Detecting Eruptions of Steamboat Geyser with Convolutional Neural Networks

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Introduction
Steamboat Geyser, located in Norris Geyser Basin, Yellowstone National Park, WY, was dormant for several years prior to 15 March 2018. Now the active geyser with the tallest eruptions in the world, it erupted 32 times in 2018, as many times as in the preceding 35 years. In response to this unexpected active period, I designed and implemented the Steamboat Geyser Eruption Alert System (SGEAS), a text message alert system that derives its predictive skill from an ensemble of convolutional neural networks that detect eruption signatures in real-time seismograph traces.

Instrumentation
• Nanometrics Trillium 240 seismograph
• Three-channel (east-north-up)
• 100 Hz sampling rate
• Data are available online in real-time
• Within walking distance of Steamboat Geyser

Seismic data representations
• Seismic trace: time series of instrument displacement
• HHE, HHN, and HHZ traces record displacement along the east-west, north-south, and vertical axes, respectively
• Short-time Fourier transform (STFT): shows how the frequency content of a seismic trace changes over time

Classical detection methods don’t work
• z-detection, the short-term average / long-term average (STA/LTA) method and its variants, ...
• Not suitable for detecting eruptions because of high sensitivity to man-made noise such as visitor footsteps (Trnkoczy 1998)
• Compare: an eruption trace (the 27 May traces above) and an ambient noise trace (the 07 October traces above)
• Seismic noise due to visitors is frequently larger in amplitude than eruption signatures, as shown in the above traces

Convolutional neural network (CNN) method
• Used a CNN to transform an HHZ STFT into an activity indicator and alert the system operator if that indicator exceeds a fixed threshold
• CNNs are mathematical models that use successive convolutions and non-linear function applications to approximate functions
• CNNs have many trainable numerical parameters, allowing them to represent a large class of functions (think many-parameter regression)
• Training data consist of three years of seismic data broken into 20-minute STFTs labeled 1 (0) if an eruption signature is present (absent)

Implementation
• Chose a residual CNN architecture (pictured below)
• Used ensembling (bootstrap aggregation) for variance reduction
• Implemented all subprograms with Python
• Acquired and processed seismic data with ObsPy
• Computed STFTs with SciPy
• Implemented CNNs with Keras
• Used the Twilio SMS API to send text message alerts

Real-world performance
• Has been online during 15 eruptions
• Detected 14 (93%) of those eruptions
• Produced zero false positives
• Has low latency (typically less than three minutes)
• Conclusion: SGEAS works well in practice and its low latency can help in-person observers arrive quickly enough to take notes

References
• Steamboat Geyser photo credit: US National Park Service.
• IRIS DMC Web Services. https://service.iris.edu/.
• Chollet, et al. Keras. https://keras.io/.

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