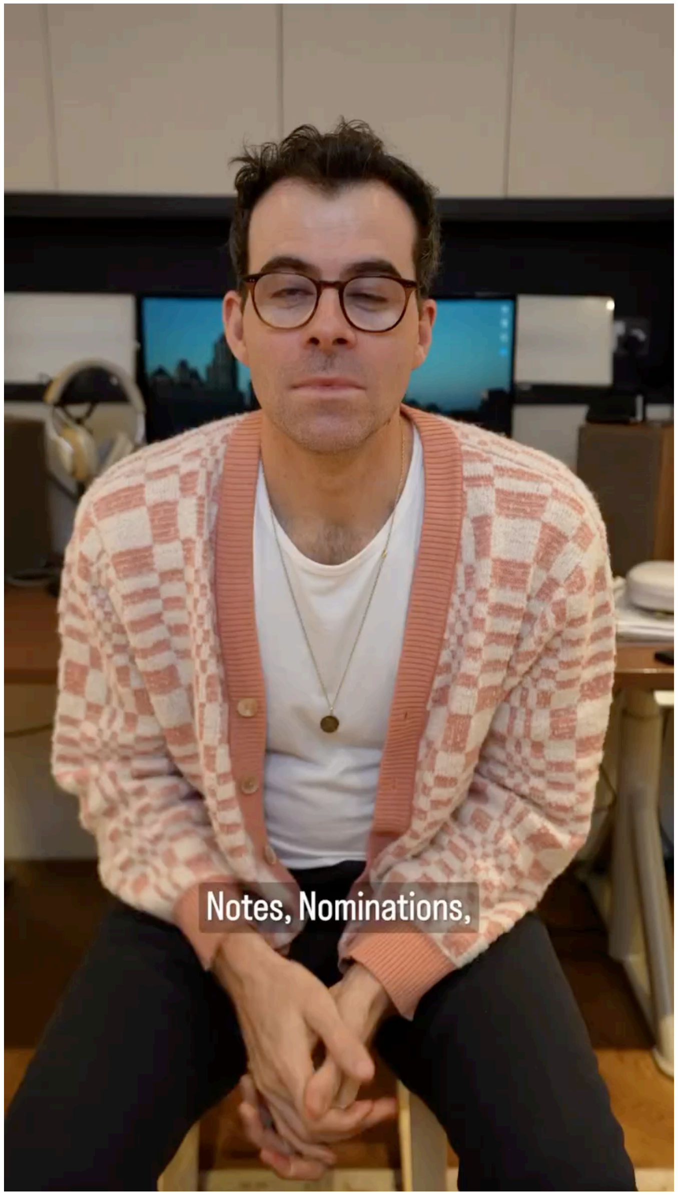


Growth example
by Avika P:

Country comparisons, launching new social features only in a few select countries for testing: "Nominations", "Candid Stories", "Group Profiles" only launched in Canada, Taiwan, and Chile

submit examples on Ed in the "Lectures" category for 1% extra credit

Feed Me

CS 278 | Stanford University | Michael Bernstein

Announcements

Project proposal + prototype due Monday

Assignment 2 will be released after the project proposal is turned in, and will be due after one week

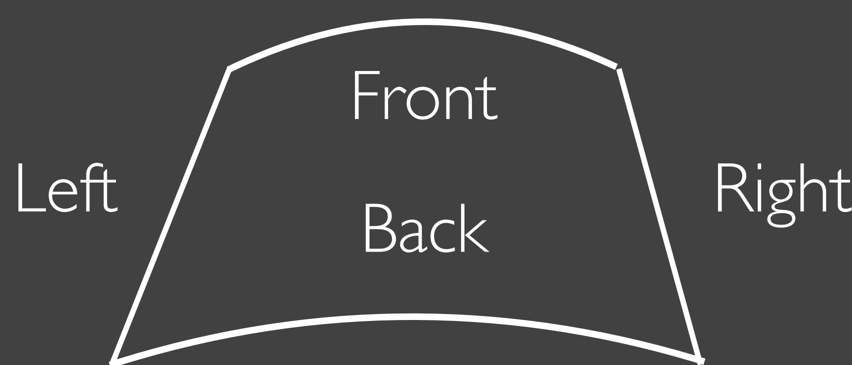
No lecture next Tuesday — Michael @ CHI 2023

Attendance

Time for chaos!

We've been testing this out: please be gentle

Turn up your phone's brightness



Most viral memes

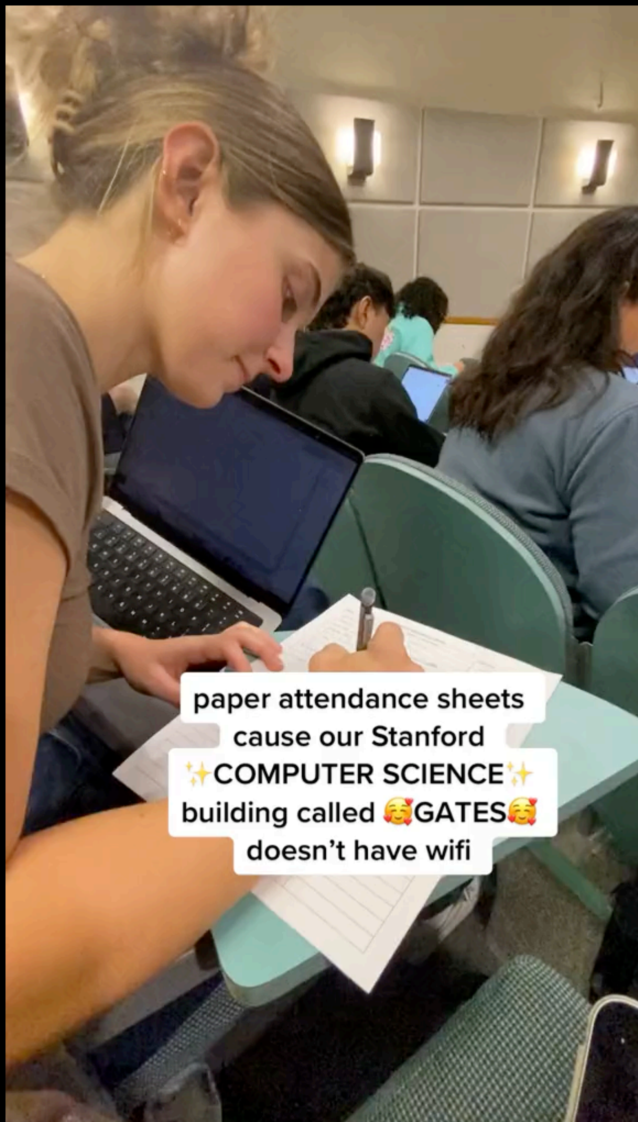
Assignment 1: Going Viral

As voted by the internet or by the class

Viral online (1.1M views)
+ #1 voted by class

by Jason L.

