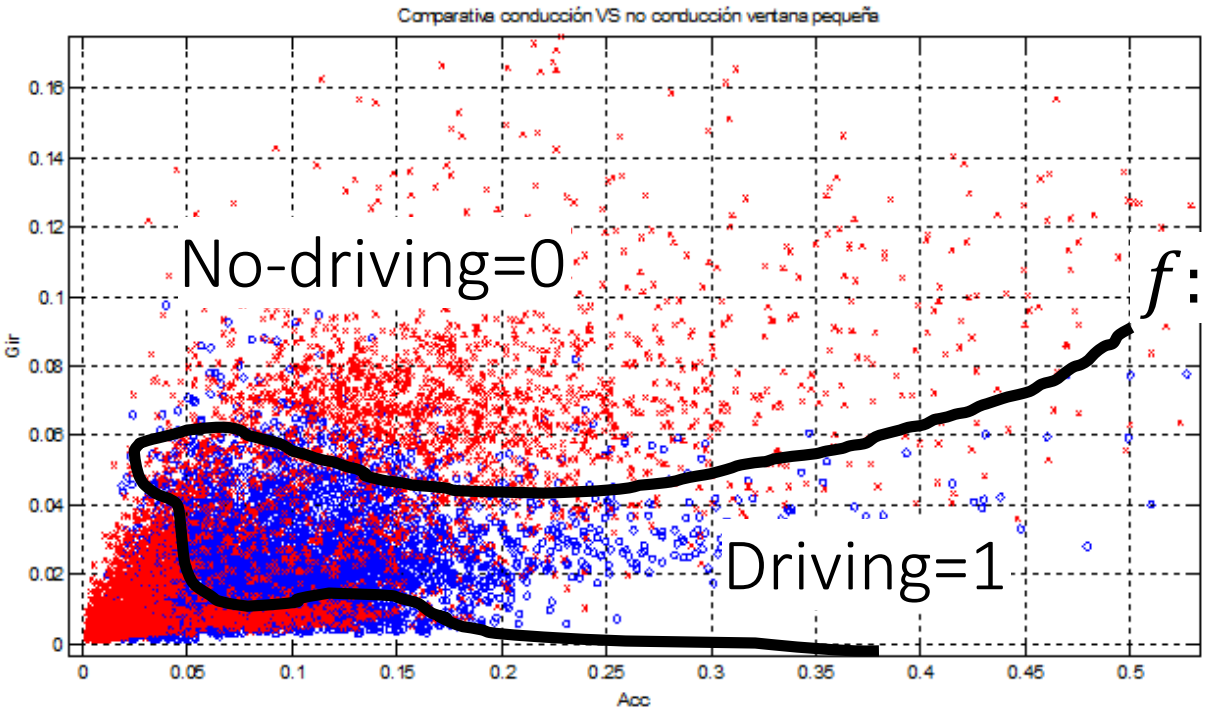
$$\mathbf{x}^{\mathrm{T}}\mathbf{w}$$

Logistic Regression

From linear classifiers TO Neural Networks

Nonlinear **decision function?**

x_2



$f: R^K \rightarrow R$

x_1

Non-linear decision functions

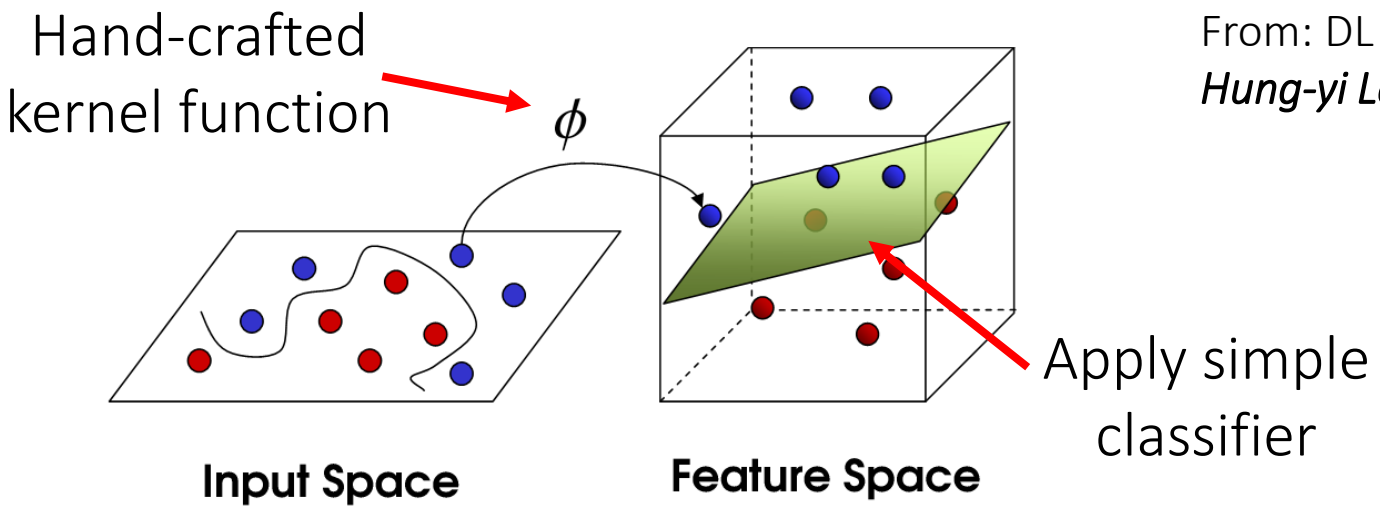
$$y = x_1 w_1 + x_1^2 w_2 + x_1^3 w_3 + x_1 x_2 w_4 + \cdots + b$$

A linear model of transformed inputs:

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

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

SVM



From: DL Tutorial
Hung-yi Lee

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

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

1. Feature engineering (based on expert knowledge) $\phi(.)$

2. Use a very generic $\phi(.)$ as kernel machines (e.g. SVM, RBF kernel)

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

1. Feature engineering (based on expert knowledge) $\phi(.)$

2. Use a very generic $\phi(.)$ as kernel machines (e.g. SVM, RBF kernel)

3. The strategy of Deep Learning : to learn $\phi(.)$

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

Now we have:

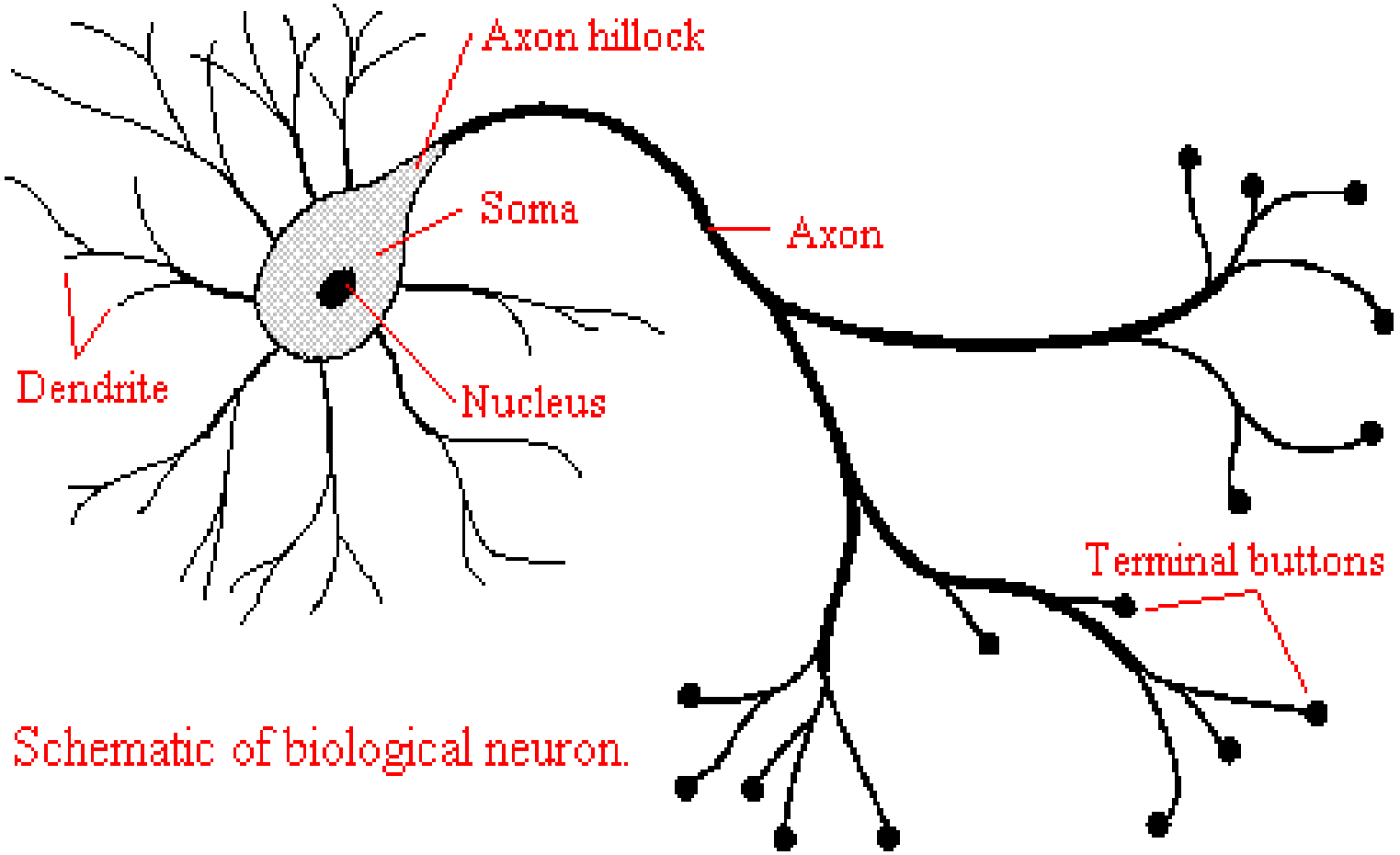
- Parameters $\boldsymbol{\theta}$ that we use to learn $\phi(\mathbf{x})$ from a broad class of functions
- Parameters $\mathbf{w}$ that map $\boldsymbol{\phi}(\mathbf{x})$ to he desired output

BUT .... what $\phi(.)$?

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

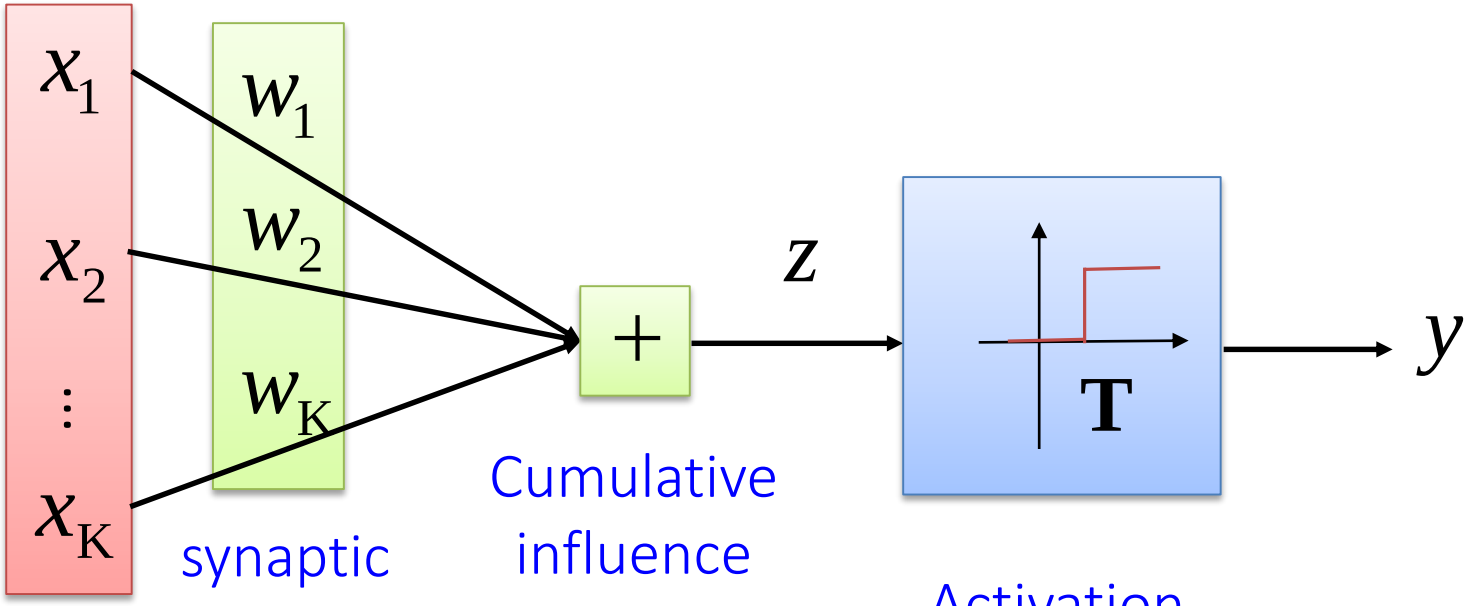
The DL approach: learn $\phi(\mathbf{x})$

…from a broad class of functions

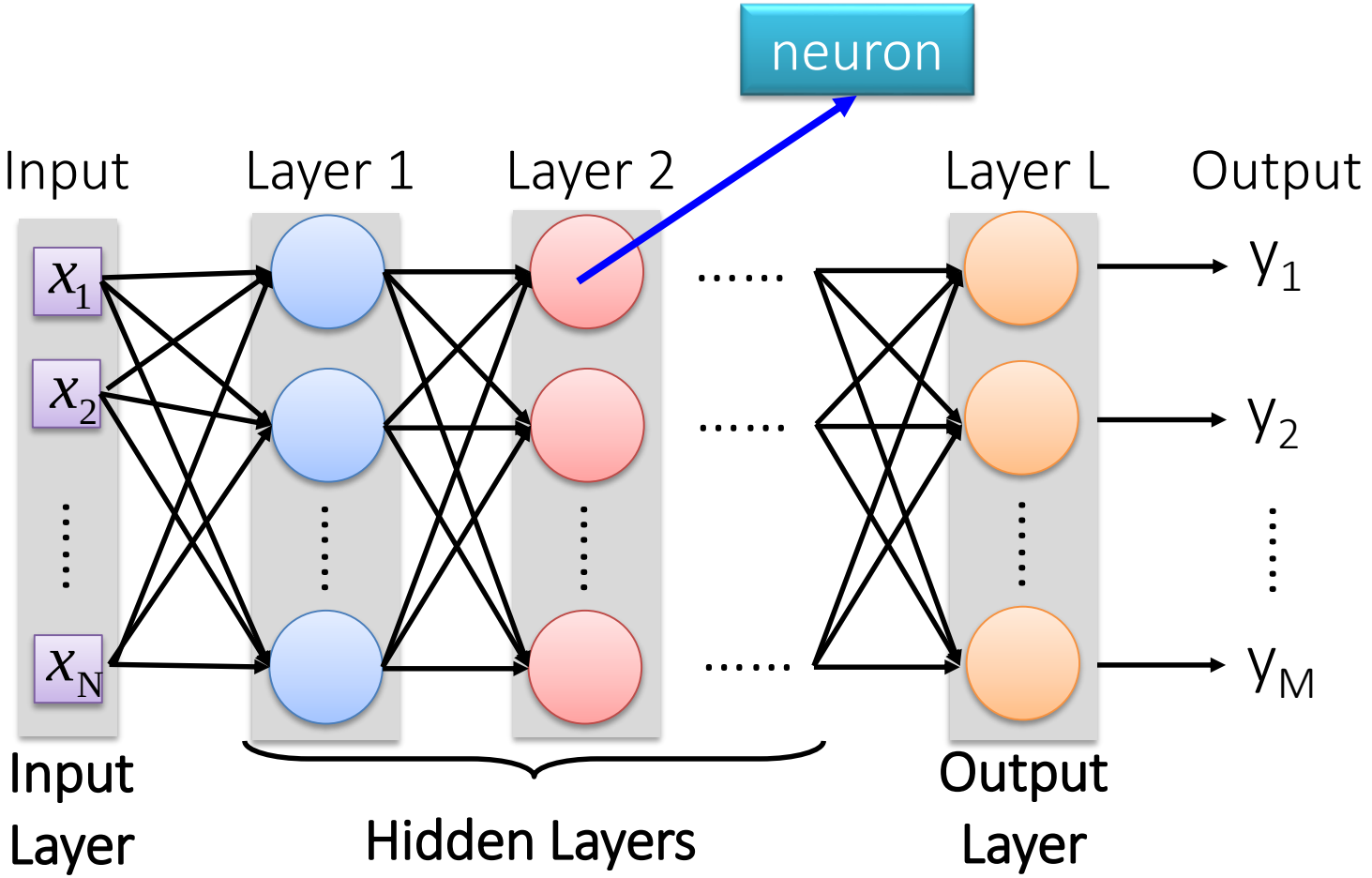


Schematic of biological neuron.

Naïve Neuron approach….

