

A large group of fluffy yellow chicks are gathered in a wooden brooder. The chicks are in various poses, some looking towards the camera and others looking away. The background is slightly blurred, emphasizing the chicks in the foreground.

# AUDIOT ADVANCED PROJECT, TEAM ADVI, SUMMER 2024

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CHLOE POMEROY

CHRISTOPHER SNIFFEN



A photograph of several chickens in a grassy field with trees in the background. The image is semi-transparent, serving as a background for the text.

## WHO IS THE SPONSOR?

- AudioT is a startup company developing analytics to monitor poultry well-being through audio sensors (microphones) placed in large-scale poultry houses. The value proposition of the company is that identifying threats to the birds' well-being quickly will allow farmers to react quickly to problems, improving the quality of life for the animals while limiting economic risks due to environmental or mechanical incidents for the farmers.
- The AudioT approach to this problem is to productize an ensemble of analytics models that take in noisy, raw audio from microphones distributed throughout the poultry houses, isolate the chicken vocalizations, and then identify anomalies in the chicken vocalizations in order to alert the farmer to potential problems.

# WHAT IS THE TEAM'S OBJECTIVE?

- The AudioT vision is predicated on the ability of models to effectively isolate chicken vocalizations from other noises such as farming machinery. The approach to this problem taken by AudioT is to use Hidden Markov Models (HMMs) to classify audio files by profiling the background noise into different states. If the HMMs function effectively, then separate de-noising and anomaly detection models can be used for each state to effectively identify anomalies in the chicken vocalizations. Currently, AudioT only has a very basic HMM that can classify time series audio as night or day for a single microphone and a single flock. This semester the team is charged with extending this basic model to generalize across different noise profiles, flocks and locations.



# BACKGROUND

- During the Spring 2024 semester, another OMSA practicum team successfully implemented the first Hidden Markov Models (HMMs) on features generated from raw audio files for AudioT. This HMM was trained to differentiate between night and day within the poultry houses. While these models were able to predict night and day as hidden states, they were not robust to unexpected noises.
- Chloe and Chris are charged with extending this work, first replicating and confirming the results of their predecessors and then testing the ability of the HMMs to generalize across different flocks and locations. The team will be working to improve model performance by including additional hidden states in an attempt to accommodate unexpected noises. Finally, the team will be experimenting with feature engineering and additional features as a way to improve the models and reduce overfitting.





## WHAT HAS THE TEAM DONE SO FAR?

- The team has received a crash course on poultry farming, to include basic familiarization with the relevant machinery and sounds. The team has also worked through a lot of information on audio signal processing, the core domain expertise needed for this project.
- The team has reproduced previous HMM training results, verifying both the accuracy results and the limitations of previous modeling. The team brainstormed alternative approaches and discussed the overall vision for the AudioT product, clarifying the particular problem that AudioT wants this team to solve.
- The team has generated features for four different flocks using the current methods, based on AudioT's data holdings, and used this data to show that the current HMM models do not generalize across different flocks and locations.




## NEXT STEPS: FOUR SPECIFIC LINES OF EFFORT

- Over the remainder of the semester, the team intends to work on the following four specific
  - Experiment with the feature engineering approach using audio compression in order to improve the HMM's ability differentiate between different noise sources.
  - Experiment with varying numbers of hidden states and hyperparameter tuning in order to expand on the ability of the HMM to classify different noise profiles.
  - Incorporate bird age as a separate feature to help the HMM generalize better to other flocks.
  - Experiment with semi-supervised and supervised variants of HMMs and compare the results to the unsupervised models
  - Experiment with small-scale neural networks as an alternative classification approach




# THE TEAM'S APPROACH: FEATURE ENGINEERING

A brown egg is positioned in the lower-left area of the slide, casting a soft shadow to its right. It is partially obscured by the vertical line that separates the title from the list.

