
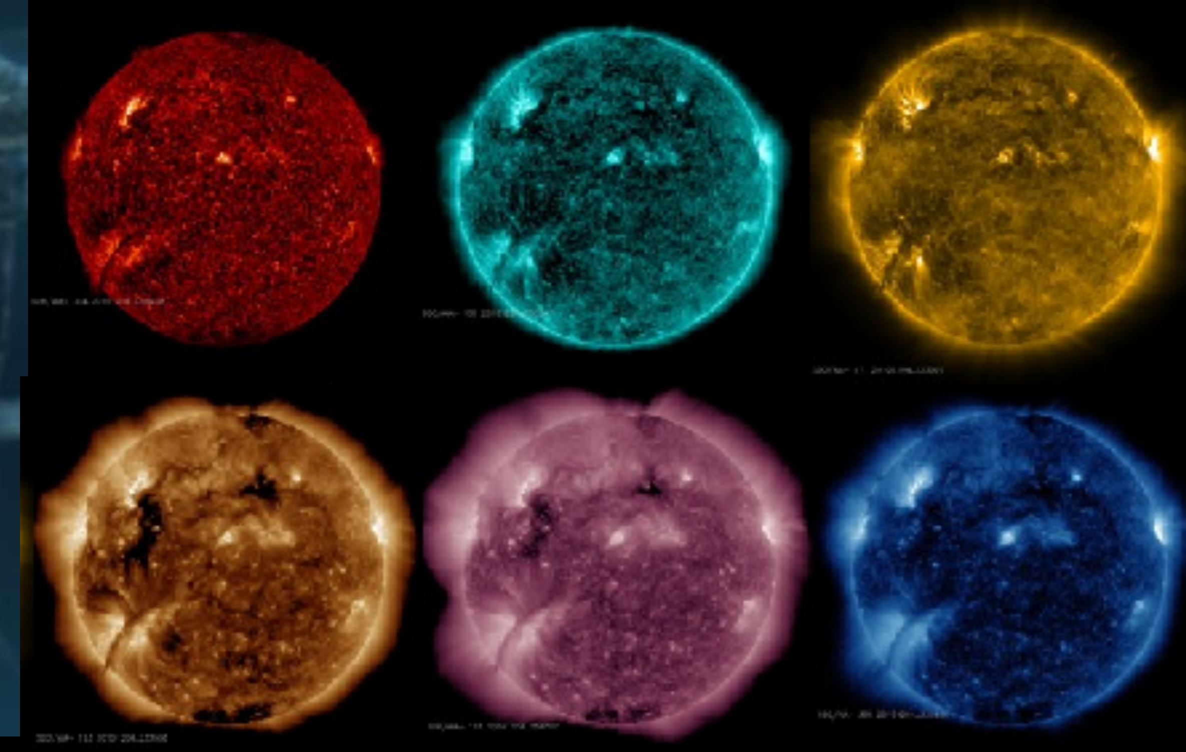

MACHINE LEARNING IN SOLAR PHYSICS

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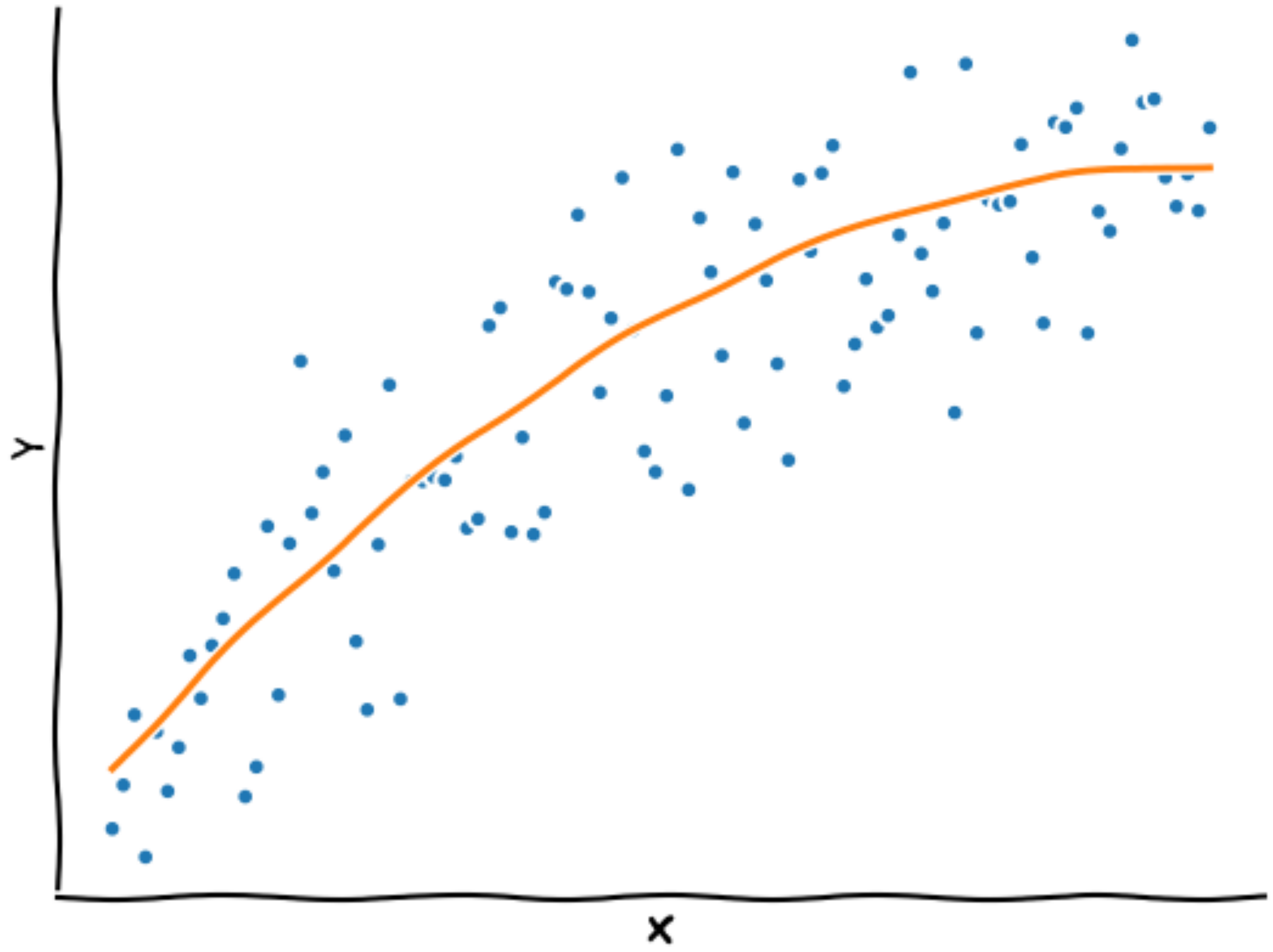
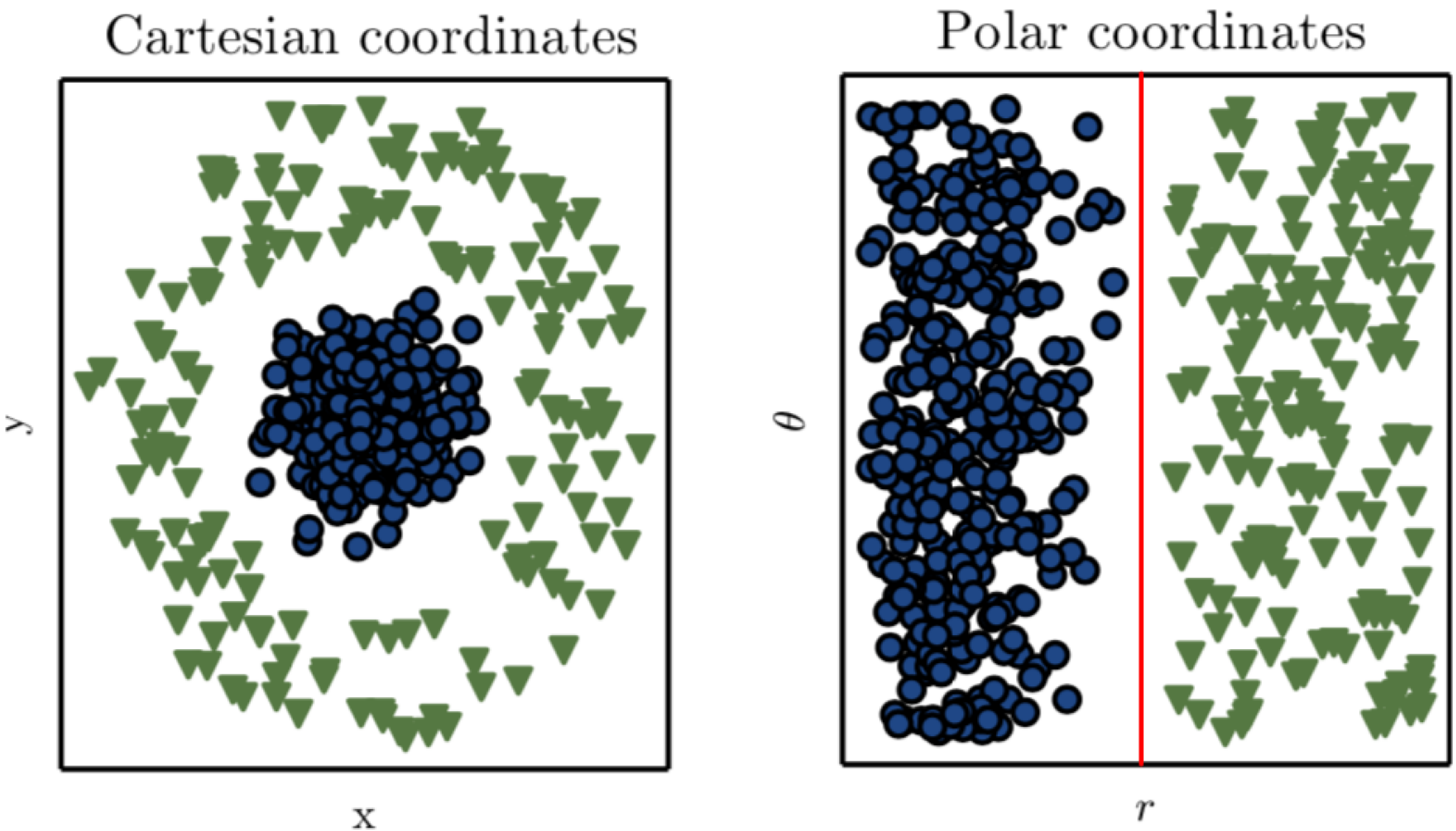
what is machine learning?

