\>>> Introduction to Deep Learning

\>>> The force Awakens

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Date: October 19, 2017

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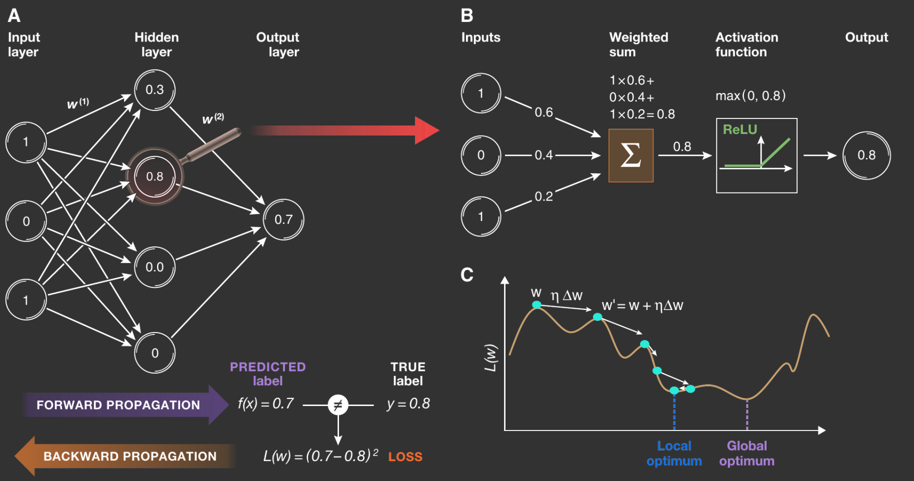
[1] http://imaglabs.org/
[2] http://conf.scipyla.org/
[3] https://www.meetup.com/Patagonia-Python-Meetup/

## >>> 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.

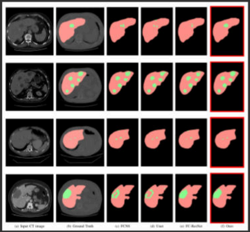
# >>> Neural Nets

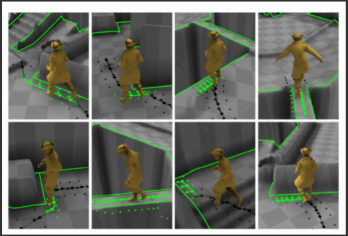


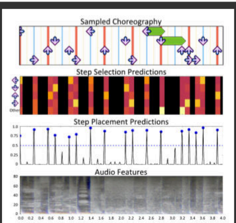

* http://onlinelibrary.wiley.com/doi/10.15252/msb.20156651/full

# >>> 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

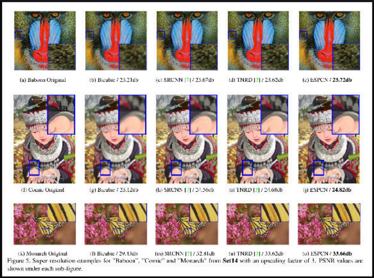
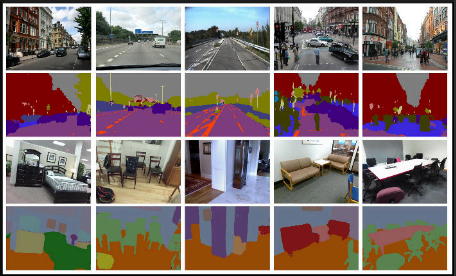
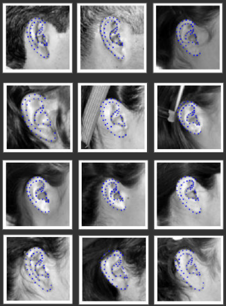


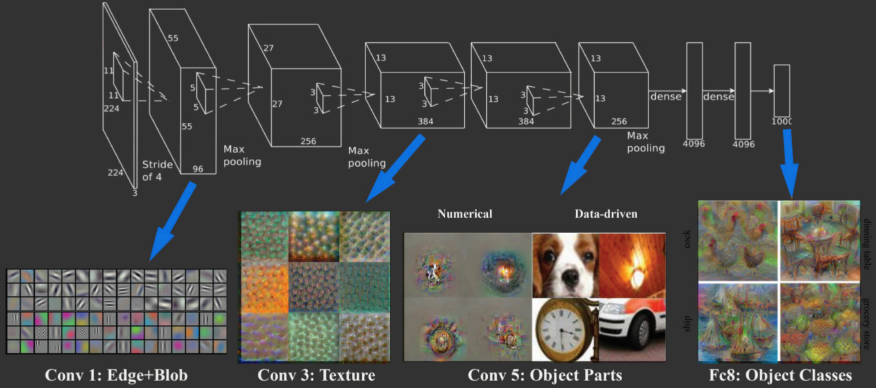
Figure 5. Super-resolution examples for "Baboon", "Comic" and "Monarch" from **Set14** with an upscaling factor of 3. PSNR values are shown under each sub-figure.





