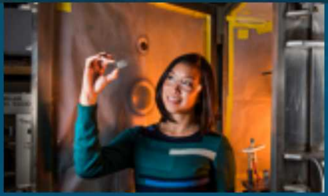
Sandia National Laboratories

SAND2018-13608C

Infrasound Event Classification: A Comparison of Machine Learning Approaches



PRESENTED BY

Sarah Albert and Lisa Linville

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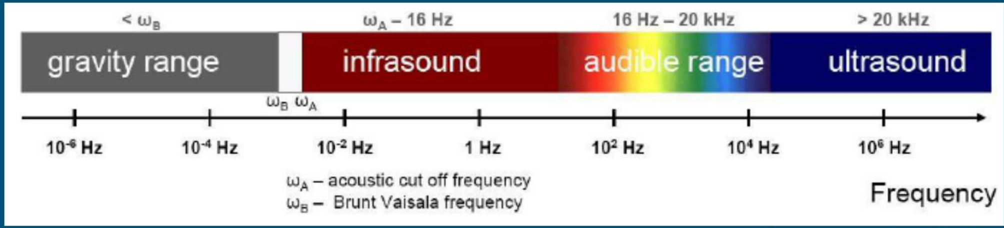
SAND2018-XXXX

Outline

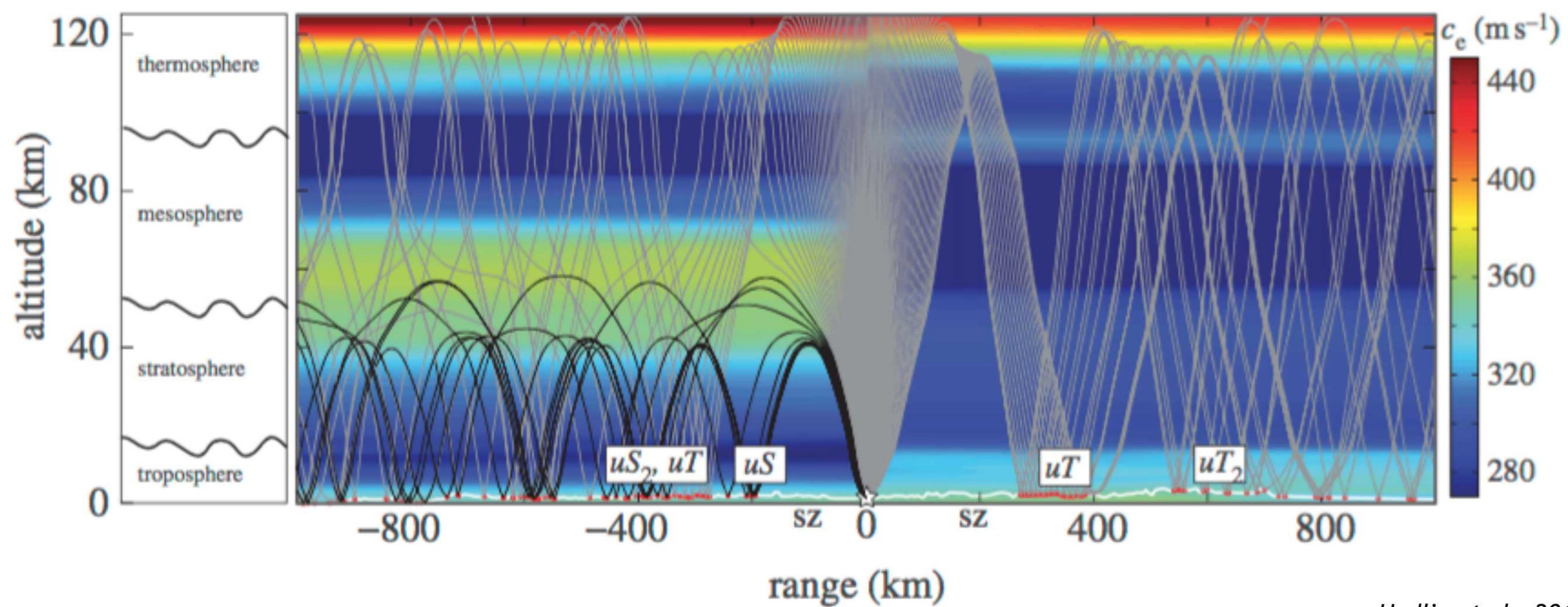
What is Infrasound?

Low-frequency sound (0.01 – 20 Hz)

