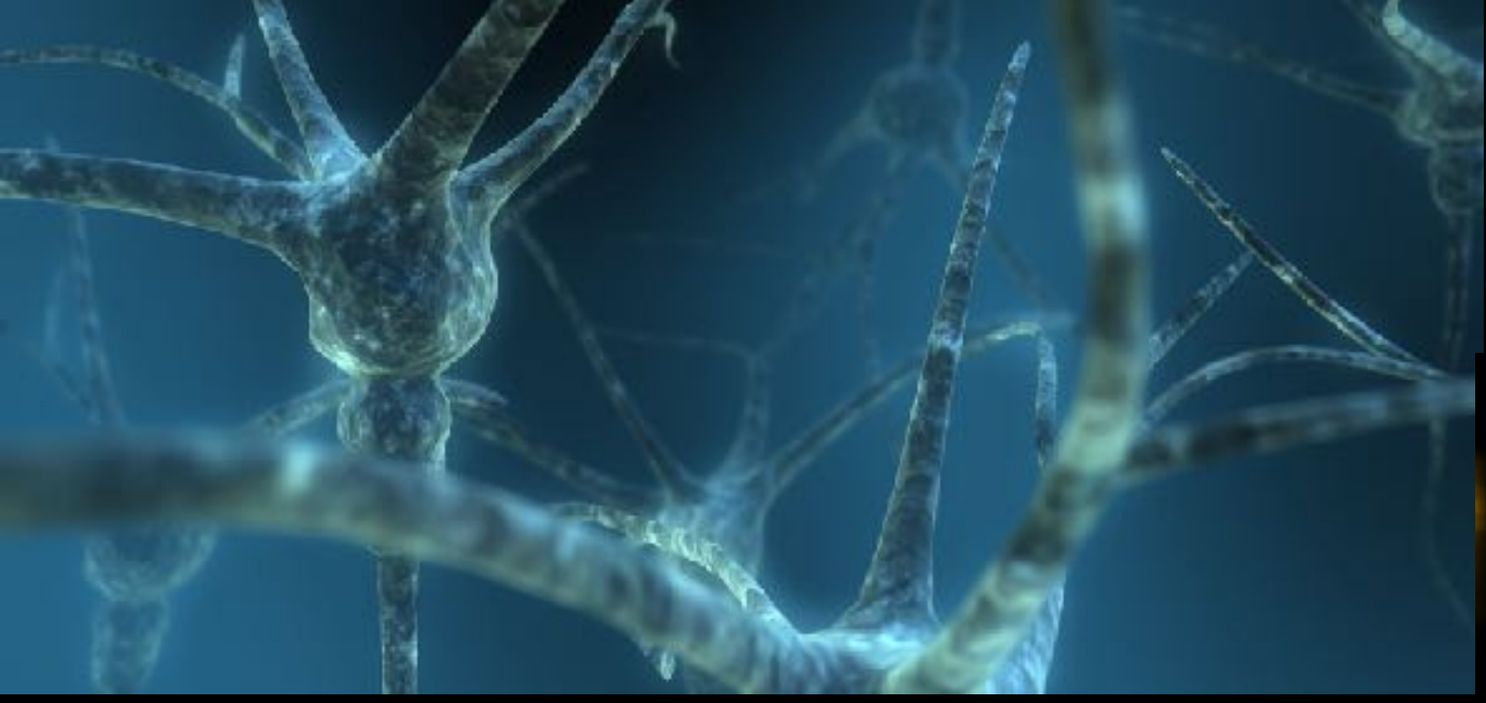
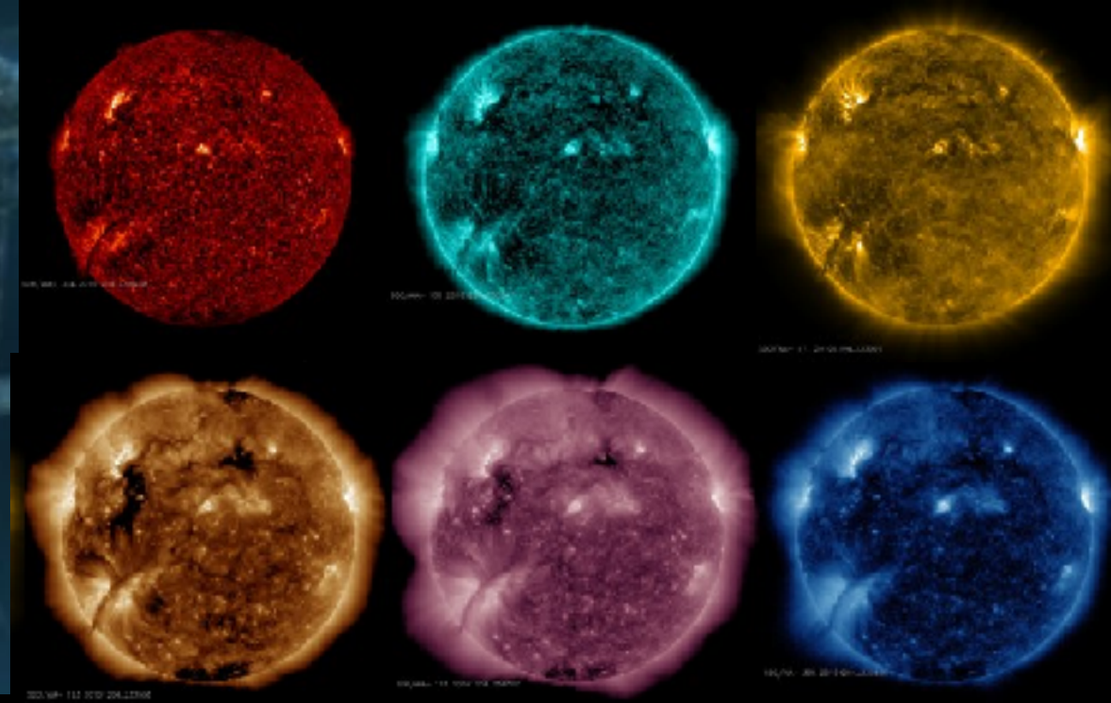




BASICS OF DEEP LEARNING

a. asensio ramos
@aasensior
github.com/aasensio

CONTENT

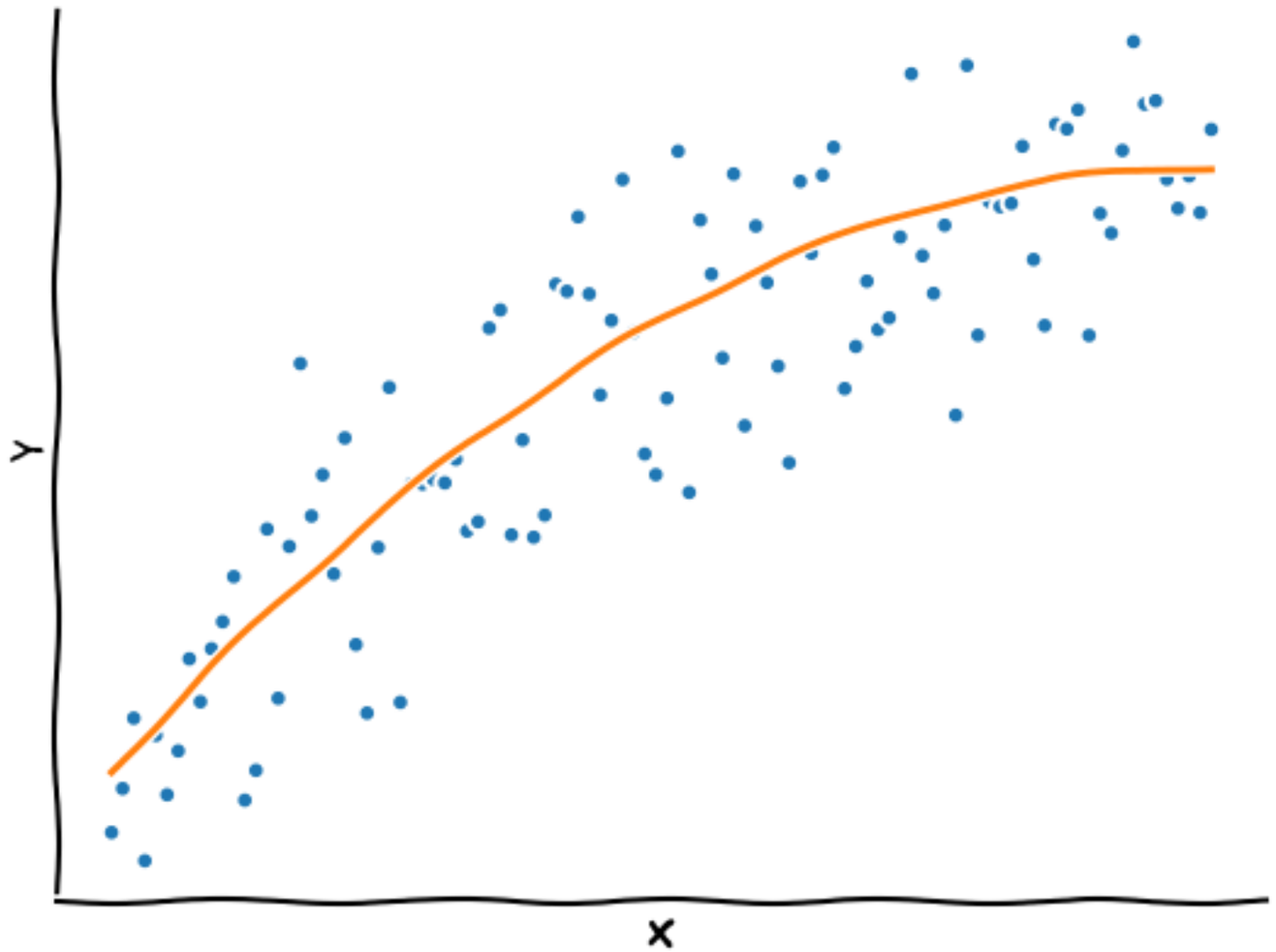
- Introduction
- Neural networks
  - Basics : supervised vs unsupervised, regression, classification, deep learning
  - Architecture of a neural network
    - Types of neural networks: fully connected, convolutional, recurrent
    - Activation functions
    - Pooling
    - Residual connections
    - Batch normalization
  - Training
    - Loss functions and stochastic gradient descent
    - Backpropagation
- Applications in Solar Physics and other fields
- Practical example

Introduction

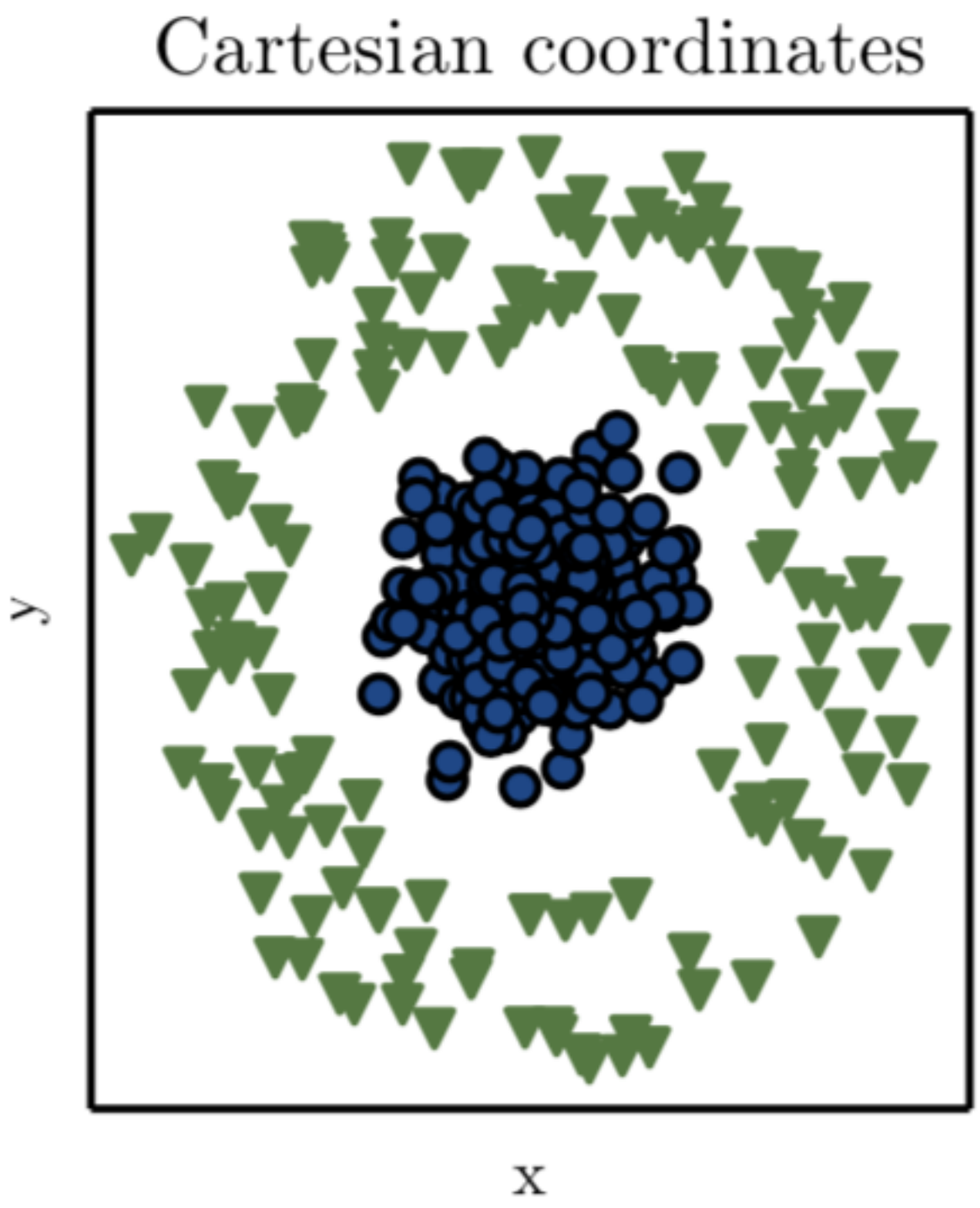
what is machine learning?

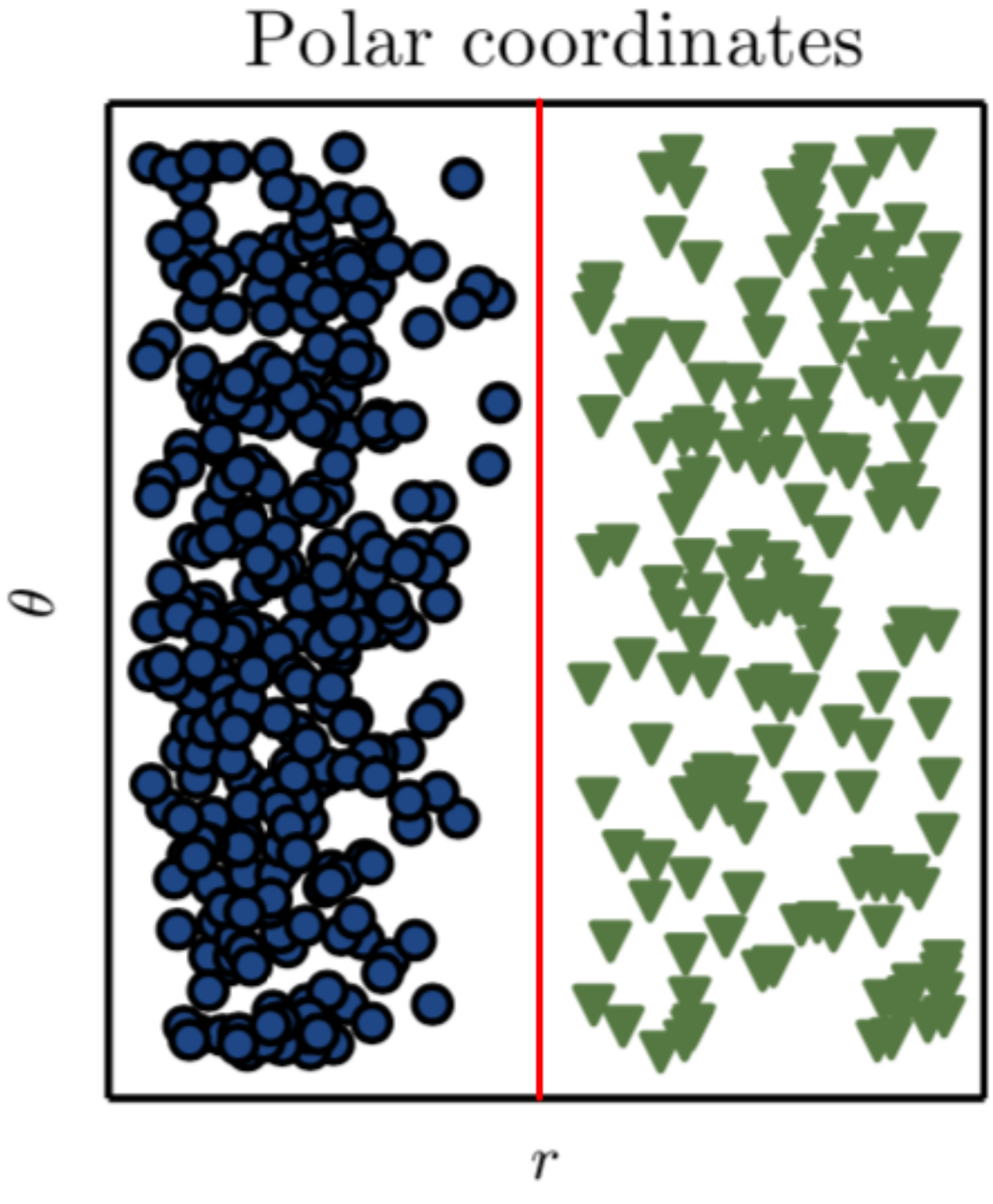
the focus of Machine Learning (ML) is to give computers the ability to learn from data, so that they may accomplish tasks that humans have difficulty expressing in pure code

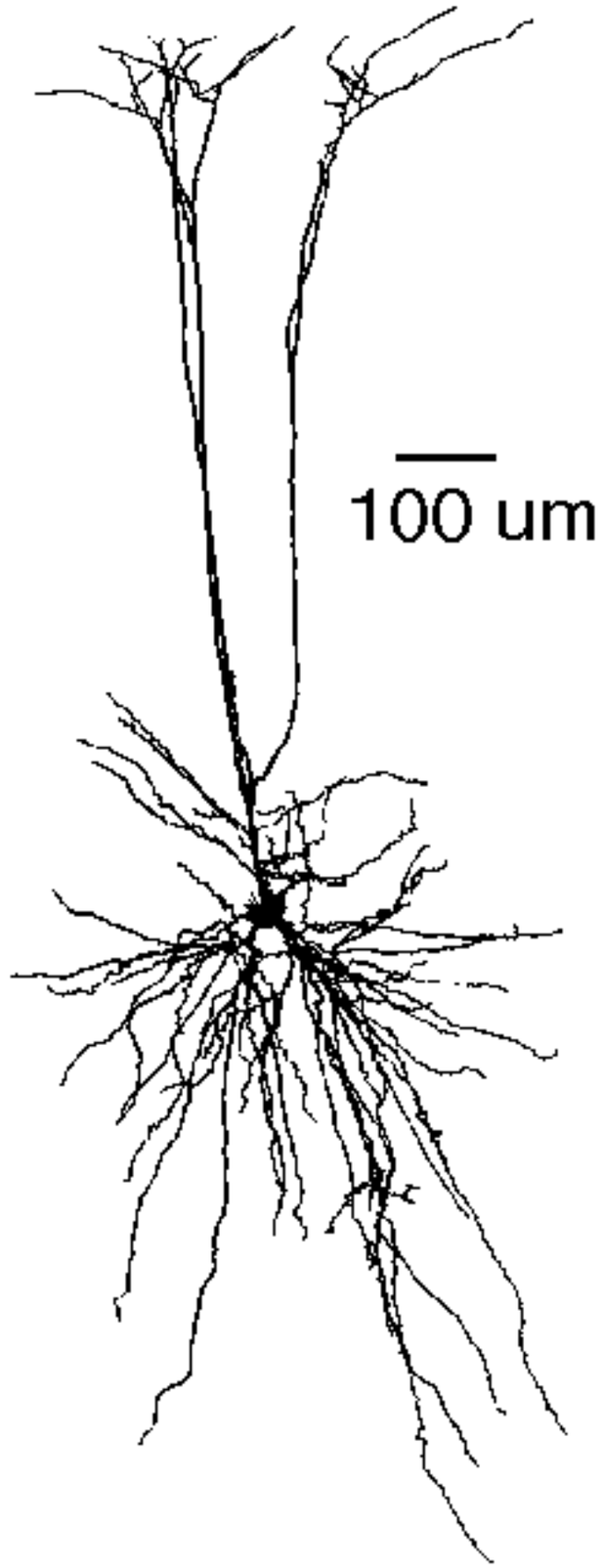
REGRESSION



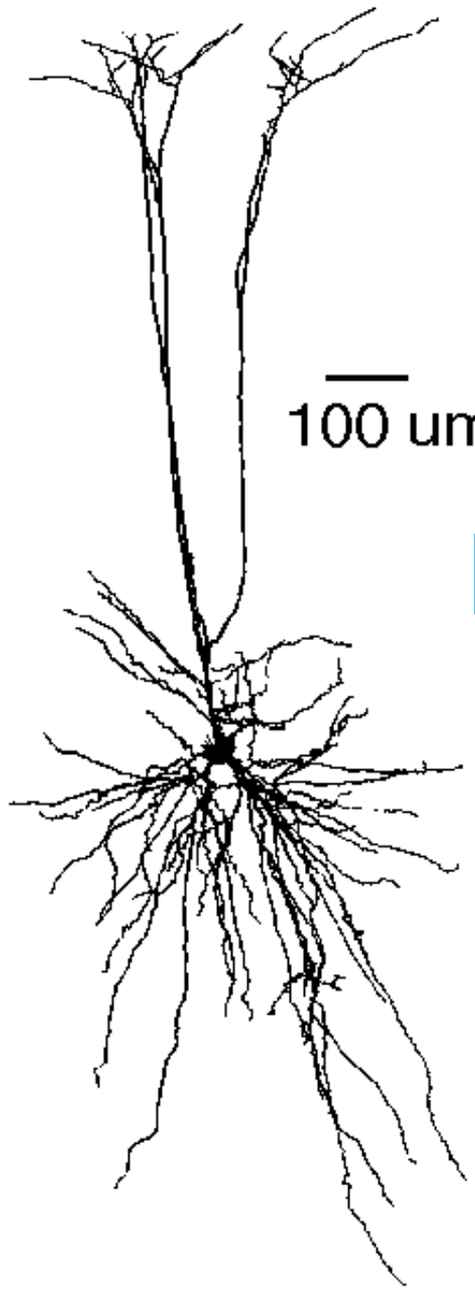
CLASSIFICATION

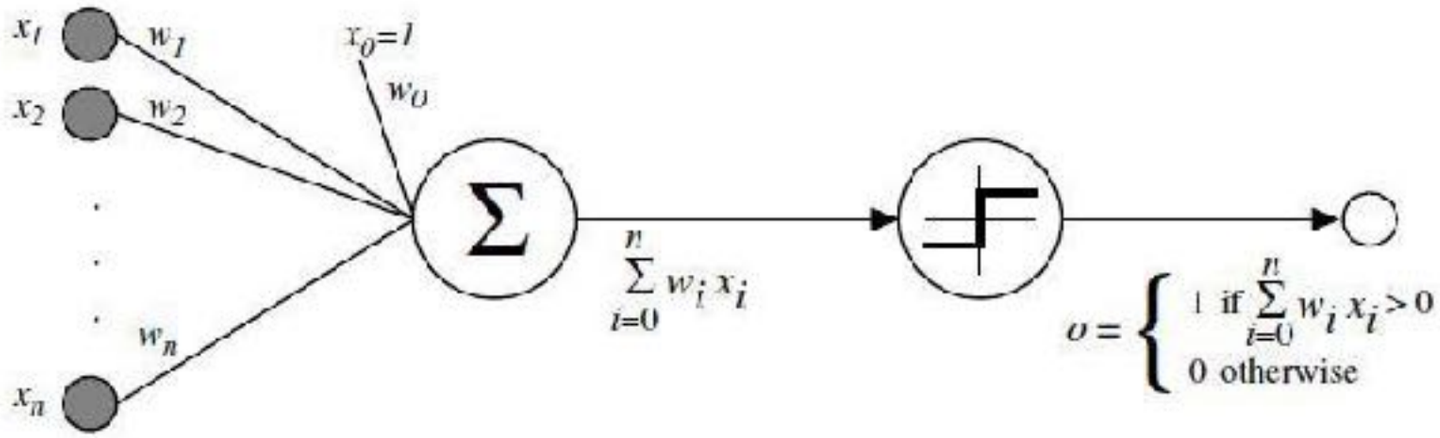




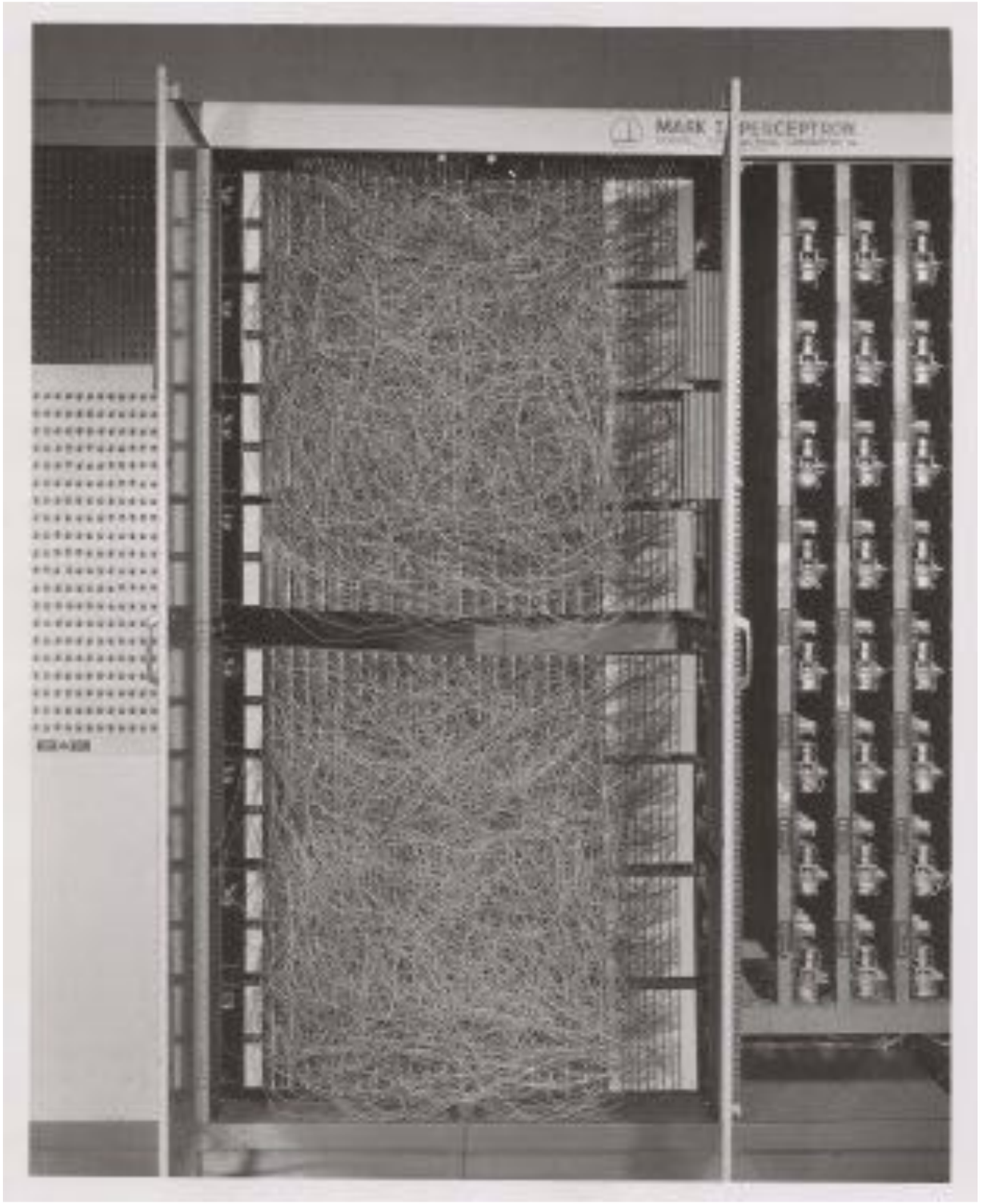

100 um

ARTIFICIAL NEURAL NETWORKS



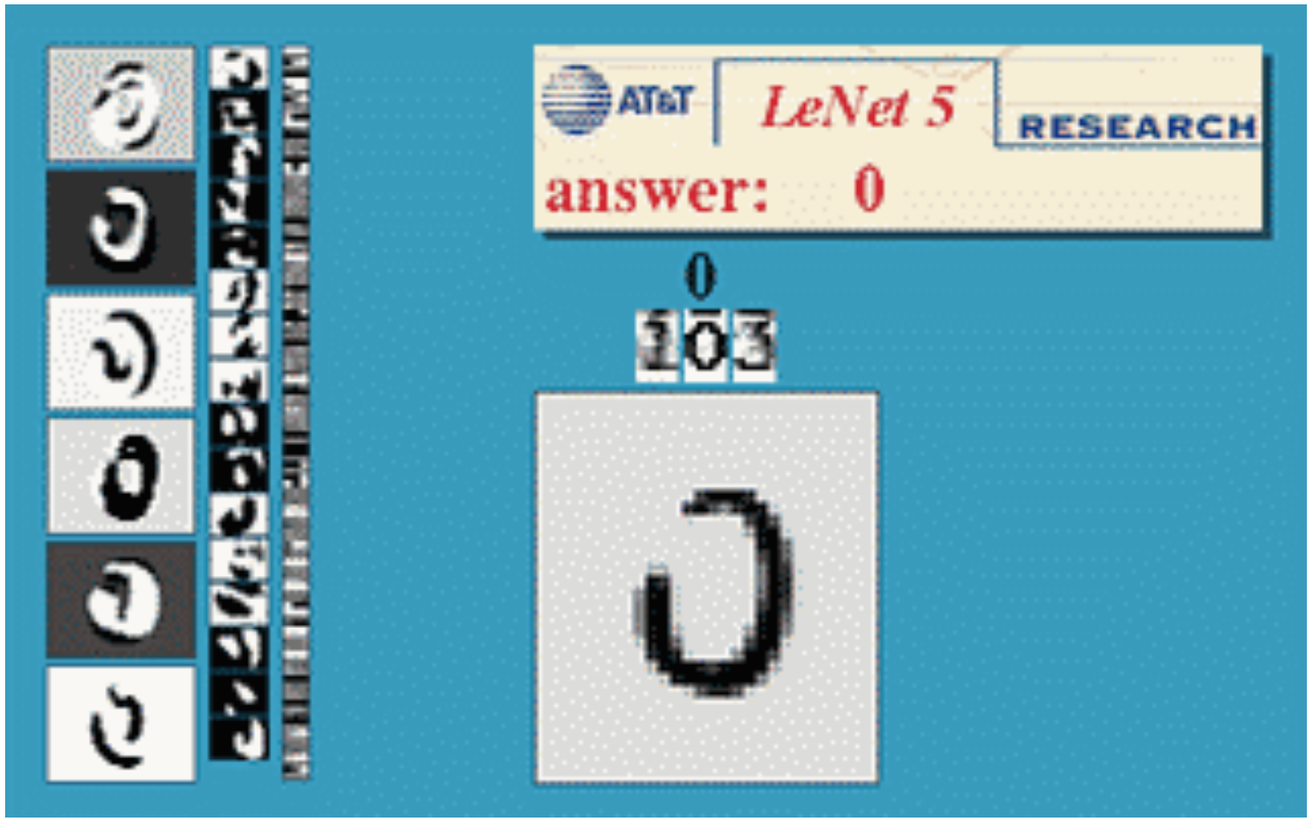


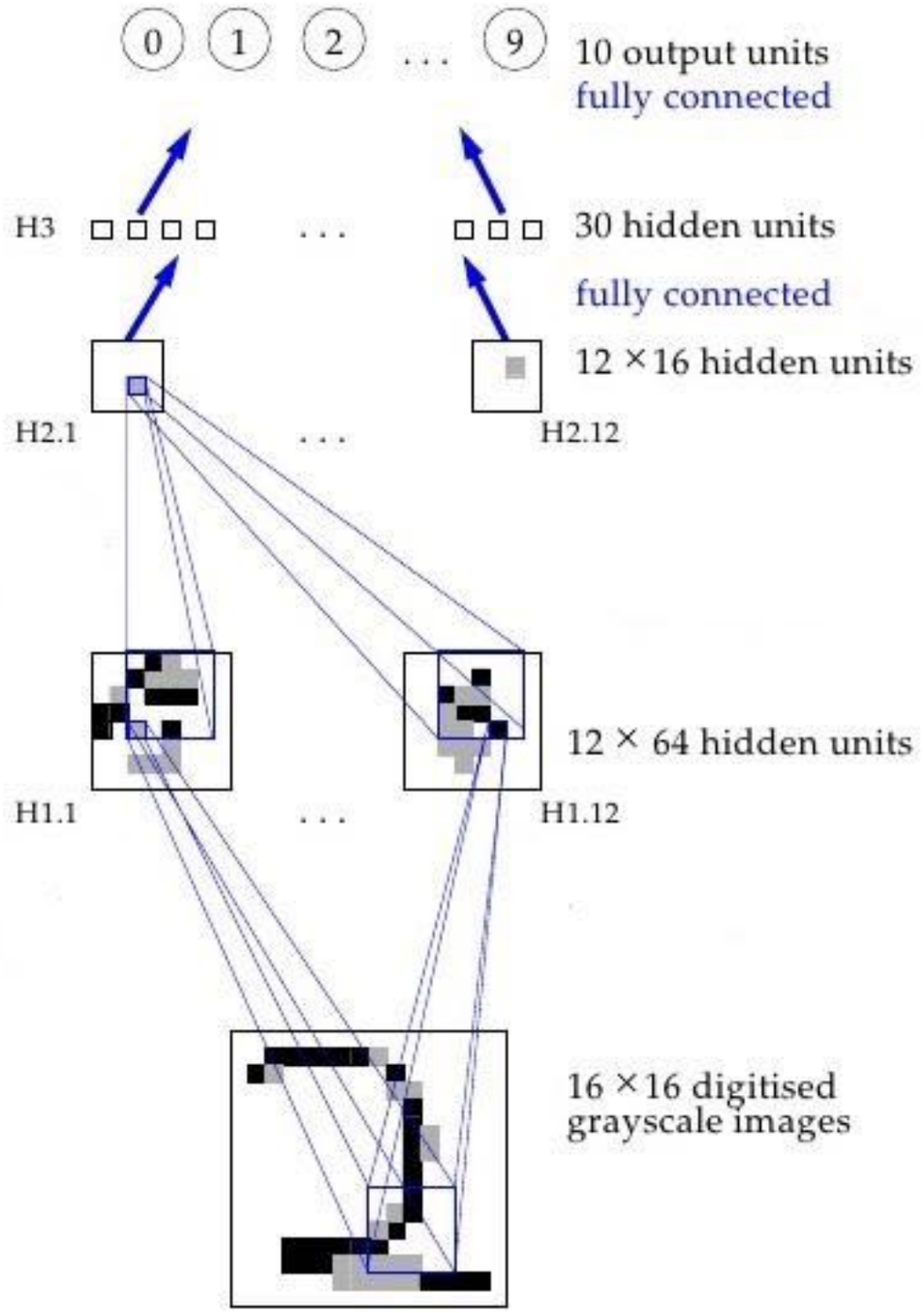
MARK I PERCEPTRON : FRANK ROSENBLATT



Source: Arvin Calspan Advanced Technology Center; Hecht-Nielsen, R. Neurocomputing (Reading, Mass.: Addison-Wesley, 1990)

CONVOLUTIONAL NEURAL NETWORKS : YANN LACUN



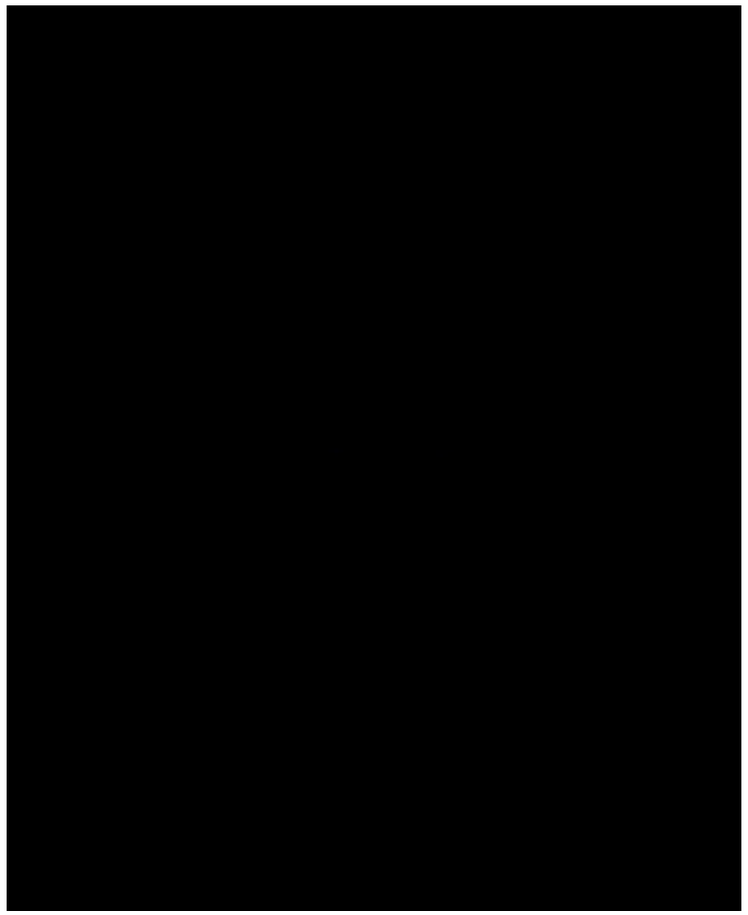


CONVOLUTIONAL NEURAL NETWORKS : YANN LECUN

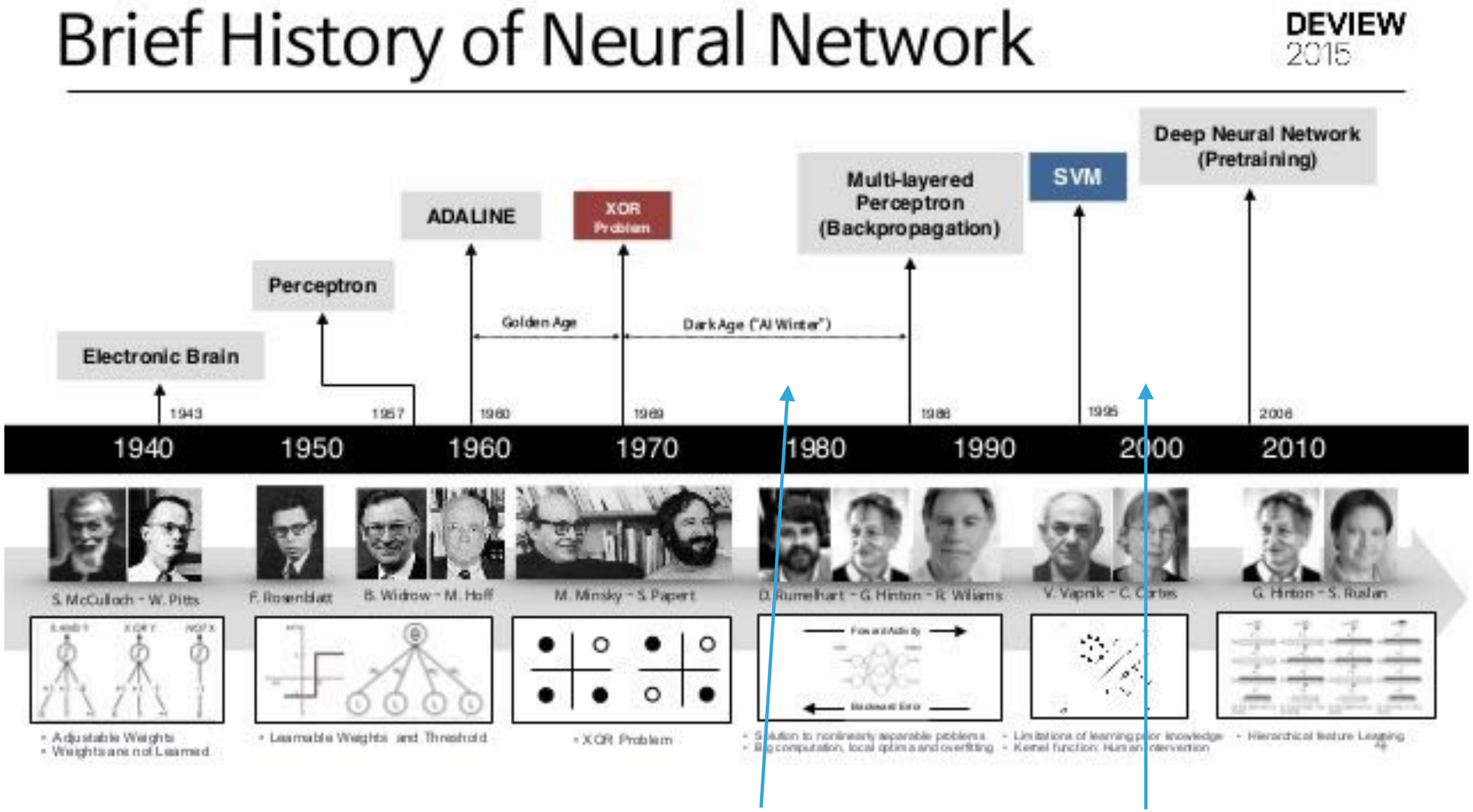
RANDOM PLAYER

TRAINED PLAYER

After 240 min of training



AI WINTERS



1ST AI WINTER

2ND AI WINTER

BE PERSEVERANT

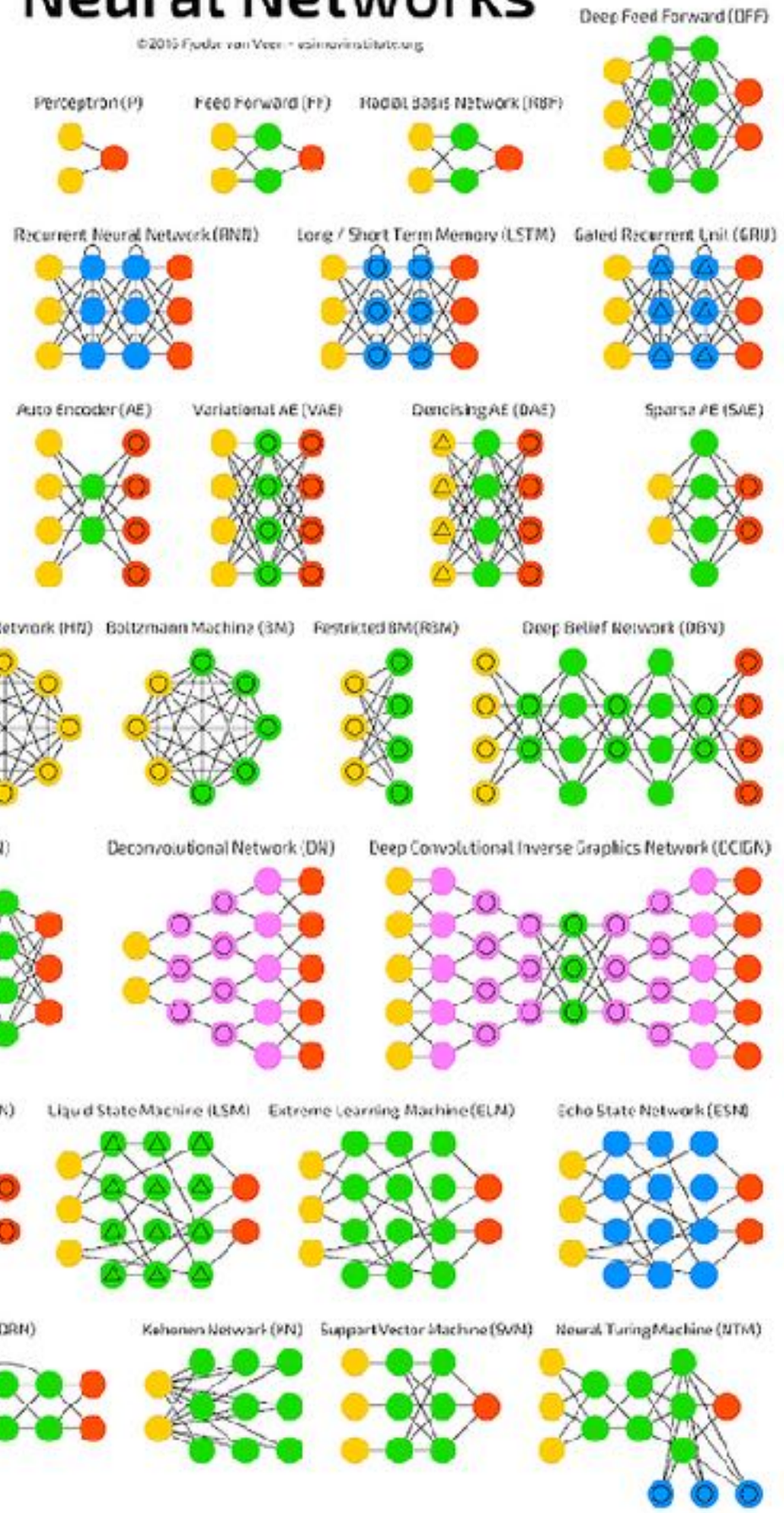
Yoshua Bengio
Montreal University

Yann LeCun
Facebook+NYU

Geoffrey Hinton
Google+Toronto

A mostly complete chart of

Neural Networks



CURSE OF DIMENSIONALITY

CURSE OF DIMENSIONALITY

CURSE OF DIMENSIONALITY

CURSE OF DIMENSIONALITY

Dimension: 1

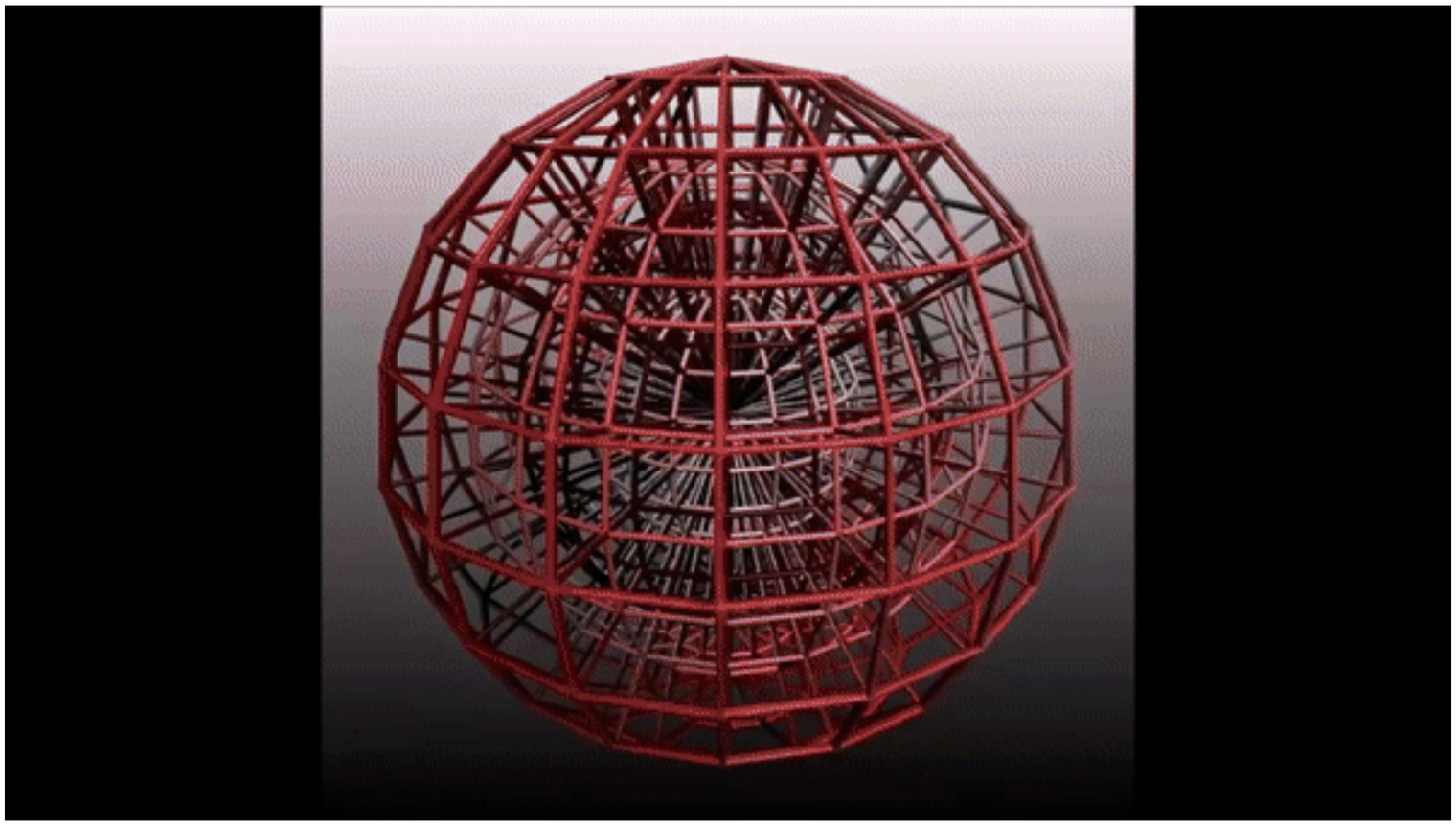
CURSE OF DIMENSIONALITY

Dimension: 2

CURSE OF DIMENSIONALITY

Dimension: 3

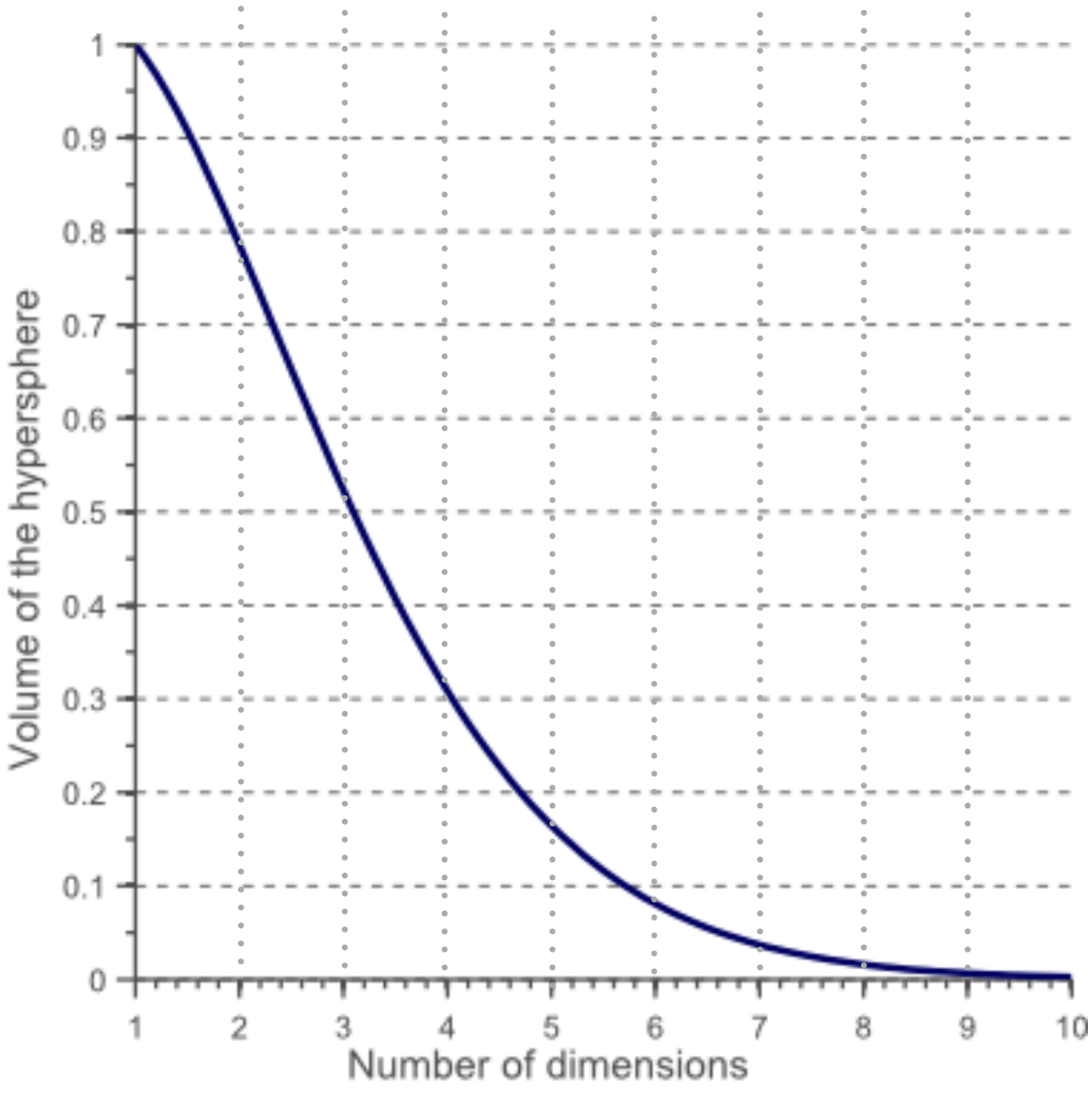
CURSE OF DIMENSIONALITY



Dimension: 4

HOW MUCH VOLUME I CAN FILL?

$$V(d) = \frac{\pi^{d/2}}{\Gamma\left(\frac{d}{2}+1\right)}\left(\frac{1}{2}\right)^d$$



but is deep learning really a hype?