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

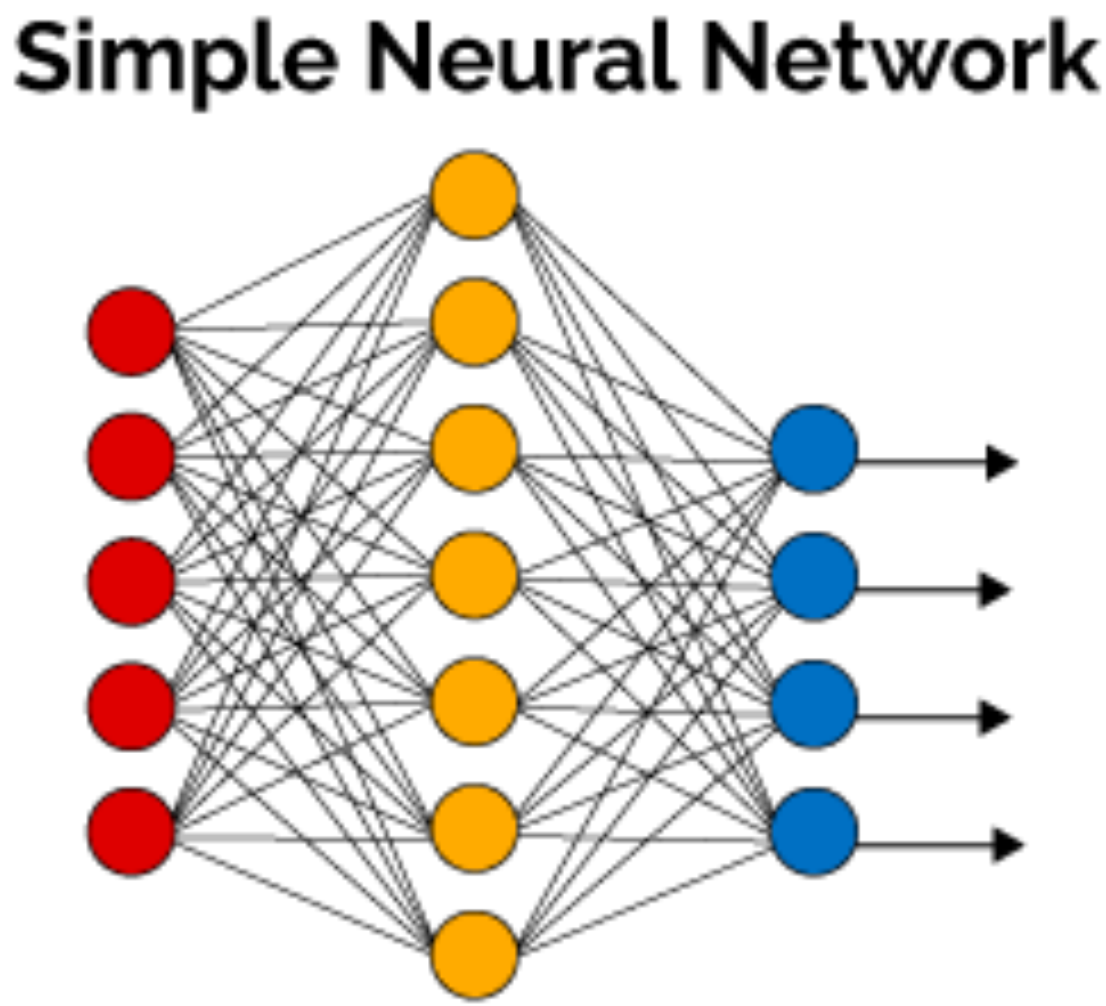
REGRESSION



CLASSIFICATION



NEURAL NETWORKS

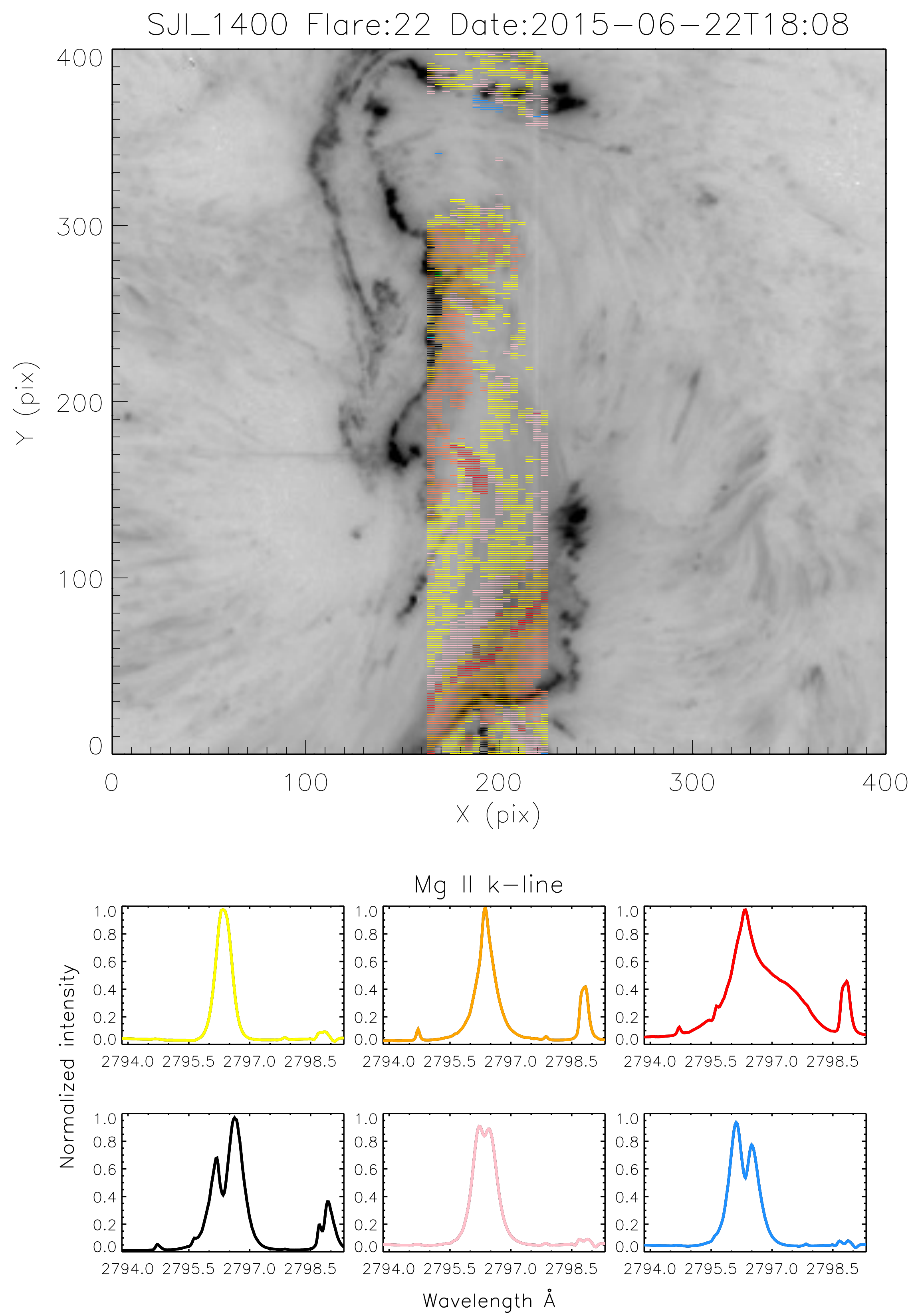


classical machine learning

CLASSICAL MACHINE LEARNING

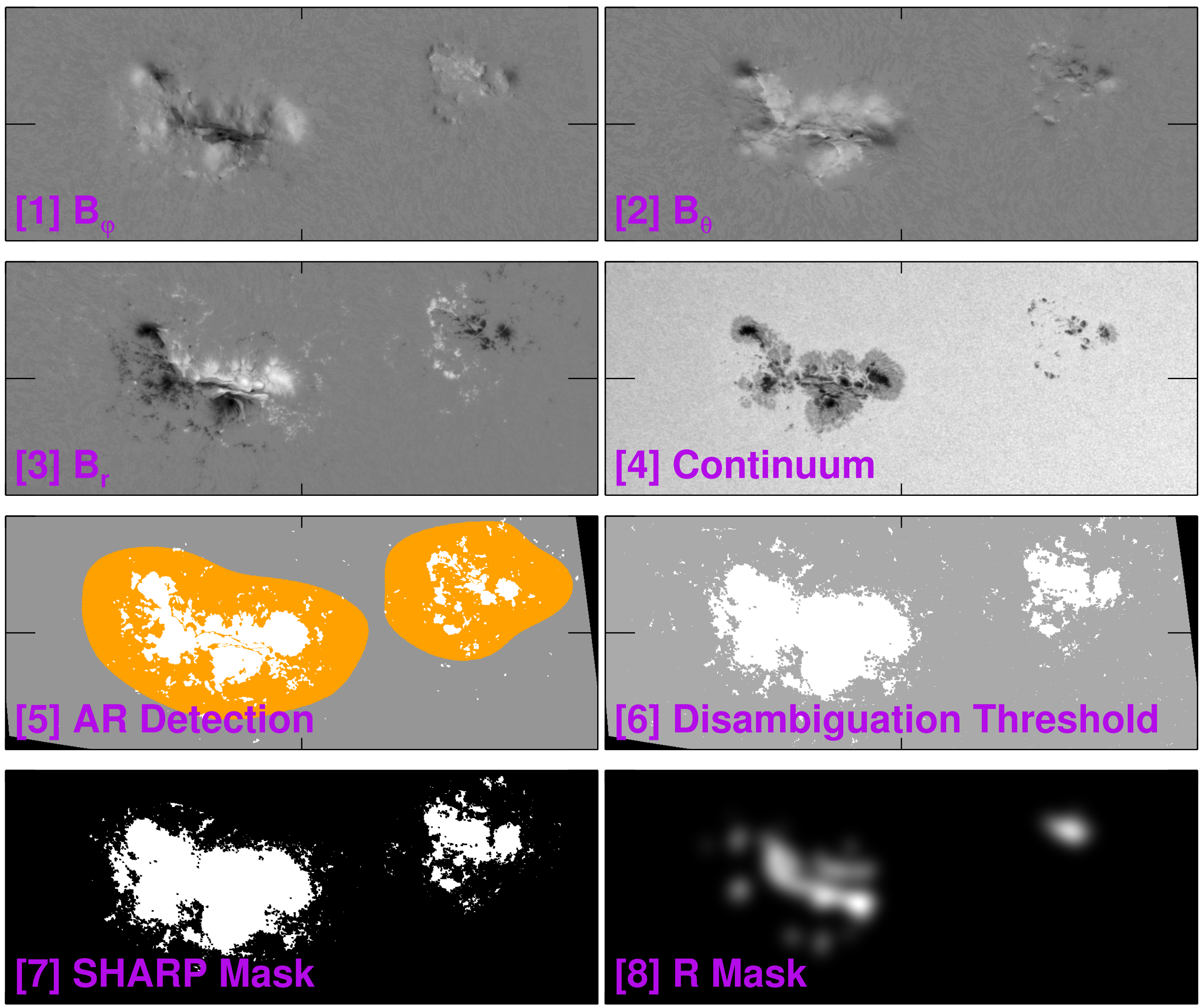
- Principal component analysis (PCA)
- k-nearest neighbors (k-NN)
- Support vector machines (SVM)
- Artificial neural networks (ANN)
- Random forests (RF)
- Gaussian Process (GP)
- …

K-NN CLASSIFICATION OF FLARE MG II K



Panos et al. (2018)

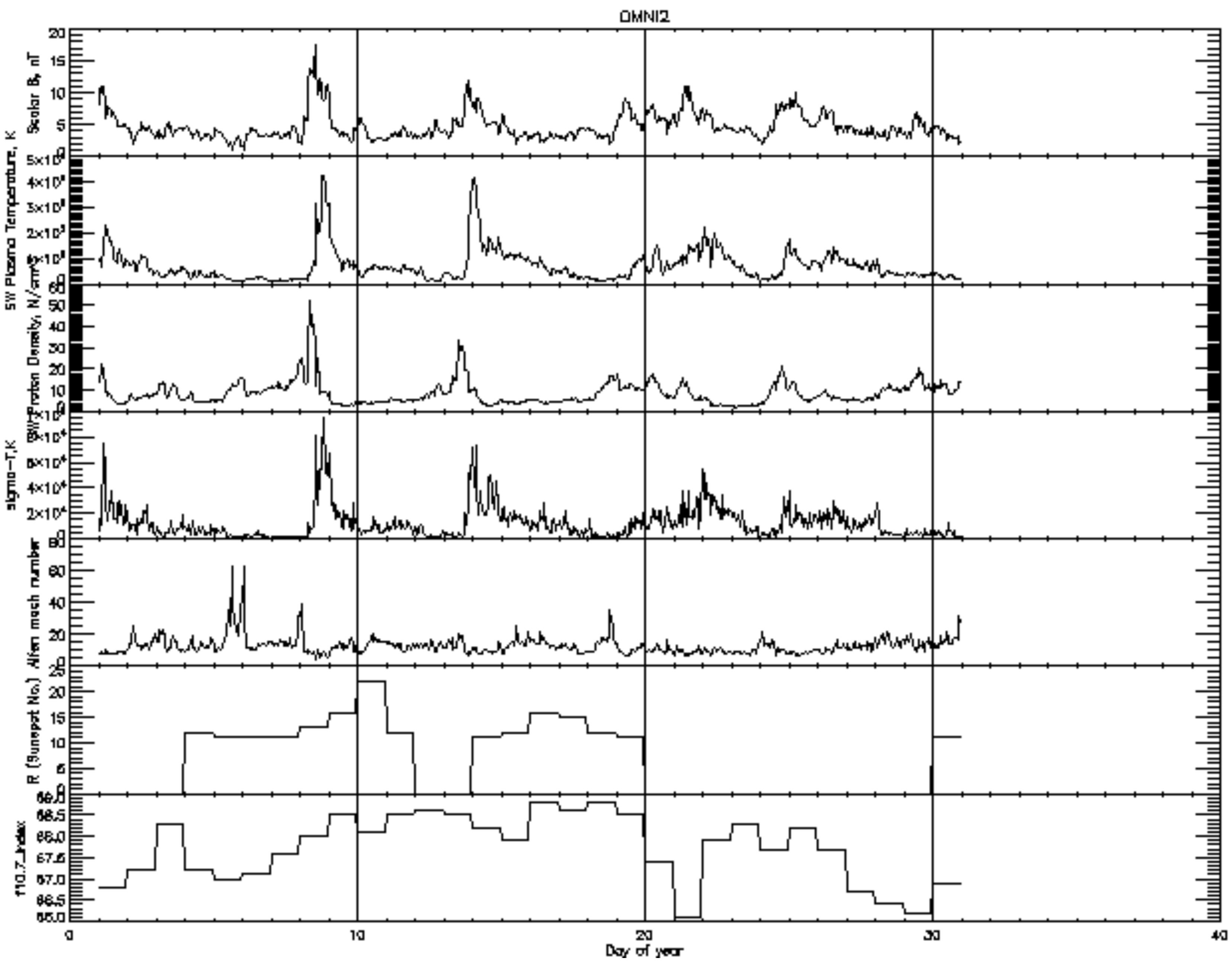
SOLAR FLARE PREDICTION



Keyword	Description	Formula
TOTUSJH	Total unsigned current helicity	$H_{c_{total}} \propto \sum \lvert B_z \cdot J_z \rvert$
TOTBSQ	Total magnitude of Lorenz force	$F \propto \sum B^2$
TOTUSJZ	Total unsigned vertical current	$J_{z_{total}} = \sum \lvert J_z \rvert dA$
ABSNJZH	Absolute value of the net current per polarity	$H_{c_{abs}} \propto \lvert \sum B_z \cdot J_z \rvert$
SAVNCPP	Sum of the modules of the net current per polarity	$J_{z_{sum}} \propto \lvert \sum^{B_z^+} J_z dA \rvert + \lvert \sum^{B_z^-} J_z dA \rvert$
USFLUX	Total unsigned flux	$\Phi = \sum \lvert B_z \rvert dA$
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 Lorentz 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	$\overline{\gamma} = \frac{1}{N} \sum arctan\left(\frac{B_h}{B_z}\right)$
MEANGBT	Mean gradient of total field	$\overline{\lvert \nabla B_{tot} \rvert} = \frac{1}{N} \sum \sqrt{\left(\frac{\partial B}{\partial x}\right)^2 + \left(\frac{\partial B}{\partial y}\right)^2}$
MEANGBZ	Mean gradient of vertical field	$\overline{\lvert \nabla B_z \rvert} = \frac{1}{N} \sum \sqrt{\left(\frac{\partial B_z}{\partial x}\right)^2 + \left(\frac{\partial B_z}{\partial y}\right)^2}$
MEANGBH	Mean gradient of horizontal field	$\overline{\lvert \nabla B_h \rvert} = \frac{1}{N} \sum \sqrt{\left(\frac{\partial B_h}{\partial x}\right)^2 + \left(\frac{\partial B_h}{\partial y}\right)^2}$
MEANJZH	Mean current helicity (B_z contribution)	$\overline{H_c} \propto \frac{1}{N} \sum B_z \cdot J_z$
TOTFY	Sum of y-component of Lorentz force	$F_y \propto \sum B_y B_z dA$
MEANJZD	Mean vertical current density	$\overline{J_z} \propto \frac{1}{N} \sum \left(\frac{\partial B_y}{\partial x} - \frac{\partial B_x}{\partial y}\right)$
TOTFX	Sum of x-component of Lorentz force	$F_x \propto -\sum B_x B_z dA$
EPSY	Sum of y-component of normalized Lorentz force	$\delta F_y \propto \frac{-\sum B_y B_z}{\sum B^2}$
EPSX	Sum of x-component of normalized Lorentz force	$\delta F_x \propto \frac{\sum B_x B_z}{\sum B^2}$

Bobra & Couvidat (2014)

SOLAR WIND CLASSIFICATION



Camporeale, Carè & Borovsky (2017)

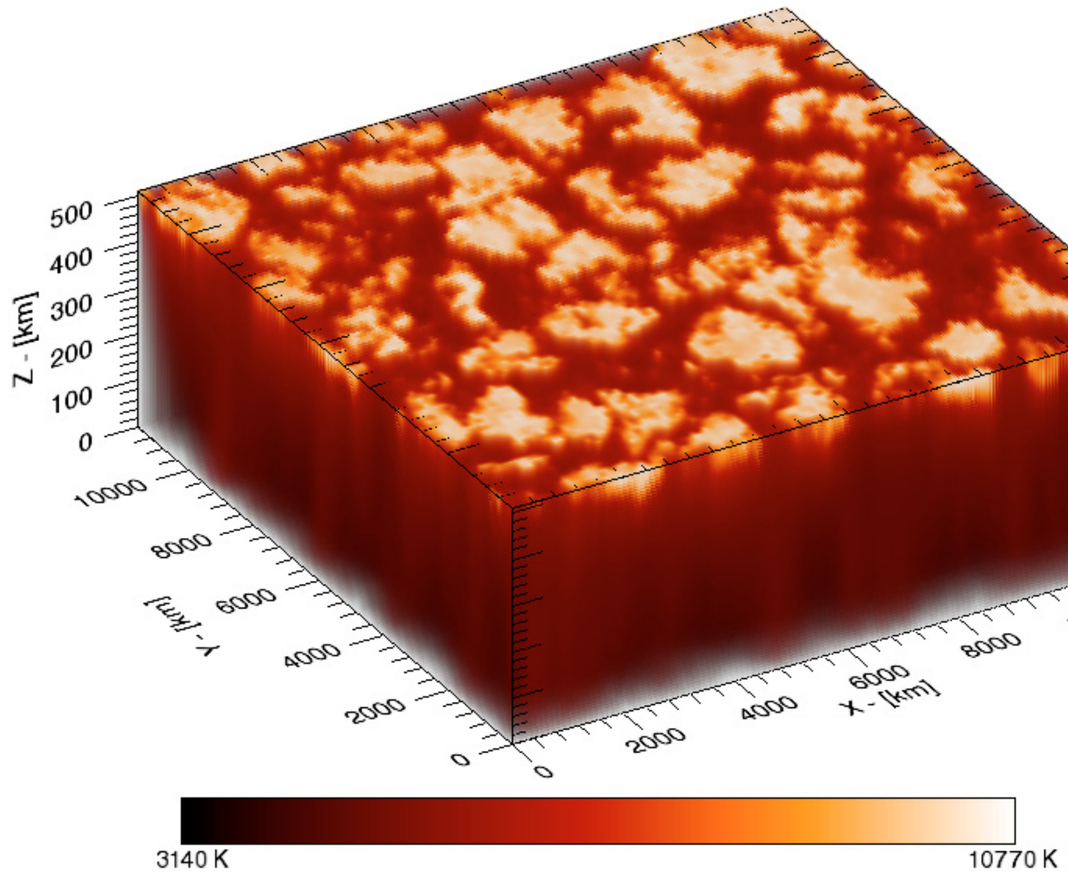
- ejecta
- coronal hole
- streamer belt
- sector reversal

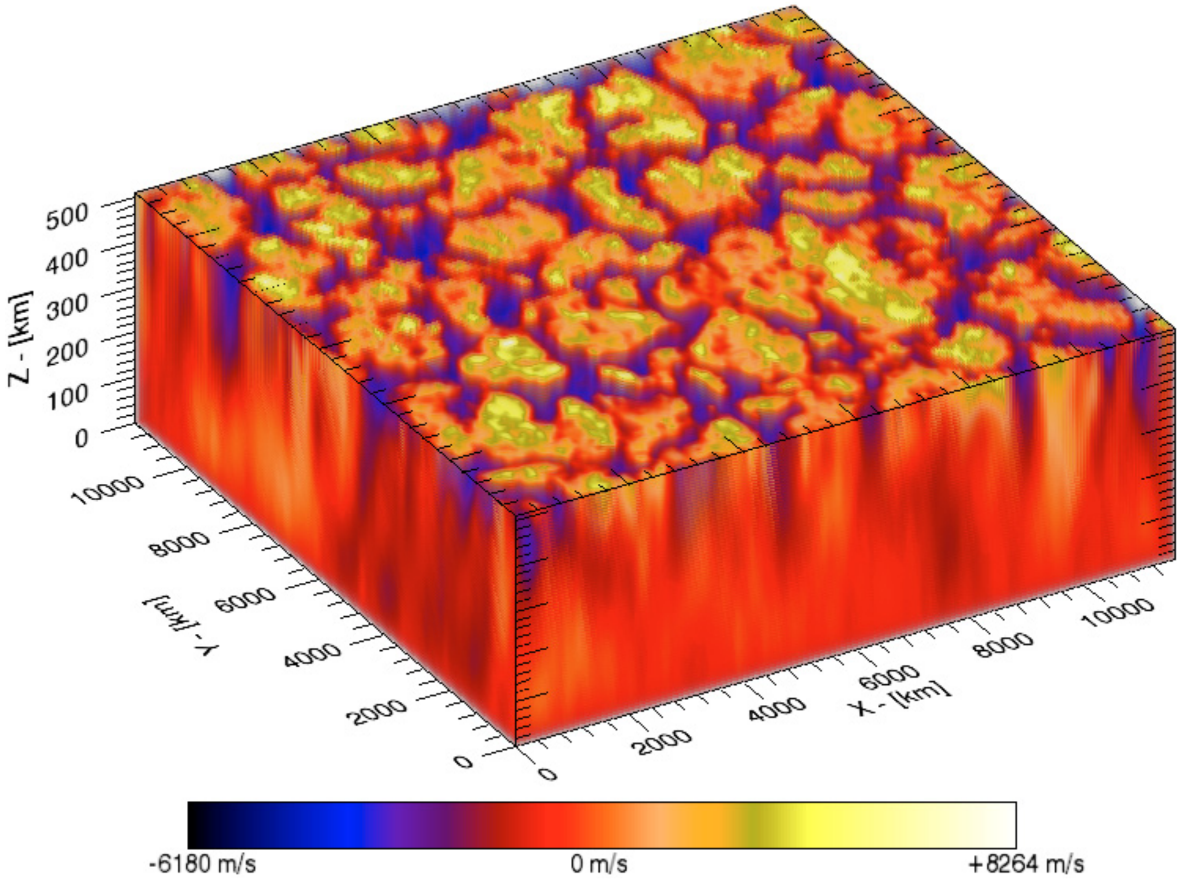
SOLAR WIND CLASSIFICATION

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

	Observed category			
Prediction	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

