Astrophysical J and D factors in dwarf spheroidal galaxies – an overview

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Indirect detection in γ-rays and ν

The gamma or neutrino flux in given by:

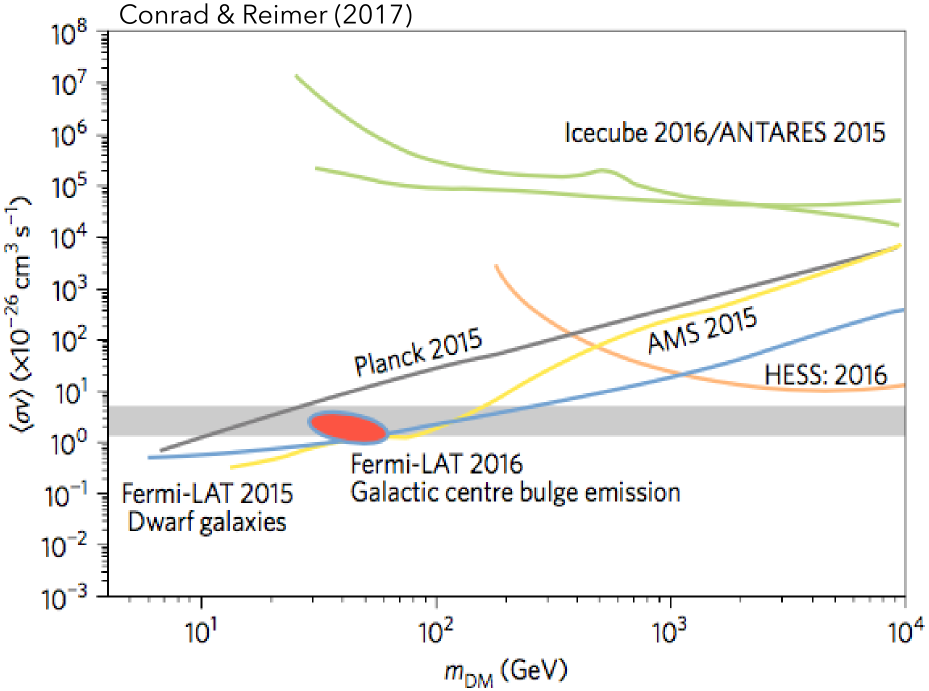
$$\frac{d\Phi_\gamma}{dE_\gamma}(E_\gamma,\psi,\theta,\Delta\Omega) = \underbrace{\frac{d\Phi_\gamma^{PP}}{dE_\gamma}(E_\gamma)}_{\text{Particle physics}} \times \underbrace{J(\psi,\theta,\Delta\Omega)}_{\text{Astrophysics}}$$

$$\frac{d\Phi^{\rm PP}}{dE}(E) = \frac{1}{4\pi}\sum_f \frac{dN^f_{\gamma,\nu}}{dE} B_f \times \begin{cases} \dfrac{\sigma v}{m_\chi^2 \delta} & \text{(annihilation)} \\ \dfrac{1}{\tau\, m_\chi} & \text{(decay)}, \end{cases}$$

$$J(\psi,\theta,\Delta\Omega) = \int_0^{\Delta\Omega}\int_{\rm l.o.s} \rho^2(l(\psi,\theta))dl\, d\Omega$$

$$D(\psi,\theta,\Delta\Omega) = \int_0^{\Delta\Omega}\int_{\rm l.o.s} \rho(l(\psi,\theta))dl\, d\Omega$$

Conrad & Reimer (2017)



- J and D values and uncertainties must be robustly determined to put constraints on DM candidate
- Signal/constraints depends crucially on DM distribution
- Favoured targets include:
  - Galactic centre
  - Dark Galactic clumps
  - Galaxy clusters
  - DSph galaxies → very competitive

Outline

1. J and D factors from spherical Jeans analysis
   - Principle
   - Limitations and choosing an optimal setup
   - Result overview

2. Other considerations
   - Sample contamination
   - Accounting for triaxiality

From kinematics to DM profile: the Jeans analysis

- Light profile and velocity dispersion

$I(R)$ $\qquad\qquad$ $\sigma_p^2(R)$

Deprojection - Projection

ν $\qquad\qquad$ $\bar{v_r^2}$

- Jeans equation: solve for νv_r^2

Anisotropy $\beta_{\rm ani} = 1 - \bar{v_\theta^2}/\bar{v_r^2}$

$$\boxed{\frac{1}{\nu}\frac{d}{dr}(\nu\bar{v_r^2}) + 2\frac{\beta_{\rm ani}\bar{v_r^2}}{r} = -\frac{GM(r)}{r^2}}$$

Enclosed mass

$$M(r) = \int_0^r 4\pi s^2 \rho(s) ds$$

- Dark matter profile, e.g.

$$\rho_{\rm DM}^{\rm Zhao}(r) = \frac{\rho_s}{(r/r_s)^\gamma \cdot [1 + (r/r_s)^\alpha]^{(\beta-\gamma)/\alpha}}$$

$$\rho_{\rm DM}^{\rm Einasto}(r) = \rho_{-2} \exp\left\{-\frac{2}{\alpha}\left[\left(\frac{r}{r_{-2}}\right)^\alpha - 1\right]\right\}$$

Getting the J- and D-factors: the Jeans analysis

- Light profile and velocity dispersion

$I(R)$ → **Deprojection - Projection** → ν

$\bar{v_r^2}$ → **Deprojection - Projection** → $\sigma_p^2(R)$

- Jeans equation: solve for $\nu \bar{v_r^2}$

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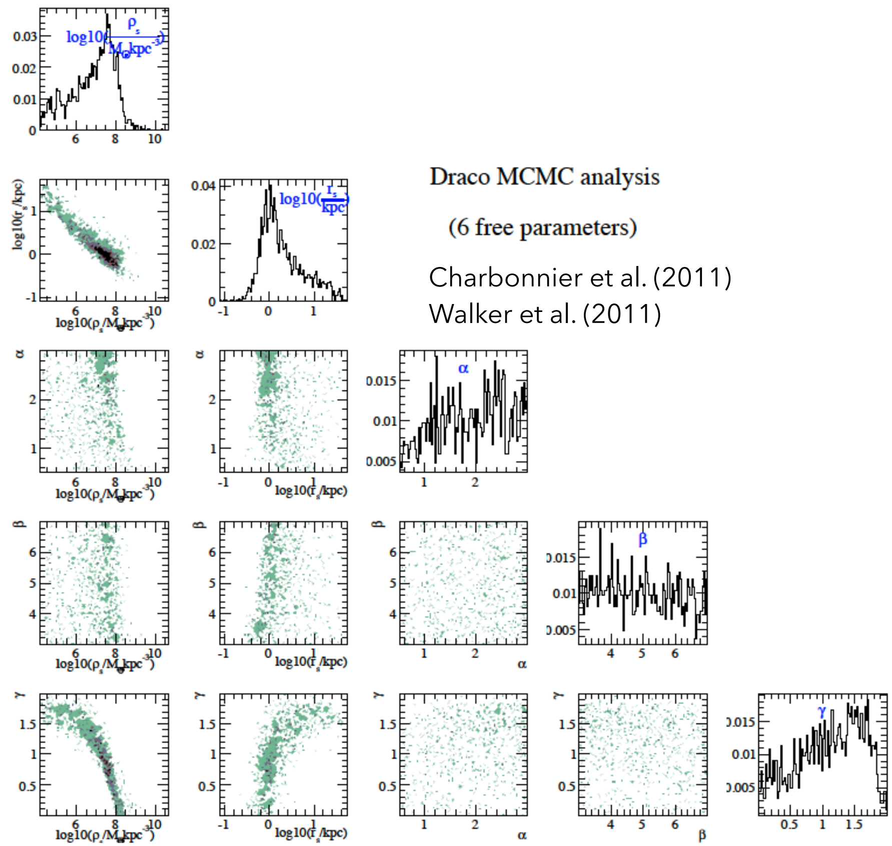
Fitting DM profile: χ^2 or Bayesian inference (MCMC, MultiNest) to sample the posterior of the parameters (anisotropy = nuisance parameter)