Baidu's Andrew Ng on Deep Learning and Innovation in Silicon Valley

Nervana Systems raises $3.3M to build hardware designed for deep learning

by Derrick Harris Aug. 21, 2014 - 5:48 AM PST

Artificially Intelligent Robot Scientists Could Be Next Project for Google's AI Firm

Deep learning might help you get an ultrasound at Walgreens

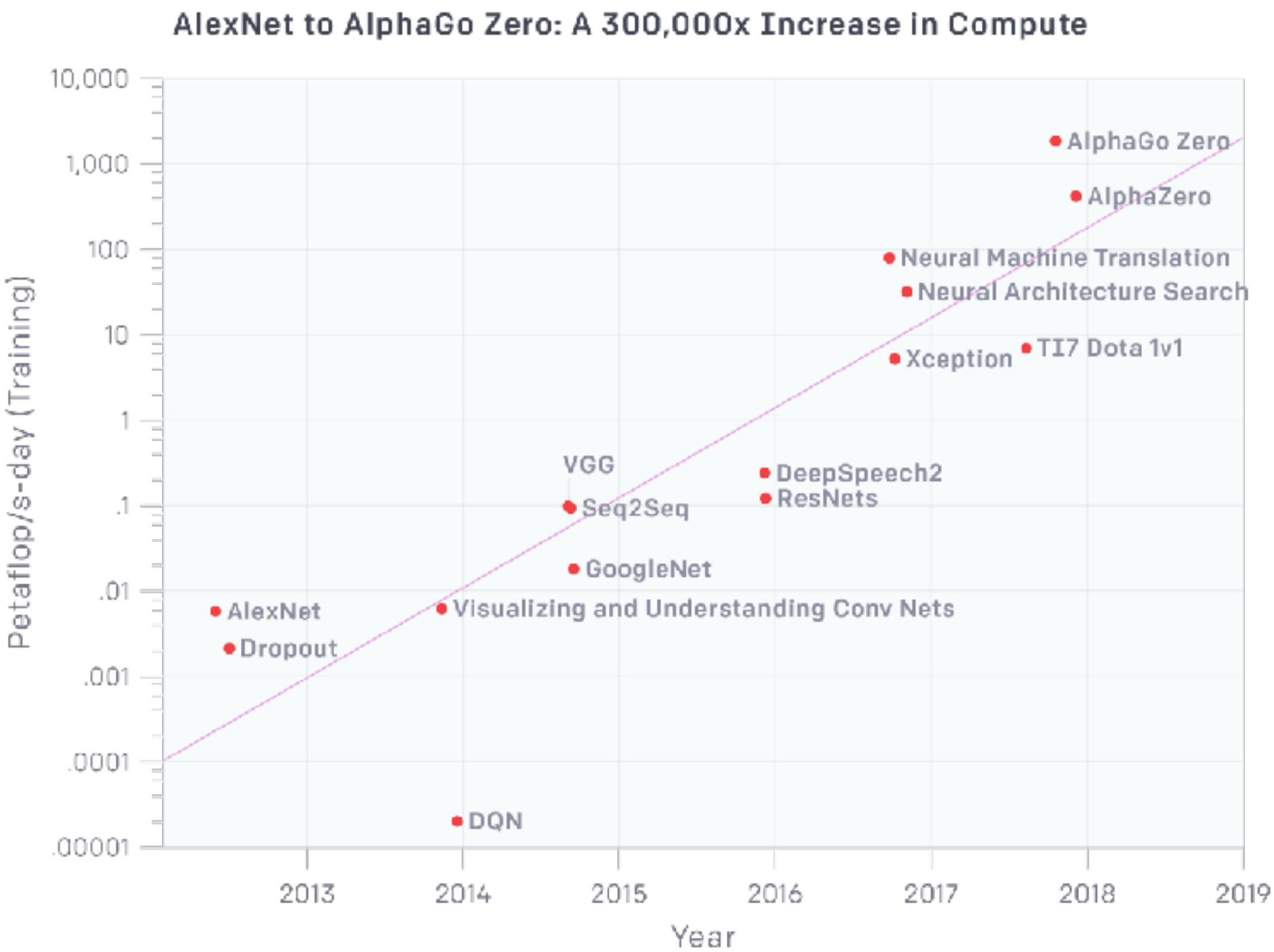
by Derrick Harris Nov. 20, 20..

A Googler's Quest to Teach Machines How to Understand Emotions

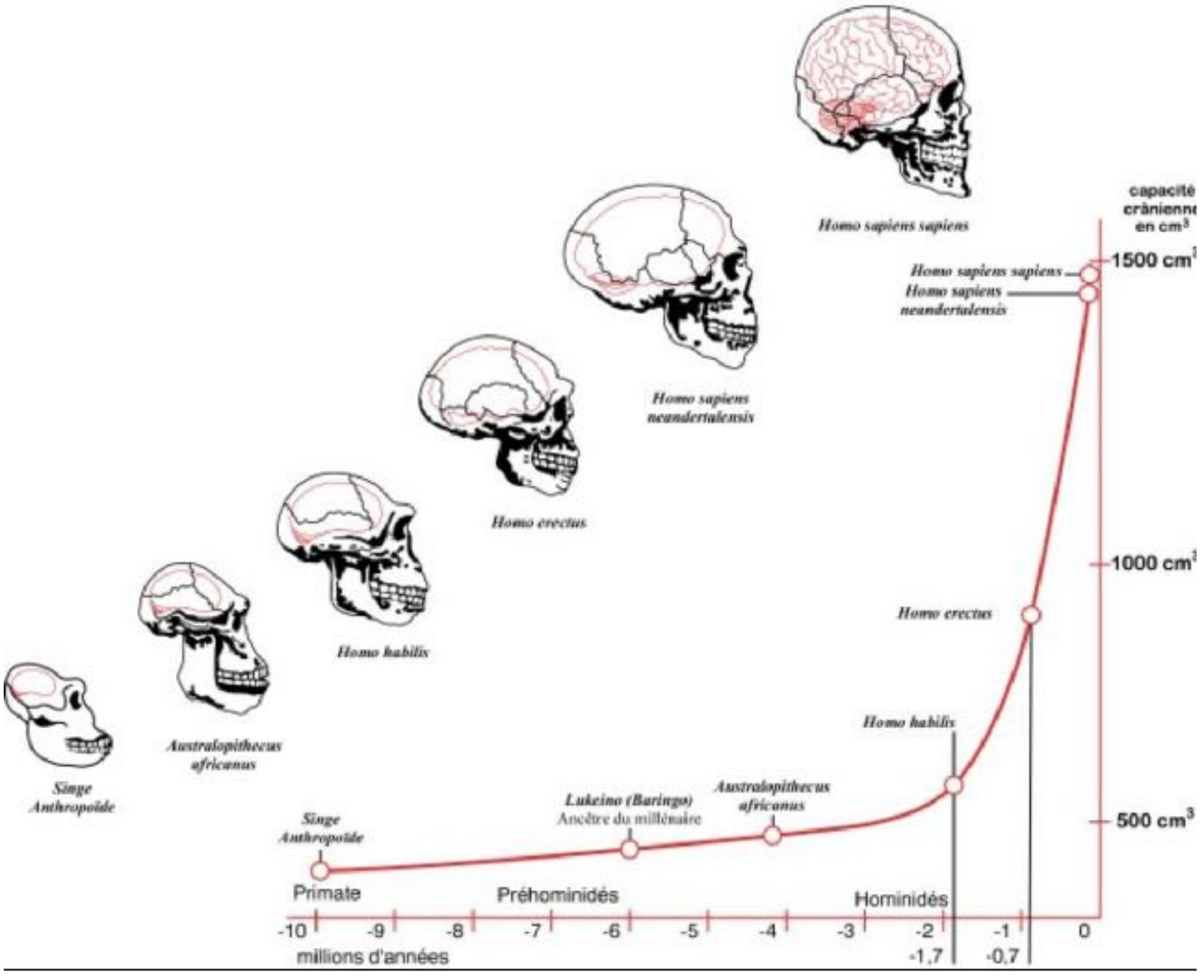
Google, Spotify, & Pandora bet a computer could generate a better playlist than you can

Butterfly Network Hopes to Bring Deep Learning AI to Medicine

Enlitic picks up $2M to help diagnose diseases with deep learning



https://blog.openai.com/ai-and-compute


Singe Anthropoïde
Australopithecus africanus
Homo habilis
Homo erectus
Homo sapiens neandertalensis
Homo sapiens sapiens
capacité crânienne en cm3
1500 cm3
1000 cm3
500 cm3
Homo sapiens sapiens
Homo sapiens neandertalensis
Homo erectus
Homo habilis
Australopithecus africanus
Lukeino (Baringo)
Ancêtre du millénaire
Singe Anthropoïde
Primate
Préhominidés
Hominidés
-10
-9
-8
-7
-6
-5
-4
-3
-2
-1
0
-1,7
-0,7
millions d'années

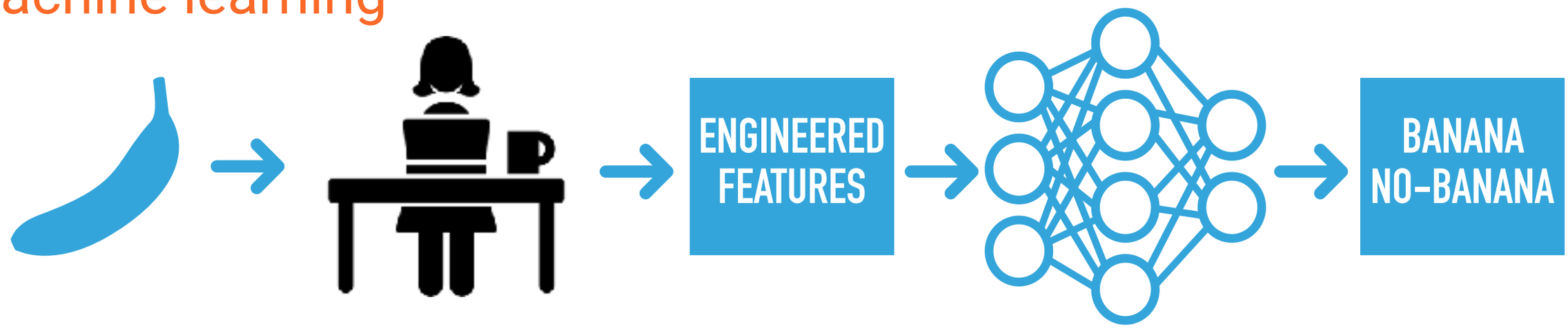
WHERE ARE WE NOW?

Brock et al. (2018)

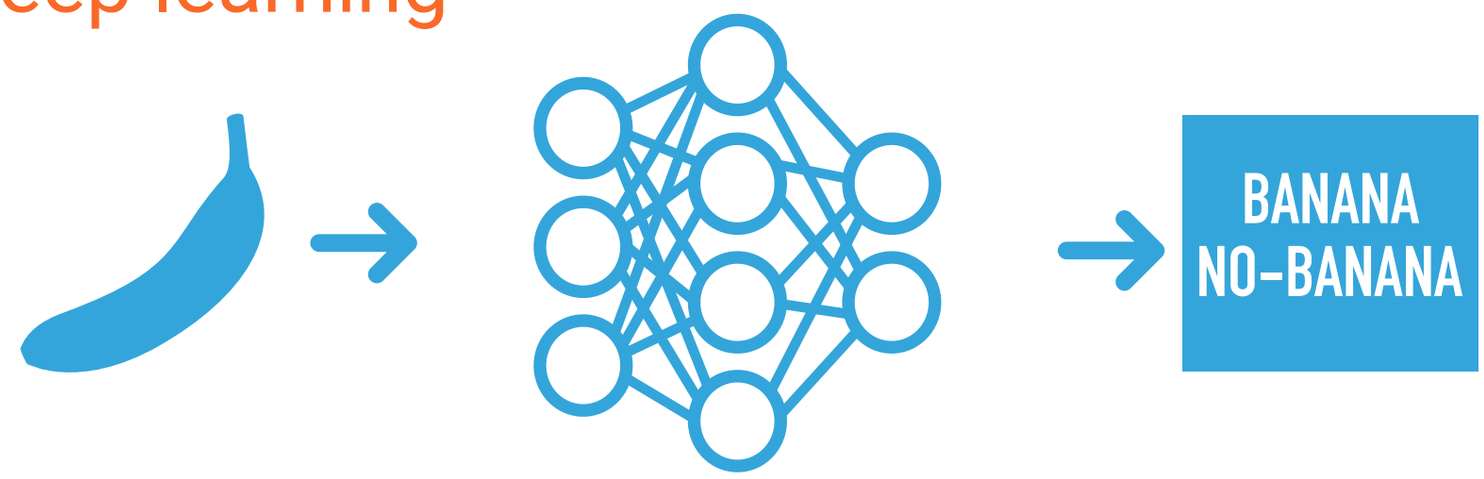
Basics

CLASSICAL MACHINE LEARNING VS. DEEP LEARNING

Machine learning

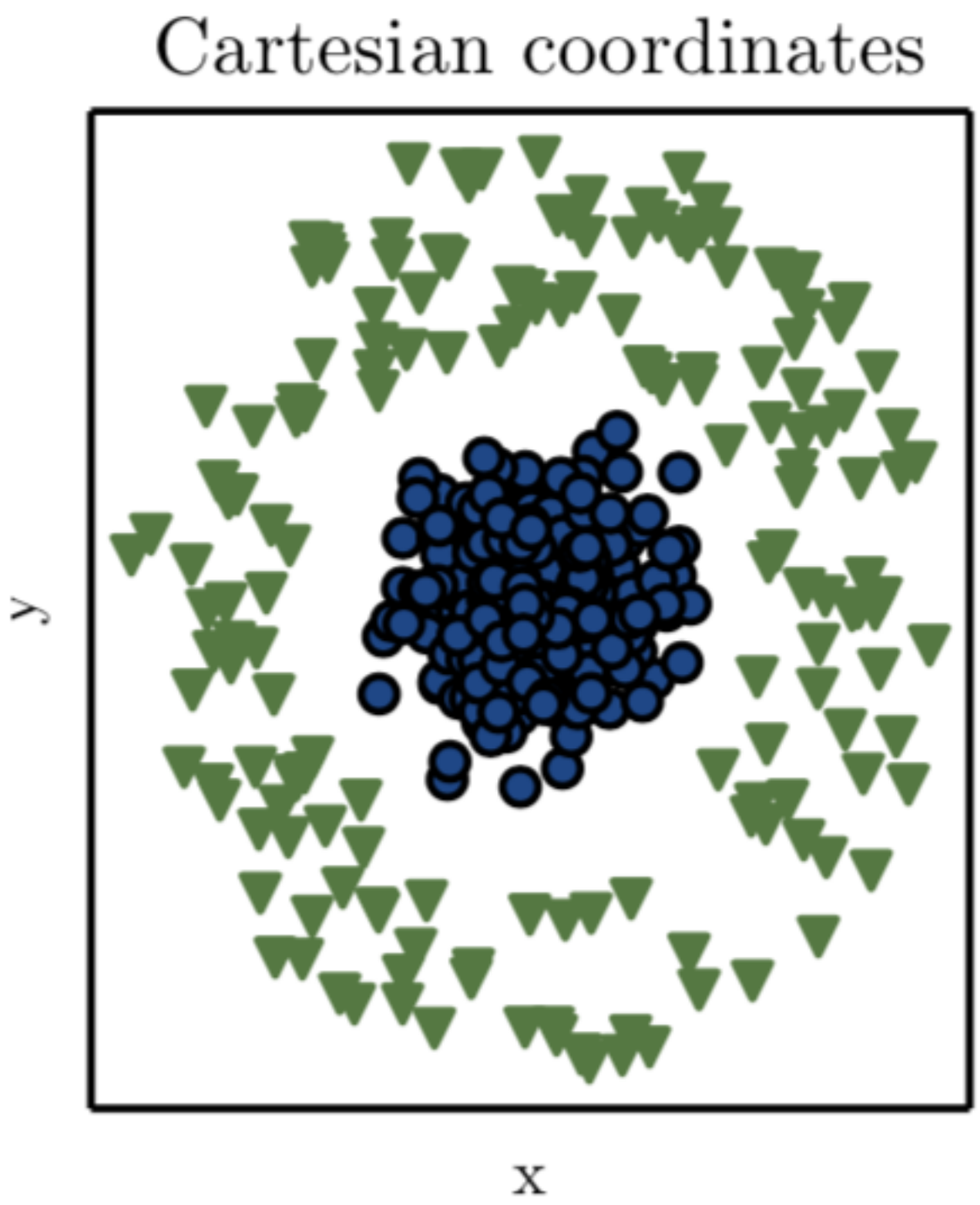


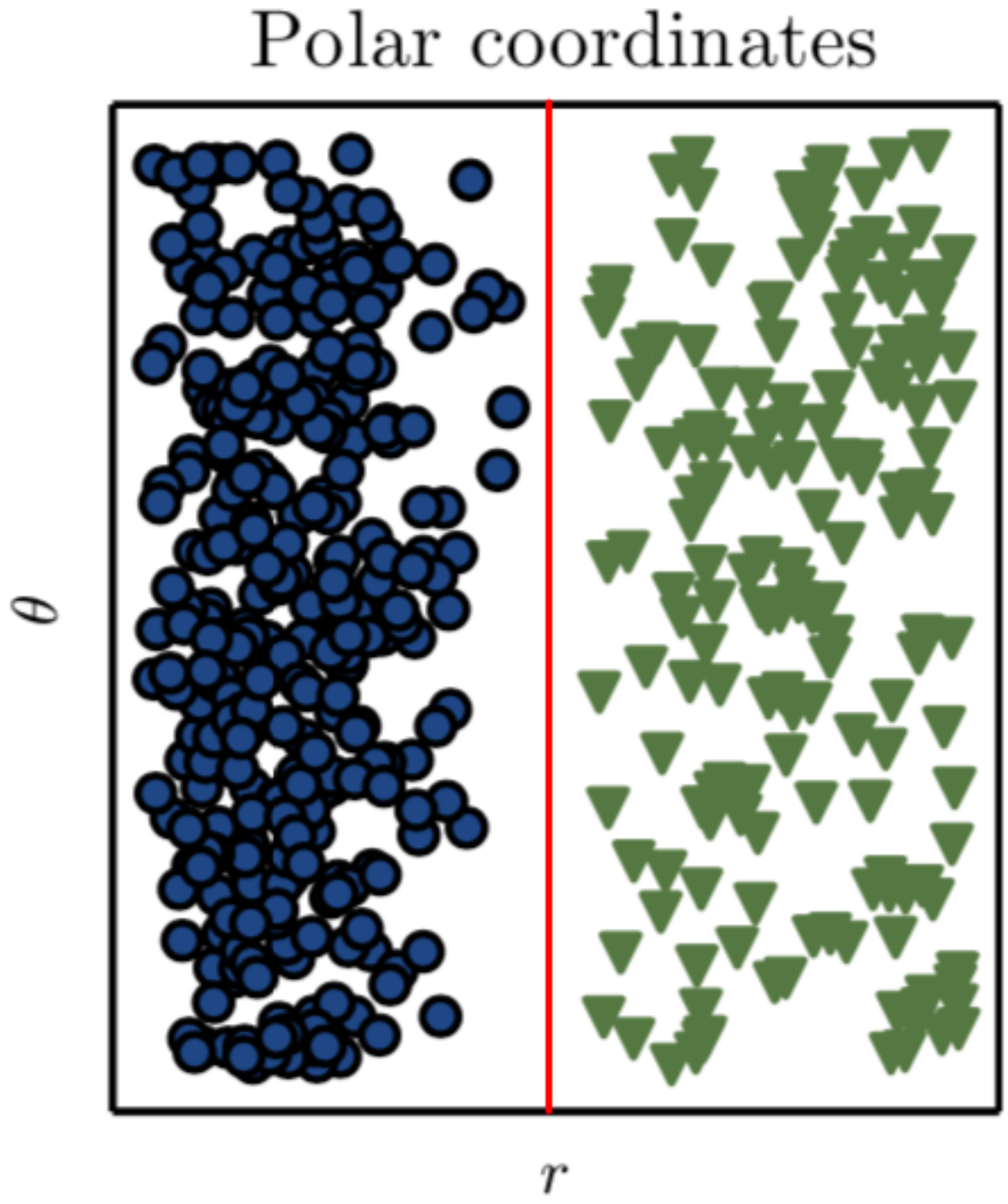
Deep learning



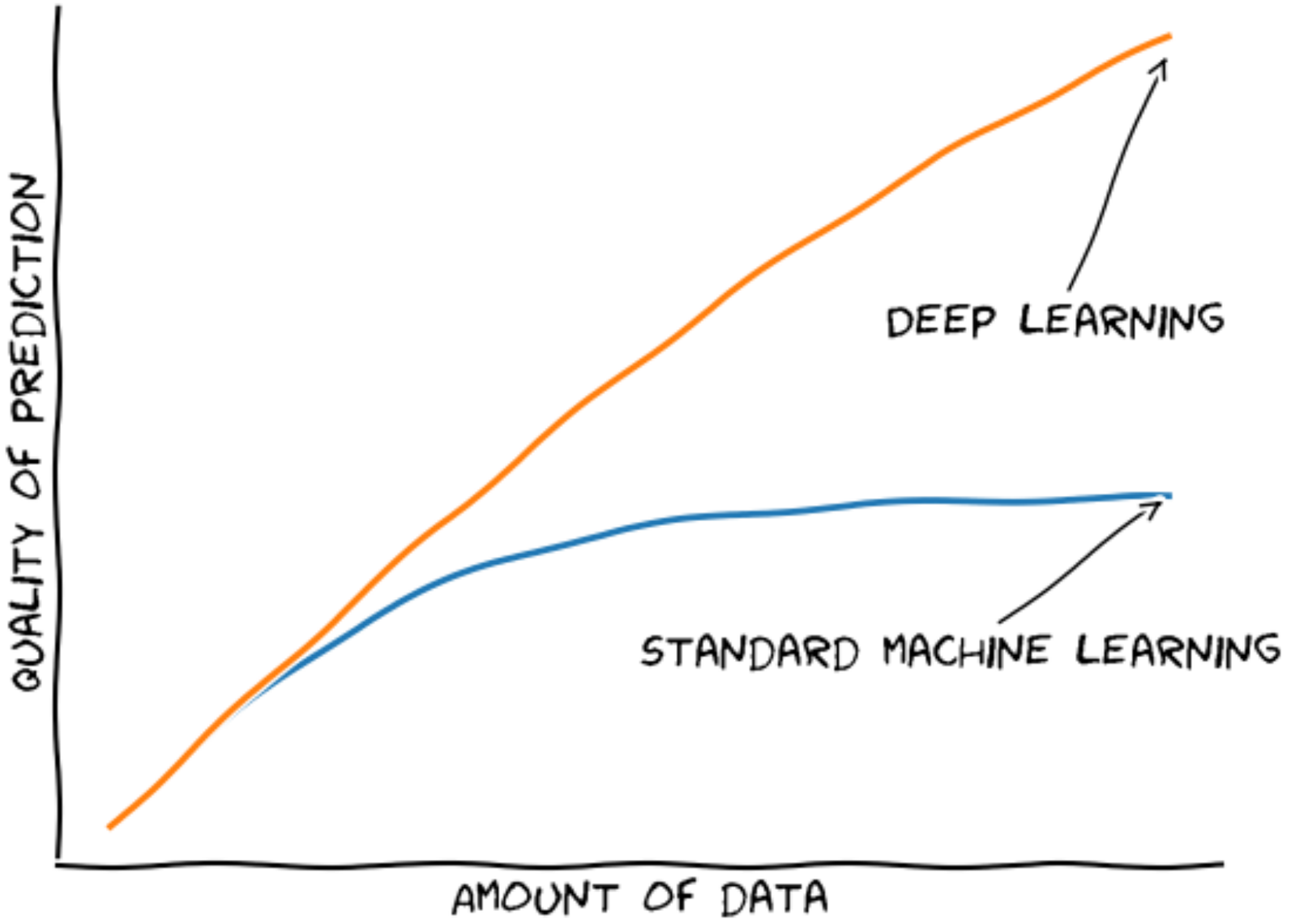
Credits: freepik.com

CLASSICAL MACHINE LEARNING VS. DEEP LEARNING

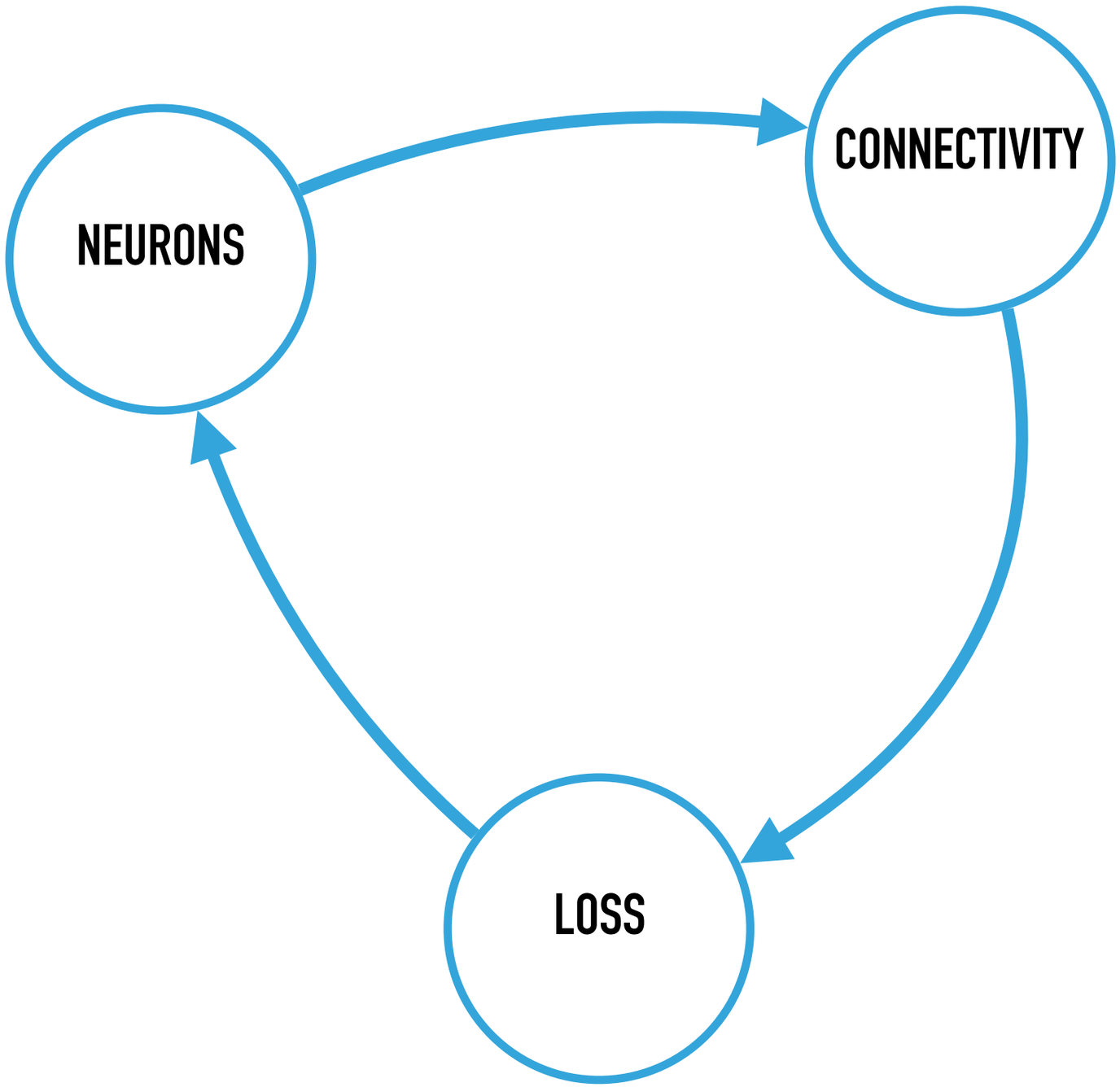




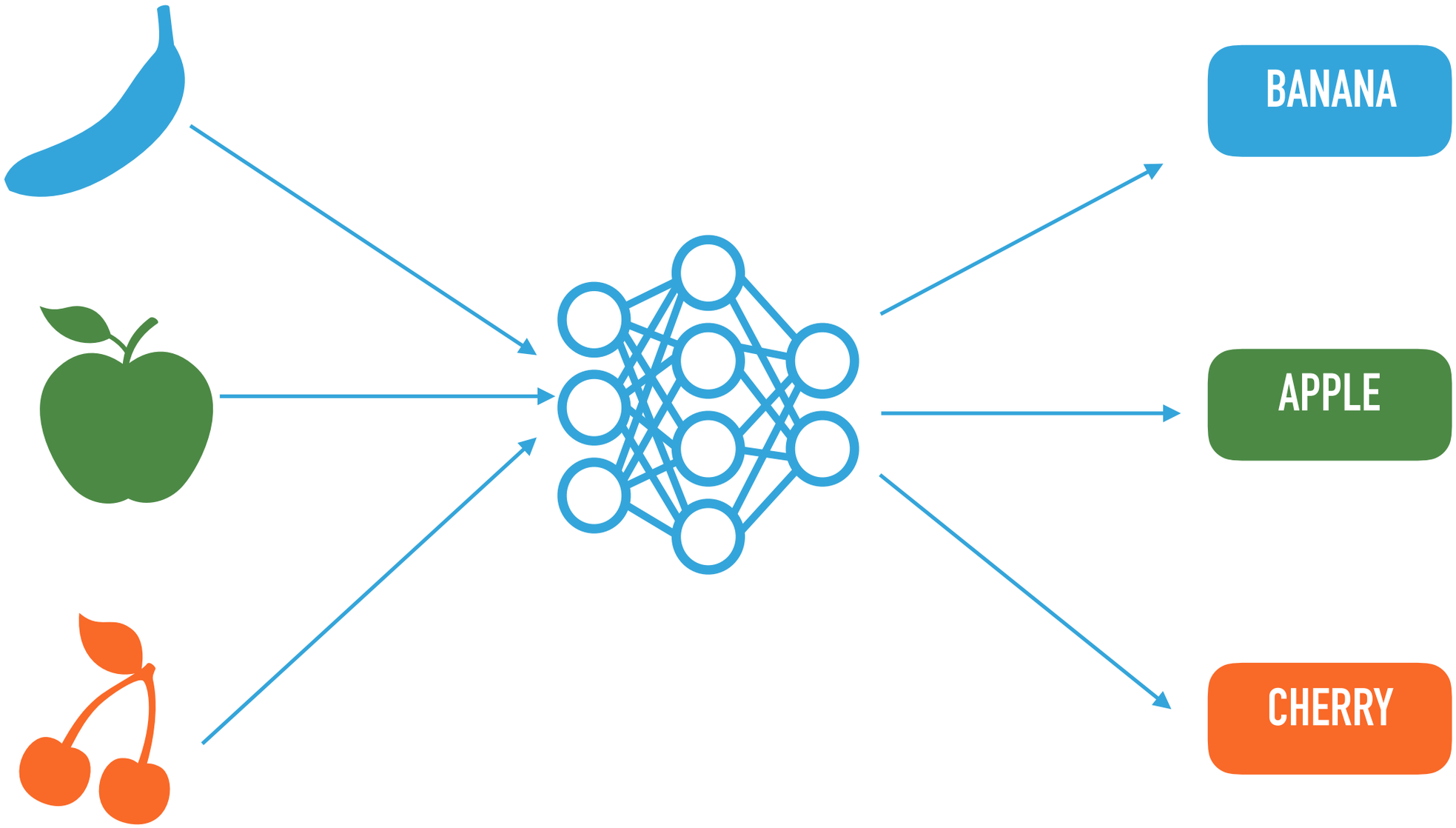
WHY DEEP LEARNING?



NEURAL NETWORKS : INGREDIENTS

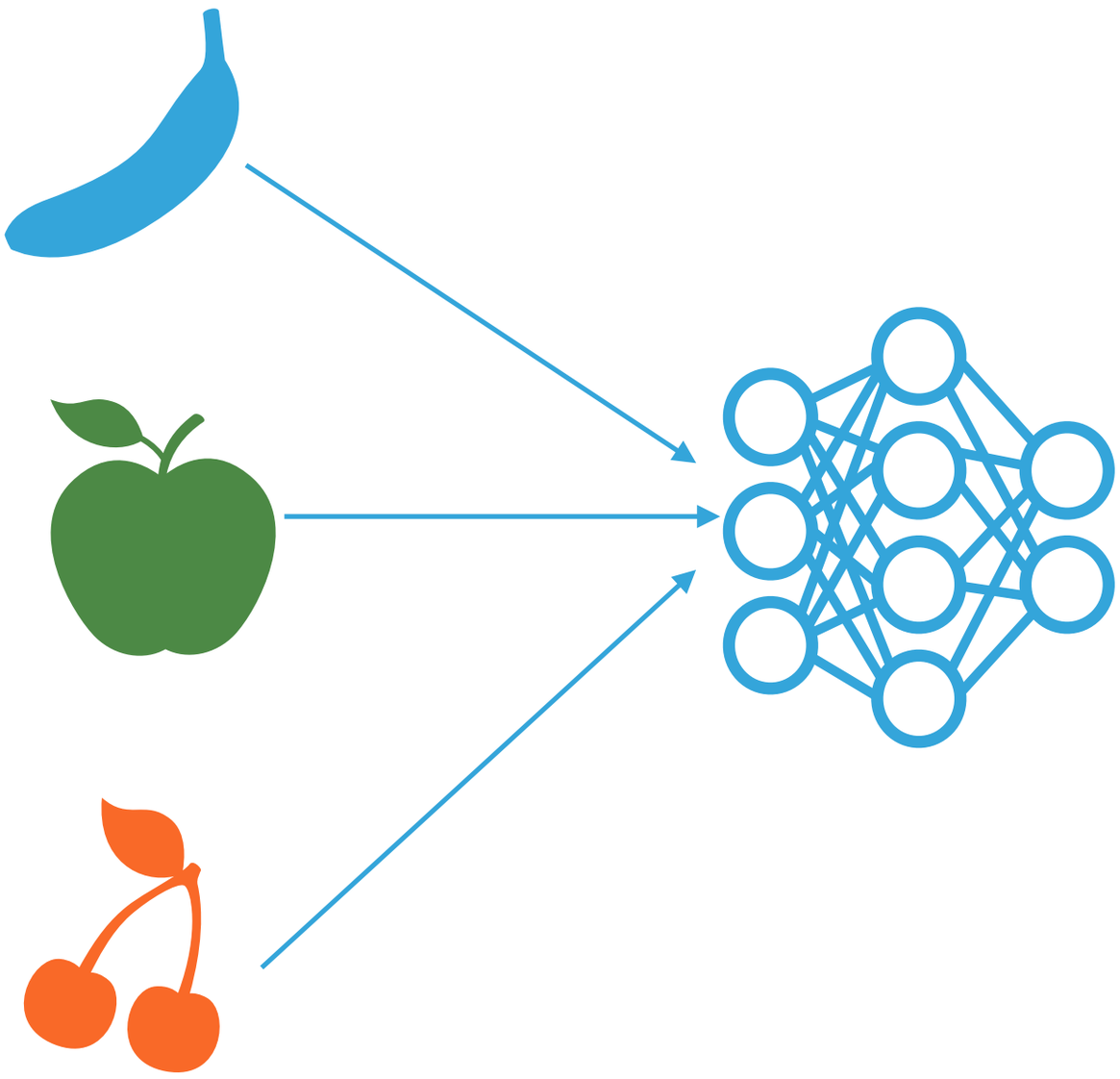


SUPERVISED TRAINING



Prediction, classification, regression, image2image, …

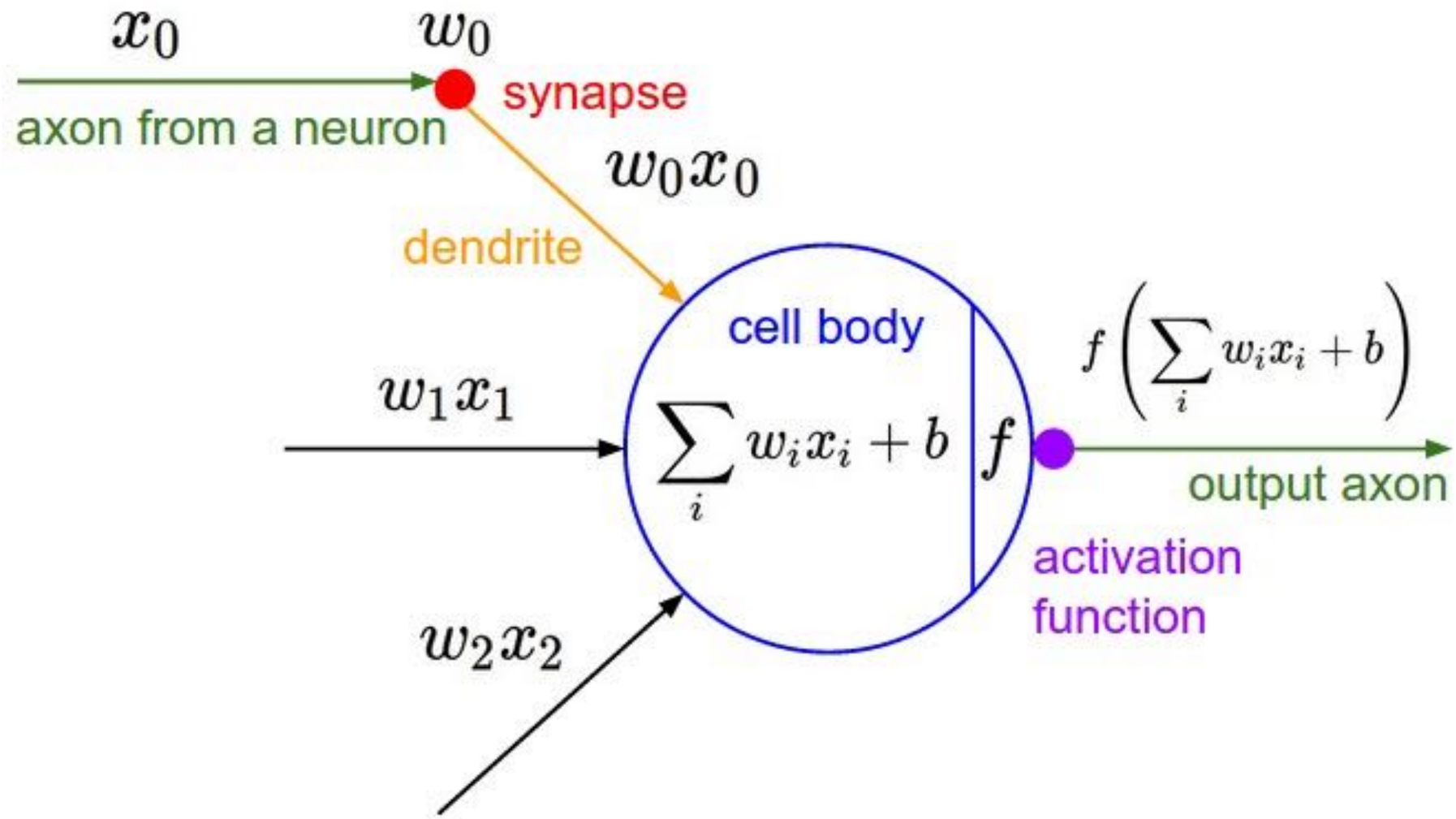
UNSUPERVISED TRAINING



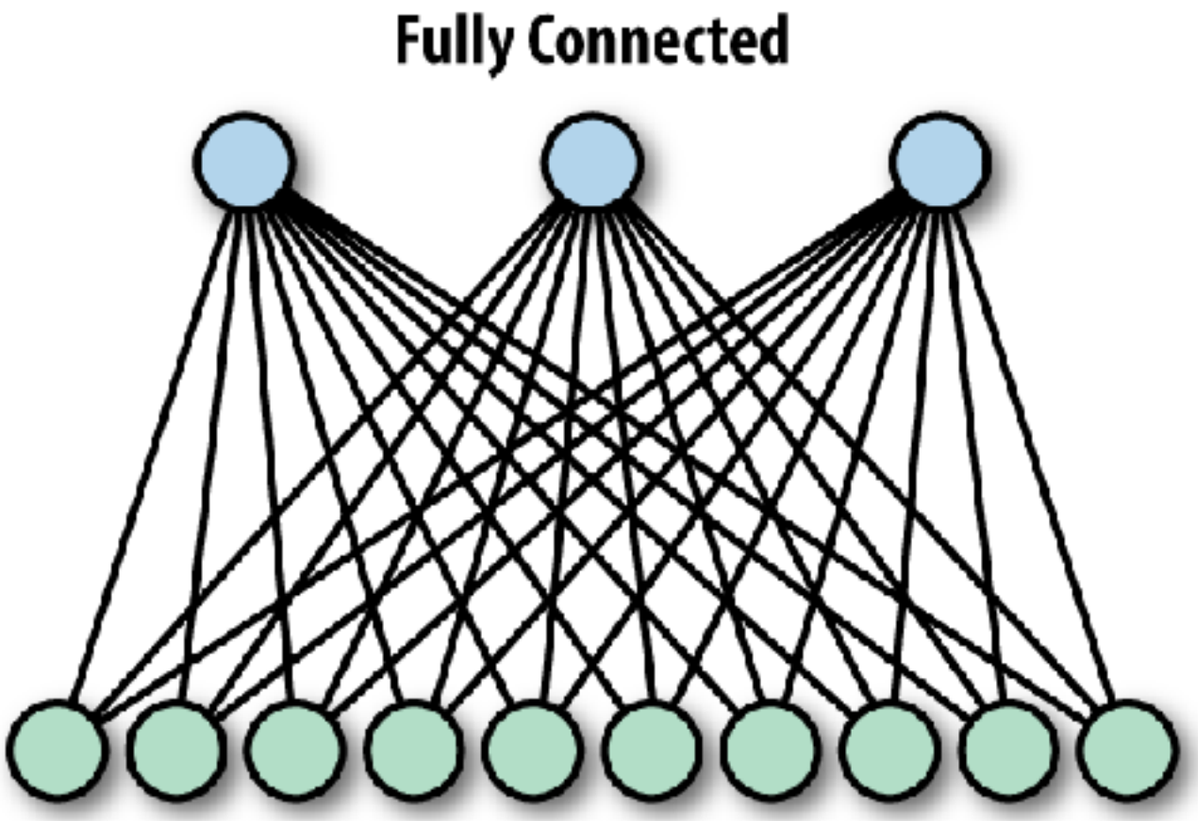
Clustering, feature extraction, generative models,...

