Firefly: a browser-based interactive 3D data visualization tool for millions of data points

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ABSTRACT

We present Firefly, a new browser-based interactive tool for visualizing 3D particle data sets. On a typical personal computer, Firefly can simultaneously render and enable real-time interactions with \( \gtrsim 10 \) million particles, and can interactively explore datasets with billions of particles using the included custom-built octree render engine. Once created, viewing a Firefly visualization requires no installation and is immediately usable in most modern internet browsers simply by visiting a URL. As a result, a Firefly visualization works out-of-the-box on most devices including smartphones and tablets. Firefly is primarily developed for researchers to explore their own data, but can also be useful to communicate results to researchers/collaborators and as an effective public outreach tool. Every element of the user interface can be customized and disabled, enabling easy adaptation of the same visualization for different audiences with little additional effort. Creating a new Firefly visualization is simple with the provided Python data pre-processor (PDPP) that translates input data to a Firefly-compatible format and provides helpful methods for hosting instances of Firefly both locally and on the internet. In addition to visualizing the positions of particles, users can visualize vector fields (e.g., velocities) and also filter and color points by scalar fields. We share three examples of Firefly applied to astronomical datasets: 1) the FIRE cosmological zoom-in simulations, 2) the SDSS galaxy catalog, and 3) Gaia DR3. A gallery of additional interactive demos is available at alexgurvi.ch/Firefly.

Keywords: scientific visualization — visual analytics

1. INTRODUCTION

As datasets of all kinds become larger and more complex, exploring and extracting information from them has become commensurately more difficult. In particular, with advancements in modern computer processors and data collecting instruments, the size of astronomical datasets has grown by orders of magnitude in the last two decades (e.g., SDSS: York et al. 2000, Blanton et al. 2017; Gaia: Gaia Collaboration et al. 2016, Babusiaux et al. 2022; anticipated data output of V. Rubin Observatory Ivezic et al. 2019) The scale and complexity of these massive datasets makes it difficult to grasp their full scientific content through traditional analysis and statistical methods alone.

Hydrodynamic cosmological simulations are an important example of a complex dataset in astronomy that benefits from 3D visualization. They are extremely rich in information, and the larger the volume (or the higher the resolution) the more structures that can be easily missed by standard pipeline analysis tools. Their output typically consists of 3D spatial coordinates annotated with various scalar quantities for each resolution element. However, as the number of resolution elements in these simulations increases, interactive visualization becomes increasingly more difficult.

A common visualization workflow for these kinds of simulations is to produce a series of 2D projections or slices of the 3D dataset (using e.g. FIRE Studio, Gurvich 2022). These 2D images are often stitched together from a rotating perspective into an animation, to give a sense of three-dimensionality. However, constructing a publication-quality static image (or movie) often requires a priori knowledge of the most important portion and features of the data to view. Additionally, relevant
Interactive visualization enables users to interrogate a dataset in real time, e.g., through manipulating the camera location, filtering out portions of data, coloring portions of data differently, etc. Moreover, interactive visualization is a powerful tool for building intuition about a dataset and enabling serendipitous scientific discovery, which can be particularly important for large and complex datasets. However, effective interactive visualization is technically challenging, as it requires the ability to render dozens of frames per second while also reacting to user input, and therefore the field has struggled to keep up with the pace at which data has ballooned. In addition to the technical hurdles, it is also challenging to design visualization software that is both accessible to creators and end-users. In this paper we present a new general-purpose web-based interactive visualization tool, Firefly\(^1\), that addresses many of these visualization challenges and draws from the successes of previous visualization software.

One field that has contributed greatly to the 3D interactive visualization landscape is photogrammetry, which visualizes point-based data taken from Laser Imaging, Detection, and Ranging (LIDAR) equipped drones. Modern photogrammetric datasets can contain as many as 43 trillion data points\(^2\). A popular approach for visualizing these datasets is to use highly optimized point-based rendering methods (e.g., Martinez-Rubi et al. 2015; Schütz 2016). These special purpose softwares are well optimized to handle hundreds of billions of data points at a time to produce interactive topographical maps\(^3\). We borrow and adapt some of their successful techniques (e.g., progressive rendering of massive particle data sets, and browser-based viewers) in Firefly.

Unlike many other fields in science, Astronomy has a highly heterogenous audience and data structure. Astronomers span from observers to theorists to computer modelers to instrumentation engineers (and any combination of these). Astronomy also has a historical ability to engage wide swaths of the public. Furthermore, the wide range of data taken across the electromagnetic spectrum (from different telescopes) and differences in modeling/simulation codes produces a similarly wide range in data formats and requirements.

Thus, many astronomy tools have been developed to visualize specific data, each filling it’s own niche. For example, much of the current software for visualizing Gaia data is purpose built in order to handle the data volume and to interface directly with the Gaia archive (e.g., the Gaia archive visualization service Moitinho et al. 2017 and VAEX Breddels & Veljanoski 2018).

There are also many existing tools for general-purpose (interactive) visualization of different astronomical datasets. A non-exhaustive list includes Partiview (Levy 2003), yt (Turk et al. 2011), ParaView (Ayachit 2015), pyshviewer (Benitez-Llambay 2015), IGM-Vis (Burchett et al. 2019), and Polyphorm (Elek et al. 2020). Each software fills a niche in its community and, as a result, has its own interface, data structures, and limitations. One approach to bridge the gap between communities is Glue (Robitaille et al. 2019), which creates a unified interface and data input framework for multiple specialized visualization and analysis softwares using “plugins”. Python’s Matplotlib (Hunter 2007) is another very popular tool in the astronomy community for visualizing modest sized data sets (e.g., thousands of points).

In creating Firefly we have attempted to include many of the successful features of previous tools while also addressing needs that we were unable to find in existing tools. Our aim is to create software that:

- supports any array data

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1 This package should not be confused with the serendipitously named web-based visualization software firefly, from Caltech-IPAC/github.com/Caltech-IPAC/firefly), a general tool for retrieving and viewing astronomy FITS files.

2 See for example the public dataset of LIDAR readings across the US provided by the US Geological Service at: registry.opendata.aws/usgs-lidar which can be interactively explored at: usgs.entwine.io

3 See for example this interactive visualization of Cook County Illinois
Firefly enables interrogation of large data sets ($\gtrsim 10^6 - 10^9$ points) in real time from within a web browser without any installation and allows for customization of aspects of the visualization and elements of the user interface through shareable app-state configuration files to tailor visualizations for any audience. Firefly is configured to visualize any three-dimensional dataset (though it will likely produce the best results if those dimensions are spatial $x,y,z$). Firefly also has specific tools for visualizing particle velocities (a common attribute of many observed and simulated astronomical data sets) or any other vector field. Users can also specify scalar fields to color/filterSCALE the particles. In this sense, Firefly is flexible enough to be applied in any context in which there are three dimensions that one would like to visualize in a web browser.

In the following sections, we describe how to use Firefly and provide an in-depth description of the code. In §2 we use illustrative example use-cases to highlight the key features of Firefly. In §3 we showcase example Firefly visualizations of astronomical datasets. In §4, we evaluate the performance of Firefly for different sized datasets. Finally, in §5 we summarize and conclude.

The appendices contain detailed information about the implementation and usage of many of Firefly’s features. In Appendix A we describe how to use the various elements of the user interface in a Firefly web application. In Appendix B we describe how to use the provided Python data pre-processor (PDPP) to create new Firefly visualizations, generate settings files, and host instances of Firefly both locally and on the internet. In Appendix C we describe the inner workings of the web application. In Appendix D we describe the (optional) progressive rendering scheme for visualizing datasets which have been pre-formatted as an octree (allowing Firefly to scale to datasets of $\gtrsim 10^9$ particles).

2. USE CASES AND KEY FEATURES

Firefly is a flexible application with many features that can be enabled/disabled using the same dataset without fundamentally altering the code. In this section we provide some example use cases in order to highlight key features of Firefly that can be used to create a tailored experience. We categorize the use cases based on the intended audience and/or purpose: interactively exploring one’s own data (§2.1), sharing results with other scientists and collaborators (§2.2), and public outreach and broader science communication (§2.3).

Many of the features described below require a Flask-enabled Firefly server, which allows communication between a live Python interpreter and a Javascript interpreter using websockets (for details, see Grinberg 2018). A Flask-enabled Firefly server can be launched locally using the firefly command, which is made available when Firefly is pip installed, with the --method=flask command-line argument. Additional information about installing and using Firefly with Flask is available in Appendix B.3.

Lastly, we note that the features we highlight in the sections below can easily be mixed and matched to create a compelling Firefly experience for any audience. Additional features and information are available in the documentation. To help guide the reader to the text they may be most interested in, in each of the following subsections we first provide a bulleted list of features to be discussed and then use bold font within the subsequent narrative to point the reader to where these specific features are mentioned.

2.1. Research tool for data exploration

In this section we discuss the following features:

- the Python data pre-processor (PDPP)
- coloring/filtering by an attribute
- plotting the velocity vector field
- moving the rotation anchor
- extrapolating position along velocity vectors
- embedding Firefly in a jupyter notebook
- accessing data on a remote server and streaming a scene rendered on another computer

Firefly is a powerful and versatile tool for researchers to interactively explore their own data in real time.
The first step in creating any Firefly visualization is to process the dataset using Firefly’s built-in Python data pre-processor (PDPP; see Appendix B). The Python data pre-processor can interpret a range of common data file formats (e.g., csv and hdf5; additional file formats can also be added by modifying the source code). Typical data will consist of discrete particles that each have x,y,z coordinates, and any number of additional attributes (e.g., velocity, temperature, density, etc.). The most straight-forward procedure is to use Firefly’s PDPP to save a copy of the pre-processed data to disk and then launch Firefly within a web browser (see Appendix C). Firefly will then read in and visualize the pre-processed data and allow the researcher to interactively e.g., color and/or filter data based on an attribute.

As a concrete example, a researcher who is interested in the 3D morphology of high-temperature regions in their particle data set could filter out all particles below their temperature threshold. Then the researcher could toggle the camera mode from the default “trackball controls” (which rotates the scene) to “fly controls” in order to move around the data volume. By flying the camera into one of these high-temperature regions and switching back into trackball controls they can reposition the rotation anchor at the new location to visually inspect the morphology of each region and note their locations for potential future detailed follow-up investigations. Perhaps the researcher is also interested in the magnitudes and directions of the velocities in these high-temperature regions; in that case, they can color the points by velocity and plot velocity vectors rather than individual scatter points (e.g., see Figure 1 (a) and (b)). The researcher could also select to (linearly) extrapolate the particle positions along the direction of the velocity vectors in a loop of a given duration to give an intuitive sense of how the material will flow over time by enabling the “animate velocities” checkbox.

