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Raja Giryes

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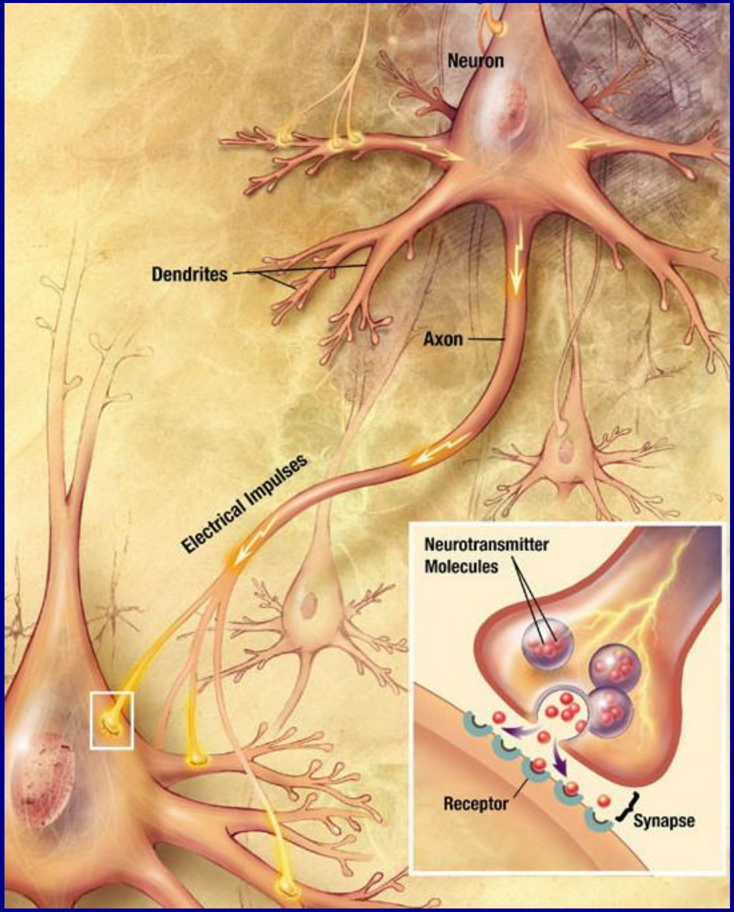
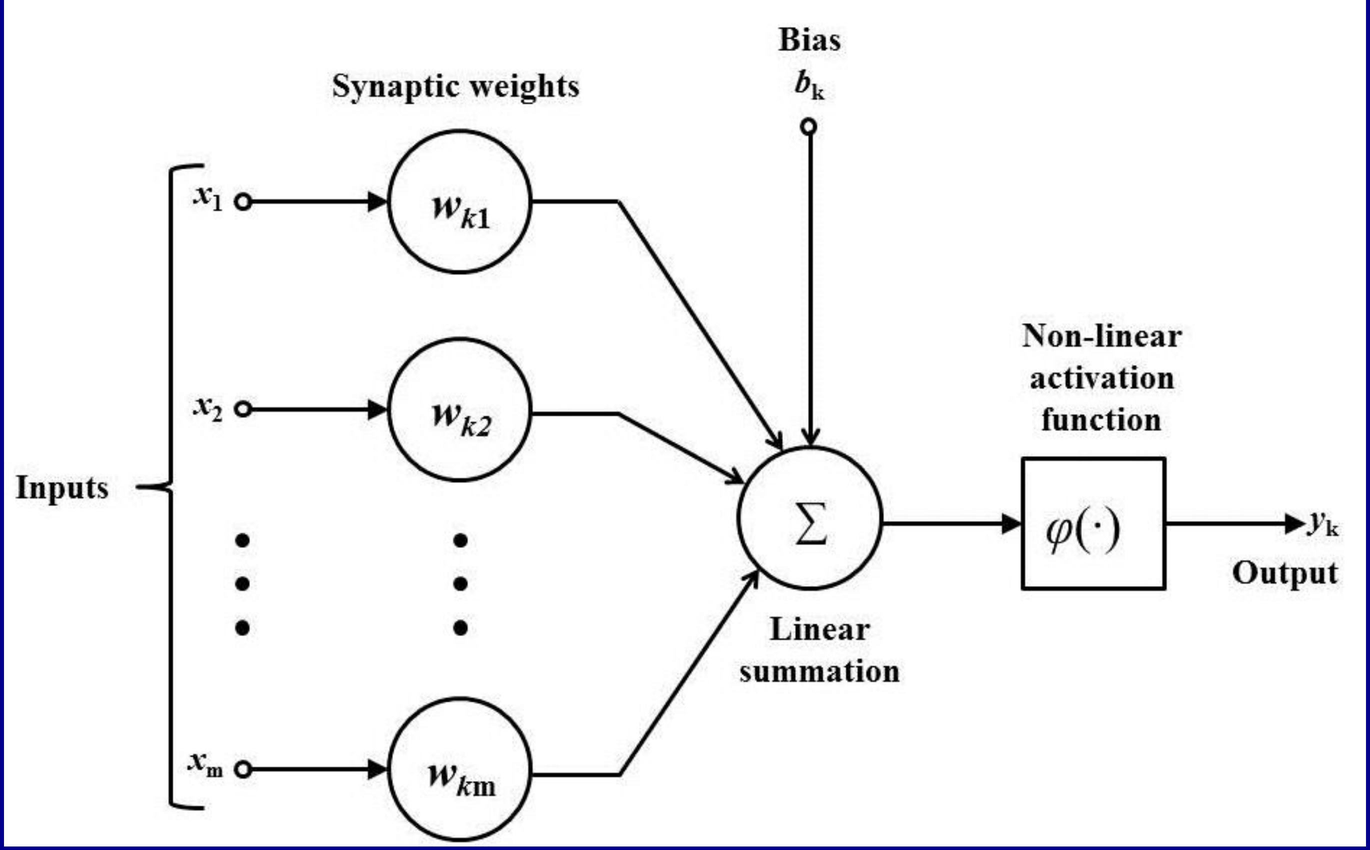
ISSI international team
Juan Cabrera

