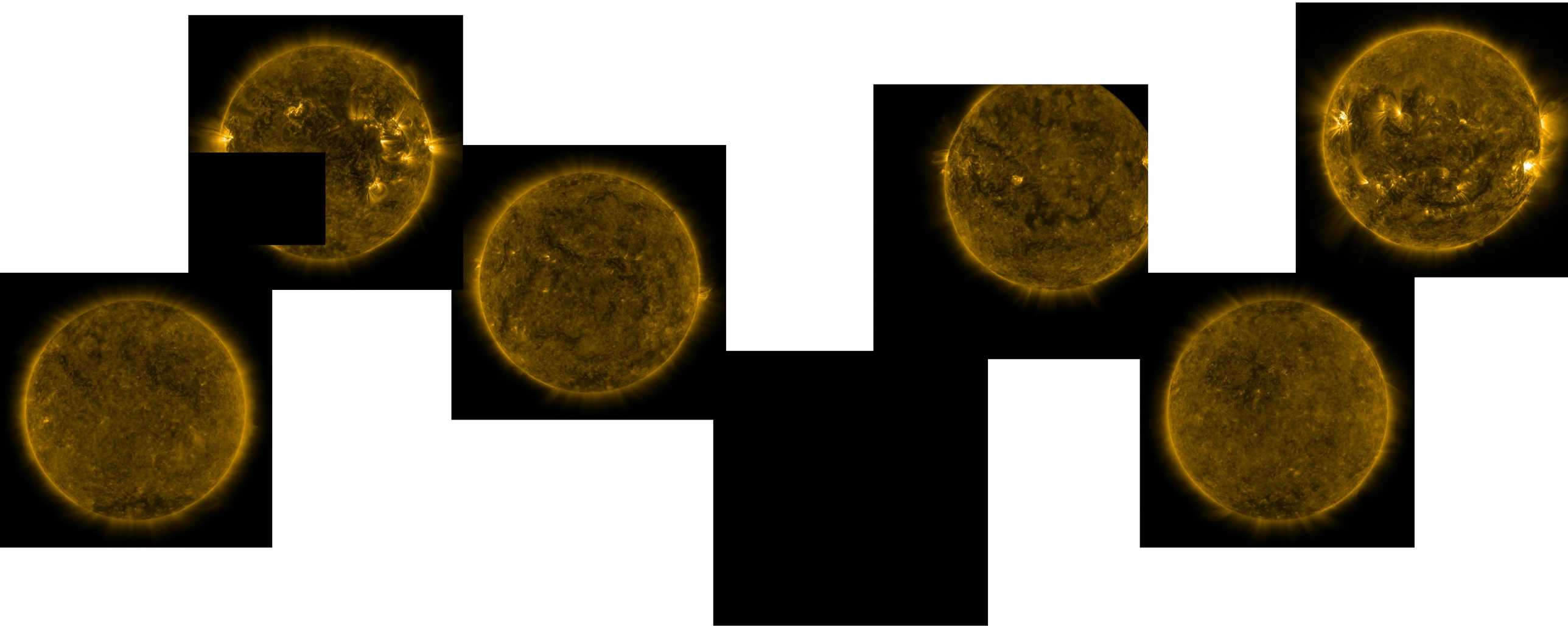
University of Applied Sciences and Arts
Northwestern Switzerland

Unsupervised event detection in heliophysics

ML Helio 2022

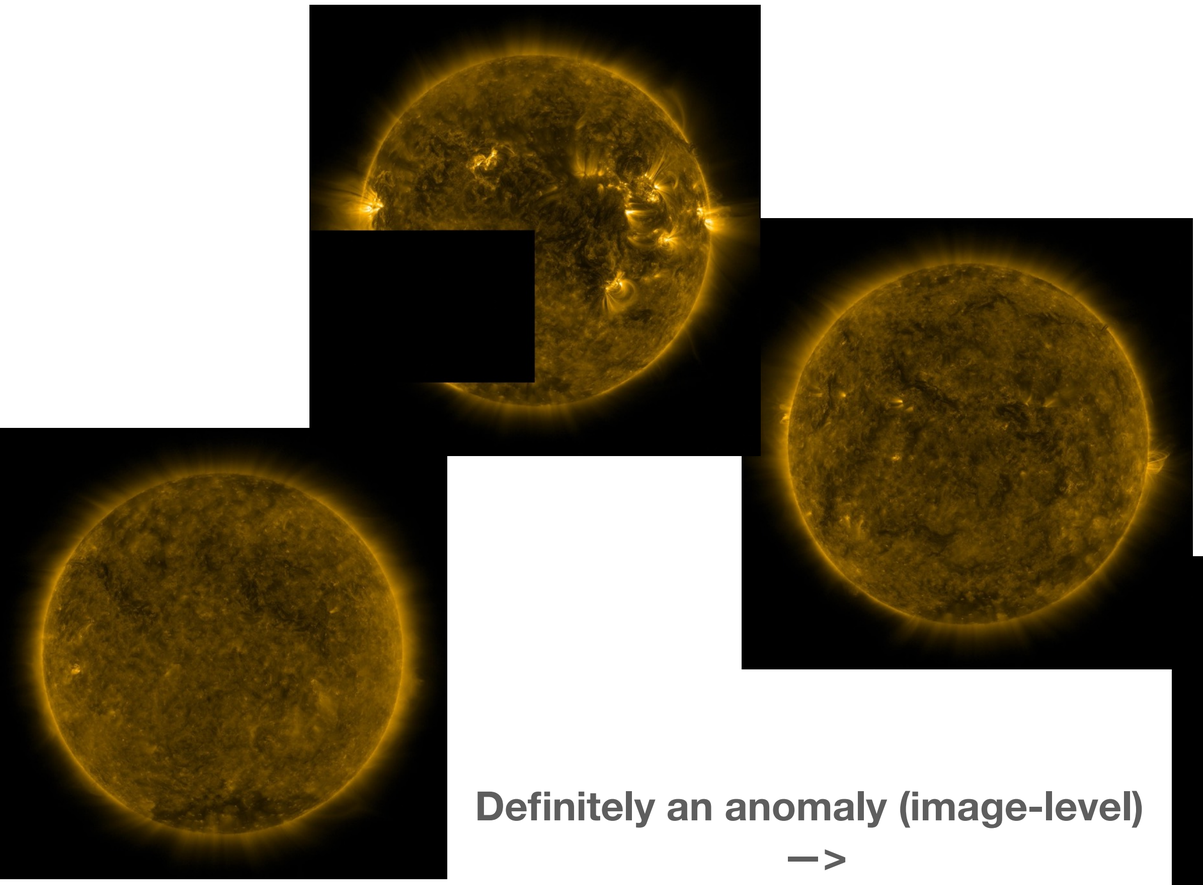
Marius Giger & André Csillaghy - 23.03.2022 - FHNW - Institute for Data Science (i4DS)

Spot the anomaly

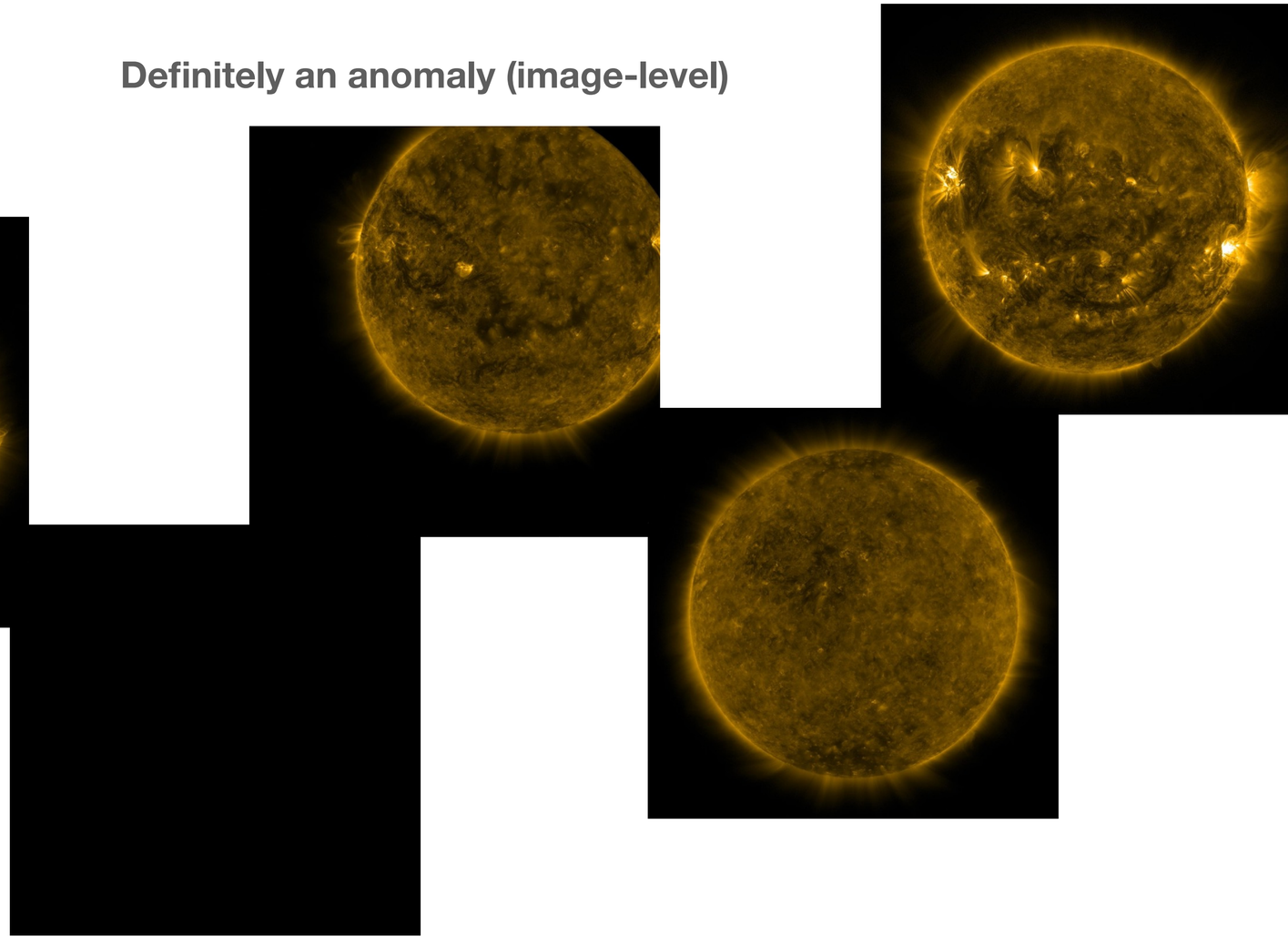


Spot the anomaly

Definitely an anomaly (image-level)



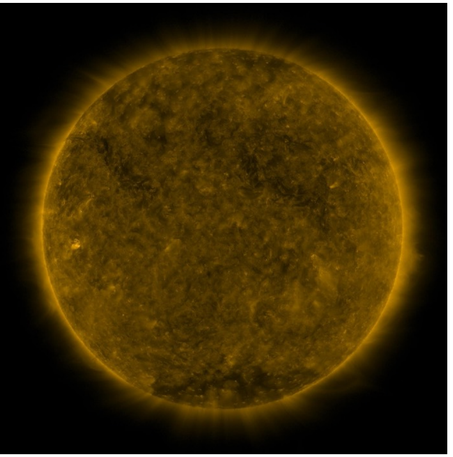
Definitely an anomaly (image-level)

