DARK SKY SIMULATIONS: EARLY DATA RELEASE

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ABSTRACT

The Dark Sky Simulations are an ongoing series of cosmological N-body simulations designed to provide a quantitative and accessible model of the evolution of the large-scale Universe. Such models are essential for many aspects of the study of dark matter and dark energy, since we lack a sufficiently accurate analytic model of non-linear gravitational clustering. In July 2014, we made available to the general community our early data release, consisting of over 55 Terabytes of simulation data products, including our largest simulation to date, which used $1.07 \times 10^{12}$ (10240\textsuperscript{3}) particles in a volume $8h^{-1}$Gpc across. Our simulations were performed with 2HOT, a purely tree-based adaptive N-body method, running on 200,000 processors of the Titan supercomputer, with data analysis enabled by yt. We provide an overview of the derived halo catalogs, mass function, power spectra and light cone data. We show self-consistency in the mass function and mass power spectrum at the 1\% level over a range of more than 1000 in particle mass. We also present a novel method to distribute and access very large datasets, based on an abstraction of the World Wide Web (WWW) as a file system, remote memory-mapped file access semantics, and a space-filling curve index. This method has been implemented for our data release, and provides a means to not only query stored results such as halo catalogs, but also to design and deploy new analysis techniques on large distributed datasets.

\texttt{Subject headings:} cosmology: theory — methods: numerical

1. INTRODUCTION

In the past 40 years we have witnessed tremendous growth in the availability and utility of computational techniques and resources. This has led to an equally astounding increase in the quality and accuracy of N-body simulations of cosmological structure formation, starting with $\sim 1000$ particles in early works to the current work (Figure 1) with 9 orders of magnitude more particles (Peebles 1970, Press and Schechter 1974, Davis et al. 1985, Efstathiou 1990, Jenkins et al. 1998, Klypin et al. 1999, Springel 2005, Springel et al. 2005, Klypin et al. 2011, Angulo et al. 2012, Alimi et al. 2012). N-body simulations form a major pillar of our understanding of the cosmological standard model; they are an essential link in the chain which connects particle physics to cosmology, and similarly between the first few seconds of the Universe to its current state. Predictions from numerical models are now critical to almost every aspect of precision studies of dark matter and dark energy, due to the intrinsic non-linearity of the gravitational evolution of matter in the Universe. Current and upcoming optical surveys that probe baryon acoustic oscillations (BAO), the galaxy power spectrum, weak gravitational lensing, and the abundances of galaxy clusters all require support from numerical simulations to guide observational campaigns and interpret their results (Hu and White 1996, Eisenstein 1990, Jenkins et al. 1998, Klypin et al. 1999, Springel 2005, Springel et al. 2005, Klypin et al. 2011, Angulo et al. 2012, Alimi et al. 2012).

Surveys in the X-ray and sub-millimeter wavelengths provide an alternate view of the high-temperature plasma that sits in the deep gravitational potential wells of the dark matter, and provide an alternate constraint on the abundances of the most massive collapsed objects in the Universe (Planck Collaboration et al. 2013b, Mantz et al. 2014). Existing and future observational data motivate our work to understand theoretically a variety of spatial scales. The next generation of surveys will span very large volumes; for example, the Dark Energy Spectroscopic Instrument (DESI) (Levi et al. 2013) will survey $\sim 30$ million galaxies and quasars over 14000 sq. degrees beyond $z \sim 2.3$, spanning a volume of $\sim 50$ (Gpc $h^{-1}$)$^3$. The Large Synoptic Survey Telescope (LSST) (Ivezic et al. 2008) will survey half the sky, detecting $L^*$ galaxies over a volume of roughly 100 (Gpc $h^{-1}$)$^3$. Planck is already able to identify massive galaxy clusters over the entire sky, beyond $z \sim 1$ (Planck Collaboration et al. 2013a). Achieving the science goals of these surveys requires realistic mock catalogs based on numerical simulations that calculate the non-linear evolution of structure and predict the dependence of survey observables on cosmological parameters. They also require that these simulations be of sufficiently large volumes to calculate the statistics of rare objects and to calculate covariances between observables—this requires multiple realizations as large as survey volumes.

On the largest scales, the universe is populated by clusters of galaxies, connected by filaments, bordering cosmic voids. The statistics of the distribution of these structures can be used in a variety of methods to constrain fundamental cosmological parameters. For example, the number of objects in the Universe of a given mass, the mass function, is...
sensitive to cosmological parameters such as the matter density, $\Omega_m$, the initial power spectrum of density fluctuations, and the dark energy equation of state. Especially for very massive clusters (above $10^{15}$ solar masses [$M_\odot/h$]) the mass function is a sensitive probe of cosmology. For these reasons, the mass function is a major target of current observational programs. Precisely modeling the mass function at these scales is an enormous challenge for numerical simulations, since both statistical and systematic errors conspire to prevent the emergence of an accurate theoretical model (see Reed et al. (2013) and references therein). The dynamic range in mass and convergence tests necessary to model systematic errors requires multiple simulations at different resolutions, since even a $10^{12}$ particle simulation does not have sufficient statistical power by itself.

While galaxies and clusters of galaxies account for large concentrations of mass, cosmic voids that grow from regions of local divergence are the underdense regions that comprise most of the volume in the Universe (Sutter et al. 2014). Today, over two thousand voids have been detected in galaxy redshift surveys [http://www.cosmicvoids.net](http://www.cosmicvoids.net) and they offer excellent probes of cosmology via their size distributions, shapes, internal dynamics, and correlations with the Cosmic Microwave Background, as well as unique probes of magnetic fields and galaxy evolution. Voids are only observed in the galaxy distributions, and galaxies are sparse, biased tracers of the underlying dark matter. However, voids are typically studied from a theoretical perspective only in dark matter $N$-body simulations. The identification of voids is sensitive to survey density and geometry in a highly non-trivial fashion; to make direct contact with observed voids we must perform large-volume, high-resolution simulations to capture the structure and dynamics of dark matter, map the dark matter to a galaxy population, place the galaxies on a lightcone, apply realistic survey masks, and identify and characterize the voids.

It is theorized that small perturbations, referred to as baryon acoustic oscillations (BAO) and possibly excited during an inflationary epoch, launched sound waves in the photon-dominated baryon plasma. As the Universe expanded and the plasma cooled, eventually these perturbations were “frozen-in” at the time of recombination, and are seen as the fluctuations in the Cosmic Microwave Background (Bennett et al. 2012; PlanckCollaboration et al. 2013; Levi et al. 2013). These small fluctuations are thought to lead to an imprint in the spatial distribution of large scale structure, which can be measured directly by a number of galaxy surveys (Eisenstein et al. 2005; Anderson et al. 2014; Beutler et al. 2011; Levi et al. 2013) and in upcoming low-frequency radio surveys (Johnston et al. 2008; Dewdney et al. 2009). The BAO signal has been detected at $\sim 10\sigma$ in the Sloan Digital Sky Survey (SDSS-III) Data Release 11 (DR11) Baryon Oscillation Spectroscopic Survey (BOSS) galaxy samples (Anderson et al. 2014). In principle the precise structure of the galaxy distribution can be used to probe cosmological parameters. Our theoretical models need to keep up with the tremendous advances in observational data, and high quality dark matter simulations can be used provide a bridge between observational and theoretical cosmology. The most basic statistical measures of galaxy clustering are the power spectrum and the two-point correlation function. By producing high-quality databases of galaxy tracers (i.e. “mock catalogs”), cosmological simulations are able to probe observed galaxy distributions (Peacock and Smith 2000; Wechsler et al. 2006; Tinker et al. 2012; Reddick et al. 2014). Galaxy velocities can also be used for directly testing cosmology (Johnston et al. 2012).

The rigorous statistical and systematic demands of upcoming surveys requires the computational cosmology community to design and deliver high quality simulations that can be used to further our understanding of cosmological theory.
and the large scale structure of our universe. Our measurements of the Universe are sufficiently refined such that we now require both large statistical volumes and accurate, high-performance methods. Kuhlen et al. (2012) reviews the prior state-of-the-art in numerical simulations of the Dark Universe, the largest being the “DEUS FUR” 550 billion particle simulation (Alimi et al. 2012) performed with the RAMSES adaptive particle-mesh code (Teyssier 2002). Other simulations/codes at the $10^{11}$ particle scale are HR3 (Kim et al. 2011) using GOTPM (Dubinski et al. 2004), Millennium-XXL (Angulo et al. 2012) with GADGET3 (Springel 2005), Jubilee (Watson et al. 2013) with CUBEP3M (Harnois-Deraps et al. 2012), and Bolshoi/BolshoiP (Klypin et al. 2011) with ART (Kravtsov et al. 1999). Other codes that have advertised capability at the $10^{12}$ particle scale are HACC (Habib et al. 2013) and Gordon Bell prize winner Green (Ishiyama et al. 2012). The method most commonly used for accessing these simulations are relational databases which allow SQL queries to halo catalogs or other data from the simulations (Lemson and Consortium 2006; Riebe et al. 2013).

A potentially disturbing observation is that the research cycle associated with cutting-edge simulations is dominated not by the runtime of the simulation itself, but in the time to both extract scientific results and (if at all) make the simulation data publicly available. This indicates that porting existing analysis tools, validating results, and developing new analysis techniques have not received the same attention as our primary simulation codes. This is not a new phenomenon; in our own work for the 1992 Gordon Bell prize (Warren and Salmon 1992), it took another two years for scientific results to become available (Zurek et al. 1994). Recent examples of a similar timescale are the Millennium-XXL simulation completed in Summer 2010 with results submitted in March, 2012 (Angulo et al. 2012), and the DEUS FUR simulation completed in March 2012, with results in Rasera et al. (2014). This highlights the fact that software development and data-analysis are less amenable to acceleration from advances in computer hardware, and warrants additional attention regarding the most productive allocation of resources to support sustainable software and simulations.

Computational techniques have progressed so rapidly that the time to run a state-of-the-art simulation following 13.8 billion years of cosmic history takes only days on modern supercomputer architectures. However, this progress has not come without a cost. The time to design, develop, debug, and deploy a simulation can take years. After the completion of a simulation, the time to disseminate the main results takes months or years. Public data releases can take years to happen, if at all. There are many reasons for the significant delays in dissemination, both technical and social. Simulations of these type produce raw datasets that are measured in hundreds of Terabytes or even Petabytes, with even reduced halo catalogs reaching Terabyte in size. Even on high speed networks, data transfer of just a single snapshot can take as long as the original simulation. Socially, there is both the concern that a mistake will be discovered and the worry that others will make important discoveries with the publicly released data, thereby curtailing the scientific accomplishments of the simulators. However, despite these concerns, we believe it is of immense value to the community for everyone to release their simulation data as soon as possible. A mistake found by another can be fixed, and a new iteration of a simulation can be undertaken. A discovery made by outsiders is only possible through the community for everyone to release their simulation data as soon as possible. A discovery made by others will be found by others, and correct attribution makes that known.

