Recommender Algorithms

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OUTLINE

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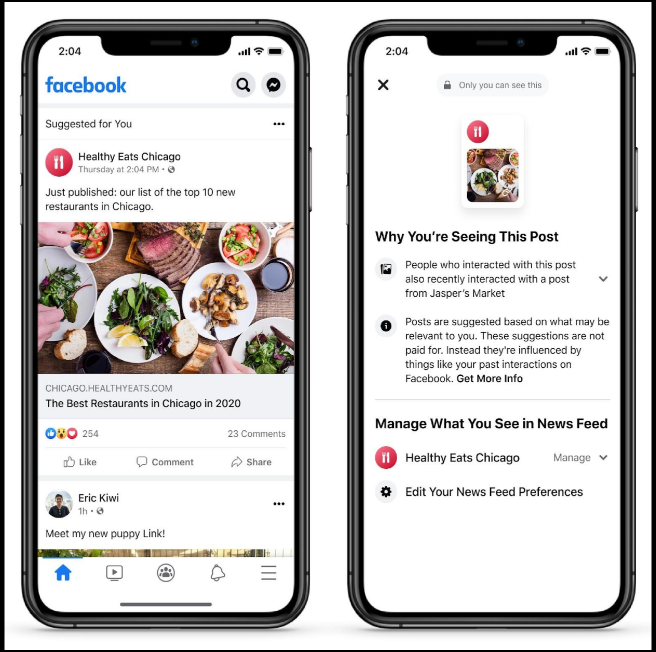
What is a Recommender Algorithm ?

“THE ALGORITHM”



Applications of recommender algorithms

- **Content delivery**
- Retail
- Advertising
- Search
- Social platforms
- Finance
- Health
- etc.

The problem it addresses

- 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 priorities contribute to a general 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

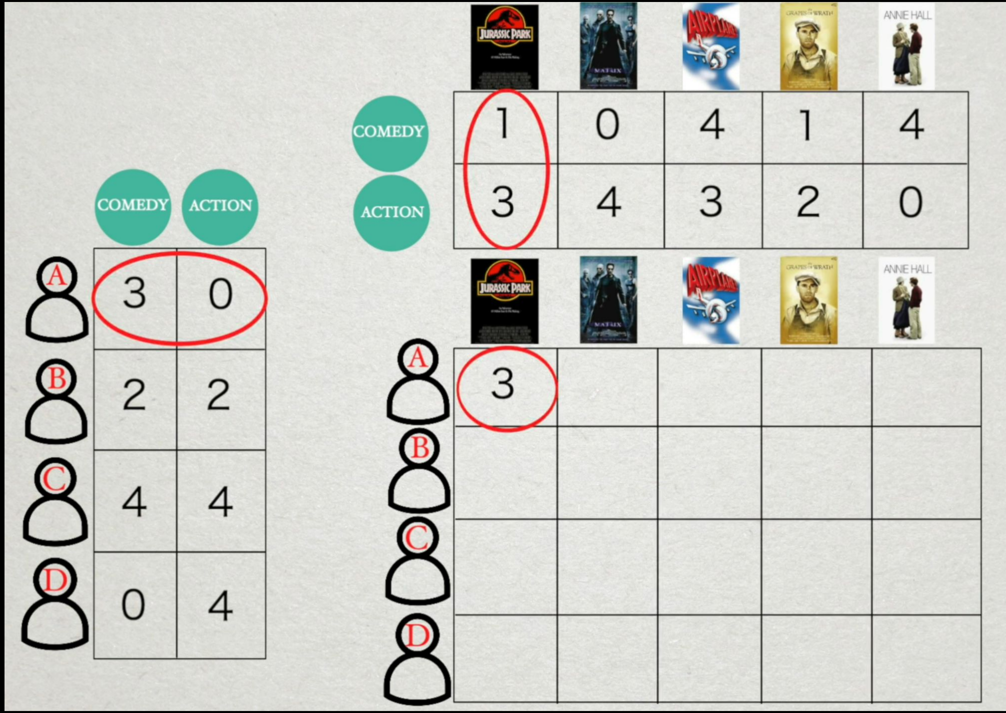
History & Algorithm Overview

Recommender Algorithm Origins - Content-Based Filtering

Uses similarity between items to recommend new items that are similar to what the user likes.

