JIRC 2017



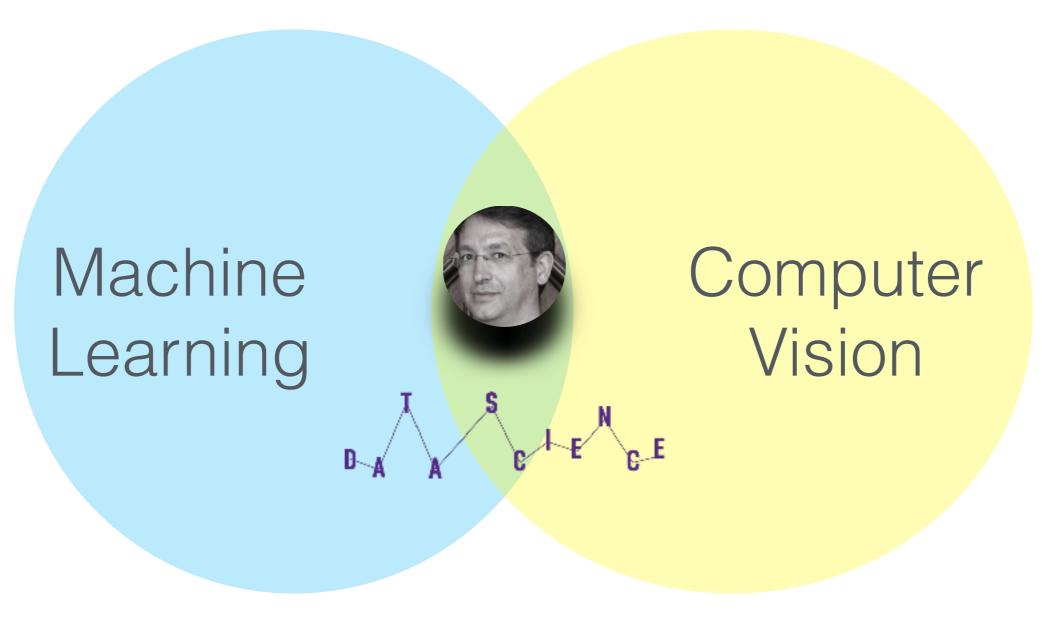
Images from https://distill.pub/2017/feature-visualization/

LET'S OPEN THE DEEP LEARNING BLACK BOX! JORDI VITRIÀ



jordi.vitria@ub.edu

Departament de Matemàtiques i Informàtica Universitat de Barcelona



Since 2007, I am a Full Professor at the Mathematics & Computer Science Department, Universitat de Barcelona. Before that I spent 20 years on the faculty of the CS Department at the Universitat Autonoma de de Barcelona. I am the Director of the Data Science & Big Data Postgraduate Course and the Foundations of Data Science Master at UB. I am the leader of the DataScience@UB group, whose objective is to promote technology transfer.



Some examples of our research (that involve **deep learning** methods)

end-to-end learning

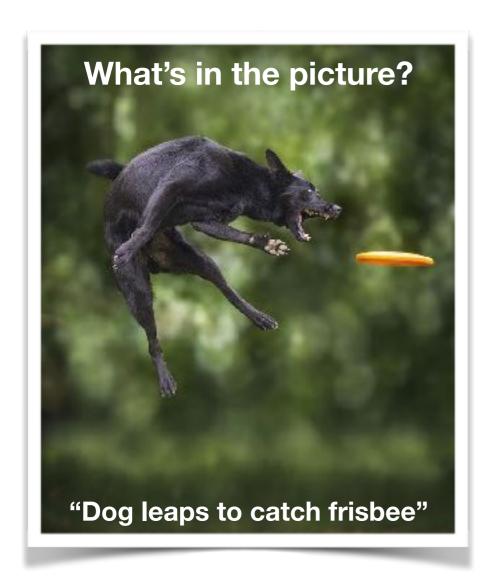
deep neural networks

"black box" learning...



Extracting non visual attributes from images using CNN.

Non-visual attributes are those attributes of an image that can be inferred from visual information but do not have a clear correspondence on the image.







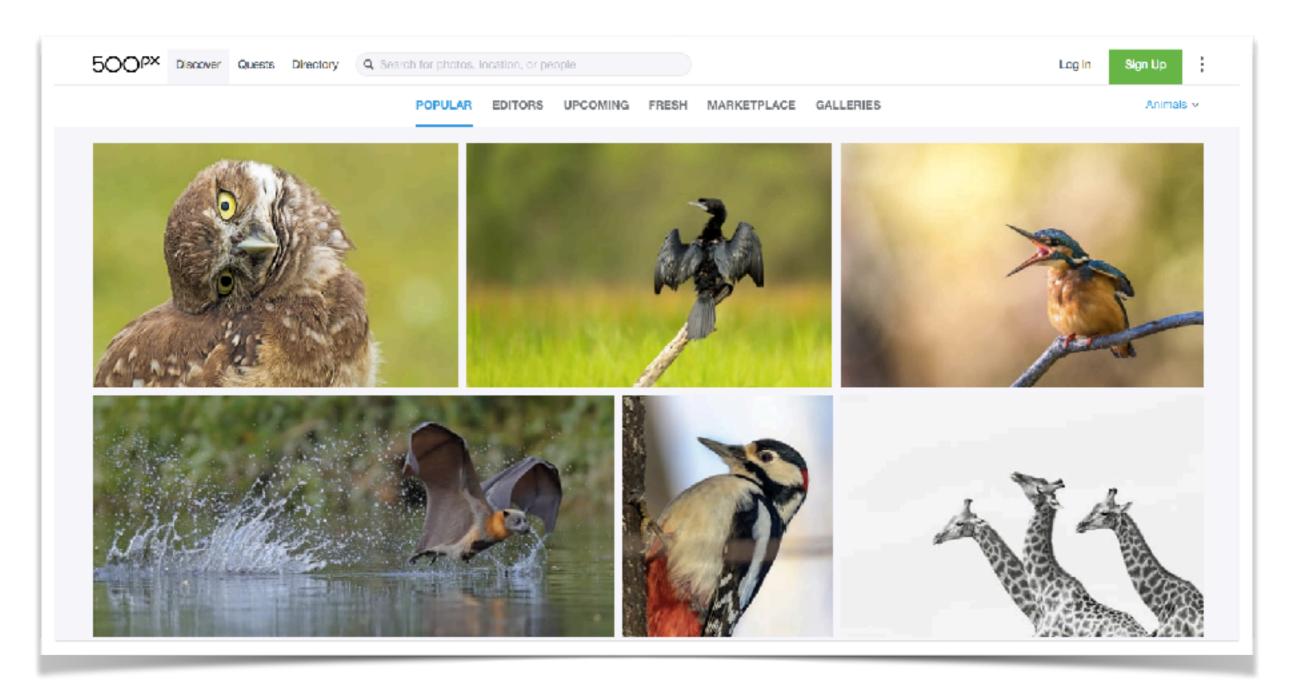




Which apartment is, a priori, more successful on Airbnb?



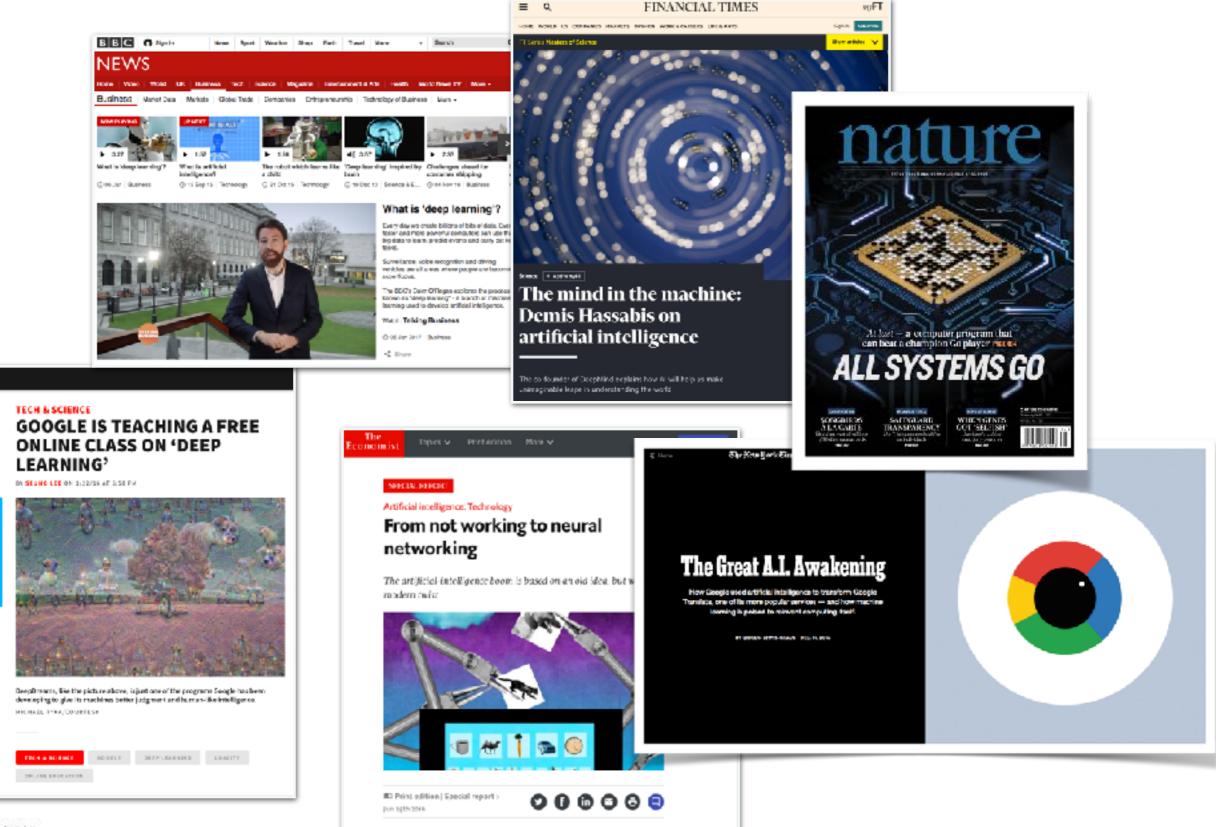
Online photo marketplace



Which is the expected popularity of these images?



