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COMPUTATIONAL
RELATIVITY AND
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R·I·T

Multimessenger parameter and population inference

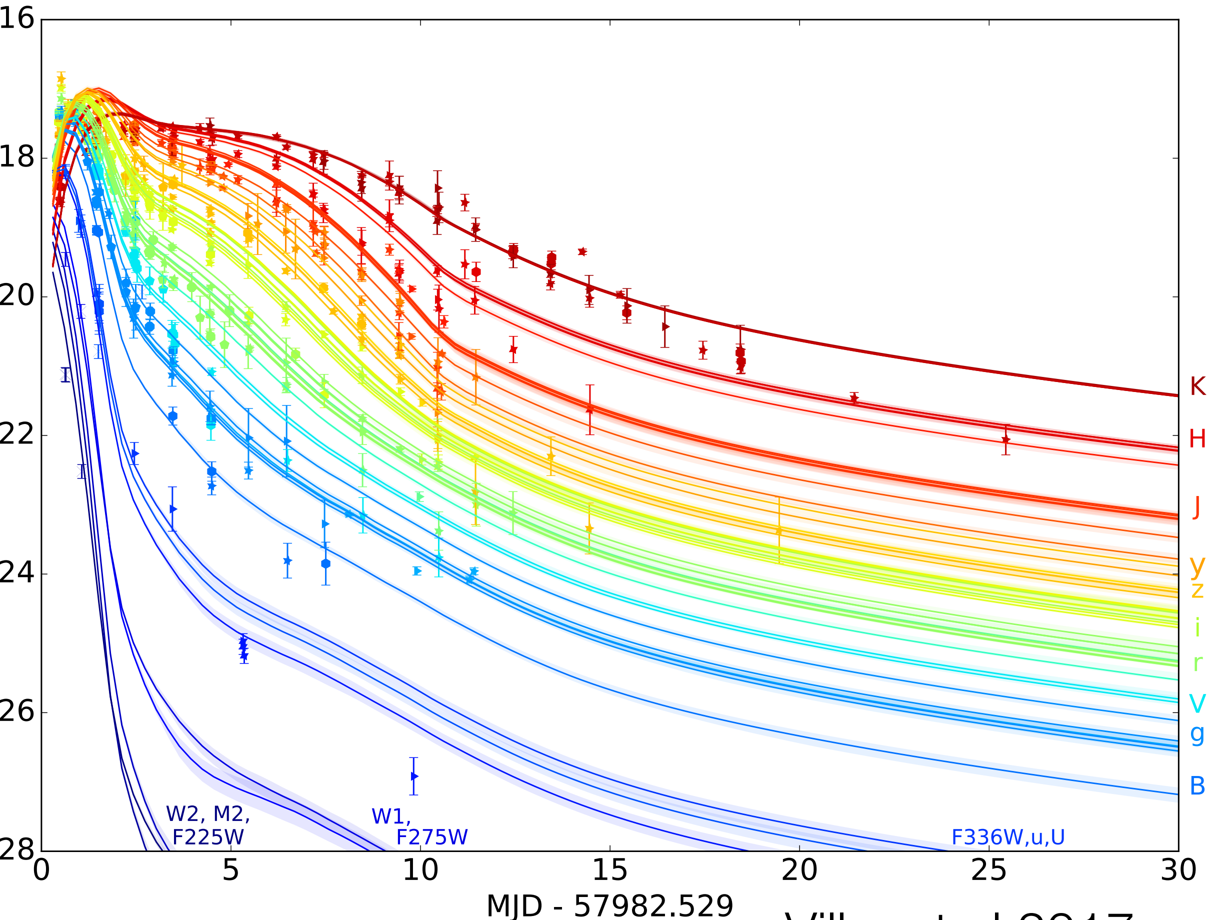
Richard O'Shaughnessy

2022 05 24 INT Workshop "The r-process and the nuclear EOS after LIGO-Virgo's third observing run"

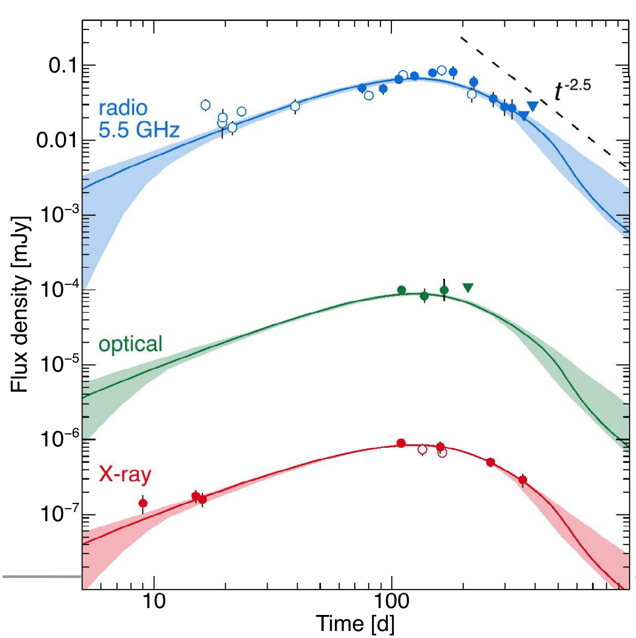
LIGO DCC G2200781

Introduction by example: Single transients

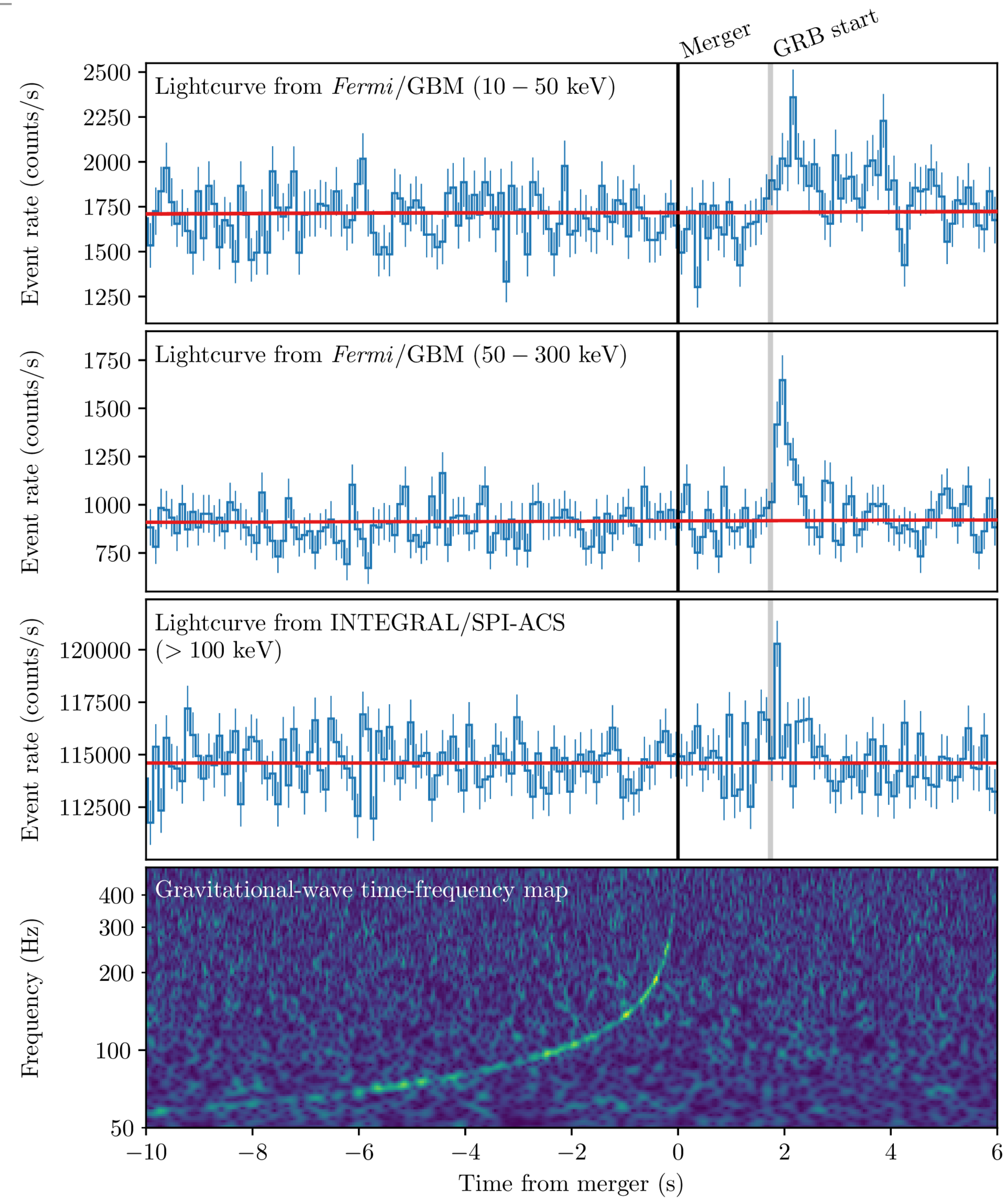
- **Example: GW170817**



Villar et al 2017



Troja et al 2018 (1808.06617)

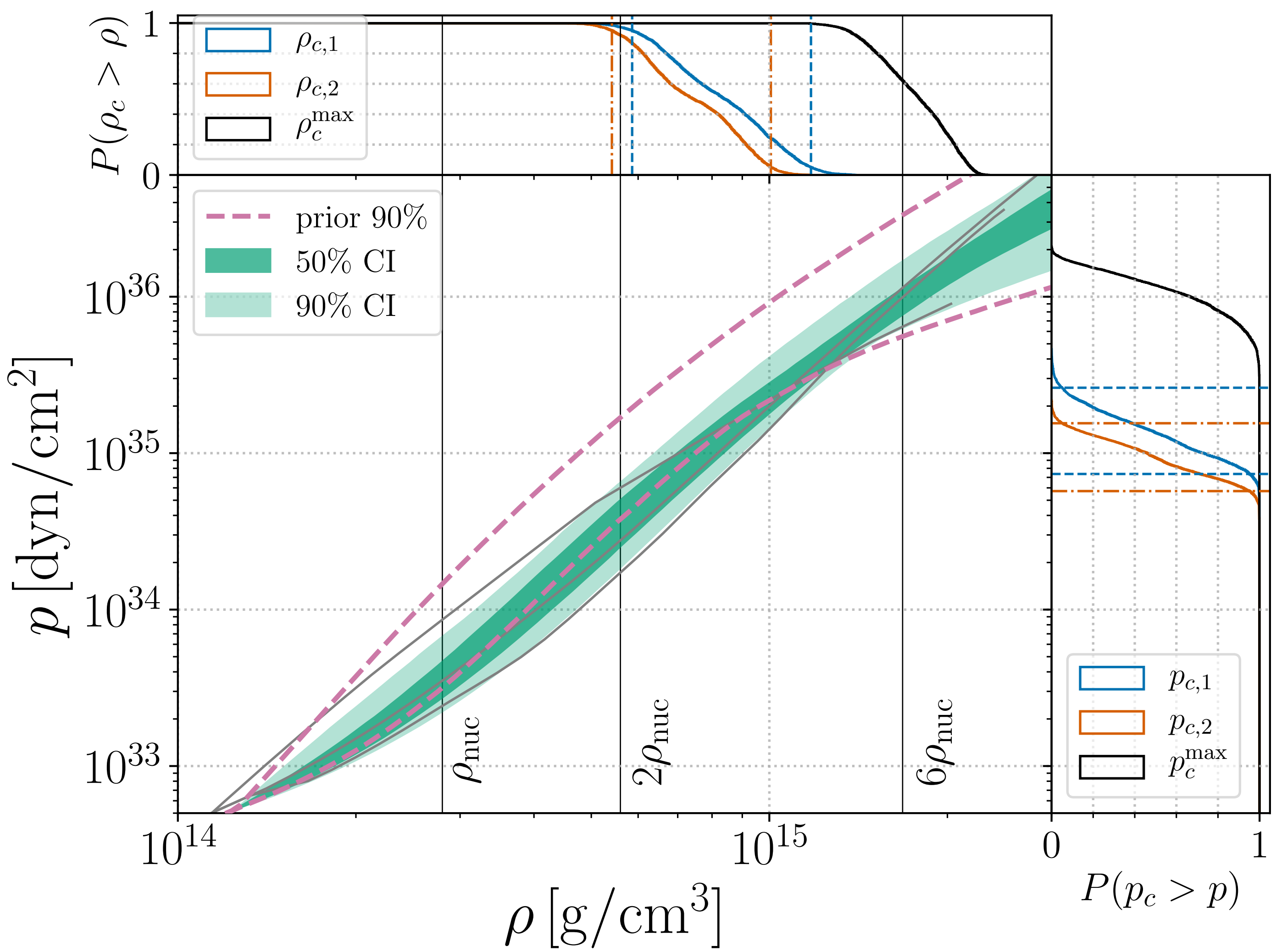


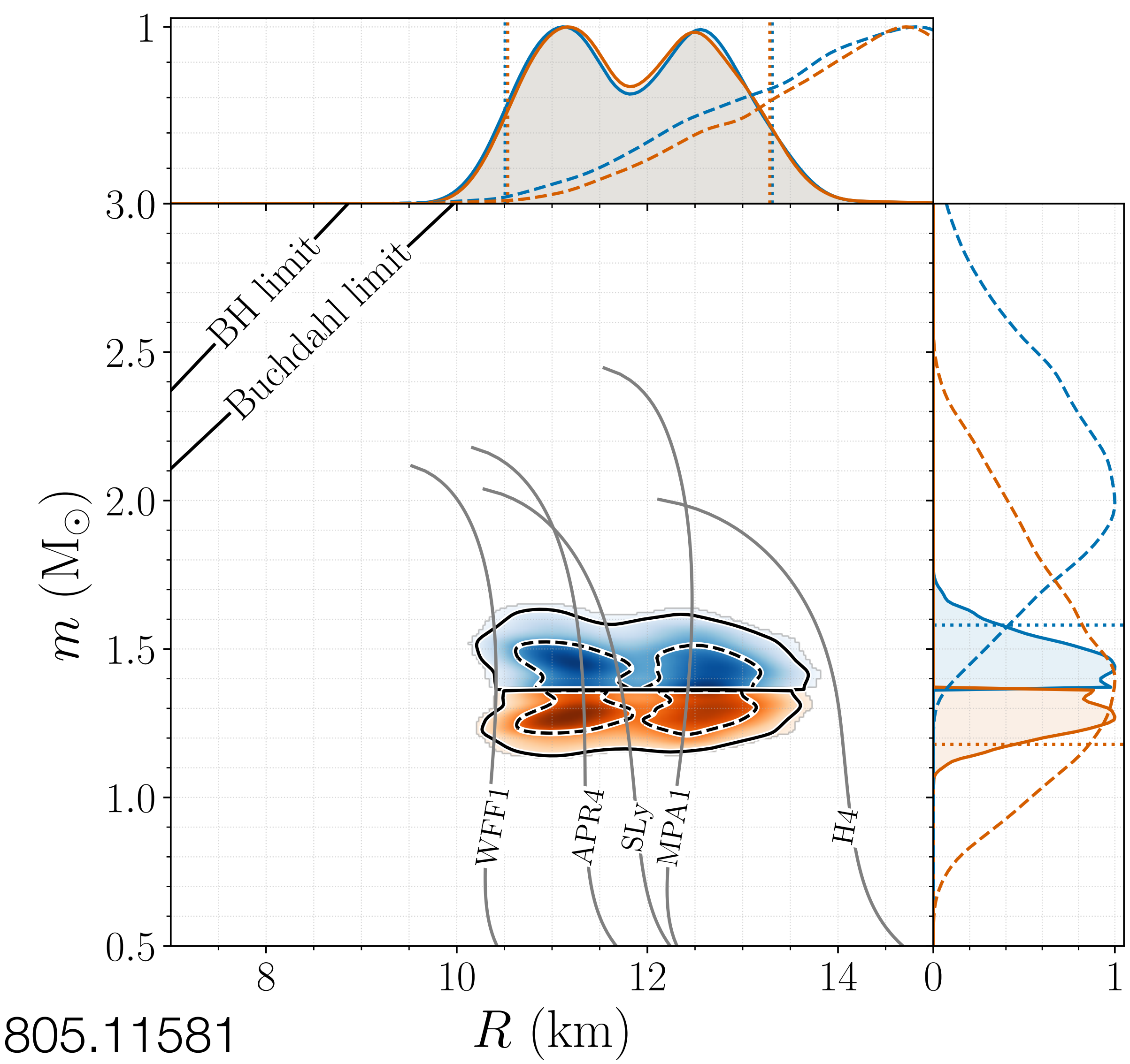
Abbott et al 2017

Nuclear equation of state (as of n=1 BNS)

