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

Uwaila Ekhator, Mason Youngblood,
Vicken Hillis

BOISE STATE UNIVERSITY

Stony Brook University

Tackling Climate Change with Machine Learning Workshop
NeurIPS 2025

NEURAL INFORMATION PROCESSING SYSTEMS

Climate Change AI

Background

- Climate change has severe effects on ecosystems and human societies. January 2025 was the warmest ever, according to the WMO[1].
- Despite scientific evidence, climate skepticism persists, amplified by social media platforms like X (formerly Twitter).
- In 2022, 850,000 tweets on X contained climate-skeptic language, the highest recorded[2].

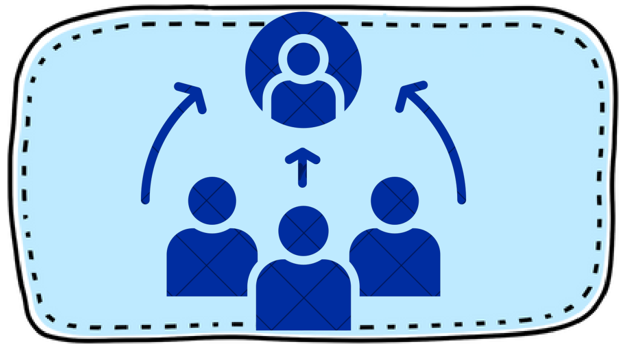
[1]https://wmo.int/media/news/january-2025-sees-record-global-temperatures-despite-la-nina
[2]https://www.thetimes.com/business-money/technology/article/climate-sceptic-tweets-surge- after-musks-twitter-takeover-5mtvnwqzb
Image source: https://www.canva.com/photos/MAENYN4o_AU/

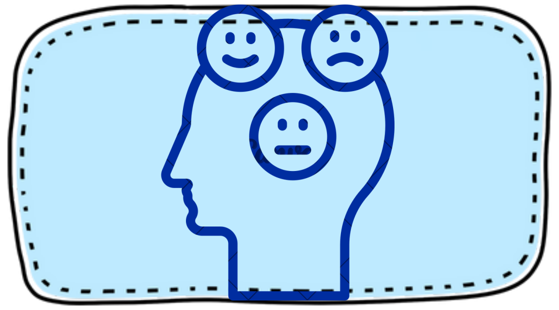
Motivation & Objective

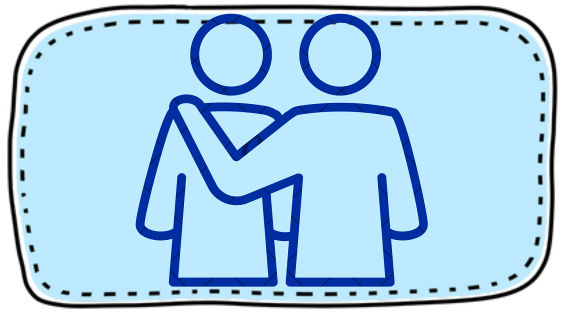
- Skepticism weakens the perceived urgency for action; therefore, understanding the mechanisms that drive the spread of climate skepticism online is important.
- We propose a methodological approach combining **agent-based simulation** with **deep-learning-based simulation inference** to identify which **social learning strategies (SLS) or biases** drive the spread of climate skepticism on X.

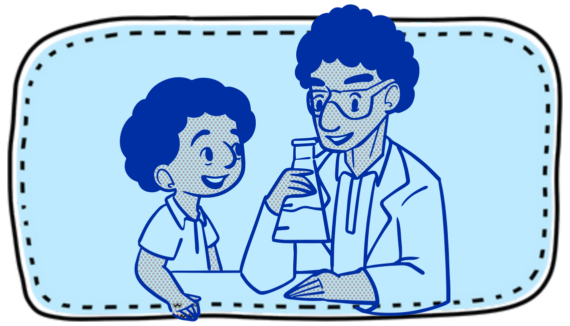
Image source: https://www.iberdrola.com/corporate-governance/governance-sustainability-system/environment-climate-change-policies/climate-action-policy