Is Deep Learning Overhyped?





Objectives

1. What is Deep Learning?

or how to train large and highly complex models with deeply cascaded nonlinearities by using automatic differentiation and several tricks.

Deep Learning is not magic.

2. What are the main applications of Deep Learning?

computer vision, natural language, speech, recommenders, time series, etc.

3. What are the main limitations of Deep Learning?

Deep Learning is not the final machine learning method.

4. How to build deep learning models?

Keras, Tensorflow...





History





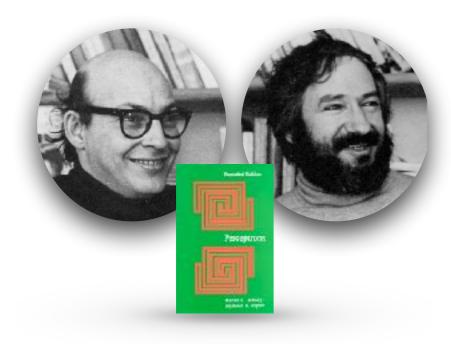




- In 1943, neurophysiologist Warren McCulloch and mathematician Walter Pitts wrote a paper on how neurons might work. In order to describe how neurons in the brain might work, they modeled a simple neural network using electrical circuits.
- In 1949, Donald **Hebb** wrote *The Organization of Behavior*, a work which pointed out the fact that neural pathways are strengthened each time they are used, a concept fundamentally essential to the ways in which humans learn. If two nerves fire at the same time, he argued, the connection between them is enhanced.
- In 1957 **Frank Rosenblatt** attempted to build a kind of mechanical brain called the **Perceptron**, which was billed as "a machine which senses, recognizes, remembers, and responds like the human mind".



• In 1962, **Widrow & Hoff** developed a learning procedure that examines the value before the weight adjusts it (i.e. 0 or 1) according to the rule: Weight Change = (Pre-Weight line value) * (Error / (Number of Inputs)). It is based on the idea that while one active perceptron may have a big error, one can adjust the weight values to distribute it across the network, or at least to adjacent perceptrons.



• A critical book written in 1969 by **Marvin Minsky** and his collaborator **Seymour Papert** showed that Rosenblatt's original system was painfully limited, literally blind to some simple logical functions like "exclusive-or" (As in, you can have the cake or the pie, but not both). What had become known as the field of "neural networks" all but disappeared.



First neural network winter is coming











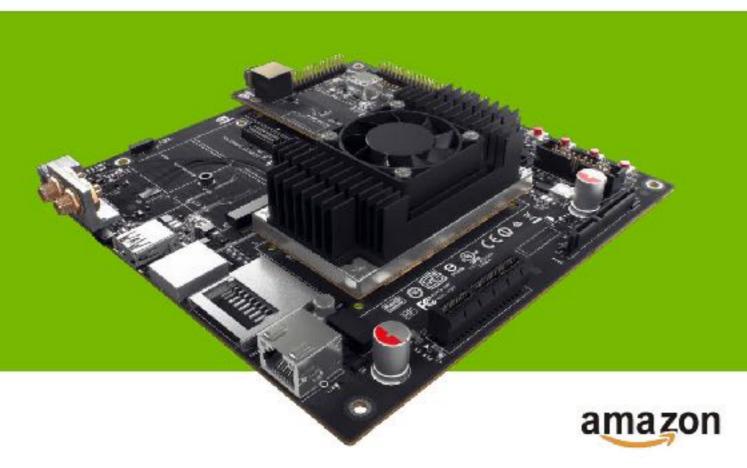
- In 1982, interest in the field was renewed. **John Hopfield** of Caltech presented a paper to the National Academy of Sciences. His approach was to create more useful machines by using bidirectional lines. Previously, the connections between neurons was only one way.
- In 1986, the problem was how to extend the Widrow-Hoff rule to multiple layers. Three independent groups of researchers, which included David E. Rumelhart, Geoffrey E. Hinton and Ronald J. Williams, came up with similar ideas which are now called backpropagation networks because it distributes pattern recognition errors throughout the network.
- From 1986 to mid 90's new developments arised: convolutional neural networks (Y.LeCun), unsupervised learning (Y.Bengio), RBM (G.Hinton), etc. But, by this point new machine learning methods had begun to also emerge, and people were again beginning to be skeptical of neural nets since they seemed so intuition-based and since computers were still barely able to meet their computational needs.

Second neural network winter is coming



- With the ascent of Support Vector Machines and the failure of backpropagation, the early 2000s were a dark time for neural net research.
- Then, what every researcher must dream of actually happened: G.Hinton, S.Osindero, and Y.W.Teh published a paper in 2006 that was seen as a breakthrough, a breakthrough significant enough to rekindle interest in neural nets: A fast learning algorithm for **deep** belief nets.
- After that, following Moore's law, computers got dozens of times faster (GPUs) since the slow days of the 90s, making learning with large datasets and many layers much more tractable.





Jetson TX1 Developer Kit \$599 retail \$299 edu Pre-order Nov 12 Shipping Nov 16 (US) Intl to follow

