Environmental Noise Contamination Detection

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Project Motivation

- Noise reduction is being targeted by regulatory agencies around the world
- Community noise testing is expensive
- Noise certification testing done at remote locations
- Noise contamination still possible from birds, insects, livestock, wildlife, and road traffic
- Noise contamination can increase recorded noise levels
- Personnel used to monitor recordings for contamination

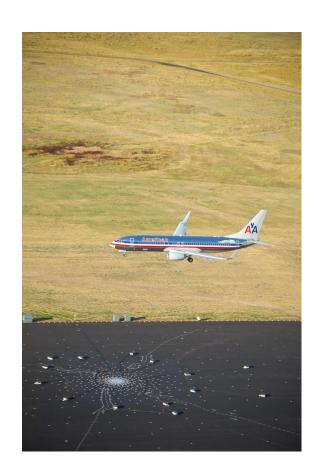


Project Goal

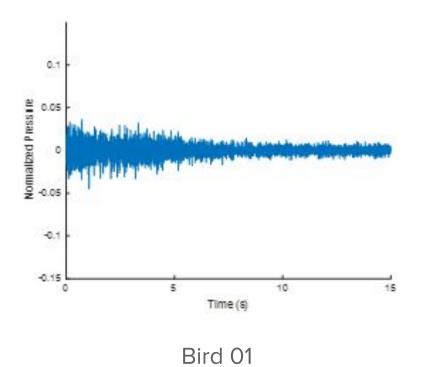
- Research the feasibility of automating the detection of environmental noise contamination contained in acoustic measurements for aircraft community noise testing
 - Investigate wide range of feature and model types
 - Document performance and recommendations to proceed

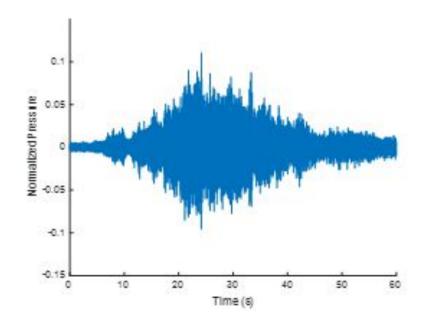
<u>Bird 01</u>

Plane 08



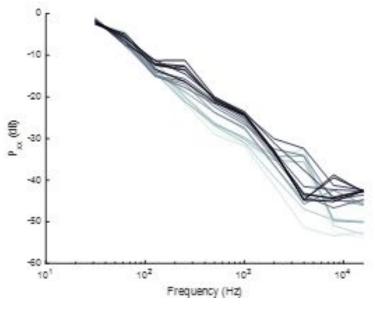
Data Example-Time Series

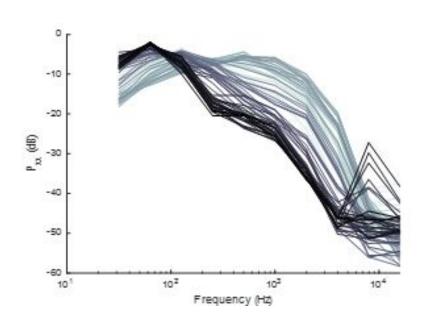




Plane 08

Data Example-Octave Spectrum





Bird 01 Plane 08

Data

Data

- 66 audio files from Boeing Test & Evaluation
 - Wave file recordings
 - Anonymized by an unknown normalization factor
 - 49 aircraft (737, A350, Q400 turboprop, etc)
 - o 10 ambient
 - o 7 contamination
- 6 audio file from US National Parks Service
 - Public domain data
 - Non-consistent sampling rate and uncalibrated levels
 - Crickets, bison, common raven, sparrow, Steller's jay, and yellow-rumped warbler
- Total of 233 MB of audio



Project Challenges

- How to turn audio recordings into features?
 - Separate into blocks
 - Process each block for features
 - Accumulate feature sets as function of time
 - Does this make streaming processing difficult later?
- How to quantify contamination levels?
 - Only use audio recordings that are of only a single noise source
 - Combine aircraft or ambient with contamination examples to create contaminated audio
 - Allows for control of signal-to-noise ratio

