A Unified Deep Learning Framework for Ground Motion Prediction Before, During, and After Earthquakes

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Accurate ground motion prediction remains fundamental to earthquake science and engineering. While the rapid expansion of seismic monitoring networks has generated unprecedented data volumes, traditional ground motion prediction equations that rely on simplified empirical relationships cannot fully exploit this wealth of information. Meanwhile, near-fault ground motions from large earthquakes are particularly destructive when rupture directivity and basin effects amplify intensity measures. Yet, the scarcity of near-fault observations makes it difficult for empirical methods to capture high-fidelity directivity effects and their associated uncertainties. Physics-based simulations such as CyberShake offer a promising alternative by generating massive earthquake scenarios with varied rupture realizations. Still, their substantial computational and storage demands make it impractical to produce high-resolution hazard maps without significant interpolation. Together, these limitations motivate a unified deep learning approach that can learn directly from both observational and simulated ground-motion data.

We introduce QuakeFormer, a Transformer-based architecture that addresses three critical ground-motion prediction scenarios, as shown in Fig. 1: before (intensity estimation), during (early warning), and after (spatial interpolation) earthquakes. We employ a novel masked training strategy that randomly masks seismic stations and waveforms, enabling the model to learn complex source characteristics, propagation paths, and site effects directly from observational data. By leveraging the Transformer's strong capability to learn complex data patterns and generalize through interpolation and extrapolation, QuakeFormer outperforms state-of-the-art methods across all three tasks while reducing epistemic uncertainty. Trained on over 4 million ground-motion records from California, the total residual in the estimation task is reduced by 20% and 10% compared with mainstream ergodic and non-ergodic models, respectively. When 50% of stations are made available, the between-event residual drops by half, and the model progressively refines its interpolation toward the observed field. When applied to early warning, the unified model

exhibits superior performance on magnitude prediction and regional intensity warning, highlighting the benefits of cross-task knowledge transfer.

We further extend the Transformer framework to physics-based simulation data by training on the CyberShake dataset, conditioned on complex finite-fault geometries. A key challenge is that, unlike simplified point sources, finite-fault ruptures are not easily parameterizable due to their varied segment geometries (strike, dip, rake) and the spatial dependencies between faults and sites. We overcome this by discretizing faults into segments characterized by specific locations, orientations, and other attributes, then encoding these segments into a fault sequence that is fused with a site sequence representing the locations of interest. The spatial encoding and attention mechanism within the Transformer naturally capture the dependencies between fault segments and sites. Results demonstrate that this model successfully reproduces directivity and basin effects, surpassing the point-source baseline. Moreover, by using only 50% of the available sites, it outperforms Kriging interpolation applied to 100% of the sites.

By distilling physical knowledge from both billions of simulated ground motions and millions of observational records, this unified framework demonstrates the potential of deep learning to serve as a non-ergodic ground motion model. It offers a scalable and generalizable tool for rapid post-event emergency response, long-term seismic hazard analysis, and earthquake hazard mitigation as seismic datasets continue to grow.

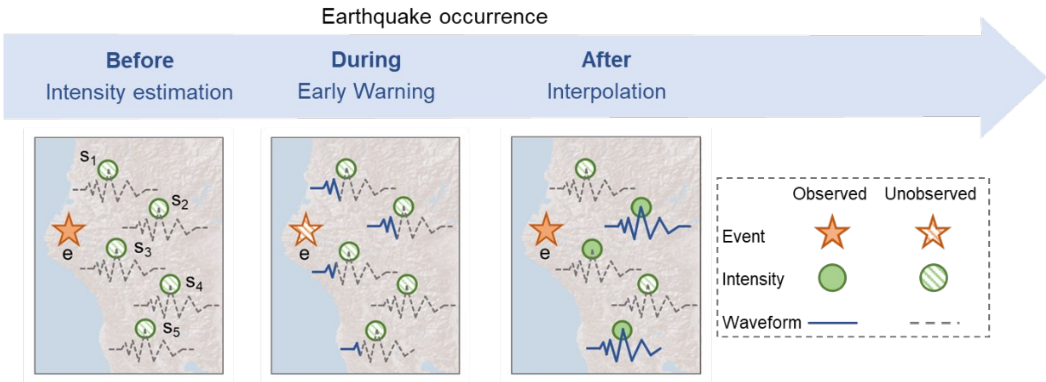

Fig 1: Ground motion intensity prediction before, during and after earthquakes