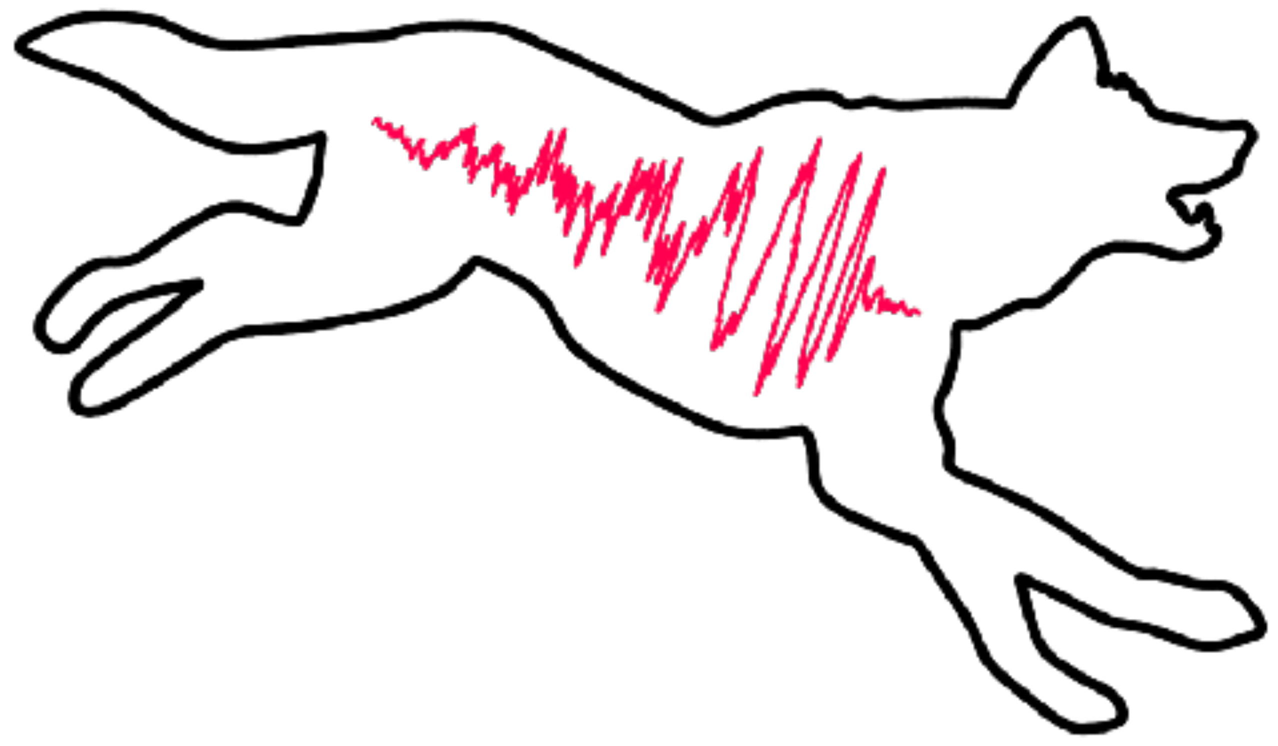
Flexible Gravitational-Wave Parameter Estimation with Transformers



Annalena Kofler, 18.12.2025

ML Algorithms Group, LIGO

Transformers for GW data

- Increasing number of papers that use transformers:
  - Denoising Previous talk!
  - Detection Jiang & Luo ICPR 2022, Chatterjee et al. arXiv 2025, Joshi & Prix arXiv 2025
  - Glitch classification Chatterjee et al. arXiv 2025
  - Waveform generation Shi et al., PRD 2024
  - Parameter estimation Papalini et al. Class. Quantum Grav. 2025
- Strength of transformers: **Variable sequence length**

  → Flexible parameter estimation

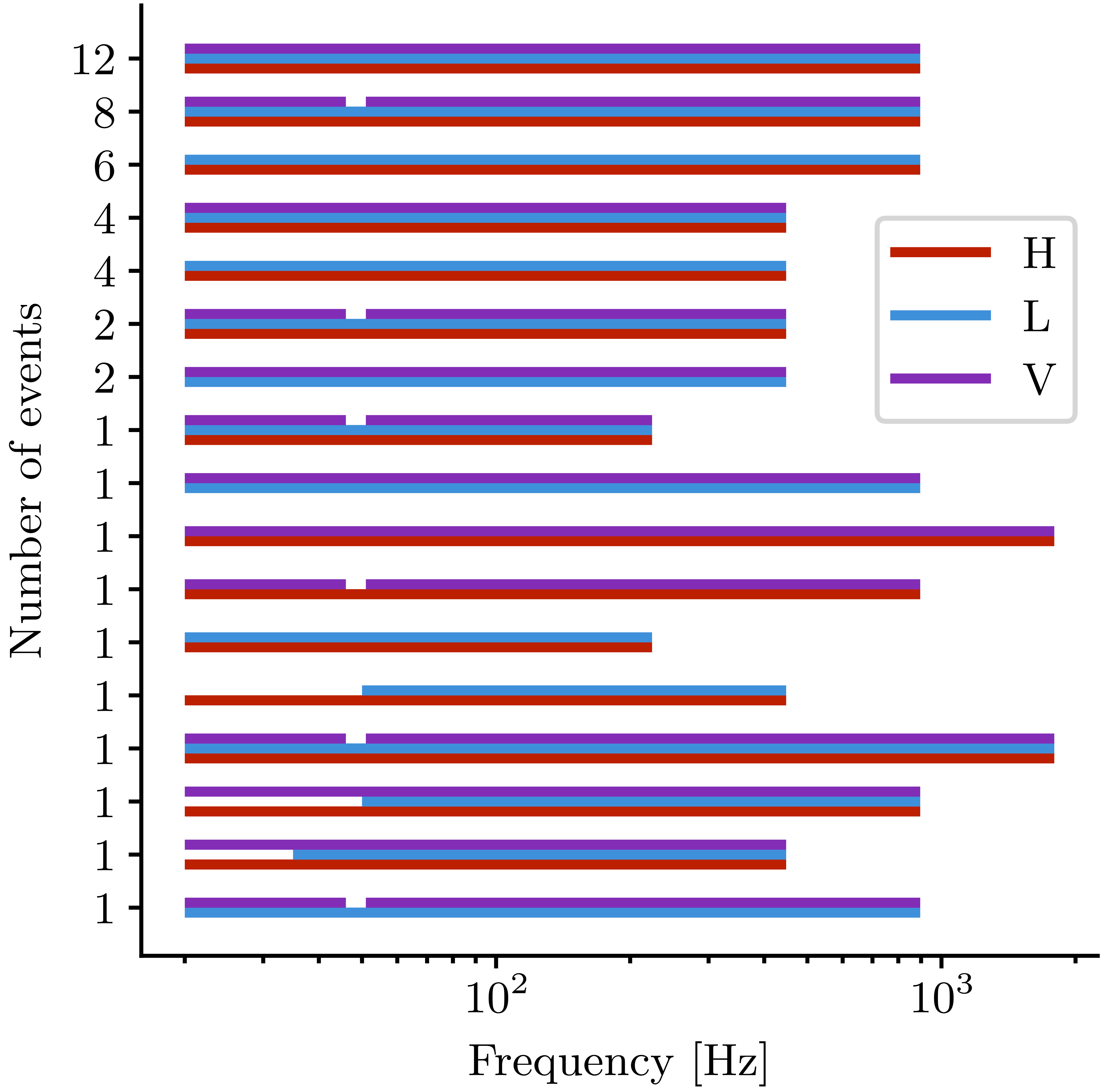
6 Tokens	I	love	gravit	ational	waves	!			
9 Tokens	Gravit	ational	wave	data	analysis	is	the	best	.

Why do we need flexible parameter estimation?

Example: Official O3 LVK analysis

- 48 events with 17 different data configurations
    - Different detectors
    - Different frequency ranges