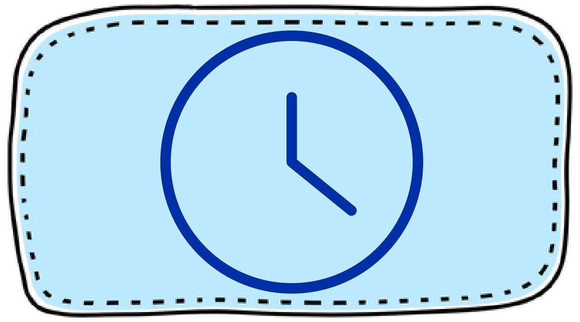
Social Learning Biases


Frequency bias


Content bias


Similarity bias


Demonstrator bias


Age dependence

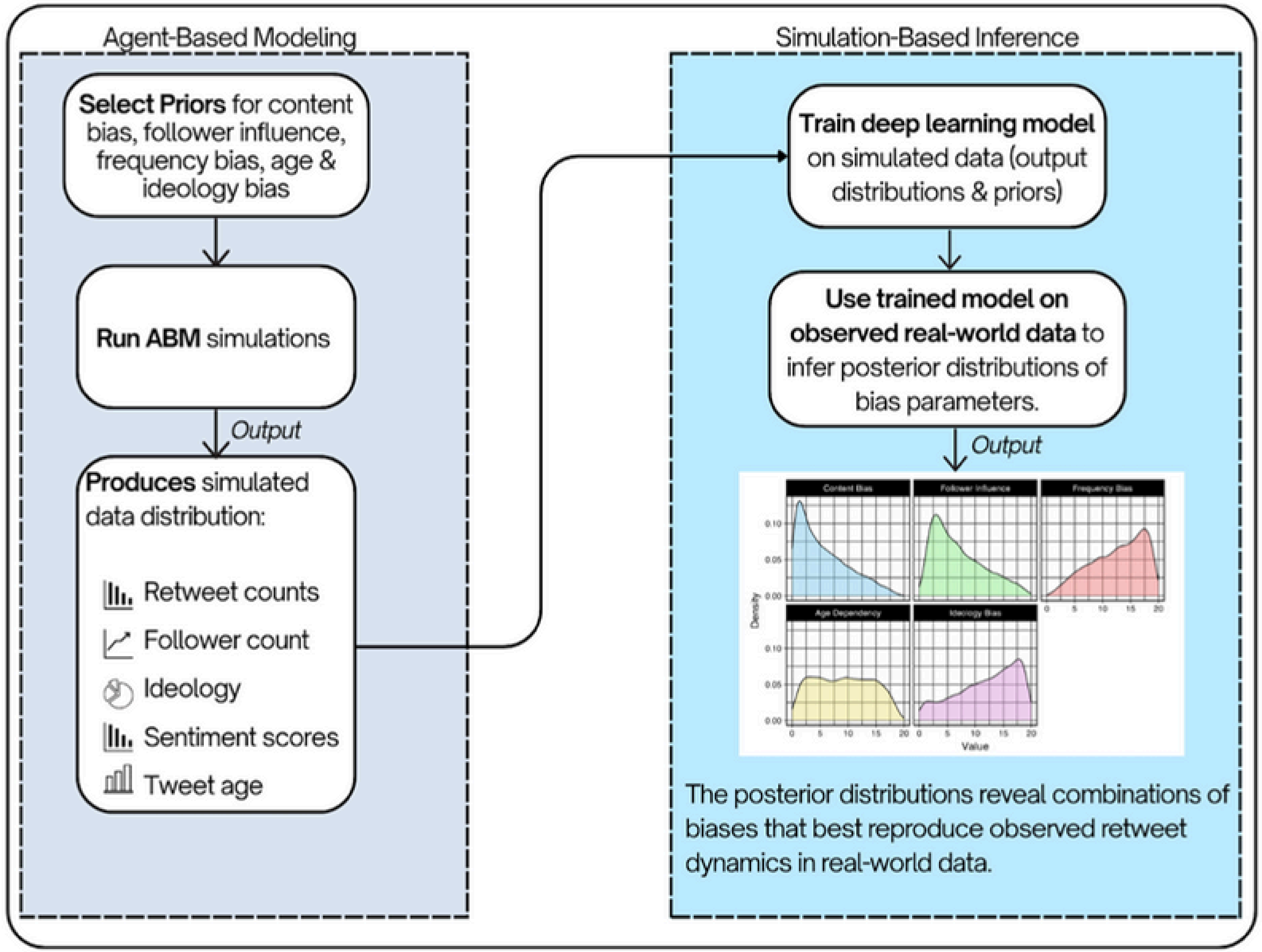
- Social learning strategies (SLS)-> underlying biases guiding what, when, and whom people copy.
- Individual learning is costly, so people resort to social learning.

