

MarineSomniac

An Interactive Sleep Stage Scoring Tool



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PROBLEM STATEMENT

The current methodologies for sleep scoring and behavioral analysis in marine mammals, specifically Northern Elephant Seals, are predominantly tailored for human data and require extensive technical expertise in software and data science. This presents a significant barrier for ecologists and researchers who need accessible, automated tools to analyze complex electrophysiological and motion data. The lack of tailored solutions hinders the ability to accurately classify sleep states and respiratory conditions in these animals, which is crucial for understanding their behavior and physiology in both natural and controlled environments.

Therefore, the goal of this project is to develop a robust, scalable, and user-friendly analytical toolkit that can process multi-channel time-series data from Northern Elephant Seals, accurately classify various behavioral states, and provide insights that are easily interpretable by researchers with varying levels of technical expertise. Furthermore, this project aims to bridge the gap between advanced data science techniques and practical ecological research, facilitating better understanding and conservation of marine mammals. This work also serves as a stepping stone to not only facilitate better understanding and conservation of marine mammals but also land mammals. The insights derived from this investigative effort will hopefully become building blocks for future research in aiding conservation efforts in the field of ecology.

DATA SCIENCE PIPELINE

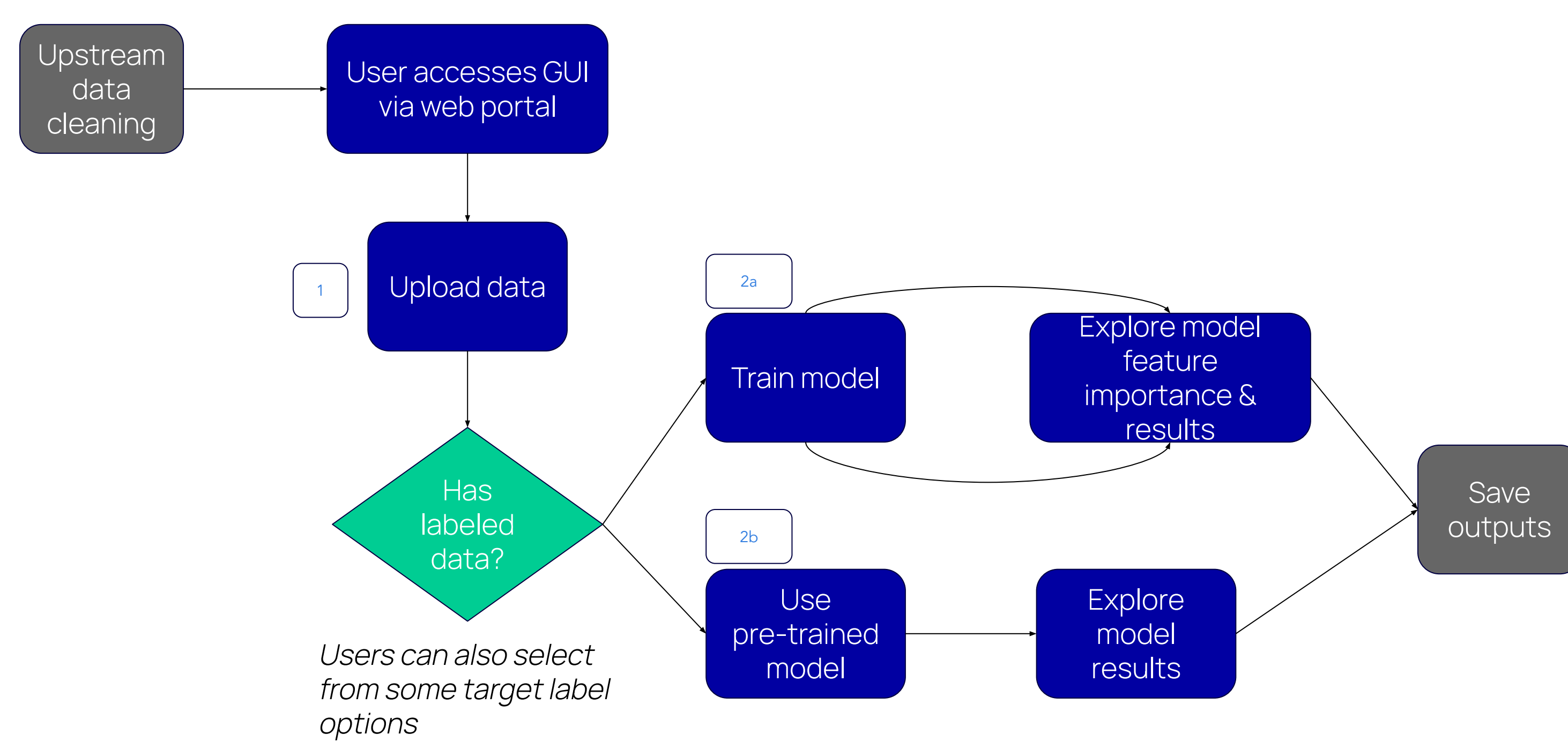
- Acquire:** Data was previously gathered by Dr. Kendall-Bar. The raw signal data captured through the animal sensors was then prepared. Dr. Kendall-Bar also had manually classified sleep, behavioral, and respiratory stages. The signal data was shared as EDF and the labels were in CSV files with corresponding timestamps. The final source data included a rich dataset collected from various instruments including EEG, ECG, and motion sensors. The data collection process involved deploying custom non-invasive head caps and waterproof housings on the seals to record their physiological and environmental parameters.
- Prepare:** The identification of methods for preliminary analysis was driven by the need to understand the complex electrophysiological and motion data collected from Northern Elephant Seals. The project began with Exploratory Data Analysis (EDA) to uncover patterns and insights within the dataset. Tools such as MNE-Python were employed to handle and visualize the EDF files containing electrophysiological data. This