

MACHINE LEARNING IN SOLAR PHYSICS

a. asensio ramos

@aasensior

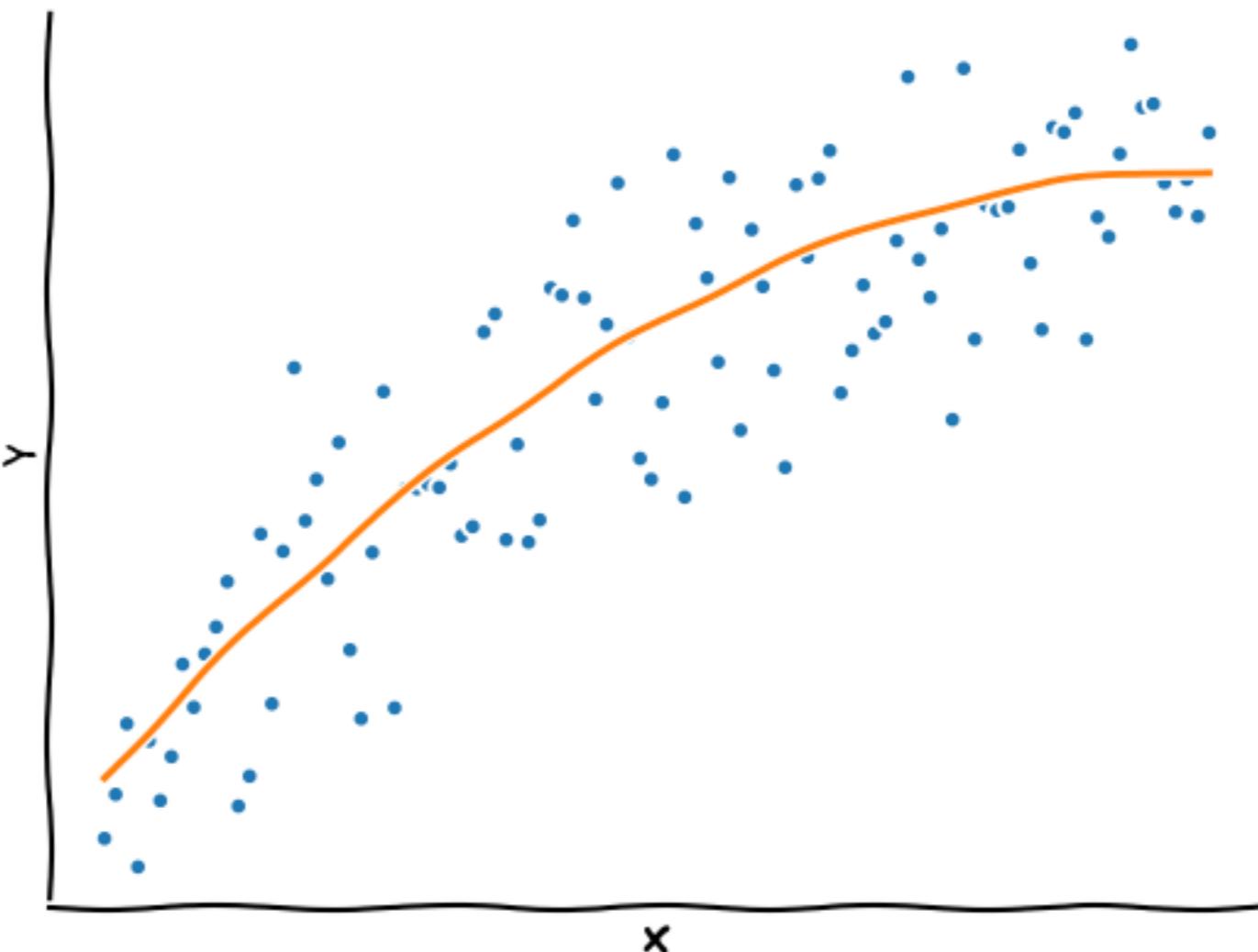
github.com/aasensio



what is machine learning?

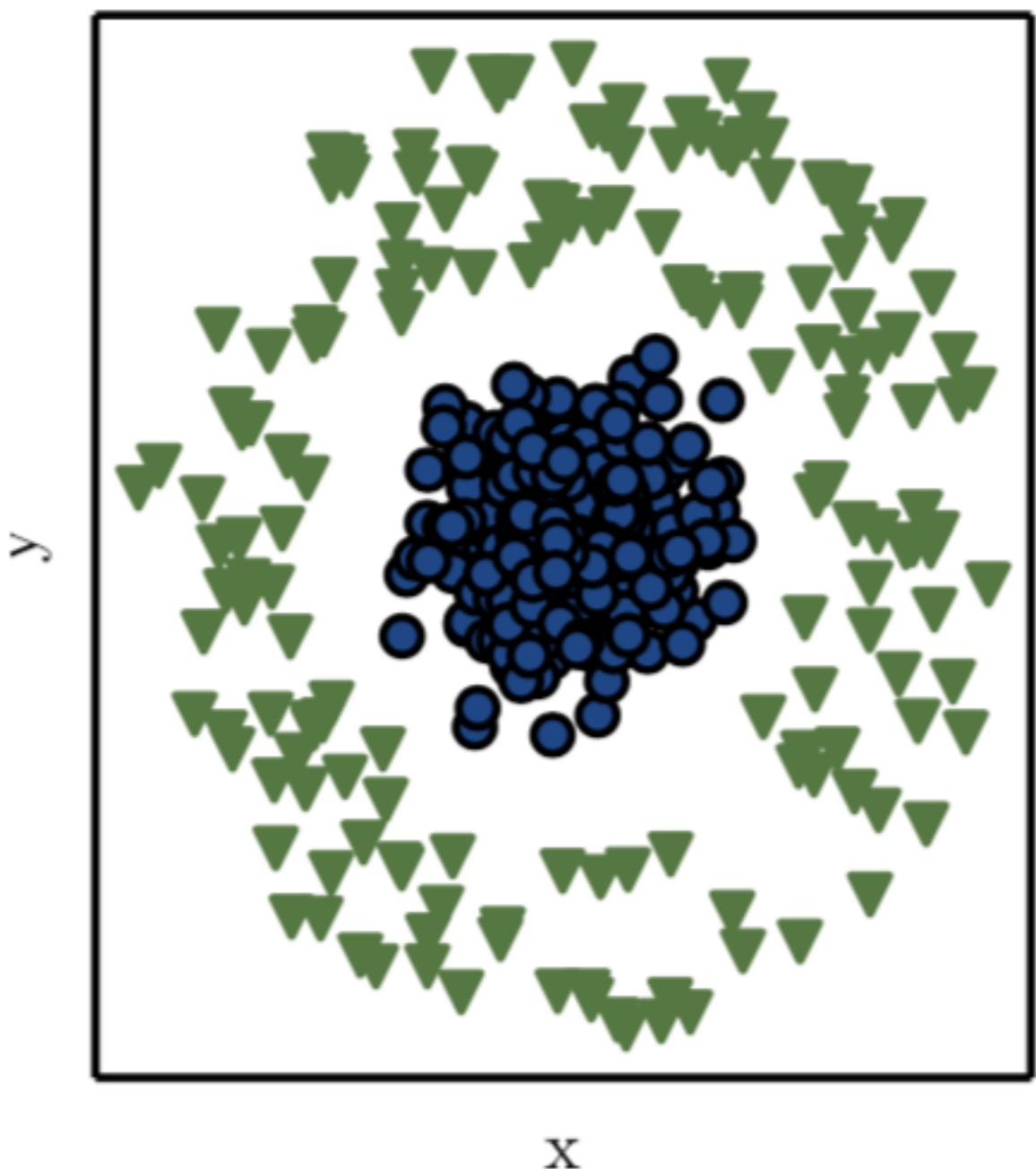
Using statistical techniques to give computers the ability to progressively improve performance on a specific task with data, without being explicitly programmed.

REGRESSION

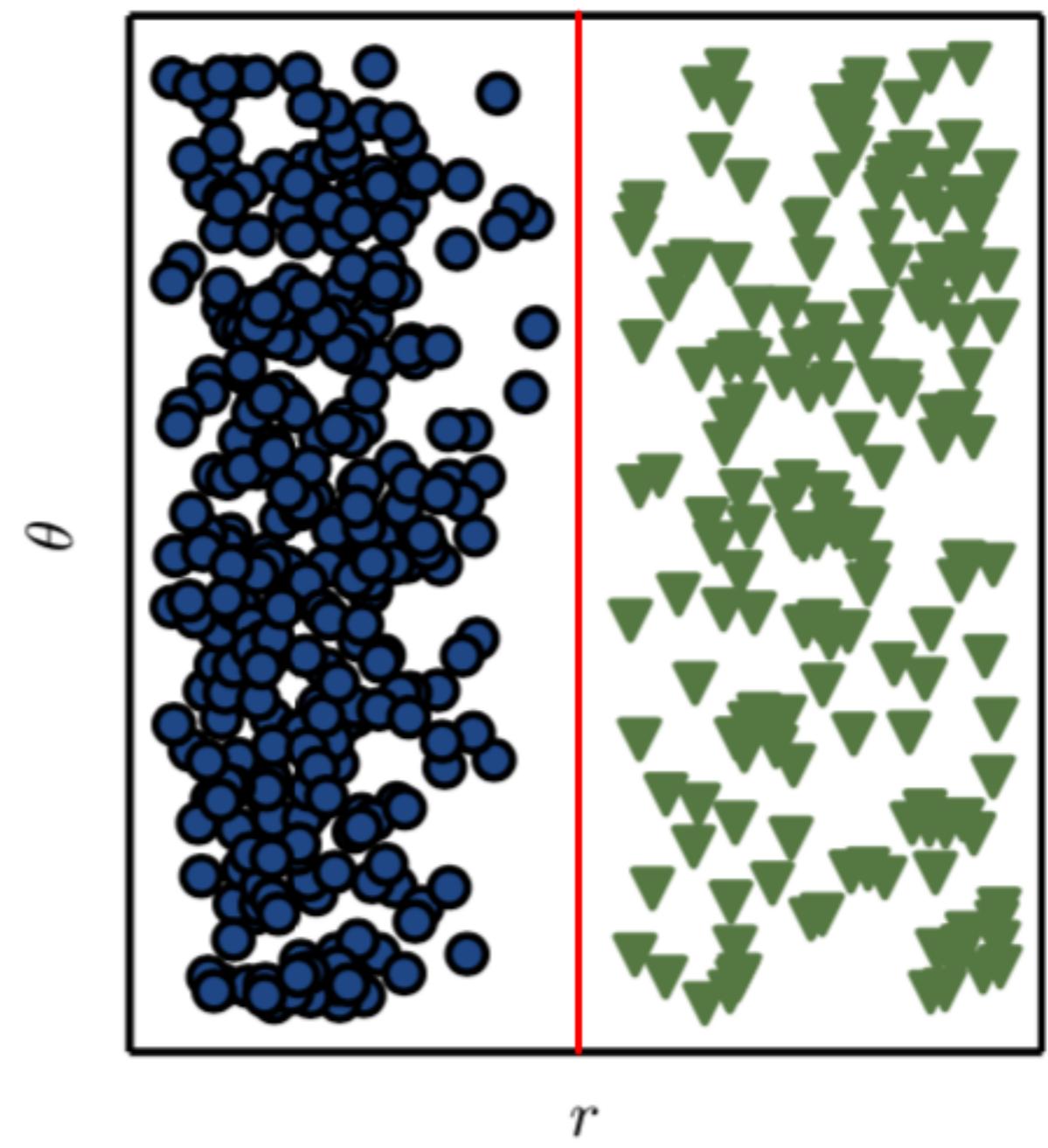


CLASSIFICATION

Cartesian coordinates

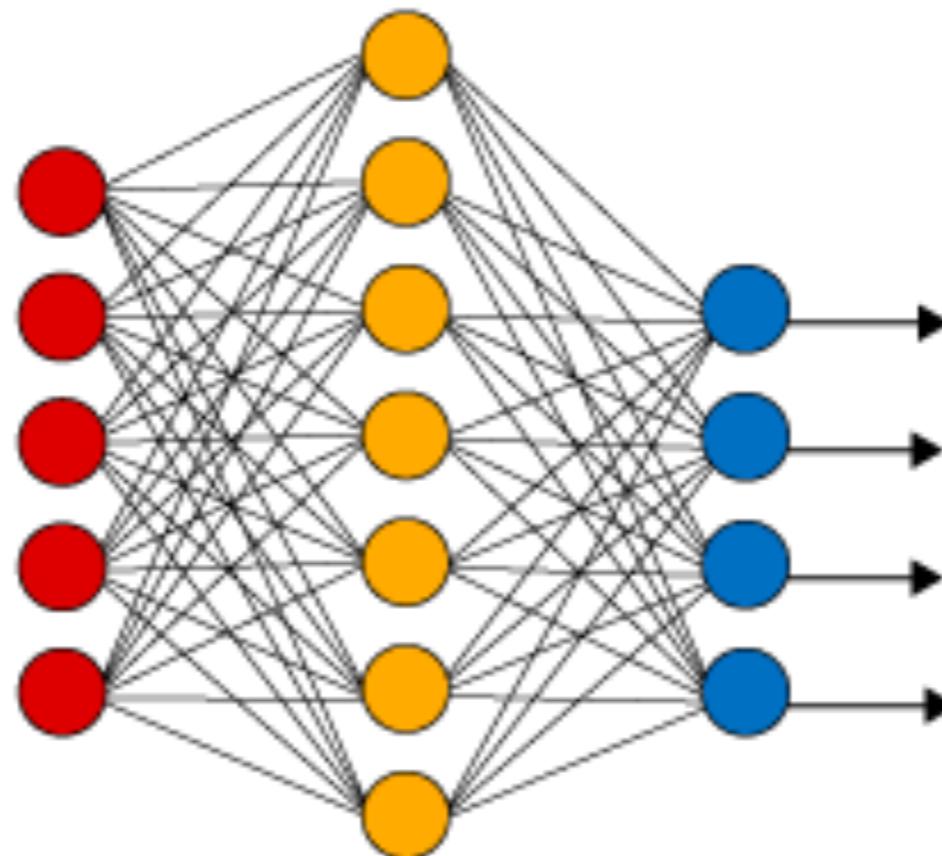


Polar coordinates



NEURAL NETWORKS

Simple Neural Network

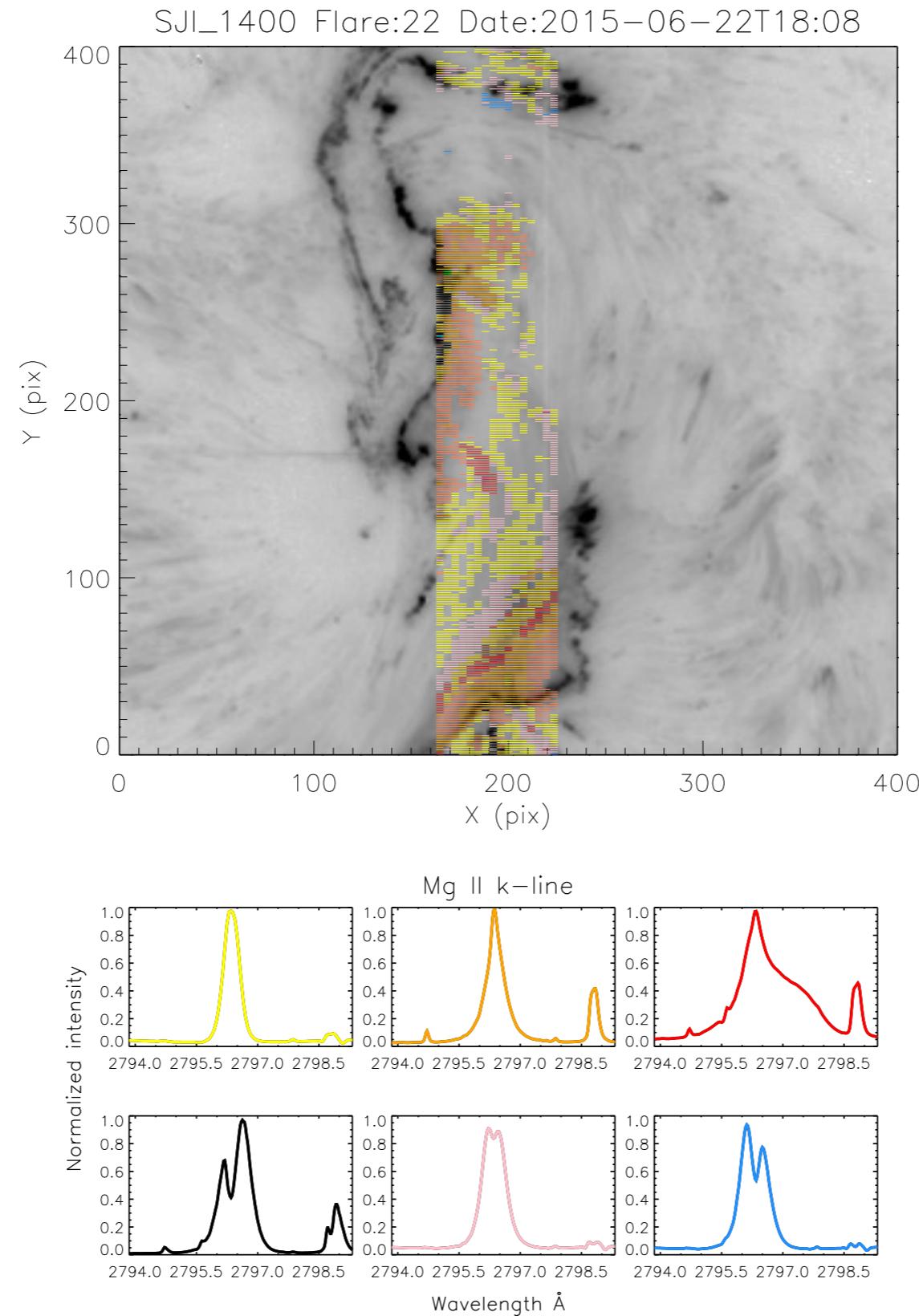


classical machine learning

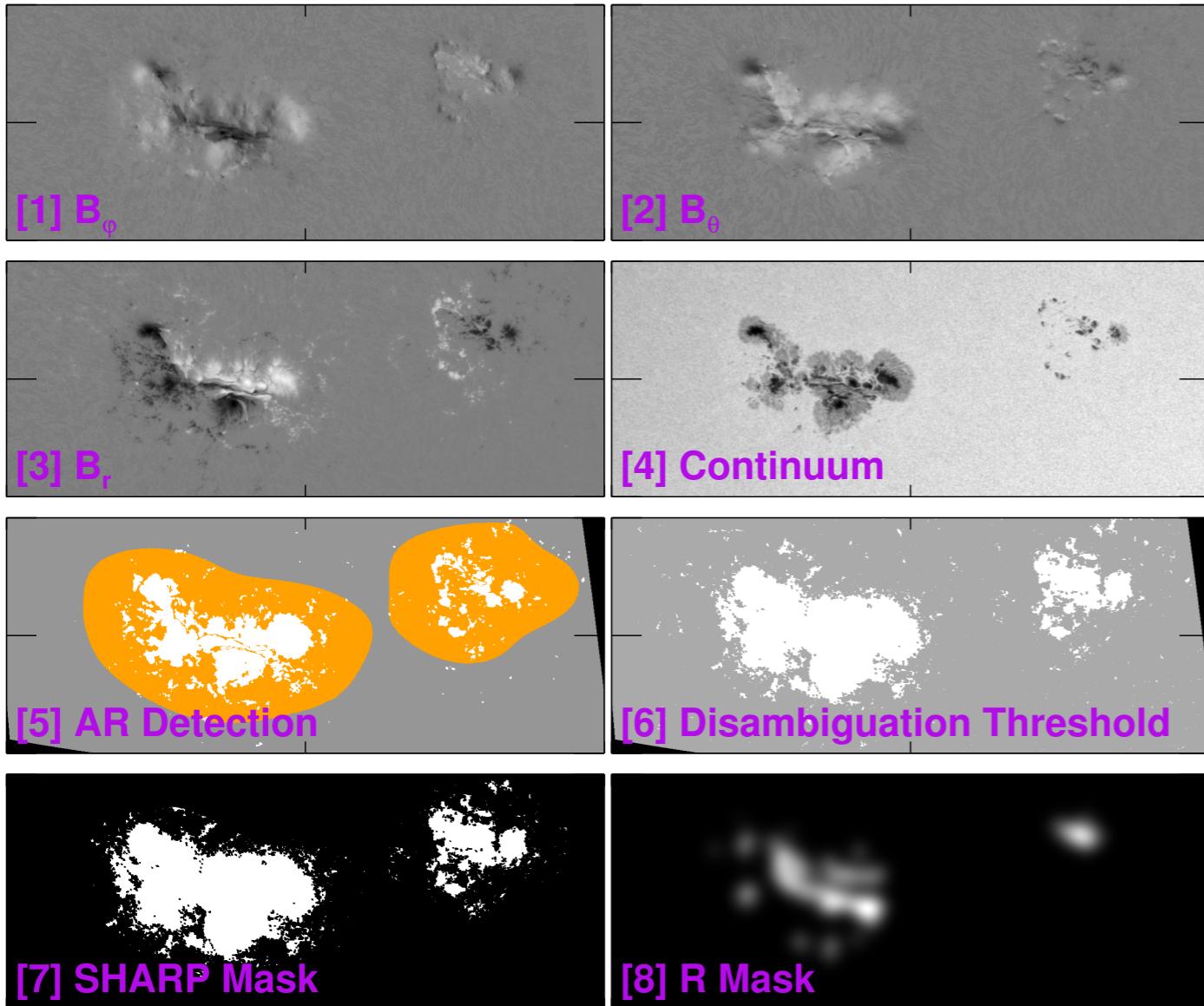
CLASSICAL MACHINE LEARNING

- ▶ Principal component analysis (PCA)
- ▶ k-nearest neighbors (k-NN)
- ▶ Support vector machines (SVM)
- ▶ Artificial neural networks (ANN)
- ▶ Random forests (RF)
- ▶ Gaussian Process (GP)
- ▶ ...