Data Preprocessing

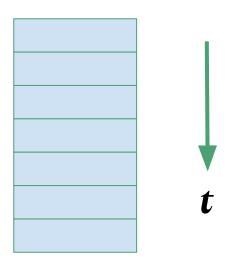
For each audio signal



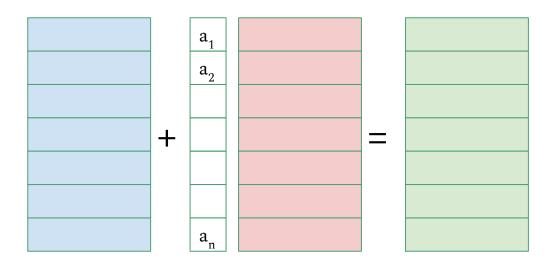
Separate into (overlapping) blocks



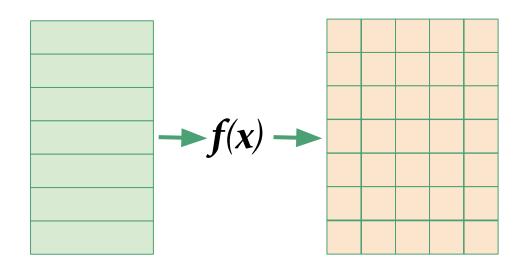
Stack the blocks



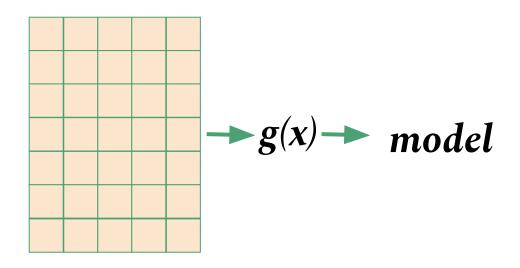
Add contamination (adjust levels of each block to achieve SNR)



Generate features



Train the model



Feature Set and Model Exploration

Initial Broad Investigation-Features

- Octave Spectrum
 - Full octave with 10 features
 - ½ octave with 29 features
- Mel-frequency Cepstral Coefficients
 - o 13 features
- Modified Mel-frequency Cepstral Coefficients
 - Extended frequency range up to 20 kHz
 - 13 features
 - 26 features

FFT

- \circ $\Delta f = 25$ Hz with 799 features
- \circ $\Delta f = 100 \text{ Hz with } 200 \text{ features}$
- Continuous Wavelet Transform
 - Scalograms
 - Scalograms bag-of-features with500 features
- Discrete Wavelet Transform
 - Wavelet Variance (Percival UW)
 - Shannon entropy
 - Mean/SD of subband coefficients
 - Coiflet, Haar, Daubechies
 - 2-5 levels of transform
 - 7, 13, 17, 49 features

Initial Broad Investigation-Models

- Logistic Regression
- Trees
 - o Fine
 - Medium
 - Coarse
- SVM
 - Linear
 - Quadratic
 - Cubic
 - Gaussian (Fine, Medium, Coarse)

- Ensembles / Forests
 - Boosted
 - Bagged
- Subspace KNN
- Neural Nets
 - Shallow
 - Convolutional
 - Long Short Term Memory

