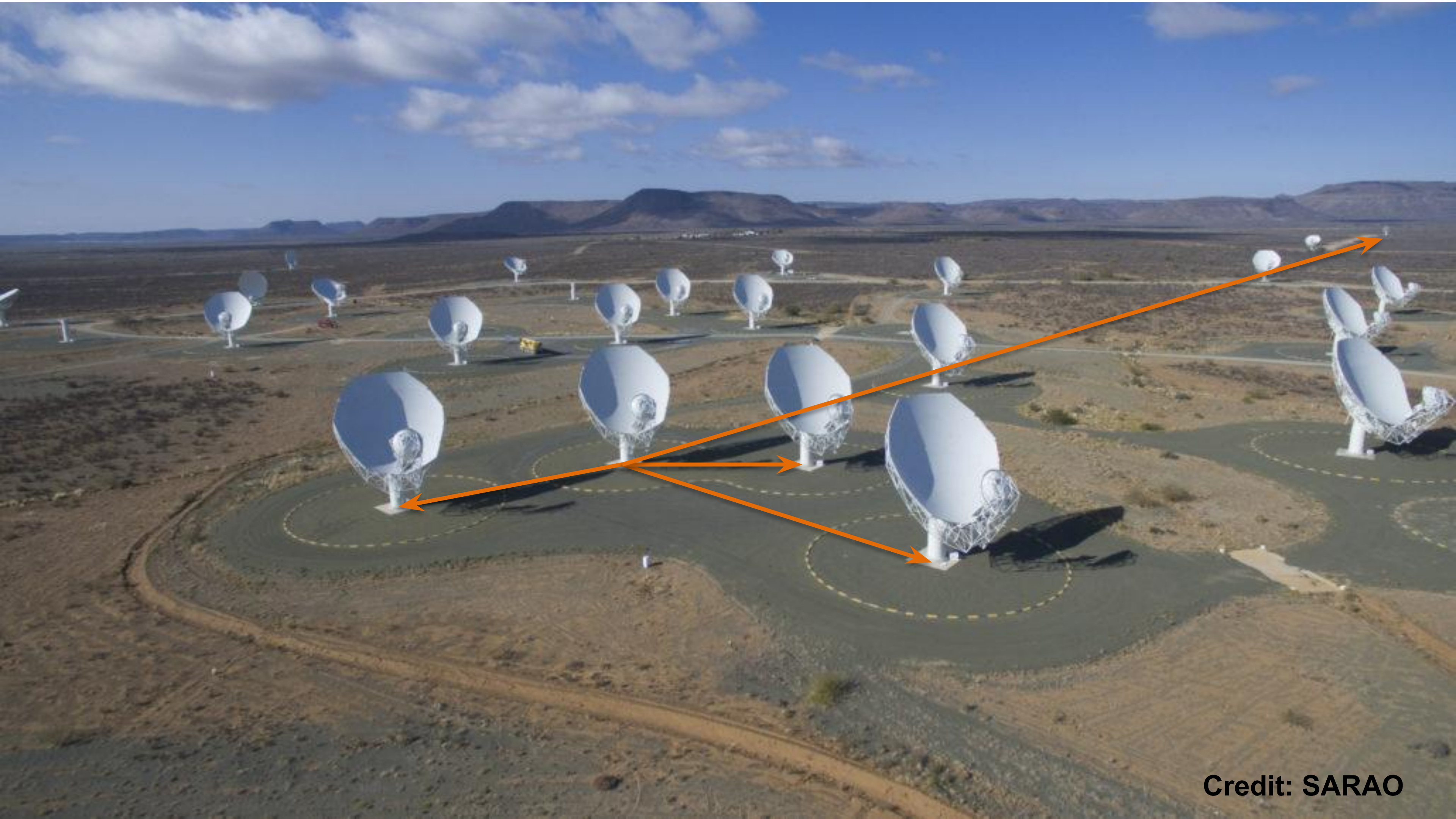
Machine Learning & Techniques: Building Trustworthy Models for Scientific Discovery

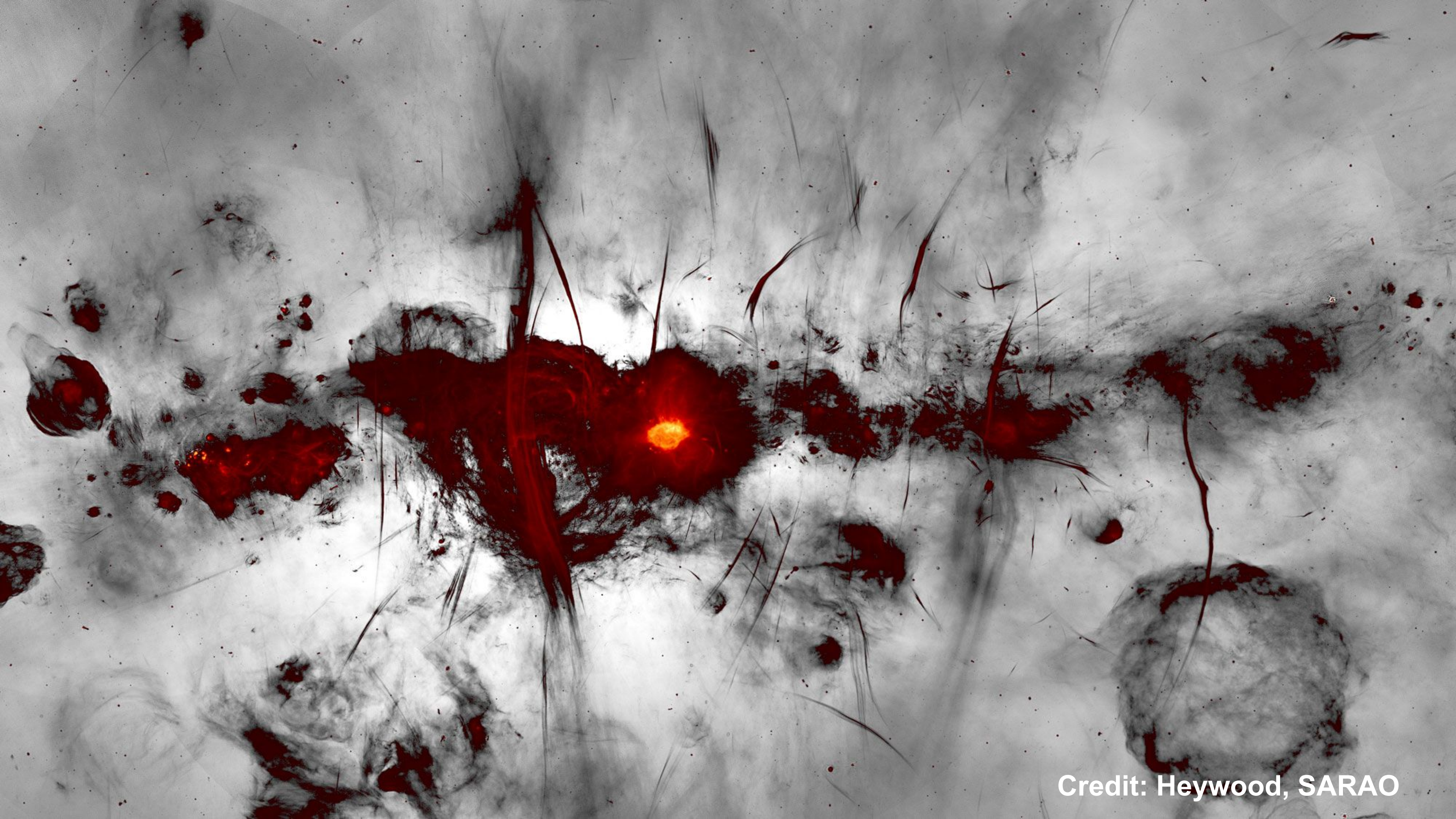
Nadeem Oozeer[1,2]

1 Radio Astronomy Research Group (RARG) - SARAO

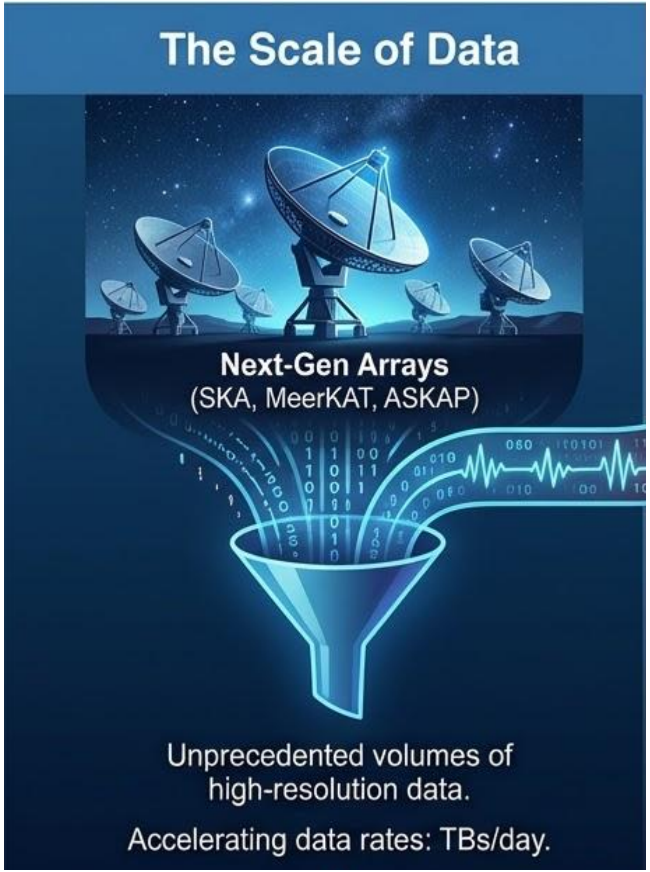
2 Rhodes University

Disclaimer: T&Cs apply to images.