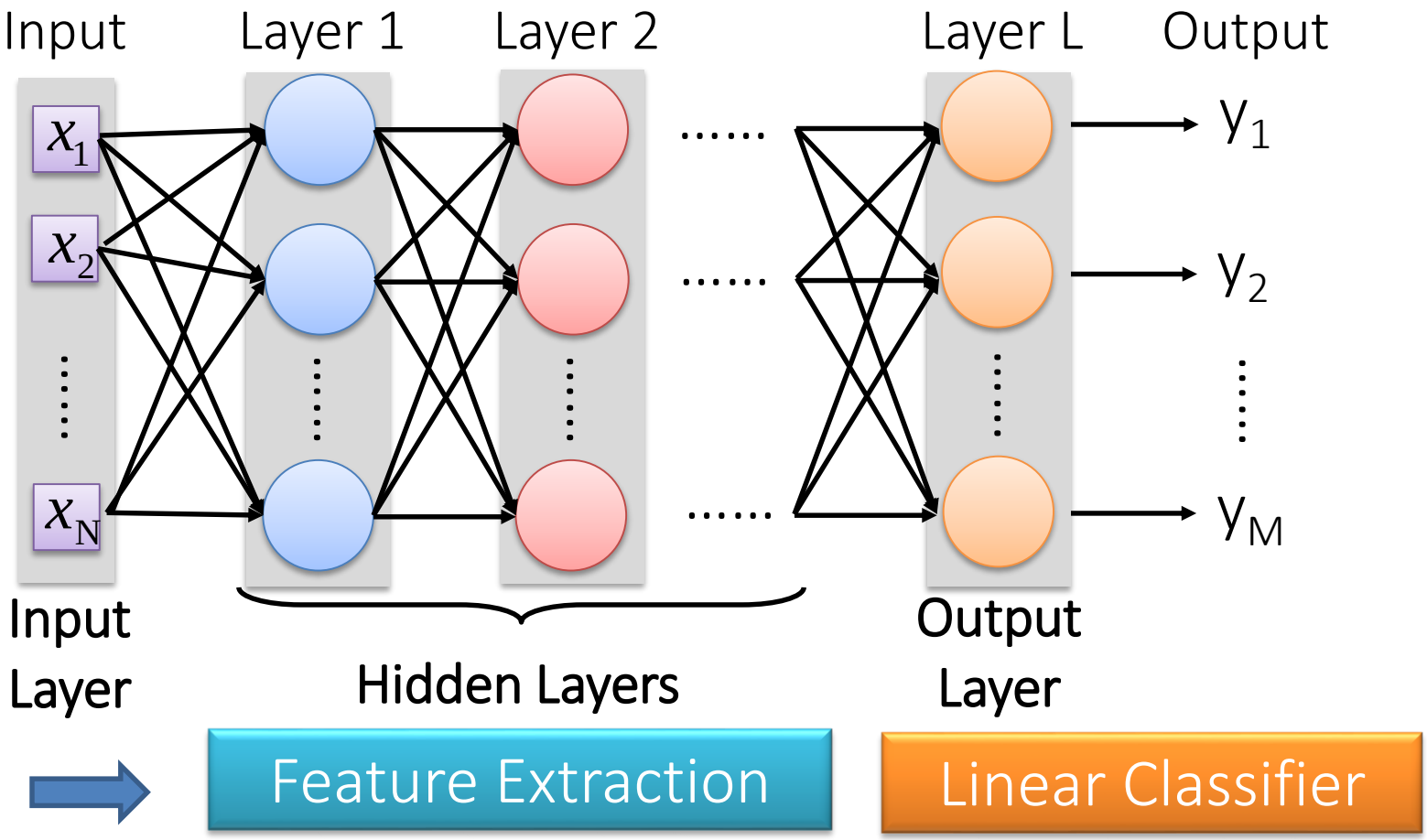


Neural Network (from Hung-yi Lee "Deep Learning Tutorial")



Deep means many hidden layers

Feature Extraction + Final Linear Classifier



From linear classifiers TO Neural Networks

- Parameters $\boldsymbol{\theta}$ that we use to learn $\phi(.)$ from a broad class of functions

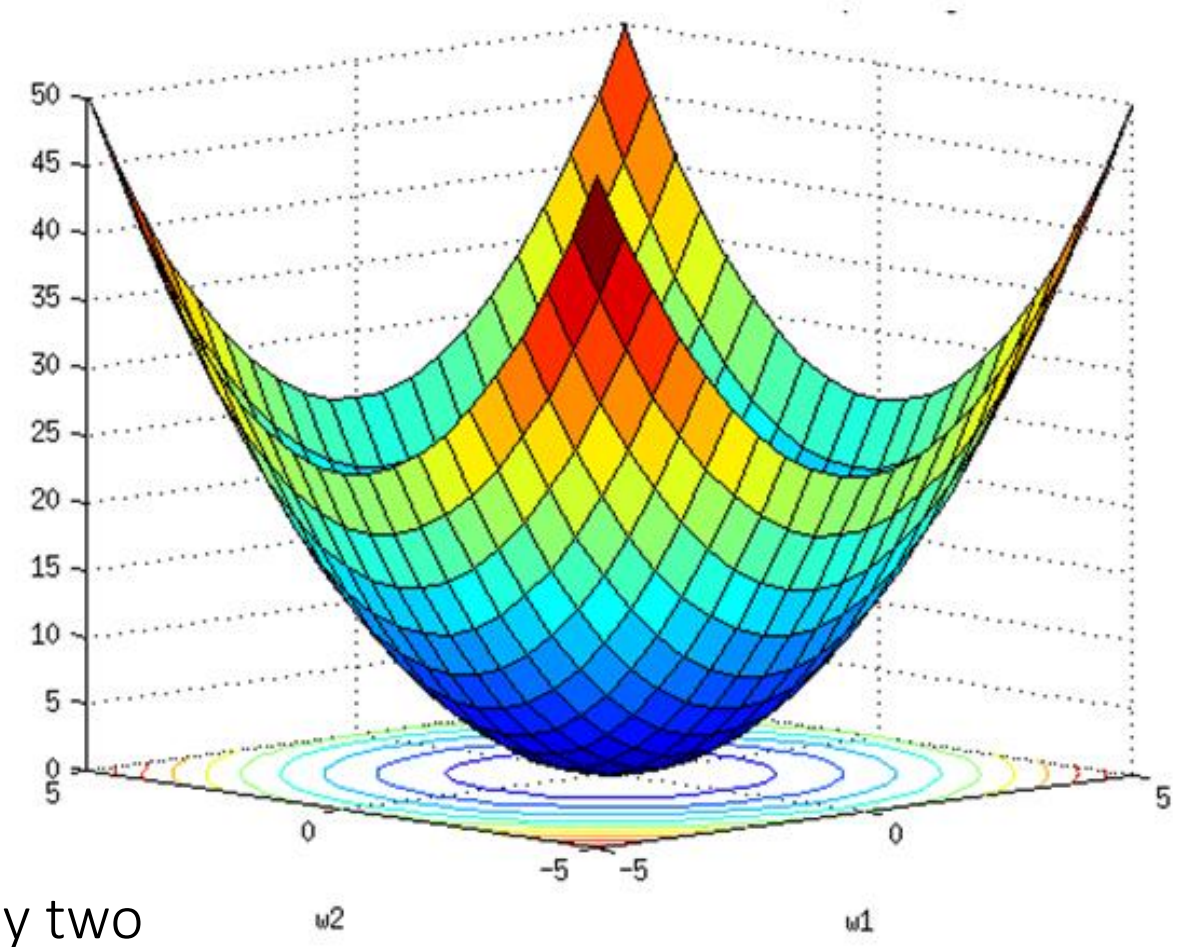
- Weights and thresholds are estimated from training examples:
  - to minimize a **loss function** (i.e. similarity between NN outputs y and desired outputs $\hat{y}$)

OPTIMIZATION

Gradient Descent

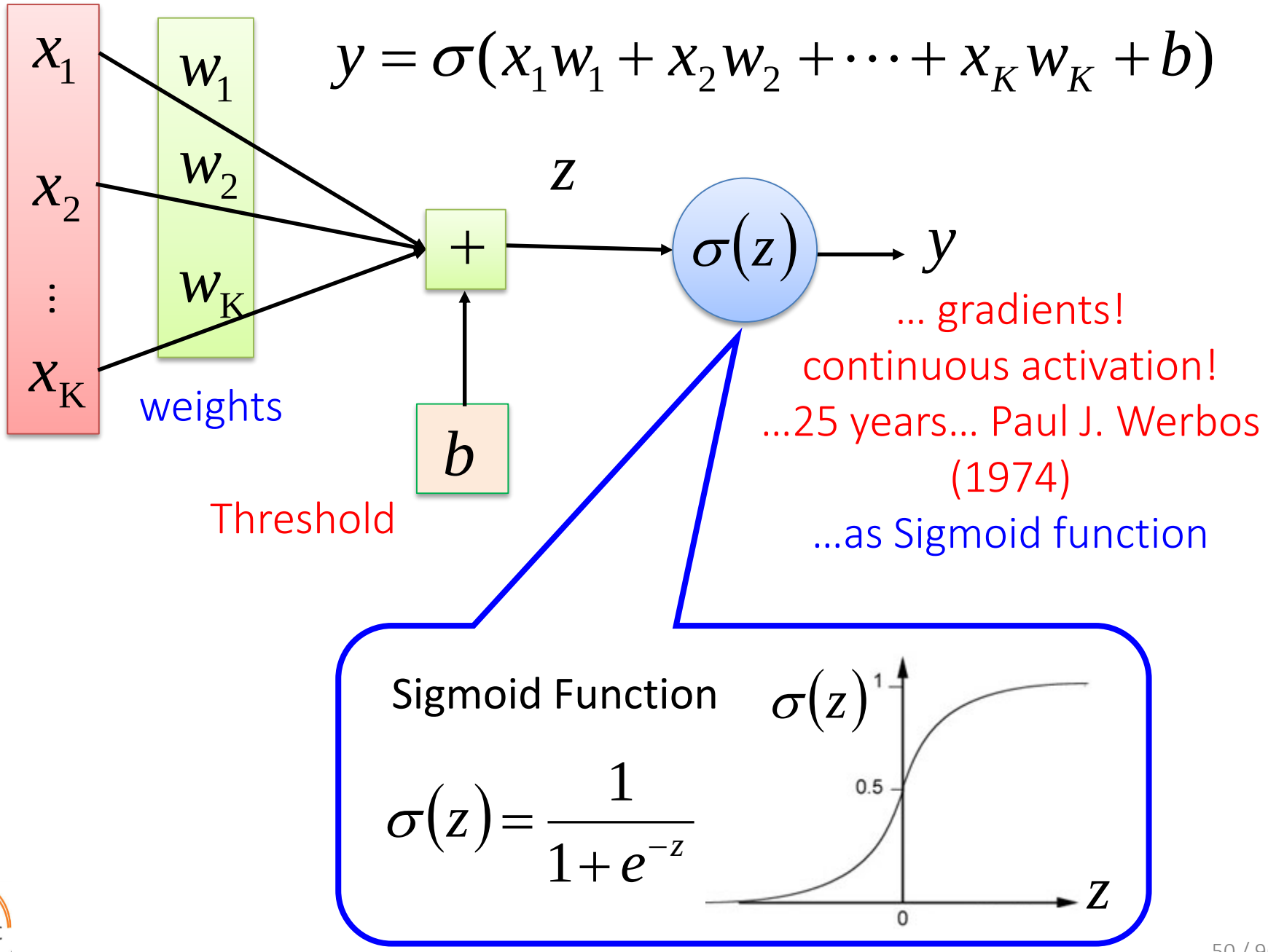
Cost
Or
Loss function

$C(\theta)$

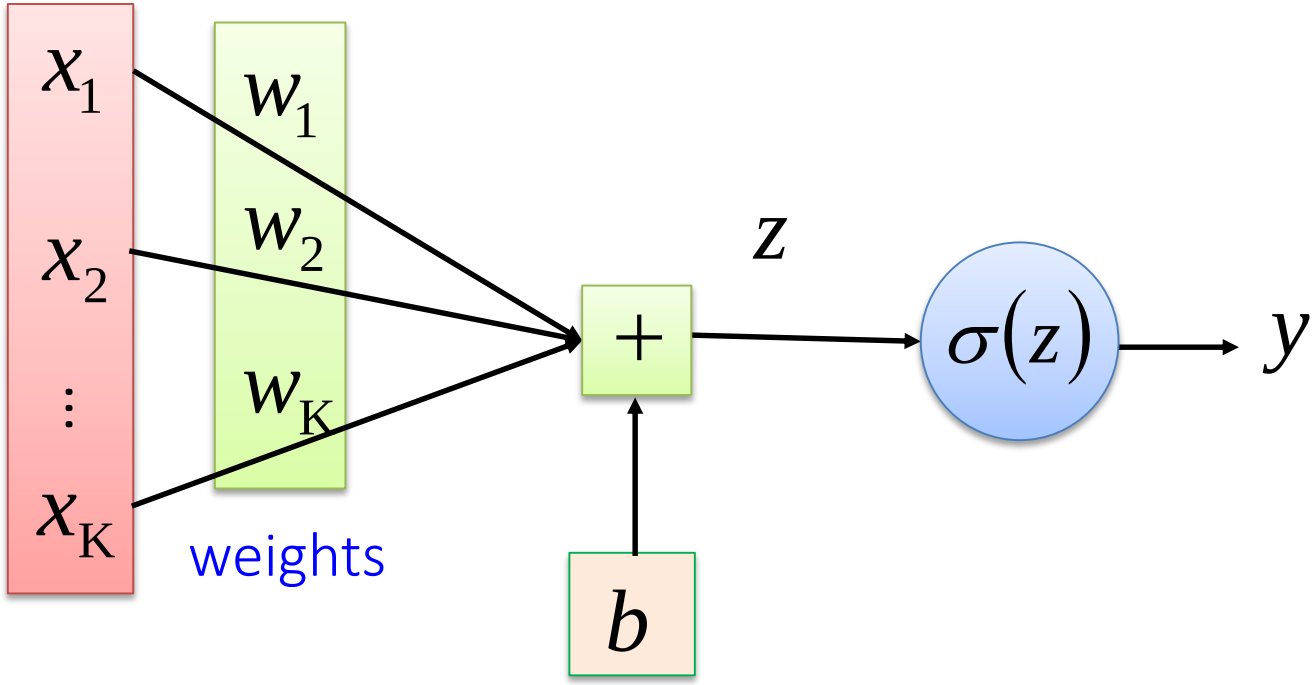


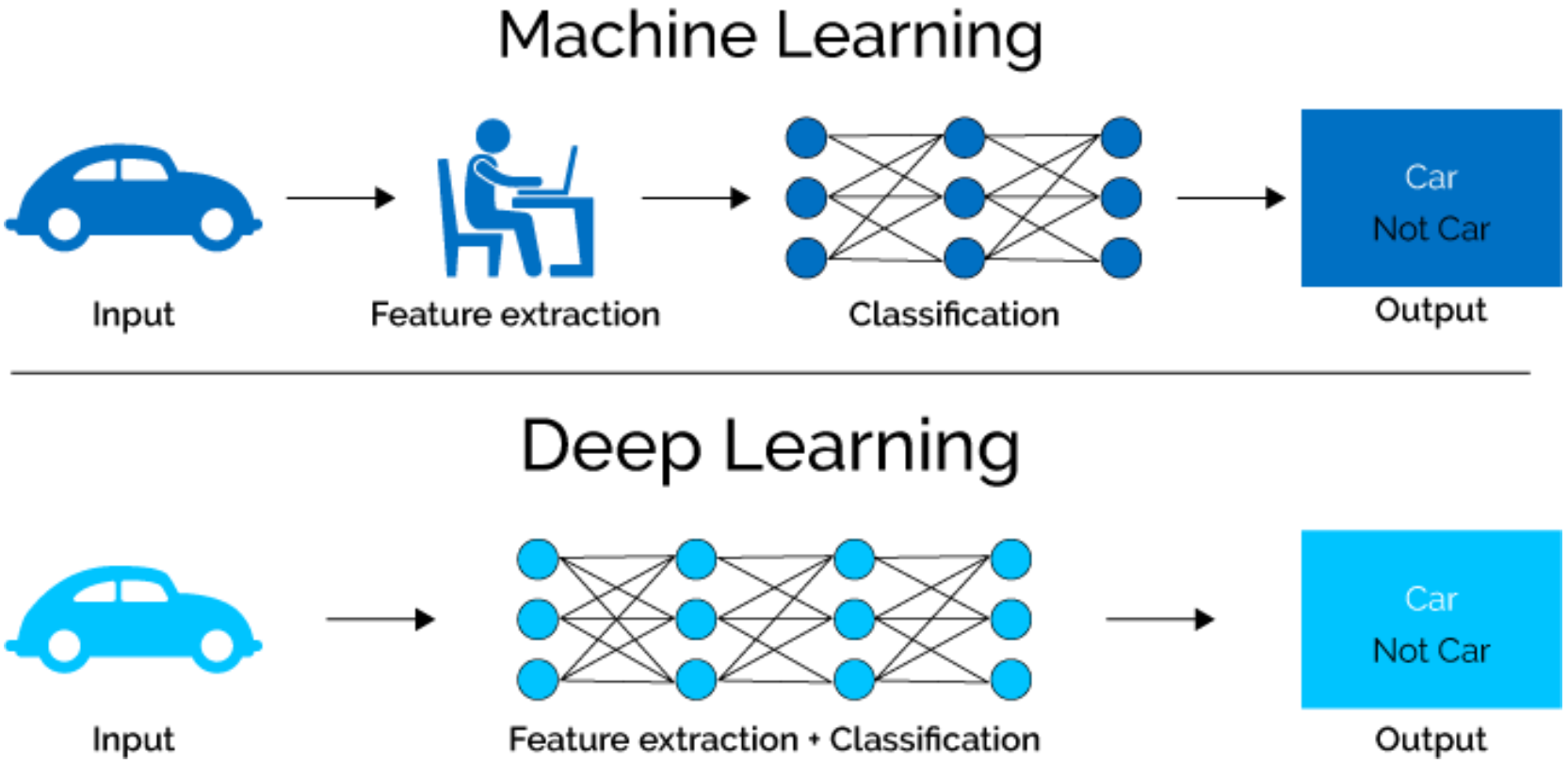
Assume there are only two parameters w_1 and w_2 in a network.