Open source software projects have led the open data field, as a rapid increase in the availability of software developed in the open has led to burgeoning communities of developers in many astrophysical projects (yt, astropy, and sunpy to only name a few of the Python-based projects). A primary goal of this project is to adopt some of the fundamental concepts of the open source community, and translate them to open data for state of the art cosmological simulations. We aim to decrease the barrier to entry for accessing and analyzing data, and increase the speed of iteration and pace of scientific inquiry. Through a set of ongoing simulations, we begin this progress by releasing both reduced and raw data products from a set of cosmological simulations, including a simulation utilizing over a trillion particles. We hope to use input and feedback from the broader community to help shape our future data releases, and ultimately the types of simulations to be run. Our hope is that these data products enable discovery pertaining to many areas of research in cosmology. In particular, our trillion particle simulation is included in our current release; this is state-of-the-art in terms of mass resolution for its cosmological volume, and should offer tremendous insight into the largest scales and structures in our Universe.

While experts can be trained to interact with large datasets on parallel file systems, we aimed to create an interface to the data that is novel, simple, and extensible, with the aims of allowing people with a wide range of technical abilities and interests to explore the data. In principle, high school students interested in physics and/or computation should be capable of accessing subsets of a trillion particle dataset and studying the structure of the dark matter potential in a sample galaxy cluster. Researchers in large scale data visualization should be able to load halo catalogs into 3D models of our universe, and explore alternate representation methods for high-dimensional datasets. Digital artists or game designers may even be inclined to use our data as input for their personal work.

In what follows we describe the simulation setup, data analysis pipeline, and data access methods. We also describe our initial data validation through the analysis of the $z = 0$ mass function, power spectra, and a brief comparison to the Planck Sunyaev-Zel’dovich galaxy cluster catalog. We end with a proposed set of community standards for fostering growth in computational cosmology both within and exterior to the confines of the Dark Sky Simulations project.

2. SOFTWARE & HARDWARE

2.1. 2HOT
2HOT is an adaptive treecode N-body method whose operation count scales as $N \log N$ in the number of particles. It is described in [Warren (2013)], which we summarize here, and offer additional details relevant to the Dark Sky Simulations Early Data Release. Almost 30 years ago, the field of N-body simulations was revolutionized by the introduction of methods which allow N-body simulations to be performed on arbitrary collections of bodies in a time much less than $O(N^2)$, without imposition of a lattice (Appel 1985; Barnes and Hut 1986; Greengard and Rokhlin 1987). They have in common the use of a truncated expansion to approximate the contribution of many bodies with a single interaction. The resulting complexity is usually determined to be $O(N)$ or $O(N \log N)$, which allows computations using orders of magnitude more particles. These methods represent a system of $N$ bodies in a hierarchical manner by the use of a spatial tree data structure. Aggregations of bodies at various levels of detail form the internal nodes of the tree (cells). These methods obtain greatly increased efficiency by approximating the forces on particles. Properly used, these methods do not contribute significantly to the total solution error. This is because the force errors are exceeded by or are comparable to the time integration error and discretization error. Treecodes offer the best computational efficiency when force resolution at small scales is important. 2HOT is distinguished from other current cosmology simulation approaches at the petascale by not having a particle-mesh component, using a pure treecode avoiding the potentially problematic transition scale between PM and tree forces inherent with TreePM approaches, and offering additional flexibility for high-resolution simulations with a large dynamic range in particle masses.

The code has been evolving for over 20 years on many computational platforms. We began with the very earliest generations of distributed-memory message-passing parallel machines (an architecture which now dominates the arena of high-performance computing), the Intel iPSC/860, Ncube machines, and the Caltech/JPL Mark III (Warren and Salmon 1988; Warren et al. 1992). This original version of the code was abandoned after it won a Gordon Bell Performance Prize in 1992 (Warren and Salmon 1992), due to various flaws inherent in the code, which was ported from a serial version. A new version of the code was initially described in Warren and Salmon (1993). Since then, our hashed oct-tree (HOT) algorithm has been extended and optimized to be applicable to more general problems such as incompressible fluid flow with the vortex particle method (Ploumhans et al. 2002) and astrophysical gas dynamics with smoothed particle hydrodynamics (SPH) (Fryer et al. 2006). The code also won the Gordon Bell performance prize again in 1997, with absolute performance reaching 3.40 GHz on ASCI Red on a 320 million particle simulation, as well as obtaining a Gordon Bell price/performance prize on the Loki Beowulf cluster (Warren et al. 1997) and the Avalon Beowulf cluster (Warren et al. 1998).

The basic algorithm may be divided into several stages. First, particles are domain decomposed into spatial groups. Second, a distributed tree data structure is constructed. In the main stage of the algorithm, this tree is traversed independently in each processor, with requests for non-local data being generated as needed. In our implementation, we assign a key to each particle, which is based on Morton ordering (Samet 1990). This maps the points in 3-dimensional space to a 1-dimensional list, while maintaining as much spatial locality as possible. The domain decomposition is obtained by splitting this list into pieces. The Morton ordered key labeling scheme implicitly defines the topology of the tree, and makes it possible to easily compute the key of a parent, daughter, or boundary cell for a given key. A hash table is used in order to translate the key into a pointer to the location where the cell data are stored. This level of indirection through a hash table can also be used to catch accesses to non-local data, and allows us to request and receive data from other processors using the global key name space. We have developed an efficient mechanism for latency hiding in the tree traversal phase of the algorithm, which is critical to high performance.

A recent major effort on code development has added many additional features to the code, being designated in the naming transition from HOT to 2HOT. Accuracy and error behavior have been improved significantly for cosmological volumes through the use of a technique to subtract the uniform background density (Warren 2013), correcting for small-scale discretization error, and using a Dehnen $K1$ compensating smoothing kernel (Dehnen 2001) for small-scale force softening. We use an adaptive symplectic integrator (Quinn et al. 1997) and an efficient implementation of periodic boundary conditions using a high-order ($p = 8$) multipole local expansion (Challacombe et al. 1997; Mchnik 2009) which accounts for the periodic boundary effects to near single-precision floating point accuracy (one part in $10^{-7}$). We adjust the error tolerance parameter to limit absolute errors to 0.1% of the rms peculiar acceleration. Our code and parameters have been extensively tested and refined with thousands of simulations to test accuracy and convergence across multiple dimensions of timestep, smoothing length, smoothing type, error tolerance parameters, and mass resolution.

The 2HOT code is written in the C programming language. We utilize a variety of gcc extensions, the most important of which is the vector_size attribute, which directs the compiler to use SSE or AVX vector instructions on Intel architectures. Using gcc with vector_size has eliminated the need to write the gravitational inner loops in assembly language to obtain good performance on CPU-only architectures. We have implemented the GPU portions of our code in both CUDA and OpenCL, with the CUDA versions performing somewhat better at present. We use a purely message-passing programming model, implemented in MPI. In order to hide latency, the tree-traversal phase of our algorithm uses an active message abstraction implemented inside MPI with our own “asynchronous batched messages” routines. Our 2HOT software does not depend on any external libraries.

Treecodes place heavy demands on the various subsystems of modern parallel computers. This results in very poor performance for algorithms which have been designed without careful consideration of message latency, memory bandwidth, instruction-level parallelism and the limitations inherent in deep memory hierarchies. The space-filling curve domain decomposition approach we proposed in Warren and Salmon (1993) has been widely adopted in both application codes (e.g. Griebel and Zumbusch 1999; Fryxell et al. 2000; Springel 2005; Gittings et al. 2008; Jetley
Our claim that such orderings are also beneficial for improving memory hierarchy performance has also been validated (Mellor-Crummey et al. 1999; Springel 2005). Our method converts a d-dimensional set of data elements into a 1-dimensional list, while maintaining as much spatial locality in the list as possible. This allows us to neatly domain decompose any set of spatial data. The idea is simply to cut the one-dimensional list of sorted elements into \( N_p \) (number of processors) equal pieces, weighted by the amount of work corresponding to each element. The implementation of the domain decomposition is practically identical to a parallel sorting algorithm, with the modification that the amount of data that ends up in each processor is weighted by the work associated with each item. The mapping of spatial co-ordinates to integer keys converts the domain decomposition problem into a generalized parallel sort. The method we use is similar to the sample sort described in Solomonik and Kale (2010). Note that after the initial decomposition, the Alltoall communication pattern is very sparse, since usually elements will only move to a small number of neighboring domains during a timestep. This also allows significant optimization of the sample sort, since the samples can be well-placed with respect to the splits in the previous decomposition. In Warren and Salmon (1995) we describe a tree traversal abstraction which enables a variety of interactions to be expressed between “source” and “sink” nodes in tree data structures. This abstraction has since been termed dual-tree traversal (Yokota 2012). The dual-tree traversal is a key component of our initial approach to increase the instruction-level parallelism in the code to better enable GPU architectures. It is also relevant to a number of data analysis tasks, such as neighbor-finding and computing correlation functions.

In this earlier work we used the fact that particles which are spatially near each other tend to have very similar cell interaction lists. By updating the particles in an order which takes advantage of their spatial proximity, we improved the performance of the memory hierarchy. Going beyond this optimization with dual-tree traversal, we can bundle a set of \( m \) source cells which have interactions in common with a set of \( n \) sink particles (contained within a sink cell), and perform the full \( m \times n \) interactions on this block. This further improves cache behavior on CPU architectures, and enables a simple way for GPU co-processors to provide reasonable speedup, even in the face of limited peripheral bus bandwidth. We can further perform data reorganization on the source cells (such as swizzling from an array-of-structures to a structure-of-arrays for SIMD processors) to improve performance, and have this cost shared among the \( n \) sinks. In an \( m \times n \) interaction scheme, the interaction vector for a single sink is computed in several stages, which requires writing the intermediate results back to memory multiple times. For current architectures, the write bandwidth available is easily sufficient to support the \( m \times n \) blocking.

