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Estimating Seismic Moment Tensors based on Bayesian Machine Learning

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Estimating fast earthquakes' source mechanism is essential for near real time hazard assessments, which are based on shakemaps and further downstream analysis such as physics based aftershock probability calculations. The model and data uncertainties associated to the estimated source mechanism are also crucial. We propose a Baysian Machine Learning algorithm trained on normalized synthetic waveforms for estimating the full moment tensor of earthquakes almost instantaneously with associated source parameter uncertainties.

A prior assumption is an appropriate location of the earthquakes along with its associated uncertainties. Here, this is obtained by already established Machine learning based algorithms, where the training data set is computed by forward calculations of synthetic waveforms based on Green's functions calculated for a specified 1-D velocity model using the Pyrocko software package. The learned labels, which are the information learned by the Machine Learning algorithm associated to the data, are the moment tensor components, described with only five unique parameters. For predefined locations in an area of interest we train a full independent Bayesian Convolutional Neural Network (BNN).

With variational inference the weights of the network are not scalar but represent a distribution of weights for the activation of neurons. Each evaluation of input data into our BNN yields therefore to a set of predictions with associated probabilities. This allows us to evaluate an ensemble of possible source mechanisms for each evaluation of input waveform data.

As a test set, we trained our models for an area south of the Coso geothermal field in California for a fixed set of broadband stations at maximum 150 km distance. We validate our approach with a subset of earthquakes from the Ridgecrest 2019-2020 sequence. For this data set we compare the results of the estimates of our Machine Learning based approach with independently determined focal mechanism and moment tensors. Overall, we benchmark our approach with data unseen during the training process of the Machine Learning models and show its capabilities for generating similar source mechanism estimations as independent studies within only a few seconds processing time per earthquake. We finally apply the method to seismic data of a research network monitoring the area around two south-german geothermal power plants. Our approach demonstrates the potential of Machine Learning for being implemented in operational frameworks for fast earthquake source mechanism estimation with associated uncertainties.