>>> Introducción a Deep Learning con Python

>>> El despertar de la fuerza

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>>> $ whoami

1. Doctoranda en Cs de la Computación, trabajando en el Centro de Investigación Patagónico (CENPAT-CONICET) dentro del Grupo de Investigación en Biología Evolutiva Humana (GIBEH).
2. Miembro del Laboratorio de Ciencias de las Imágenes[1] (LCI - Bahia Blanca).
3. Pythonera desde 2009, entusiasta del software libre.
4. Feliz miembro de LinuxChixAr.
5. Co-organizadora de SciPy Latinoamericana[2] (2013, 2014) y del Grupo Patagonia Python Meetup[3].
6. Docente de la UNPSJB.

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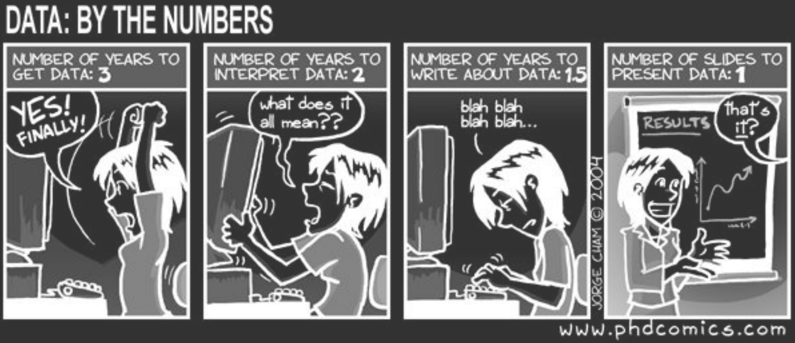
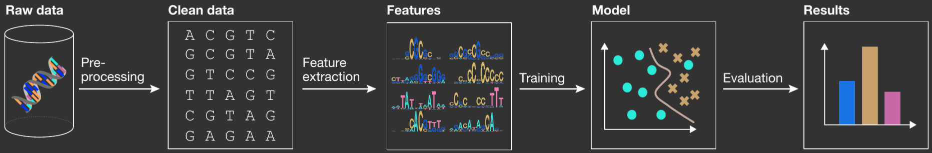
[1] http://imaglabs.org/
[2] http://conf.scipyla.org/
[3] https://www.meetup.com/Patagonia-Python-Meetup/

>>> Aprendizaje Supervisado

Consiste en inferir una función a partir de valores etiquetados. Estos valores tienen la forma de (X_i, y_i), donde X_i es el valor de entrada y y_i es el valor de salida correspondiente. En etapa de entrenamiento se comparan los valores generados por la función inferida vs. los valores reales y_i para reducir el error y mejorar la función generada.