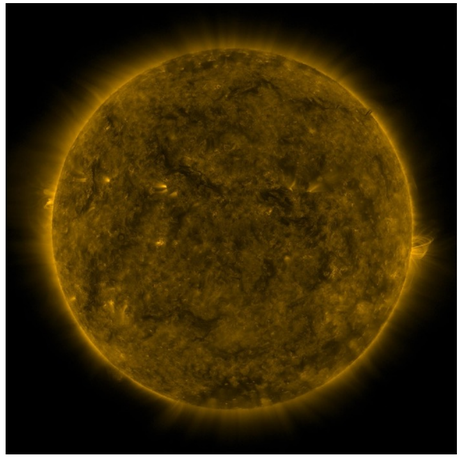


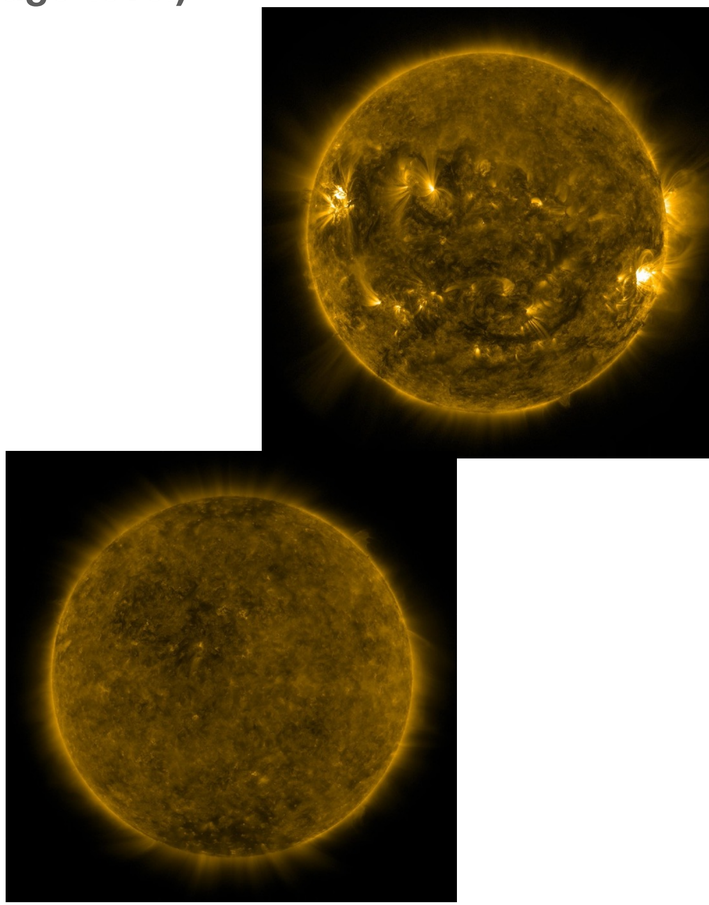
Definitely an anomaly (image-level)
—>

Spot the anomaly

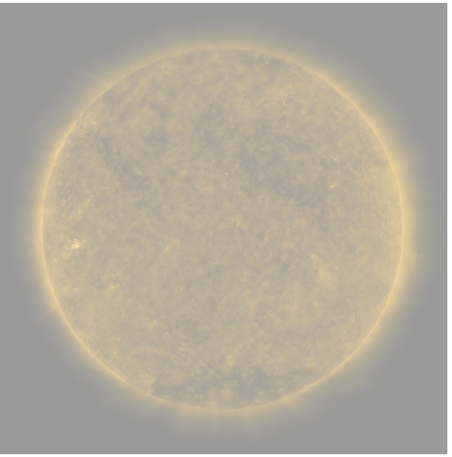
A lot of activity (image-level)
—>

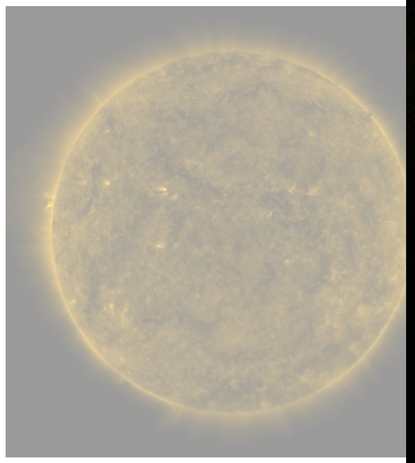


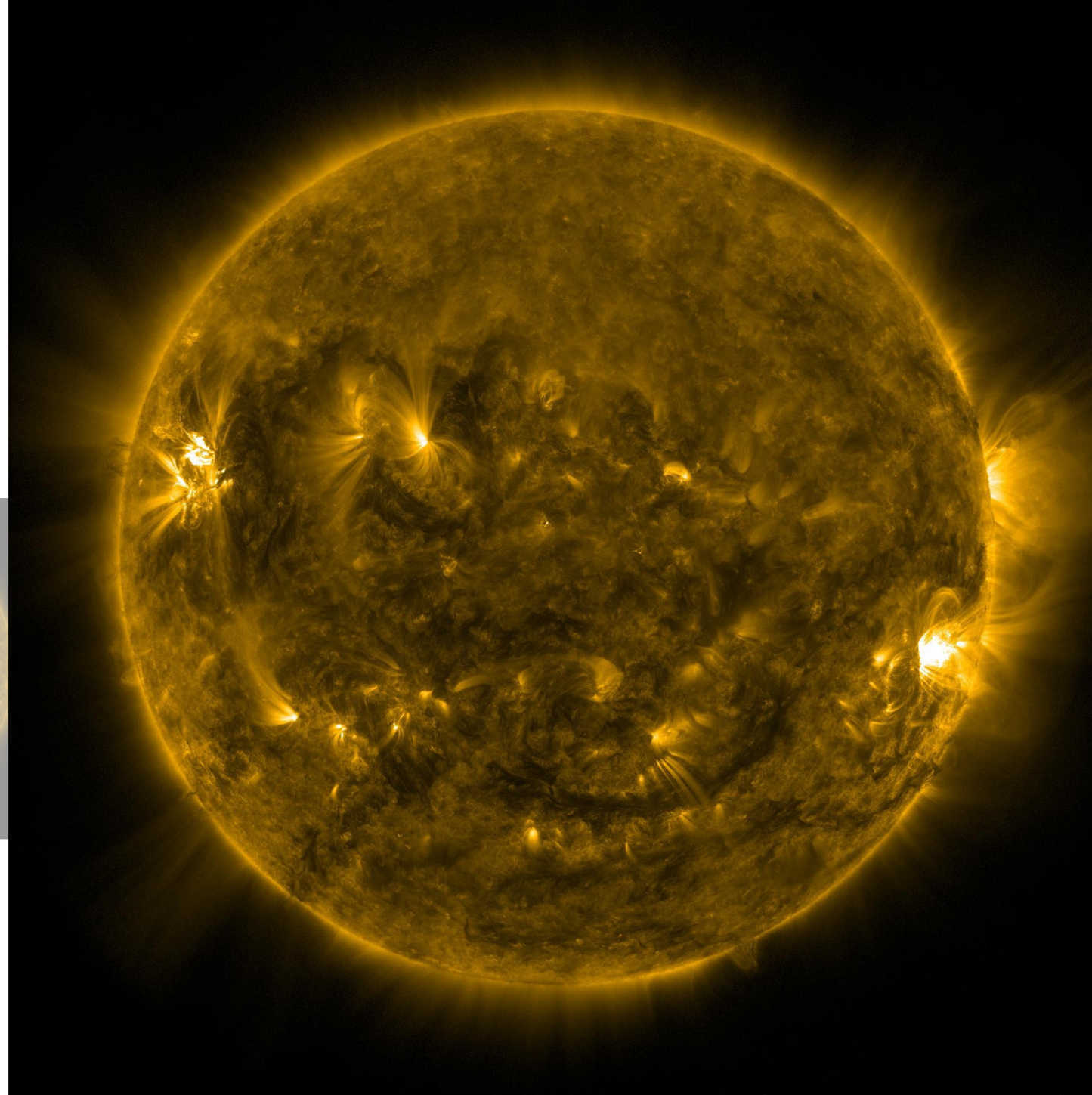




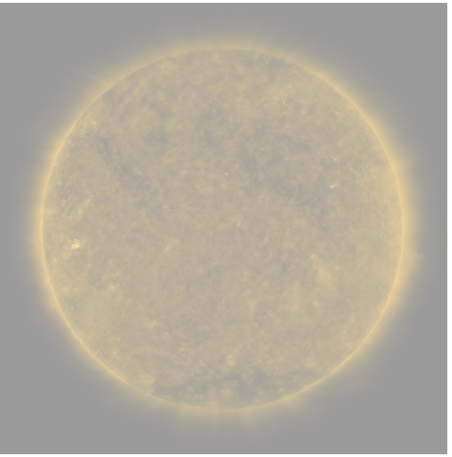
Spot the anomaly

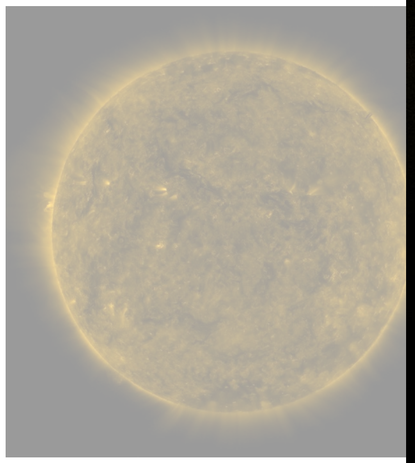


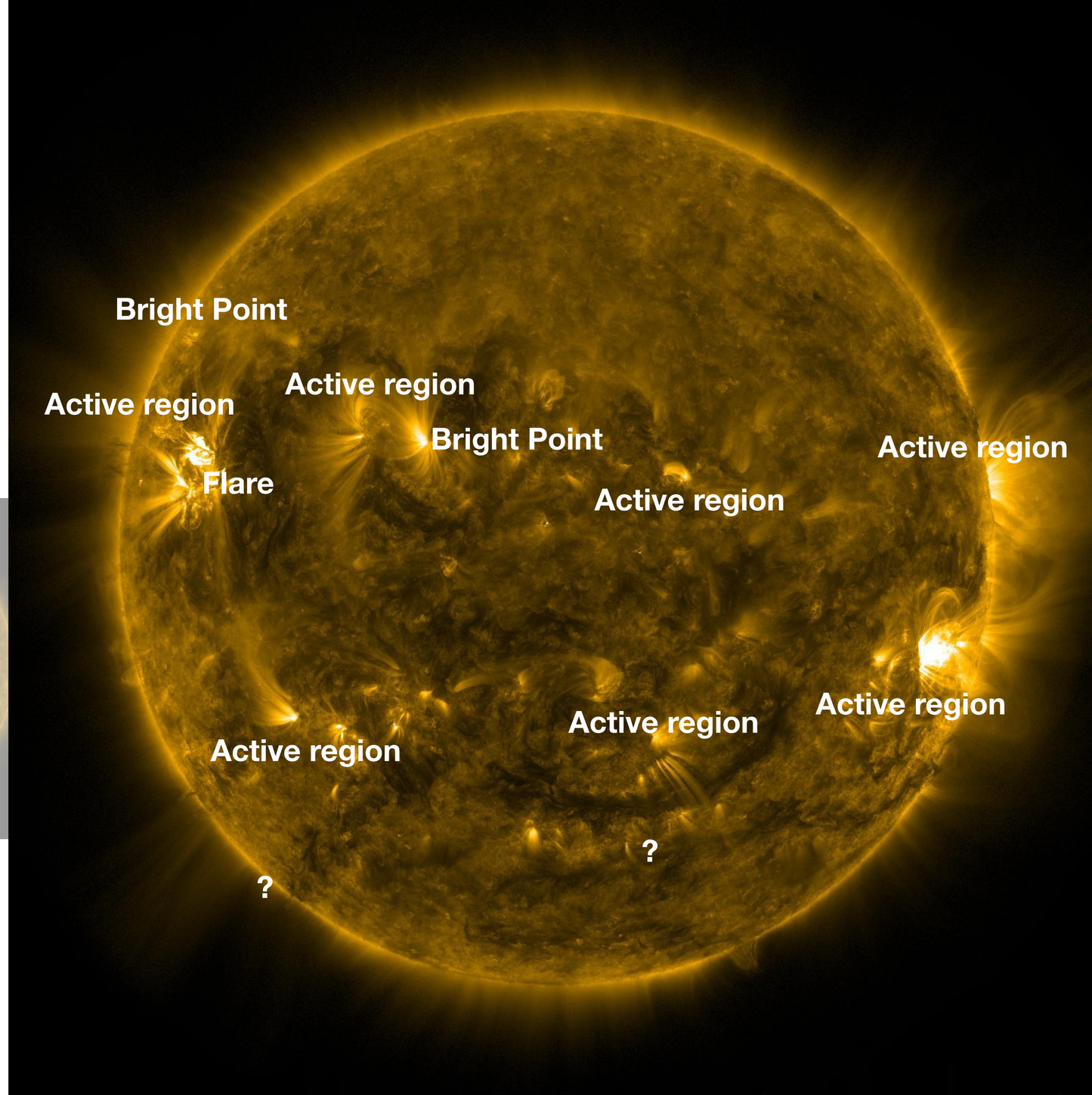




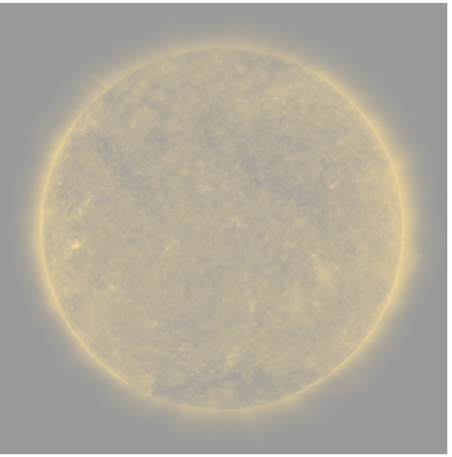
Spot the anomaly

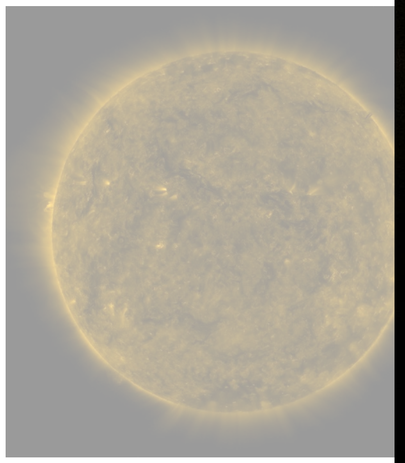


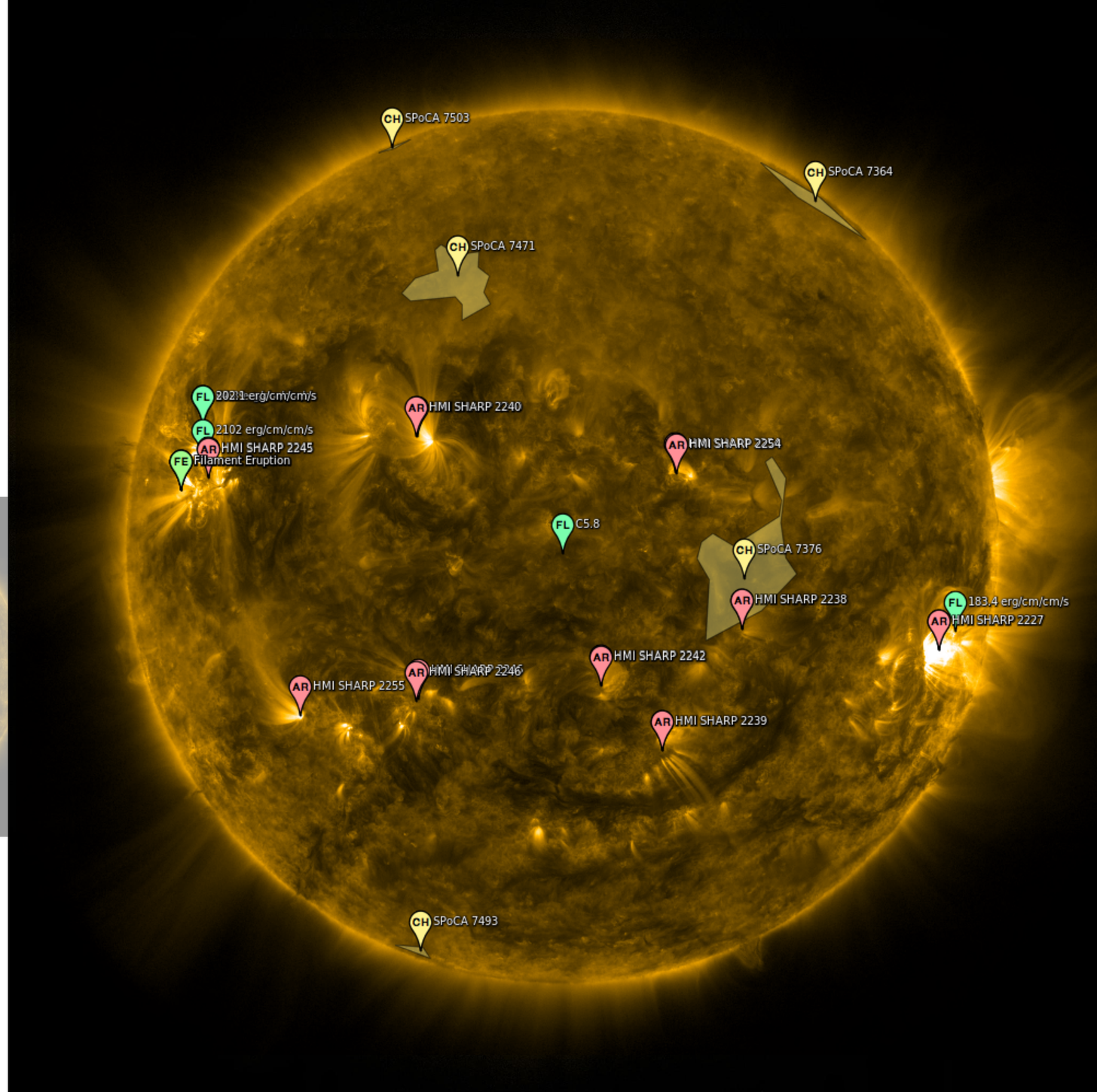




Spot the anomaly







What is normal?

- Normality highly depends on the application
- Working hypothesis: *all regions that are not quiet Sun are anomalous*
- Other definitions:
  - *Complex active regions are abnormal (focussing on event type)*