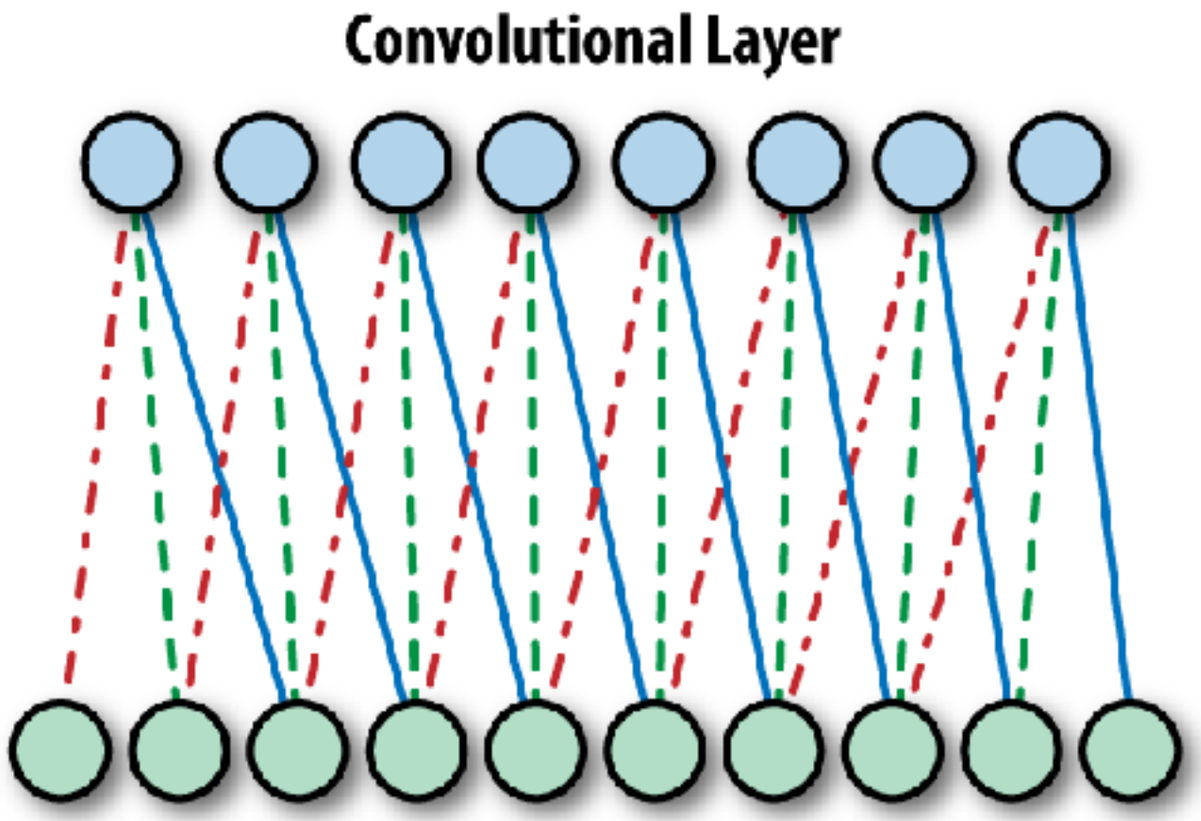
Arquitecture of a neural network

THE BASICS : A NEURON

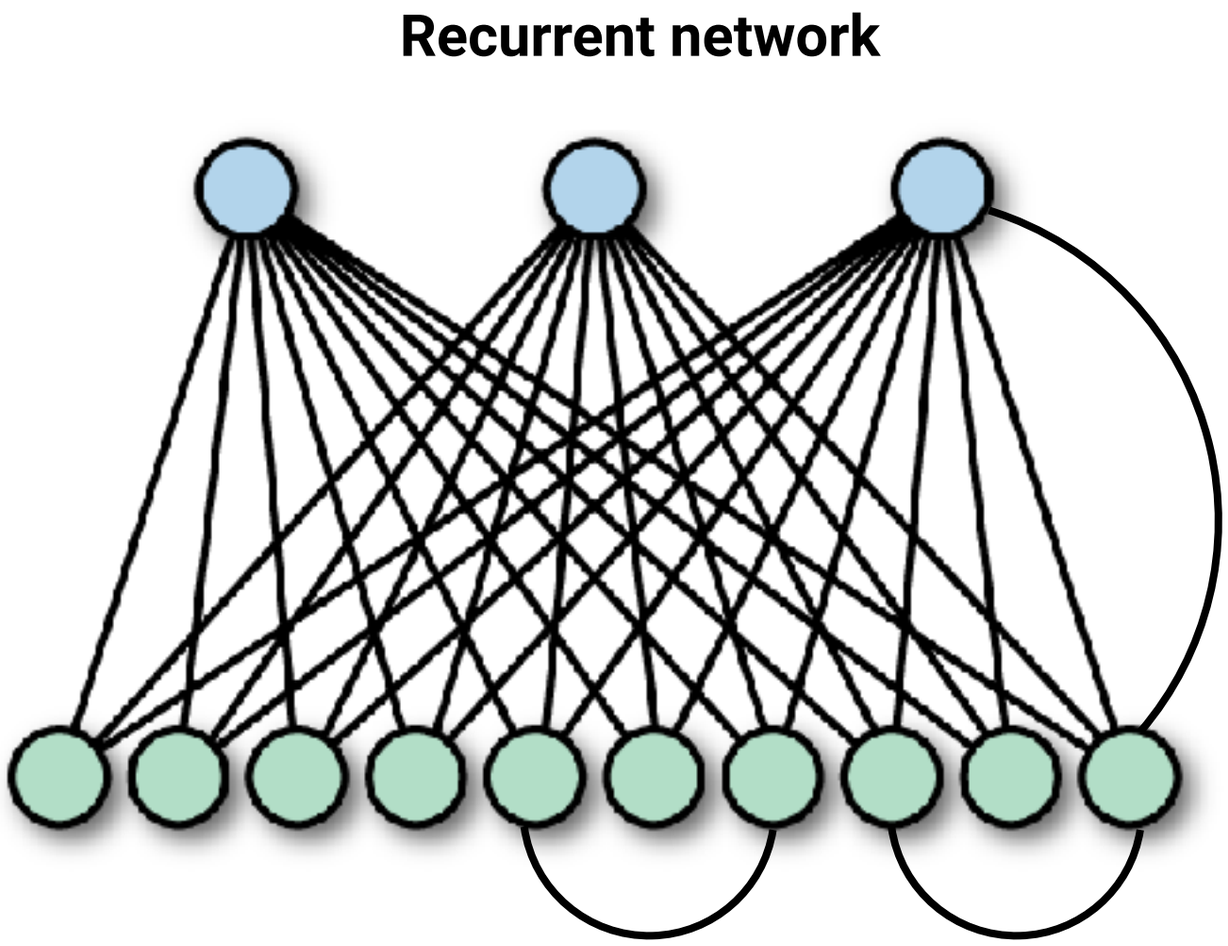


TYPES OF NEURAL NETWORKS

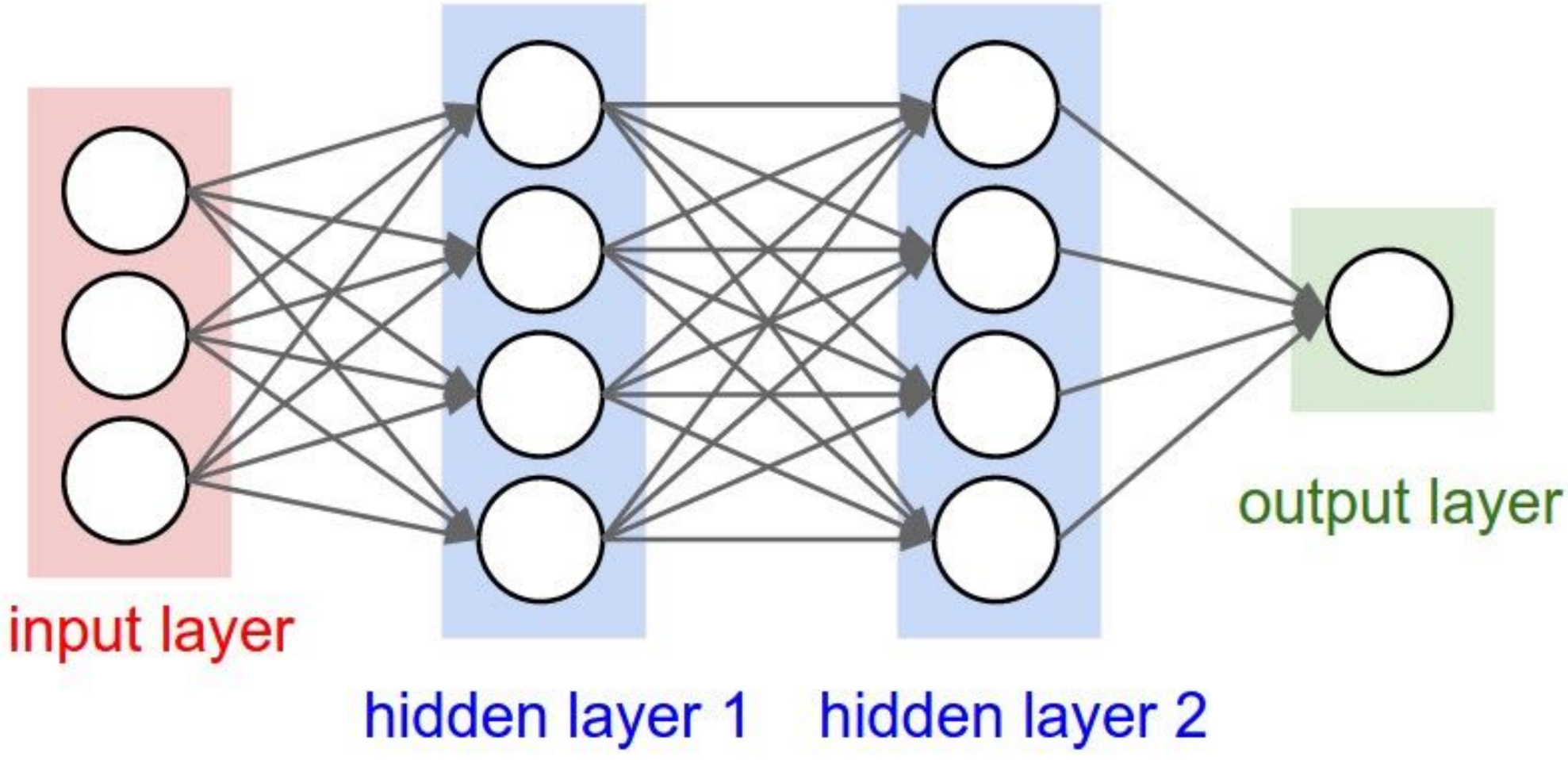




TYPES OF NEURAL NETWORKS

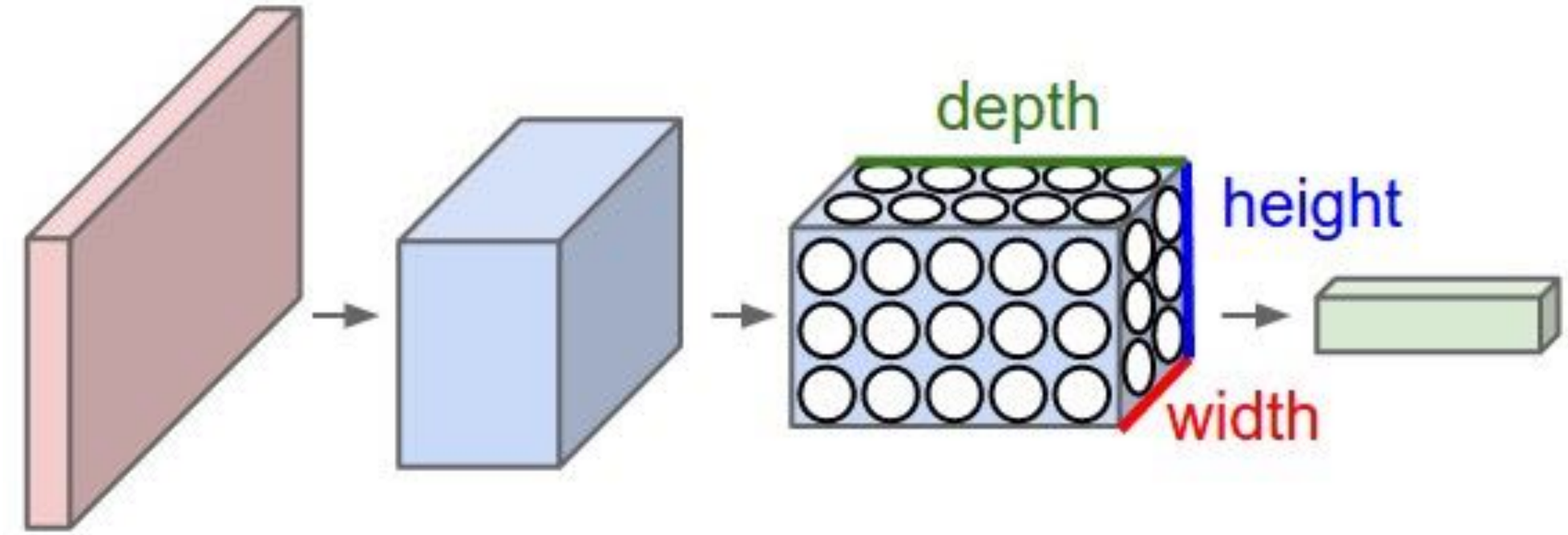


FULLY CONNECTED NEURAL NETWORK



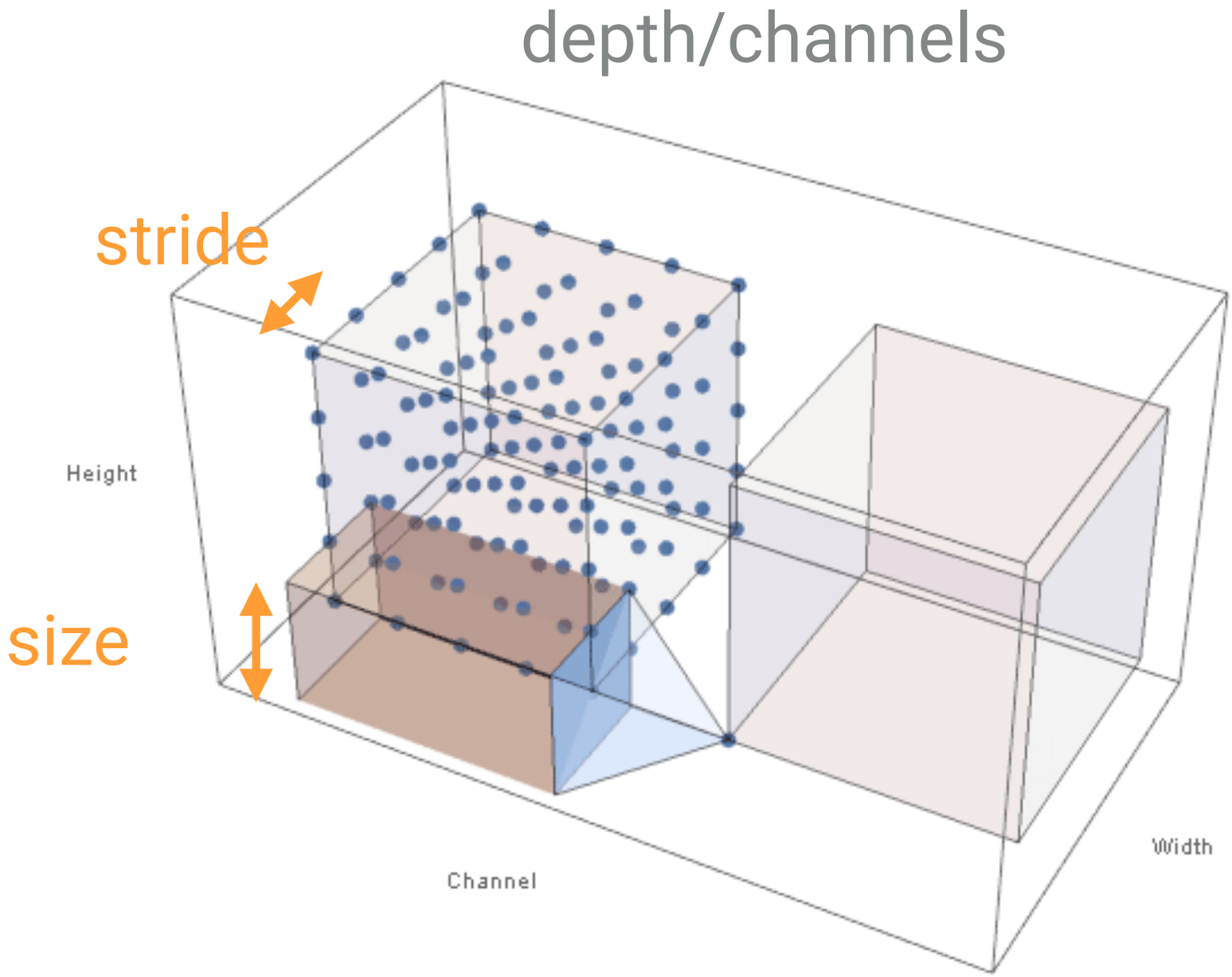
$$N = N_{\text{in}} N_{\text{hid1}} + N_{\text{hid1}} N_{\text{hid2}} + N_{\text{hid2}} N_{\text{out}}$$

CONVOLUTIONAL NEURAL NETWORK

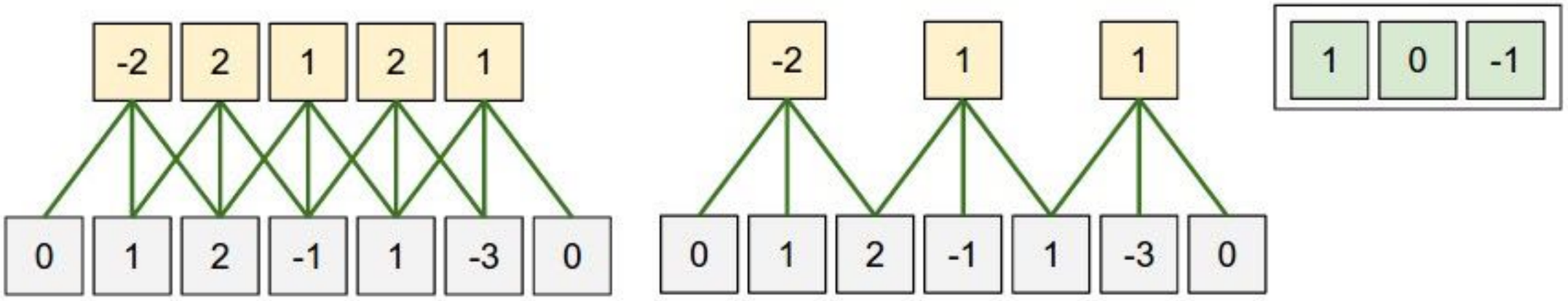


$$N = N_{\text{in}} N_{\text{ker}} d_{\text{ker}}^2$$

CONVOLUTION



STRIDE



$$\frac{W - K + 2P}{S} + 1$$

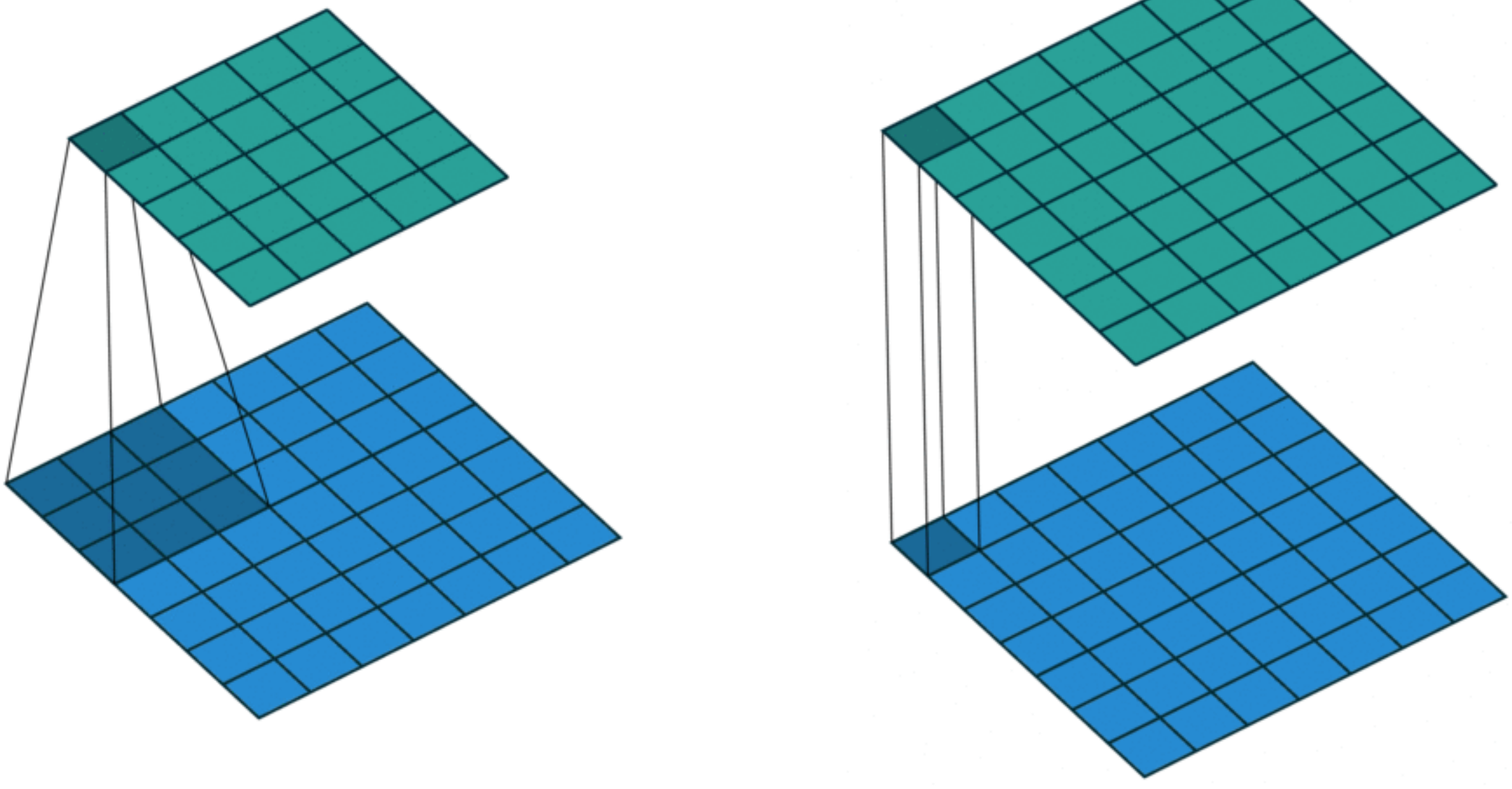
W: volume size

K: kernel size

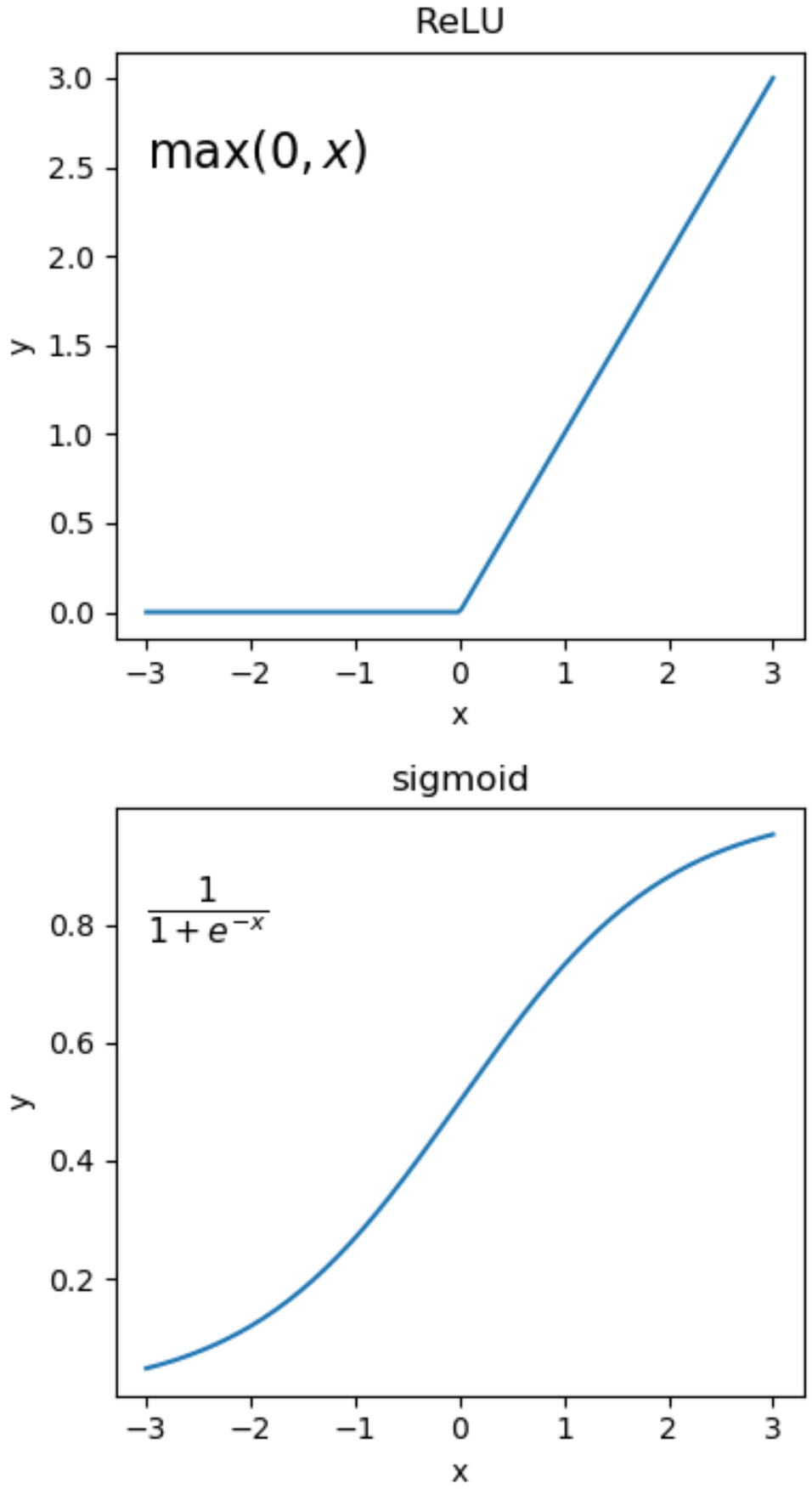
P: zero padding

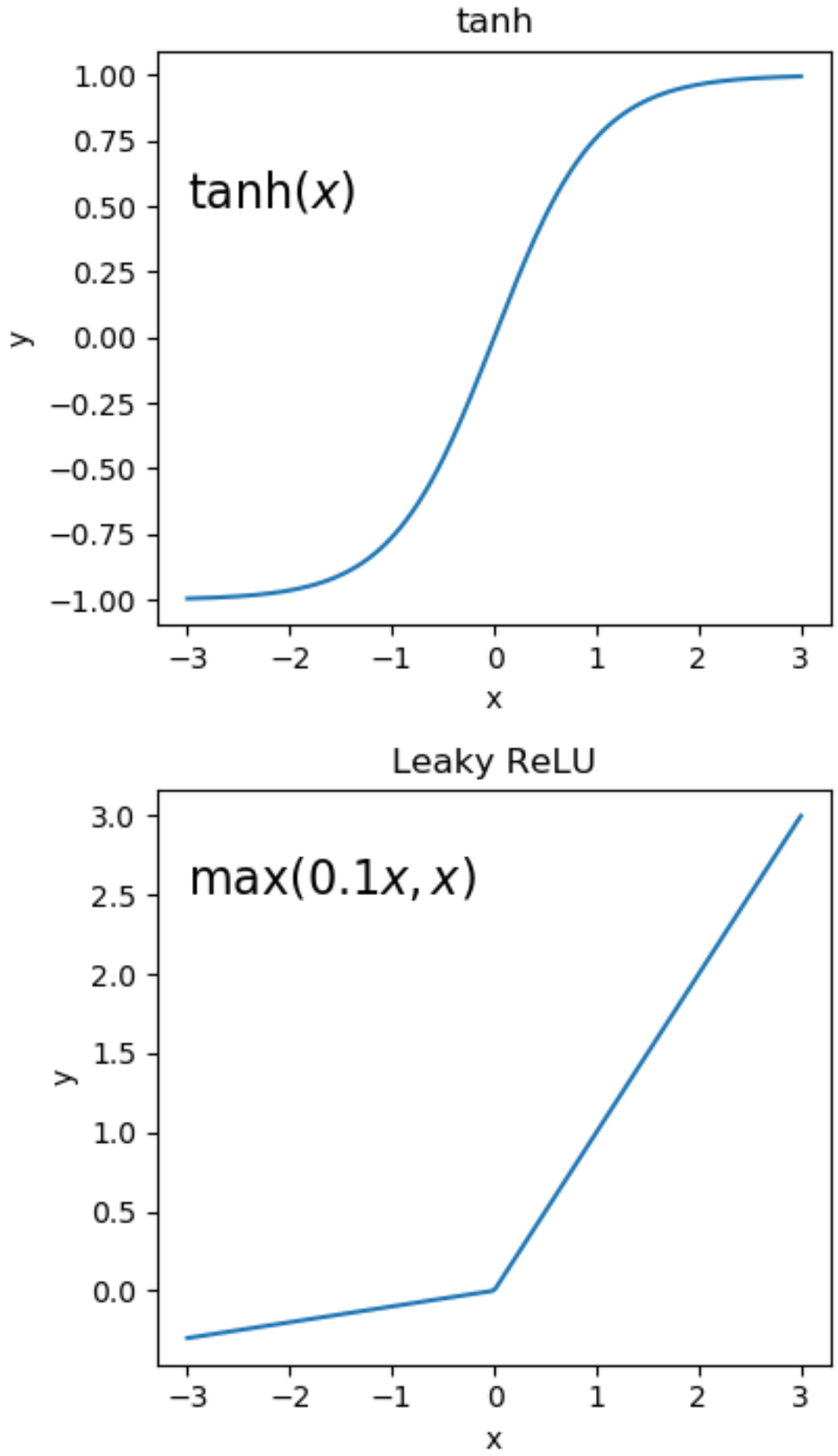
S: stride

1X1 CONVOLUTION

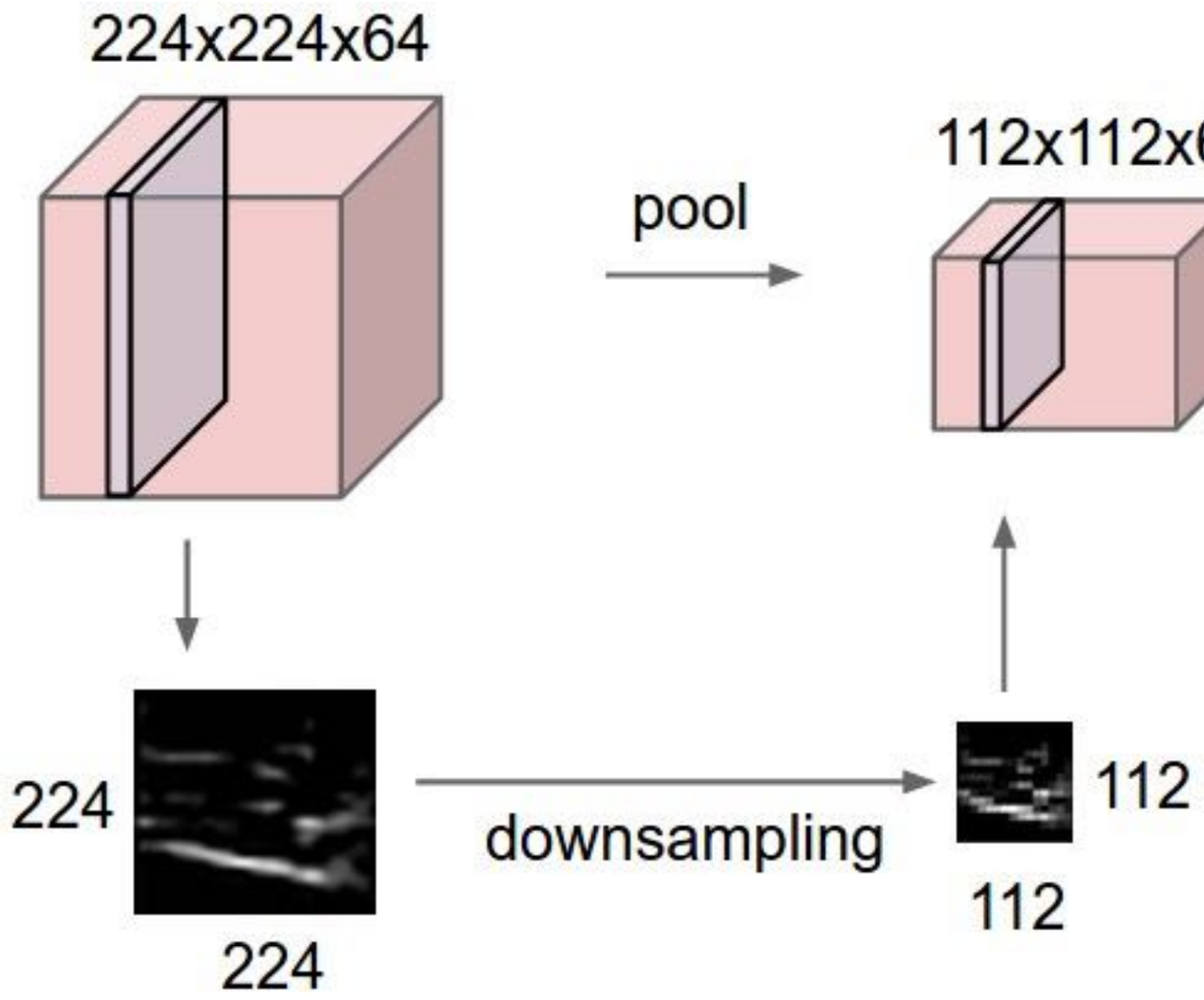


ACTIVATION FUNCTION

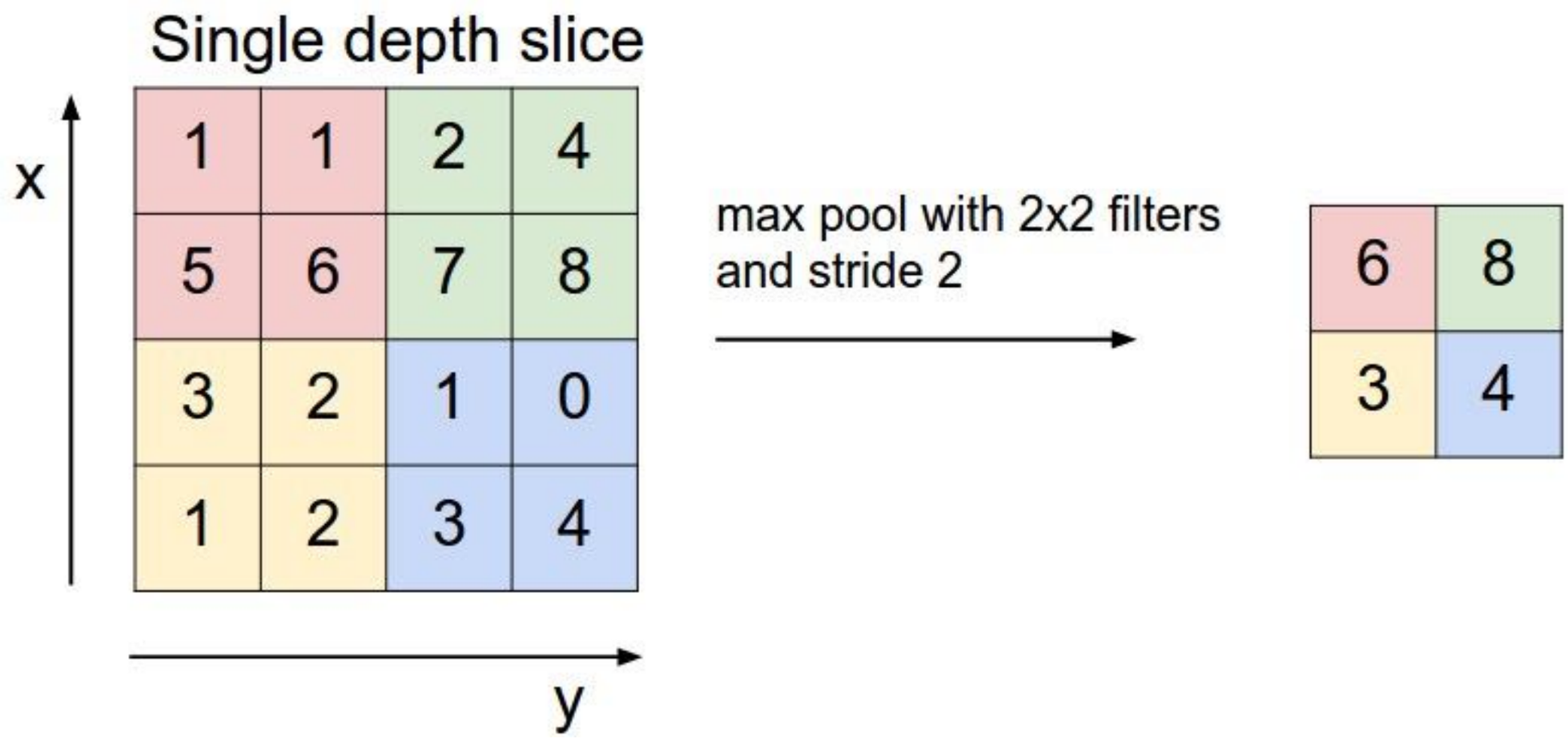




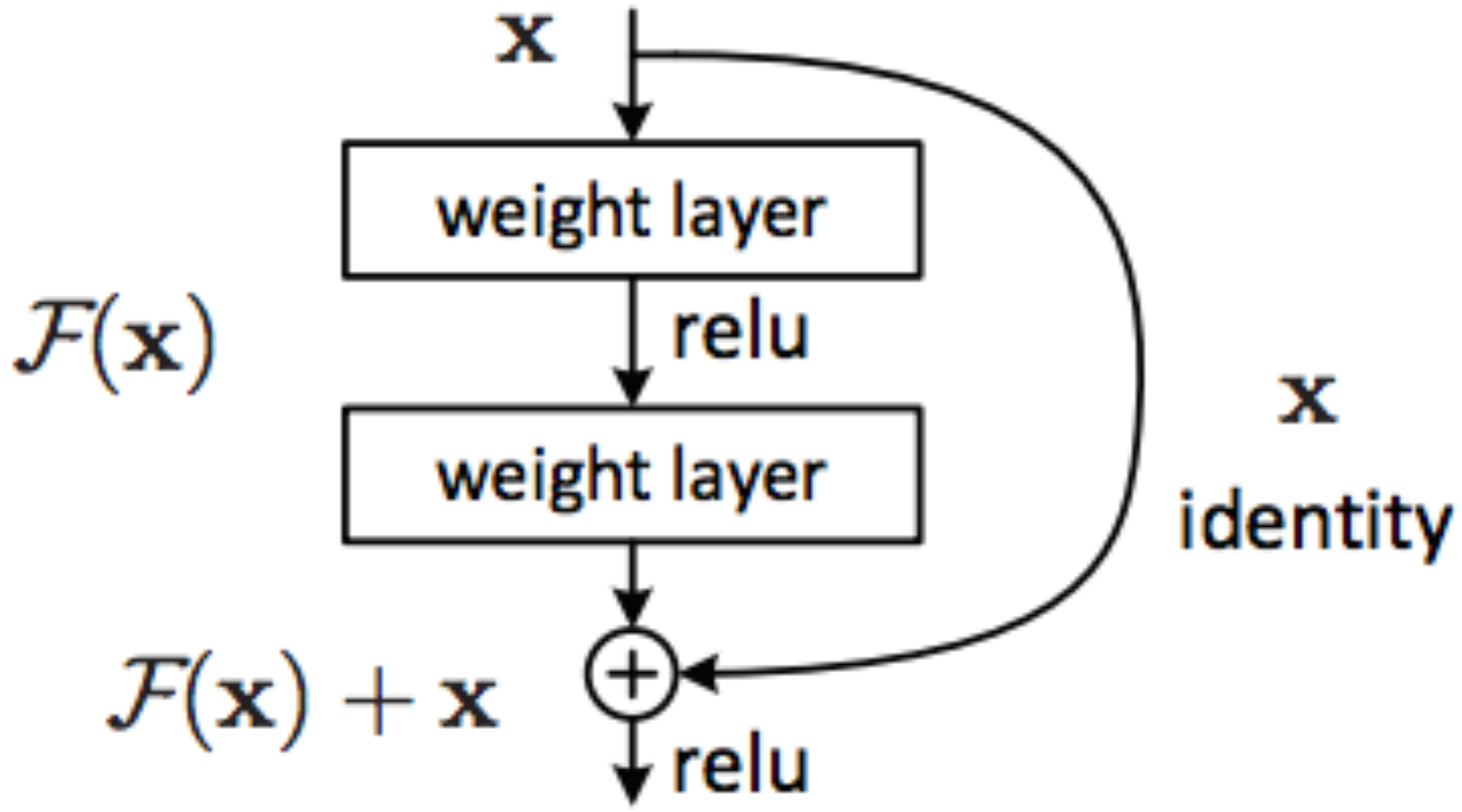
POOLING

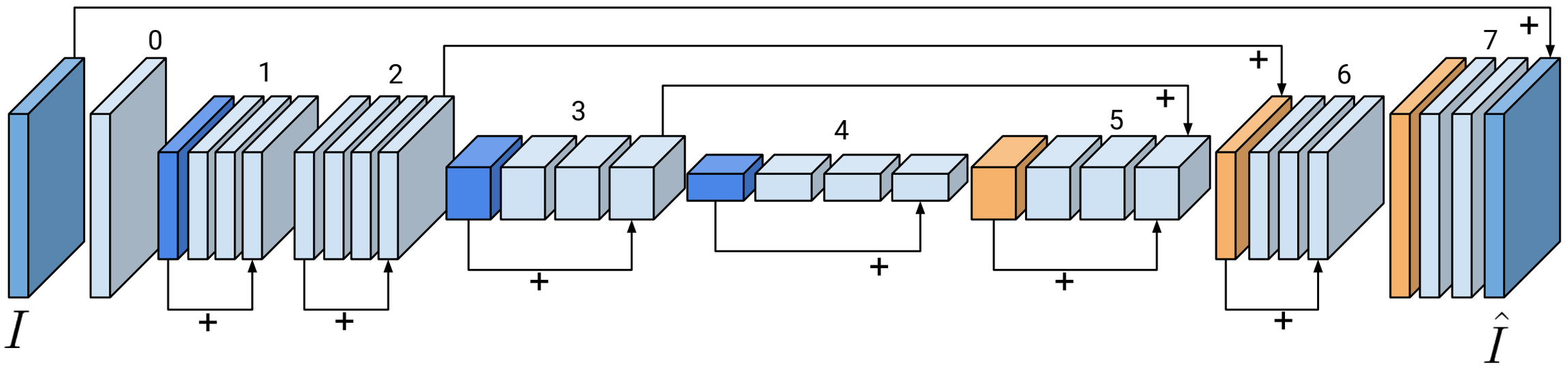


MAX-POOLING


Single depth slice
x
y
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2x2 filters
and stride 2
6 8
3 4

RESIDUAL CONNECTION





BATCH NORMALIZATION

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

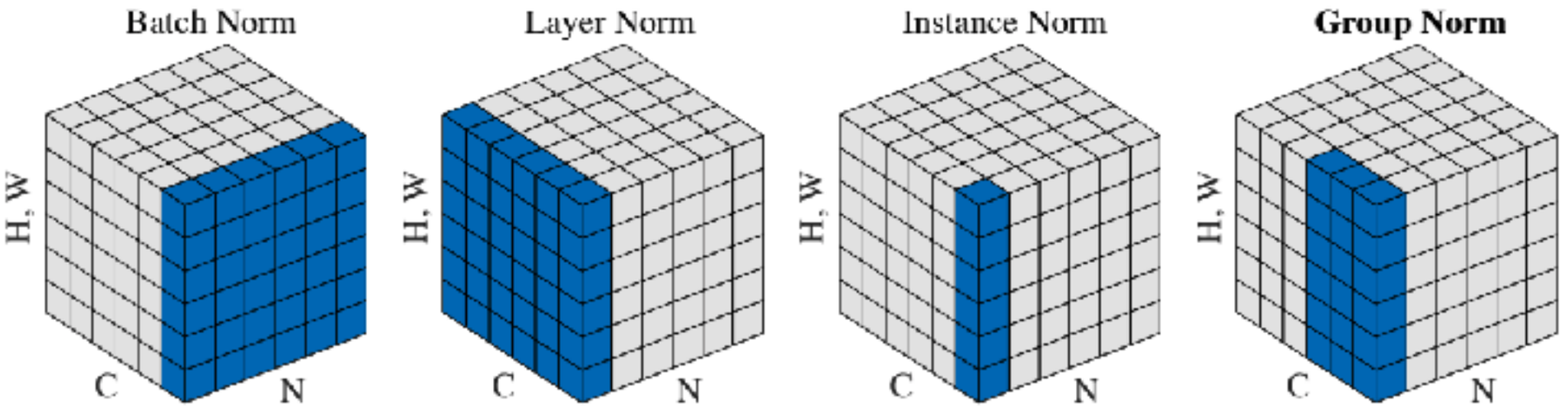
$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.

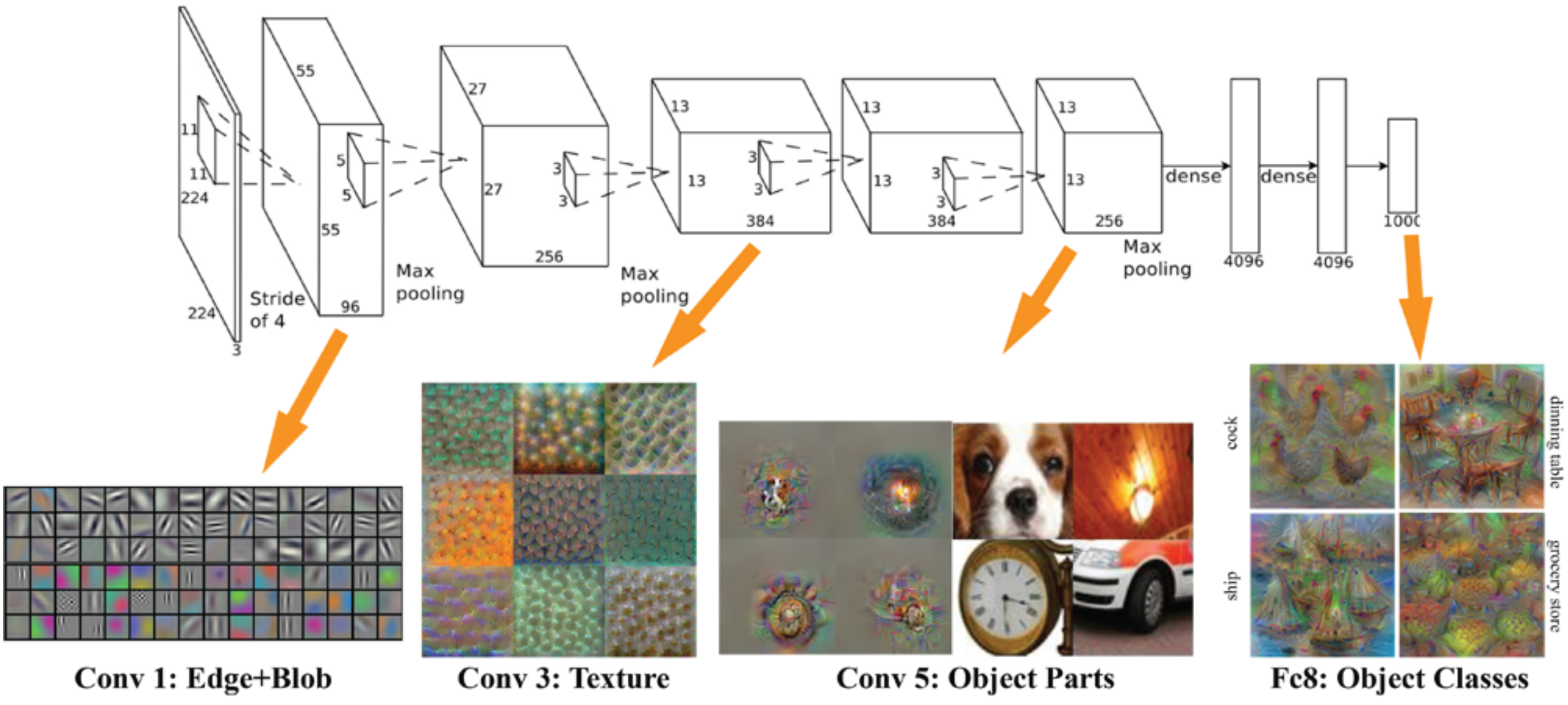
Ioffe & Szegedy (2015)

BATCH NORMALIZATION

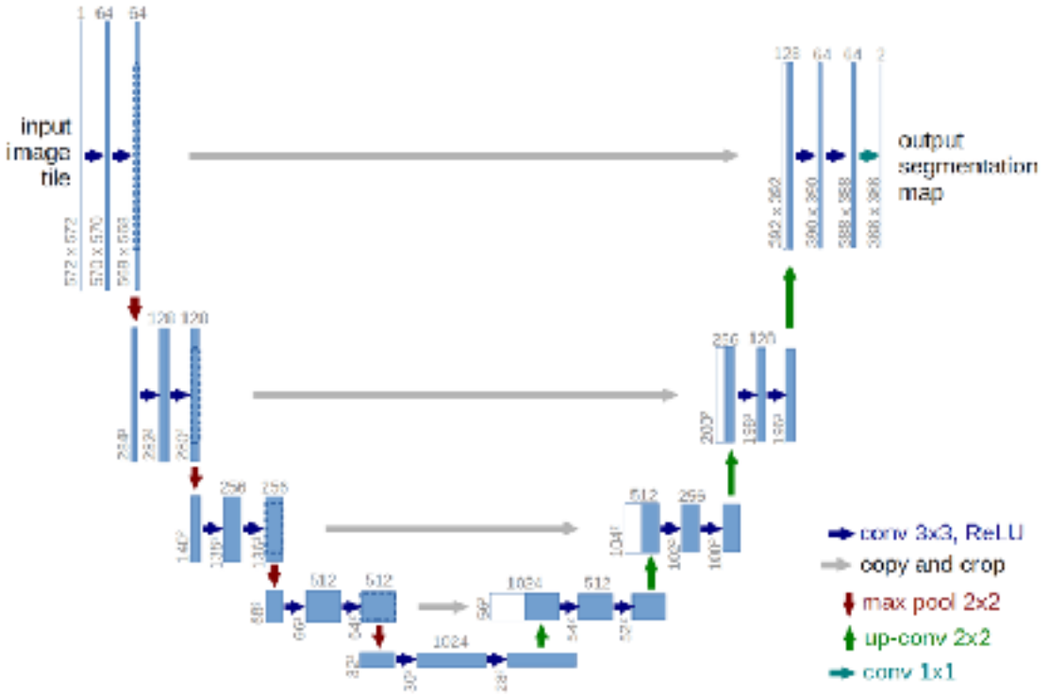


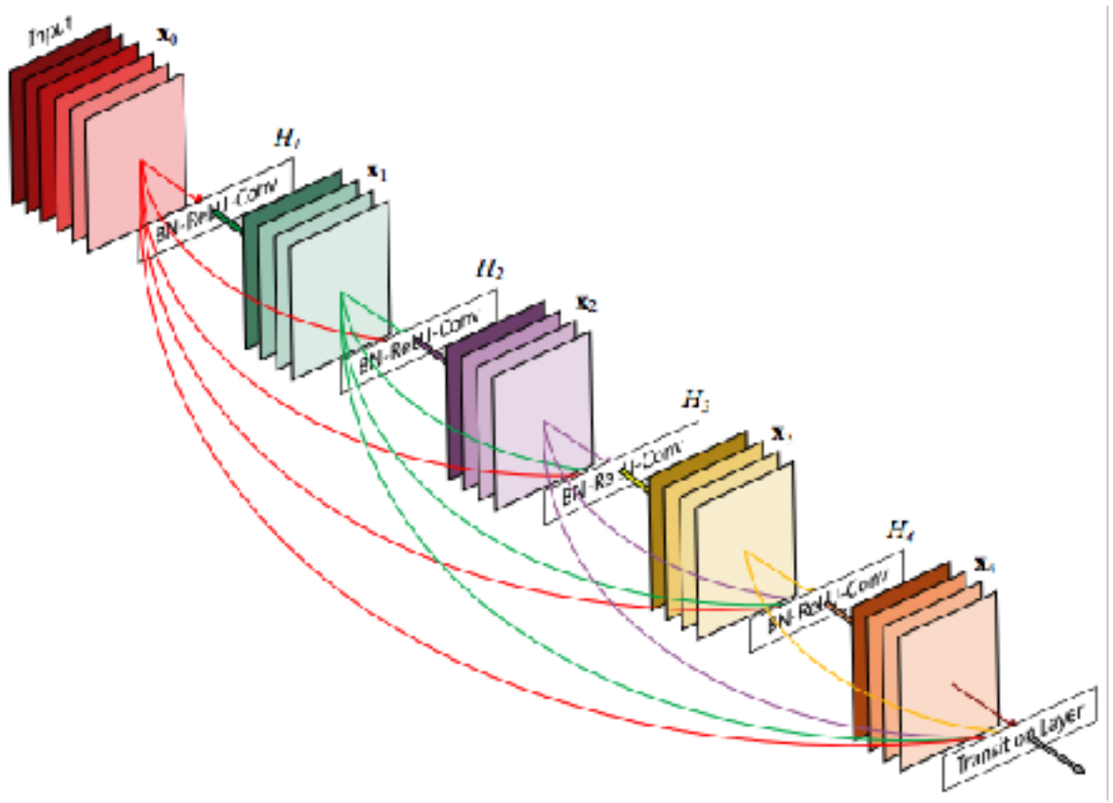
Wu & He (2018)

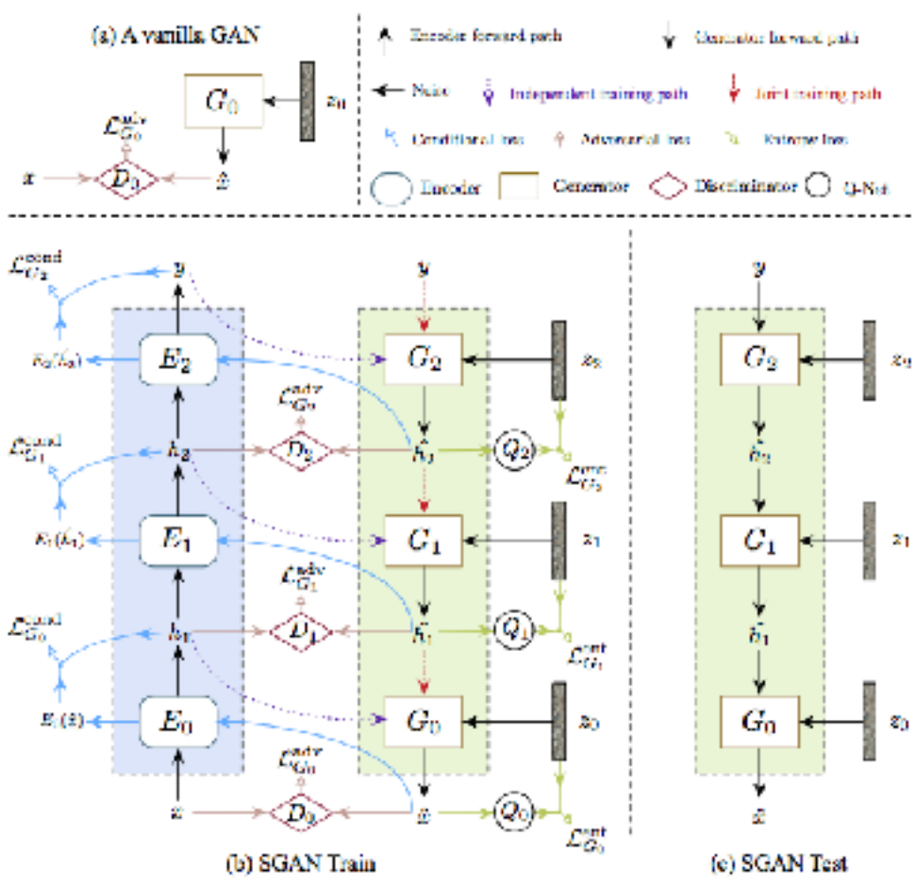
MULTISCALE ANALYSIS

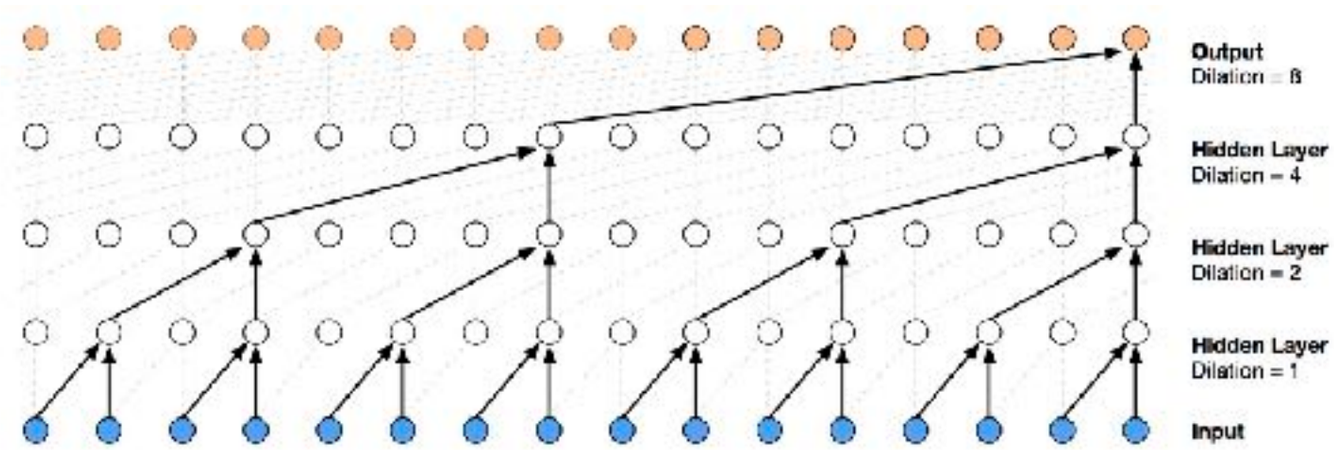


ENORMOUS LANDSCAPE









TWO RULES TO DECIDE THE ARCHITECTURE

Read a lot!

Experiment a lot!

Still not in books: arxiv!