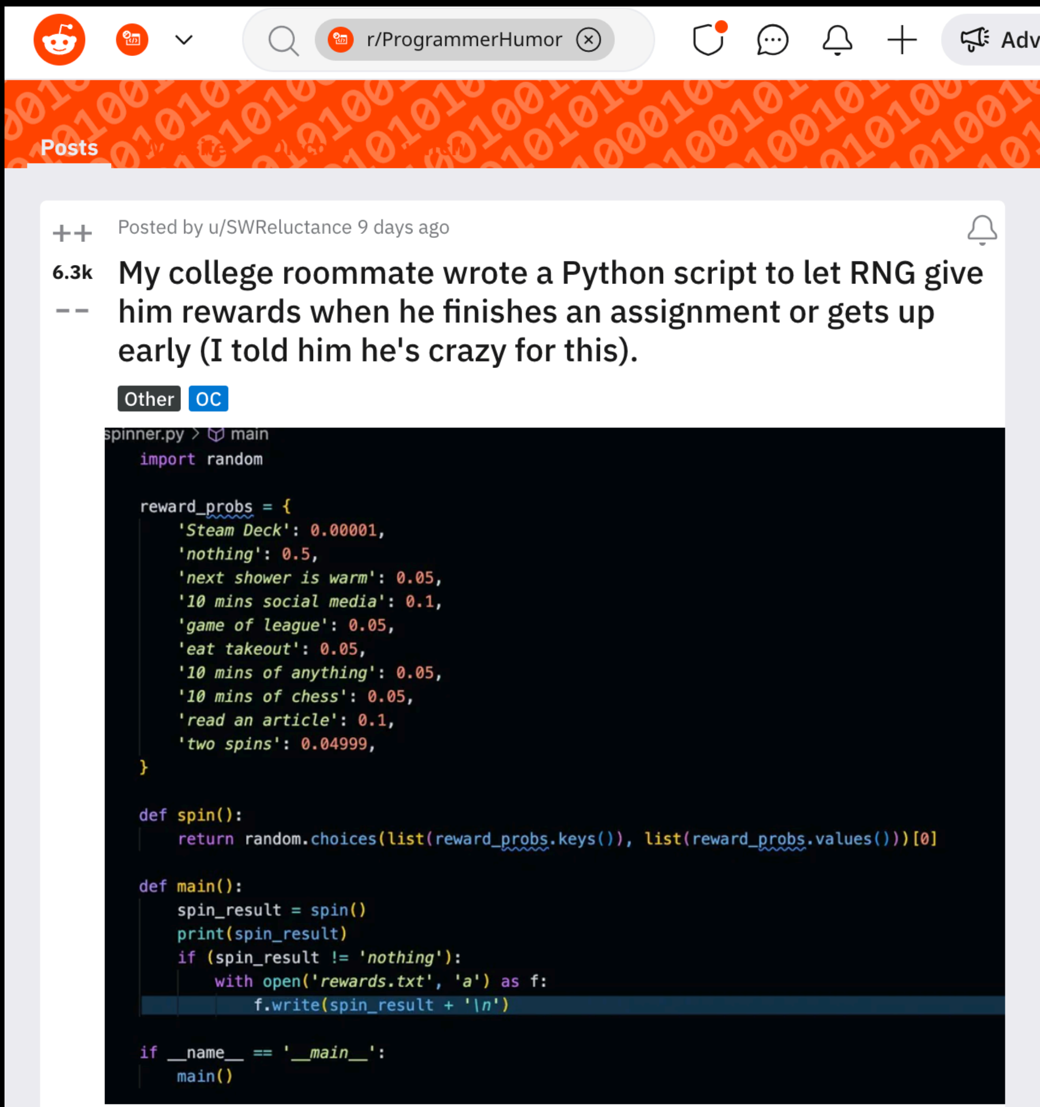
https://www.tiktok.com/@horsebeforecouch/video/7219792981576977706



Viral online (150k views)

by Kathryn R.

https://www.tiktok.com/@katdancer6/video/7219349090159643947



Viral online (600k views)

by Sauren K.

https://www.reddit.com/r/ProgrammerHumor/comments/12h12v0/my_college_roommate_wrote_a_python_script_to_let/

#2 voted by class

by Rui Y.

#3 voted by class

by Luca W.

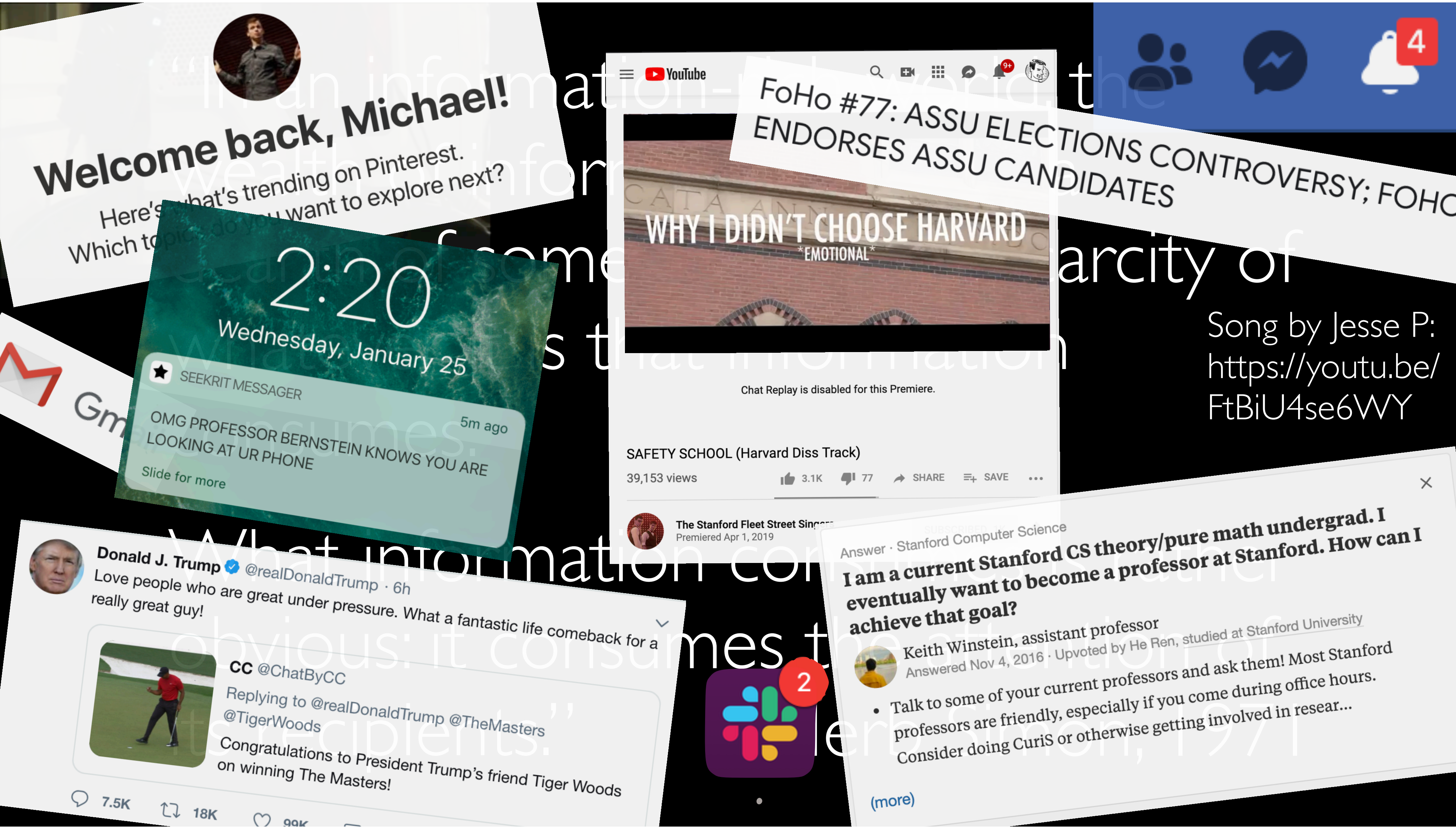
Last time: growing pains

Communities can't maintain the same design as they grow. Newcomers change the dynamics, even if they absorb the norms—and oftentimes they don't absorb the norms.

Growth begets contention and rulemaking, which can push off newcomers

"In an information-rich world, the wealth of information means a dearth of something else: a scarcity of whatever it is that information consumes.

What information consumes is rather obvious: it consumes the attention of its recipients." - Herb Simon, 1971



Welcome back, Michael!
Here's what's trending on Pinterest.
Which topic do you want to explore next?
2:20
Wednesday, January 25
SEEKRIT MESSAGER
5m ago
OMG PROFESSOR BERNSTEIN KNOWS YOU ARE LOOKING AT UR PHONE
Slide for more
YouTube
WHY I DIDN'T CHOOSE HARVARD
EMOTIONAL
Chat Replay is disabled for this Premiere.
SAFETY SCHOOL (Harvard Diss Track)
39,153 views
3.1K
77
SHARE
SAVE
Premiered Apr 1, 2019
FoHo #77: ASSU ELECTIONS CONTROVERSY; FOHO ENDORSES ASSU CANDIDATES
4
Song by Jesse P: https://youtu.be/FtBiU4se6WY
Donald J. Trump @realDonaldTrump · 6h
Love people who are great under pressure. What a fantastic life comeback for a really great guy!
CC @ChatByCC
Replying to @realDonaldTrump @TheMasters @TigerWoods
Congratulations to President Trump's friend Tiger Woods on winning The Masters!
7.5K
18K
2
Answer · Stanford Computer Science
I am a current Stanford CS theory/pure math undergrad. I eventually want to become a professor at Stanford. How can I achieve that goal?
Keith Winstein, assistant professor
Answered Nov 4, 2016 · Upvoted by He Ren, studied at Stanford University
Talk to some of your current professors and ask them! Most Stanford professors are friendly, especially if you come during office hours. Consider doing CuriS or otherwise getting involved in resear...
(more)