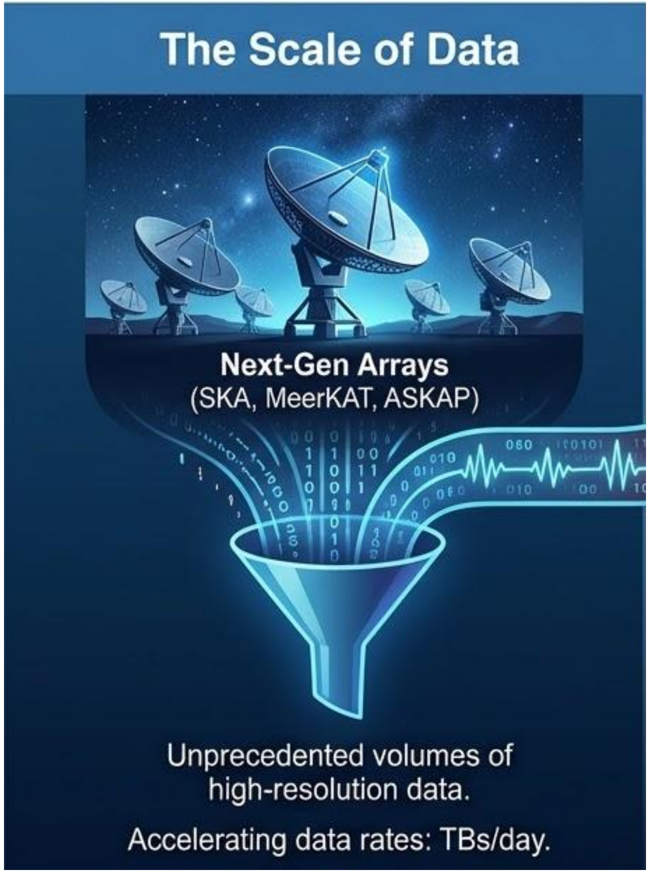

Credit: SARAO


Credit: Heywood, SARAO

The Scale of Modern Radio Astronomy & The ML Solution



In the early 1990s, the **Very Large Array (VLA)** produced data at a rate of approximately **tens of megabytes (MB) per hour**,



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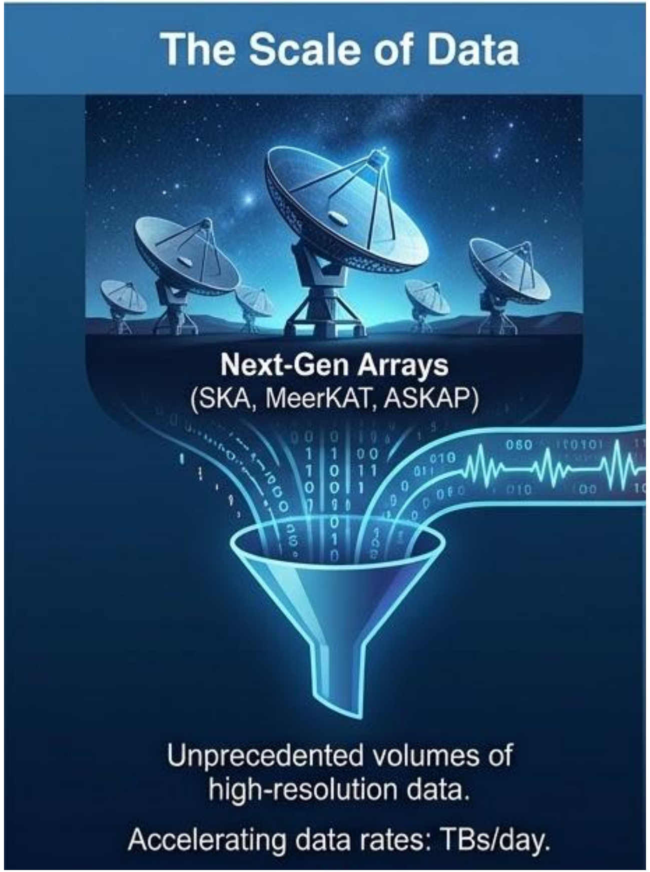

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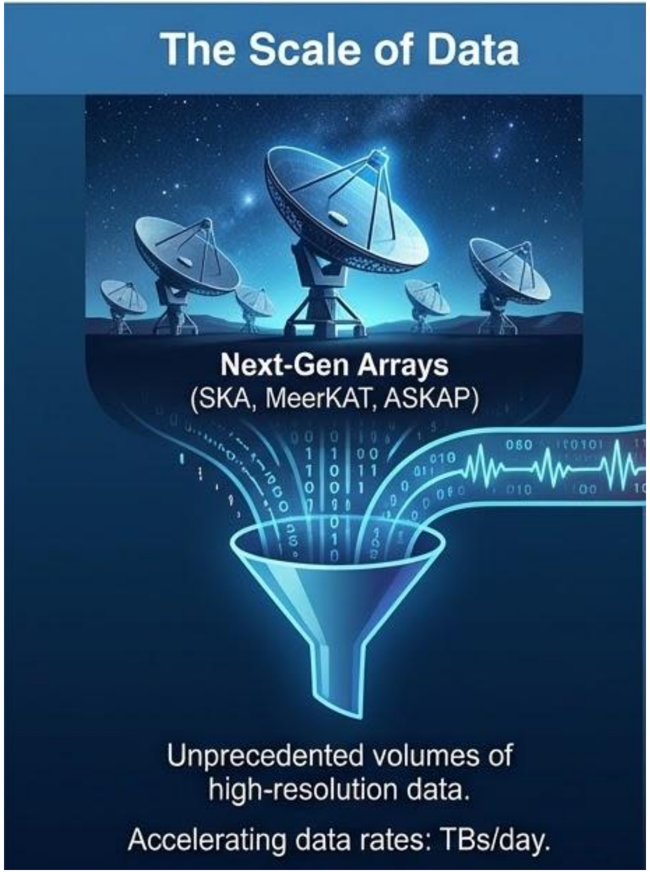

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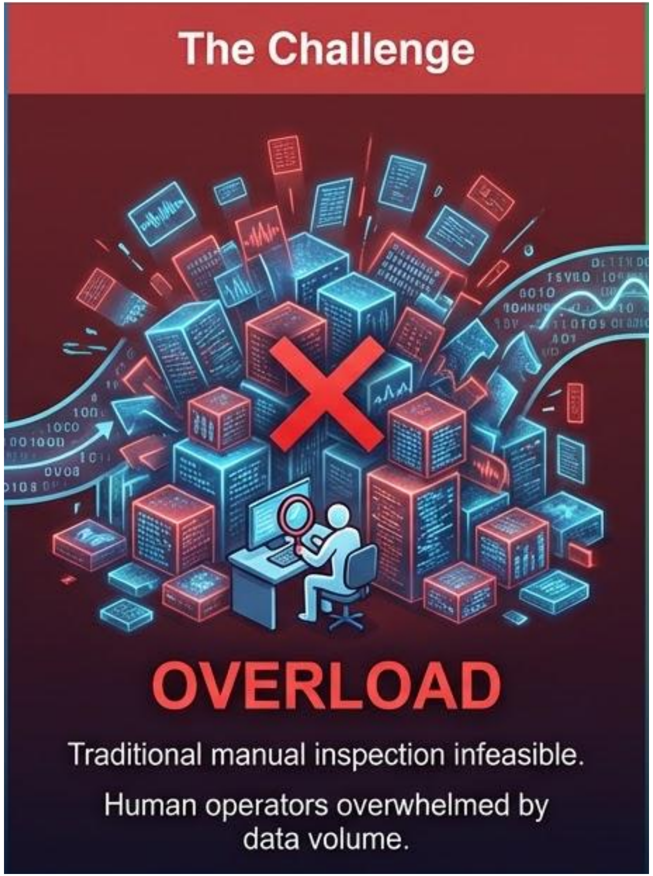
SKA mid expected to produce roughly **1,800 to 3,600 TB (1.8 to 3.6 PB) per hour**

