Trinity College Dublin
Coláiste na Tríonóide, Baile Átha Cliath
The University of Dublin

Using supervised machine learning to automatically detect type II and III solar radio bursts

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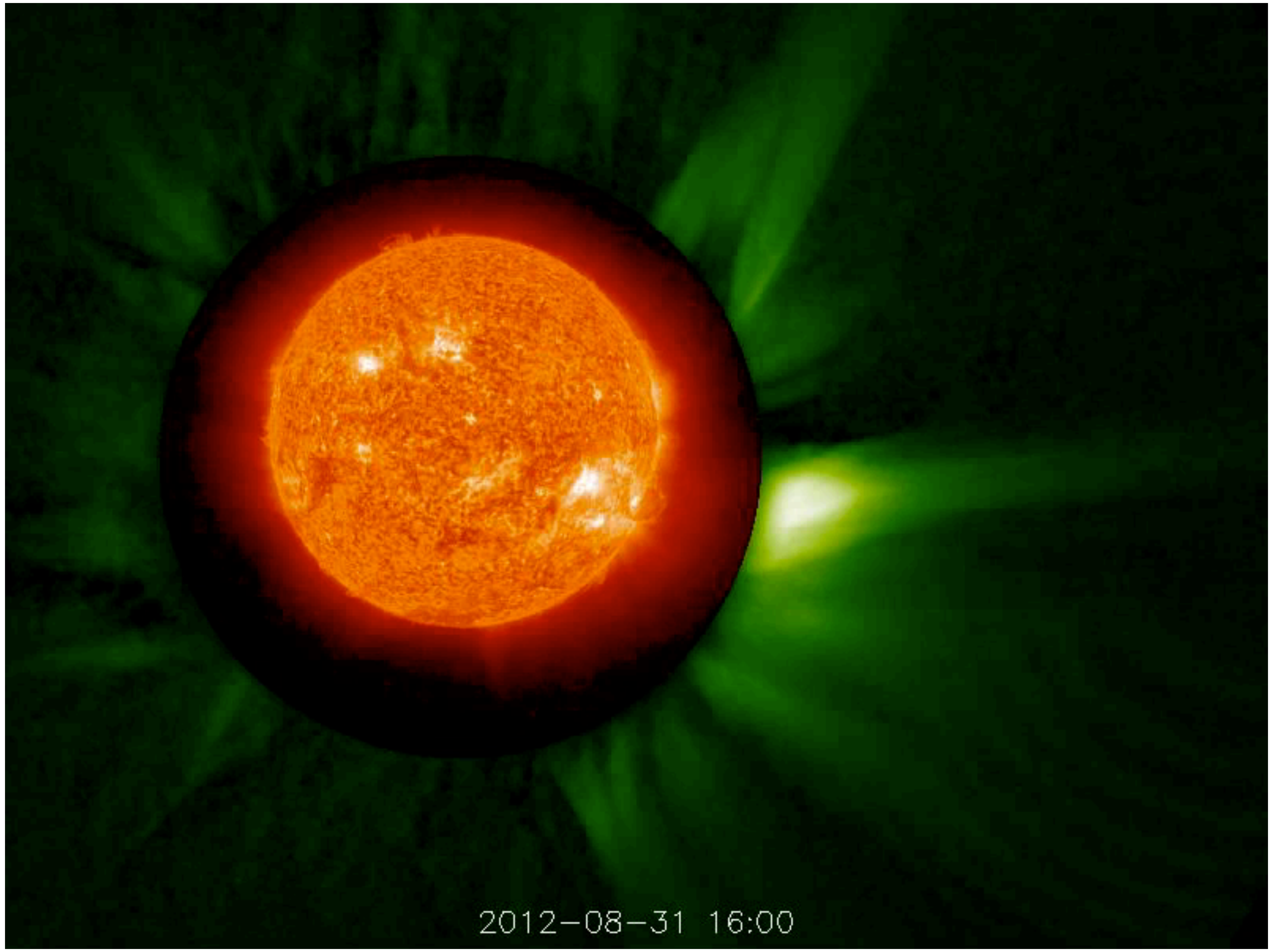
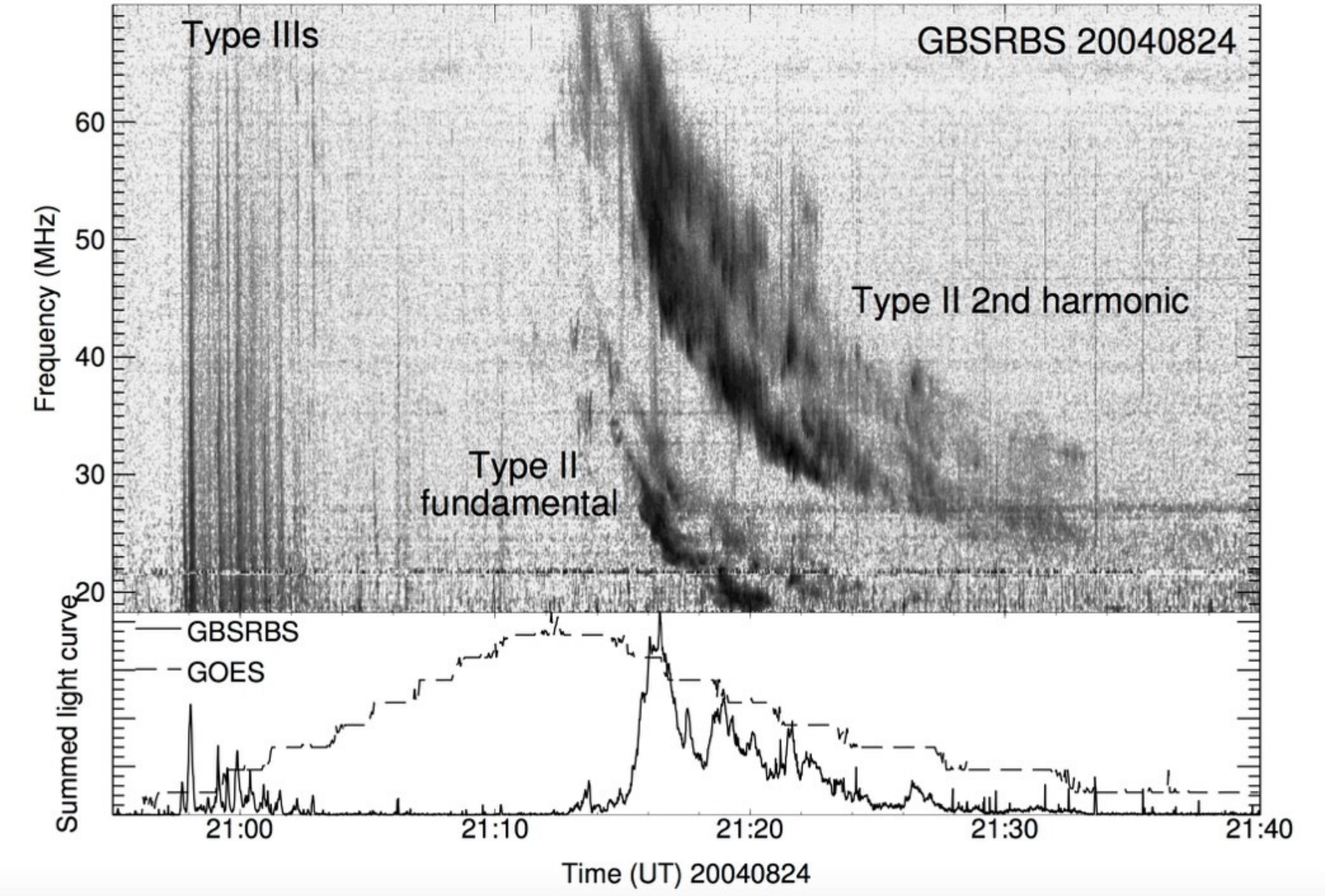
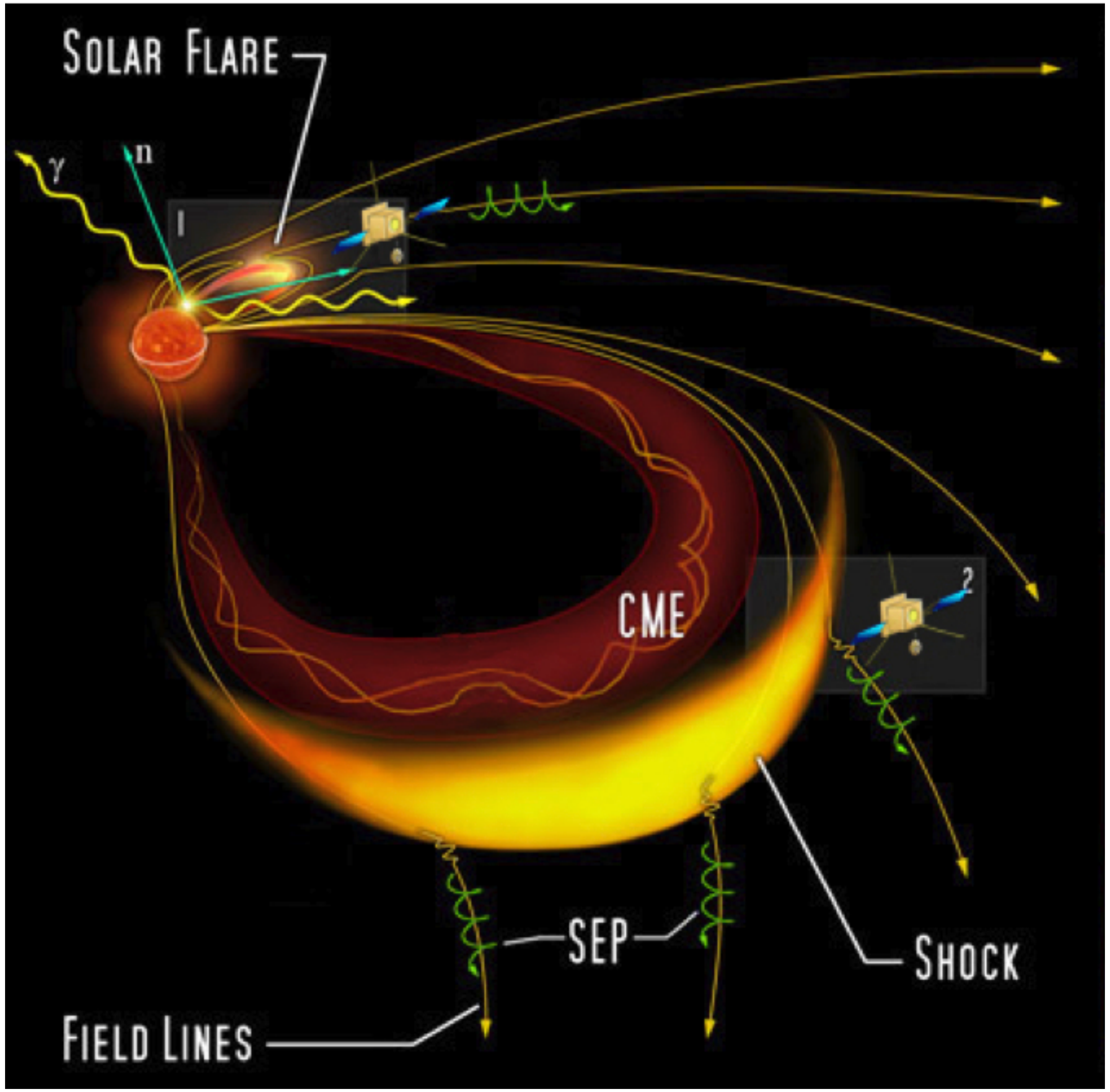
Institiúid Ard-Léinn Bhaile Átha Cliath | Dublin Institute for Advanced Studies
European Commission
LOFAR4SW
I-LOFAR
Exploring the Radio Universe from Ireland