Information overload causes attention underprovision

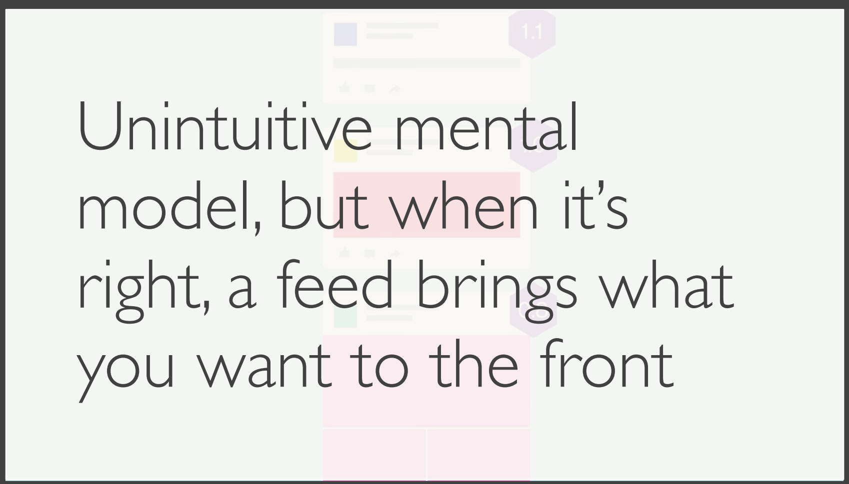
As Usenet groups grow in size, members (1) respond to simpler messages, (2) generate simpler responses, and (3) are more likely to leave. [Jones, Ravid, and Rafaeli 2004]

As a subreddit gets larger, its users cluster their comments around a smaller and smaller proportion of posts [Lin et al. 2017]

Fewer than half of Reddit's most popular links get noticed and upvoted the first time they were submitted to the site [Gilbert 2013]

Designing for info overload

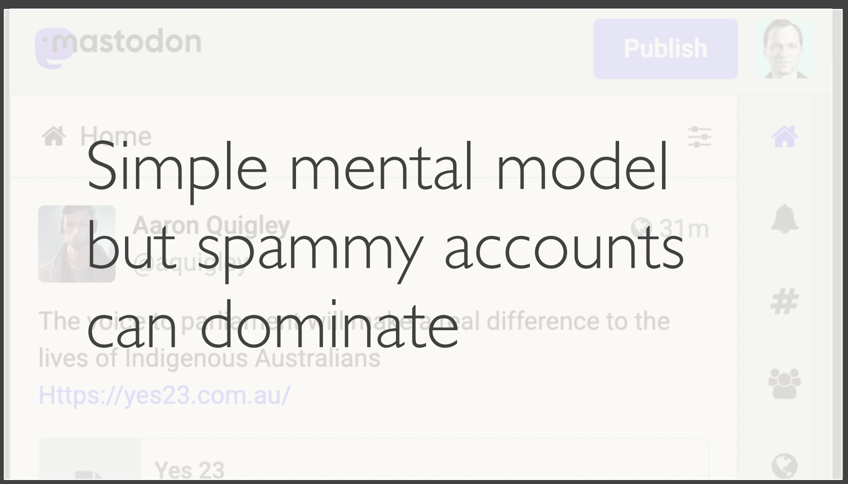
Ranking



Unintuitive mental model, but when it's right, a feed brings what you want to the front

Facebook
Twitter
Pinterest
Instagram
Reddit
TikTok

Chronological

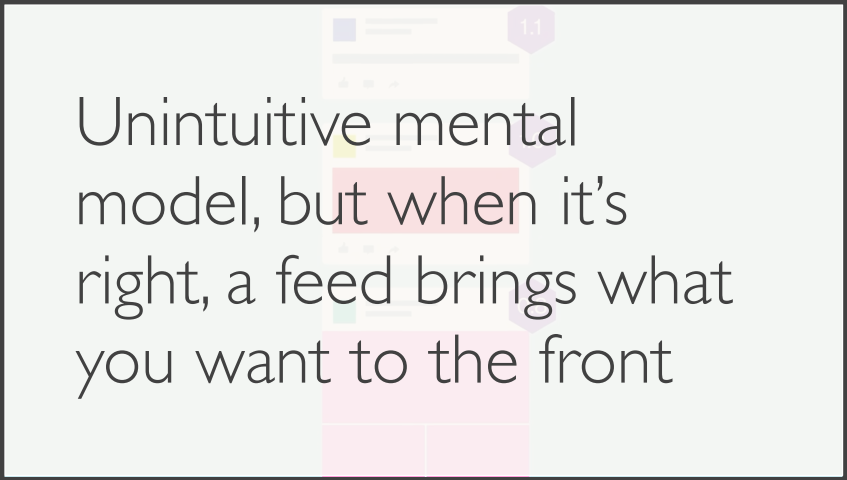


Simple mental model but spammy accounts can dominate

Mastodon
Email
Slack
iMessage
WhatsApp
Discord

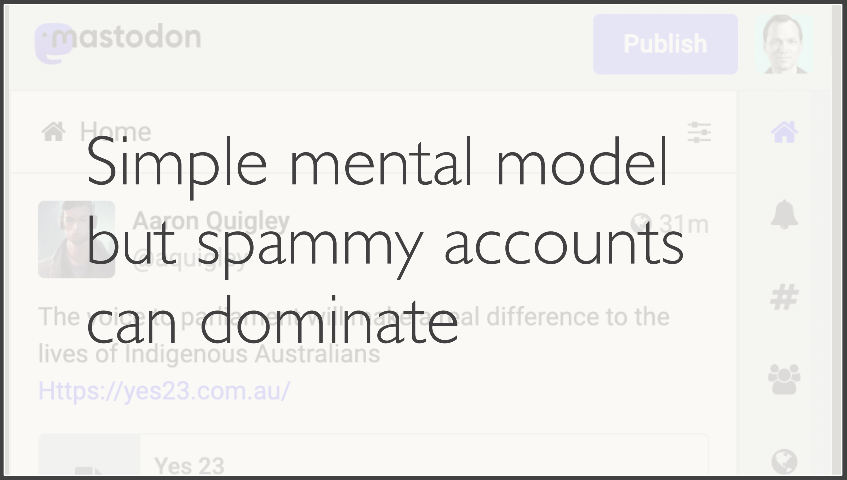
Designing for info overload

Ranking



Unintuitive mental model, but when it's right, a feed brings what you want to the front

Chronological



Simple mental model but spammy accounts can dominate

How do you think a system should be directing attention in an overloaded community? [2min]

Designing for info overload

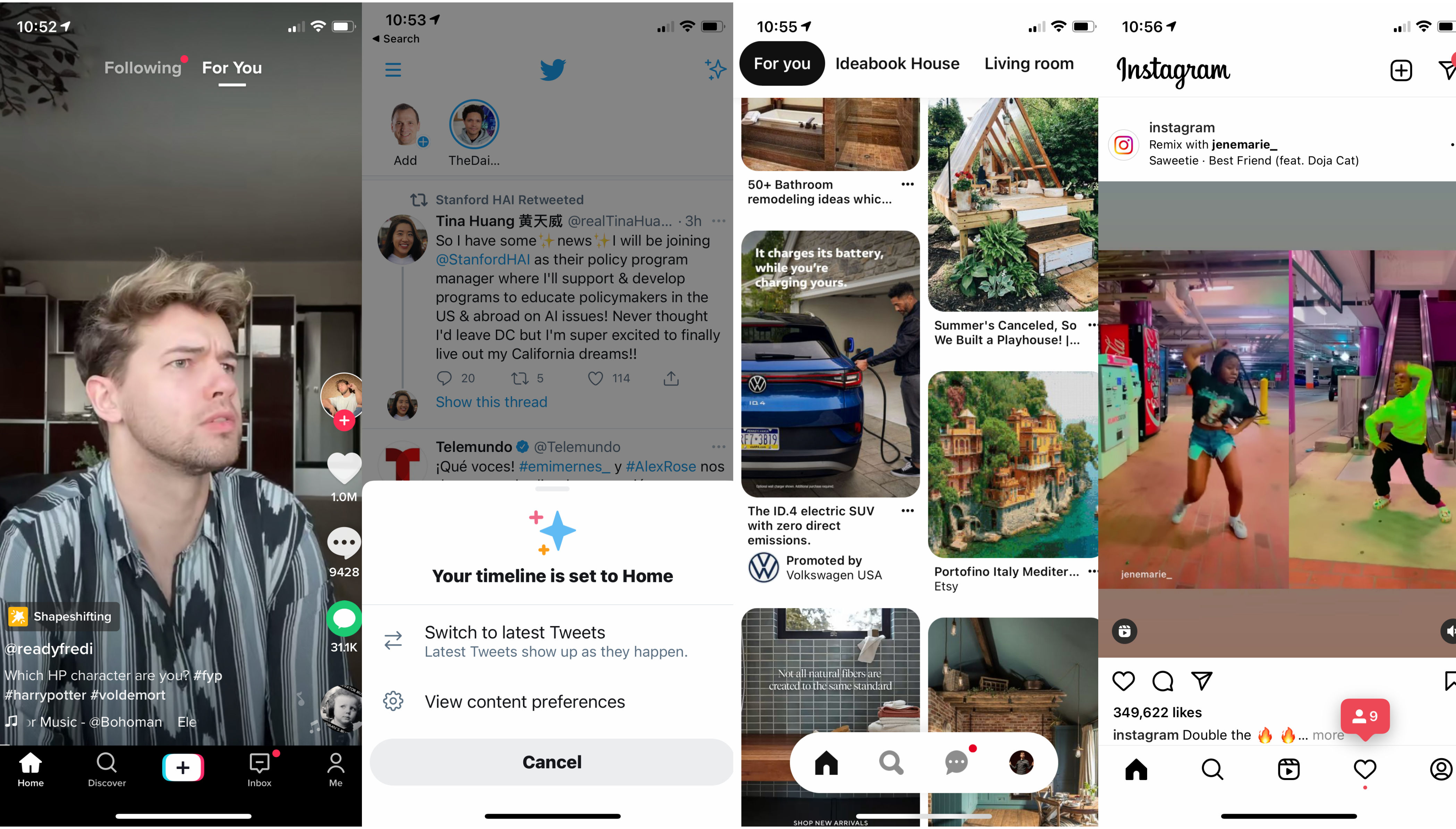
"Algorithms are unavoidable here. Even sorting posts by friends in chronological order or videos by overall popularity is algorithmic; and often it is unclear there is a single, simple baseline algorithm."
- Dean Eckles, MIT, to the US Senate [2021]

