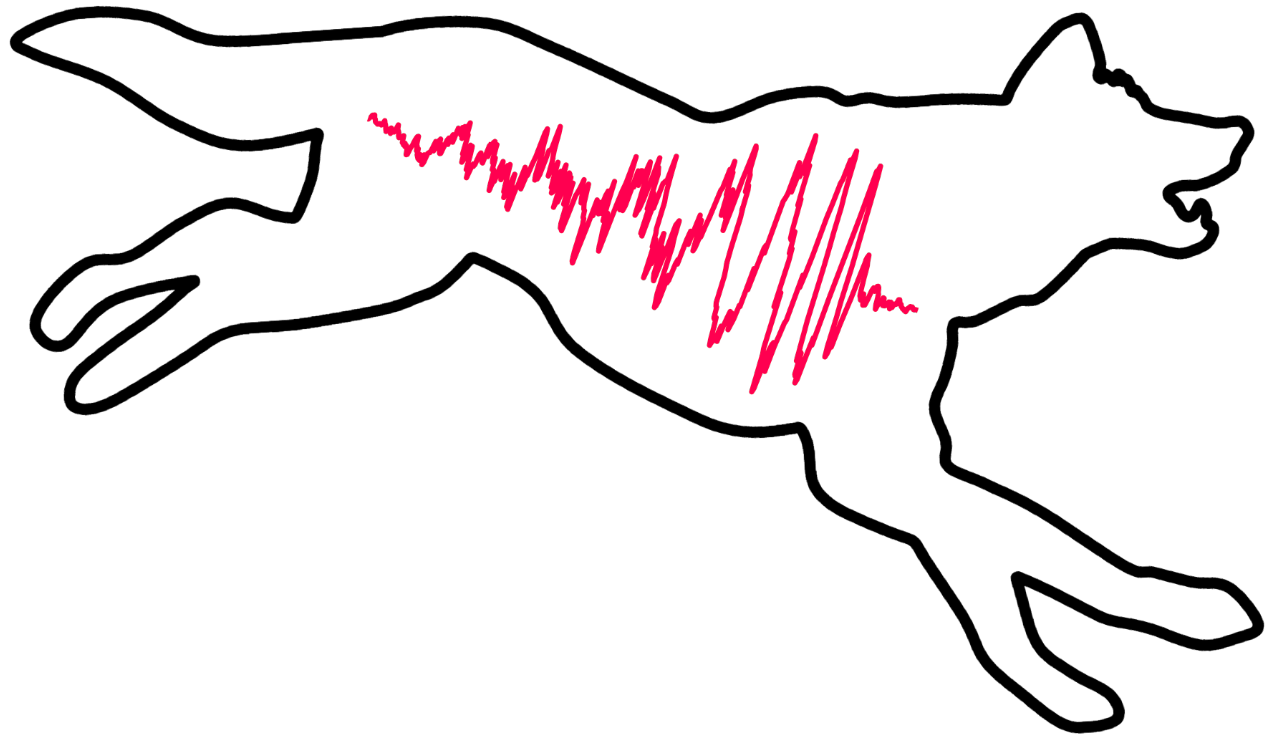
MAX PLANCK INSTITUTE
FOR INTELLIGENT SYSTEMS

Posterior Estimation with DINGO

An (incomplete) Summary



Annalena Kofler, 25.04.2024

AIslands 2024

The Dingo Pack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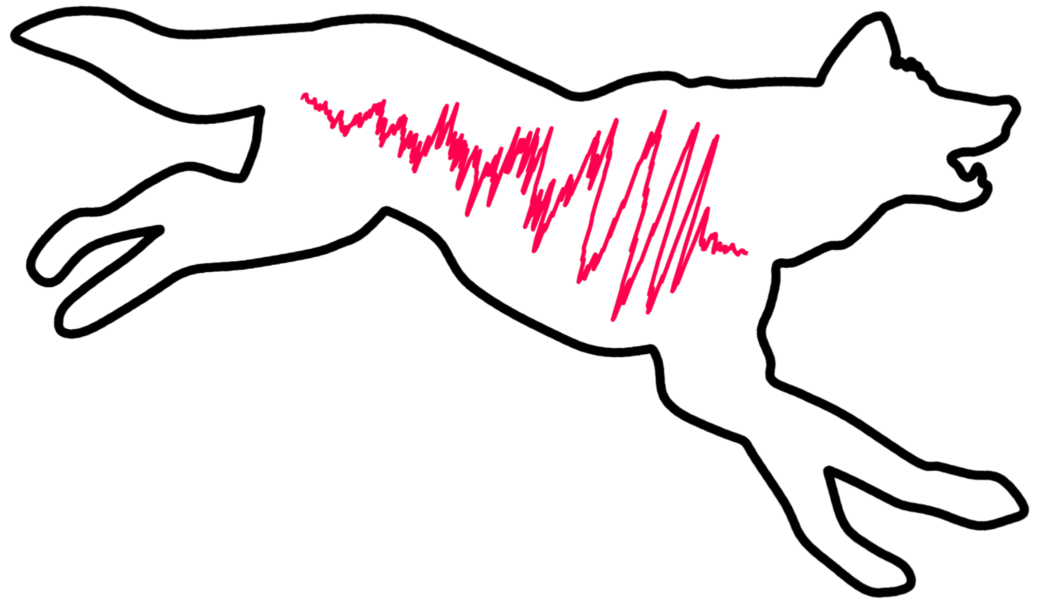
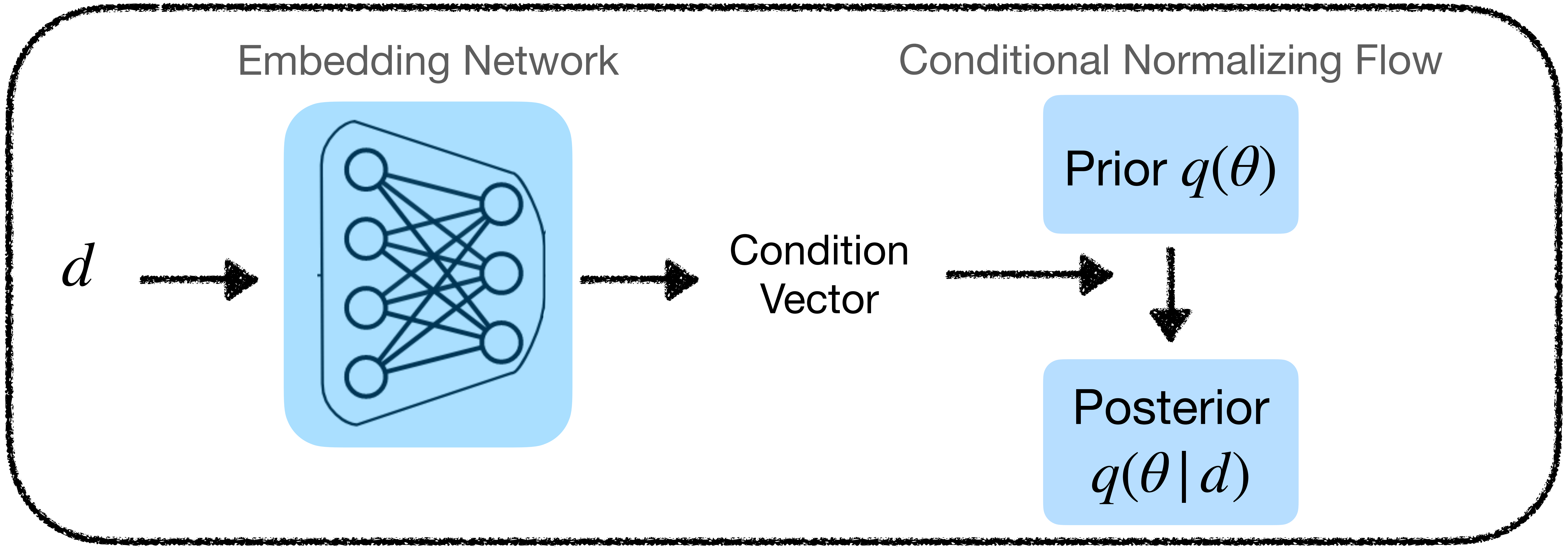


What is DINGO?