- The current approach to feature engineering is to take raw .flac audio files and extract mel-frequency cepstral coefficients. These features are designed to remove extraneous noise and preserve the chicken vocalizations.
- We are currently extracting 13 mel-frequency coefficients, and AudioT hypothesizes that we may be able to reduce overfitting and create more generalizable models by grouping these instead into 3-5 coefficients.
- Alternatively, the team hypothesizes that this noise reduction may limit the ability of the HMM to accurately identify noise profiles, since much of the noise information is eliminated in the processing. The intent is to experiment with both less granular and more granular coefficients.

## THE TEAM'S APPROACH: MODEL ENGINEERING

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- The current HMM implementation has two hidden states: night and day. The model performs fairly well on these highly predictable states, but the presence of less predictable machinery noise, such as fans and feed augers, is a significant challenge.
- AudioT has asked the team to experiment with varying numbers of states, in order to find the optimal number of states to classify the noise profiles effectively. Chloe and Chris also feel that the current parameterization of the HMM is probably not optimal, and so they plan to work on optimizing the number of states and the parameters, with the goal of improved accuracy and generalization. This work will require significant effort in data labeling in order to validate improvements in model performance.



## THE TEAM'S APPROACH: ADDITIONAL FEATURES

- Currently, only the actual raw audio is used for feature generation within the AudioT modeling ensemble. AudioT has suggested that adding bird age – that is, the flock maturity as ‘days old’ or perhaps weeks – may also help the model fit on the information of interest.
- The team will work with the birds’ age as an additional feature to determine whether or not it improves model performance.

## THE TEAM'S APPROACH: ALTERNATIVE MODELS

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- AudioT has invested significant time and energy into its current modeling approach with HMMs, and has significant expertise in this model type and signal processing in general to draw upon.
- The team has talked to AudioT about trying semi-supervised and supervised HMMs to see how they compare to the unsupervised HMMs.
- However, in considering the company's objectives with a fresh perspective, the team feels that recent advances in deep learning may make neural networks a compelling option for the audio classification task. Time allowing, the team hopes to do some basic experimentation to investigate the possibility.



# CHALLENGES

- The most significant challenge the team has faced so far is that the only data labels available are the date and time of the recording. From this limited data, the team is able to extrapolate night and day states as well as the age of a flock, however the only means for examining the noise content of an audio file (i.e. is there fan noise present?) is by either listening to the audio or viewing the waveform. This limits model options to unsupervised approaches in general and makes it difficult to measure success.
- Another significant limitation is the fragmented data and software storage. AudioT uses Github repositories to store and version code, but the team does not have access to all of the code or know the extent of some key aspects of AudioT's past experiments (i.e. how far has feature engineering already been investigated?). AudioT has been extremely helpful in helping the team locate and use relevant code and data, but it has taken a lot of time and effort to do so.

# WORK DISTRIBUTION

Task	Description	Team Member Contributions
Downloading and extracting features	Running feature extraction for a flock (~2 months worth of minute-by-minute data)	Both Chloe and Chris extracted features for 2 flocks each. Chloe identified which data to use based on microphones had the most complete data.
Reproducing previous experiments	Trying to replicate the previous semester's work of identifying clear night/day states using our extracted data	Both Chloe and Chris replicated previous experiments with data from different flocks/microphones. Chris validated that the models overfit and do not generalize well and Chloe looked at making adjustments for missing data.
Alternative Models	Testing alternative model approaches	Chris will work on creating a proof of concept with a small neural network and Chloe will work with supervised HMMs
Feature Engineering	Experimenting with the features	Chloe will experiment with different levels of granularity for the mel-frequency features
Model Engineering	Experimenting with different numbers of states and hyperparameter tuning	Chris will experiment with different numbers of states with the original HMM algorithm and tune the hyperparameters to look at how this compares to the initial model.
Midterm Report	Creating the powerpoint presentation	Chris created the presentation and all the initial slides. Chloe looked over these and made a few content changes, as well as adding the contributions table.
Final Report	Creating the final report	Chloe will create the initial report and Chris will add his thoughts, experiments and findings