K-NN CLASSIFICATION OF FLARE MG II K



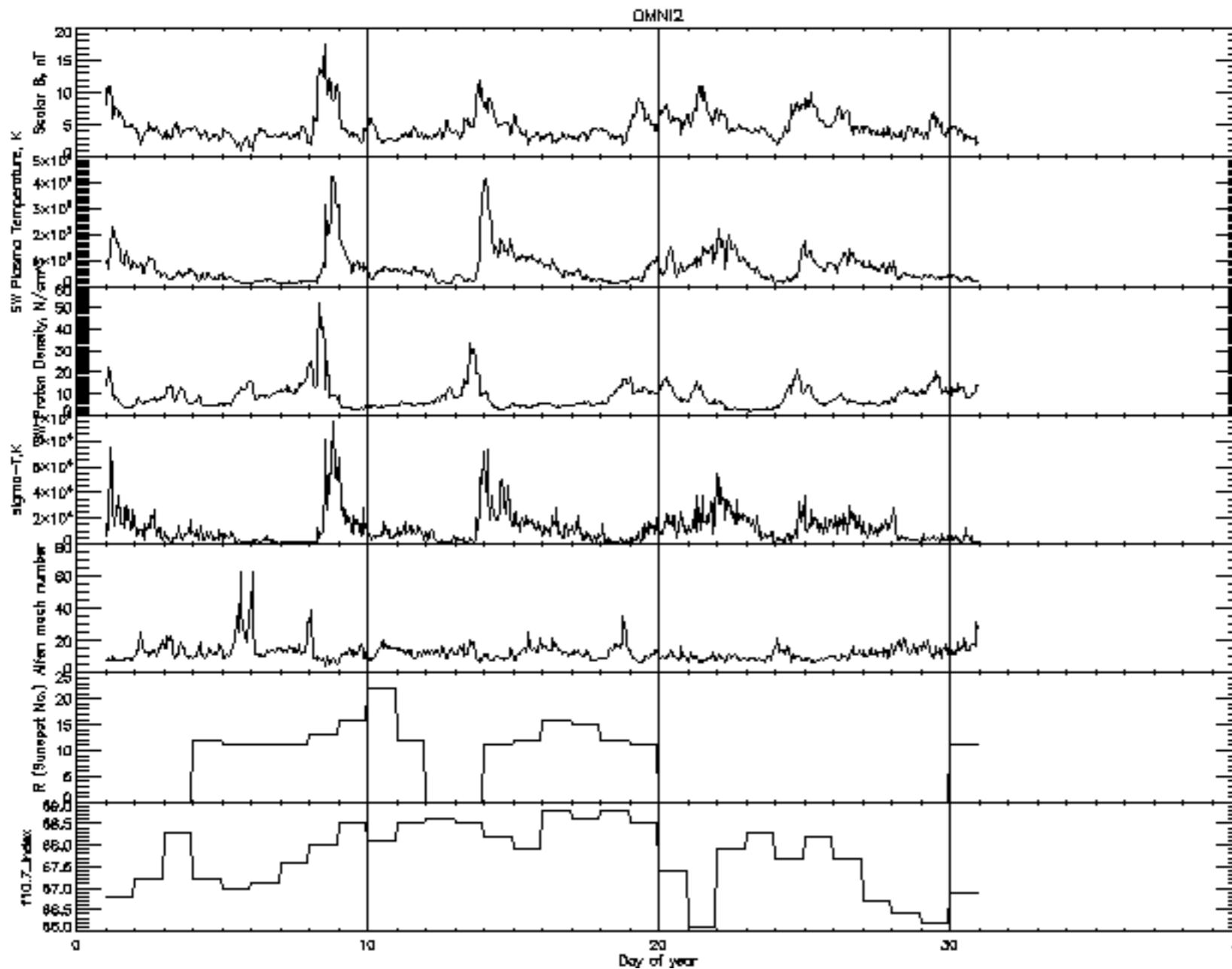
SOLAR FLARE PREDICTION



Keyword	Description	Formula
TOTUSJH	Total unsigned current helicity	$H_{c_{total}} \propto \sum B_z \cdot J_z $
TOTBSQ	Total magnitude of Lorenz force	$F \propto \sum B^2$
TOTUSJZ	Total unsigned vertical current	$J_{z_{total}} = \sum J_z dA$
ABSNJZH	Absolute value of the net current per polarity	$H_{c_{abs}} \propto \sum B_z \cdot J_z $
SAVNCP	Sum of the modules of the net current per polarity	$J_{z_{sum}} \propto \sum J_z dA + \sum B_z^- dA $
USFLUX	Total unsigned flux	$\Phi = \sum B_z dA$
AREA-ACR	Area of strong field pixels in the active region	$Area = \sum Pixels$
TOTFZ	Sum of z-component of Lorenz force	$F_z \propto \sum (B_x^2 + B_y^2 - B_z^2)dA$
EPSZ	Sum of z-component of normalized Lorenz force	$\delta F_z \propto \frac{\sum (B_x^2 + B_y^2 - B_z^2)}{\sum B^2}$
MEANGAM	Mean angle of field from radial	$\bar{\gamma} = \frac{1}{N} \sum \arctan\left(\frac{B_h}{B_z}\right)$
MEANGBT	Mean gradient of total field	$ \nabla B_{tot} = \frac{1}{N} \sum \sqrt{\left(\frac{\partial B}{\partial x}\right)^2 + \left(\frac{\partial B}{\partial y}\right)^2}$
MEANGBZ	Mean gradient of vertical field	$ \nabla B_z = \frac{1}{N} \sum \sqrt{\left(\frac{\partial B_z}{\partial x}\right)^2 + \left(\frac{\partial B_z}{\partial y}\right)^2}$
MEANGBH	Mean gradient of horizontal field	$ \nabla B_h = \frac{1}{N} \sum \sqrt{\left(\frac{\partial B_h}{\partial x}\right)^2 + \left(\frac{\partial B_h}{\partial y}\right)^2}$
MEANJZH	Mean current helicity (B_z contribution)	$H_c \propto \frac{1}{N} \sum B_z \cdot J_z$
TOTFY	Sum of y-component of Lorenz force	$F_y \propto \sum B_y B_z dA$
MEANJZD	Mean vertical current density	$\bar{J}_z \propto \frac{1}{N} \sum \left(\frac{\partial B_y}{\partial x} - \frac{\partial B_x}{\partial y} \right)$
TOTFX	Sum of x-component of Lorenz force	$F_x \propto - \sum B_x B_z dA$
EPSY	Sum of y-component of normalized Lorenz force	$\delta F_y \propto \frac{-\sum B_y B_z}{\sum B^2}$
EPSX	Sum of x-component of normalized Lorenz force	$\delta F_x \propto \frac{\sum B_x B_z}{\sum B^2}$

Bobra & Couvidat (2014)

SOLAR WIND CLASSIFICATION



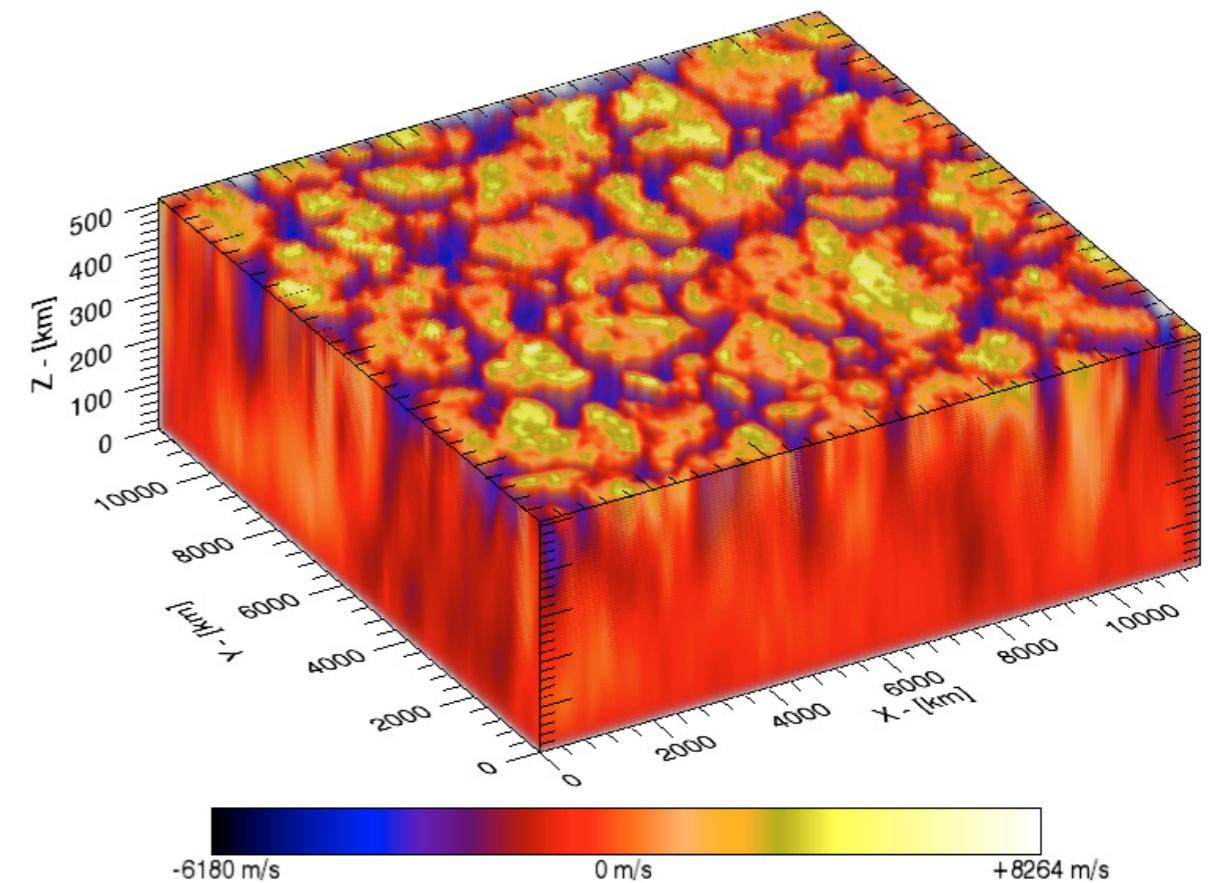
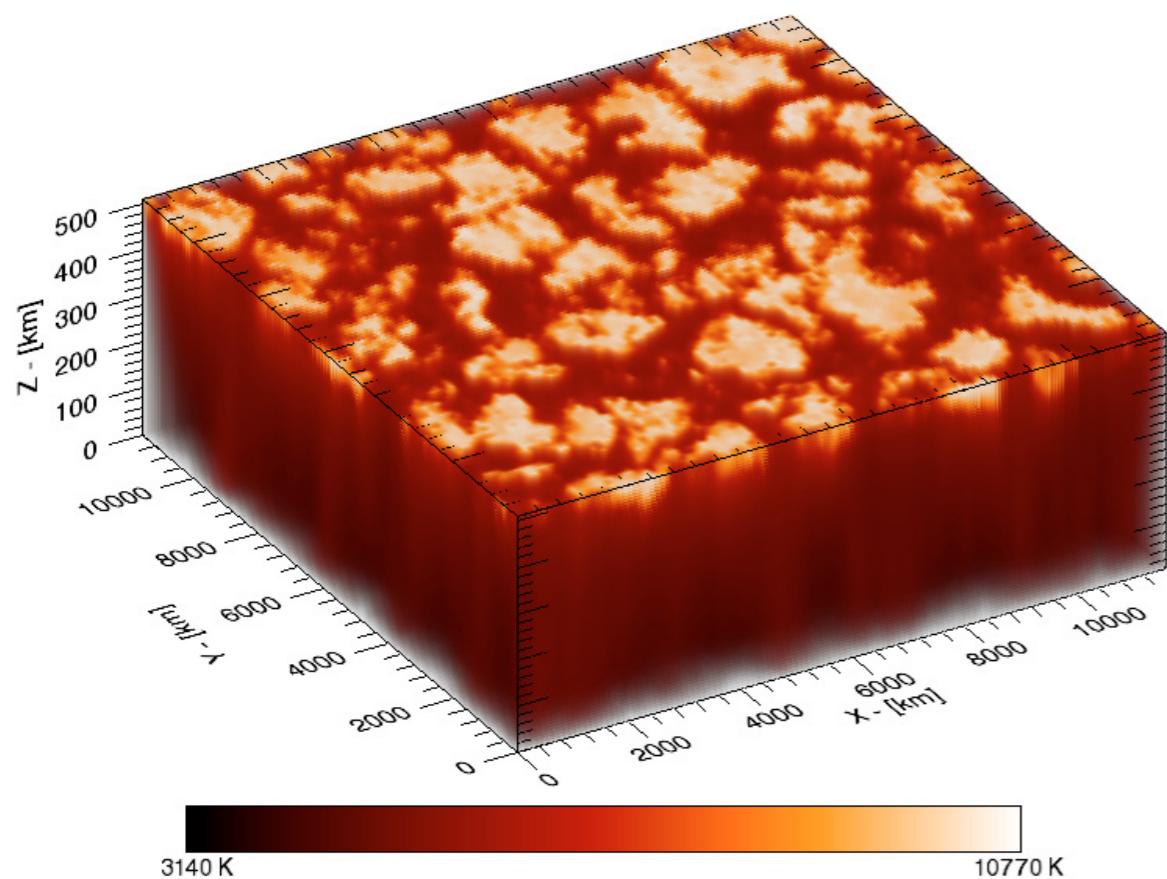
- ▶ ejecta
- ▶ coronal hole
- ▶ streamer belt
- ▶ sector reversal

SOLAR WIND CLASSIFICATION

$$\mathbf{y} \sim \text{GP}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

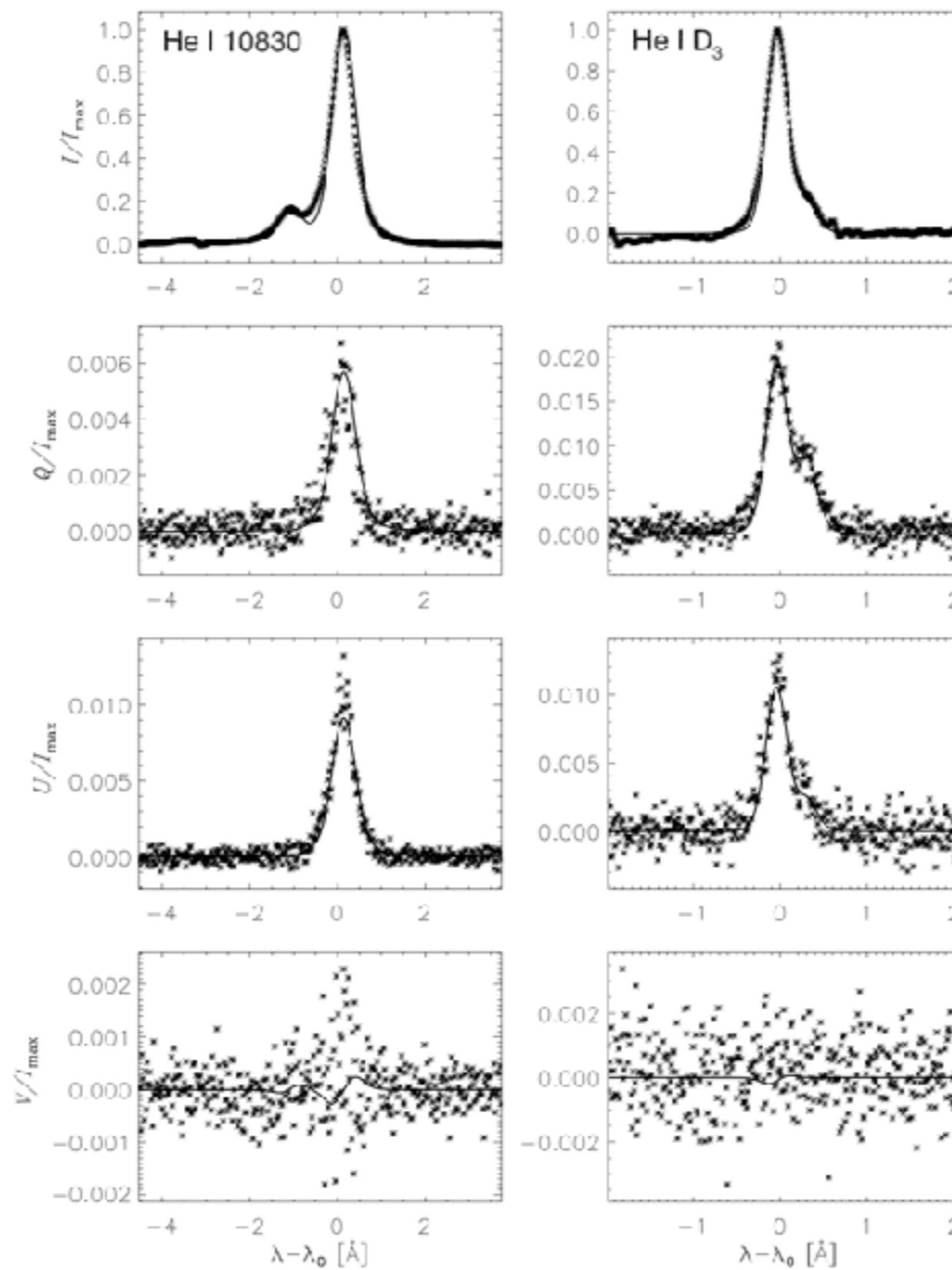
Prediction	Observed category			
	Ejecta	Coronal hole	Sector reversal	Streamer belt
Ejecta	94.8	0.2	1.6	1.4
Coronal hole origin	0.8	99.6	0.5	0.2
Sector reversal origin	1.8	0.1	96.6	0.8
Streamer belt origin	2.5	0.1	1.3	97.7

PHOTOSPHERIC SPECTROPOL INVERSIONS



Carroll & Kopf (2007)