Training of a neural network

LOSS FUNCTIONS

Mean squared error

$$L = \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2}{n}$$

Mean absolute error

$$L = \frac{\sum_{i=1}^{n} \left| y_i - \hat{y}_i \right|}{n}$$

Cross-entropy

$$L = -\left(y_i \log \left(\hat{y}_i \right) + \left(1 - y_i \right) \log \left(1 - \hat{y}_i \right) \right)$$

TRAINING: USE THE SIMPLEST YOU CAN THINK OF

Gradient descent

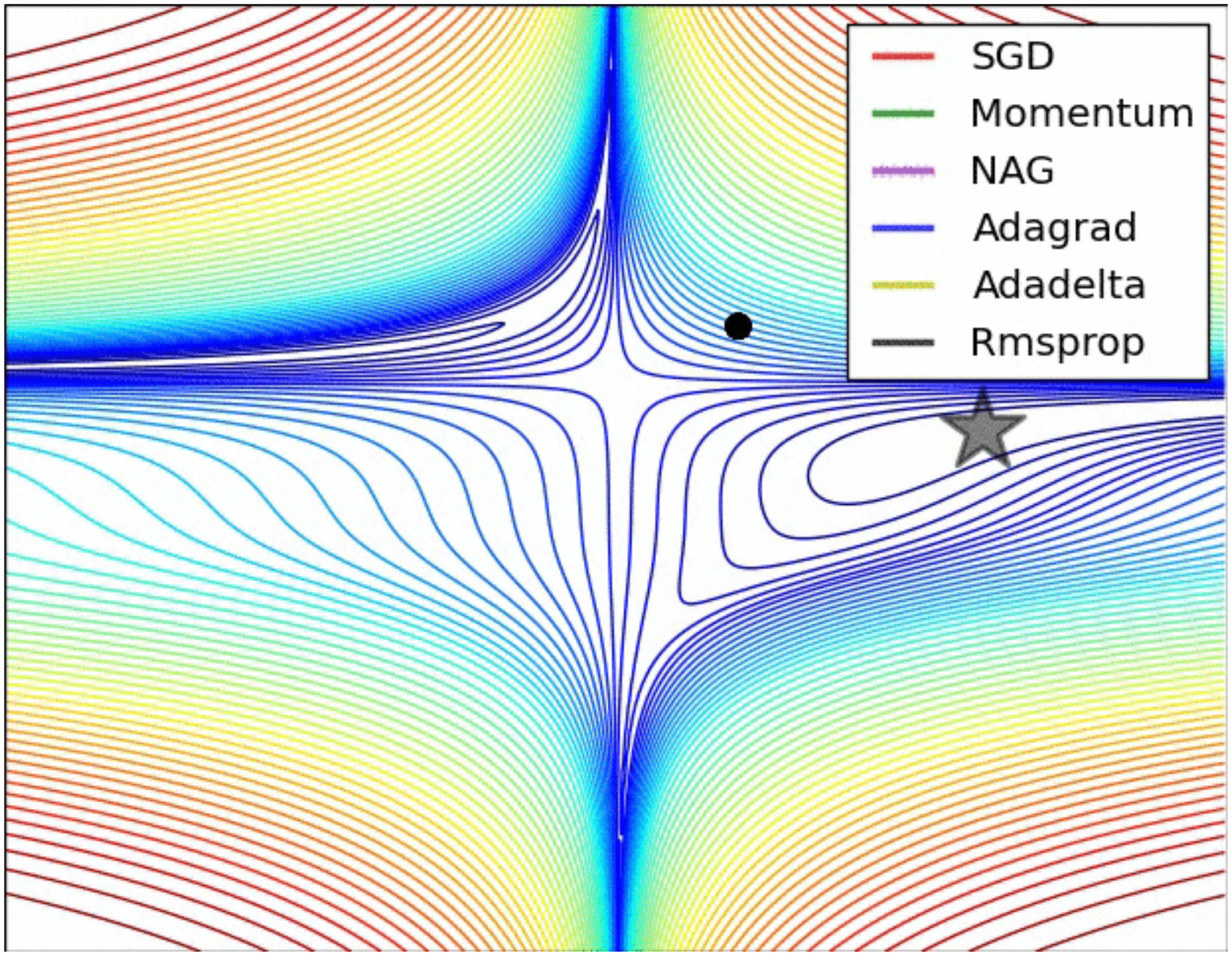
$$\theta_{i+1} = \theta_i - h\nabla_\theta f(\theta, \mathbf{T})$$

Stochastic gradient descent

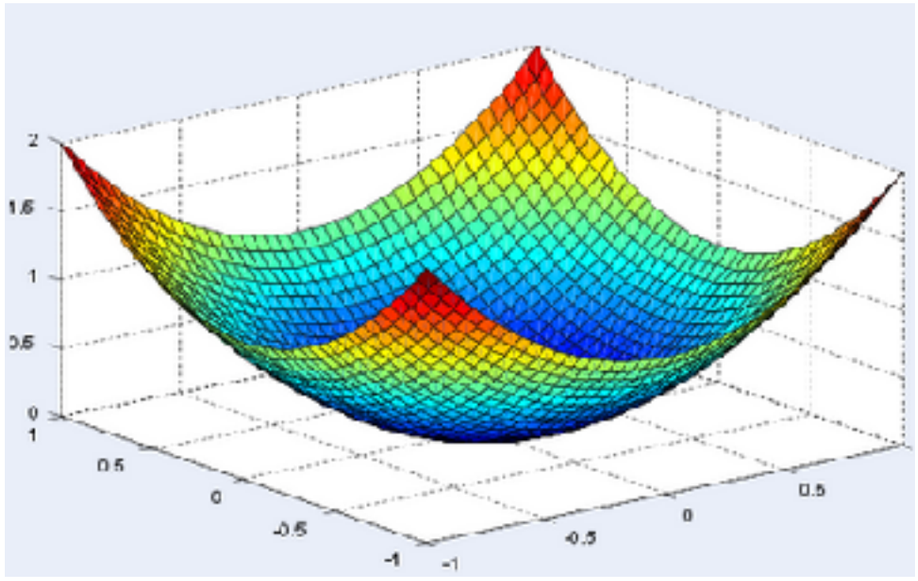
$$\theta_{i+1} = \theta_i - h\nabla_\theta f(\theta, \mathbf{T}_{\text{subset}})$$

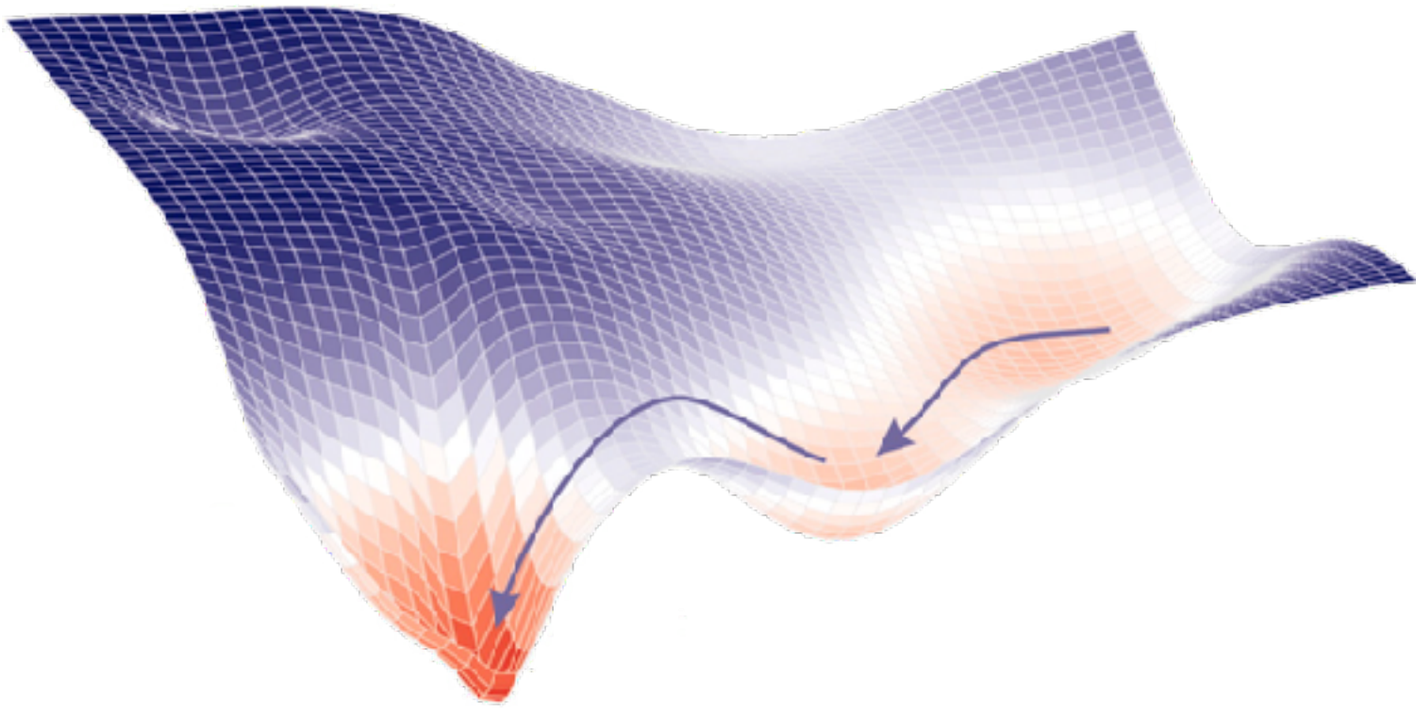
TRAINING

$$\theta_{i+1} = \theta_i - h\nabla_\theta f(\theta, \mathbf{T}_{\text{subset}})$$

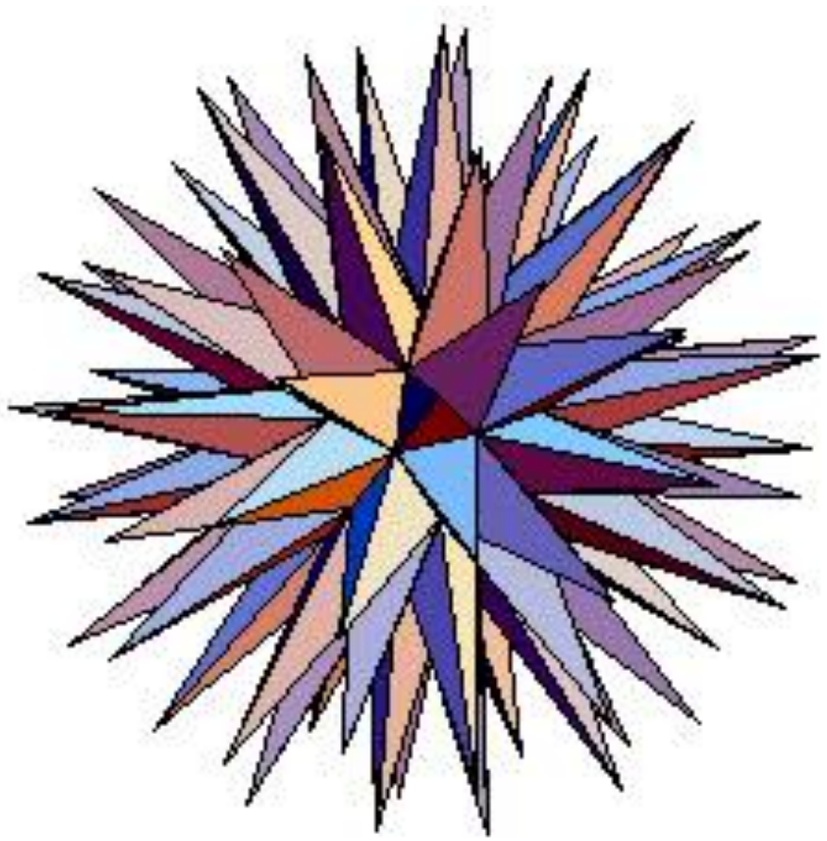


CONVEXITY VS. NON-CONVEXITY





CURSE OF DIMENSIONALITY



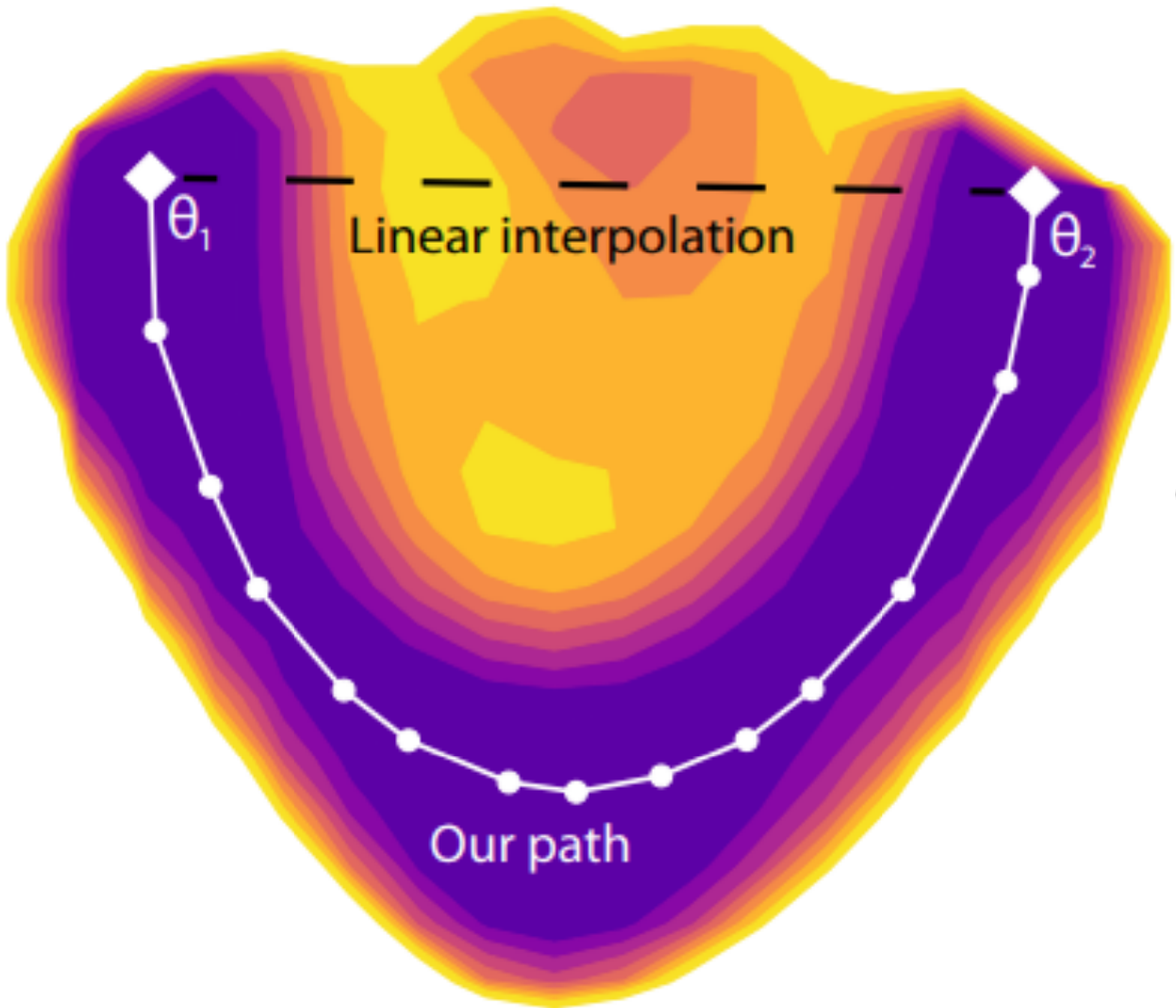
N. directions forming angles between 88 and 92 degrees

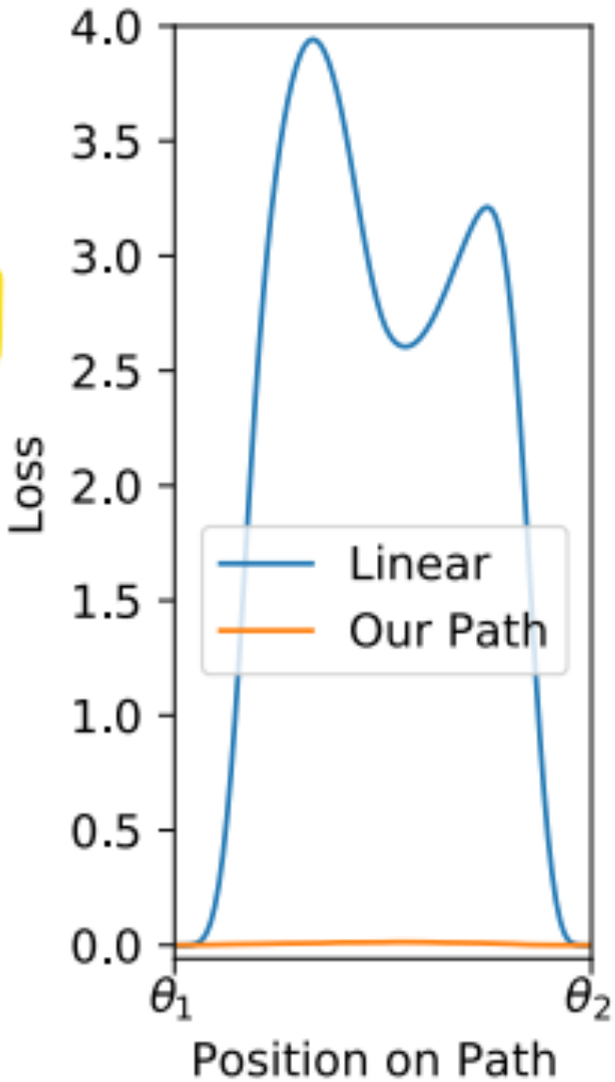
$$\mathbb{R}^2 \rightarrow 2$$

$$\mathbb{R}^3 \rightarrow 2$$

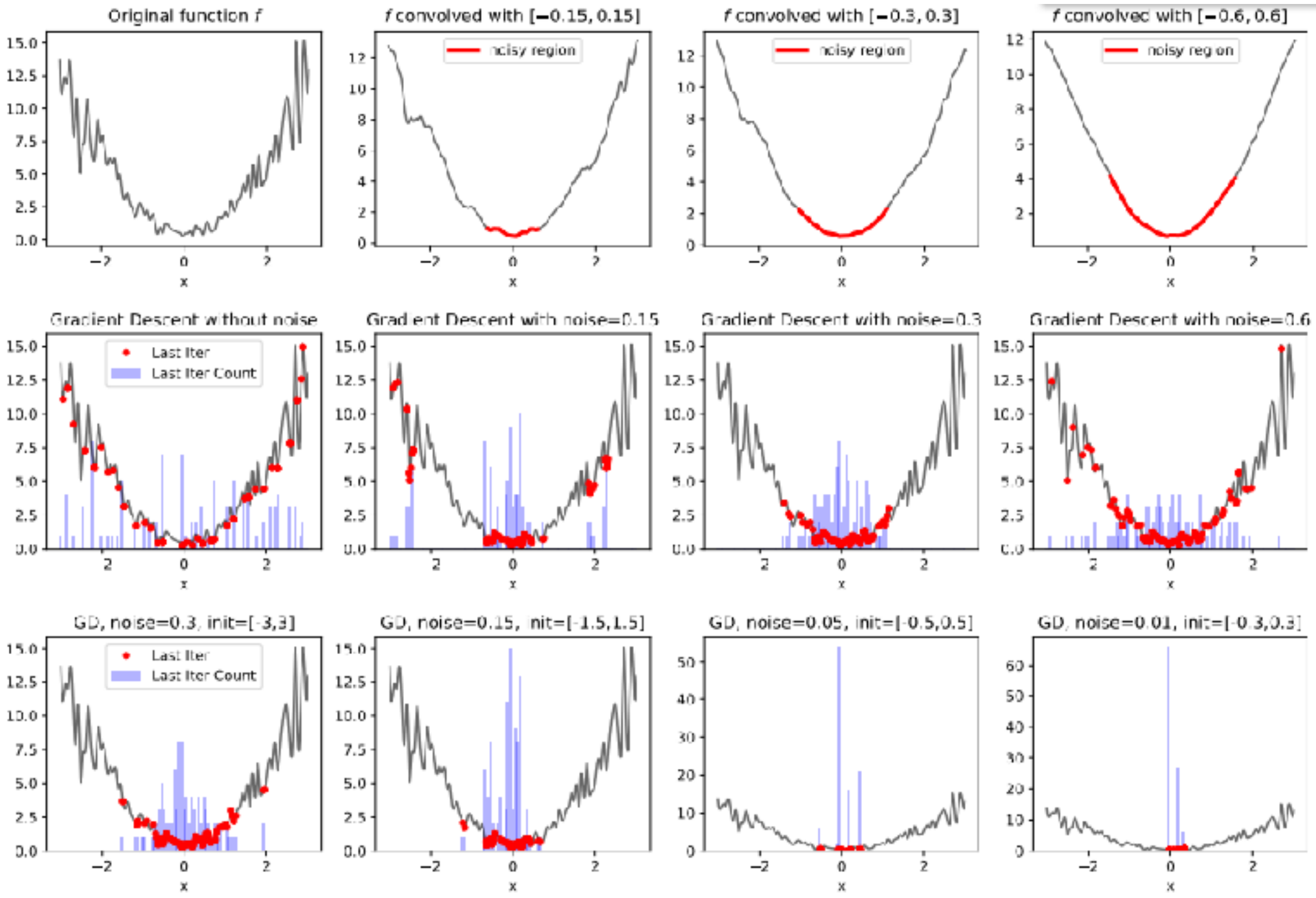
$$\mathbb{R}^d \rightarrow \exp(cd)$$

ALL MINIMA ARE EQUIVALENT





SGD MODIFIES THE LOSS FUNCTION



Backpropagation

HOW TO EFFICIENTLY COMPUTE THE GRADIENT

$$L = g(\mathbf{y})$$

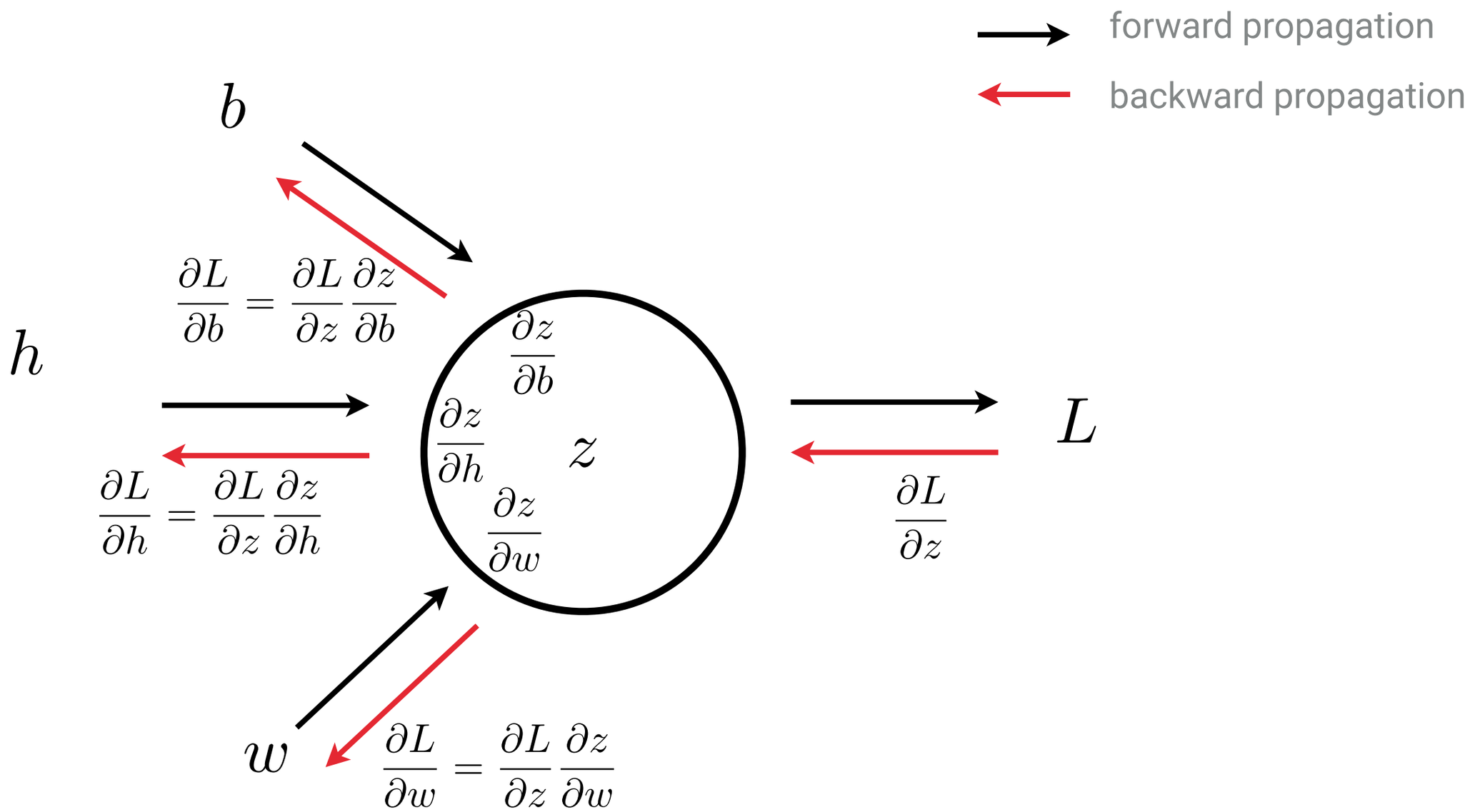
$$\mathbf{y} = f(\mathbf{x})$$

$$L = g(f(\mathbf{x}))$$

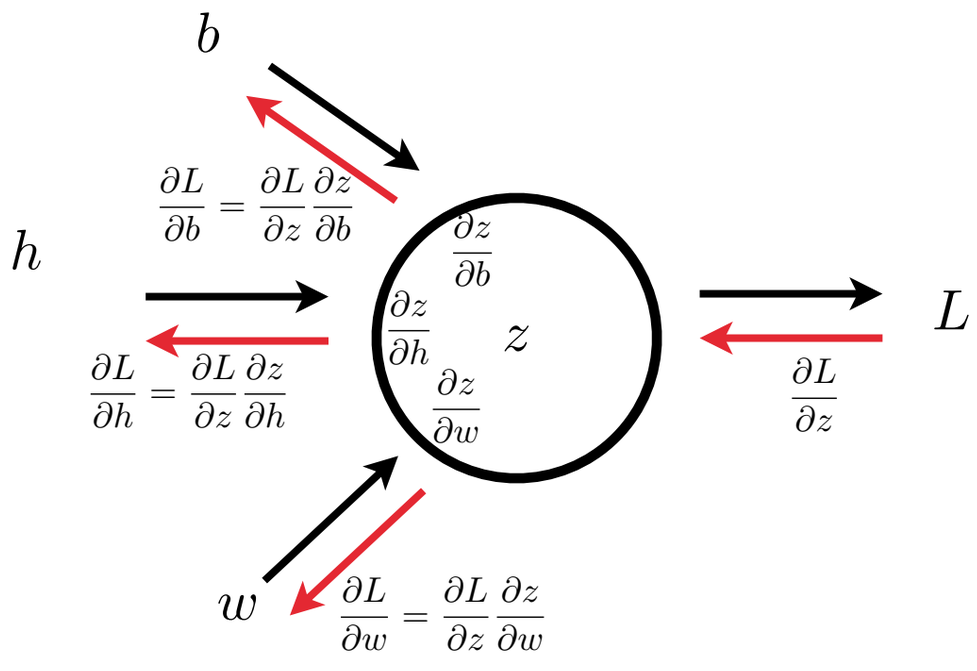
$$\frac{\partial L}{\partial \mathbf{x}} = J^T \frac{\partial L}{\partial \mathbf{y}} = \frac{\partial \mathbf{y}}{\partial \mathbf{x}} \frac{\partial L}{\partial \mathbf{y}}$$

$$J^T = \begin{pmatrix} \frac{\partial y_1}{\partial x_1} & \cdots & \frac{\partial y_m}{\partial x_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_1}{\partial x_n} & \cdots & \frac{\partial y_m}{\partial x_n} \end{pmatrix}$$

HOW TO EFFICIENTLY COMPUTE THE GRADIENT



HOW TO EFFICIENTLY COMPUTE THE GRADIENT




```
class node(object):
 def forward(z):
  output = f(z)
  return output

 def backward(z, dLdz):
  J = jacobian(z)
  return J.dot(dLdz)
```

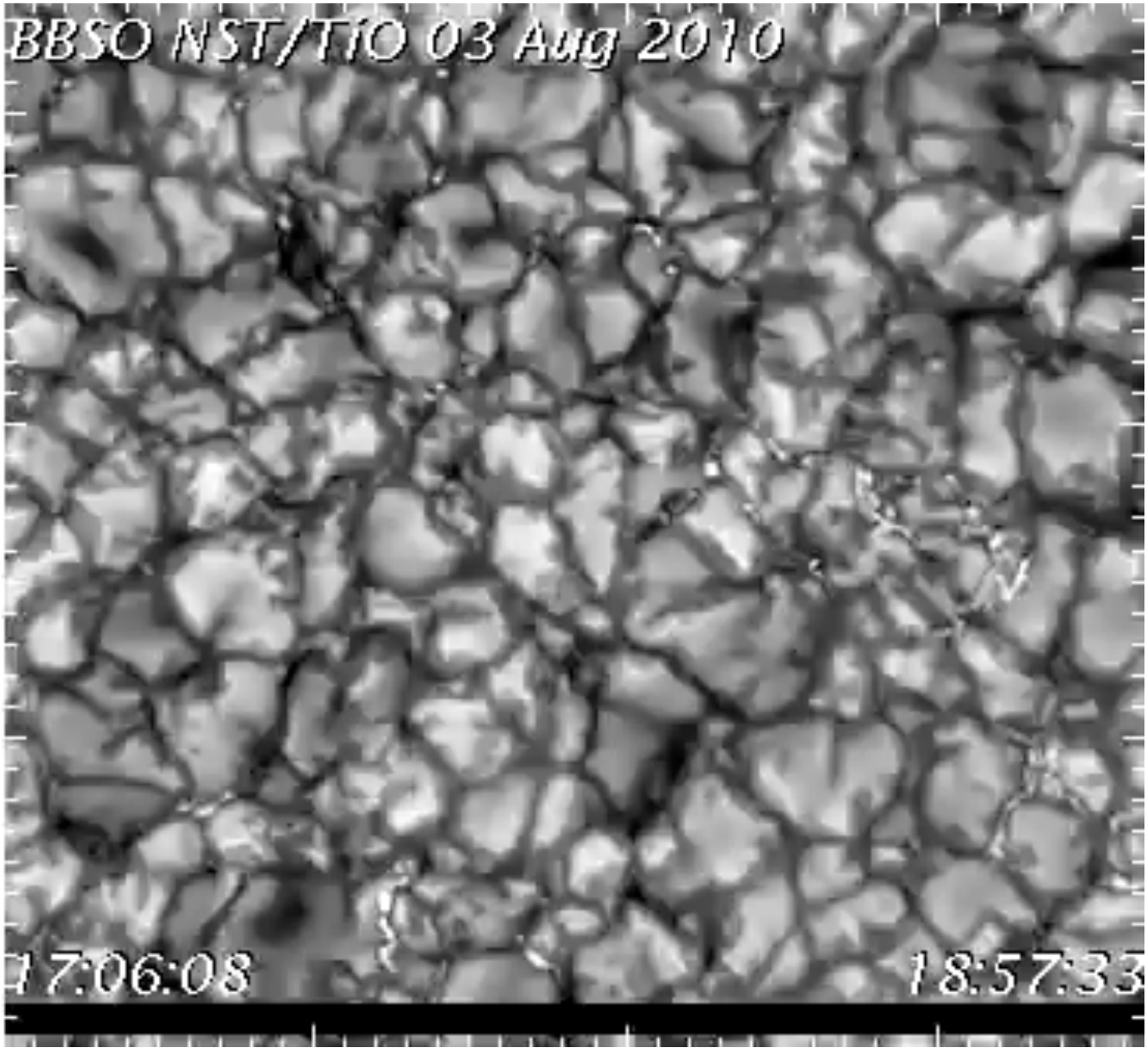
Applications in Solar Physics

PROBLEMS TACKLED SO FAR

- Measuring velocities
- Enhancing HMI images
- Multiframe blind deconvolution
- Fast inversion of Stokes profiles
- Farside imaging
- Classification of solar structures
- Physical conditions in flares

measuring velocities

MEASURING VELOCITIES



MEASURING VELOCITIES

Longitudinal component

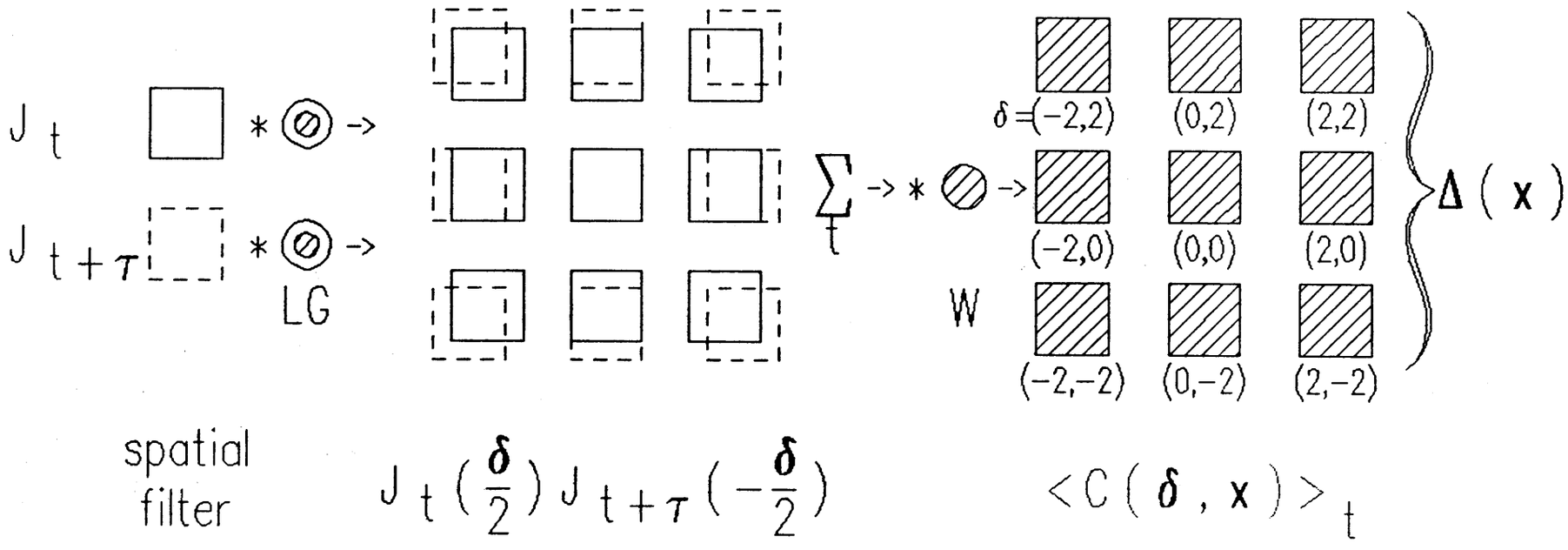
- Can be measured with Doppler effect using spectroscopy
- Physical meaning

Transverse component

- Cannot be spectroscopically measured
- Not obvious physical meaning
- Different depending on selection of “corks”

MEASURING VELOCITIES IN THE PLANE OF THE SKY

November & Simon (1988) - Local correlation tracking

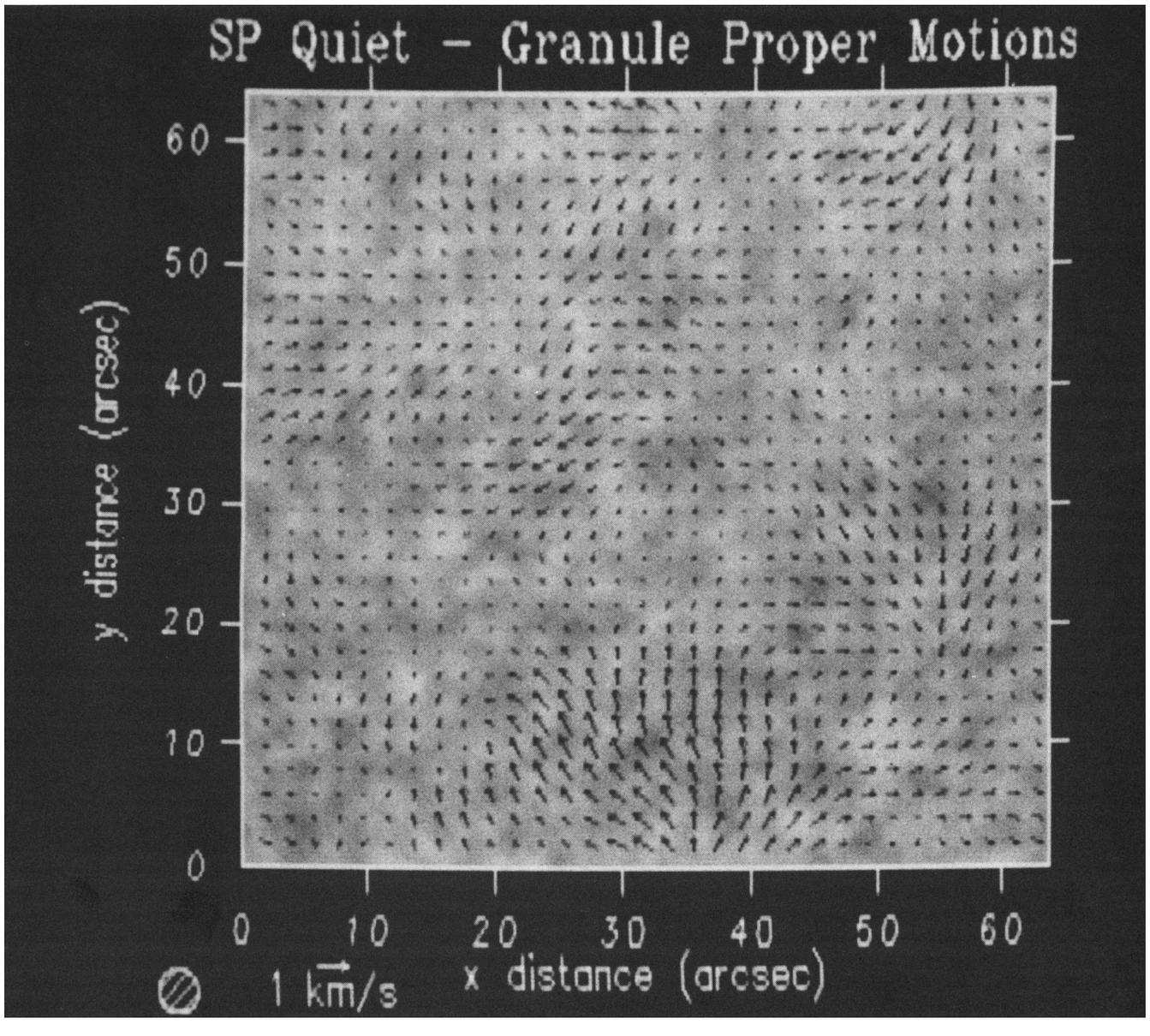


spatial filter

$$J_t\left(\frac{\delta}{2}\right) J_{t+\tau}\left(-\frac{\delta}{2}\right) \qquad \langle C(\delta, x)\rangle_t$$

MEASURING VELOCITIES IN THE PLANE OF THE SKY

November & Simon (1988) - Local correlation tracking



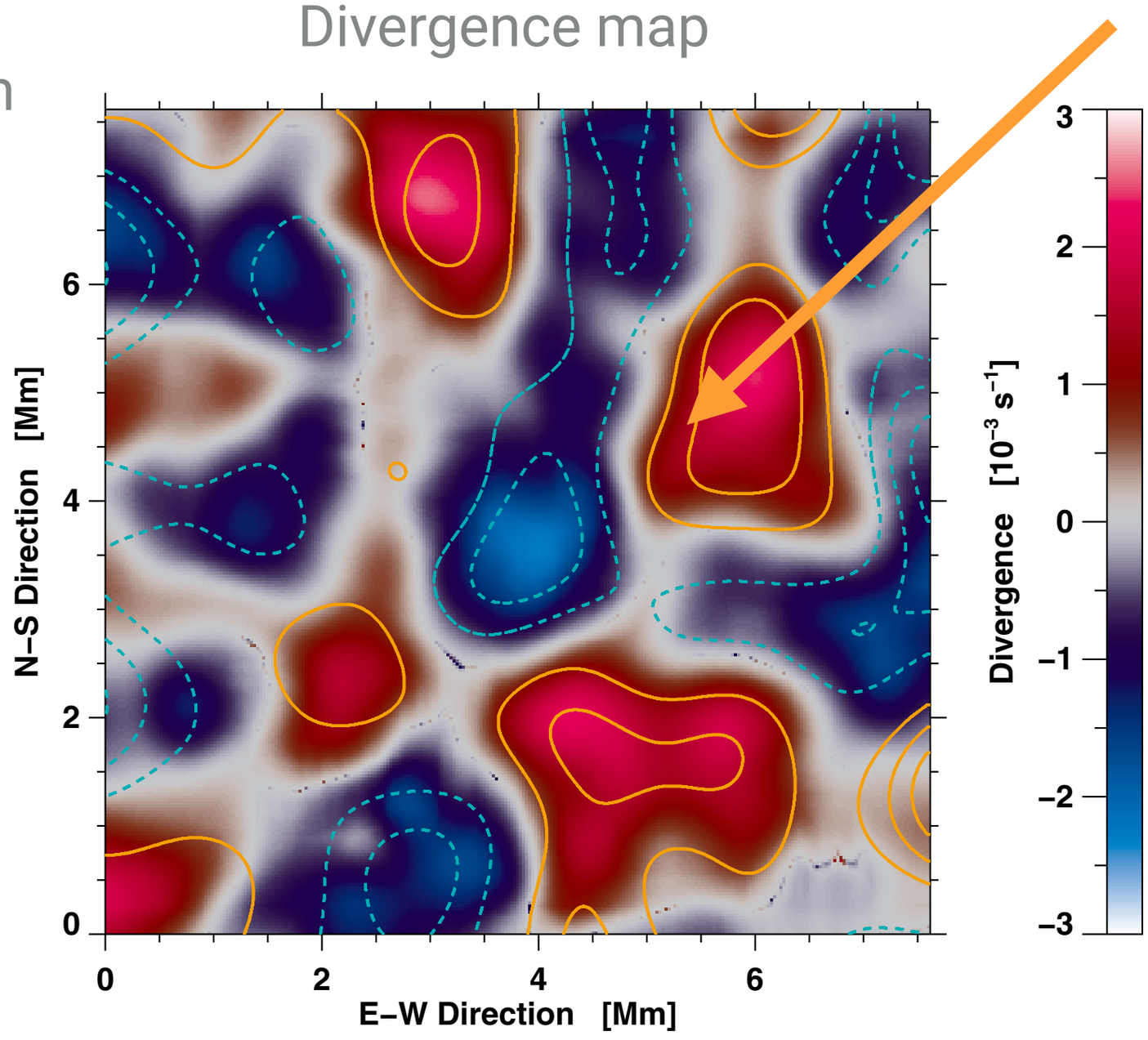
- Spatial correlation window
- Temporal correlation window
- Noise sensitive

LCT VS. SIMULATIONS

Average time 1 h

FWHM = 1200 km

1-hour average
from simulations

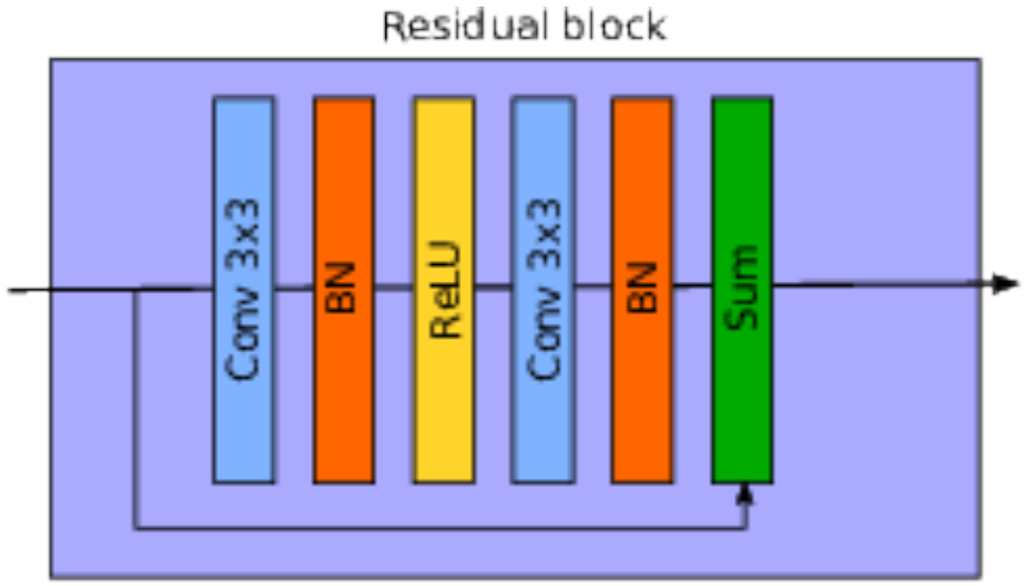


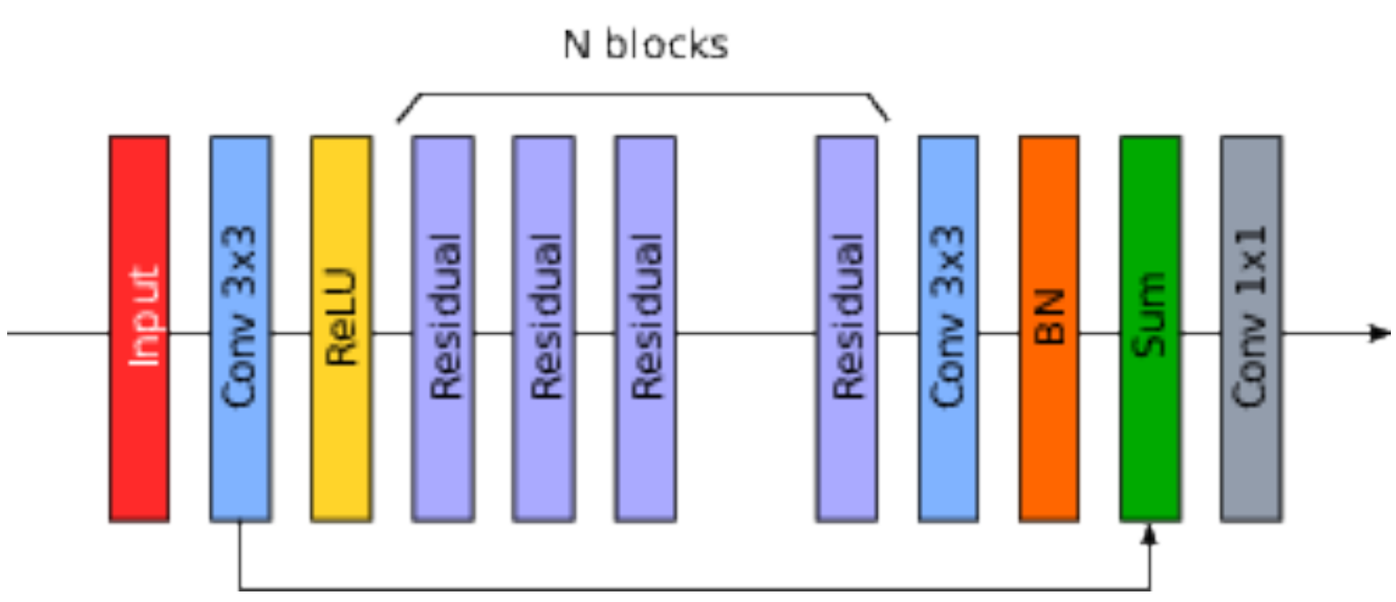
Verma & Denker (2013)

LIST OF DESIRES: DEEPVEL

- End-to-end approach
- Scale to any image size
- Be fast
- Easy to train

DEEPVEL: ARCHITECTURE





Asensio Ramos, Requerey & Vitas (2017)

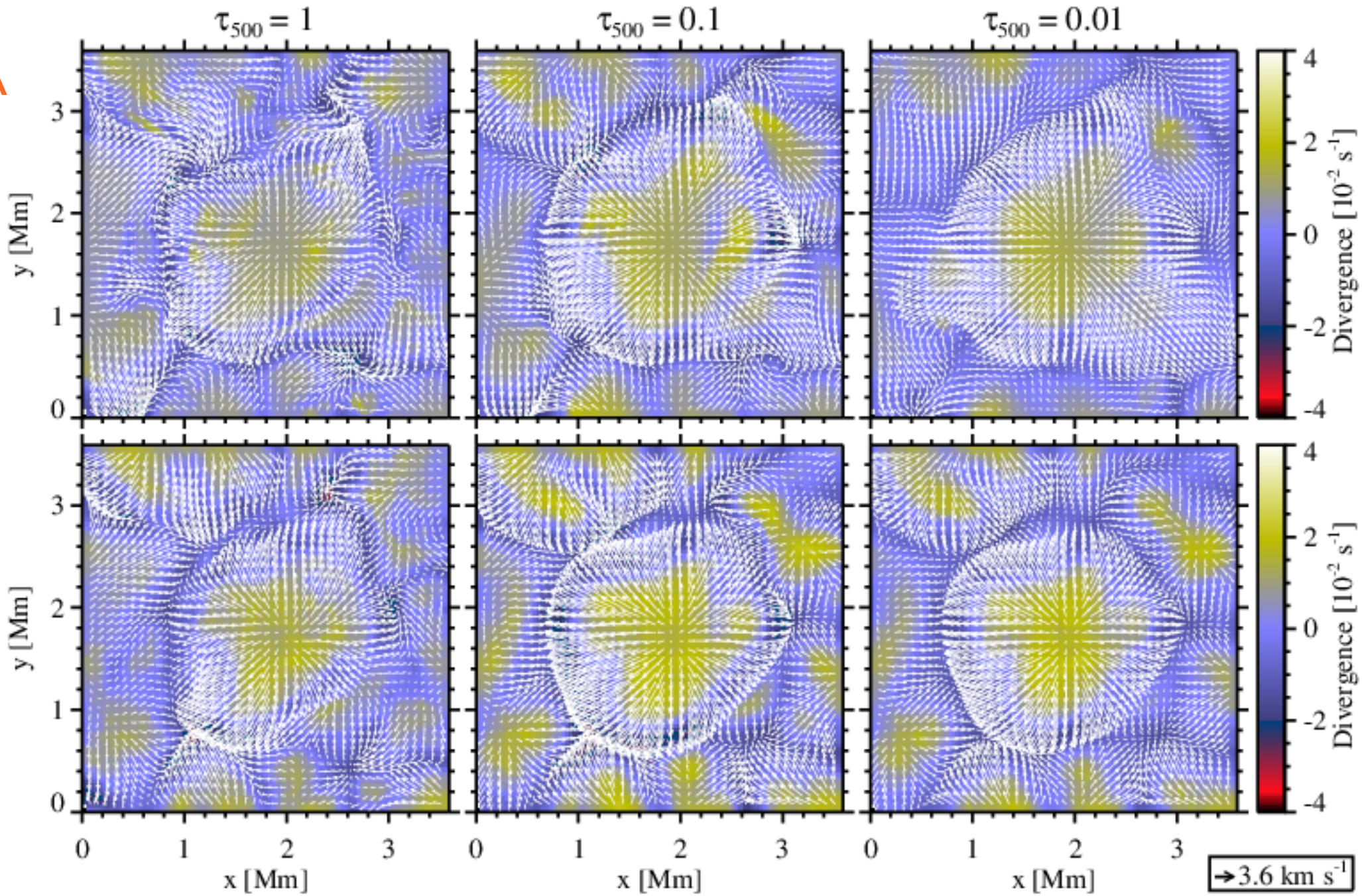
DEEPVEL: TRAINING WITH SIMULATIONS

- Synthetic images from Stein & Nordlund (2012) + degradation
- We extract 30000 pairs of patches of 50x50 pixels separated by 30 s
- The outputs are maps of v_x and v_y at τ=1,0.1,0.01
- Loss function : ℓ_2 -norm between predicted and simulated velocities
- Trained with ADAM optimizer with β=10^{-4} for 900k steps

