Ideas for Citizen Science in Astronomy

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Abstract

We review the expanding, newly internet-enabled, and rapidly-evolving field of citizen science, focusing on research projects in stellar, extragalactic and planetary astronomy that have benefited from the participation of members of the public, often in large numbers. We find these volunteers making contributions to astronomy in a variety of ways: making and analyzing new observations, visually classifying features in images and light curves, exploring models constrained by astronomical datasets, and initiating new scientific enquiries. The most productive citizen astronomy projects involve close collaboration between the professionals and amateurs involved, and occupy scientific niches not easily filled by great observatories or machine learning methods: citizen astronomers are typically motivated by being of service to science, as well as an interest in the subject. In the coming years we expect participation and productivity in citizen astronomy to increase, as survey datasets get larger and citizen science platforms become more efficient. Opportunities include engaging the public in ever more advanced analyses, and facilitating citizen-led enquiry by designing professional user interfaces and analysis tools with citizens in mind.

CONTENTS

1 INTRODUCTION

The term "citizen science" refers to the activities of people who are not paid to carry out scientific research ("citizens"), but who make intellectual contributions to scientific research nonetheless.[1] Citizen scientists come from all walks of life, and their contributions are diverse, both in type and research area. This review is about the astronomy projects they have participated in to date, the tasks they have performed, and how astronomy has benefited – and could benefit further – from their efforts.

The earliest example of collaboration between professional and amateur astronomers seems to have been Edmund Halley's call for observations of the 1715 total eclipse of the Sun which crossed central England (Halley 1716).[2] Since then there has been a long tradition of amateur observers making important discover-

[1]In this review we differentiate between the data collection and data analysis to which citizens contribute, and distributed "grid" computing farmed out to processors owned by citizens. We omit the latter since it does not fit our definition of citizen science as involving *intellectual* contributions from citizens; the Oxford English Dictionary defines citizen science as "*scientific work* undertaken by members of the general public, often in collaboration with or under the direction of professional scientists and scientific institutions" (our emphasis).

[2]Citizen observations proved useful; Halley's colleagues at Oxford were clouded out, and those in Cambridge were "oppressed by too much Company, so that, though the heavens were very favourable, [they] missed both the time of the beginning of the Eclipse and that of total darkness."

ies and significant sustained contributions. However, the advent of the world wide web has changed the face of professional and amateur collaboration, providing new opportunities and accelerating the sharing of information. People are now connected to each other on a scale that has never happened before. Citizens can interact with professional scientists via a range of media, including purpose-built citizen science websites which increase the potential for shared data analysis and exploration, as well as for data collection. Meanwhile, communities of citizens have sprung into existence as like-minded people have been able to find and talk to each other in a way that is almost independent of their geographical location. The result has been an exponential increase in citizen involvement in science. The field is evolving very quickly, with more and more professional scientists becoming aware of the possibilities offered by collaborating with, for example, specialists operating outside the usual parameters of professional astronomical observation, or tens of thousands of people eager to perform microtasks in their spare time.

Our aim in this work is to review the astronomical (and occasionally wider) literature for productive citizen science projects, and distill the characteristics that made these case studies successful. As our title states, this is a review of ideas for astronomy: we will look forward as well as back, and try to answer the following questions. What are the particular niches that citizen science fills, in our field? What traits do successful citizen astronomy projects share? What is the potential of citizen science in astronomy, and how can it be realized? Citizen science has a significant impact on its participants, whether they be sitting in a university office or in front of a home computer or mobile phone screen.

This review is organised as follows. Astronomy research typically starts with observations: so do we, in Section 2. We then proceed to consider visual classification, data modeling and finally citizen-led enquiry in Sections 3–5. With this overview in place, we take a look in Section 6 at the population of citizens who take part in astronomical research. In Section 7 we speculate on potential citizen contributions to astronomy in the future, and finish with some concluding remarks in Section 8.

2 AMATEUR OBSERVING

There is currently an active community of well-equipped amateur observers making astronomical observations of great utility. The steady improvements and increasing affordability of digital technology, in addition to the ease of data sharing and communications, have considerably expanded the realm of amateur astronomy in the past two decades. Meanwhile, professional observatories are always over-subscribed, with resources necessarily being divided between particular areas of sky, or samples of objects, or on a few astronomical questions: tuning the parameters of professional observations to optimize all possible scientific enquiries would seem an impossible task. What types of niches does this leave for amateur observers to fill? What are the strengths that amateur observers can play to?

Discovery and characterisation of asteroids and comets. Small solar system objects moving against the fixed-star background can be detected in a set of CCD frames either by eye or by automated software. Targets include near-earth asteroids (NEAs, with orbits intersecting those of the terrestrial planets), main belt asteroids between Mars and Jupiter, and comets. The extreme familiarity of some citizen astronomers with a particular region of sky, planet or nebula, allows them to immediately identify peculiarities or new features. A protocol for citizen discovery has been established: the position of any new object is compared to existing catalogues, and if no existing details are found then the new discovery and its ephemerides can be reported to the IAU Minor Planet Center.[3] If observations are repeated for at least two nights by one or several observers, then a new denomination is provisionally assigned to the discovery, and an electronic circular reports the discovery to the wider world. For example, the NEA 2012 DA14 was initially reported by a team of amateur observers affiliated with the La Sagra Sky Survey at the Astronomical Observatory of Mallorca (Spain), and subsequently characterised by professional astronomers during its closest approach in February 2013 (e.g., de León et al. 2013).

As with asteroids, the majority of new comet discoveries are made by automated surveys, but a small and stable number of discoveries come from amateurs with small telescopes (Mousis et al. 2014), typically in regions poorly covered by survey telescopes (e.g., regions close to the Sun). C/2011 W3 (Lovejoy), a Kreutz sungrazer comet, is one such example, discovered by T. Lovejoy and circulated via the Central Bureau for Astronomical Telegrams (CBAT) (e.g., Sekanina & Chodas 2012). The Oort cloud comet C/2012 S1 (ISON) was spotted by V. Nevski and A. Novichonok in images from the International Scientific Optical Network, which spurred a major international effort to observe its perihelion passage as it disintegrated (Sekanina & Kracht 2014). At the time of writing, an international citizen network, managed via the 'Co-ordinated Observations of Comets (CIOC)' group[4], is hoping to provide worldwide coverage of the close approach of C/2013A Siding Spring with Mars in Oct 2014. Amateurs are also contributing to the search for a sub-category of objects with a detectable cometary coma within the asteroid belt. Recent discoveries of these main belt

[3] `http://www.minorplanetcenter.net`

[4] `http://cometcampaign.org/comet-siding-spring`

comets, which appear to be asteroids that are actively venting their volatiles at perihelion, are beginning to blur the distinction between asteroids and comets. The T3 project, a collaboration between the University of Rome and several amateur observers, began in 2005 with the detection of a coma around asteroid 2005 SB216 (Buzzi et al. 2006), and has gone on to detect at least eight main belt comets (Mousis et al. 2014). These early citizen science discoveries, followed up by professional astronomers, have generated new insights into the properties and variety of comets, and the dynamic and evolving nature of our solar system. The discovery of Comet Shoemaker-Levy 9 (co-discovered by amateur observer D. Levy) before its collision with Jupiter (Harrington et al. 2004) is a classic example. In general, it is the global distribution of citizen observers and the long-baselines of their observations that enable new discoveries of minor bodies in our solar system.

Long timescale planet monitoring. Planetary atmospheres make tantalising targets for citizen observers, being large, bright, colourful and highly variable from night to night (e.g., Figure 1). The long-term monitoring provided by the network of amateur astronomers provides valuable insights into the meteorology of these worlds, tracking the motions of clouds, waves and storms as they are transported by atmospheric winds to probe the physical and chemical processes shaping their climates. For example, the global distribution of giant planet observers permits global monitoring of Jupiter and Saturn as they rotate over 10 hours. Citizens upload raw filtered images and colour composites, organised by date and time, to online servers, such as the Planetary Virtual Observatory and Laboratory (PVOL[5]) maintained for the International Outer

[5] `http://www.pvol.ehu.es/pvol`

Planets Watch (IOPW Hueso et al. 2010). Those images can be used by amateurs and professionals alike to study quantitatively the visible activity, including measuring wind speeds from erupting plumes (Sánchez-Lavega et al. 2008), investigating the strength and changes to the large vortices (e.g., the 2006 reddening of Jupiter's Oval BA, Simon-Miller et al. 2006), and determining the life cycle of the belt/zone structure (Fletcher et al. 2011, Sánchez-Lavega et al. 1996). For Saturn, a close collaboration between citizen scientists and Cassini spacecraft scientists (known as Saturn Storm Watch) has allowed correlation of lightning-related radio emissions detected by the spacecraft with visible cloud structures on the disc (e.g., Fischer et al. 2011), which would not have been possible with the targeted regional views provided by Cassini's cameras alone. Furthermore, it was the amateur community that first spotted the eruption of Saturn's enormous 2010-2011 storm system, which was monitored over several months (Sánchez-Lavega et al. 2012).

Video monitoring has been used by citizen observers to enable high resolution "lucky" imaging of Jupiter. The best images, at moments of clear seeing, from the high-resolution video frames are selected, extracted and stacked together, using custom software to correct for the distortions associated with the telescope optics and residual atmospheric seeing. Software written by citizen scientists for free distribution to active observers, such as Registax[6] and Autostakkert[7], allows them to process their own video files, thus avoiding the need for transfer of large datasets to some centralised server (see Mousis et al. 2014, for a thorough review). Descriptive records of morphological changes are maintained and continuously updated by organisations of citizen scientists such as the British

[6] `http://www.astronomie.be/registax`

[7] `http://www.autostakkert.com`

Astronomical Association (BAA) and the Association of Lunar and Planetary Observers (ALPO and ALPO-Japan). The BAA's Jupiter section[8] is a team of amateurs with substantial expertise in Jupiter's appearance (Rogers 1995); their regular bulletins describe the changing appearance of the banded structure and the emergence of new turbulent structures and weather phenomena, and keep a record of the long-term atmospheric changes.

Amateur observing also provides long-term monitoring in the inner solar system. Discrete cloud features can be used to study the super-rotation of the Venusian atmosphere, and the occurrence of a mysterious ultraviolet absorber at high altitudes. For example, the Venus Ground-Based Image Active Archive was created by ESA to provide contextual observations supporting the Venus Express mission (Barentsen & Koschny 2008). Groups such as the International Society of Mars Observers (ISMO[9]), the British Astronomical Association (BAA) and the International Mars Watch program quantitatively and qualitatively assess amateur images of the red planet, and while citizen observations of Uranus and Neptune require telescopes with diameters exceeding 25 cm, there have been confirmed reports of atmospheric banding and discrete cloud features when near-infrared filters (to maximise the contrast between the white clouds and the dark background) and long exposure times of tens of minutes are used. Citizen monitoring of all of these worlds (summarised in Figure 1) provides the long-baseline, flexible and high frequency imaging complementary to that returned by orbital and surface missions.

Solar System Impacts. The increasing adoption of video monitoring of planetary targets means that unexpected, short-lived events on the surfaces of

[8] `http://www.britastro.org/jupiter`

[9] `http://www.mars.dti.ne.jp/~cmo/ISMO.html`

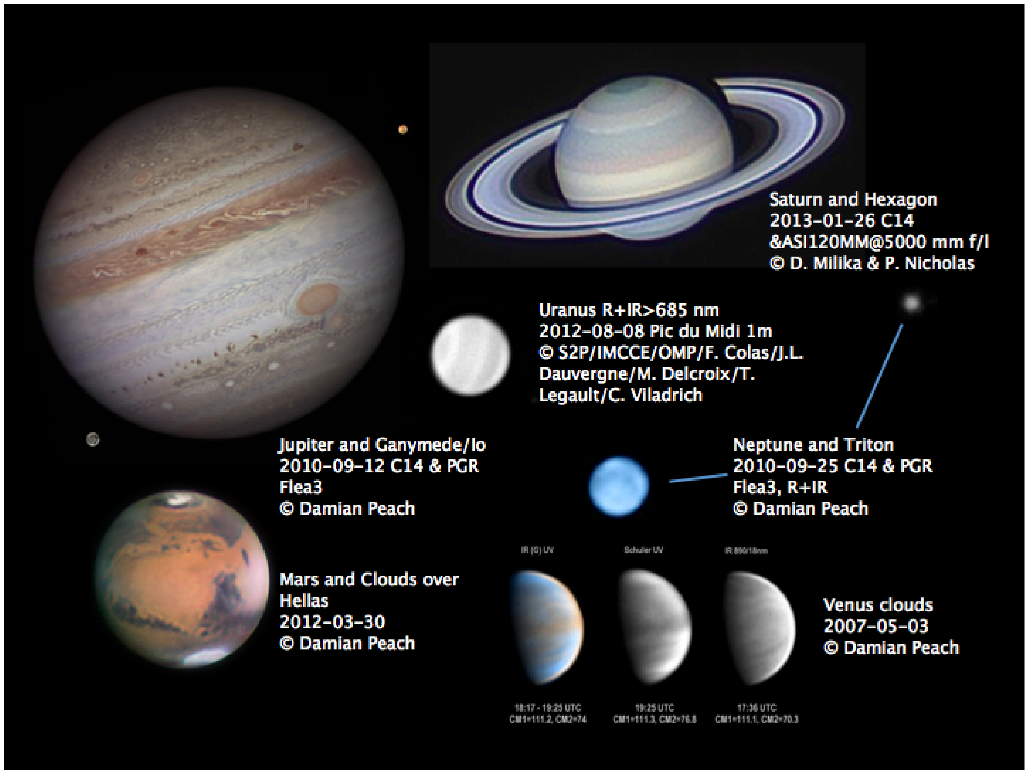

Figure 1: Examples of high-fidelity images obtained by amateur planetary observers. Credit: Damian Peach (UK) for Venus, Mars and Neptune images; Christopher Go (Philippines) for Jupiter; Darryl Pfitzner Milika and Patricia Nicholas (Australia) for Saturn; and Anthony Wesley (Australia) for Uranus (see Mousis et al. 2014, for a thorough review of amateur planetary astronomy).

those bodies are now more likely to be observed by citizen astronomers than by professional observatories. For example, an impact scar near Jupiter's south polar region was first discovered in imaging by Australian amateur Anthony Wesley on July 19th, 2009. This led to an international campaign of professional observations to understand the asteroidal collision that had created the scar (e.g., de Pater et al. 2010, Hammel et al. 2010, Orton et al. 2011). Although the 2009 impact was out of view from the Earth, at least three flashes have been confirmed between 2010 and 2012, and the light curves used to determine the sizes and frequency of objects colliding with Jupiter (e.g., Hueso et al. 2013) (Figure 2). Citizen scientists have developed free software to allow observers to search for impact flashes in an automated way (e.g., Jupiter impact detections[10] and LunarScan from the ALPO Lunar Meteoritic Impact Search for transient impact flashes recorded on the Moon[11]).