- DINGO = **D**eep **IN**ference for **G**ravitational wave **O**bservations

DINGO Model



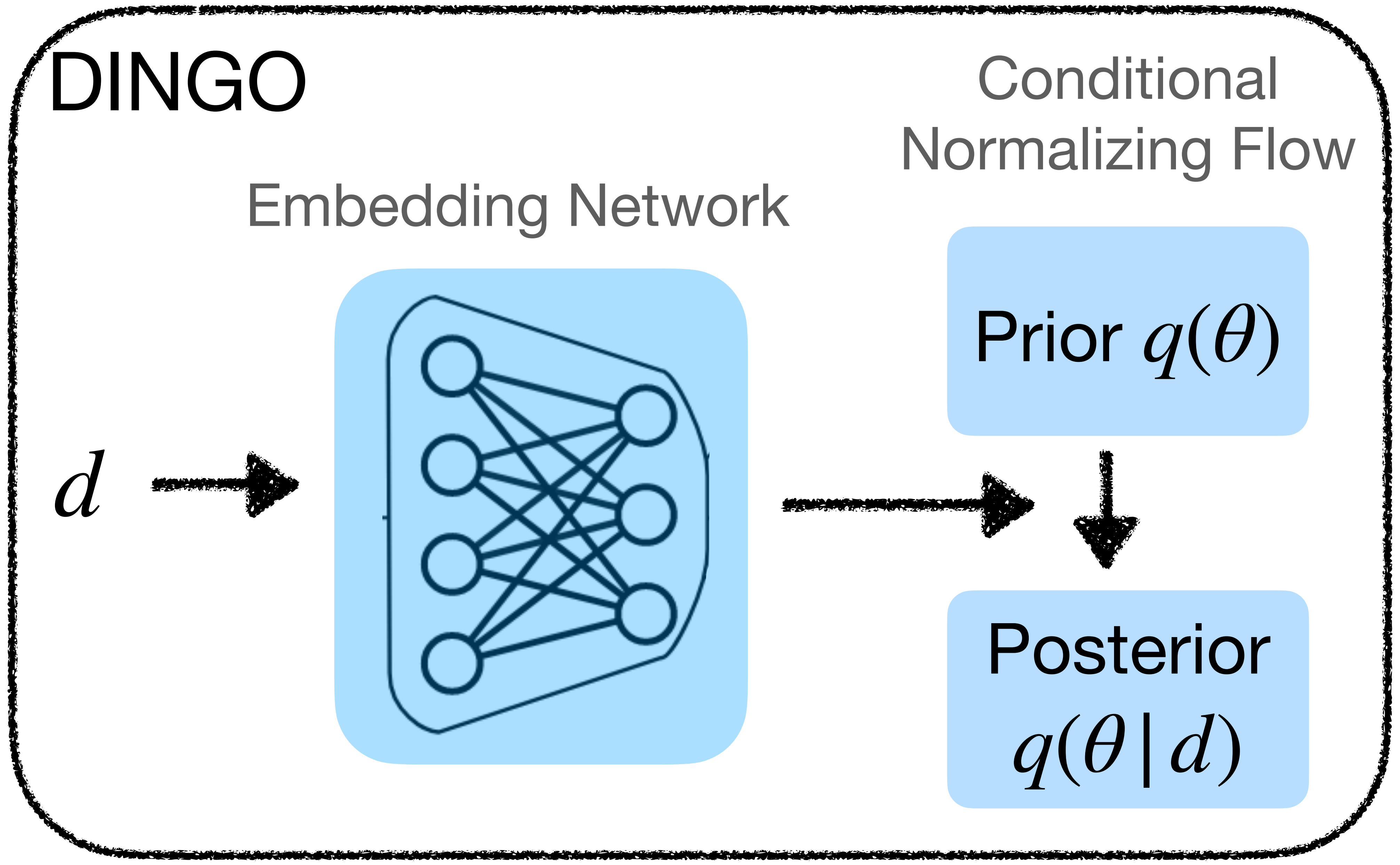
d: Data θ: Parameters

Dax+, PRL 2021

How to train DINGO?

- Sample from prior θ
- Simulate data: $d =$ signal + noise
- Evaluate DINGO Model
- Minimize negative log likelihood

$$\mathscr{L} = -\frac{1}{N} \sum_{\substack{\theta^{(i)} \sim p(\theta) \\ d^{(i)} \sim p(d \mid \theta^{(i)})}} \log q(\theta^{(i)} \mid d^{(i)})$$



