[Bird Song Identification]

[Gold Team]

Data Science Capstone Project
Launch Report

Date:

[04/18/2024]

Team Members:

Name: Jonathan Watkins

Name: Joseph Trybala

Name: Max Song

[The purpose of this report is initiating a new project. It provides an overview description of the project. It includes three major sections: The System/Product, The Team, and The Project Plan.]

The System/Product

System/Product Name: Bird Song Identification

Introduction:

[Describe the background information, motivation, and goals of your Data Science capstone project. What are the deliverables of your project?]

Birds are integral to numerous scientific fields including but not limited to biology, ecology, geography, and zoology, and are particularly renowned for their vocalizations. These are divided into two classes: calls and songs, with the latter being complex, elongated vocal patterns prominently used (or *sung* as it were) during the breeding season (Disabato et al. 2021, Wada 2010). Birdsong, rich in variability and complexity, presents an acoustic challenge across these disciplines. Each bird possesses their unique song repertoire, almost as if speaking its language or *dialect*, influenced by diverse environmental factors and specific to its habitat.

Biogeography examines how species are distributed geographically. Since Darwin's demonstration of divergence and speciation using Galapagos finches, the distribution of bird species has been critical in biogeographical research. Over recent years, there has been a growing interest in bird distributions and biogeography–driven largely by conservation concerns (Jetz et al. 2012).

Bird identification poses a well-known challenge for ornithologists and has been long regarded as a scientific pursuit. Experts delve into various factors of bird life, encompassing their habitat preferences, anatomical features, vocalizations, distribution patterns, and ecological influence. Observing, studying, or monitoring birds serves several practical purposes. Scientists frequently utilize birds as a means to explore and comprehend ecosystems for multiple reasons: their abundance, responsiveness to environmental shifts, manageability compared to other species, ubiquity, and visibility make them advantageous subjects for study (A. Marini et al. 2015)

Historically, the accurate identification of bird species relied heavily on these vocal signatures, especially in such cases where physical identifying markers were insufficient or ambiguous. The evolution of audio recording technology has not only enhanced species identification but has also become pivotal in studying population dynamics, song evolution, and more recently, even the impacts of climate change (Gallagher 2015, Wada 2010).

The recent advent of sophisticated audio technology and the proliferation of advanced machine learning tools have revolutionized birdsong analysis (Disabato et al. 202l, Mehyadin et al. 2021, Rivera et al. 2023, Sprengel et al. 2016, Tang et al. 2024). Today, automated systems can identify and classify birdsongs. Access to open-source datasets, collected by volunteers, has democratized this field, offering non-commercial teams both the opportunity and ability to develop models that accurately distinguish and identify birds and their species.

Deliverable: A model capable of identification of species of birds based on birdsong. With 2 group members touting a music background and 2 group members with a birding background, we decided to work with audio that pertains to birds.There is research in this field already, mostly coming from Cornell University. Cornell hosted a data science competition 4 years ago on this exact subject via Kaggle (Howard et al, 2020) With others having attempted this project, we felt there was enough material for us to learn from and enough room to grow. After achieving success in species identification we seek to parse birdsong syntax applying current academic theory in practice. From literature review, this has not been done before.

Highlighted Features:

[Write it in bullet forms.]

EDA

- Collect and collate data
- Scope analysis
  - Is it possible to work with all species with samples available to us?
- Testing of data with random sampling.
  - Average volume, volume min/max, volume extrema
- Clean data
  - After checking volume extrema we expect there to be audio samples with poor differentiation (which could indicate faint bird noise). We intend to cut poorly differentiated samples wholesale, there is enough data available for us to excise coarsely.

Model

- Sound waveform parsing
  - Cutting down larger samples to uniform chunks to aid model
- Waveform to spectrogram
  - The current understood method is taking audio data and converting to visual with spectrograms.
- Spectrogram cleaning
  - Suppressing or elevating decibel ranges, and elevating patterns through machine vision techniques
- Training of model on cleaned spectrograms
  - Spectrograms are provided alongside species labels
- Testing
  - Sound acquisition: Either through outside recording or using testing holdout set
- Species identification based on bird call using model
- Bonus: Bird Song Syntactic Parsing for certain species. May require data labeling.

Sponsor or Proxy User:

[If you have an external sponsor or real user, please describe who they are and how you will work with them.]

