# EarthquakeNPP:

## Benchmark Datasets for Earthquake Forecasting with Neural Point Processes

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# Neural Point Processes

- Promise greater flexibility and improvements over classical forecasting models.
- Belong to the same statistical family as the Epidemic-Type Aftershock Sequence (ETAS) model.
- Replace the typical point process parameterizations with neural networks $\phi(\cdot)$.

Either directly modeling the intensity function,

$$\lambda(t, \mathrm{x}|\mathcal{H}_t) = \phi(t, \mathrm{x}, \mathcal{H}_t),$$

the triggering kernel [4, 3],

$$\lambda(t, \mathrm{x}|\mathcal{H}_t) = \mu + \sum_{t_i < t} \phi(t - t_i, \mathrm{x} - \mathrm{x}_i, \mathcal{H}_{t_i})$$

or the next-event probability density [1],

$$p(t, \mathrm{x}|\mathcal{H}_t) = \phi(t, \mathrm{x}, \mathcal{H}_t)$$

# Existing Benchmark in ML community [1]

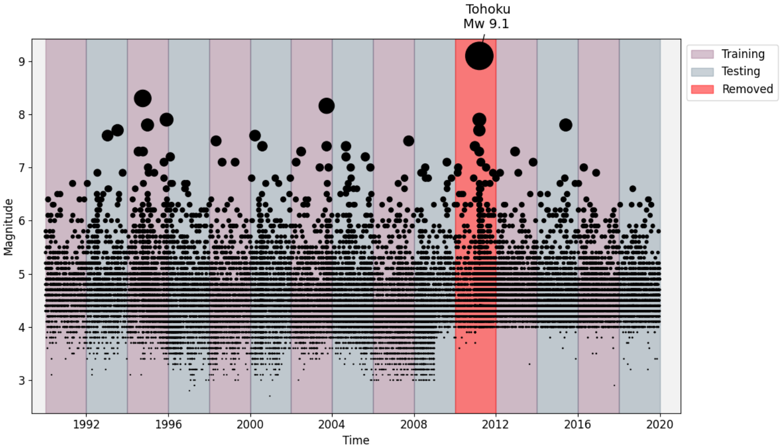


**Figure:** *ANSS Comprehensive Earthquake Catalog, focusing on Japan from 1990 to 2020, used in the machine learning community to benchmark NPPs. Earthquakes above $M_w 2.5$ are considered and the data is partitioned for training and testing in an alternating patern. The authors also exclude the Tōhoku earthquake sequence, under the pretext of removing outliers.*

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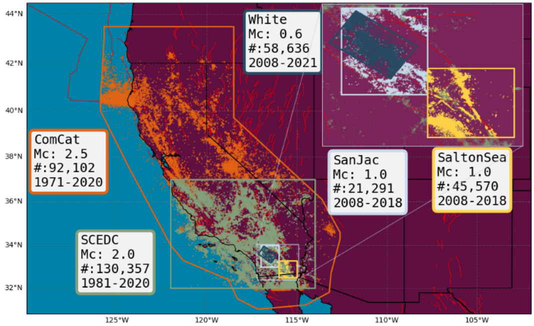
# EarthquakeNPP: Benchmark Datasets for Earthquake Forecasting with Neural Point Processes

EarthquakeNPP is an expanding collection of benchmark datasets designed to facilitate testing of Neural Point Processes (NPPs) on earthquake data. The datasets are accompanied by an implementation of the Epidemic-Type Aftershock Sequence (ETAS) model, currently considered the benchmark forecasting model in the seismology community. Derived from publicly available raw data, these datasets undergo processing and configuration to support forecasting experiments relevant to stakeholders in seismology. The datasets cover various regions of California, representing typical forecasting zones and the data commonly available to forecast issuers. Several datasets include much smaller magnitude earthquakes thanks to modern algorithms for detection and dense seismic networks.




**EarthquakeNPP: Benchmark Datasets for Earthquake Forecasting with Neural Point Processes**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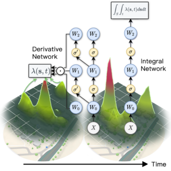
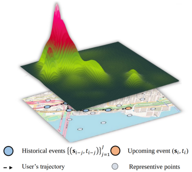
# Models

Includes an implementation of the ETAS model [2],

$$\lambda(t, \mathrm{x}|\mathcal{H}_t) = \mu + \sum_{t_i<t} \frac{e^{-(t-t_i)/\tau} \cdot k \cdot e^{a(m_i-M_c)}}{(t-t_i+c)^{1+\omega} \cdot \left(||\mathrm{x}-\mathrm{x}_i||_2^2 + d \cdot e^{\gamma(m_i-M_c)}\right)^{1+\rho}}$$

Deep-STPP [4], Auto-STPP [3], Neural-STPP [1]




Evaluation of models using the event-based log-likelihood

$$\log p(\mathcal{H}_T) = \underbrace{\sum_{i=0}^{n} \log \lambda(t_i|\mathcal{H}_{t_i}) - \int_{T_0}^{T_1} \int_{\mathcal{S}} \lambda(s, \mathrm{z}|\mathcal{H}_s) d\mathrm{z} ds}_{\text{Temporal log-likelihood}} + \underbrace{\sum_{i=0}^{n} \log f(\mathrm{x}_i|t_i, \mathcal{H}_{t_i})}_{\text{Spatial log-likelihood}},$$