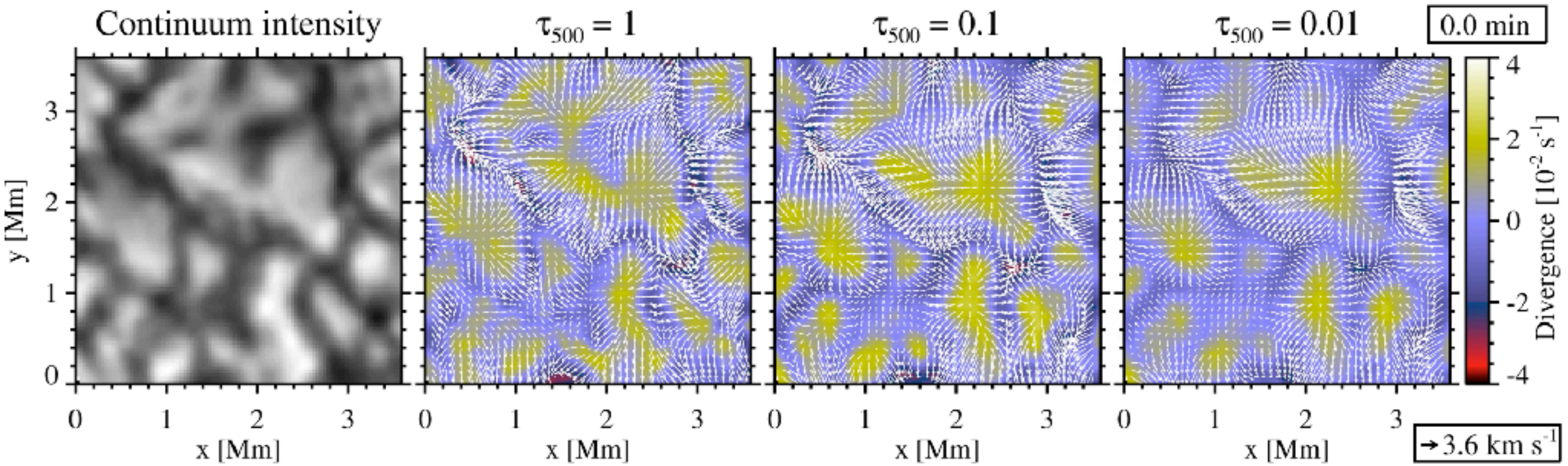
VALIDATION

MANCHA

DeepVel



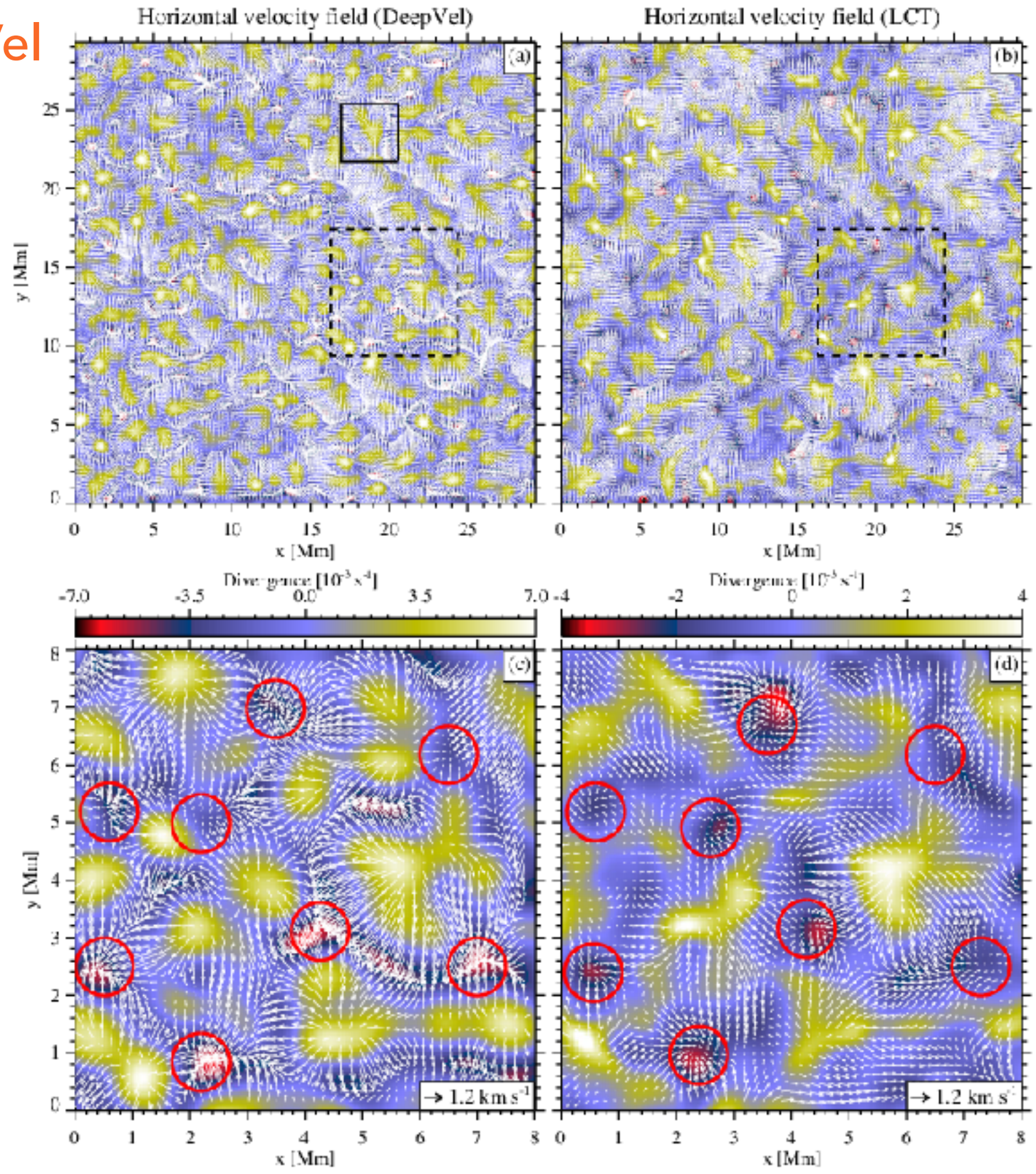
DEEPVEL https://github.com/aasensio/deepvel



Asensio Ramos, Requerey & Vitas (2017)

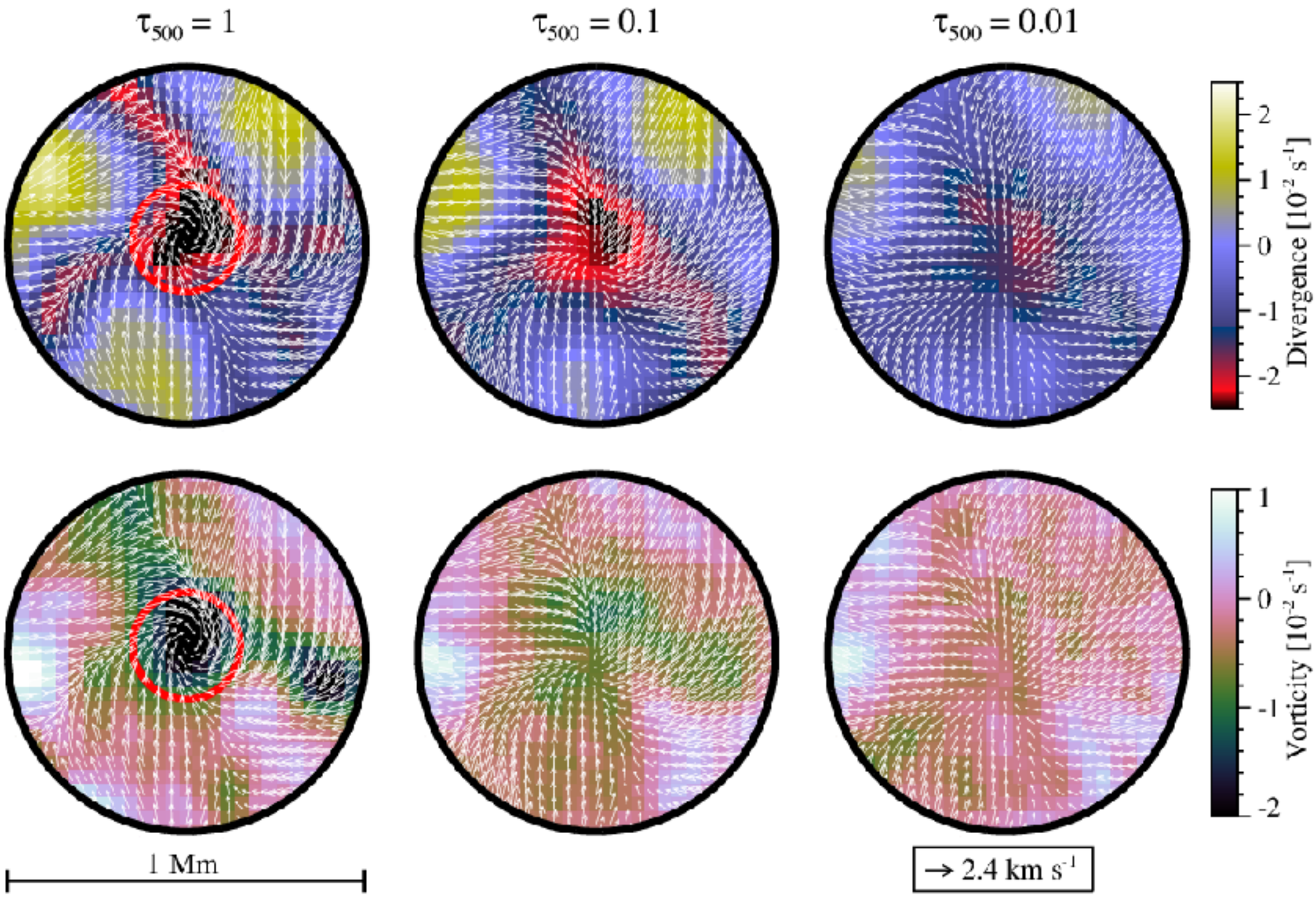
AVERAGE PROPERTIES

DeepVel



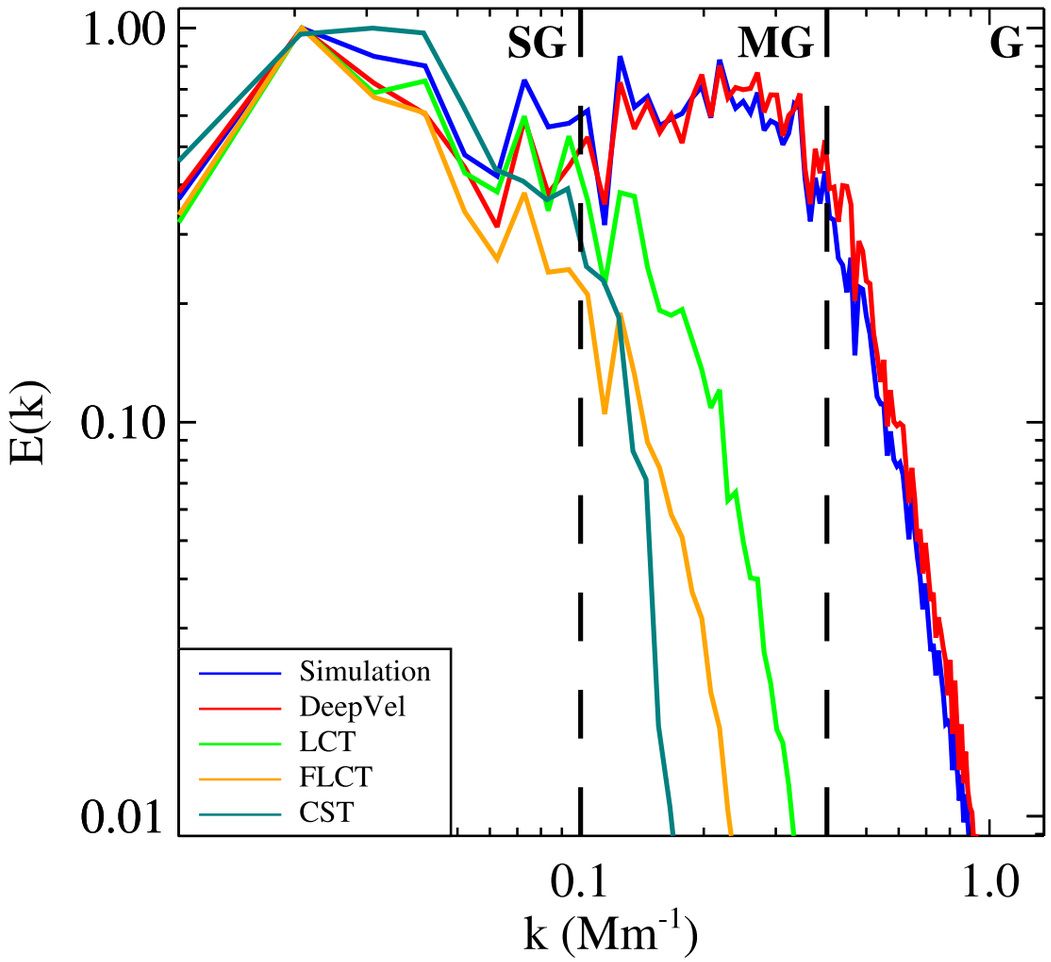
LCT

SMALL SCALE VORTEX FLOWS

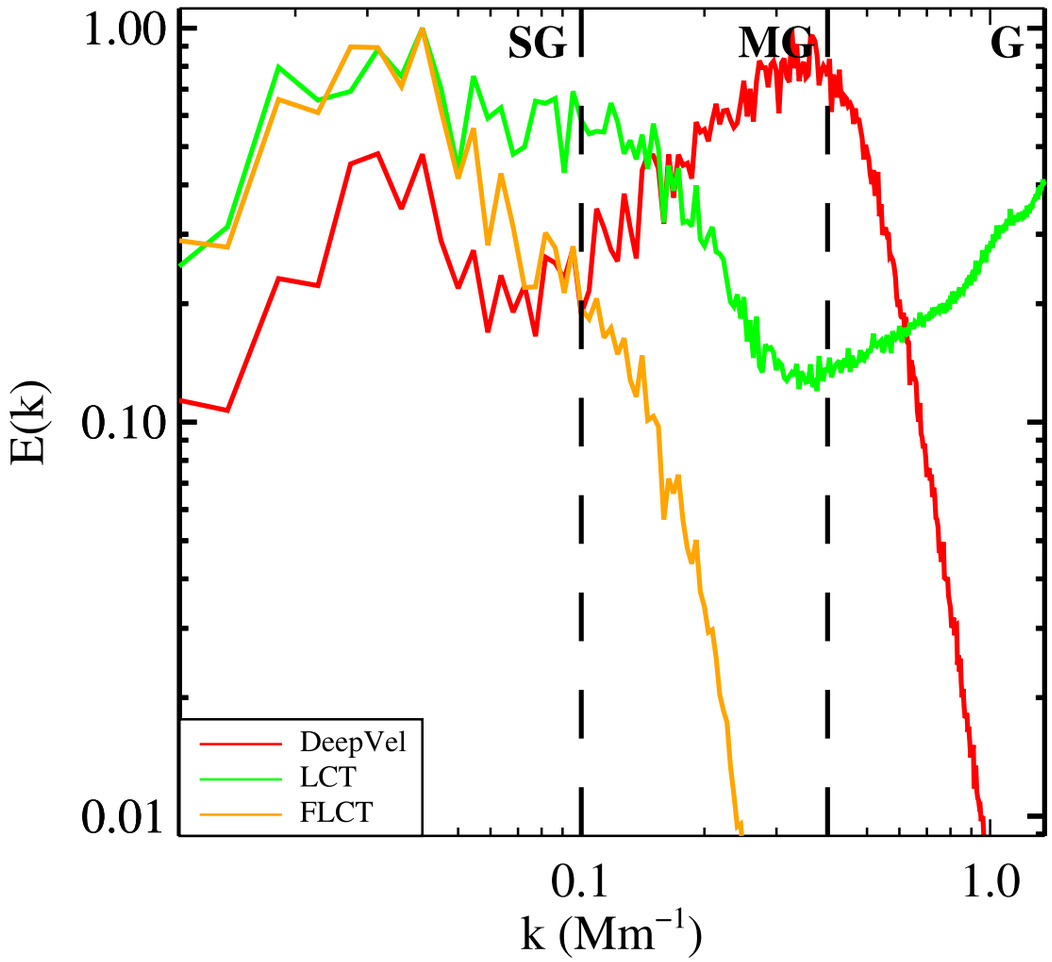


KINETIC ENERGY SPECTRUM

Simulations



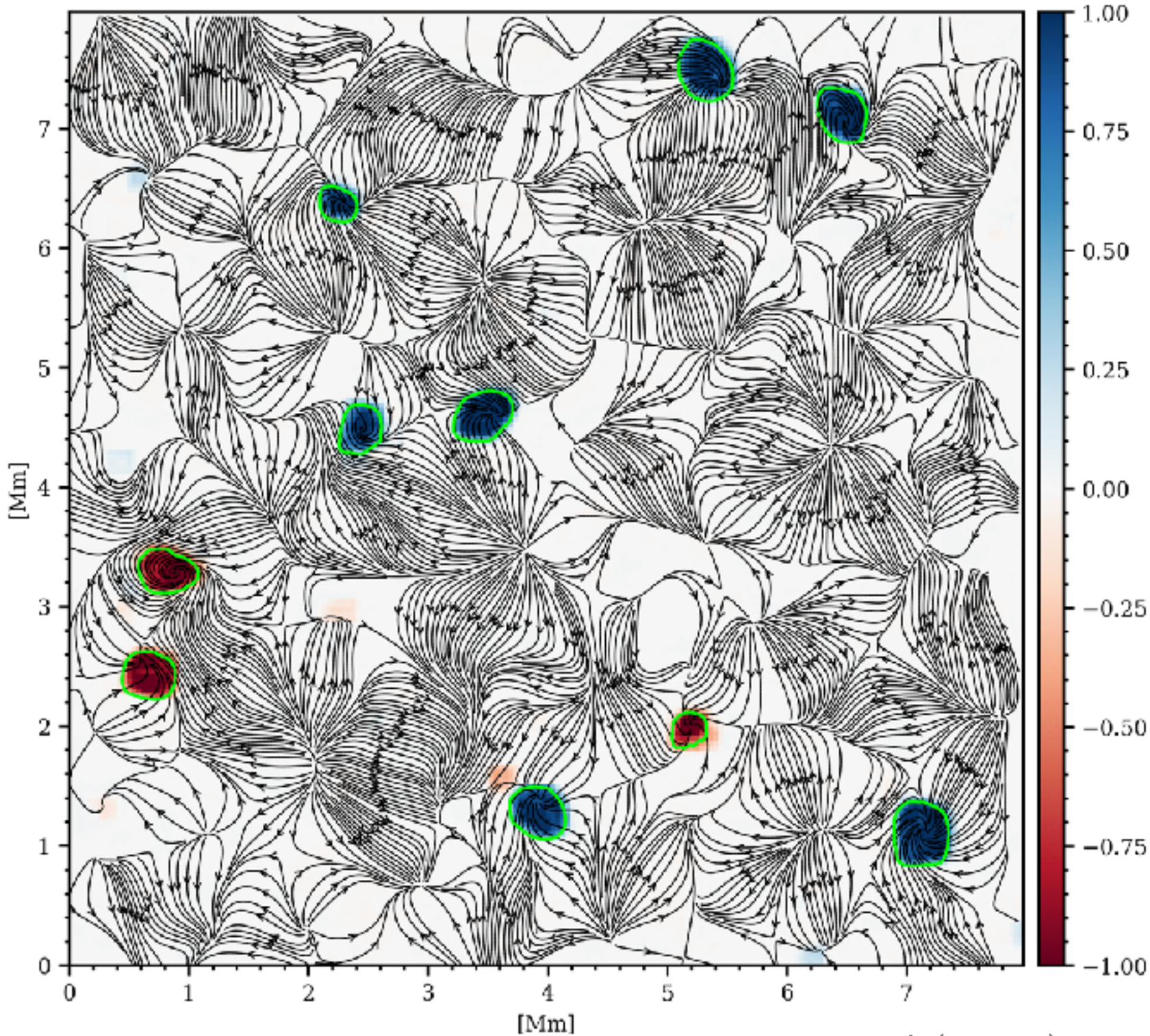
SDO/HMI



Tremblay et al. (2018)

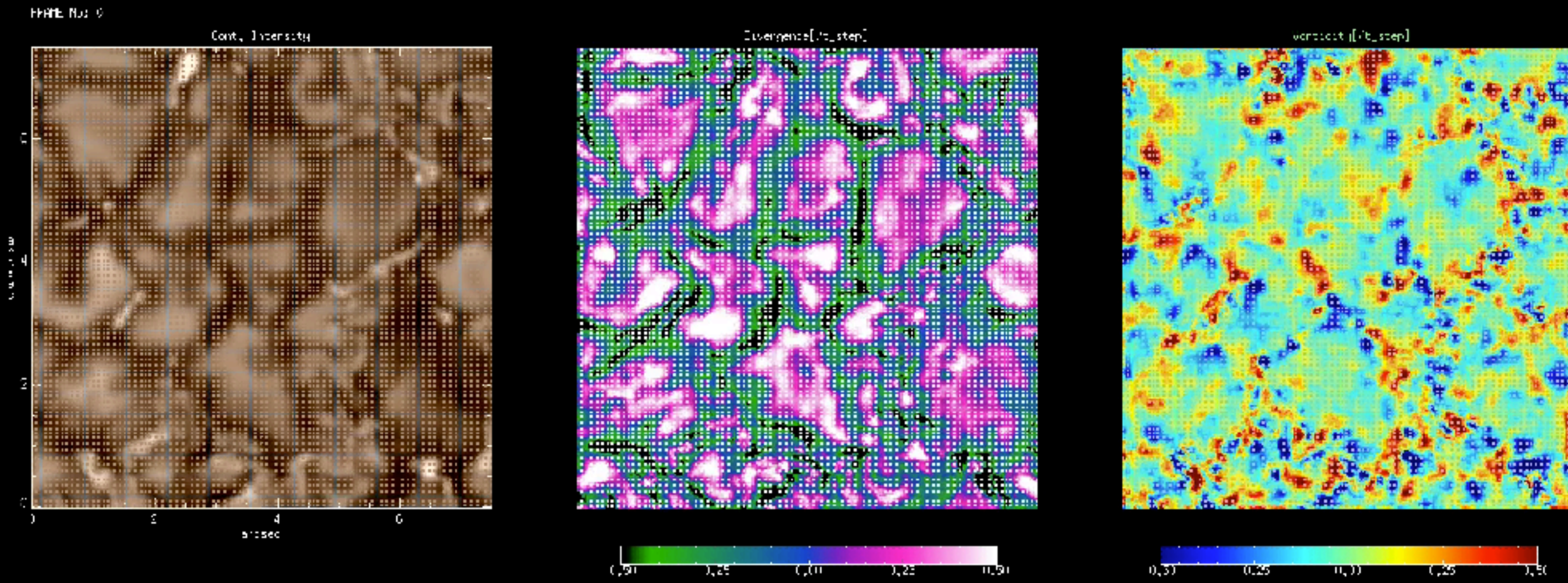
VORTEX DETECTION

DeepVortex



Requerey et al. (in prep)

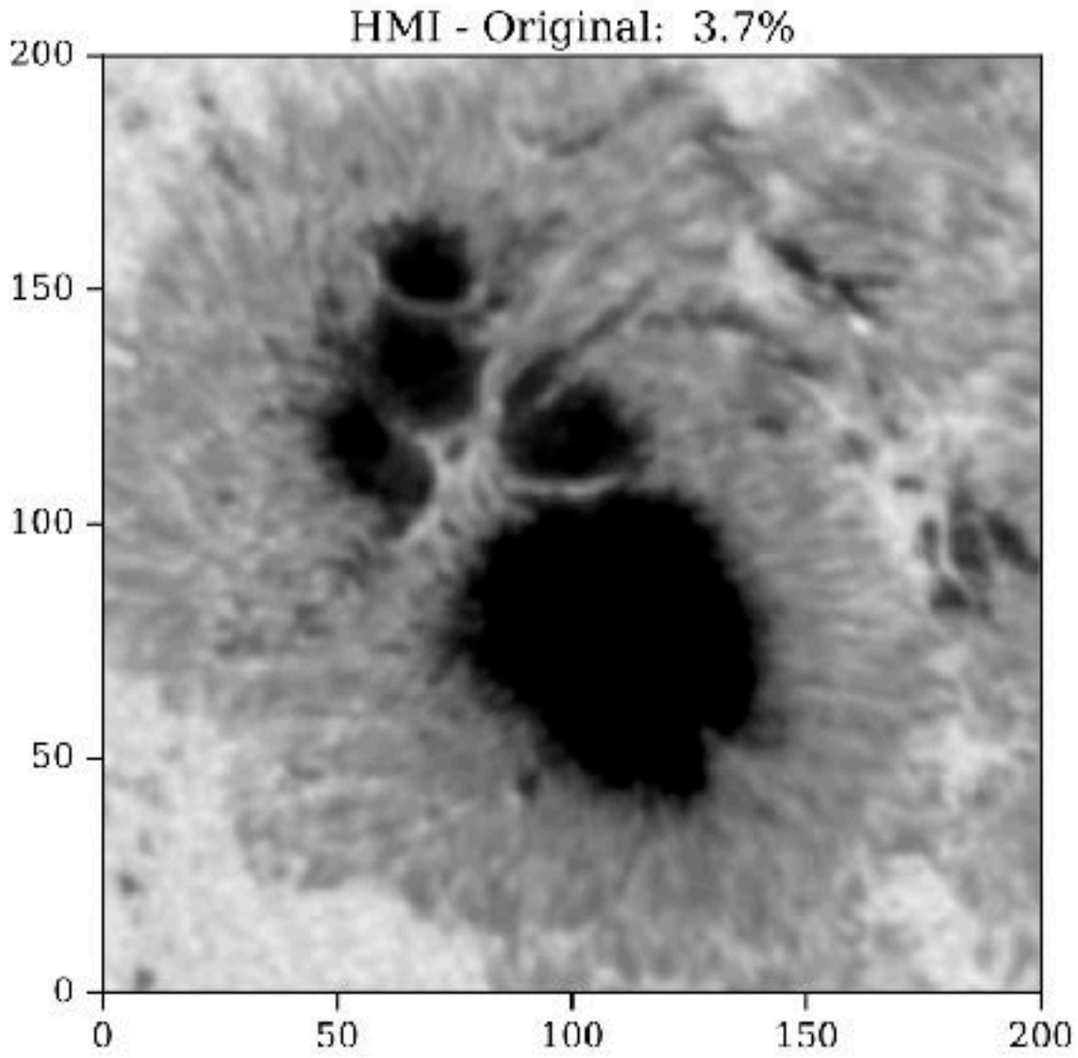
CORKS EVOLUTION

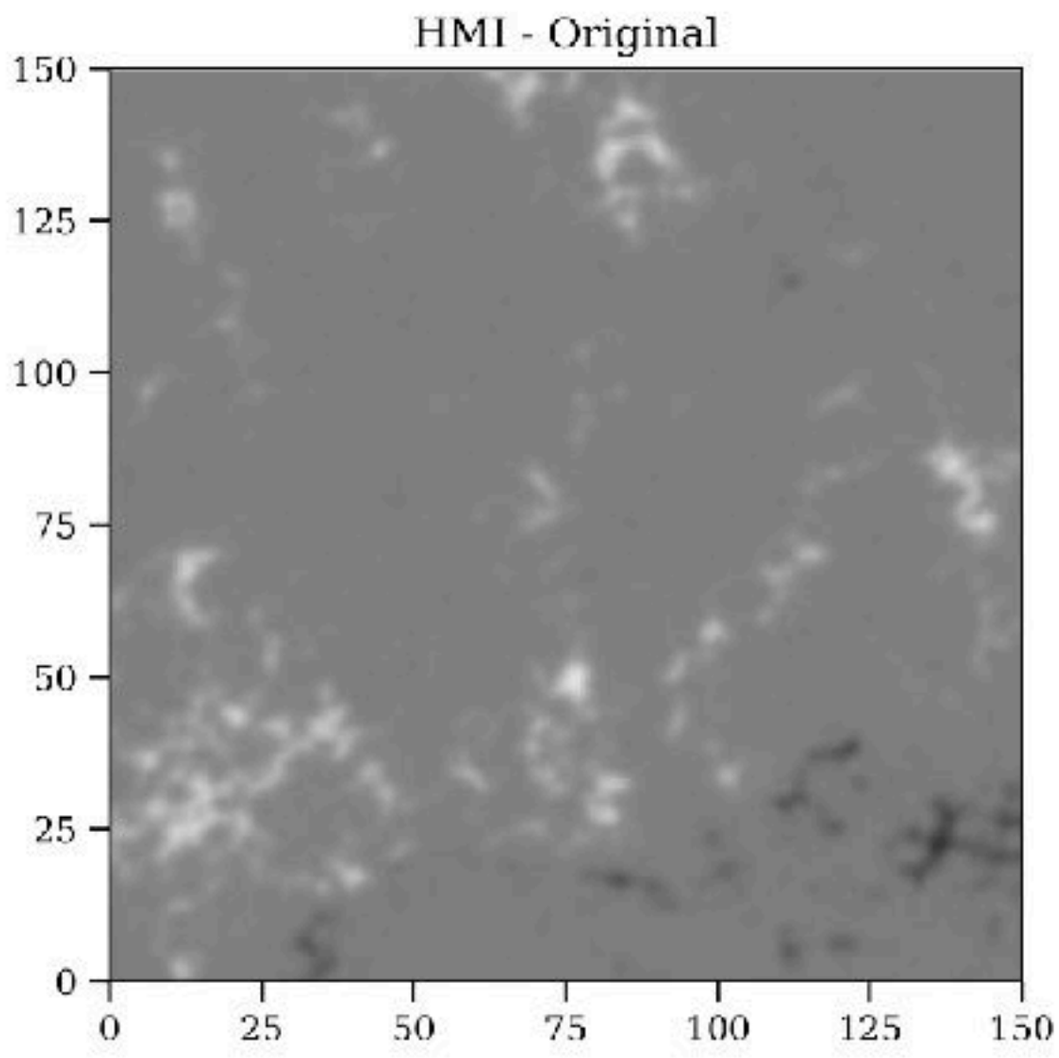


Rouppe van der Voort (private comm)

enhancing HMI images

HMI: 24/7 BUT NOT ENOUGH SPATIAL RESOLUTION





ENHANCE:

Low-res image

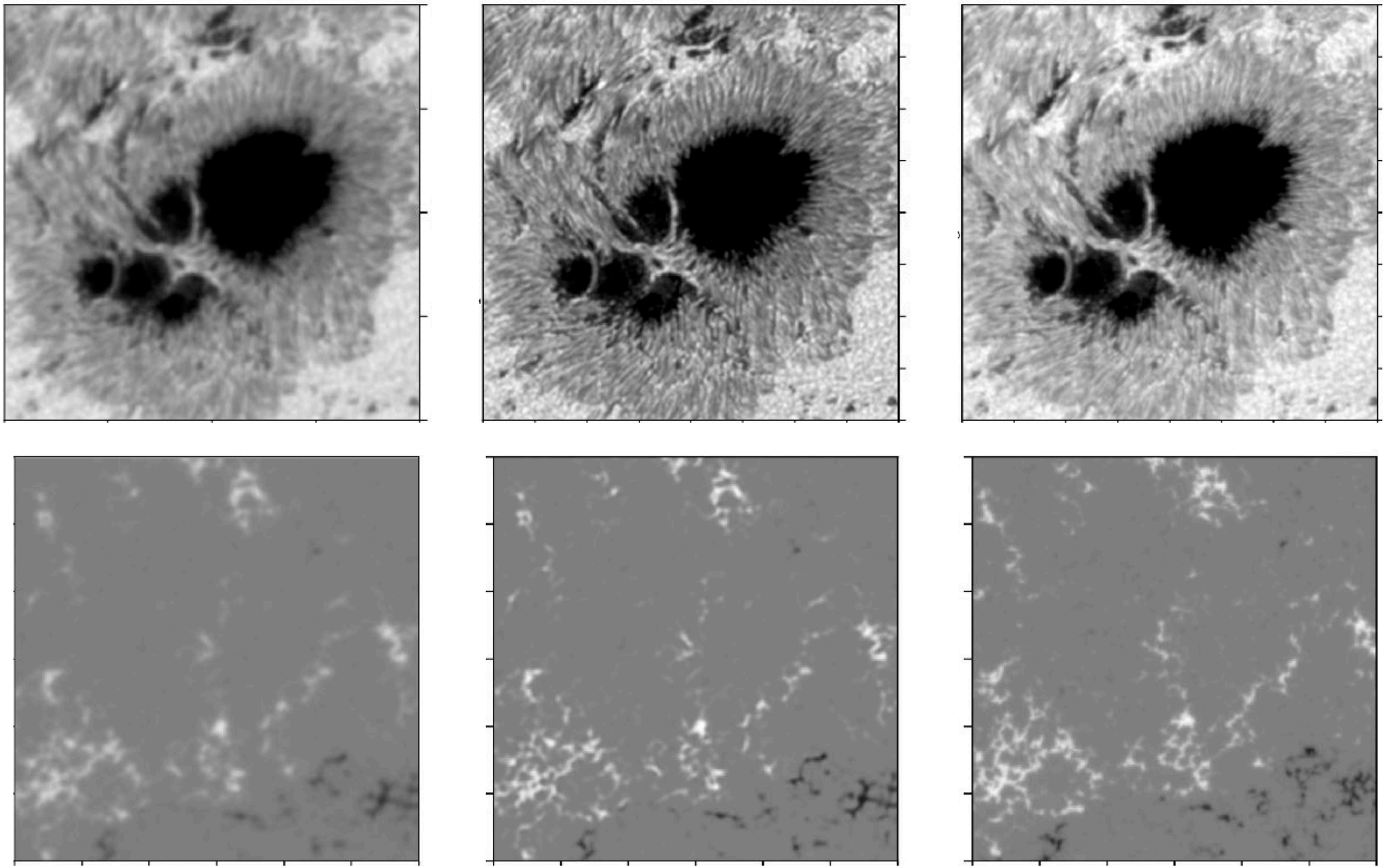
- Trained on simulations (courtesy of M. Cheung)
- End-to-end deep neural network
- Continuum + magnetograms

ENHANCE: SINGLE IMAGE SUPERRESOLUTION

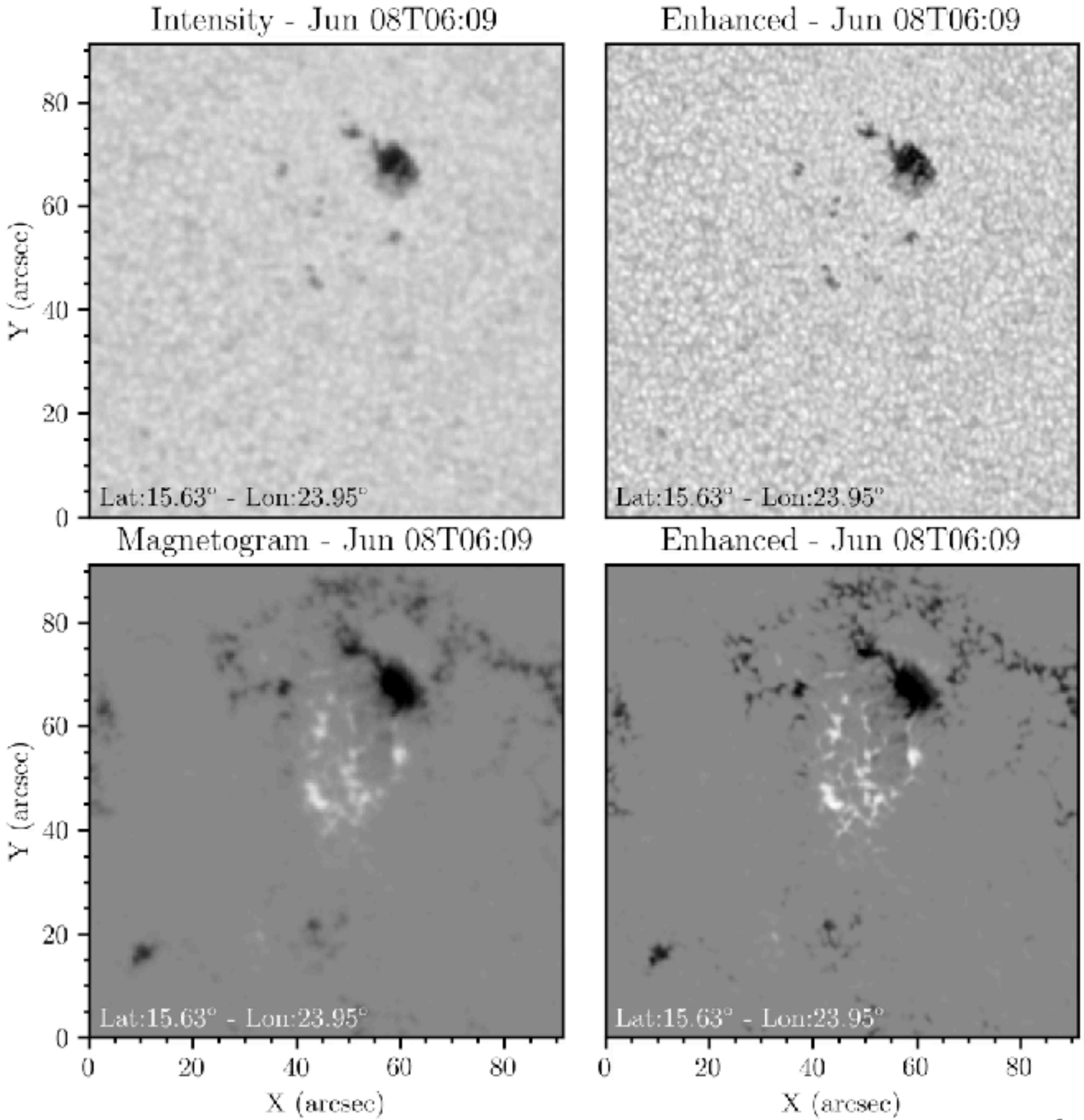
HMI

Neural network

Hinode



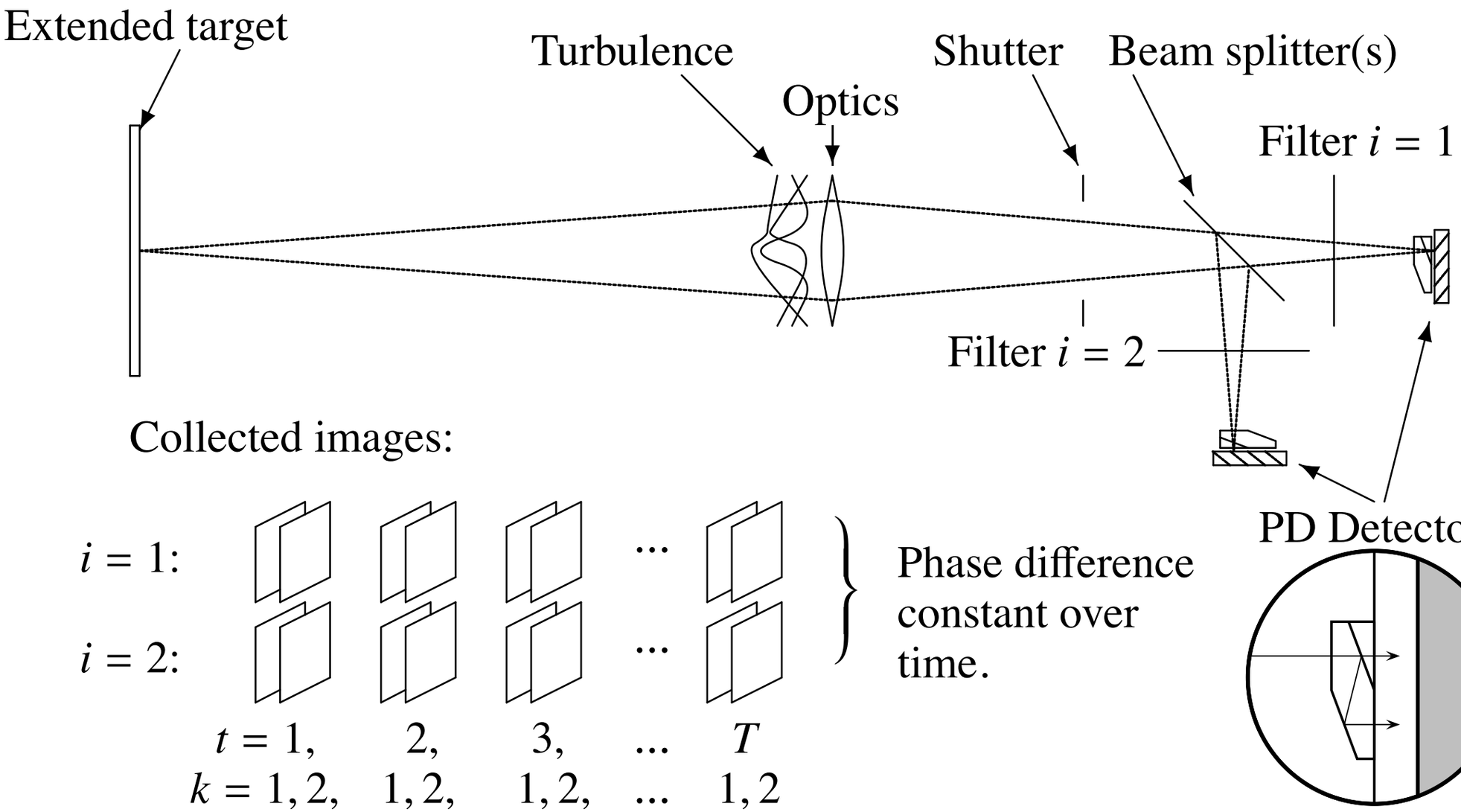
ENHANCE https://github.com/cdiazbas/enhance



courtesy of S. Castellanos Durán

real-time multiframe deconvolution

MULTIFRAME BLIND DECONVOLUTION



van Noort et al. (2005)

MULTIFRAME BLIND DECONV : MAX-LIKELIHOOD

Observed frames

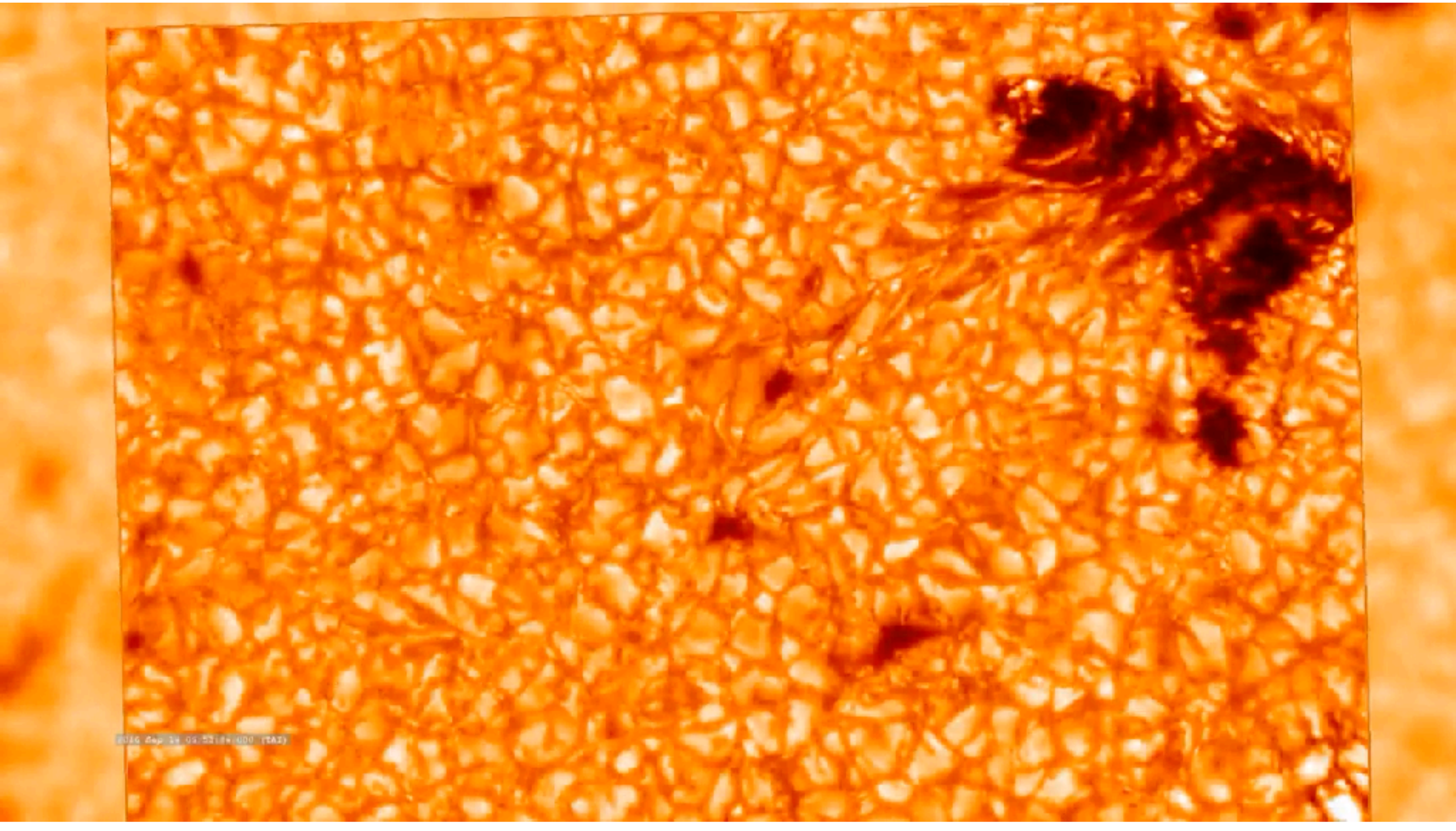
Optical transfer function

$$L_i\left(\boldsymbol{\alpha}_i\right) = \sum_u \left[\sum_j^J \left|D_{ij}\right|^2 - \frac{\left|\sum_j^J D_{ij}^* \hat{S}_{ij}\right|^2}{\sum_j^J \left|\hat{S}_{ij}\right|^2 + \gamma_i} \right]$$

$$P_{ij} = A_{ij} \exp\left\{\mathrm{i}\phi_{ij}\right\}$$

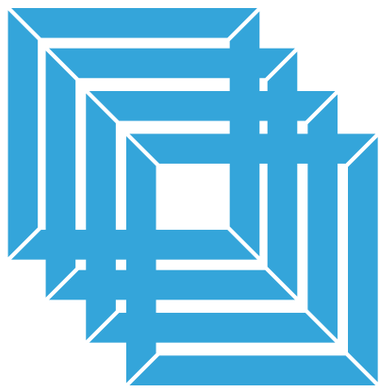
van Noort et al. (2005)

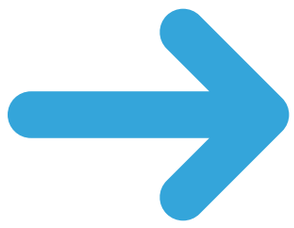
MULTIFRAME BLIND DECONVOLUTION

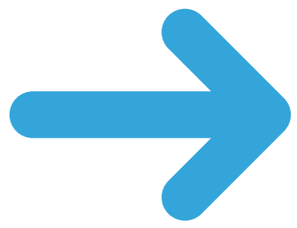


MULTIFRAME BLIND DECONVOLUTION

Short-exposure burst





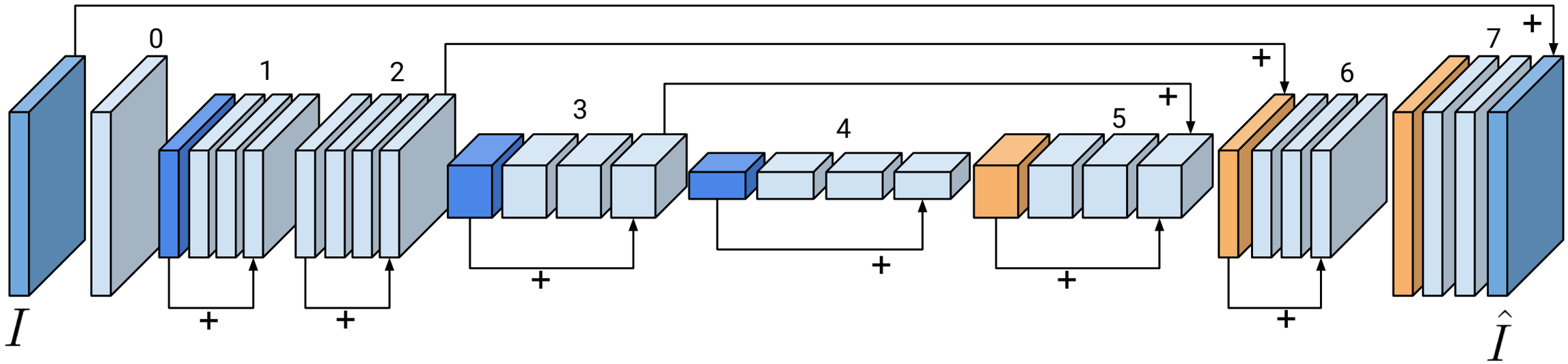


Deconvolved image

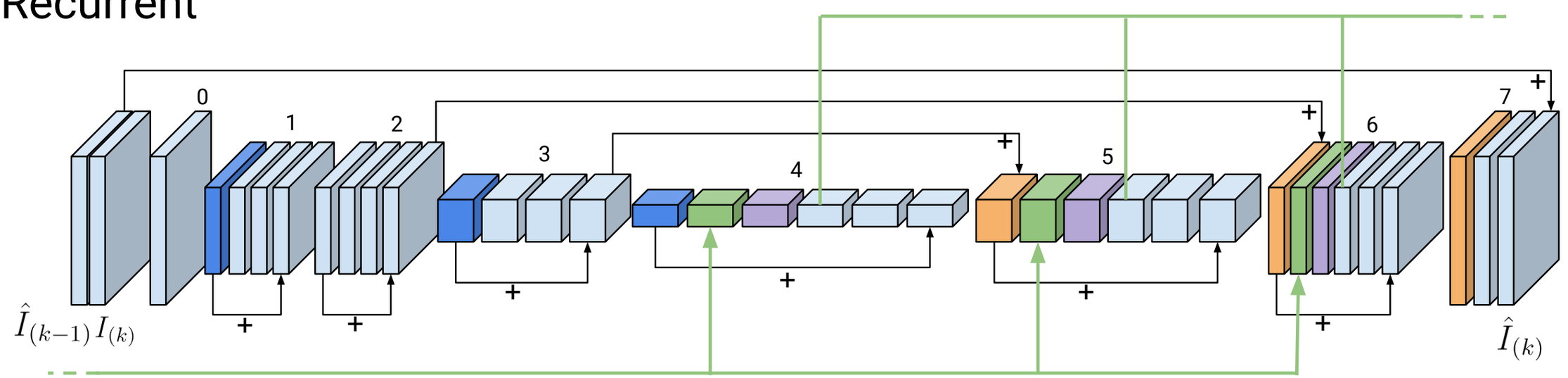
- Trained on CRISP@SST Fe I 630 nm and Ca II 854 nm deconvolved data
- End-to-end deep neural network
- Asensio Ramos et al. (A&A, arXiv:1806.07150)
- 1k x 1k images at ~100 Hz
- https://github.com/aasensio/learned_mfbd