Can travel thousands of kilometers

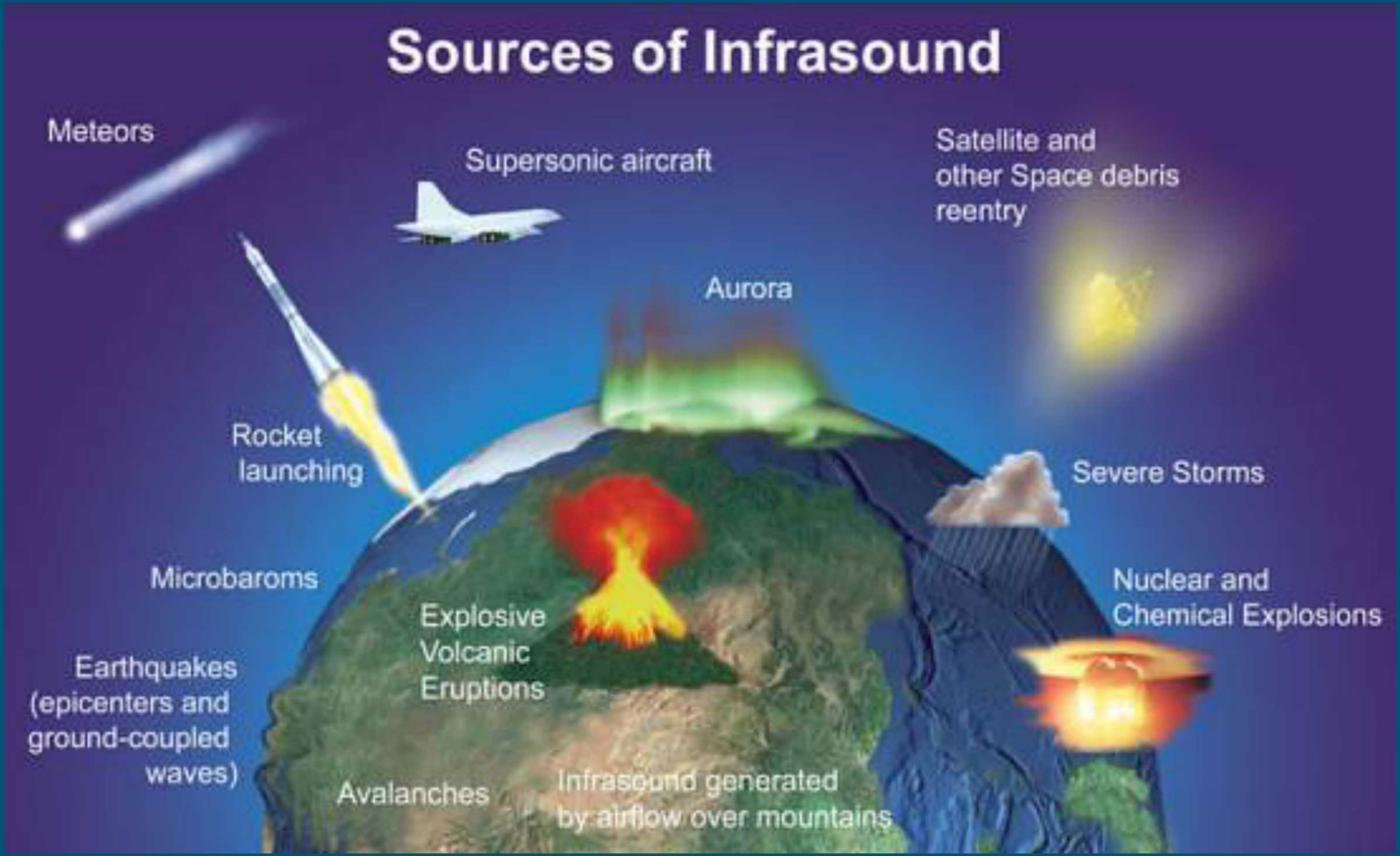


Bittner et al., 2010



Hedlin et al., 2010

What is Infrasound?



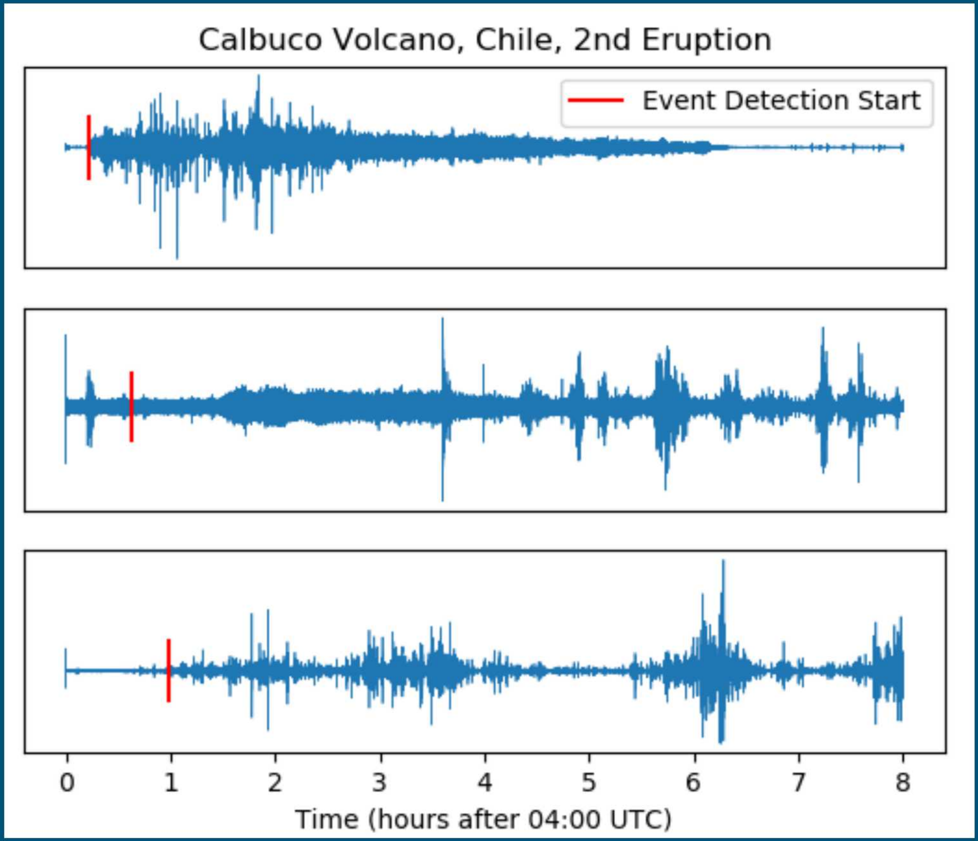
https://neuroresearchproject.com/2013/02/19/1289/

The Infrasound Categorization Problem

Nearly impossible to categorize events by eye

Infrasound propagates through a dynamic atmosphere
- Signals from the same event can look very different
- Distance from source to sensor
- Frequency content
- Atmospheric conditions

Analysts require ground truth
- Seismic, satellite, etc.



Why Machine Learning and Deep Learning?

