

Quantifying Echo-Chamber Formation in Personalized News Feeds

6.3950/6.3952 AIDMS : Final Project

Group 23: Salma Bouzit, Fiona Daly, Olivia Honeycutt, Tina Zhang

Motivation

Problem

Personalized feeds reinforce user preferences, creating echo chambers.

Impact

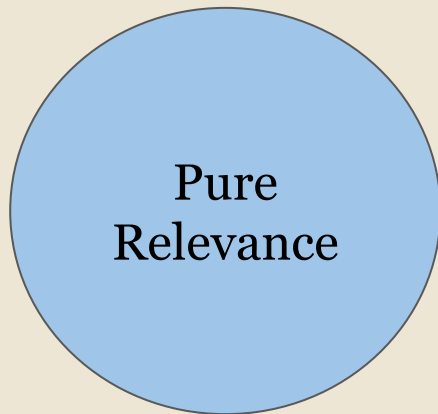
Increased polarization and reduced exposure to diverse viewpoints.

Goal

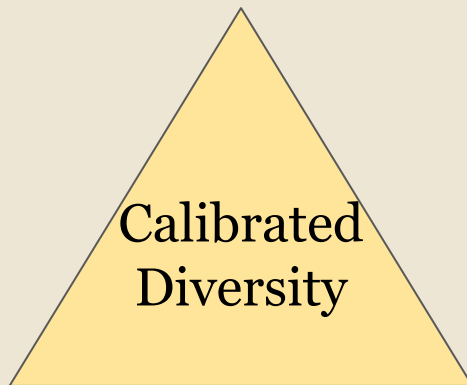
Quantify how echo chambers form across personalization strategies and domains



3 Commonly Studied Recommendation Algorithms



Recommend topics purely **by similarity** to a user's past



Balance preferred topics with contrasting perspectives



Deliberately **include** a few unexpected or cross-ideological pieces

Methods

A banner image for the MIND dataset. It features a dark blue, textured background resembling water or a sky. In the lower center, there is a dark, rocky island or cliff. The text 'MIND: Microsoft News Dataset' is centered in a white, bold, sans-serif font. Below it, in a smaller white font, is the subtitle 'A Large-Scale English Dataset for News Recommendation Research'.

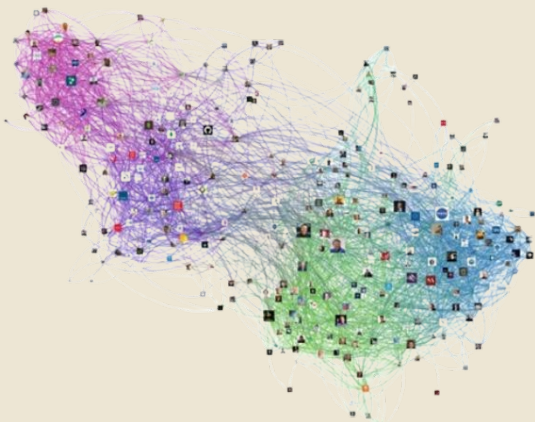
MIND: Microsoft News Dataset

A Large-Scale English Dataset for News Recommendation Research

- ❑ MIND dataset of user **click behavior** and **click history** on news articles
- ❑ Algorithms **recommend articles** to **users** based on each user's past news clicks.
- ❑ Track echo chamber formation with chosen **evaluation methods**.

Pre-existing Evaluation Methods

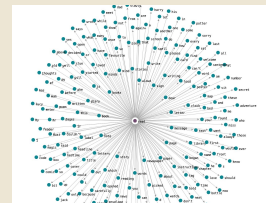
Homophily



Hartmann et al. (2024)