Draco MCMC analysis

(6 free parameters)

Charbonnier et al. (2011)
Walker et al. (2011)

→ Infer median and CIs of all derived quantities, e.g. J and D factors

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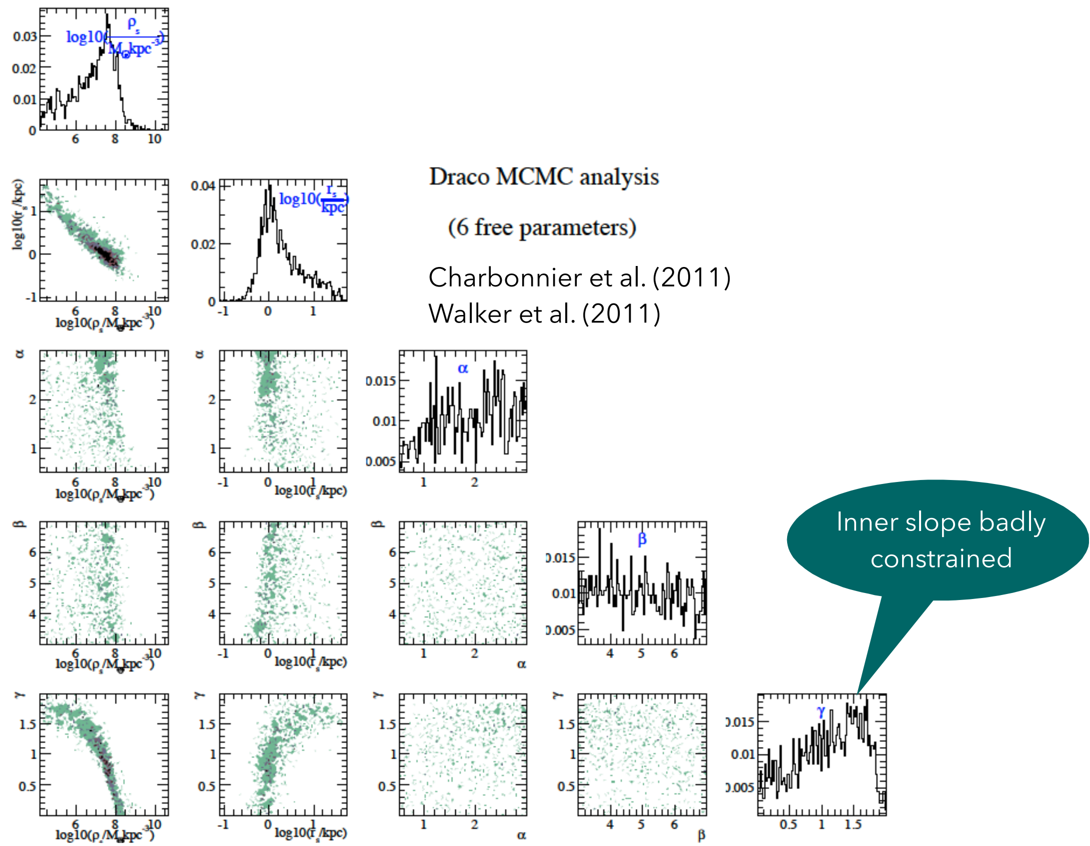

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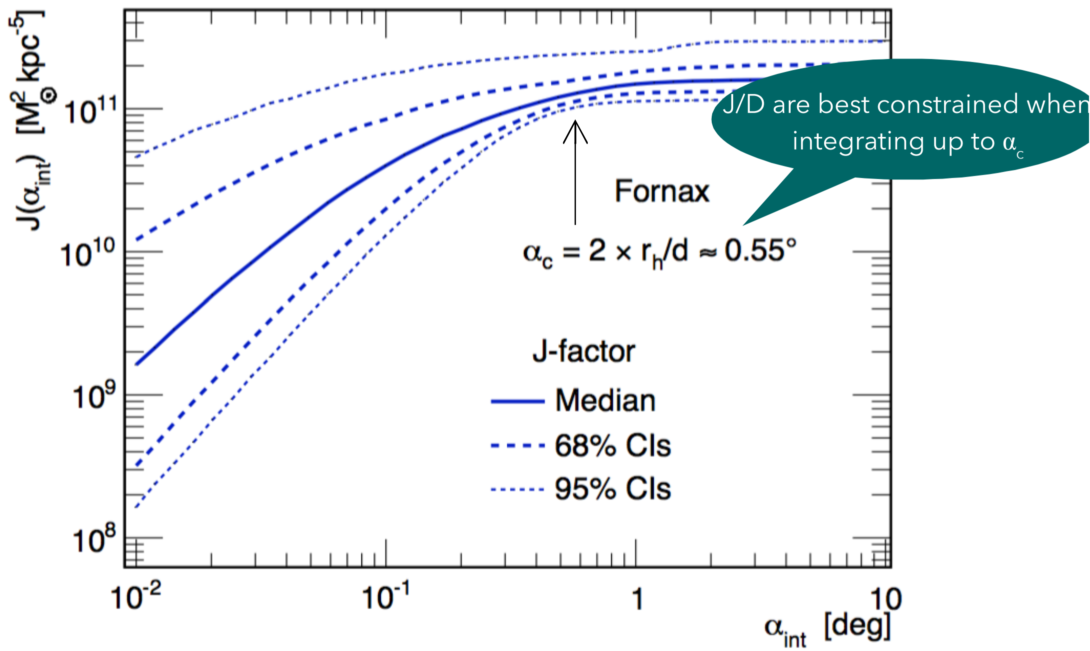

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Jeans equation assumes

- Spherical symmetry
- Dynamical equilibrium
- No rotation

Hope for the best

Parametric approach

- Light profile parametrisation *(Plummer, King, Sersic)*
- Anisotropy parametrisation *(zero, constant, β(r))*
- DM profile parametrisation *(NFW, core, Zhao, Einasto)*

Bayesian inference needs

- Likelihood (binned or unbinned)
- Priors (range, lin or log)

Different choices
=
Different results

Is there a "safe"/optimal setup for the Jeans analysis?
[Bonnivard et al. (2015)]

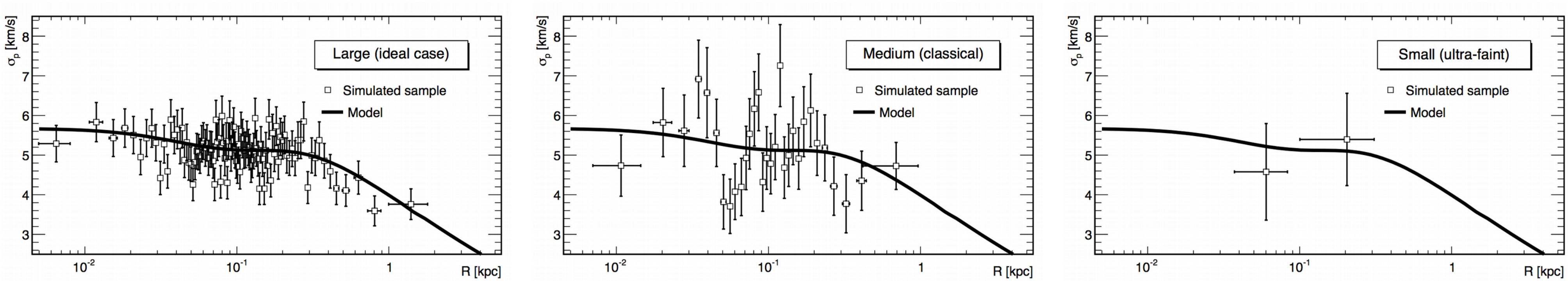
Mock dSph datasets

Walker et al. (2011)
Charbonnier et al. (2011) "Gaia Challenge"