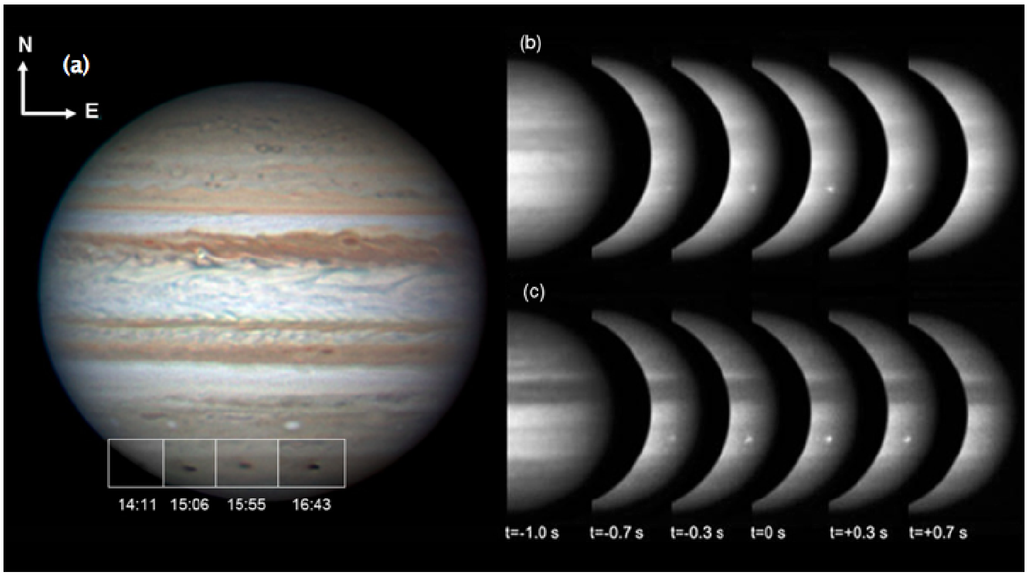

Figure 2: Citizen science contributions to monitoring of impacts in the Jupiter system. (a) Dark impact scar in Jupiter's atmosphere imaged by Anthony Wesley on July 19th 2009 (Sánchez-Lavega et al. 2010). (b) The evolution of a smaller bolide impact on June 3rd 2010 at red wavelengths, also imaged by Wesley. (c) The evolution at blue wavelengths by Christopher Go, figure from Hueso et al. (2010).

Transiting and Microlensing Exoplanets. Amateur observers have contributed to several exoplanet investigations, responding to detections made by professional surveys and making important contributions to the light curves of

[10]http://www.pvol.ehu.es/software

[11]http://alpo-astronomy.org/lunarupload/lunimpacts.htm

the targets. In the case of exoplanet transits, the challenge is to measure the 1% diminution in starlight as a giant planet transits in front of its parent star. Mousis et al. (2014) point out three methods whereby amateurs can contribute to the characterisation of exoplanetary systems: first, by frequent observations of known transits to refine ephemeris; second, by searching for transit time variations that can reveal additional planets in a system; and third, by searching for previously unidentified transits in known planetary systems (e.g., the discovery of the transit of HD 80606b from a 30 cm telescope near London, Fossey, Waldmann & Kipping 2009). A further interesting example of citizen contribution to exoplanet observations is the characterisation of the transit candidate KOI-961 (Muirhead et al. 2012), during which amateur astronomer Kevin Apps pointed out to the professional observing team the close similarity of the stellar spectrum to that of Barnard's star, enabling them to carry out an unusually sensitive differential analysis.

In a planetary microlensing event, significant brightening of the background star is required to make a planet orbiting the microlens visible at all; if additional caustic crossings are caused, the resulting exoplanetary microlensing feature is of just several days duration, calling for high frequency, on demand monitoring – a situation well matched to the capability of a global network of small telescope observers (see e.g. Christie 2006). High magnification events detected by the OGLE[12] and MOA[13] surveys have been broadcast by the microFUN[14] and PLANET[15] networks (now merged) to globally-distributed professional and amateur observers to follow up. These collaborations have been very successful,

[12] `http://ogle.astrouw.edu.pl/`

[13] `http://www.phys.canterbury.ac.nz/moa`

[14] `http://www.astronomy.ohio-state.edu/~microfun`

[15] `http://planet.iap.fr`

helping enable characterisation of over a dozen exoplanet systems (see e.g. Gould et al. 2014, Udalski et al. 2005, and references therein). (A similarly responsive network of citizen observertories is assembling as the RECON project, which aims to measure the size of Kuiper belt objects from the width of their occultation shadows as they pass over the West coast of the U.S.[16])

Variable Star Monitoring: the AAVSO. The American Association of Variable Star Observers (AAVSO) supports and coordinates the efforts of about 2000 amateurs (over a five-year window) who are interested in monitoring variable stars. In each of the last five years, the community has made over a million observations, either visually or with digital techniques, and logged them into a shared, public database[17] with over 100 years of continuous data on many stars. The AAVSO provides a number of services to assist the volunteers, including training material, an online data entry tool that carries out basic error checking, finding charts with calibrated photometry, a catalog of known variable stars that is more extensive than the General Catalog of Variable Stars (GCVS), and data analysis tools such as light curve generation and period determination. Staff and volunteers perform quality control on the submitted data. Despite its name, AAVSO observers are located all over the world, with two thirds of the observer base residing outside of the U.S. Some of the community's larger telescopes can be operated robotically, and have been linked together into a network, AAVSOnet. The AAVSO is also engaged in the NSF-funded AAVSO Photometric All-Sky Survey (APASS[18]), a survey of the entire sky in 8 bandpasses ($BVu'g'r'i'z'Y$) for stars between 7th and 17th magnitude. The APASS data processing and

[16] `http://tnorecon.net/`

[17] `http://www.aavso.org`

[18] `http://www.aavso.org/apass`

calibration is being done in collaboration with professional astronomers, and the data is being released at approximately annual intervals.

The distributed nature of the AAVSO community means that it can produce continuous light curves for stars at all declinations. The AAVSO data has been used extensively by professional astronomers needing the most up-to-date optical measurements of stellar variability in, for example, the SS Cyg system (Miller-Jones et al. 2013), optical light curves taken simultaneously with monitoring being carried out by space telescopes and/or at different wavelengths (see *e.g.* Szkody et al. 2013, for a successful joint AAVSO–HST program), or who are performing long baseline data mining analysis of variable star populations.

The AAVSO, in partnership with several professional astronomers and education specialists, successfully coordinated the NSF-funded "Citizen Sky" project to monitor the 2009-2011 eclipse of the epsilon Aurigae binary star system. The results from this campaign (Stencel 2012)[19] were used by Kloppenborg et al. (2010) to help interpret their interferometric imaging of the obscuring disk in the system. AAVSO observers are not only active participants in the data collection process, but also perform original research and publish their results, and so are involved at every level of Citizen Science.

The Whole Earth Blazar Telescope. Similar in organisational spirit to the AAVSO's variable star monitoring, the Whole Earth Blazar Telescope project[20] coordinates the continuous monitoring of blazars at over 40 amateur and professional optical and radio observatories, most recently in support of the Fermi and AGILE space telescopes in the GASP long-term monitoring program.

[19] The results from the Citizen Sky project are presented in a special issue of the JAAVSO at `http://www.aavso.org/jaavso-v40n2`

[20] `http://www.to.astro.it/blazars/webt/`

The observations taken by this global network have been published in over 50 peer-reviewed papers since 1998. The large number of observatories involved gives the system both a fast response time, and a large capacity for ongoing high cadence observations, enabling blazar outbursts to be monitored intensively for several months soon after they are detected (*e.g.* Raiteri et al. 2008), and rapid variability to be captured (*e.g.* Böttcher et al. 2005).

Extragalactic Transients: Supernovae and GRBs. An extremely productive area of citizen astronomy has been the discovery and early characterisation of supernovae. Since the early 1980's, amateur astronomers have consistently made very important contributions to the search for nearby supernovae. For example, both Type 1B prototype objects (SN1983N and SN1984L, Porter & Filippenko 1987) were discovered by amateur astronomer Robert Evans, who has visually identified 42 new supernovae alone. Since 2010, amateur astronomers have discovered supernovae at the rate of about 150–180 per year, approximately 10% of the total.[21] While professional surveys have now overtaken them in terms of total numbers of supernovae found, amateur astronomers continue to discover nearby and peculiar objects in significant numbers. These citizens observe as individuals and in teams. For example, the Puckett Observatory World Supernova Search,[22] a collaboration between 26 amateur astronomers coordinated by Tim Puckett, has found 15–20 supernovae per year, including seven of the 25 known Type 1ax class (Foley et al. 2013). The small but dedicated worldwide community of amateur astronomers searching for supernovae communicate with each other via email and their club or observatory websites, and report discoveries directly

[21] See e.g. `http://www.rochesterastronomy.org/sn2013/snstats.html` for a citizen-compiled summary of recent supernova discovery statistics.

[22] `http://www.cometwatch.com/supernovasearch/discoveries.html`

to the IAU via its Central Bureau for Astronomical Telegrams.[23] This is the primary interaction between amateurs and professionals in this area: the citizen observers are self-organised and simply provide a very valuable discovery service: the Puckett Observatory notes that, to date, 22 peer-reviewed publications have been written on the supernovae they have discovered. Optical transients associated with Gamma Ray Bursts (GRBs) have also been discovered by amateur astronomers who were able to supply the required rapid response (Oksanen et al. 2008). Again, results were reported via a telegram system, the Gamma-ray Burst Coordinate Network[24] (Monard 2003, Oksanen 2007).

The example case studies in this section illustrate a thriving synergy between amateur and professional observations, and several instances of productive professional-amateur ("Pro-Am") collaboration. While the solar system provides some of the most amenable targets for amateur observation (Mousis et al. 2014), "deep sky" observations by the non-professional community provide important further insight into the capabilities of citizen astronomers. In particular, we can identify three advantages held by amateur astronomers that have enabled them to make authentic contributions to science.

The first is *time availability*. Determinations of meteor frequencies or blazar microvariability require observations on short timescales (minutes), whereas the slow evolution of giant planets or periodic variable stars occur on longer timescales (years and decades). Amateur observations can be frequent and repetitive, but also long standing. The second, related, advantage is that of *flexibility*: whenever a new phenomenon is discovered, citizen observers will be keen to catch a

[23] `http://www.cbat.eps.harvard.edu/index.html`

[24] `http://gcn.gsfc.nasa.gov/`

glimpse irrespective of the scientific value of their observations. This reaction can be near-instantaneous, and, when made by a networked community, provides naturally well-sampled coverage across the globe. The third advantage is *contextual*. Professional observations are often taken in a very different wavelength range, focus on a narrower spatial region, or employ spectroscopic techniques that do not yield images. In some situations, near-simultaneous wide field optical imaging by citizen scientists provides very useful additional constraints on the process of interest.

"Passive Observing." While amateur astronomers have acquired a great deal of very useful data, the general population is better equipped than ever to image the sky and make that data available for scientific analysis. This has been demonstrated by two recent professionally-led projects that made use of a largely passive observing community connected via online social networks not usually associated with astronomy.