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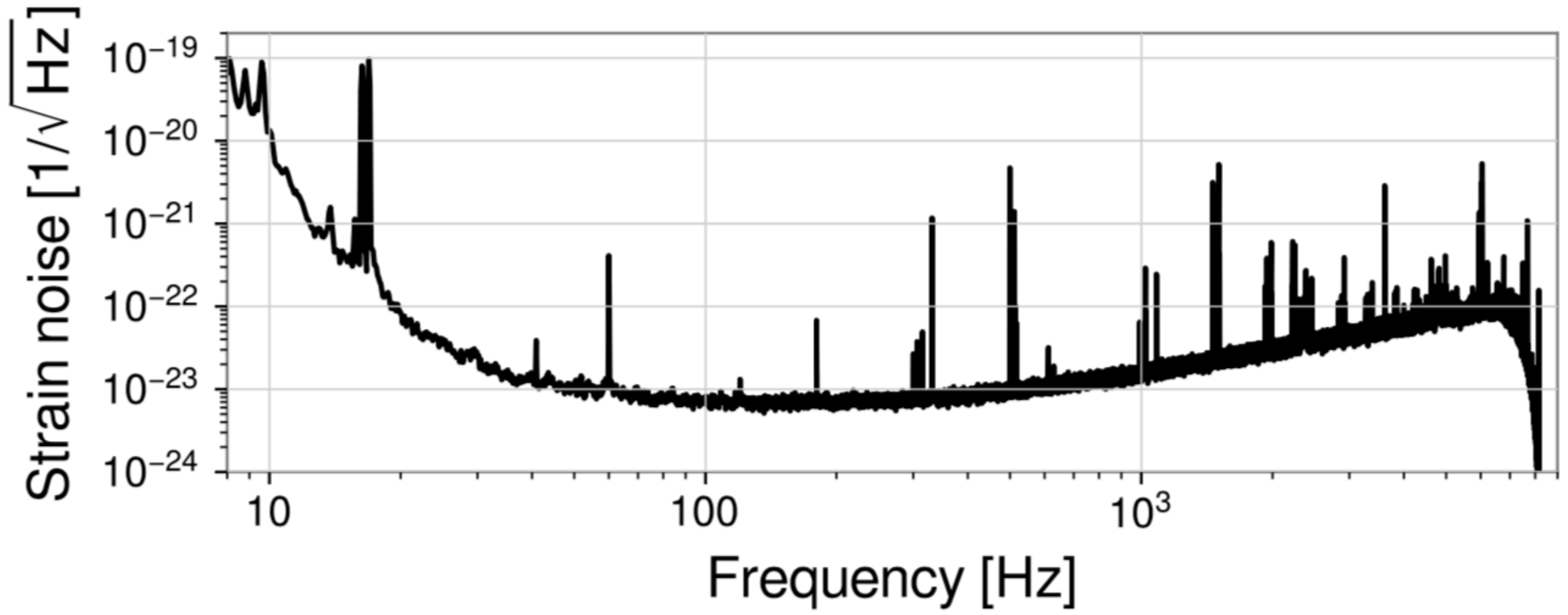
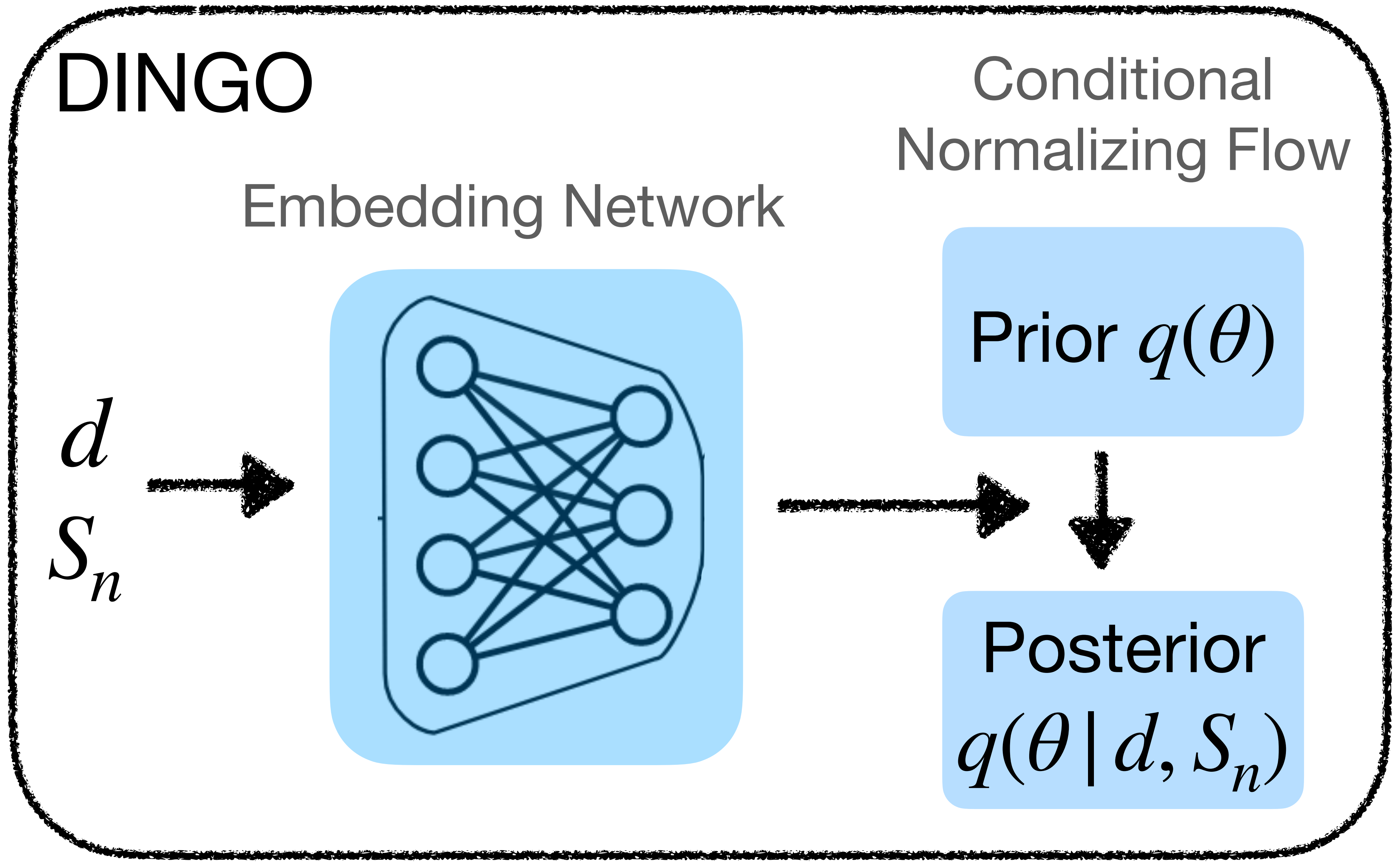
Changing PSDs

- Detector noise $S_n(f)$ varies from event to event
  → augment training to include collection of PSDs $S_n(f) \rightarrow \{S_n^{(i)}(f)\}$

1. Sample PSD $\quad S_n^{(i)} \sim p(S_n)$
2. Generate noise $\quad n^{(i)} \sim \mathcal{N}(0,\, S_n^{(i)})$
3. Add signal $\quad d^{(i)} = h(\theta^{(i)}) + n^{(i)}$





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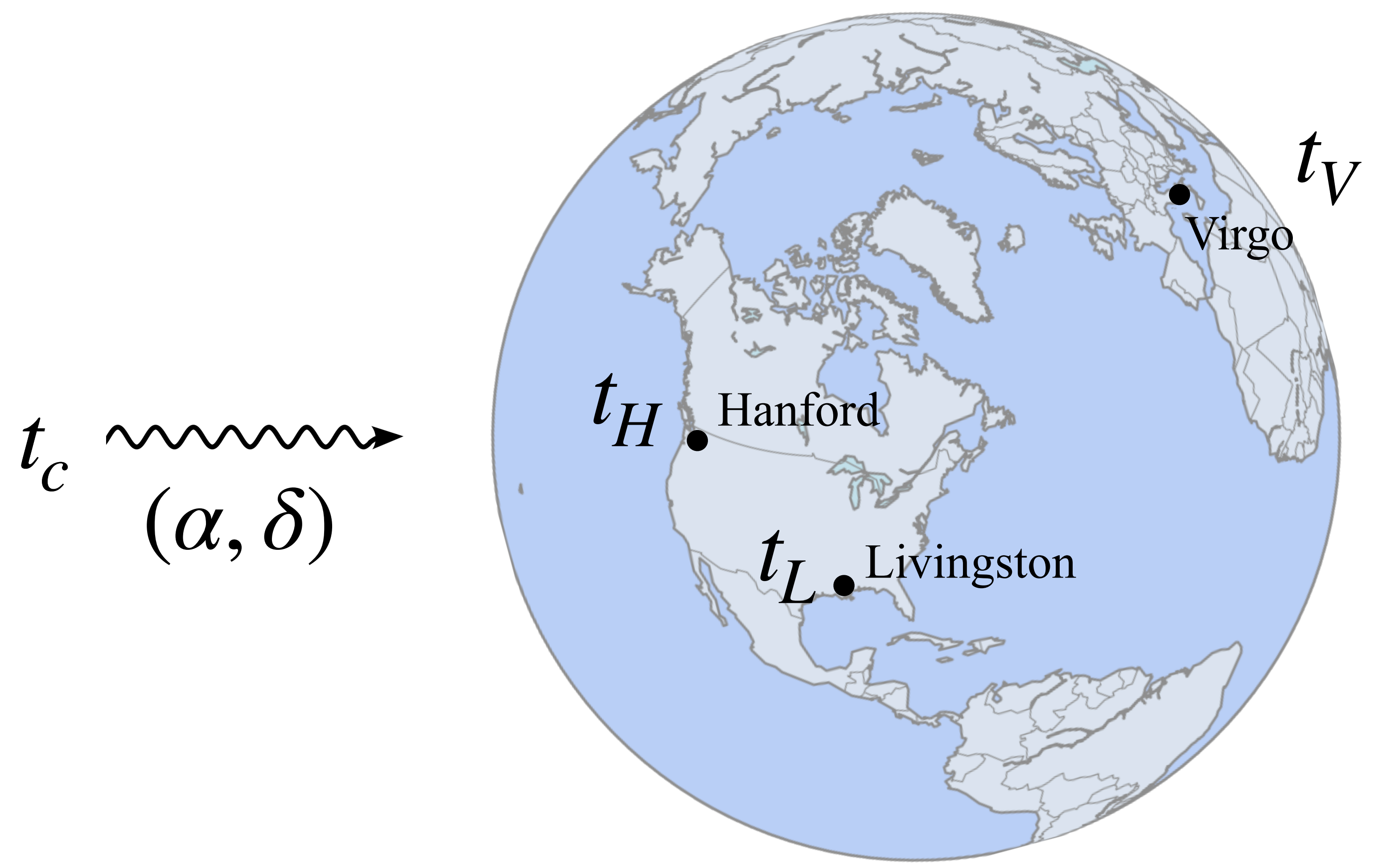
Simplifying Data using Symmetries