	Mock data	Spherical*	Spherical°	Triaxial†
98 models	# of models	64	32	2
DM profile	γ	[0, 1]	$0-1$	$0.23-1$
	r_s [kpc]	[0.2, 1]	1	1.5
Light profile	γ^*	[0, 0.7]	$0.1-1$	0.23
	r_s^* [kpc]	[0.1, 1]	[0.1, 1]	0.81
Anisotropy	$\beta_{\rm ani}$ profile	Cst	Cst+Osipkov	Baes & van Hese

Each model is sampled to mimick:

- Ulltrafaint dSph (N*=30)
- Classical dSph (N*=10^3)
- Ideal dSph (N*=10^4)



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- True J-factors are known for all mock dSph galaxies
- Run analysis on all mock dSphs allowing for fits with the “wrong” parametrisations

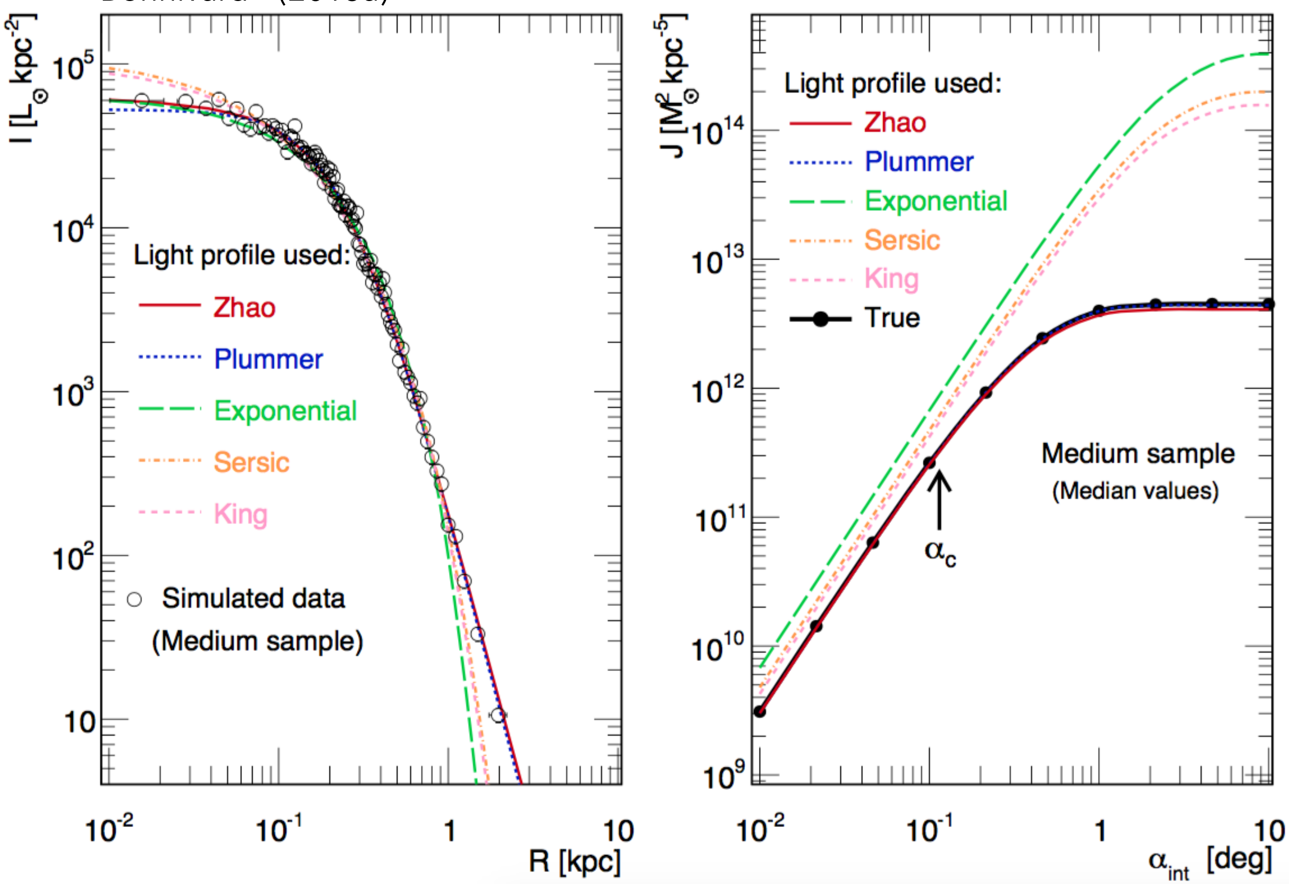
How are the reconstructed J-factors affected?

→ Identify the most important ingredients and define a safe(r) way to use the spherical Jeans analysis.

Mock dSph datasets: light profile

NB: the light profile is fitted first, then used in the Jeans analysis

Bonnivard+ (2015a)



Choice of light profile:

- Zhao (5 parameters)
- Sersic, King (3 parameters)
- Plummer, Exp (2 parameters)

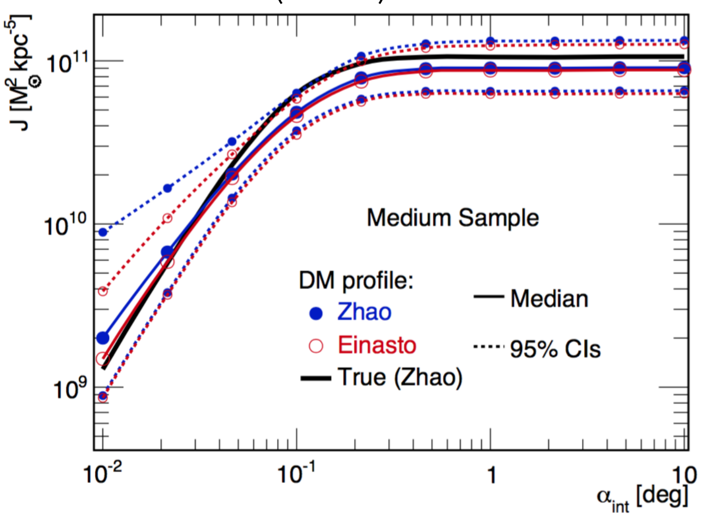
Undershooting I(R) at large radii

→ bias in J-factor

Select Zhao parametrisation as more flexible to describe the light profile

Mock dSph datasets: DM density profile

Bonnivard+ (2015a)



Choice of DM profiles:

- Zhao (5 parameters)
- Einasto (3 parameters)

Median value + CIs not affected

Independent on sample size

Select Einasto parametrisation as less free parameters
→ Speed-up MCMC

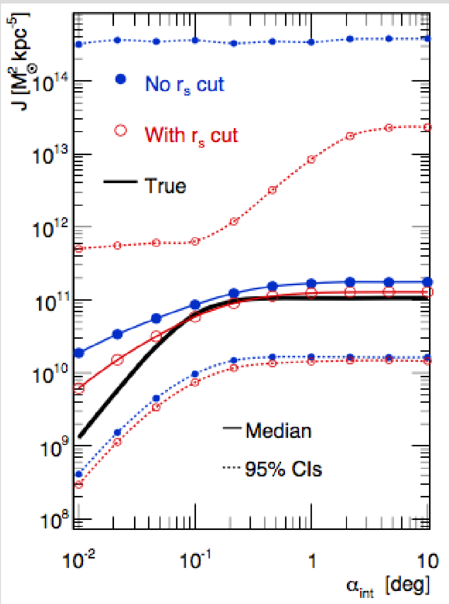
Priors

Einasto slope: very steep inner slopes disfavoured by sims and data and give rise to large upper CIs (not shown)

$$0.12 < \alpha^E < 1$$

→ (conservative <σv>)

