

TSB-based learning model

- Under the recent SB-based learning framework [Vargas 2021, De Bortoli 2021, Chen 2022]

- **Learnable** models $(Z_t(\theta), \hat{Z}_t(\hat{\theta}))$ for optimal policies (Z_t, \hat{Z}_t)

- NNs, graph/simplicial NNs

- **Trainable** objective relating the TSBP objective and the models

$$\mathcal{L}_{TSB}(x_0) = \mathbb{E} [\log \nu_1(X_1)] - \int_0^1 \mathbb{E} \left[\frac{1}{2} \|Z_t\|^2 + \frac{1}{2} \|\hat{Z}_t\|^2 + \nabla \cdot (g_t \hat{Z}_t - f_t) + \hat{Z}_t^\top Z_t \right] dt$$

- Particular choices of models give topological variants

- diffusion models using score-matching [Song et al. 2021]

$$Z_t = 0, \quad \hat{Z}_t = g_t \nabla \log p_{t|0}$$

- Diffusion bridge models based on Doob's h -transform for a particular final distri.

- Probability flow ODE: flow-matching [Lipman et al. 2022]

TSB-learning model

$$Z_t \approx Z_t(\theta) \quad l(x_0; \phi)$$

$$\tilde{Z}_t \approx \tilde{Z}_t(\phi) \quad l(x_1; \theta)$$

Learnable

Trainable

Topological signal generation

- TSB-based models vs. SB-based models
- Generative modeling

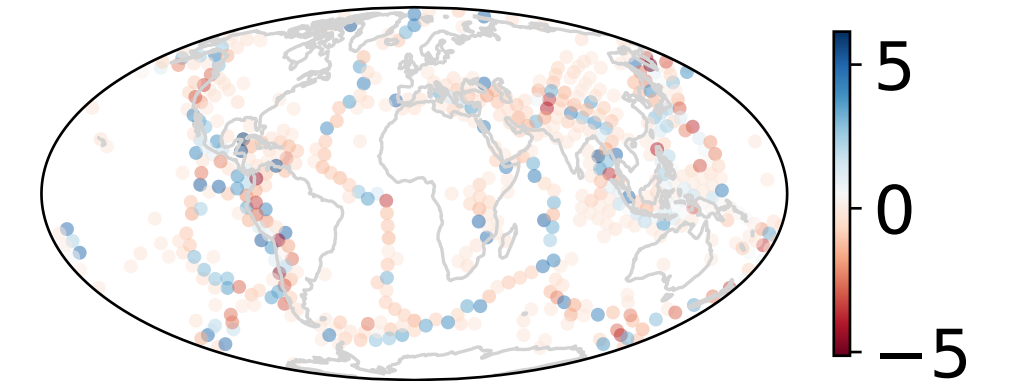
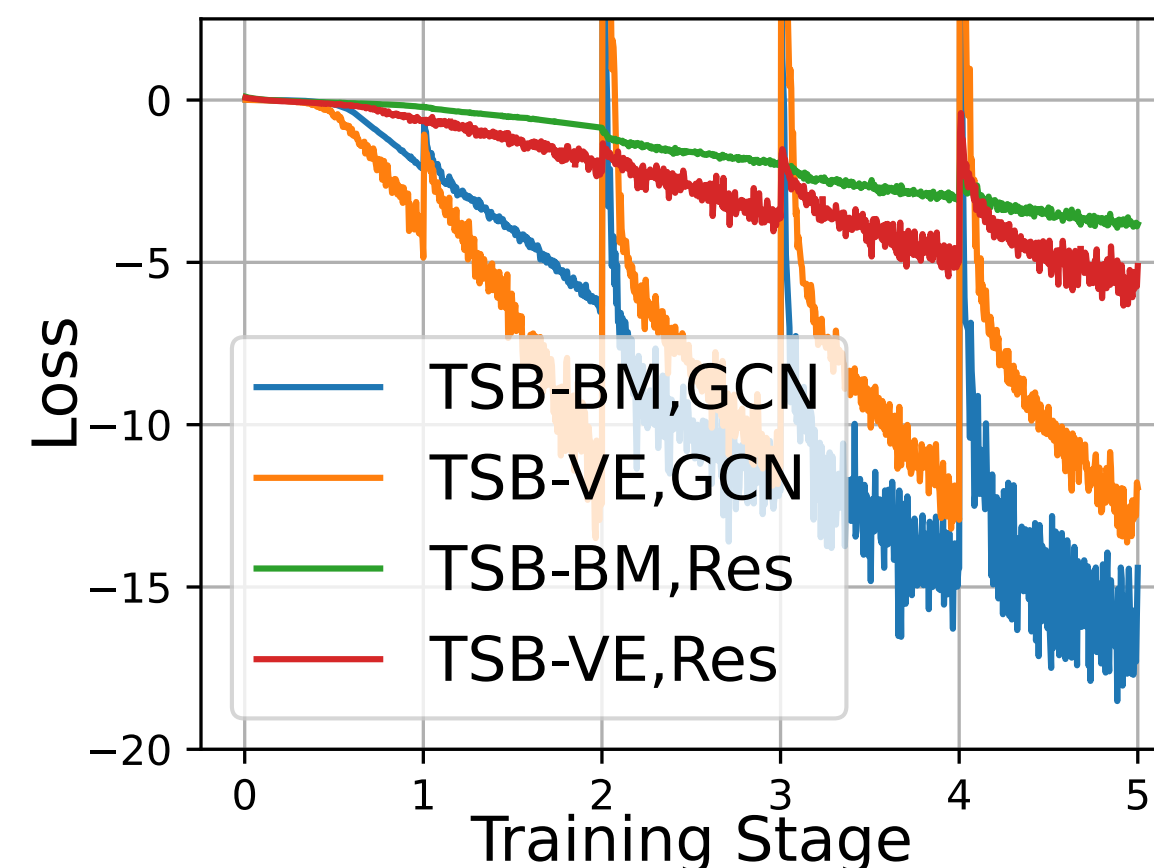