Firefly can also run while embedded within a Jupyter notebook (Appendix B.4). In this mode, it is often most effective to use a Flask-enabled server to launch Firefly, e.g., using the firefly --method=flask command from the terminal. However the Firefly server is launched, a Firefly visualization can then be embedded as an IFrame in the Jupyter notebook:

```python
from IPython.display import IFrame
IFrame('http://localhost:<port>/',)
```

Then, the researcher can work directly within the Jupyter notebook to manipulate their data, process it for Firefly, and send (POST) the data directly to their Firefly server (a task that is conveniently wrapped by the Reader.sendDataViaFlask method of the Python PDPP). As a result, the researcher can load their data and interactively explore it in Firefly as easily as they would make static visualizations or scientific plots with the same footprint on disk (i.e., without having to double the size of the dataset by copying it on disk in Firefly compatible format).

If the researcher’s local machine does not have sufficient resources, they can connect to a high-performance computer (HPC) where they process the data and launch a Firefly server. By port forwarding, the researcher could view and manipulate Firefly on their local computer while accessing the Firefly server on the HPC. In this scenario, the researcher’s web browser on their local machine will read the data stored on the HPC without having to manually copy data over to the local machine. Alternatively, the researcher could launch a web browser directly on the HPC and only “stream” the visual content to their local computer (using the <ip-address>:<port>/stream entry point, which is only available when Firefly is launched with a Flask-enabled server; note that firewalls on some centrally managed HPCs might prohibit this streaming method). Here the local computer does not load in any data other than the rasterized frame-by-frame images from the HPC. The quality of the rasterized image is automatically degraded in order to preserve a minimum FPS (which can be configured using the --framerate=<fps> command line argument when Firefly is launched). Detailed instructions on this procedure is available in the documentation.

2.2. Collaborative tool for sharing results with peers

In this section we discuss the following features:

- mirroring a view between two computers
- preset startup settings files for specific views
- exporting standalone Firefly instances

In this category of use we envision the following scenarios: 1) a researcher communicating with a collaborator live via videoconferencing software and 2) a researcher sharing the results of a recent paper on a stand-alone website.

In scenario 1), a researcher can set up Firefly using the --method=flask command line argument as above. At this point the researcher could simply share their screen via Zoom in order to illustrate their point using Firefly. However, this can often introduce latency which can be frustrating and, in the worst cases, actively confusing if the framerate is exceptionally low.
Instead, if the researcher sets up their router to allow incoming connections through the port Firefly is served on, this would allow their collaborator to access their Firefly session by visiting the corresponding `<ip-address>:<port>/viewer` entry point; The view from the researcher’s Firefly session would then be mirrored and rendered on their collaborator’s computer.

In scenario 2), a researcher desires to create a Firefly visualization that they can provide as supplemental data to a publication that readers can freely access asynchronously. To do so, the researcher can first create their Firefly visualization locally. They can optionally use Firefly to generate a `start-up settings file` that will initialize the view at start-up to an exact position and with applied filters and colormap. This process can be repeated with different datasets, e.g., separated in time, in order to create a multi-dataset visualization. We provide easy-to-use functions in Firefly’s PDPP that can export standalone Firefly instances. To export a Firefly instance the PDPP creates a new directory containing only the necessary Firefly source files and data that is ready to be uploaded to a personal web server, or to copy this local Firefly visualization to GitHub Pages (a free web-hosting service provided by GitHub).

Once the visualization is hosted online, the researcher can include the url in their publication and on their own personal website to direct readers to the interactive visualization where they can learn more about the research in an engaging and unique way.

2.3. **Public outreach tool for science communication**

In this section we discuss the following features:

- splitting the view and user interface into separate windows
- enabling/disabling elements of the user interface
- pre-defining a camera path
- VR compatibility

In this category, we envision two scenarios: 1) a researcher speaking in front of an audience and 2) a museum visitor exploring data within a Firefly visualization as part of an exhibit.

In scenario 1) the researcher launches Firefly with a Flask-enabled server using the `--method=flask` command line argument. This allows the researcher to split the view into two different browser windows: one with only the visualization imagery, and another with the user-interface controls. The researcher can access the `localhost:<port>/viewer` entry point on the display visible to their audience and the `localhost:<port>/gui` entry point on a hand-held device. In doing so, the researcher is able to interactively control the view from Firefly without revealing the controls interface to the audience, making for a cleaner, simpler, and more engaging viewing experience.

In scenario 2) the researcher could create a Firefly visualization and restrict aspects of the user interface using the settings file in order to simplify the experience and reduce the amount of “visual clutter” in the user-interface in order to make it easier for an inexperienced user to navigate. The researcher can also, optionally, define a camera path that viewers will automatically be flown along. This allows the researcher to highlight specific aspects of the visualization while still allowing the viewer to interactively change aspects of the visualization (like the colormap and filters). If the museum has a VR headset available, the `localhost:<port>/VR` entry point will enable basic camera controls using the orientation of a VR headset so that visitors can put on the VR headset and immerse themselves in the data.

3. **EXAMPLE FIREFLY VISUALIZATIONS OF ASTRONOMICAL DATASETS**

To demonstrate the flexibility of Firefly, we provide three concrete examples of Firefly applied to different astronomical datasets and the Jupyter notebooks we used to create them.

1. a z=0 snapshot from the FIRE-2 simulations\(^4\) (Hopkins et al. 2018)
2. a higher resolution counterpart snapshot from the FIRE-2 simulation public data release (Wetzel et al. 2022)
3. the SDSS galaxy catalog from DR17 (Meert et al. 2018) with morphological classification from Galaxy Zoo (Lintott et al. 2008, 2011)
4. nearly 1.5\(\times\)\(10^9\) stars from Gaia DR3 (Gaia Collaboration et al. 2016; Babusiaux et al. 2022)

These and other examples can be found in the gallery at alexbgurvi.ch/Firefly.

3.1. **FIRE simulations**

For these examples, we use snapshot 600 (corresponding to redshift \(z = 0\)) of the m12b_res5700 and m12b_res7100 simulations (described in Garrison-Kimmel et al. 2019). The first is a low(er) resolution

\(^4\) See the FIRE project web site: http://fire.northwestern.edu.
Figure 1. Screen captures of the Firefly web application in different modes visualizing the example datasets presented in §3. (a): An example dataset from the FIRE simulations. In this example, we highlight the existence of a fast moving biconical outflow of hot gas by colormapping by velocity, scaling the particle sizes by temperature, and plotting velocity vectors. (b): A second, higher resolution, example dataset from the FIRE simulations. In this example, we highlight the flocculent spiral structure of the galactic disk using the column density projection mode. (c): The SDSS galaxy catalog, split into categories by Galaxy Zoo classifications. In this example, we contrast the spatial distributions of different morphologically classified galaxies by coloring each particle group (split by classification) a fixed color (red: elliptical, blue: disk, yellow: uncertain). (d): A view from inside Gaia DR3, where points are individual stars colored by the difference in their measured blue band (bp) and red band (rp) magnitudes available. The galactic plane is clearly visible in the dirth of detected stars and the bp-rp of stars at its edges is indicative of dust reddening. These visualizations are available to explore interactively at alexbgurvi.ch/Firefly.

counterpart of the second, which is from the FIRE-2 public data release (Wetzel et al. 2022). The Jupyter notebooks we use to generate these instances of Firefly are available at github.com/agurvich/FIRE_lowres and github.com/agurvich/FIRE_hires. The high resolution simulation, m12b_res7100, can be obtained from the FlatHUB, an online data repository provided by the Flatiron Institute. The top panels of Figure 1 show screenshots of these datasets (available to explore interactively at alexbgurvi.ch/FIRE_lowres and alexbgurvi.ch/FIRE_hires).

Both datasets contains 4 particle types: gas, stars, high resolution dark matter (HRDM), and low resolution dark matter (LRDM). Each particle type has coordinates, velocities, and masses which we use to calculate the center of mass of the simulation box and the velocity of the center of mass. For each particle type we additionally compute the distance to the center of mass (GCRadius; “galactocentric radius”) and the magnitude of the velocity (Velocity) as additional “derived” scalar fields in order to track them in Firefly for filtering and colormapping. In addition to these two scalar fields, we also track the (log_{10} of the) Temperature and Density for the gas particles and the stellar age (AgeGyr) for the star particles.

The low resolution dataset contains 6.2 million gas particles, 3.3 million star particles, 9.3 million HRDM particles and 3 million LRDM particles. The high resolution dataset contains 58 million gas particles, 17 million star particles, 70 million HRDM particles and 7 million HRDM particles. However, given that not all the particles are necessary to create an informative interactive visualization and that computational resources may be limited for some users, we reduce the HRDM and LRDM by a factor of 10× (50×) for the low (high) resolution dataset. Additionally we apply 7× (10×) reduction factors to the gas (star) particles for the high resolution dataset in order to fit within browser memory.
restrictions (in §3.3 we explore an alternate approach to circumventing this browser memory restriction for an extremely large, \( \gtrsim 10^9 \) particle, dataset). Table 1 summarizes the number of particles and scalar fields included in these Firefly visualizations, including the decimation factors where applicable.

We begin with the low resolution m12b_res57000 example. To avoid obscuring the galaxy at the center of the box we initialize the HRDM GCRadius filter to hide all particles within 300 kpc; if we didn’t do this then the view near the galaxy would be obscured by a volume filling screen of dark matter particles. We use the PDPP to apply this filter at startup, rather than doing it interactively at startup for two reasons: 1) it’s more user friendly and 2) it avoids performance issues if you have a bunch of particles overlapping in the same pixel (see §1 for a detailed breakdown of how this scales). We also colormap the gas particles according to the magnitude of their velocities and enable velocity vectors. By default the vector sizes (i.e., both their lengths and widths) are also set by the magnitude of their velocities. This approach of using color and size to doubly encode information is a best practice in creating accessible visualization. Here we instead choose to scale the vector sizes according to the \( \log_{10} \) of their temperature. The ability to scale sizes by another quantity enables us to take this double-encoding approach for any quantity, not just velocities. With these settings, the visualization (see Figure 1a) highlights a fast moving biconical outflow (yellow) driven by stellar feedback from the center of the main galaxy surrounded by a swirling inflow of slower moving and cooler gas (purple) both above and below the disk plane (blue). Interestingly, the trajectory of the biconical outflow is clearly perturbed by the presence of the inflowing material as the jet bends noticeably before continuing on to large radii (\( \sim 100s \) of kpc). The presence of the biconical outflow (and its deflection) in this dataset went unnoticed until we produced this visualization, demonstrating the utility of 3D interactive visualization for exploration.

