EMRI kludges:

What they are, why they’re important, and how to *end* them

Alvin Chua

JPL-Caltech

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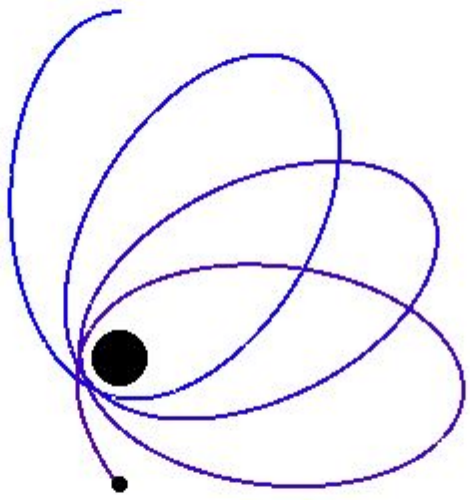
Jet Propulsion Laboratory
California Institute of Technology

Outline

- What's a kludge?
- An inventory of EMRI kludges
  - Analytic kludge (AK)
  - Numerical kludge (NK)
  - Augmented analytic kludge (AAK)
- Kludges in LISA preparatory science
- The EMRI data analysis problem
- Paving the way to surrogates
  - Existing pieces
  - Compression & interpolation
  - Strategies & coordination



What’s a kludge?

- Some particularly apt dictionary definitions:

  “Any construction or practice, typically crude yet effective, designed to solve a problem temporarily or expediently”

L. Preiss

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  “An ill-assorted collection of poorly matching parts, forming a distressing whole”

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What’s a kludge?

- Some particularly apt dictionary definitions:

“Any construction or practice, typically crude yet effective, designed to solve a problem temporarily or expediently”

“An ill-assorted collection of poorly matching parts, forming a distressing whole”

“A badly written or makeshift piece of software”

L. Preiss

What's an EMRI kludge model?

- **if** Efficiency-oriented
  - Feasible for bulk use in data analysis algorithms
- **and** End-to-end
  - Source parameters ⟶ trajectory ⟶ orbit ⟶ waveform ⟶ detector response
- **and** Extensive
  - Describes generic Kerr orbits (intrinsic) & observer dependence (extrinsic)
- **and not** Fully relativistic
  - At least one component uses flat-space approximation
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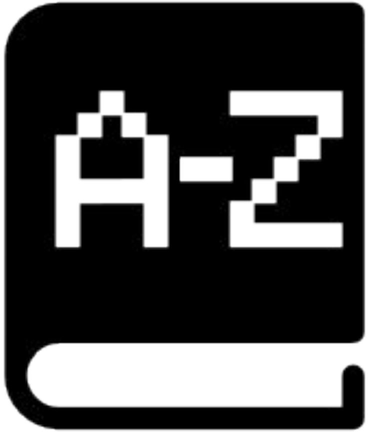
- **then** It’s a kludge!
- Disclaimer: This is my personal, completely non-standard definition
  - But really the only one you should use

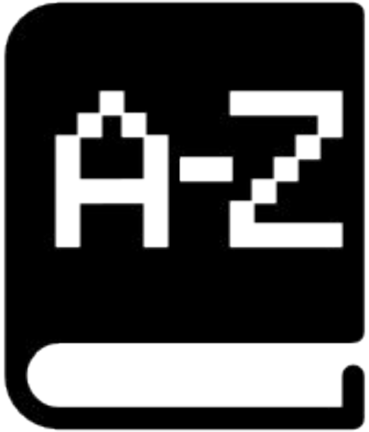
While we’re defining terms…

- Waveform model:
    - Not efficiency-oriented + fully relativistic
- Template model:
    - Efficiency-oriented + end-to-end + extensive



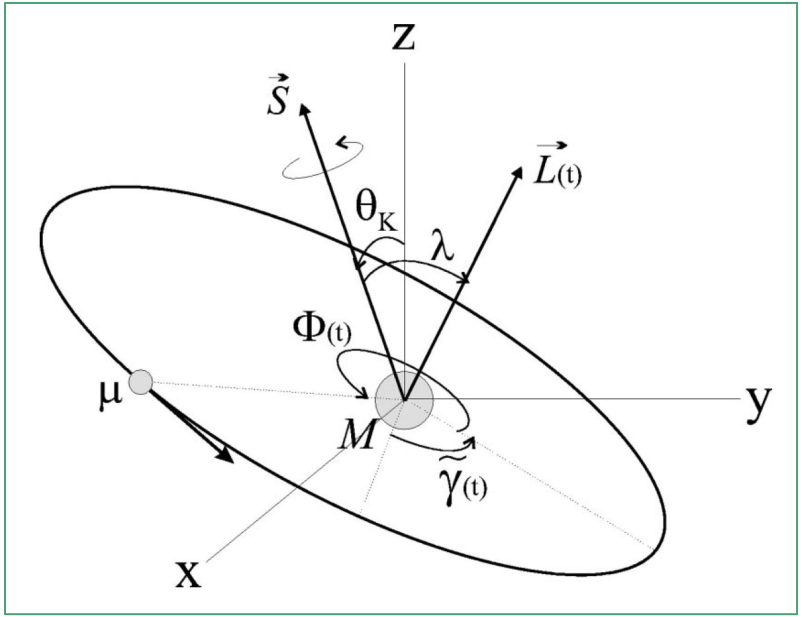
While we’re defining terms…

- Waveform model:
  - Not efficiency-oriented + fully relativistic
- Template model:
  - Efficiency-oriented + end-to-end + extensive
- Surrogate model:
  - Efficiency-oriented + end-to-end + extensive + fully relativistic
  - i.e., a surrogate is a template model that is not a kludge
  - Can (probably will) be phenomenological & not self-consistent
  - Nomenclature is compatible with the NR ROM surrogates
- Approximant:
  - LIGO-speak for a surrogate



Analytic kludge (AK)

- Barack & Cutler, 2004
- PN inspiral trajectory
  - Mixed-order fluxes for (p,e)
  - Assume constant inclination
- Flat-space orbital evolution
  - Instantaneous Keplerian ellipses
  - Add PN precession



Barack & Cutler (2004)