Lang & Hogg (2012) used more than 2000 images scraped from the photo sharing website Flickr as inputs to a reconstruction of the orbit of Comet Holmes. This comet was bright enough to be visible with the naked eye during its 2007 apparition, and a large number of photographs were taken of it and uploaded. Lang & Hogg were able to astrometrically calibrate many of the images using their automatic image registration software, *astrometry.net* (Lang et al. 2010). The calibrated images trace out the trajectory of the comet, producing a result which is close to that obtained from the JPL Horizons system (Giorgini et al. 1997). Estimates of orbital parameters from Flickr images alone are accurate, when compared to the JPL Horizons values, to within a few standard deviations. As the authors point out, while in this case the photographers did not realize they were participating in a scientific study, the potential of combining powerful calibration software with large amounts of citizen-supplied imaging data is made clear. This method of "unconscious" citizen science may prove to have significant value in fields beyond astronomy too, if models of the statistical sampling can be developed: for example, ecological studies of wildlife photographs submitted to sites like Flickr are likely to happen in the next few years.

Another form of passive observing occurs when dramatic impacts capture attention. Video footage of the fireball and shockwave of the February 2013 Chelyabinsk meteor (Popova et al. 2013) proved essential in scientifically characterising the impactor and its likely origins, despite the fact that these records were largely captured accidentally by autonomous security cameras. Trajectories reconstructed from these records even permitted the recovery of meteorites from a debris field on the ground. While statistics on meteor flux and impacts are currently actively provided via a global network of citizen scientists, sharing and publicising their observations of meteors via the International Meteor Organisation (IMO[25]), visual observations of meteors can also be tracked with no such active participation. By searching the archive of short text messages submitted to the web service Twitter, Barentsen et al. (priv. comm.) were able to detect several new meteor showers. Naked-eye observers had spotted shooting stars and tweeted about them to their followers, giving rise to a detectable signal in the stream of tweets that night. At present, when most people image the night sky they don't think of themselves contributing to science, but these projects show just how low the barrier to entry to citizen astronomy could be.

[25] `http://www.imo.net`

3 VISUAL CLASSIFICATION

Observing the night sky with a telescope is perhaps the most familiar of the activities of amateur astronomers, but as the previous section showed, citizens are also actively involved in the processing and interpretation of the data they have taken. In this and the next section we look at projects where much larger archival astronomical datasets have been made available to crowds of citizens, who are asked to inspect images and light curves, and help describe and characterize the features in them. Despite significant advances in machine learning and computer vision, the visual inspection of data remains an important part of astronomy, as it continues to take advantage of the amazing human capacity for visual pattern recognition. While many in the 1990s predicted that the increasing size of astronomical datasets would make such time-intensive inspection impossible, the extensive reach of the world wide web has enabled the involvement of hundreds of thousands of citizen scientists in this form of "crowd-sourced" data analysis.

3.1 Crowd-sourced Classification in Astronomy

Stardust@home. While significant preliminary work had been carried out by NASA's "clickworkers" (see below), the project that first illustrated the potential of crowd-sourcing for astronomical purposes was Stardust@home[26]. The team asked volunteers to scan through images of samples returned from Comet Wild-2 by the *Stardust* mission, attracted a large audience to the apparently unprepossessing task of looking for dust grains in an effort to identify samples of material from outside our Solar System. The site was built on BOSSA, an early attempt to build a generalized platform for such crowd-sourcing projects, and

[26] `http://stardustathome.ssl.berkeley.edu/`

featured a stringent test which volunteers had to pass before their classifications would be counted. Despite this hurdle, more than 20,000 people took part, and a variety of dust grains were removed from the aerogel for further study, contributing two of the seven candidate interstellar grains presented in a recent Science paper (Westphal et al. 2014). Perhaps the most significant long-term impact of Stardust@home, though, was the demonstration that large amounts of volunteer effort were available even for such seemingly uninspiring tasks such as hunting dust grains in images unlikely to be described as intrinsically beautiful, and that, with a suitable website design and stringent testing, scientifically valuable results could be obtained.

Galaxy morphology with Galaxy Zoo

The Stardust@home experience directly inspired the development of Galaxy Zoo, perhaps the most prominent scientific crowd-sourcing project to date. Galaxy Zoo was built on the continued importance of morphological classification of galaxies, first introduced in a systematic fashion by Hubble, and later developed by, among others, de Vaucouleurs. While the morphology of a galaxy is closely related to its other properties, such as colour, star formation history, dynamics, concentration and so on, it is not entirely defined by them: there is more information in resolved images of galaxies than is captured in these observables. One approach was to develop simple proxies (e.g CAS (Conselice 2006)), but these are at best approximations for true morphology.

In an effort to prepare for large surveys, such as the Sloan Digital Sky Survey (SDSS), Lahav et al. (1995,1996), and later, Ball et al. (2004) developed neural networks trained on small samples of expert classified images,[27] in order to au-

[27] The Lahav papers are perhaps as interesting for their psychology as for their astrophysics,

tomate the process of classification, arguing that the size of the then-upcoming surveys left no place for visual classification.

The performance of these automatic classifiers depended on the input parameters, including colour, magnitude and size. These variables correlate well with morphology, but are not themselves morphological, and when included they dominate the classification. In particular, for galaxies which do not fit the general trends, such as spirals with dominant bulges, or star-forming ellipticals, automated classifiers, whether using these simple measures or more complex proxies for morphology such as texture, fail to match the performance of expert classifiers (Lintott et al. 2008). As a result, Schawinski et al. (2007), Nair & Abraham (2010), and others have spent substantial amounts of time visually classifying tens of thousands of galaxies.

Inspired by Stardust@home, a small group led by one of the authors (Lintott) created Galaxy Zoo in 2007 to provide basic classifications of SDSS galaxies[28] Classifiers were presented with a coloured image centered on and scaled to one of more than 800,000 galaxies, and could select from one of six options to characterise that object's morphology: clockwise, anti clockwise and edge-on spirals, ellipticals, mergers and "star/don't know." Aside from an easily-passed initial test, little knowledge was required or indeed presented to classifiers, enabling them to proceed quickly to doing something real shortly after arriving at the site; this approach, in contrast to Stardust@home, was successful in encouraging large numbers of visitors to participate. This tactic – in which both passing and sustained engagement provide substantial contributions – is illustrated in Fig-

as the classifications reveal the relations between the senior classifiers employed to be experts.

[28]The original Galaxy Zoo is preserved at `http://zoo1.galaxyzoo.org` with the current incarnation at `http://www.galaxyzoo.org`.

ure 3 which shows results from Galaxy Zoo 2. This later version of the project asked for more detailed classifications via a decision tree containing questions such as ‘How prominent is the bulge?’, and later iterations of the project have applied a similar approach to galaxies drawn from *Hubble Space Telescope* surveys including GEMS (Rix et al. 2004), GOODS (Giavalisco et al. 2004), COSMOS (Koekemoer et al. 2007, Scoville et al. 2007) and CANDELS (Grogin et al. 2011, Koekemoer et al. 2011).

To date, several hundred thousand people have participated in the Galaxy Zoo project. However, such figures would be meaningless if the classifications provided were not suitable for science. With sufficient effort to ensure each galaxy is classified multiple times (as many as 80 for many Galaxy Zoo images), these independent classifications need to be combined into a consensus. As discussed in later sections, this can become complex, but for Galaxy Zoo a simple weighting which rewards consistency, first described in Land et al. (2008), was deemed sufficient. Importantly, combining classifications provides not only the assignment of a label but, in the vote fraction in a particular category, an indication of the reliability of the classification. This allows more subtle biases, such as the propensity for small, faint or distant galaxies to appear as elliptical regardless of their true morphology, to be measured and accounted for (see Bamford et al. 2009). The net result is that the Galaxy Zoo classifications are an excellent match for results from expert classification, and have produced science ranging from studies of red spirals (Masters et al. 2010) to investigations of spiral spin (Slosar et al. 2009). A full review of Galaxy Zoo science is beyond the scope of this review; a review of the project and many early science results can be found in Fortson et al. (2012), a summary of more recent science results can be found in Willett et al. (2013).

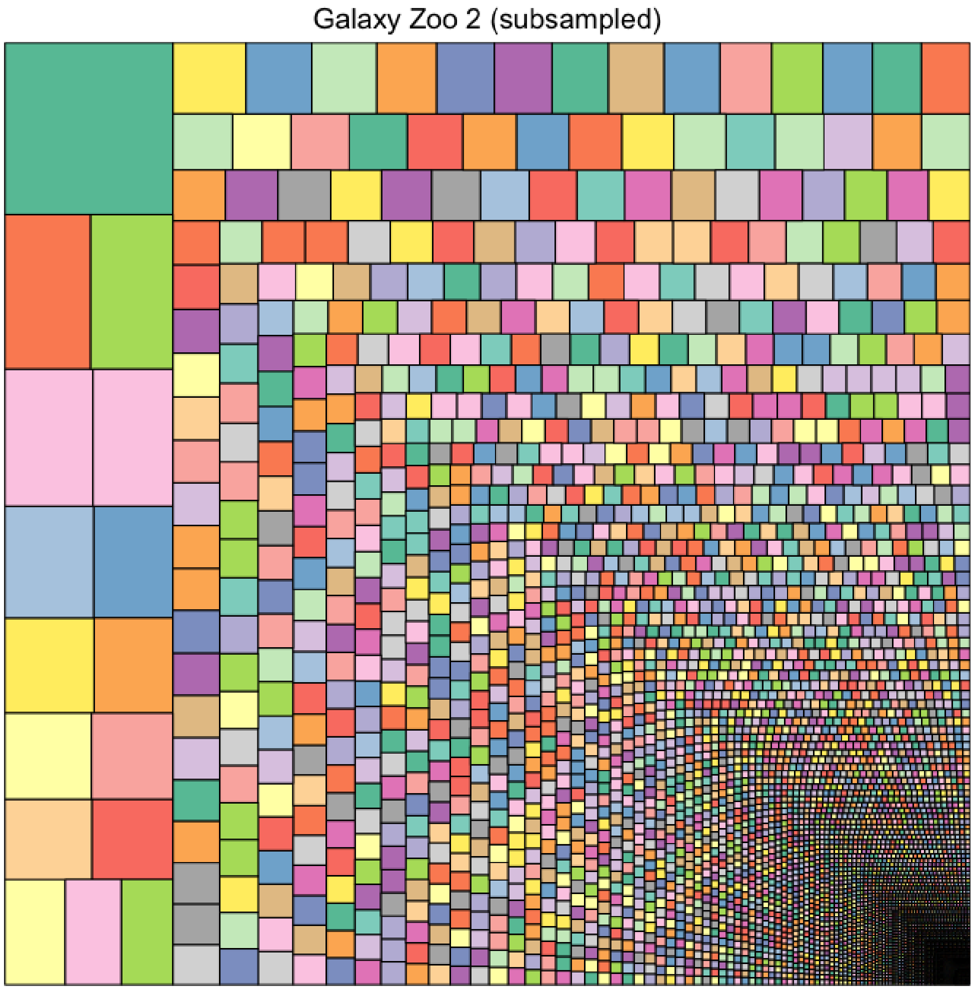

Figure 3: Distribution of effort amongst 5000 randomly selected volunteers from Galaxy Zoo 2. The area of each square represents the classifications of a single user; colours are randomly assigned. The diagram illustrates the importance of designing for both committed and new volunteers as both contribute significantly; ignoring one or the other would greatly reduce the project's utility. Figure made by K. Willett using code by P. Brohan.

It is worth noting that some of the project's most important results have been the result not of interaction with the main classification interface, but represent rather serendipitous discoveries made by participants. We return to these in

Section 5 below.

Surfaces of solar system bodies: Moon Zoo, Moonwatch. If studying galaxies remains, at least in part, a visual pursuit, then the same is certainly true of planetary science. NASA's Clickworkers[29], which asked volunteers to identify craters on the Martian surface, lays claim to be the oldest astronomical crowd-sourcing project. The consensus results matched those available from experts at the time, but failed to go beyond this promising start to produce results of real scientific value. More recently, interfaces inviting classifiers to look at the Moon, Mercury, Mars and Vesta have been launched and attracted significant numbers of classifications; however, although preliminary results have been promising (Kanefsky, Barlow & Gulick 2001), these projects have yet to produce datasets that have been used by the planetary science community in the same way that Galaxy Zoo has by the astronomical community. The recent release of the first paper from the Cosmoquest Moon Mappers project (Robbins et al. 2014) may indicate that this will change.

Tracking Features in Giant Planet Atmospheres: WinJUPOS Not all astronomical crowd-sourced visual classification is led by professional scientists. JUPOS[30] is an amateur astronomy project involving a global network of citizen observers to monitor the appearance of planetary atmospheres. Recent software developments have provided a much more quantitative perspective on these citizen observations. The WinJUPOS software was developed by a team of citizen scientists led by G. Hahn; it allows multiple images of a giant planet to be stacked with a correction for the rapid rotation of Jupiter or Saturn (once every 10 hours), then re-projected onto a latitude-longitude coordinate system,

[29] http://www.nasaclickworkers.com/

[30] `http://jupos.privat.t-online.de`

so that the precise positional details of atmospheric features can be determined via “point-and-click,” relying on the citizen’s ability to identify features on the planetary disc visually.

