



a place of mind

Periodicity Searches with Arrays (a segue to machine learning)

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Aspen, Colorado

with direction from: [Ingrid Stairs](#)
lots of help from: [Weiwei Zhu](#) (UBC Postdoc)
Erik Madsen (UBC Master's student)

Outline:

- **Survey modes with arrays**
 - New possibility: bispectrum

- **Automated searches for pulsars**
 - Image-based AI search for pulsars using deep-learning algorithms
(big props: Weiwei Zhu, Ingrid Stairs)
(smaller props: Erik Madsen)

An array of observing modes

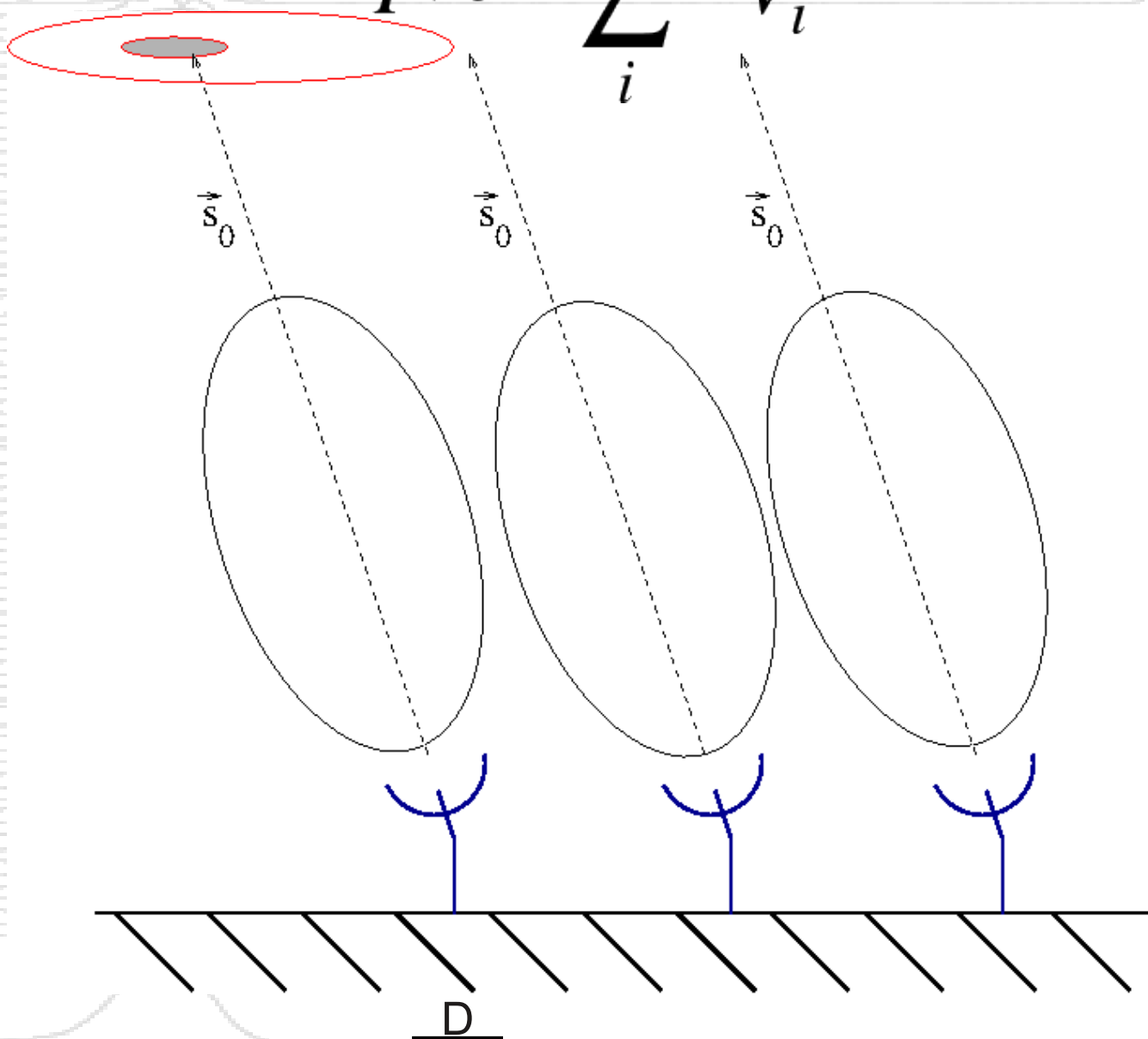
- Incoherent Sum**

Each element provides an independent observation

Intensity \sim voltage²

