

Mode Counting in Acoustic Signals

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The Agenda

- The Problem
- The Data
- Model Architectures
- Results
 - Comparing Model Performance
 - Effect of Channels on Performance
 - Channel Padding
- Future Work



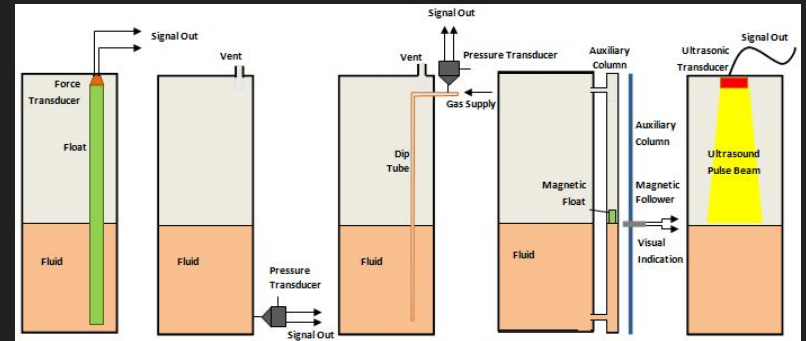
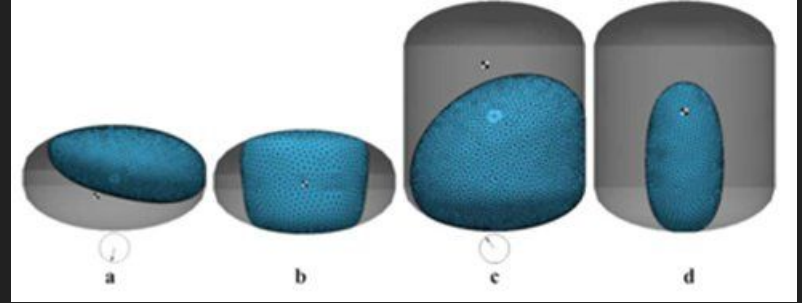
The Problem

Measure the volume of fluid in a tank
... in space

Measuring Tank Volume: Zero Gravity

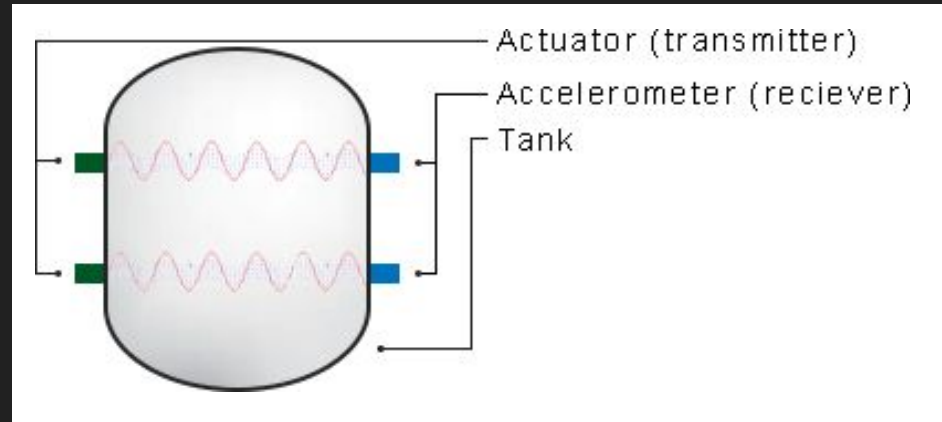
- Liquids behave differently in low-gravity environments
- Traditional sensors will not work

Liquid doesn't settle to the bottom of tank in low-gravity

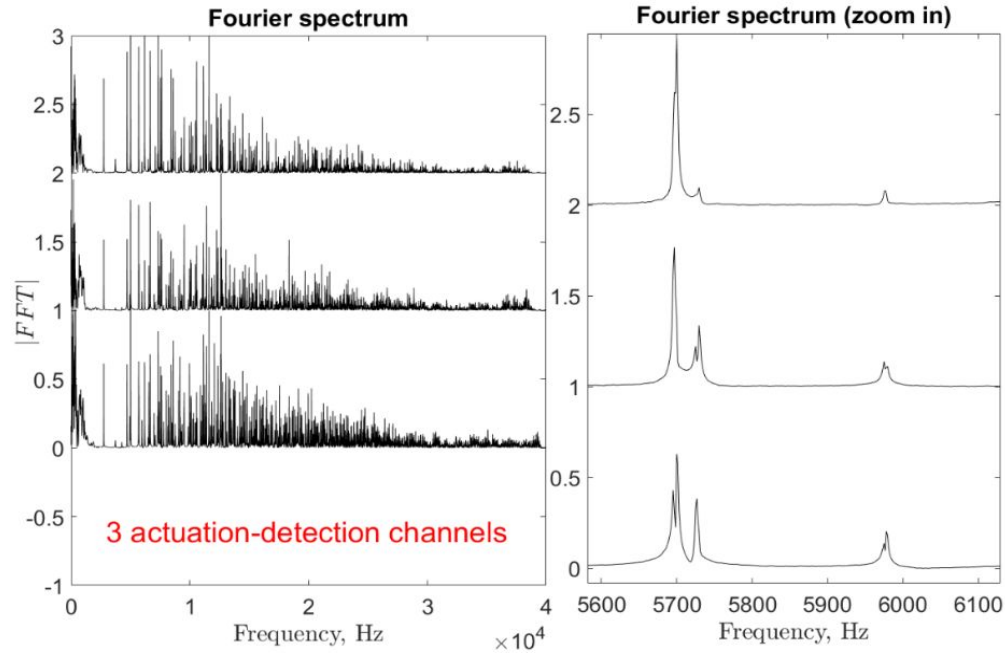


Spectral Mass Gauging in Unsettled Liquids

- Estimate the **volume** of unsettled liquids in **low-gravity**
- Acoustic resonances