By doing this over many nights surrounding Jupiter’s opposition, the community builds up enormous drift charts, comprising tens of thousands of positional measurements for these features, ranging from the tiniest convective structure being moved by the jet streams, to the largest vortices (e.g. Hahn 1996). The charts reveal the dynamic interactions within the jovian weather layer, and the long-term stability of their zonal jets (see e.g., the regular bulletins provided by the Jupiter section of the British Astronomical Association). The positions can be extrapolated forward in time, enabling targeted observations by professional observatories or even visiting spacecraft. The Juno mission, scheduled to arrive at Jupiter in 2016, is reliant on the citizen observer community to provide this sort of contextual mapping for the close-in observations from the orbiter. This long-term record of Jupiter’s visible appearance by citizen scientists has proven to be an invaluable resource for the giant planet community.

Time domain astronomy: Supernova Zoo and Planet Hunters The three defining characteristics of “Big Data” have come to be accepted as volume, velocity and variety. Time-domain astronomy projects, that indeed require the immediate inspection of challenging volumes of live, high velocity, complex data, can benefit from citizen science, as shown by two recent projects, Supernova Zoo and Planet Hunters. While transients such as supernovae or asteroids can often be found through the use of automatic routines, visual inspection is still used by many professional science teams as part of their process of selecting candidates for follow-up.

The most successful attempt to use crowd-sourcing to attack these problems to date has been the offshoot of Galaxy Zoo described in Smith et al. (2011). Data from the Palomar Transient Factory (Law et al. 2009) was automatically processed and images of candidate supernovae uploaded on a nightly basis; this triggered an email to volunteers who, upon responding, were shown the new image, a reference image and the difference between the two. By analyzing the answers given by the volunteers to a series of questions, candidates were sorted into three categories, roughly corresponding to "probable supernova," "likely astrophysical but non-supernova transient" and "artifact." The results were displayed on a webpage and used by the science team to select targets for follow-up. Despite the Supernova Zoo site attracting many fewer classifiers than Galaxy Zoo, it was highly effective in sorting through data, with consensus typically reached on all images within 15 minutes of the initial email being sent.

The large dataset generated by this project was used by Brink et al. (2013) to develop a supervised learning approach to automatic classification for PTF transients. The performance of this routine, which for a false-positive rate of 1% is more than 90% complete, depends on the kind of large training set that can be generated by crowds of inspectors; this suggests a future path for large surveys in which citizen science provides initial, training data and is followed by machines taking on the remaining bulk of the work. Encouragingly, Brink et al.'s method, which makes use of a set of 42 features extracted from survey images, has performance which is insensitive to a small fraction of mislabeled training data, suggesting that the requirements for accuracy of citizen science projects which aim to calibrate later machine learning may be less stringent than otherwise thought.

A different approach to crowd-sourced classification in time-domain astronomy is exemplified by the Planet Hunters project,[31] which asks volunteers to examine light curves drawn from the dataset provided by the *Kepler*mission in order to identify interesting events in retrospect. While the task of identifying transits from extrasolar planets is, at first glance, one which seems more suited for automated than for human analysis, the success of Planet Hunters in identifying more than fifty planet candidates missed by the automatic routines suggests that there remains a role for inspection by eye in cases where the relevant science requires samples of high completeness. Several of the planets found by Planet Hunters are unusual: PH1b, the project's first confirmed planet (Schwamb et al. 2013) and a circumbinary, is the first planet known in a four-star system. Others, including the more than forty candidates identified by (Schmitt et al. 2014, Wang et al. 2013), might have been expected to be recovered by more conventional searches. Planet Hunters, therefore, is acting as an independent test of the *Kepler*pipeline's efficiency (Schwamb et al. 2012) and has inspired improvements in subsequent analysis (Batalha et al. 2013). A recent redesign of the project, launched in September 2014, aims to provide a 'first-look' at data from the Kepler extended mission, emphasising rapid analysis through a system which quickly identifies potential transits and then asks experienced volunteers to review them.

Using existing tools: Near Earth Asteroid precovery and RAD@home. Online visual classification does not necessarily require a custom-built interface. Solano et al. (2014) describe an online classification project carried out by the Spanish Virtual Observatory (SVO) to refine the orbits of Near Earth Astroids (NEAs) using archival images from the Sloan Digital Sky Survey. Over 3000

[31] `http://planethunters.org`

volunteers inspected pairs of images looking for and marking moving objects, leading to the improvement of 6% of known NEAs. While designed and funded as an outreach project, the SVO made use of the *Aladin*[32] VO science user interface tool in use by professional astronomers, and enabled the submission of results via the Minor Planet Circular system.

Citizen scientists utilising publically-available video data from observatories such as SOHO and STEREO and their choice of graphics software have been able to discover numerous sungrazing comets (Section 2). Indeed, the majority of 2000+ SOHO sungrazer discoveries have been due to dedicated amateurs over 15+ years of operation, e.g.,][]12battams, reporting their observations to professional observers via the Sungrazer Project[33].

Similar in spirit to these projects is the RAD@Home project (Hota et al. 2014), a "a zero-funded, zero-infrastructure, human-resource network" using free web services and public astronomical data archives to organise and enable citizen astronomy research. The community of volunteers was formed around a Facebook group,[34] and its initial investigations have focused on morphological identification of massive spiral galaxies hosting radio loud AGN (Hota et al. 2011) in the GMRT TGSS survey imaging. Some of the RAD@home volunteers have co-authored follow-up proposals, mentored by the project's PI. We return to the enabling of volunteers to "graduate" to more advanced activites in Sections 4 and 5 below.

[32] `http://aladin.u-strasbg.fr`

[33] `http://sungrazer.nrl.navy.mil/`

[34] `https://www.facebook.com/groups/RADathome`

3.2 Classification Analysis

In most visual classification projects, working on archived image data with little time pressure, the random assignment of task to classifier, followed by simple, democratic treatment of the classifications has been judged sufficient. However, the need for rapid processing of images in time domain astronomy projects has prompted the investigation of more efficient analyses of the classification data. Using the Supernova Zoo project's archive as a test, Simpson et al. (2012) developed a Bayesian method, IBCC, for assessing classifier performance; in this view, each classification provides information both about the subject of the classification and about the classifier themselves. Classifier performance given subject properties can thus be predicted and an optimum set of task assignments calculated. Moreover, work by Simpson et al., as well as Kamar, Hacker & Horvitz (2012) and Waterhouse (2013) on Galaxy Zoo data, suggests that accuracy can be maintained with as few as 30% of classifications. This sort of optimization will be increasingly important for online citizen science, especially in projects that use a live stream of data, rather than an archive, since the classification analysis will need to be done in real time.

Rare event detection: Space Warps Steps towards real-time classification analysis have been taken in the Space Warps project.[35] Space Warps is a rare object search: volunteers are shown deep sky survey images and asked to mark features that look as though they are gravitationally lensed galaxies or quasars (Marshall et al, More et al in prep.). Extensive training is provided via an ongoing tutorial that includes simulated lenses and known non-lenses, and immediate pop-up feedback as to whether these training images were correctly classified.

[35] `http://spacewarps.org`

Because real lenses are rare (appearing once every 10^{2-4} images, depending on the dataset), the primary goal is to reject the multitude of uninteresting images so that new ones can be inspected – and this drives the need for efficiency. Marshall et al (in prep.) derived a simplified version of the IBCC classification analysis that updates a probablistic model of both the subjects and the agents that represent the classifiers in a statistically online manner (enabling, in principle, real-time analysis). This analysis was run daily during each of the Space Warps projects, and subjects retired from the stream as they crossed a low probability threshold. This algorithm is being implemented into the web application itself for future datasets.

The increased efficiency of visual classification projects that will come with real-time analysis will enable feedback on the projects' progress to be given much more promptly – an important part of the collaboration between professionals and amateurs in crowd-sourcing projects.

3.3 Visual Classification in Other Fields

Although, as described in the previous section, astronomical analysis led the development of citizen science as a data analysis tool, it has quickly been adopted by other fields. In some cases, this adoption has been explicit. The tools developed for Stardust@home were developed into a general purpose library for citizen science, BOSSA. Both this and the Zooniverse platform (which hosts many of the examples described above) support projects from fields as diverse as ecology and papyrology. This diversity allows general lessons about project design to be drawn; indeed, this is an active area of research for academic fields as diverse as computer science, economics and social science. A recent paper by Crowston et al. (2014), for example, compares Planet Hunters and Seafloor Explorer, a Zooniverse project which explores the health of fisheries off the coast of North America, finding in both cases that volunteers who are new to the project seek out "practice proxies" – examples of apparently correct behaviour from amongst material accumulated in the informal social spaces that accompany the main project.

Projects from other fields can also suggest strategies which could be adopted by future citizen astronomy projects. For example, future projects involving analysis of survey data which has been collected for a multitude of purposes may require a more sophisticated model for data analysis than the simple decision tree presented by projects such as Galaxy Zoo.

Snapshot Serengeti This project invites the visual classification of animals in photographs from more than two hundred motion-sensitive "camera traps" installed in the Serengeti National Park, and enables a particularly sophisticated volunteer response. Driven in part by the need for an interface which allows volunteers to state the obvious (for example, identifying elephants, lions or zebras) and also to provide more obscure classification (for example, distinguishing between different species of gazelle), a variety of classification paths are presented. In addition to just clicking buttons identifying species, volunteers can opt for a decision tree-like approach, or choose from a variety of similar species ("Looks like an antelope...") or search the descriptions provided in order to make an informed classification ("Show me all animals whose descriptions involve 'ears' "). This hybrid model has proved successful not only in encouraging classification, but also in encouraging learning; over a Snapshot Serengeti classifier's "career" they are increasingly likely to chose more direct routes.

Visual inspection of 3-D biological scans: Eyewire Another aspect of project strategy, and design, relates to the engagement of the volunteers. The online citizen astronomy projects developed so far have tended to emphasise co-operation between volunteers, and the results being due to a team effort. Elsewhere, experiments with a more competitive approach to citizen science, "gamifying" the activity, have been performed. The Eyewire project[36], based at MIT, seeks to supplement machine learning identification of neurons in three-dimensional scans. Notably, this project incorporated some "gamified" elements into its design. Participants in the project, who are asked to identify connected regions throughout a three-dimensional scan, earn points based on participation and also have a separate, publicly visible, accuracy score. In addition to overall leader boards, the project also runs short challenges including a regular Friday "happy hour" in which participants compete on specific problems. Eyewire is also notable for its other strong community elements, with a chat room open and available to all participants in the project (supplemented, incidentally, by a "bot" built by a participant which answers frequently asked questions from new users). Its first result, which drew on mapping of so-called 'starburst' neurons, was published in mid-2014 (Kim et al. 2014).

4 DATA MODELLING

New understanding of the world comes from the interpretation – fitting – of data with a physical model. Such "data modelling" often involves technical difficulties that computers may find hard to overcome, associated with complex and/or computationally expensive likelihood functions. Humans, by applying their de-

[36] `http://www.eyewire.org`

veloped intuition, can contribute a great deal to the exploration of a model's parameter space by closing in quickly on those configurations that fit the data well. This process can be particularly satisfying, rather like solving a puzzle. Meanwhile, many "machine learning" techniques effective in one field can often be adapted to astronomical problems: there are plenty of citizens with the skills to do this. How have citizen scientists been involved in model making and data fitting in astronomy, and other fields, to date?

The Milky Way Project (MWP[37]). Simpson et al. (2012) provided volunteers with a fairly flexible set of annulus-drawing tools, for annotating circularly-symmetric "bubble" features in colour-composite (24.0, 8.0 and 4.5μm) infrared images from surveys carried out by the Spitzer space telescope (Figure 4). These bubbles are hypothesized to have been caused by recently-formed high mass stars at the centre each. The (bubble) model in this case is simple and recognizable, making both the interface construction and its operation relatively straightforward. The large sample of bubble models have been used to investigate the possibility of further star formation being triggered at the bubble surfaces (Kendrew et al. 2012). A subsequent effort (Beaumont et al. 2014) used data provided by the project to train a machine learning algorithm, *Brut*, in bubble finding. *Brut* is able to identify a small number of sources which were not identified in the Simpson et al. catalog. These bubbles were difficult for humans to identify, owing to their lying close to bright sources, and so having low contrast relative to their surroundings.

In addition, *Brut* has proved effective at identifying suspect bubbles included in the previous (pre-citizen) surveys. Given the relatively small size of the MWP

[37] http://milkywayproject.org

sample, the main use of machine learning here has been to provide an independent check on the citizen classification data; for larger samples, as discussed below, an approach in which machine learning is trained on citizen science data, and gradually takes over the classification task could be considered.

Modelling Lens Candidates The Space Warps project (Section 3.2) has an informal data modeling element. The classification interface is restricted to enabling identification of candidate gravitationally-lensed features, but all the images are available via the project's discussion forum. A small team of volunteers (including several citizens who helped design the project) has engaged in modeling some of the identified lens candidates using web-based software developed and supported by the project science team.[38] Results from a small test program show that the Einstein radii (proportional to the lens galaxy masses) derived by the ensemble of citizens are as accurate as those derived by experts (Kueng et al, in prep.). A pilot collaborative modeling analysis was carried out and written up by a small group of Space Warps volunteers[39] (Capella_05 2014).