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


$y = \sigma(x_1 w_1 + x_2 w_2 + \cdots + x_K w_K + b)$
x_1
x_2
x_K
w_1
w_2
w_K
weights
z
$+$
b
Threshold
$\sigma(z)$
y
... gradients!
continuous activation!
...25 years... Paul J. Werbos
(1974)
...as Sigmoid function
Sigmoid Function
$\sigma(z) = \frac{1}{1+e^{-z}}$
$\sigma(z)$
1
0.5
0
z

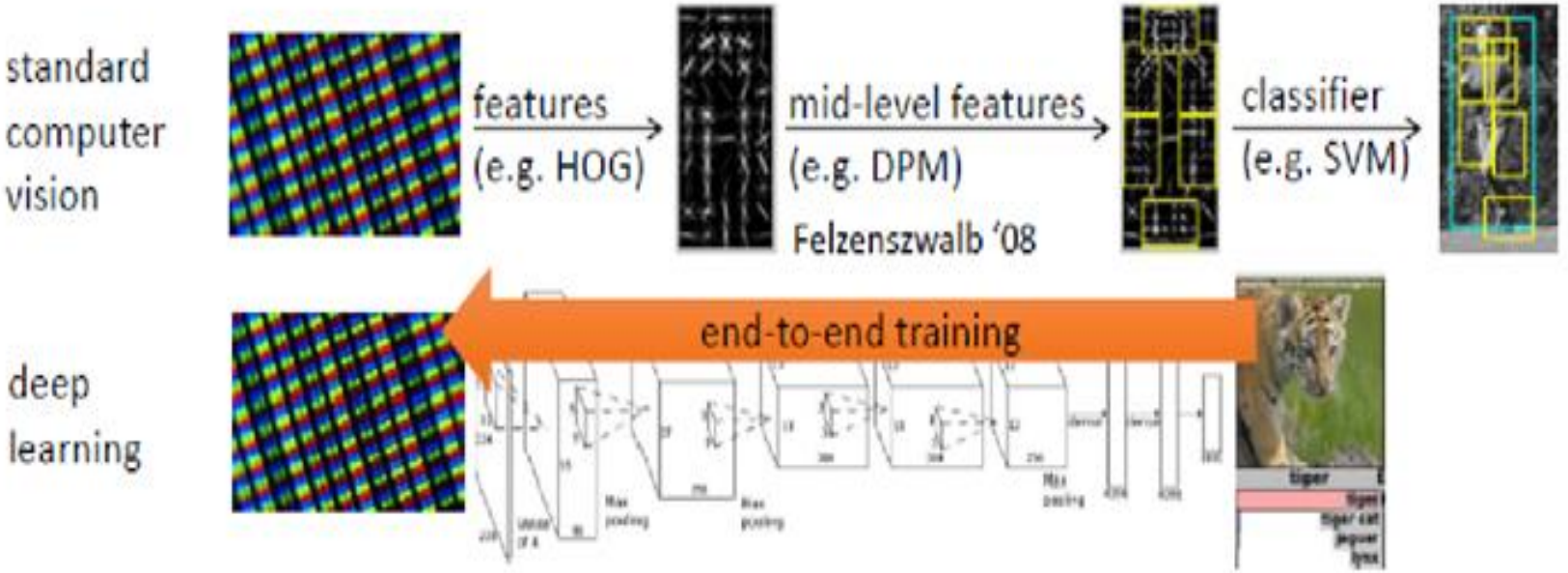
But recall that this is also: logistic regression!




Machine Learning
Input
Feature extraction
Classification
Car
Not Car
Output
Deep Learning
Input
Feature extraction + Classification
Car
Not Car
Output

End-to-end

REVOLUTION!



Towards End-to-End Speech Recognition

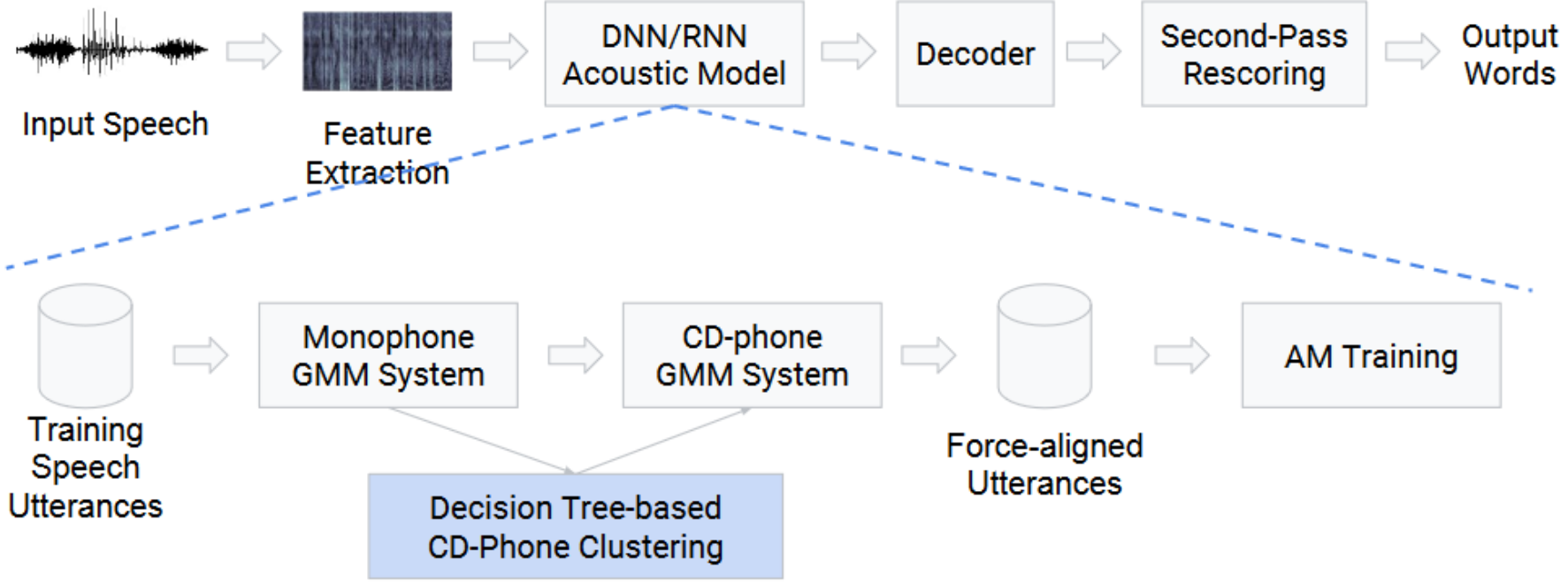
Bo Li, Yanzhang He, Shuo-Yiin Chang

ISCSLP Tutorial 4

Nov. 26, 2018

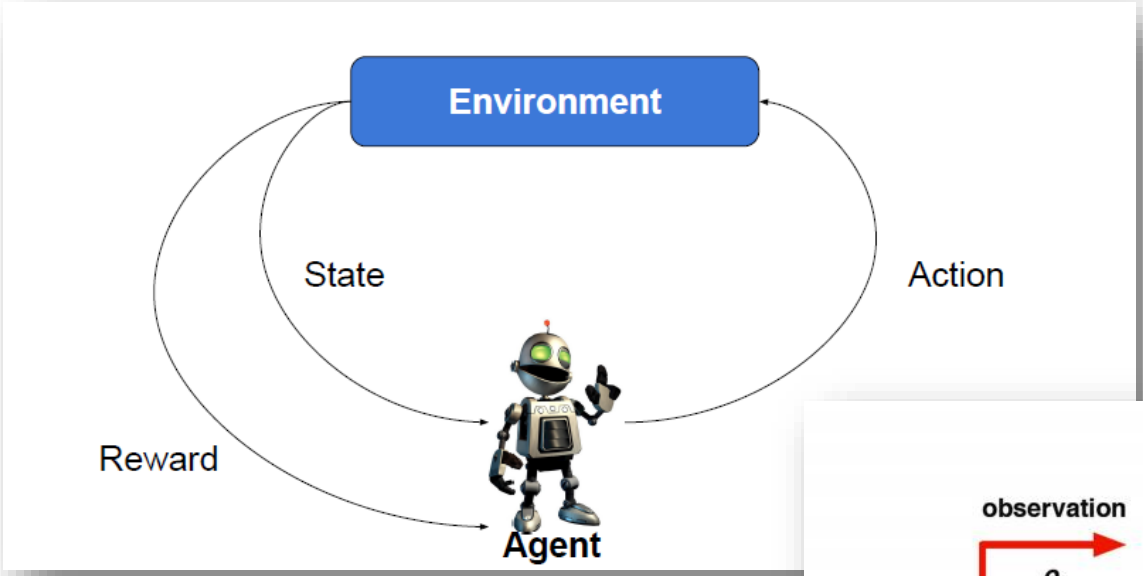
Conventional ASR

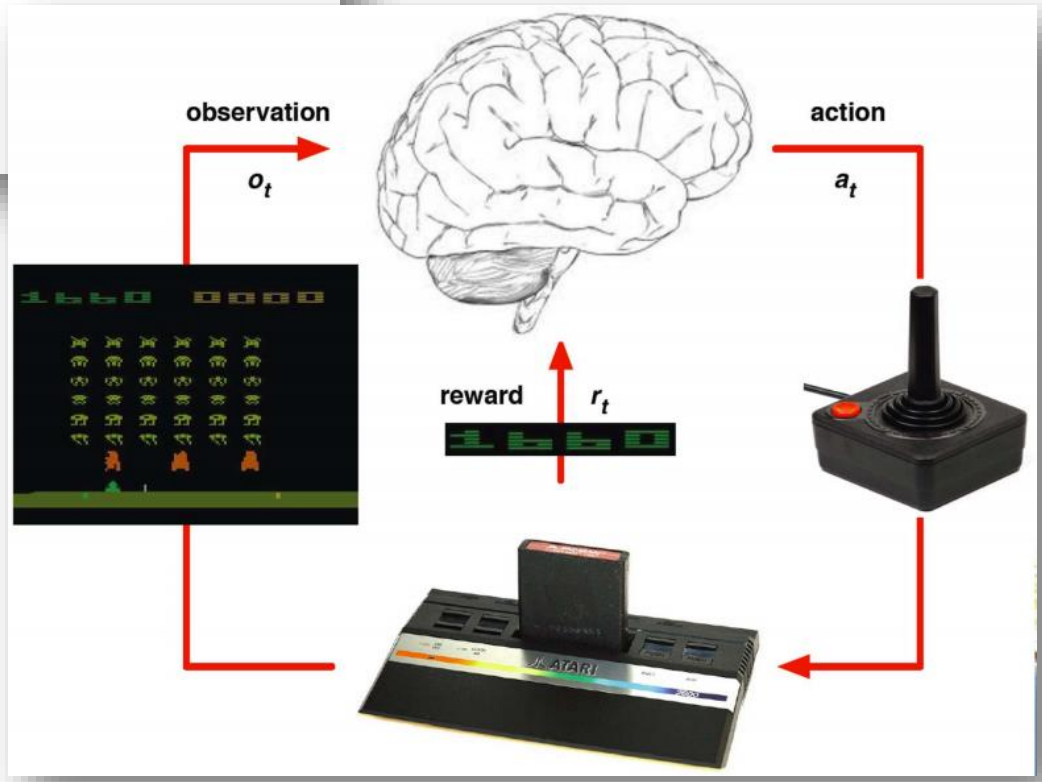
AM Training



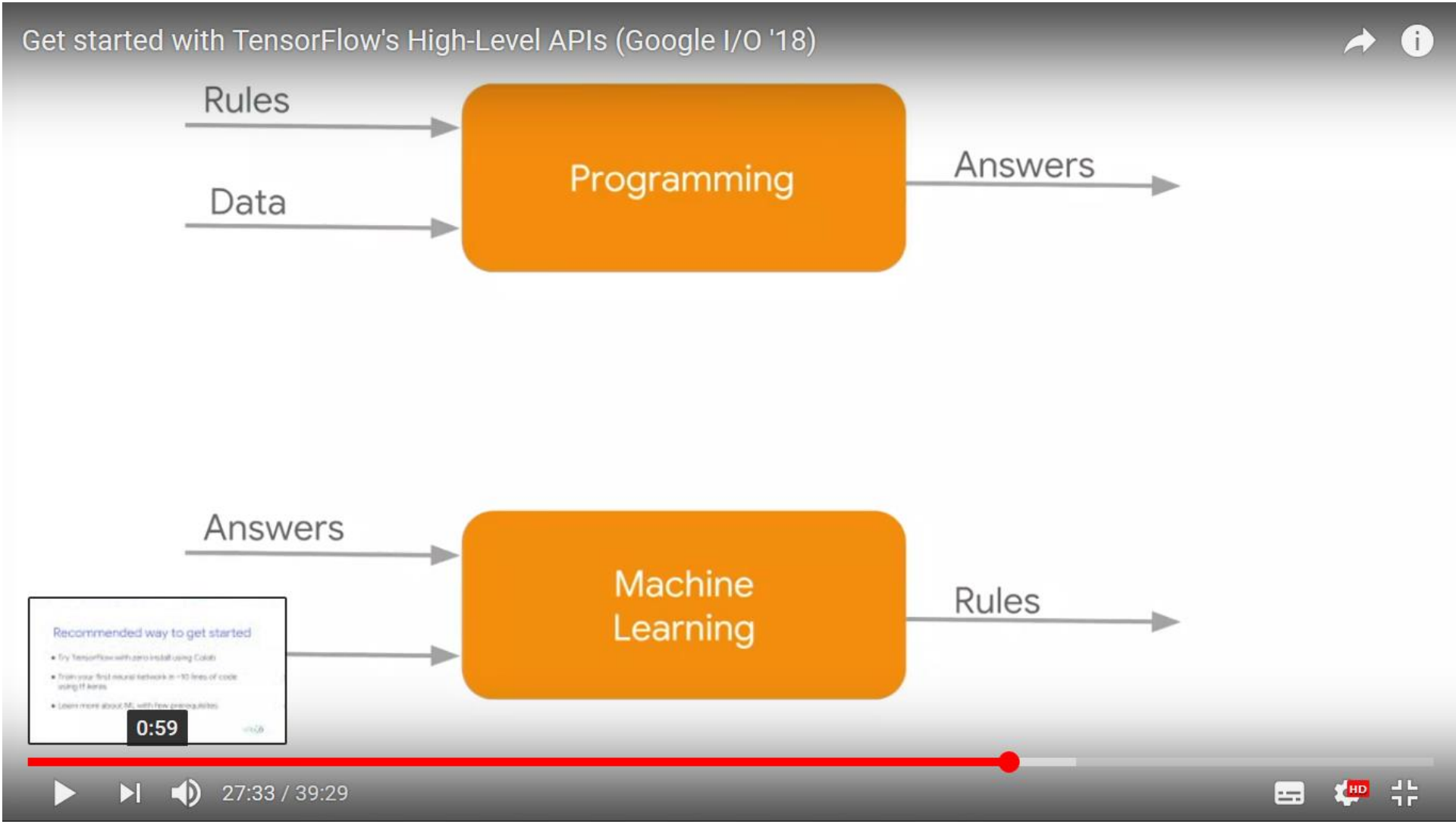
Google

What's Reinforcement Learning?





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


Get started with TensorFlow's High-Level APIs (Google I/O '18)
Rules
Data
Programming
Answers
Answers
Machine Learning
Rules
Recommended way to get started
0:59
27:33 / 39:29

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

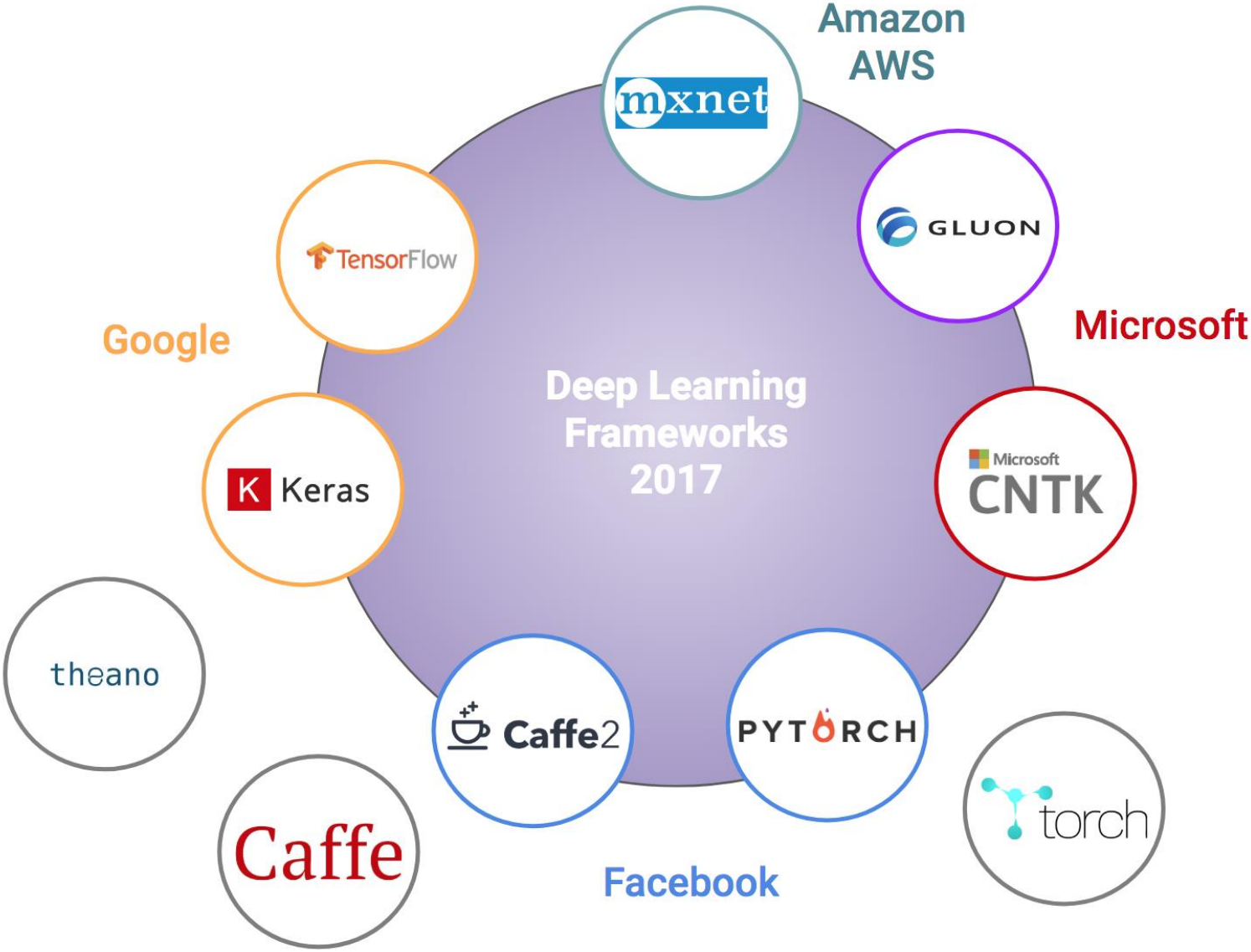
Nvidia CEO Jensen Huang at the company's developer conference in San Jose, California.