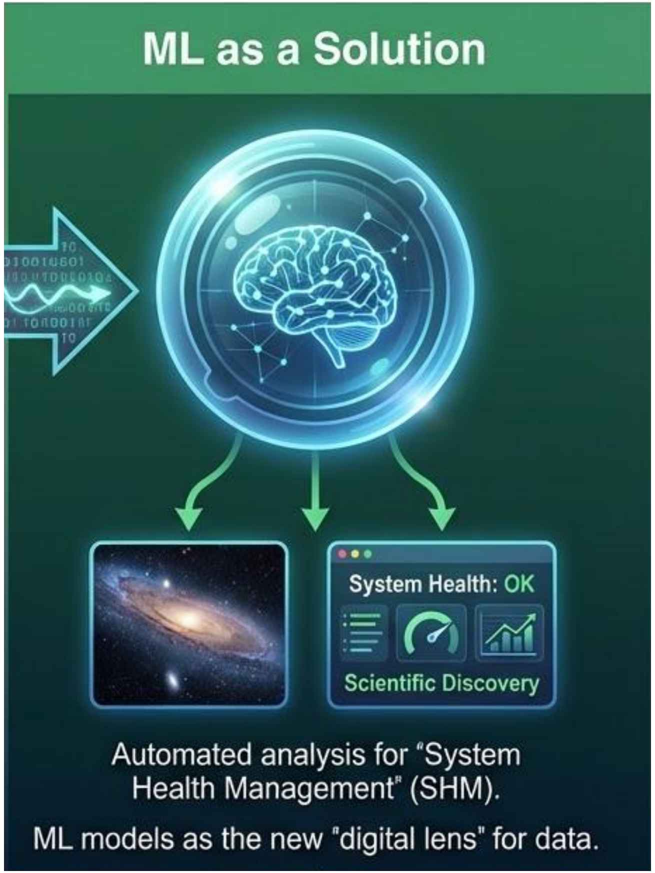
AIPS

CASA
Common Astronomy Software Applications

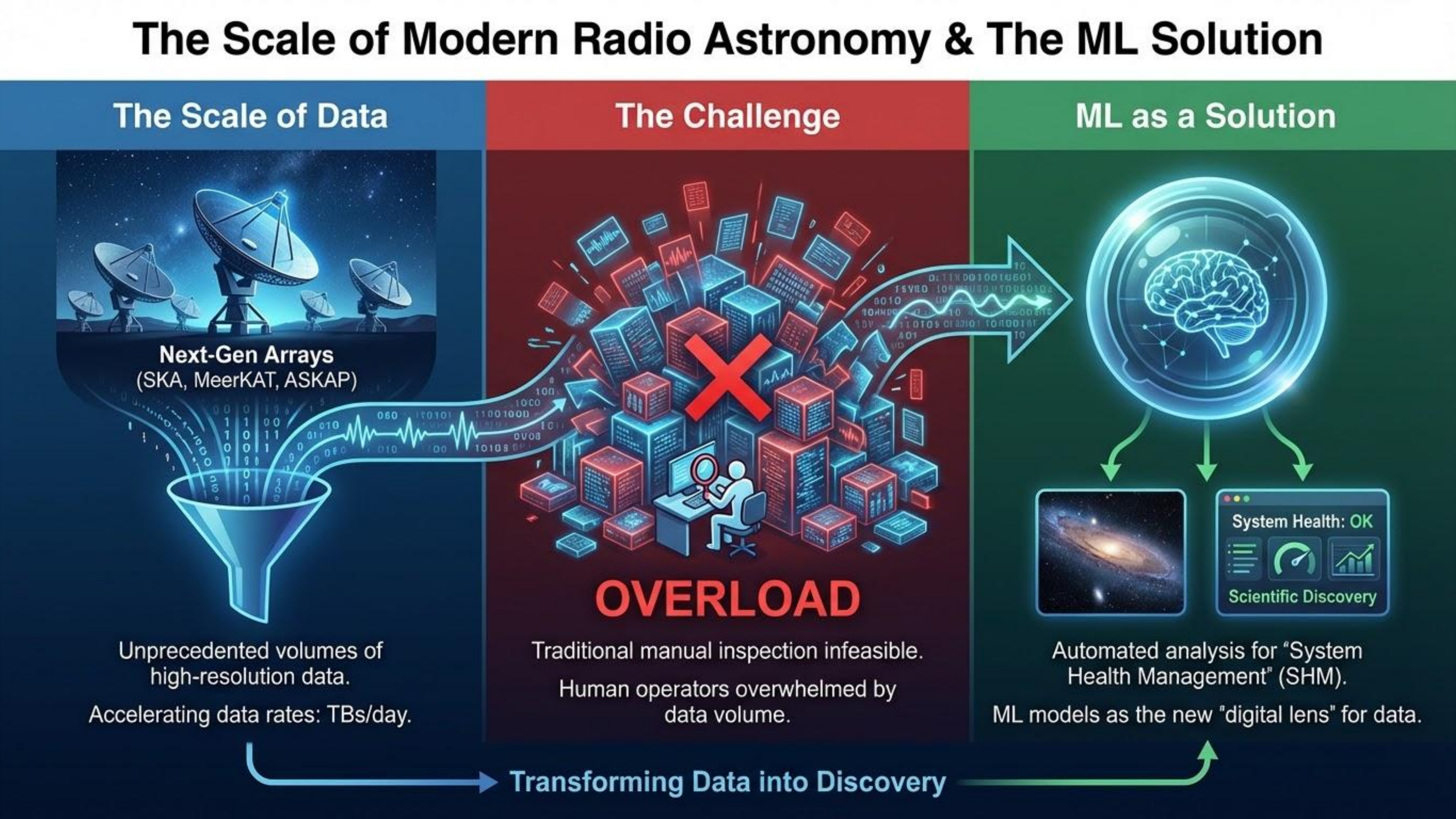


CARTA

https://ratt.center
RATT
Centre For Radio Astronomy Techniques & Technologies • Rhodes University



ML as a Solution
System Health: OK
Scientific Discovery
Automated analysis for "System Health Management" (SHM).
ML models as the new "digital lens" for data.


The Scale of Modern Radio Astronomy & The ML Solution
The Scale of Data
Next-Gen Arrays
(SKA, MeerKAT, ASKAP)
Unprecedented volumes of high-resolution data.
Accelerating data rates: TBs/day.
The Challenge
OVERLOAD
Traditional manual inspection infeasible.
Human operators overwhelmed by data volume.
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Transforming Data into Discovery

Key Applications in Radio Astronomy

Key Applications in Radio Astronomy

Source Characterisation

Automating the detection, classification, and identification of radio sources from image data.

DeepSource: Point Source Detection using Deep Learning in Radio Astronomy Images

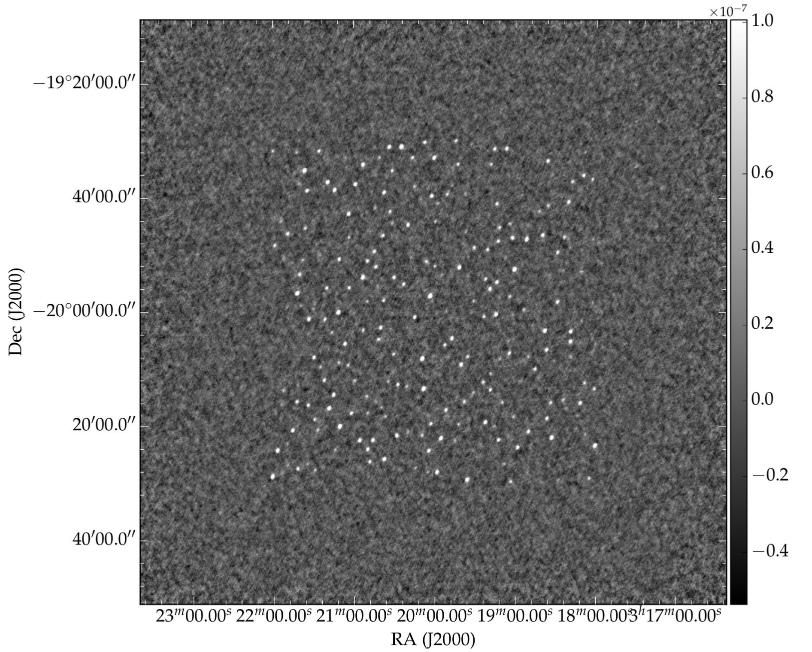
A. Vafaei Sadr, E. E. Vos, B. A. Bassett, Z. Hosenie, N. Oozeer, M. Lochner

Goal

Improve detection of faint radio sources in interferometric images where noise and artefacts make classical methods struggle.

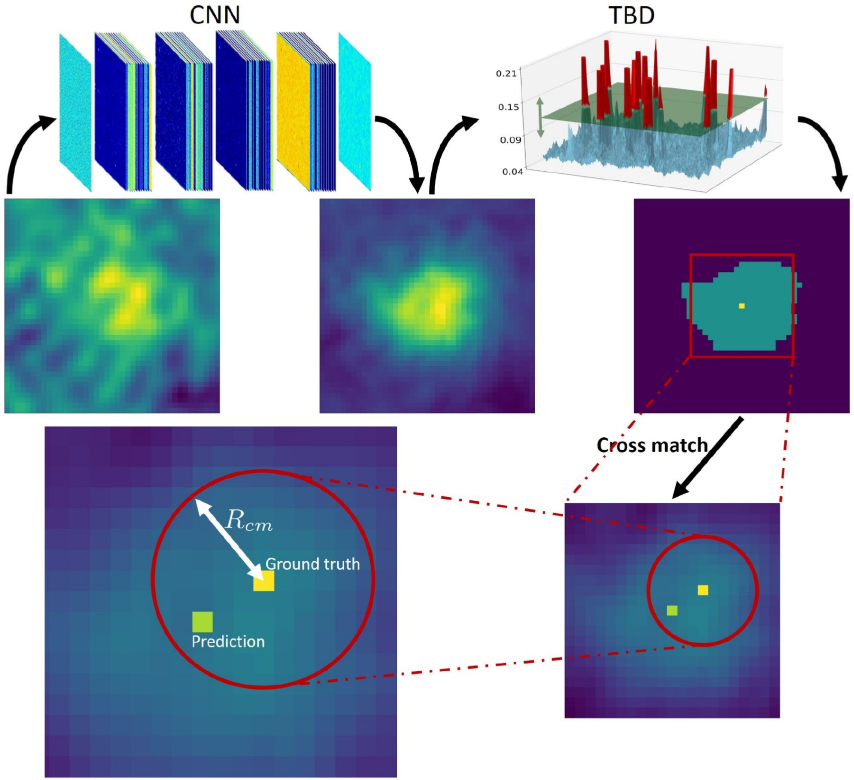
Comparison

Compared with PyBDSF, a standard radio source finder.



