

Fast and accurate evaluation of black hole Green's functions using surrogate models

Chad Galley, California Institute of Technology

with Barry Wardell (University College Dublin)

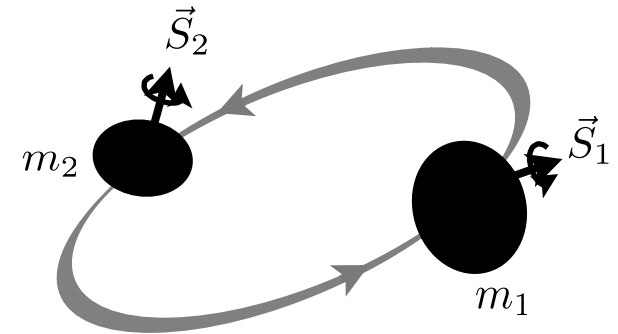
GR21, New York City, July 11, 2016

Caltech

Compact binaries

Numerical relativity has proven success approximating compact binary evolutions

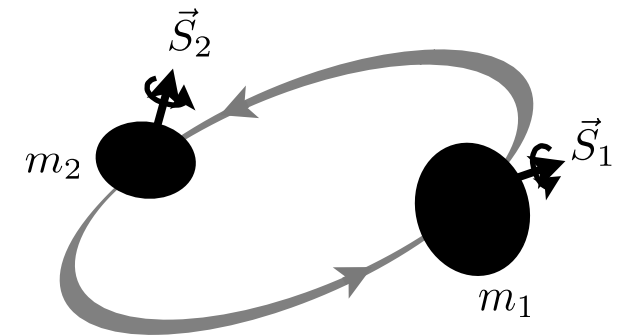
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- Challenging for much smaller mass ratios



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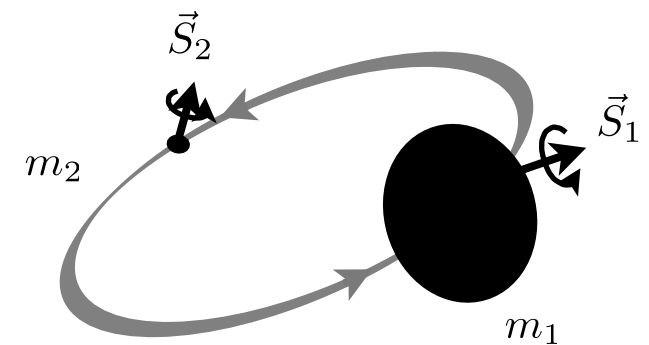
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Complementary description provided by [self-force](#) framework where mass ratio is an expansion parameter for perturbation theory

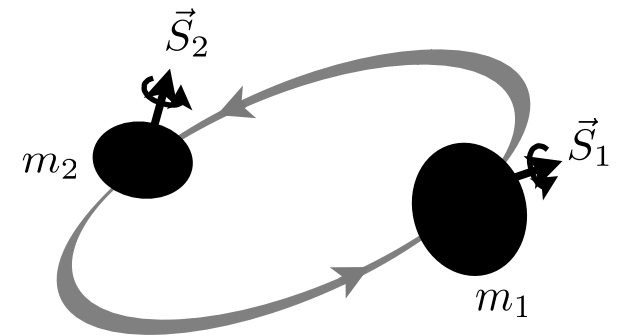
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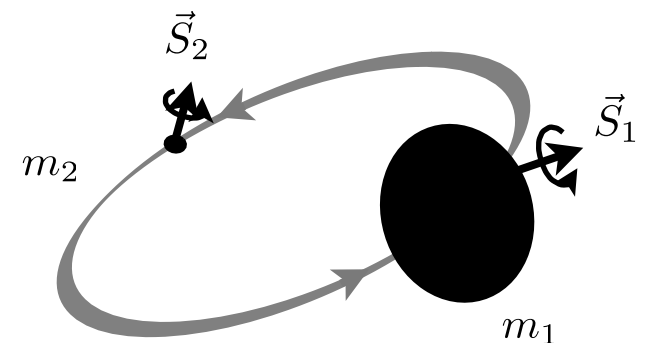
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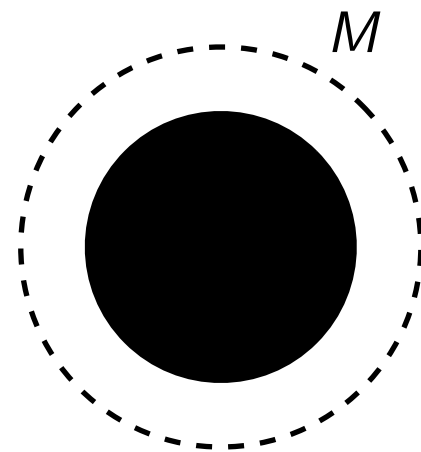


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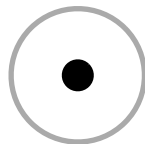
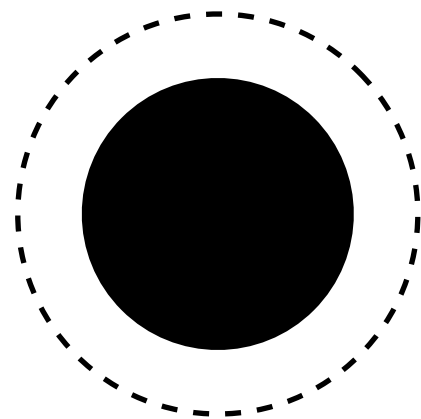
What is self-force?



● m

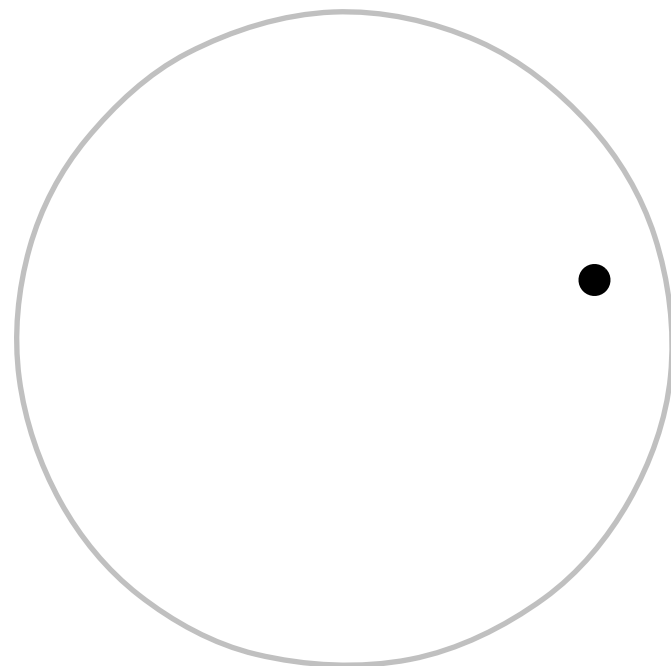
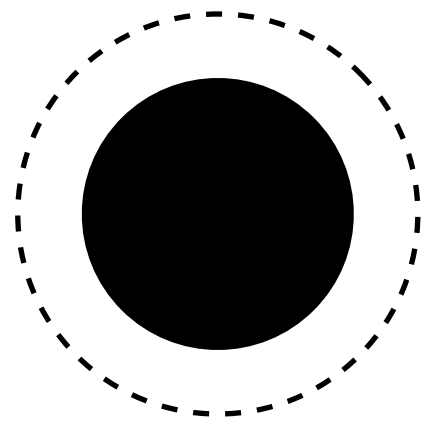
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radiation reaction
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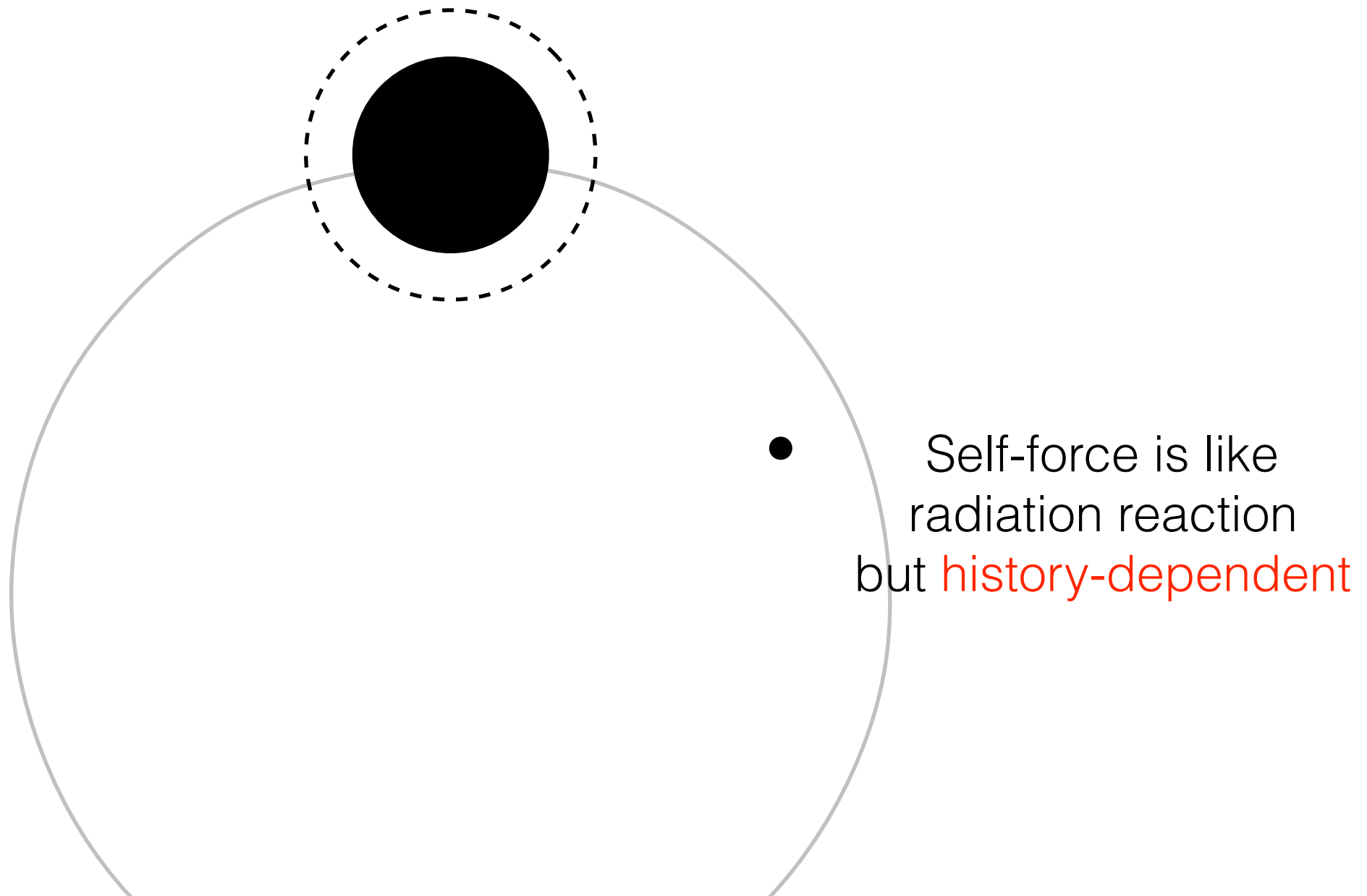
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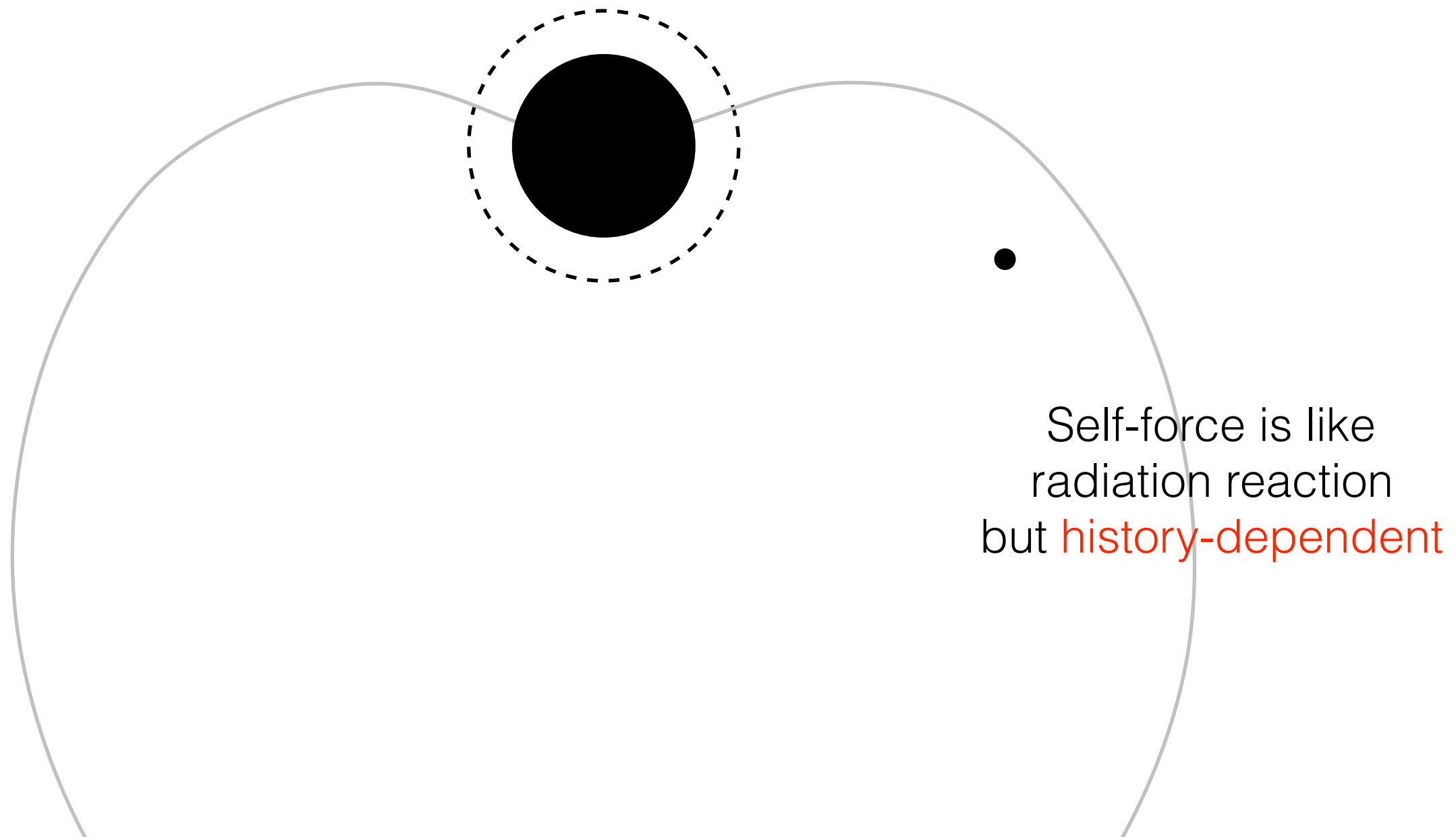


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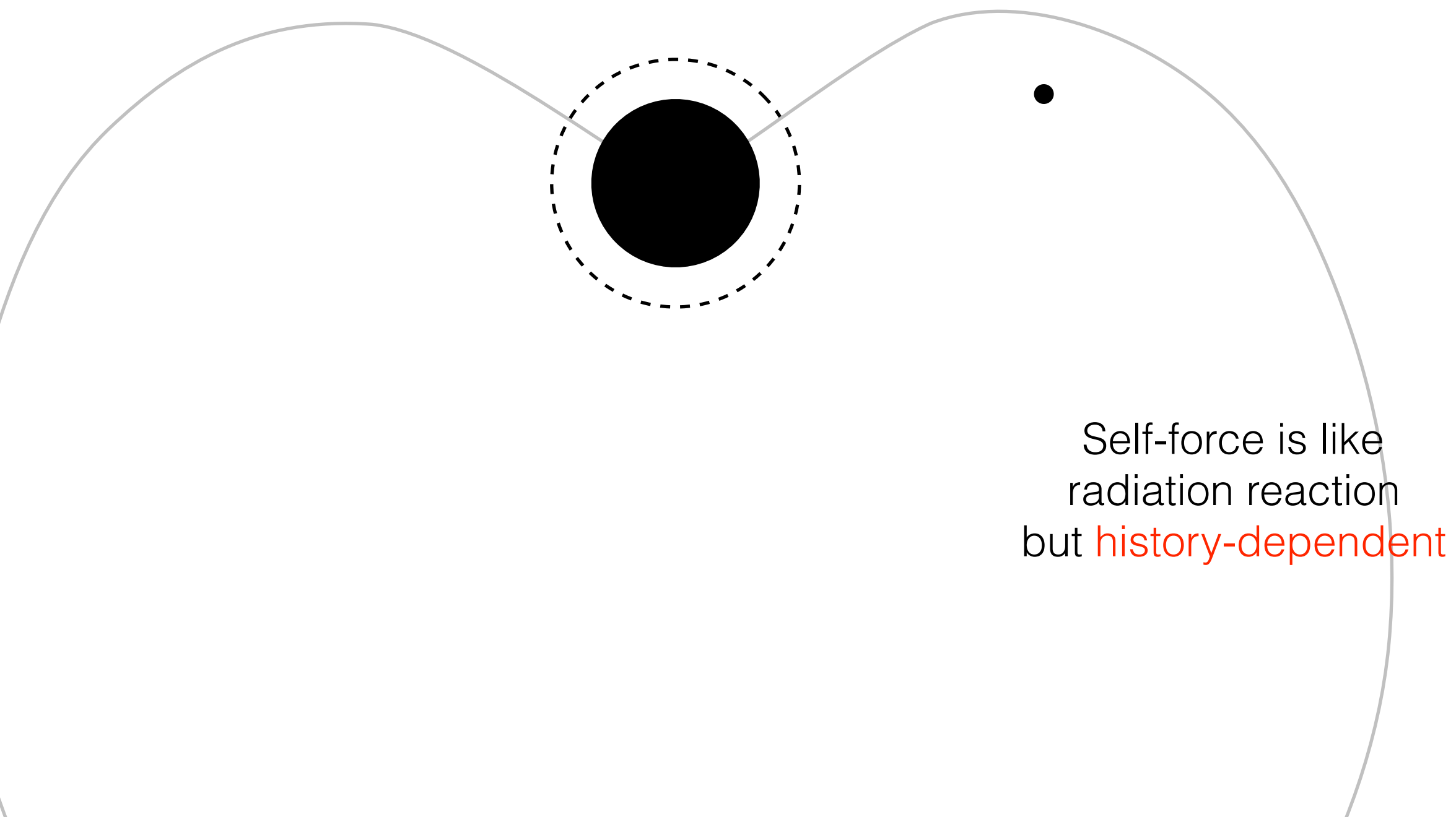
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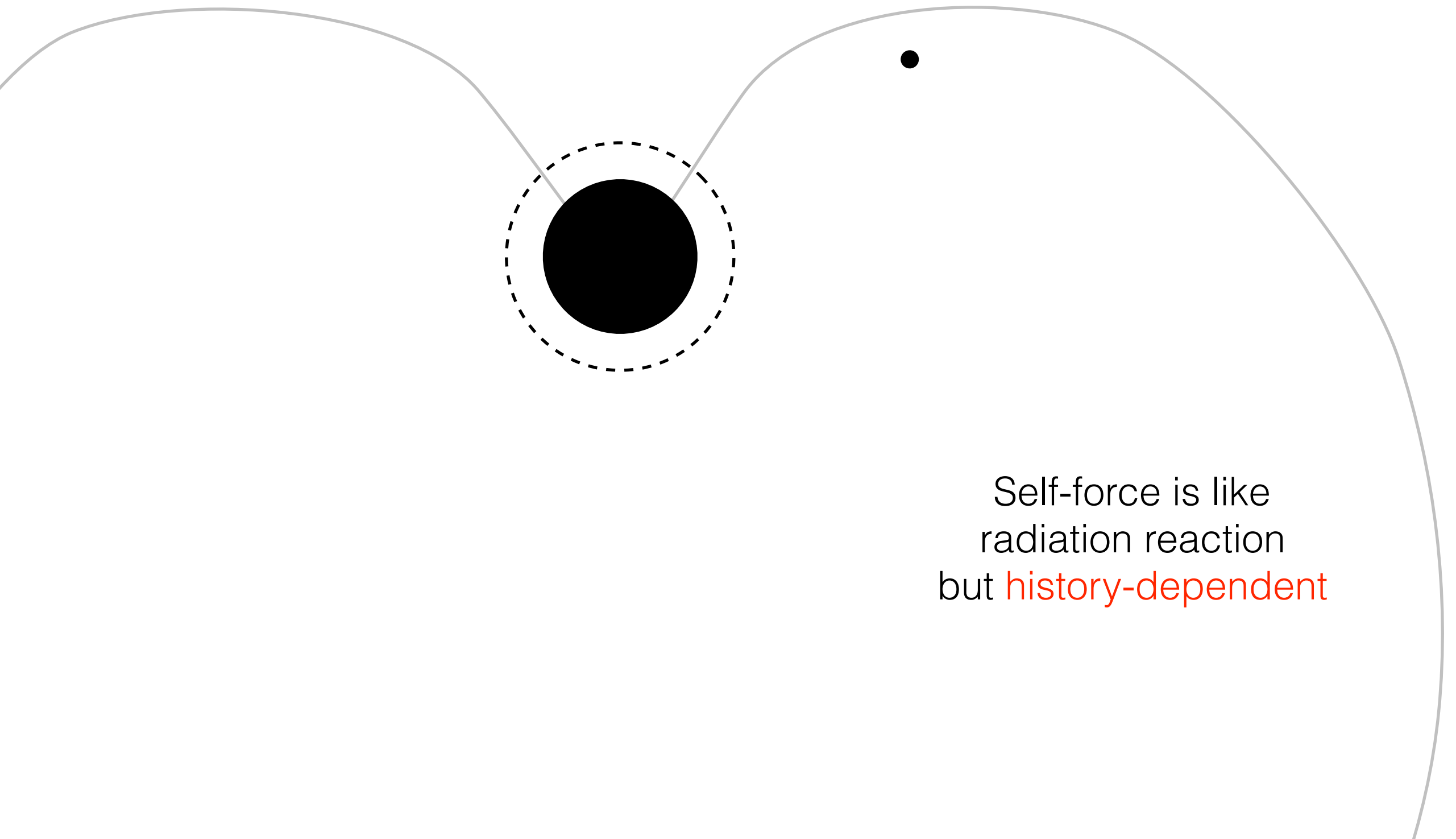
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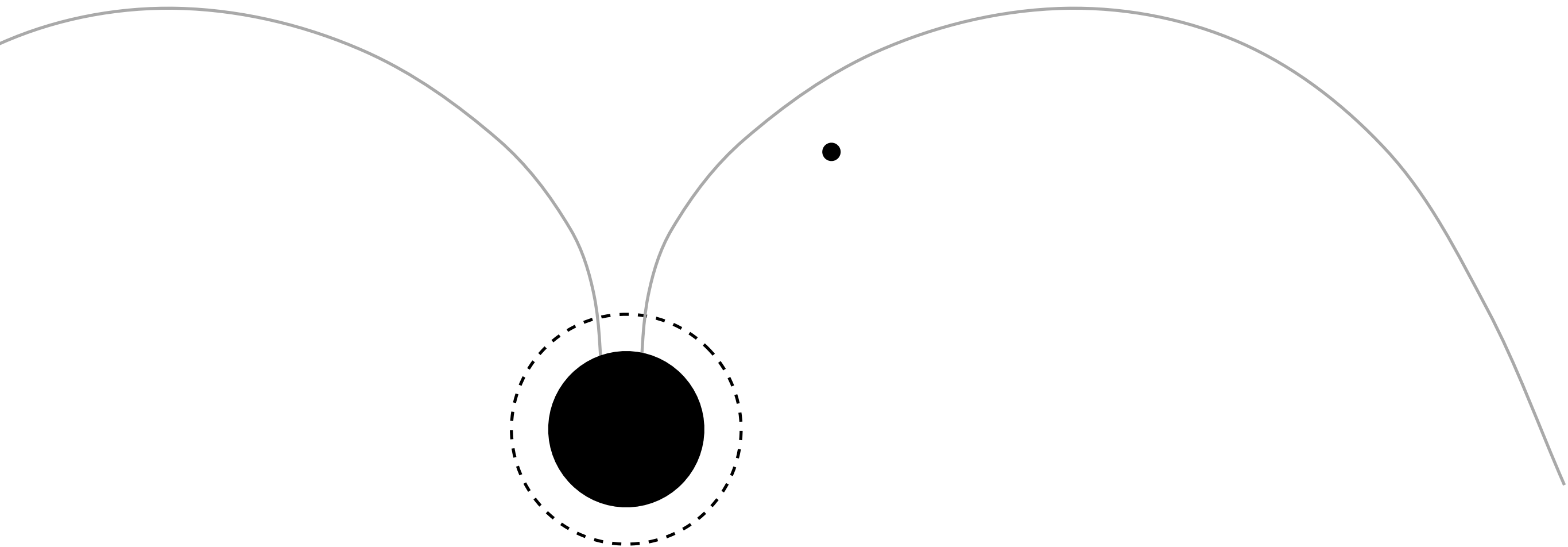


