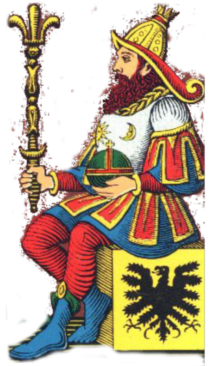
Artificial Intelligence for Flare Imaging and Forecasting

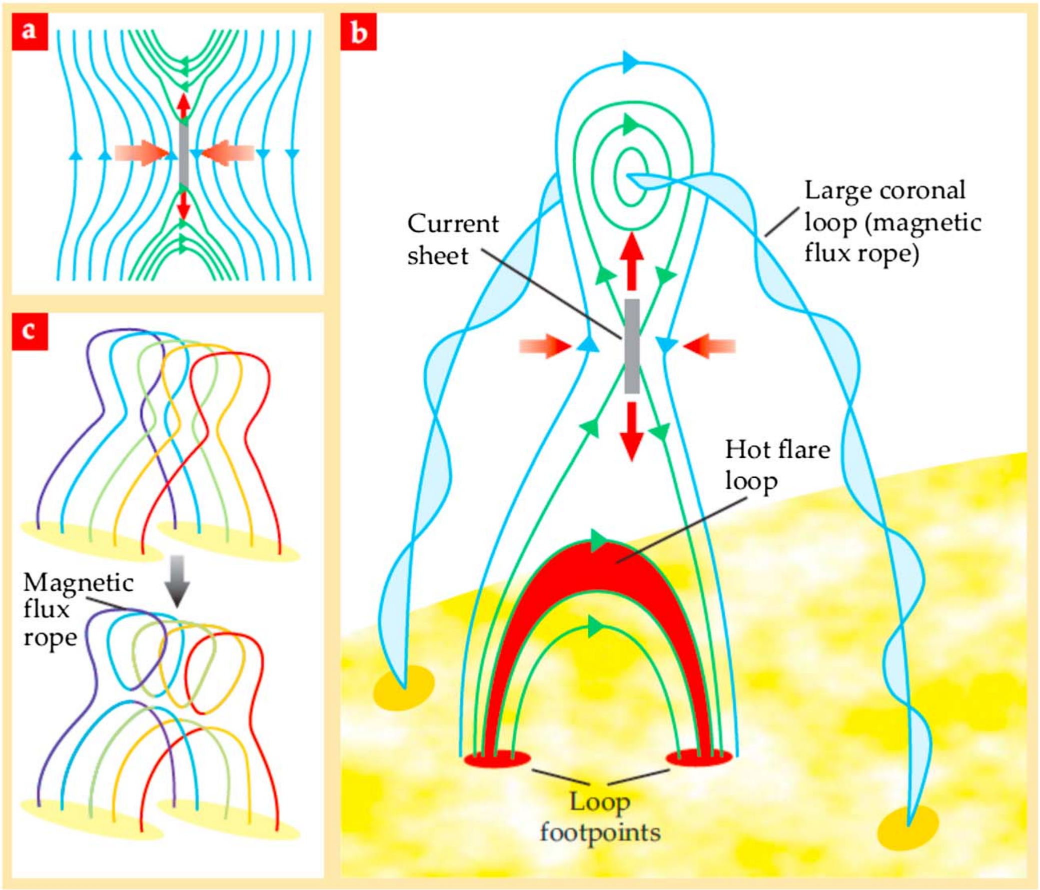
Paolo Massa, MIDA, Department of Mathematics, University of Genoa

February 28, 2022, Western Kentucky University,
Department of Physics and Astronomy



Solar flares

- Sudden release of energy due to **magnetic reconnection**
- Acceleration of electrons and ions
- Emission of radiation at any wavelengths (including UV, EUV and X-rays)

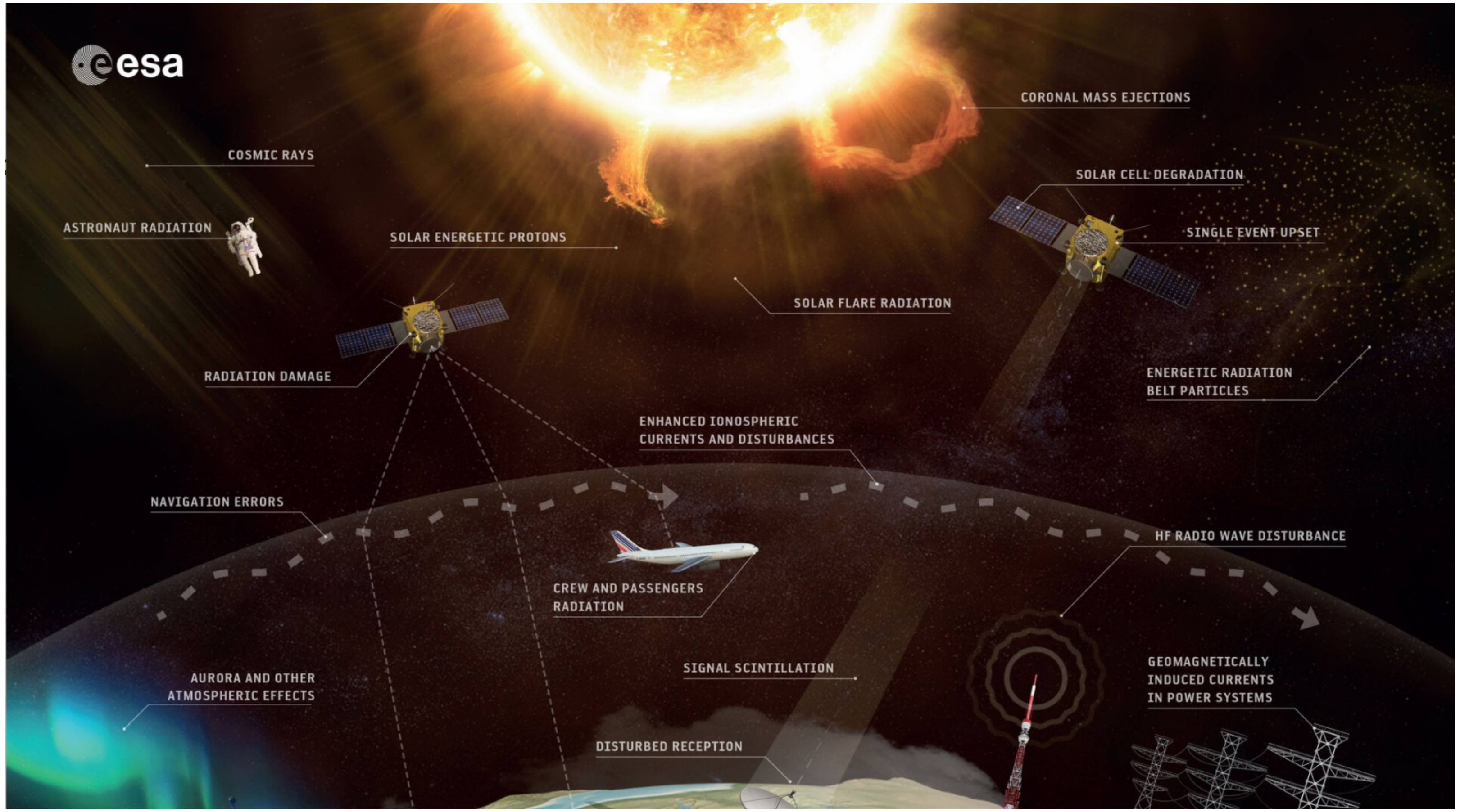


(Holman, 2012)

Solar flares

Credits: NASA website (https://svs.gsfc.nasa.gov/cgi-bin/details.cgi?aid=11199)

Solar flares and Space Weather



Outline

Solar flares

Outline

Solar flares

Indirect X-ray imaging

Outline

Solar flares

Indirect X-ray imaging

Forecasting
or
Nowcasting

Outline

Solar flares

Indirect X-ray imaging

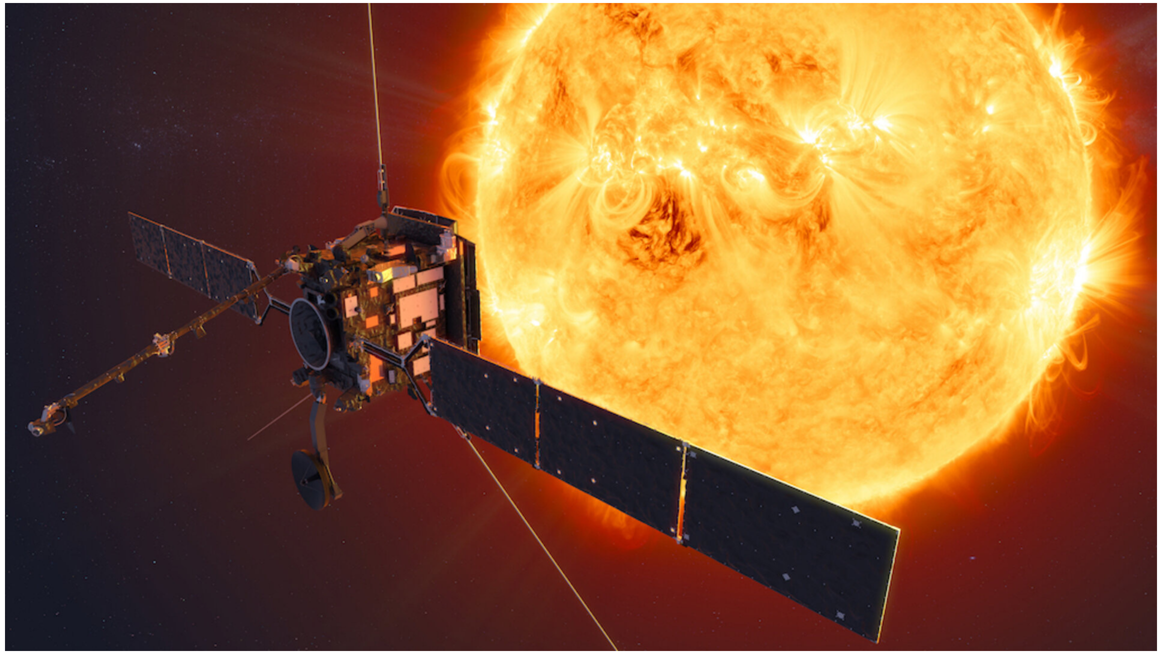
Artificial Intelligence

Forecasting or Nowcasting

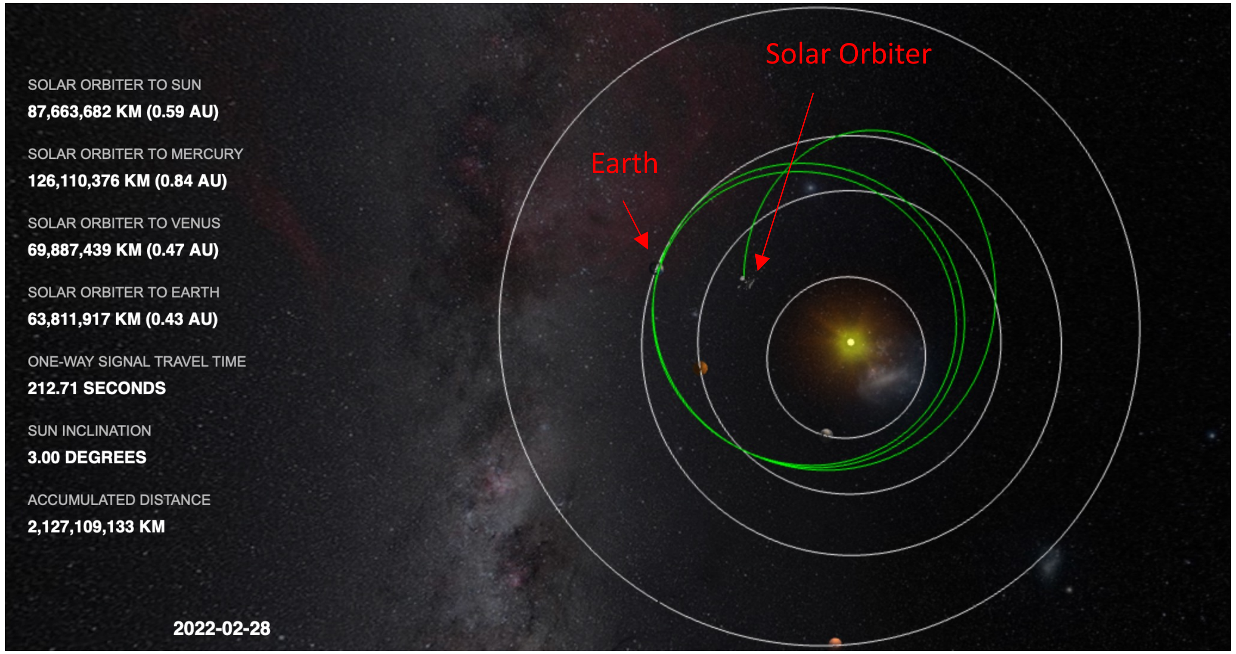
Indirect X-ray imaging

STIX in Solar Orbiter

Solar Orbiter: ESA mission launched on February 10, 2020



(credits: ESA website)



(https://solarorbiter.esac.esa.int/where/)

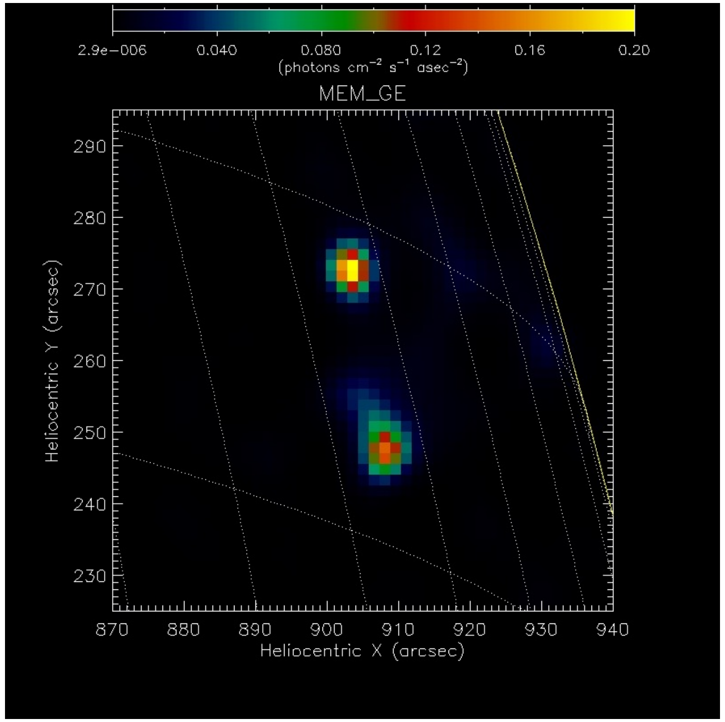
The STIX instrument

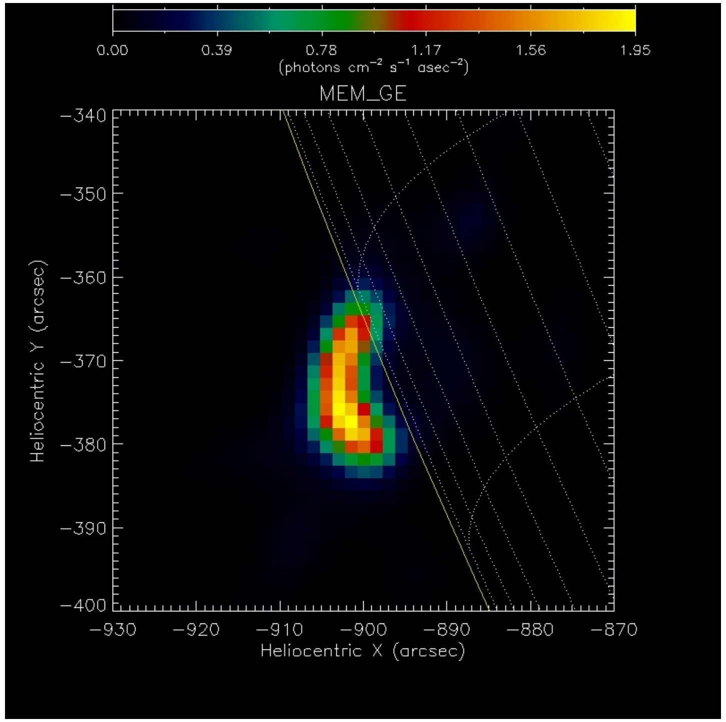
- **STIX**: Spectrometer/Telescope for Imaging X-rays
- **Scientific goal:** provide information on electrons accelerated during a solar flare and on the plasma temperature
- **How:** by measuring X-ray photons emitted by bremsstrahlung

The STIX instrument

- **STIX**: Spectrometer/Telescope for Imaging X-rays
- **Scientific goal:** provide information on electrons accelerated during a solar flare and on the plasma temperature
- **How:** by measuring X-ray photons emitted by bremsstrahlung

Images of solar flare X-ray emissions
(from RHESSI data (Lin et al. , 2002))