Acoustic Resonances



Global vs local

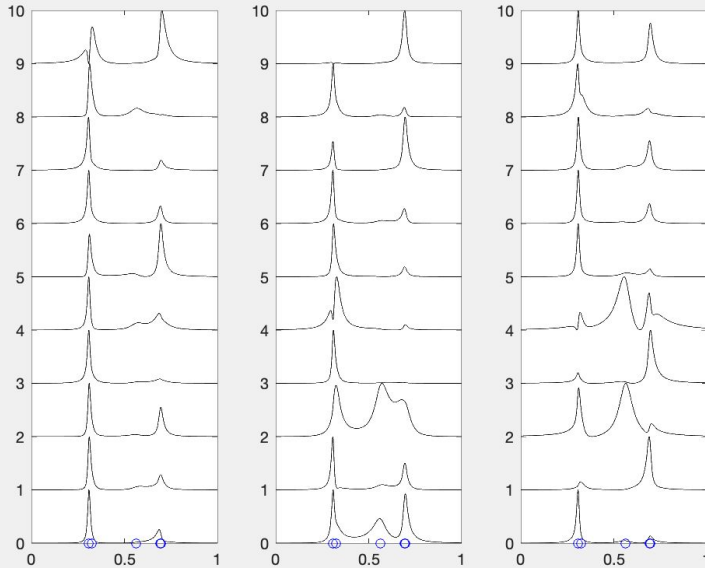
Multiple channels

Shell modes vs **liquid** modes

The Data



The Data



Original MATLAB spectrum visualization

- The original MATLAB script generates **simulated Fourier-transformed data**
- **Users manually estimate** where the modes are located by pressing 1
- The **correct mode locations** are later displayed with blue circles

The Task: Use the MATLAB code to easily **generate a large amount of simulated data** with specified parameters

Dataset Parameters

NMax:	Maximum number of resonances
NMaxS:	Maximum number of shell modes in a spectral window
NC:	Number of channels
Gamma:	Damping of each resonance
dG:	Variation of gamma
dGS:	Variation of gamma for shell modes
Omega:	Frequency of each mode
Scale:	Width of a window

The Data

- Data is optionally sharded
- Data is saved as JSON format
- Stored on AWS server / S3 bucket
- Command line tool to generate new sets

Parameters

```
(venv) (base) [Nathan DATA-Capstone (master ✖)]$ python datagen/run_gen.py
Spectra are stored in this directory. : test_set
Number of instances to create [10000]: 100
How many spectra to put in each shard (0 = no shard) [0]: 50
Number of channels to generate [10.0]: 10
Maximum number of modes [5.0]: 4
Maximum number of shell peaks [5.0]: 5
Scale or width of window [1.0]: 1
Omega Shift [10.0]: 5
Variation of Gamma [0.5]: .5
Gamma variation of shell modes [1.8]: 1.8
Creating generator...
Saving training data into 2 shards.

Generating 50 spectra for shard #1 (100 left)...
  Making SpectraLoader...
  Splitting data...
    42 Train, 8 Test

Generating 50 spectra for shard #2 (50 left)...
  Making SpectraLoader...
  Splitting data...
    42 Train, 8 Test
  Saving training data...
    Saved 50 spectra
  Saving training data...
    Saved 34 spectra
  Saving testing data...
    Saved 16 spectra

Saving info...
Saved 100 spectra to /Users/Nathan/Documents/Programming_Projects/DATA-Caps
Done.
```

Model Architecture

Model Development

Neural Networks

- **Features extraction** would be non-trivial
- **Noise** and shell modes **filtering** would be non-trivial
- Existing Research

Loss Function

- Categorical Cross Entropy
- Poisson Loss
- Macro Averaged Mean Absolute Error

Model Architectures

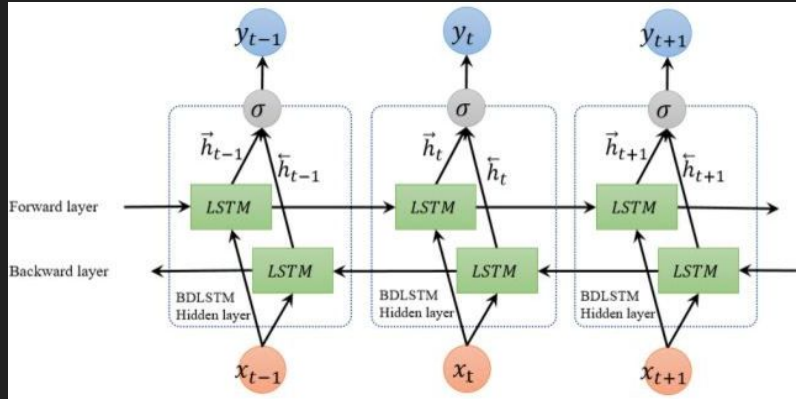
CNN

Bidirectional LSTM

Ensemble CNN

CNN + LSTM

Attention



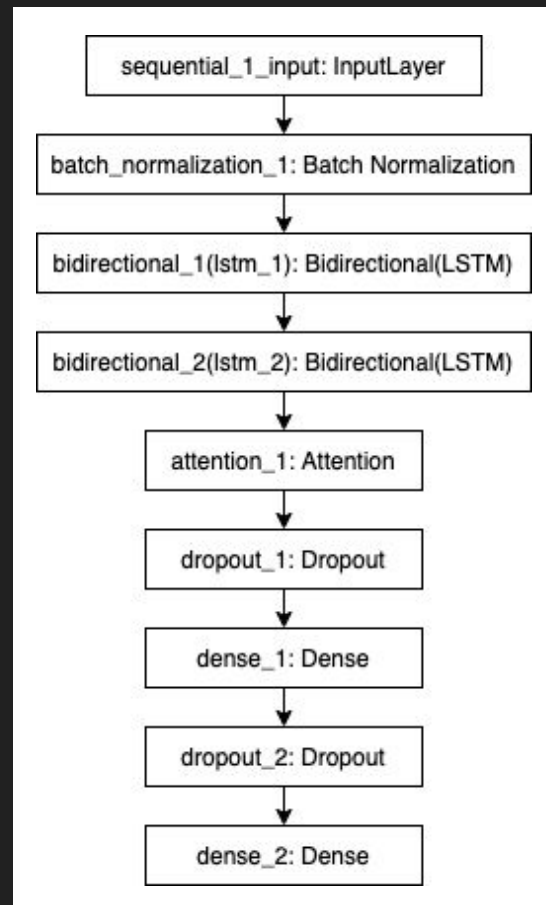
Results

Results Overview

- **Evaluating Performance** of 3 Model Architectures
- Effect of **Variable Channels**
- Channel Padding

