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Unbinned Non-Parametric Spherical Jeans Mass Estimation with B-Splines - WORK IN PROGRESS

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ABSTRACT
Spherical Jeans modeling is widely used to estimate mass profiles of systems from star clusters to galactic stellar halos to clusters of galaxies. It derives the cumulative mass profile, $M(<r)$, from kinematics of tracers of the potential under the assumptions of spherical symmetry and dynamical equilibrium. We consider the application of Jeans modeling to mapping the outer reaches of the Milky Way, specifically to determine the dark matter distribution from field halo stars. We present a novel unbinned non-parametric routine for solving the spherical Jeans equation by fitting B-Splines to the 3-dimensional velocity and density profiles of halo stars obtained by the Gaia survey and spectroscopic surveys such as DESI and LSST. While most implementations of Jeans assume parametric forms for these profiles, B-Splines provide non-parametric fit curves and conv or accuracy of their derivatives. Despite Jeans modeling's prevalence, there is little work quantifying the errors introduced when breaking the assumptions. We validate our routine on several progressively more complex and realistic mock datasets that break these assumptions in different ways. We find that our routine recovers the mass profiles of equilibrium systems with even quite flattened halos and systems including a stellar disk and bulge excellently ($\leq 5\%$ error). We also perform tests with non-equilibrium, non-spherical models from the Latte cosmological simulations, which also perform well ($\leq 15\%$ error). This larger error suggests that the output of spherical Jeans modeling is more sensitive to deviations from dynamical equilibrium than deviations from sphericity.

Key words: – galaxies: halo – galaxies: kinematics and dynamics – galaxies: structure

1 INTRODUCTION

In the context of applying spherical Jeans modeling to halos to study their dark matter distribution, most established implementations use binning and or power law functions (Kafle et al. 2018, Xue et al. 2008, Gnedin et al. 2010) to evaluate the spherical Jeans equation on the data. These methodologies have been favored because they are relatively easy to implement and, in some cases, align well with theory. For example, Gnedin 2010 assigns a power law relation to the density profile beyond 25 kpc, agreeing with an NFW profile. These approaches have their limitations, however. Power laws are parametric fit curves, which may not be perfectly representative of the true velocity or density profiles, and binning adds variation based how bins are chosen and gives less accurate derivatives. Both methods, power laws and binning, introduce obscured biases into the mass profile. Recently, Jeans routines that use other methods have been developed (Genina et al. 2020), although most still take parametric forms for the velocity and or density profiles.

Irrespective of implementation, there is little work done to understand the errors introduced when breaking either of the assumptions. This is relevant because real potentials of Milky Way-like disk galaxies are not spherically symmetric nor are they in dynamical equilibrium. To responsibly use spherical Jeans modeling, we must have a detailed understanding of the effect breaking these assumptions has on the resulting mass profile.

We build a diverse suite of mock datasets to validate our B-Spline routine on and constrain the behavior of spherical Jeans modeling when its assumptions are broken. Along with mocks from the Latte cosmological simulations (Wetzel et al. 2016), we generate our own mock datasets using `Agama` (Vasiliev 2019), an efficient all-purpose galactic modeling package. The results from each mock dataset teach us more about how the quality of the Jeans estimate changes in relation to the geometry of the system in question.

On top of the base cosmological simulation mocks, we also use Latte's Gaia mocks, Ananke (Sanderson et al. 2018), and apply a DESI footprint over them. These take us a step closer to mimicking

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the data we will get from Gaia and DESI. Once available, we will execute our Jeans routine on the Gaia and DESI data to construct a mass profile of the Milky Way.

2 MOCK DATA

The mocks we generate using `Agama` are all in equilibrium but vary in their deviations from sphericity. We set a baseline for the systematic error in our routine using a model containing just a spherical halo in equilibrium. This satisfies both assumptions, so we expect a perfect estimation with Jeans. We create variations of this initial model by flattening the halo and adding a disk and bulge. From the Latte simulations, we use m12f, m12i, and m12m.

2.1 `Agama` mocks

The "Halo alone" mocks contain only a spheroidal halo with axis ratio q varying from $q = 1.00$ (spherical) to $q = 0.80$.

The mock labeled "Halo, Disk, Bulge" has a spherical halo, a disk, and a spherical bulge. Each component is scaled to be Milky Way-like with halo and disk mass and scale radius from (Bland-Hawthorn & Gerhard 2016). We perform a mass-weighted average to combine thin and thick disk parameters into a composite disk. The bulge is spherical and described in (McMillan 2017). We also create variations of this mock for additional tests. We explore the routine's sensitivity to input contamination by sampling fractions of the disk particles into the input and sensitivity to radially varying anisotropy by recreating the system with an Osipkov-Merritt profile (Osipkov 1979, Merritt 1985a, Merritt 1985b).

2.2 Latte mocks

The tests with Latte mocks include m12f, m12i, and m12m. The metallicity cut we employ here is done so with various threshold values: stars with $[\mathrm{M/H}] \leq -2.0, -1.5, -1.0$ are designated as halo stars and thus used for input into for Jeans modeling.