For the second example (see Figure 1b), we show the high resolution counterpart m12b_res7100. Here we use the column density project mode, which emphasizes the flocculent (roughly “fluffy” and discontinuous) spiral structure of the galactic disk. The column density projection mode counts the number of particles that overlap each pixel and applies a colormap to this per-pixel number density. This is critical for analyzing the high resolution dataset; otherwise the high density of particles quickly saturates the screen, making it difficult to identify structure. By accumulating the data in each pixel and then assigning a color based on density, we produce a more meaningful visualization that can be more easily interpreted scientifically. In this case we assign a meaningful color to the pixel by colormaping the \( \log_{10} \) of the \( \log_{10} \) of the projected number of particles in each pixel, which is proportional to the total mass along the line of sight, using the magma colormap from Matplotlib. Using the column density mode, and in particular the \( \log_{10} \) normalization, helps identify the surface density contrasts, which are typically 2–3 orders of magnitude, which define the spiral arms of the galaxy. Without projecting and \( \log_{10} \) normalizing the disk would appear uniform across its face due to the large number of particles saturating the pixel values and the spiral structure would not be visible.

This high(er) resolution version uses the same initial starting conditions as the lower resolution simulation shown in panel (a), however interestingly, a biconical outflow does not appear in this higher resolution version (when viewed in column density or using the previous visualization settings used for the low resolution dataset). Contrasting between these two different resolution simulations could help us understand how such outflows are launched and in what kinds of galaxies. Concretely, even if one was to explain this difference as a “resolution artifact” then, by contrasting these two simulations to isolate the physics that is unresolved in the lower resolution simulation, we can identify a key component to driving these sorts of outflows. Most importantly, the outflows can’t be explained by differences in the macroscopic properties of the galaxy like the total mass, gas/(baryon) fraction, star formation rate, stellar mass, because they are numerically converged between the high and low resolution simulations. Instead, by honing in on the key differing attributes of these simulations we can, hopefully, identify the driving attributes of galaxies which are observed to launch similar outflows in the real universe.

### 3.2. SDSS DR17

For this example, we use DR17 of the SDSS galaxy survey which can be obtained from the online repository (Meert et al. 2018). The Jupyter notebook we use to download the data and generate this instance of Firefly is available at github.com/agurvich/SDSS_test. Each of the 670722 galaxies in the sample has RA and Dec sky coordinates along with an estimated redshift. We use astropy (Astropy Collaboration et al. 2013, 2018) to convert these into x,y, and z coordinates in 3D space. The Meert et al. (2018) dataset also includes probabilities for basic morphological classifications from the citizen science project Galaxy Zoo for each galaxy, which we use to partition the dataset into three categories (Lintott
et al. 2008, 2011). We choose to categorize galaxies with $P(\text{disk}) \geq 0.5$ and $P(\text{elliptical}) < 0.5$ as “likely disks,” galaxies with $P(\text{elliptical}) \geq 0.5$ and $P(\text{disk}) < 0.5$ as “likely ellipticals,” and galaxies with both $P(\text{disk}) < 0.5$ and $P(\text{elliptical}) < 0.5$ as “uncertain.” The number of galaxies that fall into each category is listed in Table 1.

In addition to the morphological probabilities, Meert et al. (2018) also include distance modulus, gri apparent magnitudes, extinctions, and k-corrections which we use to calculate absolute magnitudes. From these absolute magnitudes we calculate the corresponding luminosities to calculate absolute magnitudes. From these absolute magnitudes, extinctions, and k-corrections which we use for the different particle groups, their sizes, whether they have 3D velocities, and the number of scalar fields for each example dataset.

Table 1.

| Particle group | $N_{\text{particles}}$ | 3D velocities | $N_{\text{fields}}$ |
|----------------|------------------------|---------------|---------------------|
| FIRE - m12b_res7100 - snapshot 600 | | | |
| Gas            | 8,369,779 (7×)         | ✓             | 4                   |
| Stars          | 1,686,946 (10×)        | ✓             | 3                   |
| HRDM           | 1,490,740 (50×)        | ✓             | 2                   |
| LRDM           | 135,019 (50×)          | ✓             | 2                   |
| FIRE - m12b_res57000 - snapshot 600 | | | |
| Gas            | 6,225,729              | ✓             | 4                   |
| Stars          | 3,264,723              | ✓             | 3                   |
| HRDM           | 932,304 (10×)          | ✓             | 2                   |
| LRDM           | 304,226 (10×)          | ✓             | 2                   |
| SDSS DR17      | | | |
| Disks          | 311,212                | ×             | 6                   |
| Ellipticals    | 252,715                | ×             | 6                   |
| Uncertain      | 106,795                | ×             | 6                   |
| Total          | 670,722                | ×             | 6                   |
| Gaia DR3       | | | |
| no RV          | 1,467,744,818          | ×             | 2                   |
| RV sample      | 33,812,18              | ✓             | 3                   |

Table 1. the different particle groups, their sizes, whether they have 3D velocities, and the number of scalar fields for each example dataset.

Their gri magnitudes. We initially disable this particle group using the PDPP so as not to overlap with the partitioned particle groups but include it so that we can toggle between.

The resulting visualization (shown in Figure 1c) reveals a number of interesting features in the SDSS data. First, we that the nearest and furthest galaxies are all classified as uncertain. Enabling the gri magnitude colored particle group (and disabling the morphologically classified particle groups) shows that the nearest galaxies have very low absolute magnitudes (the particles appear nearly black) suggesting that the reason they are classified as uncertain is because they are dimmer (smaller/lower mass) galaxies which are only detected as a result of their (relative) proximity and thus are more likely to be irregular. On the other hand, the furthest galaxies are also the most difficult to detect and are less likely to have obvious features for the citizen scientists to classify.

If we switch the view back to the morphological classifications, change the blending mode from additive to normal, and enable the depth buffer checkbox, the pixel color value we see represents the morphology of the galaxy closest to the camera’s current perspective along each line of sight. This is a valuable viewing mode to differentiate the colors of overlapping particles and the normal+depth blending mode is enabled automatically when the colormap is enabled.

By comparing the frequency of the blue points to red points as a function of distance from the center we can see that with increasing redshift disks become much rarer in the dataset compared to ellipticals. We can estimate the maximum redshift the bulk of disk galaxies are contained within by interactively moving the redshift filter minimum handle to show that at a redshift of $z \gtrsim 0.2$, ellipticals dominate the galaxy population (see Figure 2). There are likely two effects at play that lead to this relative dirth of disks for redshift $z \gtrsim 0.2$ in the dataset: 1) the physical effect that disks are actually
rarer as one looks further back in time (a phenomenon known as “disk-settling,” see e.g. Kassin et al. 2012) and 2) the observational effect that higher mass galaxies (which are preferentially elliptical) are brighter and therefore can be seen from further away. The ease with which these effects can be illustrated and communicated (e.g., in a public lecture or museum setting) by interactively exploring the dataset, again, demonstrates the power of interactive visualization.

3.3. Gaia DR3

For our final example, we use the latest data release from Gaia, DR3 Gaia Collaboration et al. (2016); Babusiaux et al. (2022). The dataset contains RA, Dec, parallax, proper motions in RA and Dec, radial velocity, BP-RP color, and g-band magnitude. We again use astropy to convert the RA, Dec and parallax to 3D positions for all stars. Where radial velocity data is available we also include proper motions and radial velocities to calculate the 6 dimensional cartesian position and velocity phase space. Following this, we use the g-band magnitude to scale the particle radii. Lastly, we use the measured difference in blue band and red band magnitudes (bp-rp) to colormap the stars.

The full DR3 dataset has 1,467,744,818 sources, of which 33,812,183 have radial velocity measurements which are required for the full 6d phase space position (x,y,z + vx,vy,vz). The sheer volume of data for this dataset is more than most web browsers will allow a single tab to use, even if the hardware is available. Most browsers will only allow ~2-3 GB of data to be stored in memory; the Gaia data is ~250 GB in total on disk. Thus in order to interactively explore large datasets like Gaia, we implement and employ a progressive rendering scheme which only loads the data from disk which is currently in the camera’s view. We do this by reorganizing the data such that spatially collocated particles are grouped on disk in files which are indexed by octants of an octree.

Our algorithm for building the octree in Python, as well as walking it and loading the necessary data in Javascript, is described in detail in Appendix D. In short, we start building the octree by defining a bounding box which contains the 99% of the particles closest to the center of mass and iteratively sort those particles within the box into octants (and then sub-octants, sub-sub-octants, etc.) with a refinement criterion based on a (configurable) maximum allowable number of particles. To accommodate extremely large datasets (like this example) our implementation does not require the entire dataset ever be loaded into memory at a time and allows multiple worker threads to contribute to building the octree in parallel. Using a single node with 52 cores on the Quest HPC at Northwestern, we built this octree in ~45 minutes. To determine which data to load in Javascript, we loop through the nodes of the octree and determine: 1) whether any of the vertices are onscreen and 2) the distance from the node center to the camera. If the node is onscreen and the distance to the camera is such that the node covers multiple pixels, then the data indexed by the node is queued to be loaded from disk.

Once the data is indexed into an octree and loaded into Firefly (see Figure 1d), we can immediately see interesting features. Firstly, there is a dirth of stars along a dark streak which, evidently, traces out the galactic midplane where dust attenuation is strong enough to prevent the detection of any stars along the line of sight. Second, the stars which are along the edges of the galactic midplane have colors that are redder than those stars that are further away owing to the reddening effect of interstellar dust. Lastly, by enabling the “animate velocities” feature (i.e., extrapolating the positions of particles along the direction of their velocity vectors) we can see that there are (hyper-velocity) stars which move much faster than the galactic average. It is also possible to look for co-moving groups of stars to visually identify astrometric binaries and even star clusters and associations. The sheer volume of data makes this last activity challenging through visual inspection alone, but could be facilitated by first identifying candidate groups (e.g., by using a friends-of-friends or clump finding algorithm in pre-processing) and adding these as an additional particle group of a different color.

