Insights into deep learning for earthquake magnitude and location estimation

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The estimation of earthquake source parameters, in particular magnitude and location, in real time is one of the key tasks for earthquake early warning and rapid response. In recent years, several publications introduced deep learning approaches for these fast assessment tasks. Deep learning is well suited for these tasks, as it can work directly on waveforms and can learn features and their relation from data.

A drawback of deep learning models is their lack of interpretability, i.e., it is usually unknown what reasoning the network uses. Due to this issue, it is also hard to estimate how the model will handle new data whose properties differ in some aspects from the training set, for example earthquakes in previously seismically quite regions. The discussions of previous studies usually focused on the average performance of models and did not consider this point in any detail.

Here we analyze a deep learning model for real time magnitude and location estimation through targeted experiments and a qualitative error analysis. We conduct our analysis on three large scale regional data sets from regions with diverse seismotectonic settings and network properties: Italy and Japan with dense networks (station spacing down to 10 km) of strong motion sensors, and North Chile with a sparser network (station spacing around 40 km) of broadband stations.

We obtained several key insights. First, the deep learning model does not seem to follow the classical approaches for magnitude and location estimation. For magnitude, one would classically expect the model to estimate attenuation, but the network rather seems to focus its attention on the spectral composition of the waveforms. For location, one would expect a triangulation approach, but our experiments instead show indications of a fingerprinting approach. Second, we can pinpoint the effect of training data size on model performance. For example, a four times larger training set reduces average errors for both magnitude and location prediction by more than half, and reduces the required time for real time assessment by a factor of four. Third, the model fails for events with few similar training examples. For magnitude, this means that the largest event is systematically underestimated. For location, events in regions with few events in the training set tend to get mislocated to regions with more training events. These characteristics can have severe consequences in downstream tasks like early warning and need to be taken into account for future model development and evaluation.