Learning to Identify Extragalactic Radio Sources

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Slides: http://www.mso.anu.edu.au/~alger/review-2020

Australian National University

DATA 61

CSIRO


ADACS
ASTRONOMY DATA AND COMPUTING SERVICES
NCRIS
Curtin University
PAWSEY
Automated Cross-identification of Wide-area Radio Surveys
OVERVIEW
Estimating the Extended Radio Luminosity Function
by Learning from Citizen Scientists
HB
MÜNCHEN
Milch
WELCOME
HOME
BERSEPHONE
WARDEN

Acknowledgements

   

Australian National University | RESEARCH SCHOOL OF ASTRONOMY & ASTROPHYSICS
ANU College of Science

POSSUM
POLARISATION SKY SURVEY OF THE UNIVERSE'S MAGNETISM

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$$\mathrm{sign}\left(\sigma\left(\sum_{i=1}^{n} \alpha_i k(x_i, x)\right)\right)$$

ASA Astronomical Society of Australia

The two-way street of interdisciplinary work

Apply domain knowledge in another field
Easier to communicate results
Focus on results that are meaningful

Better understanding of domain by formalisation
New or novel applications of existing ideas
Better communication of methods

"Machine learning really forces you to think very hard about the precision of your domain knowledge, because you're trying to make this machine do a thing you have in your head."
— Cheng on a panel at C3DIS 2019

Three components of my PhD

PART I:

Combining citizen science,
machine learning,
and astronomy

PART II:

Making radio
luminosity functions

PART III:

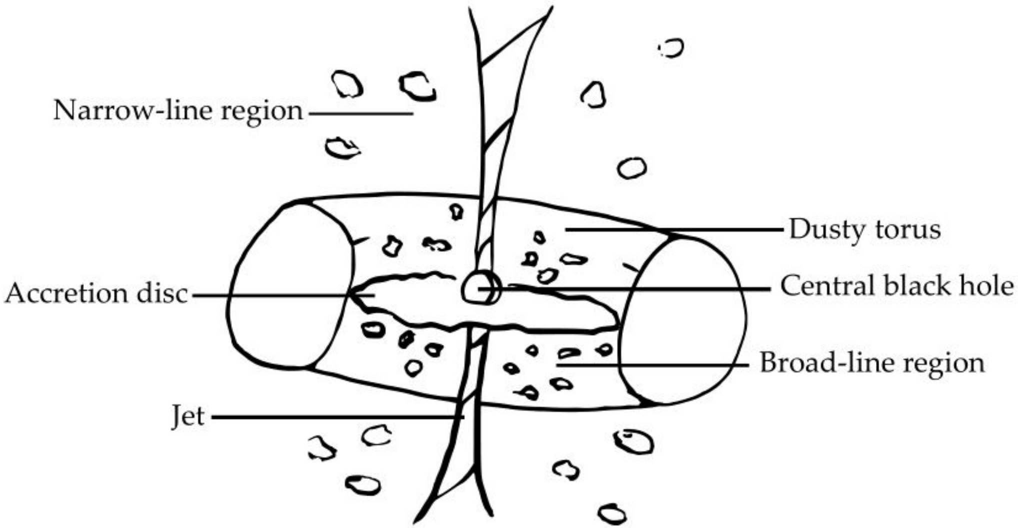
Classifying polarised
radio sources

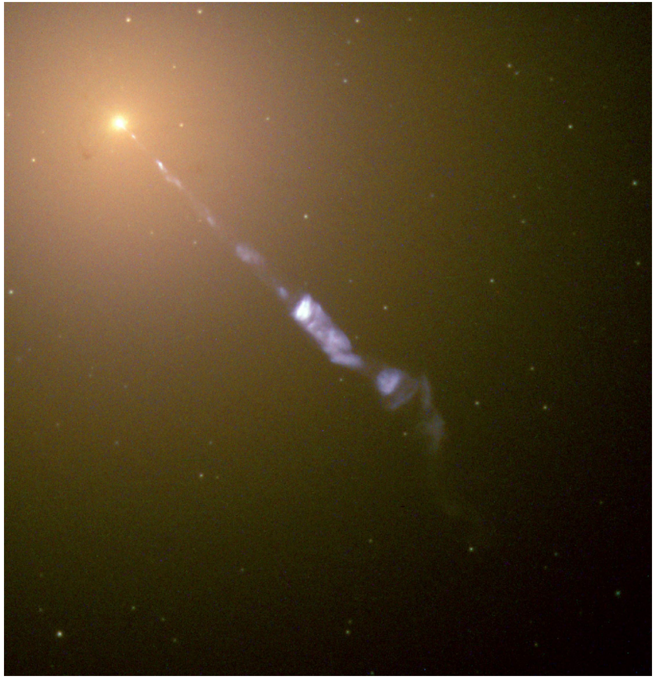
Learning to identify extragalactic radio sources

PART I:

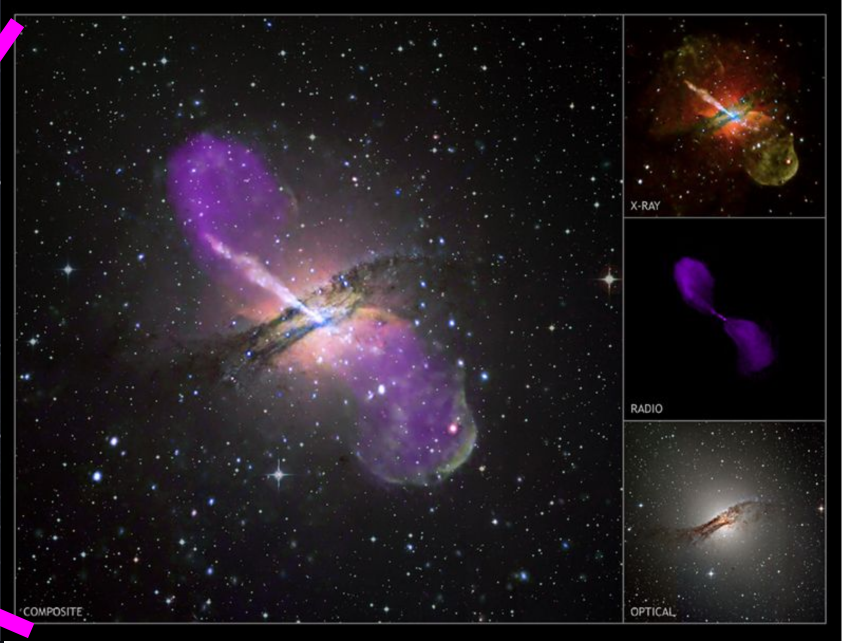
Radio galaxies, citizen science, and binary classification

Active galactic nuclei





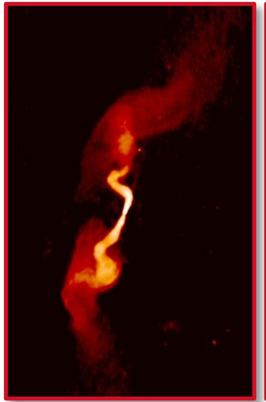
M87. Image: NASA

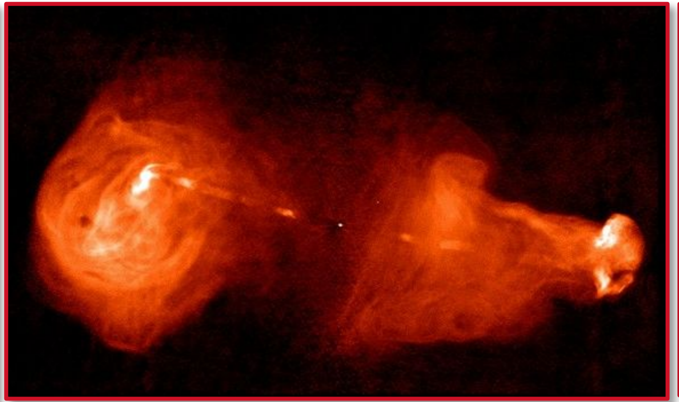


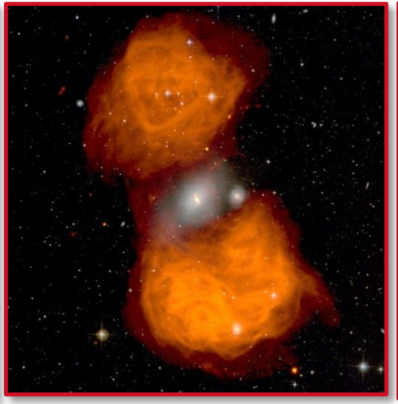
Centaurus A, a radio galaxy 13 million light years away.

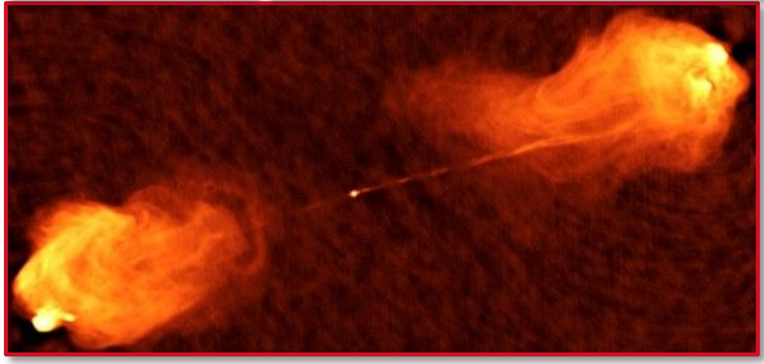
Top: NASA/CXC/R.Kraft (CfA), et al.; NSF/VLA/M.Hardcastle (U Hertfordshire) et al.; ESO/M.Rejkuba (ESO-Garching) et al.
Left: Ilana Feain, Tim Cornwell & Ron Ekers (CSIRO/ATNF); R. Morganti (ASTRON); N. Junkes (MPIfR); Shaun Amy, CSIRO

A zoo of radio galaxies



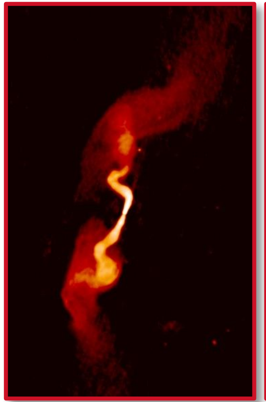
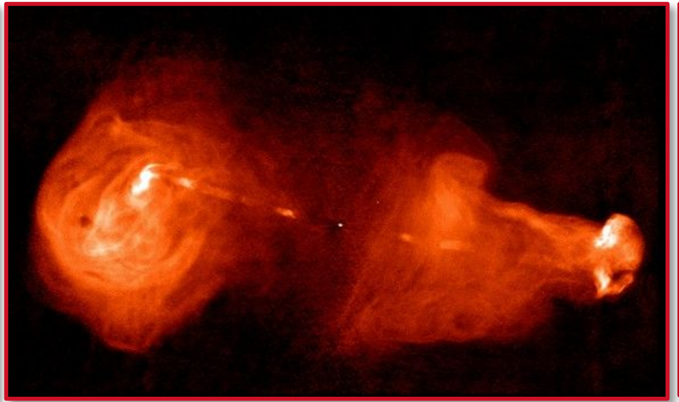
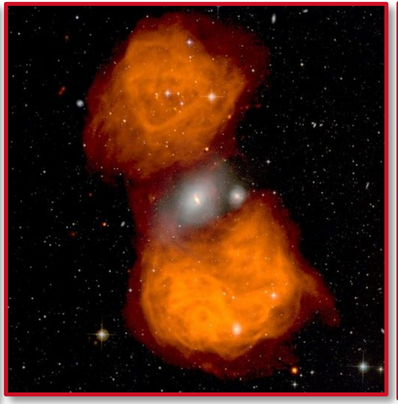


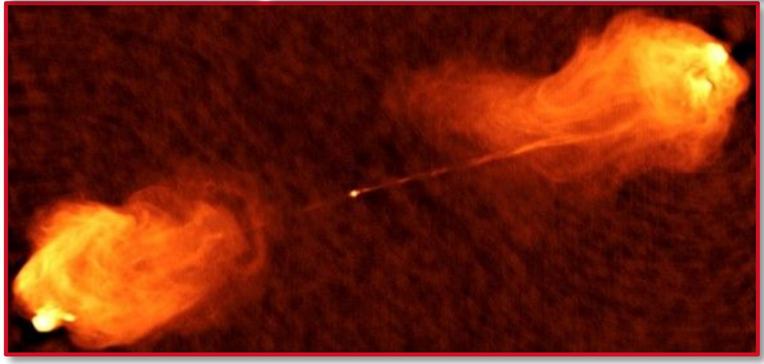




Images: NRAO/AUI via Julie Banfield

A radio galaxy zoo 🤔

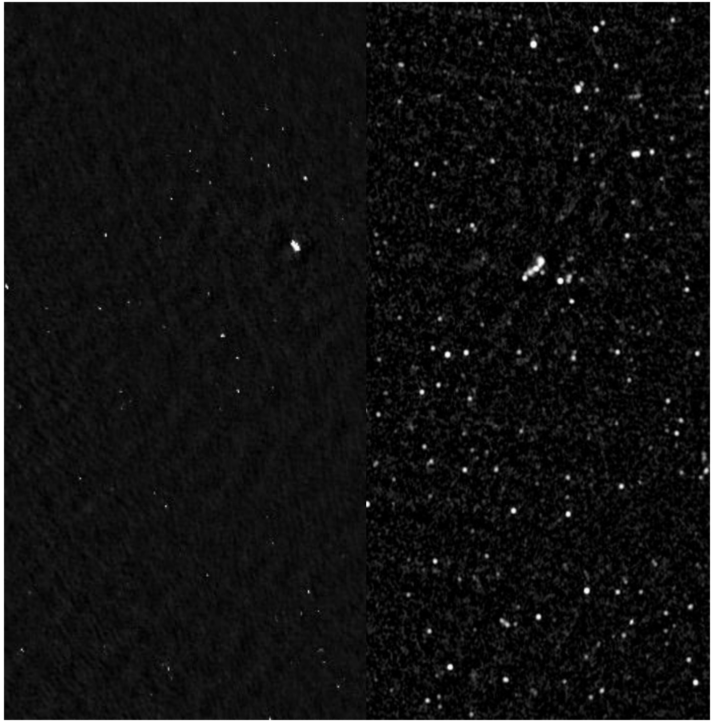






Images: NRAO/AUI via Julie Banfield

Wide radio surveys see AGN

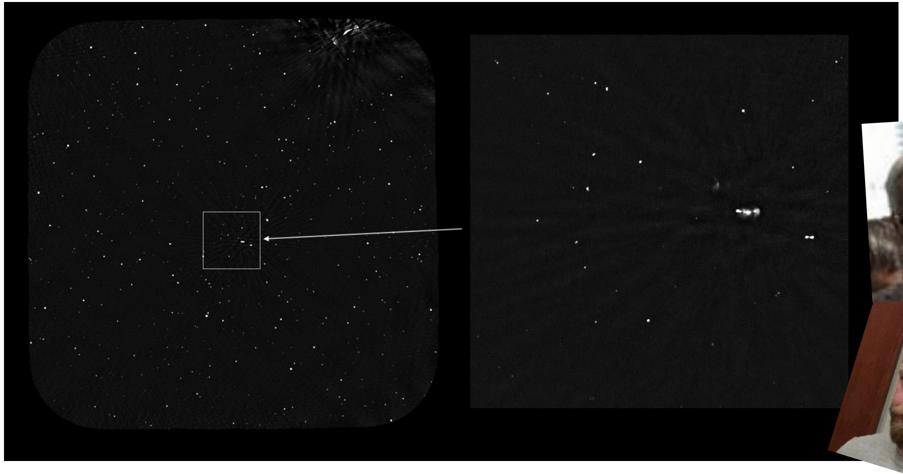
- ~70% of sources in wide-area radio surveys are AGN
- AGN have complicated extended structure

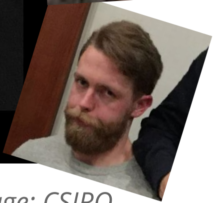


Images: TGSS (left) and NVSS (right)

We have too much data

- Surveys like VLA-FIRST generate more data than we can look at
- Surveys like ASKAP-EMU generate more data than we can *store*
- ASKAP can already survey the whole sky in 2 weeks





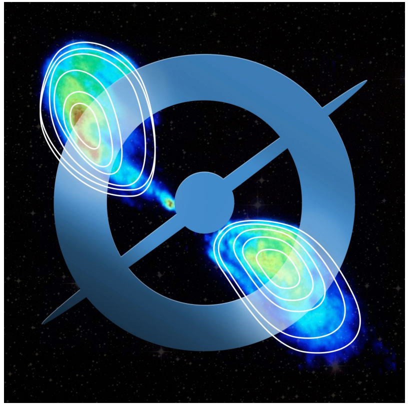
A tile of the Rapid ASKAP Continuum Survey. *Image: CSIRO*

Australian SKA Pathfinder.
Image: CSIRO

The Very Large Array.
Image: NRAO

Strategies for data-at-scale

- Crowdsourcing (e.g. Radio Galaxy Zoo, Gravity Spy)
  - **Fast**: RGZ classified 75000 galaxies in just 3 years
  - **Serendipitous**: Citizen scientists are endlessly curious
  - **Noisy**: Non-experts are not experts
- Asking students very nicely to look at all the data
  - **Slower**: Students are slow and grumpy
  - **Opportunity** cost: More fruitful things to do
  - **Incomplete**: We can’t see all the data, so we miss things
- Machine learning
  - **Fast**: Computers are well-known to be quite speedy
  - **Hard to interpret**: Much state-of-the-art ML research is black magic
  - **Tricky**: Given a problem, how do we make ML work for it?



What is citizen science?

"Citizen science projects involve non-professionals taking part in crowdsourcing, data analysis, and data collection. The idea is to break down big tasks into understandable components that anyone can perform."

— Robert Simpson (Zooniverse), [The Conversation, 15/08/13]

What is machine learning?

"Machine learning is the statistics kept at the back of the textbook."

— Anonymous RSAA researcher

"Machine learning is about designing algorithms that automatically extract valuable information from data."

— *Mathematics for Machine Learning*,
Deisenroth, Faisal & Ong

What is machine learning?

"Actually running logistic regression, after feature vectors and labels were all set up, went particularly fast, leading to the remark: 'and I thought machine learning was difficult'! In this lies what I identify as the 'TV Chef Problem': if all the ingredients are prepared earlier, the task looks easy. However, this hides that sourcing and preparing those ingredients, as well as determining if you've even got the right recipe, is where the real difficulty and ambiguity lies. Watching the TV Chef is effortless, but answering 'is this meal right?' can be really hard."

— James Gardner, ANU undergraduate

Citizen science + machine learning

- Machine learning:
  Finding useful information from data
  - Formalise problem as an unknown function
  - Approximate that function from labelled data
- Citizen science:
  Get people to solve problems well-suited for people to solve

*Use **machine learning** to approximate how **citizen scientists** label data, then use the approximation to label radio surveys.*

Different wavelengths, different physics

Optical
Image: ESO/WFI/M.Rejkuba et al.

Infrared
Image: NASA

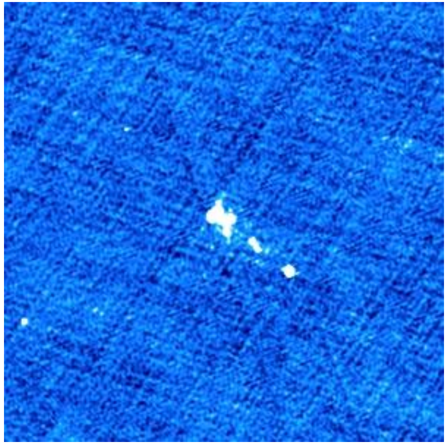
X-ray
Image: NASA/CXC/U.Birmingham/M.Burke et al.