The Jupyter notebook we use to generate this instance of Firefly is available at the github repo and the resulting visualization is available to explore interactively at alexbgiurvi.ch/Firefly.

4. PERFORMANCE TESTING

Because Firefly runs locally in the browser, its performance is determined by the client’s hardware. A Firefly visualization can run on essentially any device that has a WebGL-enabled browser, though performance can vary significantly. For instance, a Firefly visualization can be created and viewed locally on a personal laptop. Alternatively, the visualization could be hosted on a powerful HPC, e.g., with many GB of available RAM and a powerful graphics processor. As described in §2 above, there are two modes to access the visual content from the HPC server: 1) port forwarding (in which case performance is limited by the client hardware; i.e. the user’s laptop) and 2) the /stream entry point (in which case performance is limited by the HPC hardware and the user’s internet connection speed). Nonetheless, the most com-
mon mode of using Firefly will no doubt rely on the computing resources available on a standard consumer grade laptop.

The general criteria and limitations that govern the performance with which a given dataset is loaded and visualized interactively are as follows:

- space on disk that the data occupies (limited by available hard drive space)
- amount of RAM required to store the dataset in memory (limited by the amount of RAM installed and possibly further limited by the amount of RAM allowed within the browser)
- time to load the data from disk into RAM (limited by the CPU clock speed)
- time to render an individual frame (limited by the GPU)

In this section, we provide benchmarks run using a Macbook Air (M1, 2020) running macOS Monterey Version 12.3.1 with 8 GB of RAM purchased in March of 2022. The guidance here is intended to convey confidence that a modern personal computer can run Firefly interactively with a large dataset; one does not need a purpose built workstation. However, each dataset is unique, and the only way to know if a dataset will run well in Firefly is to make an attempt.

4.1. Memory limitations and startup

Our first set of benchmarks aim to measure the amount of memory (both on disk and in RAM) required to load in datasets of different sizes, as well as the time required to load the data from disk into RAM.

The size of the dataset on disk can be calculated exactly. In this case we use a dataset from the FIRE simulations and apply different decimations to achieve different numbers of particles. In this dataset, we include 3 coordinates \((x, y, z)\), 3 velocities \((v_x, v_y, v_z)\), and 4 scalar fields (the density, temperature, galactocentric radius, and magnitude of the velocity) for each particle (10 single precision floats per particle). The top panel of Figure 3 shows that the binary .ffly format scales exactly as predicted except at the lowest end (where the data volume is comparable to the size of the .ffly file headers).

The .JSON format is inflated by a factor of \(\sim 3\) by comparison. We can understand this by estimating the number of characters that would be required to represent a single precision floating point number since .JSON is a text-based format. The number of digits in the typical string representation of a single precision floating
Figure 4. performance benchmarks for the framerate of a Firefly visualization as a function of number of overlapping particles. In general, the bottleneck for performance during the visualization is how many particles in a pixel are overlapping (and for how many pixels this number is $\gg 1$). Top: schematic diagrams of the two tests we perform: 1) placing many particles at the origin (left) and 2) distributing many particles in a cube of fixed size. In both cases, we vary both the number of particles and their diameter. Scale bars illustrate the mapping between dataspace (in “units”) and screen space (in pixels) from a fixed camera distance 2 units for consumer grade monitor with a 1920x1080 resolution. In all tests, we move the camera along a predefined path orbiting the origin with radius of 2 units. Bottom: quantitative results of varying the number and diameter of particles for both the overlapping particle (left 2 panels) and cube (right-most panel) setup. In both of these extreme cases of particle density, we find that interactive framerates are achievable.

Note that writing to disk is only necessary if hosting on the internet or if using an octree. Otherwise, writing to disk can be totally avoided if the data is sent via Flask instead which does not require writing intermediate files to disk at all.

The space that each particle occupies in RAM once the application is started is less obvious. In addition to the raw data as it exists on disk, there are additional arrays that must be created like: RGBA color arrays (4 additional floats) and particle sizes (1 additional float). The coordinate and velocity arrays must also be copied into special purpose buffers (6 additional floats), as well as the scalar field currently being colormapped (1 float; even if colormapping is disabled this buffer must be filled with 0s). As well, copies of subsets of the data are made as filters are applied, colormaps are computed, etc. making it difficult to exactly predict the memory footprint as a function of the number of particles and scalar fields.

Finally, and perhaps only relevant for small datasets, the various Javascript libraries we employ have to be loaded as well (representing a constant offset). The middle panel of Figure 3 measures the memory usage as reported by Chrome’s internal memory usage API (window.performance.memory.totalJSHeapSize). In it we see that, as one would expect, there is not a significant difference between whether the data is loaded from .JSON or .ffly format.

Lastly, the time required to load the data from disk into RAM will vary substantially between different datasets and computers. In particular, the speed and condition of the RAM, the speed of the CPU, and the speed of the hard drive will all play a role. Any other processes running on the computer will also effectively slow down Firefly’s ability to read in data. The bottom panel of Figure 3 shows the measured timings for this specific combination of dataset and hardware both for
Figure 5. Performance benchmarks for pre-formatting sample FIRE data as an octree using the Firefly PDPP. Top: the number of nodes in the constructed octree as a function of the number of particles in the dataset and the maximum number of particles in a node before it is refined into child nodes (yellow $10^3$, red $10^4$, and blue $10^5$). Bottom: the time elapsed constructing the octree. The dashed lines in both panels show fitting functions (defined by the black annotations in each panel) to the data for each $N_{\text{max node}}$. Generally, octrees with fewer but larger nodes take less total time to generate but appear more “chunky” than those with more numerous and smaller nodes.

4.2. Interactivity in the web application

The number of frames rendered per second (FPS) determines whether the app is experienced “interactively.” For our purposes here, we’ll define an interactive FPS as being above 15 FPS. In Firefly, the FPS falls steeply when many particles overlap one-another, and even more steeply when this is true for many pixels on the screen. The issue being that the hardware accelerated rendering is performed on each pixel independently (and in parallel as threads are available). Thus, when the work required to render an individual pixel increases, it acts as a bottleneck for the application as a whole (note that this is generally true for all graphics rendering processes). As you add more particles and the number of overlapping particles increases, or if the size of each of the particles increases, the FPS will drop, eventually below our interactive threshold.

To give a rough idea of this limitation we consider two idealized scenarios: 1) maximally overlapping particles all placed at the origin (top-left of Figure 4) and 2) a cube of uniformly distributed particles between ±0.5 in each coordinate axis centered on the origin (top-right of Figure 4). In both scenarios we place the camera on a fixed path circling the origin at a radius $r = 2$. To automate these tests we use Puppeteer, a Node.js module that allows users to interact with a basic Chromium web browser using scripted commands. The Puppeteer script we use for these tests is available at the Firefly Github repository.

In general, the bottom panels of Figure 4 demonstrate that interactive framerates are easily achievable for moderately sized particles (∼12px from this camera distance) for up to $10^5 - 10^6$ overlapping particles. Thus by manually adjusting the particle size multiplier as the camera distance increases/decreases, users should be able to maintain interactivity without hitting performance bottlenecks except in the most extreme cases of particle density.

4.3. Using an octree

Pre-formatting a dataset as an octree using the PDPP may allow users to avoid some of the limitations described in the previous sections while still visualizing the entire dataset (albeit not all simultaneously). However, there is the obvious upfront time and storage costs of re-writing the data to disk and of processing the data into an octree format.

Octree files are only supported in binary format, so their size on disk will scale the same as in the top panel of Figure 3. The number of nodes in the octree will determine the level of granularity (or “chunking”) in the visualization as raw particle data is loaded. In general, having more nodes will produce a visualization that more closely resembles the raw particle data since the nodes will be smaller and faster to load. The maximum number of particles a node can contain before being further refined determines how many total nodes there will be in the octree. The top panel of Figure 5 shows how the number of nodes scales with the number of particles for three different values of the maximum number of particles per node. In all three cases, the number of nodes scales linearly with the number of particles. The storage space on disk is constant regardless of the number of nodes except in the limit of small numbers of particles in which case the metadata of the octree structure can approach the total size of the particle dataset, as in the top panel of Figure 3.
The additional time it takes to build octrees with more nodes at fixed number of particles can be significant. The bottom panel of Figure 5 demonstrates that, as one might expect, the average time to build a node, \( \alpha \), is longer for larger nodes. Also, the total time to build the octree scales more steeply, \( \beta \), with larger nodes. Despite the larger \( \alpha \) and \( \beta \) for larger nodes, the total time is still shorter as \( N_{\text{max node}} \) is increased. Thus, we recommend users err on the side of larger nodes in general and we set the default maximum number of particles per node in the PDPP to \( 10^7 \). Users who wish to visualize their own data using Firefly’s octree mode can (and should) experiment with the octree parameters within the PDPP to achieve their desired visual effect within Firefly, using the results of these performance tests as a guide.

5. CONCLUSION

In this paper we introduce and describe the inner workings of Firefly, a browser-based 3D interactive visualization software for particle data. Firefly is lightweight, portable, and performant. Viewing a Firefly visualization requires no installation; users need only to visit a URL to immediately explore a pre-configured dataset. Because Firefly is browser based, it is automatically compatible with any device or operating system whose internet browser supports WebGL (which is typically true of most popular browsers, e.g., Google Chrome, Mozilla Firefox, Safari, etc.). Firefly is capable of displaying \( \gtrsim 10 \) million points simultaneously, limited by the amount of RAM available to the browser (which is 2-3 GB/tab in most web browsers). This limitation can be circumvented by pre-processing data into an octree which allows Firefly to load on demand only that data which is currently in the camera view. This allows Firefly to visualize datasets with \( \gtrsim 10^9 \) particles, like Gaia DR3 (albeit not in its entirety simultaneously). Through the user interface, users can interactively apply filters and colormaps to create new perspectives that can be exported as a screenshot or as a settings file to be imported into another Firefly session (or more computationally expensive rendering tool).