Previous attempts in graduate school used cross correlation:

- Only ~30% accuracy
- Limited to one location – Sakurajima Volcano

Other studies using ML on infrasound data have shown promising results:

Author(s)	# Events (Train/ Test)	Classifications	Station Layout	Avg. Source to Sensor Distance	Method	Accuracy
Ham and Park, 2002	246/210	Event type: volcano, mountain waves, impulsive, "no event"	Single station	Some $\geq$ 250 km, others unknown	NN	100%
Cannata et al., 2011	665/610	Volcano vent location	Network	$\leq$ 5 km	SVM	88%
Thuring et al., 2015	29/30	Avalanche detection	Single station	$\leq$ 5 km	SVM	57%
Li et al., 2016	88/15	Event type: eathquake, volcano, tsunami	Single station	unknown	SVM	86%

A Global, Labeled, Infrasound Event Catalog

Labeled infrasound event catalog

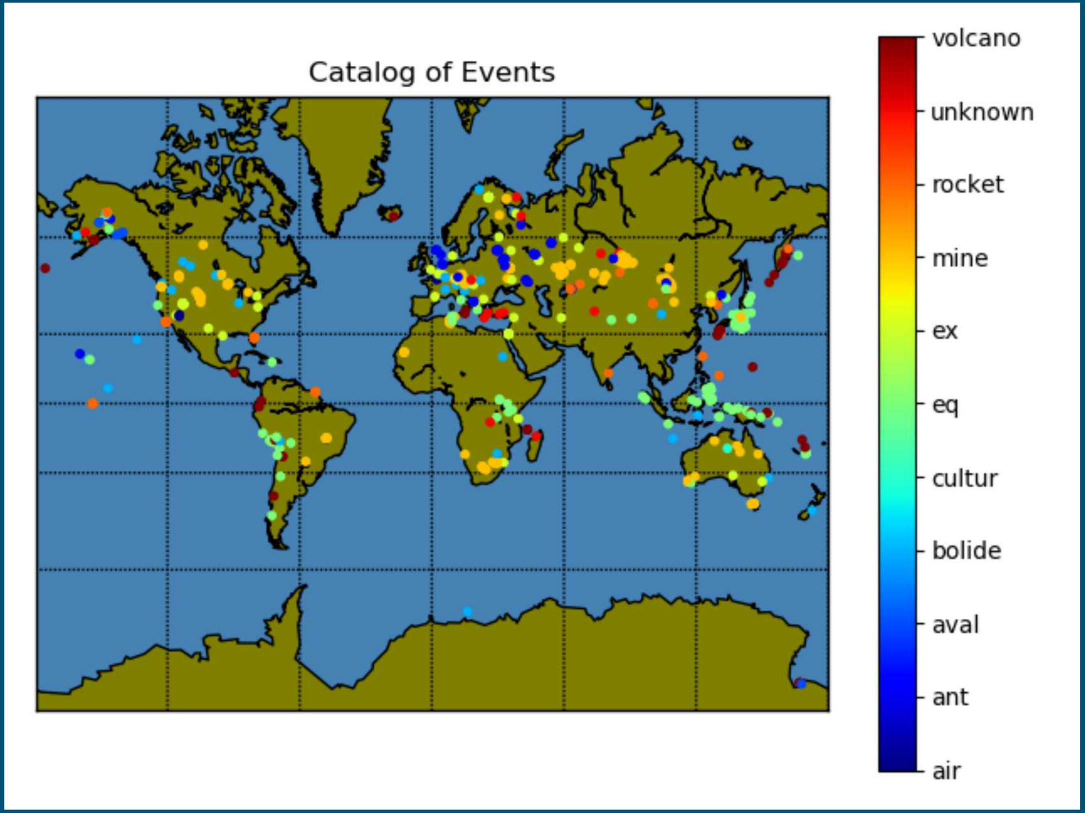
- IMS catalog with local, regional, and global events

717 events

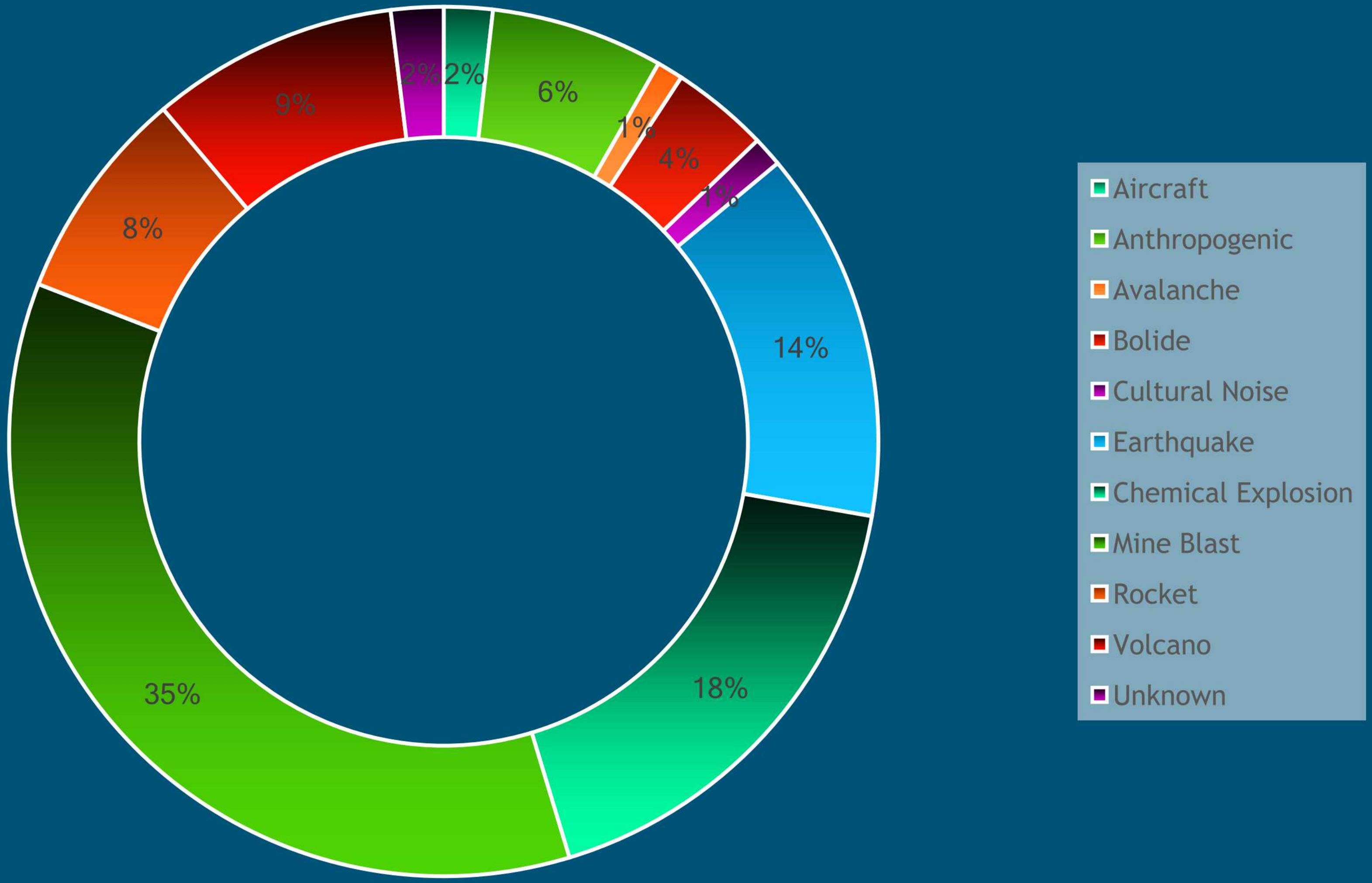
- Recorded at multiple stations
- Each station consists of at least 3 sensors
- Some events have multiple subevents