Galaxy Zoo: Mergers This has been perhaps the most advanced attempt at data modeling in astronomical web-based citizen science (Holincheck et al. 2010, Wallin et al. 2010). Here, simple N-body simulations of galaxy mergers were performed in a Java applet, and the results selected according to visual similarity to images of galaxy mergers (previously identified in the Galaxy Zoo project). A key hypothesis here is that the inspectors of the simulation outputs would be able to find matches to the data more readily than a computer could, for two reasons. First is that humans are good at *vague* pattern matching: they

[38] `http://mite.physik.uzh.ch`

[39] See `http://talk.spacewarps.org/#/boards/BSW0000006/discussions/DSW00008fr` for the forum thread that was used.

do not get distracted by detailed pixel value comparisons but instead have an intuitive understanding of when one object is "like" another. The second is that initializing a galaxy merger simulation requires a large number of parameters to be set – and it's this high dimensionality that makes the space of possible models hard to explore for a machine. Humans should be able to navigate the space using their intuition, which is partly physical and partly learned from experience gained from playing with the system. Initial tests on the merging system Arp 86 showed the crowd converging on a single location in parameter space, and that the simulated mergers at this location do indeed strongly resemble the Arp 86 system. The authors have since collected thousands of citizen-generated models for a sample of a large number SDSS merging systems (Holincheck et al, in preparation, Figure 4).

Protein Modeling with Foldit One of the most successful examples of crowd-sourced, "manual" data modeling is the online multi-player 3-D protein modeling game, Foldit (Cooper et al. 2010)[40] In this pioneering project, players compete in teams to find the best – that is, the lowest free energy – molecular structures for particular protein "puzzles." These puzzles are naturally visualizable in three dimensions, but they nevertheless involve thousands of degrees of freedom, in a parameter space that is notoriously hard to explore. Under the hood is the professional Rosetta structure prediction methodology; the player's scores are simply the negative of the Rosetta-computed energy. Foldit provides an accessible interface to the Rosetta toolkit, which provides multiple ways to interact with the protein structure as the global minimum energy solution is sought. The Rosetta model parameter free energy hyper-surface is completely

[40] `http://fold.it`

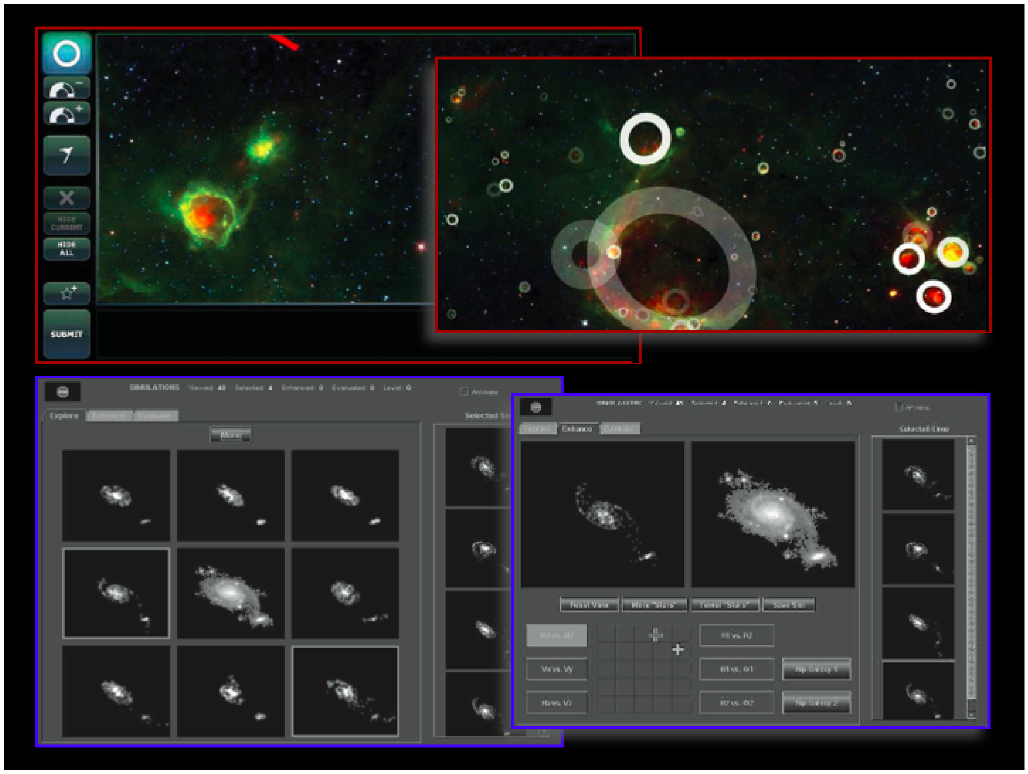

Figure 4: Examples of image modeling in web-based citizen science projects. Top row: star formation "bubble" identification and interpretation in Spitzer images in the Milky Way Project, with the annotation interface shown on the left, and some example (selected, averaged) bubbles on the right. Images from Simpson et al. (2012). Bottom row: matching N-body simulated merging galaxies to SDSS images in the Galaxy Zoo Mergers project (left), and exploring parameter space two parameters at a time to refine the models (right). Screenshots from Holincheck et al. (2010).

analogous to the complex likelihood surface of any non-linear model, the kind of model that is to be found in planetary system dynamics, gravitational lenses, merging galaxies, and many other astrophysical data analysis situations.

Results from Foldit have been very encouraging, with the players discovering several new protein configurations, leading to improved enzyme performance

(Eiben et al. 2012) and new understanding of retroviral drug design (Khatib et al. 2011b). The team have suggested several features of Foldit that appear to them to have underpinned its success. Recipes for manipulating the protein structures (that codify strategies) can be shared within teams, and later made available by the Foldit team to the whole community – these algorithms evolve rapidly as different players modify them, and can rival (if not out-perform) strategies developed by professional scientists (Khatib et al. 2011a). The game provides multiple sources of motivation (competition between players, collaboration within a team, short term scores, long term status) which appeal to a variety of players.

Online Data Challenges We now turn to data modeling by citizens implementing machine learning techniques in astronomy, via analysis challenges organised by members of the professional astrophysics community. The measurement of weak gravitational lensing by large scale structure ("cosmic shear") relies on the measurement of the shapes of distant, faint galaxies with extreme accuracy. Blind galaxy shape estimation challenges have had an enormous impact on the field, revealing biases present in existing techniques, and providing a way for researchers outside the world of professional cosmology to participate. In particular, the GREAT08 challenge (Bridle et al. 2010) saw very successful entries from two (out of a total of 11) teams of researchers from outside of astronomy (albeit still professional researchers), including the winner. A companion, somewhat streamlined galaxy shape measurement challenge, "Mapping Dark Matter," was hosted at the Kaggle website[41] (Kitching et al. 2012b). The wider reach of this platform led to over 70 teams making over 700 entries to the competition; many of the teams did not contain professional astronomers, although most were

[41] `http://www.kaggle.com/c/mdm`

still from academia.

In a comparison with the GREAT challenges, the Kitching et al. found a factor of several improvement in shear accuracy over comparable previous challenges, and suggested two interesting explanations for this success. First, the challenge was designed to be as accessible as possible, with an extensive training set of data that needed very little explanation; in this way the challenge was geared towards *idea generation*. Second, they noted that the competitive nature of the challenge (a webpage leaderboard was updated in real time as entries were submitted) seemed to stimulate the analysts into improving their submissions. Kaggle offers cash prizes, which will have had some effect as well (the pot was $3000 for this challenge, even if indirectly).

Two more astronomical Kaggle challenges have since been set. The first involved inferring the positions of dark matter halos based on their weak lensing effects (Harvey et al. 2014)[42] This challenge attracted the attention of 357 teams, perhaps due to its larger prizes, and led to an improvement in halo position accuracy of 30%. It also sparked some debate in its forums as to the design of the challenge: the models used to generate the data, the size of the test datasets (and consequent stability of the leaderboard), the choice of leaderboard metric and so on. These issues are also of generic importance for scientists looking to crowd-source algorithm development. It is interesting to note that the Kaggle forums are a useful resource for the Kaggle development team: the citizens who are active there do influence the design of the site infrastructure and challenge rules (D. Harvey, priv. comm.).

The most recent Kaggle astronomy challenge was to reproduce the Galaxy Zoo 2

[42] `http://www.kaggle.com/c/DarkWorlds`

crowd-sourced galaxy morphologies based on automated measurements of the SDSS color composite JPEG images.[43] 329 teams entered the challenge, including professional astronomers, academics specializing in non-astronomy areas, teams from university courses, and members of the public (K. Willett, priv. comm.). The top performing algorithms were able to reproduce detailed morphologies, including features on scales of only a few pixels and those with highly non-symmetric geometries, that were originally generated by crowd-sourced annotations (Willett et al., in prep.). All of the leading entries also used various implementations of convolutional neural networks (convnets); the results suggest that convnets offer one of the best candidates for automated machine learning trained on gold standard data in larger, future surveys (see Section 7.2).

Like Foldit's "recipes," the Kaggle challenges are crowd-sourcing the development of new algorithms. As data science plays an increasingly important role in industry and commerce, we might expect the number of citizens interested in applying their skills to science problems in their spare time to grow. The challenge is to present those problems in meaningful ways, to enable high value contributions to be made. While members of this community may not identify as "citizen astronomers," there is clearly an opportunity for citizen data scientists to play an important support role.

5 CITIZEN-LED ENQUIRY

The previous sections have focused on specific, and somewhat isolated activities in which citizens have participated. In most cases, the community's involvement has been a *contribution* to a scientific investigation defined by professionals. The

[43] `http://www.kaggle.com/c/galaxy-zoo-the-galaxy-challenge`

most important part of any scientific investigation is the question at its heart: what is it we are trying to find out about the universe? In this section we look at some cases where the process of enquiry, the science itself, has been led by citizens. While citizen scientists have published as first authors in research journals (Hui 2013; Liang, Liang & Weisberg 2014, see e.g.), this is still a fairly rare occurrence. Instead, we focus on some collaborative projects where the asking of science questions by citizens is supported and guided by professionals.

In principle, this is an area of great potential. The constraints of funding proposals and management of research groups can often mean that professional scientists focus very narrowly on particular topics of research, specializing in particular techniques or datasets. Steering away from this course implies taking risks with time management, and allocation of resources to an ultimately fruitless research area can be detrimental to careers. Citizen scientists are largely free of these managerial and budgetary constraints, and are able to devote their attentions to whatever topics interest them. Moreover, we might expect outsiders to ask some unusual questions, and make connections and suggestions that highly focused professionals may not have thought of.

The Galaxy Zoo Forum.

The best known serendipitous discovery emerging from the Galaxy Zoo project is "Hanny's Voorwerp" (Lintott et al. 2009), a galaxy-scale light echo which reveals a recent ($\sim 100,000$ years ago) shutdown of AGN activity in IC 2497, a neighboring spiral galaxy (Keel et al. 2012b). The discovery of the Voorwerp was first recorded in the Galaxy Zoo forum a few weeks after the project started, and inspired a more systematic search for similar phenomena in other galaxies. This project, made possible by the deep engagement in the forum community of Galaxy Zoo science team member Bill Keel, succeeded in finding more than forty instances of clouds which appear to have been ionized by AGN activity. One-third of such systems show signs of similar significant drops in AGN activity on timescales of tens of thousands of years (Keel et al. 2012a).

The ability of the Zoo volunteers to carry out their own research, moving far beyond the mere “clockwork” required by the main interface, is best illustrated by the discovery of the Galaxy Zoo Green Peas (Cardamone et al. 2009). These small, round and, in SDSS imaging, green, systems are dwarf galaxies with specific star formation rates which are unprecedented in the local Universe, matched only by high-redshift Lyman-break galaxies. Volunteers not only identified these systems, but organized a systematic search and further review of them. This effort included the use of tools designed by SDSS for professional astronomers to acquire and study spectroscopic data. Other projects, such as the systematic search for overlapping galaxies (Keel et al. 2013) in order to study the dust distribution and attenuation law (Keel et al. 2014), were initially directed by professional members of the Galaxy Zoo team but thenceforth drew on the enthusiasm and ability of volunteers.

While the discovery of the Peas and other similar projects demonstrates the exploration ability of the Galaxy Zoo citizen community, it is important to note that the simpler, initial interaction provided by the main classification interface was necessary in order to develop that community in the first place. The participants in the citizen scientists’ investigation of the Peas did not arrive on the site wanting to dig into spectra or confident of their ability to do so; these were the results of their participation. The project acted as an “engine of motivation” in inspiring its participants to become more involved.

Lightcurve analysis on Planet Hunters *Talk*.

The data modelling examples of Section 4 all involved modeling infrastructure provided by either the project's developers or their science teams. Planet Hunters provides a case where citizens have carried out their own modeling analysis, using their own tools. Critical to this endeavour was the ability of a small, and increasingly expert, group of volunteers to identify objects worthy of further analysis. For Galaxy Zoo, the forum had served this purpose but, as the project matured, participation in discussions became restricted to a small and decreasing fraction of the community. Planet Hunters was the first Zooniverse project to introduce an integrated discussion tool, known as *Talk*. Classifiers were asked, after viewing each light curve, whether they wanted to discuss what they had seen; more advanced users could then harvest interesting candidates from these posts. For example, the candidates presented in Lintott et al. (2013) were initially collated by volunteers.