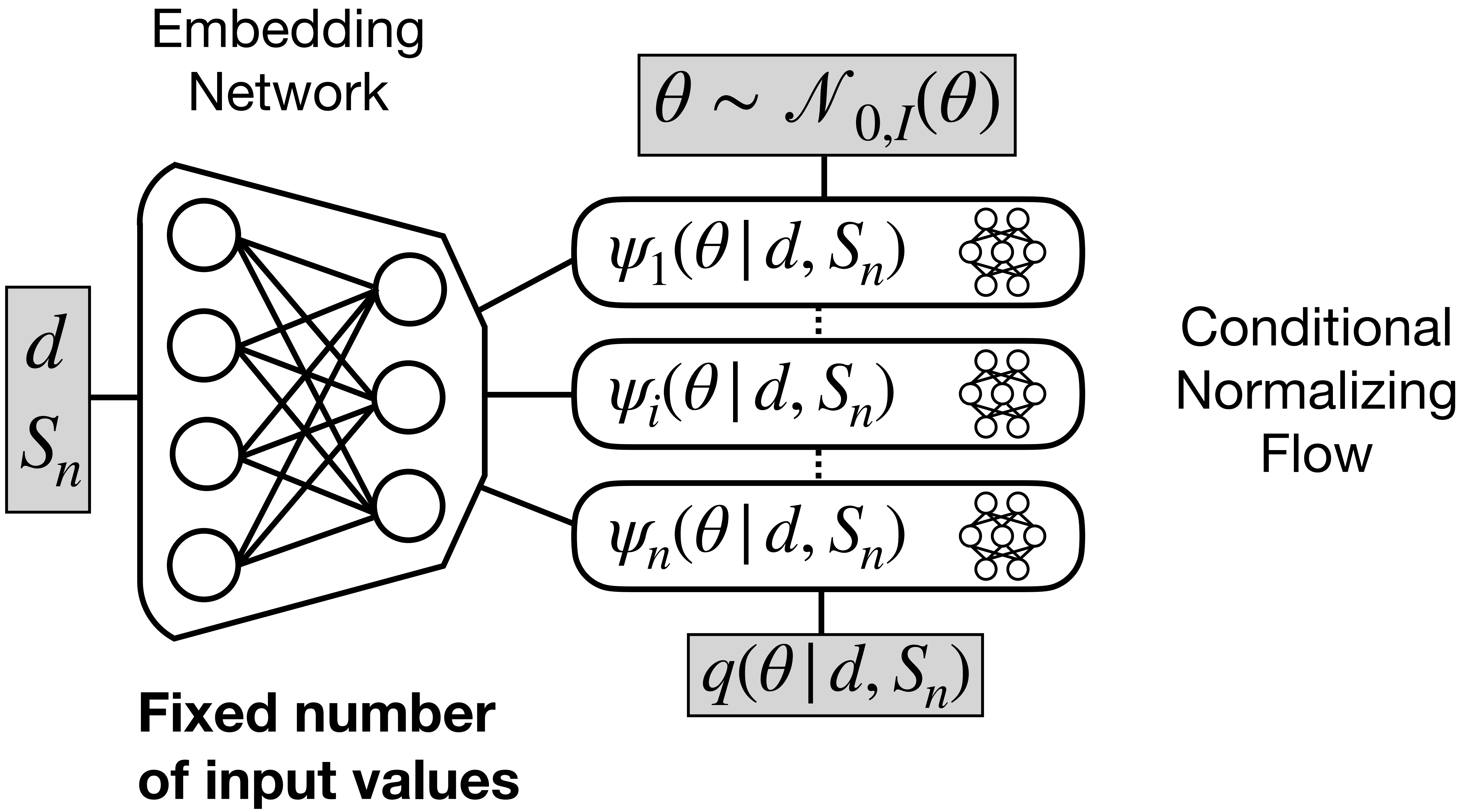
Problem:
Amortized ML approaches like DINGO[1] cannot deal with changing inputs!



[1]Dax+, PRL 2021

Why is the DINGO architecture not flexible?

- Compress data d and noise PSD S_n via embedding network
- Train with negative log-likelihood loss $\mathscr{L} = \mathbb{E}_{p(\theta),p(S_n),p(d|\theta,S_n)}\left[-\log q(\theta\,|\,d, S_n)\right]$

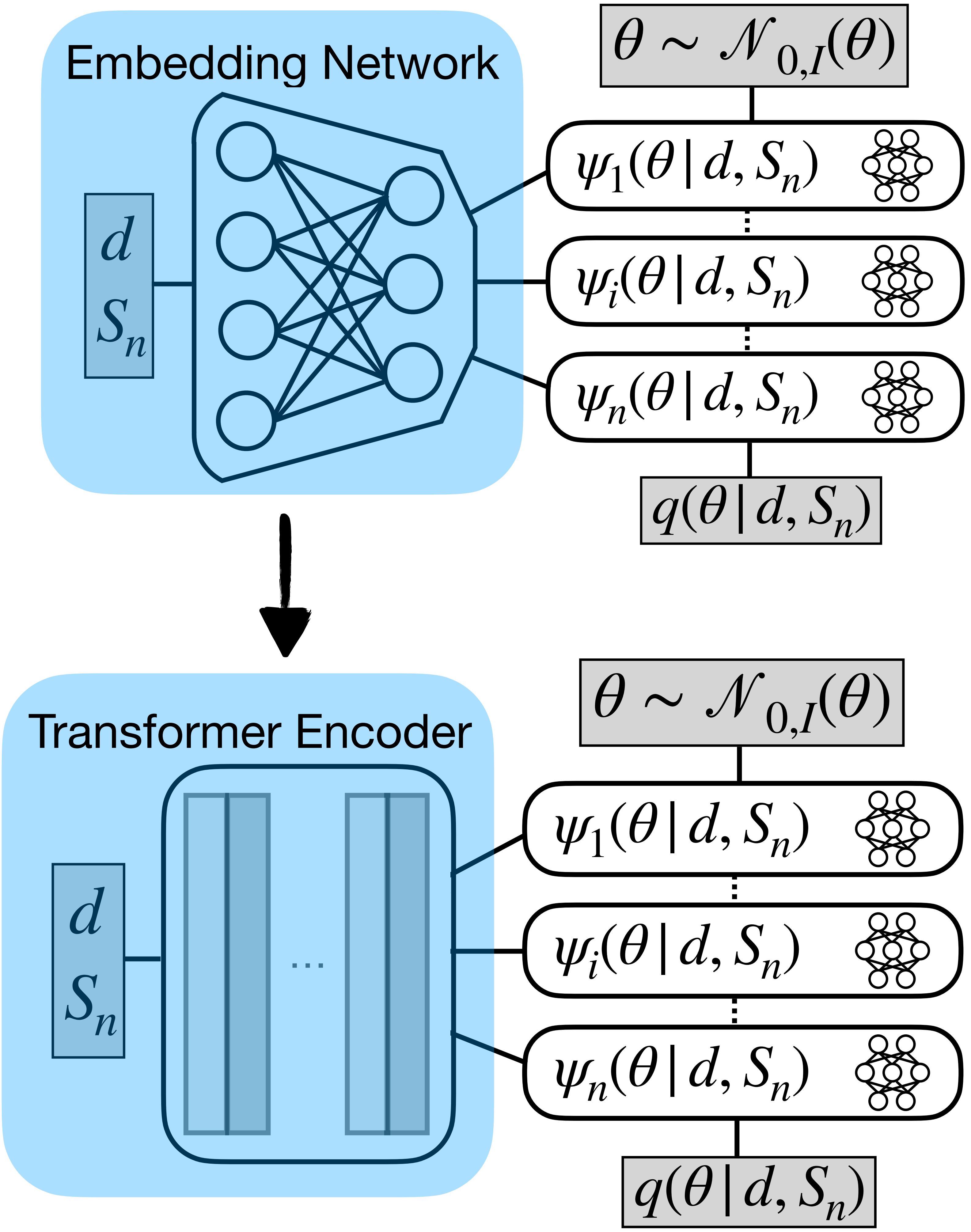


Dax+, PRL 2021

How do we make DINGO flexible?

- Replace fixed embedding network with transformer encoder[2]
- Train with signals of varying shapes
- Adjust exact data analysis settings at inference time

⇒ **DINGO-T1** (Transformer version 1)