Scale radius: Asking $r_s^{\rm DM} \geq r_s^\star$ drastically reduces upper CIs



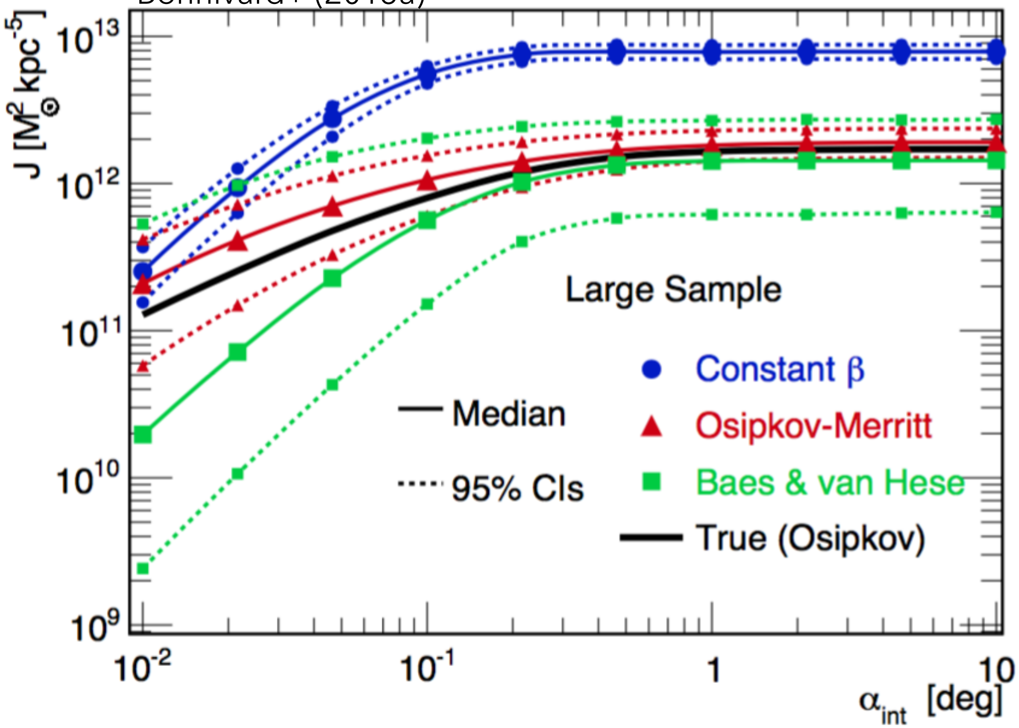
Truncation radius ?

- tidal radius
- $\rho_{dsph} = \rho_{Gal}$
- outermost star

[Geringer-Sameth+ 2015]

Mock dSph datasets: anisotropy profile

Bonnivard+ (2015a)



Choice of anisotropy profiles:

- Constant (β_0, 1 parameter)
- Osipkov-Merritt (β(r), 1 parameter)
- Baes (β(r), 4 parameters)

'Bad' anisotropy choice
→ bias in J-factor

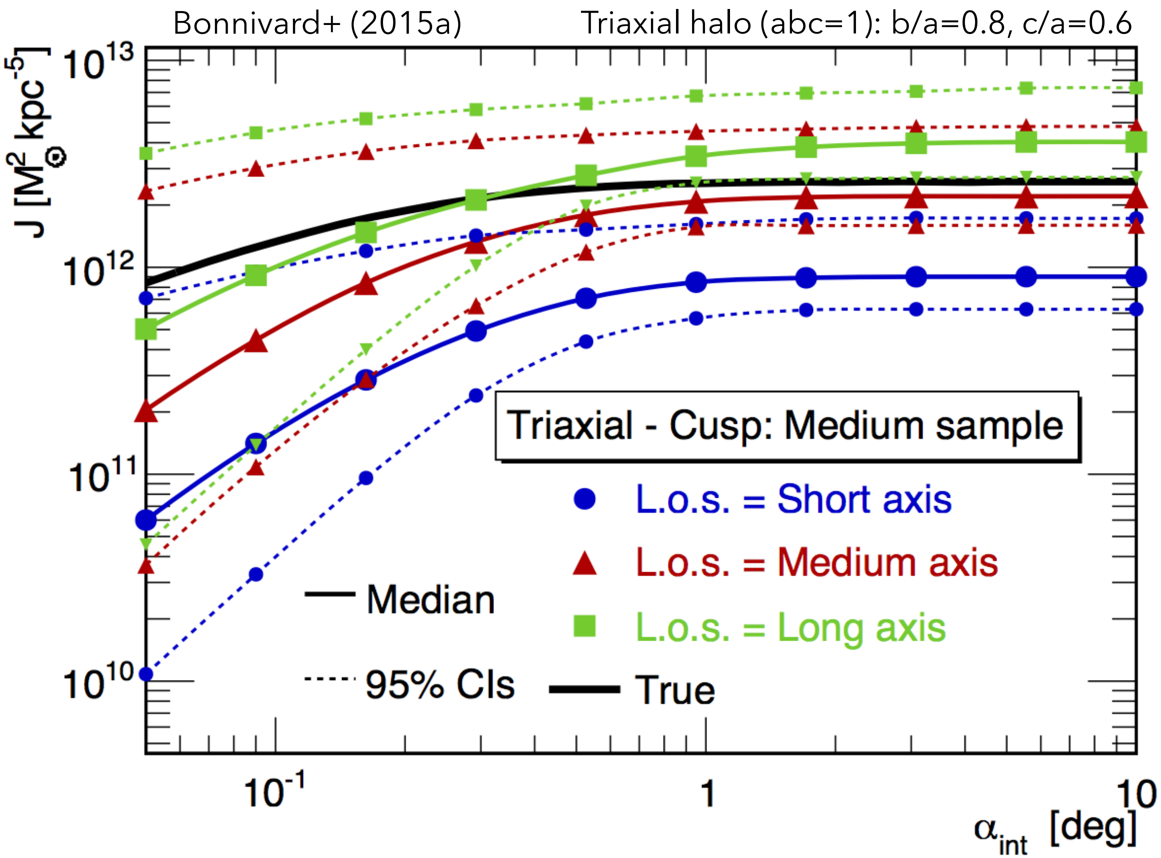
NB: Less critical for ultrafaint dSphs
→ larger error bars encompass the 'true' value

+ anisotropy cut: avoid non-physical models with $\beta_{\rm ani}(r) \leq -\frac{1}{2}\frac{\mathrm{d}\log \nu(r)}{\mathrm{d}\log(r)}$, (Ciotti & Morganti 2010)

For classical dSphs, use Baes & van Hese anisotropy profile (but time consuming)

For ultrafaint dSphs, constant anisotropy profile suffices (and runs much faster)

Mock dSph datasets: triaxiality



Simulations → DM halos are triaxial

Observations → signs of ellipticity

1) Known triaxiality parameters but unknown orientation
   → ~30% uncertainty

2) Spherical Jeans analysis on triaxial data
   → Bias J up to factor ~ 2.5 ⚠
   → Truth may not be encompassed in 95% CIs.

