# Detection of Fast Radio Bursts using a hybrid neural architecture

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# General Context

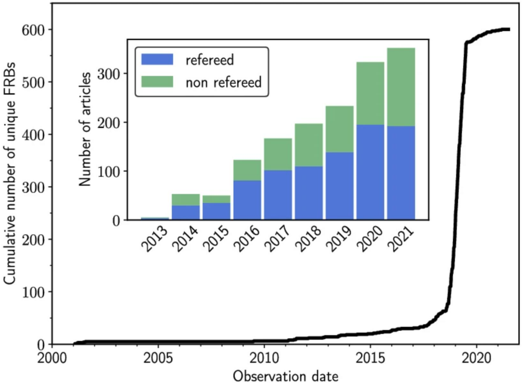



Figure: Cumulative number of published, unique FRB sources as a function of their arrival time at the Earth. Image courtesy of [1]

# Fast Radio Bursts in a Nutshell

- Bright ($< 10^{44}$ erg $s^-1$) and short ($\sim$ ms)
- High event rate ($\sim$ 5.000/sky/day)
- Extragalactic (predominately)
- One-off events and repeaters.

Useful as cosmological probe to study:

- The intergalactic medium.
- The missing baryons.

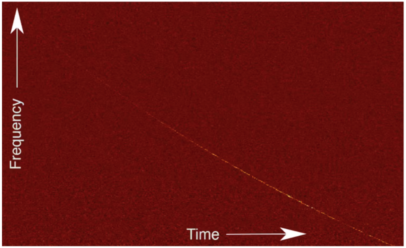
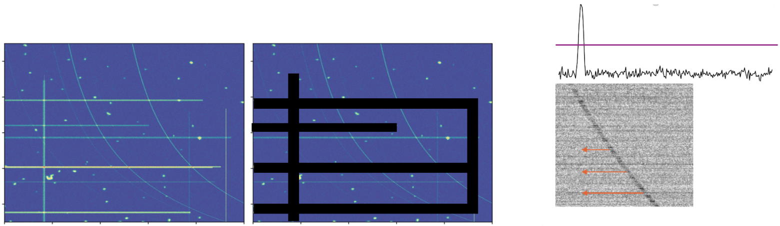



Figure: A typical FRB

# SoTA methods for FRB detection



*Raw spectrogram*     1) *RFI Masking*     2) *De − dispersion*

$$t_2 - t_1 \simeq \left\{\frac{1}{\nu_2^2} - \frac{1}{\nu_1^2}\right\} \times DM_{grid}$$

Traditional pipelines for transient detection

- (-) Computational complexity.
- **(-) An abundance of False positives.**

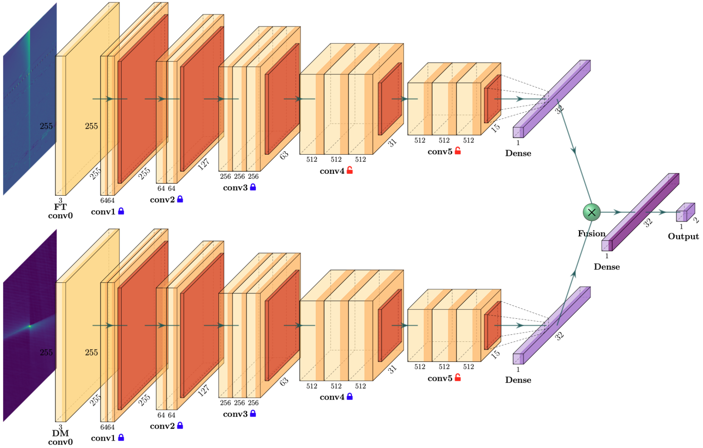
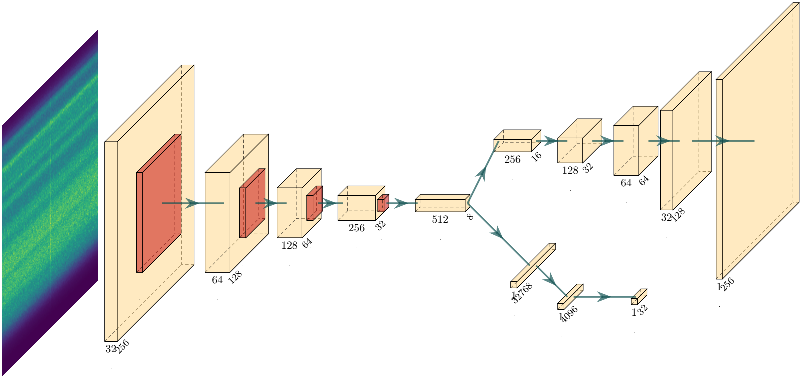