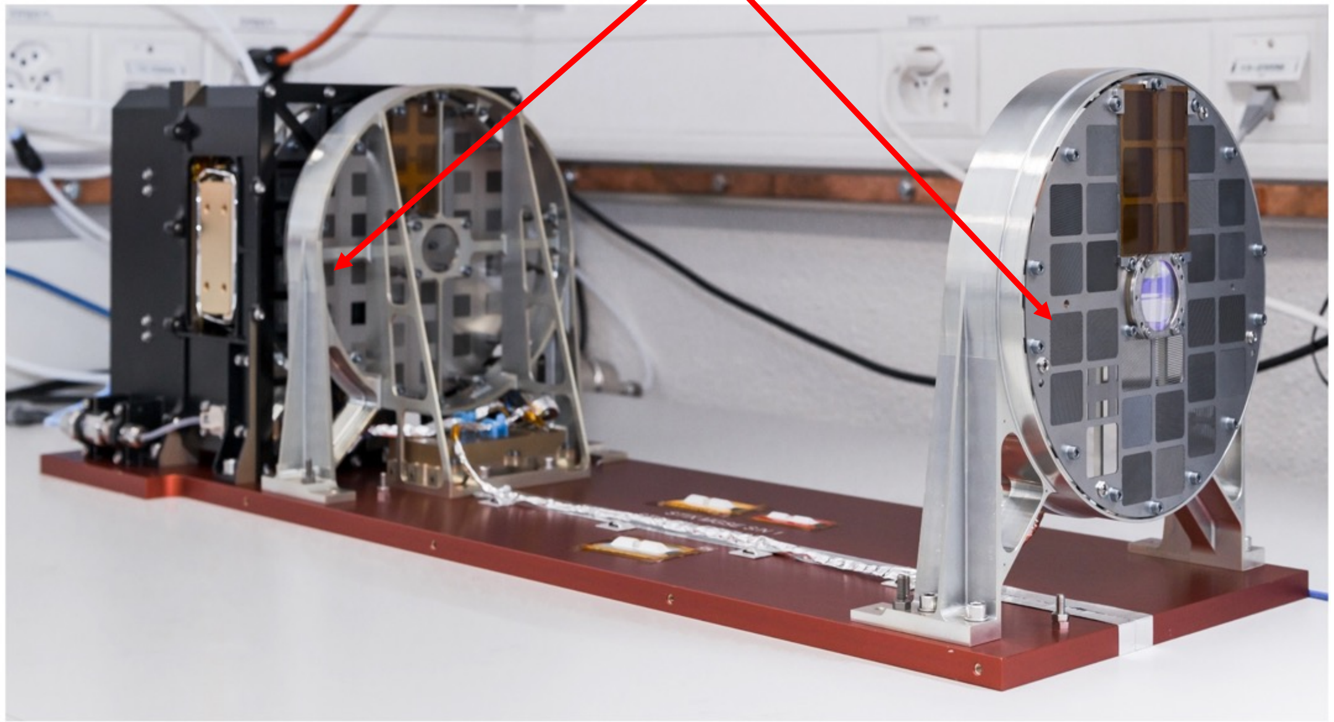




STIX imaging objective: reconstruct the image of the flaring X-ray emission form indirect measurements

The STIX instrument

Sub-collimator = front grid + rear grid + detector



(Krucker et al., 2020)

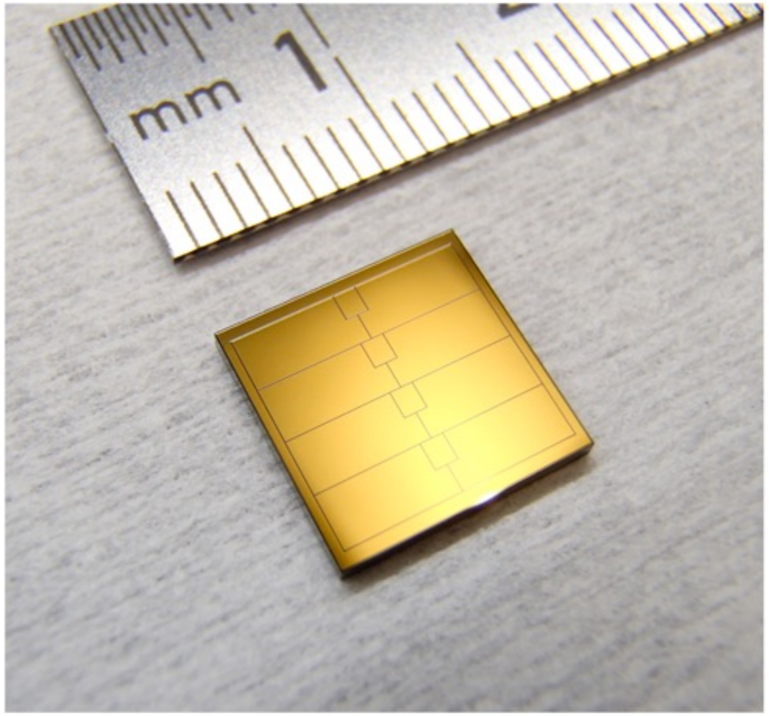
- Bi-grid imaging system

- STIX consists of 32 subcollimators:
  - 30 are used for imaging
  - Coarse Flare Locator
  - Background monitor

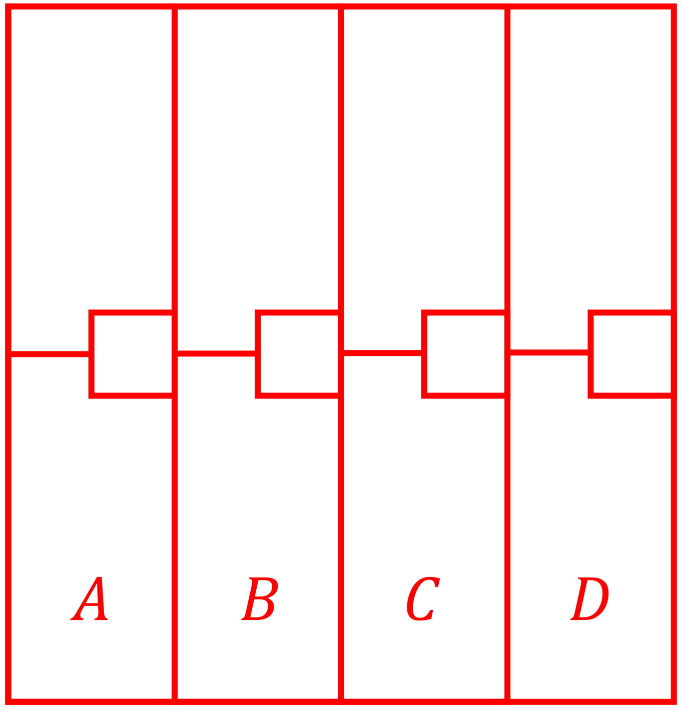
The STIX instrument

STIX Cadmium-Telluride detector

(Meuris et al., 2015)

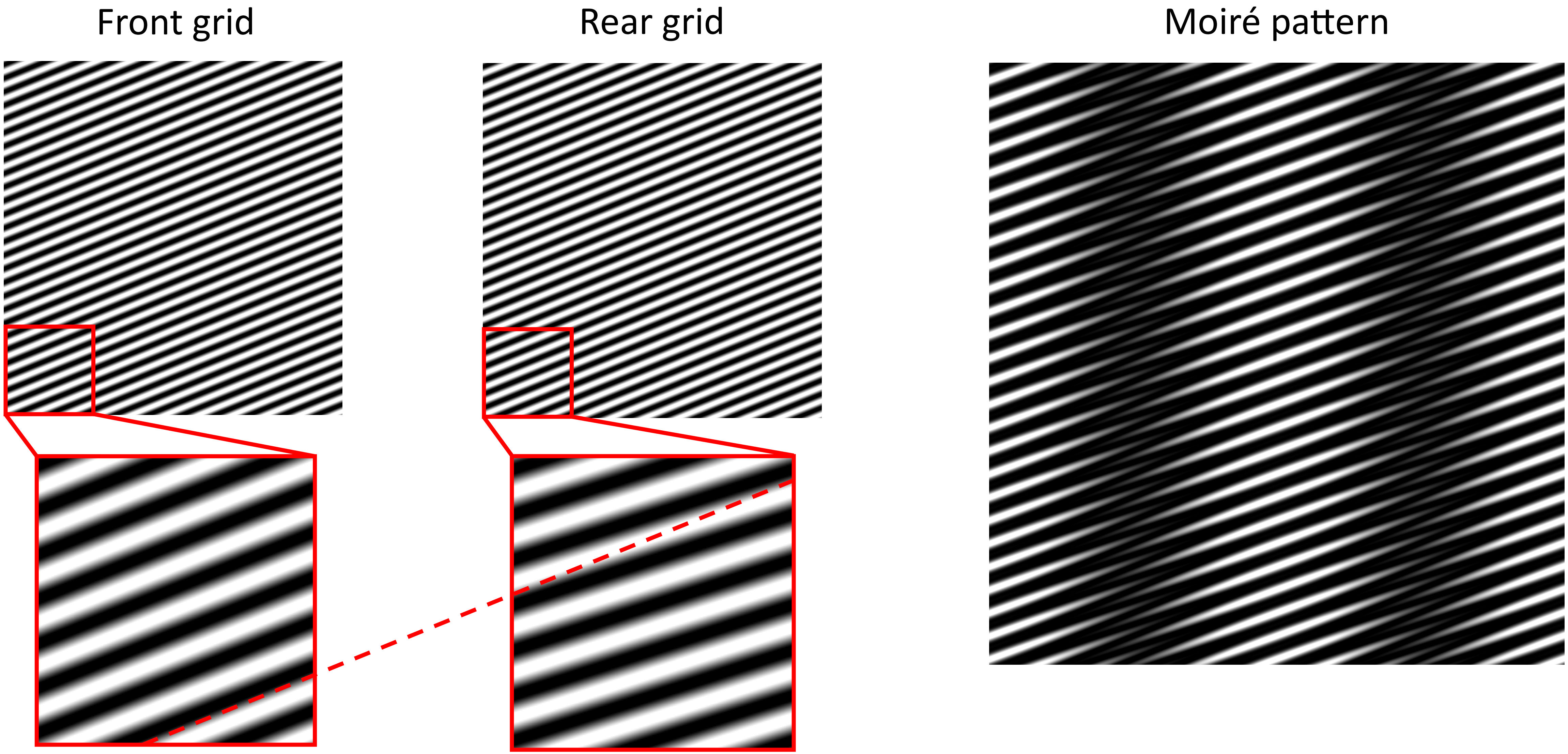


(Krucker et al., 2020)

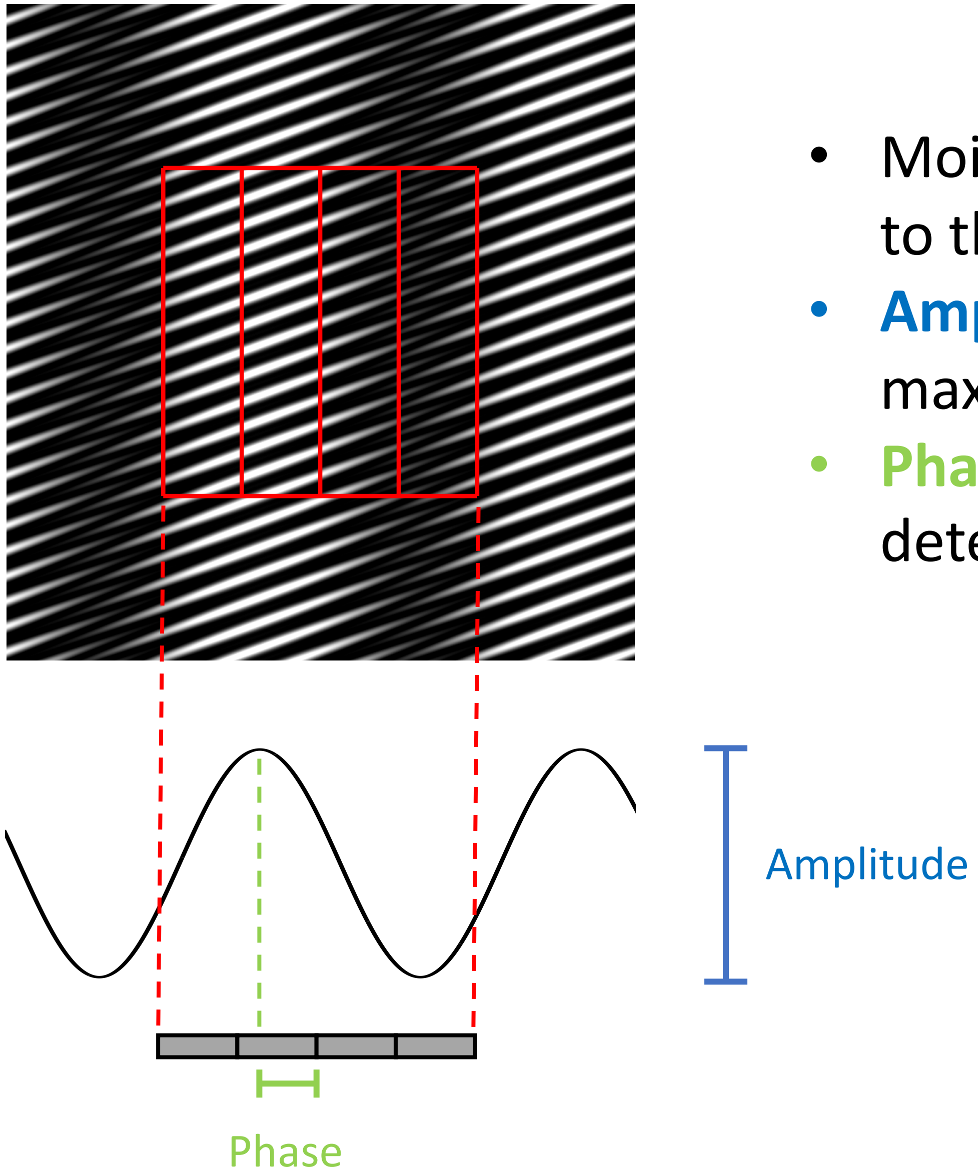


A, B, C and D: number of counts recorded by the detector pixels

The STIX imaging concept



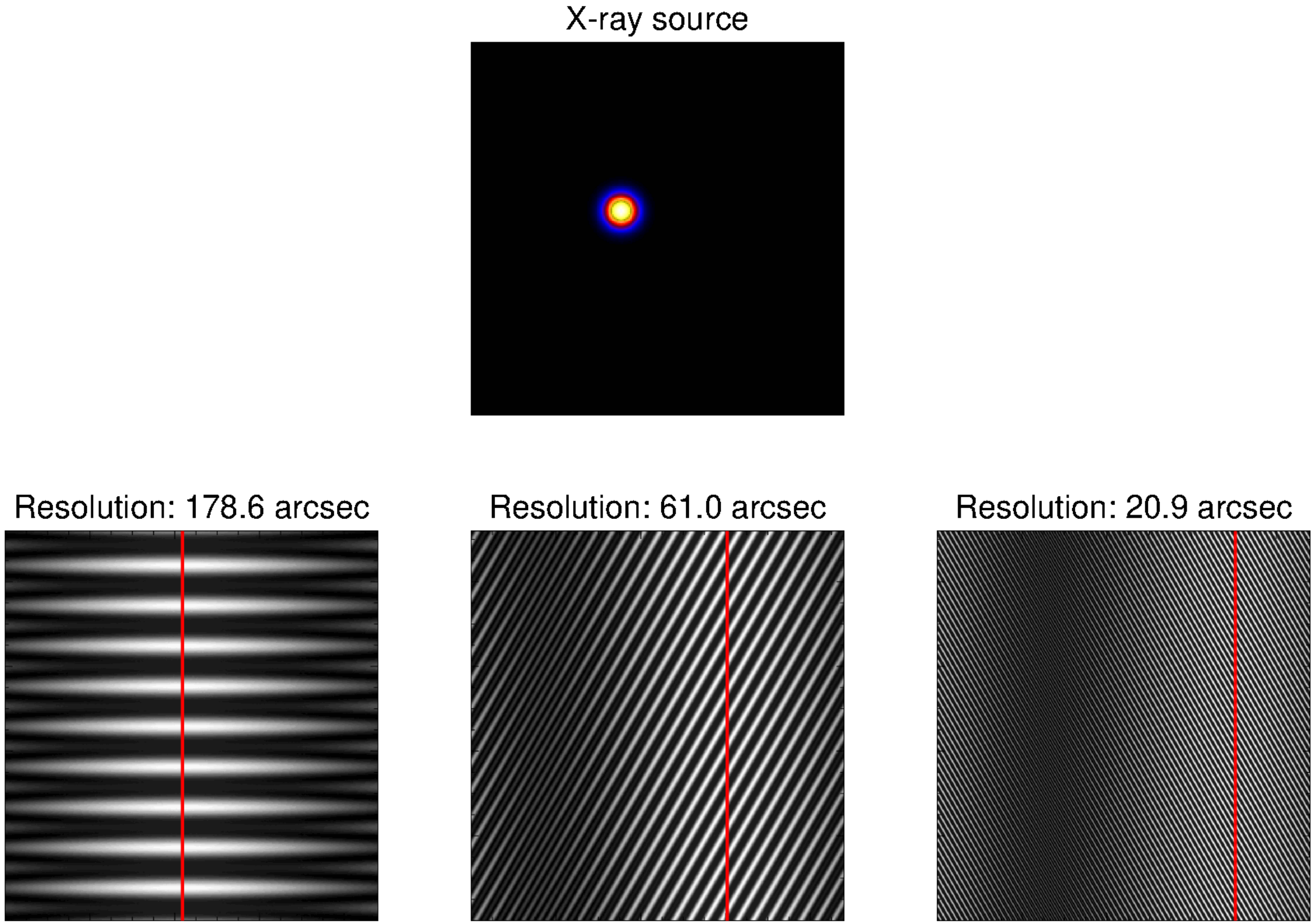
The STIX imaging concept



- Moiré pattern: sinusoidal wave with period equal to the detector width
- **Amplitude**: half of the difference between the maximum and the minimum of the pattern
- **Phase**: location of the peak of the pattern w.r.t. the detector center