Today

Feed ranking algorithms: how they work

- Global rankings a la upvote
- Personalized rankings a la the For You Page
- Feeds' objective functions — what are we optimizing for?

Feeds are echo chambers: are feeds echo chambers?
[Gilbert, Bergstrom, and Karahalios 2009]


10:52
Following
For You
1.0M
9428
31.1K
Shapeshifting
@readyfredi
Which HP character are you? #fyp #harrypotter #voldemort
r Music - @Bohoman Ele
Home
Discover
Inbox
Me
10:53
◂ Search
Add
TheDai...
Stanford HAI Retweeted
Tina Huang 黄天威 @realTinaHua... · 3h
So I have some ✨news✨ I will be joining @StanfordHAI as their policy program manager where I'll support & develop programs to educate policymakers in the US & abroad on AI issues! Never thought I'd leave DC but I'm super excited to finally live out my California dreams!!
20
5
114
Show this thread
Telemundo @Telemundo
¡Qué voces! #emimernes_ y #AlexRose nos
Your timeline is set to Home
Switch to latest Tweets
Latest Tweets show up as they happen.
View content preferences
Cancel
10:55
For you
Ideabook House
Living room
50+ Bathroom remodeling ideas whic...
Summer's Canceled, So We Built a Playhouse! |...
It charges its battery, while you're charging yours.
The ID.4 electric SUV with zero direct emissions.
Promoted by Volkswagen USA
Portofino Italy Mediter...
Etsy
Not all natural fibers are created to the same standard
SHOP NEW ARRIVALS
10:56
Instagram
instagram
Remix with jenemarie_
Saweetie · Best Friend (feat. Doja Cat)
jenemarie_
349,622 likes
instagram Double the 🔥 🔥... more
9

Global ranking

Used by the traditional Reddit "hot" ranking or the Fizz ranking or Hacker News

First shot: how many upvotes does it have?

- e.g., 100 upvotes ranked above 10 upvotes
- …but this ignores if lots of people saw it but a large % disliked it

Global ranking

Reddit, Fizz, and Hacker News also have downvote data!

Second shot: upvotes – downvotes

- e.g., 10 upvotes + 1 downvote ranked above 100 upvotes + 100 downvotes
- …but this ranking would never stay fresh! The most popular items of all time would never change.

Global ranking

Final shot: decay over time

$\log(\max(\text{upvotes} - \text{downvotes}, 1))$

Why log? [30sec]

Because the most popular posts have orders of magnitude more upvotes than others: without the log transform, the top posts would never decay fast enough, relative to the other posts

Finally, decay the log score over time

(Reddit did a linear penalty, Hacker News is more exponential. The choice depends on what exactly you're aiming for.)

Personalized feed: machine learning

1) Featurize
2) Predict
3) Calculate objective
4) Rank

1) Featurize

- Tie strength w/ MSB: 6
- Content type: mobile phone photo
- Platform: iPhone
- Vision algorithm: stuffed animal, bear
- Text features (e.g., BERT embeddings)
- Interactions so far: 101
- % haha reactions: 15%
- Day of year
- Age of content
- Internet: 10 mbps

[ ]

Personalized feed: machine learning

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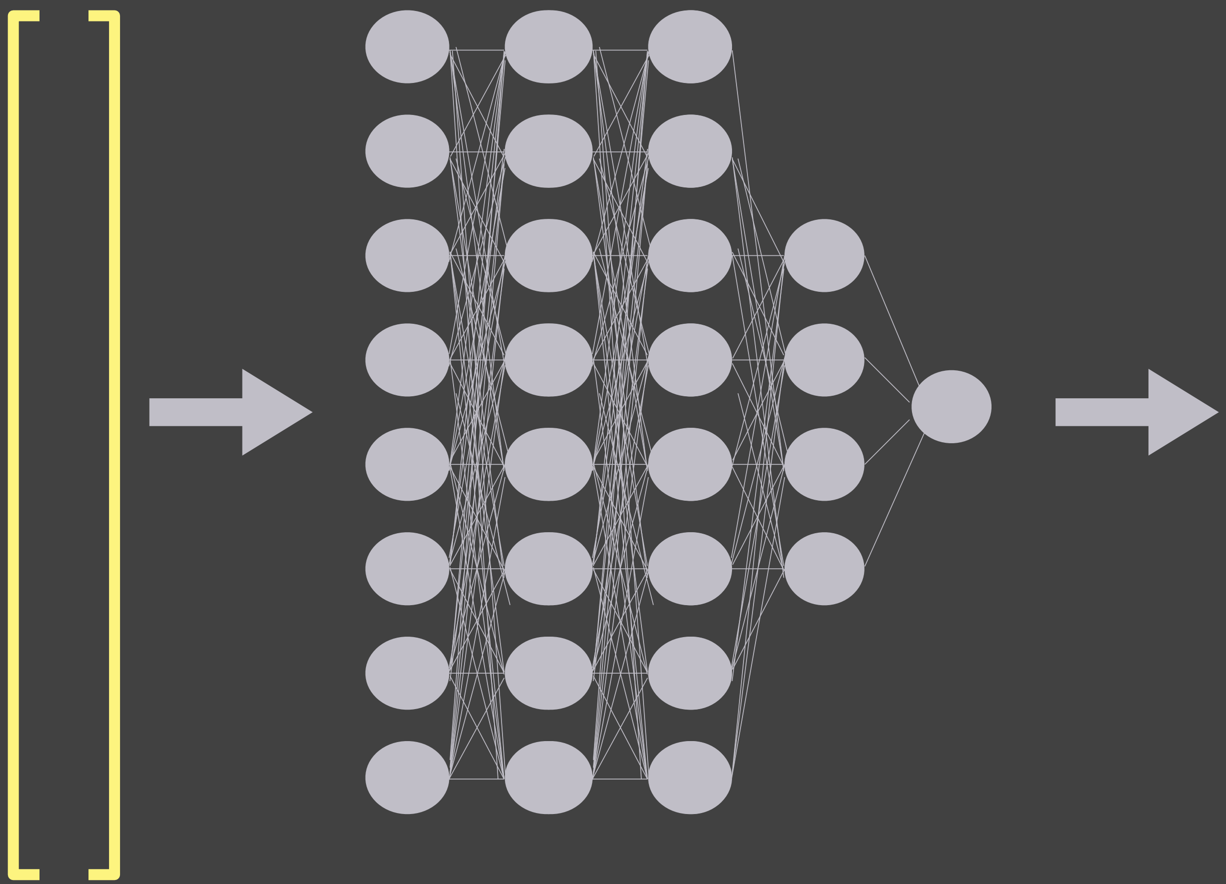
- Day of year
- Age of content
- Internet: 10 mbps