Cannot do much about it as dSphs actual shapes and orientations are unknown…

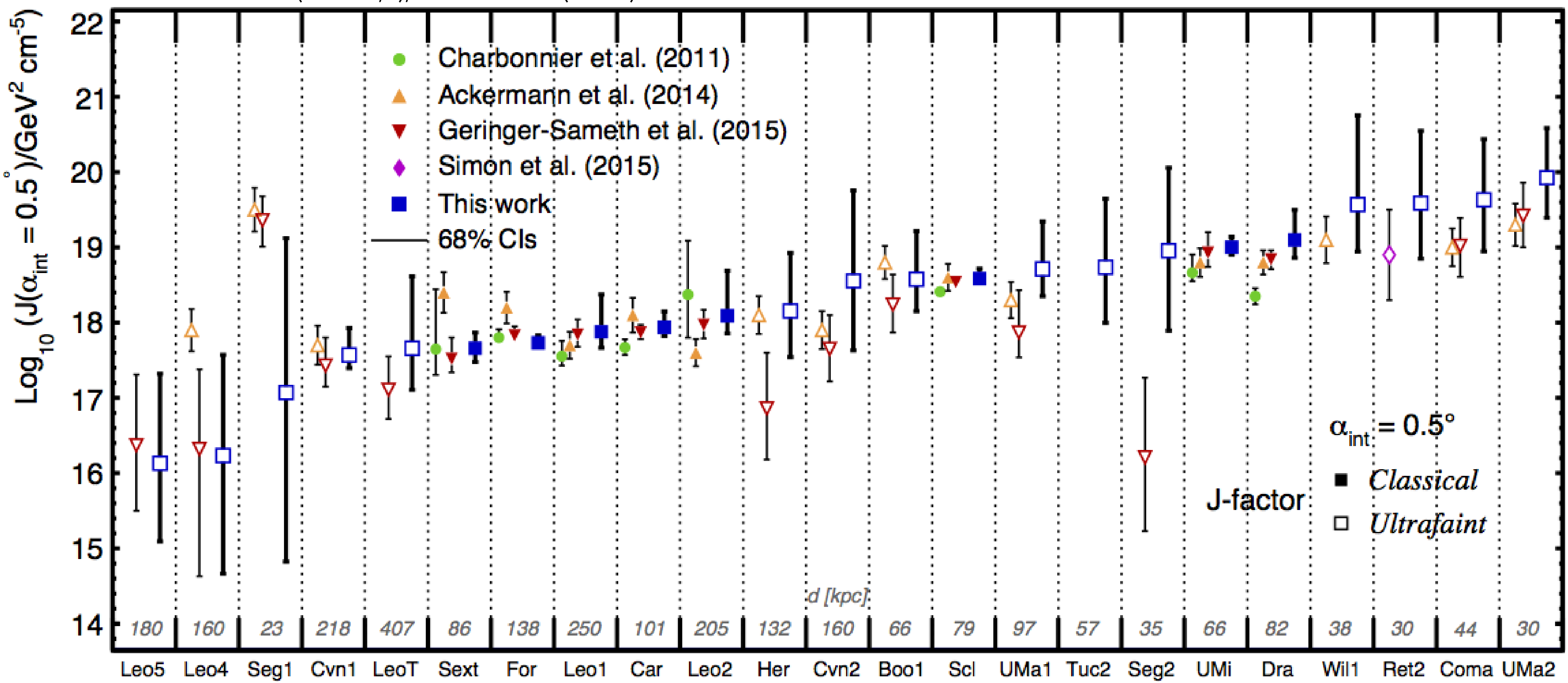
So, keep working assuming spherical symmetry but consider adding extra systematic error in the error budget

Mock dSph datasets: biases and uncertainties

	Annihilation			**Decay**		
	Ultra-faint	*Classical*	*Ideal*	*Ultra-faint*	*Classical*	*Ideal*
Bias from:	$J^{\rm median}/J^{\rm true}(\alpha_c^J)$			$D^{\rm median}/D^{\rm true}(\alpha_c^D)$		
Einasto vs Zhao	none	none	none	none	none	none
Wrong $\beta_{\rm ani}$	none	$\lesssim 3$	$\lesssim 10$	none	$\lesssim 2.5$	$\lesssim 2$
Wrong $I^{\rm light}$	$\lesssim 2$	$\lesssim 3$	$\lesssim 3$	$\lesssim 1.5$	$\lesssim 4$	$\lesssim 4$
Triaxiality	$\lesssim 2.5$	$\lesssim 2.5$	$\lesssim 2.5$	$\lesssim 2$	$\lesssim 2$	$\lesssim 2$
Uncertainties†:	$J^{\pm 95\%\rm CI}/J^{\rm median}(\alpha_c^J)$			$D^{\pm 95\%\rm CI}/D^{\rm median}(\alpha_c^D)$		
Maximum knowledge	$\lesssim 20$	$\lesssim 2$	$\lesssim 1.5$	$\lesssim 8$	$\lesssim 1.5$	$\lesssim 1.25$
$\rho_{\rm DM}^{\rm Einasto} + \beta_{\rm ani}^{\rm Baes}$ modelling	$\lesssim 20$	$\lesssim 4$	$\lesssim 2.5$	$\lesssim 10$	$\lesssim 2$	$\lesssim 2$

J-factors: Application to real dSph data ($\alpha_{int} = 0.5^{\circ}$)

Bonnivard et al. (2015b,c), Walker et al. (2016)



- Larger error bars to ultrafaint dSph [except for the *Fermi-LAT* 2014 analysis, which assumed universal dSph properties from numerical simulations (Martinez 2015)].

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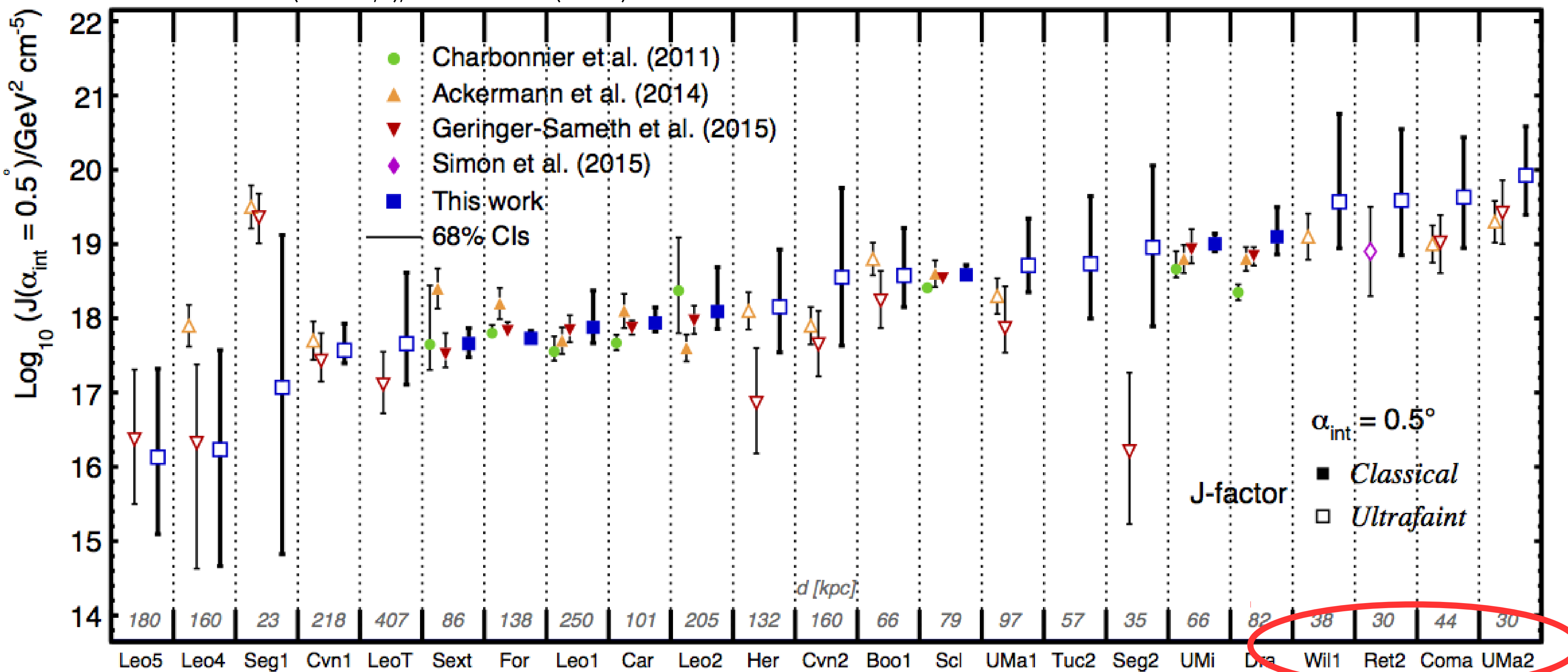