Firefly is bundled with a custom Python data preprocessor (PDPP). This PDPP can format user data, customize the UI, host local Firefly servers, and help users create standalone versions of Firefly they can host on the internet. These features allow users to conveniently create, share, and explore streamlined and intuitive Firefly visualizations for different audiences without having to change any of the source code.

When used locally, Firefly has additional features that are available when it is served by a Flask-enabled server, which provides a Python-Javascript interface using websockets. These websockets allow users to split the UI and viewer into different windows, explore their scene in VR, stream the rendered image to a client, and pass data to an active Firefly instance without having to write it to disk. The last feature is especially useful as it enables users to interactively load and visualize their data seamlessly in a Jupyter notebook.

The source code to run Firefly locally or to generate new instances of Firefly to host on the web is easily obtained using the pip install firefly command from a terminal. It can also be downloaded and built from its Github repository (github.com/ageller/Firefly). Detailed Instructions for using Firefly and its PDPP can be found online at alexbguerti.ch/Firefly along with a gallery of example Firefly instances and a link to the source code repository.

We also present three examples of applying Firefly to astronomical datasets: 1) the FIRE cosmological simulations, 2) the SDSS galaxy catalog, and 3) the Gaia DR3 dataset. The Python code used to produce these examples are packaged alongside the source code and particle data in their respective Github repositories. Though we have presented Firefly in the context of these specific examples, we emphasize that Firefly can be used to visualize any three dimensional dataset, whether those dimensions are spatial or not. Higher dimensional datasets can be visualized using colormaps and filters.

Development of Firefly is ongoing and this paper is linked to the release of the 3.1 version of the code. New features, like greater support for datasets that vary with time, and volume rendering particle data with spatial extent. For an up-to-date list of features and planned changes please consult the project’s homepage, alexbguerti.ch/Firefly.

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APPENDIX

A. HOW TO USE A FIREFLY VISUALIZATION

In this section we describe how to navigate around a Firefly visualization within a web browser. In general, to create a new visualization a user first will need to process their data with our Python utilities, which we will describe in the subsequent section. Here we assume that the user already has access to a live Firefly visualization (e.g., one of the examples that we provide on alexbgurvi.ch/Firefly).

The visual side of Firefly is a primarily Javascript application that uses the three.js library to create a WebGL rendering canvas. Along with the WebGL rendering canvas, the three.js library also provides useful primitive objects for representing and manipulating the scene. Additionally, we use kaitai.io to build custom Javascript binary data loaders and the d3.js library to both: 1) load .JSON data/settings files and 2) procedurally create elements of the user interface (UI).

Figure 1 shows example Firefly scenes. The bulk of the screen space is devoted to the rendered scene and a collapsible UI appears on the left side of the screen by default (though it can be clicked and dragged to any position on the screen if desired). Clicking and dragging outside of the UI will move the camera; more information on this is provided in the following subsection.

A.1. Manipulating the 3D scene

Users navigate the camera through the visualization using mouse and keyboard inputs. The mapping between mouse movements and key presses is split between two control modes: “trackball controls” and “fly controls.” Pressing the space bar, or checking the lock camera check box in the UI, toggles between these two control modes.

Trackball controls, which use only the mouse, are enabled by default. In this camera mode, the view focuses on and orbits a “camera center” when users click the left mouse button and drag the mouse. The user can also zoom in and out by scrolling up or down and pan the camera center by holding the right mouse button and dragging. After moving the camera in trackball controls mode, it will briefly continue moving to provide a sense of inertia.

In fly controls, the primary input device is instead the keyboard, and the camera is moved freely about the scene (without orbiting about a fixed center as with trackball controls). Users move forward or backward using the “W” and “S” keys, left or right with the “A” and “D” keys, and vertically up or down using the “R” and “F” keys. Clicking and dragging the mouse up or down (left or right) in this mode will pitch (yaw) the camera. Holding the “shift” key in combination with any of the above will reduce the speed for fine-adjustment. Users can also press the “4” or “.” keys to increase or decrease the default fly speed (respectively).

In addition to interactively exploring a dataset using the mouse and keyboard, Firefly has a UI which starts collapsed in the top left corner by default. Clicking the three bars (“x” that takes its place) will expand (re-collapse) the interface. The user interface is organized hierarchically in order to keep the interface compact. At the top level, the user interface is split into two categories: 1) general controls which affect the application as a whole (§A.2) and 2) any number of particle group controls which affect only individual particle groups (§A.3). Users can navigate through the hierarchy by clicking on labeled buttons to move downwards, and clicking on the back arrow to move upwards. Users interact with the visualization through buttons, checkboxes, drop-down menus, text entry boxes, one-sided sliders, two-sided sliders, and color pickers. Since the UI is procedurally generated using d3.js to add HTML divs to the DOM, each section, and their individual elements, can be disabled independently by adding a unique “path” identifier to the GUIExcludeList (see Appendix B below).

A.2. User interface: general controls

The general controls, shown in Figure A1, control global aspects of the visualization and are split into three categories: 1) data, which contains controls for adjusting or replacing the current dataset; 2) camera, which contains information about the current camera location and controls for modifying the camera view; and 3) projection, which allows users to toggle the column density projection mode and adjust the colormapping.

A.2.1. General Controls: Data

Clicking the “Data” button in the main/general UI pane will reveal the main/general/data pane (see Figure A1d). In this pane, there are buttons, sliders, and text entry boxes that allow the user to control various aspects of, or change entirely, the currently viewed data set. The first UI element is a slider and text box combination which applies a global decimation factor to reduce the number of particles on screen in all particle groups (for performance or personal preference).
The “Load New Data” button allows Firefly to directly open new pre-formatted Firefly datasets or to directly convert .csv and .hdf5 files. This button only appears if the user is running Firefly through a Flask-enabled server, described in Appendix B.3. In the latter scenario, the files are parsed through the Python utilities described in Appendix B and sent directly to the running Firefly instance without having to write intermediate Firefly files to disk. For .csv files, Firefly assumes that individual files contain data for a single particle group. Each file must at least contain columns with names of “x”, “y”, and “z.” For a given .hdf5 file, Firefly can accommodate different particle types within a single file if they are split into different HDF5 groups. Each particle type must contain a “Coordinates” key (pointing to the x, y, z spatial locations of each particle) or “x”, “y”, and “z” keys. We describe how to load one’s own data in more detail in Appendix B below and in the documentation.

Lastly, the values of the settings which define the current visualization view can be collectively exported or imported through the “Save” and “Load Settings” buttons. This can be particularly useful if a user has defined a specific view on their data that they want to be able to reproduce later and/or share with a colleague. The settings can also be reset to their initial values from the application startup using the “Initial Settings” button.

A.2.2. General Controls: Camera

Clicking the “Camera” button in the main/general UI pane will reveal the main/general/camera pane (see Figure A1e). In this UI pane, the camera’s position and orientation are printed in read only text boxes. This may be useful if, for example, a user desires to copy the camera settings into another application that will perform more computationally intensive rendering for publication. There are also two checkboxes, one labeled “Lock” which toggles the camera control mode between fly and trackball (see Appendix A.1 above) controls (just as the space bar does), and a second, labeled “Tween,” which will move the camera along a pre-defined path, according to keyframe locations and durations defined in the tween file ( tweenParams.json by default). This check box only appears if there is an existing TweenParams.json file linked to the dataset (see Appendix B below).

Next, there are three buttons for saving the camera position, resetting the camera to the most recently saved camera position, and refocusing the camera. The first two buttons allow users to store a saved camera position and then reset the view to that saved camera position at any time. If the reset camera position button is pressed before the save camera position button then the camera is reset to the original position from initialization. The refocus button reorients the camera to face the origin.

In trackball controls, the “Friction” slider allows a user to change how quickly the camera decelerates after movement with smaller values allowing the camera to move for longer (with 0 making the camera continue to move forever). In fly controls, the same slider determines the speed of motion (in addition to the “+” and “-” keys mentioned above).

The camera view can also be horizontally duplicated and slightly offset to produce a stereoscopic effect that modern 3D televisions and monitors can overlay to make 3D scenes with polarized glasses. The “Stereo” checkbox will enable stereo mode, and the adjacent slider controls the strength of the 3D effect by changing the stereo separation.

The canvas can also be expanded to take up the full screen area using the “full screen” button when the application is not already in Full Screen mode. Additionally, it is also possible to export static images by clicking the “Take snapshot” button. The default resolution of these images depends on the user’s computer monitor and the size of the browser window, but the resolution can be specified manually in the text entry boxes within the button to produce large format images for print or publication if so desired.
Figure A2. UI elements that affect the individual particle groups independently. The format of this figure is analogous to that of Figure A1.

A.2.3. General Controls: Projection

Clicking the “Projection” button in the main/general UI pane will reveal the main/general/projection pane (see Figure A1c). In this pane, there are checkboxes, sliders, and drop-down menus which allow the user to enable and adjust Firefly’s column density projection mode.

When column density mode is enabled particles are first rendered to a texture buffer rather than directly to the canvas in order to sum up the number of particles within a given pixel. This number is then used to draw a color from the colormap selected from the drop-down menu in the UI. There is also a checkbox to first take the $\log_{10}$ of the particle count before applying the colormap if so desired. Lastly, there is a two-handled slider which controls the colormap limits.

A.3. User interface: particle controls

Within a dataset, it is common for there to be different categories or types of data. For example, in cosmological hydrodynamic simulations, there are often at least gas, star, and dark matter particles. In Firefly these different categories are represented as particle groups. More broadly, particle groups are subsets of data that will share certain characteristics in the visualization like size, shape, and color.

Clicking the “Particles” button in the main pane (Figure A2a) will reveal the main/particles pane (Figure A2b). Figure A2 illustrates how the various (sub-)panes of the particle UI are organized hierarchically. Each particle group has its own pane in the main/particles window whose controls affect only that particle group. The sub-panes for each particle group are structured identically but only show the relevant fields/limits/etc. corresponding to that particle group. Clicking the downward facing arrow on the right edge of the particle group’s row in the main/particles pane will expand that particle group’s base UI pane and reveal the: general, velocities, filters, and colormap sub-panes (see Figure A2c). The downward facing arrow will transform into an upward facing arrow which, when clicked, will re-collapse the base pane. There are three basic controls for every particle group, which are visible regardless of whether the base pane is expanded: 1) a switch to toggle visibility, 2) a slider+text box to change the particle radius scale factor, and 3) a color picker to change the particle group’s color.