Intelligent Machines

The U.S. Military Wants Its Autonomous Machines to Explain Themselves

The latest machine-learning techniques are essentially black boxes. DARPA is funding a number of efforts to open them up.

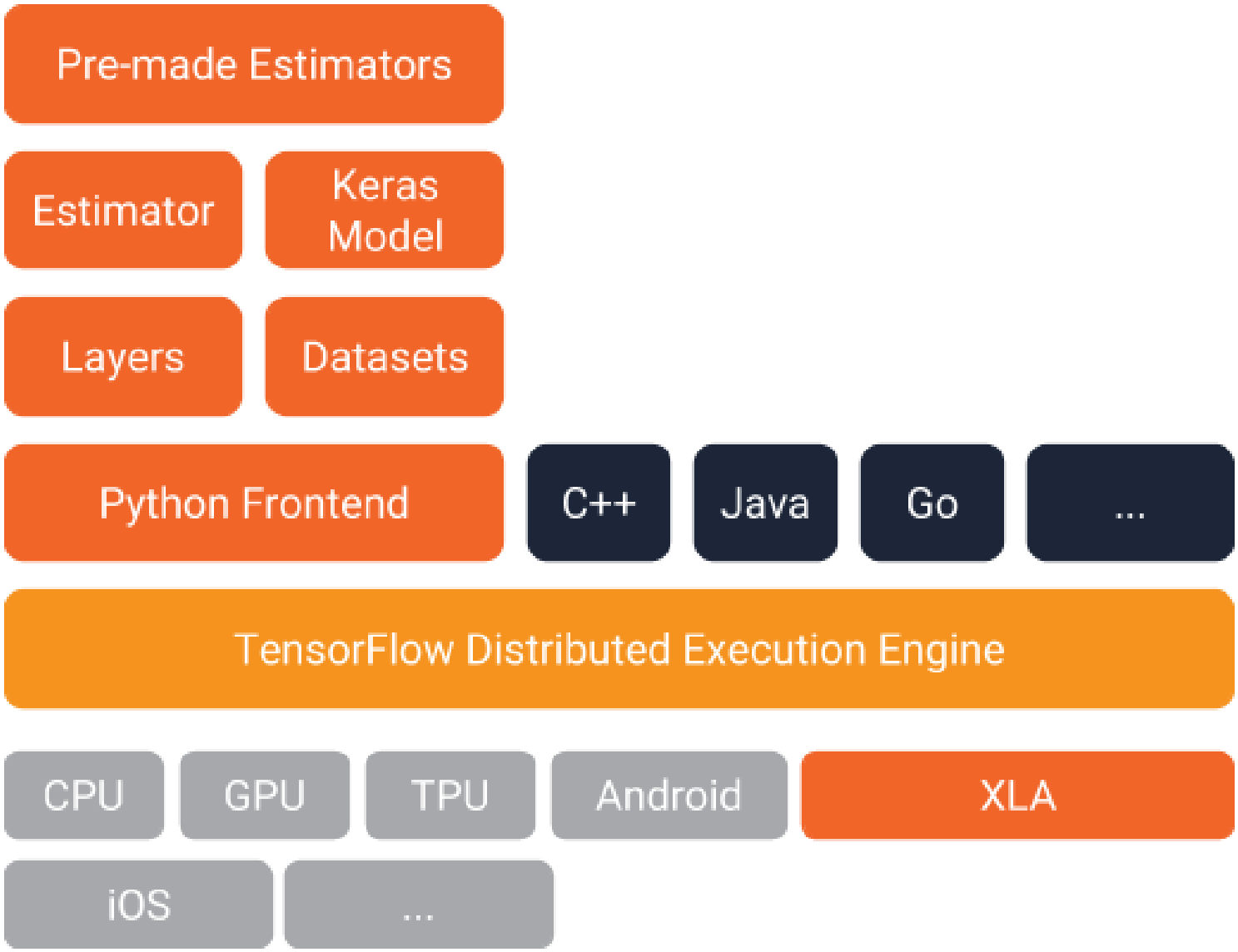
by Will Knight March 14, 2017

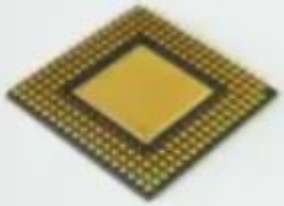


https://towardsdatascience.com/battle-of-the-deep-learning-frameworks-part-i-cff0e3841750

Google TensorFlow

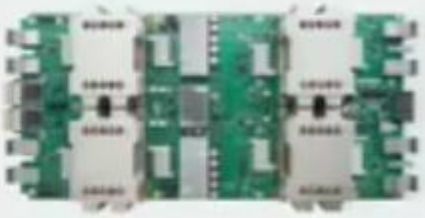
- Library for writing “machine intelligence” algorithms
- Very popular for deep learning and neural networks
- Can also be used for general purpose numerical computations
- Interface in C++ and Python


Pre-made Estimators
Estimator
Keras Model
Layers
Datasets
Python Frontend
C++
Java
Go
...
TensorFlow Distributed Execution Engine
CPU
GPU
TPU
Android
XLA
iOS
...



CPU

GPU



Cloud TPU

Android

iOS

Embedded Devices


API styles
tf.keras
Estimators
Eager execution
Deferred execution

Deep Learning: some on-line resources

Keras Tutorial: Deep Learning in Python

10 Best Machine Learning & Deep Learning Courses [2019 UPDATED]

https://digitaldefynd.com/best-machine-learning-and-deep-learning-courses/

Keras: The Python Deep Learning library

Keras

Guiding principles

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

BUT WHERE to (play) run your programs (scripts) ?

BUT WHERE to (play) run your programs (scripts)

- Your local machine (ANACONDA)
- On **the cloud**
  - Google Colaboratory
    https://colab.research.google.com/notebooks/welcome.ipynb
  - Kaggle kernels (powered by Google)
    https://www.kaggle.com/docs/kernels
  - IBM Cognitive Labs
    https://labs.cognitiveclass.ai

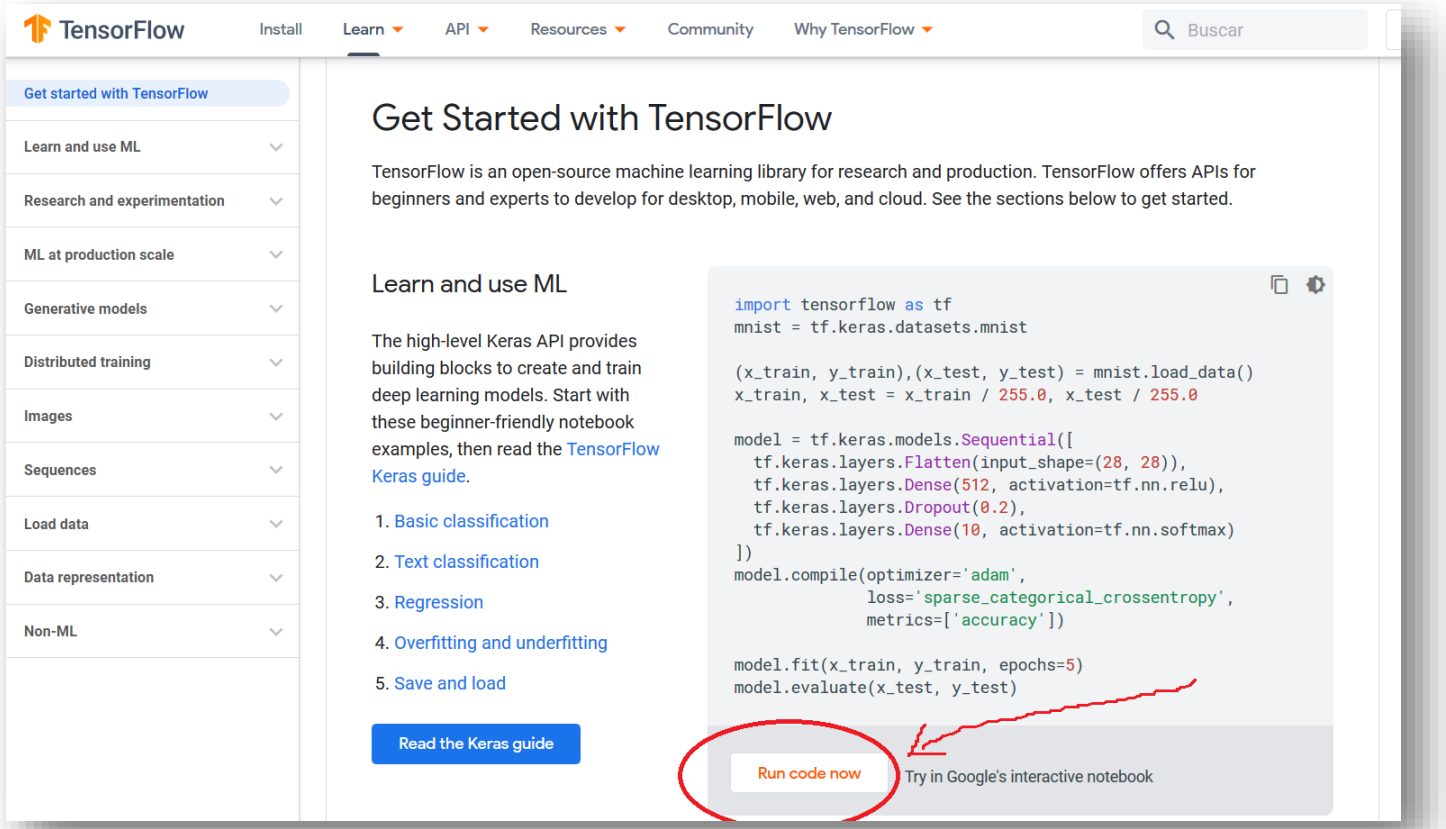
Training and Testing:

MNIST

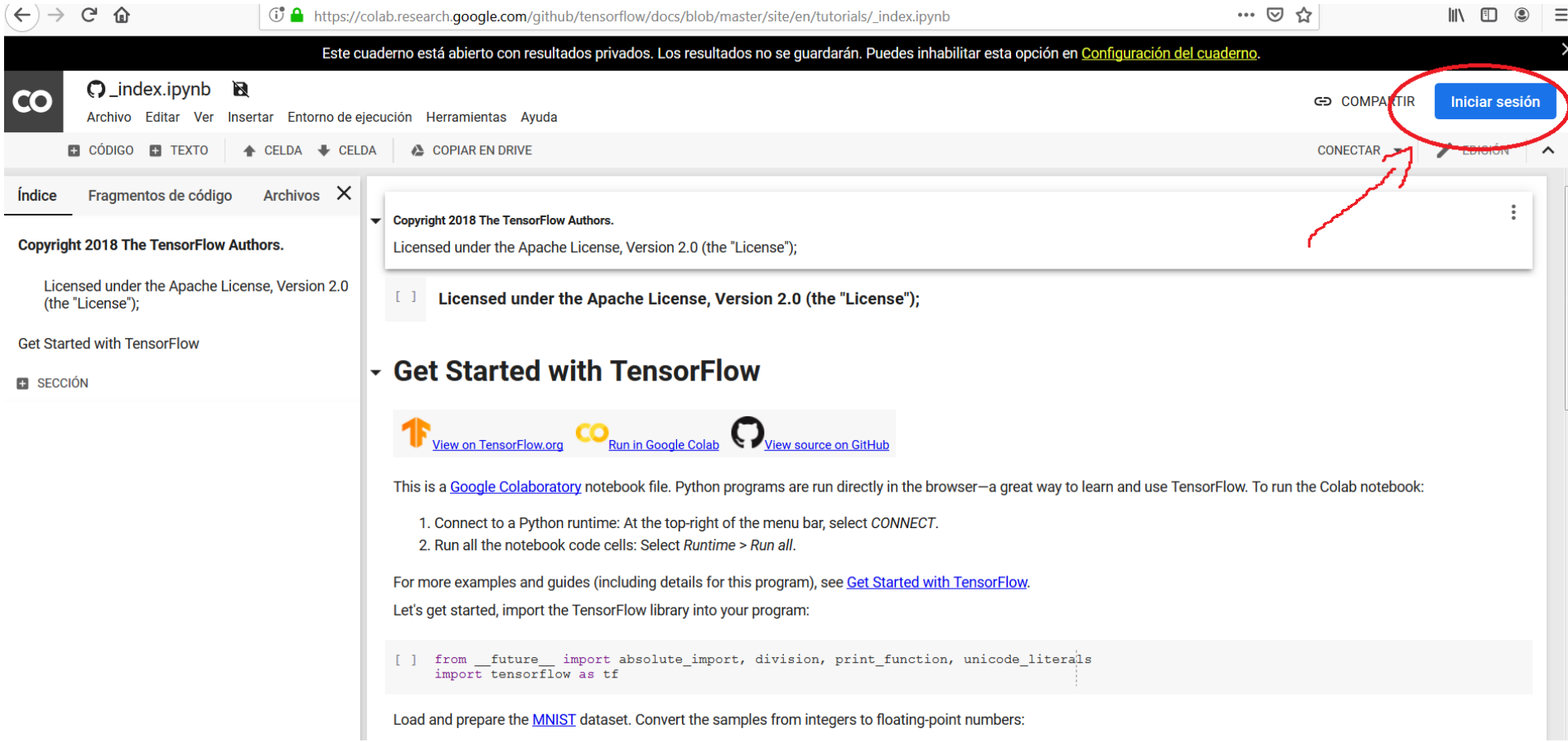
Deep Learning Hello World!