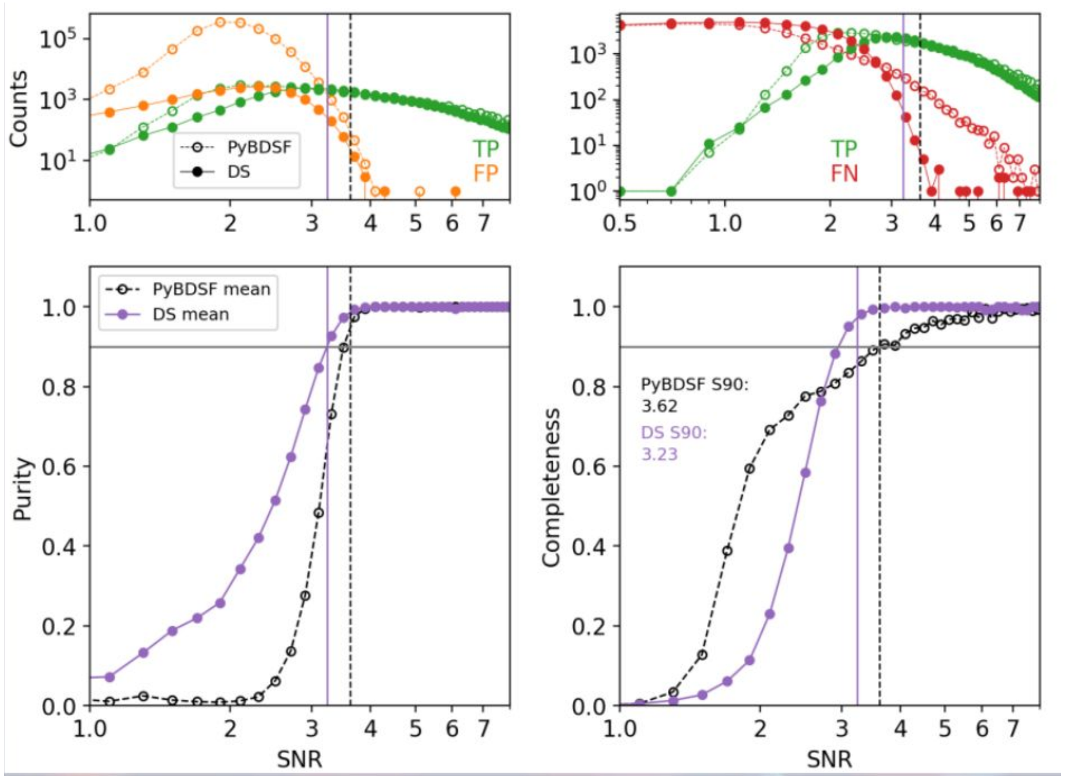
https://github.com/vafaei-ar/deepsource

- Train CNN to learn noise/background & point source
- Probability map of source



$$\text{Completeness}\,(f) = \frac{TP\,(f)}{TP\,(f) + FN\,(f)}$$

$$Purity\,(f) = \frac{TP\,(f)}{TP\,(f) + FP\,(f)}$$



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Anomaly Detection

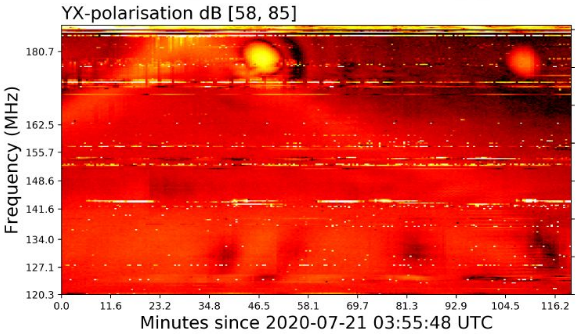
Identifying unexpected events like electronic failures, miscalibrated observations, or environmental effects like lightning storms.

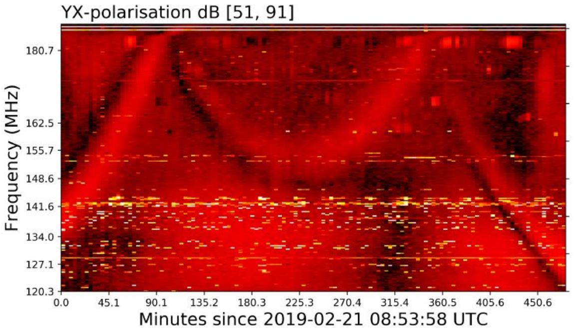
Machine-learning-driven anomaly detection in radio astronomy spectrograms (ROAD)

Source: A&A, 680, A57 (2023) - https://www.aanda.org/articles/aa/full_html/2023/12/aa47182-23/aa47182-23.html

Data & Methodology

- Use LOFAR autocorrelation spectrograms (~7000 samples)
- 10 labelled anomaly types
- Train a self-supervised model using:
  - Context prediction (predict missing regions)
  - Reconstruction loss (autoencoder-like)





Results & Key Takeaway

- Results:
  - Real-time: <1 ms per spectrogram
  - Anomaly detection F2 ≈ 0.92, false positive ~2%
- Takeaway:
  - Self-supervised ML can monitor telescope health and discover unexpected events without requiring large labelled datasets—important for SKA-scale operations.

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RFI Mitigation

Detecting and removing Radio Frequency Interference (RFI) from increasingly difficult environments populated by massive satellite networks.

Insights into the Aerospace RF Spectrum from Radio Astronomy Observations

Nadeem Oozeer[1,2], Isaac Sihlangu[1,2], Bruce Bassett*

Karoo Array Telescope: Historical Probability RFI (KATHPRFI)

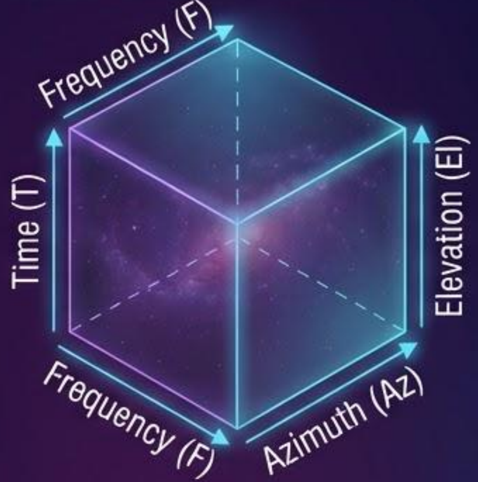
Software & Data Stack, Dimensions, and Publication

Software & Data Stack

- Python
- Numpy
- Numba
- Dask
- Zarr/ Xarray
- T, F, B, Az, El

24 x 4096 x 2016 x 8 x 24

Data Dimensions (T, F, B, Az, El)



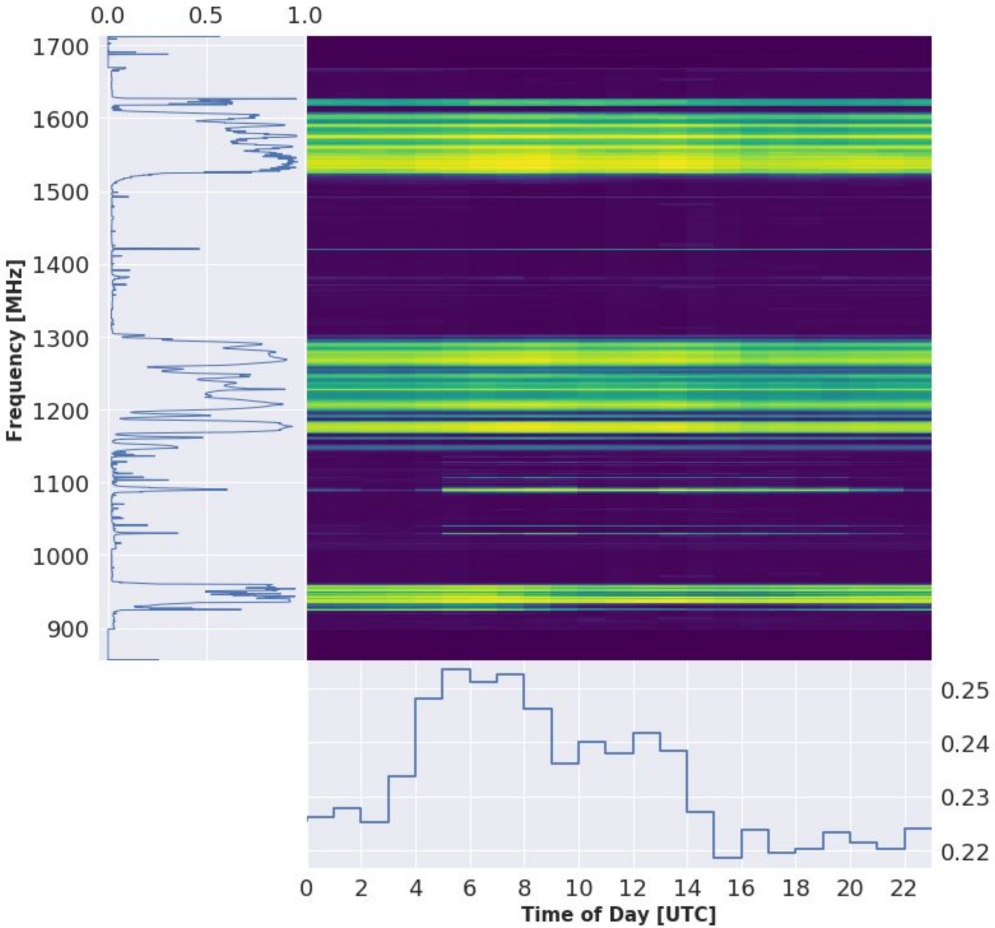
Publication Details

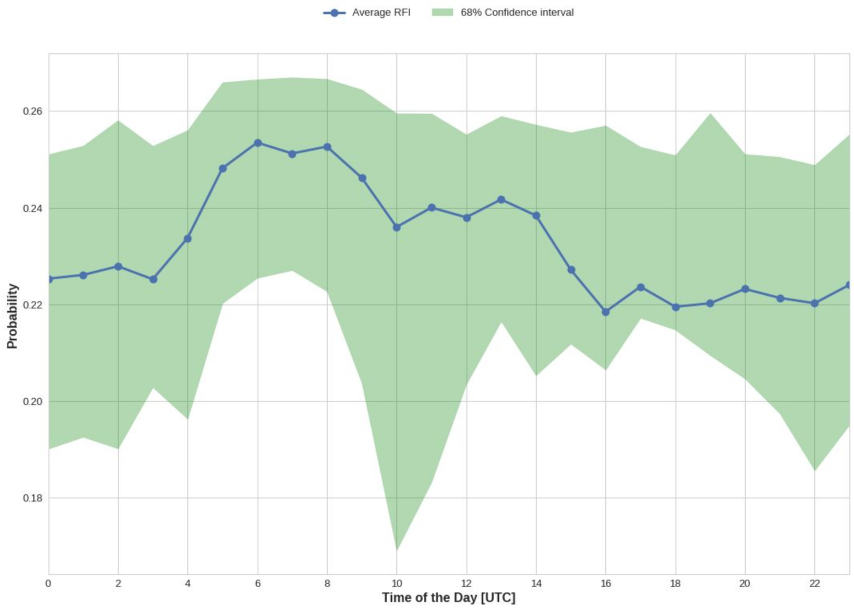
J. of Astronomical Telescopes, Instruments, and Systems, 8(1), 011003 (2021).