- (Chirp) mass (one data point = consistent with galactic)
- (Aligned part of) spin small, consistent with galactic
- Tides and the nuclear EOS

require $\Lambda = \Lambda(m)$

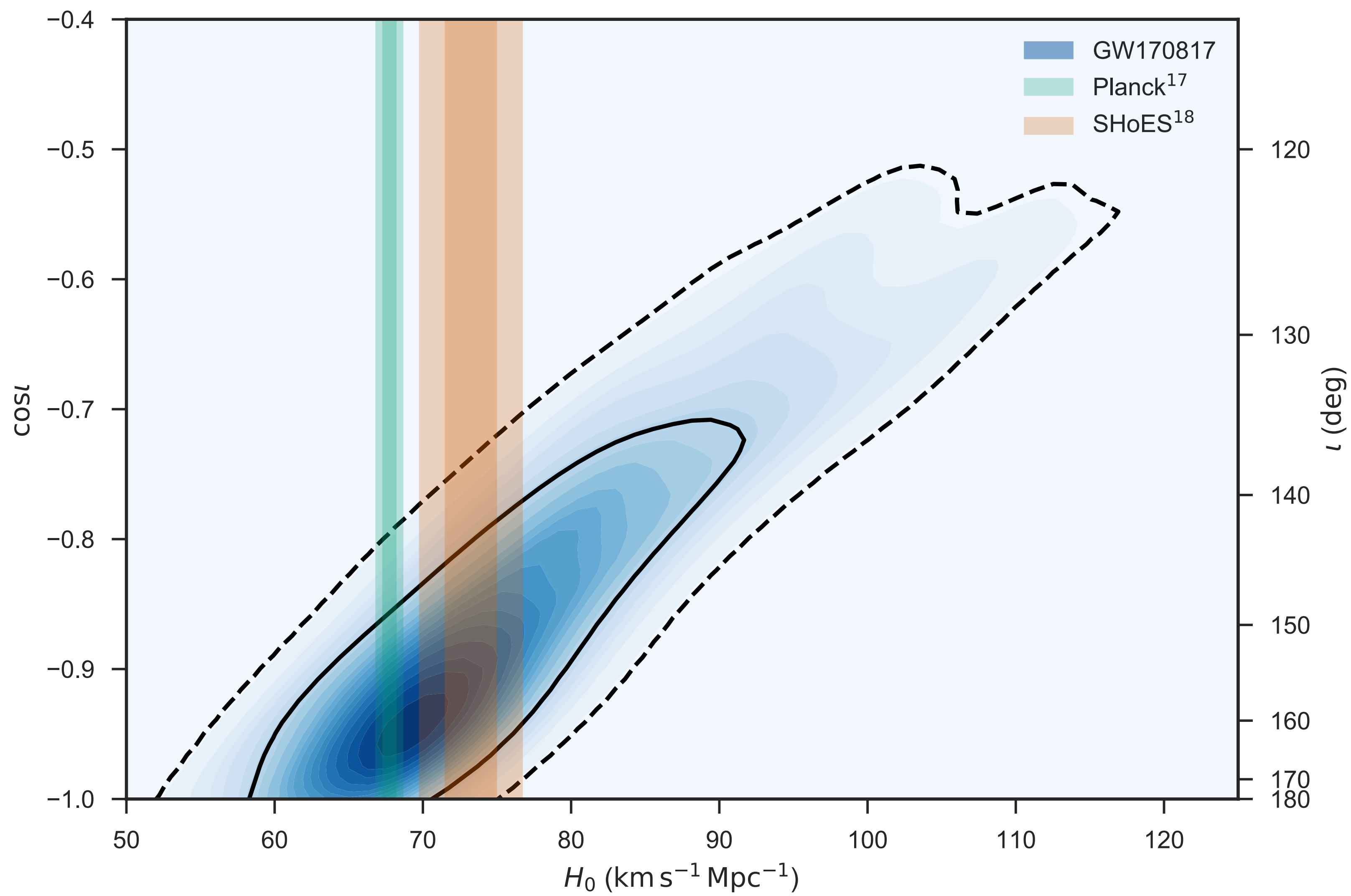




Abbott et al 1805.11581

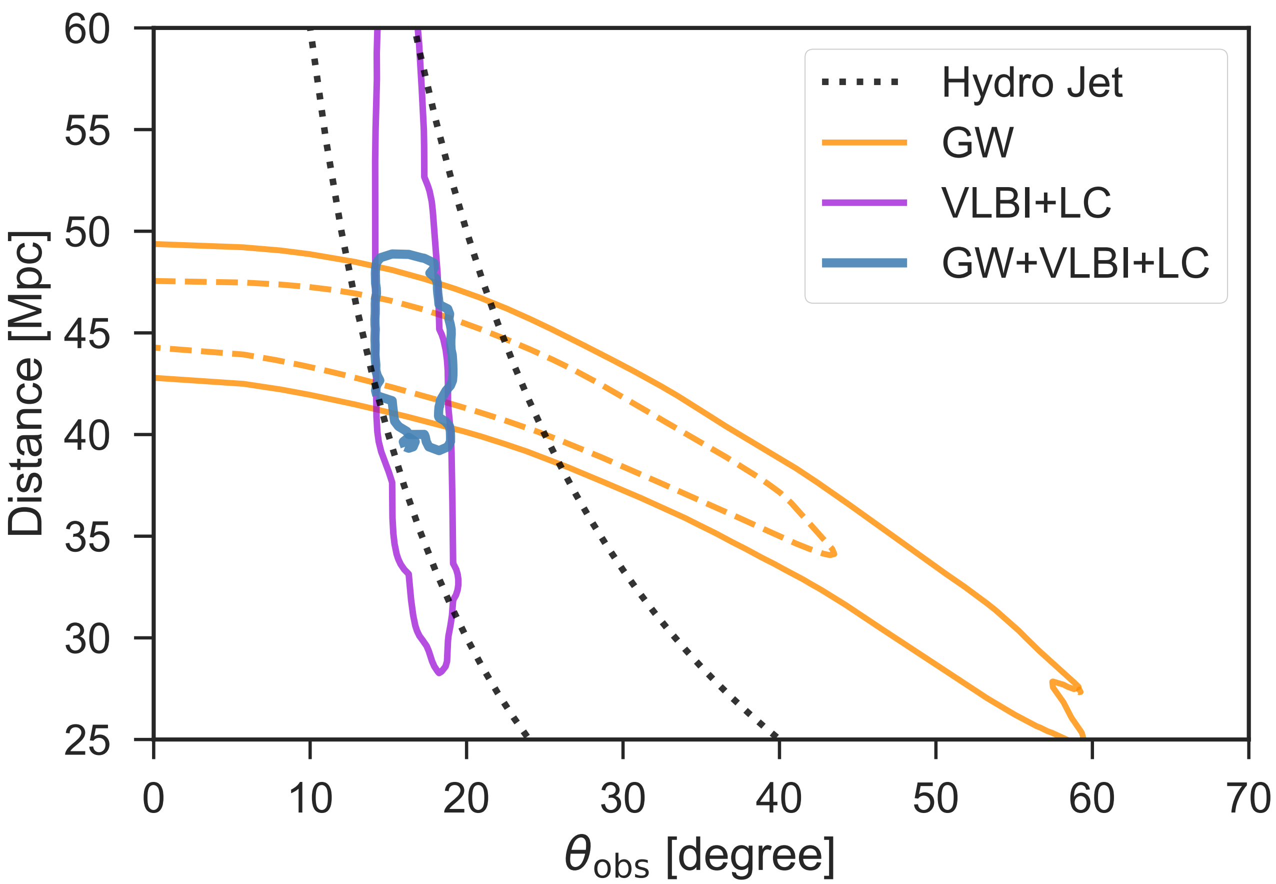
Multimessenger inference has broad return

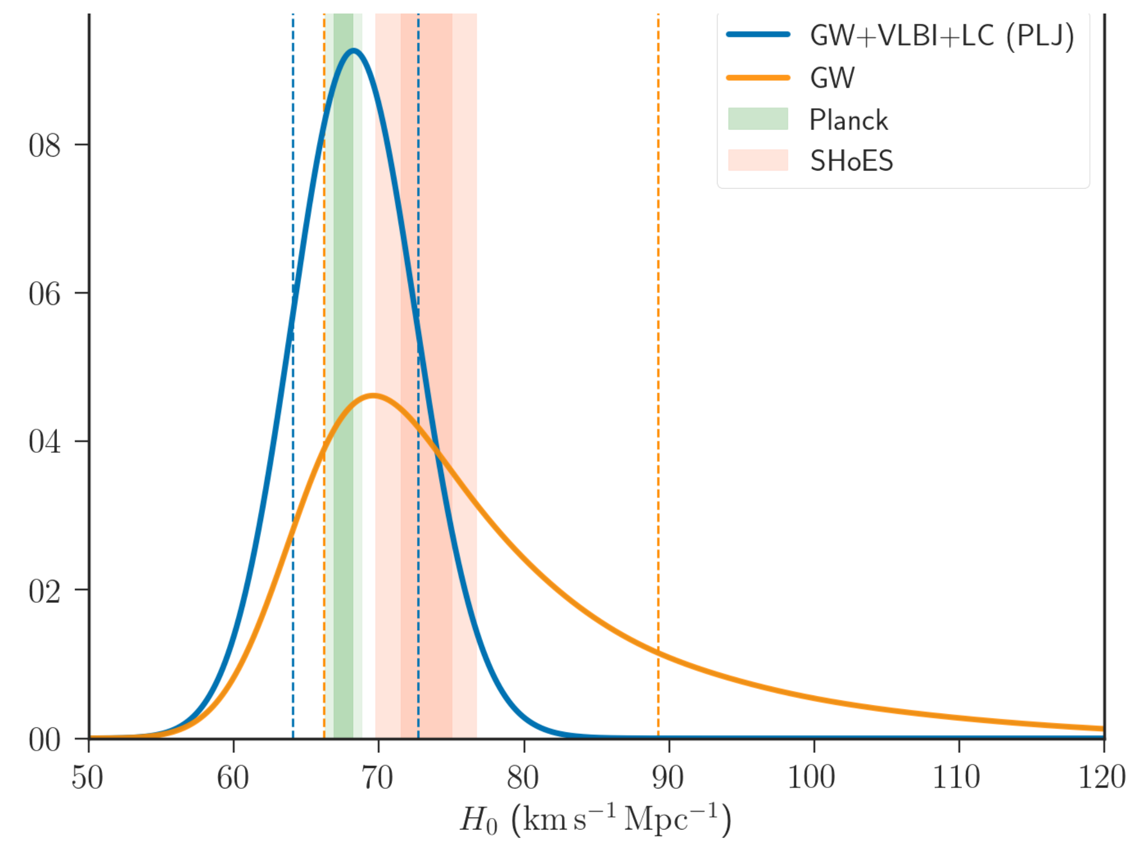
- Hubble constant measurements: very sensitive to inclination degeneracy



Multimessenger inference has broad return

- Hubble constant measurements: very sensitive to inclination degeneracy
  - Observations of jet break that degeneracy
  - Example: Radio VLBI jet constraints

