Astronomy and Computing 5 (2014) 35–44

Contents lists available at ScienceDirect

Astronomy and Computing

journal homepage: www.elsevier.com/locate/ascom

Full length article

Observing Dark Worlds: A crowdsourcing experiment for dark matter mapping

D. Harvey[a,*], T.D. Kitching[b], J. Noah-Vanhoucke[c], B. Hamner[c], T. Salimans[d], A.M. Pires[e]

[a] SUPA, University of Edinburgh, Royal Observatory, Blackford Hill, Edinburgh EH9 3HJ, UK

[b] Mullard Space Science Laboratory, University College London, Holmbury St Mary, Dorking, Surrey RH5 6NT, UK

[c] Kaggle, Inc., 188 King St. Suite 502, San Francisco, CA 94107, USA

[d] Erasmus University, Rotterdam, The Netherlands

[e] Department of Mathematics and CEMAT, Instituto Superior Técnico, University of Lisbon, Av. Rovisco, Pais, 1049-001 Lisboa, Portugal

ARTICLE INFO

Article history:
Received 4 November 2013
Accepted 16 April 2014

Keywords:
Cosmology
Dark matter — galaxies
Clusters — gravitational lensing
Weak

ABSTRACT

We present the results and conclusions from the citizen science competition 'Observing Dark Worlds', where we asked participants to calculate the positions of dark matter halos from 120 catalogues of simulated weak lensing galaxy data, using computational methods. In partnership with Kaggle (http://www.kaggle.com), 357 users participated in the competition which saw 2278 downloads of the data and 3358 submissions. We found that the best algorithms improved on the benchmark code, LENSTOOL by $>30\%$ and could measure the positions of $>3\times10^{14}M_\odot$ halos to $<5''$ and $<10^{14}M_\odot$ to within $1'$. In this paper, we present a brief overview of the winning algorithms with links to available code.

1. Introduction

Dark matter dominates the mass content of the Universe (see for example Massey et al., 2010 for reviews), in particular on galaxy and galaxy cluster scales where the ratio of total mass to observed baryonic matter is a factor of at least 10–100. In fact approximately 30% of the total energy budget of the Universe is in the form of non-baryonic matter (Planck Collaboration et al., 2013). Further constraining the nature of dark matter has become one of the most important problems in physics (Peter, 2012). However, despite the macroscopic total abundance of this non-baryonic component of the Universe being well determined, the understanding of the subatomic physics of dark natter is not; if indeed dark matter is a subatomic particle at all. Under the assumption that dark matter is a non-relativistic particle when it decouples from baryonic, ordinary, matter in the early universe, and that it is collisionless, one can qualitatively reconstruct the observed large scale structure in N-body simulations (Davis et al., 1985), with the baryonic physics (Semboloni et al., 2011) limiting our knowledge at the sub megaparsec scales. Dark matter is hypothesised to exist in clouds of particles that self-gravitate into bound systems, these clouds are referred to as dark matter 'halos' since observationally dark matter appears to have concentrations that are highest in clouds that surround baryonic matter.

It is hypothesised, from N-body simulations, that there are several problems with the collisionless dark matter paradigm at small scales, where predictions begin to depart from measurements in data. These are the 'too big to fail problem' (Boylan-Kolchin et al., 2011), and 'the cuspy halo problem' (Dubinski and Carlberg, 1991). The former refers to the observation that N-body simulations predict far more large sub-halos in galaxies that exhibit star formation than we see in the Milky Way, the latter refers to the observation that galactic halos have 'cores' (a high density of dark matter) which are inconsistent with those predicted by N-body simulations (Navarro et al., 1997). In order to reconcile these inconsistencies, one can invoke a variety of mechanisms that add complexity to the collisionless dark matter scenario (so-called Cold dark matter or CDM paradigm). For example warm dark matter, self interacting dark matter (SIDM), and the impact of baryons on CDM all have the potential to account for the observed differences (Spergel and Steinhardt, 2000; Firmani et al., 2000), or N-body simulations are not representative of the Universe in some other respect.

It has been observed that the highest ratio of mass-to-light, i.e. the largest concentrations of dark matter, are in galaxy clusters.

* Corresponding author. Tel.: +44 7725896492.
E-mail addresses: davidharvey1986@googlemail.com, drh@roe.ac.uk (D. Harvey), t.kitching@ucl.ac.uk (T.D. Kitching).

http://dx.doi.org/10.1016/j.ascom.2014.04.003
2213-1337/

These clusters are therefore the best available astronomical 'laboratories' to study the properties of dark matter because not only is there a relative overabundance, but there is also a relatively large amount of baryonic matter against which dark matter properties can be calibrated and compared. Previous work studying the distribution of dark matter in galaxy clusters has led to discoveries of colliding clusters and evidence of dark matter (Clowe et al., 2004, 2006; Bradač et al., 2006, 2008; Merten et al., 2011; Dawson et al., 2012; Mahdavi et al., 2007; Clowe et al., 2012; Jee et al., 2012).