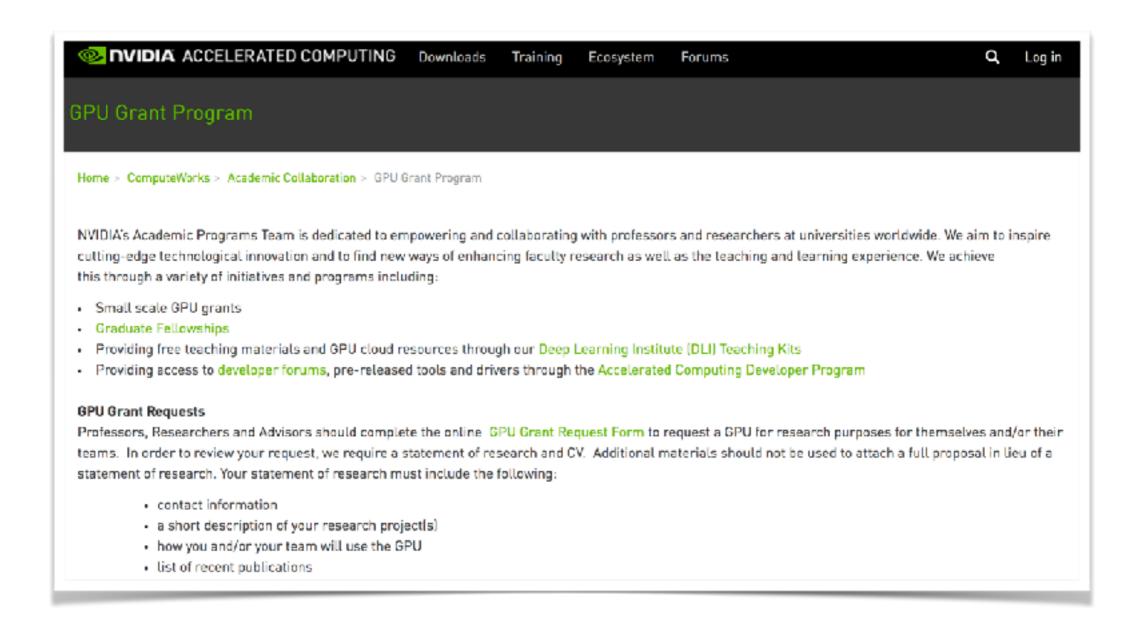






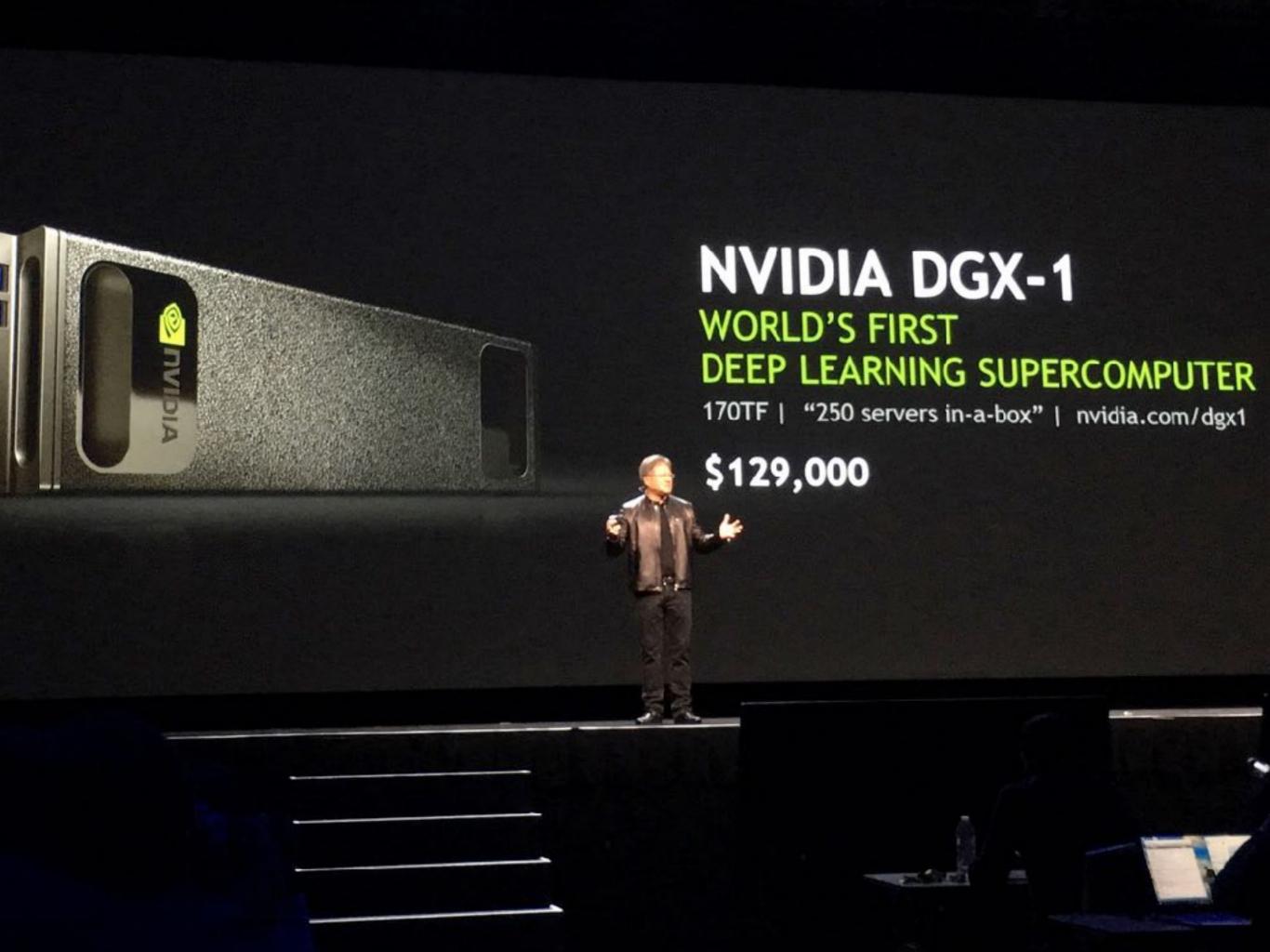


GPU democratization



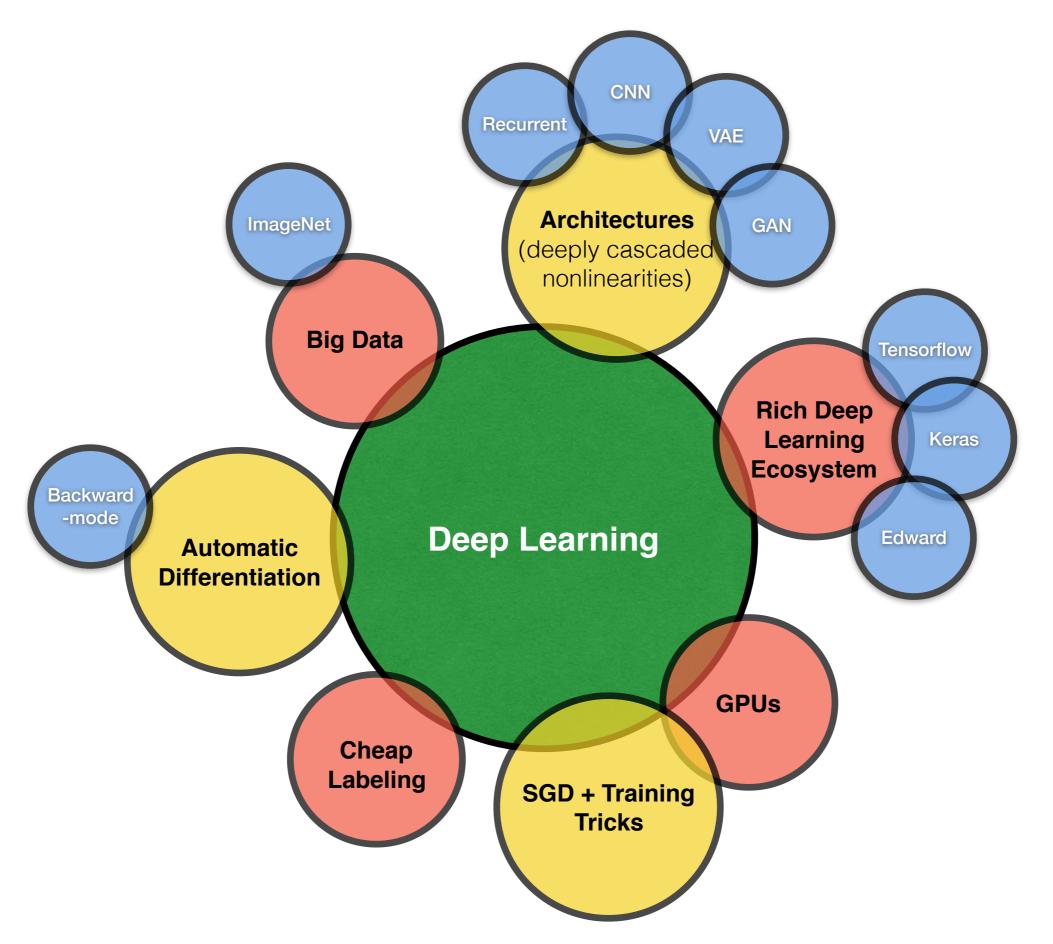
Thank you NVIDIA!





Definitions

- Neural Networks (NN) is a beautiful biologicallyinspired programming paradigm which enables a computer to learn from observational data.
- Deep Learning (DL) is a powerful set of techniques (and tricks) for learning in deep neural networks.
- NN and DL currently provide the best solutions to many problems in image recognition, speech recognition, and natural language processing.





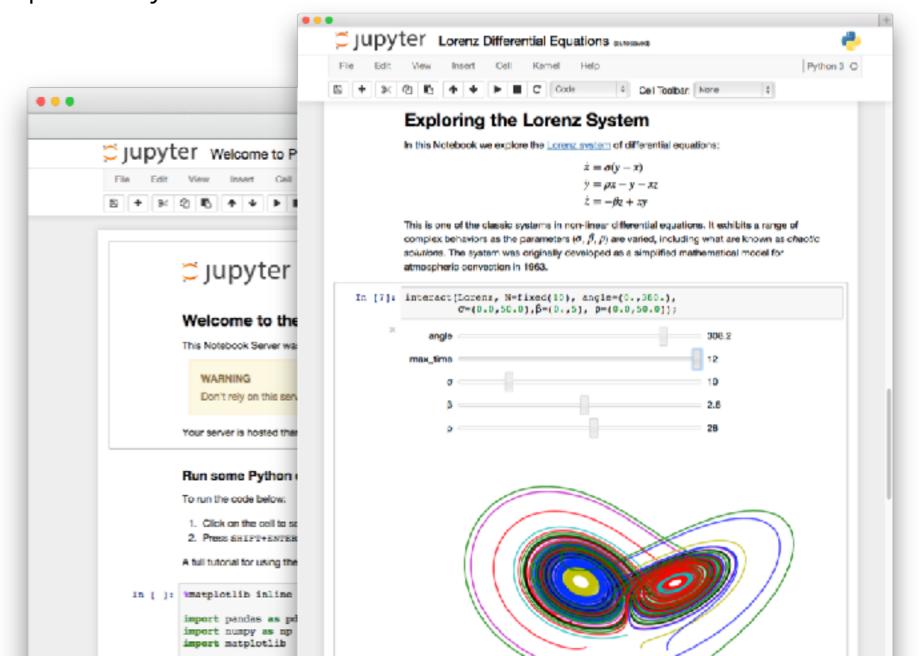
Our objectives

- Optimization and Automatic Differentiation
- Programming a Neural Network
- Design and Train a Deep Model



Approach

We will illustrate all contents with **Jupyter notebooks**, a web application that allows you to create and share documents that contain live code, equations, visualizations and explanatory text.





Approach

docker

We will use a **Docker Container**.

Docker provides the ability to build a runtime environment that not only remains isolated from other running containers, but also can be deployed to multiple locations in a repeatable way.

Docker also uses a text document – a Dockerfile – that contains all the commands to assemble an image, which will meet our need to document the build environment.

Finally, Docker's runtime options enable us to attach GPU devices when deploying on remote servers.



