





Dynamical models of the Milky Way nuclear star cluster

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Dynamical modelling overview: input data

(individual stars) positions, magnitudes proper motions μ_i line-of-sight velocities $V_{\text{LoS},i}$

(unresolved)

surface brightness profile integrated-light kinematics (line-of-sight only)

x, **v** – intrinsic (model) coordinates; **X**, **V** \equiv { V_{LoS} , μ_X , μ_Y } – observed data indices: *i* – stars;

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surface brightness profile / integrated-light kinematics (line-of-sight only) $\Sigma(\mathbf{X})$ deprojection \Downarrow luminosity density $j(\mathbf{x})$ mass-to-light ratio \Downarrow mass density $\rho_{\star}(\mathbf{x})$ Poisson eq \Downarrow $\Phi(\mathbf{x}) = -\frac{GM_{\bullet}}{r} + \Phi_{\star}(\mathbf{x}) + \dots$

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 $\Sigma(\mathbf{X})$

(optional) spatial binning

velocity moments $\overline{\mathbf{V}}^{(b)}$. $\sigma^{(b)}$ at $\mathbf{X}^{(b)}$ velocity moments $\overline{\mathbf{V}}^{(b)}$, $\sigma^{(b)}$ at $\mathbf{X}^{(b)}$. velocity distribution functions $\mathbf{f}^{(b)}(\mathbf{V})$, often parameterised by Gauss-Hermite moments $v_0, \varsigma, h_3, h_4, \ldots$

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input kinematic data

(individual stars)

 $\mathbf{X}_i, \mathbf{V}_i$

(binned)

 $\overline{\mathbf{V}}^{(b)}$, $oldsymbol{\sigma}^{(b)}$ or

Gauss-Hermite moments $v_0, \varsigma, h_3, h_4, \ldots$, or full VDF $\mathfrak{f}^{(b)}(\mathbf{V})$

indices: i - stars; b - bins;

orbit fitting of multi-epoch observations

[Genzel+ 2003+; Ghez+ 2003+; GRAVITY 2018+]

input kinematic data

(individual stars)

 $\mathbf{X}_i, \mathbf{V}_i$ (t)

(binned)

 $\overline{\mathbf{V}}^{(b)}$, $\pmb{\sigma}^{(b)}$ or

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orbit fitting of multi-epoch observations [Genzel+ 2003+; Ghez+ 2003+; GRAVITY 2018+] input kinematic data Jeans equations: $\rho_{\star}(\mathbf{x}), \ \Phi(\mathbf{x}) \Rightarrow \overline{\mathbf{V}}^{\text{mod}}(\mathbf{X}), \ \sigma^{\text{mod}}(\mathbf{X})$ (individual stars) , compare with binned $\overline{\mathbf{V}}^{(b)}$, $\sigma^{(b)}$ at $\mathbf{X}^{(b)}$ X_i, V_i [Schödel+ 2009; Do+ 2013; Feldmeier+2014; Fritz+ 2016] or "discrete Jeans" – assume a Gaussian DF (binned) $f(\mathbf{V}_i) = \mathcal{N}(\mathbf{V}_i; \ \overline{\mathbf{V}}^{mod}, \sigma^{mod} \text{ at } \mathbf{X}_i) \quad [D_{0+2020}]$ $\overline{\mathbf{V}}^{(b)}$. $\sigma^{(b)}$ or *DF-based models* with parameters *p*: evaluate $f(\mathcal{I}(\mathbf{x}, \mathbf{v}; \Phi), \mathbf{p})$ at each star; Gauss-Hermite moments $v_0, \varsigma, h_3, h_4, \ldots$, or integrals of motion \mathcal{I} depend on Φ [Chatzopoulos+ 2015: Magorrian+ 2019: this study] full VDF $f^{(b)}(\mathbf{V})$ Schwarzschild orbit-superposition models $f(\mathcal{I}) = \sum_{k=1}^{N_{\text{orbits}}} w_k \,\delta(\mathcal{I} - \mathcal{I}_k[\Phi])$ compare model VDFs $f^{(b)}$ or GH moments [Feldmeier+ 2017] indices: i - stars; b - bins; k - orbits

Distribution functions

DF $f(\mathbf{x}, \mathbf{v})$ offers a complete description of the stellar population:

Jeans' theorem: in a steady state, DF must be a function of integrals of motion $f(\mathcal{I}(\mathbf{x}, \mathbf{v}; \Phi))$, for which it may be convenient to use actions J.



