Benchmarking seismic phase associators: Insights from synthetic scenarios.

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Introduction

This study systematically evaluates five seismic phase associators, including machine learning options, using synthetic datasets designed to mimic the seismic activity of subduction zones. These datasets, created with the NonLinLoc raytracer and realistic station and velocity setups, featured various event depths and introduced errors and omissions to replicate real-world conditions. Under project MILESTONE, we compared the effectiveness of **PhaseLink [Ross et al., 2019], GaMMA [Zhu et al., 2022], REAL [Zhang et al., 2019], GENIE [McBrearty and Beroza, 2023], and PyOcto [Münchmeyer, 2024]** across scenarios like low and high noise levels, out-of-network events, and complex aftershock sequences. We tested each associator's performance, highlighting significant differences in their performance.

Benchmark Setup and Parameter Optimization

We generated synthetic seismic events using the NonLinLoc raytracer and a Northern Chile velocity model [Graeber and Asch, 1999], observed by the CX network of the IPOC. Events were set within a 24-hour window, with arrival times calculated according to McBrearty and Beroza [2023], subjected to a random distance cutoff of [160,500] km, noise addition (1-2%), and random station dropouts (20%). False picks were also incorporated to mimic realistic data conditions. Various seismic phase associators were applied to this dataset under different noise scenarios, assessing their performance based on precision, recall, and F1 scores. Each run was limited to 24 hours, with "event matches" defined as detected events sharing at least 50% of their seismic phases with a reference event from the synthetic catalog, ensuring only substantial overlaps were recognized as true positives.

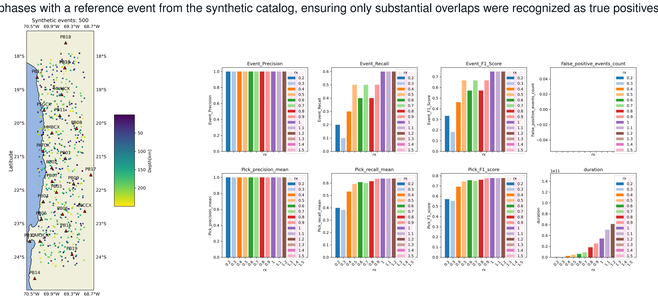

Figure 1. Station configuration and synthetic seismic event distribution example. Red triangles represent the IPOC network's seismic stations, with an example set of 500 events (Left). Effects of varying the Rx search range at a station's initiating pick on REAL's performance. It demonstrates the optimization of association capabilities by comparing different metrics (Right).

Parameter optimization for each associator was methodically conducted by iteratively adjusting one parameter at a time, assessing its impact on performance metrics and runtimes. This approach enabled precise tuning of each associator's settings to optimal levels for diverse scenarios, ensuring robust and comparative performance analysis.
To offer a glimpse into this intricate procedure, we list some of these pivotal parameters for each associator:

GaMMA

- DBSCAN Utilization: Controlled by use_dbscan, this influences whether the algorithm will segment a sequence of picks into clusters based on proximity and density.
- Specified the values for P and S waves, it critically influences travel time calculations.

PhaseLink

- Trained using the same velocity model as the synthetic data it is applied.
- Using n_train_samples=1e7, trained on 500 epochs, n_min_nucl=3, false_picks=35

Genie

- n_epochs=18000, thresh_assoc=0.2 (Threshold to declare src-arrival association).
- dist_range: [30000, 1000000] (The spatial window over which to sample max distance of source-station moveouts in m, per event.
- tc_win=12.0 (Temporal window (s) to link events in Local Marching)
- step=5 (Temporal step size to predict source outputs over, and stack overlapping portions)

REAL

- rx=1 (Search range in horizontal at the station with the initiating picking degree), rh=250 (Search range in depth).
- tdx=0.1 (search grid size for epicenter in degree), tdh=10(search grid size for depth in km).
- nrt =2 (Helps accommodate inaccuracy of velocity model and pick uncertainty)

PyOcto

- time_before: 300 (Overlap between consecutive time slices)
- pick_match_tolerance: 2.0 (Max difference in predicted and observed time for associating a pick)
- n_picks=10 (Minimum required number of picks for an event)
- n_p_and_s_picks=4 (Minimum required number of stations with both P and S pick)

Event-level metrics

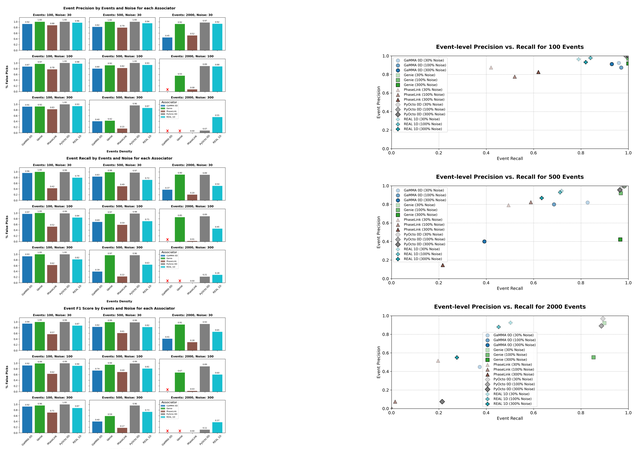

Figure 2. Comparing precision, recall, F1 score, and computation duration across seismic event association algorithms under different noise levels and event density (Left). Event-level Precision vs. Recall across noise levels for seismic phase associators. Each subplot shows performance under varying event counts and noise levels. Marker opacity increases with noise, illustrating associator sensitivity. Scatter plots highlight precision-recall trade-offs, with distinct markers for comparison (Right).