https://doi.org/10.1117/1.JATIS.8.1.011003

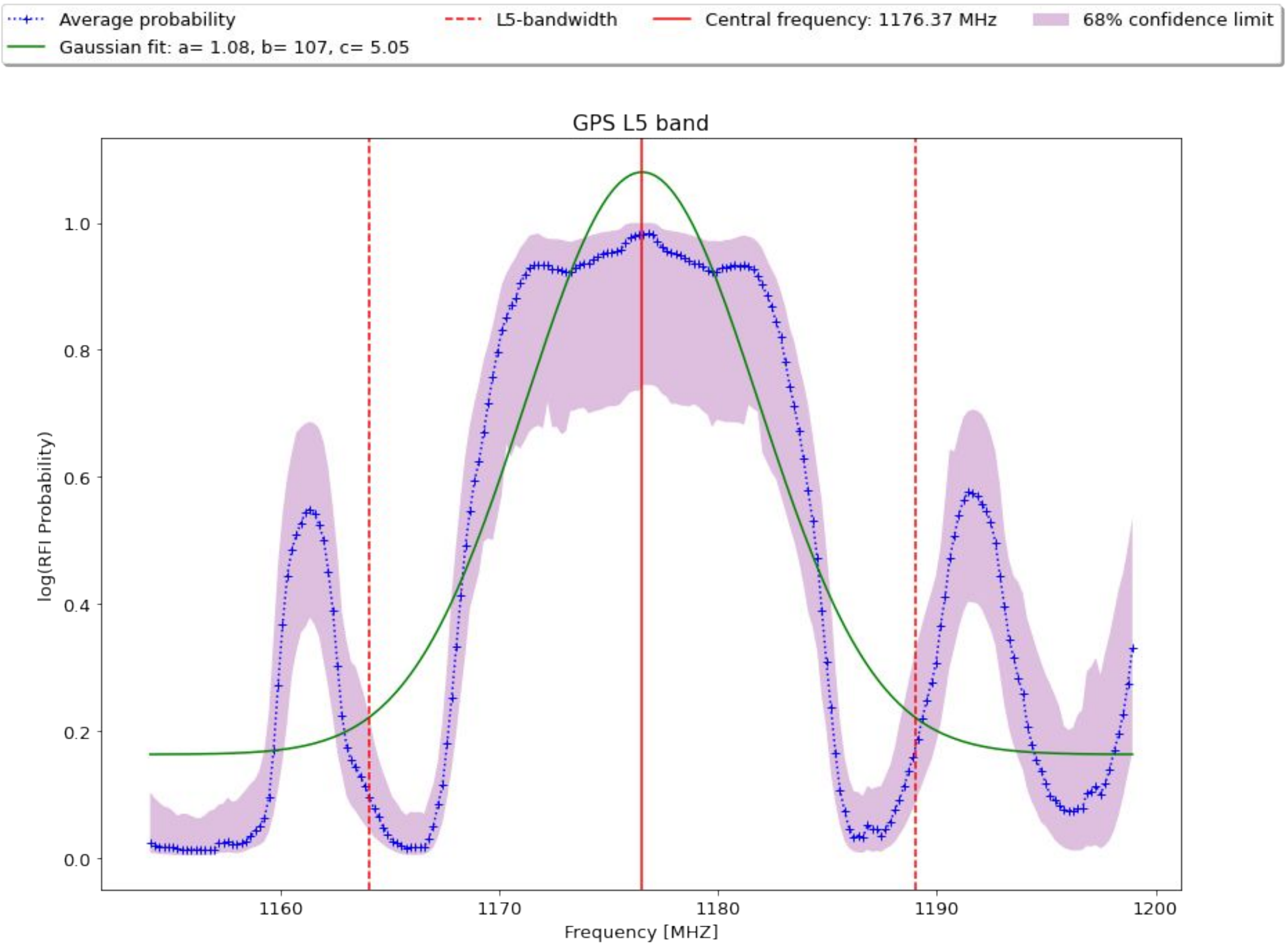
Isaac Sihlangu et al.

L - Band Results

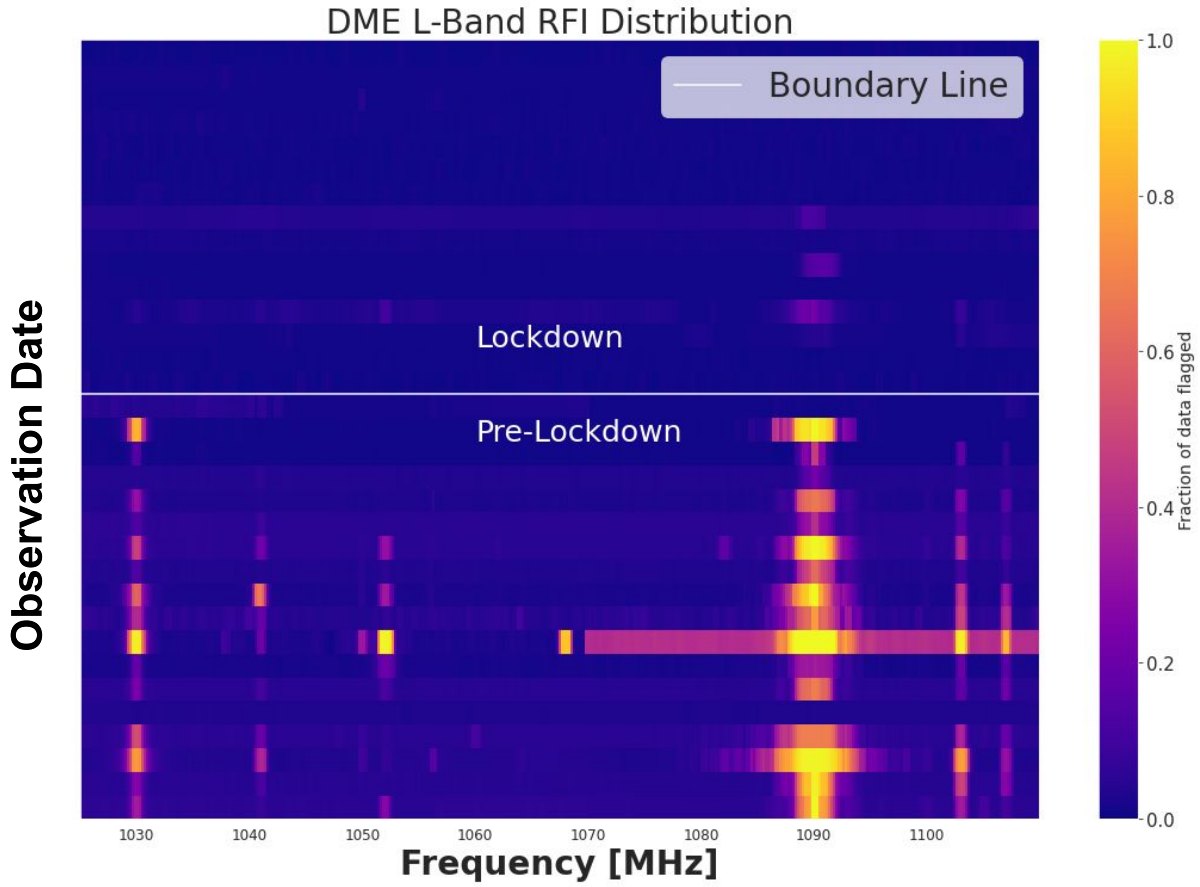




- Not much difference between Night and day time
- Known RFI bands (DME, GPS and GNSS) populate the frequency band
- Confidence level on the probability


Average probability
Gaussian fit: a= 1.08, b= 107, c= 5.05
L5-bandwidth
Central frequency: 1176.37 MHz
68% confidence limit
GPS L5 band
log(RFI Probability)
Frequency [MHZ]
0.0
0.2
0.4
0.6
0.8
1.0
1160
1170
1180
1190
1200

Automatic Dependent Surveillance–Broadcast (ADS-B)



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Transient Detection

Finding rare and sudden events, such as flaring stars or scintillating galaxies, that appear only briefly in observations.

Using LLMs to Interpret Astronomical Images & Explain Classifications

Based on Stoppa et al., Nature Astronomy (2025)

1. PROBLEM

Modern sky surveys detect millions of transient events (supernovae, variable stars, artefacts). Human inspection is impossible.

2. IDEA

Use Large Language Models (LLMs) to interpret astronomical images and explain classifications in text, like an astronomer.

3. METHOD

- Provide LLMs with transient images (e.g., difference images).
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4. KEY RESULT

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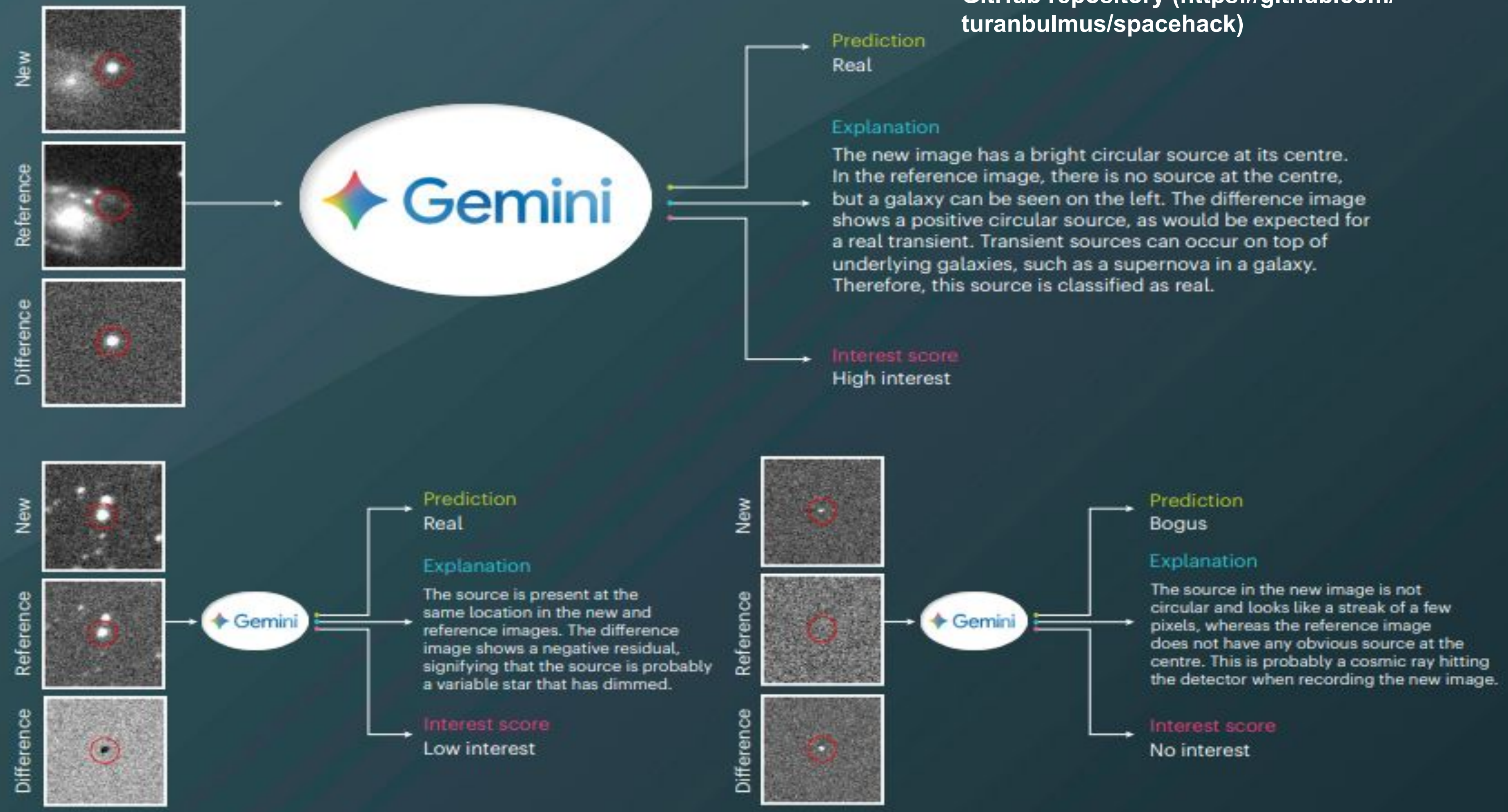
5. WHY IT MATTERS

