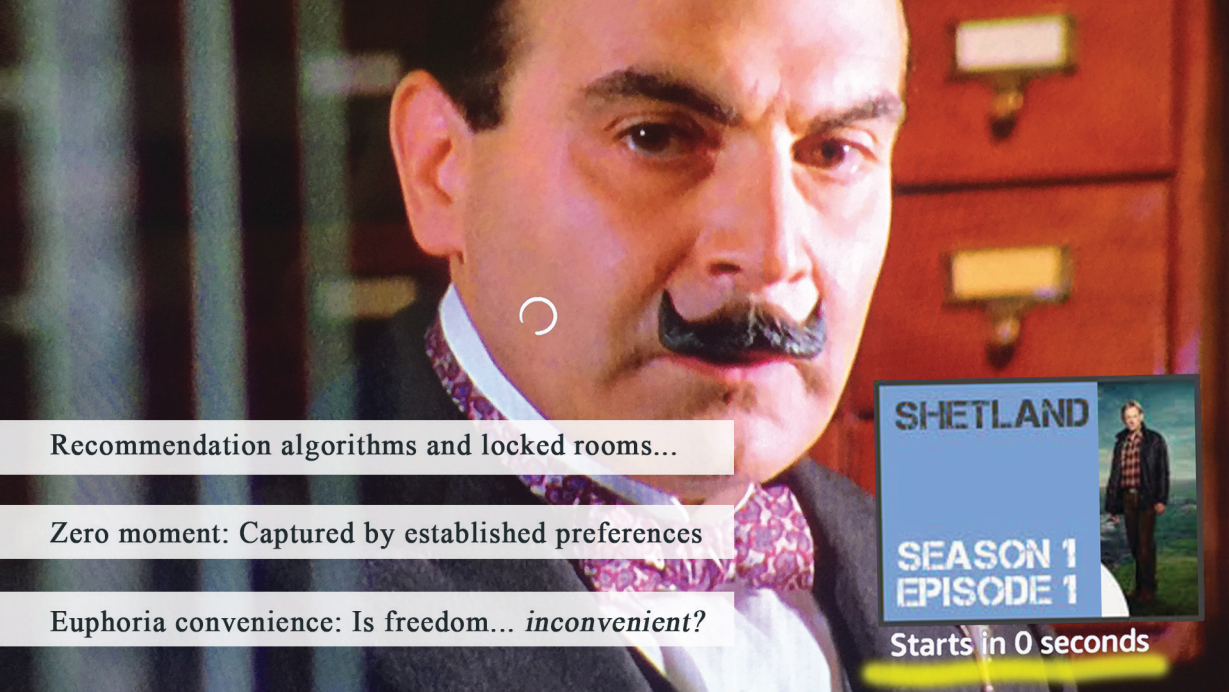
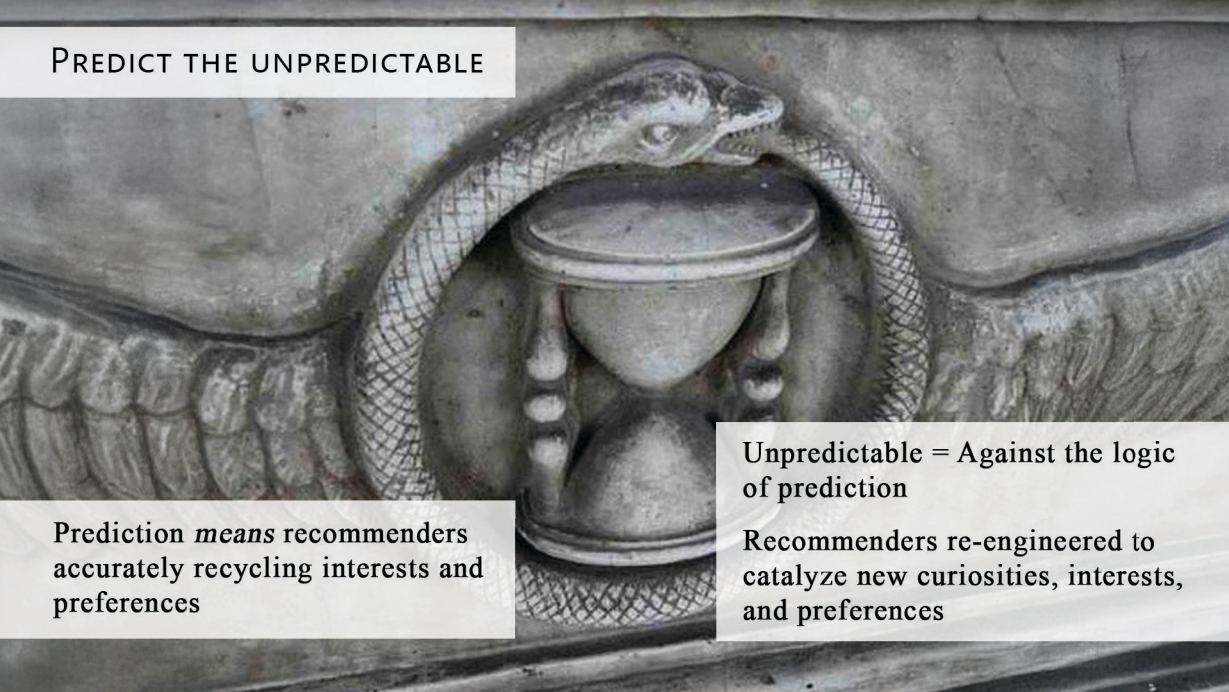
*Locke, John. (1689). *Essay Concerning Human Understanding*.