[3]https://www.nature.com/collections/feibciaebg

Image Source

Proposed Framework

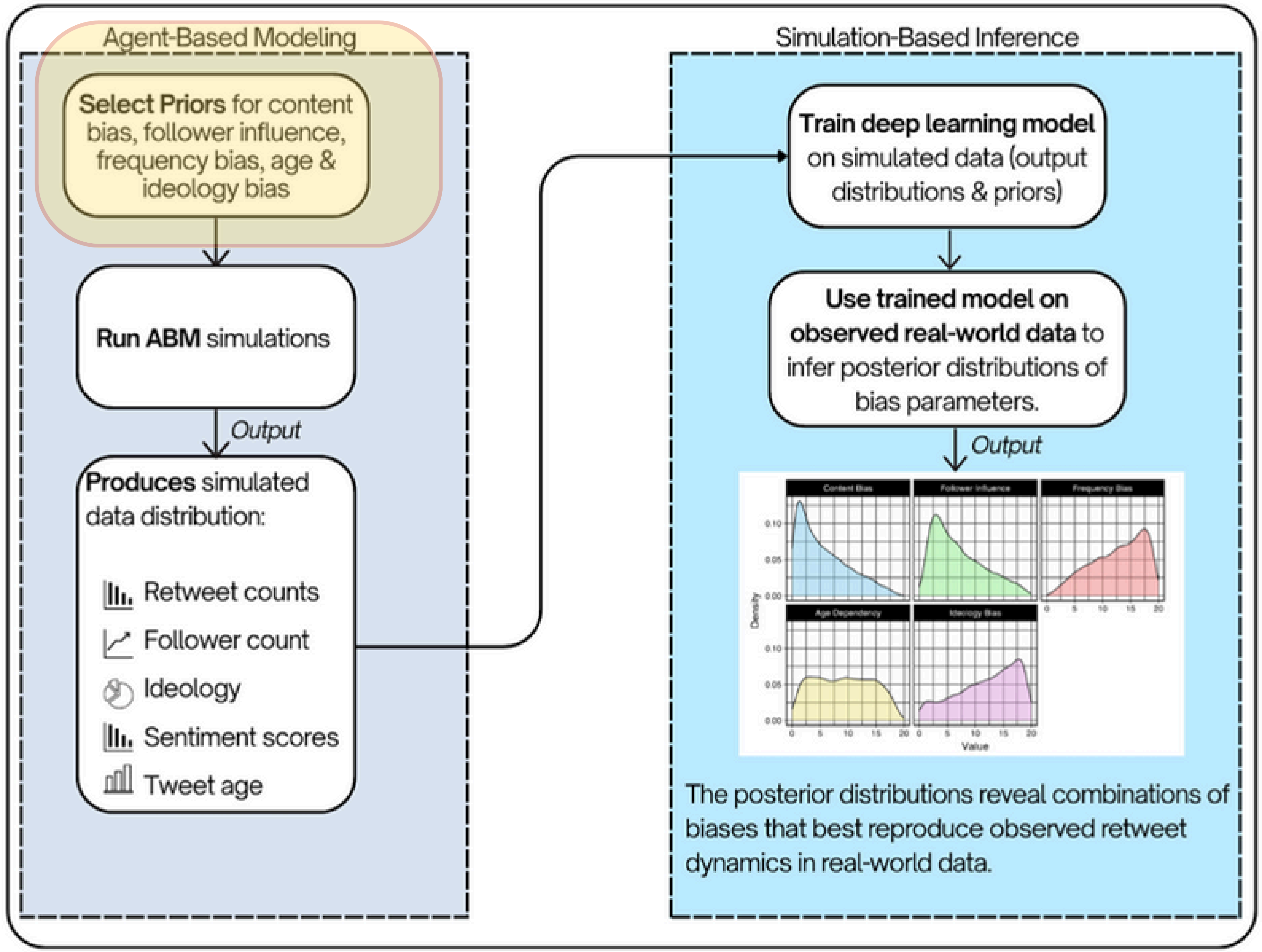
Dataset: a large sample of climate change X data (n = 507,358) curated by Brady et al in 2017.



Proposed Framework

Stages of our framework:

- **Prior distributions**: range of possible parameter values based on assumptions or prior knowledge.