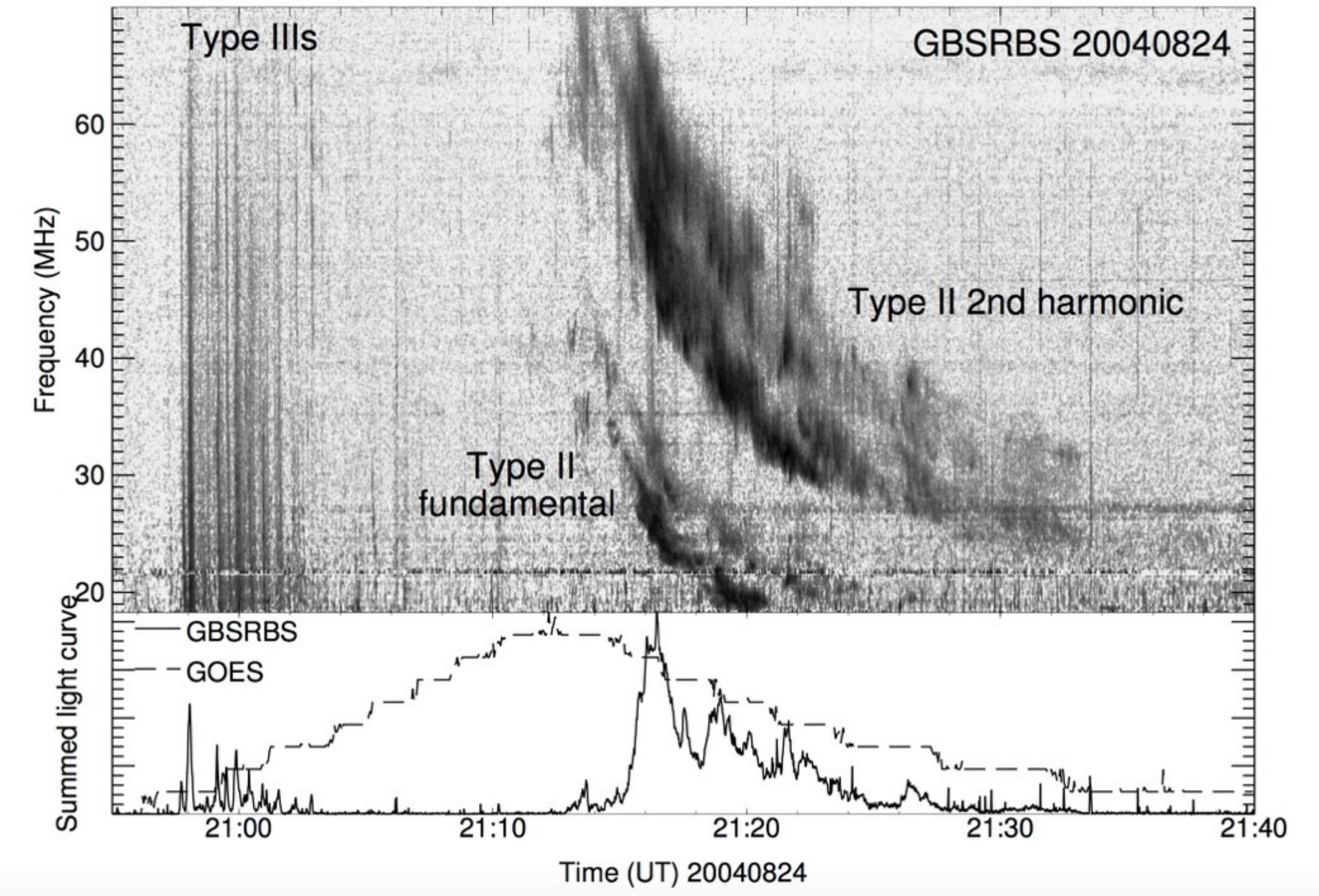
Coronal mass ejections and radio bursts





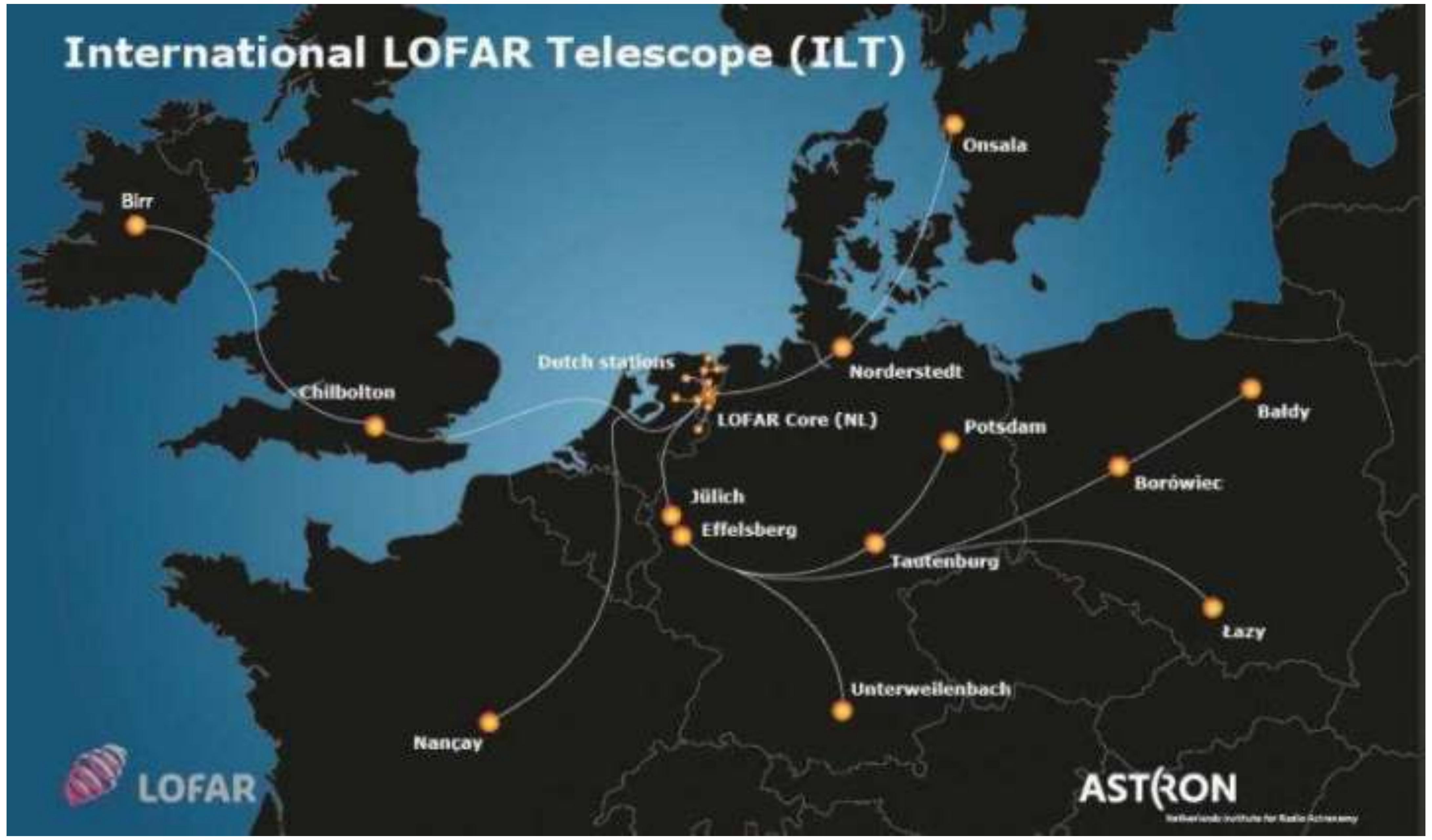
Coronal mass ejections and radio bursts

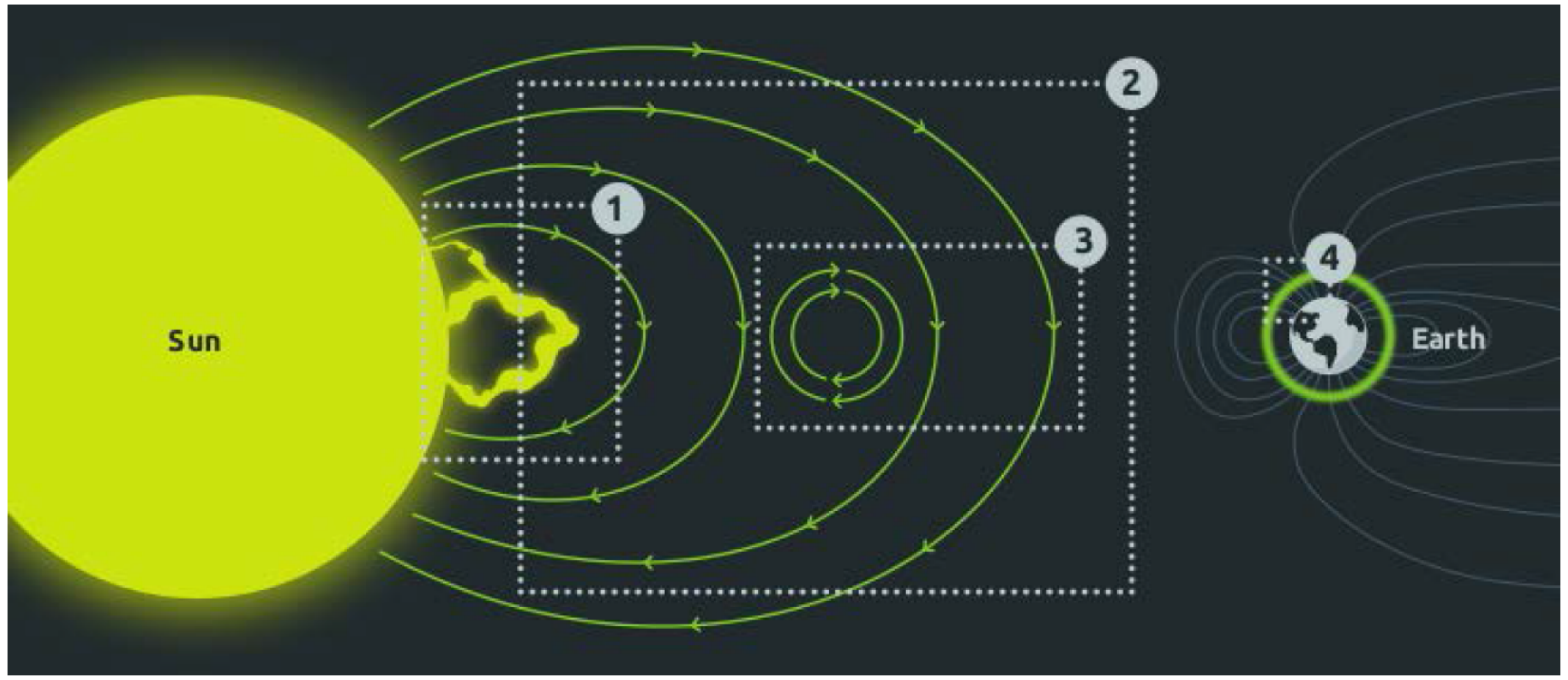




- Type II burst - CME-driven shock
- Type III burst - Electron beams on open B-field
- **Notoriously difficult to detect/classify**

Why do we need an automated detection algorithm?



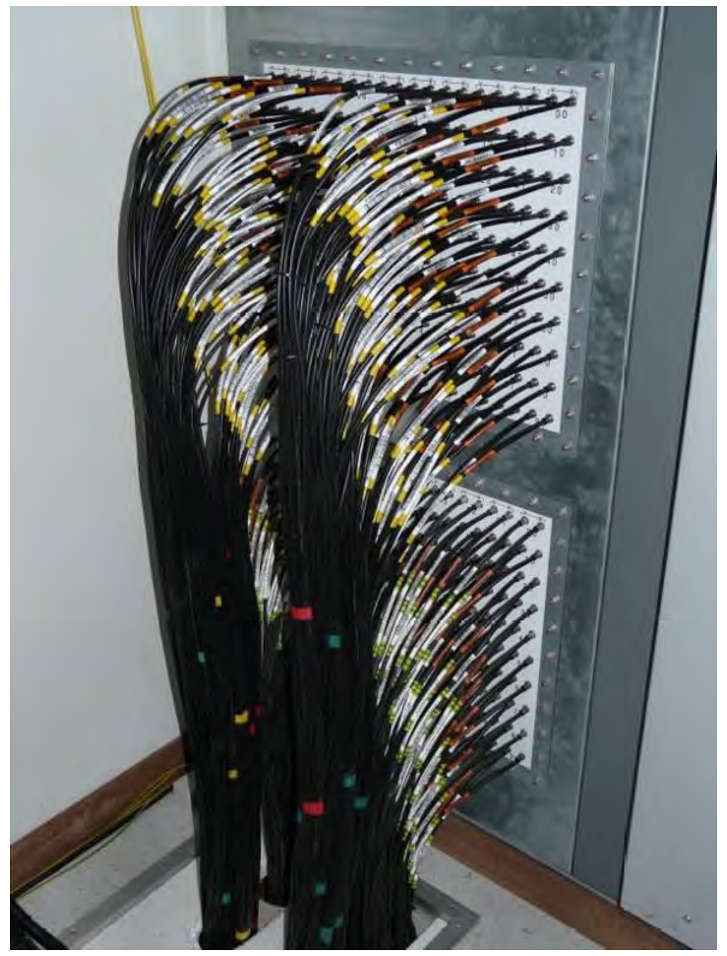


- International LOFAR telescope
- Interferometer @10 - 240 MHz
- ~50 stations and counting
  - Each can produce ~3 Gb s^{-1}
- H2020 project; 8 European partners, lead by ASTRON.
- Upgrade LOFAR to observe heliosphere constantly
- Operate as a space weather instrument.
  - We need automated data pipelines

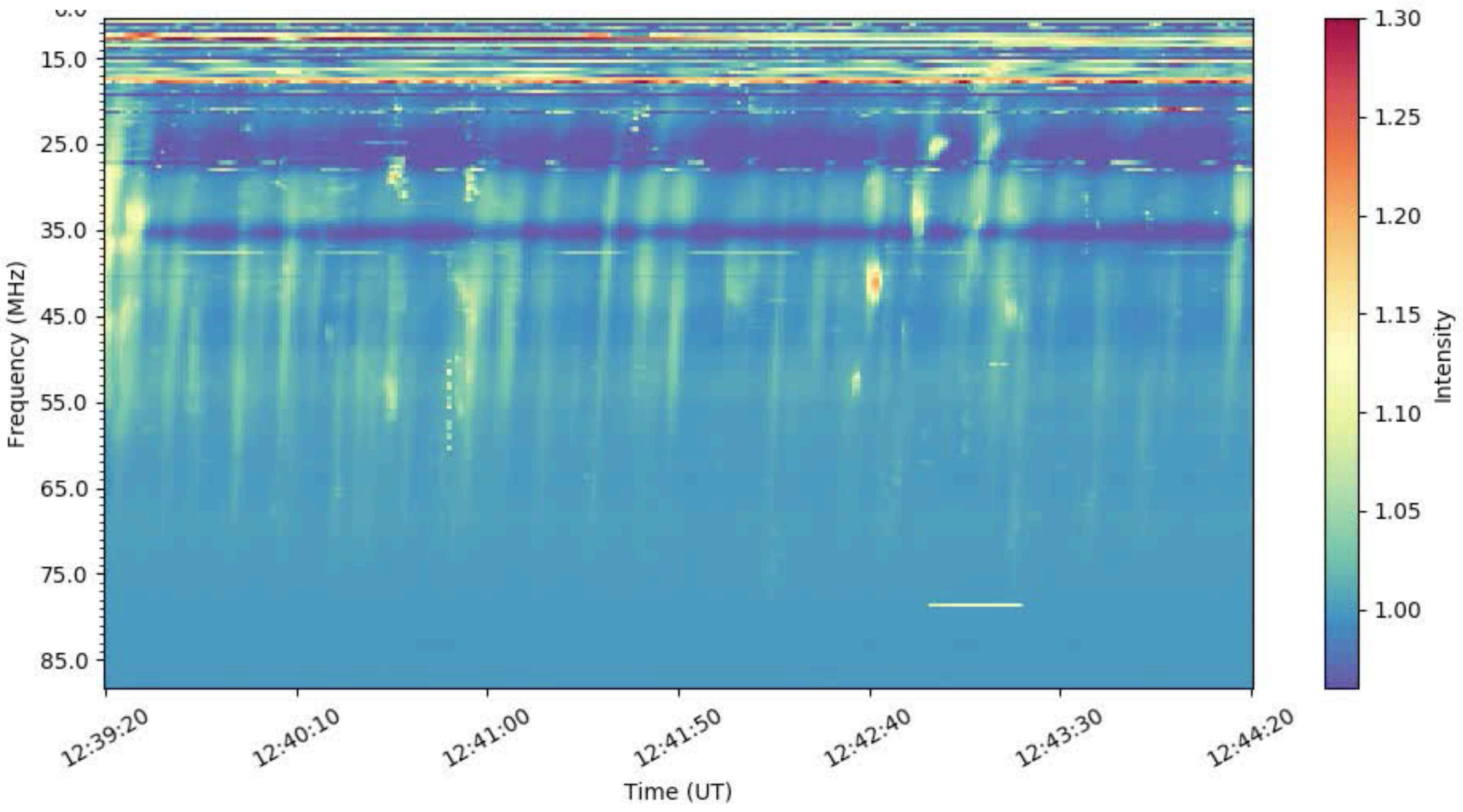
LOFAR4SW

www.lofar4sw.eu

ILOFAR and REALTA



- Data output
  - 488 frequencies each at 5μs sampling
  - Records ~4 TB hr^{-1}
- Type III every 1-10 seconds
- Can we detect them all?



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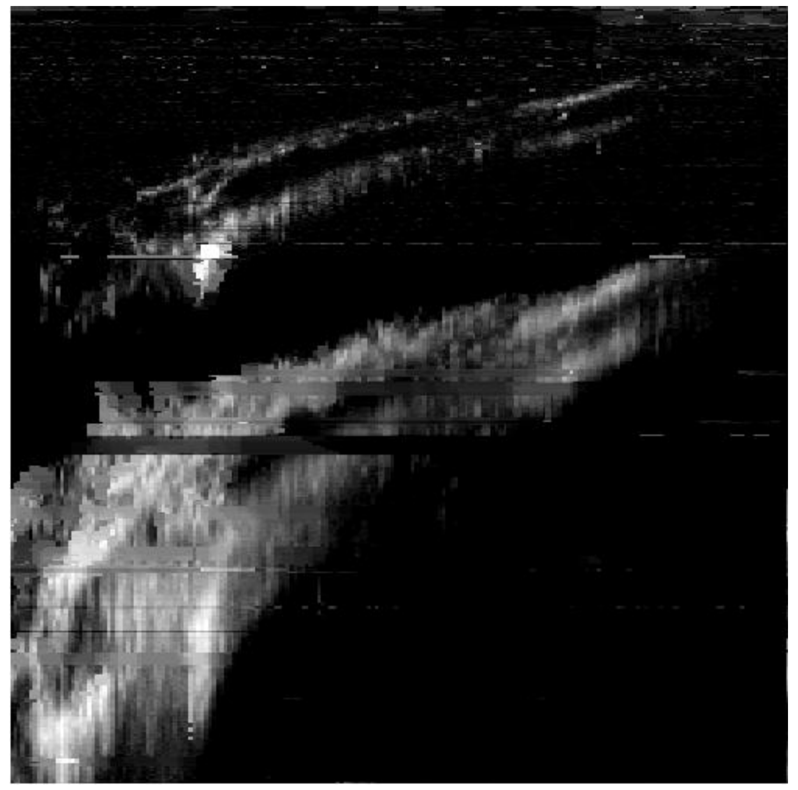
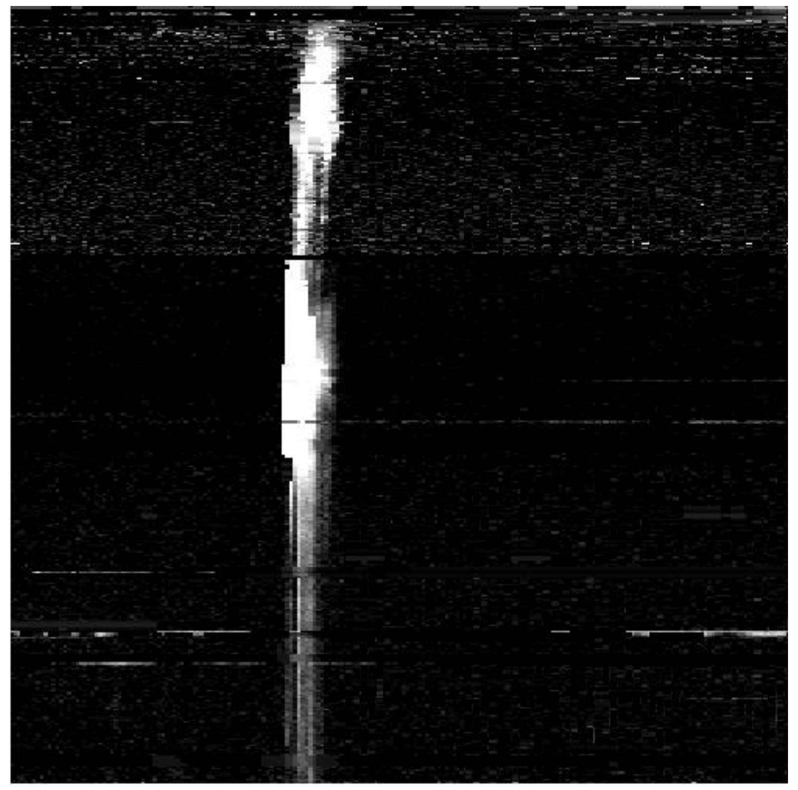
Training data - RSTN Observations

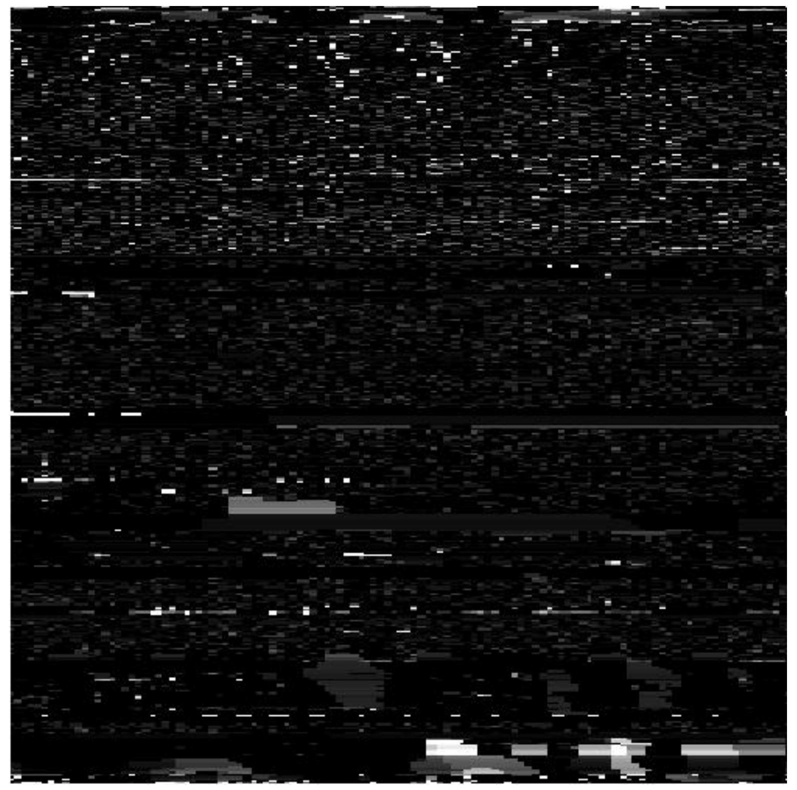
- SWPC event lists from 1996 to present.
- Download data from Radio Solar Telescope Network (RSTN)
- Had to be cleaned for RFI and background subtracted.



