

Stony Brook University

# Tracking the Spread of Climate Change Skepticism on X with Simulations and Deep Learning



**METHODOLOGY** 

Uwaila Ekhator, Mason Youngblood, Vicken Hillis

uwailaekhator@u.boisestate.edu, masonyoungblood@gmail.com, vickenhillis@boisestate.edu



#### **INTRODUCTION**

Despite escalating climate impacts, skepticism persists and spreads rapidly through social media [1, 2], which amplifies misinformation and weakens the urgency for action [3, 4, 5]. Understanding the mechanisms behind this spread is critical for effective climate communication.

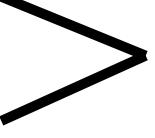
Research Question: Which social learning biases best explain how climate beliefs spread on X?

#### **OBJECTIVE**

We propose an agent-based modeling & simulation-based inference framework to reveal which **social learning biases** shape climate change conversations on X, offering insights to improve online climate dialogue.

### PRELIMINARY FINDINGS

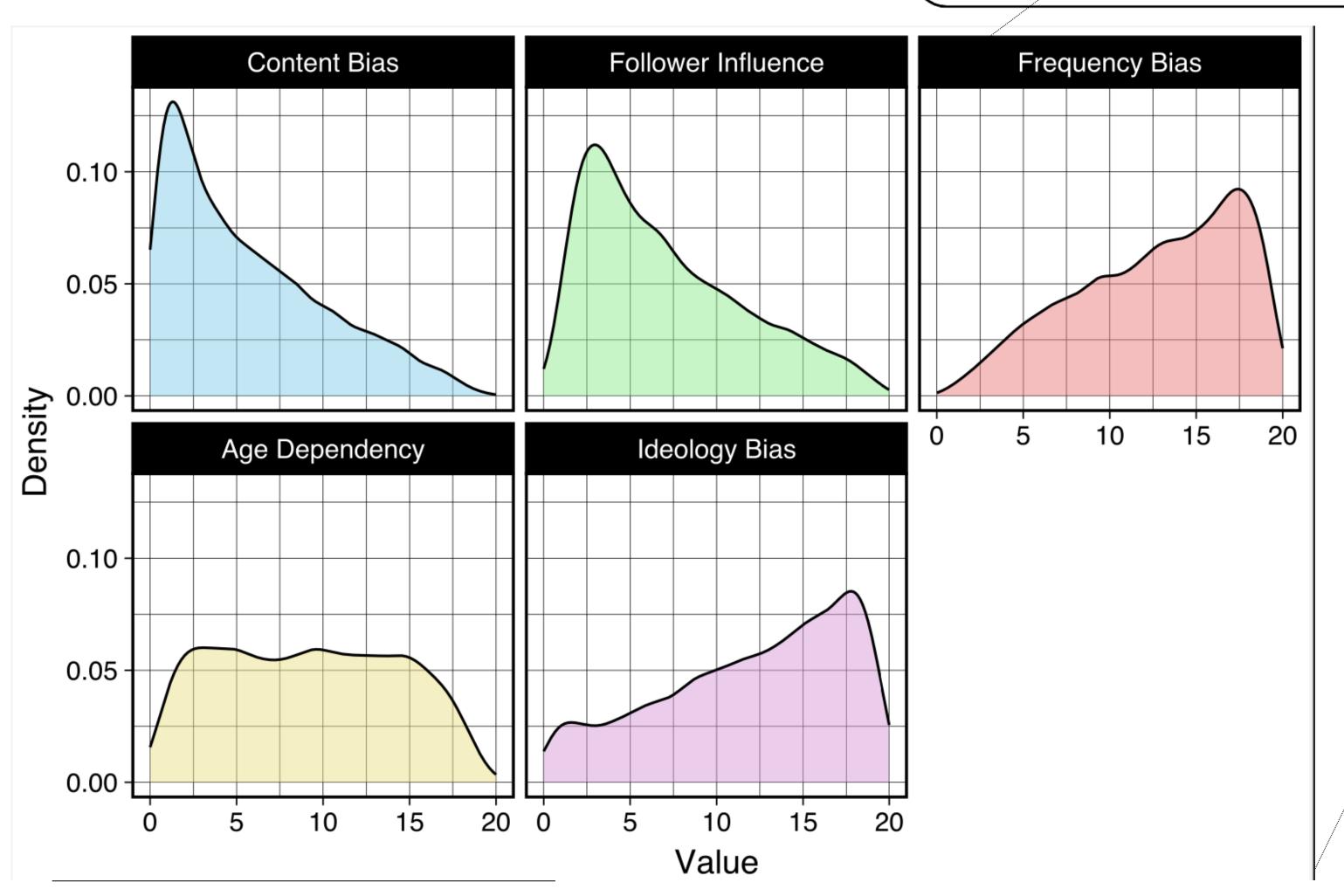
Frequency & Ideology effects



**Content & Follower** influence

Preliminary GLMM analysis revealed that retweeting is ~40% higher within ideological groups, which aligns with the result above.

#### social learning biases Age dependence Content bias Agent-Based Modeling Simulation-Based Inference Select Priors for content Train deep learning model bias, follower influence, on simulated data (output frequency bias, age & ideology bias distributions & priors) Use trained model on observed real-world data to **Run ABM** simulations infer posterior distributions of bias parameters. Output Output **Produces** simulated data distribution: III. Retweet counts Ideology III. Sentiment scores The posterior distributions reveal combinations of biases that best reproduce observed retweet dynamics in real-world data.,



#### **FUTURE WORK**

Use (Generalized Linear **Mixed Models**) GLMMs to test whether retweeting behavior differs across ideological communities in the data.

# **IMPACTS**

The insights from our work will help: (1) identify biases (e.g., if users have a bias towards negative tweets, moderators might design controls to limit the spread of negative or misleading content).

(2) Guide policy makers and climate communicators on message framing.

## REFERENCES

- [1] IPCC. Summary for Policymakers. IPCC, Geneva, Switzerland, 2023.
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- [4] Yanmengqian Zhou and Lijiang Shen. Confirmation bias and the persistence of misinformation on climate change. Communication Research, 49(4):500–523, 2022.
- [5] Matthew J. Hornsey et al. Climate skepticism decreases when the planet gets hotter and conservative support wanes. Global Environmental Change, 74:102492,129 2022.130