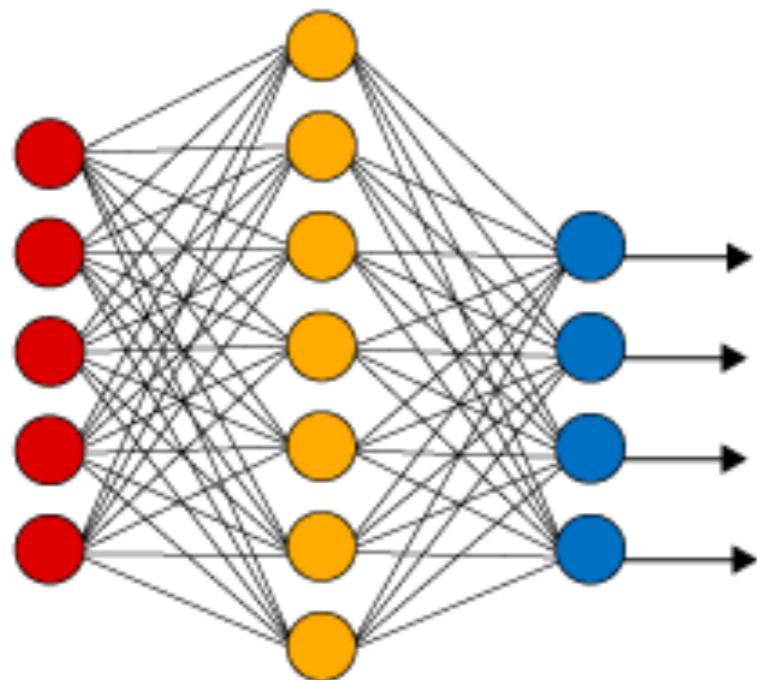
CHROMOSPHERIC SPECTROPOL INVERSIONS



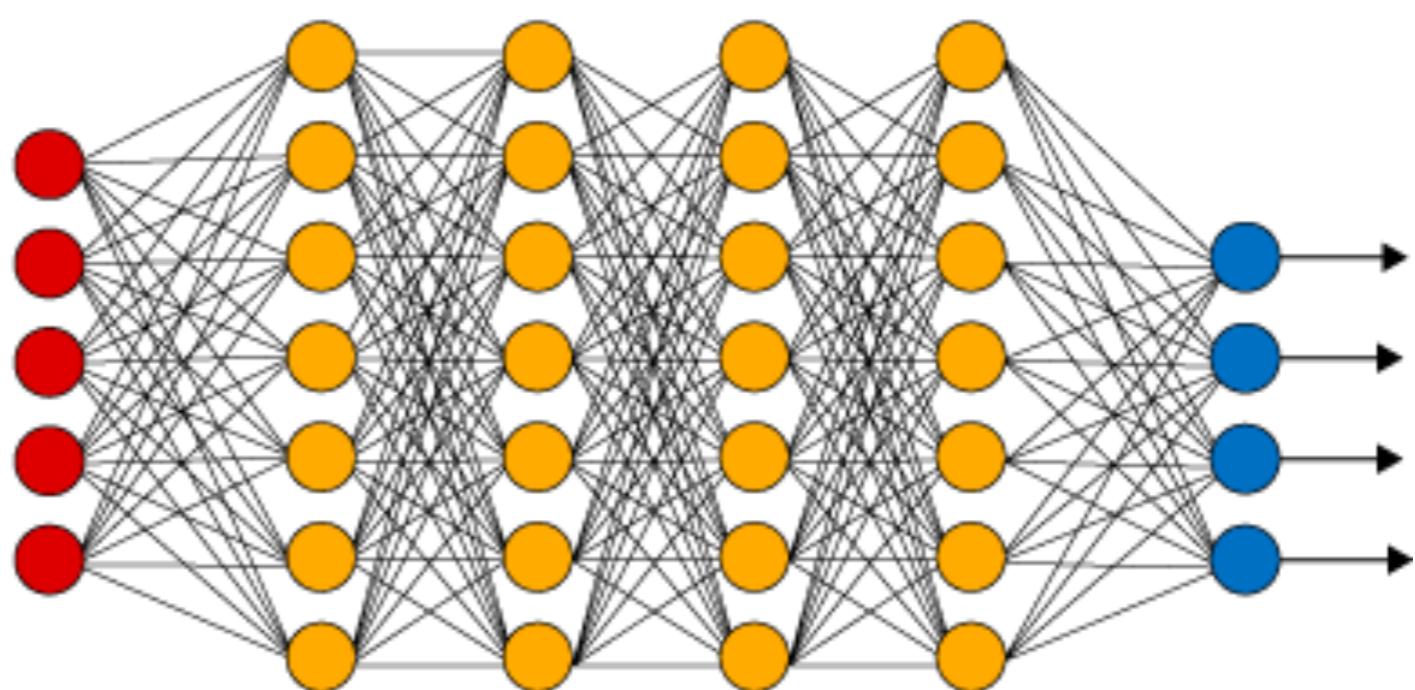
Casini et al. (2009)

deep learning

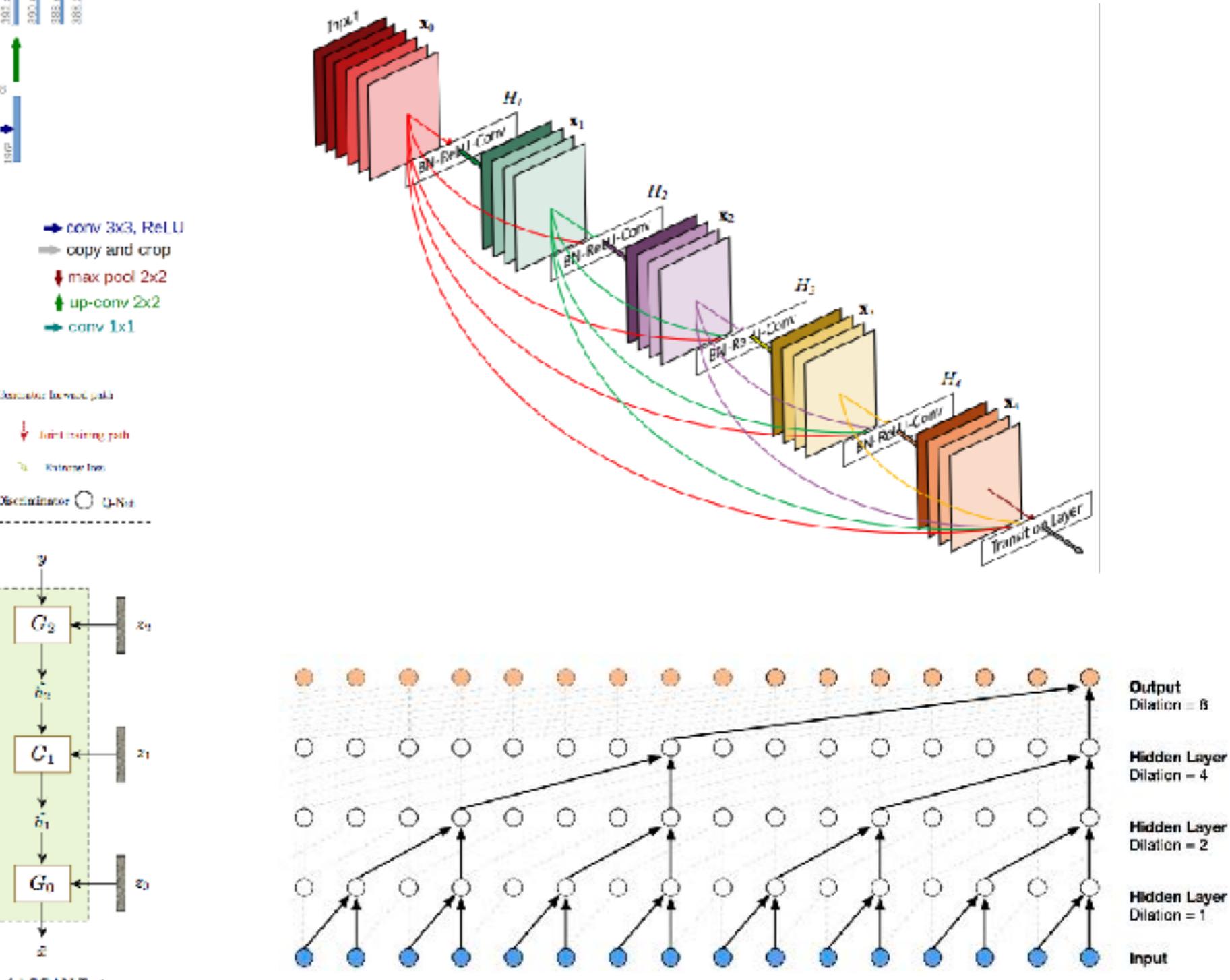
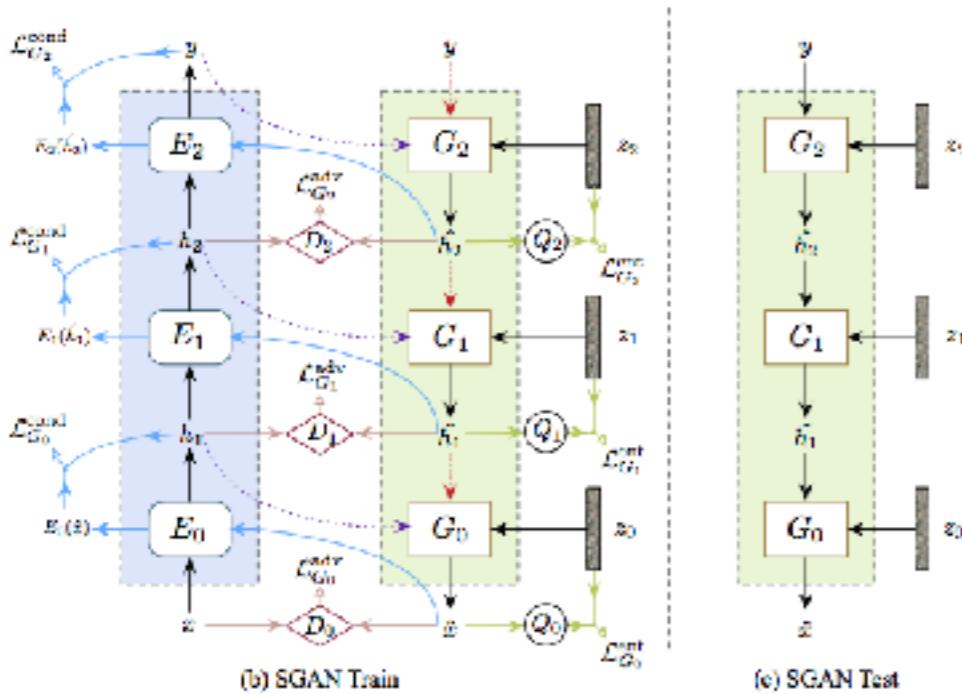
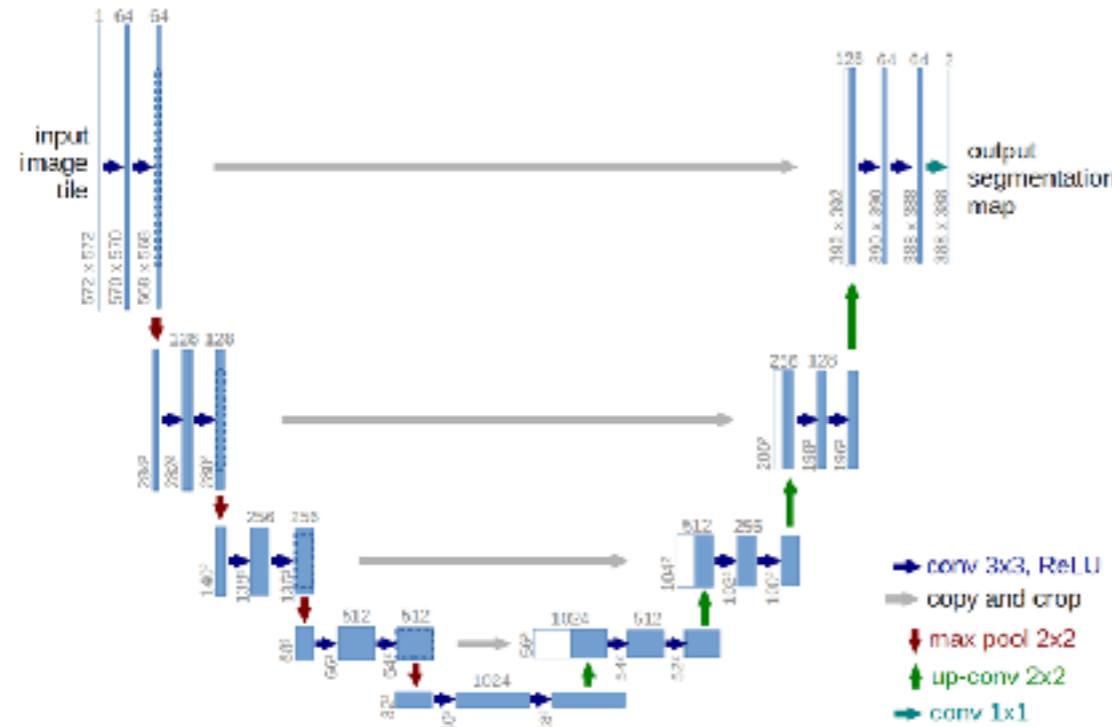
Simple Neural Network