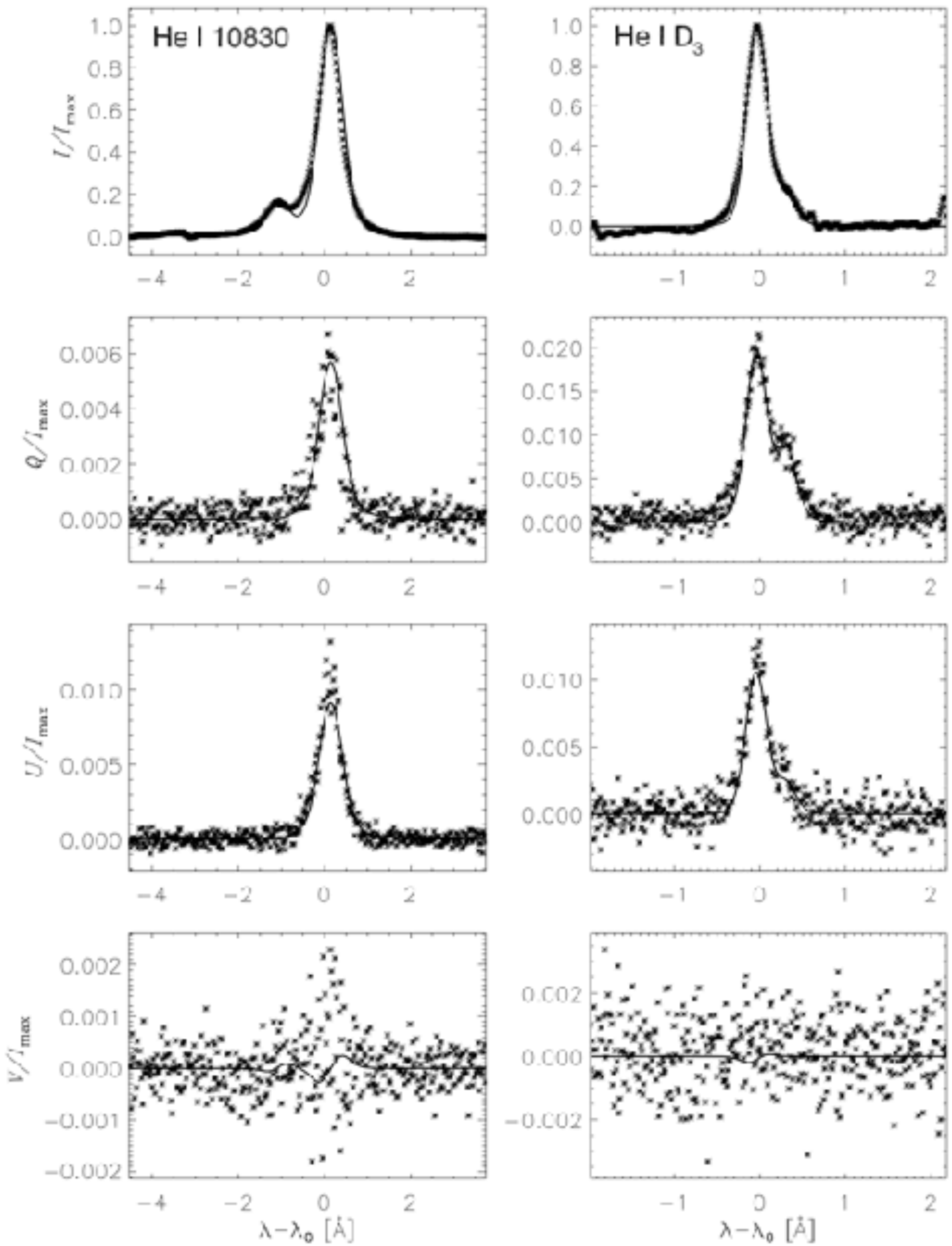
PHOTOSPHERIC SPECTROPOL INVERSIONS





Carroll & Kopf (2007)

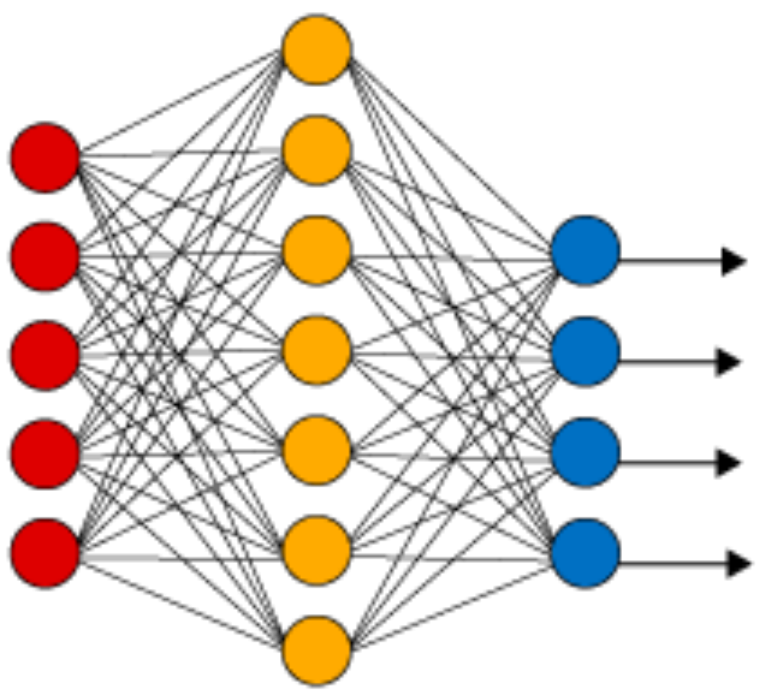
CHROMOSPHERIC SPECTROPOL INVERSIONS



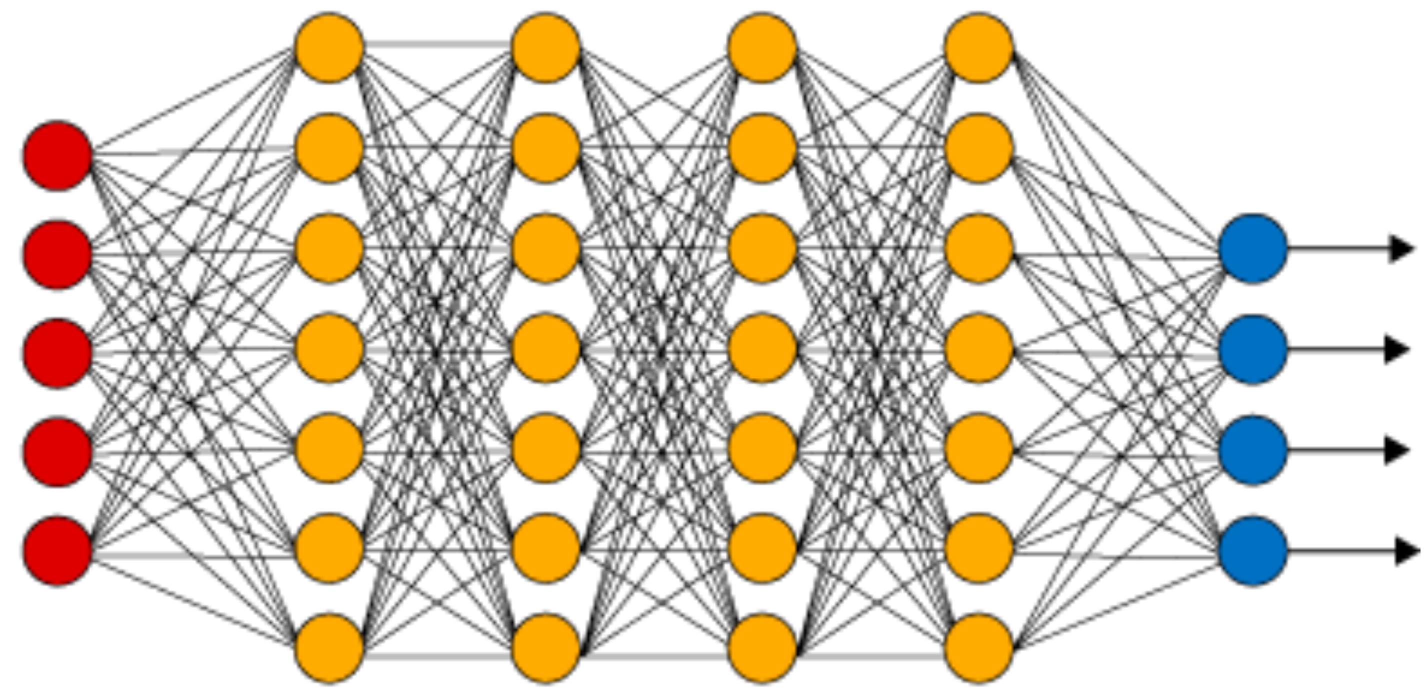
Casini et al. (2009)