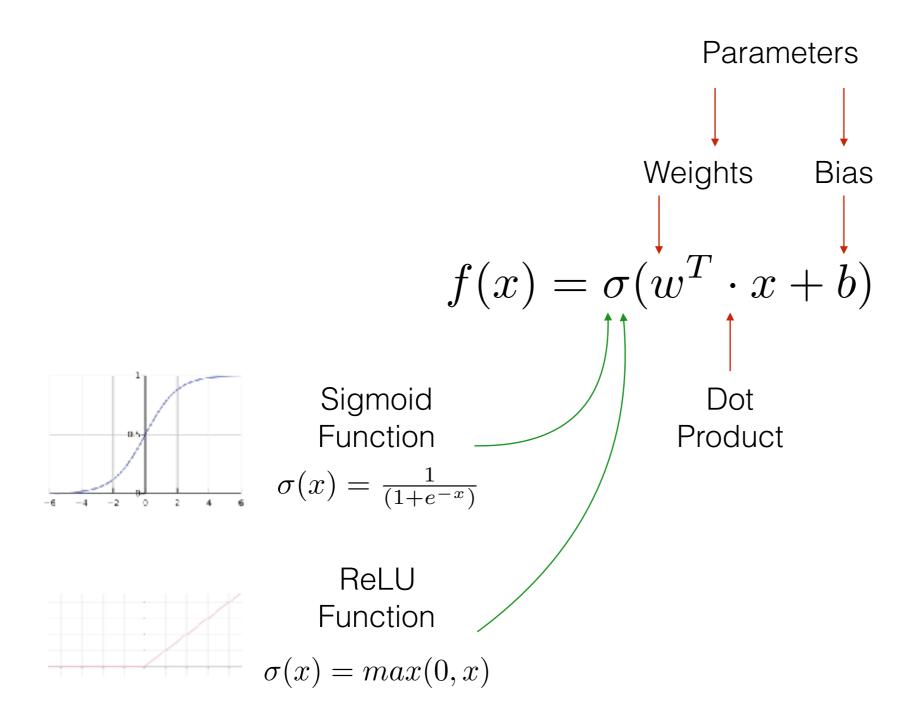
The problem: machine learning

Numeric features that characterize your cases

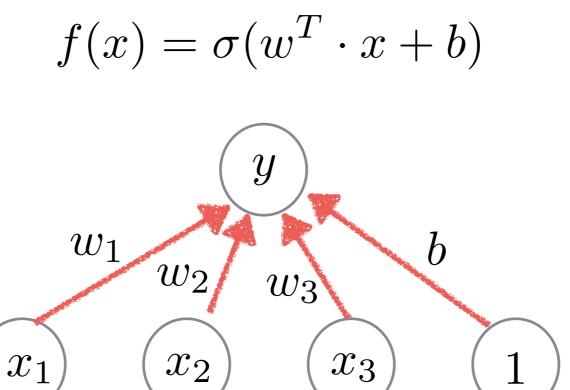
Your desired outcomes

Training data: a set of $(x^{(m)}, y^{(m)})$ pairs. Learn a function $f_w : x \to y$ to predict on new inputs x.

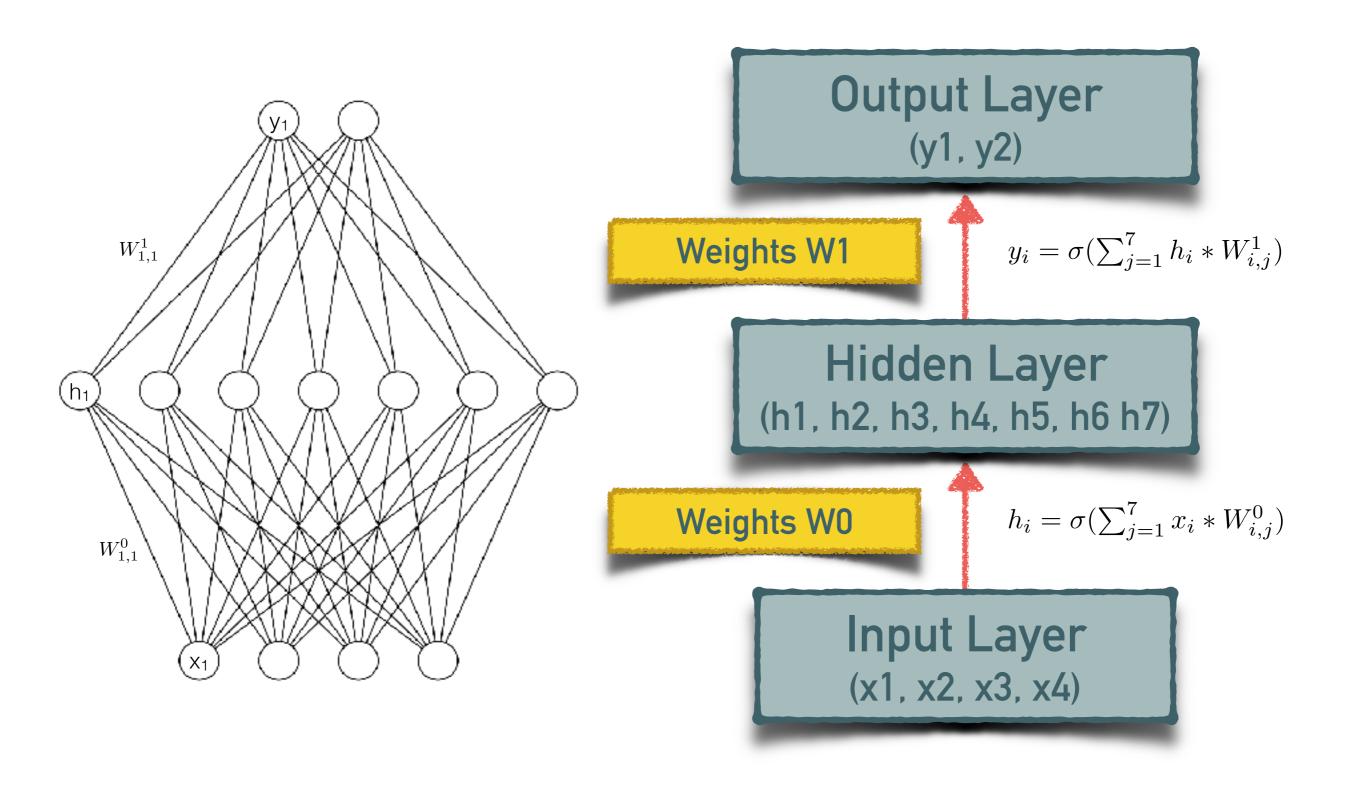
- 1. Choose a model function family f_w .
- 2. Optimize parameters w.







Graphical Representation



- How to find the parameters of the function?
- We can use optimization techniques (minimizing a function, the loss function, that measures the discrepancy between the outcomes of a model and the desired outcomes.
- To optimize, we must compute the derivative of every parameter with respect to the loss function.
- But we have (possibly) millions of parameters and the loss function is a (possibly) large composition of functions...



Automatic Differentiation

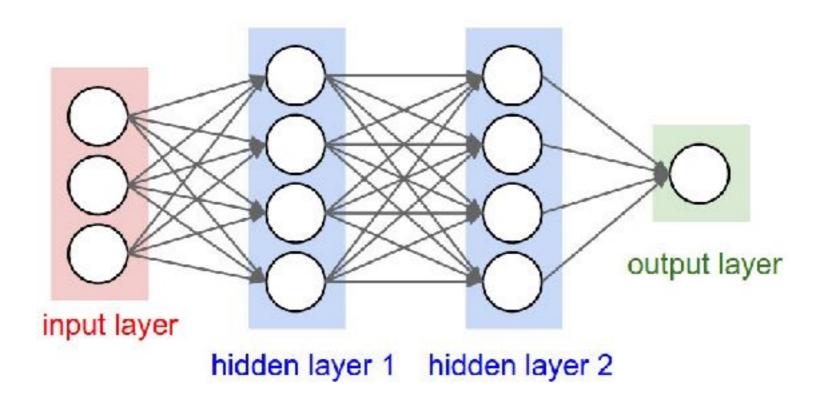
```
import autograd.numpy as np # Thinly-wrapped version of Numpy
from autograd import grad
def taylor_sine(x): # Taylor approximation to sine function
    ans = currterm = x
   i = 0
    while np.abs(currterm) > 0.001:
        currterm = -currterm * x^{**2} / ((2 * i + 3) * (2 * i + 2))
        ans = ans + currterm
        i += 1
    return ans
grad_sine = grad(taylor_sine)
print "Gradient of sin(pi) is", grad_sine(np.pi)
```



SGD-based logistic regression

```
import autograd.numpy as np
from autograd import grad
def sigmoid(x):
    return 0.5*(np.tanh(x) + 1)
def logistic_predictions(weights, inputs):
    # Outputs probability of a label being true according to logistic model.
    return sigmoid(np.dot(inputs, weights))
def training loss(weights):
    # Training loss is the negative log-likelihood of the training labels.
    preds = logistic_predictions(weights, inputs)
    label_probabilities = preds * targets + (1 - preds) * (1 - targets)
    return -np.sum(np.log(label probabilities))
# Build a toy dataset.
inputs = np.array([[0.52, 1.12, 0.77],
                   [0.88, -1.08, 0.15],
                   [0.52, 0.06, -1.30],
                   [0.74, -2.49, 1.39]])
targets = np.array([True, True, False, True])
# Define a function that returns gradients of training loss using autograd.
training_gradient_fun = grad(training_loss)
# Optimize weights using gradient descent.
weights = np.array([0.0, 0.0, 0.0])
print "Initial loss:", training_loss(weights)
for i in xrange(100):
    weights -= training_gradient_fun(weights) * 0.01
print "Trained loss:", training loss(weights)
```

