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Learning to Identify Extragalactic 2 Radio Sources

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6 Doctor of Philosophy
7 of The Australian National University



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¹²

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13 I declare that the research presented in this thesis represents original work that I
14 carried out during my candidature at the Australian National University, except for
15 contributions to multi-author papers incorporated in the thesis where my contribu-
16 tions are specified in this Statement of Contribution.

- 17 • *Radio Galaxy Zoo: Machine learning for radio source host galaxy cross-identification*,
18 by **M. J. Alger**, J. K. Banfield, C. S. Ong, L. Rudnick, O. I. Wong, C. Wolf, H.
19 Andernach, R. P. Norris, and S. S. Shabala. Published in 2018 in the *Monthly*
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- 21 • *Radio Galaxy Zoo: Radio luminosity functions of extended sources*, by **M. J. Alger**,
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29 For all three papers I wrote the entirety of the content, produced all figures ex-
30 cept where noted, and conducted all experiments. Other authors reviewed the papers,
31 made suggestions, discussed ideas, and vitally contributed to the Radio Galaxy Zoo
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To Shirley and Bob.

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73 Abstract

74 Radio observations of actively accreting supermassive black holes outside of the galaxy
75 can provide insight into the history of galaxies and their evolution. With the construc-
76 tion of fast new radio telescopes and the undertaking of large new radio surveys in the
77 lead-up to the Square Kilometre Array (SKA), radio astronomy faces a ‘data deluge’
78 where traditional methods of data analysis cannot keep up with the scale of the data.
79 Astronomers are increasingly looking to machine learning to provide ways of handling
80 large-scale data like these. This thesis introduces machine learning methods for use
81 in wide-area radio surveys and demonstrate demonstrates their application to radio
82 astronomy data. To help understand the issues facing large-scale wide-area radio sur-
83 veys, and contribute toward their solutions, we consider the problems of automated
84 radio-infrared cross-identification and Faraday complexity classification.

85 We developed an automated machine learning method for cross-identifying radio
86 objects with their infrared counterparts, training the algorithm with data from the cit-
87 izen science project Radio Galaxy Zoo. The trained result performed comparably to
88 an algorithm trained on expert cross-identifications, demonstrating the benefit of non-
89 expert labelling in radio astronomy. By examining the theoretical maximum accuracy
90 of this algorithm we showed that existing pilot studies for future surveys were not
91 sufficiently large enough to train machine learning methods. We showed the utility of
92 our cross-identification algorithm by applying it instead to a large survey, Faint Images
93 of the Radio Sky at Twenty Centimeters (FIRST), producing the largest catalogue of
94 cross-identified extended sources available at the time of writing. From this catalogue,
95 we calculated a mid-infrared-divided fractional radio luminosity function as well as
96 an estimate of energy injected into the intergalactic medium by active galactic nuclei
97 jets—one of the first applications of machine learning to radio astronomy to obtain a
98 physics result. A key result from this work was that the limitation in our sample size
99 was not due to the number of radio objects cross-identified but rather by the number
100 of available redshift measurements. Finally, we developed interpretable features for
101 spectropolarimetric measurements of radio sources and used these features to design
102 a machine learning algorithm that can identify Faraday complexity, while the features
103 themselves may be used for other tasks. The methods in this thesis will be applicable
104 to future radio surveys such as the Evolutionary Map of the Universe (EMU) contin-
105 uum survey and the Polarised Sky Survey of the Universe’s Magnetism (POSSUM),
106 as well as surveys produced with the SKA, allowing the development of higher reso-
107 lution radio luminosity functions, better estimates of the impact of radio galaxies on
108 their environments, faster analysis of polarised surveys, and better quality rotation
109 measure grids.

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List of Constants

³⁵⁶ The values of the following constants, except where otherwise noted, are drawn from
³⁵⁷ the NIST Reference on Constants, Units, and Uncertainty (Mohr et al., 2019) which
³⁵⁸ itself draws from the 2018 CODATA recommended values.

Symbol	Unit	Name	Value
ϵ_0	F m^{-1}	Vacuum permittivity	$8.8541878128(13) \times 10^{-12}$
G	$\text{m}^3 \text{ kg}^{-1} \text{ s}^{-2}$	Gravitational constant	$6.67430(15) \times 10^{-11}$
m_p	kg	Proton mass	$1.67262192369(51) \times 10^{-27}$
m_e	kg	Electron mass	$9.1093837015(28) \times 10^{-31}$
c	m s^{-1}	Speed of light	2.99792458×10^8
σ_T	m^2	Thomson cross section	$6.6524587321(60) \times 10^{-29}$

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359 List of Abbreviations

360 The following list summarises abbreviations that are commonly used in this thesis.

- 361 • AGN: active galactic nuclei, energetic objects at the centre of galaxies
- 362 • ASKAP: Australian Square Kilometre Array Pathfinder, a next-generation radio
363 telescope in Murchison
- 364 • ATCA: Australia Telescope Compact Array, a radio telescope in Narrabri
- 365 • CNN: convolutional neural network, a classifier which works on images and
366 spectra
- 367 • EMU: Evolutionary Map of the Universe, an upcoming large radio survey
- 368 • FDF: Faraday dispersion function, a representation of a polarisation spectrum
- 369 • FIRST: Faint Images of the Radio Sky at Twenty Centimeters, a large radio survey
- 370 • FRI: Fanaroff-Riley type I, an edge-darkened radio galaxy
- 371 • FRII: Fanaroff-Riley type II, an **edge-brightened** **edge-brightened** radio galaxy
- 372 • ISM: interstellar medium, the stuff between stars
- 373 • LR: logistic regression, a classification model
- 374 • MWA: Murchison Widefield Array, a next-generation radio telescope in Murchi-
375 son
- 376 • NVSS: NRAO VLA Sky Survey, a large radio survey
- 377 • POSSUM: Polarisation Sky Survey of the Universe's Magnetism, an upcoming
378 large radio polarisation survey
- 379 • RACS: Rapid ASKAP Continuum Survey, a new large radio survey
- 380 • RF: random forests, a classification model
- 381 • RGZ: Radio Galaxy Zoo, a citizen science project to cross-identify and aggregate
382 radio sources
- 383 • RLF: radio luminosity function, a description of how common radio galaxies of
384 different energies are

- 385 • RM: rotation measure, the amount of Faraday rotation between a polarised source
386 and an observer
- 387 • RMSF: rotation measure spread function, the kernel convolving a FDF
- 388 • SDSS: Sloan Digital Sky Survey, a large optical spectroscopic and photometric
389 survey
- 390 • SFR: star formation rate, the recent rate of star formation
- 391 • SKA: Square Kilometre Array, a next-generation radio telescope yet to be built
- 392 • SNR: signal-to-noise ratio, the ratio of total intensity to noise level
- 393 • SWIRE: *Spitzer* Wide-area Infrared Extragalactic Survey, a deep infrared survey
- 394 • VLA: Very Large Array, a radio telescope in New Mexico
- 395 • WISE: *Wide-field Infrared Survey Explorer*, a space-based infrared telescope
- 396 • XGB: extreme gradient boosted trees, a classification model

398 Introduction

399 Many great results come from study at the intersection of two fields, and the combina-
400 tion of astronomy and informatics is no exception. The resulting interdisciplinary field
401 is called *astroinformatics*, and concerns the application of statistical and machine learn-
402 ing techniques to problems in astronomy and astrophysics. Machine learning, a col-
403 lection of methods for formalising and solving data-driven problems at scale, is a nat-
404 ural fit for radio astronomy: Radio astronomy faces a ‘data deluge’ thanks to new and
405 upgraded telescopes and associated wide-area surveys to be undertaken with them.
406 The goal in the near future is to be able to process data—and conduct science on that
407 data—on the fly as the volume of data grows too large to store. This is a requirement
408 for the Square Kilometre Array (SKA), a grand international undertaking to build a
409 distributed radio array across Western Australia and South Africa with an intended
410 collecting area of one square kilometre. There exists no comparable telescope today.
411 The SKA will be able to perform new tests of general relativity, help pin down the large-
412 scale structure of the Universe, investigate the mysteries of the epoch of reionisation,
413 probe the history of galaxy evolution to new extents, and perhaps make unexpected
414 new discoveries (Diamond, 2017).

415 The SKA will have technical challenges unlike any so far in radio astronomy. Raw
416 data will stream from the telescope antennae at 2 petabytes per second, and up to 300
417 petabytes per year of science data is expected to be generated (Diamond, 2017). This
418 is a phenomenal amount of data, much of which won’t be stored, and the community
419 expectation is that machine learning will provide avenues to conduct science with such
420 a large dataset. Precursor projects to the SKA have begun to investigate these pathways
421 (e.g. Bonaldi et al., 2020; Kapinska, 2020; Mostert et al., 2021).

422 Even without the SKA, the data deluge has already begun. Three precursor tele-
423 scopes have been constructed: the Australian Square Kilometre Array Pathfinder
424 (ASKAP) and Murchison Widefield Array (MWA) in Western Australia, and MeerKAT
425 in South Africa. While MeerKAT will eventually form part of the SKA itself, all three
426 are already online and generating science data at astonishing rates. ASKAP will soon
427 conduct six surveys of the entire southern radio sky: the Evolutionary Map of the Uni-
428 verse (EMU; Kapinska, 2020; Norris et al., 2011), the Widefield ASKAP L-Band Legacy
429 All-Sky Blind Survey (Koribalski et al., 2020, WALLABY), the First Large Absorption
430 Survey in HI (FLASH), an ASKAP Survey for Variables and Slow Transients (VAST;
431 Murphy et al., 2013), the Galactic ASKAP Spectral Line Survey (GASKAP), and the

Polarisation Sky Survey of the Universe’s Magnetism (POSSUM); as well as the deeper but smaller Deep Investigation of Neutral Gas Origins (DINGO) and the Commensal Real-Time ASKAP Fast-Transients survey (CRAFT; Macquart et al., 2010). Atop these future surveys, the recent Rapid ASKAP Continuum Survey (RACS; McConnell et al., 2020) has redefined our knowledge of the southern radio sky with shallow observations at 15 arcsecond resolution—compare to the previous largest radio survey, the NRAO VLA Sky Survey (NVSS; Condon et al., 1998), with 45 arcsecond resolution over the northern sky.

Machine learning methods for radio astronomy will be developed for and tested upon surveys like RACS and EMU. The path between an astronomical problem and a machine learning problem, however, is not a straightforward one. The goal when casting an astronomy question as something mathematical or computational is to convert the question into one with a known method of solution, such as classification or regression. Along the way, astronomical concepts and assumptions need to be turned into something a computer can deal with. Despite the wide availability of machine learning software and tools, there is no automatic or easy way to make this transformation. This necessitates research in astroinformatics.

This thesis concerns applications of machine learning to radio astronomy for the identification of extended extragalactic radio sources in wide-area surveys. We will present new methods of cross-identifying radio objects with their corresponding infrared and optical observations, demonstrate the applicability of these methods to existing wide-area radio surveys (shedding light on radio source population astronomy along the way), and develop a new way to identify complexity in polarised radio sources.

1.1 Problems in extragalactic radio astronomy

Galaxies produce radio emission through a variety of methods. The main emission mechanisms are star formation and active galactic nuclei (AGN, Section 2.3) and only the latter show extended structure well beyond the galaxy itself. AGN are the central focus of this thesis. They are intensely energetic objects at the centre of galaxies, which actively accrete matter and eject huge jets of plasma that develop into extended lobes over huge distances. Radio astronomy has many uses for AGN: ~~their~~Their energy scales provide a test-bed for high energy physics, and the extremely bright lobes and jets can be seen throughout the Universemaking AGN an accessible probe of the distant and old Universe.

AGN are thought to be critical to galaxy evolution and perhaps the early reionisation of the Universe (Bosch-Ramon, 2018), but their exact role in their host galaxies is an open question. The radiative and mechanical energy released by AGN impacts the interstellar medium (ISM) and is a key component of contemporary galaxy simulations and models (Morganti, 2017). The quenching of star formation due to AGN activity is called *AGN feedback*, the idea being that the energy expelled from an AGN is returned to the ISM of the galaxy, heating the gas so it cannot condense into stars. The

473 different impacts of radiative and mechanical energy, the location and scales within
474 the galaxy for which star formation is quenched, and whether star formation material
475 is ejected from the galaxy by the AGN are all open questions (Husemann & Harrison,
476 2018). One of our key results in Chapter 5 is an estimation of the mechanical energy
477 contributed to the intergalactic medium by AGN. Solving these questions requires an
478 understanding of AGN at both small and large scales, as well as connecting AGN to
479 their host galaxies at other wavelengths so that redshift, emission lines, star formation
480 rates, etc. can be determined. Chapter 4 describes our new method for performing
481 such cross-identifications.

482 The large scales of AGN also provide insight into the larger-scale structure of the
483 Universe. Giant radio galaxies for example (Section 2.3.1) are difficult to identify due
484 to their size and disconnected appearance (Section 2.6), but are so large that they can
485 be used to probe galaxy clusters (Banfield et al., 2016) and even the large-scale struc-
486 ture of the Universe (Reiprich et al., 2020). Other large-scale effects seem to exist, such
487 as the apparent alignment of radio galaxies ([Contigiani et al., 2017; Panwar et al., 2020](#))
488 ([Contigiani et al., 2017; Panwar et al., 2020; Taylor & Jagannathan, 2016](#)), though inves-
489 tigation continues as to whether this effect is real or due to some unknown systematic
490 bias. New radio surveys will reveal more radio sources than ever before, and if they can
491 be identified, radio structures in these surveys will allow us to investigate the structure
492 of the Universe.

493 The magnetic structure of AGN and their extended lobes may be probed by ra-
494 dio polarimetry observations (Anderson et al., 2015; Grant, 2011). Through polarisation,
495 though, extragalactic AGN can provide insight into our own [Galaxy: the galaxy:](#)
496 [The](#) Faraday depth and complexity (Section 2.2.2) of extragalactic radio sources can
497 be used to quantify local magnetic fields. With more polarised radio sources to be
498 revealed through upcoming wide-area polarisation surveys, the magnetic field of the
499 Milky Way and its surrounding intergalactic medium can be better resolved. Polarime-
500 try also allows us to determine some aspects of the structure of unresolved extragalac-
501 tic sources, even though we cannot spatially see that structure: [Spatially](#) [Spatially](#) ex-
502 tended, polarised radio sources may have different polarisation spectra to those which
503 are spatially compact when projected onto the sky.

504 Other problems in radio astronomy relate to the new level of data that we are about
505 to obtain from large telescopes like the SKA, which we discuss in Section 1.2.

506 1.2 Big data in astronomy

507 The scale of radio data underpins many of the methodology problems facing radio as-
508 tronomy. There are two main scientific benefits that come from large-scale data: better
509 statistics and more unusual objects. However, methods for dealing with radio data at
510 scale are still very much in their infancy, and need to be developed before instruments
511 like ASKAP and MeerKAT can be used to their full potential.

512 Many results in astronomy are statistical, from measuring the expansion of the
513 Universe to understanding the distribution of galaxy properties. With more observa-

514 tions, we can not just only narrow the uncertainty of these results, but also diversify
 515 them diversify them as well. When the number of objects under study is large, we can
 516 subdivide the population into subpopulations based on their physical properties and
 517 determine a statistic on each subpopulation. This can help understand the physical ba-
 518 sis behind the statistic, or remove unwanted subpopulations from analysis. Even with
 519 less data it is still possible to subdivide or filter populations, but this will dramatically
 520 raise the uncertainty in the results due to the low sample size of each bin. An example
 521 of such a statistic is the radio luminosity function (RLF), which describes the density of
 522 radio sources throughout the Universe. It can be divided into a fractional RLF to exam-
 523 ine the distribution of subpopulations, or to remove the effect of star-forming galaxies.
 524 We use large datasets to improve the uncertainty of RLFs and subdivide RLFs by the
 525 infrared properties of the population in Chapter 5.

526 With large datasets, highly unusual or rare objects are more likely to be included.
 527 Much of astronomy has been pushed forward by serendipitous discoveries, and (pro-
 528 vided we have some way of combing through the dataset) large datasets should pro-
 529 vide a wealth of such discoveries to be found. These may be found either through
 530 identifying objects where statistical methods seem to fail, or perhaps through direct
 531 searches (Norris, 2017a). By applying machine learning techniques, we found-find a
 532 number of new, rare giant radio galaxies in Chapter 5.

533 But with the benefits of big data come new challenges. At these new scales, the abil-
 534 ity to store all of our science data is no longer a given. Many methods that previously
 535 had the luxury to run over a whole dataset at their own pace will now need to process
 536 data on-the-fly. This is in contrast to how most science observations are currently per-
 537 formed, with new discoveries coming from legacy surveys many years after they were
 538 conducted. Many discoveries are unplanned, and losing the ability to make serendip-
 539 itous discoveries would be a major blow to astronomy (Norris, 2017a): how-How can
 540 we deal with so much data but still retain the ability to discover the unknown? Even
 541 with storage, the scale is tremendous: FIRST, for example, contains around 900 000
 542 sources, of which very few were manually labelled. Over 10 000 volunteers labelled in-
 543 teresting objects in FIRST over four years of the Radio Galaxy Zoo project, with 75 000
 544 aggregated labels passing quality assurance testing. While a phenomenal and, in ra-
 545 dio, unparalleled labelling effort, it pales in comparison to the estimated 70 000 000
 546 sources that EMU will find (Banfield et al., 2015).

547 1.3 Machine learning in astronomy

548 Machine learning is the process and practice of designing algorithms that automati-
 549 cally find and exploit useful patterns in data (Deisenroth et al., 2020). It is best suited
 550 for scenarios where these patterns are hard to encode by hand. Typically hard-to-
 551 describe problems might include data exploration, data visualisation, or interpolation.
 552 We face a deluge of data, and our existing methods for data analysis and astronomical
 553 discovery are hard to automate due to the often complex, visual-imagery-based nature
 554 of much of astronomy. This is where machine learning comes in: if we can-If we could

555 find a way to encode the processes underpinning astronomy as algorithms, we could
556 apply them at scale. Machine learning has found much success in other fields with sim-
557 ilar difficult-to-describe problems like image classification and outlier identification.

558 From the other direction, machine learning finds interesting and unique applica-
559 tions in radio astronomy. Radio images are usually quite different from images in the
560 typical image analysis problems faced in computer science. Standard assumptions are
561 frequently broken: ~~noise~~ Noise is correlated across the image, objects can be different
562 shapes when viewed at different wavelengths, and the number of colours in an image
563 may be in the hundreds. Data points are spatially located and can be close together or
564 far apart in ways that are not solely based on how they look or behave. We often do not
565 have the option of obtaining more data, sometimes because it is prohibitively expen-
566 sive (e.g. to undertake a new survey) and sometimes because it simply does not exist
567 (as we only have one Universe to look at or because the event is a transient one-off).
568 The burgeoning field of astroinformatics promises to prove interesting.

569 1.4 How this thesis fits in

570 Current methods of identifying radio sources in wide-area radio surveys work best for
571 compact, isolated objects. As resolution and depth of radio surveys ~~increases~~ increase
572 in the lead-up to the SKA, these limitations are becoming more apparent: ~~resolution~~
573 Resolution increases apparent complexity and depth increases the number of radio
574 sources visible in any given patch of sky.

575 Source identification is critical for analysis of radio sources in large-scale surveys
576 whether one is interested in individual sources or their bulk properties. Without solv-
577 ing issues like cross-identification and Faraday complexity we will not be able to make
578 full use of the SKA when it arrives. As we will discuss in Section 2.5, cross-identification
579 of radio sources with their counterparts in infrared or optical is key to understanding
580 these sources. Many radio galaxy properties can only be derived from non-radio ob-
581 servations of the galaxy, the stellar component of which can be traced by emission in
582 the infrared and optical. This can yield properties including distance, star formation
583 rate, and even mass of the central black hole powering the radio source itself. We de-
584 velop an automated machine learning method for cross-identification in Chapter 4 and
585 apply it to obtain physical results in Chapter 5.

586 Bulk analysis of polarised sources greatly benefits from being able to assess their
587 Faraday complexity. The most important application is perhaps in the development of
588 so-called *rotation measure grids*, which help characterise the magnetic field of the Milky
589 Way and surrounding intergalactic medium. Without knowing which sources are com-
590 plex and which are not, we cannot estimate the grid reliably. A fast way to estimate
591 Faraday complexity also allows us to quickly determine which sources may need fol-
592 lowing up, either with more expensive algorithms or further observations. Chapter 6
593 details our development of an automated Faraday complexity classifier.

594 **1.5 Thesis outline**

595 We begin by introducing key concepts from radio astronomy in Chapter 2, including
 596 radio active galactic nuclei (AGN), as well as motivations for and difficulties in cross-
 597 identifying observed radio emission from AGN. In Chapter 3 ~~introduces we introduce~~
 598 machine learning and ~~describes~~describe the machine learning background required
 599 for the remainder of the thesis. These chapters together comprise the background
 600 knowledge.

601 Chapter 4 is my paper *Radio Galaxy Zoo: Machine learning for radio source host galaxy*
 602 *cross-identification* (Alger et al., 2018). This chapter describes a new ~~,~~ machine learning
 603 method for cross-identifying extended radio emission with host galaxies in the
 604 infrared. We apply this approach to cross-identifying all extended radio sources in
 605 the Faint Images of the Radio Sky at Twenty Centimeters radio survey (FIRST; Becker
 606 et al., 1995) with their infrared counterparts in AllWISE (Cutri et al., 2013) and use the
 607 resulting catalogue of cross-identifications to create a fractional radio luminosity func-
 608 tion in Chapter 5, which itself is my paper *Radio Galaxy Zoo: Radio luminosity functions*
 609 *of extended sources* (Alger et al., in prep.). Chapter 6 is my paper *Interpretable Faraday*
 610 *Complexity Classification* (Alger et al., 2021), which introduces an interpretable method
 611 for classifying radio emission as Faraday complex or simple, which could be used to
 612 identify whether it is an extended source that is below the resolution limit. In Chap-
 613 ter 7 ~~provides we provide~~ a discussion of the insights gained from the findings of this
 614 thesis and ~~suggests~~suggest future directions for research building on our results.

615 **1.6 Contributions**

616 My main contributions to radio astroinformatics in this thesis are:

- 617 • I introduce a new method for cross-identifying radio emission which can learn
 618 from existing catalogues, the first application of machine learning to radio cross-
 619 identification (Chapter 4);
- 620 • I demonstrate an application of this new method to the creation of fractional ra-
 621 dio luminosity functions, which require considerably more cross-identifications
 622 than non-fractional radio luminosity functions, in the process creating the largest
 623 available catalogue of extended, cross-identified radio sources (Chapter 5);
- 624 • I produce a fractional radio luminosity function with divisions based on mid-
 625 infrared colours associated with the host galaxies of the radio emission, helping
 626 to understand how radio galaxies evolve throughout the Universe (Chapter 5);
- 627 • I highlight the requirement of considerably more redshifts in understanding fu-
 628 ture wide-area radio surveys (Chapter 5);
- 629 • I introduce a new method to identify Faraday complexity using an interpretable
 630 classifier, as well as features for Faraday dispersion functions which can be used
 631 for other machine learning tasks (Chapter 6); and

-
- ⁶³² • I apply machine learning to real radio spectropolarimetric data for the first time
⁶³³ (Chapter 6).

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634 1.7 Works produced during this PhD

635 During my PhD, I had the good fortune to collaborate with many talented authors
 636 and contribute to a number of related works. The following is a list of papers which I
 637 co-authored in this time:

- 638 • *Radio Galaxy Zoo: Machine learning for radio source host galaxy cross-identification*
 639 (2018). **M. J. Alger**, J. K. Banfield, C. S. Ong, L. Rudnick, O. I. Wong, C. Wolf,
 640 H. Andernach, R. P. Norris, and S. S. Shabala. *Monthly Notices of the Royal Astro-*
 641 *nomical Society* 478, pp. 5547–5563. [This is the content of Chapter 4 with minor](#)
 642 [modifications.](#)
- 643 • *Radio Galaxy Zoo: Radio luminosity functions of extended sources* (in prep.). **M. J.**
 644 **Alger**, O. I. Wong, C. S. Ong, N. M. McClure-Griffiths, H. Andernach, L. Rudnick,
 645 S. S. Shabala, A. F. Garon, J. K. Banfield, A. D. Kapińska, R. P. Norris, and A. J. M.
 646 Thomson. [This is the content of Chapter 5 with minor modifications.](#)
- 647 • *Interpretable Faraday Complexity Classification* ([in press 2021](#)). **M. J. Alger**, J. D. Liv-
 648 ington, N. M. McClure-Griffiths, J. L. Nabaglo., O. I. Wong, and C. S. Ong. *Pub-*
 649 *lications of the Astronomical Society of Australia* –38, E022. [This is the content of](#)
 650 [Chapter 6 with minor modifications.](#)
- 651 • *Radio Galaxy Zoo Data Release 1: visual identification of 75,641 radio morphologies from*
 652 *the FIRST and ATLAS surveys* (in prep.). O. I. Wong, A. F. Garon, **M. J. Alger**, K.
 653 W. Willett, L. Rudnick, J. K. Banfield, J. Swan, S. S. Shabala, H. Andernach, R. P.
 654 Norris, B. D. Simmons, A. D. Kapińska, N. Seymour, et al.
- 655 • *Radio Galaxy Zoo: CLARAN - a deep learning classifier for radio morphologies* (2019).
 656 C. Wu, O. I. Wong, L. Rudnick, S. S. Shabala, **M. J. Alger**, J. K. Banfield, C. S. Ong,
 657 S. V. White, A. F. Garon, R. P. Norris, H. Andernach, J. Tate, V. Lukic, H. Tang,
 658 K. Schawinski, and F. I. Diakogiannis. *Monthly Notices of the Royal Astronomical*
 659 *Society* 482, pp. 1211–1230.
- 660 • *Heightened Faraday Complexity in the inner 1 kpc of the Galactic Centre* (2021), by J.
 661 D. Livingston, N. M. McClure-Griffiths, B. M. Gaensler, A. Seta, and **M. J. Alger**.
 662 *Monthly Notices of the Royal Astronomical Society* 502, pp. 3814–3828.
- 663 • *Radio Galaxy Zoo: Unsupervised Clustering of Convolutionally Auto-encoded Radio-*
 664 *astronomical Images* (2019). N. O. Ralph, R. P. Norris, G. Fang, L. A. F. Park, T. J.
 665 Galvin, **M. J. Alger**, H. Andernach, C. Lintott, L. Rudnick, S. S. Shabala, and O. I.
 666 Wong. *Publications of the Astronomical Society of the Pacific* 131, 108011.
- 667 • *Radio Galaxy Zoo: Knowledge Transfer Using Rotationally Invariant Self-organizing*
 668 *Maps* (2019). T. J. Galvin, M. Huynh, R. P. Norris, X. R. Wang, E. Hopkins, O. I.
 669 Wong, S. S. Shabala, L. Rudnick, **M. J. Alger**, and K. L. Polsterer. *Publications of*
 670 *the Astronomical Society of the Pacific* 131, 108009.

671 I also gave a number of conference talks:

- 672 • *Machine Learning Methods for Radio Host Cross-Identification with Crowdsourced La-*
673 *bels*, presented in 2017 at the seventh SKA Pathfinder Radio Continuum Survey
674 meeting, Perth, Australia.
- 675 • *Learning to Cross-identify Wide-area Radio Surveys with Radio Galaxy Zoo: Data chal-*
676 *lenges in citizen science*, presented in 2018 at the Collaborative Conference on Com-
677 putational and Data Intensive Science, Melbourne, Australia.
- 678 • *Radio luminosity functions with Radio Galaxy Zoo and machine learning*, presented
679 in 2019 at the ninth SKA Pathfinder Radio Continuum Survey meeting, Lisbon,
680 Portugal.
- 681 • *Radio luminosity functions with machine learning and Radio Galaxy Zoo*, presented in
682 2019 at the Annual Scientific Meeting of the Astronomical Society of Australia.
- 683 • *Extracting Meaningful Features from Early-Science Radio Data*, presented in 2019 at
684 the Collaborative Conference on Computational and Data Intensive Science, Can-
685 berra, Australia.
- 686 • *Extracting Meaningful Features from Early-Science Radio Data*, presented in 2019 at
687 Artificial Intelligence in Astronomy, Garching, Germany.

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689 Radio Sources

690 As its title suggests, this thesis ~~is focused~~focuses on the identification of extended ra-
 691 dio sources. This chapter introduces extended radio sources, describing what we see
 692 when we look at the sky with radio eyes and radio telescopes. We will discuss the dif-
 693 ferent kinds of radio sources that we can observe, how they are distributed throughout
 694 the Universe, and key issues surrounding their identification. We will start by looking
 695 at the extragalactic radio sky, introducing what it is that we see through radio tele-
 696 scopes (Section 2.1). Then, we will describe the physics behind radio emission, includ-
 697 ing the emission mechanisms that allow us to observe active galactic nuclei in radio,
 698 and how radio polarisation can help us determine aspects of distant magnetic fields
 699 (Section 2.2). From there we will turn to active galactic nuclei as they ~~will be are~~are the
 700 objects of interest in this thesis (Section 2.3): ~~what~~What do they look like, how are
 701 they structured, and what do they do? Finally, we will cover three different tasks we
 702 may face when presented with a collection of observed AGN, including classification
 703 (Section 2.4), cross-identification (Section 2.5), and source aggregation (Section 2.6).

704 **2.1 The Extragalactic Radio Sky**

705 The extragalactic sky appears quite different at different wavelengths. While an op-
 706 tical observer may look at a distant galaxy and see spirals and halos, an infrared ob-
 707 server will see discs and dust. What does the radio astronomer see? Figure 2.1 shows
 708 a false-colour image of the radio sky from 72–231 MHz. The plane of the Milky Way
 709 is clearly visible through the centre, but nearly every other object in this image is a
 710 galaxy. These galaxies fall into two main categories: those that emit radio due to star
 711 formation (called *star-forming galaxies*), and those that emit radio due to *active galactic*
 712 *nuclei* (AGN; called *radio galaxies* in this thesis). AGN can be observed at many fre-
 713 quencies: ~~for~~For the remainder of this thesis, except where otherwise noted, ‘AGN’
 714 refers to *radio AGN*.

715 Non-AGN emission from distant galaxies traces the recent star-formation rate (SFR).
 716 Besides low-power thermal emission, stellar radio emission from galaxies mainly comes
 717 from massive ($\gtrsim 8 M_{\odot}$) stars ~~through~~ two emission mechanisms. The first is through
 718 H II regions, which are ionised by such stars. The ionised electrons emit bremsstrahlung
 719 radiation at radio wavelengths. The second emission mechanism is supernovae. Mas-

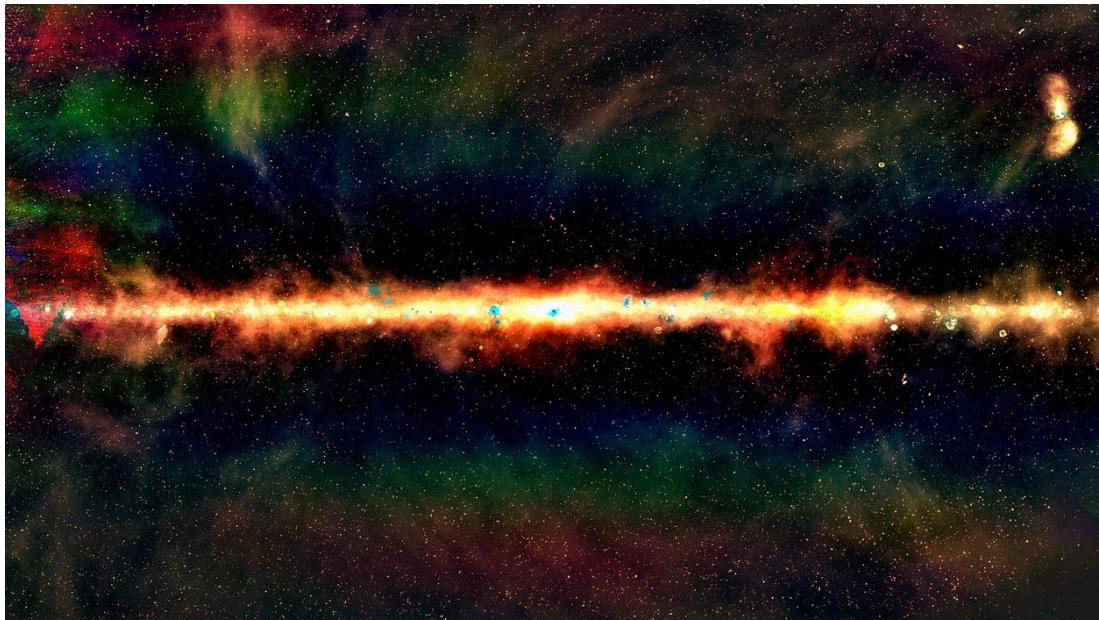


Figure 2.1: False-colour image of the radio sky from the GLEAM survey. (Image: Natasha Hurley-Walker, Curtin University/ICRAR; Hurley-Walker et al., 2017)

720 massive stars may end their lives in Type II and Type Ib supernovae, which can result in super-
 721 nova remnants. These remnants emit Interaction between the supernova remnant
 722 and the interstellar medium (ISM) causes the emission of synchrotron radiation. Mass-
 723 sive stars like these are short-lived (a few 10^6 yr), and the corresponding emitting
 724 electrons have similarly short lifetimes ($\lesssim 10^8$ yr). The radio effects of these stars are
 725 therefore also short-lived, which is why radio emission traces the recent SFR (Condon,
 726 1992). Star formation-associated emission is mainly found in the dise discs of spiral
 727 galaxies, as this is where the star formation rate is highest. In particular, there is no
 728 star-forming radio emission extending outside of the galaxy proper. The radio power
 729 emitted by these galaxies at 1.4 GHz is on the order of 10^{18} – 10^{23} W Hz $^{-1}$ (Condon,
 730 1992). For a radio survey like the NRAO VLA Sky Survey (NVSS; Condon et al., 1998),
 731 with a detection limit of 2.3 mJy, this luminosity range corresponds to a maximum red-
 732 shift range of 0.0004–0.1272 (corresponding to 6×10^6 – 1.646×10^9 yr lookback time¹).
 733 Upcoming surveys such as the Evolutionary Map of the Universe (EMU; Norris et al.,
 734 2011), with 5σ detection thresholds of 50 μ Jy (Norris et al., 2011), will push this red-
 735 shift range to 0.0030–0.6684 (corresponding to 4.2×10^7 – 6.261×10^9 yr lookback time).

736 AGN are energetic objects at the centre of galaxies, powered by accretion into super-
 737 massive black holes. The extended, strongly-magnetised plasma they eject emits
 738 synchrotron radiation from accelerating relativistic electrons, which is what we see
 739 when we observe a radio galaxy. The radio luminosity of a radio galaxy can range
 740 from 10^{20} – 10^{28} W Hz $^{-1}$ (Pracy et al., 2016) at 1.4 GHz, making them some of the most

¹Assuming cosmological parameters from Chapter 5. Calculated using “A Cosmology Calculator for the World Wide Web” (Wright, 2006).

741 luminous objects in the Universe. They are therefore visible throughout the Universe,
742 with the most distant AGN detected at a redshift of 7.5 (Bañados et al., 2018). De-
743 pending on the orientation and type of AGN, as well as its interaction with its host
744 galaxy, the radio emission may extend far beyond the galaxy itself—up to megaparsec
745 scales—and this emission may have complex structure. Perhaps the most impressive
746 local example is Centaurus A (Cen A), the prominent double-lobed cloud in the upper-
747 right of Figure 2.1 extending over 8 degrees across the sky. Section 2.3 discusses AGN
748 in more detail.

749 Most ~~radio galaxies are~~ AGN emission is compact and unresolved in any given
750 radio survey due to the distance at which ~~they~~ it can be detected and ~~their~~ the orien-
751 tation or type of the galaxy. This means that ~~their~~ observed structure does not always
752 help to distinguish AGN radio emission from star-forming radio emission. How can
753 we tell these apart? Synchrotron emission has a considerably steeper spectral index
754 than bremsstrahlung, but synchrotron emission dominates the bremsstrahlung in star-
755 forming galaxies at 1.4 GHz (Condon, 1992). Truly star-forming galaxies can be distin-
756 guished from AGN host galaxies by using optical spectroscopy (e.g. Groves & Kewley,
757 2007; Mauch & Sadler, 2007), but radio emission is detectable at much greater dis-
758 tances than those at which good quality optical spectra can be obtained~~at~~, making this
759 solution impractical for many galaxies. Separating star-forming galaxies from AGN
760 host galaxies at radio wavelengths remains a difficult problem in radio astronomy.

761 Polarised radio surveys can provide extra information. While radio emission due
762 to star formation tends to not have detectable polarisation, AGN may be very strongly
763 polarised. This makes polarisation an excellent indicator of whether a source is an
764 AGN, though very incomplete: ~~many AGN will also~~ Many AGN do not have detectable
765 polarisation, and the polarised intensity is usually less than ~~ten~~ 10 per cent of the total
766 radio intensity, meaning we detect far fewer polarised radio sources than we do radio
767 sources in general.

768 From the size scales described above, it should be clear that a survey of extended ra-
769 dio sources ~~will be is~~ dominated by AGN. Nevertheless, star-forming galaxies present
770 a significant part of the radio population, and the fraction of the radio sky they com-
771 prise varies significantly with survey parameters.

772 2.2 Radio emission

773 Electromagnetic radiation in radio frequencies—about 10 MHz–1 THz (Condon & Ran-
774 som, 2016)—is called *radio emission*. This is a very broad range of frequencies and so
775 radio astronomy covers a very broad range of astrophysical phenomena, from cosmo-
776 logical background radiation to neutron stars. The focus of this thesis is the excit-
777 ing, dynamic, and so-called ‘violent universe’ of radio galaxies. These galaxies are ob-
778 served through their emission of synchrotron radiation and are studied through their
779 observed physical structure, the intensity and spectroscopic properties of their radia-
780 tion, and the polarisation and spectropolarimetric properties that are uniquely visible
781 in radio. This section introduces synchrotron radiation and radio polarisation.

782 **2.2.1 Synchrotron radiation**

Most radio emission from radio galaxies is *synchrotron radiation*, produced by relativistic charged particles accelerating in a magnetic field. A non-relativistic charged particle ~~will spiral spirals~~ with a fixed angular frequency when it moves in a magnetic field in a process called *gyro radiation*. Synchrotron radiation is a relativistic effect: ~~it~~-~~It~~ can be thought of as gyro radiation which has been Lorentz transformed to energies much greater than mc^2 . The spectrum of optically thin synchrotron radiation follows a power law (Condon & Ransom, 2016):

$$S(\nu) \propto \nu^\alpha. \quad (2.1)$$

where ν is the frequency of radiation and α is called the *spectral index*². It is related to the energy distribution of the emitting electrons: ~~assuming~~. Assuming that the electron energy distribution follows a power law (~~which it generally does, Rybicki & Lightman, 2008~~) (which it generally does; Rybicki & Lightman, 2008), where the number density of electrons at a given energy E is given by

$$n(E) \propto E^\Gamma, \quad (2.2)$$

then

$$\alpha = \frac{\Gamma - 1}{2}. \quad (2.3)$$

783 The spectral index for synchrotron radiation tends to range from -2 to 0 (Condon &
784 Ransom, 2016) with spectral indices greater than 0 called ‘inverted’ spectra.

785 **2.2.2 Polarisation**

786 Electromagnetic radiation consists of waves of self-propagating, orthogonal electric
787 and magnetic fields. The orthogonality of these two waves allows us to characterise
788 the radiation just by the electric field. As a transverse wave, the electric field travels at
789 an angle in the plane perpendicular to the line-of-sight. This angle and its behaviour
790 is called the *polarisation* of the wave.

The polarisation can be characterised by decomposing the electric field into orthogonal components E_x and E_y , letting \hat{z} denote the axis of propagation:

$$\vec{E} = (\hat{x}E_x \exp(i\varphi_x) + \hat{y}E_y \exp(i\varphi_y)) \exp(i(\vec{k} \cdot \hat{z} - \omega t)). \quad (2.4)$$

In an astronomical context, \hat{z} is the line-of-sight from the source of the radiation to the observer. \vec{k} is the *wave vector* which points in the direction of travel and has magnitude $2\pi/\lambda$, and $\omega = 2\pi\nu$ is the *angular frequency*. φ_x and φ_y are the phase offsets of each component. As this wave propagates along the line-of-sight toward an observer, the electric field oscillates in an ellipse across the $x-y$ plane. When the two components are in phase, this ellipse is degenerate and the radiation is called *linearly polarised*. When the two components are perfectly out of phase, the ellipse is a circle, and the radiation is called *circularly polarised*. Of course, any ellipse in between these extremes is

²Note that the sign of α varies by convention, and both $S \propto \nu^\alpha$ and $S \propto \nu^{-\alpha}$ exist in the literature.

also possible. For this reason, we decompose the polarisation into linearly polarised components and a circularly polarised component, called *Stokes parameters* (Condon & Ransom, 2016; Stokes, 1851). These are:

$$I = \frac{1}{R_0} \mathbb{E}_t [E_x^2 + E_y^2], \quad (2.5)$$

$$Q = \frac{1}{R_0} \mathbb{E}_t [E_x^2 - E_y^2], \quad (2.6)$$

$$U = \frac{1}{R_0} \mathbb{E}_t [2E_x E_y \cos(\varphi_x - \varphi_y)], \quad (2.7)$$

$$V = \frac{1}{R_0} \mathbb{E}_t [2E_x E_y \sin(\varphi_x - \varphi_y)]. \quad (2.8)$$

\mathbb{E}_t denotes the expectation value over time. I is the *total intensity* of the radiation. Q and U together describe the linear polarisation and ~~together can be~~ are used to define the *polarisation angle* χ :

$$\tan(2\chi) = \frac{U}{Q}. \quad (2.9)$$

V is the circular polarisation and describes the eccentricity of the ellipse. For most extragalactic sources, the contribution of circular polarisation is tremendously small, especially compared to that of linear polarisation, and can be assumed to be zero (Rayner et al., 2000; Saikia & Salter, 1988). Incoherent radiation may be composed of radiation with many different polarisations, and these polarisations may fully or partially cancel out: ~~this~~. This is called *unpolarised* or ~~partially-polarised~~ partially polarised radiation respectively. The total intensity of polarised radiation is called the *polarised intensity* P and is given by

$$P^2 = Q^2 + U^2 + V^2. \quad (2.10)$$

Note that $P^2 \leq I^2$. The *fractional polarisation* is the ratio between these two intensities:

$$p = \frac{P}{I}. \quad (2.11)$$

The synchrotron radiation from radio galaxies is polarised, though this polarisation is not always detectable as the polarised signal tends to be much weaker than the total intensity, ~~on the order of ten per cent (O'Sullivan et al., 2015)~~ (on the order of 10 per cent; O'Sullivan et al., 2015). Additionally, the most common non-AGN cause for radio emission is star formation, which does not generally have detectable polarisation in extragalactic surveys. Polarisation is therefore an excellent way to confirm that a radio source is an AGN.

Polarisation can also be used to describe the magnetic structure of both the radio galaxy jets and lobes as well as the intervening medium. As polarised light from distant galaxies makes its way to us, magnetised plasma along the way can cause the polarisation angle to rotate due to the Faraday effect. The amount of rotation is called the *Faraday depth* ϕ , and is related to the electron density n_e and the line-of-sight magnetic

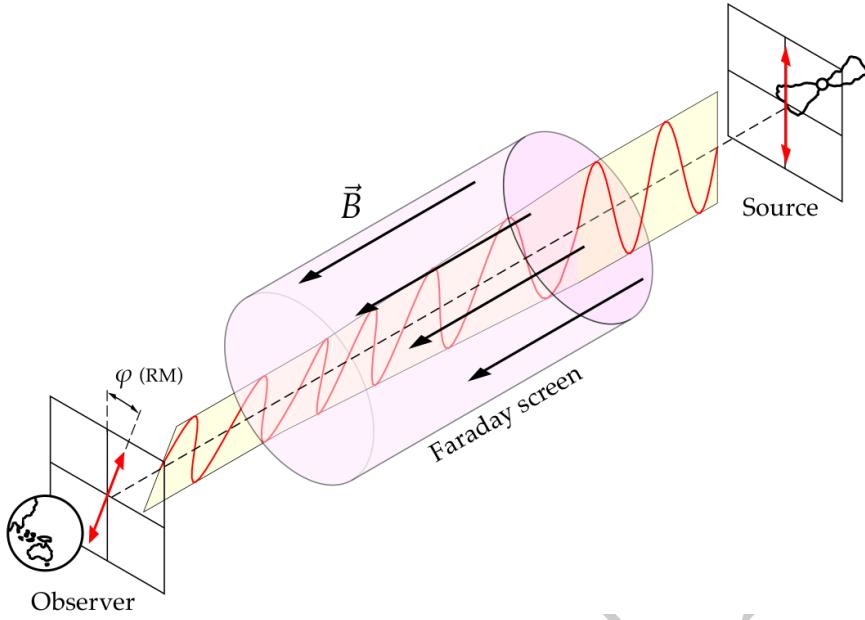


Figure 2.2: The Faraday effect for a single Faraday screen with magnetic field \vec{B} inducing a Faraday rotation of ϕ . Adapted from a figure by Bob Mellish.

field strength $\vec{B} \cdot \hat{z}$ of the intervening medium:

$$\phi(x, y) = \frac{e^3}{8\pi^2 \epsilon_0 m_e^2 c^3} \int_{\text{there}}^{\text{here}} n_e(x, y, z) \vec{B}(x, y, z) \cdot d\vec{z} \text{ rad m}^{-2}. \quad (2.12)$$

Here $d\vec{r}$ is the infinitesimal path length in pc (Brentjens & de Bruyn, 2005). Within the synthesised beam of a radio telescope there may be multiple lines-of-sight that go through different media and hence have different Faraday depths. An example of this is a radio galaxy that is sufficiently far away that its structure is unresolved by the telescope, and yet has different polarisation properties across its breadth. The leading constant of Equation 2.12 is around $2.62 \times 10^{-13} \text{ T}^{-1}$, more commonly written as $0.812 \text{ pc } \mu\text{G}^{-1} \text{ cm}^{-1}$ in CGS units with B in μG and z in pc. The amount of polarised radiation at each Faraday depth can be characterised by the *Faraday dispersion function* (FDF) or *Faraday spectrum* of the source, usually denoted $F(\phi) \in \mathbb{C}$. F is defined implicitly by its relationship with the polarised radiation P observed at wavelength λ :

$$P(\lambda^2) = \int_{-\infty}^{\infty} F(\phi) e^{2i\lambda^2\phi} d\phi. \quad (2.13)$$

⁷⁹⁷ One useful way of thinking about this equation is that F is the decomposition of $P(\lambda^2)$ into complex sinusoids of the form $e^{2i\lambda^2\phi}$.

⁷⁹⁸ If observed radiation has precisely one Faraday depth ϕ , then the polarised structure is called a *Faraday screen* and the source is called *Faraday simple*. In this degenerate case, the relationship between the polarisation angle χ and the squared wavelength λ^2

is linear:

$$\chi = \chi_0 + \phi\lambda^2, \quad (2.14)$$

and the FDF is a delta distribution:

$$F(\phi) = \delta(\phi - \phi). \quad (2.15)$$

799 ϕ is then called the *rotation measure* (RM). If the source is not Faraday simple, then it
800 is called *Faraday complex*, and the question of whether a source is Faraday simple or
801 Faraday complex is called *Faraday complexity*. A diagram of a Faraday screen is shown
802 in Figure 2.2. Until very recently, the frequency resolution of polarised surveys was
803 insufficient to meaningfully separate most complex arrangements of Faraday depths,
804 and so most sources were assumed to be simple and characterised entirely in terms of
805 their rotation measure (e.g. Taylor et al., 2009). Advancing telescope technology and
806 emphasis on polarisation science has opened new frontiers in spectropolarimetry and
807 upcoming and ongoing surveys (e.g. RACS and POSSUM) will likely report Faraday
808 complexity and produce Faraday depth catalogues instead of rotation measures.

If the polarised spectrum of a Faraday complex source is observed at multiple frequencies, then the multiple Faraday depths comprising it can be disentangled even though they spatially overlap in the radio image. This can provide insight into the polarised structure of the source as well as the intervening medium. This disentanglement is accomplished by inverting Equation 2.13, a process called *RM synthesis* (Brentjens & de Bruyn, 2005):

$$F(\phi) = \int_{-\infty}^{\infty} P(\lambda^2) e^{-2i\lambda^2\phi} d\lambda^2. \quad (2.16)$$

In reality we do not observe $P(\lambda^2)$ at all wavelengths nor with infinite resolution. In RM synthesis this is accounted for by the introduction of a *weighting function* (or *windowing function*, e.g. Heald, 2008) $W(\lambda^2)$. $W(\lambda^2)$ is nonzero if and only if an observation was taken with wavelength λ . Substituting $P(\lambda^2) \rightarrow P(\lambda^2)W(\lambda^2)$ into Equation 2.16 results in a sum which can be numerically evaluated:

$$F(\phi) \approx \int_{-\infty}^{\infty} P(\lambda^2)W(\lambda^2) e^{-2i\lambda^2\phi} d\lambda^2 = \sum_{j=1}^J P(\lambda_j^2)W(\lambda_j^2) e^{-2i\lambda_j^2\phi}. \quad (2.17)$$

809 $P(\lambda_j^2)$ is the observed polarisation at the j th value of wavelength, $W(\lambda_j^2)$ is the corre-
810 sponding j th weight, and J is the total number of wavelengths for which measurements
811 were taken. The weighting function W is analogous to the weighting function in radio
812 synthesis imaging. The most common choices of W are 1) uniform weighting³ with
813 $W(\lambda_j^2) = 1$ for all nonzero values, and 2) weighting by the inverse variance at each
814 wavelength.

Of course, no physical source has a precise Faraday depth, as there is always in-

³The analogous weighting scheme in radio synthesis imaging would be natural weighting rather than uniform—an unfortunate overlap in terminology.

trinsic scatter. Along the ~~line of sight~~^{line-of-sight}, if we assume ~~Gaussian noise in an otherwise constant that~~^{n_e is observed with random Gaussian noise} i.e. $n_e(z) \sim \mathcal{N}(\bar{n}_e, \sigma_{n_e}^2)$, and ~~a constant that~~^{B is constant} for simplicity, then we find:

$$\phi \sim \mathcal{N}\left(\frac{e^3}{8\pi^2\epsilon_0 m_e^2 c^3} B \bar{n}_e, \frac{e^3}{8\pi^2\epsilon_0 m_e^2 c^3} B \sigma_{n_e}^2\right), \quad (2.18)$$

that is, the depth has an uncertainty proportional to the magnetic field strength and the noise in n_e . A similar result follows for noise in B only. There is no analytic solution for noise in both B and n_e , but if we approximate the integrand as a Gaussian by calculating the mean and variance, we find:

$$\phi \sim \mathcal{N}\left(\frac{e^3}{8\pi^2\epsilon_0 m_e^2 c^3} \frac{\bar{n}_e \sigma_B^2 + \bar{B} \sigma_{n_e}^2}{\sigma_B^2 + \sigma_{n_e}^2}, \frac{e^3}{8\pi^2\epsilon_0 m_e^2 c^3} \frac{\sigma_{n_e}^2 \sigma_B^2}{\sigma_{n_e}^2 + \sigma_B^2}\right). \quad (2.19)$$

815 We observe multiple lines-of-sight that are coalesced into one within the beam. Due
 816 to this noise, even with constant n_e and B across a source, we can see multiple Faraday
 817 depths as each line-of-sight is a sample from the above distribution.

818 2.3 Radio galaxies and active galactic nuclei

819 AGN are some of the most energetic objects in the Universe. They both provide a labo-
 820 ratory for extreme physics and are a key part of the life cycle of a galaxy (Heckman &
 821 Best, 2014). Powered by a supermassive black hole, they convert gravitational poten-
 822 tial energy into intense electromagnetic radiation at a broad range of frequencies. AGN
 823 that produce strong radio emission are called radio AGN, and methods of observing
 824 the complex structures that these radio AGN form as radio galaxies are the focus of
 825 this thesis.

826 2.3.1 What we see when we look at AGN

827 Observations are the crux of astronomy. While there are many models of how AGN
 828 evolve and how they interact with their surroundings—and indeed, the actual struc-
 829 ture of an AGN is very much an open question in astronomy—the evidence presented
 830 by observations is reliable and a good place to start discussing the structure, behaviour,
 831 and importance of AGN throughout the Universe.

832 As powerful sources of radio emission, radio AGN and their associated extended
 833 structure can be seen throughout the Universe. Sufficiently close or large radio galax-
 834 ies can be resolved by telescopes and their structure examined, while more distant
 835 or smaller radio galaxies may be unresolved and point-like. A well-resolved radio
 836 galaxy can be a striking thing: ~~from~~^{From} the central AGN extend two opposing,
 837 tightly-collimated jets, which widen into huge lobes of radio-bright plasma. These
 838 lobes may have further structure, particularly bright regions called *hot-spots*, and the
 839 jets and lobes may be bent and distorted as they travel away from their host galaxy.

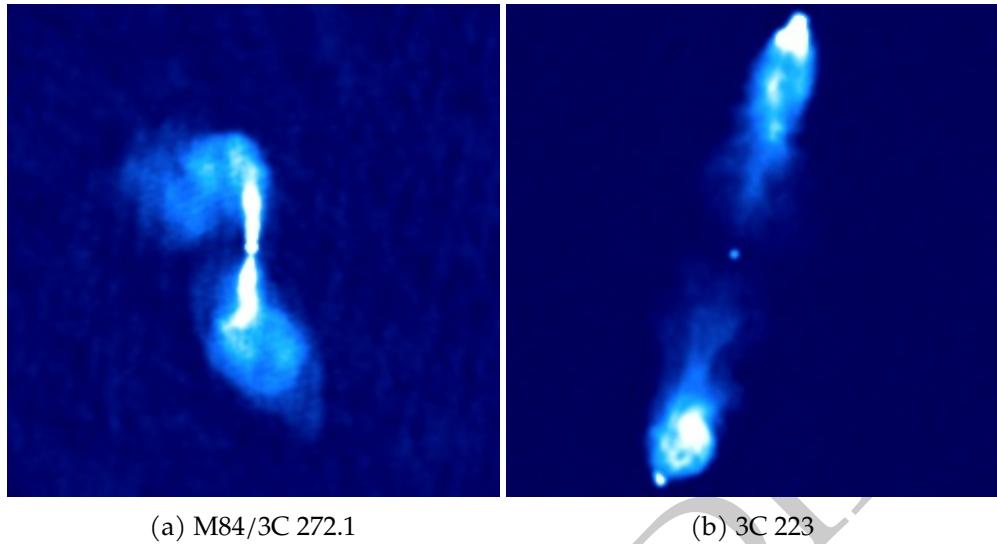


Figure 2.3: Examples of (a) a FRI (Laing & Bridle, 1987) and (b) a FRII radio galaxy (Leahy & Perley, 1991). Both are shown with an arcsinh stretch and were observed with the VLA.

For any given radio galaxy, some of these features may or may not be present. In particular, radio galaxies are often divided into two classes based on the kinds of extended structure that are visible, called Fanaroff-Riley type I (FRI) and Fanaroff-Riley type II (FRII) radio galaxies. FRI have wavy, diffuse lobes, appearing brighter toward the host galaxy and dimming further out (e.g. Figure 2.3a). FRII, on the other hand, have long, tightly-collimated jets and sharp-edged lobes with bright hot-spots (Urry & Padovani, 1995) at the very end of the lobes, and are brighter further away from the host galaxy (e.g. Figure 2.3b). FRII are also generally higher-luminosity (Fanaroff & Riley, 1974) than FRI, and therefore make up the majority of observed extended radio sources throughout the Universe. However, this is by no means the clear-cut divide it was once thought to be (Mingo et al., 2019) with the difference now being attributed largely to environmental effects rather than jet power. The current understanding is that FRII jets remain at relativistic energies up until the edge of the lobe, where they terminate in a shock that appears as a hot-spot, while FRI jets decelerate within the galaxy itself (Hardcastle & Croston, 2020). This sharp difference in extended structure begins with environmental interactions at the very centre of the galaxy.

