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Classification in Time Domain Astrophysics

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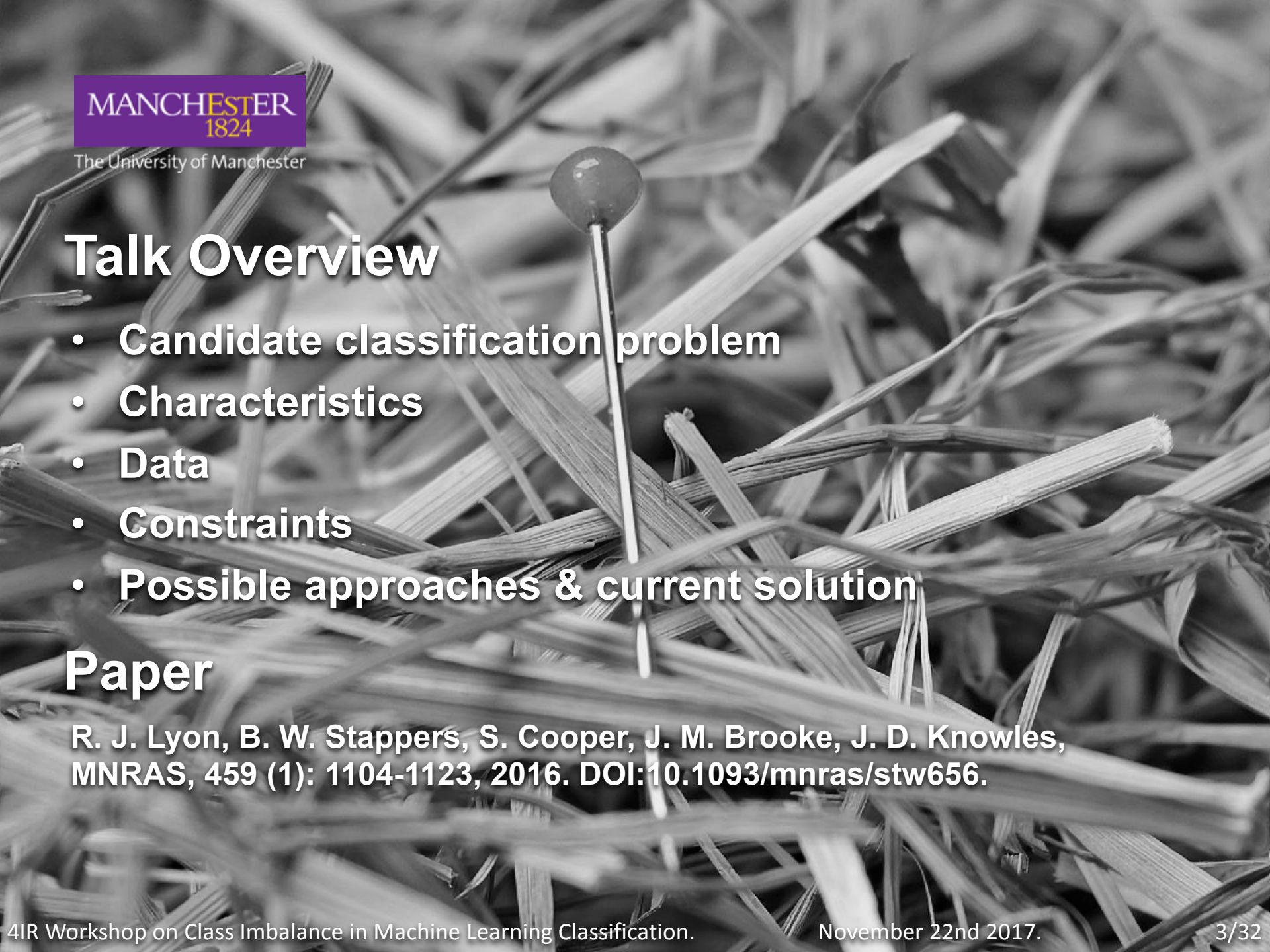
Collaborators

- John Brooke (retired)
- Sally Cooper (University of Manchester)
- DRAGNET team (Hessels et. al.)
- Joshua Knowles (University of Birmingham)
- Lina Levin-Preston (University of Manchester)
- Mitchell Mickaliger (University of Manchester)
- Ben Stappers (University of Manchester)
- Chia Min Tan (University of Manchester)
- SKA Group Time Domain Team (Oxford, INAF)



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Talk Overview

- Candidate classification problem
- Characteristics
- Data
- Constraints
- Possible approaches & current solution

Paper

R. J. Lyon, B. W. Stappers, S. Cooper, J. M. Brooke, J. D. Knowles, MNRAS, 459 (1): 1104-1123, 2016. DOI:10.1093/mnras/stw656.

Candidate Selection

- Goal: automatically categorise signals
- A classification problem
- Heavily imbalanced data
- Encountered on-line and off-line
- Data non-stationary
- Input data not i.i.d
- Data labelling costly
- Real-time constraints
- Conceptually simple, difficult in practice!

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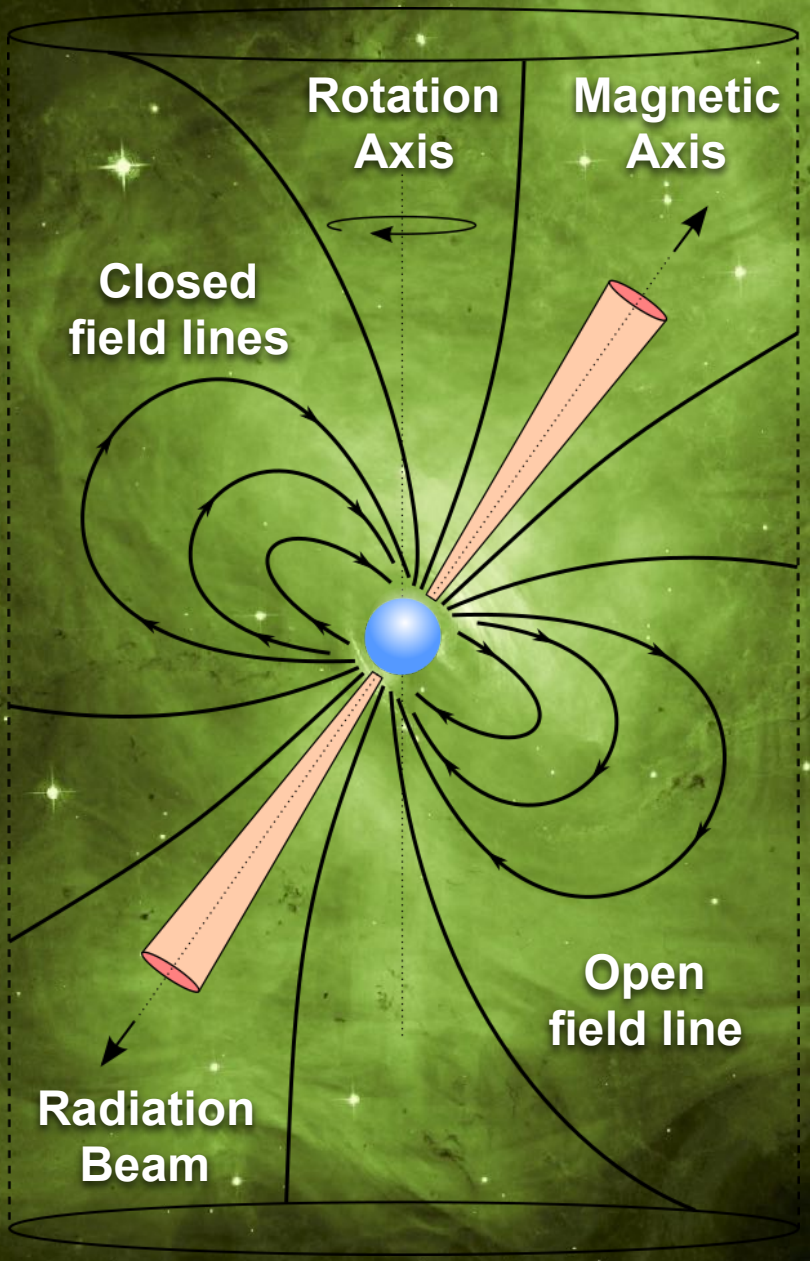
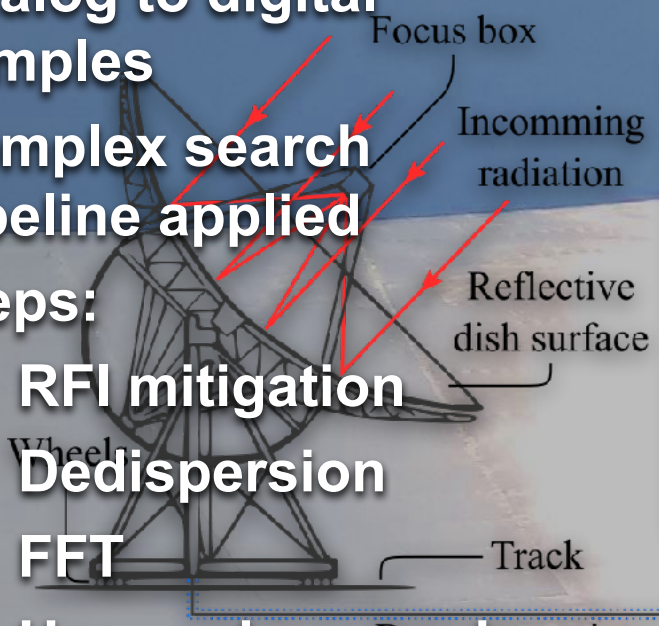
Pulsars