Variety of events

- Suffers from class imbalance
- Complex/diverse labels in some of the classes

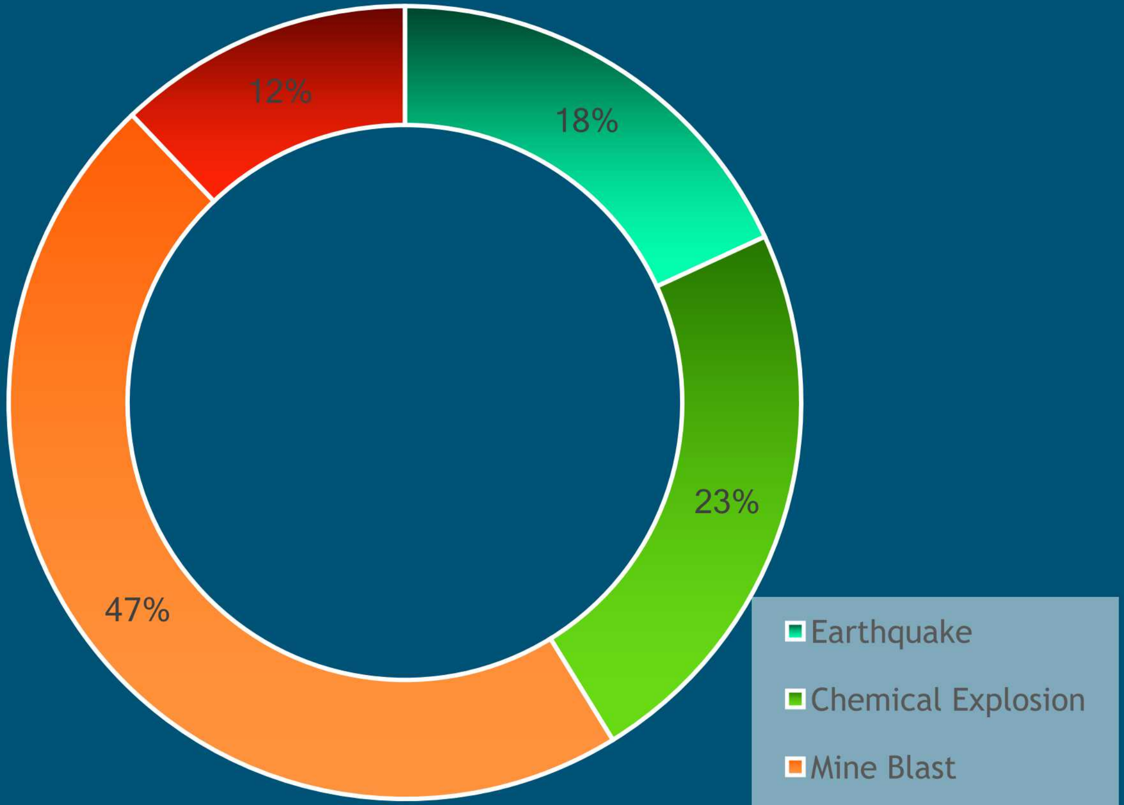


Event Class Imbalance



Focus on Four Most Abundant Classes

1. Earthquakes
2. Chemical explosions
3. Mining explosions
4. Volcanic eruptions



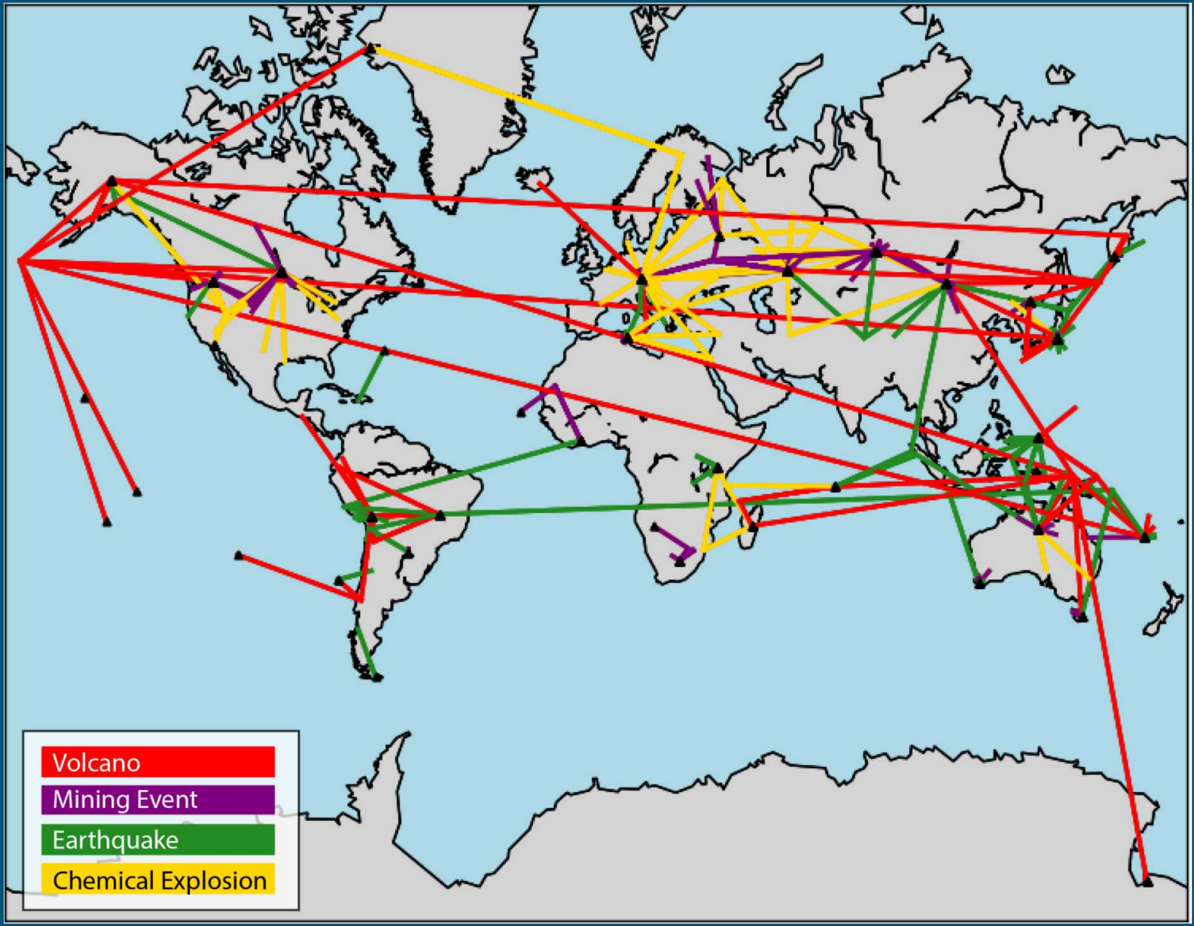
Focus on Four Most Abundant Classes

Most common event types for the IMS

Of interest for monitoring purposes

New catalog:
- 519 events
- More balanced, lacking volcanic eruptions

Most events detected at global distance (≥ 250 km)



Two Approaches to a Solution

Method 1: SVM

2 feature extraction methods:
Spectral Entropy (Li et al., 2016)

- Wavelet Singular Spectrum Entropy
- Wavelet Power Spectrum Entropy
- Wavelet Energy Spectrum Entropy

Physical Features

- Amplitude (mean, max, rms, std)
- Energy