If user A has watched many action and comedy movies, then the system can recommend action-comedy movies to them.

Also, demographic filtering



Advantages

- Model is specific to each user, so it does not require large amounts of data on all users of the platform.
- Can help users discover new interests
- The model can capture the specific interests of a user, and can recommend niche items that few other users show interest in

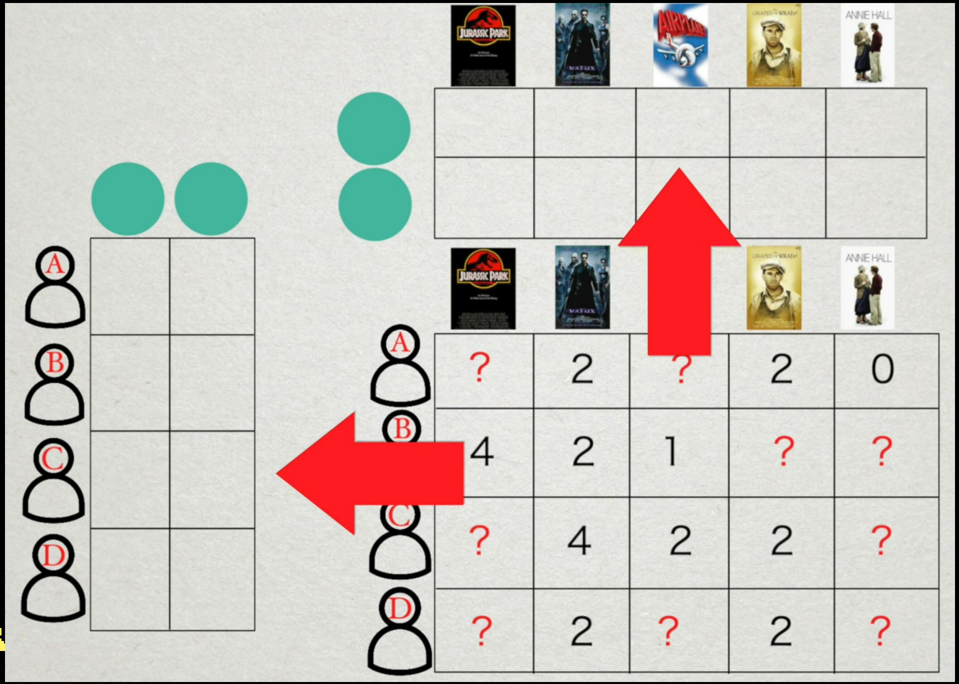
Disadvantages

- Features are hand-engineered to some extent, requiring a lot of domain knowledge and overhead
- Model is only as good as its explicit features
- Becomes less useful as user interests evolve, or may not have a complete picture of a user's interests due to a lack of data

Recommender Algorithm Evolution - Collaborative Filtering

Uses similarities between groups of users (through latent features) to provide recommendation.

If user A is similar to user B, and user B likes movie 1, then the system can recommend movie 1 to user A (even if user A hasn't seen any movies similar to movie 1).



The Netflix Prize

Matrix Factorization for Collaborative Filtering

Embedding model

- In this case, given a rating matrix *(m x n)*, where the model learns user and item embedding matrices *U (m x d)*, *V (n x d)* that, when factored, produces a good approximation of the original matrix
- Original matrix has *O(nm)* entries, while the embedding matrices *U*, *V* have *O((n+m)d)* where the embedding dimension *d* is usually smaller than *m* or *n* — *This is compression!*

Matrix Factorization for Collaborative Filtering

There are many ways to go about building these models

General steps:

1. **Select an objective function** (a.k.a. loss or cost)
    a. Squared distance
    b. Singular Value Decomposition (SVD)
    c. Alternating Least Squares (ALS)
2. (OPTIONAL) **Optimize objective function**
    a. Regularization (reduce overfitting)
3. **Minimize the objective function**
    a. Stochastic gradient descent (SGD)
    b. Weighted Alternating Least Squares (WALS)