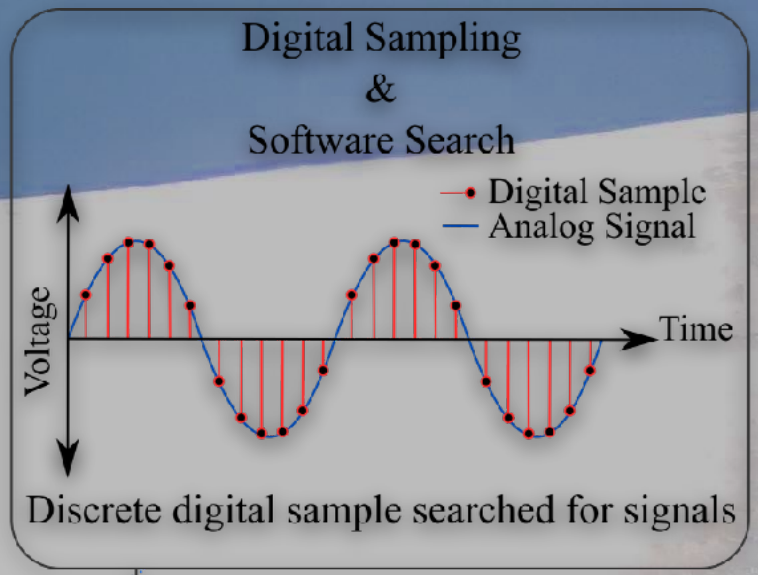
- Stellar remnats
- Very dense
- ~20 km diameter
- Produce radio emission
- Very useful for science



Data Capture

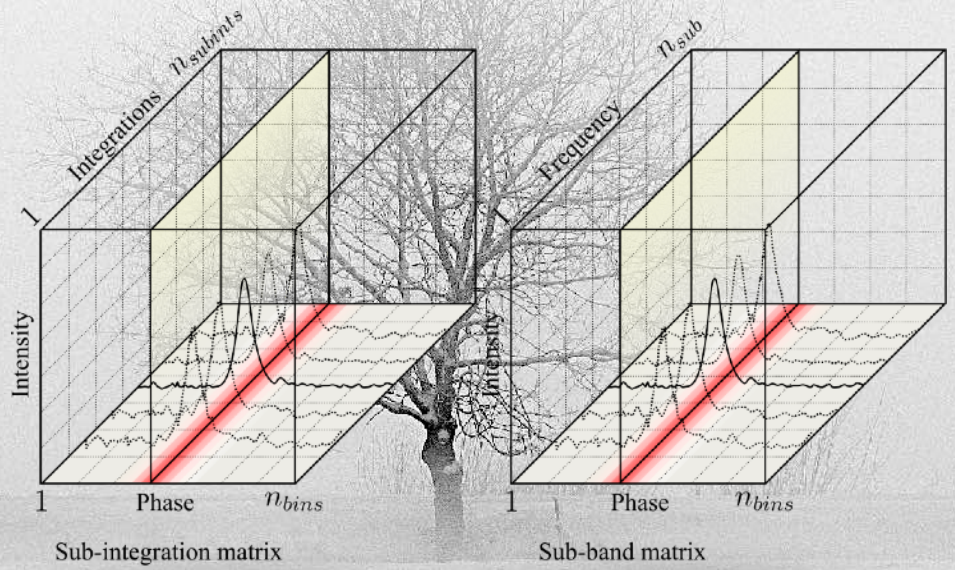
- Analog to digital samples
- Complex search pipeline applied
- Steps:
  - RFI mitigation
  - Dedispersion
  - FFT
  - Harmonic summing
  - Detection
  - Sifting



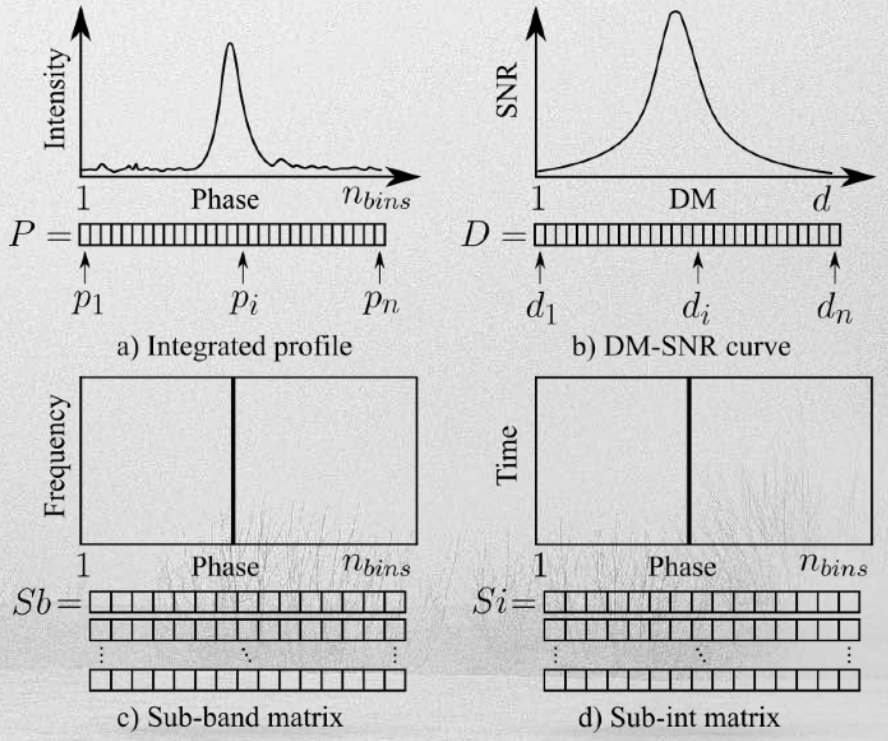


Data Products (1)