Pick-level metrics

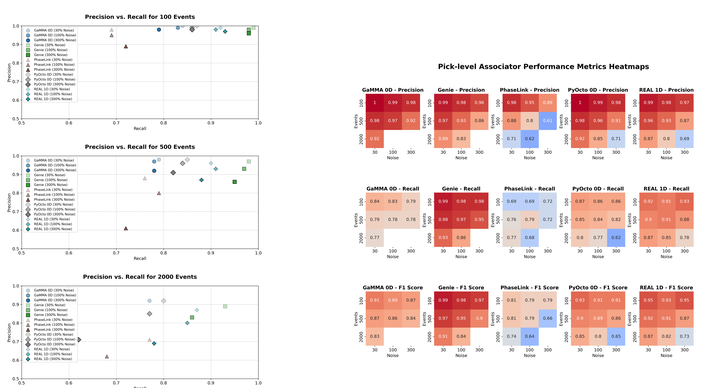

Figure 3. Pick-level Precision vs. Recall across noise levels for seismic phase associators. Each subplot shows performance under varying event counts and noise levels. Marker opacity increases with noise, illustrating associator sensitivity. Scatter plots highlight precision-recall trade-offs, with distinct markers for comparison. (Left). Performance metrics for seismic phase associators across varying noise levels and event densities, depicted through heatmaps. Each panel captures the mean performance derived from individual events that successfully matched our synthetic ground truth (Right).

Processing Runtimes

Our approach to assessing runtime encompasses the period from the initiation of the model to the generation of its outputs. However, it's important to note that this measurement does not account for preprocessing steps such as the construction of the velocity model, or the model training for the deep learning.

Figure 4. Logarithmic scale comparison of processing duration against the total number of picks for various seismic phase associators.

Out-of-network insights

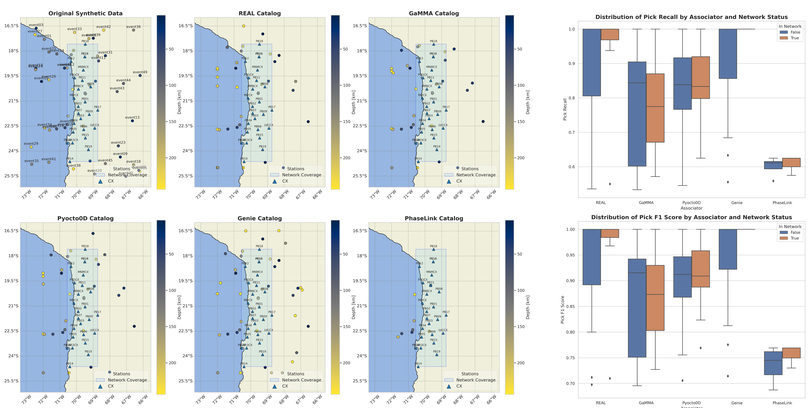

Figure 5. Seismic event locations by associators overlaid on network coverage. Subplots show results for one associator, with synthetic events for reference. Events are color-coded by depth, and stations are marked by triangles. The blue rectangle outlines network coverage (Left). Analysis of associator performance on phase association within and outside network coverage. Boxplots illustrate pick-level metrics. In-network vs. out-of-network events highlight coverage impact (Right).

Summary and future work

Although Genie performed well in our case study, it failed to converge in the last scenario. It is important to note that Genie was not fully optimized and it was the first time applied to a subduction setting. Further enhancements, such as leveraging GPU acceleration, are expected to improve its performance significantly. Although REAL using a 1D velocity model demonstrated the best performance in the most complex scenarios, PyOcto exhibited outstanding performance, achieving the best balance between processing times and effectiveness. Future work will include evaluation of all homogeneous and 1D versions of the associators, as well as improve Genie optimization and tests not only in subduction settings but also in a shallow seismicity setting.

References

F. M. Graeber and G. Asch. Three-dimensional models ofpwave velocity andP-to-Svelocity ratio in the southern central andes by simultaneous inversion of local earthquake data. *J. Geophys. Res.*, 104(B9):20237–20256, Sept. 1999.

I. W. McBrearty and G. C. Beroza. Earthquake phase association with graph neural networks. *Bull. Seismol. Soc. Am.*, 113(2):524–547, Apr. 2023.

J. Münchmeyer. PyOcto: A high-throughput seismic phase associator. *Seismica*, 3(1), Jan. 2024.

Z. E. Ross, Y. Yue, M.-A. Meier, E. Hauksson, and T. H. Heaton. PhaseLink: A deep learning approach to seismic phase association. *J. Geophys. Res. [Solid Earth]*, 124(1):856–869, Jan. 2019.

M. Zhang, W. L. Ellsworth, and G. C. Beroza. Rapid earthquake association and location. *Seismol. Res. Lett.*, 90(6):2276–2284, Nov. 2019.

W. Zhu, I. W. McBrearty, S. M. Mousavi, W. L. Ellsworth, and G. C. Beroza. Earthquake phase association using a bayesian gaussian mixture model. *J. Geophys. Res. [Solid Earth]*, 127(5), May 2022.