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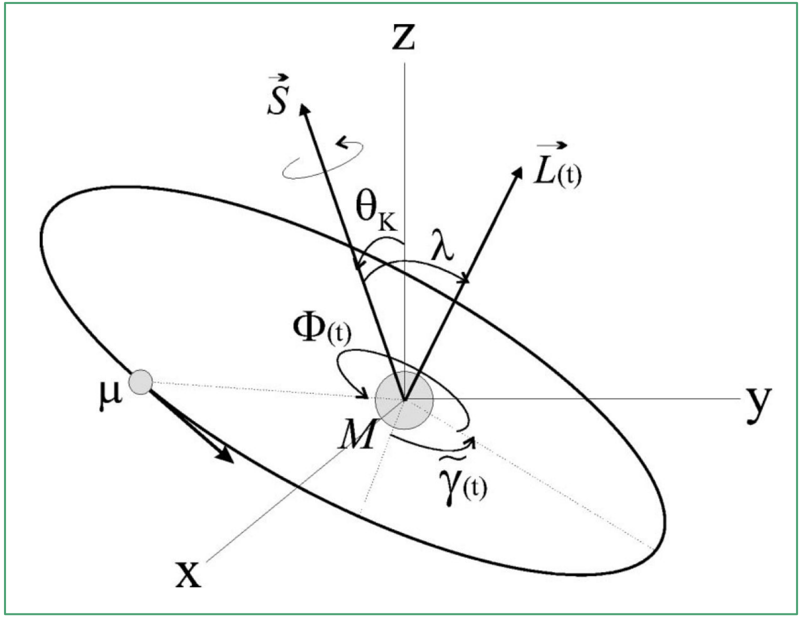
- Flat-space waveform generation
  - Peters-Mathews decomposition
  - Hence quadrupolar
- Time-domain detector response
  - Long-wavelength approximation
  - Extended to t/f rigid-equal-arm TDIs (Babak)



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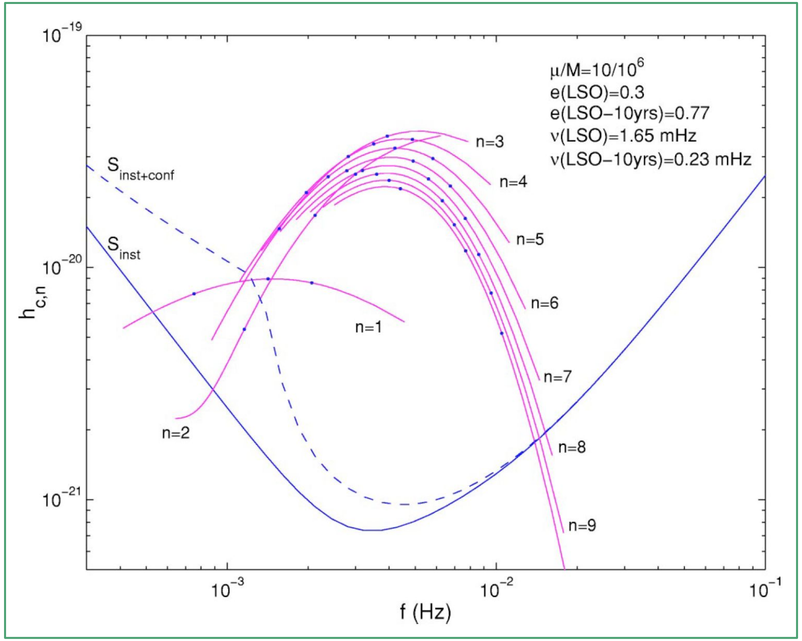
- Strengths:
  - Fast to generate at low eccentricity (< 0.5)
  - Fast to generate for long signals
  - Constructed from harmonic decomposition



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- Strengths:
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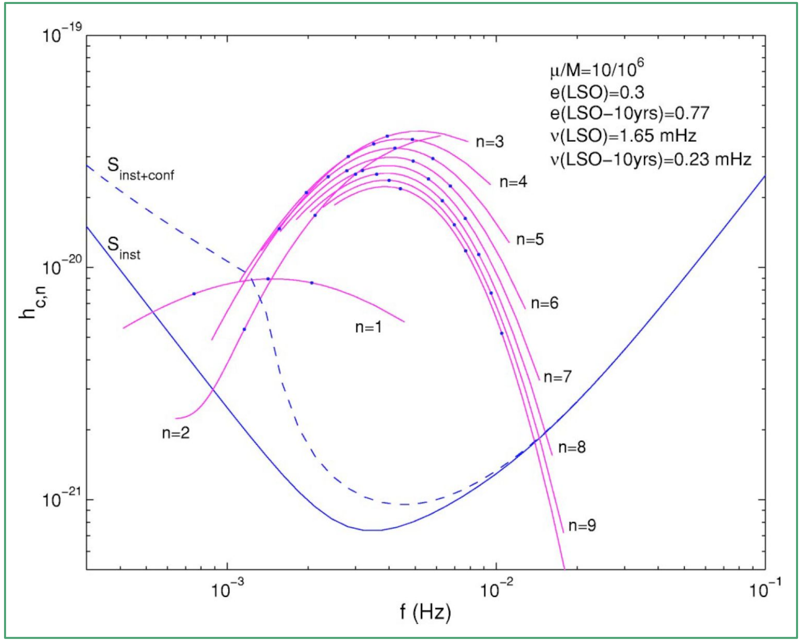
- Weaknesses:
  - Unphysical instantaneous frequencies
  - Limited performance at high eccentricity



Barack & Cutler (2004)

Numerical kludge (NK)

- Babak et al., 2007
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  - Mixed-order fluxes for (p,e,i)
  - Fit to adiabatic trajectories
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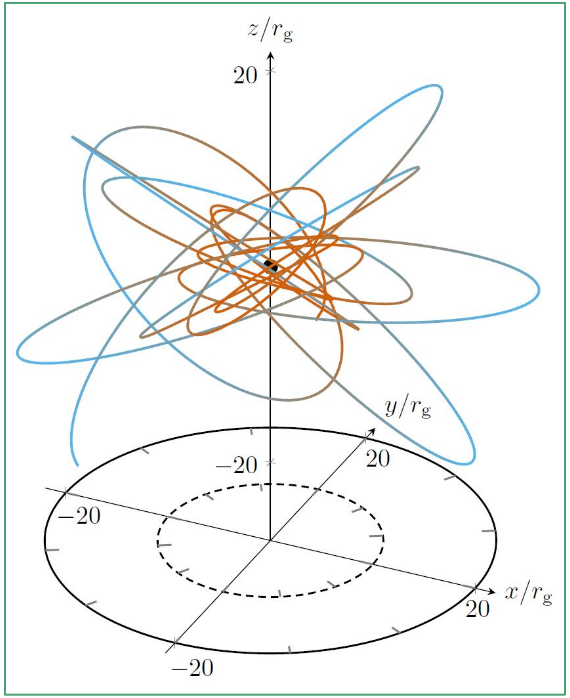
  - Precession naturally included