Data produced via signal processing

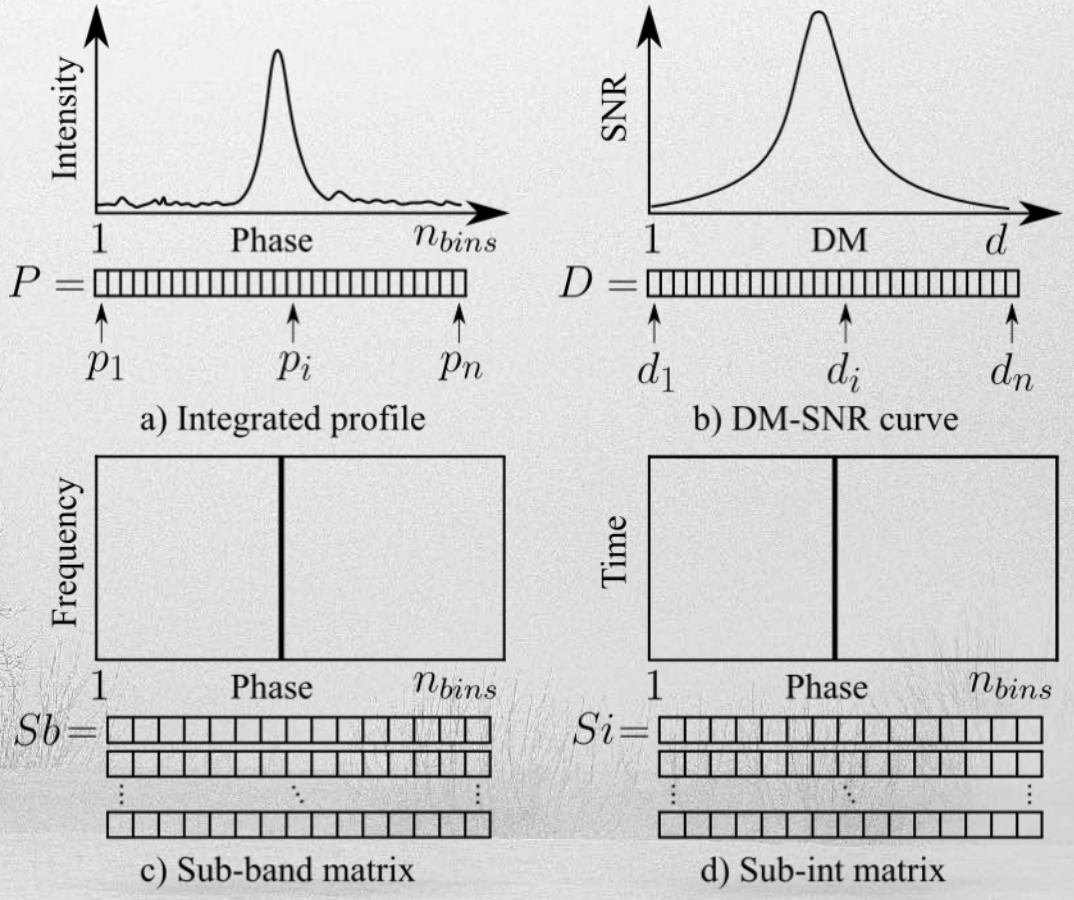


Reduced data



Data Products (2)

- A candidate file
- Describes a signal detection
- Covers time and frequency space
- At least one per detection (duplicates!)
- Classification appears simple - things do get fuzzy!



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What to look out for

- Clear pulse with a defined peak
- Evidence that the signal persists in time, i.e. an indication of a periodic source
- Evidence that the signal persists in frequency - pulsars are broadband emitters
- A DM value greater than zero
- Evidence of other effects, such as scintillation?

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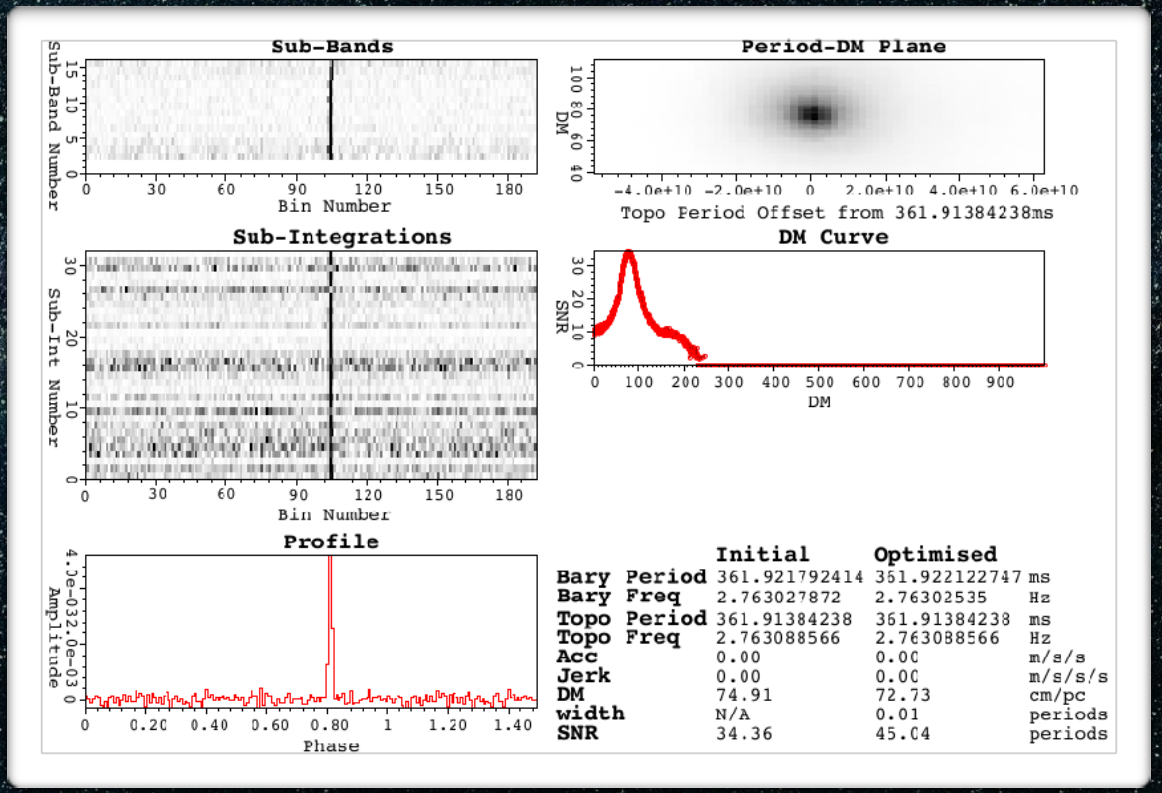
Candidate Examples (1)

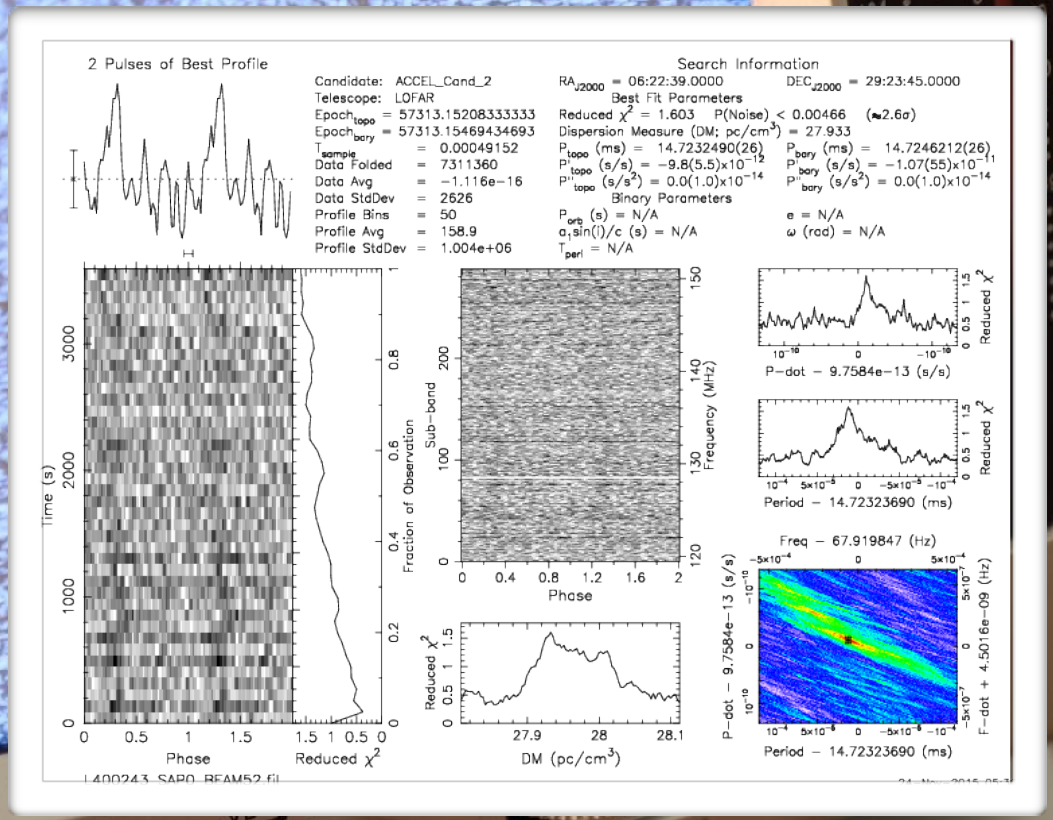
- Defined peak
- Clear DM-SNR peak
- Consistent in time
- Persistant in frequency
- Obvious pulsar!