A radio galaxy can be tremendously extended, with increasingly many radio galaxies being found with a length of over one megaparsec. Such large galaxies are called *giant radio galaxies*, but even non-giants are still quite big, regularly extending well outside the stellar component of the host galaxy. We will discuss the extended structure in Section 2.3.2. Appendix 5.J lists some giants discovered during the work of this thesis.

An AGN interacts with its host galaxy, and so the host galaxy of an AGN can also provide interesting insights into the structure and behaviour of the AGN. Early research indicated that the split between FRI and FRII radio galaxies was dependent on the mid-infrared and optical brightness (and therefore density) of the host galaxy (Bicknell, 1995; Ledlow & Owen, 1996) though more recent work suggests this may

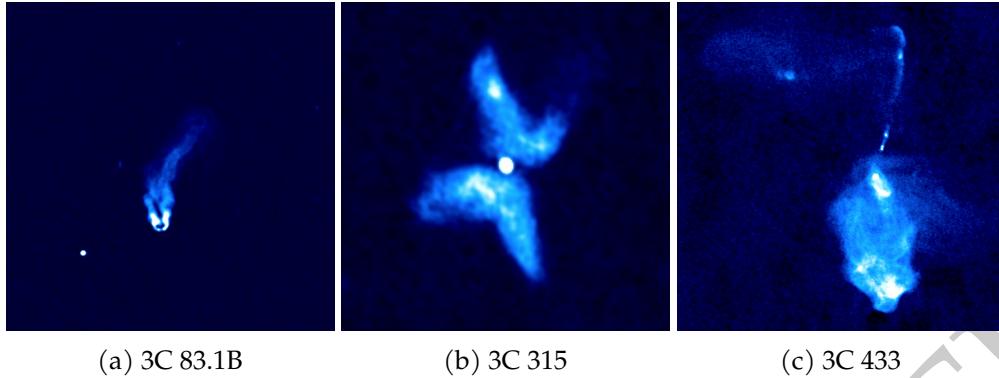


Figure 2.4: Radio galaxies, displayed with an arcsinh colour scale. All images were taken with the VLA. (a) is a narrow-angled tail radio galaxy (Leahy et al., n.d.), (b) is an X-shaped radio galaxy (Leahy et al., 1986), and (c) is a very unusually-shaped radio galaxy (Black et al., 1992).

not be a strong effect if it exists at all (Hardcastle & Croston, 2020). Chapter 5 investigates the distribution of radio luminosities conditioned on the mid-infrared colour of the host galaxy.

2.3.2 Extended structure

The jets and lobes of AGN can be very extended, with the largest known radio galaxies measuring over 4 Mpc end-to-end (Machalski et al., 2011). This is a much larger size than the radii of the host galaxies, and so the jets and lobes of AGN are uniquely poised to interact with the local environment. Environmental interactions both within and outside the host galaxy warp and distort the jets and lobes. Within the galaxy, the jets drive a bubble of energy in the [interstellar medium \(ISM; Mukherjee et al., 2016\)](#) [ISM \(Mukherjee et al., 2016\)](#), transferring energy into the ISM with different effects depending on the jet power (Mukherjee et al., 2018); the ISM on the other hand suppresses the jets and distorts them to varying amounts depending on the degree of interaction (Mukherjee et al., 2018). Outside the galaxy, the jets and lobes are bent by the intra-cluster medium and neighbouring galaxies (ICM; Garon et al., 2019; Rodman et al., 2019) and this structure may even be used as a probe for cluster environments (Banfield et al., 2016; Sakelliou et al., 2008).

The strong interaction of AGN with their [environment environments](#) leads to a great variety of exotic-shaped radio galaxies. Some morphological classes of this ‘radio galaxy zoo’ include X-shaped galaxies, which have two sets of lobes roughly perpendicular to each other; wide- and narrow-angled tail galaxies, which are bent about the core with large and small angles respectively; head-tail galaxies, which are so bent that the two lobes seem to be the same or nearly the same; double-doubles, which have two sets of lobes on each side; and many, many more. Some examples of radio galaxies with interesting structure are shown in Figure 2.4. Large-scale automated identification of these galaxies can be tricky owing to their variety, extent, and often disconnected structure.

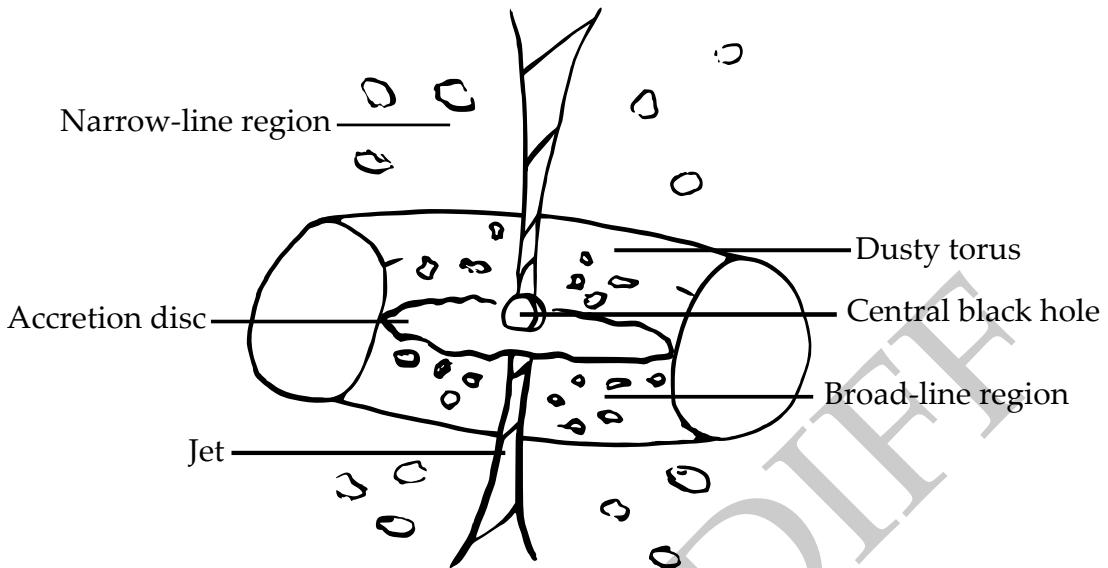


Figure 2.5: The unified model of AGN.

893 AGN cores tend to have flat or inverted spectral indices around -0.5–1 (Condon
 894 & Ransom, 2016; Randall et al., 2012). Moving out from the host galaxy, the spectral
 895 index steepens as the electrons are older and less energetic, with the spectral index
 896 of the lobes usually at about -0.7 (Condon & Ransom, 2016). The hot-spots of FRII
 897 galaxies have spectral indices between -0.5 – -0.7, becoming shallower as the electrons
 898 reaccelerate. These are only general trends: ~~the~~ The spectral structure within lobes
 899 can be very complex (Treichel et al., 2001). The jets do not strongly emit and are only
 900 detectable for particularly deep observations or nearby radio galaxies.

901 2.3.3 The unified model

902 At their core, AGN are an accreting *supermassive black hole*: a body so dense that even
 903 light cannot escape its gravitational pull, with mass on the order of 10^7 – $10^9 M_\odot$ (Mar-
 904 coni & Hunt, 2003). Such black holes seem to exist at the centres of galaxies and these
 905 galaxies are called *host galaxies*. The current understanding of the structure of an AGN
 906 is as follows (Urry & Padovani, 1995). The black hole is surrounded by an accretion
 907 disc emitting in ultraviolet and X-ray. Beyond this is the broad-line region, named for
 908 the Doppler-broadened emission lines emitted by the energetic clouds of material sur-
 909 rounding the accretion disc. The broad-line region and accretion disc are themselves
 910 surrounded by a dusty torus (or some other disc-like structure) which prevents light
 911 from the centre of the AGN being observed from the sides. Further still from the accre-
 912 tion disc is the narrow-line region, where lower-energy gas produces narrow emission
 913 lines. From either side of the disc, an AGN produces two collimated outflows of rel-
 914 ativistic plasma called jets, and these jets may interact with gas in the host galaxy to
 915 produce bright radio emission. The jets are not always visible. As the jets disperse fur-
 916 ther out from the centre of the AGN they widen into plumes of plasma known as *lobes*.

917 This model of AGN unifies different observed classes of AGN by their orientation and
 918 luminosity, and is hence known as the *unified model* (Antonucci, 1993). Recent work
 919 suggests that the unified model of AGN is not the full story (e.g. Zhuang & Ho, 2020).

There are many different ways to divide the set of radio AGN into classes. By morphology, radio AGN are often divided by the structure of the jets and lobes, with FRI and FRII the most striking examples. AGN can also be divided into *radiative-mode* and *jet-mode* by how they expel their energy (Heckman & Best, 2014). Radiative-mode AGN produce radiative energy in amounts higher than 1 per cent of their Eddington limit, while jet-mode AGN mainly output energy through their jets. The Eddington limit describes the maximum luminosity that a compact object can emit, and is given in Equation 2.20 (Rybicki & Lightman, 2008):

$$L_{\text{Eddington}}(M) = \frac{4\pi GMm_p c}{\sigma_T} \quad (2.20)$$

920 where M is the mass of the compact object.

921 Optical emission observed near the centre of the AGN can be used to divide radio
 922 AGN into broad-line and narrow-line galaxies. The former have broad spectral lines
 923 while the latter have narrow spectral lines, with broader spectral lines indicative of
 924 higher thermal energies. The most common interpretation, under the unified model,
 925 is that broad-line AGN are those seen end-on and narrow-line are those seen edge-on
 926 with the dusty torus obscuring the broad-line region. These narrow-line galaxies are
 927 usually the only ones for which we see significant extended structure.

928 2.3.4 Polarised structure

929 The magnetic field of AGN is thought to be critical to their structure (Sikora & Begelman, 2013). A strong magnetic field is required to eject and collimate the jets (Lovelace,
 930 1976) and the magnetic environment influences the structure of the jets (O'Sullivan et
 931 al., 2015). Polarisation provides a probe for measuring this magnetic field. Radiative-
 932 and jet-mode AGN have different fractional polarisations, with jet-mode AGN hav-
 933 ing a much wider range of fractional polarisations ($p \sim [0, 30]$ per cent) compared to
 934 radiative-mode AGN (limited to $p \lesssim 15$ per cent), with this difference attributable to
 935 the magnetic environment (O'Sullivan et al., 2015). Steep-spectrum ($\alpha > 0.5$) and flat-
 936 spectrum ($\alpha < 0.5$) AGN have differing fractional polarisations, with steep-spectrum
 937 sources having much higher fractional polarisation for frequencies > 5 GHz and flat-
 938 spectrum sources having higher fractional polarisation for frequencies < 1 GHz due
 939 to frequency-dependent depolarisation of the steep-spectrum sources (Saikia & Salter,
 940 1988). **Hotspots** of FRII radio galaxies have low polarisation (< 10 per cent)
 941 while the more diffuse sections may have much greater polarisation (> 20 per cent)
 942 (Saikia & Salter, 1988). The direction of the magnetic field is correlated with the direc-
 943 tion of **patterns** in the total intensity of the source (Saikia & Salter, 1988).

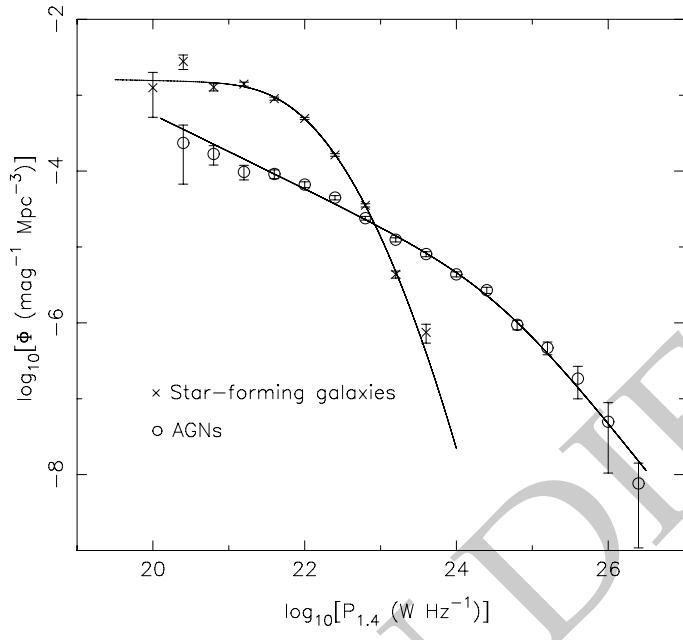


Figure 2.6: RLF for star-forming galaxies and AGN, from Mauch and Sadler (2007).

2.3.5 AGN luminosity

The distribution of AGN luminosities throughout the Universe can be characterised by the *radio luminosity function* (RLF). This describes the density of AGN within luminosity bins at a given frequency. The RLF at 1.4 GHz from Mauch and Sadler (2007) is shown in Figure 2.6. 1.4 GHz is arguably the most common large-scale survey frequency as it detects the easily observed 21 cm hydrogen line, but this RLF can be scaled to different frequencies by assuming a constant spectral index ($\alpha = -0.7$ for a typical AGN). In Chapter 5, we will use a machine learning-derived radio source catalogue to estimate a RLF for extended radio objects.

2.3.6 The role of AGN

AGN are an important part of galaxy evolution, though the exact mechanisms of this are not currently known. Understanding galaxy evolution requires understanding the links between it and AGN, and thus requires the study of AGN.

There are established relationships between AGN parameters and galaxy parameters: ~~the~~ The mass of the central black hole is correlated with the stellar mass and velocity dispersion near the core in elliptical galaxies (Cattaneo et al., 2009) as well as the luminosity of the bulge (Kormendy & Richstone, 1995). Massive galaxies seem to be more likely to contain an AGN rather than an inactive galactic nucleus (Hardcastle & Croston, 2020). The large-scale behaviour of AGN (e.g. the Fanaroff-Riley divide) may be caused by interactions within the host galaxy (Hardcastle & Croston, 2020) and this interaction would be a significant energy contribution to the ~~interstellar~~

966 mediumISM.

967 Perhaps the biggest topic in this field is that of *AGN feedback*, the role of AGN in the
 968 enhancement or quenching of star formation within their host galaxies. Star formation
 969 requires cold gas; AGN can push gas out of the galaxy (Zubovas & King, 2012) or heat
 970 it so that it can no longer form stars. But the rapid expansion of AGN jets can produce
 971 shocks in the local environment, compressing gas, triggering collapse of gas clouds,
 972 and potentially increasing the star formation rate (Zubovas et al., 2014).

973 For a review of the role of AGN within galaxy evolution, see Kormendy and Ho
 974 (2013). For a detailed review of the current understanding of AGN, see Hardcastle
 975 and Croston (2020).

976 2.4 Classifying AGN

977 As discussed in Section 2.3.3, radio galaxies fall into many classes. Understanding the
 978 mechanisms underlying these class distinctions is critical to understanding AGN. As
 979 we have no way to directly see the core of an AGN (it's far too small to resolve at the
 980 distances AGN occur and may also be occluded), our only method to investigate AGN
 981 is to look at their large-scale behaviour. Some classes may relate to the fundamental
 982 AGN core, some may be environmental, and some may be due to observation effects.
 983 Much of our knowledge about AGN (such as the unified model) come from analysing
 984 these classes and their differences. To investigate classes of AGN a large sample of
 985 each class is required, and source classification approaches can divide a large dataset
 986 from a radio survey into useful subsets. Knowing what class a source is may also help
 987 analyse its properties as we can estimate its expected behaviour, perhaps with the aid
 988 of models and simulations. Some classes may have interesting structure or properties
 989 that can only be observed with additional detailed observations, so identifying which
 990 sources require follow-up is a tightly related problem in radio astronomy. An excellent,
 991 though now somewhat dated, summary of radio source classification is the review
 992 paper by Urry and Padovani (1995), which we recommend for further reading.

993 Deciding which class a given radio galaxy falls into may be challenging, and doing
 994 this automatically even more so. This section discusses approaches to classifying radio
 995 galaxies.

996 2.4.1 Statistical and manual classification of AGN

997 Manual and statistical approaches to classifying AGN have dominated the radio as-
 998 tronomy literature until very recently, due to the comparative lack of computational
 999 power as well as a lack of good automated methods. Manual methods amount to ex-
 1000 amining the structure of a resolved source and determining its class: ~~this~~. This is how
 1001 we usually identify bent radio galaxies, head-tail radio galaxies, X-shaped radio galax-
 1002 ies, and those radio galaxies with more unusual morphologies. Statistical approaches
 1003 identify properties of the source that can be combined and thresholded to separate
 1004 the sources into categories en masse. Modern machine learning techniques for classi-
 1005 fication of radio sources can be thought of as an extension of these statistical methods,

1006 where the properties and their combinations are identified automatically, but we will
1007 discuss these separately in Section 2.4.2.

1008 Arguably the most well-known radio classification scheme, FRI and FRII, was orig-
1009 inally defined on well-resolved radio galaxies by computing the ratio of the distance
1010 between the regions of highest brightness on opposite lobes and the total extent of the
1011 radio emission (Fanaroff & Riley, 1974). Sources with a ratio under 0.5 were called FRI
1012 and those with a ratio greater than 0.5 were called FRII. This classification has over time
1013 evolved into a less precise divide, with classification generally now morphological and
1014 based on the structure (diffuse, wavy plumes versus hot-spots and lobes for FRI and
1015 FRII respectively). The FRI and FRII divide has been further complicated by other re-
1016 lated categorisations such as the so-called “Fanaroff-Riley type 0” sources which seem
1017 to be the lower end of a continuum of radio sources with diffuse plumes (Capetti et al.,
1018 2020; Garofalo & Singh, 2019) as well as hybrid morphology radio sources (HyMoRS)
1019 which appear to be FRI on one side and FRII on the other (Gopal-Krishna & Wiita, 2000;
1020 Kapińska et al., 2017). Many classes are defined by explicitly statistical means; for ex-
1021 ample, steep- and flat-spectrum sources are divided by spectral index at $\alpha = 0.5$ (Urry
1022 & Padovani, 1995). For convenient analysis, radio sources are often also grouped into
1023 “observational” classes that don’t have a physical analogue based on their apparent
1024 structure, e.g. the GLEAM survey classifies radio sources into the number of apparent
1025 components, which is highly dependent on the observational parameters (White et al.,
1026 2020).

1027 More unusual or more loosely defined classes, such as X-shaped radio galaxies
1028 and giants, have often been identified by manual searches through large datasets, e.g.
1029 Cheung (2007), Dabhade et al. (2020) and notably the recent ROGUE I catalogue of
1030 32 616 morphologically classified radio galaxies (Żywucka et al., 2020). These searches
1031 are often aided by computer algorithms (e.g. Dabhade et al., 2020; Proctor, 2011).

1032 Radio sources are also more generally classified, such as into AGN or non-AGN
1033 emission (Koziel-Wierzbowska et al., 2020), often using optical emission lines or opti-
1034 cal/infrared magnitude.

1035 2.4.2 Machine learning classification of AGN

1036 Machine learning based approaches for radio source classification are rapidly evolv-
1037 ing as the amount of radio data available through big surveys increases. Advances
1038 in tooling, such as the wide availability of hardware-accelerated automatic differentia-
1039 tion software, have also contributed to an explosion in machine learning applications
1040 in astronomy by making machine learning techniques more available to astronomy
1041 researchers.

1042 Morphological classification of galaxies with machine learning began in optical as-
1043 tronomy, probably due to the large sample sizes of well-resolved galaxies previously
1044 available. The earliest such paper is likely the application of neural networks to the
1045 task by Storrie-Lombardi et al. in 1992. From here, the field applied other classifica-
1046 tion algorithms such as decision trees (e.g. Owens et al., 1996). The Sloan Digital Sky
1047 Survey (SDSS) brought an explosion of new data in 2003, and new experiments in clas-

1048 sification soon followed (e.g. Ball et al., 2006; Ball et al., 2004). The Galaxy Zoo project
 1049 leveraged hundreds of thousands of volunteers to produce an astonishingly large set
 1050 of labelled optical galaxies from SDSS and subsequent papers used this as a training
 1051 set for machine learning methods (Banerji et al., 2010; Dieleman et al., 2015; Zhu et al.,
 1052 2019).

1053 While machine learning has been used in radio astronomy for some time ([Condon et al., 1998](#), e.g. the NVSS
 1054 ([e.g. the NVSS used neural networks to detect sidelobes](#); [Condon et al., 1998](#)) its first ap-
 1055 plication to radio source classification was most likely to identifying quasar candi-
 1056 dates (Carballo et al., 2004) in Faint Images of the Radio Sky at Twenty Centimeters
 1057 (FIRST; Becker et al., 1995). Proctor (2006) applied decision tree ensembles to identify
 1058 bent double morphologies in FIRST, manually selecting features to characterise radio
 1059 sources, while Bastien et al. (2017) used shapelet analysis to obtain features to feed into
 1060 their decision tree ensembles. 2011–12 marked a revolution in computer vision with
 1061 the discovery that deep convolutional neural networks (known as early as 1989, see
 1062 LeCun et al., 1989), boosted dramatically by widely available training data generated
 1063 by the internet and a huge increase in computational power from GPUs, could achieve
 1064 greater-than-human performance on image classification tasks. Deep neural networks
 1065 have since found use for morphological classification of radio sources, such as FRI vs.
 1066 FRII (Aniyan & Thorat, 2017; Bowles et al., 2020; Lukic et al., 2019; Ma et al., 2019b;
 1067 Samudre et al., 2020; Tang et al., 2019; see also Ma et al., 2018), compact vs. extended
 1068 sources (Alhassan et al., 2018; Lukic et al., 2018; Lukic et al., 2019), and observational
 1069 classes (Galvin et al., 2019; Ralph et al., 2019).

1070 There are also many works on classification of radio sources besides morphology.
 1071 Machine learning has been applied to AGN classification tasks including blazar classi-
 1072 fication (Arsioli & Dedin, 2020) and radio loudness (Beaklini et al., 2020). Deep learn-
 1073 ing is also prevalent on this topic, with deep learning finding applications in Faraday
 1074 complexity classification (Brown et al., 2018) and notably in transient detection (Agar-
 1075 wal et al., 2020; Balakrishnan et al., 2020; Connor & van Leeuwen, 2018; Guo et al.,
 1076 2019; Lin et al., 2020; Wang et al., 2019; Zhang et al., 2020).

1077 It is worth contrasting these machine learning approaches with non-machine learn-
 1078 ing automated approaches, as the two are often conflated in the literature. Mingo et
 1079 al. (2019), for example, use an automated version of detecting the brightness gradi-
 1080 ent of extended radio sources to determine whether they are FRI or FRII en masse
 1081 and apply this approach to the LoTSS survey. Segal et al. (2019) apply an information
 1082 theoretic approach to estimating morphological complexity of a source. The key dif-
 1083 ference between a machine learning automated approach and a non-machine learning
 1084 automated approach is that the former has the capacity to change its behaviour based
 1085 on available data, while the latter does not—though note that this is not necessarily a
 1086 bad thing.

1087 2.5 Cross-identification

1088 *Cross-identification* is the problem of matching an observed astronomical object at one
1089 wavelength with its counterpart in a survey at some other wavelength. Sometimes
1090 the counterpart in question can be obvious, such as when the object being matched is
1091 compact and well-aligned in both wavelengths. This is not the case for radio, though:
1092 ~~radio~~^{Radio} galaxies can be very extended and, due to environmental interactions, this
1093 extended structure may be complicated and have no obvious relationship to the galaxy
1094 at other wavelengths. The galaxy itself in radio cross-identification is called the *host*
1095 *galaxy* as it hosts the central AGN.

1096 2.5.1 Why do we need to cross-identify?

1097 Radio spectra do not generally contain much information besides the spectral index: as
1098 Jim Condon purportedly said, "There's nothing as useless as a radio source". Most in-
1099 formation about extragalactic sources is gleaned from other wavelengths, with optical
1100 and infrared showing physically meaningful differences due to emission and absorp-
1101 tion at these wavelengths. For this reason radio sources are typically cross-identified
1102 with their counterparts at other wavelengths to get information. Key features of a host
1103 galaxy that may be obtained from optical or infrared observations include its redshift,
1104 mass, star formation rate, and composition. From these we may also determine prop-
1105 erties of the radio plasma, most notably its physical extent and radio luminosity, both
1106 of which require knowing the redshift.

1107 2.5.2 Methods for cross-identification

1108 Most small radio surveys are cross-identified by astronomers, visually comparing the
1109 radio image to the optical or infrared image (e.g. Middelberg et al., 2008; Norris et
1110 al., 2006). The largest such catalogue is the ROGUE I catalogue with over 32 000
1111 cross-identifications (Żywucka et al., 2020). The Radio Galaxy Zoo project (Banfield
1112 et al., 2015) extended manual cross-identification to larger scales by crowdsourcing,
1113 asking volunteers online to cross-identify FIRST and ATLAS resulting in 75 000 cross-
1114 identified extended sources. This is the largest manually cross-identified source cat-
1115 alogue ever, by citizen scientists rather than professional astronomers—though this
1116 distinction does not seem to matter as the accuracy of cross-identifications in Radio
1117 Galaxy Zoo is still quite high, and there is an upper limit to how well even astronomers
1118 can cross-identify large surveys (Banfield et al., 2015; Wong et al., in prep.).

1119 2.5.2.1 Positional matching

1120 The simplest automated method for cross-identification is simply to look for the closest
1121 optical or infrared galaxy to some radio emission, a strategy called *positional matching* or
1122 *nearest neighbours*⁴. The distance to the nearest potential host galaxy is usually limited

⁴Not to be confused with the machine learning algorithm also called 'nearest neighbours', which does not make an appearance in this thesis.

to some small value, so that distant spurious relations are excluded. This distance is usually about $5''$ for infrared and $1''$ for optical but may be much further. Some authors modify this approach ~~to~~by selecting the nearest *bright* galaxy or adding some other constraints (e.g. Kimball & Ivezić, 2008). This approach generally works quite well for compact objects but extended radio structures may overlap with unrelated galaxies on the sky, leading to spurious cross-identifications.

The rate of spurious identification with this approach can be estimated by a simple model, assuming that the true host galaxy is not visible (either too faint or not nearby). Assume that a small circular region of the sky with radius a contains K potential host galaxies. The probability that a randomly selected potential host galaxy is within r rad of a given point is r^2/a^2 , with $r < a$. The probability of no potential host galaxy falling within r rad of a given point is therefore $(1 - r^2/a^2)^K$ and the probability of coincidental cross-identification is $1 - (1 - r^2/a^2)^K$. The AllWISE survey contains 747 634 026 infrared sources, over 4π sr, so it has an average source density of approximately $6 \times 10^7 \text{ sr}^{-1}$. With $r = 5''$, and $a = 1^\circ$ (corresponding to an area of $9.57 \times 10^{-4} \text{ sr}$ and thus 57 420 sources), we have a coincidental cross-identification rate of 10.5 per cent when the host galaxy is not visible.

2.5.2.2 Other automated methods

With very few non-trivial cross-identification methods in existence, the field is still very much in its infancy. Other automated methods for cross-identification can be grouped into machine learning and non-machine learning approaches. The two non-machine learning approaches are a Bayesian geometric model fitting approach (Fan et al., 2020; Fan et al., 2015) and a likelihood ratio approach (Weston et al., 2018; Weston, 2020). In Chapter 4 we introduce the very first machine learning approach for radio-infrared cross-identification (Alger et al., 2018). Galvin et al. (2020) later developed a hybrid machine learning and manual labelling approach to cross-identification.

2.6 Aggregating Radio Components

Unlike emission from galaxies observed at other wavelengths, the extended emission from radio galaxies can be disconnected when observed: ~~a~~A single radio galaxy may appear in observations as multiple discrete components. This is partly due to inhomogeneous emission over the radio galaxy structure—e.g. FRII hot-spots can be much brighter than the rest of the galaxy, so they ~~might~~may be visible while the rest of the galaxy is too faint to see—and partly due to the technique through which many radio observations are made, *interferometry*, which may screen out diffuse emission.

This potential of a radio galaxy to be split into multiple discrete blobs of emission also leads to a linguistic ambiguity not present at other wavelengths. A *radio source* may be either a single physical object that emits radio, or a single blob of disconnected radio emission. The same is true for *radio object*. There is no agreed-upon terminology. We will therefore adopt the following terminology from this point on, adapted from our paper (Alger et al., 2018) based on the Radio Galaxy Zoo terminology: ~~a~~A *radio source*



(a) The 64m telescope (Murriyang) at Parkes Observatory

(b) ATCA near Narrabri

Figure 2.7: (a) A single-dish telescope and (b) an array. Images: CSIRO.

or *radio galaxy* refers to all radio emission observed that comes from a single physical object, and a *radio component* refers to a single, contiguous region of radio emission above the noise level of an observation. ~~We will avoid using *radio object*.~~ Note that in the literature a *radio component* may be either a Gaussian fit to an observation or it may be a region of connected emission; in works where the former is the case (particularly in source-finding literature) the latter is often called a *radio island*.

Since radio galaxies can appear disconnected, aggregating observed radio components into physical sources is integral to understanding radio galaxies. Aggregating disparate components into a single source is important for two reasons. Firstly, without all components, the total luminosity of a source is dramatically underestimated. Secondly, we need all components to accurately examine the morphology of the source.

2.6.1 Missing emission in radio observations

Radio observations ~~may be made either with~~ are made with either single-dish telescopes, like the famous Parkes Radio Telescope (Murriyang), or radio arrays, like the Australia Telescope Compact Array (ATCA), both shown in Figure 2.7. Both have their advantages. Single-dish telescopes are able to measure absolute brightnesses (while arrays can only measure relative brightnesses, and must therefore be calibrated to a source of known brightness). Interferometric arrays can achieve incredibly high resolution, as the resolution is inversely proportional to the distance between the most distant array elements (while the resolution of single dish telescopes is inversely proportional to the diameter of the dish).

Radio telescopes can be thought of as sampling the *u-v plane*, the Fourier transform of the sky. The *u-v* plane is perpendicular to the line-of-sight. Each pair of antennae in an array samples two points on this plane, each corresponding to the vector between the antennae projected onto the *u-v* plane, called a *baseline*. Longer baselines therefore correspond to higher (spatial) frequencies, which is why long baselines provide

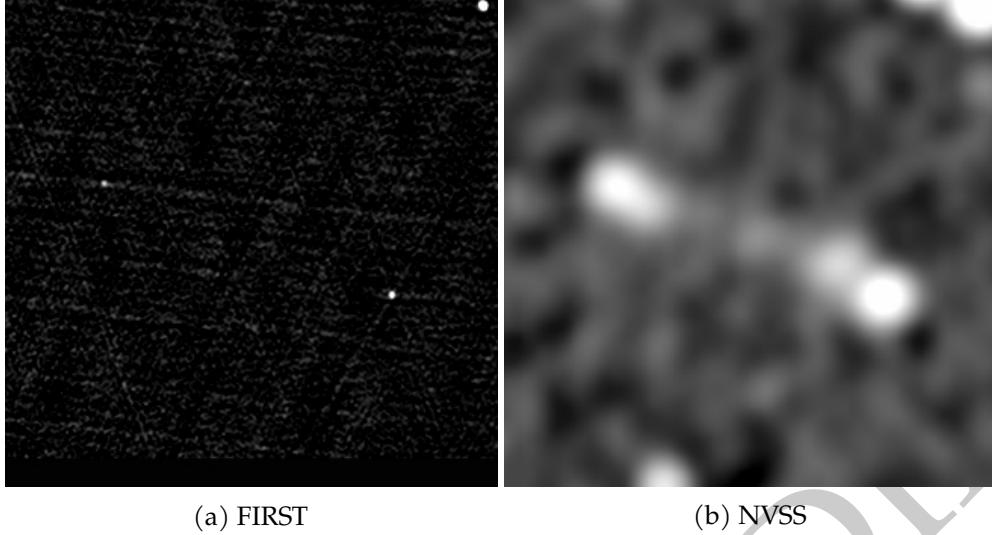


Figure 2.8: A fairly diffuse FRII, J0016+0420, observed with the VLA in the (a) FIRST (Becker et al., 1995) and (b) NVSS (Condon et al., 1998) surveys. (GRG1 from Dabhade et al., 2017)

high resolution. Diffuse emission is characterised mainly by low (spatial) frequency components, while compact emission is characterised by a broad range of frequency components, ~~so~~. This means that large angular scale, diffuse emission both a) takes up less space on the u - v plane than compact sources and b) occupies spaces much closer to the origin on the u - v plane. Some intuition on this can be obtained by examining the Fourier transform of a 2D Gaussian:

$$\mathcal{F}_{x,y} \left[\frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} \right] = e^{-2\sigma^2\pi^2(u^2+v^2)}. \quad (2.21)$$

From this equation we can see that the Fourier transform of a fairly *compact* Gaussian (small σ) would be quite broad, taking up many frequencies in the u - v plane, while a very *diffuse* Gaussian (large σ) would have a very narrow Fourier transform. The upshot of this is that long baselines sacrifice sensitivity to diffuse emission for high resolution. Single-dish radio telescopes are unable to make the same tradeoff, as they are only able to sample a disc centred on the origin⁵. This loss of larger scale diffuse emission is often called *resolving out*. An example of this is shown in Figure 2.8, where (a) and (b) are the same radio galaxy observed with the same telescope, the Very Large Array, with the only difference being that the VLA was in the B configuration for (a) and the D configuration for (b). The B configuration moves the antennae of the VLA far apart, while the D configuration keeps them close together.

⁵This is, incidentally, why single-dish telescopes can measure the absolute brightness while arrays cannot: ~~there~~There is no way to measure the origin in the u - v plane as there is no way for two array antennae to be infinitely close together (forming a zero-length baseline), and the origin contains the absolute brightness information, much like how the centre of a Fourier transform contains the mean.

1196 **2.6.2 Methods of aggregation**

1197 Most large radio catalogues are of *components* rather than sources, most likely because
1198 manual methods remain the best way to aggregate components into sources. Many
1199 component catalogues have source catalogues of some interesting subset later derived
1200 from them by manual inspection (e.g. Dabhadé et al., 2017). Such manual searches
1201 are often assisted by automated methods (e.g. Proctor, 2011). The Radio Galaxy Zoo
1202 citizen science project has also, with the help of over 10 000 volunteers, aggregated
1203 over 75 000 sources from FIRST (Wong et al. in prep.) and ATLAS (Banfield et al.,
1204 2015), which is one of the largest (if not the largest) extant catalogues of manually
1205 aggregated sources.

1206 Automated methods have been developing steadily as data volumes ~~have grown~~ grow.
1207 A Bayesian approach, fitting models of sources to component locations, was intro-
1208 duced by Fan et al. (2015) and later expanded upon (Fan et al., 2020). Machine learn-
1209 ing methods have also become increasingly popular. Proctor (2016) aggregated radio
1210 components using a decision tree classifier and used the results to search for giant
1211 radio galaxies (see also Proctor, 2006, 2011). Wu et al. (2019) applied a deep learn-
1212 ing model to identify radio sources from an image of radio components, training this
1213 model on the Radio Galaxy Zoo FIRST dataset. Most recently Galvin et al. (2020) used
1214 a nested self-organising map, a kind of neural network, to cluster similar sources and
1215 then aggregated them into sources using manual labelling of the clusters and some
1216 heuristics.

1217 Any method for cross-identification of components can also be used to aggregate
1218 components. Cross-identify all components with their host galaxies, then components
1219 that share a host are almost always part of the same radio source. It is this approach
1220 ~~that~~ we will later take to aggregating sources in Chapter 5. There is no obvious in-
1221 verse algorithm (to go from aggregate sources to cross-identifications) although some
1222 algorithms attempt to solve both problems simultaneously (Fan et al., 2020; Fan et al.,
1223 2015).

1224 **2.7 Summary: radio sources**

1225 The radio sky is vibrant and exciting, and current and new wide-area radio surveys are
1226 opening up new avenues of exploring this space. In this chapter we introduced radio
1227 sources that you might see in the radio sky, including the often-extended AGN. We dis-
1228 cussed their radio emission and emission mechanisms, and described some aspects of
1229 their morphology and structure. We also looked at ways that radio sources can be clas-
1230 sified, aggregated, and cross-identified with their counterparts at other wavelengths.
1231 In the next chapter, we will introduce machine learning concepts that we will use to
1232 develop methods for exploiting the vast amount of data ~~that~~ radio telescopes provide
1233 on radio sources.

REVISION DIFF

1235 **Machine Learning for
1236 Astroinformatics**

1237 Machine learning was once described to me by an anonymous supervisor as “the statistics
1238 kept at the back of the textbook”. But even accepting its grounding in statistics,
1239 is this really an accurate description of the field? I think of machine learning as a
1240 combination of three pieces: a data-driven way of formalising predictive problemsand
1241 a way of converting between different kinds of statistical problems, as well as an
1242 accompanying-and-a set of methods and practices for handling data and uncertainty.
1243 The eventual goal is to design some method or algorithm that automatically discov-
1244 ers useful patterns in (potentially very large) data-setsdatasets. There are three core
1245 components of machine learning: the data, the model, and learning (Deisenroth et al.,
1246 2020). Before discussing these, we will look at the kinds of problems that machine
1247 learning solves.

1248 **3.1 Prediction**

1249 Machine learning aims to solve *prediction tasks*: problems where we have some data
1250 and we seek some kind of output based on that data. Central to prediction tasks are
1251 predictors, the objects we train based on data.

1252 **3.1.1 Predictors**

1253 A *predictor* is an object that makes predictions based on an input. A predictor can be a
1254 function or a probabilistic model, depending on the machine learning approach being
1255 undertaken.

As a function, a predictor maps from some input domain \mathcal{X} into some output do-
main \mathcal{Y} , and is usually written as

$$f : \mathcal{X} \rightarrow \mathcal{Y}. \quad (3.1)$$

1256 \mathcal{X} and \mathcal{Y} are commonly (but certainly not always) a real vector space \mathbb{R}^n . Because the
1257 goal of machine learning involves *finding* a suitable function f for the task at hand, the
1258 set of functions is usually constrained. For example, if $\mathcal{X} = \mathbb{R}^n$, we might require that

1259 f is a linear function $\mathbb{R}^n \rightarrow \mathbb{R}$, easily parametrised by $n + 1$ constants. This constraint is
1260 called a *model*. Models are often (but not always) parametrised and training the model
1261 refers to finding a good set of parameters. The parameters are sometimes called *weights*.
1262 To avoid ambiguity, parameters of the model that are not changed during training are
1263 called *hyperparameters* and may include regularisation terms, constraints, or variations
1264 of the model.

1265 Some predictors can be described as a probabilistic model. In this case a predictor is
1266 a joint probability distribution between observations and hidden parameters (Deisen-
1267 roth et al., 2020). Using a probabilistic predictor allows us to formally describe and
1268 work with uncertainty both in the input space and output space. Such a predictor is
1269 usually parametrised by a finite set of parameters, which already includes most com-
1270 mon probability distributions.

1271 We ~~will~~ generally assume that our data are generated from some unobserved, true
1272 function called the *groundtruth*. This might be a physical process, or a complicated
1273 sampling function from some unknown vector space. The assumptions we make on
1274 this generative function can greatly change the way we approach machine learning
1275 problems.

1276 In some sense, the goal of machine learning is to identify a good predictor from
1277 within the space of all possible predictors. Of course, this begs the question: ~~what~~
1278 What is a ‘good’ predictor? We will return to this when we discuss learning, but for
1279 now, a good predictor is one that approximates the groundtruth well.

1280 3.1.2 Classification

1281 *Classification* is the machine learning task of predicting discrete, unstructured values
1282 (Deisenroth et al., 2020). These values are called *classes*. Classification is arguably the
1283 most important prediction task, as many other problems can be formalised as classi-
1284 fication. Astronomy has its fair share of classification tasks, from classical astronomy
1285 tasks like galaxy morphology classification (appearing in machine learning literature
1286 as e.g. Dieleman et al., 2015) to transient detection (e.g. Scalzo et al., 2017); see Sec-
1287 tion 2.4 for more examples.

1288 A classification problem seeks a predictor where \mathcal{Y} represents a finite, discrete set
1289 of classes. Classification tasks are usually delineated by the number of classes: ~~there~~
1290 There are either two classes or more than two classes. The former are called *binary*
1291 *classification* tasks and the latter are *multiclass classification* tasks. The reason for this
1292 split is that binary classes are dramatically easier to reason about and analyse, and
1293 many special cases exist for binary where they do not for multiclass.

1294 \mathcal{Y} for a binary task is usually represented as $\mathcal{Y} = \{0, 1\}$. 1 is called the *positive class*;
1295 0 is called the *negative class*.

1296 An easy way to see why many tasks can be formalised as classification can be found
1297 by taking any prediction problem $\mathcal{X} \rightarrow \mathcal{Y}$ and reinterpreting it as the binary classifica-
1298 tion problem $\mathcal{X} \times \mathcal{Y} \rightarrow \{0, 1\}$, i.e. instead of taking an input and predicting an output,
1299 take an input and a potential output and determine if they should be related. Of course
1300 this is not always the most efficient way to solve a prediction problem but the many

1301 known properties of classification make it an appealing framework to cast problems
1302 into. In Chapter 4, we will cast the radio astronomy problem of cross-matching galaxies
1303 seen in different wavelengths into a binary classification problem, and in Chapter 6
1304 we will classify radio observations as Faraday complex or Faraday simple.

1305 There are three different formalisms for the output of a binary classifier. The output
1306 may be a *score*, a *class probability estimate*, or a *predicted class*. A predicted class is what
1307 first comes to mind as a representation of binary classes: ~~the~~The classifier outputs ei-
1308 ther 0 or 1, with no way of representing ambiguity. A class probability estimate is a
1309 number from 0 to 1 which represents the probability that an example is in the positive
1310 class, i.e. if f is a classifier then $f(x) = p(y = 1 | x)$. Class probability estimates may
1311 be output by probabilistic classifiers, or may be estimated from non-probabilistic classi-
1312 fiers. Finally, a score is a value that tends to be larger for elements of the positive class,
1313 with less ambiguous examples being given a higher score. Scores are often converted
1314 into class probability estimates by applying a sigmoid (see Section 3.4.1). There are
1315 multiple ways to generalise these concepts to multiclass classification. Having a score
1316 or a class probability estimate can be more useful than only having a predicted class.
1317 For example, you could sort your examples by how likely they are to be a member
1318 of the positive class. This underpins our approach to casting cross-identification as
1319 binary classification in Chapter 4.

1320 3.1.3 Regression

1321 The other main kind of supervised prediction task is *regression*, which is the machine
1322 learning task of predicting ordered (and usually continuous) values. In a regression
1323 problem, we seek a predictor where \mathcal{Y} is a set of ordered values, usually a subset of
1324 \mathbb{R}^k for some positive natural k . Regression is ubiquitous in astronomy, from simple
1325 linear relationships like the famous Tully-Fisher relation (Tully & Fisher, 1977) to es-
1326 timation of redshifts from photometric observations (called *photometric redshifts*; first
1327 introduced by Baum, 1962). ~~We will This thesis does~~ not directly address any regres-
1328 sion problems~~in this thesis, but we will~~, but does make use of their results.

1329 3.2 Data and representation

1330 Machine learning is centred on data and the extraction of useful information from that
1331 data. Data can include anything from numeric information, documents, or images,
1332 to spectra or galaxies. A collection of data is called a *dataset* and an element of this
1333 dataset is (interchangably) called an *example* or *instance*. Generally, data are not easy to
1334 work with in their original form and must be converted into a numerical representation
1335 before use. We usually convert our data into real vectors in \mathbb{R}^n as it is relatively easy
1336 to work with both numerically and analytically. Each axis of this vector space is called
1337 a *feature* and the space as a whole is called the *feature space*. Features are non-trivial
1338 to choose, and finding good features often requires the expertise of a human who is
1339 well-versed in the original dataset (a *domain expert*). The process of finding features is
1340 called *feature selection*, *feature design*, or *feature engineering*.

What makes a feature good? Intuitively, we want to transform our data into a space where it is easy to work with: a space where properties we care about are obvious, easy to extract, behave nicely, and work well with our model. For this reason, features will vary tremendously depending on the problem being faced, and the same data may be represented in many different ways. Much of early machine learning literature focused on finding good methods to automatically develop features (generally called *feature extraction*), and much early applied machine learning focused on identifying these features manually so that good predictors could be easily found. An astronomical example is Proctor (2006), who developed features for representing radio galaxies for the purpose of sorting them. State-of-the-art models like deep neural networks (e.g. Dieleman et al., 2015) can be viewed as developing their own task-specific features as part of their training (see Section 3.4.3). These deep learning features can be useful (e.g. when it is hard or slow to define good features manually), but are usually hard to interpret. A good feature space ~~will have has~~ a structure that reflects the components of the intrinsic structure of the input data which are useful for the prediction task at hand. Good features may also be useful in other related tasks, such as dataset exploration, dataset visualisation, or other prediction tasks. Chapter 6 largely focuses on finding good features for identifying Faraday complexity in polarised sources.

Labels comprise another very important piece of the machine learning puzzle. Training a predictor with supervised learning requires some known pairs of inputs and outputs, and the known outputs are called labels. Like features, labels also need to be encoded in some way, and this depends on the specific task. Much like features, we want to embed the labels into a space which is easy to work with and has a meaningful structure. For problems where we know the outputs we wish to obtain, this can be a lot simpler than feature selection. For example, a binary classification problem ~~will have has~~ only two possible outputs. Common representations for ~~this would be these are~~ $\{0, 1\}$ as described in Section 3.1.2, but we could also represent the labels as $\{[1, 0]^T, [0, 1]^T\}$, called a *one-hot encoding*. The advantage of the former is its simplicity and ease of integration into binary classification equations, but the advantage of the latter is that it is easily extended into multiclass classification without imposing order on the classes. Despite being simpler to encode, labels can carry a lot more difficulty than features due to their comparative rarity: ~~in-In~~ essence, features are cheap and labels are expensive. We will discuss labels in more detail in Section 3.5.

3.3 Loss functions

Training a model is the process of using data to find a good predictor that fits the model's constraints. This is generally achieved by minimising a *loss* (also called *error* or *cost*) function over the model.

Put simply, a loss function is a function of a predictor and a dataset which is chosen to be a proxy for how good the predictor is at predicting that dataset. We try to choose loss functions that are high-valued for a predictor that poorly describes the dataset, and are low-valued for a predictor that well-describes the dataset. Sometimes (and

in both cases listed in this section) the loss is minimised at zero, when the predictor perfectly captures the dataset (though whether this is possible, or whether this is even a desired result, is another question).

What should the loss function be for a given problem? The answer is not always obvious. Take for example a binary classification problem. The “obvious” loss would be the complement of the accuracy: the rate at which the predictor incorrectly guesses the label. This is easy to compute and we would like our predictor to have a high accuracy. But this is not a good choice: it is tremendously hard to work with as it takes on discrete values, because the accuracy is the number of correct predictions divided by the total number of examples. It is hard to motivate with probabilistic arguments. Finally, it is unclear how the accuracy should work in the case of a probabilistic model.

Instead, the loss function is usually derived by making assumptions on the structure of the data and task. The main assumption we usually make is that data are drawn *independently and identically distributed* (IID), that is, each example is drawn from the same distribution and is not dependent on any other examples. We also assume a structure of the noise in the observed labels: training data are almost never completely accurate, and so there will be so there is usually intrinsic noise in the distribution of labels about their unobserved “true” value. To demonstrate these assumptions, we will now derive loss functions for regression and binary classification. The loss function we derive depends on the model we assume for the noise; for example, assuming Gaussian noise gives us the common least-squares loss.

3.3.1 Loss function for regression

To derive a loss function for regression, let us assume that our labels are a random variable y modelled by a predictor $y = f(x)$. Further, let us assume that a predicted y is normally distributed about its true value, i.e.

$$y \sim \mathcal{N}(\mu, \sigma^2) \quad (3.2)$$

for the true mean μ and standard deviation σ where \mathcal{N} is the normal distribution:

$$\mathcal{N}(a | \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(a-\mu)^2}{2\sigma^2}}. \quad (3.3)$$

Under this assumption the probability that y is equal to a target t given an example x is

$$p(y = t | x) = \mathcal{N}(t | f(x), \sigma^2). \quad (3.4)$$

What would the probability be of observing a set of targets $T = \{t_1, \dots, t_n\}$ given corresponding examples $X = \{x_1, \dots, x_n\}$? Letting $Y = \{y_1, \dots, y_n\}$ be random variables like y , the joint probability distribution $p(Y = T | X)$ is

$$p(Y = T | X) = \prod_{i=1}^n p(y_i = t_i | x_i) \quad (3.5)$$

by using our independence assumption. We can then substitute the normal distribution:

$$p(Y = T | X) = \prod_{i=1}^n \mathcal{N}(t_i | f(x_i), \sigma^2). \quad (3.6)$$

$p(Y | X)$ is called the *likelihood*. We would like to maximise this likelihood over f , which is called a *maximum likelihood* approach to finding a predictor. It is, however, not very easy to work with in this current form. Maximising the likelihood is equivalent to minimising its negative logarithm, so we write:

$$\mathcal{L}(f; T, X) = - \sum_{i=1}^n \log \mathcal{N}(t_i | f(x_i), \sigma^2) \quad (3.7)$$

where \mathcal{L} is the *negative log-likelihood*, a loss function. We can simplify this dramatically by cancelling the logarithm and the exponential within the normal distribution:

$$\mathcal{L}(f; T, X) = \sum_{i=1}^n \frac{(t_i - f(x_i))^2}{2\sigma^2} \quad (3.8)$$

and by noting that arbitrary scaling of \mathcal{L} does not change the minimising f we can scale \mathcal{L} by σ^2 and arrive at the *sum-of-squares error*, also known as the *least-squares error*, the most common loss function for regression:

$$\mathcal{L}(f; T, X) = \frac{1}{2} \sum_{i=1}^n (t_i - f(x_i))^2. \quad (3.9)$$

The factor of half helps keep the derivative tidy:

$$\frac{d\mathcal{L}}{d\theta}(f; T, X) = \sum_{i=1}^n (t_i - f(x_i)) \frac{df}{d\theta}(x_i). \quad (3.10)$$

1404 3.3.2 Loss function for binary classification

Now we will calculate a loss function for binary classification. As for regression, we first assume a form for the noise. Assume that our labels are a random variable $y \in \{0, 1\}$ and that the prediction y is drawn from a Bernoulli distribution based on a predictor $f(x)$:

$$p(y = t | x) = \mathcal{B}(t; f(x)). \quad (3.11)$$

The Bernoulli distribution is parametrised by one parameter, usually called $p \in (0, 1)$, and in this case set to $f(x)$. It is:

$$\mathcal{B}(a; p) = p^a (1 - p)^{1-a}. \quad (3.12)$$

It can be thought of as a biased coin toss with a probability p of tossing heads. To gain some intuition into how this expression works, imagine setting a to 0 and then to 1. Continuing to derive the loss function, we once again determine the likelihood

making the IID assumption:

$$p(Y = T \mid X) = \prod_{i=1}^n p(y_i = t_i \mid x_i) = \prod_{i=1}^n f(x_i)^{t_i} (1 - f(x_i))^{1-t_i}. \quad (3.13)$$

Then we find the negative log-likelihood and hence what is known as the *binary cross-entropy loss* for binary classification:

$$\mathcal{L}(f; T, X) = - \sum_{i=1}^n \log \left(f(x_i)^{t_i} (1 - f(x_i))^{1-t_i} \right) \quad (3.14)$$

$$= - \sum_{i=1}^n t_i \log f(x_i) + (1 - t_i) \log(1 - f(x_i)). \quad (3.15)$$

1405 This is the standard loss used for logistic regression (Section 3.4.1).

1406 **3.3.3 Gradient descent**

Given a loss function and a parametrised model, how can we find parameters for the model that minimise the loss function? There are many optimisation strategies but if both the loss function and model are differentiable with respect to the parameters then we can employ a particularly efficient approach: *gradient descent*. Assume we have a model $f(x; \vec{w})$ parametrised by some vector \vec{w} and a loss function $\mathcal{L}(\vec{w}; T, X)$. Then the value of \vec{w} after the $k+1$ th update of gradient descent is

$$\vec{w}^{(k+1)} = \vec{w}^{(k)} - \lambda \nabla_{\vec{w}} \mathcal{L}(\vec{w}^{(k)}; T, X) \quad (3.16)$$

1407 where $\lambda > 0$ is a small scalar called the *learning rate*. With an appropriately small choice
1408 of λ \vec{w} will converge to a local minimum of \mathcal{L} . Many variations on this concept exist
1409 which attempt to avoid local minima, such as introducing a ‘momentum’ term that
1410 accumulates as multiple iterations move \vec{w} in the same direction. If the loss function
1411 is convex, then any minimum is the global minimum (there are no local minima).

1412 **3.4 Models**

1413 This section describes some common models for classification. There are a plethora of
1414 different classification models and variations on these models, but I will present here
1415 only those relevant to this thesis: logistic regression, decision tree ensembles, and neu-
1416 ral networks. These are, not coincidentally, also the most common models in astroinfor-
1417 matics. Logistic regression provides reliable and interpretable results. Decision tree
1418 ensembles are a fantastic off-the-shelf choice which work on a large variety of datasets.
1419 Neural networks have ~~proved~~-proven extremely effective for a wide variety of tasks,
1420 especially in computer vision.

1421 **3.4.1 Logistic regression**

1422 *Logistic regression* is a linear, binary, probabilistic classifier. Linear classifiers can only
 1423 separate classes using a hyperplane in the feature space, with objects on one side of the plane being assigned to one class and objects on the other side being assigned to the other. A binary classifier works on binary classification tasks. Probabilistic classifiers, as discussed in Section 3.1.2, have outputs interpretable as class probabilities.

1426 Logistic regression in a d -dimensional feature space is parametrised by a *weights vector* $w \in \mathbb{R}^d$. Given a set of features $x \in \mathbb{R}^d$, logistic regression is:

$$f(x; w) = \sigma(w^T x) \quad (3.17)$$

where σ is the *logistic function* or *sigmoid*, which is a monotonic and bijective function:

$$\sigma(a) = \frac{1}{1 + e^{-a}}. \quad (3.18)$$

1427 The output of logistic regression applied to an example x is the probability that x is
 1428 in the positive class. σ , and thus logistic regression, has a domain of $(-\infty, \infty)$ and a
 1429 range of $(0, 1)$. This enforces the output to be like a probability. $w^T x = 0$ defines a
 1430 d -dimensional hyperplane, called the *separating hyperplane* or *decision surface*. Logistic
 1431 regression is differentiable, which allows us to optimise its parameters w using
 1432 gradient descent. Interpreting the classifier is possible through examining the weights
 1433 vector, with a larger absolute value of a weight corresponding to a ‘more important’
 1434 feature. The weights from logistic regression can be used to produce scores or class
 1435 probability estimates (Section 3.1.2): $w^T x$ is a score, $\sigma(x^T x)$ is a class probability esti-
 1436 mate, and thresholding either the score or the class probability estimate at 0 gives a
 1437 discrete class.

1438 A limitation of logistic regression is its sensitivity to scale. Features need to be of
 1439 approximately the same order of magnitude and should have a standard deviation of
 1440 approximately 1. An implicit assumption is that each ~~features~~ feature has a mean of 0
 1441 across the dataset. This can be enforced by normalising and scaling: subtract the mean
 1442 of the dataset and divide by the new standard deviation.

1443 We apply logistic regression to binary classification problems in Chapter 4 and
 1444 Chapter 6.

1445 **3.4.2 Decision tree ensembles**

1446 A *decision tree* is a non-linear classifier. It repeatedly splits a dataset based on binary
 1447 comparisons until every subset contains only one class (or mostly one class, with the
 1448 amount of purity left as a hyperparameter). Each split only uses one feature for the
 1449 comparison, making decision trees relatively easy to visualise and interpret. However,
 1450 because of this, each split is axis-parallel, which can be a limitation for some datasets.
 1451 They are not sensitive to scale and do not require a zero mean, making them easy to
 1452 apply without preprocessing a dataset.

1453 Key limitations of a decision tree are:

- 1454 • They can only output a prediction, not a confidence of this prediction or a score
1455 of how likely an instance is to be found within each class.
- 1456 • Small changes to the dataset or training method can result in large changes to
1457 the tree.
- 1458 • They tend toward overfitting the training set.
- 1459 • With many low-information features, decision trees have quite poor performance
1460 (Breiman, 2001).