- Posterior should be …
  … equivariant wrt. overall coalescence time t_c

- Frequency-domain data
  → time shift = multiplication by $e^{2\pi i f \cdot \delta t}$



Simplifying Data using Symmetries

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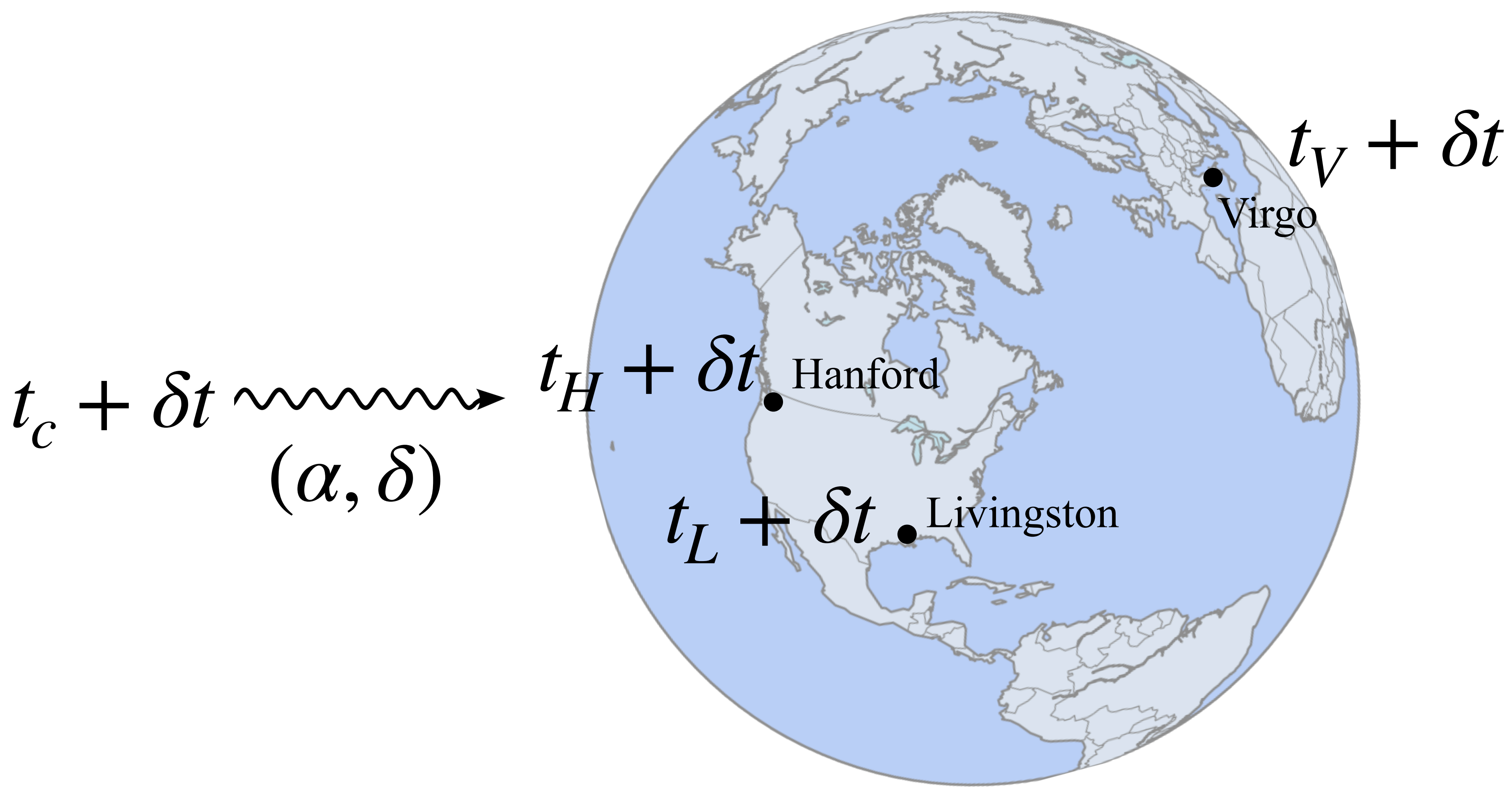

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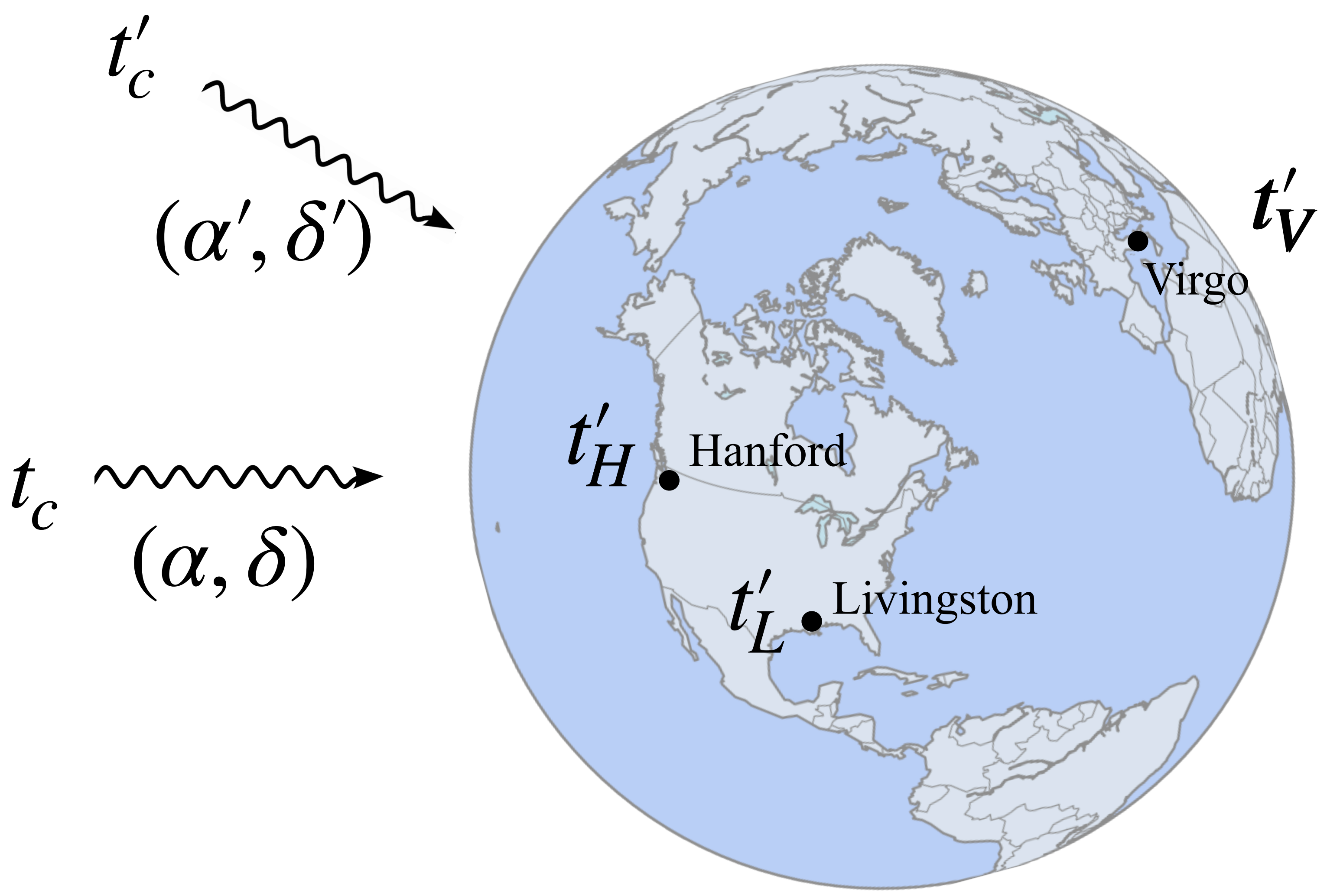
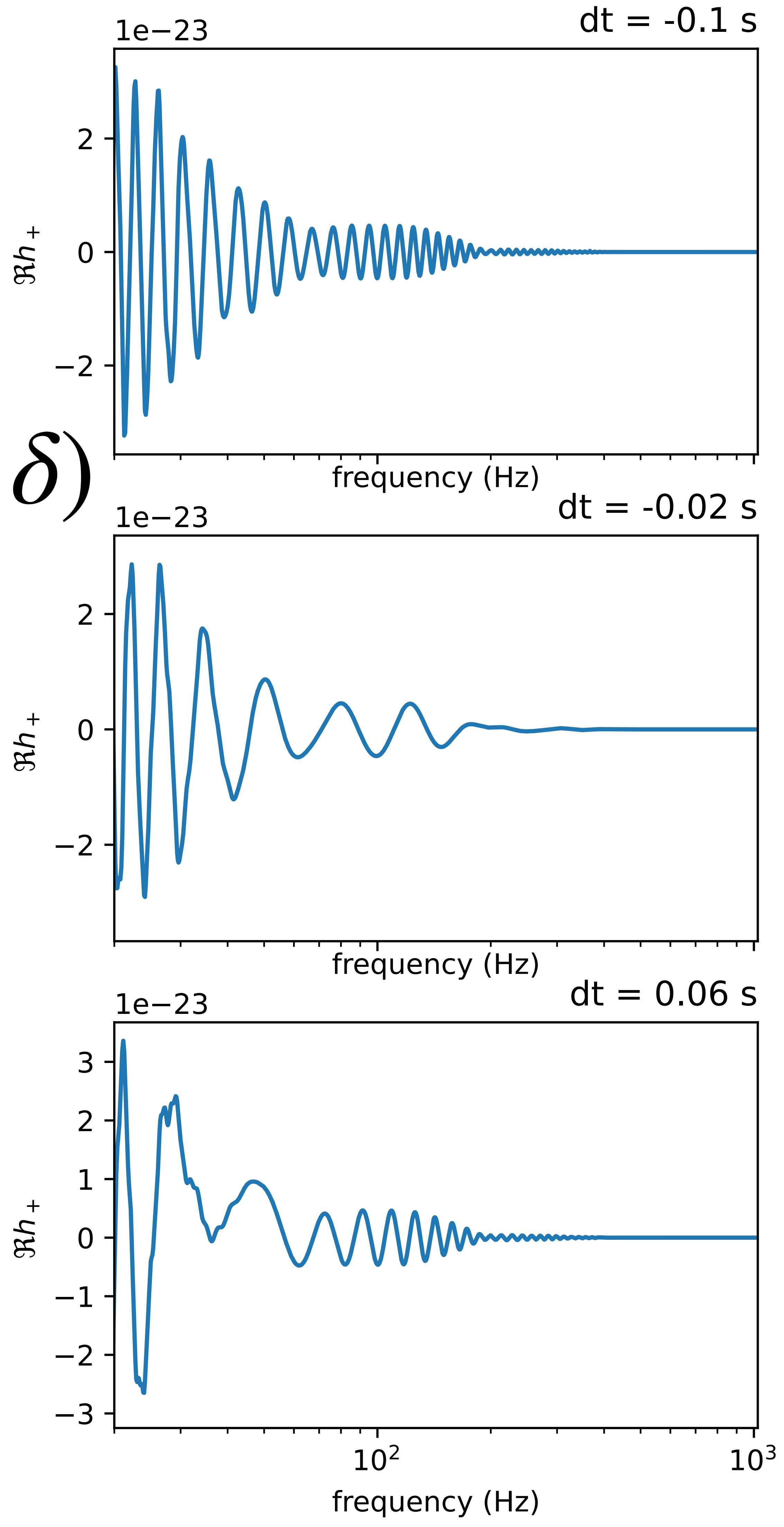
Simplifying Data using Symmetries