Credit: HTRU Collaboration.

Candidate Examples (2)

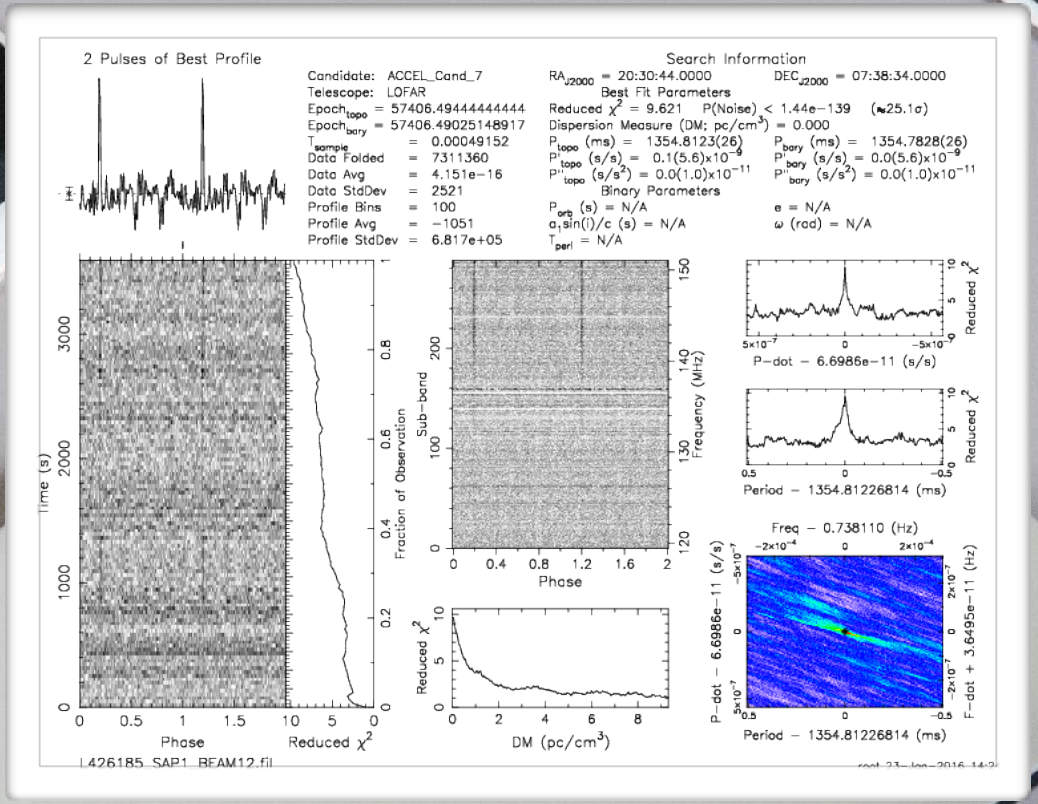
- Clearly defined peak?
- Some persistence in time?
- A DM value > zero
- Labelled as noise



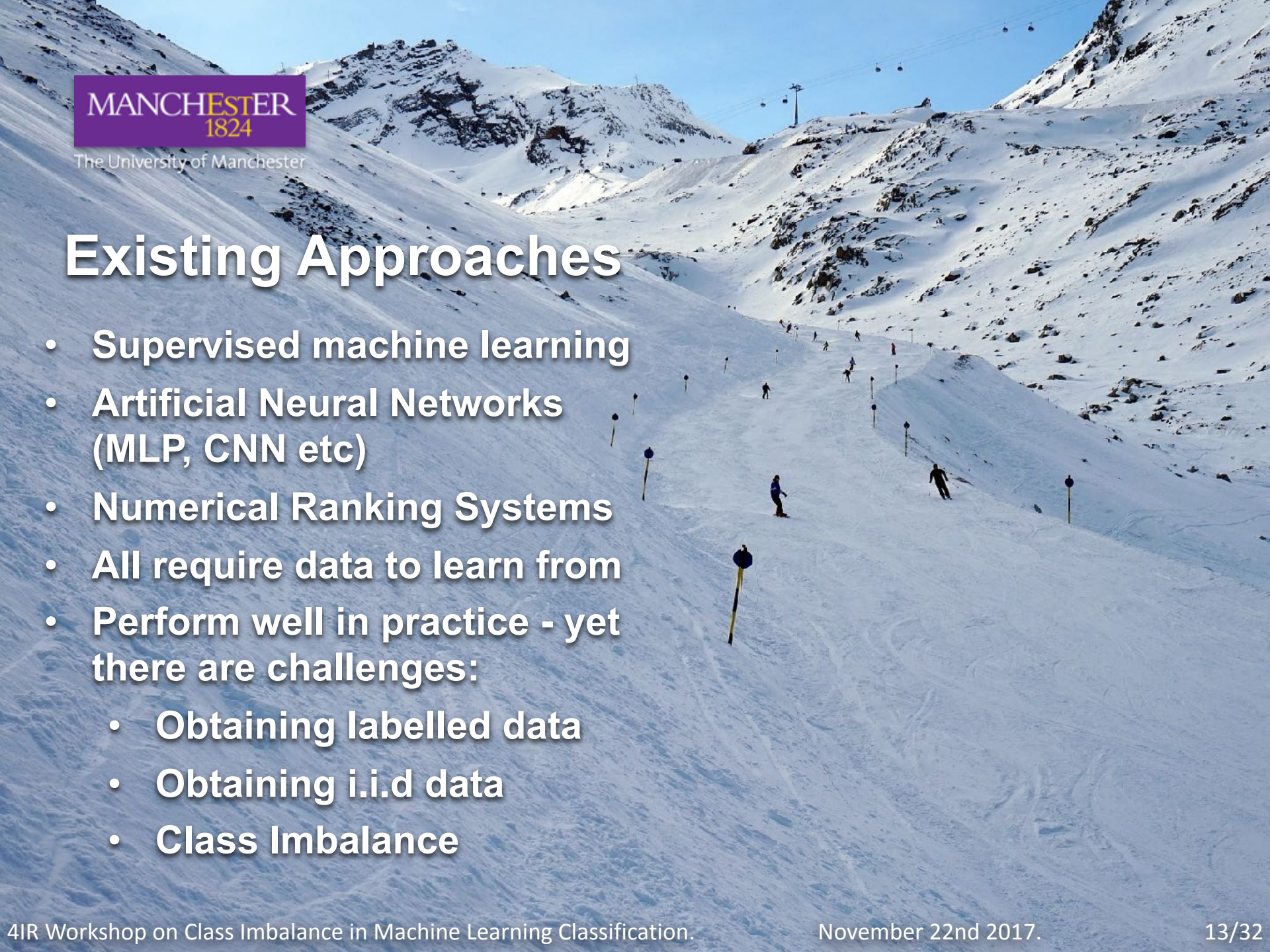
Credit: LOTAAS Collaboration (Chia Min Tan et. al.).