Radio
Image: NSF/VLA/Univ.Hertfordshire/M.Hardcastle

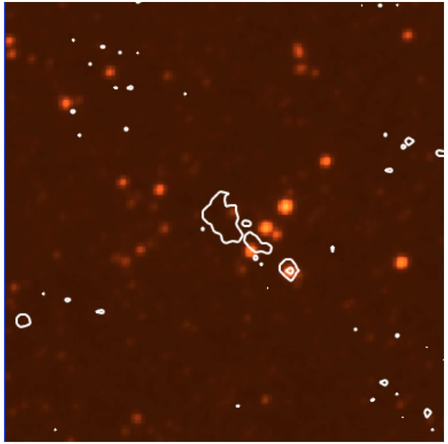
Images of Centaurus A at different wavelengths.

Radio/infrared cross-identification

- Problem:
  - Match radio emission to the corresponding galaxy in infrared
  - Important for understanding galaxies throughout cosmic time
- Hard:
  - Radio emission can be very extended across the sky
  - Often no clear relationship between radio emission and the emitting galaxy



A radio galaxy imaged with the VLA, a radio telescope.
Image: FIRST

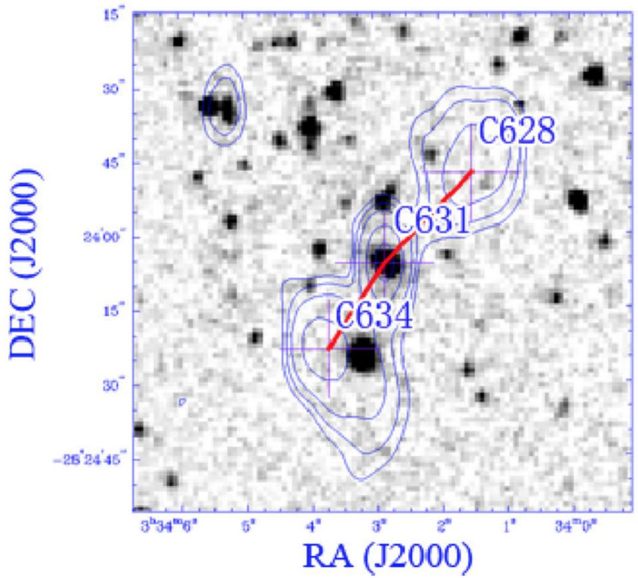


The same patch of sky imaged with *WISE*, an infrared telescope. White contours show the radio image on the left.
Image: WISE

Radio/infrared cross-identification

Past approaches:

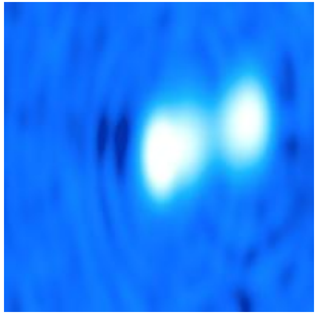
- Manual
- Crowdsourcing
- Positional matching
- Bayesian methods
- Likelihood ratio



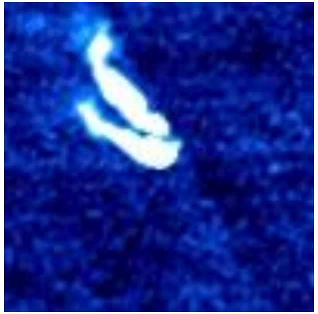
Bayesian model fit to a radio triple.
Image: ATLAS (radio), SWIRE (infrared), Fan et al. 2015

Radio Galaxy Zoo

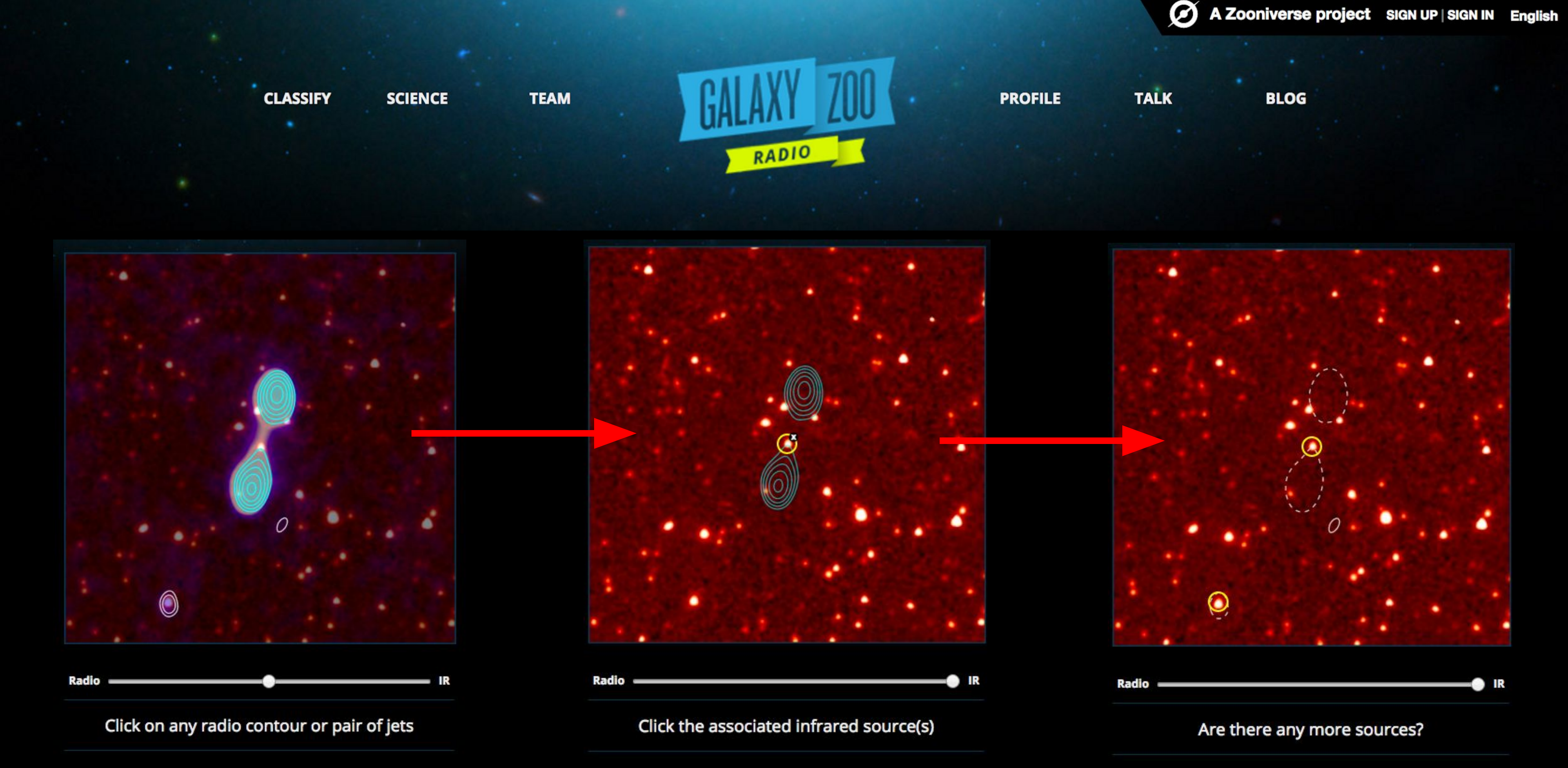
- Crowdsourced, citizen science project
- ~75000 labelled radio objects in 3 years
- Volunteers identify infrared galaxy counterparts to radio emission



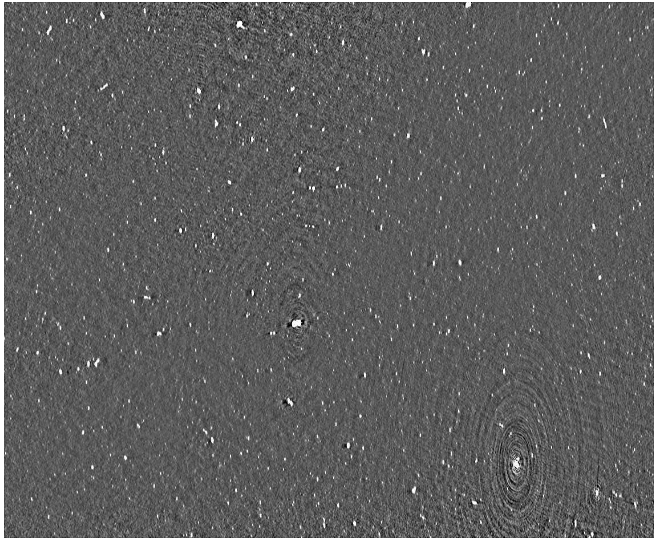
An image from the Australia Telescope Compact Array.



An image from the Very Large Array.

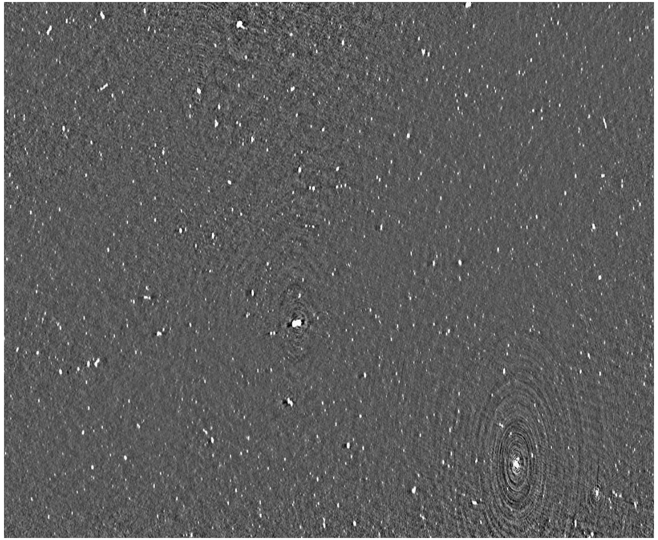

A Zooniverse project
SIGN UP | SIGN IN
English
CLASSIFY
SCIENCE
TEAM
GALAXY ZOO
RADIO
PROFILE
TALK
BLOG
Radio
IR
Click on any radio contour or pair of jets
Radio
IR
Click the associated infrared source(s)
Radio
IR
Are there any more sources?

Australia Telescope Large Area Survey – *Chandra* Deep Field (South)



ATLAS observations of CDFS.
Image: ATLAS, Franzen+2015

ATLAS–CDFS

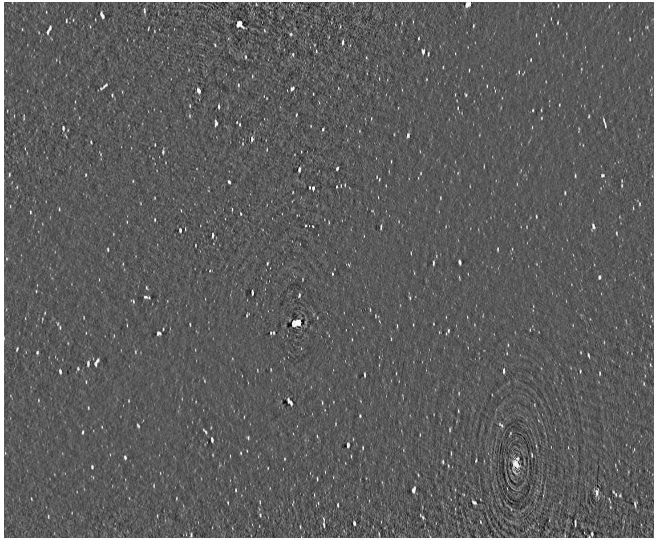


ATLAS observations of CDFS.
Image: ATLAS, Franzen+2015

Corner image: Freepik.com

ATLAS–CDFS

- ~2000 radio sources cross-identified with *Spitzer* images by Radio Galaxy Zoo
- ~500 sources cross-identified by experts (Norris+2006)
  - and now also ~2000 cross-identified by Jesse Swan
- Pilot study for Evolutionary Map of the Universe (EMU) with ASKAP



ATLAS observations of CDFS.
Image: ATLAS, Franzen+2015

The Gomeroi people are the traditional custodians of the land that ATCA is built on.

ATLAS machine learning cross-identification

Simple goals:

- Design a machine learning algorithm for cross-identification
- Train on Radio Galaxy Zoo cross-identifications
- Cross-identify ATLAS-CDFS
- Compare to expert cross-identifications

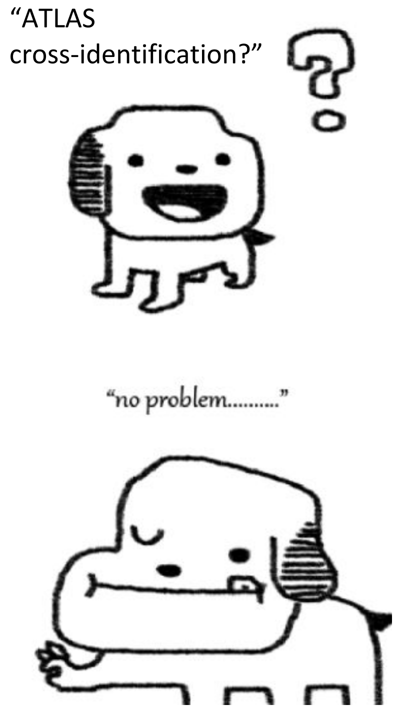
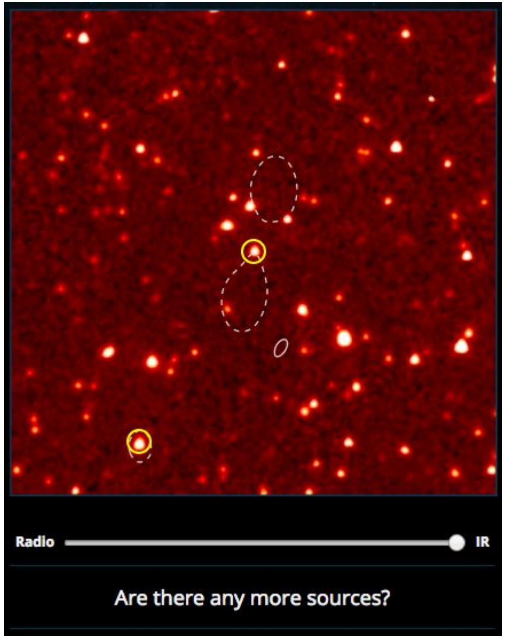


Image: Brian Lee

Machine learning can only answer some questions



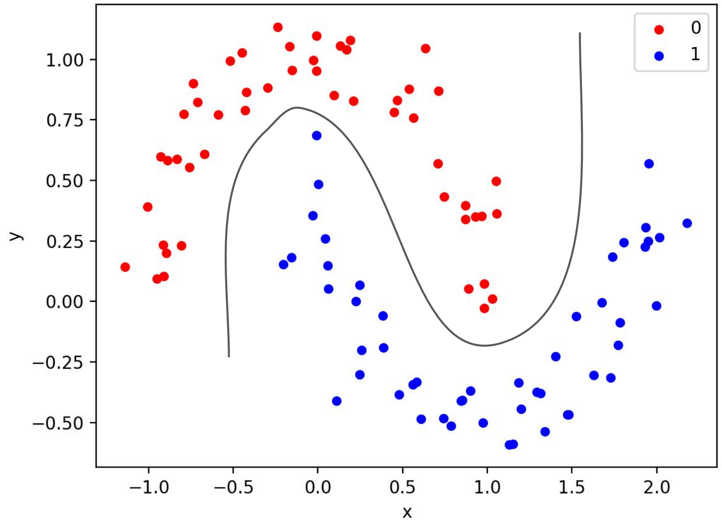
How do you turn an astrophysics question like “Where’s the host galaxy?” into a machine learning question?

Binary classification

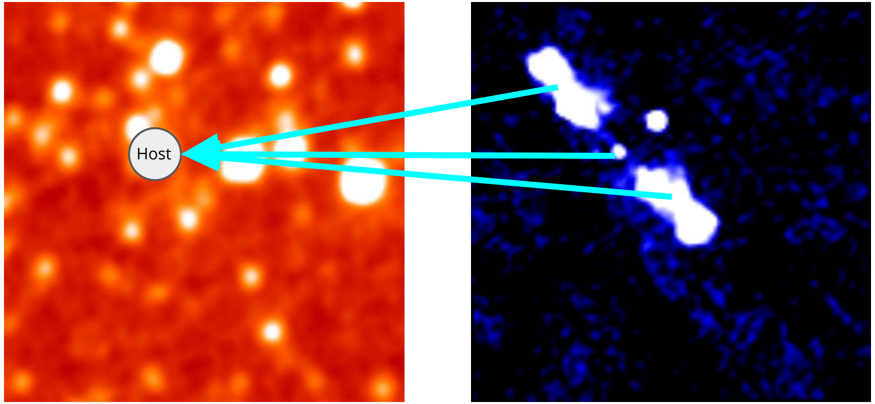
- Find a function that separates objects into two classes
- Well-understood

Equivalent:
$h(x) = g(x) > 0$
$g(x) = \sigma(f(x))$

$$\begin{cases} f : \mathbb{R}^d \to \mathbb{R} \\ g : \mathbb{R}^d \to [0, 1] \\ h : \mathbb{R}^d \to \{\top, \perp\} \end{cases}$$

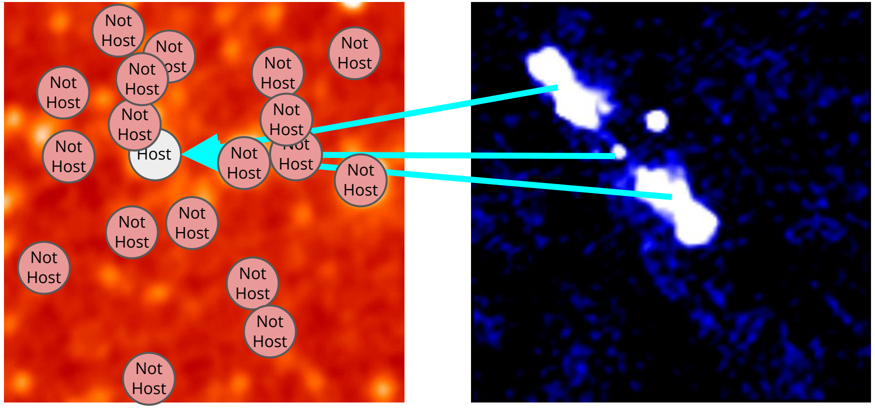


Learning from Radio Galaxy Zoo



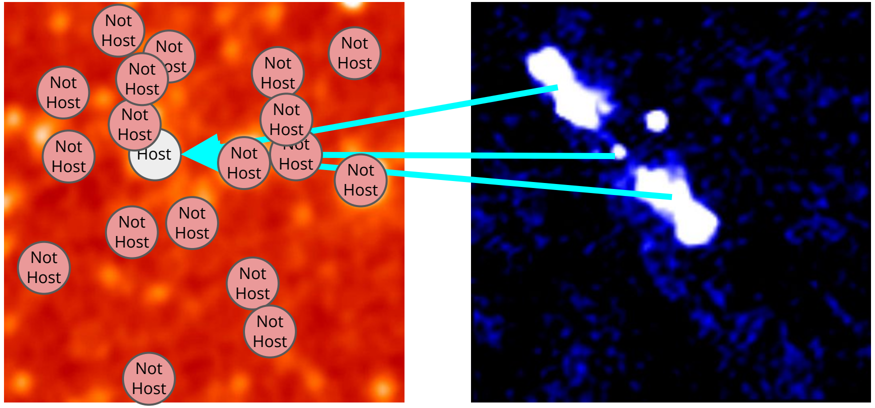
- Assign hosts positive labels

Learning from Radio Galaxy Zoo

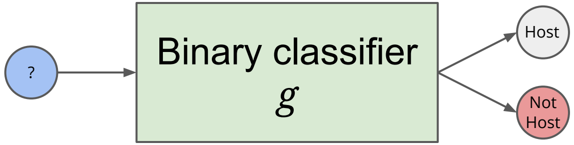


- Assign hosts positive labels
- Assign everything else negative labels

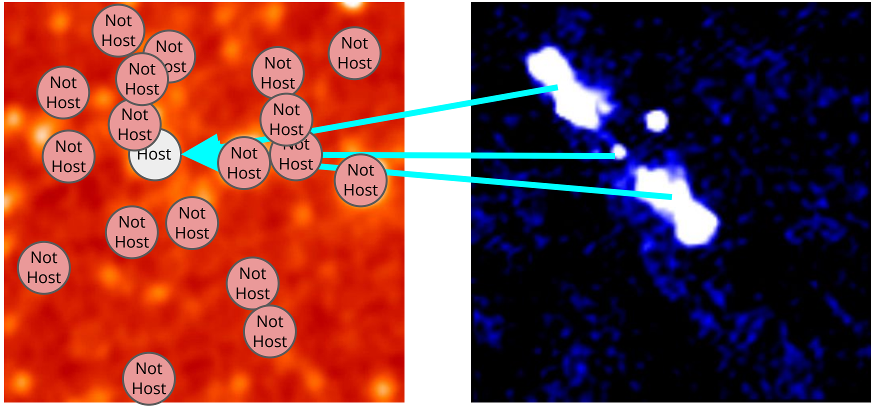
Learning from Radio Galaxy Zoo



- Assign hosts positive labels
- Assign everything else negative labels
- Train classifier to identify *host* and *not host* classes