This is the key to our approach on Titan enabling high performance from the GPUs: we bundle multiple particles with a single interaction list to increase the computational intensity. This allows the full GPU performance to be sustained without being severely limited from PCI-Express bandwidth. In more detail, the computational intensity of our inner loop is 2 flops per byte. With an achievable PCI bandwidth of 5 Gbytes/sec on Titan, we need to increase the flops/byte by a factor of 200 to support a 2 Tflop GPU. We achieve this by packaging 200 or more particles with the same interaction list and sending them to the GPU. Finding more than 200 particles which share the same cell interactions is only possible given the framework of the \texttt{2Hot} code, which provides the grouping and multiple acceptance tests to arrange the computation suitably. Even then, this technique only works for about 80% of the interactions, with the rest near the leaf nodes of the tree not being able to be sufficiently grouped.

A second round of GPU optimizations was required to manage most of the remaining interactions near the leaf nodes. In particular, pre-staging a large block of particle positions and terminating the tree traversal once less than 80 particles remained in a cell (handling the rest with direct interactions) and bundling partial lists for leaf level quadrupole and hexadecapole interactions allows us to perform 97% of the gravitational interactions on the GPU, with all of the tree traversal logic handled by the CPU.

As a scaling comparison (see Table 2.1), we have run the \texttt{2Hot} code on the same small cosmology problem using a single node of the Titan supercomputer, as well as Eos (an Intel Xeon E5-2670 processor-based Cray XC30 also at Oak Ridge National Laboratory) a desktop Haswell processor, and an Amazon Elastic Compute Cloud (EC2) current generation \texttt{c3.8xlarge} and older \texttt{c1.large} instance. We quote performance in particles updated per second per node (p/s/n), where our 5.9 Petaflop result described in Section 3.1 below corresponds to 10240\(^3/110/12288 = 7.94 \times 10^5\) p/s/n, or 64\% efficiency scaling from 1 node to 12288 nodes.

The most scientifically relevant metric for evaluating gravitational N-body simulations is not Petaflops, but how many particles are updated per second, at an accuracy sufficient to accurately represent the physics involved. In 1997, we obtained a performance of 3 million particles updated per second at an RMS force accuracy better than \(10^{-3}\) (Warren et al. 1997). Our current performance results are about 8 billion particles per second, with an equivalent force accuracy about 10 times better. Whether this accuracy is sufficient, or if accuracy can be sacrificed without adversely affecting the scientific results, is an area of current research.

### 2.2. SDF

We use the Self-Describing File (SDF) interface, originally designed and implemented for our early parallel simulations (Warren and Salmon 1992), with an implementation of the interface recently released under an open-source license (Salmon and Warren 2014). The basic aims of the SDF library are to be simple, flexible, extensible and most importantly, scalable to millions of processing elements. By writing analysis software which uses the SDF interface, the differences between data formats can be encapsulated, allowing software to read multiple data layouts and formats, without requiring recompilation each time a field is added, or a new data format needs to be supported. The SDF format consists of a human-readable ASCII header followed by raw binary data. The header is intended to support
### Table 1

| Node Description          | Cores (MHz) | Perf. (p/s/n) |
|---------------------------|-------------|---------------|
| Opteron 6274/K20x         | 30, 2000    | 12.25 · 10^4  |
| Opteron 6274              | 16, 2000    | 2.54 · 10^5   |
| Xeon E5-2670 (HT)         | 32, 2600    | 6.37 · 10^4   |
| Xeon E5-2670              | 16, 2600    | 5.78 · 10^5   |
| EC2 c3.8xlarge            | 32, 2800    | 3.91 · 10^5   |
| EC2 c1.xlarge             | 8, 1800     | 1.00 · 10^5   |
| Core i5-4570              | 4, 3200     | 2.50 · 10^5   |

Performance measured in particles updated per second per node (p/s/n) for a variety of computational platforms. The top line is a Titan node (including the NVIDIA K20x GPU counted as 14 cores), which is 4.8x faster than the second line (without the GPU). The third and fourth lines compare a Cray XC30 node with and without hyperthreading. The Amazon EC2 results had a well defined price, which was $0.263 per hour for the c3.8xlarge instance, and $0.064 for the c1.xlarge instance. Performing an equivalent number of particle updates as our large ds14_a run using Amazon EC2 resources would have cost at least $200,000 at the current Amazon spot price, or $1.3 million for on-demand ($1.68/hr) c3.8xlarge resources.

metadata that describes the data, its pedigree, checksums of the data contained within it, and its layout on disk or in memory. The header also provides all the information needed for any processor in a parallel machine to independently read its own portion of a dataset. Note that the interface is capable of describing other existing data formats (such as the GADGET and Tipsy formats commonly used for cosmological datasets). In this regard, it is distinguished from libraries such as HDF5 [Folk et al. 1999], which cannot describe existing data without going through a conversion process. Each line in the header that includes an * is interpreted as a key-value dictionary pair. Other lines are interpreted as comments or internal SDF parameters. The structure of the binary data is encoded using a structure descriptor closely analogous to a C language structure declaration. One is allowed to have as many fixed-length arrays as desired followed by an optional arbitrary length array as the last entry (whose length can be determined by the structure size and file length). We note that while the majority of the data presented in this EDR follows the format described above, there are occasional instances where the data is not fully described by the header and requires the use of additional metadata that is provided within the file.

The major portion of our data is stored in spatial Morton order (also known as Z or N ordering), meaning that the sequential particles or halos on disk lie along a space filling curve. We further expose this embedded spatial structure in the file by creating an auxiliary file, which we refer to as the Morton index midx file. This midx file is constructed by first choosing a level in the oct-tree hierarchy to bin particles. The full particle dataset is then searched to find the first particle offset and the total number of particles within each leaf node in the tree. These values are mapped to the Morton index Key. This file has an extension with the naming convention .midx% level, where level corresponds to the level of the oct-tree that was constructed to bin the particles. For example, .midx7 corresponds to a Morton index file that bins particles into (2^7)^3 cells. The midx file itself is also stored in the SDF format. We typically use higher level midx files for progressively larger data.

Because the size of an individual SDF file can be many Terabytes, we have utilized the concept of a memory-mapped file in two separate implementations. The first is exposed through the Python interface using a Numpy memmap. This creates an “out-of-core” view of the complete data file. We have utilized this technique for the majority of our early science results, and have been satisfied with its performance and ease-of-use.

Our second implementation extends this concept to file stored on the World Wide Web (WWW), and utilizes a local page-cache mechanism to address a remote file through a thin wrapper that exposes binary data to Numpy. This approach transparently takes advantage of the enormous investment in multiple technologies which have been developed to improve the performance and reliability of generic WWW resources. We released this software at the time of this manuscript’s submission (Turk et al. 2014b). This is the first instance that we are aware of that directly exposes binary data hosted on the WWW into local memory in a running Python session. We note that this interface may be useful for future large astronomical surveys, as we will later describe how we use this technology to address individual files that are 34 TB in size, similar to the expected size of individual data products from SKA-1 survey in 2020 (Kitazeff et al. 2014).

### 2.3. yt

From the data perspective, 2HOT can be thought of as a highly efficient method to create vast amounts of unstructured data. We therefore required an analysis framework that is both capable of ingesting Terabytes of data and allows for rapid design and development phases for analysis. For this reason we have utilized and extended yt, an open-source analysis and visualization package written primarily in Python, which our team has experience in applying to both large unigrid simulations (such as the 3600^3 radiation-hydrodynamics simulation mentioned in Norman et al. (2013)) and deep Adaptive Mesh Refinement simulations of the first stars (Turk et al. 2009). yt is parallelized using mpi4py (Dalcín et al. 2008), which we have exposed on 2048 nodes (32768 cores) of the Titan supercomputer in this work.

yt was originally designed to manage data output by patch-based Adaptive Mesh Refinement (AMR) astrophysical simulations. Recent versions have restructured the underlying engine to shift the focus from AMR simulations to other

\[ 1 \text{TB} \equiv 10^{12} \text{bytes} \]
forms of data such as octree, unstructured mesh, and as used here, particle-based datasets. During this transition, the focus of yt has shifted to enable faster and more flexible indexing methods, which are utilized here to great extent, ensuring that even the very largest of datasets can be analyzed with proper care taken to enable multi-level indexing and on-demand data loading.

In this work we have used yt as a base upon which we build access methods to both local and remote (on the WWW via thingking) Petascale datasets. We required a system that enabled ease of deployment, ease of access, and minimized the burden on the individual researcher interested in examining the data — and perhaps most importantly, we rejected any solution that obfuscated the data in any way. For this reason, rather than presenting a SQL frontend, or a science gateway for exploring pre-selected data products and results, we have instead taken a hybrid approach that preserves access to the underlying data, while still making accessible the reduced data products. Our extensions include adding an SDF frontend that can utilize the midx index for spatially querying large datasets (up to 34 TB at the time of this writing). These additions are being actively reviewed through the yt projects peer review system, and in the meantime can be used through a fork that can be located through our project website (http://darksky.slac.stanford.edu).

The current version of yt also provides support for loading halo catalogs generated by ROCKSTAR as particle datasets, enabling selection, processing and visualization of the halo objects. We envision users loading the halo catalogs, determining the regions of interest to them in the full dataset, and then (transparently) utilizing the multi-level indexing system described above to load only the subselection of particles that are relevant to their research questions. While it would normally be completely intractable for a researcher to analyze a 34 TB file of particles, this approach will make it convenient and straightforward.

2.4. Halo Finding

To identify dark matter halos and substructure we use the ROCKSTAR algorithm (Behroozi et al. 2013). This halo-finding approach is based on adaptive hierarchical refinement of friends-of-friends groups in both position and velocity. It has been tested extensively and compared with other halo finders in Knebe et al. (2011), showing excellent, and in many cases superior, performance when compared with other approaches.

While we have previously used the basic ROCKSTAR code successfully for simulations with 69 billion particles using 10,000 CPUs, several features of the code were not ideal for the computing environment on the Titan system. In particular, the client-server model of computation in ROCKSTAR requires using a file descriptor for each pair of communicating processes, and the limit on open file descriptors for each CPU on Titan is 32768. In addition, we have found it preferable to use a smaller number of CPUs to process the data in pieces, which enables the use of less capable computing resources for analysis (rather than requiring a machine with over 70 Tbytes of RAM to process the simulation all at once).