A.3.1. Particle Controls: General

Clicking the “General” button in the base particle UI pane will reveal the base/general pane (see Figure A2e). In the first row is a “Blending Mode” drop-down menu and “Depth” checkbox. The blending mode menu allows users to adjust how the colors of overlapping particles are blended. The default mode, additive, adds the RGB values after multiplying by opacity. Other modes include “normal” (as additive but ignoring opacity), “subtractive” (takes the difference of the RGB values). The depth checkbox enables the “depth buffer”, which will render the particles in order from farthest to nearest to the camera; this can be useful when combined with “normal” blending to show the color of the nearest particle to the camera for each pixel (important when using a colormap). Next is the “N” slider, which can be used to set the maximum number of particles shown. The “N” slider is analogous to the decimation slider in the main/general/data UI pane (Figure A1d) but for individual particle groups. It can be used to downsample the visualization in order to get a more coarse-grained view without having to create separate input files. If the input data for this particle group has scalar fields flagged as being allowed to scale the particle radii (see Appendix B below), an additional dropdown will be available to change the radius scaling variable for the particle group. This is set to “None” by default, i.e., all particles in that group are the same size.

A.3.2. Particle controls: velocities

If the dataset includes velocity data then the “Velocities” button will be shown in the base pane. Clicking the “Velocities” button will reveal the base/velocities pane (see Figure A2f). Within this pane, there is a
A.3.3. Particle controls: colormap

If the dataset includes scalar field values that have been flagged to colormap, then the “Colormap” button will appear in the base particle UI pane. Clicking will reveal the base/colormap pane (see Figure A2d). The “Colormap” checkbox toggles the color of each particle in the group between the fixed color for the group and the color corresponding to the particle’s value in the selected scalar field array. The user can choose which colormap to use and which scalar field to colormap by using adjacent dropdown menus. When colormapping is enabled an additional tab is added to the side of the user interface that contains a colorbar mapping between the scalar field values and the corresponding colors. This colorbar is updated automatically if the user changes any of the colormap settings.

The available colormaps are defined in the colormaps.jpg file in the firefly/src directory (mostly drawing colormaps from Python’s Matplotlib library, Hunter 2007). This file contains rows of different colormaps whose row index corresponds to their position in a list defined within the colormap_names.json file, which is read when Firefly is initialized. Replacing these files can allow users to apply custom colormaps if so desired.

The lower and upper limits on the colormap in the two-sided slider are set to the minimum and maximum values for the given field by default, but can also be specified in the settings file. Firefly stores the colormap limits for each field separately, so when the user switches between fields the limits will automatically change to those corresponding to the newly selected scalar field.

A.3.4. Particle controls: filters

If the dataset includes scalar field values that have been flagged to filter by, then the “Filters” button will appear in the base particle UI pane. Clicking will reveal the base/filters pane (see Figure A2g). Filters apply additively and can be stacked in order to restrict the visualization to a specific region of phase space. Filters and their limits are only applied on a per-particle-group basis even if different particle groups share the same filterable scalar field.

Analogously to the colormap pane, there is a dropdown menu containing the field names that are flagged for filtering and the minimum and maximum limits within the two-sided slider are set to the minimum and maximum field values by default (but can also be specified in the settings file). There are also two checkboxes: one for inverting the filter to exclude particles whose scalar field values fall within the limits and one for enabling filter “playback” mode. Playback mode will automatically shift the selected region of the two-sided filter slider along the length of the filter limits. Playback allows users to quickly explore isocontours of specific variables without having to manually move the filter handles themselves.

B. THE PYTHON DATA PRE-PROCESSOR (PDPP)

In addition to the core visualization functions described in Appendix A, Firefly includes a Python interface to facilitate: 1) converting particle data to properly formatted Firefly files, 2) customizing the user interface and startup settings of a Firefly visualization, and 3) hosting local and remote Firefly servers. To create a new Firefly visualization or host a local Firefly server, users must first obtain a copy of the source code and install the PDPP. The development version of the code is available from its Github repository while the latest stable version can be obtained from the Python Package Index (PYPI) and automatically installed using the pip install firefly command. Example Jupyter Notebooks (along with YouTube video tutorials) demonstrating the usage of the PDPP are available in the documentation.

B.1. Formatting particle data with the PDPP

Users convert their data into Firefly files in either ASCII .JSON (inefficient but portable) or binary .ffly (efficient but only interpretable by Firefly) containing the coordinate, velocity, and any additional scalar field data associated with each point. .ffly files are read using kaitai.io, a flexible framework which allows developers to semantically describe their data using .ksy.
configuration files and produce data loading routines for any number of programming languages. We provide the .ksy files we used to produce the Javascript files for loading .ffly files alongside the source code of Firefly (though most users should not need to use them unless they intend to modify the .ffly file format).

Whether .JSON or .ffly, each particle group is broken up into chunks across a set of files, rather than being saved as a single large file, to improve performance when loading data into the web application. We find that 10,000 entries per file is a good size for chunking but users may find that performance varies depending on the particular system they are running Firefly on and are encouraged to experiment with different chunking (using the n_particles_per_file attribute of the firefly.Reader class). Each file must be listed in the manifest filenames.json file, which is populated automatically when data is loaded into a firefly.Reader instance, so that Firefly knows to load it in. Manifest files must be listed in the startup file, startup.json, which is automatically generated by the PDPP when new datasets are created.

As in the web application, the PDPP organizes data into separate particle groups. We provide the firefly.ParticleGroup class, which holds the data and performs basic data validation. Each particle group must have a set of coordinates which represent the x, y, and z locations of each particle in the web application. They can also optionally contain velocity and RGBA color arrays, along with any number of scalar field arrays to use to filter, colormap, or scale the radius of the corresponding points. These optional arrays are expected to share indices with the coordinate data and so must have an entry for every particle within a particle group. Once data is ingested into a firefly.ParticleGroup instance, the .writeToDisk method can produce Firefly files. For more information, examples, and tutorials see the documentation.

B.2. Customizing the UI and startup settings

The user can customize the UI to start the application from a specific camera location, set filter/colormap limits, or even disable any UI element using a settings.json file. This allows users to produce instantly sharable visualizations that start from the exact perspective they desire and to tailor their visualizations to different audiences by restricting the level of interactivity available. In addition to describing the state of the web application at startup, settings files can also be imported through the “Load Settings” button of the UI. Likewise, settings files can be created by clicking the “Save Settings” button in the UI.

However, most users will find that it is easiest to generate settings files by hand using the firefly.Settings class. The firefly.Settings class is implemented as a restricted dictionary with key validation, raising an error if an invalid setting is accessed and providing a best guess alternative key. Settings are organized into two broad categories: those that affect the entire application and those that affect individual particle groups. For settings that affect individual particle groups, we use a nested dictionary structure where the particle group’s UIName indexes the value for that setting (e.g. settings[‘sizeMult’][‘Gas’]=1). Within these two broad categories each is split into a handful of sub-categories: startup, UI, filter, colormap, and velocity for the per-particle-group settings. All settings can be accessed from the firefly.Settings instance.

To disable elements of the UI, users can add unique identifying paths, which are case insensitive, to the GUIExcludeList in their settings.json file. Paths are structured hierarchically, e.g., the path for main/general/data/decimation would disable the decimation slider in the main/general/data pane whereas main/general/data would hide the data button on the main/general pane and main/general would hide the general button on the main pane. If users would prefer to disable the UI entirely, then the UI key in the settings.json should be set to False. Paths for per-particle-group panes begin with the name of the particle group, e.g. Gas/onoff and Gas/dropdown/velocities/velocityCheckBox.

Users can also pre-define camera paths using a tweenParams.json file generated by a firefly.tweenParams instance. Camera paths are defined by a sequence of key frame camera coordinates that are linearly interpolated between for a specified duration between each frame. Once the last keyframe is reached the path will wrap around and loop through the keyframe list again until tweening is disabled (by unchecking the tween checkbox in the main/general/camera pane).

Both settings.json and tweenParams.json files can have any name so long as they are correctly referenced in the manifest file (i.e., they are attached to a firefly.Reader instance).

B.3. Hosting local and remote Firefly servers

To explore a custom instance of Firefly, a user must host these files (along with the Firefly source code) either on the internet (as is done for the examples in the gallery at alexbgurvi.ch/Firefly) or locally using the http module in the Python 3 standard library (in-
voked as `python -m http.server` from the command line while located inside the Firefly source directory). Users can also host the files locally using **Flask**, a Python backend that effectively connects the browser to a Python interpreter and enables numerous additional Firefly features, including the ability to split the visualization and user interface into different browser windows, stream the visualization from one computer to another, explore data in virtual reality and to pass data directly to Firefly without saving Firefly files to disk (which can take-up significant hard-drive space). These features are accessed by visiting different urls in a web browser (which we refer to as “entry points,” as described in Appendix C.1.1).

The PDPP offers multiple ways to launch Flask servers: 1) the `spawnFireflyServer` function which can be used from in a Python script or Jupyter notebook and 2) the `firefly` terminal command which is added to the user’s path when Firefly is installed (e.g., via pip). It also includes a convenient interface for POST’ing new data using the `Reader.sendDataViaFlask` method.

Lastly, the PDPP makes it convenient and easy to host new instances of firefly on the internet using the `Reader.copyFireflySourceToTarget` method. By default, `Reader.copyFireflySourceToTarget` will copy only the necessary Javascript, data, and settings files to the specified path. However, if users create a GitHub OAuth authentication token, save it to their computer as a text file, and pass the path to that text file, a new GitHub repository can be automatically created with GitHub pages enabled. Thus, with one line users can immediately push their data to the internet and share the url with a collaborator without extensive background knowledge of web hosting. More details can be found in the documentation.

**B.4. Embedding Firefly within a Jupyter notebook**

Jupyter notebooks are powerful engines for interactively analyzing and interpreting data. In light of their growing popularity, we have also included a convenient interface for launching Firefly servers and embedding Firefly visualizations all within the confines of a Jupyter notebook. To take advantage of this feature users need only:

1. launch a Firefly server as a background subprocess using the `spawnFireflyServer` function
2. access the local url from within the Jupyter notebook using an IFrame
3. explore the data from within the IFrame
4. (optional) interactively change the dataset using the `sendDataViaFlask` method
5. close the server when no longer required using the `closeAllFireflyServers`

More detailed instructions and examples are available in the documentation.