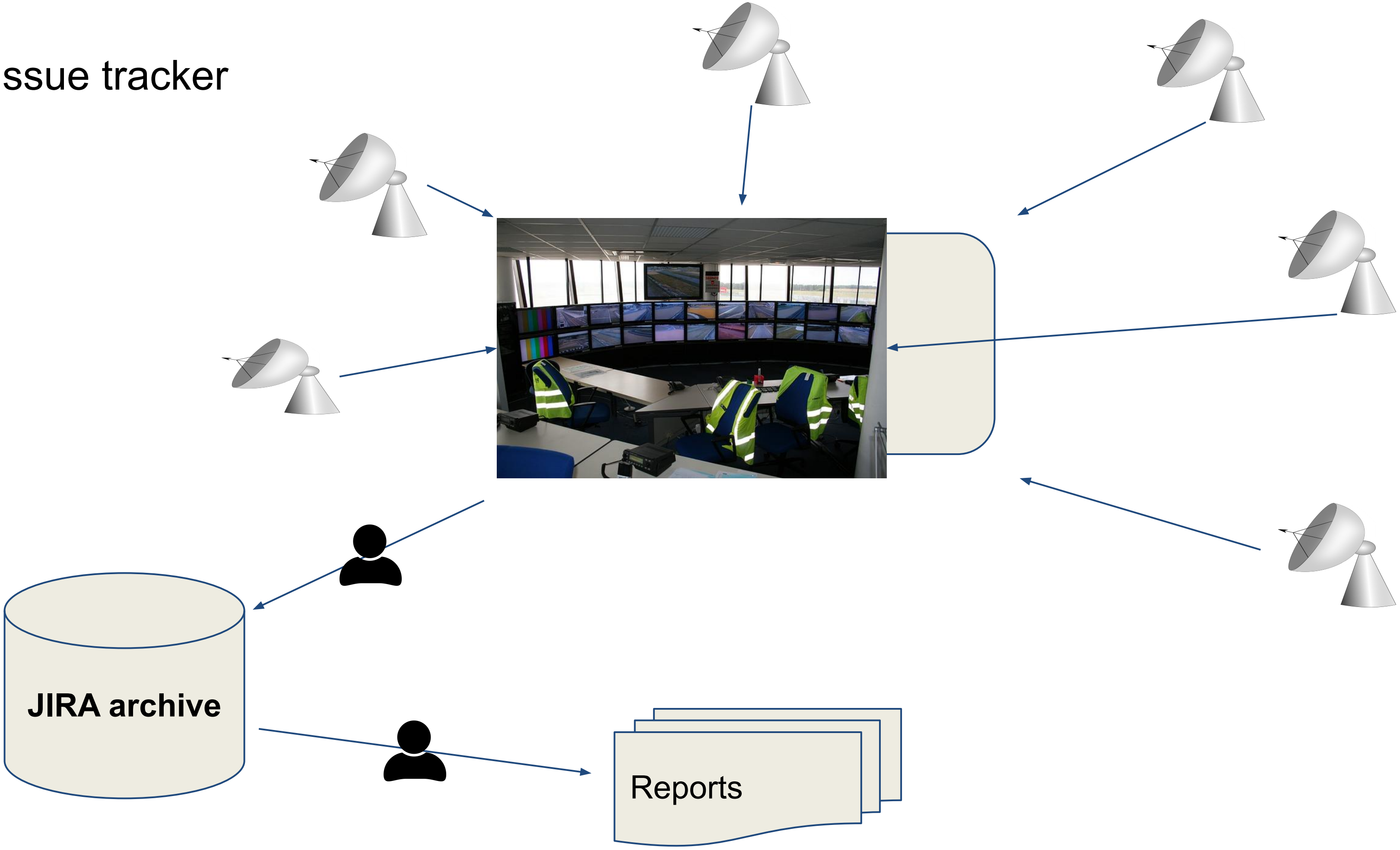
Future surveys (LSST, SKA) will have millions of alerts/night. Explainable AI helps:

- Filter alerts
- Debug pipelines
- Understand ML decisions.

GitHub repository (https://github.com/turanbulmus/spacehack)



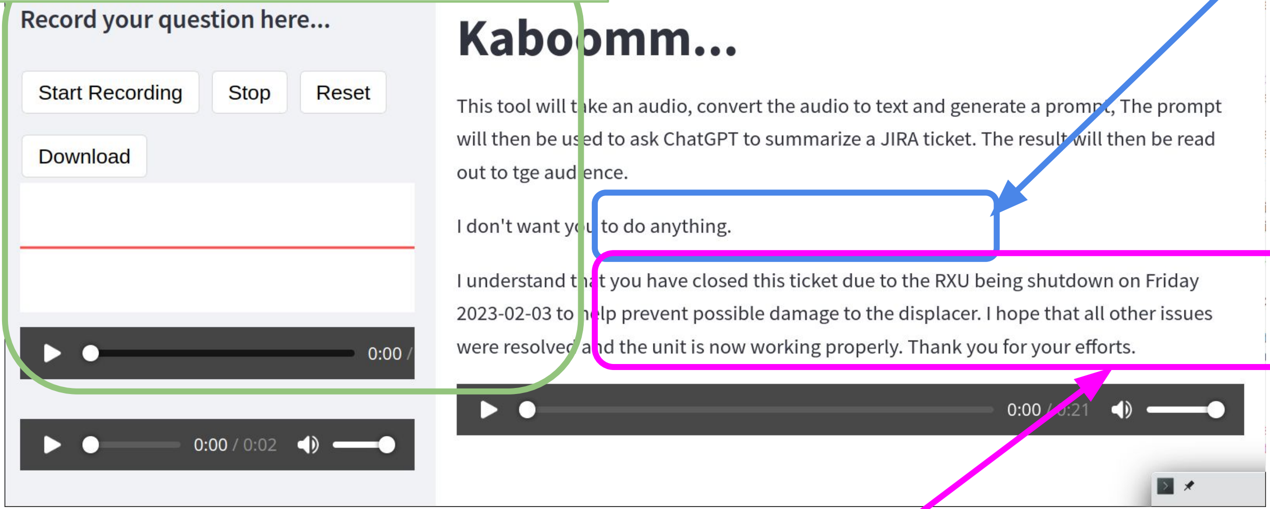
Issue tracker



What? - Under the hood

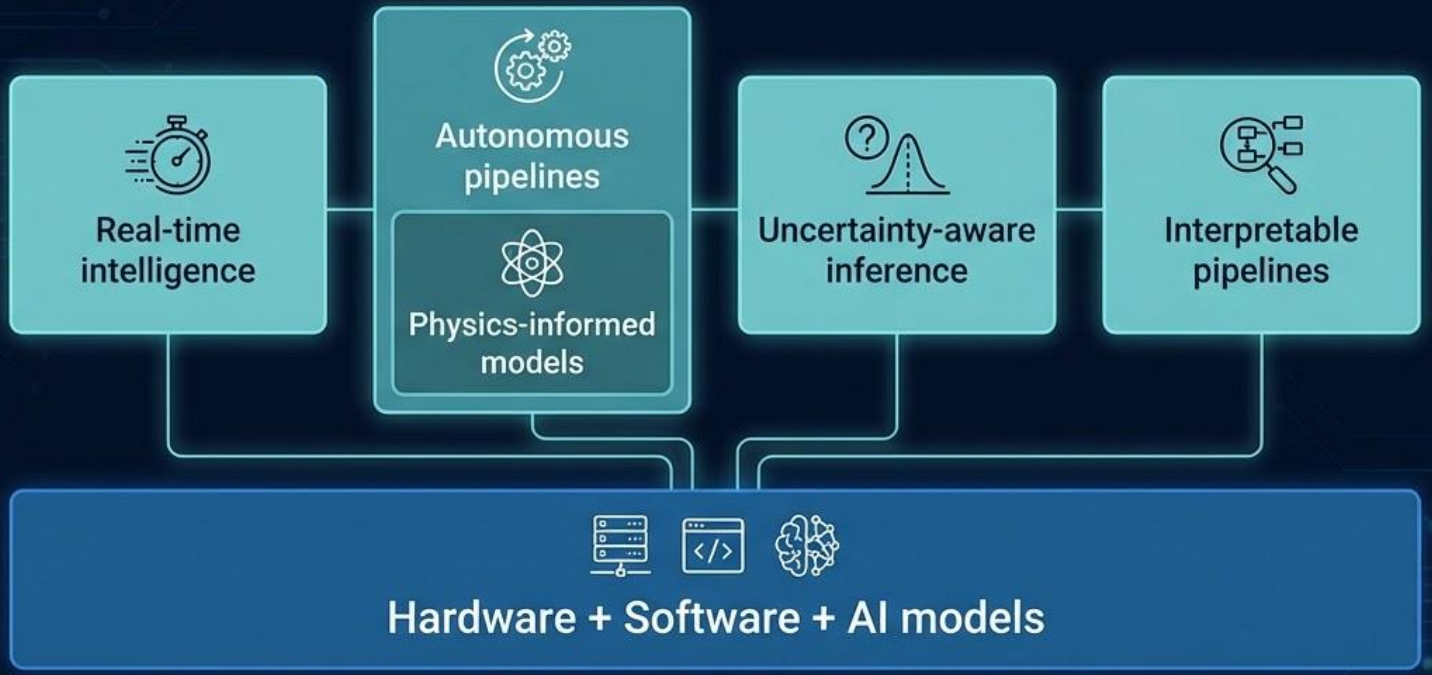
Audio-to-text - Whisper (**OpenAI**)