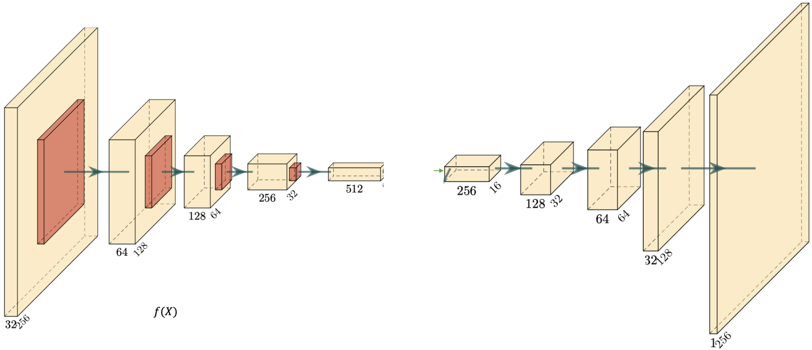

Figure: Fast Extragalactic Transient SearCH (FETCH)

- (-) Trained on **balanced** RFI/FRB datasets.

# Proposed Architecture



# Multi-head architecture

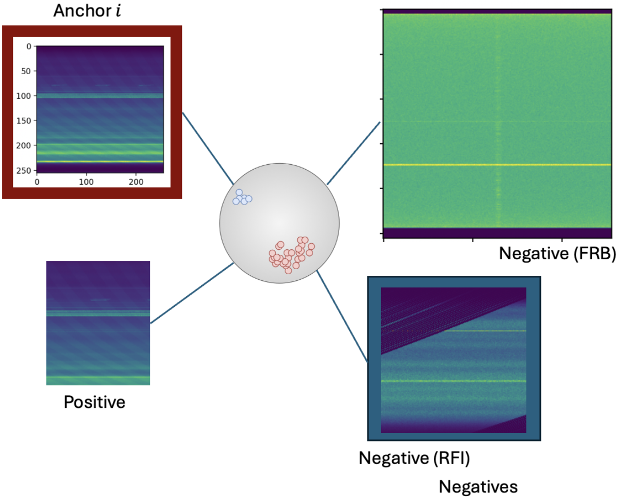



A common feature extractor: $f(\mathbf{X})$ ( a standard CNN encoder).

A reconstruction head (mirror architecture of $f$) **trained on the majority class only (RFI)**

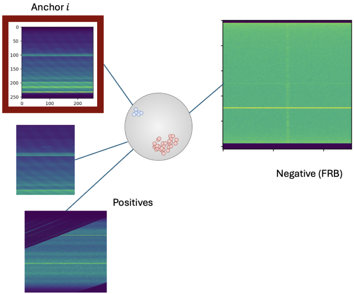
$$\mathcal{L}_{\text{rec}}(\mathbf{X}) = \|g^{(r)}(f(\mathbf{X})) - \mathbf{X}\|_F^2 \tag{1}$$

# Self-supervised contrastive learning




Self-supervised contrastive learning

# Supervised contrastive learning

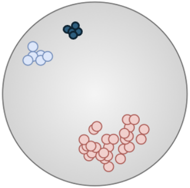



$$\mathcal{L}_{\text{con}}(\mathbf{X}) = \sum_{i \in \mathcal{B}} \frac{-1}{|\mathcal{A}_i|} \sum_{q \in \mathcal{A}_i} \log \frac{\exp(\mathbf{z}_i \cdot \mathbf{z}_q / \tau)}{\sum_{a \in \mathcal{B}_i} \exp(\mathbf{z}_i \cdot \mathbf{z}_a / \tau)},$$

$$\mathbf{z}_i = g^{(c)}(f(\mathbf{X}_i)). \qquad (2)$$

## Contrastive head

- The contrastive head is an Multi-Layer Perceptron (MLP) denoted $g^{(c)}$.