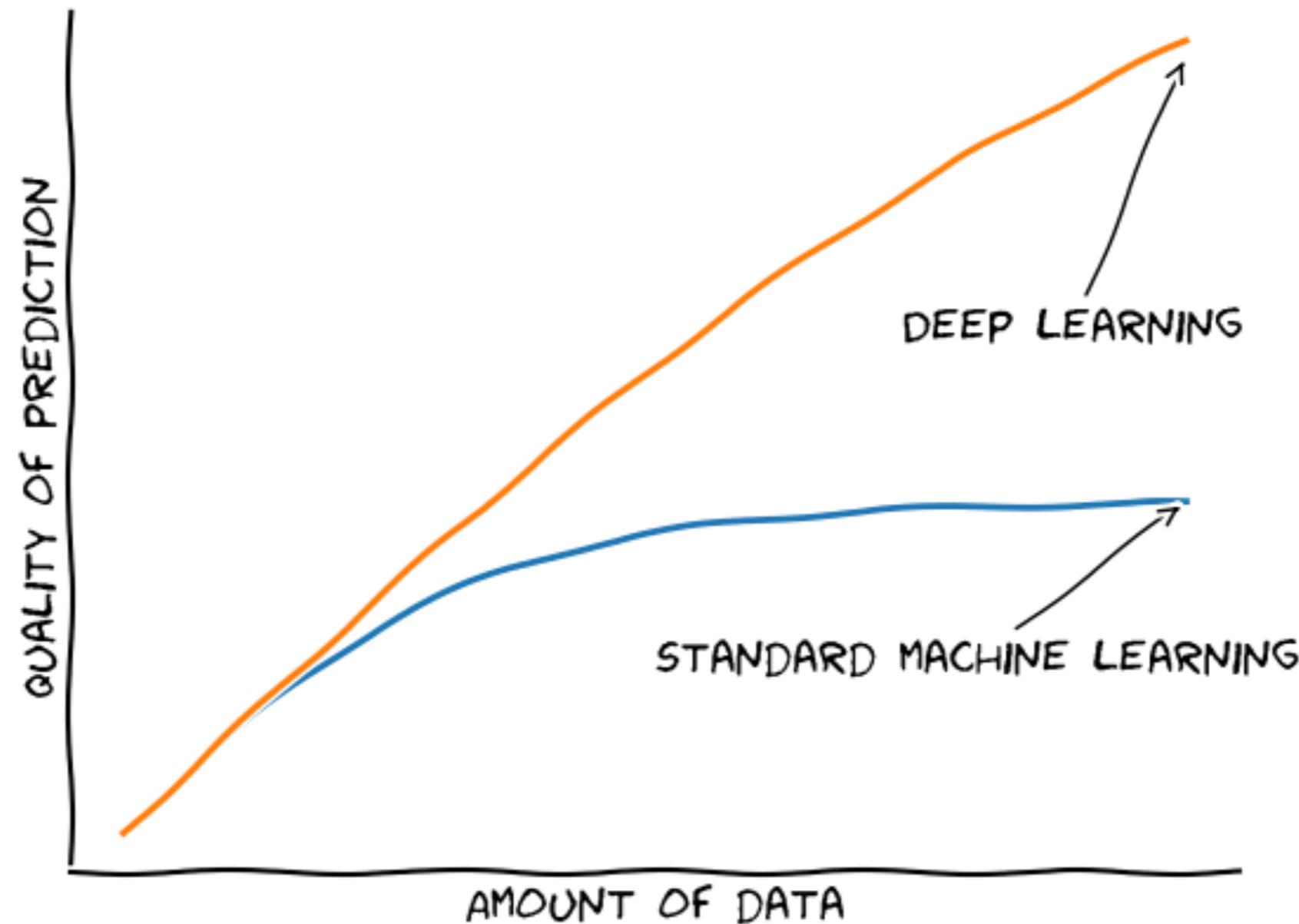


Deep Learning Neural Network

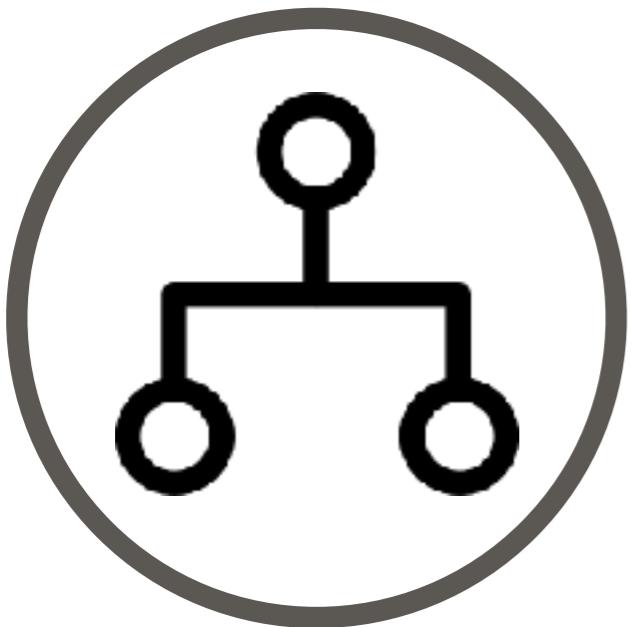


ENORMOUS LANDSCAPE

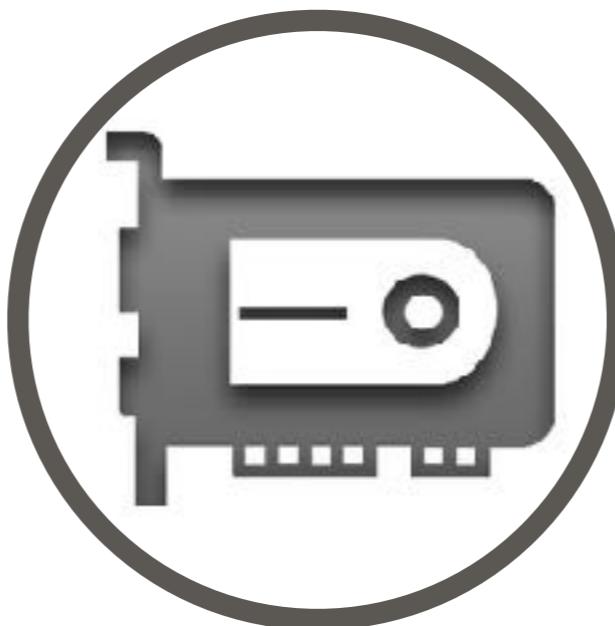




Algorithms



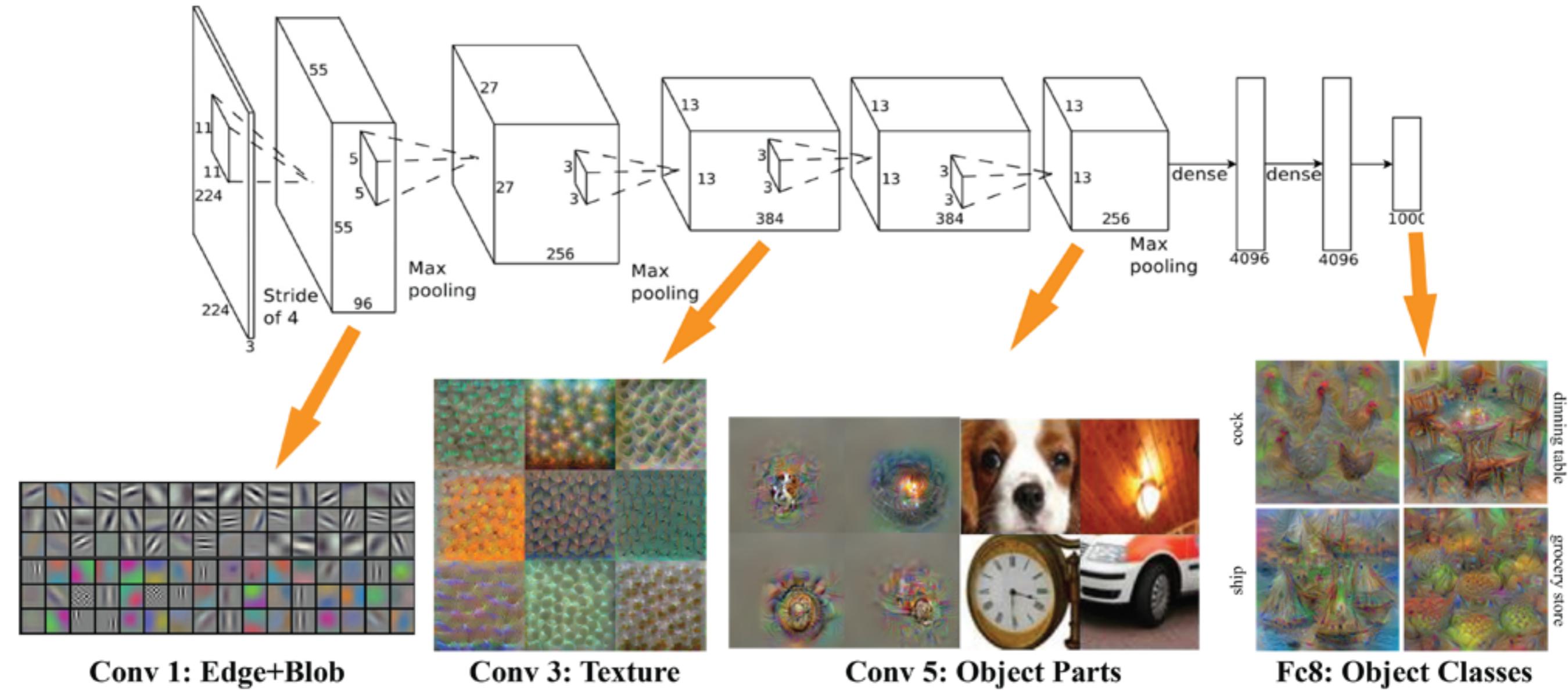
Hardware



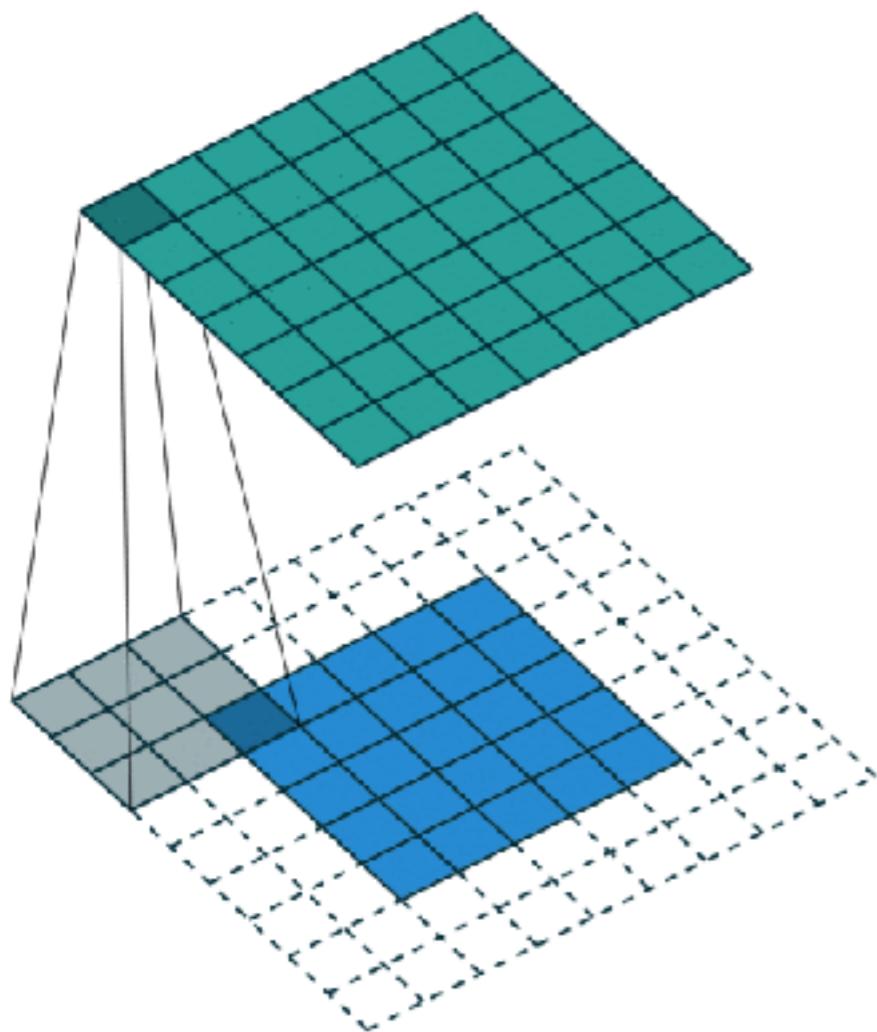
Data



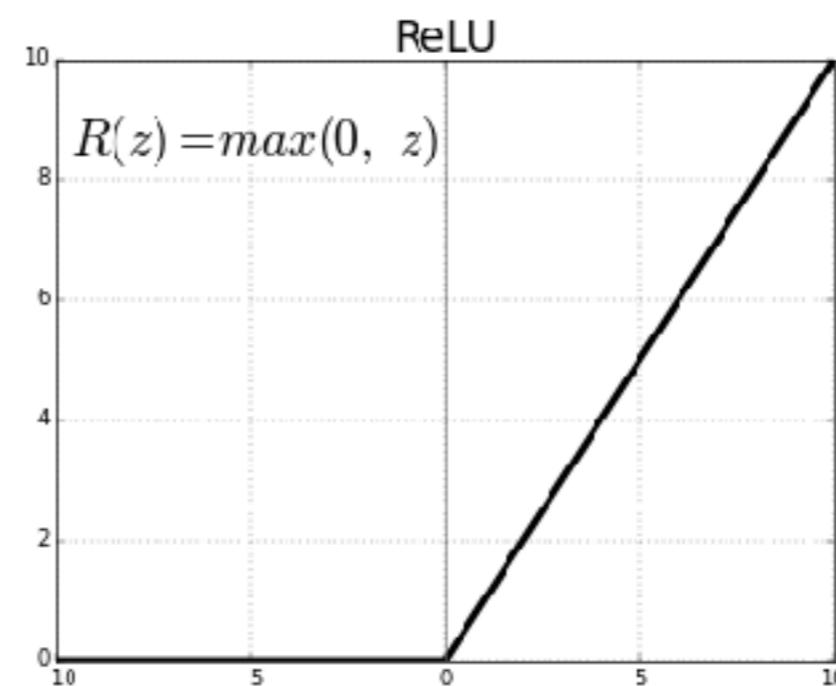
MULTISCALE ANALYSIS



BASIC INGREDIENTS



Convolution



Activation

$$f = \|\mathbf{O} - \mathbf{T}\|_2^2$$

Loss

TRAINING

Gradient descent

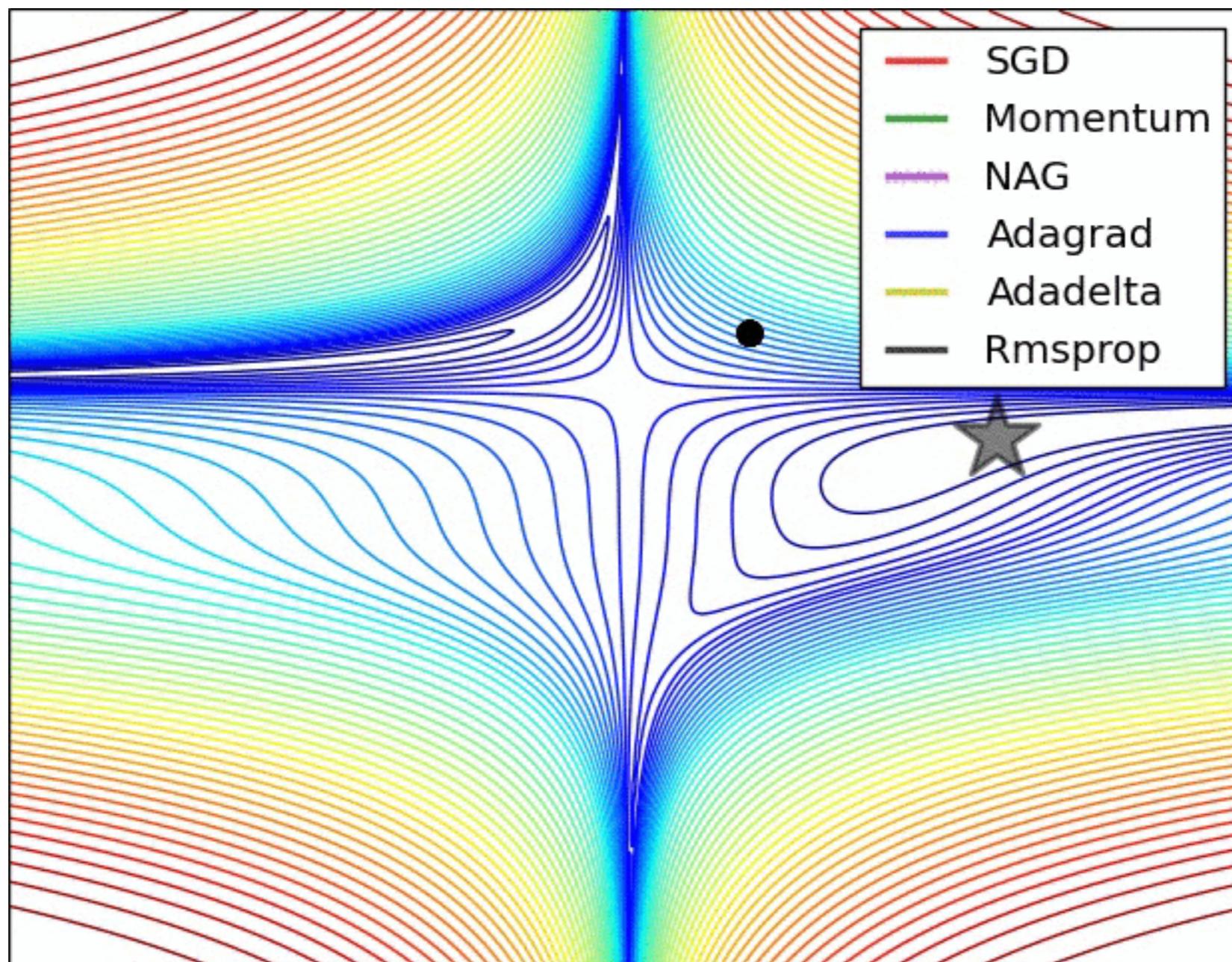
$$\theta_{i+1} = \theta_i - h \nabla_{\theta} f(\theta, \mathbf{T})$$