Table 1: Generative modeling results (NLL).

	SB-BM	SB-VE	SB-VP	TSB-BM	TSB-VE	TSB-VP
Seismic, Res	2.78 ± 0.01	2.94 ± 0.03	2.28 ± 0.02	2.13 ± 0.01	2.22 ± 0.02	2.00 ± 0.02
Seismic, GCN	2.71 ± 0.03	2.73 ± 0.05	2.01 ± 0.03	1.82 ± 0.02	1.53 ± 0.03	1.51 ± 0.02
Traffic, Res	0.82 ± 0.00	0.77 ± 0.00	0.79 ± 0.00	0.40 ± 0.00	0.01 ± 0.00	0.02 ± 0.00
Traffic, SNN	0.18 ± 0.02	-0.42 ± 0.01	-0.09 ± 0.01	-0.83 ± 0.05	-1.26 ± 0.05	-1.01 ± 0.03

- Effect of policy models
 - ResBlock vs. topological NNs



Method	Seismic magnitudes		Traffic flows	
	W_1	W_2	W_1	W_2
SB-BM	11.73 ± 0.05	8.29 ± 0.04	18.69 ± 0.02	13.36 ± 0.01
SB-VE	11.49 ± 0.04	8.13 ± 0.03	19.04 ± 0.02	13.61 ± 0.02
SB-VP	12.61 ± 0.06	8.92 ± 0.04	18.22 ± 0.03	13.02 ± 0.02
TSB-BM	9.01 ± 0.03	6.37 ± 0.03	10.57 ± 0.02	7.62 ± 0.01
TSB-VE	7.69 ± 0.04	5.44 ± 0.03	10.51 ± 0.02	7.58 ± 0.01
TSB-VP	8.40 ± 0.04	5.95 ± 0.03	9.92 ± 0.02	7.16 ± 0.01