Recommendation algorithms and locked rooms...
Zero moment: Captured by established preferences
Euphoria convenience: Is freedom... *inconvenient?*
SHETLAND
SEASON 1
EPISODE 1
Starts in 0 seconds

Challenge:
Predict the unpredictable



Predict the unpredictable

Prediction *means* recommenders accurately recycling interests and preferences

Unpredictable = Against the logic of prediction

Recommenders re-engineered to catalyze new curiosities, interests, and preferences

How today's recommenders
trap us in our own preferences

NETFLIX

Logic: Similar, Resemblance, Shared, Same

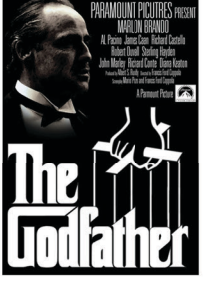
Content filtering: Shared keywords/vectors content

NETFLIX

?

Collaborative filtering: Shared keywords/vectors users NETFLIX

?



Existing preferences cannot be escaped within current recommender systems, trapping and narrowing *is* the system.

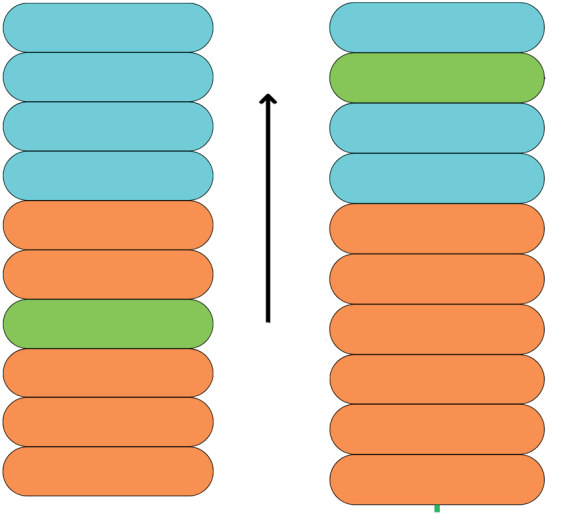
Narrowing recommendations, interests, preferences narrows recommendations, interests, preferences...

How do platforms seek variety? Serendipity

NETFLIX

1) Random “Noise-based” injection

2) Reduced similarity



“Anomalies and exceptions, partially implemented via poor similarity measures.”

E. Toms, "Serendipitous Information Retrieval", Proc. of DELOS Workshop: Information Seeking, Searching and Querying in Digital Libraries, 2000.

Antagonistic filtering:
Logic of difference
More effective serendipity

Antagonistic filtering

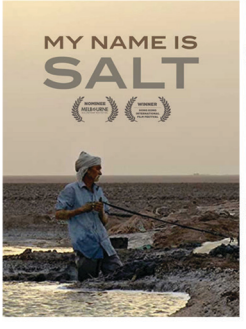
Catalyze new interests instead of recycling those already existing =

Logic of difference instead of similarity

Different, Resonance, Irreducible, Other

~~Similar~~, ~~Resemblance~~, ~~Shared~~, ~~Same~~

Antagonistic filtering: Difference *before* Similarity



?

Different age
Different gender
Different nationality
Different language
Similar taste in restaurants
Different music preferences
Different pastimes

Antagonistic filtering: Difference *before* Similarity

An international conference on...philosophy and computing

Everyone anonymously submits a favorite movie, song...