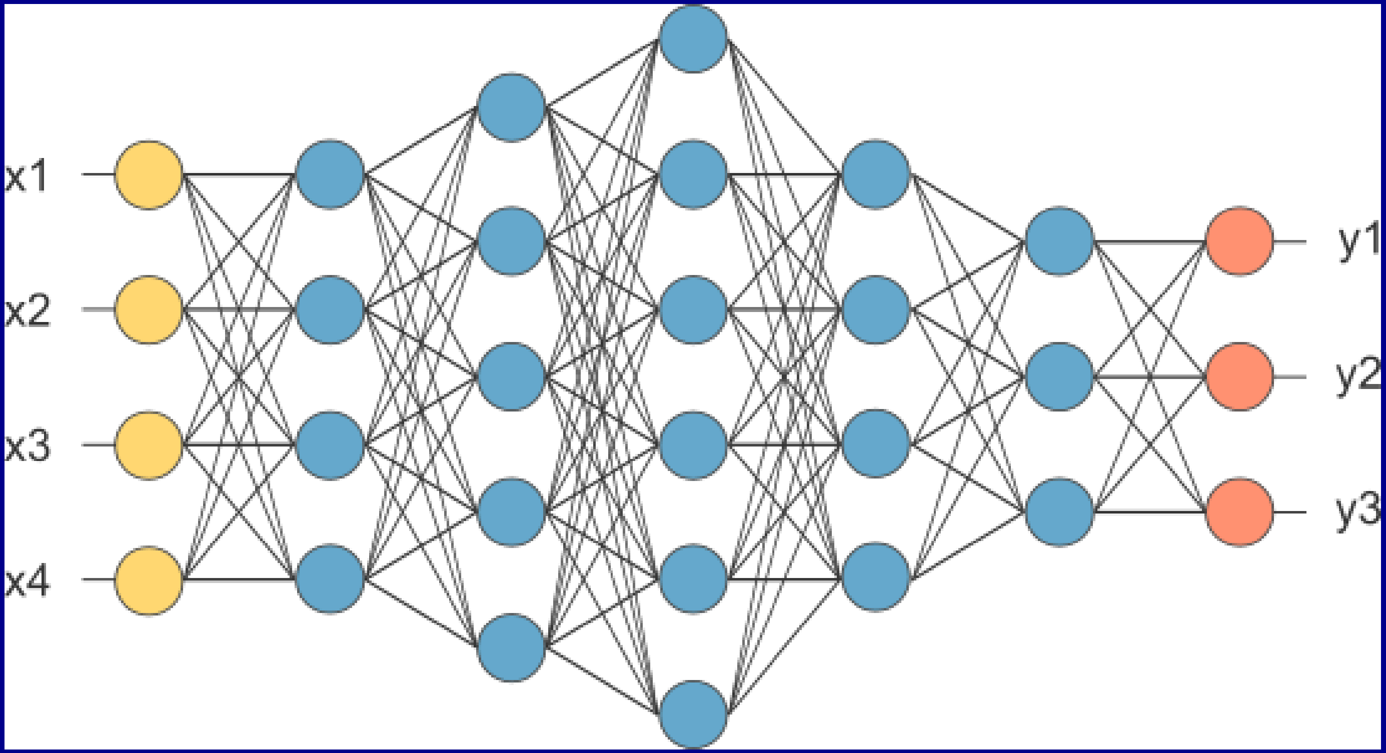
Biological Neuron



McCulloch-Pitts Neuron



Deep Neural Networks



Input Layer Hidden Layers Output Layer

Inspiration: human visual cortex

Training using Backpropagation

- Supervised learning: given examples with ground truth
- (‘training set’)
- Loss function (error quantification)
- Loss depends analytically on the synaptic weights
- Back-propagation of derivatives (chain rule) through layers
- Slowly update the synaptic weights (e.g. gradient descent, Metropolis-Hastings, etc.) to minimize loss

Deep Learning

- Comeback of neural networks (~2005)
- Depth made all the difference
- Depth (number of layers) allows significant abstraction
- Progress made possible by hardware
- Breaks records of performance

Deep Learning Revolution

- Computer vision