1461 A *decision tree ensemble* aims to reduce some of these limitations by training mul-
1462 tiple, slightly different, independently-trained decision trees. Depending on the im-
1463 plementation each constituent decision tree may only have access to some of the fea-
1464 tures or some of the data. To predict, each tree produces a prediction and ‘votes’ for
1465 this prediction; the votes ~~can be~~ are combined to produce the overall prediction (e.g.
1466 with majority voting). A simple example of such an ensemble is decision tree bagging
1467 (Breiman, 1996), which trains each tree with a random subset of the training data and
1468 takes a plurality vote. Decision tree ensembles decrease variance, increase the usabil-
1469 ity of low-information features, and increase stability of the trained model (Breiman,
1470 2001). Averaging over the classifications produced by each tree gives a number that
1471 can be interpreted as a class probability estimate.

1472 The most well-known description of decision tree ensembles is the *random forest*
1473 (Breiman, 2001), which has found common use in astronomy partly to its readily avail-
1474 able Python implementation in `scikit-learn` (Pedregosa et al., 2011). Splits are de-
1475 cided from a subset of features and training samples are randomly drawn with replace-
1476 ment from the total training set. One downside of random forests is the large number
1477 of hyperparameters that need to be set, and these vary a lot depending on the problem
1478 being addressed.

1479 We apply decision tree ensembles to binary classification problems in Chapter 4
1480 and Chapter 6.

1481 3.4.3 Convolutional neural networks

A *neural network* is a directed graph of transformations, each node representing a trans-
formation that linearly combines its inputs and applies a non-linear function called the
activation function to the result. The inputs to the graph are the features. A particularly
prominent kind of neural network is the *fully-connected neural network*, where nodes
are arranged into layers, with each node in a layer taking as input every output from
the previous layer. Each layer can then be represented by a matrix multiplication of
the outputs of the previous layer by a weight matrix, composed with the activation
function. Fully-connected K -layer neural networks have the form:

$$f(x; W_K, \dots, W_1) = h_K(x; W_K, \dots, W_1) \quad (3.19)$$

$$h_i(x; W_i, \dots, W_1) = a(W_i h_{i-1}(x; W_{i-1}, \dots, W_1)) \quad (3.20)$$

$$h_1(x; W_1) = a(W_1 x) \quad (3.21)$$

1482 where a is the activation function. h_i are called *hidden layers*. In fact, neural networks
 1483 are usually described by their layer structure rather than graph structure, with the
 1484 addition of ‘concatenation layers’ to combine outputs from previous layers. Neural
 1485 networks may be used for regression or for classification; these are structured the same
 1486 but for classification the last activation function is replaced by sigmoid (for binary
 1487 classification) or its multiclass counterpart softmax.

1488 *Convolutional neural networks* (CNN; LeCun et al., 1998) are ~~a-variant~~variants of
 1489 neural networks that are particularly well-suited to inputs that have local structure,
 1490 such as images or spectra. Layers in the network may be *dense layers* of the same form
 1491 as Equation 3.20, or *convolutional layers*, where the weights are convolved with the input
 1492 rather than multiplied. These convolutional weights are called *filters* and they are small
 1493 compared to the dimensionality of the input. CNNs are translation-invariant (Waibel
 1494 et al., 1989) and derive features from local relationships thanks to the trainable filters.

1495 We apply CNNs to binary classification problems in Chapter 4 and Chapter 5, and
 1496 compare our results to a state-of-the-art CNN in Chapter 6.

1497 3.5 Labels

1498 As described in Section 3.2, labels are the known outputs of supervised prediction
 1499 tasks. They are used for two main, distinct purposes: training and validation. Labels
 1500 for training are used to evaluate loss and determine how to update the model. Labels
 1501 for validation are used to evaluate and characterise the model’s behaviour.

1502 3.5.1 Where do labels come from?

1503 We previously said that labels were ‘expensive’. This is to be interpreted as expensive
 1504 in either or both time and money: ~~labelling~~Labelling can be a slow, manual~~process~~,
 1505 ~~and labelling can be costly~~. ~~Labelling~~and process. It is usually completed by hand,
 1506 manually examining instances and determining ~~what~~which class they belong to (for
 1507 classification) or what target they ought to be associated with (for regression). In
 1508 astronomy this usually amounts to expert astronomers examining imagery at multi-
 1509 ple wavelengths and making an educated guess as to what the true label ~~should be~~is,
 1510 but labelling may also involve follow-up observations (perhaps at higher resolution,
 1511 greater sensitivity, or at a different wavelength).

1512 An increasingly popular option for labelling large amounts of data is *citizen science*:
 1513 asking volunteers who are interested in contributing to science to label our data. Citi-
 1514 zen science projects can be a fantastic opportunity for both science and outreach. For
 1515 example, the ABC’s ‘Stargazing Live’ television programme engaged viewers and with
 1516 their help found four exoplanets in just 48 hours (Miller, 2017) and labelled 120 000
 1517 SkyMapper images¹ in just three days (Tucker, 2017). The downside of citizen science
 1518 is that non-expert labellers may be less accurate than experts, and indeed some may
 1519 even be malicious and provide intentionally incorrect labels (Zhang et al., 2016).

¹Citizen scientists actually produced around 5 million labels—these were aggregated to 120 000 to reduce noise.

1520 Astronomers often face a large collection of unlabelled data and must choose which
1521 to label. Choosing what to label is a broad topic of research separately in machine
1522 learning (often called active learning e.g. Gilyazev & Turdakov, 2018), in astronomy
1523 ('follow-up observations'), and in citizen science project design (e.g. citizen science
1524 project Snapshot Serengeti found that showing volunteers *uninteresting* images helped
1525 retain engagement; Sieland, 2015).

1526 **3.5.2 Label noise**

1527 *Label noise* is the presence of incorrect labels in the training or validation data set. In
1528 classical machine learning there is no such thing: ~~labels~~ Labels are assumed to come
1529 from some always-correct 'oracle'. In reality, though, labels can be wrong. There is
1530 intrinsic noise in data, and even expert astronomers ~~can~~ may disagree on labels due
1531 to ambiguities (e.g. around 10 per cent of Radio Galaxy Zoo is extremely divisive
1532 amongst expert labellers; Banfield et al., 2015). All is not lost for machine learning:
1533 ~~many~~ Many optimisation targets are robust to label noise (Menon et al., 2015). One
1534 way to think about this is that the loss function for machine learning 'smooths over' or
1535 'averages out' the noise.

1536 It is important to note that label noise affects training and validation differently.
1537 While it is perfectly possible to train a good model with noisy labels, performance
1538 measures are not as robust to label noise. Noise in the validation set can change the re-
1539 ported performance in unpredictable ways and wherever possible should be avoided.

1540 **3.6 Summary: machine learning**

1541 Machine learning is a field of study concerned with ways of automatically finding use-
1542 ful patterns in large datasets, formalising predictive problems, converting between dif-
1543 ferent statistical problems, and handling data and uncertainty. With the large volumes
1544 of data radio astronomy faces in the lead-up to the SKA, machine learning provides
1545 an avenue for enabling scientific discovery at scale. In this chapter we introduced key
1546 concepts of machine learning, including predictors, features, labels, and loss functions.
1547 We also highlighted classification tasks as a key kind of prediction problem that we will
1548 use to frame astronomical questions throughout this thesis and introduced three clas-
1549 sification models: logistic regression, decision tree ensembles, and CNNs. In the next
1550 chapter, we will frame the astronomical problem of cross-identification as binary clas-
1551 sification, allowing us to train a cross-identification algorithm using an existing cata-
1552 logue of cross-identifications and hopefully allowing us to cross-identify radio sources
1553 en masse.

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1555

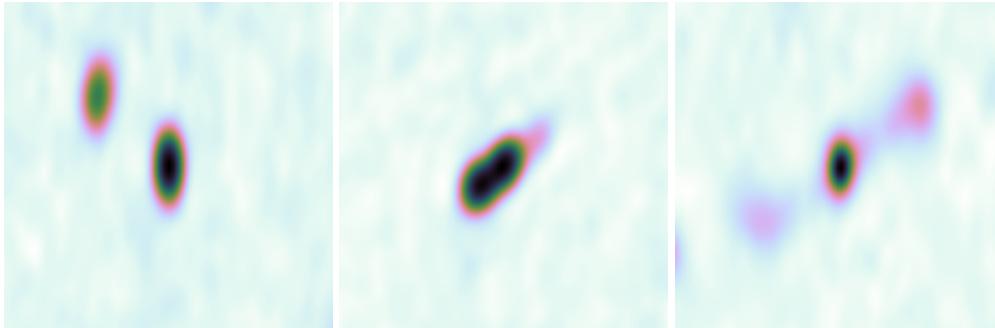
Radio Cross-identification

1556 This chapter is based on my paper *Radio Galaxy Zoo: Machine learning for radio source*
1557 *host galaxy cross-identification*, by M. J. Alger, J. K. Banfield, C. S. Ong, L. Rudnick, O. I.
1558 Wong, C. Wolf, H. Andernach, R. P. Norris, and S. S. Shabala; published in the *Monthly*
1559 *Notices of the Royal Astronomical Society* in 2018. Some minor changes have been made
1560 to match the rest of this thesis.

1561

1562 In this chapter, we consider the problem of determining the host galaxies of radio
1563 sources by cross-identification. This has traditionally been done manually, which will
1564 be intractable for upcoming and ongoing wide-area radio surveys like the Evolutionary
1565 Map of the Universe (EMU). Automated cross-identification will be critical for these
1566 future surveys, and machine learning may provide the tools to develop such methods.

1567 We applied a standard approach from computer vision to cross-identification, in-
1568 troducing one possible way of automating this problem, and explored the pros and
1569 cons of this approach. We applied our method to the 1.4 GHz Australian Telescope
1570 Large Area Survey (ATLAS) observations of the *Chandra* Deep Field South (CDFS)
1571 and the ESO Large Area ISO Survey South 1 (ELAIS-S1) fields by cross-identifying
1572 them with the *Spitzer* Wide-area Infrared Extragalactic (SWIRE) survey. We trained
1573 our method with two sets of data: expert cross-identifications of CDFS from the ini-
1574 tial ATLAS data release and crowdsourced cross-identifications of CDFS from Radio
1575 Galaxy Zoo. We found that a simple strategy of cross-identifying a radio component
1576 with the nearest galaxy performs comparably to our more complex methods, though
1577 our estimated best-case performance is near 100 per cent. ATLAS contains 87 complex
1578 radio sources that have been cross-identified by experts, so there are not enough com-
1579 plex examples to learn how to cross-identify them accurately. Much larger datasets are
1580 therefore required for training methods like ours. We also showed that training our
1581 method on Radio Galaxy Zoo cross-identifications gives comparable results to train-
1582 ing on expert cross-identifications, demonstrating the value of crowdsourced training
1583 data.



(a) Two compact components, each a compact source.
 (b) One resolved component and resolved source.
 (c) Three resolved components comprising one resolved source.

Figure 4.1: Examples showing key definitions of radio emission regions used throughout this chapter. Compact and resolved components are defined by Equation 4.1.

1584 4.1 Introduction to cross-identification

1585 Next generation radio telescopes such as the Australian SKA Pathfinder (ASKAP; John-
 1586 ston et al., 2007) and Apertif (Verheijen et al., 2008) will conduct increasingly wide,
 1587 deep, and high-resolution radio surveys, producing large amounts of data. The Evo-
 1588 lutionary Map of the Universe (EMU; Norris et al., 2011) survey using ASKAP is ex-
 1589 pected to detect over 70 million radio sources, compared to the 2.5 million radio sources
 1590 currently known (Banfield et al., 2015). An important part of processing these data
 1591 is cross-identifying observed radio emission regions with observations of their host
 1592 **galaxy galaxies** in surveys at other wavelengths.

1593 In the presence of extended radio emission, cross-identification of the host can be
 1594 a difficult task. Radio emission may extend far from the host galaxy and emission
 1595 regions from a single physical object may appear disconnected. As a result, the ob-
 1596 served structure of a radio source may have a complex relationship with the corre-
 1597 sponding host galaxy, and cross-identification in radio is much more difficult than
 1598 cross-identification at shorter wavelengths. Small surveys containing a few thousand
 1599 sources such as the Australia Telescope Large Area Survey (ATLAS; Middelberg et al.,
 1600 2008; Norris et al., 2006) can be cross-identified manually, but this is impractical for
 1601 larger surveys.

1602 One approach to cross-identification of large numbers of sources is crowdsourc-
 1603 ing, where volunteers cross-identify radio sources with their host **galaxy galaxies**. This
 1604 is the premise of Radio Galaxy Zoo¹ (Banfield et al., 2015), a citizen science project
 1605 hosted on the Zooniverse platform (Lintott et al., 2008). Volunteers are shown radio
 1606 and infrared images and are asked to cross-identify radio sources with the correspon-
 1607 ding infrared host galaxies. An explanation of the project can be found in Banfield et al.
 1608 (2015). The first data release for Radio Galaxy Zoo will provide a large dataset of over
 1609 75 000 radio-host cross-identifications and radio source morphologies (Wong et al., in

¹<https://radio.galaxyzoo.org>

1610 prep.). While this is a much larger number of visual cross-identifications than have
1611 been made by experts (e.g., Gendre & Wall, 2008; Grant et al., 2010; Middelberg et al.,
1612 2008; Norris et al., 2006; Taylor et al., 2007) it is still far short of the millions of radio
1613 sources expected to be detected in upcoming radio surveys (Norris, 2017b).

1614 Automated algorithms have been developed for cross-identification. Fan et al. (2015)
1615 applied Bayesian hypothesis testing to this problem, fitting a three-component model
1616 to extended radio sources. This was achieved under the assumption that extended
1617 radio sources are composed of a core radio component and two lobe components.
1618 The core radio component is coincident with the host galaxy, so cross-identification
1619 amounts to finding the galaxy coincident with the core radio component in the most
1620 likely model fit. This method ~~is could be~~ easily extended to use other, more complex
1621 models, but it is purely geometric. It does not incorporate other information such
1622 as the physical properties of the potential host galaxy. Additionally, there may be
1623 new classes of radio source detected in future surveys like EMU which do not fit the
1624 model. Weston et al. (2018) developed a modification of the likelihood ratio method of
1625 cross-identification (Richter, 1975) for application to ATLAS and EMU. This method
1626 does well on non-extended radio sources with approximately 70 per cent accuracy in
1627 the ATLAS fields, but does not currently handle more complex (extended or multi-
1628 component) radio sources (Norris, 2017a).

1629 One possibility is that machine learning techniques can be developed to automatically
1630 cross-identify catalogues drawn from new surveys. Machine learning describes
1631 a class of methods that learn approximations to functions. If cross-identification can
1632 be cast as a function approximation problem, then machine learning will allow ~~data~~
1633 ~~sets-datasets~~ such as Radio Galaxy Zoo to be generalised to work on new data. ~~Data~~
1634 ~~sets-Datasets~~ from citizen scientists have already been used to train machine learning
1635 methods. Some astronomical examples can be found in Marshall et al. (2015).

1636 In this chapter we cast cross-identification as a function approximation problem
1637 by applying an approach from computer vision literature. This approach casts cross-
1638 identification as the standard machine learning problem of binary classification by ask-
1639 ing whether a given infrared source is the host galaxy or not. We train our methods
1640 on expert cross-identifications and volunteer cross-identifications from Radio Galaxy
1641 Zoo. In Section 4.2 we describe the data we use to train our methods. In Section 4.3
1642 we discuss how we cast the radio host galaxy cross-identification problem as a ma-
1643 chine learning problem. In Section 4.4 we present results of applying our method
1644 to ATLAS observations of the *Chandra* Deep Field South (CDFS) and the ESO Large
1645 Area ISO Survey South 1 (ELAIS-S1) field. Our data, code and results are available at
1646 <https://radiogalaxyzoo.github.io/atlas-xid>.

1647 Throughout this chapter, a ‘radio source’ refers to all radio emission observed asso-
1648 ciated with a single host galaxy, and a ‘radio component’ refers to a single, contiguous
1649 region of radio emission. Multiple components may arise from a single source. A
1650 ‘compact’ source is composed of a single unresolved component. Equation 4.1 shows
1651 the definition of a resolved component. We assume that all unresolved components
1652 are compact sources, i.e. we assume that each unresolved component has its own host

Table 4.1: Catalogues of ATLAS/SWIRE cross-identifications for the CDFS and ELAIS-S1 fields. The method used to generate each catalogue is shown, along with the number of radio components cross-identified in each field.

Catalogue	Method	CDFS	ELAIS-S1
Norris et al. (2006)	Manual	784	0
Middelberg et al. (2008)	Manual	0	1366
Fan et al. (2015)	Bayesian models	784	0
Weston et al. (2018)	Likelihood ratio	3078	2113
Wong et al. (in prep.)	Crowdsourcing	2460	0

1653 galaxy². An ‘extended’ source is a non-compact source, i.e. resolved single-component
 1654 sources or a multi-component source. Figure 4.1 illustrates these definitions.

1655 4.2 Data

1656 We use radio data from the Australia Telescope Large Area Survey (ATLAS; Franzen
 1657 et al., 2015; Norris et al., 2006), infrared data from the *Spitzer* Wide-area Infrared
 1658 Extragalactic survey (SWIRE; Lonsdale et al., 2003; Surace et al., 2005), and cross-
 1659 identifications of these surveys from the citizen science project Radio Galaxy Zoo (Ban-
 1660 field et al., 2015). Radio Galaxy Zoo also includes cross-identifications of sources in
 1661 Faint Images of the Radio Sky at Twenty Centimeters (FIRST; White et al., 1997) and
 1662 the AllWISE survey (Cutri et al., 2013), though we focus only on Radio Galaxy Zoo
 1663 data from ATLAS and SWIRE.

1664 4.2.1 ATLAS

1665 ATLAS is a pilot survey for the EMU (Norris et al., 2011) survey, which will cover
 1666 the entire sky south of +30 deg and is expected to detect approximately 70 million
 1667 new radio sources. 95 per cent of these sources will be single-component sources, but
 1668 the remaining 5 per cent pose a considerable challenge to current automated cross-
 1669 identification methods (Norris et al., 2011). EMU will be conducted at the same depth
 1670 and resolution as ATLAS, so methods developed for processing ATLAS data are ex-
 1671 pected to work for EMU. ATLAS is a wide-area radio survey of the CDFS and ELAIS-
 1672 S1 fields at 1.4 GHz with a sensitivity of 14 and 17 $\mu\text{Jy beam}^{-1}$ on CDFS and ELAIS-S1
 1673 respectively. CDFS covers 3.6 deg² and contains 3034 radio components above a signal-
 1674 to-noise ratio of 5. ELAIS-S1 covers 2.7 deg² and contains 2084 radio components above
 1675 a signal-to-noise ratio of 5 (Franzen et al., 2015). The images of CDFS and ELAIS-S1
 1676 have angular resolutions of 16 by 7 and 12 by 8 arcsec respectively, with pixel sizes
 1677 of 1.5 arcsec px⁻¹. Table 4.1 summarises catalogues that contain cross-identifications
 1678 of radio components in ATLAS with host galaxies in SWIRE. In the present work, we

²This will be incorrect if the unresolved components are actually compact lobes or **hotspots**, but determining which components correspond to unique radio sources is outside the scope of this thesis.

1679 train methods on CDFS³ and test these methods on both CDFS and ELAIS-S1. This
1680 ensures helps confirm that our methods are transferable to different areas of the sky
1681 observed by the same telescope, as will be the case for EMU.

1682 4.2.2 SWIRE

1683 SWIRE is a wide-area infrared survey at the four IRAC wavelengths 3.6, 4.5, 5.8, and
1684 8.0 μm (Lonsdale et al., 2003; Surace et al., 2005). It covers eight fields, including CDFS
1685 and ELAIS-S1. SWIRE is the source of infrared observations for cross-identification
1686 with ATLAS. SWIRE has catalogued 221,535 infrared objects in CDFS and 186,059 in-
1687 frared objects in ELAIS-S1 above a signal-to-noise ratio of 5.

1688 4.2.3 Radio Galaxy Zoo

1689 Radio Galaxy Zoo asks volunteers to cross-identify radio components with their in-
1690 frared host galaxies. There are a total of 2460 radio components in Radio Galaxy Zoo
1691 sourced from ATLAS observations of CDFS. These components are cross-identified by
1692 Radio Galaxy Zoo participants with host galaxies detected in SWIRE. A more detailed
1693 description can be found in Banfield et al. (2015) and a full description of how the Ra-
1694 dio Galaxy Zoo catalogue used in this work⁴ is generated can be found in Wong et al.
1695 (in prep.).

1696 The ATLAS CDFS radio components that appear in Radio Galaxy Zoo are drawn
1697 from a prerelease version of the third data release of ATLAS by Franzen et al. (2015).
1698 In this release, each radio component was fit with a two-dimensional Gaussian. De-
1699 pending on the residual of the fit, more than one Gaussian may be fit to one region of
1700 radio emission. Each of these Gaussian fits is listed as a radio component in the ATLAS
1701 component catalogue. The brightest radio component from the multiple-Gaussian fit
1702 is called the ‘primary component’. If there was is only one Gaussian fit then this Gaus-
1703 sian is the primary component. Each primary component found in the ATLAS compo-
1704 nent catalogue appears in Radio Galaxy Zoo. Non-primary components may appear
1705 within the image of a primary component, but do not have their own entry in Radio
1706 Galaxy Zoo. We will henceforth only discuss the primary components.

1707 4.3 Method

1708 The aim of this chapter is to express cross-identification in a form that will allow us
1709 to apply standard machine learning tools and methods. We use an approach from
1710 computer vision to cast cross-identification as binary classification.

³Radio Galaxy Zoo only contains CDFS sources and so we cannot train methods on ELAIS-S1.

⁴The Radio Galaxy Zoo Data Release 1 catalogue will only include cross-identifications for which over 65 per cent of volunteers agree. However, we use a preliminary catalogue containing volunteer cross-identifications for all components.

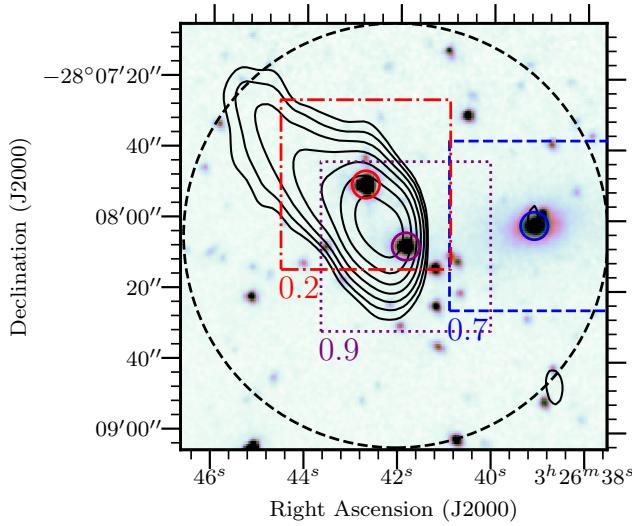


Figure 4.2: An example of finding the host galaxy of a radio source using our sliding-window method. The background image is a $3.6\text{ }\mu\text{m}$ image from SWIRE. The contours show ATLAS radio data and start at 4σ , increasing geometrically by a factor of 2. Boxes represent ‘windows’ centred on candidate host galaxies, which are circled. The pixels in each window are used to represent the candidate that the window is centred on. The scores of each candidate would be calculated by a binary classifier using the window as input, and these scores are shown below each window. The scores shown are for illustration only. In this example, the galaxy coincident with the centre window would be chosen as the host galaxy, as this window has the highest score. The dashed circle shows the $1'$ radius from which candidate host galaxies are selected. For clarity, not all candidate host galaxies are shown.

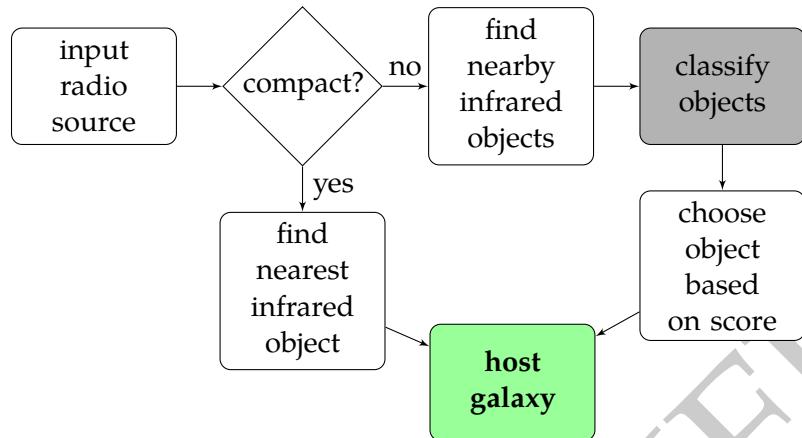


Figure 4.3: Our cross-identification method once a binary classifier has been trained. As input we accept a radio component. If the component is compact, we assume it is a compact source and select the nearest infrared object as the host galaxy. If the component is resolved, we use the binary classifier to score all nearby infrared objects and select the highest-scored object as the host galaxy. Compact and resolved components are defined in Equation 4.1.

1711 4.3.1 Cross-identification as binary classification

1712 We propose a two-step method for host galaxy cross-identification which we will de-
 1713 scribe now. Given a radio component, we want to find the corresponding host galaxy.
 1714 The input is a $2' \times 2'$ radio image of the sky centred on a radio component and po-
 1715 tentially other information about objects in the image (such as the redshift or infrared
 1716 colour). Images at other wavelengths (notably infrared) might be useful, but we defer
 1717 this for now as it complicates the task. We ~~choose~~ choose a $2' \times 2'$ image to match the
 1718 size of the images used by Radio Galaxy Zoo. To avoid solving the separate task of
 1719 identifying which radio components are associated with the same source, we assume
 1720 that each radio image represents a single extended source⁵. Radio cross-identification
 1721 can then be formalised as follows: given a radio image centred on a radio com-
 1722 ponent, locate the host galaxy of the source containing this radio component. This is a
 1723 standard computer vision problem called ‘object detection’, and we apply a common
 1724 technique called a ‘sliding-window’ (Rowley et al., 1996).

1725 In sliding-window object detection, we want to find an object in an image. We
 1726 develop a function to score each location in the image such that the highest-scored
 1727 location coincides with the desired object. Square image cutouts called ‘windows’ are
 1728 taken centred on each location and these windows are used to represent that location
 1729 in our scoring function. To find the infrared host galaxy, we choose the location with
 1730 the highest score. To improve the efficiency of this process when applied to cross-
 1731 identification, we only consider windows coincident with infrared sources detected in
 1732 SWIRE. We call these infrared sources ‘candidate host galaxies’. For this chapter, there
 1733 is no use in scoring locations without infrared sources as that would not lead to a host

⁵Limitations of this assumption are discussed in Section 4.3.2.

1734 identification anyway. Using candidate host galaxies instead of pixels also allows us to
 1735 include ancillary information about the candidate host galaxies, such as their infrared
 1736 colours and redshifts. We refer to the maximum distance a candidate host galaxy can
 1737 be separated from a radio component as the ‘search radius’ and take this radius to be 1
 1738 arcmin. To score each candidate host galaxy we use a ‘binary classifier’, which we will
 1739 define now.

Algorithm 1: Cross-identifying a radio component given a radio image of the component, a catalogue of infrared candidate host galaxies \mathcal{G} , and a binary classifier. σ is a parameter of the method.

Data:

A 2×2 arcmin radio image of a radio component

A set of infrared candidate host galaxies \mathcal{G}

A binary classifier $f : \mathbb{R}^k \rightarrow \mathbb{R}$

Result: A galaxy $g \in \mathcal{G}$

$max \leftarrow -\infty;$

$host \leftarrow \emptyset;$

for $g \in \mathcal{G}$ **do**

$x \leftarrow$ a k -dimensional vector representation of g (Section 4.3.3);

$d \leftarrow$ distance between g and the radio component;

$score \leftarrow f(x) \times \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{d^2}{2\sigma^2}\right);$

if $score > max$ **then**

$max \leftarrow score;$

$host \leftarrow g;$

end

end

return $host$

1740 Binary classification is a common method in machine learning where objects are to
 1741 be assigned to one of two classes, called the ‘positive’ and ‘negative’ classes. This as-
 1742 signment is represented by the probability that an object is in the positive class. A
 1743 ‘binary classifier’ is a function mapping from an object to such a probability. Our
 1744 formulation of cross-identification is equivalent to binary classification of candidate
 1745 host galaxies: the positive class represents host galaxies, the negative class represents
 1746 non-host galaxies, and to cross-identify a radio component we find the candidate host
 1747 galaxy maximising the positive class probability. In other words, the binary classifier
 1748 is exactly the sliding-window scoring function. We therefore split cross-identification
 1749 into two separate tasks: the ‘candidate classification task’ where, given a candidate
 1750 host galaxy, we wish to determine whether it is a host galaxy of *any* radio component;
 1751 and the ‘cross-identification task’ where, given a specific radio component, we wish to
 1752 find its host galaxy. The candidate classification task is a traditional machine learning
 1753 problem which results in a binary classifier. To avoid ambiguity and recognise that
 1754 the values output by a binary classifier are not true probabilities, we will refer to the
 1755 outputs of the binary classifier as ‘scores’ in line with the sliding-window approach

described above. The cross-identification task maximises over scores output by this classifier. Our approach is illustrated in Figure 4.2 and described in Algorithm 1. We refer to the binary classifier scoring a candidate host galaxy as f . To implement f as a function that accepts candidate host galaxies as input, we need to represent candidate host galaxies by vectors. We describe this in Section 4.3.3. There are many options for modelling f . In this chapter we apply three different models: logistic regression, random forests, and convolutional neural networks.

We cross-identify each radio component in turn. The classifier f provides a score for each candidate host galaxy. This score indicates how much the candidate looks like a host galaxy, independent of which radio component we are currently cross-identifying. If there are other nearby host galaxies, then multiple candidate hosts may have high scores (e.g. Figure 4.4). This difficulty is necessary—a classifier with dependence on the radio object would be impossible to train. We need multiple positive examples (i.e. host galaxies) to train a binary classifier, but for any specific radio component there is only one host galaxy. As a result, the candidate classification task aims to answer the general question of whether a given galaxy is the host galaxy of *any* radio component, while the cross-identification task attempts to cross-identify a *specific* radio component. To distinguish between candidate host galaxies with high scores, we weight the scores by a Gaussian function of angular separation between the candidates and the radio component. The width of the Gaussian, σ , controls the influence of the Gaussian on the final cross-identification. When σ is small, our approach is equivalent to a nearest neighbours approach where we select the nearest infrared object to the radio component as the host galaxy. In the limit where $\sigma \rightarrow \infty$, we maximise the score output by the classifier as above. We take $\sigma = 30''$ as this was the best value found by a grid search maximising cross-identification accuracy. Note that the optimum width will depend on the density of radio sources on the sky, the angular separation of the host galaxy and its radio components and the angular resolution of the survey.

We can improve upon this method by cross-identifying compact radio sources separately from extended sources, as compact sources are much easier to cross-identify. For a compact source, the nearest SWIRE object may be identified as the host galaxy (*a nearest neighbours approach*), or a more complex method such as likelihood ratios may be applied (see Weston et al., 2018). We cross-identify compact sources separately in our pipeline and this process is shown in Figure 4.3.

4.3.2 Limitations of our approach

We make a number of assumptions to relate the cross-identification task to the candidate classification task:

1. For any radio component, the $2' \times 2'$ image centred on the component contains components of only one radio source.
2. For any radio component, the $2' \times 2'$ image centred on the component contains all components of this source.

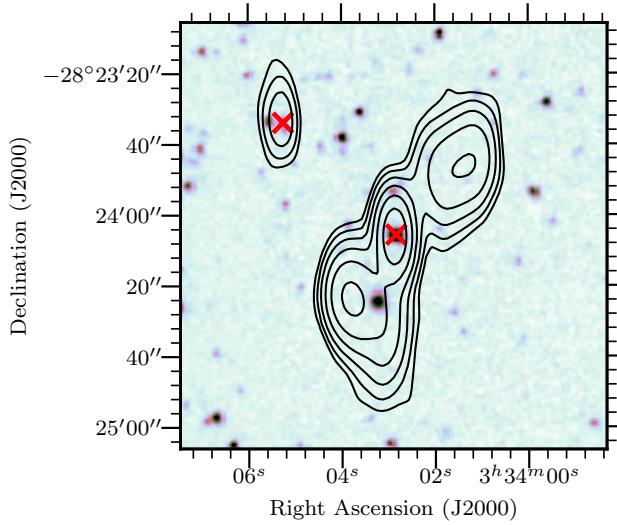


Figure 4.4: A $2'$ -wide radio image centred on ATLAS3_J033402.87-282405.8C. This radio source breaks the assumption that there are no other radio sources within 1 arcmin of the source. Another radio source is visible to the upper-left. Host galaxies found by Radio Galaxy Zoo volunteers are shown by crosses. The background image is a $3.6\text{ }\mu\text{m}$ image from SWIRE. The contours show ATLAS radio data and start at 4σ , increasing geometrically by a factor of 2.

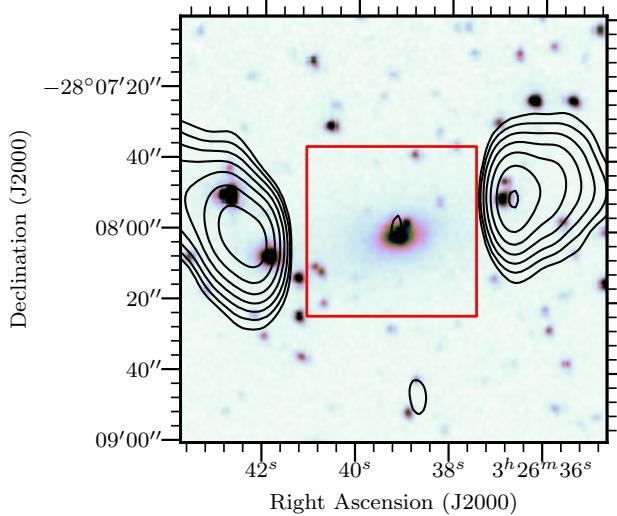


Figure 4.5: An example of a radio source where the window centred on the host galaxy, shown as a rectangle, does not contain enough radio information to correctly identify the galaxy as the host. The background image is a $3.6\text{ }\mu\text{m}$ image from SWIRE. The contours show ATLAS radio data and start at 4σ , increasing geometrically by a factor of 2.

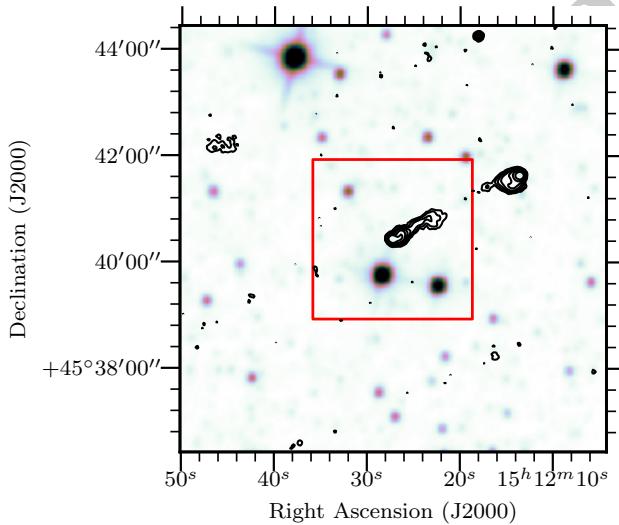


Figure 4.6: A 8'-wide radio image from FIRST, centred on FIRST J151227.2+454026. The 3'-wide red box indicates the boundaries of the image of this radio component shown to volunteers in Radio Galaxy Zoo. This radio source breaks our assumption that the whole radio source is visible in the chosen radius. As one of the components of the radio source is outside of the image, a volunteer (or automated algorithm) looking at the 3'-wide image may be unable to determine that this is a radio double or locate the host galaxy. The background image is a 3.4 μm image from WISE. The contours show FIRST radio data, starting at 4σ and increasing geometrically by a factor of 2.

-
- 1796 3. The host galaxy of a radio component is within the 1 arcmin search radius around
 1797 the component, measured from the centre of the Gaussian fit.
- 1798 4. The host galaxy of a radio component is closer on the sky to the radio component
 1799 than the host galaxy of any other radio component.
- 1800 5. The host galaxy appears in the SWIRE catalogue.

1801 These assumptions limit the effectiveness of our approach, regardless of how accurate
 1802 our binary classifier may be. Examples of radio sources that break these respective
 1803 assumptions are:

- 1804 1. A radio source less than 1' away from another radio source.
- 1805 2. A radio source with an angular size greater than 2'.
- 1806 3. A radio source with a component greater than 1' away from the host galaxy.
- 1807 4. A two-component radio source with another host galaxy between a component
 1808 and the true host galaxy.
- 1809 5. An infrared-faint radio source (as in Collier et al., 2014).

1810 The main limitations are problems of scale in choosing the candidate search radius
 1811 and the size of the windows representing candidates. If the search radius is too small,
 1812 we may not consider the host galaxy as a candidate. If the search radius is too large, we
 1813 may consider multiple host galaxies (though this is mostly mitigated by the Gaussian
 1814 weighting). If the window is too small, radio emission may extend past the edges of
 1815 the window and we may miss critical information required to identify the galaxy as a
 1816 host galaxy. If the window is too large, then irrelevant information will be included
 1817 and it may be difficult or computationally expensive to score. We chose choose a win-
 1818 dow size of 32×32 pixels, corresponding to approximately $48'' \times 48''$ in ATLAS. This
 1819 is shown as squares in Figure 4.2 and Figure 4.5. These kinds of size problems are dif-
 1820 ficult even for non-automated methods as radio sources can be extremely wide—for
 1821 example, Radio Galaxy Zoo found a radio giant that spanned over three different im-
 1822 ages presented to volunteers and the full source was only cross-identified by the efforts
 1823 of citizen scientists (Banfield et al., 2015). An example of a radio image where part of
 1824 the radio source is outside the search radius is shown in Figure 4.6.

1825 In weighting the scores by a Gaussian function of angular separation, we implicitly
 1826 assume that the host galaxy of a radio component is closer to that radio component
 1827 than any other host galaxy. If this assumption is not true then the incorrect host galaxy
 1828 may be identified, though this is rare.

1829 We only need to require that the host galaxy appears in SWIRE to incorporate
 1830 galaxy-specific features (Section 4.3.3) and to improve efficiency. Our method is ap-
 1831 plicable even when host galaxies are not detected in the infrared by considering every
 1832 pixel of the radio image as a candidate location as would be done in the original com-
 1833 puter vision approach. If the host galaxy location does not correspond to an infrared
 1834 source, the radio source would can be classified as infrared-faint.

1835 Our assumptions impose an upper bound on how well we can cross-identify radio
 1836 sources. We estimate this upper bound in Section 4.4.1.

1837 **4.3.3 Feature vector representation of infrared sources**

1838 Inputs to binary classifiers must be represented by an array of real values called feature
 1839 vectors. We therefore need to choose a feature vector representation of our candidate
 1840 host galaxies. Candidate hosts are sourced from the SWIRE catalogue (Section 4.2.2).
 1841 We represent each candidate host with 1034 real-valued features, combining the win-
 1842 dows centred on each candidate (Section 4.3.1) with ancillary infrared data from the
 1843 SWIRE catalogue. For a given candidate host, these features are:

- 1844 • the 6 base-10 logarithms of the ratios of fluxes of the candidate host at the four
 1845 IRAC wavelengths (the ‘colours’ of the candidate);
- 1846 • the flux of the host at 3.6 μm ;
- 1847 • the stellarity index of the host at both 3.6 and 4.5 μm ;
- 1848 • the radial distance between the candidate host and the nearest radio component
 1849 in the ATLAS catalogue; and
- 1850 • a 32×32 pixel image from ATLAS (approximately $48'' \times 48''$), centred on the
 1851 candidate host (the window).

1852 The infrared colours provide insight into the properties of the candidate host galaxy
 1853 (Grant, 2011). The 3.6 and 4.5 μm fluxes trace both galaxies with faint polycyclic aro-
 1854 matic hydrocarbon (PAH) emission (i.e. late-type, usually star-forming galaxies) and
 1855 elliptical galaxies dominated by old stellar populations. The 5.8 μm flux selects galax-
 1856 ies where the infrared emission is dominated by non-equilibrium emission of dust
 1857 grains due to active galactic nuclei, while the 8.0 μm flux traces strong PAH emission
 1858 at low redshift (Sajina et al., 2005). The stellarity index is a value in the SWIRE cata-
 1859 logue that represents how likely the object is to be a star rather than a galaxy (Surace
 1860 et al., 2005). It was estimated by a neural network in SExtractor (Bertin & Arnouts,
 1861 1996).

1862 We use the 32×32 pixels of each radio window as independent features for all
 1863 binary classification models, with the convolutional neural network automatically ex-
 1864 tracting features that are relevant. Other features of the radio components may be
 1865 used instead of just relying on the pixel values, but there has been limited research on
 1866 extracting such features: Proctor (2006) describes hand-selected features for radio dou-
 1867 bles in FIRST, and Aniyan and Thorat (2017) and Lukic et al. (2018) make use of deep
 1868 convolutional neural networks which automatically extract features as part of classifi-
 1869 cation. A more comprehensive investigation of features is a good avenue for potential
 1870 improvement in our pipeline but this is beyond the scope of this initial study.

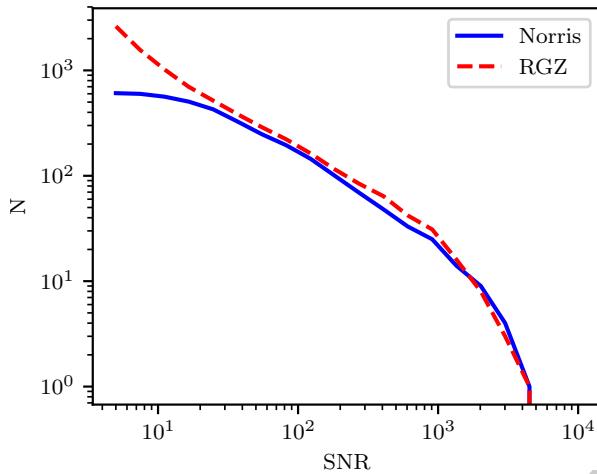


Figure 4.7: Cumulative number of radio components (N) in the expert (Norris) and Radio Galaxy Zoo (RGZ) training sets with different signal-to-noise ratios (SNR).

1871 4.3.4 Binary Classifiers

1872 We use three different binary classification models: logistic regression, convolutional
 1873 neural networks, and random forests. These models cover three different approaches
 1874 to machine learning. Logistic regression is a probabilistic binary classification model.
 1875 It is linear in the feature space and outputs the probability that the input has a positive
 1876 label (Bishop, 2006, Chap. 4). Convolutional neural networks (CNN) are biologically-
 1877 inspired prediction models with image inputs. They have recently produced good
 1878 results on large image-based datasets in astronomy (Dieleman et al., 2015; Lukic et al.,
 1879 2018, e.g.). Random forests are an ensemble of decision trees (Breiman, 2001). They
 1880 consider multiple subsamples of the training set, where each bootstrap subsample is
 1881 sampled with replacement from the training set. To classify a new data point, the ran-
 1882 dom forest takes the weighted average of all classifications produced by each decision
 1883 tree. [For a more detailed description of these models, see Appendix 4.A.](#)

1884 4.3.5 Labels

1885 The Radio Galaxy Zoo and Norris et al. (2006) cross-identification catalogues must be
 1886 converted to binary labels for infrared objects so that they can be used to train binary
 1887 classifiers. There are two challenges with this conversion:

- 1888 • We can only say that an object is a host galaxy, not which radio object it is associ-
 1889 ated with, and
- 1890 • We cannot disambiguate between non-host infrared objects and host galaxies that
 1891 ~~were~~ [are](#) not in the cross-identification catalogue.

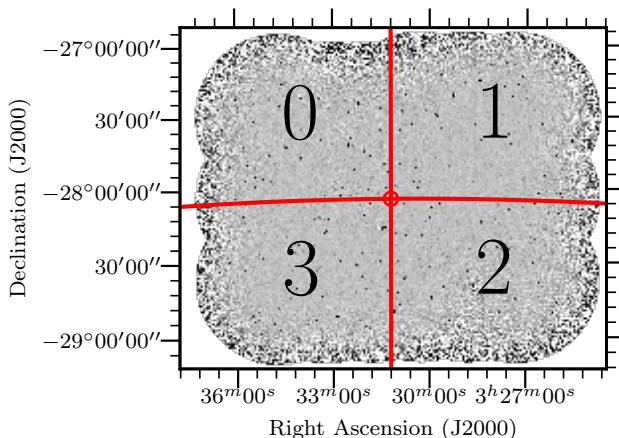


Figure 4.8: CDFS field training and testing quadrants labelled 0 – 3. The central dot is located at $\alpha = 03^{\text{h}}31^{\text{m}}12^{\text{s}}$, $\delta = -28^{\circ}06'00''$. The quadrants ~~were~~are chosen such that there are similar numbers of radio sources in each quadrant.

Table 4.2: Number of compact and resolved radio objects in each CDFS quadrant. Radio Galaxy Zoo (RGZ) has more cross-identifications than the expert catalogue (Norris et al., 2006) provides as it uses a deeper data release of ATLAS, and so has more objects in each quadrant for training.

Quadrant	Compact	Resolved	Compact (RGZ)	Resolved (RGZ)
0	126	24	410	43
1	99	21	659	54
2	61	24	555	57
3	95	18	631	51
<i>Total</i>	381	87	2255	205

We use the Gaussian weighting described in Section 4.3.1 to address the first issue. The second issue is known as a ‘positive-unlabelled’ classification problem, which is a binary classification problem where we only observe labels for the positive class. We treat unlabelled objects as negative examples following Menon et al. (2015). That is, we make the naïve assumption that any infrared object in the SWIRE catalogue not identified as a host galaxy in a cross-identification catalogue is not a host galaxy at all.

We first generate positive labels from a cross-identification catalogue. We decide that if an infrared object is listed in the catalogue, then it is assigned a positive label as a host galaxy. We then assign every other galaxy a negative label. This has some problems—an example is that if the cross-identification catalogue did not include a radio object (e.g. it was below the signal-to-noise ratio) then the host galaxy of that radio object would receive a negative label. This occurs with Norris et al. (2006) cross-identifications, as these are associated with the first data release of ATLAS. The first data release went to a 5σ flux density level of $S_{1.4} \geq 200 \mu\text{Jy beam}^{-1}$ (Norris et al., 2006), compared to $S_{1.4} \geq 85 \mu\text{Jy beam}^{-1}$ for the third data release used by Radio Galaxy Zoo (Franzen et al., 2015). The labels from Norris et al. (2006) may therefore disagree with labels from Radio Galaxy Zoo even if they are both plausible. The difference in training set size at different flux cutoffs is shown in Figure 4.7. We train and test our binary classifiers on infrared objects within a 1 arcmin radius of an ATLAS radio component.

4.3.6 Experimental Setup

We trained binary classifiers on infrared objects in the CDFS field using two sets of labels. One label set was derived from Radio Galaxy Zoo cross-identifications and the other was derived from the Norris et al. (2006) cross-identification catalogue. We refer to these as the ‘Radio Galaxy Zoo labels’ and the ‘expert labels’ respectively. We divided the CDFS field into four quadrants for training and testing. The quadrants were divided with a common corner at $\alpha = 03^{\text{h}}31^{\text{m}}12^{\text{s}}, \delta = -28^{\circ}06'00''$ as shown in Figure 4.8. For each trial, one quadrant was used to extract test examples and the other three quadrants were used for training examples.

We further divided the radio components into compact and resolved. Compact components are cross-identified by fitting a 2D Gaussian (as in Norris et al., 2006) and we would expect any machine learning approach for host cross-identification to attain high accuracy on this set. A radio component was considered resolved if

$$\ln \left(\frac{S_{\text{int}}}{S_{\text{peak}}} \right) > 2 \sqrt{\left(\frac{\sigma_{S_{\text{int}}}}{S_{\text{int}}} \right)^2 + \left(\frac{\sigma_{S_{\text{peak}}}}{S_{\text{peak}}} \right)^2}, \quad (4.1)$$

where S_{int} is the integrated flux density, S_{peak} is the peak flux density, $\sigma_{S_{\text{int}}}$ is the uncertainty in integrated flux density and $\sigma_{S_{\text{peak}}}$ is the uncertainty in peak flux density (following Franzen et al., 2015).

Candidate hosts were selected from the SWIRE catalogue. For a given subset of radio components, all SWIRE objects within 1 arcmin of all radio components in the

subset were added to the associated SWIRE subset. In results for the candidate classification task, we refer to SWIRE objects within 1 arcmin of a compact radio component as part of the ‘compact set’, and SWIRE objects within 1 arcmin of a resolved radio component as part of the ‘resolved set’.

To reduce bias in the testing data due to the expert labels being generated from a shallower data release of ATLAS, a SWIRE object was only included in the test set if it was within 1 arcmin of a radio object with a SWIRE cross-identification in both the Norris et al. (2006) catalogue and the Radio Galaxy Zoo catalogue.

Each binary classifier was trained on the training examples and used to score the test examples. These scores were thresholded to generate labels which could be directly compared to the expert labels. We then computed the ‘balanced accuracy’ of these predicted labels. Balanced accuracy is the average of the accuracy on the positive class and the accuracy on the negative class, and is not sensitive to class imbalance. The candidate classification task has highly imbalanced classes—in our total set of SWIRE objects within 1 arcmin of an ATLAS object, only 4 per cent have positive labels. Our threshold was chosen to maximise the balanced accuracy on predicted labels of the training set. Only examples within 1 arcmin of ATLAS objects in the first ATLAS data release (Norris et al., 2006) were used to compute balanced accuracy, as these were the only ATLAS objects with expert labels.

We then used the scores to predict the host galaxy for each radio component cross-identified by both Norris et al. (2006) and Radio Galaxy Zoo. We followed Algorithm 1: ~~the~~^{The} score of each SWIRE object within 1 arcmin of a given radio component was weighted by a Gaussian function of angular separation from the radio component and the object with the highest weighted score was chosen as the host galaxy. The cross-identification accuracy was then estimated as the fraction of the predicted host galaxies that matched the Norris et al. (2006) cross-identifications.

4.4 Results

In this section we present accuracies of our method trained on CDFS and applied to CDFS and ELAIS-S1, as well as results motivating our accuracy measures and estimates of upper and lower bounds for cross-identification accuracy using our method.

4.4.1 Application to ATLAS-CDFS

We can assess trained binary classifiers either by their performance on the candidate classification task or by their performance on the cross-identification task when used in our method. Both performances are useful: ~~performance~~^{Performance} on the candidate classification task provides a robust and simple way to compare binary classifiers without the limitations of our specific formulation, and performance on the cross-identification task can be compared with other cross-identification methods. We therefore report two sets of accuracies: balanced accuracy for the galaxy classification task and accuracy for the cross-identification task. These accuracy measures are correlated and we show this correlation in Figure 4.9. Fitting a line of best fit with `scipy`

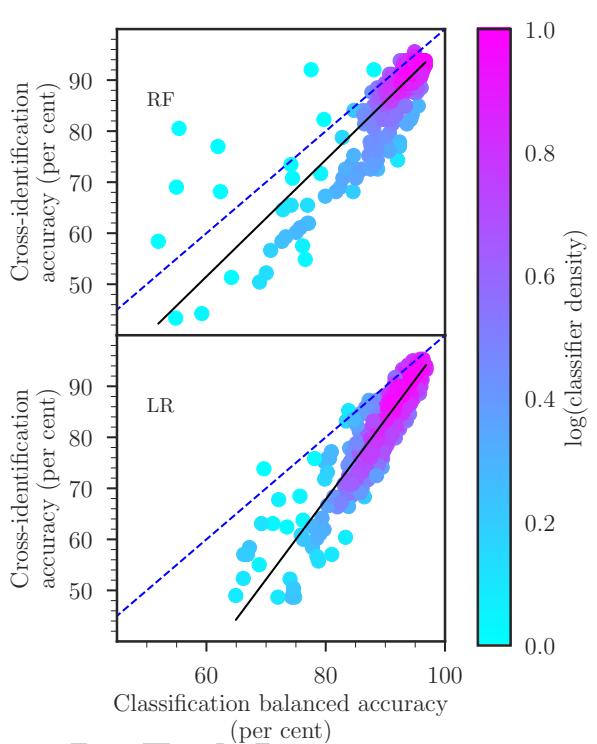


Figure 4.9: Balanced accuracy on the candidate classification task plotted against accuracy on the cross-identification task. ‘RF’ indicates results from random forests, and ‘LR’ indicates results from logistic regression. Binary classifiers were trained on random, small subsets of the training data to artificially restrict their accuracies. Colour shows the density of points on the plot estimated by a Gaussian kernel density estimate. The solid lines indicate the best linear fit; these fits have $R^2 = 0.92$ for logistic regression and $R^2 = 0.87$ for random forests. The dashed line shows the line where cross-identification accuracy and candidate classification accuracy are equal. We did not include convolutional neural networks in this test, as training them is very computationally expensive. There are 640 trials shown per classification model. These results exclude binary classifiers with balanced accuracies less than 51 per cent, as these are essentially random.

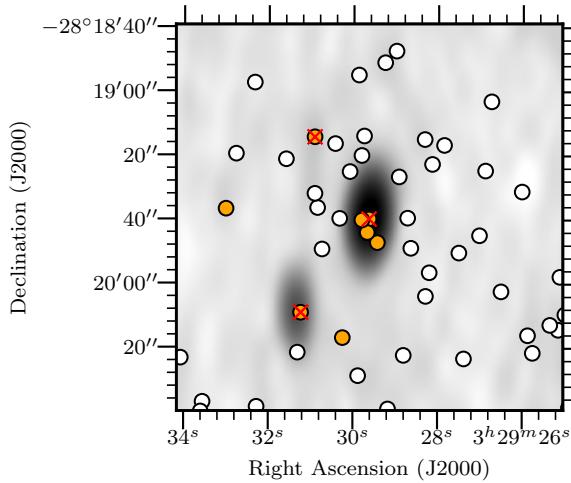


Figure 4.10: Predicted host galaxies in the candidate classification task for ATLAS3 J032929.61-281938.9. The background image is an ATLAS radio image. Radio Galaxy Zoo host galaxies are marked by crosses. SWIRE candidate host galaxies are circles coloured by the score output by a logistic regression binary classifier. The scores are thresholded to obtain labels, as when we compute balanced accuracy. Orange circles have been assigned a ‘positive’ label by a logistic regression binary classifier and white otherwise. Note that there are more predicted host galaxies than there are radio components, so not all of the predicted host galaxies would be assigned as host galaxies in the cross-identification task.

gives $R^2 = 0.92$ for logistic regression and $R^2 = 0.87$ for random forests. While performance on the candidate classification task is correlated with performance on the cross-identification task, balanced accuracy does not completely capture the effectiveness of a binary classifier applied to the cross-identification task. This is because while our binary classifiers output real-valued scores, these scores are thresholded to compute the balanced accuracy. In the candidate classification task, the binary classifier only needs to ensure that host galaxies are scored higher than non-host galaxies. This means that after thresholding there can be many ‘false positives’ that do not affect cross-identification. An example of this is shown in Figure 4.10, where the classifier has identified 8 eight ‘host galaxies’. However, there are only three true host galaxies in this image—one per radio component—and so in the cross-identification task, only three of these galaxies will be identified as hosts.