$$(I_V \propto V_V^2)$$

$$I \sim \sum_i^{N_{\text{antenna}}} V_i^2$$



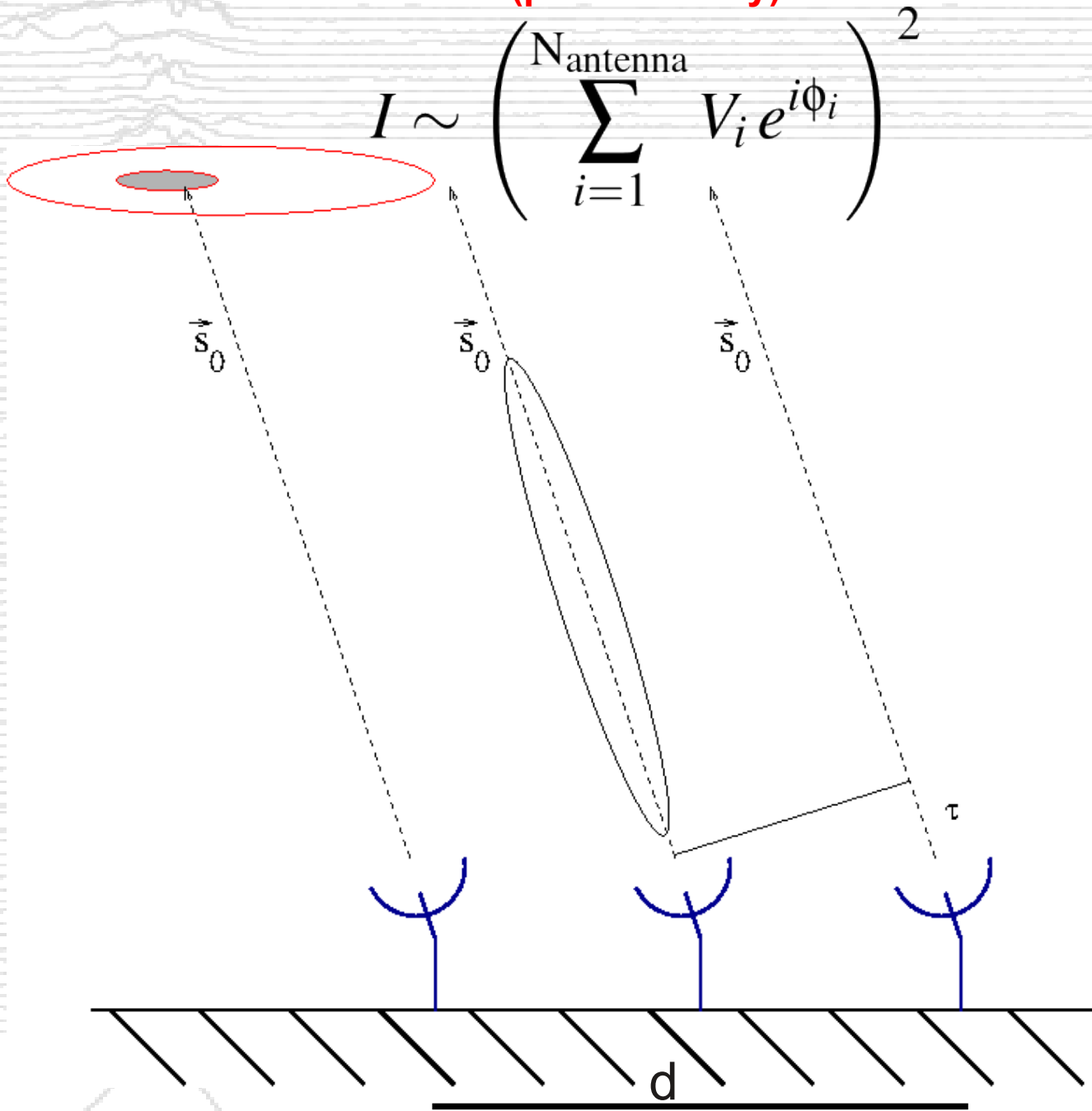
- Resolution** determined by **dish size** D . typically $O(1\text{deg})$

$$\theta_D = 1.22 \frac{\lambda}{D}$$

- FoV** $\sim \theta_D$
- Sensitivity** $\sim \sqrt{N_a}$
- Easy to implement

An array of observing modes

- **Coherent Sum (phased array)** Similar to double slit experiment



- **Resolution** determined by **array size** d . typically $O(1'')$

$$\theta_d \simeq \frac{\lambda}{d}$$

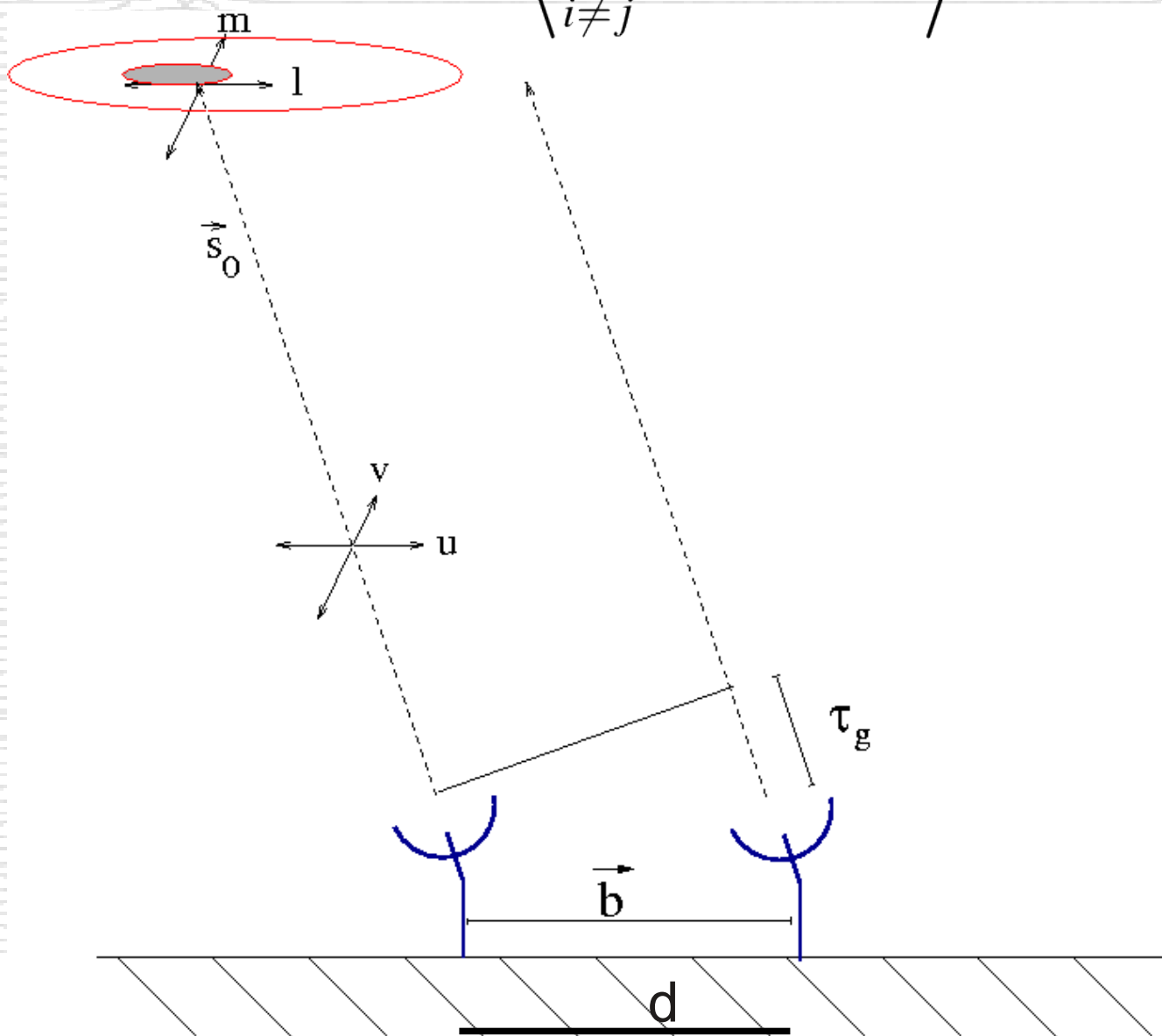
- **FoV** $\sim N_{\text{beams}} \theta_d$
- **Sensitivity** $\sim N_a$
- Survey possible if correlator can form many array beams