  - Scene parsing, face recognition, handwriting recognition, etc.
- Speech recognition
- Automatic machine translation
- Genomics (e.g. roles of non-coding DNA sequences)
- Drug discovery (e.g. predict metabolic fate of a molecule)
- Autonomous cars
- … and many more

Essential Ingredients

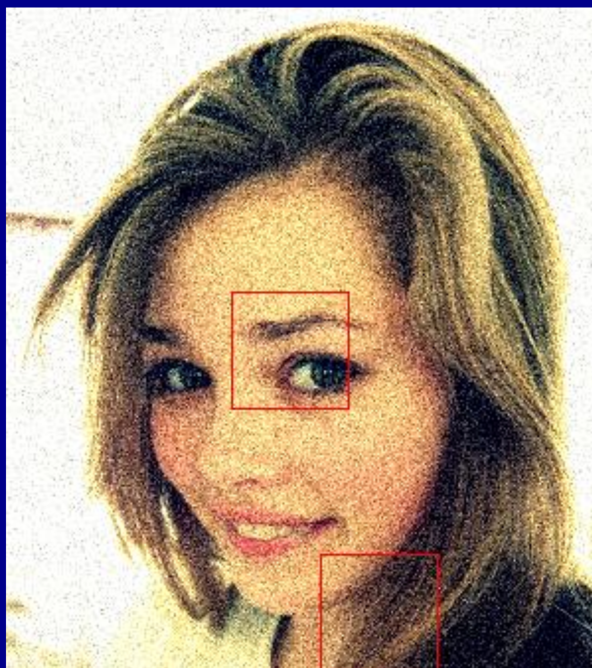
- Large and comprehensive training set
- Deep network (many layers)
- Adequate network architecture
  - Convolutional neural networks (ConvNets)
  - Fully Convolutional networks (FCN)
  - Recurrent neural networks (RNN)
  - Residual networks (ResNets)
- Back-propagation scheme

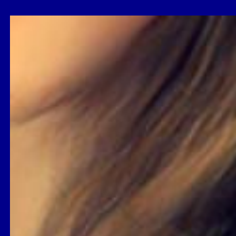
Typical Task #1: Image Classification

Microsoft competition: dogs vs. cats (Kaggle dataset)
Design a code that will distinguish between cats and dogs

98.9% right! (Pierre Sermanet, 2014)

