\>>> Introduction to Deep Learning
\>>> The force Awakens

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>>> $ whoami

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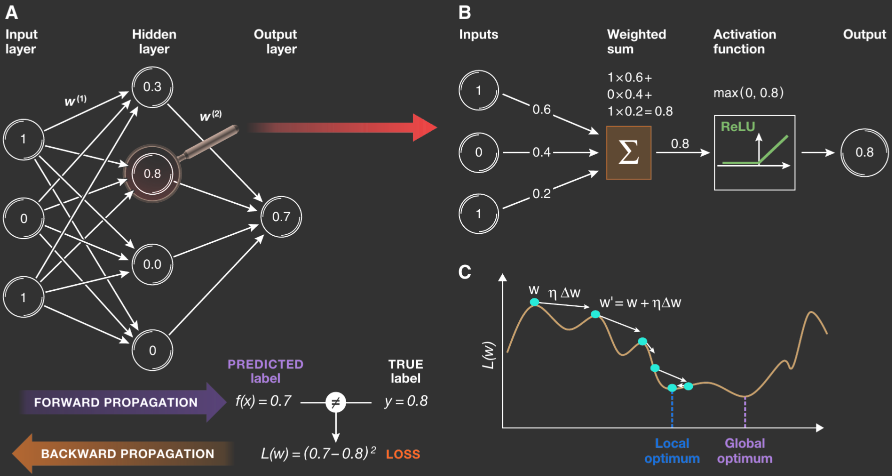
2. Member of the Image Sciences Lab (LCI - Bahia Blanca).
3. Professor at Engineering Department, Patagonian University UNPSJB.
4. Pythonista since 2008.
5. Happy member of LinuxChixAr.
6. Co-organizer of SciPy Latinoamericana[1] (2013, 2014) and Patagonia Python Meetup.

[1] http://conf.scipyla.org/

>>> Supervised Learning

It consists of inferring a function from labeled values. These values have the form of (X_i, y_i), where X_i is the input value and y_i is the corresponding output value. In the training stage, the values generated by the inferred function are compared with the actual values y_i to reduce the error and improve the generated function.

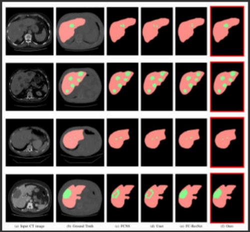
>>> Neural Nets

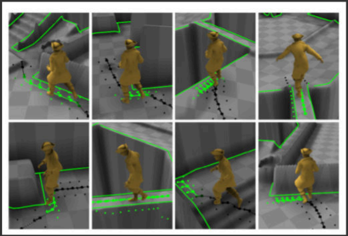


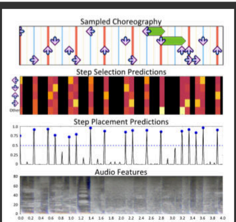
* http://onlinelibrary.wiley.com/doi/10.15252/msb.20156651/full

>>> What is Deep Learning?

Deep learning allows computational models composed of several processing layers to learn representations about data with multiple levels of abstraction and, through this, to discover precise representations in large volumes of data autonomously.







>>> Some nice applications examples

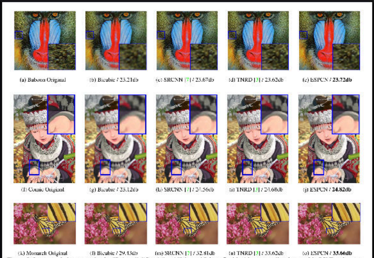
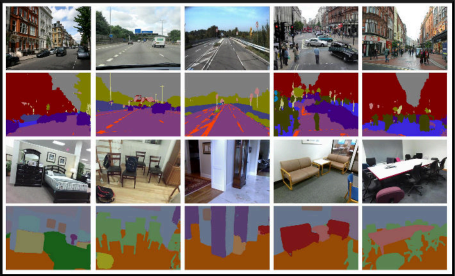
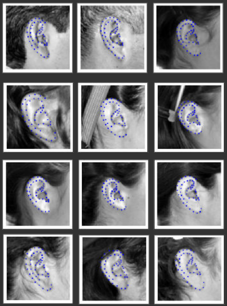