In our implementation, we take advantage of the modularity of the ROCKSTAR algorithm and use only the function interface find_subs() via the yt-3.0 halo finding interface. We process each spatial domain independently, with yt loading the spatially indexed particle data for a domain and finding the initial FOF groups. We add a buffer region to each domain to contain any particles from a halo near the domain edge ($6h^{-1}$Mpc is sufficient for halo masses up to $10^{15}h^{-1}M_{\odot}$). These groups are then passed to ROCKSTAR find_subs(). For strict spherical overdensity masses, yt performs the same post-processing steps to assign particles which were missed by the FOF group to halos, and to identify parent/sub-halo relationships. We have validated our implementation by comparing it with unmodified ROCKSTAR for smaller ($4096^3$) simulations. For a 1.07 trillion particle dataset, our complete halo finding process takes about 6 hours on 1024 CPUs.

2.5. Computational Hardware

The complete Titan Cray XK7 system (Bland 2012) at Oak Ridge National Laboratory contains 18,688 compute nodes, each containing a 16-core 2200 MHz XMD Opteron 6274 with 32 GB of 1600 MHz DDR3 memory, paired across a PCI-Express 2.0 bus with an NVIDIA Tesla K20x GPU with 6 GB of memory. The Cray Gemini interconnect (Alverson et al. 2010) provides roughly 8 Gbytes/sec of bi-directional bandwidth per node at the hardware level, with MPI latencies quoted as 1.5 microseconds or less. Titan host nodes currently run the SUSE Linux Enterprise Server 11 SP1 (x86_64) with current kernel 2.6.32.59 (Cray Inc.), with latencies quoted as 1.5 microseconds or less. Titan host nodes currently run the SUSE Linux Enterprise Server 11 SP1 (x86_64) with current kernel 2.6.32.59. Processing nodes run Cray’s Compute Node Linux, designed to minimize interference between operating system services and application scalability.

2.6. Additional Software

All of our software was compiled with system installed gcc (Stallman 1989) version 4.8.2 20131016 (Cray Inc.), with the addition of NVIDIA’s LLVM-based nvcc (Frigo and Johnson 1998) (system version 5.5.0) for two CUDA-specific files. Significant software dependencies used via the system modules interface include cray-mpich/6.2.0 (Snir 1998; Gropp 2003; Bosilca et al. 2002), ftw/3.3.0.3 (Frigo and Johnson 1998) and gsl/1.16 (Galassi et al. 2007).

We additionally installed roughly 40 additional packages that were not available on the system, or were out-of-date including g++ 7.6.90 (system version 7.5.1), Mercurial (O’Sullivan 2009) (not available on system), git 1.8.5 (Torvalds and Hamano 2005) (system version 1.6.0), Python 2.7.6 (Van Rossum and Drake Jr 1995) (system version 2.6.8), MPI for Python (Dalcín et al. 2008), Cython (Behnel et al. 2011), Numpy (Oliphant 2006) and matplotlib (Hunter 2007). We have additionally made extensive use of the bbcp program (Hanushevsky et al. 2001) to transfer hundreds of Tbytes of data between Oak Ridge, LANL, SLAC and NERSC, as well as efficiently copy data between local systems.
3. THE DARK SKY SIMULATIONS

We have performed a series of calculations that vary in particle number from 2048$^3$ to 10240$^3$ and in comoving cosmological volumes from 100$h^{-1}$Mpc to 8$h^{-1}$Gpc on a side, as shown in Table 2. The set of simulations released in this Early Data Release (EDR) are part of a larger effort (Warren et al. 2014) enabled through a 2014 INCITEd computing grant at Oak Ridge National Laboratory. Additionally, one of the small volume boxes was run on the LANL Mustang supercomputer. All of these simulations utilize the exact same cosmology with $(\Omega_m, \Omega_b, \Omega_\Lambda, h_{100}, \sigma_8) = (0.295, 0.0468, 0.705, 0.688, 0.835)$, detailed in Table 3. Initial conditions were calculated using a modified version of 2LPTic (Crocce et al. 2006). The input power spectrum was calculated from a million step Markov Chain Monte Carlo calculation using MontePython (Audren et al. 2012) and CLASS, the Cosmic Linear Anisotropy Solving System (Blas et al. 2011). Observational constraints used as inputs included Planck (PlanckCollaboration et al. 2013), BOSS (Delubac et al. 2014) and BICEP2 (BICEP2Collaboration et al. 2014). The raw Markov Chain data the input cosmology was based on is publicly available (Warren 2014).

| Simulation | $\sqrt{N}$ | $L \ [h^{-1}$Mpc$]$ | $M_p \ [h^{-1}$M$_\odot]$ | $r \ [h^{-1}$kpc$]$ | $z_{	ext{init}}$ | timesteps |
|------------|------------|----------------|----------------|----------------|-------------|-----------|
| ds14a      | 10240      | 8000           | 3.9 $\cdot 10^{10}$ | 36.8           | 93          | 543       |
| ds14g,1600,4096 | 4096     | 1600           | 4.9 $\cdot 10^{9}$ | 18.4           | 135         | 563       |
| ds14g,800,4096  | 4096     | 800            | 6.1 $\cdot 10^{8}$ | 9.2            | 183         | 983       |
| ds14g,200,2048   | 2048     | 200            | 7.6 $\cdot 10^{7}$ | 4.6            | 240         | 1835      |
| ds14g,100,2048   | 2048     | 100            | 9.5 $\cdot 10^{6}$ | 2.3            | 297         | 3539      |

**TABLE 2**

Dark Sky Simulations. For each simulation, the name, particle count, box size, particle mass, Plummer equivalent softening length, starting redshift and number of timesteps are shown above.

| Param   | best-fit | mean±$\sigma$ | 95% lower | 95% upper |
|---------|----------|---------------|----------|----------|
| $\Omega_0$ | 2.201    | 2.214±0.025   | 2.165    | 2.263    |
| $\omega_{\text{cib}}$ | 0.118    | 0.1175±0.0014 | 0.1146   | 0.1204   |
| $H_0$    | 68.46    | 68.81±0.064   | 67.48    | 70.13    |
| $10^{+9}A_s$ | 2.18    | 2.187±0.052   | 2.076    | 2.296    |
| $n_s$    | 0.9688   | 0.9676±0.0054 | 0.9568   | 0.9785   |
| $\tau_{\text{reio}}$ | 0.08755  | 0.09062±0.0012 | 0.06518  | 0.1156   |
| $\omega$ | 0.1511   | 0.1737±0.0035 | 0.09785  | 0.2526   |
| $\Omega_\Lambda$ | 0.7012  | 0.7048±0.0085 | 0.688    | 0.7211   |
| $Y_{\text{He}}$ | 0.2477  | 0.2477±0.0001 | 0.2475   | 0.2479   |
| $\sigma_8$ | 0.8355   | 0.8344±0.0012 | 0.811    | 0.858    |

**TABLE 3**

Cosmological Parameters. See Warren (2014) for details. Our simulations use the parameters in the mean value column. The values of any parameters not specified are available in the CLASS.ini file in the data repository.

### 3.1. The ds14a and ds14g Simulations

On April 18-19, 2014, we ran the ds14a simulation from redshift $z = 93$ to $z = 0$ with 1,073,741,824,000 (10240$^3$) particles on 12,288 nodes (196,608 CPU cores and 12,288 NVIDIA K20x GPUs) of the Titan system at Oak Ridge National Laboratory, which represents approximately 2/3 of the total machine. The simulation was of a cubical region of space 8,000$h^{-1}$Mpc (comoving) across; a region large enough to contain the entire visible Universe older than 2.8 billion years in a light cone to a redshift of 2.3 for an observer at the center of the simulation volume. The simulation carried out $3.14 \times 10^{20}$ floating point operations (0.3 zettaflops). We saved 16 particle dumps totaling 540 Thytes, as well as 69 subsamples of the data totaling 34 Thytes, and 34 Thytes of data in two light cones (one from the center, and one from the lower left corner). Had we attempted the same calculation with a simple $O(N^3)$ algorithm, it would have taken about ten million times as many operations and approximately 37 thousand years on the same hardware to obtain the answer. During the initial stages of the simulation, a single timestep required about 110 seconds, for a performance of 5.9 Petaflops. At the end of the simulation, where significant clustering increases the tree traversal overhead we perform a timestep in 135 seconds, for a performance of 4.3 Petaflops.

Our aggregate performance over the entire 33 hour and 50 minute period was 2.58 Petaflops, due to nearly 40% overhead from disk I/O. This overhead was due in large part to the fact that MPI I/O on the Titan system was limited to only 160 of the roughly 1000 Lustre Object Storage Targets (OST) on each of the two Titan Atlas filesystems. We

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12 http://www.doeleadershipcomputing.org/incite-awards/
13 We perform somewhat more flops per timestep at late times
have demonstrated I/O performance using equivalent POSIX I/O benchmarks nearly 8 times higher, which will reduce I/O overhead to less than 5% for our next run (with an as yet undetermined cost in development time to replace what we thought was the proper MPI interface to use to avoid performance surprise). We also saved more checkpoint files than were necessary, given the new input (surprising to us!) that we encountered no failures during a 34 hour run.

In addition to the ds14.a simulation, we have performed a number of lower particle count simulations with progressively better spatial and mass resolution. These simulations have thus far been used to provide means for convergence tests, but in and of themselves enable a number of additional projects. At this time, only z = 0 data is available, but we expect to release additional snapshots, halo catalogs, and merger trees in the future.

4. EARLY SCIENCE RESULTS

While this manuscript’s primary purpose is to announce the Dark Sky Simulations campaign and encourage peer review of the data and development of compatible tools and feedback on its direction, we present present several state-of-the-art scientific results that have been enabled by these simulations. In the following two sections we present the $M_{200b}$ halo mass function, followed by an initial power spectra analysis and a comparison to the Planck Sunyaev-Zel’dovich all-sky galaxy cluster catalog.