3 ANALYSIS METHODS

Starting with the spherical Jeans equation presented in (Binney & Tremaine 2008), we solve for $M(<r)$ and apply the derivative power rule to simplify:

$$M(<r) = -\frac{r\overline{v_r^2}}{G}\left(\frac{\mathrm{d}\ln\rho}{\mathrm{d}\ln r} + \frac{\mathrm{d}\ln\overline{v_r^2}}{\mathrm{d}\ln r} + 2\beta\right) \tag{1}$$

The terms v_r^2, v_ϕ^2 = and v_θ^2 are the square of the radial, azimuthal, and polar velocities respectively, $\rho(r)$ is the tracer number density, r is the spherical radius measured from the center of the system, and G is the gravitational constant. The velocity anisotropy parameter β is defined as

$$\beta = 1 - \frac{\overline{v_\theta^2} + \overline{v_\phi^2}}{2\overline{v_r^2}} \tag{2}$$

$\beta < 0$ indicates excess tangential velocity, $\beta = 0$ indicates velocity isotropy, and $\beta > 0$ indicates excess radial velocity.

We perform penalized spline regression to fit B-Splines to v_r^2, v_ϕ^2, v_θ^2, and a penalized spline density estimate to calculate ρ. All of the B-Splines are functions of $\ln r$ and have logarithmically spaced knots. We find that this best captures the large range of values the velocity and density profiles take.

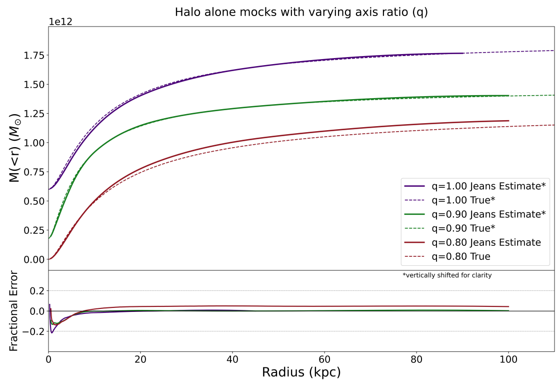

Figure 1. Results of three 'halo alone' mock datasets with $q = 1.00, 0.90, 0.80$. The error due to flattening only appears in the $q = 0.80$ mock and is steady around 5% at most radii. The estimations on the $q = 1.00$ and $q = 0.90$ perform excellently with almost no error at all. The deviation at small radii in all three mocks – and later mocks – is likely due to noise in the simulation.

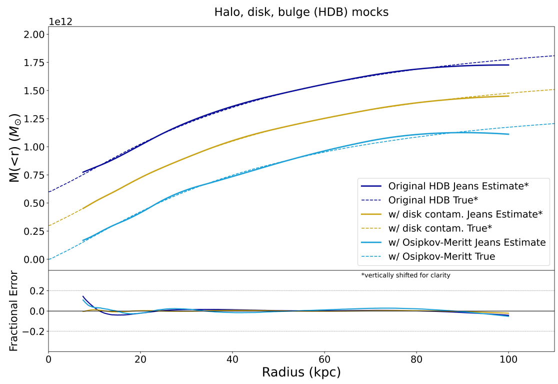

Figure 2. All variations of the 'halo, disk, bulge' mock perform very well. These tests primarily assesses how the inclusion of a disk and bulge to break sphericity affects the routine accuracy. Further, the introduction of disk contamination and a radially varying anisotropy profile have almost no affect on the high accuracy. All three 'halo, disk, bulge' mocks have ≤ 5% error at most radii.

4 RESULTS

Results are preliminary, but I'll include some plots here.

Halo alone results 1;

Halo, disk, bulge 2;

Latte 3

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We also used the following software packages: matplotlib

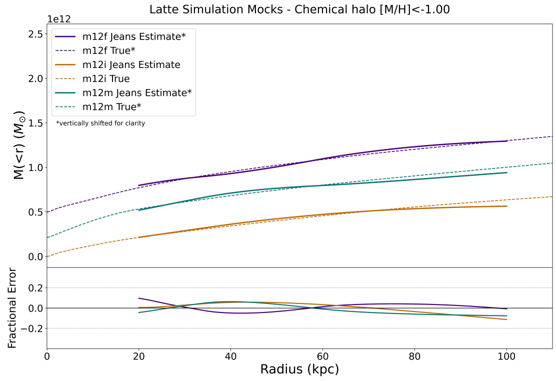

Figure 3. Despite the introduction of significant halo substructure and tidal streams with these Latte mocks, the accuracy of the routine remains quite good: $\leq$ 15% error. These estimated $M(< r)$ profiles exhibit an oscillating pattern between over- and under-estimating, likely due to the presence of different satellites and streams at different radii.

(Hunter 2007), numpy (van der Walt et al. 2011), scipy (Jones et al. 2001)

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