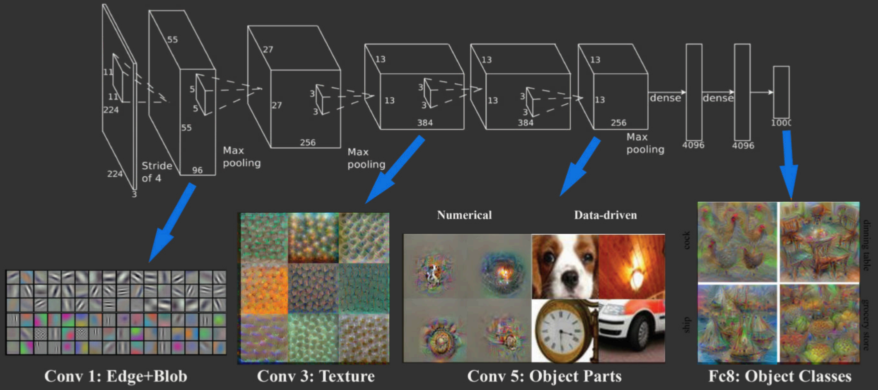
Figure 5. Super-resolution examples for "Baboon", "Comic" and "Monarch" from **Set14** with an upscaling factor of 3. PSNR values are shown under each sub-figure.





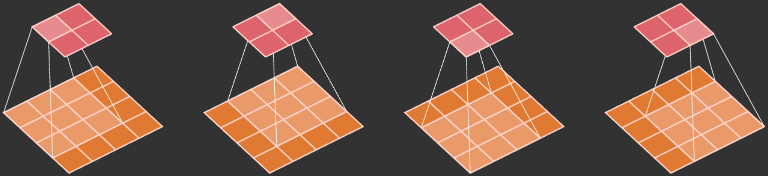
>>> ConvNets

A classic architecture ConvNet is given by two stages. The first stage focuses on extracting discriminant characteristics at different levels of abstraction and the second focuses on classification based on the characteristics previously obtained.



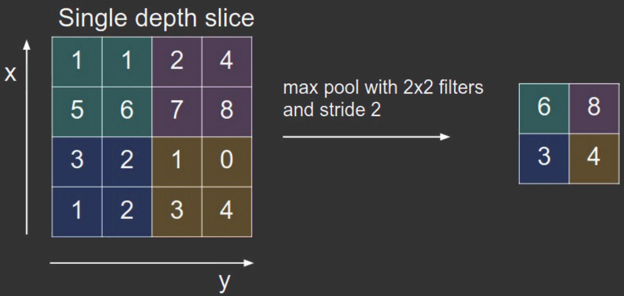
>>> Convolution Layer

Important concepts: number of kernels and their size, slide and zero padding.



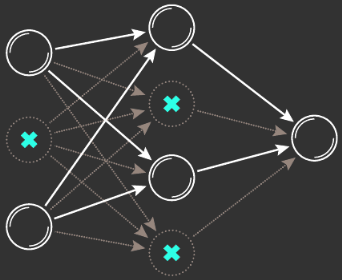
* A guide to convolution arithmetic for deep learning. Dumoulin, Vincent and Visin, Francesco.

>>> Max-Pooling



* http://cs231n.github.io/convolutional-networks/#pool

>>> Dropout



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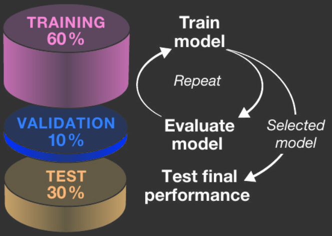
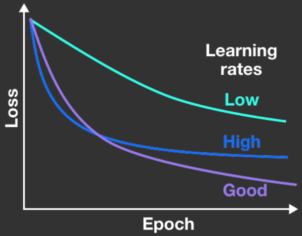
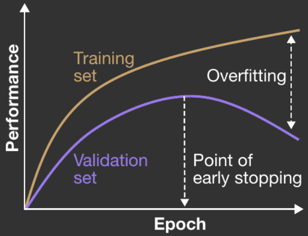
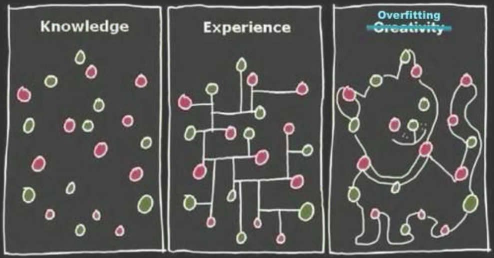
>>> Training, Validation and Evaluation