Their involvement was not limited to collecting Planet Hunters candidates. Making use of the *Kepler*archive, these advanced users were able to investigate the full set of data for candidate stars, producing periodograms and making fits to transits to derive planet candidate properties. Some of this analysis, for example checking the *Kepler*field for background sources, can be carried out online with tools originally intended for professional astronomers, but much was done offline using Excel or other software.[44] PH1b (Section 3.1) was one of the systems discovered in this way, as indeed were the candidates in the Wang et al. (2013) and Schmitt et al. (2014) papers. Nor was this sort of work restricted

[44]The expense of IDL licenses was a major barrier to further modelling; much of the software used by the *Kepler*team is written in this proprietary language.

to planet candidates; interesting variable stars, including several new RR Lyrae systems, and cataclysmic variables (e.g. Kato & Osaki 2014) have been discovered and analysed by Planet Hunters volunteers. This pattern of work, in which more experienced or specialised volunteers follow up on serendipitous discoveries identified initially by classifiers working in the main interface, is explicitly encouraged in the new version of Planet Hunters, when comments can be made on light-curves without leaving the main interface.

Galaxy Zoo: Quench. Examples such as those above show that advanced work is possible within distributed citizen science projects, but that this requires volunteers to take on such tasks themselves. In order to increase the number, and perhaps the diversity, of volunteers moving beyond simple classification, experiments have been conducted to provide more scaffolded experiences. One of the most ambitious was the Galaxy Zoo: Quench project[45] (Trouille et al. in prep.) which offered volunteers the opportunity to "experience science from beginning to end."

In this project, classification of a sample of potential post-merger galaxies selected from the main Galaxy Zoo sample was followed by open exploration of both the classification data and the metadata for these galaxies (available from the Sloan Digital Sky Survey) by the volunteers, enabled by a "dashboard.[46]" 3298 users participated in the classification stage, and around 25% of those Zooniverse-registered users who did so took part in data analysis. These results contributed to a discussion from which a set of astrophysically interesting conclusions were formulated by a small number of participants (10), with support from the project science team.

[45] `http://quench.galaxyzoo.org`

[46] `http://tools.zooniverse.org/#/dashboards/galaxy_zoo`

Galaxy Zoo: Quench demonstrated that a hierarchical approach, with simple tasks leading to more advanced analysis, can be successful in encouraging large numbers of volunteers to move beyond simple classification; the number working with the data was much higher as a percentage of participants than in Planet Hunters, a project with success in volunteer user engagement. However, engagement with the literature (either by reading or writing) required close collaboration with the professionals involved. One interesting feature of the Quench project was its teething problems: issues with the data were discovered by the citizens, and needed to be fixed. (Similar problems have been encountered in Kaggle challenges.) While this caused the project to slow down and lose engagement somewhat, it does illustrate a key feature of citizen-led enquiry, namely that the same book-keeping, cleaning and calibration problems will arise in these projects just as they do in professional ones, and the limiting factor may well be the amount of professional effort available. The challenge is to enable the crowd to solve them quickly and keep investigating.

6 UNDERSTANDING THE CITIZENS

Having surveyed some of the activities involving citizen scientists, we can now consider some questions about this community itself. Who participates in citizen science, and what motivates them?

6.1 Demographics

Who is participating in citizen astronomy? We might expect the demographics to vary with activity, and with the level of commitment required. We have some understanding of at least the former division from two studies that were carried out approximately simultaneously, one of the community participating in Galaxy Zoo, and another of the American Association of Variable Star Observers (AAVSO). Raddick et al. (2013) surveyed the Galaxy Zoo volunteer community to investigate their motivations (Section 6.2 below), via a voluntary online questionnaire. The 11,000 self-selected Galaxy Zoo users identified as 80% male, with both genders having an approximately uniform distribution in age between their mid-twenties and late fifties. (Responses from volunteers under 18 were removed). The authors point out that this is close to the US internet user age distribution, except for slight but significant excesses in numbers of post-50s males, post-retirement people of both genders, and a deficit in males under 30. The survey respondents also tended to be more highly educated than average US internet users, with most holding at least an undergraduate degree, and around a quarter having a masters or doctorate. Very similar findings were reported by Gugliucci, Gay & Bracey (2014) from a survey of COSMOQUEST project participants.

These findings can be compared with a survey of the members of AAVSO: Price & Paxson (2012) received over 600 responses (corresponding to about a quarter of the society's members). The education levels of the AAVSO repondents matches the Galaxy Zoo community very closely; the AAVSO age distribution is more peaked (in the mid fifties), with a similar post-60 decline but also a marked absence of younger people. The online nature of the Galaxy Zoo project seems to have increased the participation of younger (pre middle-age) people. Likewise, the Galaxy Zoo gender bias, while itself extreme, is less so than at AAVSO, where some 92% of survey respondents were male. One additional piece of information provided by the AAVSO survey is the profession of the variable star observers: most (nearly 60%) of the survey respondents were found to be working in science, computer science, engineering and education.

The Galaxy Zoo and AAVSO communities differ by more than just the nature of their activity. The smaller AAVSO community is arguably more engaged in its research, in the sense that a larger fraction of its membership is active in taking observations and contributing to analyses. It would be very interesting to know how citizen scientist motivation varied with the level of participation: dividing the Galaxy Zoo community into volunteers that contribute to the forum and those who do not could be interesting; perhaps more so would be to repeat the analysis of Raddick et al. over a wide range of projects, and look for trends there. The emergent picture thus far, however, is of a well-educated (and often scientifically trained) but male-dominated citizen science community, whose female and younger membership is likely to have been, at least in part, enabled via projects being hosted online. Continuing to lower the barriers to entry for currently under-represented demographic groups would seem both important, and within reach.

6.2 Motivation

What motivates citizen scientists? The two demographic studies referred to above also covered this question; having previously (Raddick et al. 2010) identified 12 categories of motivation in an earlier pilot study, Raddick et al. (2013) asked the 170,000 Galaxy Zoo volunteers at the time to comment on how motivated they were by each of these categories, and which was their primary motivation. The 6% who responded gave consistent answers to those given by around 900 forum users who responded in a separate appeal, allowing conclusions about this presumably more engaged sub-population to be drawn. A desire to *contribute* to science was found to be the dominant primary motivation, being selected by 40% of respondents. *Astronomy*, *science*, *vastness*, *beauty* and *discovery* were all motivation categories that were found to very important to the volunteers, while *fun*, *learning* and *community* were less important.

The AAVSO demographic survey (Price & Paxson 2012) found similar results: over a third of variable star observers cited *involvement in science and research* as their primary source of motivation. However, a similar number gave an *interest in variable stars* as theirs, perhaps reflecting a stronger focus on the science questions involved than is present in the Galaxy Zoo community. Both groups of citizen scientists are clearly quite serious in their reasons for taking part: their motivations are actually very close to those of professional scientists, as many readers of this review will recognize. Perhaps surprisingly, the participants in online data analysis citizen science projects seem to a large extent to be a distinct community from those who participate in more traditional amateur astronomical activities. Galaxy Zoo classifiers, for example, are not, for the most part, regular amateur observers.

While research on the skill, and conceptual understanding, that people aquire while participating in citizen science activities is still in its early stages, there are some hints that continued engagement is correlated with both performance in the task at hand, and understanding of the physics and astronomy underlying the task. Prather et al. (2013) offered Galaxy Zoo and Moon Zoo volunteers the opportunity to take questionnaires that tested their understanding of the astrophysics associated with each project, and found that performance on this questionnaire correlated with high levels of participation in the projects. In a quantitative analysis of ten of the Zooniverse projects, Luczak-Roesch et al.

(2014) detected significant shifts towards more advanced vocabulary used on the discussion boards over the lifetime of each project. In the Space Warps project, the probabilistic model for the crowd includes a measure of each classifier's skill; a strong correlation is seen between a classifier's skill, and the number of images they have seen (Marshall et al, in prep.). It seems as though the skillful classifiers remain engaged in the project for a long time, while almost no long-term participants have low skill – an observation consistent with the volunteers being motivated by contributing to science. Interestingly, Luczak-Roesch et al. (2014) found a strong correlation between the number of classifications performed, and the number of contributions to the comment or discussion boards, with two thirds of the latter being contributed by 1% of the volunteers showing above average engagement. Community interaction seems to be particularly important for dedicated volunteers, even if it may not be what they would give as their primary motivation.

6.3 Competition or Collaboration?

As seen in Section 3.3 and Section 4 above, non-astronomical projects may have much to teach us about "gamification" as a motivator – the inclusion, either explicitly or implicitly, of game-like mechanics such as scores, "badges" or other rewards, leaderboards, and so on. The Foldit team presents a strong case for games as drivers of activity in citizen science, and the Kaggle challenges depend on competition to stimulate engagement. However, an early experiment with Galaxy Zoo showed that the addition of a score de-incentivised poor classifiers, but also resulted in the best classifiers leaving, presumably having been satisfied once a top score was achieved. A recent study by Eveleigh et al. (2013) of the

Zooniverse's Old Weather project, which included basic rankings for classifiers, also highlighted these dangers, identifying volunteers who were alienated by the addition of this game-like score. They felt discouraged when top scores could not be matched, and worried about data quality if the scoring scheme rewarded quantity of classifications rather than accuracy. Taking seriously the finding that citizen scientists are motivated by a perception of authentic participation in research, it seems right to be cautious about introducing elements which are, or which are perceived to be, in tension with this primary motivation.

Moreover, the introduction of a significant incentivizing scheme relies on an accurate model of what "correct" behaviour would look like. This may prove to be a significant barrier to accuracy if such a model is not available. For example, in Planet Hunters, such a model would not have included unusual systems such as PH1b. Where a strong incentive scheme results in near-uniform classifier behaviour, a loss of flexibility in later data analysis could be incurred. A strong comparison of the type of reward structure utilized by Eyewire and the approach used by projects such as Galaxy Zoo is needed, in order to inform future project design.

The surveys described in the previous section reveal a community of people many of whom may have left academic science behind as soon as they finished their education, but whose passion for astronomy and the desire to be part of the scientific process drives them to actively observe the night sky or to participate in the analysis of large datasets. While "community" was not found to be a strong stated motivator for the Galaxy Zoo volunteers, it is nevertheless very important for those who participate in the discussions. For these more engaged volunteers, being part of a community (albeit a distributed one) seems to bring great enjoyment and satisfaction, as they unite under this shared interest which may be far removed from their "normal" lives.

The binding together of these community is reflected in the language they use: Zooniverse volunteers refer to themselves as "Zooites," for example. It is interesting to note that *approachable* project names are almost universal in citizen science, and perhaps function as ice-breakers in their nascent communities. Through improved forum design, more recent Zooniverse projects have sought to further widen participation in community discussion, hypothesizing not that it will more strongly motivate people, but because it will help them make better contributions. Tests of hypotheses like this should be helpful in guiding citizen science project design.

7 THE FUTURE OF CITIZEN ASTRONOMY

During this review a picture has emerged of two types of very active and engaged citizen astronomy community, which we might label observers and classifiers. Although these communities come together in differing ways (by self-assembly through local groups linked by national and international networks, or by joining online projects built by professional organisations), they have reached a similar degree of internet-enabled connectedness, both with each other and with the groups of professional astronomers with whom they collaborate. They also share the common motivation of being involved in, and contributing to, science. In this section we look ahead, to the next decade or so, and discuss the likely paths that citizen astronomy will take, as the available technology advances and professional astronomy evolves. In it we try to identify the niches that citizens might best occupy in this changing environment, and also some key challenges that those who find themselves planning citizen science projects are likely to have to face.

7.1 The Future of Citizen Observing

In professional astronomy, the wide field survey era is upon us: SDSS provided the data for Galaxy Zoo, and other, larger surveys are planned or underway. Key science drivers for projects such as LSST and the Square Kilometer Array include mapping cosmological structure back into the reionisation era, and further opening the time domain; these will yield datasets of significantly increased volume, throughput rates, and complexity. Follow up observations of new discoveries made at greater depths will be made with giant facilities such as ALMA and the various planned Extremely Large Telescopes, while distributed arrays of robotic telescopes, operating in remote regions with excellent atmospheric conditions, and trained to observe a target in a regular fashion over multiple nights will be able to take advantage of wealth of new transient phenomena.

These future advances in technology may in one sense widen the gap between citizen scientists and professionals again. For example, networked telescopes capable of quasi-continuous observations over 24 hour periods could be used to develop a consistent high-quality dataset for cloud tracking on Venus, Mars or the giant planets; as the images would be homogenous, we can envisage automated software identifying morphological peculiarities over time, replacing the crowd-sourced citizen analysis currently underway. However, such an investment would require both international funding and considerable time and effort: the availability of citizen observers will remain a factor.

However, the advances in hardware becoming available to citizen observers suggest other roles that they could play. Larger optics, more sensitive cameras, and spectral coverage extending to longer wavelengths in the infrared could permit citizen investigations of Uranus and Neptune, the Kuiper Belt objects, and a wider variety of bright variable objects. Transits of extrasolar planets in front of their parent stars would be permitted from modest observatories provided they had stable conditions. New platforms might also become available to the citizen scientist, including balloon-borne observatories that provide crisper and more detailed observations of astronomical targets. We can expect to see the networks of citizen deep sky observers investigating new bright transients found in the wide field surveys, while continuing to expand their own surveys.