Advantages

- No domain knowledge or hand-engineering features necessary, as latent features emerge
- Model can help users discover new interests

Disadvantages

- Cold-start problem
  - Sparse rating matrices
- Scaling
  - Computational complexity

Modern Recommender Algorithms - Deep Neural Networks (e.g. YouTube)

Two stage pipeline:

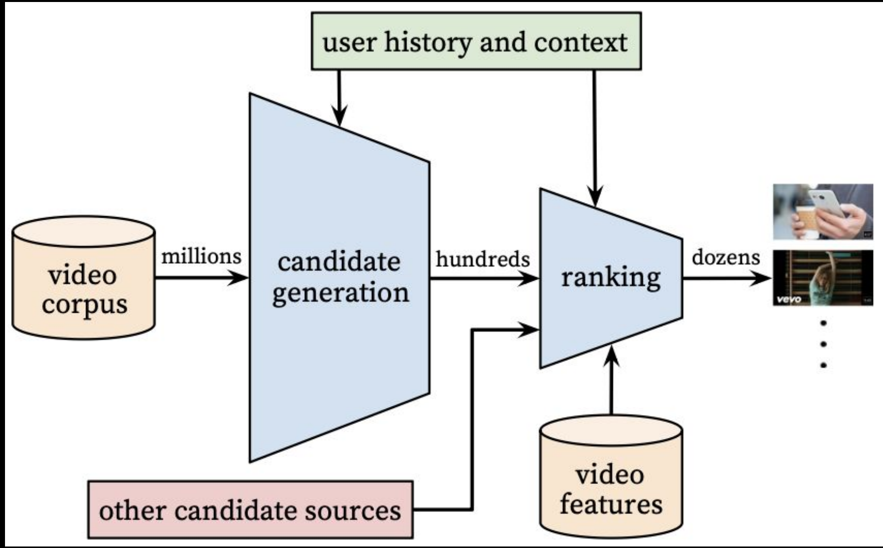
1. **Candidate Generation** (Rough Personalization)