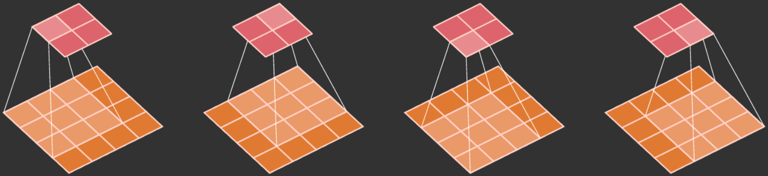
## >>> ConvNets

A classic *ConvNet* architecture 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.



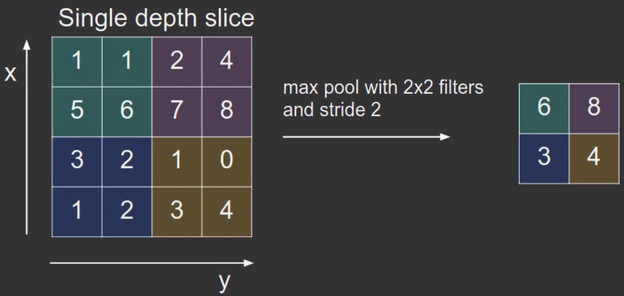
## >>> Convolution Layer

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



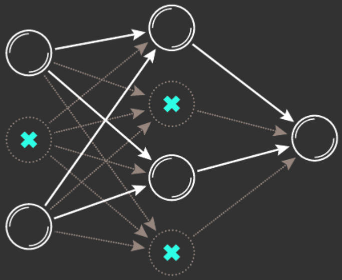
* A guide to convolution arithmetic for deep learning. Dumoulin, Vincent and Visin, Francesco.

# >>> Max-Pooling




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

# >>> Dropout



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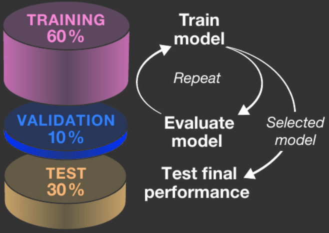
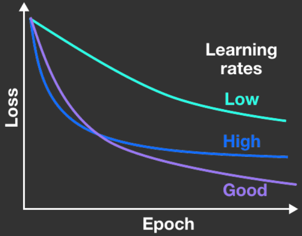
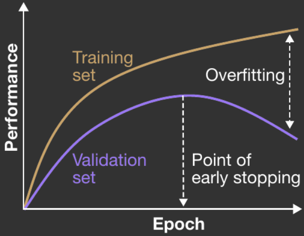
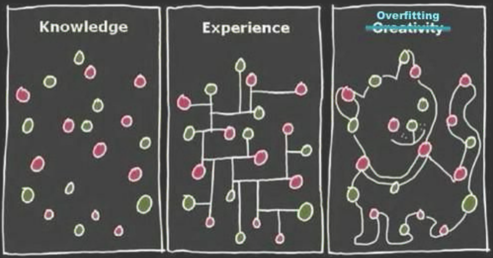
## >>> Training, Validation and Evaluation




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

# >>> Technologies

Py.17

scikit learn

OpenCV

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

Lasagne

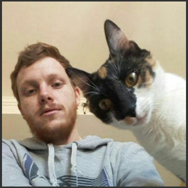
matplotlib

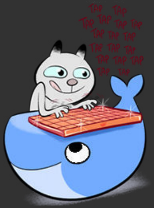
## >>> Setup

* $ 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!

Py.17

# >>> Next Stop

## 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.

Under review as a conference paper at ICLR 2017

## 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 backprojection 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].

# >>> Other Libraries for Deep Learning with Python

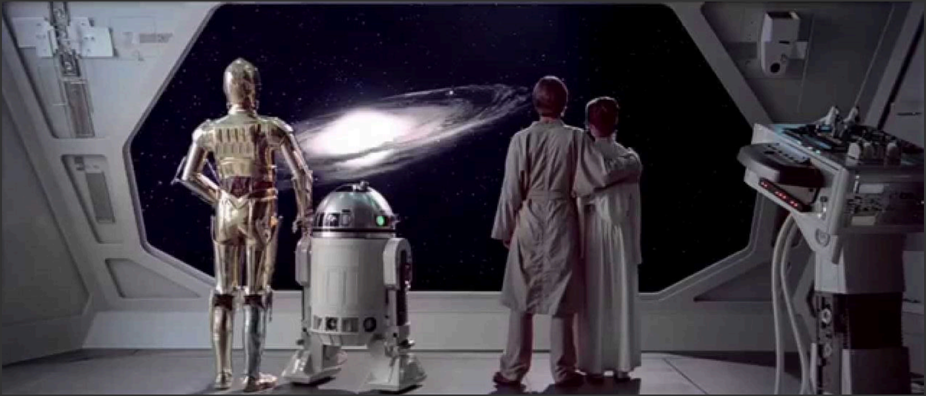
PYTORCH

TensorFlow™

K 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 ..


* Yann, L. (1998). Efficient backprop. Neural networks: tricks of the trade (Vol. 53).
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* 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.

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* Shwartz-Ziv, R., & Tishby, N. (2017). Opening the Black Box of Deep Neural Networks via Information. arXiv, 1-19.
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