Our Selected Methods

Semantic Diversity



Centroid Distance

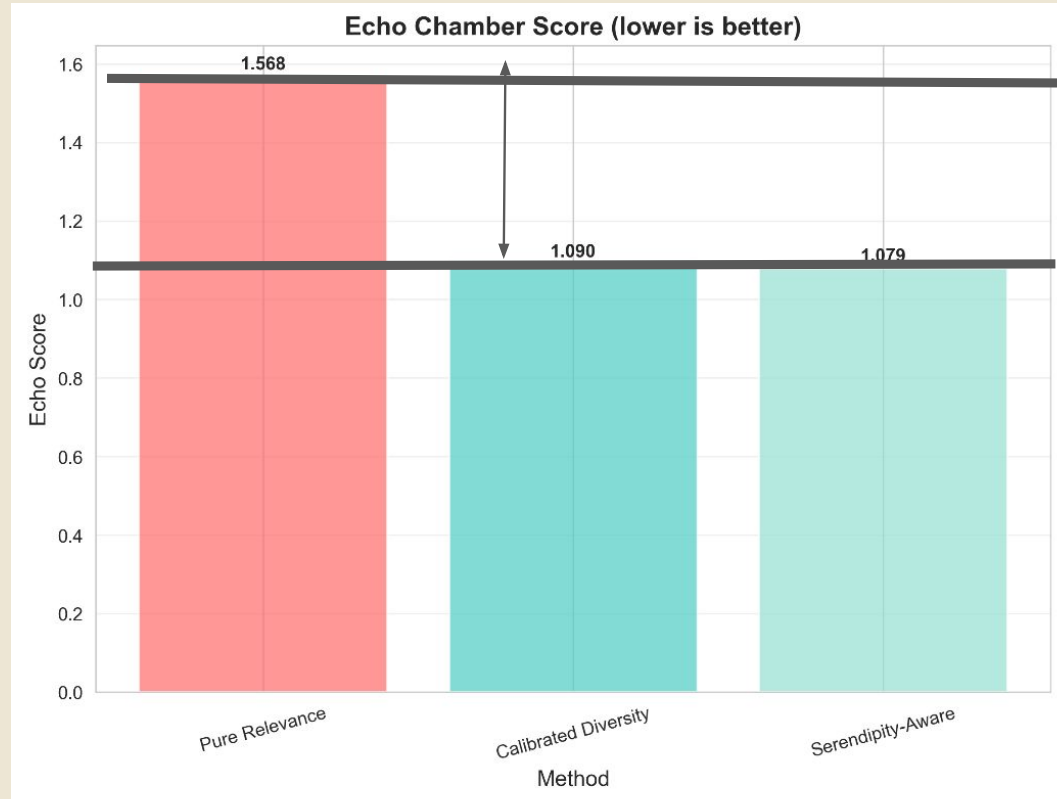


LLM Evaluation

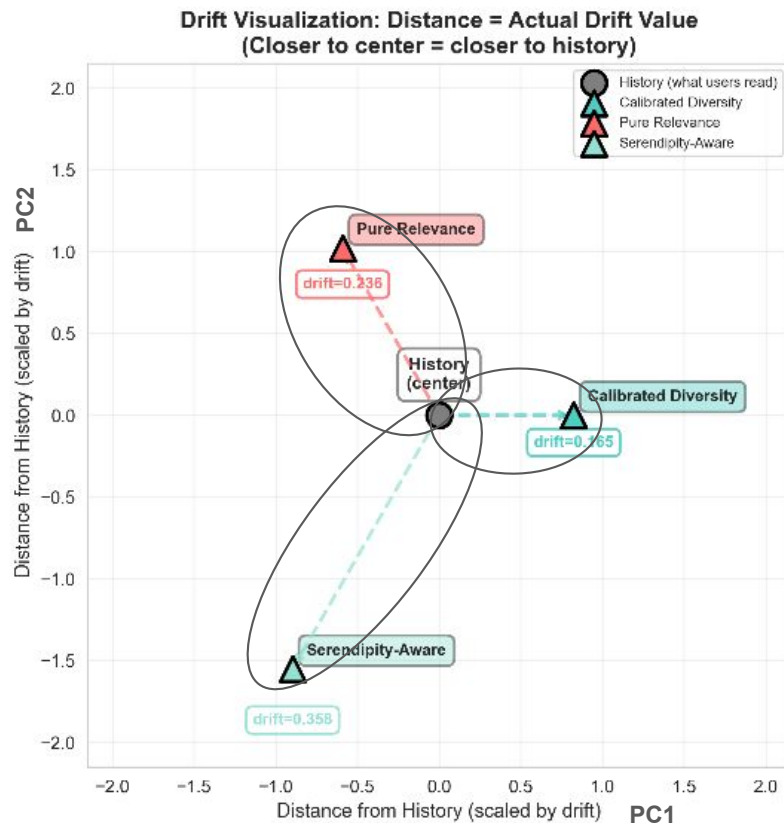


Findings - 1. Semantic Diversity

$$\text{Echo Score} = \frac{\text{History Diversity}}{\text{Recommendation Diversity}}$$