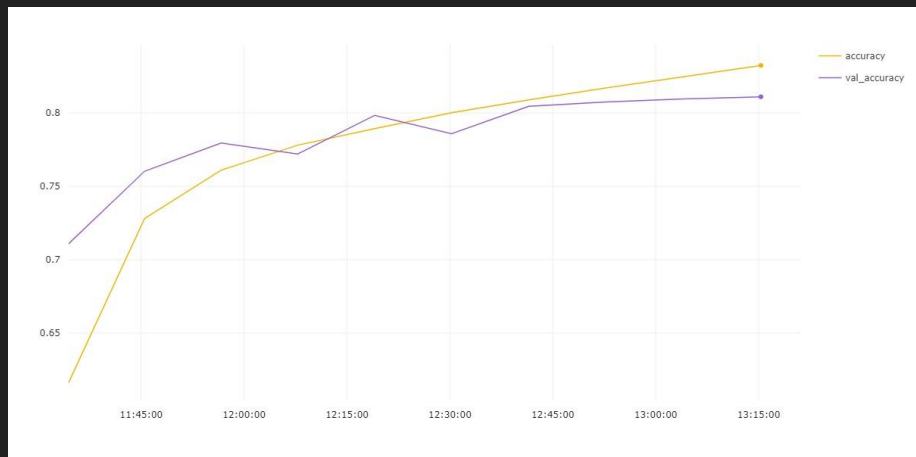
LSTM Model

- One of our initial models
- **Bidirectional LSTM**
- **Attention Layer**

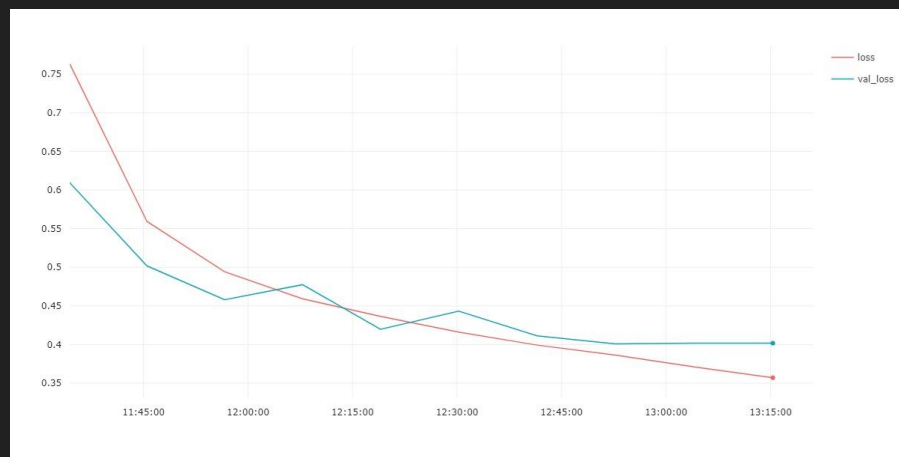


LSTM Model

Training Accuracy
Validation Accuracy



Training Loss
Validation Loss



LSTM Model Results

1v2v3v4 Classifier	Predict 1	Predict 2	Predict 3	Predict 4
Actual 1	250	0	0	0
Actual 2	1	245	4	0
Actual 3	0	38	180	32
Actual 4	0	8	98	144

Evaluated with:
50 channels
Omega Shift = 10
Delta Gamma = 0.5
Delta Gamma Shell = 0.5
Max Modes = 4
Max Shell Modes = 5

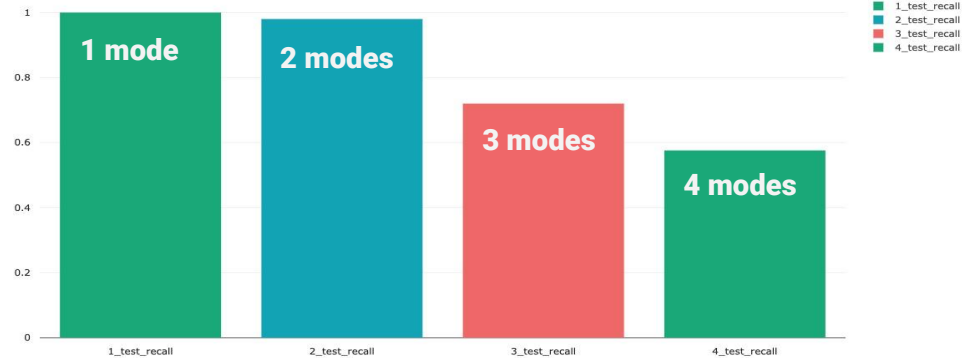
Test Accuracy: 81.1%
Test Loss: 0.401
Test MAE: 0.118
Test MSE: 0.064

LSTM Model Results

Precision / Recall
by Class (number of modes)