Learning from Radio Galaxy Zoo



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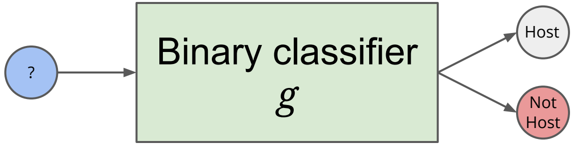
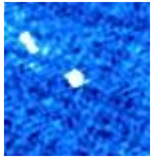
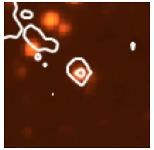
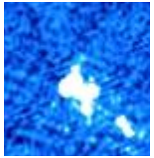
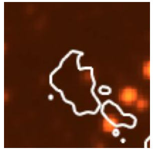


$$\mathrm{xid} : \mathrm{Radio} \to \mathrm{IR}$$

$$\mathrm{xid}(r) = \underset{i\, \in\, \mathrm{IR\ objects}}{\mathrm{argmax}}\ g(i)\ \mathcal{N}(r, i)$$

Cross-identification as binary classification

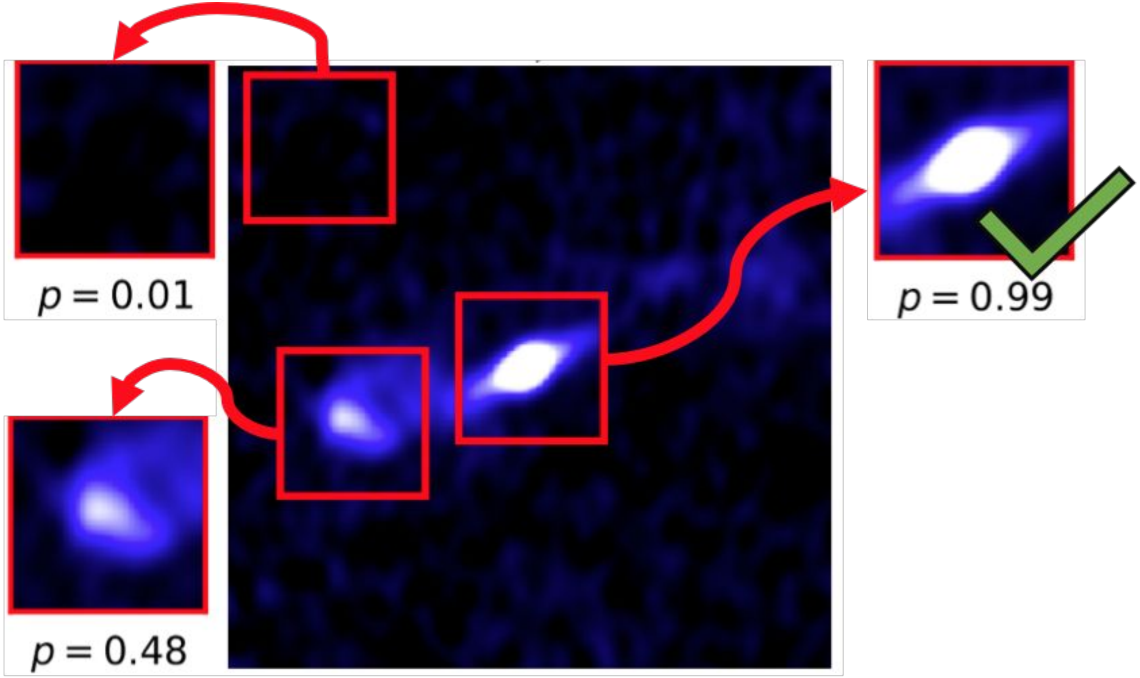
$($  ,  $) \longrightarrow 1$

$($  ,  $) \longrightarrow 0$

Representation of galaxy

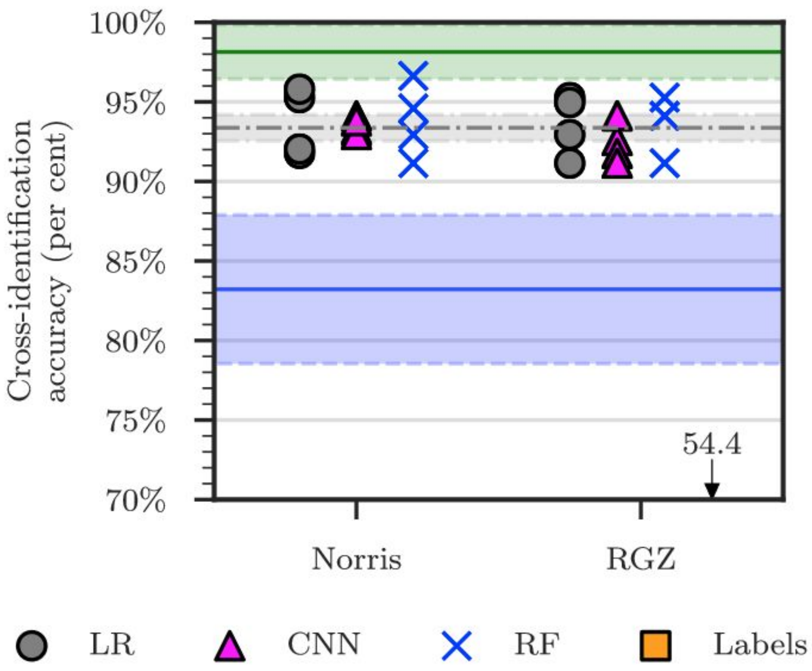
Whether galaxy has an AGN

Cross-identification as binary classification



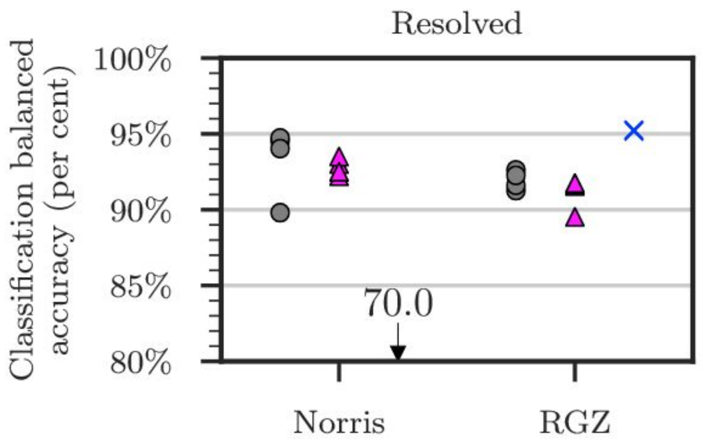
Surprising results on ATLAS-CDFS

- Positional matching beats all other literature
  - Never tested in this context before!
- No classifier appreciably better than positional matching
- Radio Galaxy Zoo shockingly low accuracy
  - But we know from other validation work that Radio Galaxy Zoo should be accurate...



Surprising results on ATLAS-ELAIS-S1

- Apply classifiers to another patch of sky observed in the *same* survey
- Some classifiers dramatically worse, but only when trained on expert labels



Findings summary

- Machine learning for cross-identification requires much larger dataset
- ATLAS-CDFS may not be good training data for EMU
  - Dire implications!
- Some classifiers can be highly sensitive to simple changes in survey parameters
- Radio Galaxy Zoo-trained methods were comparable to expert-trained methods, even though the labels were noisy

New hypotheses

- ATLAS-CDFS not big enough, or too simple, to train good methods
  - Train and test on FIRST instead, n ~ 900 000?
- A sufficiently good binary classifier will give good cross-identification results
  - The core method works!
- Big difference in resolution

Aside: Three contexts for labelling tasks

1. Tasks labellers (e.g. volunteers) are good at
2. Tasks machine learning is good at
3. Physics questions we want to answer

Summary of Part I

- We learned a lot about Radio Galaxy Zoo by trying to use it for machine learning
- We learned a lot about how useful ATLAS is as a pilot survey
- We learned a lot about why the naïve approach works

By thinking about our problems in a machine learning context,
we learned lessons about our data and methods we otherwise wouldn't have.

Learning to identify extragalactic radio sources

PART II:

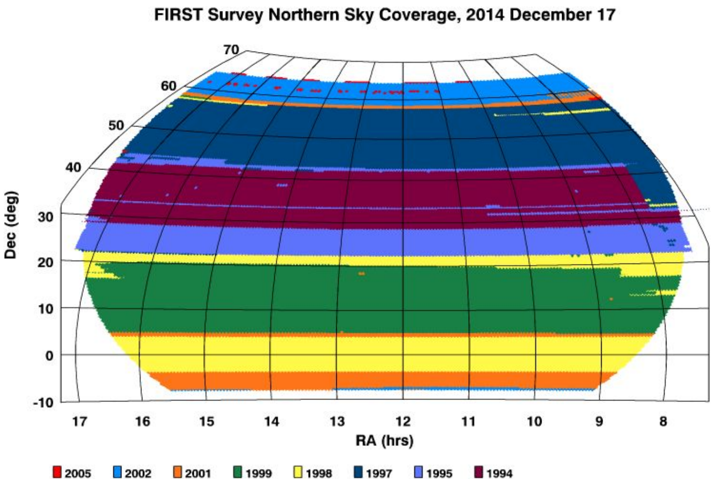
Doing new astronomy with old data

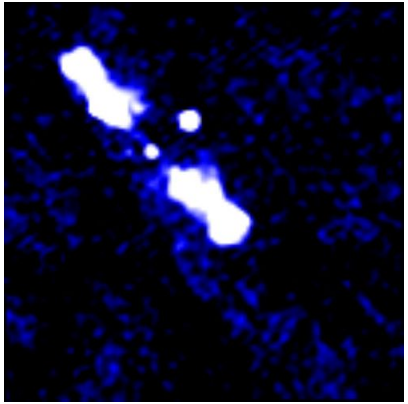
Faint Image of the Radio Sky at Twenty-Centimeters

FIRST

FIRST

- ~900 000 radio sources
- ~75 000 cross-identified with *WISE* images by Radio Galaxy Zoo
- Many more interesting objects





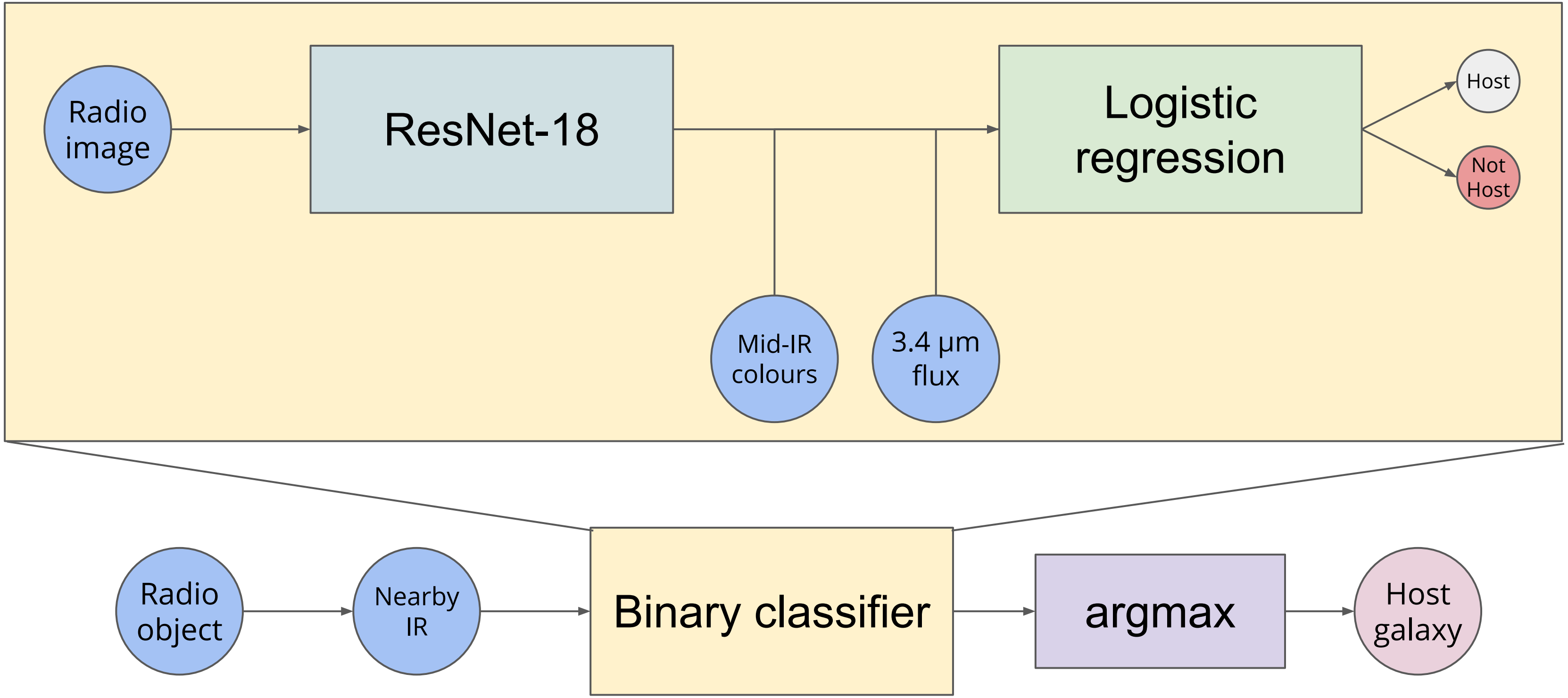
ATLAS to FIRST

- ATLAS
    - Pilot survey for EMU, so looks like new data
    - Small, n ~ 2000
    - Many (~90%+) simple sources
    - ~12” resolution
    - Reliably cross-identified by experts
- FIRST
    - Legacy survey
    - Large, n ~ 900 000
    - Many (~20%) complex sources
    - ~5” resolution
    - Not cross-identified by experts

FIRST cross-identification goals

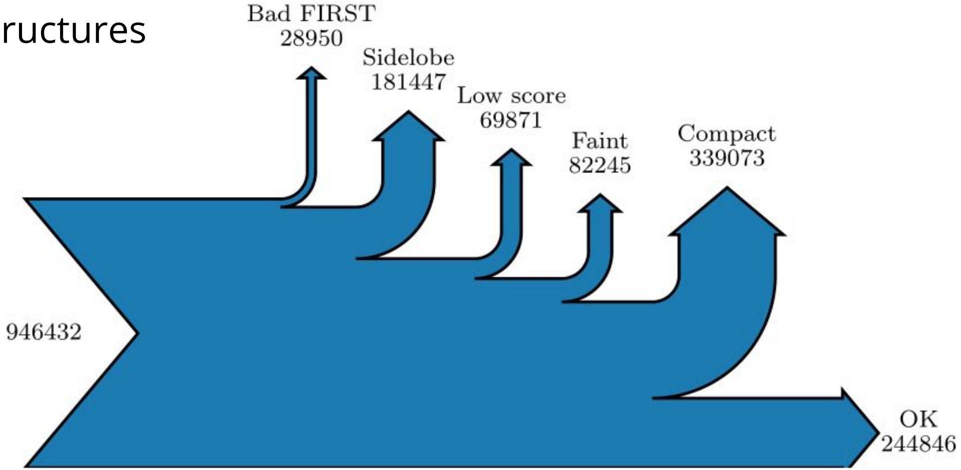
1. Prove our cross-identification method works
2. Do useful astronomy (with legacy data)

New binary classification model



New dataset

- 75 000 radio objects cross-identified by citizen scientists
  - *Much* higher accuracy than for ATLAS images
- 250 000 radio objects
  - Interesting and complex extended structures



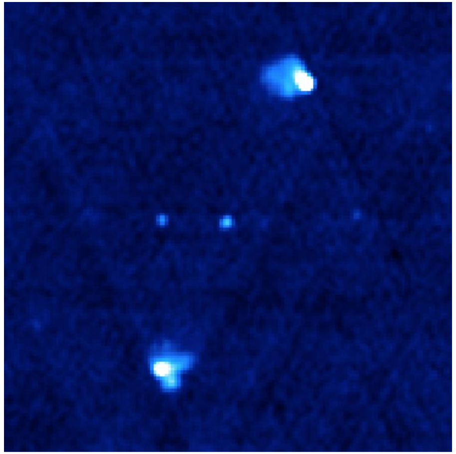
New results

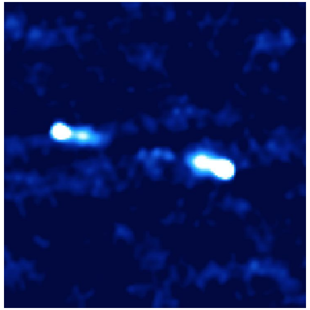
- Our method works!
  - 89.5 ± 0.8% binary classification accuracy
  - Confirmation of our earlier hypotheses about sample size
- Aggregated 250 000 radio objects into 150 000 radio sources
- 35 000 galaxies with redshifts in SDSS
- We call this catalogue ***RGZ-Ex***

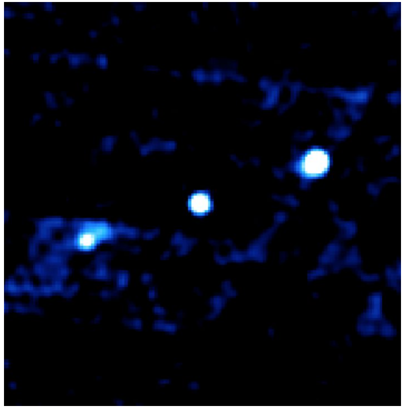
What should we do with the largest catalogue of extended radio galaxies in existence?