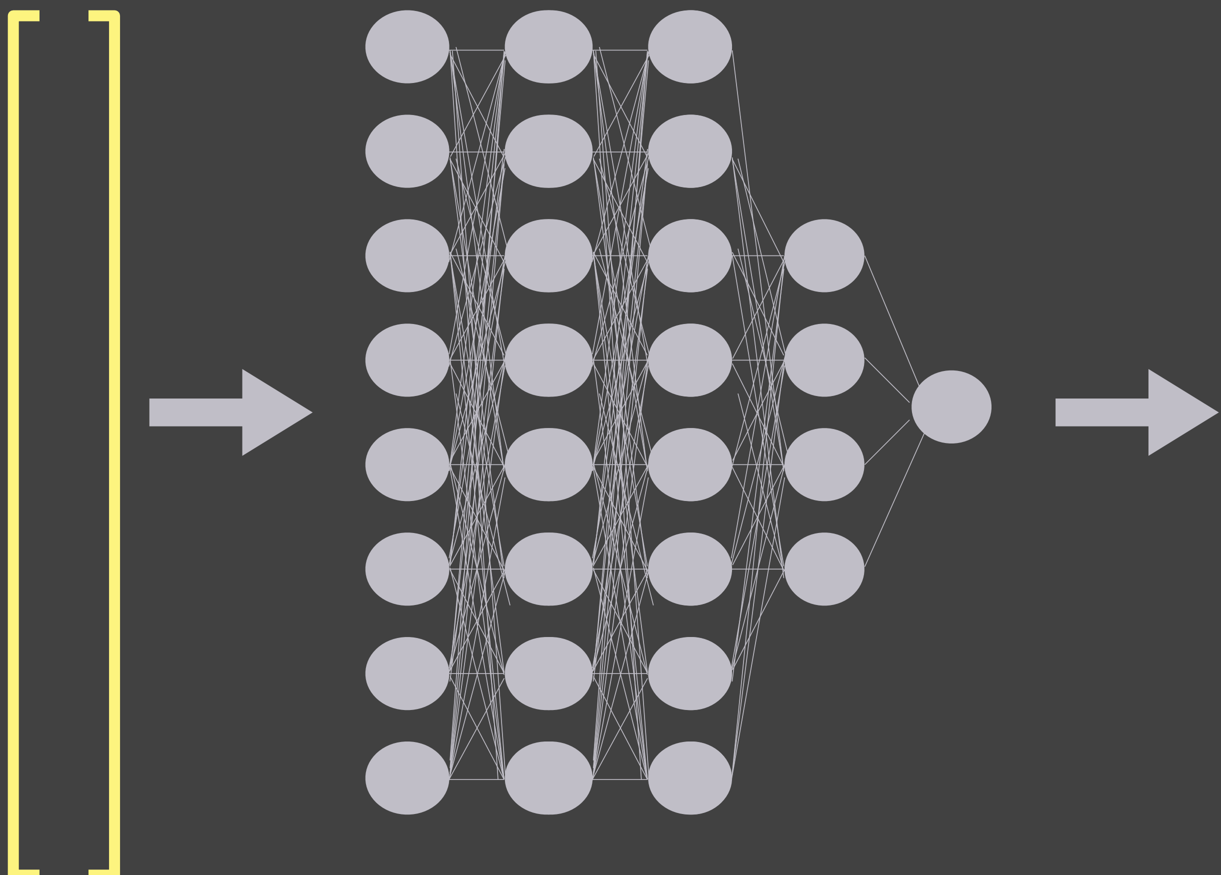
2) Predict



Probability of clicking "like"

P(like)

2) Predict



Models for each outcome of interest

P(like)

P(watch)

P(hide)

P(share)

P(comment)

P(click)

P(follow)

2) Predict

How do we train these deep learning algorithms?

Training data: prior behavior on the platform

> As you browse, scroll, and click, and as others do, the system builds models to predict your behavior toward future unseen posts

Personalized feed: machine learning

1) Featurize
2) Predict
3) Calculate objective
4) Rank

3) Calculate objective

So what do we do with all of these predictions?

P(like) P(watch) P(comment) P(click) P(share) P(hide) P(follow)

We define an objective: an algorithm to combine and weight the predictions

Intuitively: how many points does each predicted behavior get?

$$\sum_{p \in \text{predictions}} \text{weight}_p \cdot p$$

Objectives in use

Facebook: "Meaningful Social Interactions": a weighted average of Likes, Reactions, Reshares, and Comments

Facebook overhauls News Fee
favor of 'meaningful social
interactions'

Refresh of the News Feed algorithm will de-prioriti
content shared by media and businesses in favor of
that produced by friends and family, Zuckerberg say

Julia Carrie Wong *in San Francisco*

Interaction type	weight
Like	1
Reaction	1.5
Reshare	1.5
Comment	15-20

Source: https://knightcolumbia.org/content/understanding-social-media-recommendation-algorithms

Objectives in use

Twitter's open sourced algorithm:

75 points if predicted that, if you reply, the author will reply back

27 points if predicted that you'd reply

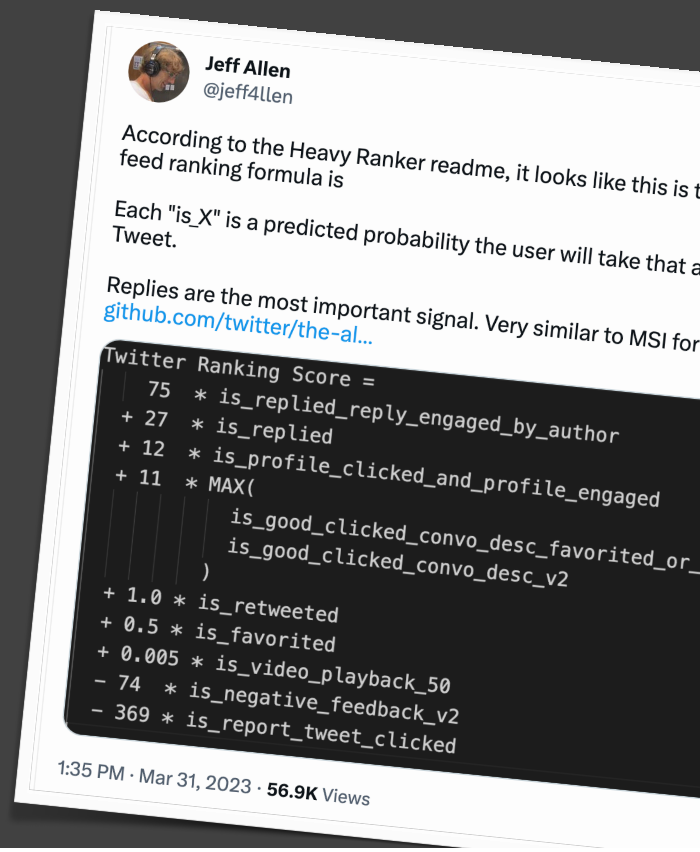
12 points if predicted that you engage with the author's Twitter profile

1 point if predicted that you'll retweet

0.5 points if predicted that you'll favorite

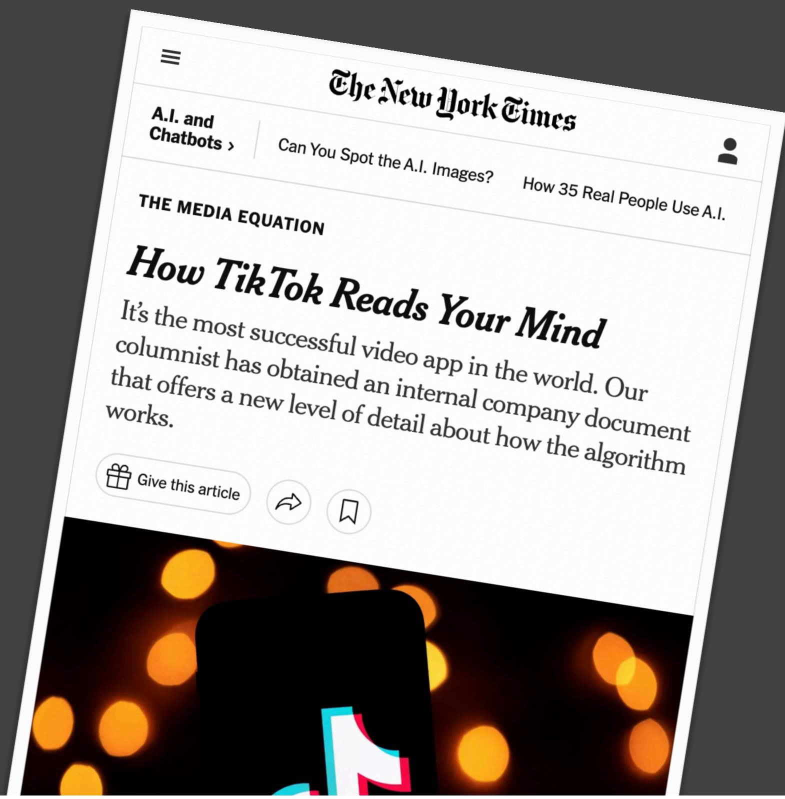
-74 points if predicted that you'll give negative feedback ("not interested", mute, block)