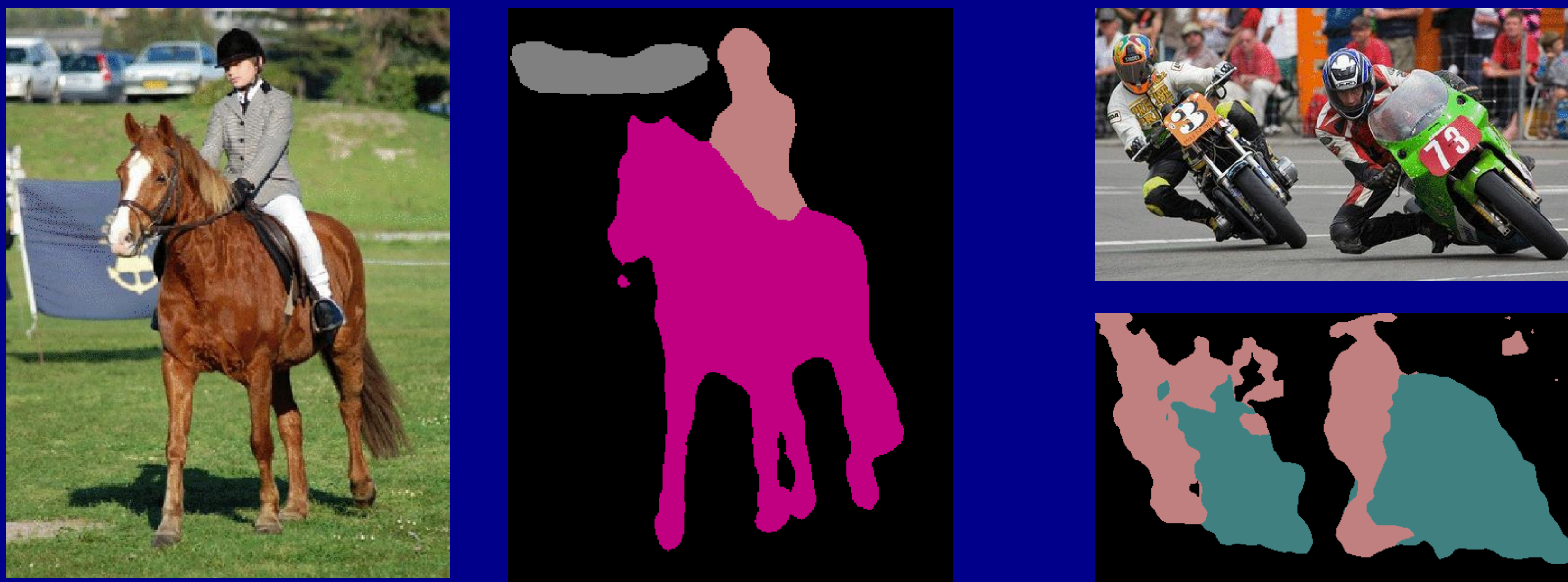
Typical Task #2: Image Denoising





Remez et al. 2017

Typical Task #3: Image Segmentation



Shelhamer et al. 2017

Relevant Tasks for PLATO

- Transit detection (‘classification’, #1)
- Detrending (‘denoising’, #2)
- Individual transit identification (‘segmentation’, #3)
- Estimates of false positive/negative rates

Feasibility Study

- Cadence 5 min
- Time span ~21 days
- (6144 samples)
- Training set:
  - 83333 lightcurves with transits
  - 83333 lightcurves with no transits

Feasibility Study

- GP Simulated red noise:

$$k(t_i - t_j) = A_s^2 \exp\left[-\left(\frac{t_i - t_j}{\lambda_s}\right)^2\right] + A_q^2 \exp\left[-\frac{\sin^2[\pi(t_i - t_j)/T_q]}{2} - \left(\frac{t_i - t_j}{\lambda_q}\right)^2\right] + A_w^2 \delta(t_i - t_j)$$

- $A_s \sim 20 - 500$ ppm, $A_q \sim 2 - 500$ ppm
- $A_w = 140 \exp[0.2(M - M_{min})]$
- $M \sim 10 - 16$
- $\lambda_s \sim 1$ min – 10 hours, $T_q \sim 10 - 500$ hours
- $\lambda_q \sim 16.6 - 500$ hours