N/A

Issues:

[Are there any potential issues in data acquisition for the project? Do you have the expertise or stakeholder who can help you to understand and interpret the insights extracted in the project?]

We have access to several birders, we have contacted Cornell's Ornithology lab and they are receptive to discussion, and we can compare results against current commercial products for performance. We already have the dataset required and are able to access alternatives readily. We are stating that the birdsong syntax parsing is a bonus goal as we are guessing at the feasibility of that while knowing that the primary goal is achievable.

1. Failsafe 1: Quality Assurance of Data
    a. We are committed to assuring the highest quality of data for our dataset. We acknowledge that despite advancements, data collected by volunteers still require a level of data integrity.
    b. We commit to this through the implementation of data validation checks as necessary to ensure said integrity and uphold accuracy in our dataset(s).
    c. We shall use automated scripts to detect any anomalies, inconsistencies, or missing/incomplete data.
2. Failsafe 2: Use of Alternative Data Sources
    a. We have identified secondary and tertiary data sources, i.e. datasets that can serve as backups should our primary dataset(s) fail to meet the project's requirements or if there are any gaps with respect to data completeness.
    b. All datasets are to be publicly available datasets from reputable sources. Reputable shall be defined as a data source with no known inconsistencies or issues.
3. Failsafe 3: Scalable Data Processing Framework
    a. As applicable for this phase of the DSCI591 Capstone Project, we aim to design a flexible, scalable data processing pipeline able to efficiently handle increases in data volume and complexity.
    b. Should the need arise for it, we may use/employ cloud storage and/or services with capabilities to auto-scale for the proper management of computational resources dynamically, which ensures that the project is adaptable to varying loads without disruption.

The Team

Team Name:

[You will be assigned a team number in the first week of class, e.g. G1. You may also pick a creative name such as SmartHealth. In this example, your team name will be G1-SmartMedia. The team name will be used in all reports and presentations in this quarter.]

G1-GoldTeam

Team Members and their specialties:

[Discuss with your team members about your individual experience, strength, and interest. Identify the role of each member. For example, one of you will be the team leader who coordinates the whole team. Some of you may focus on data acquisition, some may be doing data-preprocessing and cleaning, some may do exploratory data analytics, modeling, etc.]

Joseph Trybala has a basic blend of Data Science skills earned through the 2 years of the MSDS degree at Drexel University. He has experience with Data Analytics and a Google Professional certificate to back it. He has domain knowledge from casual birding, but not enough to be an SME so we will be relying on academic literature and birders with more experience. He has no experience working with audio data and would like to change that. Responsible for meeting scheduling, editing, EDA, model structuring, model training, and submission, and will pick up wherever necessary.

Max Song brings a unique interdisciplinary background to the Drexel MSDS program, merging a solid foundation in psychology from the University of Pittsburgh, with minors in Chinese and English writing. His previous professional experience in mental health and therapy, particularly working with clients with autism and in mental hospitals, has honed his empathetic and analytical skills, which are critical in any data-driven field. As a seasoned musician, having played the cello competitively throughout most of his life and currently engaging as a DJ and music producer, Max has a strong connection with audio data. His technical experience includes working with .wav files and developing projects such as a music recommendation system, a music lyric generation pipeline, and a model to predict popular songs from track metadata. Despite his limited exposure to ornithology, Max is eager to dive into the world of birdsong identification. He is looking forward to assisting in sourcing academic literature and data on birdsongs, in addition to EDA. His prior work with audio and music data uniquely positions him to contribute to the technical aspects of the project.

Jonathan Watkins has honed a fundamental ‘array’ of Data Science competencies through his journey in Drexel’s MSDS program. His academic and professional pursuits span from linguistics to supply chain management and underscore a multidisciplinary approach. Having worked on projects like creating a predictive model for stock prices, using cloud technologies to correlate factors that influence pavement conditions of provincial highways in Ontario, Canada, all the way to working on models to help capture and explain the spread of Dengue in Brazil, he demonstrates continued eagerness to apply his learning to complex real-world challenges. Despite his limited exposure to audio data, Jonathan is keen to expand his expertise into this novel area armed with the tools Drexel has provided him. As such, he is looking forward to becoming a pseudo-SME in birdsongs by the end of the project. He aims to contribute to the group through his storytelling and strong writing skills, eye for visual details related to EDA, and adaptability as the capstone project requires.