Broad Investigation Results

	#	Block	Logistic		Medium		Boosted trees	Bagged trees		Quadratic		Fine Gaussian	Medium Gaussian	Coarse Gaussian	Subspace			
Model Performance for SNR 6 dB	Features	length (s)	regression	Fine tree	tree	Coarse tree	ensemble	ensemble	Linear SVM	SVM	Cubic SVM	SVM	SVM	SVIM	KNN	Neural Net	CNN	LSTM NN
Cepstral	13	1	75.8%	83.1%	81.1%	75.6%	85.0%	86.8%	77.2%	87.3%	89.1%	85.7%	88.0%	80.4%				
Cepstral	13		78.3%	85.2%	82.5%	76.3%	86.3%	88.2%	79.0%	89.5%	91.9%	88.6%	89.3%	80.5%		86.7%		
Cepstral	26		78.0%	81.8%	78.9%	75.6%	85.0%	85.5%	79.0%	88.8%	89.7%	76.3%	88.1%	79.7%				
Cepstral	26		80.2%	85.2%	81.4%	74.3%	85.9%	88.3%	80.4%	90.7%	92.8%	80.9%	90.3%	79.7%		92.5%		61.8%
1/3 Octaves	29		70.7%	83.7%	80.2%	75.3%	85.1%	89.0%	70.3%	77.5%	81.2%	71.9%	75.4%	70.1%				
1/3 Octaves	29	2	72.8%	87.5%	82.8%	77.3%	87.5%	91.9%	71.7%	79.7%	83.8%	76.6%	76.5%	71.5%		71.5%		
Octaves	10		67.3%	82.0%	79.4%	72.7%	82.2%	86.3%	66.6%	76.4%	80.0%	78.0%	75.6%	66.8%				
Octaves	10	2	67.8%	84.7%	80.6%	73.7%	84.2%	89.0%	66.5%	77.0%	81.2%	81.1%	76.8%	66.9%		77.4%		
MFCC	13	2	76.3%	82.0%	78.2%	72.1%	83.5%	85.3%	76.8%	85.2%	87.4%	83.8%	87.0%	77.0%				
MFCC	13	1	74.1%	80.4%	78.9%	68.8%	81.6%	82.9%	75.3%	83.0%	84.6%	80.5%	84.8%	76.4%		77.5%		
FFT (25 Hz resolution)	799		1	78.4%	75.8%	70.0%												
FFT (100 Hz resolution)	200		68.3%	76.8%	74.0%	69.6%												
CWT Scalogram	150528	1															92.9%	
CWT Scalogram	150528	3															85.1%	
CWT Scalogram	150528		i														83.3%	
CWT Scalogram Bag of Features			81.0%	75.5%	74.2%	73.3%	82.1%	82.0%	83.1%	86.4%	87.1%	60.5%	86.1%	79.9%				
CWT Scalogram Bag of Features			80.7%	73.2%	73.7%	75.3%	84.8%	82.7%	86.7%	87.7%	88.6%	59.1%	87.9%	81.6%				
CWT Scalogram Bag of Features	500	5	55.0%	73.0%	74.1%	70.6%	82.3%	81.7%	88.0%	89.4%	90.9%	60.2%	87.7%	81.6%				
DWT (Coiflet2, 4 levels)	29		70.0%	90.4%	88.3%	78.1%	91.2%	93.1%	80.1%	86.2%	88.6%	84.8%	82.3%	76.0%		81.5%		76.4%
DWT (Coiflet2, 4 levels)	29	2	75.4%	91.6%	88.1%	80.1%	91.0%	93.3%	80.5%	87.3%	90.5%	85.8%	82.4%	77.6%		81.5%		78.2%
DWT (Coiflet2, 5 levels)	49	2	81.5%	91.7%	89.1%	79.3%	92.3%	94.2%	82.1%	88.0%	90.6%	87.2%	83.5%	78.8%		82.3%		
DWT (Coiflet2, 5 levels, Hampel Filter)	49	2	81.0%	91.7%	88.7%	79.3%	92.1%	94.0%	82.0%	88.9%	91.5%	87.6%	83.8%	76.8%	76.5%	84.9%		
DWT (Coiflet2, 4 levels, Hampel Filter)	29	2	70.1%	92.1%	88.6%	80.0%	91.1%	93.5%	80.7%	87.9%	90.8%	86.3%	82.7%	77.8%		83.1%		
DWT (Coiflet2, 3 levels, Hampel Filter)	17	2	67.1%	89.7%	87.5%	78.1%	89.6%	92.9%	79.0%	84.4%	52.0%	85.9%	81.1%	76.5%	81.3%	81.4%		
DWT (Debauchies4, 4 levels)	29	1	64.4%	90.1%	86.0%	81.1%	88.9%	91.6%	77.2%	80.6%	51.4%	81.5%	77.6%	66.1%	71.1%			
DWT (Haar, 4 levels)	29	1	53.8%	77.0%	73.1%	68.7%	76.4%	80.5%	71.5%	76.4%	58.7%	76.1%	73.9%	70.4%	67.1%			
DWT (Coiflet2, 4 levels, no entropy)	25	2	71.6%	90.6%	85.7%	81.6%	88.3%	92.1%	79.2%	57.1%	49.9%	76.3%	67.9%	61.0%	54.1%			
DWT (Coiflet2, 2 levels)	7	2	70.1%	89.0%	84.6%	78.9%	88.2%	92.3%	68.8%	71.8%	53.9%	77.7%	74.0%	61.5%	73.7%			