  - *Active regions that lead to a flare in the next 1h are abnormal (flare forecasting)*
  - *Large brightness changes in a short amount of time are abnormal (including temporal dimension)*

👉 *Quiet Sun is the normal state*

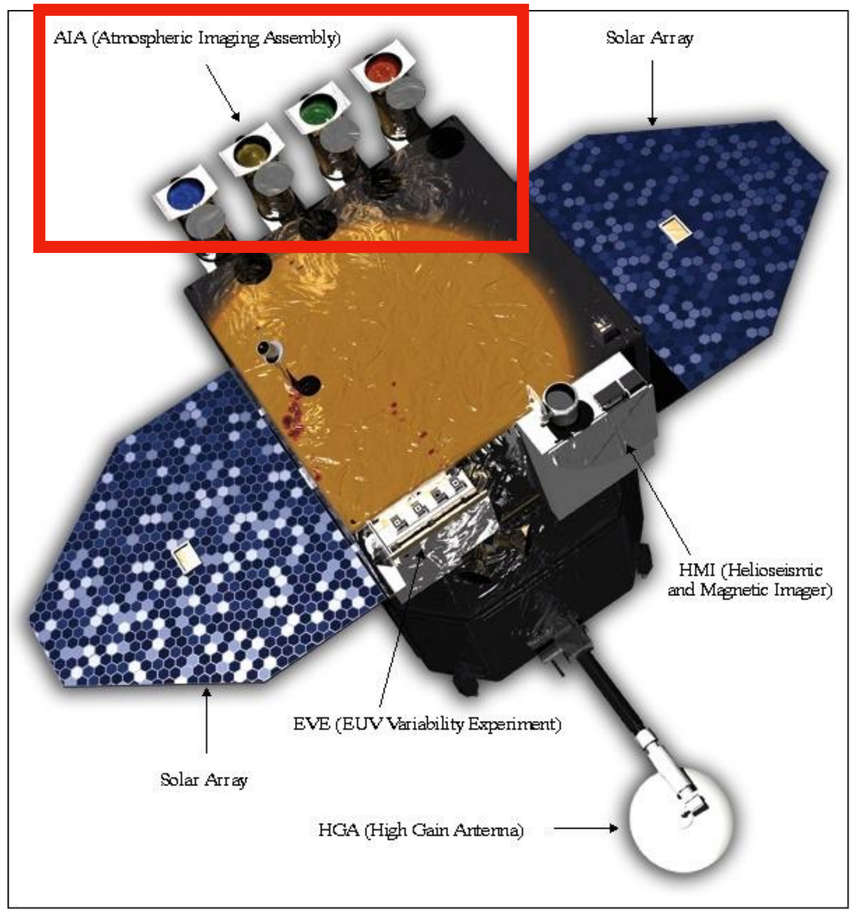
Research Objectives

- ✓ Uncover unknown/interesting structures **(novelty/anomaly detection)**
- ✓ Find ways to overcome the data bottleneck of annotated data, missing or incomplete labels **(unsupervised learning)**
- ✓ Automatically detect different solar phenomena **(representation learning)**
- ✓ Make use of the full available datasets

Data

Solar Dynamics Observatory (SDO)

- EUV images from SDO AIA
- Single channel observations (AIA 171)
- Machine-learning ready data: Curated Image Parameter Dataset *(Ahmadzadeh et al., 2019)* and SDO ML Dataset v1 *(Galvez et al., 2019)*

