

# Recommender Algorithms

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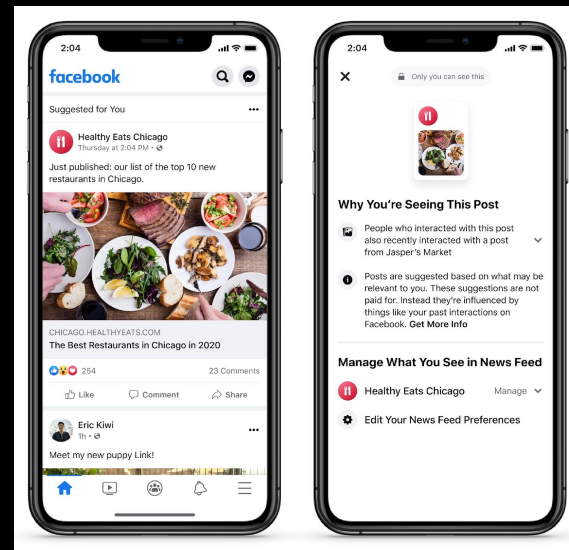
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# OUTLINE

- (1) What is a Recommender Algorithm?
- (2) History of Development
- (3) Privacy Considerations
- (4) Fairness & Ethics Considerations
  - (a) General
  - (b) Emotional/Psychological
  - (c) Radicalization
- (5) Possible Solutions

What is a Recommender  
Algorithm ?

# “THE ALGORITHM”



# The problem it addresses - Maximizing user's time

- Many companies using recommender algorithms collect and & sell user data to advertisers & other third-parties
- Others operate on a subscription model (Netflix), and aim to keep their subscribers paying
- Both of these lead priorities to the primary goal of **maximizing time spent by users on the platform**—to maximize profits

Recommender algorithms are the key to achieving this goal, providing users with content they are most likely to enjoy