Type II
x1000

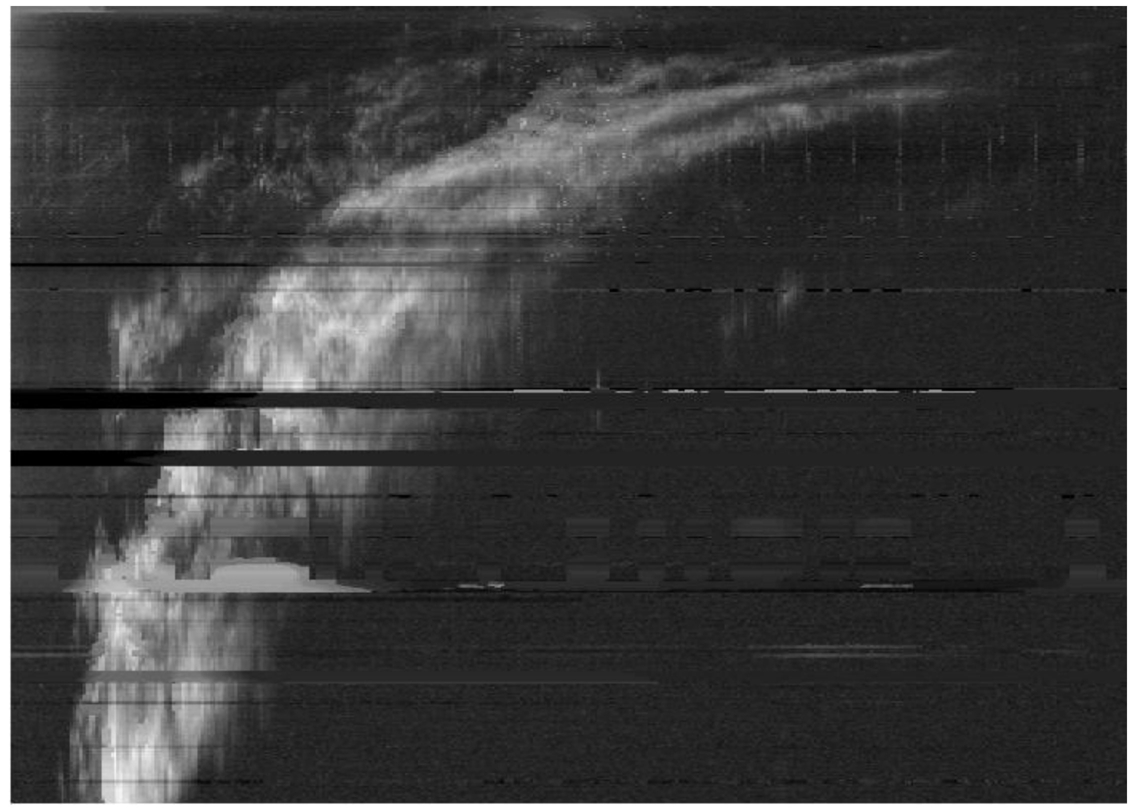


Type III
x1000

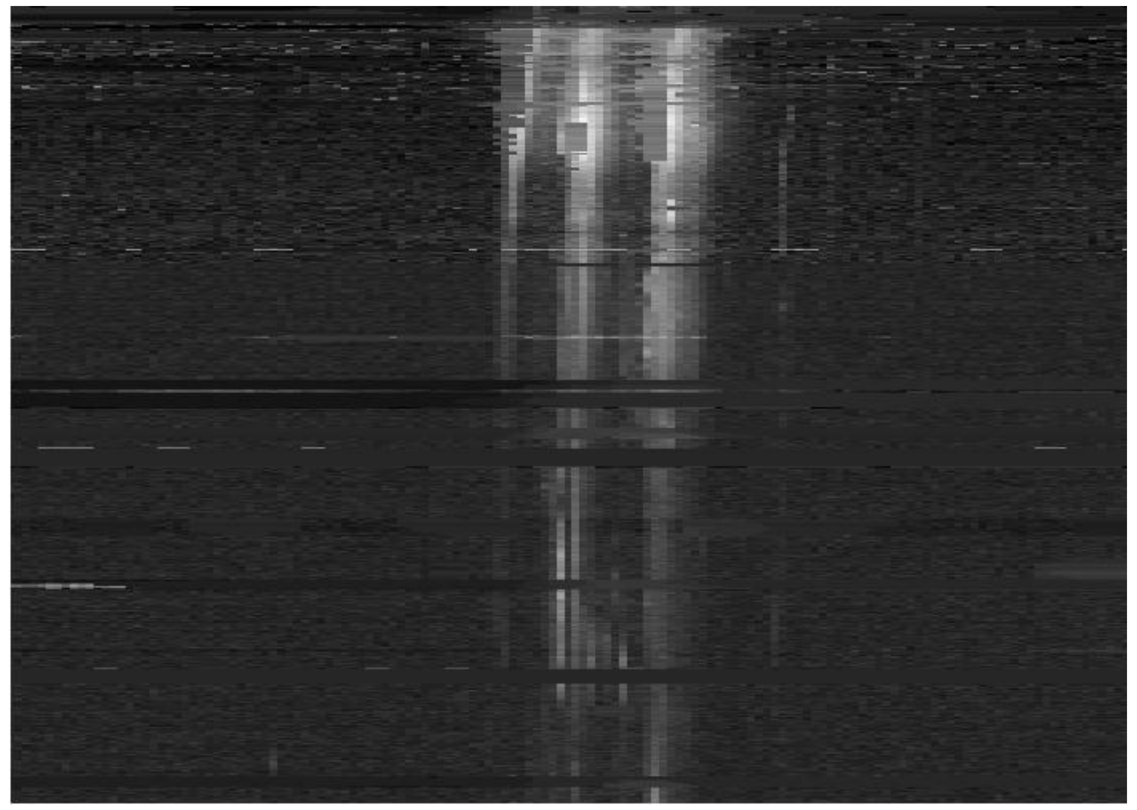


No burst
x1000

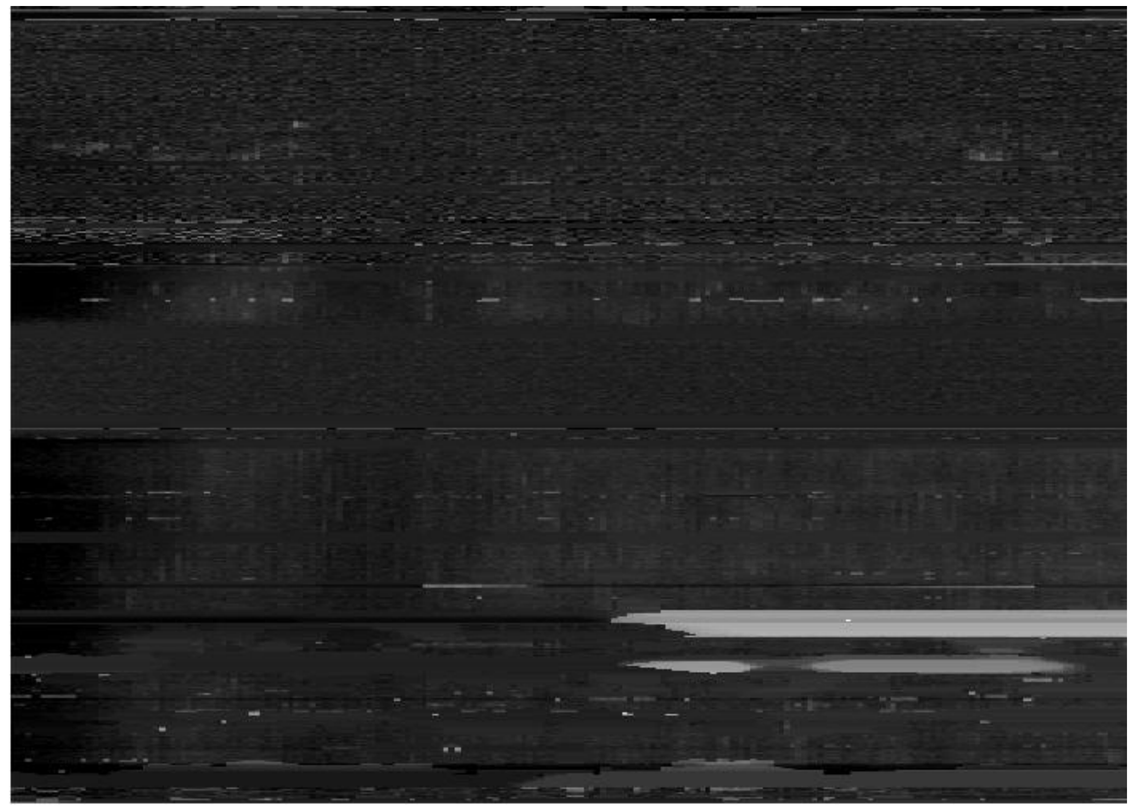
Radio burst classification - Support Vector Machine



Type II
x1000

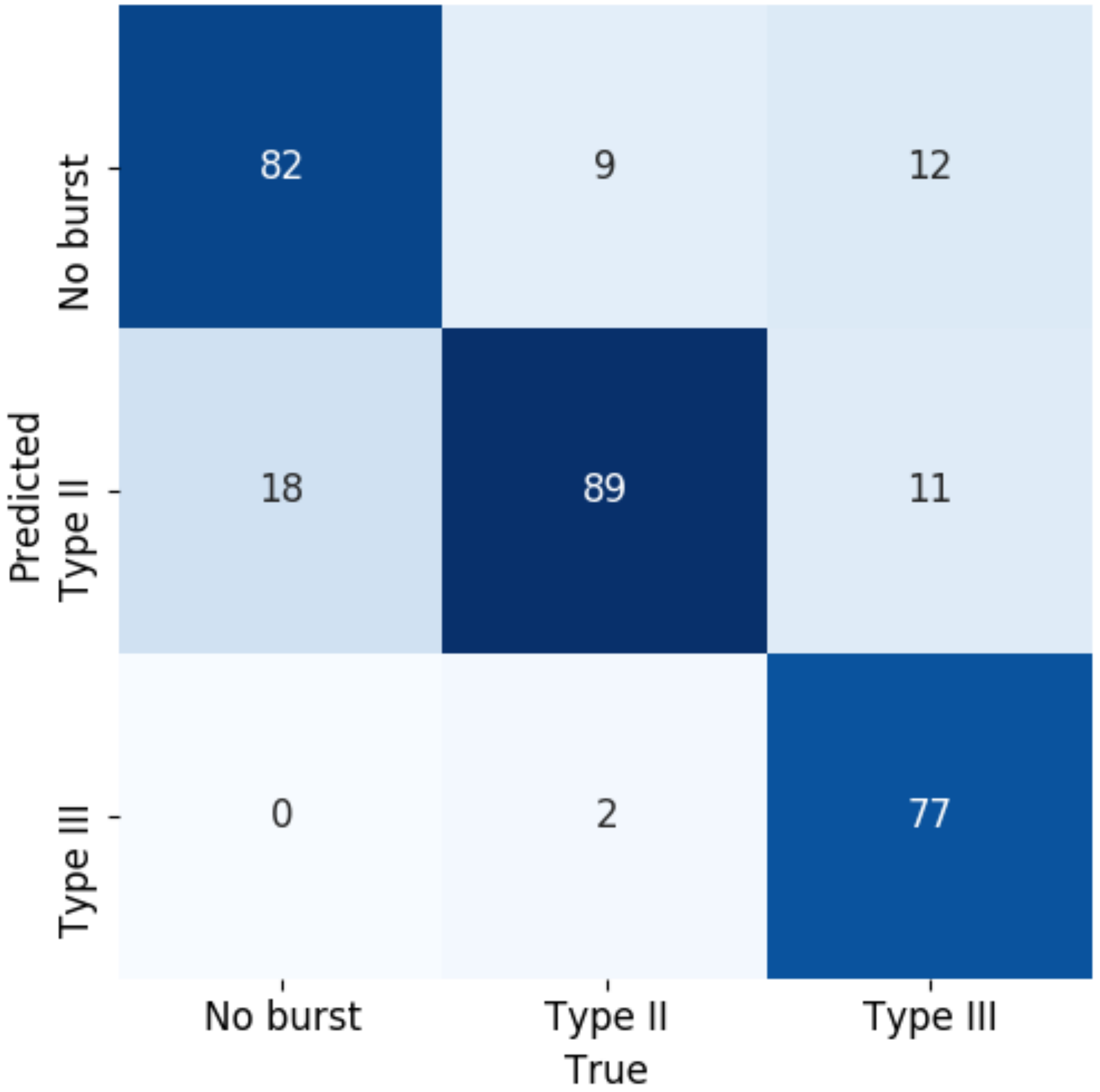


Type III
x1000

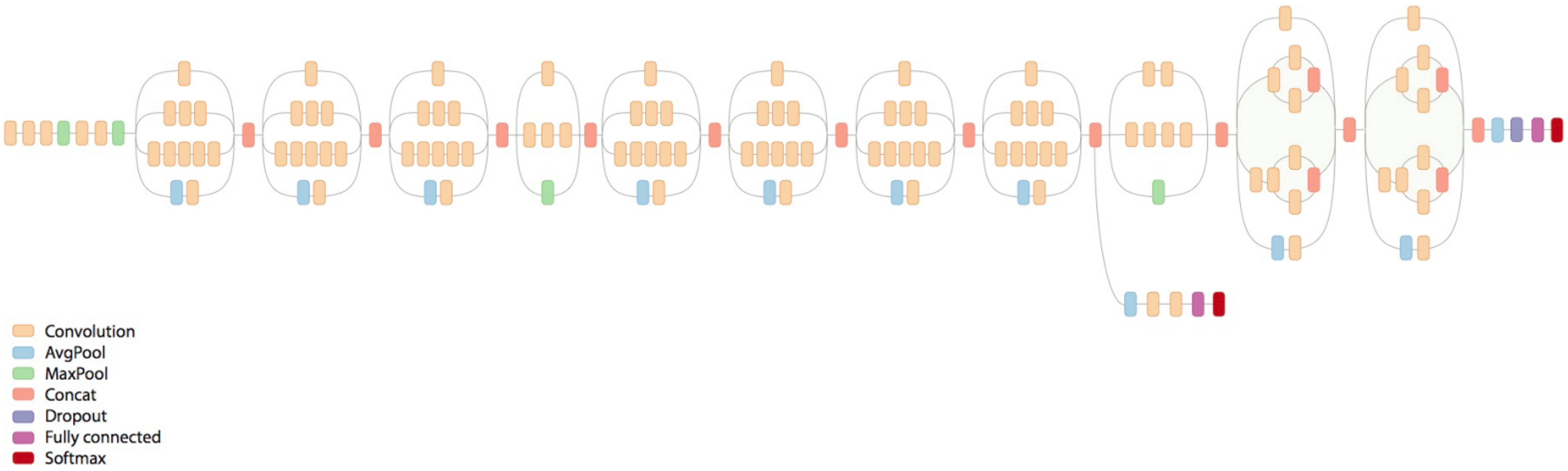


No burst
x1000

- Multi-class SVM
- Implement in Scikit-learn
- Kernel: RBF
- Accuracy on test set of 300 images is ~82%



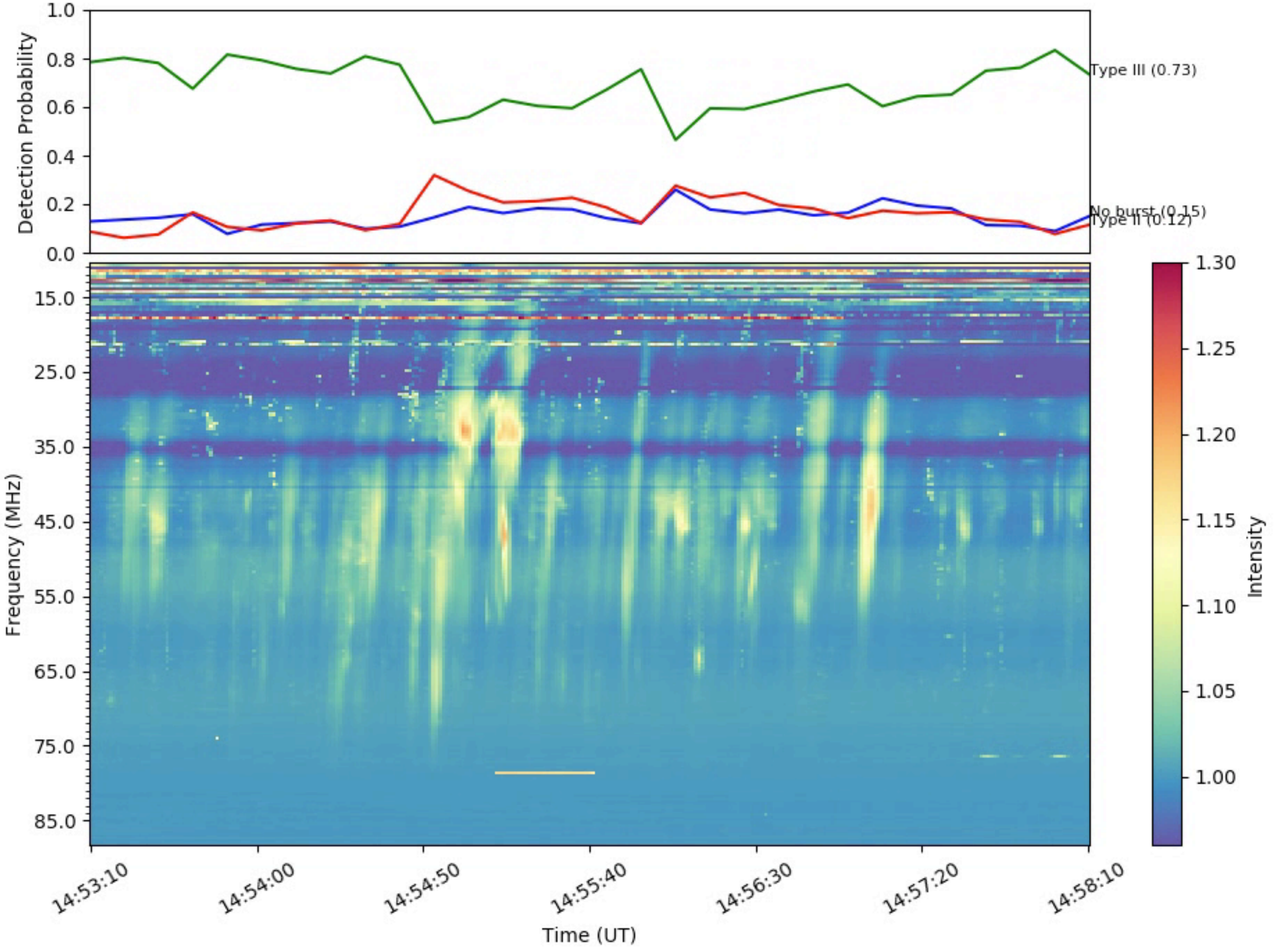
Radio burst classification - Inception-v3 CNN



- Built by Google (Szegedy et al. 2015).
- Previous winner of the ImageNet competition
- Problem!
  - Has millions of parameters
  - Needs millions of training examples to avoid underdetermination
- Solution;
  - Transfer learning;
    - Use pre-trained Inception model
    - Only train the last fully-connected layer

- Results:
  - Trained on RSTN data
  - Approx 50 epochs of training
  - Achieves ~90% on RSTN test set (300 images)
  - Works well on ILOFAR!