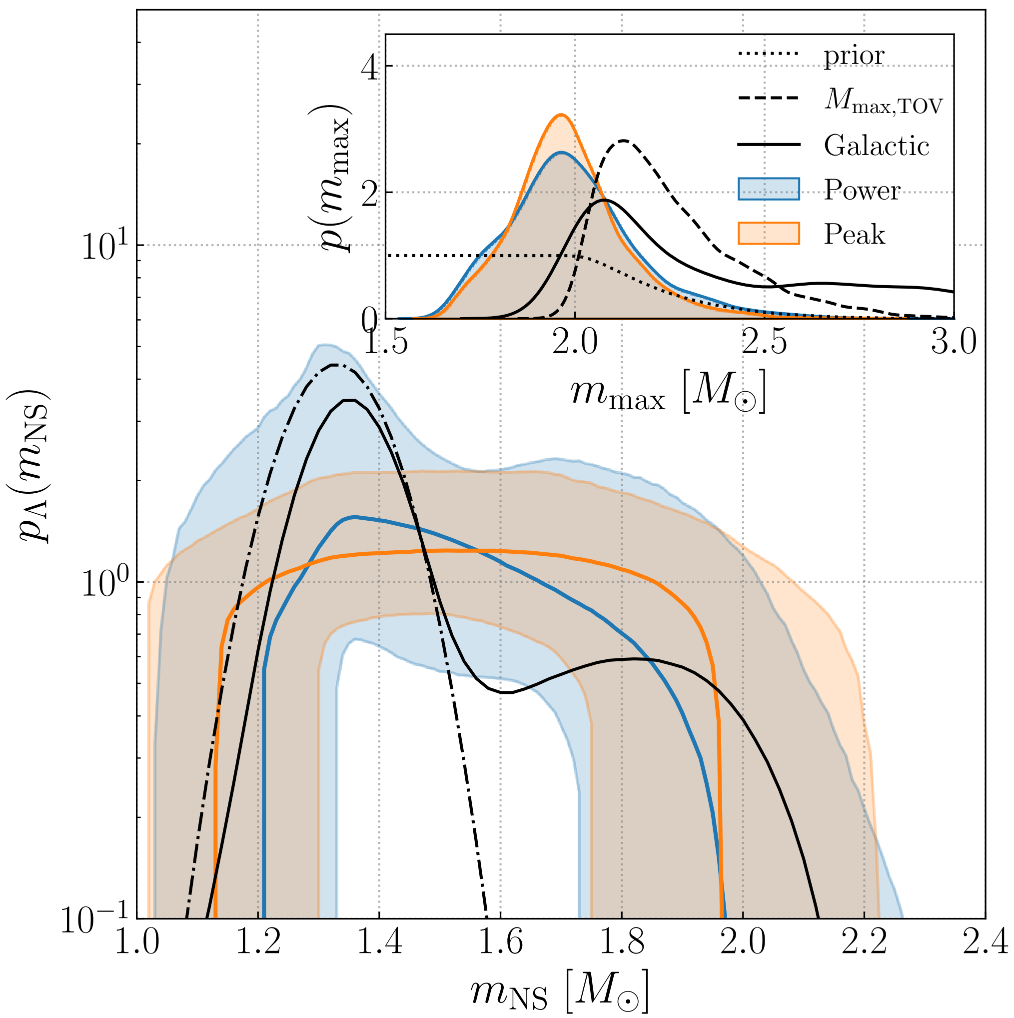


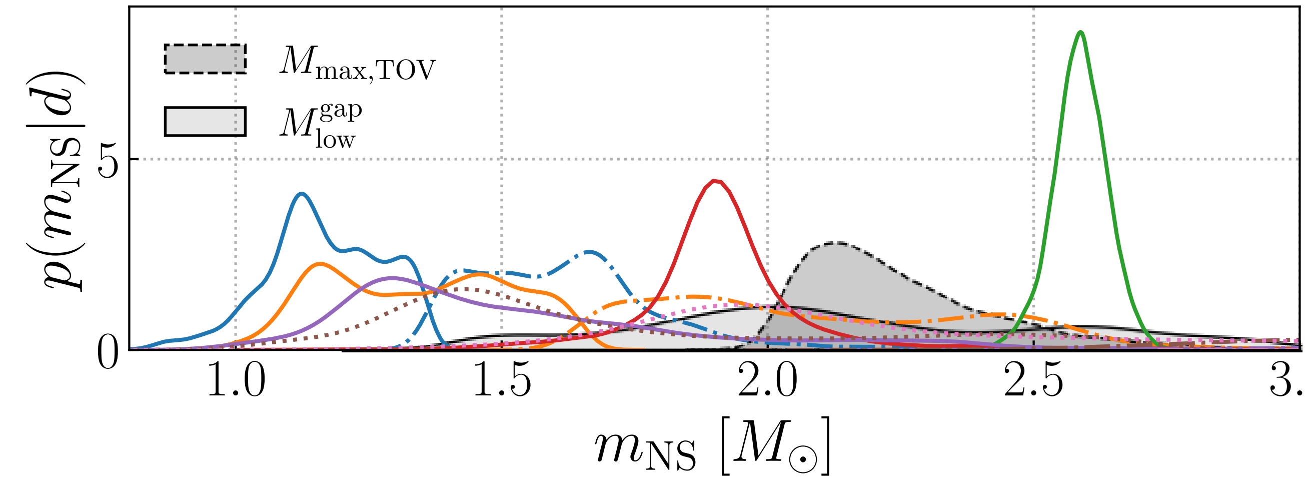


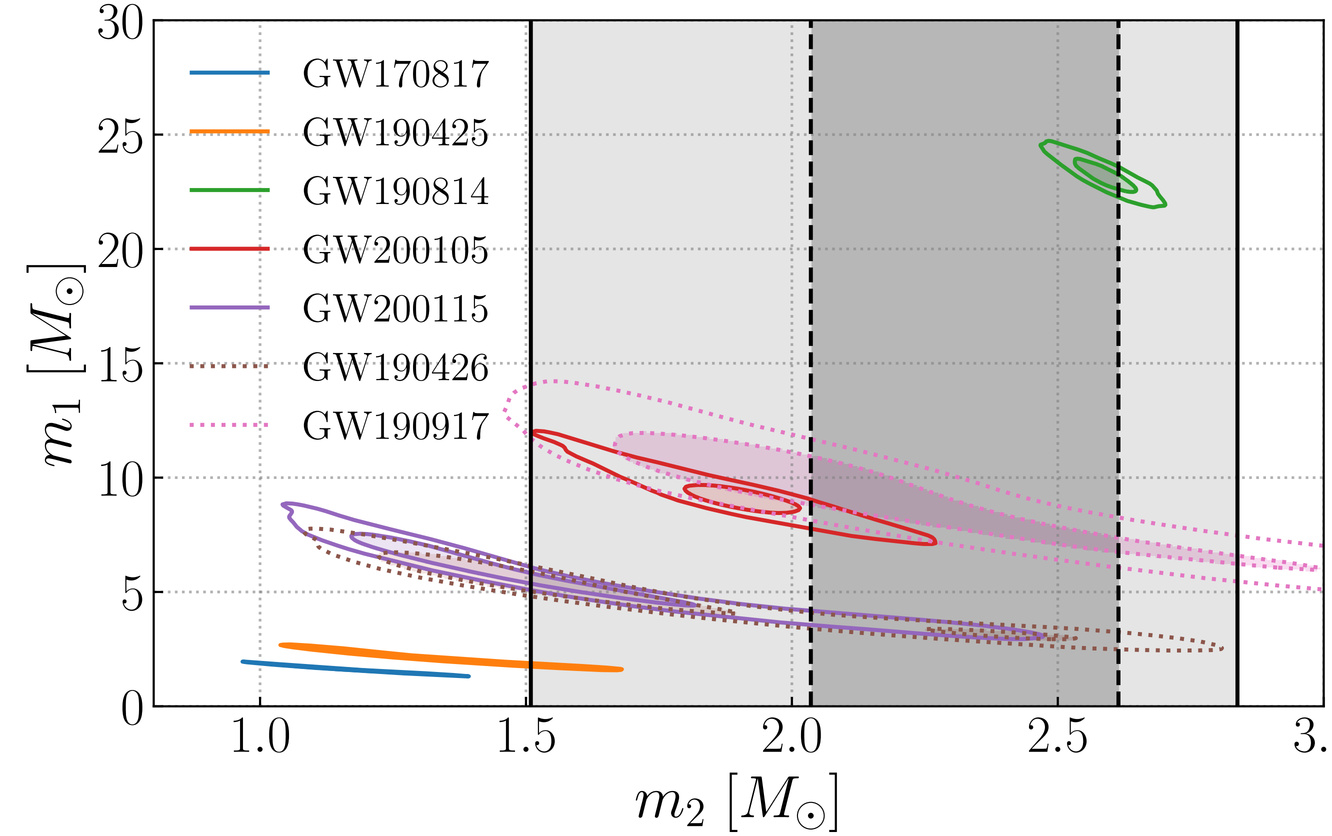
Hotokezaka 1806.10596

Introduction by example: Multiple transients

- **Example: NS mass distribution**





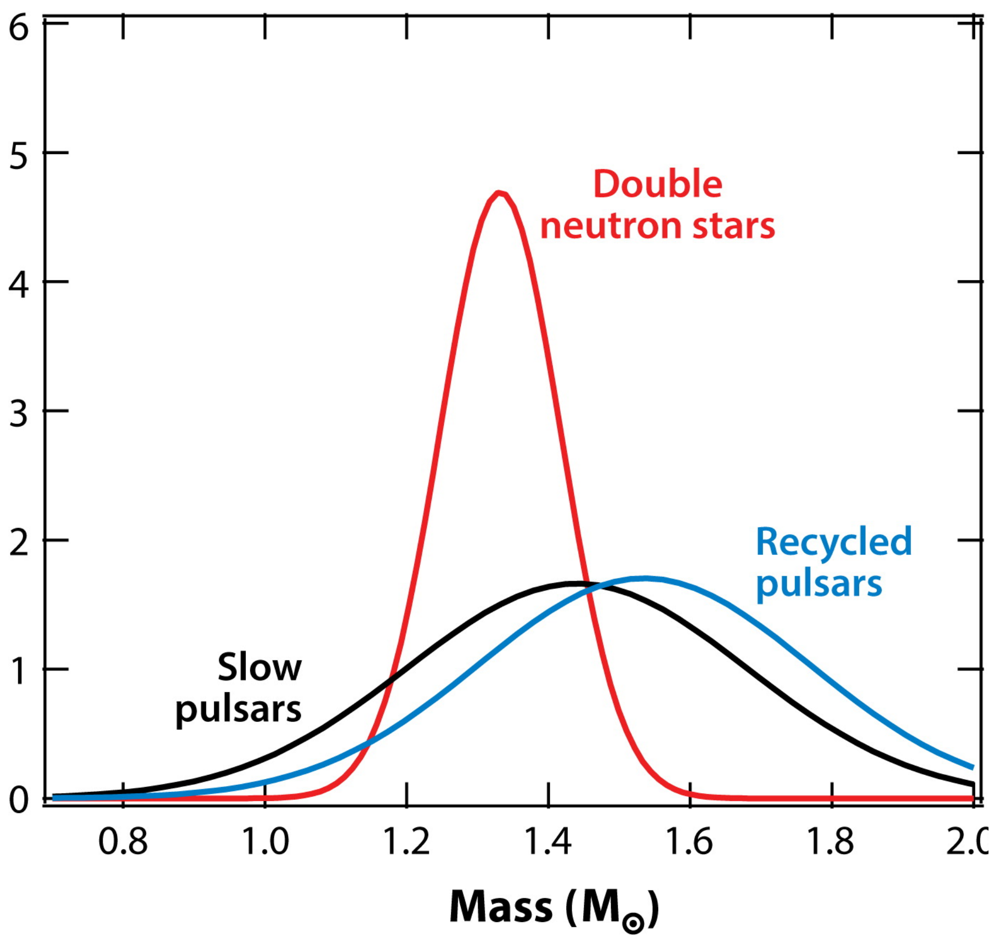


Abbott et al 2111.03634

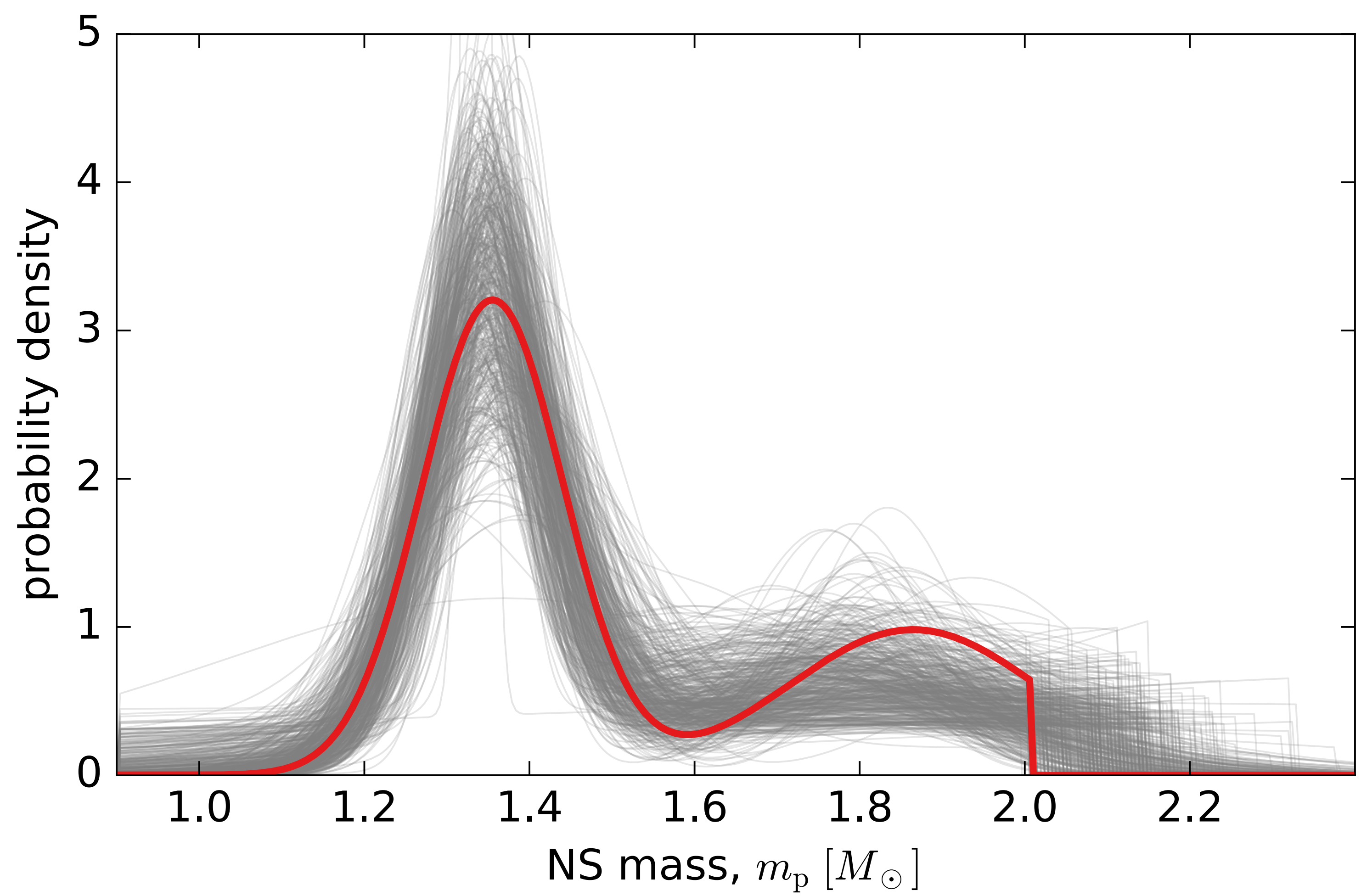
Introduction by example: Adding non-transients

- Many multi messenger probes of NS / BNS properties, like masses, spins, …
    - Pulsar observations most numerous -> mass distribution

also X-ray NS observations for radius: see AWS yesterday



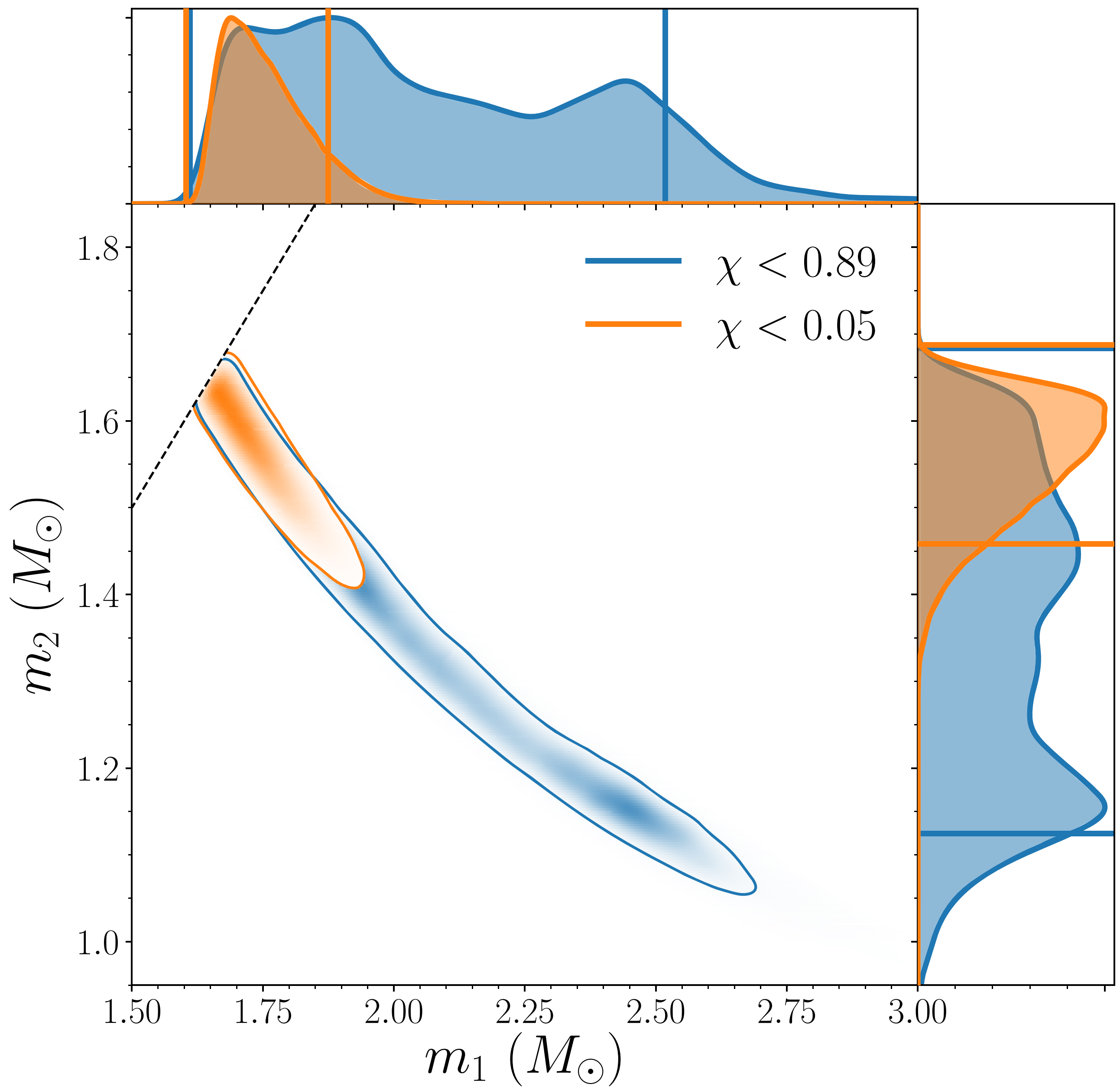
Ozel and Freire 1603.02698



Alsing et al 2018

How our measurements correlate mass/spin/tides

- Prior knowledge about NS (here, spins) strongly impacts interpretation of NS masses (and thereby tidal constraints)



Abbott et al 2020 (190425z)

Outline

- Motivation
- Single transients
    - Method review
    - Adding ingredients: GW data/model, EM data/model, EOS, …

  Lange et al 2022
  Ristic et al 2021 2105.07013

- Population analysis of (mostly) one set of observables

  Abbott et al 2021 2111.03634
  Wysocki et al 2020 2001.01747
  Al-Mamun et al 2020 2008.12817

- Adding heterogeneous additional inputs

  Holmbeck et al 2021 2110.06432
  Ristic et al 2022

- Putting it all together: tools and tricks of the trade

Single transients: Methods review

- Standard Bayesian: likelihood * prior

$$\frac{\mathcal{L}(x)p(x)}{\int dx \mathcal{L}(x)p(x)}$$

- Usually performed by (some kind of) Monte Carlo integration -> **fair draw samples** x_k

Single transients: Methods review

- Standard

$$\frac{\mathcal{L}(x)p(x)}{\int dx \mathcal{L}(x)p(x)}$$

- Likelihood requires **detailed forward model of observation**:
  - Simplified (inspiral-dominated GW, disk/ejecta EM) approach:

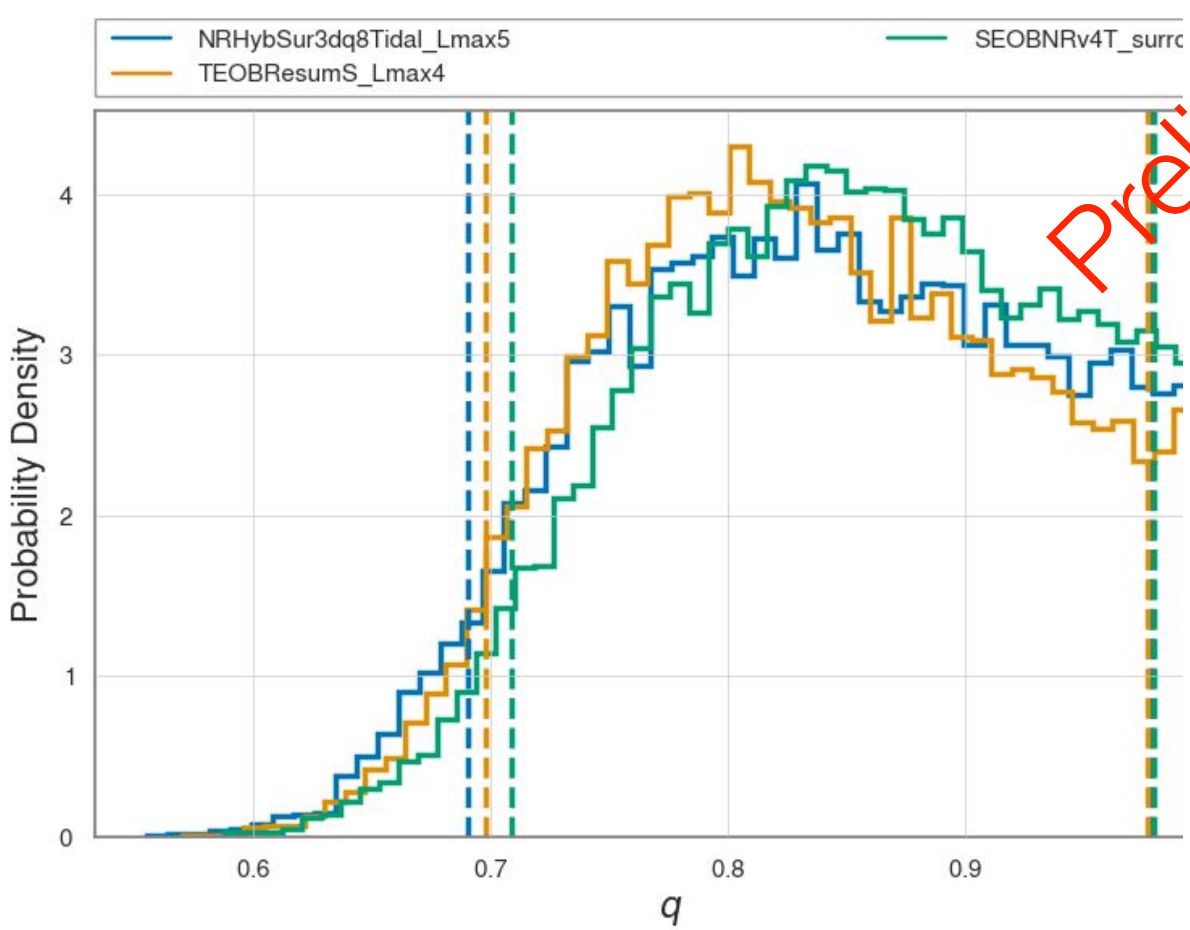
$$\mathcal{L}(x) = \mathcal{L}_{GW}(x, \mathrm{tides}(x, EOS))\mathcal{L}_{EM}(\mathrm{ejecta}(x, EOS))$$

    - GW model for binary evolution and merger
    - tides from EOS
    - Ejecta from binary parameters, EOS/tides, including
      - mass, velocity, composition, angular distribution
    - (anisotropic) EM model from binary ejecta/disk

GW-only analysis (with ‘free’ tides)

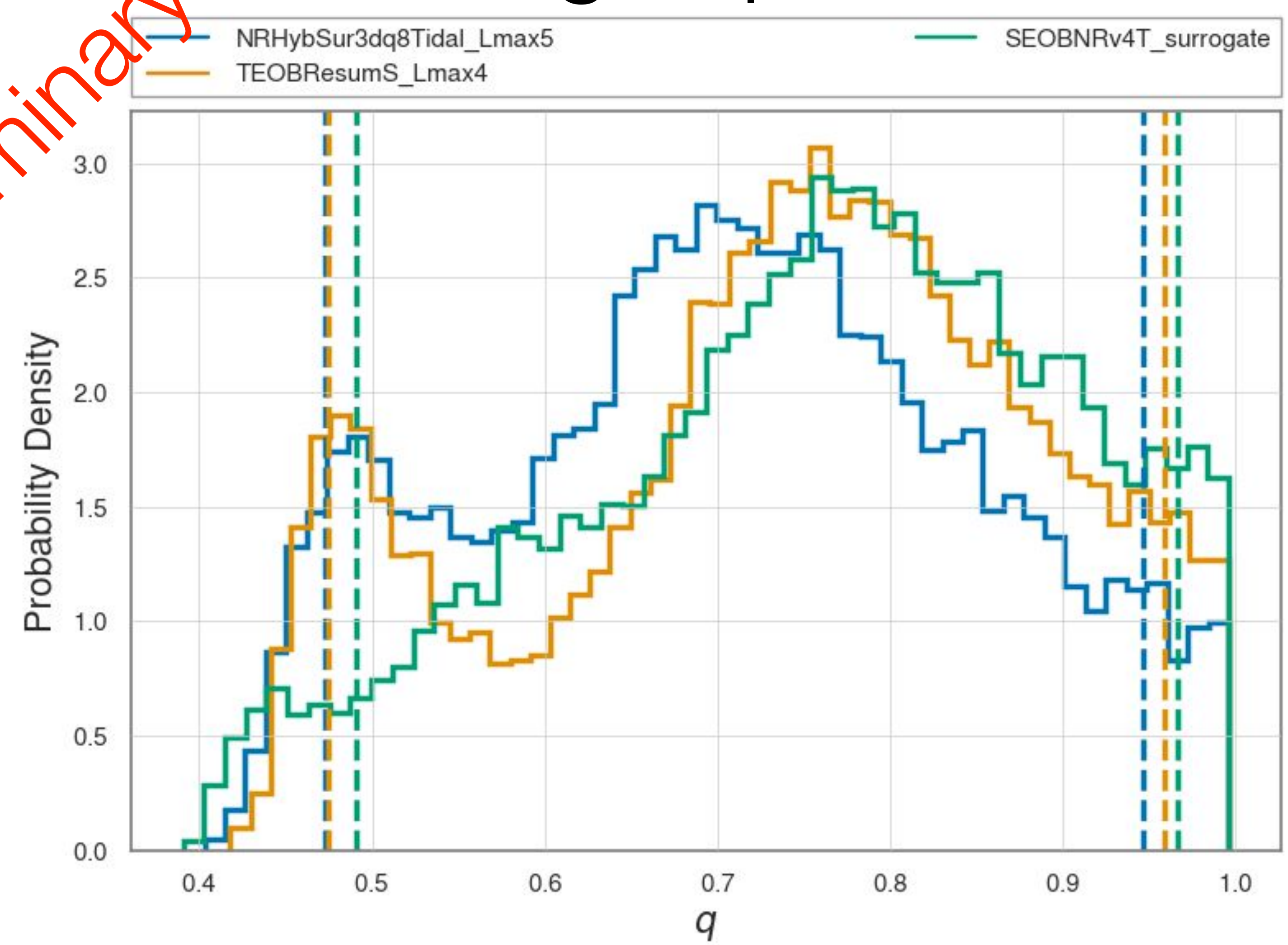
- GW systematics of merging NS tricky : tides **at end**
  - Reanalyses with latest HM models -> different mass ratio? p(q)