- Posterior should be …
  … equivariant wrt. overall coalescence time t_c
  … approximately equivariant wrt. changes in sky position (α, δ)

- Frequency-domain data
  → time shift = multiplication by $e^{2\pi i f \cdot \delta t}$

- Hard to learn just from data



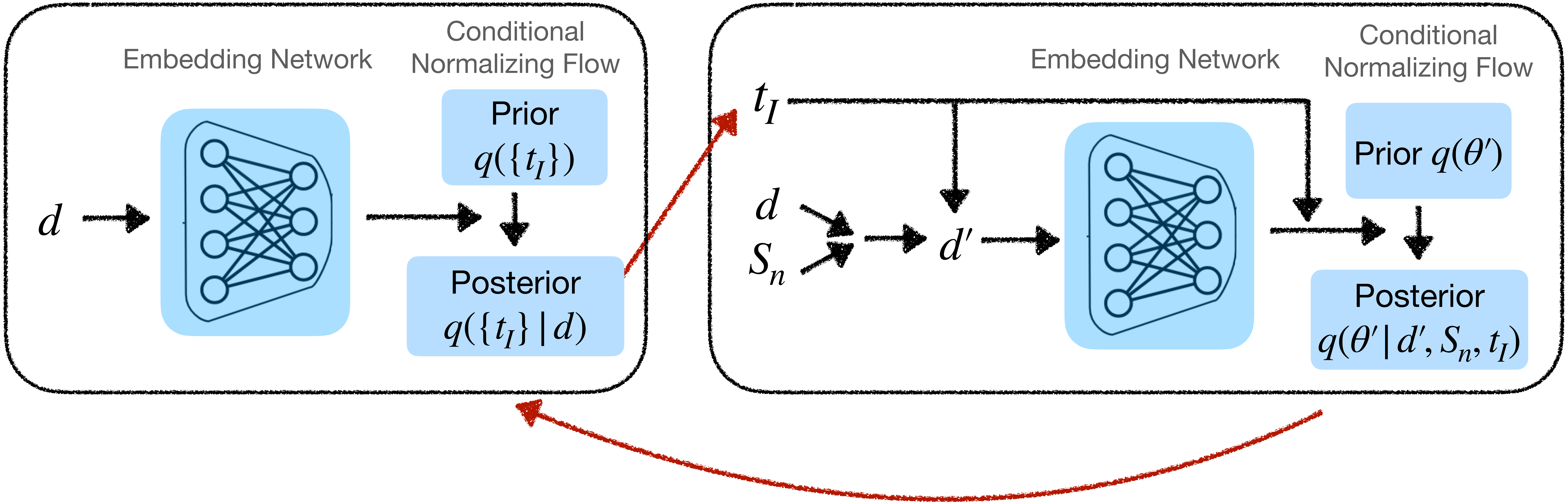


GNPE = Group-equivariant NPE

- Standardize data within band around $t_I = 0$
- Gibbs Sampling:
  - Start with blurred proxy $t_I + \epsilon_I$ with $\epsilon_I \sim \kappa(\epsilon_I)$
  - Learn approximate distribution $q_{\text{init}}(\{t_I\}_{I=H,L,V} \,|\, d)$ for time shift
  - Time-translate data $d' = d(t_I = 0)$
  - Train conditional density estimator $q(\theta' \,|\, d', t_I + \epsilon_I)$