# History & Algorithm Overview

# Recommender Algorithm Origins - Collaborative Filtering

■	.9	-.8	1	1	-.9
▲	-.2	-.8	-1	.9	1
					
	Harry Potter	The Triplets of Belleville	Shrek	The Dark Knight Rises	Memento

●	◆
1	.1
-1	0
.2	-1
.1	1



✓		✓	✓	
	✓			✓
✓	✓	✓		
		?	✓	✓

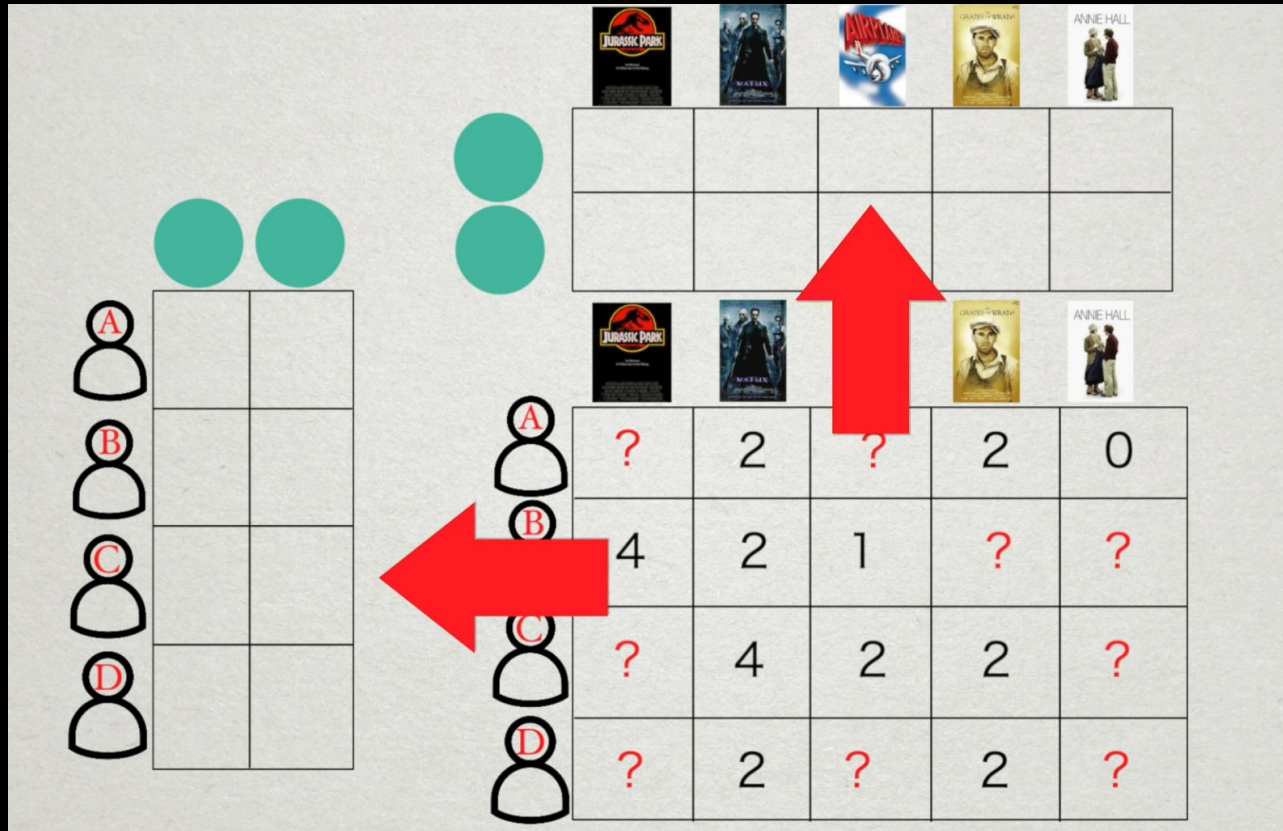
■ arthouse <-> blockbuster

▲ children's <-> adult's

● preference for arthouse <-> blockbuster

◆ preference for children's <-> adult's

# Recommender Algorithm Evolution - Matrix Factorization





# Modern Recommender Algorithms - Deep Neural Networks (Ex. Youtube)

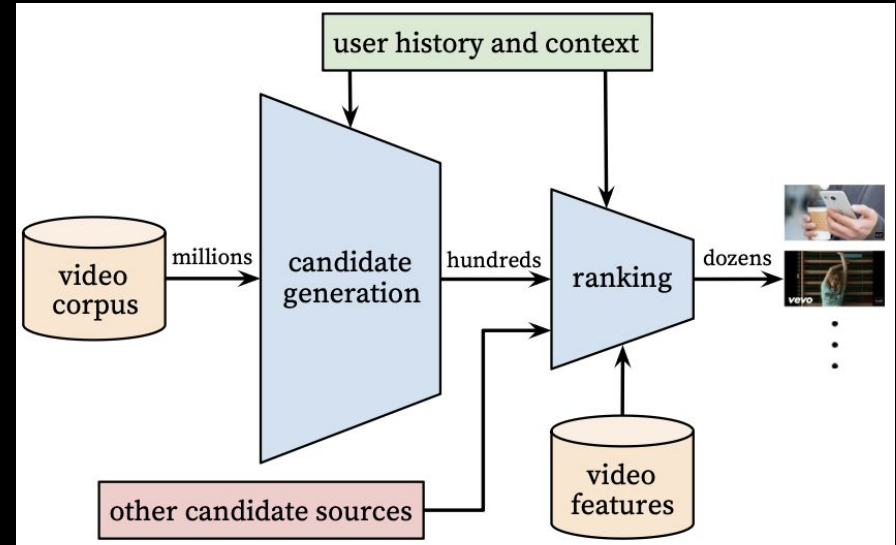
Two stage pipeline:

## 1. Candidate Generation (Rough Personalization)

Input: user's watch history, search history, and basic demographics (location, age, device).

## 2. Ranking (Fine-Tuned Personalization)

Input: More features (hundreds) like channel history, time since last watch, click frequency etc.



# Privacy

“Does the system know who I am? How much does it know?”



# Concerns

## User Profiling:

- Systems track many things (searches, clicks, time spent) to build a profile.

## Inference & sensitive attribute disclosure:



- Even if you didn't tell the system your age, gender, or medical condition, algorithms might infer it from your behaviour

## Lack of control / transparency

- Users may not know what data is used, whether they can control it, or how to opt out.

# Trade-off

## Personalization vs privacy

- The more personalized recommendations get, the more data is used - this can reduce privacy.



# Fairness & Ethics

“Is it morally acceptable for a company to design the algorithm so that I stay longer even if it harms my well-being?”



### Popularity bias & “rich get richer”

- “Niche books... accounted for 30–40% of Amazon book sales.”



### Unequal exposure for creators/groups

- “Popularity can derive from historical and structural inequalities, which means favoring popular items can be unfair towards protected groups.”

### Reduced user autonomy & manipulation

- Preferences shaped even if users “think” they’re choosing freely

### Opaque decision-making

- Users have no visibility into why something is recommended



# Emotional/Psychological Impact

“Recommendations can affect how we feel, what we believe, and our habits.”



### Addiction & continuous scrolling

- The system learns what keeps you engaged



### Mood-based content loops (sad -> sadder)

- Content often reflected or amplified users' emotional expression

### Self-image & unrealistic standards

- Exposure to idealised physical appearance and lifestyle content was associated with lower self-esteem

### Echo-chambers & emotional escalation

- Recommendations can trap you in narrow emotional/ideological loops.



# Algorithmic Radicalization<sup>u</sup>

“A serious risk: how recommender systems may push users toward extreme or radicalised content.”





## Engagement loop rewards extreme content

- Content that triggers strong emotion often yields high engagement



## Progressive escalation path

- A user might start with “mild” content and gradually be recommended more extreme content.

## Filter bubbles & narrow world-views

- The system may increasingly show similar content, reducing exposure to opposing views



# Solutions & Mitigations

“What can be done: both technically and from a design/ethical standpoint.”

# Solutions to Privacy Concerns



## Federated Learning / On-device processing

- Instead of sending all your data to central server, compute recommendations partly on your device
- Share only aggregated updates. (keeps raw data local)



## User control & transparency

- Give clear options: “See what data we use”, “Delete your data”, “Turn off personalized recommendations”.
- Show “why was I recommended this?” logs.



# Solutions to Fairness & Ethical Concerns



Include fairness/diversity objectives

- Shift algorithm goal: not just “keep you longer”, but “serve you well” and “treat creators fairly”.



Expose reasoning: “Why was this recommended?”

Design for well-being, not only attention

- Algorithms can detect signs of negative loops (emotional or ideological) and moderate.

Independent audits of recommendation outcomes (exposure, fairness, emotional impact)



# Why corporations ultimately don't care about implementing solutions

Goals of **product** recommender systems:

- Better understand what the user wants
- Increase user satisfaction
- Increase number of items sold
- Sell more diverse items



Goals of **content** recommender systems:

- Better understand what the user wants
- Increase user satisfaction
- Increase user's total content consumption time
- Maximize ad revenue



# References



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THANK YOU!

Questions ?

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