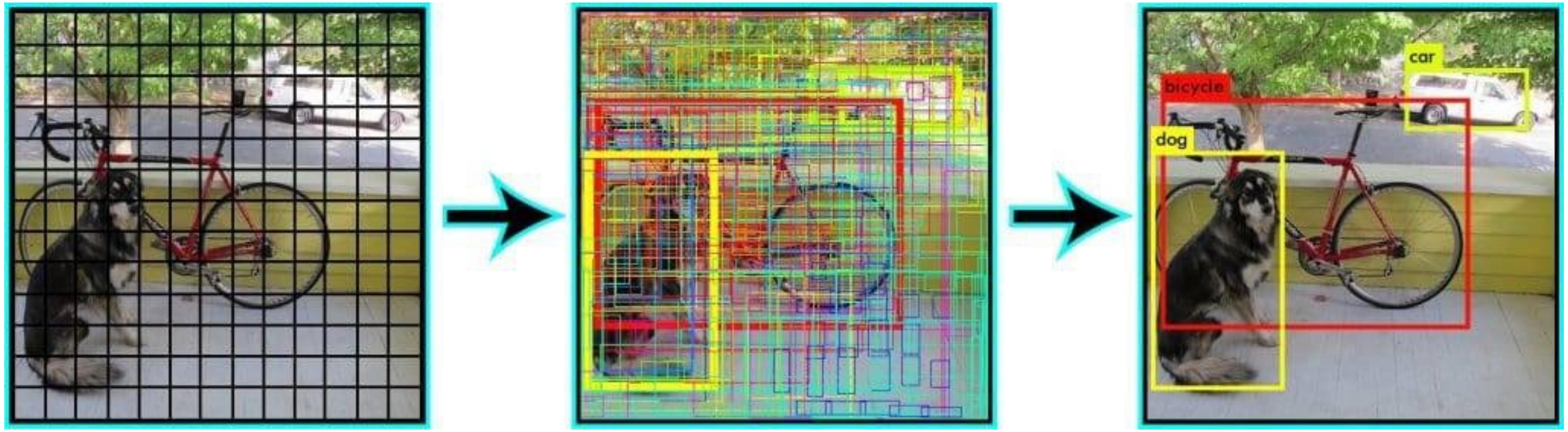
Radio burst classification - Inception CNN



- Trained on RSTN
- Applied to I-LOFAR
- Can recognise:
  - Type III bursts
  - Type II bursts
  - No bursts (true negatives)

- Does this only for the entire frame.
  - Can we located the bursts?

Radio burst classification - You Only Look Once (YOLO) v3



Loss function= $\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2$ Box position

$$+ \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(\sqrt{w_i} - \sqrt{\hat{w}_i}\right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i}\right)^2$$ Box width/height

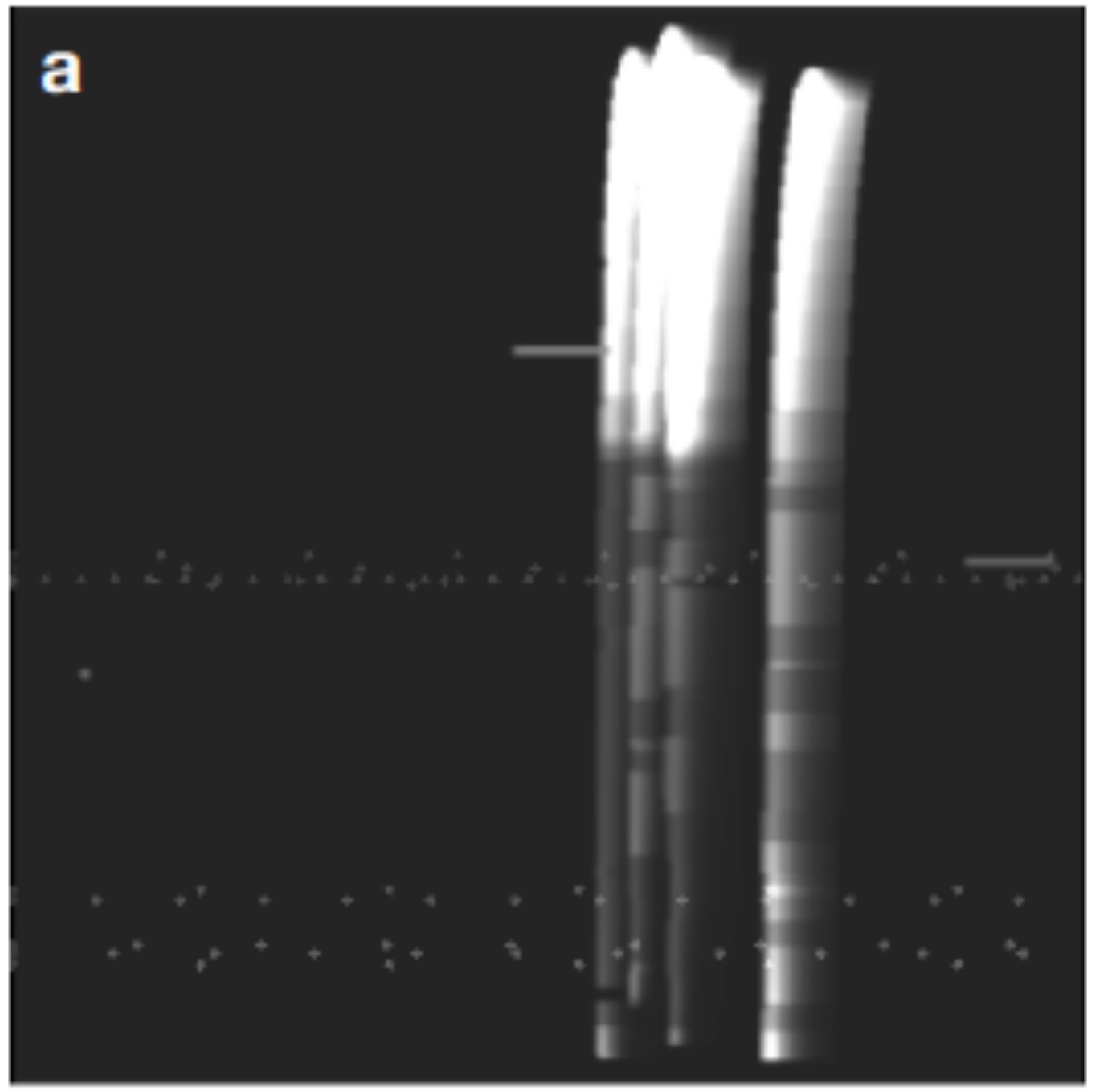
$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i\right)^2$$

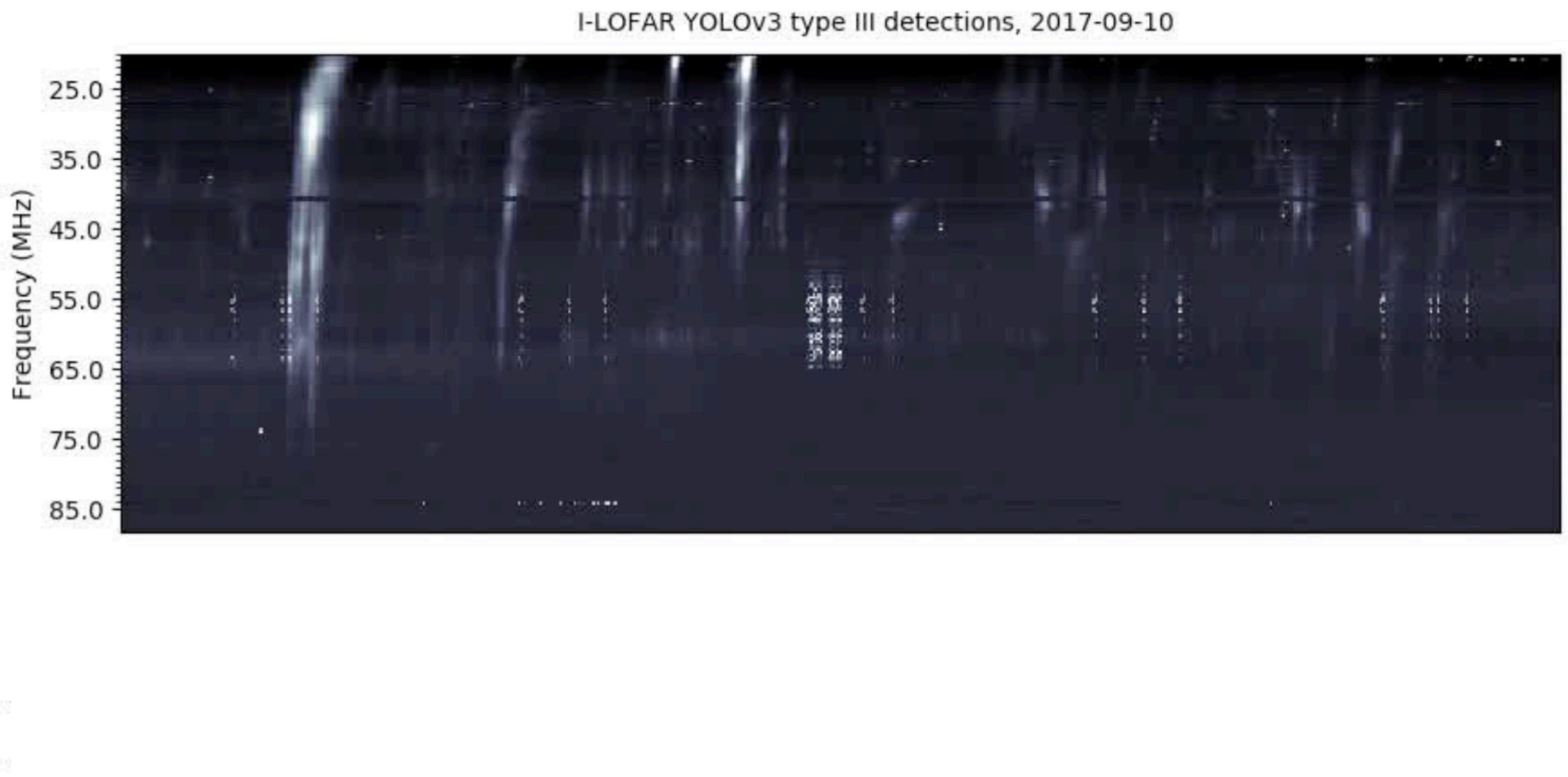
$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i\right)^2$$ 'Objectness' scores

$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \quad (3)$$ Classification probability

- One of fastest object detection and classification algorithms (Redmon et al. 2016).
- Loss function includes:
  - Usual classification probability
  - Parameters of correct box position, size
  - Object confidence scores

Radio burst classification - You Only Look Once (YOLO) v3

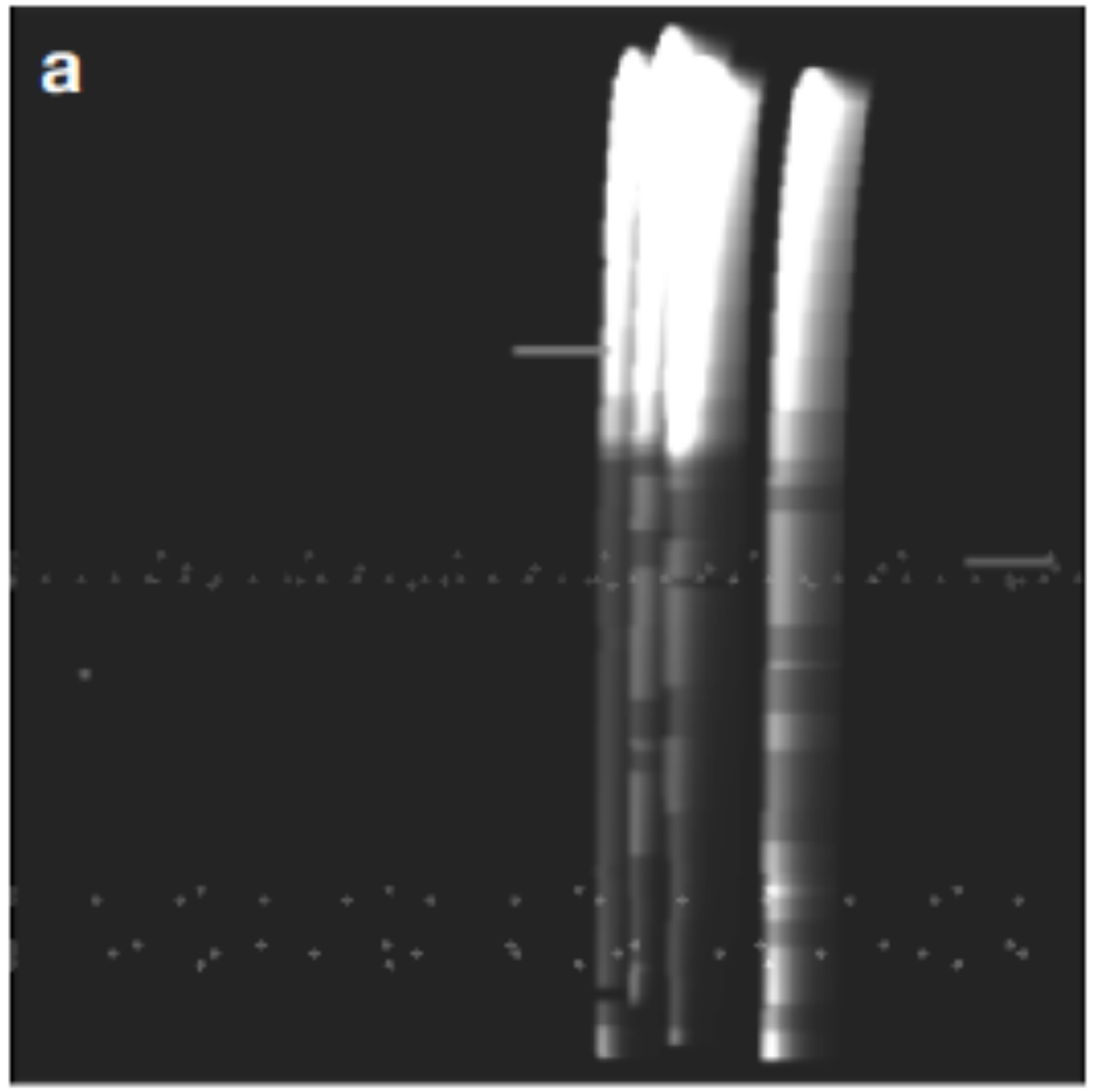


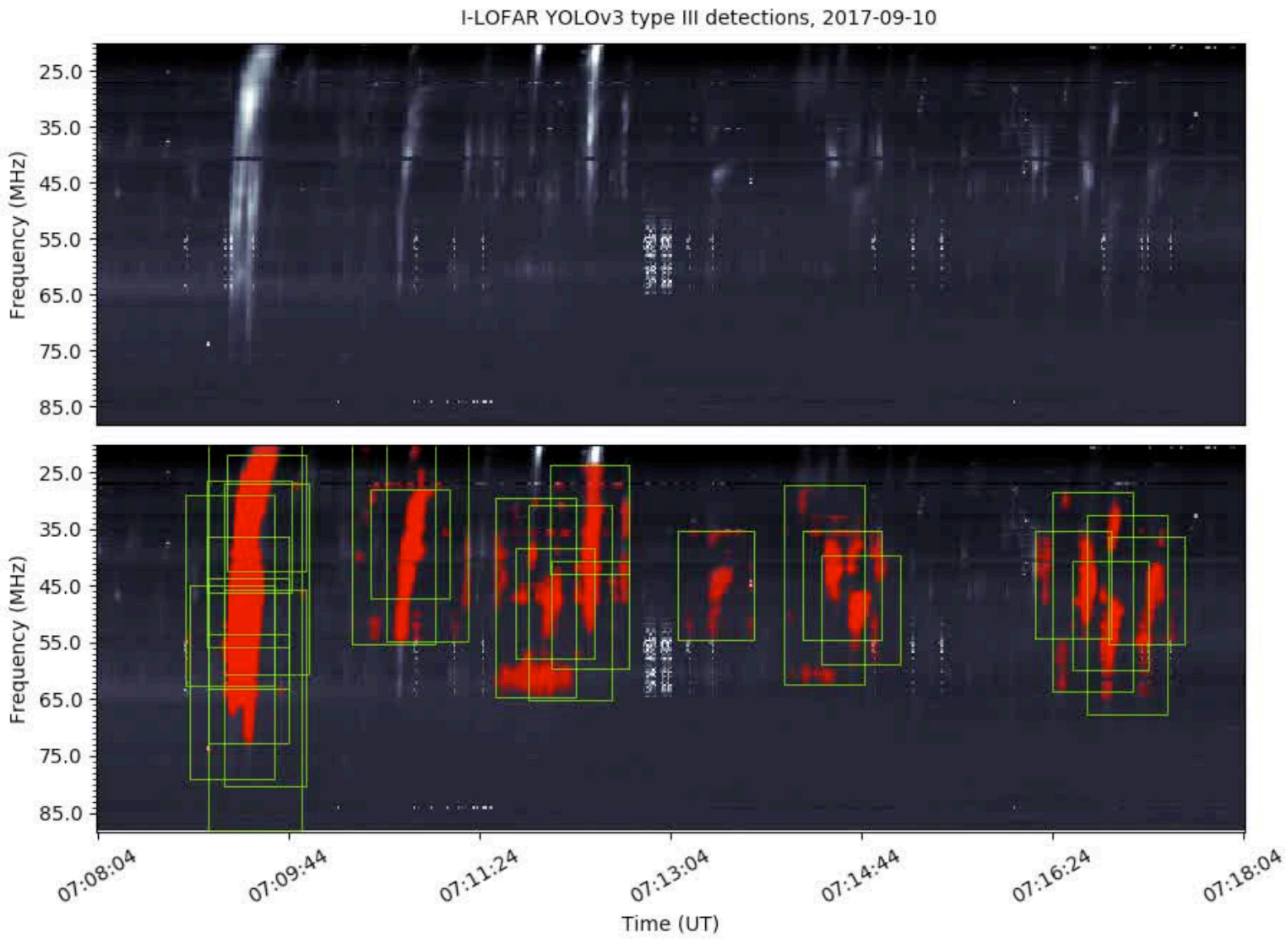


- Train on ~50,000 simulated type IIIs
  - Supply box position, width, height
  - Requires a GPU

- Evaluate on real data (ILOFAR)
- Initial results promising.