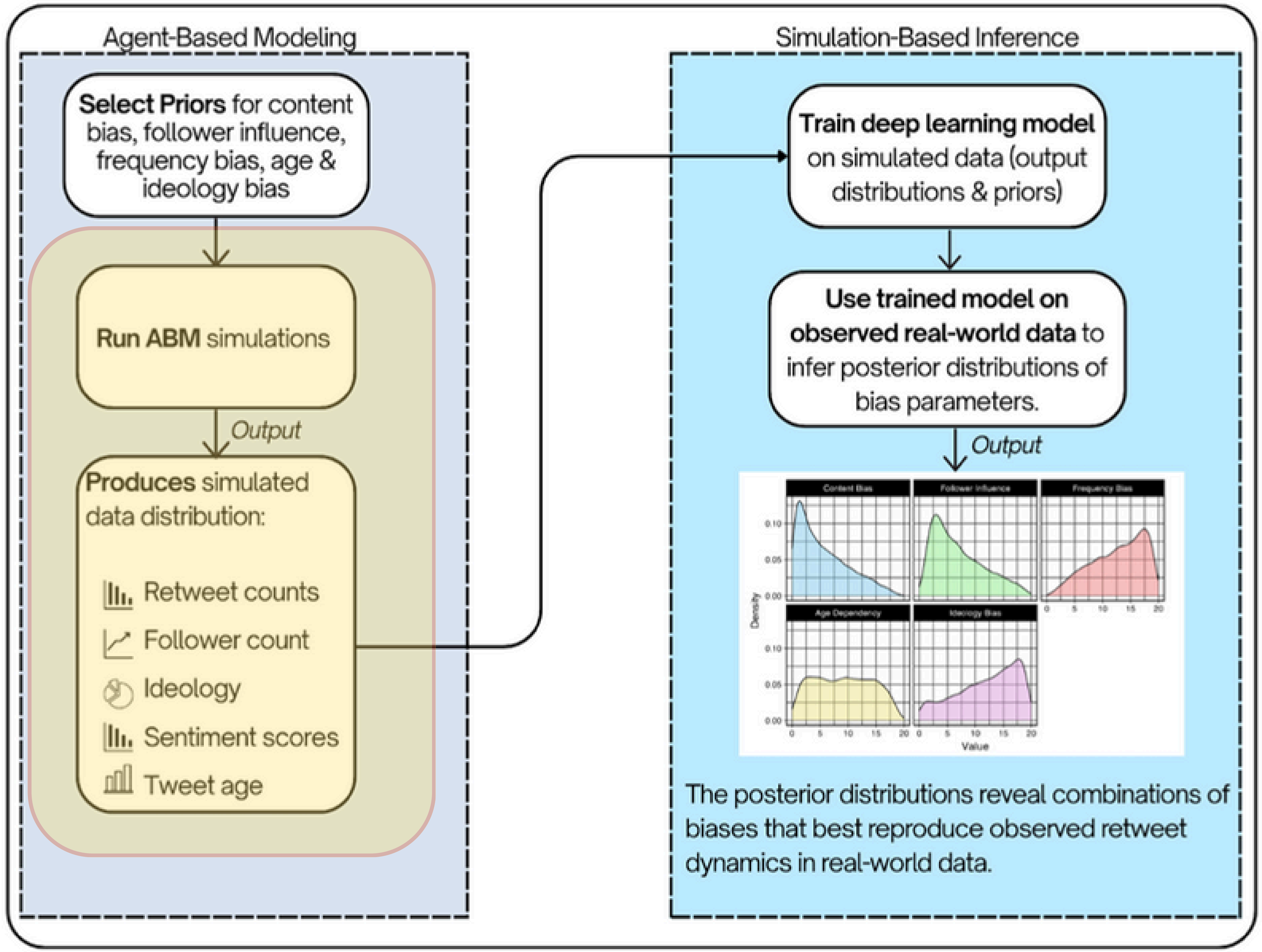
Proposed Framework

Stages of our framework:

ABM: Our ABM simulates interactions between a population of X users with:

- follower counts (T),
- activity levels (r),
- ideologies (G)
- probabilities of tweeting original tweets (μ)

from real users in the observed data.



Proposed Framework

Stages of our framework:

ABM:

Baseline attractiveness for retweeting:

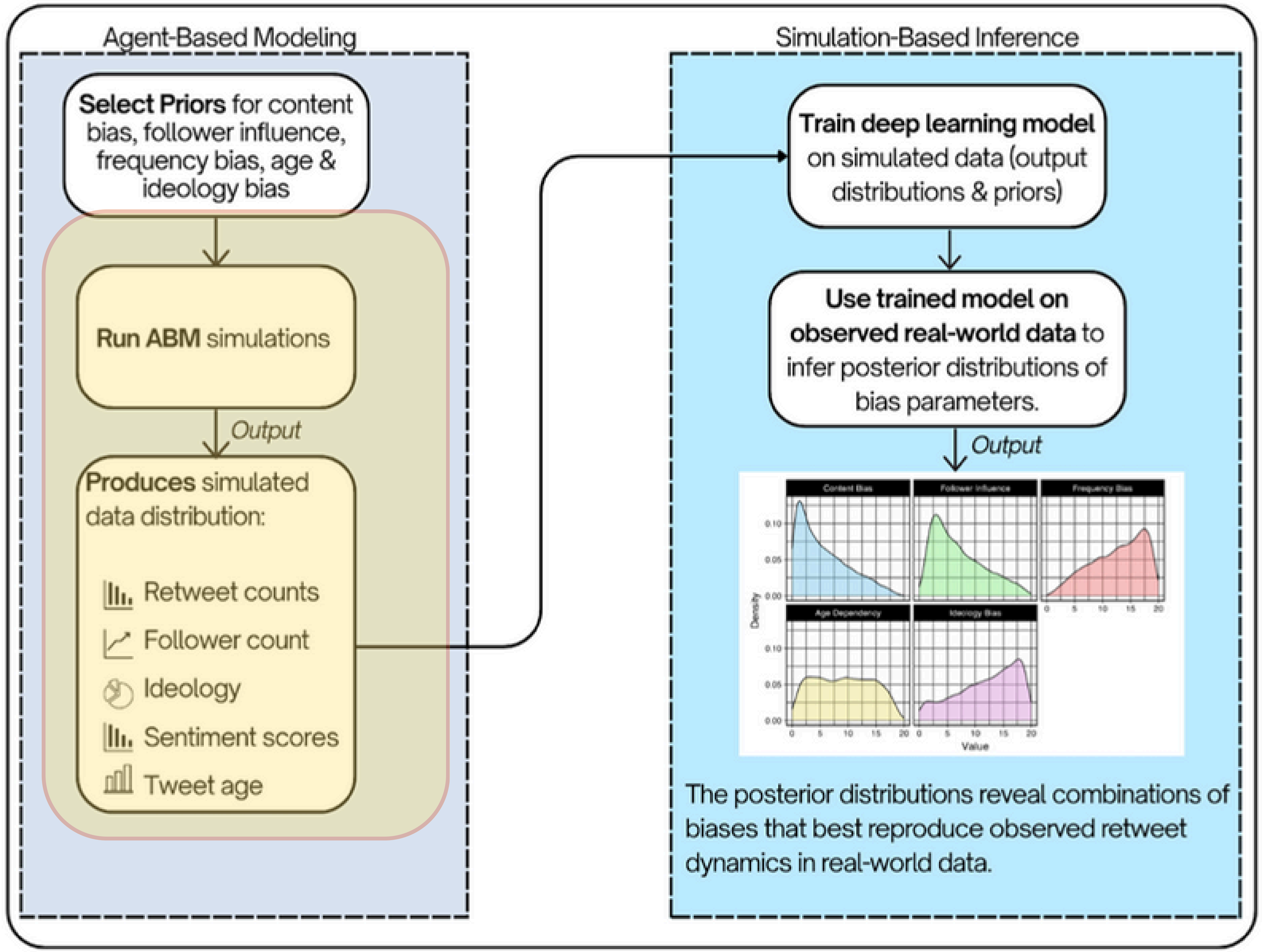
$$b_x = s(\log F_x)^a \cdot s(\log T_x)^d \cdot s(M_x)^c \cdot s(\text{age}_x)^{-g}$$