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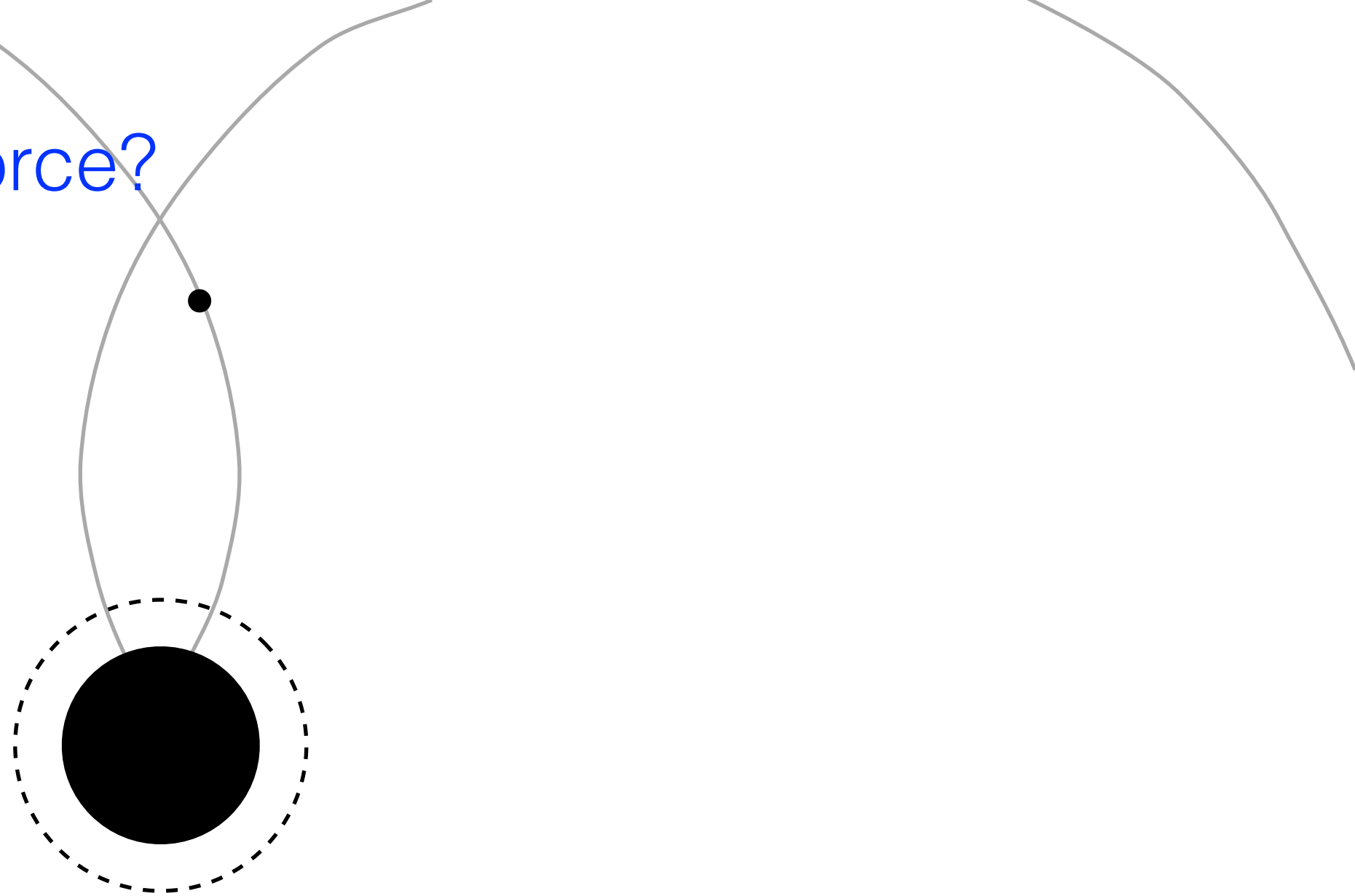
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Self-force

Gravitational self-force is described by the MiSaTaQuWa equation
Mino, Sasaki, Tanaka (96); Quinn, Wald (96)

$$a^\mu = \frac{m}{2} P^{\mu\nu\alpha\beta} \lim_{\epsilon \rightarrow 0^+} \int_{-\infty}^{\tau-\epsilon} d\tau' \nabla_\nu G^{\text{ret}}_{\alpha\beta\gamma'\delta'}(z^\mu(\tau), z^{\mu'}(\tau')) u^{\gamma'} u^{\delta'}$$

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The Green's function is **central** to understanding and describing self-force effects

$$\square_x G(x, x') = \frac{\delta^4(x - x')}{\sqrt{-g(x)}} \implies \phi(x) = \int d^4x' \sqrt{-g(x')} G(x, x') J(x')$$

- x is **field** point; x' is **source/base** point; G is a **biscalar/bitensor**

Green's functions

Green's functions

What are the **advantages** of using Green's functions?

- **Compute only once** for every source
- Nearly all physical quantities of interest are calculated via convolution integrals
- **Arbitrary** motion for self-force *Wardell, CRG et al (14)*
- Geometric interpretation *Zenginoglu & CRG (12), Wardell, CRG et al (14)*
- Higher-order self-force
- Self-consistent (higher-order) self-forced evolution
- Self-consistent inspiral waveforms
- Arguably straightforward to implement once known

(show movie)
Credit: B. Wardell

Numerical Green's functions

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Numerical Green's functions are **globally valid approximations** but utilizing analytic approximations at **early** and **late** times is extremely helpful for self-force calculations

- Quasi-local expansions *Ottewill & Wardell (08); Wardell's thesis*
- Pade approximants *Casals et al (09)*
- Method of matched expansions *Anderson & Wiseman (05); Casals et al (13)*

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When these analytical approximations (e.g., in Schwarzschild) are available we use numerical Green's functions for **intermediate** times

What are the **disadvantages** of using Green's functions?

- Analytically, very difficult to calculate in curved spacetimes
Casals, Nolan (16)
- Numerically, computationally expensive
- Large data sets (G depends on **two** space-time points!)

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101 modes	~30GB (~200 GB)
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Goal:

Find a way for Green's functions to be efficient and accurate to use for practical self-force and related computations.

The goal

To quickly predict accurate solutions to the Green's function wave equation that are otherwise too slow and too large for practical use

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- *Reduced basis* (compression in source & field points)
- *Empirical interpolation* (compression in time)
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The result

An accurate *surrogate model* to generate new Green's function data on demand

Surrogate models for gravitational waveforms have been built successfully for:

- Non-spinning Effective One-Body (*EOBNRv2*)
Field, CRG, et al PRX (14)
- Spin-aligned Effective One-Body (*SEOBNRv2*)
Purrer (15)
- Non-spinning Numerical Relativity (*SpEC*)
Blackman, Field, CRG et al PRL (15)
- 4d precession, Numerical Relativity (*SpEC*) (*see J. Blackman's talk*)
(in prep)
- Tidal Effective One-Body (*see S. Bernuzzi's talk*)
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However, some steps for building a Green's function surrogate are necessarily **different** than for waveforms

- Provides one with **dynamics**, **field content**, and **waveforms**
- Source and field points are **time-dependent** for worldline convolutions

Surrogate building: Initial stuff

see *Wardell, CRG et al (14)*
for details of numerical
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$$\Delta t = 0.1M$$

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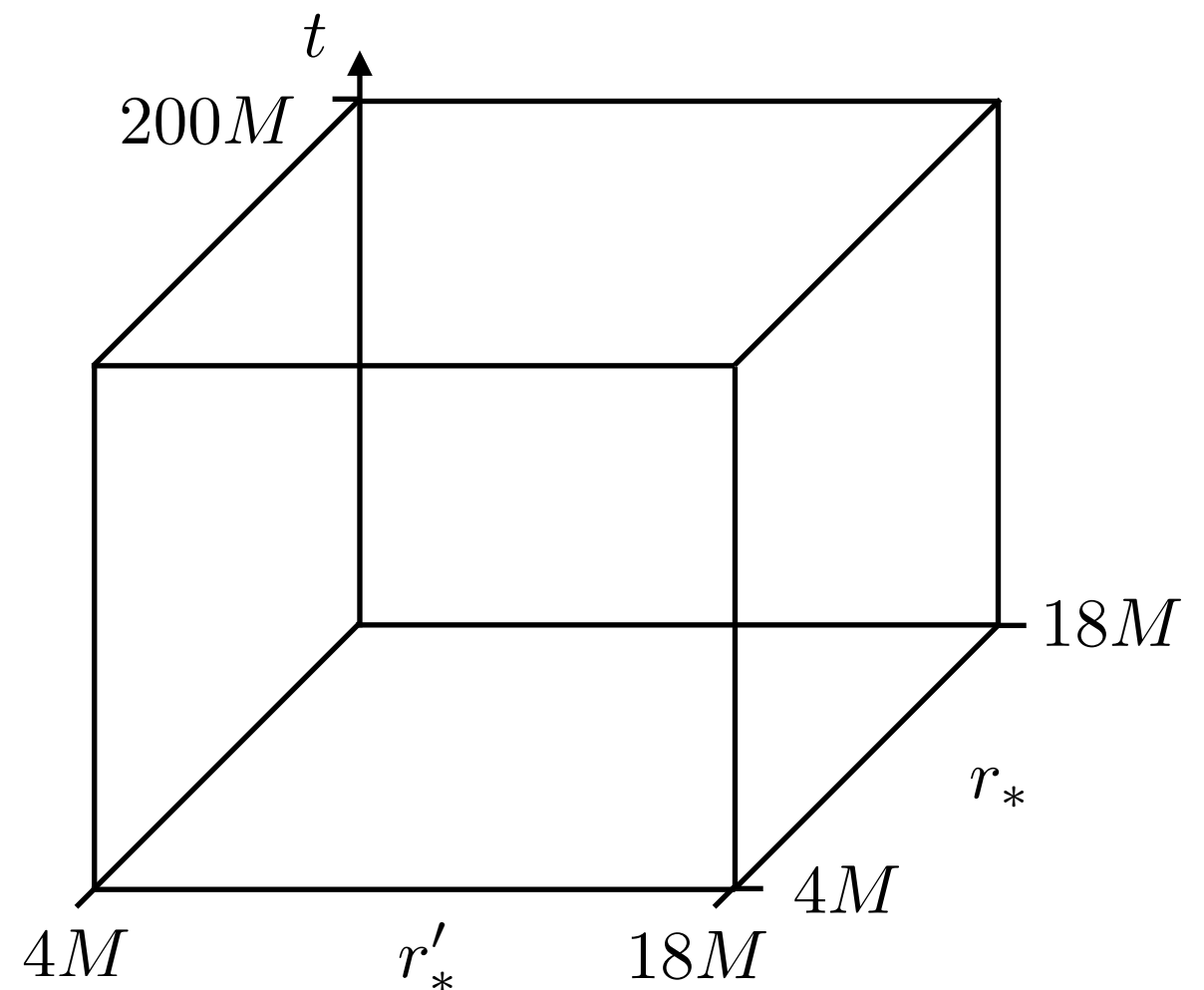
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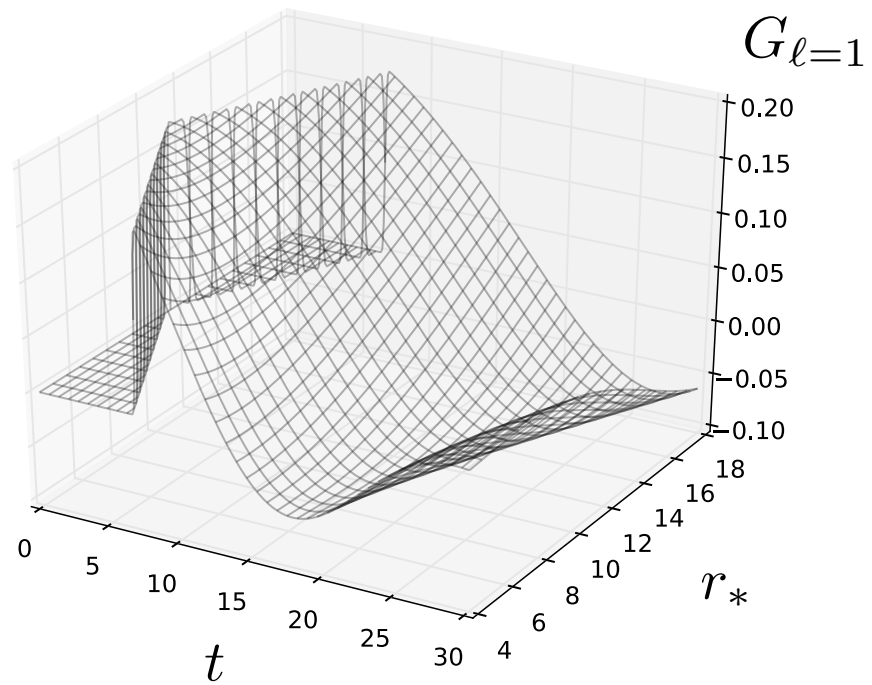
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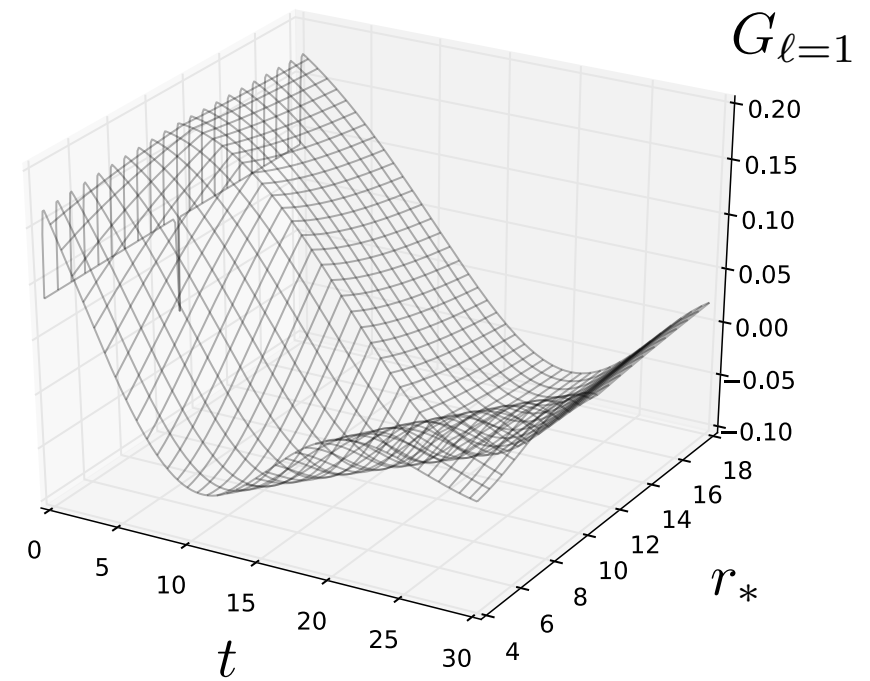
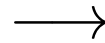
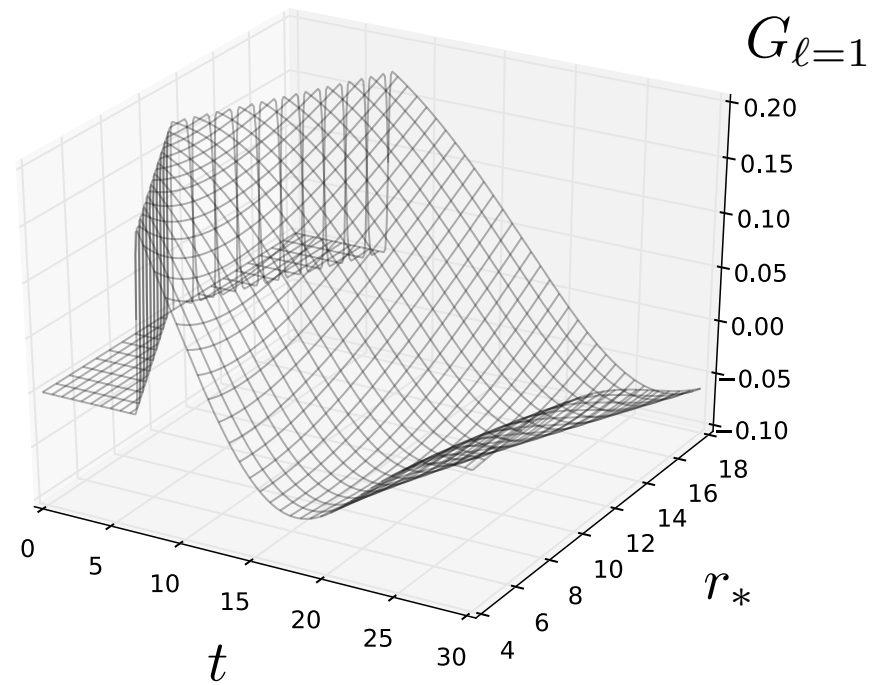
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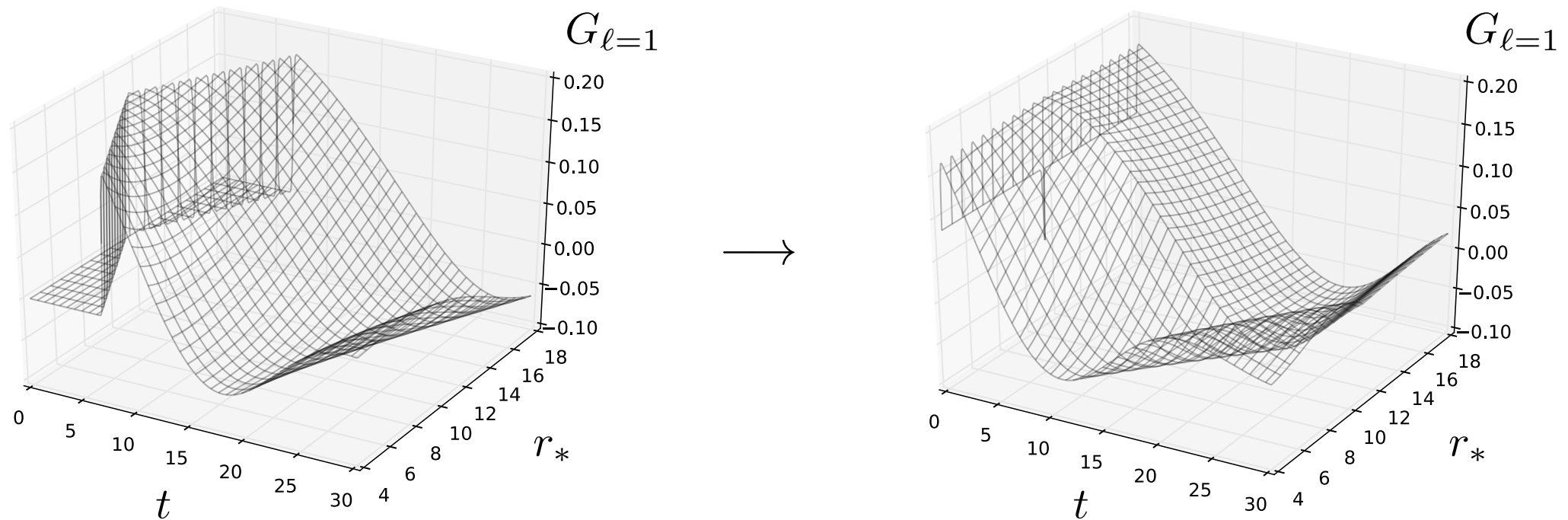
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- In addition, to reduce high-frequency noise we introduce a smoothing factor *Wardell, CRG et al (14)*

$$G(x^\alpha, x'^\alpha) \approx \frac{1}{rr'} \sum_{\ell=0}^{\ell_{\max}} P_\ell(\cos \theta) (2\ell + 1) e^{-\ell^2 / 2\ell_{\text{cut}}^2} G_\ell(t - t'; r_*, r'_*)$$