Candidate Examples (3)

- Clearly defined peak?
- Some persistence in time?
- Some persistence in frequency?
- RFI



Credit: LOTAAS Collaboration (Chia Min Tan et. al.).



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Existing Approaches

- Supervised machine learning
- Artificial Neural Networks (MLP, CNN etc)
- Numerical Ranking Systems
- All require data to learn from
- Perform well in practice - yet there are challenges:
  - Obtaining labelled data
  - Obtaining i.i.d data
  - Class Imbalance

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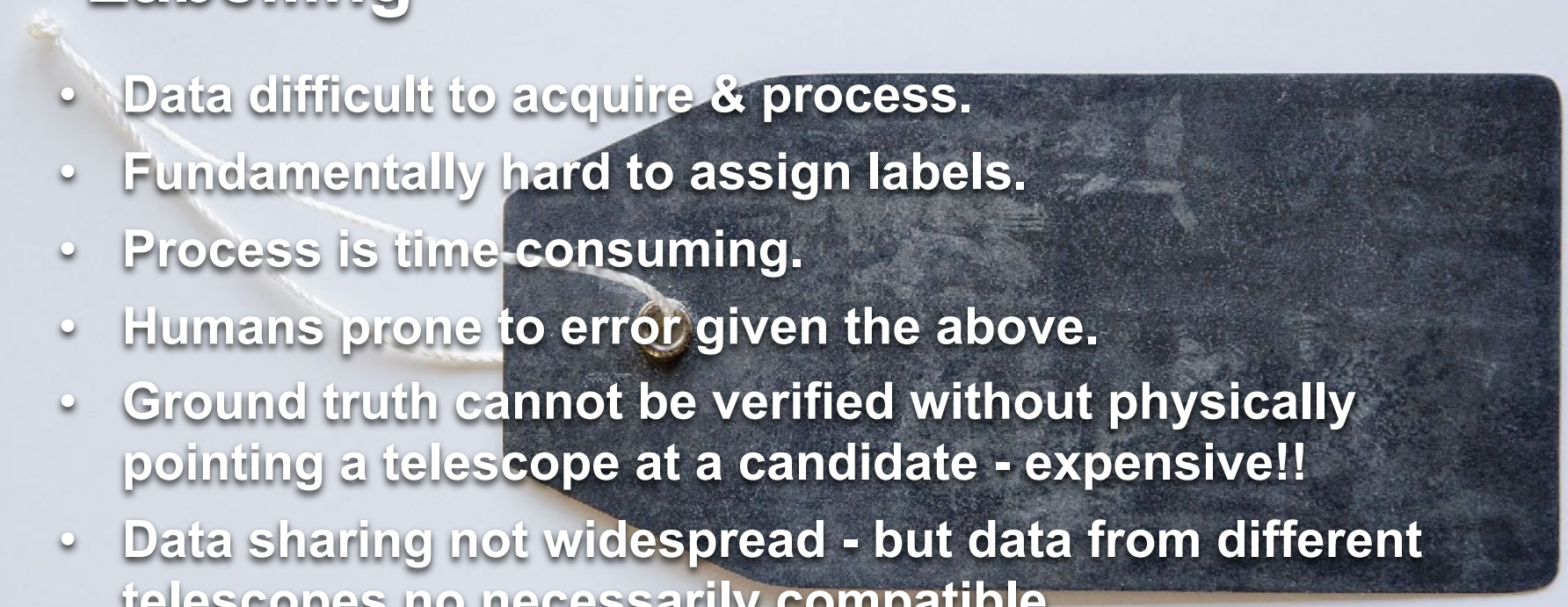
Labelling



- Data difficult to acquire & process.
- Fundamentally hard to assign labels.
- Process is time consuming.
- Humans prone to error given the above.
- Ground truth cannot be verified without physically pointing a telescope at a candidate - expensive!!
- Data sharing not widespread - but data from different telescopes no necessarily compatible…

i.i.d. Assumption

- Feature distributions can change, causing a drop in accuracy due to i.i.d violation.
- Mostly occurs when training data differs from real-word data.
- Also occurs when data is subject to distributional drift.

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Class Imbalance (1)

- Class ratios are skewed toward one or more category
- For pulsar search ratio is 1 pulsar to 10,000 non-pulsar examples (not a worse case)
- Imbalance can be intrinsic or extrinsic
- Given that class distributions drift over time, we have a difficult problem
- What are it's characteristics? What does the imbalance actually do?

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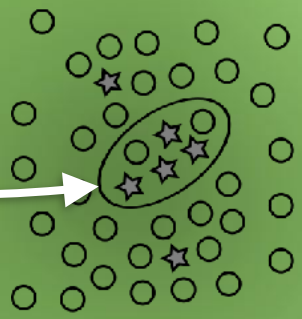
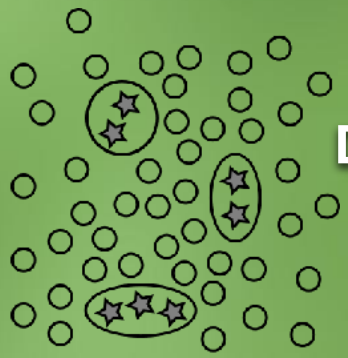
Class Imbalance (2)

Class overlap



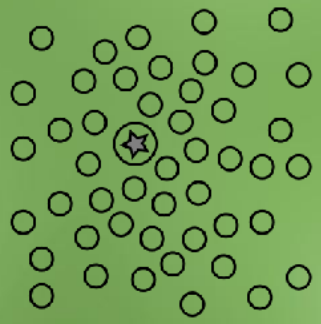
a)



b)

Disjuncts

Absolute rarity



c)

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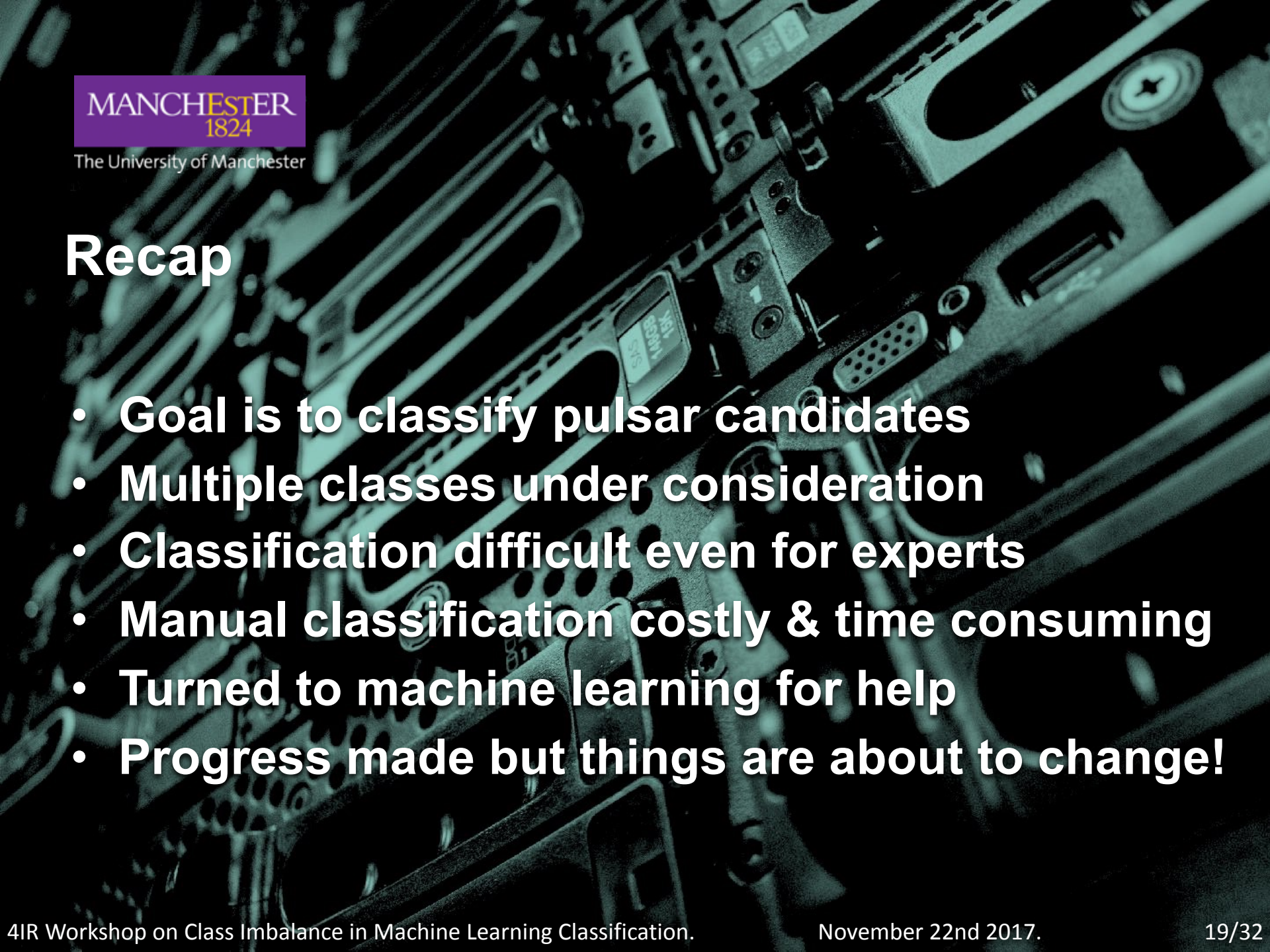
Potential Solutions?