Ideological differences:

$$G_{u,y} = |\text{ideology}_u - \text{ideology}_y|, \quad \text{for each tweet } y \in q$$

Final retweet probability:

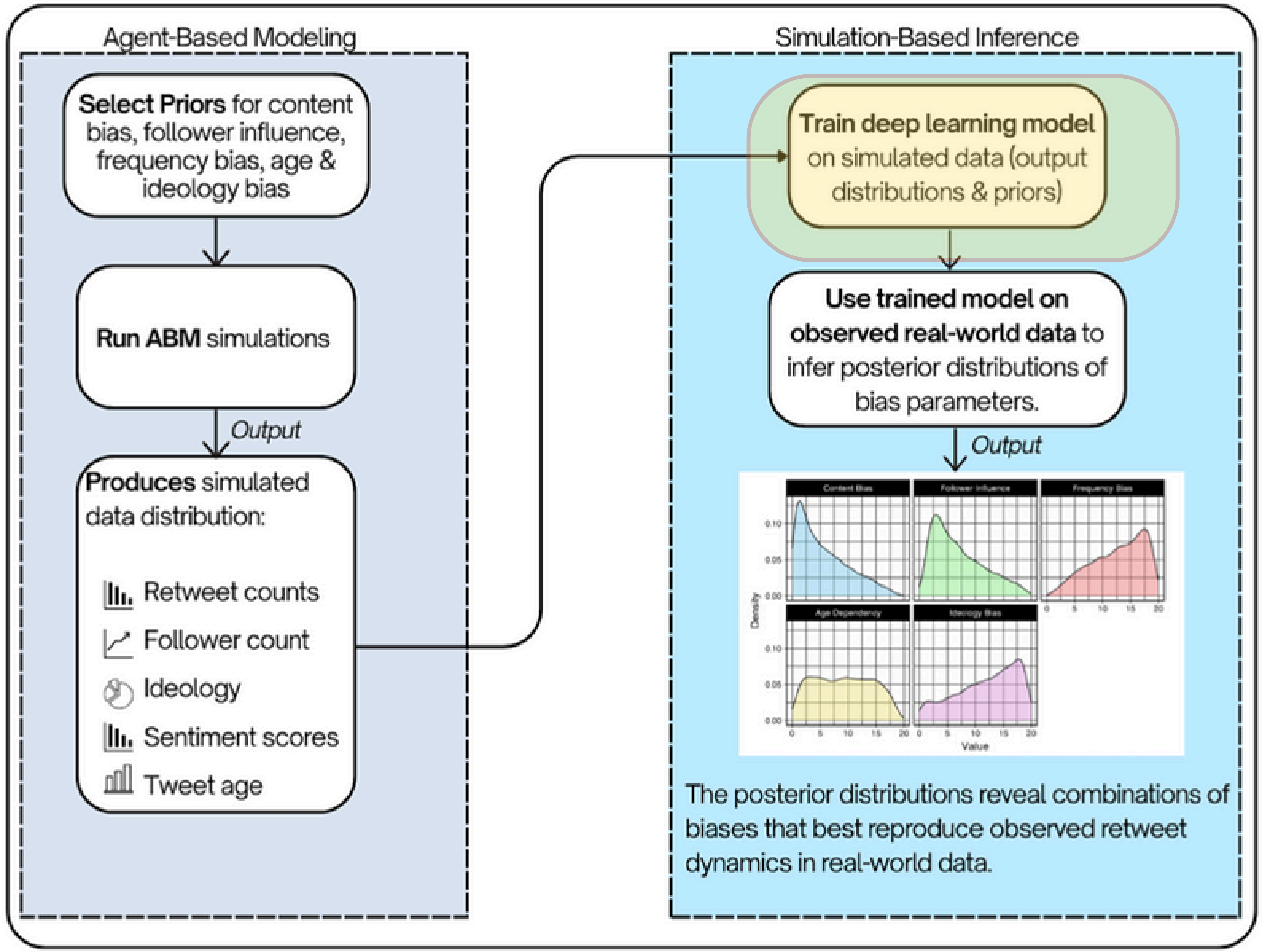
$$P_{u,y} = \frac{b_y \cdot s(G_{u,y})^k}{\sum_{z \in q} b_z \cdot s(G_{u,z})^k}$$