- **demanding on correlator and storage-intensive**

An array of observing modes

- **Cross-Correlate** Gives the spatial coherence function

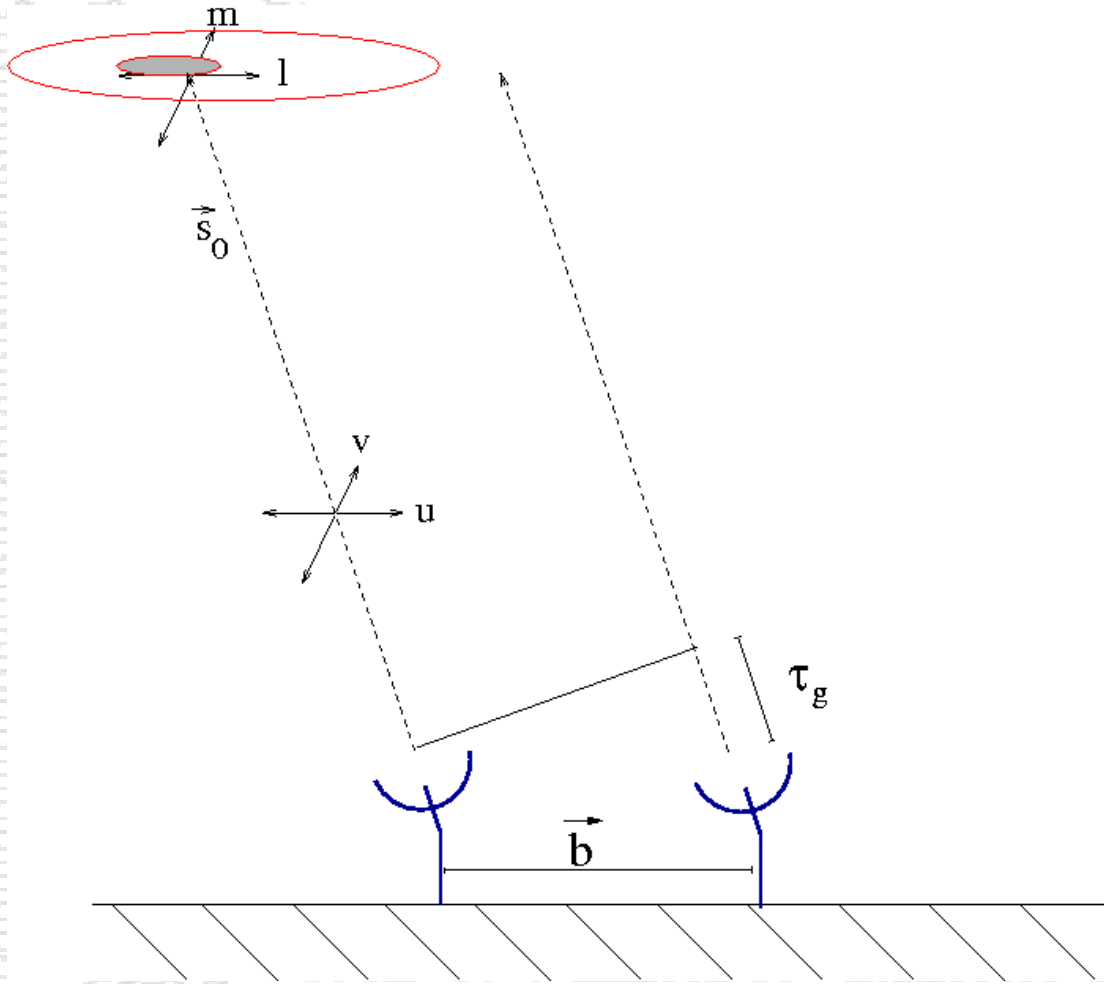
$$\left\langle \sum_{i \neq j} V_i V_j^*(u, v)_{ij} \right\rangle$$



- Resolution determined by **array size** d
- FoV determined by **dish size** D
- Sensitivity $\sim N_a$
- Easier on correlator but **data intensive**
- Pushes complexity to post-processing

An array of observing modes

- **Cross-Correlate**



$$\begin{aligned} N_{\text{pixels}} &\sim \left(\frac{\Theta_{\text{dish}}}{\Theta_{\text{array}}} \right)^2 \\ &\sim \left(\frac{d_{\text{array}}}{D_{\text{dish}}} \right)^2 \\ &\sim \left(\frac{10^4 \text{ m}}{10^1 \text{ m}} \right)^2 \end{aligned}$$

Ultimately we want to form timeseries.
The images give $O(10^{5-6})$ cells (beams) on the sky

Typical survey gets \sim **50 candidates/beam**

Bi-curious?

Periodicity search the bispectrum

$$b_{ijk} = \underbrace{V_{ij} \cdot V_{jk} \cdot V_{ki}}_{\text{measured}} = \underbrace{\tilde{V}_{ij} \cdot \tilde{V}_{jk} \cdot \tilde{V}_{ki}}_{\text{true}}$$

Benefits:

- Removes antenna-based errors

$$\underbrace{V_{ij}}_{\text{measured}} = \underbrace{\tilde{V}_{ij}}_{\text{true}} \underbrace{e^{i(\phi_i + \phi_j)}}_{\text{error}}$$

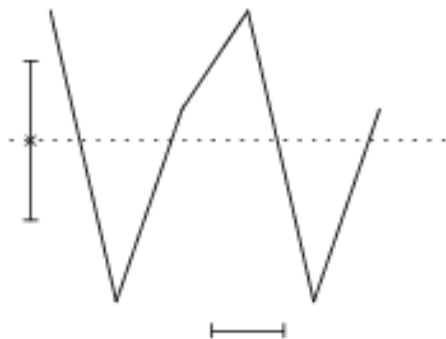
- $S/N \propto N_a$ Across the primary beam
- It's a single timeseries

A test set: JVLA commissioning data

- The observations:
 - 7 antenna
 - 64 2 MHz channels (L-band)
 - 12 millisecond samples
 - Tracking the Crab Pulsar
33 ms period

