Validating Few-shot Bird Vocalisation Detection through Causal Explanations (REX)

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1 Introduction

Autonomous acoustic monitoring is becoming an increasingly important tool for conservation efforts and ecosystem health assessment. However, biodiversity monitoring using deep learning on bioacoustic data is limited by sparse labeled data, making few-shot learning approaches particularly promising for this domain. This approach raises the following critical question: *Do these models learn biologically meaningful acoustic features or exploit spurious dataset patterns?*

Current explainability tools (LIME, SHAP) show *which* features influence decisions but not *whether those features are causally necessary*. For conservation applications, this distinction is crucial as false or missed detections could have cascading consequences.

Our approach: We propose applying REX, a causal explainability method, to validate few-shot bioacoustic models before field deployment. ReX identifies minimal sufficient features for classification, enabling biological validation of model reasoning.

Planned validation: DCASE 2024 Task 5 benchmark [1] followed by Sensing the Forest real-world recordings from Alice Holt forest.

Keywords: Bioacoustics, Explainable AI, Few-shot Learning, Causal Explanations, Biodiversity Monitoring

2 ReX: Causal Explanations for Audio

REX [2] is a tool for explainble AI (XAI) based on actual causality [3]. Unlike popular XAI tools such as LIME [4] or SHAP [5] which produce *saliency maps* measuring feature contribution, REX finds causal explanations by isolating the input features required to reproduce the original classification. These isolated features are a *sufficient cause* for that classification. In our demo, you will see – and hear – sufficient and necessary explanations for audio classification. We will also demonstrate that, once you know the cause of a classification, it can be used to manipulate the model.

ReX: Causal Responsibility Explanations for AI documentation

3 Sensing the Forest

Sensing the Forest is a project exploring arts, science, and climate change. Two DIY, solar-powered, off-grid audio recorders [6] were deployed in Alice Holt forest to capture soundscape recordings over a year, aiming to support biodiversity monitoring and climate awareness through community science [7]. This motivates our need for interpretable, validated models before applying bird vocalisation detection to the Sensing the Forest dataset.

Sensing the Forest website

4 Future work

1. **Baseline Validation:** Train prototypical networks on DCASE 2024 Task 5 BirdVox subset and establish performance benchmark for bird vocalisation detection [8].

2. **REX Integration:** Adapt ReX for audio analysis to identify minimal sufficient features for classification. Compare identified features with established ornithological acoustic characteristics.

3. **Real-world Validation:** Deploy validated models on Sensing the Forest Alice Holt recordings and assess model robustness across different acoustic environments.

Expected Outcomes: Development of an interpretable validation framework for few-shot bioacoustic models, enabling more confident deployment in conservation applications.

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