The STIX imaging concept

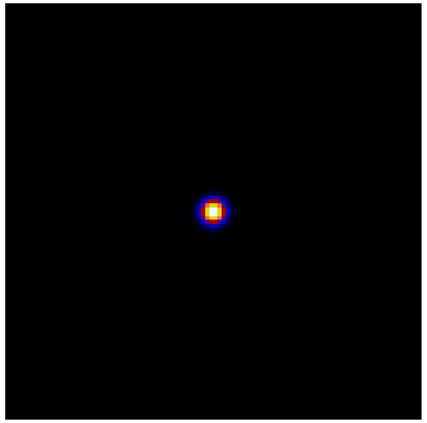
The phase of a Moiré pattern is sensitive to the X-ray source location



The STIX imaging concept

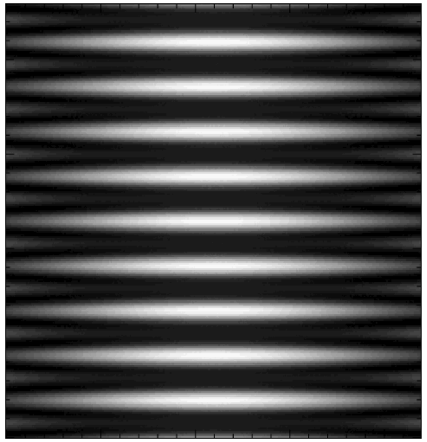
The amplitude of a Moiré pattern is sensitive to the X-ray source size and shape

X-ray source

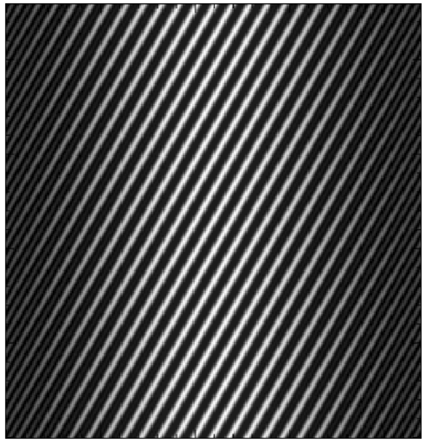


FWHM from 12 to 120 arcsec

Resolution: 178.6 arcsec



Resolution: 61.0 arcsec



Resolution: 20.9 arcsec

The STIX imaging concept

Photon count measurements A, B, C and D

The STIX imaging concept

Photon count measurements A, B, C and D → Amplitude and phase of the Moiré pattern

The STIX imaging concept

Photon count measurements A, B, C and D → Amplitude and phase of the Moiré pattern → information on size and location of the X-ray source

The STIX imaging concept

Photon count measurements A, B, C and D → Amplitude and phase of the Moiré pattern → information on size and location of the X-ray source → Amplitude and phase of a Fourier component of the X-ray emission (**visibility**)

Definition: Visibility

- $\phi(x, y)$: intensity of the X-ray radiation emitted from (x, y) on the Sun surface;
- (u, v): angular frequency.

Then, the visibility value is given by

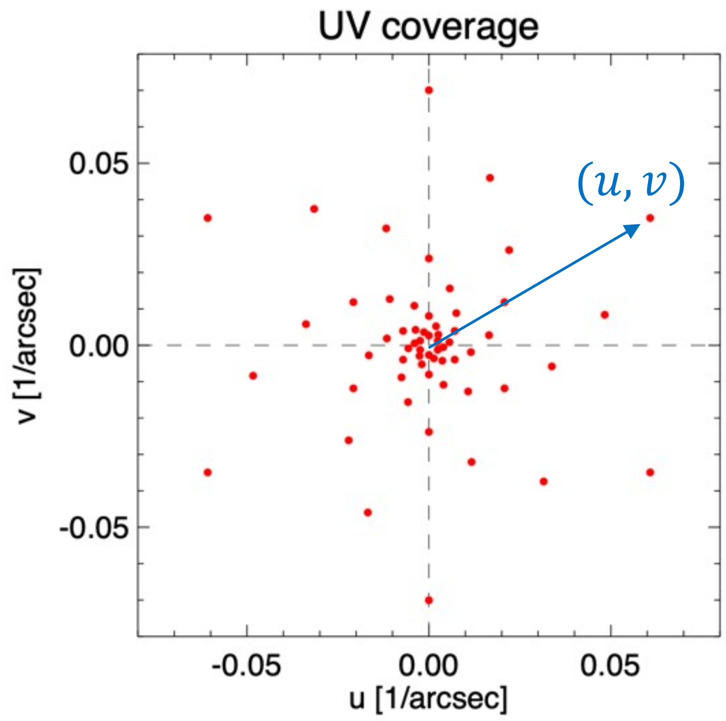
$$V(u, v) = \iint \phi(x, y) e^{2\pi i(xu+yv)} dxdy$$

STIX imaging problem

What is known:

- $(u_1, v_1), \dots, (u_{30}, v_{30})$: determined by hardware parameters of the grids
- $\boldsymbol{V} = (V_1, \dots, V_{30})$: determined by photon count measurements

What is unknown: $\phi(x, y)$



(Krucker et al., 2020)

STIX imaging problem

What is known:

- $(u_1, v_1), \dots, (u_{30}, v_{30})$: determined by hardware parameters of the grids
- $\boldsymbol{V} = (V_1, \dots, V_{30})$: determined by photon count measurements

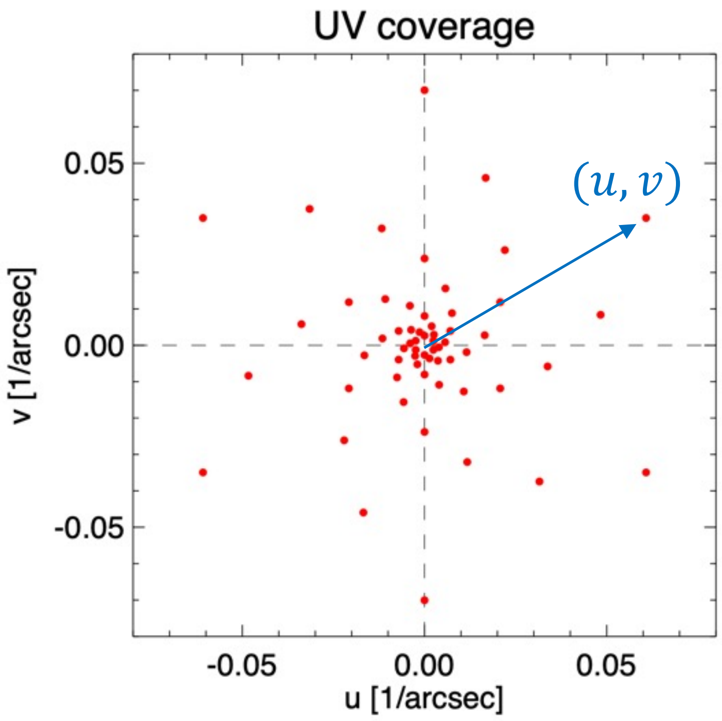
What is unknown: $\phi(x, y)$

Image reconstruction problem for STIX:

$$F\phi = \boldsymbol{V}$$

Where:

- ϕ is the image to reconstruct
- F is the Fourier transform
- $\boldsymbol{V}$ is the complex array of visibilities



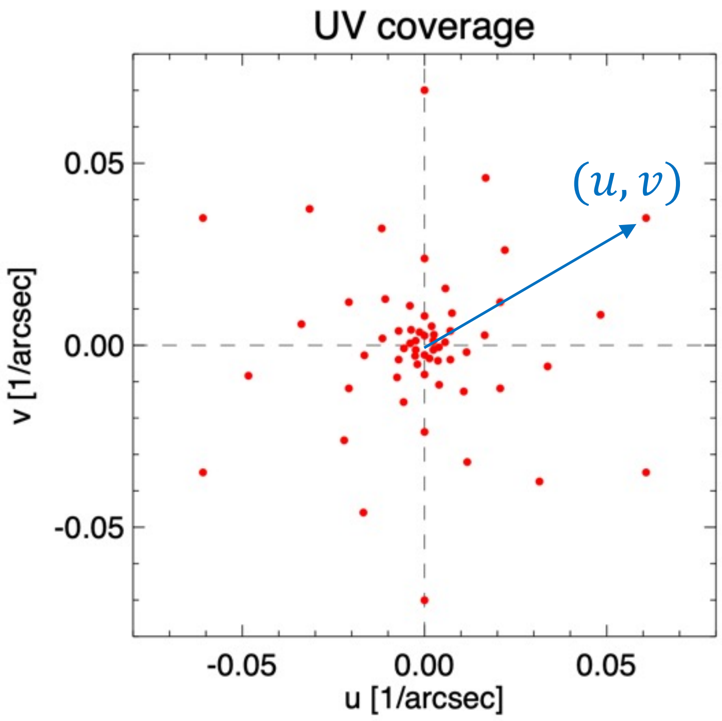
(Krucker et al., 2020)

STIX imaging problem

What is known:

- $(u_1, v_1), \dots, (u_{30}, v_{30})$: determined by hardware parameters of the grids
- $\boldsymbol{V} = (V_1, \dots, V_{30})$: determined by photon count measurements

What is unknown: $\phi(x, y)$



(Krucker et al., 2020)

Image reconstruction problem for STIX:

$$F\phi = \boldsymbol{V}$$

Where:

- ϕ is the image to reconstruct
- F is the Fourier transform
- $\boldsymbol{V}$ is the complex array of visibilities

- No analytic solution $\phi = F^{-1}\boldsymbol{V}$
- Numerical solution by means of AI methods

MEM_GE (Massa et al., 2020)

Solves the maximum-entropy regularized problem

$$\arg\min_{\phi \geq 0} \chi^2(\phi) - \lambda H(\phi)$$

$$\text{with} \sum_j \phi_j = f$$

where

$$\chi^2(\phi) = \sum_i \frac{|(\mathcal{F}\phi)_i - V_i|^2}{\sigma_i^2} \qquad H(\phi) = -\sum_j \phi_j \log\left(\frac{\phi_j}{me}\right)$$

MEM_GE (Massa et al., 2020)

Solves the maximum-entropy regularized problem

$$\arg\min_{\phi\geq 0} \chi^2(\phi) - \lambda H(\phi)$$

$$\text{with} \sum_j \phi_j = f$$

where

$$\boxed{\chi^2(\phi) = \sum_i \frac{|(\mathcal{F}\phi)_i - V_i|^2}{\sigma_i^2}}$$

Data fitting

$$H(\phi) = -\sum_j \phi_j \log\left(\frac{\phi_j}{me}\right)$$

MEM_GE (Massa et al., 2020)

Solves the maximum-entropy regularized problem

$$\arg\min_{\phi \geq 0} \chi^2(\phi) - \lambda H(\phi)$$

$$\text{with} \sum_j \phi_j = f$$

where

$$\chi^2(\phi) = \sum_i \frac{|(\mathcal{F}\phi)_i - V_i|^2}{\sigma_i^2}$$

$$\boxed{H(\phi) = -\sum_j \phi_j \log\left(\frac{\phi_j}{me}\right)}$$

Regularization

MEM_GE (Massa et al., 2020)

Solves the maximum-entropy regularized problem

$$\arg\min_{\phi \geq 0} \chi^2(\phi) - \lambda H(\phi)$$

$$\text{with} \sum_j \phi_j = f$$

Regularization parameter

where

$$\chi^2(\phi) = \sum_i \frac{|(\mathcal{F}\phi)_i - V_i|^2}{\sigma_i^2} \qquad H(\phi) = -\sum_j \phi_j \log\left(\frac{\phi_j}{me}\right)$$

MEM_GE (Massa et al., 2020)

Solves the maximum-entropy regularized problem

Positivity constraint

$$\underset{\boxed{\phi \geq 0}}{\arg\min}\, \chi^2(\phi) - \lambda H(\phi)$$

$$\text{with} \sum_j \phi_j = f$$

where

$$\chi^2(\phi) = \sum_i \frac{|(\mathcal{F}\phi)_i - V_i|^2}{\sigma_i^2} \qquad H(\phi) = -\sum_j \phi_j \log\left(\frac{\phi_j}{me}\right)$$

MEM_GE (Massa et al., 2020)

Solves the maximum-entropy regularized problem

$$\arg\min_{\phi \geq 0} \chi^2(\phi) - \lambda H(\phi)$$

$$\boxed{\text{with} \sum_j \phi_j = f}$$

Flux constraint

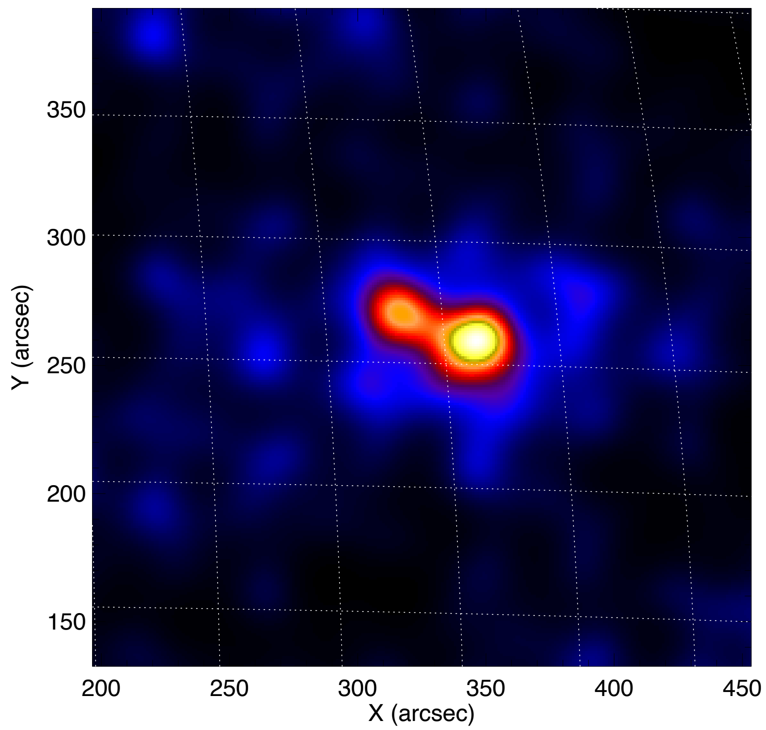
where

$$\chi^2(\phi) = \sum_i \frac{|(\mathcal{F}\phi)_i - V_i|^2}{\sigma_i^2} \qquad H(\phi) = -\sum_j \phi_j \log\left(\frac{\phi_j}{me}\right)$$

MEM_GE (Massa et al., 2020)

λ: finds a tradeoff between data fitting and regularization

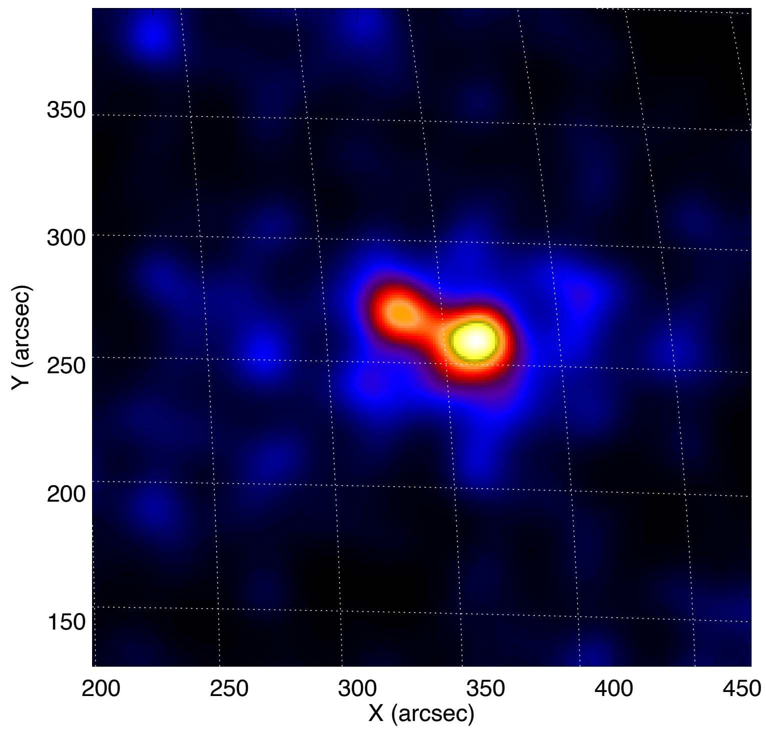
Large λ



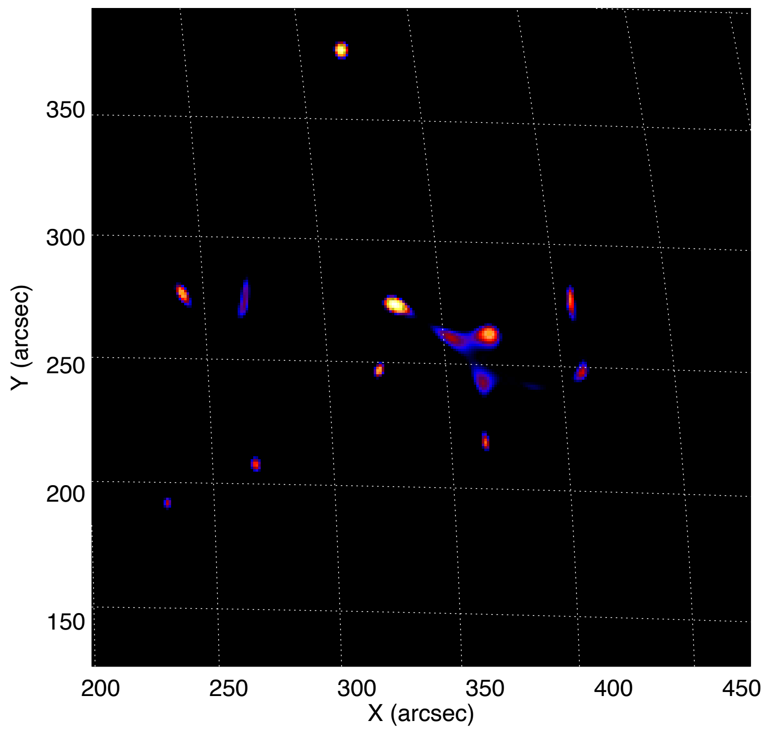
MEM_GE (Massa et al., 2020)