Proposed Framework

Stages of our framework:

SBI: We will conduct SBI using BayesFlow in Python, a library that uses amortized deep neural networks to approximate the posterior distributions of parameters in a generative mode.

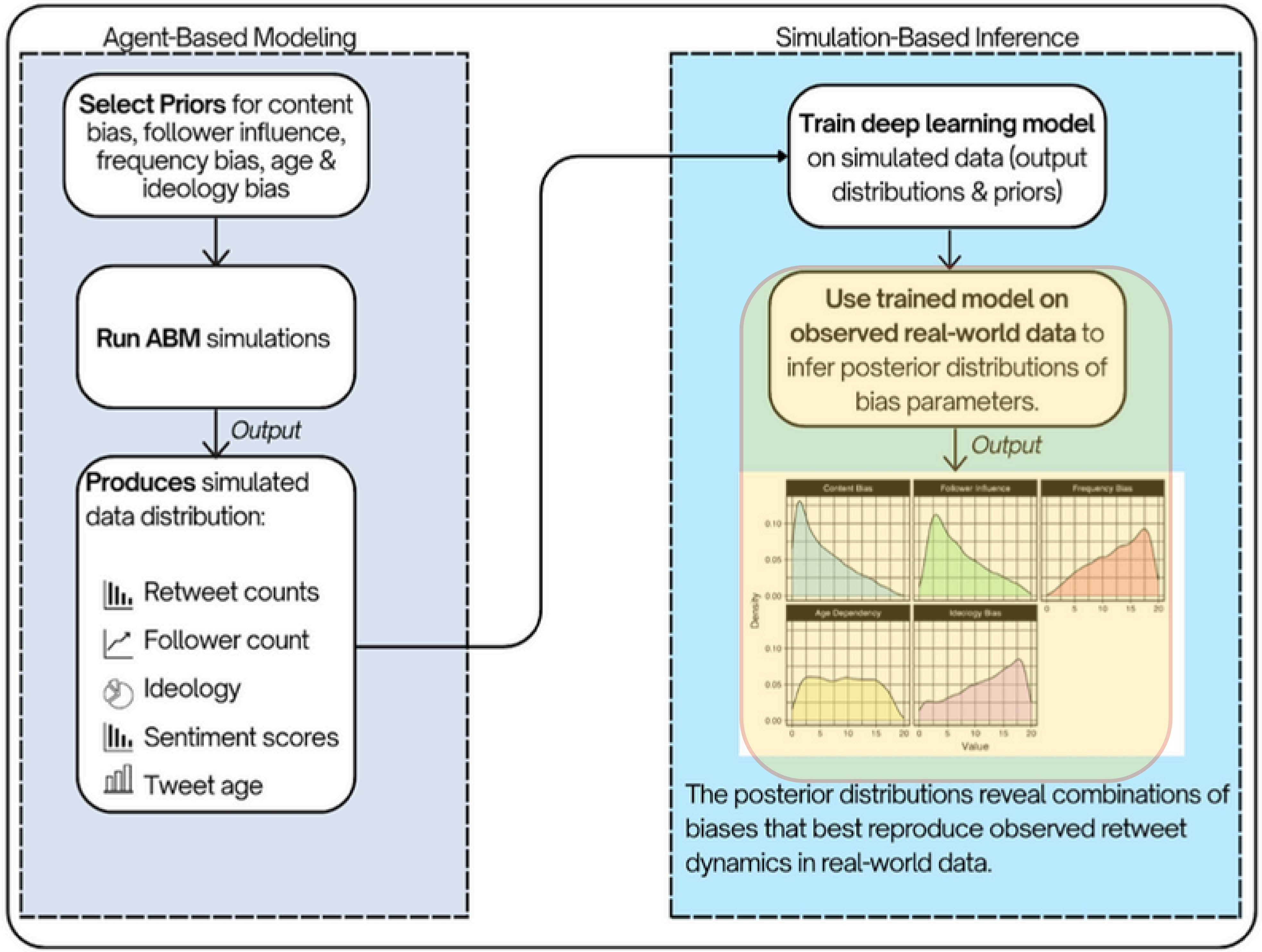


Proposed Framework

Stages of our framework:

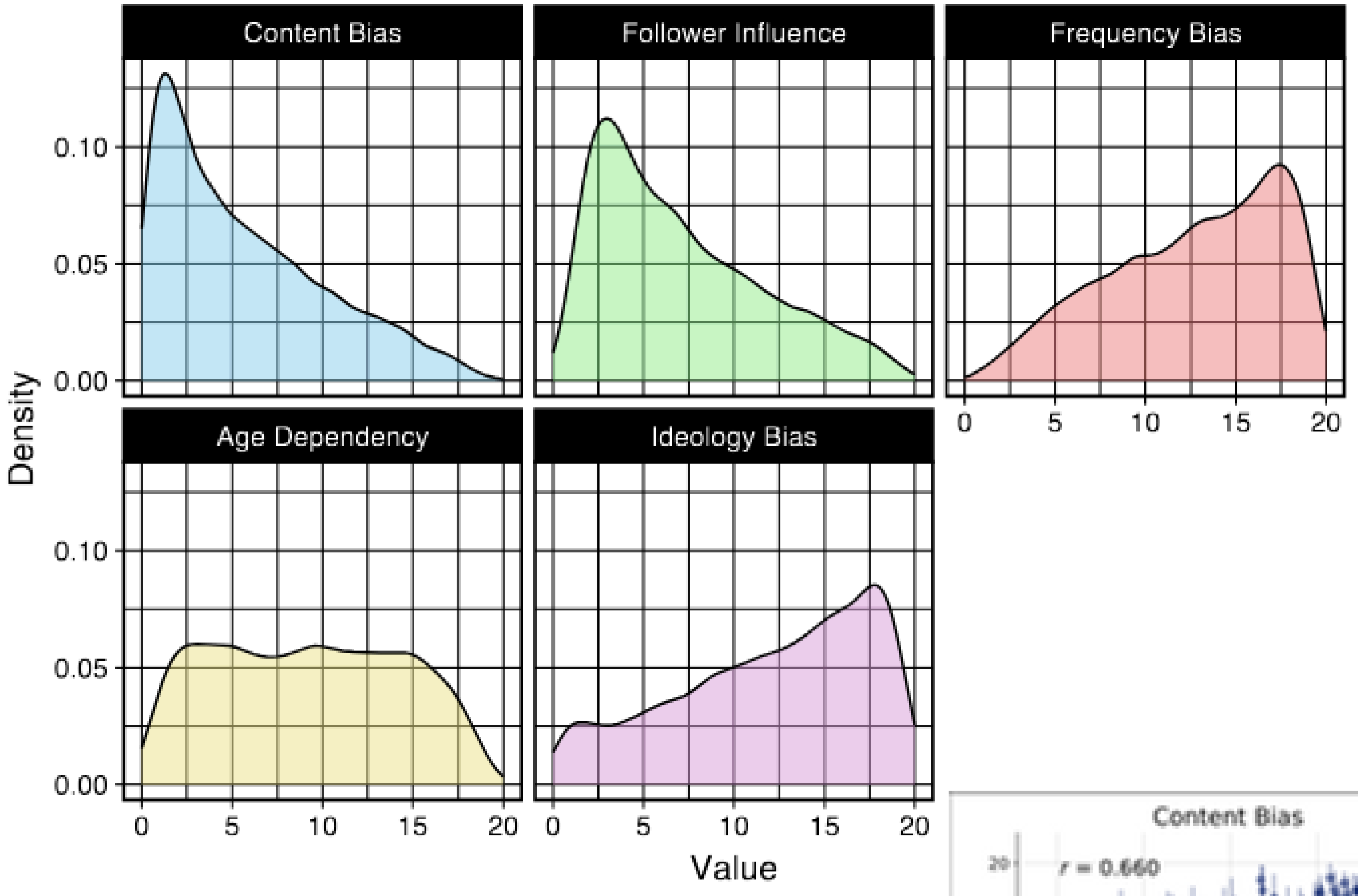
SBI: We will apply the trained neural network to produce posterior predictions for each parameter in the ABM, based on the five distributions computed from the real data.

The posterior distributions reveal the combinations of biases that best reproduce the retweet dynamics in the real dataset.

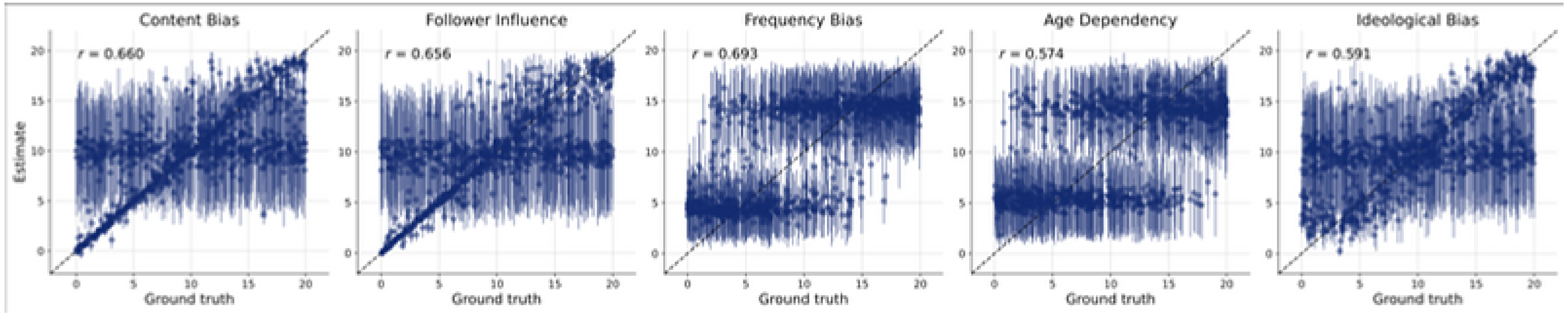


Preliminary Result

Posterior distribution for each parameter.