Observations/Comments

- If accuracy is low, confusion matrix tends to be skewed with high false negative rate
- Conventional models and shallow neural networks achieve >90% accuracy
- Long short term memory network not performing as expected
 - Likely requires creating unique, varying input sequences for training
- GPUs only necessary for training convolutional neural network

Remaining Project Work

Remaining Work

- Down select to only 3 feature/model combinations
- Optimization of model hyperparameters
- Increase performance metric to include
 - Accuracy
 - F1 score
 - False positive rate
 - False negative rate
- Detailed study of performance for:
 - Varying SNR
 - Percent of signal block contaminated
 - Randomization of blocks contaminated
- Monte Carlo simulation of randomized parameters
 - To simulate real-world scenario

Select Feature/Models

- Wavelets (Coiflet2, 5 level, T=2s)/bagged trees
 - Best overall with accuracy of 94.2% (best overall)
- Wavelets (Coiflet2, 4 level, T=2s)/bagged trees
 - Accuracy of 93.3% (4rd best overall)
- Cepstral (26 feature T=2 s)/cubic SVM
 - O Best non-NN, non-wavelet performer with accuracy of 92.8% (7th best overall)

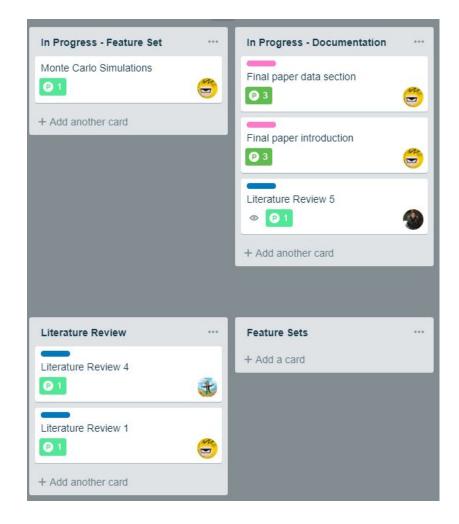
- *Coiflet2*: Coiflet wavelet with 2 vanishing moments
- T = 2s: block length

Work Tracking

- Using Trello to track our work
 - Agile Tools
- 5 Story Points = ~ 1 Week of Work
- ~60 points of work remaining after 2/6

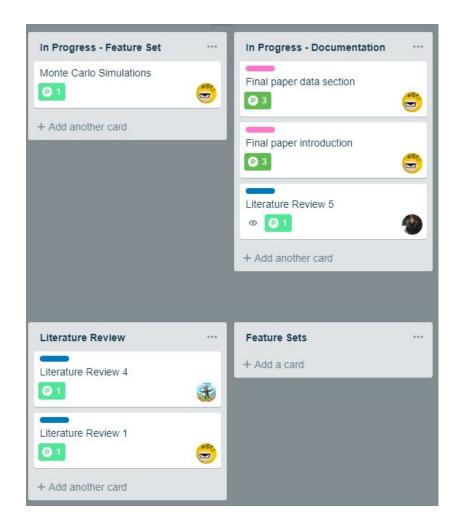
Workflow

- Stories are added to separate backlog lists
- 2. Stories are moved to In Progress
- 3. Stories are closed or removed



Remaining Work

Epic	Story Points					
In Progress - Feature Set	1 points					
In Progress - Documentation	7 points					
In Progress - Course Assignments	3 points					
In Progress - Machine Learning	5 points					
Poster Session	6 points					
Machine Learning	25 points					
Literature Review	2 points					
Documentation	6 points					
Course Assignments	3 points					



Q&A