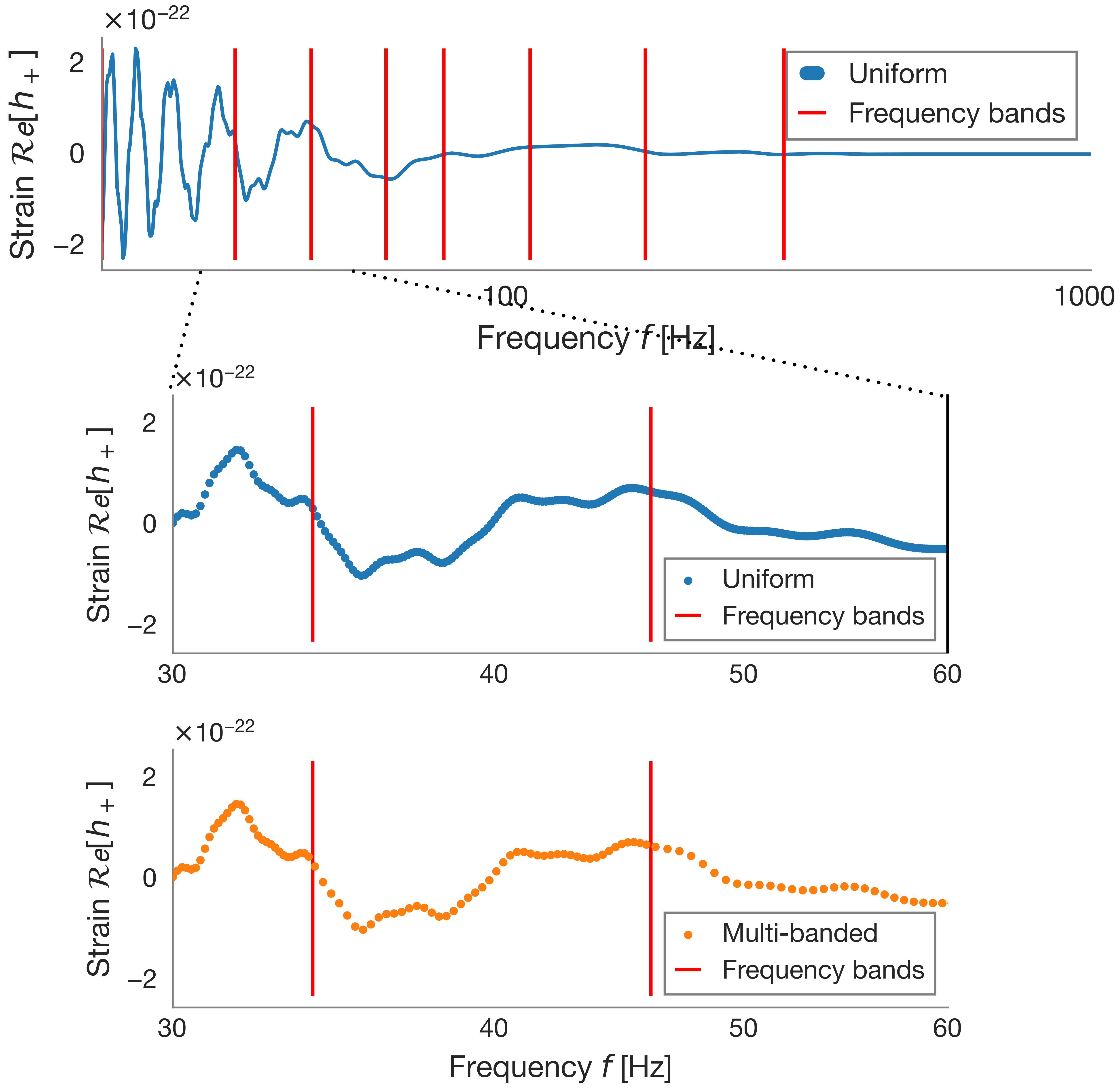
[2]Similar to Papalini+

Previous work (relevant for this talk)

- **Conditioning** on measured ASD
  Dax+ PRL 2021, ICLR 2022
- **Importance sampling** to validate model & reweigh samples towards true posterior
  Dax+ PRL 2023

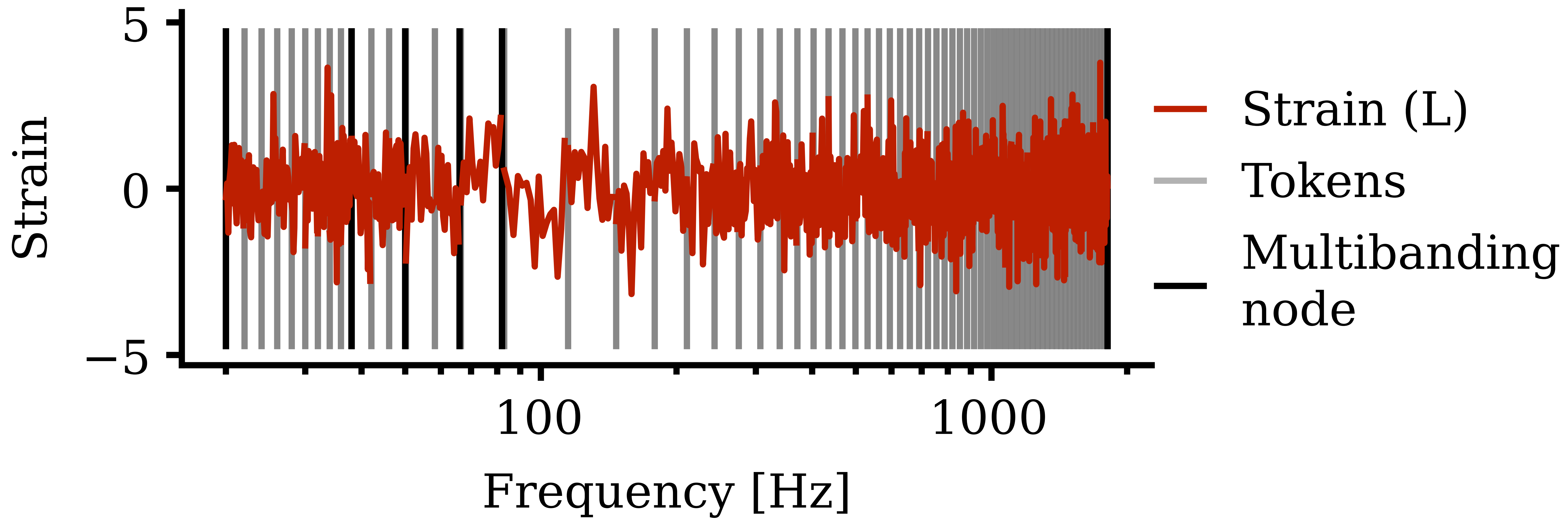
$$\text{Efficiency: } \epsilon = \frac{N_{\text{eff}}}{N}$$

- **“Multibanding”**: Data compression
  Dax+ Nature 2025



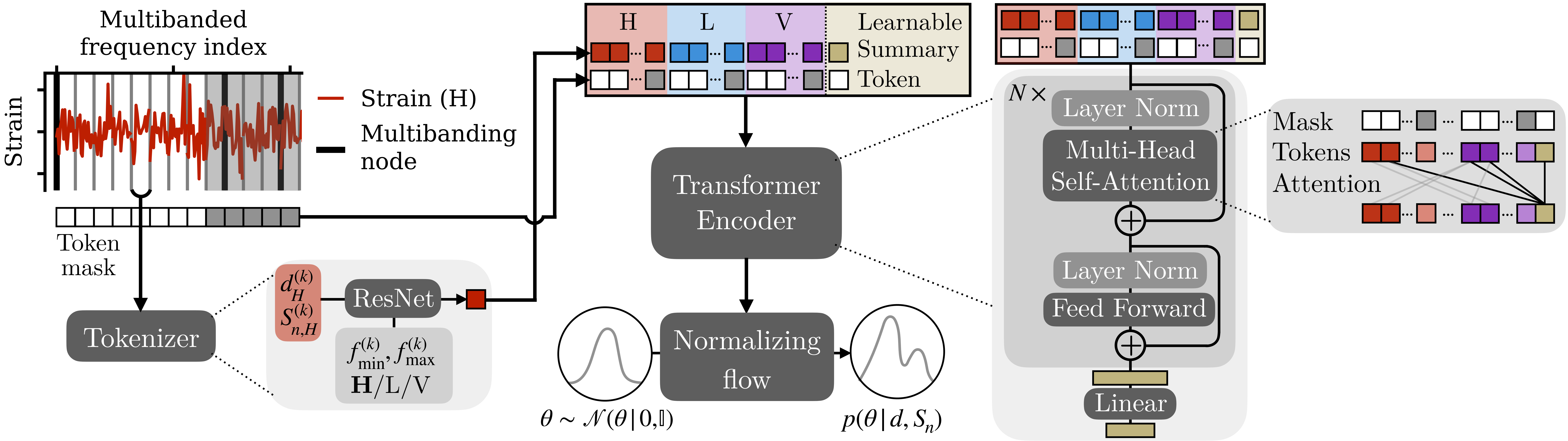
Preparing token segments

- Extend multibanding:
  - Resolution should be consistent within a token segment
  - Tokens should have same number of strain values
  - Nodes of multibanded frequency domain should align with token boundaries



DINGO-T1 Architecture

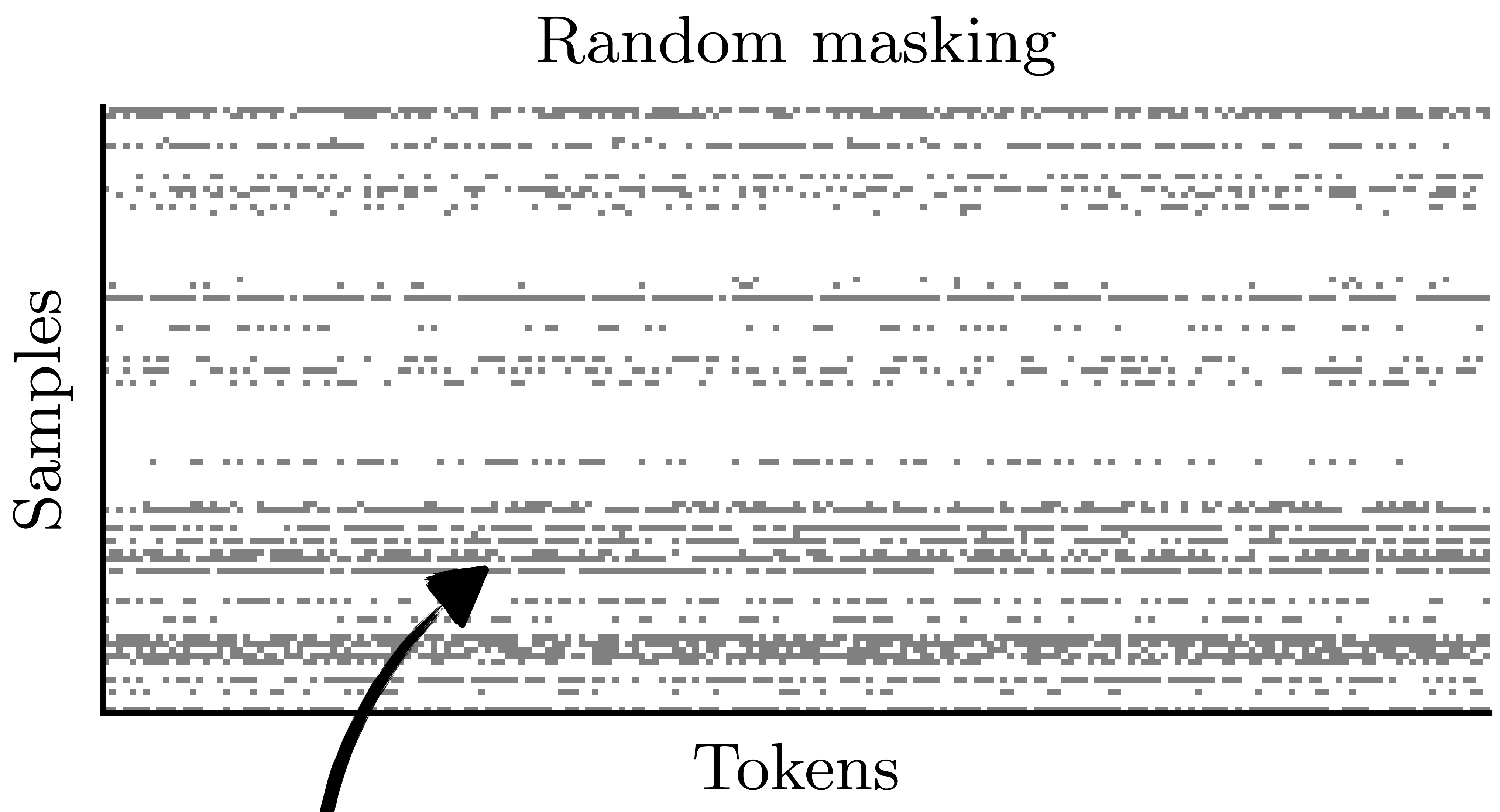
- Shared tokenizer across detector and frequencies
- Extract information via summary token
- End-to-end training