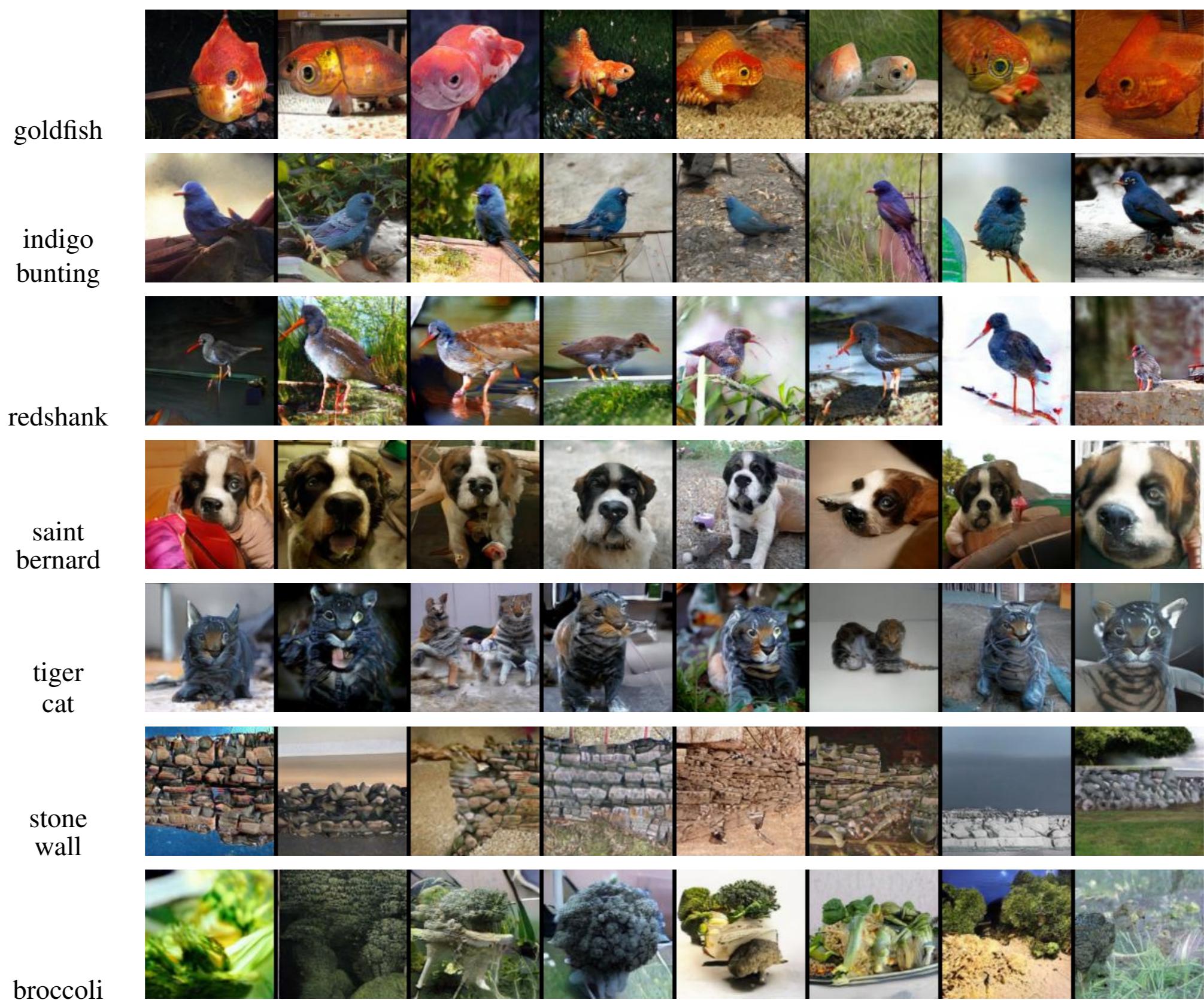
Stochastic gradient descent

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

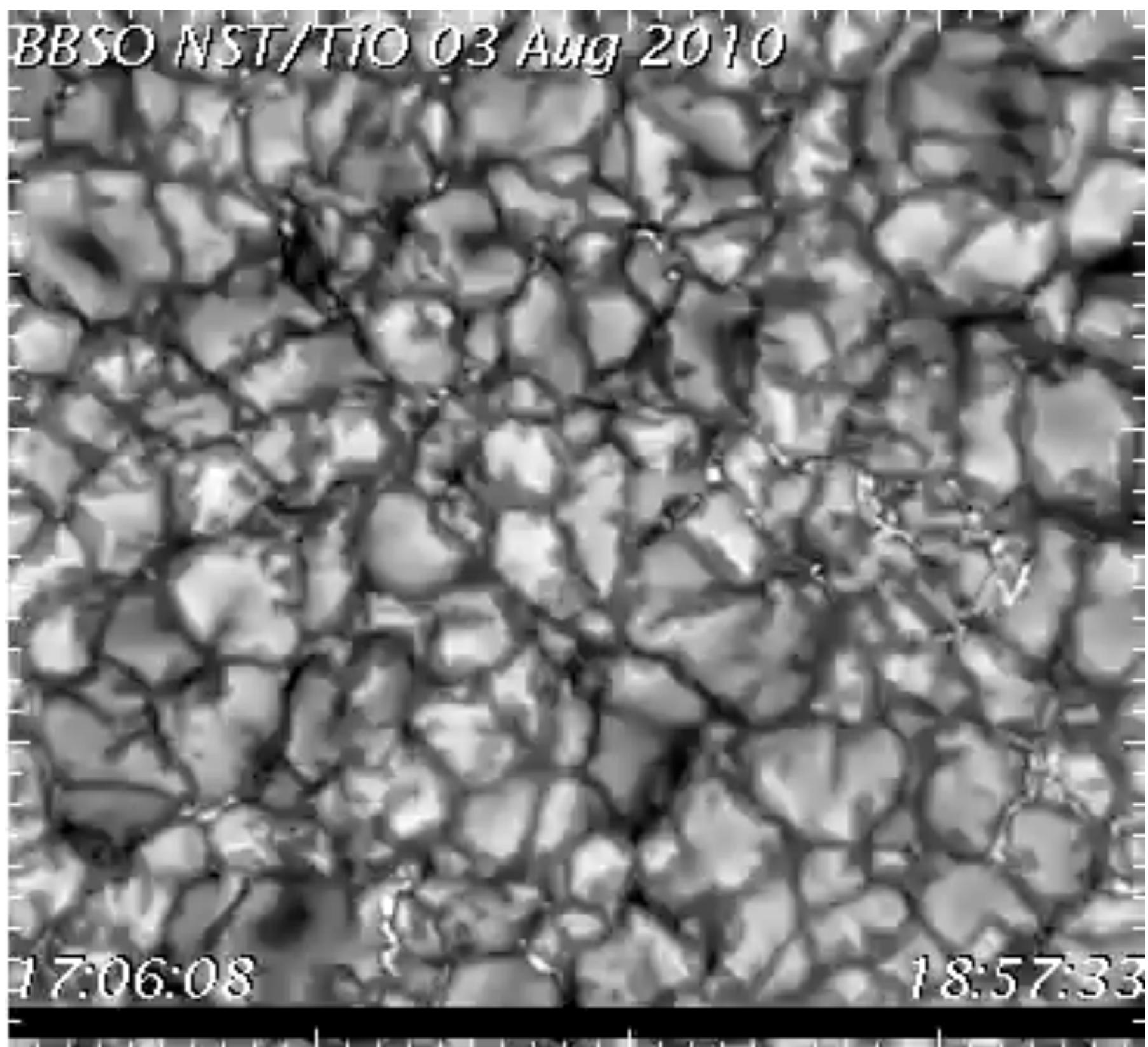
TRAINING

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



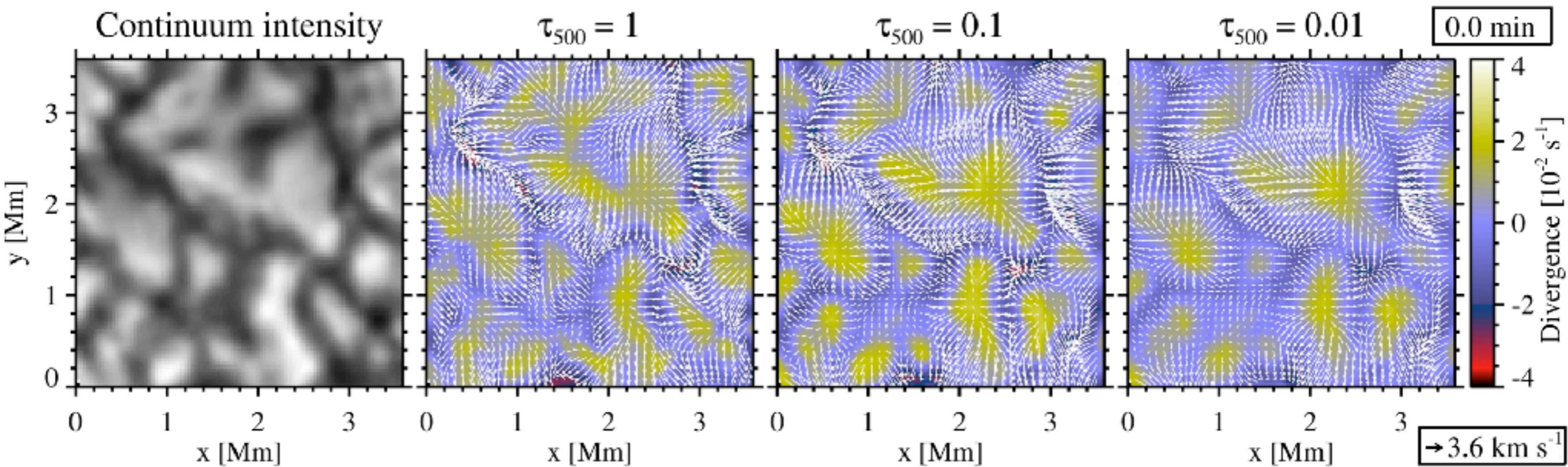


measuring velocities



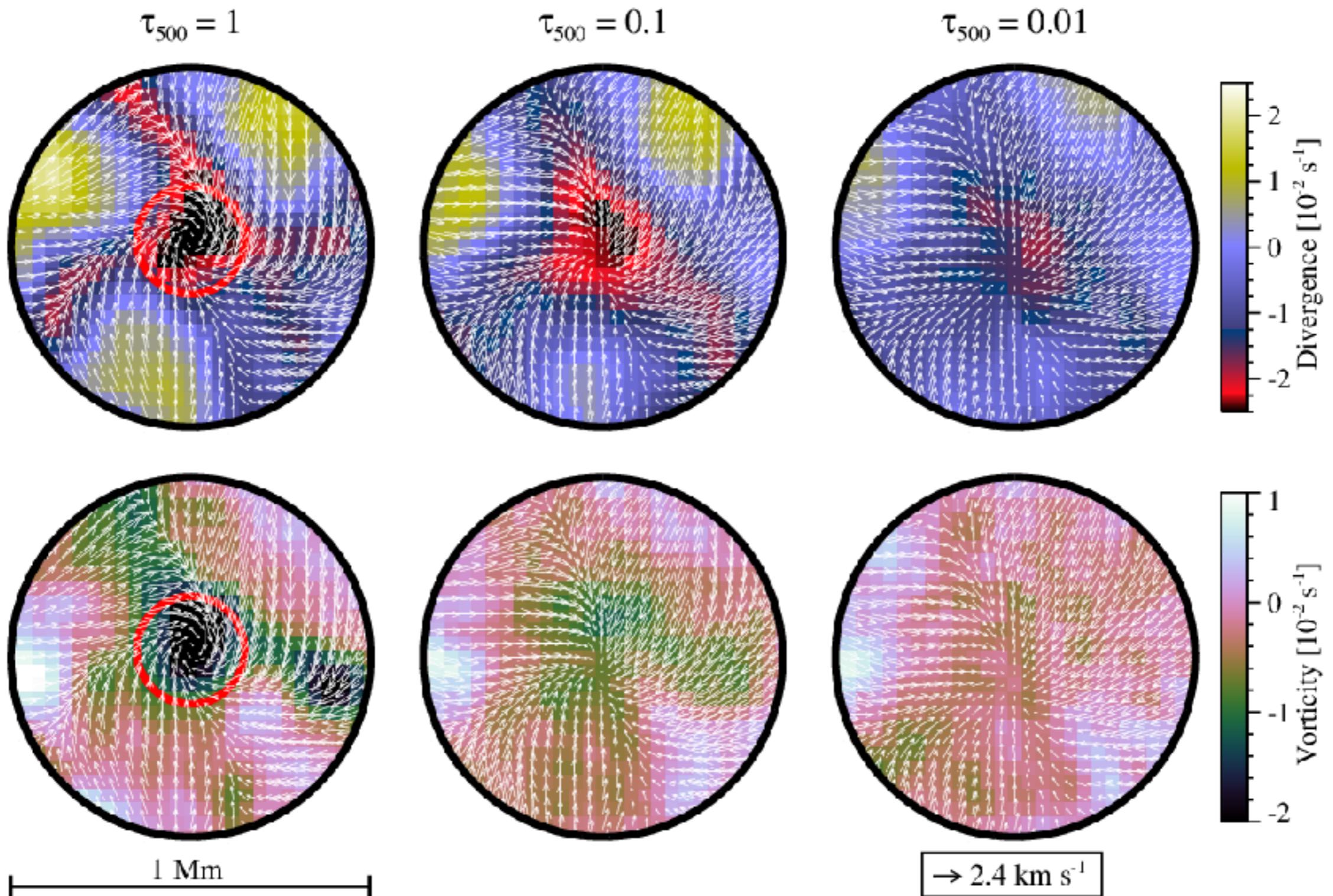
DEEPVEL

- ▶ Trained on simulations (Stein & Nordlund, 2012)
- ▶ End-to-end deep neural network
- ▶ Outputs are maps of v_x and v_y at $\tau=1, 0.1, 0.01$
- ▶ <https://github.com/aasensio/deepvel>



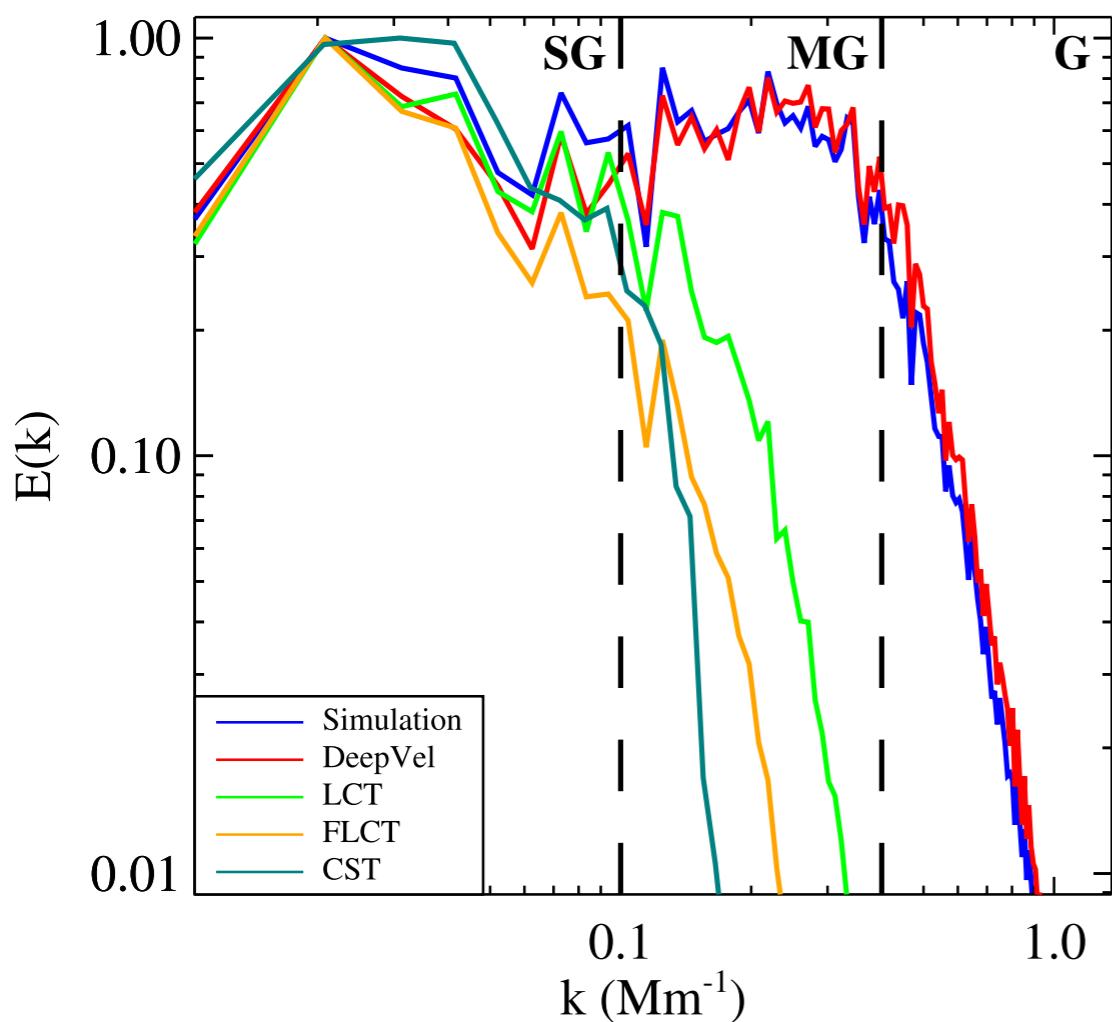
Asensio Ramos, Requerey & Vitas (2017)

SMALL SCALE VORTEX FLOWS

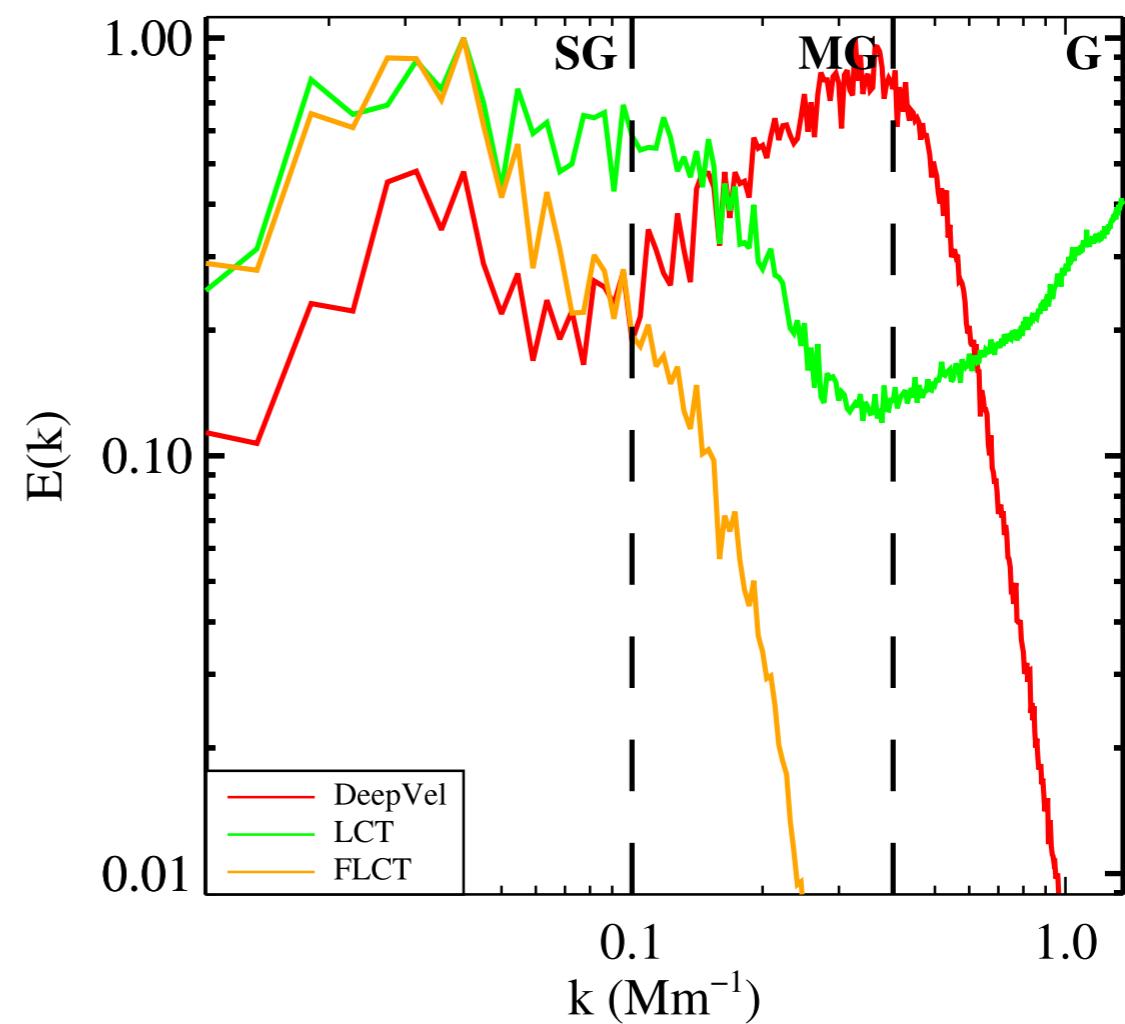


KINETIC ENERGY SPECTRUM

Simulations



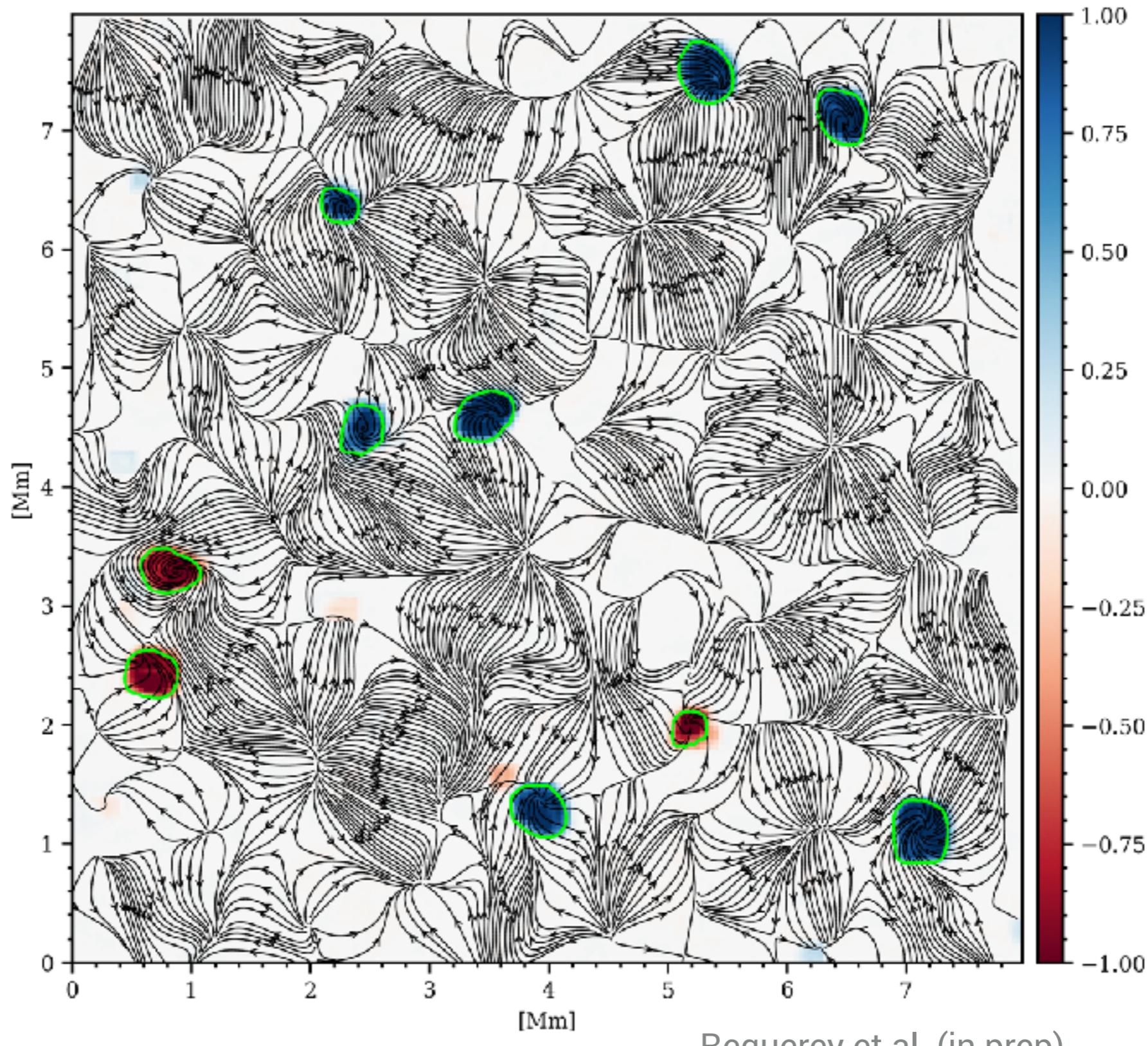
SDO/HMI



Tremblay et al. (2018)

VORTEX DETECTION

DeepVortex



Requerey et al. (in prep)

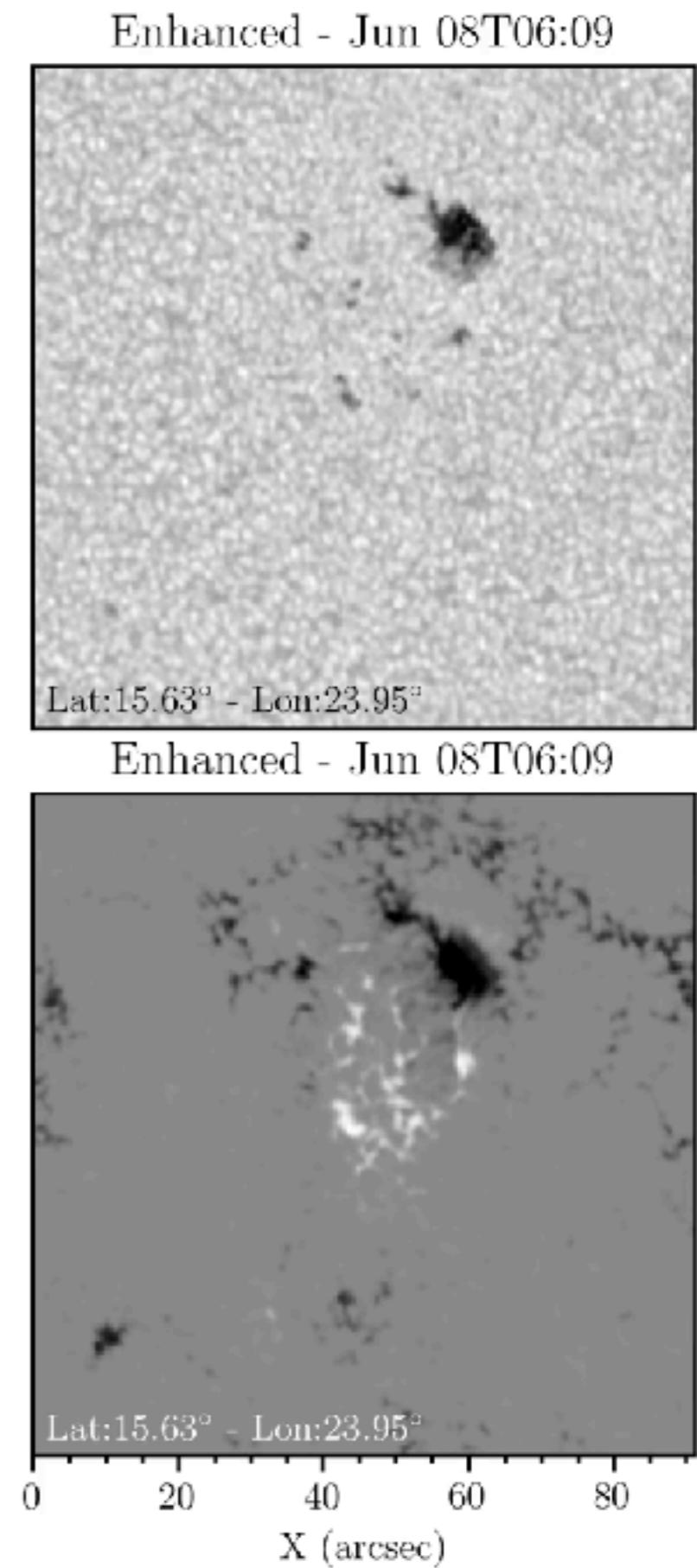
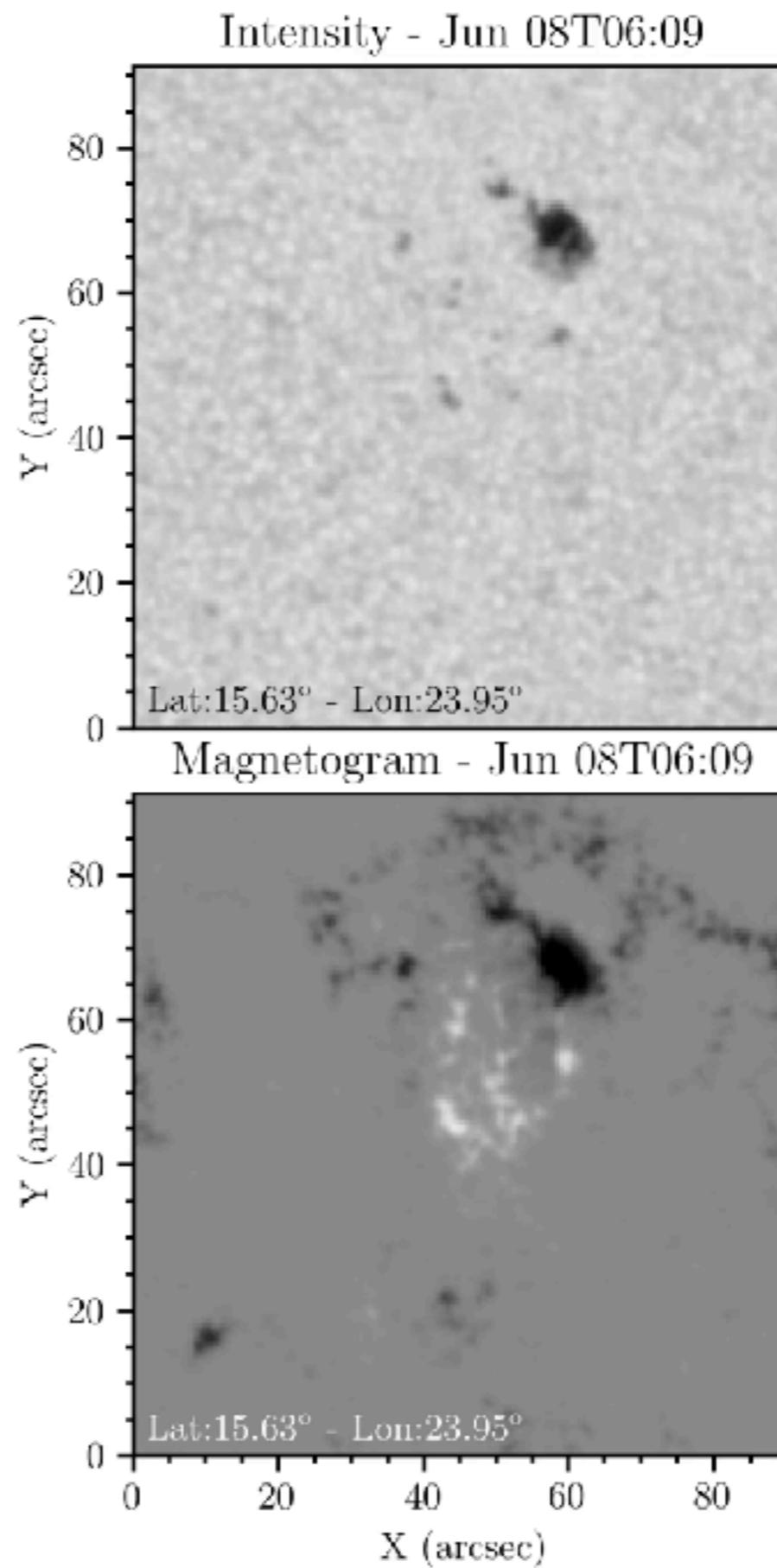
enhancing HMI images