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

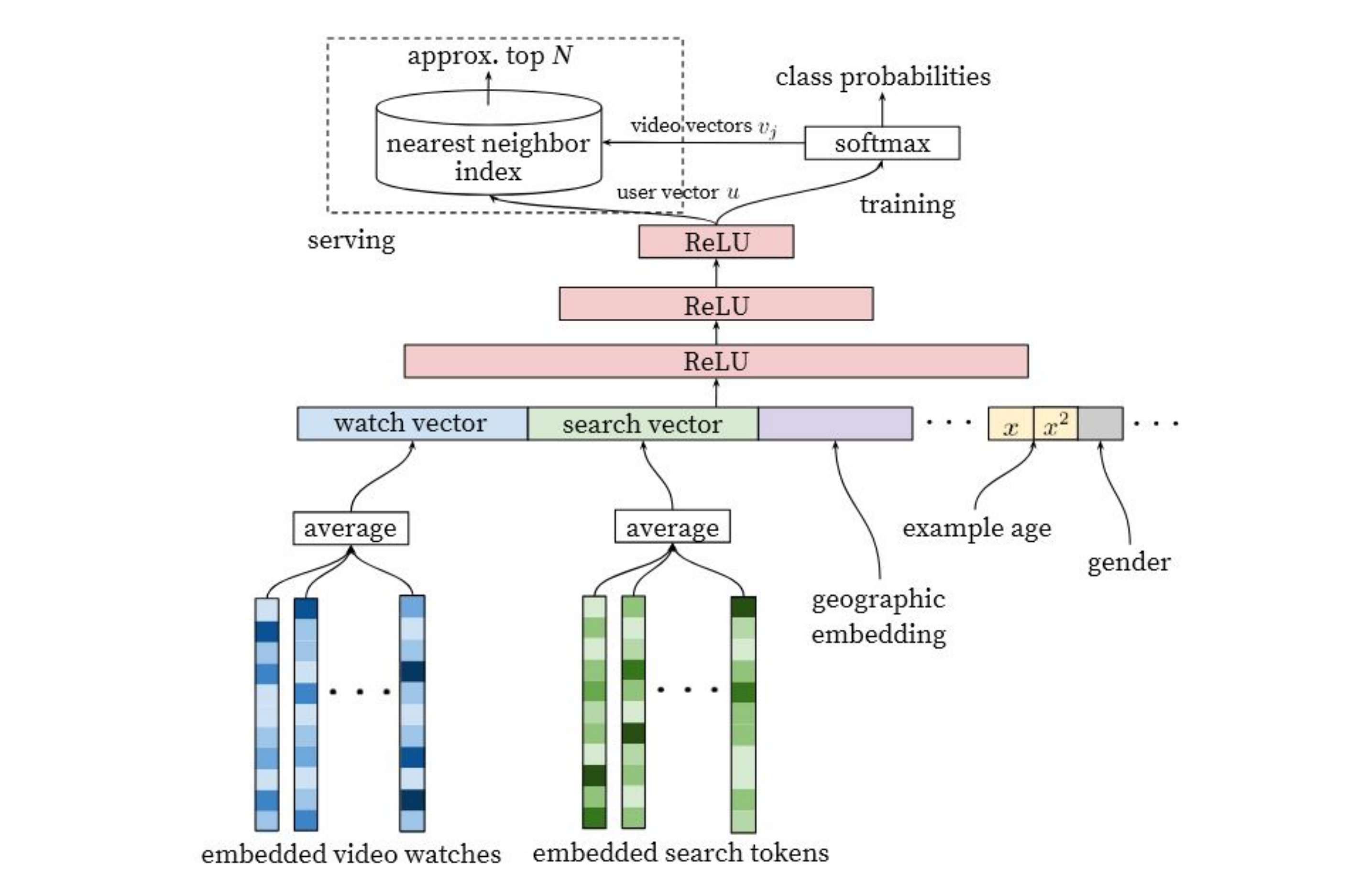
Eliminate 99.9% of irrelevant videos.

2. **Ranking** (Fine-Tuned Personalization)