A test set: JVLA commissioning data

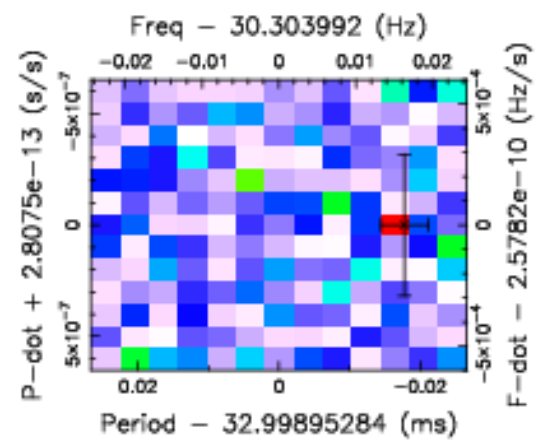
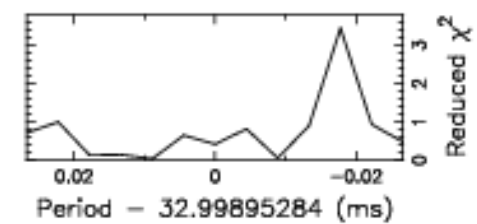
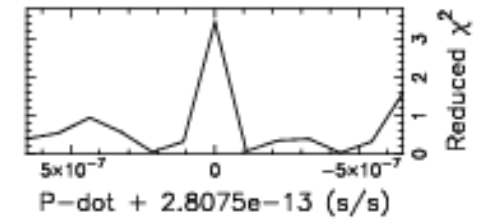
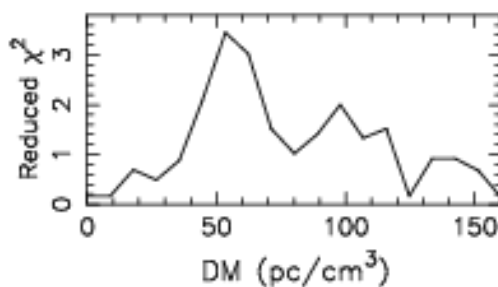
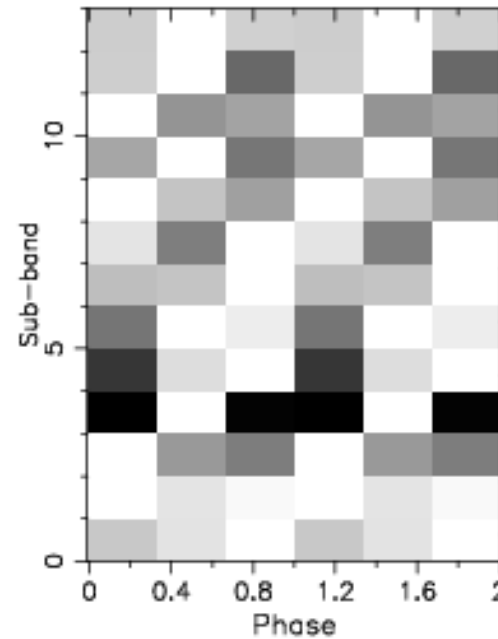
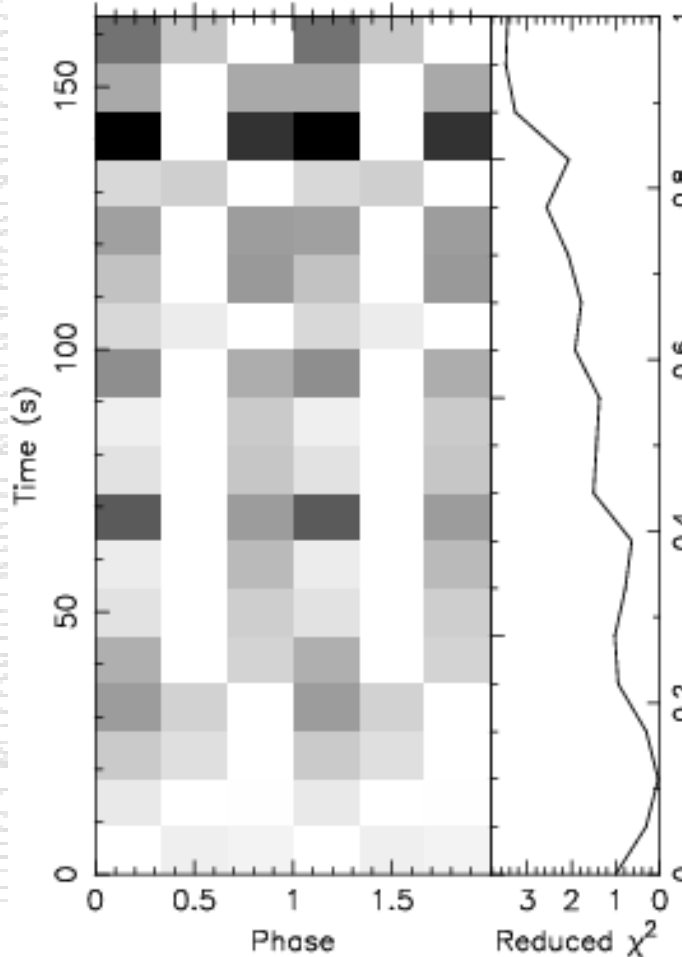
2 Pulses of Best Profile