- Duration
- Fundamental frequency
- Number of zero crossings
- Spectral analysis (spread, centroid)
- Skewness around fundamental frequency
- Source to sensor distance
- SNR

Method 2: CNN

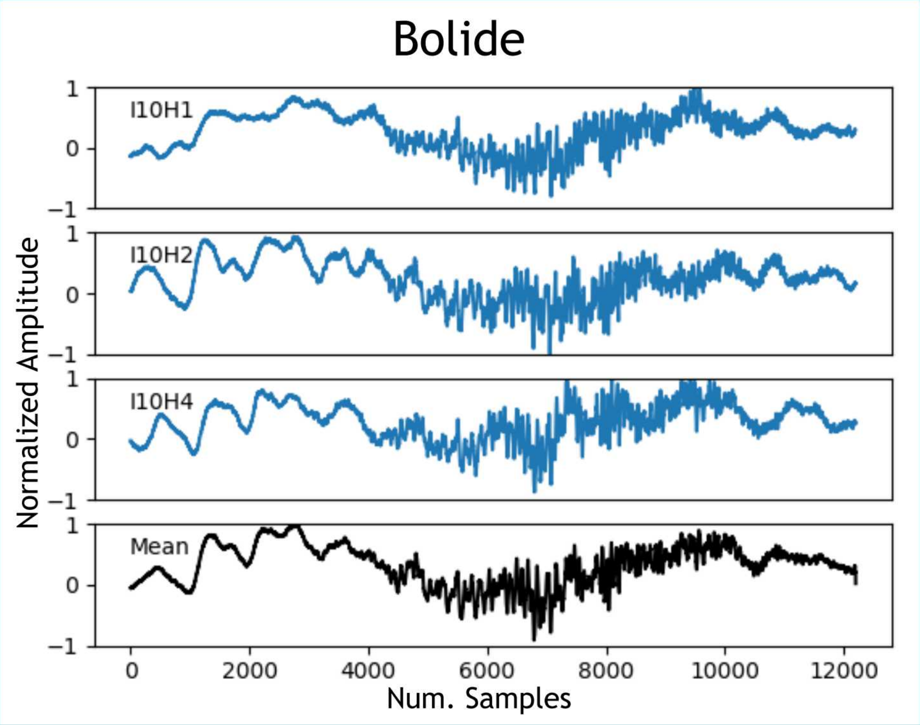
- Demonstrated success on a variety of analogous tasks
- Testing in seismic domain indicates that performs nearly as well as RNN (LSTM) for sequences of similar length, but is more compact
- Higher capacity to model the data
  - Limited training data in this study

SVM Dataset

615 stations recorded 519 events

Signal duration encompasses all phases
- Detrended
- Data was time-shifted and averaged for each station

4-fold cross validation
- Initially randomly chose 25% of each class for each partition (4 fixed partitions)
- 64 mining events
- 38 chemical explosions
- 26 volcanic eruptions
- 25 earthquakes