GNPE = Group-equivariant NPE

- Include condition on t_I in DINGO



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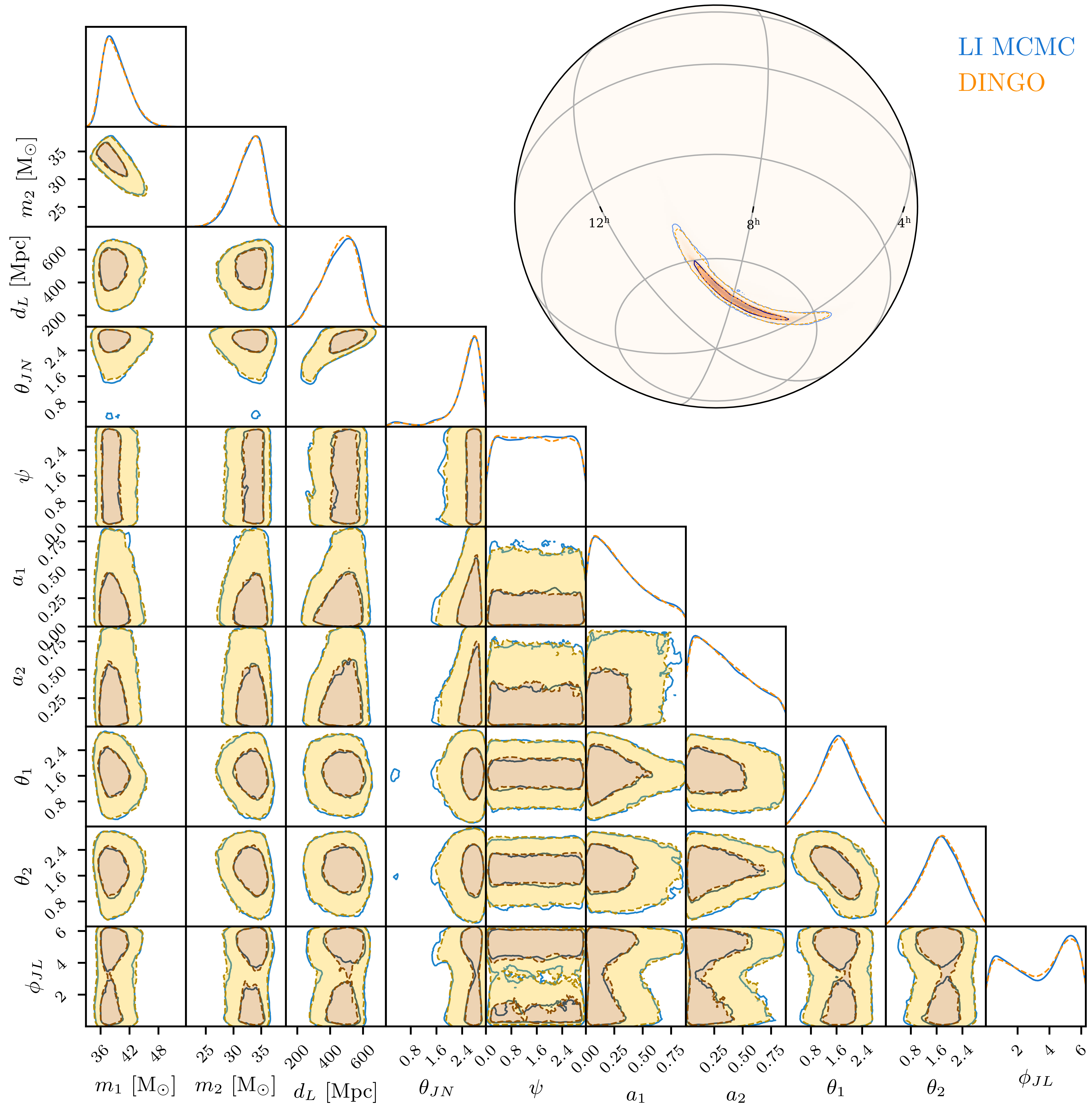
DINGO with GNPE

- Very good agreement with standard techniques
- $\sim 10^7$ training examples
  $\sim 10^8$ network parameters
- Training: $\sim$ few days
  Inference: $\sim$ few minutes



Dax+, PRL 2021

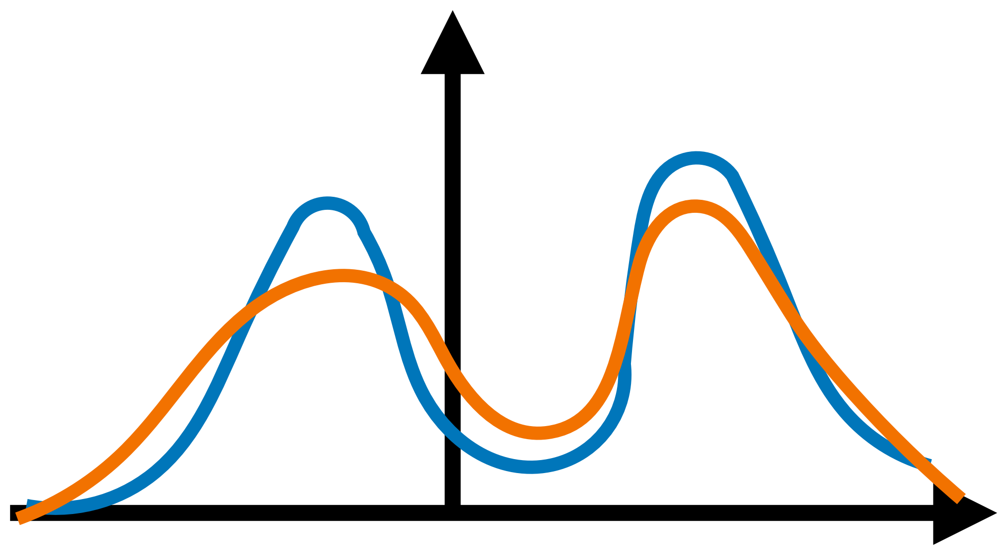
Verifying Results: DINGO-IS

- Neural Importance Sampling to compare learned NPE density and likelihood

$$w_i \propto \frac{p(\theta_i)p(d\,|\,\theta_i)}{q(\theta_i\,|\,d)}$$

Target = Likelihood x Prior

Proposal (NPE)



- Effective Sample Size:

$$n_{\text{eff}} = \frac{\left(\sum_i w_i\right)^2}{\sum_i w_i^2}$$

- Evidence: $$p(d) \approx \frac{1}{N}\sum_{i=1}^{N} w_i$$

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Verifying Results: DINGO-IS

- Failure cases flagged via low sample efficiency ϵ
- Out-of-distribution data: = inconsistent with noise or signal model