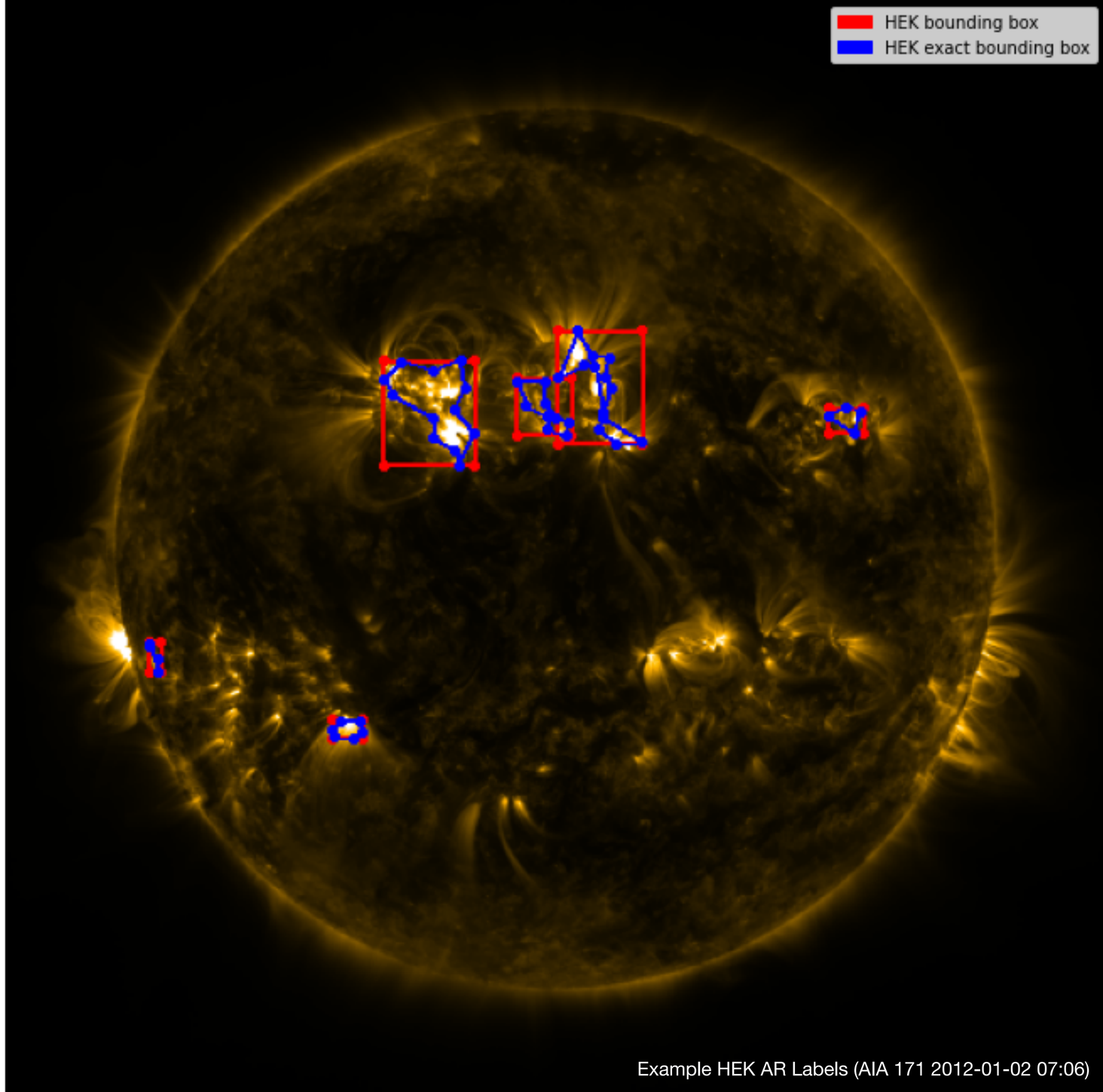


SDO spacecraft, Image Source: NASA

👉 DMLab API is very useful to retrieve a specific set of data from the Curated Image Parameter Dataset

Existing labels

- Heliophysics Event Knowledgebase (HEK)
  - Resulting artefacts of FFT algorithms
  - Other algorithms and manual observations
- Expert-curated datasets e.g. DeepSDO event dataset *(Baek et al., 2021)*
- Many more



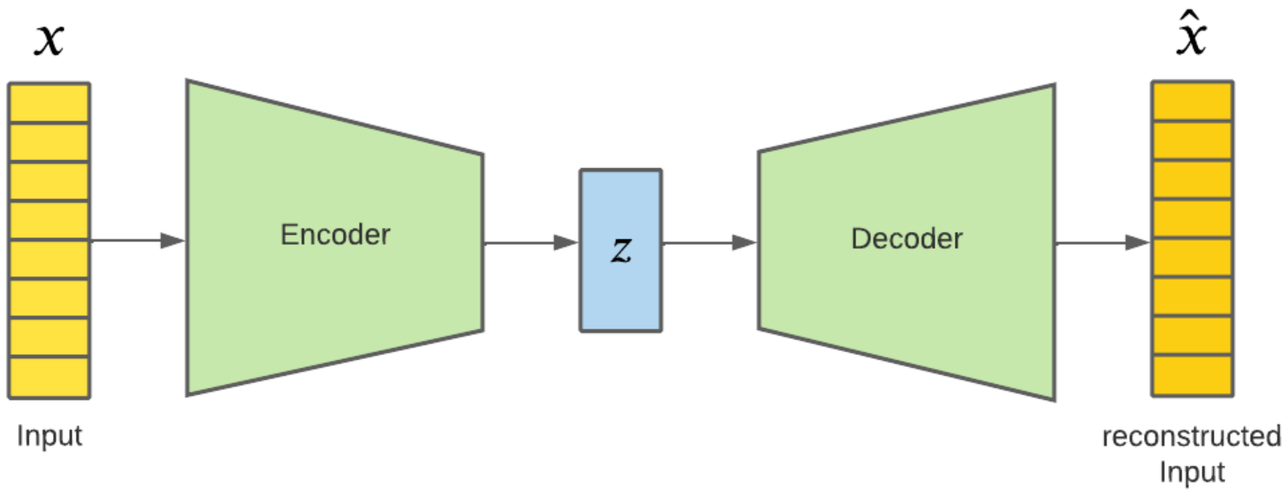
Example HEK AR Labels (AIA 171 2012-01-02 07:06)

Challenges

- Evaluating model output (samples, regions of interest)
- Data complexity (Spatio-temporal observations, dynamics at different time-scales, non-stationary data, spherical shape)

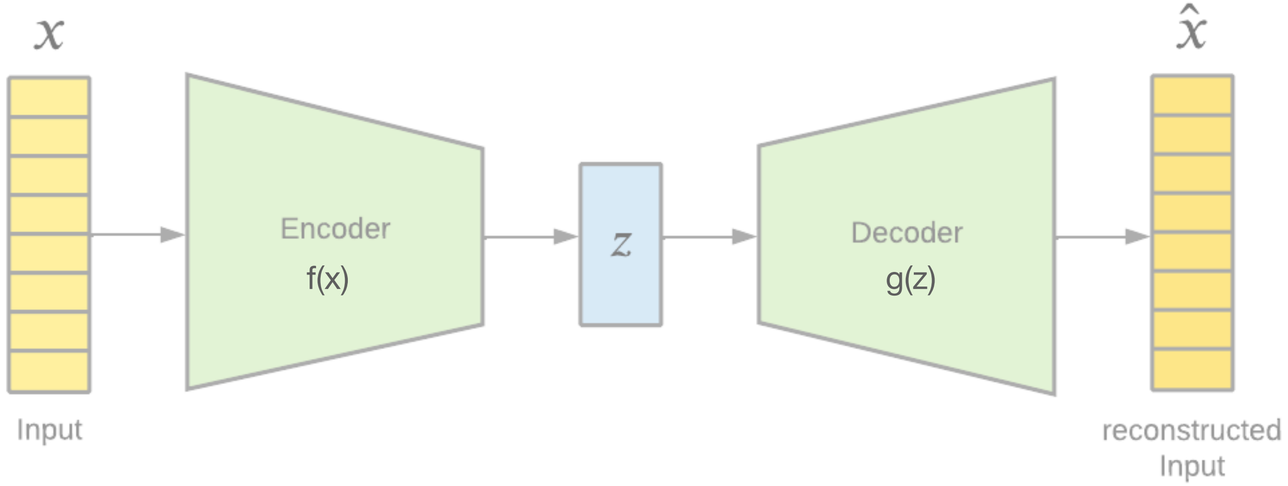
Anomaly Detection using Auto Encoders (AE)

What is an AE?



also refer to *(Kingma and Welling, 2019)*

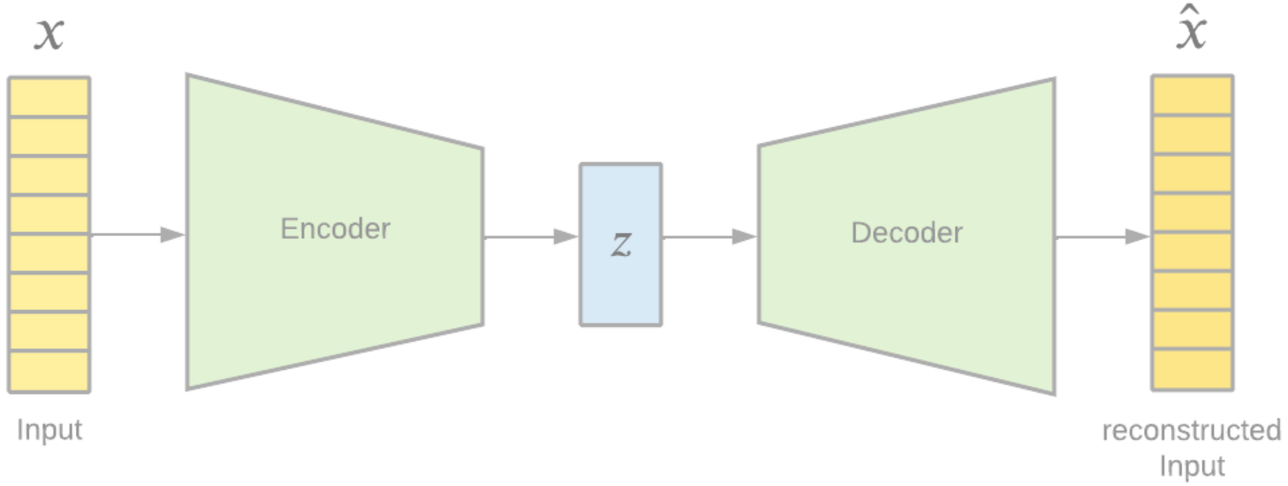
What is an AE?