Action–angle variables

Orbits in axisymmetric potentials look like "rectangular tori" with three parameters defining the shape:

angular momentum $J_{\phi} \equiv L_z = R_g v_{\text{circ}}(R_g)$ determines the overall size of the orbit ("guiding radius" R_g); radial action J_R defines the extent of radial oscillations; vertical action J_z does the same for vertical oscillations.

Actions are computed in the Stäckel approximation [Binney 2012], as implemented in AGAMA [Vasiliev 2019].



Iterative construction of self-consistent dynamical models

A model can be fully specified by its DF $f(\mathcal{I})$, and the density $\rho(\mathbf{x})$ and potential $\Phi(\mathbf{x})$ follow from it (e.g. a King model).

However, to compute $\rho(\mathbf{x}) = \iiint f(\mathcal{I}(\mathbf{x}, \mathbf{v}; \Phi)) d^3\mathbf{v}$, one needs to know the potential, which is, in turn, linked to density by the Poisson equation $\nabla^2 \Phi = 4\pi G\rho$.

Thus we have a circular dependency, which is resolved using an iterative approach [Kuijken & Dubinski 1995; Widrow+ 2005; Binney 2014; Piffl+ 2015; Binney & Vasiliev 2023, 2024].

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Likelihood of a DF-based model

[spatial] selection function $S(\mathbf{x})$ – fraction of stars included in the kinematic sample



Modelling workflow

- Adopt parameters p describing the NSC DF (e.g., mass, inner/outer slope, anisotropy, rotation) and BH mass M_•; the NSD DF is kept fixed.
- Construct the self-consistent model
- Compute the 1d velocity distribution functions (VDFs) f^(b)(v_{x,y,z} | x^(b)) in ∼ 100 spatial bins.
- Evaluate the likelihood *L* of the observed dataset given the model VDFs (sum of NSC and NSD).
 - Repeat with a different choice of parameters p in the MCMC loop.

Note that there is no binning of observational data! bins are only used to construct spatially varying model VDFs, and each star's contribution to the likelihood is summed up separately. We also do not input any information about the density profile (although be could..)





(figure originally presented at the "Dense stellar systems" workshop in Heidelberg, Novermber 2018)







What happens?



- Enclosed mass in the radial range 1–2 pc is the same in models with free and fixed (true) *M*_•, but the radial profiles differ.
- Stellar density profile has a similar shape (a mild cusp ρ ∝ r⁻¹) in both cases, somewhat shallower than inferred from the photometric observations

[Gallego-Cano+ 2018, Schödel+ 2018].

Note that it was not explicitly put into the model!

Why a lower M_{\bullet} is preferred by models?

difference in log-likelihood between models with free and fixed M_{\bullet}



- Most of the difference comes from PM;
- v_{LoS} data alone cannot constrain the SMBH mass well, even though they cover a much larger spatial region.

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Discussion

Testing the DF fitting method on mock data: $M_{\bullet, \text{best-fit}} \simeq (3.9 \pm 0.2) \times 10^6 M_{\odot}$, close to the actual value.

Possible culprits:

- some features in the data? unlikely, tried two independent PM datasets (Schödel+ 2009; Fritz+ 2016) with no significant difference in results.
- biases from model mismatch (limitations of the functional form of the DF) (e.g., it becomes necessarily isotropic in the limit of a cusp slope r^{-3/2})

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OTOH a *dynamical* model with ~ 10 free parameters in the DF fits the VDFs in ~ 20 bins just as well as *empirical* B-spline fits to VDFs with 10 free parameters per bin!



Summary

- DF-based models offer a more detailed description of the NSC + NSD system than just the first two velocity moments;
- The bias in the recovery of SMBH mass is puzzling, possibly owes to limitations of the adopted functional form of the DF;
- A caveat for measuring IMBH masses in globular clusters?

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- A caveat for measuring IMBH masses in globular clusters?

"I have all data and tools, but what to do with the results??"