- Generate artificial examples to train on?
- Random over or under-sampling?
- Ditch binary classification, try anomaly/outlier/ novelty detection, one-class learning, semi-supervised learning?
- Must be careful - this is a discovery discipline, and we can't introduce bias.
- What about unknowns?



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Recap

- Goal is to classify pulsar candidates
- Multiple classes under consideration
- Classification difficult even for experts
- Manual classification costly & time consuming
- Turned to machine learning for help
- Progress made but things are about to change!

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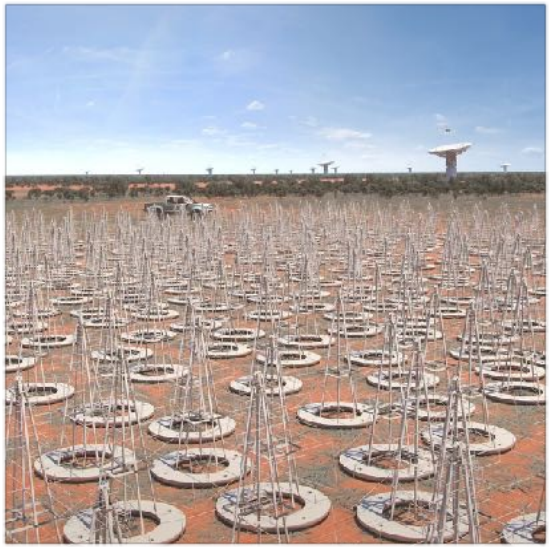
Square Kilometre Array

Two telescopes, one HUGE processing challenge.



Credit: SKAO

- Changes the classification problem
- Greatly increases data capture rate
- Requires real-time computation
- Introduces a number of constraints

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Constraints

- Computational constraints - must be resource efficient
- Real-time constraints - must process the data quickly
- Storage constraints - only a portion of the data can be stored
- Architectural constraints - must run our systems on a massive heterogeneous computing resource, the SDP
- Archiving constraints - must archive our data with along with metadata, allowing audit and tracking
- Operational constraints - the system must be tuneable by users whilst executing autonomously
- Then there's cost, scalability, maintainability….

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SKA Data rates

- Enormous.
- Reduced data products alone 1.08 GB each.
- One data product per beam, per scan.
- Real-time constraints dictate data transfer rate.
- ~50 PB for a single all-sky survey = billions of candidates.
- See DOI: 10.5281/zenodo.836715

	SKA-Low (500 beams)	SKA-Mid (1500 beams)
Data per beam (GB)	~1.08	~1.08
Data per scan (TB)	~0.54	~1.62
Approx. Data rate Gbit/s	~43.22	~130.66

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Real-time Constraints

- Data storage restrictions mean we can't store everything.
- For pulsars we must process data as quickly as possible.
- For transients, real-time processing important for rapid followup.
- Must make a decision quickly.
- Also constrained by computational power available.

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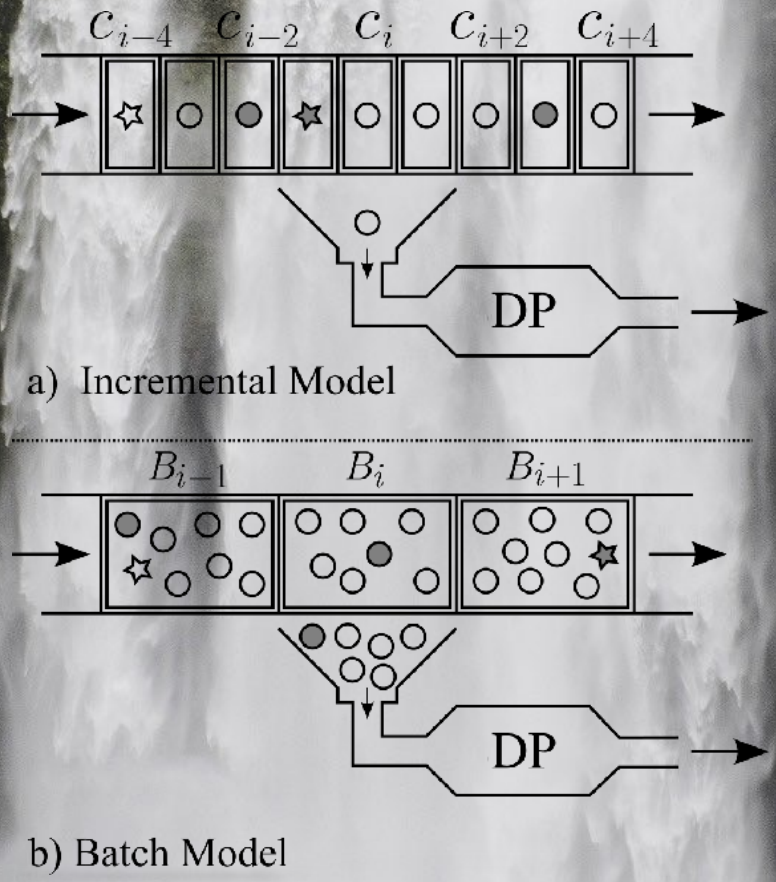
Steaming Data

- High data rates and real-time constraints, require a streaming model.
- Makes traditional off-line learning impractical.