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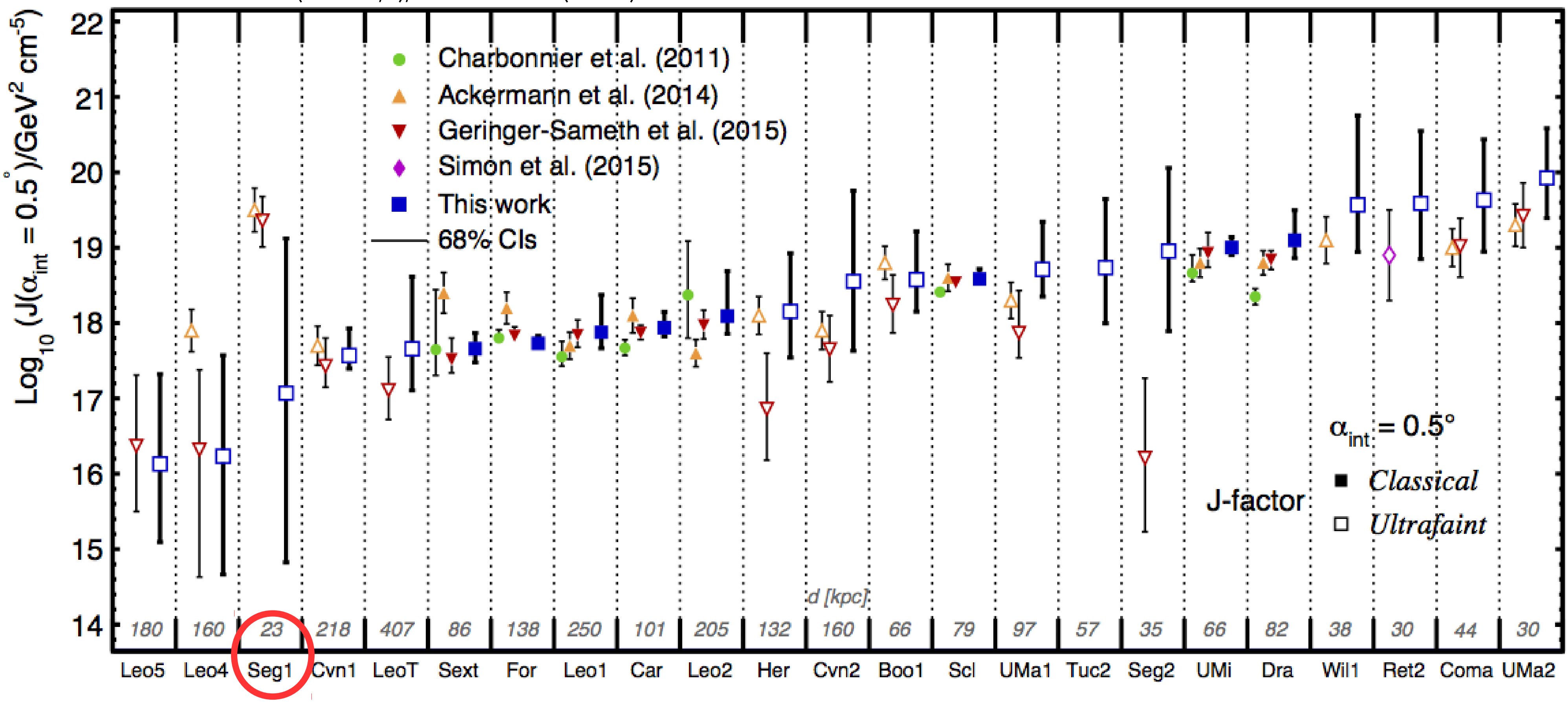

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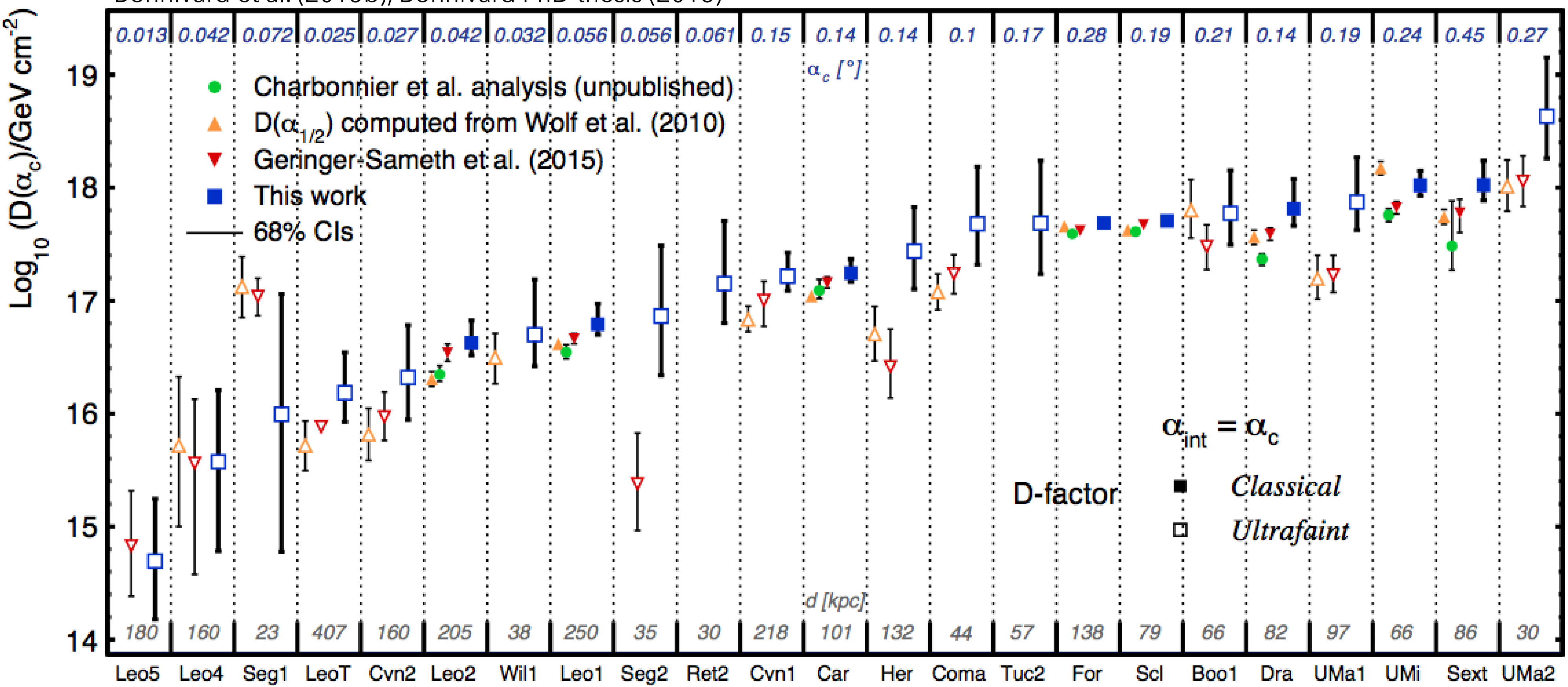
- Distance is the main driver → simple scaling to estimate J when no spectroscopic data (e.g. Drlica-Wagner et al. (2015), Albert et al. (2017))
- Segue I is found discrepant with other estimates and very uncertain: possibly suggests stellar contamination [cf. Part 2]

D-factors: Application to real dSph data ($\alpha_{int} = \alpha_c$)

Bonnivard et al. (2015b), Bonnivard PhD thesis (2016)



- Reshuffling of the best targets when considering D-factors; UMa2 remains an excellent option
- For decay, emission is less peaked and outer regions play an important role → halo truncation radius becomes an important parameter; point-like assumption fails.