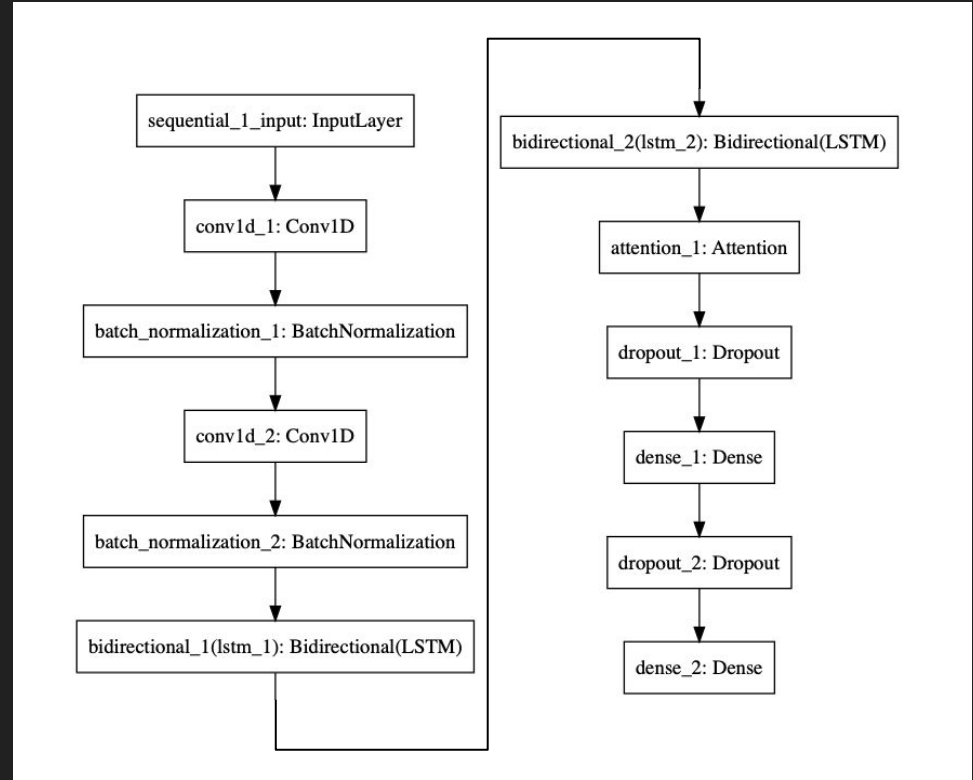
Recall

Precision



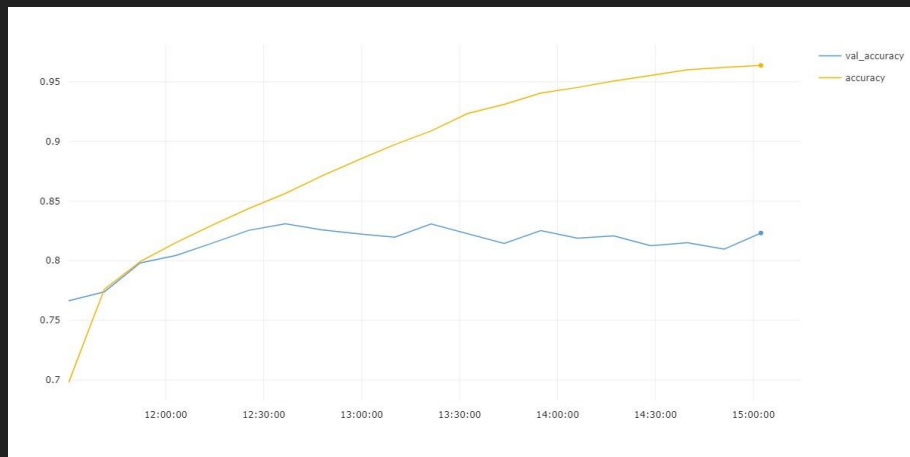
1D CNN + LSTM Model

- Additional two **convolutional layers**
- **1D** Convolutions

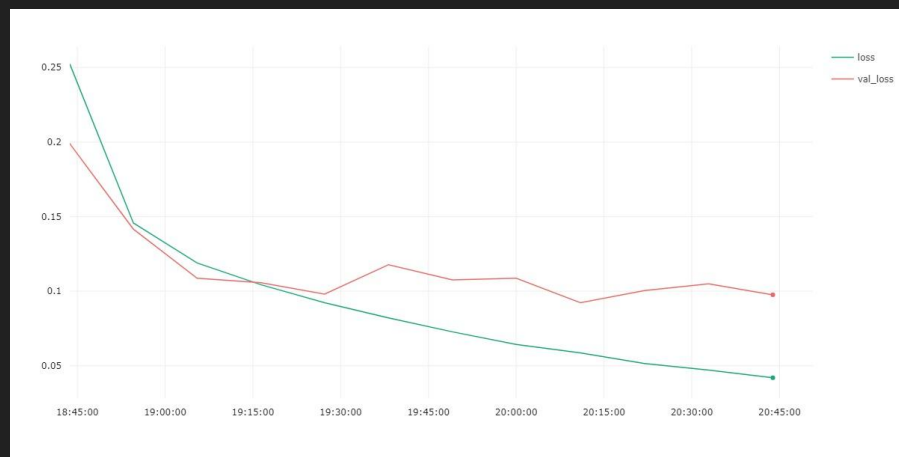


1D CNN + LSTM Model

Training Accuracy
Validation Accuracy



Training Loss
Validation Loss



1D CNN + LSTM Model Results

Evaluated with:
50 channels
Omega Shift = 10
Delta Gamma = 0.5
Delta Gamma Shell = 0.5
Max Modes = 4
Max Shell Modes = 5

1v2v3v4 Classifier	Predict 1	Predict 2	Predict 3	Predict 4
Actual 1	250	0	0	0
Actual 2	1	241	8	0
Actual 3	0	21	169	60
Actual 4	0	3	79	168

Test Accuracy: 82.3%
Test Loss: 0.659
Test MAE: 0.092
Test MSE: 0.073

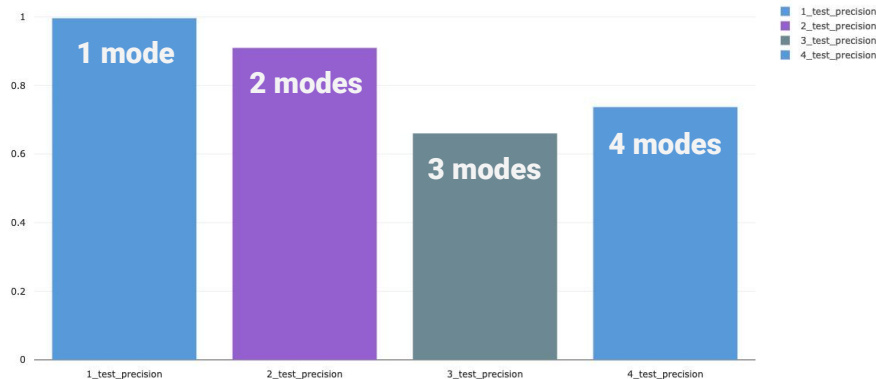
1D CNN + LSTM Model Results

Precision / Recall
by Class (number of modes)

