DeepTremor: Californian Earthquake Projection with Deep Generative Spatiotemporal RNNs

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CS 236

Overview

California's Earthquake Early Warning (EEW) system utilizes a sparse network of seismic monitoring stations to detect and forecast the severity of earthquakes that occur across the state. However, current methods for predicting the spatiotemporal effects of an earthquake are slow, tend to propagate errors in initial measurements, and are generally inaccurate.

In this project, a collaboration with the Ellsworth Lab, we explore the use of recurrent networks to achieve fast spatiotemporal inference times and accurate forecasting of an earthquake's progression.

Dataset

- 35,680 earthquakes across 15 stations in the California Integrated (CI) Seismic Network.
- Events from the Jun - Sept 2019 earthquake swarm in the Ridgecrest region of Southern California.
- Raw data is composed of accelerometer readings at 100Hz.
- Subsample data and smooth by calculating average magnitude of acceleration at each second. One earthquake is 60s.

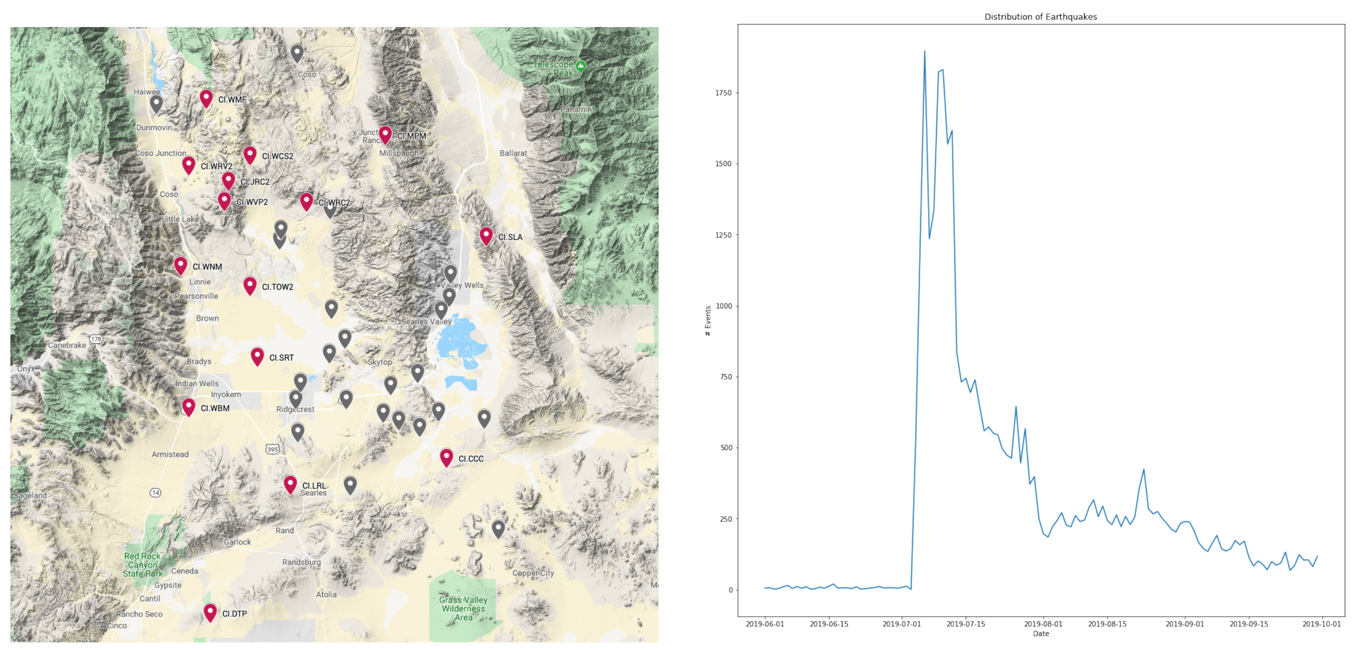

Figure 1: Left: Map of stations in the Ridgecrest area. Project focuses on red stations. Right: Distribution of earthquakes from June 1 - Sept 30, 2019.