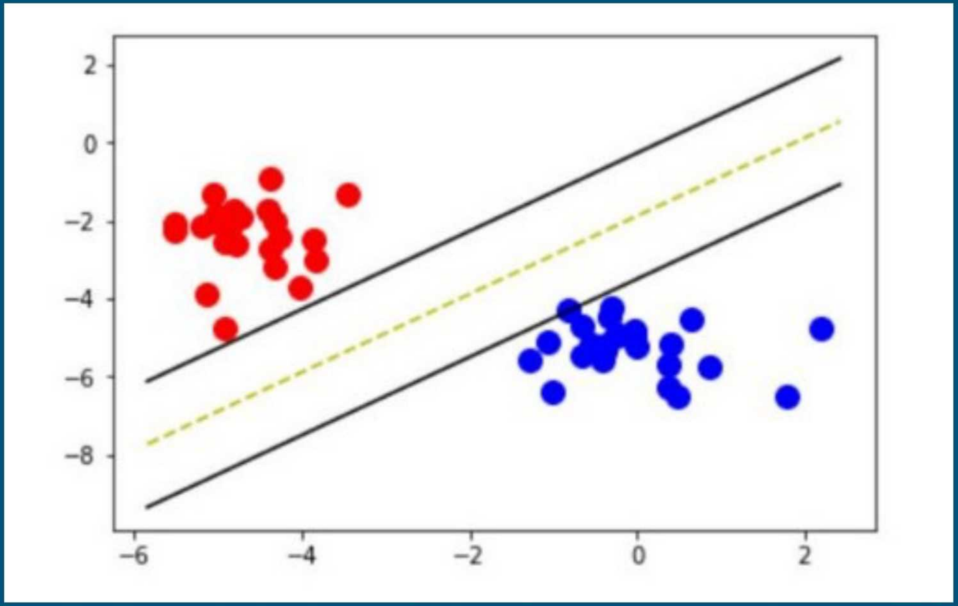


What is a Support Vector Machine (SVM)?

Supervised machine learning
- Requires labeled data, cannot cluster data on its own

Commonly used for classification and regression analysis

Model aims to identify a set of hyperplanes that maximize the distance between the nearest data points in each category
- Can be linear or nonlinear (requires a kernel trick)



https://medium.com/machine-learning-101/chapter-2-svm-support-vector-machine-theory-f0812effc72

SVM Results – Spectral Entropy

50-60% accuracy

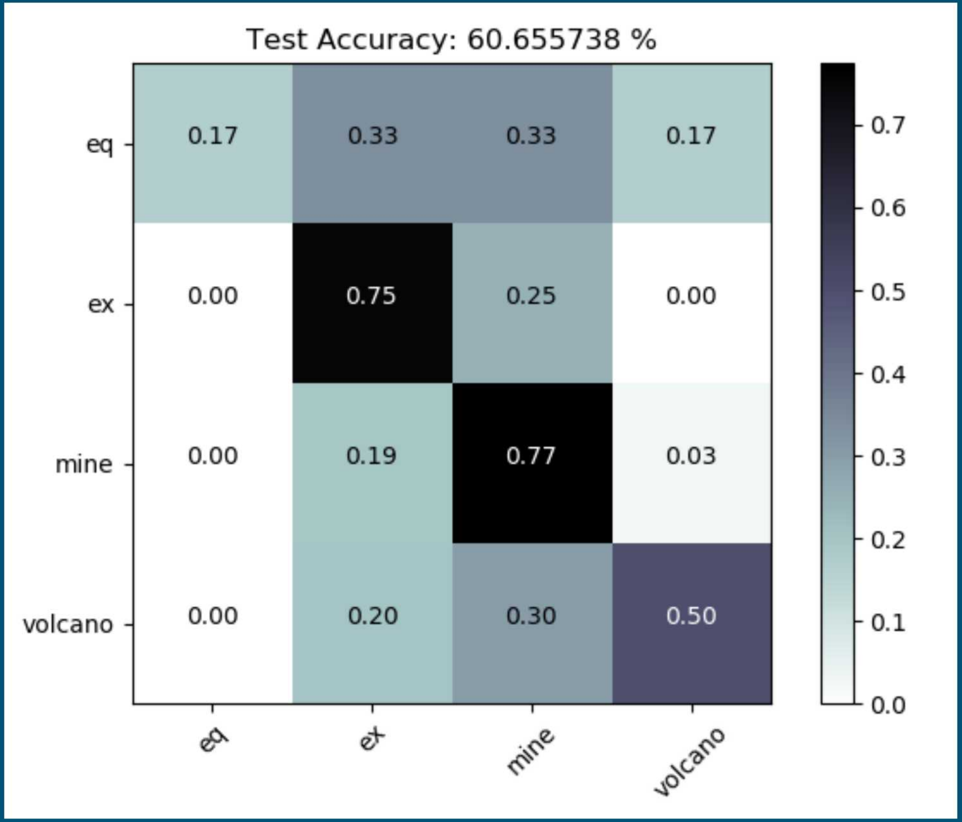
Many false classifications as mining events

- Predicts mining events correctly 77% of the time
- Often predicts other classes as mining events