deep learning

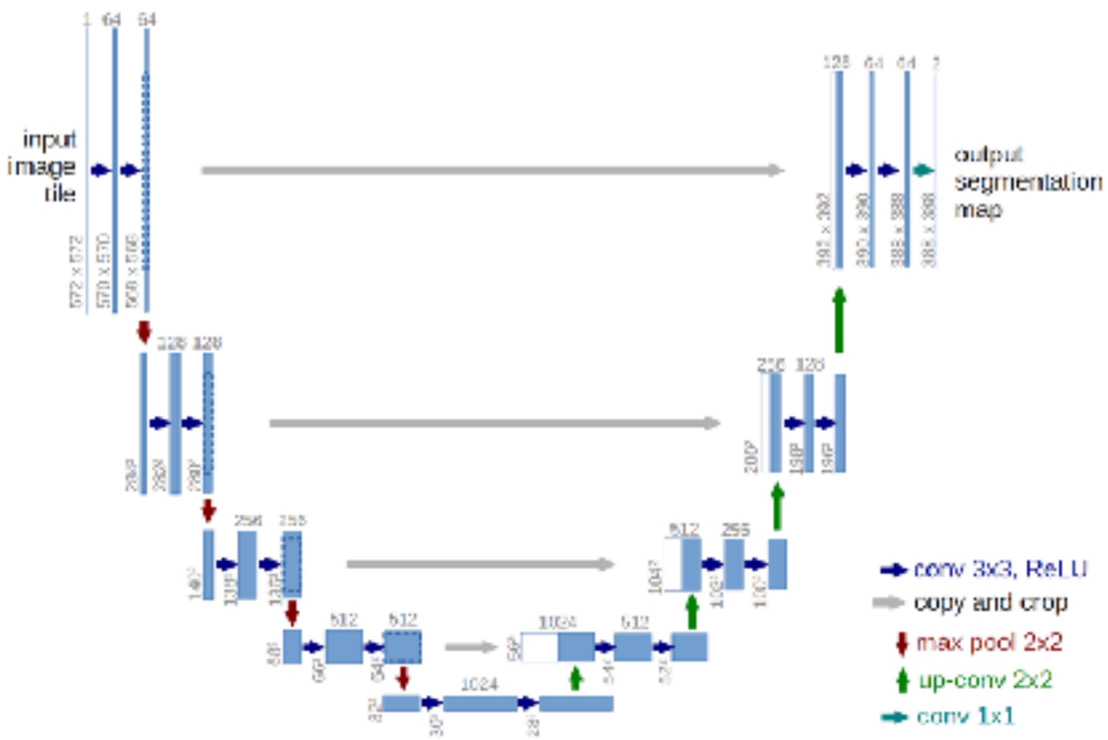
Simple Neural Network

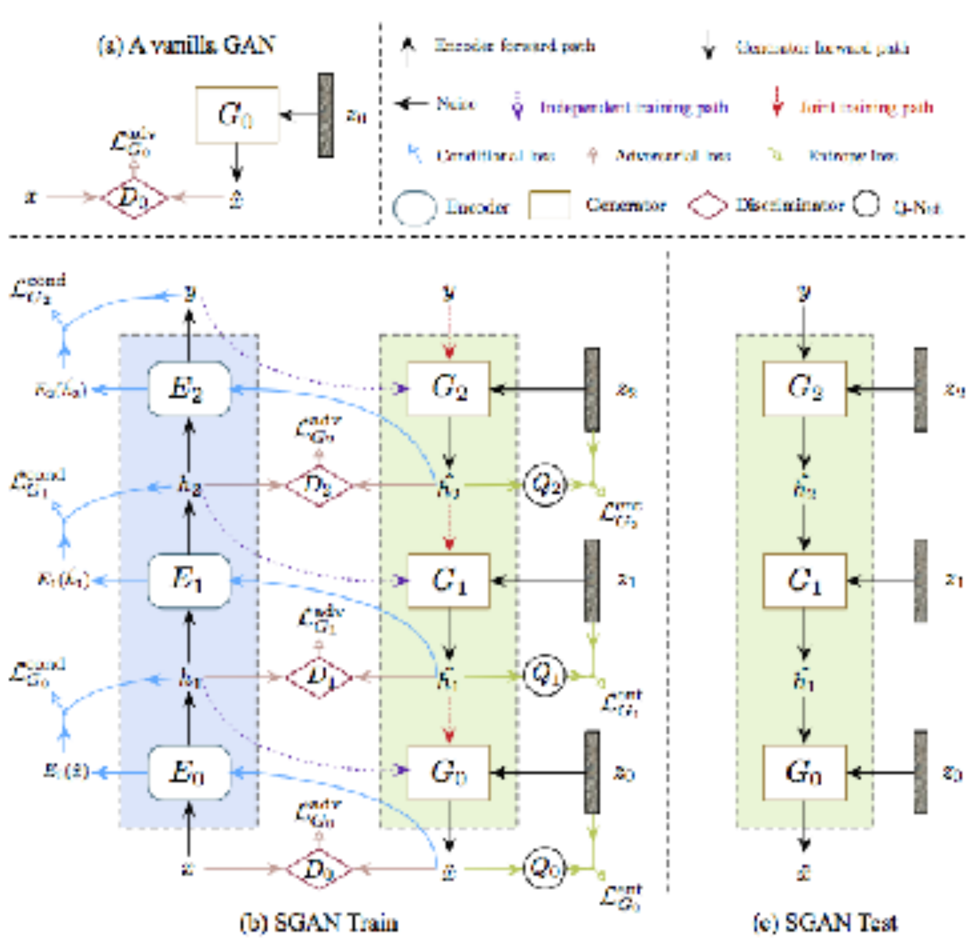


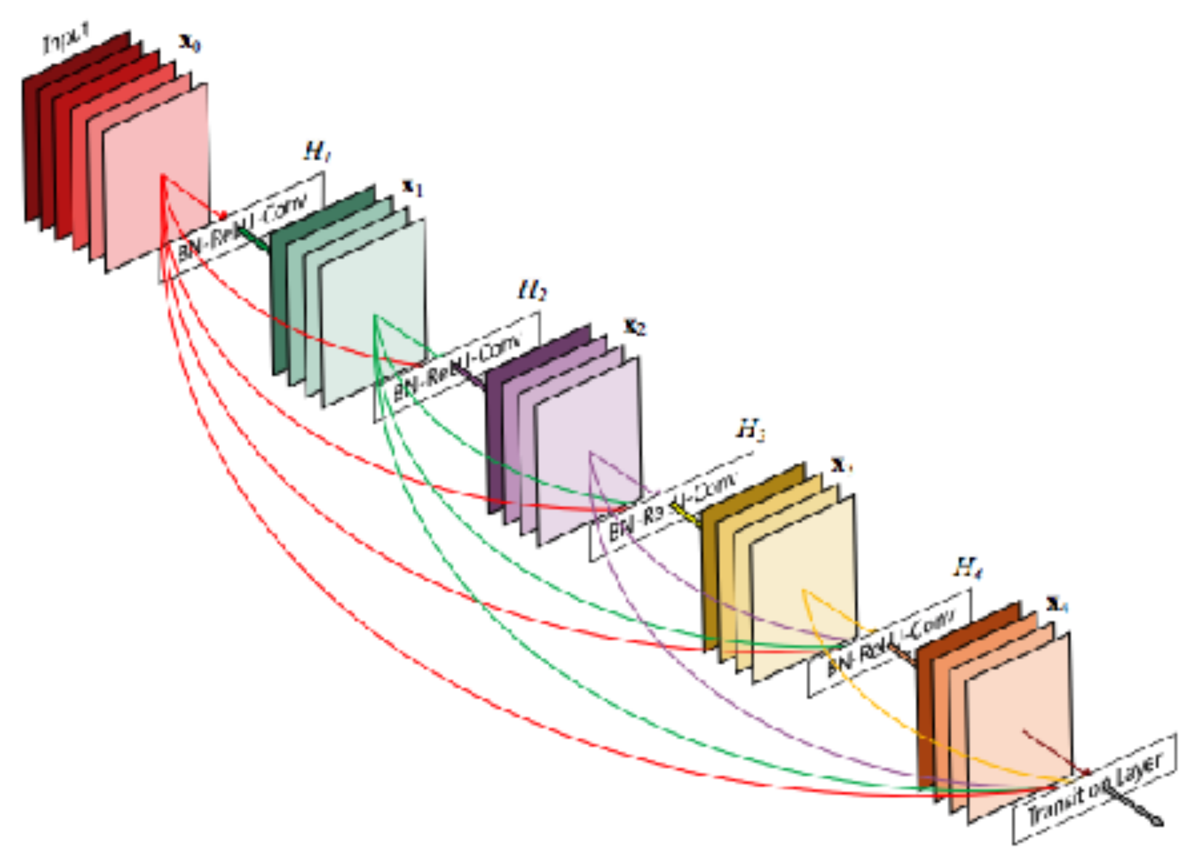
Deep Learning Neural Network

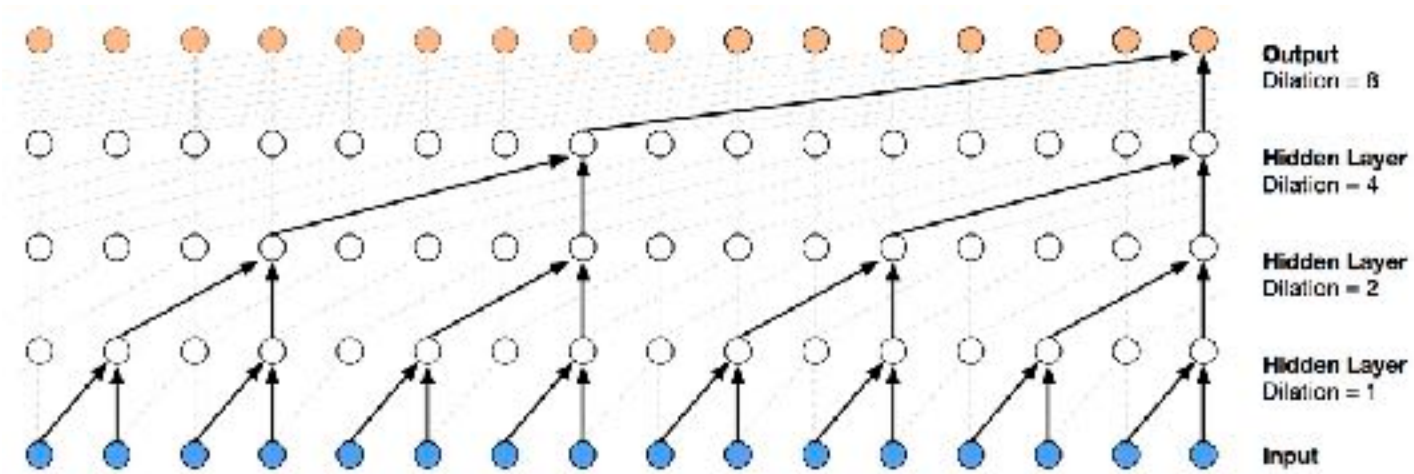


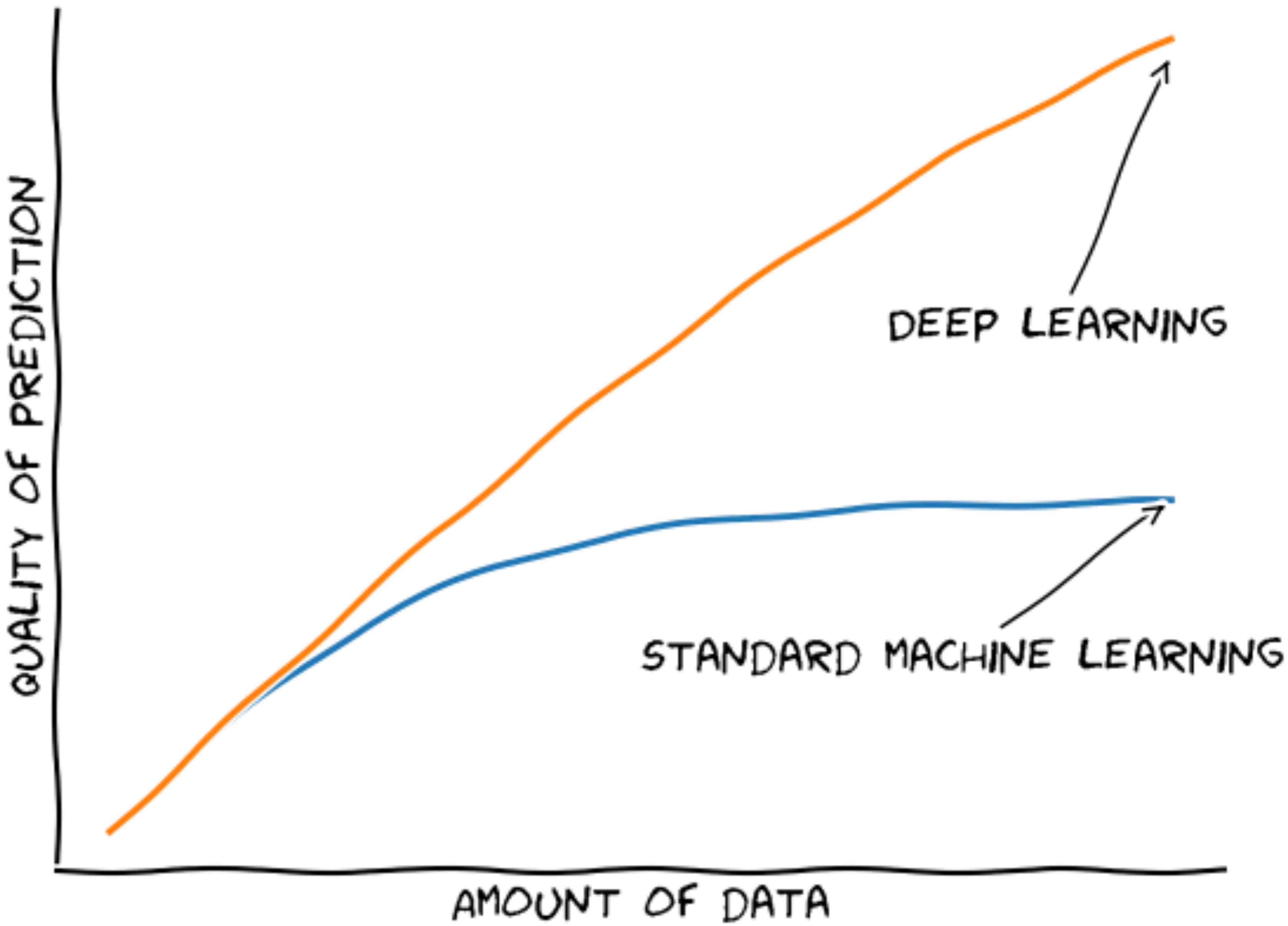
ENORMOUS LANDSCAPE



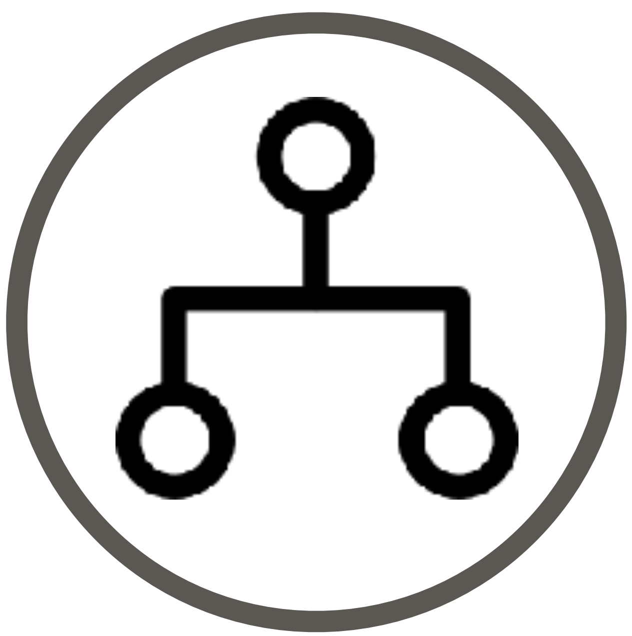




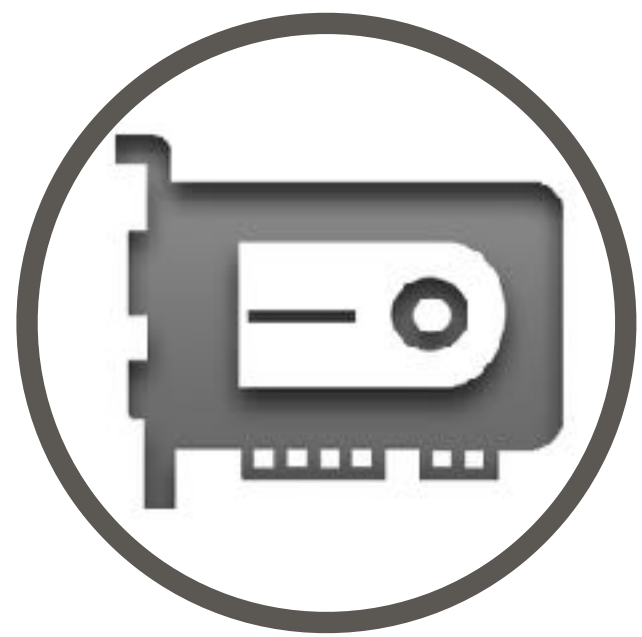



QUALITY OF PREDICTION
DEEP LEARNING
STANDARD MACHINE LEARNING
AMOUNT OF DATA

Algorithms

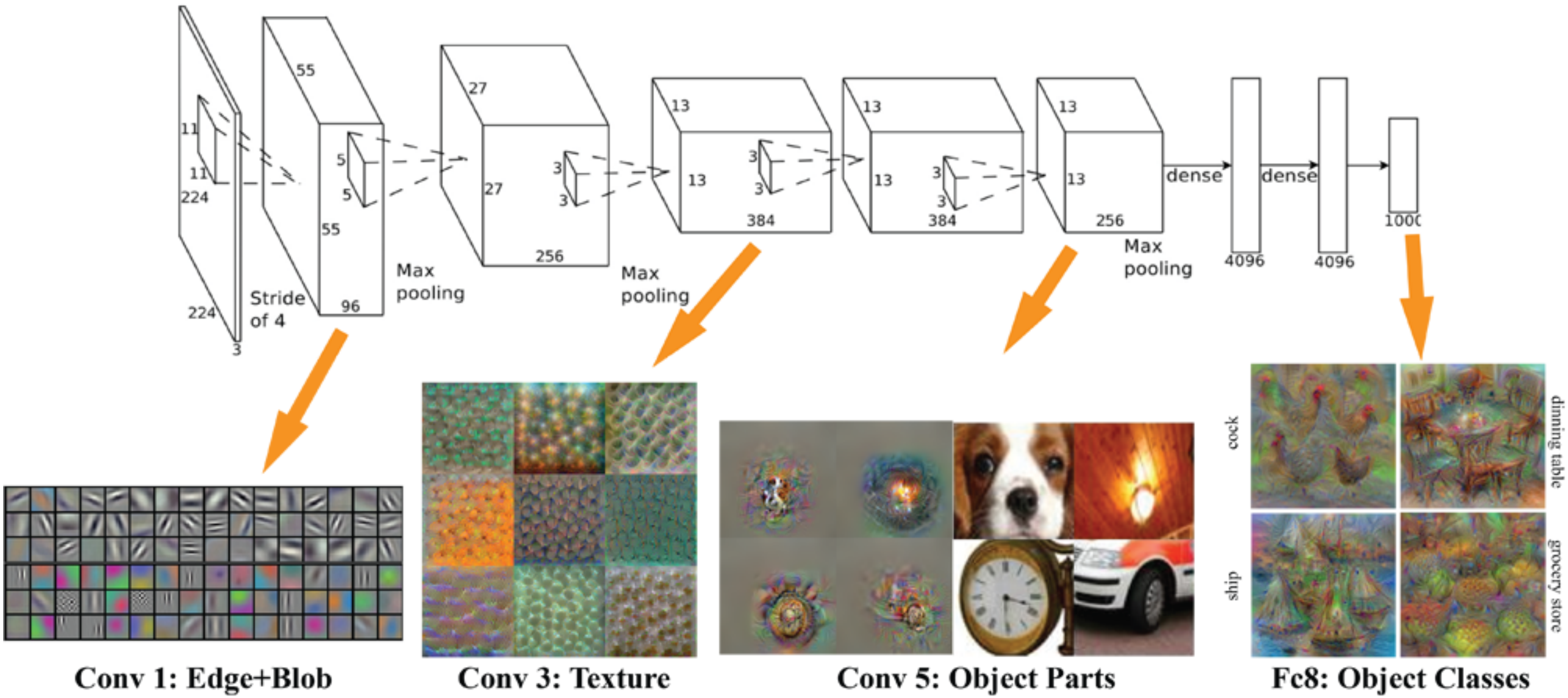


Hardware

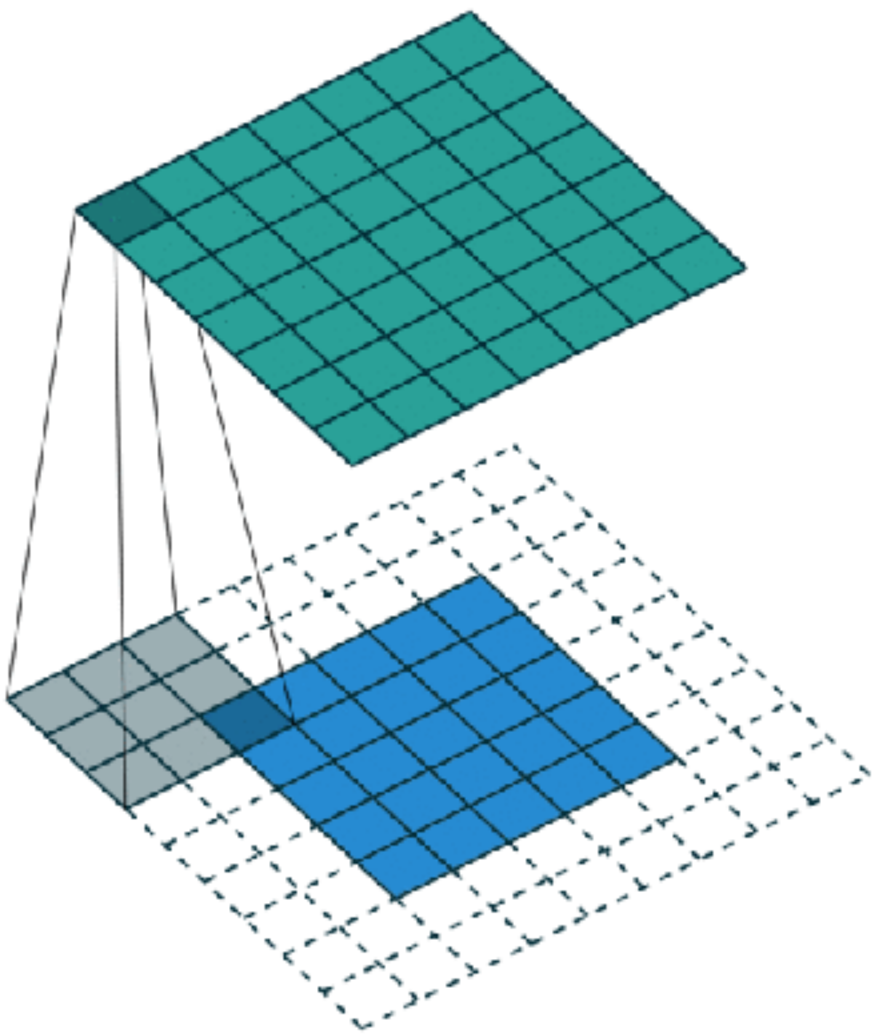


Data

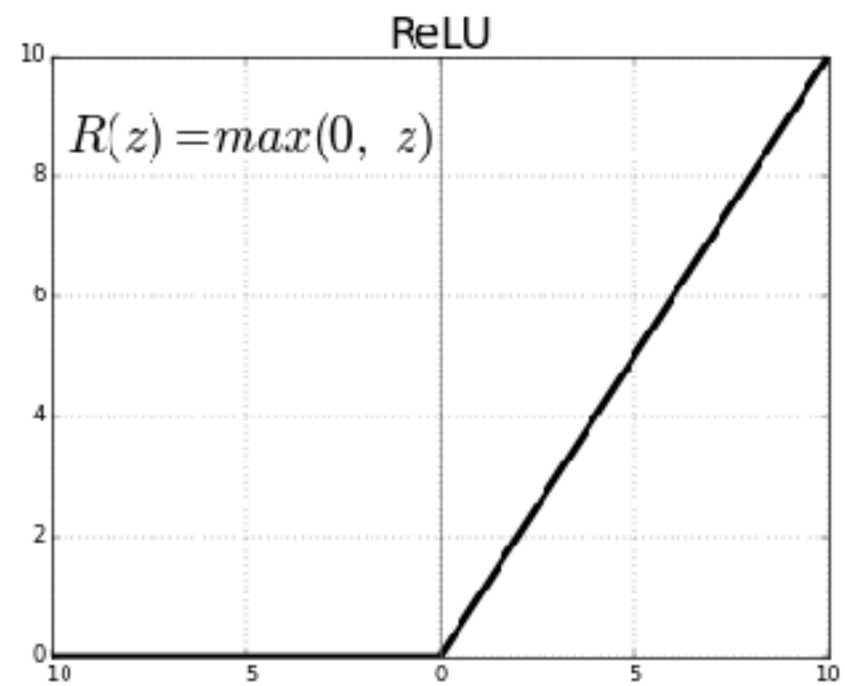
MULTISCALE ANALYSIS



BASIC INGREDIENTS



Convolution



Activation

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

Loss

TRAINING

Gradient descent

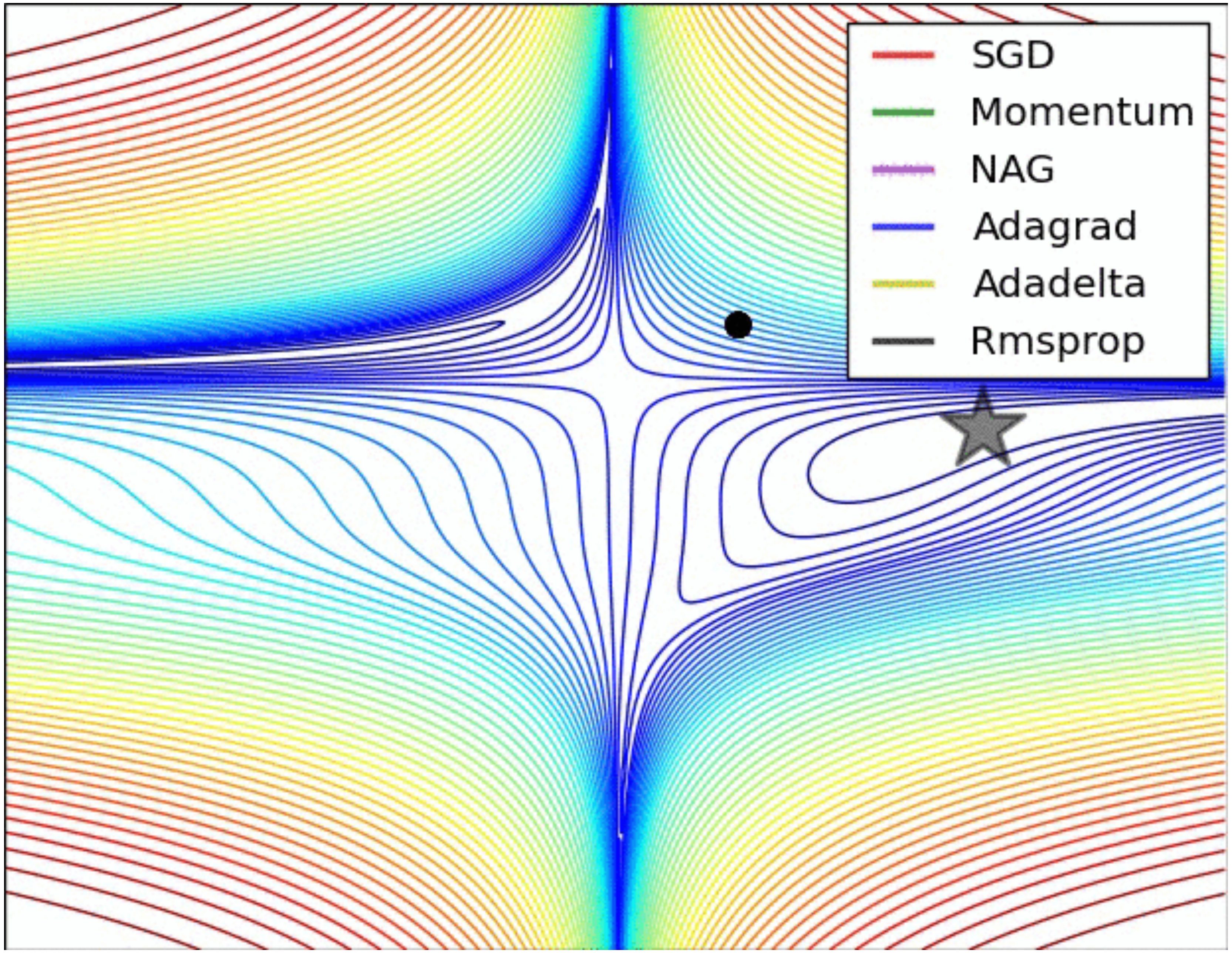
$$\theta_{i+1} = \theta_i - h\nabla_\theta f(\theta, \mathbf{T})$$