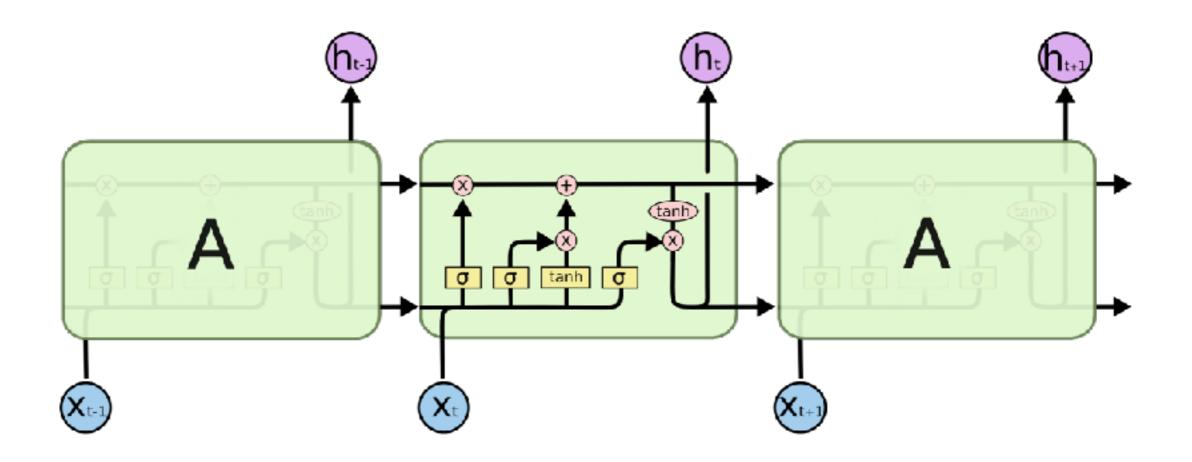
Architectures



Each layer is a function, acting on the output of a previous layer. As a whole, the network is a chain of composed functions. This chain of composed functions is optimized to perform a task.