In Figure 4.11 we plot the balanced accuracies of our classification models on the candidate classification task and the cross-identification accuracies of our method using each of these models. Results are shown for both the resolved and compact sets. For comparison, we also plot the cross-identification accuracy of Radio Galaxy Zoo and a nearest neighbours approach, as well as estimates for upper and lower limits on the cross-identification accuracy. We estimate the upper limit on performance by assigning all true host galaxies a score of 1 and assigning all other candidate host galaxies a score of 0. This is equivalent to ‘perfectly’ solving the candidate classification task and

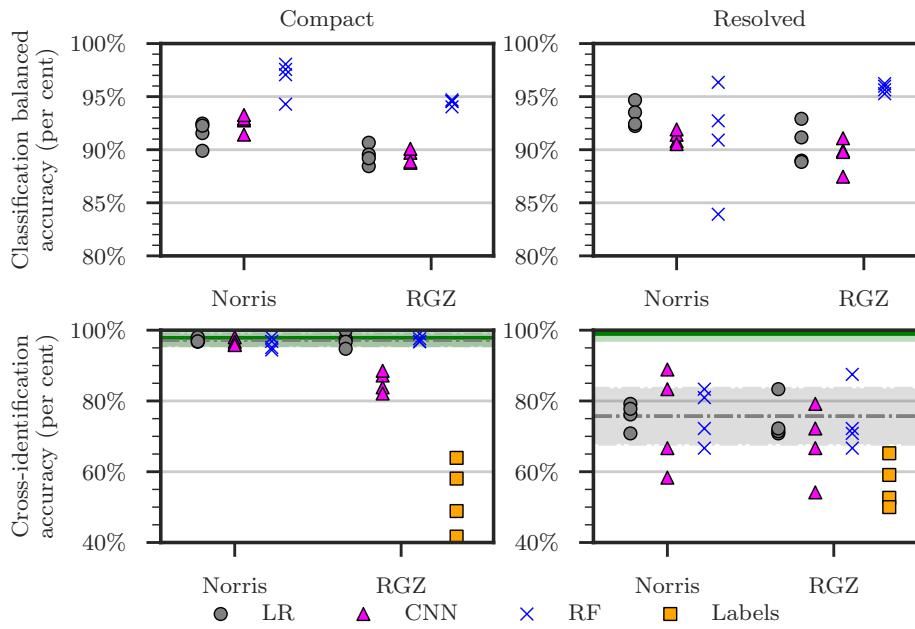


Figure 4.11: Performance of our method with logistic regression ('LR'), convolutional neural networks ('CNN') and random forest ('RF') binary classifiers. 'Norris' indicates the performance of binary classifiers trained on the expert labels and 'RGZ' indicates the performance of binary classifiers trained on the Radio Galaxy Zoo labels. One point is shown per binary classifier per testing quadrant. The training and testing sets have been split into compact (left) and resolved (right) objects. Shown for comparison is the accuracy of the Radio Galaxy Zoo consensus cross-identifications on the cross-identification task, shown as 'Labels'. The cross-identification accuracy attained by a perfect binary classifier is shown by a solid green line, and the cross-identification accuracy of a nearest neighbours approach is shown by a dashed grey line. The standard deviation of these accuracies across the four CDFS quadrants is shown by the shaded area. Note that the pipeline shown in Figure 4.3 is not used for these results.

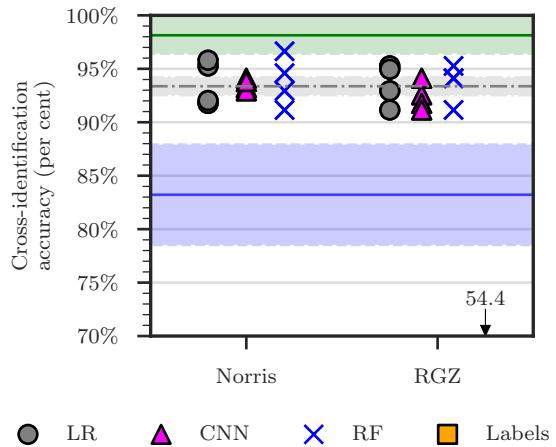


Figure 4.12: Performance of our approach using different binary classifiers on the cross-identification task. Markers and lines are as in Figure 4.11. The blue solid line indicates the performance of a random binary classifier and represents the minimum accuracy we expect to obtain. The standard deviation of this accuracy across 25 trials and 4 quadrants is shaded. The accuracy of Radio Galaxy Zoo on the cross-identification task is below the axis and is instead marked by an arrow with the mean accuracy. Note that the pipeline shown in Figure 4.3 is used here, so compact objects are cross-identified in the same way regardless of binary classifier model.

1986 so represents the best possible cross-identification performance achievable with our
 1987 method. We estimate the lower limit on performance by assigning random scores to
 1988 each candidate host galaxy. We expect any useful binary classifier to produce better re-
 1989 sults than this, so this represents the lowest expected cross-identification performance.
 1990 The upper estimates, lower estimates, and nearest neighbour nearest neighbour accuracy
 1991 are shown as horizontal lines in Figure 4.11.

1992 In Figure 4.12 we plot the performance of our method using different binary classi-
 1993 fication models, as well as the performance of Radio Galaxy Zoo, nearest neighbours,
 1994 and the perfect and random binary classifiers τ on the full set of ATLAS DR1 radio
 1995 components using the pipeline in Figure 4.3. The accuracy associated with each clas-
 1996 sification model and training label set averaged across all four quadrants is shown in
 1997 Appendix 4.B.

1998 Differences between accuracies across training labels are well within one standard
 1999 deviation computed across the four quadrants, with convolutional neural networks on
 2000 compact objects as the only exception. The spread of accuracies is similar for both sets
 2001 of training labels, with the exception of random forests. The balanced accuracies of
 2002 random forests trained on expert labels have a considerably higher spread than those
 2003 trained on Radio Galaxy Zoo labels, likely because of the small size of the expert train-
 2004 ing set—there are less than half the number of objects in the expert-labelled training set
 2005 than the number of objects in the Radio Galaxy Zoo-labelled training set (Table 4.2).

2006 Radio Galaxy Zoo-trained methods significantly outperform Radio Galaxy Zoo

cross-identifications. Additionally, despite poor performance of Radio Galaxy Zoo on the cross-identification task, methods trained on these cross-identifications still perform comparably to those trained on expert labels. This is because incorrect Radio Galaxy Zoo cross-identifications can be thought of as a source of noise in the labels which is ‘averaged out’ in training. This shows the usefulness of crowdsourced training data, even when the data is noisy.

Our method performs comparably to a nearest neighbours approach. For compact objects, this is to be expected—indeed, nearest neighbours attains nearly 100 per cent accuracy on the compact test set. Our results do not improve on nearest neighbours for resolved objects. However, our method does allow for improvement on nearest neighbours with a sufficiently good binary classifier: a-A ‘perfect’ binary classifier attains nearly 100 per cent accuracy on resolved sources. This shows that our method may be useful provided that a good binary classifier can be trained. The most obvious place for improvement is in feature selection: we-We use pixels of radio images directly and these are likely not conducive to good performance on the candidate classification task. Convolutional neural networks, which are able to extract features from images, *should* work better, but these require far more training data than the other methods we have that we applied and the small size of ATLAS thus limits their performance.

We noted in Section 4.3.5 that the test set of expert labels, derived from the initial ATLAS data release, was less deep than the third data release used by Radio Galaxy Zoo and this chapter, introducing a source of label noise in the testing labels. Specifically, true host galaxies may be misidentified as non-host galaxies if the associated radio source was is below the 5 signal-to-noise limit in ATLAS DR1 but not in ATLAS DR3. This has the effect of reducing the accuracy for Radio Galaxy Zoo-trained classifiers.

We report the scores predicted by each classifier for each SWIRE object in Appendix 4.C and the predicted cross-identification for each ATLAS object in Appendix 4.D. Scores reported-we report for a given object were predicted by binary classifiers tested on the quadrant containing that object. The reported scores are not weighted.

In Figure 4.17 we show 5-five resolved sources where the most classifiers disagreed on the correct cross-identification.

4.4.2 Application to ATLAS-ELAIS-S1

We applied the method trained on CDFS to perform cross-identification on the ELAIS-S1 field. Both CDFS and ELAIS-S1 were imaged by the same radio telescope to similar sensitivities and angular resolution for the ATLAS survey. We can use the SWIRE cross-identifications made by Middelberg et al. (2008) to derive another set of expert labels, and hence determine how accurate our method is. If our method generalises well across different parts of the sky, then we expect CDFS-trained classifiers to have comparable performance between ELAIS-S1 and CDFS. In Figure 4.13 we plot the performance of CDFS-trained classification models on the candidate classification task and the performance of our method on the cross-identification task using these mod-

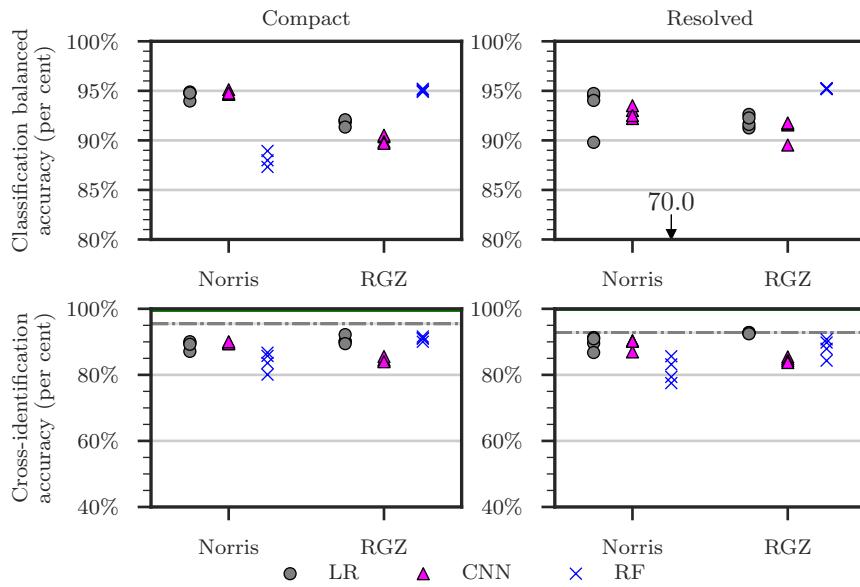


Figure 4.13: Performance of different classification models trained on CDFS and tested on resolved and compact sources in ELAIS-S1. Points represent classification models trained on different quadrants of CDFS, with markers, lines, and axes as in Figure 4.11. The balanced accuracy of expert-trained random forest binary classifiers falls below the axis and the corresponding mean accuracy is shown by an arrow. The estimated best attainable accuracy is almost 100 per cent.

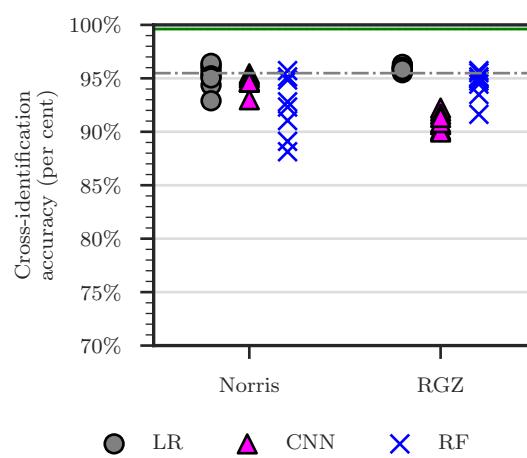


Figure 4.14: Performance of different classifiers trained on CDFS and tested on ELAIS-S1. Markers are as in Figure 4.12 and horizontal lines are as in Figure 4.13. Note that the pipeline shown in Figure 4.3 is used here, so compact objects are cross-identified in the same way regardless of binary classifier model.

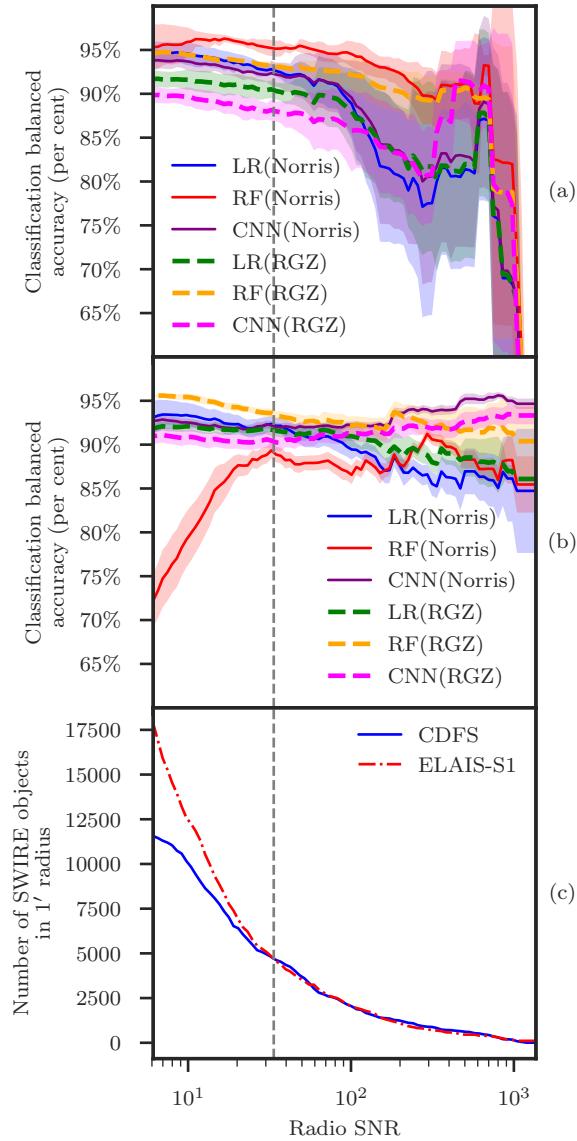


Figure 4.15: (a) Balanced accuracies of classifiers trained and tested on CDFS with different signal-to-noise ratio (SNR) cutoffs for the test set. A SWIRE object is included in the test set if it is within 1' of a radio component with greater SNR than the cutoff. Lines of different colour indicate different classifier/training labels combinations, where LR is logistic regression, RF is random forests, CNN is convolutional neural networks, and Norris and RGZ are the expert and Radio Galaxy Zoo label sets respectively. Filled areas represent standard deviations across CDFS quadrants. (b) Balanced accuracies of classifiers trained on CDFS and tested on ELAIS-S1. (c) A cumulative distribution plot of SWIRE objects associated with a radio object with greater SNR than the cutoff. The grey dashed line shows the SNR level at which the number of SWIRE objects above the cutoff is equal for CDFS and ELAIS-S1. This cutoff level is approximately at a SNR of 34.

2048 els. We also plot the cross-identification accuracy of a nearest neighbours approach⁶.
 2049 In Figure 4.14 we plot the performance of our method on the full set of ELAIS-S1 AT-
 2050 LAS DR1 radio components using the pipeline in Figure 4.3. We list the corresponding
 2051 accuracies in Appendix 4.B.

2052 Cross-identification results from ELAIS-S1 are similar to those for CDFS, showing
 2053 that our method trained on CDFS performs comparably well on ELAIS-S1. However,
 2054 nearest neighbours outperforms most methods on ELAIS-S1. This is likely because
 2055 there is a much higher percentage of compact objects in ELAIS-S1 than in CDFS. The
 2056 maximum achievable accuracy we have estimated for ELAIS-S1 is very close to 100
 2057 per cent, so (as for CDFS) a very accurate binary classifier would outperform nearest
 2058 neighbours.

2059 One interesting difference between the ATLAS fields is that random forests trained
 2060 on expert labels perform well on CDFS but poorly on ELAIS-S1. This is not the case for
 2061 logistic regression or convolutional neural networks trained on expert labels, nor is it
 2062 the case for random forests trained on Radio Galaxy Zoo. We hypothesise that this is
 2063 because the ELAIS-S1 cross-identification catalogue (Middelberg et al., 2008) labelled
 2064 fainter radio components than the CDFS cross-identification catalogue (Norris et al.,
 2065 2006) due to noise from the very bright source ATCDFS_J032836.53-284156.0 in CDFS.
 2066 Classifiers trained on CDFS expert labels may thus be biased toward brighter radio
 2067 components compared to ELAIS-S1. Radio Galaxy Zoo uses a preliminary version of
 2068 the third data release of ATLAS (Franzen et al., 2015) and so classifiers trained on the
 2069 Radio Galaxy Zoo labels may be less biased toward brighter sources compared to those
 2070 trained on the expert labels. To test this hypothesis we tested each classification model
 2071 against test sets with a signal-to-noise ratio (SNR) cutoff. A SWIRE object was only
 2072 included in the test set for a given cutoff if it was located within 1' of a radio component
 2073 with a SNR above the cutoff. The balanced accuracies for each classifier at each cutoff
 2074 are shown in Figure 4.15(a) and (b) and the distribution of test set size for each cutoff
 2075 is shown in Figure 4.15(c). Figure 4.15(c) shows that ELAIS-S1 indeed has more faint
 2076 objects in its test set than the CDFS test set, with the SNR for which the two fields reach
 2077 the same test set size (approximately 34) indicated by the dashed vertical line on each
 2078 plot. For CDFS, all classifiers perform reasonably well across cutoffs, with performance
 2079 dropping as the size of the test set becomes small. For ELAIS-S1, logistic regression and
 2080 convolutional neural networks perform comparably across all SNR cutoffs, but random
 2081 forests do not. While random forests trained on Radio Galaxy Zoo labels perform
 2082 comparably to other classifiers across all SNR cutoffs, random forests trained on expert
 2083 labels show a considerable drop in performance below the dashed line.

2084 4.5 Discussion

2085 Based on the ATLAS sample, our main result is that it is possible to cast radio host
 2086 galaxy cross-identification as a machine learning task for which standard methods can

⁶We cannot directly compare our method applied to ELAIS-S1 with Radio Galaxy Zoo, as Radio Galaxy Zoo does not include ELAIS-S1.

2087 be applied. These methods can then be trained with a variety of label sets derived
 2088 from cross-identification catalogues. While our methods have not outperformed near-
 2089 est neighbours, we have demonstrated that for a very accurate binary classifier, good
 2090 cross-identification results can be obtained using our method. Future work could com-
 2091 bine multiple catalogues or physical priors to boost performance.

2092 Nearest neighbours approaches outperform most methods we investigated, no-
 2093 tably including Radio Galaxy Zoo. This is due to the large number of compact or
 2094 partially-resolved objects in ATLAS. This result shows that for compact and partially-
 2095 resolved objects, methods that do not use machine learning such as a nearest neigh-
 2096 bours approach or likelihood ratio (Weston et al., 2018) should be preferred to ma-
 2097 chine learning methods. It also shows that ATLAS is not an ideal ~~data set~~ dataset for
 2098 developing machine learning methods like ours. Our use of ATLAS is motivated by its
 2099 status as a pilot survey for EMU, so methods developed for ATLAS should also work
 2100 for EMU. New methods developed should work well with extended radio sources, but
 2101 this goal is almost unsupported by ATLAS as it has very few examples of such sources.
 2102 This makes both training and testing difficult—there are too few extended sources to
 2103 train on and performance on such a small test set may be unreliable. Larger ~~data sets~~
 2104 datasets with many extended sources like FIRST exist, but these are considerably less
 2105 deep than and at a different resolution to EMU, so there is no reason to expect methods
 2106 trained on such ~~data sets~~ datasets to be applicable to EMU.

2107 The accuracies of our trained cross-identification methods generally fall far below
 2108 the estimated best possible accuracy attainable using our approach, indicated by the
 2109 green-shaded areas in Figures 4.12 and 4.14. The balanced accuracies attained by our
 2110 binary classifiers indicate that there is significant room for improvement in classifica-
 2111 tion. The classification accuracy could be improved by better model selection and more
 2112 training data, particularly for convolutional neural networks. There is a huge variety
 2113 of ways to build a convolutional neural network, and we have only investigated one ar-
 2114 chitecture. For an exploration of different convolutional neural network architectures
 2115 applied to radio astronomy, see Lukic et al. (2018). Convolutional neural networks
 2116 generally require more training data than other machine learning models and we have
 2117 only trained our networks on a few hundred sources. We would expect performance
 2118 on the classification task to greatly increase with larger training sets.

2119 Another problem is that of the window size used to select radio features. Increasing
 2120 window size would increase computational expense, but provide more information to
 2121 the models. Results are also highly sensitive to how large the window size is compared
 2122 to the size of the radio source we are trying to cross-identify, with large angular sizes
 2123 requiring large window sizes to ensure that the features contain all the information
 2124 needed to localise the host galaxy. An ideal implementation of our method would
 2125 most likely represent a galaxy using radio images taken at multiple window sizes, but
 2126 this is considerably more expensive.

2127 Larger training sets, better model selection, and larger window sizes would im-
 2128 prove performance, but only so far: ~~we~~-We would still be bounded above by the es-
 2129 timated ‘perfect’ classifier accuracy. From this point, the performance can only be
 2130 improved by addressing our broken assumptions. We detailed these assumptions in

2131 Section 4.3.2, and we will discuss here how our method could be adapted to avoid these
2132 assumptions. Our assumption that the host galaxy is contained within the search radius
2133 could be improved by dynamically choosing the search radius, perhaps based
2134 on the angular extent of the radio emission, or the redshift of candidate hosts. Radio
2135 morphology information may allow us to select relevant radio data and hence relax the
2136 assumption that a 1'-wide radio image represents just one, whole radio source. Finally,
2137 our assumption that the host galaxy is detected in infrared is technically not needed,
2138 as the sliding-window approach we have employed will still work even if there are
2139 no detected host galaxies—instead of classifying candidate hosts, simply classify each
2140 pixel in the radio image. The downside of removing candidate hosts is that we are no
2141 longer able to reliably incorporate host galaxy information such as colour and redshift,
2142 though this could be resolved by treating pixels as potentially undetected candidate
2143 hosts with noisy features.

2144 We observe that Radio Galaxy Zoo-trained methods perform comparably to meth-
2145 ods trained on expert labels. This shows that the crowdsourced labels from Radio
2146 Galaxy Zoo will provide a valuable source of training data for future machine learn-
2147 ing methods in radio astronomy.

2148 Compared to nearest neighbours, cross-identification accuracy on ELAIS-S1 is lower
2149 than on CDFS. Particularly notable is that our performance on compact objects is very
2150 low for ELAIS-S1, while it was near-optimal for CDFS. These differences may be for
2151 a number of reasons. ELAIS-S1 has beam size and noise profile different from CDFS
2152 (even though both were imaged with the same telescope), so it is possible that our
2153 methods over-adapted to the beam and noise of CDFS. Additionally, CDFS contains a
2154 very bright source which may have caused artefacts throughout the field that are not
2155 present in ELAIS-S1. Further work is required to understand the differences between
2156 the fields and their effect on performance.

2157 Figure 4.15 reveals interesting behaviour of different classifier models at different
2158 flux cutoffs. Logistic regression and convolutional neural networks seem relatively
2159 independent of flux, with these models performing well on the fainter ELAIS-S1 com-
2160 ponents even when they were trained on the generally brighter components in CDFS.
2161 Conversely, random forests were sensitive to the changes in flux distribution between
2162 datasets. This shows that not all models behave similarly on radio data, and it is
2163 therefore important to investigate multiple models when developing machine learn-
2164 ing methods for radio astronomy.

2165 Appendix 4.E (see Figure 4.17) shows examples of incorrectly cross-identified com-
2166 ponents in CDFS. On no such component do all classifiers agree. This raises the possi-
2167 bility of using the level of disagreement of an ensemble of binary classifiers as a mea-
2168 sure of the difficulty of cross-identifying a radio component, analogous to the consen-
2169 sus level for Radio Galaxy Zoo volunteers.

2170 Our methods can be easily incorporated into other cross-identification methods or
2171 used as an extra data source for source detection. For example, the scores output by
2172 our binary classifiers could be used to disambiguate between candidate host galaxies
2173 selected by model-based algorithms, or used to weight candidate host galaxies while
2174 a source detector attempts to associate radio components. Our method can also be

2175 extended using other data sources: ~~for~~^{For} example, information from source identifi-
 2176 cation algorithms could be incorporated into the feature set of candidate host galaxies.

2177 **4.6 Summary**

2178 We presented a machine learning approach for cross-identification of radio compo-
 2179 nents with their corresponding infrared host ~~galaxy~~^{galaxies}. Using the CDFS field of
 2180 ATLAS as a training set we trained our methods on expert and crowdsourced cross-
 2181 identification catalogues. Applying these methods on both fields of ATLAS, we found
 2182 that:

- 2183 • Our method trained on ATLAS observations of CDFS generalised to ATLAS ob-
 2184 servations of ELAIS-S1, demonstrating that training on a single patch of sky is
 2185 a feasible option for training machine learning methods for wide-area radio sur-
 2186 veys;
- 2187 • Performance was comparable to nearest neighbours even on resolved sources,
 2188 showing that nearest neighbours is useful for datasets consisting mostly of unre-
 2189 solved sources such as ATLAS and EMU;
- 2190 • Radio Galaxy Zoo-trained models performed comparably to expert-trained mod-
 2191 els and outperformed Radio Galaxy Zoo, showing that crowdsourced labels are
 2192 useful for training machine learning methods for cross-identification even when
 2193 these labels are noisy;
- 2194 • ATLAS does not contain sufficient data to train or test machine learning cross-
 2195 identification methods for extended radio sources. This suggests that if machine
 2196 learning methods are to be used on EMU, a larger area of sky will be required
 2197 for training and testing these methods. However, existing surveys like FIRST are
 2198 likely too different from EMU to expect good generalisation.

2199 While our cross-identification performance is not as high as desired, we make no
 2200 assumptions on the binary classification model used in our methods and so we expect
 2201 the performance to be improved by further experimentation and model selection. Our
 2202 method provides a useful framework for generalising cross-identification catalogues
 2203 to other areas of the sky from the same radio survey and can be incorporated into
 2204 existing methods. We have shown that citizen science can provide a useful dataset for
 2205 training machine learning methods in the radio domain. Chapter 5 will extend this
 2206 approach and confirm that dataset size is a key limitation by successfully applying it
 2207 to a considerably larger dataset: FIRST.

2208 **4.7 Acknowledgements**

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 2210 more than 11 000 volunteers in the Radio Galaxy Zoo project. Their contributions are

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4.A Classification models

This appendix describes the three different models we used for binary classification in this chapter: logistic regression, convolutional neural networks, and random forests.

4.A.1 Logistic regression

Logistic regression is linear in the feature space and outputs the probability that the input has a positive label. The model is (Bishop, 2006):

$$f(\vec{x}) = \sigma(\vec{w}^T \vec{x} + b) , \quad (4.2)$$

where $\vec{w} \in \mathbb{R}^D$ is a vector of parameters, $b \in \mathbb{R}$ is a bias term, $\vec{x} \in \mathbb{R}^D$ is the feature vector representation of a candidate host, and $\sigma : \mathbb{R} \rightarrow \mathbb{R}$ is the logistic sigmoid function:

$$\sigma(a) = (1 + \exp(-a))^{-1} . \quad (4.3)$$

The logistic regression model is fully differentiable, and the parameters \vec{w} can therefore be learned using gradient-based optimisation methods. We used the scikit-learn (Pedregosa et al., 2011) implementation of logistic regression with balanced classes.

4.A.2 Convolutional neural networks

Convolutional neural networks (CNN) are a biologically-inspired prediction model for prediction with image inputs. The input image is convolved with a number of

2241 filters to produce output images called feature maps. These feature maps can then
 2242 be convolved again with other filters on subsequent layers, producing a network of
 2243 convolutions. The whole network is differentiable with respect to the values of the
 2244 filters and the filters can be learned using gradient-based optimisation methods. The
 2245 final layer of the network is logistic regression, with the convolved outputs as input
 2246 features. For more detail, see subsection II.A, LeCun et al. (1998). We used KERAS
 2247 (Chollet et al., 2015) to implement our CNN, accounting for class imbalance by reweighting
 2248 the classes.

2249 CNNs have recently produced good results on large image-based datasets in astronomy
 2250 (Dieleman et al., 2015; Lukic et al., 2018, e.g.). We employed only a simple CNN model
 2251 in Chapter 4 as a proof of concept that CNNs may be used for class probability prediction
 2252 on radio images. The model architecture we used is shown in Figure 4.16.

2253 4.A.3 Random forests

2254 Random forests are an ensemble of decision trees (Breiman, 2001). They consider
 2255 multiple subsamples of the training set, where each subsample is sampled with replacement
 2256 from the training set. For each subsample a decision tree classifier is constructed by
 2257 repeatedly making axis-parallel splits based on individual features. In a random forest
 2258 the split decision is taken based on a random subset of features. To classify a new data
 2259 point, the random forest takes the weighted average of all classifications produced by
 2260 each decision tree. In Chapter 4 we used the scikit-learn (Pedregosa et al., 2011)
 2261 implementation of random forests with 10 trees, the information entropy split criterion,
 2262 a minimum leaf size of 45, and balanced classes.

2263 4.B Accuracy tables

2264 This section contains tables of accuracy for our cross-identification method applied
 2265 to CDFS and ELAIS-S1. In Table 4.3 and Table 4.4 we list the balanced accuracies
 2266 of our Chapter 4 classifiers on the cross-identification task for CDFS and ELAIS-S1
 2267 respectively, averaged over each set of training quadrants. In Table 4.5 and Table 4.6
 2268 we list the balanced accuracies of classifiers on the cross-identification task for CDFS
 2269 and ELAIS-S1 respectively, averaged over each set of training quadrants.

2270 4.C SWIRE object scores

2271 This appendix contains scores predicted by our Chapter 4 binary classifiers for each
 2272 SWIRE object within 1' of a radio component in CDFS and ELAIS-S1. Scores for SWIRE CDFS
 2273 objects are shown in Table 4.7 and scores for SWIRE ELAIS-S1 are shown in Table 4.8.
 2274 For CDFS, the score for an object in a quadrant is predicted by binary classifiers trained
 2275 on all other quadrants. For ELAIS-S1, we show the scores predicted by binary classifiers
 2276 trained on each CDFS quadrant. Note that these scores have *not* been weighted by

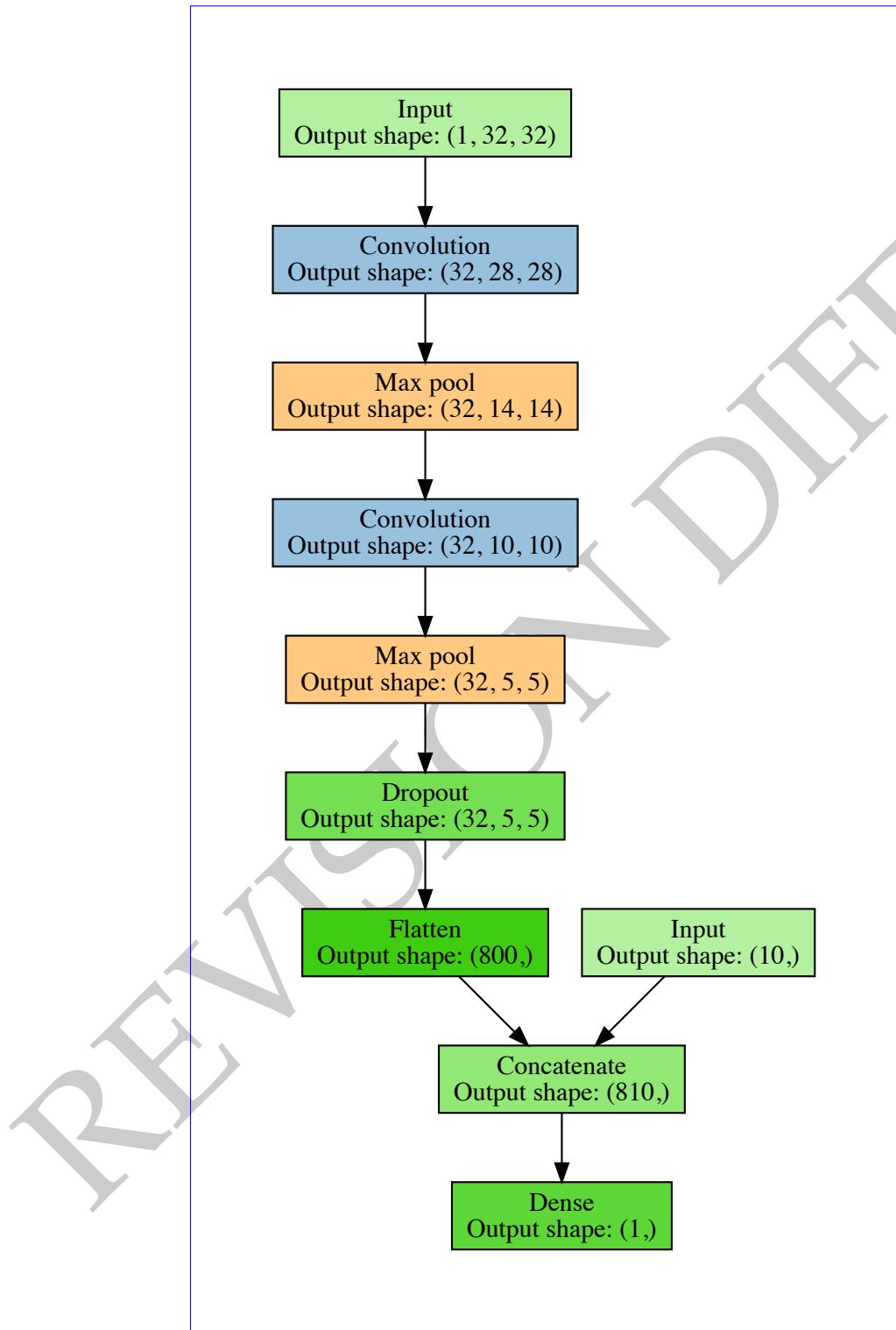


Figure 4.16: Architecture of our CNN. Parenthesised numbers indicate the size of output layers as a tuple (width, height, depth). The concatenate layer flattens the output of the previous layer and adds the 10 features derived from the candidate host in SWIRE, i.e. the flux ratios, stellarity indices, and distance. The dropout layer randomly sets 25 per cent of its inputs to zero during training to prevent overfitting. Diagram based on <https://github.com/dnouri/nolearn>.

Table 4.3: Balanced accuracies for different binary classification models trained and tested on SWIRE objects in CDFS. The ‘Labeller’ column states what set of training labels were used to train the classifier, and the ‘Classifier’ column states what classification model was used. ‘CNN’ is a convolutional neural network, ‘LR’ is logistic regression and ‘RF’ is random forests. Accuracies are evaluated against the expert label set derived from Norris et al. (2006). The standard deviation of balanced accuracies evaluated across the four quadrants of CDFS (Figure 4.8) is also shown. The ‘compact’ set refers to SWIRE objects within 1' of a compact radio component, the ‘resolved’ set refers to SWIRE objects within 1' of a resolved radio component, and ‘all’ is the union of these sets.

Labeller	Classifier	Mean ‘Compact’ accuracy (per cent)	Mean ‘Resolved’ accuracy (per cent)	Mean ‘All’ accuracy (per cent)
Norris	LR	91.5 ± 1.0	93.2 ± 1.0	93.0 ± 1.2
	CNN	92.6 ± 0.7	91.2 ± 0.5	92.0 ± 0.6
	RF	96.7 ± 1.5	91.0 ± 4.5	96.0 ± 2.5
RGZ	LR	89.5 ± 0.8	90.5 ± 1.7	90.2 ± 0.8
	CNN	89.4 ± 0.6	89.6 ± 1.3	89.4 ± 0.5
	RF	94.5 ± 0.2	95.8 ± 0.4	94.7 ± 0.3

Table 4.4: Balanced accuracies for different binary classification models trained on SWIRE objects in CDFS and tested on SWIRE objects in ELAIS-S1. Columns and abbreviations are as in Table 4.3. Accuracies are evaluated against the expert label set derived from Middelberg et al. (2008). The standard deviations of balanced accuracies of models trained on the four subsets of CDFS (Figure 4.8) are also shown.

Labeller	Classifier	Mean ‘Compact’ accuracy (per cent)	Mean ‘Resolved’ accuracy (per cent)	Mean ‘All’ accuracy (per cent)
Norris	LR	94.6 ± 0.4	93.3 ± 2.0	95.3 ± 0.1
	CNN	94.8 ± 0.2	92.8 ± 0.5	94.4 ± 0.2
	RF	85.9 ± 3.8	70.0 ± 2.8	86.6 ± 3.2
RGZ	LR	91.8 ± 0.3	91.9 ± 0.5	92.0 ± 0.2
	CNN	90.1 ± 0.3	91.1 ± 0.9	90.2 ± 0.3
	RF	95.1 ± 0.1	95.2 ± 0.0	95.2 ± 0.3

Table 4.5: Cross-identification accuracies for different classification models on CDFS. The ‘Labeller’ column states what set of training labels were used to train the method, and the ‘Classifier’ column states what classification model was used. ‘CNN’ is a convolutional neural network, ‘LR’ is logistic regression, ‘RF’ is random forests, and ‘Labels’ is the accuracy of the label set itself. ‘Perfect’ indicates that the true labels of the test set were used and hence represents an upper bound on cross-identification accuracy with our method. ‘NN’ is a nearest neighbours approach. Accuracies are evaluated against the expert label set, so ‘Norris’ labels are 100 per cent accurate by definition. The standard deviation of accuracies evaluated across the four quadrants of CDFS (Figure 4.8) is also shown.

Labeller	Classifier	Mean ‘Compact’ accuracy (per cent)	Mean ‘Resolved’ accuracy (per cent)	Mean ‘All’ accuracy (per cent)
Norris	NN	97.2 ± 1.7	75.7 ± 7.9	93.4 ± 0.8
	Random	97.9 ± 2.2	22.3 ± 9.2	83.2 ± 4.7
	Labels	100.0 ± 0.0	100.0 ± 0.0	100.0 ± 0.0
	Perfect	97.9 ± 2.2	99.0 ± 1.8	98.1 ± 1.7
	LR	97.3 ± 0.5	76.0 ± 3.2	93.7 ± 1.8
	CNN	96.6 ± 0.9	74.3 ± 12.3	93.5 ± 0.5
RGZ	RF	96.1 ± 1.4	75.8 ± 6.7	93.8 ± 2.0
	Labels	53.1 ± 8.5	56.7 ± 5.9	54.4 ± 5.9
	LR	97.3 ± 1.9	74.5 ± 5.1	93.6 ± 1.7
	CNN	85.4 ± 2.6	68.1 ± 9.2	92.4 ± 1.1
	RF	97.5 ± 0.9	74.3 ± 7.9	93.7 ± 1.5

Table 4.6: Cross-identification accuracies for different classification models on ELAIS-S1. Columns and abbreviations are as in Table 4.5. Accuracies are evaluated against the expert label set derived from Middelberg et al. (2008) cross-identifications. The standard deviation of accuracies evaluated across models trained on the four quadrants of CDFS (Figure 4.8) is also shown.

Labeller	Classifier	Mean ‘Compact’ accuracy (per cent)	Mean ‘Resolved’ accuracy (per cent)	Mean ‘All’ accuracy (per cent)
Middelberg	NN	95.5 ± 0.0	92.8 ± 0.0	95.5 ± 0.0
	Random	61.9 ± 1.1	26.6 ± 2.1	61.9 ± 1.1
	Perfect	99.6 ± 0.0	99.8 ± 0.0	99.6 ± 0.0
	LR	89.0 ± 1.1	89.7 ± 1.8	94.4 ± 0.9
	CNN	89.7 ± 0.3	89.4 ± 1.4	94.3 ± 0.7
	RF	83.8 ± 5.6	82.3 ± 4.1	90.6 ± 2.1
Norris	LR	90.5 ± 1.0	92.7 ± 0.2	95.9 ± 0.1
	CNN	84.6 ± 0.6	84.6 ± 0.6	91.8 ± 0.3
	RF	91.3 ± 1.0	90.3 ± 2.4	94.7 ± 1.2
RGZ	Labels	100.0 ± 0.0	100.0 ± 0.0	100.0 ± 0.0
	LR	97.3 ± 1.9	74.5 ± 5.1	93.6 ± 1.7
	CNN	85.4 ± 2.6	68.1 ± 9.2	92.4 ± 1.1

2277 Gaussians. These are partial tables, and the full tables are available online at the
 2278 Monthly Notices of the Royal Astronomical Society website⁷.

2279 The columns of the score tables are defined as follows:

- 2280 • *SWIRE*—SWIRE designation for candidate host galaxy.
- 2281 • *RA*—Right ascension (J2000).
- 2282 • *Dec*—Declination (J2000).
- 2283 • *Expert host*—Whether the candidate host galaxy is a host galaxy according to
 2284 Norris et al. (2006) or Middelberg et al. (2008) cross-identifications of CDFS and
 2285 ELAIS-S1 respectively.
- 2286 • *RGZ host*—Whether the candidate host galaxy is a host galaxy according to Radio
 2287 Galaxy Zoo cross-identifications (Wong et al., in prep.). This is always ‘no’ for
 2288 ELAIS-S1 objects.
- 2289 • *C/L/D*—Score assigned by binary classifier C trained on label set L of D candidate
 2290 host galaxies. C may be ‘CNN’, ‘LR’ or ‘RF’ for CNN, logistic regression, or
 2291 random forests respectively. L may be ‘Norris’ or ‘RGZ’ for expert and Radio
 2292 Galaxy Zoo labels respectively. D may be ‘All’, ‘Compact’, or ‘Resolved’ for each
 2293 respective subset defined in Section 4.3.6.

2294 4.D ATLAS component cross-identifications

2295 This section contains cross-identifications predicted by our cross-identification method
 2296 for each ATLAS radio component in CDFS and ELAIS-S1. Cross-identifications for
 2297 ATLAS CDFS components are shown in Table 4.9 and cross-identifications for ATLAS ELAIS-S1
 2298 are shown in Table 4.10. For CDFS, the cross-identification for a component in a quadrant
 2299 is predicted using our method with binary classifiers trained on all other quadrants.
 2300 For ELAIS-S1, we show the cross-identifications predicted by our method using binary
 2301 classifiers trained on each CDFS quadrant. For CDFS, we also show the Radio Galaxy
 2302 Zoo consensus, which is a proxy for the difficulty of cross-identifying a component
 2303 (Wong et al., in prep.). These are partial tables, and the full tables are available online
 2304 at the Monthly Notices of the Royal Astronomical Society website⁸.

2305 The columns of the cross-identification tables are defined as follows:

- 2306 • *ATLAS*—ATLAS designation for radio component.
- 2307 • *RA*—Right ascension of radio component (J2000).
- 2308 • *Dec*—Declination of radio component (J2000).
- 2309 • *CID*—Radio Galaxy Zoo component ID.

⁷<https://doi.org/10.1093/mnras/sty1308>

⁸<https://doi.org/10.1093/mnras/sty1308>

Table 4.7: Scores output by our trained classifiers for SWIRE CDFS candidate host galaxies. Columns are defined in Appendix 4.C. Full table electronic.

Table 4.8: Scores output by our trained classifiers for SWIRE ELAIS-S1 candidate host galaxies. Columns are defined in Appendix 4.C. Full table electronic.

	RA	Dec	Expert	RGZ	CNN	RGZ						
	host	host	host	All	Compact	Resolved	All	Compact	Resolved	All	Compact	Resolved
J002925.73-440256.2	7.3572	-44.0490	yes	0.9537	0.8638	0.5552	0.9195	0.9037	0.9371			
J002926.14-440249.0	7.3590	-44.0470	no	0.7361	0.8752	0.5640	0.7740	0.7474	0.7952			
J002926.52-440247.0	7.3605	-44.0464	no	0.3390	0.8338	0.5556	0.7275	0.6894	0.7197			
J002926.63-440301.1	7.3610	-44.0503	no	0.2108	0.8251	0.5623	0.3434	0.3306	0.3292			
J002927.13-440232.6	7.3631	-44.0424	no	0.0339	0.8479	0.5669	0.5853	0.5148	0.5159			
J002927.28-440245.3	7.3637	-44.0459	no	0.0406	0.8345	0.5540	0.2702	0.2340	0.2133			
J002927.44-440238.5	7.3644	-44.0440	no	0.0116	0.8267	0.5746	0.2228	0.2182	0.2028			
J002928.08-440230.3	7.3670	-44.0418	no	0.0024	0.8626	0.5791	0.2297	0.1963	0.1549			
J002928.11-440312.7	7.3671	-44.0535	no	0.0011	0.8159	0.5514	0.0377	0.0384	0.0271			
J002928.80-440306.8	7.3700	-44.0519	no	0.0003	0.8405	0.5668	0.0236	0.0226	0.0136			
<hr/>												
LR												
All	Compact	Resolved	All	Compact	Resolved	All	Compact	Resolved	All	Compact	Resolved	
0.9722	0.9955	0.8769	0.9933	0.9934	0.9658	0.8824	0.9664	0.7950	0.8078	0.9227	0.7677	
0.4669	0.0111	0.4249	0.3926	0.2220	0.5947	0.2077	0.0000	0.1613	0.1876	0.0852	0.4546	
0.2264	0.0254	0.2389	0.6275	0.3033	0.6812	0.1347	0.0857	0.399	0.3582	0.4854	0.5347	
0.0603	0.0007	0.0734	0.0688	0.0141	0.1581	0.0917	0.0000	0.0399	0.2846	0.1245	0.2833	
0.0248	0.0334	0.0301	0.5735	0.5065	0.5265	0.1977	0.1507	0.0000	0.3334	0.6593	0.3995	
0.0173	0.0016	0.0359	0.1056	0.0492	0.1456	0.0000	0.0000	0.0000	0.0000	0.0000	0.0287	
0.0064	0.0049	0.0187	0.1981	0.1534	0.1493	0.0000	0.0000	0.0000	0.1565	0.1634	0.1284	
0.0020	0.0005	0.0239	0.1337	0.1001	0.1310	0.0000	0.0000	0.0358	0.0000	0.0000	0.0190	
0.0008	0.0013	0.0280	0.0361	0.0205	0.1171	0.0000	0.0000	0.0873	0.0383	0.0000	0.0000	
0.0004	0.0014	0.0095	0.0339	0.0408	0.0136	0.0000	0.0000	0.1114	0.1480	0.1584		

- 2310 • *Zooniverse ID*—Radio Galaxy Zoo Zooniverse ID.
- 2311 • *Norris/Middleberg*—Designation of SWIRE cross-identification from Norris et al. (2006)
- 2312 or Middleberg et al. (2008) for CDFS and ELAIS-S1 respectively.
- 2313 • *Norris/Middleberg RA*—Right ascension of SWIRE cross-identification from Norris et al. (2006)
- 2314 or Middleberg et al. (2008) for CDFS and ELAIS-S1 respectively.
- 2315 • *Norris/Middleberg Dec*—Right ascension of SWIRE cross-identification from Norris et al. (2006)
- 2316 or Middleberg et al. (2008) for CDFS and ELAIS-S1 respectively.
- 2317 • *RGZ*—Designation of SWIRE cross-identification from Radio Galaxy Zoo (Wong et al., in prep.)
- 2318 ~
- 2319 • *RGZ RA*—Right ascension of SWIRE cross-identification from Radio Galaxy Zoo
- 2320 (Wong et al., in prep.).
- 2321 • *RGZ Dec*—Right ascension of SWIRE cross-identification from Radio Galaxy Zoo
- 2322 (Wong et al., in prep.).
- 2323 • *RGZ radio consensus*—Percentage agreement of Radio Galaxy Zoo volunteers on
- 2324 the radio component configuration.
- 2325 • *RGZ IR consensus*—Percentage agreement of Radio Galaxy Zoo volunteers on the
- 2326 host galaxy of this radio component.
- 2327 • *C / L / D*—Designation of SWIRE cross-identification made by our method using
- 2328 classification model C trained on label set L of D candidate host galaxies. C may
- 2329 be ‘CNN’, ‘LR’ or ‘RF’ for CNN, logistic regression or random forests respectively.
- 2330 L may be ‘Norris’ or ‘RGZ’ for expert and Radio Galaxy Zoo labels respectively.
- 2331 D may be ‘All’, ‘Compact’, or ‘Resolved’ for each respective subset defined in
- 2332 Section 4.3.6.~
- 2333 • *C / L / D RA*—Right ascension (J2000) of SWIRE cross-identification made by
- 2334 our method using classification model C trained on label set L of D candidate
- 2335 host galaxies. C, L, and D are defined as for designation.
- 2336 • *C / L / D Dec*—Declination (J2000) of SWIRE cross-identification made by our
- 2337 method using classification model C trained on label set L of D candidate host
- 2338 galaxies. C, L, and D are defined as for designation.

2339 4.E *Cross-identification figures*

2340 Figure 4.17 shows figures of our cross-identifications of each ATLAS radio component
 2341 in CDFS and ELAIS-S1. There are just five examples shown here, but all 469 examples
 2342 are available online at the *Monthly Notices of the Royal Astronomical Society* website⁹.

⁹<https://doi.org/10.1093/mnras/sty1308>

Table 4.9: Cross-identifications for ATLAS-CDFS components. Columns are defined in Appendix 4.D. Full table electronic.

ATLAS	RA	Dec	CID	Zooniverse ID	Norris		RGZ		RGZ	
					RA	Dec	RA	Dec	radio consensus	IR consensus
J032602-32-284708.1C	51.5117	-28.7856	C10412	ARG003rb2	J032603-15-284708.5	51.5132	-28.7857	J032615-41-284630.7	51.5642	-28.7752
J032615-49-284629.4C	51.5646	-28.7749	C10614	ARG003fr	J032615-41-284630.7	51.5642	-28.7752	J032615-41-284630.7	51.5642	-28.7752
J032615-55-280559.8C	51.5648	-28.1000	C10820	ARG003fb	J032615-52-280559.8	51.5647	-28.1000	J032615-52-280559.8	51.5647	-28.1000
J032617-35-280710.2C	51.5723	-28.1195	C10050C1	ARG003r2	J032617-39-280707.2	51.5746	-28.1187	J032617-39-280707.2	51.5746	-28.1187
J032625-13-280909.8C	51.6047	-28.1527	C10409	ARG003ra2	J032623-19-280910.1	51.6050	-28.1528	J032625-19-280910.1	51.6050	-28.1528
J032629-10-280650.1C	51.6213	-28.1139	C10963	ARG003rd	J032629-13-280650.7	51.6214	-28.1141	J032626-14-280656.7	51.6114	-28.1102
J032629-51-284652.7C	51.6234	-28.6813	C10394	ARG003re	J032629-54-284655.8	51.6231	-28.6822	J032629-54-284655.8	51.6231	-28.6822
J032629-52-284753.5C	51.6247	-28.7982	C10229	ARG003rw	J032629-81-284754.4	51.6242	-28.7985	J032629-81-284754.4	51.6242	-28.7985
J032630-06-283657.3C	51.6278	-28.6159	C10172C1	ARG003r5	J032630-64-283658.0	51.6277	-28.6161	J032628-56-283744.8	51.6191	-28.6291
J032634-59-280228.8C	51.6441	-28.3397	C10757	ARG003r9	J032634-58-280228.8	51.6441	-28.3397	J032631-96-281941.0	51.6329	-28.3281

Compact	Norris		CNN		LR		RGZ	
	RA	Dec	RA	Dec	RA	Dec	RA	Dec
J032602-36-284711.5	51.5098	-28.7865	J032602-36-284711.5	51.5098	-28.7865	J032602-36-284711.5	51.5098	-28.7865
J032615-31-284630.7	51.5642	-28.7732	J032615-31-284630.7	51.5642	-28.7732	J032615-31-284630.7	51.5642	-28.7732
J032615-52-280559.8	51.5647	-28.1000	J032615-52-280559.8	51.5647	-28.1000	J032615-52-280559.8	51.5647	-28.1000
J032617-59-280707.2	51.5746	-28.1187	J032617-59-280707.2	51.5746	-28.1187	J032617-59-280707.2	51.5746	-28.1187
J032621-19-280901.0	51.6050	-28.1528	J032621-19-280901.0	51.6050	-28.1528	J032621-19-280901.0	51.6050	-28.1528
J032629-13-280650.7	51.6214	-28.1141	J032629-13-280650.7	51.6214	-28.1141	J032629-13-280650.7	51.6214	-28.1141
J032629-54-284651.9	51.6231	-28.6811	J032629-54-284651.9	51.6231	-28.6811	J032629-54-284651.9	51.6231	-28.6811
J032629-81-284754.4	51.6242	-28.7985	J032629-81-284754.4	51.6242	-28.7985	J032629-81-284754.4	51.6242	-28.7985
J032630-04-283658.0	51.6277	-28.6161	J032630-04-283658.0	51.6277	-28.6161	J032630-04-283658.0	51.6277	-28.6161
J032634-58-280228.8	51.6441	-28.3397	J032634-58-280228.8	51.6441	-28.3397	J032634-58-280228.8	51.6441	-28.3397

Table 4.10: Cross-identifications for ATLAS ELAIS-S1 components. Columns are defined in Appendix 4.D. Full table electronic.