Go to:

https://www.tensorflow.org/tutorials

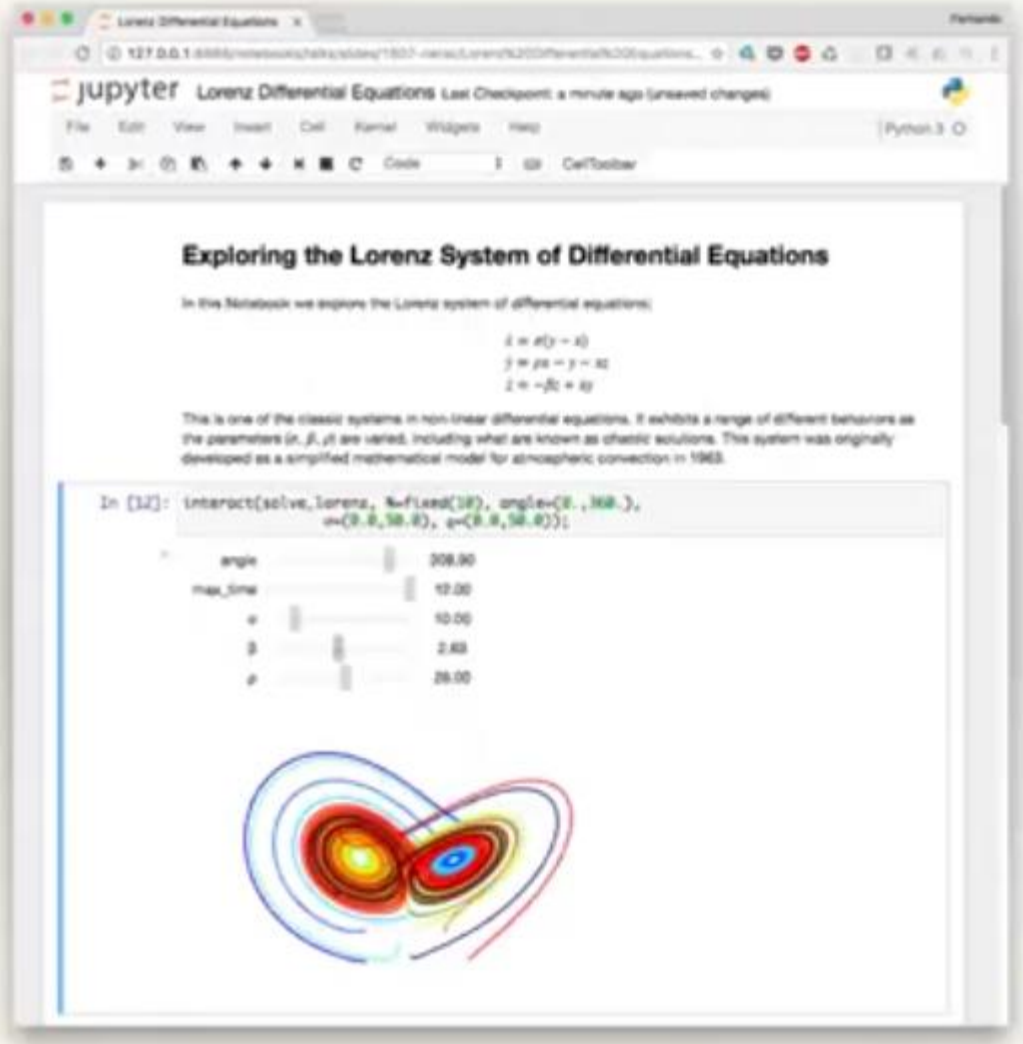


To Run it: You must login using your Gmail account

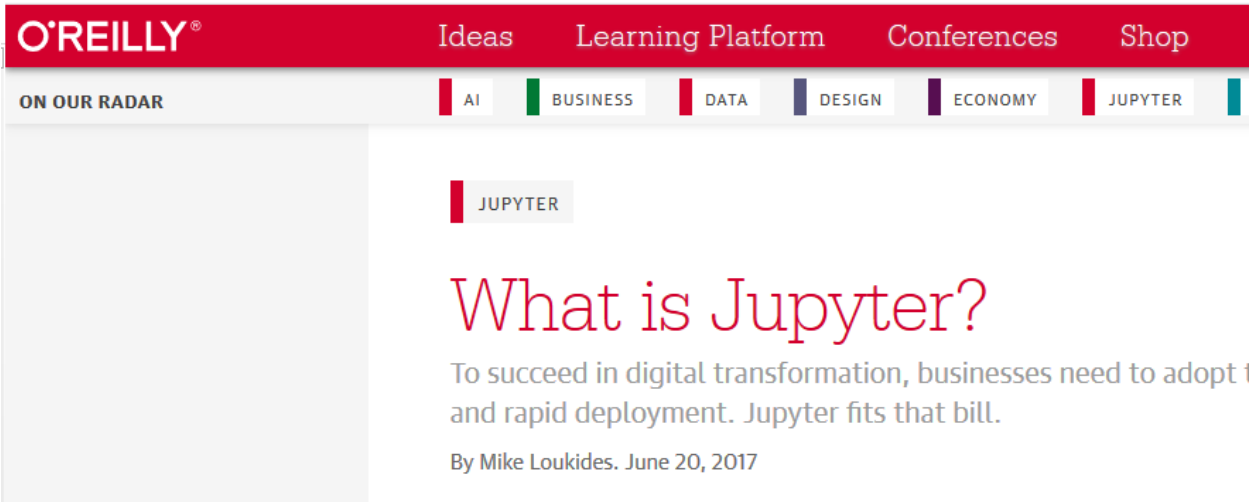


The Jupyter Notebook

- Rich web client
- Text & math
- Code
- Results
- Share, reproduce.




Gateways 2016: Fernando Perez on Project Jupyter
Jupyter Protocol
is language agnostic
jupyter
julia
python
IP[y]:
IPython
6:49 / 48:08



The Jupyter architecture: Jupyter is built from three parts:

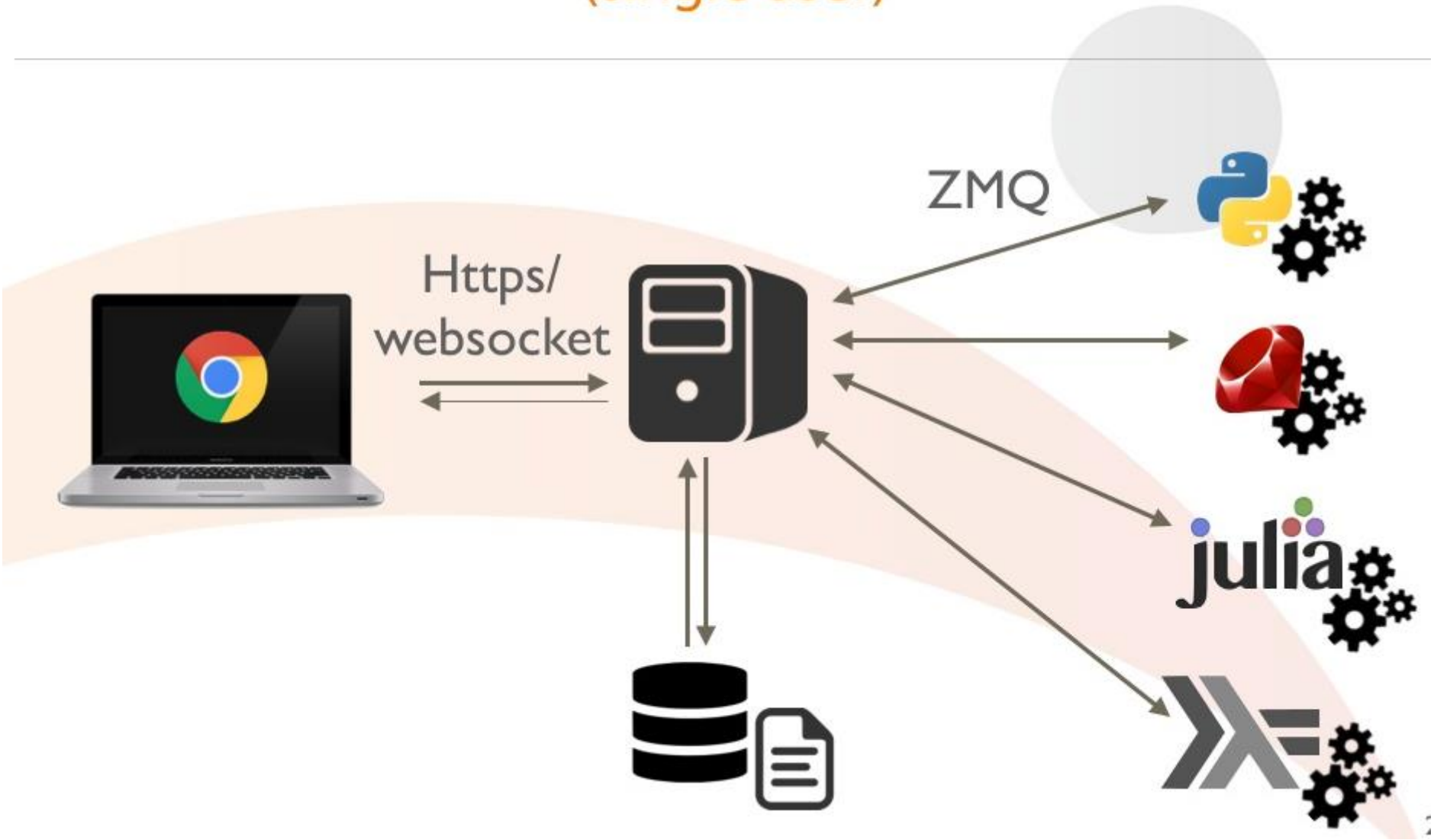
1. **The notebook front end**. The front end allows you to edit and run notebooks (JavaScript application)

2. **The Jupyter server**, which is either a relatively simple application that runs on your laptop, or a multi-user server. The Jupyter project's JupyterHub is the most widely used multi-user server for Jupyter.

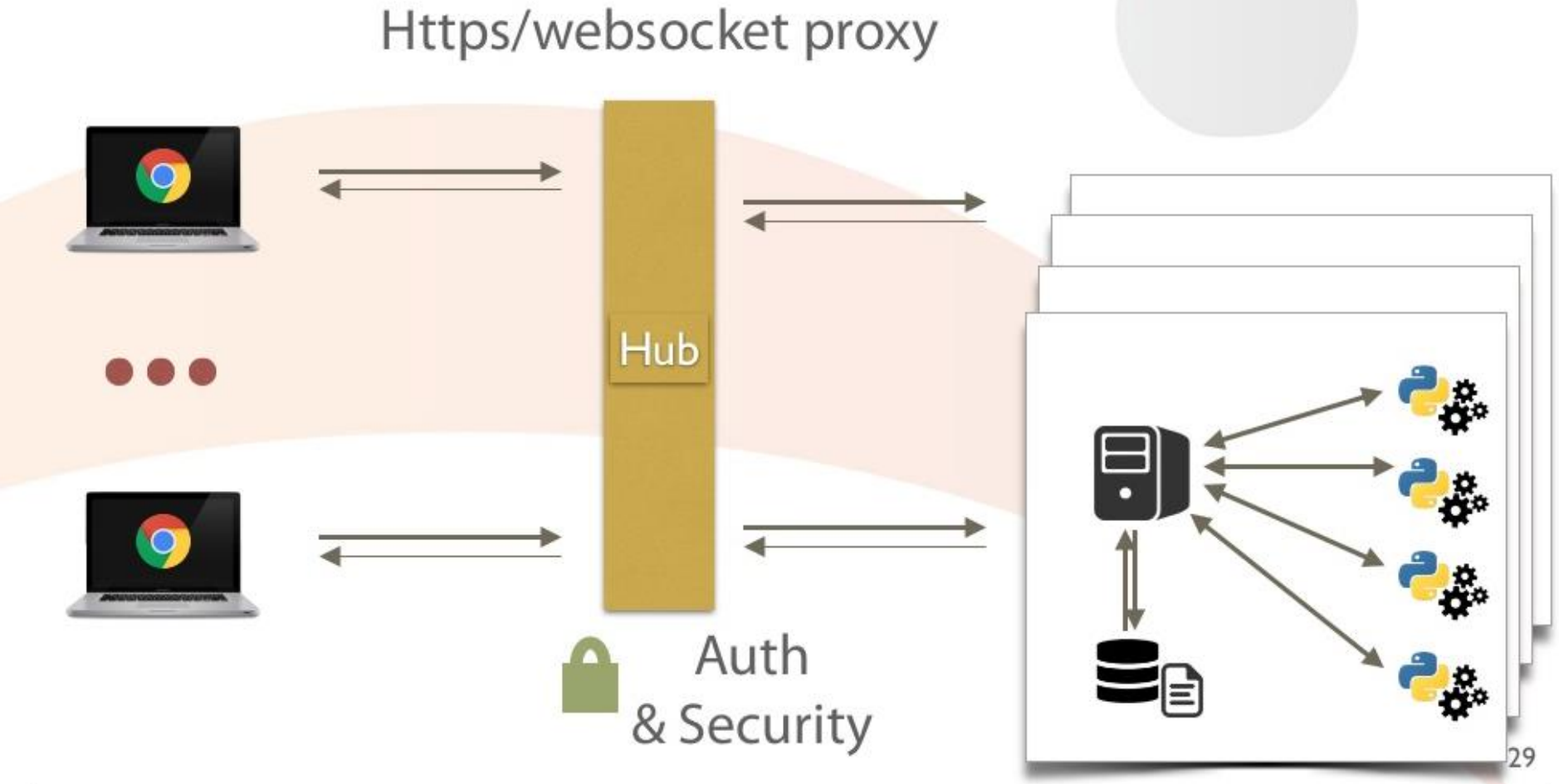
3. **The kernel protocol**, which allows the server to offload the task of running code to a language-specific kernel. Jupyter ships with kernels for Python 2 and Python 3, but kernels for many other languages are available.

The networking architecture

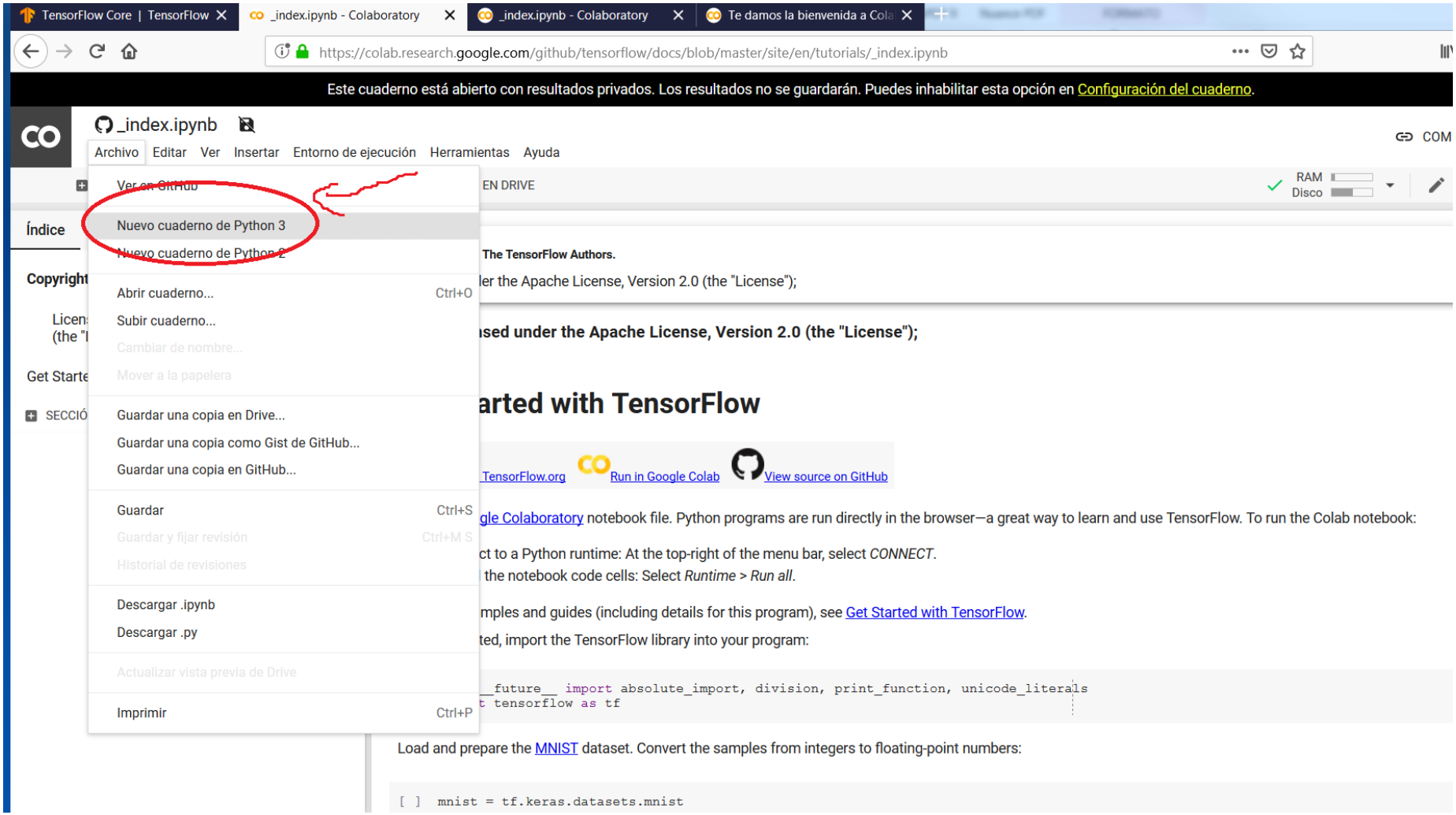
(single user)