initial exploration revealed significant features, such as the prominence of delta waves (0.5 - 4 Hz) in EEG signals during slow-wave sleep, which contrasted with their absence in REM sleep and minimal presence in other stages. Using EDA was significant because it allowed the team to identify key characteristics and anomalies in the data, guiding subsequent analytical steps. For example, the identification of delta waves as a critical feature influenced the decision to include spectral power calculations in the feature extraction process. This method also highlighted the need for careful preprocessing, such as time alignment of labels and removal of outliers, ensuring the integrity of the data used for model training. To generate features, we used a variety of methods, including from existing time series and signal processing packages, to help calculate dimensions like mean, standard deviation, delta/alpha/beta. powers, low frequency and very low frequency heart rate.
- Model:** Once data was processed and new features were generated, simple classification models like logistic regression, decision tree and random forest were all deployed. The decision tree/random forest models yielded more promising results. After more analysis and some research, a LightGBM classifier ended up being the preferred choice. Existing sleep classification packages for human sleep such as yasa also employed a LightGBM classifier, so there was some existing precedent. The LightGBM classifier also had a feature importance scoring tool that allowed for further model training and optimization.
- Scale:** Scaling MarineSomniac involves adding features that will allow ecologists and researchers to train models not just on marine mammals but also other mammals and animals in the wild. The hope is to expand features and capabilities of this project such that polysomnographic data can be studied and trained on for various animals while accepting various forms of data. This will allow research in the area of environmental conservation and animal physiology.
- Report:** MarineSomniac successfully classified sleep states in Northern Elephant Seals, with the LightGBM classifier improving accuracy to 80.1% and better detecting SWS and REM stages. Key metrics, including overall and per-class accuracy, highlighted the model's performance. Visualizations comparing heart rate and EEG signals with true and predicted sleep states provided clear insights into model effectiveness. Features like delta spectral power and heart rate variability were emphasized for accurate classification. These findings, supported by detailed metrics and visual aids, aim to facilitate further research and application in marine mammal sleep studies.

