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Machine Learning Predicts Laboratory Earthquakes in a Meter-scale Rock-friction Experiment

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Machine learning (ML) has been used to study the predictability of laboratory earthquakes. However, the question remains whether or not this approach can be applied in a tectonic setting where one may have to rely on sparse earthquake catalogs, and where important timescales vary by orders of magnitude. We first applied ML to a synthetic seismicity catalog, generated by continuum models of a rate-and-state fault with frictional heterogeneities, containing foreshocks, mainshocks, and aftershocks that nucleate in a similar manner. We developed a network representation of the seismicity catalog to calculate the input features and found that the trained ML model can predict the time to mainshock with great accuracy, from the scale of decades to minutes. Based on the simulation results, we then applied our method to the data from a meter-scale rock-friction laboratory experiment. Remarkably, we found that the trained ML model can predict the time to failure with great accuracy, from the scale of tens of seconds down to milliseconds.

1. Introduction

Recent studies demonstrated that machine learning (ML) can predict laboratory fast and slow slip events, through instantaneous monitoring of continuous acoustic emissions (AEs). For example, Rouet-Leduc et al. (2017) showed that the statistical features of AEs, notably the evolution of their variance, provide predictability of the time to failure in the double direct-shear experiment. While the study has provided new insights into the slip phenomenon on a fault plane, there are at least two major questions to apply the ML-based approach to forecast real earthquakes, as mentioned in the abstract. To partially address these issues, we first use a 2D fully-dynamic earthquake-cycle simulation with regular frictional heterogeneity on the 1D fault (Ito & Kaneko, 2023) and develop the catalog-based ML approach to predict multi-scale mainshock cycles. Based on the simulation work, in this study, we apply our developed method to the catalog of a meter-scale rock-friction experiment (Yamashita et al., 2021) and test whether or how it works.

2. Materials & Method

We use a catalog and shear stress data in a meter-scale rock-friction experiment (Yamashita et al., 2021). Figure 1 shows the schematic of the experimental facilities (Figure from Yamashita et al., 2021). We developed a new approach, "network representation" (Figure 2), to quantify the earthquake pattern by using only catalog information (hypocenter, magnitude, and event origin time). We define a network as a group of specific numbers of consecutive earthquakes and abstract the catalog information by computing statistics of catalogs within each network. ML is trained using the abstracted catalog information with the time remaining before the next laboratory failure. Thus, the trained ML model attempts to predict future information, the time to failure, by monitoring the current and past earthquake patterns. In addition to predicting the time to failure, we also attempt to predict the shear stress data by monitoring the foreshock activity, as tested in previous works (e.g., Rouet-Leduc et al., 2018; Shreedharan et al., 2021).

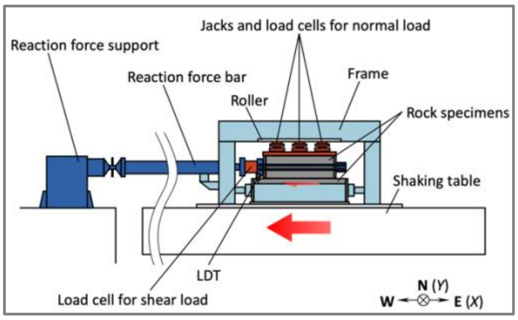

Figure 1: A schematic illustration of the experimental facility used in Yamashita et al., 2021.

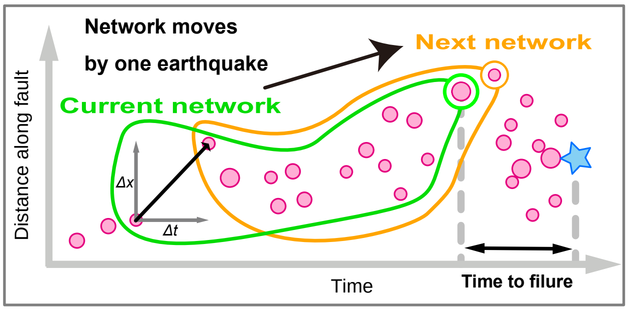

Figure 2: A schematic illustration of network representation. Earthquake groups enclosed by green and orange lines correspond to the current and next network. The catalog information is abstracted in each network and connected with the time to failure.

3. Result & Discussion

Figure 3 shows that the trained ML model can accurately predict both the time remaining before the next laboratory failure (future information) and shear stress (current fault physical state).

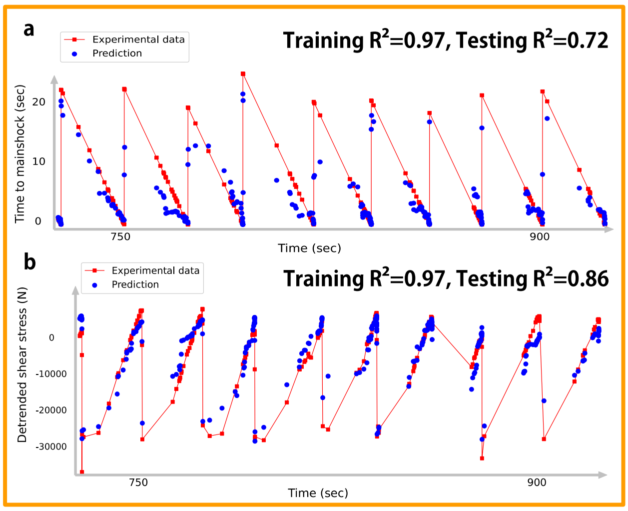

Figure 3: Prediction of time to failure (a) and detrended shear stress (b) by the trained ML model. We evaluate the performance by the coefficient of determination R^2.

Based on the output of the trained ML model, the increase in seismic moment (or magnitude) and the decrease in recurrence interval of events averaged over certain networks provide the predictability of laboratory earthquakes and shear stress. These features will correspond to the decrease in the b-value or the acceleration of the event rate before the laboratory failure, as observed in Yamashita et al., 2021. Our approach to quantifying the earthquake pattern can capture the precursory foreshock activity, and this is the reason why ML can predict laboratory earthquakes and shear stress in this study. Ongoing work is traying to speculate the physical mechanism of predictability by combining the simulation and experimental results.

4. Conclusions

We showed that the trained machine-learning model by monitoring the foreshock activity can accurately predict the time to mainshock and shear stress in a meter-scale rock-friction laboratory experiment. The increase in seismic moment and the decrease in event recurrence averaged over certain networks have the predictive power of time to failure and shear stress. Our result will offer clues as to why machine learning can predict laboratory earthquakes.

References

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