ENHANCE: SINGLE IMAGE SUPERRESOLUTION



- ▶ Trained on simulations (courtesy of M. Cheung)
- ▶ End-to-end deep neural network
- ▶ Continuum + magnetograms
- ▶ <https://github.com/cdiazbas/enhance>

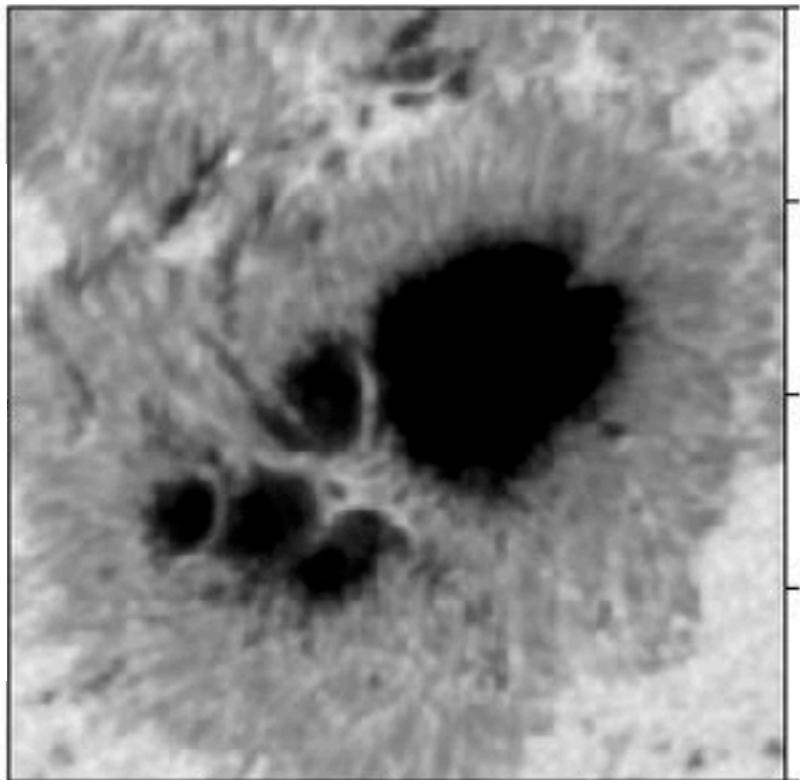
ENHANCE



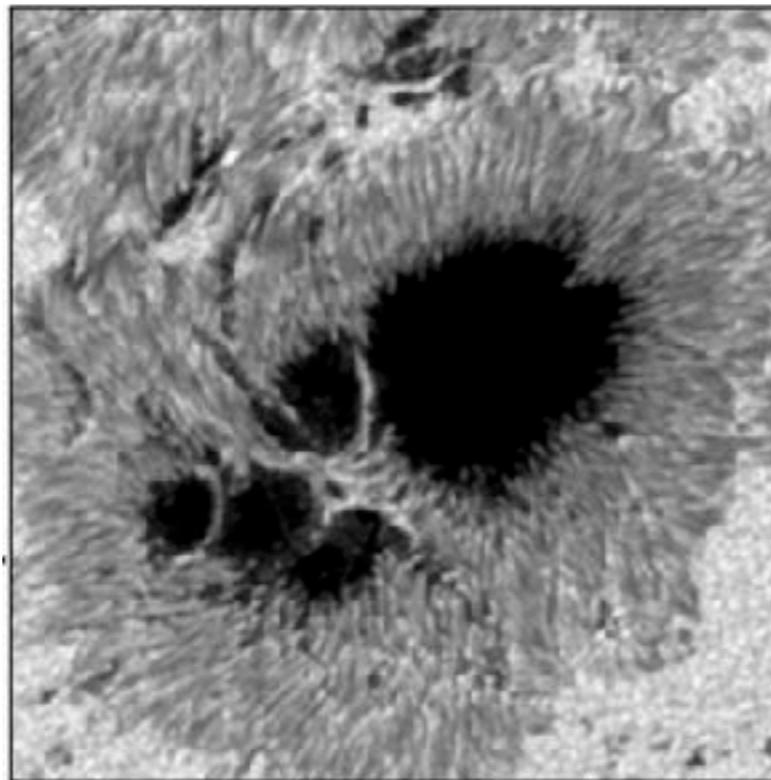
courtesy of S. Castellanos Durán

ENHANCE

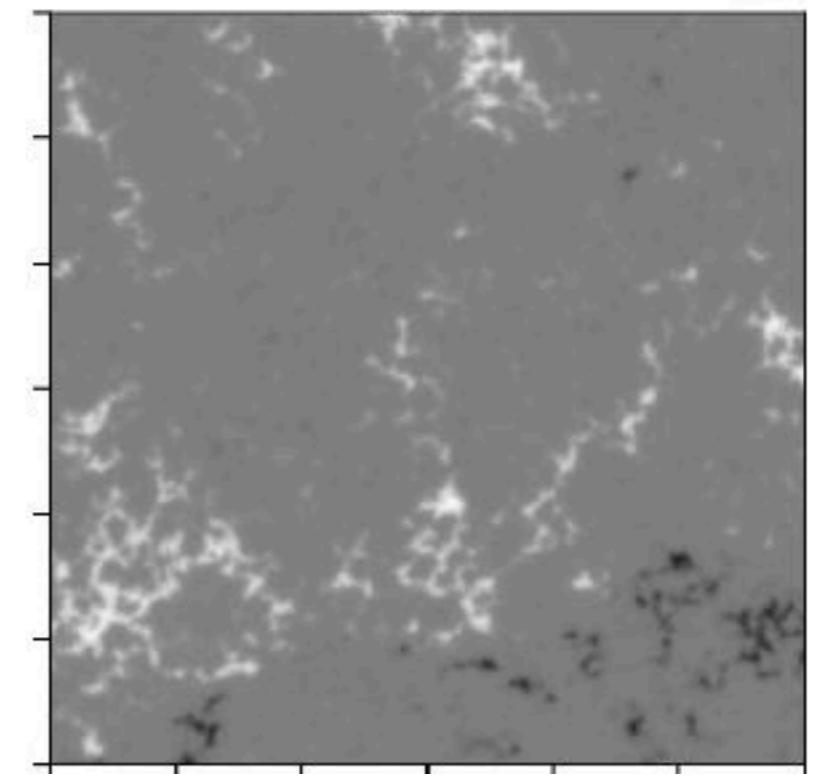
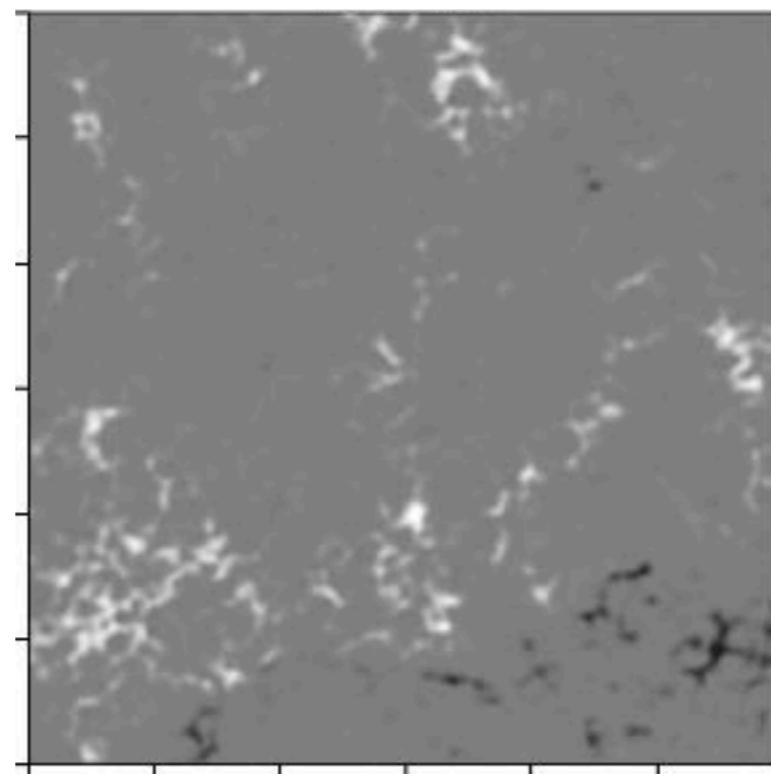
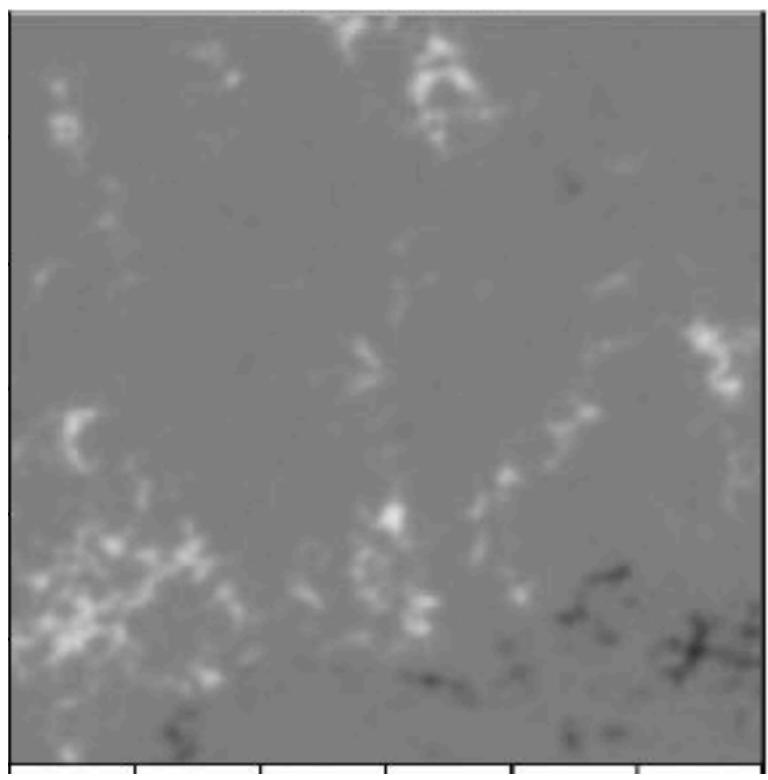
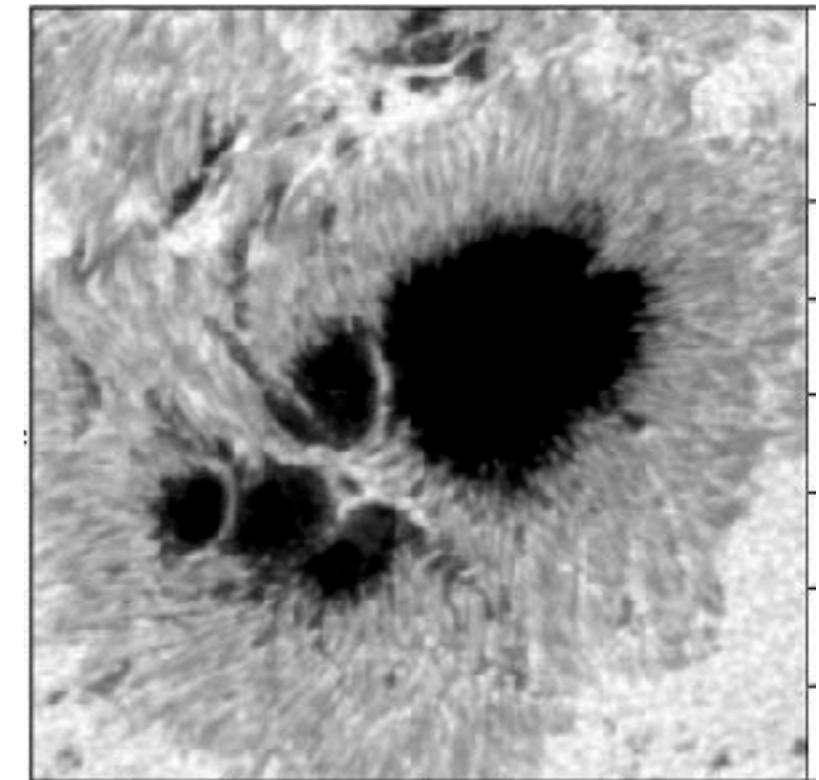
HMI



Neural network



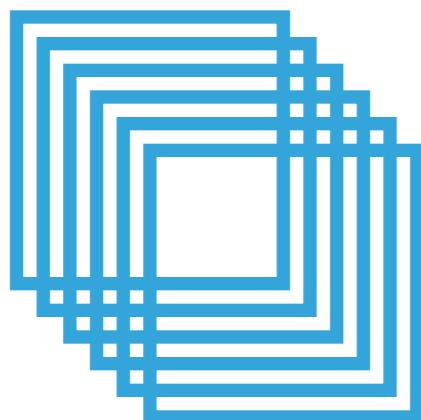
Hinode



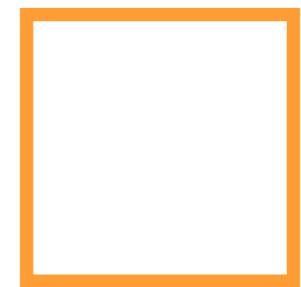
real-time multiframe deconvolution

MULTIFRAME BLIND DECONVOLUTION

Short-exposure burst



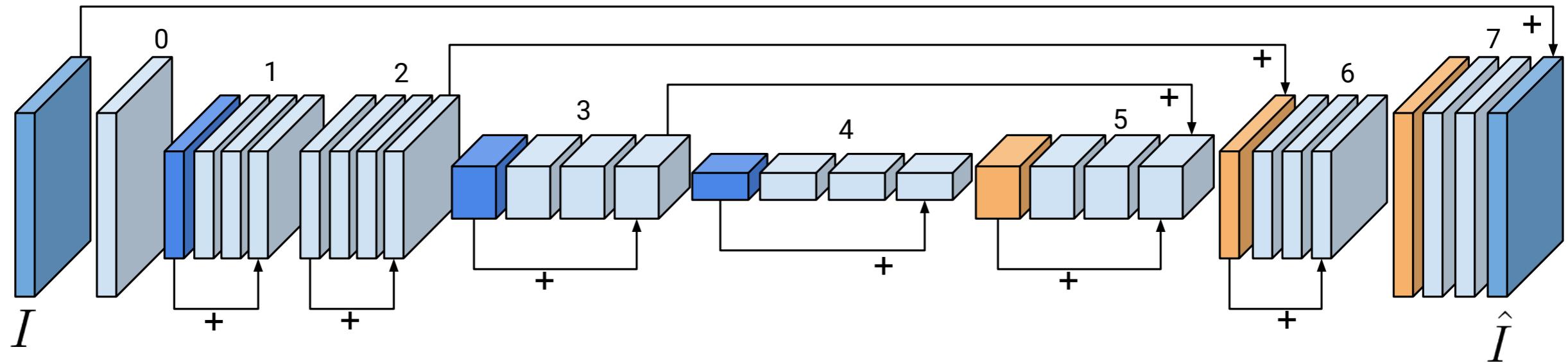
Deconvolved image



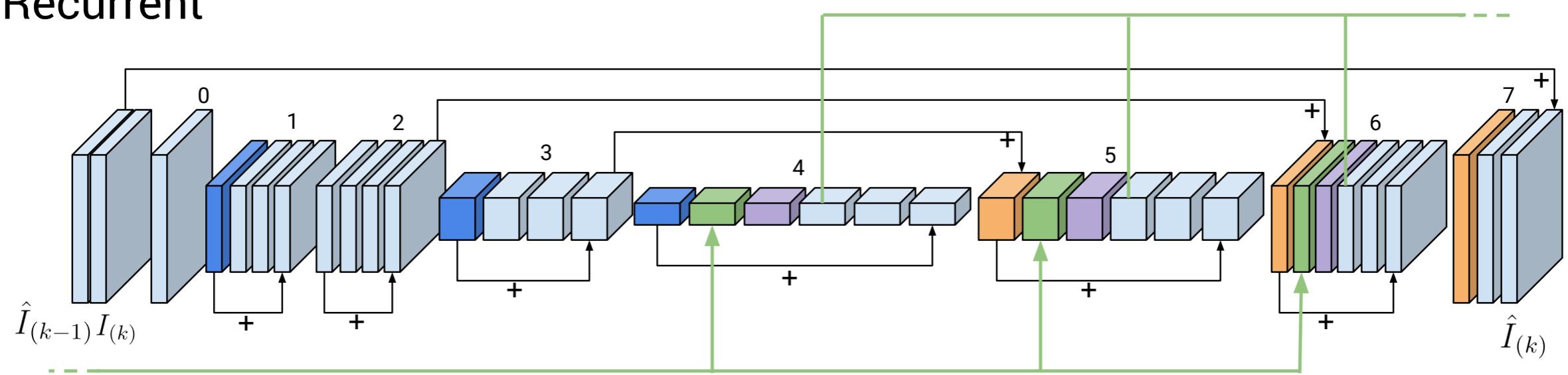
- ▶ Trained on CRISP@SST Fe I 630 nm and Ca II 854 nm deconvolved data
- ▶ End-to-end deep neural network
- ▶ Asensio Ramos et al. (submitted)
- ▶ Deconvolves 1k x 1k images at ~100 Hz
- ▶ https://github.com/aasensio/learned_mfbd

