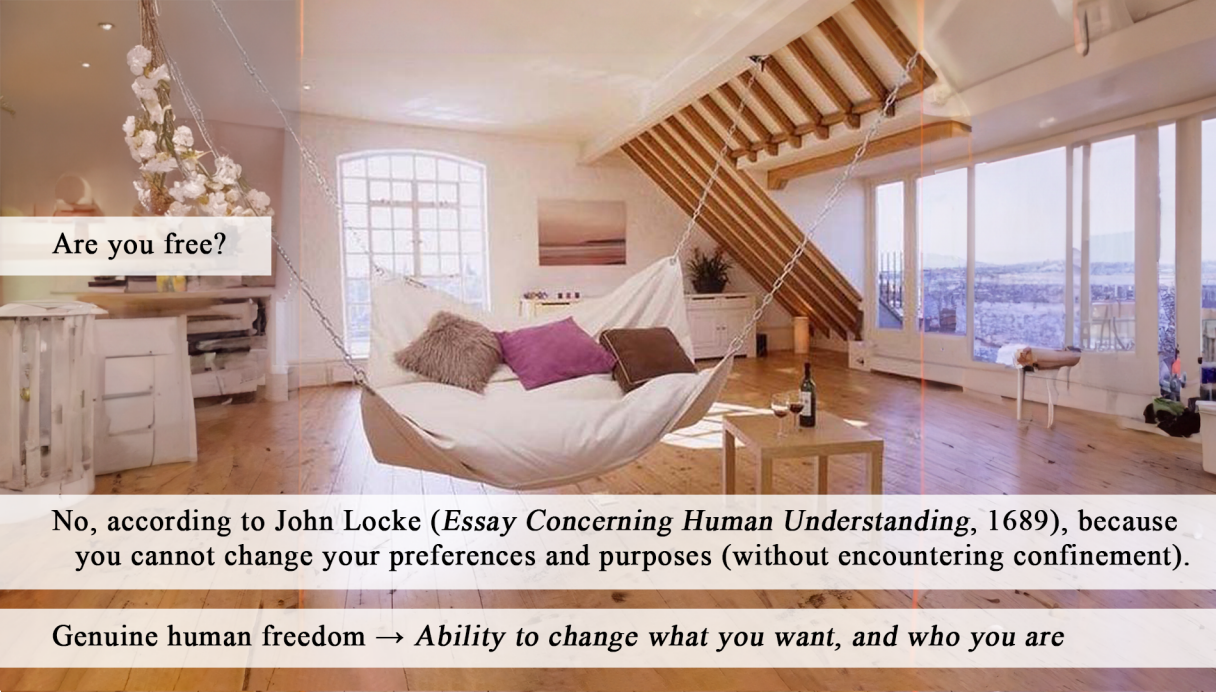


THOUGHT EXPERIMENT: *WHAT IS HUMAN FREEDOM?*

You're inside a pleasurable room that you don't want to leave.
Silently, someone locks the door from the outside.

Are you free?





Are you free?

No, according to John Locke (*Essay Concerning Human Understanding*, 1689), because you cannot change your preferences and purposes (without encountering confinement).

Genuine human freedom → *Ability to change what you want, and who you are*

HOW DO AI RECOMMENDATION ALGORITHMS RESEMBLE THE LOCKED ROOM?



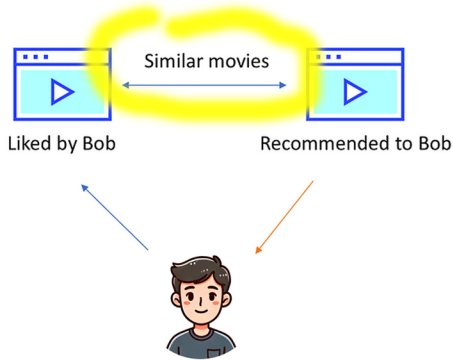
Zero moment: Captured by established preferences
Get what you want, but hard to want something else...
Hard to be *curious*



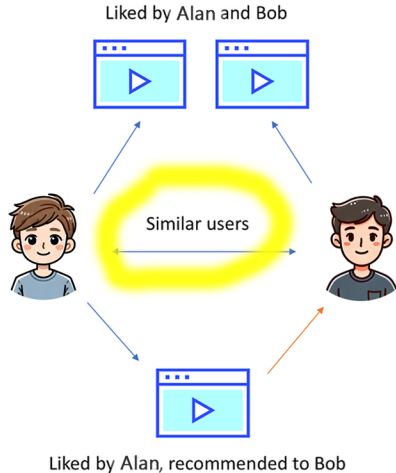
Starts in 0 seconds

HOW RECOMMENDATIONS TRAP ME AS WHO I AM: **NETFLIX**

Content-based filtering



Collaborative filtering



PROBLEM

Recommendation algorithms limit human freedom

↳ Capture us within our established interests, preferences...