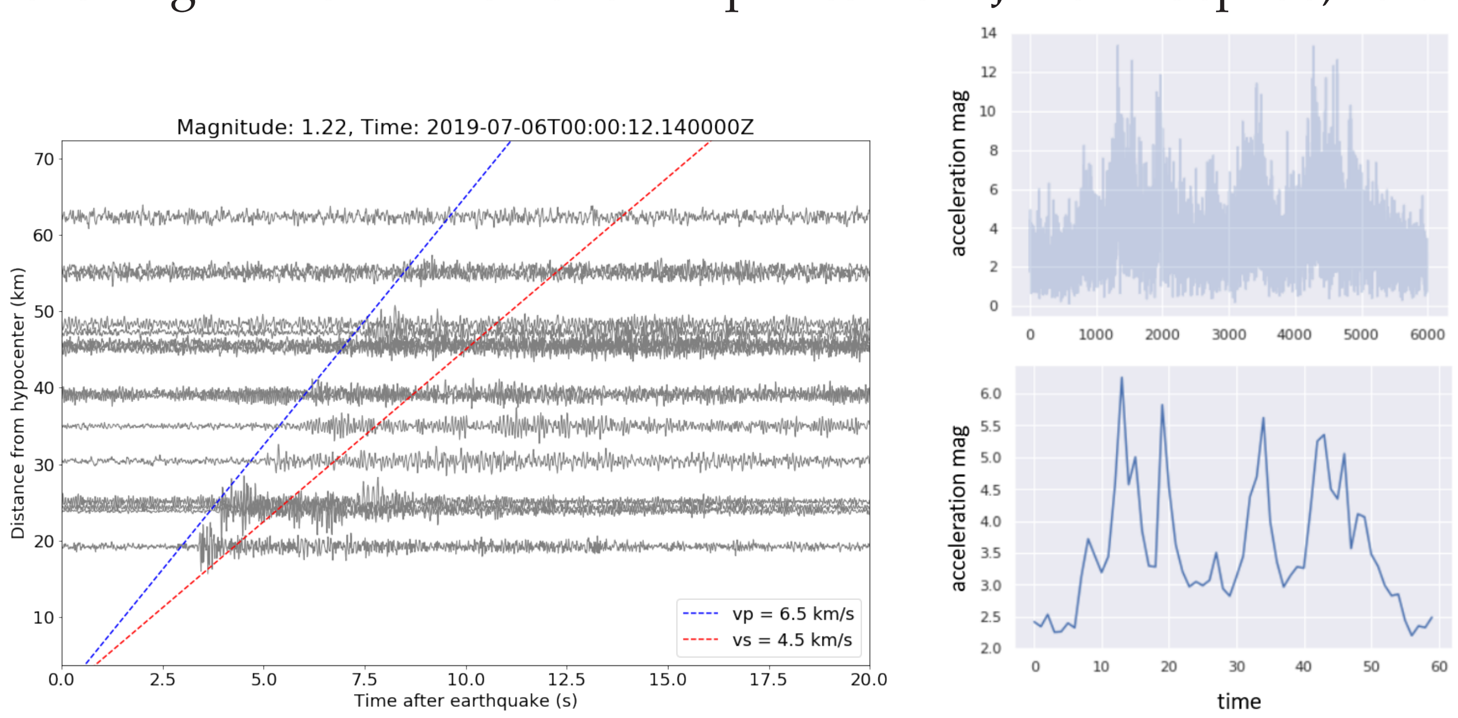

Figure 2: Left: Example of an earthquake propagating over time. Right: Subsampling of earthquake accelerometer data.