Berry et al. (2019)

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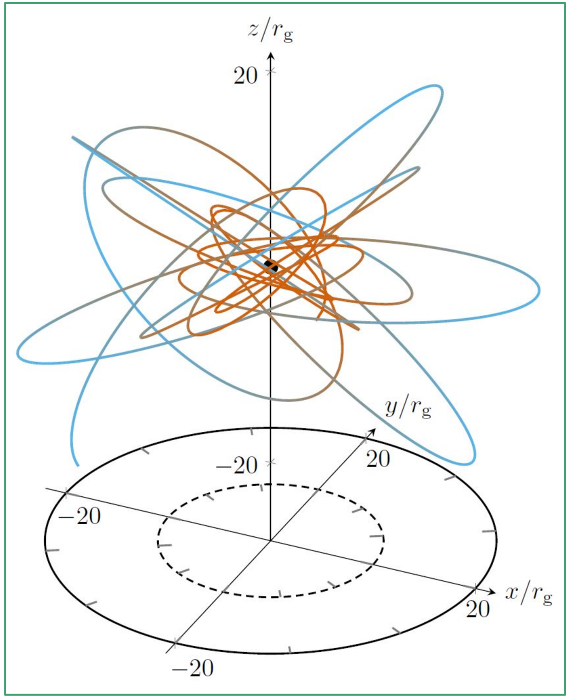
- PN inspiral trajectory
  - Mixed-order fluxes for (p,e,i)
  - Fit to adiabatic trajectories
- Curved-space orbital evolution
  - Instantaneous Kerr geodesics
  - Precession naturally included
- Flat-space waveform generation
  - Associate curved & flat coordinates
  - Several multipolar prescriptions
- Time-domain detector response
  - Only long-wavelength approximation
  - Needs LISA simulator for accurate response



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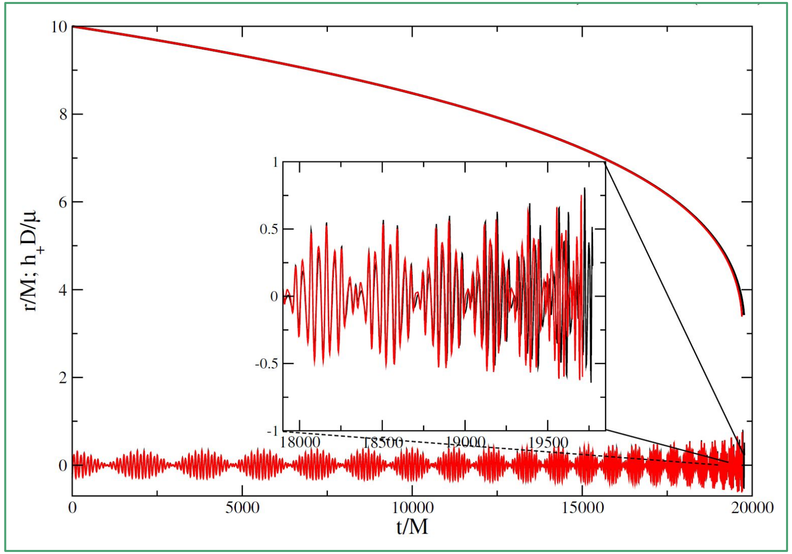

Babak et al. (2007)

Numerical kludge (NK)

- Strengths:
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  - Much faster than relativistic models
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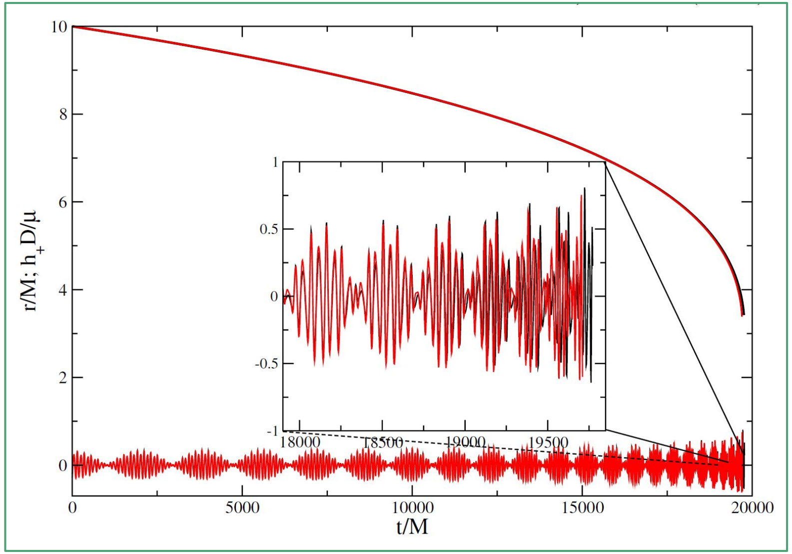
- Weaknesses:
  - Multipole formalism is inefficient
  - Weak-field approximation is inaccurate at high eccentricity (see talk by Osburn)
  - No easy harmonic decomposition



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Augmented analytic kludge (AAK)

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- PN inspiral trajectory
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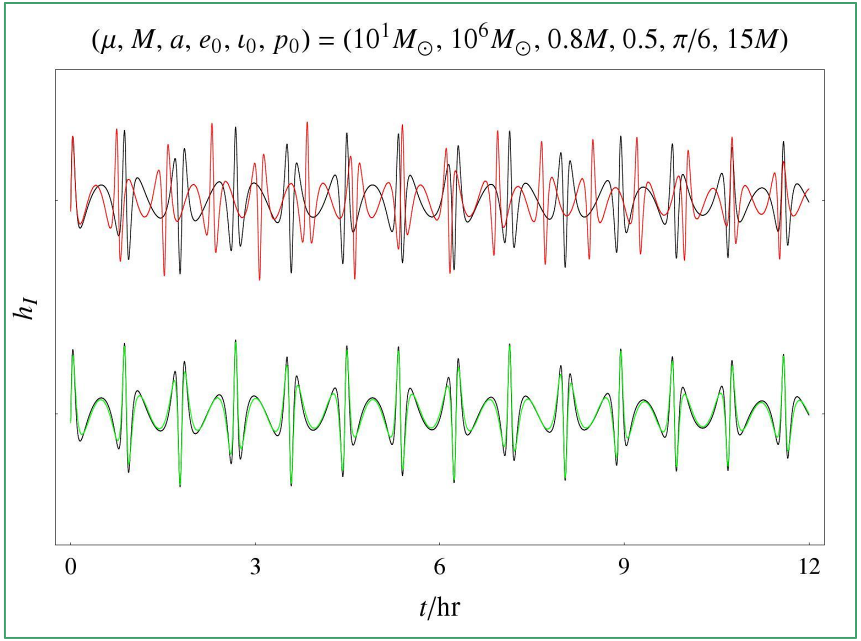
  - Local fit to NK trajectories
- Flat-space orbital evolution
  - Map to Kerr instantaneous frequencies
  - Otherwise same as AK