Very bad at categorizing earthquakes

- Often categorized as explosions or mining events

Request for more "physical" features that have been used with seismic

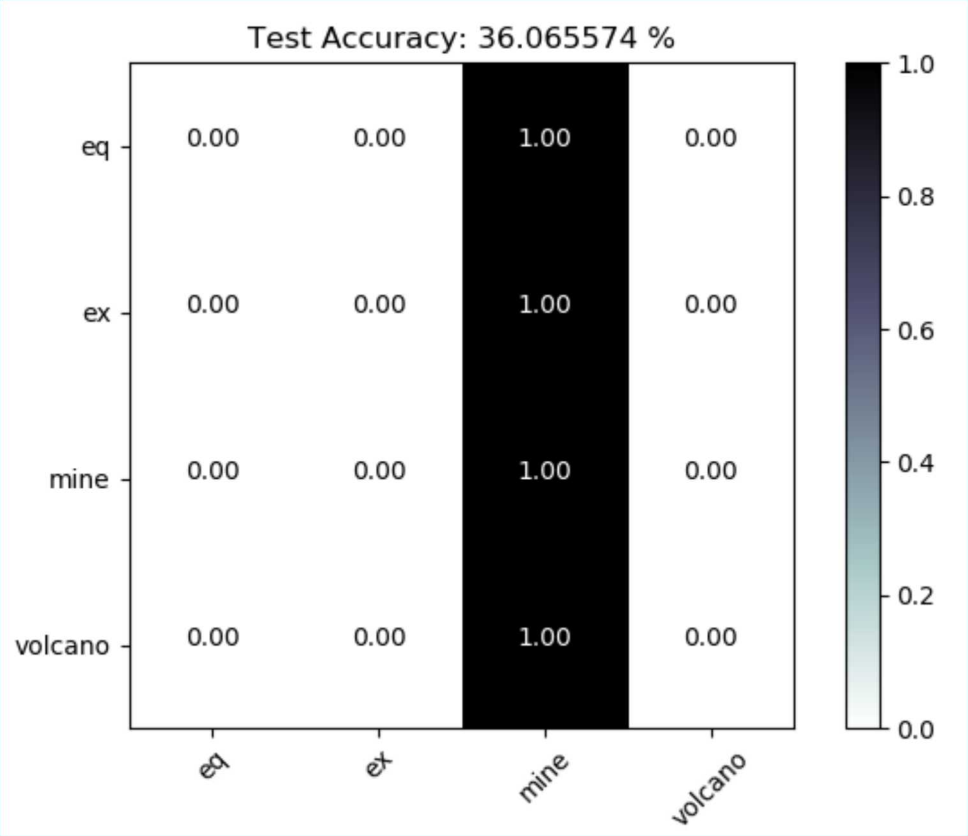


SVM Results – “Physical” Features

30-40% accuracy

Everything categorized as a mining event

These features do not describe the waveforms



CNN Dataset

615 stations recorded 519 events
- Only top 4 classes

Fixed signal duration to 475 sec (2 std median signal length)
- Detrended
- Tapered (1%)
- Normalized spectrogram computed for CNN
  - Temporal resolution: 1 time bin = 60 seconds
- Data was time-shifted and averaged for each station

4-fold cross validation
- Initially randomly chose 25% of each class for each partition (4 fixed partitions)
- 64 mining events
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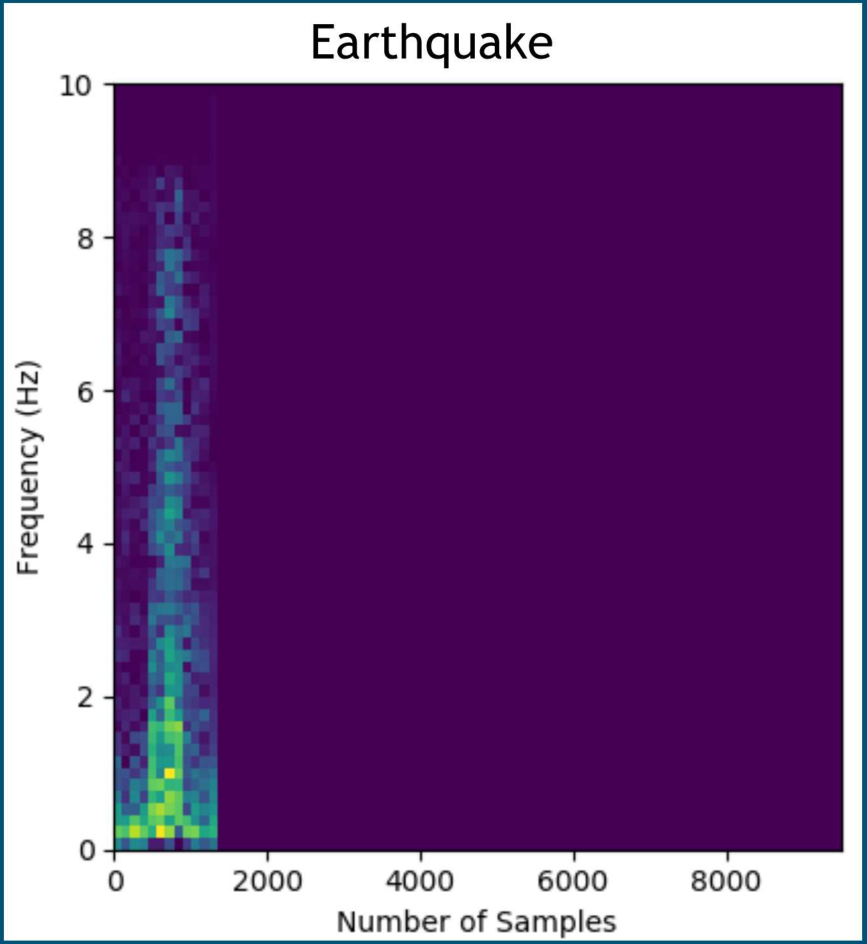


What is a Convolutional Neural Network (CNN)?