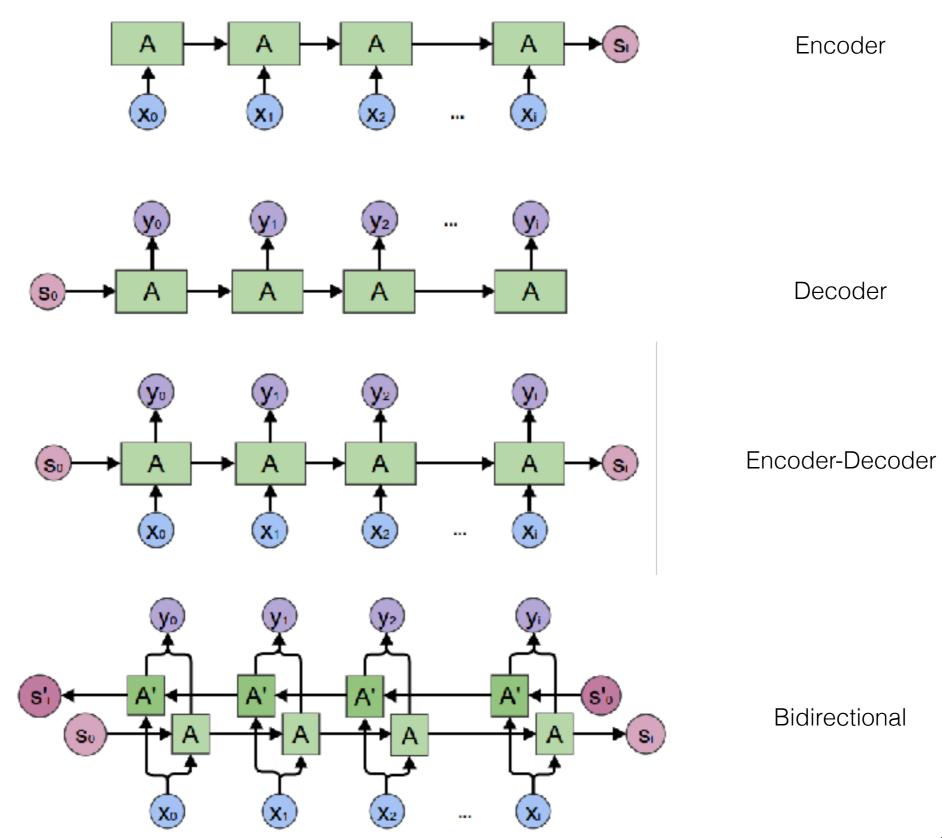


Recurrent neural layer model



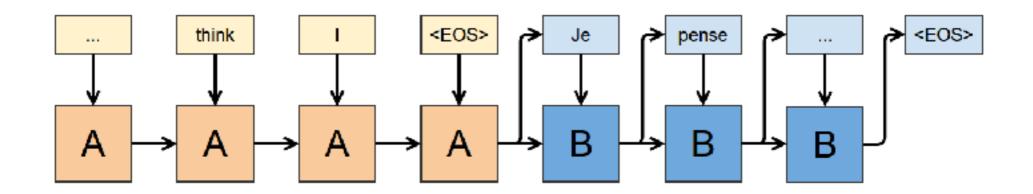


Recurrent neural layer model



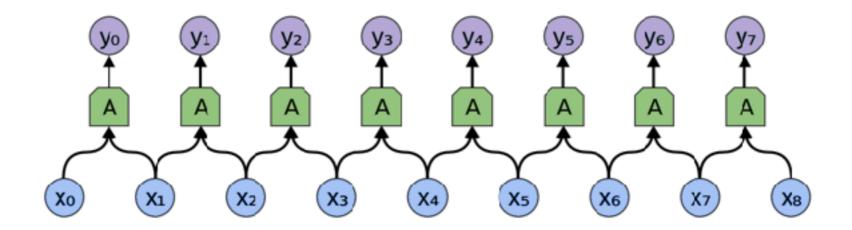


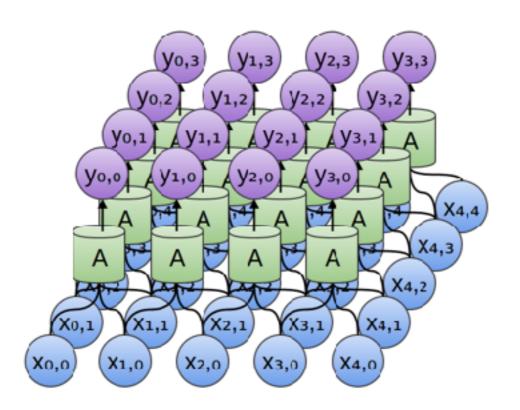
Recurrent neural layer model





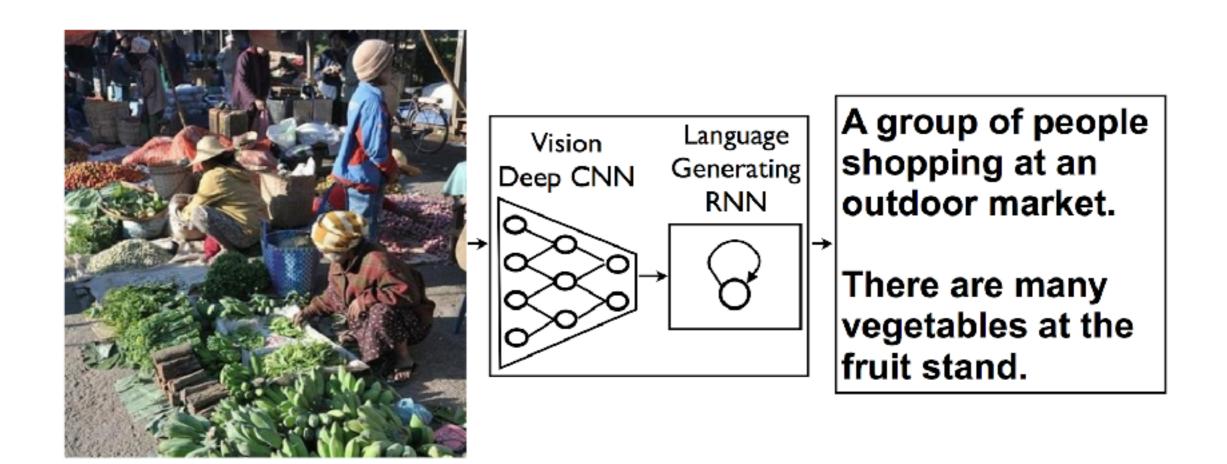
Convolutional neural layer model



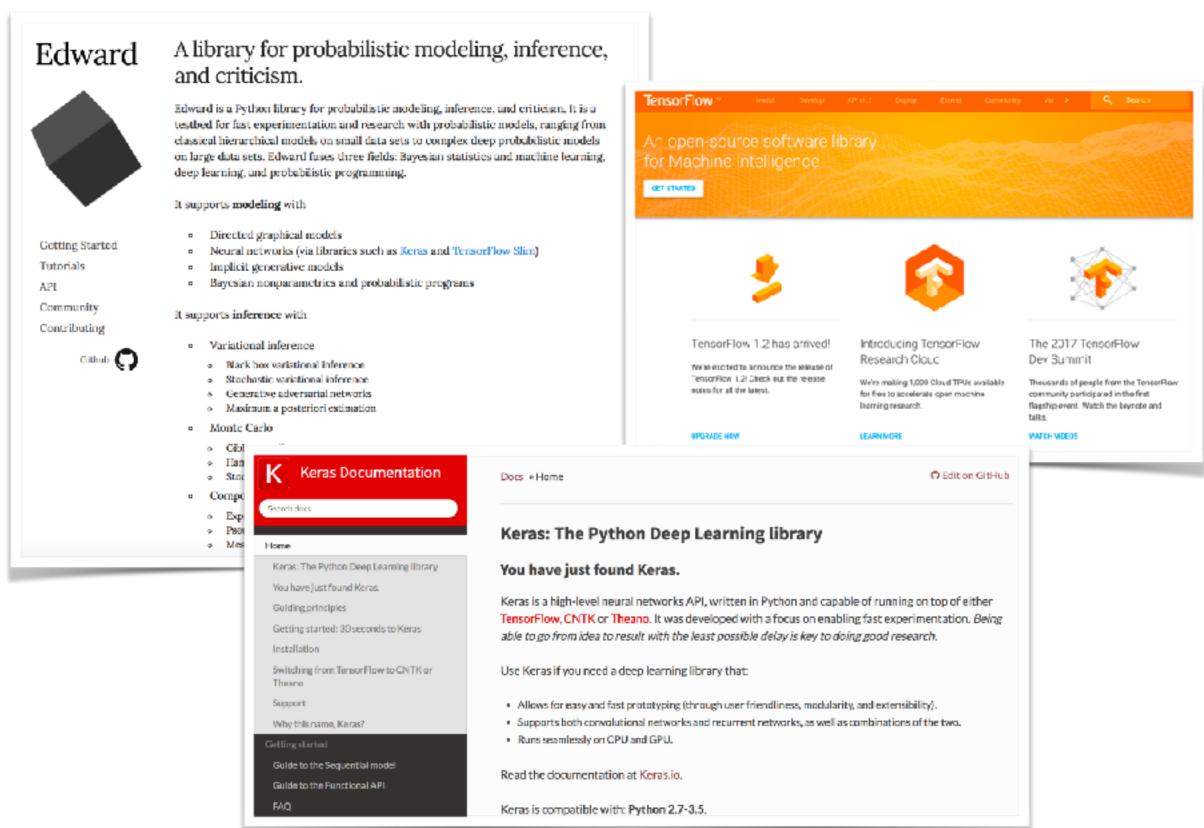




CNN + RNN



Deep Learning Ecosystem



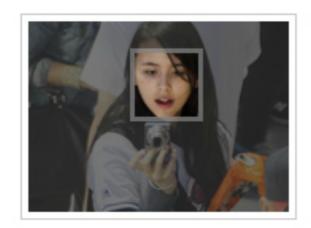


"Classical" applications: object classification, detection and segmentation.

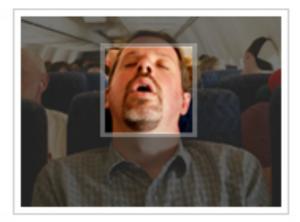




Face recognition.







Who is this?

Who is this?

Who is this?







Who is this?

Who is this?

Who is this?

DeepFace (Facebook): Accuracy of 97.35%



New applications: navigation and mapping.





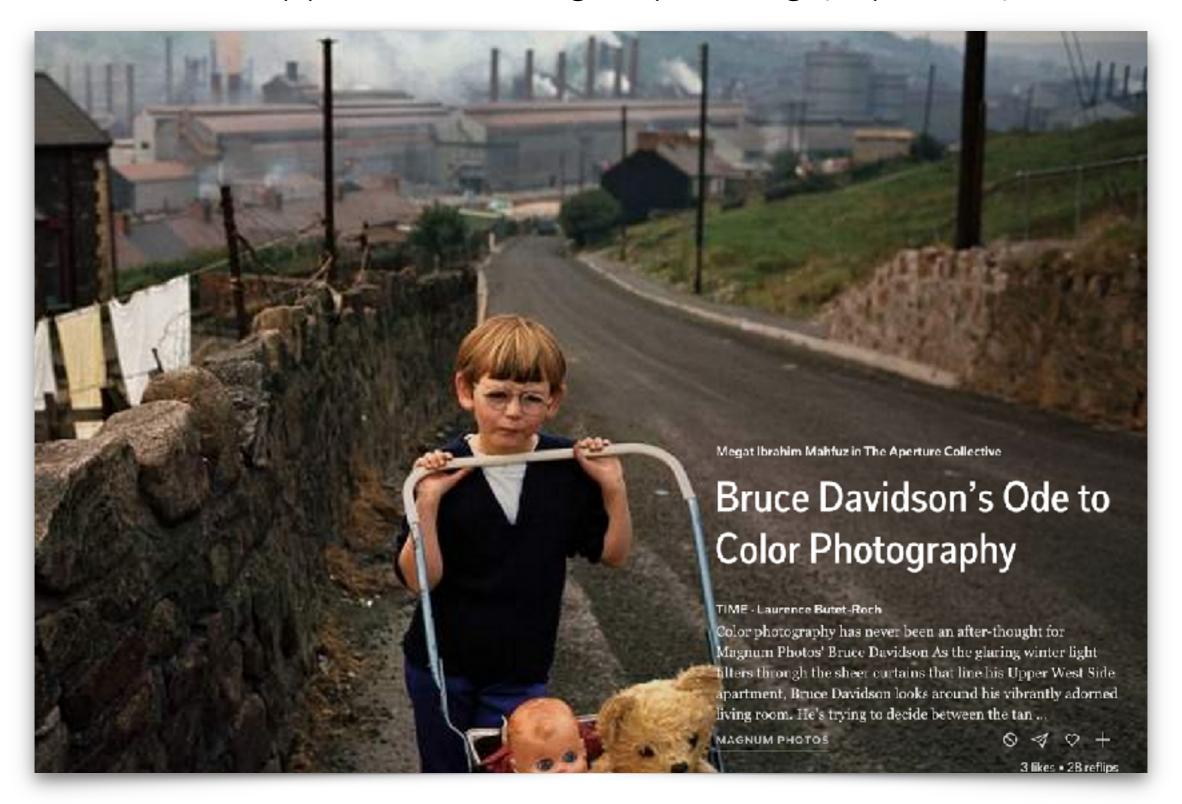
New applications: Image Upscaling (Flipboard)



http://engineering.flipboard.com/2015/05/scaling-convnets/



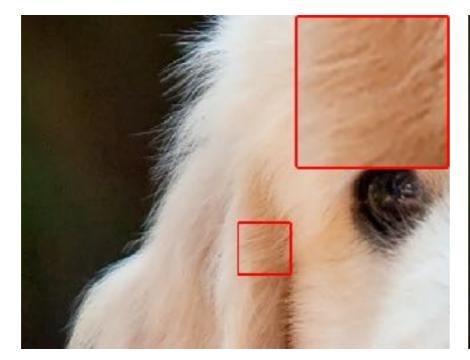
New applications: Image Upscaling (Flipboard)

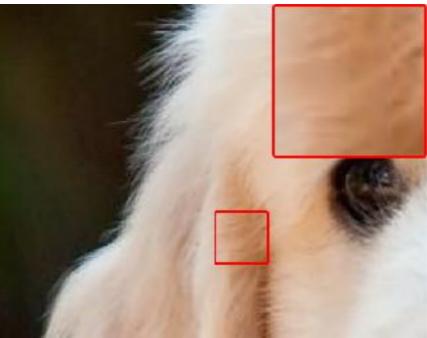


http://engineering.flipboard.com/2015/05/scaling-convnets/



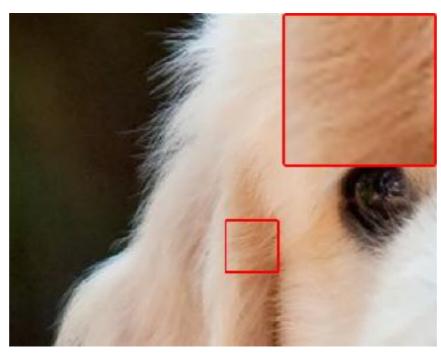
New applications: Image Upscaling (Flipboard)