4.1. Halo Mass Function

One of our primary scientific goals is to improve upon the spherical overdensity (SO) mass function derived in Tinker et al. (2008), which has a quoted accuracy for virial masses of 5% up to $10^{15} h^{-1} M_{\odot}$. To give some sense of the computational advantages enabling this improvement, in the 30 years since the seminal work of Press and Schechter (1974), the number of particles in a simulation has increased from one thousand to one trillion (a factor of $10^{10}$). We rely on progress in creating initial conditions (Crocce et al. 2006; Blas et al. 2011), algorithms (Warren 2013), computing capability (Blundell 2012) and analysis (Tinker et al. 2011; Behroozi et al. 2013) to increase the volume simulated and analyzed at high fidelity. We also use a better-constrained input cosmology (Bennett et al. 2012; Anderson et al. 2014; Delubac et al. 2014; BICEP2 Collaboration et al. 2014; Adren et al. 2012; Warren 2014), reducing the effects of non-universality in applying the Tinker et al. (2008) mass function to the current standard cosmological model. While the mass function is almost independent of epoch, cosmological parameters and initial power spectrum (as suggested by Press and Schechter (1974) and demonstrated by Jenkins et al. 2001 at the 10-30% level), more detailed work has shown this universality is not obtained more precisely (e.g. Tinker et al. 2008; Courtin et al. 2011; Bhattacharya et al. 2011).

For large masses, the Tinker et al. (2008) fit obtains most of its statistical power from the 50 realizations of the larger-volume WMAP1 L1280 ($(1280 h^{-1} \text{Mpc})^3$) simulations. Since the WMAP1 cosmology lies considerably outside current observational constraints, any non-universality in the translation from WMAP1 to the currently favored cosmology should be added to the 5% error budget. We analyze here roughly 5 times as much volume ($512 h^{-3} \text{Gpc}^3$) as Tinker et al. (2008), with particle masses ($3.9 \times 10^{10} h^{-1} M_{\odot}$) about 15x smaller than the L1280 simulations. It remains to be demonstrated if we are within reach of the sub-percent statistical accuracy required for discriminating Dark Energy models from future surveys, as calculated by Wu et al. (2010).

Reed et al. (2013) present a number of detailed tests of requirements for the recovery of the mass function to percent level accuracy, and present parameter guidelines for doing so. Their requirements for the “very challenging prospect” of a simulation with a light cone to replicate the volume accessible to future cluster surveys with sufficient mass resolution to avoid sensitivity to simulation parameters are essentially met by our current simulation (we obtain 800 particles per halo of mass $M = 10^{13.5} h^{-1} M_{\odot}$ rather than the suggested 1000, but our mass resolution is better than those of the large-volume tests they present, which reduces the sensitivity somewhat). As a stringent test of both simulation and halo-finding consistency, we use the ROCKSTAR halo finder (Behroozi et al. 2013) to select halos in a series of five simulations with particle masses varying between each by a factor of 8, for an overall dynamic range in mass of $4096 (9.53 \times 10^6 h^{-1} M_{\odot}$ to $3.90 \times 10^{10} h^{-1} M_{\odot}$).

The largest systematic error we have identified primarily affects the mass of the smallest halos (less than 800 particles), and is related to the initial evolution of clustering on the inter-particle scale. Representing a mode with too few particles results in it growing more slowly than it should. This loss of small-scale power is made worse by starting at higher redshift (because the error has longer to accumulate before non-linear clustering takes over) so the use of 2LPT initial conditions is required to allow a simulation to start at an appropriate redshift. However, even 2LPT initial conditions will lose small-scale power if started at a redshift higher than they need. The correction term to the truncation error is exactly the same mathematical form as deconvolving a cloud-in-cell density interpolation, so we enable the CORRECT_CIC flag in the initial conditions generator, even when starting with particles on a grid. Note that this correction will not apply to codes which compute short-range forces with a Fourier method, since the force kernel may already apply “sharpening” with the same effect.

In order to compare our theoretical and numerical models with the universe, we require a reliable calibration of the correlation between an observable and a quantity measurable from our simulation data. Since observational data do not provide halo masses neatly derived at a fixed overdensity, the relationship between measurable and observable is non-trivial. At the levels of accuracy required for next-generation surveys, the details are important. In particular, the best definition of “halo mass” in a simulation will be influenced by the computational complexity of the cosmological parameter estimation it is used for, as well as the ability to connect it with an observed halo mass. Even algorithmic choices will affect the precise definition of a spherical overdensity halo mass at the 1% level (Knebe et al. 2011). A
Fig. 2.— The top panel shows the number of halos per mass bin compared with Tinker et al. (2008) for the five Dark Sky Simulations introduced in this paper, over six orders of magnitude in halo mass. Each decade in mass is split into eight logarithmically spaced bins. The error bars indicate the Poisson error for each bin. The ratio between the number of halos and Tinker et al. (2008) is shown in the lower panel, on a linear y-axis. The simulations are internally consistent at the 1% level for halos with more than \( \approx 800 \) particles. Lighter points in the lower panel denote halos with 100-800 particles, which are consistent at the 3% level.

measure which yields mass functions which are self-similar and parameterized simply in terms of the details of the cosmological parameters and initial conditions would be ideal, but none of the currently favored measures of halo mass meets this goal. Part of our motivation for providing raw particle data and the framework to apply different mass measures is to encourage exploration of alternative definitions which may suit either theoretical models or particular observational programs better than the currently used spherical overdensity.

We have also identified halos in the light cone dataset, which places an observer at the center of the ds14.a simulation volume. At a radius of \( 4h^{-1} \) Gpc, this yields data out to \( z \sim 2.3 \). Within this volume, we identify 1.85 billion halos with 20 particles or more. This data can be used in a variety of contexts, both observational and theoretical. Observationally, this dataset can be used for creating mock galaxy catalogs (Berlind and Weinberg 2002), weak lensing predictions, and large scale clustering predictions. Of particular interest is the distribution and clustering of the largest halos in the Universe. Figure 5 shows halo masses as a function of redshift in the ds14.a.1c000 dataset. The largest halo has an \( M_{200b} \) mass of \( 4.35 \times 10^{15}h^{-1}M_{\odot} \), and is at a distance of \( 631h^{-1}Mpc \) (a redshift of \( z = 0.22 \)). This can be compared with theoretical predictions such as Holz and Perlmutter (2012), where they determined the most massive object in the universe should be \( M_{200b} = 3.8 \times 10^{15}M_{\odot} \). We note that they assumed a slightly different cosmology, and notably a slightly lower \( \sigma_8 = 0.801 \). A detailed analysis of the statistics of the most massive halos is forthcoming.

\[
dN(M)/d\ln(M) \left[ (h/Mpc) \right]^3
\]
4.2. Power Spectra

The matter power spectrum is a convenient statistic for probing the time-evolution of spatial clustering of matter in the Universe. Measuring the matter and galaxy power spectrum (and its inverse Fourier transform, the correlation function), on linear and non-linear scales, both directly and indirectly, is one of the major goals of many ongoing and proposed observational projects: Pan-STARRs (Kaiser et al. 2002), BOSS (Anderson et al. 2014), DES (DE-SCollaboration 2005), SPT (Hou et al. 2014), WiggleZ (Marin et al. 2013), Planck (PlanckCollaboration et al. 2013), LSST (Ivezic et al. 2008), SKA (Dewdney et al. 2009), DESI (Levi et al. 2013), Euclid (Amendola et al. 2013). Notable theoretical approaches for calculating the non-linear power spectrum from an initial linear spectrum and the cosmological parameters are the ‘scaling Ansatz’ of Hamilton et al. (1991) and its extension to the HALOFIT model of Smith et al. (2003), with further recent refinement by Takahashi et al. (2012). At mildly non-linear scales perturbation theory approaches have been successful (e.g. Taruya et al. (2012)). Other approaches are based on fitting the results of N-body simulations with an “emulator” (Heitmann et al. 2008, 2014) or neural network (Agarwal et al. 2014).

![Power spectra](image)

**Fig. 3.**— Power spectra at $z = 0$ for the five simulations presented here. Top: As a function of wavenumber, $k$, the measured power spectra are shown. Lower: The power spectra are shown relative to a spline fit of the combined simulation data. Error bars on the largest spatial modes show their expected variance. Vertical ticks indicate the Nyquist frequency of the initial conditions for each simulation. Shot noise corrections are not applied, except for the 8000$h^{-1}$Mpc box, where the spectrum is shown with and without (light gray) a shot noise correction.

In addition to being sensitive to cosmological parameters, the power spectrum is influenced by the volume, mass resolution and code parameters used for the simulation. A necessary (but not sufficient) condition for a well-behaved simulation model is that the measurement of relevant physical quantities be independent of these non-physical parameters. It is often difficult to measure these sensitivities, since performing a simulation with a large volume (to reduce statistical errors) and high mass resolution (to probe small spatial scales) soon becomes prohibitively expensive to
compute.

Within the current suite of Dark Sky Simulations, we have both large volume and good mass resolution, providing an opportunity to check the sensitivity of the power spectrum to non-physical parameters. These tests are complementatory to the previous comparison of the power spectrum evolved from the same initial conditions using the 2HOT and GADGET (Springel 2005) codes that were presented in Warren (2013). In Figure 3 we show the power spectrum measured from five simulations differing in mass resolution by factors of 8. It is to be noted on the log-log scale of the top panel that the measured power spectra differ by less than the width of the line over most of the spatial scale. To minimize distortions from the precise form of the mass interpolation at small scales, we perform large (4096^3) FFTs, and perform multiple FFTs with the spectrum folded up to a factor of 8 to probe high k without approaching the Nyquist limit of the FFT.

The lower panel of Figure 3 shows the power spectra on a linear scale, divided by a spline fit to our data. The spline uses the 8000h^{-1}Mpc data up to k = 2, 800h^{-1}Mpc from k = 2 to k = 10, and 200h^{-1}Mpc data beyond k = 10. The most obvious 10% difference between simulations is due to the “cosmic variance” of the smaller 100 and 200h^{-1}Mpc volumes. The three larger volume simulations show remarkable agreement (well below the 1% level) over the range from where the mode variance is small, down to spatial scales near the mean inter-particle spacing. The vertical ticks represent the Nyquist frequency of the initial conditions, representing the spatial scale below which there is no information when the simulation begins. Our convergence results near the mean inter-particle spacing echo the conclusions of Splinter et al. (1998), that increased force resolution must be accompanied by sufficient mass resolution, and that results below the inter-particle scale are subject to larger systematic errors.

In Figure 4 we show our results compared with FrankenEmu (Heitmann et al. 2014), HALOFIT (Takahashi et al. 2012) as generated from the CAMB code (Lewis et al. 2000), RegPT (Taruya et al. 2012) and the linear power spectrum. The matching of the wiggles at the BAO scale in HALOFIT differs from our results at the 2% level. The agreement at large scales with the FrankenEmu+h emulator is very good. FrankenEmu also matches up to k=10 within their quoted 5% accuracy. Since FrankenEmu was not calibrated using this specific cosmology within the emulator framework, errors at the 5% level are expected by k = 10, as was the case for their M000 test cosmology. Perturbation theory results from RegPT are not a particularly good match at z = 0 where the system is highly evolved, but at z = 1 in the right panel of the figure where perturbation theory would be expected to match to higher k, RegPT matches our results extremely well up to k = 0.3.