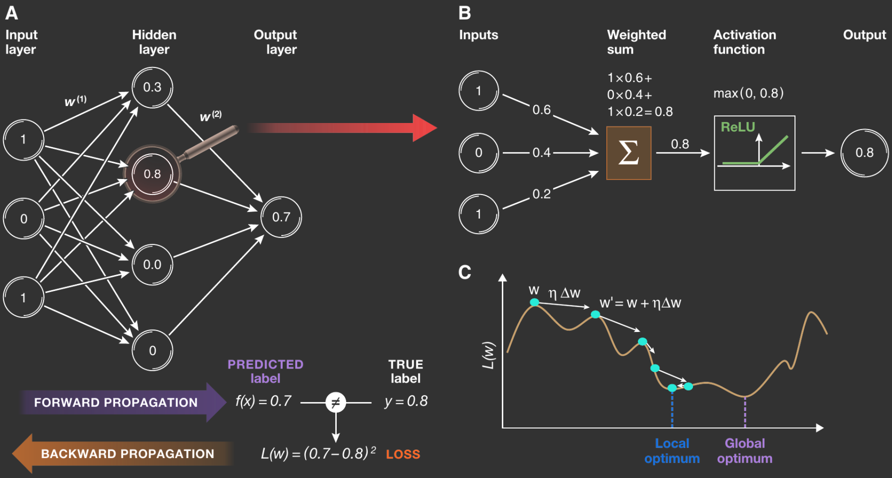
>>> Pasos clásicos de análisis de datos





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

>>> Redes Neuronales



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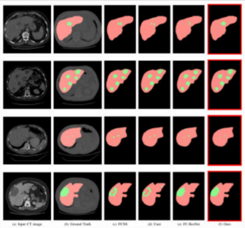
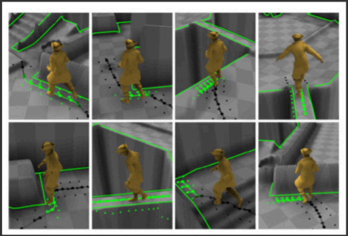
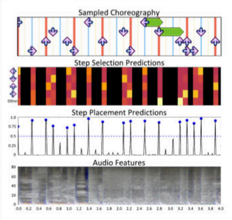
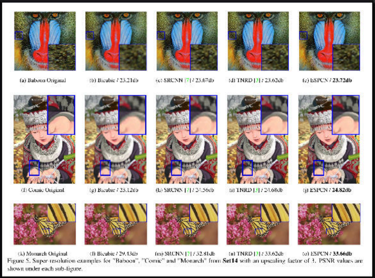
Deep learning permite que modelos computacionales compuestos por varias capas de procesamiento puedan aprender representaciones sobre datos con múltiples niveles de abstracción y, mediante esto, descubrir representaciones precisas en grandes volúmenes de datos de forma autónoma.

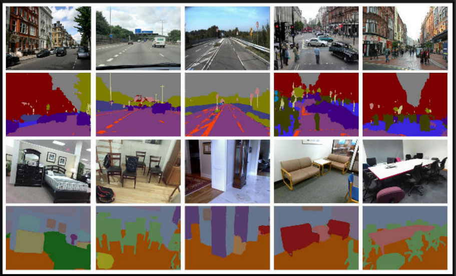


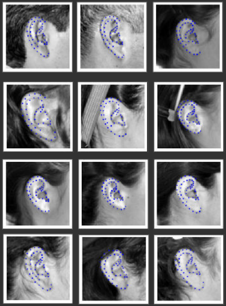




>>> Algunas Aplicaciones

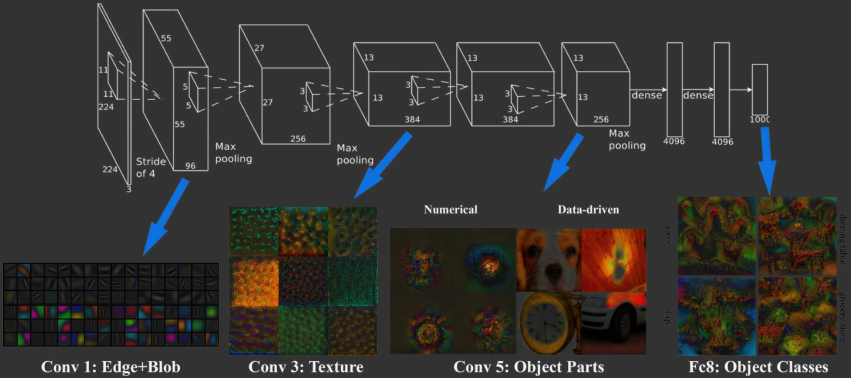






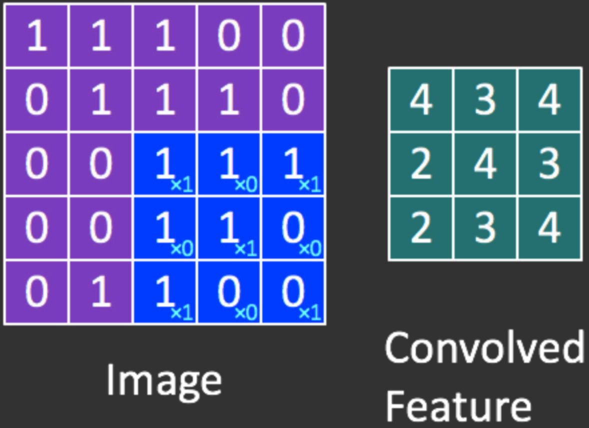
>>> ConvNets

Una arquitectura clásica de *ConvNet* esta dada por dos etapas. La primer etapa se enfoca en extraer características discriminantes a distintos niveles de abstracción y la segunda se enfoca en la clasificación a partir de las características obtenidas previamente.