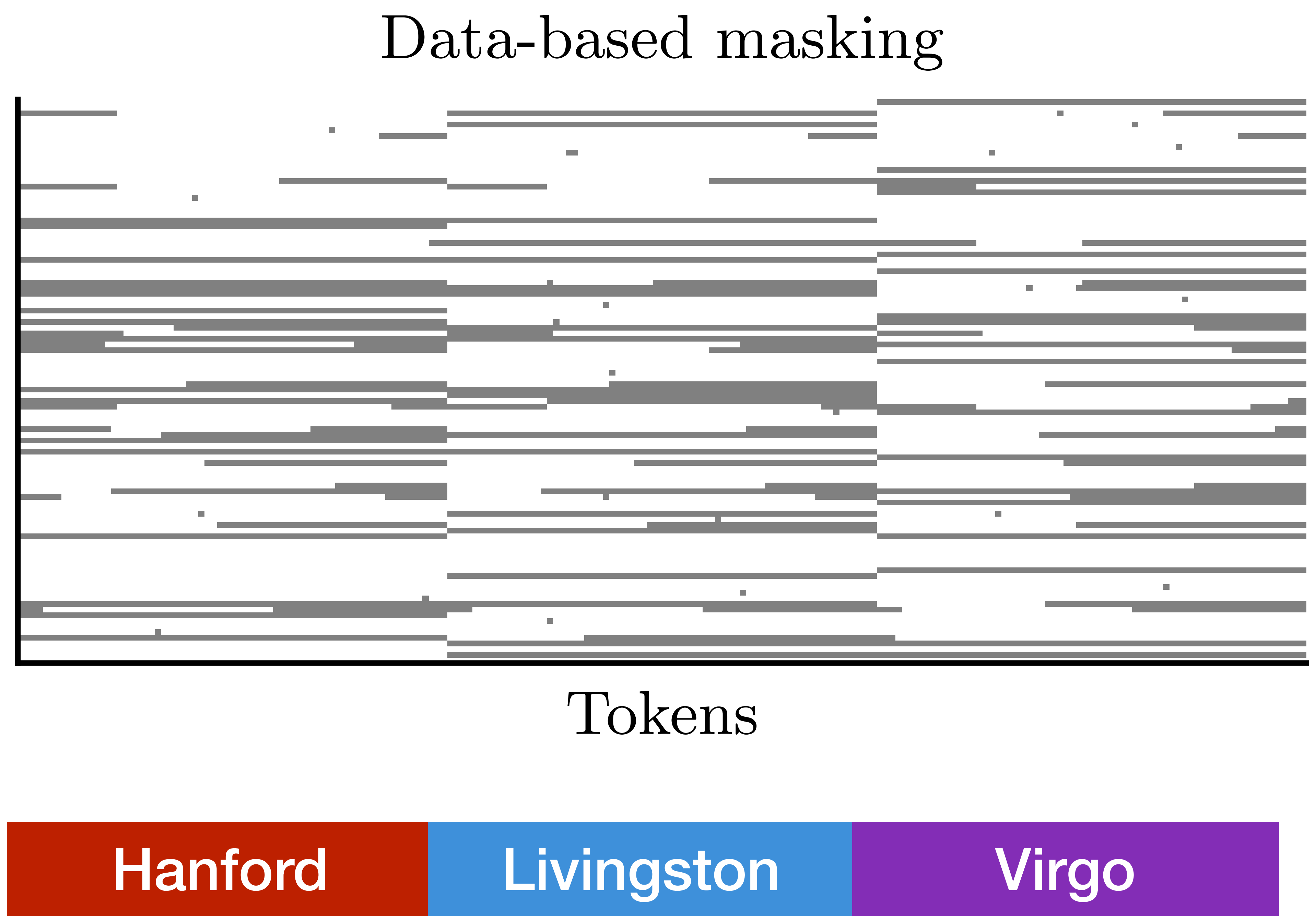
Training a flexible model

- Loss: $$\mathscr{L} = \mathbb{E}_{p(\theta)p(S_n)p(d|\theta,S_n)p(m)}\left[-\log q\left(\theta \,|\, m(d), m(S_n)\right)\right]$$

- Two masking strategies $m \sim p(m)$:

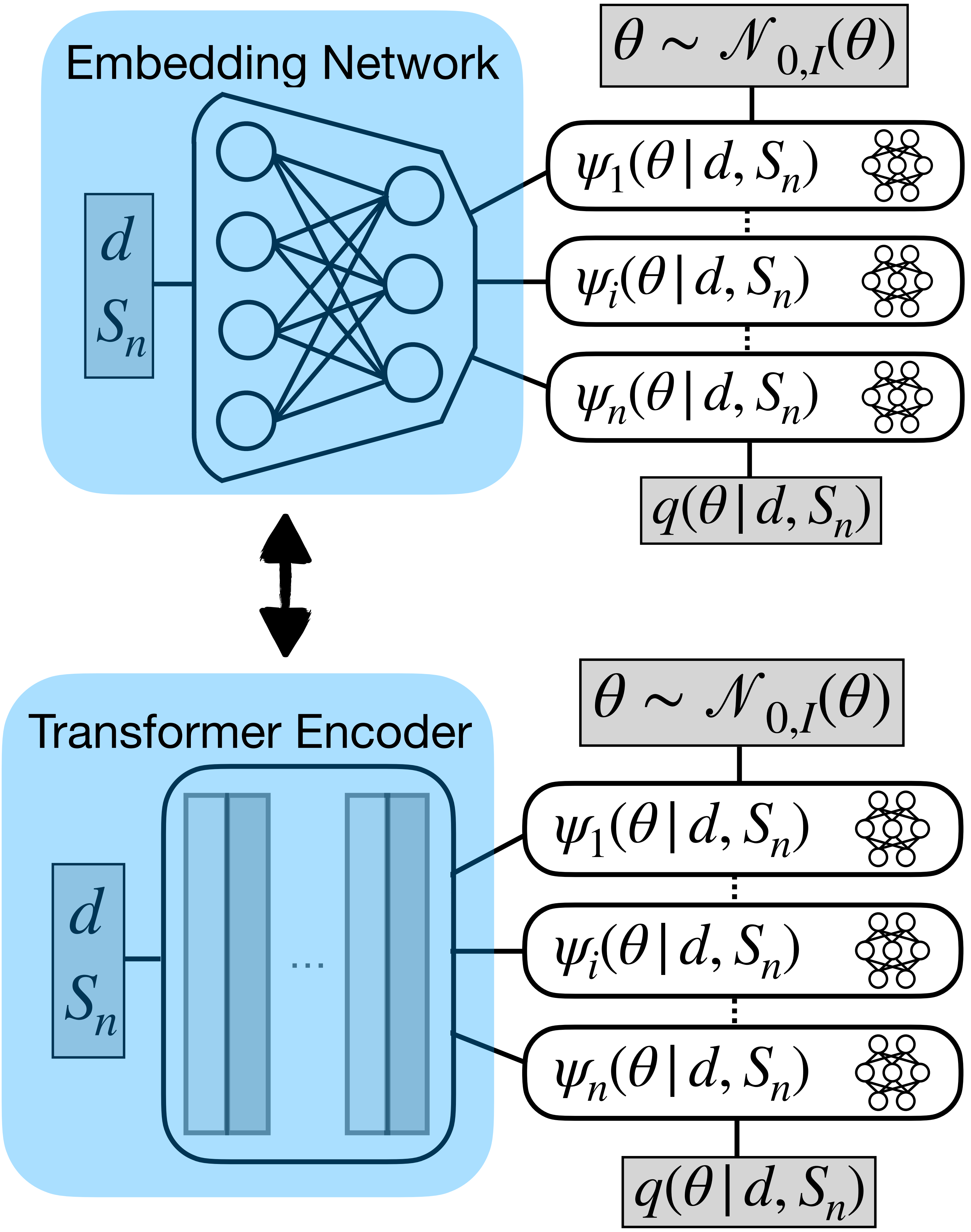


No physics domain knowledge included



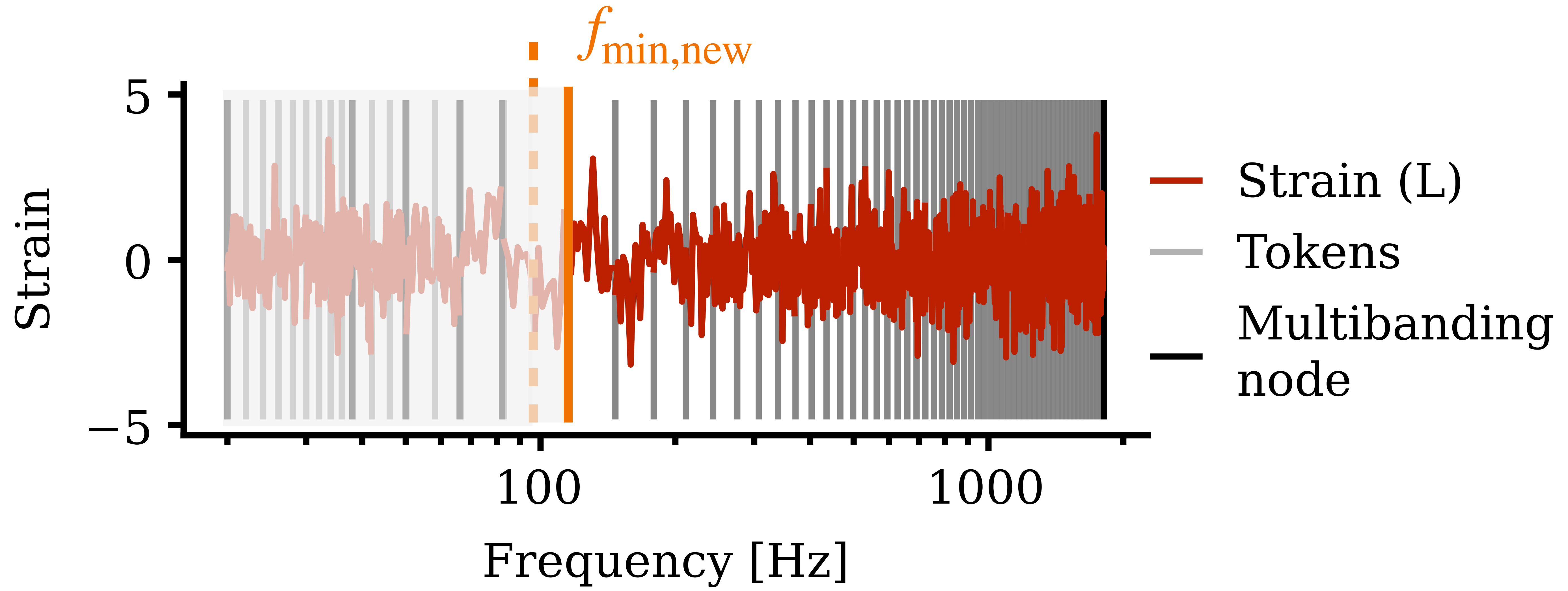
Training a flexible model

- Train with $2.5 \cdot 10^7$ IMRPhenomXPHM waveforms and $\sim 10^3$ noise curves
- Distributed data-parallel training on 8 A100 GPUs $\rightarrow \sim$ 8 days
- Baseline: NPE with ResNet embedding network



Data analysis settings during inference

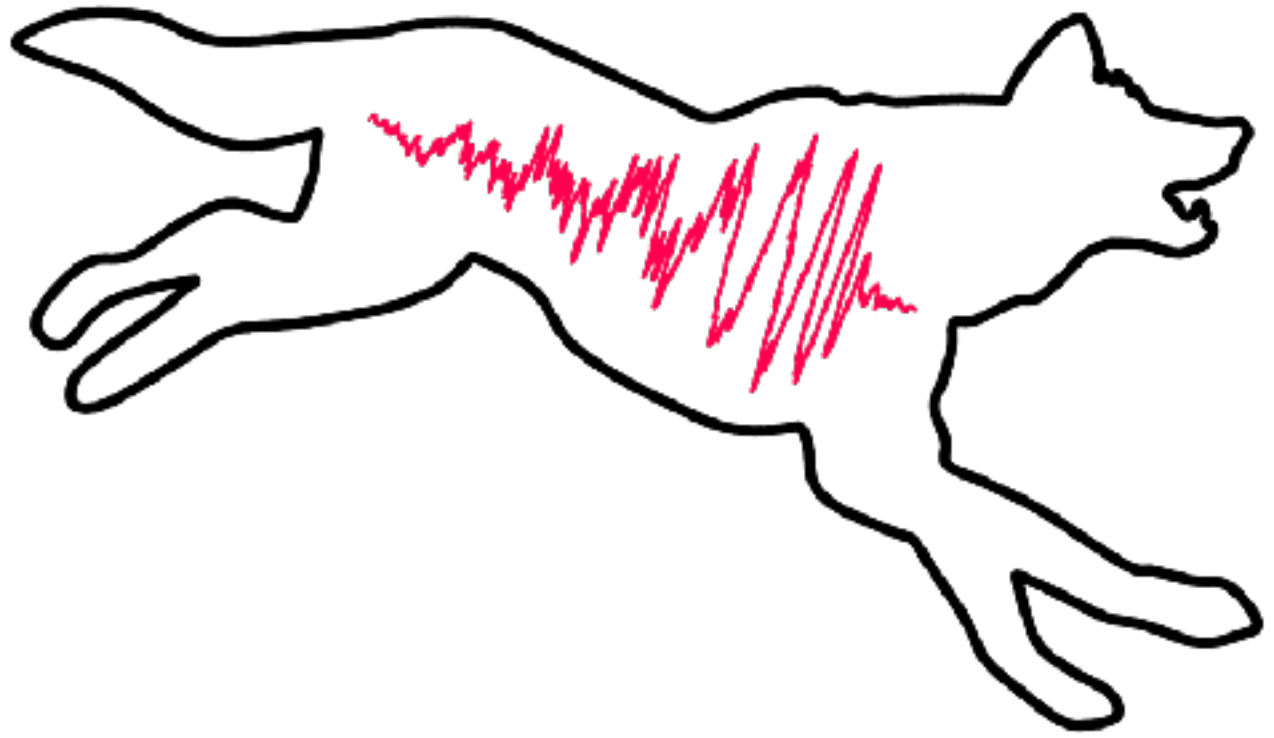
- Remove token inclusively by masking unwanted tokens
- Perform importance sampling on uniform frequency domain



→ Result independent of multi-banding and masking

→ Correct for potential information loss

Results

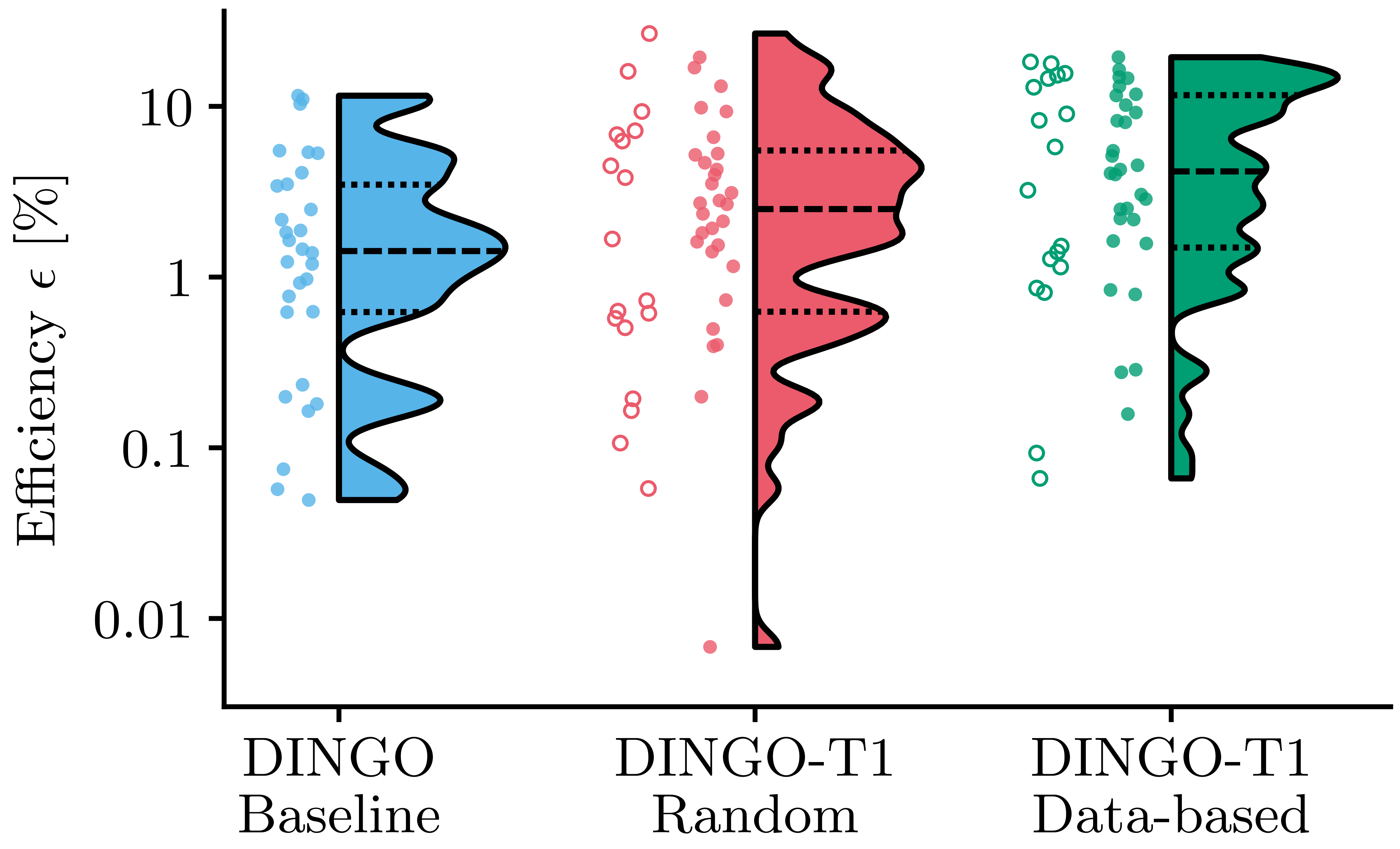


- What masking strategy works best?
- What can we do with a flexible model?