→ Identification of events with known issues with data quality or modeling

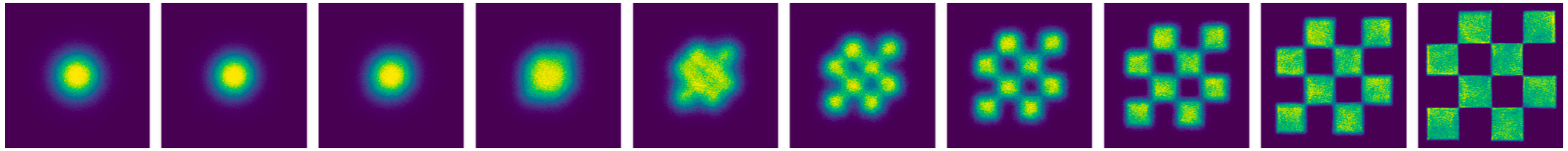
Event	$\log p(d)$	ϵ	Event	$\log p(d)$	ϵ	Event	$\log p(d)$	ϵ
GW190408	-16178.332 ± 0.012	6.9%	GW190727	-15992.017 ± 0.009	10.3%	GW191230	-15913.798 ± 0.009	12.2%
_181802	-16178.172 ± 0.010	9.3%	_060333	-15992.428 ± 0.005	30.8%	_180458	-15913.918 ± 0.010	8.8%
GW190413	-15571.413 ± 0.006	22.5%	GW190731	-16376.777 ± 0.005	32.6%	GW200128	-16305.128 ± 0.013	6.1%
_052954	-15571.391 ± 0.005	26.3%	_140936	-16376.763 ± 0.005	31.0%	_022011	-16304.510 ± 0.007	18.3%
GW190413	-16399.331 ± 0.009	12.4%	GW190803	-16132.409 ± 0.006	21.4%	‡GW200129	-16226.851 ± 0.109	0.1%
_134308	-16399.139 ± 0.014	4.7%	_022701	-16132.408 ± 0.005	27.8%	_065458	-16231.203 ± 0.051	0.4%
GW190421	-15983.248 ± 0.008	15.3%	GW190805	-16073.261 ± 0.006	20.0%	GW200208	-16136.381 ± 0.007	16.6%
_213856	-15983.131 ± 0.010	9.4%	_211137	-16073.656 ± 0.007	16.6%	_130117	-16136.531 ± 0.009	11.2%
GW190503	-16582.865 ± 0.022	2.0%	GW190828	-16137.220 ± 0.009	12.2%	GW200208	-16775.200 ± 0.011	7.4%
_185404	-16583.352 ± 0.027	1.4%	_063405	-16136.799 ± 0.010	9.1%	_222617	-16774.582 ± 0.021	2.2%
GW190513	-15946.462 ± 0.043	0.6%	GW190909	-16061.634 ± 0.011	7.4%	GW200209	-16383.847 ± 0.009	12.5%
_205428	-15946.581 ± 0.017	3.4%	_114149	-16061.275 ± 0.016	3.8%	_085452	-16384.157 ± 0.025	1.6%
GW190514	-16556.466 ± 0.009	11.6%	GW190915	-16083.960 ± 0.015	20.8%	GW200216	-16215.703 ± 0.017	3.4%
_065416	-16556.314 ± 0.017	3.5%	_235702	-16083.937 ± 0.027	4.8%	_220804	-16215.540 ± 0.018	3.1%
GW190517	-16271.048 ± 0.027	1.3%	GW190926	-16015.813 ± 0.019	2.8%	GW200219	-16133.457 ± 0.011	9.6%
_055101	-16272.428 ± 0.034	0.9%	_050336	-16015.861 ± 0.009	12.1%	_094415	-16133.157 ± 0.017	4.0%
GW190519	-15991.171 ± 0.008	15.2%	GW190929	-16146.666 ± 0.018	3.2%	GW200220	-16303.782 ± 0.007	17.3%
_153544	-15991.287 ± 0.068	0.2%	_012149	-16146.591 ± 0.021	2.4%	_061928	-16303.087 ± 0.026	1.5%
GW190521	-16008.876 ± 0.008	13.4%	GW191109	-17925.064 ± 0.025	1.7%	GW200220	-16136.600 ± 0.008	13.2%
_074359	-16008.037 ± 0.015	4.2%	_010717	-17922.762 ± 0.041	0.6%	_124850	-16136.519 ± 0.037	0.7%
GW190527	-16119.012 ± 0.008	13.8%	GW191127	-16759.328 ± 0.019	2.7%	GW200224	-16138.613 ± 0.006	22.5%
_092055	-16118.781 ± 0.013	6.1%	_050227	-16758.102 ± 0.029	1.2%	_222234	-16139.101 ± 0.006	21.4%
GW190602	-16036.993 ± 0.006	25.0%	‡GW191204	-15984.455 ± 0.015	4.2%	‡GW200308	-16173.938 ± 0.013	6.0%
_175927	-16037.529 ± 0.006	23.5%	_110529	-15983.618 ± 0.063	0.3%	_173609	-16173.692 ± 0.025	1.7%
GW190701	-16521.381 ± 0.040	0.6%	GW191215	-16001.286 ± 0.013	5.8%	GW200311	-16117.505 ± 0.011	7.4%
_203306	-16521.609 ± 0.010	10.1%	_223052	-16000.846 ± 0.052	0.4%	_115853	-16117.583 ± 0.009	11.9%
GW190719	-15850.492 ± 0.008	13.4%	GW191222	-15871.521 ± 0.007	16.5%	‡GW200322	-16313.568 ± 0.307	0.0%
_215514	-15850.339 ± 0.011	8.0%	_033537	-15871.450 ± 0.005	25.8%	_091133	-16313.110 ± 0.105	0.1%

Table II. 42 BBH events from GWTC-3 analyzed with DINGO-IS. We report the log evidence $\log p(d)$ and the sample efficiency ϵ for the two waveform models IMRPhenomXPHM (upper rows) and SEOBNRv4PHM (lower rows). Highlighting colors indicate the sample efficiency (green: high; yellow: medium; orange/red: low); DINGO-IS results can be trusted for medium and high ϵ (see Supplemental Material). Events in gray suffer from data quality issues [1, 21]. ‡See remarks on these events in text.

How to improve DINGO?

- Larger networks?
  $\rightarrow$ (discrete) normalizing flows do not scale well beyond $\sim 10^8$ trainable parameters and ~ 15 inference parameters