Diabolical: Not restricted by opposition of others, but by similarity with *our own past*

NOTE

Film recommendations are insignificant form of imprisonment, but...

Netflix

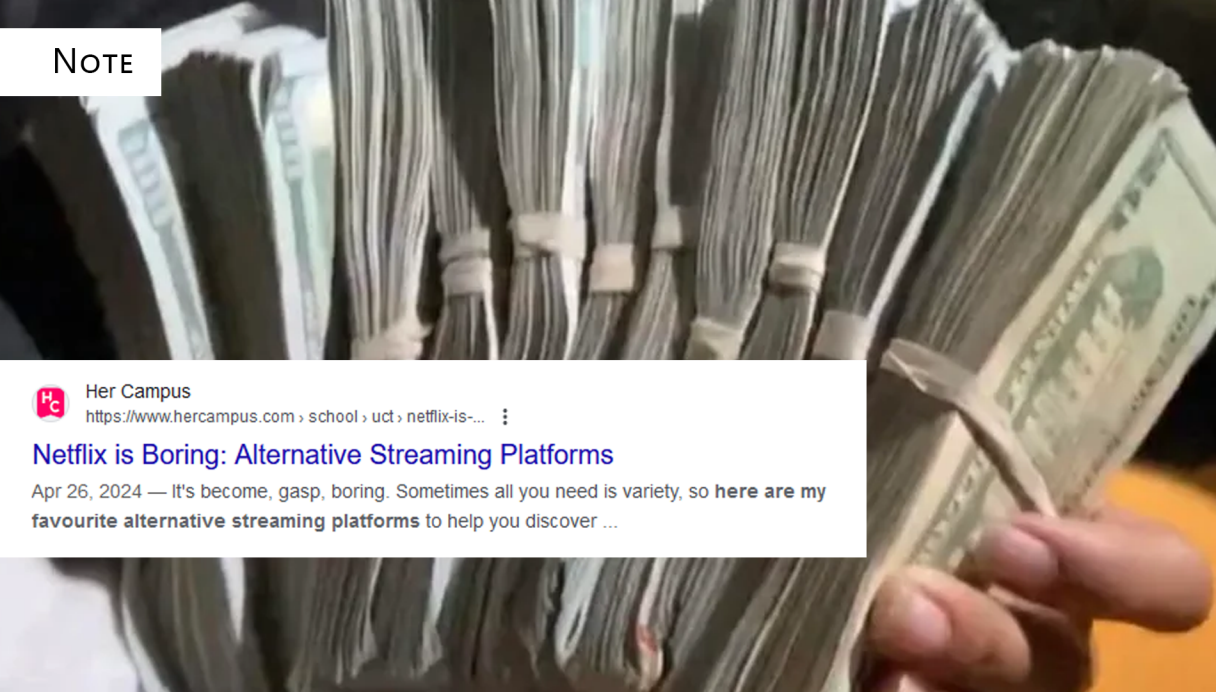
Twitter/X (Social media echo chambers)

LinkedIn

Tinder

So many options, *need* recommendations...





NOTE



Her Campus

<https://www.hercampus.com> › school › uct › netflix-is-... ⋮

Netflix is Boring: Alternative Streaming Platforms

Apr 26, 2024 — It's become, gasp, boring. Sometimes all you need is variety, so **here are my favourite alternative streaming platforms** to help you discover ...

SOLUTION

Recommendation algorithms re-engineered to catalyze new curiosities, interests, and preferences



Expand human freedom (ethics)
Diminish social media echo chambers (society)
Maintain user loyalty (business)

How?