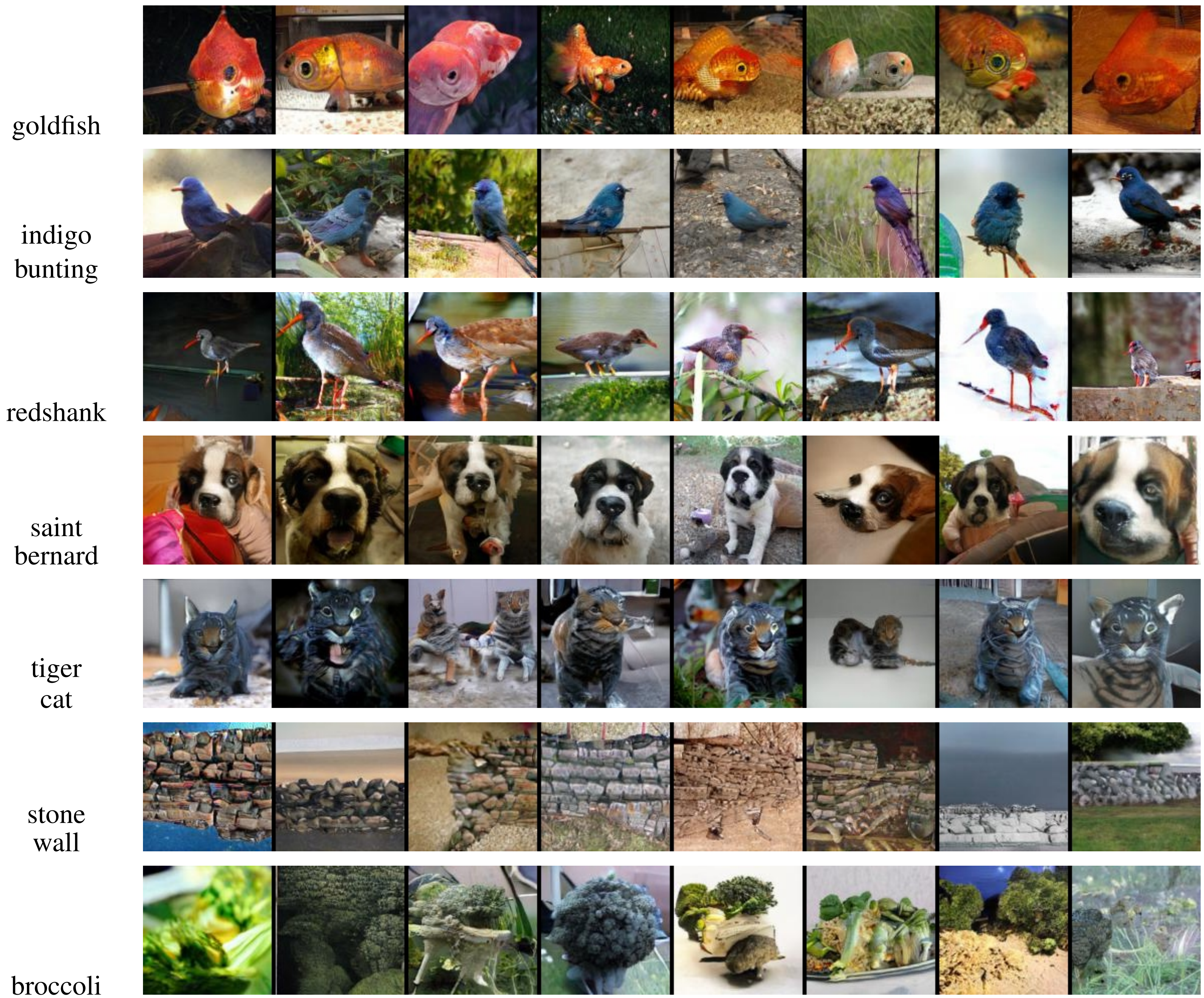
Stochastic gradient descent

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

TRAINING

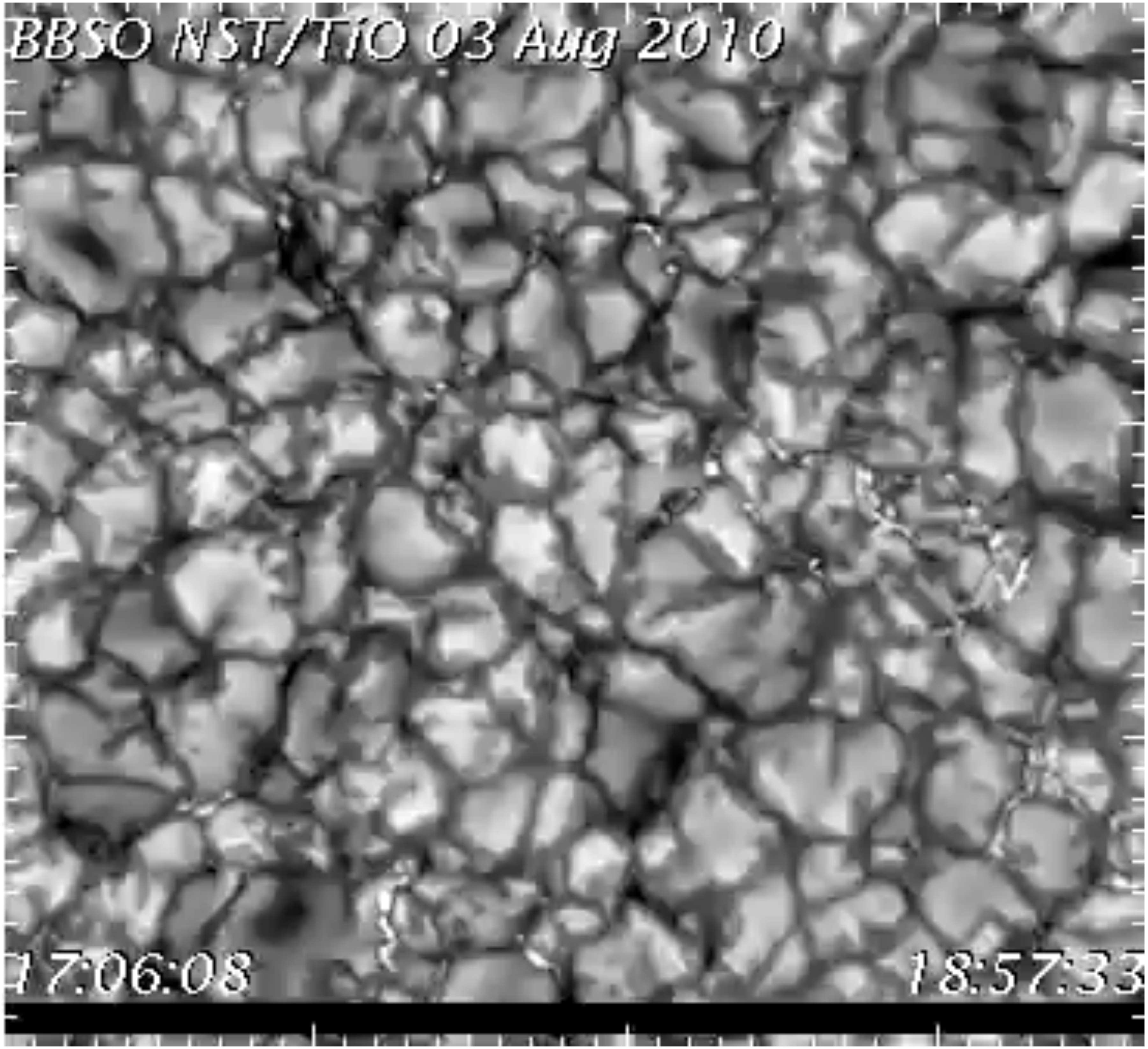
$$\theta_{i+1} = \theta_i - h\nabla_\theta f(\theta, \mathbf{T}_{\text{subset}})$$





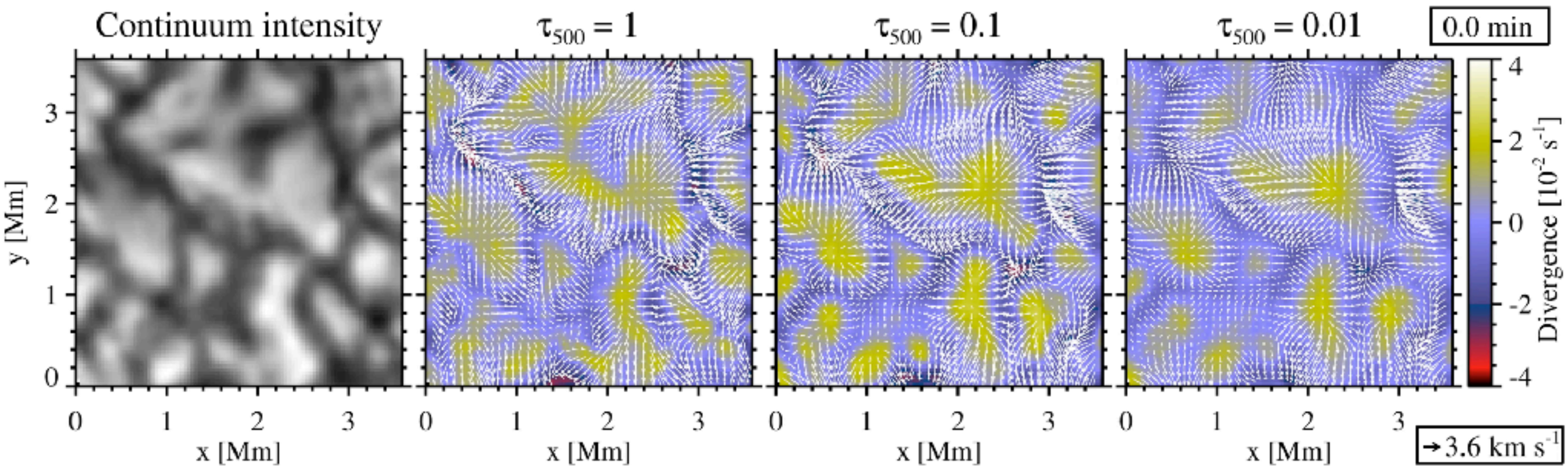
Zhang et al. (2018)