Process

START WITH DIFFERENCES

Difference: Movie preferences

Difference: Age

Difference: Language

...

THEN SEEK: ONE SIMILARITY

Shared: Favorite restaurants

Or shared: Music

Or shared: Pastime

Or shared: Profession

...

THEREFORE: RECOMMEND

One person's enjoyed movie recommended to other

Purpose: Open ***new range or genre*** of interests*

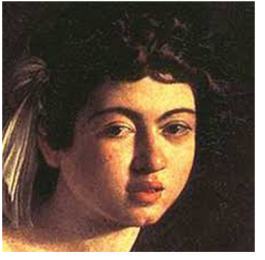
*Definition + metric of "Serendipity"

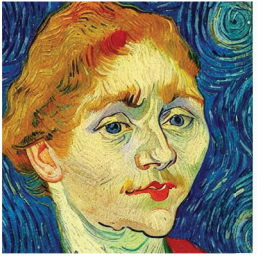
Antagonistic filtering
Intuitions, concepts...

Intuition: Opposites attract (Sometimes)

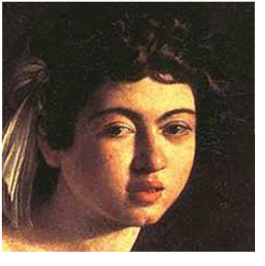
Concept: Accuracy *versus* Provocation

Same but Different = Accuracy
(Current model for recommending from one to the other)





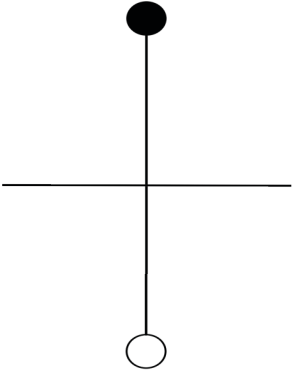
Different but the Same = Provocation + Curiosity
(Proposed model for recommending from one to the other)

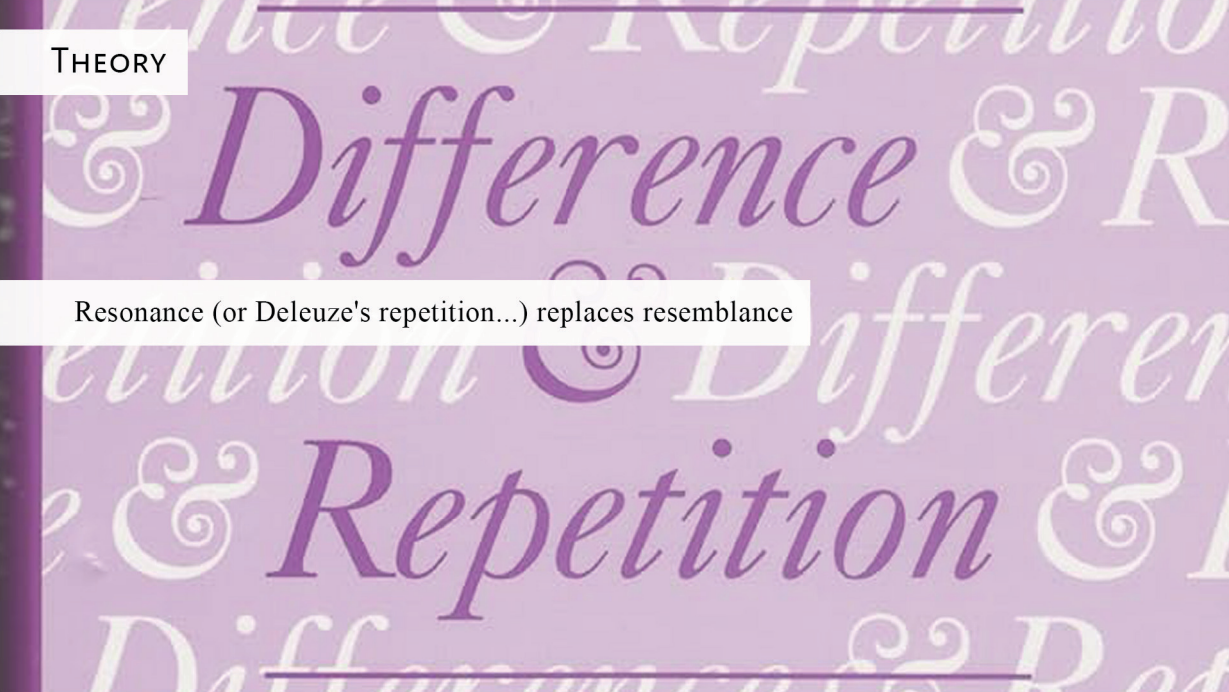


Concept: Different ≠ Less resemblance

Difference is a positive quality, not privation of resemblance

*Orthogonality





Resonance (or Deleuze's repetition...) replaces resemblance

Theory

Resonance (or Deleuze's repetition...) replaces resemblance

Theory

"Diversity of diversity"

Individual versus aggregate effects of recommenders: Tyranny of quality

Ethics

Cross domain recommending and privacy...