ATLAS	RA	Dec	CID	Zooniverse ID	Middelberg		RCZ		IR		
					RA	Dec	RA	Dec	radio consensus	IR consensus	
J002925.6-440256.8	7:3570~	-44.091~	C0375	J002925.73-440256.2	7:3572~	-44.090~	J002925.73-440256.2	7:3572~	-44.090~	J002925.73-440256.2	
J002938.9-432946.7	7:4092~	-43.4963~	C0832	J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	
J002940.1-340309.2	7:4172~	-44.0526~	C0374	J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	
J002943.14-440812.3	7:4298~	-44.1368~	C0302	J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	
J002944.5-433627.8	7:4335~	-43.6077~	C0272	J002944.36-433630.2	7:4348~	-43.6094~	J002944.36-433630.2	7:4348~	-43.6094~	J002944.36-433630.2	
J002945.3-432148.5	7:4388~	-43.3635~	C0943.1~	J002945.64-432149.3	7:4402~	-43.3637~	J002945.64-432149.3	7:4402~	-43.3637~	J002945.64-432149.3	
J002946.14-432149.1~	7:4423~	-43.3637~	C0943~	J002946.64-432149.3	7:4402~	-43.3637~	J002946.64-432149.3	7:4402~	-43.3637~	J002946.64-432149.3	
J002949.89-440541.4~	7:4579~	-44.0648~	C0345	J002949.90-440541.4	7:4580~	-44.0649~	J002949.90-440541.4	7:4580~	-44.0649~	J002949.90-440541.4	
J002951.13-432354.3	7:4631~	-43.3984~	C0924~	J002951.14-432355.3	7:4631~	-43.3987~	J002951.14-432355.3	7:4631~	-43.3987~	J002951.14-432355.3	
J002951.19-440556.6~	7:4633~	-44.0901~	C0942~	J002951.26-440556.4	7:4636~	-44.0900~	J002951.26-440556.4	7:4636~	-44.0900~	J002951.26-440556.4	
CNN											
Norris											
Compact		Resolved		RA		RA		RA		RA	
J002925.73-440256.2	7:3572~	-44.0490~	J002925.73-440256.2	7:3572~	-44.0490~	J002925.73-440256.2	7:3572~	-44.0490~	J002925.73-440256.2	7:3572~	-44.0490~
J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	7:4087~	-43.4967~
J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	7:4175~	-44.0527~
J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	7:4298~	-44.1371~
J002944.36-433630.2~	7:4348~	-43.6094~	J002944.36-433630.2~	7:4348~	-43.6094~	J002944.36-433630.2~	7:4348~	-43.6094~	J002944.36-433630.2~	7:4348~	-43.6094~
J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~
J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~
J002951.14-440546.1~	7:4644~	-44.0962~	J002951.14-440546.1~	7:4644~	-44.0962~	J002951.14-440546.1~	7:4644~	-44.0962~	J002951.14-440546.1~	7:4644~	-44.0962~
J002951.14-440546.1~	7:4631~	-43.3987~	J002951.14-440546.1~	7:4631~	-43.3987~	J002951.14-440546.1~	7:4631~	-43.3987~	J002951.14-440546.1~	7:4631~	-43.3987~
J002951.26-440556.4~	7:4636~	-44.0900~	J002951.26-440556.4~	7:4636~	-44.0900~	J002951.26-440556.4~	7:4636~	-44.0900~	J002951.26-440556.4~	7:4636~	-44.0900~
LR											
Compact		Resolved		RA		RA		RA		RA	
J002925.73-440256.2	7:3572~	-44.0490~	J002925.73-440256.2	7:3572~	-44.0490~	J002925.73-440256.2	7:3572~	-44.0490~	J002925.73-440256.2	7:3572~	-44.0490~
J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	7:4087~	-43.4967~
J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	7:4175~	-44.0527~
J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	7:4298~	-44.1371~
J002944.36-433630.2~	7:4348~	-43.6094~	J002944.36-433630.2~	7:4348~	-43.6094~	J002944.36-433630.2~	7:4348~	-43.6094~	J002944.36-433630.2~	7:4348~	-43.6094~
J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~
J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~
J002951.14-440546.1~	7:4644~	-44.0962~	J002951.14-440546.1~	7:4644~	-44.0962~	J002951.14-440546.1~	7:4644~	-44.0962~	J002951.14-440546.1~	7:4644~	-44.0962~
J002951.14-440546.1~	7:4631~	-43.3987~	J002951.14-440546.1~	7:4631~	-43.3987~	J002951.14-440546.1~	7:4631~	-43.3987~	J002951.14-440546.1~	7:4631~	-43.3987~
J002951.26-440556.4~	7:4636~	-44.0900~	J002951.26-440556.4~	7:4636~	-44.0900~	J002951.26-440556.4~	7:4636~	-44.0900~	J002951.26-440556.4~	7:4636~	-44.0900~
RF											
Norris		Resolved		RA		RA		RA		RA	
J002925.73-440256.2	7:3572~	-44.0490~	J002925.73-440256.2	7:3572~	-44.0490~	J002925.73-440256.2	7:3572~	-44.0490~	J002925.73-440256.2	7:3572~	-44.0490~
J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	7:4087~	-43.4967~	J002938.07-432947.9	7:4087~	-43.4967~
J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	7:4175~	-44.0527~	J002940.19-440309.6	7:4175~	-44.0527~
J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	7:4298~	-44.1371~	J002943.15-440813.6	7:4298~	-44.1371~
J002944.36-433630.2~	7:4348~	-43.6094~	J002944.36-433630.2~	7:4348~	-43.6094~	J002944.36-433630.2~	7:4348~	-43.6094~	J002944.36-433630.2~	7:4348~	-43.6094~
J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~
J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~	J002945.64-432149.3~	7:4402~	-43.3637~
J002951.14-440546.1~	7:4644~	-44.0962~	J002951.14-440546.1~	7:4644~	-44.0962~	J002951.14-440546.1~	7:4644~	-44.0962~	J002951.14-440546.1~	7:4644~	-44.0962~
J002951.14-440546.1~	7:4631~	-43.3987~	J002951.14-440546.1~	7:4631~	-43.3987~	J002951.14-440546.1~	7:4631~	-43.3987~	J002951.14-440546.1~	7:4631~	-43.3987~
J002951.26-440556.4~	7:4636~	-44.0900~	J002951.26-440556.4~	7:4636~	-44.0900~	J002951.26-440556.4~	7:4636~	-44.0900~	J002951.26-440556.4~	7:4636~	-44.0900~

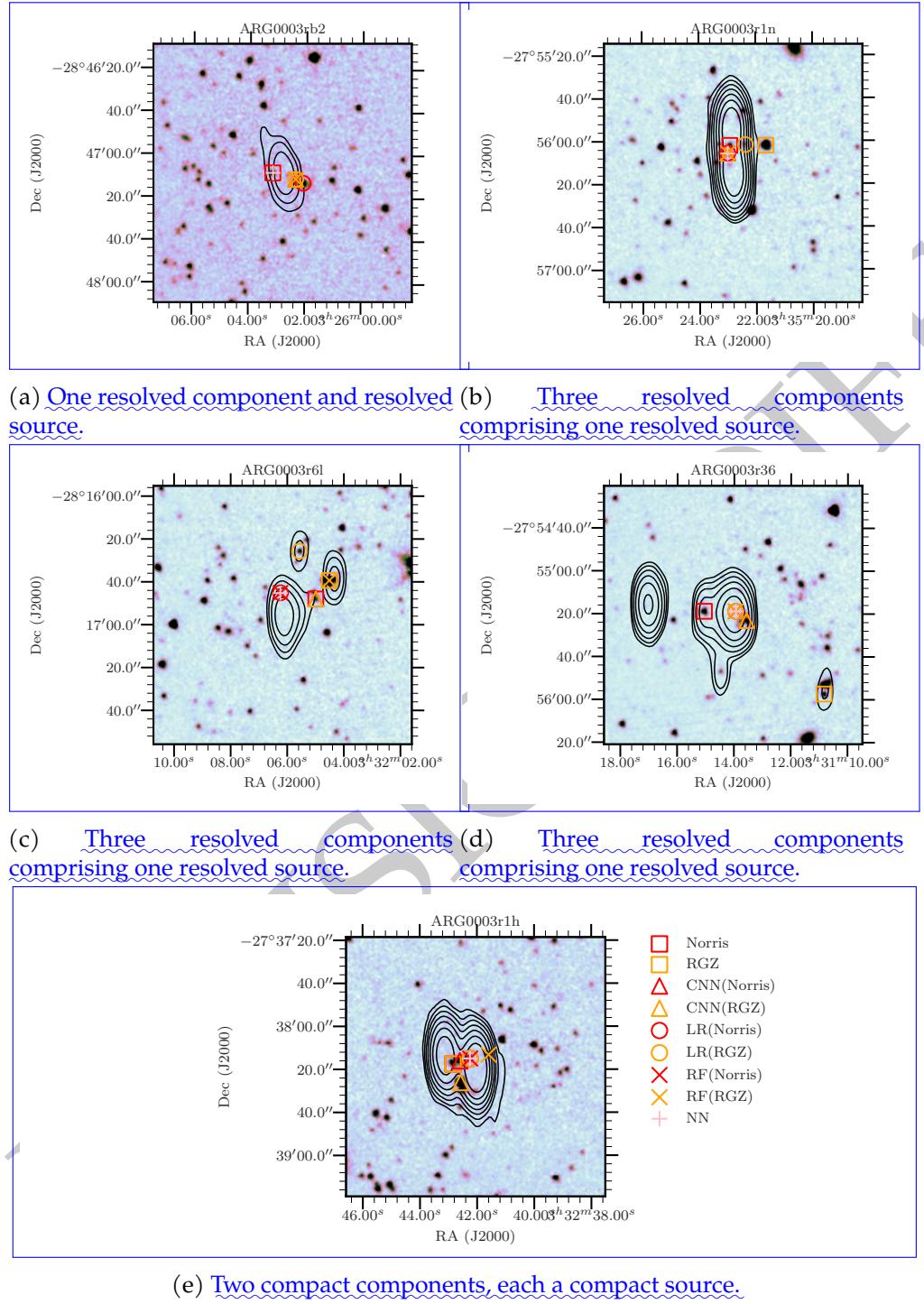


Figure 4.17: Examples of resolved sources with high disagreement between cross-identifiers. The contours show ATLAS radio data and start at 4σ , increasing geometrically by a factor of 2. The background image is the $3.6 \mu\text{m}$ SWIRE image. Binary classifier model/training set combinations are denoted $C(S)$ where C is the binary classifier model and S is the training set. ‘LR’ is logistic regression, ‘CNN’ is convolutional neural networks, and ‘RF’ is random forests. ‘Norris’ refers to the expert labels and ‘RGZ’ refers to the Radio Galaxy Zoo labels. The cross-identification made by nearest neighbours is shown by ‘NN’.

2344

Radio Luminosity Functions

2345 This chapter is based on my paper *Radio Galaxy Zoo: Radio Luminosity Functions of Ex-
2346 tended Sources*, by M. J. Alger, O. I. Wong, C. S. Ong, N. M. McClure-Griffiths, H. An-
2347 dernach, L. Rudnick, S. S. Shabala, A. F. Garon, J. K. Banfield, A. D. Kapińska, R. P.
2348 Norris, and A. J. M. Thomson; to be submitted. Some minor changes have been made
2349 to match the rest of this thesis.

2350

2351 In Chapter 4, we concluded that our machine learning cross-identification approach
2352 was sound in principle, but the small size and lack of morphological complexity in AT-
2353 LAS prevented training a good classifier. To demonstrate this, we turned our attention
2354 to the Faint Images of the Radio Sky at Twenty Centimeters (FIRST) survey, which con-
2355 tained many more sources and many more morphologically complex sources due to its
2356 higher resolution and sample size. If cross-identification of this dataset was successful,
2357 we could use the resulting cross-identification catalogue to investigate statistical prop-
2358 erties of radio galaxies at larger scales than previously possible. The object of interest
2359 would be the radio luminosity function (RLF), a statistical description of how common
2360 radio galaxies of various luminosities are throughout the [universe](#)[Universe](#). The RLF
2361 would be specific to only extended radio galaxies, and it is this class of galaxies that we
2362 would expect to maximally impact its local environment through direct, mechanical
2363 energy input.

2364 In this chapter, we use a machine learning model trained on the Radio Galaxy Zoo
2365 citizen science project to cross-identify 244 846 radio components of extended radio
2366 sources from FIRST with 158 337 host galaxies observed in the mid-infrared from the
2367 AllWISE source catalogue. 34 305 hosts have a spectroscopic redshift in the Sloan Digi-
2368 tal Sky Survey (SDSS). This is the largest available sample of cross-identified extended
2369 radio sources to date at the time of writing. The large sample size allows us to estimate
2370 the RLF of extended radio galaxies and to further characterise the sample with frac-
2371 tional radio luminosity functions. The extended source RLF can be used to estimate the
2372 mechanical energy injected into the local [environment](#)[environments](#) of active galactic
2373 nuclei (AGN). We estimate from the observed radio emission that inferred extended
2374 radio jets from AGN contribute between 1.3×10^{30} and $1.2 \times 10^{32} \text{ W Mpc}^{-3}$ of mech-
2375 ical energy to their environment throughout the low-redshift ($z < 0.6$) Universe. By
2376 further visual verification we also find 40 radio galaxies with projected size larger than

²³⁷⁷ 1 Mpc. Our results directly demonstrate the impact that automated machine learning
²³⁷⁸ methods could have on future wide-area radio surveys.

²³⁷⁹ **5.1 Introduction**

²³⁸⁰ Radio active galactic nuclei (AGN) are some of the most violent and energetic objects
²³⁸¹ in the Universe. Supermassive black holes at the ~~centre~~-centres of galaxies can produce
²³⁸² large, luminous radio jets that may feed lobes extending up to megaparsec scales. As
²³⁸³ a vital part of galaxy evolution, we want to understand how radio AGN interact with
²³⁸⁴ their host galaxies, in what kinds of galaxies these AGN are found, and how these
²³⁸⁵ populations change over cosmic time.

²³⁸⁶ Mechanical energy from AGN is needed to explain the star-formation history of
²³⁸⁷ galaxies throughout the Universe (e.g. Hardcastle & Croston, 2020; Raouf et al., 2017).
²³⁸⁸ The radio luminosity function (RLF) of extended radio sources ~~would characterise~~
²³⁸⁹ characterises the energy output of galaxies capable of significant energy impact into
²³⁹⁰ their local environment. The local RLF of primarily compact sources is estimated and
²³⁹¹ described in detail by Mauch and Sadler (2007), Pracy et al. (2016) and Condon et al.
²³⁹² (2019), each with complete volume-limited samples. However, the RLF of extended
²³⁹³ radio sources has not been characterised as a separate sample, because estimating this
²³⁹⁴ RLF would need a large number of extended sources with known redshifts. Such red-
²³⁹⁵ shifts are usually obtained by cross-matching the radio sources with their host galaxies
²³⁹⁶ in the optical or infrared. While this cross-matching is relatively straightforward for
²³⁹⁷ compact/unresolved sources, and can therefore be automated (e.g. Kimball & Ivezić,
²³⁹⁸ 2008), extended radio emission may be complex and may not be co-located with the
²³⁹⁹ host galaxy. Cross-identification of complex, extended sources is therefore usually
²⁴⁰⁰ done manually, limiting the sample size.

²⁴⁰¹ Wide-area radio surveys like the Very Large Array Faint Images of the Sky at Twenty
²⁴⁰² Centimeters survey (FIRST; White et al., 1997) have led to catalogues of hundreds of
²⁴⁰³ thousands of radio objects, most of which are associated with radio AGN (Sadler et
²⁴⁰⁴ al., 2002). While individual galaxy properties vary significantly between galaxies, the
²⁴⁰⁵ large sample size of such surveys allows us to examine reliable bulk statistics that may
²⁴⁰⁶ tightly constrain models and ~~theory~~ theories of radio galaxy evolution and formation
²⁴⁰⁷ (Condon, 1992). With a sufficiently large sample (of size N such that $N \gg \sqrt{N}$; Con-
²⁴⁰⁸ don, 1991) we can also divide the RLF into fractions based on the physical properties
²⁴⁰⁹ of each galaxy. These *fractional RLFs* show how different physical processes comprise
²⁴¹⁰ the luminosity distribution, and can be used to investigate how these processes relate
²⁴¹¹ to the properties of the AGN.

In this chapter we calculate the RLF for extended radio sources in FIRST. Throughout this chapter we define an *extended radio source* as a collection of extended radio components with the same host galaxy, and following Banfield et al. (2015) we define an *extended radio component* as a radio component which fulfils Equation 5.1:

$$\frac{S_{\text{peak}}}{S_{\text{int}}} < 1 - \frac{0.1}{\log_{10}(S_{\text{peak}}/1 \text{ mJy})}, \quad (5.1)$$

where S_{peak} is the peak radio flux density and S_{int} is the integrated radio flux density. We define *radio components* as Gaussians fit to radio emission, *radio islands* as connected patches of radio emission above a local 4σ value, and *radio sources* as sets of radio islands or components associated with the same galaxy. The radio flux density of a source is the sum of the flux densities of the components according to the FIRST catalogue. The (*infrared*) *host galaxy* of a radio source or component is defined as the infrared galaxy associated with the radio emitter. A *cross-identification* is an association of a host galaxy with one or more radio components or islands. We define *candidate host galaxies* (or simply *candidates*) as infrared objects that are near a radio component on the sky and thus may potentially be the host galaxy of that component.

Upcoming radio surveys such as the Evolutionary Map of the Universe (EMU; Norris et al., 2011) are expected to increase the number of complex radio sources to around 7 million (Banfield et al., 2015). Manual, expert cross-identification for such surveys will be impractical. One way forward could be to ask non-expert volunteers for help with manual cross-identification, which ~~is was~~ the approach taken by Radio Galaxy Zoo (RGZ; Banfield et al., 2015). This is called *citizen science* and has been employed successfully in many fields with large datasets (Marshall et al., 2015). Even this approach is not sufficient for 7 million sources, though, with RGZ cross-identifying around 75 000 sources in four years. Machine learning provides a potential pathway to obtaining useful physics from such large samples.

In this chapter, we train a machine learning model based on Alger et al. (2018), using RGZ as training data, and use this model to automatically cross-identify 244 846 radio components catalogued by FIRST. This results in 34 305 sources with spectroscopic redshifts. This is the largest available catalogue of extended radio source cross-identifications. We call our catalogue *RGZ-extrapolated* or *RGZ-Ex*. Due to our large sample size we are able to further divide the source population by properties of the host galaxies. We refer to the trained machine learning model and the associated cross-identification algorithm jointly as *binary cross-identification*, or *BXID*. Note that there are two stages to our automated approach: ~~firstFirst~~, we train BXID using an existing catalogue of cross-identified sources; second, we generate new cross-identifications for radio components not in the training catalogue. We refer to these stages as *training* and *prediction* respectively. Our data sources are described in Section 5.2. Our approach is discussed in Section 5.3. Radio luminosity functions of extended sources are presented in Section 5.4 and we discuss these functions in Section 5.5.

Throughout this chapter we assume a flat Λ -CDM cosmology of $H_0 = 69.3 \text{ km s}^{-1} \text{ Mpc}^{-1}$, $\Omega_m = 0.287$. These are the cosmological parameters from the Nine-year Wilkinson Microwave Anisotropy Probe (WMAP9; Hinshaw et al., 2013).

5.2 Data

In this section we describe how we obtain our training and prediction data. To enable the estimation of the extended RLF, we apply a number of selection criteria to the data which are shown in Figure 5.6.

2453 **5.2.1 RGZ**

2454 RGZ is a citizen science project that aims to cross-identify complex radio sources with
 2455 mid-infrared host galaxies with the help of volunteers. The first RGZ data release con-
 2456 tains around 75 000 cross-identifications of a random subset of extended sources in
 2457 FIRST with their host galaxies in AllWISE. For more details on RGZ see Banfield et al.
 2458 (2015). This catalogue has also been used in other machine learning contexts, includ-
 2459 ing supervised learning for source aggregation (Wu et al., 2019) and unsupervised
 2460 learning methods (Galvin et al., 2019; Ralph et al., 2019). We discard the RGZ sources
 2461 without a host galaxy detected in AllWISE and use the remaining 41 446 sources for
 2462 training.

2463 The RGZ catalogue only contains sources with at least 0.65 weighted volunteer
 2464 agreement, equivalent to approximately 80 per cent reliability. This implicitly selects
 2465 for less complex sources, since the volunteer agreement is a proxy for the difficulty of
 2466 cross-identifying a source (Wong et al. in prep.).

2467 **5.2.2 FIRST**

2468 We use radio imagery and select radio components from the FIRST survey and associ-
 2469 ated catalogue respectively (Helfand et al., 2015; White et al., 1997). FIRST is a 1.4 GHz
 2470 radio survey covering 10 575 deg² of the sky north of Dec = −10° with an angular res-
 2471 olution of 5.4''. At a detection limit of 1 mJy, the catalogue contains 946 432 radio
 2472 components.

2473 For both training and prediction, we make use of image cutouts from FIRST cen-
 2474 tered on mid-infrared candidate hosts. We predict host galaxies for the 244 846 ex-
 2475 tended FIRST components detected at > 10 σ (about 1.5 mJy beam^{−1}, per Banfield
 2476 et al., 2015) that have complete radio imagery for all candidate hosts. The numbers of
 2477 objects removed by our quality filters are shown in Appendix 5.F.

2478 **5.2.3 AllWISE**

2479 We use the sky coordinates and magnitudes from the AllWISE (Cutri et al., 2013) cata-
 2480 logue during training and prediction. AllWISE is an all-sky catalogue of mid-infrared
 2481 objects detected by the *Wide-field Infrared Survey Explorer* (WISE Wright et al., 2010) at
 2482 3.4, 4.6, 12, and 22 μm wavelengths (called W1–W4, respectively). AllWISE contains
 2483 over 747 million objects detected above 5 σ at 3.4 and 4.6 μm. WISE has an angular
 2484 resolution of 6.1'' and 6.4'' at these wavelengths, respectively.

2485 We store AllWISE objects in a MongoDB¹ database with a geospatial index on the
 2486 right ascension and declination. This allows us to perform fast spatial lookups. The
 2487 geospatial index in MongoDB assumes a perfectly spherical Earth with a fixed radius,
 2488 allowing us to use it for sky coordinate searches. We use the right ascension and decli-
 2489 nation of AllWISE sources to generate candidate hosts by searching for infrared sources
 2490 near FIRST components.

¹<https://www.mongodb.com/>

Table 5.1: Medians and standard deviations used to normalise input features [for our classifiers](#).

Feature	Median	Standard deviation
Radio image	13.2 μ Jy	3.01 mJy
W1 – W2	0.289 mag	0.378 mag
W1 – W3	4.350 mag	1.067 mag
W1 – W4	7.853 mag	1.144 mag
W2 – W3	4.016 mag	0.958 mag
W2 – W4	7.541 mag	1.046 mag
W3 – W4	3.518 mag	0.409 mag
W1	16.659 mag	1.154 mag

2491 5.2.4 SDSS

2492 While we do not use data from the Sloan Digital Sky Survey Data Release 15 (SDSS;
 2493 Aguado et al., 2019) for training or prediction, we do use SDSS for spectroscopic red-
 2494 shifts of our host galaxies. These redshifts are required to calculate the radio **luminosity**
 2495 **luminosities** of our sources. We use CDS X-Match² to match each infrared host galaxy
 2496 to the closest source imaged by SDSS to within 5''. This results in 34 305 spectroscopic
 2497 redshifts for our 158 337 total host galaxies. To estimate the rate of false association
 2498 with SDSS sources, we add a 1' offset to all host positions and redo the matching pro-
 2499 cess. With this method we estimate a 0.4 per cent rate of false association.

2500 5.3 Method

2501 We apply the binary classification cross-identification method (BXID) following Alger
 2502 et al. (2018). This method casts cross-identification as a classification problem where
 2503 infrared ‘candidate host galaxies’ are classified as either being host galaxies or not. A
 2504 classifier is trained on examples of host galaxies and non-host galaxies drawn from
 2505 a cross-identification catalogue, for which we use RGZ. Other related algorithms de-
 2506 veloped to automatically cross-identify radio objects include Bayesian methods (Fan
 2507 et al., 2015), likelihood ratio (Weston et al., 2018), positional matching (e.g. Kimball &
 2508 Ivezić, 2008; Middelberg et al., 2008; Norris et al., 2006), and positional/image hybrid
 2509 approaches (van Velzen et al., 2012), but these methods do not make use of existing
 2510 cross-identification catalogues and most assume compact radio sources or that the pro-
 2511 jected radio emission overlaps the host galaxy.

We represent candidate host galaxies by a $2' \times 2'$ radio image from FIRST centred on that galaxy, the 3.4μ m magnitude, and the six colours (magnitude differences) derived from the four *WISE* wavelengths. Unknown values of infrared flux were set to their upper limits in AllWISE. We note that many W3 – W4 colours are missing, so this feature may be less useful than the others. We normalise the colours and **magnitude magnitudes** by subtracting the median and dividing by the standard deviation. We

²<http://cdsxmatch.u-strasbg.fr/>

normalise each pixel in each radio image by subtracting the median, dividing by the standard deviation, and applying a logistic function (σ ; Equation 5.2) to account for the high dynamic range of radio images.

$$\sigma(a) = \frac{1}{1 + \exp(-a)} \quad (5.2)$$

2512 The medians and standard deviations are reported in Table 5.1. These values are com-
2513 puted across the training set.

2514 For each FIRST component we generate a set of candidate host galaxies. An AllWISE
2515 object is considered a candidate host for a radio component if it is within $\sqrt{2} \times 1.5'$ of
2516 the centre of the two-dimensional Gaussian fit for that component. This search radius
2517 is the maximum angular distance that a host galaxy can be located in RGZ due to the 3'-
2518 wide square images shown to volunteers. Candidate hosts are assigned binary labels:
2519 All candidates identified as host galaxies in RGZ are assigned a positive label and all
2520 others are assigned a negative label. Following Alger et al. (2018) we train a convolutional
2521 neural network (CNN) on the labelled candidate hosts. We base our model on
2522 ResNet18 (He et al., 2016) pretrained on the ImageNet classification task, with the final
2523 layer removed and replaced by a logistic regression model. Non-image features (i.e.
2524 colours and the 3.6 μm magnitude) are concatenated with the features that are output
2525 by the final ResNet18 layer. Using Adam (Kingma & Ba, 2015) to optimise our weights,
2526 we train this model on our task until binary cross-entropy loss starts to increase on a
2527 randomly-selected 20 per cent validation set. We use PyTorch (Paszke et al., 2017) to
2528 implement this model. The scores of each FIRST component are weighted by a one-
2529 dimensional Gaussian function of angular separation, and the candidate maximising
2530 this weighted score is selected as the host galaxy. We set the standard deviation of the
2531 Gaussian to 120'' as this provides good empirical results.

2532 92 per cent of the host galaxies in RGZ ~~are-were~~ also detected as host galaxies in
2533 RGZ-Ex. The mean volunteer agreement on all RGZ sources with detected hosts was
2534 95^{+5}_{-13} per cent, compared to 88^{+12}_{-17} per cent for sources with hosts not in RGZ-Ex. In-
2535 correct cross-identifications can be considered a source of noise in the statistics. In
2536 future work we will design a way for BXID to output an ‘uncertainty’ so ~~that~~ sources
2537 with uncertain cross-identifications can be removed from calculations. We quantify
2538 the reliability of RGZ-Ex in Section 5.3.1.

2539 We note that BXID necessarily identifies a host galaxy for all radio emission, even
2540 when it does not make sense to do so. In our current work we treat this as a source of
2541 noise. Future extensions to BXID will allow it to output ‘no detected host’.

2542 5.3.1 Visual verification

2543 To quantify the reliability of RGZ-Ex, ~~some of the authors~~ ~~we~~ (M.A., O.W., A.K., N.M.,
2544 and A.T.) visually verified a randomly selected set of 200 radio components/host galaxy
2545 pairs in RGZ-Ex. For each pair we decided whether the radio component matched its
2546 identified host or not. This allowed us to estimate the accuracy of radio component-
2547 infrared host pairs identified by BXID. Verification of component-host pairs is noisy

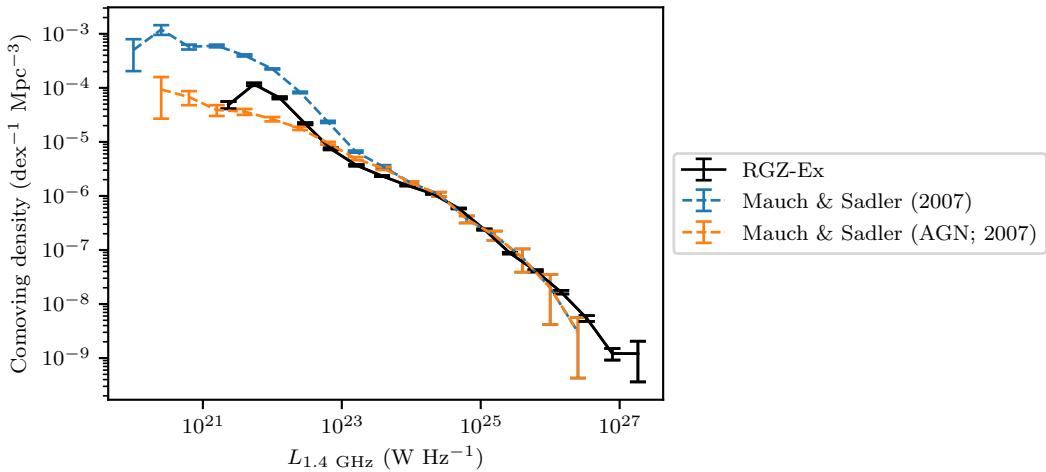


Figure 5.1: RGZ-Ex radio luminosity function compared with the RLFS of Mauch and Sadler (2007).

and sometimes even subjective, so each author looked at all 200 components. If an author was unsure about a pair, they were allowed to ignore it and the verification was treated as missing label data. We then aggregated these verifications following the aggregation approach introduced by Dawid and Skene (1979). This approach jointly estimates the accuracy of each author along with the aggregated verification by maximising the joint likelihood. Note that this approach is able to handle missing label data. We propagated the uncertainty in the accuracy with a Monte Carlo approach, sampling aggregated verifications from the probabilities resulting from the Dawid and Skene model. The estimated accuracy of BXID ~~is was~~ (89.5 ± 0.8) per cent. It is interesting to note from our results that even astronomers disagree significantly on the radio cross-identification task, with agreement between authors ranging from 50 to 100 per cent across the verification components. We report the full verification set in Appendix 5.G.

5.4 Radio luminosity functions

In this section we present our radio luminosity functions (RLFs) derived from the RGZ-Ex catalogue. We first eliminated sources and components with high sidelobe probability according to the FIRST catalogue and low BXID scores (see Appendix 5.F for a diagram of this filtering process). To calculate each RLF we followed the $1/V_{\max}$ method (Schmidt, 1968). This method accounts for the effects of Malmquist bias, which is a systematic bias against sources at greater distances. We describe this approach in ~~We limit~~ Appendix 5.H. We limited our sample to radio sources with 1.4 GHz integrated flux density of at least 2 mJy associated with host galaxies brighter than magnitude 17 at 3.4 μ m, a spectroscopic redshift $0.02 \leq z \leq 0.6$, and an *i*-band magnitude < 20 . We chose these limits based on the distribution of redshifts and in-

frared magnitudes as well as the sensitivity of FIRST. We then ~~remove~~removed sources with unusually high or low $W1 - W1$ magnitude for their redshift (more than ~~3~~three standard deviations from the mean) because many such sources ~~have~~had incorrect spectroscopic redshifts, e.g. blazars. There ~~are~~were 24 743 sources matching all criteria. We ~~assume~~assumed a spectral index of $\alpha = -0.7$ (as is common in literature, e.g. Condon et al., 2002) with flux density $f \propto \nu^\alpha$ where ν is the frequency. We ~~calculate~~calculated the k -corrected radio luminosity (Kochanek et al., 2001) as follows:

$$L = \frac{4\pi f d^2}{1+z} (1+z)^{-\alpha} \quad (5.3)$$

where z is redshift and d is luminosity distance (a function of z). Uncertainties in comoving density ~~are~~were estimated as described in Appendix 5.H. Completeness estimates are shown in Appendix 5.I. We discuss biases in our methods and results in Section 5.5.1.

We ~~compare~~compared our RLFs with Mauch and Sadler (2007), who estimated RLFs from 7 824 manually cross-identified radio sources in the NRAO VLA Sky Survey (NVSS; Condon et al., 1998). Their RLFs were split into AGN and star-forming radio sources. While we ~~do~~did not make this split explicitly in our catalogue, we ~~expect~~expected both RGZ-Ex and RGZ to be dominated by AGN due to the selection criterion of being extended in the selected redshift volume. We note that the redshift range used in our work, $0.02 < z < 0.6$, differs from the $0.003 < z < 0.3$ range used by Mauch and Sadler (2007).

In Figure 5.1 we show the RLF derived from RGZ-Ex along with the RLFs from Mauch and Sadler (2007). There is good agreement between all three luminosity functions for luminosities greater than 10^{23} W Hz $^{-1}$ and below this luminosity the RGZ-Ex RLF is bounded above by the Mauch and Sadler (2007) RLF. RGZ-Ex generally finds less comoving density than Mauch and Sadler (2007), which we attribute to our requirement for extent. We suggest that the peak in RGZ-Ex RLF at approximately 10^{22} W Hz $^{-1}$ is due to our sample containing a small fraction of star-forming galaxies. Our criterion, however, ~~does~~cut out most star-forming regions as these are often compact, which is why we report lower densities than the star-forming RLF of Mauch and Sadler (2007).

The WISE colour-colour plot, shown for RGZ-Ex in Figure 5.2, is often used to categorise galaxies at different evolutionary stages into four mid-infrared colour regions that are typically populated by 1) spheroidals or elliptical galaxies; 2) quasi-stellar objects (QSOs), Seyferts or powerful AGN; 3) starbursting or luminous infrared galaxies (LIRGs); and 4) the intermediate region where the other three regions overlap. The horizontal axis, $W2 - W3$, separates early- and late-type galaxies, with the star-forming late-type galaxies appearing redder (further to the right) (Wright et al., 2010). The vertical axis, $W1 - W2$, separates inactive galaxies from AGN with strongly radiating accretion discs (Sadler et al., 2014). In Figure 5.3 we show the radio luminosity function split by host galaxy location in the mid-infrared colour-colour plot as defined by Jarrett et al. (2017).

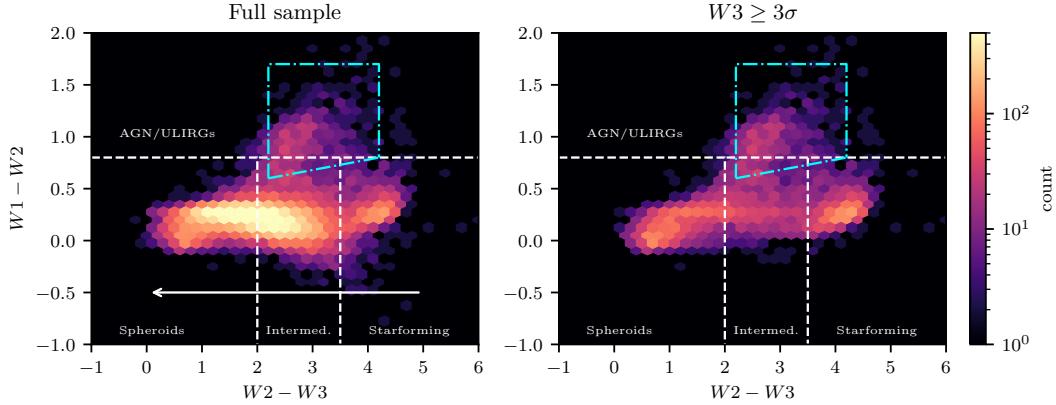


Figure 5.2: *WISE* colour-colour distributions. The dashed grey lines show simple host galaxy class divisions from Jarrett et al. (2017). These classes are labelled in the plot. The blue dot-dashed line shows the empirical optical/infrared AGN criteria from Jarrett et al. (2011). The arrow shows the direction that galaxies would shift with fainter $W3$ magnitudes. The right plot limits the sample to only sources with $W3 \geq 3\sigma$.

Many sources have $W3$ detections with low signal-to-noise, limiting our ability to subdivide our sample. We plot both the RLFs for the sample with only $W3 \geq 3\sigma$ as well as the RLFs for the full sample in Figure 5.3. For the full sample we use the lower magnitude limit from AllWISE as the $W3$ magnitude (which is an upper flux limit). Using the upper flux limit as the real $W3$ flux has the effect of increasing $W2 - W3$ compared to a real detection, so objects appear further to the right of the colour-colour diagram (Figure 5.2) than they ought to. This means that due to $W3$ limits, objects that should be in the spheroid set ~~will instead~~ appear in the intermediate and star-forming sets, and objects from the intermediate set ~~will instead~~ appear in the star-forming set.

At low luminosities, our extended source RLF is dominated by galaxies with infrared colours consistent with star formation. The fraction of the RLF composed of the star-forming set drops off rapidly for $L_{1.4 \text{ GHz}} > 10^{22} \text{ W Hz}^{-1}$, as expected for galaxies with radio emission dominated by star formation (e.g. Mauch & Sadler, 2007). However, the RLF slope flattens out again beyond $10^{24} \text{ W Hz}^{-1}$, suggesting a second source population. This population has many missing $W3$ measurements, and these are likely intermediates or spheroids incorrectly included in the star-forming set. We therefore suggest that the low-luminosity RGZ-Ex sample mostly contains nearby galaxies with radio emission due to star formation, which appear extended in FIRST as they are close enough for FIRST to resolve their disc (greater than 20 kpc at $z = 0.2$). The remaining fraction of star-forming sources found by Mauch and Sadler (2007), shown in Figure 5.1, would not be resolved in FIRST, as they are small or distant.

Spheroids, which are hosts in the mid-infrared region corresponding to ellipticals and stars (Wright et al., 2010), comprise the majority of radio galaxies at $10^{23} \text{ W Hz}^{-1}$, and have a peak density at $10^{22} \text{ W Hz}^{-1}$. The common host galaxies for radio-loud AGN tend to be passively-evolving spheroids. It is not surprising that they are more

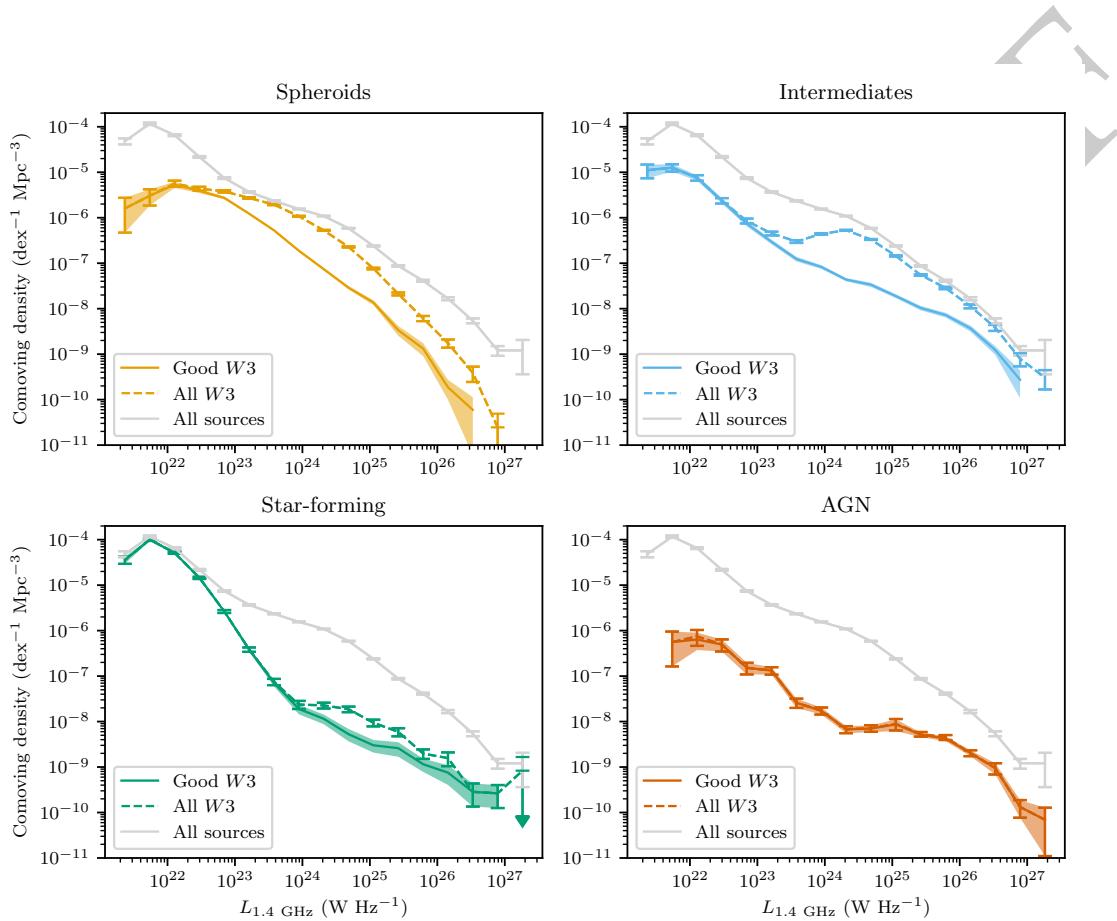


Figure 5.3: RLFs split by host galaxy location in the WISE colour-colour plot (Figure 5.2), using our automated cross-identifications. The grey line is the total RLF for all sources. Solid lines have good W3 detections and dashed lines include W3 with low signal-to-noise.

common than star-forming galaxies at luminosities greater than $10^{22} \text{ W Hz}^{-1}$. Above $10^{25} \text{ W Hz}^{-1}$ they are less common than intermediate galaxies and their contribution to the luminosity function drops rapidly. This is likely due to the loss of W3 detections moving spheroids into the intermediate set, and we hypothesise that with deeper W3 observations spheroids may dominate above $10^{25} \text{ W Hz}^{-1}$.

Sources with hosts in the mid-infrared AGN region of the colour-colour diagram (Figure 5.2) make up the smallest contribution to the radio luminosity function. They have a steadily decreasing density from their lowest observed $L_{1.4 \text{ GHz}}$ of $10^{22} \text{ W Hz}^{-1}$ to their highest of $10^{27} \text{ W Hz}^{-1}$, but are present in all luminosity bins except for the very lowest. This is a set with a very low fraction of spectroscopic SDSS matches for the *WISE* host galaxies. 26 per cent of hosts outside the *WISE* AGN region have an SDSS match, compared to just 12 per cent of hosts inside the *WISE* AGN region. This is likely due to the incomplete sampling of QSOs in the SDSS spectroscopic survey or redshift evolution effects (Strauss et al., 2002). The fraction of the RLF contributed by galaxies classed as mid-infrared AGN increases above $10^{25} \text{ W Hz}^{-1}$, meaning that high-luminosity radio AGN are also more likely to be infrared AGN than at lower radio luminosities. Note that the AGN set is unaffected by missing W3 detections, as the AGN set is based only on $W_1 - W_2$.

Galaxies residing in the intermediate mid-infrared colour region can be populated by both early- and late-type galaxies, which have a mix of processes occurring within them. These ‘intermediate sources’ dominate in most luminosity ranges, and above $10^{24} \text{ W Hz}^{-1}$ they comprise the vast majority of our sample. As intermediate-type galaxies fall between star-forming galaxies and passive ellipticals on the mid-infrared colour-colour plane, they do not have a clear morphological class and are composed of overlapping subsets of sources. The most luminous radio AGN are almost entirely found in this set of galaxies. In fact, as radio luminosity increases, the density fraction shifts from spheroids toward intermediate galaxies, likely due to missing W3 moving objects from the spheroid set into the intermediate set.

In Figure 5.4 we show the radio luminosity function for different ranges of projected physical extent of their radio emission. We estimate the angular extent as the angular distance between the most separated components in a multi-component source. This result is complementary to other Radio Galaxy Zoo studies on the effect of the environment on the size and asymmetry of the observed extended radio emission (Garon et al., 2019; Rodman et al., 2019).

5.5 Discussion

5.5.1 Biases and uncertainties

Biases enter our work due to our chosen samples and methods. Our training set, RGZ, is biased toward sources smaller than $1.5'$ and limited above by $\sqrt{2} \times 3'$ due to the $3' \times 3'$ cutout size of the RGZ user interface. RGZ volunteers preferentially select host galaxies that are brighter in W_1 , so we expect RGZ to overrepresent the number of sources with W_1 -bright host galaxies.

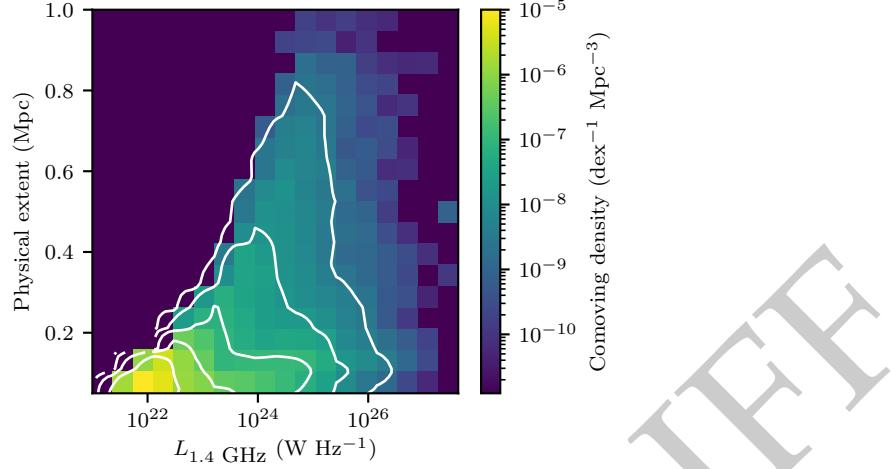


Figure 5.4: Bivariate radio luminosity function showing radio luminosity against projected physical extent. Contours are on a log scale, starting at the median and increasing by 10 per cent per contour.

2661 These biases may affect our trained algorithm: ~~for~~For example, the overabundance
 2662 of W1-bright host galaxies in RGZ may cause our algorithm to be less accurate when
 2663 unassociated bright galaxies are in the field of view. Without knowing the true distri-
 2664 bution of host galaxies, however, it is difficult to quantify the effect of such biases on
 2665 our trained method.

2666 FIRST itself is also biased. Helfand et al. (2015) describe several reasons why FIRST
 2667 flux may be systematically underestimated. Most of these effects are insignificant for
 2668 extended objects in our sample or are corrected in the FIRST catalogue from which
 2669 we draw our flux information. The exception is the ‘resolving out’ of diffuse and low
 2670 surface brightness radio emission by the Very Large Array in its B configuration. This
 2671 means that we lose flux on most nearby radio galaxies (especially those with very dif-
 2672 fuse components) and may miss diffuse or dim radio galaxies entirely. More diffuse
 2673 radio galaxies such as Fanaroff-Riley type I (FRI; Fanaroff & Riley, 1974) galaxies tend
 2674 to be toward the low end of the radio-loud luminosity distribution, about $10^{23} \text{ W Hz}^{-1}$
 2675 (Best, 2009), so we expect that losing diffuse sources would lower our estimates of
 2676 density around this luminosity. Large, extended lobes such as those associated with
 2677 Fanaroff-Riley type II (FRII; Fanaroff & Riley, 1974) galaxies may also be resolved out,
 2678 so by the same mechanism we expect to lose an increasing amount of flux with increas-
 2679 ing source angular size. This effect is compounded by flux loss at 1.4 GHz associated
 2680 with synchrotron losses and adiabatic expansion losses (Blundell et al., 1999).

2681 Our host galaxy redshifts may be biased. Incorrectly identifying the host galaxy
 2682 may introduce sources with incorrect redshifts into the RLF, an effect which will be
 2683 dominated by misidentifying galaxies as hosts where the true host is not detected.
 2684 Since we are matching to optical spectra in SDSS to find redshifts, we are biased to-
 2685 toward brighter host galaxies ~~that~~which are more likely to have such spectra. With-

2686 out an optically-complete ~~sample~~—~~currently sample~~—~~currently~~ impossible on such
 2687 scales—this effect is unavoidable. Brighter optical sources appear at lower redshifts,
 2688 so we likely undersample higher-redshift (and hence higher-luminosity) galaxies.

2689 Our requirement for radio emission to be extended ~~will miss~~~~misses~~ radio galaxies
 2690 that would be resolved and extended if they were not aligned with the ~~line of~~
 2691 ~~sight~~~~line-of-sight~~. We therefore must be underestimating the population of extended
 2692 sources (though assuming a random distribution of orientations, the majority of galaxies
 2693 ~~will not be~~~~are not~~ aligned close to the ~~line of sight~~~~line-of-sight~~). The requirement
 2694 for extended radio emission ~~will also impose~~~~also imposes~~ a lower limit on linear size,
 2695 which ~~will vary~~~~varies~~ with redshift: ~~at~~ At $z = 0.6$ the effect will be strongest and we
 2696 will see no sources with linear size under 33.5 kpc. This ~~will cause~~~~causes~~ us to un-
 2697 derestimate the population of radio galaxies with linear sizes between 10–30 kpc. On
 2698 the other hand, we ~~have likely avoided~~~~likely avoid~~ significant overestimation of radio
 2699 luminosity due to relativistic beaming, since we filter out sources aligned along the
 2700 ~~line of sight~~~~line-of-sight~~.

2701 We ~~have estimated~~~~estimate~~ uncertainties in our RLF from Poisson noise in the his-
 2702 togram bins. We ~~have likely underestimated~~~~likely underestimate~~ these uncertainties
 2703 as it is difficult to estimate uncertainty in our algorithm, though in future we anticipate
 2704 that we can employ an ensemble of classifiers to estimate this (e.g. Lakshminarayanan
 2705 et al., 2017).

2706 5.5.2 Extended radio galaxies in the low- z Universe

2707 Our total RLFs are consistent with the idea that large, extended radio sources are
 2708 typically hosted by massive ellipticals (Best et al., 2005). These RLFs match exist-
 2709 ing RLFs such as that of Mauch and Sadler (2007), except at radio luminosities be-
 2710 low 10^{22} W Hz $^{-1}$. This is unsurprising since we employ a requirement for extended
 2711 emission, and, besides very nearby star-forming galaxies, FRII comprise most of the
 2712 population of extended radio objects. The fractional RLF split by mid-infrared colour,
 2713 Figure 5.3, shows that spheroids reach peak density at a radio luminosity associated
 2714 with a drop in density of intermediates, and intermediates begin to dominate the RLF
 2715 as the spheroid density drops. Together, these mid-infrared classes of galaxy form the
 2716 bulk of the extended radio galaxy RLF.

2717 We see a significant star-forming population in our extended sample, which means
 2718 that we are likely resolving some discs in radio. While the $1/V_{\max}$ method ensures that
 2719 our RLFs account for similar galaxies throughout the Universe, even though we only
 2720 resolve very nearby discs, some of the star-forming population is not included. The
 2721 difference between our RLF and existing RLFs must be due to the latter containing
 2722 low-luminosity sources that are compact even when very nearby.

2723 Can we use our RLFs to estimate the kinetic energy contribution of AGN to the
 2724 galaxy halo and beyond? The extended population of AGN ~~will be~~~~is~~ the population
 2725 that contributes ~~the~~ most mechanical energy: ~~the~~~~The~~ major part of the energy in the
 2726 jet expands the radio lobes, drives shocks~~or~~ or is stored in the jet magnetic field, rather
 2727 than being emitted as radiation (Godfrey & Shabala, 2016; Hardcastle & Krause, 2014).

Extended radio sources should therefore represent the bulk of AGN feedback: ~~radio Radio~~ galaxies with extended jets ~~will~~ inject mechanical energy out to larger distances from the core of the host galaxies than those with smaller jets. This is supported by e.g. Turner and Shabala (2015), who found that extended sources ~~comprised~~ comprise the bulk of the mechanical energy contribution. By assuming a relationship between radio luminosity and radio jet mechanical energy, we can use our extended source RLFs to estimate the contribution of extended AGN to energy in the intergalactic/circumgalactic medium (IGM/CGM). But assuming such a relationship is not without problems: ~~the The~~ radio lobe luminosity experiences significant evolution (e.g. Bicknell et al., 1997), the surrounding IGM/CGM may interact with the radio lobe expansion in non-trivial ways (e.g. Hardcastle & Krause, 2013) and the relationship between the mechanical energy and radio luminosity has high scatter on individual radio sources (Hardcastle & Krause, 2013). With our sample size, these effects should be diminished, and with these caveats in mind we will estimate the energy contribution of extended sources to the IGM. We assume a scaling relation of $\ln Q = \beta \ln L_\nu + Q_0$, where Q is the jet power and L_ν is the monochromatic radio luminosity at frequency ν . The values for β and Q_0 vary significantly across the literature, based on different physical assumptions and samples. Willott et al. (1999) presented a widely-used relationship:

$$\ln Q = \ln(f^{3/2} 3 \times 10^{38}) + \frac{6}{7} \ln \left[\frac{L_{151 \text{ MHz}}}{10^{28} \text{ W Hz}^{-1}} \right], \quad (5.4)$$

with a scaling constant $1 \leq f \leq 20$ and Q in watts. Other models exist with different slopes, e.g. Bîrzan et al. (2008) suggest that $\beta \approx 0.5 - 0.7$ and Cavagnolo et al. (2010) find $\beta \approx 0.7$. ~~Godfrey and Shabala (2016) Shabala and Godfrey (2013) show that the scalings presented by Willott et al. (1999) are consistent with independent theoretical modelling for high-power radio galaxies. Godfrey and Shabala (2016) on the other hand~~ provide a summary of the literature in this field and suggest that these correlations are from mutual distance dependence rather than intrinsic relationships. They find that there is no strong empirical evidence for such a correlation in either FRI or FRII. However, their theoretical models suggest $\beta \approx 0.5, 0.8$ for FRI and FRII respectively, which is consistent with Willott et al. (1999). ~~Shabala and Godfrey (2013) on the other hand show that the scalings presented by Willott et al. (1999) are consistent with independent theoretical modelling for high-power radio galaxies. The relationship between luminosity and kinetic energy is not yet settled, but we can still use this popular scaling method both to explore the consequences of our RLFs and for comparison with previous work.~~

Scaling the frequency to 1.4 GHz, and assuming a spectral index of $\alpha = -0.7$, $\beta = 6/7$, and $Q_0 = \ln(f^{3/2}) + 89.9$, we can write the Willott et al. (1999) relation as

$$\ln(Q) = \ln(f^{3/2}) + 89.9 + \frac{6}{7} \ln \left[\frac{L_{1400 \text{ MHz}}}{10^{28} \text{ W Hz}^{-1}} \right]. \quad (5.5)$$

~~Assuming $f \in [1, 20]$ gives $Q_0 \in [89.9, 94.4]$. Integrating over our RLF we find $Q \in [1.3 \times 10^{30}, 1.2 \times 10^{32}] \text{ W Mpc}^{-3}$. This is likely a lower limit as we are missing ex-~~

2740 tended radio sources oriented along our line-of-sight and nearby diffuse extended ra-
2741 dio sources (e.g. FRI), and Shabala (2018) argues that many ‘compact’ AGN may in
2742 fact be extended but below the sensitivity of surveys such as FIRST. Our results are con-
2743 sistent with other literature (e.g Hardcastle et al., 2019, who estimated the energy contribution as $7 \times$
2744 (e.g. Hardcastle et al., 2019, who estimated the energy contribution as $7 \times 10^{31} \text{ W Mpc}^{-3}$)
2745 .

2746 **5.5.3 Future work**

2747 With such a large sample size, further partitioning of the RLF into subsamples is pos-
2748 sible. Any combination of the features investigated here, plus further host galaxy and
2749 radio properties, could be used to generate fractional RLFs. Automated classifiers such
2750 as ClaRAN (Wu et al., 2019) or feature extractors such as PINK (Galvin et al., 2019; Pol-
2751 sterer et al., 2015; Ralph et al., 2019) could provide a way to divide the RLF by radio
2752 morphology. These methods provide a way of dividing galaxy classes based directly
2753 on the radio image, rather than the host galaxy like we have done here, and so should
2754 not be affected by extinction or redshift in the same way as our sample. Such sub-
2755 samples would lend insight into how radio power is connected to radio morphology
2756 and generation mechanisms. Cross-matching with other surveys such as NVSS or the
2757 150 MHz TIFR GMRT Sky Survey would provide properties such as the spectral index
2758 and observations of diffuse emission missed by FIRST (as used by Kimball & Ivezić,
2759 2008). Such properties could also be used to create interesting and insightful fractional
2760 RLFs.

2761 While we have not investigated the link between extended sources and their local
2762 environments, this will be the focus of future work. Environment will heavily factor
2763 into the source sizes, morphologies, and so on, following work such as Rodman et al.
2764 (2019) and Garon et al. (2019).

2765 Ongoing radio surveys such as EMU, VLASS (Lacy et al., 2020), and LoTSS
2766 (Shimwell et al., 2019) will greatly increase the number of extended sources. How-
2767 ever, our sample size limitations in this chapter are not from FIRST, but from SDSS:
2768 until Until next-generation spectroscopic surveys are available, redshifts will be the
2769 limiting factor. To significantly increase our sample size would require much greater
2770 numbers of redshifts.

2771 **5.6 Summary**

2772 Extended radio sources provide an opportunity to study the interaction between AGN
2773 and their large-scale environments. We trained the binary cross-identification method
2774 on the Radio Galaxy Zoo to generate the largest sample of reliably cross-identified,
2775 extended radio sources, and this large sample allows allowed us to investigate their
2776 bulk distributions in new, detailed ways. We estimated radio luminosity functions
2777 split by mid-infrared colour, physical extent, and redshift. Despite our extendedness
2778 criterion, we found a significant star-forming population. We estimated that extended
2779 AGN contribute between 1.3×10^{30} and $1.2 \times 10^{32} \text{ W Mpc}^{-3}$ of mechanical energy to

their environment environments. Ongoing and future surveys such as EMU will provide even greater numbers of extended radio sources, and our combination of machine learning and astronomy methodology will allow these samples to be cross-identified and investigated efficiently and reliably.

5.7 Acknowledgements

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5.F Sankey diagrams

This section presents Sankey diagrams showing the filtering of components and sources from the full FIRST sample in this chapter. A Sankey diagram shows the order and number of objects removed from a sample. Figure 5.5 shows the filtering of components and Figure 5.6 shows the filtering of sources. The component filters are ‘Bad FIRST’ for components on the edge of FIRST with incomplete images, ‘Sidelobe’ for components with high sidelobe probability, ‘Low score’ for components with only low-scoring candidate hosts, ‘Faint’ for components with less than 10 signal-to-noise according to the FIRST catalogue, and ‘Compact’ for components that do not have extended radio emission according to Equation 5.1. Sources were removed after each component filter if they no longer contained any components.