λ: finds a tradeoff between data fitting and regularization

Large λ



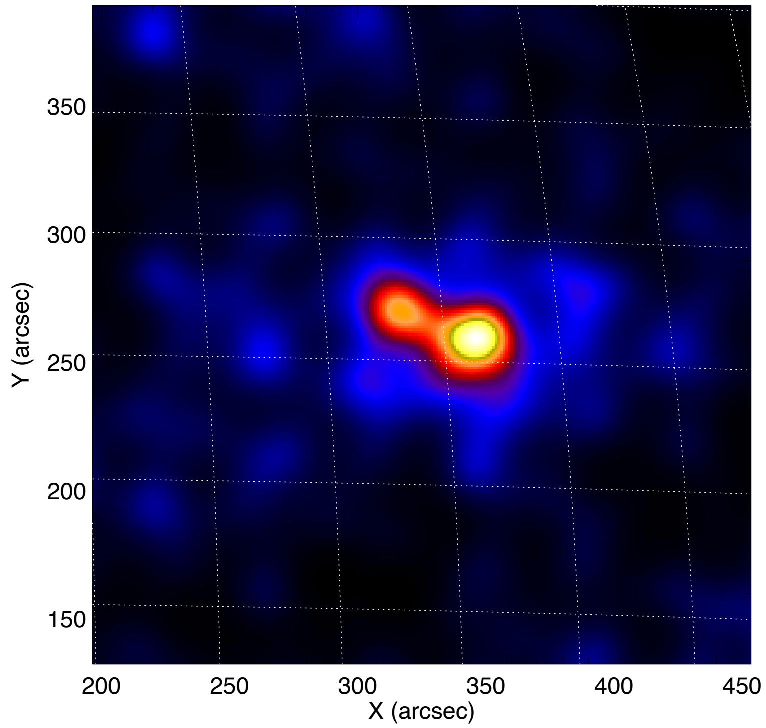
Low λ



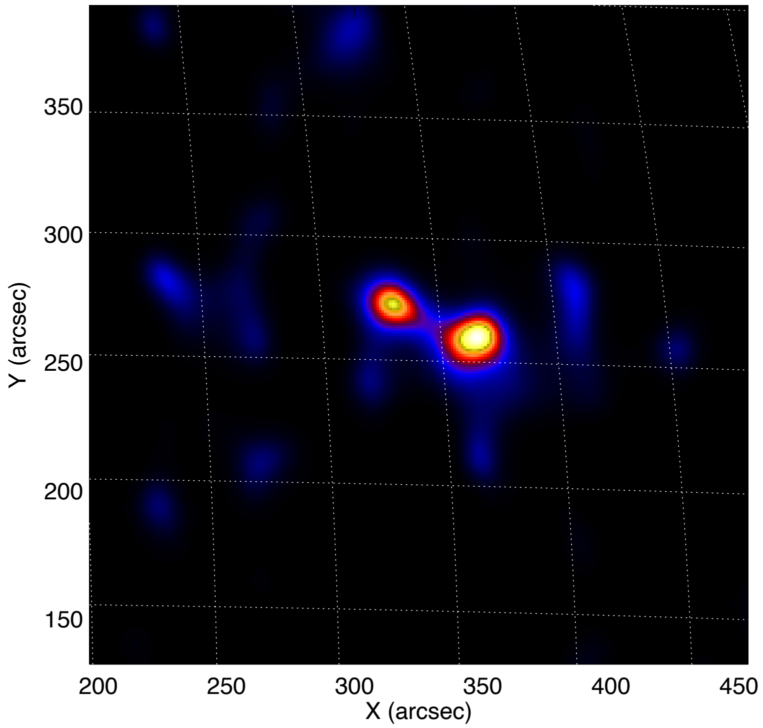
MEM_GE (Massa et al., 2020)

λ: finds a tradeoff between data fitting and regularization

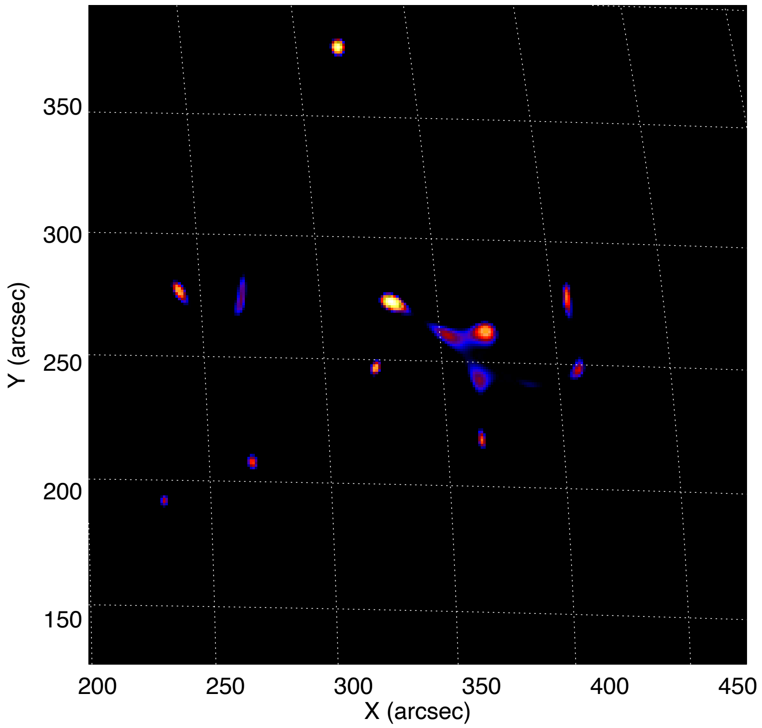
Large λ



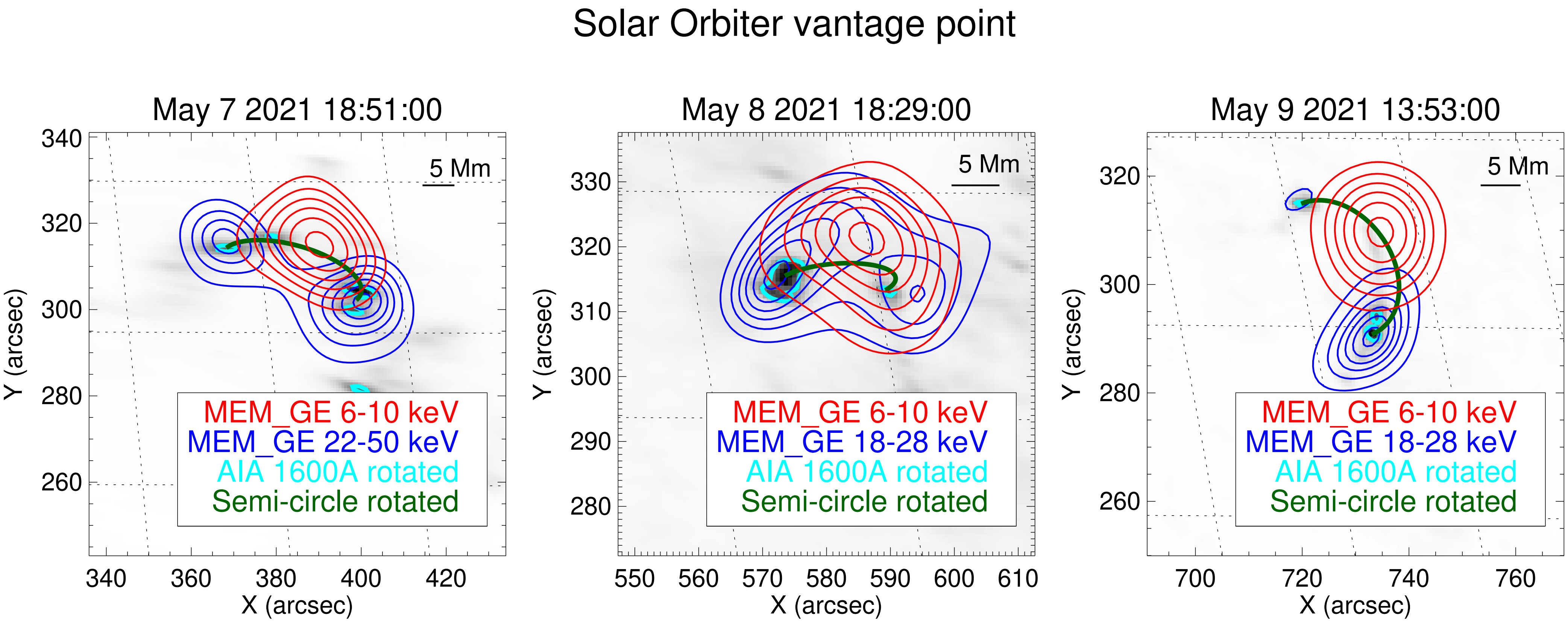
Tradeoff



Low λ



May 2021 events (Massa et al., 2022)



Flare forecasting/nowcasting

Flare forecasting/nowcasting

Goal: predict the occurrence of a flare on a timescale of hours/minutes

Flare forecasting/nowcasting

Goal: predict the occurrence of a flare on a timescale of hours/minutes

Why?

Prevent damages on the Earth

Support sounding rockets campaigns

Flare forecasting/nowcasting

Problem: how can we predict a flare?

Flare forecasting/nowcasting

Problem: how can we predict a flare?

Solar data
(e.g. images, time series, videos)

Flare forecasting/nowcasting

Problem: how can we predict a flare?

Solar data
(e.g. images, time series, videos)

Flare occurrence
(yes/no)

Flare forecasting/nowcasting

Problem: how can we predict a flare?

Solar data (e.g. images, time series, videos)

Model

Flare occurrence (yes/no)

Flare forecasting/nowcasting

Problem: how can we predict a flare?

Solar data (e.g. images, time series, videos)

Model

Flare occurrence (yes/no)

Unknown, but we can *learn* it from a dataset of examples

Flare forecasting/nowcasting – Supervised learning

- The model is a **parametric** function $f_W\colon \mathbb{R}^M \to [0,1]$

Flare forecasting/nowcasting – Supervised learning

- The model is a **parametric** function $f_{\boxed{W}}: \mathbb{R}^M \rightarrow [0,1]$

Set of parameters

Flare forecasting/nowcasting – Supervised learning

- The model is a **parametric** function $f_W\colon \boxed{\mathbb{R}^M} \to [0,1]$

Data space

Flare forecasting/nowcasting – Supervised learning

- The model is a **parametric** function $f_W : \mathbb{R}^M \rightarrow \boxed{[0,1]}$

Probability of occurrence

Flare forecasting/nowcasting – Supervised learning

- The model is a **parametric** function $f_W : \mathbb{R}^M \rightarrow [0,1]$
- Dataset: pairs $\{(x_i, y_i)\}_{i=1}^N$

Flare forecasting/nowcasting – Supervised learning

- The model is a **parametric** function $f_W: \mathbb{R}^M \to [0,1]$
- Dataset: pairs $\{(\boxed{x_i,} y_i)\}_{i=1}^N$

Feature or data
(e.g. image)

Flare forecasting/nowcasting – Supervised learning

- The model is a **parametric** function $f_W\colon \mathbb{R}^M \rightarrow [0,1]$
- Dataset: pairs $\{(x_i, \boxed{y_i})\}_{i=1}^{N}$

Label (0=no flare, 1=flare)

Flare forecasting/nowcasting – Supervised learning

- The model is a **parametric** function $f_W : \mathbb{R}^M \to [0,1]$
- Dataset: pairs $\{(x_i, y_i)\}_{i=1}^N$
- **Training phase**: determine W^* so that $f_{W^*}(x_i) \approx y_i$ for all i. It is addressed as the optimization problem

$$W^* = argmin_W \frac{1}{N} \sum_{i=1}^{N} L(f_W(x_i), y_i) + R(W)$$

Flare forecasting/nowcasting – Supervised learning

- The model is a **parametric** function $f_W : \mathbb{R}^M \to [0,1]$
- Dataset: pairs $\{(x_i, y_i)\}_{i=1}^N$
- **Training phase**: determine W^* so that $f_{W^*}(x_i) \approx y_i$ for all i. It is addressed as the optimization problem

$$W^* = argmin_W \frac{1}{N} \sum_{i=1}^{N} \boxed{L(f_W(x_i), y_i)} + R(W)$$

Loss function: for binary classification it is the cross-entropy function
$L(p, q) = -q \log(p) - (1-q) \log(1-p)$

Flare forecasting/nowcasting – Supervised learning

- The model is a **parametric** function $f_W: \mathbb{R}^M \rightarrow [0,1]$
- Dataset: pairs $\{(x_i, y_i)\}_{i=1}^N$
- **Training phase**: determine W^* so that $f_{W^*}(x_i) \approx y_i$ for all i. It is addressed as the optimization problem

$$W^* = argmin_W \frac{1}{N} \sum_{i=1}^{N} L(f_W(x_i), y_i) + \boxed{R(W)}$$

Regularization: usually, $R(W) = \lambda ||W||^2$, where λ is the regularization parameter

Flare forecasting/nowcasting – Supervised learning

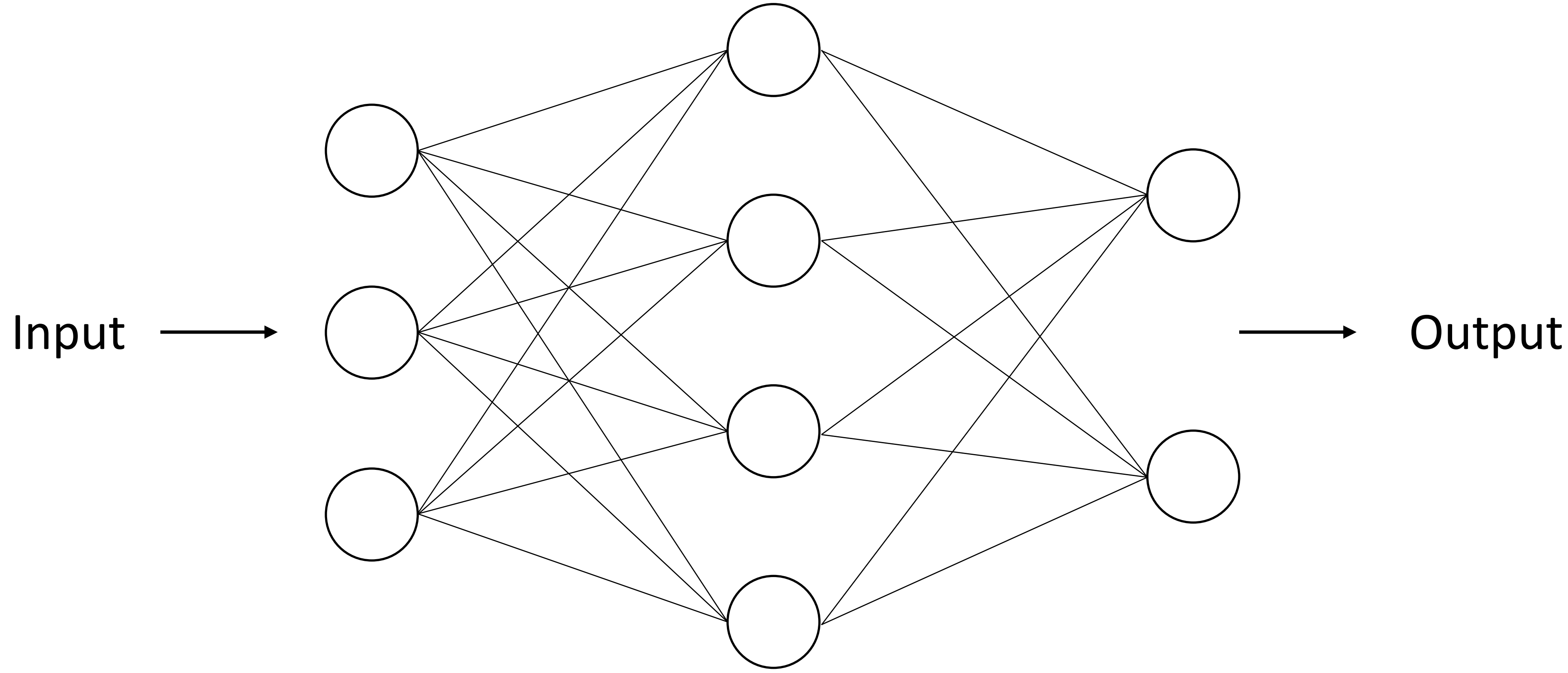
- The model is a **parametric** function $f_W: \mathbb{R}^M \rightarrow [0,1]$
- Dataset: pairs $\{(x_i, y_i)\}_{i=1}^N$
- **Training phase**: determine W^* so that $f_{W^*}(x_i) \approx y_i$ for all i. It is addressed as the optimization problem