Methods

Model Inputs: Earthquake broken down into t-second sliding windows of mag data from 15 stations.
Model Outputs: The ith t-second window is used to predict the magnitude of acceleration for the $i+t+k$th timestep (note: for these results we used $k = 1$).
Data Normalization: Correct for large variance in earthquake readings by normalizing magnitudes.
Class Balancing: Correct for imbalance between small and large earthquakes by upsampling large earthquakes.
Model Architecture: Three-layer LSTM (depicted below)
Loss Function: Mean Absolute Error: $\frac{1}{n}\sum_{i=0}^{n}|\hat{y}-y|$

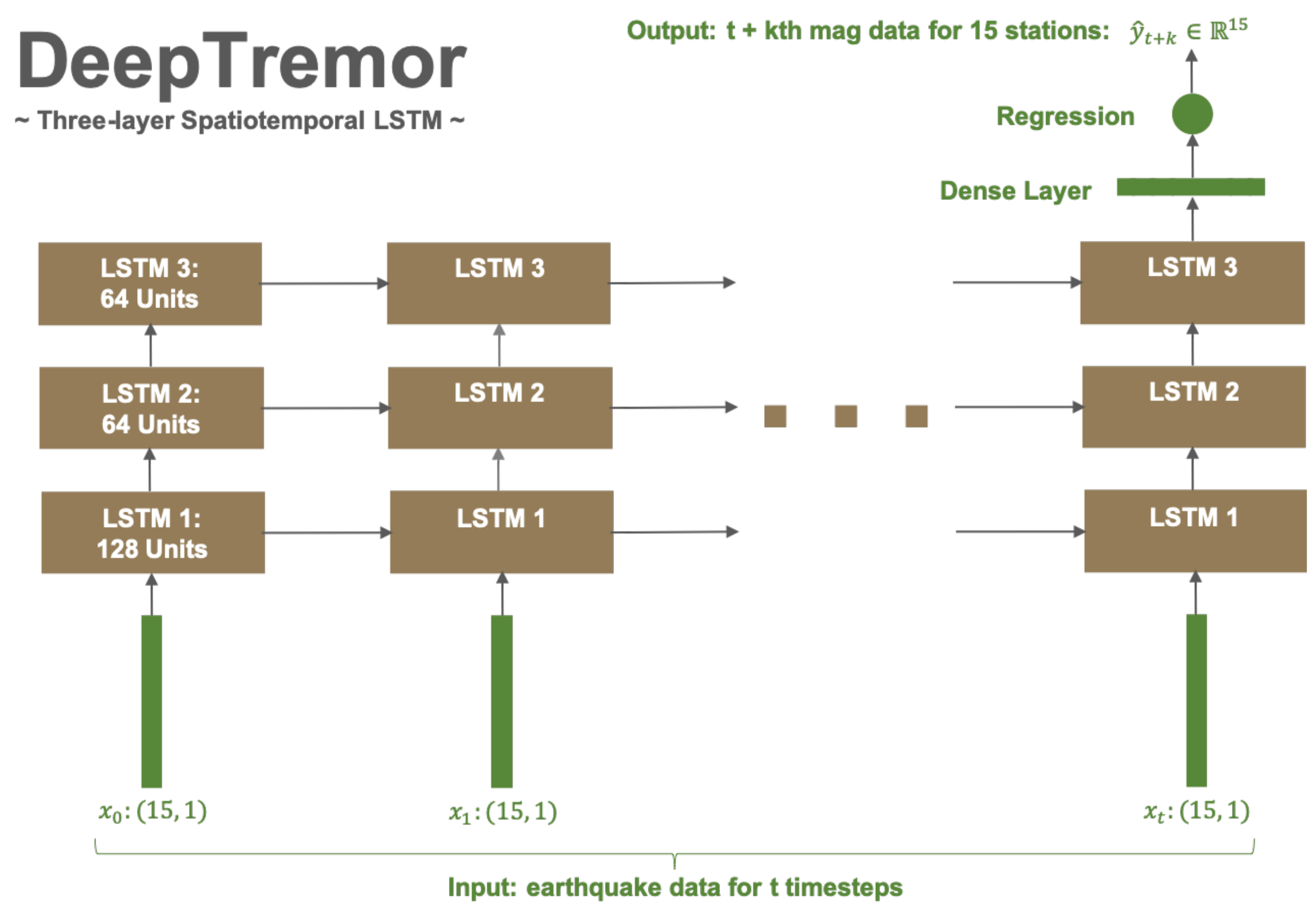

Figure 3: DeepTremor three-layer spatiotemporal LSTM architecture

Analysis

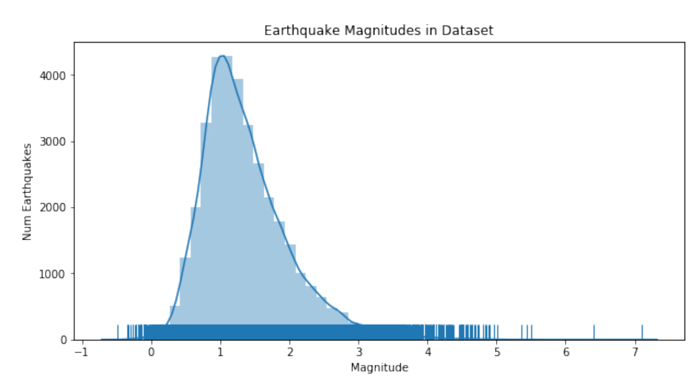

Figure 4: Our dataset contains significant imbalance of magnitudes.

Log-Magitude (Richter)	MAE	% MAE
$m \leq 1$	2.53	4.38
$1 < m \leq 3$	6.08	2.86
$3 < m \leq 5$	140.43	2.73
$5 < m$	5723.29	2.28

Table 1: MAE values for different classes of earthquakes, **Overall: 3.7%**

Results

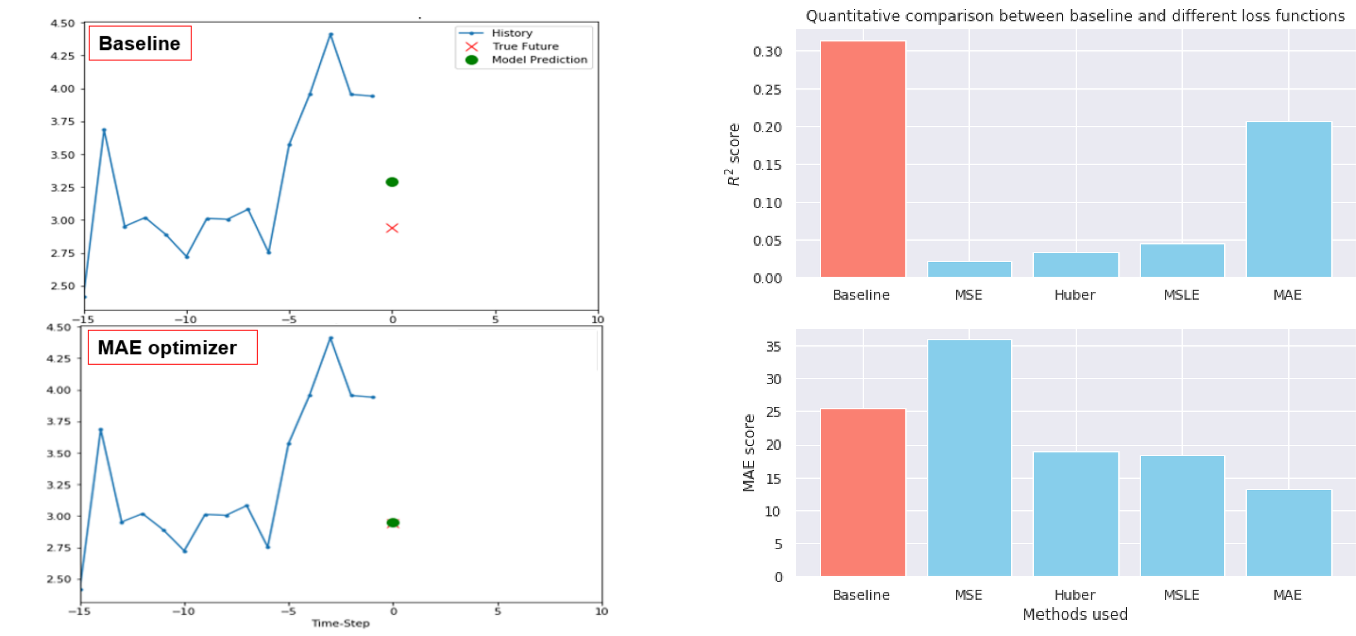

Figure 5: Left: Comparison of baseline vs MAE optimizer prediction on one future timestep. Right: Comparison of error rates of different loss functions.