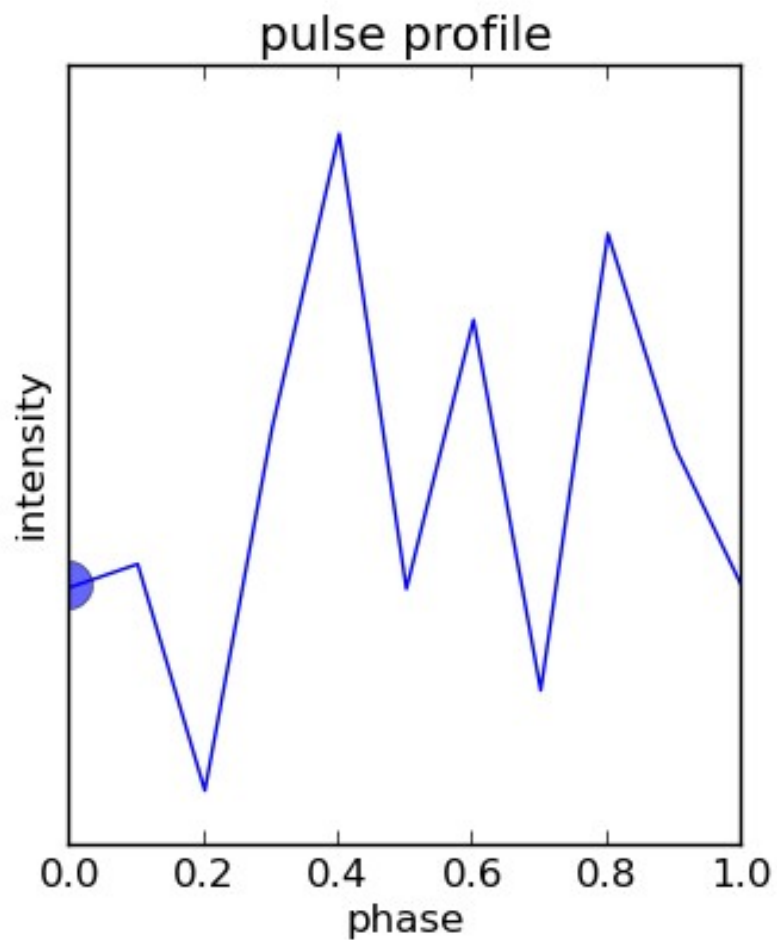
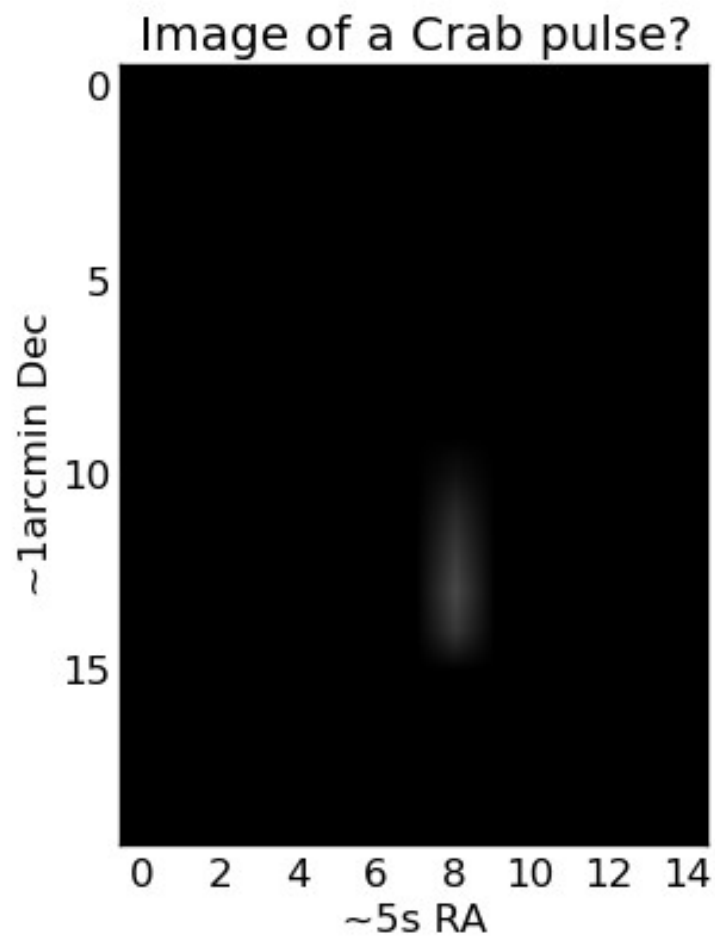
Candidate: 33.00ms_Cand
 Telescope: VLA
 Epoch_{topo} = 55747.79041666666
 Epoch_{bary} = 55747.78563300457
 T_{sample} = 0.012
 Data Folded = 13608
 Data Avg = 1126
 Data StdDev = 114
 Profile Bins = 3
 Profile Avg = 5.109e+06
 Profile StdDev = 7681

Search Information

RA_{J2000} = 05:34:31.9500 DEC_{J2000} = 22:00:52.1000
 Best Fit Parameters
 Reduced χ^2 = 3.448 P(Noise) < 0.0318 ($\approx 1.9\sigma$)
 Dispersion Measure (DM; pc/cm³) = 53.427
 P_{topo} (ms) = 32.9812(33) P_{bary} (ms) = 32.9822(33)
 P_{dot} (s/s) = 0.0(3.2)x10⁻⁷ P_{dot} (s/s) = 0.0(3.2)x10⁻⁷
 P_{ddot} (s/s²) = 0.0(1.3)x10⁻⁸ P_{ddot} (s/s²) = 0.0(1.3)x10⁻⁸
 Binary Parameters
 P_{orb} (s) = N/A e = N/A
 a₁sin(i)/c (s) = N/A ω (rad) = N/A
 T_{peri} = N/A



A test set: JVLA commissioning data



- The observations:

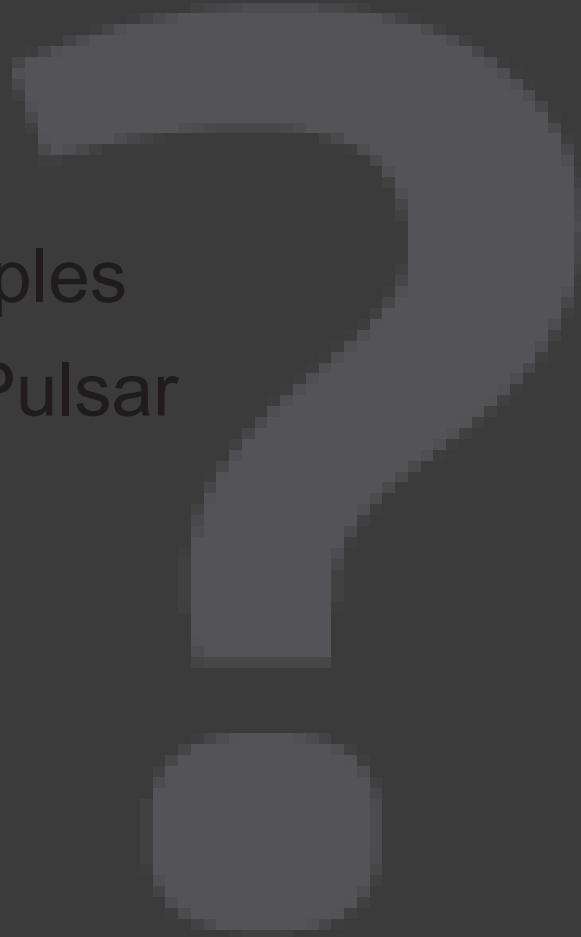
- 7 antenna

- 64 2MHz channels

- 12 millisecond samples

- Tracking the Crab Pulsar

33 ms period



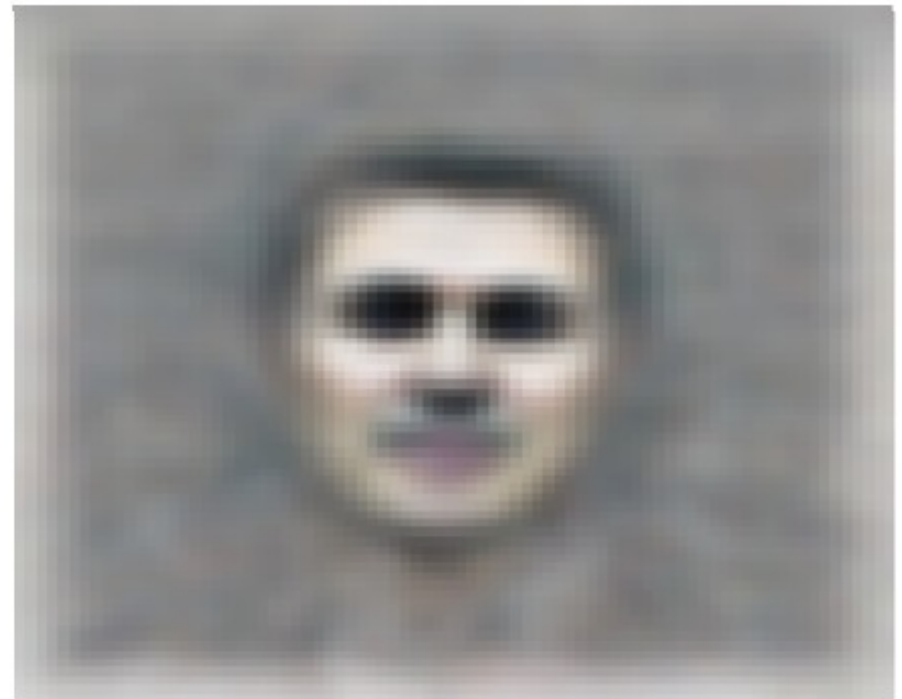
Big data is motivating the use of
automated data analysis.

**Image based Machine Learning
(Pattern Recognition)**

Using deep learning: The essence of youtube

- *Building high-level features using large scale unsupervised learning*
arxiv.org/abs/1112.6209v5.pdf
(Ng et al.)

Feed 10 million 200x200 pixel images into a Neural Network

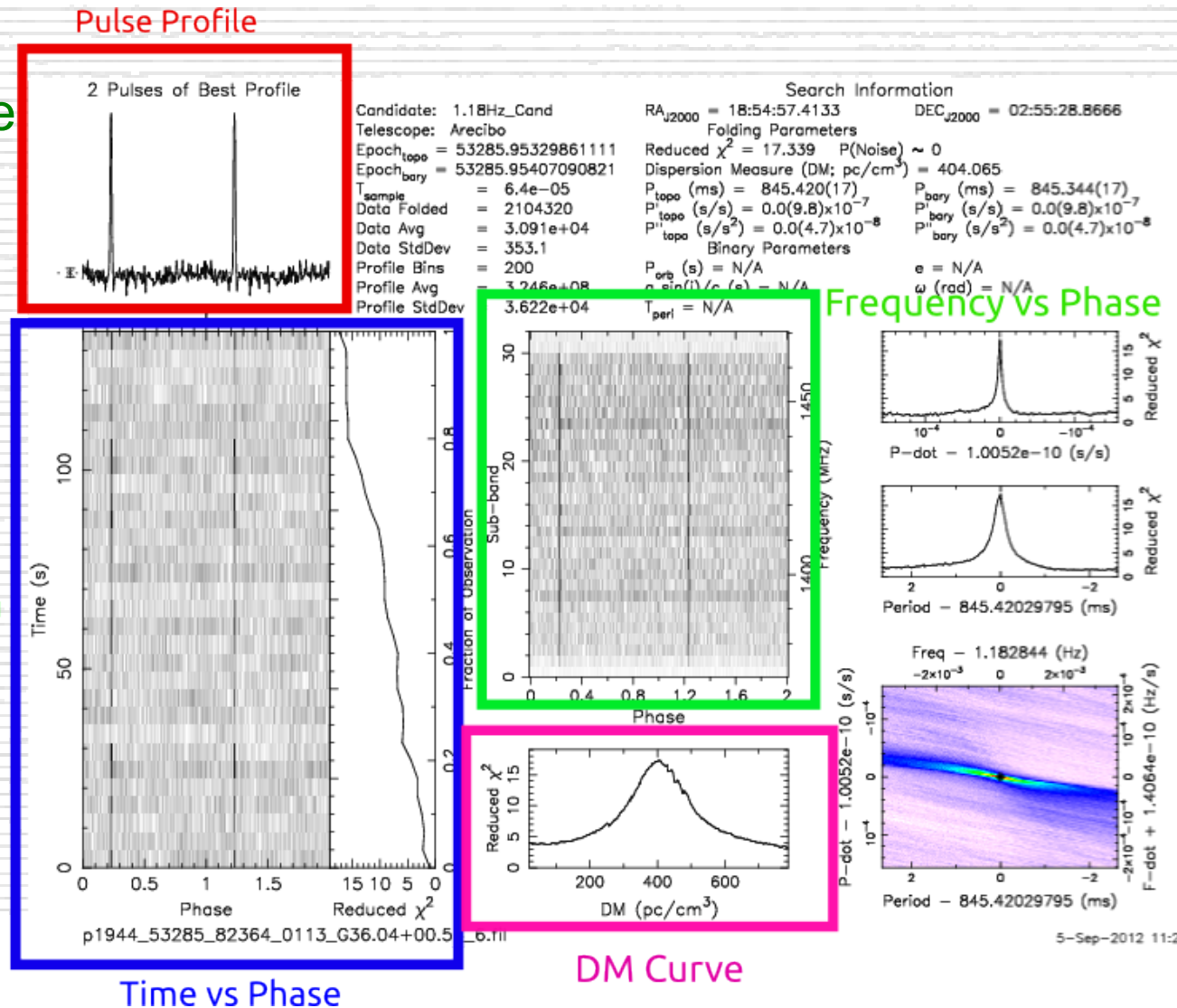
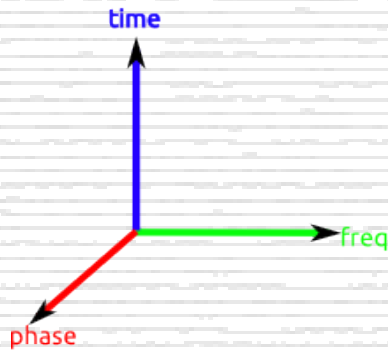