Recall

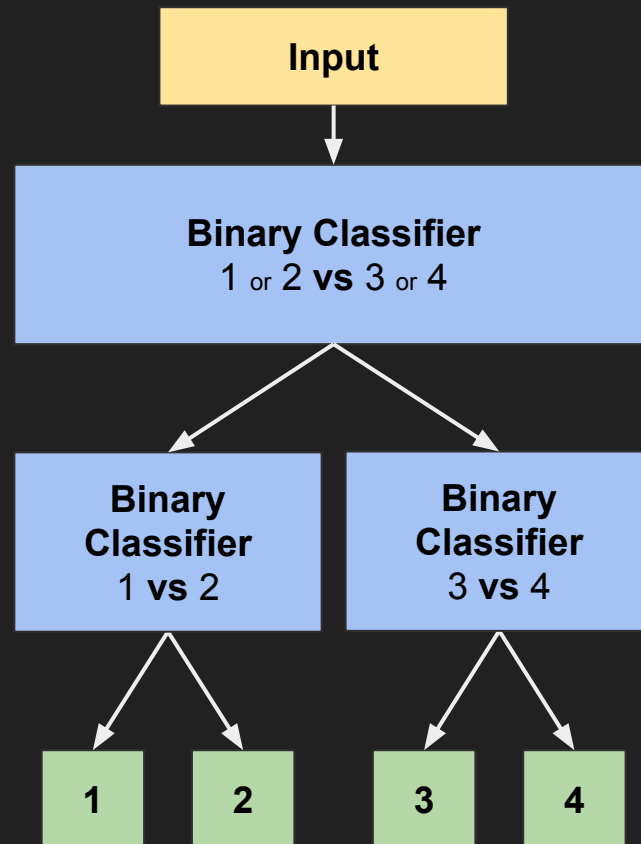


Precision



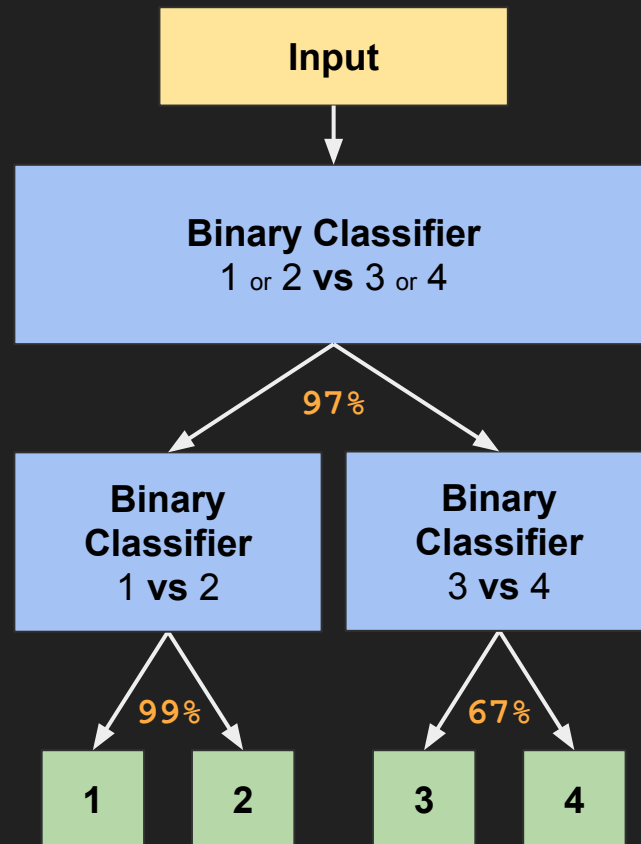
1D CNN + LSTM Binary Ensemble

- Three **binary** classifiers to classify **1-4 modes**
- Same architecture as 1D CNN + LSTM



1D CNN + LSTM Binary Ensemble

- Three **binary** classifiers to classify **1-4 modes**
- Same architecture as 1D CNN + LSTM