Radio burst classification - You Only Look Once (YOLO) v3





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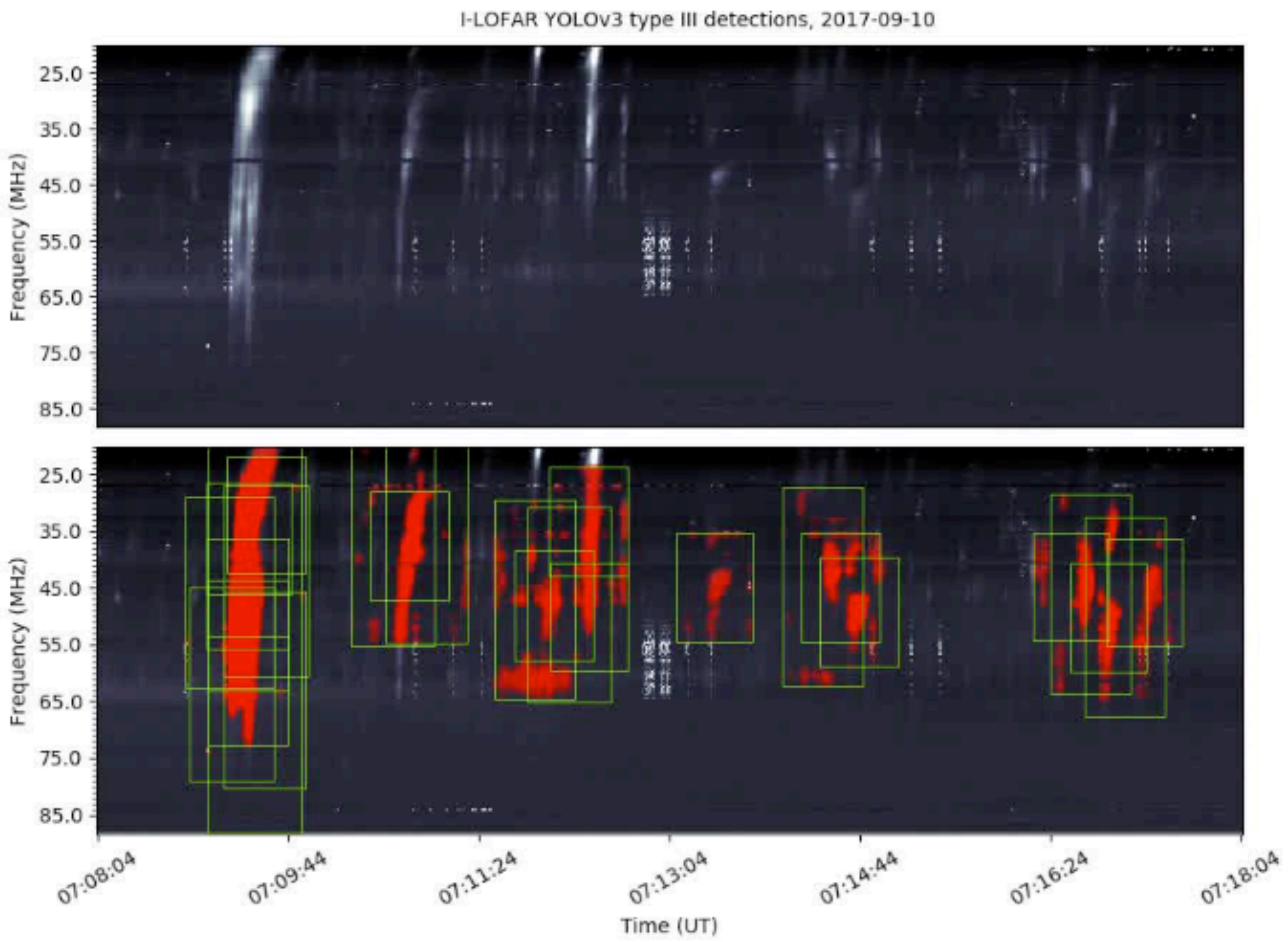
Conclusions

- **Instrument like LOFAR generate TB/hour**
- **Need to classify this data**
- **Machine learning has shown potential**
  - Support vector machine
  - Inception-v3
  - YOLO-v3
  - Need to investigate other CNN architectures (all suggestions welcome!)
- **Will be implemented on ILOFAR and possibly LOFAR4SW**



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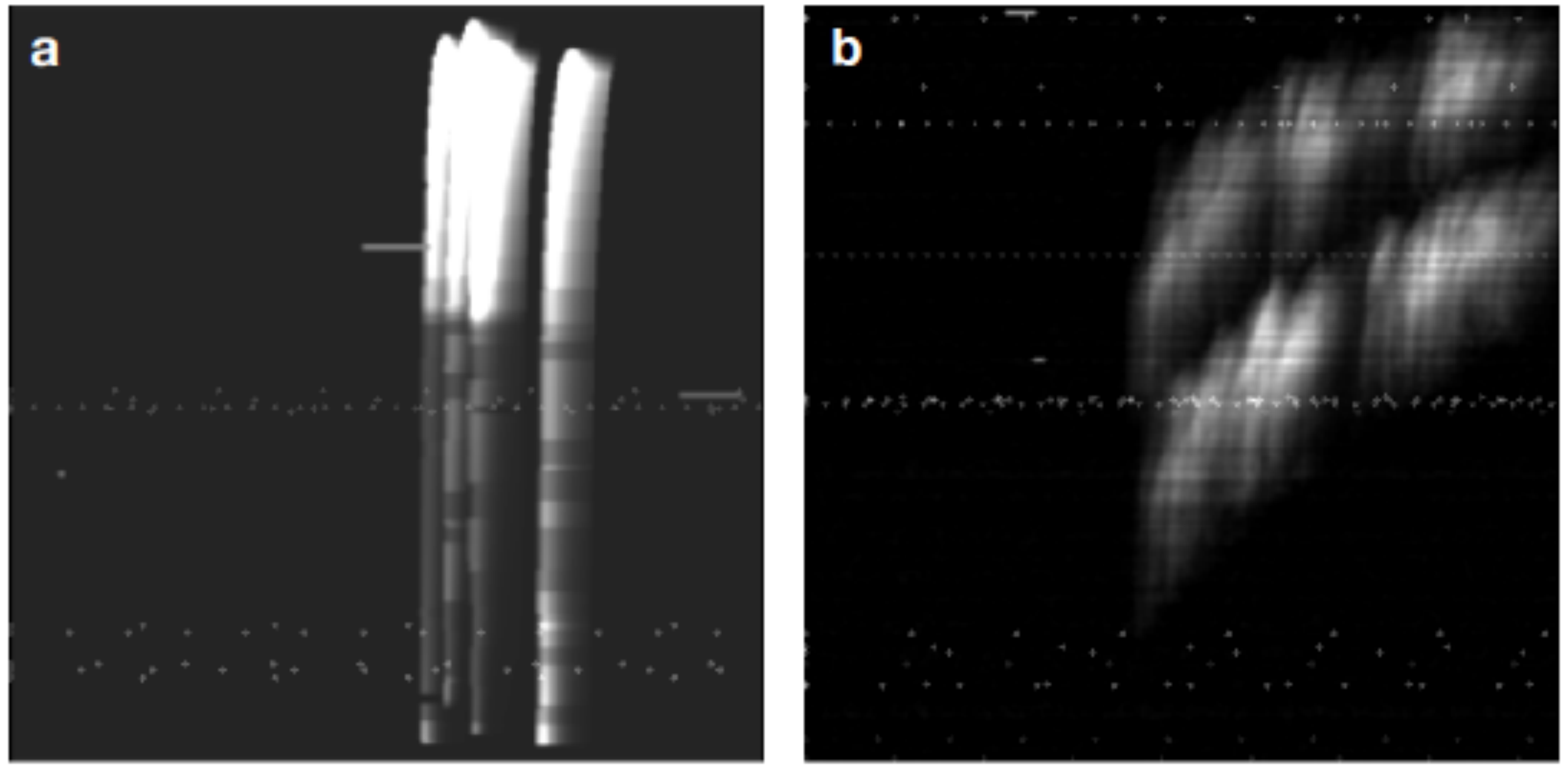
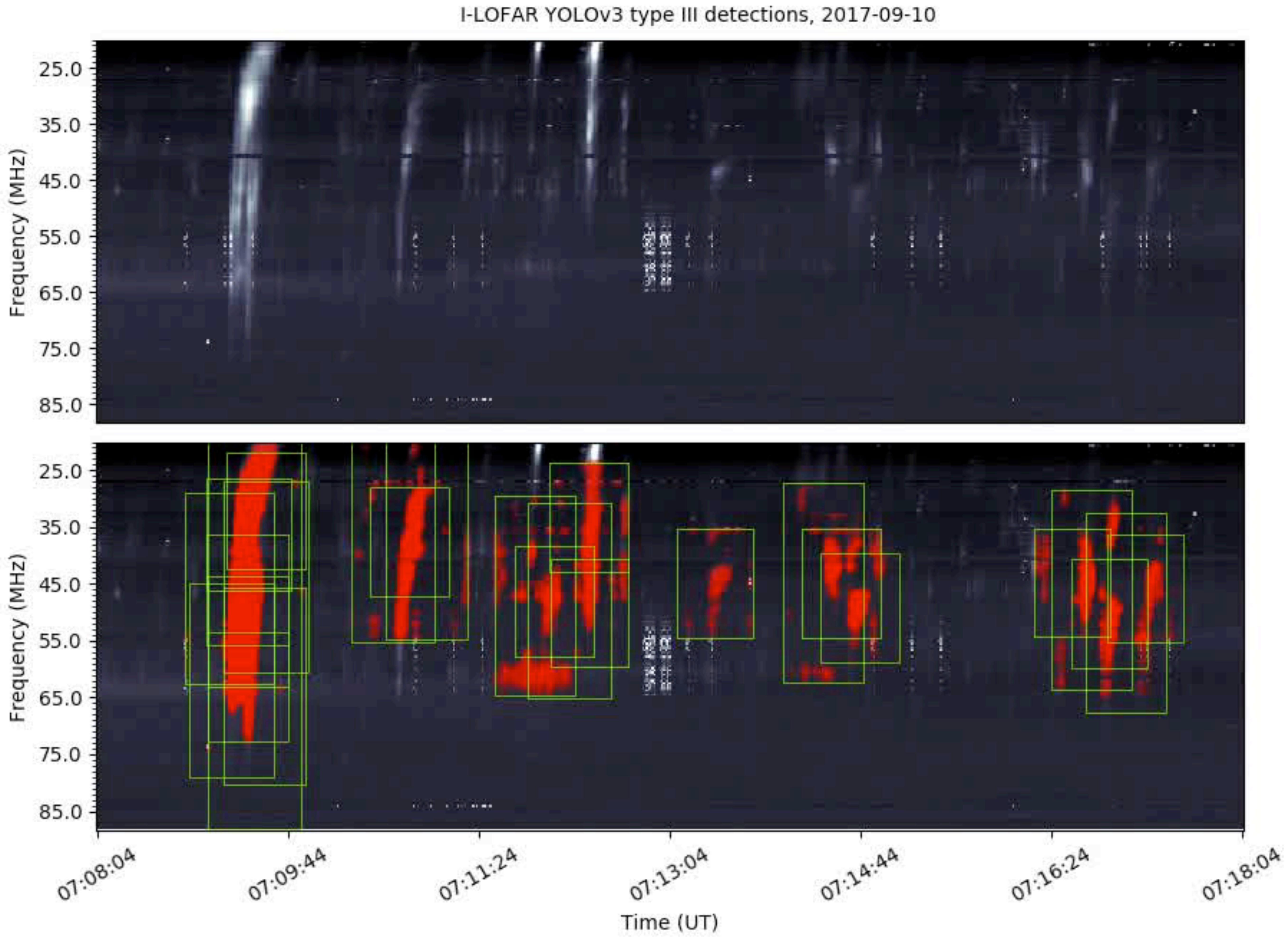
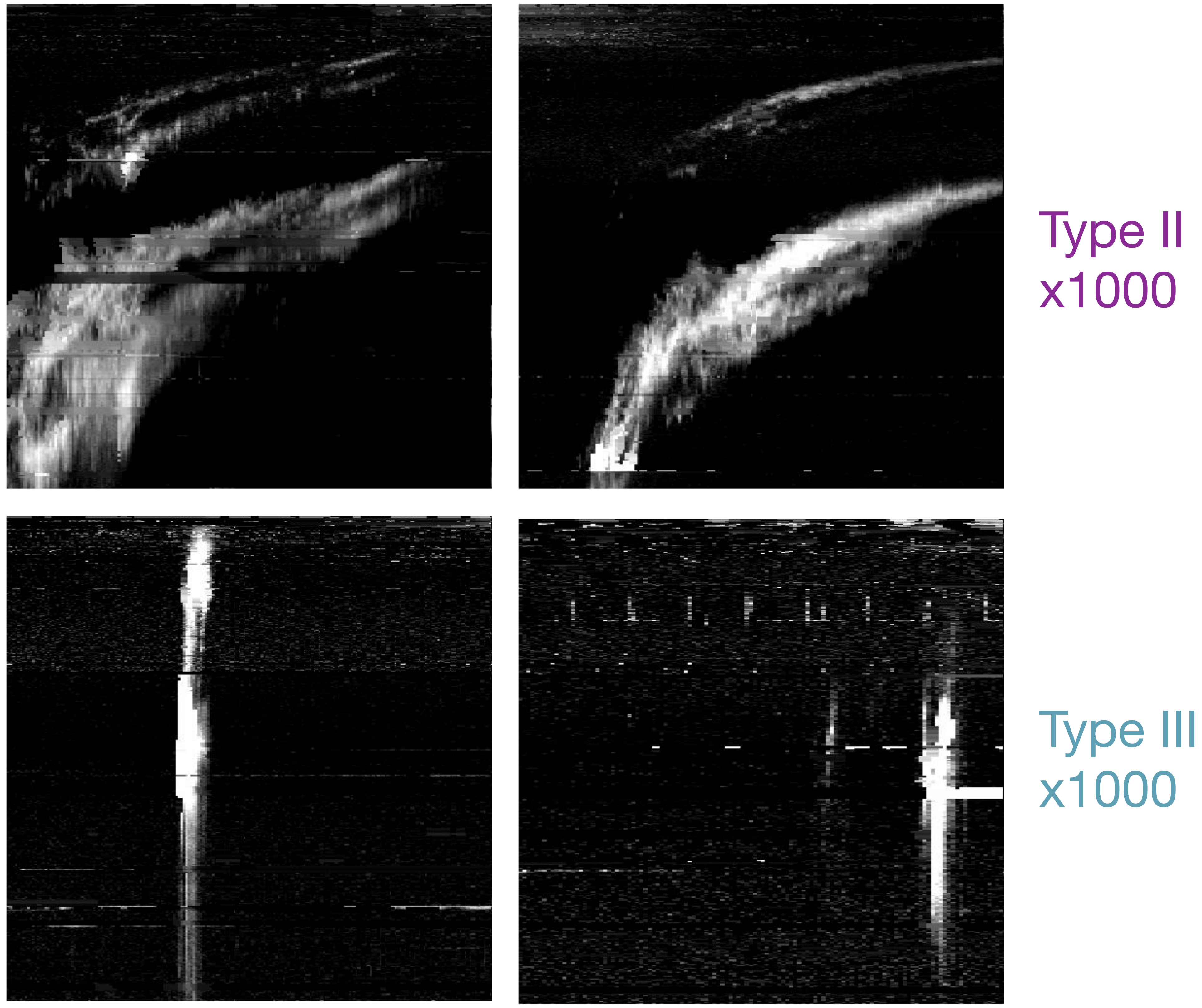
Backups: Radio burst classification - You Only Look Once (YOLO) v3





- ~50,000 simulated examples of each class
- Trained on NVIDIA Tesla K80
- ~1 hour for 1 epoch of training
- Initial results promising
- Problem with heavily saturated radio bursts