AI: DIFFERENCE *BEFORE* SIMILARITY

Recommendations



Unfamiliar (Unexpected/Novel/Diverse)

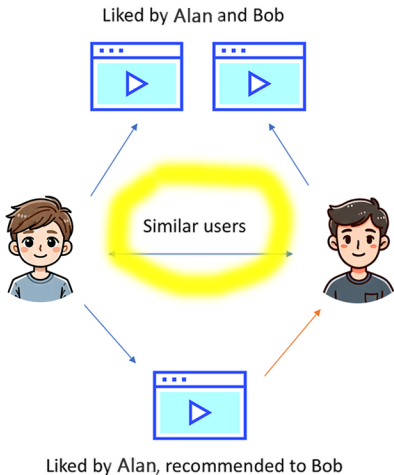
= Not imitating past selections, not technically accurate

Engaging (Provoking curiosity + exploration)

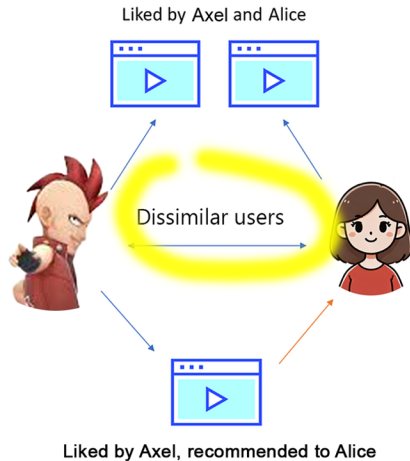
= Relevant to who user *could* be, not to who user *is*

AI: ANTAGONISTIC FILTERING (DIFFERENCE *BEFORE* SIMILARITY)

Collaborative filtering



Antagonistic filtering



AI: PROVOCATION IS BETTER THAN ACCURACY



Same but different...

or

Different but the same...

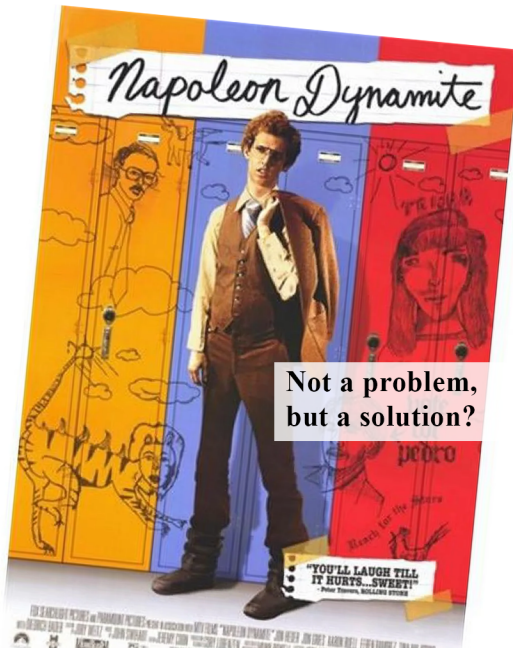
AI: EXAMPLES POSSIBLE PROVOCATIONS

MY NAME IS SALT



Same but different...
or
Different but the same...

Napoleon Dynamite



Not a problem,
but a solution?

AI: CURRENT RESEARCH: SERENDIPITY, EXPLORE/EXPLOIT

Deep Learning Models for Serendipity Recommendations: A Survey and New Perspectives

success has been achieved in recommender systems to capture complex user-item relationships from data and provide accurate recommendations towards users' preferences (e.g., [1–4]). However, these deep learning-based recommender systems often suffer from a narrow focus on users' historical behavior and excessive pursuit of recommendation accuracy (e.g., precision on relevance, recall on relevance, etc.). Consequently, these systems tend to overlook unexpected yet valuable items, and only recommend items that users are already familiar with, which might make them feel bored and dissatisfied [5–7]. This problem parallels the "filter bubble" phenomenon observed in news agencies [8], where users are exposed only to information that aligns with their viewpoints, leading to a repetitive stream of homogeneous recommendations [9]. Additionally, recommender systems often neglect unpopular or "long-tail" items [10] buried among a vast array of options, favoring popular items for better algorithmic accuracy [11]. While the systems increasingly enhance the recommendation accuracy, the results

CONCLUSION

Recommendation algorithms can do more than give us what we want, they can also help us to want new things



*Catalyze human freedom (Do good)
+ Commercially valuable (Do well)*

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Interested in collaborating?

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