1D CNN + LSTM Binary Ensemble

Training Accuracy

1|2 v 3|4

Validation Accuracy

1|2 v 3|4

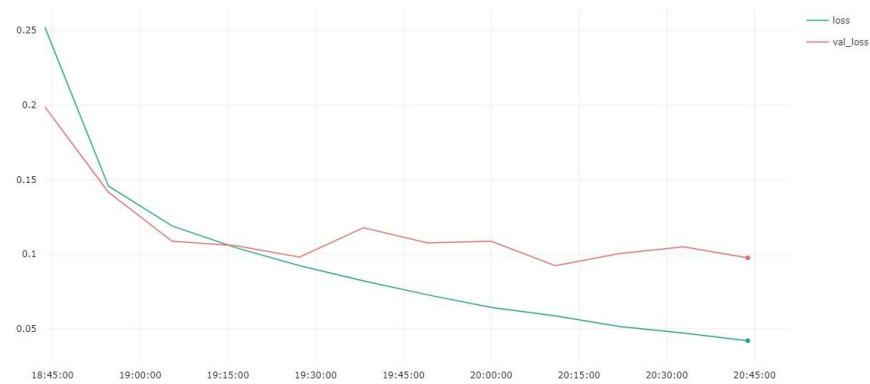


Training Loss

1|2 v 3|4

Validation Loss

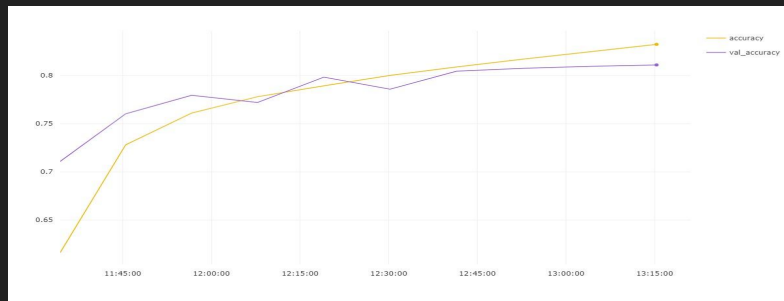
1|2 v 3|4



1D CNN + LSTM Binary Ensemble

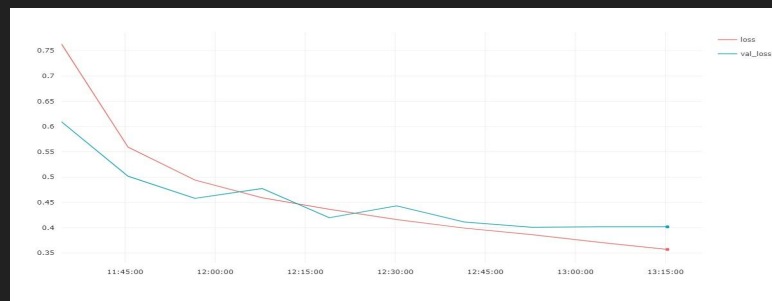
Training Accuracy
Validation Accuracy

1 v 2
1 v 2



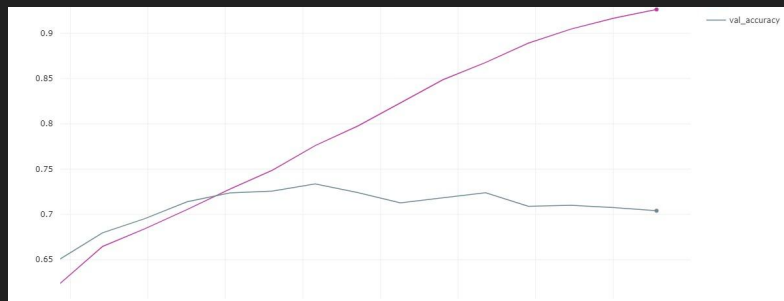
Training Loss
Validation Loss

1 v 2
1 v 2



Training Accuracy
Validation Accuracy

3 v 4
3 v 4

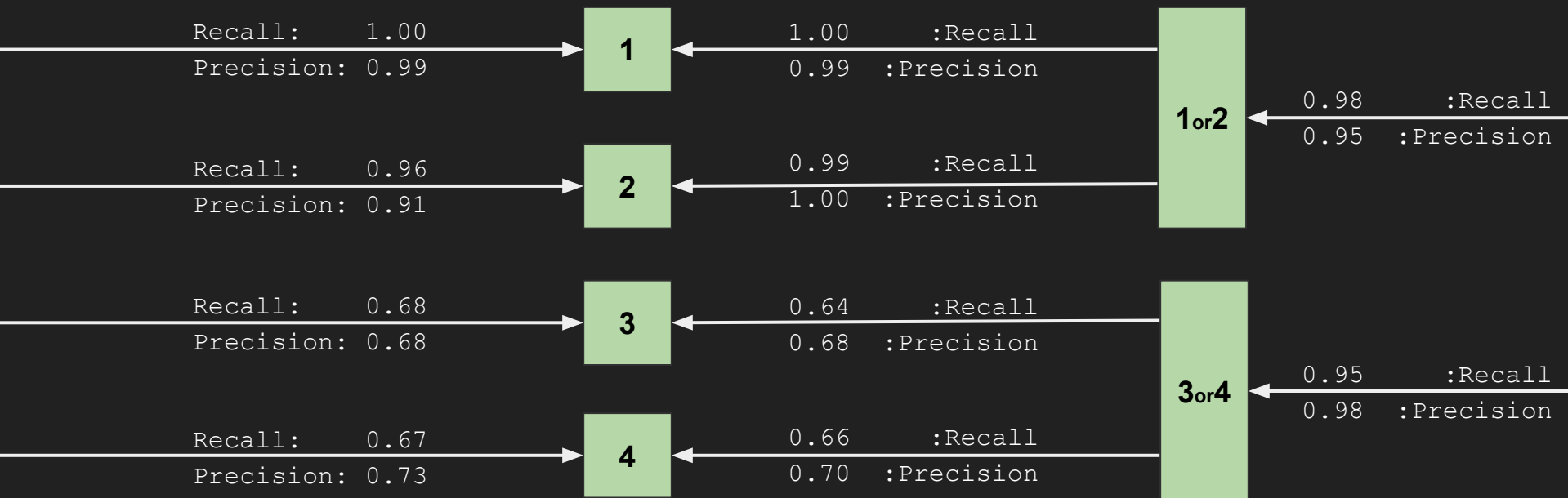


Training Loss
Validation Loss

3 v 4
3 v 4



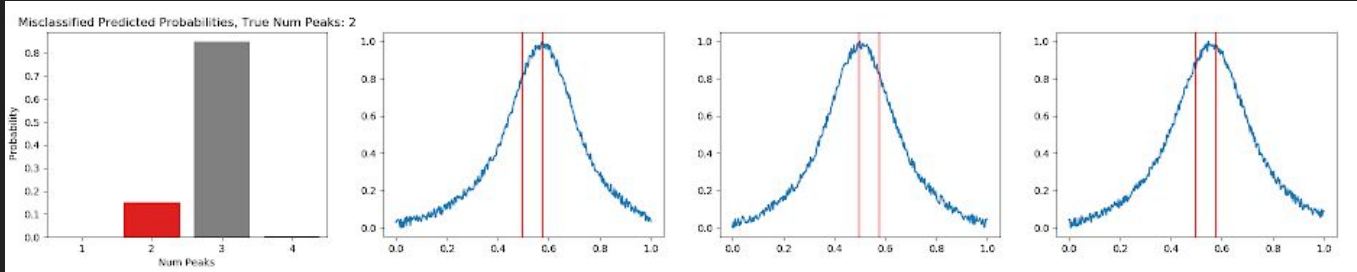
'All-in-One' Categorical vs Binary Ensemble Classifier