ARCHITECTURES

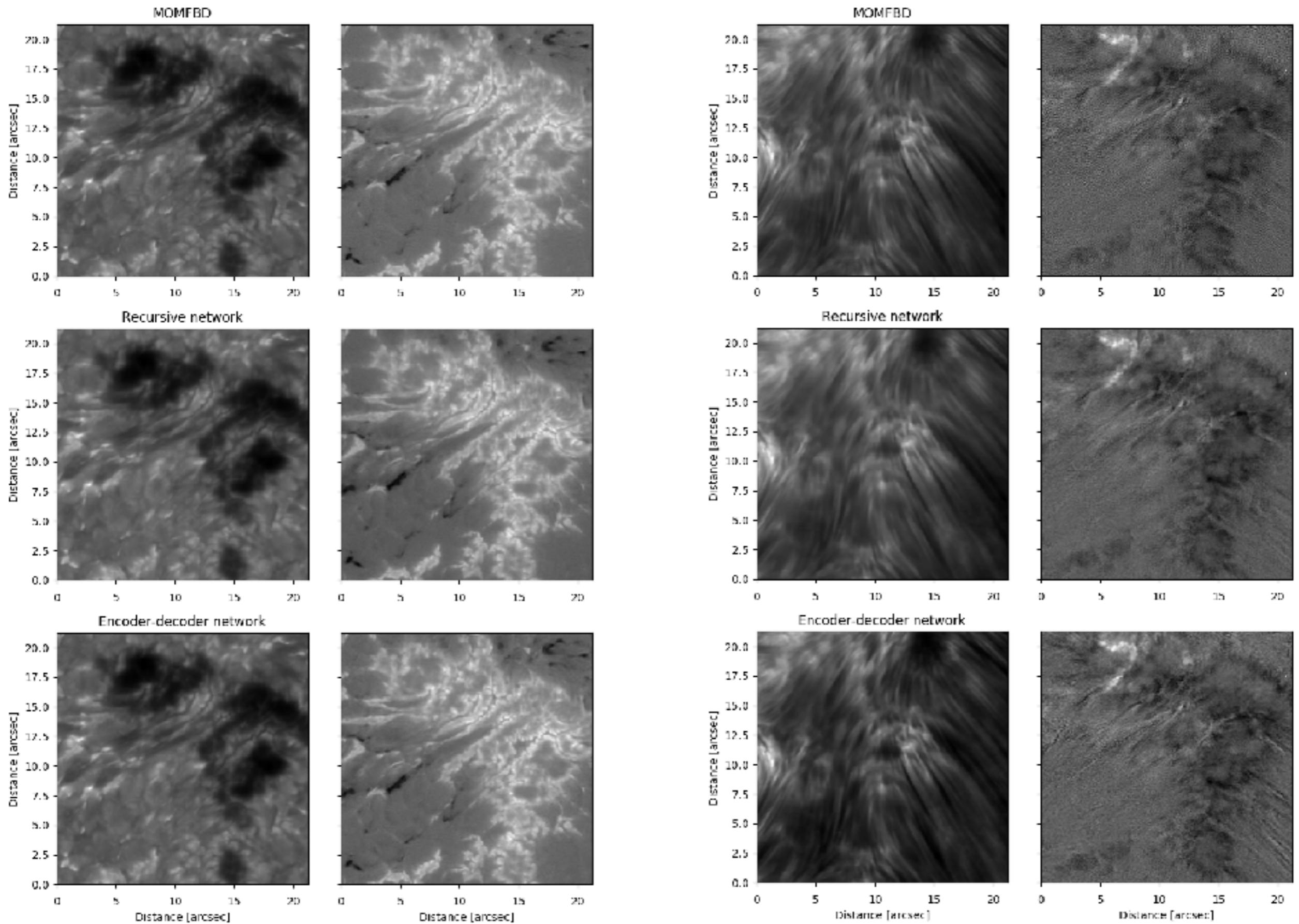
Encoder-decoder



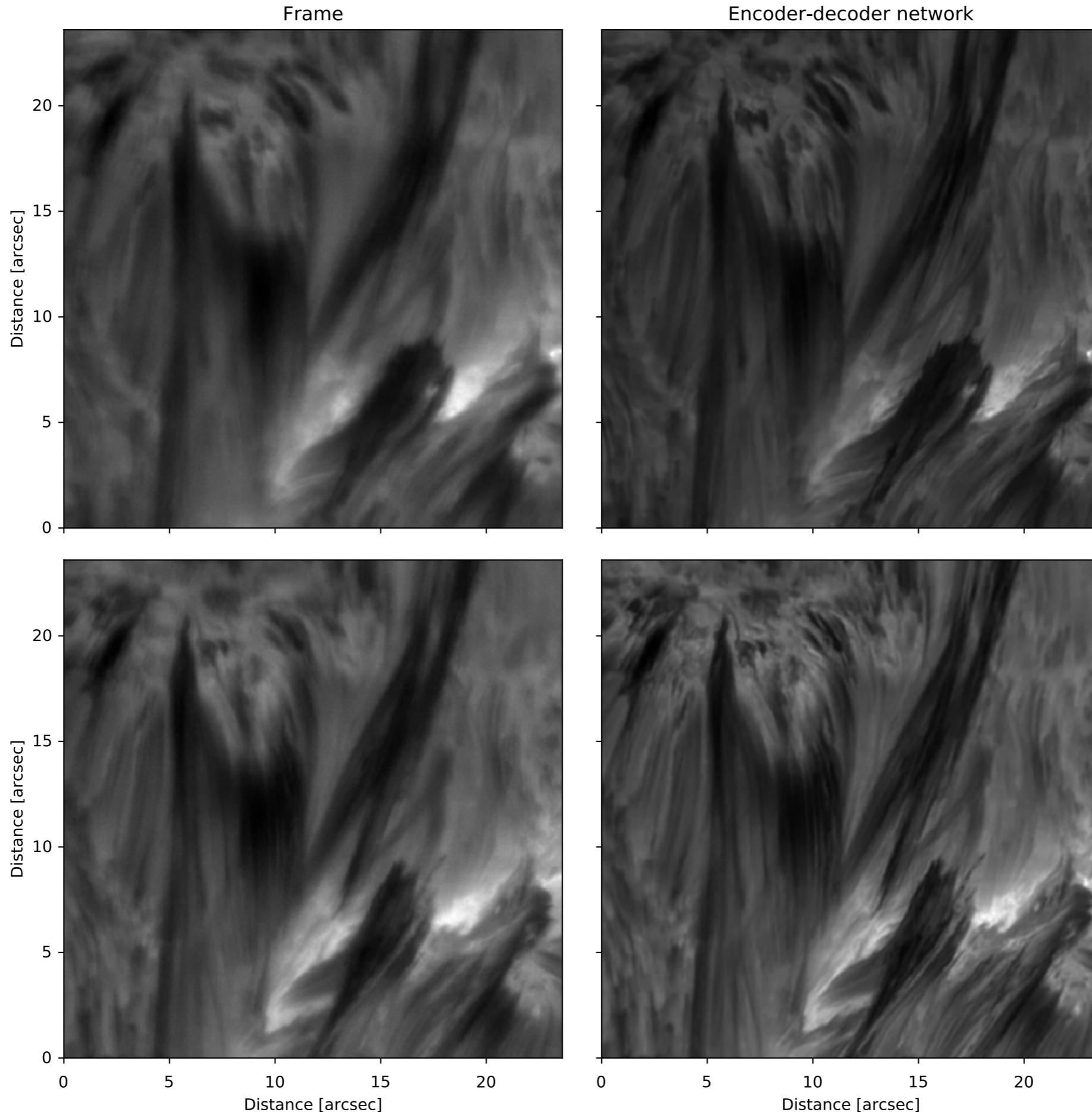
Recurrent



POLARIMETRY



GENERALIZATION



SEE ALSO...

Learning to correct for atmospheric seeing from solar observations
John Armstrong and Lyndsay Fletcher
University of Glasgow
j.armstrong.2@research.gla.ac.uk

1. Introduction
Atmospheric seeing is ubiquitous in ground-based astronomy^[1]. We propose a post-processing correction for seeing using a machine learning algorithm known as generative adversarial network^[2] (GAN). This provides a kernel-free deblurring technique. In models assuming some blur kernel explicitly it is hard to deal with occluded (optically thick) regions without a complex kernel estimation^[3]. This is avoided in our model.

2. Discriminator and generator
There are two parts to a GAN: discriminator (D) and generator (G). The goal of the generator is to fool the discriminator into thinking the data that it has created is real. The discriminator wants to classify whether or not data is real. The two play a game against each other and train simultaneously.

3. Blur Model
Fig. 3: SCT^[4] image pre- and post-blurred

Blur image via randomly offsetting image w.r.t. itself twice 312 during 100

4. CRISP Ca II 8542Å Correction
Blurry → Sharp → Corrected

Fig. 4: Correcting a CRISP observation of the 2014-09-08 flare.

5. Conclusion

- Reconstructs lines well from CRISP data.
- This shows that the image deblurring works perceptually and preserves spectral integrity. This implies that the method can be used to correct for atmospheric seeing.

References

- [1] S. Seach, R. L. Dunn, M. J. A. Clark, "Ground-based solar seeing", *Proc. Roy. Soc. A*, 2007, 463, 2075-2092.
- [2] Goodfellow, I., Bengio, Y., Courville, A., "Generative Adversarial Networks", *NIPS 2014*, 2014, 2672-2679.
- [3] K. Cho, D. Kim, S. Lee, "A generative adversarial network for image deblurring", *CVPR 2017*, 2017, 109-117.
- [4] Armstrong, J., Fletcher, L., "Learning to correct for atmospheric seeing from solar observations", *ASIAA 2018*, 2018, 1-10.

The diagram illustrates the GAN architecture. It starts with 'Raw' data input. The 'Discriminator' (D) takes the data and divides it into 64, 128, 256, 512 segments. Each segment is classified as 'real' or 'fake'. The 'Generator' (G) takes the raw data and adds what it has learned from the blurry image for comparison with the sharp image. The generator's output is then processed by the discriminator to produce the final 'Corrected' image.

3D inversion of Stokes profiles

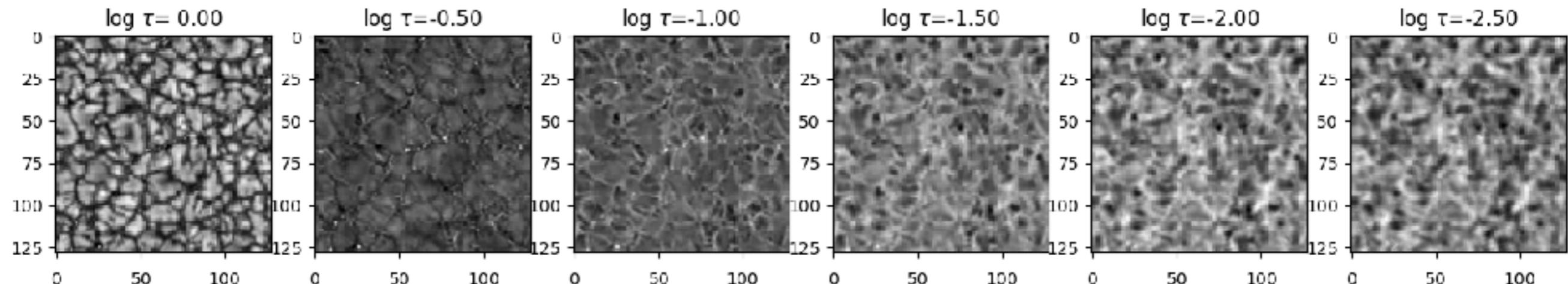
3D INVERSION OF STOKES PROFILES



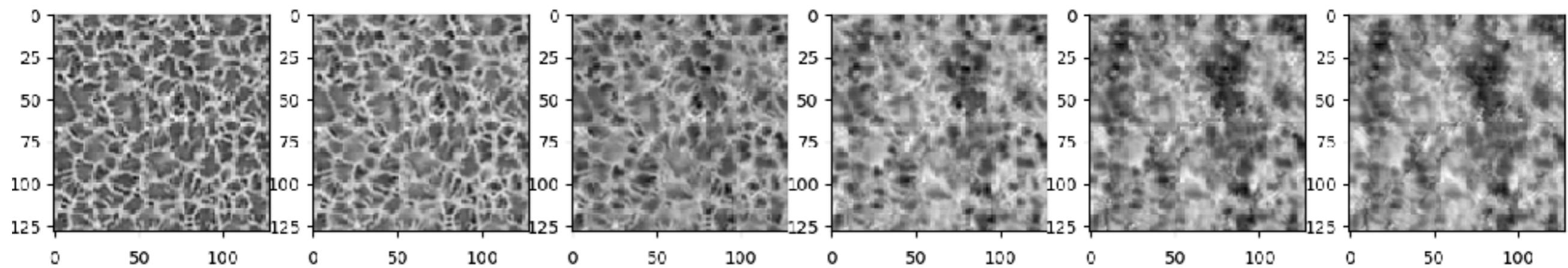
- ▶ Trained on 3D MHD magnetoconvection sims (still too few snapshots)
- ▶ End-to-end deep neural network
- ▶ Severe augmenting during training
- ▶ Still without polarimetry