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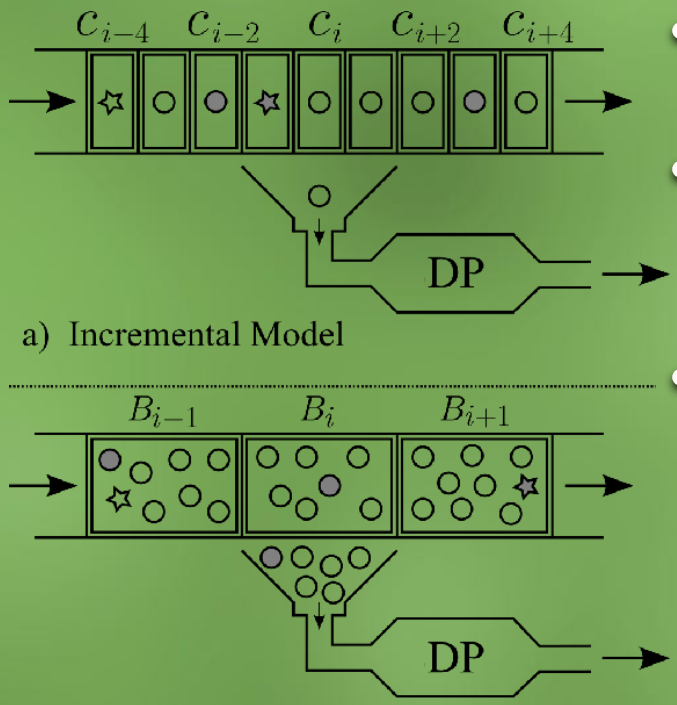
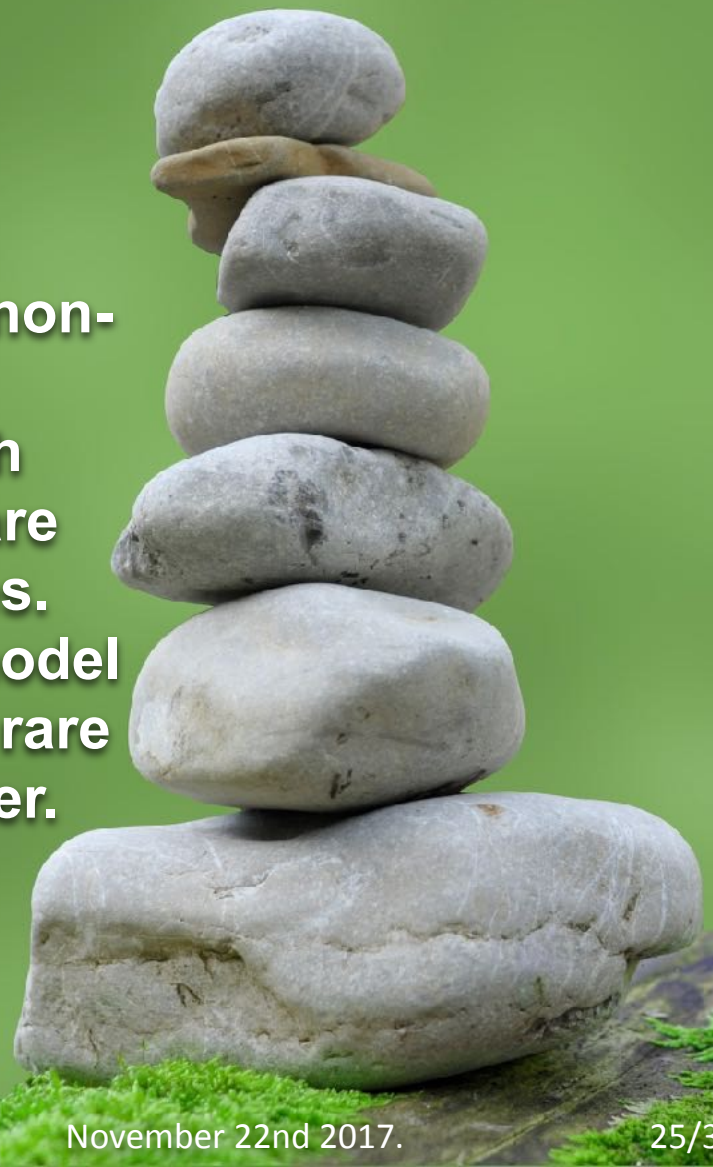
Class Imbalance Worsens



- Worsened by non-stationarity.
- Arbitrary batch contains no rare class examples.
- Incremental model might not see rare examples either.



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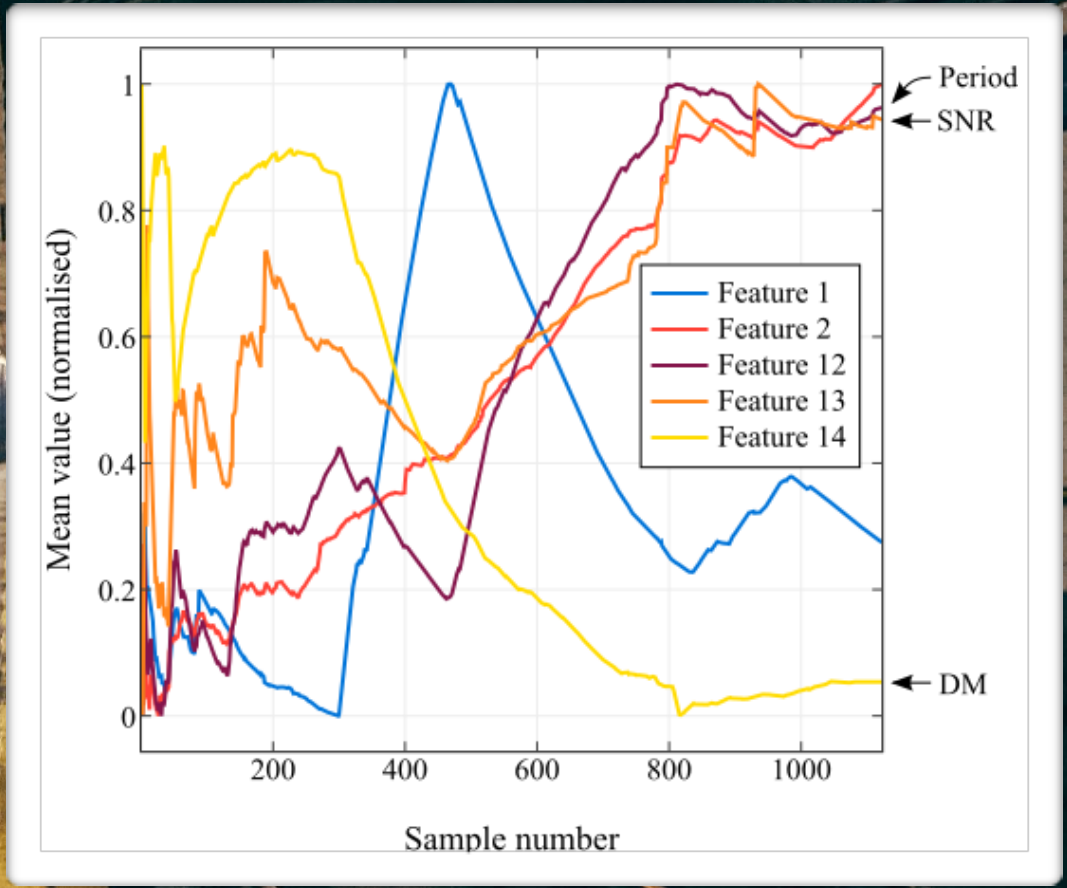
Non-stationarity (1)

- Data distributions changes over time
- Can affect one or more classes
- Cause violations in i.i.d assumption
- Evidence?



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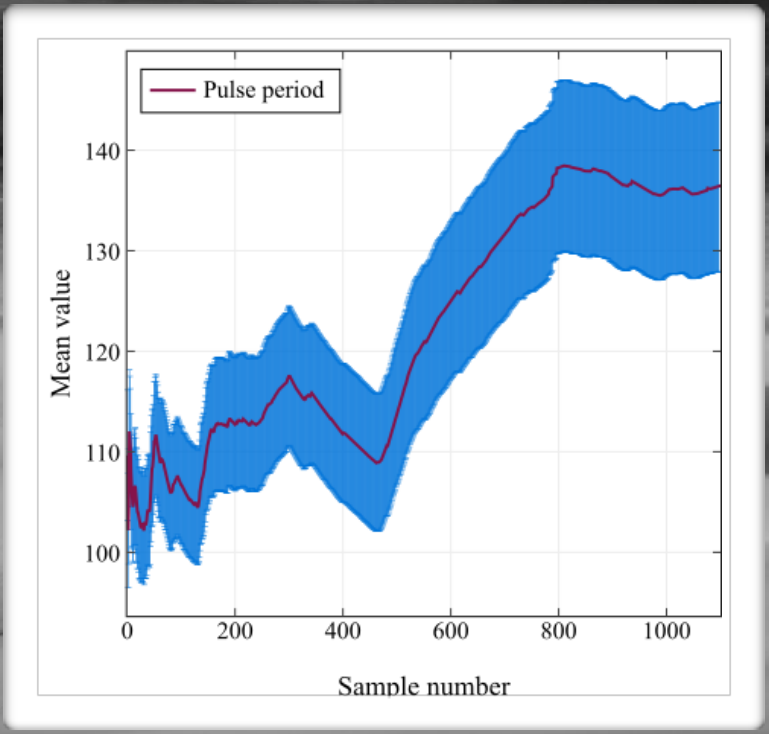
Non-stationarity (2)