Freedom and authenticity?

Personal identity and responsibility?

...?

Antagonistic filtering
Technical

TECHNICAL

4 Strategies for recommending based on difference

Cross-domain

Clustering & bridging

Contrary

Orthogonality

Technical

Cross-domain (Resonance)

- Different movie preferences
- Different age
- Different gender
- Different nationality
- Different language
- Similar taste in restaurants
- Different music preferences
- Different pastimes

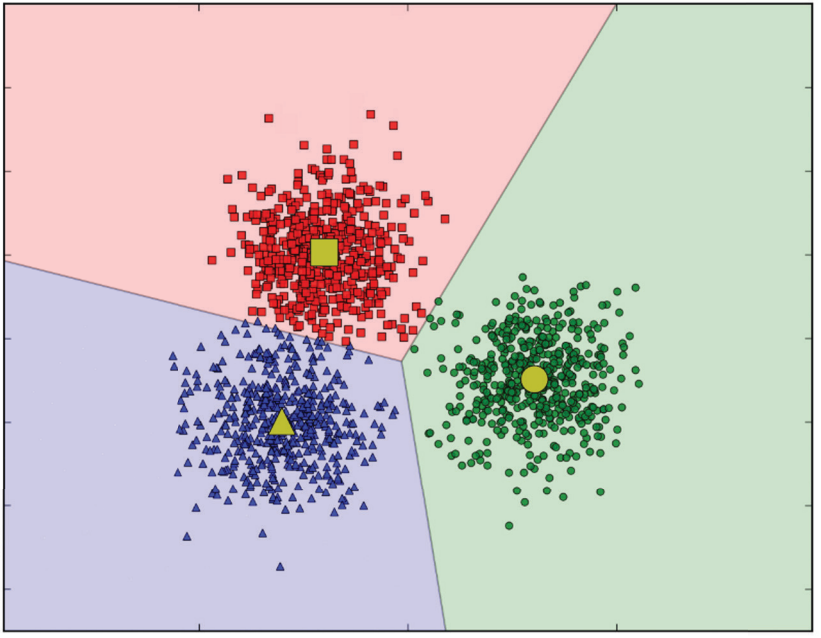
Technical

Clustering & bridging

Which direction promises escape velocity?

*Escape into new set of interests.

Movie clusters *or* user clusters *or* cross-domain...

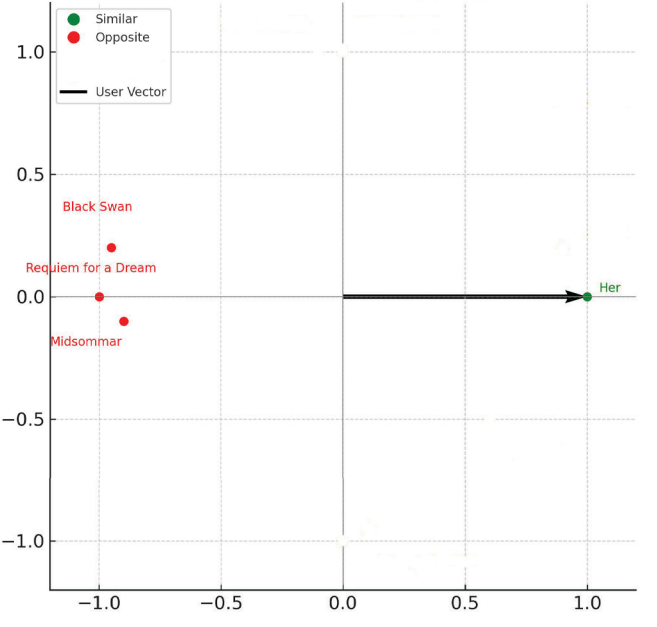


Technical

Contrary

Opposites attract?