Team Communication:

[How do you communicate with each other? Provide some details about the schedules of meetings, communication tools, documents sharing, etc. It is particularly important if your team have both on-campus and online students.]

We have established a communication protocol collectively to ensure successful collaboration and effective project management throughout the project. This involves utilizing a dedicated chat platform all group members are comfortable with, allowing for continuous team dialogue. Weekly synchronous checkpoint meetings complement this. These meetings serve to delineate objectives and strategize on the equitable workload distribution among our team. Both document and output management have been centralized through the use of a Google Drive folder. This approach helps to streamline our workflow and facilitate efficient information exchange, ensuring immediate access to the latest updated project advancements and resources.

Team Issues:

[Identify any issues such as skill levels and scheduling problem that constitute risks for the project and discuss how you will address these issues.]

Throughout this first phase of the project, we may encounter challenges, particularly concerning the dataset. We have addressed the majority of these concerns in the main issue section of this document. We recognize that the project involves unfamiliar material, nevertheless, we are confident our foundational knowledge is sufficient to navigate through and address the complexities of the work effectively.

As of the time of the creation of this document, we do neither foresee nor anticipate any direct scheduling conflicts. As stated in the section “Team Communication”, we agree to handle and communicate any issues promptly allowing for accommodations. Any knowledge gaps in our team will be handled as encountered. The aim of picking a project that was new to us was to widen our knowledge base, so knowledge gaps are not only expected but hoped for.

Table of Contributions

The table below identifies contributors to various sections of this document.

	Section	Writing	Editing
1	**Project**	**All**	**All**
2	**Team**	**All**	**All**
3	**Plan**	**None**	**None**

Grading

The grade is given on the basis of quality, clarity, presentation, completeness, and writing of each section in the report. This is the grade of the group. Individual grades will be assigned at the end of the term when peer reviews are collected.

References

Disabato, S., Canonaco, G., & Flikkema, P. G. (2021). *Birdsong detection at the edge with deep learning.* IEEE Transactions on Smart Computing, https://doi.org/10.1109/TSC.2021.3097234

Gallagher, T. (2015, January 15). The birth of natural sound recording. *Living Bird Magazine*. Retrieved from https://www.allaboutbirds.org/news/the-birth-of-natural-sound-recording/

Howard, Addison, et al. "Cornell Birdcall Identification." *Kaggle*, 2020, www.kaggle.com/competitions/birdsong-recognition.

Jetz, W., Thomas, G. H., Joy, J. B., Hartmann, K., & Mooers, A. O. (2012, October 31). *The global diversity of birds in space and Time*. Nature News. https://www.nature.com/articles/nature11631

Marini, A., Turatti, A. J., Britto, A. S., & Koerich, A. L. (2015). *Visual and acoustic identification of bird species | IEEE conference publication | IEEE Xplore*. Visual and acoustic identification of bird species. https://ieeexplore.ieee.org/abstract/document/7178383/

Mehyadin, A. E., Abdulazeez, A. M., & Hasan, D. A. (2021). *Birds Sound Classification Based on Machine Learning Algorithms*. Retrieved from https://www.researchgate.net/publication/352523116_Birds_Sound_Classification_Based_on_Machine_Learning_Algorithms

Rivera, M., Edwards, J. A., Hauber, M. E., & Woolley, S. M. N. (2023). *Machine learning and statistical classification of birdsong link vocal acoustic features with phylogeny*. Scientific Reports, 3. https://doi.org/10.1038/s41598-023-33825-5

Sprengel, E., Jaggi, M., Kilcher, Y., & Hofmann, T. (2016). *Audio based bird species identification using deep learning techniques*. LifeCLEF 2016. Retrieved from https://infoscience.epfl.ch/record/229232/files/16090547.pdf

Tang, Y., Liu, C., & Yuan, X. (2024). *Recognition of bird species with birdsong records using machine learning methods*. Plos One. https://doi.org/10.1371/journal.pone.0297988

Wada, H. (2010). The development of birdsong. *Nature Education Knowledge*, 3(10), 86. Retrieved from https://www.nature.com/scitable/knowledge/library/the-development-of-birdsong-16133266/