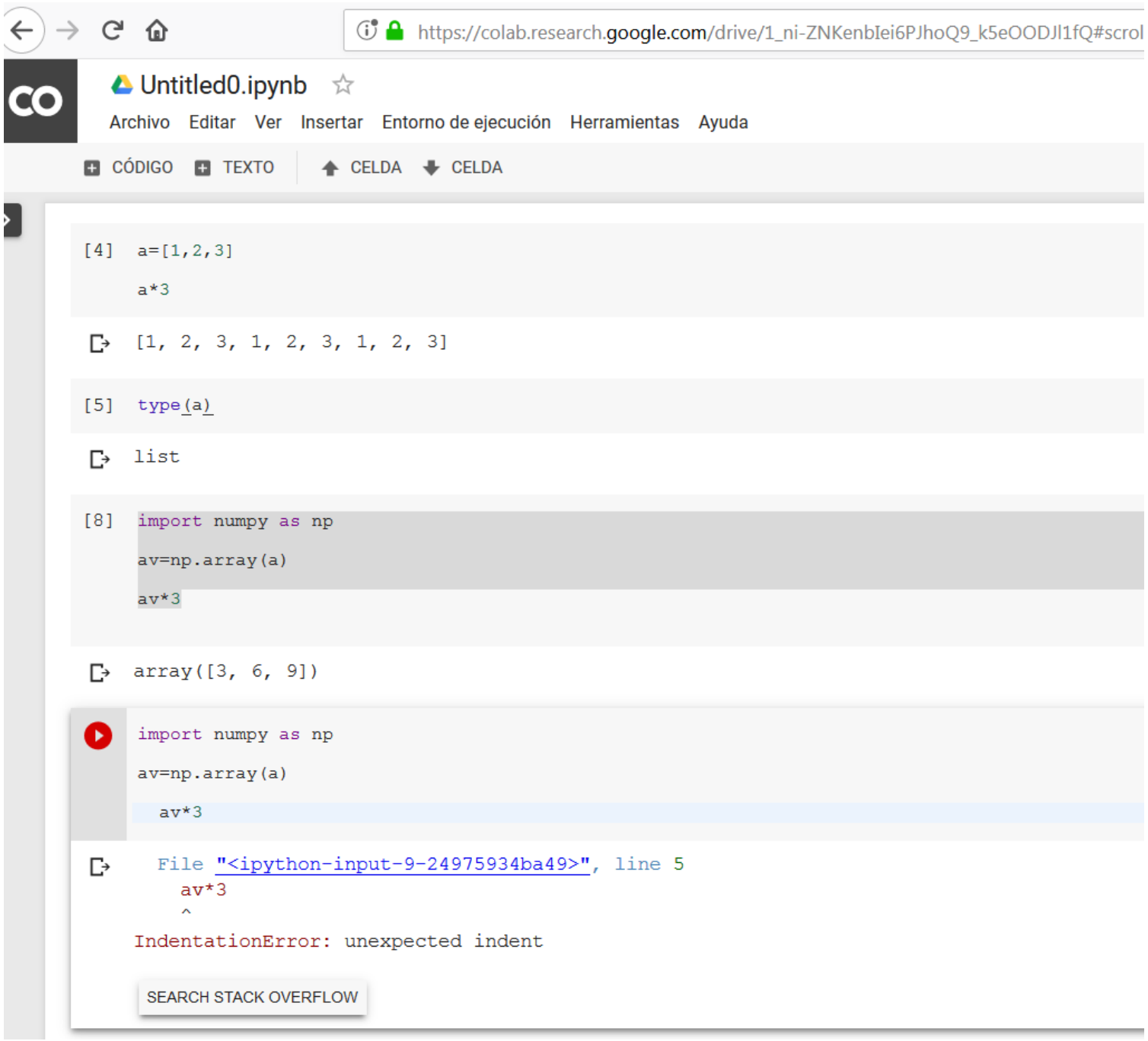


jupyterHub

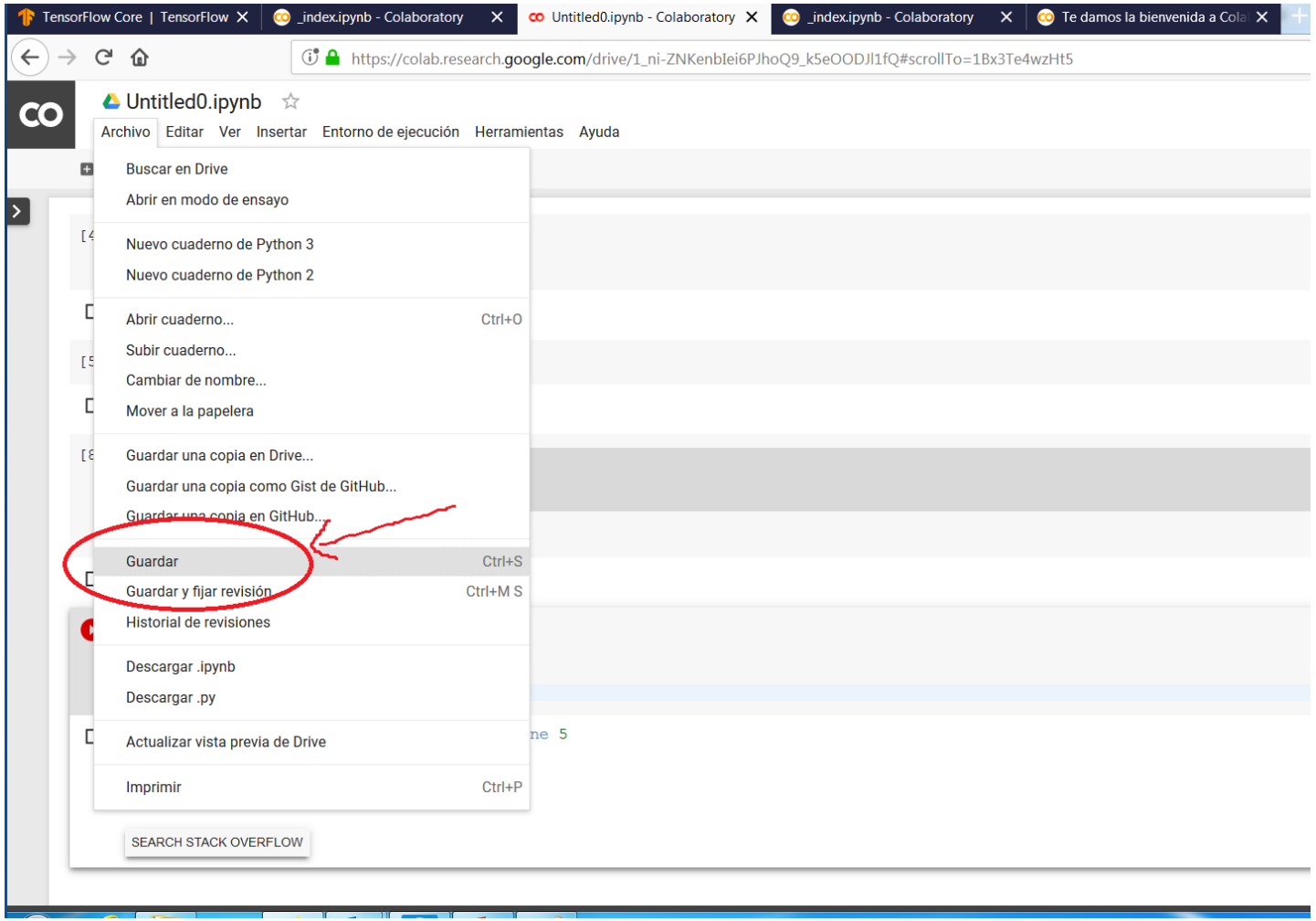


Now CREATE YOUR OWN Python 3 Notebook



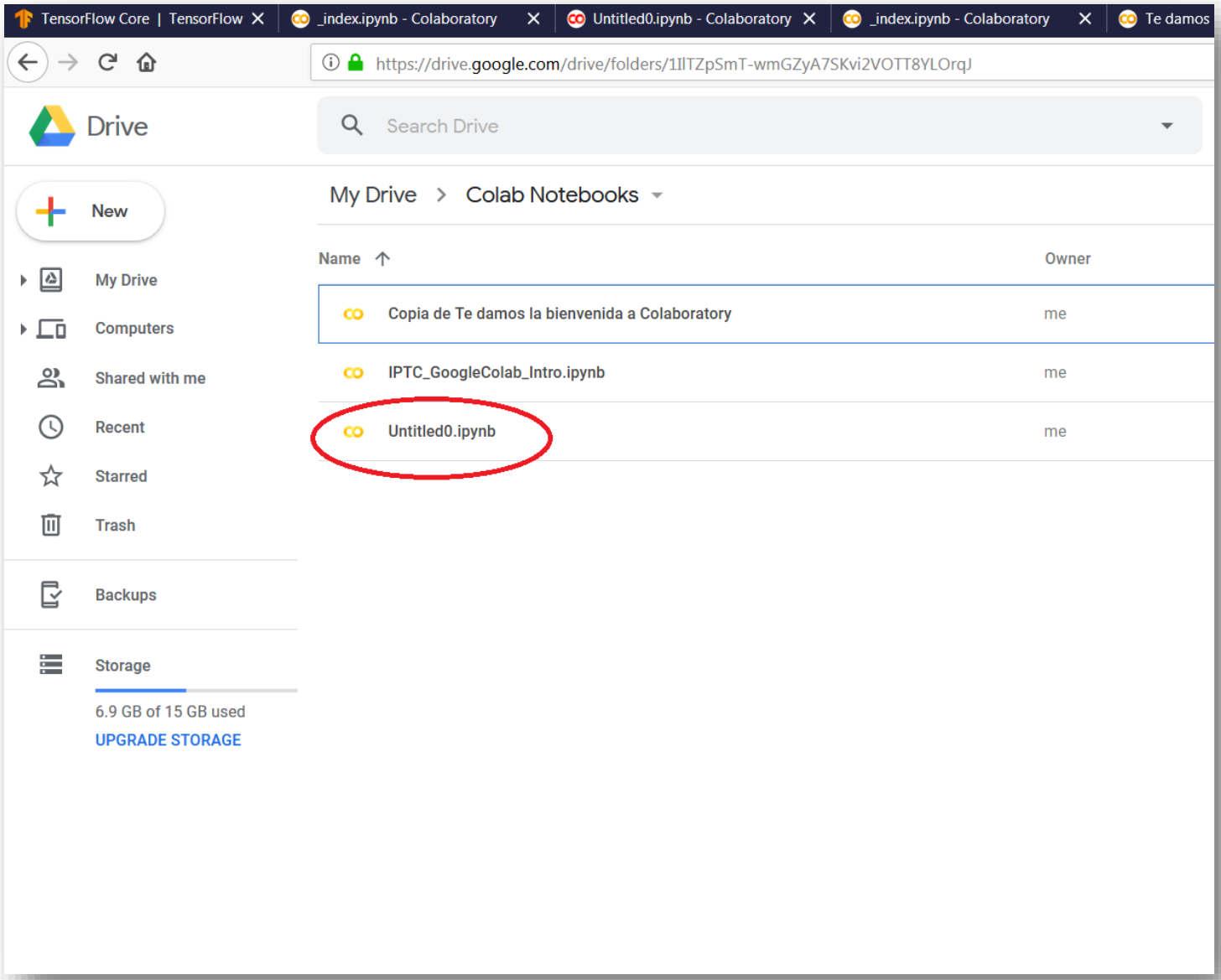

https://colab.research.google.com/drive/1_ni-ZNKenbIei6PJhoQ9_k5eOODJl1fQ#scrol
Untitled0.ipynb
Archivo Editar Ver Insertar Entorno de ejecución Herramientas Ayuda
CÓDIGO TEXTO CELDA CELDA
[4] a=[1,2,3]
a*3
[1, 2, 3, 1, 2, 3, 1, 2, 3]
[5] type(a)
list
[8] import numpy as np
av=np.array(a)
av*3
array([3, 6, 9])
import numpy as np
av=np.array(a)
av*3
File "<ipython-input-9-24975934ba49>", line 5
av*3
^
IndentationError: unexpected indent
SEARCH STACK OVERFLOW

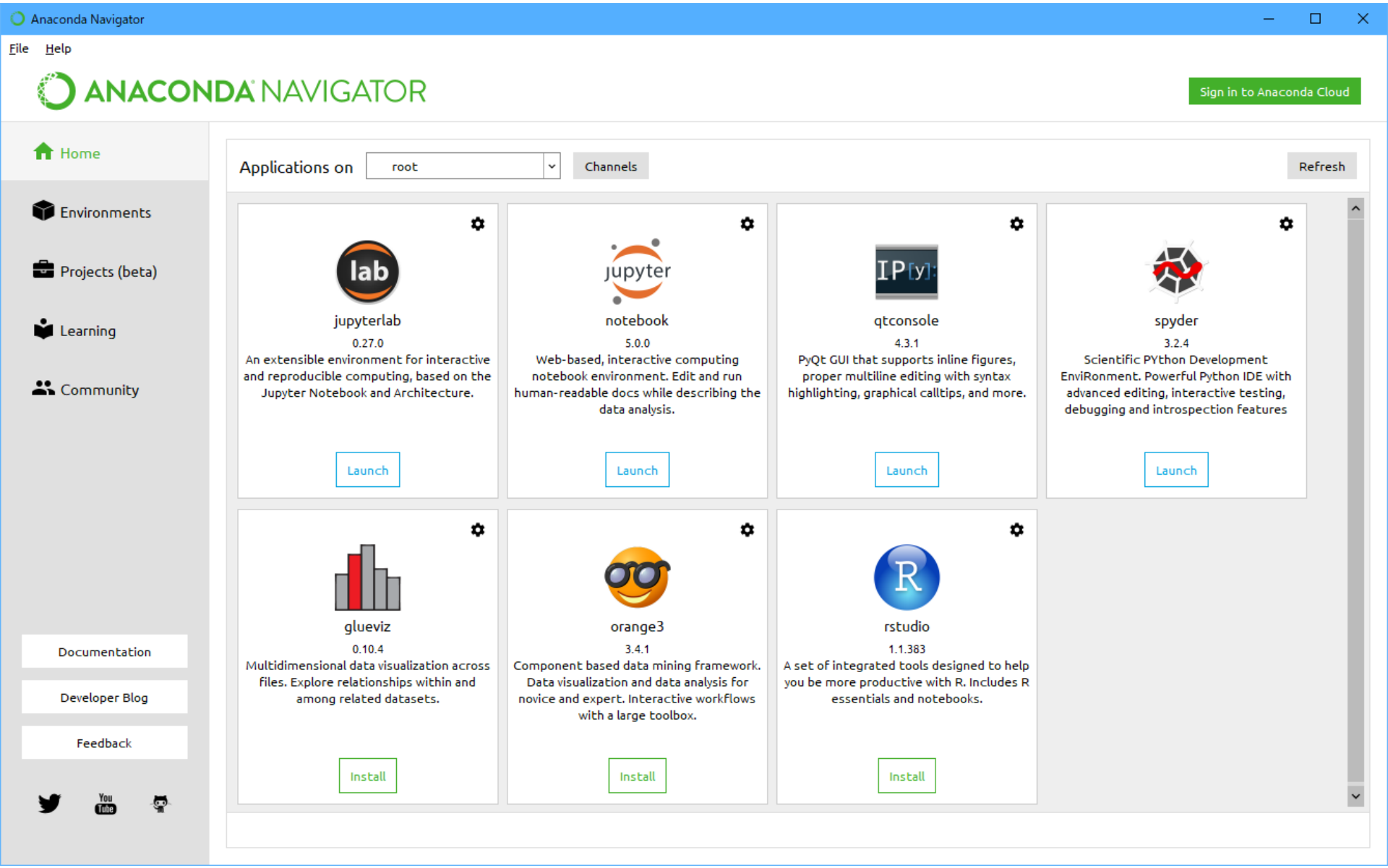
Save it....



WHERE?

By default it is saved into your Google Drive under folder “Colab Notebooks”



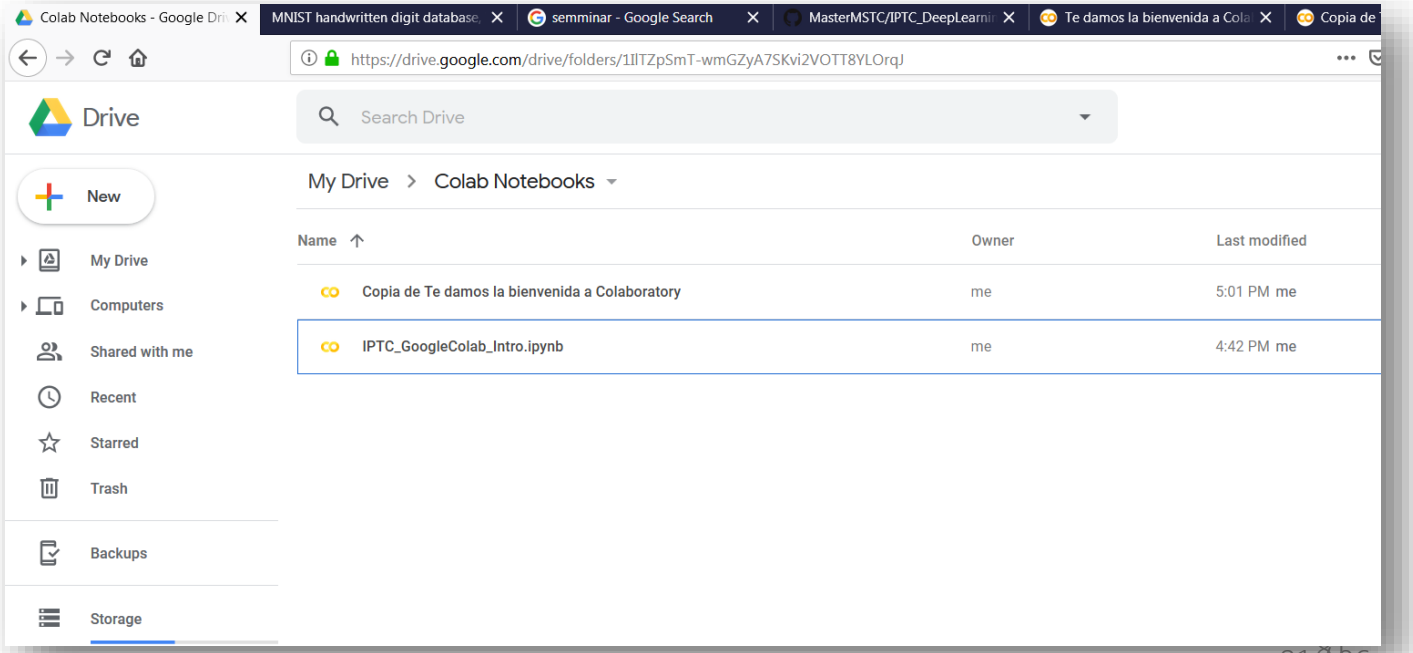

Anaconda Navigator
File
Help
ANACONDA NAVIGATOR
Sign in to Anaconda Cloud
Home
Environments
Projects (beta)
Learning
Community
Documentation
Developer Blog
Feedback
Applications on
root
Channels
Refresh
jupyterlab
0.27.0
An extensible environment for interactive and reproducible computing, based on the Jupyter Notebook and Architecture.
Launch
notebook
5.0.0
Web-based, interactive computing notebook environment. Edit and run human-readable docs while describing the data analysis.
Launch
qtconsole
4.3.1
PyQt GUI that supports inline figures, proper multiline editing with syntax highlighting, graphical calltips, and more.
Launch
spyder
3.2.4
Scientific PYthon Development EnviRonment. Powerful Python IDE with advanced editing, interactive testing, debugging and introspection features
Launch
glueviz
0.10.4
Multidimensional data visualization across files. Explore relationships within and among related datasets.
Install
orange3
3.4.1
Component based data mining framework. Data visualization and data analysis for novice and expert. Interactive workflows with a large toolbox.
Install
rstudio
1.1.383
A set of integrated tools designed to help you be more productive with R. Includes R essentials and notebooks.
Install

