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Deep learning for laboratory earthquake prediction and autoregressive forecasting of fault zone stress

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Earthquakes forecasting and prediction have long, and in some cases sordid, histories but recent work has rekindled interest in this area based on advances in short-term early warning, hazard assessment for human induced seismicity and successful prediction of laboratory earthquakes.

In the lab, frictional stick-slip events provide an analog for the full seismic cycle and such experiments have played a central role in understanding the onset of failure and the dynamics of earthquake rupture. Lab earthquakes are also ideal targets for machine learning (ML) techniques because they can be produced in long sequences under a wide range of controlled conditions. Indeed, recent work shows that labquakes can be predicted from fault zone acoustic emissions (AE). Here, we generalize these results and explore additional ML and deep learning (DL) methods for labquake prediction. Key questions include whether improved ML/DL methods can outperform existing models, including prediction based on limited training, or if such methods can successfully forecast beyond a single seismic cycle for aperiodic failure. We describe significant improvements to existing methods of labquake prediction using simple AE statistics (variance) and DL models such as Long-Short Term Memory (LSTM) and Convolution Neural Network (CNN). We demonstrate: 1) that LSTMs and CNNs predict labquakes under a variety of conditions, including pre-seismic creep, aperiodic events and alternating slow and fast events and 2) that fault zone stress can be predicted with fidelity (accuracy in terms of $R2 > 0.92$), confirming that acoustic energy is a fingerprint of the fault zone stress. We predict also time to start of failure (TTsF) and time to the end of Failure (TTeF). Interestingly, TTeF is successfully predicted in all seismic cycles, while the TTsF prediction varies with the amount of fault creep before an event. We also report on a novel autoregressive forecasting method to predict future fault zone states, focusing on shear stress. This forecasting model is distinct from existing predictive models, which predict only the current state. We compare three modern approaches in sequence modeling framework: LSTM, Temporal Convolution Network (TCN) and Transformer Network (TF). Results are encouraging in forecasting the shear stress at long-term future horizons, autoregressively. Our ML/DL prediction models outperform the state of the art and our autoregressive model represents a novel forecasting framework that could enhance current methods of earthquake forecasting.