MULTIFRAME BLIND DECONVOLUTION

Encoder-decoder

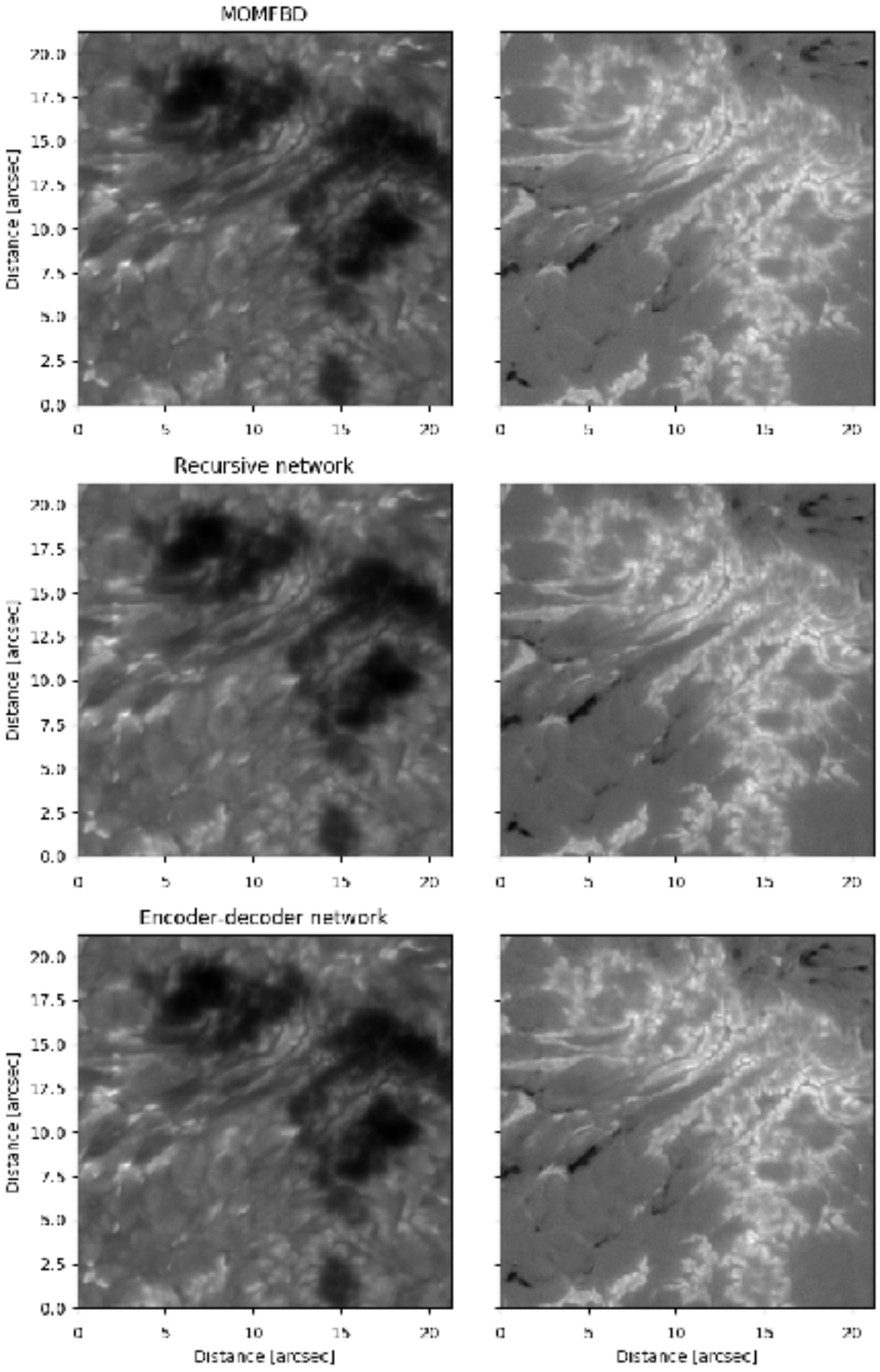


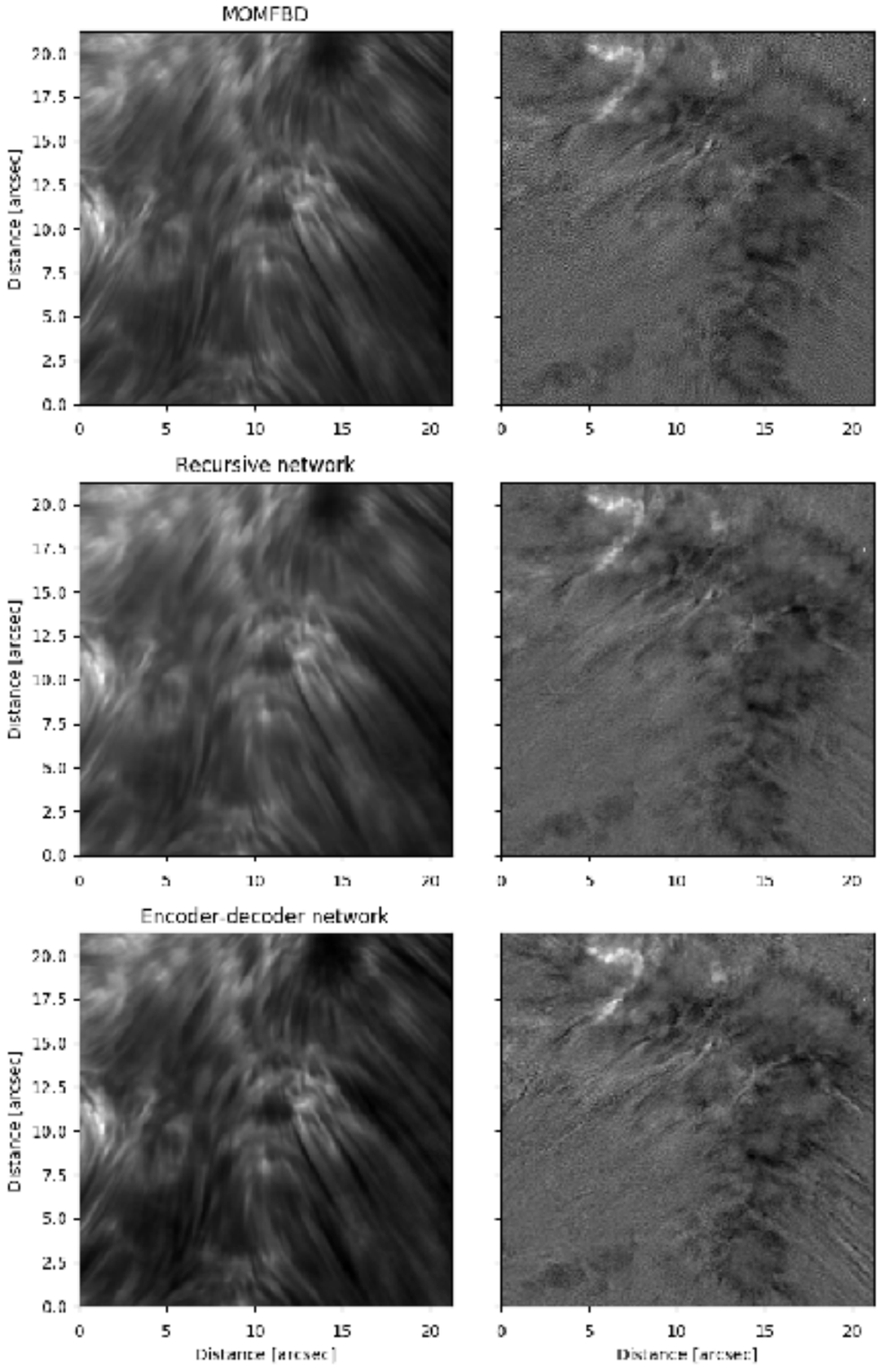
Recurrent



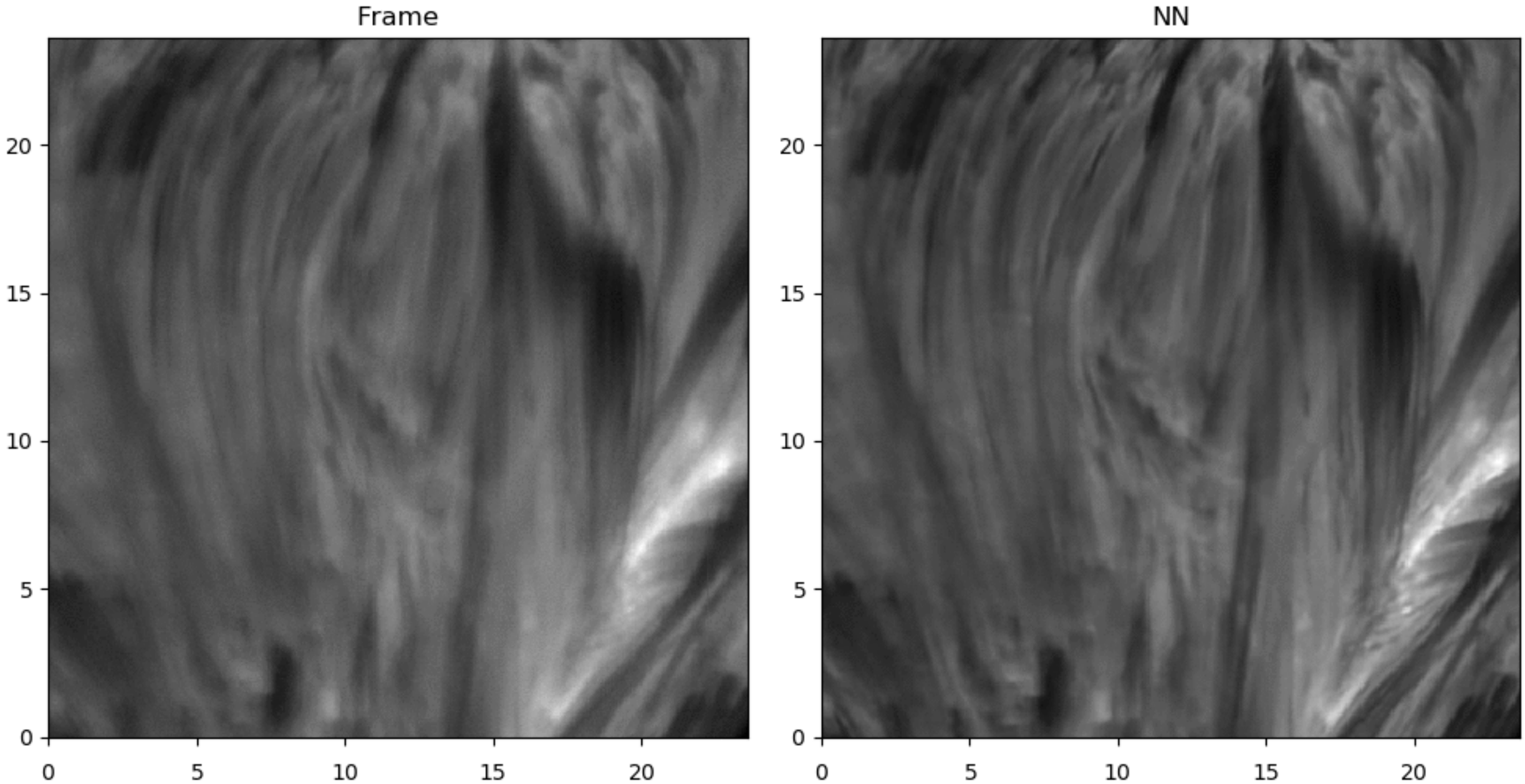
https://github.com/aasensio/learned_mfbd

POLARIMETRY



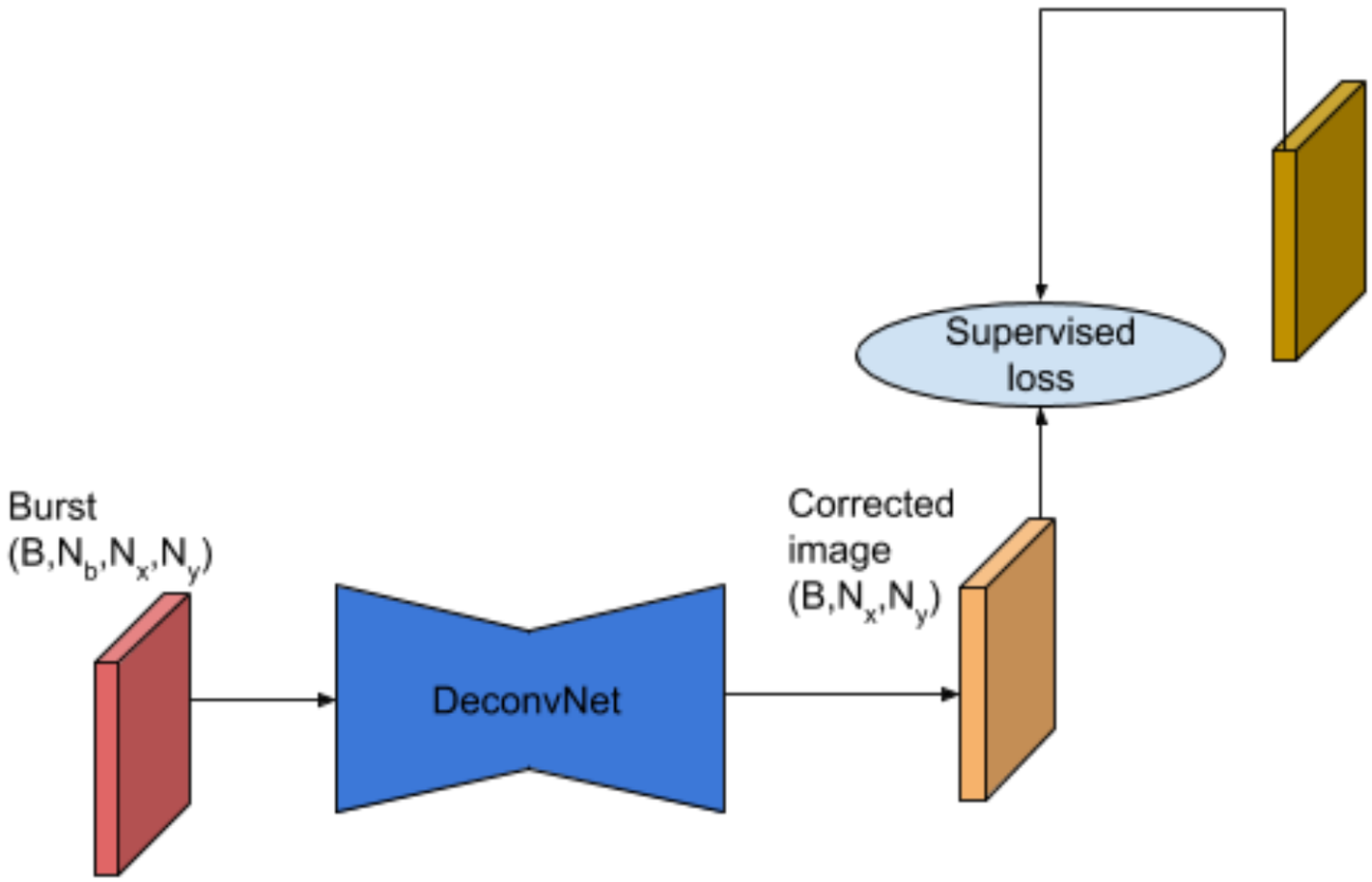


GENERALIZATION TO UNSEEN DATA

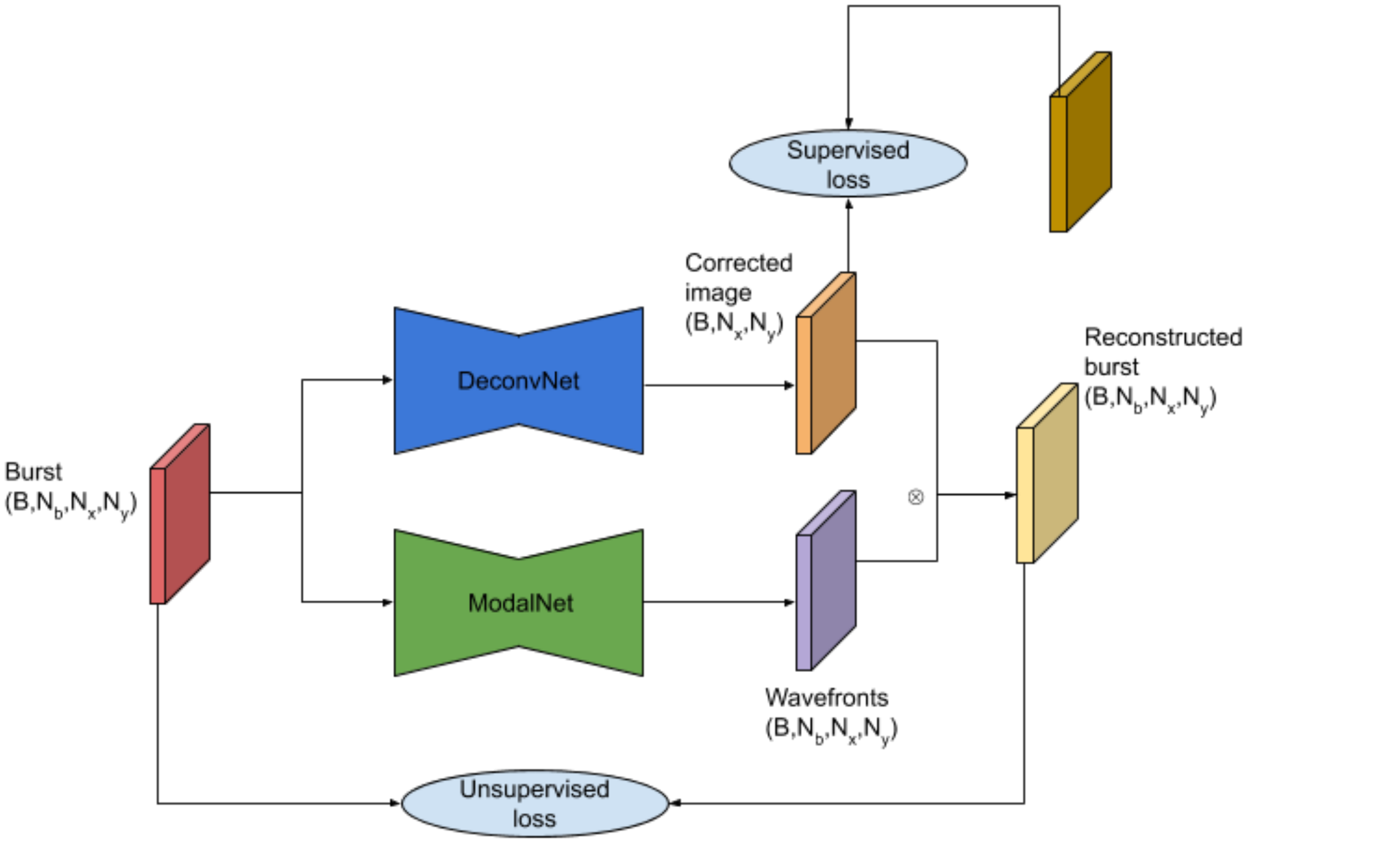


100 images/s

WIP : UNSUPERVISED TRAINING



WIP : UNSUPERVISED TRAINING



fast inversion of Stokes profiles

CLASSICAL INVERSION OF STOKES PROFILES

$$\mathbf{S}(\lambda) = f(\mathbf{p}, \lambda)$$

T, B, v, …

Stokes vector

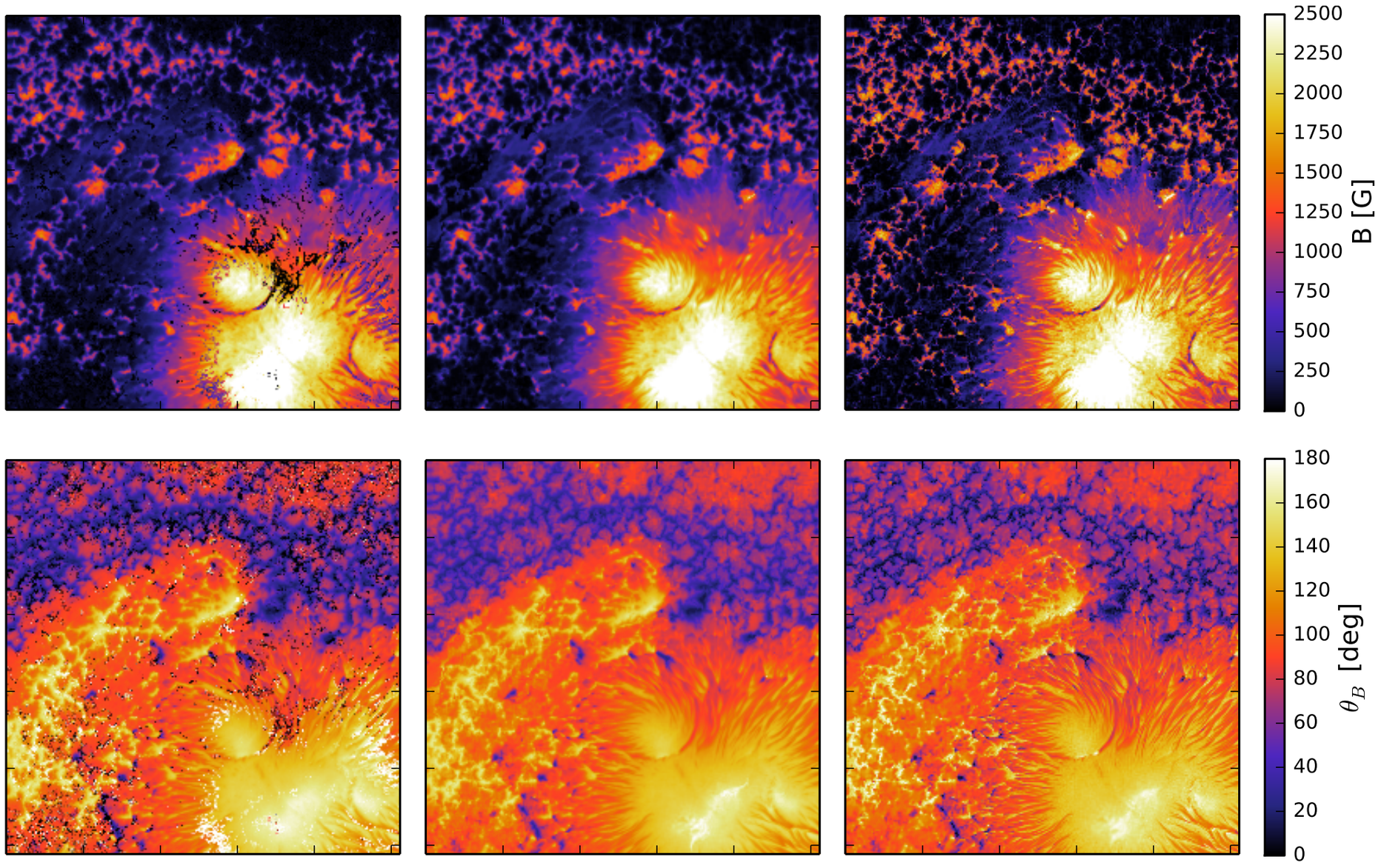
Radiative transfer+QM

$$L = \sum_{ij} \left[S_i(\lambda_j) - f_i(\mathbf{p}, \lambda_j) \right]^2$$

- Optimized with Levenberg-Marquardt
- Gradients are difficult to compute (non-linear + non-local forward)

SPARSITY CONSTRAINTS

$$L = \sum_{ij} \left[S_i(\lambda_j) - f_i(\mathbf{p}, \lambda_j) \right]^2 + \lambda \| \mathbf{W}^T \mathbf{p} \|_0$$

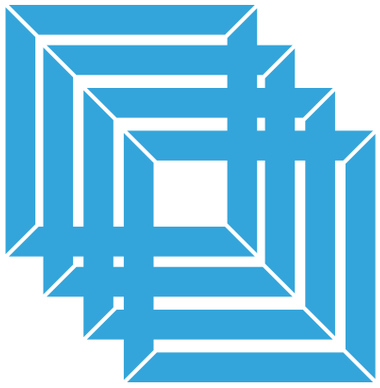


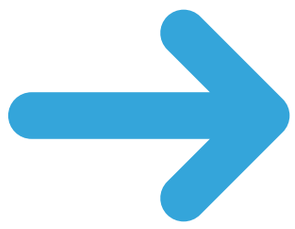
Pixel-by-pixel Sparse Sparse+deconv

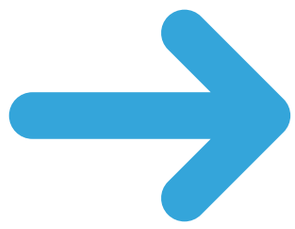
Asensio Ramos & de la Cruz Rodríguez (2013)

CAN WE TRAIN END-TO-END?

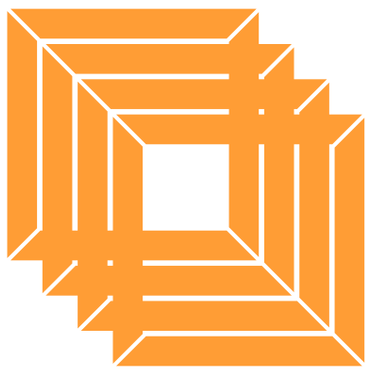
Observed Stokes profiles





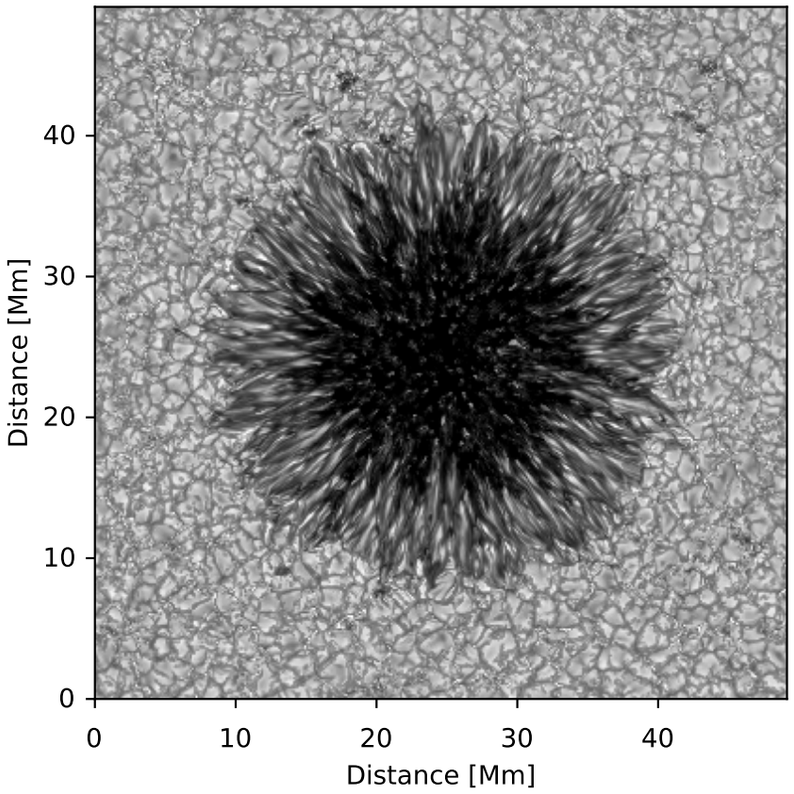


3D cube physical parameters

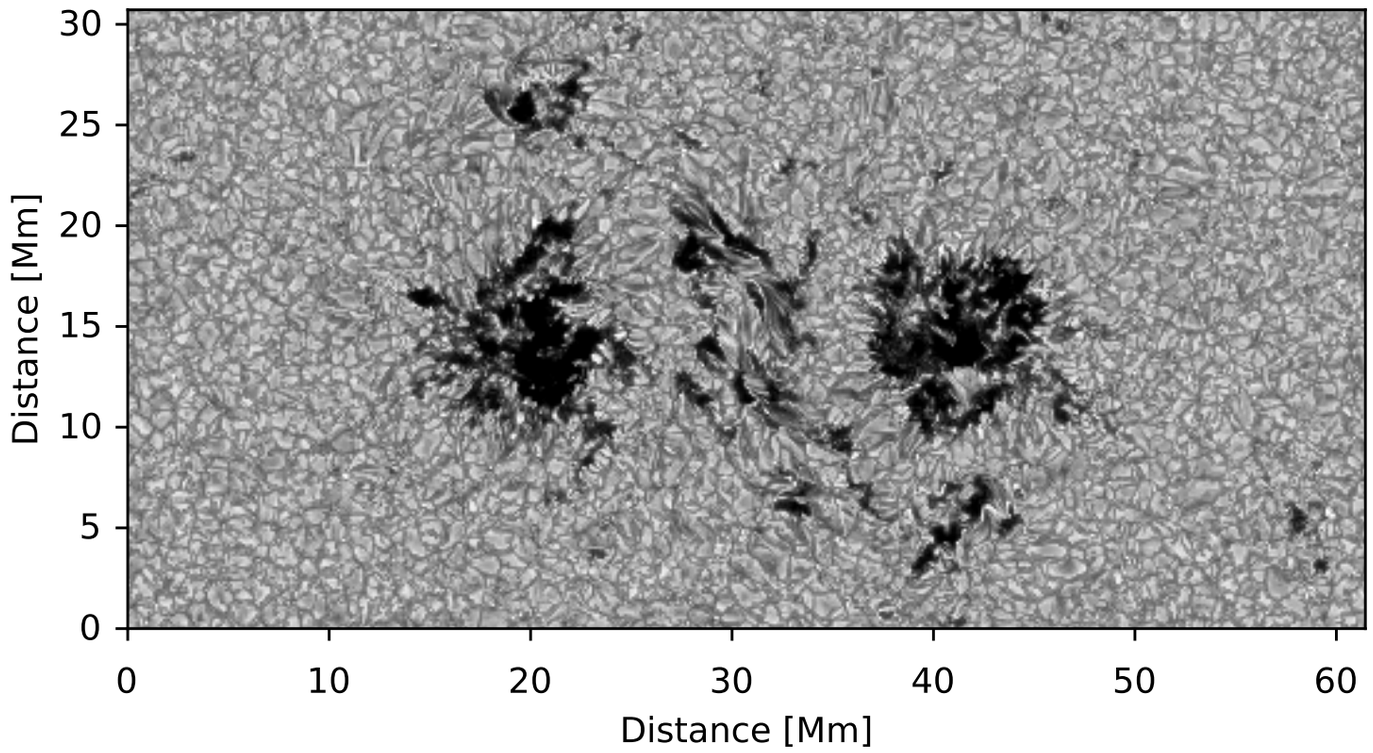


TRAINING SETS

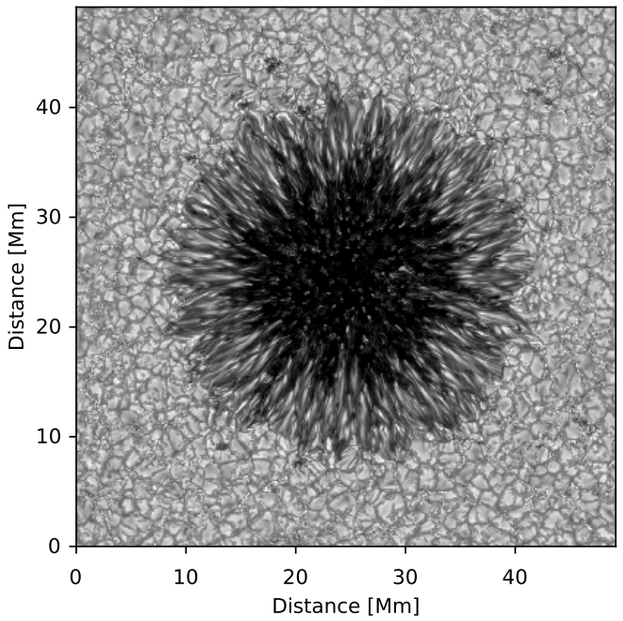
Rempel et al. (2012)



Cheung et al. (2010)



DEGRADING TRAINING SETS



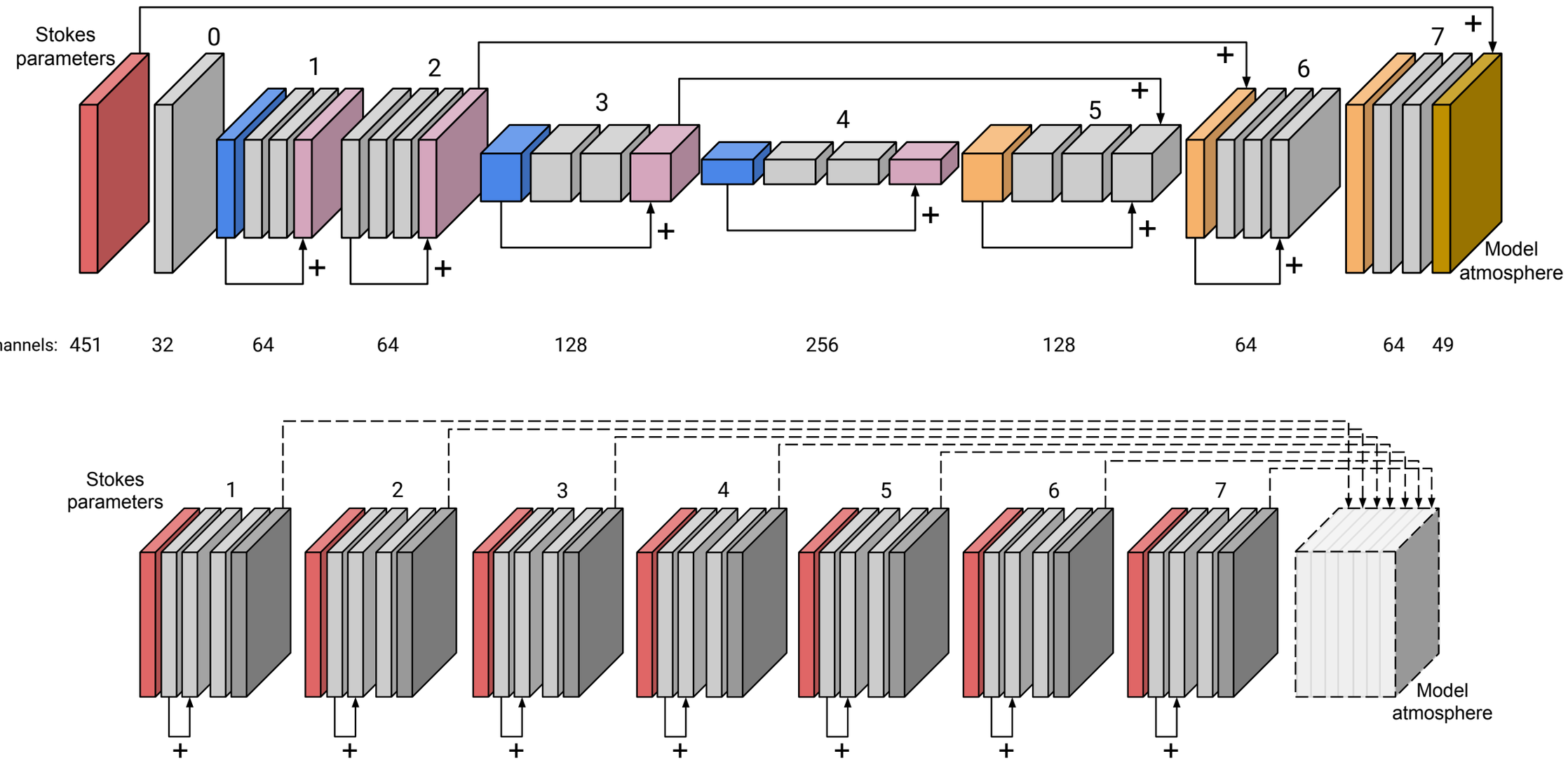
Stokes profiles

LTE SPECTRAL SYNTHESIS → SPATIAL SMEARING → SPECTRAL SMEARING → SPATIAL BINNING

OPTICAL DEPTH SURFACES → SPATIAL BINNING

Physical models

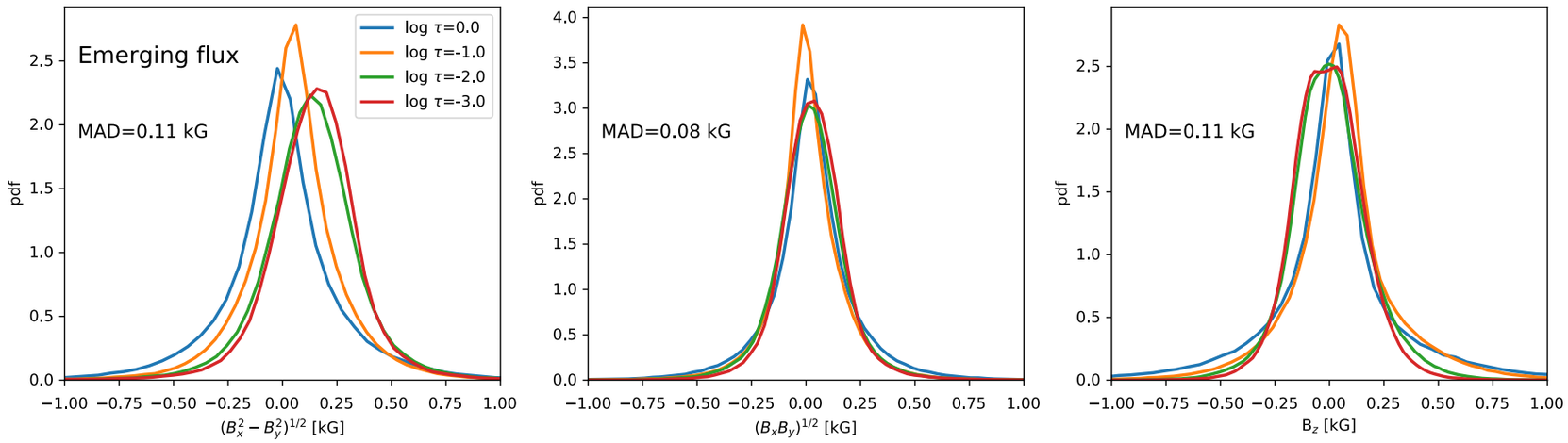
ARCHITECTURES

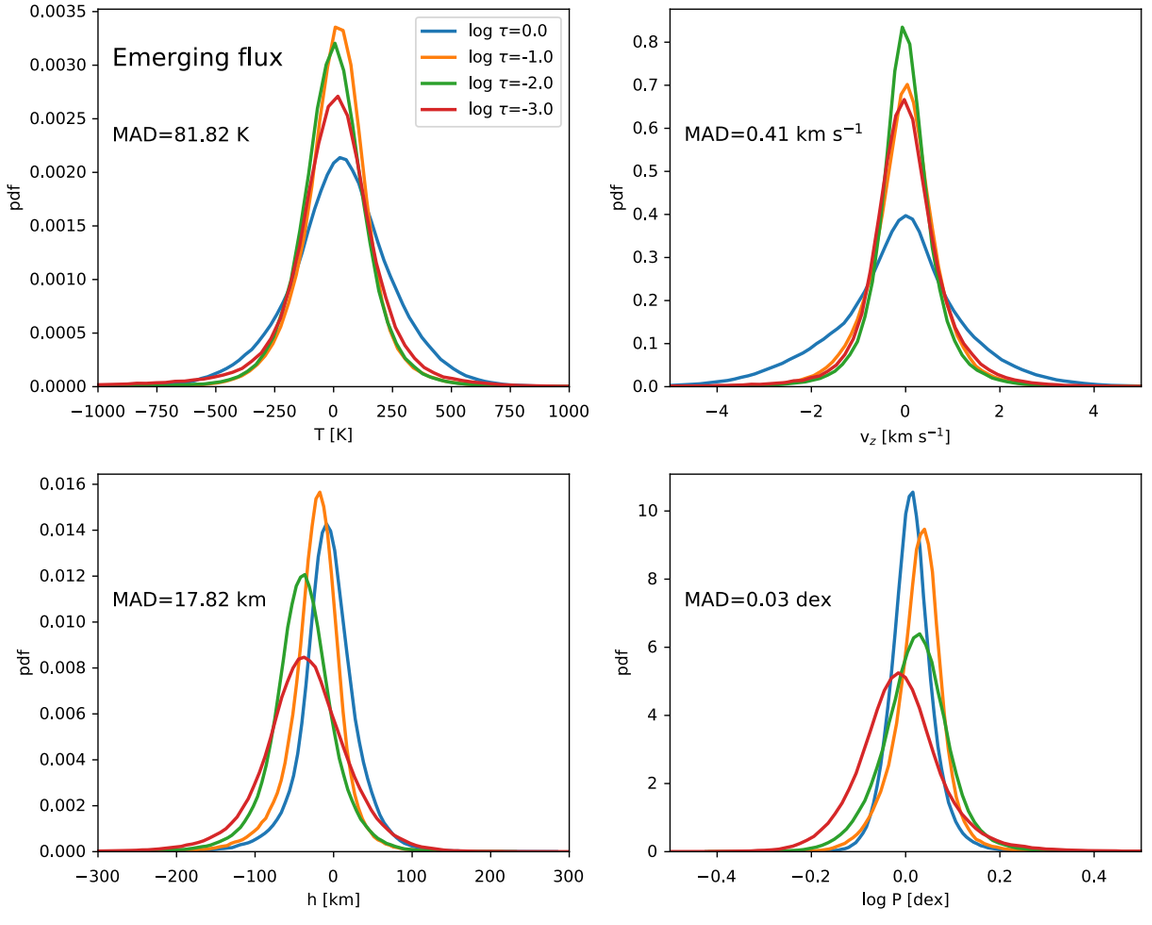


180 ms per inversion on 512x512

30 minutes for all Hinode observations

VALIDATION


Emerging flux
MAD=0.11 kG
log τ=0.0
log τ=-1.0
log τ=-2.0
log τ=-3.0
pdf
$(B_x^2 - B_y^2)^{1/2}$ [kG]
MAD=0.08 kG
$(B_x B_y)^{1/2}$ [kG]
MAD=0.11 kG
B_z [kG]


Emerging flux
MAD=81.82 K
log τ=0.0
log τ=-1.0
log τ=-2.0
log τ=-3.0
pdf
T [K]
MAD=0.41 km s^{-1}
v_z [km s^{-1}]
MAD=17.82 km
h [km]
MAD=0.03 dex
log P [dex]