Text-to-prompt (**ChatGPT**)

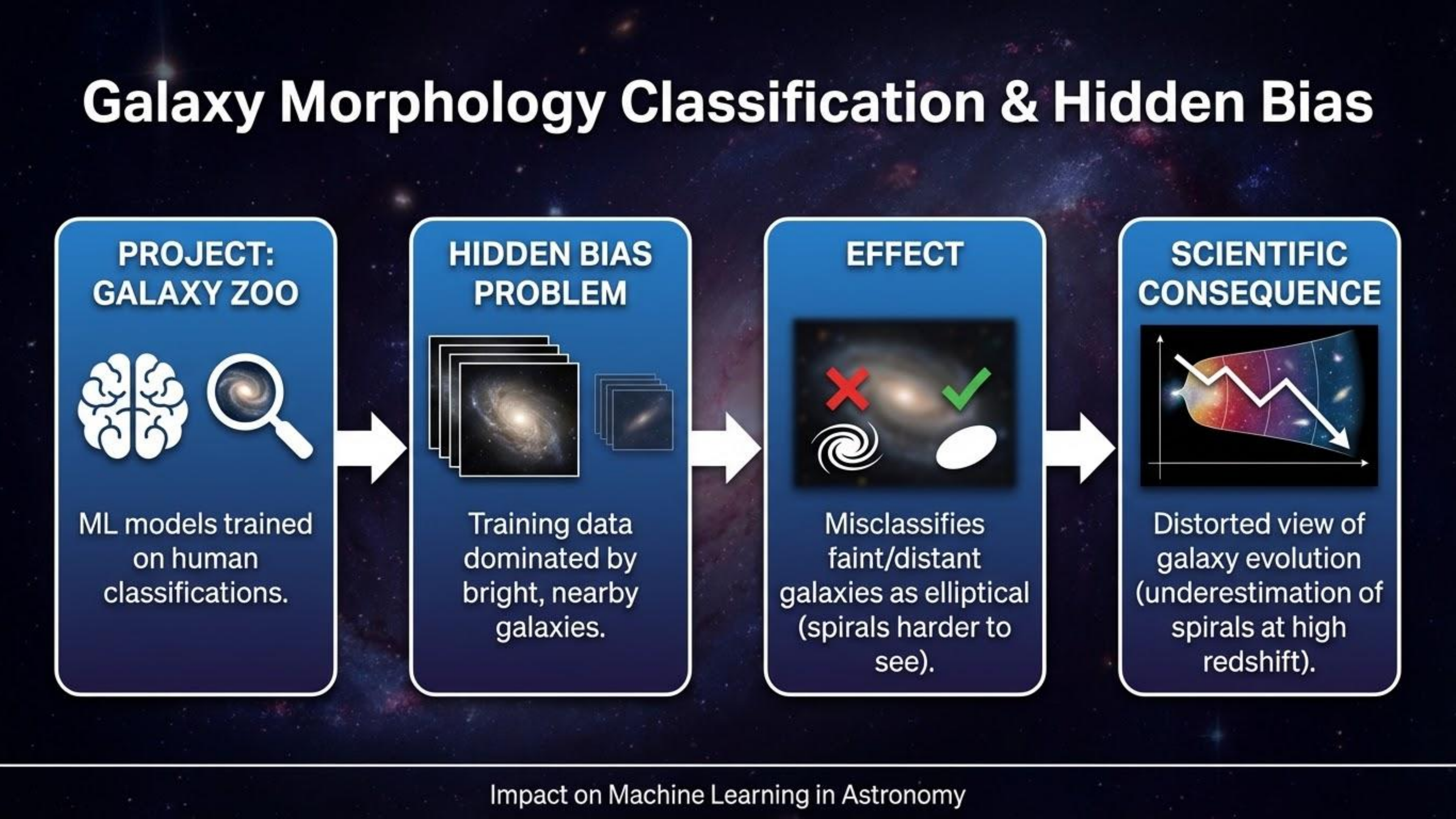


ChatGPT ⟵ JIRA issues (**JIRA api**) ⟶ Summarisation (text)

Observatory Stack



Risks of AI in scientific research

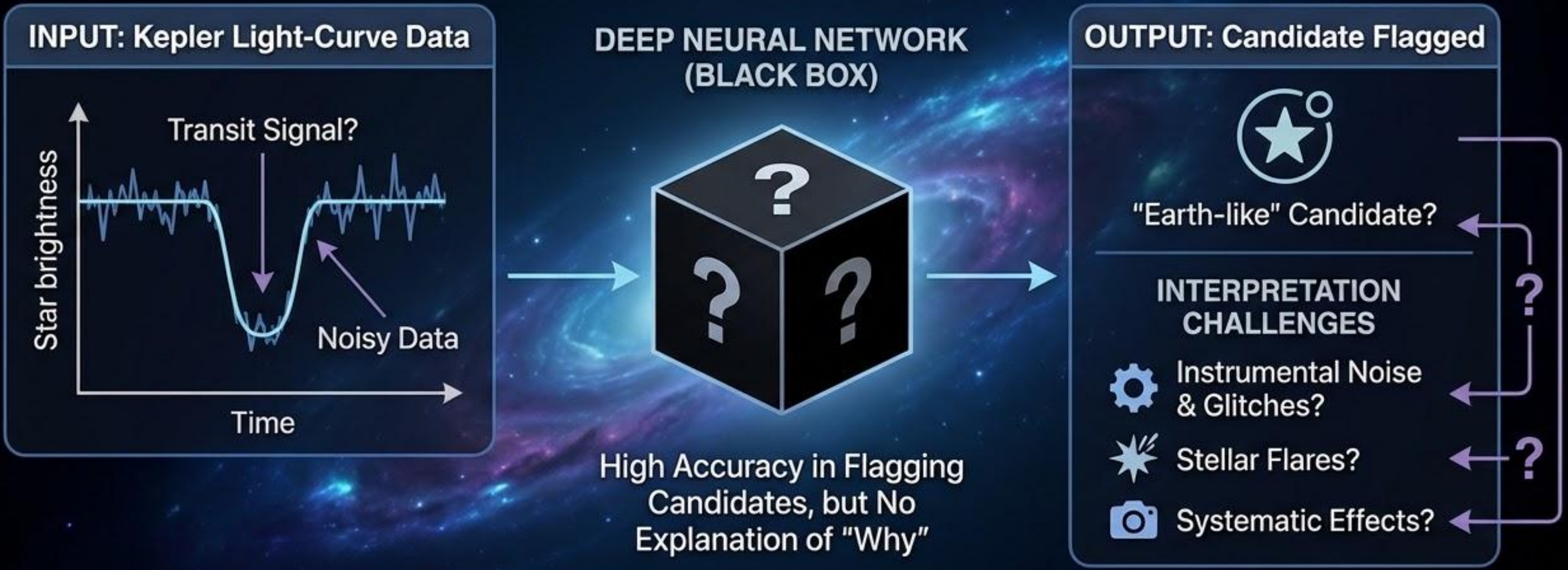


Galaxy Morphology Classification & Hidden Bias
PROJECT: GALAXY ZOO
ML models trained on human classifications.
HIDDEN BIAS PROBLEM
Training data dominated by bright, nearby galaxies.
EFFECT
Misclassifies faint/distant galaxies as elliptical (spirals harder to see).
SCIENTIFIC CONSEQUENCE
Distorted view of galaxy evolution (underestimation of spirals at high redshift).
Impact on Machine Learning in Astronomy

Reproducibility Concerns/Crisis in ML

- Reproducibility issues come from software variations and random seeds.
- Incomplete reporting compounds these problems in ML-based astronomy.
- Solutions include environment virtualization and strict provenance tracking.

The “Black Box” Problem: Exoplanet Detection with DNNs



Consequence: Lack of interpretability risks unverified “false positives”, hindering scientific confirmation of physical characteristics.

Conclusion

- **Data is exploding**
  - Next-generation telescopes produce TB–PB scale data, beyond human inspection.
- **ML is now part of the instrument**
  - Algorithms increasingly sit alongside antennas and correlators in the discovery chain.
- **Intelligent pipelines enable new science**
  - ML enables scalable detection of sources, transients, anomalies, and RFI mitigation.
- **Trust and interpretability are essential**
  - We must address bias, black-box decisions, and reproducibility to maintain scientific integrity.

"The next discoveries will not only depend on better telescopes, but on better intelligence interpreting the Universe."

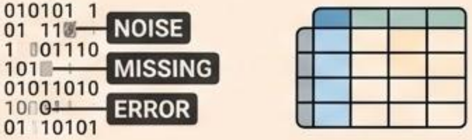
Extra Slides

Critical Challenges & Future Trends

Interpretability

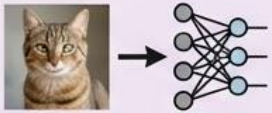
Highly complex models often lack transparency, making it difficult to fully understand the scientific conclusions they produce.