measuring velocities


BBSO NST/TiO 03 Aug 2010
17:06:08
18:57:33

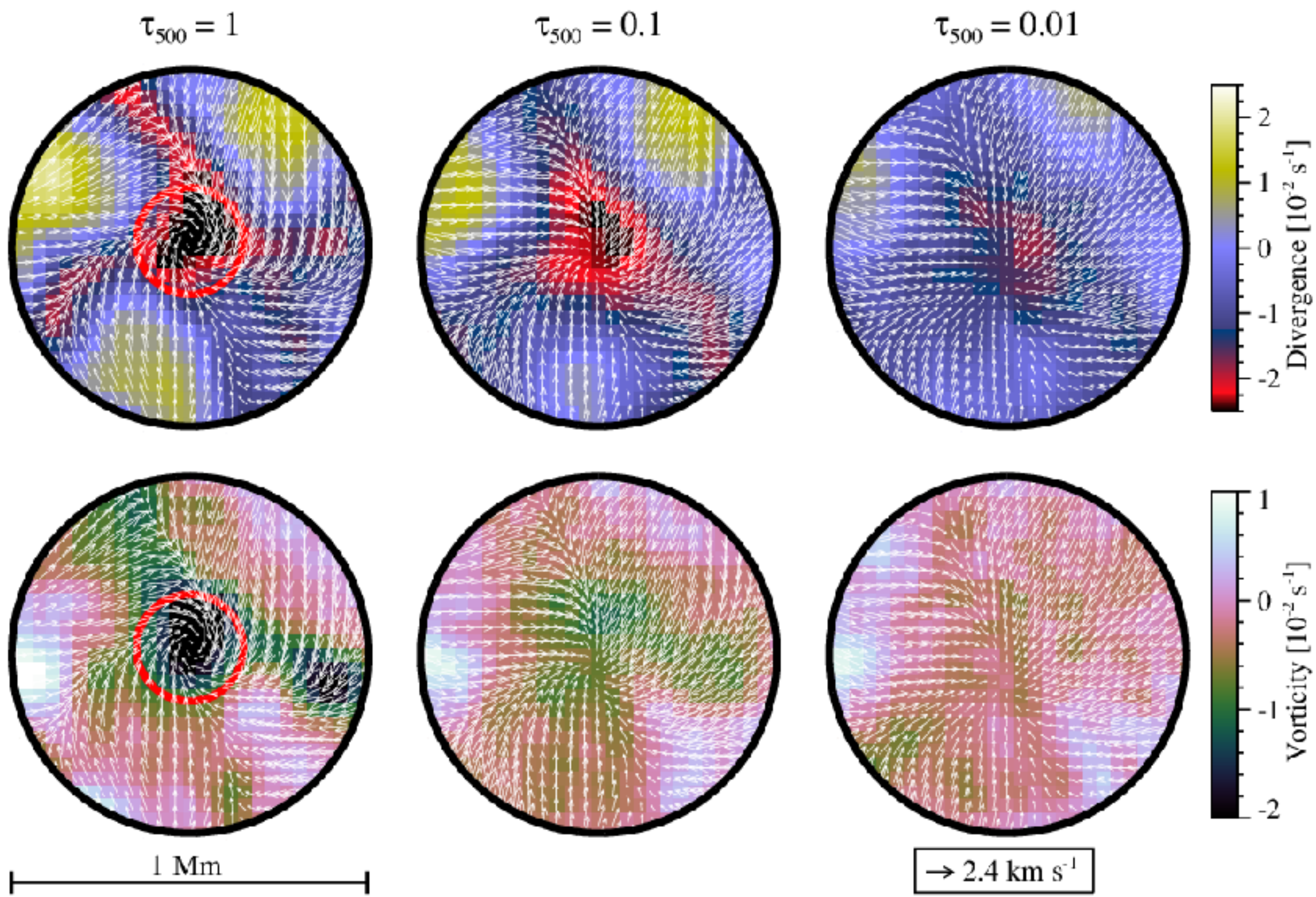
DEEPVEL

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

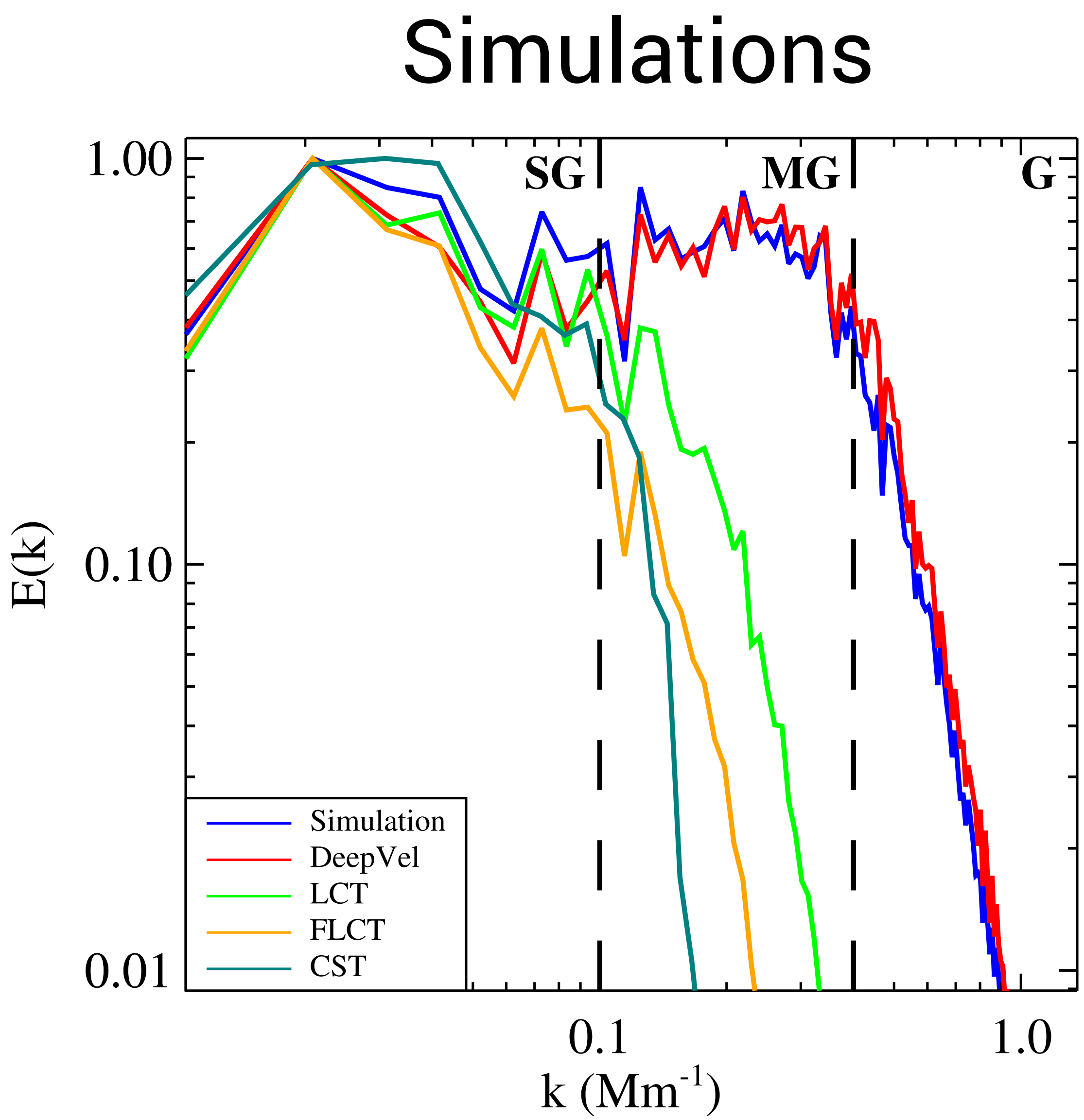


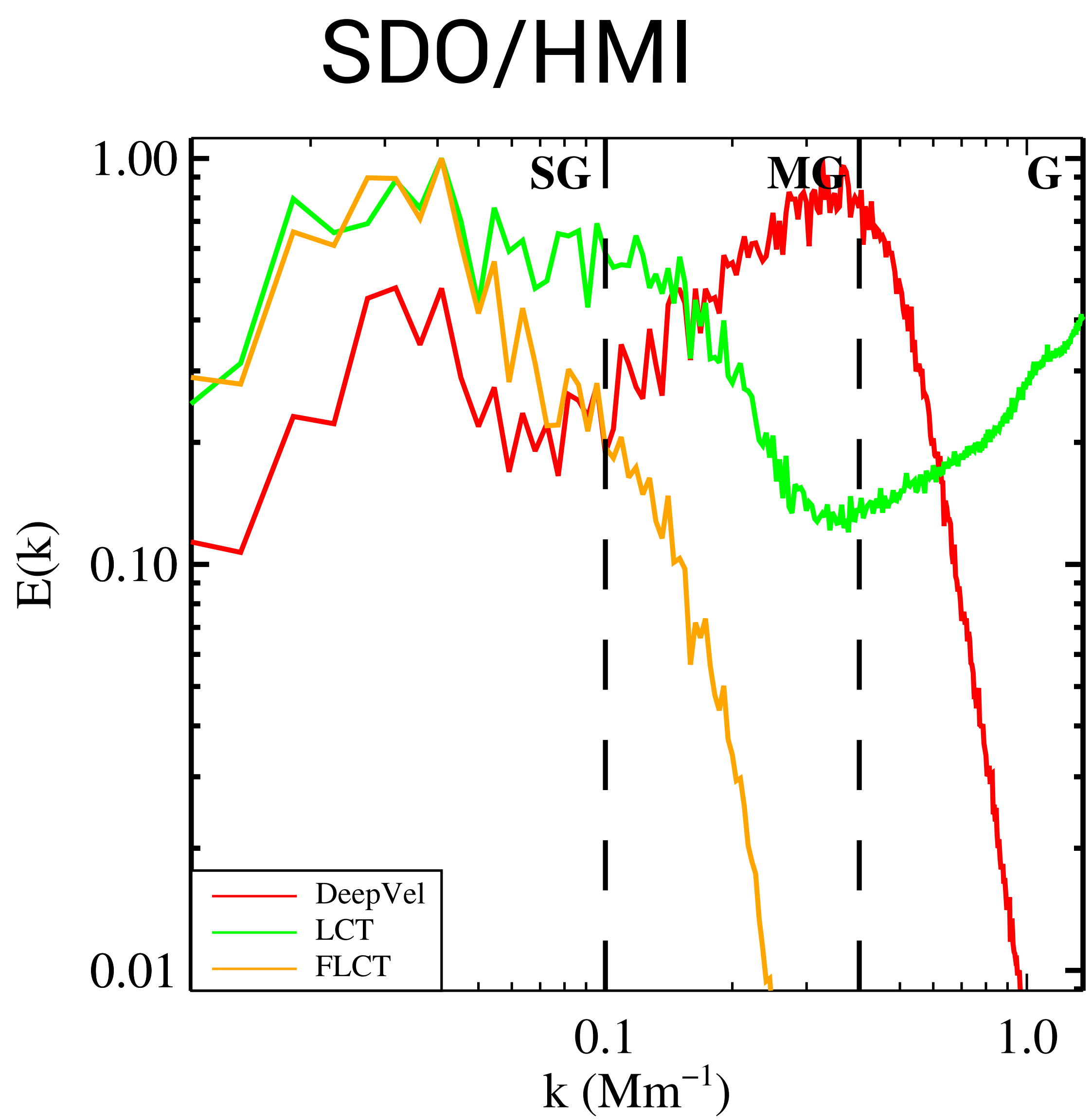
Asensio Ramos, Requerey & Vitas (2017)

SMALL SCALE VORTEX FLOWS



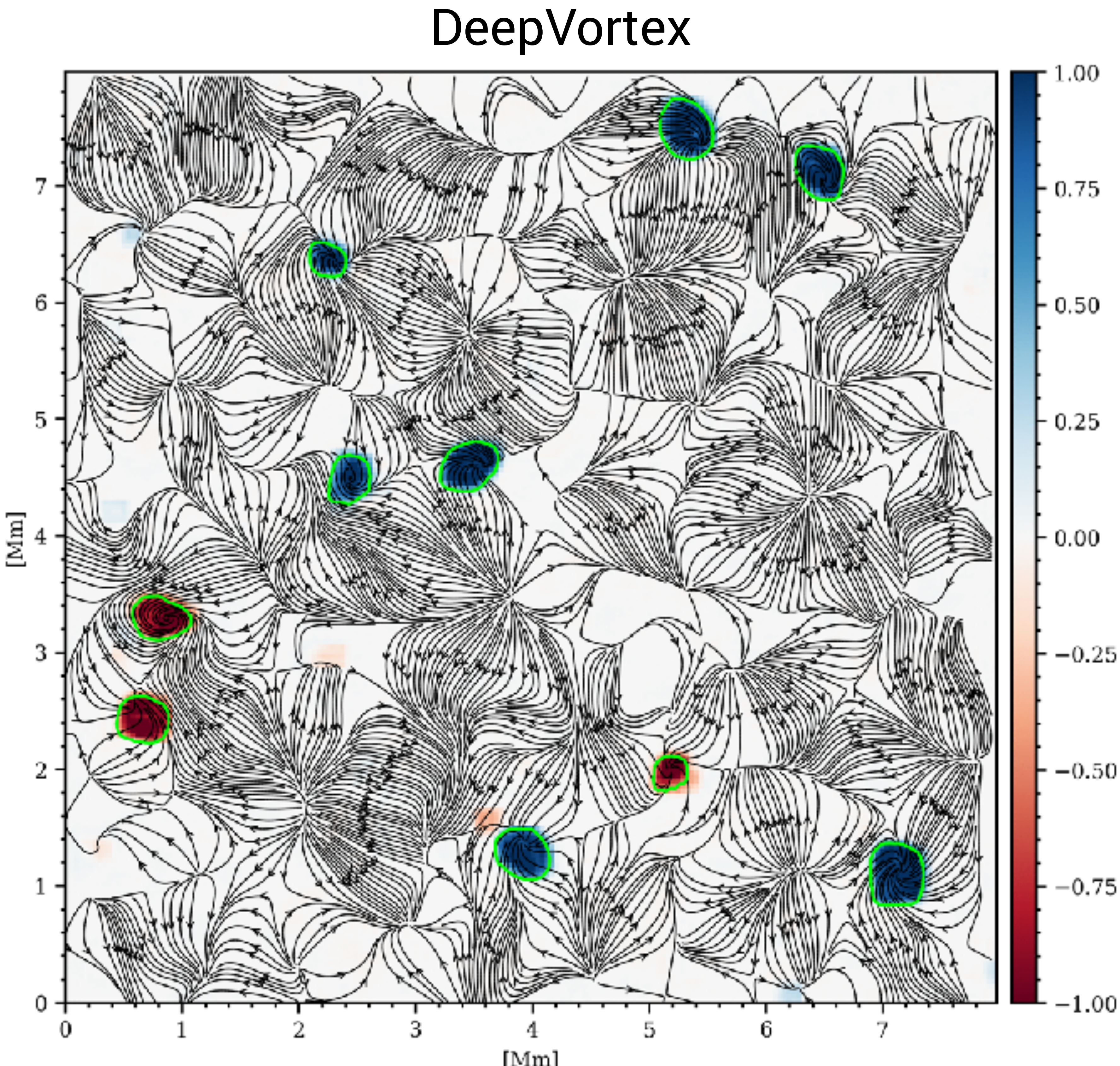
KINETIC ENERGY SPECTRUM





Tremblay et al. (2018)

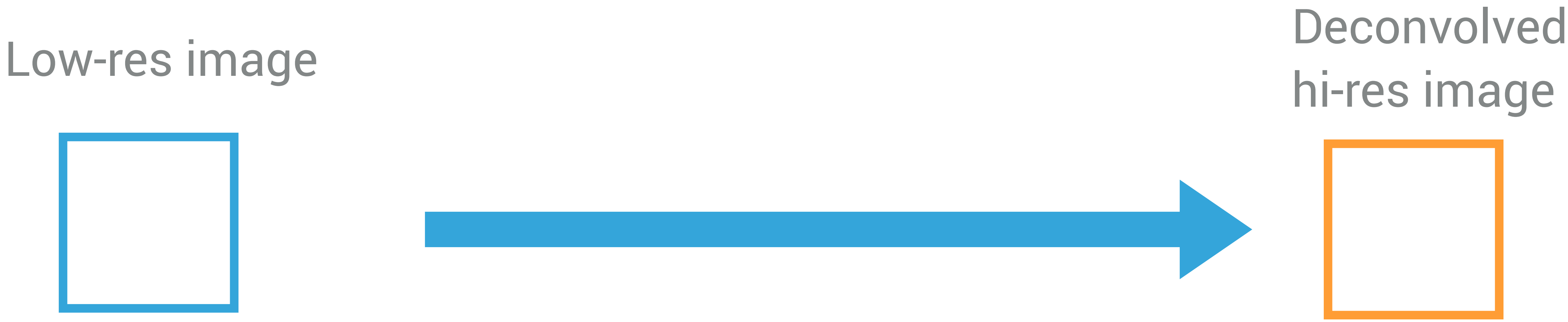
VORTEX DETECTION



Requerey et al. (in prep)

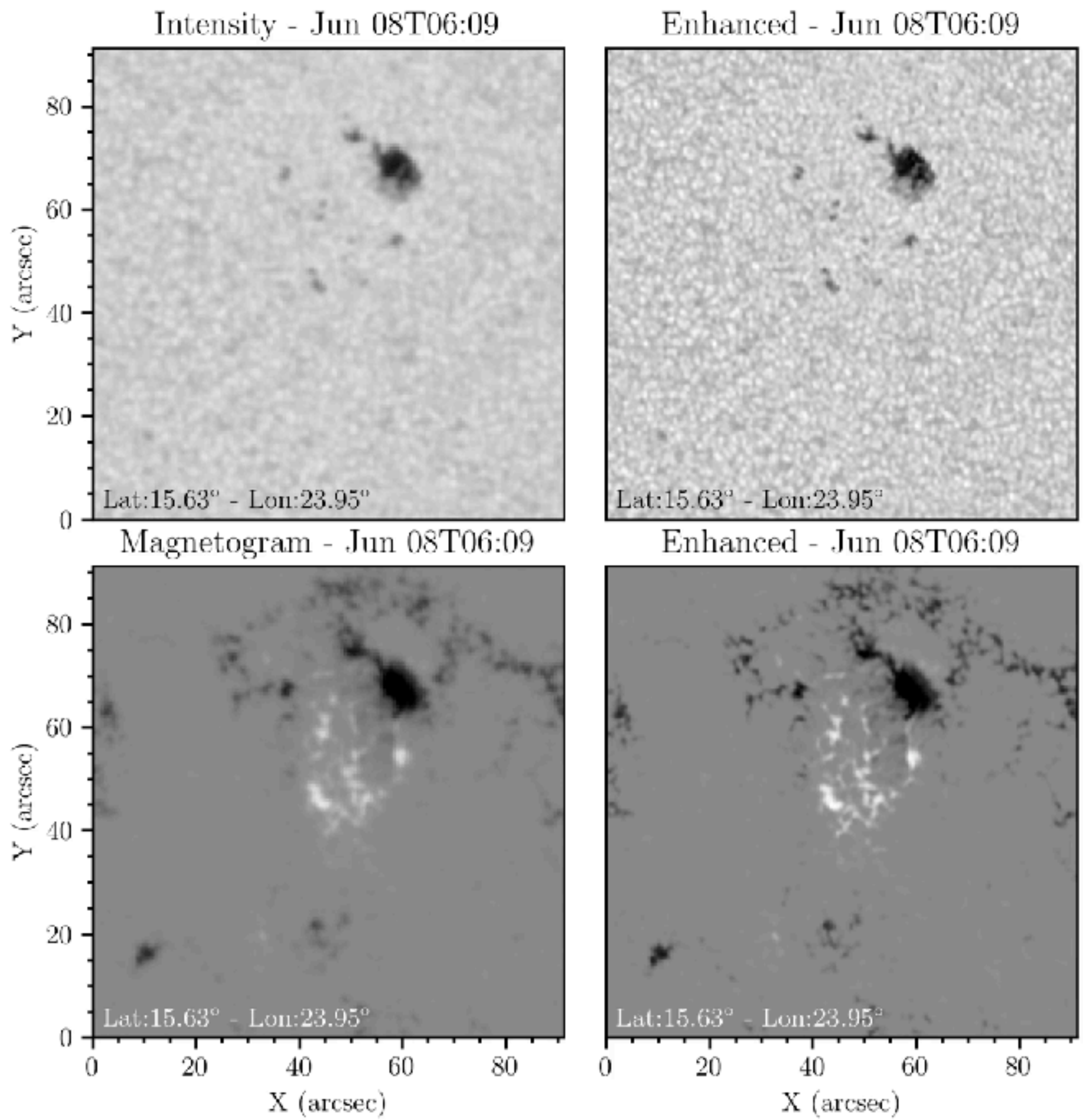
enhancing HMI images

ENHANCE: SINGLE IMAGE SUPERRESOLUTION



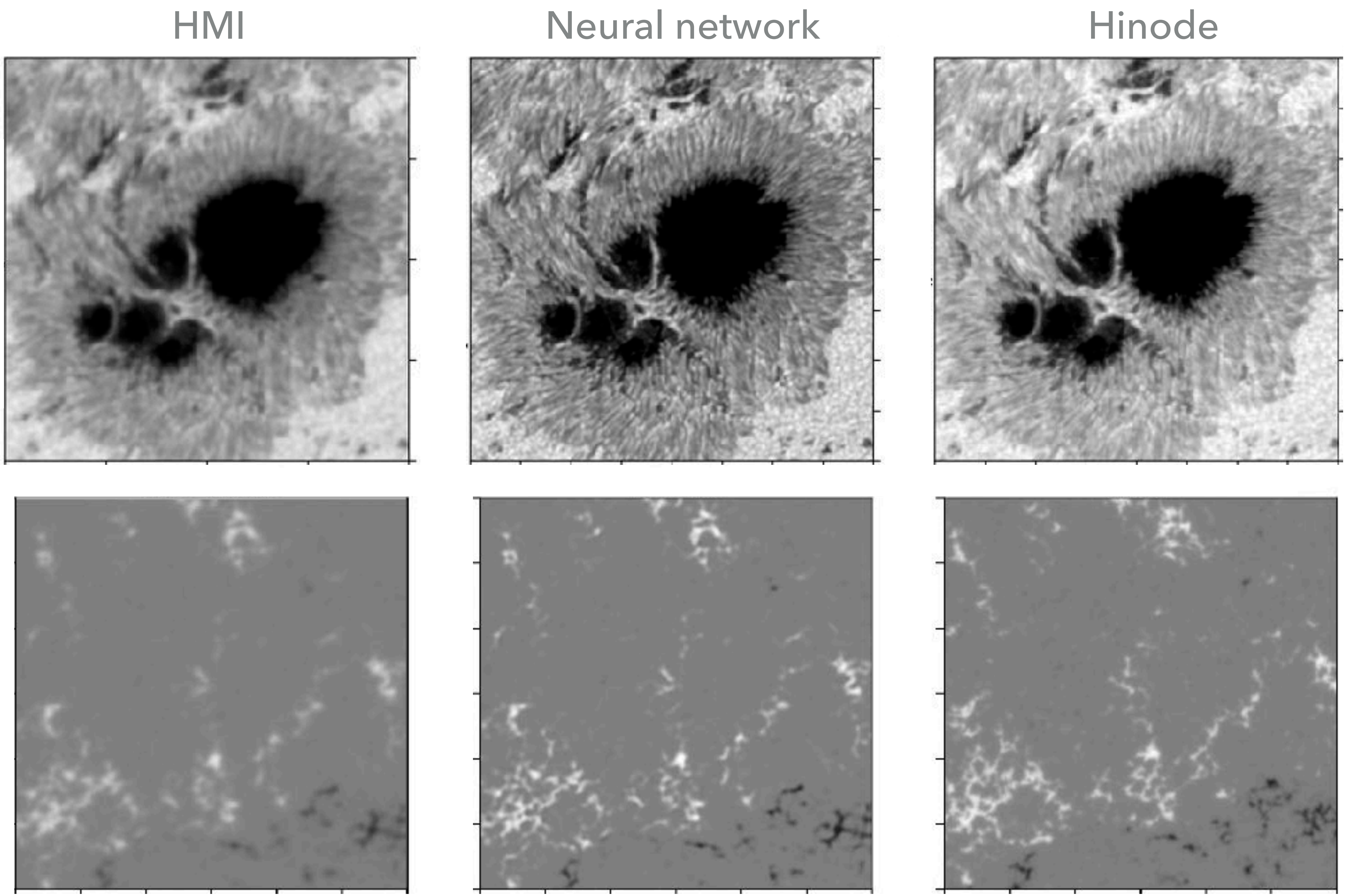
- Trained on simulations (courtesy of M. Cheung)
- End-to-end deep neural network
- Continuum + magnetograms
- https://github.com/cdiazbas/enhance