Automated Pulsar Classifier

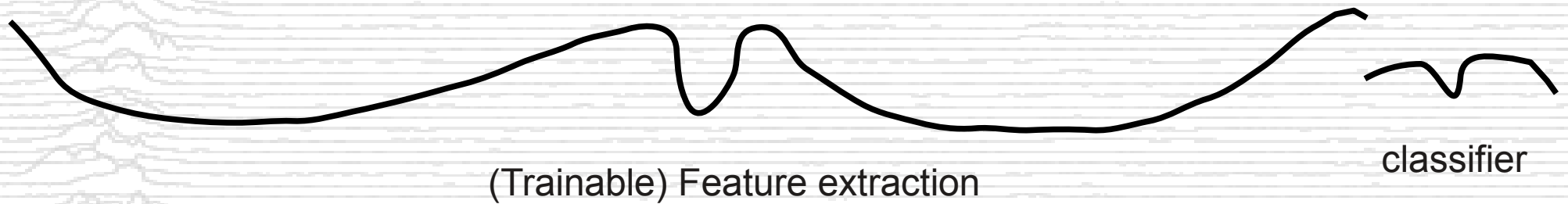
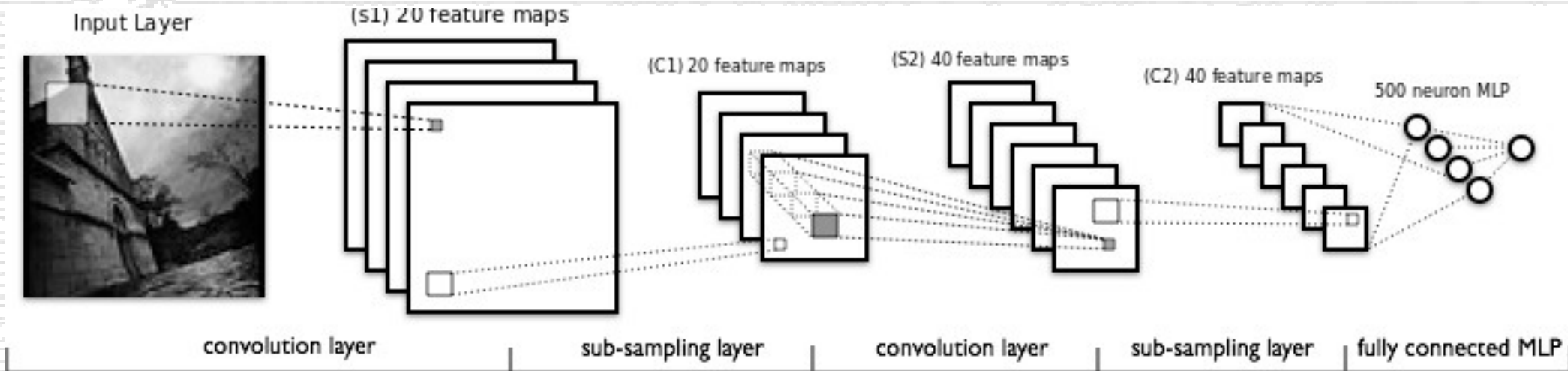
- A combination of **4 image plots** and **3 machine learning algorithms**:

- Logistic Regression
- Support Vector Machine
- (deep) Neural Network

- **9 resultant predictions** are then run through another AI algorithm

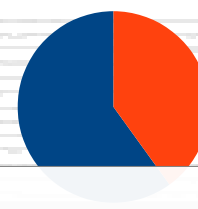


Our best sub-classifier: ConvNet, working on intervals subplot



- Convolutional layer: apply 4 filters to each **local** patch on the original image
- Subsample and apply another convolutional layer
- hierarchical learning: low-level features to mid-level invariant representations

AI Performance

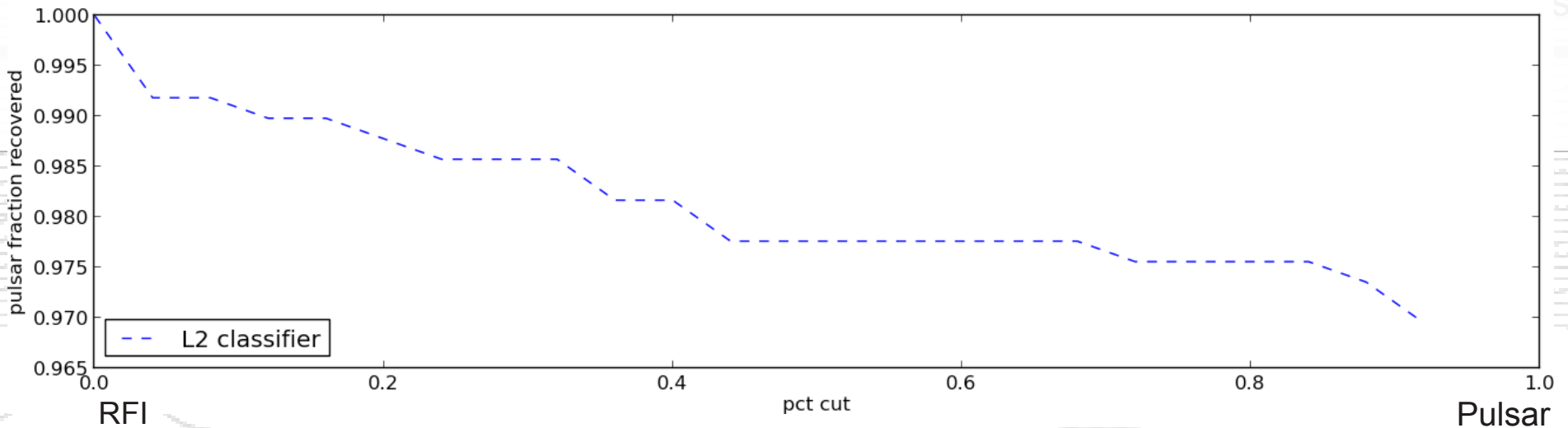
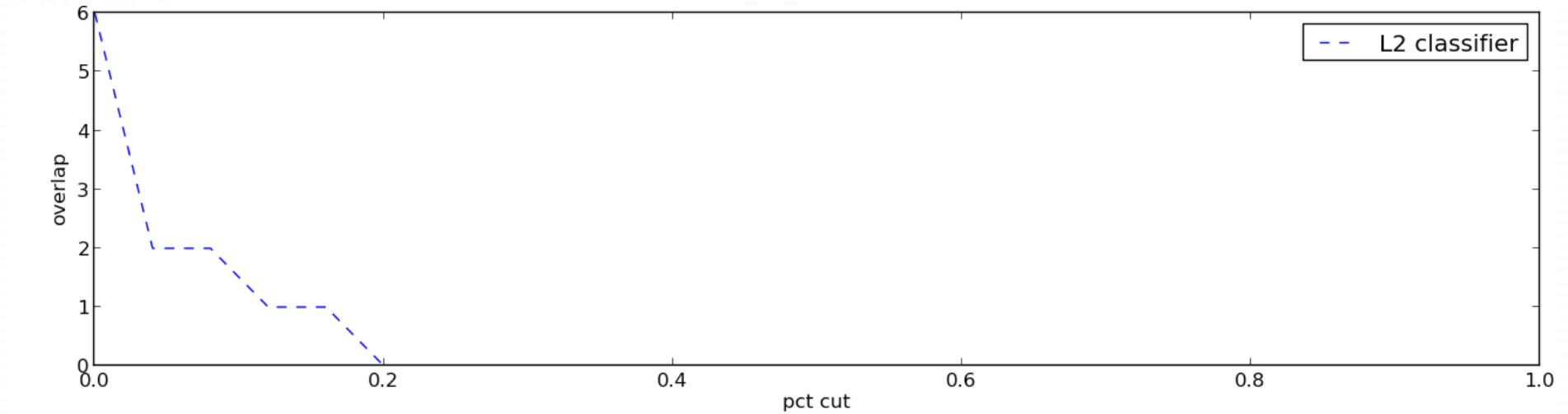