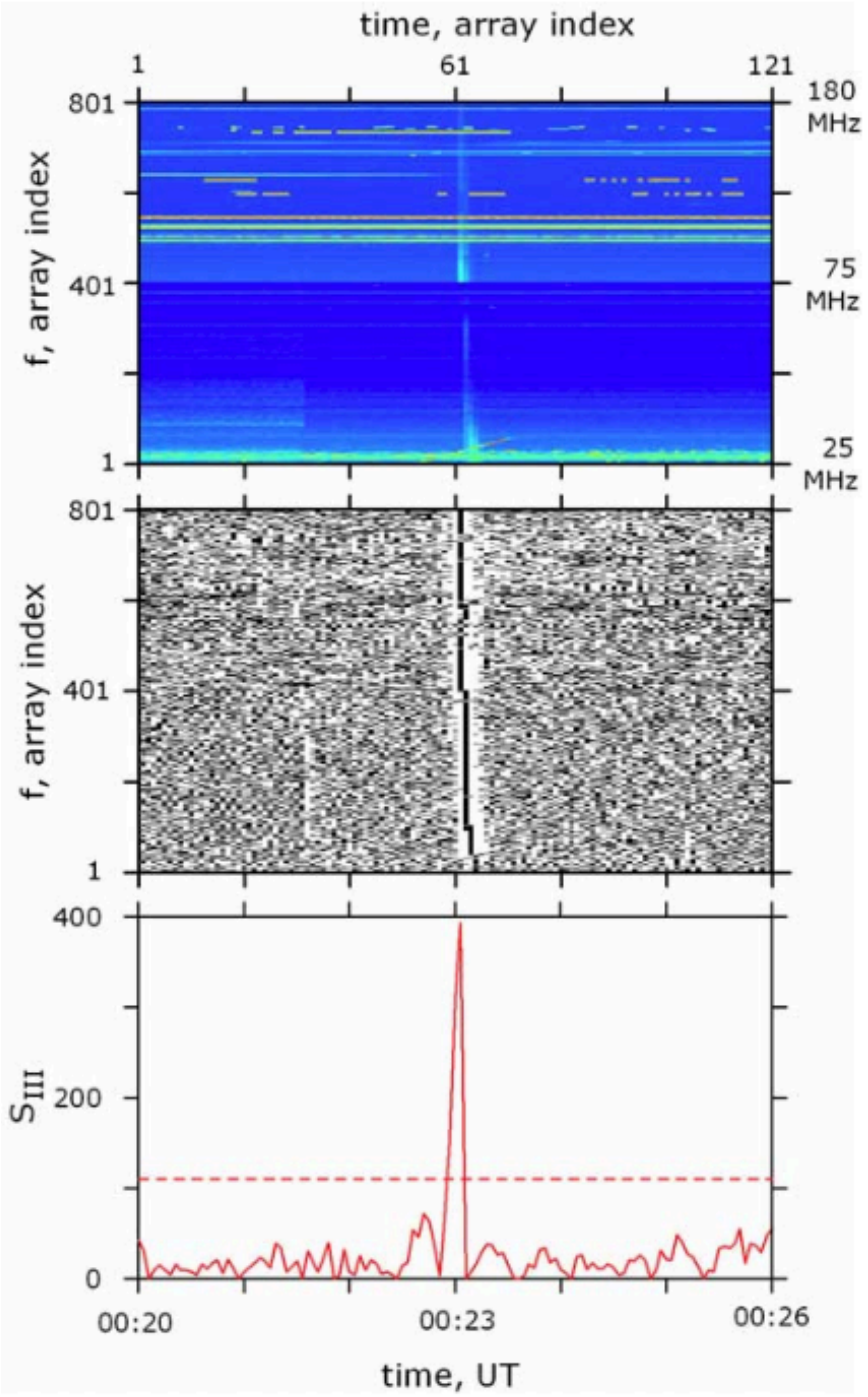
Training data - RSTN Observations



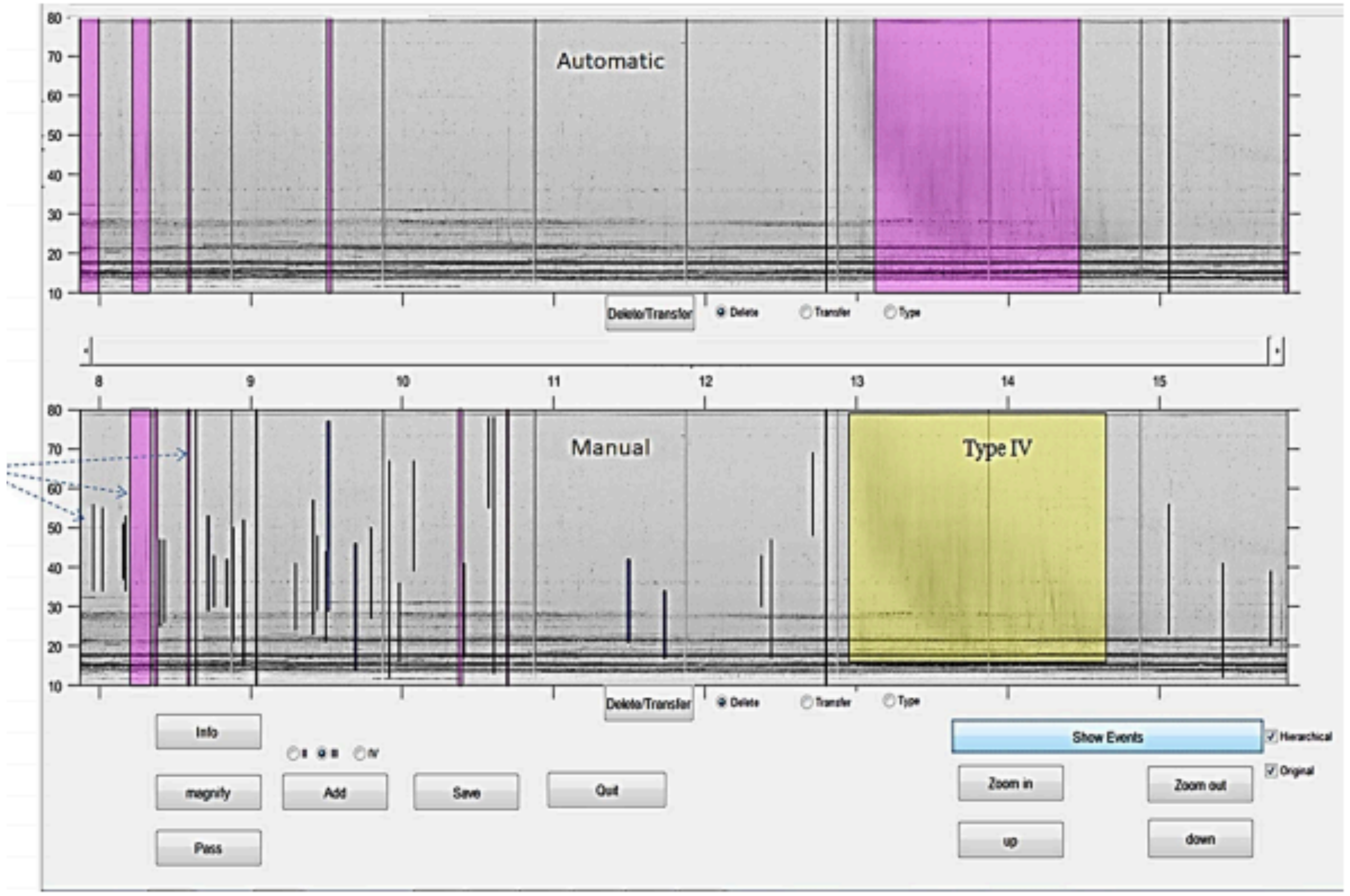
- SWPC event lists from 1996 to present.
- Initially thousands of bursts
  - Some mis-labelled
  - Some with terrible RFI
- Had to be cleaned for RFI and background subtracted.
- Downsampled to 50x50 pixels

Radio Burst Detection and Classification: Existing methods

Lobzin et al. (2009)

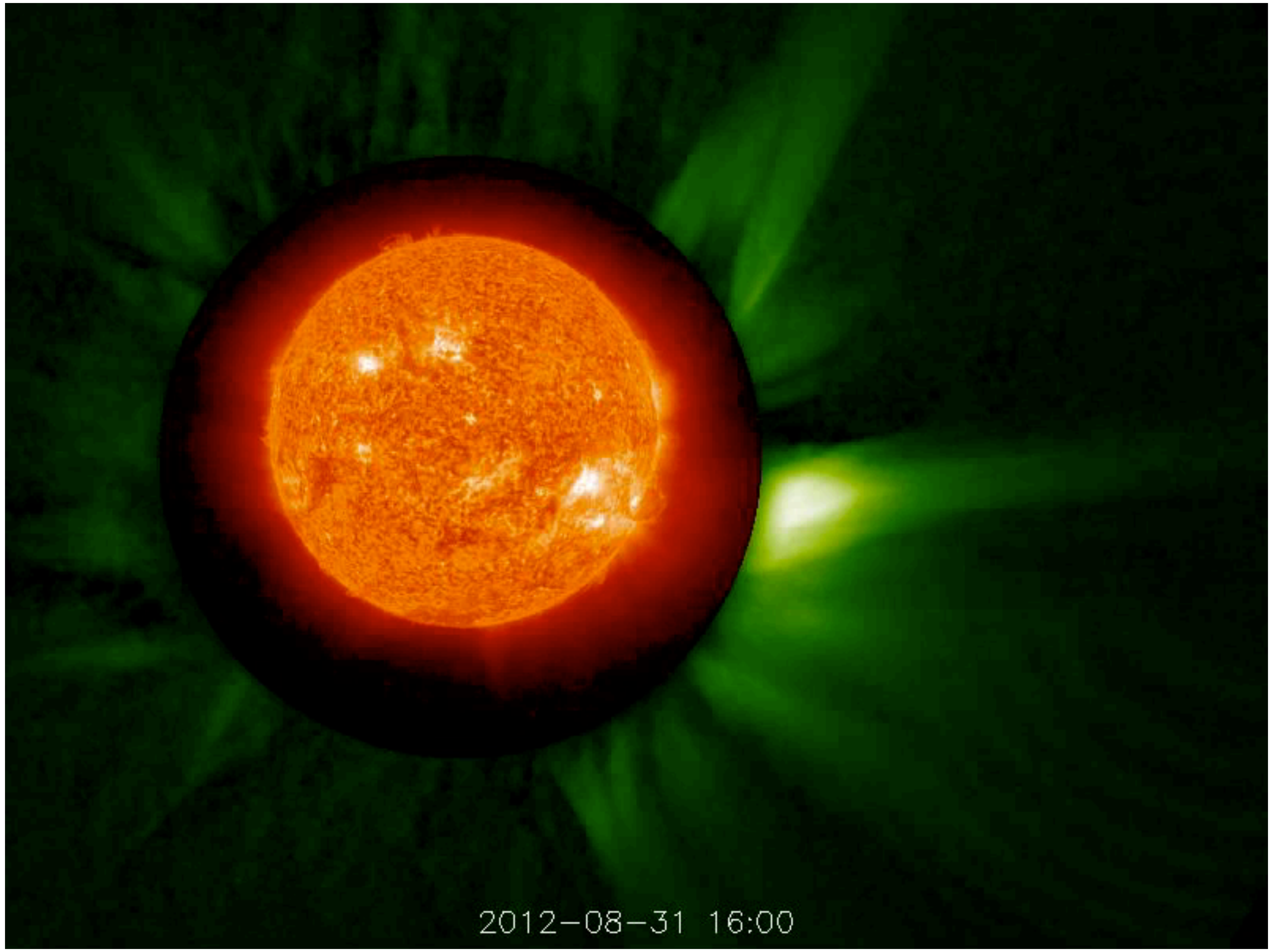


Salman et al. (2018)



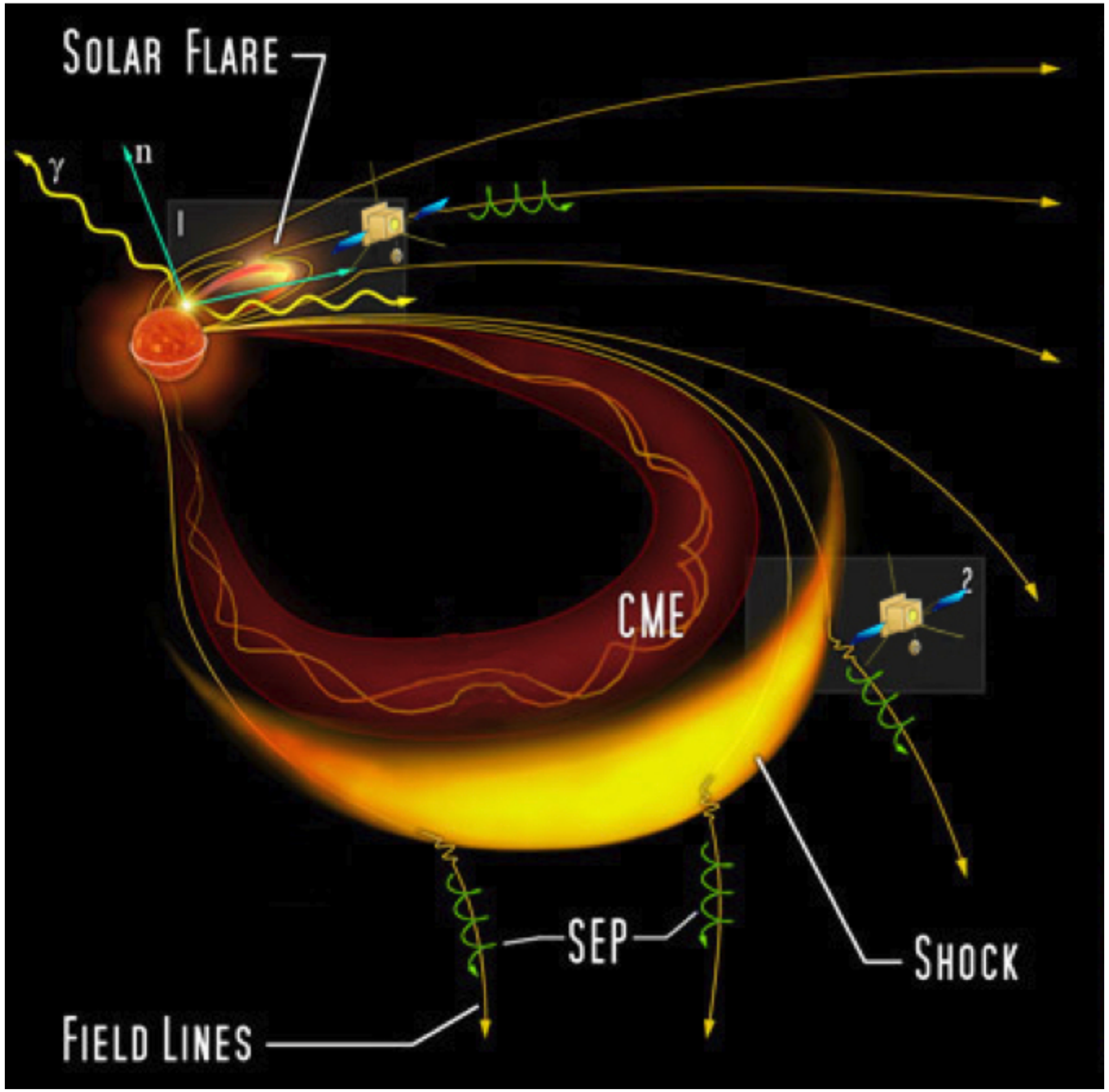
- **Hough transform,** see:
  - Type III bursts: Lobzin et al. (2009, 2010), Bonnin et al. (2011) - ~84% accuracy
  - Type II bursts: Lobzin et al. (2010) - ~80% accuracy
  - Herringbones: Carley et al. (2015)
- **Constant false alarm rate (CRAF)** detection:
  - Type II, III, IV bursts: Salman et al. (2018) - ~70% accuracy
- **Deep Learning (CNNs):**
  - Type IVs in GHz: Ma et al. (2017) - ~82% accuracy