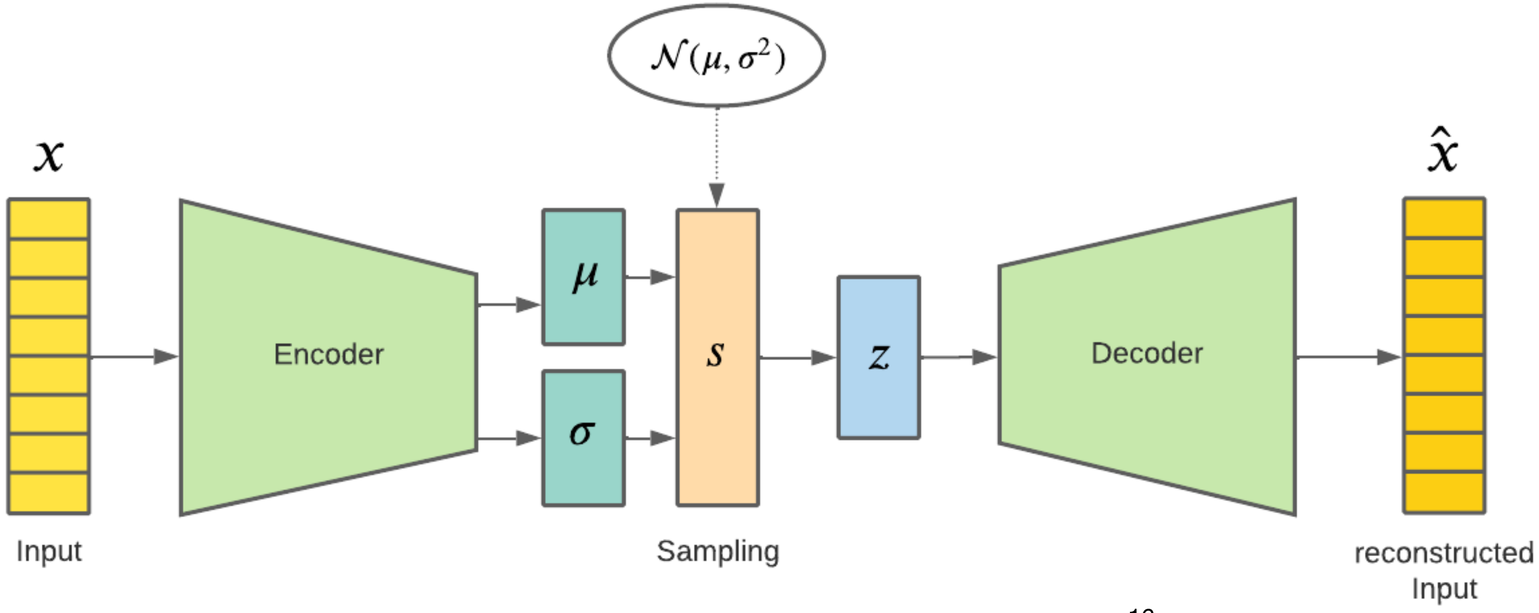
$$L_{AE} = L_{rec}(x, g(f(x)))$$

also refer to *(Kingma and Welling, 2019)*

What is a VAE?



$$L_{AE} = L_{rec}(x, g(f(x)))$$



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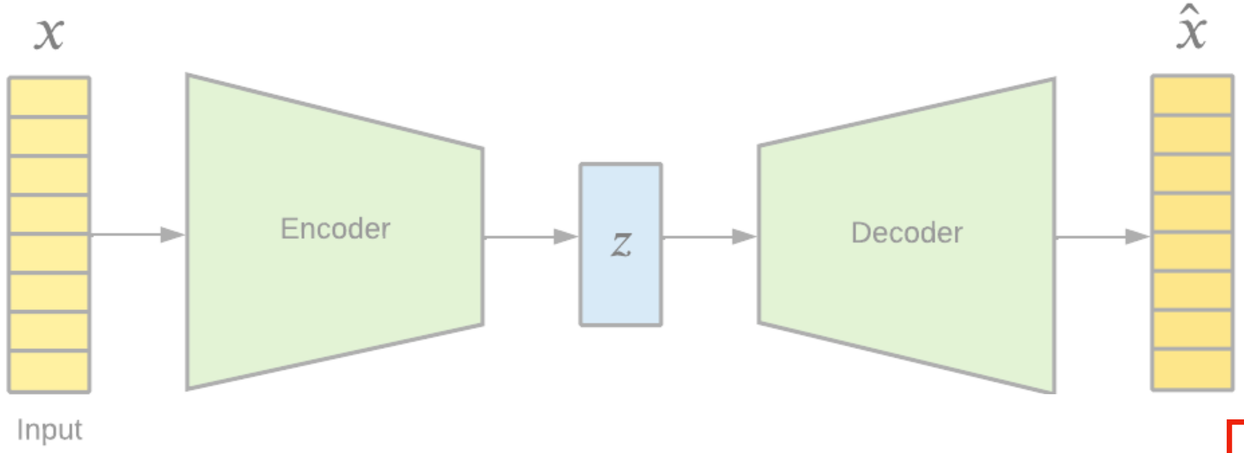
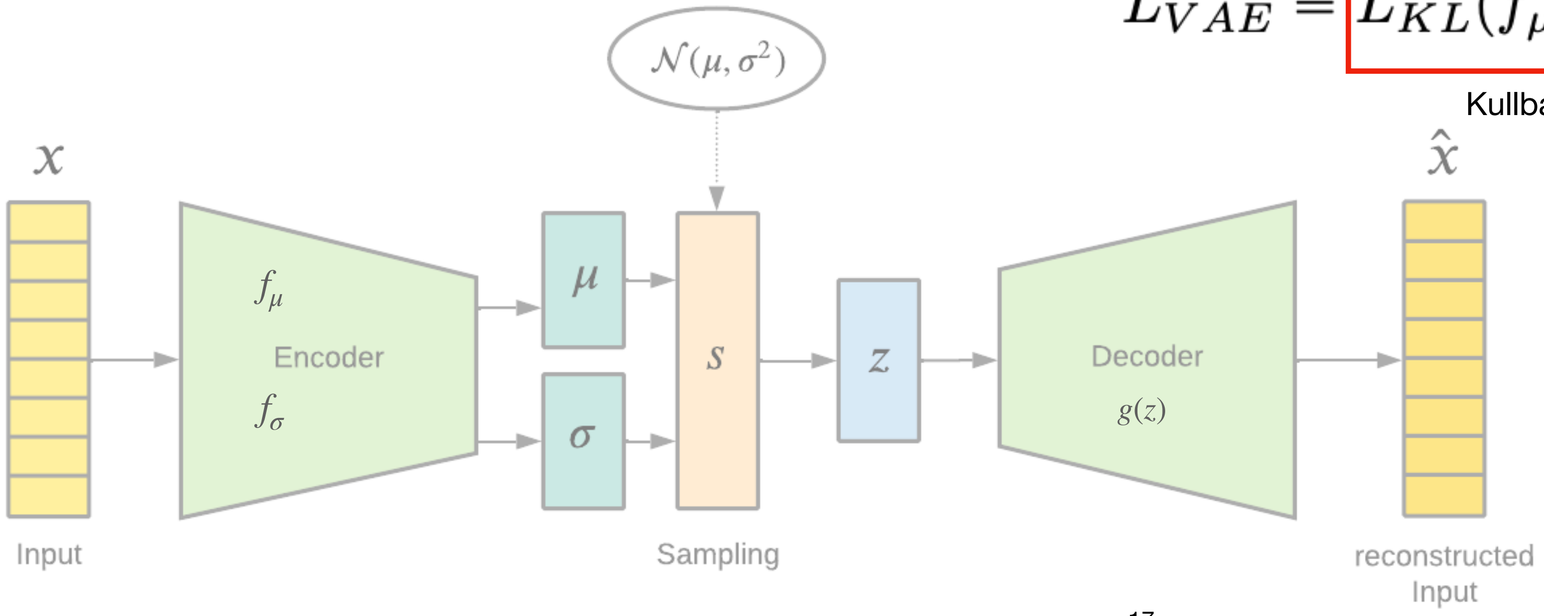
What is a VAE?



$$L_{AE} = L_{rec}(x, g(f(x)))$$

$$L_{VAE} = \boxed{L_{KL}(f_\mu(x), f_\sigma(x)^2))} + L_{rec_{VAE}}(x, g(z))$$

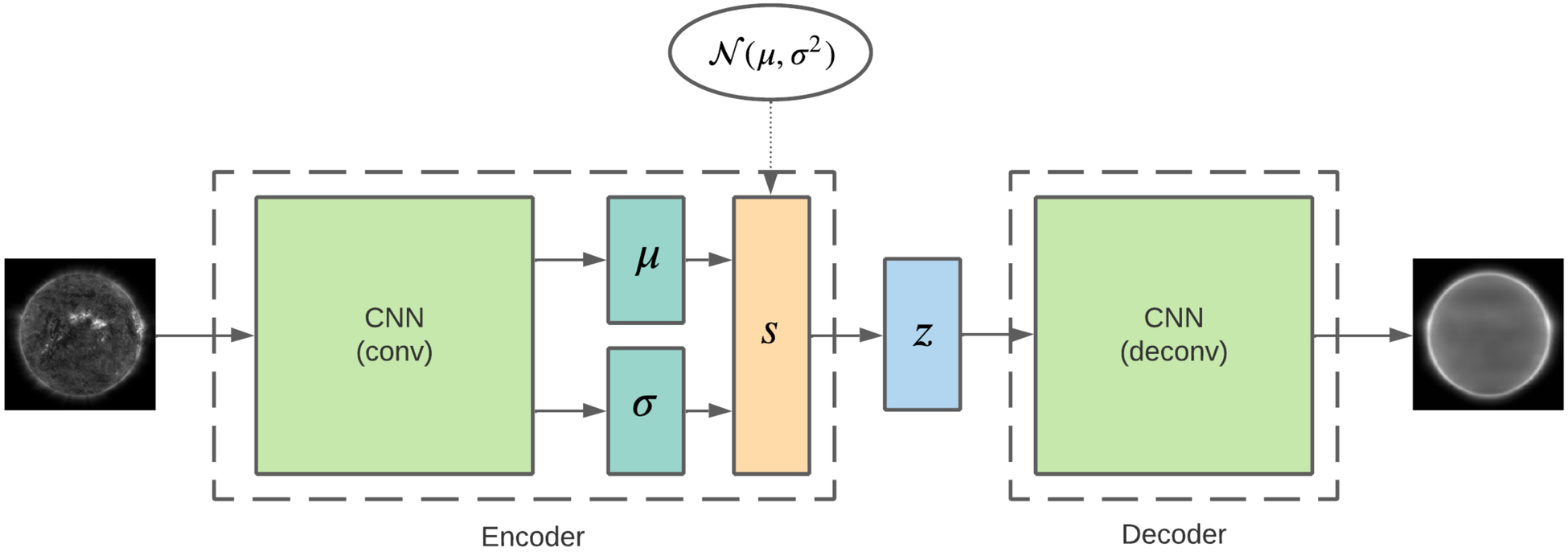
Kullback-Leibler divergence



also refer to *(Kingma and Welling, 2019)*

What is a Convolutional VAE?

- For images both Encoder/Decoder usually are CNNs
- Model inputs are full-disk AIA images (in our case AIA 171)



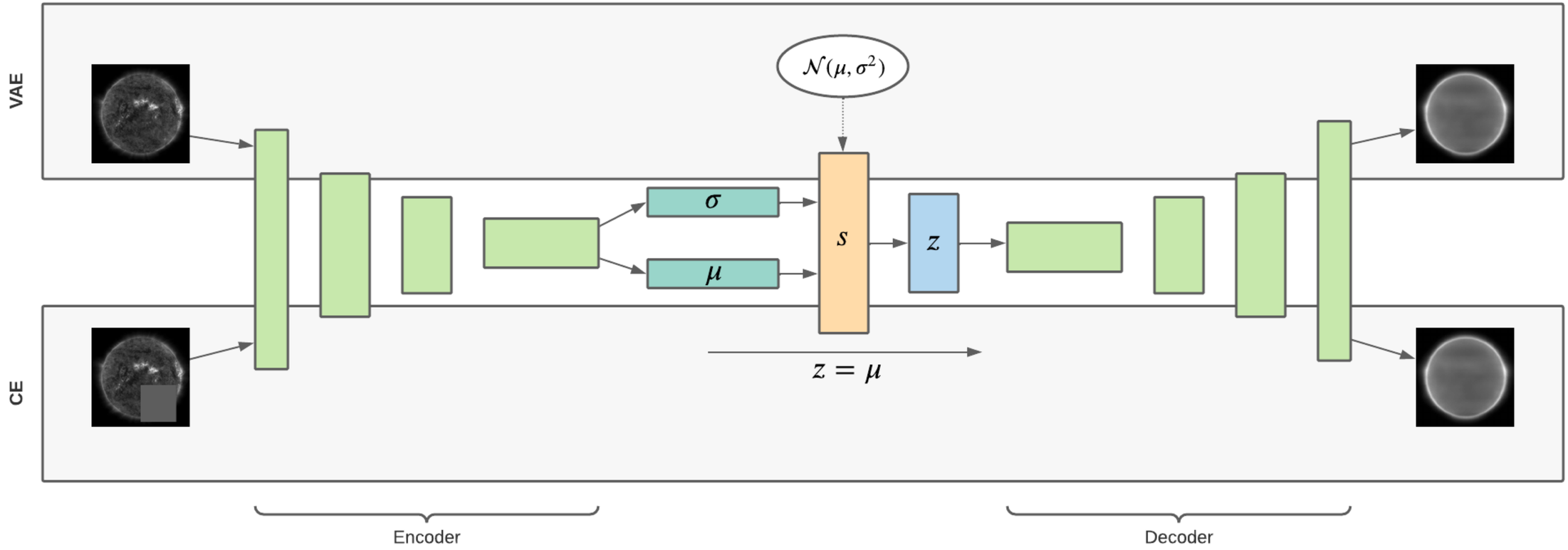
Unsupervised Anomaly Detection with ceVAE

Context-Encoding Variational Autoencoder

What is ceVAE?