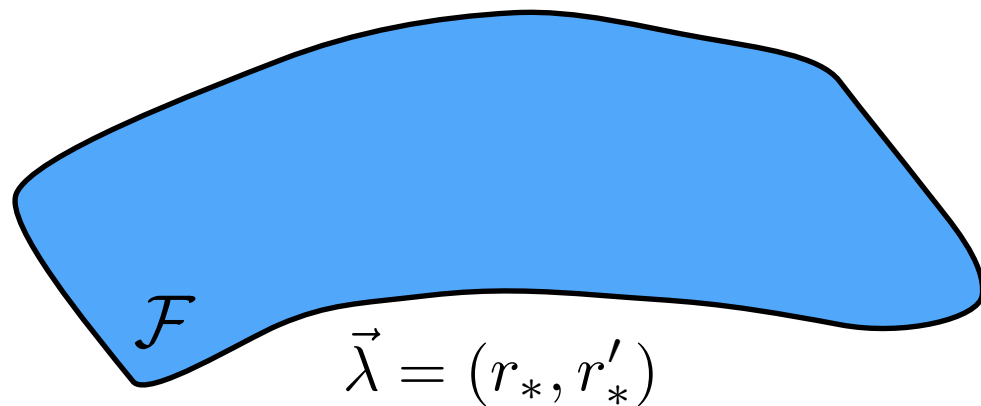
$$\ell_{\max} = 100$$

$$\ell_{\text{cut}} = \ell_{\max} / 5$$

1) Reduced basis via greedy algorithm

Can find a linear approximation space that is *nearly* optimal

Set of functions \mathcal{F}

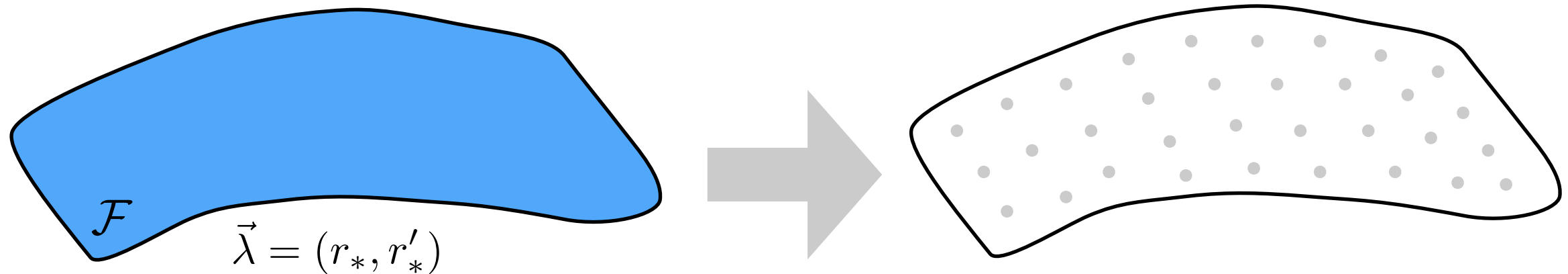


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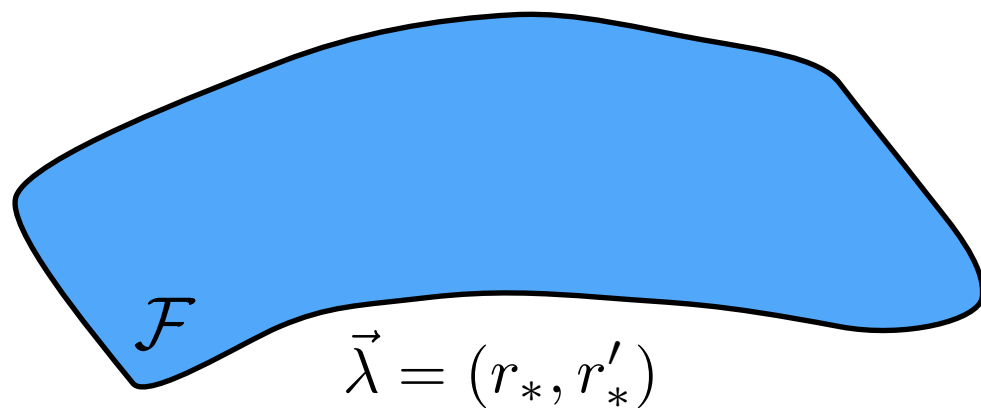
"Training space"



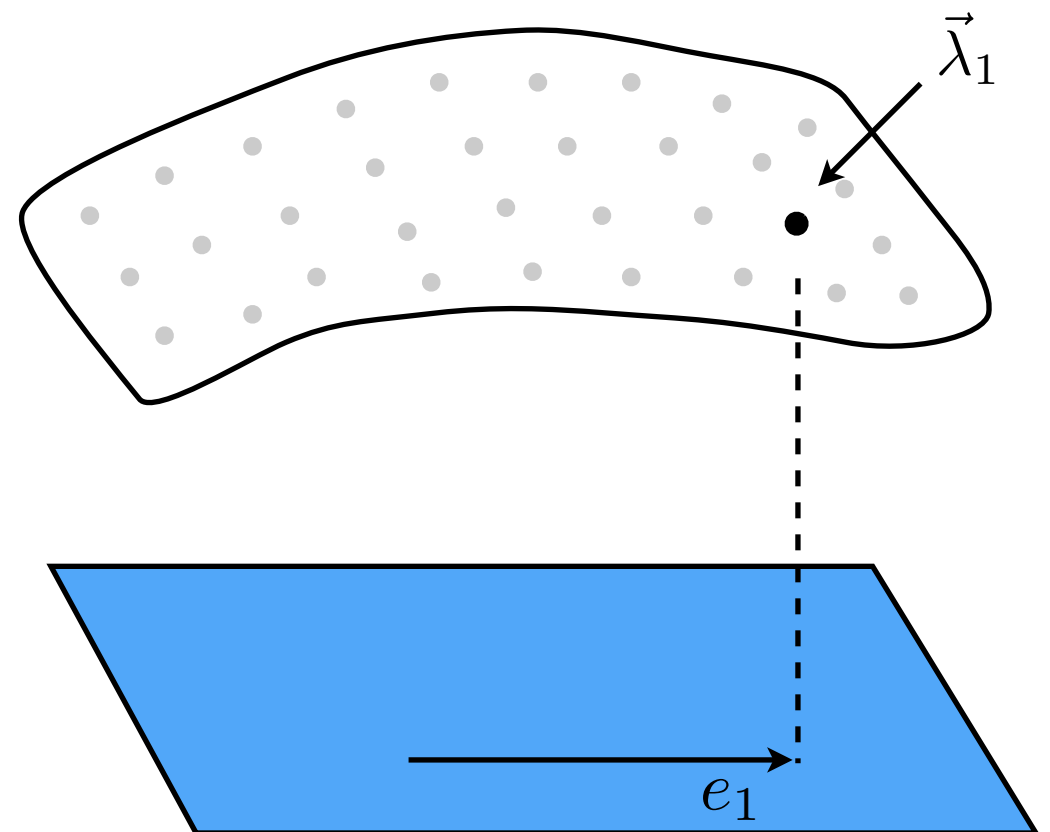
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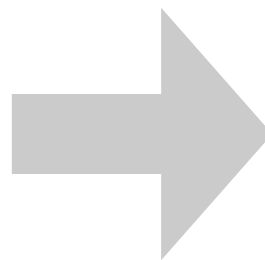
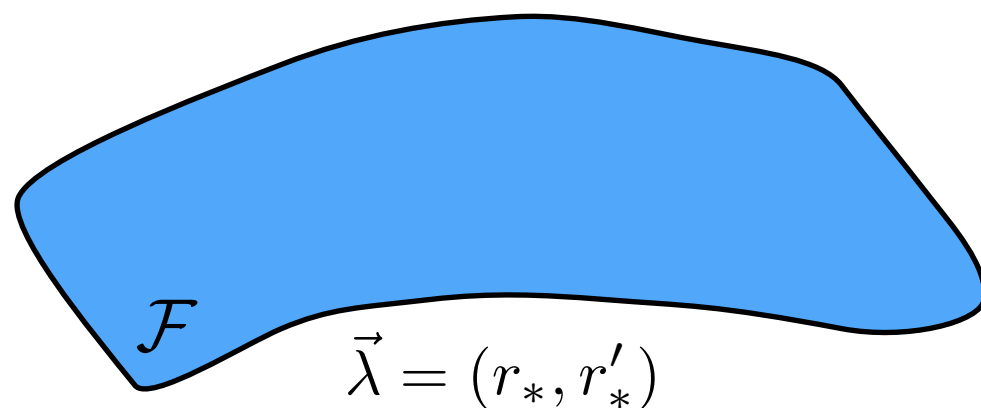


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 $e_1 = G_\ell(t; \vec{\lambda}_1), C_1 = \{e_1\}$

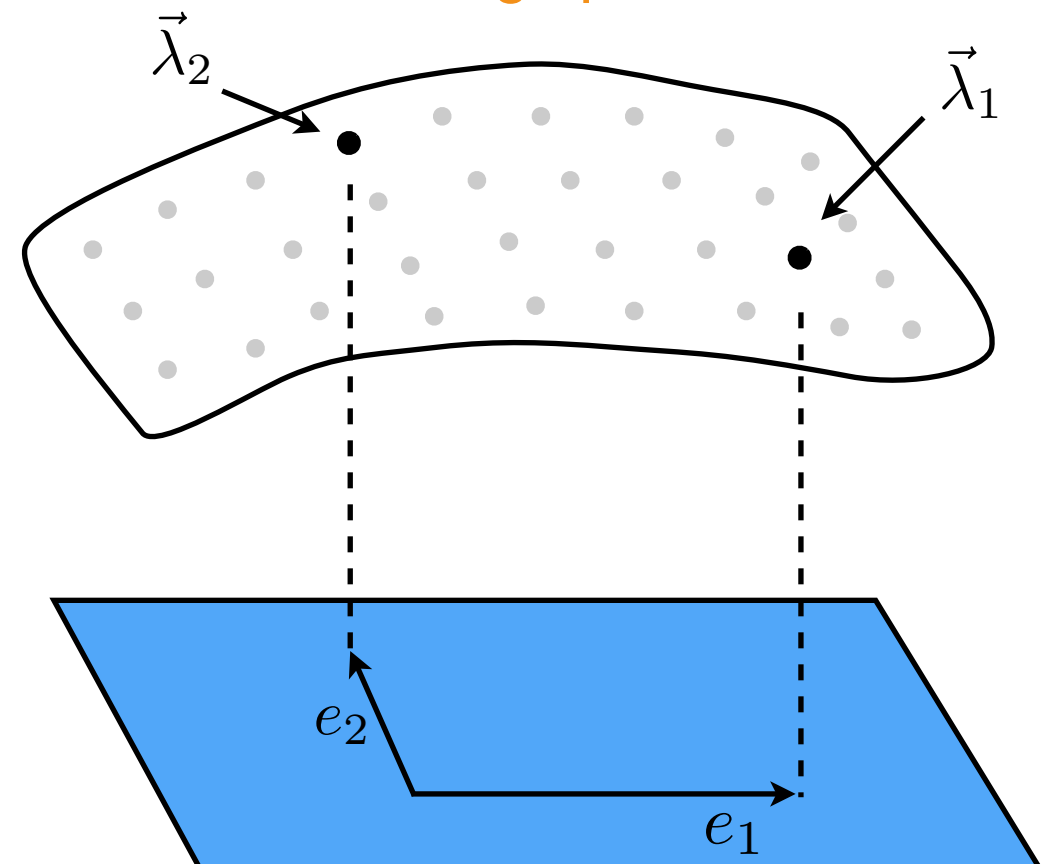
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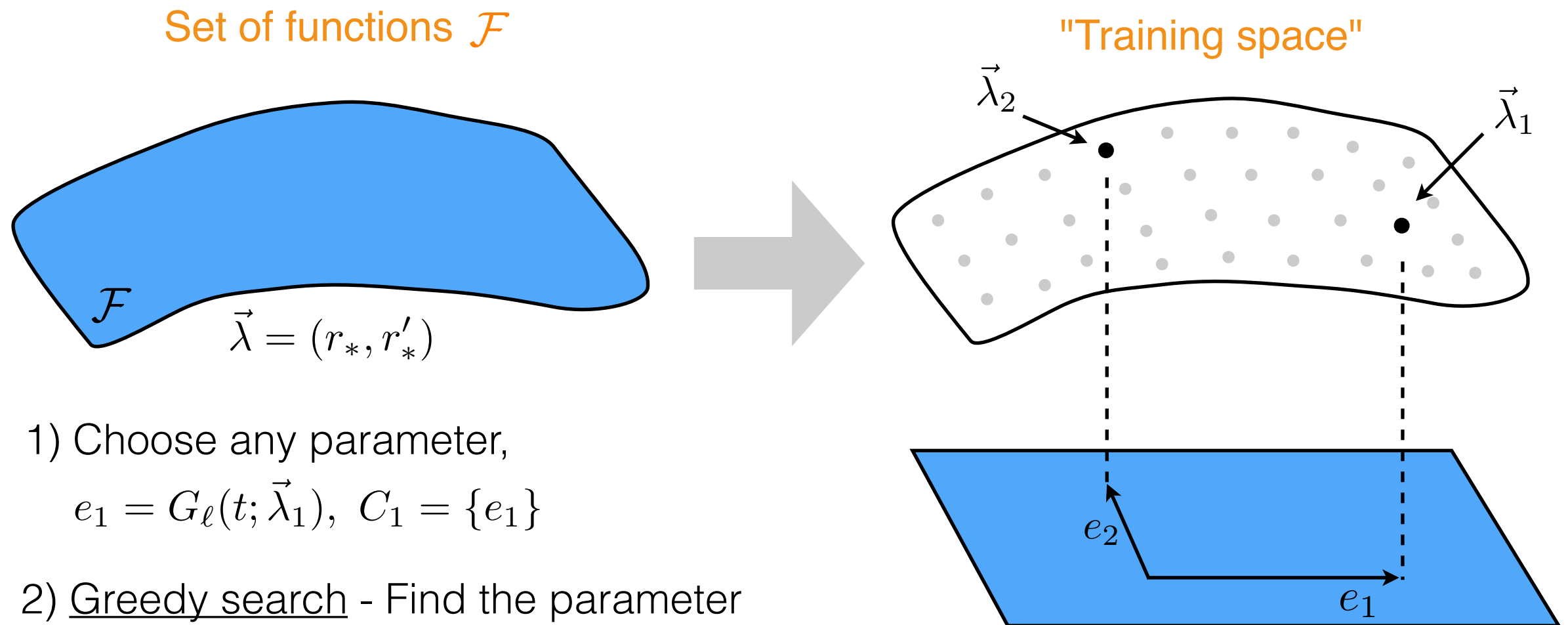
$$e_1 = G_\ell(t; \vec{\lambda}_1), \quad C_1 = \{e_1\}$$

2) Greedy search - Find the parameter that maximizes:

$$\max_t |G_\ell(t; \vec{\lambda}) - P_1[G_\ell(t; \vec{\lambda})]|, \quad P_1[\cdot] = e_1 \langle e_1, \cdot \rangle$$

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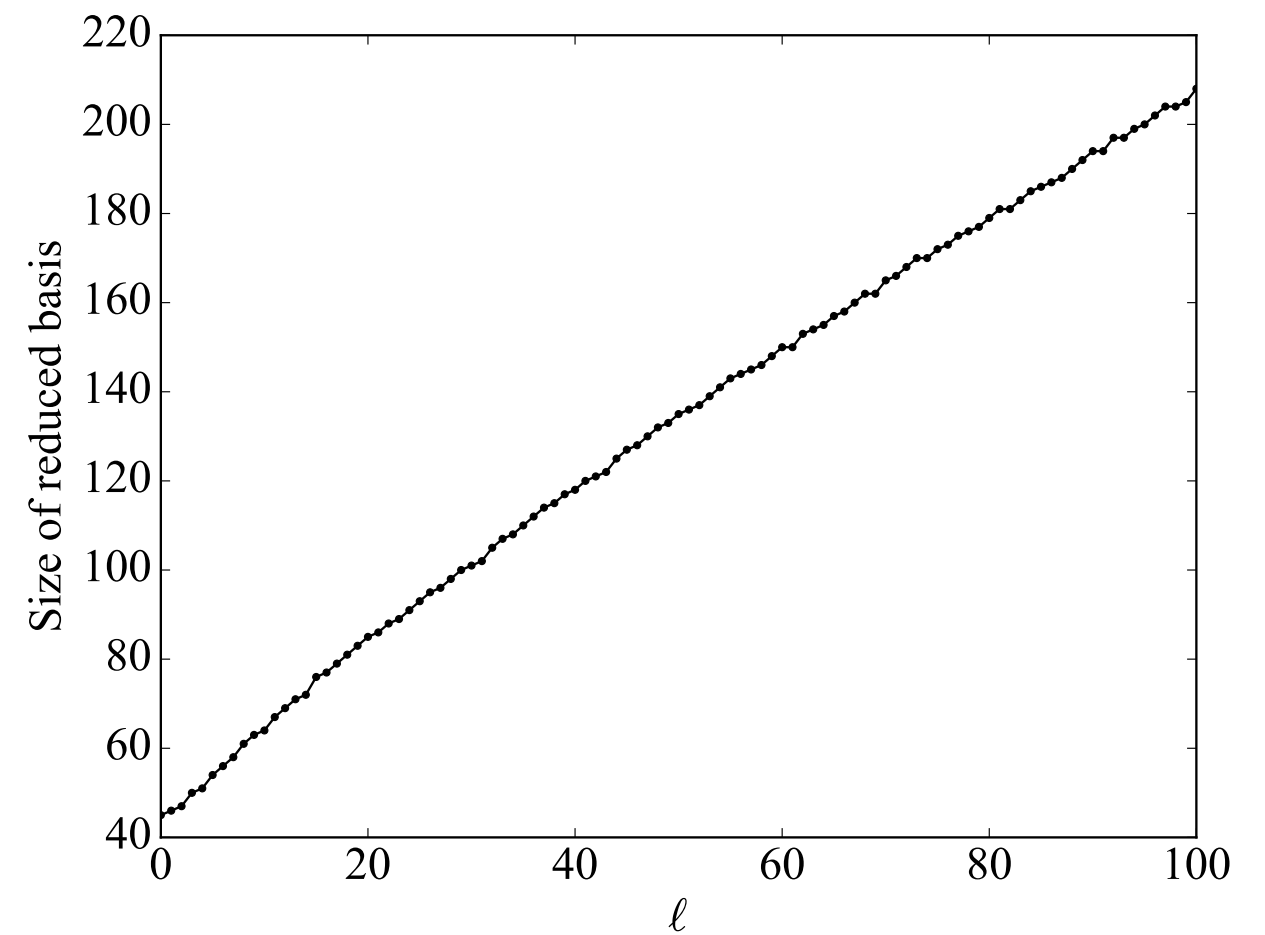
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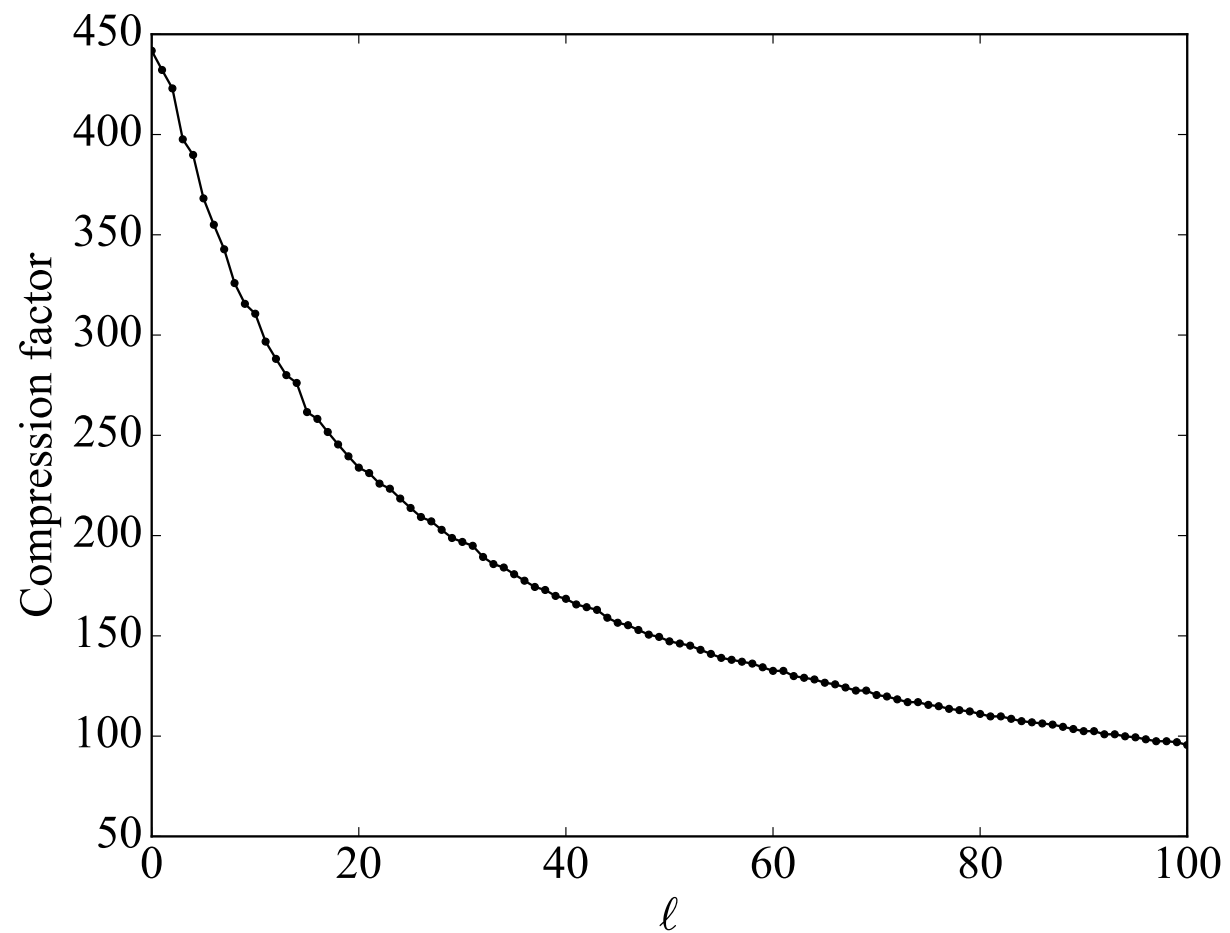
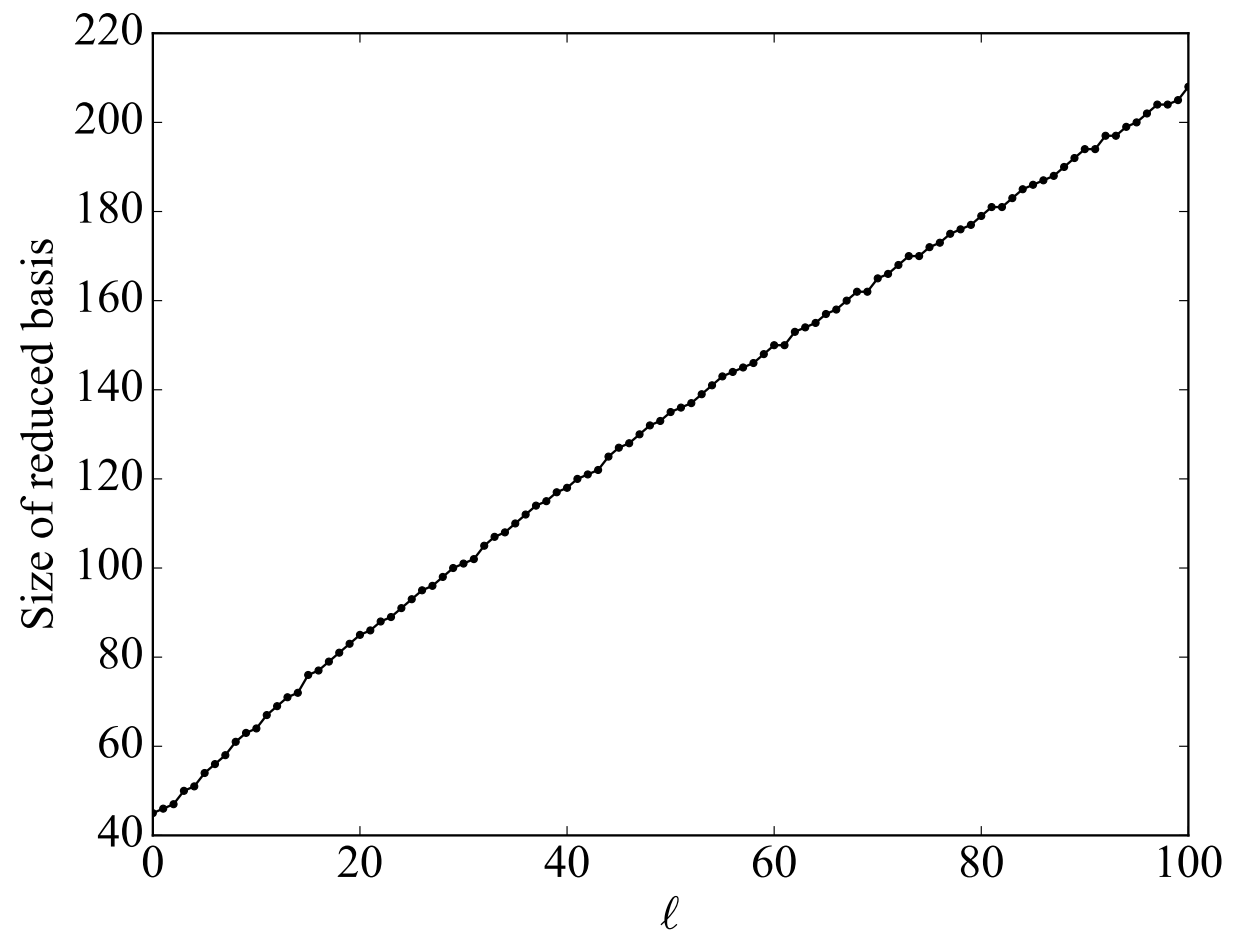
3) Orthogonalization to get basis vector e_2