Please go to our MSTC GitHub:
https://github.com/MasterMSTC/IPTC_DeepLearning

…and copy from Notebooks:

IPTC_GoogleColab_Intro.ipynb

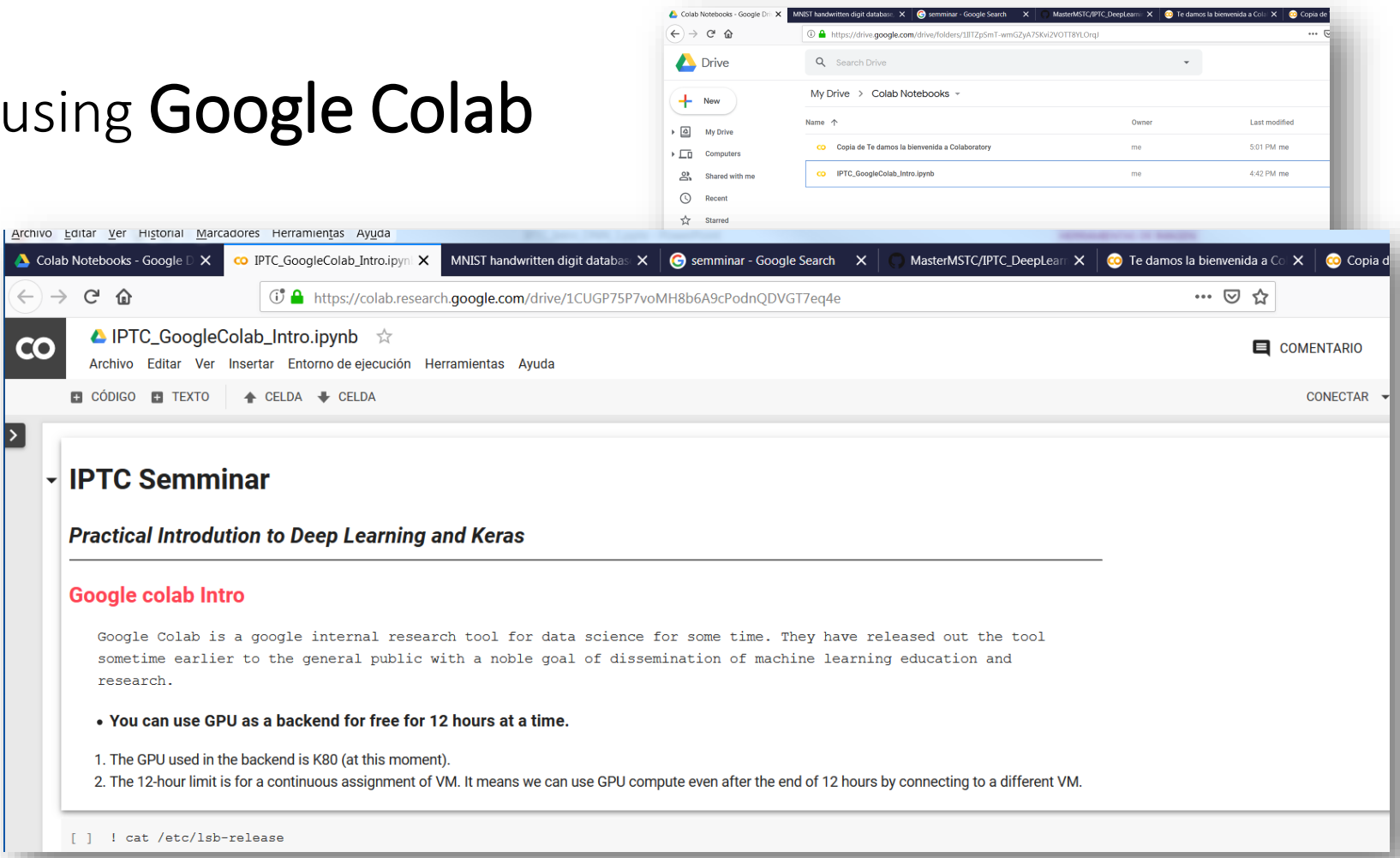
in to your: Google Drive



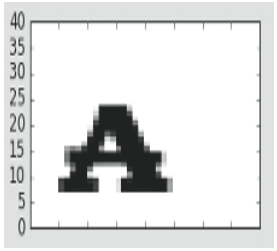
Now, from your Google Drive open the Notebook

IPTC_GoogleColab_Intro.ipynb

…using **Google Colab**



Let's try to develop an Image Classifier using a FeedForward Network



Hidden layer 1
128

Hidden layer 2
32

Output layer
5

Output
Probabilities

x_1

x_2

x_{1296}

Softmax

0.1

Font 1

0.4

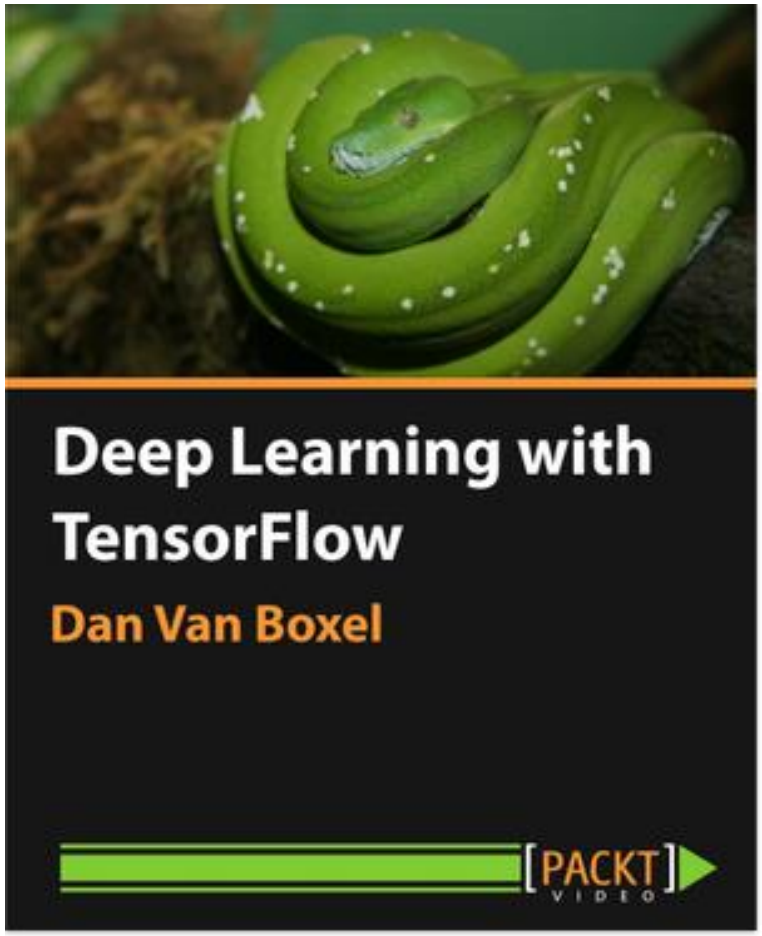
Font 2

0.2

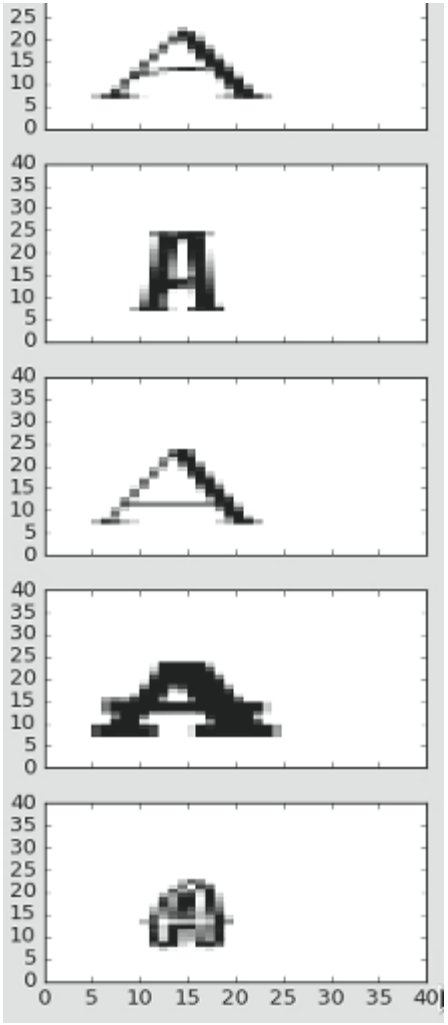
Font 5

Font type Recognition

Keras



One-hot-encoding (OHE)



Categories	Number of Categories (N=5)				
Type 1	1	0	0	0	0
Type 2	0	1	0	0	0
Type 3	0	0	1	0	0
Type 4	0	0	0	1	0
Type 5	0	0	0	0	1

Softmax Layer

The output of a Classifier is a categorical variable

- In **REGRESSION** the output *y* is a Numerical variable
- BUT in **CLASSIFICATION** *y* is a Categorical one

So: How to represent Categorical variables?

y = {cats, dogs, birds, ants}

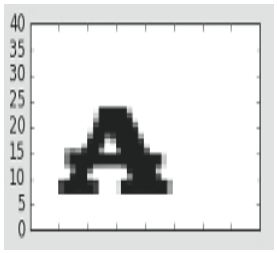
- Why not just to assign "1", "2" , "3" ?

OHE : One-Hot encoding

cats :	1 0 0 0
dogs:	0 1 0 0
birds:	0 0 1 0
ants:	0 0 0 1

- ...and what for a LARGE number of categories (as words!) .... **sparsity** (a lot of zeros)....

On **Day-3** we will talk about:
embeddings
Great in NLP
(Natural Language Processing)



Hidden layer 1
128

Hidden layer 2
32

Output layer
5

Output
Probabilities

x_1

x_2

x_{1296}

Softmax

0.1

Font 1

0.4

Font 2

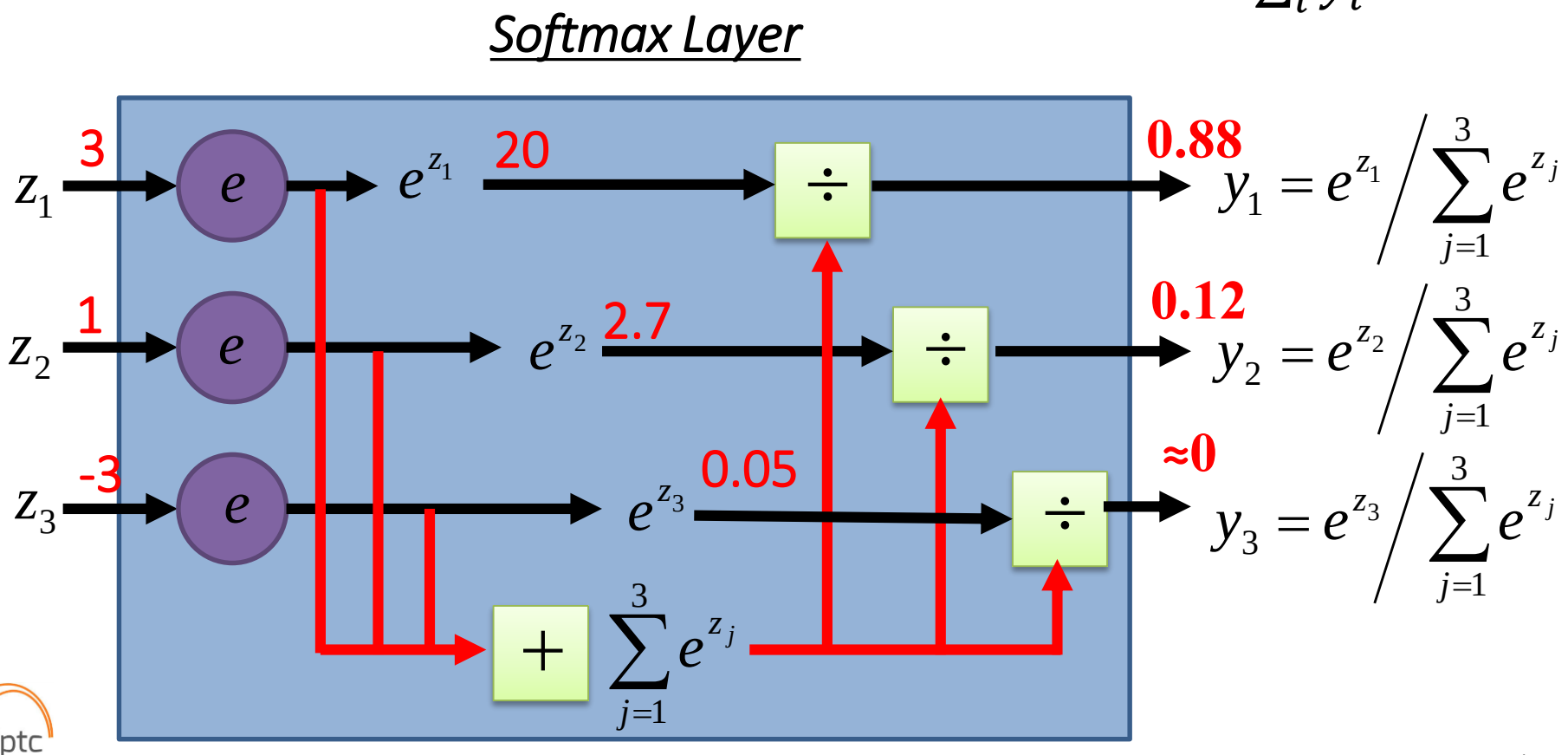
0.2

Font 5

Softmax layer as the output layer

Probability:

- $1 > y_i > 0$
- $\sum_i y_i = 1$



Font type Recognition

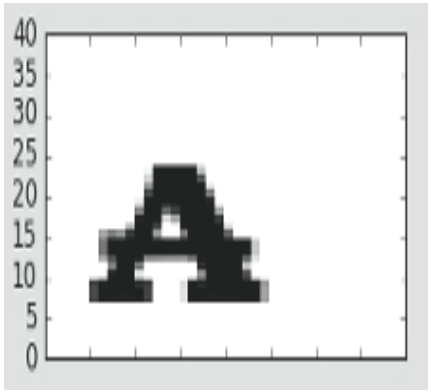
IPTC_Keras_FontReco_FeedFordward.ipynb

Available at:

https://github.com/MasterMSTC/IPTC_DeepLearning

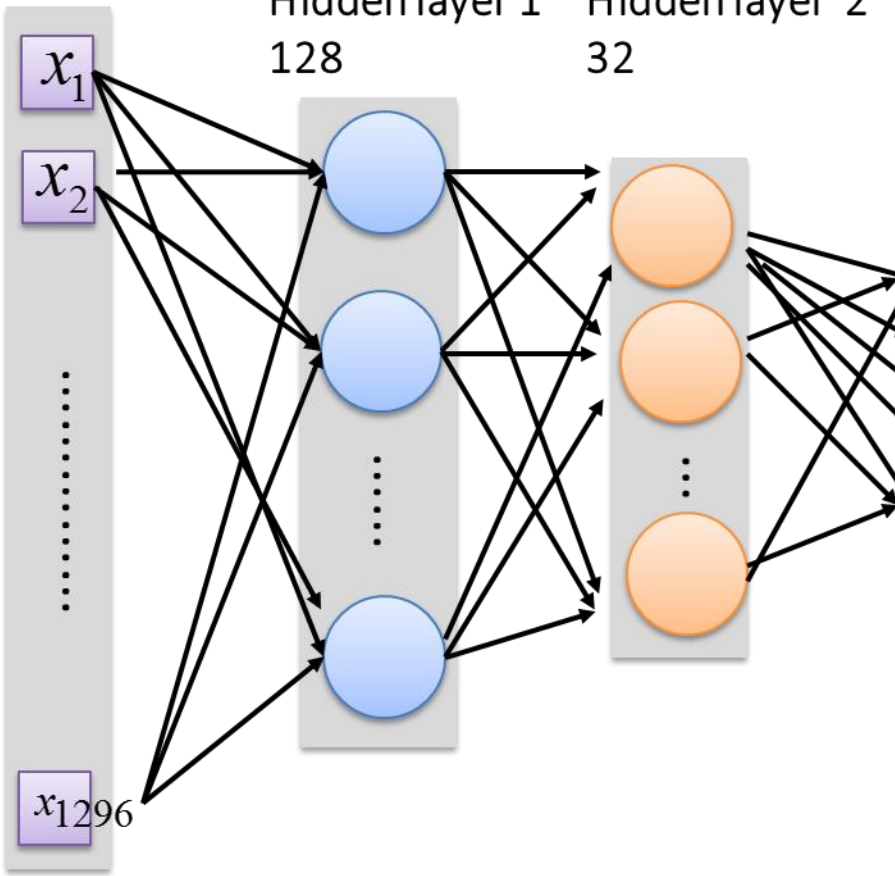
Reshape
(we need a 1D input)