Data Quality

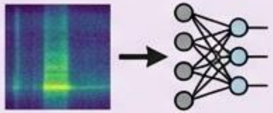


'Dirty data'—including noise, missing values, and incorrect labels—remains a major bottleneck in model performance.

Domain Adaptation



Natural Images



Astro Data

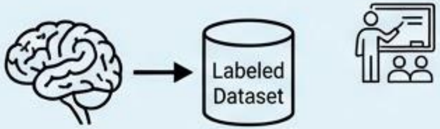
Models pre-trained on natural images often perform poorly on astronomical spectrograms; domain-specific pre-training is essential.

Future Directions

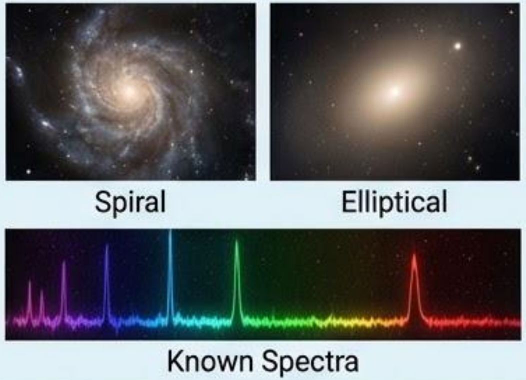
Focus on improving computational efficiency, developing more interpretable models, and integrating cross-band data for multi-dimensional analysis.

Machine Learning Paradigms in Radio Astronomy

Supervised Learning

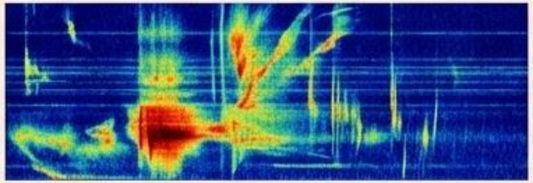


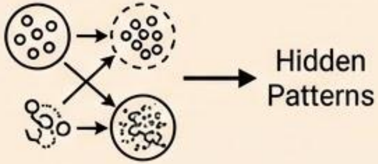
Used for fundamental tasks like classifying galaxies by their morphology (shape) or identifying known stellar spectra.



Unsupervised Learning

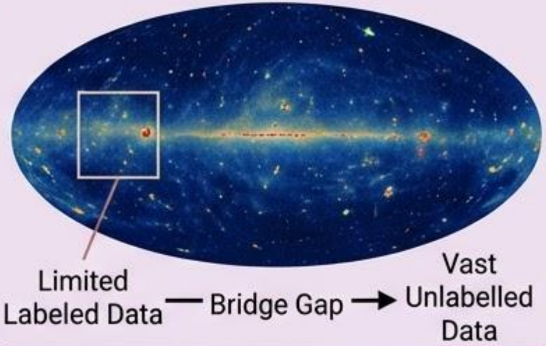
Essential for finding hidden patterns or variations in solar radio data and linking them to underlying physical theories.





Self-Supervised Learning (SSL)

A powerful tool for learning from the vast amounts of **unlabelled** data abundant in radio astronomy, **bridging the gap** between limited manually annotated datasets.

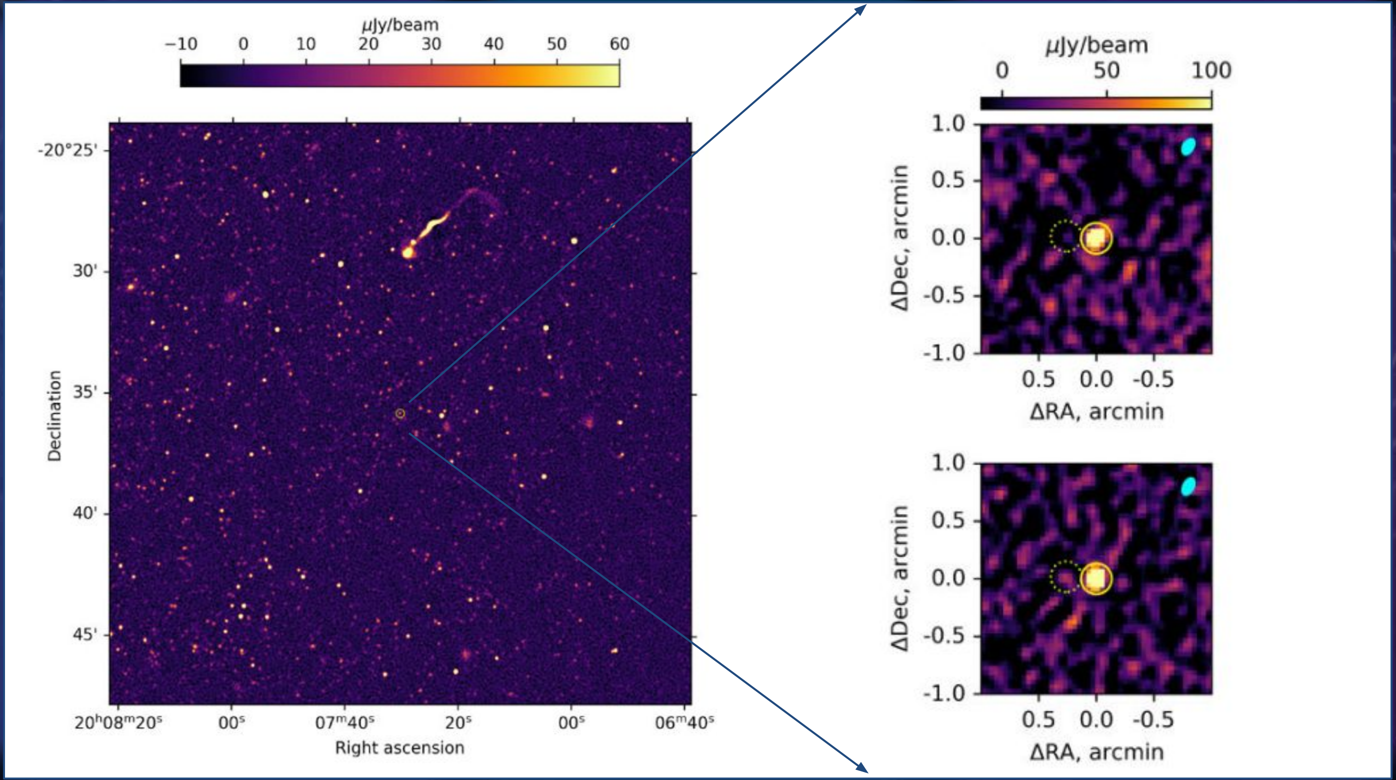


Mining the time axis with TRON – II. MeerKAT detects a stellar radio flare from a distant RS CVn candidate

MNRAS **538**, L89–L93 (2025) - O. M. Smirnov *et al.*

1. What the paper tries to do

- Search MeerKAT data for radio transients (minutes–hours scale).
- Utilize the TRON pipeline to scan calibrated images and light curves for such events.



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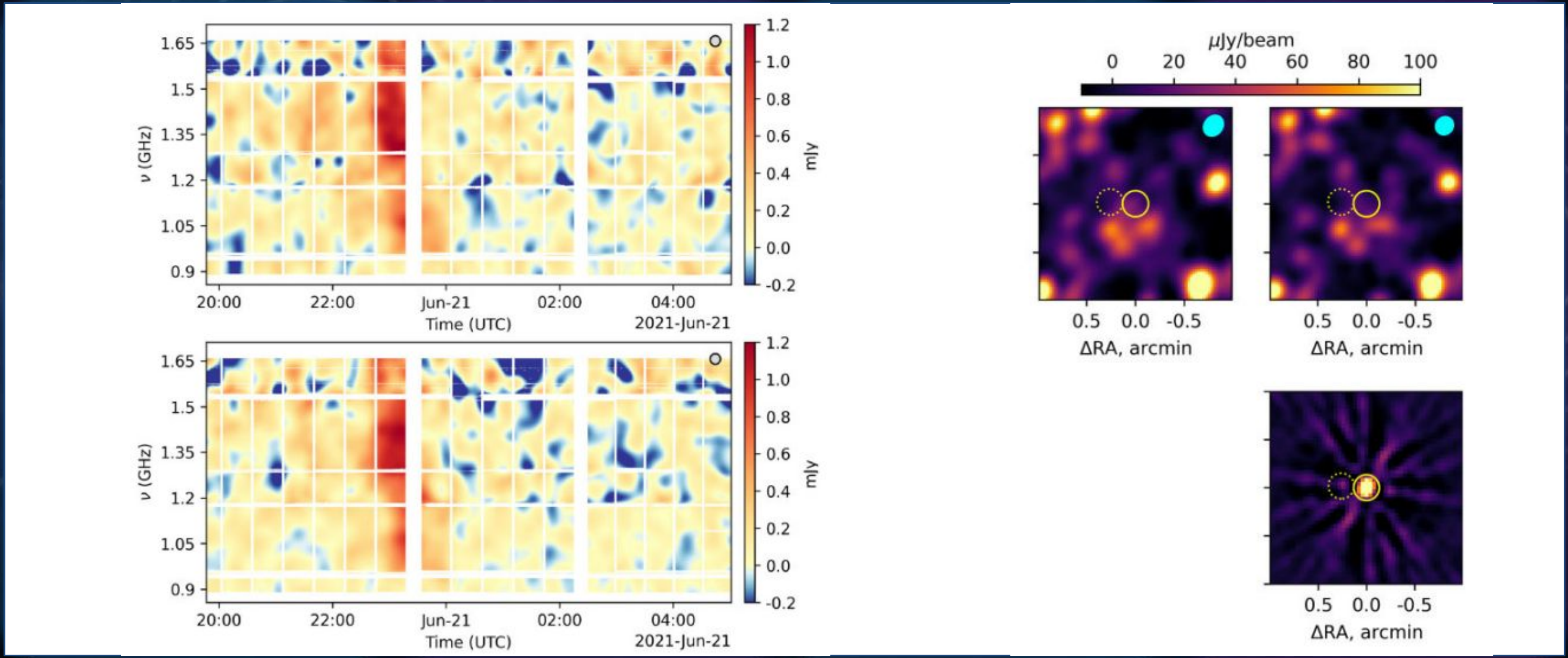

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