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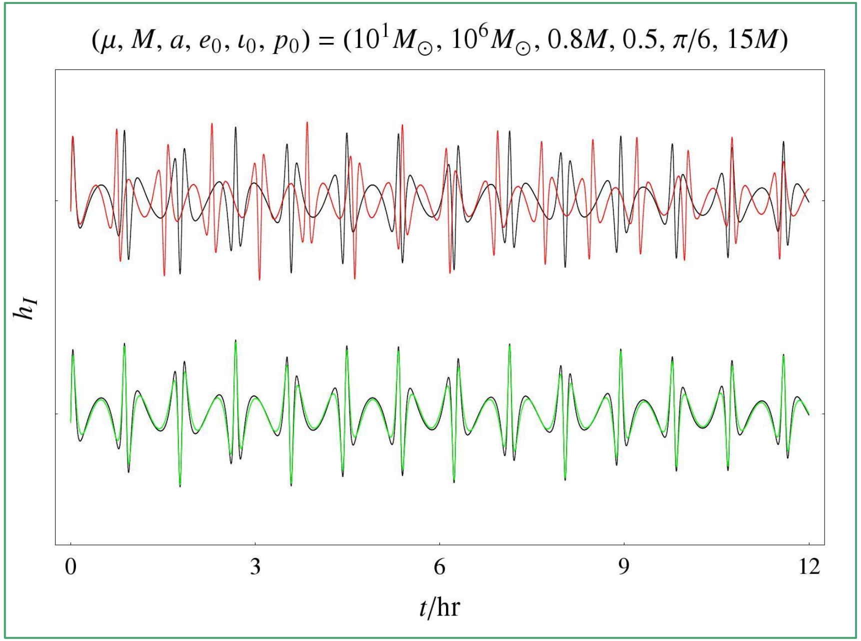

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Augmented analytic kludge (AAK)

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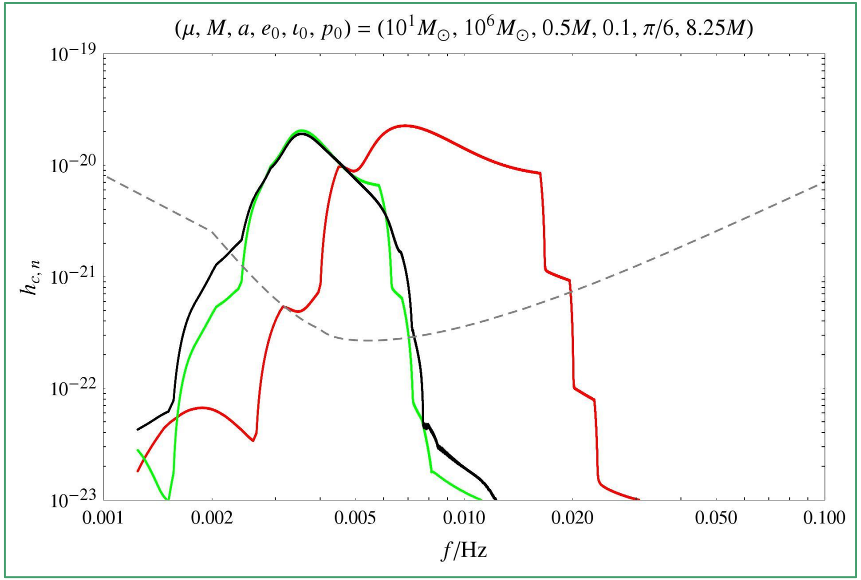
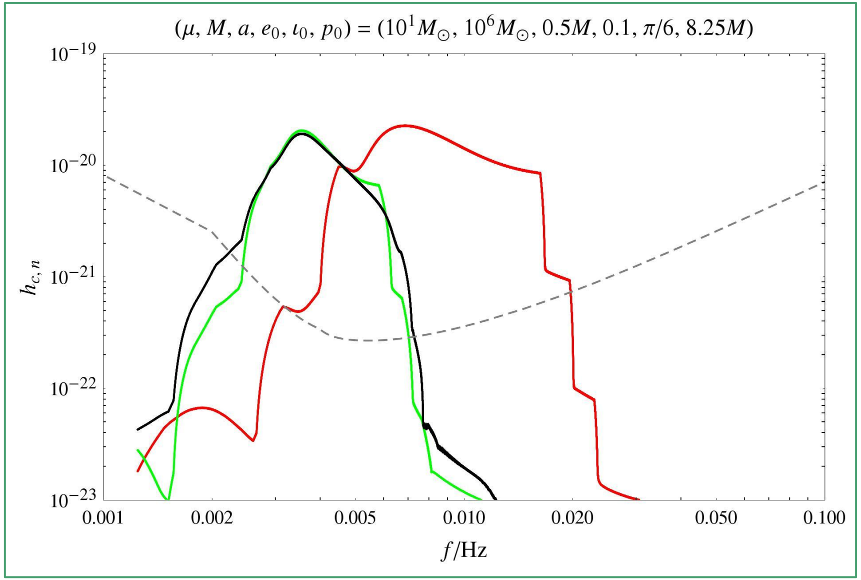
  - Improved implementation
  - Actually being maintained by postdoc



Chua, Moore & Gair (2017)

Augmented analytic kludge (AAK)

- Strengths:
  - Same as AK
  - Good agreement with NK waveforms
  - Improved implementation
  - Actually being maintained by postdoc
- Weaknesses:
  - Limited performance at high eccentricity
  - Frequency map ill-defined at plunge