New giant radio galaxies

- Giant radio galaxies are >1 Mpc long
- Very difficult to locate as their components can be very spread out
- We found 40 giant radio galaxies
    - Most were not known to literature

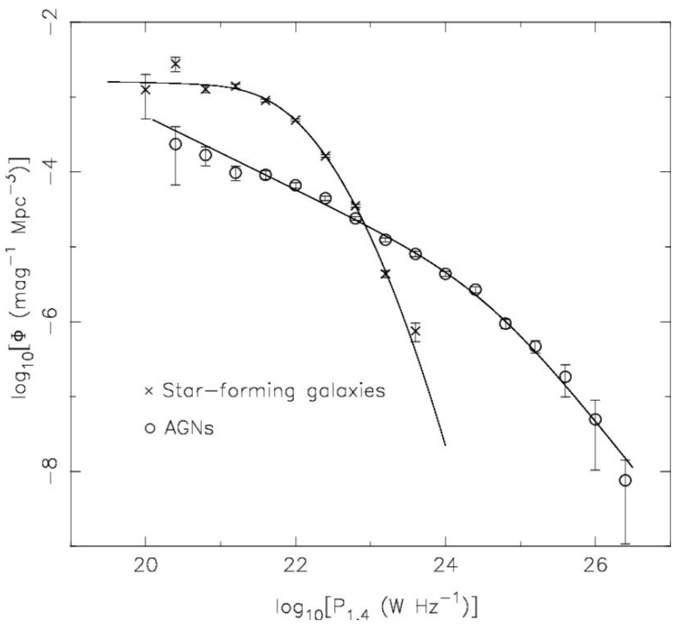






Radio luminosity functions

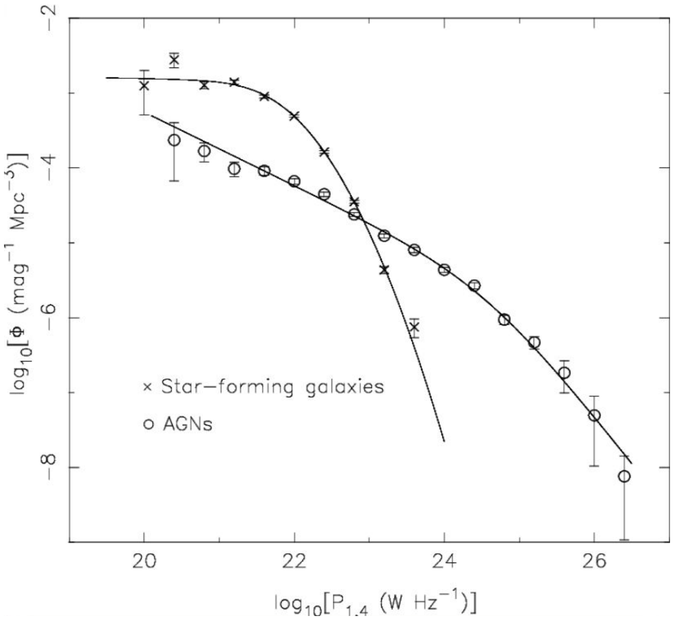
- Comoving density of radio sources as a function of radio luminosity
    - Distribution of radio source luminosities in a *physically meaningful* way



Radio luminosity function divided into radio due to star formation and radio due to AGN.
Image: Mauch & Sadler (2007)

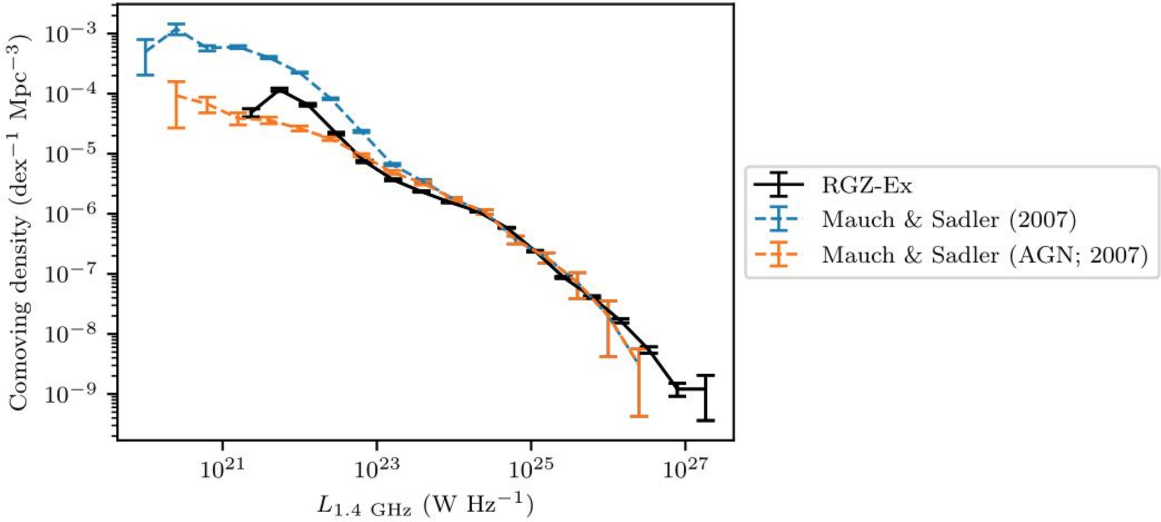
Radio luminosity functions

- Comoving density of radio sources as a function of radio luminosity
  - Distribution of radio source luminosities in a *physically meaningful* way
- Fractional radio luminosity functions
  - Luminosity distribution of physically-selected subsets may be different
  - Helps understand evolution and structure of radio galaxies

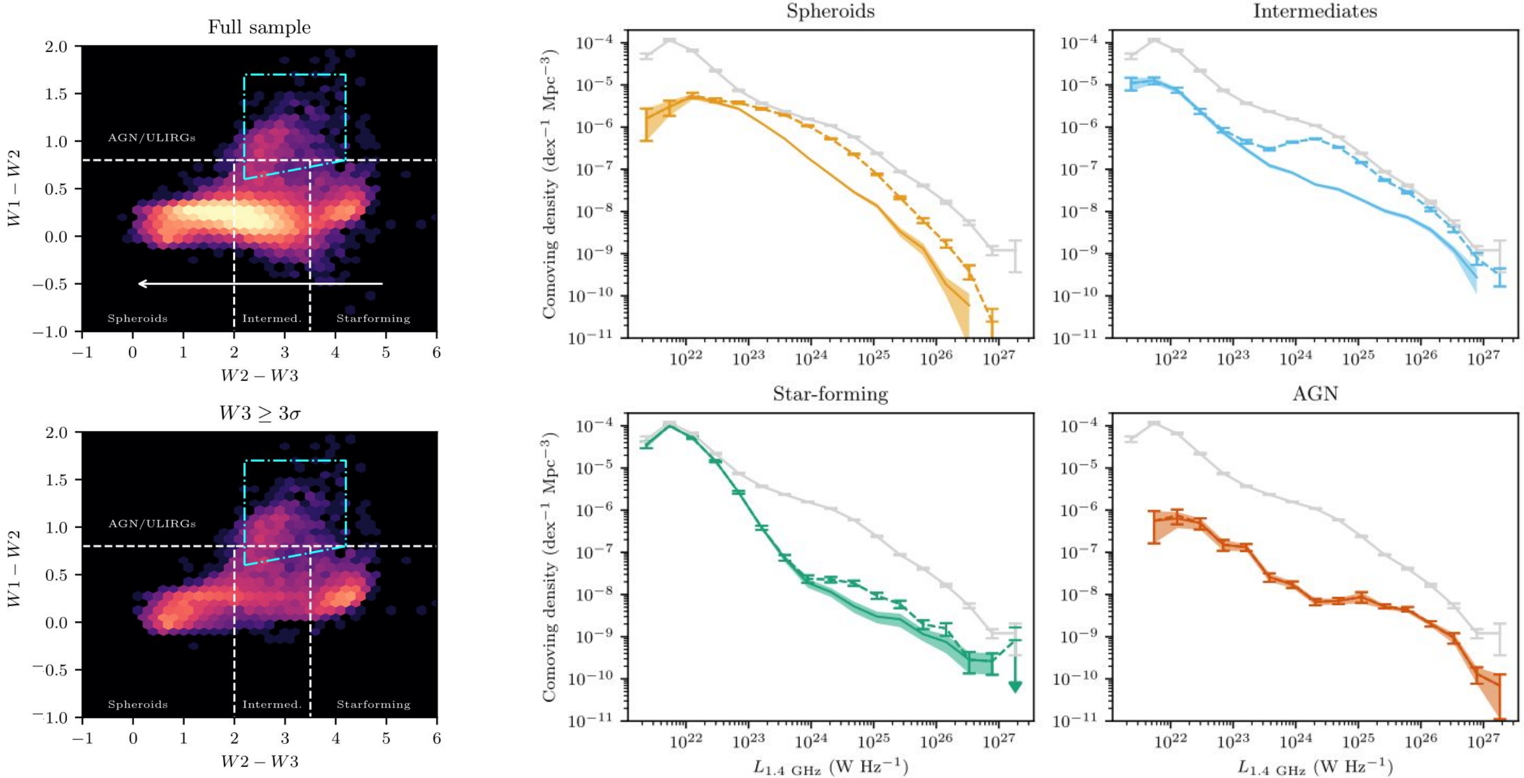


Radio luminosity function divided into radio due to star formation and radio due to AGN.
Image: Mauch & Sadler (2007)

Luminosity function of extended sources



Fractional luminosity functions



Looking forward: EMU

- FIRST gave very different results to previous work on EMU-ATLAS
  - Much lower source density on sky
  - Higher angular resolution — more extended sources
  - More training and prediction data
- Generalisation to EMU will be non-trivial

Image: James Garlick via ABC News

Summary of Part II

- We proved our method works
- We showed that FIRST and ATLAS are different when it comes to automation
- We found ways to look through our data without explicitly developing them
- We made a useful physics product

Different datasets can give vastly different results — and not always in a way you might expect.

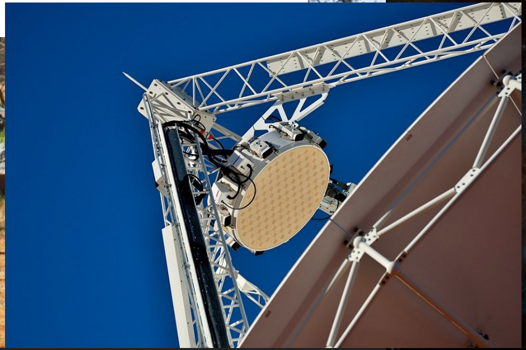
Learning to identify extragalactic radio sources

PART III:

But what about the magnetic fields?

Australian Square Kilometre Array Pathfinder

- Huge 30 deg^2 field of view
- Fast!
- 32 antennae
- >2 PB of science data so far



The Wajarri Yamatji people are the traditional custodians of the land that ASKAP is built on.

Image: CSIRO

Data are coming fast

- Two main projects on ASKAP
- Evolutionary Map of the Universe
- Widefield ASKAP L-Band Legacy All-Sky Blind Survey

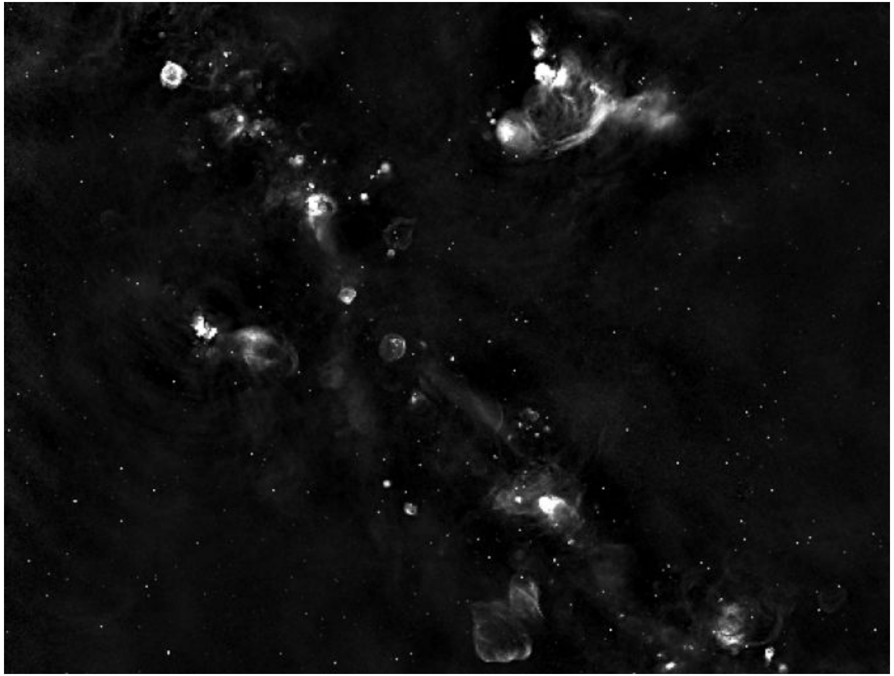


Image: Early science ASKAP-EMU data, via Ray Norris.

Data are coming fast

- Two main projects on ASKAP
- EMU
- WALLABY

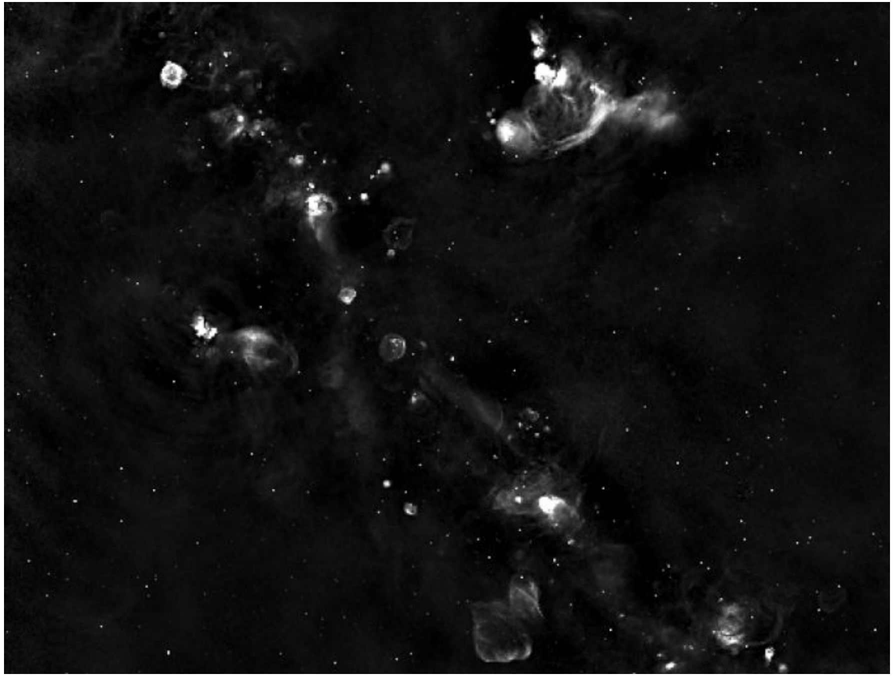


Image: Early science ASKAP-EMU data, via Ray Norris.

Data are coming fast

- Two main projects on ASKAP
  - EMU
  - WALLABY
- Eight simultaneous projects
  - Galactic ASKAP Spectral Line Survey
  - Polarization Sky Survey of the Universe's Magnetism
  - First Large Absorption Survey in HI
  - Variables and Slow Transients
  - Commensal Real-time ASKAP Fast Transients
  - Deep Investigations of Neutral Gas Origins
  - Compact Objects with ASKAP: Surveys and Timing
  - Meeting the Long Baseline Specifications for the SKA

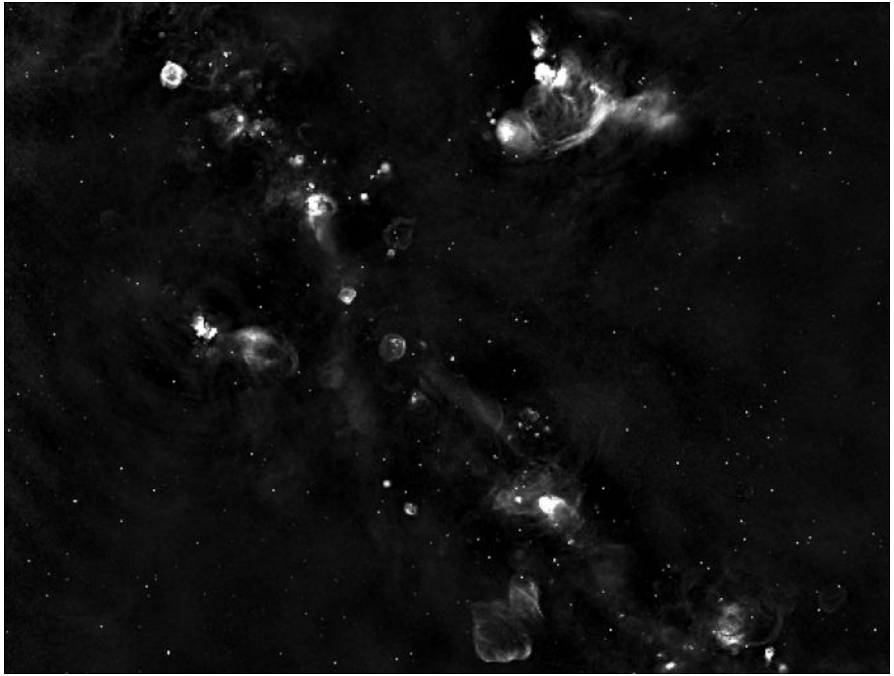


Image: Early science ASKAP-EMU data, via Ray Norris.

Data are coming fast

- Two main projects on ASKAP
  - EMU
  - WALLABY
- Eight simultaneous projects
  - GASKAP
  - POSSUM
  - FLASH
  - VAST
  - CRAFT
  - DINGO
  - COAST
  - ASKAP VLBI

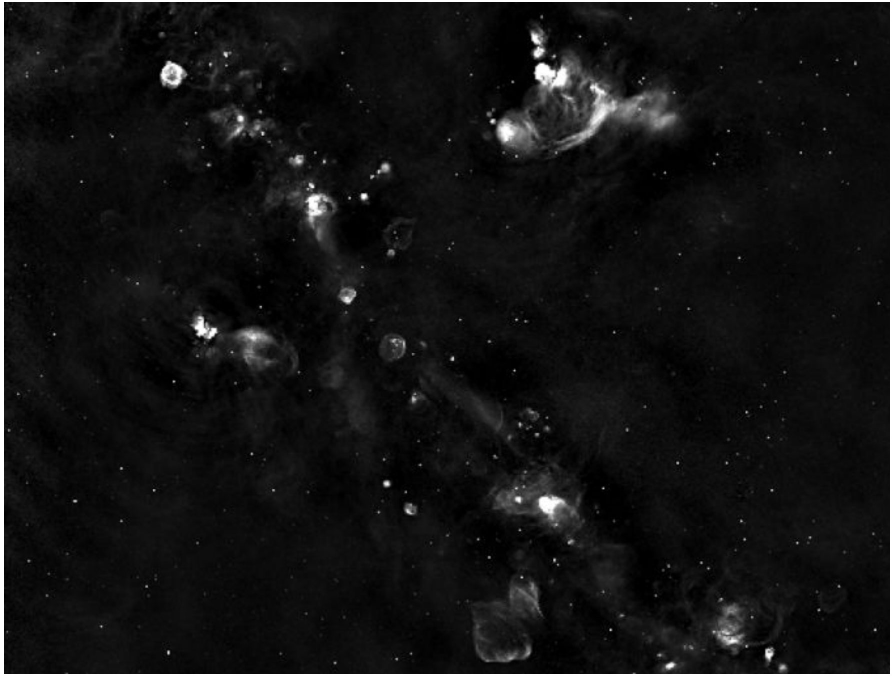
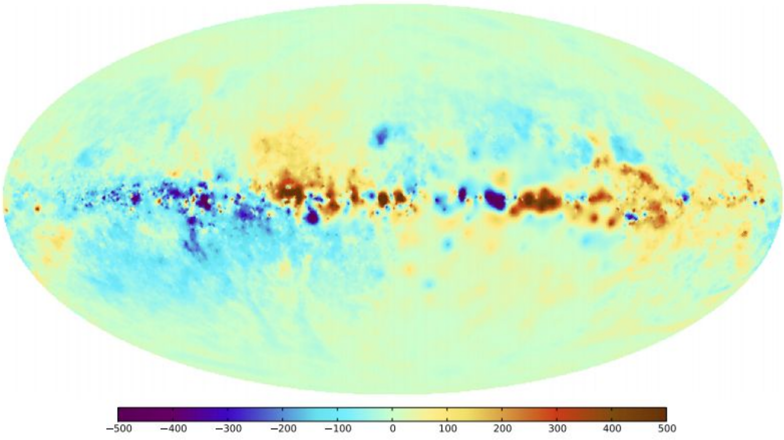


Image: Early science ASKAP-EMU data, via Ray Norris.

