Laboratory earthquake prediction using supervised machine learning applied on controlled-source ultrasonic amplitudes and velocities

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1. Background
In previous works, we implement ∼100 statistical features of the acoustic signal into a gradient boosted tree algorithm to predict the instantaneous shear stress. Despite this success, we still lack a fundamental understanding of how/why the ML predictions work.

2. Key Questions

A. Can features of transmitted elastic waves serve as a proxy to the instantaneous shear stress?
B. By using active source ultrasonic, can we derive a physical explanation behind the ML predictions?

3. Methods

Fig. 1. A. Red curve shows measured shear stress as a function experimental run time. Middle plot depicts measured shear stress in red with ML predictions in blue for testing data with $R^2 = .80$. Bottom subplot shows acoustic variance (power) as a function of time. B. Acoustic power as a function of shear stress. Symbols are color coded corresponding to the time to failure and red curves represent average values. Black line represents linear fit between acoustic power and shear stress (After Hulbert et al. 2019).

Fig. 2. A schematic of the biaxial testing apparatus and Western granite blocks used in this study. The setup is instrumented with a load cell and direct current differential transformer (DCDT) transducer in the vertical (shear) and horizontal (normal) stress directions. P-wave polarized piezoelectric transducers on either side of the double-direct shear setup transmit and receive a 500 kHz pulse. A blow-up of a typical wave recorded by the receiver shows the p-wave arrival at ~33 μs. P-wave amplitude is calculated as a peak-to-peak amplitude of the red portion of the waveform. Timeshift is the change in travel time of the first wavelet. A positive timeshift represents reduced velocity and negative timeshift represents increased velocity relative to an initial master waveform.

4. Relationship between seismic properties and preseismic slip

Fig. 3. Seismic amplitudes decrease during the preseismic stage as slip rate on the fault increases for (A) fast elastodynamic earthquakes and (C) slow earthquakes. The scaling between amplitudes and slip rate is log-linear for (B) fast earthquakes and (D) slow slip events with similar slopes of -1.0 unit reduction in amplitude per decade increase in slip rate. The amplitude continuously decreases as the fault approaches failure. Notice that the maximum velocity and amplitude minima coincide.

Fig. 4. Seismic timeshifts (as proxy for velocities) first decrease until the fault is close to failure and subsequently increase rapidly for (A) fast earthquakes and (B) slow earthquakes. In velocity space, this translates to an increase in seismic velocities until the fault is close to failure, with a subsequent reduction just prior to failure. As the fault begins to slip seismically, the timeshift maximum (or velocity minimum) correlates well with the minimum shear stress. The temporal timeshift trends do not systematically track the slip rate on the fault as well as the amplitudes do (see Fig. 3).

5. Machine learning predicts laboratory earthquakes

Fig. 5. ML prediction based on dataset trained using seismic amplitudes as the sole feature. The model performs well with $R^2 = 0.8$. The model fits the stress minima well and slightly underpredicts the peaks.

Fig. 6. ML prediction based on dataset trained using changes in seismic travel-times as the sole feature. The model performs well with $R^2 = 0.8$. The model fits the stress minima well and slightly underpredicts the peaks.

6. Conclusions

• We train a ML model to predict the shear stress state of faults for slow and fast laboratory earthquakes with good accuracy and an $R^2 = 0.8$.
• The training is based on features tracking the fault slip rate and stressing rate, which are well founded in the physics of fault friction.
• The model predicts the stress minima well while underpredicting the maxima.

References