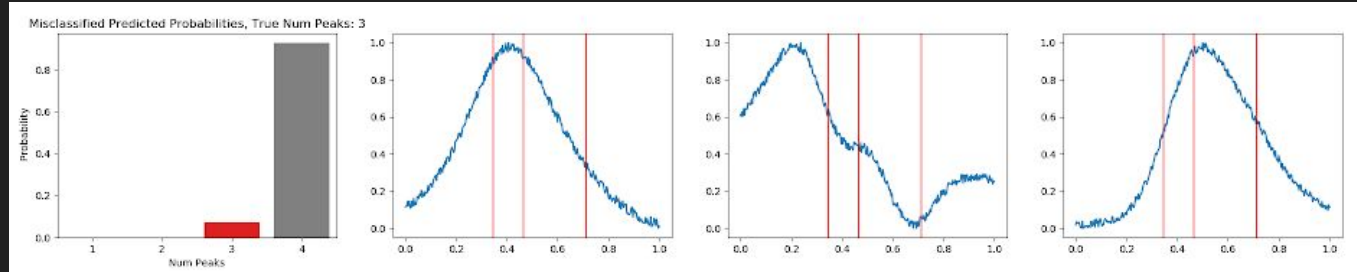
* Scores are calculated independently of parent classifier

Model Evaluation Visualizations

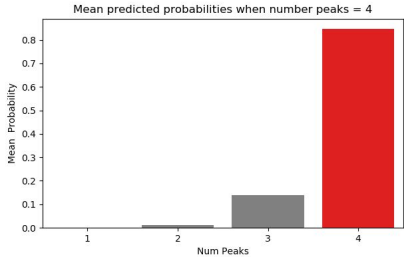
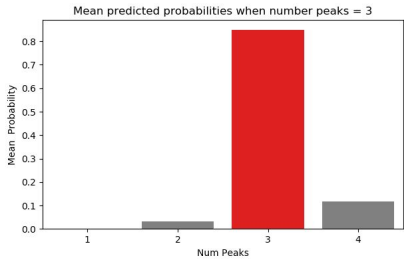
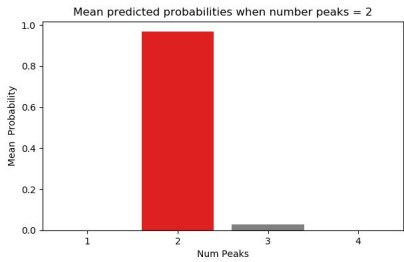
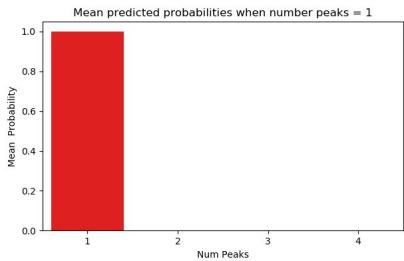
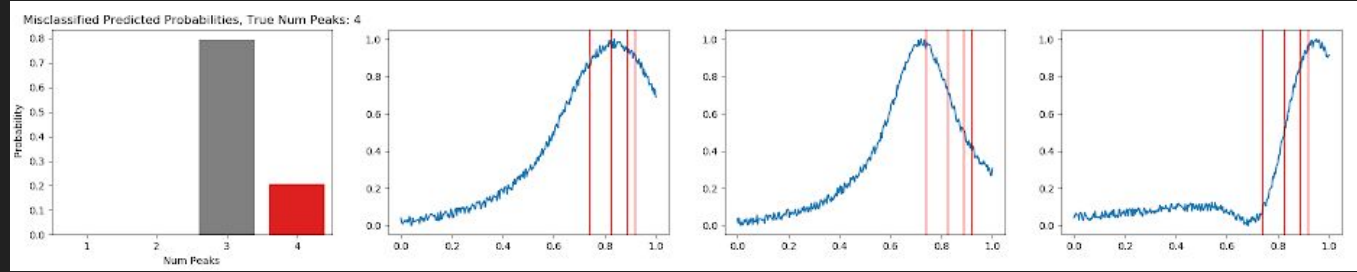
Misclassified spectrum with 2 modes