Original

Bicubic



Model

http://engineering.flipboard.com/2015/05/scaling-convnets/



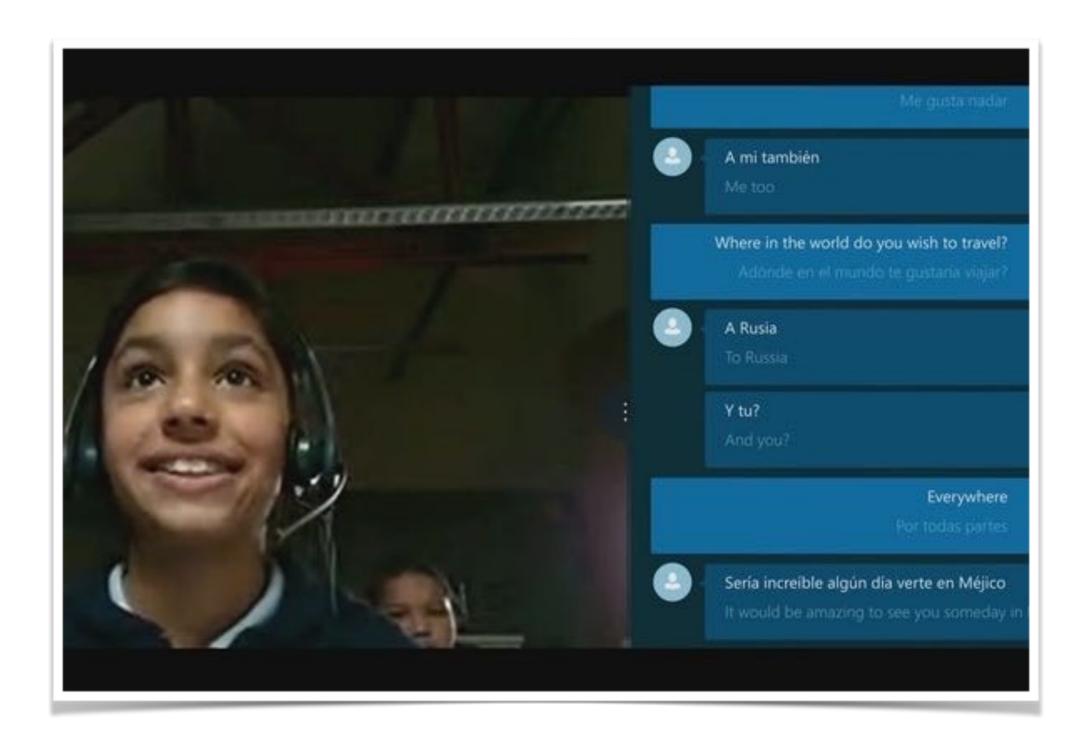
New applications: Automatic Image Captioning



http://blogs.technet.com/b/machinelearning/archive/2014/11/18/rapid-progress-in-automatic-image-captioning.aspx

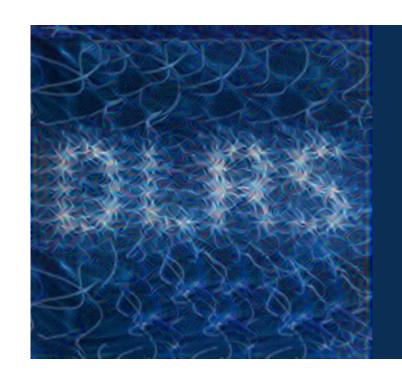


Speech translation





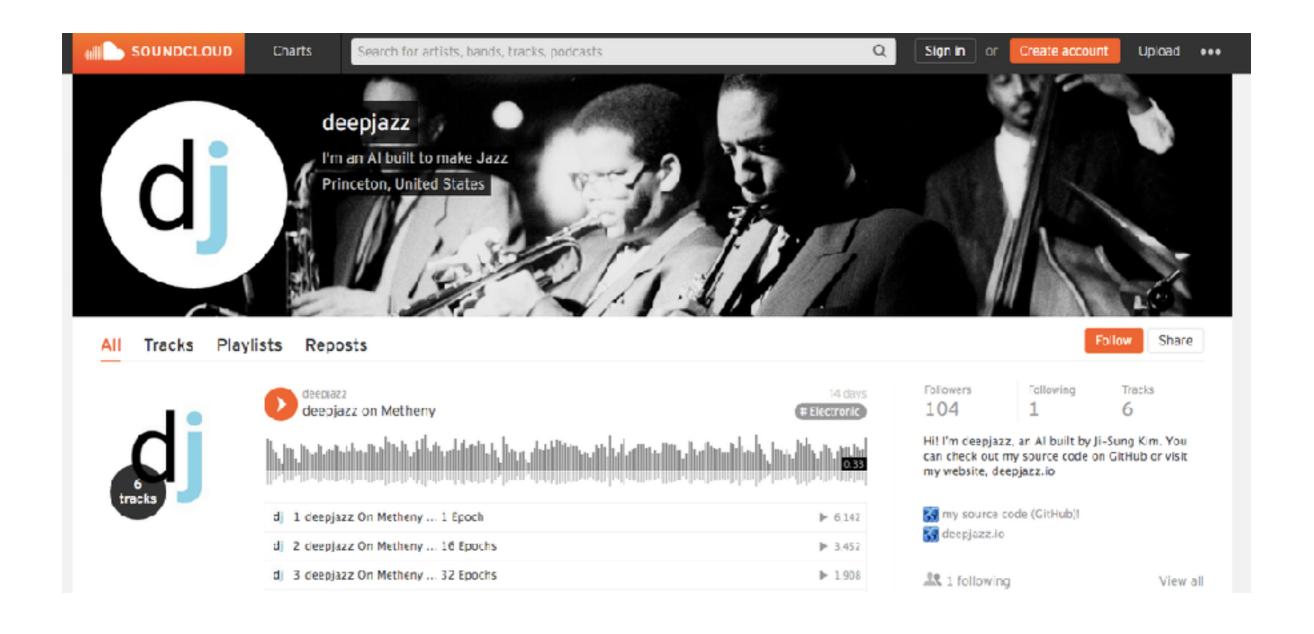
Recommenders



1st Workshop on Deep Learning for Recommender Systems

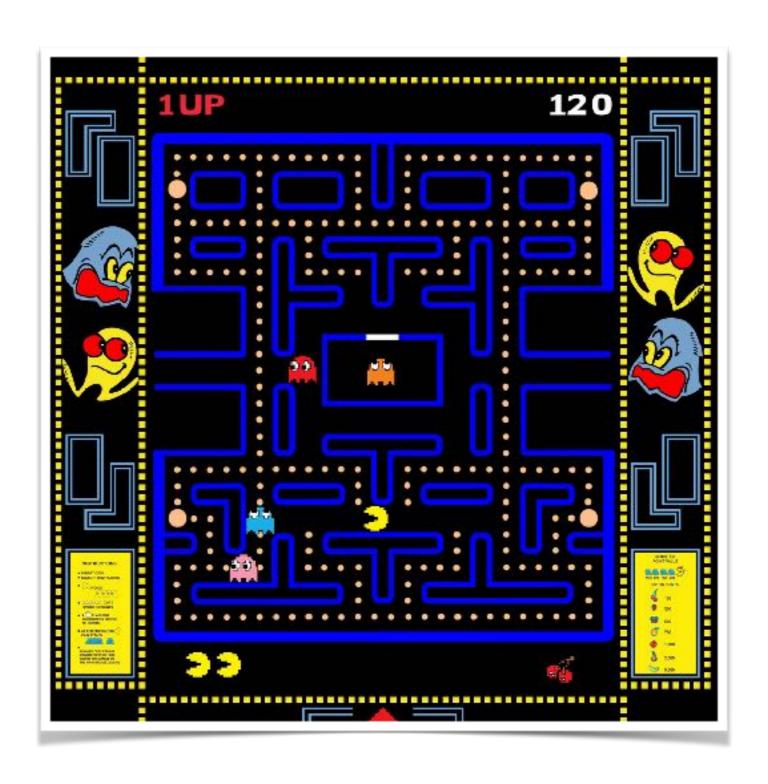
in conjunction with RecSys 2016 15 September 2016, Boston, USA

Music Generation





Reinforcement learning.





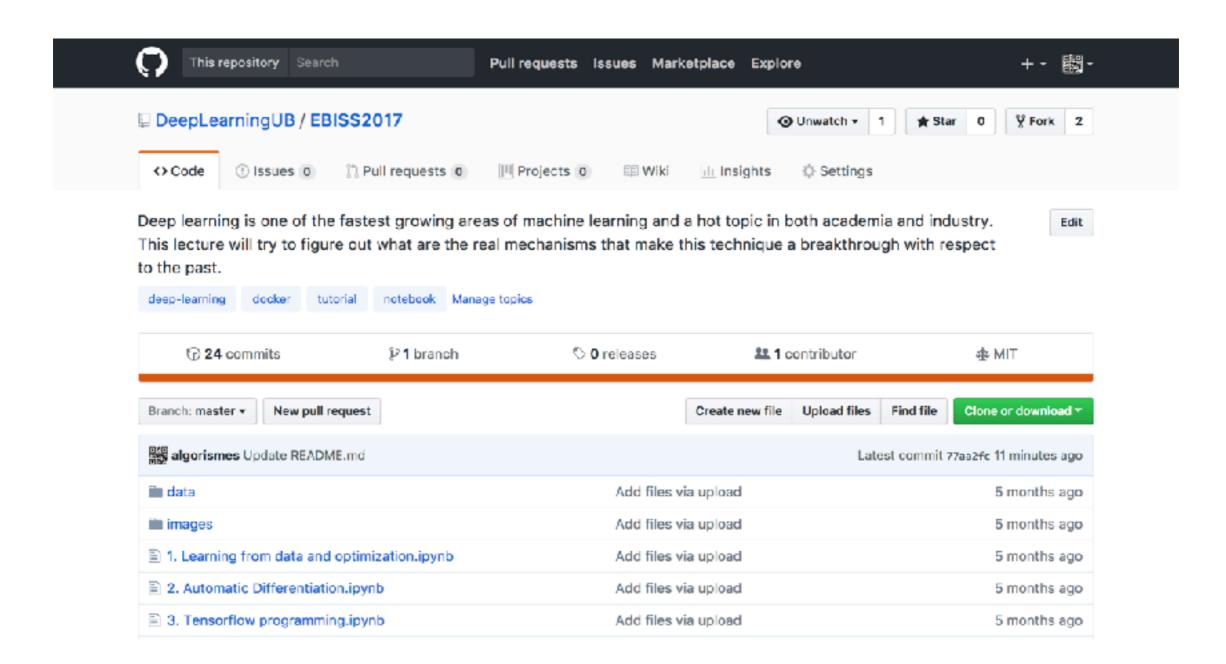
Go





Hands On!