-369 points if predicted that you'll report it



Objectives in use

TikTok: watching, liking, commenting



The New York Times

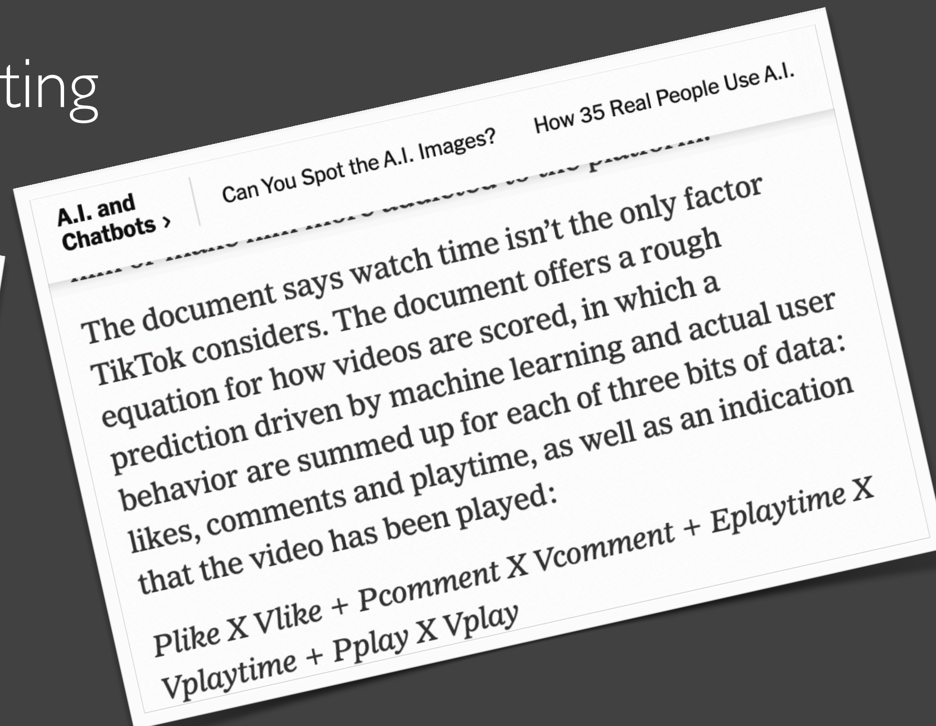
A.I. and Chatbots › Can You Spot the A.I. Images? How 35 Real People Use A.I.

THE MEDIA EQUATION

How TikTok Reads Your Mind

It's the most successful video app in the world. Our columnist has obtained an internal company document that offers a new level of detail about how the algorithm works.

Give this article



A.I. and Chatbots › Can You Spot the A.I. Images? How 35 Real People Use A.I.

The document says watch time isn't the only factor TikTok considers. The document offers a rough equation for how videos are scored, in which a prediction driven by machine learning and actual user behavior are summed up for each of three bits of data: likes, comments and playtime, as well as an indication that the video has been played:

Plike X Vlike + Pcomment X Vcomment + Eplaytime X Vplaytime + Pplay X Vplay

$$\sum_{p \in \text{predictions}} \text{weight}_p \cdot p$$

This is why we talk about feeds as being driven by engagement

Engagement is typically a shorthand for behaviors that the platform can observe: e.g., likes

But, optimizing for engagement can create negative outcomes. What are they, and what could we do about them? [2min]

This is also why feeds include predictions for global objectives

Indirect impacts: if we show this to you, and you leave a comment, will it make a better experience for the user who posted it?

Long-term impacts: what impact will this have on your wellbeing? [Burke and Kraut 2016; Stray 2020]

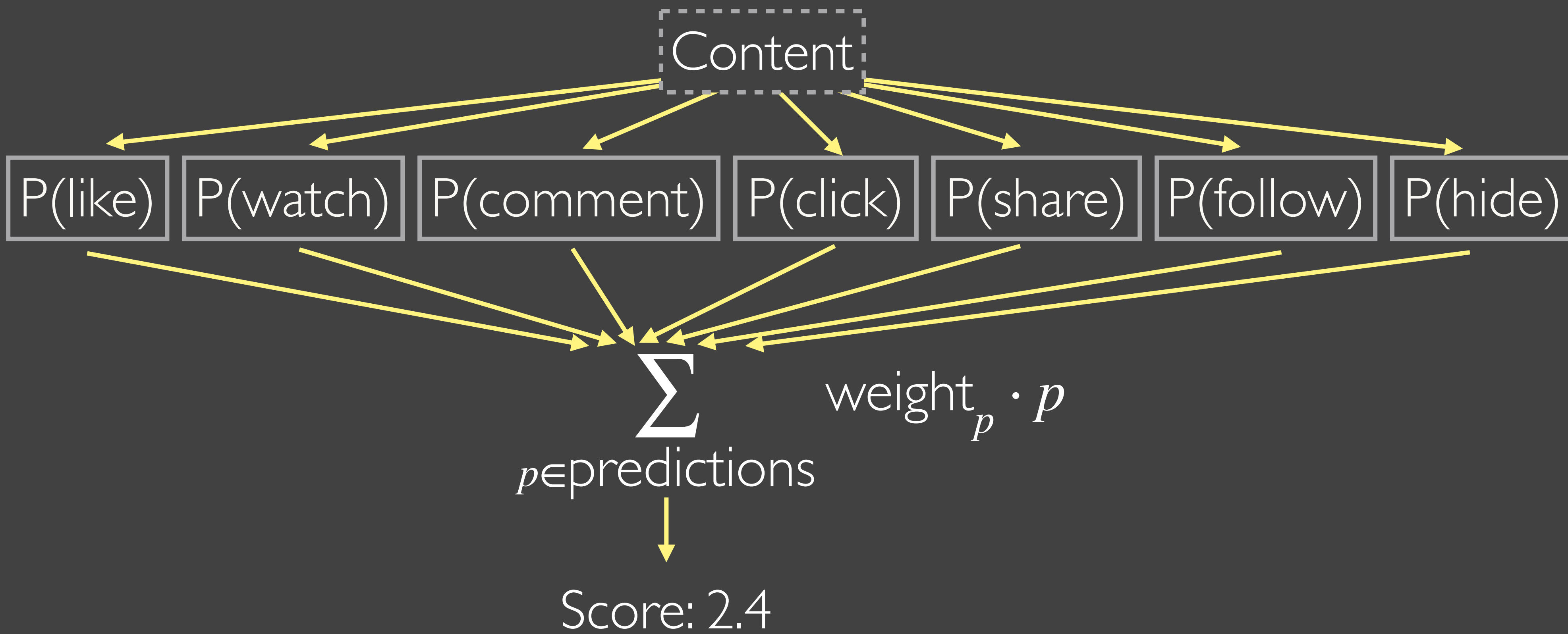
News Feed quality: We've made several changes to News Feed to provide more opportunities for meaningful interactions and reduce passive consumption of low-quality content — even if it decreases some of our engagement metrics in the short term. We demote things like clickbait headlines and false news, even though people often click on those links a a high rate. We optimize ranking so posts from the friends you care abou most are more likely to appear at the top of your feed because that's what people tell us in surveys that they want to see. Similarly, our rank promotes posts that are personally informative. We also recently redesigned the comments feature to foster better conversations.

This is also why feeds include predictions for global objectives

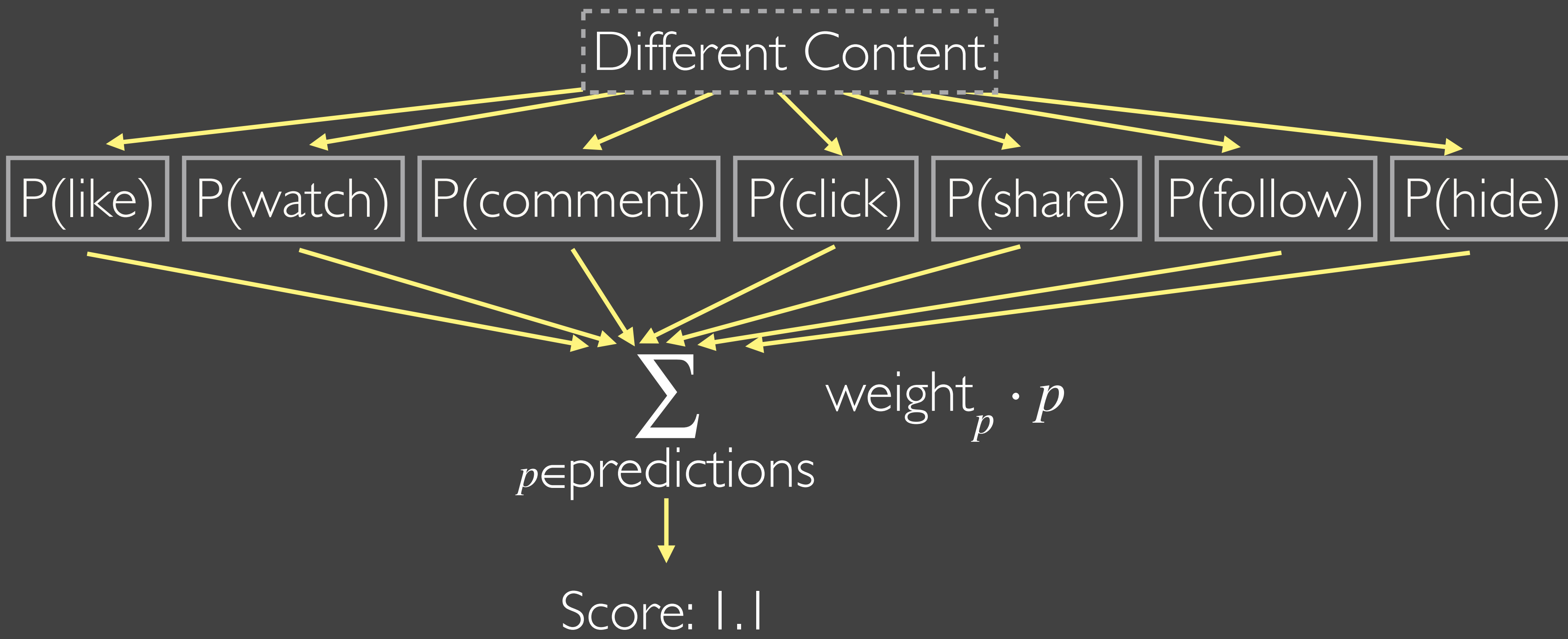
Impacts estimated via survey: machine learning models trained on survey responses — some users have surveys injected into their feed where they rate whether a particular item is important, informative, funny, or makes them feel connected [Eckles 2021]