In this paper we focus on the technique of gravitational lensing as a probe of the dark matter distribution. According to general relativity, the presence of mass acts to distort the path of photons through the Universe relative to the path that would have been take in the absence of mass (Bartelmann and Schneider, 2001; Refregier, 2003; Hoekstra et al., 2008; Massey et al., 2010). Gravitational lensing therefore, probes the total mass along the path of a photon and, because our Universe is dominated by dark matter, has become the primary technique for mapping dark matter. The ability to independently measure the distribution of the total matter content, without some assumed relation between observed galaxies and the underlying gravitational potential means that gravitational lensing is less sensitive to potential astrophysical systematics. In galaxy clusters, gravitational lensing effects can result in multiple images of galaxies and highly distorted images; so-called strong lensing occurs in the regime where the lensing mass is large. However every galaxy is lensed by some amount; an effect that does not result in multiple images or strong distortions but only causes a change in the observed ellipticity of the source galaxy: so-called 'weak lensing'. The small change in ellipticity caused by weak lensing is referred to as 'shear'.

In this paper we will present the analysis of simulated weak lensing data around simulated galaxy clusters. The analysis of these simulations, in an effort to improve the algorithms that are used to infer the mass distribution from weak lensing data, were used to define a citizen science competition that was crowdsourced to the public.

1.1. Standard approaches to dark matter reconstruction

The fidelity with which algorithms are required to map the dark matter distribution in galaxy clusters depends on the range of scales in question. Although it is possible to map the distribution of matter using galaxy velocities it has become increasingly popular to use gravitational lensing to determine the total matter distribution. There are several approaches that have been developed within the field of weak lensing where algorithms are split mainly into two categories based on the type of model used:

- Parametric methods involve fitting a physical model to the data and constraining a number of parameters in that model.
- Non-parametric methods attempt to directly convert from the measured shear to some projected mass density.

For a recent review of the standard approaches see Jullo et al. (2013).

Throughout this paper we shall refer to the benchmark code LENSTOOL. LENSTOOL (Jullo et al., 2007) is a public strong and weak lensing gravitational mass reconstruction method that fits dark matter halos, parameterised by a parametric radial profile, to data and determines posterior probabilities for the parameters via a Bayesian sampling method. For a full description of how LENSTOOL works please see Jullo et al. (2007), however, simply, it works by:

1. Taking a user input number of halos, which have with them the desired halo profile and associated parameters (e.g. mass, position etc.)
2. It then selects a random sample of parameters from within the priors given by the user and then converts the data, which are the shapes galaxies in the image plane, back to the source plane, undoing the lensing affect caused by the sampled dark matter halo.
3. These unlensed galaxies should represent the intrinsic shape of the galaxy which will be drawn from an assumed Gaussian distribution with a mean of zero and variance also given by the user. Using a chi-square test it then finds how well the parameters which converted the galaxies to the source plane did at recovering the expected intrinsic ellipticity distribution.
4. It then resamples the posterior depending on the likelihood of the next parameter set chosen.
5. It will continue to build up a representation of the posterior surface, over a predetermined number of samples.
6. 10 simultaneous sampling chains are run, each with 1000 samples, in order to avoid local maxima, after which the maximum likelihood position is chosen and selected as the estimate for the position of the halo.

Given 50″ priors (not applied to this competition), Harvey et al. (2013a) found that the accuracy of LENSTOOL is roughly $\sim 10''$ for a halo of mass $\sim 10^{13} M_{\odot}$, and is robust to most potential systematics involved in parametric fitting. This code was run on the competition and presented in this paper in order to provide benchmark analysis on individual scores.

1.2. Expert citizen science

Citizen science has recently become a productive tool in the analysis of large complicated databases for which algorithms are unable to provide reliable results. Pioneering this work in science is the Zooinverse.[1] The Zooniverse is a database of various projects including (amongst others), Moon craters, whale sounds and galaxies. In each case, a sample of images/sounds or other data is presented to a user (a 'citizen'), who is then guided through steps to classify that sample into a particular category based on their personal judgement. In many cases, such as the identification of complex galaxy morphologies, human-based classification is more reliable than current automated algorithms. The science is achieved through the statistical analysis of the human-classified data sets.

The success of using humans to classify large databases of complicated objects relies on the number of humans doing the classification to be large, to avoid individual subjectivity (although there are common inter-subjective biases in human object recognition that need to be found and quantified). There are many advantages of using a large population to solve a classification problem (i.e. 'crowdsourcing'). However there are two regimes in which the human-classification mode of crowdsourcing a problem is limited

- When the data set, or the number of classification categories, becomes too large for a population of humans to analyse in a reasonable time period. An example would be a database of several billion astronomical objects, each of which needed many minutes of classification.

[1] https://www.zooniverse.org.