4.3. Comparison to Planck SZ Cluster Catalogs

One motivation for the large 8^-1Gpc volume is given by full sky galaxy cluster surveys. For example, Reed et al. (2013) point out that the full-sky volume corresponding to z = 2 could be achieved through a simulation with a box size of 8h^-1Gpc on a side, with enough mass resolution to populate halos with $M \gtrsim 10^{13.5} h^{-1} M_{\odot}$ with $N \sim 1000$ dark matter particles. ds14.a nearly achieves this, having $N \sim 800$ particles in the desired mass halo. As such, this simulation provides a unique opportunity for comparison with on-going surveys. In order to showcase this opportunity, we demonstrate its use in creating a simple mock SZ cluster catalog. Properly constructing a full SZ mock catalog is beyond the scope of this work, and the current presentation should be viewed as a demonstration.
We use the results shown in Figure 3 of Planck Collaboration et al. (2013b) to construct a minimum mass filter (as defined w.r.t $M_{500c}$) as a function of redshift. Here we use both the “Deep” and “Mean” estimates from their study. In Figure 5 we show the positions on the simulated sky, the histogram of clusters as a function of redshift, and the masses of the galaxy clusters as a function of redshift. Figure 5 can be directly compared with Figure 2 and 24 from Planck Collaboration et al. (2013a). We see a quite striking agreement between the Planck “Mean” estimate with their (Figure 24) Planck-MCXC sample, and between the Planck “Deep” estimate with the combined set of their “Planck clusters with redshift” distribution.

![Figure 5: Top: Positions of all simulated galaxy clusters that would be visible in an all-sky survey of the ds14.a light cone dataset using the Planck 2013 Deep estimates. Bottom-left: The number of galaxy clusters visible as a function of redshift (in $\Delta z = 0.05$ bins), assuming limits from two minimum mass estimates from Planck Collaboration et al. (2013b). Bottom-right: Masses of galaxy clusters in the light cone dataset as a function of redshift. Red points indicate those that would be visible with the Planck Deep filter, while black denote all Dark Sky clusters with $M_{500c} \geq 10^{14} M_\odot$.]

5. AVAILABLE DATA PRODUCTS

In this first data release our goal is to provide enough public data to enable state-of-the-art scientific research, as well as provide a testbed for the public interface. A list of available data products as of July 2014 is listed in Table 4. Raw data can be downloaded directly from the web without authentication. While the exact HTTP address may migrate as server usage is evaluated, we will keep an updated python package darksky_catalog\textsuperscript{14} that can be used to alias a given simulation data product to its current uniform resource locator (URL). Updated information will also

\textsuperscript{14} https://bitbucket.org/darksysims/darksky_catalog
be kept on our project website (http://darksky.slac.stanford.edu). As well as directly accessing data through a web browser, we provide advanced access methods through yt, detailed at the end of this Section.

| Simulation   | Description                  | Size    |
|--------------|------------------------------|---------|
| ds14_a       | \(z = 0\) Particle Data     | 34 TB   |
| ds14_a       | Halo Catalog \(z < 2.3\)   | 349 GB  |
| ds14_a       | Lightcone Data \(z < 2.3\) | 16 TB   |
| ds14_a       | Lightcone Halo Catalog       | 155 GB  |
| ds14_g,1600,4096 | \(z = 0\) Particle Data   | 2 TB    |
| ds14_g,800,4096   | \(z = 0\) Particle Data    | 2 TB    |
| ds14_g,200,2048   | \(z = 0\) Particle Data    | 256 GB  |
| ds14_g,100,2048   | \(z = 0\) Particle Data    | 256 GB  |

TABLE 4
Available datasets as of July, 2014. A full listing is available at the project website.

The datasets in this EDR fall roughly into three categories: raw particle data, halo catalogs, and reduced data. Raw particle data, and halo catalogs are stored in single SDF files for each snapshot/redshift. This leads to individual files that are up to 34 TB in size. In addition to the primary SDF file, we create a “Morton index file” (midx), detailed in 2.2 that allows for efficient spatial queries (see Figure 6). By combining the raw particle dataset and a midx file, sub-selection and bounding box queries can be executed on laptop-scale computational resources while addressing an arbitrarily large simulation. Particle datasets store particle position \((x, y, z)\) and particle velocity \((v_x, v_y, v_z)\) each as a 32-bit float, and a particle unique identifier, \(id\), as a 64-bit int. Halo catalogs store a variety of halo quantities calculated using Rockstar (Behroozi et al. 2013), described in Section 2.4.

![Morton ordered data](image)

**Fig. 6.** Morton ordered data. A small subset of particles from the ds14_a simulation, connected in order as they are sorted on-disk. The color indicates increasing offset in the file. The recursive “Z-order” pattern can be seen. Spatial queries that are aligned with octants result in a single read, after which particles may be filtered quickly in-memory.

In addition to raw particle snapshots, during runtime we output two light cone datasets, one from a corner of the simulation volume and one from the center. At this time we are releasing the lightcone from the center of the box, which covers the full sky out to a redshift of \(z = 2.3\). Halos found from this lightcone are also released. A slice through the halos found in the lightcone dataset is shown in Figure 9.

Data can be browsed and directly downloaded using a common web browser. However, given the data volume of the raw particle data, we do not recommend directly downloading an entire file. Instead, we have provided a simple remote interface through the commonly used yt analysis and visualization software. In this way, a researcher may directly query a sub-volume of the domain and download only what is needed for their analysis. These fast spatial
Fig. 7.— A 10 deg slice of halos above $10^{13} M_\odot$ found in the ds14 dataset. Each point is colored by its proper radial velocity from the center. The top panel shows the full radial extent of the halo catalog, which covers $z < 2.3$. The bottom panel is a zoom on $z < 0.25$. This represents $1/18th$ of the halos in the lightcone dataset.
queries are enabled by storing the majority of the data products (raw particle, halo catalogs) in “Morton order” on the server. Each particle is described by 32 bytes, and therefore loading a million particles around a halo in \texttt{ds14\_a} requires downloading 32MB. The average broadband internet speed in the U.S. (July, 2014) is 25.1 Mbps\[^{15}\], meaning that an average household could load this data in less than 10 seconds. Well-connected institutions would presumably be faster. Given a bounding box and Morton index file, offsets and lengths can be used with an HTTP range request to return the desired data. These queries are cached locally such that once loaded, particle data can be analyzed in-memory without any special requirements on the server. An example analysis is shown in Figure 8 that utilizes helper functions from the \texttt{darksky\_catalog} to remotely load the particles around the most massive halo in the \texttt{ds14\_a} simulation into \texttt{yt}, and project the dark matter density along the line of sight.

![Figure 8](http://bitbucket.org/darksysims)

Fig. 8.— Halo loaded remotely by \texttt{yt} that uses the the \texttt{darksky\_catalog} abstraction layer to redirect to datasets hosted on the WWW. Code used to generate the figure can be found in the project repository at \texttt{http://bitbucket.org/darksysims}.

6. COMMUNITY STANDARDS

The full stack of open-source software utilized to create this data—from the operating system, to the file systems, the compilers, numerical libraries, and even the software used to typeset this paper—is the product of the efforts of thousands upon thousands of individuals. In most of these cases, we are afforded the benefit of decades of an enormous and largely intangible investment in shared software development. We are releasing this data in the spirit of open science and open software development, with the intention of making it \textit{immediately} usable to individuals with a wide range of skills and interests, encouraging the sharing and reuse of derived data products, and perhaps most importantly, removing ourselves as obstacles to its use. By doing so, we are attempting to participate in a material way in the development of future scientific endeavors, as we have benefited from the open release of software and data in the past. The value and quantity of this data vastly exceeds our ability to mine it for insight; we do not wish to see its utility bottlenecked by our own limitations.

On one hand, we would like the data to be usable with as little bureaucratic or viral licensing overhead as possible. On the other, we do not wish that it be used for unfair advantage. To support these goals, we hope to foster the

\[^{15}\text{http://www.netindex.com/download/2,1/United-States/}\]
In this work we present the first public data release from the ongoing “Dark Sky Simulations” cosmological simulation campaign. These first five simulations include one of the largest simulations carried out to date, with $10^{240}$ particles in an $(8h^{-1}\text{Gpc})^3$ volume. The main findings from our work can be summarized as the following:

- A single-method hierarchical tree approach to the N-body gravitational problem is computationally feasible, accurate, and performant on modern HPC architectures.

- Using this method, we’ve carried out a suite of state-of-the-art cosmological simulations, hereafter referred to as the Dark Sky Simulations.

- We present results comparing the mass function and power spectra to demonstrate the quality of our simulations. We find internal consistency between different box sizes at the 1% level over more than 3 orders of magnitude in particle number. Comparisons with results in the literature agree at the 1-10% level depending on scale.

- The ds14_a light cone dataset and associated halo catalog provide a unique resource to make predictions for the large volumes probed by current and upcoming sky surveys; we use all-sky Sunyaev-Zel’dovich effect cluster counts as an example application.

- Interacting with data from Petascale supercomputing simulations is algorithmically challenging; We have designed and implemented a novel data access approach that is simple, extensible, and demonstrated its capability of interacting with individual files that are 34 TB in size over the Internet.

- We have reduced the time to the dissemination phase of our research by providing open access to a significant portion of the raw data from our simulations less than three months after the simulation was run, totalling more than 55 TB of publicly accessible datasets.
We encourage the use and further analysis of these data as well as feedback on the accuracy and accessibility of the data. We will be updating and adding to the contents of the data release, including new simulations, and encourage feedback on which data products and simulation suites would be most useful. We will notify the community through the project website and discussion forum. The computational resources required to generate these data were only a small fraction of our currently allocated computing time, so we expect the amount of and variety of scientifically useful data products to grow rapidly.