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EMRI Kludge Suite

- Software suite with all 3 kludges & common interface
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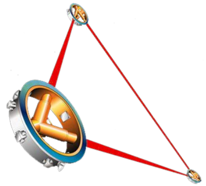
- Usage
    - Executables in ./bin: Waveforms (all models), TDIs (AK/AAK), phases (AAK)
    - Template files in ./examples: Source/waveform parameters, model settings
    - Import Python module AAKwrapper, example usage in AAKdemo.py
    - Caveat utilitor: Limited domain validation & error handling

EMRI Kludge Suite

Model	Trajectory	Orbit	Waveform/response	Accuracy	Speed
AK	- Mixed-order PN fluxes	- Evolving Keplerian ellipses	- Peters-Mathews approximation to quadrupole - Rigid-equal-arm approximation (TDIs)	- Instantaneous frequencies too high - Schwarzschild plunge handling - Qualitative use only	- Fast, but less speedup over NK for shorter waveforms or more eccentric orbits
AAK	- 3PN O(e^6) fluxes - Locally fitted to NK trajectories	- Evolving Keplerian ellipses - Instantaneous frequencies mapped to Kerr	- Peters-Mathews approximation to quadrupole - Rigid-equal-arm approximation (TDIs)	- Phase-accurate w.r.t. NK waveforms, for 2-6 months - Approximate Kerr plunge handling	- Same as AK, but slightly faster due to streamlining
NK	- Mixed-order PN fluxes - Fitted to adiabatic trajectories	- Evolving Kerr geodesics	- Quadrupole - Long-wavelength approximation (h_I,II)	- Phase-accurate w.r.t. adiabatic waveforms, down to 2-3 r_ISCO - Kerr plunge handling	- Order of magnitude slower than AK/AAK on average

Kludges in LISA preparatory science



- Data analysis
  - Synthetic data sets
    - MLDCs, 2006-2011 (using AK); LDCs, 2018-present (transitioning from AK to AAK)
  - Search algorithms
    - Babak, Gair & Porter, 2009 + Cornish, 2011 + Wang, Shang & Babak, 2012 + several others (all using lossy, kludge-informed, harmonic decomposition techniques)
  - Inference algorithms
    - Ali et al., 2012 (short data segments); not much else (even kludges are still too slow)

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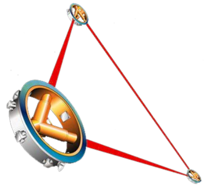

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  - Degeneracies & confusion
    - Chua & Cutler, in prep. (mapping out the likelihood surface); Barack & Cutler, 2004 + Karnesis, Chua & Babak, in prep. (unresolvable EMRI background)
  - Systematics (theoretical errors)
    - Huerta & Gair, 2009 (effect of conservative corrections); Berry et al., 2016 (effect of resonances); Chua et al., in prep. (error marginalization)

Kludges in LISA preparatory science

- Mission performance
  - Detection rates
    - Gair et al., 2004 (using AK); Babak et al., 2017 + several other reports/proposals (*still* using AK); Chua, Moore & Gair, 2017 (using AAK)
  - Parameter estimation precision (statistical errors)
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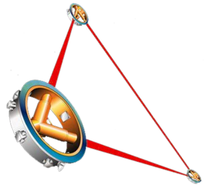

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- Science applications
  - Fundamental physics (tests of gravity)
    - Glampedakis & Babak, 2006 + Barack & Cutler, 2007 + Chua et al., 2018 (generic Kerr deviations); Canizares, Gair & Sopuerta, 2012 (dynamical Chern-Simons); possibly others
  - Astrophysics & cosmology
    - Sesana et al., 2008 (WD EMRIs); Han & Chen, 2019 (b-EMRIs); surprisingly not much else (heuristic analysis, or just use cited rates/precision)

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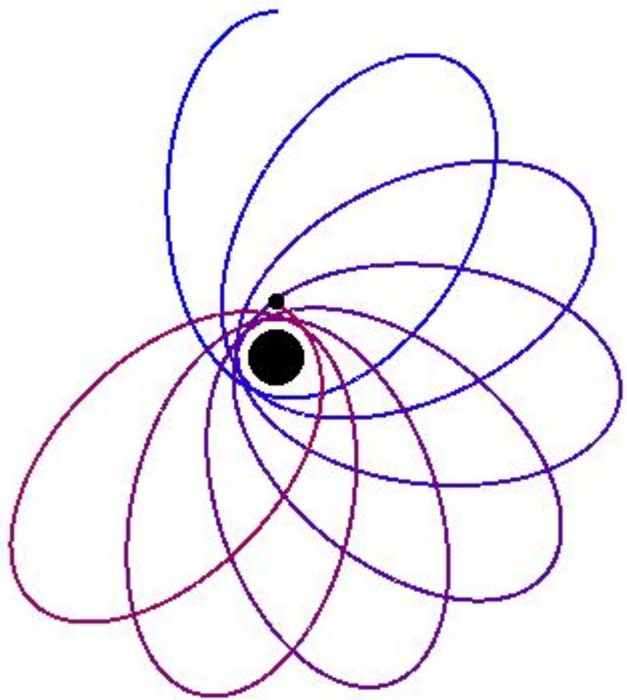
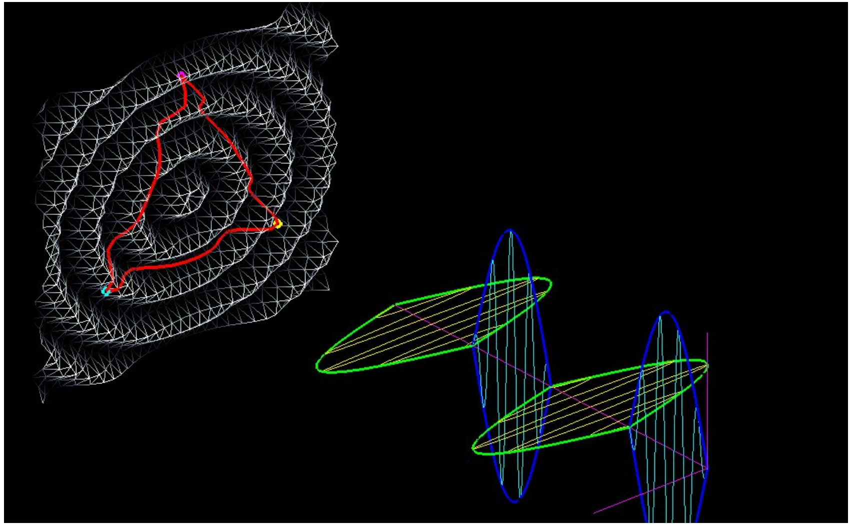