**C. THE JAVASCRIPT APPLICATION**

Figures C1 and C2 illustrate the control flow of the web application from entering a Firefly url to the interactive rendering loop. We describe each of these steps in detail below but, in brief, these steps are:

1. First, a user visits one of a Firefly server’s “entry points” (§C.1.1) to initialize the web application in the browser tab’s Javascript interpreter.
2. Then the startup file, `startup.json`, is read to determine which dataset to load. If multiple datasets are listed in the startup file the user is presented with a dropdown list to select from.
3. Next, the settings and particle data files specified in the manifest file, `filenames.json`, are opened using d3.js, and/or kaitai.io where binary particle data in .ffly format is specified.
4. A three.js WebGL renderer is initialized and resized to fit the window. The renderer’s keyboard/mouse controls mode and camera properties are set according to the input settings.
5. three.js material and geometry objects corresponding to each particle group are created and the geometry buffers are filled with coordinate, velocity (if available), and colormap (if enabled) data.
6. The UI is generated (using d3.js, described in Appendix A) and the settings for filters, particle sizes, etc. from the input settings are applied.
7. After the GUI and viewer are initialized, the application enters the visualization render loop which continuously checks the UI and updates the corresponding values in the three.js material objects and geometry buffer.

**C.1. Start-up and initialization**

Unless a new dataset is loaded through the user interface, steps 1-6 above (i.e., excluding the render loop) are only performed once when Firefly is initialized. These steps configure the application, load in data, and create the objects necessary to visualize the dataset.
Launch from entry point, e.g. INDEX.HTML

Choose dataset from STARTUP.JSON

Read corresponding FILENAMES.JSON

Create WebGL canvas

Create three.js Particle Mesh

Create Material & Geometry

Fill Geometry buffers

Build octree

Generate User Interface

Create UI elements w/ D3.js

Disable flagged elements

Figure C1. An illustration of the Firefly web application control flow at initialization. The steps outlined here are executed only once, in contrast to the components of the interactive render loop which are repeated many times a second (illustrated in Figure C2). Major steps are in larger boxes and control flow proceeds from top to bottom. Sub-steps are in smaller boxes and proceed horizontally from left to right. Colors indicate which aspect of the application handles the step: viewer in black, UI in orange, and the optional octree build in purple (Appendix D). Major steps are executed sequentially, except for “Generating the User Interface” and “Creating three.js Particle Mesh”, which occur in parallel.

C.1.1. Startup: visiting an entry point

An entry point, in this context, is a url that is accessed to initialize the web application. There are four possible entry points for Firefly:

1. /index
2. /combined
3. /gui & /viewer
4. /data_input
5. /stream
6. /VR

If Firefly is being hosted over the internet or using a local http server, then only the /index.html entry point will work. For instance, on a local server, one would point their browser to localhost:8000/index to access the first entry point. The other entry points require Flask. If no entry point is specified /index is implied. Once the Firefly source files have been delivered by the server to the client browser, the application is launched into the mode corresponding to the entry point.

The /combined entry point (which shares an alias with the /index and blank / entry points) shows the default Firefly web application with user interface and viewer combined in one browser tab. The /gui and /viewer entry point pair allows a user to split the user interface and visualization view between two separate windows (or devices on the same network). By connecting a primary device like a computer with a high-end graphics card connected to a large screen to the /viewer entry point, and a second device like an iPad or smartphone to the /gui entry point, a user can manipulate the visualization remotely in a manner ideal for presentations or public outreach activities. POST'ing Firefly formatted data to the /data_input entry point updates the data currently being viewed without having to write it to disk. The /stream entry point displays a rasterized version of the visualization scene allowing users to render the Firefly scene on a powerful workstation and view it from a less powerful computer. Lastly, the /VR entry point is experimental and can be used to view Firefly with a VR headset (e.g., Google cardboard) with limited navigational controls. For additional details on how to use Flask, and which features require Flask, see the documentation.

C.1.2. Startup: selecting a dataset

The first step performed by Firefly is to look for input data to visualize. The input dataset is specified by the startup file, startup.json in the Firefly/data directory. The contents of startup.json are a dictionary mapping of key-value pairs with numbered indices starting at 0 as keys mapped to the relative path of different dataset directories with respect to the static directory. For browser security purposes, all files loaded by the application must be accessible as sub-directories of the static directory in the source code (e.g., within the static/data directory). If a user prefers to store their data elsewhere in their computer, one way to achieve this for local servers is to create a symbolic link from the data’s location on disk to the static/data directory (which the PDPP will do for users automatically).

An example startup file might look like:
If only a single key-value pair exists in the startup.json file, then Firefly will automatically begin loading the data in that directory. If multiple entries are provided (as in the example above), Firefly will prompt the user to choose which data set to load. If the startup.json file does not exist then Firefly will prompt the user to select a directory manually using a file browser.

Each directory provided in startup.json must contain a manifest file, filenames.json, that identifies the filenames of the settings and particle data files within the directory. This is created automatically by the PDPP.

C.1.3. Startup: loading settings and particle data

Once the data directory is identified, Firefly attempts to load the data listed in the filenames.json manifest file. The manifest file includes entries for the settings file (.JSON extension) and every file containing particle data (.JSON and/or .ffly extensions). If Firefly does not find a filenames.json manifest file and it is not being served from a Flask-enabled server, it will raise a Javascript alert in the browser indicating it cannot load the data. If Firefly is served from a Flask-enabled server, it will attempt to load every .csv or .hdf5 file contained in the directory chosen from the startup.json file using the PDPP. If no .csv or .hdf5 files are found, the same error is raised.

The manifest file also allows users to break up large particle datasets into multiple files. There are several advantages to using multiple smaller files rather than using a single large file (which may crash some browsers in their attempt to load it). Separating the particles into a series of smaller files allows us to provide a well-defined status bar, representing the fraction of particle files that have been opened, to be presented to the user while the data is loading. Lastly, it is common for web-hosting services (like Github pages, a popular and free web-hosting service) to have strict individual file size limits; separating the data into multiple files, each under the size limit, can allow the user to host these data online more easily.

Once the data is loaded, the settings are imported from the settings .JSON file using d3.js. These settings are used to set the default values of the visualization, e.g., the filter limits, colormap attributes, particle sizes, which aspects of the user interface to include, etc.

C.1.4. Startup: creating the renderer

The rendering canvas is a three.js WebGL renderer. If stereo mode is requested at startup (within the settings file), this is set now. Otherwise the user can toggle into stereo mode through the user interface.

The camera is initialized, and attached to either the trackball or fly controls control mode (see Appendix A.1). The render distance is effectively infinite by default but only particles that are large enough to cover multiple pixels are drawn.

C.1.5. Startup: making material and geometry objects

After the UI is generated and the canvas is initialized, Firefly creates a three.js point cloud object for each particle group and copies the data into its memory buffers. Each point has, at minimum, a three-dimensional coordinate, size, and opacity. If per-particle RGBA colors or a colormappable field are provided then corresponding memory buffers are initialized and filled with the corresponding values. If velocity vectors are provided, then each velocity’s magnitude is rescaled to the interval [0, 1] defined by the minimum and maximum velocities of that particle group. The unit vector pointing along the direction of velocity and the new normalization are stored in a flattened \( N_{\text{part}} \times 4 \) array and passed to a velocity vector geometry buffer. Otherwise, dummy buffers are initialized containing all zeroes because the fragment and vertex shaders require them.

C.1.6. Startup: generating the UI

Firefly uses d3.js to generate the DOM elements which make up the UI dynamically upon loading in the data and settings files. Within the settings file, the user can specify which of the controls to exclude from the UI using the GUIExcludeList setting (see Appendix B.2). Additionally, individual particle group panels are automatically customized according to the available data in each particle group (e.g., the velocity vector controls are not shown as an option if velocities were not provided with the data).

Many of the elements of the UI shown in Figures A1 and A2 are generated with “vanilla” HTML+CSS+JS code, though some use specialized Javascript libraries. Specifically: 1) the one- and two-sided sliders used for adjusting floating point parameters use the noUiSlider library, 2) we use the wNumb library to format and interpret many of the numbers displayed in the UI (particularly in connection to the sliders), and 3) the color picker uses the spectrum library, which itself requires jQuery.

C.2. The main render loop

Once all of the data and settings files are loaded, the application enters the render loop. The render loop uses the requestAnimationFrame function to repeatedly call the animate function. Using requestAnimationFrame
(rather than, say, a while(true) loop) allows the browser to conserve resources when the user is on a different tab by pausing the app entirely. It also takes advantage of knowing the display’s refresh rate to avoid rendering faster than the display can actually update. Typical modern displays have 60 hz refresh rates corresponding to a maximum of 60 renders per second. The median frame rate over the 100 most recent renders can be displayed in the application if the showFPS setting is set to true.

The steps of the render loop are:

1. Check the UI state to determine if any values have changed (e.g., filter or colormap values, particle group on/off toggle, velocity vector checkbox, etc.) and update the particle meshes with new particle sizes/colors as needed.

2. Draw the particles to either the canvas or to a buffer for remapping (projection mode) or saving to disk (take snapshot button).

3. Check the loop duration and determine if the app should pause the loop if rendering is taking longer than 1.5 seconds/frame to avoid freezing the user’s computer.

C.2.1. Render loop: checking the UI state and updating particle geometry and material objects

Because the application is interactive, users can change parameters of the visualization through the user interface and using the mouse and keyboard throughout the render loop. At the beginning of each render pass, changes to the UI are noted and applied to the particle geometry and material objects as needed.

In general, creating and disposing of three.js geometry objects is (relatively) computationally expensive. So, instead of creating a new object whenever a UI element is changed we update all of the relevant geometry buffers registered to the three.js scene in order to enact the corresponding change. Most changes do not impact performance. However operations that require looping over every particle in the Javascript interpreter,
can potentially slow down the frame rate for large numbers of particles.

The most frequent action that requires looping over every particle is changing the size and alpha values to show/(hide) a given particle when filter limits are applied. If the user moves the position of a filter handle, then the code loops through each particle to set its size and alpha values to zero if it is outside the filter range (or reset its size and alpha values to their original values if it was previously outside the filter boundaries but no longer is). As a result, moving the filter handles can temporarily introduce latency for large datasets (\( \geq 10^6 \) particles) until the filter limits are applied. Changing the colormap variable (or toggling the colormap on/off) also requires looping over every particle in order to set the colormap scalar field value for each particle in the geometry buffer. After these expensive operations are completed, the framerate and interactivity return to normal.