$$W^* = argmin_W \ \frac{1}{N}\sum_{i=1}^{N} L(f_W(x_i), y_i) + R(W)$$

- f_{W^*} should be able to make accurate predictions from unseen data

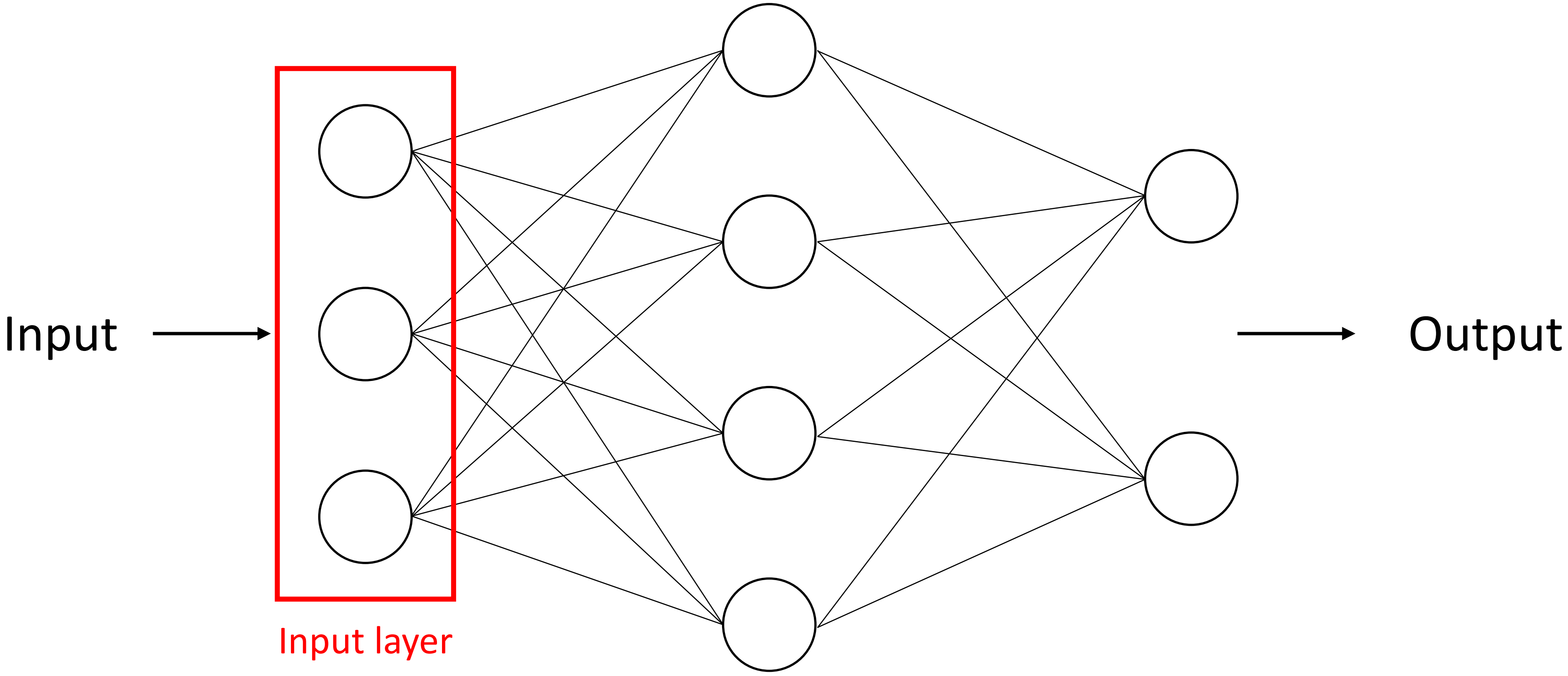
Flare forecasting/nowcasting – Supervised learning

What is the model f_W? Possible choice: **neural network**



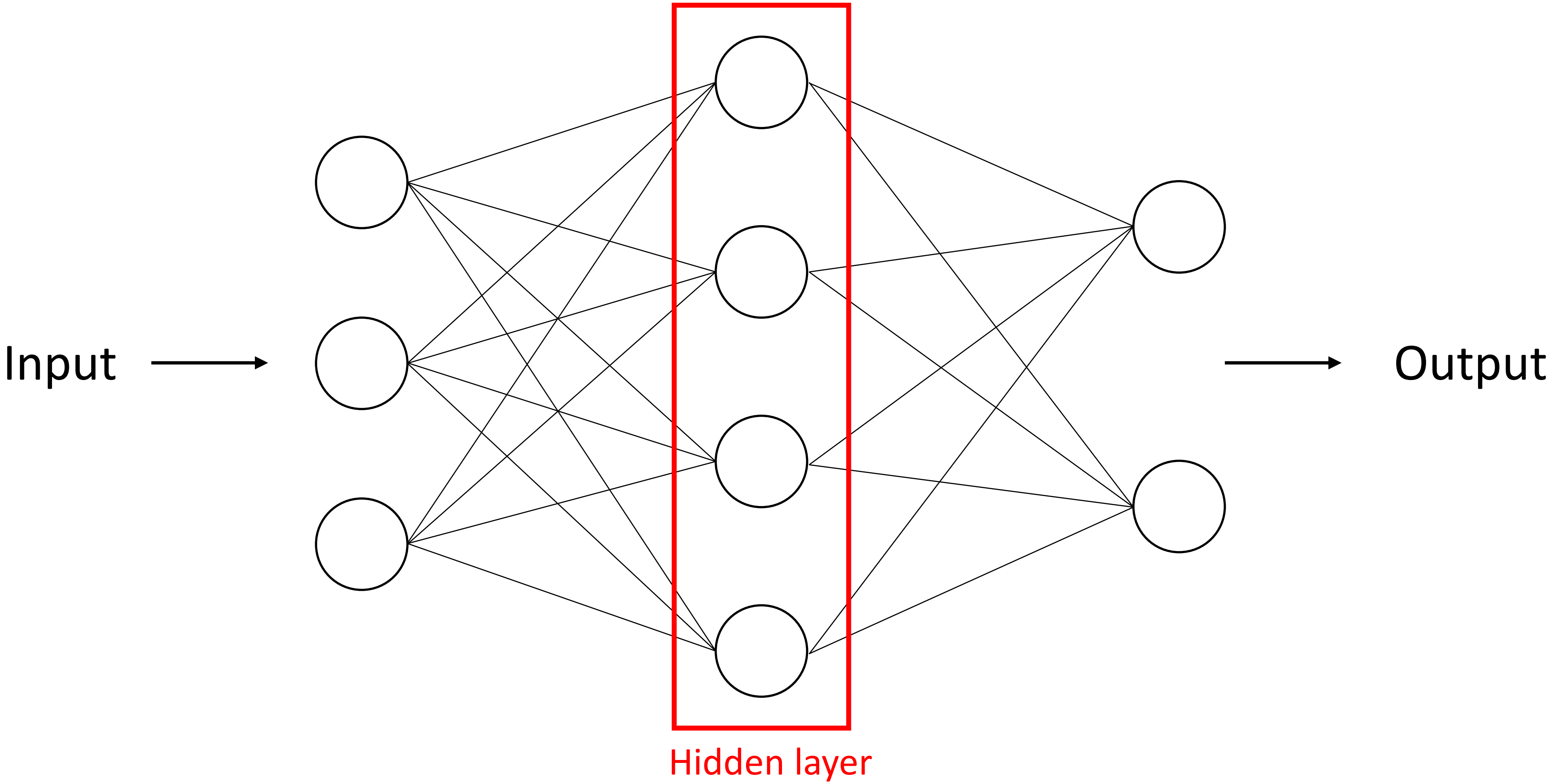
Flare forecasting/nowcasting – Supervised learning

What is the model f_W? Possible choice: **neural network**



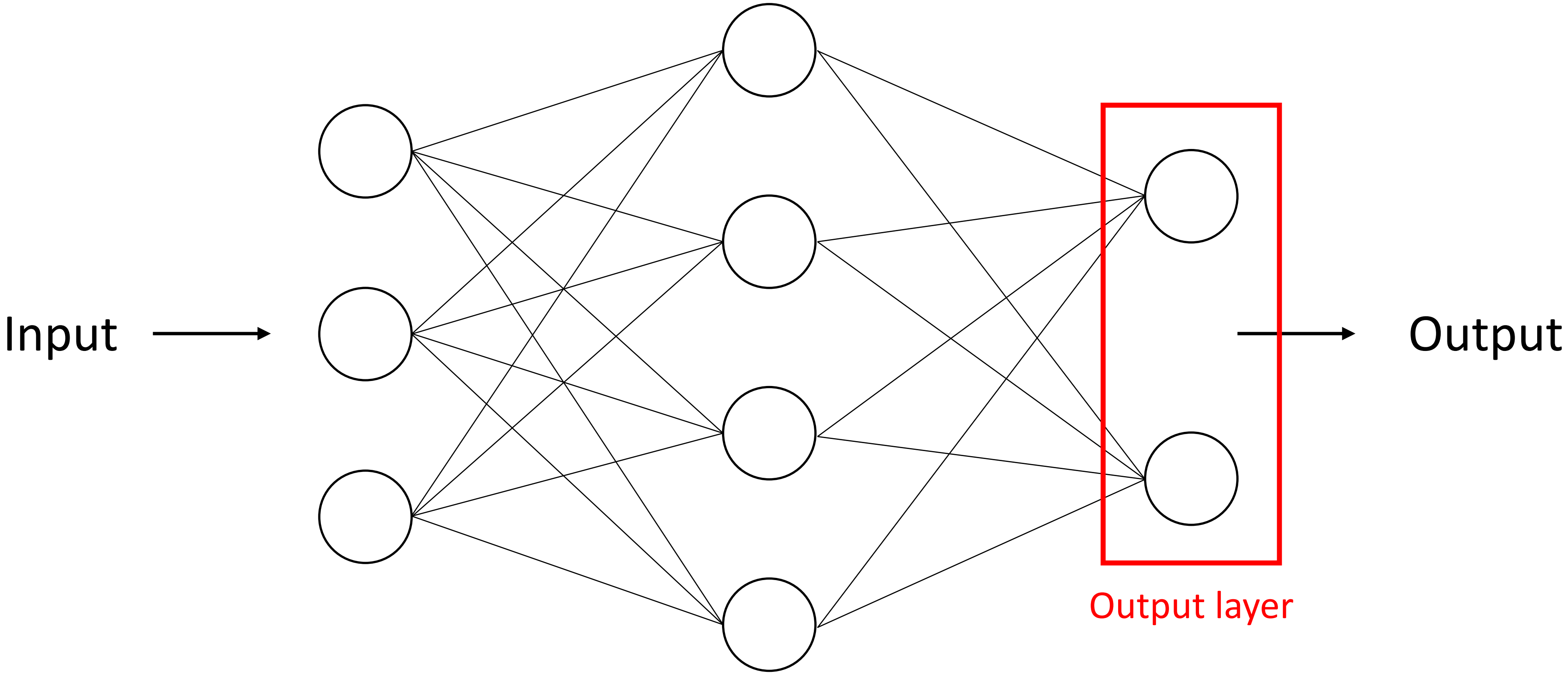
Flare forecasting/nowcasting – Supervised learning

What is the model f_W? Possible choice: **neural network**



Flare forecasting/nowcasting – Supervised learning

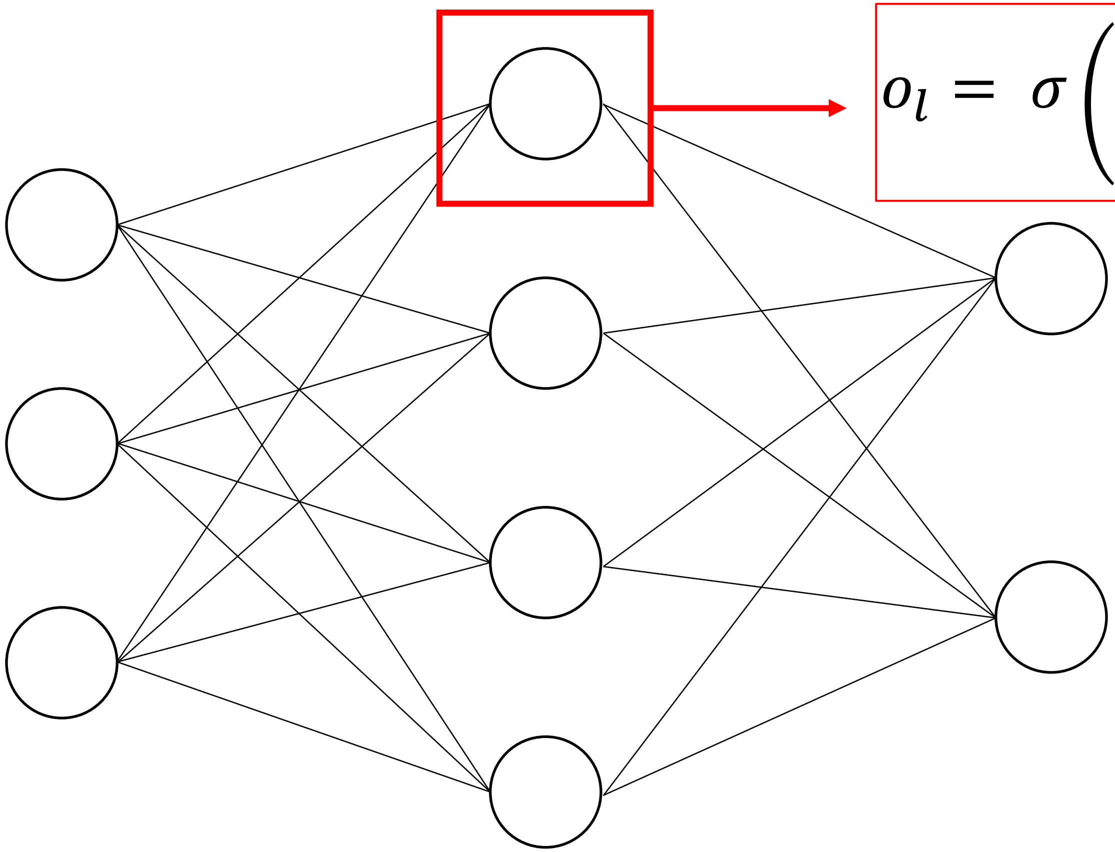
What is the model f_W? Possible choice: **neural network**



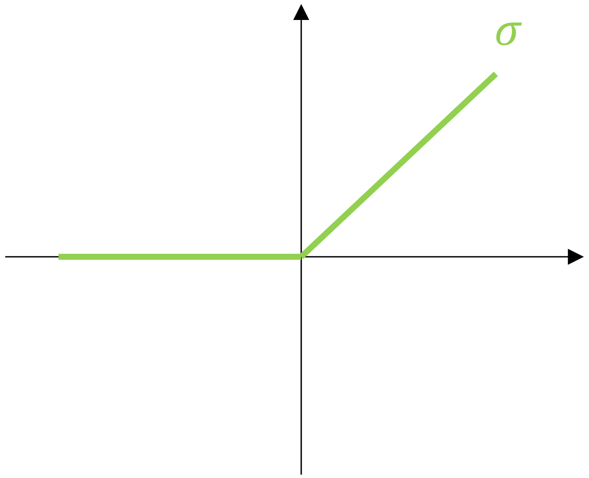
Flare forecasting/nowcasting – Supervised learning

What is the model f_W? Possible choice: **neural network**

Input

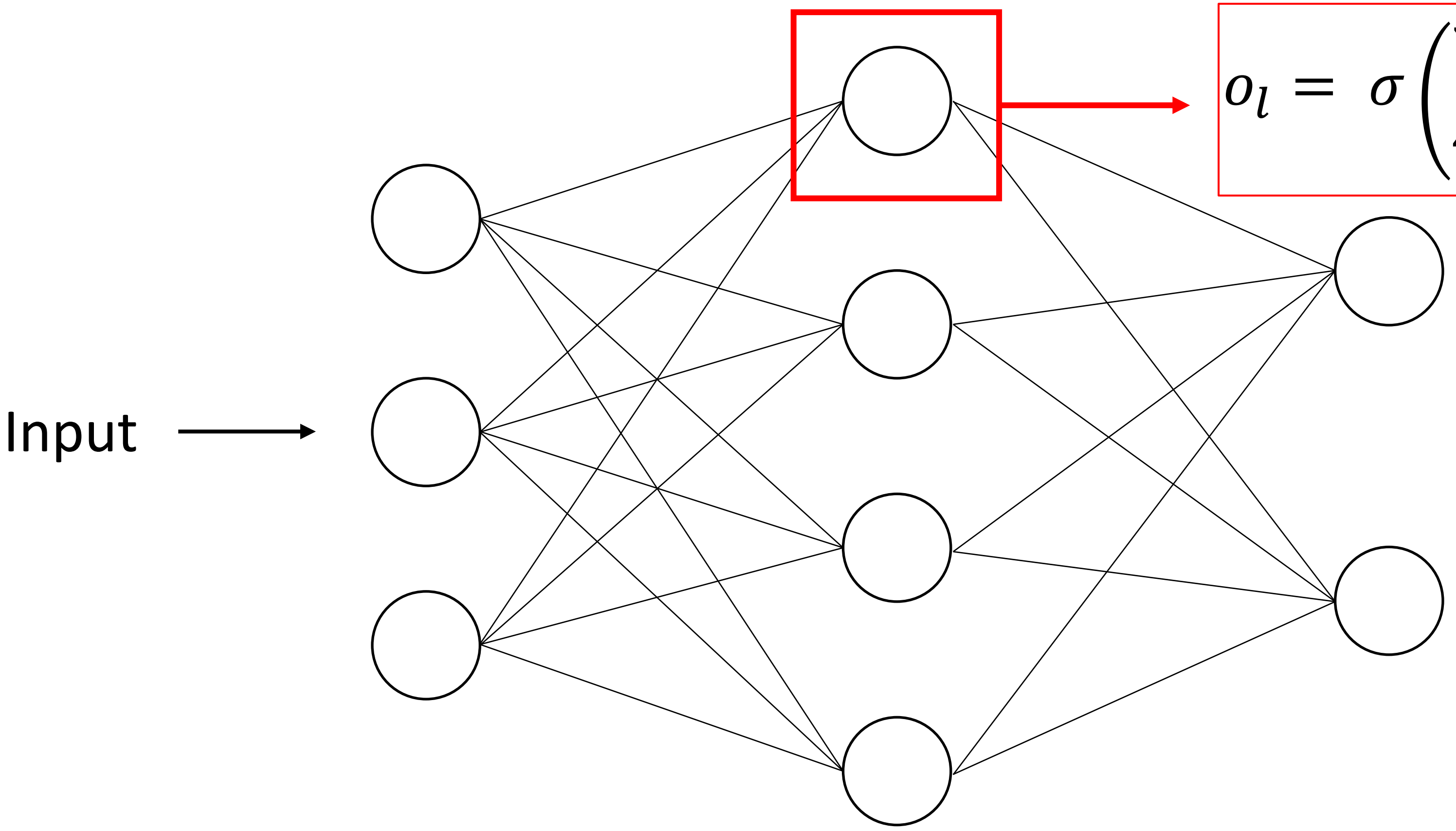


$$o_l = \sigma\left(\sum_j w_{lj}\, x_j + b_l\right)$$



Flare forecasting/nowcasting – Supervised learning

What is the model f_W? Possible choice: **neural network**



$$o_l = \sigma\left(\sum_j w_{lj}\, x_j + b_l\right)$$

The set of parameters is
$W = \{w_{lj}, b_l\}_{jl}$

Flare forecasting/nowcasting – Supervised learning

- Model evaluation on a **test set**

Flare forecasting/nowcasting – Supervised learning

- Model evaluation on a **test set**
- **Skill scores:**

Predicted

Observed	Positive	Negative
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TP)