■ Training (60%)
■ cross-validation (40%)

• Precision
• Recall
• Completeness

Current Performance:
trained on 355 pulsars, 860 harmonics, 1950 RFIs PALFA candidates

$P = \frac{TP}{TP + FP}$ Predicted Positive
 $R = \frac{TP}{TP + FN}$ True Pulsars
F1 = 0.995



As applied to 600,000 GBNCC candidates

- $N(P > .25) = 4934$ (recall: we trained on PALFA candidates)

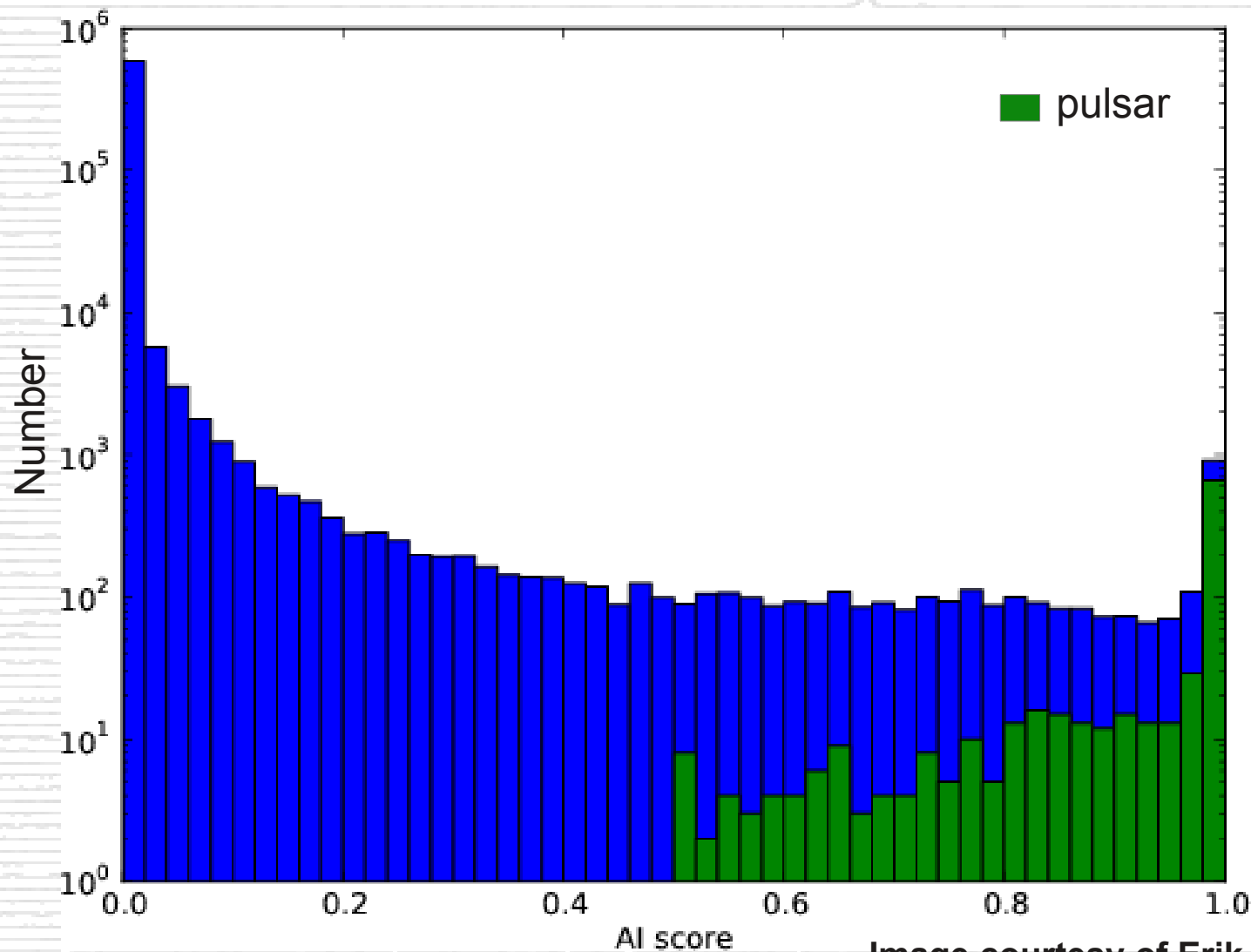


Image courtesy of Erik Madsen

AI has found 3 PALFA pulsars, waiting for follow-up observations on several more

Summary

- The **bispectrum** is a simple timeseries one can search for pulsed candidates
- **AI and deep learning** can play a role in pulsar data mining
(Zhu et al., in prep)
- See the UBC team about incorporating the above into your survey