Key features of LISA data analysis

- Problem 0: Instrument/noise model
  - Complicated dynamical orbits
  - Complicated instrument response (TDIs)
  - Non-stationary noise
  - Gaps & glitches



N. Douillet

Key features of LISA data analysis

- Problem 0: Instrument/noise model
  - Complicated dynamical orbits
  - Complicated instrument response (TDIs)
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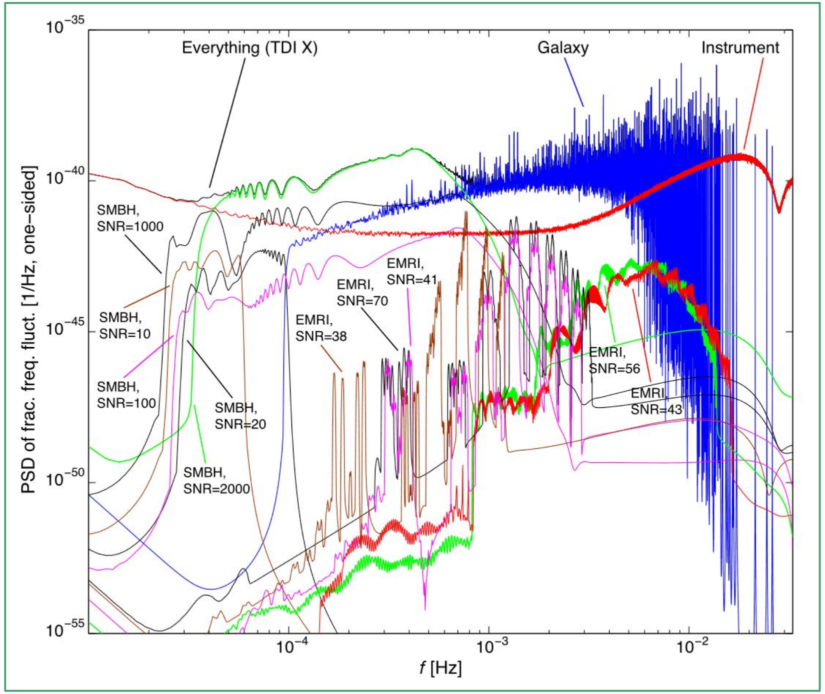
  - Gaps & glitches
- Problem 1: Signal confusion
  - Many signals overlap in time/frequency: Galactic binaries + SMBH mergers + EMRIs
  - Cannot just subtract then move on
  - Global-solution algorithm is required
  - Not practical to do fully simultaneous fit
  - Separate source pipelines communicating



Arnaud et al. (2007)

Key features of LISA data analysis

- Problem 2: Global search
  - Parameter space can be massive:
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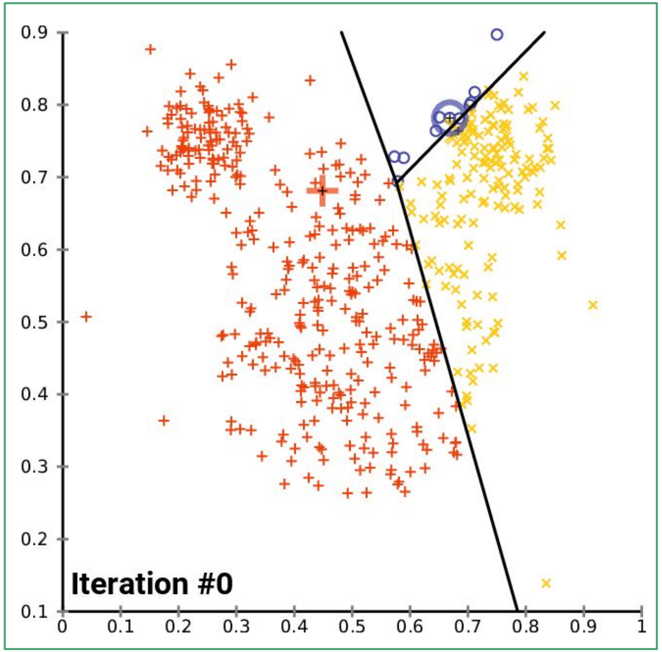
  - Credible regions can be very localized
  - Stochastic search algorithms are required
  - Search is hierarchical & needs multiple passes



Wikimedia

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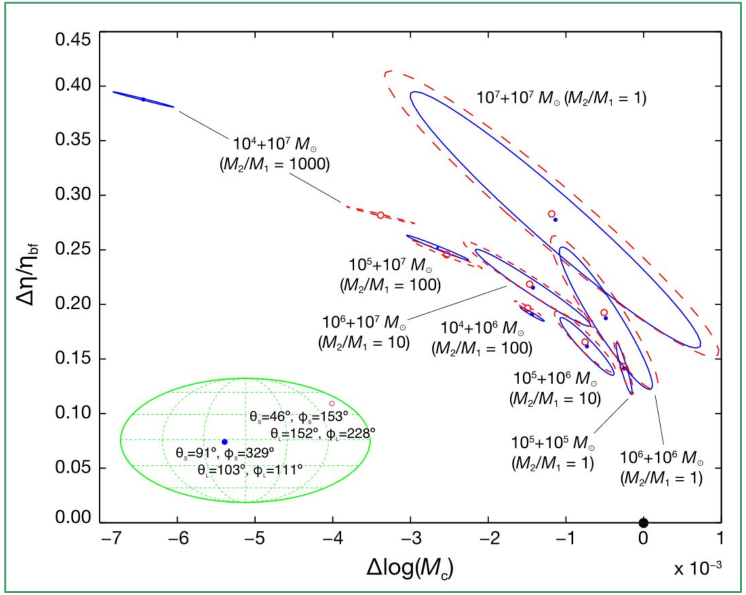
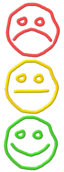
- Problem 3: Modeling accuracy
  - Bias when theoretical error > statistical error
  - Only for strong-field, high-SNR sources
  - Most interesting, but most difficult to model
  - Need to understand errors for waveforms, minimize loss of accuracy for templates
  - Could be addressed from data analysis end



Cutler & Vallisneri (2007)

The EMRI data analysis problem

- Galactic binaries
  - Confusion: Severe (resolvable + background)
  - Search: Low SNR & many signals to resolve, but templates are inexpensive
  - Modeling: No problem



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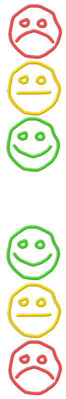

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  - Search: Expensive templates & localized, but high SNR & fewer signals to find
  - Modeling: Difficult (NR)
- EMRIs
  - Confusion: Maybe (uncertain event rates, possibly severe degeneracies)
  - Search: Expensive templates, highly localized, moderate SNR, possibly many signals
  - Modeling: Difficult (SF)

Will kludges be good enough?