- Alternative: Flow Matching Lipman et al., ICLR 2023



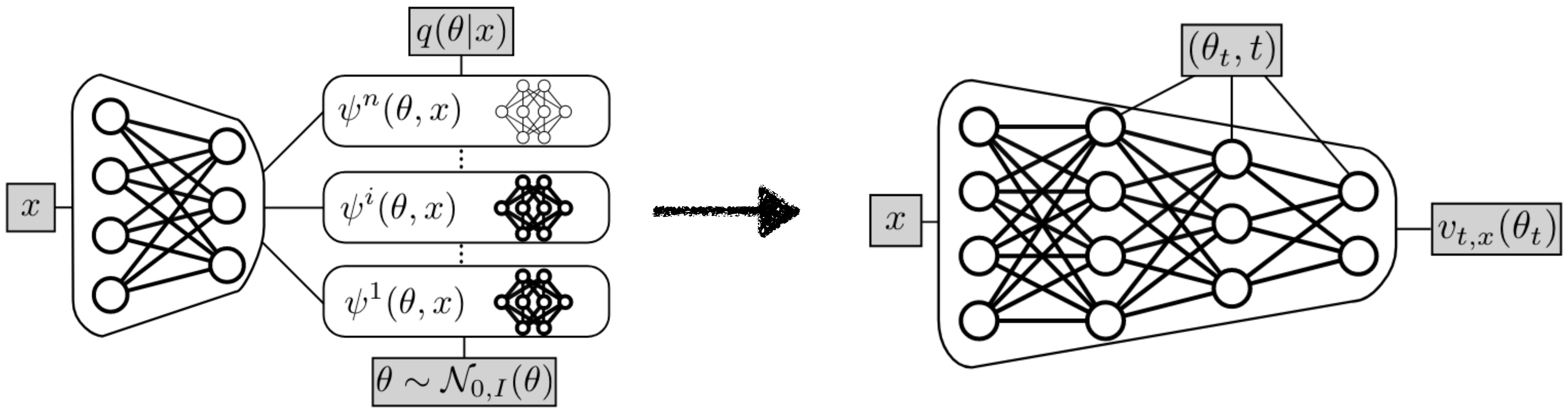
Flow Matching w/ OT

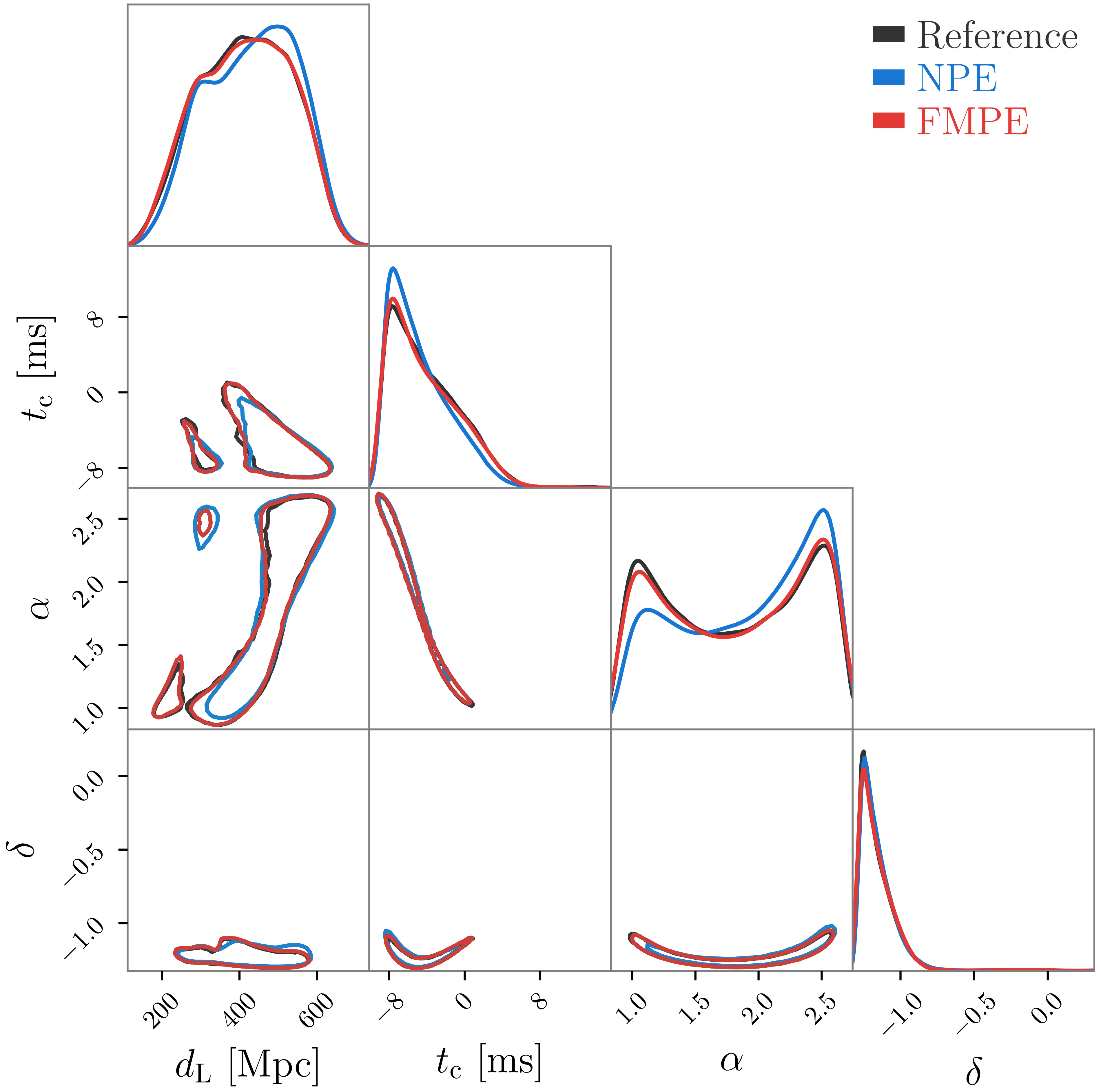
$t = 0$ $\longrightarrow t$ $t = 1$

- Network learns vector field $$\frac{\mathrm{d}\theta_t}{\mathrm{d}t} = v_{t,d}(\theta_t)$$

Flow Matching Posterior Estimation

- Estimate posterior with flow matching





- Outperforms NPE with discrete flows
  - Faster training
  - Better scaling to larger networks

Dax+, NeurIPS 2023

Where/How is DINGO used?

- Analyze large collection of observations
  - Learn population posterior directly   Leyde et al., 2023
  - Evidence for eccentricity → Nihar's talk on Monday   Gupte et al., 2024
- DINGO approved in internal LIGO review 🥳
  → Evaluation of O4 events!

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Take-Aways for DINGO

- Accurate inference for BBHs in seconds - minutes
  → Rapid inference of large number of events
- Validation of results with Importance Sampling
- Ready to be used:
  Code @ https://github.com/dingo-gw/dingo, Documentation, Tutorials

Outlook

- Extension to BNS → Max talk on Friday
- New architectures to deliver ever-improving performance

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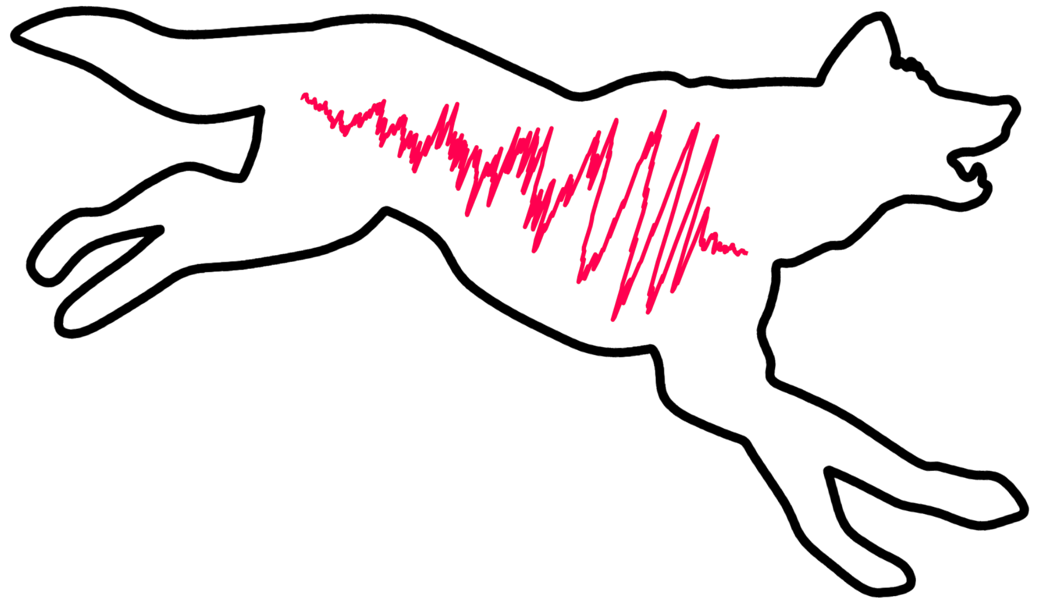
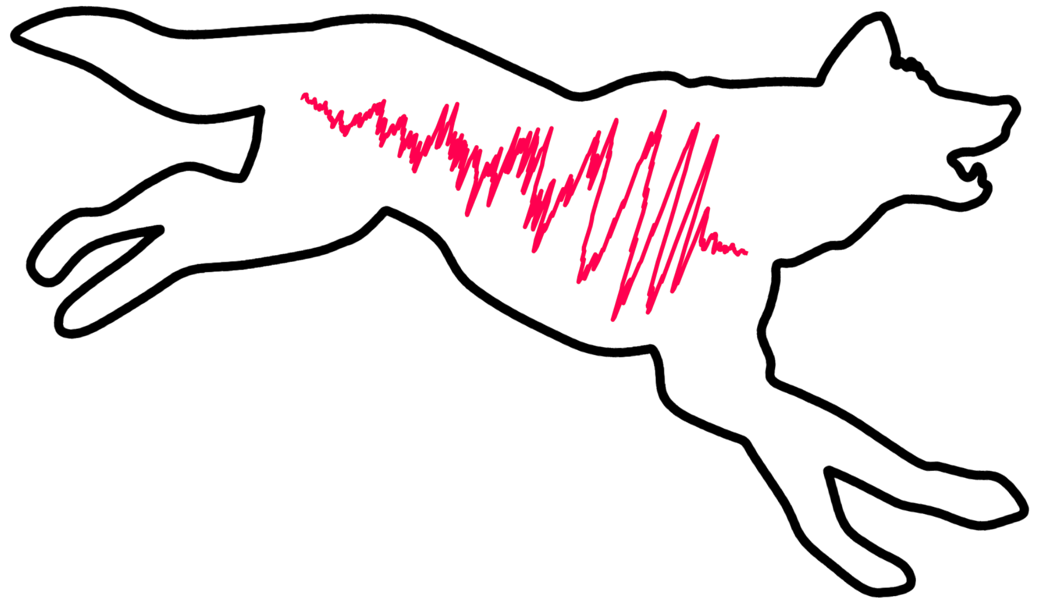


Discussion Questions

- Do you know of other scenarios where DINGO can be applied?
- Do you want to use DINGO or know people that are looking into using DINGO?

Thank you!

Do you have any questions?



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- Gupte et al., Evidence for eccentricity in the population of binary black holes observed by LIGO-Virgo-KAGRA, arXiv:2404.14286v1, 2024
- Dax et al. in preparation, 2024