Comparing masking strategies

- 48 O3 events with 17 different data analysis settings
- Distribution over sample efficiencies:

Median efficiency	2-detector	3-detector
DINGO-T1 Random	1.2%	2.7%
DINGO-T1 Data-based	**4.5%**	**4.2%**

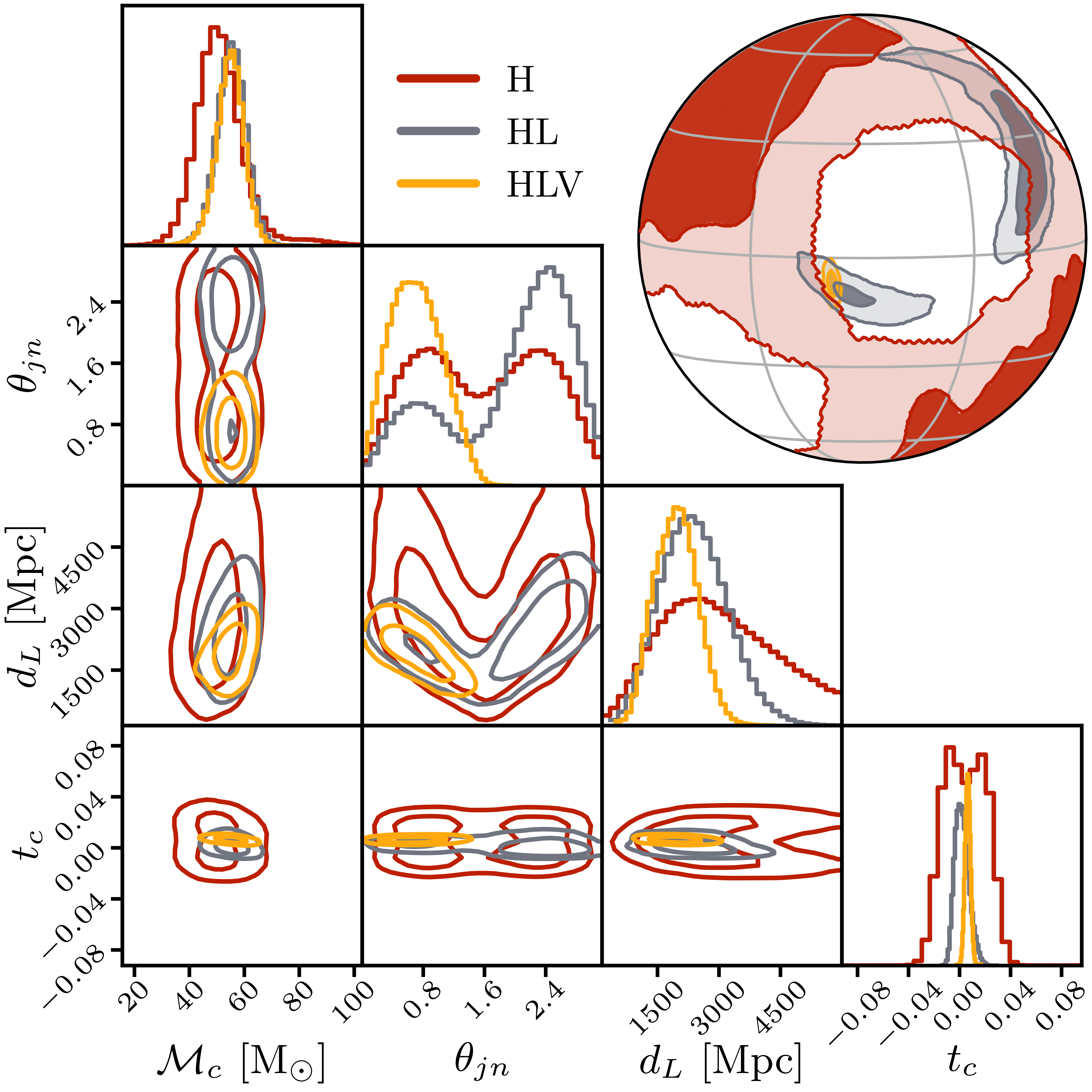


○ 2-detector events (HL, HV, LV)
● 3-detector events (HLV)

Conclusion: Data-based masking wins ⇒ DINGO-T1

Applications: Posteriors under different detectors

- How is the posterior affected when analyzing an event in different detectors?
- Example: GW190701_203306
- Sky position changes a lot (expected)



Applications: Posteriors under different detectors

- Inference with DINGO-T1:
  - Initial sampling < 10s
  - Importance sampling: 5 - 10min
- Analyze all events in different detectors (264 individual PE runs)
- Computationally infeasible with standard samplers

Event	Detectors	HLV	HL	HV	LV	H	L	V
GW190408_181802	HLV	8.07 %	8.28 %	0.64 %	1.35 %	2.79 %	6.71 %	62.23 %
GW190413_052954	HLV	11.77 %	9.52 %	2.41 %	0.74 %	9.5 %	18.61 %	37.48 %
GW190413_134308$^{*\dagger L}$	HLV	4.52 %	7.84 %	8.29 %	1.36 %	21.16 %	11.78 %	32.2 %
GW190426_190642	HLV	0.79 %	2.27 %	7.41 %	0.0 %	29.53 %	0.04 %	49.52 %
GW190503_185404^{*L}	HLV	1.57 %	1.31 %	1.0 %	0.41 %	17.09 %	2.14 %	60.85 %
GW190513_205428^{*L}	HLV	0.16 %	0.52 %	4.19 %	2.04 %	11.74 %	4.17 %	22.9 %
GW190517_055101	HLV	2.17 %	4.28 %	1.79 %	0.27 %	1.36 %	0.36 %	13.06 %
GW190519_153544	HLV	4.26 %	0.85 %	3.71 %	4.88 %	3.38 %	9.09 %	59.66 %
GW190602_175927	HLV	13.09 %	13.18 %	28.09 %	5.4 %	27.24 %	15.95 %	26.58 %
GW190701_203306^{*L}	HLV	14.83 %	14.05 %	9.13 %	5.45 %	31.43 %	5.93 %	38.78 %
GW190706_222641	HLV	2.49 %	5.65 %	13.73 %	6.21 %	0.1 %	10.14 %	27.66 %
GW190727_060333$^{\cdot L}$	HLV	0.84 %	17.6 %	2.95 %	3.29 %	5.09 %	0.45 %	23.71 %
GW190803_022701	HLV	16.39 %	28.23 %	19.48 %	9.04 %	28.74 %	7.89 %	42.92 %
GW190828_063405	HLV	3.99 %	17.35 %	8.7 %	7.11 %	24.58 %	9.26 %	64.41 %
GW190915_235702	HLV	8.23 %	13.56 %	0.89 %	5.24 %	1.9 %	14.02 %	42.52 %
GW190916_200658	HLV	19.41 %	20.19 %	5.16 %	18.13 %	11.2 %	27.25 %	42.29 %
GW190926_050336	HLV	1.63 %	4.25 %	11.17 %	12.38 %	16.39 %	19.97 %	53.75 %
GW190929_012149	HLV	3.04 %	4.74 %	10.61 %	0.0 %	24.68 %	0.01 %	50.24 %
GW191127_050227$^{\diamond H}$	HLV	0.28 %	0.97 %	8.21 %	5.15 %	16.13 %	28.83 %	6.04 %
GW191215_223052	HLV	4.05 %	5.79 %	5.13 %	1.25 %	6.55 %	2.02 %	56.09 %
GW191230_180458	HLV	14.61 %	8.4 %	2.68 %	16.51 %	7.79 %	16.88 %	58.75 %
GW200129_065458$^{\ddagger L}$	HLV	0.29 %	0.29 %	2.16 %	0.01 %	14.15 %	0.07 %	2.66 %
GW200208_130117	HLV	11.58 %	12.15 %	5.17 %	5.99 %	32.27 %	8.9 %	17.75 %
GW200208_222617	HLV	2.86 %	2.47 %	4.73 %	0.05 %	5.55 %	18.82 %	18.48 %
GW200209_085452	HLV	2.52 %	11.06 %	3.55 %	16.62 %	9.66 %	34.08 %	41.28 %
GW200216_220804	HLV	2.2 %	12.56 %	12.41 %	7.44 %	21.27 %	10.96 %	52.1 %
GW200219_094415	HLV	5.12 %	7.36 %	3.27 %	2.77 %	11.76 %	11.09 %	1.9 %
GW200220_061928	HLV	10.17 %	18.1 %	6.07 %	7.68 %	8.67 %	11.95 %	61.93 %
GW200224_222234	HLV	5.49 %	7.18 %	1.65 %	6.85 %	10.2 %	20.89 %	4.01 %
GW200311_115853	HLV	9.2 %	5.56 %	11.57 %	4.81 %	7.71 %	4.23 %	3.64 %
GW190421_213856	HL	-	17.8 %	-	-	10.08 %	17.4 %	-
GW190514_065416$^{*\dagger L}$	HL	-	15.22 %	-	-	19.48 %	4.83 %	-
GW190521_074359	HL	-	1.28 %	-	-	7.24 %	1.26 %	-
GW190527_092055	HL	-	9.04 %	-	-	2.95 %	5.56 %	-
GW190719_215514	HL	-	14.56 %	-	-	17.56 %	0.05 %	-
GW190731_140936	HL	-	18.22 %	-	-	38.6 %	4.69 %	-
GW191109_010717$^{\diamond HL}$	HL	-	1.52 %	-	-	0.11 %	5.15 %	-
GW191204_110529	HL	-	0.07 %	-	-	19.49 %	13.28 %	-
GW191222_033537	HL	-	15.61 %	-	-	6.84 %	16.18 %	-
GW200128_022011	HL	-	8.28 %	-	-	38.67 %	18.79 %	-
GW200220_124850	HL	-	12.94 %	-	-	23.86 %	15.56 %	-
GW200306_093714	HL	-	0.09 %	-	-	6.0 %	0.08 %	-
GW190925_232845	HV	-	-	0.86 %	-	8.16 %	-	16.97 %
GW200302_015811	HV	-	-	1.4 %	-	2.25 %	-	31.8 %
GW190620_030421	LV	-	-	-	0.81 %	-	1.5 %	55.53 %
GW190630_185205	LV	-	-	-	1.15 %	-	7.98 %	16.08 %
GW190910_112807	LV	-	-	-	3.22 %	-	4.2 %	19.1 %
GW200112_155838	LV	-	-	-	5.79 %	-	16.7 %	20.93 %