Findings - 2. Centroid Distance

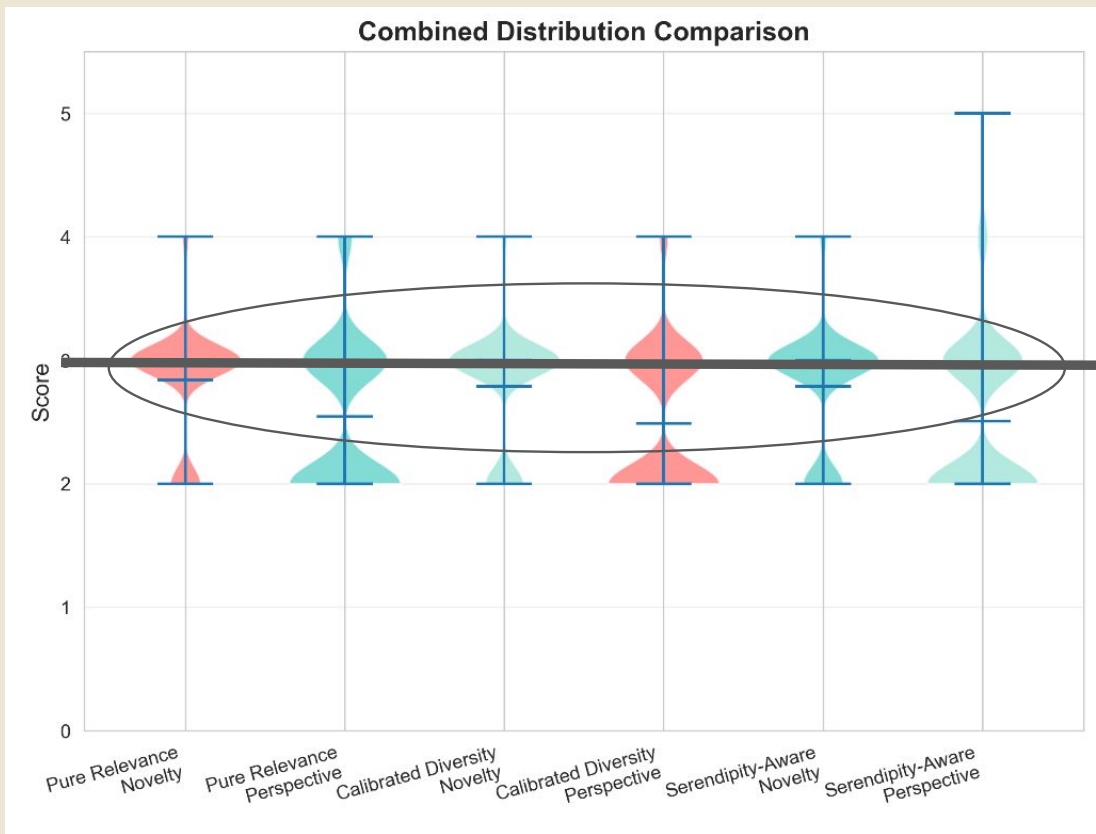


Serendipity-Aware: 0.358

Pure-Relevance: 0.236

Calibrated Diversity: 0.165

Findings - 3. LLM Evaluation (Microsoft Phi-2)



Novelty:

1 = same topics as history

5 = very different topics

Perspective:

1 = same viewpoint as history

5 = diverse viewpoints

Conclusion

Metrics

- **Pure relevance** leads to the **highest** echo-chamber effects, while **serendipity-aware** is **best at mitigating** echo-chamber effects.

Future Work

- Testing **political bias classifier** on politically charged datasets (Twitter, partisan news).
- **Fine-tune LLMs** for echo-chamber detection.

Key Takeaway:
Embedding-based metrics outperform LLM-based metrics.

Thank you for your time!

Any questions?