Feed diversity: penalize feeds that are all the same kind of content

Sum it up


Content
P(like)
P(watch)
P(comment)
P(click)
P(share)
P(follow)
P(hide)
$\sum_{p \in \text{predictions}} \text{weight}_p \cdot p$
Score: 2.4

Sum it up

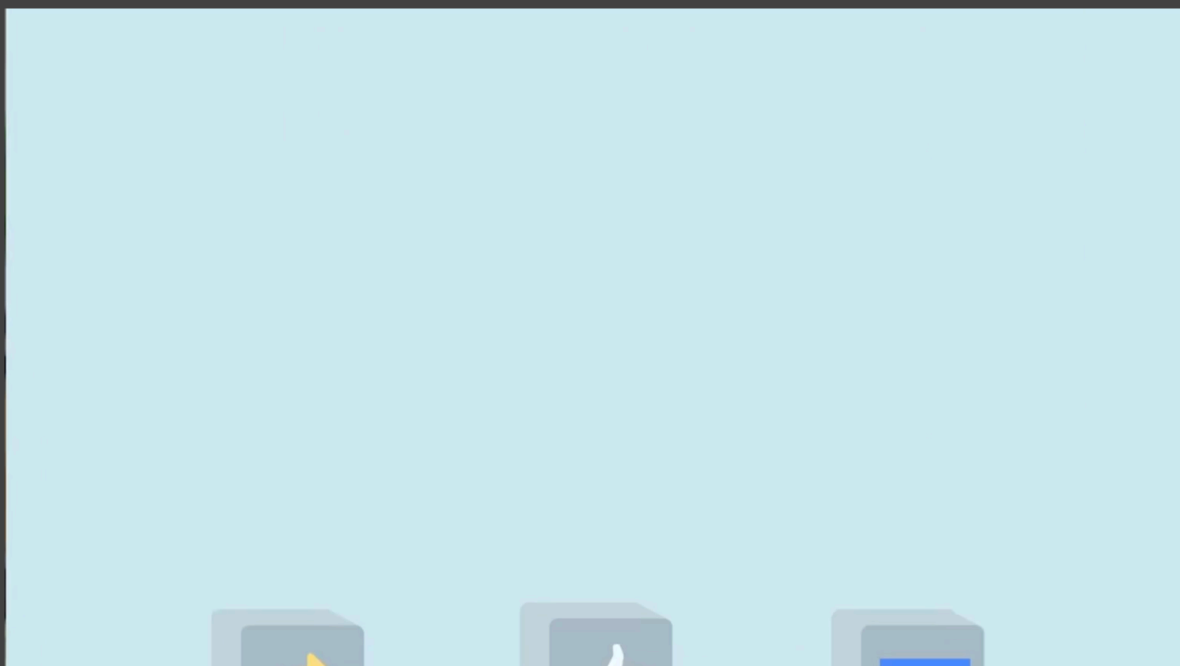


Different Content
P(like)
P(watch)
P(comment)
P(click)
P(share)
P(follow)
P(hide)
$\sum_{p \in \text{predictions}} \text{weight}_p \cdot p$
Score: 1.1

Personalized feed: machine learning

1) Featurize
2) Predict
3) Calculate objective
4) Rank

4) Rank

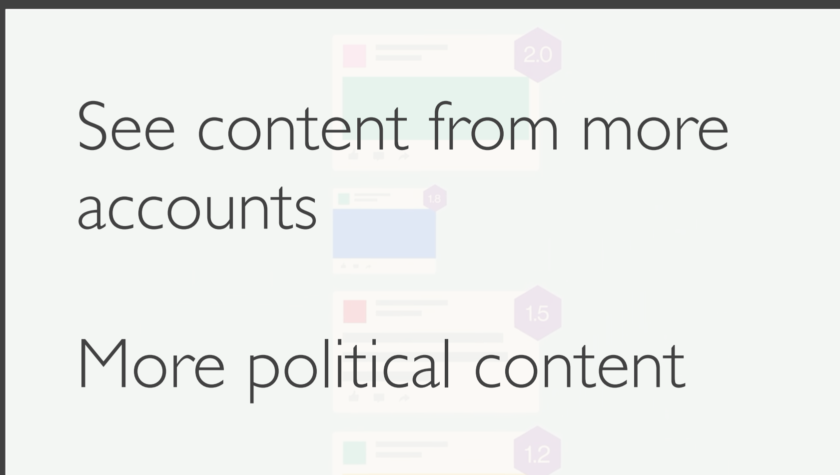


[Facebook]

Rank the items in the feed by their score

Outcomes of ranking

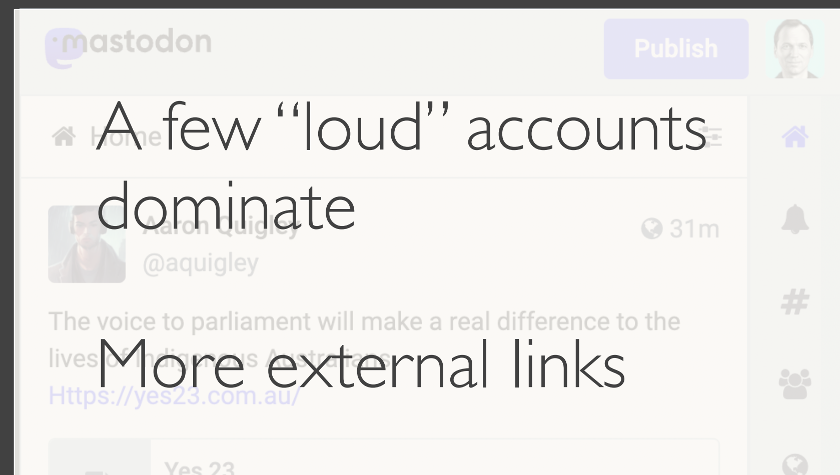
Ranking (on Twitter)



See content from more accounts

More political content

Chronological (on Twitter)



A few "loud" accounts dominate

More external links

[Bandy and Diakopoulos 2021]

How decisions get made

Typically, the platform runs an A/B test on, say, 1% of its users to test the impact of a feed ranking change on its metrics

Often, in practice, the criterion is, "does this move up your desired metrics without harming our other metrics?"

The New York Times

A.I. and Chatbots › | Can You Spot the A.I. Images? | How 35 Real People Use A.I.

Facebook Struggles to Balance Civility and Growth

Employees and executives are battling over how to reduce misinformation and hate speech without hurting ... bottom line.

So the team trained a machine-learning algorithm to predict posts that users would consider "bad for the world" and demote them in news feeds. In early tests, the new algorithm successfully reduced the visibility of objectionable content. But it also lowered the number of times users opened Facebook, an internal metric known as "sessions" that executives monitor closely.

"The results were good except that it led to a decrease in sessions, which motivated us to try a different approach," according to a summary of the results, which was posted to Facebook's internal network and reviewed by The Times.