5.G Visual verification results

In Section 5.3.1 we described our visual verification of the BXID method. We list the radio components in the verification set in Table 5.2. Each row of the table contains the FIRST component, its AllWISE host galaxy according to BXID, and whether the association is correct according to our visual verification. If a verifier was particularly

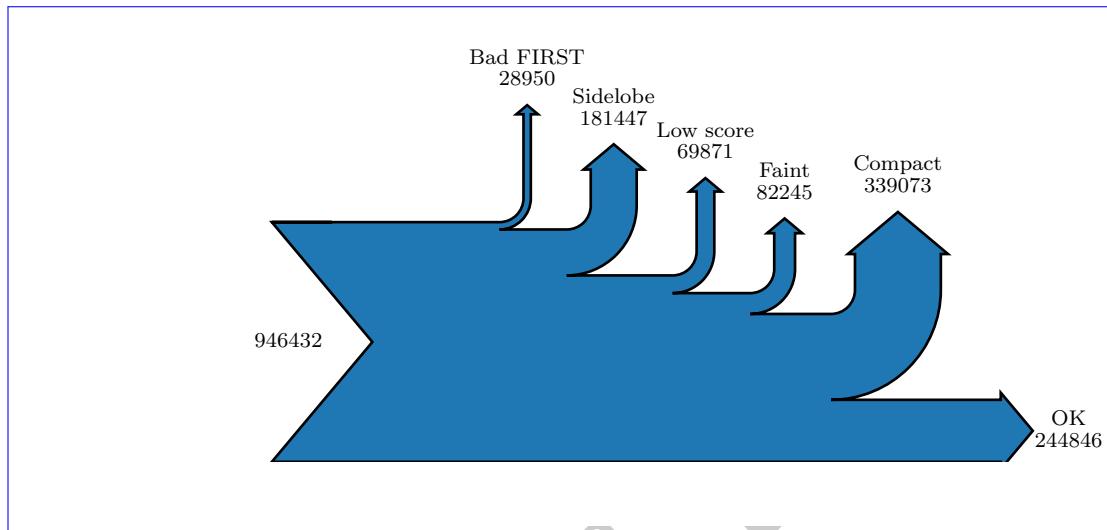


Figure 5.5: Number of components removed from FIRST by each filter.

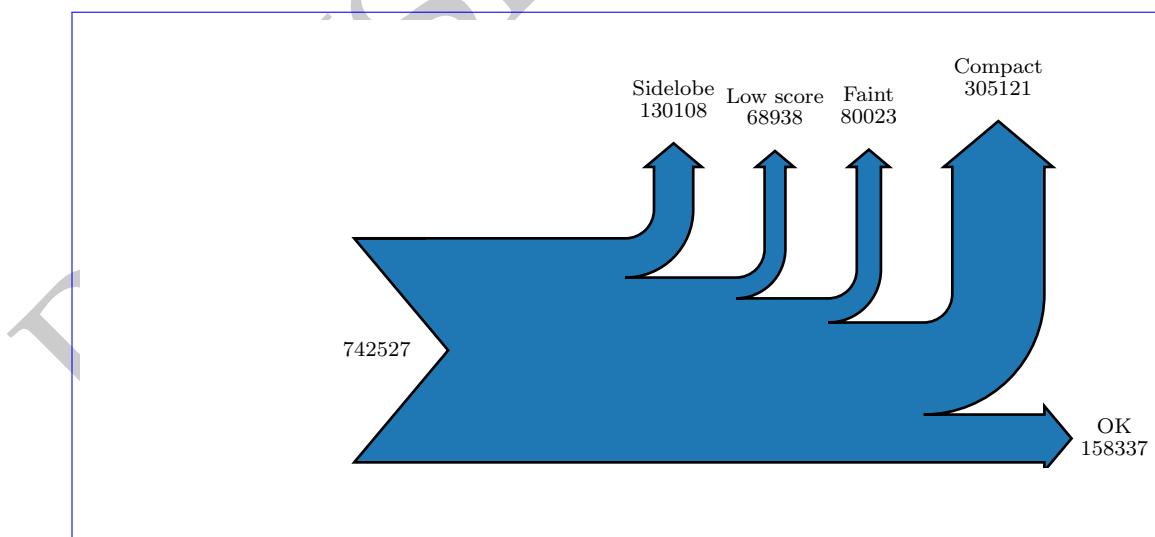


Figure 5.6: Number of sources removed by each filter.

2817 unsure about an object, they were able to skip this object, and so are not accounted for
 2818 in the verification for that object. Verification was weighted by the Dawid and Skene (1979)
 2819 maximum likelihood model.

2820 5.H Radio luminosity function

2821 We computed the radio luminosity function following the $1/V_{\max}$ method (Schmidt, 1968).
 2822 We performed the following steps:

- 2823 1. Remove all radio sources that do not fit the selection criteria. This applies for
 2824 both radio and infrared properties, so we choose a minimum radio flux density
 2825 f_{\min} and a maximum infrared magnitude $m_{\max,ir}$, as well as redshift limits z_{lower}
 2826 and z_{upper} .
2. For each source, compute the maximum redshift that the source could have been observed within the selection criteria. We find this redshift by first numerically solving Equation 5.3 for z with L as the luminosity of each radio source and $f = f_{\min}$ to obtain the maximum redshift z_{radio} at which the source could be observed in radio. We similarly find the maximum redshift that the infrared host galaxy could be observed at within the selection criteria, z_{ir} , by numerically solving Equation 5.6. $d(z_{\text{ir}})$ is the luminosity distance at a redshift z_{ir} , d is the luminosity distance of the host galaxy, and m is the apparent magnitude of the host galaxy, all in the infrared.

$$2827 5 \log_{10} \left(\frac{d(z_{\text{ir}})}{d} \right) + m = m_{\max,ir} \quad (5.6)$$

2828 The maximum redshift that the source could have been observed within the selection criteria is then $z_{\max} = \min(z_{\text{ir}}, z_{\text{radio}}, z_{\text{upper}})$.

- 2829 3. For each source, compute the comoving volume V_{\max} at redshift z_{\max} .
4. The count for each luminosity bin is the sum over $1/V_{\max}$ for each source in the bin. We divide these counts by the estimated completeness (Appendix 5.I) to account for redshift incompleteness. We account for the fact FIRST does not cover the whole sky by multiplying by the total area of the sky divided by the area of our selection.

2830 After computing the luminosity function, we estimate the uncertainty in each bin
 2831 using Poisson statistics, \sqrt{N} for a bin count N .

2832 5.I Redshift completeness estimate

2833 Figure 5.7 shows the estimated completeness of our RLF sample in Chapter 5 as a
 2834 function of W_1 and $W_1 - W_2$. We followed the same method as Pracy et al. (2016).

Table 5.2: Validation objects. ‘Agree’ is whether or not the verifiers agreed with BXID associating the given FIRST object with the given AllWISE object.

FIRST	AllWISE	Agree	FIRST	AllWISE	Agree
J000234.9-001421	J000242.35-001320.5	n	J094009.5+600403	J094011.55+600357.6	n
J002841.1+141654	J002840.37+141652.7	y	J094023.7+135123	J094023.73+135125.2	y
J003731.4+000156	J003731.26+000146.7	y	J094324.5+435341	J094324.61+435342.0	y
J005407.5-011158	J005407.61-011158.9	y	J094650.8+382015	J094650.44+382010.9	y
J011210.3+002203	J011210.41+002201.9	y	J095011.8+455319	J095011.82+455320.0	y
J012342.4+015849	J012342.24+015850.4	y	J095113.5+180211	J095113.82+180204.2	n
J013015.1+110653	J013015.16+110653.4	y	J095242.4+222638	J095242.45+222638.0	y
J013107.7+070343	J013102.02+070332.0	y	J095538.7+013546	J095539.20+013546.1	y
J014247.9-000039	J014247.81-000040.3	y	J095609.9+363441	J095609.30+363445.4	y
J014250.0-000032	J014247.81-000040.3	n	J095811.8+225056	J095811.90+225055.5	y
J020222.3+030138	J020223.20+030150.4	y	J100019.2+263516	J100018.84+263527.5	y
J020333.8+000853	J020336.94+000759.3	y	J101315.9+064520	J101316.51+064519.0	y
J021840.1-032311	J021840.13-032306.0	y	J101455.2-004716	J101455.30-004718.3	y
J023022.0+010834	J023022.11+010840.0	y	J102153.5+260429	J102153.52+260429.6	y
J024245.3-022535	J024245.35-022534.6	y	J102354.7+390653	J102354.88+390654.0	y
J025901.0+005350	J025901.50+005346.1	y	J102620.4+303600	J102620.46+303550.4	y
J033204.1-004757	J033204.15-004757.1	y	J102710.4+460254	J102714.81+460256.4	n
J073033.2+390413	J073033.21+390412.9	y	J102955.9+424906	J102955.96+424906.7	y
J073954.1+481810	J073954.87+481759.5	y	J103503.9+102404	J103503.92+102403.6	y
J074504.9+331247	J074504.81+331256.2	y	J103839.9+331200	J103839.94+331201.1	y
J074640.4+421709	J074640.45+421709.1	y	J104030.5+211624	J104031.09+211620.6	n
J074707.9+171719	J074708.35+171726.5	y	J104533.8+430025	J104535.22+430020.8	y
J075043.6+274838	J075043.35+274844.8	n	J104907.5+322903	J104907.91+322906.6	y
J075050.3+331937	J075051.25+331905.0	y	J105146.9+552257	J105147.40+552308.4	y
J075422.2+311253	J075422.35+311252.5	y	J105257.5+105418	J105257.53+105421.5	y
J075637.0+212006	J075636.65+212001.4	y	J105521.6+372641	J105521.24+372652.4	y
J082326.1+141438	J082326.34+141435.9	y	J105758.8+321605	J105758.84+321605.3	y
J082422.5+351121	J082422.65+351114.6	y	J110104.9+151618	J110104.90+151618.2	y
J082925.9+462618	J082926.02+462618.5	y	J110353.2+352320	J110353.37+352319.9	y
J083512.4+175441	J083512.45+175441.1	y	J110414.4+481345	J110423.08+481311.0	n
J084133.5+402035	J084133.40+402042.8	y	J111057.7+220756	J111057.18+220758.3	y
J084238.4+405305	J084238.38+405306.6	n	J111208.5+275207	J111201.79+275053.8	n
J084417.3+315845	J084417.92+315845.9	y	J111225.2+233159	J111225.30+233157.9	y
J084728.5+360700	J084728.24+360714.6	y	J111726.3+375336	J111726.35+375337.0	y
J084905.5+111448	J084905.51+111447.8	y	J111746.1+261151	J111746.18+261150.9	y
J085236.8+262006	J085236.11+262013.4	y	J111854.3+424708	J111854.45+424652.8	y
J085415.6+524930	J085415.62+524936.7	y	J112124.4+640417	J112125.02+640408.6	y
J090623.2+300746	J090622.87+300743.9	y	J112135.3+352330	J112135.44+352324.9	y
J091745.1+275049	J091745.89+275103.8	y	J112550.9+200631	J112558.75+200554.3	y
J091752.0+431614	J091752.14+431612.7	y	J112859.7+260923	J112859.86+260911.3	y
J092014.4+302907	J092013.95+302859.3	y	J113201.1+442639	J113201.23+442639.4	y
J092140.5+540118	J092140.24+540121.1	y	J113302.5+355408	J113301.80+355415.3	y
J092213.0+542157	J092213.03+542157.2	y	J113712.7+263301	J113711.86+263335.1	y
J092406.9+562703	J092406.47+562656.2	y	J113756.3+471314	J113756.31+471314.1	y
J092713.1+105841	J092713.14+105839.8	y	J113906.6+230602	J113906.68+230602.1	y
J093108.6+613447	J093108.63+613447.2	y	J114325.0+600721	J114323.90+600737.1	y
J093239.6+052308	J093237.71+052240.7	n	J114759.7+370305	J114759.22+370311.2	y
J093627.8+103610	J093627.87+103609.7	y	J114916.7+083022	J114916.33+083040.5	n
J093645.2+561435	J093645.89+561434.2	y	J115010.9+063340	J115010.93+063340.5	y
J094006.8+482651	J094006.92+482649.2	y	J115308.6+374851	J115316.96+374850.0	y

FIRST	AllWISE	Agree	FIRST	AllWISE	Agree
J115448.7+472222	J115448.67+472223.7	y	J142829.5+070836	J142829.60+070836.3	y
J115603.7+584704	J115603.48+584706.1	y	J143411.0+170036	J143411.18+170035.7	y
J115605.9+343230	J115605.64+343229.4	y	J143624.0-001057	J143623.89-001100.8	y
J115653.0+572338	J115645.38+572151.7	y	J143742.6+104412	J143742.69+104412.8	y
J120138.0+230922	J120137.97+230922.2	y	J143840.8+475355	J143841.08+475356.1	y
J120752.8+533808	J120752.85+533807.3	y	J143909.1+430847	J143909.08+430847.8	y
J120943.3-021934	J120942.89-021943.0	y	J144135.8+102246	J144135.91+102245.1	y
J121045.6+190225	J121045.68+190227.0	y	J144333.6+275229	J144333.02+275250.2	y
J121207.6+115412	J121207.72+115413.8	y	J145012.3+471739	J145012.33+471738.7	y
J121211.3+485951	J121211.86+485952.0	y	J145103.7+452459	J145102.66+452520.5	n
J121406.7+002634	J121406.73+002635.0	y	J145401.6+141009	J145401.70+141009.6	y
J122518.0+350258	J122517.85+350301.9	y	J150158.7+191413	J150158.87+191405.3	y
J122525.1+451530	J122524.71+451508.5	y	J150743.9+352720	J150743.62+352724.1	y
J122640.9+430508	J122640.82+430509.2	y	J151141.6-003209	J151142.01-003213.0	y
J123429.8+260107	J123434.79+260134.3	n	J151315.5+403107	J151315.56+403107.7	y
J123633.1+100928	J123633.12+100928.7	y	J151518.7+230256	J151518.67+230257.3	y
J124839.3+411522	J124839.42+411522.3	n	J151703.6+105947	J151703.68+105947.6	y
J125129.2+551012	J125128.76+551009.3	y	J151736.8+610856	J151736.83+610857.7	y
J130005.8+524801	J130006.14+524803.0	y	J152121.6+281635	J152120.68+281626.2	y
J130132.1+511351	J130132.32+511352.5	y	J152714.8+310425	J152714.88+310424.7	y
J131104.4+464936	J131104.45+464934.0	y	J153428.9+272134	J153429.68+272120.8	y
J131452.2+252811	J131446.81+252820.8	n	J154245.3+100919	J154245.71+100917.8	y
J132033.8+332639	J132033.59+332639.0	n	J154901.6+103159	J154901.40+103152.6	y
J132257.5+191134	J132257.53+191133.9	y	J154925.2+395316	J154926.17+395303.7	y
J132529.3+230734	J132529.35+230733.8	y	J155206.3-005348	J155206.58-005339.3	y
J132546.8+052453	J132546.86+052454.1	y	J155457.3+344637	J155458.45+344644.7	y
J132637.7+112110	J132637.92+112108.8	y	J155743.5+272752	J155743.52+272752.8	y
J132831.8+104339	J132831.88+104338.8	y	J160130.0+083848	J160130.07+083850.7	y
J132932.3+131839	J132932.32+131839.6	y	J160534.8+441220	J160535.55+441221.5	y
J133022.8+311904	J133022.83+311902.8	y	J160859.2+400135	J160901.32+400230.7	n
J133453.3+405653	J133454.13+405650.6	y	J161545.4+231617	J161545.14+231617.2	y
J133741.1+124302	J133741.13+124303.1	y	J161930.4+085533	J161930.51+085532.6	y
J133823.6+103337	J133823.67+103341.9	y	J162228.0+264743	J162228.70+264736.7	y
J134651.2+415154	J134651.06+415156.1	y	J162750.4+473624	J162750.55+473623.5	y
J134704.3+110622	J134704.35+110622.7	y	J162904.2+470852	J162904.34+470853.0	y
J134752.7+555046	J134752.71+555048.6	y	J163038.7+214740	J163037.43+214748.9	n
J134831.7+164325	J134831.57+164328.2	y	J163323.6+424051	J163323.61+424051.9	y
J134949.8+385539	J134949.93+385542.8	y	J163327.5+242426	J163327.87+242427.4	y
J135106.5+074534	J135106.50+074534.2	y	J163533.8+454557	J163534.00+454554.3	y
J135107.7+615502	J135107.75+615502.1	y	J164211.2+512029	J164211.27+512029.3	y
J135658.5+134028	J135659.15+134017.0	y	J165549.1+375923	J165549.01+375923.6	y
J135833.9+180021	J135834.03+180020.4	y	J165620.0+363402	J165619.89+363403.9	y
J140630.7+554017	J140629.32+554009.9	y	J165700.5+474820	J165659.58+474809.0	y
J140804.2+503019	J140804.10+503021.1	y	J171406.2+292712	J171404.16+292704.0	n
J141226.7+454125	J141226.54+454125.5	y	J172126.4+374446	J172126.46+374446.6	y
J141245.0+495213	J141243.84+495206.4	y	J222627.7-005010	J222627.77-005010.8	y
J141317.4+325306	J141317.50+325306.8	y	J223636.4-013827	J223636.48-013827.2	y
J141723.8+543639	J141724.33+543629.5	y	J225619.0+143257	J225621.96+143351.4	y
J141938.8+312146	J141940.16+312138.8	y	J232410.1+001315	J232410.15+001314.5	y
J142515.3+175526	J142513.89+175525.7	y	J234727.9-000919	J234727.65-000912.9	y

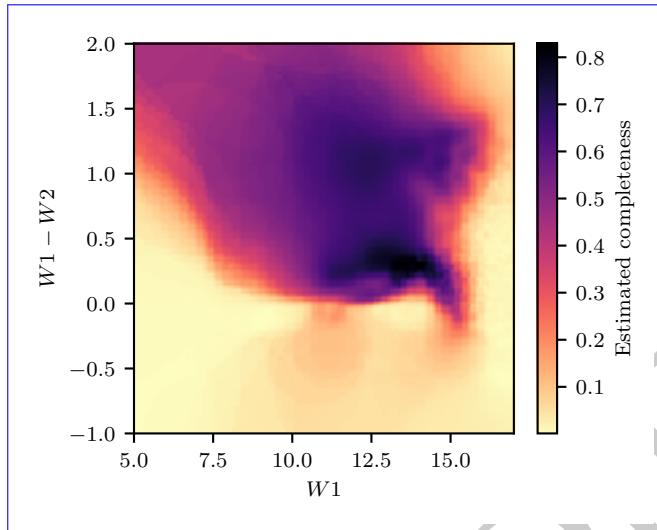


Figure 5.7: Estimated completeness as a function of mid-infrared colour and magnitude.

for this estimation, averaging completeness over circles centred on each source. Each source is associated with a circle of radius equal to the distance to its 50th nearest neighbour in the W_1 and $W_1 - W_2$ plane. This appendix was originally part of Alger et al. (in prep.)
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5.J Giant radio galaxies

This appendix describes our search for giant radio galaxies in RGZ-Ex, and the results of this search. To identify radio sources we assumed that if any two components had the same host galaxy then they were part of the same source. This would be a reasonable assumption if all host galaxies were correctly identified, which was not the case. This assumption therefore introduced spurious sources due to galaxies incorrectly identified as host galaxies: Not all sources used in this chapter are real sources, and in particular sources of large angular size are likely to be incorrect. Nevertheless RGZ-Ex provides a useful catalogue of *candidate* radio sources, and visual follow-up can confirm whether sources of interest are real.

H.A. and M.J.A. examined all 296 candidate sources in the RGZ-Ex catalogue with an estimated physical extent larger than 1 Mpc. Of these, 40 were real giant radio galaxies, which we show in Table 5.3. We defined ‘giant radio galaxy’ as a radio galaxy with emission extended to physical sizes ≥ 1.0 Mpc. Other thresholds, such as 0.7 Mpc, also exist in literature. The physical extents of the remaining 256 candidate sources were overestimated mostly due to sidelobes/artefacts (103), incorrect source grouping (82), or incorrect SDSS matches (21). The citizen scientists who identified giants were WizardHowl, DolorousEdd, antikodon, csunjoto, sisifolibre, JeanTate, JKD, PADV, and firejuggler. H.A., together with his summer students, had previously identified 29 of these giants.

Table 5.3: Giant radio galaxies found in RGZ-Ex. ‘LLS’ is the projected linear size of the source as measured by the maximum angular distance between radio components. The RA/Dec are the coordinates of the host galaxy. s/p indicates spectroscopic/photometric redshift. ^LExisting in literature. ^RAlso found by RGZ citizen scientists. [†]Misidentified SDSS host, manually corrected to obtain redshift.

AllWISE host (WISEA)	RA (J2000)	Dec (J2000)	z	LLS (Mpc)	
J004210.18-080011.3	10.54	-8.00	0.65 ± 0.14	1.6	p
J021008.48+011839.6 ^L	32.54	1.31	0.86524 ± 0.00001	1.2	s
J075858.29+355643.6 ^R	119.74	35.95	0.74748 ± 0.00013	1.0	s
J080831.68+473523.9 ^R	122.13	47.59	0.58854 ± 0.00016	1.1	s
J083034.78+231124.6	127.64	23.19	0.94 ± 0.13	1.1	p
J090604.03+011114.2	136.52	1.19	0.7975 ± 0.0004	1.6	s
J093256.81+074212.2	143.24	7.70	1.0032 ± 0.0003	1.1	s
J093526.80+051729.8 ^R	143.86	5.29	0.84 ± 0.04	1.2	p
J094238.72+114337.9	145.66	11.73	0.49 ± 0.05	1.2	p
J094835.60+535946.4 ^R	147.15	54.00	0.64 ± 0.10	1.2	p
J095706.12+292439.2	149.28	29.41	0.71 ± 0.12	1.5	p
J102335.25+433208.0	155.90	43.54	0.75 ± 0.09	1.5	p
J102933.99+210345.8 ^R	157.39	21.06	0.82407 ± 0.00008	1.1	s
J103043.98+355451.2 ^R	157.68	35.91	0.64074 ± 0.00008	1.2	s
J104449.92+234525.6 [†]	161.20	23.76	0.57712 ± 0.00009	1.6	s
J110655.98+624759.8 ^R	166.73	62.80	0.84379 ± 0.00004	1.1	s
J112900.68+635543.2	172.25	63.93	0.71 ± 0.06	1.1	p
J112948.20+243922.6	172.45	24.66	0.79 ± 0.07	1.1	p
J114553.67-003304.7	176.47	-0.55	2.0522 ± 0.0006	1.3	s
J121111.26+534840.4	182.80	53.81	0.74 ± 0.14	1.1	p
J121152.04+304232.4 ^R	182.97	30.71	0.47102 ± 0.00012	1.3	s
J121944.73+174121.3	184.94	17.69	1.5129 ± 0.0009	1.0	s
J123735.89+544814.4 ^R	189.40	54.80	1.0271 ± 0.0006	1.2	s
J123819.16+113444.8	189.58	11.58	0.80 ± 0.08	1.2	p
J123846.84-032857.5 [†]	189.70	-3.48	0.67 ± 0.07	1.5	p
J131625.00+272042.8	199.10	27.35	0.69092 ± 0.00004	1.0	s
J133307.00+045048.6 ^R	203.28	4.85	1.40534 ± 0.00016	1.1	s
J141933.36+104706.4 ^R	214.89	10.79	0.33973 ± 0.00003	1.0	s
J142008.45+185422.7 ^R	215.04	18.91	0.63 ± 0.04	1.4	p
J145057.28+530007.7 ^L	222.74	53.00	0.91662 ± 0.00009	1.3	s
J150012.18+604941.3	225.05	60.83	1.6626 ± 0.0007	1.2	s
J153547.13+432245.0 ^R	233.95	43.38	0.63891 ± 0.00007	1.3	s
J154631.18+194819.9	236.63	19.81	0.5917 ± 0.0002	1.4	s
J160852.10+561110.2 ^R	242.22	56.19	1.3196 ± 0.0003	1.3	s
J162200.48+364044.0	245.50	36.68	1.9994 ± 0.0002	1.1	s
J163004.35+103321.9 ^R	247.52	10.56	0.85 ± 0.09	1.2	p
J163125.75+200224.1 ^R	247.86	20.04	0.62662 ± 0.00013	1.0	s
J165055.46+394446.6	252.73	39.75	0.58829 ± 0.00013	1.1	s
J232410.33+045309.6	351.04	4.89	0.76 ± 0.06	1.4	p
J234440.02-003231.6	356.17	-0.54	0.5014 ± 0.0001	1.0	s

2864 Note that this is a particularly challenging set: Sources that were misidentified
2865 often have unusually large estimated extents due to the inclusion of spurious components.
2866 The error rate in this set therefore does not reflect the rest of the catalogue.

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2868

Faraday Complexity

2869 This chapter is based on my paper *Interpretable Faraday Complexity Classification*, by M.
2870 J. Alger, J. D. Livingston, N. M. McClure-Griffiths, J. L. Nabaglo, O. I. Wong, and C.
2871 S. Ong; accepted and to be published by the *Publications of the Astronomical Society of
2872 Australia*.

2873 In the last two chapters we developed and applied a way of automatically cross-
2874 identifying radio sources, which will allow us to quickly extract useful information
2875 from wide-area radio continuum surveys like EMU. These are not the only radio sur-
2876 veys that will be conducted in the lead-up to the SKA, however. Polarisation sky sur-
2877 veys like POSSUM can provide very different information about the radio sky. One
2878 piece of information that ~~could~~can be determined from polarised observations is the
2879 Faraday complexity of a radio source. A complex source may be separated from us
2880 as observers by some magnetised structure, or it ~~might~~may have extended structure
2881 across the sky, even if we cannot resolve the source spatially. This tells us something
2882 about the intervening Universe or the physical structure of the source, respectively.
2883 This chapter develops a new machine learning method of classifying sources as Far-
2884 day complex or simple.

2885 Faraday complexity describes whether a spectropolarimetric observation has sim-
2886 ple or complex magnetic structure. Quickly determining the Faraday complexity of a
2887 spectropolarimetric observation is important for processing large, polarised radio sur-
2888 veys. Finding simple sources lets us build rotation measure grids, and finding complex
2889 sources lets us follow these sources up with slower analysis techniques or further ob-
2890 servations. We introduce five features that can be used to train simple, interpretable
2891 machine learning classifiers for estimating Faraday complexity. We train logistic re-
2892 gression and extreme gradient boosted tree classifiers on simulated polarised spectra
2893 using our features, analyse their behaviour, and demonstrate that our features are ef-
2894 fective for both simulated and real data. This is the first application of machine learn-
2895 ing methods to real spectropolarimetry data. With 95 per cent accuracy on simulated
2896 ASKAP data and 90 per cent accuracy on simulated ATCA data, our method performs
2897 comparably to state-of-the-art convolutional neural networks while being simpler and
2898 easier to interpret. Logistic regression trained with our features behaves sensibly on
2899 real data and its outputs are useful for sorting polarised sources by apparent Faraday
2900 complexity.

2901 6.1 Introduction

2902 As polarised radiation from distant galaxies makes its way to us, magnetised plasma
 2903 along the way can cause the polarisation angle to change due to the Faraday effect.
 2904 The amount of rotation depends on the squared wavelength of the radiation, and the
 2905 rotation per squared wavelength is called the Faraday depth. Multiple Faraday depths
 2906 may exist along one line-of-sight, and if a polarised source is observed at multiple
 2907 wavelengths then these multiple depths can be disentangled. This can provide insight
 2908 into the polarised structure of the source or the intervening medium.

2909 Faraday rotation measure synthesis (RM synthesis) is a technique for decomposing
 2910 a spectropolarimetric observation into flux at its Faraday depths ϕ , the resulting distri-
 2911 bution of depths being called a *Faraday dispersion function* (FDF) or a *Faraday spectrum*.
 2912 It was introduced by Brentjens and de Bruyn (2005) as a way to rapidly and reliably
 2913 analyse the polarisation structure of complex and high-Faraday depth polarised obser-
 2914 vations.

2915 A *Faraday simple* observation is one for which there is only one Faraday depth, and
 2916 in this simple case the Faraday depth is also known as a *rotation measure* (RM). All Far-
 2917 aday simple observations can be modelled as a polarised source with a thermal plasma
 2918 of constant electron density and magnetic field (a ‘Faraday screen’; Anderson et al.,
 2919 2015; Brentjens & de Bruyn, 2005) between the observer and the source. A *Faraday*
 2920 *complex* observation is one which is not Faraday simple, and may differ from a Faraday
 2921 simple source due to plasma emission or composition of multiple screens (Brentjens
 2922 & de Bruyn, 2005). The complexity of a source tells us important details about the
 2923 polarised structure of the source and along the line-of-sight, such as whether the in-
 2924 tervening medium emits polarised radiation, or whether there are turbulent magnetic
 2925 fields or different electron densities in the neighbourhood. The complexity of nearby
 2926 sources taken together can tell us about the magneto-ionic structure of the galactic and
 2927 intergalactic medium between the sources and us as observers. O’Sullivan et al. (2017)
 2928 show examples of simple and complex sources, and Figure 6.1 and Figure 6.2 show an
 2929 example of a simulated simple and complex FDF respectively.

2930 Identifying when an observation is Faraday complex is an important problem in po-
 2931 larised surveys (Sun et al., 2015), and with current surveys such as the Polarised Sky
 2932 Survey of the Universe’s Magnetism (POSSUM) larger than ever before, methods that
 2933 can quickly characterise Faraday complexity en masse are increasingly useful. Being
 2934 able to identify which sources are simple lets us produce a reliable rotation measure
 2935 grid from background sources, and being able to identify which sources might be com-
 2936 plex allows us to find sources to follow-up with slower polarisation analysis methods
 2937 that may require manual oversight, such as QU fitting (as seen in e.g. Miyashita et al.,
 2938 2019; O’Sullivan et al., 2017). In this [paper](#)[chapter](#), we introduce five simple, inter-
 2939 pretable features representing polarised spectra, use these features to train machine
 2940 learning classifiers to identify Faraday complexity, and demonstrate their effective-
 2941 ness on real and simulated data. We construct our features by comparing observed
 2942 polarised sources to idealised polarised sources. The features are intuitive and can be
 2943 estimated from real FDFs.

2944 Section 6.2 provides a background to our work, including a summary of prior work
2945 and our assumptions on FDFs. Section 6.3 describes our approach to the Faraday com-
2946 plexity problem. Section 6.4 explains how we trained and evaluated our method. Fi-
2947 nally, Section 6.5 discusses these results.

2948 6.2 Faraday Complexitycomplexity

2949 Faraday complexity is an observational property of a source: ~~if If~~ multiple Faraday
2950 depths are observed within the same apparent source (e.g. due to multiple lines-of-
2951 sight being combined within a beam), then the source is complex. A source composed
2952 of multiple Faraday screens may produce observations consistent with many models
2953 (Sun et al., 2015), including simple sources, so there is some overlap between simple
2954 and complex sources. Faraday thickness is also a source of Faraday complexity: ~~when~~
2955 When the intervening medium between a polarised source and the observer also emits
2956 polarised light, the FDF cannot be characterised by a simple Faraday screen. As dis-
2957 cussed in Section 6.2.2 we defer Faraday thick sources to future work. In this section
2958 we summarise existing methods of Faraday complexity estimation and explain our as-
2959 sumptions and model of simple and complex polarised FDFs.

2960 6.2.1 Prior work

2961 There are multiple ways to estimate Faraday complexity, including detecting non-
2962 linearity in $\chi(\lambda^2)$ (Goldstein & Reed, 1984), change in fractional polarisation as a func-
2963 tion of frequency (Farnes et al., 2014), non-sinusoidal variation in fractional polari-
2964 sation in Stokes Q and U (O’Sullivan et al., 2012), counting components in the FDF
2965 (Law et al., 2011), minimising the Bayesian information criterion (BIC) over a range of
2966 simple and complex models (called *QU fitting*; O’Sullivan et al., 2017), the method of
2967 Faraday moments (Anderson et al., 2015; Brown, 2011), and deep convolutional neural
2968 network classifiers (CNNs; Brown et al., 2018). See Sun et al. (2015) for a comparison
2969 of these methods.

2970 The most common approaches to estimating complexity are QU fitting
2971 (e.g. O’Sullivan et al., 2017) and Faraday moments (e.g. Anderson et al., 2015). To our
2972 knowledge there is currently no literature examining the accuracy of QU fitting when
2973 applied to complexity classification specifically, though Miyashita et al. (2019) analyse
2974 its effectiveness on identifying the structure of two-component sources. Brown (2011)
2975 ~~suggested~~ suggests Faraday moments as a method to identify complexity, a method
2976 later used by Farnes et al. (2014) and Anderson et al. (2015), but again no literature
2977 examines the accuracy. CNNs are the current state-of-the-art with an accuracy of 94.9
2978 per cent (Brown et al., 2018) on simulated ASKAP Band 1 and 3 data, and we will
2979 compare our results to this method.

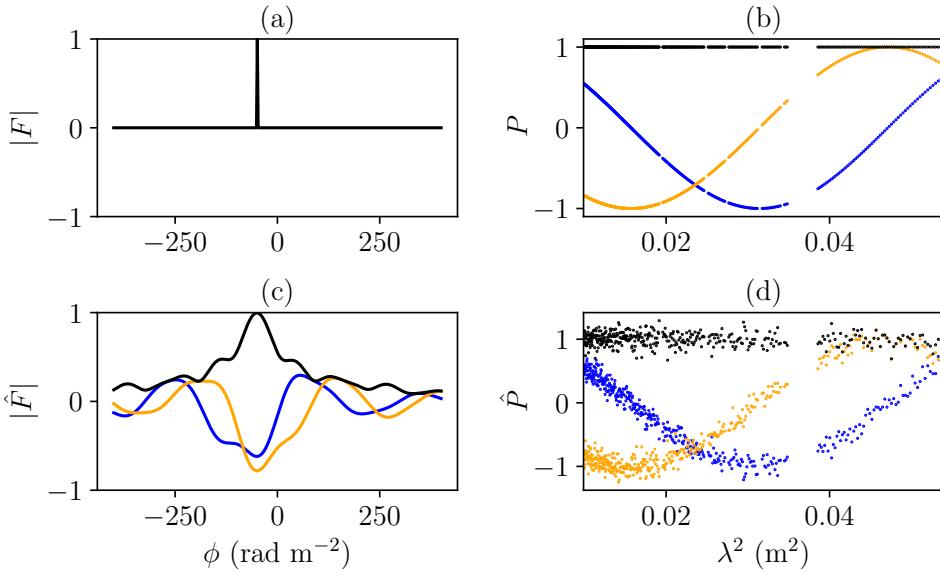


Figure 6.1: A simple FDF and its corresponding polarised spectra: (a) groundtruth FDF F , (b) noise-free polarised spectrum P , (c) noisy observed FDF \hat{F} , (d) noisy polarised spectrum \hat{P} . Blue and orange mark real and imaginary components respectively.

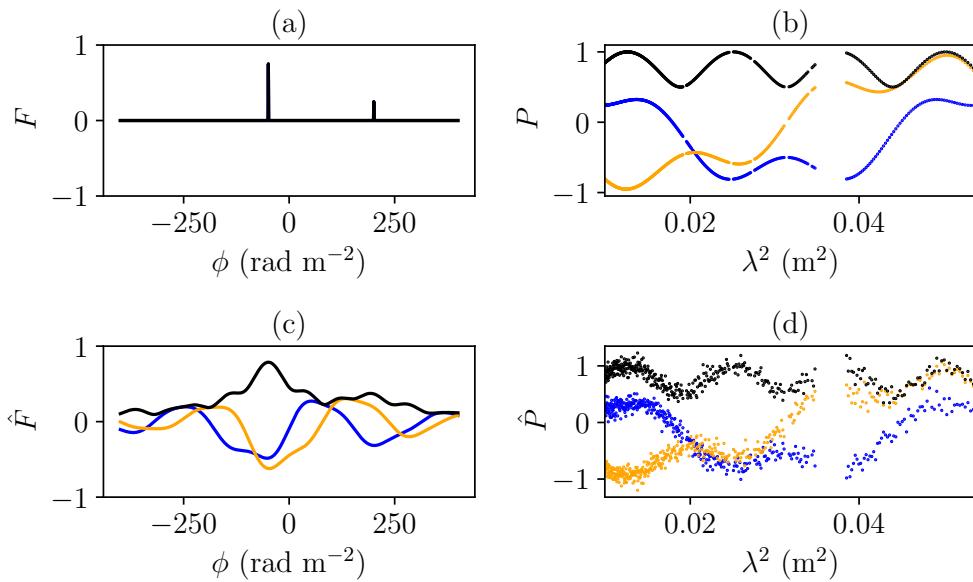


Figure 6.2: A complex FDF and its corresponding polarised spectra: (a) groundtruth FDF F , (b) noise-free polarised spectrum P , (c) noisy observed FDF \hat{F} , (d) noisy polarised spectrum \hat{P} . Blue and orange mark real and imaginary components respectively.

2980 **6.2.2 Assumptions on Faraday dispersion functions**

Before we can classify FDFs as Faraday complex or Faraday simple, we need to define FDFs and any assumptions we make about them. An FDF is a function that maps Faraday depth ϕ to complex polarisation. It is the distribution of Faraday depths in an observed polarisation spectrum. For a given observation, we assume that there is a true, noise-free FDF F composed of at most two Faraday screens. This accounts for most actual sources (Anderson et al., 2015) and extension to three screens would cover most of the remainder—O’Sullivan et al. (2017) found that 89 per cent of their sources were best explained by two or less fewer screens, while the remainder were best explained by three screens. We model the screens by Dirac delta distributions:

$$F(\phi) = A_0\delta(\phi - \phi_0) + A_1\delta(\phi - \phi_1). \quad (6.1)$$

A_0 and A_1 are the polarised flux of each Faraday screen, and ϕ_0 and ϕ_1 are the Faraday depths of the respective screens. With this model, a Faraday simple source is one which has $A_0 = 0$, $A_1 = 0$, or $\phi_0 = \phi_1$. By using delta distributions to model each screen, we are assuming that there is no internal Faraday dispersion (which is typically associated with diffuse emission rather than the mostly-compact mostly compact sources we expect to find in wide-area polarised surveys). F generates a polarised spectrum of the form shown in Equation 6.2:

$$P(\lambda^2) = A_0e^{2i\phi_0\lambda^2} + A_1e^{2i\phi_1\lambda^2}. \quad (6.2)$$

Such a spectrum would be observed as noisy samples from a number of squared wavelengths $\lambda_j^2, j \in [1, \dots, D]$. We model this noise as a complex Gaussian with standard deviation σ and call the noisy observed spectrum \hat{P} :

$$\hat{P}(\lambda_j^2) \sim \mathcal{N}(P(\lambda_j^2), \sigma^2). \quad (6.3)$$

The constant variance of the noise is a simplifying assumption which may not hold for real data, and exploring this is a topic for future work. By performing RM synthesis (Brentjens & de Bruyn, 2005) on \hat{P} with uniform weighting we arrive at an observed FDF:

$$\hat{F}(\phi) = \frac{1}{D} \sum_{j=1}^D \hat{P}(\lambda_j^2) e^{-2i\phi\lambda_j^2}. \quad (6.4)$$

2981 Examples of F , \hat{F} , P , and \hat{P} for simple and complex observations are shown in Figure 6.1
 2982 and Figure 6.2 respectively. Note that there are two reasons that the observed FDF \hat{F}
 2983 does not match the groundtruth FDF F . The first is the noise in \hat{P} . The second arises
 2984 from the incomplete sampling of \hat{P} .

2985 We do not consider external or internal Faraday dispersion in this work. External
 2986 Faraday dispersion would broaden the delta functions of Equation 6.1 into peaks, and
 2987 internal Faraday dispersion would broaden them into top-hat functions. All sources
 2988 have at least a small amount of dispersion as the Faraday depth is a bulk property

2989 of the intervening medium and is subject to noise, but the assumption we make is
 2990 that this dispersion is sufficiently small that the groundtruth FDFs are well-modelled
 2991 with delta functions. Faraday thick sources would also invalidate our assumptions,
 2992 and we assume that there are none in our data as Faraday thickness can be consistent
 2993 with a two-component model depending on the wavelength sampling (e.g. Brentjens
 2994 & de Bruyn, 2005; Ma et al., 2019a). Nevertheless some external Faraday dispersion
 2995 ~~would be is~~ covered by our model, as depending on observing parameters Faraday
 2996 thick sources may appear as two screens (Van Eck et al., 2017).

2997 To simulate observed FDFs we follow the method of Brown et al. (2018), which we
 2998 describe in Appendix 6.K.

2999 6.3 Classification approach

3000 The Faraday complexity classification problem is as follows: Given an FDF \hat{F} , is it Far-
 3001 day complex or Faraday simple? In this section we describe the features that we have
 3002 developed to address this problem, which can be used in any standard machine learn-
 3003 ing classifier. We trained two classifiers on these features, which we describe here also.

3004 6.3.1 Features

Our features are based on a simple idea: ~~all~~All simple FDFs look essentially the same,
 up to scaling and translation, while complex FDFs may deviate. A noise-free peak-
 normalised simple FDF \hat{F}_{simple} has the form:

$$\hat{F}_{\text{simple}}(\phi; \phi_s) = R(\phi - \phi_s). \quad (6.5)$$

where R is the rotation measure spread function (RMSF), the Fourier transform of the
 wavelength sampling function which is 1 at all observed wavelengths and 0 otherwise.
 ϕ_s traces out a curve in the space of all possible FDFs. In other words, \hat{F}_{simple} is a
 manifold parametrised by ϕ_s . Our features are derived from relating an observed FDF
 to the manifold of simple FDFs (the ‘simple manifold’). We measure the distance of
 an observed FDF to the simple manifold using distance measure D_f , that ~~take~~takes all
 values of the FDF into account:

$$\xi_f(\hat{F}) = \min_{\phi_s \in \mathbb{R}} D_f(\hat{F}(\phi) \parallel \hat{F}_{\text{simple}}(\phi; \phi_s)). \quad (6.6)$$

3005 We propose two distances that have nice properties:

- 3006 • invariant over changes in complex phase,
- 3007 • translationally invariant in Faraday depth,
- 3008 • zero for Faraday simple sources (i.e. when $A_0 = 0$, $A_1 = 0$, or $\phi_0 = \phi_1$) when
 3009 there is no noise,

- 3010 • symmetric in components (i.e. swapping $A_0 \leftrightarrow A_1$ and $\phi_0 \leftrightarrow \phi_1$ should not
3011 change the distance),
- 3012 • increasing as A_0 and A_1 become closer to each other, and
- 3013 • increasing as screen separation $|\phi_0 - \phi_1|$ increases over a large range.

3014 Our features are constructed from this distance and its minimiser. In other words we
3015 look for the simple FDF \hat{F}_{simple} that is “**closest**” ‘**closest**’ to the observed FDF \hat{F} . The
3016 minimiser ϕ_s is the Faraday depth of the simple FDF.

3017 While we could choose any distance that operates on functions, we used the 2-
3018 Wasserstein (W_2) distance (Equation 6.7) and the Euclidean distance (Equation 6.9).
3019 The W_2 distance operates on probability distributions and can be thought of as the min-
3020 imum cost to ‘move’ one probability distribution to the other, where the cost of moving
3021 one unit of probability mass is the squared distance it is moved. Under W_2 distance,
3022 the minimiser ϕ_w in Equation 6.6 can be interpreted as the Faraday depth that the FDF
3023 \hat{F} would be observed to have if its complexity was unresolved (i.e. the weighted mean
3024 of its components). The Euclidean distance is the square root of the least-squares loss
3025 which is often used for fitting \hat{F}_{simple} to the FDF \hat{F} . Under Euclidean distance, the
3026 minimiser ϕ_s is equivalent to the depth of the best-fitting single component under as-
3027 sumption of Gaussian noise in \hat{F} . We calculated the W_2 distance using Python Optimal
3028 Transport (Flamary & Courty, 2017), and we calculated the Euclidean distance using
3029 `scipy.spatial.distance.euclidean` (Virtanen et al., 2020). Further intuition about
3030 the two distances is provided in Section 6.3.2.

We denote by ϕ_w and ϕ_e , the Faraday depth of the simple FDF that minimises the
respective distances (2-Wasserstein and Euclidean).

$$\begin{aligned}\phi_w &= \underset{\phi_w}{\operatorname{argmin}} D_{W_2}(\hat{F}(\phi) \| \hat{F}_{\text{simple}}(\phi; \phi_w)), \\ \phi_e &= \underset{\phi_e}{\operatorname{argmin}} D_E(\hat{F}(\phi) \| \hat{F}_{\text{simple}}(\phi; \phi_e)).\end{aligned}$$

These features are depicted on an example FDF in Figure 6.3. For simple observed
FDFs, the fitted Faraday depths ϕ_w and ϕ_e both tend to be close to the peak of the
observed FDF. However for complex observed FDFs, ϕ_w tends to be at the average
depth between the two major peaks of the observed FDF, being closer to the higher
peak. For notation convenience, we denote the Faraday depth of the observed FDF
that has largest magnitude as ϕ_a , i.e.

$$\phi_a = \underset{\phi_a}{\operatorname{argmax}} |\hat{F}(\phi_a)|.$$

3031 Note that in practice $\phi_a \approx \phi_e$. For complex observed FDFs, the values of Faraday
3032 depths ϕ_w and ϕ_a tend to differ (essentially by a proportion of the location of the second
3033 screen). The difference between ϕ_w and ϕ_a therefore provides useful information to
3034 identify complex FDFs. When the observed FDF is simple, the 2-Wasserstein fit **will**
3035 **overlap** **overlaps** significantly, hence the observed magnitudes $\hat{F}(\phi_w)$ and $\hat{F}(\phi_a)$ will

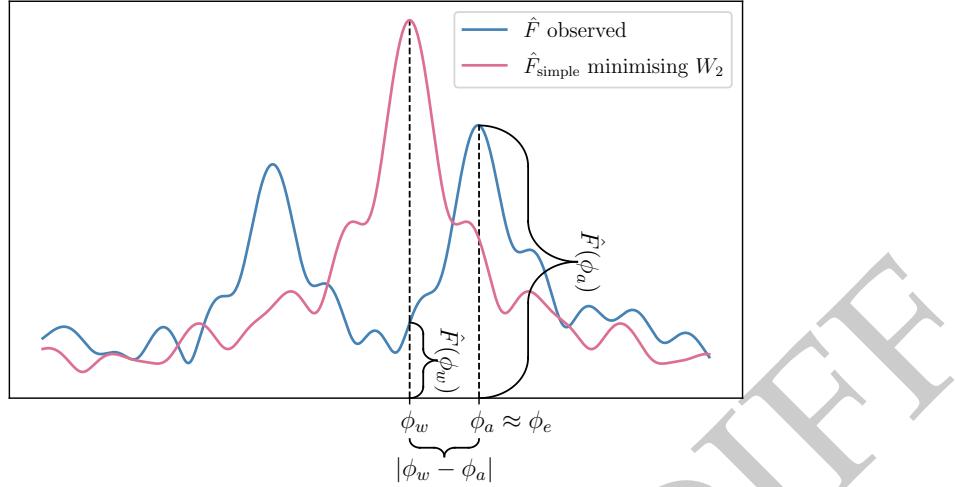


Figure 6.3: An example of how an observed FDF \hat{F} relates to our features. ϕ_w is the W_2 -minimising Faraday depth, and ϕ_a is the \hat{F} -maximising Faraday depth (approximately equal to the Euclidean-minimising Faraday depth). The remaining two features are the W_2 and Euclidean distances between the depicted FDFs.

be similar. However, for complex FDFs, ϕ_w and ϕ_a are at different depths, leading to different values of $\hat{F}(\phi_w)$ and $\hat{F}(\phi_a)$. Therefore the magnitudes of the observed FDFs at the depths ϕ_w and ϕ_a indicate how different the observed FDF is from a simple FDF.

In summary, we provide the following features to the classifier:

- $\log |\phi_w - \phi_a|,$
- $\log \hat{F}(\phi_w),$
- $\log \hat{F}(\phi_a),$
- $\log D_{W_2}(\hat{F}(\phi) \parallel \hat{F}_{\text{simple}}(\phi; \phi_w)),$
- $\log D_E(\hat{F}(\phi) \parallel \hat{F}_{\text{simple}}(\phi; \phi_e)),$

where D_E is the Euclidean distance, D_{W_2} is the W_2 distance, ϕ_a is the Faraday depth of the FDF peak, ϕ_w is the minimiser for W_2 distance, and ϕ_e is the minimiser for Euclidean distance.

6.3.2 Interpreting distances

Interestingly, in the case where there is no RMSF, Equation 6.6 with W_2 distance reduces to the Faraday moment already in common use:

$$D_{W_2}(F) = \min_{\phi_w \in \mathbb{R}} D_{W_2}(F(\phi) \parallel F_{\text{simple}}(\phi; \phi_w)) \quad (6.7)$$

$$= \left(\frac{A_0 A_1}{(A_0 + A_1)^2} (\phi_0 - \phi_1)^2 \right)^{1/2}. \quad (6.8)$$

See Appendix 6.L for the corresponding calculation. In this sense, the W_2 distance can be thought of as a generalised Faraday moment, and conversely an interpretation of Faraday moments as a distance from the simple manifold in the case where there is no RMSF. Euclidean distance behaves quite differently in this case, and the resulting distance measure is totally independent of Faraday depth:

$$D_E(F) = \min_{\phi_e \in \mathbb{R}} D_E(F(\phi) \parallel F_{\text{simple}}(\phi; \phi_e)) \quad (6.9)$$

$$= \sqrt{2} \frac{\min(A_0, A_1)}{A_0 + A_1}. \quad (6.10)$$

3049 See Appendix 6.M for the corresponding calculation.

3050 6.3.3 Classifiers

3051 We trained two classifiers on simulated observations using these features: logistic re-
3052 gression (LR) and extreme gradient boosted trees (XGB). These classifiers are useful
3053 together for understanding Faraday complexity classification. LR is a linear classifier
3054 that is readily interpretable by examining the weights it applies to each feature, and
3055 is one of the simplest possible classifiers. XGB is a powerful off-the-shelf non-linear
3056 ensemble classifier, and is an example of a decision tree ensemble which are widely
3057 used in astronomy (e.g. Hložek et al., 2020; Machado Poletti Valle et al., 2020). We
3058 used the scikit-learn implementation of LR and we ~~use-used~~ the XGBoost library
3059 for XGB. We optimised hyperparameters for XGB using a fork of xgboost-tuner¹ as
3060 utilised by Zhu et al. (2020). We used 1-000-1000 iterations of randomised parameter
3061 tuning and the hyperparameters we found are tabulated in Table 6.2. We optimised
3062 hyperparameters for LR using a 5-fold cross-validation grid search implemented in
3063 sklearn.model_selection.GridSearchCV. The resulting hyperparameters are tabu-
3064 lated in Table 6.3 in the Appendix Appendix 6.N.

3065 6.4 Experimental method and results

3066 We applied our classifiers to classify simulated (Section 6.4.2 and 6.4.3) and real (Sec-
3067 tion 6.4.4) FDFs. We replicated the experimental setup of Brown et al. (2018) for
3068 comparison with the state-of-the-art CNN classification method, and we also applied
3069 our method to 142 real FDFs observed with the Australia Telescope Compact Array
3070 (ATCA) from Livingston et al. (2021) and O’Sullivan et al. (2017).

3071 6.4.1 Data

3072 6.4.1.1 Simulated training and validation data

3073 Our classifiers were trained and validated on simulated FDFs. We produced two sets of
3074 simulated FDFs, one for comparison with the state-of-the-art method in the literature

3075¹<https://github.com/chengsoonong/xgboost-tuner>

and one for application to our observed FDFs (described in Section 6.4.1.2). We refer to the former as the ‘ASKAP’ dataset as it uses frequencies from the Australian Square Kilometre Array Pathfinder 12-antenna early science configuration. These frequencies included 900 channels from 700–1300 and 1500–1800 MHz and were used to generate simulated training and validation data by Brown et al. (2018). We refer to the latter as the ‘ATCA’ dataset as it uses frequencies from the 1–3 GHz configuration of the ATCA. These frequencies included 394 channels from 1.29–3.02 GHz and match our real data. We simulated Faraday depths from -50 to 50 rad m^{-2} for the ‘ASKAP’ dataset (matching Brown) and -500 to 500 rad m^{-2} for the ‘ATCA’ dataset.

For each dataset, we simulated 100 000 FDFs, approximately half simple and half complex. We randomly allocated half of these FDFs to a training set and reserved the remaining half for validation. Each FDF had complex Gaussian noise added to the corresponding polarisation spectrum. For the ‘ASKAP’ dataset, we sampled the standard deviation of the noise uniformly between 0 and $\sigma_{\max} = 0.333$, matching the dataset of Brown et al. (2018). For the ‘ATCA’ dataset, we fit a log-normal distribution to the standard deviations of O’Sullivan’s data (O’Sullivan et al., 2017) from which we sampled our values of σ :

$$\sigma \sim \frac{1}{0.63\sqrt{2\pi}\sigma} \exp\left(-\frac{\log(50\sigma - 0.5)^2}{2 \times 0.63^2}\right) \quad (6.11)$$

6.4.1.2 Observational data

We used two real datasets containing a total of 142 sources: 42 polarised spectra from Livingston et al. (2020, submitted) and 100 polarised spectra from O’Sullivan et al. (2017). These datasets were observed in similar frequency ranges on the same telescope (with different binning), but are in different parts of the sky. The Livingston data were taken near the Galactic Centre, and the O’Sullivan data were taken away from the plane of the Galaxy. There are more Faraday complex sources near the Galactic Centre compared to more Faraday simple sources away from the plane of the Galaxy (Livingston et al.). The similar frequency channels used in the two datasets result in almost identical RMSFs over the Faraday depth range we considered (-500 to 500 rad m⁻²), so we expected that the classifiers would work equally well on both datasets with no need to re-train. We discarded the 26 Livingston sources with modelled Faraday depths outside of this Faraday depth range, which we do not expect to affect the applicability of our methods to wide-area surveys because these fairly high depths are not common.

Livingston et al. (2021) used RM-CLEAN (Heald, 2008) to identify significant components in their FDFs. Some of these components had very high Faraday depths up to 2000 rad m⁻², but we chose to ignore these components in this paper chapter as they are much larger than might be expected in a wide-area survey like POSSUM. They used the second Faraday moment (Brown, 2011) to estimate Faraday complexity, with Faraday depths determined using `scipy.signal.find_peaks` on the cleaned FDFs, with a cutoff of 7 times the noise of the polarised spectrum. Using this method, they

3106 estimated that 89 per cent of their sources were Faraday complex i.e. had a Faraday
 3107 moment greater than ~~0-zero~~.

3108 O’Sullivan et al. (2017) used the QU-fitting and model selection technique described
 3109 in O’Sullivan et al. (2012). The QU-fitting models contained up to three Faraday screen
 3110 components as well as a term for internal and external Faraday dispersion. We ignore
 3111 the Faraday thickness and dispersion for the purposes of this ~~paperchapter~~, as most
 3112 sources were not found to have Faraday thickness and dispersion is beyond the scope
 3113 of our current work. 37 sources had just one component, 52 had two, and the remaining
 3114 11 had three.

3115 6.4.2 Results on ‘ASKAP’ dataset

Table 6.1: Confusion matrix entries for LR and XGB on ‘ASKAP’ and ‘ATCA’ simulated datasets, and the CNN confusion matrix entries adapted from Brown et al. (2018).

	'ASKAP'			'ATCA'	
	LR	XGB	CNN	LR	XGB
True negative rate	0.99	0.99	0.97	0.92	0.91
False positive rate	0.01	0.01	0.03	0.08	0.09
False negative rate	0.10	0.09	0.07	0.16	0.10
True positive rate	0.90	0.91	0.93	0.84	0.90

3116 The ~~accuracy accuracies~~ of the LR and XGB classifiers on the ‘ASKAP’ testing set
 3117 ~~was-were~~ 94.4 and 95.1 per cent respectively. The rates of true and false identifications
 3118 are summarised in Table 6.1. These results are very close to the CNN presented by
 3119 Brown et al. (2018), with a slightly higher true negative rate and a slightly lower true
 3120 positive rate (recalling that positive sources are complex, and negative sources are
 3121 simple). The accuracy of the CNN was 94.9 ~~per cent~~, slightly lower than our XGB
 3122 classifier and slightly higher than our LR classifier. Both of our classifiers therefore
 3123 ~~produce produced~~ similar classification performance to the CNN, with faster training
 3124 time and easier interpretation.

3125 6.4.3 Results on ‘ATCA’ dataset

3126 The ~~accuracy accuracies~~ of the LR and XGB classifiers on the ‘ATCA’ dataset ~~was-were~~
 3127 89.2 and 90.5 per cent respectively. The major differences between the ‘ATCA’ and the
 3128 ‘ASKAP’ experiments are the range of the simulated Faraday depths and the distribu-
 3129 tion of noise levels. The ‘ASKAP’ dataset, to match past CNN work, only included
 3130 depths from -50 to 50 rad m^{-2} , while the ‘ATCA’ dataset includes depths from -500
 3131 to 500 rad m^{-2} . The rates of true and false identifications are again shown in Table 6.1.