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$$

Flare forecasting/nowcasting – Supervised learning

- Model evaluation on a **test set**
- **Skill scores:**

Predicted

Observed	Positive	Negative
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TP)

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

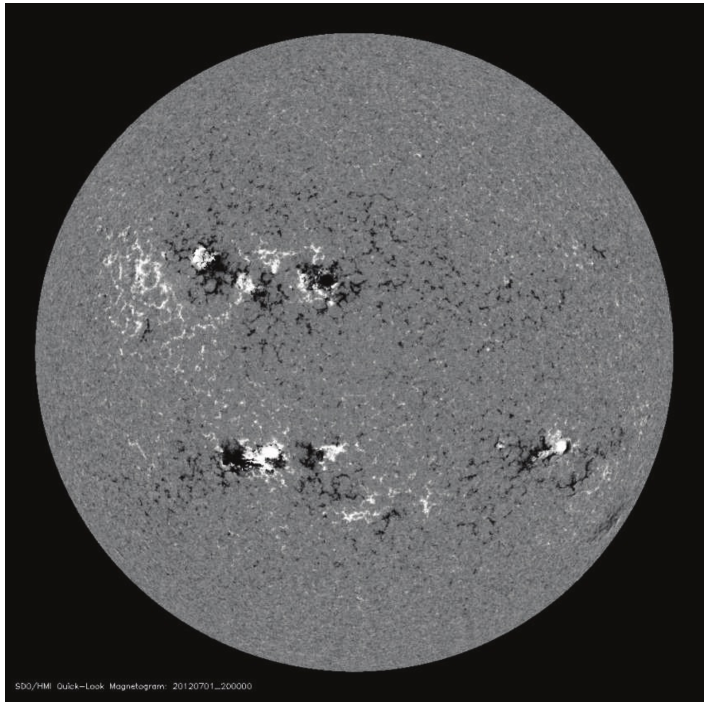
Not suited for rare events

$$TSS = \frac{TP}{TP+FN} - \frac{FP}{FP+TN}$$

Flare forecasting

SDO/HMI (Scherrer et al, 2012)

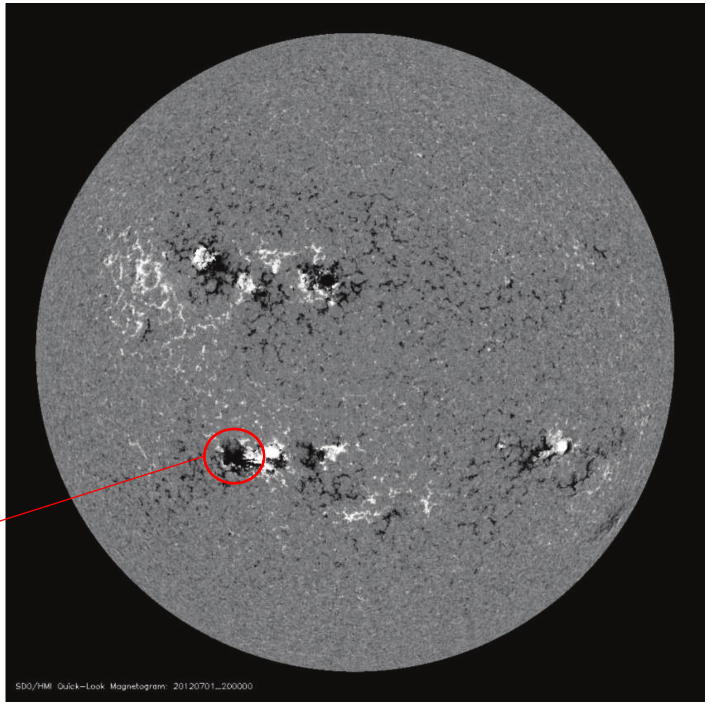
- Helioseismic and Magnetic Imager on-board the Solar Dynamics Observatory (SDO/HMI)
- Measures the magnetic field on the Sun



SDO/HMI (Scherrer et al, 2012)

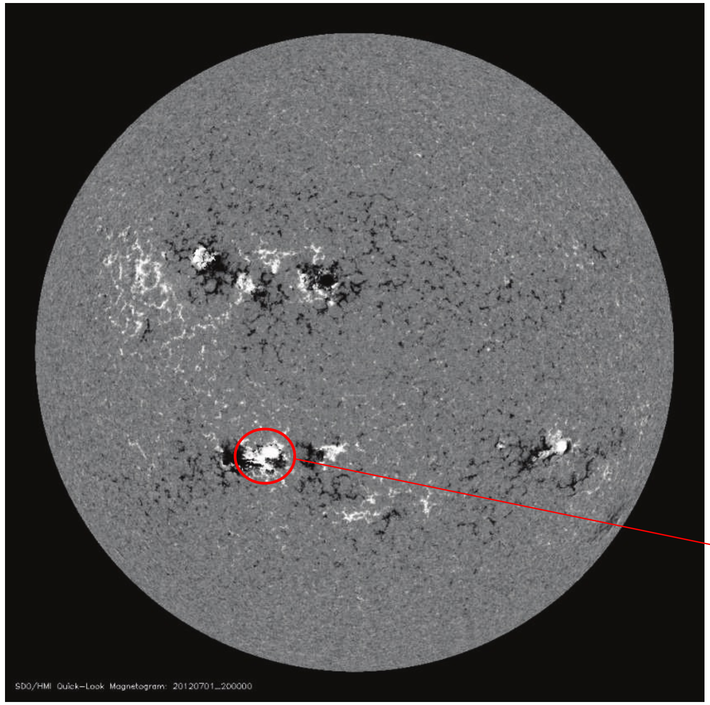
- Helioseismic and Magnetic Imager on-board the Solar Dynamics Observatory (SDO/HMI)
- Measures the magnetic field on the Sun

Pointing away from Earth



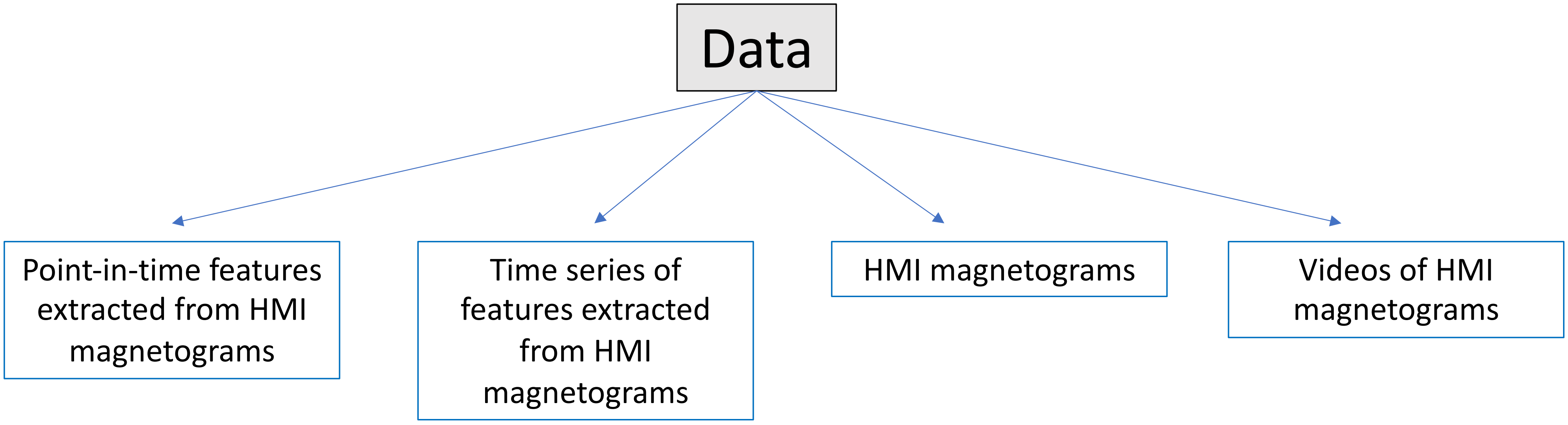
SDO/HMI (Scherrer et al, 2012)

- Helioseismic and Magnetic Imager on-board the Solar Dynamics Observatory (SDO/HMI)
- Measures the magnetic field on the Sun

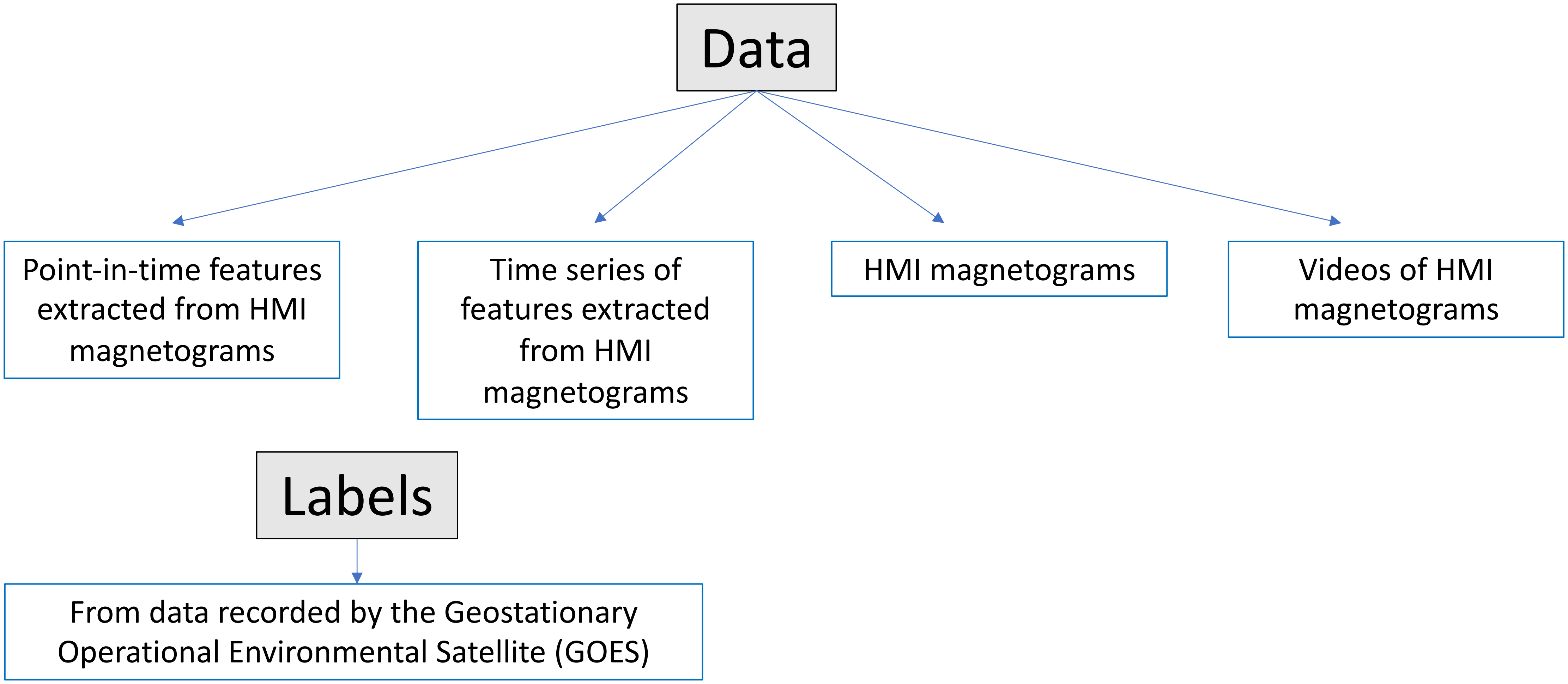


Coming toward Earth

Flare forecasting from SDO/HMI data



Flare forecasting from SDO/HMI data



Flare forecasting from SDO/HMI data

Data

- Point-in-time features extracted from HMI magnetograms
- Time series of features extracted from HMI magnetograms
- HMI magnetograms
- Videos of HMI magnetograms

Labels

- From data recorded by the Geostationary Operational Environmental Satellite (GOES)

MIDA (http://mida.dima.unige.it) papers:

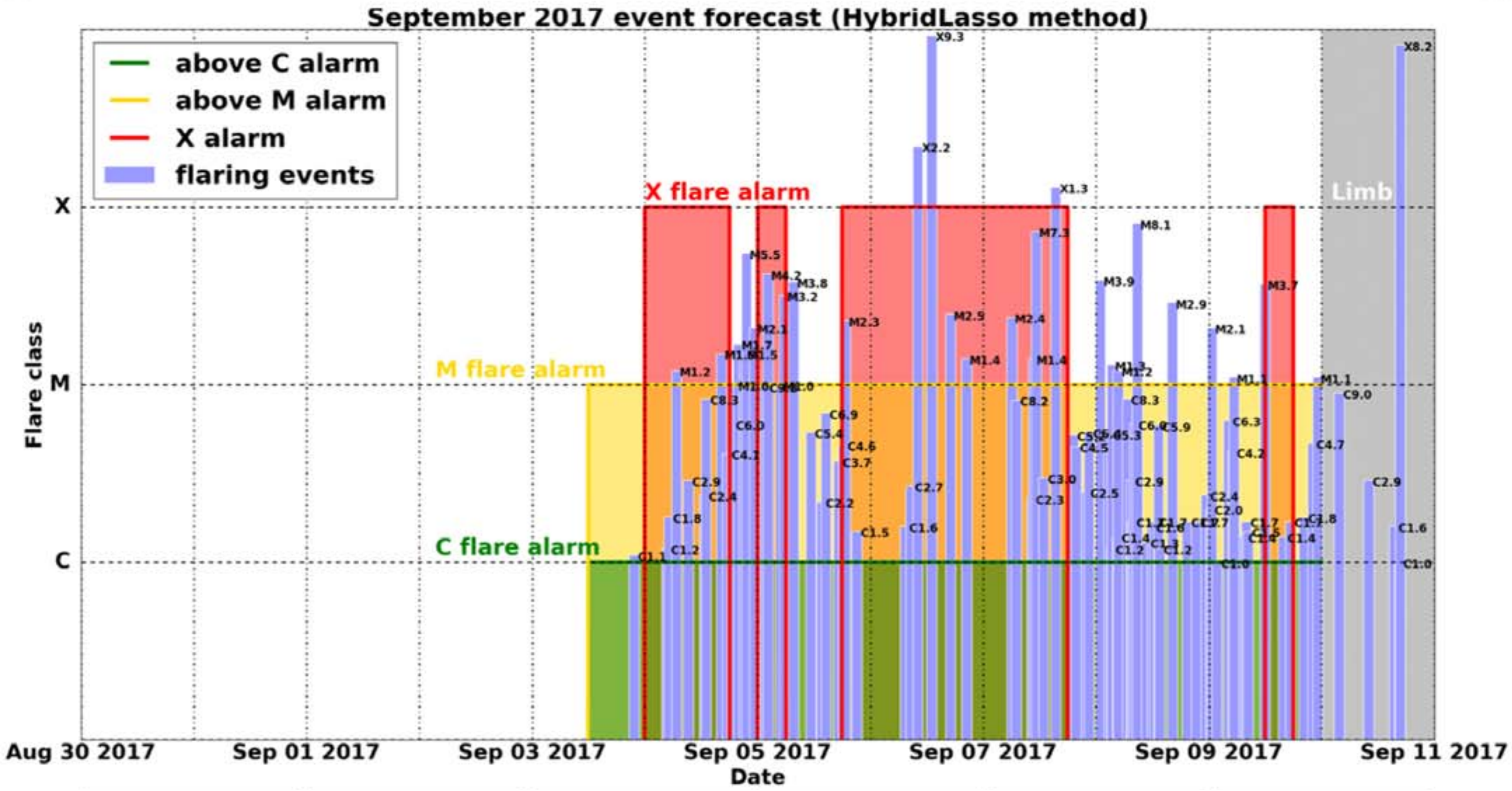
- Guastavino et al., *Implementation paradigm for supervised flare forecasting studies: a deep learning application with video data*, arxiv (2021)
- Georgulis et al., *The flare likelihood and region eruption forecasting (FLARECAST) project: flare forecasting in the big data & machine learning era* (2021)

Flare forecasting from SDO/HMI data

Does it work?