Low spin



Preliminary

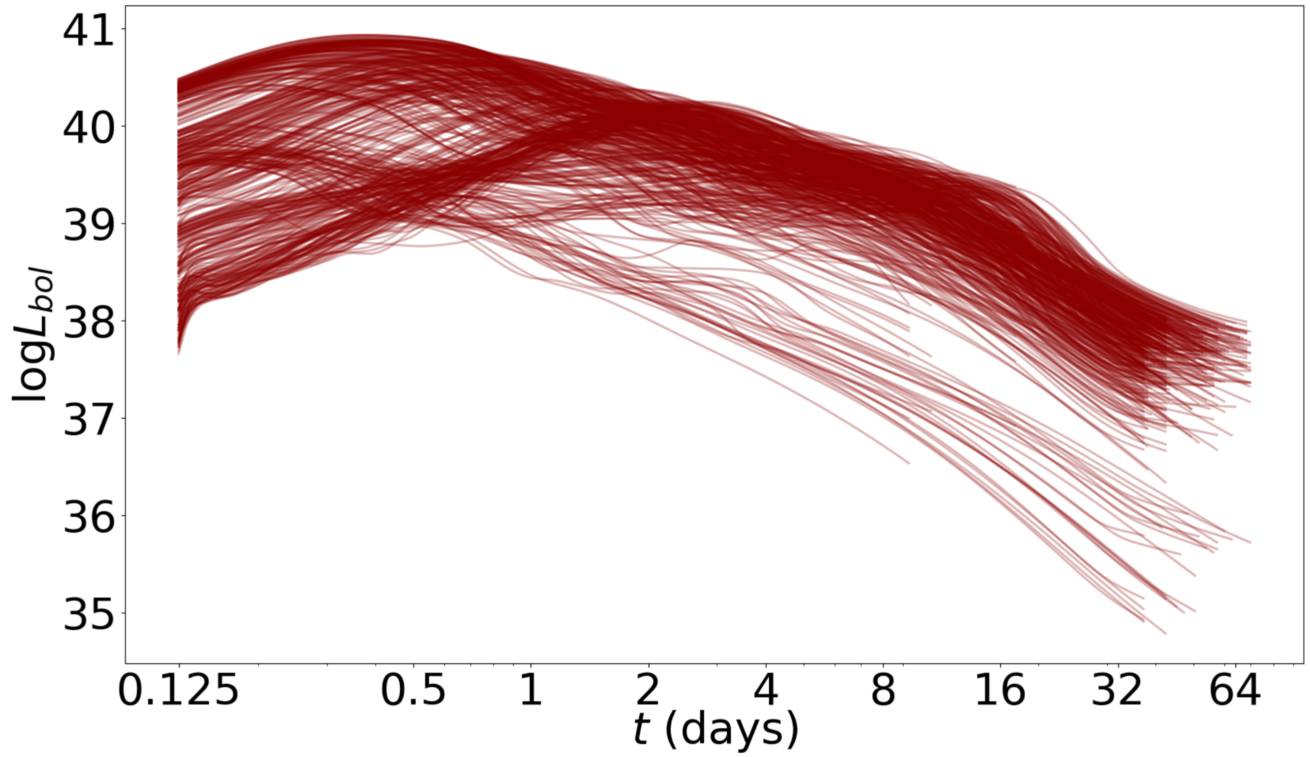
High spin



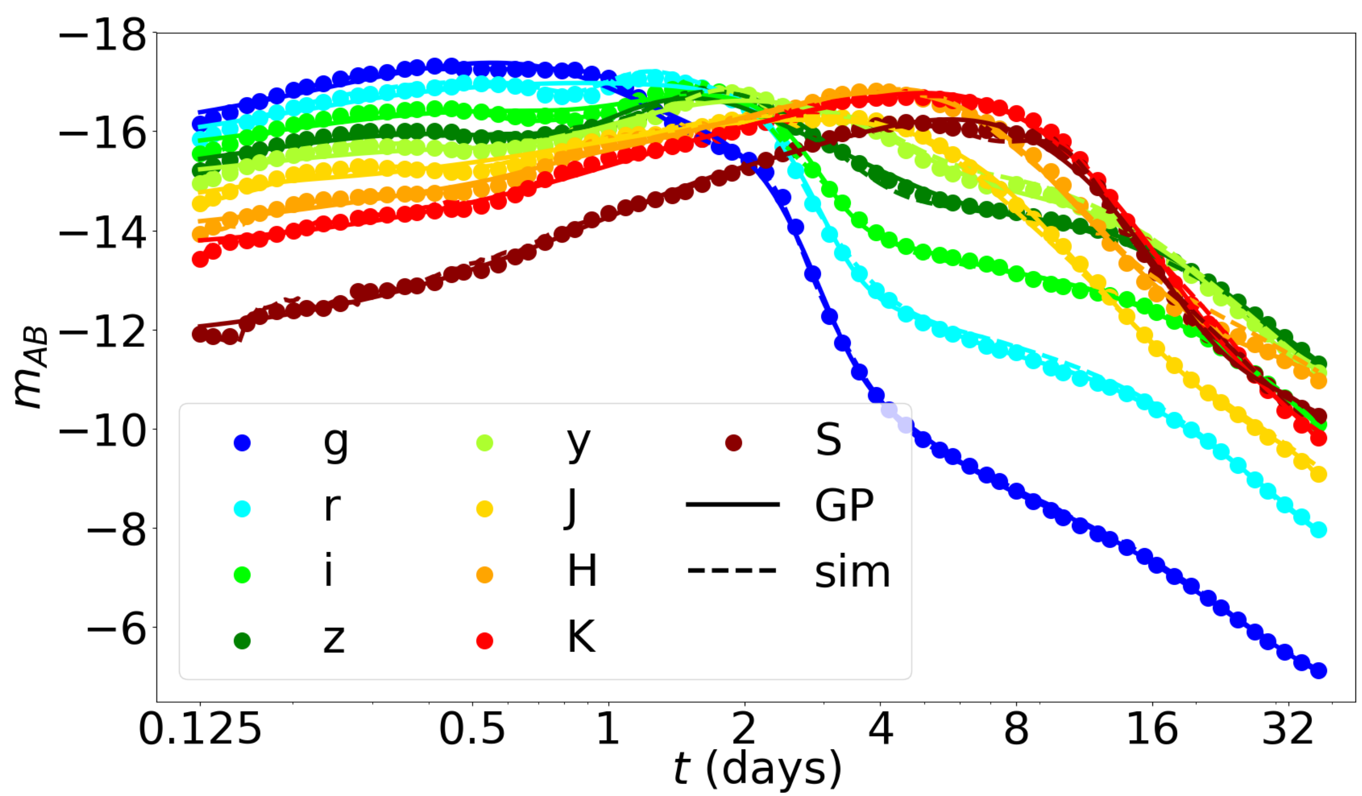
Lange et al 2022, in prep

Kilonova light curves: A surrogate model

- Detailed models (opacity; multicomponent; composition;...); actively-learned library



- Interpolate time, 2-component **mass/velocity**



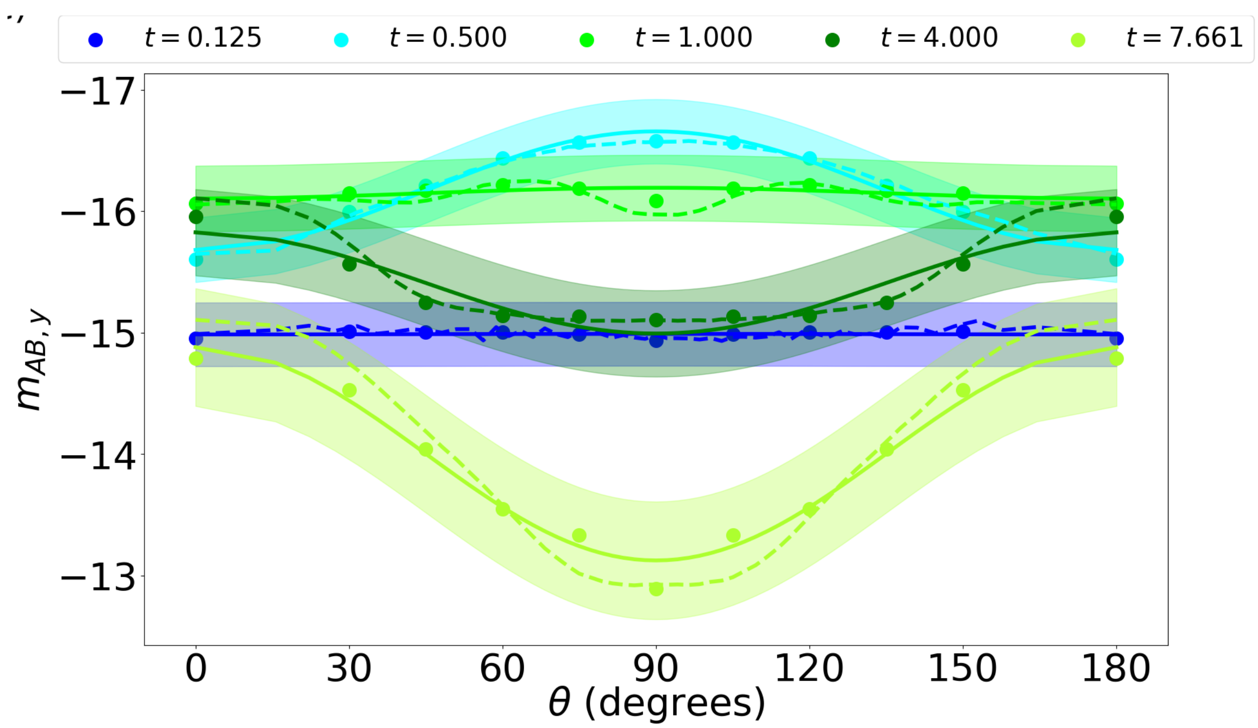
interpolation reliable in time

Ristic et al , Phys Rev Research 2021

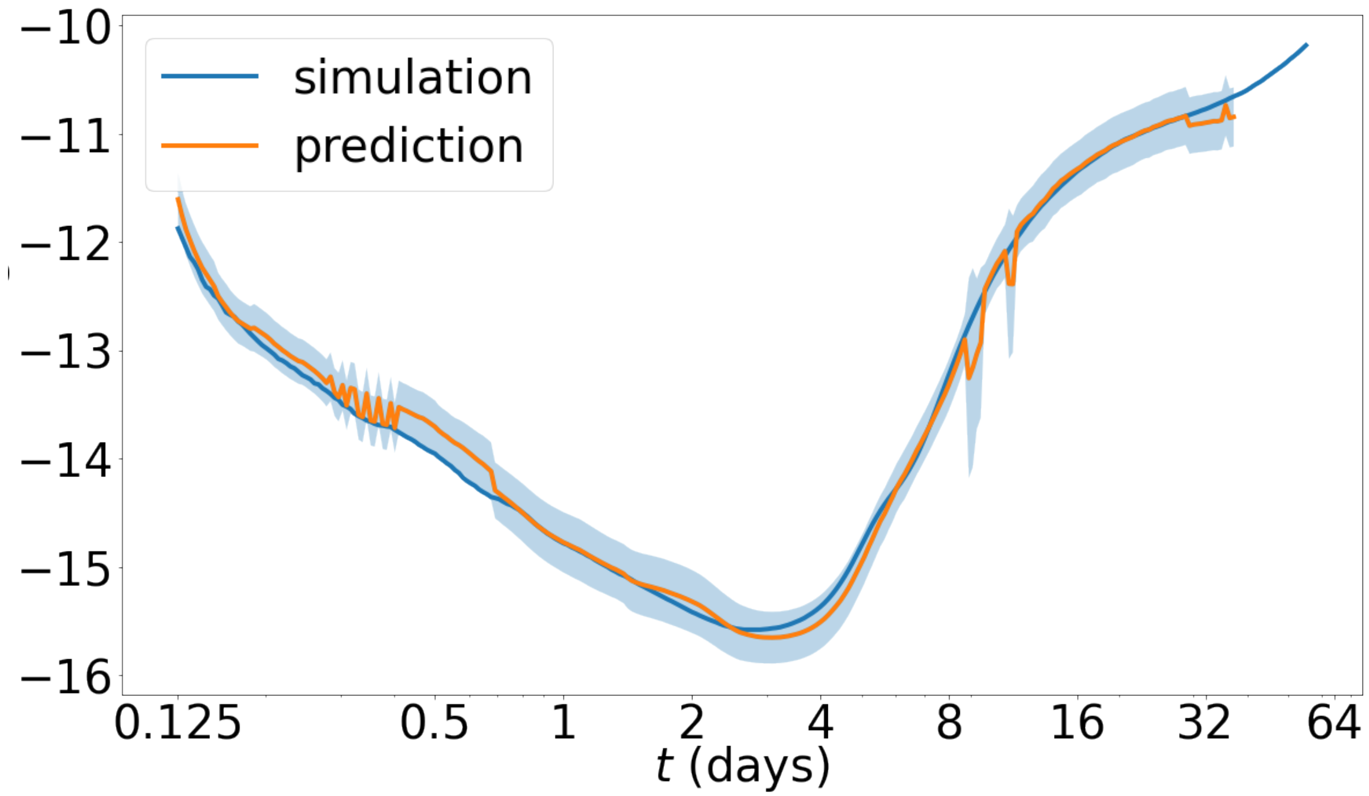
Kilonova light curves: A surrogate model

- Detailed models (opacity; multicomponent; composition;…); actively-learned library
- Interpolate Includes **mass/velocity**, **angle**, **wavelength (color)**
  - **arbitrary observing bands & source redshift**

angle interpolation



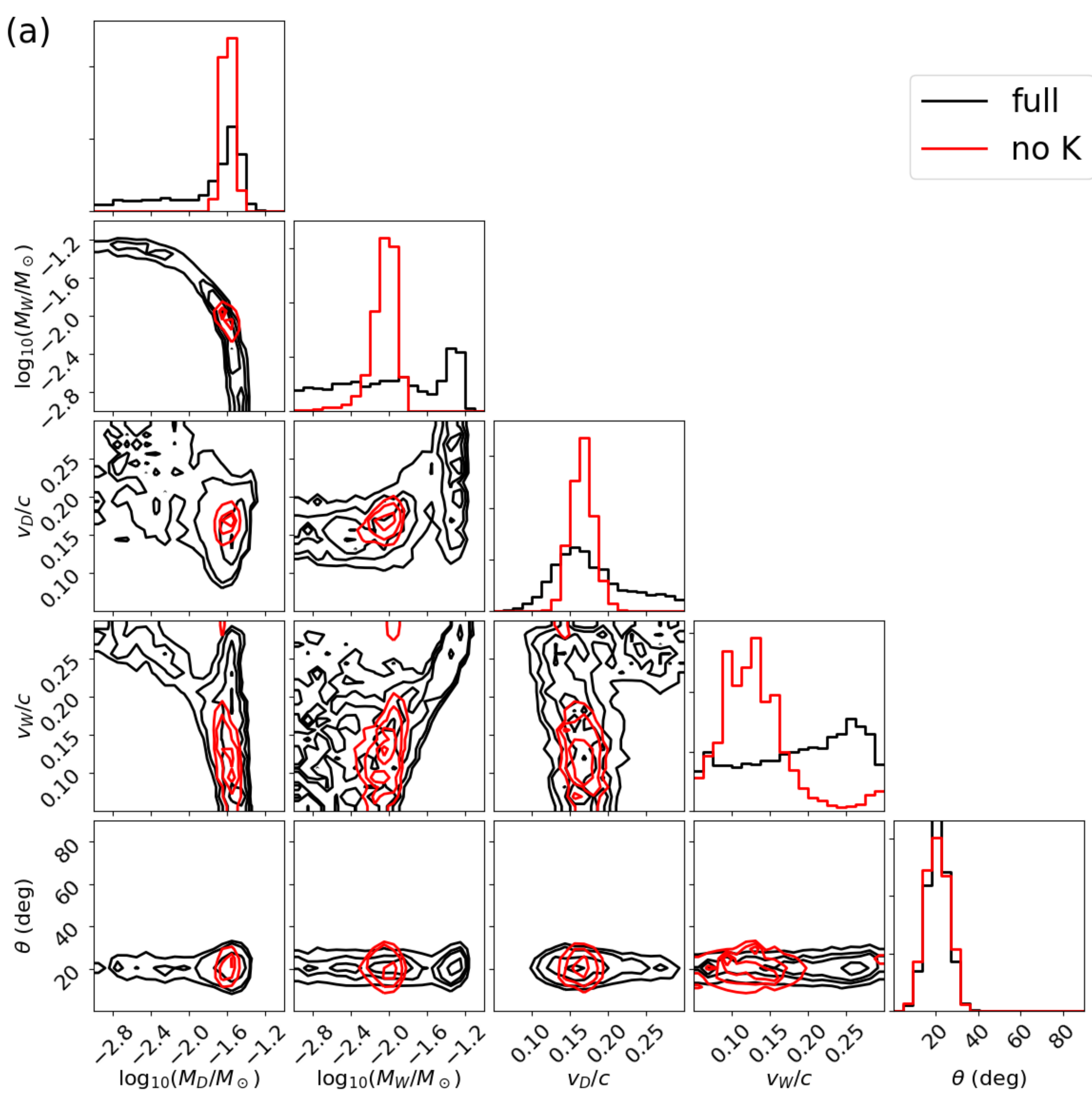
wavelength interpolation
(vs untrained filter)