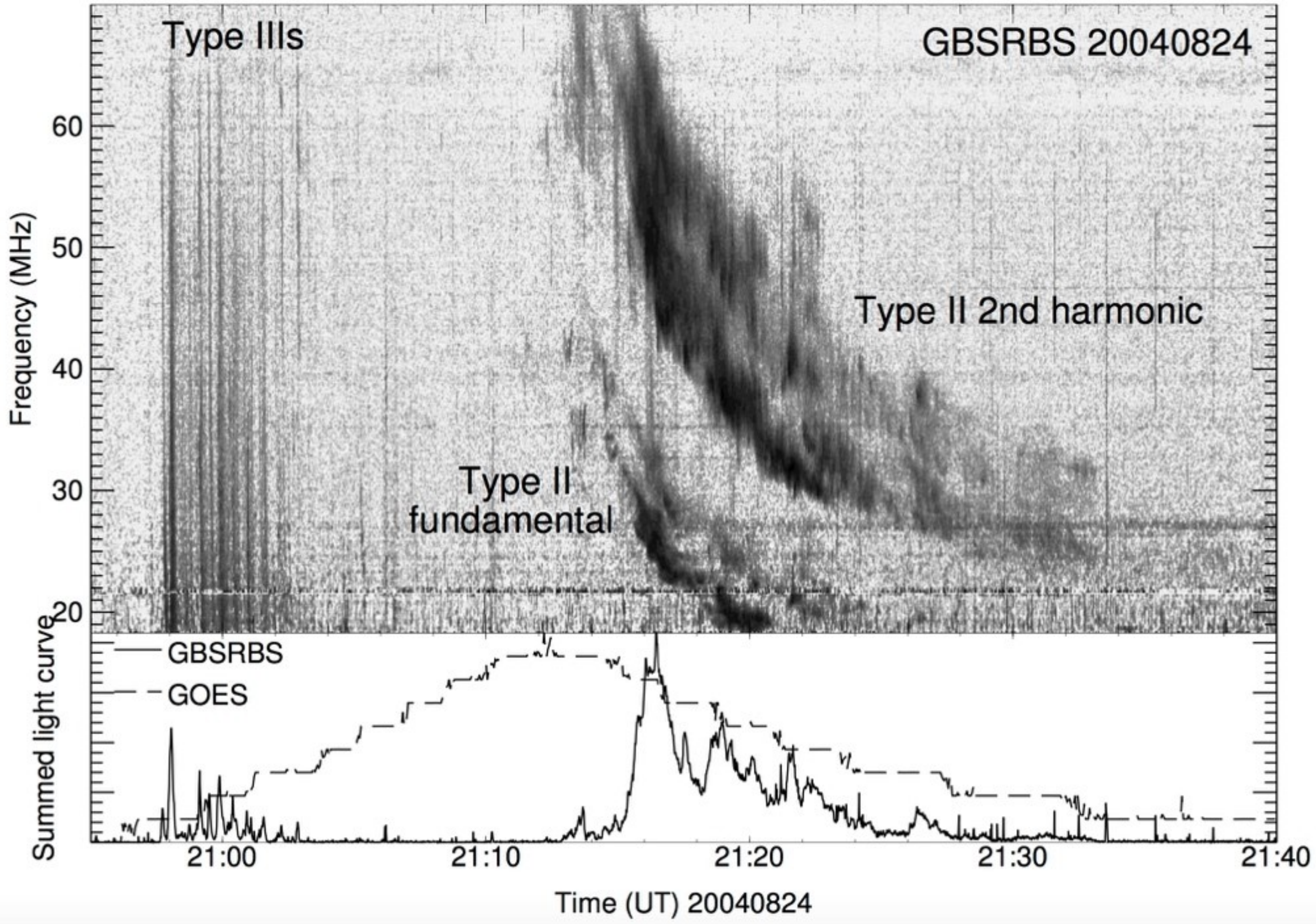
Coronal mass ejections and radio bursts



- Observed mostly in white-light coronagraphs
  - Speed of up to 3000 km s^{-1}
  - Mass of 10^{12} kg
  - Energy of 10^{25} J
  - Associated with a variety of radio bursts

Coronal mass ejections and radio bursts





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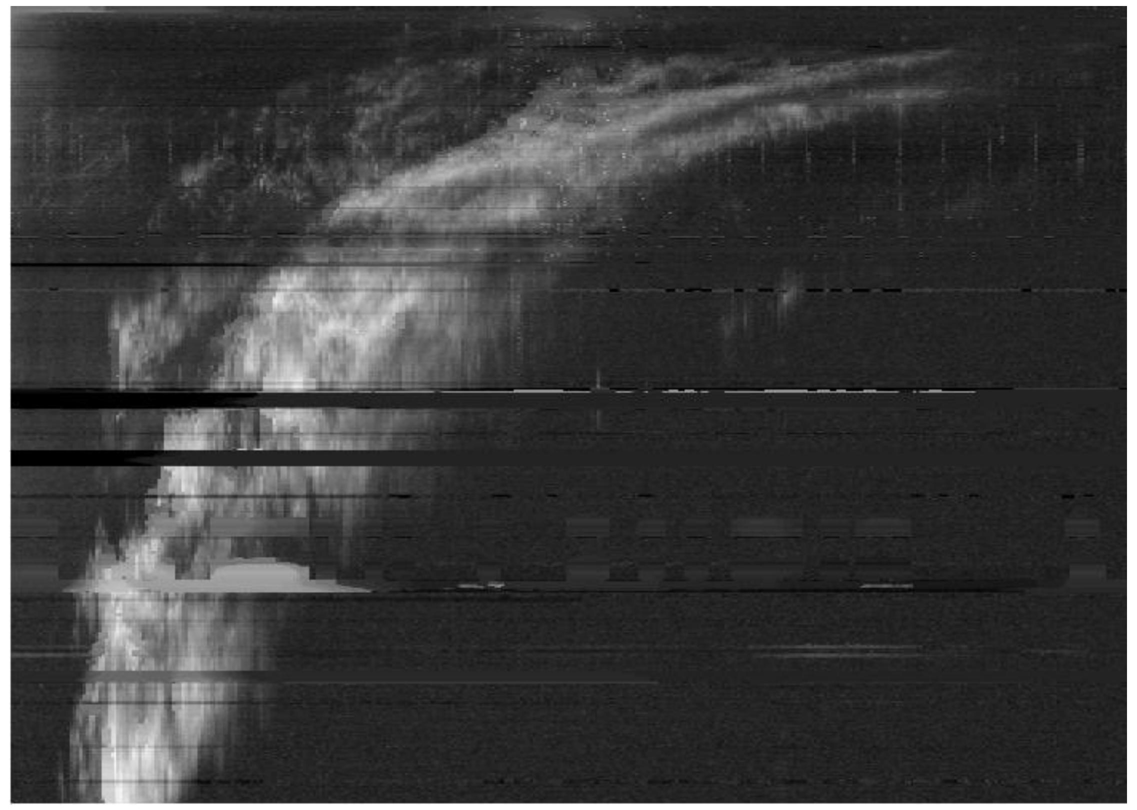
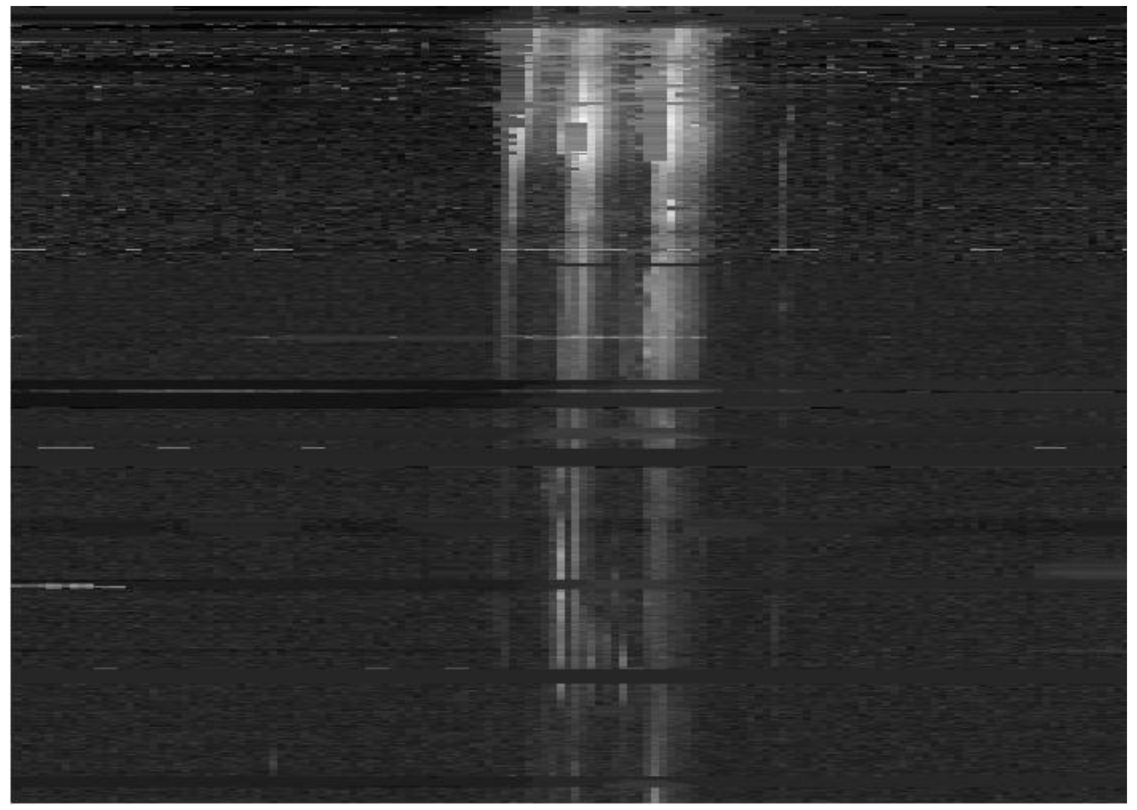
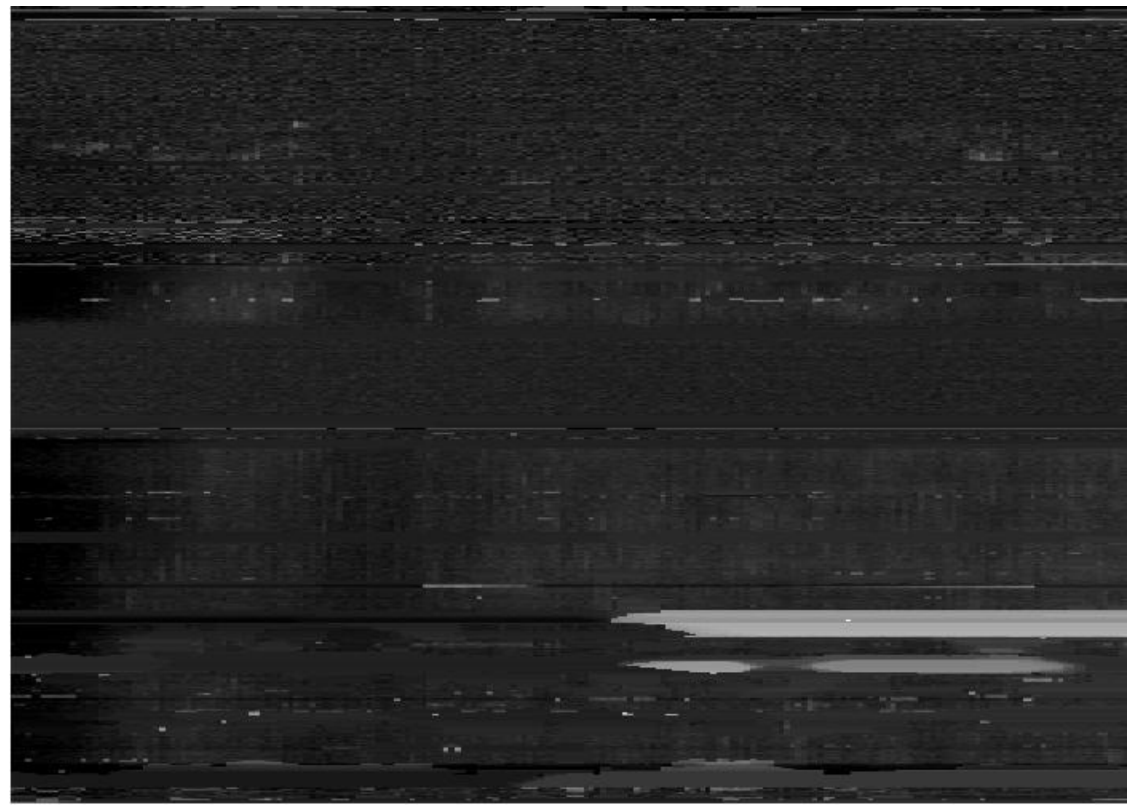
Radio burst classification - Support Vector Machine



Type II
x1000



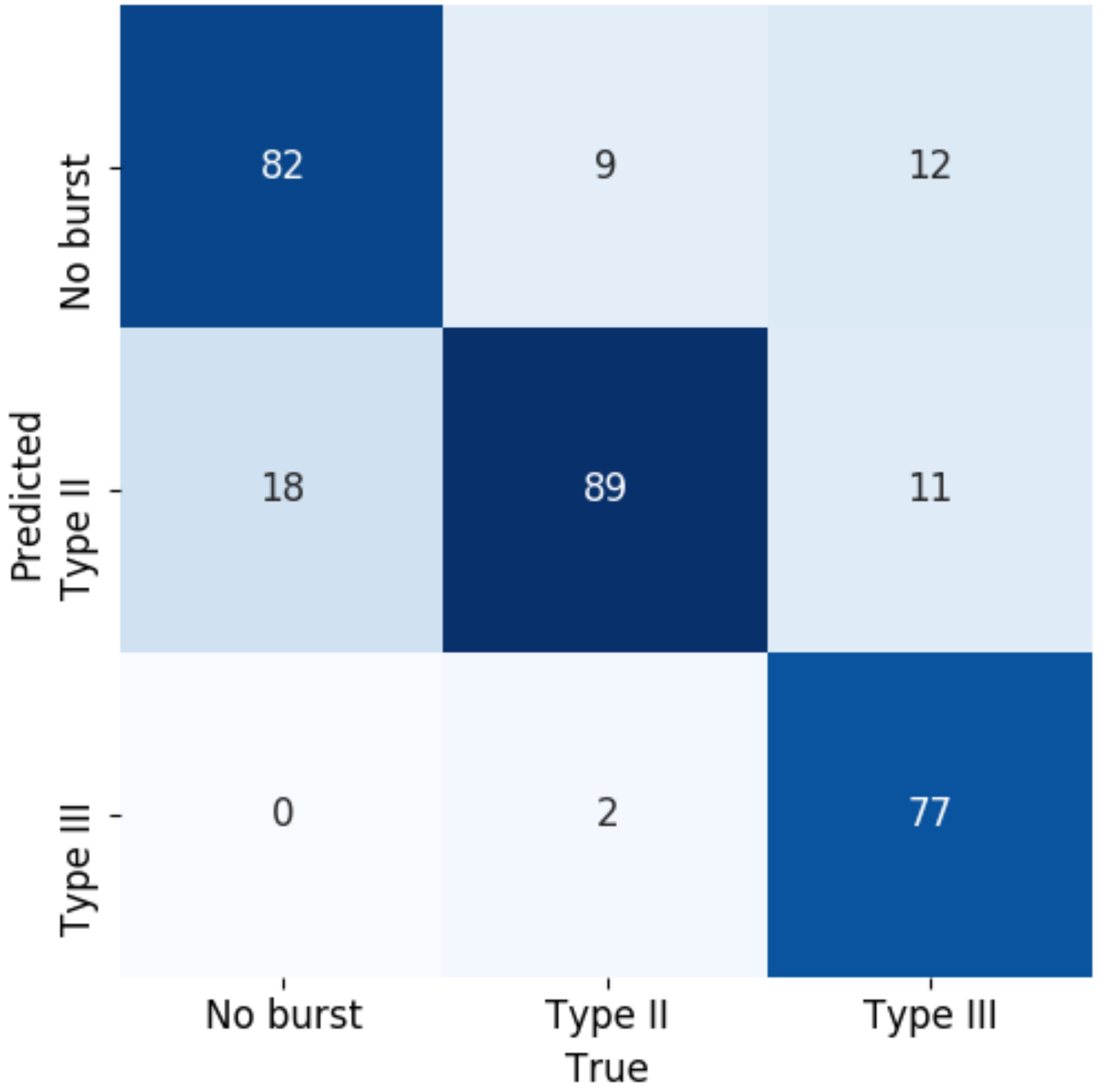
Type III
x1000



No burst
x1000

Table 1. Classification metrics for SVM on the RSTN data set.

	precision	recall	f1-score	support
No burst	0.80	0.82	0.81	100
Type II	0.75	0.89	0.82	100
Type III	0.97	0.77	0.86	100
avg/total	0.84	0.83	0.83	300