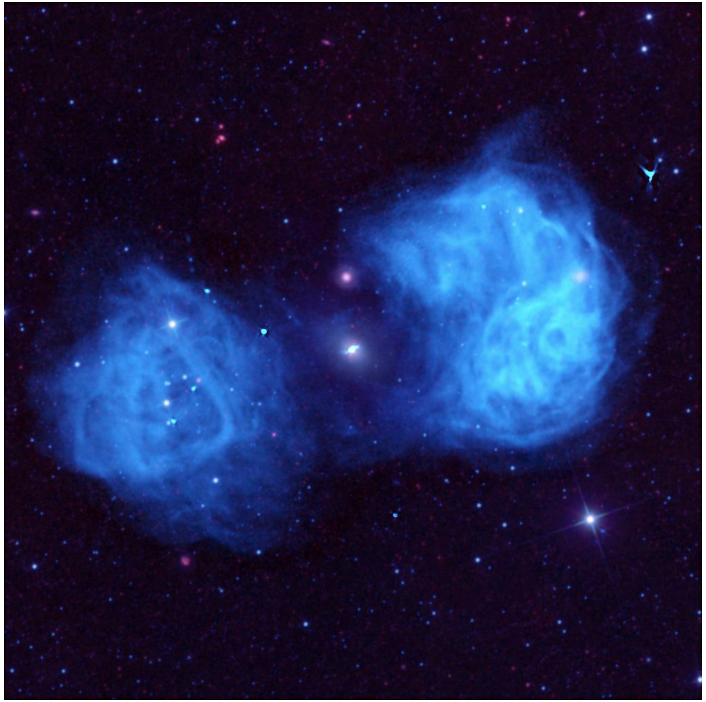
POSSUM

- Polarised “all-sky” survey to complement EMU
- ~1 000 000 polarised radio sources
- Broad benefits to astronomical magnetic field research

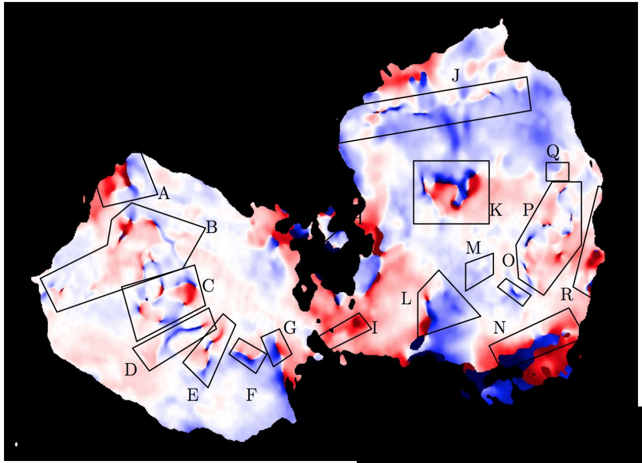


Oppermann+12 Faraday map of the galaxy.

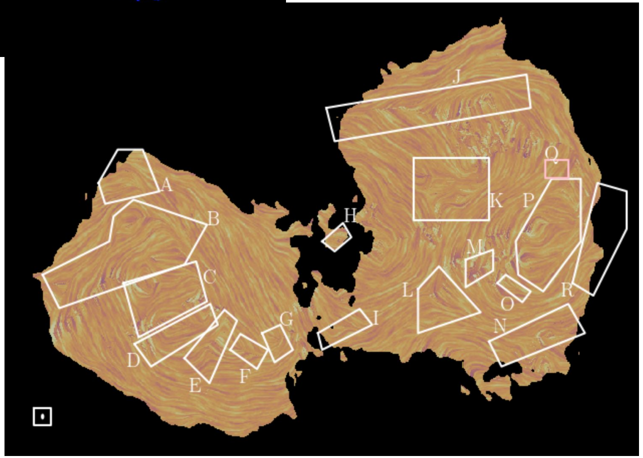
Polarisation



Fornax A in radio continuum (DRAO).



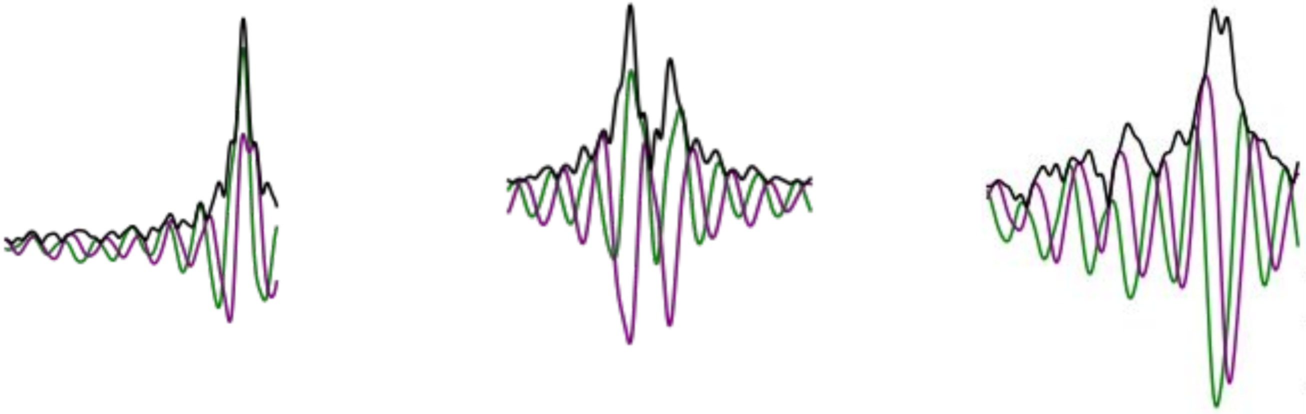
Peak Faraday depth (Anderson+18).



Magnetic field orientation (Anderson+18).

Faraday complexity

- Simple sources are useful for investigating the magnetic fields in between you and the source
- Complex sources are useful to identify for follow-up with slower (or even manual) reduction methods

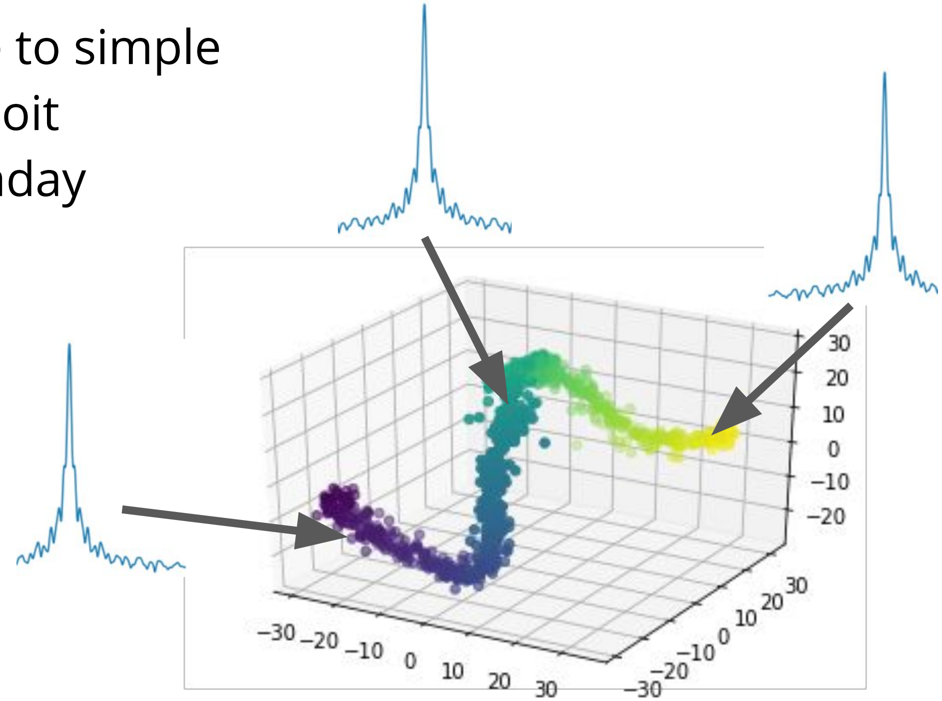


Detecting Faraday complexity

- Plot the angle against squared wavelength and see if it's a line?
- Deconvolve (hard!) to try and get the number of components?
- Machine learning?
    - Convolutional neural networks seem to do an excellent job (94.9% accuracy on simulated early science POSSUM data)
    - But are very complicated, hard to understand

Simple Faraday spectra lie on a manifold

- There is a fundamental structure to simple Faraday spectra that we can exploit
- Faraday spectra with similar Faraday depths are “next to” each other



Simple Faraday spectra lie on a manifold

- There is a fundamental structure to simple Faraday spectra that we can exploit
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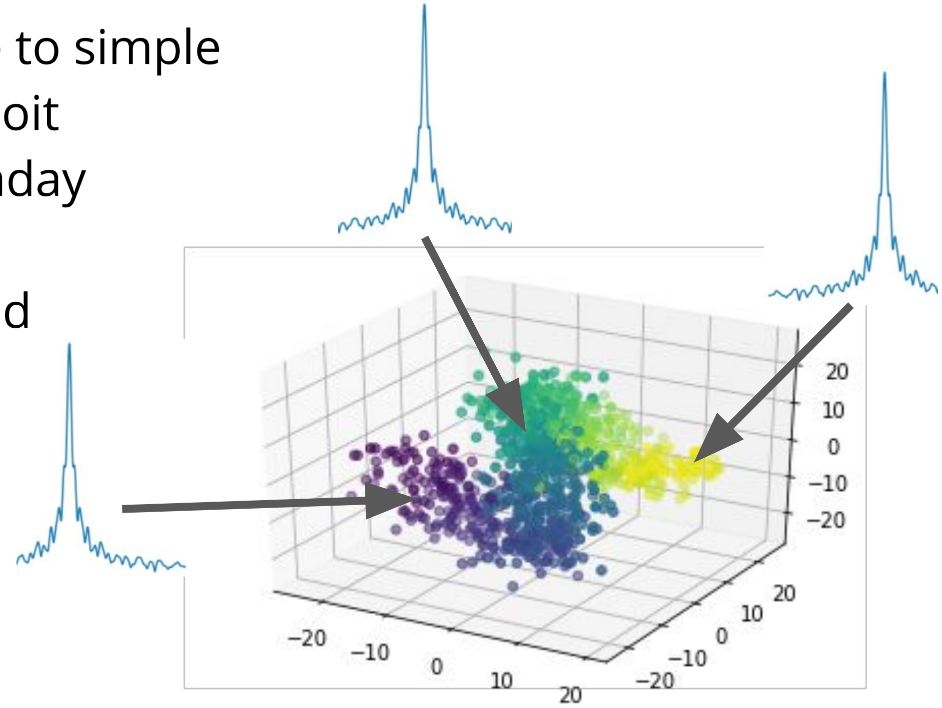
- Width of the manifold determined by the noise level



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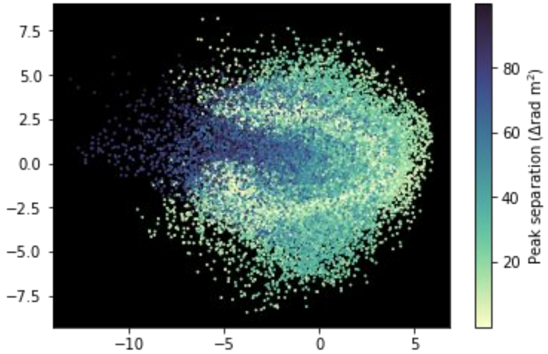
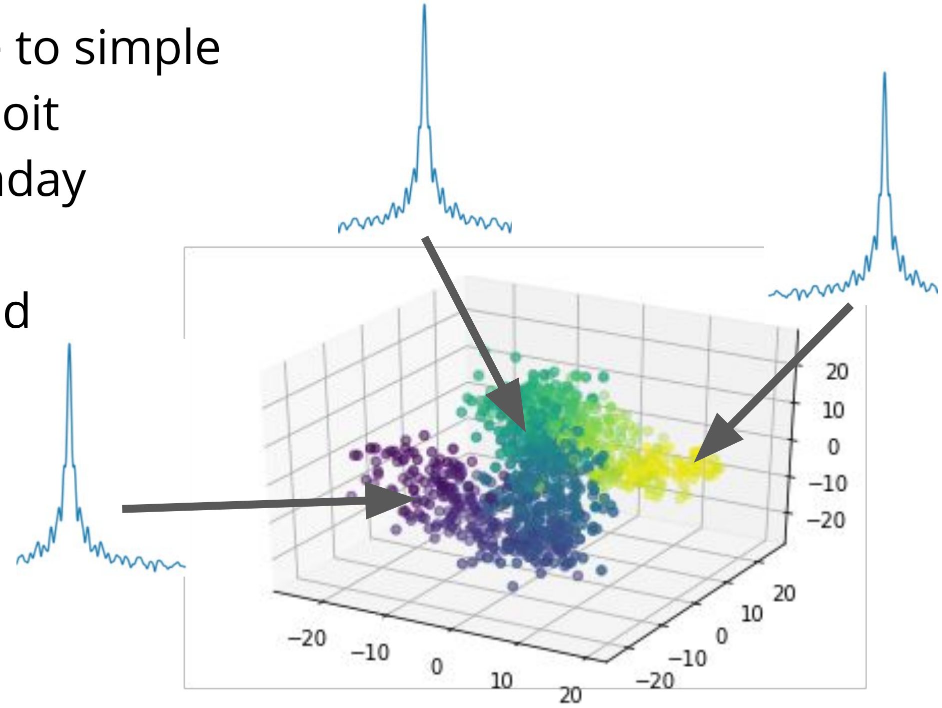
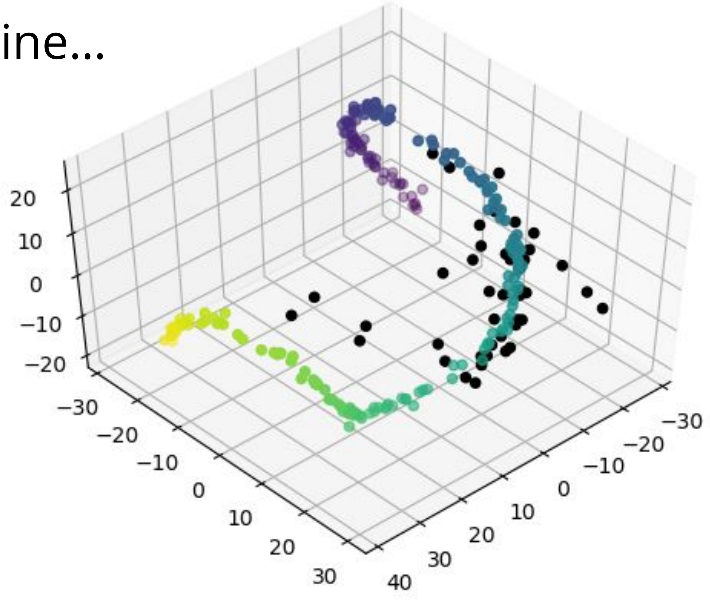




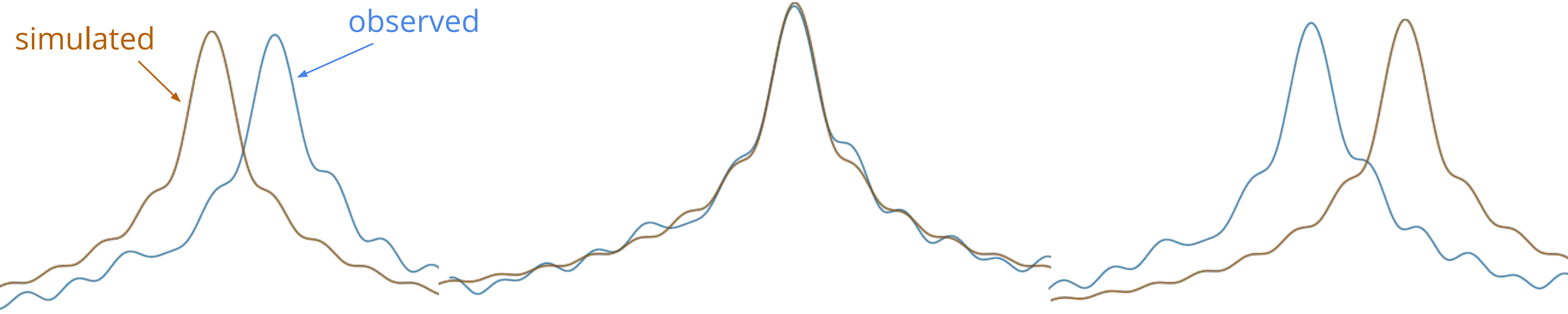
Simple Faraday spectra lie on a manifold

- Project real data onto the manifold
- The closer to the noise-free simple line...
  - The simpler?
  - The less noisy?
  - Fundamentally unclear, since complex Faraday spectra can look just like noisy simple Faraday spectra



Characterise Faraday spectra by simple ones

Slide a simulated simple Faraday spectrum across observation to find the best fit.



Too far left... Perfect fit! Too far right...

Characterise Faraday spectra by simple ones

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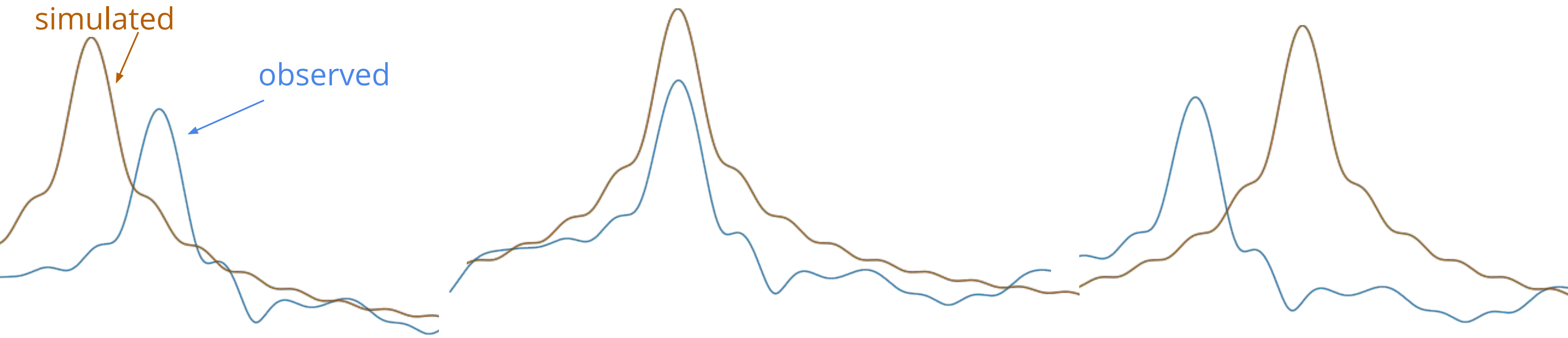

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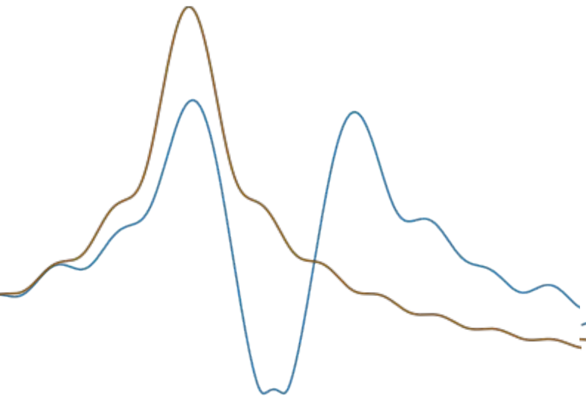
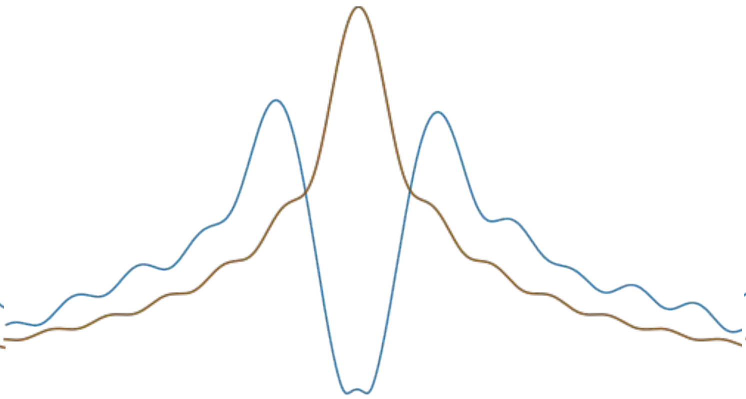
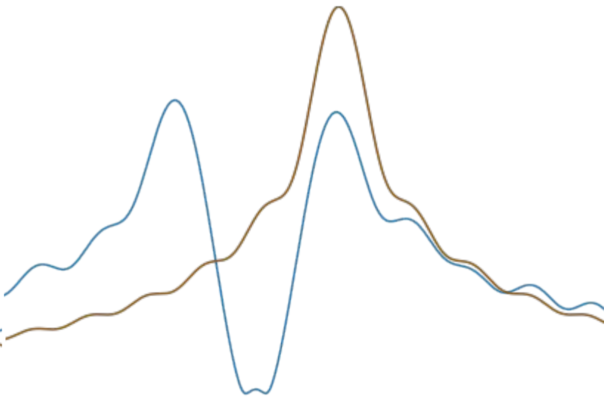


Perfect fit?