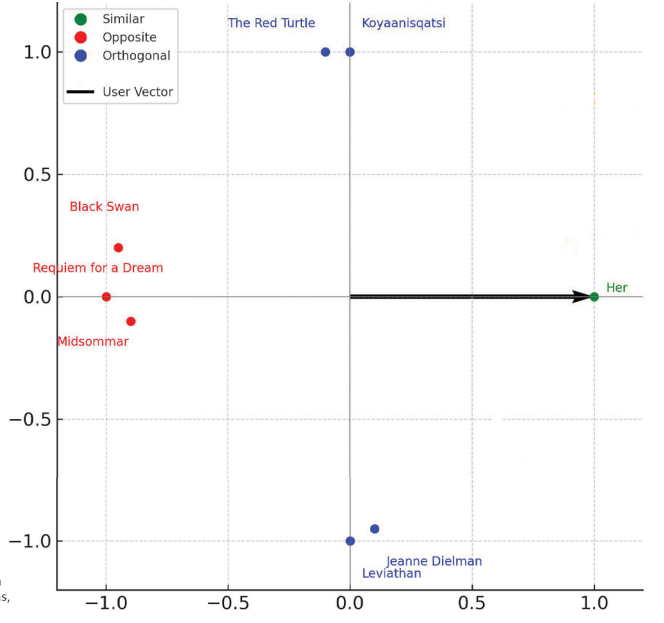
Cross-domain contrast between *users* not movies with relevant connection



Technical

Orthogonal

Movies *or* users
that move independently
of likes and dislikes



Iaquinta, Leo, Marco De Gemmis, Pasquale Lops, Giovanni Semeraro, Michele Filannino, and Piero Molino. 2008. "Introducing serendipity in a content-based recommender system." In 2008 eighth international conference on hybrid intelligent systems, pp. 168-173. IEEE, 2008.

Technical

Bridging Score

$$\text{Score}_{\text{bridging}}(i,u) = \underbrace{\text{avg\_pairwise\_dist}(U_{\text{liked}}(i))}_{\text{Bridging}} \times \underbrace{\text{partial\_alignment}(i,u)}_{\substack{\text{Personalization} \\ \textbf{Cross-domain} \\ \textbf{or} \\ \textbf{Collaborative}}} \times \underbrace{\text{novelty}(i,u)}_{\text{Newness}} \times \underbrace{\text{quality}(i)}_{\text{Engagement Potential}} \times \underbrace{\text{coherence}(i)}_{\text{Internal Consistency}}$$

Contrastive Score

$$\text{Score}_{\text{contrast}}(i,u) = \underbrace{(-\cos(i,u))}_{\text{Contrast}} \times \underbrace{\text{partial\_alignment}(i,u)}_{\substack{\text{Personalization} \\ \textbf{Cross-domain} \\ \textbf{or} \\ \textbf{Collaborative}}} \times \underbrace{\text{novelty}(i,u)}_{\text{Newness}} \times \underbrace{\text{quality}(i)}_{\text{Engagement Potential}} \times \underbrace{\text{coherence}(i)}_{\text{Internal Consistency}}$$

Orthogonal Score

$$\text{Score}_{\text{orthogonal}}(i,u) = \underbrace{(1 - |\cos(i,u)|)}_{\text{Orthogonality}} \times \underbrace{\text{partial\_alignment}(i,u)}_{\substack{\text{Personalization} \\ \textbf{Cross-domain} \\ \textbf{or} \\ \textbf{Collaborative}}} \times \underbrace{\text{novelty}(i,u)}_{\text{Newness}} \times \underbrace{\text{quality}(i)}_{\text{Engagement Potential}} \times \underbrace{\text{coherence}(i)}_{\text{Internal Consistency}}$$

Technical: What counts as success?

Open new kind of interest.
"Diversity *of* diversity," not just new interest within established preferences

Benchmark: Better than random…

Orthogonality as best bet..?

Conclusions

Antagonistic filtering: Conceptual and technical strategies

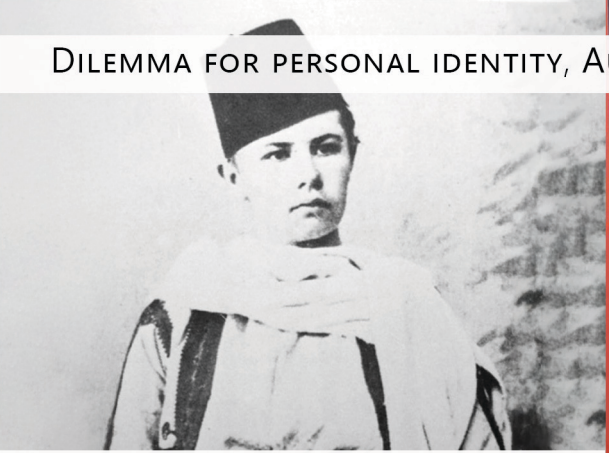
Unfamiliar (Unexpected/Novel/Diverse)
= Not imitating past selections
= Provocation replaces accuracy in evaluating success

Engaging (Provoking curiosity + exploration)
= Relevant to who user *could* be, not to who user *is*

Colab

* 2 way street... are there other approaches or strategies?