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   - Sample contamination
   - Accounting for triaxiality → See Mauro's talk

Identifying and handling contamination

- Hard cuts from some diagnosis (CMD, σ-clipping on $v_{l.o.s}$, metallicity, location) → member yes/no
  (see Battaglia, Helmi & Breddels 2013 for a review)
  → use all stars that pass the cut into likelihood

- Membership probability *Pi:* Expectation-maximisation (Walker+ 2009), Bayesian method (Martinez+ 2011)
  → cut to select 'members' : .e.g $P_i > 0.95$ (1)
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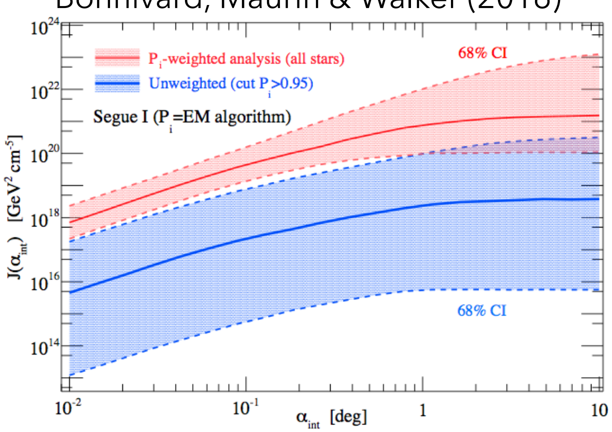
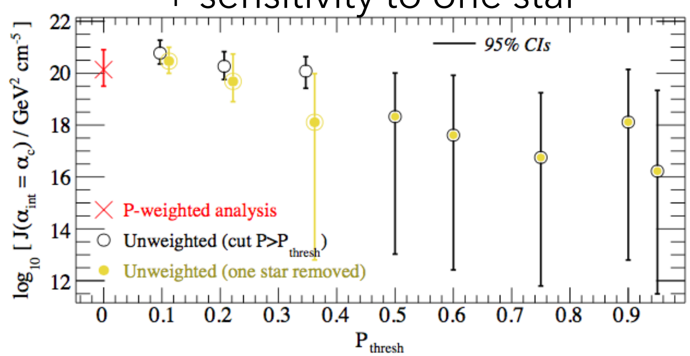
- Simulations of contaminated ultrafaint samples (Bonnivard, Maurin, Walker 2016) show that:
  → they have a 'large' values of N(0.05< *Pi*< 0.95) / N(*Pi*>10^{-3}) [=0.19 for Segue 1]
  → J-factors differ when performing Jeans using (1) or (2)

Bonnivard, Maurin & Walker (2016)



+ sensitivity to one star



- Segue I has peculiar behaviour
→ caution advised when using J.

- Among classical, Fornax shows sign of slight contamination.

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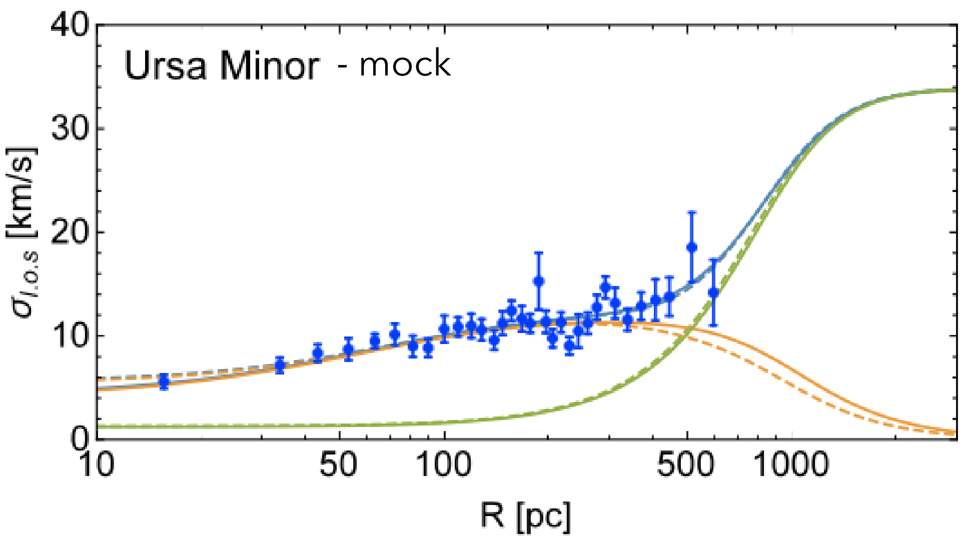
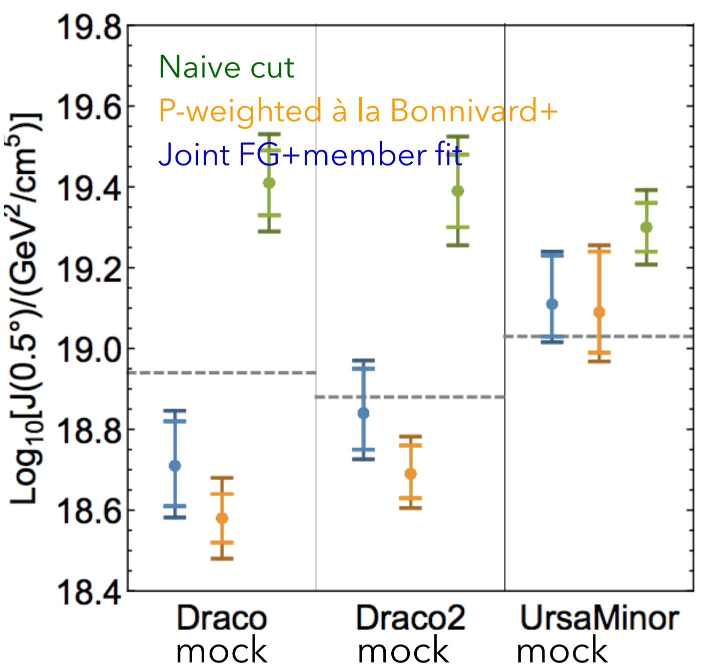
  → use all stars that pass the cut into likelihood

- Then, joint foreground + member likelihood e.g.
  → Bonnivard, Maurin, Walker (2016, Appendix A, similar result to P-weighted likelihood)
  → Ichikawa et al. (2017) : simulations + naive cut + standard Jeans (Zhao DM, Plummer light, constant anisotropy) + foreground prior from control region

$$-2\ln\mathcal{L} = -2\sum_i \ln(s\,f_{\rm Mem}(v_i,R_i) + (1-s)f_{\rm FG}(v_i,R_i))$$