Encoding Semantic Information

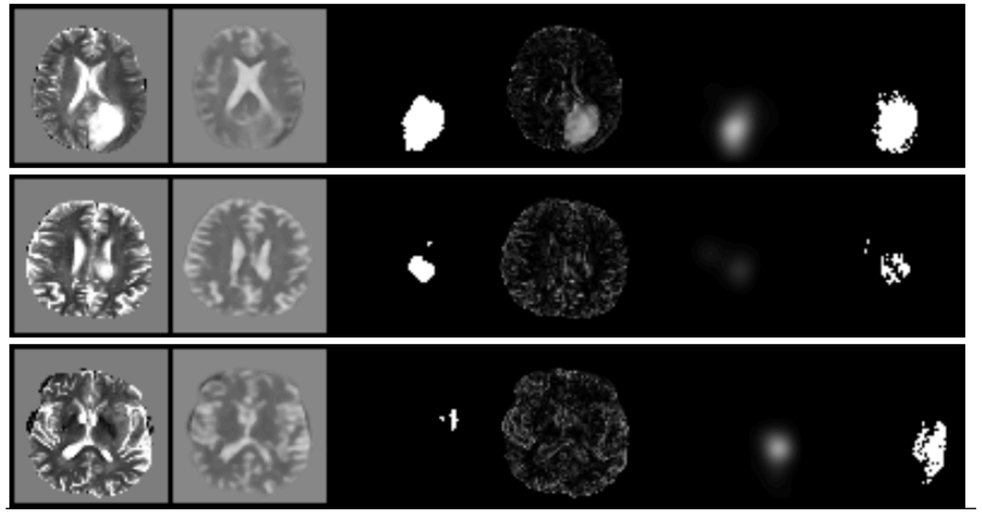
- Combination of a Context Encoder and a Variational Autoencoder (VAE)



Context-Encoding VAE (ceVAE)

Encode Semantic Information in the Latent Space

- Approach from the medical domain for detection of brain tumours *(Zimmerer et al., 2018)*
- Finding and localizing out-of-distribution images and pixels
- Combination of a Context Encoder and a Variational Autoencoder (VAE)
  - CE: denoising auto encoder which masks out local patches of the input, allows capturing semantic information of the input
  - VAE: standard Variational Auto Encoder



ceVAE applied to medical images, The 1st, 2nd, and 3rd row show a good, medium, and failure case, image source Zimmerer et al., 2018

Context-Encoding VAE

Encode Semantic Information in the Latent Space

- Imposing additional constraints on the latent space
- Loss function for the ceVAE model

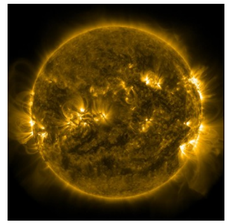
$$L_{ceVAE} = L_{KL}(f_\mu(x), f_\sigma(x)^2) + L_{rec_{VAE}}(x, g(z)) + \boxed{L_{rec_{CE}}(x, g(f_\mu(\tilde{x})))}$$

Anomaly Scoring

Image-level

- Express likelihood of an image sample by computing the Evidence Lower Bound (ELBO):

$$\log p(x) \approx L_{KL}(x) + L_{rec_{VAE}}(x, g(f(x)))$$



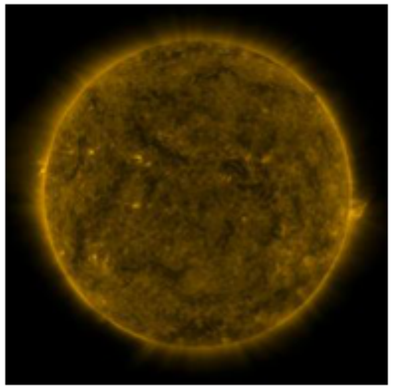
$\approx log\ p(x)$ →

0.078

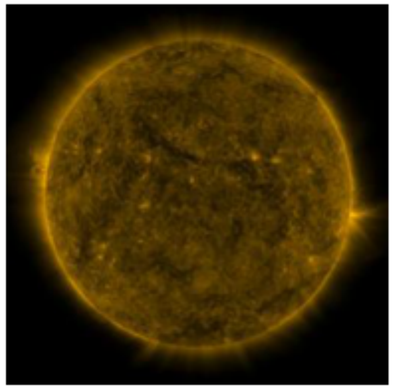
Results

Image-level scoring, low scores

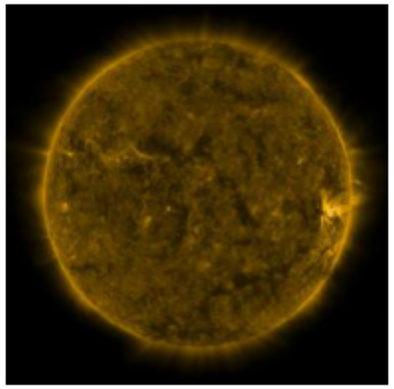
2016-12-11T000000__171
with score 0.03188



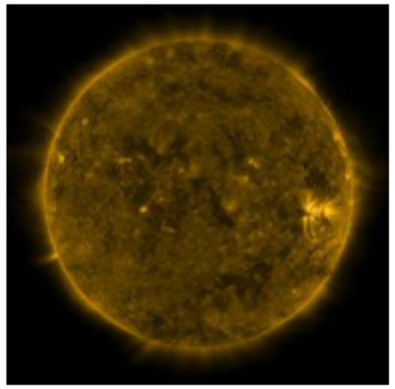
2016-12-11T060000__171
with score 0.03214



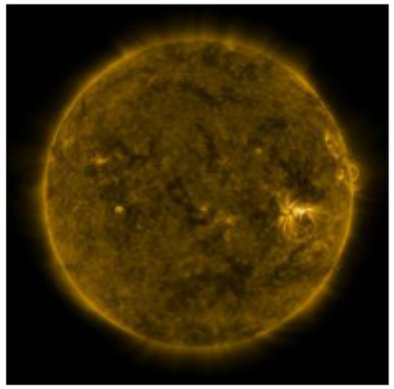
2016-12-08T060000__171
with score 0.03239



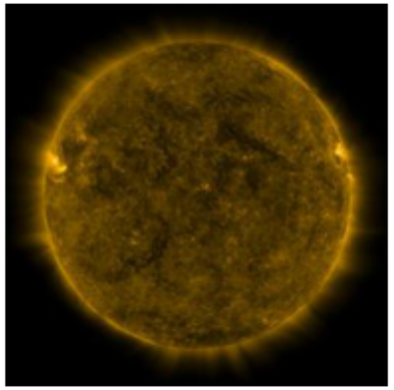
2016-12-07T120000__171
with score 0.03249



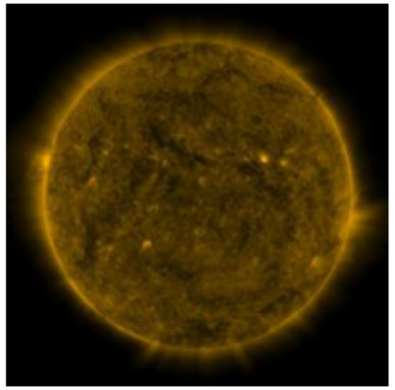
2016-12-06T180000__171
with score 0.03253



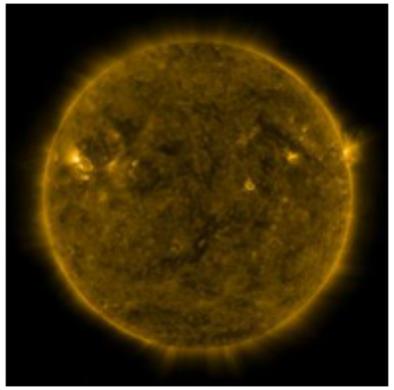
2016-12-14T000000__171
with score 0.03259



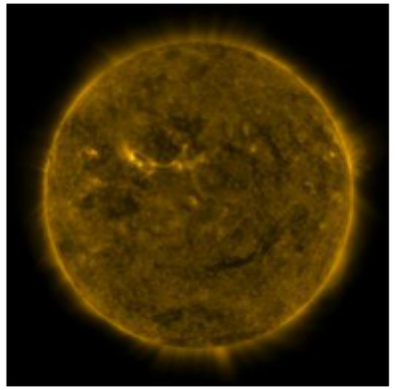
2016-12-11T120000__171
with score 0.03269



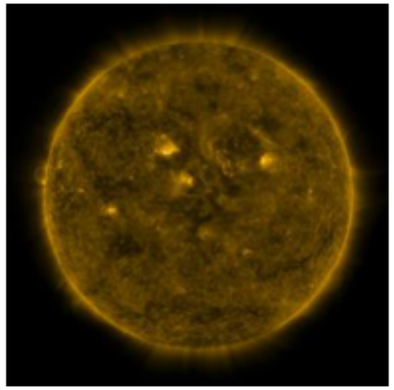
2016-12-15T060000__171
with score 0.03270



2016-12-17T060000__171
with score 0.03274



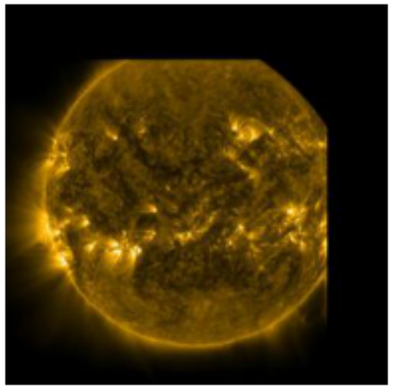
2016-12-19T180000__171
with score 0.03276