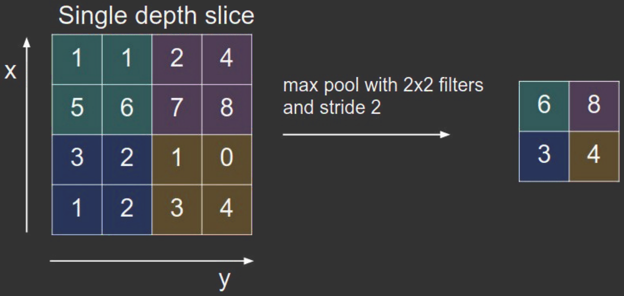
>>> Capa de convolución

Conceptos importantes: cantidad de kernels o filtros y su tamaño, paso y relleno de ceros.



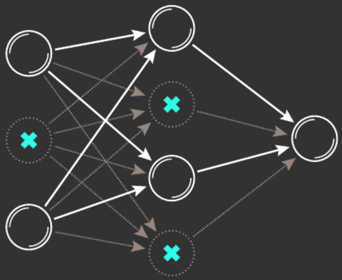
* http://ufldl.stanford.edu/tutorial/supervised/FeatureExtractionUsingConvolution/

>>> Max-Pooling



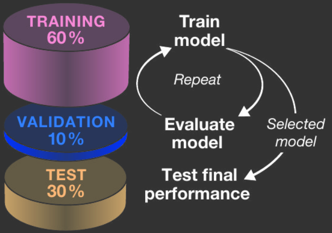
* http://cs231n.github.io/convolutional-networks/#pool

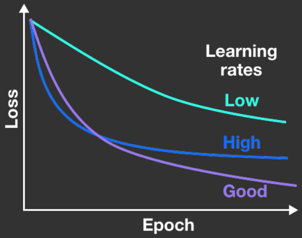
>>> Dropout

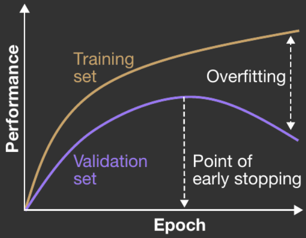


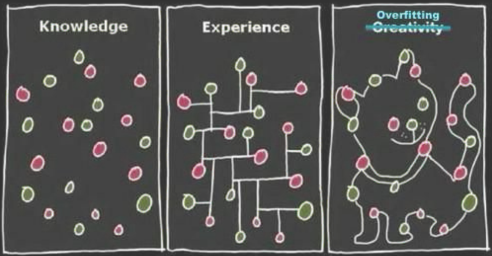
* http://onlinelibrary.wiley.com/doi/10.15252/msb.20156651/full

>>> Entrenamiento, Validación y Evaluación









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

>>> Tecnologías

scikit learn

pandas $y_it = \beta' x_{it} + \mu_i + \epsilon_{it}$

Lasagne

OpenCV

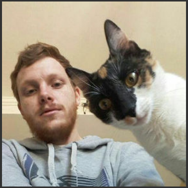
matplotlib

>>> Instalación

* $ 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

O con Docker:

* Docker-nvidia (https://github.com/NVIDIA/nvidia-docker)
* pull en Docker Hub $ docker pull pablo1n7/tatooine.



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

>>> Demo Time!

>>> Siguiente parada

Under review as a conference paper at ICLR 2017

Large-Scale Evolution of Image Classifiers

Esteban Real [1] Sherry Moore [1] Andrew Selle [1] Saurabh Saxena [1]
Yutaka Leon Suematsu [2] Jie Tan [1] Quoc V. Le [1] Alexey Kurakin [1]

Abstract

Neural networks have proven effective at solving difficult problems but designing their architectures can be challenging, even for image classification problems alone. Our goal is to minimize human participation, so we employ evolutionary algorithms to discover such networks automatically. Despite significant computational requirements, we show that it is now possible to evolve models with accuracies within the range of those published in the last year. Specifically, we employ simple evolutionary techniques at unprecedented scales to discover models for the CIFAR-10 and CIFAR-100 datasets, starting from trivial initial conditions and reaching accuracies of 94.6% (95.6% for ensemble) and

It is therefore not surprising that in recent years, techniques to automatically discover these architectures have been gaining popularity (Bergstra & Bengio, 2012; Snoek et al., 2012; Han et al., 2015; Baker et al., 2016; Zoph & Le, 2016). One of the earliest such "neuro-discovery" methods was *neuro-evolution* (Miller et al., 1989; Stanley & Miikkulainen, 2002; Stanley, 2007; Bayer et al., 2009; Stanley et al., 2009; Breuel & Shafait, 2010; Pugh & Stanley, 2013; Kim & Rigazio, 2015; Zaremba, 2015; Fernando et al., 2016; Morse & Stanley, 2016). Despite the promising results, the deep learning community generally perceives evolutionary algorithms to be incapable of matching the accuracies of hand-designed models (Verbancsics & Harguess, 2013; Baker et al., 2016; Zoph & Le, 2016). In this paper, we show that it is possible to evolve such competitive models today, given enough computational power.