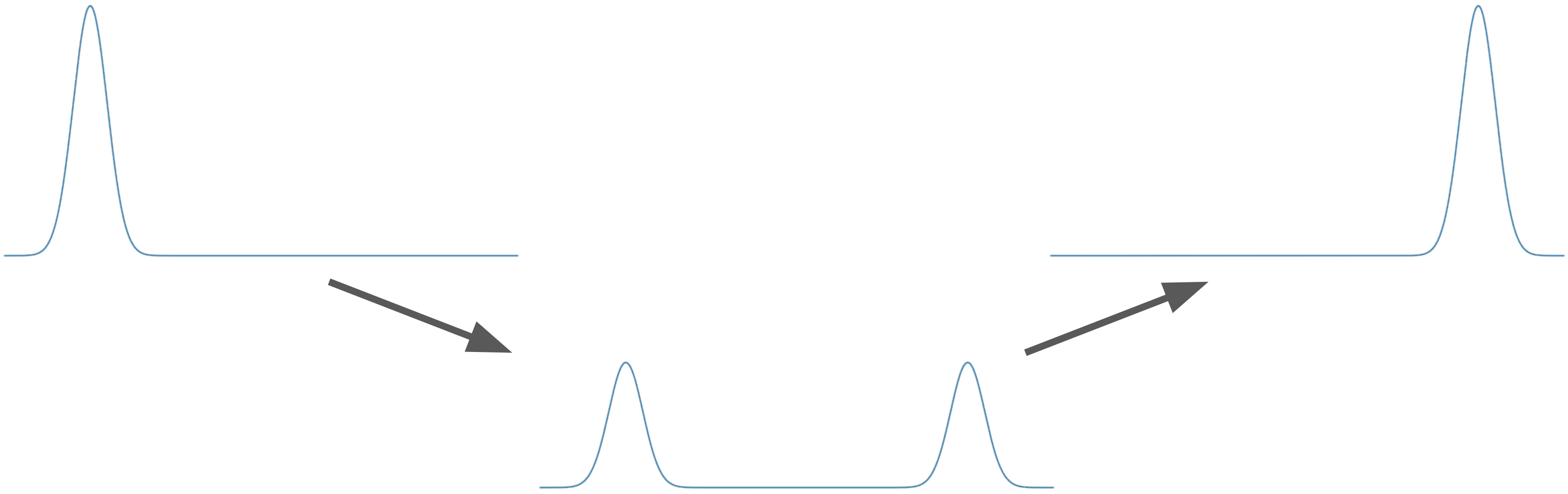
Perfect fit?



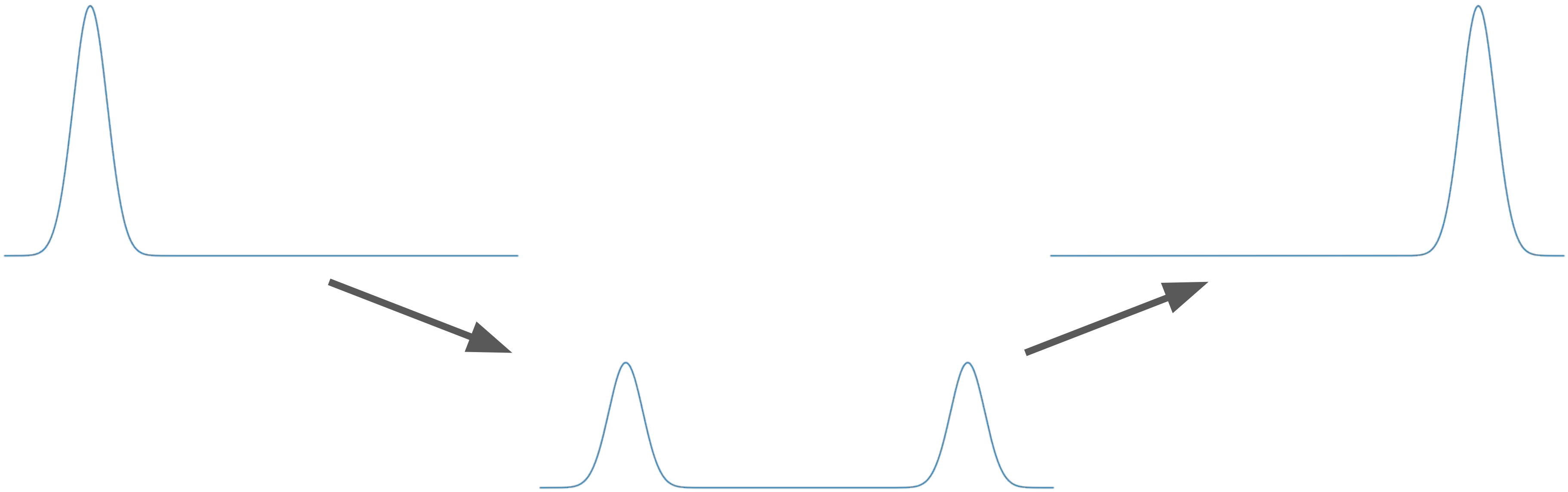
Perfect fit?

Distances between Faraday spectra

Distances between Faraday spectra

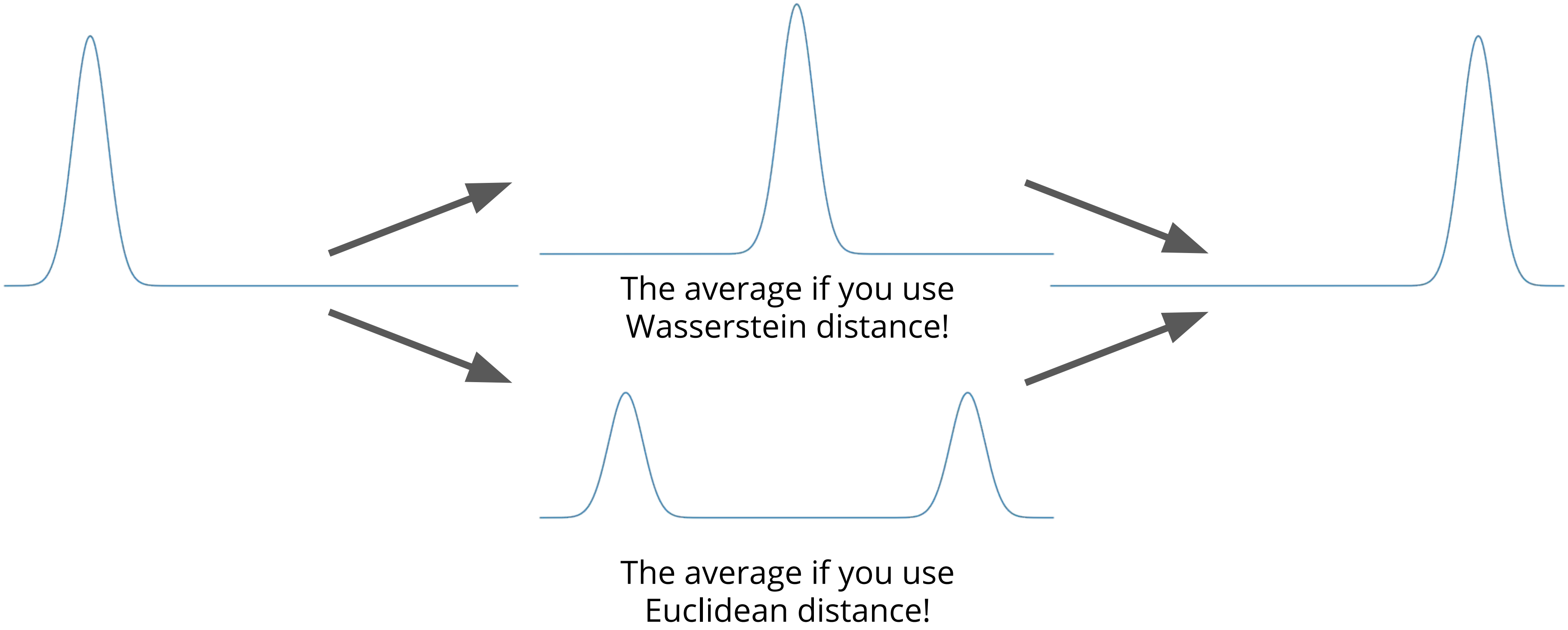


Distances between Faraday spectra



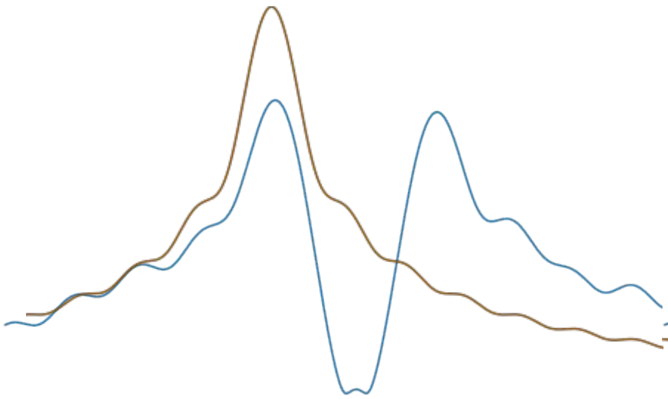
The average if you use
Euclidean distance!

Distances between Faraday spectra

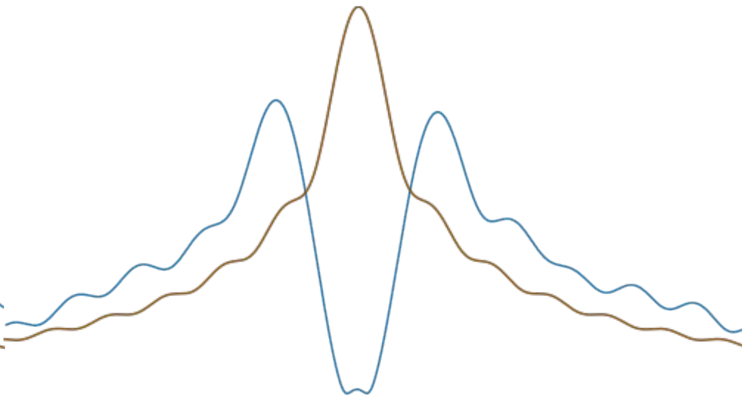


Characterise Faraday spectra by simple ones

Slide a simulated simple Faraday spectrum across observation to find the best fit.



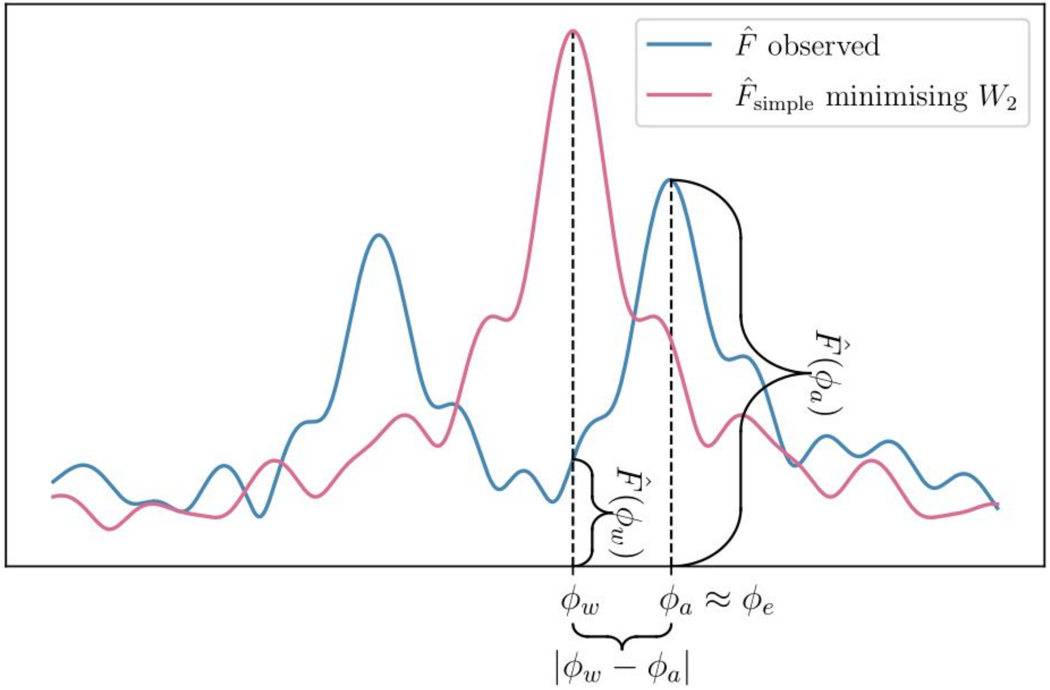
Best fit for
Euclidean distance



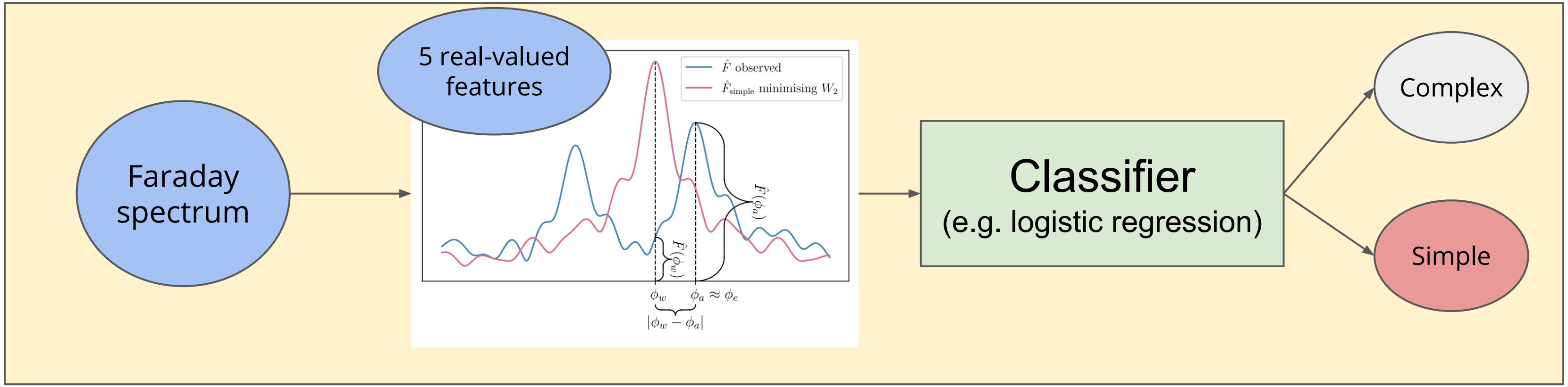
Best fit for
Wasserstein distance

Characterise Faraday spectra (attempt 2)

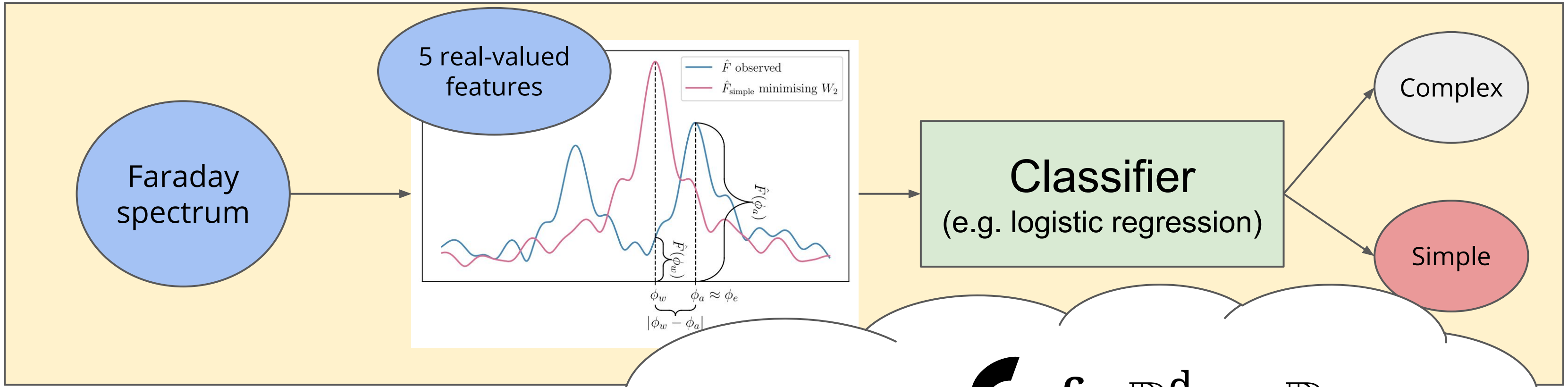
- Wasserstein minimiser
- Euclidean minimiser
- Distance between these minimisers
- Polarised flux at each minimising depth



Faraday complexity classification



Faraday complexity classification



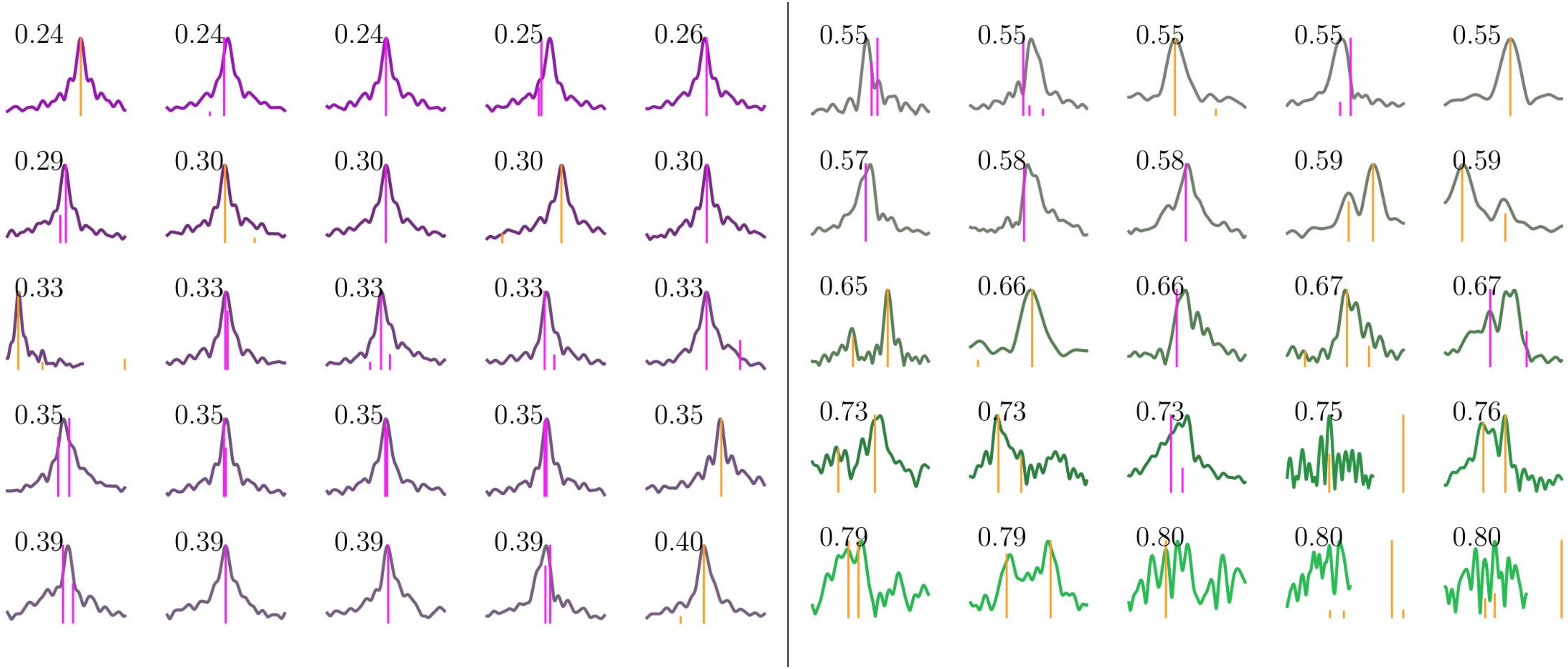
Equivalent:

$h(x) = g(x) > 0$

$g(x) = \sigma(f(x))$

$$\begin{cases} f : \mathbb{R}^d \longrightarrow \mathbb{R} \\ g : \mathbb{R}^d \longrightarrow [0, 1] \\ h : \mathbb{R}^d \longrightarrow \{\top, \perp\} \end{cases}$$

Classifying real observations



Comparison to neural networks

- State-of-the-art convolutional neural network accuracy: 94.9%
- Accuracy with logistic regression: 94.4%
- Accuracy with random forests: **95.1%**

A simple classifier with 5 real-valued features
beats convolutional neural networks!