- Likely causes?
- Consequences: labelled data becomes less helpful over time
- Particularly problematic for RFI classes
- Selection effects higher up processing chain?
- Requires adaptable learning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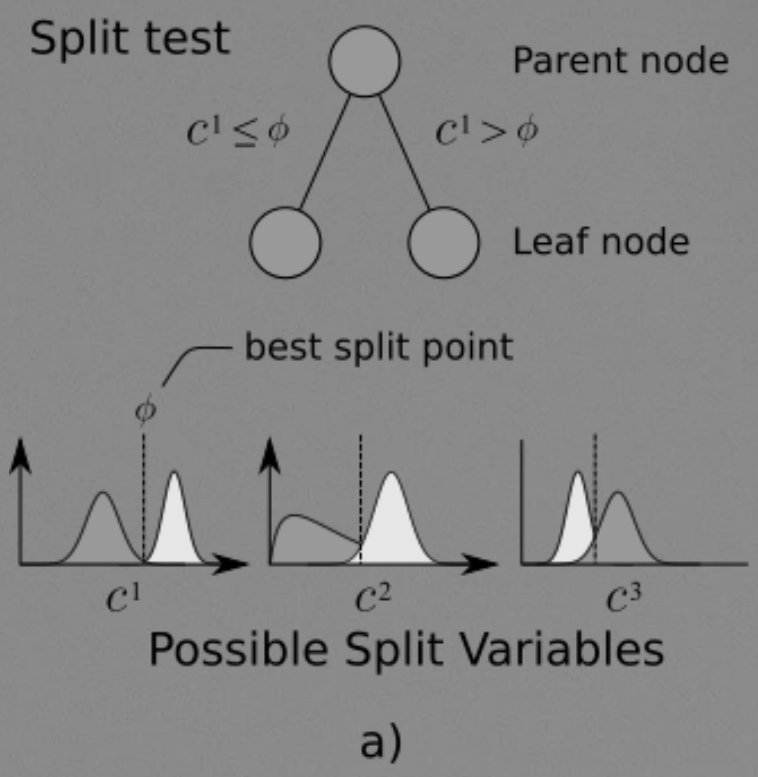
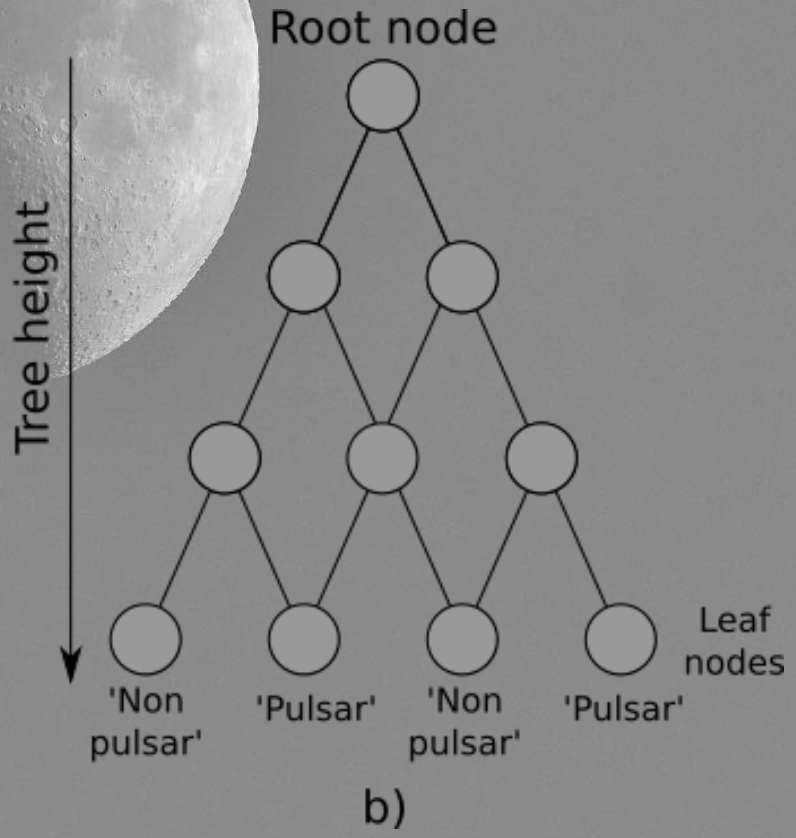
Tree Learning





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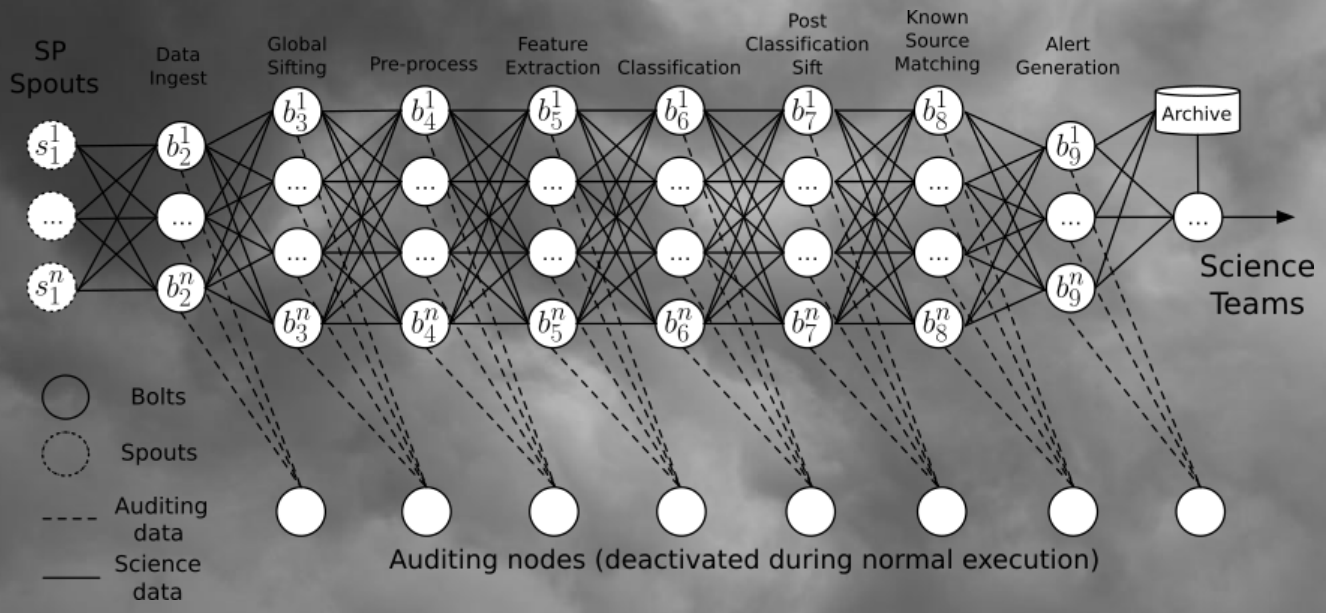
Experimental Prototypes



Credit: Lyon et. al. in prep.

99.9 % Accuracy

81 % Recall

225 second processing time

Progress but not enough!

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The Future

- 50 years since Gordon Moore's paper "Cramming more components onto integrated circuits", Electronics, Volume 38, Number 8, April 19, 1965.
- Computing power increasing - GPUs/multi-processors.
- This may mean more data.
- More sophisticated computing and analytics?
- More systems and technologies to learn?
- As a community we can meet these challenges.

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Questions & Thank For Listening

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- SKA image credit: the SKA Organisation.

More Information:

Paper DOI:10.1093/mnras/stw656.

Notebook DOI: 10.5281/zenodo.883.844

Dataset DOI: 10.6084/m9.figshare.3080389.v1 or https://archive.ics.uci.edu/ml/datasets/HTRU2