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REFERENCES

S. Agarwal, F. B. Abdella, H. A. Feldman, O. Lahav, and S. A. Thomas. pkann – II: a non-linear matter power spectrum interpolator developed using artificial neural networks. Monthly Notices of the Royal Astronomical Society, page stuo90, Feb. 2014. URL http://mnras.oxfordjournals.org/content/early/2014/02/09/mnras.stuo90

J. Allini et al. DEUS full observable (LambdaCDM universe simulation: the numerical challenge. arXiv:1206.2838, June 2012. URL http://arxiv.org/abs/1206.2838

R. Alverson, D. Roweth, and L. Kaplan. The gemini system interconnect. In 2010 IEEE 18th Annual Symposium on High Performance Interconnects (HOTI), pages 83–87, Aug. 2010.

L. Amendola et al. Cosmology and fundamental physics with the euclid satellite. Living Reviews in Relativity, 16:6, Sept. 2013. URL http://adsabs.harvard.edu/abs/2013LRR....16....6A

L. Anderson et al. The clustering of galaxies in the SDSS-III Baryon Oscillation Spectroscopic Survey: baryon acoustic oscillations in the Data Releases 10 and 11 Galaxy samples. MNRAS, 441:24–62, June 2014.

B. Blas, J. Lesgourgues, K. Benabed, and S. Prunet. Conservative constraints on early cosmology: an illustration of the monte python cosmological parameter inference code. arXiv:1210.7183 [astro-ph], Oct. 2012. URL http://arxiv.org/abs/1210.7183

J. Barnes and P. Hut. A hierarchical O(N log n) force-calculation algorithm. Nature, 324(6096):446–449, Dec. 1986. URL http://www.nature.com/nature/journal/v324/n6096/abs/324446a0.html

S. Behnel, R. Bradshaw, C. Citro, L. Dalcin, D. Seljebotn, and K. Smith. Cython: The best of both worlds. Computing in Science Engineering, 13(2):31–39, 2011. URL http://www.cs.ucsb.edu/~rbradshaw/other/other.html

P. S. Behroozi, R. H. Wechsler, and H. Wu. The ROCKSTAR phase-space temporal halo finder and the velocity offsets of cluster cores. The Astrophysical Journal, 762(2):109, Jan. 2013. URL http://iopscience.iop.org/0004-637X/762/2/109

C. L. Bennett et al. Nine-Year Wilkinson microwave anisotropy probe (WMAP) observations: Final maps and results. arXiv:1212.5225 [astro-ph], Dec. 2012. URL http://arxiv.org/abs/1212.5225

A. A. Berlind and D. H. Weinberg. The Halo Occupation Distribution: Toward an Empirical Determination of the Relation between Galaxies and Mass. ApJ, 575:587–616, Aug. 2002.

F. Beutler et al. The 6dF Galaxy Survey: baryon acoustic oscillations and the local Hubble constant. MNRAS, 416:3017–3032, Oct. 2011.

B. Blas, J. Lesgourgues, and T. Tram. The cosmic linear anisotropy solving system (CLASS). part II: approximation schemes. Journal of Cosmology and Astroparticle Physics, 2011(07):034, July 2011. URL http://iopscience.iop.org/1475-7516/2011/07/034
G. Bosilca et al. MPICH-V: toward a scalable fault tolerant MPI for volatile nodes. In Supercomputing, ACM/IEEE 2002 Conference, pages 29–29, Nov. 2002.

M. Challacombe, C. White, and M. Head-Gordon. Periodic boundary conditions and the fast multipole method. The Journal of Chemical Physics, 107(23):10131–10140, Dec. 1997. URL http://jcp.aip.org/resource/1/jcpas6/v107/i23/p10131_s1

J. Courtin, Y. Risera, J. Alimi, F. Corasaniti, V. Boucher, and A. Füzfa. Impacts of dark energy on cosmic structure formation – II. Non-universality of the halo mass function. Monthly Notices of the Royal Astronomical Society, 410(3):1911–1931, Jan. 2011. URL http://mnras.oxfordjournals.org/content/410/3/1911

M. Crocce, S. Pueblas, and R. Scoccimarro. Transients from initial conditions in cosmological simulations. Monthly Notices of the Royal Astronomical Society, 373(1):369–381, 2006. URL http://onlinelibrary.wiley.com/doi/10.1111/j.1365-2966.2006.11040.x/abstract

L. Dalcín, R. Paz, M. Storti, and J. D’Elía. MPI for python: Performance improvements and MPI2 extensions. Journal of Parallel and Distributed Computing, 68(5):655–662, May 2008. URL http://www.sciencedirect.com/science/article/pii/S0743731507001712

M. Davis, G. Efstathiou, C. S. Frenk, and S. D. M. White. The evolution of large-scale structure in the universe dominated by cold dark matter. The Astrophysical Journal, 329:271–290, 2001. URL http://adsabs.harvard.edu/abs/2001ApJ...57...111

W. Dehnen. Towards optimal softening in three-dimensional n-body codes – i. minimizing the force error. Monthly Notices of the Royal Astronomical Society, 324(2):273–291, 2001. URL http://onlinelibrary.wiley.com/doi/10.1046/j.1365-8711.2001.04239.x/abstract

T. Delucab et al. Baryon acoustic oscillations in the Ly\alpha forest of DR11 quasars. arXiv:1404.1801 [astro-ph], Apr. 2014. URL http://arxiv.org/abs/1404.1801

DESCollaboration. The dark energy survey. Journal of Parallel and Distributed Computing, 88(4):563–580, 2015. URL http://doi.acm.org/10.1145/2503210.2504566

D. Eisenstein et al. Detection of the Baryon Acoustic Peak in the Large-Scale Correlation Function of SDSS Luminous Red Galaxies. ApJ, 635:560–574, Nov. 2005.

F. Dewdney, P. Hall, R. Schilizzi, and T. Lazlo. The square kilometre array. Proceedings of the IEEE, 97(8):1482–1496, Aug. 2009.

J. Dubinski, J. Kim, C. Park, and R. Humble. GOTPM: a parallel hybrid particle-mesh treecode. New Astronomy, 9(2):111–126, Feb. 2004. URL http://www.sciencedirect.com/science/article/pii/S1384107603001337

C. Efstathiou, K. H. White, and C. S. Frenk. Numerical techniques for large cosmological n-body simulations. The Astrophysical Journal Supplement Series, 57:241–260, Feb. 1988. URL http://adsabs.harvard.edu/abs/1985ApJ...287...241

K. Heitmann. HACC: extreme scaling and performance across diverse architectures. In Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis, SC 13, page 61–6:10, New York, NY, USA, 2013. ACM. ISBN 978-1-4503-2378-9. URL http://doi.acm.org/10.1145/2503210.2504566

A. J. S. Hamilton, P. Kumar, E. Lu, and A. Matthews. Reconstructing the primordial spectrum of fluctuations of the universe from the observed nonlinear clustering of galaxies. The Astrophysical Journal Letters, 374:1–14, June 1991. URL http://adsabs.harvard.edu/abs/1991ApJ...374L...1H

A. Hannuvelsky, A. Trunov, and L. Cottrell. Peer-to-Peer computing for secure high performance data copying. In Proc. of the 2001 Int. Conf. on Computing in High Energy and Nuclear Physics (CHEP 2001), Beijing, 2001.

J. Harnois-Deraps, U. Pen, I. T. Iliev, H. Merz, J. D. Emberson, and V. Desjacques. High performance P3M n-body code: CUBE.P3M. arXiv:1208.5098, Aug. 2012. URL http://arxiv.org/abs/1208.5098

K. Heitmann, M. White, S. Habib, and D. Higdon. The Lyman-\alpha forest in the universe: I. Cosmological constant and cold dark matter. Nature, 348 (6303):705–707, Dec. 1990. URL http://www.nature.com/nature/journal/v348/n6303/abs/348705a.html

D. J. Eisenstein et al. Detection of the Baryon Acoustic Peak in the Large-Scale Correlation Function of SDSS Luminous Red Galaxies, ApJ, 635:560–574, Nov. 2005.

M. Folk, A. Cheng, and K. Yates. HDF5: a file format and I/O library for high performance computing applications. In Proceedings of Supercomputing, volume 99, 1999.

M. Frigo and S. G. Johnson. FFTW: an adaptive software architecture for the FFT. In Acoustics, Speech and Signal Processing, 1998. Proceedings of the 1998 IEEE International Conference on, volume 3, page 1381–1384, 1998. URL http://ieeexplore.ieee.org/spls/abs_all.jsp?arumber=881704

C. Fryxell, G. Remillard, and M. S. Warren. SNSPH: a parallel three-dimensional smoothed particle radiation hydrodynamics code. The Astrophysical Journal, 643(1):292, May 2006. URL http://iopscience.iop.org/0004-637X/643/1/292

B. Fryzell et al. FLASH: an adaptive mesh hydrodynamics code for modeling astrophysical thermonuclear flashes. The Astrophysical Journal Supplement Series, 131(1):273, Nov. 2000. URL http://iopscience.iop.org/0067-0049/131/1/273
M. S. Warren, T. C. Germann, P. S. Lomdahl, D. M. Beazley, and J. K. Salmon. Avalon: an Alpha/Linux cluster achieves 10 gflops for $150k. In Proceedings of the 1998 ACM/IEEE conference on Supercomputing (CDROM), Supercomputing ’98, page 1–11, Washington, DC, USA, 1998. IEEE Computer Society. ISBN 0-89791-984-X. URL http://dl.acm.org/citation.cfm?id=509058.509130

M. S. Warren, A. Friedland, D. E. Holz, S. W. Skillman, P. M. Sutter, M. J. Turk, and R. H. Wechsler. Dark Sky Simulations Collaboration. Zenodo, Jul 2014. URL http://dx.doi.org/10.5281/zenodo.10777

W. A. Watson, I. T. Iliev, J. M. Diego, S. Gottlöber, A. Knebe, E. Martínez-González, and G. Yepes. Statistics of extreme objects in the juropa hubble volume simulation. arXiv e-print 1305.1976, May 2013. URL http://arxiv.org/abs/1305.1976

R. H. Wechsler, A. R. Zentner, J. S. Bullock, A. V. Kravtsov, and B. Allgood. The Dependence of Halo Clustering on Halo Formation History, Concentration, and Occupation. ApJ, 652: 71–84, Nov. 2006.

D. H. Weinberg, M. J. Mortonson, D. J. Eisenstein, C. Hirata, A. G. Riess, and E. Rozo. Observational probes of cosmic acceleration. Phys. Rep., 530:87–255, Sept. 2013.