Summary of Part III

- We can do better than a complicated machine learning model by taking advantage of the structure of the data
- We produced an interpretable way to characterise Faraday spectra
- We gained insight into the structure of Faraday spectral data

Some problems can't be solved by simple application of off-the-shelf tools.

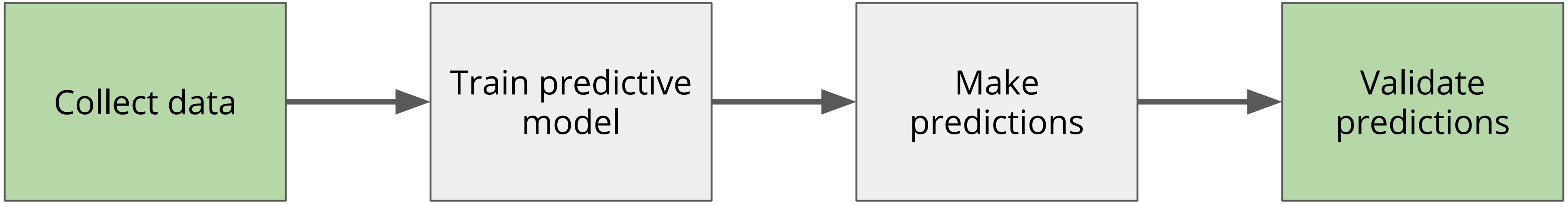
Summary

- I learned a lot about my data and methods by thinking about them from two different perspectives
- I developed and demonstrated new algorithms for cross-identification and spectropolarimetric classification
- I produced a radio cross-identification catalogue and several useful radio luminosity functions
- I identified ~40 giant radio galaxies automatically
- I introduced new ways of thinking about radio astroinformatics

Machine learning and astronomy together can solve different problems, and provide different perspectives, than either would alone.

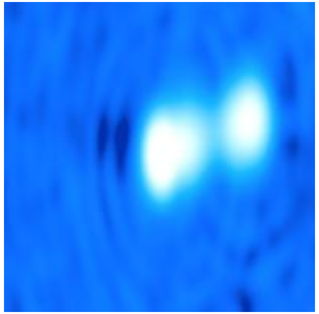
Data quality for machine learning

- Data should be
  - Accurate
  - Complete: we want to sample the full data space
  - Close to its usage
  - Understandable: we want to know when it’s wrong
- Issues in any of these affect training and evaluation

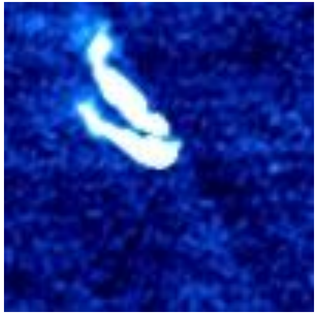


Citizen scientists are noisy

- Validating citizen scientist labels is already a hard task
- We don't know how!
    - Are some things intrinsically hard to label?
    - Are volunteers better at certain tasks?
    - Do volunteers "overfit" to some datasets?



Accuracy: 30%

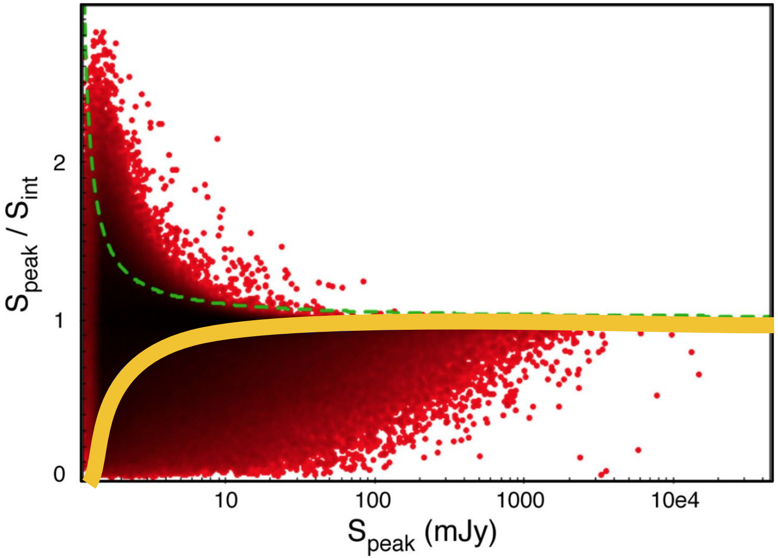


Accuracy: 80%

Accuracy of Radio Galaxy Zoo varies between ATCA (left) and VLA (right) observations. But why?

Citizen science only uses interesting objects

- We only show interesting objects
- At odds with good validation
  - Citizen science projects by design have different distributions to target distribution
  - Validation will favour particular parts of the feature space
  - Unexpected results: ML methods may fail on “simple” cases!

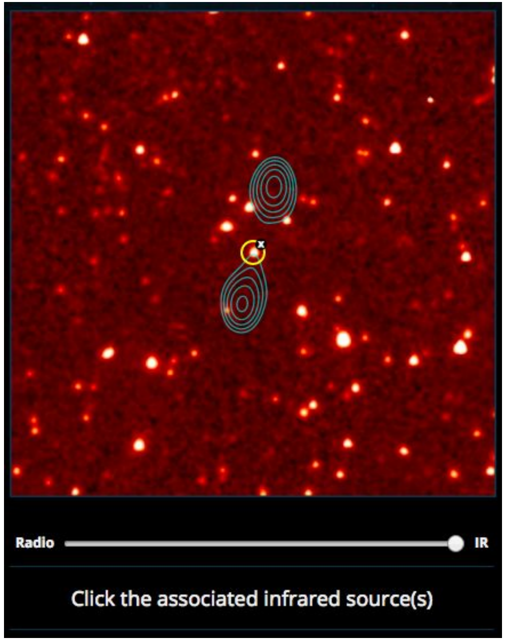


Radio Galaxy Zoo only shows objects below the gold line to volunteers.

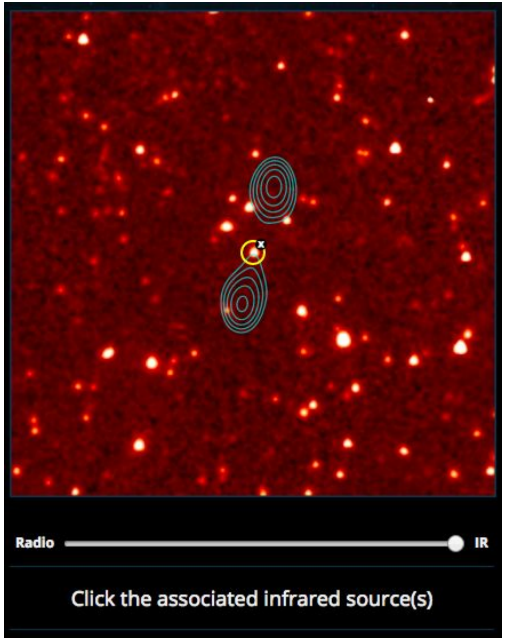
Image: Adapted from Banfield+15

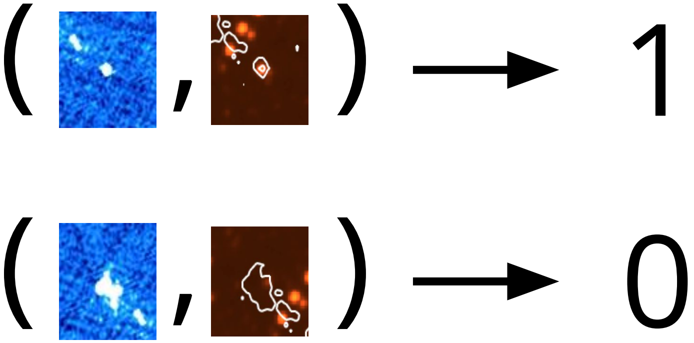
We don’t get the labels we need

- People are inherently better at some tasks than others
- We present non-experts with suitable tasks that don’t require domain knowledge
- Three distinct contexts:
    - Tasks volunteers are good at
    - Tasks ML is good at
    - Physics questions we want to answer
- Are we validating the method, or validating our data transformation?



Different tasks for volunteers and machine learning



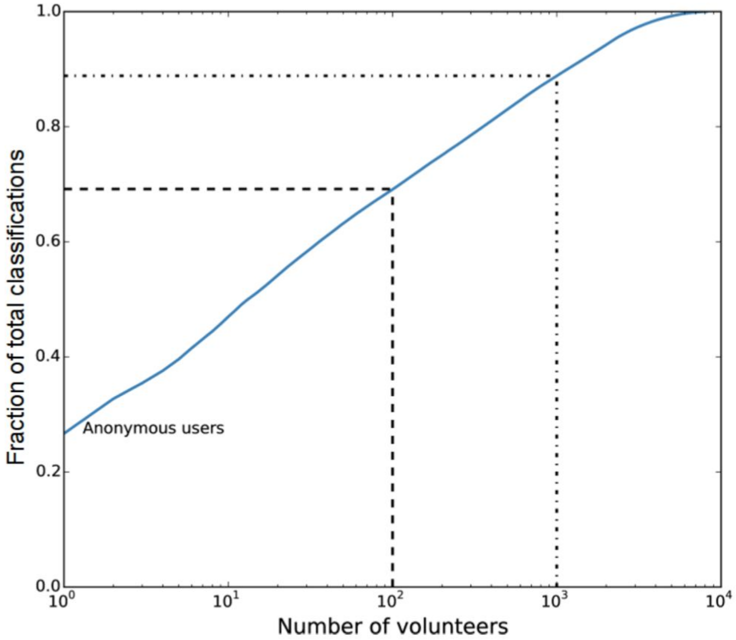


Representation of galaxy

Whether galaxy has an AGN

Noise is hard to characterise

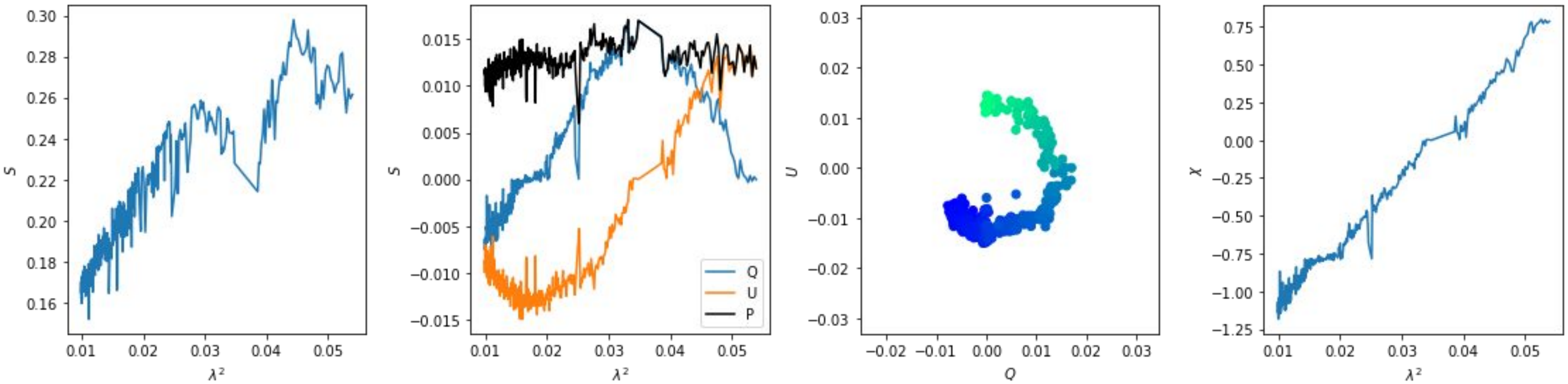
- Different tasks for citizen scientists and machine learning
  - Even when citizen science noise is quantified this doesn't map clearly to label noise or uncertainty
- 10,000s of annotators make standard label noise estimation hard
  - Joint groundtruth-model estimators fail



Cumulative distribution of classifications.

Image: Banfield+15

Polarised radio sources

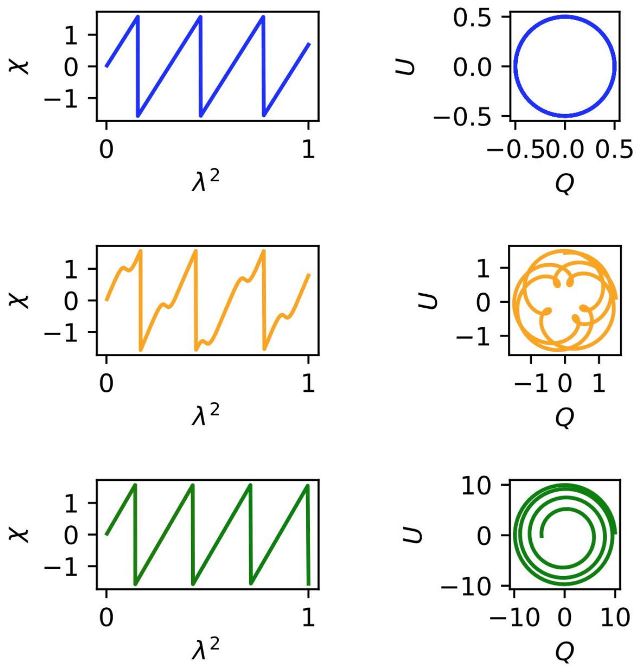


A simple polarised radio source observed with ATCA (courtesy of Jack Livingston).

Left to right: Total intensity, polarised intensity, linear polarisation plane, polarisation angle.

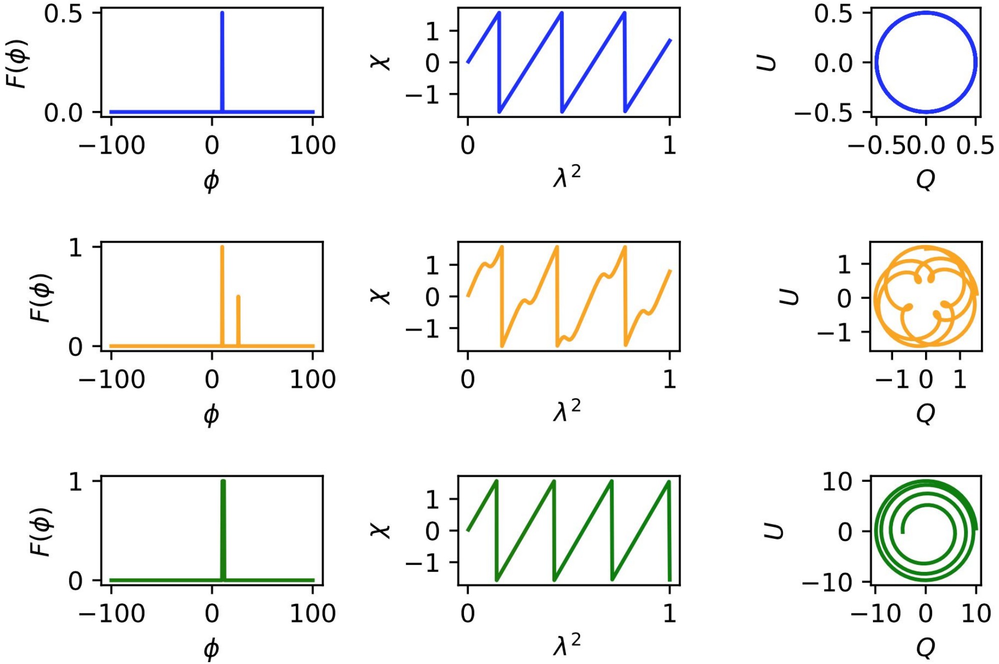
Polarised radio sources

- Simple sources (“screens”) with angle linear in squared wavelength
- Overlapping sources with superimposed rotations
- “Thick” sources with rotation and emission (“slabs”)
    - Depolarisation…



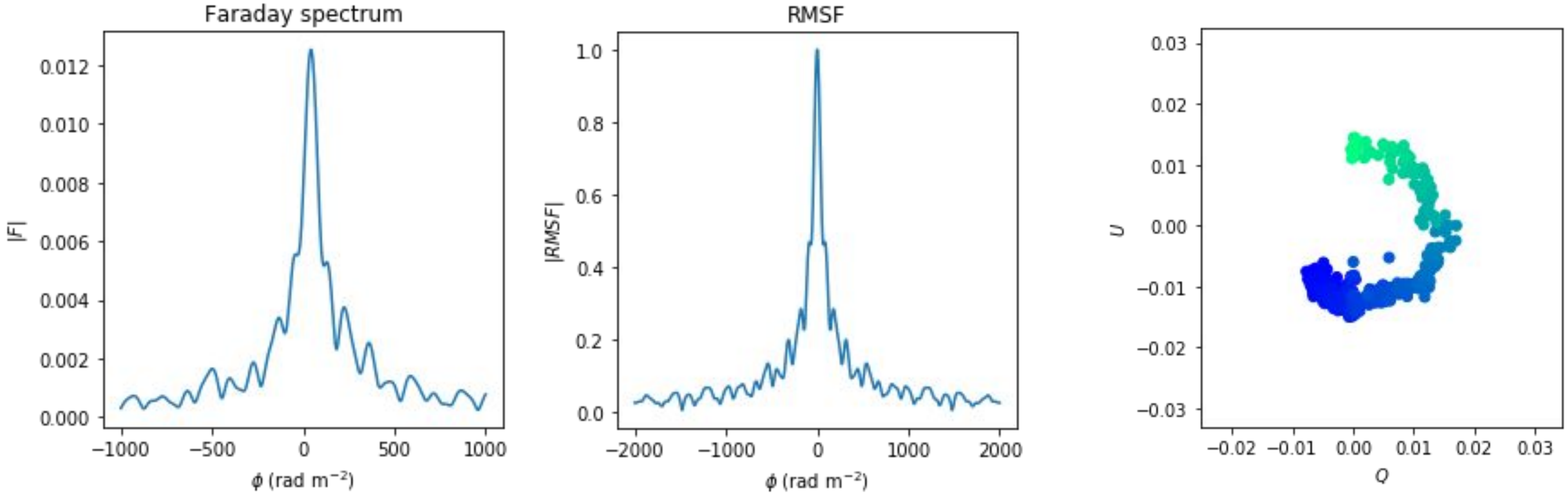
Faraday spectra

- Fourier transform* of polarised spectrum
- Conjugate axis is the *Faraday depth*
- Obvious separation of complexities



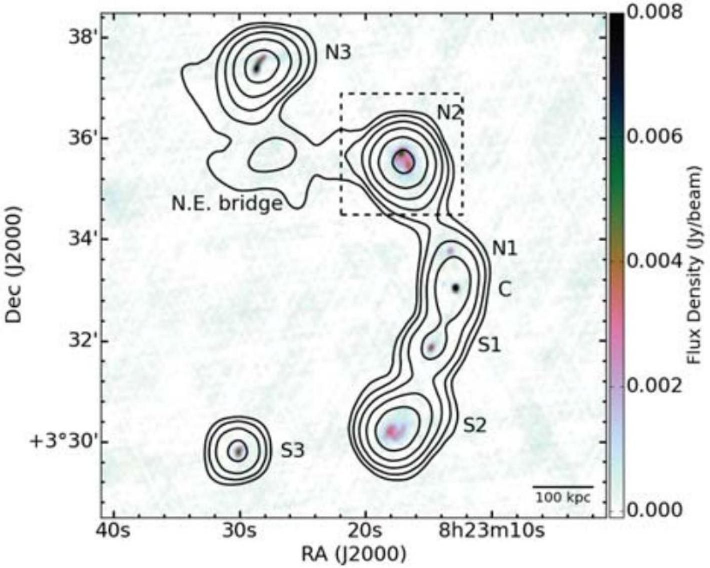
Faraday spectra

Observed spectra noisy and convolved with a spread function (RMSF):



Faraday spectrum of the previous source along with its spread function (courtesy of Jack Livingston).