Flare forecasting from SDO/HMI data

Does it work?



the 2017 September solar storm

Benvenuto et al., 2020

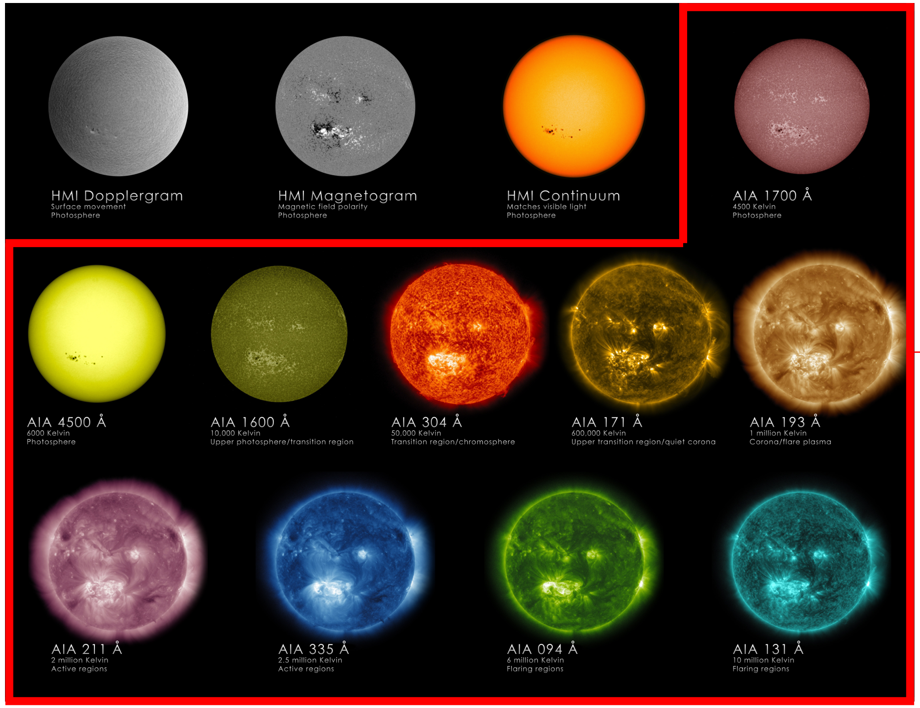
Flare nowcasting

SDO/AIA (Lemen et al. 2012)

- Atmospheric Imaging Assembly on board the Solar Dynamic Observatory

SDO/AIA (Lemen et al. 2012)

- Atmospheric Imaging Assembly on board the Solar Dynamic Observatory
- It provides full-disk images of the Sun in 10 different wavelength (7 EUV, 2 UV, 1 visible) every 12 seconds



- 131 Å
- 94 Å
- 335 Å
- 211 Å
- 193 Å
- 171 Å
- 304 Å
- 1600 Å
- 1700 Å
- 4500 Å

Credits: https://svs.gsfc.nasa.gov/cgi-bin/details.cgi?aid=11071

Flare nowcasting from SDO/AIA data

- Data are image cubes of dimension 4096 x 4096 x N_w (x N_t)

Flare nowcasting from SDO/AIA data

- Data are image cubes of dimension $\boxed{\text{4096 x 4096}}$ x N_w (x N_t)

Pixels

Flare nowcasting from SDO/AIA data

- Data are image cubes of dimension 4096 x 4096 x $\boxed{N_w}$ (x N_t)

Wavelengths

Flare nowcasting from SDO/AIA data

- Data are image cubes of dimension 4096 x 4096 x N_w (x $\boxed{N_t}$)

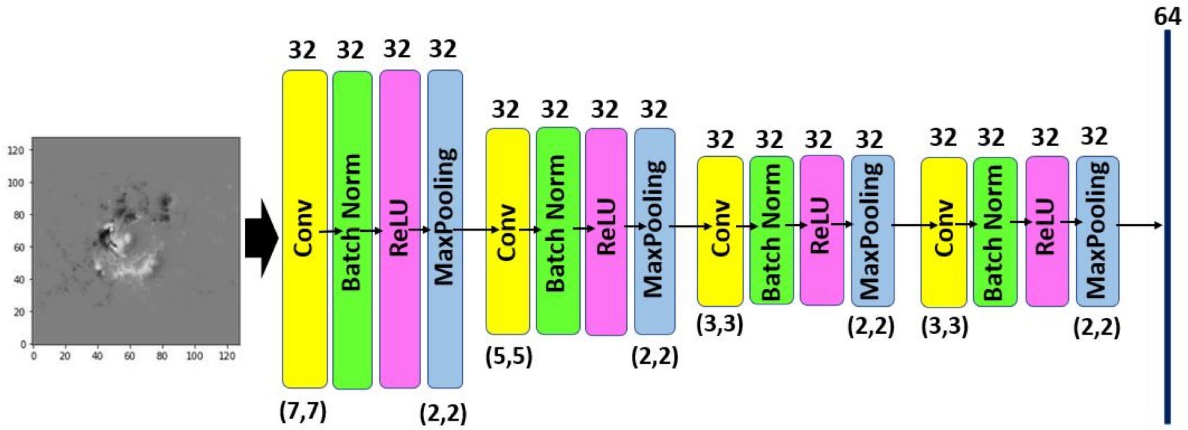
Time

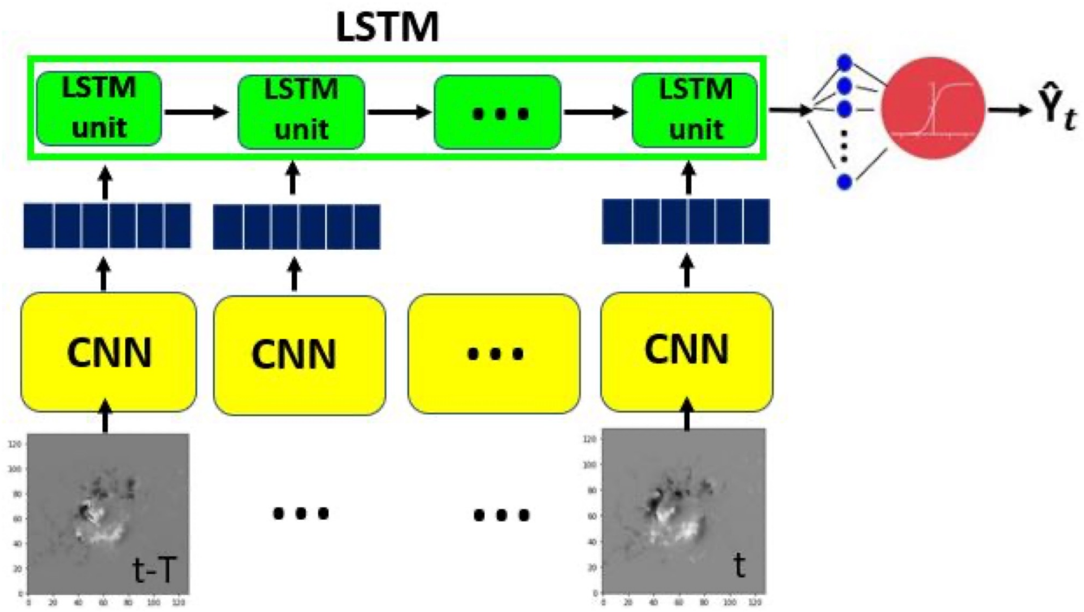
Flare nowcasting from SDO/AIA data

- Data are image cubes of dimension 4096 x 4096 x N_w (x N_t)
- **Possible approaches**:
  - Feature extraction from data cubes + NNs

Flare nowcasting from SDO/AIA data

- Data are image cubes of dimension 4096 x 4096 x N_w (x N_t)
- **Possible approaches**:
  - Feature extraction from data cubes + NNs
  - Data cubes + Convolutional Neural Networks (CNNs) or Long-term Recurrent Convolutional Networks (LRCNs)





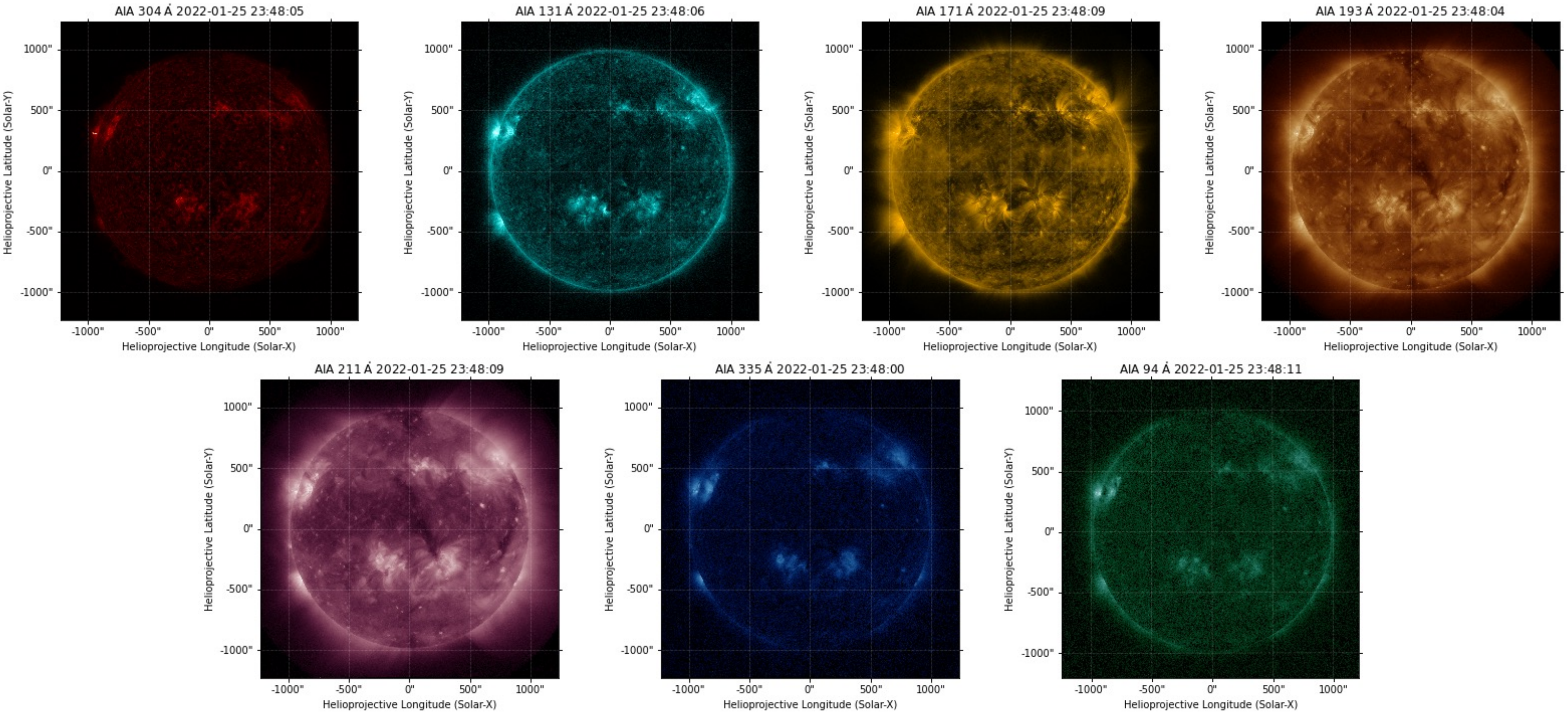
(Guastavino et al., 2021)

Flare nowcasting from SDO/AIA data

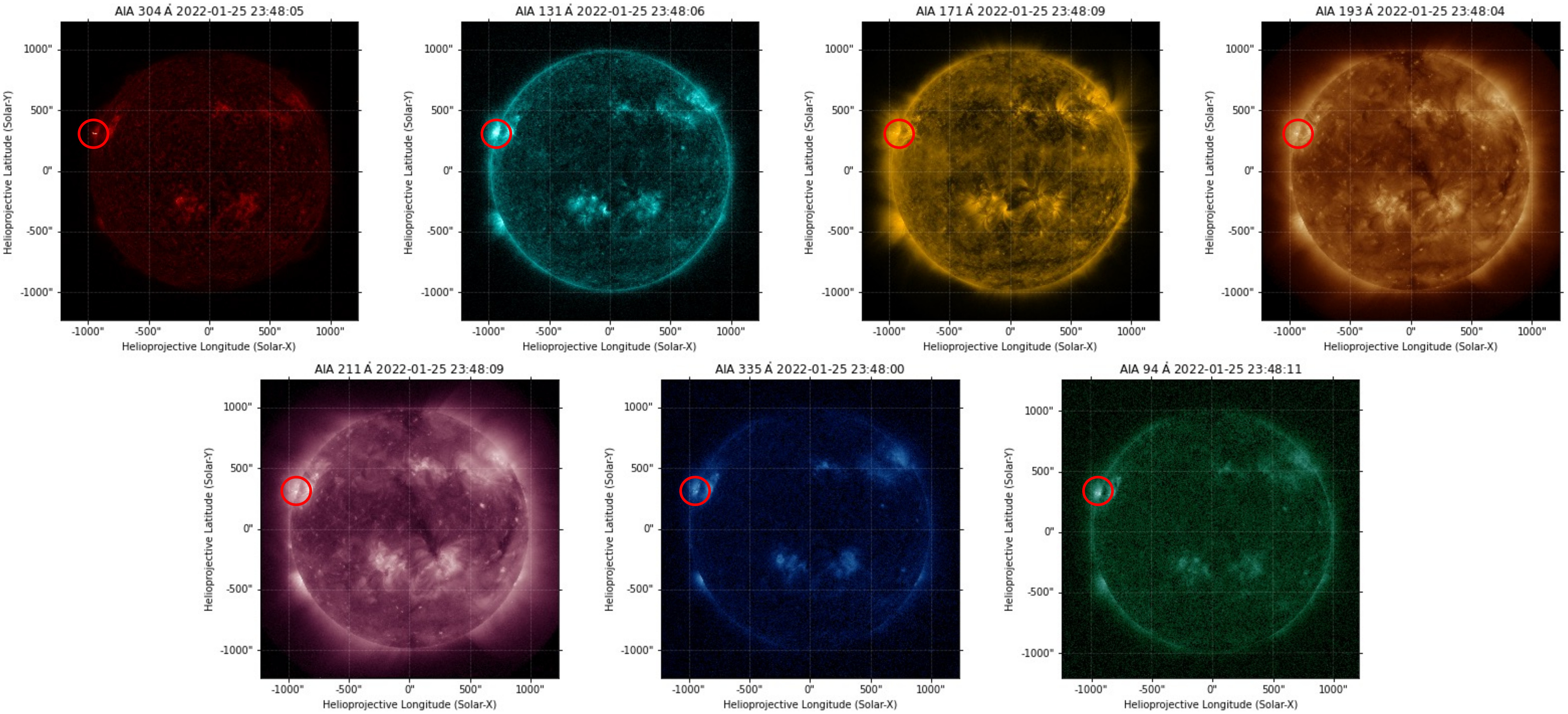
- Data are image cubes of dimension 4096 x 4096 x N_w (x N_t)
- **Possible approaches**:
  - Feature extraction from data cubes + NNs
  - Data cubes + Convolutional Neural Networks (CNNs) or Long-term Recurrent Convolutional Networks (LRCNs)
  - Data compression + CNNs or LRCNs