Misclassified spectrum with 3 modes

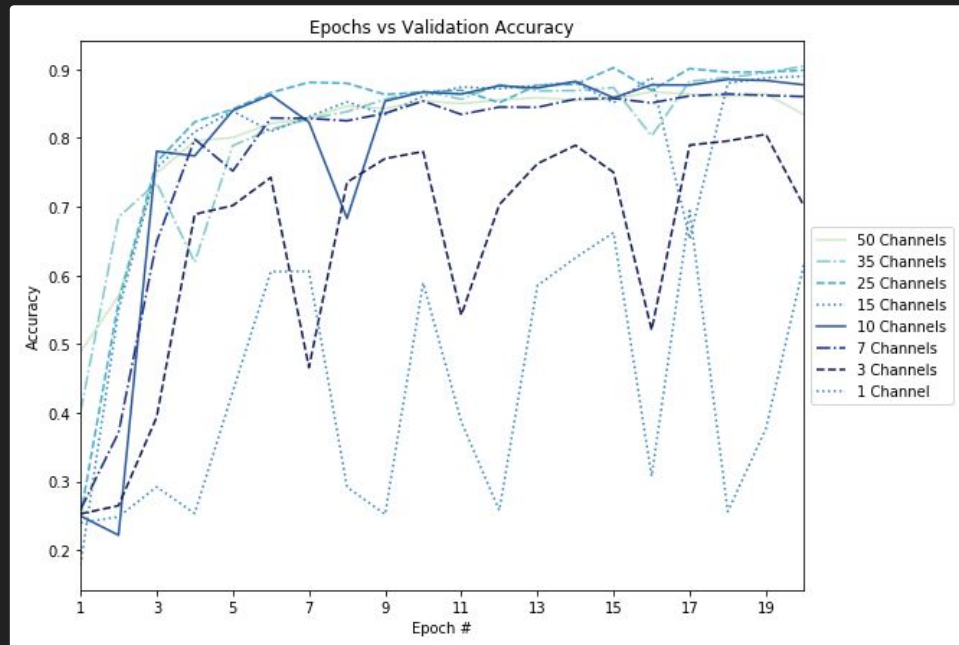


Misclassified spectrum with 4 modes

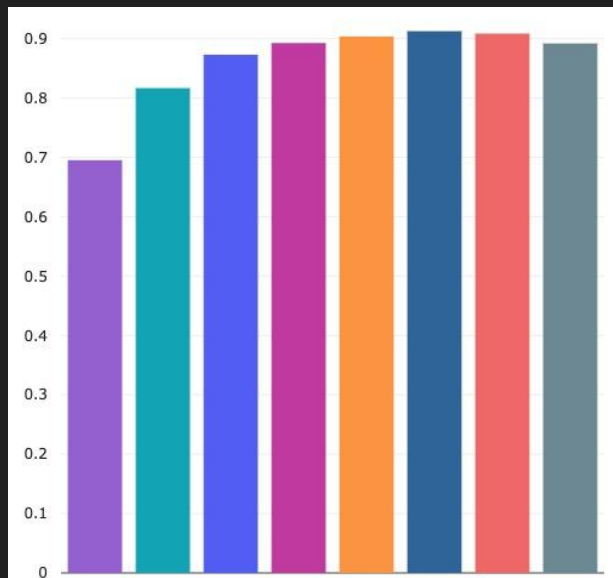


Channel Experiments

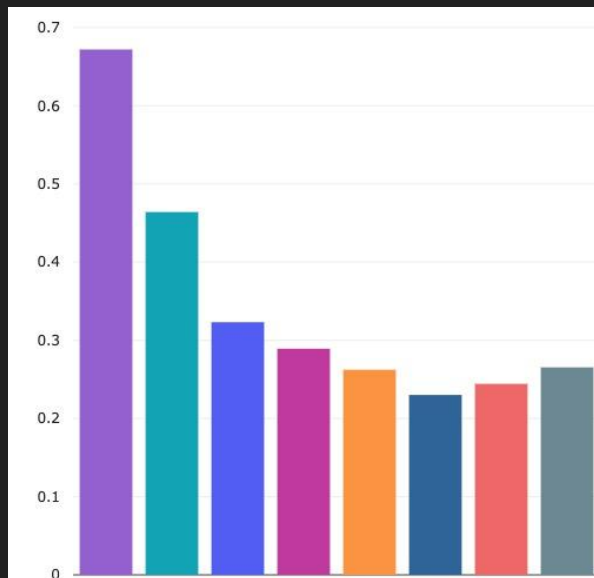
- Big improvement for 1, 3, and 7 channels
- Little difference for 10+ channels



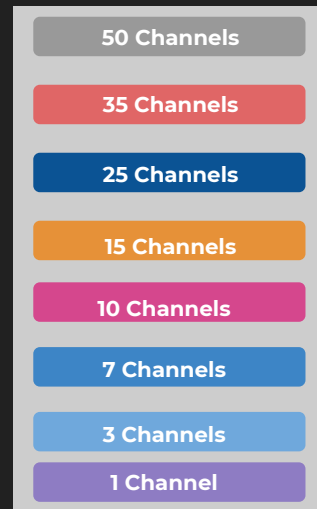
Channel Experiments



Max. Validation Accuracy



Min. Validation Loss



Channel Padding

- Want to be able to evaluate models with **different numbers of channels**
- If a **sample has less** than the number of channels a model was trained on, we pad this sample so that it fits in the model
- Padding strategies:
 - **Reflect:** Pads with the reflection of the vector mirrored on the first and last values of the vector along each axis.
 - **Symmetric:** Pads with the reflection of the vector mirrored along the edge of the array.
 - **Constant:** Pads with a constant float value, in this case "0".

```
array([[0, 1, 2],  
       [3, 4, 5]])
```

Suppose we want to pad this sample so that it has 6 "channels"

Symmetric:

```
[ [0, 1, 2],  
  [3, 4, 5],  
  [3, 4, 5],  
  [0, 1, 2],  
  [0, 1, 2],  
  [3, 4, 5] ]
```

Reflect:

```
[ [0, 1, 2],  
  [3, 4, 5],  
  [0, 1, 2],  
  [3, 4, 5],  
  [0, 1, 2],  
  [3, 4, 5] ]
```

Constant:

```
[ [0, 1, 2],  
  [3, 4, 5],  
  [0, 0, 0],  
  [0, 0, 0],  
  [0, 0, 0],  
  [0, 0, 0] ]
```


Channel Padding

Accuracy vs. Number of Original Channels



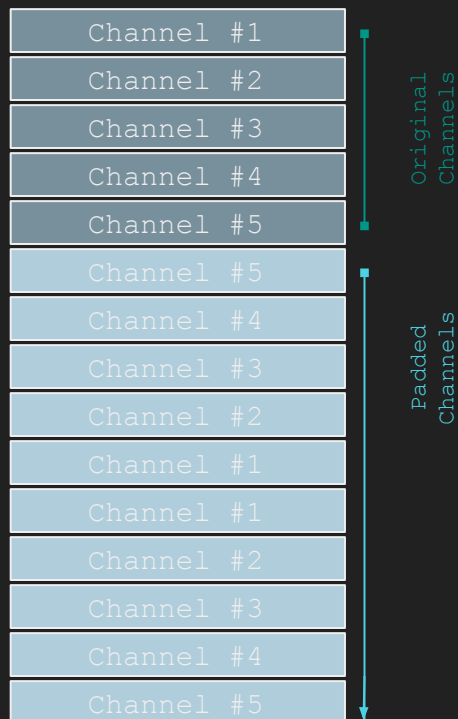
One channel, padded 49 times

No padded channels

For Example...

original_nc = 5 (45 padded)

Symmetric padding



Future Work

- Mode counting vs object detection
- Global Problem
 - Regression based approach
 - Window Slicing
- Padding Strategy vs. Training a Specific Model

Questions?