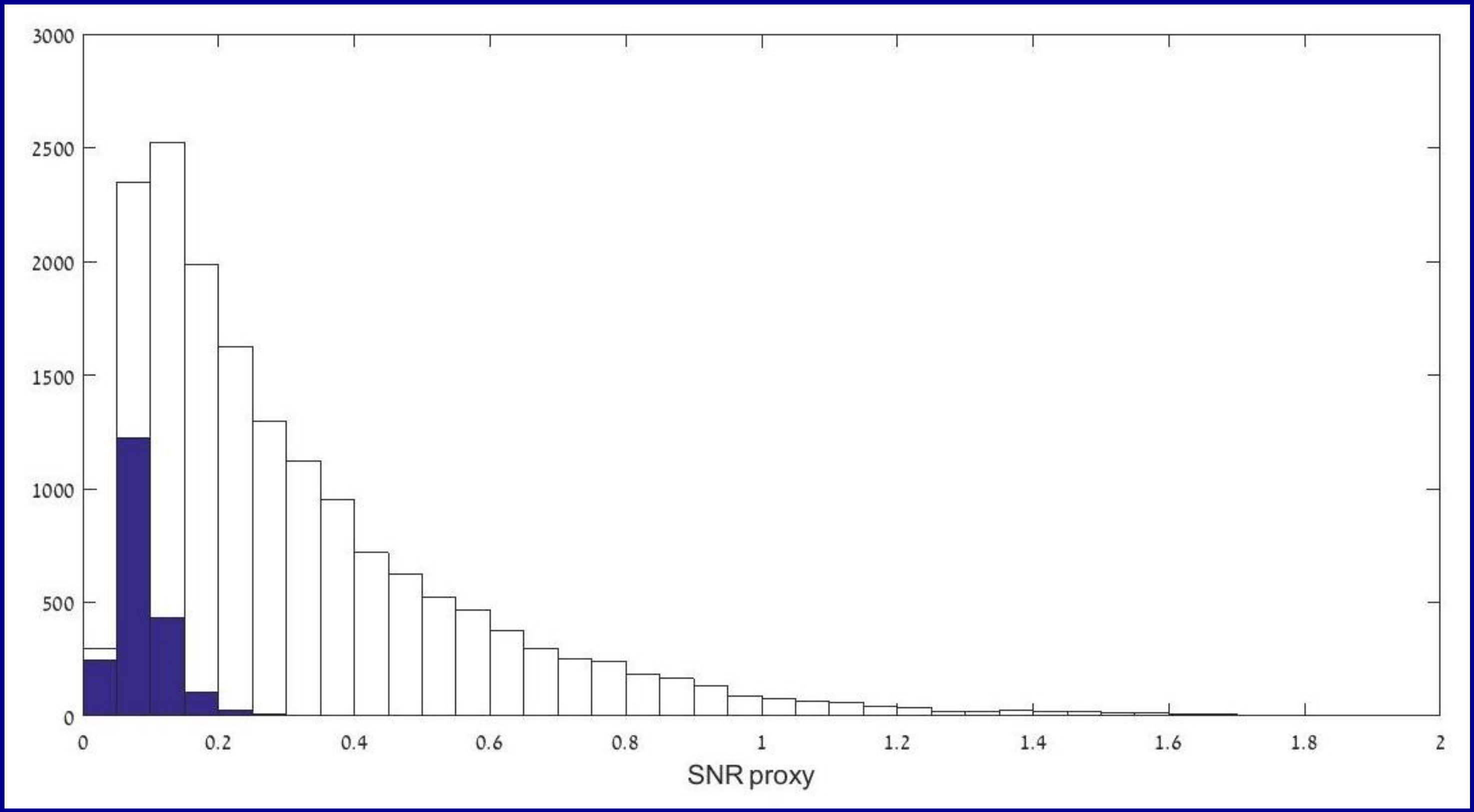
Feasibility Study

- Trapezoidal simulated transits:
- *P* ~ 16.6 hours – 4.2 days
- Depth ~ 10^{-3} – 10^{-4}
- Duration ~ 30 min – 3.3 hours