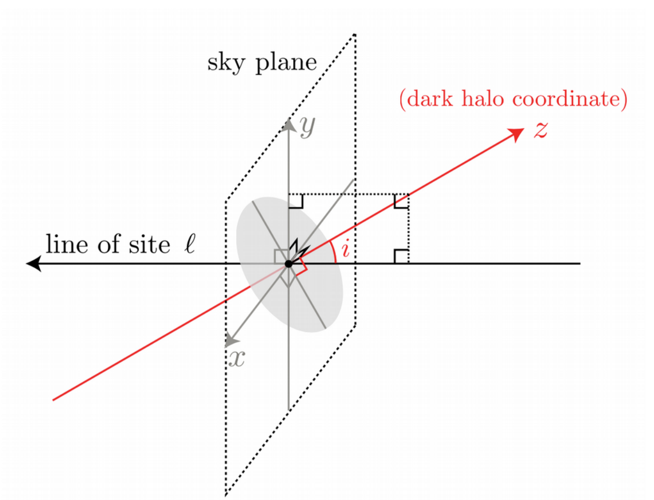




Accounting for triaxiality

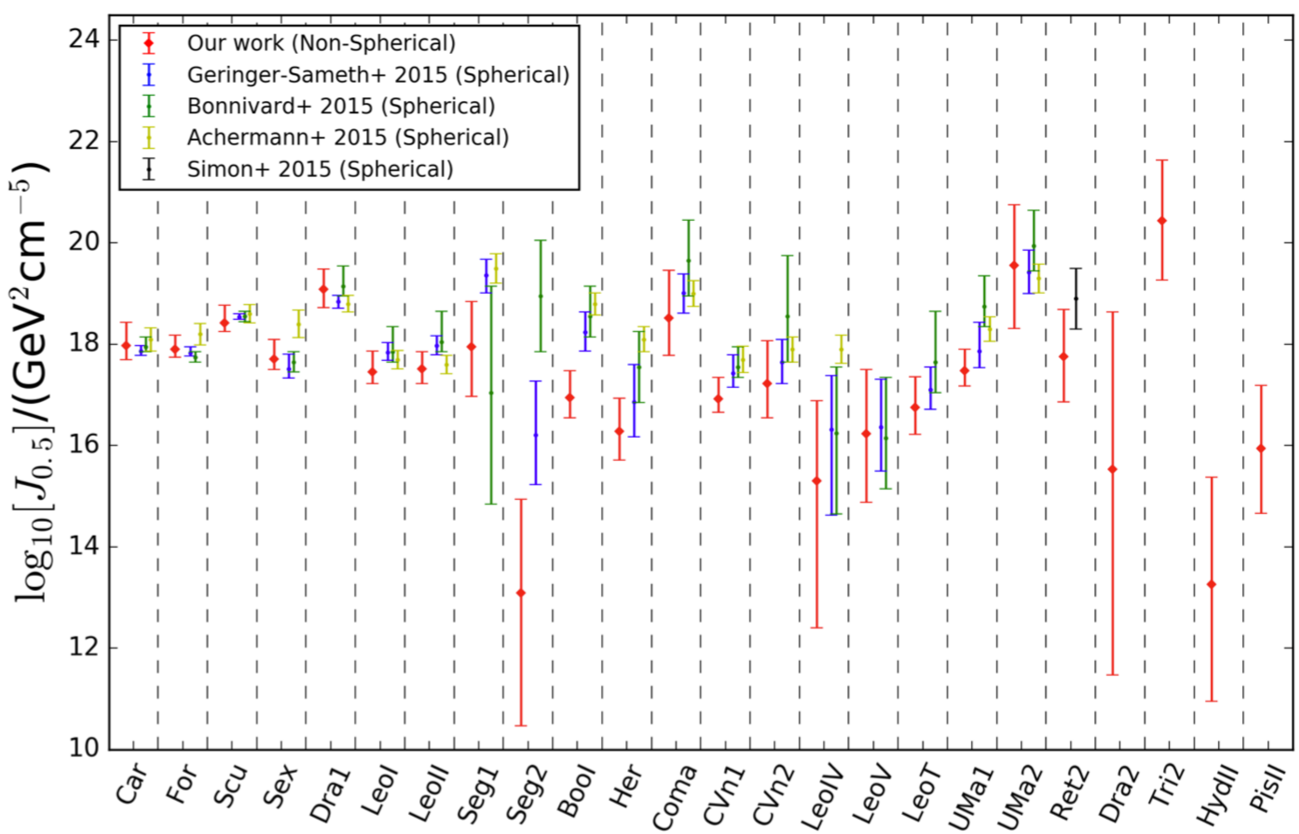
- Simulations → DM haloes are triaxial
- Observations → “light” of dSph does not necessarily look spherical
- Using spherical Jeans analysis may yield factor ~2 bias on J-factors

Hayashi & Chiba (2012), Hayashi et al. (2016) → axisymmetric Jeans analysis (oblate case)



$$\rho(R,z) = \rho_0 \left(\frac{m}{b_{\rm halo}}\right)^{\alpha} \left[1 + \left(\frac{m}{b_{\rm halo}}\right)^2\right]^{-(\alpha+3)/2}$$
$$m^2 = R^2 + z^2/Q^2,$$

→ MCMC with 6 parameters



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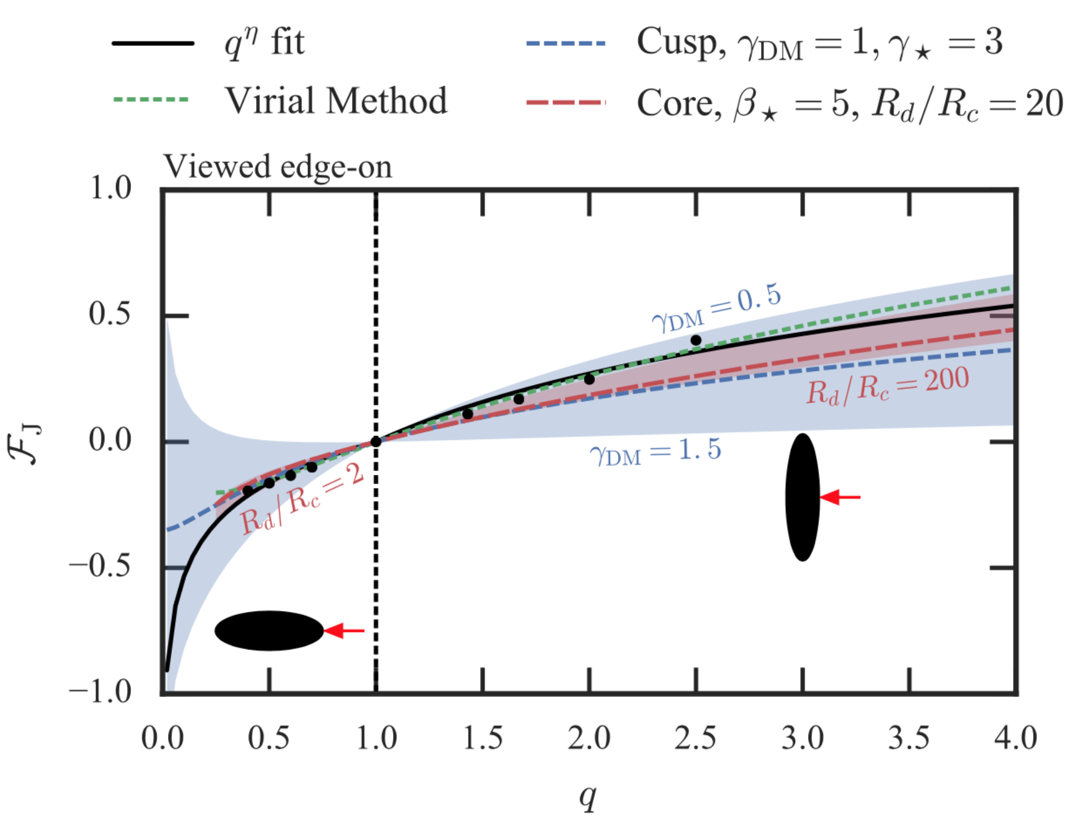
Sanders et al. (2016) → correction to J and D $\mathcal{F}_\mathrm{J} = \log_{10}(\mathrm{J}/\mathrm{J}_\mathrm{sph}),\ \mathcal{F}_\mathrm{D} = \log_{10}(\mathrm{D}/\mathrm{D}_\mathrm{sph})$ from M2M sims + analytical considerations



- Various DM/light profiles
- Prolate haloes → corr ~ 1.6
- Oblate haloes → corr ~ 0.4 – 0.75
- Triaxial haloes → factor ~2 extra uncertainty

Summary

1. Data-driven estimated J/D factors with spherical Jeans analysis + Bayesian inference

- Mock data allow optimised setup for the Jeans analysis (parametrisations + priors)
- Application to 23 dSph galaxies (overall agreement between authors)

  → For annihilation, Ursa Minor and Draco are the best 'safe' targets
  → Coma, UMa2, Ret 2 are more uncertain but possibly more promising
  → Segue 1 is problematic – possible stellar contamination

- If triaxial dSph galaxies → factor ~2 bias using spherical Jeans

2. To go further

- *Mass modeling:*

  → break mass-anisotropy degeneracy: Lokas & Mamon (2003), Walker & Penarubbia (2011), Richardson & Fairbairn (2012, 2014), Read & Steger (2017), Kovalczyk+(2017)
  → account for ellipticity/triaxiality: Hayashi et al. (2016), Sanders et al. (2016)

- *Likelihood:*

  → Include foreground component to mitigate contamination effects
  → Profile likelihood / frequentist approach (Chiappo+ 2017)