HINODE INVERSION

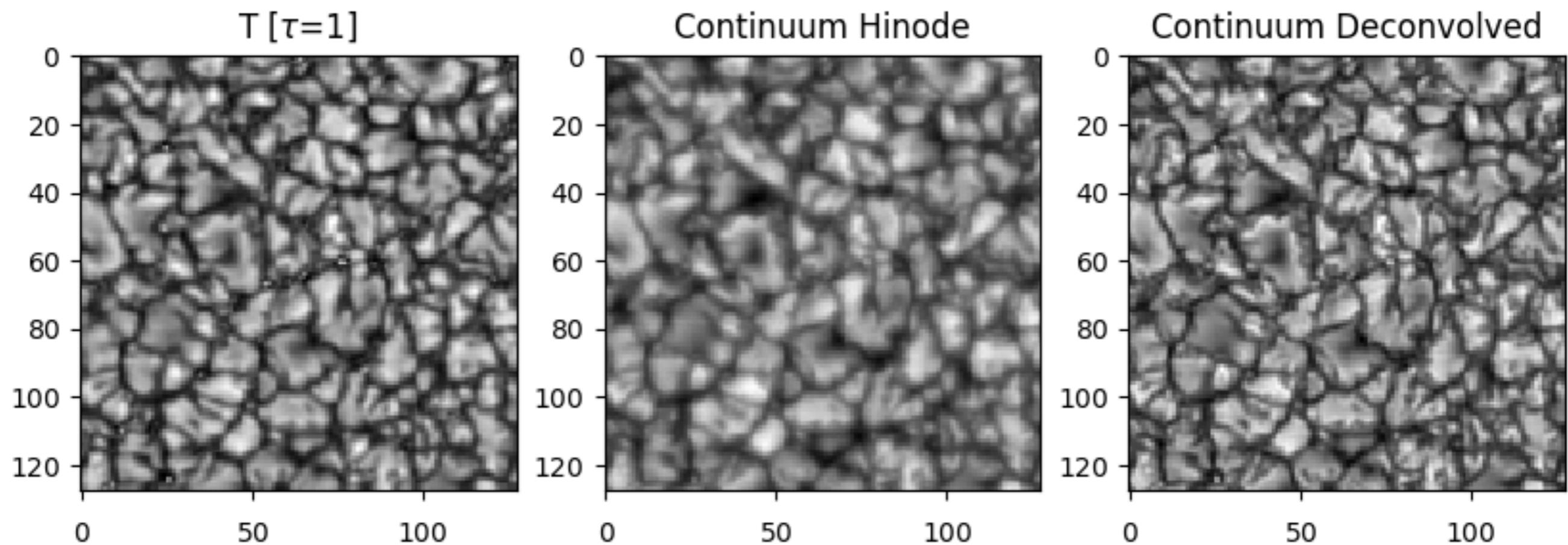
Temperature



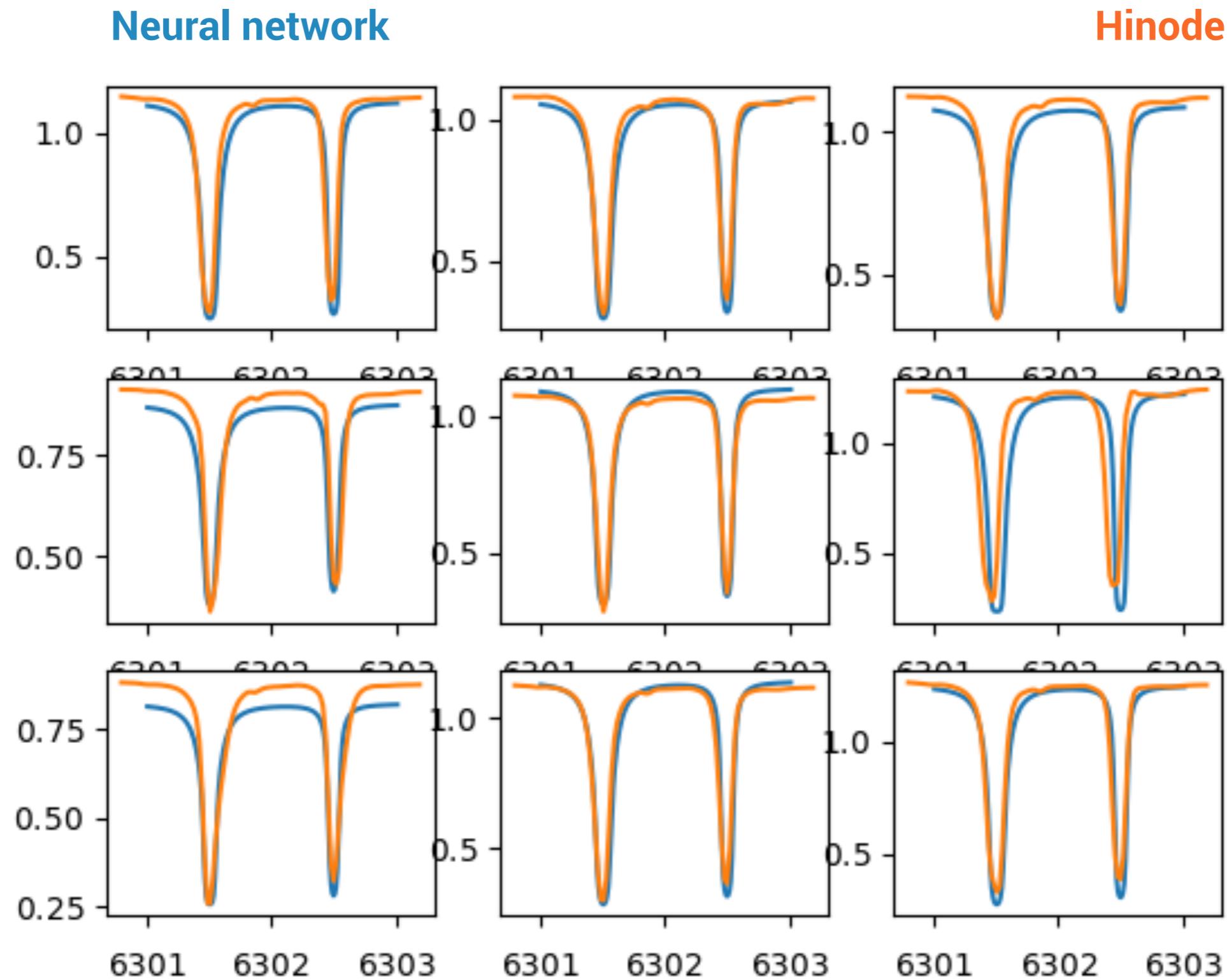
LOS velocity



INVERSION+DECONVOLUTION

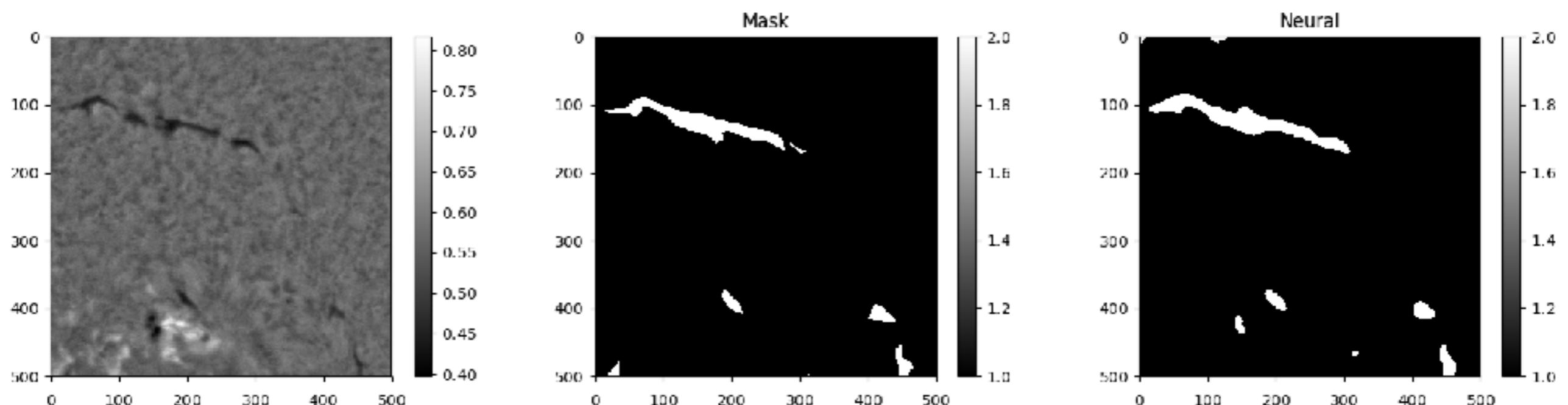


PROFILES



H α image segmentation

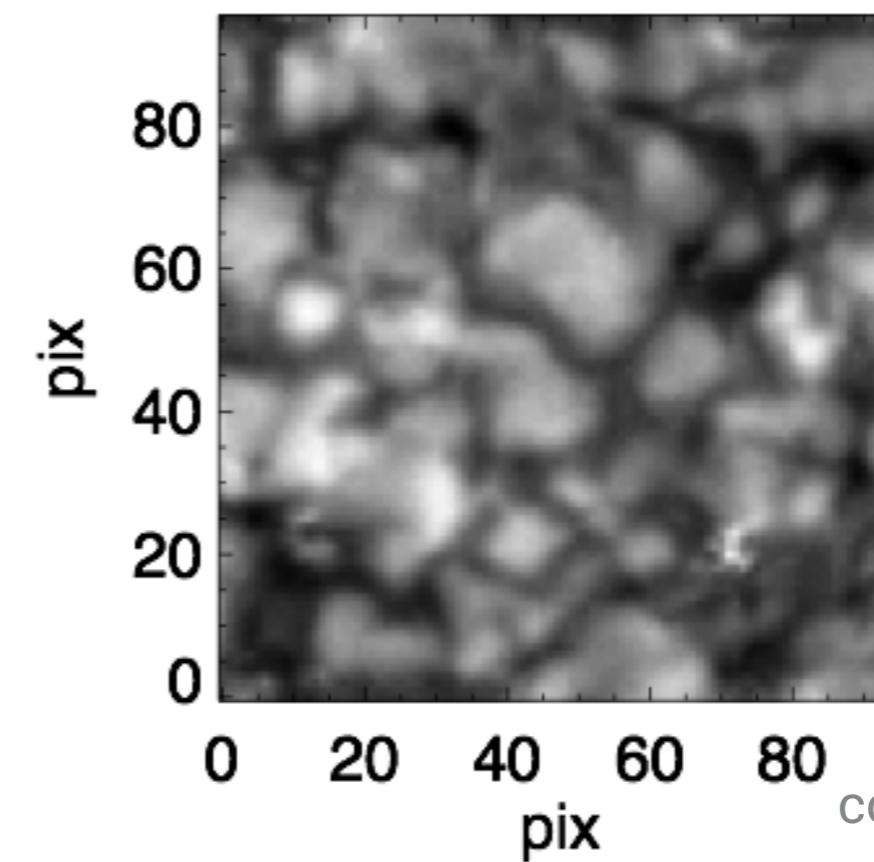
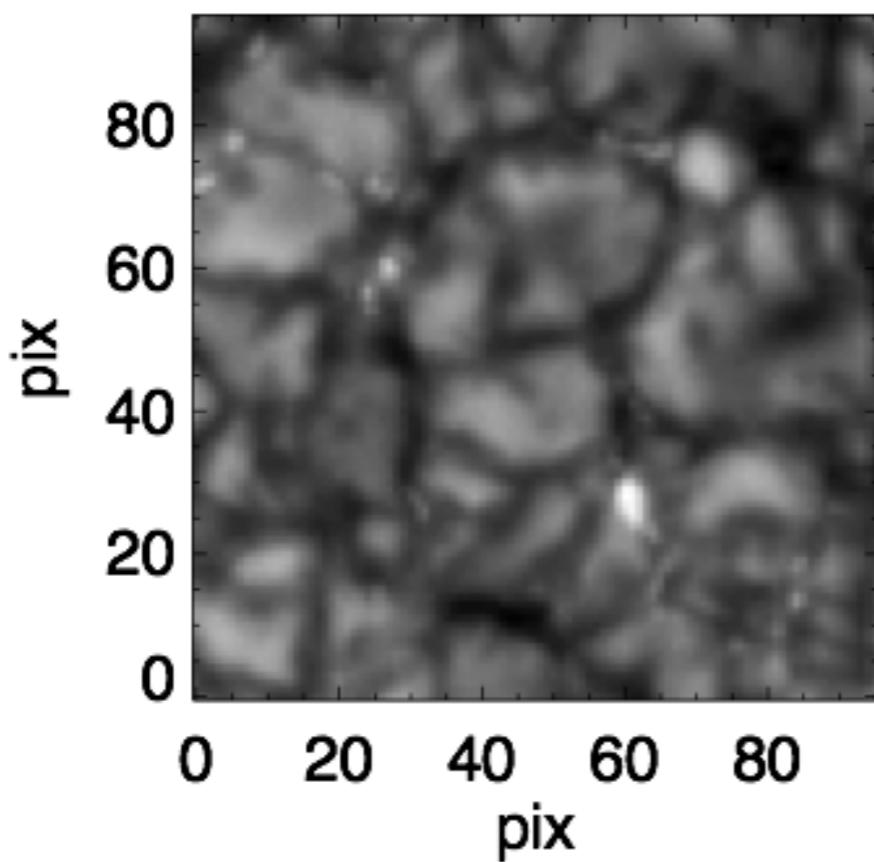
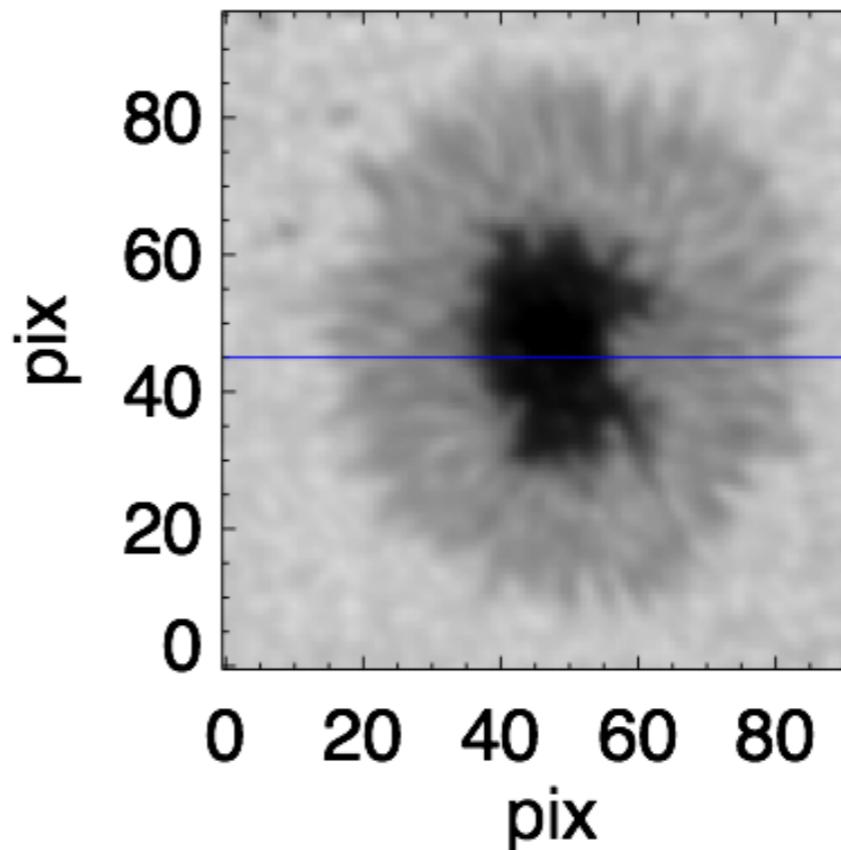
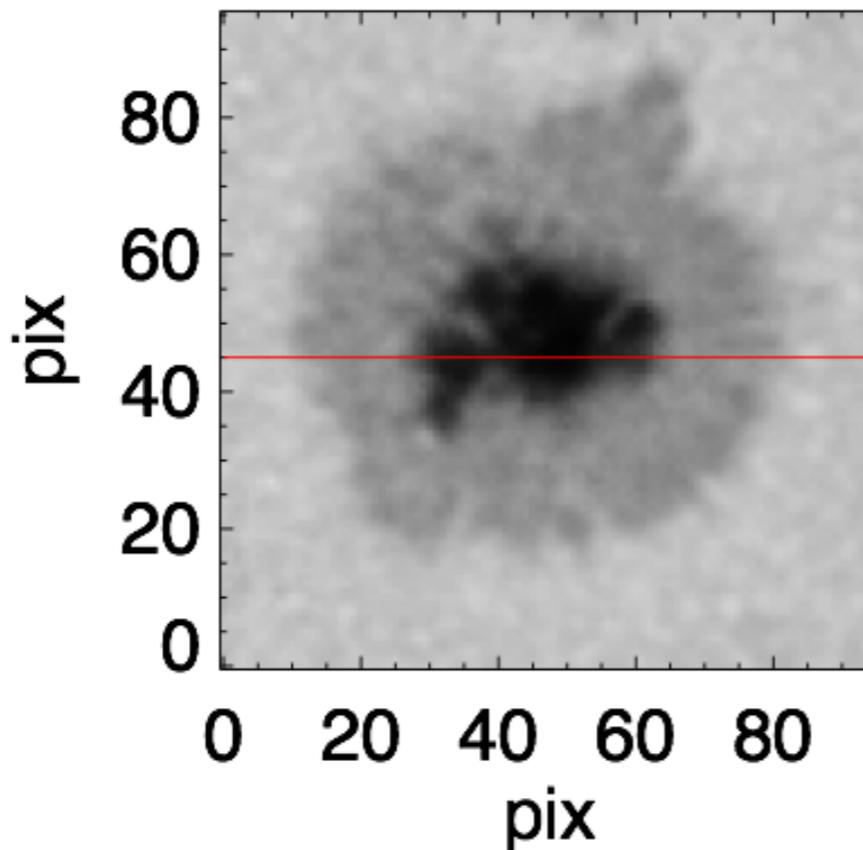
FAST SEGMENTATION



In collaboration with M. Luna

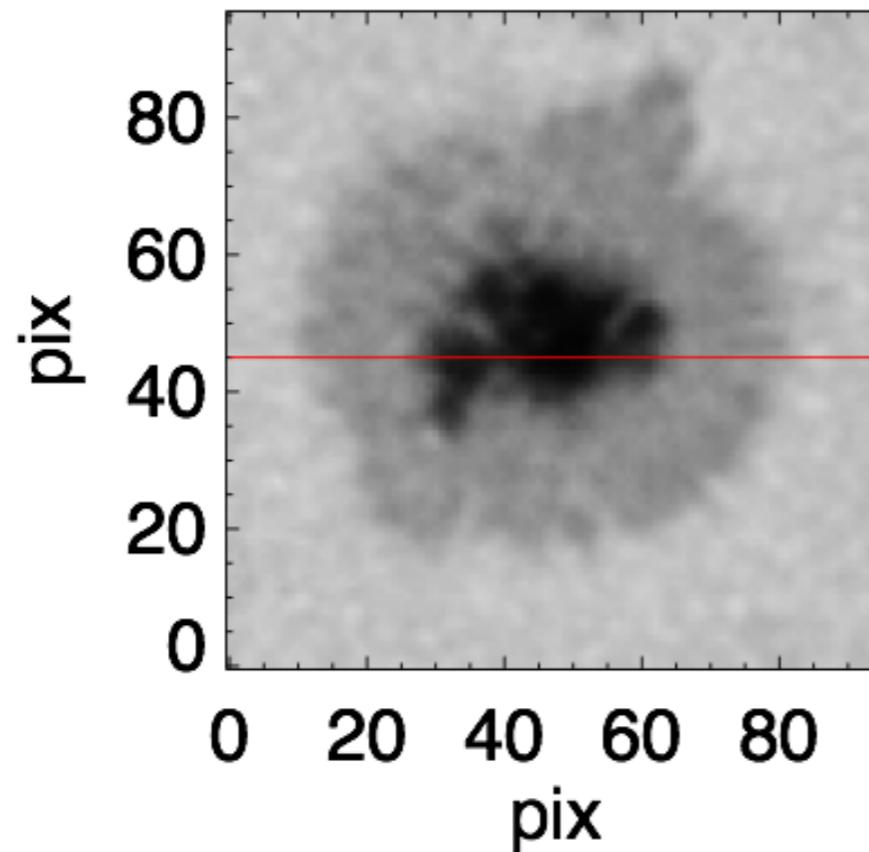
synthetic solar images

GENERATIVE ADVERSARIAL NETWORKS

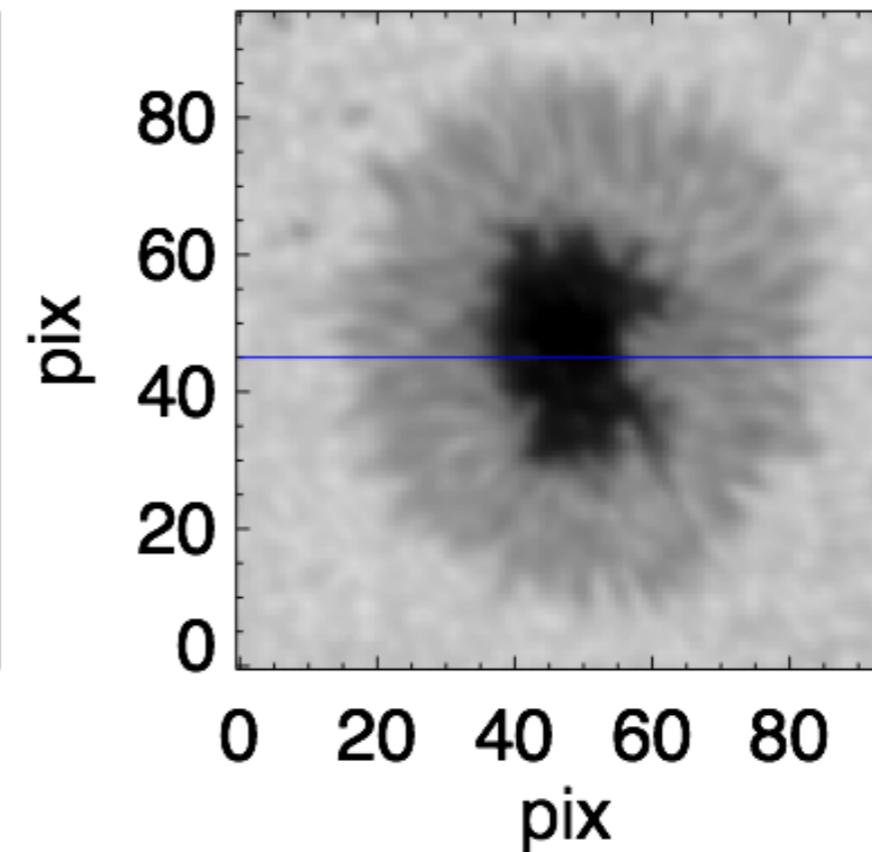


courtesy of Y. Kawabata

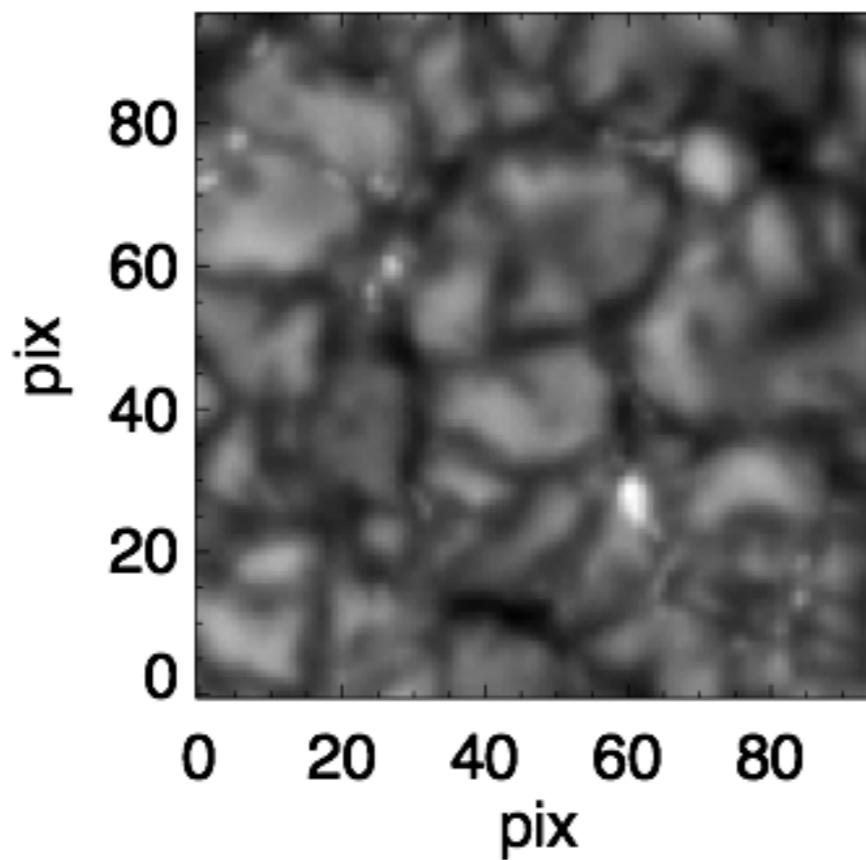
Artificial Sunspot



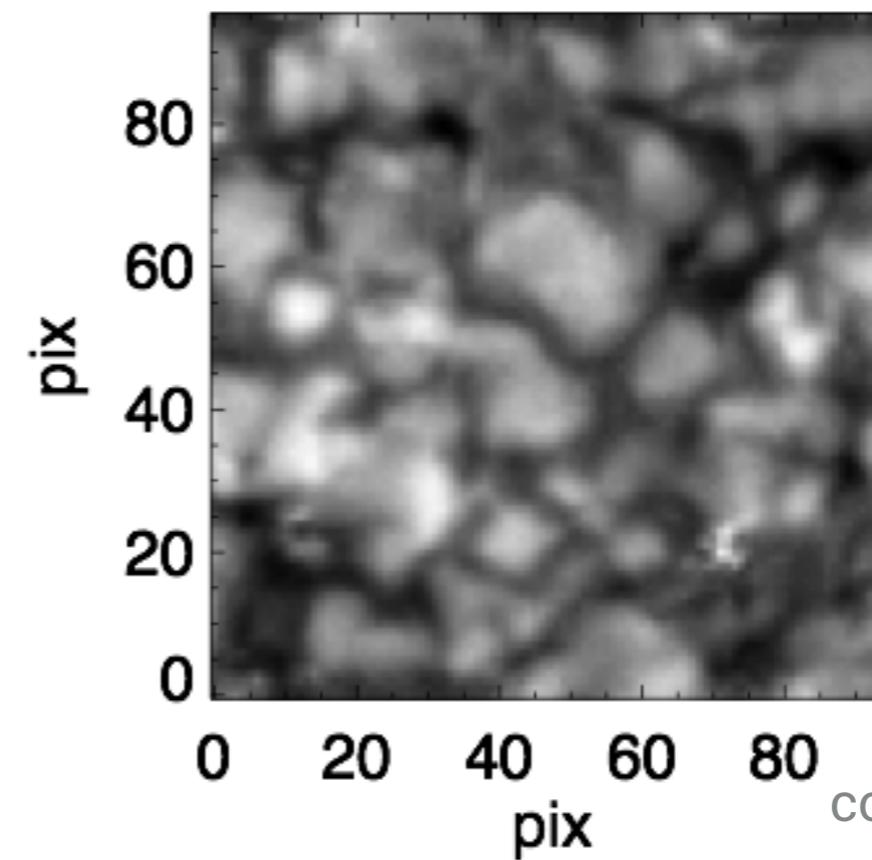
Real Sunspot



Artificial Granule



Real Granule



courtesy of Y. Kawabata

CONCLUSIONS

- many possibilities for deep learning open now in solar physics
- the machinery is prepared: we do not need to reinvent a new DL technique
 - think of a problem
 - prepare the data
 - test first already existing architectures