ENHANCE



courtesy of S. Castellanos Durán

ENHANCE



real-time multiframe deconvolution

MULTIFRAME BLIND DECONVOLUTION

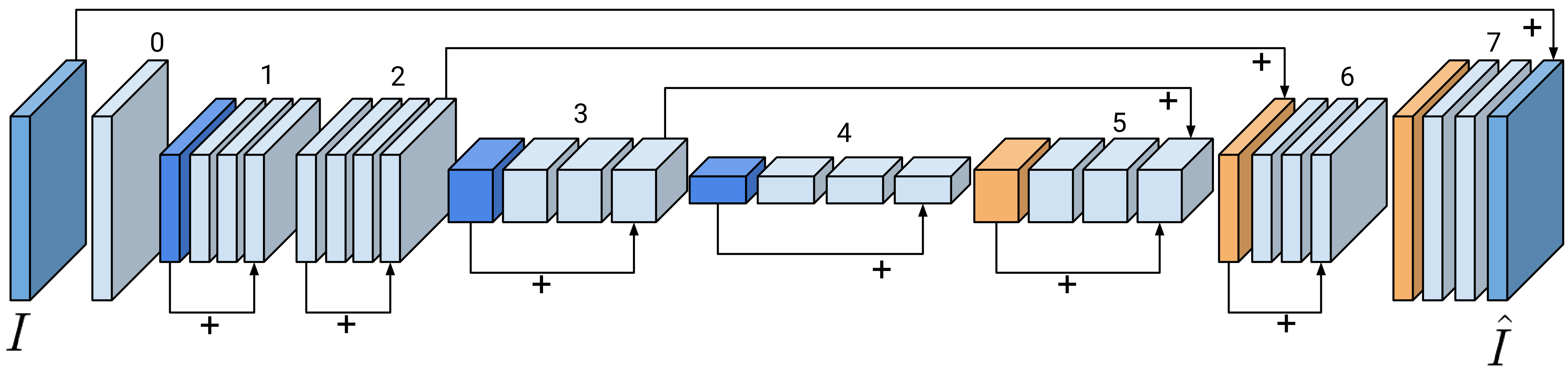
Short-exposure burst

Deconvolved image

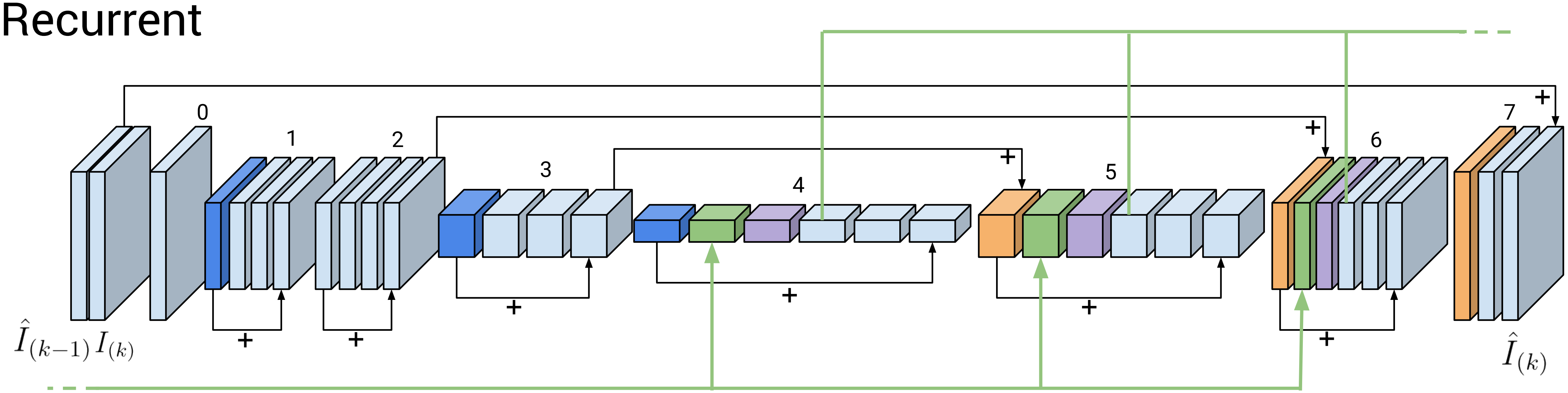
- Trained on CRISP@SST Fe I 630 nm and Ca II 854 nm deconvolved data
- End-to-end deep neural network
- Asensio Ramos et al. (submitted)
- Deconvolves 1k x 1k images at ~100 Hz
- https://github.com/aasensio/learned_mfbd

ARCHITECTURES

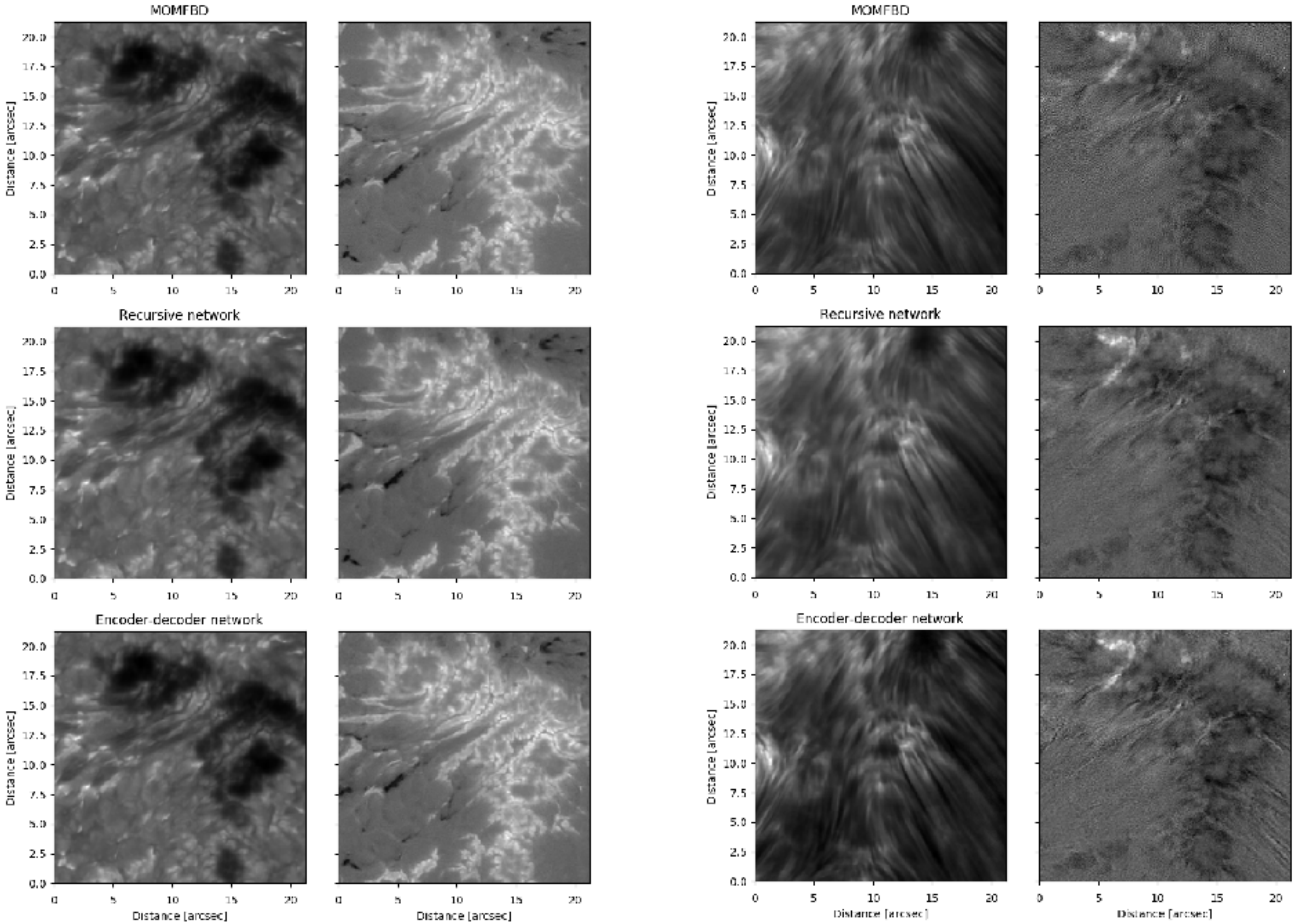
Encoder-decoder



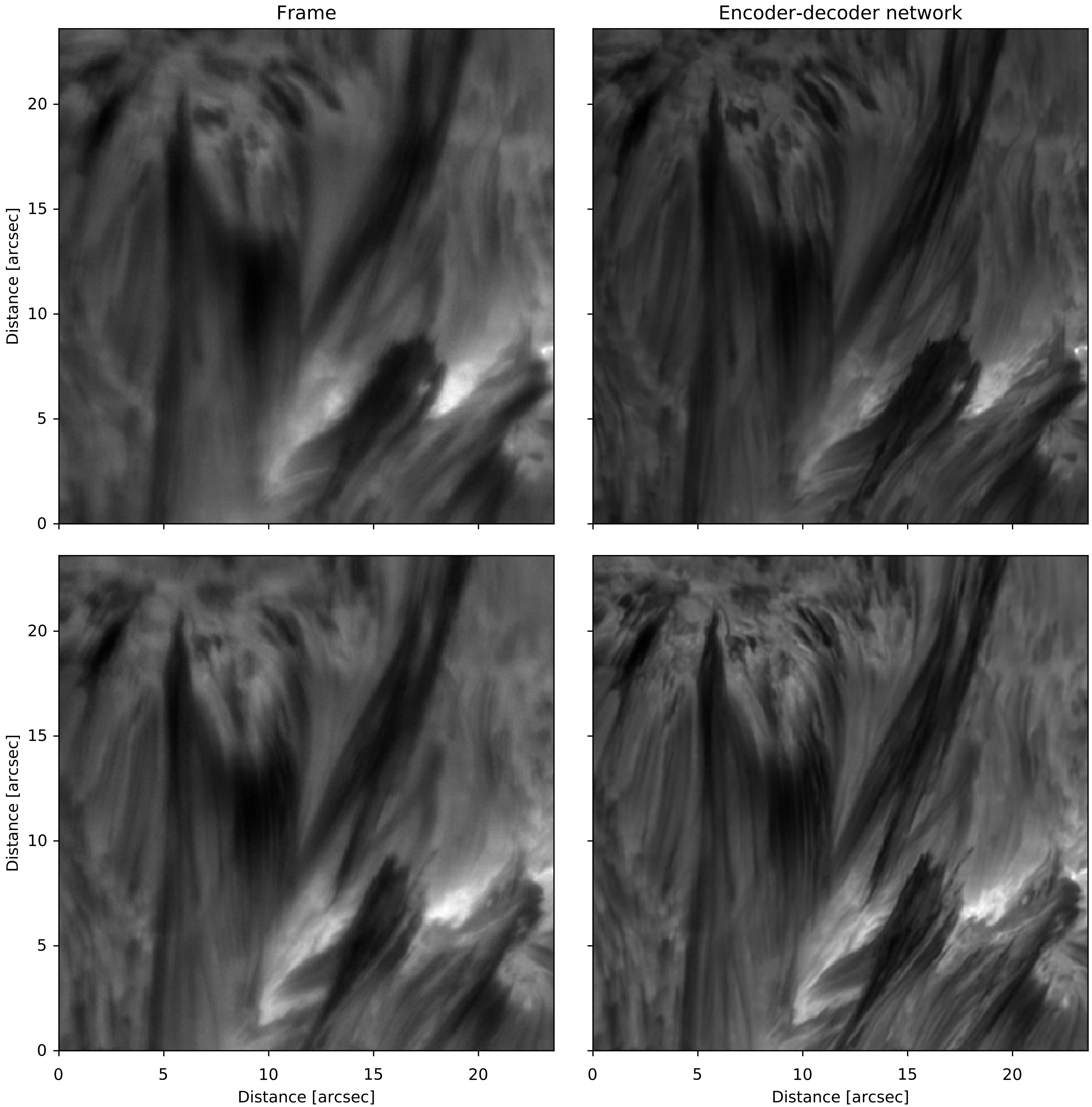
Recurrent



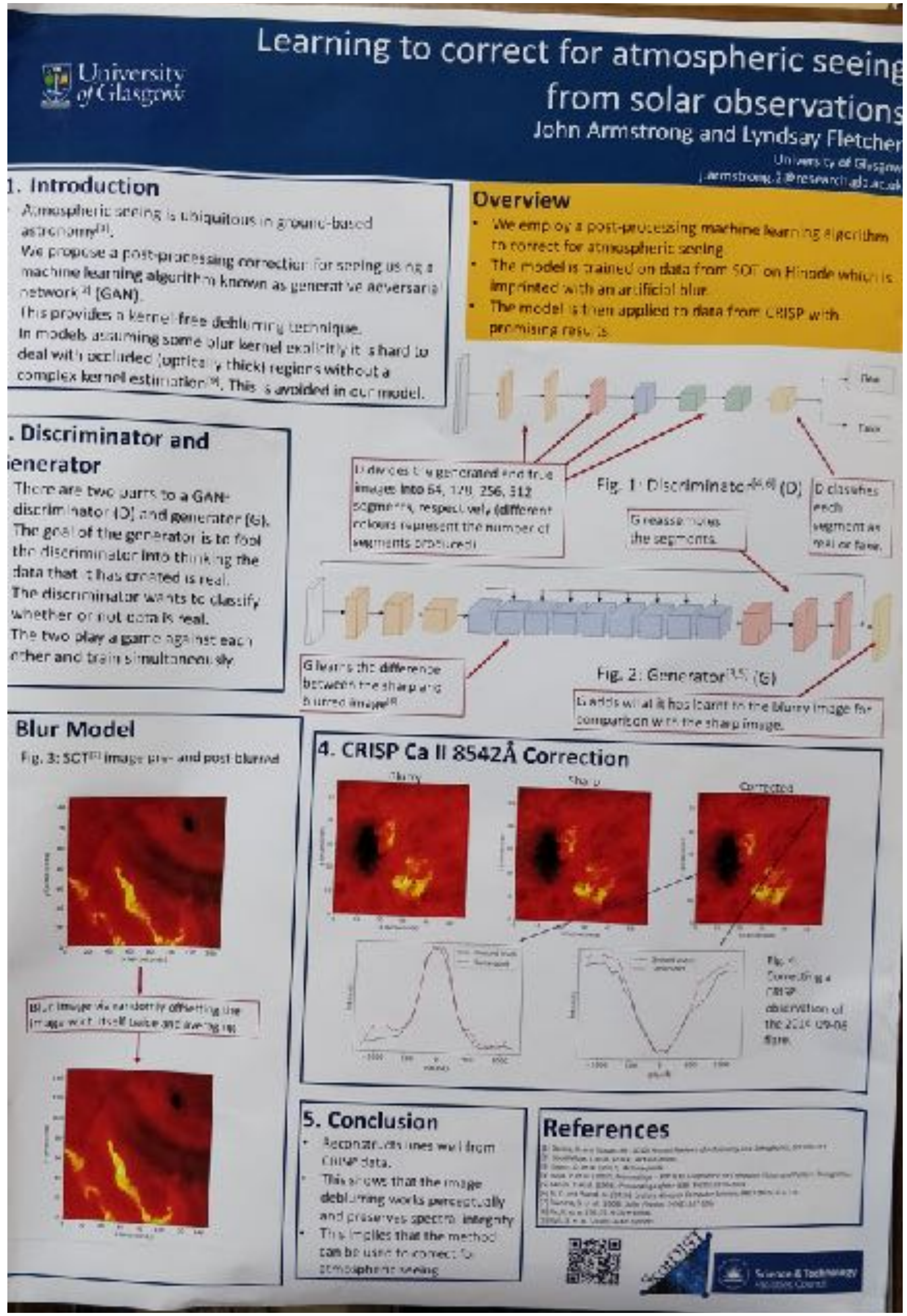
POLARIMETRY



GENERALIZATION

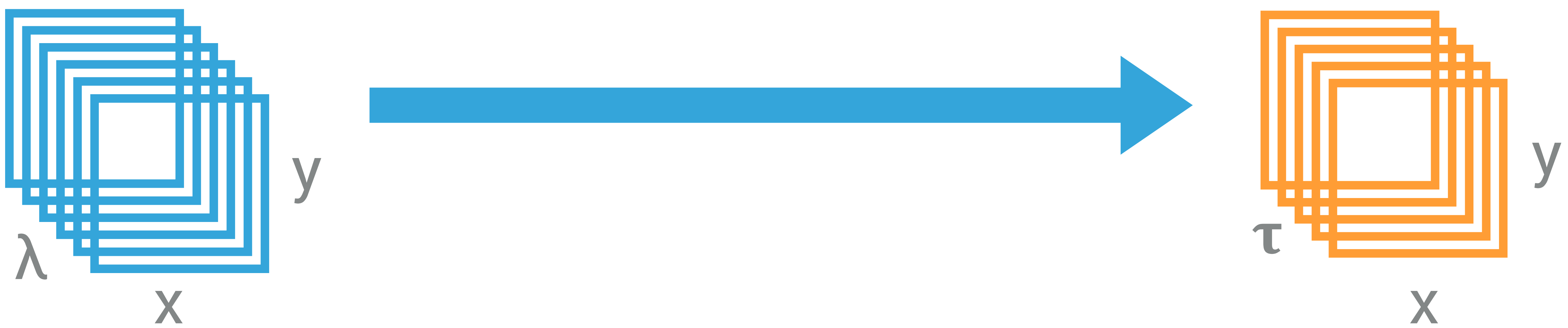


SEE ALSO…


University of Glasgow
Learning to correct for atmospheric seeing from solar observations
John Armstrong and Lyndsay Fletcher
1. Introduction
Overview
. Discriminator and
enerator
Blur Model
4. CRISP Ca II 8542Å Correction
5. Conclusion
References