3132 As we know the true Faraday depths of the components in our simulation, we can
 3133 investigate the behaviour of these classifiers as a function of physical properties. Fig-
 3134 ure 6.4 shows the mean classifier prediction as a function of component depth separa-
 3135 tion and minimum component amplitude. This is tightly related to the mean accuracy,

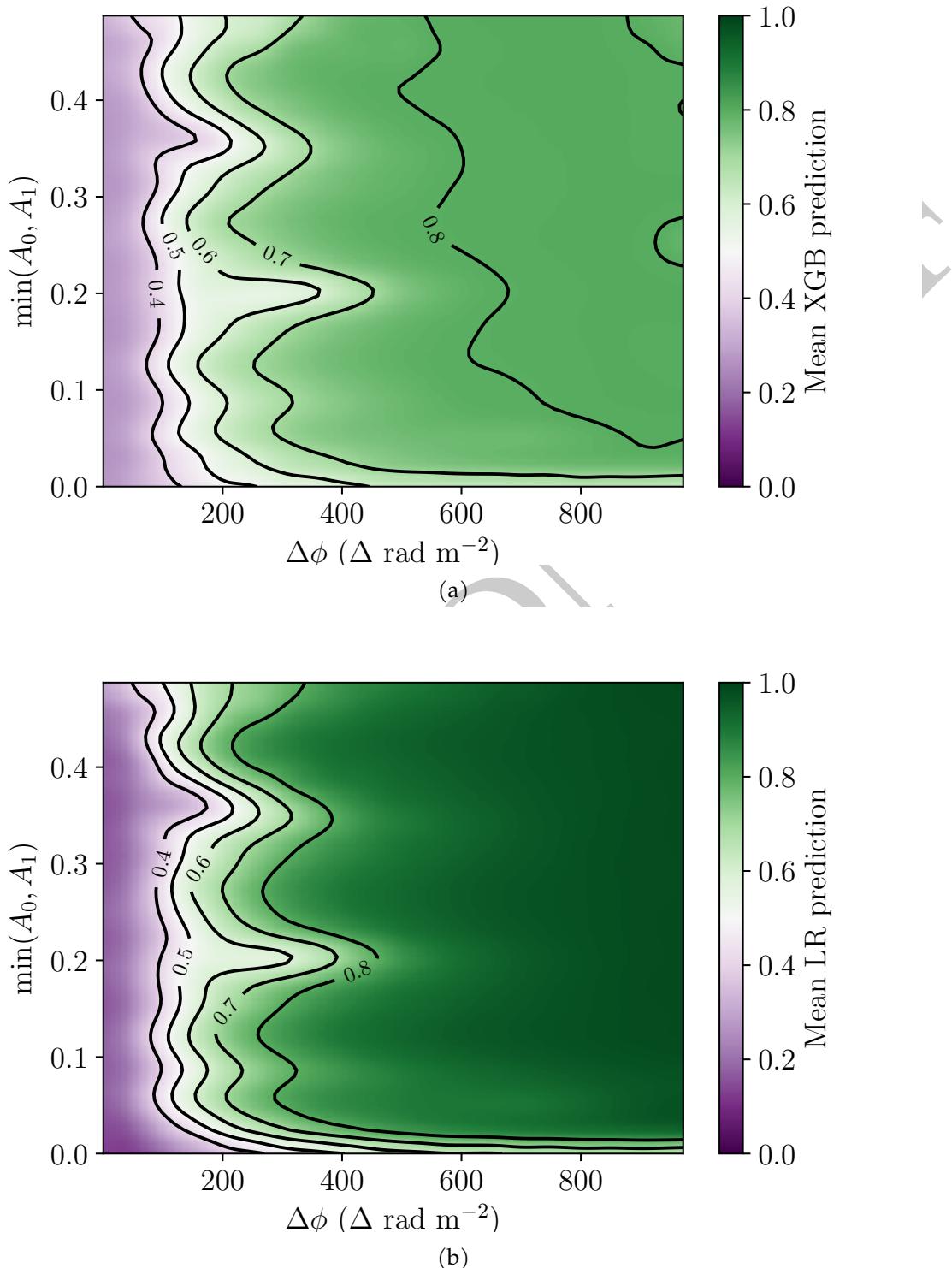


Figure 6.4: Mean prediction as a function of component depth separation and minimum component amplitude for (a) XGB and (b) LR.

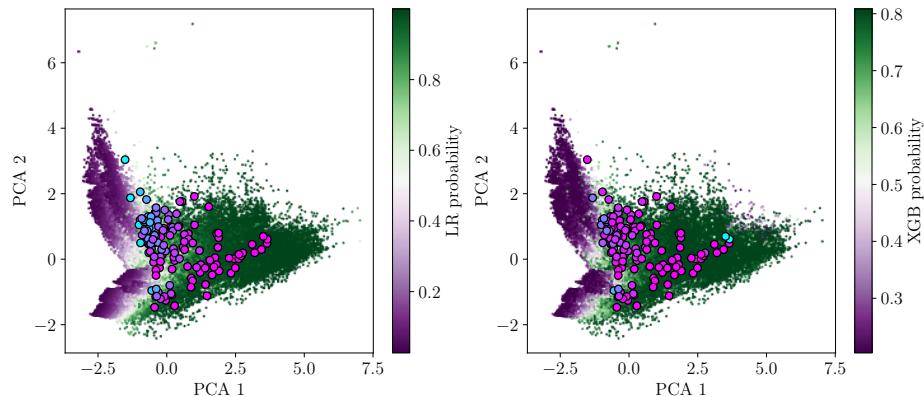


Figure 6.5: Principal component analysis for simulated data (coloured dots) with observations overlaid (black-edged circles). Observations are coloured by their XGB or LR estimated probability of being complex, with blue indicating ‘most simple’ and pink indicating ‘most complex’.

as the entire plot domain contains complex spectra besides the left and bottom edge: by thresholding the classifier prediction to a certain value, the accuracy will be one hundred per cent on the non-edge for all sources with higher prediction values.

6.4.4 Results on observed FDFs

We used the LR and XGB classifiers which were trained on the ‘ATCA’ dataset to estimate the probability that our 142 observed FDFs (Section 6.4.1.2) were Faraday complex. As these classifiers were trained on simulated data, they face the issue of the ‘domain gap’: ~~the~~-The distribution of samples from a simulation differs from the distribution of real sources, and this affects performance on real data. Solving this issue is called ‘domain adaptation’ and how to do this is an open research question in machine learning (Pan & Yang, 2010; Zhang, 2020). Nevertheless, the features of our observations mostly fall in the same region of feature space as the simulations (Figure 6.5) and so we expect reasonably good domain transfer.

Two apparently complex sources in the Livingston sample are classified as simple with high probability by XGB. These outliers are on the very edge of the training sample (Figure 6.5) and the underdensity of training data here is likely the cause of this issue. LR does not suffer the same issue, producing plausible predictions for the entire dataset, and these sources are instead classified as complex with high probability.

With a threshold of 0.5, LR predicted that 96 and 83 per cent of the Livingston and O’Sullivan sources were complex respectively. This is in line with expectations that the Livingston data should have more Faraday complex sources than the O’Sullivan data due to their location near the Galactic Centre. XGB predicted that 93 and 100 per cent of the Livingston and O’Sullivan sources were complex respectively. Livingston et al. (2021) found that 90 per cent of their sources were complex, and O’Sullivan et al. (2017)

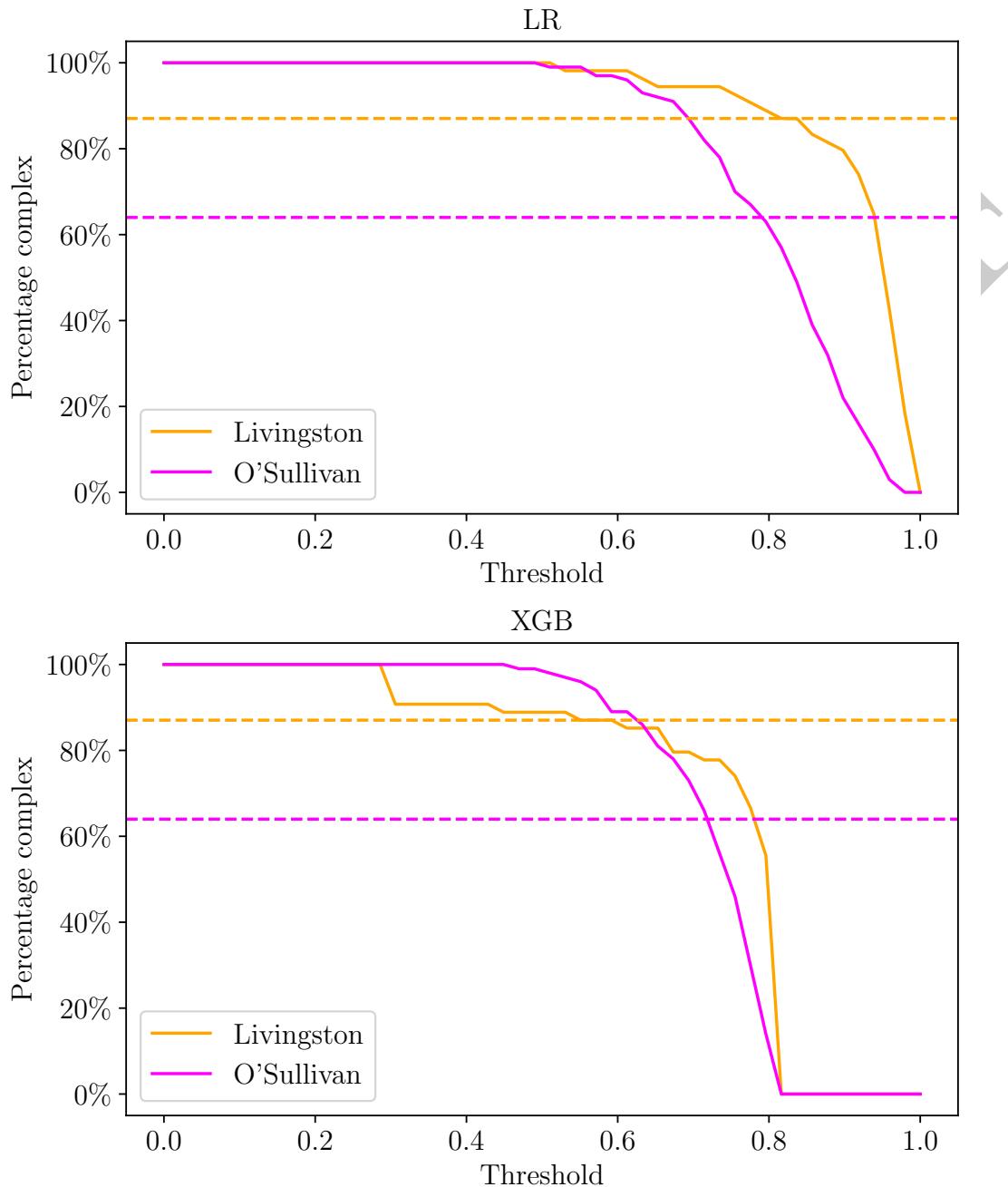


Figure 6.6: Estimated rates of Faraday complexity for the Livingston and O'Sullivan datasets as functions of threshold. The horizontal lines indicate the rates of Faraday complexity estimated by Livingston and O'Sullivan respectively.

3160 found that 64 per cent of their sources were complex. This suggests that our classifiers
3161 are overestimating complexity, though it could also be the case that the methods used
3162 by Livingston and O’Sullivan underestimate complexity. Modifying the prediction
3163 threshold from 0.5 changes the estimated rate of Faraday complexity, and we show
3164 the estimated rates against threshold for both classifiers in Figure 6.6. We suggest that
3165 this result is indicative of our probabilities being uncalibrated, and a higher threshold
3166 should be chosen in practice. We chose to keep the threshold at 0.5 as this had the
3167 highest accuracy on the simulated validation data. The very high complexity rates of
3168 XGB and two outlying classifications indicate that the XGB classifier may be overfitting
3169 to the simulation and that it is unable to generalise across the domain gap.

3170 Figure 6.7 and Figure 6.8 [in](#) Appendix 6.O show every observed FDF ordered by es-
3171 timated Faraday complexity, alongside the models predicted by Livingston and O’Sullivan
3172 et al. (2017) [for](#) LR and XGB respectively. There is a clear visual trend of increasingly
3173 complex sources with increasing predicted probability of being complex.

3174 6.5 Discussion

3175 On simulated data (Section 6.4.3) we achieve state-of-the-art accuracy. Our results on
3176 observed FDFs show that our classifiers produce plausible results, with Figure 6.7 and
3177 Figure 6.8 showing a clear trend of apparent complexity. Some issues remain: [we](#) [We](#)
3178 discuss the intrinsic overlap between simple and complex FDFs in Section 6.5.1 and
3179 the limitations of our method in Section 6.5.2.

3180 6.5.1 Complexity and seeming ‘not simple’

3181 Through this work we found our methods limited by the significant overlap between
3182 complex and simple FDFs. Complex FDFs can be consistent with simple FDFs due to
3183 close Faraday components or very small amplitudes on the secondary component, and
3184 vice versa due to noise.

3185 The main failure mode of our classifiers is misclassifying a complex source as sim-
3186 ple (Table 6.1). Whether sources with close components or small amplitudes should
3187 be considered complex is not clear, since for practical purposes they can be treated as
3188 simple: [assuming](#) [Assuming](#) the source is simple yields a very similar RM to the RM of
3189 the primary component, and thus would not negatively impact further data products
3190 such as an RM grid. The scenarios where we would want a Faraday complexity clas-
3191 sifier rather than a polarisation structure model – large-scale analysis and wide-area
3192 surveys – do not seem to be disadvantaged by considering such sources simple. Ad-
3193 ditional sources similar to these are likely hidden in presumably ‘simple’ FDFs by the
3194 frequency range and spacing of the observations, just as how these complex sources
3195 would be hidden in lower-resolution observations. Note also that misidentification of
3196 complex sources as simple is intrinsically a problem with complexity estimation even
3197 for models not well-represented by a simple FDF, as complex sources may conspire to
3198 appear as a wide range of viable models including simple (Sun et al., 2015).

Conversely, high-noise simple FDFs may be consistent with complex FDFs. One key question is how Faraday complexity estimators should behave as the noise increases: ~~should~~Should high noise result in a complex prediction or a simple prediction, given that ~~a complex or simple FDF would both~~both complex and simple FDFs ~~would~~ be consistent with a noisy FDF? Occam's razor suggests that we should choose the simplest suitable model, and so increasing noise should lead to predictions of less complexity. This is not how our classifiers operate, however: ~~high-noise~~High-noise FDFs are different to the model simple FDFs and so are predicted to be 'not simple'. In some sense our classifiers are not looking for complex sources, but are rather looking for 'not simple' sources.

6.5.2 Limitations

Our main limitations are our simplifying assumptions on FDFs and the domain gap between simulated and real observations. However, our proposed features (Section Section 6.3.1) can be applied to future improved simulations.

It is unclear what the effect of our simplifying assumptions are on the effectiveness of our simulation. The three main simplifications that may negatively affect our simulations are 1) limiting to two components, 2) assuming no external Faraday dispersion, and 3) assuming no internal Faraday dispersion (Faraday thickness). Future work will explore removing these simplifying assumptions, but will need to account for the increased difficulty in characterising the simulation with more components and no longer having Faraday screens as components. Additionally, more work will be required to make sure that the rates of internal and external Faraday dispersion match what might be expected from real sources, or risk making a simulation that has too large a range of consistent models for a given source: ~~for~~For example, a two-component source could also be explained as a sufficiently wide or resolved-out Faraday thick source or a three-component source with a small third component. This greatly complicates the classification task.

Previous machine learning work (e.g. Brown et al., 2018) has not been run before on real FDF data, so this ~~paper~~chapter is the first example of the domain gap arising in Faraday complexity classification. This is a problem that requires further research to solve. We have no good way to ensure that our simulation matches reality, so some amount of domain adaptation will always be necessary to train classifiers on simulated data and then to apply these classifiers to real data. But with the low source counts in polarisation science (high-resolution spectropolarimetric data currently numbers in the few hundreds) any machine learning method will need to be trained on simulations. This is not just a problem in Faraday complexity estimation, and domain adaptation is also an issue faced in the wider astroinformatics community: ~~large~~Large quantities of labelled data are hard to come by, and some sources are very rare (e.g. gravitational wave detections or fast radio bursts; Agarwal et al., 2020; Gebhard et al., 2019; Zevin et al., 2017). LR seems to handle the domain adaptation better than XGB, with only a slightly lower accuracy on simulated data. Our results are plausible and the distribution of our simulation well overlaps the distribution of our real data (Fig-

ure 6.5).

6.6 Conclusion

We developed a simple, interpretable machine learning method for estimating Faraday complexity. Our interpretable features were derived by comparing observed FDFs to idealised simple FDFs, which we could determine both for simulated and real observations. We demonstrated the effectiveness of our method on both simulated and real data. Using simulated data, we found that our classifiers were 95 per cent accurate, with near perfect recall (specificity) of Faraday simple sources. On simulated data that matched existing observations, our classifiers obtained an accuracy of 90 per cent. Evaluating our classifiers on real data gave the plausible results shown in Figure 6.7, and marks the first application of machine learning to observed FDFs. Future work will need to narrow the domain gap to improve transfer of classifiers trained on simulations to real, observed data.

6.7 Acknowledgements

This research was conducted in Canberra, on land for which the Ngunnawal and Ngambri people are the traditional and ongoing custodians. M.J.A. and J.D.L. were supported by the Australian Government Research Training Program. M.J.A. was supported by the Astronomical Society of Australia. The Australia Telescope Compact Array is part of the Australia Telescope National Facility which is funded by the Australian Government for operation as a National Facility managed by CSIRO. We acknowledge the Gomeroi people as the traditional owners-custodians of the Observatory site. We thank the anonymous referee for their comments on this work.

6.K Simulating observed FDFs

This appendix describes how we simulated FDFs in Chapter 6. We simulate FDFs by approximating them by arrays of complex numbers. An FDF F is approximated on the domain $[-\phi_{\max}, \phi_{\max}]$ by a vector $\vec{F} \in \mathbb{R}^d$:

$$\vec{F}_j = \sum_{k=0}^1 A_k \delta(-\phi_{\max} + j\delta\phi - \phi_k) \quad (6.12)$$

where $\delta\phi = (\phi_{\max} - \phi_{\min})/d$ and d is the number of Faraday depth samples in the FDF. \vec{F} is sampled by uniformly sampling its parameters:

$$\phi_k \in [\phi_{\min}, \phi_{\min} + \delta\phi, \dots, \phi_{\max}] \quad (6.13)$$

$$A_k \sim \mathcal{U}(0, 1). \quad (6.14)$$

We then generate a vector polarisation spectrum $\vec{P} \in \mathbb{R}^m$ from \vec{F} using a Equation 6.15:

$$\vec{P}_\ell = \sum_{j=0}^J F_j e^{2i(\phi_{\min} + j\delta_\phi) \lambda_\ell^2} d\phi. \quad (6.15)$$

λ_ℓ^2 is the discretised value of λ^2 at the ℓ th index of \vec{P} . This requires a set of λ^2 values, which depends on the dataset being simulated. These values can be treated as the channel wavelengths at which the polarisation spectrum was observed. We then add Gaussian noise with variance σ^2 to each element of \vec{P} to obtain a discretised noisy observation $\hat{\vec{P}}$. Finally, we perform RM synthesis using the Canadian Initiative for Radio Astronomy Data Analysis RM package², which is a Python module that implements a discrete version of RM synthesis:

$$\hat{F}_j = m^{-1} \sum_{\ell=1}^m \hat{P}_\ell e^{-2i(\phi_{\min} + j\delta_\phi) \lambda_\ell^2}. \quad (6.16)$$

3264 6.L 2-Wasserstein begets Faraday moments

Minimising the 2-Wasserstein distance between a model FDF and the simple manifold gives the second Faraday moment of that FDF. This appendix demonstrates that fact. Let \tilde{F} be the sum-normalised model FDF and let \tilde{S} be the sum-normalised simple model FDF:

$$\tilde{F}(\phi) = \frac{A_0 \delta(\phi - \phi_0) + A_1 \delta(\phi - \phi_1)}{A_0 + A_1} \quad (6.17)$$

$$\tilde{S}(\phi; \phi_w) = \delta(\phi - \phi_w). \quad (6.18)$$

The W_2 distance, usually defined on probability distributions, can be extended to one-dimensional complex functions A and B by normalising them:

$$D_{W_2}(A \parallel B)^2 = \inf_{\gamma \in \Gamma(A, B)} \iint_{\phi_{\min}}^{\phi_{\max}} |x - y|^2 d\gamma(x, y) \quad (6.19)$$

$$\tilde{A}(\phi) = \frac{|A(\phi)|}{\int_{\phi_{\min}}^{\phi_{\max}} |A(\theta)| d\theta} \quad (6.20)$$

$$\tilde{B}(\phi) = \frac{|B(\phi)|}{\int_{\phi_{\min}}^{\phi_{\max}} |B(\theta)| d\theta} \quad (6.21)$$

²<https://github.com/CIRADA-Tools/RM>

3265 where $\Gamma(A, B)$ is the set of couplings of A and B , i.e. the set of joint probability distributions
 3266 that marginalise to A and B ; and $\inf_{\gamma \in \Gamma(A, B)}$ is the infimum over $\Gamma(A, B)$. This can be
 3267 interpreted as the minimum cost to ‘move’ one probability distribution to the other,
 3268 where the cost of moving one unit of probability mass is the squared distance it is
 3269 moved.

The set of couplings $\Gamma(\tilde{F}, \tilde{S})$ is the set of all joint probability distributions γ such that:

$$\int_{\phi_{\min}}^{\phi_{\max}} \gamma(\phi, \varphi) d\phi = \tilde{S}(\varphi; \phi_w), \quad (6.22)$$

$$\int_{\phi_{\min}}^{\phi_{\max}} \gamma(\phi, \varphi) d\varphi = \tilde{F}(\phi). \quad (6.23)$$

The coupling that minimises the integral in Equation 6.19 is the optimal transport plan between \tilde{F} and \tilde{S} . Since \tilde{F} and \tilde{S} are defined in terms of delta functions, the optimal transport problem reduces to a discrete optimal transport problem and the optimal transport plan is:

$$\gamma(\phi, \varphi) = \frac{A_0 \delta(\phi - \phi_0) + A_1 \delta(\phi - \phi_1)}{A_0 + A_1} \delta(\varphi - \phi_w). \quad (6.24)$$

In other words, to move the probability mass of \tilde{S} to \tilde{F} , a fraction $A_0/(A_0 + A_1)$ is moved from ϕ_w to ϕ_0 and the complementary fraction $A_1/(A_0 + A_1)$ is moved from ϕ_w to ϕ_1 . Then:

$$D_{W_2}(\tilde{F} \parallel \tilde{S})^2 = \iint_{\phi_{\min}}^{\phi_{\max}} |\phi - \varphi|^2 d\gamma(\phi, \varphi) \quad (6.25)$$

$$= \frac{A_0(\phi_0 - \phi_w)^2 + A_1(\phi_1 - \phi_w)^2}{A_0 + A_1}. \quad (6.26)$$

To obtain the W_2 distance to the simple manifold, we need to minimise this over ϕ_w . Differentiate with respect to ϕ_w and set equal to zero to find:

$$\phi_w = \frac{A_0 \phi_0 + A_1 \phi_1}{A_0 + A_1}. \quad (6.27)$$

Substituting this back in, we find:

$$\zeta_{W_2}(F)^2 = \frac{A_0 A_1}{A_0 + A_1} (\phi_0 - \phi_1)^2 \quad (6.28)$$

3270 which is the Faraday moment.

3271 6.M Euclidean distance in the no-RMSF case

In this appendix we calculate the minimised Euclidean distance evaluated on a model FDF (Equation 6.1). Let \tilde{F} be the sum-normalised model FDF and let \tilde{S} be the normalised simple model FDF:

$$\tilde{F}(\phi) = \frac{A_0\delta(\phi - \phi_0) + A_1\delta(\phi - \phi_1)}{A_0 + A_1} \quad (6.29)$$

$$\tilde{S}(\phi; \phi_e) = \delta(\phi - \phi_e). \quad (6.30)$$

The Euclidean distance between \tilde{F} and \tilde{S} is then:

$$D_E(\tilde{F}(\phi) \parallel \tilde{S}(\phi; \phi_e))^2 \quad (6.31)$$

$$= \int_{\phi_{\min}}^{\phi_{\max}} |\tilde{F}(\phi) - \delta(\phi - \phi_e)|^2 d\phi. \quad (6.32)$$

Assume $\phi_0 \neq \phi_1$ (otherwise, D_E will always be either 0 or 2). If $\phi_e = \phi_0$, then:

$$D_E(\tilde{F}(\phi) \parallel \tilde{S}(\phi; \phi_e))^2 \quad (6.33)$$

$$= \frac{1}{(A_0 + A_1)^2} \int_{\phi_{\min}}^{\phi_{\max}} A_1^2 |\delta(\phi - \phi_1) - \delta(\phi - \phi_0)|^2 d\phi \quad (6.34)$$

$$= \frac{2A_1^2}{(A_0 + A_1)^2} \quad (6.35)$$

and similarly for $\phi_e = \phi_1$. If $\phi_e \neq \phi_0$ and $\phi_e \neq \phi_1$, then:

$$D_E(\tilde{F}(\phi) \parallel \tilde{S}(\phi; \phi_e))^2 = \frac{A_0^2 + A_1^2 + 1}{(A_0 + A_1)^2}. \quad (6.36)$$

The minimised Euclidean distance when $\phi_0 \neq \phi_1$ is therefore:

$$D_E(F) = \min_{\phi_e \in \mathbb{R}} D_E(F(\phi) \parallel F_{\text{simple}}(\phi; \phi_e)) \quad (6.37)$$

$$= \sqrt{2} \frac{\min(A_0, A_1)}{A_0 + A_1}. \quad (6.38)$$

3272 If $\phi_0 = \phi_1$, then the minimised Euclidean distance is 0.

3273 6.N Hyperparameters for LR and XGB

3274 This section contains tables of the hyperparameters that we used for our classifiers
 3275 in Chapter 6. Table 6.2 and Table 6.3 tabulate the hyperparameters for XGB and LR
 3276 respectively for the ‘ATCA’ dataset. Table 6.4 and Table 6.5 tabulate the hyperparameters
 3277 for XGB and LR respectively for the ‘ASKAP’ dataset.

Table 6.2: XGB hyperparameters for the ‘ATCA’ dataset.

Parameter	Value
colsample_bytree	0.912
gamma	0.532
learning_rate	0.1
max_depth	7
min_child_weight	2
scale_pos_weight	1
subsample	0.557
n_estimators	135
reg_alpha	0.968
reg_lambda	1.420

Table 6.3: LR hyperparameters for the ‘ATCA’ dataset.

Parameter	Value
penalty	L1
C	1.668

Table 6.4: XGB hyperparameters for the ‘ASKAP’ dataset.

Parameter	Value
colsample_bytree	0.865
gamma	0.256
learning_rate	0.1
max_depth	6
min_child_weight	1
scale_pos_weight	1
subsample	0.819
n_estimators	108
reg_alpha	0.049
reg_lambda	0.454

3278 6.O Predictions on real data

3279 This appendix contains Figure 6.7 and Figure 6.8. These show the predicted probability
 3280 of being Faraday complex for all real data used in Chapter 6, drawn from Livingston et al. (2021).

Table 6.5: LR hyperparameters for the 'ASKAP' dataset.

Parameter	Value
penalty	L2
C	0.464

3281 and O'Sullivan et al. (2017).

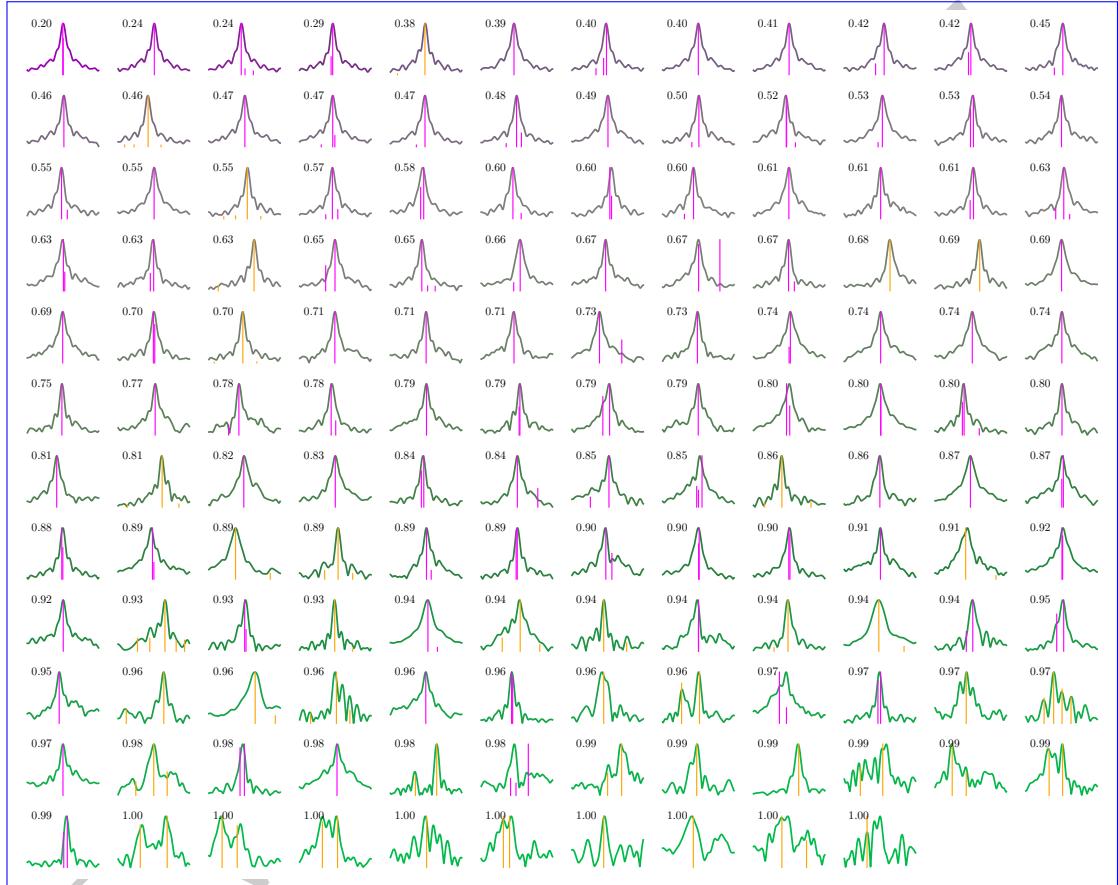


Figure 6.7: The 142 observed FDFs ordered by LR-estimated probability of being Faraday complex. Livingston-identified components are shown in orange while O'Sullivan-identified components are shown in magenta. Simpler FDFs (as deemed by the classifier) are shown in purple while more complex FDFs are shown in green, and the numbers overlaid indicate the LR estimate. A lower number indicates a lower probability that the corresponding source is complex, i.e. lower numbers correspond to simpler spectra.

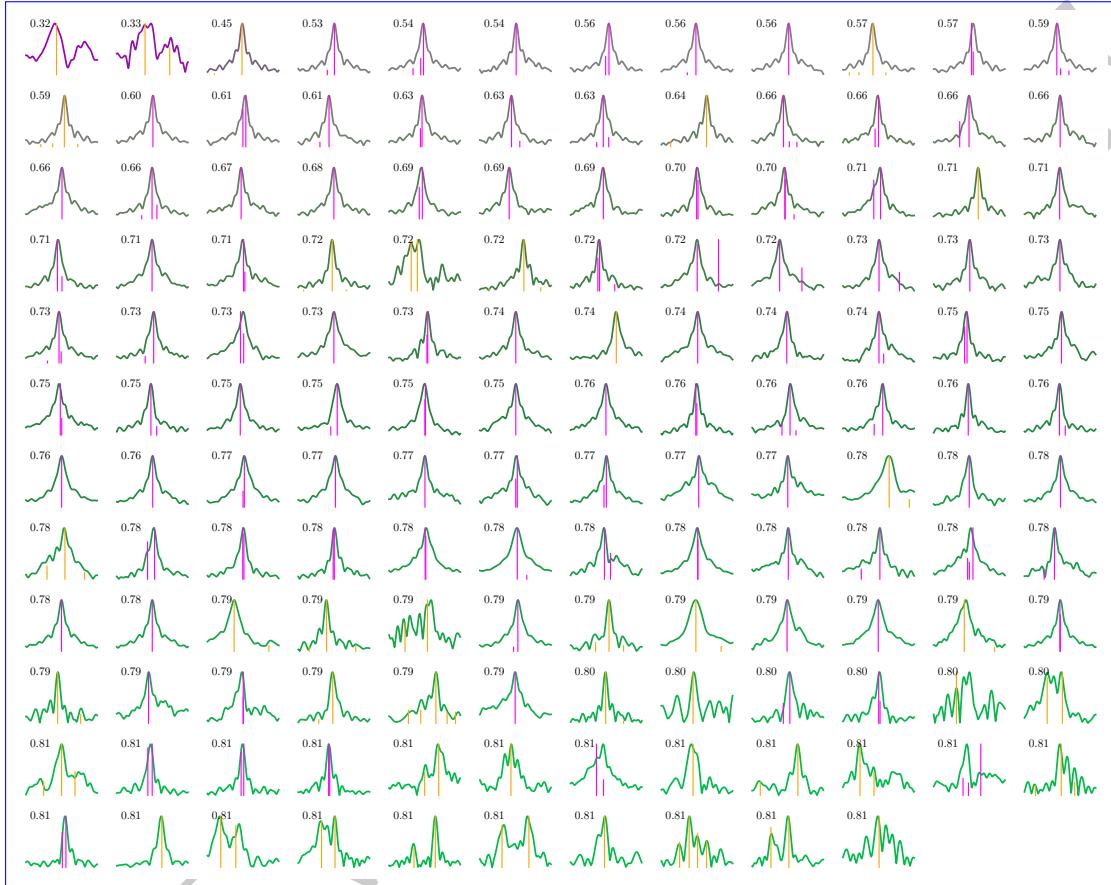


Figure 6.8: The 142 observed FDFs ordered by XCB-estimated probability of being Faraday complex. Livingston-identified components are shown in orange while O'Sullivan-identified components are shown in magenta. Simpler FDFs (as deemed by the classifier) are shown in purple while more complex FDFs are shown in green, and the numbers overlaid indicate the XGB estimate. A lower number indicates a lower probability that the corresponding source is complex, i.e. lower numbers correspond to simpler spectra.

3283 Conclusion

3284 The future of radio astronomy is immensely exciting, with upcoming radio surveys
3285 like EMU and POSSUM sure to revolutionise our understanding of the violent Uni-
3286 verse occupied by radio active galactic nuclei. Without innovative new methods for
3287 processing astronomical data at scale, however, we will be limited in what interesting
3288 physics we can learn about with these surveys. In this thesis we have explored meth-
3289 ods for identifying extragalactic radio sources in these future wide-area radio surveys.
3290 We developed a new automated cross-identification approach and a new way of classi-
3291 fying radio sources as Faraday complex or Faraday simple. We applied our methods to
3292 real data, and used our cross-identification method to directly probe the mechanical en-
3293 ergy contribution of active galactic nuclei (AGN) to the intergalactic medium (IGM).
3294 Our contributions here are all aimed at extracting more information ~~out of~~ from the
3295 very large radio surveys ~~that~~ we have begun to face.

3296 Chapter 4 developed a new approach to cross-identifying radio components with
3297 their infrared host galaxies and applied this method to the CDFS and ELAIS-S1 AT-
3298 LAS survey, a pilot survey for the upcoming ASKAP key survey EMU. This was the
3299 first application of machine learning to radio cross-identification. In the process, we
3300 demonstrated that our methods worked on ELAIS-S1 with similar performance to
3301 how they worked on CDFS, despite these being different parts of the sky. We also
3302 evaluated simple positional matching cross-identification on the ATLAS fields, show-
3303 ing better performance than either machine learning or Radio Galaxy Zoo volunteers
3304 on this dataset, which we suggest is ~~because of how due to the compact nature of~~
3305 most objects in ATLAS~~are very compact~~. Our machine learning methods performed
3306 similarly whether they were trained on expert-provided or citizen science-provided
3307 labelled datasets, clearly demonstrating the benefit of citizen science labels to radio
3308 astroinformatics even if they may be less accurate than labels provided by experts. We
3309 showed that the algorithm we ~~had~~-developed could in principle perform much better
3310 than positional matching if only its binary accuracy could be raised, perhaps with a
3311 more complex or better-trained classifier. Finally, we concluded that ATLAS was an
3312 insufficiently complex dataset to train machine learning algorithms for future radio
3313 surveys. ATLAS contains many compact sources, and while there will be many such
3314 sources in EMU and other future surveys, there will also be a zoo of partially resolved,
3315 extended, strange, ~~or-and~~ unusual morphologies. Methods designed or trained on a
3316 dataset like ATLAS, which lacks diversity of non-compact sources, will not work on

the wide range of extended radio sources that will appear. More complex and larger training sets, perhaps real or perhaps simulated, will be necessary for producing algorithms intended for use in future surveys.

To further investigate our classification-based cross-identification algorithm we needed a more complex dataset, and in Chapter 5 we turned to FIRST, a legacy survey containing around 900 000 radio components. Of these, 250 000 or so were not compact, compared to the vast majority of ATLAS. We increased the complexity of our machine learning model and trained it on this dataset along with 75 000 Radio Galaxy Zoo labels, far more than we had available for ATLAS. The resulting classifier could then be used to cross-identify every extended object in FIRST. Using the fact that any two radio components in the same radio source should also have the same host galaxy, we identified not only the host galaxies of our radio components but also their *association to associations with* other radio components. This allowed us to produce the RGZ-Ex catalogue, containing over 150 000 extended radio sources—the largest existing catalogue of extended radio sources at the time of writing. In this catalogue we identified 40 giant radio galaxies, most of which were new to literature.

Such a large catalogue enabled us to estimate a radio luminosity function (RLF) for extended radio sources, the first time a RLF has been produced for just extended sources. We could also subdivide this RLF into a fractional RLF, and we were able to produce RLFs divided by the mid-infrared colour of the host galaxy, *their* physical extent, and *their* redshift. Extended radio sources ought to be the sources which contribute the most mechanical energy to their surrounding IGM, and with an RLF dedicated solely to extended sources, we were able to estimate this energy contribution as 1.3×10^{30} and 1.2×10^{32} W Mpc $^{-3}$. Perhaps most importantly, we showed *that* our cross-identification approach works and used it to obtain a physically meaningful result. Our methods can easily be extended to new surveys, as long as sufficient host galaxy/radio component pairs are known so that the algorithm can be trained.

Our work on cross-identification allowed us to extract more information from wide-area continuum radio surveys. *To Additionally, to* help gain more use out of large polarisation surveys *as well*, we developed an interpretable Faraday complexity classifier for Faraday dispersion functions (FDFs) in Chapter 6. We constructed features that were easy to understand by measuring the distance of observations from a simple model of Faraday simple sources. Our resulting features could be calculated from both simulated and real observations. We demonstrated the effectiveness of our method on both simulated and real data and showed that on simulated data our simple methods matched the state-of-the-art convolutional neural network (CNN) classifier despite having far less parameters. This was the first application of machine learning to real spectropolarimetric data. We highlighted the domain gap between simulated and observed FDFs and suggested reframing the Faraday complexity classification task as finding simple and non-simple sources. This method will be applicable to future surveys like POSSUM.

3358 7.1 Future Work

3359 There are many ways that the research in this thesis can be extended in future. We will
3360 summarise some of these here.

3361 Our methods can be extended in a number of ways. These, which fall into two cat-
3362 egories: further applications and extensions to the algorithms. An obvious target for
3363 future work is to apply our binary cross-identification algorithm (BXID; Section 4.3.1
3364 and Section 5.3) to new and upcoming surveys like LoTSS and EMU. These promise
3365 a tremendous amount of data with new discoveries certain to be lying in wait within,
3366 and cross-identifying the radio emission with its corresponding infrared or optical host
3367 galaxy will be vital for uncovering those secrets. Similarly, we would like to apply our
3368 Faraday complexity classifier to future spectropolarimetric surveys like POSSUM.

3369 Our methodology can also be improved. Better models almost certainly exist than
3370 the CNN we applied to BXID. As we demonstrated in Chapter 6, a well thought-out
3371 model and features may best a complex model like the CNN. How well would our
3372 cross-identification approach worked-work if, say, we applied it to hand-selected fea-
3373 tures such as those chosen by Proctor (2006)? Would a search over more CNN architec-
3374 tures, like that described by Lukic et al. (2019), result in better classifiers and hence bet-
3375 ter cross-identifications? Perhaps we could even improve performance by pre-training
3376 on some unlabelled but larger dataset? A less obvious improvement to our BXID ap-
3377 proach would be to change how the classification scores are aggregated. Currently
3378 this is a weighted maximisation over candidate host galaxies, but other methods are
3379 possible. The weights could be something other than a Gaussian function of distance,
3380 from other functions of distance to an entire separate classification model. Maybe we
3381 could aggregate the scores in bulk, using some kind of algorithm that assigns radio-
3382 host relationships based on not just the radio source itself, but also on the other radio
3383 sources around it and how they have been paired to their own host galaxies.

3384 The way that our labels were generated for BXID could be improved. Our algo-
3385 rithms in Chapter 4 and Chapter 5 were trained on labels generated by Radio Galaxy
3386 Zoo. These labels were aggregated from multiple different labellers (usually 20) by
3387 majority vote, with the most common label for any given radio object being assigned
3388 as the true label in Radio Galaxy Zoo. This is not the only possible aggregation strategy,
3389 though. We employed the Dawid-Skene method (Dawid & Skene, 1979) ourselves in
3390 Section 5.3.1 to help assess the performance of our cross-identification algorithm, and
3391 this model for example may also be applied to Radio Galaxy Zoo. There are in fact ag-
3392 gregation strategies that work in tandem with a machine learning model to get better
3393 labels, such as Raykar et al. (2010). These methods simultaneously take into account
3394 the labels and the labellers, and can accommodate for different levels of ability in the
3395 labellers, or different levels of difficulty in the examples being labelled.

3396 Our RLFs could be improved. The RLF calculations in Chapter 5 are severely lim-
3397 ited by the availability of redshifts. We limit-limited our analyses to host galaxies that
3398 do-did have available spectroscopic redshifts in SDSS, but we could also employ-have
3399 employed the less-reliable but considerably more prolific photometric redshifts. These
3400 are derived from regression models rather than direct observations of redshifted spec-

tral lines, and so can be produced from photometric surveys without dedicated spectroscopy. However, without methods to handle the uncertainty introduced by photometric redshifts, the resulting RLFs would be unreliable. ~~Developing ways to not only decrease Decreasing~~ the uncertainty in photometric redshifts ~~but also to understand and incorporate the uncertainty~~ is not the only way forward. We may also develop methods for understanding and incorporating their uncertainties into downstream calculations like ~~those of the used for~~ RLFs, for example, using probabilistic programming (e.g. Bingham et al., 2019). This will allow these photometric redshifts to be used and tremendously increase sample sizes. Besides existing photometric redshifts, future surveys will also produce many more redshifts, both spectroscopic and photometric. This will be very important for surveys like EMU, which are both deep and wide with low redshift availability.

The RGZ-Ex dataset (Chapter 5) also lets us pose many other interesting science questions. We demonstrated in Appendix 5.J that rare galaxy classes can be identified from within this dataset, including examples that have never before been identified in the literature. Our dataset may be augmented with other features and used to identify unusual objects in a similar way. Besides this, our fractional RLFs could also be extended with any number of galaxy properties. One particularly interesting property could be morphology, as other algorithms in radio astroinformatics are developed which can automatically identify morphologies (e.g. Wu et al., 2019):~~such~~ Such a classifier could be used to segment RGZ-Ex and a fractional morphological RLF could be obtained. These morphologies may even be classes that are not easily separated, such as those found by self-organising maps (e.g. Polsterer et al., 2015). Of course, there are other properties that are more easily extracted, such as optical lines and colours which could be taken from SDSS using our SDSS cross-identifications.

While creating features for FDFs in Chapter 6 we demonstrated that W2 distance was a sensible distance measure between FDFs. This is useful for more than just feature construction, as it implies a geometry on the space of FDFs. This distance could be used to help gain insight on the behaviours of future algorithms that work on FDFs. A particularly exciting idea is to improve QU fitting by modifying the distance function to match ours. Our features could also be used to develop other methods for FDF analysis, like outlier detection or data visualisation.

Further research is needed to close the domain gap for FDFs. This is an interesting case study as it is such a simple case, where we know essentially all the physics behind the observations and the observations are one-dimensional. Even this is not enough, and whether through unmodelled physics (e.g. more than two screens, depolarisation) or unmodelled observational properties (e.g. radio frequency interference), simulation and observation do not fully line up. ~~This Such research~~ is critical if we want to train machine learning algorithms on simulations in the future, and we very much want to do this to augment our limited observational training data. Similarly, the domain gap must be reduced for radio continuum observations. Our results in Chapter 4 show that pilot surveys like ATLAS may not contain enough complex sources to train machine learning models, and while larger surveys like FIRST exist, transferring models from a survey undertaken with one set of observing parameters (telescope,

3445 frequency, depth, resolution...) is both non-trivial and as-yet relatively unexplored.

3446 7.2 Implications for radio citizen science

3447 Our results in Chapter 4 demonstrated that machine learning methods trained on cit-
3448 izen science labels perform comparably to those trained on expert labels, even when
3449 those labels are lower quality than expert labels. We applied this insight in Chap-
3450 ter 5 to obtain scientific results, using machine learning to extrapolate the labels to a
3451 larger dataset. While Radio Galaxy Zoo alone was not enough to fully label FIRST, Ra-
3452 dio Galaxy Zoo working in tandem with machine learning was. This is a pattern that
3453 may hold true for future surveys and applications, too. Future astronomical research
3454 at-scale may leverage the idea of people working with machine learning, sometimes
3455 called *human-in-the-loop* (e.g. Holzinger, 2016) learning, to pore through data-at-scale.

3456 7.3 Implications for wide-area radio surveys

3457 As we move toward larger and larger datasets, an important question is how applica-
3458 ble our models will be across the sky. Our results in Chapter 4 showed that we can
3459 expect some generalisation, as our model trained on one patch of sky was applicable
3460 to another without a great loss of performance. Similarly, our classifier trained on part
3461 of FIRST seemed to work well on the rest of the dataset. This is promising as it implies
3462 that limited area surveys may help develop training sets that generalise to the whole
3463 sky, potentially making the process of generating training sets considerably cheaper.

3464 With our work in Chapter 4 and 5 we demonstrated that a large set of good quality,
3465 complex data is required for training good astroinformatics algorithms. Pilot datasets
3466 like ATLAS will not work by themselves: ~~the~~^{The} sources they contain are too simple
3467 and their complex sources are too few. A sensible question to ask is, could we simu-
3468 late data for training purposes? We trained our classifier in Chapter 6 on simulated
3469 data and found that it was difficult to bridge the domain gap between simulation and
3470 observation, even in a well-understood, one-dimensional case—let alone the complex
3471 three-dimensional projected morphologies we observe in imagery. Getting across this
3472 domain gap will be difficult and will necessarily be a major topic of research in the
3473 astroinformatics field in the near future.

3474 Tying observations, simulations, and models together are the representation of the
3475 data: features. Our results in Chapter 6 show that judicious choice of features can
3476 outperform even complex and powerful models. This is good for two reasons. The
3477 first reason is that these features may be more easily interpreted. The meaning of the
3478 features may be understood to be representative of some physical property, or at least
3479 the relationship between physical reality and predictions may be more easily found.
3480 The second reason is that features may be selected which can generalise well to datasets
3481 beyond just the training set. In other words, features that are less overfit to the training
3482 set. This is of particular concern when developing predictive models on simulated
3483 training data, as features being less suited for real data than for simulations is one

3484 aspect that may contribute to the domain gap. Choosing good features in astronomy
 3485 may be more important than in many other fields ~~for-to~~ which machine learning is
 3486 applied, as while in most fields it is possible to conduct experiments, in astronomy we
 3487 only have one Universe to look at. We need to make the best use we can of the limited
 3488 radio sky.

3489 7.4 Final remarks

3490 Radio astronomy faces a deluge of data, with current and upcoming surveys delivering
 3491 incredible amounts of data for science use. While we can get a lot out of these data—
 3492 from investigations into new physics, to finding rare and unusual objects—doing so is
 3493 dependent on the development of new methods for astronomy at scale. These future
 3494 methods will necessarily be computational, and so the challenge lies in encoding the
 3495 abstract concepts of astronomy and astrophysics into a rigorously defined set of rules
 3496 that a computer can interpret and execute ~~at scaleen masse~~. This is decidedly non-
 3497 trivial, and the nuance and unique skills required to do so motivates the burgeoning
 3498 field of astroinformatics. By combining concepts from deep within the often disparate
 3499 fields of astronomy and machine learning, we hope that we will be able to make the
 3500 absolute most of the incredible new technologies and instruments that will arise in the
 3501 future of radio astronomy.

3502 7.5 Classification models

3503 ~~This appendix describes the three different models we used for binary classification in~~
 3504 ~~(logistic regression, convolutional neural networks, and random forests) and was part~~
 3505 ~~of Alger et al. (2018).~~

3506 7.4.1 Logistic Regression

3507 ~~Logistic regression is linear in the feature space and outputs the probability that the~~
 3508 ~~input has a positive label. The model is (Bishop, 2006):~~

$$f(\vec{x}) = \sigma(\vec{w}^T \vec{x} + b) ,$$

~~where $\vec{w} \in \mathbb{R}^D$ is a vector of parameters, $b \in \mathbb{R}$ is a bias term, $\vec{x} \in \mathbb{R}^D$ is the feature~~
~~vector representation of a candidate host, and $\sigma : \mathbb{R} \rightarrow \mathbb{R}$ is the logistic sigmoid function:~~

$$\sigma(a) = (1 + \exp(-a))^{-1} .$$

3509 ~~The logistic regression model is fully differentiable, and the parameters \vec{w} can therefore~~
 3510 ~~be learned using gradient-based optimisation methods. We used the scikit-learn~~
 3511 ~~(Pedregosa et al., 2011) implementation of logistic regression with balanced classes.~~

3512 7.4.1 Convolutional neural networks

3513 ~~Convolutional neural networks (CNN) are a biologically-inspired prediction model~~
3514 ~~for prediction with image inputs. The input image is convolved with a number of~~
3515 ~~filters to produce output images called feature maps. These feature maps can then~~
3516 ~~be convolved again with other filters on subsequent layers, producing a network of~~
3517 ~~convolutions. The whole network is differentiable with respect to the values of the~~
3518 ~~filters and the filters can be learned using gradient-based optimisation methods. The~~
3519 ~~final layer of the network is logistic regression, with the convolved outputs as input~~
3520 ~~features. For more detail, see subsection II.A, LeCun et al. (1998). We used KERAS~~
3521 ~~(Chollet et al., 2015) to implement our CNN, accounting for class imbalance by reweighting~~
3522 ~~the classes.~~

3523 ~~Architecture of our CNN. Parenthesised numbers indicate the size of output layers~~
3524 ~~as a tuple (width, height, depth). The concatenate layer flattens the output of the previous~~
3525 ~~layer and adds the 10 features derived from the candidate host in SWIRE, i.e. the flux~~
3526 ~~ratios, stellarity indices, and distance. The dropout layer randomly sets 25% of its~~
3527 ~~inputs to zero during training to prevent overfitting. Diagram based on .~~

3528 ~~CNNs have recently produced good results on large image-based datasets in astronomy~~
3529 ~~(Dieleman et al., 2015; Lukic et al., 2018, e.g.). We employed only a simple CNN model~~
3530 ~~in as a proof of concept that CNNs may be used for class probability prediction on radio~~
3531 ~~images. The model architecture we used is shown in .~~

3532 7.4.1 Random Forests

3533 ~~Random forests are an ensemble of decision trees (Breiman, 2001). They consider~~
3534 ~~multiple subsamples of the training set, where each subsample is sampled with replacement~~
3535 ~~from the training set. For each subsample a decision tree classifier is constructed~~
3536 ~~by repeatedly making axis-parallel splits based on individual features. In a random~~
3537 ~~forest the split decision is taken based on a random subset of features. To classify~~
3538 ~~a new data point, the random forest takes the weighted average of all classifications~~
3539 ~~produced by each decision tree. In we used the scikit-learn (Pedregosa et al., 2011)~~
3540 ~~implementation of random forests with 10 trees, the information entropy split criterion,~~
3541 ~~a minimum leaf size of 45, and balanced classes.~~

3542 7.5 Accuracy tables

3543 ~~This section contains tables of accuracy for our cross-identification method applied to~~
3544 ~~CDFS and ELAIS-S1, and was originally presented in Alger et al. (2018). In and we~~
3545 ~~list the balanced accuracies of our classifiers on the cross-identification task for CDFS~~
3546 ~~and ELAIS-S1 respectively, averaged over each set of training quadrants. In and we~~
3547 ~~list the balanced accuracies of classifiers on the cross-identification task for CDFS and~~
3548 ~~ELAIS-S1 respectively, averaged over each set of training quadrants.~~

3549 ~~Balanced accuracies for different binary classification models trained and tested on~~
3550 ~~SWIRE objects in CDFS. The ‘Labeller’ column states what set of training labels were~~

3551 used to train the classifier, and the ‘Classifier’ column states what classification model
 3552 was used. ‘CNN’ is a convolutional neural network, ‘LR’ is logistic regression and ‘RF’
 3553 is random forests. Accuracies are evaluated against the expert label set derived from
 3554 Norris et al. (2006). The standard deviation of balanced accuracies evaluated across
 3555 the four quadrants of CDFS () is also shown. The ‘compact’ set refers to SWIRE objects
 3556 within 1' of a compact radio component, the ‘resolved’ set refers to SWIRE objects
 3557 within 1' of a resolved radio component, and ‘all’ is the union of these sets. Labeller
 3558 Classifier Mean ‘Compact’ Mean ‘Resolved’ Mean ‘All’ accuracy accuracy accuracy (per
 3559 cent) (per cent) (per cent) Norris LR 91.5 ± 1.0 93.2 ± 1.0 93.0 ± 1.2 CNN 92.6 ± 0.7
 3560 91.2 ± 0.5 92.0 ± 0.6 RF 96.7 ± 1.5 91.0 ± 4.5 96.0 ± 2.5 RGZ LR 89.5 ± 0.8 90.5 ± 1.7 90.2 ± 0.8 CNN
 3561 89.4 ± 0.6 89.6 ± 1.3 RF 94.5 ± 0.2 95.8 ± 0.4 94.7 ± 0.3

3562 Balanced accuracies for different binary classification models trained on SWIRE
 3563 objects in CDFS and tested on SWIRE objects in ELAIS-S1. Columns and abbreviations
 3564 are as in . Accuracies are evaluated against the expert label set derived from Middelberg et al. (2008)
 3565 . The standard deviations of balanced accuracies of models trained on the four subsets
 3566 of CDFS () are also shown. Labeller Classifier Mean ‘Compact’ Mean ‘Resolved’ Mean
 3567 ‘All’ accuracy accuracy accuracy (per cent) (per cent) (per cent) Norris LR 94.6 ± 0.4
 3568 93.3 ± 2.0 95.3 ± 0.1 CNN 94.8 ± 0.2 92.8 ± 0.5 94.4 ± 0.2 RF 85.9 ± 3.8 70.0 ± 2.8 86.6 ± 3.2 RGZ
 3569 LR 91.8 ± 0.3 91.9 ± 0.5 92.0 ± 0.2 CNN 90.1 ± 0.3 91.1 ± 0.9 90.2 ± 0.3 RF 95.1 ± 0.1 95.2 ± 0.0
 3570 95.2 ± 0.3

3571 Cross-identification accuracies for different classification models on CDFS. The ‘Labeller’
 3572 column states what set of training labels were used to train the method, and the ‘Classifier’
 3573 column states what classification model was used. ‘CNN’ is a convolutional neural
 3574 network, ‘LR’ is logistic regression, ‘RF’ is random forests, and ‘Labels’ is the accuracy
 3575 of the label set itself. ‘Perfect’ indicates that the true labels of the test set were used and
 3576 hence represents an upper bound on cross-identification accuracy with our method.
 3577 ‘NN’ is a nearest neighbours approach. Accuracies are evaluated against the expert
 3578 label set, so ‘Norris’ labels are 100 per cent accurate by definition. The standard deviation
 3579 of accuracies evaluated across the four quadrants of CDFS () is also shown. Labeller
 3580 Classifier Mean ‘Compact’ Mean ‘Resolved’ Mean ‘All’ accuracy accuracy accuracy (per
 3581 cent) (per cent) (per cent) NN 97.2 ± 1.7 75.7 ± 7.9 93.4 ± 0.8 Random 97.9 ± 2.2
 3582 22.3 ± 9.2 83.2 ± 4.7 Norris Labels 100.0 ± 0.0 100.0 ± 0.0 100.0 ± 0.0 Perfect 97.9 ± 2.2
 3583 99.0 ± 1.8 98.1 ± 1.7 LR 97.3 ± 0.5 76.0 ± 3.2 93.7 ± 1.8 CNN 96.6 ± 0.9 74.3 ± 12.3 93.5 ± 0.5 RF
 3584 96.1 ± 1.4 75.8 ± 6.7 93.8 ± 2.0 RGZ Labels 53.1 ± 8.5 56.7 ± 5.9 54.4 ± 5.9 LR 97.3 ± 1.9
 3585 74.5 ± 5.1 93.6 ± 1.7 CNN 85.4 ± 2.6 68.1 ± 9.2 92.4 ± 1.1 RF 97.5 ± 0.9 74.3 ± 7.9 93.7 ± 1.5

3586 Cross-identification accuracies for different classification models on ELAIS-S1. Columns
 3587 and abbreviations are as in . Accuracies are evaluated against the expert label set
 3588 derived from Middelberg et al. (2008) cross-identifications. The standard deviation
 3589 of accuracies evaluated across models trained on the four quadrants of CDFS () is
 3590 also shown. Labeller Classifier Mean ‘Compact’ Mean ‘Resolved’ Mean ‘All’ accuracy
 3591 accuracy accuracy (per cent) (per cent) (per cent) NN 95.5 ± 0.0 92.8 ± 0.0 95.5 ± 0.0 Random
 3592 61.9 ± 1.1 26.6 ± 2.1 61.9 ± 1.1 Middelberg Perfect 99.6 ± 0.0 99.8 ± 0.0 99.6 ± 0.0 Norris
 3593 LR 89.0 ± 1.1 89.7 ± 1.8 94.4 ± 0.9 CNN 89.7 ± 0.3 89.4 ± 1.4 94.3 ± 0.7 RF 83.8 ± 5.6 82.3 ± 4.1
 3594 90.6 ± 2.1 RGZ LR 90.5 ± 1.0 92.7 ± 0.2 95.9 ± 0.1 CNN 84.6 ± 0.6 84.6 ± 0.6 91.8 ± 0.3 RF

3595 91.3 ± 1.0 90.3 ± 2.4 94.7 ± 1.2

3596 7.5 SWIRE object scores

3597 This appendix is from Alger et al. (2018), and contains scores predicted by our binary
 3598 classifiers for each SWIRE object within $1'$ of a radio component in CDFS and ELAIS-S1.
 3599 Scores for SWIRE CDFS objects are shown in and scores for SWIRE ELAIS-S1 are
 3600 shown in . For CDFS, the score for an object in a quadrant is predicted by binary
 3601 classifiers trained on all other quadrants. For ELAIS-S1, we show the scores predicted
 3602 by binary classifiers trained on each CDFS quadrant. Note that these scores have *not*
 3603 been weighted by Gaussians. These are partial tables, and the full tables are available
 3604 online at the *Monthly Notices of the Royal Astronomical Society* website¹.