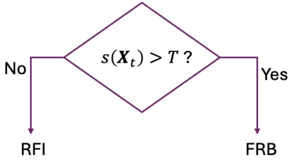


$$\mathcal{L}_{\text{con}}(\mathbf{X}) = \sum_{i \in \mathcal{B}_n} \frac{-1}{|\mathcal{Q}_i|} \sum_{q \in \mathcal{Q}_i} \log \frac{\exp(\mathbf{z}_i \cdot \mathbf{z}_q / \tau)}{\sum_{a \in \mathcal{B}_i} \exp(\mathbf{z}_i \cdot \mathbf{z}_a / \tau)}, \tag{3}$$

$$\mathbf{z}_i = g^{(c)}(f(\mathbf{X}_i). \tag{4}$$

# Anomaly scoring

For an image test $\mathbf{X}_t$, the anomaly score:



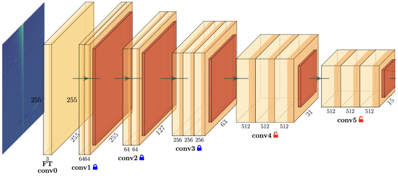

$$s(\mathbf{X}_t) = \frac{1}{\lambda}\mathcal{L}_{\text{rec}}(\mathbf{X}_t) + s_{\text{con}}(\mathbf{X}_t) \tag{5}$$

$$s_{\text{con}}(\mathbf{X}_t) = 1 - \frac{1}{|P|}\sum_{i \in P} \mathbf{z}_t \cdot \mathbf{z}_i, \tag{6}$$

# Dataset and training

| Instrument (back-end) | Source | T+V DMT | T+V FT | Test |
|---|---|---|---|---|
| FLAG (FLAG) | RFI | 32,720 | 6,000 | 2,790 |
| | Sim FRB | 20,000 | 8,500 | - |
| | Pulsar | - | - | 2,288 |
| GBT L-Band (GREENBURST) | RFI | - | 6,000 | 2,170 |
| | Sim FRB | 20,000 | 8,500 | - |
| | Pulsar | - | - | 1,376 |
| Green Bank 20m (Skynet) (GBTrans) | RFI | 9,854 | 8,000 | 2,359 |
| | Pulsar | - | 3,000 | 3,000 |
| Total | FRB | 40,000 | 20,000 | 6,664 |
| | RFI | 42,574 | 20,000 | 7,319 |

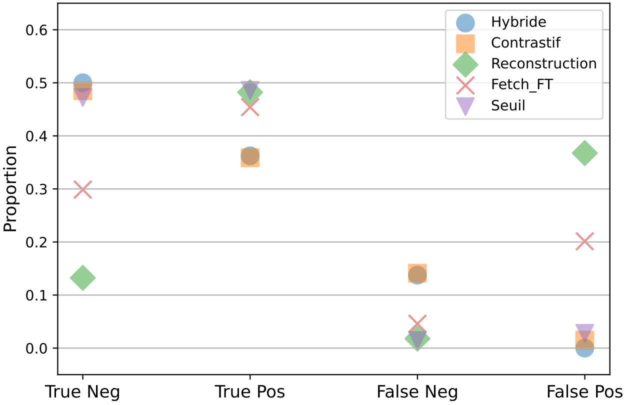
Dataset




Fetch-FT

# Results

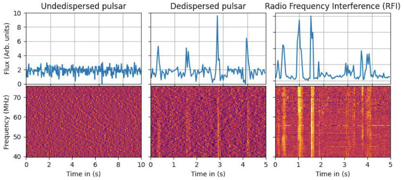
Training dataset: 80% **RFI,** 20% **(dominated by simulated FRBs). Test set is balanced.**



# Results

| Architecture | Acc (%) | ROC-AUC (%) |
|---|---|---|
| Hybride | 86.2 | 85.5 |
| Contrastive head | 84.4 | 86.8 |
| Reconstruction head | 61.5 | 52.9 |
| FETCH - FT | 75.3 | 80.9 |
| Energy thresholding | 95.8 | 97.7 |

# Conclusion and perspectives




Real Nenufar Pulsar data