$$C_2 = \{e_1, e_2\}, \quad C_1 \subset C_2$$

Basis size grows nearly linearly
with mode number



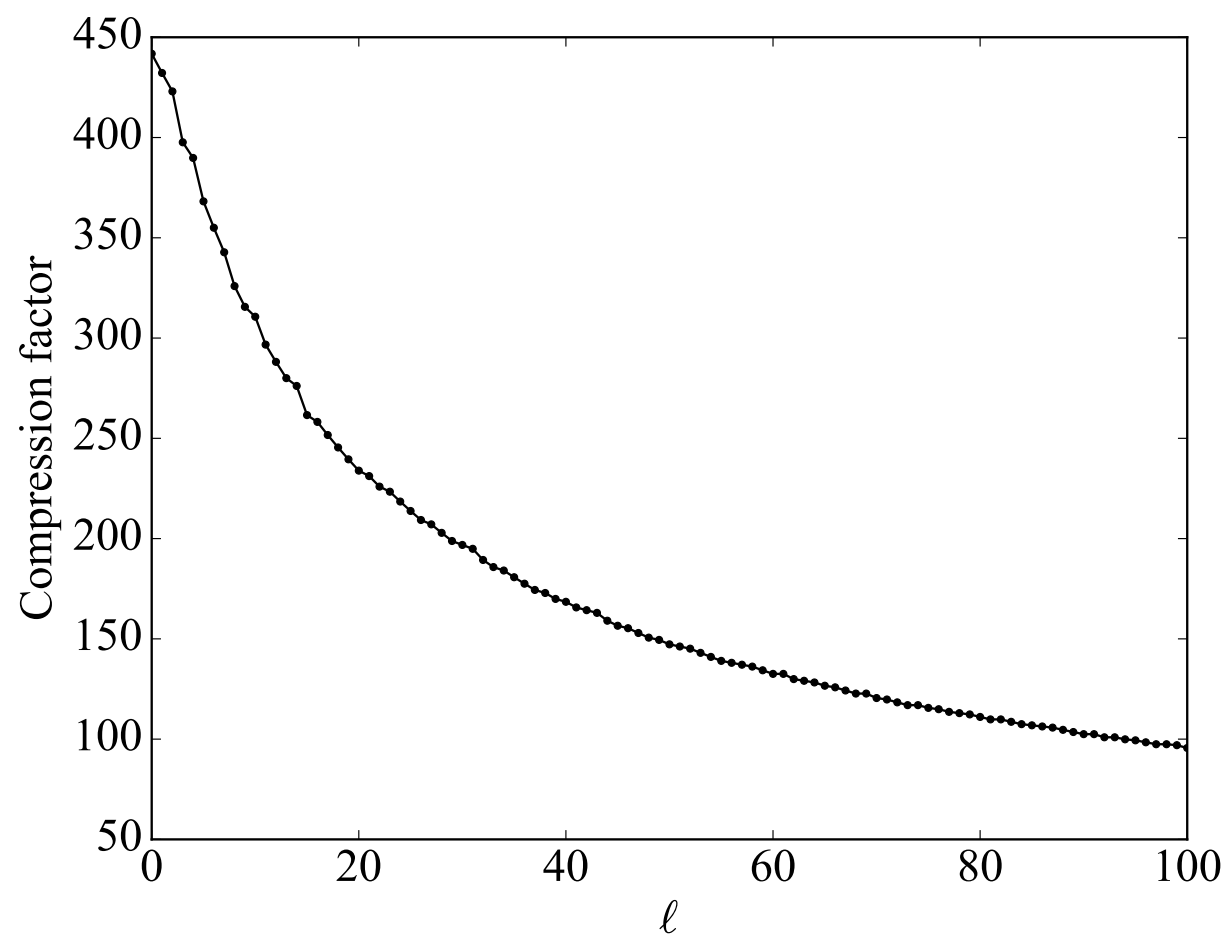
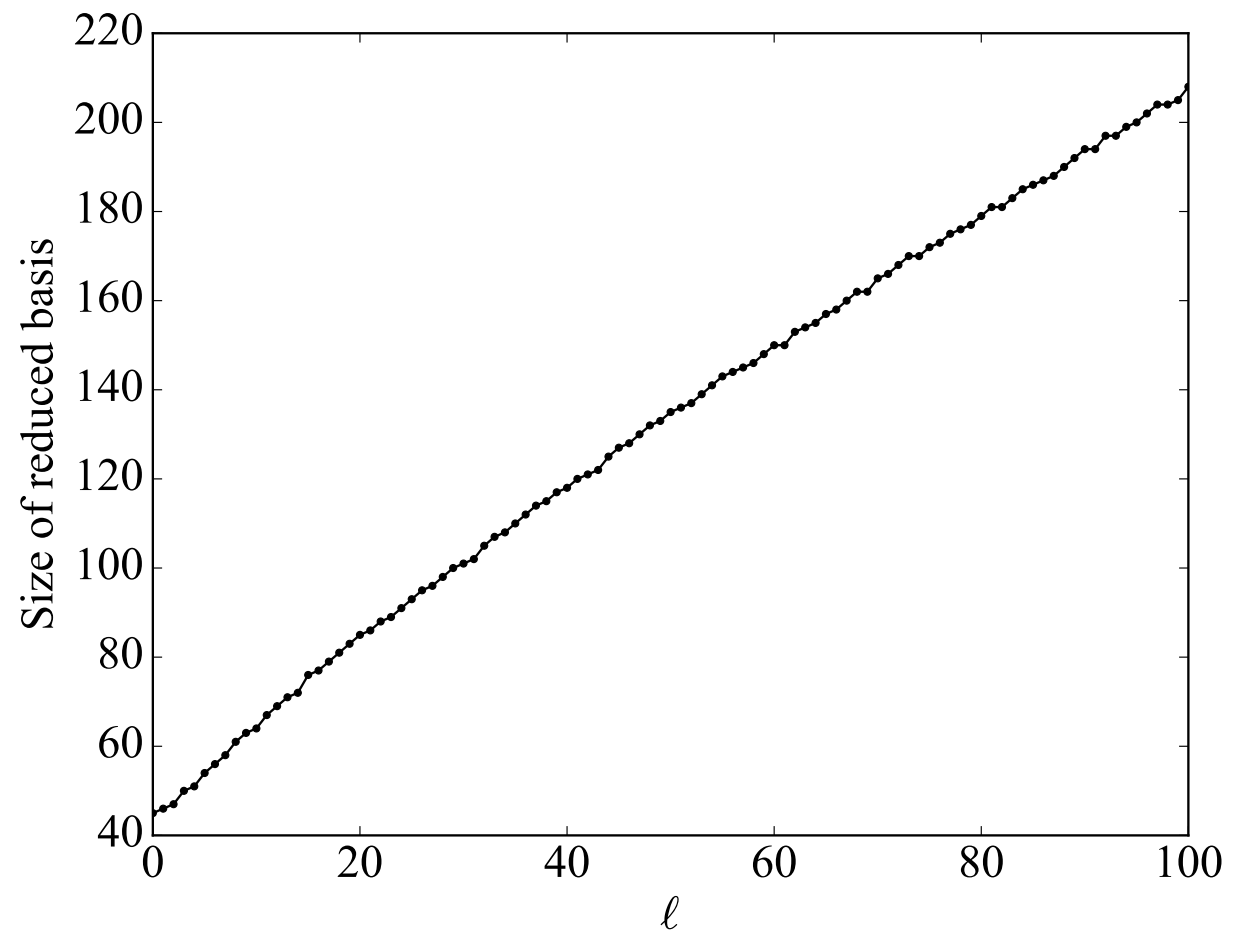
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Total compression factor:

$$C_{\text{total}} = (\ell_{\text{max}} + 1) \left(\sum_{\ell=0}^{\ell_{\text{max}}} \frac{1}{C_{\ell}} \right)^{-1} \approx 151$$

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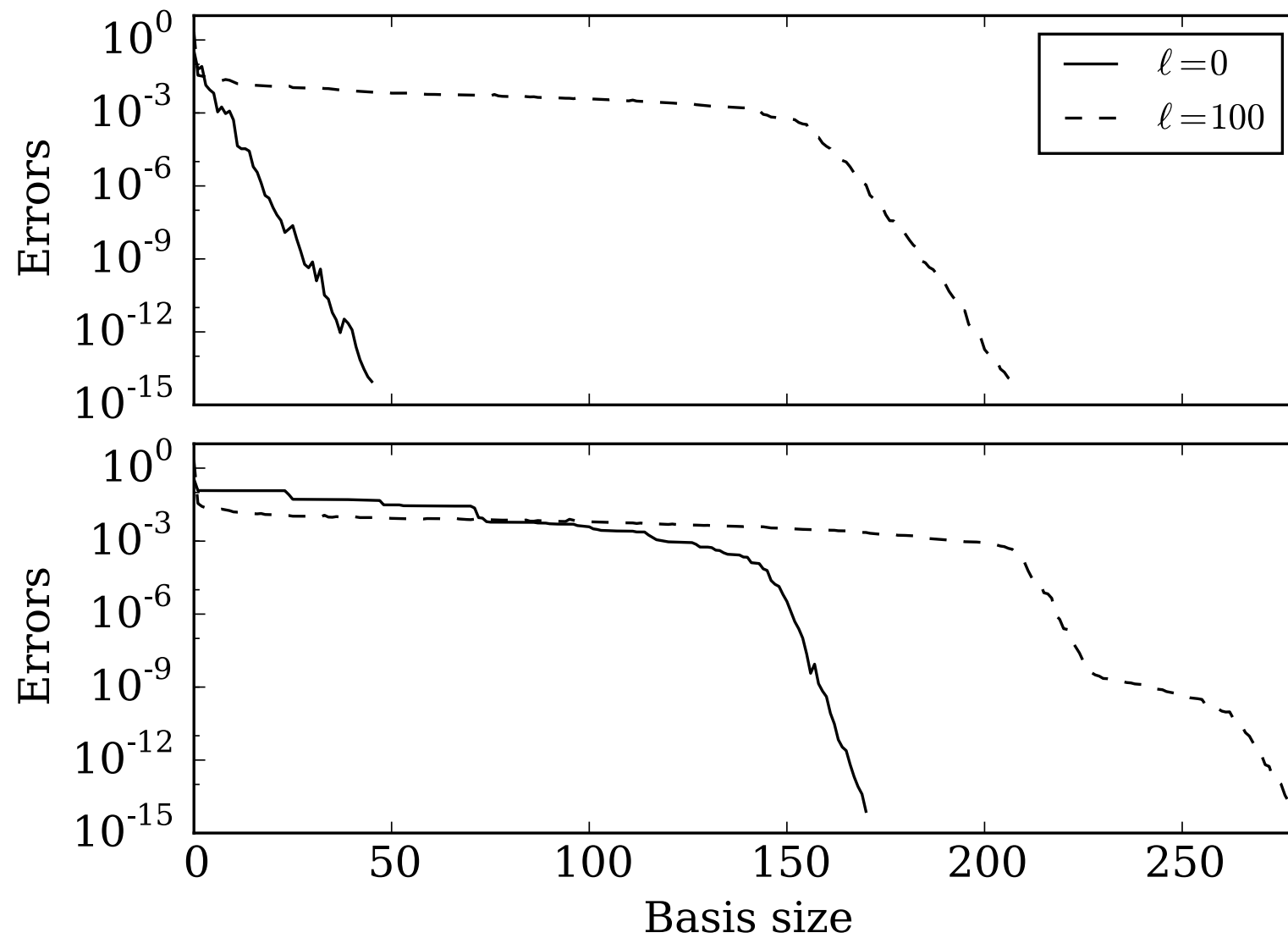


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Less than 1% of the data is
needed to capture all features
up to numerical round-off errors

Shifting by time-of-arrival



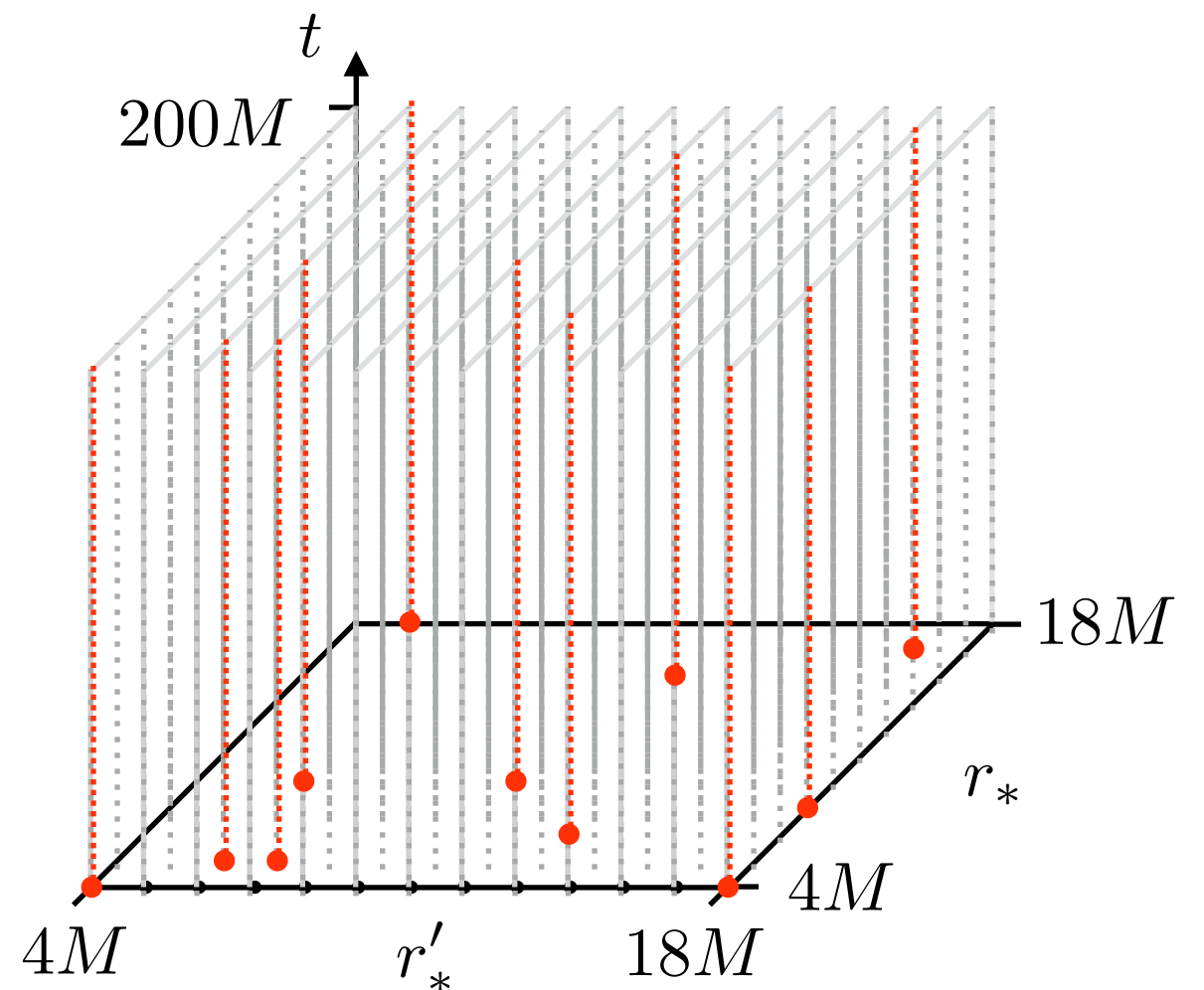
Not shifting by time-of-arrival

2) Empirical interpolation

Barrault+ (04)
Maday+ (09)

RB approximation:

$$G_\ell(t; \vec{\lambda}) \approx \sum_{i=1}^{N_\ell} C_i^\ell(\vec{\lambda}) e_i^\ell(t)$$