3605 The columns of the score tables are defined as follows:

- 3606 • *SWIRE*—SWIRE designation for candidate host galaxy.
- 3607 • *RA*—Right ascension (J2000).
- 3608 • *Dec*—Declination (J2000).
- 3609 • *Expert host*—Whether the candidate host galaxy is a host galaxy according to
 3610 Norris et al. (2006) or Middelberg et al. (2008) cross-identifications of CDFS and
 3611 ELAIS-S1 respectively.
- 3612 • *RGZ host*—Whether the candidate host galaxy is a host galaxy according to Radio
 3613 Galaxy Zoo cross-identifications (Wong et al., in prep.). This is always ‘no’ for
 3614 ELAIS-S1 objects.
- 3615 • *C/L/D*—Score assigned by binary classifier *C* trained on label set *L* of *D* candidate
 3616 host galaxies. *C* may be ‘CNN’, ‘LR’ or ‘RF’ for CNN, logistic regression or
 3617 random forests respectively. *L* may be ‘Norris’ or ‘RGZ’ for expert and Radio
 3618 Galaxy Zoo labels respectively. *D* may be ‘All’, ‘Compact’ or ‘Resolved’ for each
 3619 respective subset defined in .

3620 Scores output by our trained classifiers for SWIRE CDFS candidate host galaxies.
 3621 Columns are defined in . Full table electronic. SWIRE RA Dec Expert RGZ host host All
 3622 Compact Resolved All Compact Resolved J032603.15-284708.5 51.5132 -28.7857 yes no
 3623 0.5838 -0.4697 0.4848 -0.3754 0.3881 0.3404 J032603.39-284010.1 51.5142 -28.6695 no no
 3624 0.0373 -0.5814 0.4878 -0.7896 0.7616 0.4668 J032603.44-284210.1 51.5144 -28.7028 no no
 3625 0.0232 -0.4891 0.5101 0.4319 0.4298 0.3474 J032603.44-284222.2 51.5143 -28.7062 no no
 3626 0.0006 -0.4164 0.5216 -0.0400 0.0444 0.0276 J032603.45-284748.4 51.5144 -28.7968 no no
 3627 0.0014 -0.4914 0.4865 0.1904 0.1895 0.1467 J032603.50-284637.0 51.5146 -28.7770 no no
 3628 0.0074 -0.4144 0.5382 0.1418 0.1515 0.1166 J032603.60-284627.4 51.5150 -28.7743 no no
 3629 0.0012 -0.4578 0.5165 -0.0850 0.0904 0.0484 J032603.63-283840.5 51.5151 -28.6446 no no
 3630 0.0021 -0.4153 0.5577 0.1678 0.1746 0.1323 J032603.66-283822.8 51.5153 -28.6397 no no

3631 0.0001 0.4752 0.5009 0.0864 0.0861 0.0613 J032603.75 284014.1 51.5156 28.6706 no no
 3632 0.0547 0.3408 0.5388 0.4889 0.5242 0.7301 All Compact Resolved All Compact Resolved
 3633 All Compact Resolved All Compact Resolved 0.2489 0.0009 0.1557 0.2939 0.0007 0.1174
 3634 0.8922 0.8018 0.8732 0.7167 0.6599 0.7801 0.0183 0.1646 0.1480 0.7637 0.7065 0.6070 0.0000
 3635 0.0000 0.0000 0.1629 0.0519 0.1275 0.0155 0.0164 0.0815 0.3714 0.5626 0.2488 0.0000 0.0734
 3636 0.0000 0.1315 0.2116 0.4150 0.0005 0.0006 0.0175 0.0460 0.0810 0.0299 0.2656 0.1418 0.0000
 3637 0.7631 0.8166 0.5378 0.0013 0.0037 0.0160 0.1792 0.0663 0.1821 0.0000 0.0000 0.0000 0.0255
 3638 0.0000 0.0000 0.0047 0.0010 0.0337 0.1284 0.2198 0.0694 0.0720 0.0000 0.0000 0.6240 0.6681
 3639 0.6704 0.0008 0.0006 0.0374 0.1053 0.1424 0.0807 0.1231 0.0876 0.0000 0.8517 0.7532 0.7019
 3640 0.0021 0.0073 0.0386 0.1482 0.0403 0.1210 0.0000 0.0532 0.0000 0.0000 0.0302 0.0000 0.0001
 3641 0.0004 0.0038 0.0854 0.0447 0.0514 0.0000 0.0000 0.0000 0.0000 0.0000 0.0542 0.2712
 3642 0.2318 0.5026 0.5631 0.5032 0.0595 0.0545 0.0000 0.4289 0.0789 0.1420
 3643 Scores output by our trained classifiers for SWIRE-ELAIS-S1 candidate host galaxies.
 3644 Columns are defined in . Full table electronic. SWIRE RA Dec Expert RGZ host host
 3645 All Compact Resolved All Compact Resolved J002925.73-440256.27.3572-44.0490 yes
 3646 no 0.9537 0.8638 0.5552 0.9195 0.9037 0.9371 J002926.14-440249.07.3590-44.0470 no no
 3647 0.7361 0.8752 0.5640 0.7740 0.7474 0.7952 J002926.52-440247.07.3605-44.0464 no no 0.3390
 3648 0.8338 0.5556 0.7275 0.6894 0.7197 J002926.63-440301.17.3610-44.0503 no no 0.2108 0.8251
 3649 0.5623 0.3434 0.3306 0.3292 J002927.13-440232.67.3631-44.0424 no no 0.0339 0.8479 0.5669
 3650 0.5853 0.5148 0.5159 J002927.28-440245.37.3637-44.0459 no no 0.0406 0.8345 0.5540 0.2702
 3651 0.2340 0.2133 J002927.44-440238.57.3644-44.0440 no no 0.0116 0.8267 0.5746 0.2228 0.2182
 3652 0.2028 J002928.08-440230.37.3670-44.0418 no no 0.0024 0.8626 0.5791 0.2297 0.1963 0.1549 J002928.11-440312.7
 3653 7.3671-44.0535 no no 0.0011 0.8159 0.5514 0.0377 0.0384 0.0271 J002928.80-440306.87.3700
 3654 -44.0519 no no 0.0003 0.8405 0.5668 0.0236 0.0226 0.0136 All Compact Resolved All Compact
 3655 Resolved All Compact Resolved All Compact Resolved 0.9722 0.9955 0.8769 0.9933
 3656 0.9934 0.9658 0.8824 0.9664 0.7950 0.8078 0.9227 0.7677 0.4669 0.0111 0.4249 0.3926 0.2220
 3657 0.5947 0.2077 0.0000 0.1613 0.1876 0.0852 0.4546 0.2264 0.0254 0.2389 0.6275 0.3033 0.6812
 3658 0.1347 0.0857 0.0399 0.3582 0.4854 0.5347 0.0603 0.0007 0.0734 0.0688 0.0141 0.1581 0.0917
 3659 0.0000 0.0399 0.2846 0.1245 0.2833 0.0248 0.0334 0.0301 0.5735 0.5065 0.5265 0.1977 0.1507
 3660 0.0000 0.3334 0.6593 0.3995 0.0173 0.0016 0.0359 0.1056 0.0492 0.1456 0.0000 0.0000 0.0000
 3661 0.0000 0.0000 0.0287 0.0064 0.0049 0.0187 0.1981 0.1534 0.1493 0.0000 0.0000 0.0000 0.1565
 3662 0.1634 0.1284 0.0020 0.0005 0.0239 0.1337 0.1001 0.1310 0.0000 0.0000 0.0358 0.0000 0.0000
 3663 0.0190 0.0008 0.0013 0.0119 0.0280 0.0361 0.0205 0.1171 0.0000 0.0000 0.0873 0.0383 0.0000
 3664 0.0004 0.0014 0.0095 0.0339 0.0408 0.0136 0.0000 0.0000 0.0000 0.1114 0.1480 0.1584

3665 7.5 ATLAS component cross-identifications

3666 This section contains cross-identifications predicted by our cross-identification method
 3667 for each ATLAS radio component in CDFS and ELAIS-S1. Cross-identifications for
 3668 ATLAS-CDFS components are shown in and cross-identifications for ATLAS-ELAIS-S1
 3669 are shown in . For CDFS, the cross-identification for a component in a quadrant is
 3670 predicted using our method with binary classifiers trained on all other quadrants. For
 3671 ELAIS-S1, we show the cross-identifications predicted by our method using binary

3672 classifiers trained on each CDFS quadrant. For CDFS, we also show the Radio Galaxy
3673 Zoo consensus, which is a proxy for the difficulty of cross-identifying a component
3674 (Wong et al., in prep.). These are partial tables, and the full tables are available online
3675 at the *Monthly Notices of the Royal Astronomical Society* website¹.

3676 The columns of the cross-identification tables are defined as follows:

- 3677 • *ATLAS*—ATLAS designation for radio component.
- 3678 • *RA*—Right ascension of radio component (J2000).
- 3679 • *Dec*—Declination of radio component (J2000).
- 3680 • *CID*—Radio Galaxy Zoo component ID.
- 3681 • *Zooniverse ID*—Radio Galaxy Zoo Zooniverse ID.
- 3682 • *Norris/Middleberg*—Designation of SWIRE cross-identification from Norris et al. (2006)
3683 or Middleberg et al. (2008) for CDFS and ELAIS-S1 respectively.
- 3684 • *Norris/Middleberg RA*—Right ascension of SWIRE cross-identification from Norris et al. (2006)
3685 or Middleberg et al. (2008) for CDFS and ELAIS-S1 respectively.
- 3686 • *Norris/Middleberg Dec*—Right ascension of SWIRE cross-identification from Norris et al. (2006)
3687 or Middleberg et al. (2008) for CDFS and ELAIS-S1 respectively.
- 3688 • *RGZ*—Designation of SWIRE cross-identification from Radio Galaxy Zoo (Wong et al., in prep.)
3689 .
- 3690 • *RGZ RA*—Right ascension of SWIRE cross-identification from Radio Galaxy Zoo
3691 (Wong et al., in prep.).
- 3692 • *RGZ Dec*—Right ascension of SWIRE cross-identification from Radio Galaxy Zoo
3693 (Wong et al., in prep.).
- 3694 • *RGZ radio consensus*—Percentage agreement of Radio Galaxy Zoo volunteers on
3695 the radio component configuration.
- 3696 • *RGZ IR consensus*—Percentage agreement of Radio Galaxy Zoo volunteers on the
3697 host galaxy of this radio component.
- 3698 • *C / L / D*—Designation of SWIRE cross-identification made by our method using
3699 classification model *C* trained on label set *L* of *D* candidate host galaxies. *C* may
3700 be ‘CNN’, ‘LR’ or ‘RF’ for CNN, logistic regression or random forests respectively.
3701 *L* may be ‘Norris’ or ‘RGZ’ for expert and Radio Galaxy Zoo labels respectively.
3702 *D* may be ‘All’, ‘Compact’ or ‘Resolved’ for each respective subset defined in .
- 3703 • *C / L / D RA*—Right ascension (J2000) of SWIRE cross-identification made by
3704 our method using classification model *C* trained on label set *L* of *D* candidate
3705 host galaxies. *C*, *L* and *D* are defined as for designation.

- 3706 • $C / L / D$ Dec—Declination (J2000) of SWIRE cross-identification made by our
 3707 method using classification model C trained on label set L of D candidate host
 3708 galaxies. C , L and D are defined as for designation.

3709 Cross-identifications for ATLAS CDFS components. Columns are defined in . Full
 3710 table electronic. ATLAS RA Dec CID Zooniverse ID RA Dec RA Dec radio IR RA Dec
 3711 RA Dec consensus consensus J032602.82-284708.1C 51.5117-28.7856 CI0412 ARG0003rb2
 3712 J032603.15-284708.551.5132-28.7857 0.4516 0.3214 J032615.49-284629.4C 51.5646-28.7749
 3713 CI0614 ARG0003rfr J032615.41-284630.7 51.5642-28.7752 J032615.41-284630.7 51.5642
 3714 -28.7752 0.2941 0.8000 J032615.55-280559.8C 51.5648-28.1000 CI0320 ARG0003r8s J032615.52-280559.8
 3715 51.5647-28.1000 J032615.52-280559.8 51.5647-28.1000 0.5625 0.8333 J032617.35-280710.2C
 3716 51.5723-28.1195 CI0059C1 ARG0003r2j J032617.89-280707.2 51.5746-28.1187 J032617.89-280707.2
 3717 51.5746-28.1187 0.4146 1.0000 J032625.13-280909.8C 51.6047-28.1527 CI0409 ARG0003raz
 3718 J032625.19-280910.1 51.6050-28.1528 J032625.19-280910.1 51.6050-28.1528 0.3158 0.6667
 3719 J032629.10-280650.1C 51.6213-28.1139 CI0963 ARG0003ro4 J032629.13-280650.7 51.6214
 3720 -28.1141 J032626.74-280636.7 51.6114-28.1102 0.3333 1.0000 J032629.61-284052.7C 51.6234
 3721 -28.6813 CI0304 ARG0003r8e J032629.54-284055.8 51.6231-28.6822 J032629.54-284055.8
 3722 51.6231-28.6822 0.2676 1.0000 J032629.92-284753.5C 51.6247-28.7982 CI0120 ARG0003r3w
 3723 J032629.81-284754.4 51.6242-28.7985 J032629.81-284754.4 51.6242-28.7985 1.0000 0.8571
 3724 J032630.66-283657.3C 51.6278-28.6159 CI0172C1 ARG0003r55 J032630.64-283658.0 51.6277
 3725 -28.6161 J032628.56-283744.8 51.619-28.6291 0.3611 0.7308 J032634.59-282022.8C 51.6441
 3726 -28.3397 CI0757 ARG0003rj2 J032634.58-282022.8 51.6441-28.3397 J032631.96-281941.0
 3727 51.6332-28.3281 0.5781 0.5405 RA Dec RA Dec RA Dec RA Dec J032602.36-284711.5
 3728 51.5098-28.7865 J032602.36-284711.5 51.5098-28.7865 J032602.36-284711.5 51.5098-28.7865
 3729 J032602.36-284711.5 51.5098-28.7865 J032615.41-284630.7 51.5642-28.7752 J032615.41-284630.7
 3730 51.5642-28.7752 J032615.41-284630.7 51.5642-28.7752 J032615.41-284630.7 51.5642-28.7752 J032615.52-280559.8
 3731 51.5647-28.1000 J032615.52-280559.8 51.5647-28.1000 J032615.52-280559.8 51.5647-28.1000
 3732 J032615.52-280559.8 51.5647-28.1000 J032617.89-280707.2 51.5746-28.1187 J032617.89-280707.2
 3733 51.5746-28.1187 J032617.89-280707.2 51.5746-28.1187 J032617.89-280707.2 51.5746-28.1187 J032625.19-280910.1
 3734 51.6050-28.1528 J032625.19-280910.1 51.6050-28.1528 J032624.50-280905.9 51.6021-28.1517
 3735 J032625.19-280910.1 51.6050-28.1528 J032629.13-280650.7 51.6214-28.1141 J032629.13-280650.7
 3736 51.6214-28.1141 J032629.13-280650.7 51.6214-28.1141 J032629.13-280650.7 51.6214-28.1141 J032629.54-284051.9
 3737 51.6231-28.6811 J032629.54-284051.9 51.6231-28.6811 J032629.54-284051.9 51.6231-28.6811
 3738 J032629.54-284051.9 51.6231-28.6811 J032629.81-284754.4 51.6242-28.7985 J032629.81-284754.4
 3739 51.6242-28.7985 J032629.81-284754.4 51.6242-28.7985 J032629.81-284754.4 51.6242-28.7985 J032630.64-283658.0
 3740 51.6277-28.6161 J032630.64-283658.0 51.6277-28.6161 J032630.64-283658.0 51.6277-28.6161
 3741 J032630.64-283658.0 51.6277-28.6161 J032634.58-282022.8 51.6441-28.3397 J032634.58-282022.8
 3742 51.6441-28.3397 J032634.58-282022.8 51.6441-28.3397 J032634.58-282022.8 51.6441-28.3397 RA
 3743 Dec RA Dec RA Dec J032604.58-284650.9 51.5191-28.7808 J032602.08-284713.1
 3744 51.5087-28.787 J032602.36-284711.5 51.5098-28.7865 J032602.36-284711.5 51.5098-28.7865 J032615.41-284630.7
 3745 51.5642-28.7752 J032615.41-284630.7 51.5642-28.7752 J032615.41-284630.7 51.5642-28.7752
 3746 J032615.41-284630.7 51.5642-28.7752 J032615.52-280559.8 51.5647-28.1000 J032615.52-280559.8
 3747 51.5647-28.1000 J032615.52-280559.8 51.5647-28.1000 J032615.52-280559.8 51.5647-28.1000 J032615.86-280628.8
 3748 51.5661-28.1080 J032615.16-280742.2 51.5632-28.1284 J032615.86-280628.8 51.5661-28.1080

3749 J032618.84-280722.6 51.5785-28.1230 J032625.19-280910.1 51.6050-28.1528 J032625.19-280910.1
 3750 51.6050-28.1528 J032625.19-280910.1 51.6050-28.1528 J032625.19-280910.1 51.6050-28.1528 J032629.13-
 3751 51.6214-28.1141 J032629.13-280650.7 51.6214-28.1141 J032629.13-280650.7 51.6214-28.1141
 3752 J032629.13-280650.7 51.6214-28.1141 J032629.54-284051.9 51.6231-28.6811 J032629.54-284051.9
 3753 51.6231-28.6811 J032629.54-284051.9 51.6231-28.6811 J032629.54-284051.9 51.6231-28.6811 J032629.81-
 3754 51.6242-28.7985 J032629.81-284754.4 51.6242-28.7985 J032629.81-284754.4 51.6242-28.7985
 3755 J032629.81-284754.4 51.6242-28.7985 J032630.64-283658.0 51.6277-28.6161 J032630.64-283658.0
 3756 51.6277-28.6161 J032630.64-283658.0 51.6277-28.6161 J032630.64-283658.0 51.6277-28.6161 J032634.58-
 3757 51.6441-28.3397 J032634.58-282022.8 51.6441-28.3397 J032634.58-282022.8 51.6441-28.3397
 3758 J032634.58-282022.8 51.6441-28.3397 RA Dec RA Dec RA Dec J032603.15-284708.5
 3759 51.5132-28.7857 J032602.36-284711.5 51.5098-28.7865 J032602.36-284711.5 51.5098-28.7865
 3760 J032602.36-284711.5 51.5098-28.7865 J032615.41-284630.7 51.5642-28.7752 J032615.41-284630.7
 3761 51.5642-28.7752 J032615.41-284630.7 51.5642-28.7752 J032615.41-284630.7 51.5642-28.7752
 3762 J032615.52-280559.8 51.5647-28.1000 J032615.52-280559.8 51.5647-28.1000 J032615.52-280559.8
 3763 51.5647-28.1000 J032615.52-280559.8 51.5647-28.1000 J032617.89-280707.2 51.5746-28.1187
 3764 J032617.89-280707.2 51.5746-28.1187 J032617.89-280707.2 51.5746-28.1187 J032617.89-280707.2
 3765 51.5746-28.1187 J032625.19-280910.1 51.6050-28.1528 J032625.19-280910.1 51.6050-28.1528
 3766 J032625.19-280910.1 51.6050-28.1528 J032625.19-280910.1 51.6050-28.1528 J032629.13-280650.7
 3767 51.6214-28.1141 J032629.13-280650.7 51.6214-28.1141 J032629.13-280650.7 51.6214-28.1141
 3768 J032629.13-280650.7 51.6214-28.1141 J032629.54-284051.9 51.6231-28.6811 J032629.54-284051.9
 3769 51.6231-28.6811 J032629.54-284051.9 51.6231-28.6811 J032629.54-284051.9 51.6231-28.6811
 3770 J032630.12-284751.2 51.6255-28.7976 J032629.81-284754.4 51.6242-28.7985 J032629.81-284754.4
 3771 51.6242-28.7985 J032629.81-284754.4 51.6242-28.7985 J032630.64-283658.0 51.6277-28.6161
 3772 J032630.64-283658.0 51.6277-28.6161 J032630.64-283658.0 51.6277-28.6161 J032630.64-283658.0
 3773 51.6277-28.6161 J032634.58-282022.8 51.6441-28.3397 J032634.58-282022.8 51.6441-28.3397
 3774 J032634.58-282022.8 51.6441-28.3397 J032634.58-282022.8 51.6441-28.3397

3775 Cross-identifications for ATLAS ELAIS-S1 components. Columns are defined in
 3776 . Full-table electronic. ATLAS RA Dec CID Zooniverse ID RA Dec RA Dec radio
 3777 IR RA Dec RA Dec consensus consensus J002925.68-440256.8 7.3570-44.0491-C0375
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 3779 7.4087-43.4967 J002940.13-440309.2 7.4172-44.0526 C0374 J002940.19-440309.6 7.4175
 3780 -44.0527 J002943.14-440812.3 7.4298-44.1368 C0302 J002943.15-440813.6 7.4298-44.1371
 3781 J002944.51-433627.8 7.4355-43.6077 C0727 J002944.36-433630.2 7.4348-43.6084 J002945.31-432148.5
 3782 7.4388-43.3635 C0943.1 J002945.64-432149.3 7.4402-43.3637 J002946.14-432149.1 7.4423
 3783 -43.3637 C0943 J002945.64-432149.3 7.4402-43.3637 J002949.89-440541.4 7.4579-44.0948
 3784 C0345 J002951.13-432354.3 7.4631-43.3984 C0924 J002951.14-432355.3 7.4631-43.3987
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 3794 7.4402-43.3637 J002945.64-432149.3 7.4402-43.3637 J002945.64-432149.3 7.4402-43.3637
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 3797 7.4644-44.0962 J002951.44-440546.1 7.4644-44.0962 J002951.44-440546.1 7.4644-44.0962
 3798 J002951.44-440546.1 7.4644-44.0962 J002951.14-432355.3 7.4631-43.3987 J002951.14-432355.3
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 3800 7.4636-44.0990 J002951.44-440546.1 7.4644-44.0962 J002951.51-440617.1 7.4646-44.1048
 3801 J002951.44-440546.1 7.4644-44.0962 RA Dee RA Dee RA Dee J002925.73-440256.2
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 3803 J002925.73-440256.2 7.3572-44.0490 J002938.07-432947.9 7.4087-43.4967 J002938.07-432947.9
 3804 7.4087-43.4967 J002938.07-432947.9 7.4087-43.4967 J002938.07-432947.9 7.4087-43.4967 J002940.19-440309.6
 3805 7.4175-44.0527 J002940.19-440309.6 7.4175-44.0527 J002940.19-440309.6 7.4175-44.0527
 3806 J002940.19-440309.6 7.4175-44.0527 J002943.15-440813.6 7.4298-44.1371 J002943.15-440813.6
 3807 7.4298-44.1371 J002943.15-440813.6 7.4298-44.1371 J002943.15-440813.6 7.4298-44.1371 J002944.36-433630.2
 3808 7.4348-43.6084 J002944.36-433630.27.4348-43.6084 J002944.36-433630.27.4348-43.6084
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 3812 J002945.64-432149.3 7.4402-43.3637 J002951.26-440556.4 7.4636-44.0990 J002951.26-440556.4
 3813 7.4636-44.0990 J002951.26-440556.4 7.4636-44.0990 J002951.26-440556.4 7.4636-44.0990 J002951.14-432355.3
 3814 7.4631-43.3987 J002951.14-432355.3 7.4631-43.3987 J002951.14-432355.3 7.4631-43.3987
 3815 J002951.14-432355.3 7.4631-43.3987 J002951.26-440556.4 7.4636-44.0990 J002951.26-440556.4
 3816 7.4636-44.0990 J002951.26-440556.4 7.4636-44.0990 J002951.26-440556.4 7.4636-44.0990 RA
 3817 Dee RA Dee RA Dee J002925.73-440256.2 7.3572-44.0490 J002925.73-440256.2 7.3572-44.0490
 3818 7.3572-44.0490 J002925.73-440256.2 7.3572-44.0490 J002925.73-440256.2 7.3572-44.0490
 3819 J002938.07-432947.9 7.4087-43.4967 J002938.07-432947.9 7.4087-43.4967 J002938.07-432947.9
 3820 7.4087-43.4967 J002938.07-432947.9 7.4087-43.4967 J002940.19-440309.6 7.4175-44.0527
 3821 J002940.19-440309.6 7.4175-44.0527 J002940.19-440309.6 7.4175-44.0527 J002940.19-440309.6
 3822 7.4175-44.0527 J002943.15-440813.6 7.4298-44.1371 J002943.15-440813.6 7.4298-44.1371
 3823 J002943.15-440813.6 7.4298-44.1371 J002943.15-440813.6 7.4298-44.1371 J002944.36-433630.2
 3824 7.4348-43.6084 J002944.36-433630.27.4348-43.6084 J002944.36-433630.27.4348-43.6084
 3825 J002944.36-433630.27.4348-43.6084 J002945.64-432149.3 7.4402-43.3637 J002945.64-432149.3
 3826 7.4402-43.3637 J002945.64-432149.3 7.4402-43.3637 J002945.64-432149.3 7.4402-43.3637
 3827 J002945.64-432149.3 7.4402-43.3637 J002945.64-432149.3 7.4402-43.3637 J002945.64-432149.3
 3828 7.4402-43.3637 J002945.64-432149.3 7.4402-43.3637 J002951.26-440556.4 7.4636-44.0990
 3829 J002951.26-440556.4 7.4636-44.0990 J002949.13-440536.5 7.4547-44.0935 J002949.13-440536.5
 3830 7.4547-44.0935 J002951.14-432355.3 7.4631-43.3987 J002951.14-432355.3 7.4631-43.3987
 3831 J002951.14-432355.3 7.4631-43.3987 J002951.14-432355.3 7.4631-43.3987 J002951.26-440556.4
 3832 7.4636-44.0990 J002951.26-440556.4 7.4636-44.0990 J002951.26-440556.4 7.4636-44.0990
 3833 J002951.26-440556.4 7.4636-44.0990

3834 7.5 Cross-identification figures

3835 This section contains figures of our cross-identifications of each ATLAS radio component
 3836 in CDFS and ELAIS-S1, and was originally an appendix to Alger et al. (2018). These
 3837 are just five examples, but all 469 examples are available online at the *Monthly Notices*
 3838 of the Royal Astronomical Society website¹.

3839 One resolved component and resolved source. Three resolved components comprising
 3840 one resolved source. Three resolved components comprising one resolved source.
 3841 Three resolved components comprising one resolved source. Two compact components,
 3842 each a compact source. Examples of resolved sources with high disagreement between
 3843 cross-identifiers. The contours show ATLAS radio data and start at 4σ , increasing
 3844 geometrically by a factor of 2. The background image is the SWIRE image. Binary
 3845 classifier model/training set combinations are denoted $C(S)$ where C is the binary
 3846 classifier model and S is the training set. ‘LR’ is logistic regression, ‘CNN’ is convolutional
 3847 neural networks, and ‘RF’ is random forests. ‘Norris’ refers to the expert labels and
 3848 ‘RGZ’ refers to the Radio Galaxy Zoo labels. The cross-identification made by nearest
 3849 neighbours is shown by ‘NN’. The complete set of figures for 469 examples is available
 3850 in the supplementary information online.

3851 7.5 Sankey diagrams

3852 This section presents Sankey diagrams showing the filtering of components and sources
 3853 from the full FIRST sample in, and was originally an appendix to Alger et al. (in prep.)
 3854 . A Sankey diagram shows the order and number of objects removed from a sample.
 3855 shows the filtering of components and shows the filtering of sources. The component
 3856 filters are ‘Bad FIRST’ for components on the edge of FIRST with incomplete images,
 3857 ‘Sidelobe’ for components with high sidelobe probability, ‘Low score’ for components
 3858 with only low-scoring candidate hosts, ‘Faint’ for components with less than 10 signal-to-noise
 3859 according to the FIRST catalogue, and ‘Compact’ for components that do not have
 3860 extended radio emission according to . Sources were removed after each component
 3861 filter if they no longer contained any components.

3862 Number of components removed from FIRST by each filter.

3863 Number of sources removed by each filter.

3864 7.5 Radio luminosity function

3865 We computed the radio luminosity function following the $1/V_{\max}$ method (Schmidt, 1968)
 3866 . This appendix explains our implementation in and was originally an appendix to
 3867 Alger et al. (in prep.). We performed the following steps:

- 3868 1. Remove all radio sources that do not fit the selection criteria. This applies for
 3869 both radio and infrared properties, so we choose a minimum radio flux density

3870 f_{\min} and a maximum infrared magnitude m_{\max} , as well as redshift limits z_{lower}
 3871 and z_{upper} .

2. For each source, compute the maximum redshift that the source could have been observed within the selection criteria. We find this redshift by first numerically solving for z with L as the luminosity of each radio source and $f = f_{\min}$ to obtain the maximum redshift z_{radio} at which the source could be observed in radio. We find the maximum redshift z_{ir} that the host galaxy could be observed within the selection criteria by numerically solving for z , where $d(z)$ is the luminosity distance at a redshift z , d is the luminosity distance of the host galaxy, and m is the apparent magnitude of the host galaxy.

$$5 \log_{10} \left(\frac{d(z)}{d} \right) + m = m_{\max}$$

3872 The maximum redshift that the source could have been observed within the
 3873 selection criteria is then $z_{\max} = \min(z_{\text{ir}}, z_{\text{radio}}, z_{\text{upper}})$.

3. For each source, compute the comoving volume V_{\max} at redshift z_{\max} .
4. The count for each luminosity bin is the sum over $1/V_{\max}$ for each source in the bin. We account for the fact FIRST does not cover the whole sky by multiplying by the total area of the sky divided by the area of our selection.

3878 After computing the luminosity function, we estimate the uncertainty in each bin
 3879 using Poisson statistics, \sqrt{N} for a bin count N .

3880 7.5 Redshift completeness estimate

3881 shows the estimated completeness of our RLF sample in as a function of $W1$ and
 3882 $W1 - W2$. We followed the same method as Pracy et al. (2016) for this estimation,
 3883 averaging completeness over circles centred on each source. Each source is associated
 3884 with a circle of radius equal to the distance to its 50th nearest neighbour in the $W1$ and
 3885 $W1 - W2$ plane. This appendix was originally part of Alger et al. (in prep.).

3886 Estimated completeness as a function of mid-infrared colour and magnitude.

3887 7.5 Giant radio galaxies

3888 Giant radio galaxies found in RGZ. Ex. ‘LLS’ is the projected linear size of the source as
 3889 measured by the maximum angular distance between radio components. The RA/Dec
 3890 are the coordinates of the host galaxy. s/p indicates spectroscopic/photometric redshift.
 3891 ^LExisting in literature. ^RAlso found by RGZ citizen scientists. [†]Misidentified SDSS
 3892 host, manually corrected to obtain redshift. AllWISE host (WISEA) RA (J2000) Dec
 3893 ($J2000$) z LLS (Mpc) J004210.18-080011.3 10.54-8.00 0.65 \pm 0.14 1.6 p J021008.48+011839.6^L
 3894 32.54 1.31 0.86524 \pm 0.0001 1.2 s J075858.29+355643.6^R 119.74 35.95 0.74748 \pm 0.00013

3895 ~~1.0 sJ080831.68+473523.9^R 122.13 47.59 0.58854 ± 0.00016 1.1 sJ083034.78+231124.6 127.64~~
 3896 ~~23.19 0.94 ± 0.13 1.1 pJ090604.03+011114.2 136.52 1.19 0.7975 ± 0.0004 1.6 sJ093256.81+074212.2~~
 3897 ~~143.24 7.70 1.0032 ± 0.0003 1.1 sJ093526.80+051729.8^R 143.86 5.29 0.84 ± 0.04 1.2 pJ094238.72+114337.9~~
 3898 ~~145.66 11.73 0.49 ± 0.05 1.2 pJ094835.60+535946.4^R 147.15 54.00 0.64 ± 0.10 1.2 pJ095706.12+292439.2~~
 3899 ~~149.28 29.41 0.71 ± 0.12 1.5 pJ102335.25+433208.0 155.90 43.54 0.75 ± 0.09 1.5 pJ102933.99+210345.8^R~~
 3900 ~~157.39 21.06 0.82407 ± 0.00008 1.1 sJ103043.98+355451.2^R 157.68 35.91 0.64074 ± 0.00008~~
 3901 ~~1.2 sJ104449.92+234525.6[†] 161.20 23.76 0.57712 ± 0.00009 1.6 sJ110655.98+624759.8^R~~
 3902 ~~166.73 62.80 0.84379 ± 0.00004 1.1 sJ112900.68+635543.2 172.25 63.93 0.71 ± 0.06 1.1~~
 3903 ~~pJ112948.20+243922.6 172.45 24.66 0.79 ± 0.07 1.1 pJ114553.67-003304.7 176.47 -0.55~~
 3904 ~~2.0522 ± 0.0006 1.3 sJ121111.26+534840.4 182.80 53.81 0.74 ± 0.14 1.1 pJ121152.04+304232.4^R~~
 3905 ~~182.97 30.71 0.47102 ± 0.00012 1.3 sJ121944.73+174121.3 184.94 17.69 1.5129 ± 0.0009~~
 3906 ~~1.0 sJ123735.89+544814.4^R 189.40 54.80 1.0271 ± 0.0006 1.2 sJ123819.16+113444.8 189.58~~
 3907 ~~11.58 0.80 ± 0.08 1.2 pJ123846.84-032857.5[†] 189.70 -3.48 0.67 ± 0.07 1.5 pJ131625.00+272042.8~~
 3908 ~~199.10 27.35 0.69092 ± 0.00004 1.0 sJ133307.00+045048.6^R 203.28 4.85 1.40534 ± 0.00016~~
 3909 ~~1.1 sJ141933.36+104706.4^R 214.89 -10.79 0.33973 ± 0.00003 1.0 sJ142008.45+185422.7^R~~
 3910 ~~215.04 18.91 0.63 ± 0.04 1.4 pJ145057.28+530007.7^L 222.74 53.00 0.91662 ± 0.00009 1.3~~
 3911 ~~sJ150012.18+604941.3 225.05 60.83 1.6626 ± 0.0007 1.2 sJ153547.13+432245.0^R 233.95~~
 3912 ~~43.38 0.63891 ± 0.00007 1.3 sJ154631.18+194819.9 236.63 19.81 0.5917 ± 0.0002 1.4 sJ160852.10+561110.7~~
 3913 ~~242.22 56.19 1.3196 ± 0.0003 1.3 sJ162200.48+364044.0 245.50 36.68 1.9994 ± 0.0002 1.1~~
 3914 ~~sJ163004.35+103321.9^R 247.52 10.56 0.85 ± 0.09 1.2 pJ163125.75+200224.1^R 247.86 20.04~~
 3915 ~~0.62662 ± 0.00013 1.0 sJ165055.46+394446.6 252.73 39.75 0.58829 ± 0.00013 1.1 sJ232410.33+045309.6~~
 3916 ~~351.04 4.89 0.76 ± 0.06 1.4 pJ234440.02-003231.6 356.17 -0.54 0.5014 ± 0.0001 1.0 s~~

3917 This appendix describes our search for giant radio galaxies in RGZ-Ex, and the
 3918 results of this search. It was originally an appendix to Alger et al. (in prep.). To identify
 3919 radio sources we assumed that if any two components had the same host galaxy then
 3920 they were part of the same source. This is a reasonable assumption if all host galaxies
 3921 are correctly identified, which was not the case. This assumption therefore introduced
 3922 spurious sources due to galaxies incorrectly identified as host galaxies: not all sources
 3923 used in are real sources, and in particular sources of large angular size are likely to be
 3924 incorrect. Nevertheless RGZ-Ex provides a useful catalogue of *candidate* radio sources,
 3925 and visual follow-up can confirm whether sources of interest are real.

3926 H.A. and M.J.A. examined all 296 candidate sources in the RGZ-Ex catalogue with
 3927 an estimated physical extent larger than 1 Mpc. Of these, 40 were real giant radio
 3928 galaxies, which we show in . We defined ‘giant radio galaxy’ as a radio galaxy with
 3929 emission extended to physical sizes ≥ 1.0 Mpc. Other thresholds, such as 0.7 Mpc,
 3930 also exist in literature. The physical extents of the remaining 256 candidate sources
 3931 were overestimated mostly due to sidelobes/artefacts (103), incorrect source grouping
 3932 (82), or incorrect SDSS matches (21). The citizen scientists who identified giants are:
 3933 WizardHowl, DolorousEdd, antikodon, csunjoto, sisifolibre, JeanTate, JKD, PADV, and
 3934 firejuggler. H.A., together with his summer students, had previously identified 29 of
 3935 these giants.

3936 Note that this is a particularly challenging set: sources that are misidentified will
 3937 often have unusually large estimated extents due to the inclusion of spurious components.
 3938 The error rate in this set therefore does not reflect the rest of the catalogue.

3939 7.5 Visual verification results

3940 In we described our visual verification of the BXID method from . We list the radio
 3941 components in the verification set in . Each row of the table contains the FIRST component,
 3942 its AllWISE host galaxy according to BXID, and whether the association is correct
 3943 according to our visual verification. If an author was particularly unsure about an
 3944 object, they were able to skip this object, and so are not accounted for in the verification
 3945 for that object. Verification was weighted by the Dawid and Skene (1979) maximum
 3946 likelihood model. This appendix was originally part of (Alger et al., in prep.).

3947 Validation objects. ‘Agree’ is whether or not the authors of Alger et al. (in prep.)
 3948 agreed with BXID associating the given FIRST object with the given AllWISE object.
 3949 FIRST AllWISE AgreeJ000234.9-001421 J000242.35-001320.5 nJ002841.1+141654 J002840.37+141652.7
 3950 yJ003731.4+000156 J003731.26+000146.7 yJ005407.5-011158 J005407.61-011158.9 yJ011210.3+002203
 3951 J011210.41+002201.9 yJ012342.4+015849 J012342.24+015850.4 yJ013015.1+110653 J013015.16+110653.4
 3952 yJ013107.7+070343 J013102.02+070332.0 yJ014247.9-000039 J014247.81-000040.3 yJ014250.0-000032
 3953 J014247.81-000040.3 nJ020222.3+030138 J020223.20+030150.4 yJ020333.8+000853 J020336.94+000759.3
 3954 yJ021840.1-032311 J021840.13-032306.0 yJ023022.0+010834 J023022.11+010840.0 yJ024245.3-022535
 3955 J024245.35-022534.6 yJ025901.0+005350 J025901.50+005346.1 yJ033204.1-004757 J033204.15-004757.1
 3956 yJ073033.2+390413 J073033.21+390412.9 yJ073954.1+481810 J073954.87+481759.5 yJ074504.9+331247
 3957 J074504.81+331256.2 yJ074640.4+421709 J074640.45+421709.1 yJ074707.9+171719 J074708.35+171726.5
 3958 yJ075043.6+274838 J075043.35+274844.8 nJ075050.3+331937 J075051.25+331905.0 yJ075422.2+311253
 3959 J075422.35+311252.5 yJ075637.0+212006 J075636.65+212001.4 yJ082326.1+141438 J082326.34+141435.9
 3960 yJ082422.5+351121 J082422.65+351114.6 yJ082925.9+462618 J082926.02+462618.5 yJ083512.4+175441
 3961 J083512.45+175441.1 yJ084133.5+402035 J084133.40+402042.8 yJ084238.4+405305 J084238.38+405306.6
 3962 nJ084417.3+315845 J084417.92+315845.9 yJ084728.5+360700 J084728.24+360714.6 yJ084905.5+111448
 3963 J084905.51+111447.8 yJ085236.8+262006 J085236.11+262013.4 yJ085415.6+524930 J085415.62+524936.7
 3964 yJ090623.2+300746 J090622.87+300743.9 yJ091745.1+275049 J091745.89+275103.8 yJ091752.0+431614
 3965 J091752.14+431612.7 yJ092014.4+302907 J092013.95+302859.3 yJ092140.5+540118 J092140.24+540121.1
 3966 yJ092213.0+542157 J092213.03+542157.2 yJ092406.9+562703 J092406.47+562656.2 yJ092713.1+105841
 3967 J092713.14+105839.8 yJ093108.6+613447 J093108.63+613447.2 yJ093239.6+052308 J093237.71+052240.7
 3968 nJ093627.8+103610 J093627.87+103609.7 yJ093645.2+561435 J093645.89+561434.2 yJ094006.8+482651
 3969 J094006.92+482649.2 yFIRST AllWISE AgreeJ094009.5+600403 J094011.55+600357.6 nJ094023.7+135123
 3970 J094023.73+135125.2 yJ094324.5+435341 J094324.61+435342.0 yJ094650.8+382015 J094650.44+382010.9
 3971 yJ095011.8+455319 J095011.82+455320.0 yJ095113.5+180211 J095113.82+180204.2 nJ095242.4+222638
 3972 J095242.45+222638.0 yJ095538.7+013546 J095539.20+013546.1 yJ095609.9+363441 J095609.30+363445.4
 3973 yJ095811.8+225056 J095811.90+225055.5 yJ100019.2+263516 J100018.84+263527.5 yJ101315.9+064520
 3974 J101316.51+064519.0 yJ101455.2-004716 J101455.30-004718.3 yJ102153.5+260429 J102153.52+260429.6
 3975 yJ102354.7+390653 J102354.88+390654.0 yJ102620.4+303600 J102620.46+303550.4 yJ102710.4+460254
 3976 J102714.81+460256.4 nJ102955.9+424906 J102955.96+424906.7 yJ103503.9+102404 J103503.92+102403.6
 3977 yJ103839.9+331200 J103839.94+331201.1 yJ104030.5+211624 J104031.09+211620.6 nJ104533.8+430025
 3978 J104535.22+430020.8 yJ104907.5+322903 J104907.91+322906.6 yJ105146.9+552257 J105147.40+552308.4
 3979 yJ105257.5+105418 J105257.53+105421.5 yJ105521.6+372641 J105521.24+372652.4 yJ105758.8+321605
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 4029 y J232410.1+001315 J232410.15+001314.5 y J234727.9-000919 J234727.65-000912.9 y

4030 7.5 2-Wasserstein begets Faraday moments

Minimising the 2-Wasserstein distance between a model FDF and the simple manifold gives the second Faraday moment of that FDF. This appendix demonstrates that fact, and was originally part of Alger et al. (2021). Let \tilde{F} be the sum-normalised model FDF and let \tilde{S} be the sum-normalised simple model FDF:

$$\begin{aligned}\tilde{F}(\phi) &= \frac{A_0\delta(\phi - \phi_0) + A_1\delta(\phi - \phi_1)}{A_0 + A_1} \\ \tilde{S}(\phi; \phi_w) &= \delta(\phi - \phi_w).\end{aligned}$$

The W_2 distance, usually defined on probability distributions, can be extended to one-dimensional complex functions A and B by normalising them:

$$\begin{aligned}D_{W_2}(A \parallel B)^2 &= \inf_{\gamma \in \Gamma(A, B)} \iint_{\phi_{\min}}^{\phi_{\max}} |x - y|^2 d\gamma(x, y) \\ \tilde{A}(\phi) &= \frac{|A(\phi)|}{\int_{\phi_{\min}}^{\phi_{\max}} |A(\theta)| d\theta} \\ \tilde{B}(\phi) &= \frac{|B(\phi)|}{\int_{\phi_{\min}}^{\phi_{\max}} |B(\theta)| d\theta}\end{aligned}$$

4031 where $\Gamma(A, B)$ is the set of couplings of A and B , i.e. the set of joint probability distributions
 4032 that marginalise to A and B ; and $\inf_{\gamma \in \Gamma(A, B)}$ is the infimum over $\Gamma(A, B)$. This can be
 4033 interpreted as the minimum cost to ‘move’ one probability distribution to the other,
 4034 where the cost of moving one unit of probability mass is the squared distance it is
 4035 moved.

The set of couplings $\Gamma(\tilde{F}, \tilde{S})$ is the set of all joint probability distributions γ such that

$$\begin{aligned}\int_{\phi_{\min}}^{\phi_{\max}} \gamma(\phi, \varphi) d\phi &= \tilde{S}(\varphi; \phi_w), \\ \int_{\phi_{\min}}^{\phi_{\max}} \gamma(\phi, \varphi) d\varphi &= \tilde{F}(\phi).\end{aligned}$$

The coupling that minimises the integral in will be the optimal transport plan between

\tilde{F} and \tilde{S} . Since \tilde{F} and \tilde{S} are defined in terms of delta functions, the optimal transport problem reduces to a discrete optimal transport problem and the optimal transport plan is:

$$\gamma(\phi, \varphi) = \frac{A_0\delta(\phi - \phi_0) + A_1\delta(\phi - \phi_1)}{A_0 + A_1}\delta(\varphi - \phi_w).$$

In other words, to move the probability mass of \tilde{S} to \tilde{F} , a fraction $A_0/(A_0 + A_1)$ is moved from ϕ_w to ϕ_0 and the complementary fraction $A_1/(A_0 + A_1)$ is moved from ϕ_w to ϕ_1 . Then:

$$\begin{aligned} D_{W_2}(\tilde{F} \parallel \tilde{S})^2 &= \iint_{\phi_{\min}}^{\phi_{\max}} |\phi - \varphi|^2 d\gamma(\phi, \varphi) \\ &= \frac{A_0(\phi_0 - \phi_w)^2 + A_1(\phi_1 - \phi_w)^2}{A_0 + A_1}. \end{aligned}$$

To obtain the W_2 distance to the simple manifold, we need to minimise this over ϕ_w . Differentiate with respect to ϕ_w and set equal to zero to find

$$\phi_w = \frac{A_0\phi_0 + A_1\phi_1}{A_0 + A_1}.$$

Substituting this back in, we find

$$D_{W_2}(F)^2 = \frac{A_0 A_1}{A_0 + A_1} (\phi_0 - \phi_1)^2$$

4036 which is the Faraday moment.

4037 7.5 Euclidean distance in the no-RMSF case

In this appendix, originally from Alger et al. (2021), we calculate the minimised Euclidean distance evaluated on a model FDF (). Let \tilde{F} be the sum-normalised model FDF and let \tilde{S} be the normalised simple model FDF:

$$\tilde{F}(\phi) = \frac{A_0\delta(\phi - \phi_0) + A_1\delta(\phi - \phi_1)}{A_0 + A_1}$$

$$\tilde{S}(\phi; \phi_e) = \delta(\phi - \phi_e).$$

The Euclidean distance between \tilde{F} and \tilde{S} is then

$$\begin{aligned} & D_E(\tilde{F}(\phi) \parallel \tilde{S}(\phi; \phi_e))^2 \\ &= \int_{\phi_{\min}}^{\phi_{\max}} |\tilde{F}(\phi) - \delta(\phi - \phi_e)|^2 d\phi. \end{aligned}$$

Assume $\phi_0 \neq \phi_1$ (otherwise, D_E will always be either 0 or 2). If $\phi_e = \phi_0$, then

$$\begin{aligned} & D_E(\tilde{F}(\phi) \parallel \tilde{S}(\phi; \phi_e))^2 \\ &= \frac{1}{(A_0 + A_1)^2} \int_{\phi_{\min}}^{\phi_{\max}} A_1^2 |\delta(\phi - \phi_1) - \delta(\phi - \phi_0)|^2 d\phi \\ &= \frac{2A_1^2}{(A_0 + A_1)^2} \end{aligned}$$

and similarly for $\phi_e = \phi_1$. If $\phi_e \neq \phi_0$ and $\phi_e \neq \phi_1$, then

$$D_E(\tilde{F}(\phi) \parallel \tilde{S}(\phi; \phi_e))^2 = \frac{A_0^2 + A_1^2 + 1}{(A_0 + A_1)^2}.$$

The minimised Euclidean distance when $\phi_0 \neq \phi_1$ is therefore

$$\begin{aligned} D_E(F) &= \min_{\phi_e \in \mathbb{R}} D_E(F(\phi) \parallel F_{\text{simple}}(\phi; \phi_e)) \\ &= \sqrt{2} \frac{\min(A_0, A_1)}{A_0 + A_1}. \end{aligned}$$

4038 If $\phi_0 = \phi_1$, then the minimised Euclidean distance is 0.

4039 7.5 Hyperparameters for LR and XGB

4040 This section contains tables of the hyperparameters that we used for our classifiers in
 4041 and was originally an appendix to Alger et al. (2021). and tabulate the hyperparameters
 4042 for XGB and LR respectively for the ‘ATCA’ dataset. and tabulate the hyperparameters
 4043 for XGB and LR respectively for the ‘ASKAP’ dataset.

4044 XGB hyperparameters for the ‘ATCA’ dataset. Parameter Value colsample_bytree
 4045 0.912 gamma 0.532 learning_rate 0.1 max_depth 7 min_child_weight 2 scale_pos_weight
 4046 1 subsample 0.557 n_estimators 135 reg_alpha 0.968 reg_lambda 1.420

4047 LR hyperparameters for the ‘ATCA’ dataset. Parameter Value penalty L1 C 1.668

4048 XGB hyperparameters for the ‘ASKAP’ dataset. Parameter Value colsample_bytree
 4049 0.865 gamma 0.256 learning_rate 0.1 max_depth 6 min_child_weight 1 scale_pos_weight
 4050 1 subsample 0.819 n_estimators 108 reg_alpha 0.049 reg_lambda 0.454

4051 LR hyperparameters for the ‘ASKAP’ dataset. Parameter Value penalty L2C 0.464

4052 7.5 Predictions on real data

4053 This appendix, originally part of Alger et al. (2021), contains and . These show the
 4054 predicted probability of being Faraday complex for all real data used in , drawn from
 4055 Livingston et al. (2021) and O’Sullivan et al. (2017).

4056 The 142 observed FDFs ordered by LR-estimated probability of being Faraday complex.
 4057 Livingston-identified components are shown in orange while O’Sullivan-identified components
 4058 are shown in magenta. Simpler FDFs (as deemed by the classifier) are shown in purple
 4059 while more complex FDFs are shown in green, and the numbers overlaid indicate the
 4060 LR estimate. A lower number indicates a lower probability that the corresponding
 4061 source is complex, i.e. lower numbers correspond to simpler spectra.

4062 The 142 observed FDFs ordered by XGB-estimated probability of being Faraday
 4063 complex. Livingston-identified components are shown in orange while O’Sullivan-identified
 4064 components are shown in magenta. Simpler FDFs (as deemed by the classifier) are
 4065 shown in purple while more complex FDFs are shown in green, and the numbers
 4066 overlaid indicate the XGB estimate. A lower number indicates a lower probability
 4067 that the corresponding source is complex, i.e. lower numbers correspond to simpler
 4068 spectra.

4069 7.5 Simulating observed FDFs

This appendix was originally part of Alger et al. (2021) and describes how we simulated FDFs in . We simulated FDFs by approximating them by arrays of complex numbers. An FDF F is approximated on the domain $[-\phi_{\max}, \phi_{\max}]$ by a vector $\vec{F} \in \mathbb{R}^d$:

$$\vec{F}_j = \sum_{k=0}^1 A_k \delta(-\phi_{\max} + j\delta\phi - \phi_k)$$

where $\delta\phi = (\phi_{\max} - \phi_{\min})/d$ and d is the number of Faraday depth samples in the FDF. \vec{F} is sampled by uniformly sampling its parameters:

$$\underline{\phi_k \in [\phi_{\min}, \phi_{\min} + \delta\phi, \dots, \phi_{\max}]}$$

$$\underline{A_k \sim \mathcal{U}(0, 1)}.$$

We then generate a vector polarisation spectrum $\vec{P} \in \mathbb{R}^m$ from \vec{F} using a :

$$\vec{P}_{\ell} = \sum_{j=0}^j F_j e^{2i(\phi_{\min} + j\delta\phi)\lambda_{\ell}^2} d\phi.$$

λ_ℓ^2 is the discretised value of λ^2 at the ℓ th index of \vec{P} . This requires a set of λ^2 values, which depends on the dataset being simulated. These values can be treated as the channel wavelengths at which the polarisation spectrum was observed. We then add Gaussian noise with variance σ^2 to each element of \vec{P} to obtain a discretised noisy observation $\hat{\vec{P}}$. Finally, we perform RM synthesis using the Canadian Initiative for Radio Astronomy Data Analysis RM package¹, which is a Python module that implements a discrete version of RM synthesis:

$$\hat{F}_j = m^{-1} \sum_{\ell=1}^m \vec{P}_\ell e^{-2i(\phi_{\min} + j\delta_\phi)\lambda_\ell^2}.$$

REVISION DRAFT

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