3D inversion of Stokes profiles

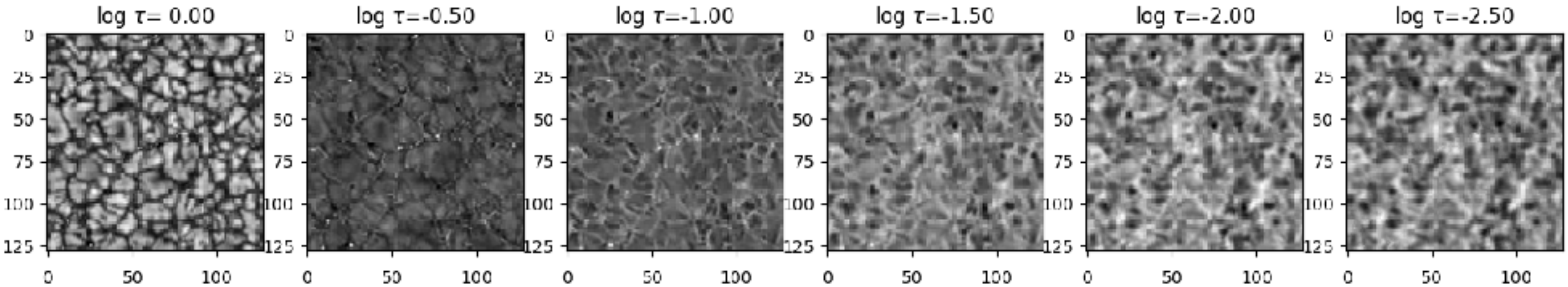
3D INVERSION OF STOKES PROFILES



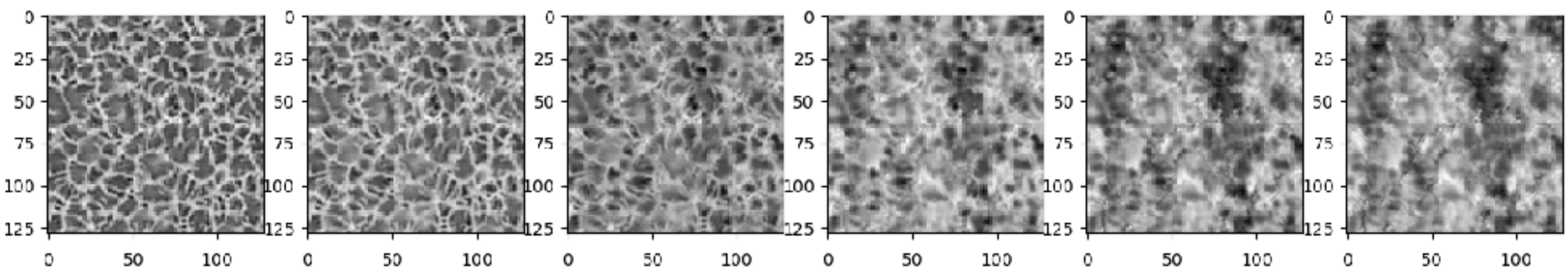
- Trained on 3D MHD magnetoconvection sims (still too few snapshots)
- End-to-end deep neural network
- Severe augmenting during training
- Still without polarimetry

HINODE INVERSION

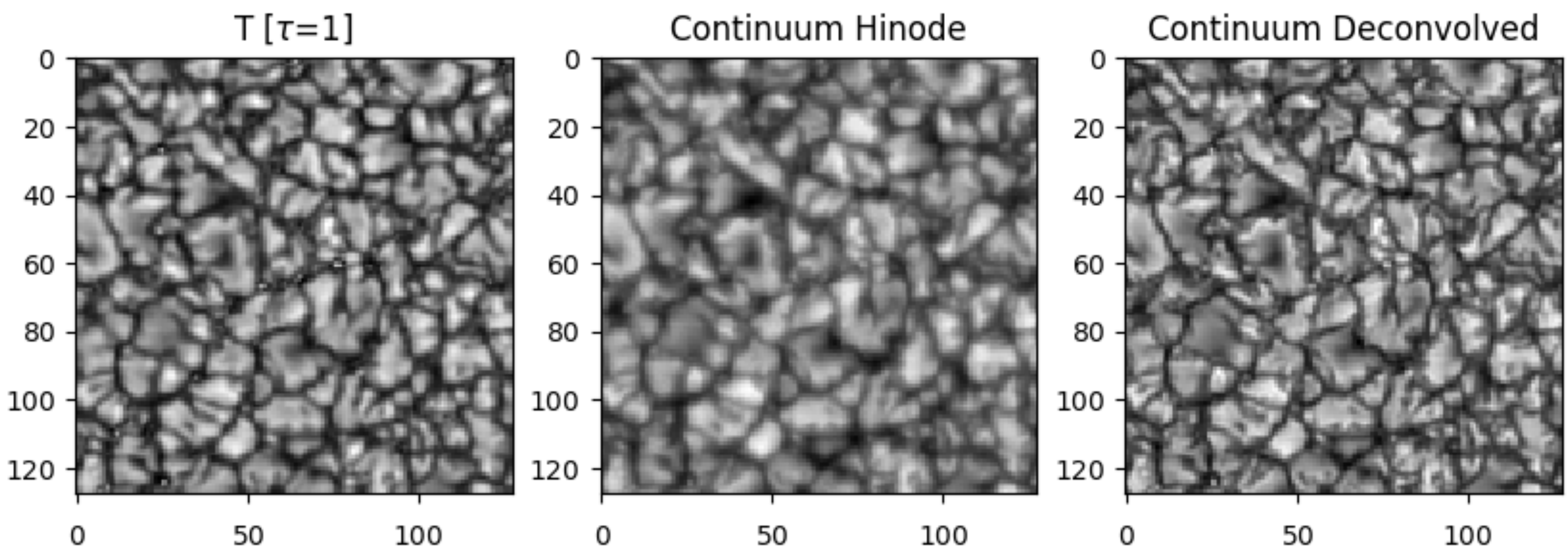
Temperature



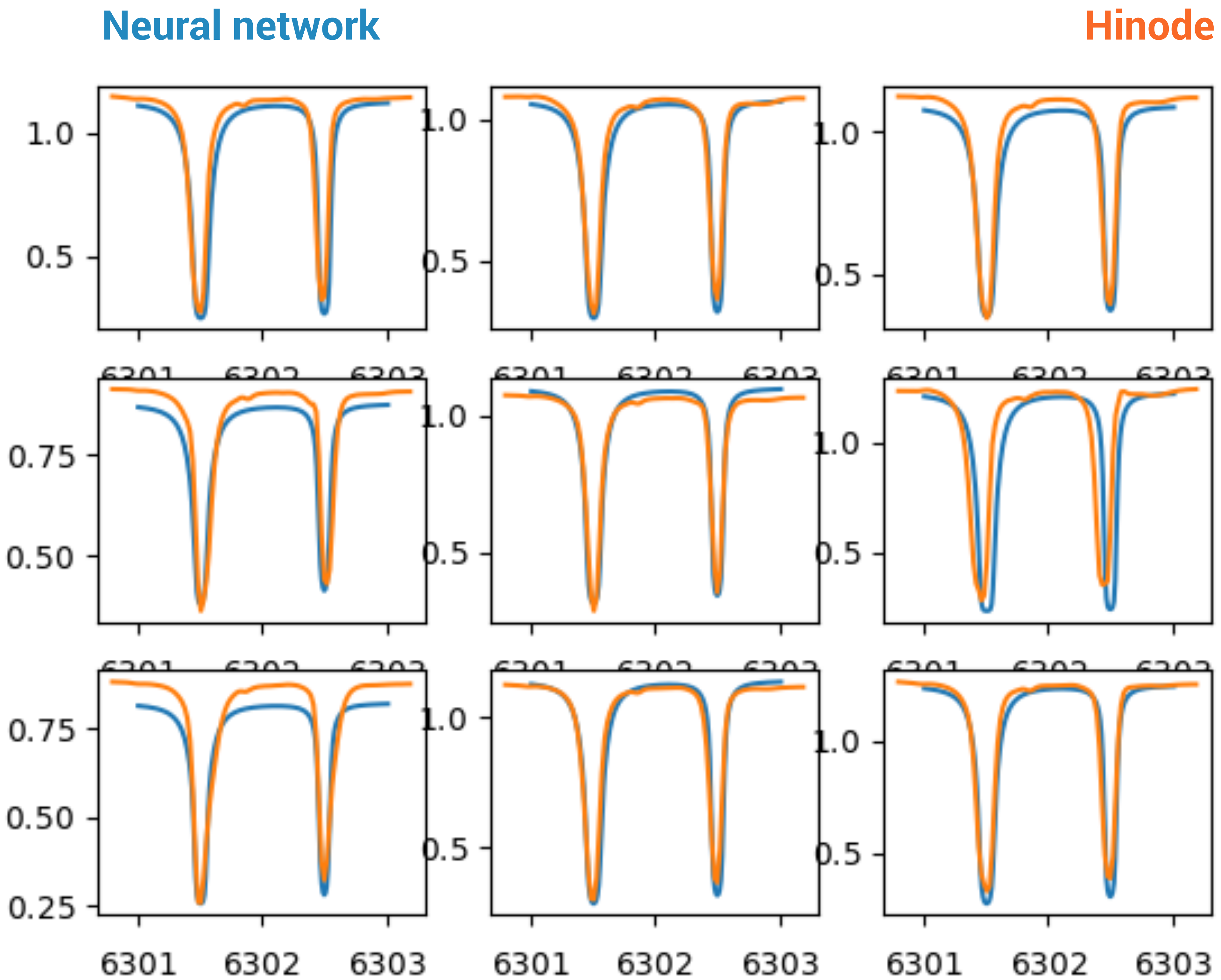
LOS velocity



INVERSION+DECONVOLUTION

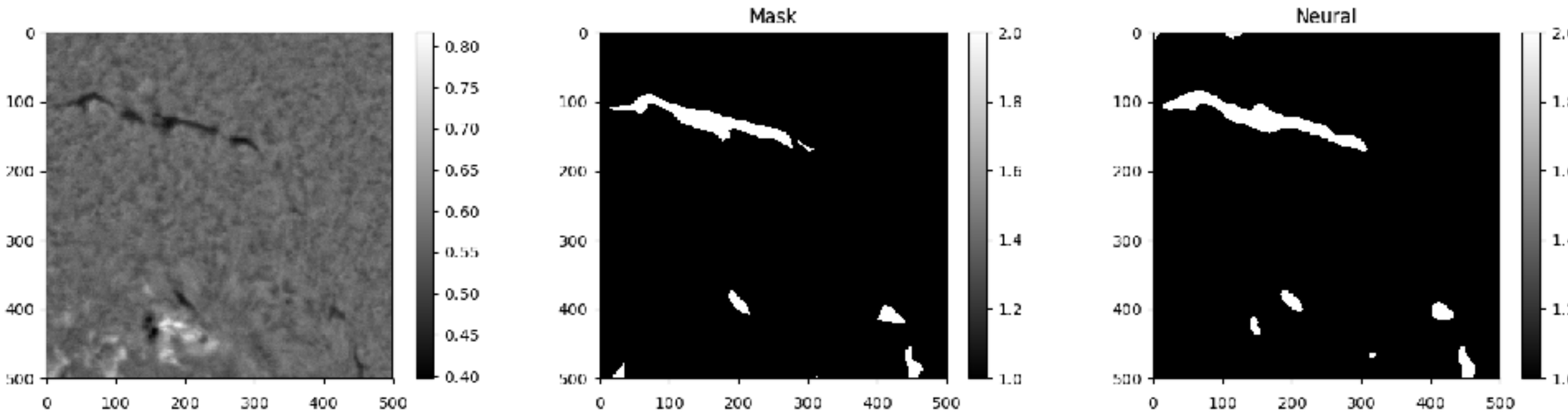


PROFILES



Hα image segmentation

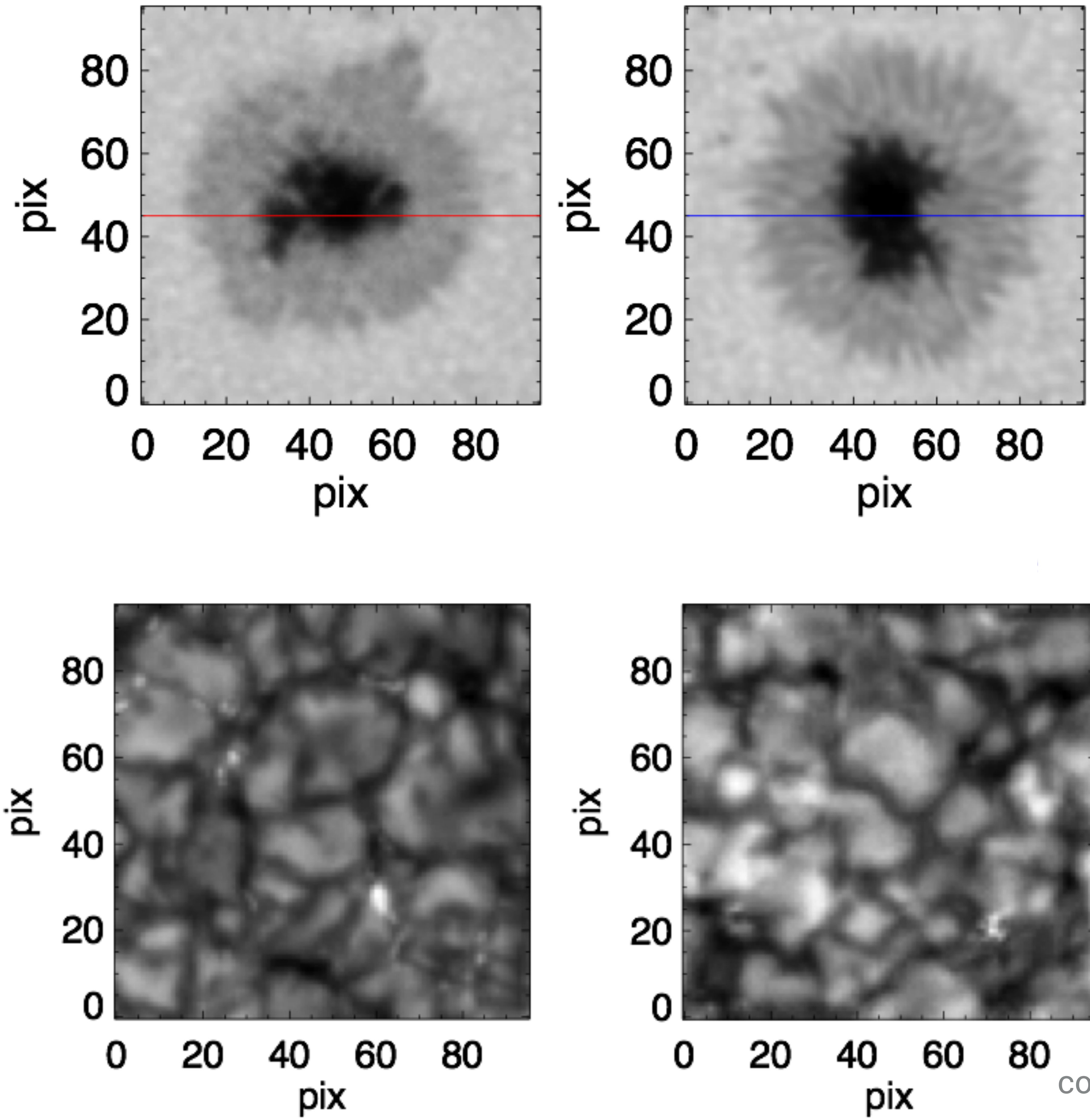
FAST SEGMENTATION



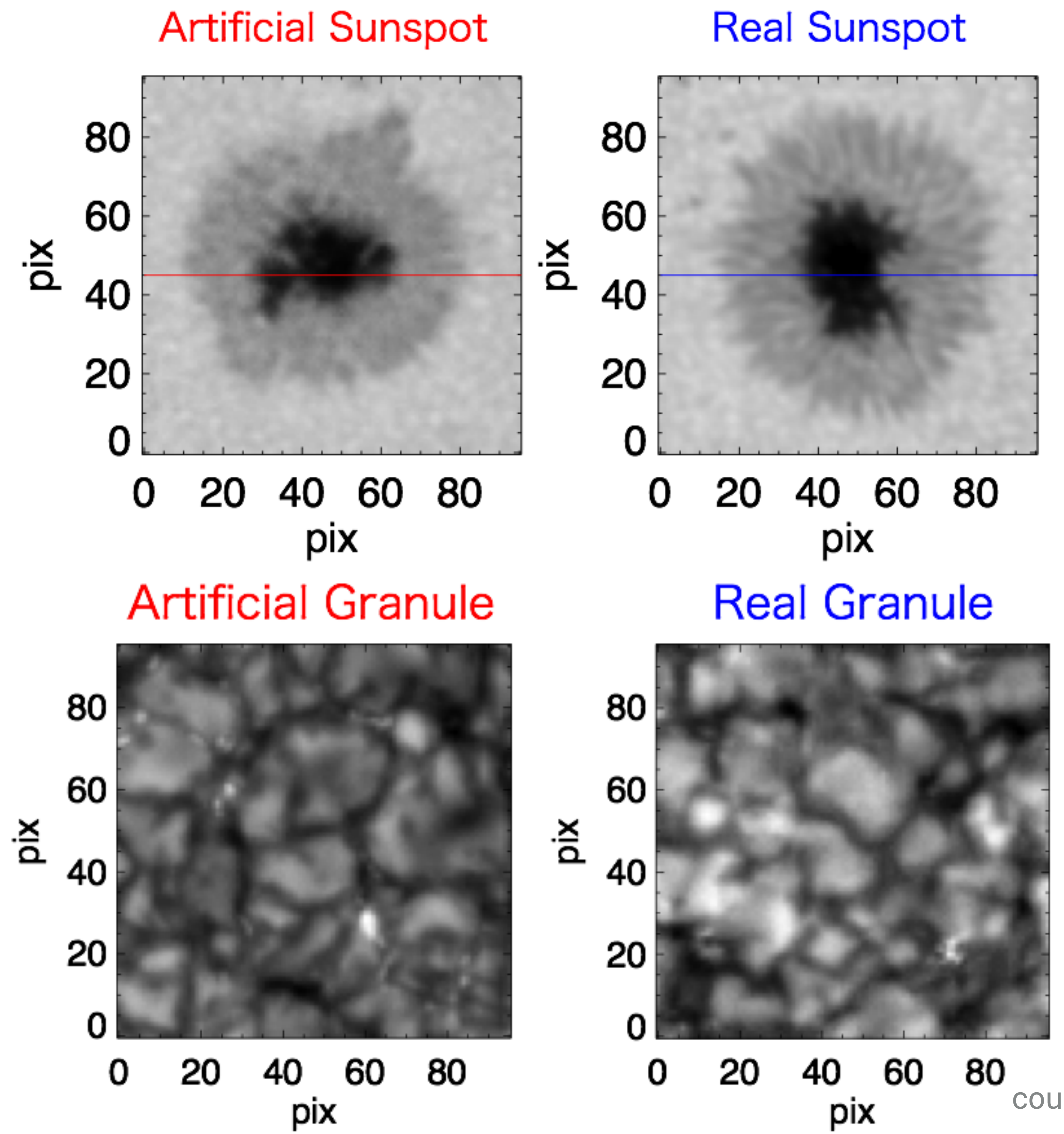
In collaboration with M. Luna

synthetic solar images

GENERATIVE ADVERSARIAL NETWORKS



courtesy of Y. Kawabata



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