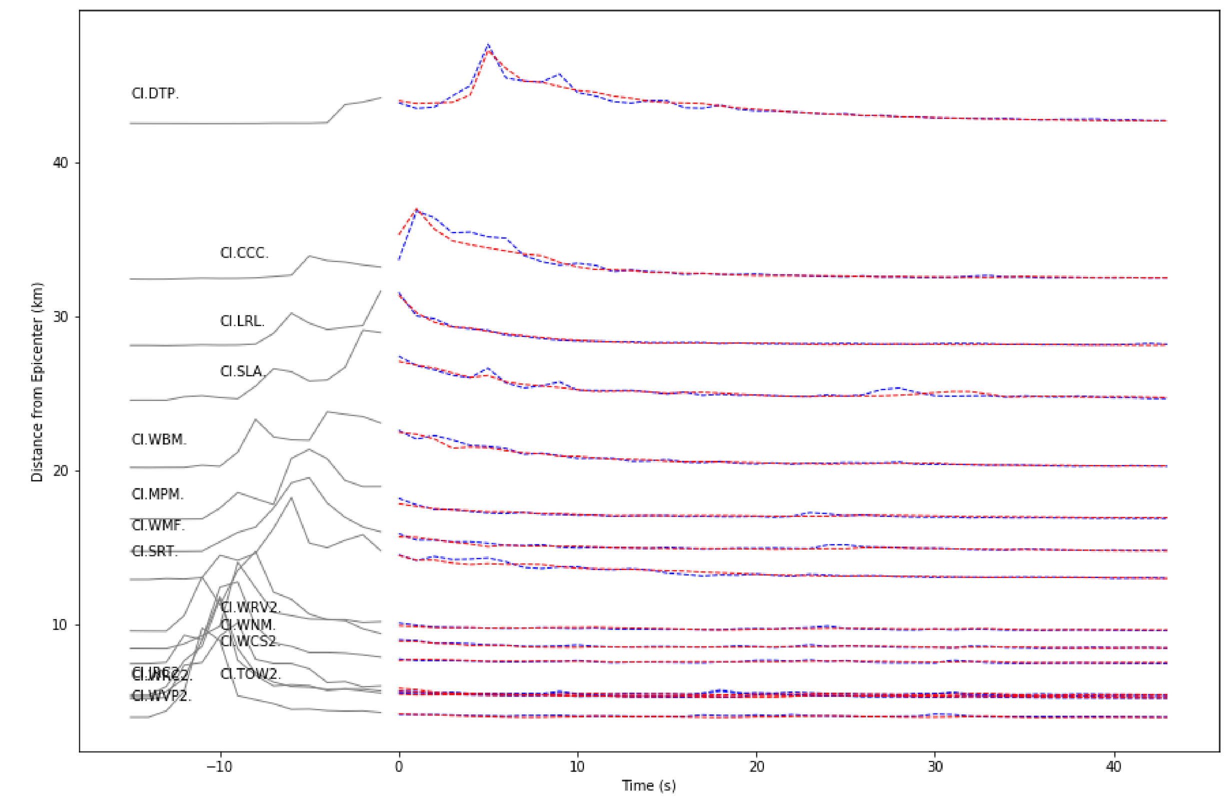

Figure 6: Example of a model prediction. Solid gray = earthquake history, dotted blue = actual, dotted red = predicted

Conclusion & Future Work

Conclusions:

- Deep spatiotemporal RNNs achieve reasonable accuracy with negligible latency
- RNNs offer a viable alternative to numerical projection methods.

Future Work:

- Project forward multiple time steps
- Deep spatial interpolation to approximate numerical methods
- Locale-agnostic earthquake projection

Acknowledgements

We would like to acknowledge **Professor William Ellsworth** from Stanford Earth for inspiring this project, and **Weiqiang Zhu**, Stanford Earth PhD candidate, whose help was essential in every stage.