Fourier transform of the images

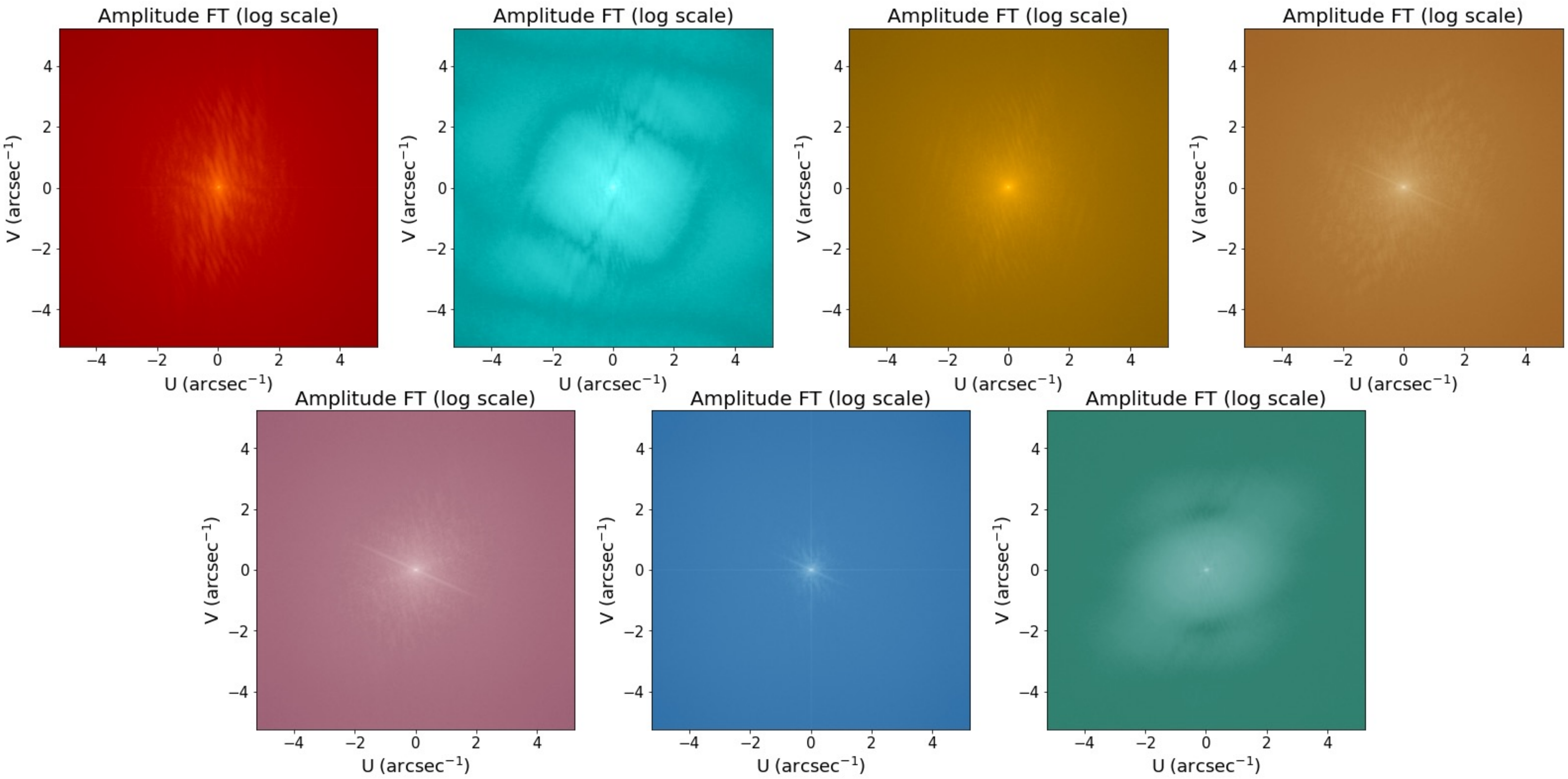
Flare nowcasting from SDO/AIA data



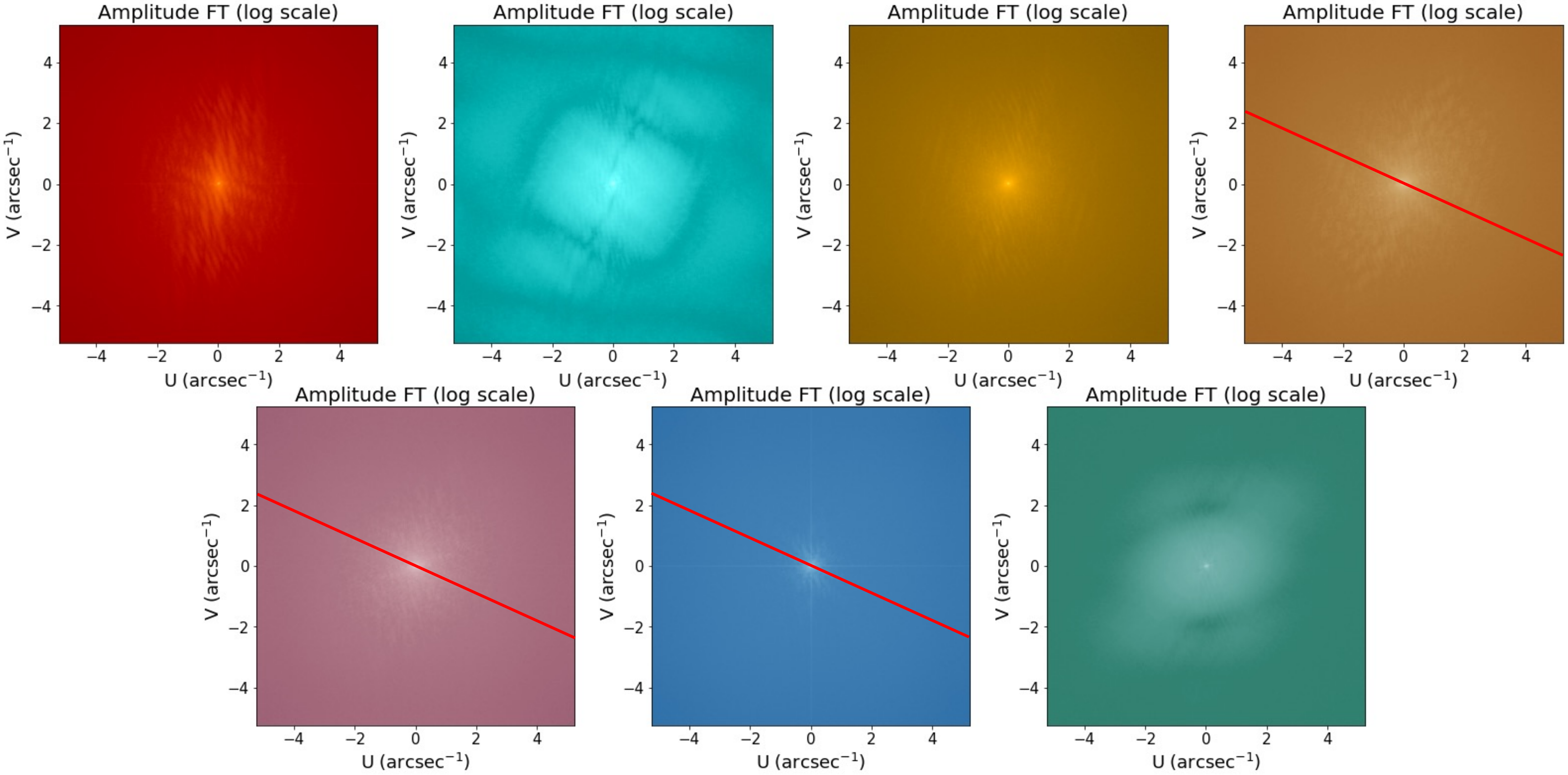
Flare nowcasting from SDO/AIA data



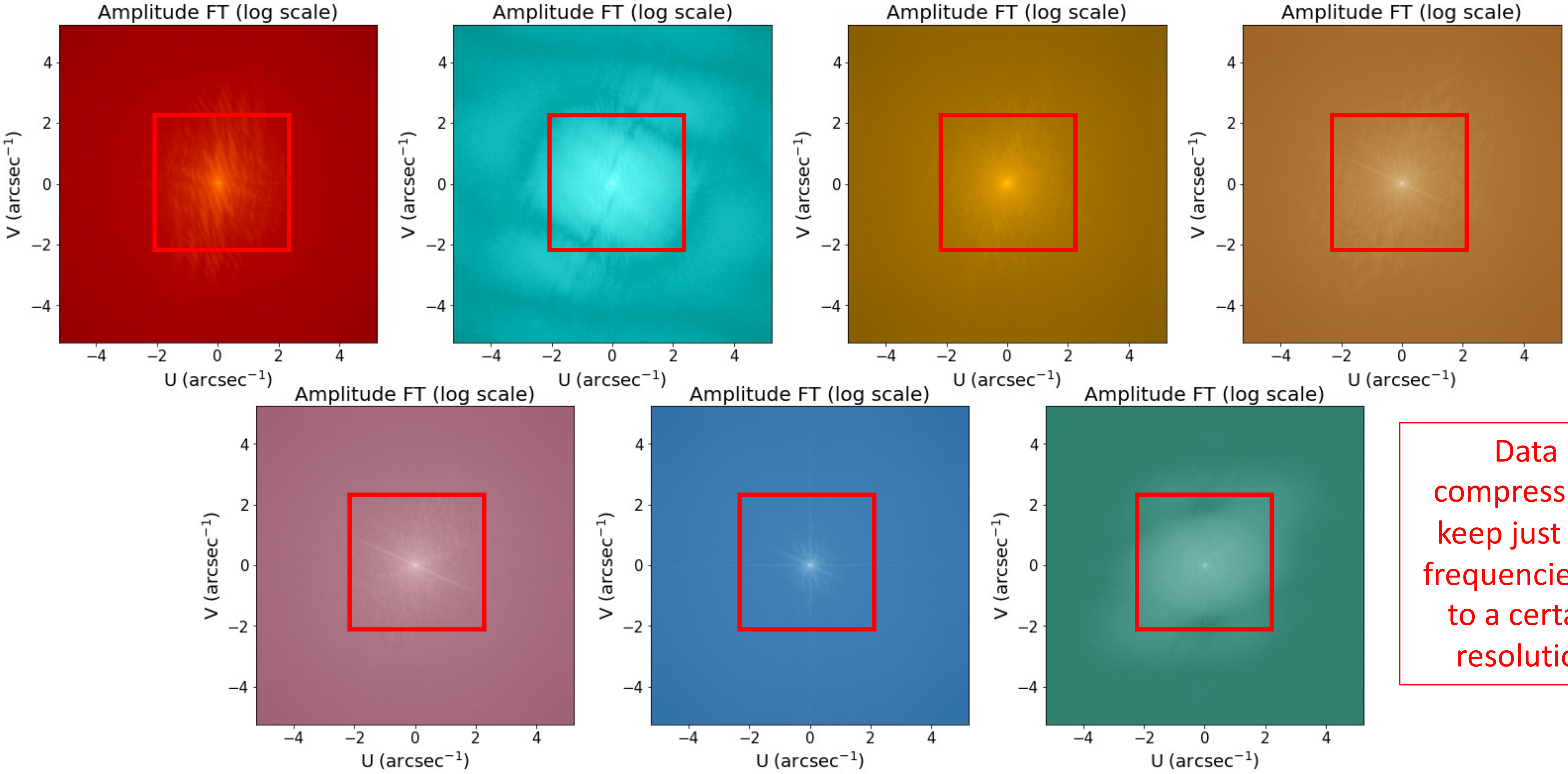
Flare nowcasting from SDO/AIA data



Flare nowcasting from SDO/AIA data



Flare nowcasting from SDO/AIA data



Data compression: keep just the frequencies up to a certain resolution

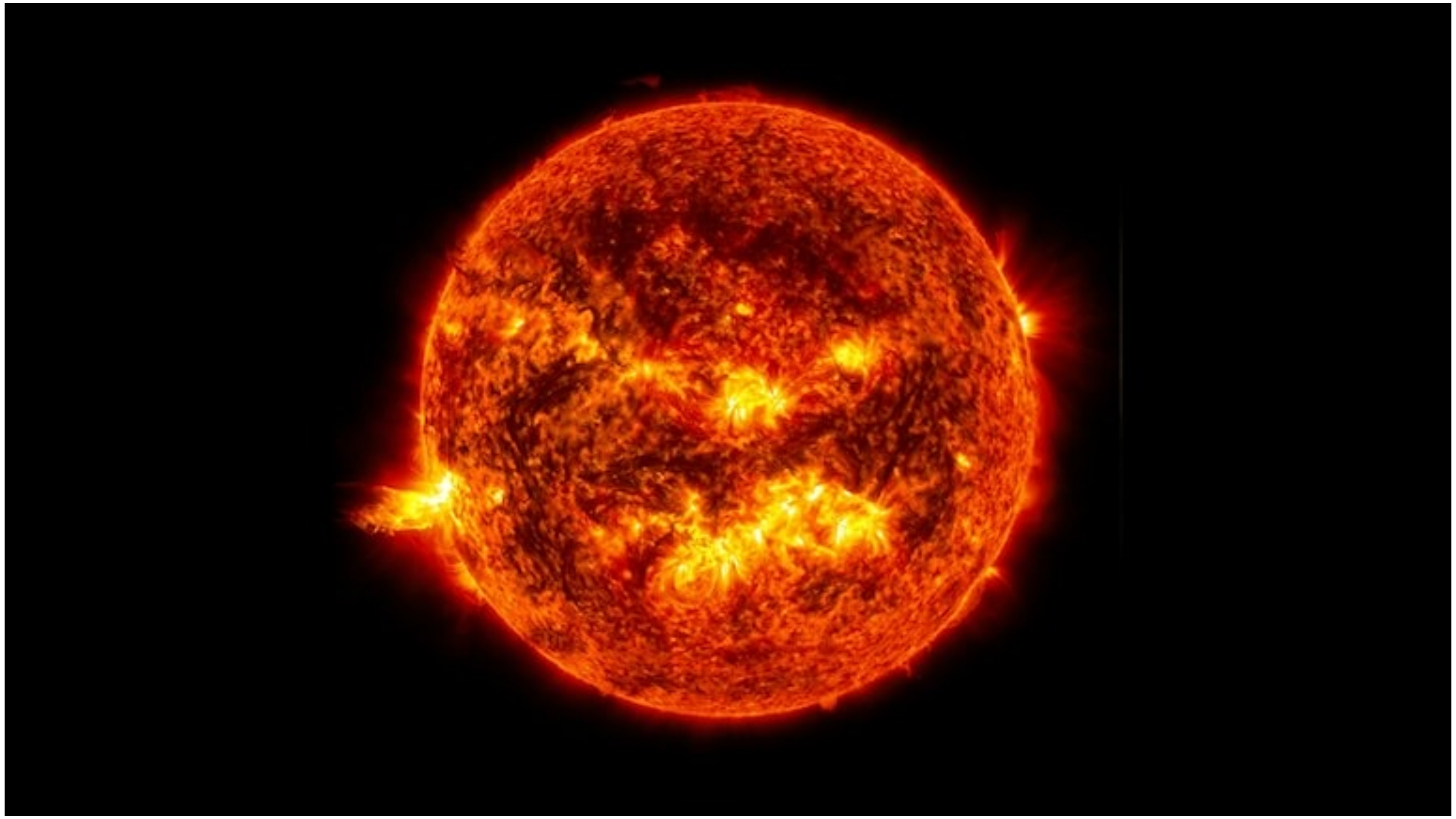
Conclusions

- We presented the STIX imaging problem and an AI method implemented to find a solution (MEM_GE)
- We described the problem of flare forecasting from SDO/HMI data and we show the results in the case of the 2017 September solar storm
- We presented possible ways to address the problem of flare nowcasting from SDO/AIA data with specific focus on data compression by means of the Fourier transform

References

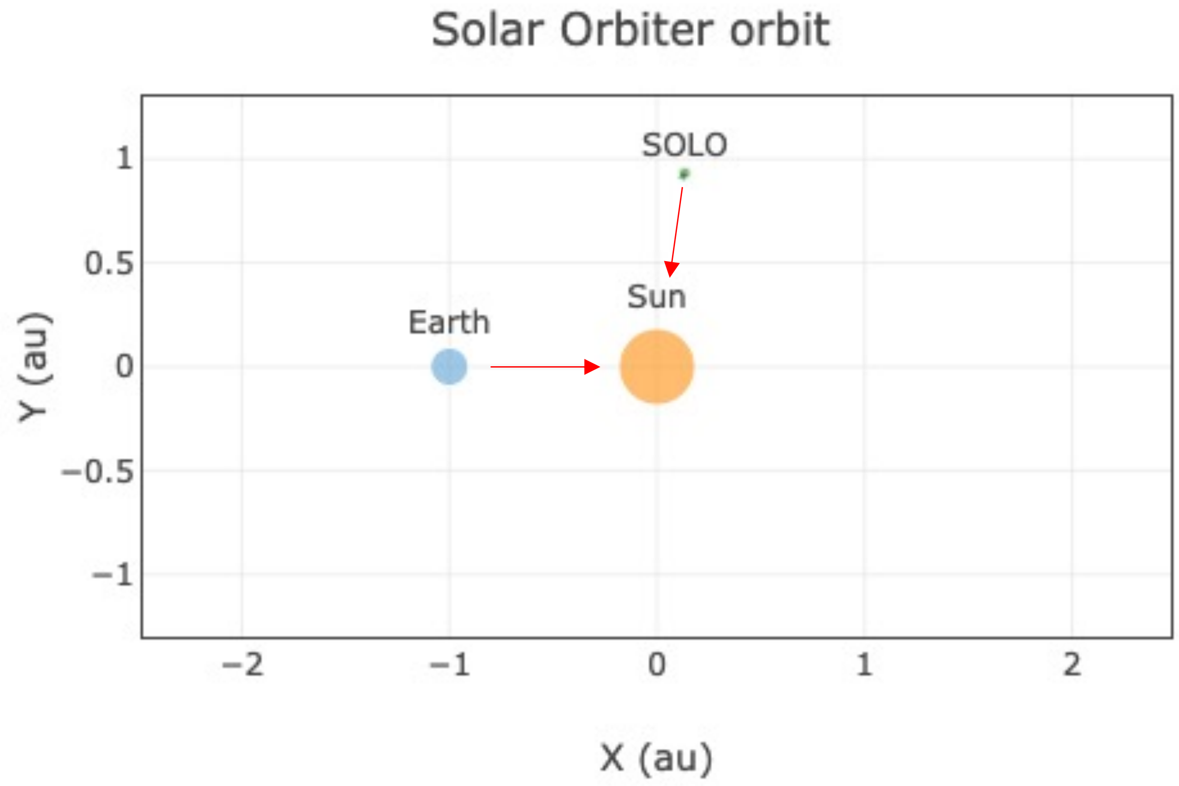
- Holman, *Solar eruptive events*, Phys. Today, 2012
- Krucker et al., *The Spectrometer/Telescope for Imaging X-rays (STIX),* A&A, 2020
- Meuris et al., *Caliste-SO, a CdTe based spectrometer for bright solar event observations in hard X-rays*, Nucl. Instrum. Methods Phys. Res. A, 2015
- Lin et al. , *The Reuven Ramaty High-Energy Solar Spectroscopic Imager (RHESSI)*, Solar Physics*,* 2002
- Massa et al., *MEM_GE: A New Maximum Entropy Method for Image Reconstruction from Solar X-Ray Visibilities*, ApJ, 2020
- Massa et al., *First hard X-ray imaging results by Solar Orbiter STIX*, arxiv, 2022
- Battaglia et al., *STIX X-ray microflare observations during the Solar Orbiter commissioning phase*, A&A, 2021
- Guastavino et al., *Implementation paradigm for supervised flare forecasting studies: a deep learning application with video data*, arxiv, 2021
- Georgulis et al., *The flare likelihood and region eruption forecasting (FLARECAST) project: flare forecasting in the big data & machine learning era,* J. Space Weather Space Clim, 2021
- Benvenuto et al., *Machine Learning as a Flaring Storm Warning Machine: Was a Warning Machine for the 2017 September Solar Flaring Storm Possible?*, ApJ Letters, 2020

Thank you for the attention!



May 2021 events (Massa et al., 2022)

Angle relative to Earth-Sun (in May 2021): 97.4° – 98.2°



AIA images rotated by means of the *reproject* Python package (see Battaglia et al., 2021)

(https://pub023.cs.technik.fhnw.ch/view/ancillary)