Feasibility Study

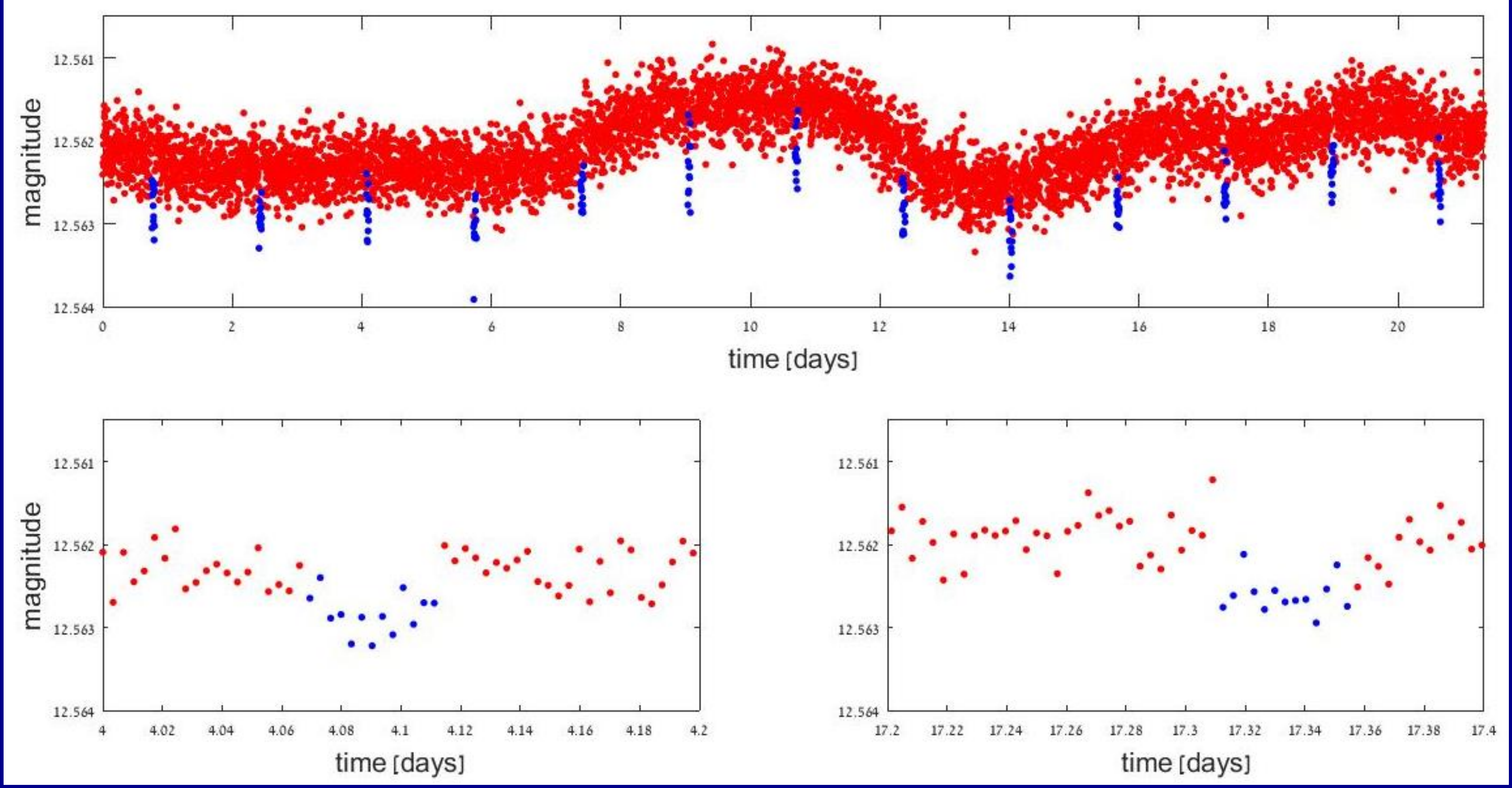
- One-layer FCN for detection
- (actually not ‘deep’ learning)
- Applied on the Fourier amplitudes
- Testing:
  - 16667 lightcurves with transits
  - 16667 lightcurves with no transits
- 7% false positives, 12% false negatives