- In terms of speed
  - Template cost: > 10^2 s (!)
  - Time samples: > 10^7 (4 years × 0.1 Hz)
  - Inner-product calls: 10^9-10^{30} (!!)
  - Barely OK for inference
  - Prohibitive for search (without sacrificing accuracy)

ORNL

$$\langle h|s\rangle = \int df\, \frac{h^*(f)s(f)}{S_n(f)}$$

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  - Assume overlaps of 0.97 with true signals
  - Barely OK for search: Lose up to half of signals (Chua, Moore & Gair, 2017)
  - Nowhere near good enough for inference

ORNL

$$O(h|s) = \frac{\langle h|s\rangle}{\sqrt{\langle h|h\rangle\langle s|s\rangle}}$$

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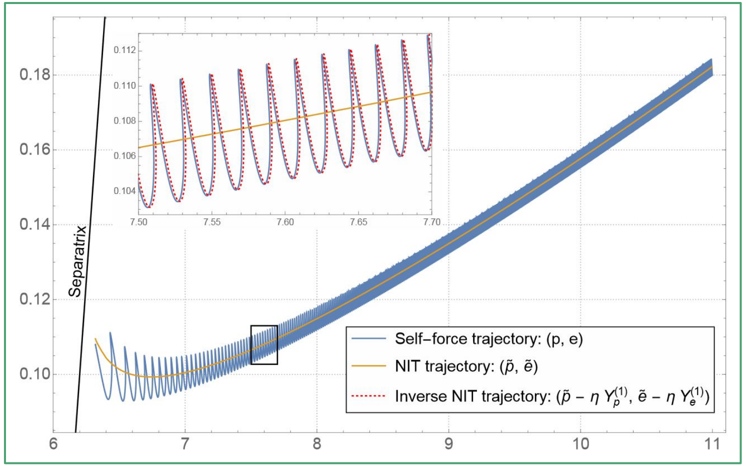
  - Nowhere near good enough for inference
- Need for surrogates & algorithms tailored to EMRI problem
  - Let's leave kludges & traditional data analysis approaches behind

ORNL

Surrogates: Existing pieces

- Trajectory & orbit
  - PN flux-based (see talks by Isoyama, Munna)
  - Teukolsky flux-based (see talk by Hughes)
  - SF-based (van de Meent & Warburton, 2018; see also talk by Osburn)



van de Meent & Warburton (2018)

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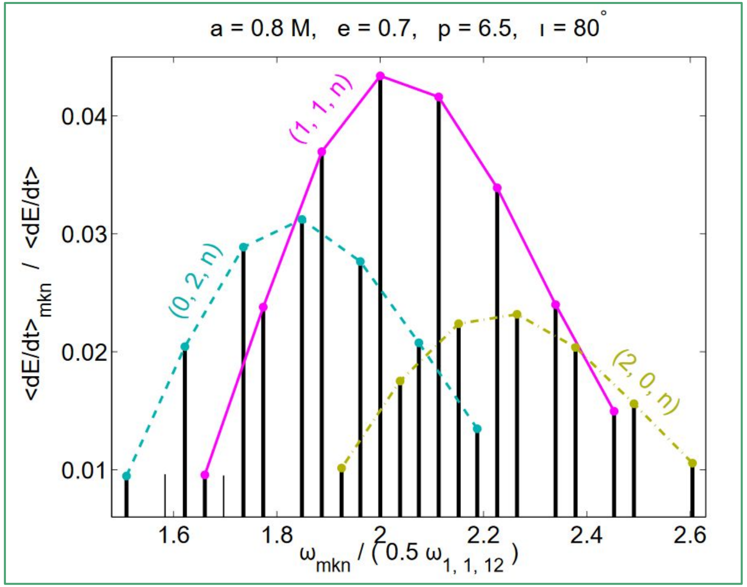
  - Teukolsky flux-based (see talk by Hughes)
  - SF-based (van de Meent & Warburton, 2018; see also talk by Osburn)
- Waveform
  - Teukolsky snapshots
  - Adiabatic (see talks by Hughes, Isoyama)
- Response
  - Approximate TDI (Babak; Marsat & Baker, 2018)



Drasco (2009)

Surrogates: Compression & interpolation

- ROM surrogates (Field et al., 2014)
    - Construct reduced basis for signal space
    - Only valid over predefined parameter domain
    - Resultant template model is fast & accurate
    - May be viable for EMRIs with smart representation

$$h(\theta) = \sum_i \alpha_i(\theta) e_i \equiv \alpha(\theta)$$

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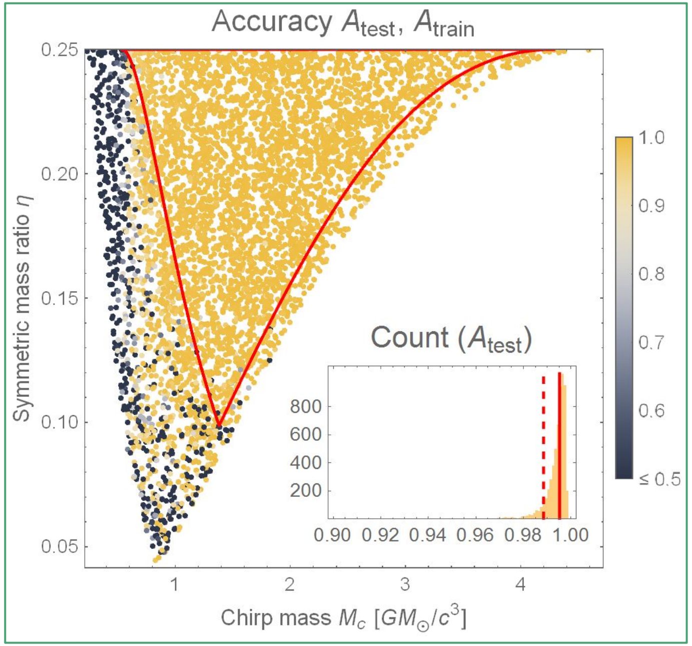
- ROMAN (Chua, Galley & Vallisneri, 2019)
    - Reduced-order modeling with artificial neurons
    - Same basis & domain as ROM surrogates
    - Comparable speed & accuracy
    - More general, connects directly to data analysis
    - Shows utility of neural-network interpolation (dimensionality, derivatives, etc.)