C.2.2. Render loop: rendering the particles

The three.js point cloud objects are rendered to the canvas using WebGL vertex and fragment shaders. To do this there are, broadly speaking, three steps:

1. determine each particle’s position and size relative to the canvas
2. determine the color of each pixel the particle overlaps
3. blend the colors according to a specified blending equation.

The vertex shader interprets the data in order to position and scale the points in the camera’s frame, accounting for camera distance, per-particle radial scaling, and the point size multiplier. It also applies a minimum and maximum point size to attempt to 1) ensure all particles are visible, even at great distance and 2) to decrease the likelihood that too many particles overlap and require blending. If the user enables velocity animation via the UI, the particle’s position is offset in the direction of its velocity vector as defined by the input values in the UI (see Figure A2f).

The fragment shader defines the color for each pixel that the particle covers. By discarding certain pixels we can draw different shapes at the location of each particle, e.g., circles or velocity vectors. Within the fragment shader, we can also: 1) apply a radial gradient in opacity (alpha) to give the particles a “fuzzy” edge or 2) change the color in a linear gradient along the velocity vector.

If a colormap is enabled, the fragment shader will also read in the colormap texture (defined by a grid of colormaps stored in the static/textures/colormaps.jpg). The colormap variable field value is remapped to the \([0, 1]\) interval using the minimum and maximum colormap limits. The remapped field value is used to sample the colormap texture in order to derive the appropriate color for the given particle. So that RGBA values of overlapping particles do not blend and produce pixel colors that do not correspond to a value on the colormap, we change the blending function and enable the depth buffer such that each pixel takes the color of the particle nearest the camera (i.e., enabling the depth buffer to perform a depth test and enforcing the “normal”, rather than “additive”, blending mode for that particle group).

If column density projection mode is enabled, then particles are first rendered to a texture buffer rather than directly to the canvas. The R channel of the texture buffer is used to accumulate the number of particles in each pixel using an additive blending function. The texture’s R channel value is then remapped to an RGB color according to a colormap (selected from the drop-down menu) then rendered to the visible canvas.

C.2.3. Render loop: deciding if the app should sleep

If a rendering pass takes longer than 1.5 seconds, a sleep screen with a warning message is shown, and the app is paused until the user clicks again. Depending on the size of the dataset (or more commonly, how many overlapping particles need to be blended on screen) the frame rate can drop. Because the entire browser is unresponsive for the duration of a rendering pass, we enforce this test to prevent users from being locked out of closing the application (and to avoid crashing the users computer). The application can be woken and the render loop re-engaged by clicking on the sleep screen.

The two most common causes of the sleep screen are: 1) switching browser tabs (in which case there is no issue) and 2) using a large point size multiplier (“size-Mult”) which causes many of the particles to overlap on top of one another and their colors to be blended (an expensive, but not valuable, calculation). In scenario 2), it is recommended that users either refresh their window to reset the point size multiplier to its default value, change the point size multiplier to a smaller value in the UI, or set a new initial size multiplier in the input settings .JSON file.

D. PROGRESSIVELY LOADING LARGE DATASETS WITH AN OCTREE

In order to visualize very large datasets (which can require more memory than is available to the browser to visualize in its entirety simultaneously), Firefly can load only that data which is nearby to and within view of the camera. To use this feature users must pre-format
their data as an “octree” using the PDPP and write the octree files to disk. An octree is a hierarchically structured scheme of partitioning space into incrementally smaller octants. Octrees are commonly used in cosmological simulations whose code makes use of adaptive mesh refinement (AMR) (e.g. Kravtsov et al. 1997; Teyssier 2002) to represent astrophysical fluids on a grid rather than with (Lagrangian) particles. We borrow the concept and apply it to particle-based data in order to partition the dataset spatially into discrete (relatively) collocated chunks that can be identified and loaded on demand.

Using a dataset that has been pre-formatted as an octree dramatically improves performance, reduces Firefly’s start-up time to nearly instantaneous, reduces the browser’s total memory usage, and allows the extent of the visualization domain to scale effectively infinitely (though importantly not all of the domain may be visualized at once). Should a user decide to pre-format their data as an octree, a single function call in the PDPP wraps the construction of the tree (described below), produces the octree binary files, and registers them to the manifest file (described in Appendix C).

We note that there are a few minor drawbacks to this approach. For one, the pre-formatting step can be computationally expensive for especially large datasets (see §4 for a quantitative benchmark). Using octree formatted data also requires that the data be saved to disk (i.e., you cannot load octree data directly into Firefly even when run locally with a Flask-enabled server). Nonetheless, utilizing an octree can provide such a significant performance boost, and can enable the visualization of extremely large datasets that are otherwise inaccessible to interactive visualization techniques, that the benefits outweigh these minor drawbacks.

Inside the Firefly application, exploring the octree is (relatively) seamless for the end-user. When a node is within the camera view and close enough that it overlaps multiple pixels it is “opened” and the raw particle data associated with that node is queued to be loaded. On the other hand, when the node no longer overlaps multiple pixels or the camera pans such that it is off-screen, the raw particle data is purged from memory freeing it up to load new data. Nodes are also forcibly closed (oldest first) to enforce a fiducial memory limit of 2 GB to prevent the app from crashing (this value can be configured by users in the settings .json file).

D.1. Building the octree using the PDPP

For our implementation of an octree, we typically group particles into nodes that contain $10^4 - 10^5$ particles each. The minimum and maximum number of particles per node can be chosen by the user, and we explore the tree construction time for different values in §4.3. Throughout the remainder of this section, we refer to the “raw” particle data associated with a node as its “buffer data.” Additionally, we also accumulate aggregate statistics while building the tree (like total mass and mass weighted scalar fields). Thus, along with pointers to any child nodes that may be associated with it, every node in the octree has its own aggregate data computed over all the particle data below it that represents the node on average and its own buffer data it is responsible for storing.

The algorithm we employ begins by first measuring the extent of the 99% of particles nearest to the center of the dataset to define the bounding box of the root node. We hold the remaining furthest 1% until after the octree has been constructed and it add as buffer data to the root node to minimize the effect of outliers on the structure of the tree (in particular, outliers can result in many empty layers of refinement that bloat the structure of the tree). Then we sort all the particles into the eight sub-octants of the root node. Any sub-octant which contains more than the maximum allowable number of particles per node “overflows” and the buffer particles are sorted into the eight sub-octants of that node. Thus the octree is spatially refined as particles are iteratively sorted by recursively applying the maximum-threshold-to-overflow criteria for each of the resulting eight child nodes (and their children, etc.). At each refinement, we merge child nodes below the minimum required particles per node back into their parents (a procedure we term “pruning”). By pruning the octree we reduce the number of extraneous nodes which may contain only a handful of particles.

Because of the inherent asymmetry in coordinates of a typical dataset, it is frequently the case that some child nodes have a particle count below the minimum threshold while their siblings do not and may even have (grand-)children of their own. Thus, by pruning the octree it is possible, and in fact frequently the case, that a node has both buffer particle data it is responsible for and children.

The octree build implementation is optimized for extremely large datasets. In particular, it can be run in parallel using multiple threads and does not require that the entire dataset be loaded into memory. It does this by breaking up the dataset into “work units” which can be split across independent tasks and then synchronized after the refinement is complete. These work units are distributed among the available worker threads using Python’s multiprocessing module.
The PDPP saves the octree’s particle data in binary format, and also creates a `.JSON` file for Firefly that contains the octree structure, accumulated aggregate data for each node, and the locations of the node centers and centers of mass.

D.2. Implementing an octree in Firefly

In the Firefly web application, an octree is represented as a Javascript object. This object is defined by the octree `.JSON` file (from PDPP) and created in the “Build Octree” step of Figure C1. An octree contains only a single particle group, though multiple octrees (one for each particle group that has an octree) can be loaded simultaneously. Each node contains pointers to the files on disk, byte sizes, and byte offsets of its buffer data in addition to its center of mass, accumulated aggregate data, bounding box, and list of children. Material and geometry mesh objects (described above in Appendix C) are dynamically created and filled with this buffer data during the render loop when nodes are opened.

The procedure of updating the octree in the render loop is visualized in the right half of Figure C2. We (un)load particle data asynchronously because the interactivity of the application is impacted by the time it takes to create (dispose) of three.js geometry meshes. When there are multiple octrees (corresponding to different particle groups), Firefly will cycle through each particle group on consecutive render passes in order to (un)load data from each particle group with equal priority. To keep track of the buffer data that needs to be asynchronously loaded or purged, each octree has its own “draw” and “remove” queues.

Each draw queue uses its own lock so that only one node’s data is loaded at a time for a given particle group. At each render pass, if the draw queue is not empty and not locked, the node nearest to the camera in the draw queue is selected and the queue is locked. The particle data associated with that node is then loaded from the corresponding binary file and the node is removed from the draw queue. Once the data is loaded from disk, new material and geometry objects are created, and the loaded data is copied into their buffers. Finally, the geometry mesh is added to the scene and the draw queue is unlocked.

Because disposing of material and geometry objects is much less expensive than creating them and adding them to the scene, the entire remove queue is emptied at each render pass. To remove a node, the material and geometry objects are disposed of, and the Javascript array data is freed (this has the effect of releasing the memory back to the application which can be monitored by a memory usage counter that can be toggled on and off with a flag in the input settings .JSON ).

After dealing with the draw and remove queues, we then update each of the queues by walking the current particle group’s octree. At each node, we decide whether that node should be opened, closed, or ignored. If the current node is on screen and covers more than one pixel from the camera perspective, the node is added to the particle group’s draw queue. If the current node has already been drawn but subtends less than 1 pixel on screen, the node is added to the particle group’s remove queue. If a node is added to either queue but also exists in its opposing queue then it is removed from the older queue (for example if a node was on screen and added to the draw queue but then exited the screen and no longer needs to be drawn).

Through this method, Firefly is able to render and interactively explore exceptionally large data sets. We provide one example of interacting with nearly $1.5 \times 10^9$ stars from Gaia DR3 in §3.3 in real time, which can only be achieved using an octree. As data sets continue to grow, Firefly’s octree rendering method will be a highly valuable tool for data exploration and public outreach.