Applications: Testing general relativity

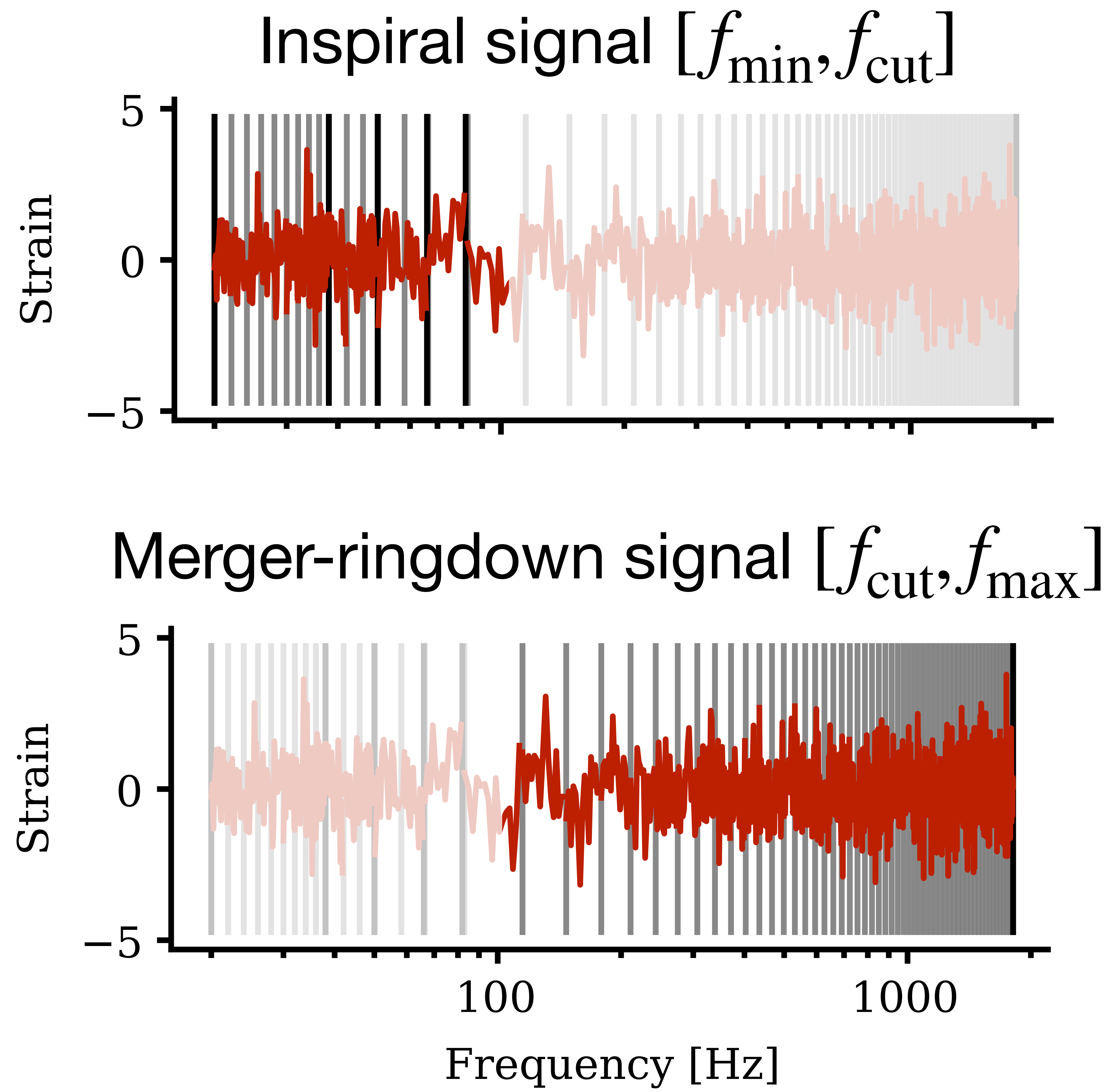
- Inspiral-merger-ringdown (IMR) consistency tests

- Do we obtain the same M_f & χ_f from different parts of the signal?

- Quantify as deviation:

$$\frac{\Delta M_f}{\overline{M}_f} = 2\frac{M_f^{\text{insp}} - M_f^{\text{postinsp}}}{M_f^{\text{insp}} + M_f^{\text{postinsp}}}$$

$$\frac{\Delta \chi_f}{\overline{\chi}_f} = 2\frac{\chi_f^{\text{insp}} - \chi_f^{\text{postinsp}}}{\chi_f^{\text{insp}} + \chi_f^{\text{postinsp}}}$$