Neural Architecture Search with Reinforcement Learning

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Abstract

Neural networks are powerful and flexible models that work well for many difficult learning tasks in image, speech and natural language understanding. Despite their success, neural networks are still hard to design. In this paper, we use a recurrent network to generate the model descriptions of neural networks and train this RNN with reinforcement learning to maximize the expected accuracy of the generated architectures on a validation set. On the CIFAR-10 dataset, our method, starting from scratch, can design a novel network architecture that rivals the best human-invented architecture in terms of test set accuracy. Our CIFAR-10 model achieves a test error rate of 3.65, which is 0.09 percent better and 1.05x faster than the previous state-of-the-art model that used a similar architectural scheme. On the Penn Treebank dataset, our model can compose a novel recurrent cell that outperforms the widely-used LSTM cell, and other state-of-the-art baselines. Our cell achieves a test set perplexity of 62.4 on the Penn Treebank, which is 3.6 perplexity better than the previous state-of-the-art model. The cell can also be transferred to the character language modeling task on PTB and achieves a state-of-the-art perplexity of 1.214.

PatternNet and PatternLRP Improving the interpretability of neural networks

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Abstract

Deep learning has significantly advanced the state of the art in machine learning. However, neural networks are often considered black boxes. There is significant effort to develop techniques that explain a classifier's decisions. Although some of these approaches have resulted in compelling visualisations, there is a lack of theory of what is actually explained. Here we present an analysis of these methods and formulate a quality criterion for explanation methods. On this ground, we propose an improved method that may serve as an extension for existing back-projection and decomposition techniques.

Do Convnets Learn Correspondence?

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Abstract

Convolutional neural nets (convnets) trained from massive labeled datasets [1] have substantially improved the state-of-the-art in image classification [2] and object detection [3]. However, visual understanding requires establishing correspondence on a finer level than object category. Given their large pooling regions and training from whole-image labels, it is not clear that convnets derive their success from an accurate correspondence model which could be used for precise localization. In this paper, we study the effectiveness of convnet activation features for tasks requiring correspondence. We present evidence that convnet features localize at a much finer scale than their receptive field sizes, that they can be used to perform intraclass aligment as well as conventional hand-engineered features, and that they outperform conventional features in keypoint prediction on objects from PASCAL VOC 2011 [4].

>>> Otras Bibliotecas para Deep Learning con Python

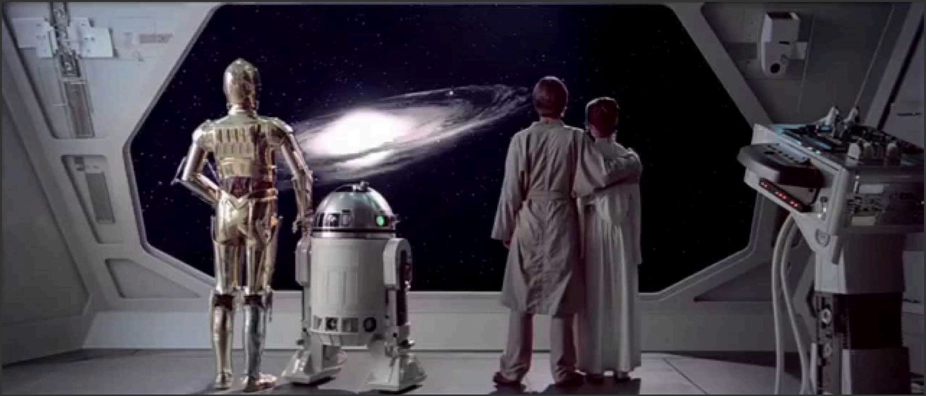
PYTORCH

TensorFlow™

K Keras

>>> Gracias!

https://github.com/celiacintas/star_wars_hackathon



* Neural Networks and Deep Learning online book
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