# Temporal log-likelihood scores

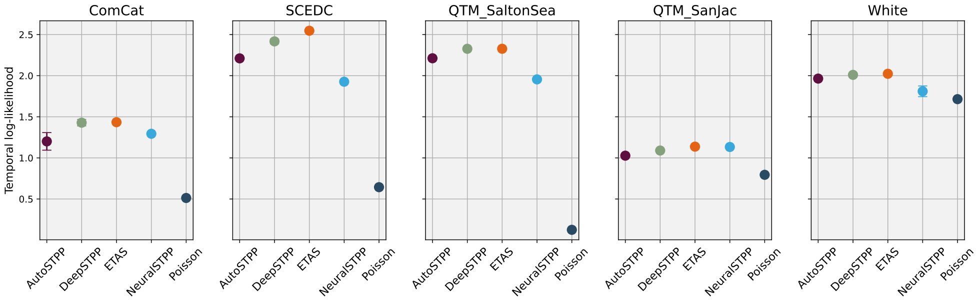



**Figure:** *Temporal log-likelihood scores for DeepSTPP [4], AutoSTPP [3], NeuralSTPP [1], ETAS [2] and a baseline Poisson model.*

# Spatial log-likelihood scores

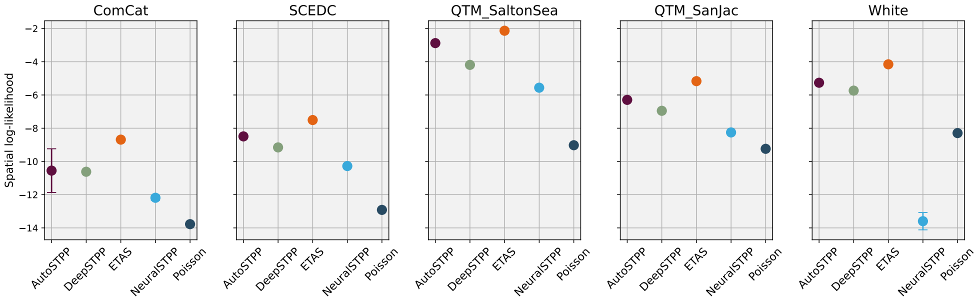
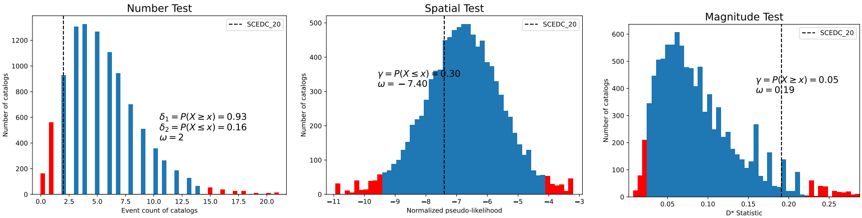
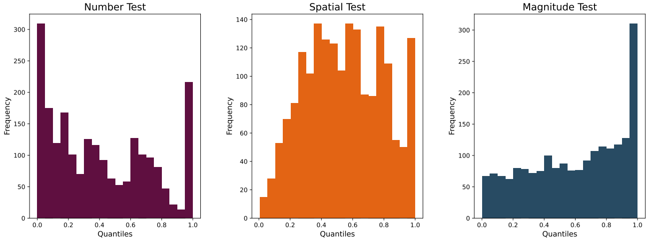


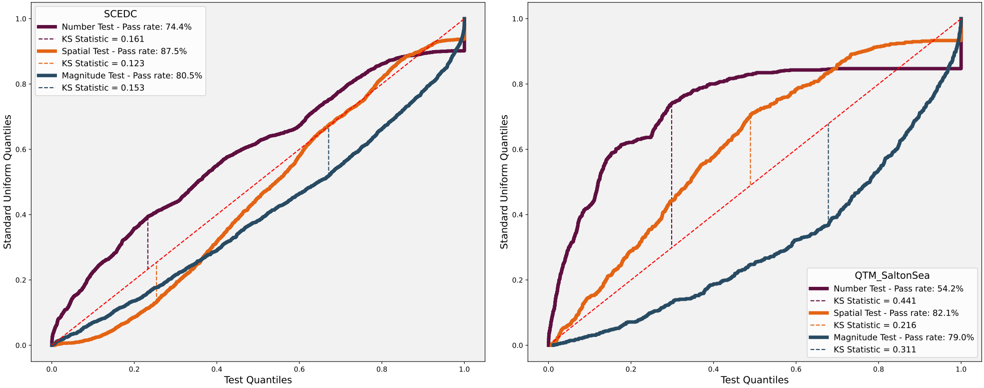

**Figure:** *Spatial log-likelihood scores for DeepSTPP [4], AutoSTPP [3], NeuralSTPP [1], ETAS [2] and a baseline Poisson model.*

# CSEP tests for daily forecasts



# QQ plots: evaluating over multiple forecasting periods



# Looking ahead

- We need to direct the future development of NPPs towards best practices in seismology.
- EarthquakeNPP is a growing platform: more models, more datasets.
- Platform for NPP development within our community.
- Provide the pathway for NPPs to be evaluated in future prospective CSEP experiments.

# References


[1] Ricky T. Q. Chen, Brandon Amos, and Maximilian Nickel. "Neural Spatio-Temporal Point Processes". In: *International Conference on Learning Representations*. 2021. URL: https://openreview.net/forum?id=XQQA6-So14.

[2] Leila Mizrahi, Nicolas Schmid, and Marta Han. *lmizrahi/etas*. Software. 2022. URL: https://doi.org/10.5281/zenodo.6583992.

[3] Zihao Zhou and Rose Yu. "Automatic Integration for Spatiotemporal Neural Point Processes". In: *Advances in Neural Information Processing Systems* 36 (2024).

[4] Zihao Zhou et al. "Neural point process for learning spatiotemporal event dynamics". In: *Learning for Dynamics and Control Conference*. PMLR. 2022, pp. 777–789.