FINAL SOLUTION ARCHITECTURE

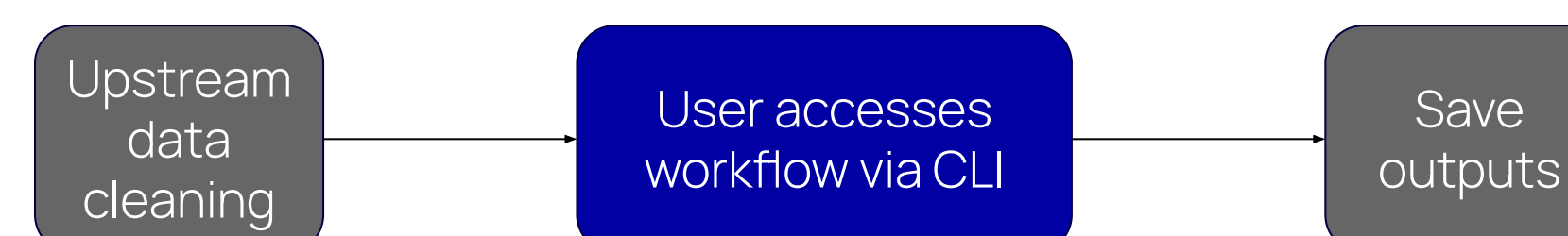
Our final solution provides two methods for interacting.

The first option is via a web UI, which would be hosted on a server and deployed in production in the future. This option would allow any user to access the GUI like a website and upload their own data, with or without labels. If they have labeled data, they would be able to train their own model and then explore the model results and the features generated by the tool. This would allow the user to then go back and re-train model based on specific features or signals and continue to iterate on the model itself. If a researcher doesn't have a sample of labeled sleep data, they would be able to use the pre-trained data as a starting point. The caveat here is that for non-seal based data, we would likely expect accuracy to be fairly low. We hope that in the future, the pre-trained model would be optimized with more and more data. The user could always then use the model output, updated any incorrect labels, and then re-submit it into the tool and train based on their species. The user is then able to save any outputs, including the model, and continue on with their research and analyses. We expect to be the primary method through which someone would use this solution.

Solution 1 (Web UI)



Solution 2 (Command Line Tool/Python Package)



INSIGHTS

- The commonly used features and techniques used to study human sleep can't always be applied to animals. It's important to test different features and assess their effectiveness.
- The transition from RandomForestClassifier to LightGBM significantly improved the overall accuracy of sleep state predictions for the seal "Wednesday," increasing it from 65% to 80.1%, with notable improvements in detecting SWS and REM stages.
- Applying a model trained on one seal (Wednesday) to other seals (HypoactiveHeidi, AshyAshley, BerthaBeauty, SnoozySuzy, and JauntingJuliette) showed varied results, indicating that while the model generalizes better than random, individual variations in the seals' signals require further customization.
- Using a leave-one-out approach, where the model is trained on data from five seals and tested on the sixth, demonstrated higher predictive accuracy, suggesting that including more diverse training data helps the model learn the varying distributions across different seals.

Model Results, per seal

Sleep State	Wednesday (validation)	Wednesday (final model)	AshyAshley	BerthaBeauty	JauntingJuliette	HypoactiveHeidi
Active Waking	91.99%	64.34%	96.39%	75.90%	54.96%	99.66%
Quiet Waking	49.43%	14.19%	12.26%	56.49%	5.97%	20.28%
Drowsiness	46.48%	0.00%	31.68%	19.14%	--	--
SWS	83.44%	70.20%	50.00%	46.70%	86.24%	44.44%
REM	63.37%	94.08%	71.64%	56.13%	59.85%	24.57%
Overall	78.18%	57.07%	66.24%	64.66%	50.25%	96.45%