Aside from pushing the observational boundaries, one challenge that amateur astronomy may face is its own big data problem. For example, solar system video monitoring projects are likely to need automated feature detection of some kind; other observing campaigns may also generate more data than is easily manipulated. Will this community take to crowd-sourcing its visual inspection? The Zooniverse platform is currently being redeveloped to enable easy upload of images and launch of projects; such a facility may be used by citizen scientists as well as by professionals.

7.2 The Future of Crowd-sourced Visual Classification

The point at which human review of data is no longer necessary has been forecast for decades, but as we have seen above, the number of problems for which manual review of images or data is still carried out is considerable. Even if the proportion of data for which human inspection is necessary decreases dramatically over the next decade (due to advances in automatic analyses), the continued growth in the size of astronomical datasets should ensure that there remains plenty for citizen scientists to do. Both LSST (Ivezic et al. 2008) and SKA scientists (Norris et al. 2013) have already considered citizen science as part of their plans for analysis. As a precursor to engaging with the latter project, Radio Galaxy Zoo[47] (Banfield et al in prep.) demonstrates a citizen science project aimed at cross-identification of sources between surveys at different wavelengths, a task that still requires human but not necessarily expert intervention. Thinking about how to deal with multiwavelength data will be critical for citizen science projects dealing with the next generation of surveys.

To understand the potential for citizen science in the era of extremely large surveys, consider the example of optical transients. The LSST system overview paper (Ivezic et al. 2008) gives a conservative estimate of $10^5 - 10^6$ alerts per night. Even if, after automated brokerage, only 1% of these require human classification, then that still might lead to $10^3 - 10^4$ objects requiring inspection and interpretation every night – roughly one every 10–100 seconds. Given the increased reliability, and likelihood of serendipitous discovery, provided by citizen inspection, we should take seriously the incorporation of open inspection into plans for LSST transients. Similar arguments (with large error bars) can be made for other surveys: inspection of transients for LOFAR already requires some human intervention (Stappers et al. 2011).

Implicit in this way of thinking is the sharing of work between human and machine classifiers. A simple example of human-machine task allocation was mentioned in Section 3.2, where machine analysis of PTF images identified those that contained candidate supernovae needing inspection by volunteers. The inclusion of human inspection changed the nature of the machine learning task:

[47] `http://radio.galaxyzoo.org`

instead of optimising for purity (producing a small but accurately classified set of candidates), the task for machine learning became one of identifying a subset of the images which contained many false positives but also a complete set of all supernovae. In this example, human and machine classification proceeded in series rather than in parallel, but more complex interactions can be imagined.

The accuracy of machine learning typically depends on the quality of the training or "gold standard" data which can be provided for the problem in question. Citizen science projects can assist by providing training sets which are orders of magnitude larger than might otherwise have been available, while work by Banerji et al. (2010) established that the confidence intervals provided by classifications from multiple volunteers can also improve machine learning accuracy. Predicting human responses (in the form of probabilities of classification) is an easier task than straightforward sorting. We might expect, therefore, intermediate-size surveys to benefit in the future from a "citizen science phase," in which data is classified by volunteers prior to the automation of the task. This pattern has already been followed by the PTF supernova project discussed above, but perhaps it is more useful to think of the citizen scientists as providing training sets on demand, so that as conditions change from night to night, or the performance of the instrument evolves over time, a small percentage of the total data is always processed by humans in order to provide a constantly updated training set.

If we are using classifications of gold standard data to assess the performance of human classifiers, it is straightforward to include machine classification in the same system. In this way, the task of classification could be shared dynamically and in real time between machine and human classifiers, improving the efficiency of the system. Significant work has already been carried out for the nearly analogous problem of assigning tasks to an ensemble of imperfect machine classifiers whose characteristics are known and for Mechanical Turk-like systems where a fixed payment is provided for a task but the problem of adding in volunteers is significantly harder. For the machine-only case, each classification task can be treated as having a known cost (perhaps the processing time necessary for a given routine), but when assigning tasks to volunteers, who are able to leave whenever they like, other costs must be taken into account. In order to create a viable system, it is, in fact, necessary to measure how *interesting* a task or set of tasks is, and this requirement may conflict with the need for efficiency. As an example, consider a Galaxy Zoo-like system which assigned the hardest galaxies to the best classifiers. This would result in a steady diet of faint fuzzy objects for the best classifiers; if they are motivated in part by the variety of images seen, then such a system would tend to systematically drive away its best classifiers. Nor is this problem necessarily resolved by simply seeding the stream of data with impressive images; an informal study of Snapshot Serengeti (Lynn, private communication) reveals that seeing more impressive images early in a classifier's career (as measured by the number of volunteers who added it to their list of favourites) tended to decrease the number of classifications received from that volunteer in the long run, presumably by setting up expectations for the rest of the data.

Considering individual classifications in isolation is clearly not sufficient; the entirety of a volunteer's career must be considered when assigning tasks. We should be wary of over-specialisation even when efficiency is paramount. Complexities like these indicate a clear need for research into novel systems for task assignment, in order to scale citizen science to the challenges of the next generation of surveys.

7.3 Advanced Citizen Activities in the Future

As we have seen in previous sections, volunteers can and do move beyond simple classification problems, and such behaviour could become increasingly important as the volume and complexity of astronomical data continues to increase. We can imagine providing user-friendly, web-based tools enabling fairly sophisticated data analysis to be performed by anyone with a browser. The experience documented above invites us to consider the possibility of teams of citizens performing analyses that currently require a significant amount of research student time. Checking survey images and catalogs for processing failures and fitting non-linear models to data are just two possibilities. Just as research students adapt and develop the tools they are first presented with, the Kaggle and Foldit experiences point strongly towards a model where citizens are also enabled to adapt and extend their tools. Open source tool code is a minimal requirement in this model; finding ways beyond this to support citizen algorithm development seems to be likely to pay off.

In terms of supporting citizen-led enquiry, an example of best practice exists in the way that the Sloan Digital Sky Survey's *sky server* provided tools for both professional (or advanced) researchers alongside simplified versions aimed primarily at educational use. This structure has the twin benefits of providing near-seamless transitions from simple to more advanced interfaces, and of providing extra pressure to make the resulting interfaces easily usable (something which benefits all users, not just citizen scientists!). Designers of science user interfaces for upcoming large projects would do well to bear these twin audiences in mind. Indeed, the more citizen-accessible the interfaces to the upcoming public wide-field survey databases can be made, the better chance we will give ourselves of enabling and supporting "bottom-up" citizen science. This term, introduced by Muki Haklay and collaborators, represents an ambition to produce citizen science projects that are driven by the participants. Moving beyond the 'top down' structure of most astronomical citizen science projects is, as we have shown, a significant challenge – but one that is, perhaps, worth taking on.

7.4 The Future of Citizen Scientific Collaboration

As well as enabling access to larger datasets, citizen science projects looking to engage larger crowds of volunteers will likely face challenges of another sort. We might expect contributing to science via large international public datasets to appeal to citizens of many nations: while translation of project materials is simple, coordinating a scientific *discussion* across multiple language barriers could prove difficult. Having a critical mass of professional scientists interacting with the citizens in each language would seem the most important factor.

Even within a single language group, collaboration is difficult to achieve with very large numbers. In the large Zooniverse projects, a hierarchical system of citizen discussion, with moderators bridging the gap between science teams and the crowd, has worked well, although it requires significant commitment and effort from both the volunteer moderators and the professional scientists involved. The pay-off seems to be high, though: as many of the smaller-scale projects in this review have shown, citizen science works best when professionals and amateurs work together as a strong collaboration. In these small groups, collaboration is natural, and can lead to highly productive teams. Scaling up to collaborations with ever larger crowds is a significant challenge.

Access by citizens to professional scientists can be somewhat improved by regular blog posts and webcasts, as many projects have found. Certainly these can supply much-needed feedback as to the utility of the citizens' efforts, as the professionals report on how the citizen-provided data is being used. We might also imagine regular broadcasts from the data-providing projects as playing a significant role in motivating and sustaining a crowd of volunteers, and MOOC-style resources may help with training. However, for the foreseeable future, astronomical surveys and other organisations will continue to seek to use citizen science as a way of *expanding* the amount of science that can be done; a short supply of committed and energetic professionals looking to work with citizens could be a bottleneck. Another way to look at this is that lareg-crowd projects which rely on significant intervention from small numbers of professionals will likely fail. Focusing on designing systems which can maximise scientific return and volunteer participation with manageable levels of intervention seems necessary.

8 CONCLUDING REMARKS

Over the last two decades, citizen astronomy has undergone a period of rapid growth, primarily due to the sharp increase in the ease with which people can form communities and work together via the world-wide web. A number of very productive "Pro-Am collaborations" have formed in order to observe a variety of bright astronomical objects in ways that capitalise on the flexibility, availability and skill of the amateur observing community. Professional-led visual classification projects have appeared, attracting three orders of magnitude more citizens to the field than were previously engaged in amateur observational research.

Citizen-classified training sets have been used to improve the performance of machine learning approaches, suggesting that we should think in terms of "human-machine partnerships." Citizens have engaged in data analysis tasks of increasing sophistication and difficulty, and experimentation in professionally-guided online "bottom up" citizen research has begun.

In this review, we have consistently seen that the best citizen science in astronomy has come from organised communities that have been asked to play to their strengths, have been guided well by their professional collaborators, and have been able to operate in niches insufficiently occupied by either professional observers or automated classification software. The citizen astronomers are passionate about their subject, and, encouragingly, are motivated by being of service. We must recognize that a critical feature of citizen science is the enabling of amateurs to make authentic contributions to the research topic in question. This, in turn, should drive us to seek out those tasks that cannot be performed by other means.

The observational and classification citizen scientist communities are similar in their diversity regarding both their motivation and their ability to contribute; this diversity means that good citizen science projects are ones that provide both a low barrier to entry, but that also provide (or support the development of) tools that enable their emergent experts to maximize their contributions to science. Indeed, the most dedicated volunteers have proved capable of developing and using a variety of advanced astronomical techniques, suggesting that we are likely to continue to see increasing numbers of citizens co-authoring papers in high impact research journals. While not everyone who takes part in a project wants to graduate to more advanced work, providing the opportunity to do so is important.

Each of the case studies presented in this review has been an experiment in citizen science: amateur and professional astronomers alike have had good ideas for ways to make use of the public's skills and abilities, tried them out, and made progress in astronomy – and in doing so revealed something about how citizen science can work. Human potential is vast: citizen astronomy seems to us to be an experiment well worth continuing.

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9 LITERATURE CITED

References

1. Ball NM, Loveday J, Fukugita M, Nakamura O, Okamura S, et al. 2004. *MNRAS* 348:1038–1046
2. Bamford SP, Nichol RC, Baldry IK, Land K, Lintott CJ, et al. 2009. *MNRAS* 393:1324–1352
3. Banerji M, Lahav O, Lintott CJ, Abdalla FB, Schawinski K, et al. 2010. *MNRAS* 406:342–353
4. Barentsen G, Koschny D. 2008. *Planetary Space Science* 56:1444–1449
5. Batalha NM, Rowe JF, Bryson ST, Barclay T, Burke CJ, et al. 2013. *ApJS* 204:24
6. Battams, K. 2012, AGU Fall Meeting Abstracts, Abstract SH21D-03
7. Beaumont C, Goodman A, Williams J, Kendrew S, Simpson R. 2014. *ArXiv e-prints: 1406.2692*
8. Böttcher M, Harvey J, Joshi M, Villata M, Raiteri CM, et al. 2005. *ApJ* 631:169–186
9. Bridle S, Balan ST, Bethge M, Gentile M, Harmeling S, et al. 2010. *MNRAS* 405:2044–2061
10. Brink H, Richards JW, Poznanski D, Bloom JS, Rice J, et al. 2013. *MNRAS* 435:1047–1060
11. Buzzi L, Pittichova J, Bernardi F, Marsden BG. 2006. *Minor Planet Electronic Circulars* :48
12. Capella_05. 2014. *Zooniverse Letters:* `http://letters.zooniverse.org/letters/86-collaborative_gravitat`

13. Cardamone C, Schawinski K, Sarzi M, Bamford SP, Bennert N, et al. 2009. *MNRAS* 399:1191–1205

14. Christie G. 2006. *Society for Astronomical Sciences Annual Symposium* 25:97

15. Conselice CJ. 2006. *MNRAS* 373:1389–1408

16. Cooper, S., Khatib, F., Treuille, A., et al. 2010. *Nature* 446:756

17. Crowston K. et al. 2014. In *17th ACM Conference on Computer Supported Co-operative Work and Social Computing (CSCW 2014)*

18. de León J, Ortiz JL, Pinilla-Alonso N, Cabrera-Lavers A, Alvarez-Candal A, et al. 2013. *A&A* 555:L2

19. de Pater I, Fletcher LN, Perez-Hoyos S, Hammel HB, Orton GS, et al. 2010. *Icarus, in press*

20. Eiben CB, Siegel JB, Bale JB, Cooper S, Khatib F, et al. 2012. *Nature Biotechnology* 30:190

21. Eveleigh A, Jennett C, Lynn S, Cox AL. 2013. *Proceedings of the First International Conference on Gameful Design, Research, and Applications* :79