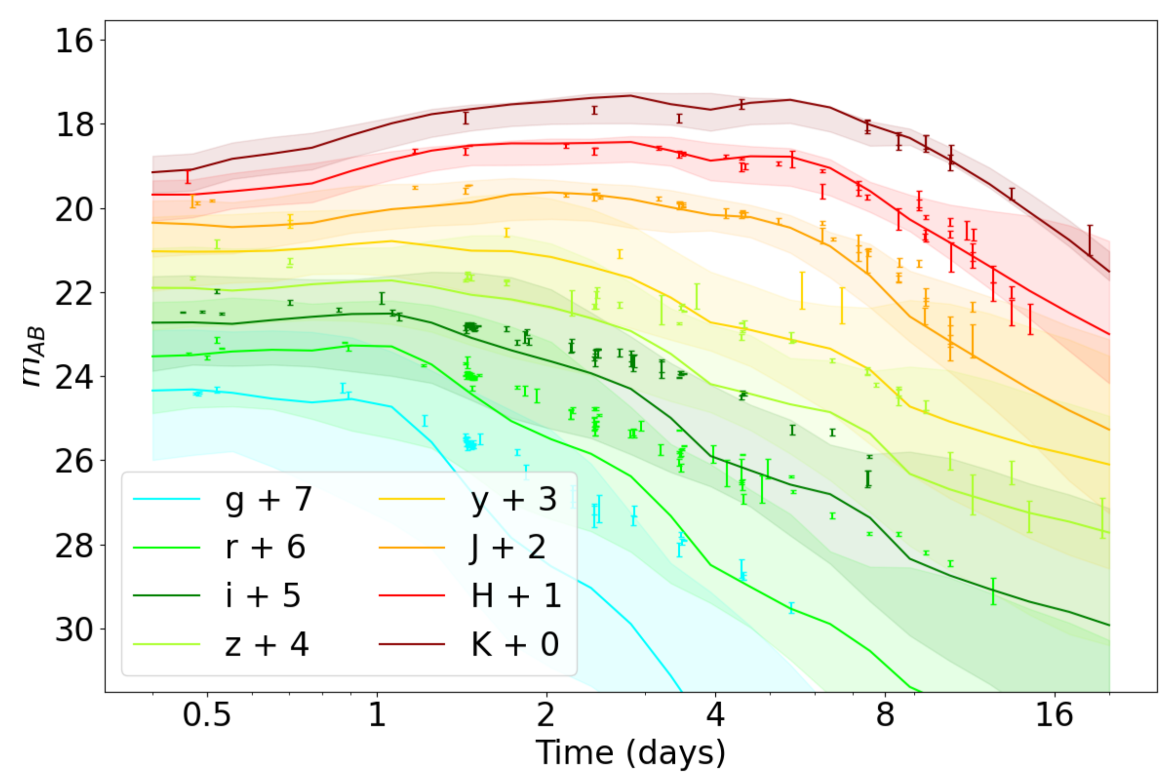


Repository: https://github.com/markoris/surrogate_kne

Kilonova-only analysis

- Can deduce ejecta properties from EM
    - GW170817, one of many examples in literature





Populations: Methods review

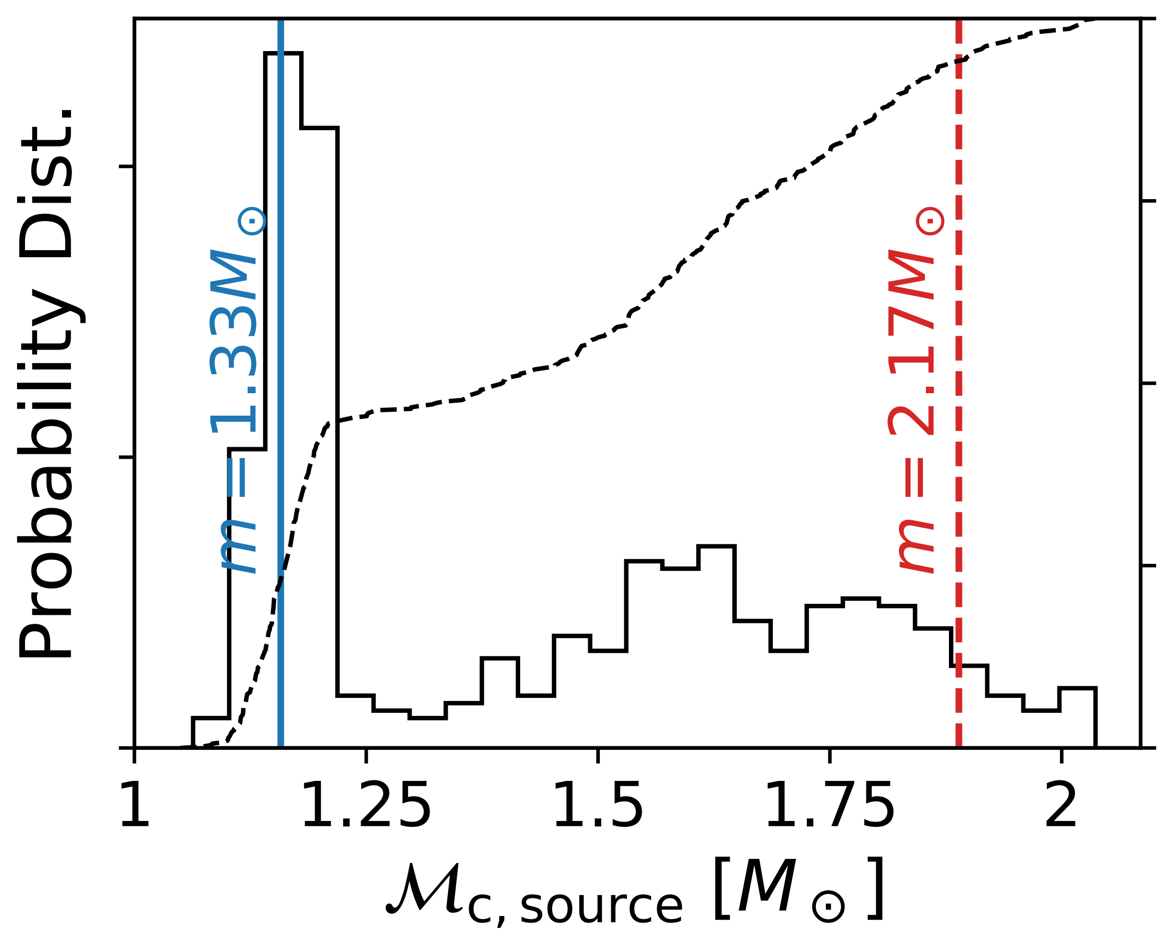
- Standard: Bayes + inhomogeneous Poisson process

$$e^{-\mu(\Lambda)} p(\Lambda) \prod_k \int dx \mathcal{L}_k(x) p(x|\Lambda)$$

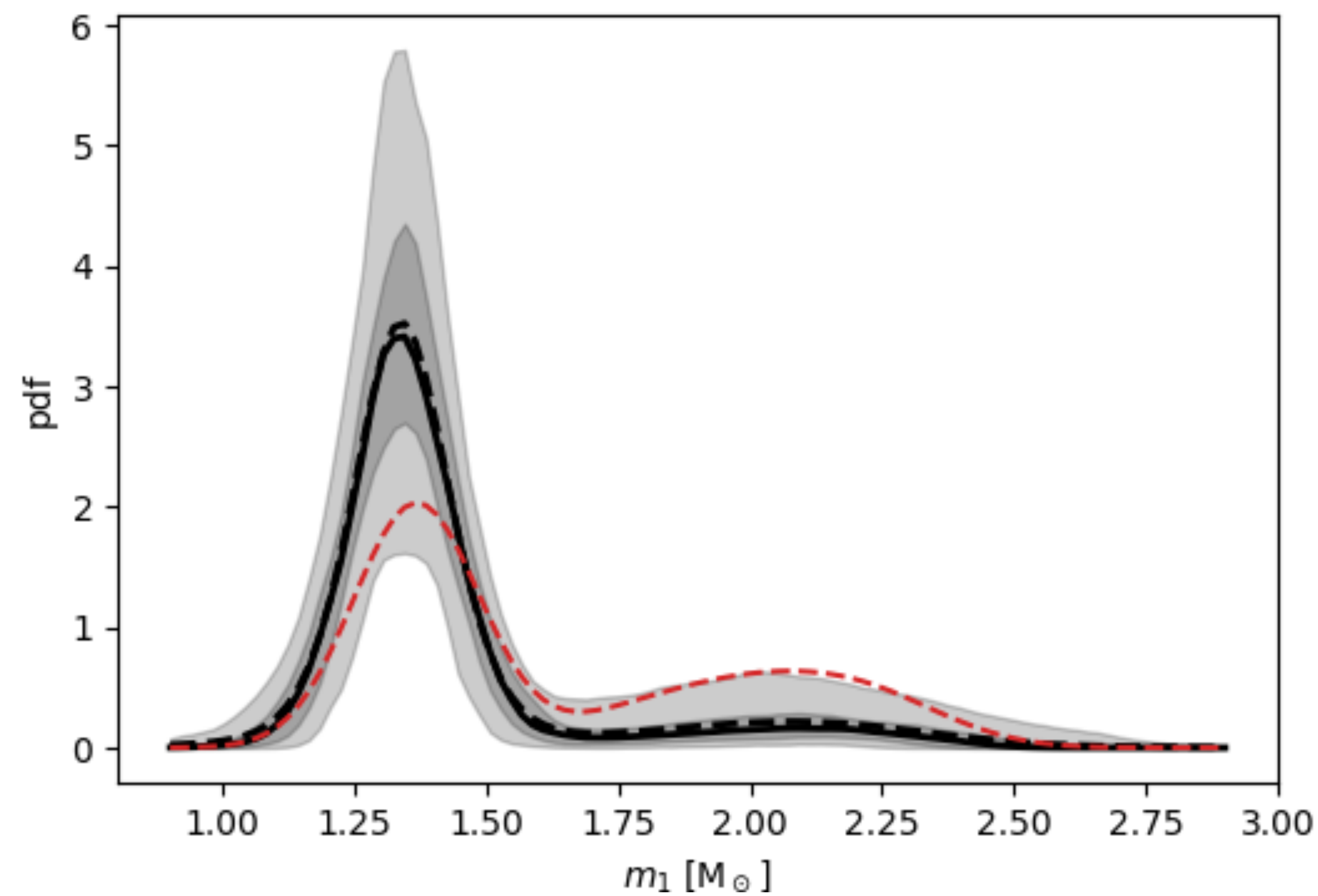
- Likelihood requires **detailed forward model of population** $p(x|\Lambda)$ including **all selection effects** $\mu(\Lambda)$ in addition to above!
  - Most models: phenomenological on current observations
    - **Fast** $p(x|\Lambda)$ but **hard to get sharp physics & generalize** for other missions
  - Realistic generative models: usually Monte Carlo, slow (>~ hours)

Synthetic GW survey of NS-NS mergers

- What happens if we combine all information, mass/spin/tides?
  - We correctly recover the mass distribution



Synthetic observed systems

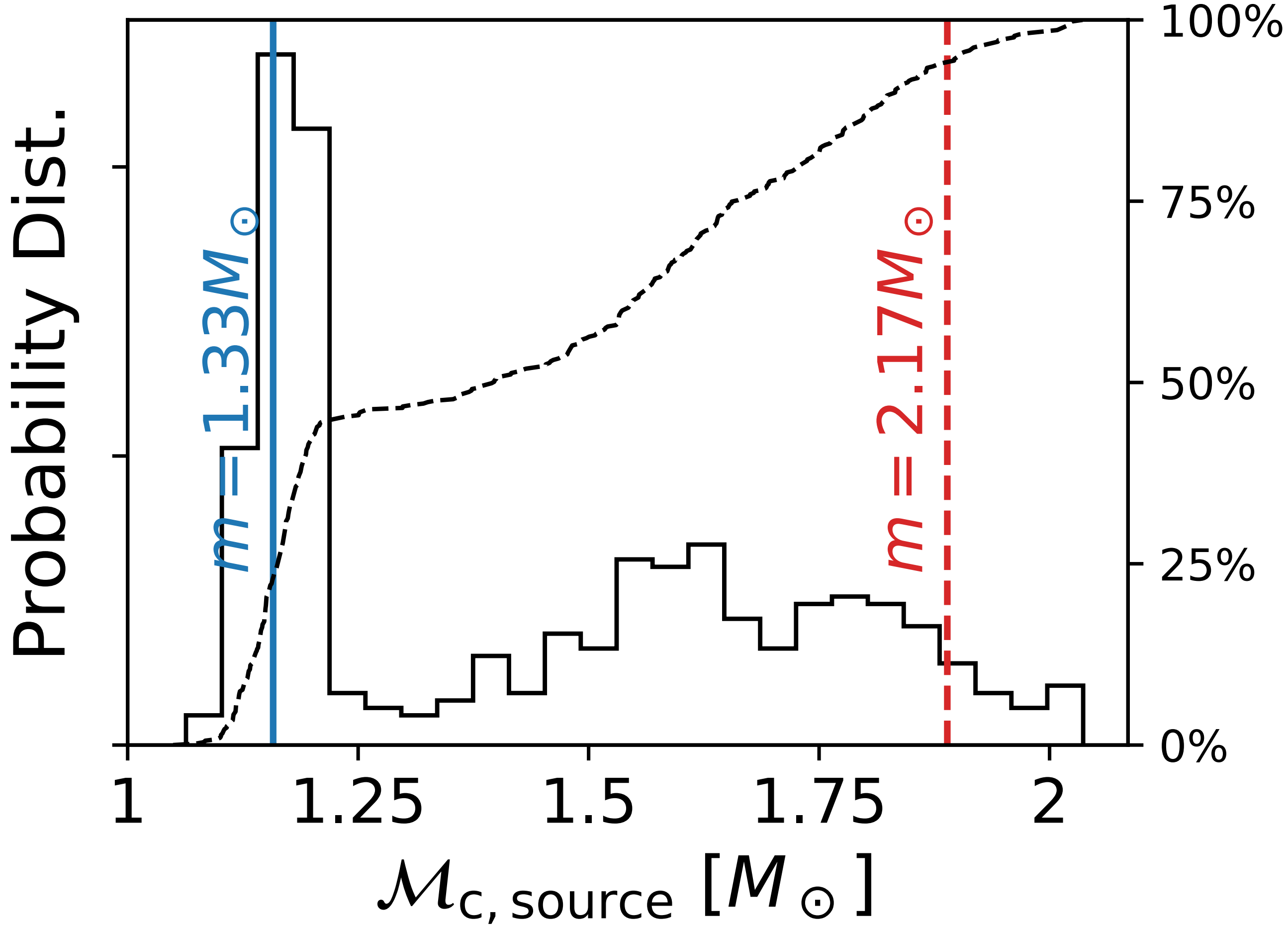


Recovery of injected population

Wysocki et al, arxiv:2001.01747

Synthetic GW survey of NS-NS mergers

- What happens if we combine all information, mass and spin?
    - & spin, and identify multiple populations



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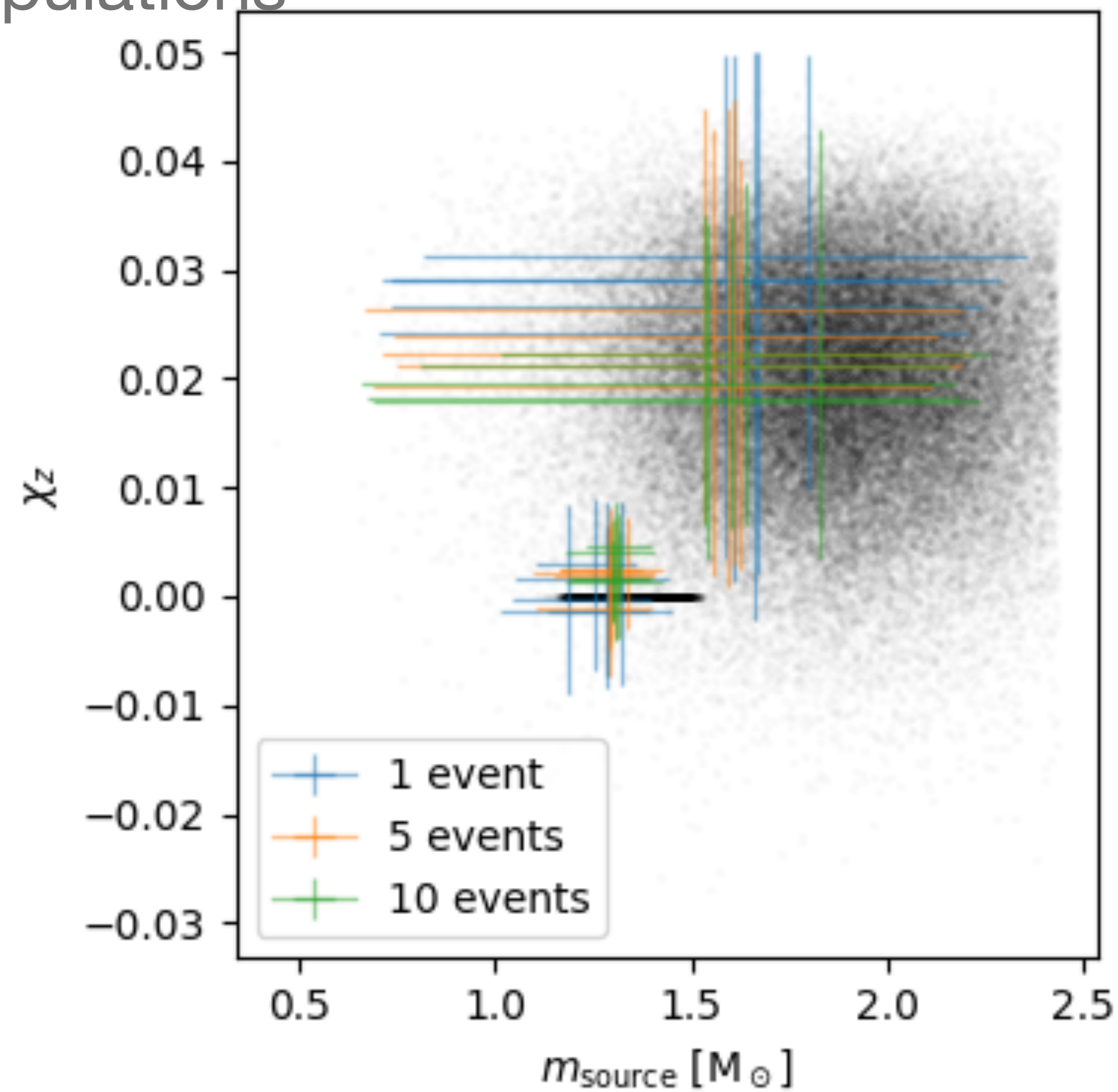