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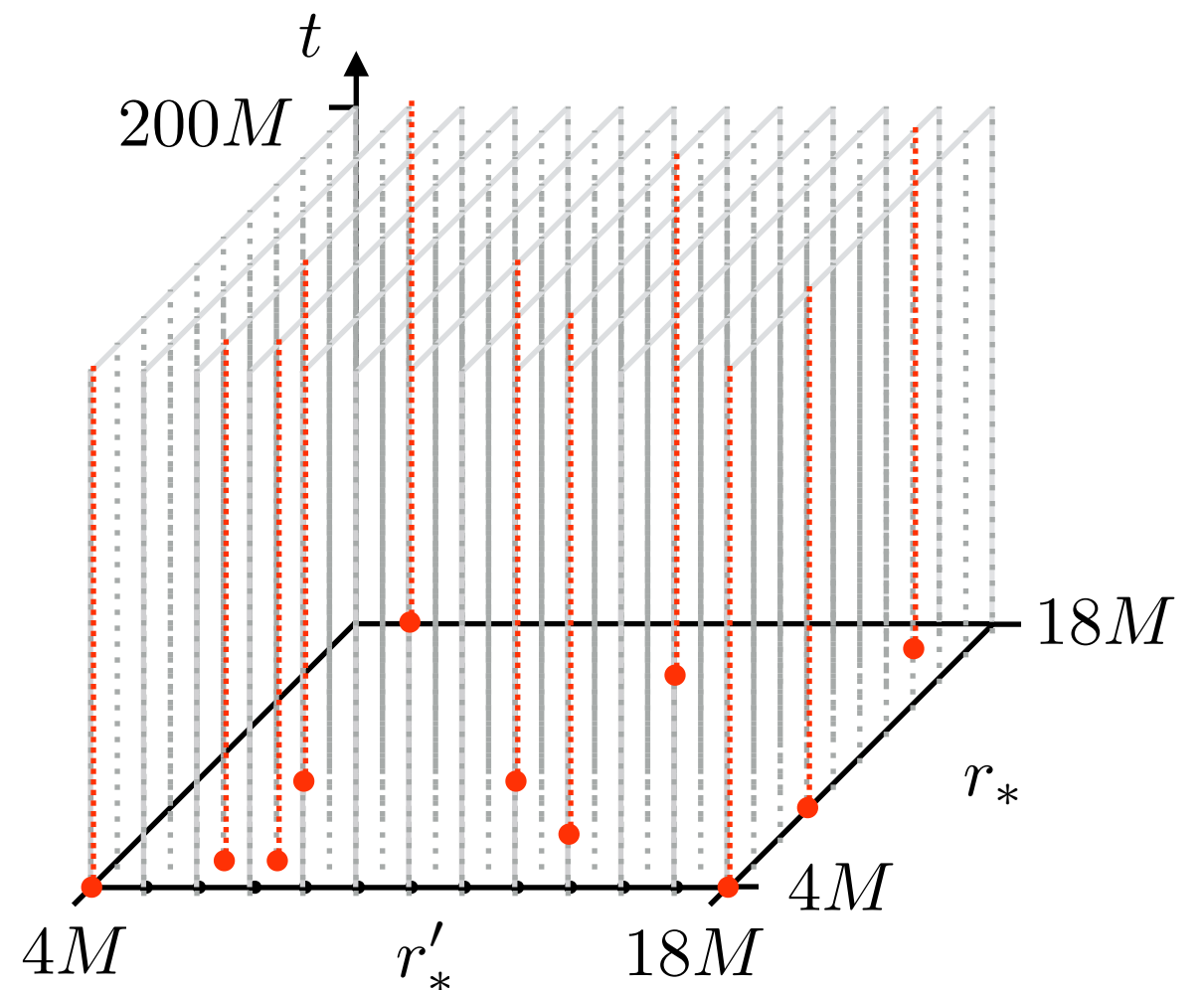
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At n time subsamples of data, $\{T_i\}_{i=1}^n$
the coefficients can be solved

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Barrault+ (04)
Maday+ (09)

RB approximation:

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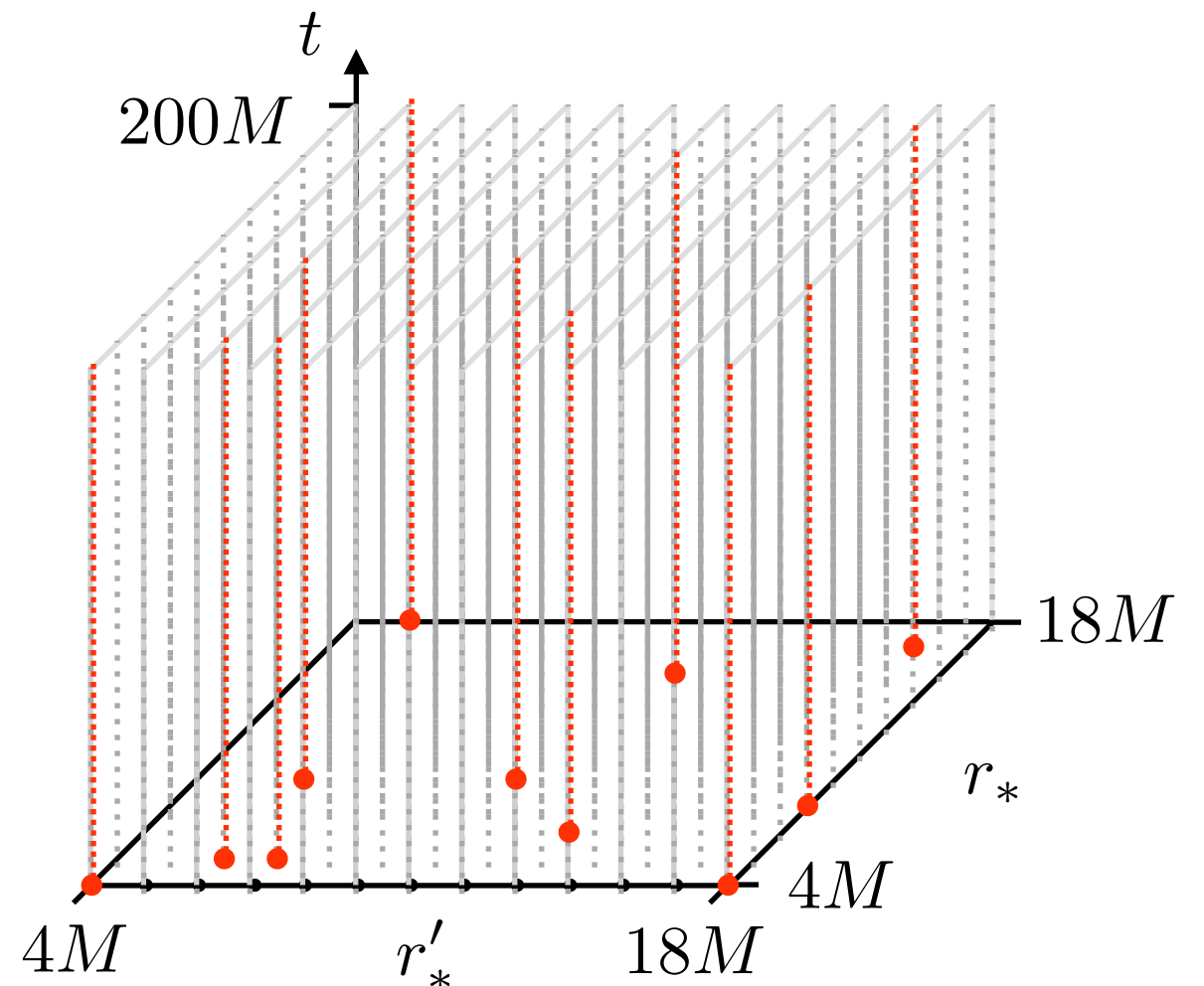
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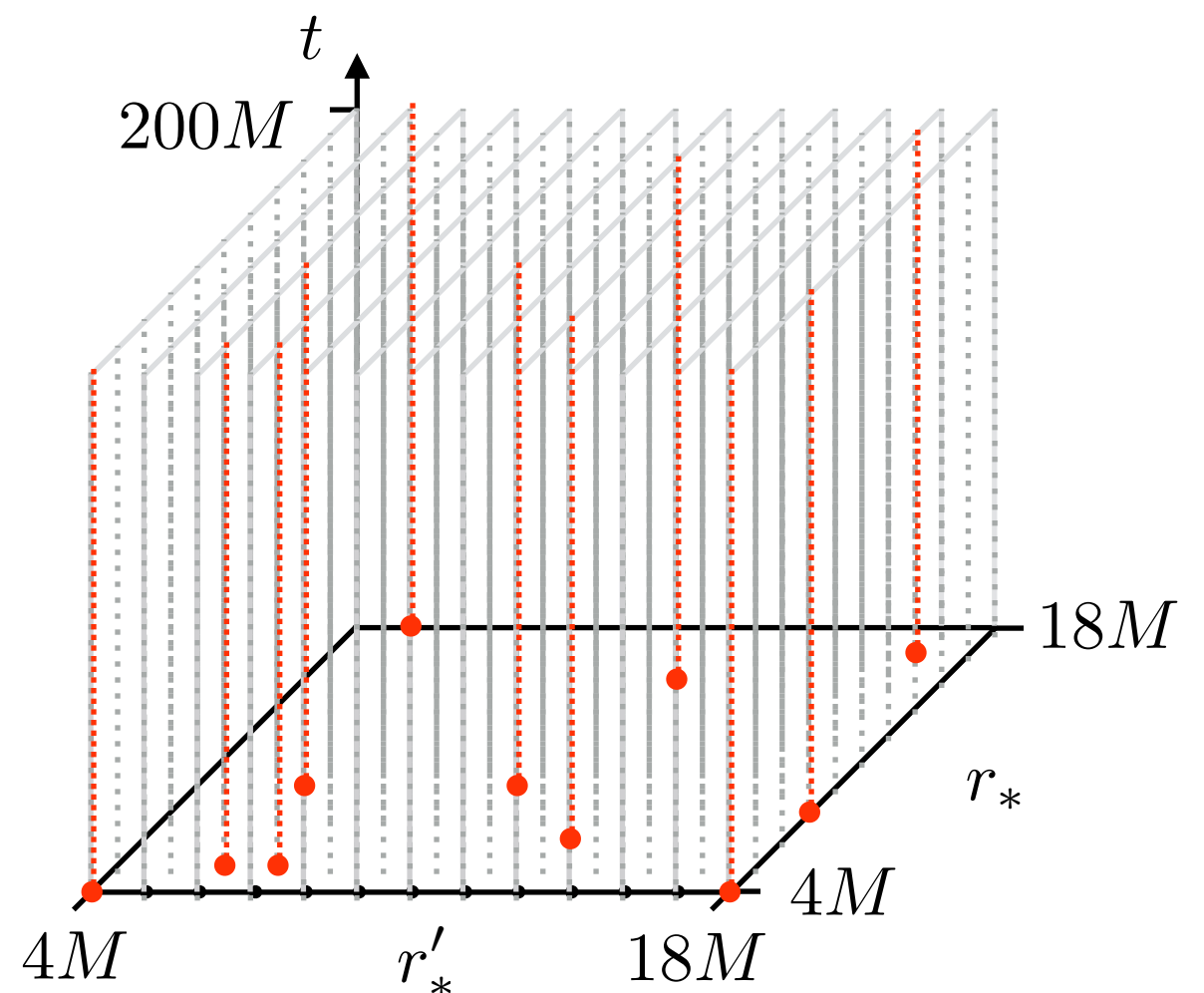
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Find the interpolation nodes through
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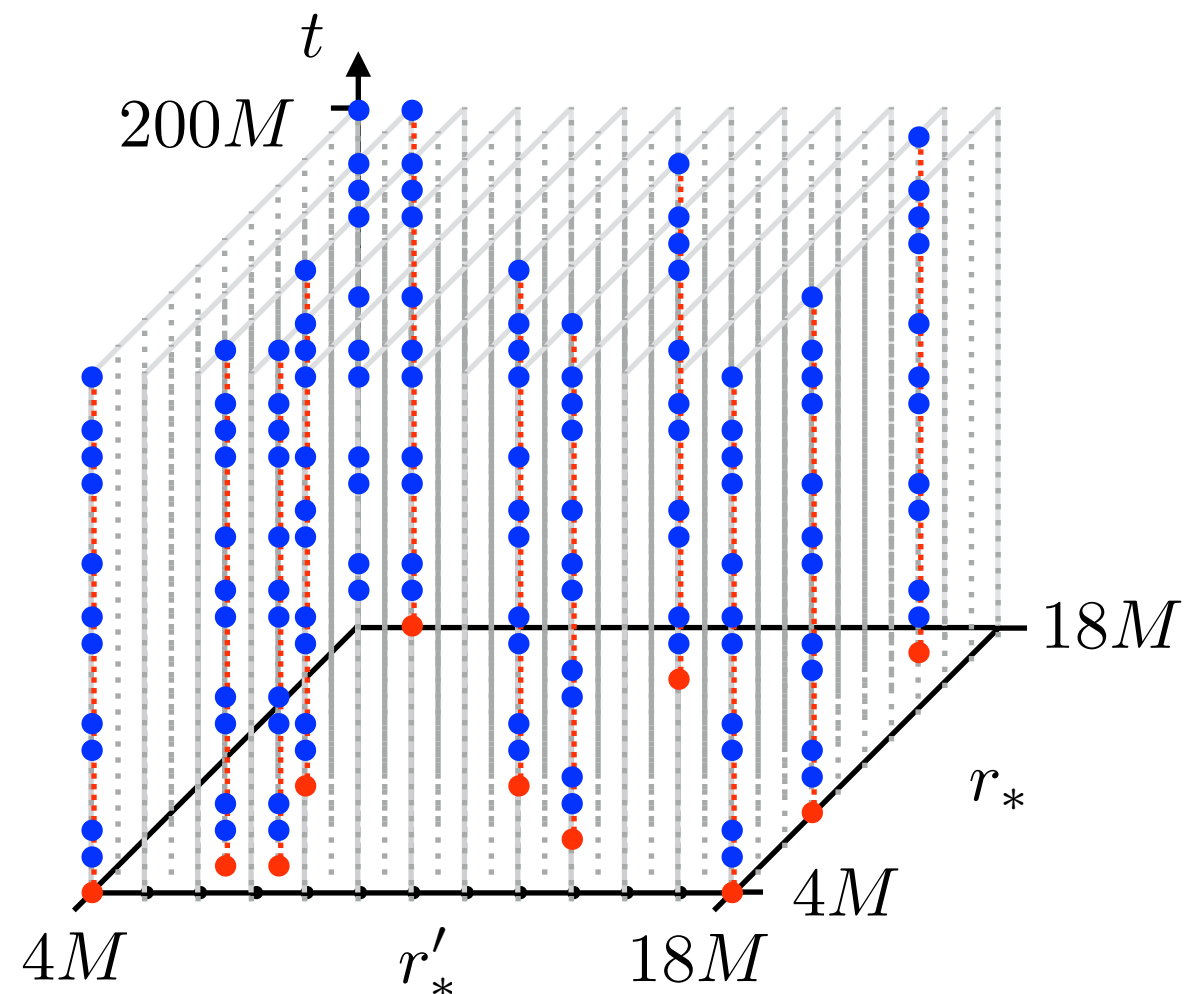
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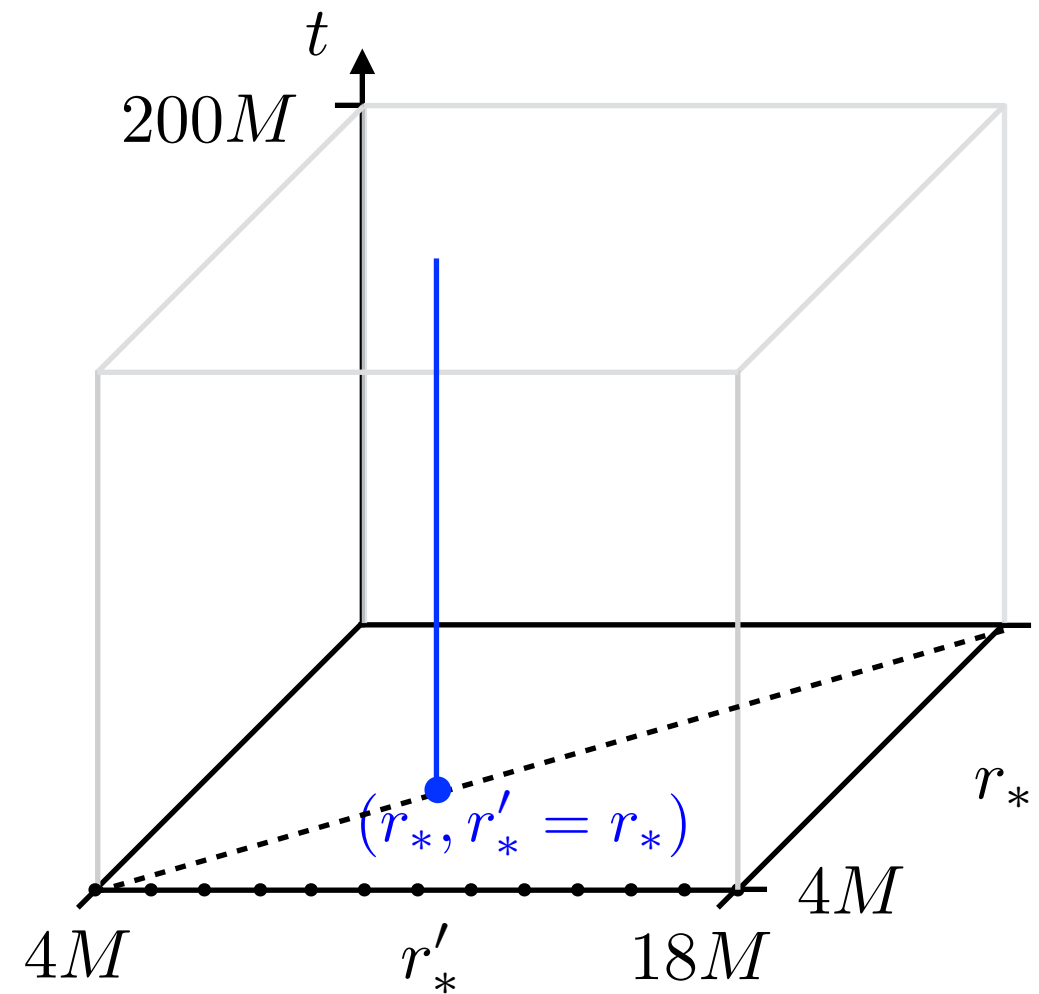
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3) Parametric fitting — $r^* = \text{constant}$

Mostly interested in computing Green's function on worldlines for self-force

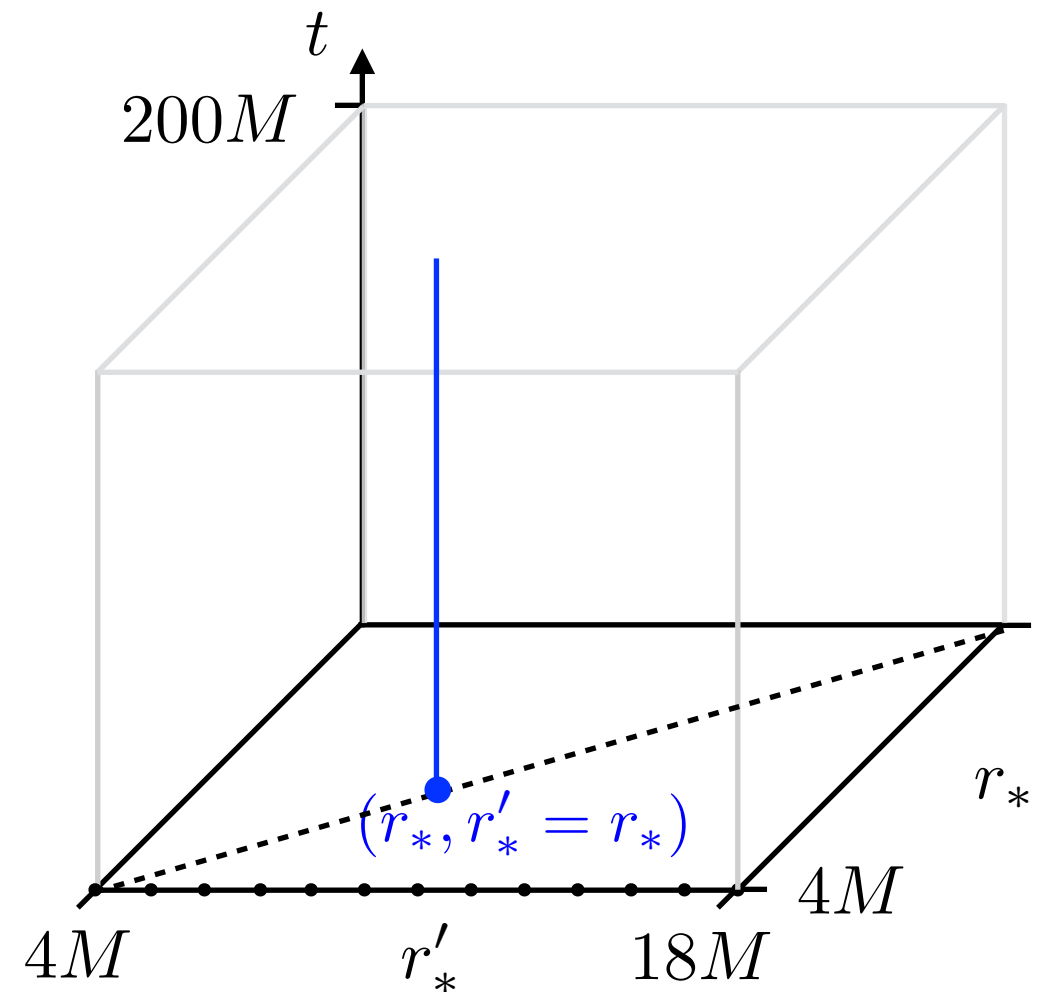


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The surrogate is simple to evaluate on worldlines with $r_* = \text{constant}$