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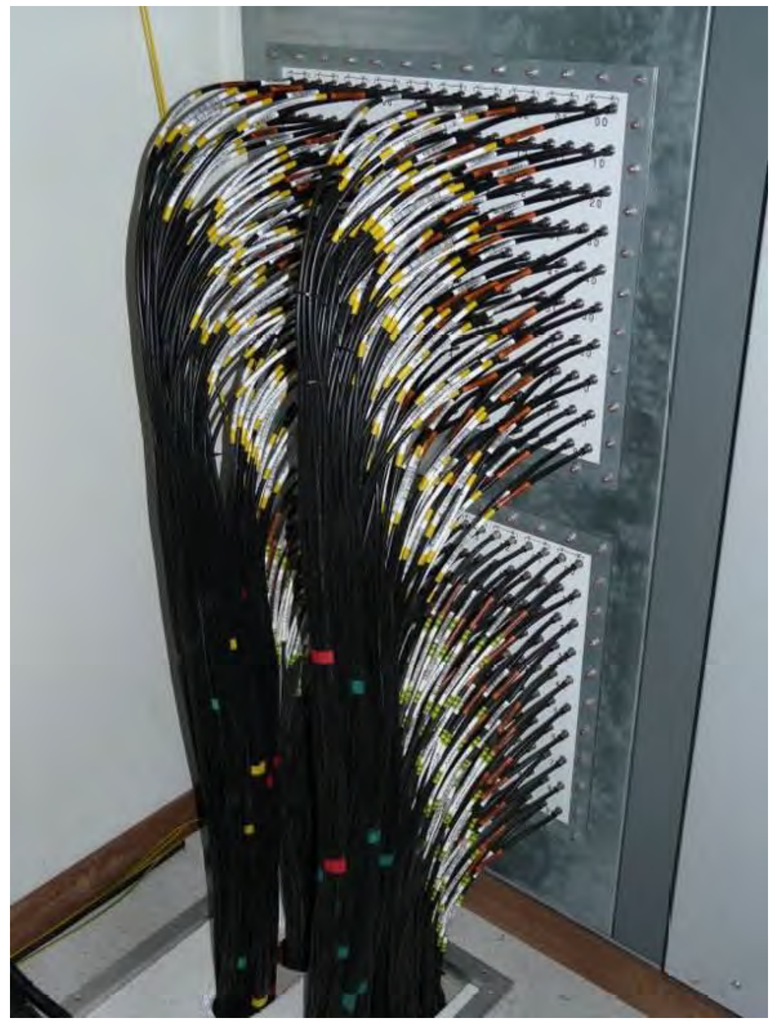
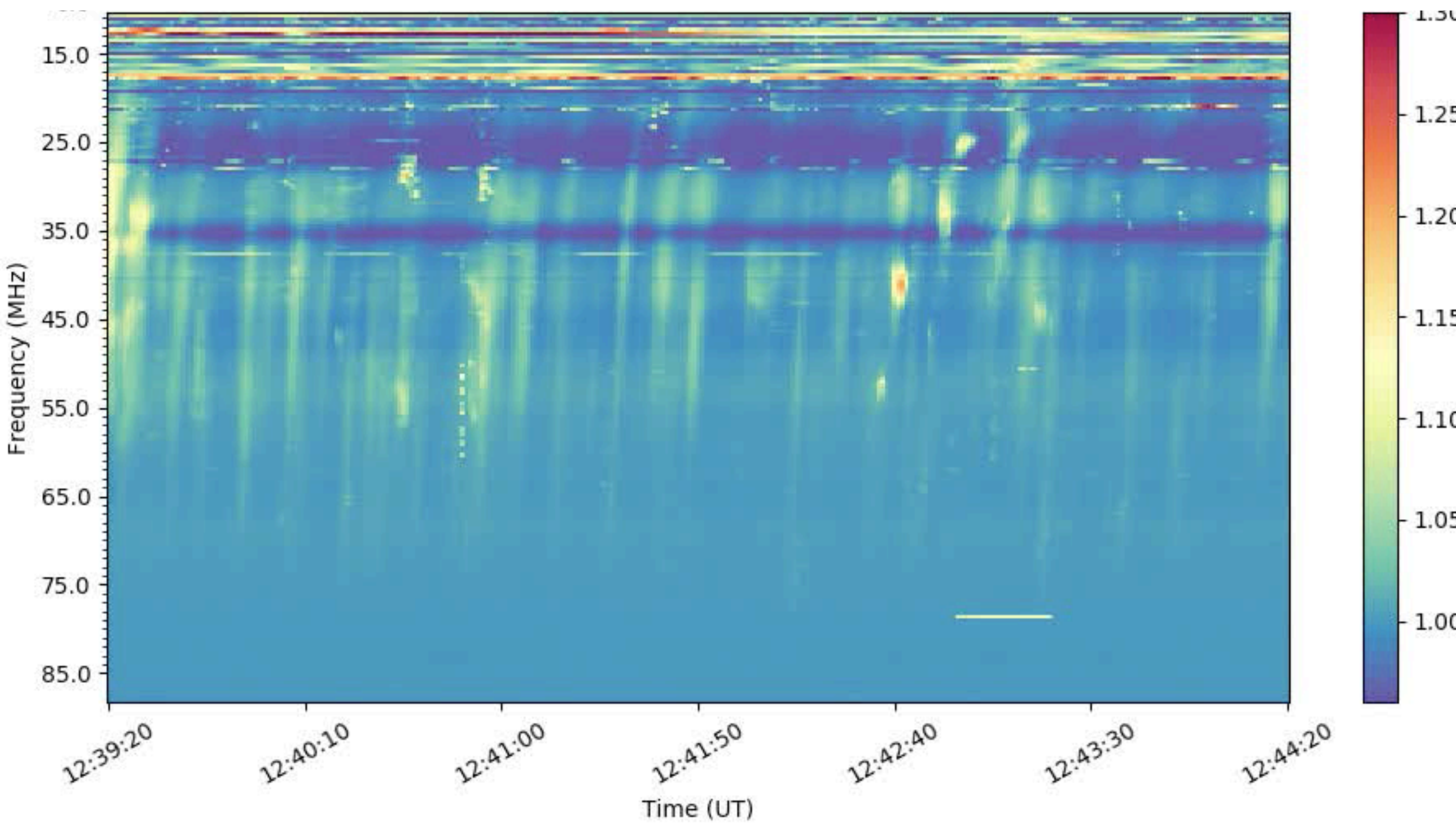
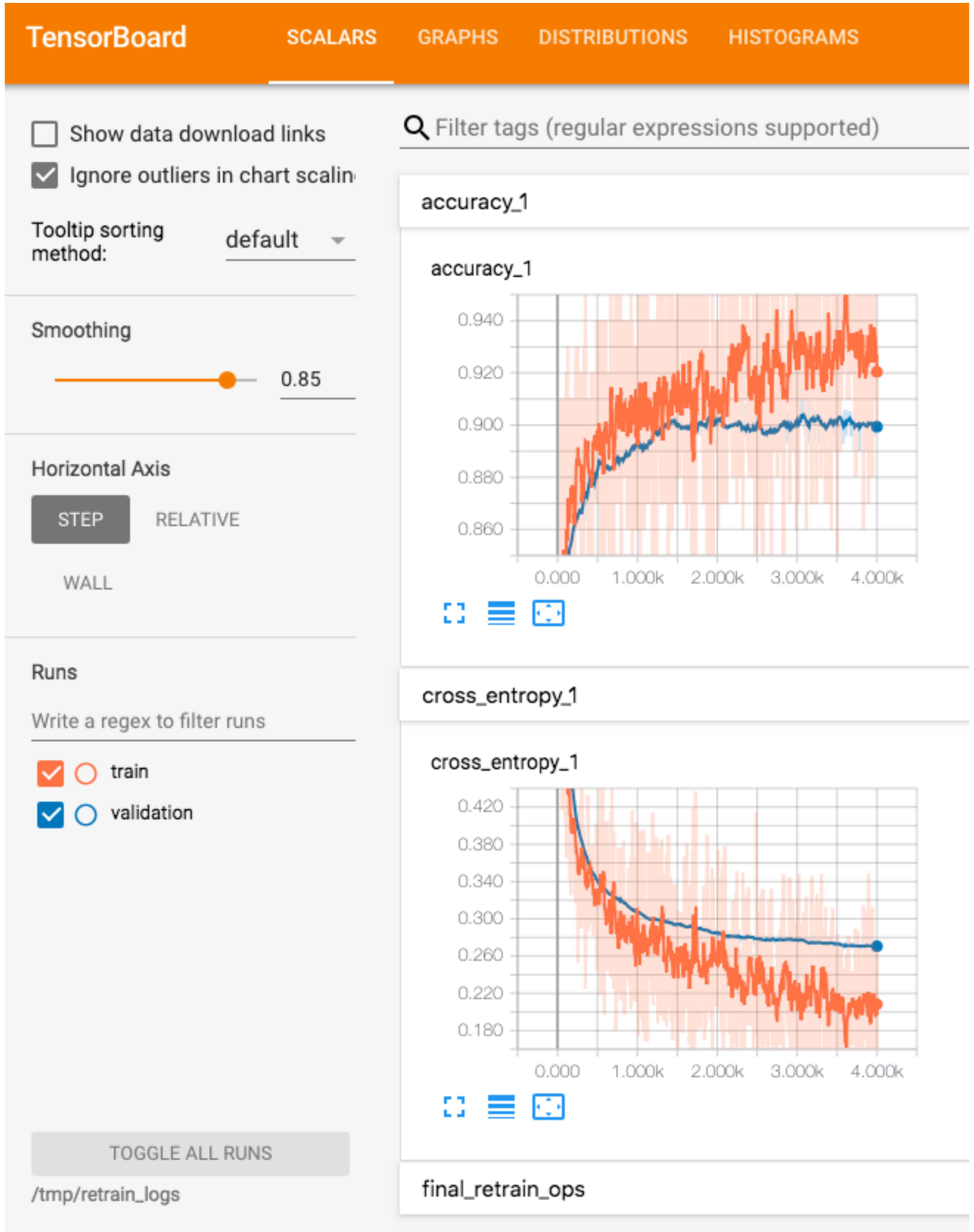
ILOFAR and REALTA



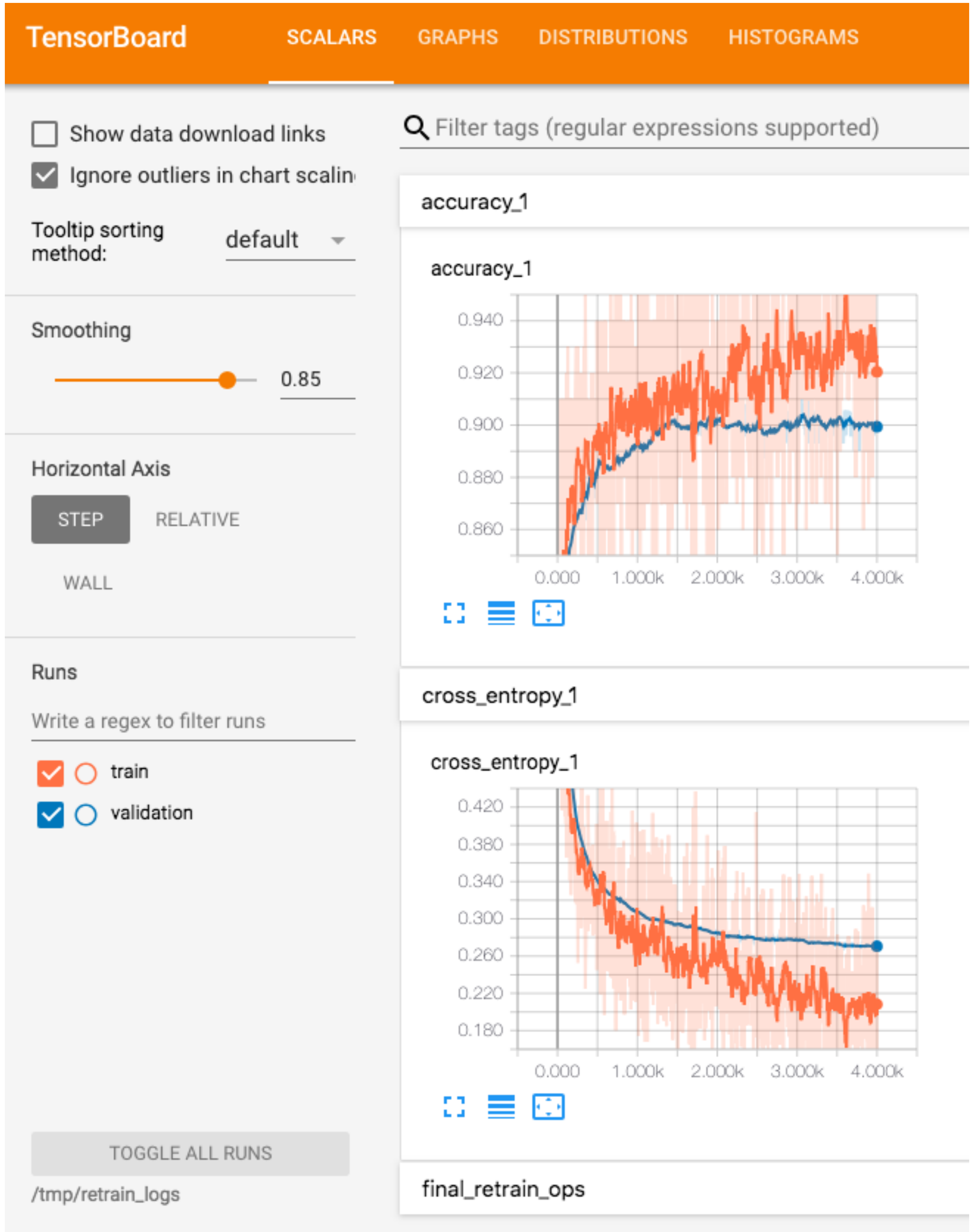
- Real-time Transient Acquisition (REALTA) cluster:
  - 488 frequencies each at 5μs time sampling
  - Records ~4 TB hr^{-1}
- Type III every 1-10 seconds
- Can we detect them all?

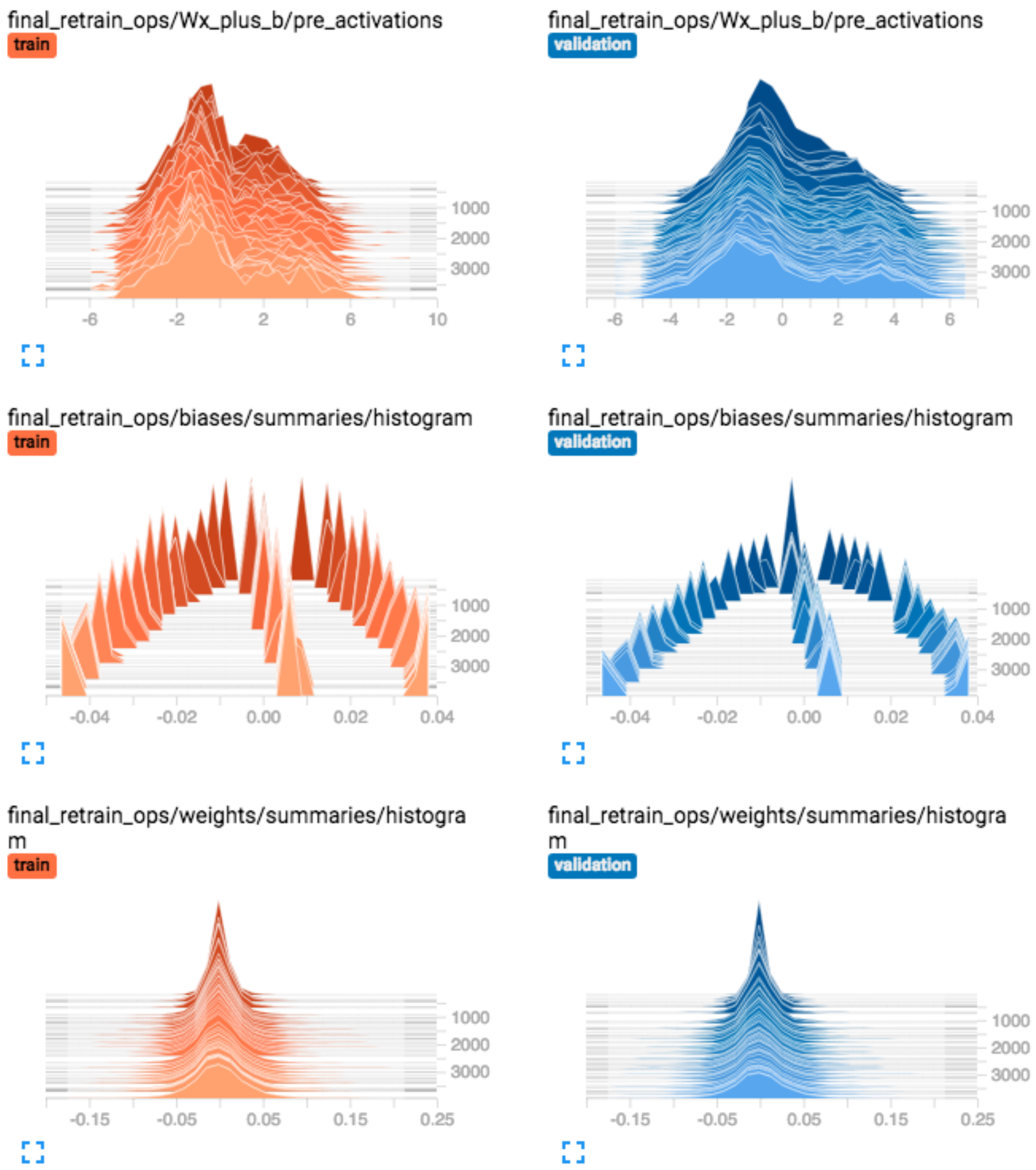


Deep Learning; Convolutional neural networks - InceptionV3

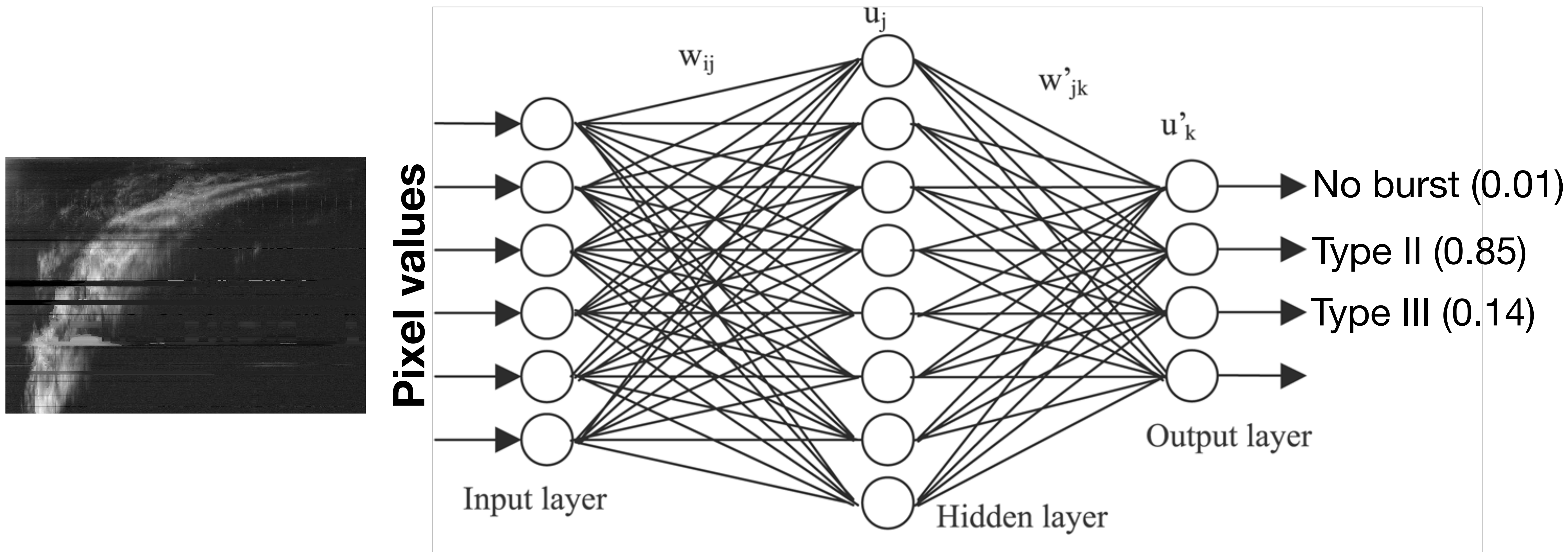


Deep Learning; Convolutional neural networks - InceptionV3





Deep Learning; Convolutional neural networks - CNNs



No burst (0.0)

Type II (1.0)

Type III (0.0)

$$x \rightarrow f(x) \rightarrow y$$