AR10933 : CONTINUUM

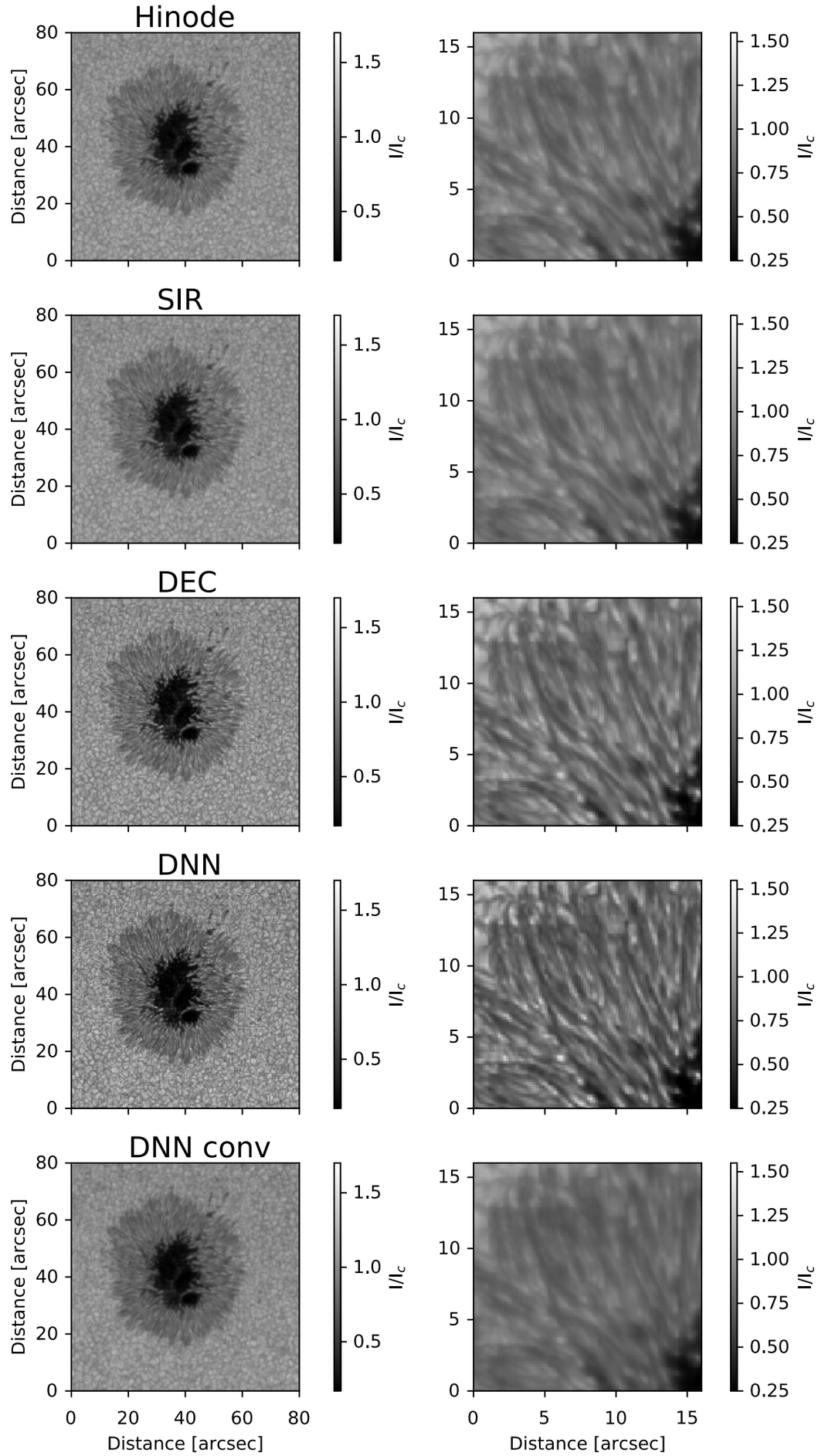
Original

SIR inversions

SIR inversions+deconvolution

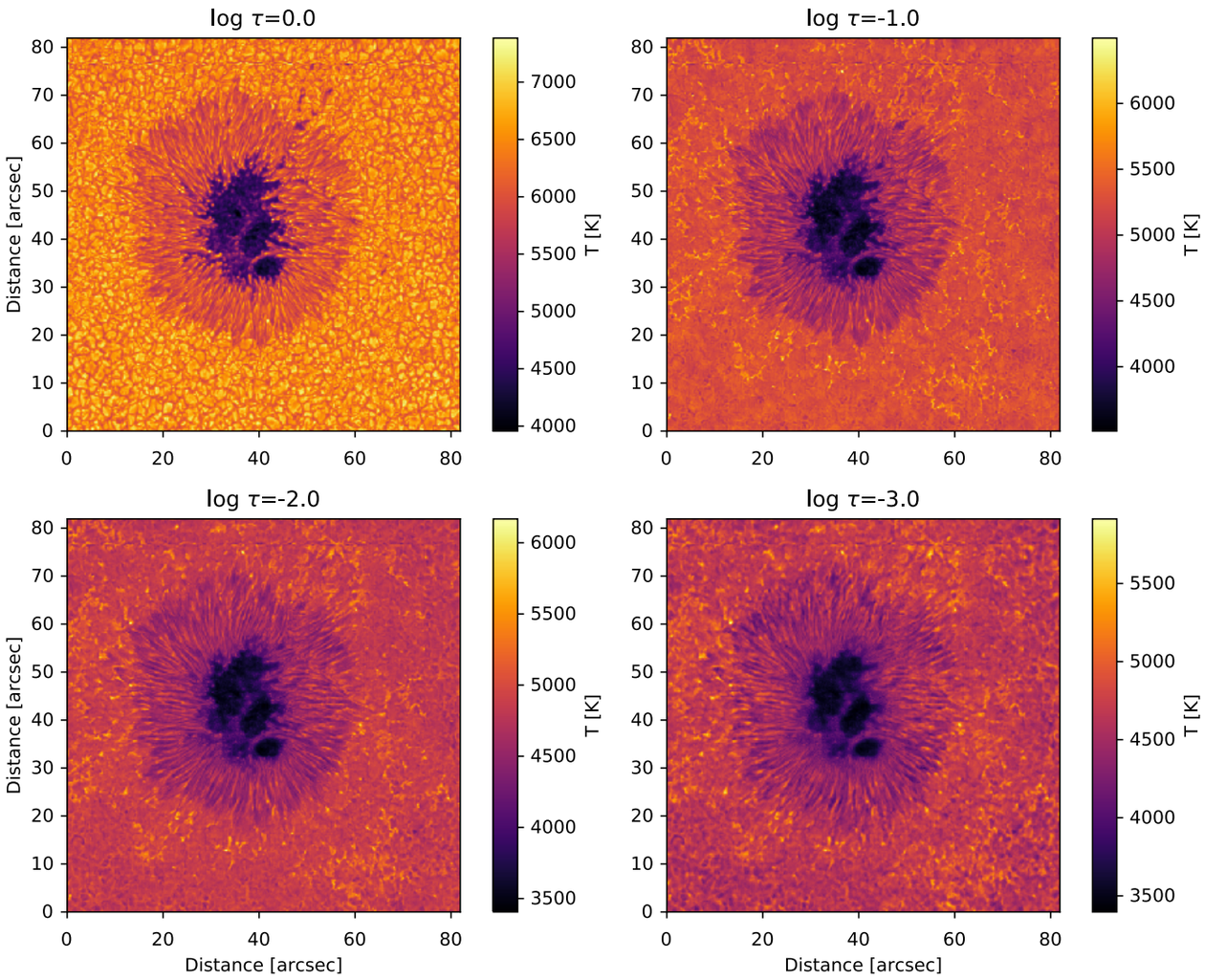
Deep neural network

Deep neural network+convolution

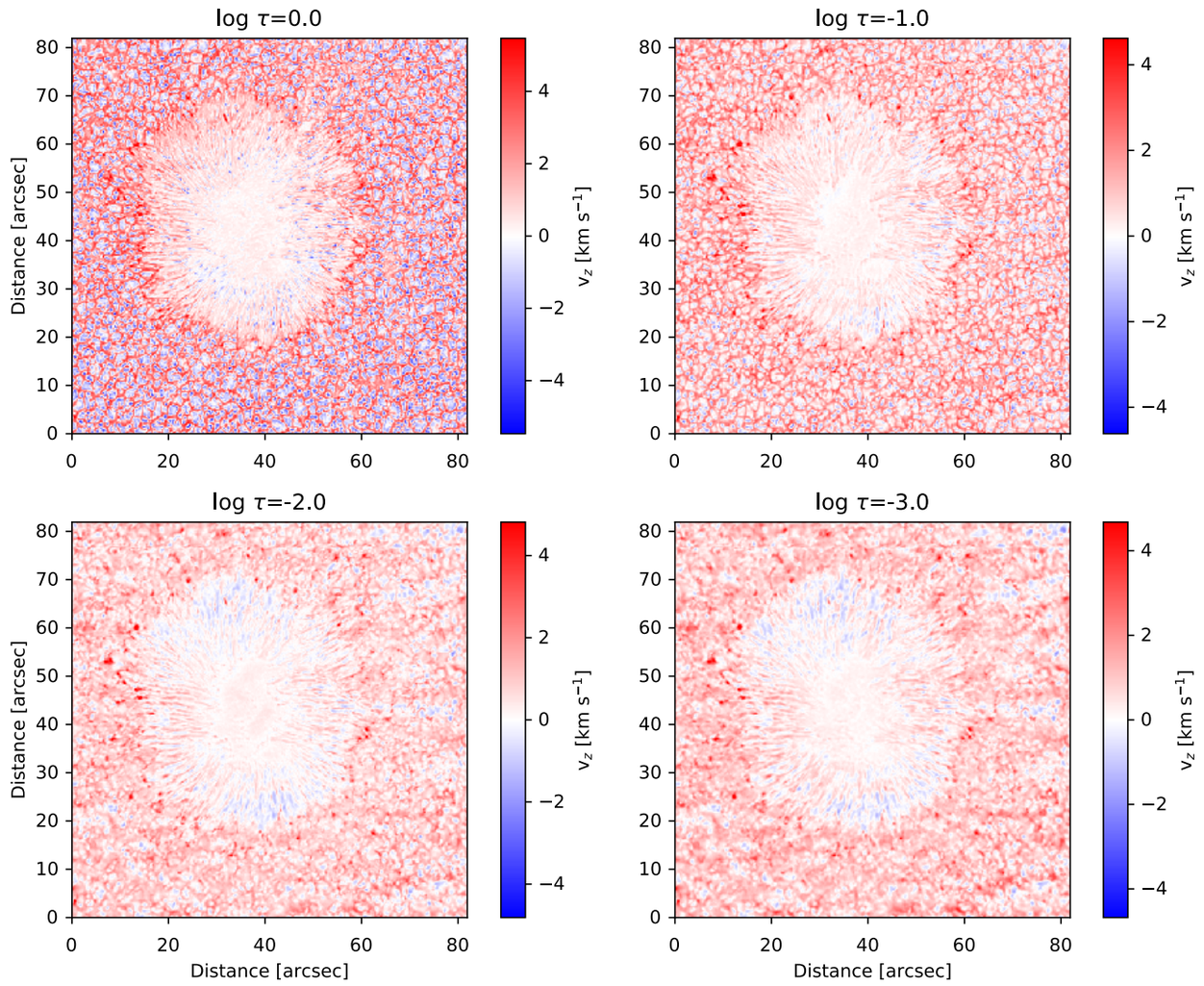


AR10933 : INFERENCE

Temperature

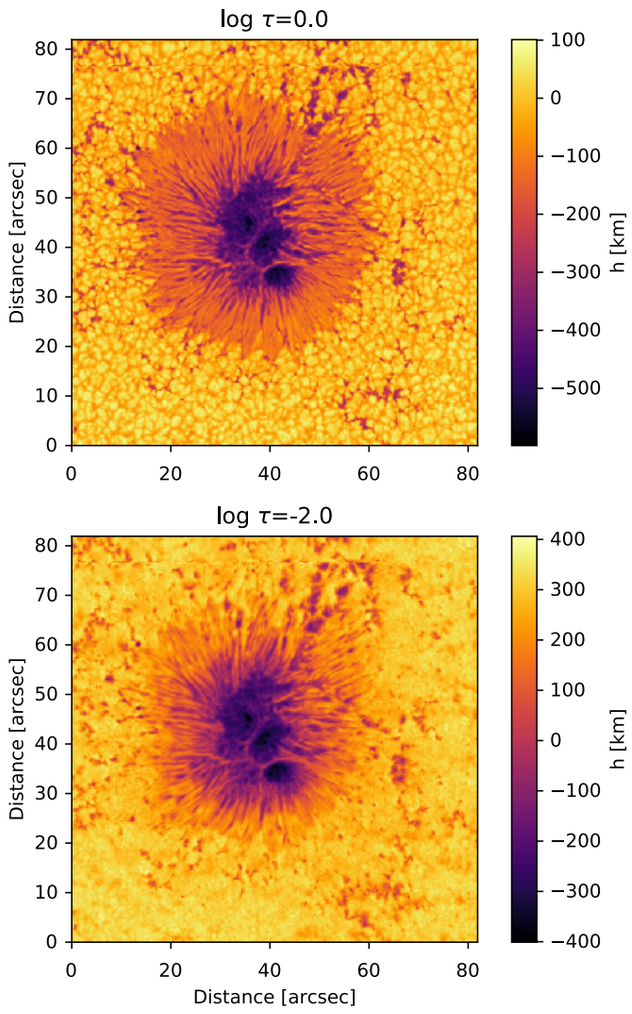


Doppler velocity

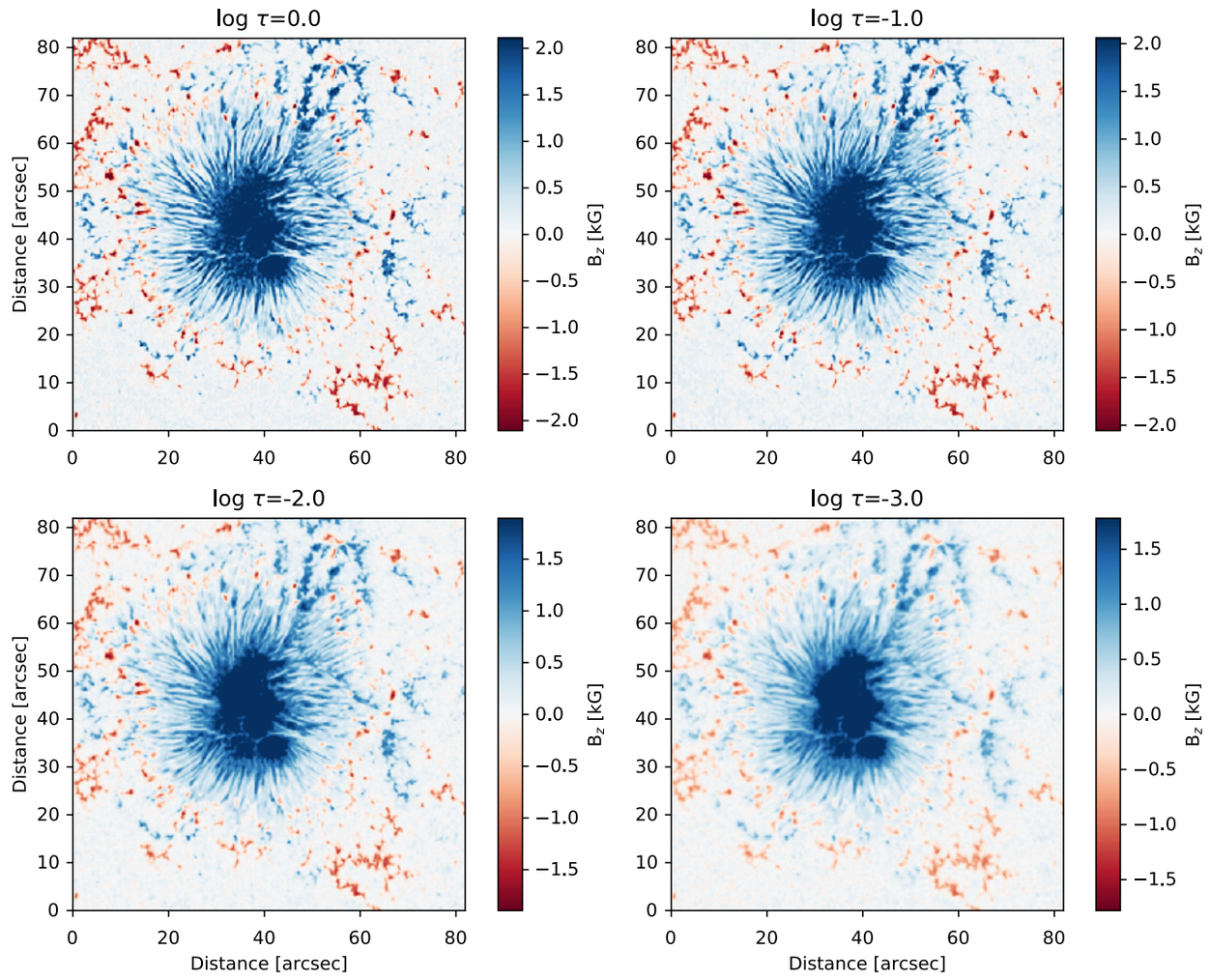


AR10933 : INFERENCE

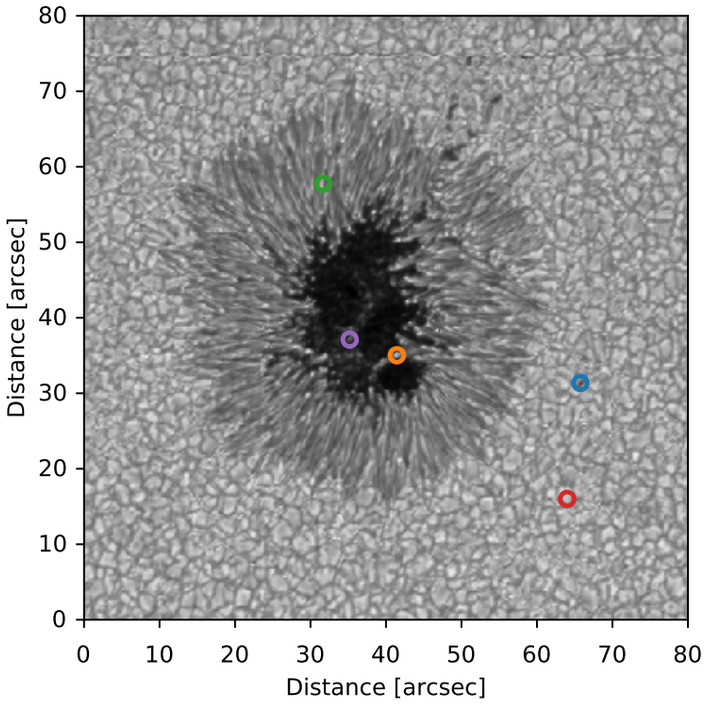
τ surfaces

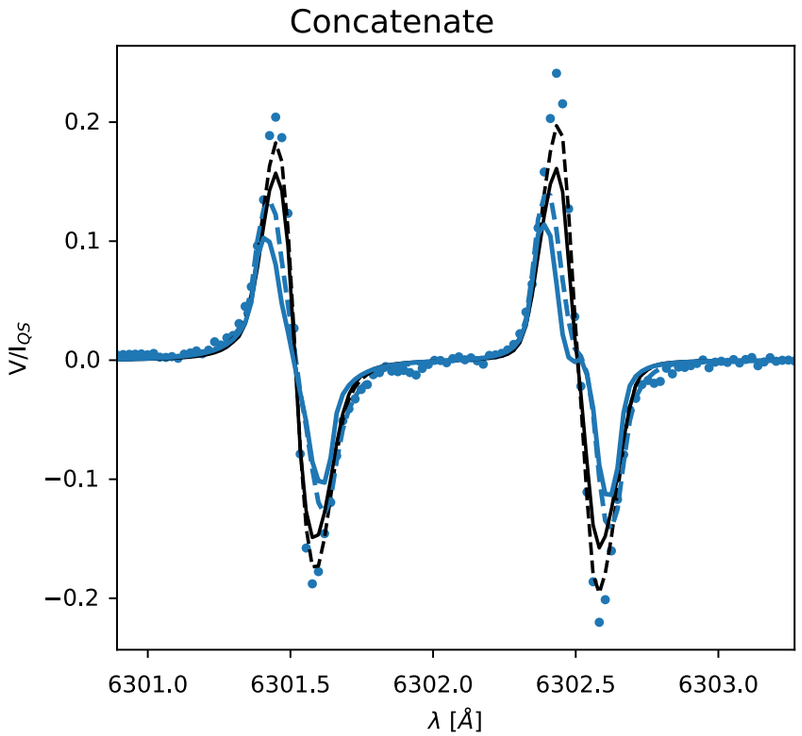


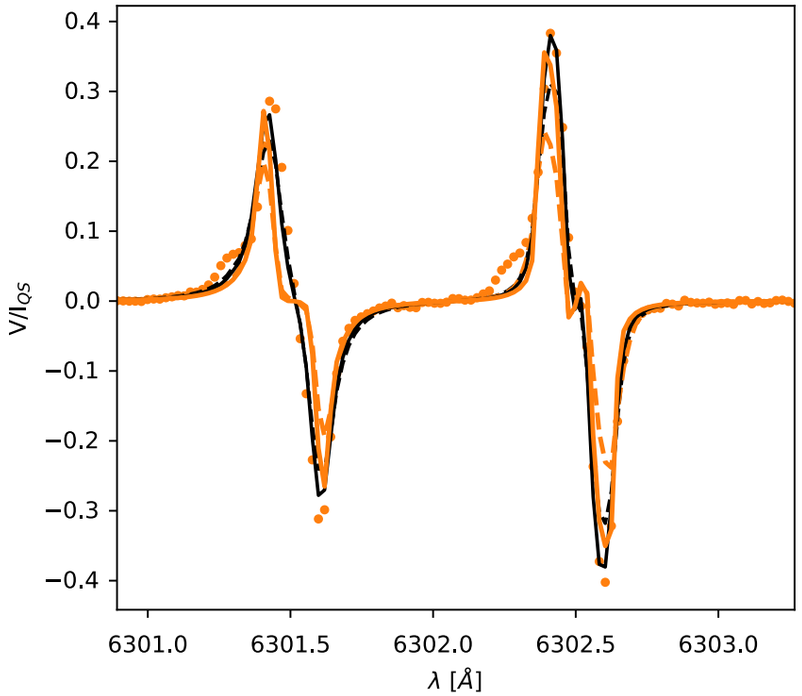
Bz

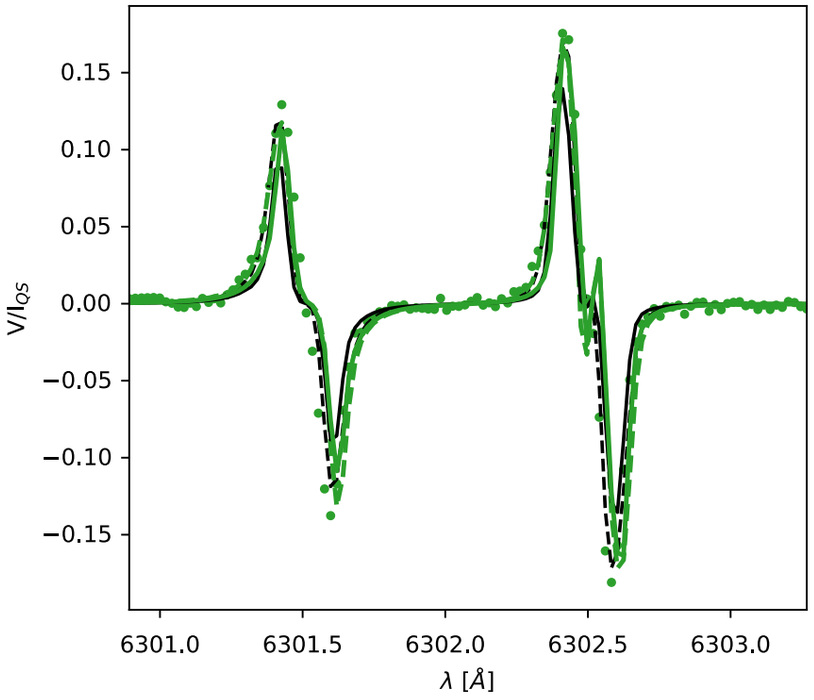


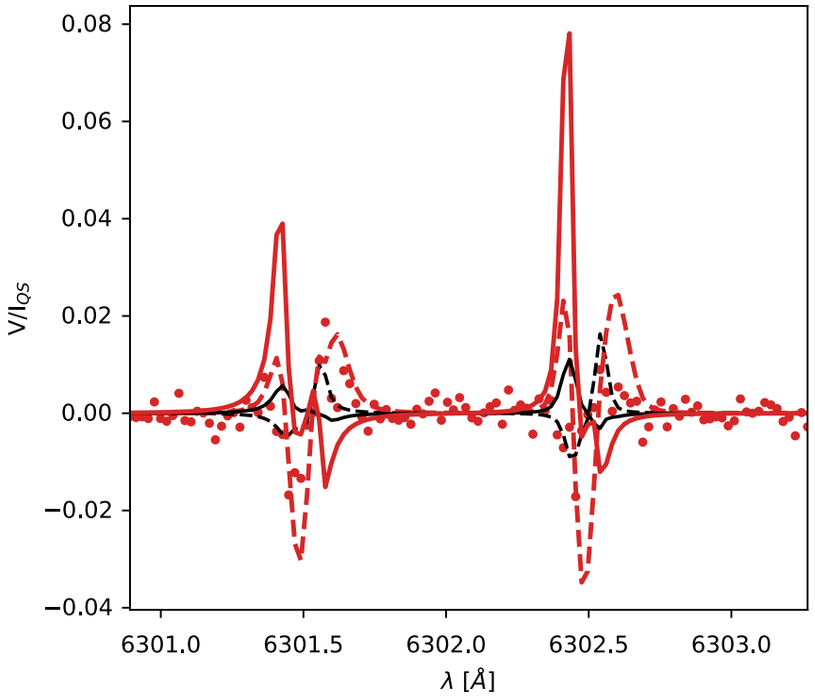
DO WE FIT THE PROFILES?

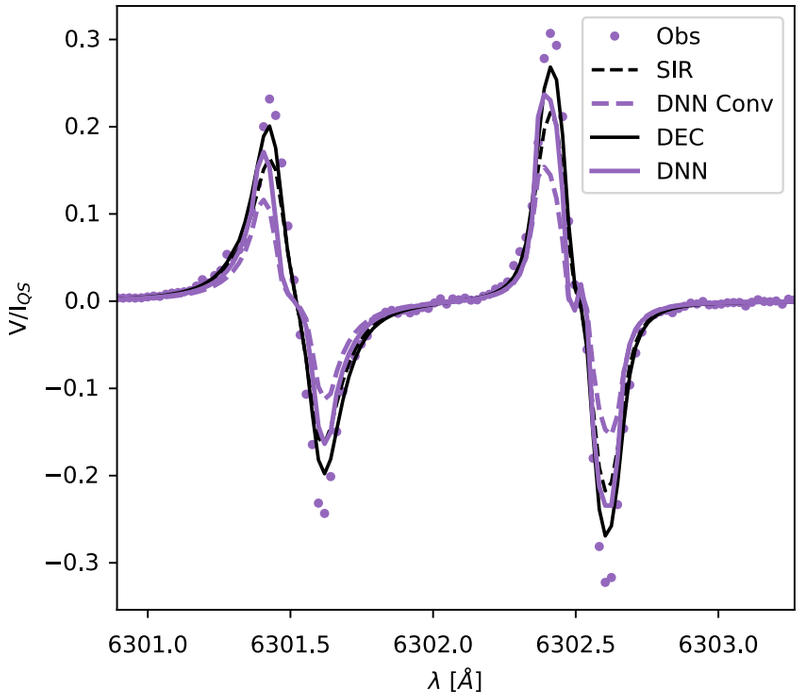




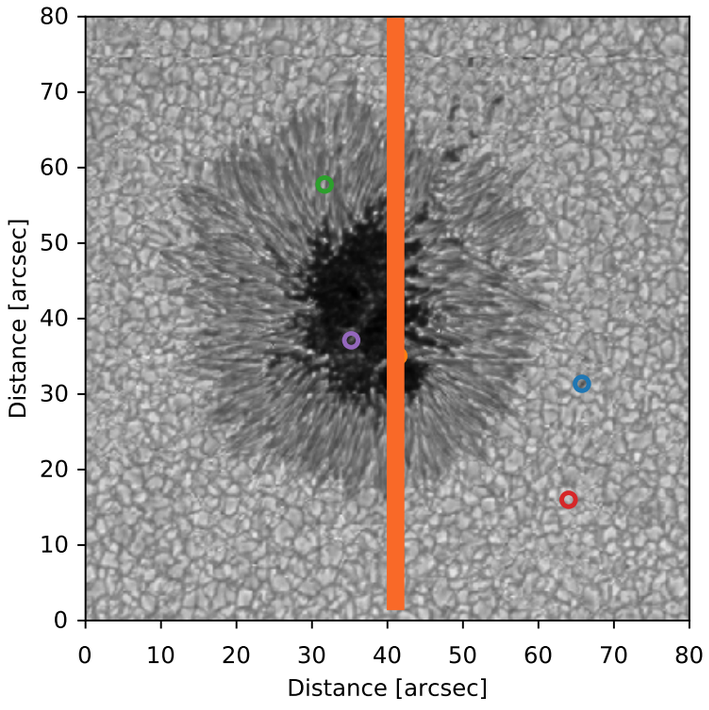


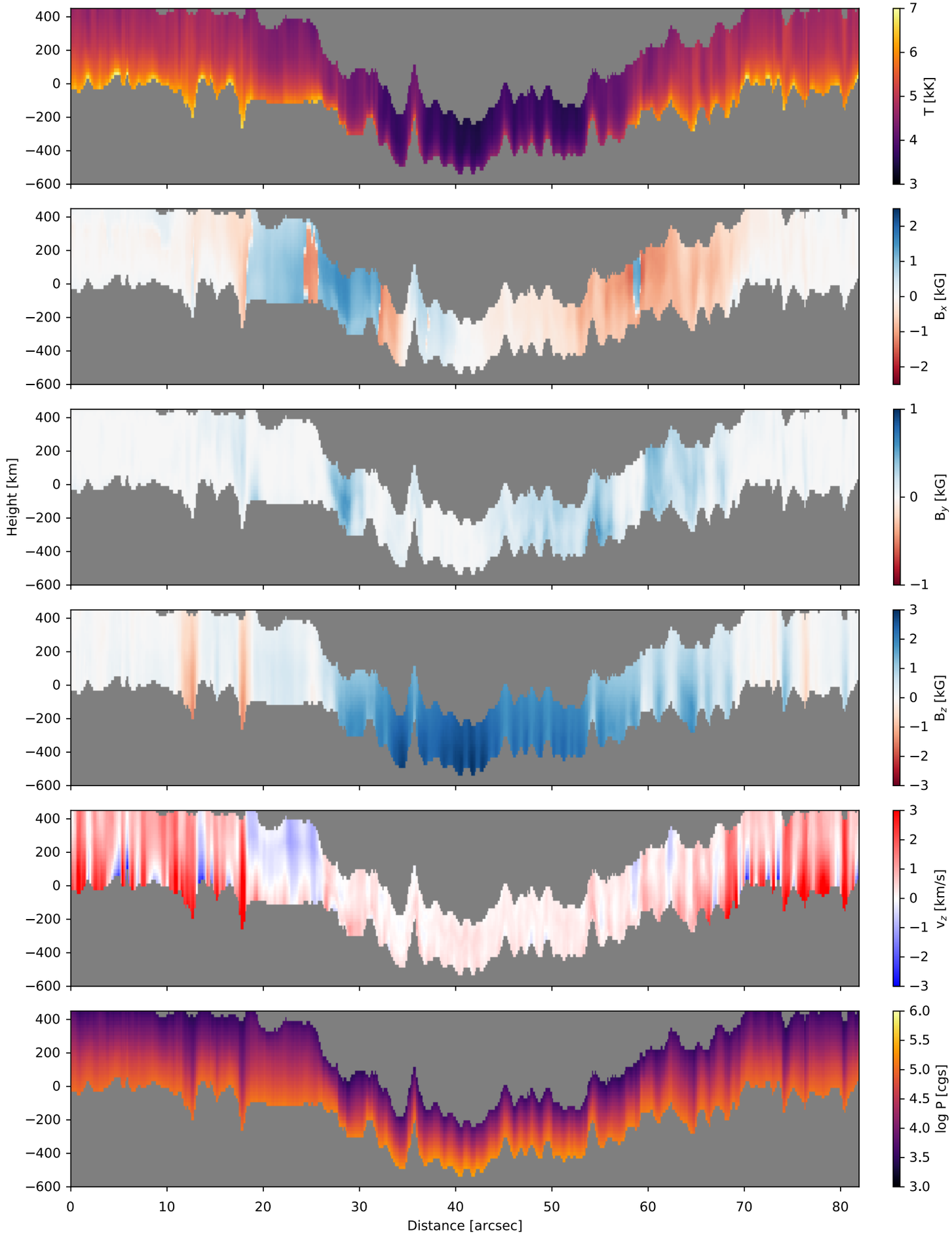






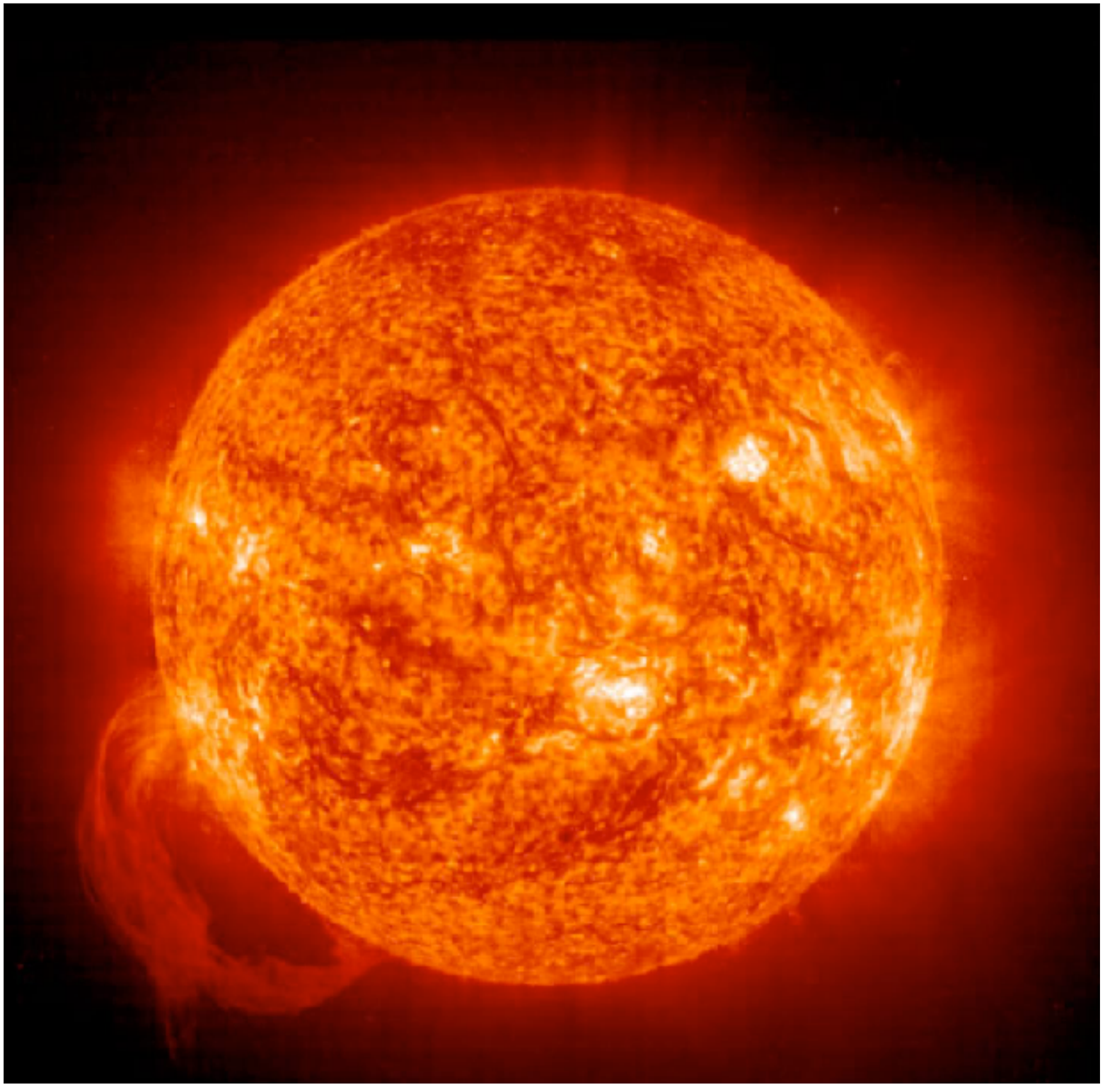
LIGHT BRIDGE





farside enhacement

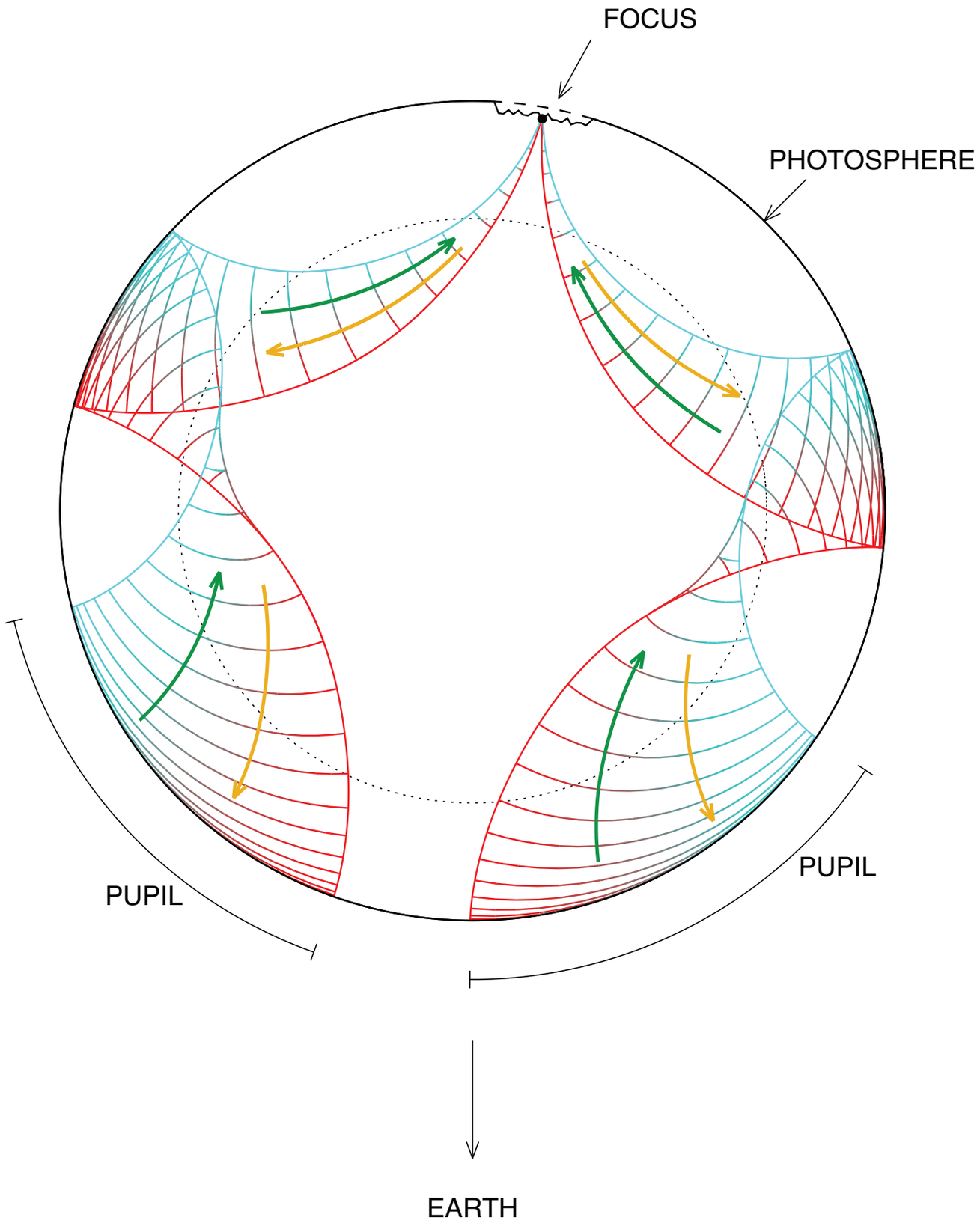
FARSIDE PROBLEM



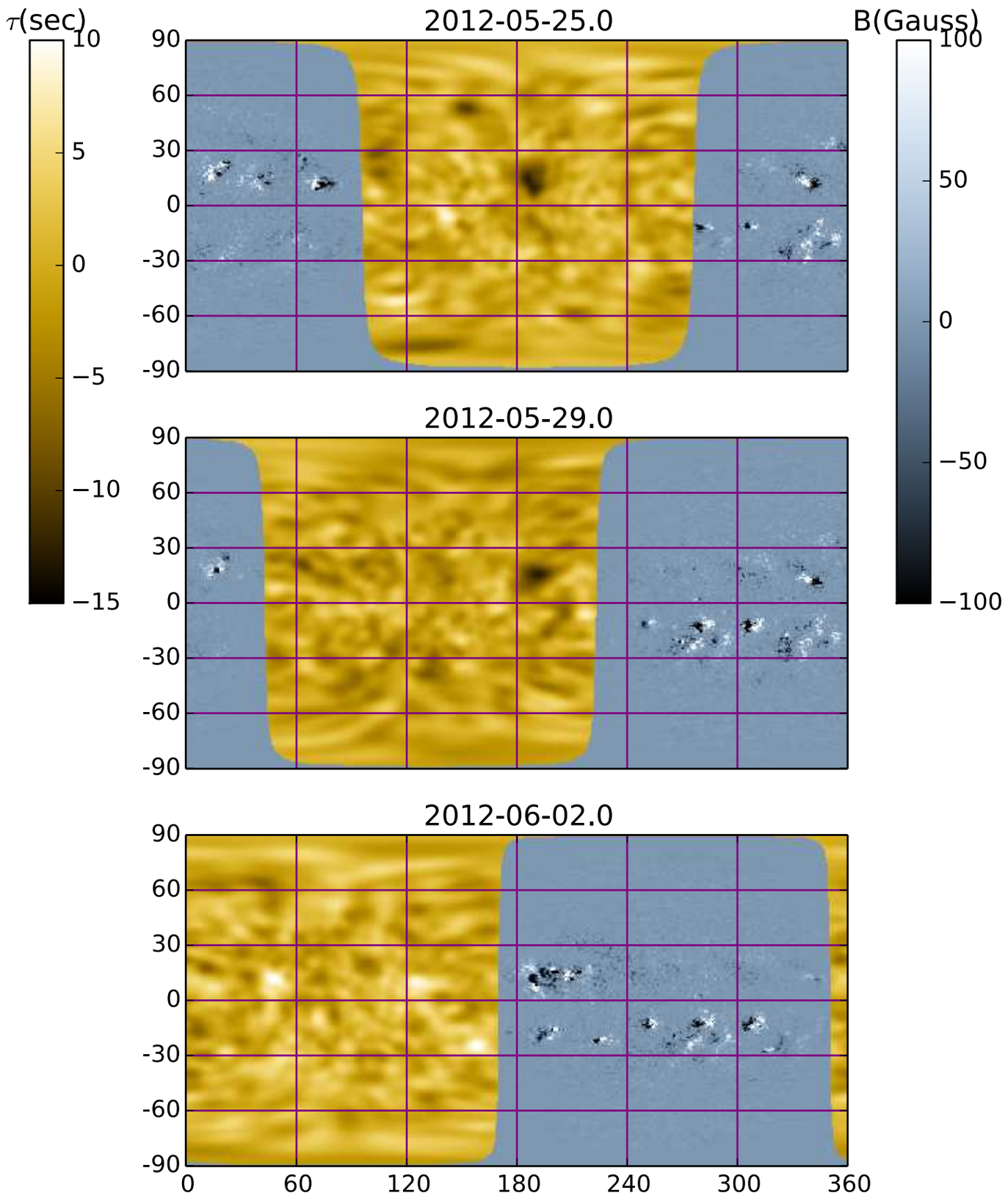
Forecasting

- Solar UV irradiance
- Global solar magnetic index
- Coronal magnetic field
- ...

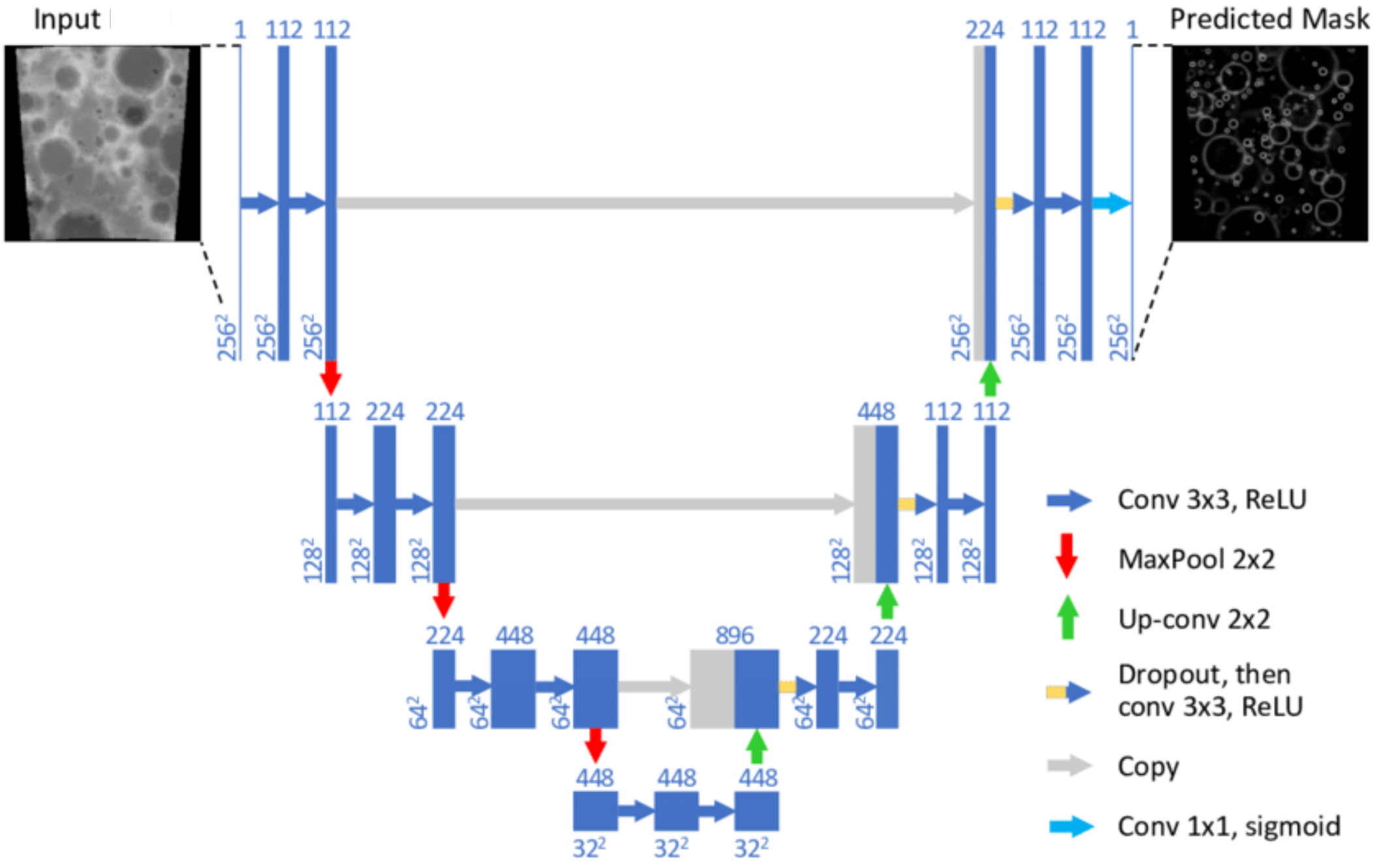
FARSIDE PROBLEM



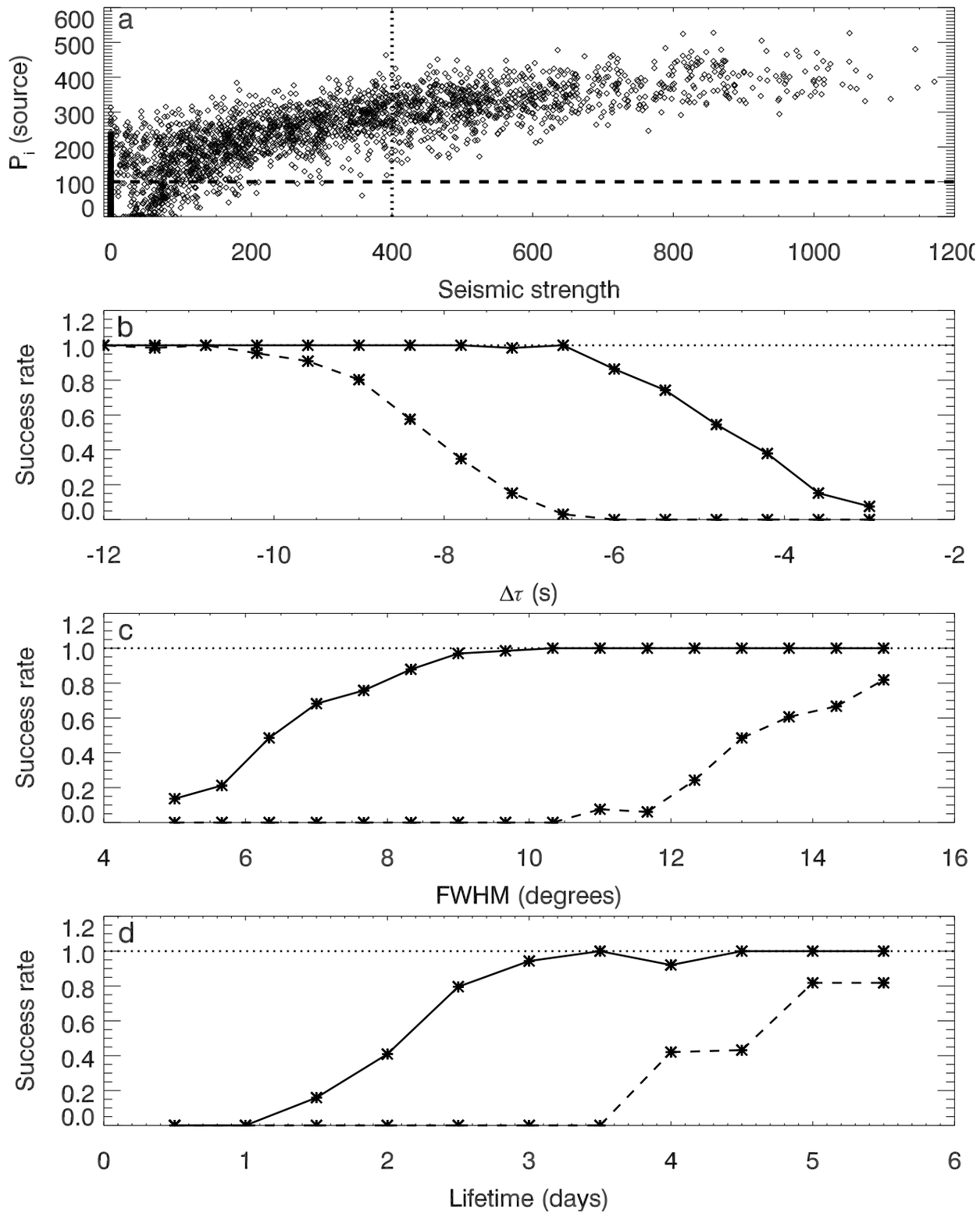
CURRENT FARSIDE PREDICTIONS



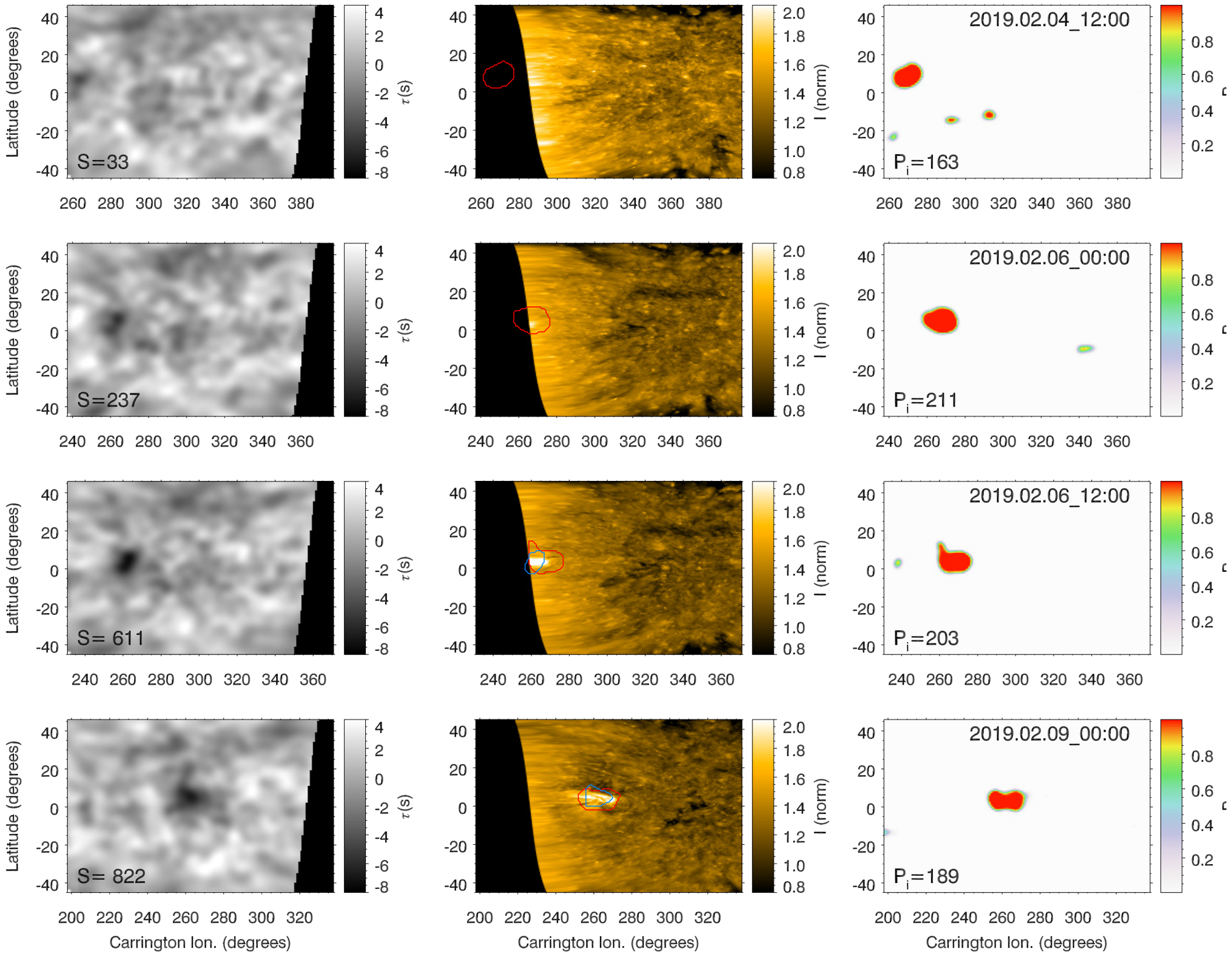
U-NET ARCHITECTURE



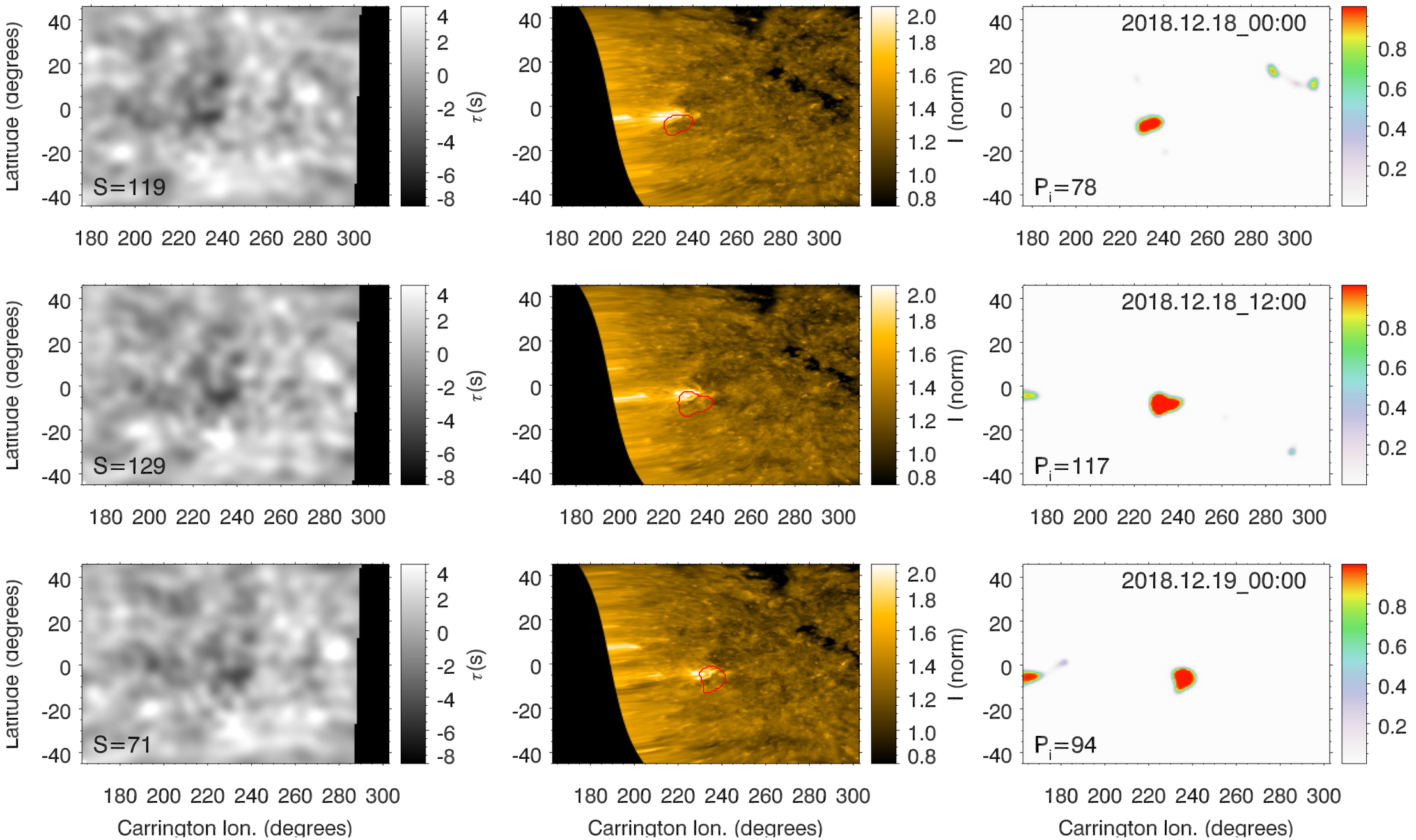
INJECTING ACTIVE REGIONS



OUR PREDICTIONS

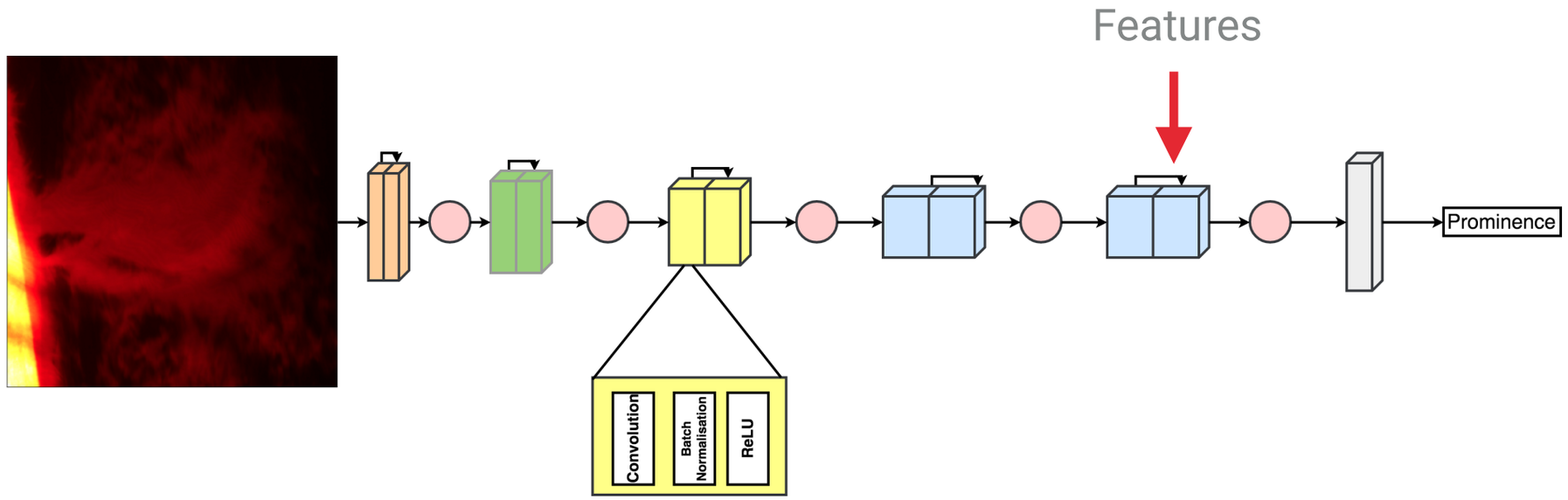


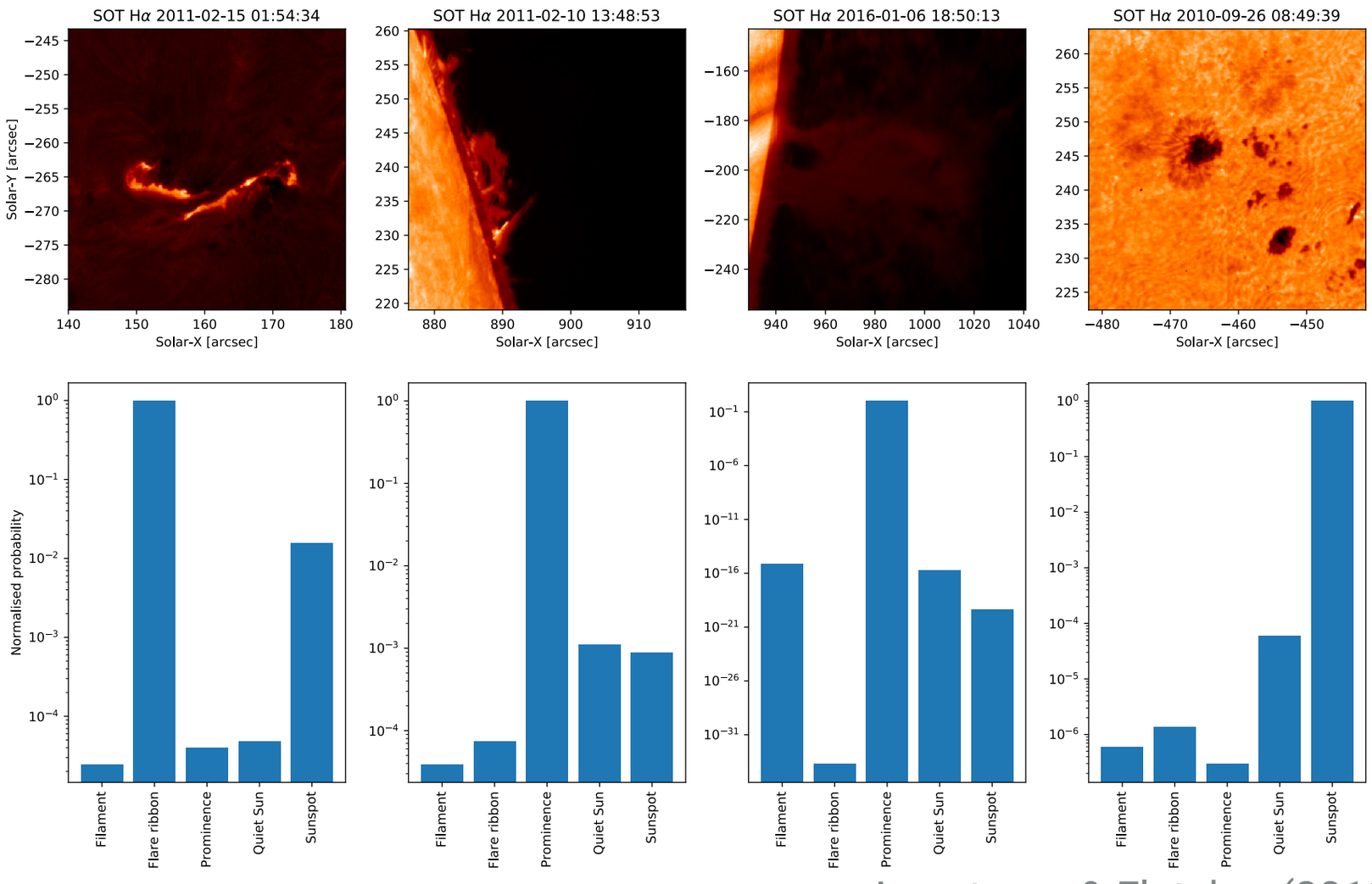
OUR PREDICTIONS



classification of solar structures

CLASSIFICATION

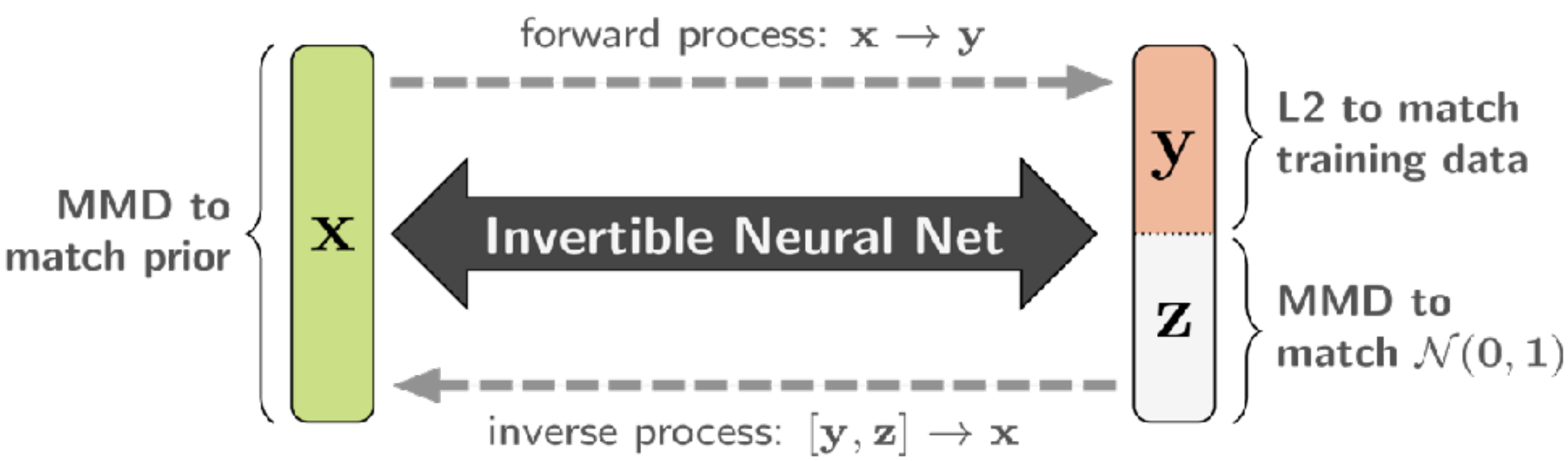




Armstrong & Fletcher (2018)