Recovery of injected population

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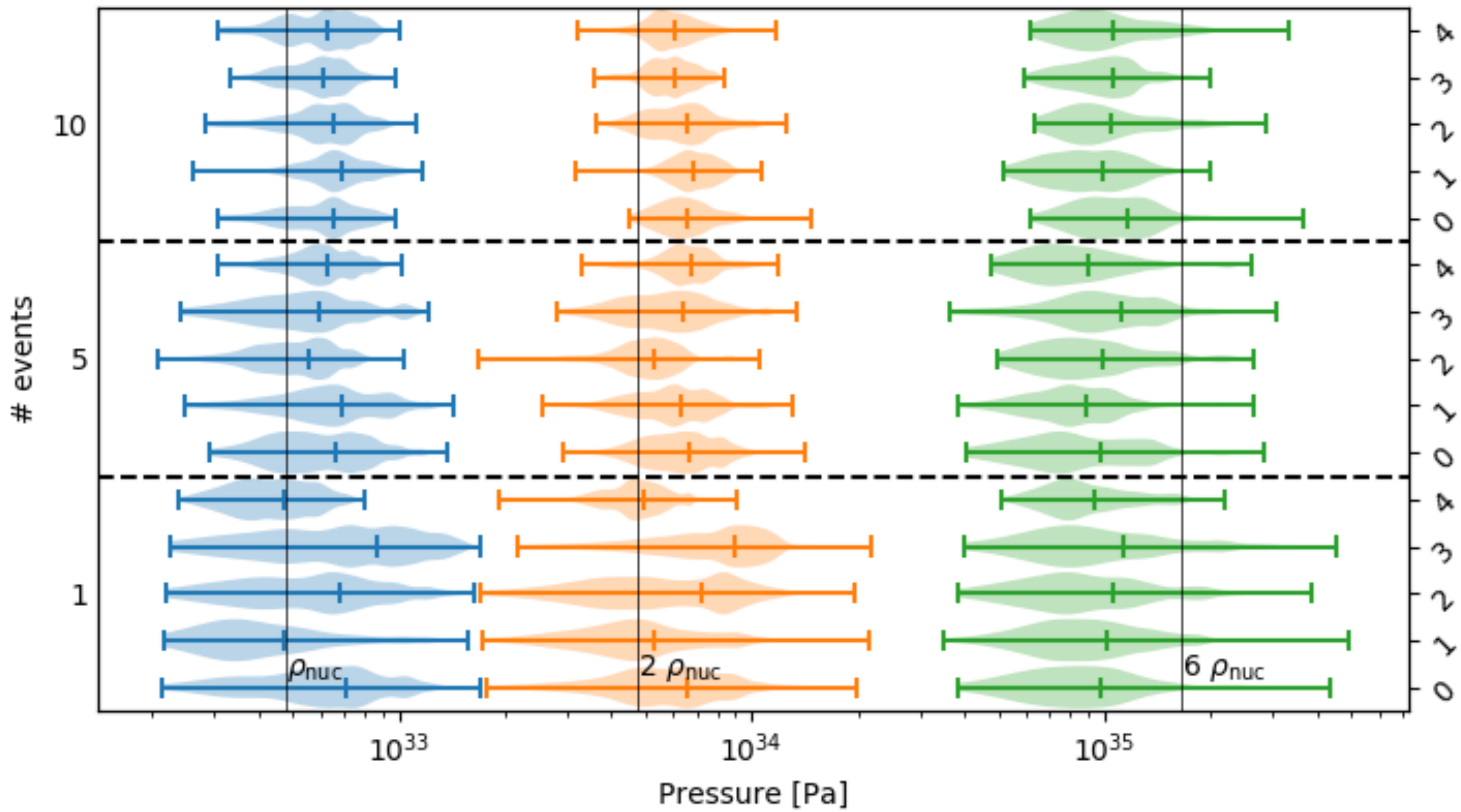
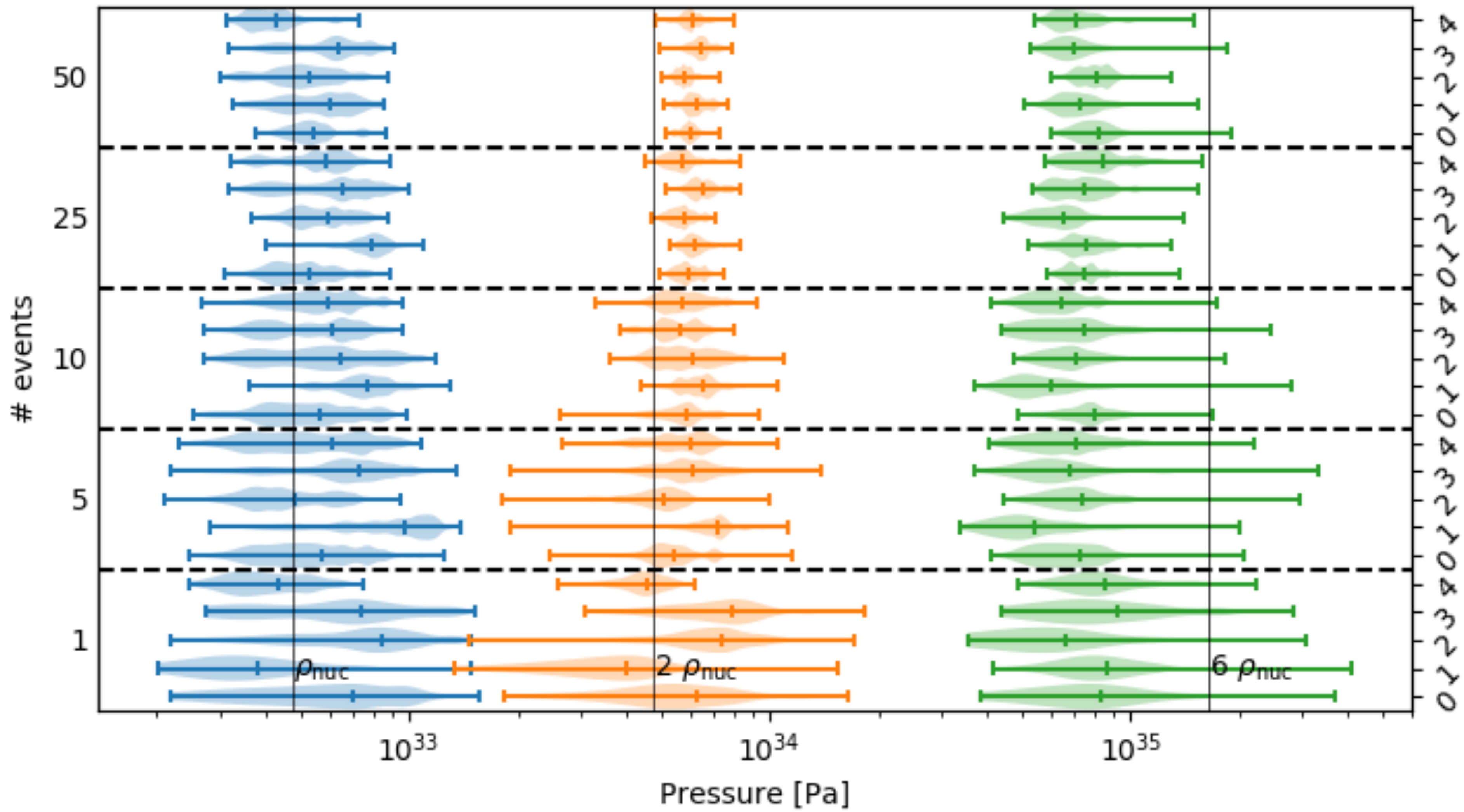
How important is joint mass/spin/EOS inference?

- Consider several small surveys of 1, 5, 10, … BNS mergers
  - Using a mass/spin model that is compatible with the data, recover EOS



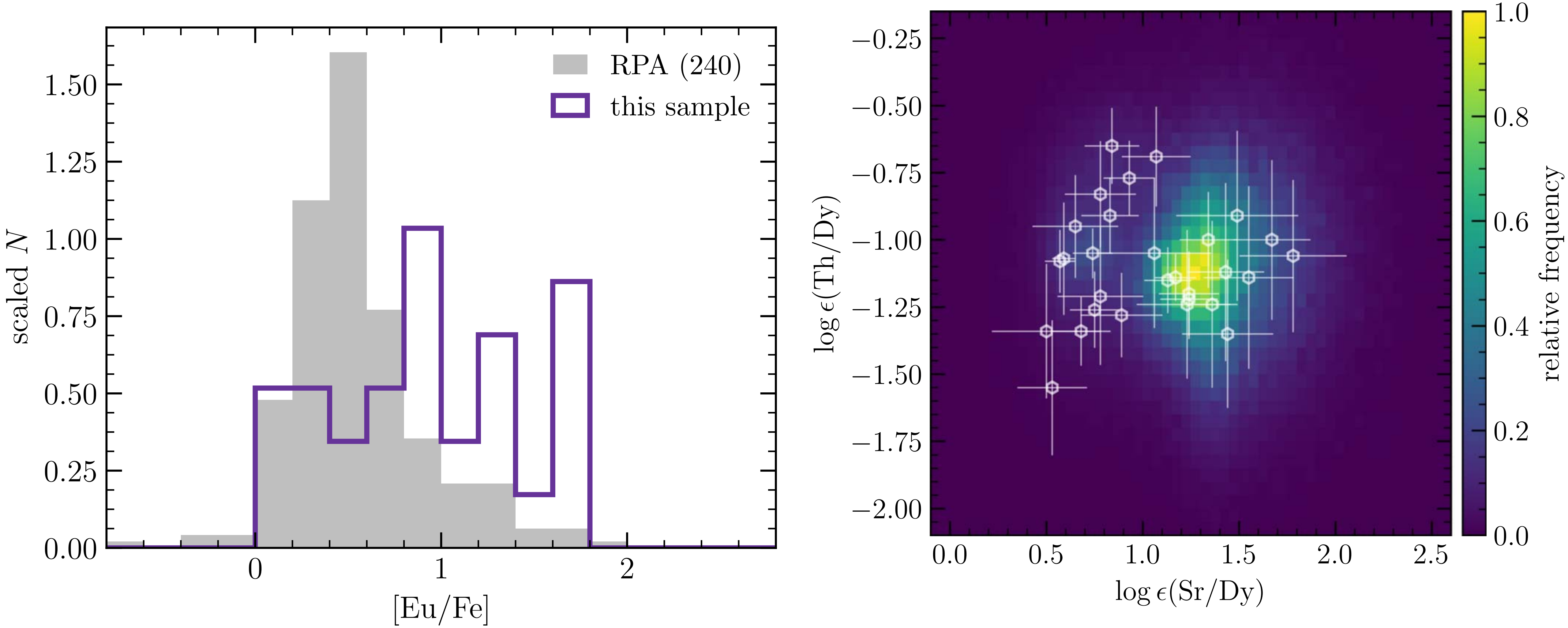
How important is joint mass/spin/EOS inference?

- Consider several small surveys of 1, 5, 10, … BNS mergers
  - Using a mass/spin model that is **oversimplified**, we **introduce biases in the recovered EOS**



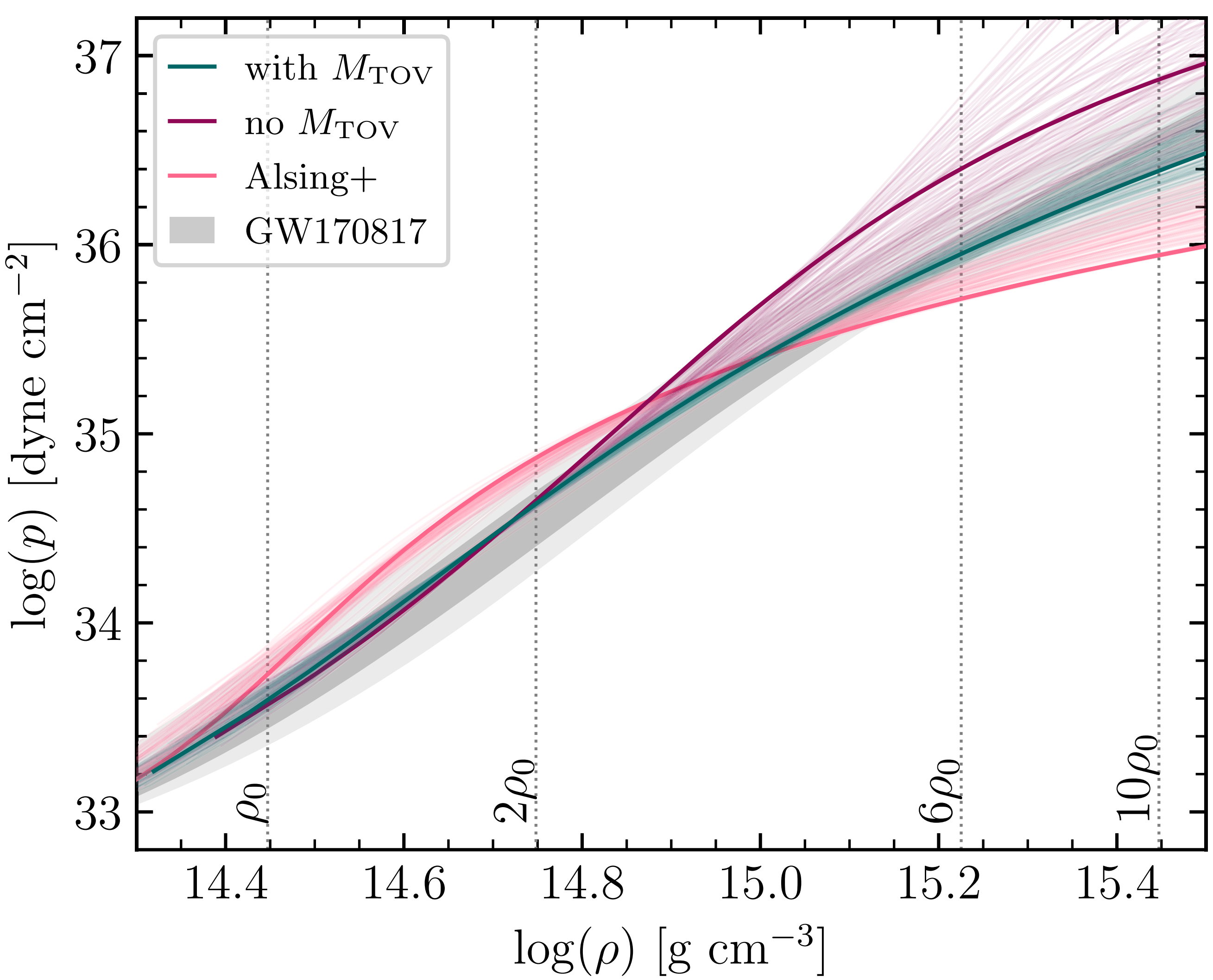
Adding other, heterogeneous observations

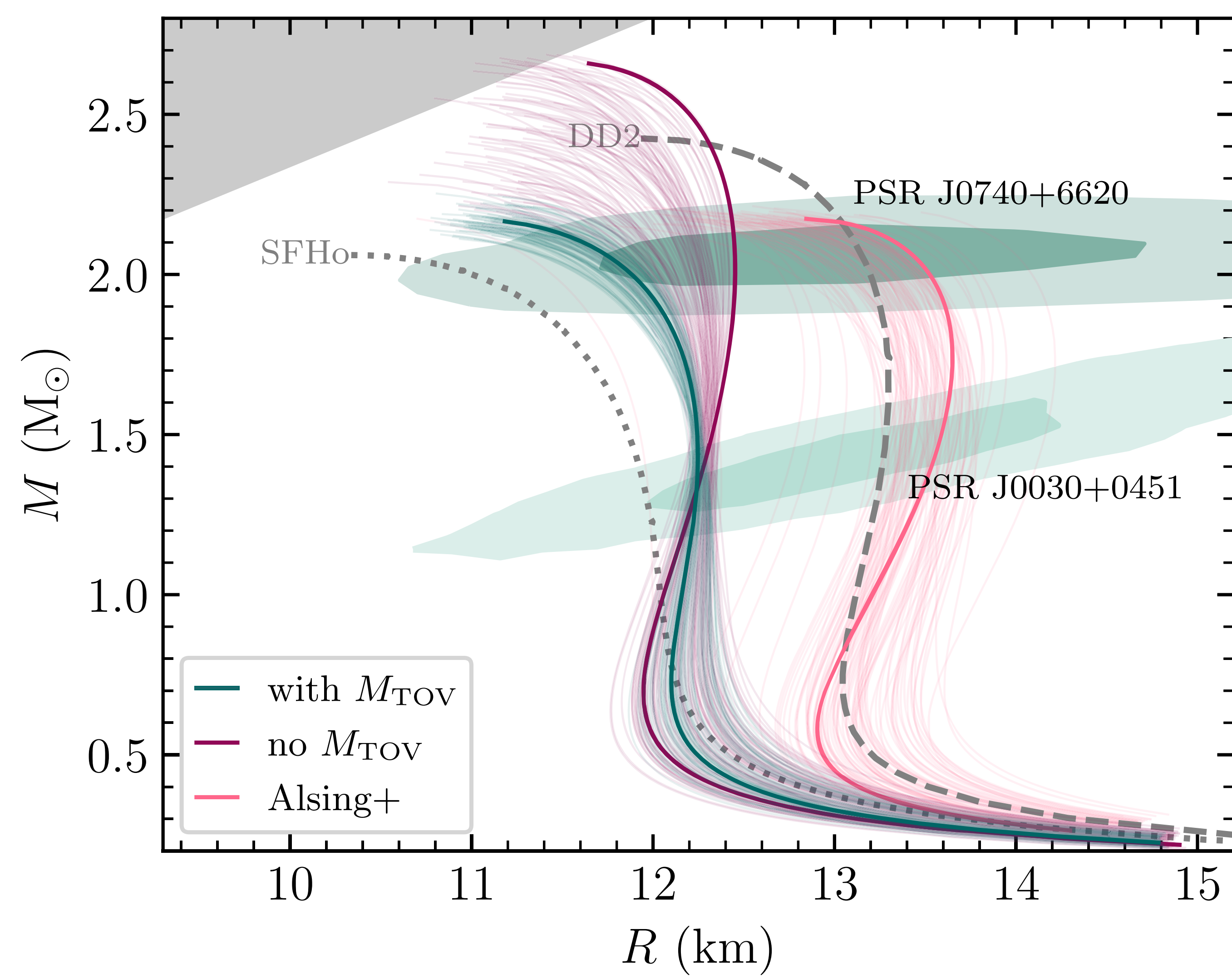
- Often we **can't** model the selection/data this carefully.
- **Example: Metal-poor stars**:
  - Selected abundance ratios + correction for selection bias
  - Construct *phenomenological* likelihood