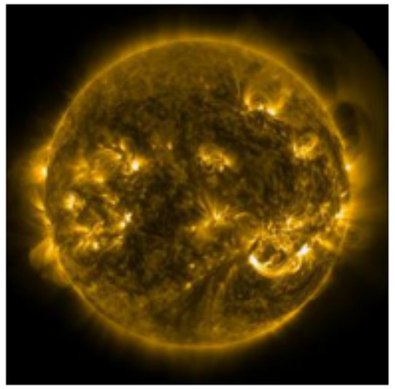
Results

Image-level scoring, high scores

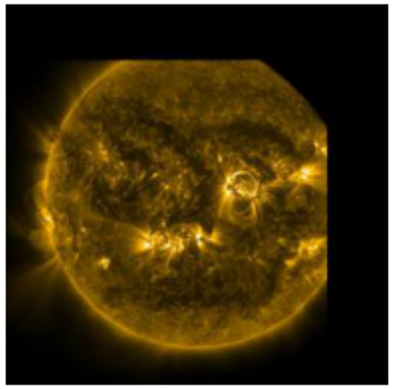
2014-04-23T180000__171
with score 0.07982



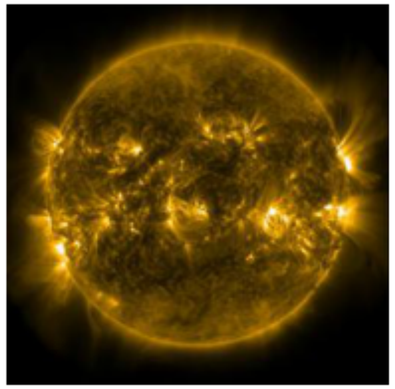
2014-12-20T060000__171
with score 0.07922



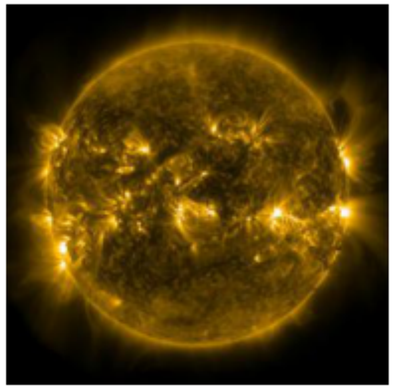
2013-10-24T180000__171
with score 0.07885



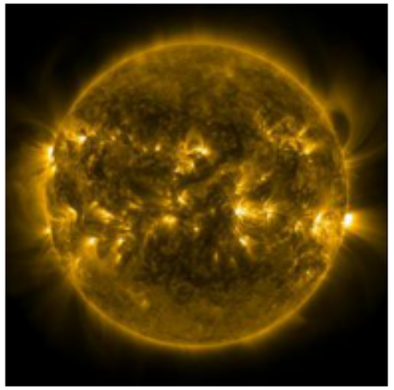
2014-03-25T120000__171
with score 0.07873



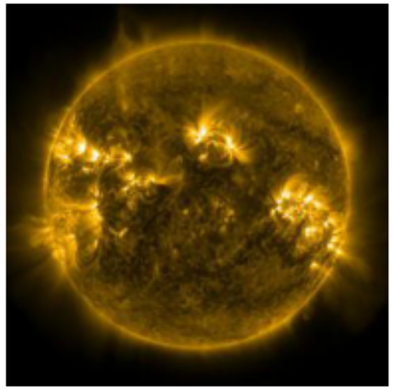
2014-03-25T180000__171
with score 0.07863



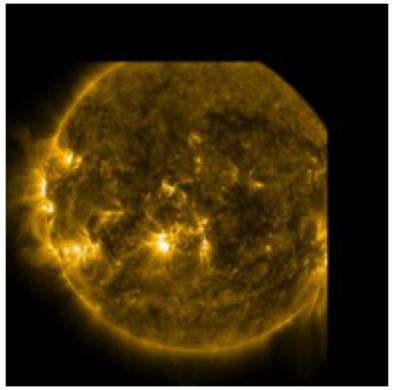
2014-03-27T120000__171
with score 0.07824



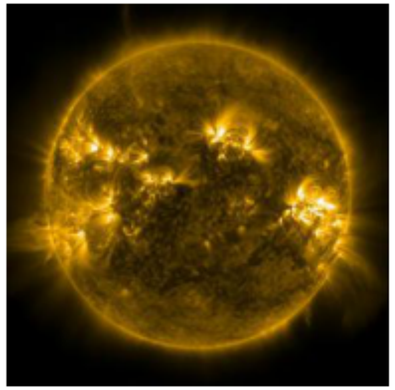
2014-02-26T060000__171
with score 0.07822



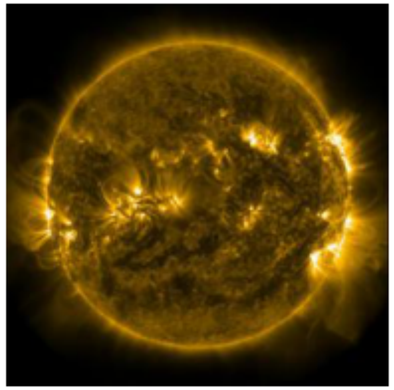
2014-11-25T180000__171
with score 0.07809



2014-02-26T180000__171
with score 0.07805



2014-03-09T060000__171
with score 0.07802

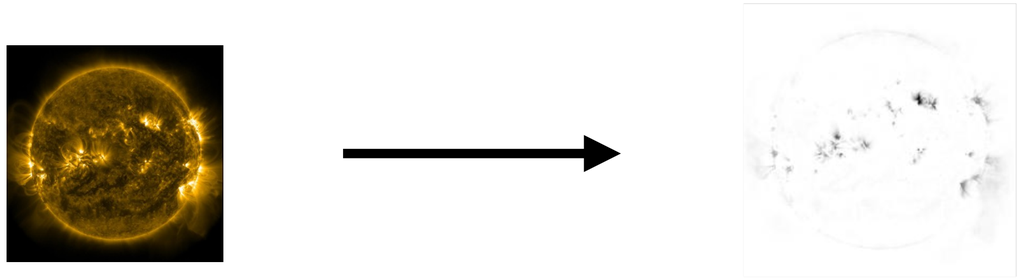


Anomaly Scoring

Pixel-level

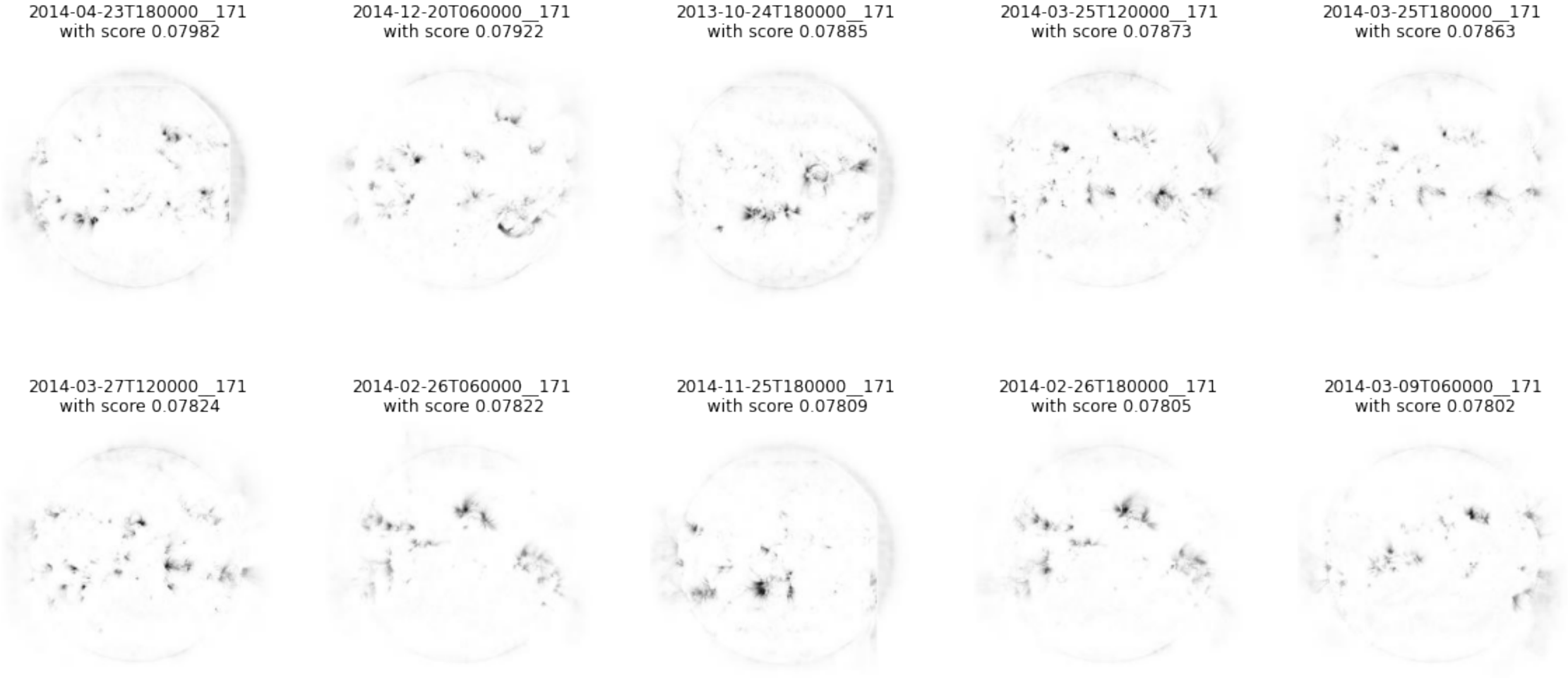
- Combine reconstruction-loss and KL-gradients by function *h* (i.e. pixel-wise multiplication)