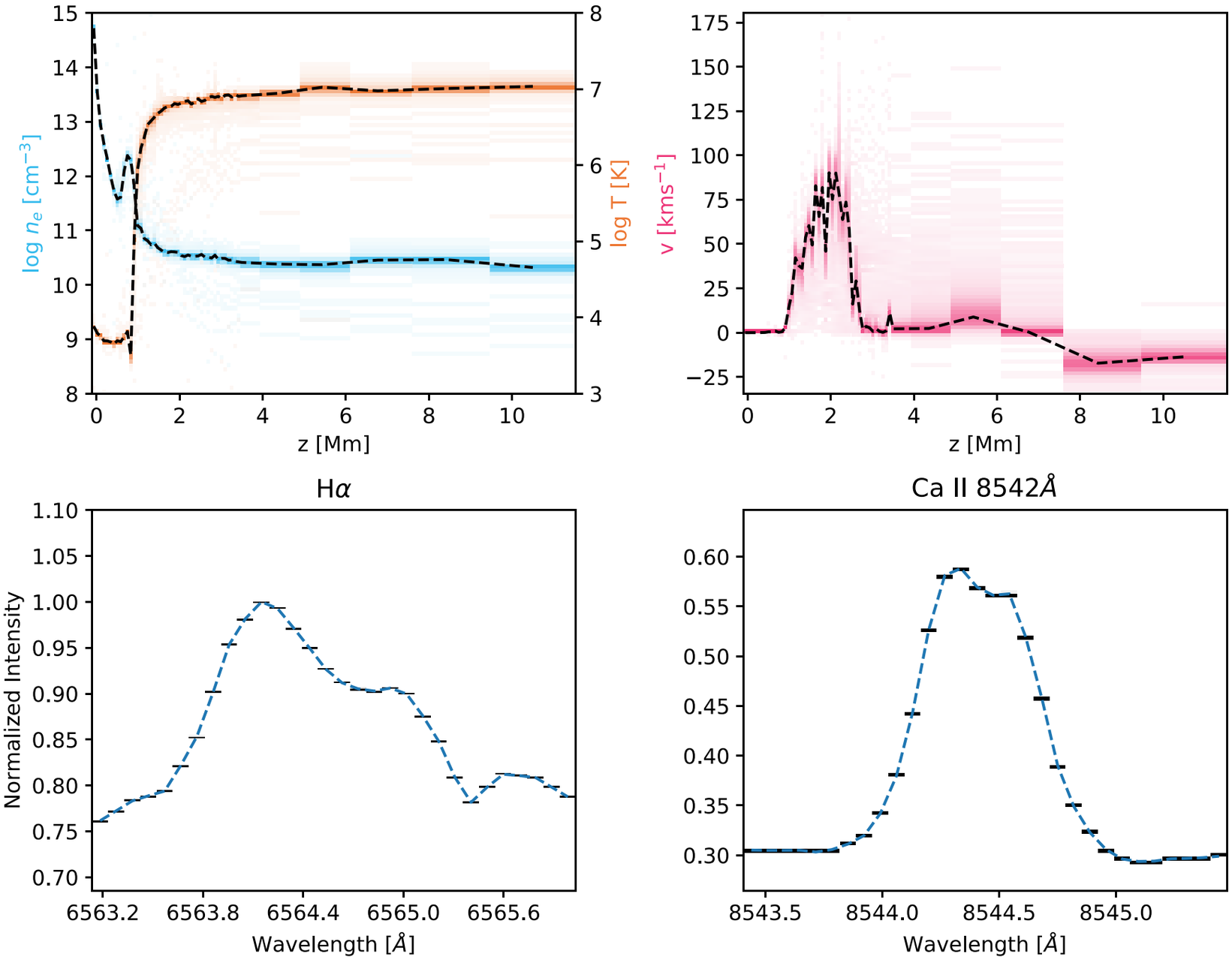
physical conditions in flares

INVERTIBLE NEURAL NETWORKS



Ardizzone et al. (2018)

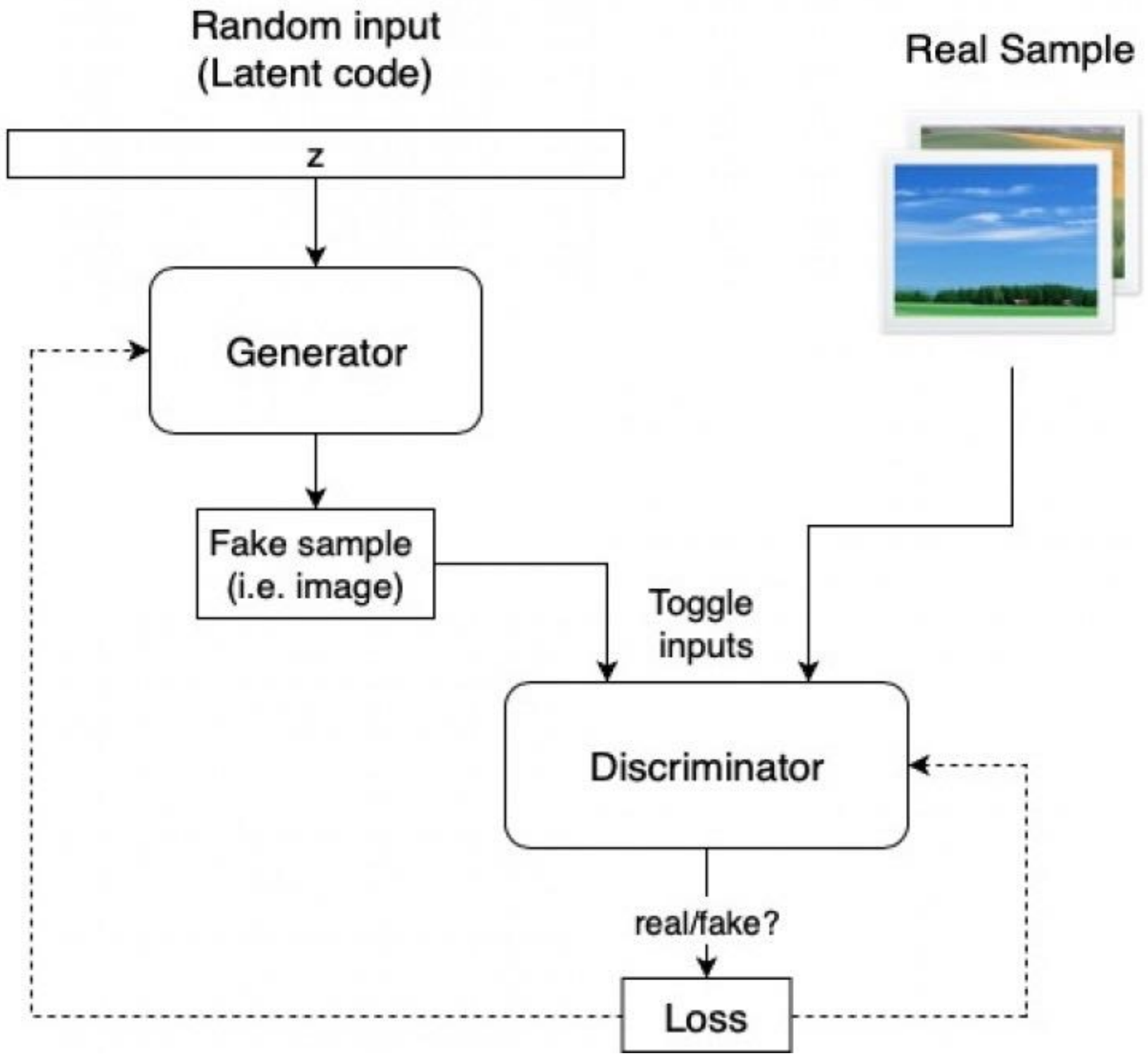
FLARE RIBBON



Osborne, Armstrong & Fletcher (2019)

Other examples…

GENERATIVE ADVERSARIAL NETWORKS



FACES

thispersondoesnotexist.com

SUPER RESOLVE GAMES

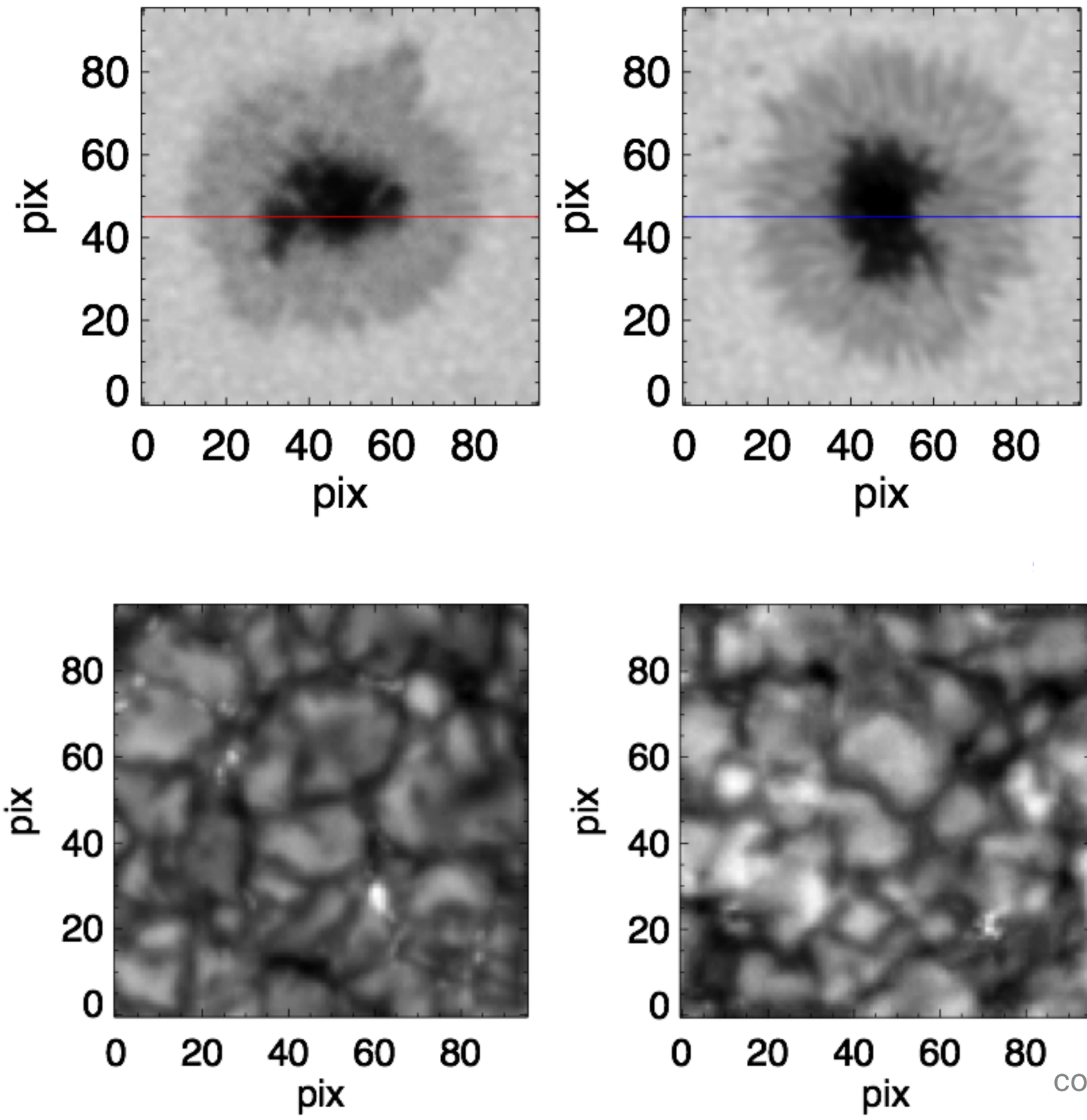
RAINDROP REMOVAL

(a) Ground truth (b) Raindrop image (c) Eigen[1] (d) Pix2pix-cGAN[10] (e) Our method

Figure 6. Results of comparing a few different methods. From left to right: ground truth, raindrop image (input), Eigen13 [1], Pix2Pix [10] and our method. Nearly all raindrops are removed by our method despite the diversity of their colors, shapes and transparency.

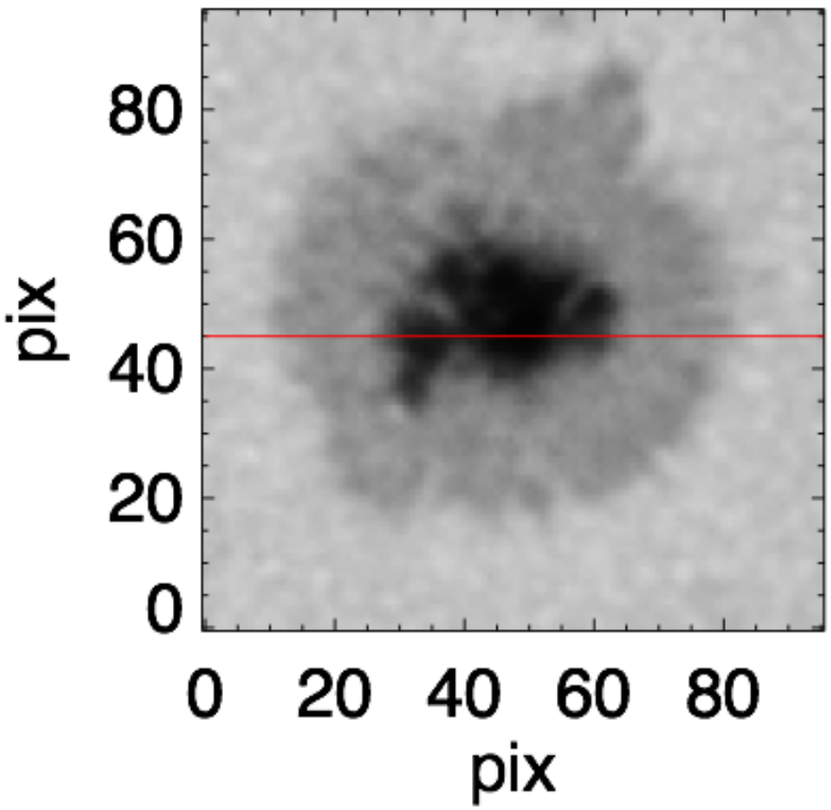
Quian et al. (2018)

GENERATIVE ADVERSARIAL NETWORKS

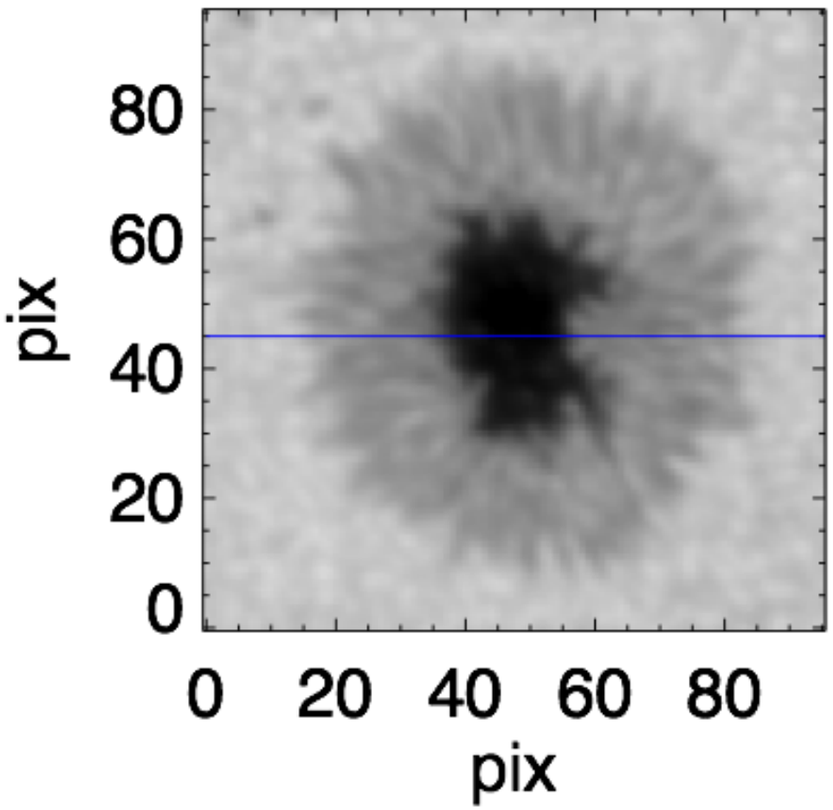


courtesy of Y. Kawabata

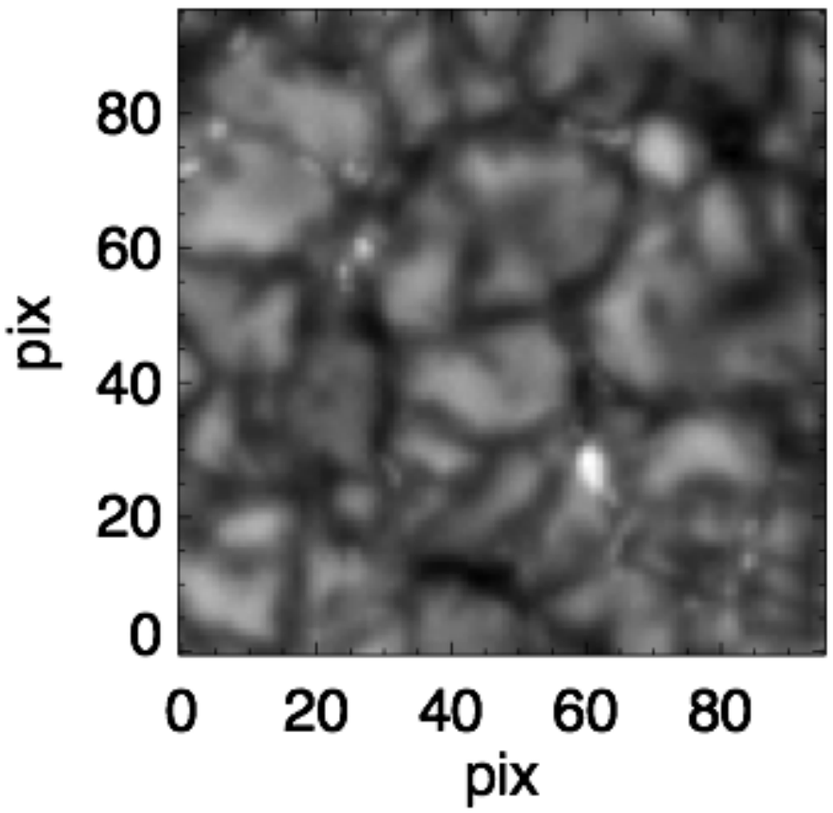
Artificial Sunspot



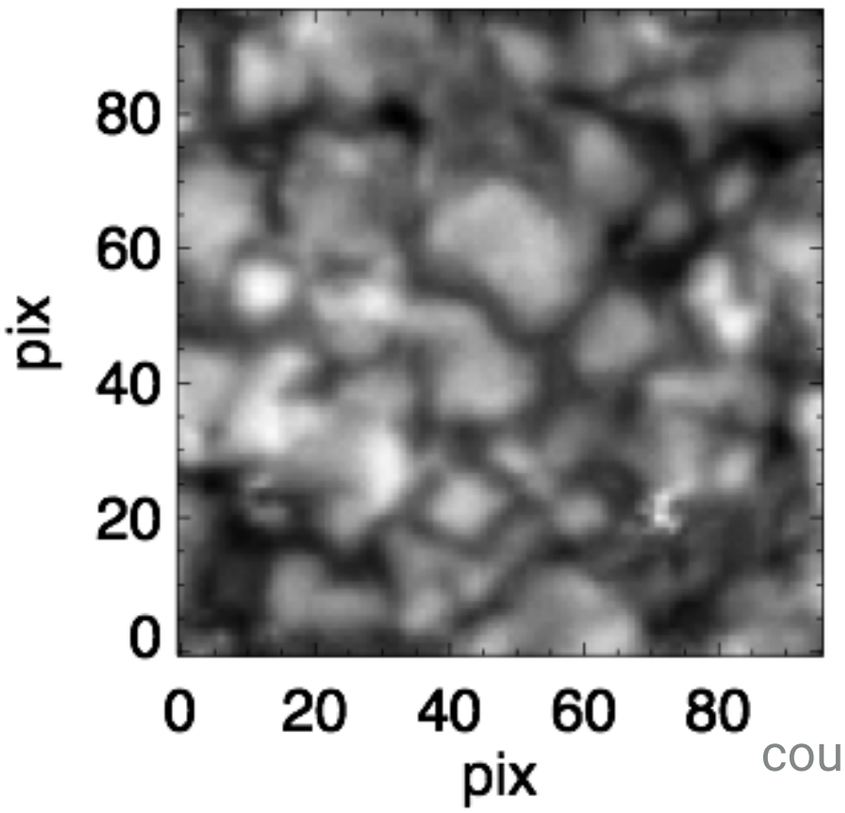
Real Sunspot



Artificial Granule

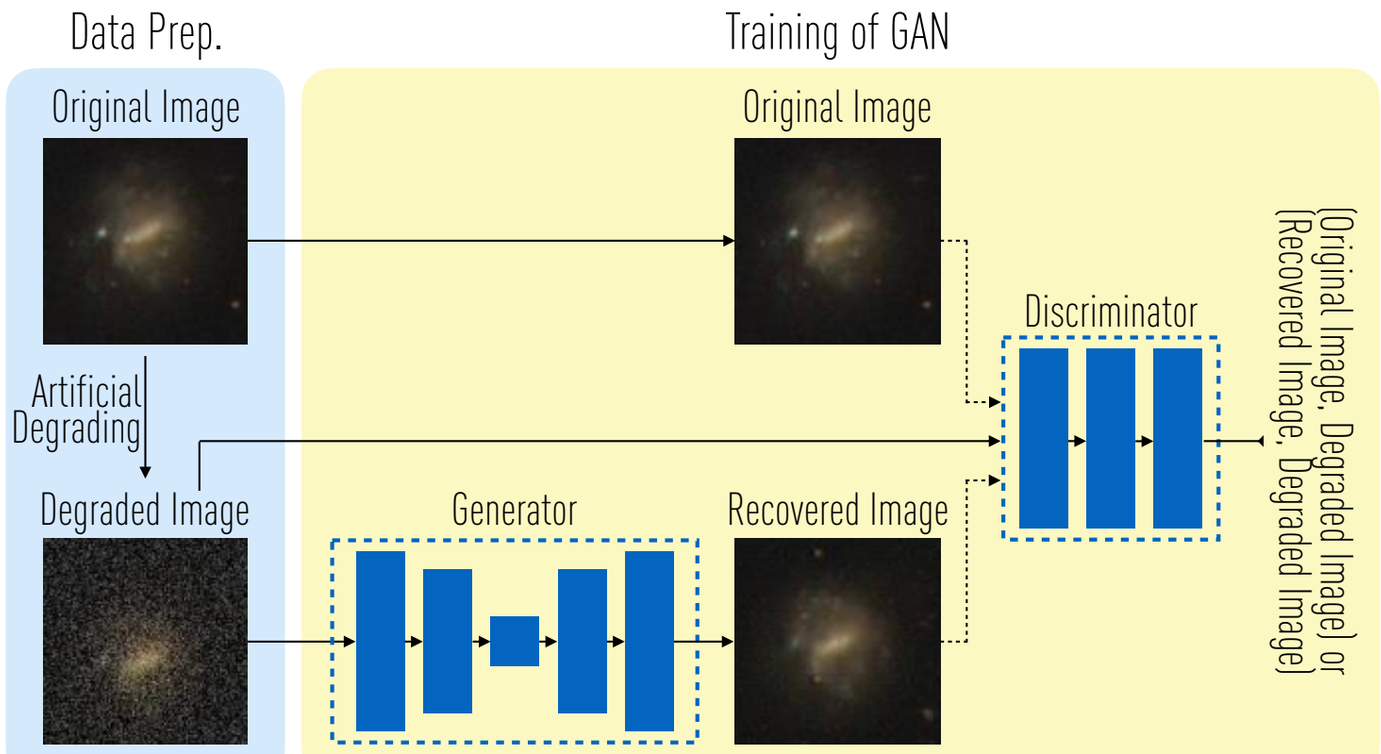


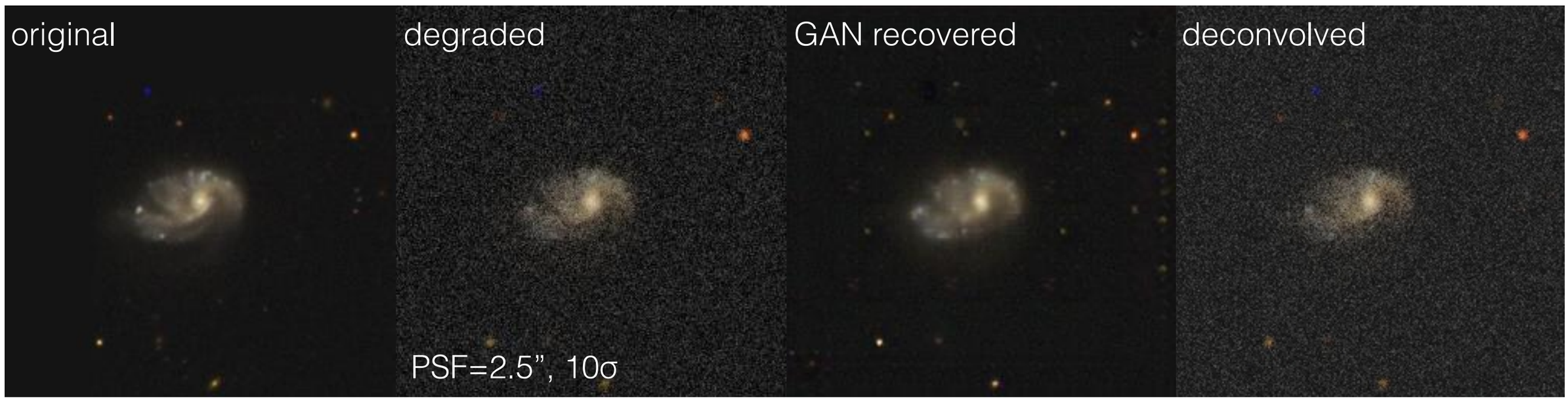
Real Granule



courtesy of Y. Kawabata

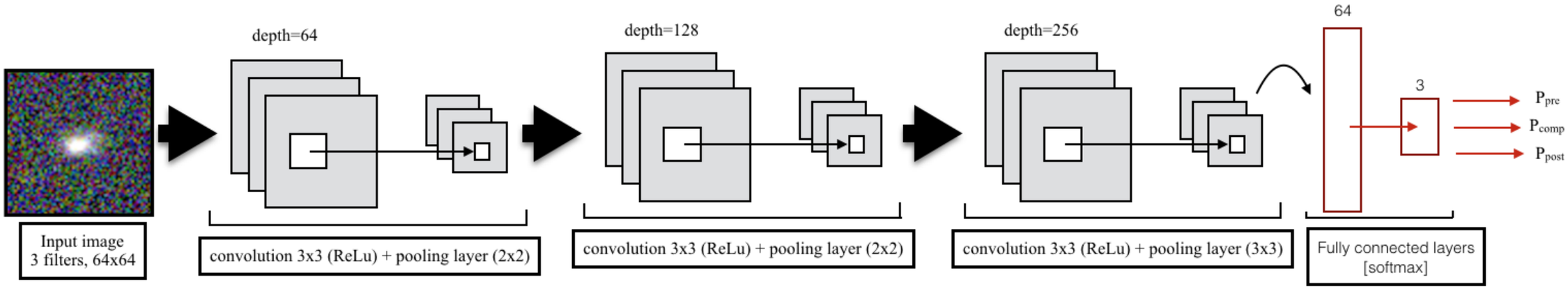
DECONVOLUTION OF GALACTIC IMAGES: GAN

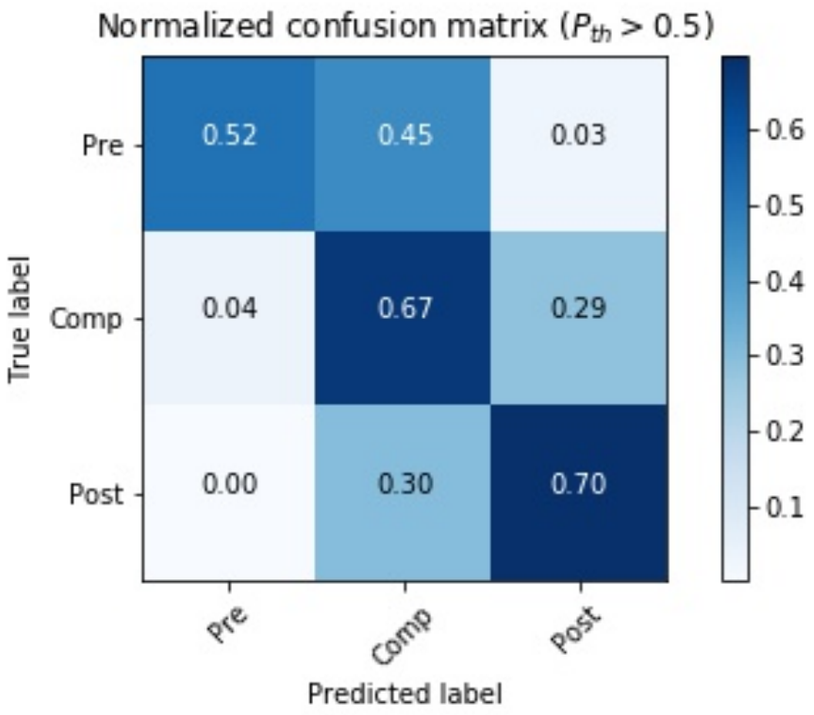




Schawinski et al (2017)

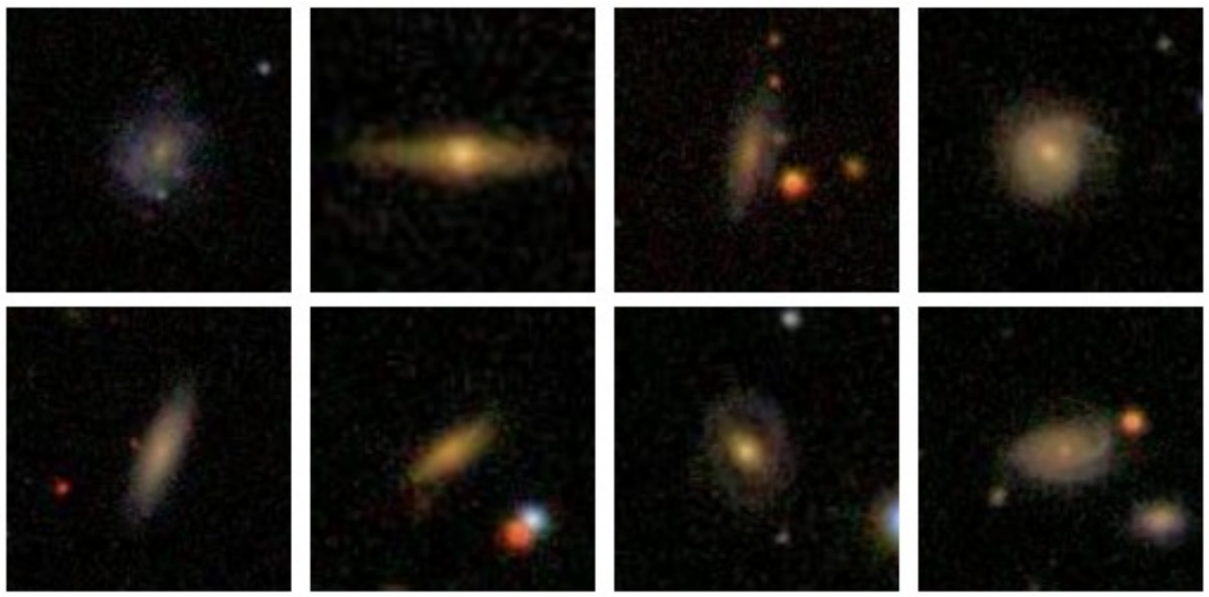
CLASSIFYING GALAXIES AT HIGH REDSHIFT

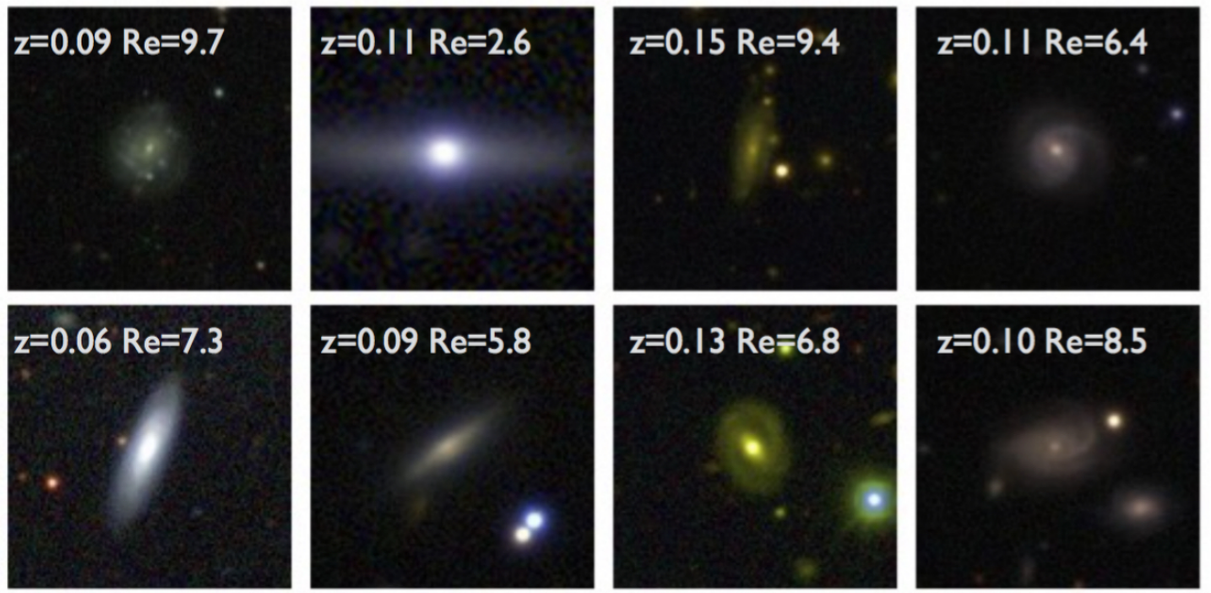


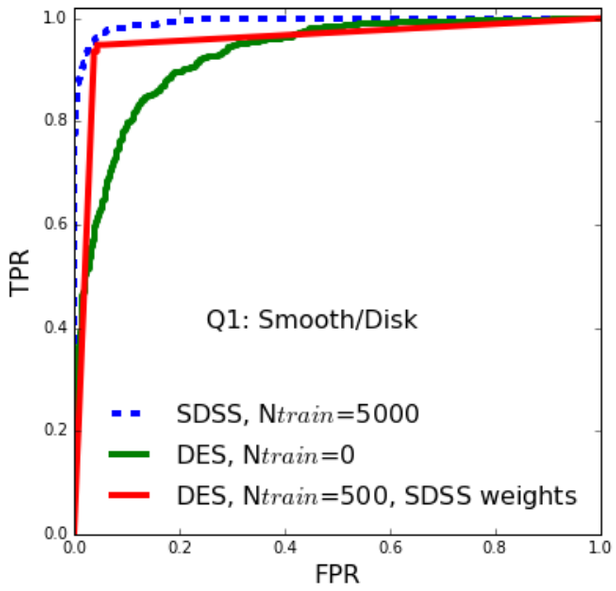


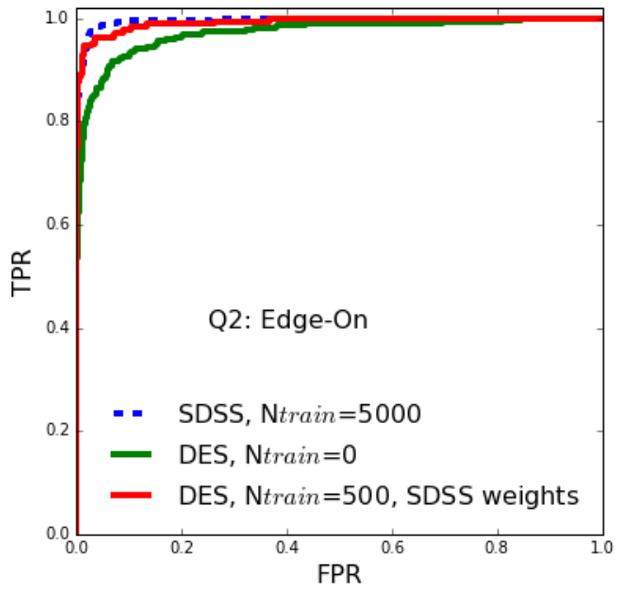
Huertas-Company et al (2018)

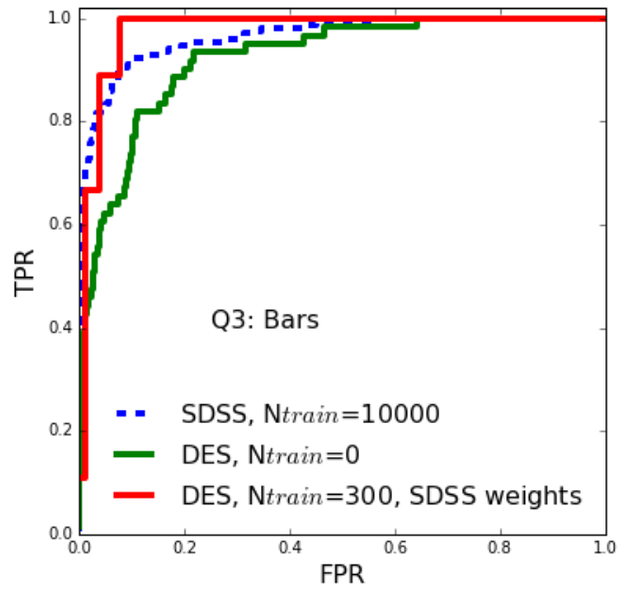
TRANSFER LEARNING FOR FUTURE SURVEYS











Domínguez-Sánchez et al (2018)

DETECTION OF GRAVITATIONAL WAVES

Deep Learning for Real-time Gravitational Wave Detection and Parameter Estimation: Results with Advanced LIGO Data

Daniel George[1,2] and E. A. Huerta[2]

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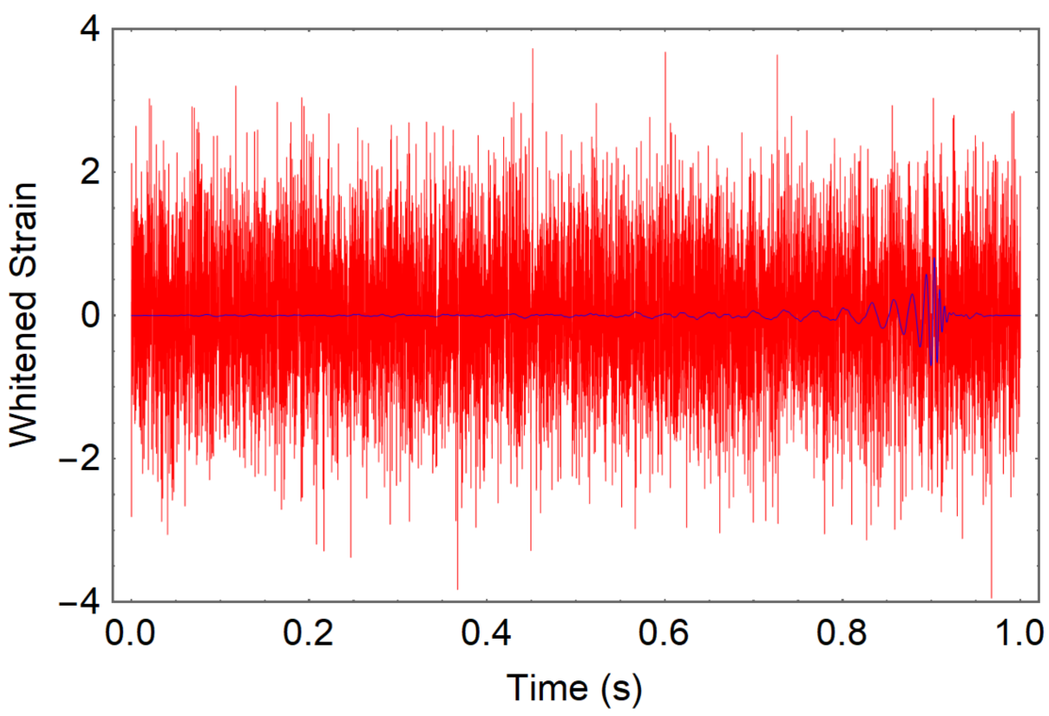
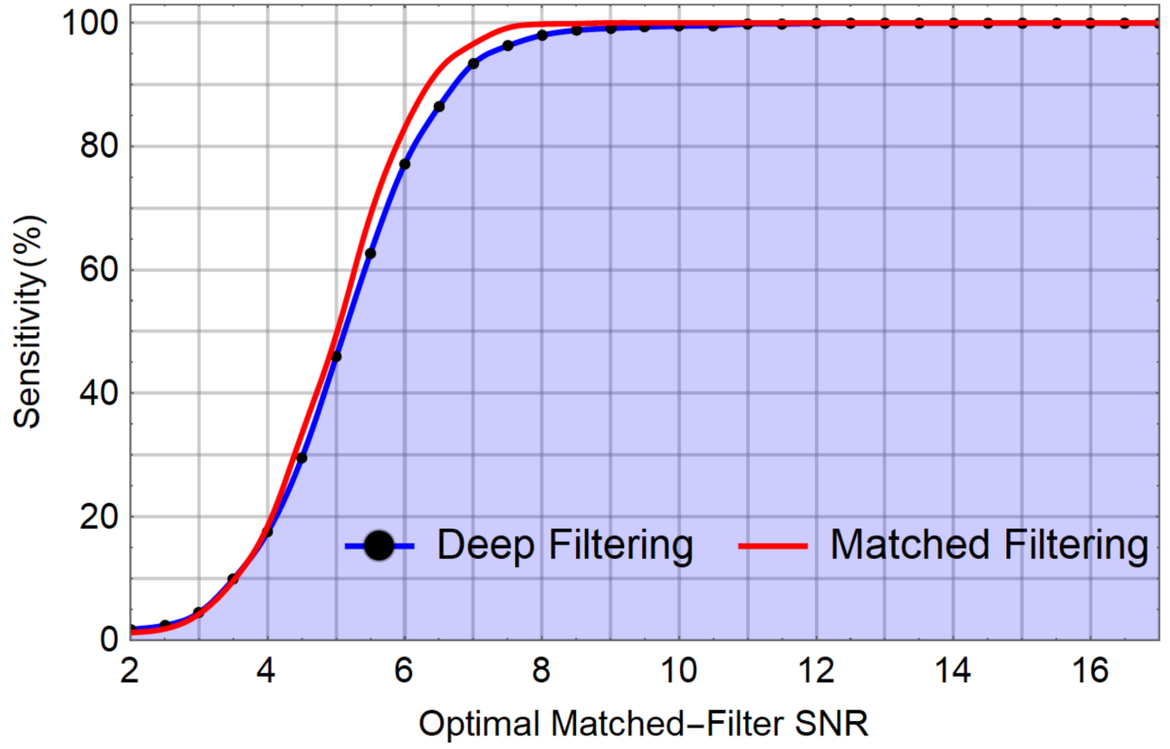
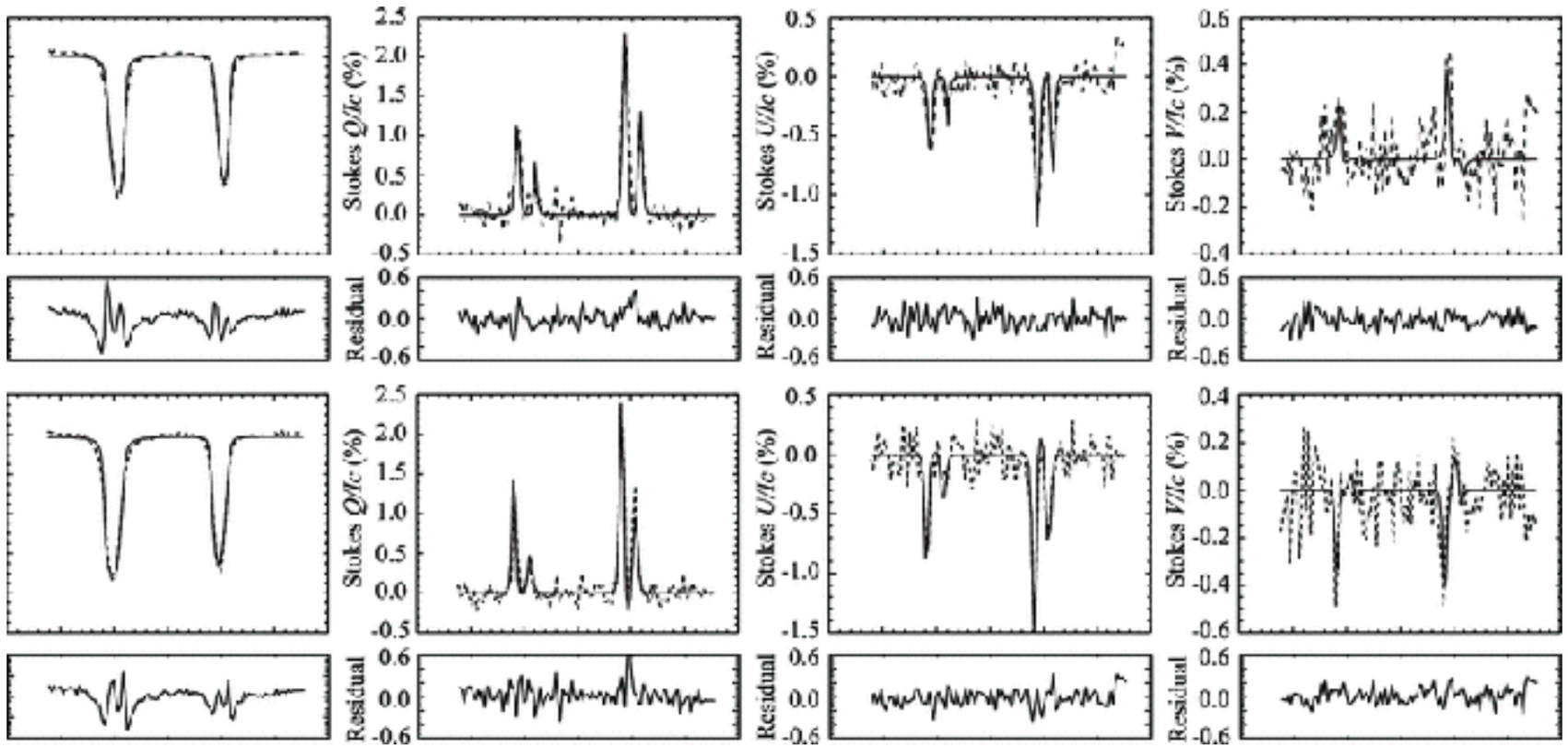


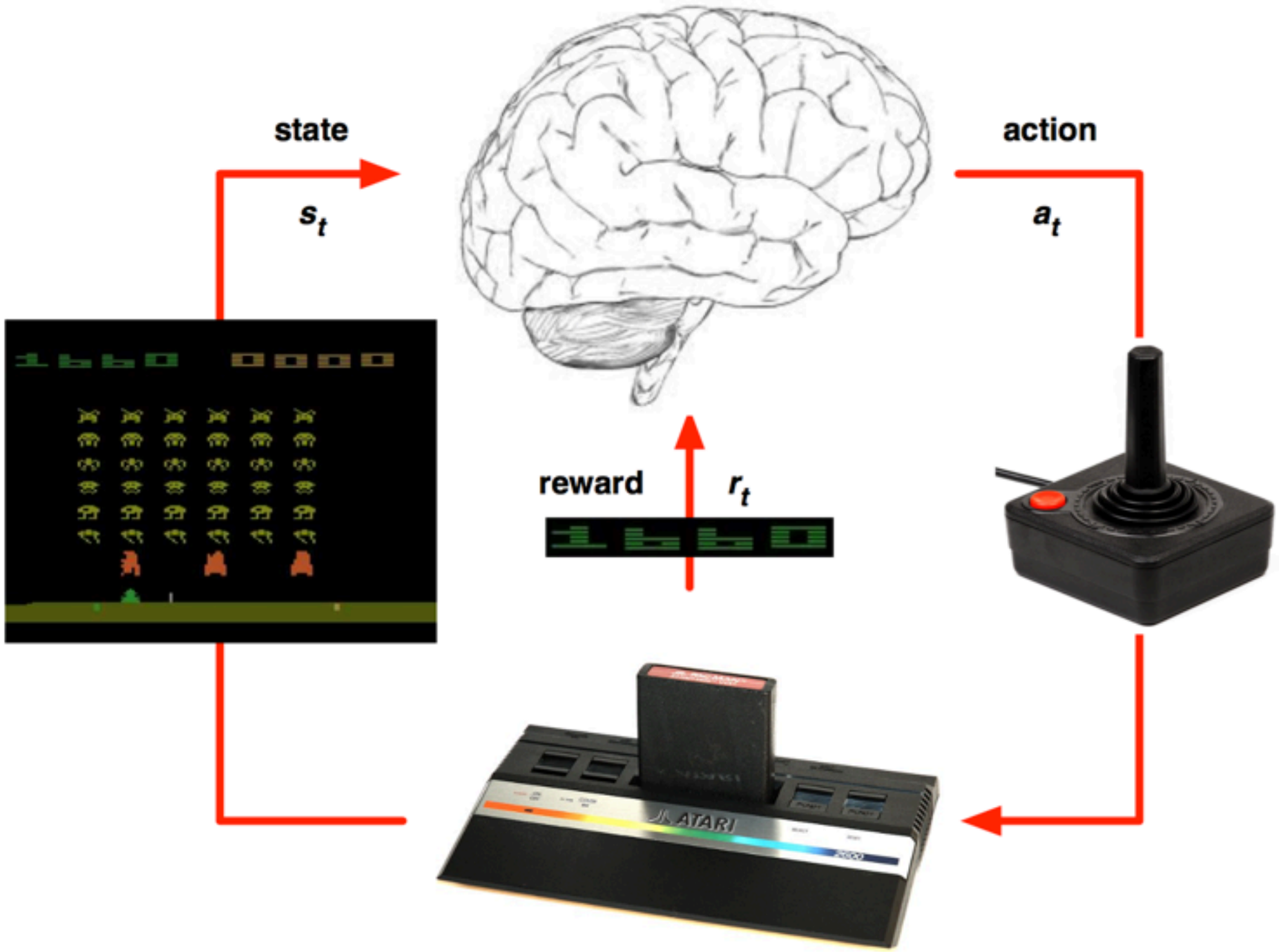


INVERSIONS WITHOUT RESPONSE FUNCTIONS



Reinforcement learning

REINFORCEMENT LEARNING



PACKAGES FOR DEEP LEARNING