Input



36 x 36 = 1296

reshape

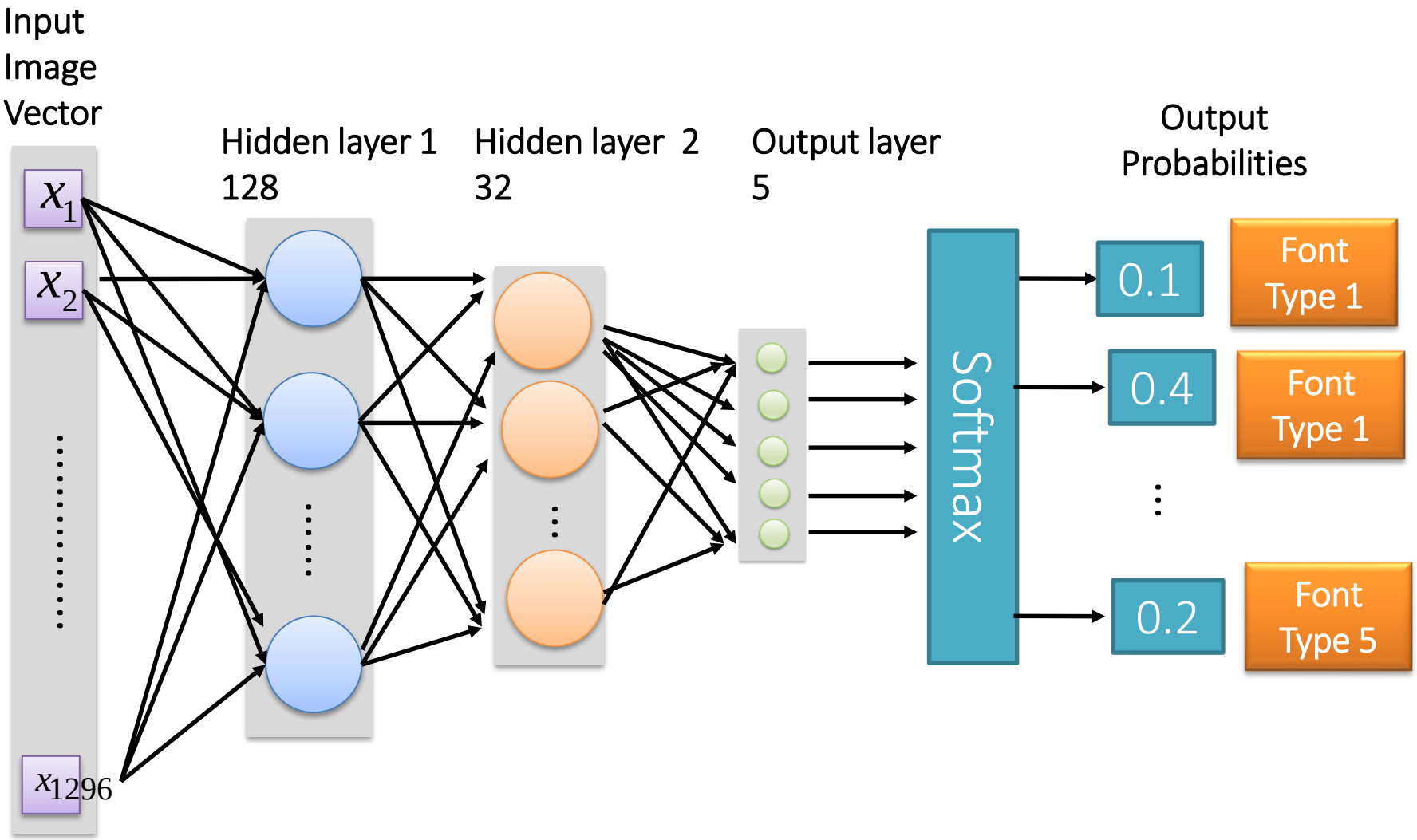


Elements [0:255]

White pixel → 0

Black pixel → 255

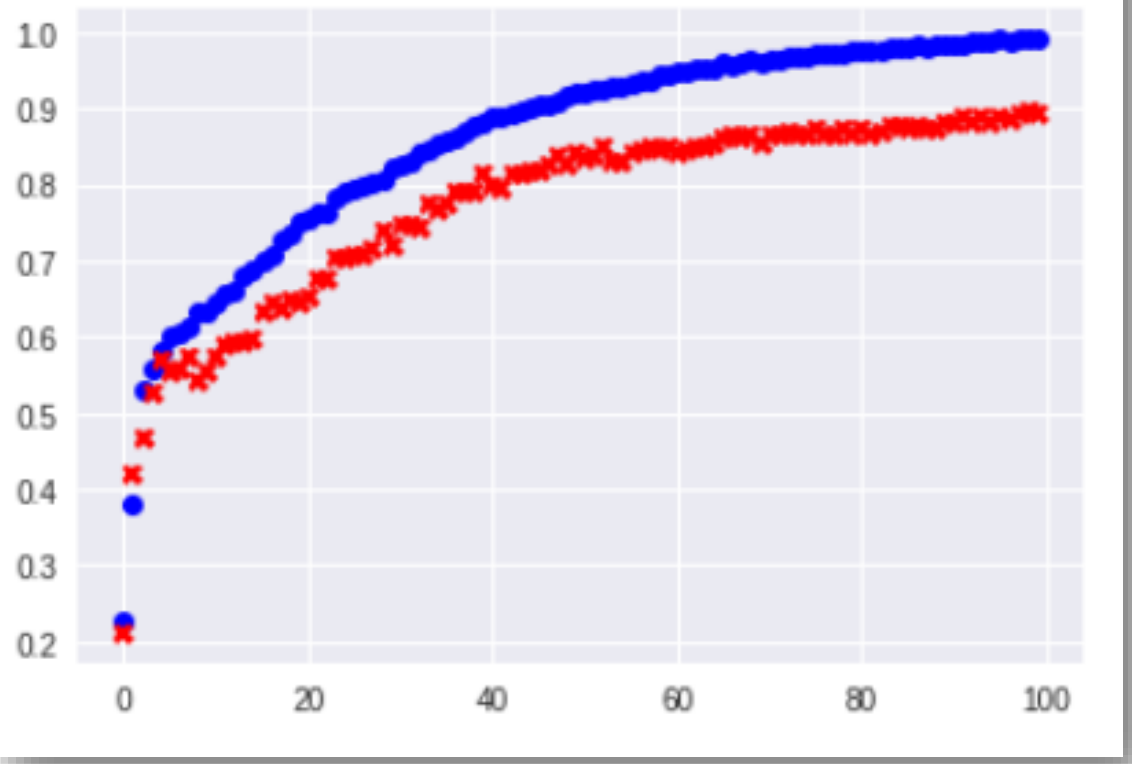
PLEASE BE AWARE OF HOW CRITICAL IS TO NORMALIZE INPUTS TO Neural Networks


Input
Image
Vector
Hidden layer 1
128
Hidden layer 2
32
Output layer
5
Output
Probabilities
x_1
x_2
x_{1296}
Softmax
0.1
0.4
0.2
Font
Type 1
Font
Type 1
Font
Type 5

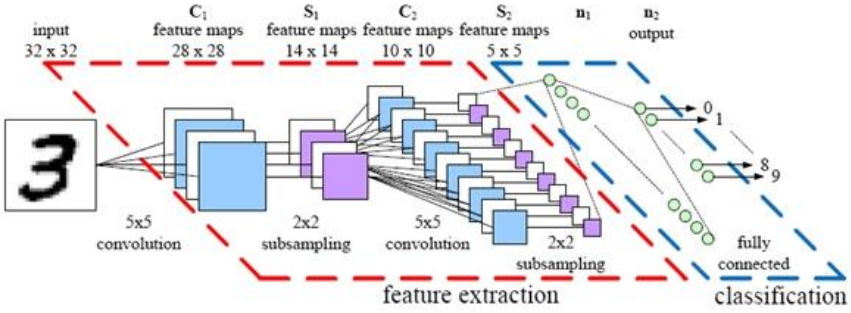
Feed Forward

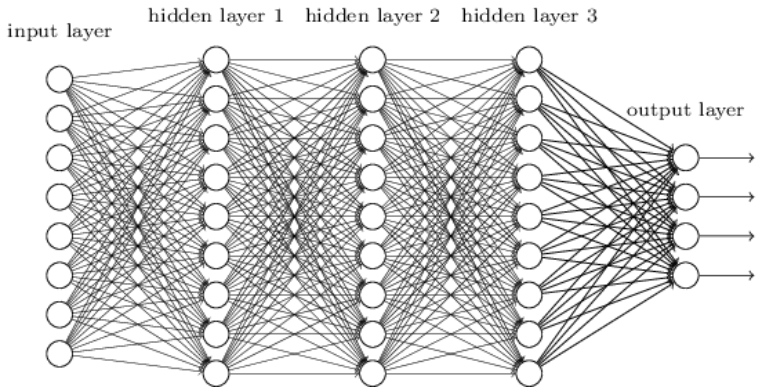
Keras

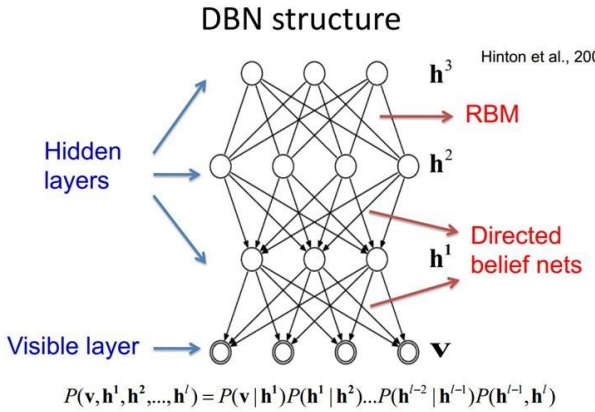
```
Train Accuracy:  0.99
Test_Accuracy:  0.89
[<matplotlib.lines.Line2D at 0x7fec4831d2b0>]
```



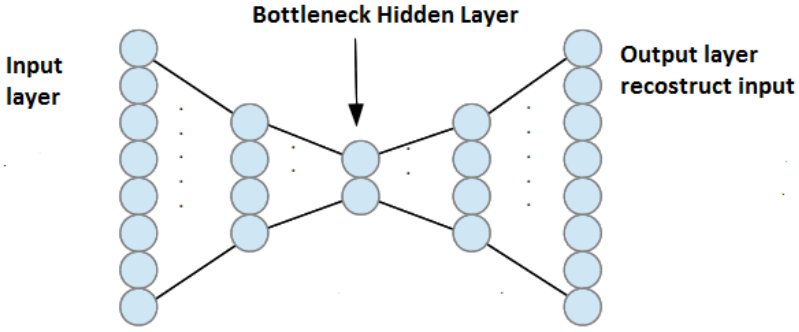
What’s next for Day-2

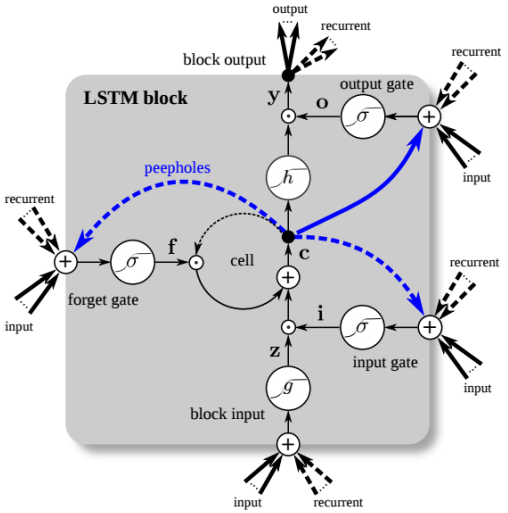


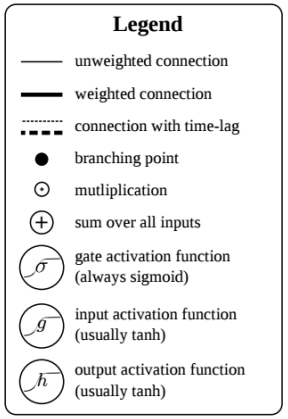




Deep Learning Architectures

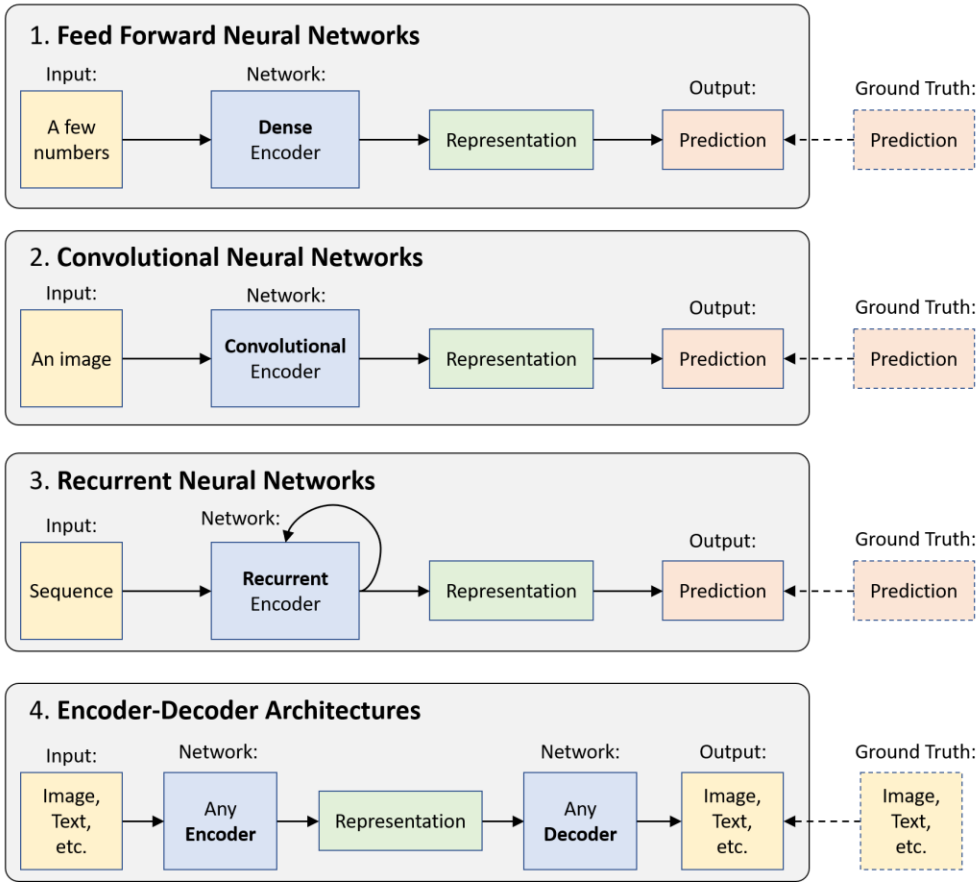




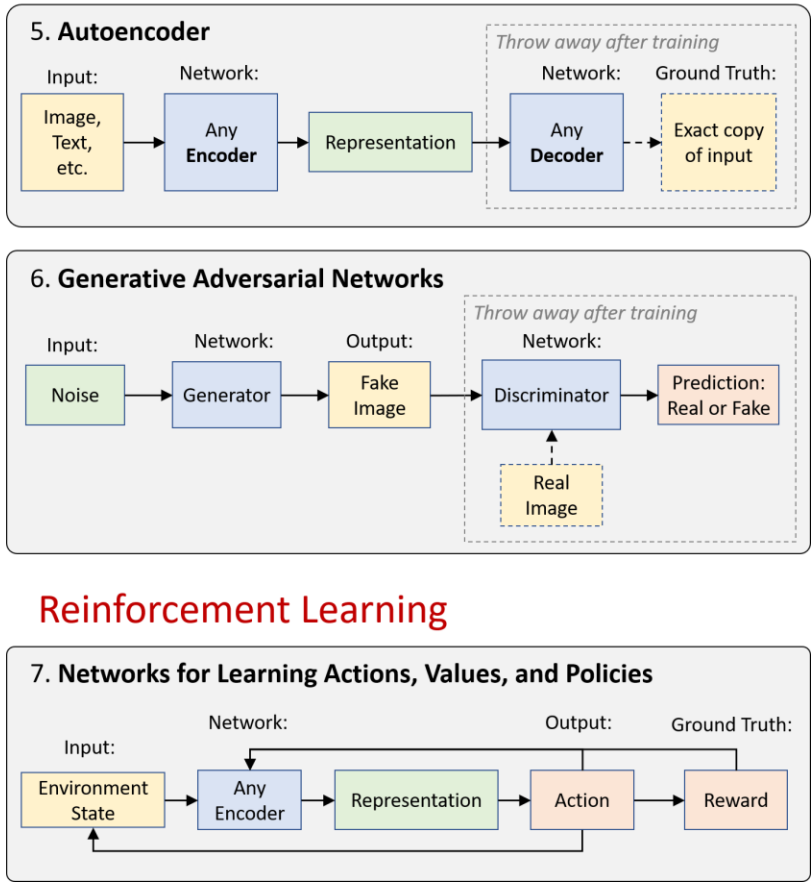


… and towards Day-3 : Deep learning basics

Supervised Learning



Unsupervised Learning



Reinforcement Learning

https://github.com/lexfridman/mit-deep-learning/blob/master/tutorial_deep_learning_basics/deep_learning_basics.ipynb

iptc
Information Processing and Telecommunications Center

Some on-line courses

Practical:

- UDACITY: Deep Learing by Google (DNN + TF)
- Udemy : Zero to Deep Learning™ with Python and Keras
- Deep Learning with TensorFlow : Packt Video (our examples today from this!)
- TensorFlow and Deep Learning without a PhD, Part 1 (Google Cloud Next '17)
  https://www.youtube.com/watch?v=u4alGiomYP4

Theory:

- Coursera Neural Networks for Machine Learning, as taught by Geoffrey Hinton (University of Toronto)
- Andrew Ng : Deep Learning and Unsupervised Feature Learning