- static worldlines
- circular geodesics
- accelerated circular worldlines



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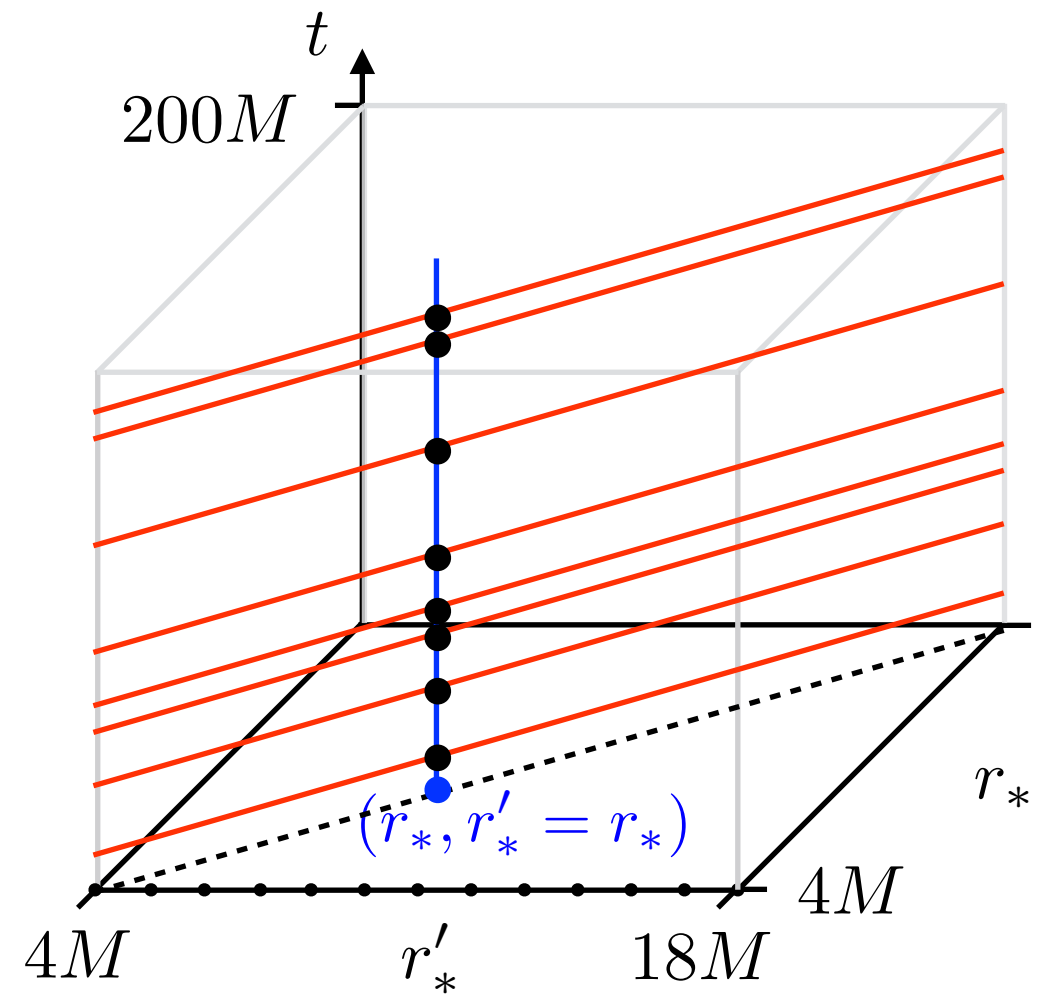
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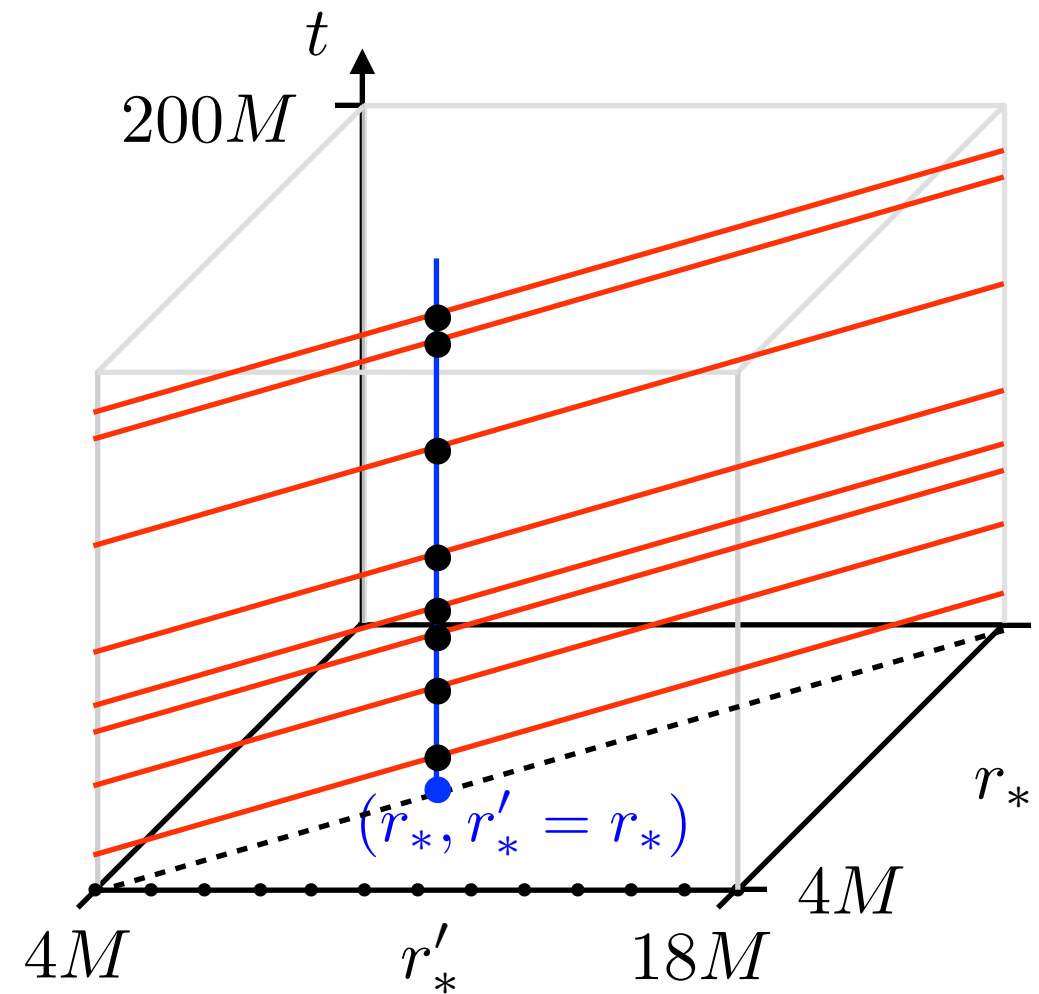
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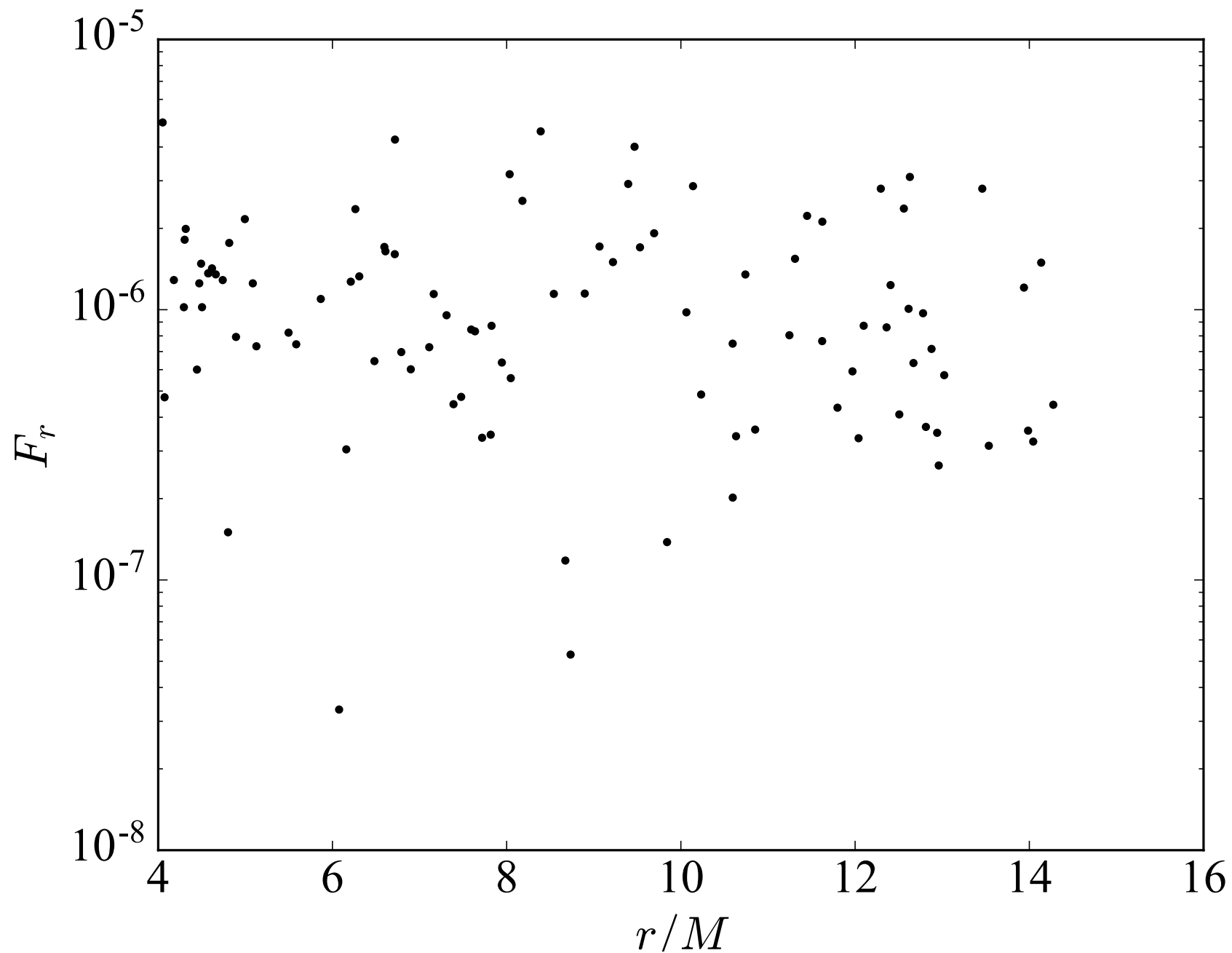
Total compression: 30GB / 192MB = 156