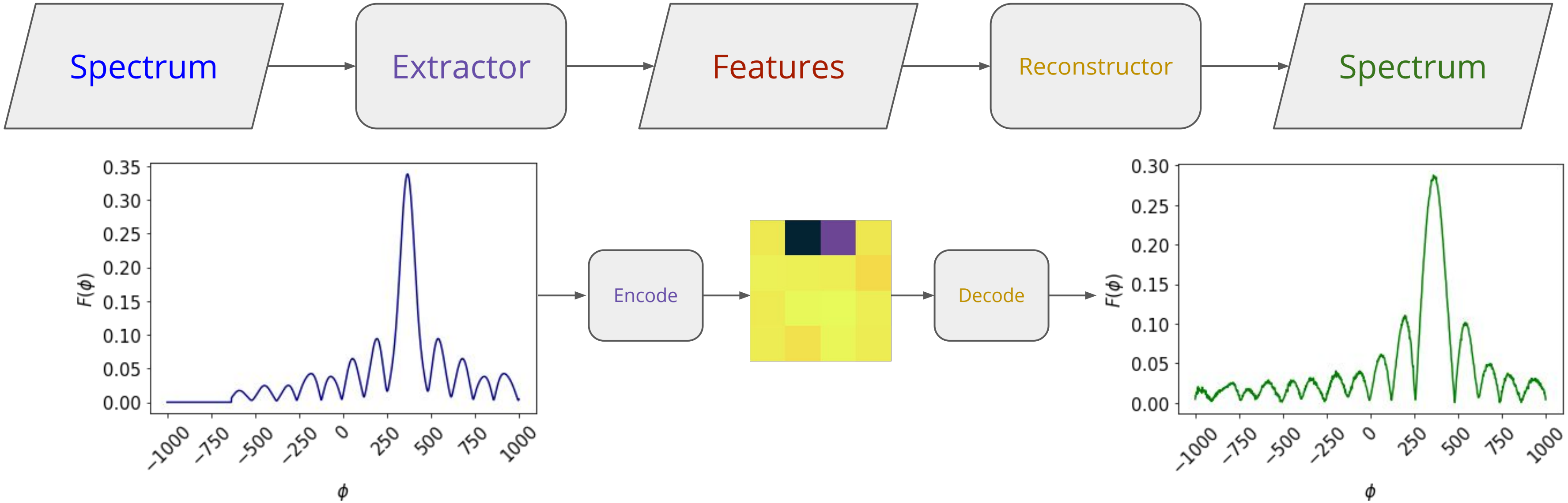
Lots of data hold lots of astrophysics



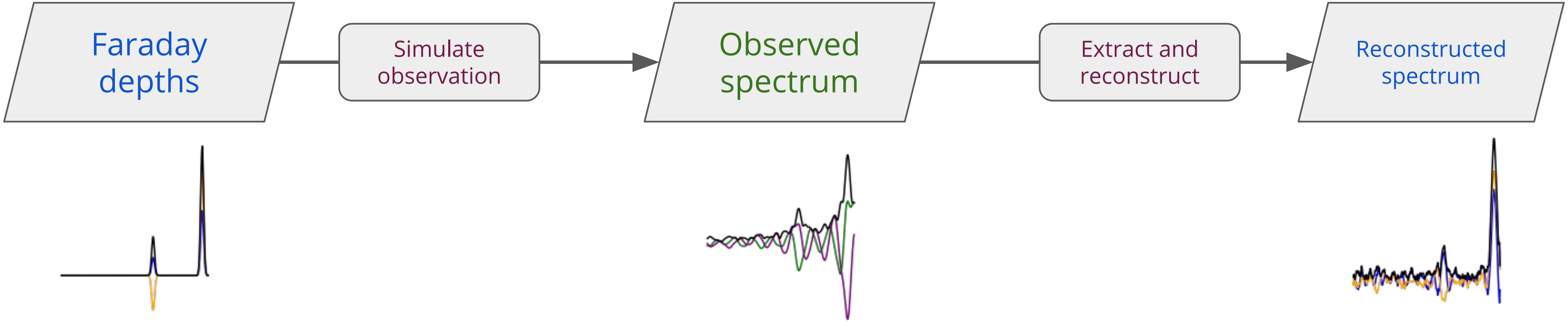
Bent, giant radio galaxy in NVSS/FIRST.
(~1 Mpc physical extent)
Image: Banfield+16

- Even 20-year old wide-area surveys like NVSS have lots of interesting astrophysics buried in them
- Much of this has come from manual inspection
- Plenty still to find

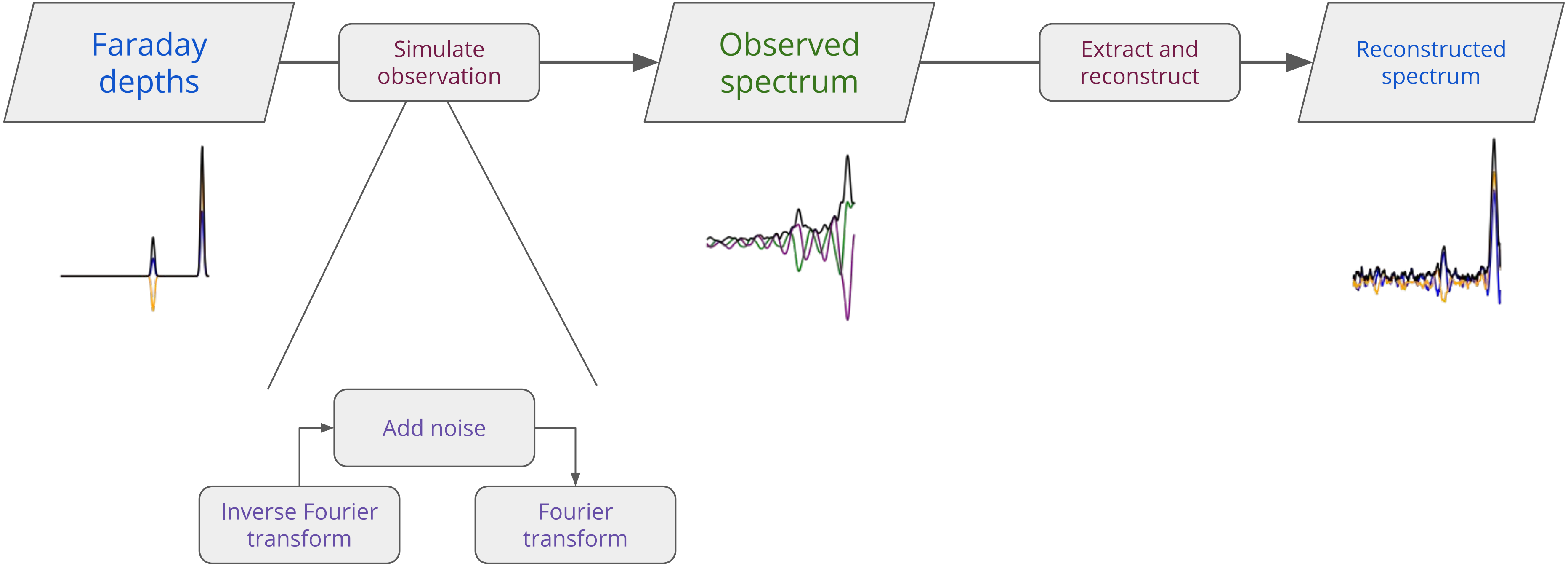
Autoencoders



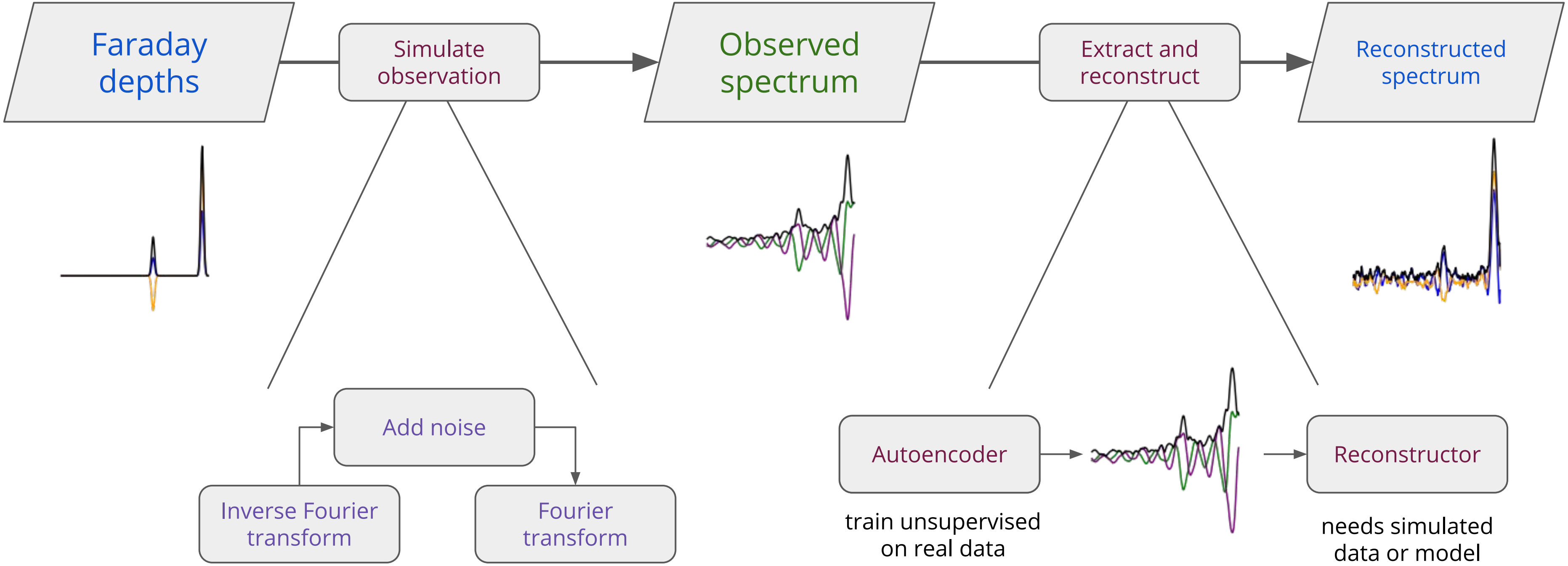
Faraday spectrum feature extractor



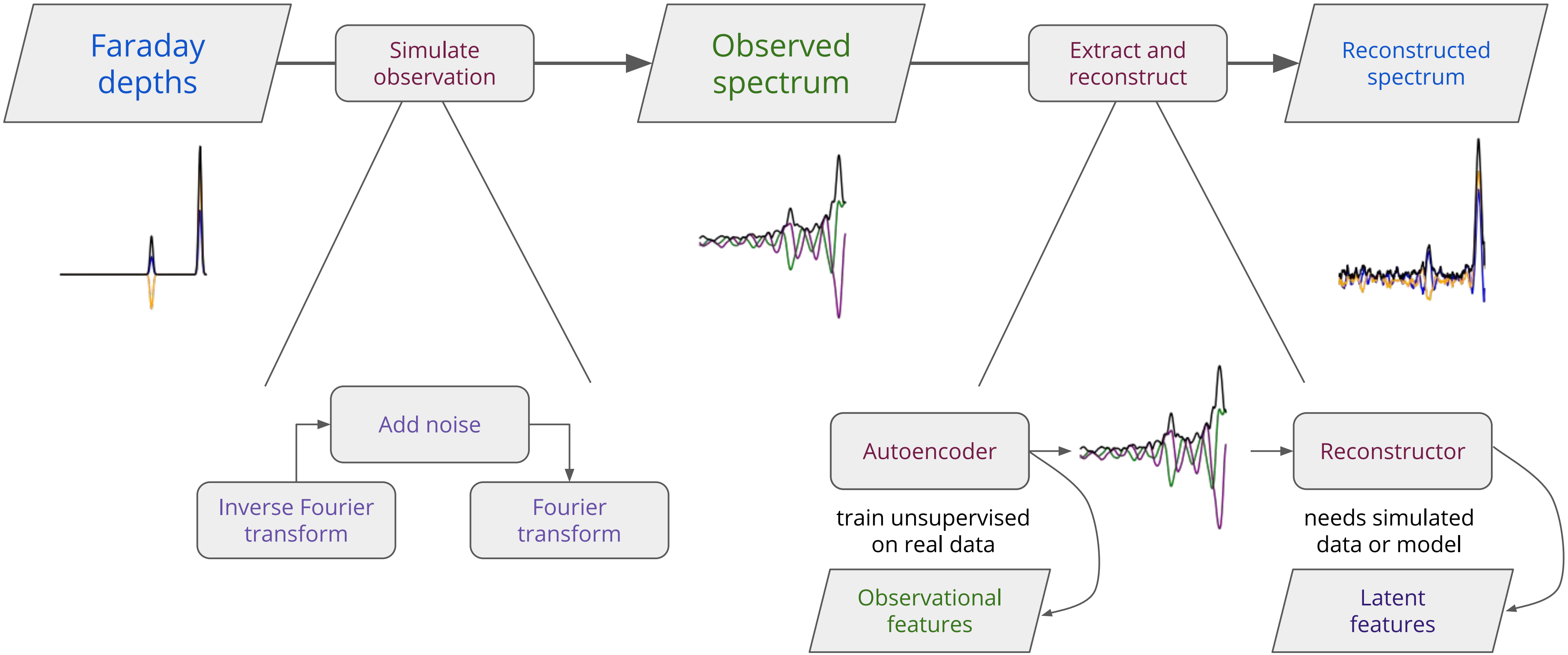
Faraday spectrum feature extractor



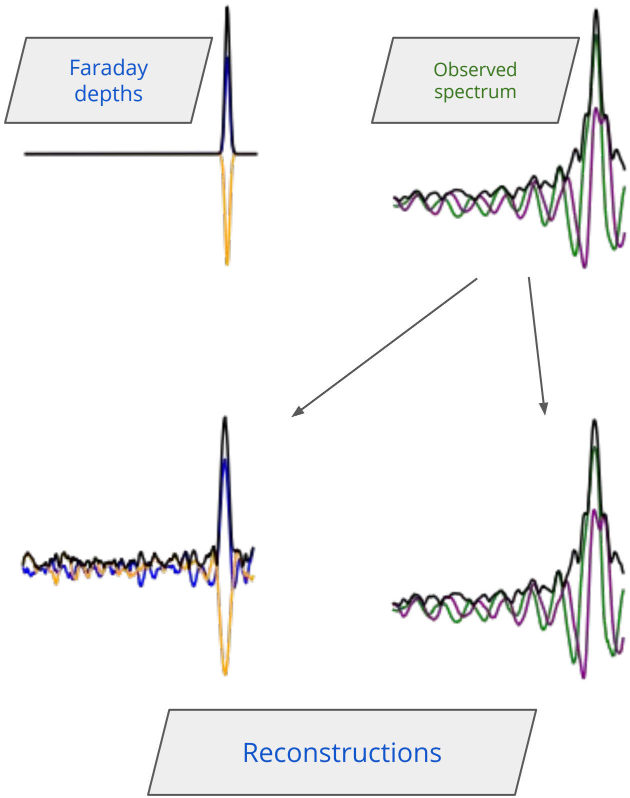
Faraday spectrum feature extractor

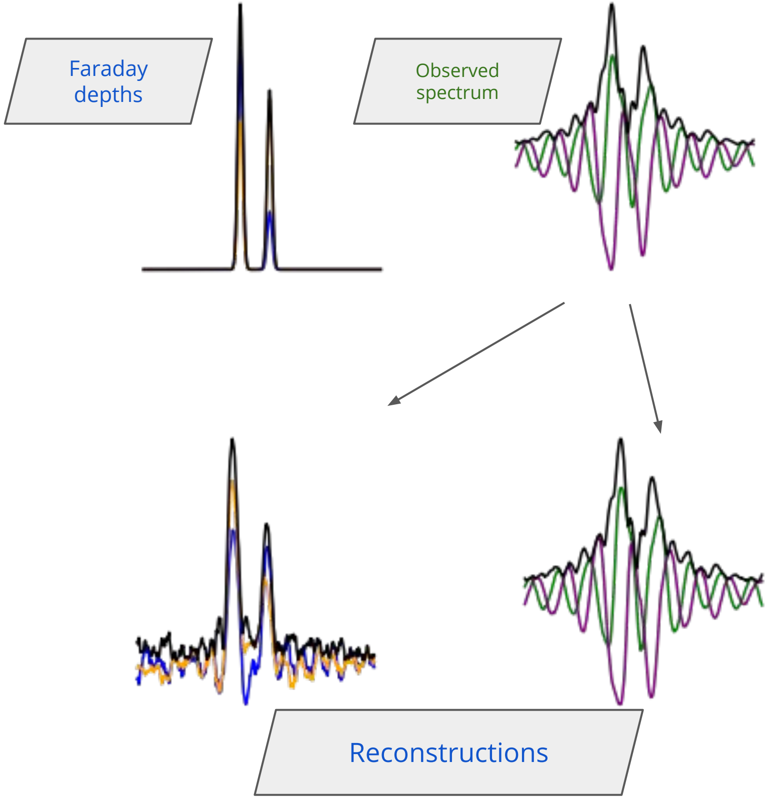


Faraday spectrum feature extractor

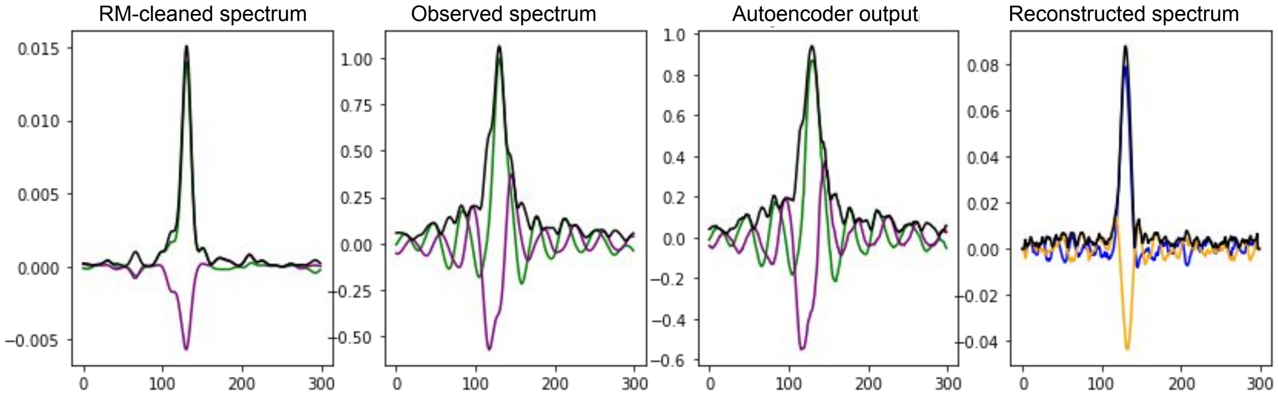


Reconstructing simulated spectra





Reconstructing real data



Polarised sources observed with ATCA (courtesy of Jack Livingston).