Open https://github.com/DeepLearningUB/EBISS2017 in your browser





Hands On!

Open a terminal window

Last login: Sun Jul 2 11:55:22 on ttys001
MacBookProJordi:~ jordi\$

Go to the working directory of your choice

```
eBISS2017 — -bash — 80×13

Last login: Sun Jul 2 11:55:22 on ttys001

MacBookProJordi:~ jordi$ cd Dropbox/eBISS2017/

MacBookProJordi:eBISS2017 jordi$
```



Hands On!

Start your docker image

```
eBISS2017 — -bash — 82×10

Last login: Sun Jul 2 12:27:25 on ttys002

MacBookProJordi:~ jordi$ cd Dropbox/eBISS2017/

MacBookProJordi:eBISS2017 jordi$ docker run -it -p 8888:8888 -v /$(pwd):/notebooks datascienceub/deepubebiss2017
```

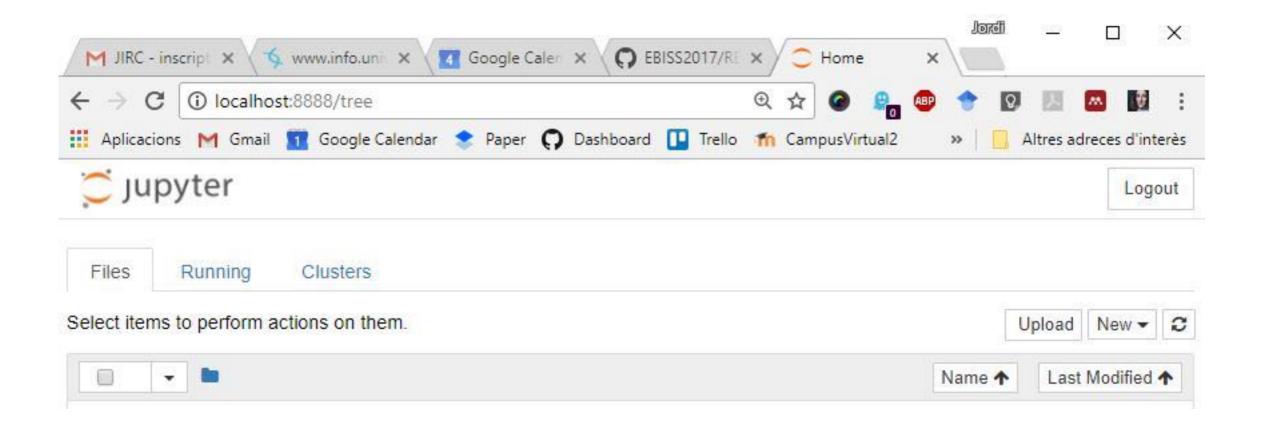
and go with your default browser to

localhost:8888

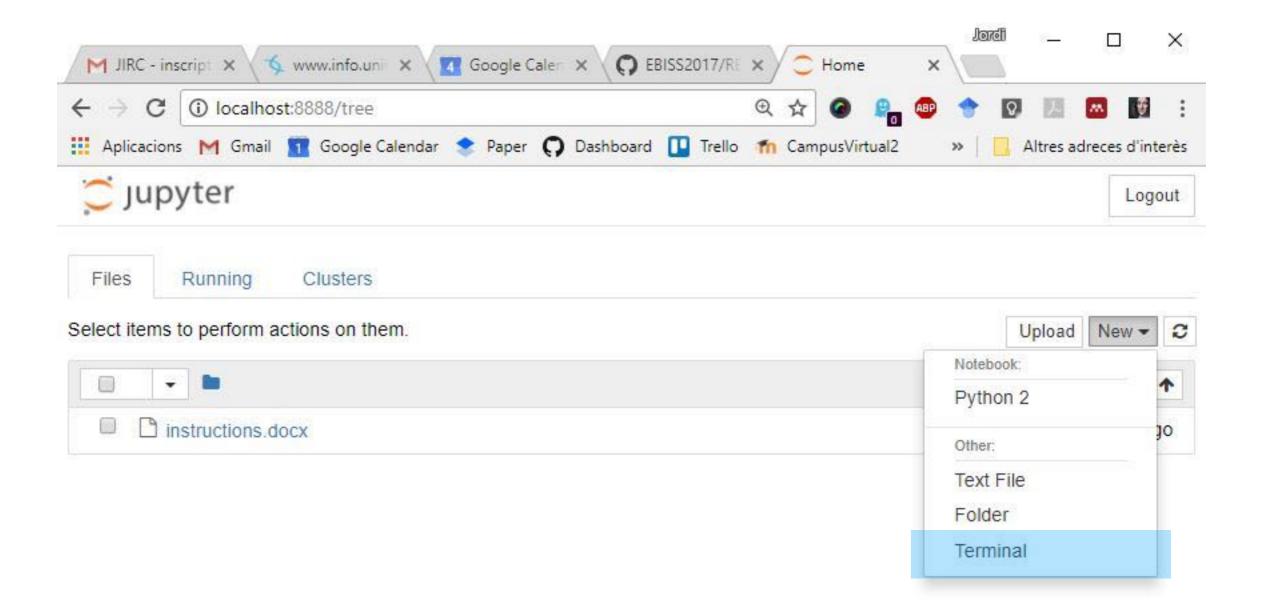
The fist time you connect you will get this message:

Copy/paste this URL into your browser when you connect for the first time, to login with a token: http://localhost:8888/?token=defbc4266e1de04bde6055ed0c0832c6e803c0efdbf74960









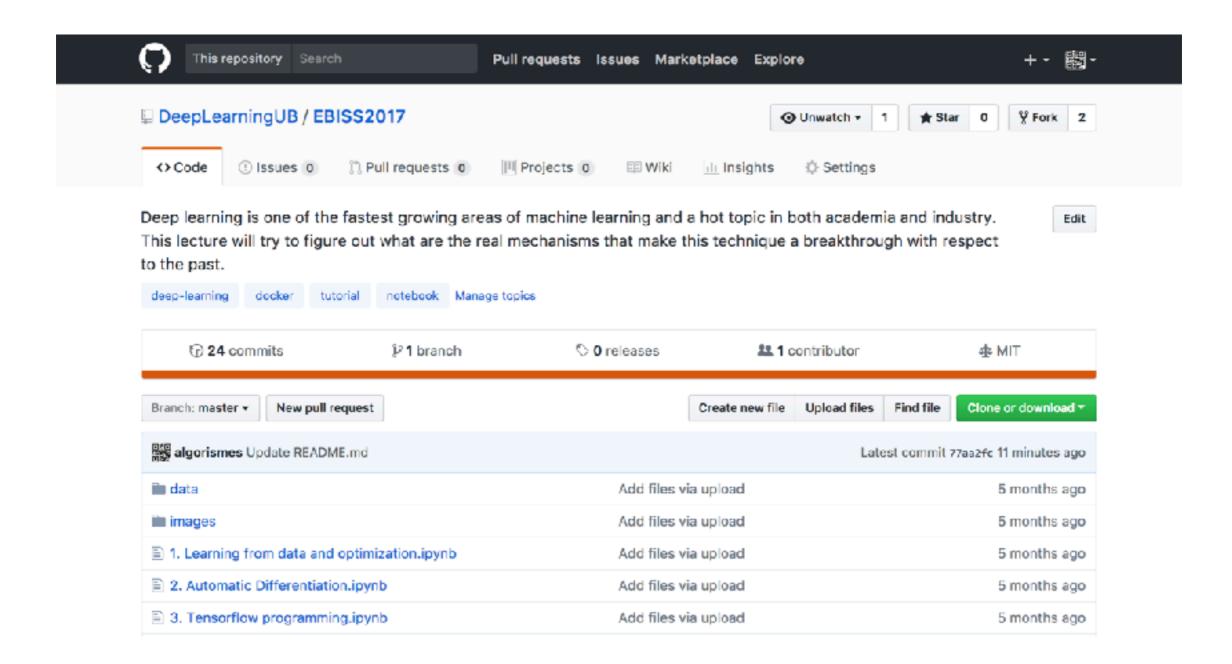


```
×
  M JIRC - in: X ( 6 xxww.info X ) T Google ( X ) C EBISS20 X
                                                                                                                     localhos: X
                 (i) localhost:8888/terminals/1
👬 Aplicacions M Gmail 🔞 Google Calendar 🌻 Paper 🞧 Dashboard 🔃 Trello 📸 CampusVirtual2.
                                                                                                                                          Altres adreces d'interes
  ijupyter 💆
                                                                                                                                                               Logout
# git clone https://github.com/DeepLearningUB/EBI552817
Cloning into 'EBISS2017'...
remote: Counting objects: 94, done.
remote: Compressing objects: 100% (8/8), done.
Unpacking objects: 32% (31/94)
```

git clone https://github.com/DeepLearningUB/EBISS2017



https://github.com/DeepLearningUB/EBISS2017





We can start to code!