Speed-up: 380s / 0.5s = 760x

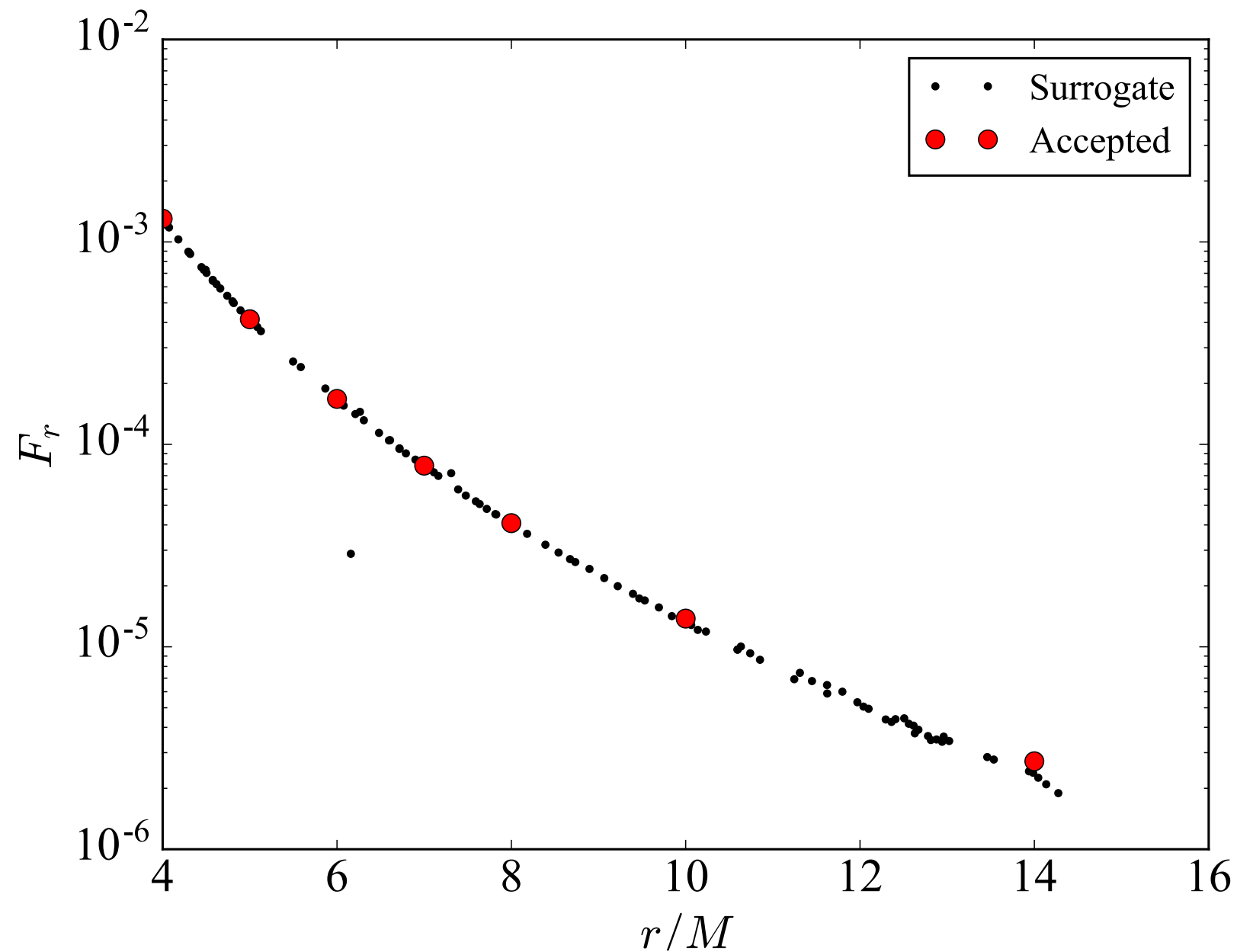


Static self-force

Analytically derived and found to be zero *Wiseman (00)*



Self-force on circular geodesics



Accepted or “truth” values computed in *Diaz-Rivera et al (04)*

3) Parametric fitting — generic case

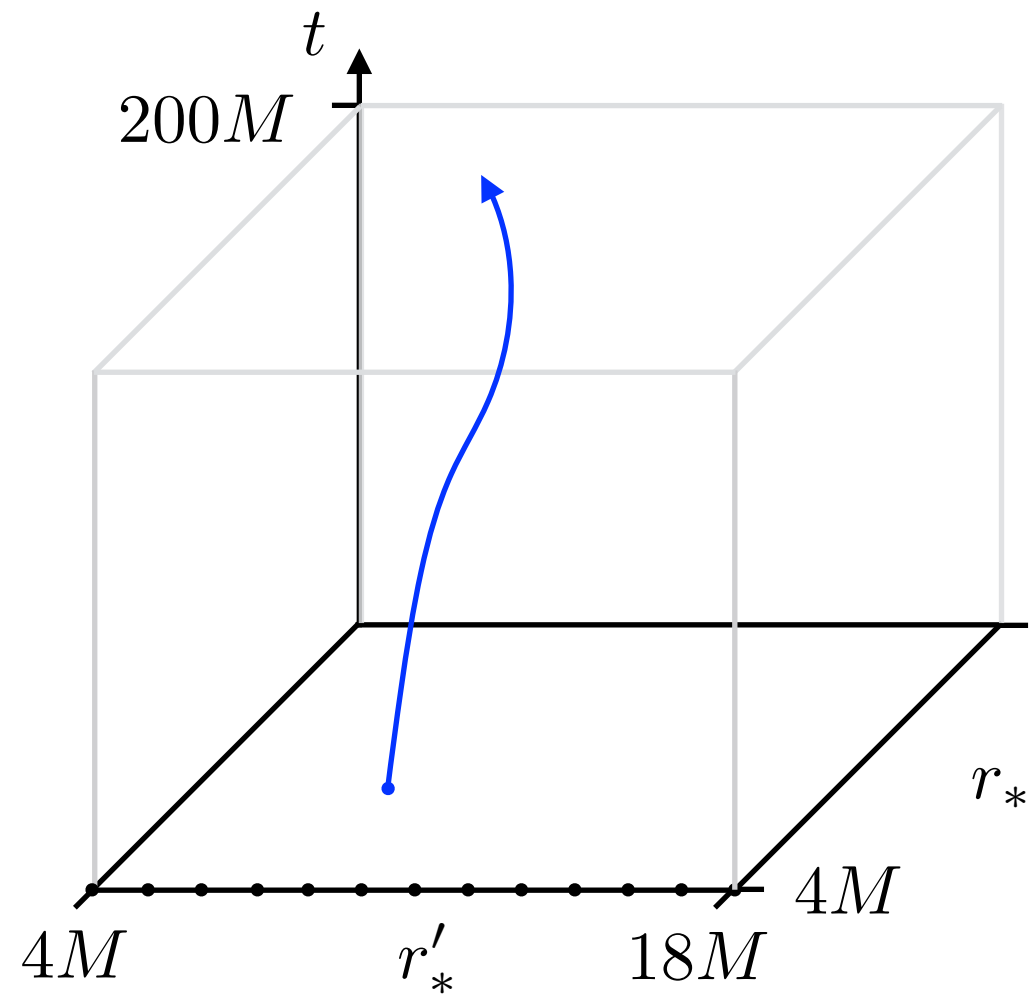
More general worldlines

$$z^\mu(t) = (t, r(t), \pi/2, \gamma(t))$$

destroy the affine nature
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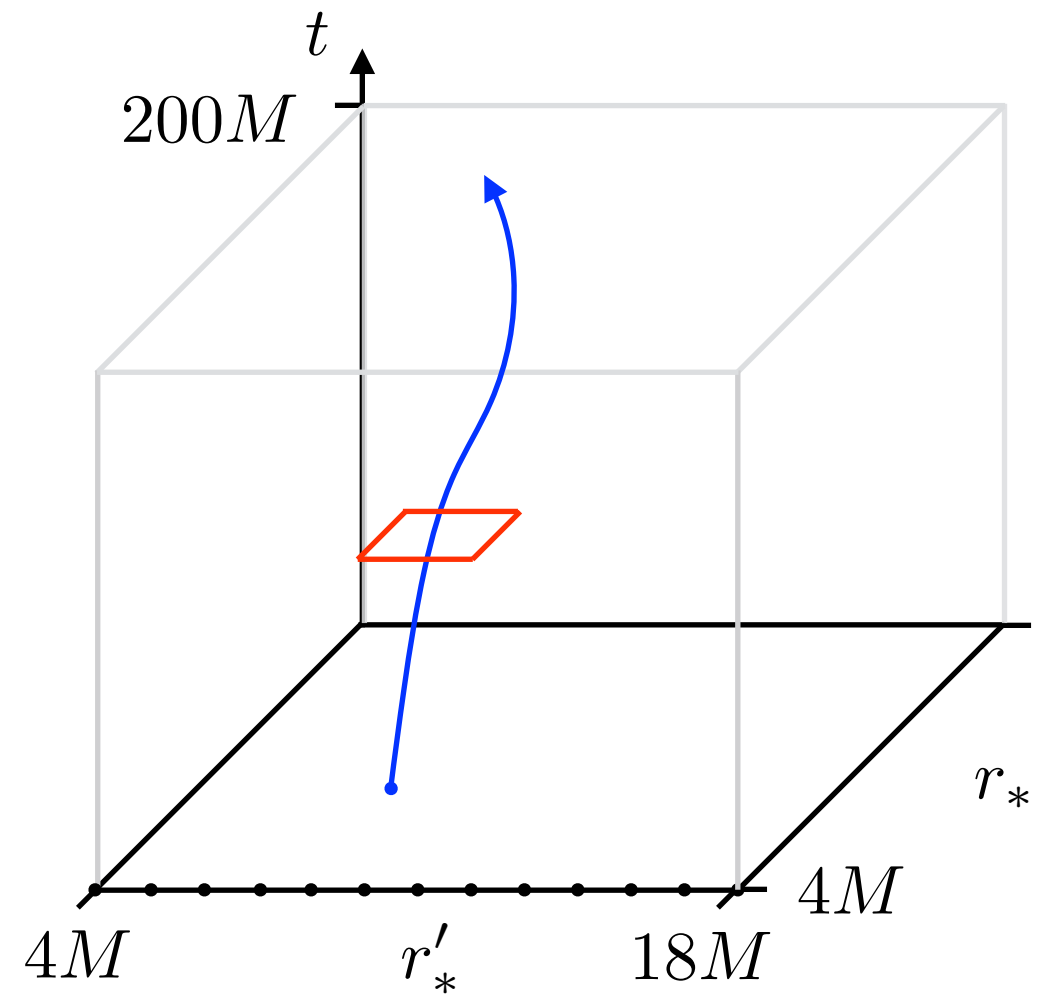
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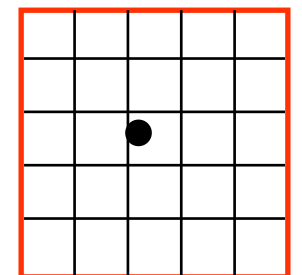
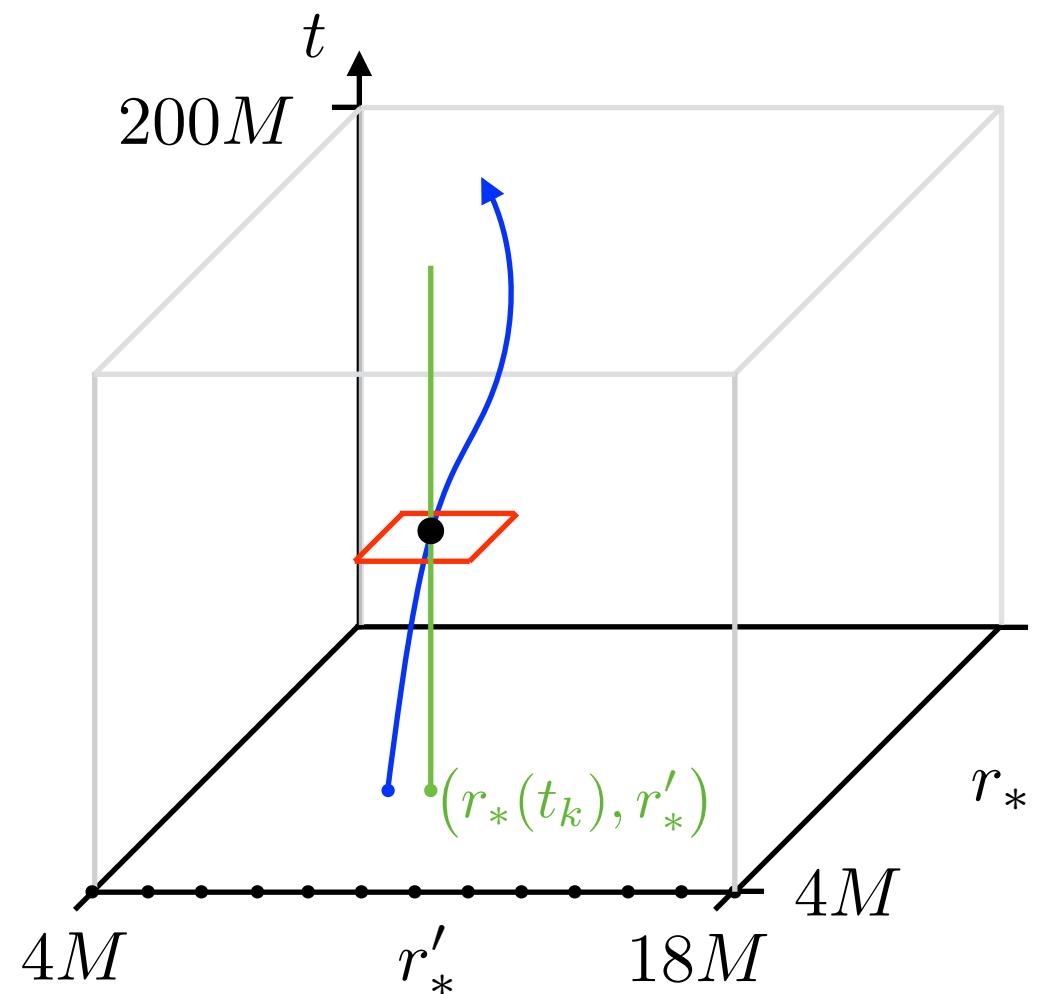
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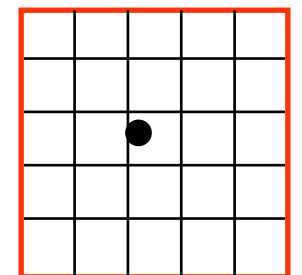
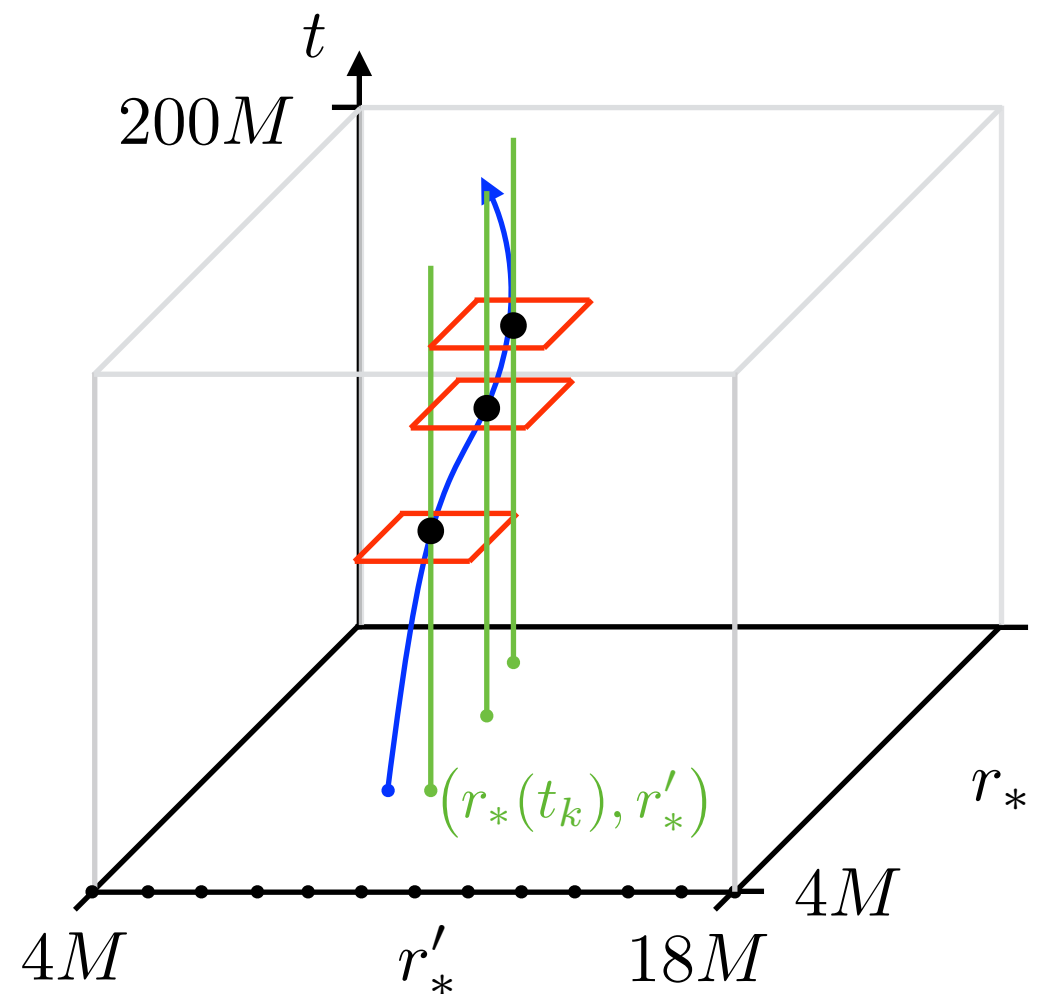
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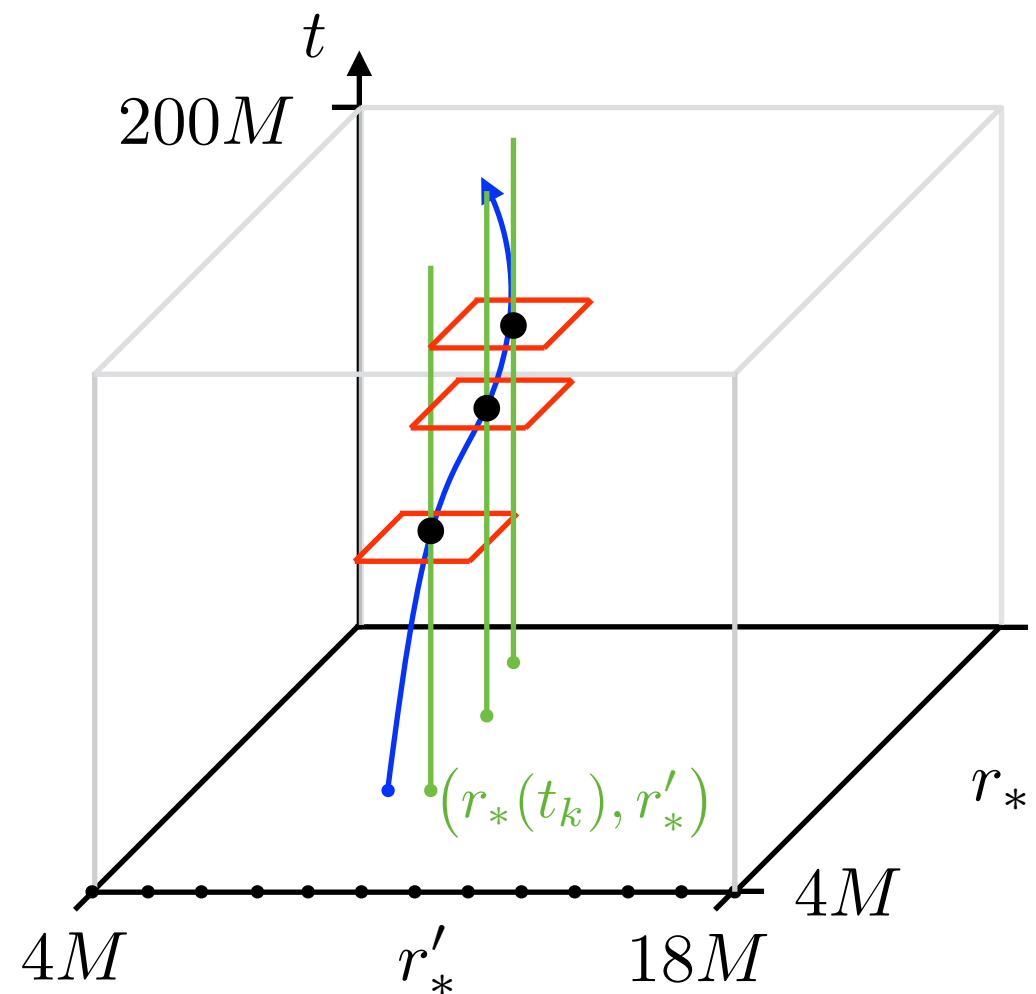
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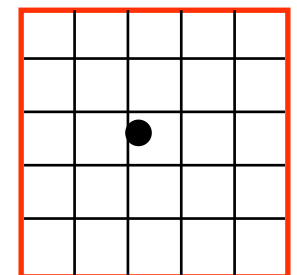
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Slower and need to
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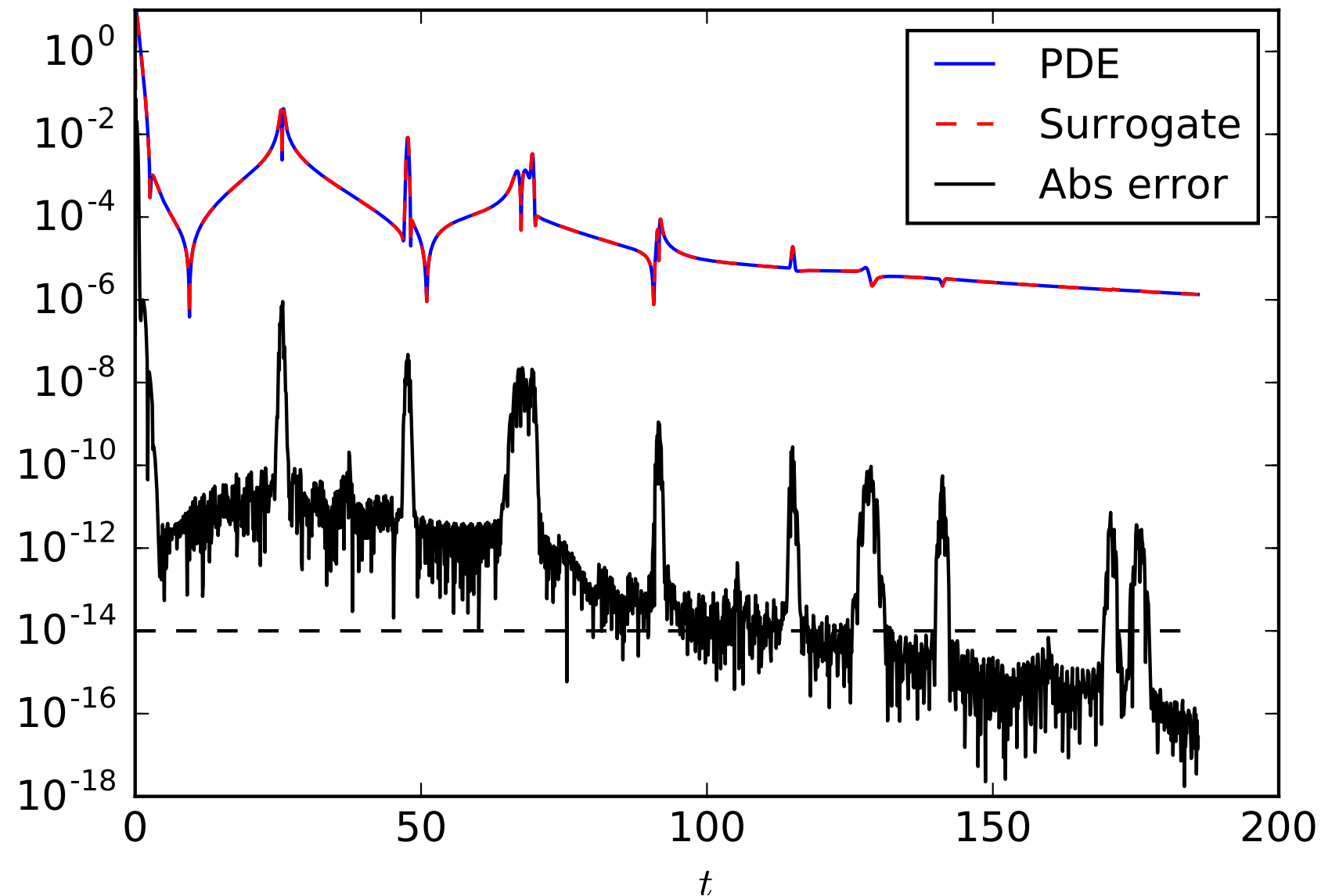


Surrogate accuracy, speed-up, and size

Eccentric geodesic orbit ($e = 0.5$, $p = 7.2$)

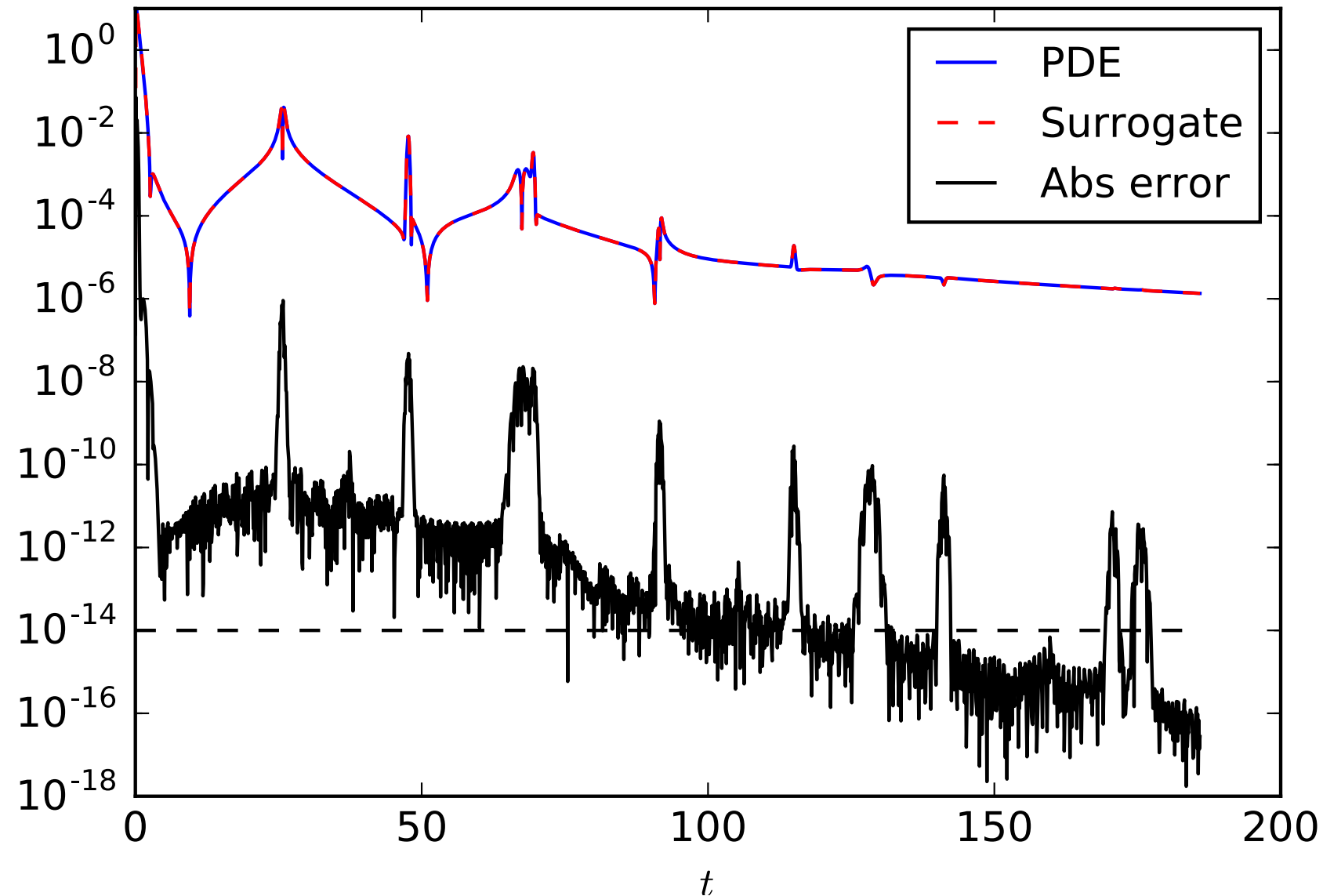
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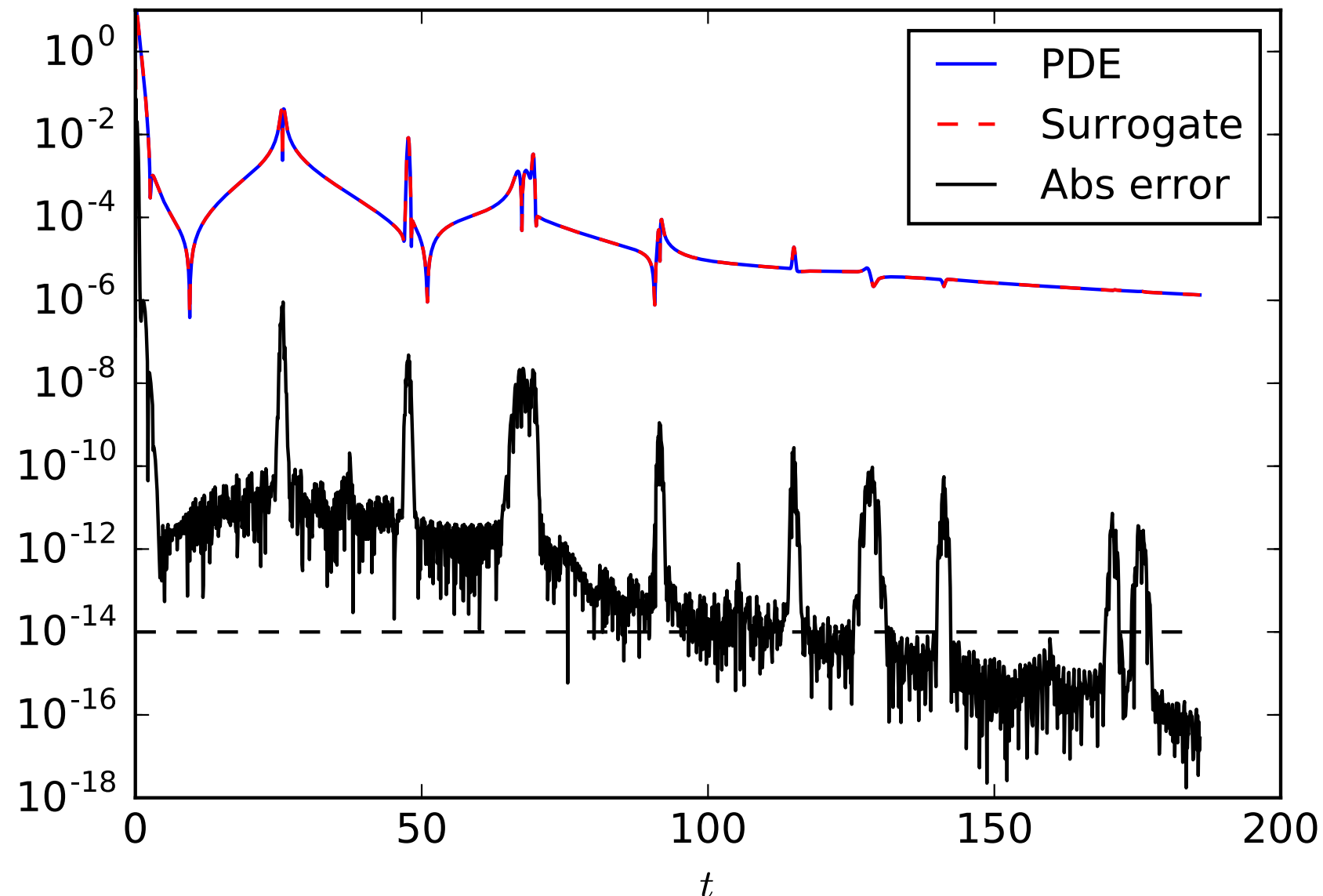


PDE	~380s
Surrogate	~25s
<hr/>	
Speed-up*	~15x

* PDE in C++
Surrogate in Python

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Physical memory: 30GB reduced to 2GB

Surrogate self-force evaluation

$$\begin{aligned} G_{\text{ret}}(z^\mu, z^{\mu'}) \\ \approx \theta(\tau - \tau_{\text{ql}}) \text{Pade}[V_{\text{ql}}(z^\mu, z^{\mu'})] \\ + \theta(\tau_{\text{ql}} - \tau) \theta(\tau - \tau_{\text{br}}) G_{\text{surr}}(z^\mu, z^{\mu'}) \\ + \theta(\tau_{\text{br}} - \tau) G_{\text{br}}(z^\mu, z^{\mu'}) \end{aligned}$$