Dilemma for personal identity, Authenticity, and freedom



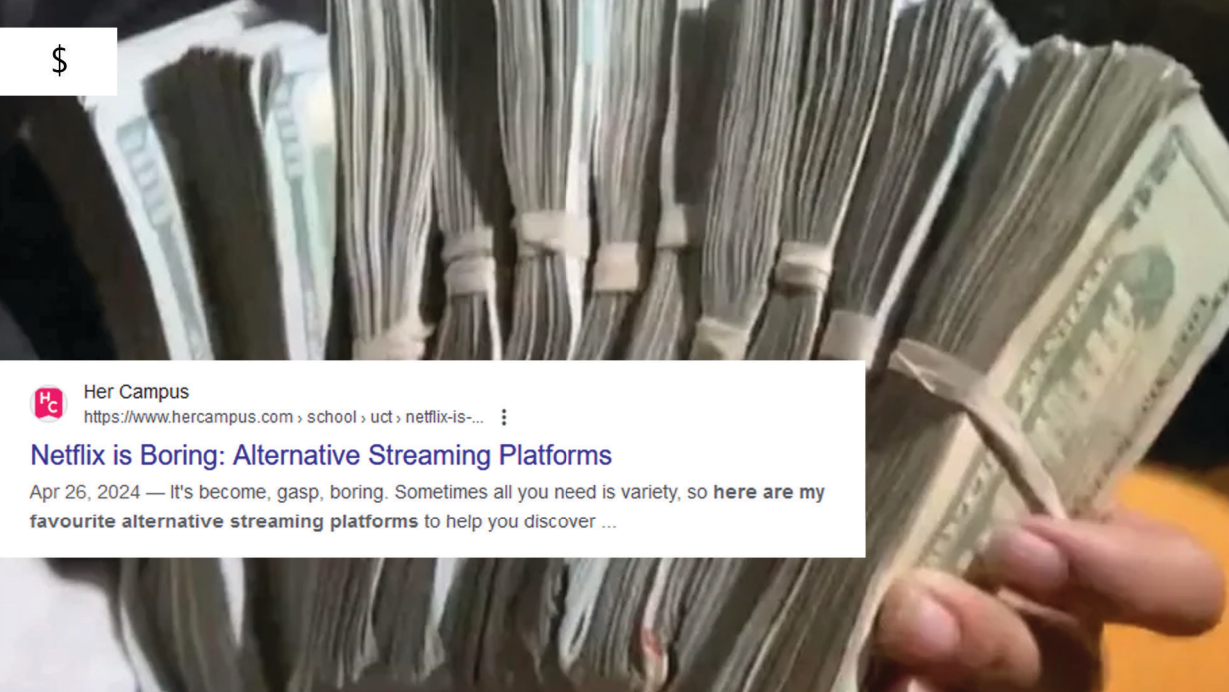
Ethics: Be who you are, or someone else?
Law: “Right to discontinuity”

Recommenders and society

Collaborative filtering as a democracy problem: users funneled into echo chambers, narrow perspectives, tribalism.

Accuracy *is* narrowing.

Antagonistic filtering ("Bridging") as a social solution?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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 ...

What is at stake with recommenders?

Philosophy + software engineering
- How do we predict the unpredictable?

Ethics
- Freedom (What counts as personal freedom/autonomy?)
- Freedom versus authenticity (as opposed to freedom supporting authenticity)
- Personal identity (Does discontinuous preferences = discontinuous personal identity?)

Law
- Right to discontinuity (as extended from the right to be forgotten)

Politics
- Filter bubbles + tribalism (Bridging based recommendations)

Business
- Profit, keep users on platform: People get bored on Netflix, Spotify, etc…

Predicting the Unpredictable

The Curiosity Engine is an NSF funded project in AI
Contact: James Brusseau, Pace University NYC, jbrusseau@pace.edu