* http://onlinelibrary.wiley.com/doi/10.15252/msb.20156651/full

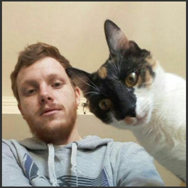
>>> Technologies

>>> Setup

- $ pip install numpy scipy pandas scikit-learn matplotlib
- $ pip install -r https://raw.githubusercontent.com/Lasagne/Lasagne/master/requirements.txt
- $ pip install https://github.com/Lasagne/Lasagne/archive/master.zip

Or with Docker:

- Docker-nvidia (https://github.com/NVIDIA/nvidia-docker)
- $ docker pull pablo1n7/tatooine:3.4 or $ docker pull pablo1n7/tatooine:2.7



* https://hub.docker.com/u/pablo1n7/

\>>> Demo Time!

>>> Next Stop

Stereotyping and Bias in the Flickr30K Dataset

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Abstract

An untested assumption behind the crowdsourced descriptions of the images in the Flickr30K dataset (Young et al., 2014) is that they "focus only on the information that can be obtained from the image alone" (Hodosh et al., 2013, p. 859). This paper presents some evidence against this assumption, and provides a list of biases and unwarranted inferences that can be found in the Flickr30K dataset. Finally, it considers methods to find examples of these, and discusses how we should deal with stereotype-driven descriptions in future applications.

Opening the black box of Deep Neural Networks via Information

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Under review as a conference paper at ICLR 2017

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>>> Other Libraries for Deep Learning with Python

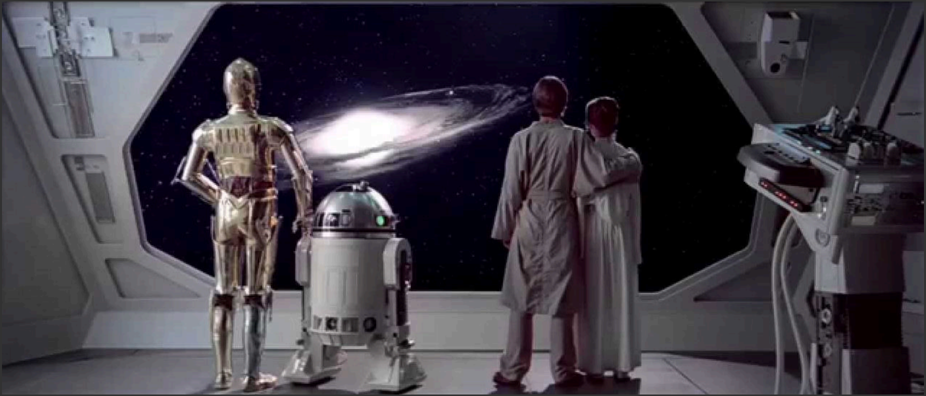
PYTORCH

TensorFlow™

Keras

\>>> Gracias!

https://github.com/celiacintas/star_wars_hackathon



* Neural Networks and Deep Learning online book
* 231n: Convolutional Neural Networks for Visual Recognition
* Unsupervised Feature Learning and Deep Learning.

>>> Nice papers to read ..

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* Krizhevsky, A., Sutskever, I., & Geoffrey E., H. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Advances in Neural Information Processing Systems 25 (NIPS2012), 1-9.

>>> Nice papers to read .. (Cont.)

* Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. Journal of Machine Learning Research, 15, 1929-1958.
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* Badrinarayanan, Vijay; Handa, Ankur; Cipolla, Roberto. SegNet: A Deep Convolutional Encoder-Decoder Architecture for Robust Semantic Pixel-Wise Labelling.

>>> Nice papers to read .. (Cont.)

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