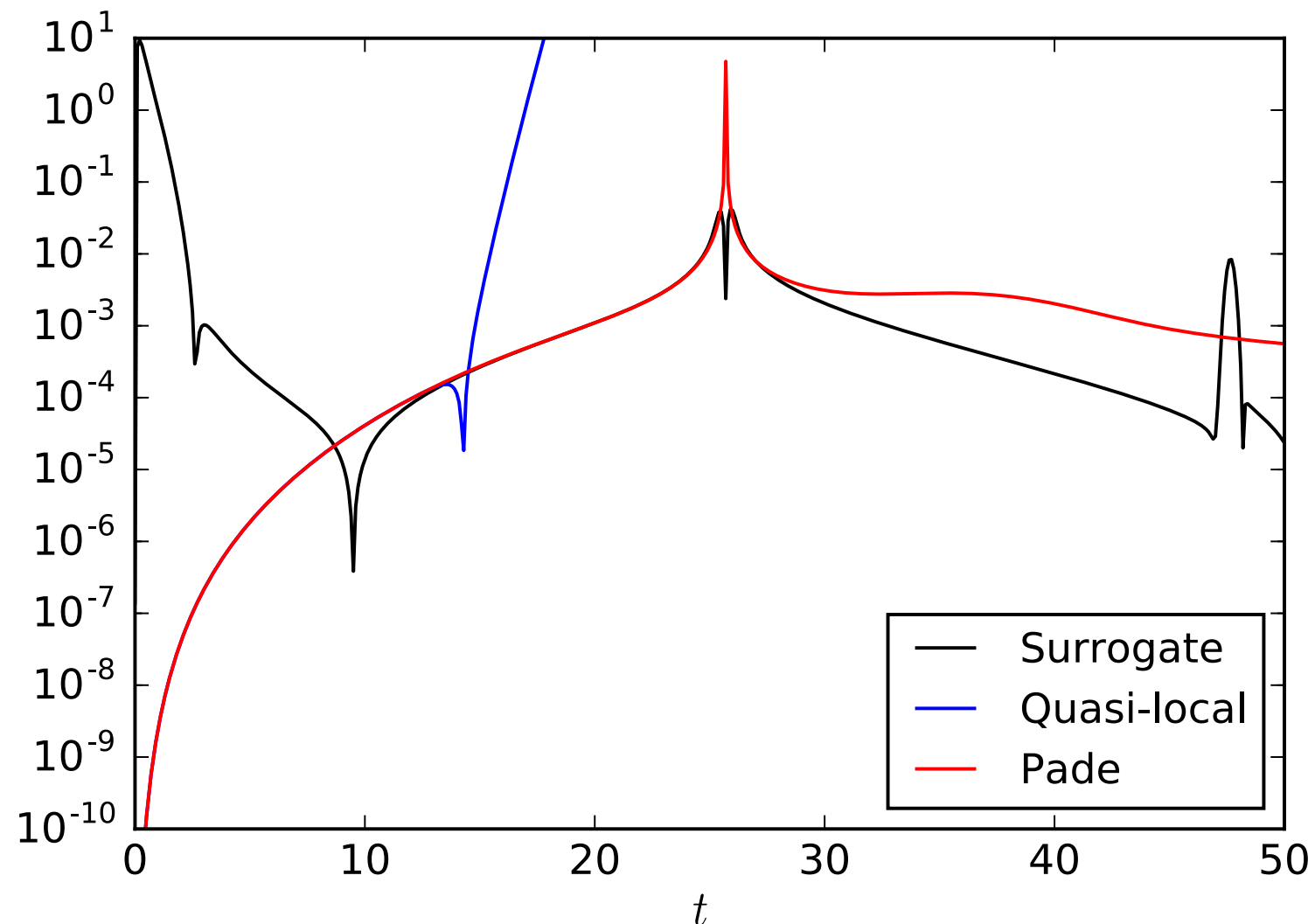
- Method of matched expansions

Anderson & Wiseman (05); Casals et al (13)

- Quasi-local expansions

Ottewill & Wardell (08); Wardell's thesis

- Pade approximants *Casals et al (09)*



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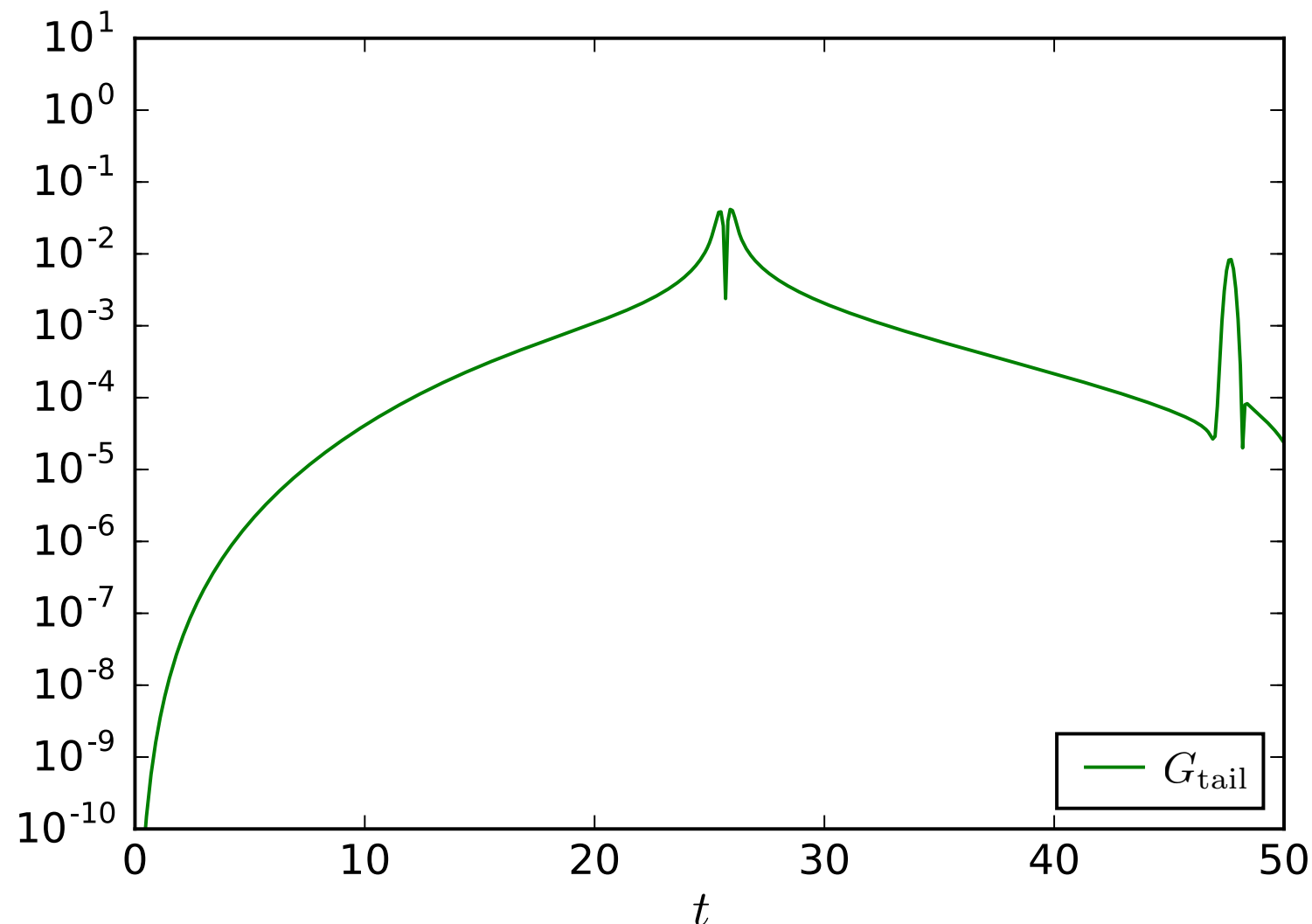
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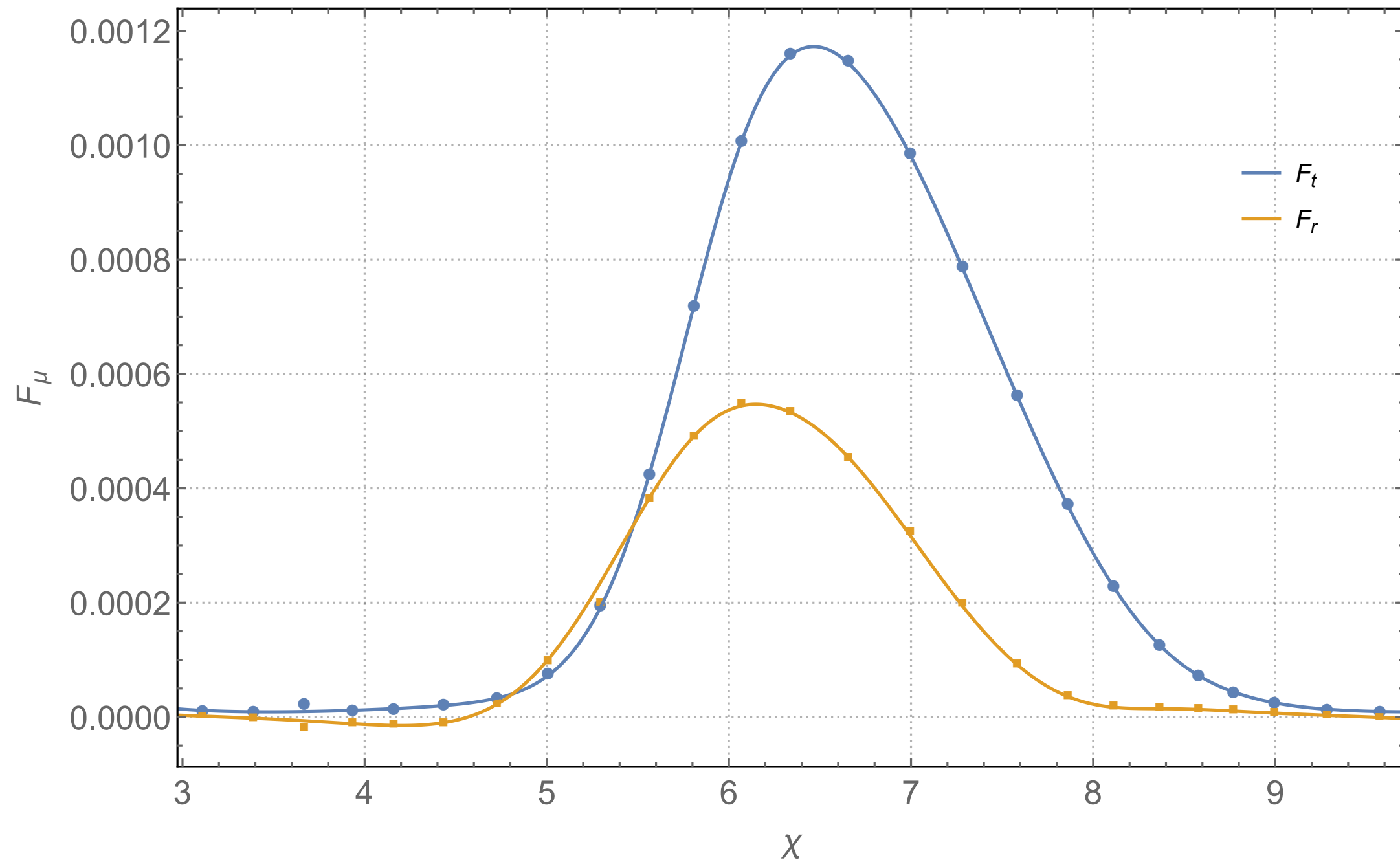
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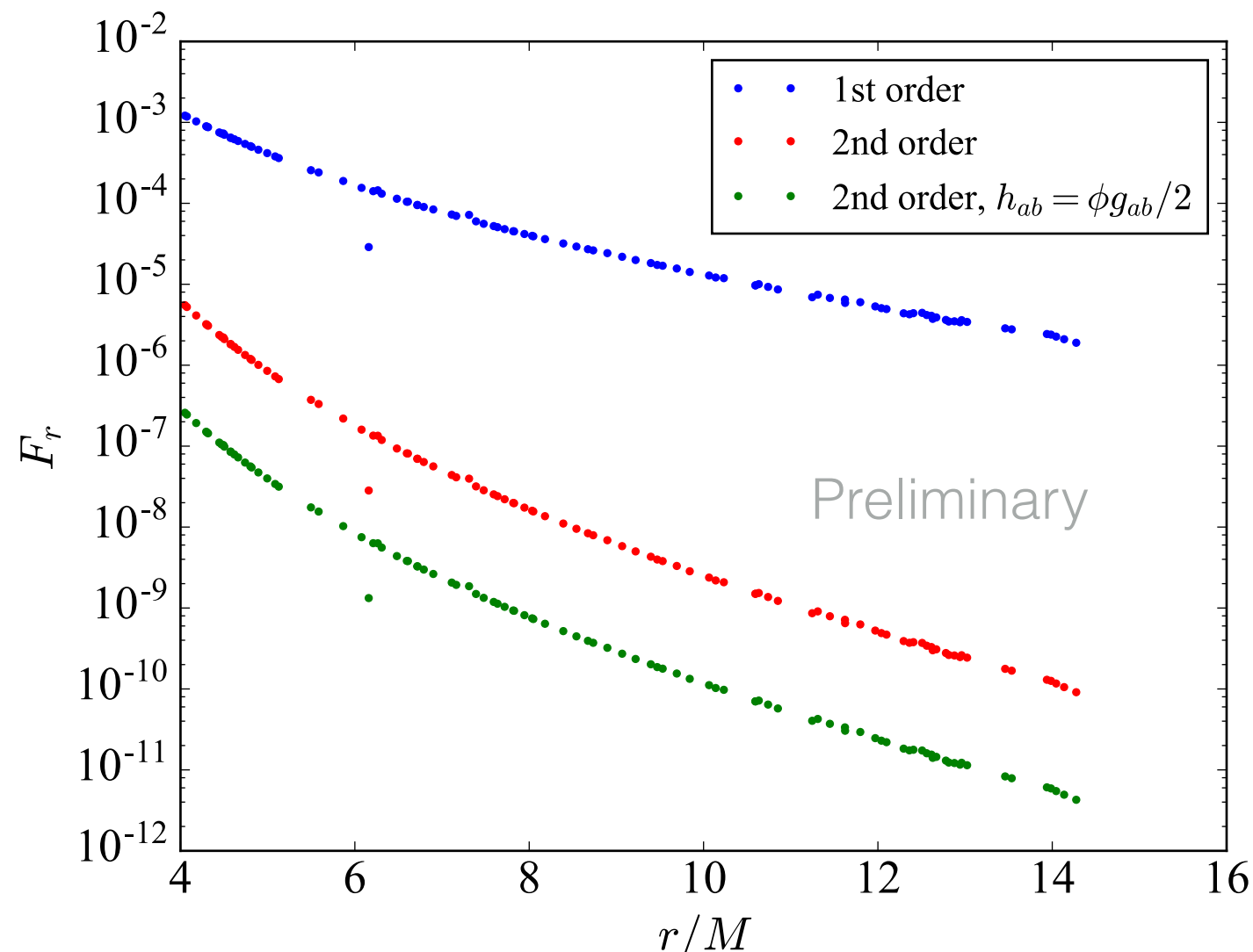


Applications

- Higher-order self-force and radiation *CRG (12a, 12b)*

$$ma^\mu \supset P^{\mu\nu} \left(\lim_{\epsilon \rightarrow 0^+} \int_{-\infty}^{\tau-\epsilon} d\tau' \nabla_\nu G_{\text{ret}}(z^\mu, z^{\mu'}) \right) \left(\lim_{\epsilon \rightarrow 0^+} \int_{-\infty}^{\tau-\epsilon} d\tau'' G_{\text{ret}}(z^\mu, z^{\mu''}) \right),$$

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- Higher-order, self-consistent evolutions
- Self-consistent field/waveform and at higher orders

$$\phi(x^\alpha) = q \int_{-\infty}^{\tau_{\text{ret}}(x)} d\tau' \left\{ \theta(\tau' - \tau_{\text{br}}) G_{\text{surr}}(x, z^{\mu'}) + \theta(\tau_{\text{br}} - \tau') G_{\text{br}}(x, z^{\mu'}) \right\}$$

- Comparing errors in osculating orbits and self-consistent evolutions (via two derivatives of the Green's function) *Pound (unpublished)*

$$F_{\text{hist}}^{\mu}(\tau) = q^2 P^{\mu\nu} \lim_{\epsilon \rightarrow 0^+} \int_{-\infty}^{\tau-\epsilon} d\tau' \nabla_{\nu} G_{\text{ret}}(z^{\mu}, z^{\mu'})$$

- Studying and visualizing basic wave propagation in black hole spacetimes
- Many similar applications in gravity plus others (e.g., NS-BH inspirals)

Summary & Outlook

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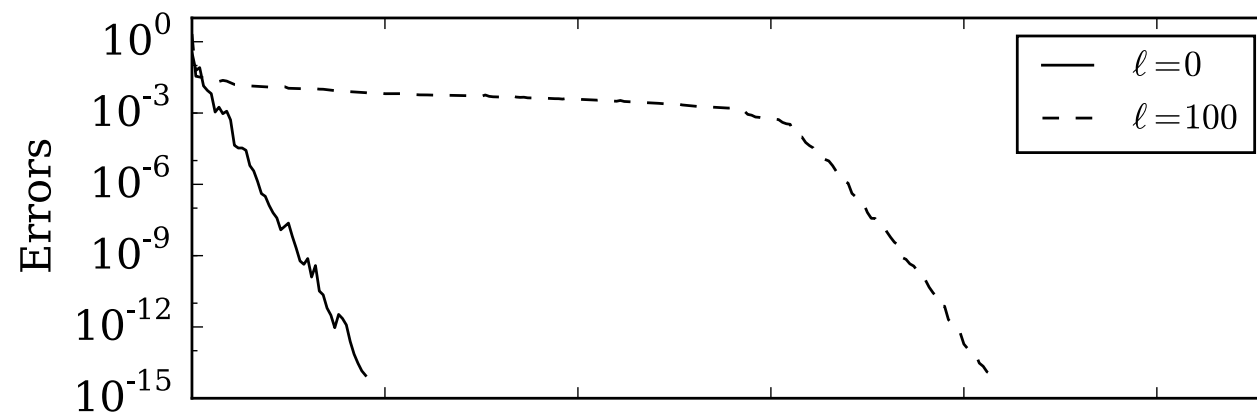
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- Extending to Kerr spacetime is straightforward but may involve (much?) larger data sets because of extra parameters and reduced symmetry
- How to compute Green's function for gravitational perturbations?
 - Lorenz gauge has unstable non-radiative modes...
 - Accuracy and speed of "metric" reconstruction from curvature scalars?

Extra slides

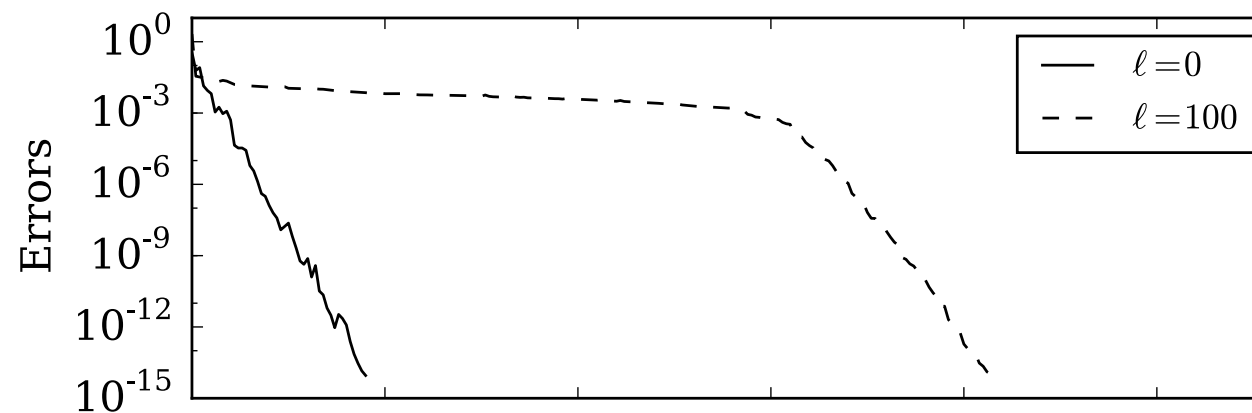
Improving the surrogate building strategy

The plateau in the max projection errors often hints that a different representation of the data may generate a more compact basis



Improving the surrogate building strategy

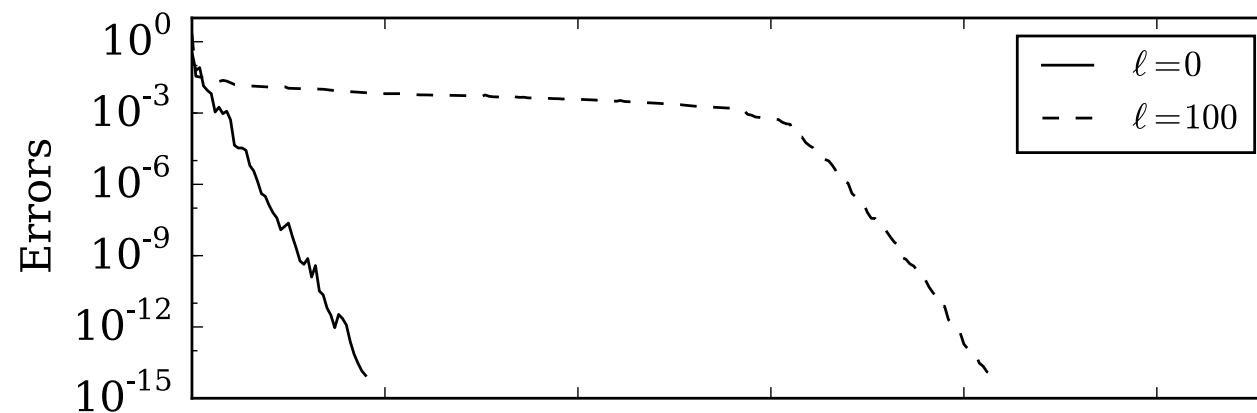
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 - “Rippling” is a problem
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 - Total basis sizes are often larger
- Some other way to represent the data?

Different and useful ways to parametrize the data?

- A more “natural” parametrization might be $\lambda = r'_*$ and regard (t, r_*) as the physical dimension

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Maybe try “invasive” approaches that project the wave equation onto the small vector space spanned by the basis