H. Wu, A. R. Zentner, and R. H. Wechsler. The impact of theoretical uncertainties in the halo mass function and halo bias on precision cosmology. The Astrophysical Journal, 713 (2):856, Apr. 2010. URL http://iopscience.iop.org/0004-637X/713/2/856

J. Wu, Z. Lin, X. Xiong, N. Y. Gnedin, and A. V. Kravtsov. Hierarchical task mapping of cell-based AMR cosmology simulations. In Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis, SC ’12, page 75:1–75:10, Los Alamitos, CA, USA, 2012. IEEE Computer Society Press. ISBN 978-1-4673-0804-5. URL http://dl.acm.org/citation.cfm?id=2388996.2389098

R. Yokota. An FMM based on dual tree traversal for many-core architectures. arXiv:1209.3516, Sept. 2012. URL http://arxiv.org/abs/1209.3516

W. H. Zurek, P. J. Quinn, J. K. Salmon, and M. S. Warren. Large-scale structure after COBE: peculiar velocities and correlations of cold dark matter halos. The Astrophysical Journal, 431:559–568, 1994.

APPENDIX

A BRIEF TOUR OF THE DARK SKY SIMULATIONS EARLY DATA RELEASE

This material is intended to be useful to a wide audience, so it starts at a very basic level. It ends at a very advanced level. Skip ahead if you need to, or slow down and review the supplemental material.

Get the Release Metadata

First, you need to get the package with the basic data release. You can use your web browser download feature to get a .zip or .tar.gz file. They can be found at https://bitbucket.org/darkskysims/data_release/downloads Or, if you prefer the command line,

wget https://bitbucket.org/darkskysims/data_release/get/default.tar.gz

declare -x DATA_RELEASE_ROOT=ds14_a

echo $DATA_RELEASE_ROOT

The file you retrieve will be named something like darkskysims-data-release-dba678c57371.tar.gz and is currently about 4 Mbytes in size. You should unpack it.

tar xzf darkskysims-data_release-dba678c57371.tar.gz

cd darkskysims-data_release-dba678c57371/ds14_a

If you are familiar with the mercurial version control system, and it is installed on your system, you can replace the steps above with

hg clone https://bitbucket.org/darkskysims/data_release
cd data_release/ds14_a

Using mercurial has additional advantages, since it can tell you if any of the files have been changed or corrupted. Read more about mercurial at http://mercurial.selenic.com/

Data Exploration

Let’s look at some metadata,

head ds14_a.1.0000.head

should produce the following output on a Unix-like operating system If you don’t have UNIX, use whatever tool is available to view an ASCII file.

```
# SDF 1.0
int header_len = 2528;
parameter byteorder = 0x78563412;
int version = 2;
int version_2HOT = 2;
int units_2HOT = 2;
int64_t npart = 107374182400;
float particle_mass = 5.6749434;
int iter = 543;
int do_periodic = 1;
```
This is an SDF header. Our raw data is distributed in the SDF format. The data_release directory just contains the initial part (.head) of this large file. Otherwise, you would need to wait to download the 34 Terabytes in the ds14_a.1.0000 file. You can read more about SDF at [http://bitbucket.org/johnSalmon/sdf](http://bitbucket.org/johnSalmon/sdf). If you browse further down in the file (perhaps using the more or less command) you will see,

double Omega0_m = 0.295037918703847;
double Omega0_lambda = 0.7048737821671822;
double Omega0_b = 0.04676431995034128;
double h_100 = 0.6880620000000001;
char length_unit[] = "kpc";
char mass_unit[] = "1e10 Msun";
char time_unit[] = "Gyr";
char velocity_unit[] = "kpc/Gyr";
char compiled_version_nln[] = "2HOT_nln-1.1.0-17-gbb2d669";
char compiled_date_nln[] = "Apr 19 2014";
char compiled_time_nln[] = "06:34:59";

That is the metadata in the SDF file which describes the cosmological parameters used, the physical units, and information describing the exact version of the code. A bit further down is the first structure declaration,

struct {
    unsigned int sha1_len;
    unsigned char sha1[20];
}[65536];

This structure describes the layout in the data file of the sha1 checksums. There are 65536 of them, each with the length of data that was checksummed and the sha1 checksum value. This allows one to verify the integrity of each segment of the 34 Terabyte file independently. Since the sha1 values are contained in the .head file in the data_release, their integrity can be verified with the checksum contained within the mercurial repository. A change to any one of the 272 trillion bits in the data file can thereby be detected.

The main purpose of the SDF header is found in the last structure definition,

struct {
    float x, y, z; /* position of body */
    float vx, vy, vz; /* velocity of body */
    int64_t ident; /* unique identifier */
}[1073741824000];

This tells us how to read the positions, velocities and identity of the particles. There are 1073741824000 of them. Where are they? We tell you in the .url file.

cat ds14_a.1.0000.url
http://darksky.slac.stanford.edu/simulations/ds14_a/ds14_a.1.0000

The full 34 TB data file is on a machine at Stanford University (feel free to explore the server at [http://darksky.slac.stanford.edu/simulations/](http://darksky.slac.stanford.edu/simulations/)). You could download it like any of the millions of other files on the Internet, but we have better ways.

**SDF-enabled Exploration**

If you like C and the command line, the SDF library is a good choice. Check out the development version from our repository and compile it. It will help for the next step if you have libcurl installed first.

    cd ..
    git clone http://bitbucket.org/darkskysims/sdf.git SDF
    cd SDF
    make

This will build an executable called SDFcvt. It can be used to browse SDF files. cp SDFcvt /usr/local/bin or elsewhere in your path if you like. Change back to the ds14_a subdirectory of the data_release, and try it out.

    cd ..\ds14_a
    ..\SDF\SDFcvt ds14_a.1.0000.head Omega0_m Omega0_lambda Omega0_b h_100
0.29503791870384699 0.7048737821671822 0.046764319950341277 0.6880620000000006

SDFcvt has parsed the cosmological values you specified from the header. Now try this,
That is the position and velocity of the trillionth particle in the data file. -n 1 specifies that you want to read 1 element from the structure -s specifies the offset in the array (Note that dsdata.org just redirects to the Stanford web site listed above. Its purpose is to make URLs shorter, so DarkSky names are easy to type, or fit on a line.)

If you see a message like this, you do not have libcurl installed

SFhdro: SFMY_Fread returns -1, errno=22

If you don’t have libcurl, read on to see how you can use our python library to access the data files over the Internet. You can also download any of the smaller data files and use SDFcvt locally.

Python-based Exploration

If you like Python, we have implemented several methods to interact with the data, both directly using Numpy arrays and through yt. Let’s start with relatively simple methods of interacting with the data. To start, you’ll need to install a few packages. The simplest method is to use pip to install some of the basic packages. To install yt, we suggest you follow their documentation (http://yt-project.org/docs/dev-3.0/installing.html).

First let’s get ThingKing:

pip install thingking
or install from source, located at http://bitbucket.org/zeropy/thingking.

ThingKing exposes data on the WWW to Python in a memory-mapped interface.

If you start up a Python interpreter, try the following:

import thingking
ds14_a = thingking.HTTPArray("http://darksky.slac.stanford.edu/simulations/ds14_a/ds14_a_1.0000")

ds14_a is now array-like, and you can do things like examine its size:

print ds14_a.size

34359739943392

That’s an array with 34 trillion elements! Let’s look at the first few. Since we did not prescribe a type to the HTTPArray, it defaults to being an array of characters. That means that if you try to print, say, the first 10 elements, you’ll see each character:

print ds14_a[:10]
[('#',) (' ',) ('S',) ('D',) ('F',) (' ',) ('1',) ('.',) ('0',) ('
',)]

That is not so useful, but if we print the data attribute that hangs off ds14_a, we get something more readable:

print ds14_a[:10].data
# SDF 1.0

Congratulations, you can now examine any part of a 34 TB file that you’d like. If you were inclined, you could use the information in the header, like the header_len value and the sizes of the variables to access the particle data. However, we’ve implemented all of that within yt, and suggest we move on to there to access the particle data in Python.

DarkSky & yt

We are working towards integrating our extensions to yt into the main yt development repository. Until then, we are maintaining a separate fork, which you can get by pulling changes from the repository at http://bitbucket.org/darkskysims/yt-dark into your local yt repository. You may also wish to just download a separate clone of this repository.

hg clone http://bitbucket.org/darkskysims/yt-dark

cd yt-dark
python setup.py install # or python setup.py develop

At this point, it would also be most useful to download the example scripts at http://bitbucket.org/darkskysims/darksky_tour Like most things, you can do this through downloading a tar file, or use mercurial:
hg clone http://bitbucket.org/darkskysims/darksky_tour
cd darksky_tour

There are a bunch of examples in here. Let's just walk through the first one, which will create a nice visualization of all the particles within a 50 Mpc box centered around the most massive galaxy cluster in ds14_a. The following is the splat_viz.py example from the darksky_tour:

```python
import yt
import numpy as np
from enhance import enhance
from yt.utilities.lib.image_utilities import add_rgba_points_to_image
from darksky_catalog import darksky

# Define a bounding box of 100 Mpc on a side.
center = np.array([-2505805.31114929, -3517306.7572399, -1639170.70554688])
width = 50.0e3 # 5 Mpc
bbox = np.array([center-width/2, center+width/2])

ds = darksky['ds14_a'].load(midx=10, bounding_box=bbox)

ad = ds.all_data()
Npix = 1024
image = np.zeros([Npix, Npix, 4], dtype='float64')

cbx = yt.visualization.color_maps.mcm.RdBu
col_field = ad['particle_velocity_z']

# Calculate image coordinates ix and iy based on what your view width is
ix = (ad['particle_position_x'] - ds.domain_left_edge[0])/ds.domain_width[0]

# Normalize the color field so that it doesn't get maxed out
col_field = (col_field - col_field.min()) / (col_field.mean() + 4*col_field.std() - col_field.min())

data = add_rgba_points_to_image(image, ix.astype('float64'), iy.astype('float64'), cbx(col_field))

# Write out a color-enhanced image
yt.write_bitmap(enhance(image), 'enhanced.png')
print 'Splatted %i particles' % ad['particle_position_x'].size
```

This imports yt, a few extras from the darksky_tour repository, and the darksky_catalog. After defining a bounding box into the entire dataset, we load the data using a midx level 10 file. The yt dataset is returned to the ds object, and we then manually splat particles onto a canvas, colored by their velocity along the line of sight, and output an image.
Fig. 9.— Particles around the most massive galaxy cluster, colored by their line-of-sight velocity, generated by the example in the Appendix. Particles are loaded over the WWW, then visualized locally.