22. Fischer G, Kurth WS, Gurnett DA, Zarka P, Dyudina UA, et al. 2011. *Nature* 475:75

23. Fletcher LN, Orton GS, Rogers JH, Simon-Miller AA, de Pater I, et al. 2011. *Icarus* 213:564–580

24. Foley RJ, Challis PJ, Chornock R, Ganeshalingam M, Li W, et al. 2013. *ApJ* 767:57

25. Fortson L, Masters K, Nichol R, Borne KD, Edmondson EM, et al. 2012. *Galaxy Zoo: Morphological Classification and Citizen Science.* 213–236

26. Fossey SJ, Waldmann IP, Kipping DM. 2009. *MNRAS* 396:L16–L20

27. Giavalisco M, Ferguson HC, Koekemoer AM, Dickinson M, Alexander DM, et al. 2004. *ApJL* 600:L93–L98

28. Giorgini JD, Yeomans DK, Chamberlin AB, Chodas PW, Jacobson RA, et al. 1997. In *Bulletin of the American Astronomical Society*, eds. MF Bietenholz, N Bartel, MP Rupen, AJ Beasley, DA Graham, VI Altunin, T Venturi, G Umana, JE Conway, vol. 29 of *Bulletin of the American Astronomical Society*

29. Godfrey D. 1988. *Icarus* 76:335

30. Gould A, Udalski A, Shin IG, Porritt I, Skowron J, et al. 2014. *Science* 345:46–49

31. Grogin NA, Kocevski DD, Faber SM, Ferguson HC, Koekemoer AM, et al. 2011. *ApJS* 197:35

32. Gugliucci N, Gay P, Bracey G. 2014. In *Ensuring STEM Literacy*, eds. G Manning J, JB Jensen, MK Hemenway, MG Gibbs, vol. 483 of *Astronomical Society of the Pacific Conference Series*

33. Hahn G. 1996. *JBAA* 106:40

34. Halley E. 1716. *Phil Trans.* :245–262

35. Hammel HB, Wong MH, Clarke JT, de Pater I, Fletcher LN, et al. 2010. *ApJ* 715:150–154

36. Harrington J, de Pater I, Brecht SH, Deming D, Meadows V, et al. 2004. *Lessons from Shoemaker-Levy 9 about Jupiter and planetary impacts*, chap. 8. Cambridge Planetary Science. Cambridge Univ. Press, New York, 159–184

37. Harvey D, Kitching TD, Noah-Vanhoucke J, Hamner B, Salimans T, Pires AM. 2014. *Astronomy and Computing* 5:35–44

38. Holincheck A, Wallin J, Borne K, Lintott C, Smith A, et al. 2010. In *Galaxy Wars: Stellar Populations and Star Formation in Interacting Galaxies*, eds. B Smith, J Higdon, S Higdon, N Bastian, vol. 423 of *Astronomical Society of the Pacific Conference Series*

39. Hota A, Croston JH, Ohyama Y, Stalin CS, Hardcastle MJ, et al. 2014. *ArXiv e-prints: 1402.3674*

40. Hota A, Sirothia SK, Ohyama Y, Konar C, Kim S, et al. 2011. *MNRAS* 417:L36–L40

41. Hueso, R., Pérez-Hoyos, S., Sánchez-Lavega, A., et al. 2013, *Astronomy and Astrophysics* 560:A55

42. Hueso R, Legarreta J, Pérez-Hoyos S, Rojas JF, Sánchez-Lavega A, Morgado A. 2010. *Planetary and Space Science* 58:1152–1159

43. Hui MT. 2013. *MNRAS* 436:1564–1575

44. Ivezic Z, Tyson JA, Acosta E, Allsman R, Anderson SF, et al. 2008. *ArXiv e-prints: 0805.2366*

45. Kamar E, Hacker S, Horvitz E. 2012. In *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2012)*, eds. Conitzer, Winikoff, Padgham, van der Hoek

46. Kanefsky B, Barlow NG, Gulick VC. 2001. In *Proceedings of the Lunar and Planetary Science Conference XXXII*

47. Kato T, Osaki Y. 2014. *PASJ* 66:L5

48. Keel WC, Chojnowski SD, Bennert VN, Schawinski K, Lintott CJ, et al. 2012a. *MNRAS* 420:878–900

49. Keel WC, Lintott CJ, Schawinski K, Bennert VN, Thomas D, et al. 2012b. *AJ* 144:66

50. Keel WC, Manning AM, Holwerda BW, Lintott CJ, Schawinski K. 2014. *AJ* 147:44

51. Keel WC, Manning AM, Holwerda BW, Mezzoprete M, Lintott CJ, et al. 2013. *PASP* 125:2–16

52. Kendrew S, Simpson R, Bressert E, Povich MS, Sherman R, et al. 2012. *ApJ* 755:71

53. Khatib F, Cooper S, Tyka MD, Xu K, Makedon I, et al. 2011a. *PNAS* 108:18949

54. Khatib F, DiMaio F, Foldit Contenders Group, Foldit Void Crushers Group, Cooper S, et al. 2011b. *Nature Structural and Molecular Biology* 18:1175

55. Kim, J. S. et al. 2014. *Nature* 509:331–336

56. Kitching TD, Rhodes J, Heymans C, Massey R, Liu Q, et al. 2012b. *ArXiv e-prints: 1204.4096*

57. Kloppenborg B, Stencel R, Monnier JD, Schaefer G, Zhao M, et al. 2010. *Nature* 464:870–872

58. Koekemoer AM, Aussel H, Calzetti D, Capak P, Giavalisco M, et al. 2007. *ApJS* 172:196–202

59. Koekemoer AM, Faber SM, Ferguson HC, Grogin NA, Kocevski DD, et al. 2011. *ApJS* 197:36

60. Lahav O, Naim A, Buta RJ, Corwin HG, de Vaucouleurs G, et al. 1995. *Science* 267:859–862

61. Lahav O, Naim A, Sodré Jr. L, Storrie-Lombardi MC. 1996. *MNRAS* 283:207

62. Land K, Slosar A, Lintott C, Andreescu D, Bamford S, et al. 2008. *MNRAS* 388:1686–1692

63. Lang D, Hogg DW. 2012. *AJ* 144:46

64. Lang D, Hogg DW, Mierle K, Blanton M, Roweis S. 2010. *AJ* 139:1782–1800

65. Law NM, Kulkarni SR, Dekany RG, Ofek EO, Quimby RM, et al. 2009. *PASP* 121:1395–1408

66. Liang ZX, Liang Y, Weisberg JM. 2014. *MNRAS* 439:3712–3718

67. Lintott CJ, Schawinski K, Keel W, van Arkel H, Bennert N, et al. 2009. *MNRAS* 399:129–140

68. Lintott CJ, Schawinski K, Slosar A, Land K, Bamford S, et al. 2008. *MNRAS* 389:1179–1189

69. Lintott CJ, Schwamb ME, Barclay T, Sharzer C, Fischer DA, et al. 2013. *AJ* 145:151

70. Luczak-Roesch M, Tinati R, Simperl E, van Kleek M, Shadbolt N, Simpson, R. 2014. *Eighth International AAAI Conference on Weblogs and Social Media*

71. Masters KL, Mosleh M, Romer AK, Nichol RC, Bamford SP, et al. 2010. *MNRAS* 405:783–799

72. Miller-Jones JCA, Sivakoff GR, Knigge C, Körding EG, Templeton M, Waagen EO. 2013. *Science* 340:950–952

73. Monard B. 2003. *GRB Coordinates Network* 2324:1

74. Mousis O, Hueso R, Beaulieu JP, Bouley S, Carry B, et al. 2014. *Experimental Astronomy*

75. Muirhead PS, Johnson JA, Apps K, Carter JA, Morton TD, et al. 2012. *ApJ* 747:144

76. Nair PB, Abraham RG. 2010. *ApJS* 186:427–456

77. Norris RP, Afonso J, Bacon D, Beck R, Bell M, et al. 2013. *Publications of the Astronomical Society of Australia* 30:20

78. Oksanen A. 2007. *GRB Coordinates Network* 6873:1

79. Oksanen A, Templeton M, Henden AA, Kann DA. 2008. *Journal of the American Association of Variable Star Observers (JAAVSO)* 36:53

80. Orton GS, Fletcher LN, Lisse CM, Chodas PW, Cheng A, et al. 2011. *Icarus* 211:587–602

81. Popova OP, Jenniskens P, Emel'yanenko V, Kartashova A, Biryukov E, et al. 2013. *Science* 342:1069–1073

82. Porter AC, Filippenko AV. 1987. *AJ* 93:1372–1380

83. Prather EE, Cormier S, Wallace CS, Lintott CJ, Raddick JM, Smith A. 2013. *Astronomy Education Review* 12:1

84. Price CA, Paxson KB. 2012. *ArXiv e-prints: 1204.3582*

85. Raddick MJ, Bracey G, Gay PL, Lintott CJ, Cardamone C, et al. 2013. *Astronomy Education Review* 12:010106

86. Raddick MJ, Bracey G, Gay PL, Lintott CJ, Murray P, et al. 2010. *Astronomy Education Review* 9:010103

87. Raiteri CM, Villata M, Larionov VM, Aller MF, Bach U, et al. 2008. *A&A* 480:339–347

88. Robbins, S. J., Antonenko, I., Kirchoff, M. R., et al. 2014, *Icarus*, 234, 109

89. Rogers J. 1995. *The Giant Planet Jupiter.* Cambridge University Press

90. Sánchez-Lavega A, del Río-Gaztelurrutia T, Delcroix M, Legarreta J, Gomez-Forrellad JM, et al. 2012. *Icarus* 220:561–576

91. Sánchez-Lavega A, Lecacheux J, Gomez JM, Colas F, Laques P, et al. 1996. *Science* 271:631–634

92. Sánchez-Lavega A, Orton GS, Hueso R, García-Melendo E, Pérez-Hoyos S, et al. 2008. *Nature* 451:437–440

93. Sánchez-Lavega A, Wesley A, Orton G, Hueso R, Perez-Hoyos S, et al. 2010. *ApJ* 715:155–159

94. Scoville N, Abraham RG, Aussel H, Barnes JE, Benson A, et al. 2007. *ApJS* 172:38–45

95. Schawinski K, Thomas D, Sarzi M, Maraston C, Kaviraj S, et al. 2007. *MNRAS* 382:1415–1431

96. Schmitt JR, Wang J, Fischer DA, Jek KJ, Moriarty JC, et al. 2014. *AJ* 148:28

97. Schwamb ME, Lintott CJ, Fischer DA, Giguere MJ, Lynn S, et al. 2012. *ApJ* 754:129

98. Schwamb ME, Orosz JA, Carter JA, Welsh WF, Fischer DA, et al. 2013. *ApJ* 768:127

99. Sekanina Z, Chodas PW. 2012. *ApJ* 757:127

100. Sekanina Z, Kracht R. 2014. *ArXiv e-prints: 1404.5968*

101. Simon-Miller AA, Conrath BJ, Gierasch PJ, Orton GS, Achterberg RK, et al. 2006. *Icarus* 180:98–112

102. Simpson E, Roberts S, Psorakis I, Smith A. 2012. *ArXiv e-prints: 1206.1831*

103. Simpson RJ, Povich MS, Kendrew S, Lintott CJ, Bressert E, et al. 2012. *MNRAS* 424:2442–2460

104. Slosar A, Land K, Bamford S, Lintott C, Andreescu D, et al. 2009. *MNRAS* 392:1225–1232

105. Smith AM, Lynn S, Sullivan M, Lintott CJ, Nugent PE, et al. 2011. *MNRAS* 412:1309–1319

106. Solano E, Rodrigo C, Pulido R, Carry B. 2014. *Astronomische Nachrichten* 335:142

107. Stencel RE. 2012. *Journal of the American Association of Variable Star Observers (JAAVSO)* 40:618

108. Szkody P, Mukadam AS, Gänsicke BT, Henden A, Sion EM, et al. 2013. *ApJ* 775:66

109. Stappers BW, Hessels JWT, Alexov A, Anderson K, Coenen T, et al. 2011. *A&A* 530:A80

110. Udalski A, Jaroszyński M, Paczyński B, Kubiak M, Szymański MK, et al. 2005. *ApJL* 628:L109–L112

111. Wallin J, Holincheck A, Borne K, Lintott C, Smith A, et al. 2010. In *Galaxy Wars: Stellar Populations and Star Formation in Interacting Galaxies*, eds. B Smith, J Higdon, S Higdon, N Bastian, vol. 423 of *Astronomical Society of the Pacific Conference Series*

112. Wang J, Fischer DA, Barclay T, Boyajian TS, Crepp JR, et al. 2013. *ApJ* 776:10

113. Waterhouse T. 2013. In *Proceedings of the 2013 conference on Computer supported cooperative work*

114. Westphal AJ, Stroud RM, Bechtel HA, Brenker FE, Butterworth AL, et al. 2014. *Science* 345:786–791

115. Willett KW, Lintott CJ, Bamford SP, Masters KL, Simmons BD, et al. 2013. *MNRAS* 435:2835–2860