$$h\left(|x - g(f(x))|, \frac{\delta(L_{KL}(x))}{\delta x}\right)$$



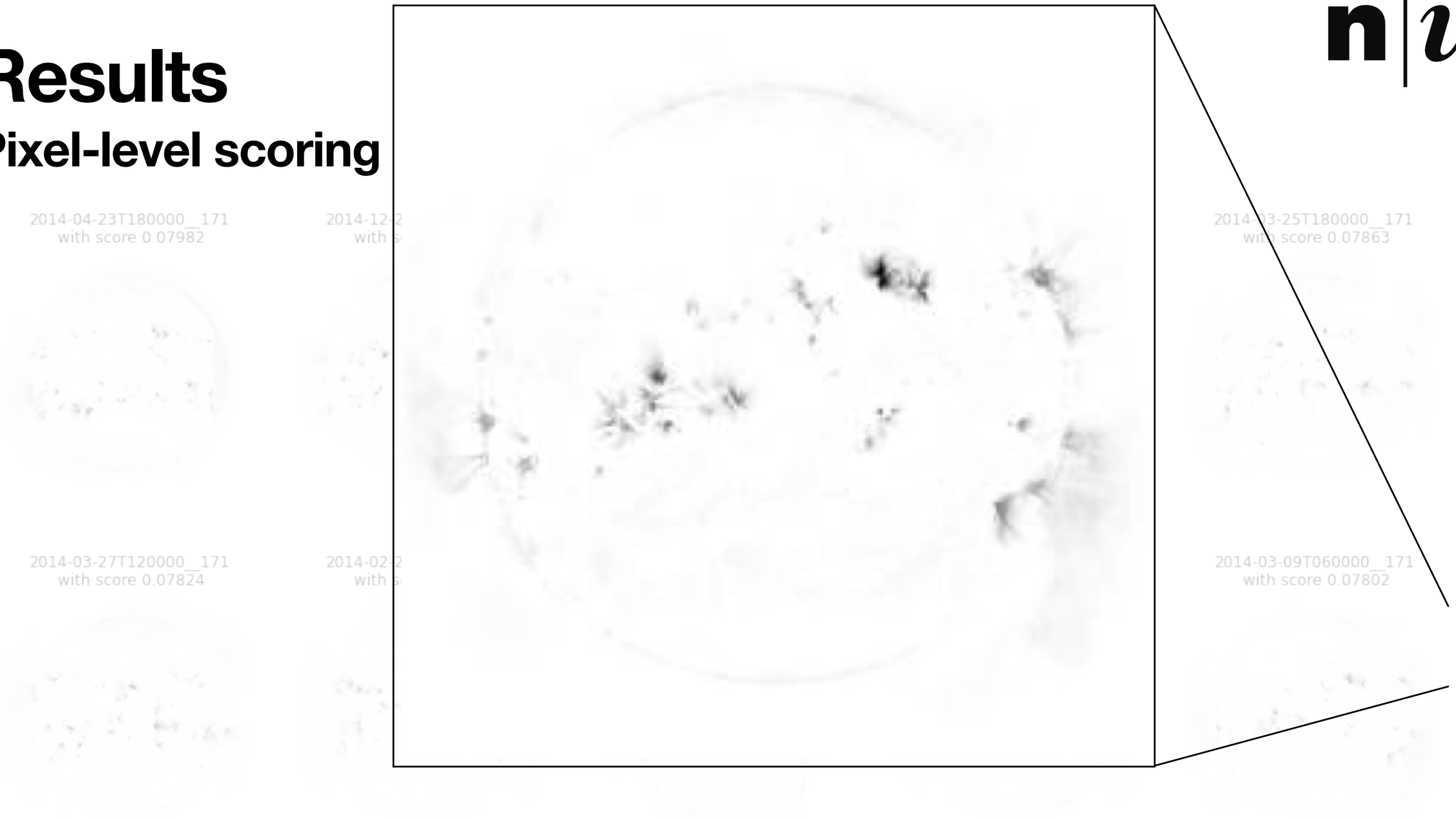
Results

Pixel-level scoring



Results

Pixel-level scoring



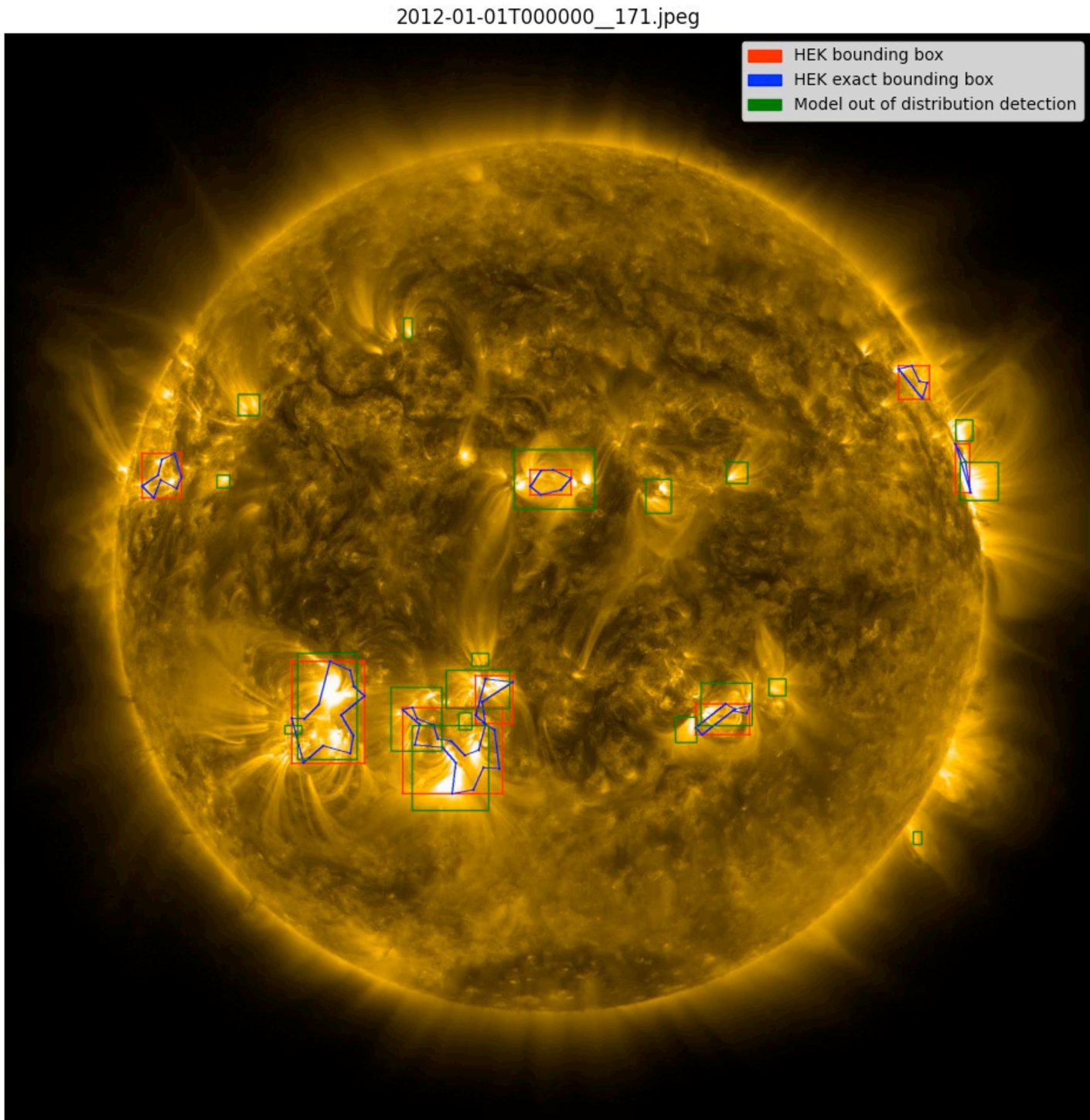
From model to application

Possible Applications

- **Search space reduction** by highlighting interesting regions for further expert/automated analysis
- **Smart downlink control** by only transmitting relevant data
- **Expert validation** by cross-validating the events reported in HEK
- **Feature Extraction** for downstream tasks such as flare prediction (such as bounding box extraction)

Bounding box Extraction

- Traditional approach with binarization
  - Otsu's adaptive thresholding of the pixel-level anomaly map
  - Teh-Chin chain approximation for bounding box extraction
- Matching with events from HEK to compute IoU
  - E.g. for Active Regions (AR) the IoU is 0.245 (rather low)

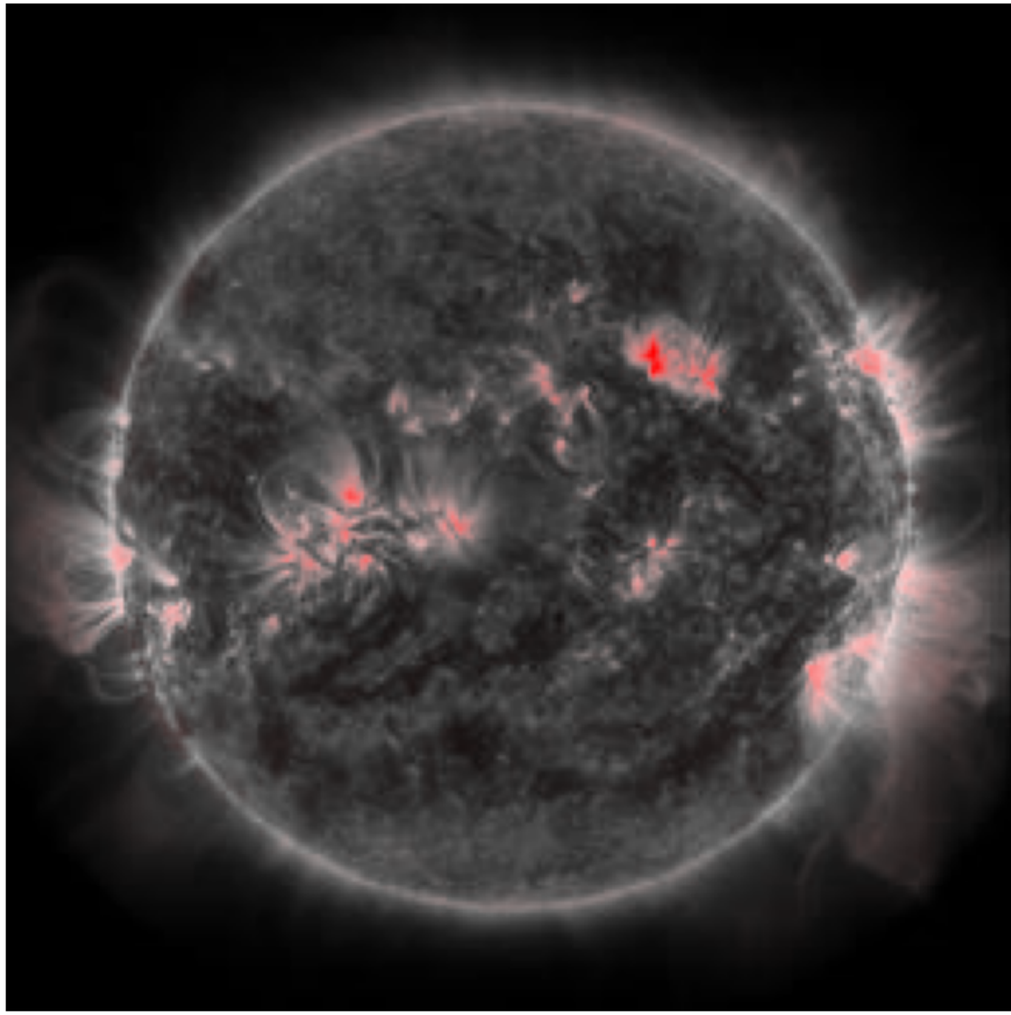


Outlook

- Find better evaluation metrics to quantify the accuracy of predicted anomalies
- This will allow providing more formal guarantees on the choice of model (AE, VAE, hyperparameters, SSL-based approach)
- Model extensions (multi-channel, temporal domain by tracking anomalies over time)
- For the application use a DL-based approach for bounding box extraction (e.g. YOLO)
- From unsupervised to semi-supervised by leveraging existing labels

In Summary

- **Adjustable:** Framework for finding and localizing regions of interest based on a definition for normality
- **No labels:** Extracting information without having any pre-existing labels (independent of human input)
- **Importance of loss:** Defining the loss such that the latent space is “well”-structured
- **VAE:** Models from the medical domain are a good starting point. Specifically, VAE-based methods show promising results —> further investigations required
- **Evaluation** ⚡: Biggest challenge: lack of evaluation/ benchmarking datasets



Overlayed anomaly map for AIA 171 2014-03-09 06:00

Thank you!

Code

- Source code is available in the sdo-cli Github repository (still work in progress)
- Contribute to awesome-helio, a curated list of available datasets and tools for machine learning in heliophysics

Q&A

References

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- [3] Baek, Ji-Hye, et al. "DeepSDO: Solar event detection using deep-learning-based object detection methods." 한국천문학회보 46.2 (2021): 46-46.
- [4] Kingma, Diederik P., and Max Welling. "An introduction to variational autoencoders." *arXiv preprint arXiv:1906.02691* (2019)
- [5] Zimmerer, David, et al. "Context-encoding variational autoencoder for unsupervised anomaly detection." *arXiv preprint arXiv:1812.05941* (2018).
- [6] Li, Chun-Liang, et al. "Cutpaste: Self-supervised learning for anomaly detection and localization." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2021.