Adding other, heterogeneous observations

- Often we **can't** model the selection/data this carefully.
- **Example: Metal-poor stars**:
  - Forward model r-process elements abundances: **get EOS model**





Summary

- Motivation
- Single transients
  - Method review
  - Adding ingredients: GW data/model, EM data/model, EOS, …

Lange et al 2022
Ristic et al 2021 2105.07013

- Population analysis of (mostly) one set of observables

Abbott et al 2021 2111.03634
Wysocki et al 2020 2001.01747
Al-Mamun et al 2020 2008.12817

- Adding heterogeneous additional inputs

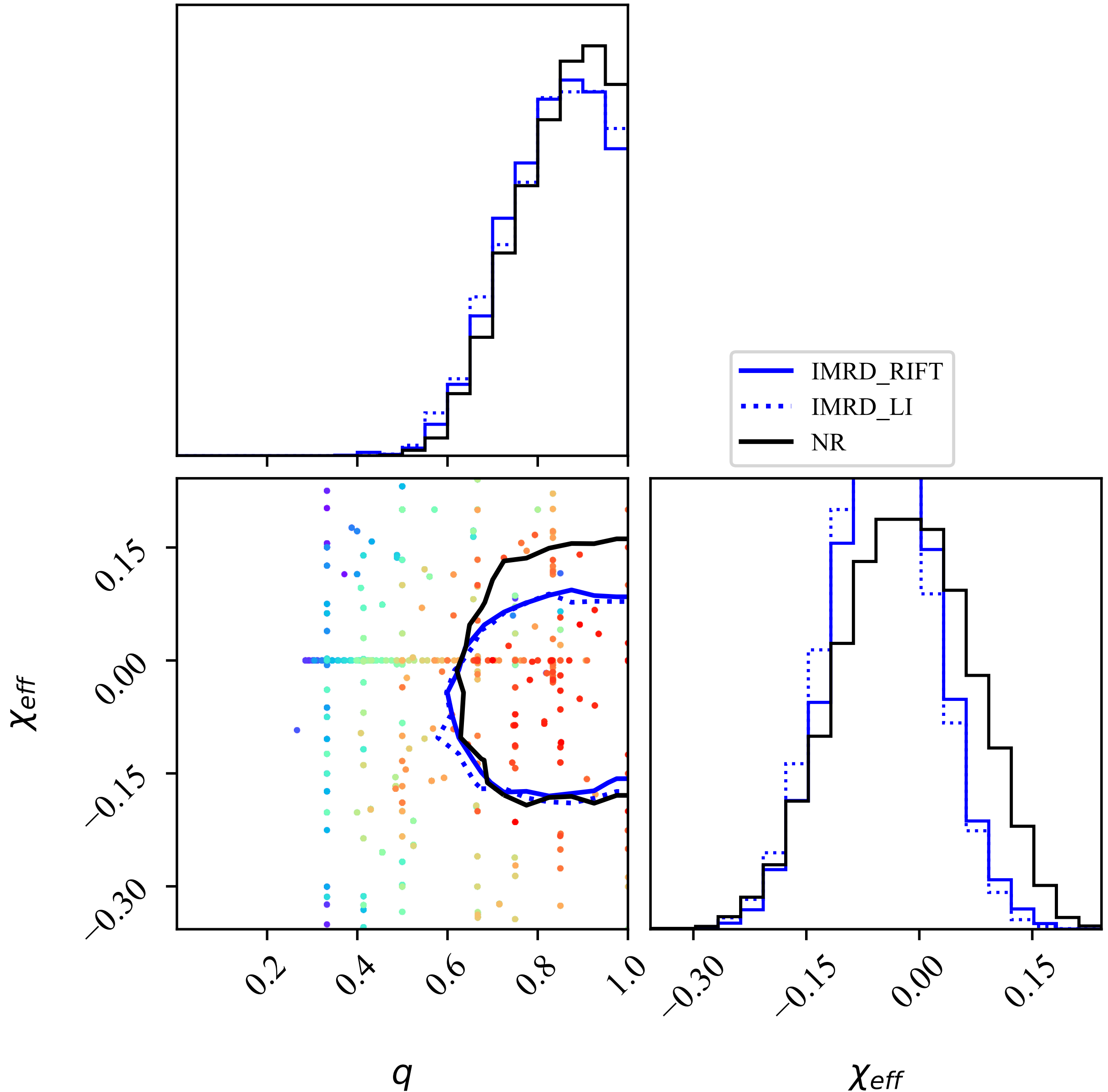
Holmbeck et al 2021 2110.06432
Ristic et al 2022

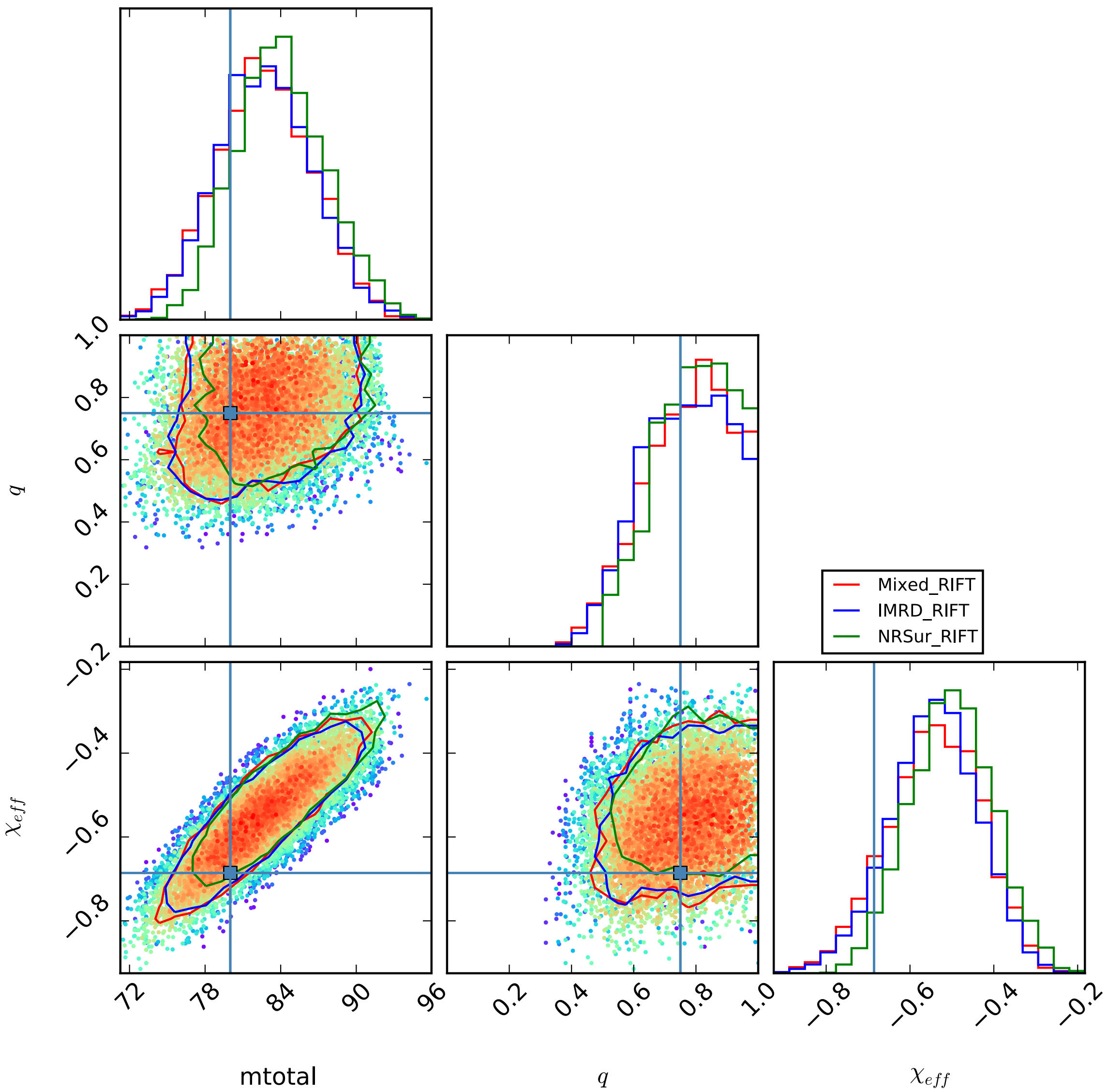
- Putting it all together: tools and tricks of the trade [**as time permits**]

Tricks of the trade

- Surrogate generative models, **or (easier)**
- Interpolate (marginal) likelihoods of costly models
  - Numerical relativity vs GW
  - GW PE

Abbott et al 1606.01262
Lange et al 1805.10457

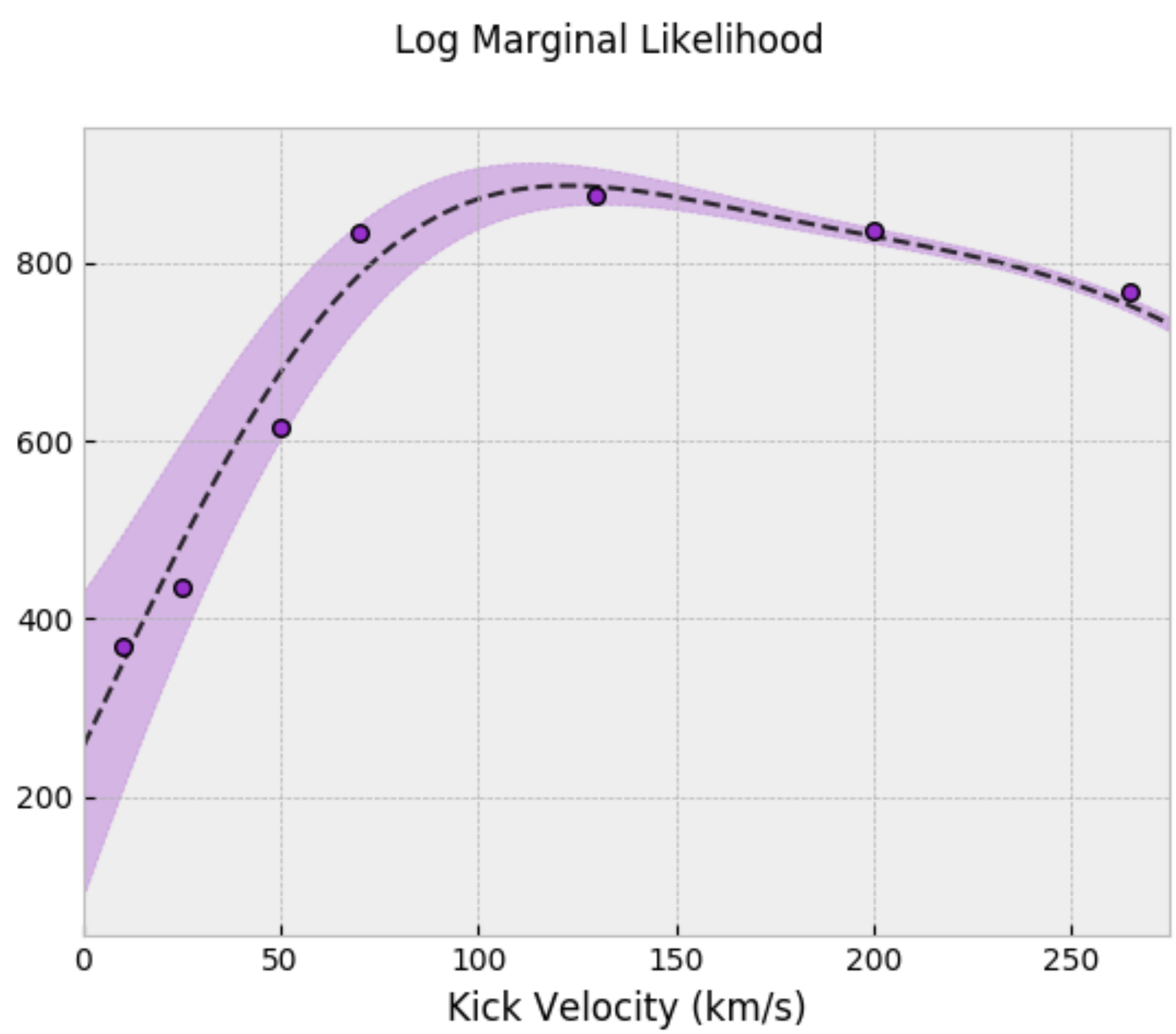




Tricks of the trade

- Surrogate generative models, **or (easier)**
- Interpolate (marginal) likelihoods of costly models
  - Numerical relativity vs GW
  - GW PE
  - Compact binary formation vs GW observation

Abbott et al 1606.01262
Lange et al 1805.10457

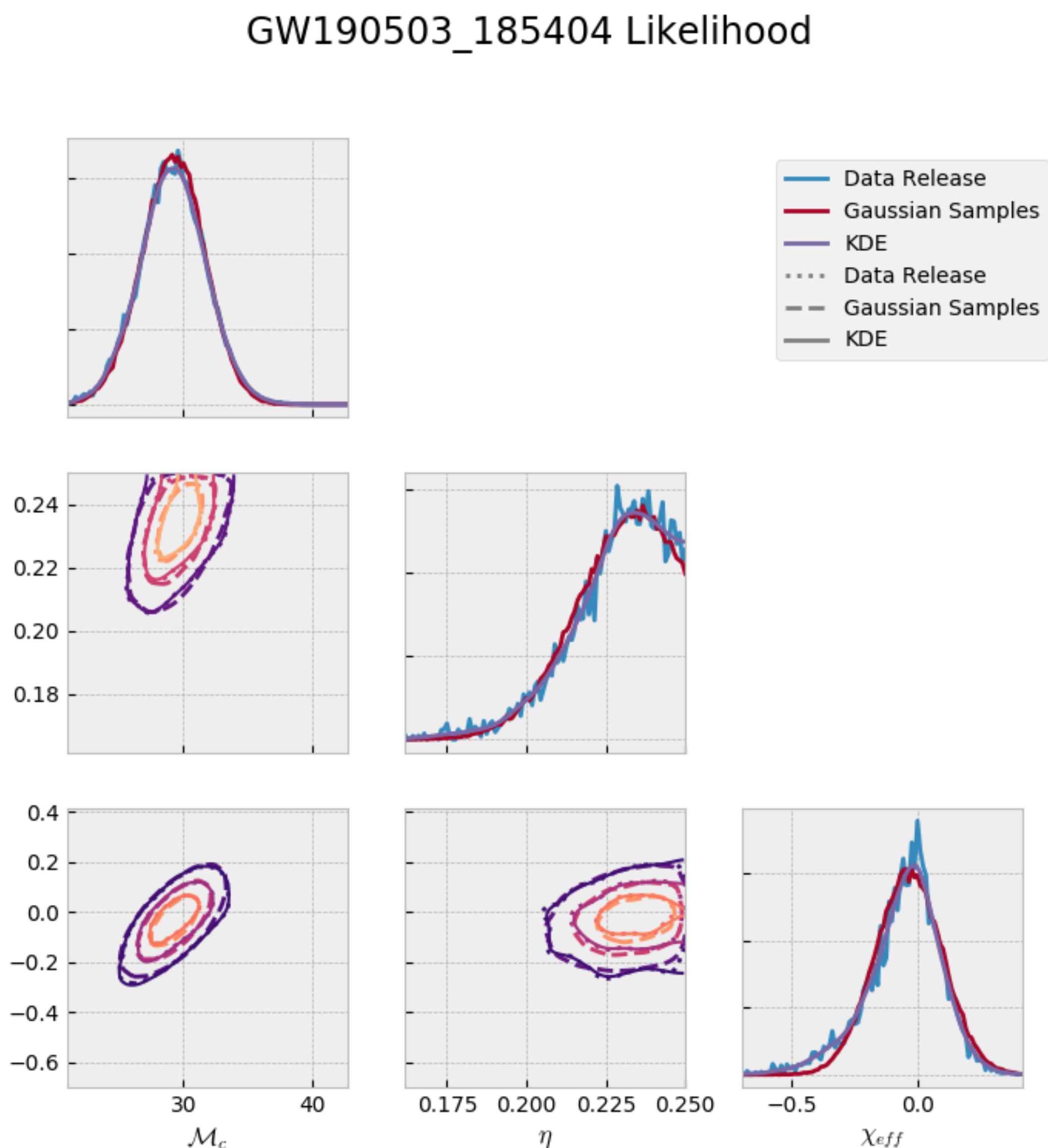


Doctor et al 2020 1911.04424
Wysocki et al 2018 PRD 97 3014
Delfavero et al 2107.13082

Tricks of the trade

- Surrogate generative models, **or (easier)**
- Interpolate (marginal) likelihoods of costly models

- Focus on **generative** models (which make multiple predictions)
- Use fast likelihoods (**gaussian**, GMM, etc) for large-scale input