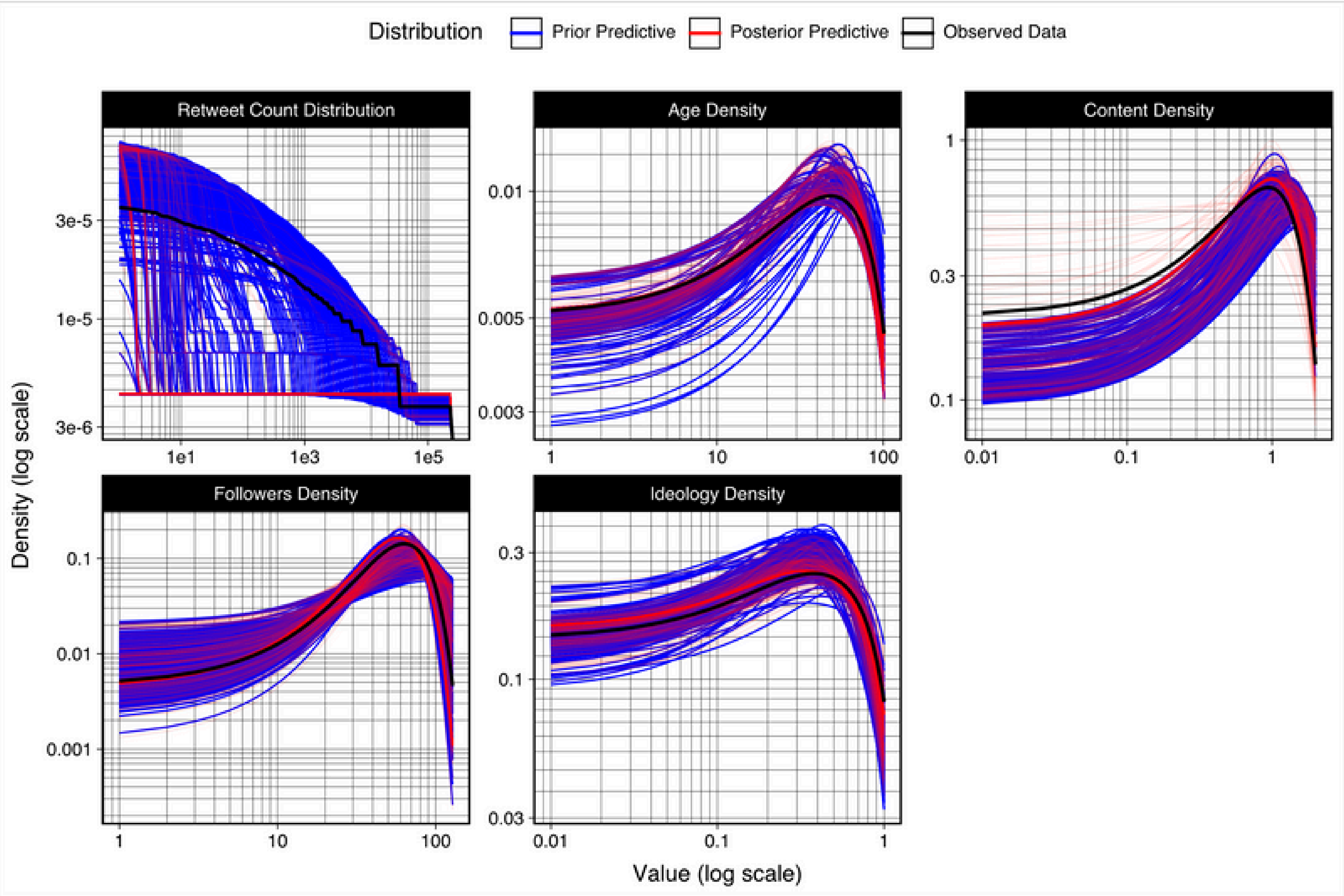


Recovery plot showing model's ability to recover known values of each parameter.



Preliminary Result

Posterior predictive checks:



Future Work

- Use (Generalized Linear Mixed Models) GLMMs to test whether retweeting behavior differs across ideological communities in the dataset

Pathways To Impact

The insights from our work will help:

- Identify social learning biases for content moderation and recommendations (e.g., if users have a bias towards negative tweets, moderators might design controls to limit the spread of negative or misleading content).
- Guide policy makers and climate communicators on message framing..

Thank You!

BOISE STATE UNIVERSITY