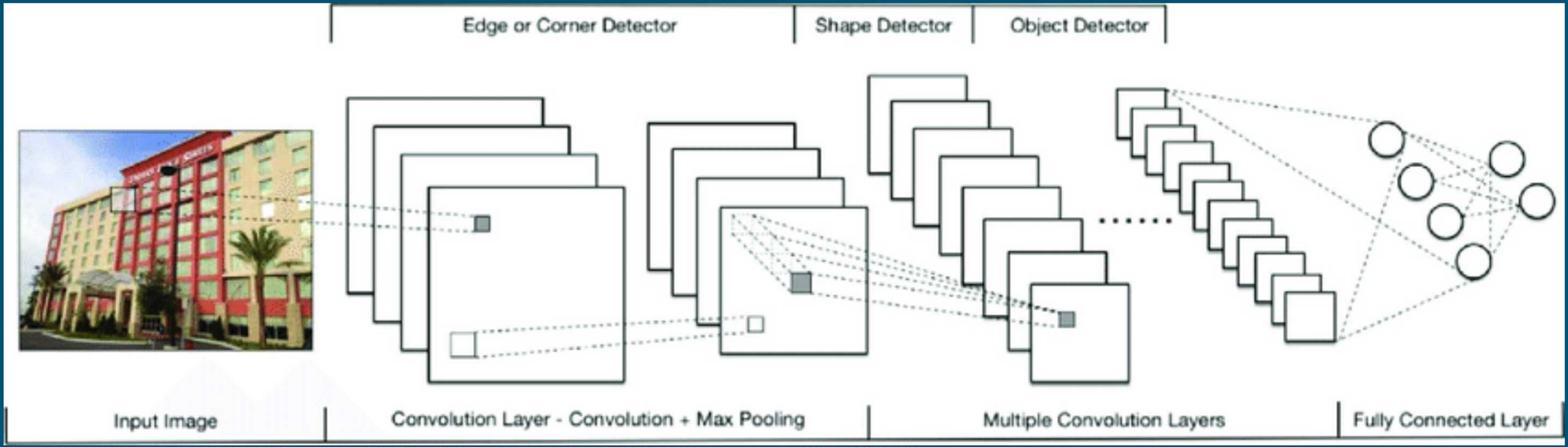
Deep, feed-forward artificial neural network

Proven highly competent at solving complex big data problems, especially in image domains.

Typically requires large amounts of data

Hidden layers, known as convolutional layers

- Receives input, transforms that input, and then passes it on to the next layer
- Filters applied to each layer (edge detector, shape detector, etc.), which help identify patterns



https://www.researchgate.net/Illustration-of-Convolutional-Neural-Network-CNN-Architecture_fig3_322477802

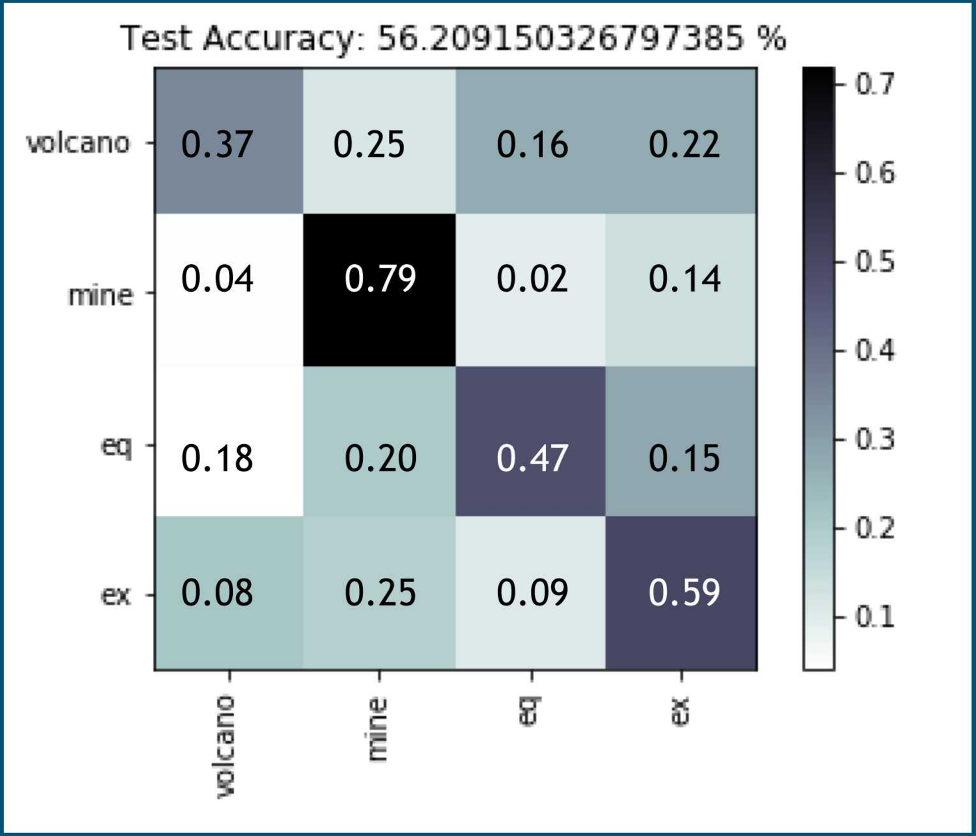
CNN Results

Current best model:

- CNN
- Best performance 60-70%:
- Not as good at classifying earthquakes

Binary tests show that the method outperforms multiclass model pairs except for with earthquakes and explosions

- No clear way to leverage binary models for multiclass classification



Conclusions

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This study	462/153	Event type: earthquake, volcano, chemical explosion, mining event	Single station and 2+ stations	≤ 15 km 15 - 250 km ≥ 250 km	SVM, CNN	50-60%

Conclusions

Highest accuracies 60-70%

- SVM seems to outperform CNN

CNN and SVM both struggle with earthquake and explosion categories

- Need to understand what is different between the two classes in order to get better accuracies

Physical features taken from seismology do not transfer over to infrasound

- Constantly changing atmosphere introduces complications
- Waveforms do not contain same obvious patterns for event types

Future Work:

Analyze SVM feature importance

Test analyst vs. CNN accuracies

Distance Tests

Distance bins: ≤15 km, 15-250 km, and ≥ 250 km

≤15 km: 3 examples

15-250 km: 183 examples, most are mining events

≥ 250 km: 429 examples, most are chemical explosions

- CNN results on binned data:
  - Prone to overfitting due to small training set vs. number of model parameters (path effects, site responses, etc.)
- Predicting distance with the model:
  - 80 % accuracy between regional and global
- Using two prediction tasks (event class + distance class):
  - Doesn't seem to offer any advantage for event classification, but also doesn't hurt
  - Results are the same (avg. ~ 50%)