Delfavero et al 2107.13082 + in prep

Good enough for tides too…

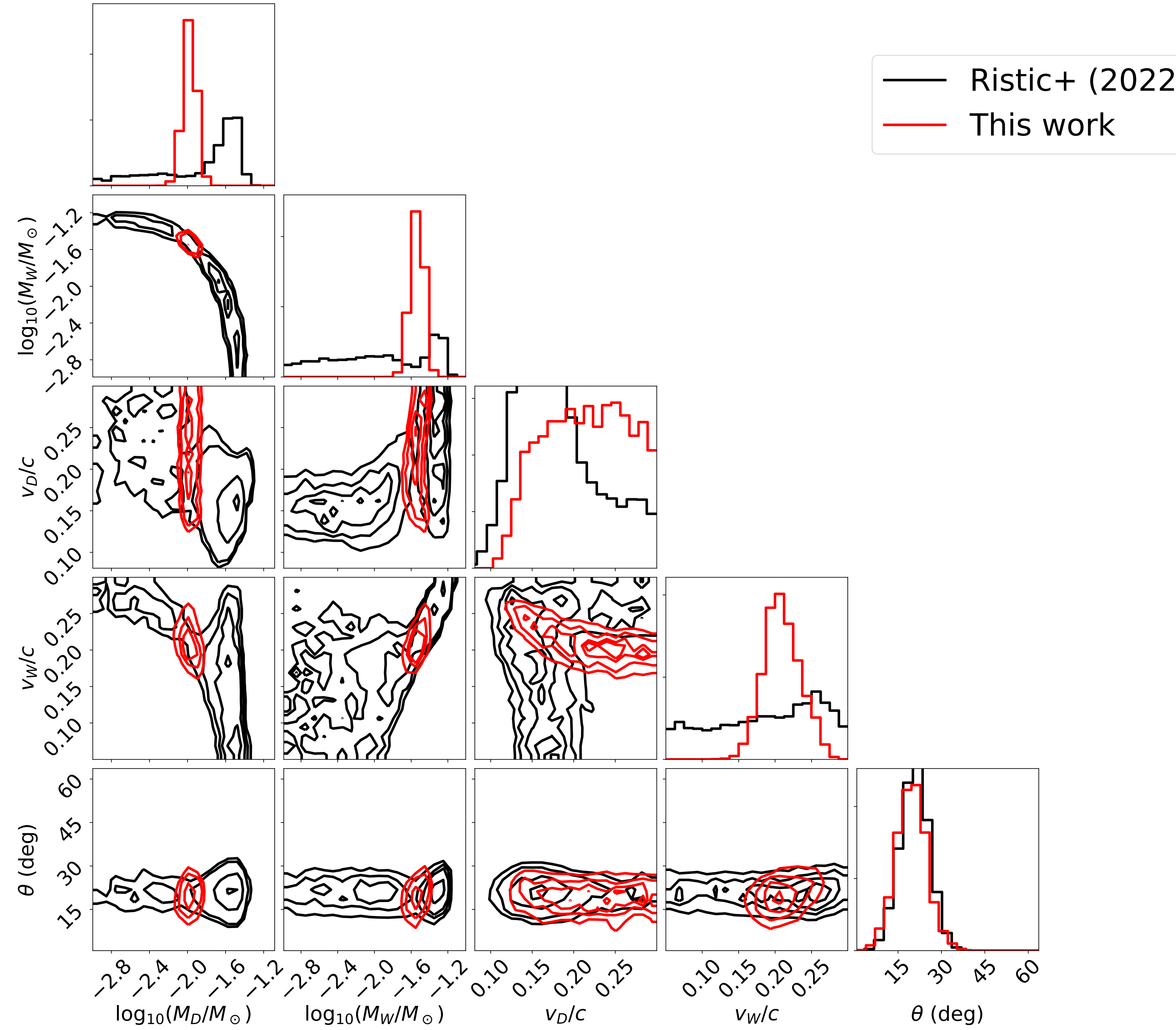
Coming soon: Concordance

- Currently: GitHub.com/oshaughn/Concordance
  - Meta-library integrating multiple inference libraries and tools

- Multiple levels of complexity: from novice to expert
  - “Annotation” mode: add GW,ejecta, EM predictions
  - Single event inference: bootstrap RIFT / EM_PE
  - Multievent parameterized inference: bootstrap PopModels, NAL, …
  - Multievent generative model inference: New (Delfavero/Wysocki)

Kilonova light curves: An r-process prior

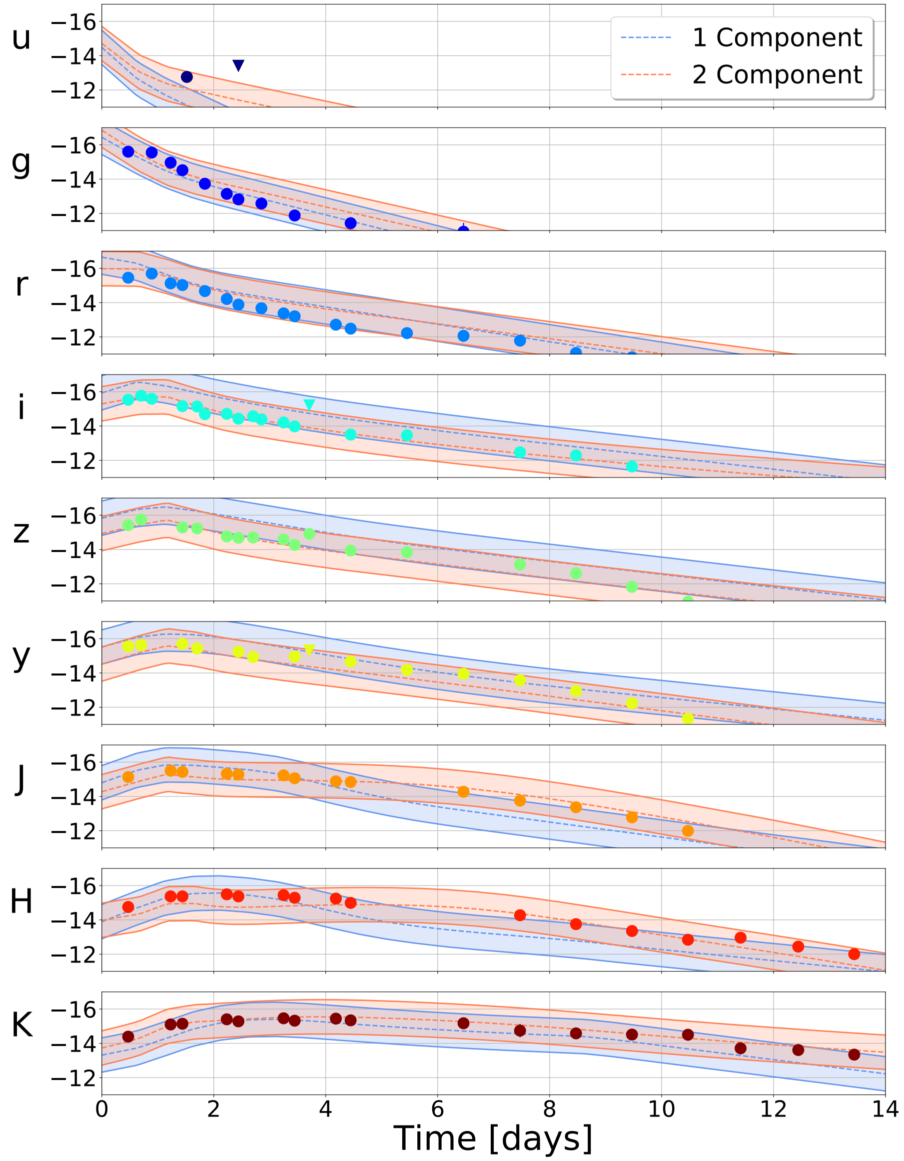
- What if GW170817 is **fiducial** and must reproduce r-process abundances?
  - Limits disk/wind ratio

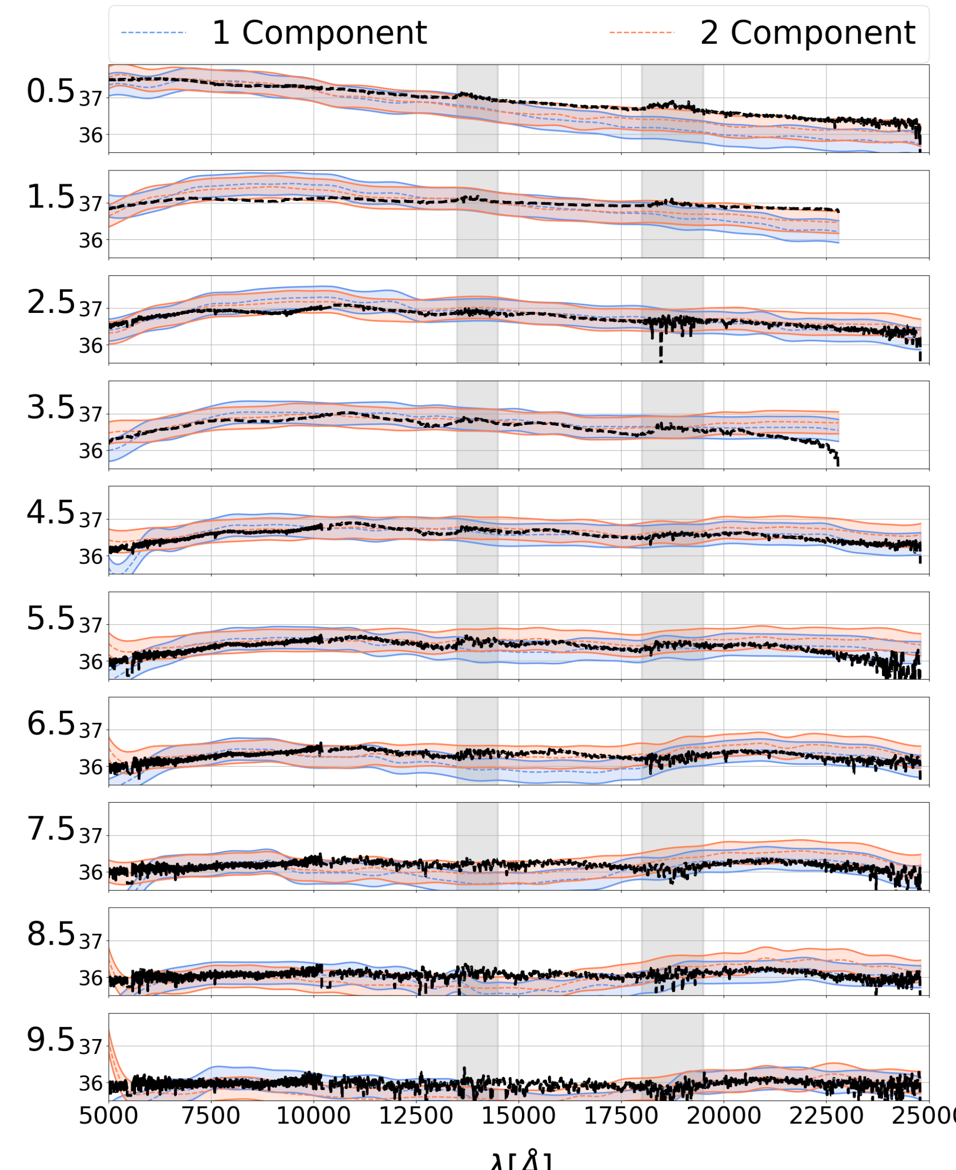


Multimessenger inference

- EM inference (and joint with GW)

Coughlin et al 2018 [multimessenger AT2017gfo] arxiv:1805.09371]





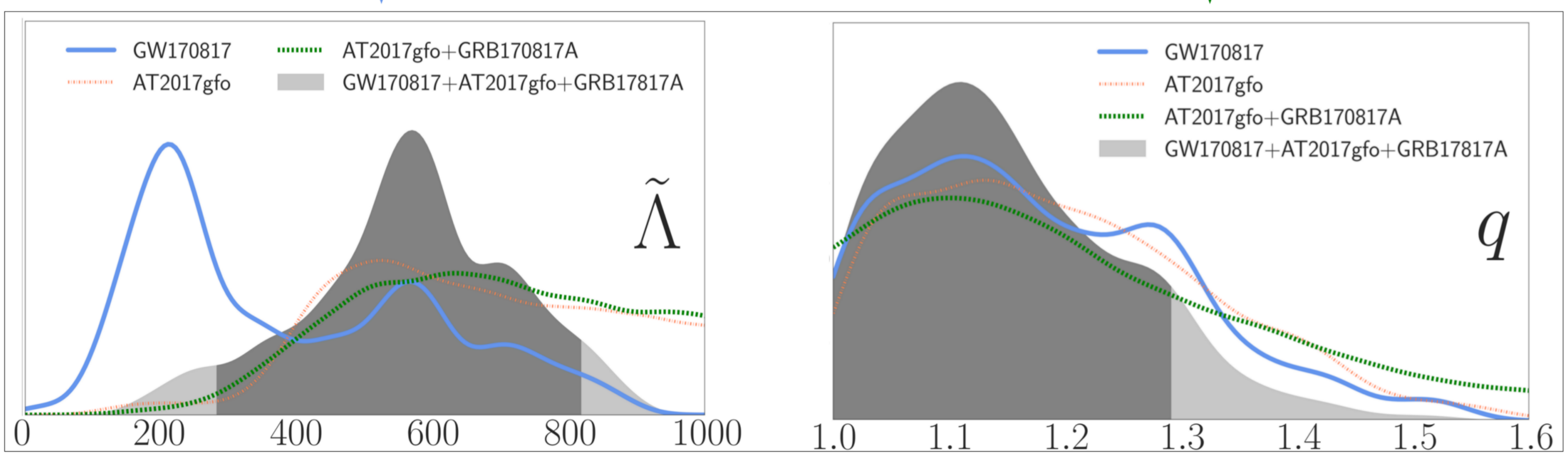
- Costly: emulators [of best models] & efficient computation important!
- Multicomponent models, including afterglow, necessary for archival work

What about for EOS?

- Must connect source to ejecta!
  - **to avoid bias, requires input to connect ejecta, dynamics** [no simplified "existence of HMNS" or "the ejecta must be…" arguments]

  - Can make strong assumptions and turn the crank … but output depends on input!

Multimessenger constraints



Coughlin et al 1812.04803

Performing and combining analyses: a review

- Joint likelihood for all selected events [inhomogeneous poisson]

Observation Model prediction

$$\mathcal{L} = e^{-\mu(\Lambda)} \prod_k \mathcal{R} \int d\lambda_k p(d_k|\lambda_k) p(\lambda_k|\Lambda)$$

$$p(\Lambda, \mathcal{R}) \propto \mathcal{L}(\Lambda, R) p(\Lambda, \mathcal{R})$$

- Features
  - Combines information from multiple events
    - Likelihoods can be heterogeneous (e.g., EM + GW info)
  - Automatically produces revised predictions for every event
  - Models, priors can fold in arbitrary astrophysics
  - Extensions can include “foreground/background” models, etc

Standard methods and their challenges

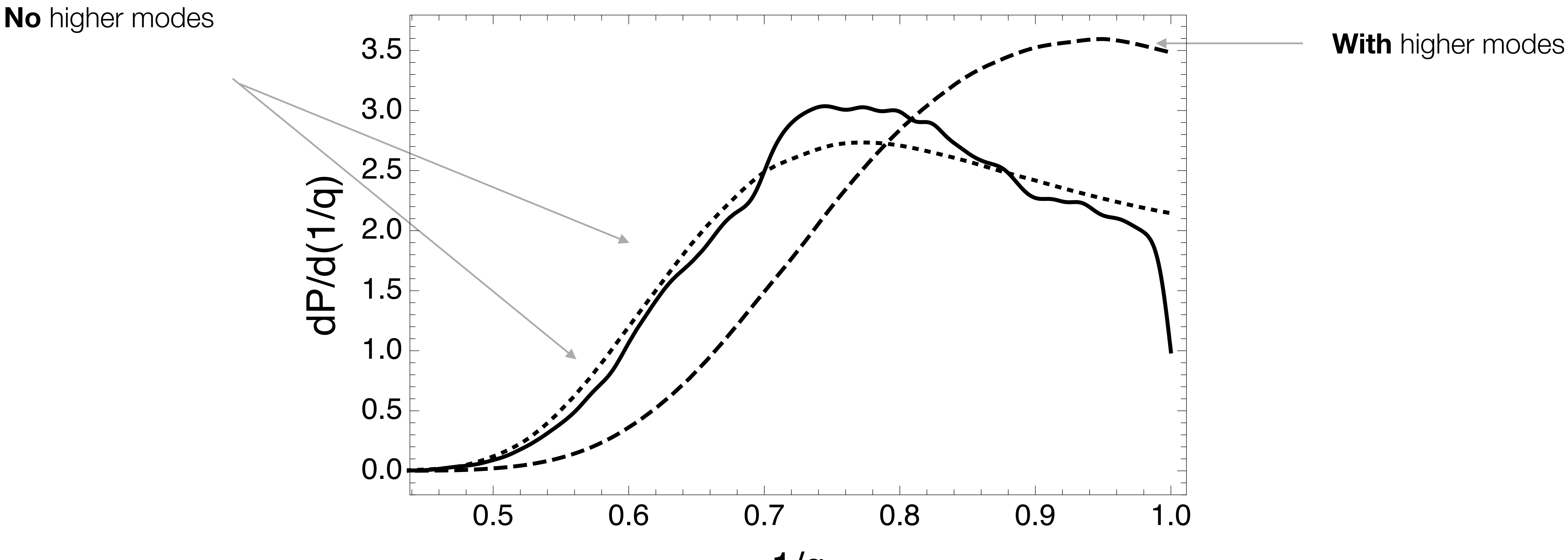
- Reweighted samples: An efficient, hierarchical evaluation method

$$\int d\lambda p(d|\lambda)p(\lambda|\Lambda) \simeq \frac{Z_{\rm ref}}{N}\sum_\alpha \frac{p(\lambda_\alpha|\Lambda)}{p_{\rm ref}(\lambda_\alpha)}$$

- Complications: Limited **density** and **size**
  - Proposed distribution can be too narrow
    - **Always** occurs for dimensional reduction $p(\lambda_1, \lambda_2, \ldots) = \delta(\lambda_1 - f(\lambda_2, \ldots))$
      - What if some population of BBHs have zero spin, equal mass, … ?
      - What about comparing EOS to data? $R = R(m)$
    - Not infrequently occurs, unless you truncate your priors to explicitly avoid it!
  - Proposed distribution can be offset from an event
    - Finite sample size & priors : **samples cover limited area, can be quite small**
    - With many events, some are outliers … few(er) samples may have support

Higher modes have an impact (relative to mod-GR)

- **Can influence conclusions**



Abbott et al PRD 94 064035 (2016)
GW150914: directly comparing to NR (=with higher modes)

- **Less important at low and comparable mass**