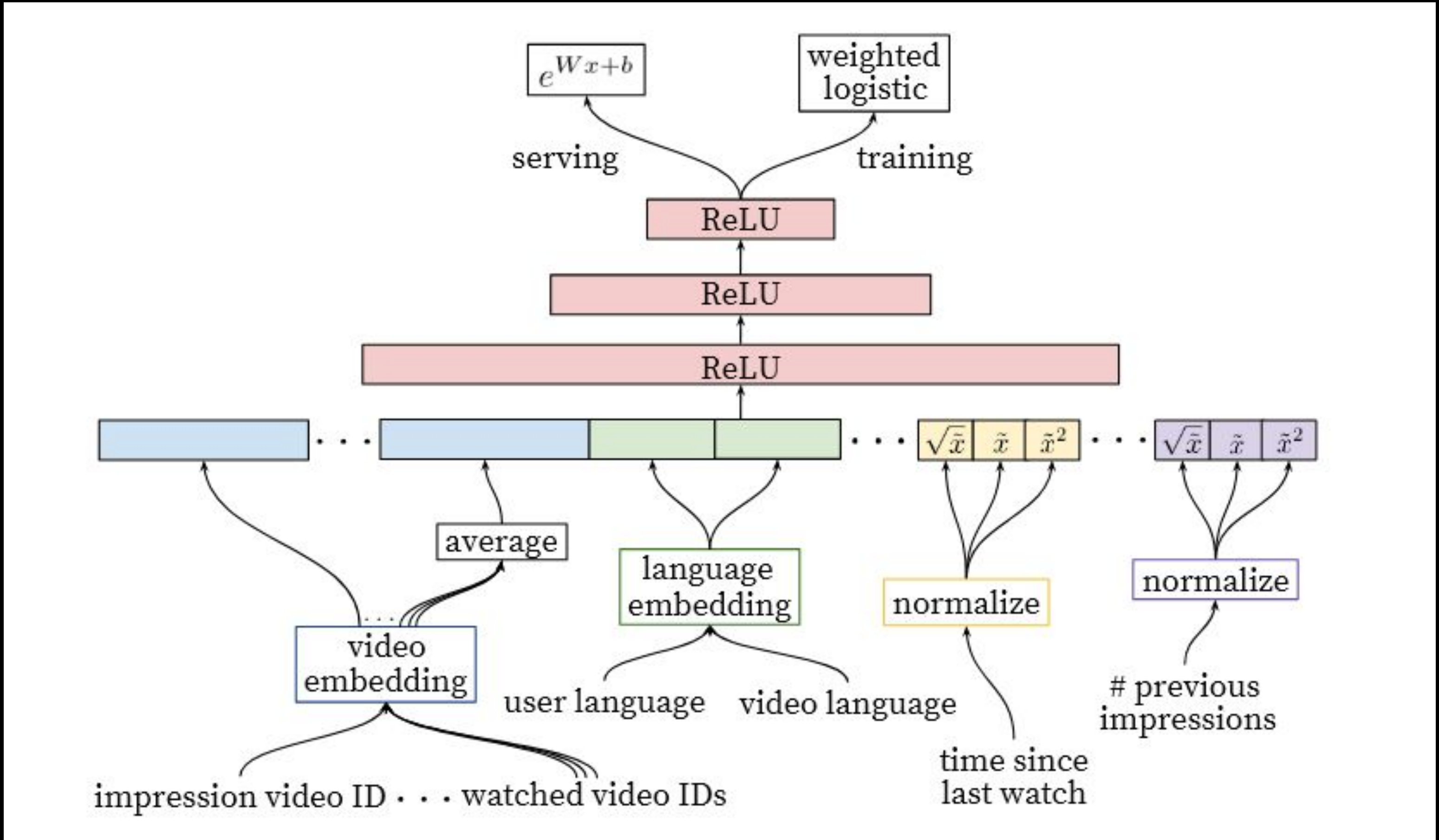
Input: More features (hundreds) like channel history, time since last watch, click frequency etc.



YouTube DNN - Candidate Generation



YouTube DNN - Ranking Network



What is in use today?

It depends.

- Domain
  - Task/Objective
  - Scale
- Computational resources
- Cold-start?

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.

Anecdote: The Netflix Prize II

- Age (not date of birth)
- Gender
- ZIP code
- Movie genre ratings (but not specific movie ratings)
- Previously rented movies

Netflix Settles Privacy Lawsuit, Cancels Prize Sequel

By Taylor Buley, Contributor. ⓘ News developer, in all senses of the phrase for The Firewall

Follow Author

Published Mar 12, 2010, 12:35pm EST, Updated Apr 24, 2013, 08:08pm EDT

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On Friday, Netflix announced on its corporate blog that it has settled a lawsuit related to its Netflix Prize, a $1 million contest that challenged machine learning experts to use Netflix's data to produce better recommendations than the movie giant could serve up themselves.

The lawsuit called attention to academic research that suggests that Netflix indirectly exposed the movie preferences of its users by publishing anonymized customer data. In the suit, plaintiff Paul Navarro and others sought an injunction preventing Netflix from going through the so-called "Netflix Prize II," a follow-up challenge that Netflix promised would offer up even more personal data such as genders and zipcodes.

Robust De-anonymization of Large Sparse Datasets

Arvind Narayanan and Vitaly Shmatikov
The University of Texas at Austin

- Minimal data needed for re-identification
  - Just 8 movie ratings (2 can be wrong) with approximate dates could identify 99% of users in Netflix's ”anonymized” 500,000-subscriber dataset
- Simple attack method: cross-database correlation (IMDb reviews)
- Complete movie viewing histories revealed private personal interests (e.g. political beliefs)

Individual preference patterns are unique enough that standard anonymization (removing names, adding noise) fails to protect privacy

- Similar vulnerabilities exist for shopping habits, browsing history, reading patterns, and any behavioural data from recommender systems

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

"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 content consumption time
- Maximize ad revenue

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THANK YOU!

Questions ?

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