Feasibility Study

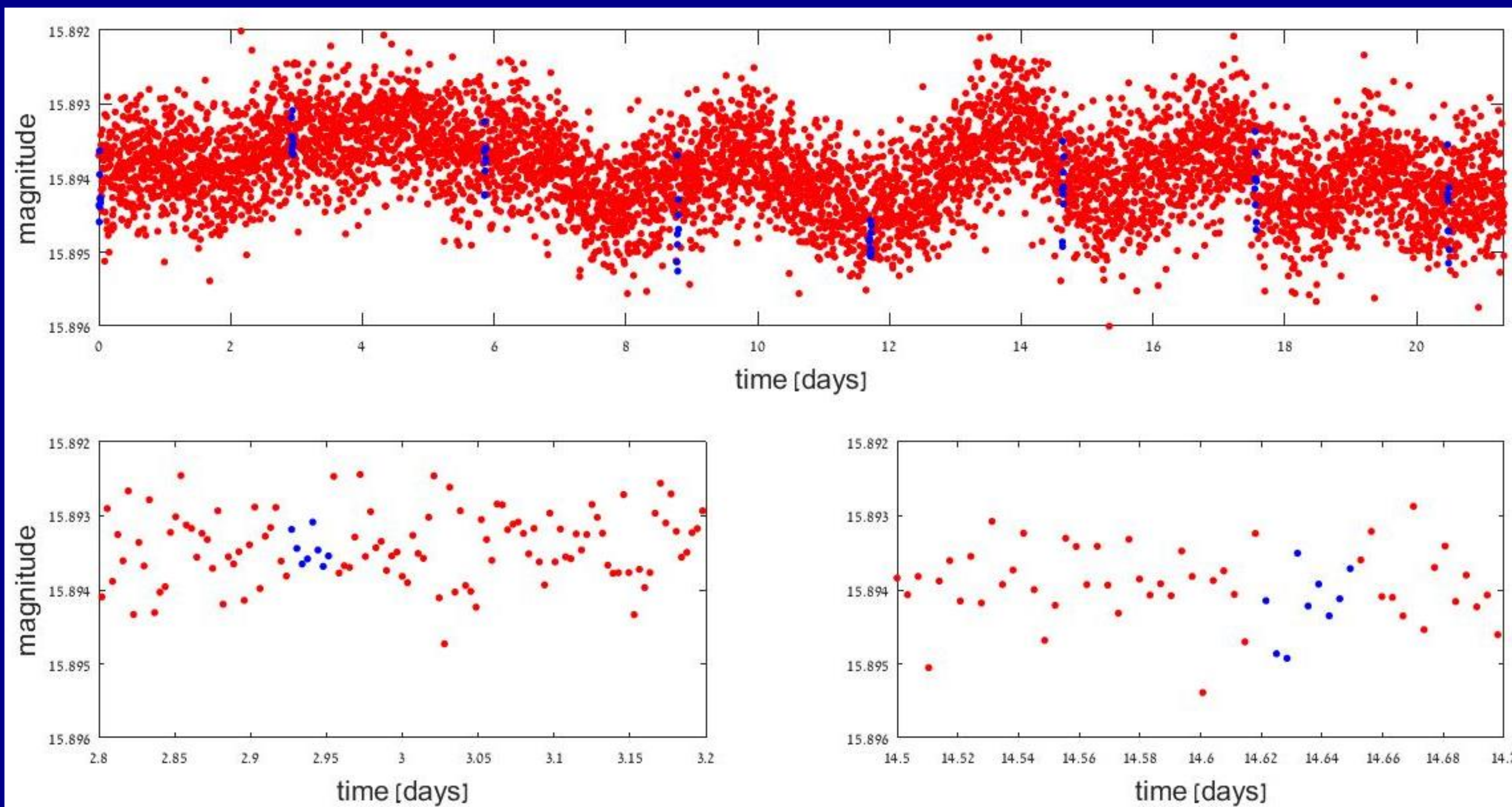


SNR proxy: $\frac{d}{\sigma}\sqrt{w/P}$

Feasibility Study



Feasibility Study



Conclusions

- Deep learning neural networks may be the way forward.
- They may achieve unprecedented results
- A fundamentally different approach