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
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

Left  Front  Back  Right
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
My college roommate wrote a Python script to let RNG give him rewards when he finishes an assignment or gets up early (I told him he's crazy for this).

```python
import random

reward_probs = {
    'Steam Deck': 0.00001,
    'nothing': 0.5,
    'next shower is warm': 0.05,
    '10 mins social media': 0.1,
    'game of league': 0.05,
    'eat takeout': 0.05,
    '10 mins of anything': 0.05,
    '10 mins of chess': 0.05,
    'read an article': 0.1,
    'two spins': 0.04999
}

def spin():
    return random.choices(list(reward_probs.keys()), list(reward_probs.values()))[0]

def main():
    spin_result = spin()
    print(spin_result)
    if (spin_result != 'nothing'):
        with open('rewards.txt', 'a') as f:
            f.write(spin_result + ',

if __name__ == '__main__':
    main()
```

https://www.reddit.com/r/ProgrammerHumor/comments/12h12v0/my_college_roommate_wrote_a_python_script_to_let/
Corporate needs you to find the differences between this picture and this picture.

They're the same picture.

#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
“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

Song by Jesse P: https://youtu.be/FtBiU4se6WY
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  Instagram  Mastodon  iMessage
Twitter  Reddit  Email  WhatsApp
Pinterest  TikTok  Slack  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]
“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 ForYou Page
  Feeds’ objective functions — what are we optimizing for?

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

\[
\log(\max(upvotes - downvotes, 1))
\]

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
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2) Predict

Probability of clicking “like”

\[ P(\text{like}) \]
2) Predict

Models for each outcome of interest

- $P(\text{like})$
- $P(\text{hide})$
- $P(\text{comment})$
- $P(\text{follow})$
- $P(\text{watch})$
- $P(\text{share})$
- $P(\text{click})$
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?

\[ \sum_{p \in \text{predictions}} \text{weight}_p \cdot p \]

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

Intuitively: how many points does each predicted behavior get?
Objectives in use

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

<table>
<thead>
<tr>
<th>Interaction type</th>
<th>weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Like</td>
<td>1</td>
</tr>
<tr>
<td>Reaction</td>
<td>1.5</td>
</tr>
<tr>
<td>Reshare</td>
<td>1.5</td>
</tr>
<tr>
<td>Comment</td>
<td>15-20</td>
</tr>
</tbody>
</table>

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

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.

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:

\[ \sum_{p \in \text{predictions}} \text{weight}_p \cdot p \]
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]
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

\[ \sum_{p \in \text{predictions}} \text{weight}_p \cdot p \]

Score: 2.4
Sum it up

\[
\sum_{p \in \text{predictions}} \text{weight}_p \cdot p
\]

Score: 1.1
Personalized feed: machine learning

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

Rank the items in the feed by their score
Outcomes of ranking

Ranking (on Twitter)

See content from more accounts
More political content

[Bandy and Diakopoulos 2021]

Chronological (on Twitter)

A few “loud” accounts dominate
More external links
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?”

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
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?

[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]

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.
References


Social Computing
CS 278 | Stanford University | Michael Bernstein

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