Chua, Galley & Vallisneri (2019)

Surrogates: Strategies & coordination

- Work in time-frequency domain
  - Lossless representation: STFT, wavelets, etc.
  - Admits native generation & data analysis
  - Best suited to nature of EMRIs & LISA
  - Can deal with non-stationarity & gaps

$$h(\tau, \omega) = \int dt\, h(t) W(t-\tau) e^{-i\omega t}$$

$$h(a, b) = \frac{1}{\sqrt{a}} \int dt\, h(t) \psi\left(\frac{t-b}{a}\right)$$

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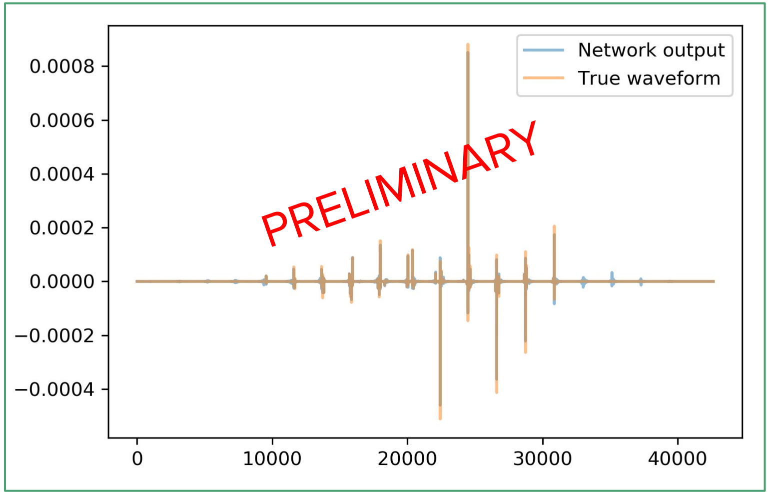

Chua et al. (in prep.)

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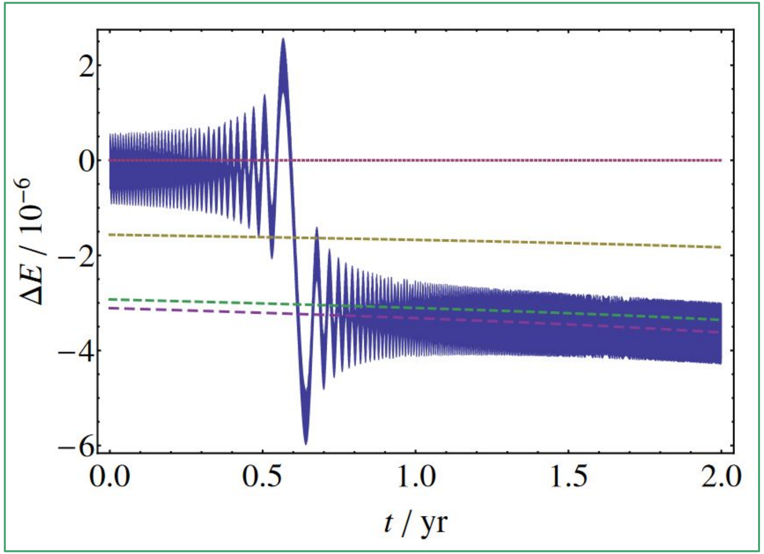
- Incorporate parallelization from the start
  - e.g., native GPU implementations
- Identify & add important missing pieces
  - Transient resonances
  - Tidal resonances? (see talk by Bonga)
  - Secondary spin? (see talks by Witzany, Kavanagh)



Berry et al. (2016)

Surrogates: Strategies & coordination

- LSG WP 1.8.3: Efficient EMRI models
  - Kludges & related tools for LDCs
  - Fast LISA response for EMRIs
  - Reduced-representation templates
  - Fast transient resonance models
  - Fast SF trajectories
  - Modern computational techniques
- Also WPs 1.2.1 (Pound), 1.2.2 (Warburton), 1.2.3 (Brito)

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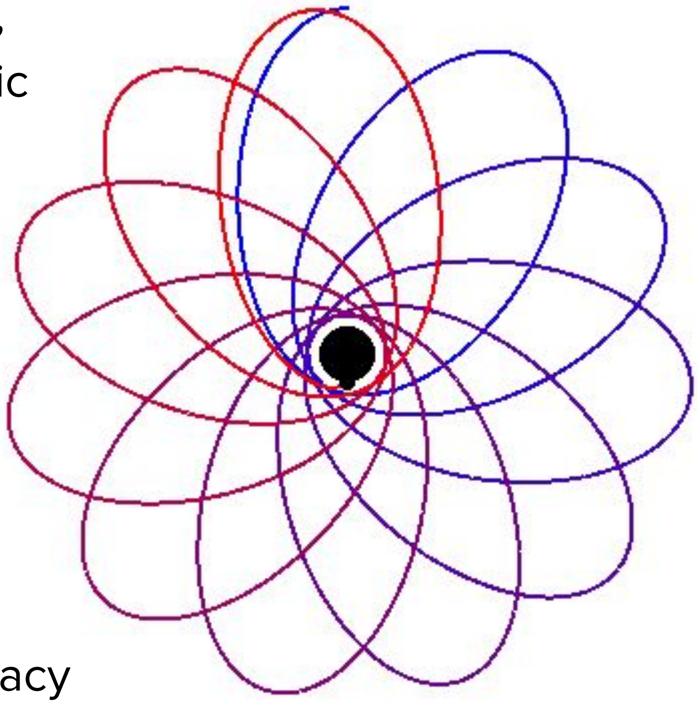
- Also WPs 1.2.1 (Pound), 1.2.2 (Warburton), 1.2.3 (Brito)
- Calling for expressions of interest/commitment
  - No need to be full or even associate LISA member
  - More at: tinyurl.com/emri-templates

Summary

- EMRI kludge models are efficiency-oriented, end-to-end, extensive, but not fully relativistic
- Kludges have fulfilled their purpose of scoping out LISA data analysis issues; they will still be relevant in the near future
- We now have some pieces to construct surrogate models that are more directly informed by perturbation theory
- These will be tailored to LISA data analysis requirements; modern computational techniques will improve both speed & accuracy



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