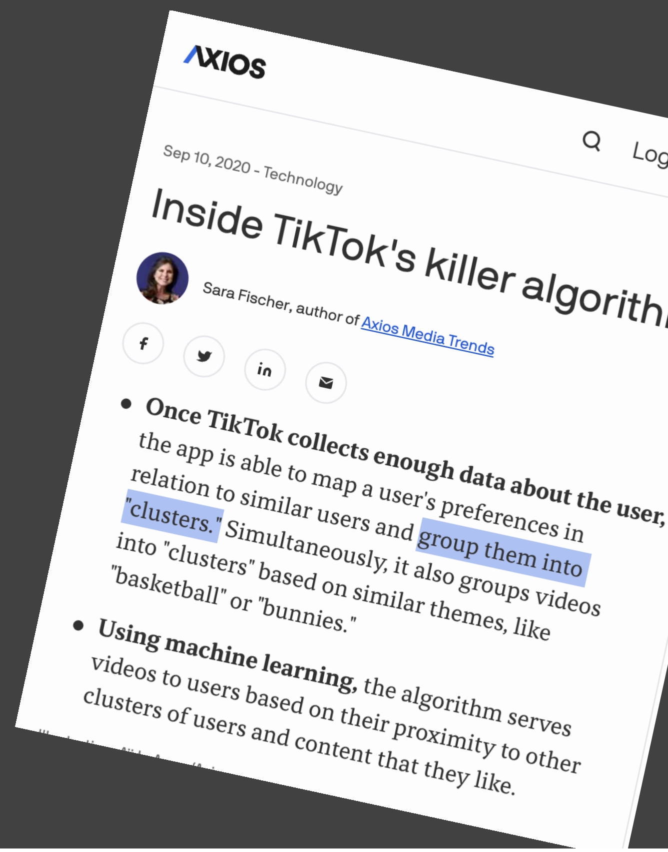
Topics I won't cover today

"Why is TikTok's feed so good?"

It's not the algorithm — it's the signals

Inventory: can it choose from every piece of content on the platform, or just the accounts you follow?

Embeddings: by structuring the deep learning model as a recommender system (think: Netflix), it can jumpstart its recommendations


AXIOS

Sep 10, 2020 - Technology

Inside TikTok's killer algorith

Sara Fischer, author of Axios Media Trends

- **Once TikTok collects enough data about the user,** the app is able to map a user's preferences in relation to similar users and group them into "clusters." Simultaneously, it also groups videos into "clusters" based on similar themes, like "basketball" or "bunnies."
- **Using machine learning,** the algorithm serves videos to users based on their proximity to other clusters of users and content that they like.

Feeds are echo chambers: are feeds echo chambers?

[Gilbert, Bergstrom, and Karahalios 2009]

Filter bubbles

Filter bubbles occur when everyone is shown only content that they like. This happens as a natural outcome of optimizing for engagement.

Example: YouTube recommendation radicalization: channels that are slightly less mainstream become recommendation gateways to more and more radical channels [Ribeiro et al. 2020]

Echo chambers

If feed algorithms only show you things that you want to see, and only shows me things that I want to see, then…

Won't the end result be an echo chamber, where we only hear people who share our opinions? Won't this further polarize our society?


PNAS

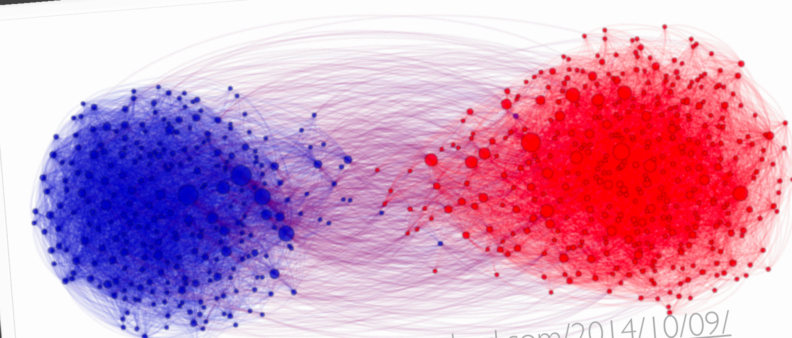
RESEARCH ARTICLE

The echo chamber effect on social media

Matteo Cinelli, Gianmarco De Francisci Morales, Alessandro Galeazzi, +1, and Michele Starnini Authors Info & Affiliations

Edited by Arild Underdal, University of Oslo, Oslo, Norway, and …
January 14, 2021 (received for review November 15, 20…

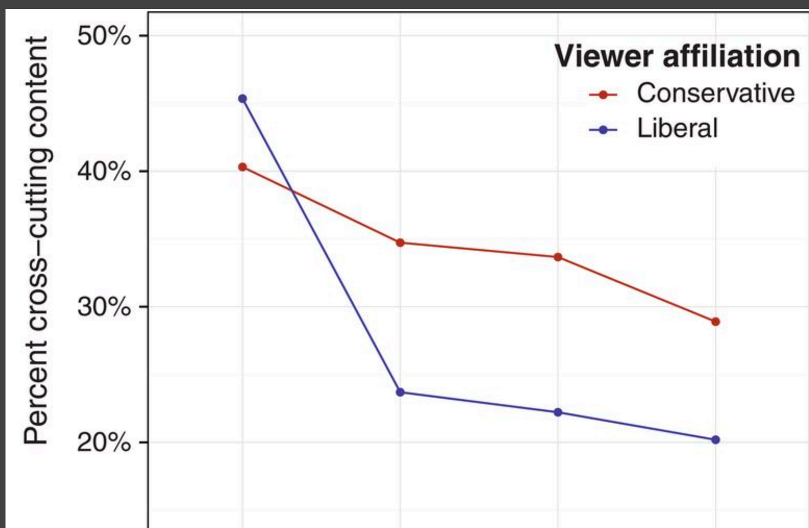
February 23, 2021 | 118 (9) e20233…
https://doi.org/10.1073/pna…



[Adamic 2004; http://allthingsgraphed.com/2014/10/09/visualizing-political-polarization/]

It’s Complicated: Part I

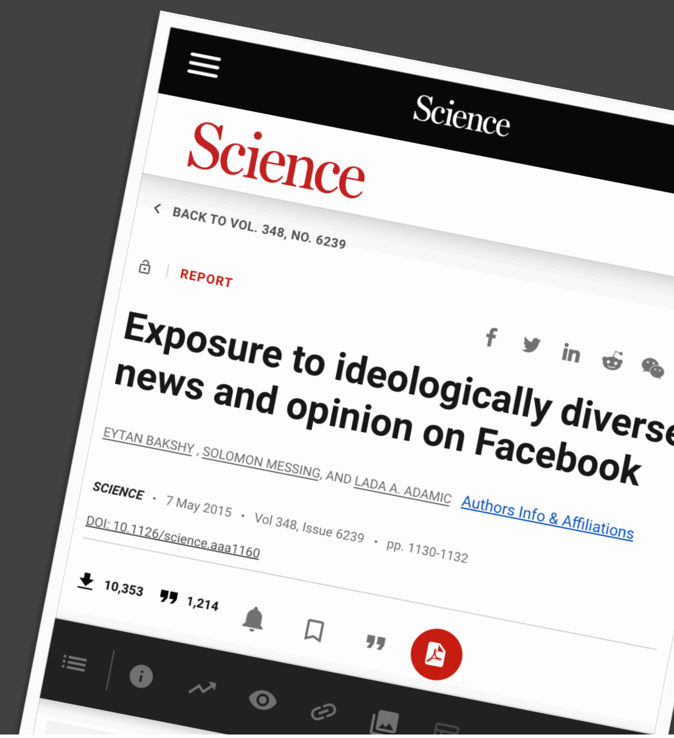
Facebook researchers studied log data to understand the composition of political news in users’ feeds [Bakshy, Messing, and Adamic 2015]



Baseline: If my feed is content from random FB users | Inventory: everything my friends share | Ranked: what my feed actually shows | Clicked: actually engaged with

The biggest drop is due to homophily: that we friend people who share our views

Surprise: the feed is having only a minor effect beyond what the inventory allows



It’s Complicated: Part II

Those who use social media are exposed to more cross-cutting ideological news than those who don’t use social media [Fletcher and Nielsen 2017]

Subscribing people to counter-partisan news sources in their feeds decreases negative attitudes toward the other political party by only 1 point on a 100-point scale [Levy 2021]

Simulations suggest that we might have it backward: that it’s not that we’re polarized because social media only exposes us to like minds, but we’re polarized because social media exposes us to a wider variety of people [Törnberg 2022]

Summary

One common strategy for managing growth is to decide on a subset of content to show users, through an algorithmic feed

- Global rankings aggregate up/downvotes, then trail off over time
- Personalized rankings predict on-platform behaviors, then assign weights to each predicted behavior to determine a score

Concerns abound about feeds creating filter bubbles and echo chambers. While there are clearly negative outcomes, the science is now catching up to what turns out to be a complicated story

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Social Computing

CS 278 | Stanford University | Michael Bernstein