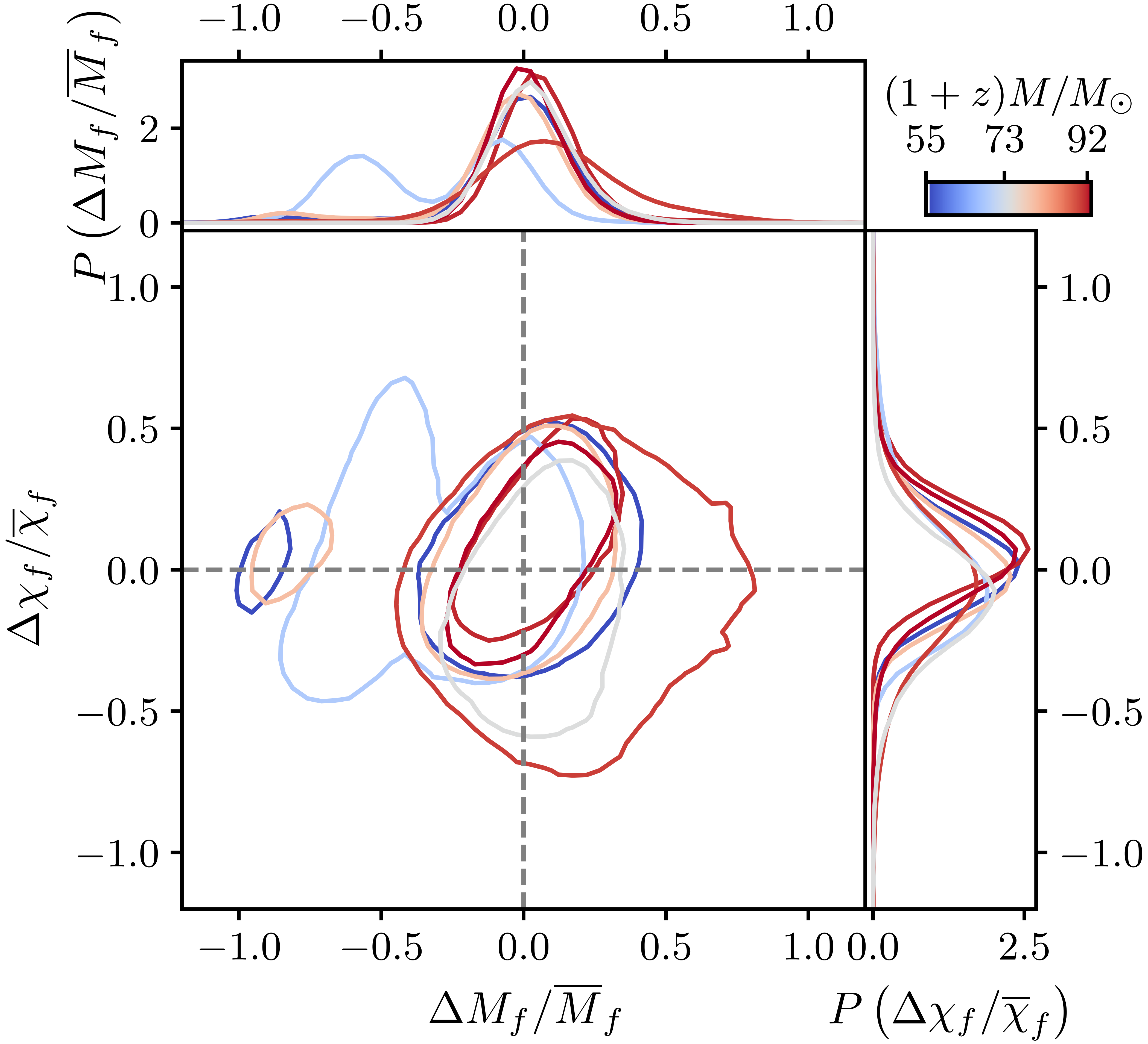
Gosh et al. 2017, arXiv:1704.06784

Applications: Testing general relativity

- 7 O3 events:

Event	Color	Frequency ranges [Hz] Inspiral	Frequency ranges [Hz] Postinspiral
GW190408_181802		[20, 164]	[164, 896]
GW190521_074359		[20, 105]	[105, 224]
GW190630_185205		[20, 135]	[135, 896]
GW190828_063205		[20, 132]	[132, 896]
GW200208_130117		[20, 98]	[98, 448]
GW200224_222234		[20, 107]	[107, 448]
GW200311_115853		[20, 122]	[102, 896]

- Theory consistent with data
  → peak at $(0{,}0)$



Summary: DINGO-T1

- Flexibility of DINGO-T1 allows us to do …

  … large scale PE analysis

  … fast re-analysis with different data analysis settings

  … IMR consistency tests

- All analyses in this paper would have required training
  94 separate DINGO models!

Further resources

- Preprint on arXiv: https://arxiv.org/abs/2512.02968
- Model publicly available on Zenodo:

November 26, 2025 (v1) | Model | Open

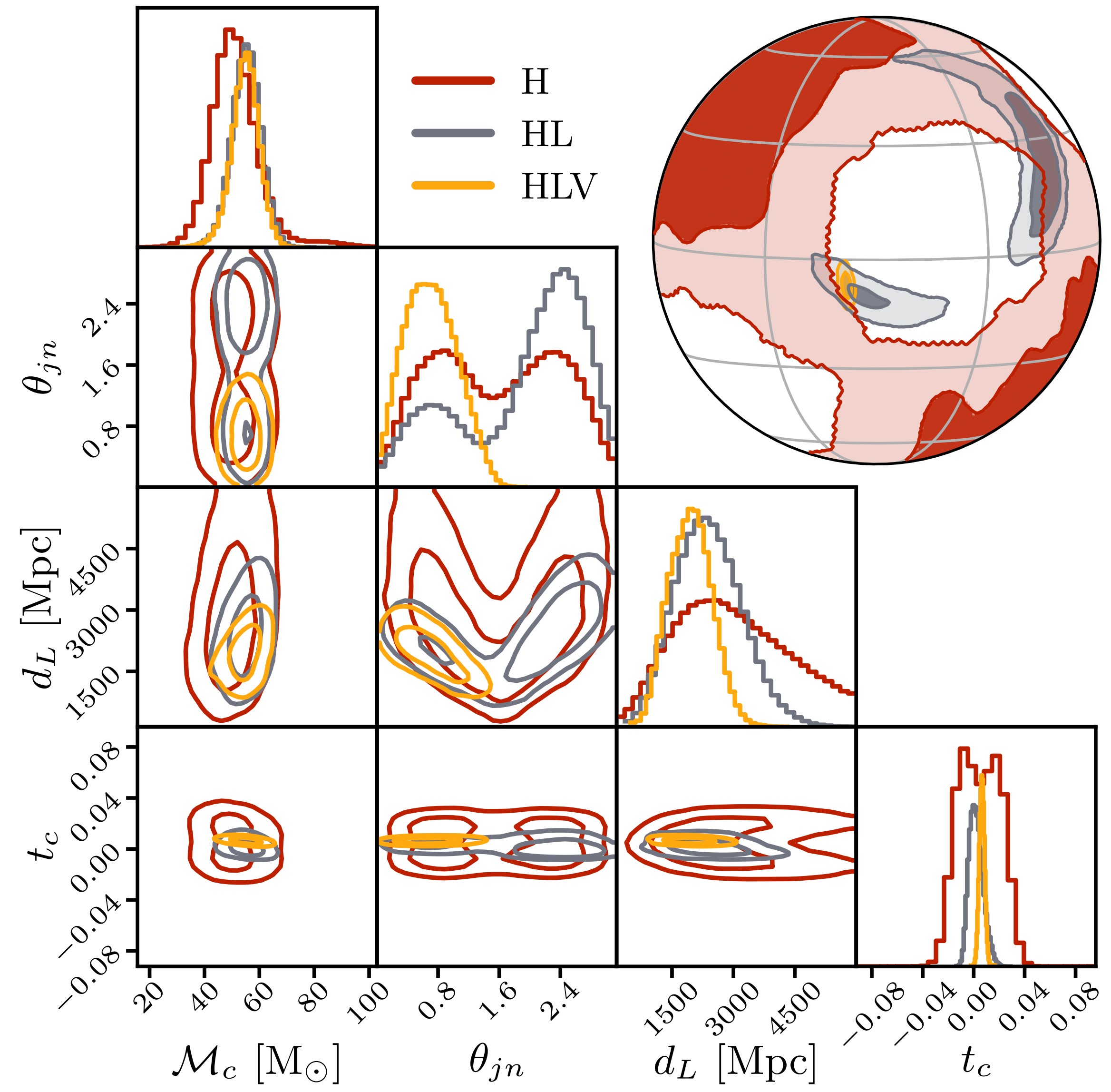
DINGO-T1 model for "Flexible Gravitational-Wave Parameter Estimation with Transformers"

Kofler, Annalena; Dax, Maximilian; Green, Stephen R.; and 6 others

DINGO-T1 and DINGO NPE baseline models for the paper "Flexible Gravitational-Wave Parameter Estimation with Transformers". How to download all files from this page If you would like to download all files on this page, you can use zenodo_get: pip install zenodo_get zenodo_get RECORD_ID_OR_DOI where the record ID for the most recent version of this page is 17726076. How to perform inference with the…

- Tutorial online: https://github.com/dingo-gw/dingo-T1

Make this plot yourself!



The Dingo Pack

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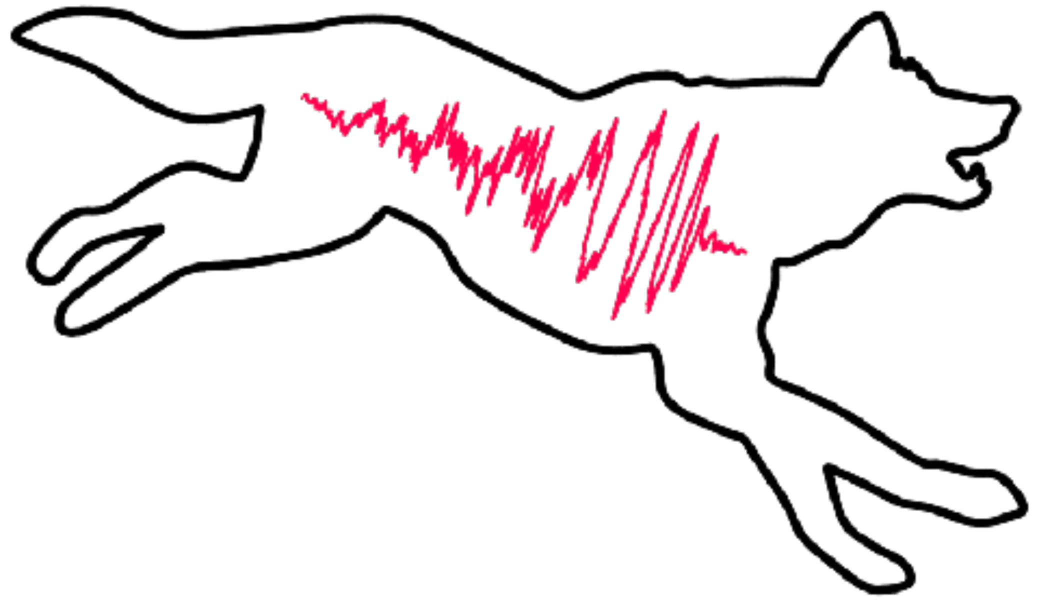
Do you have any questions?



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