Modeling Human-Software Interactions in Modern Recommender Systems

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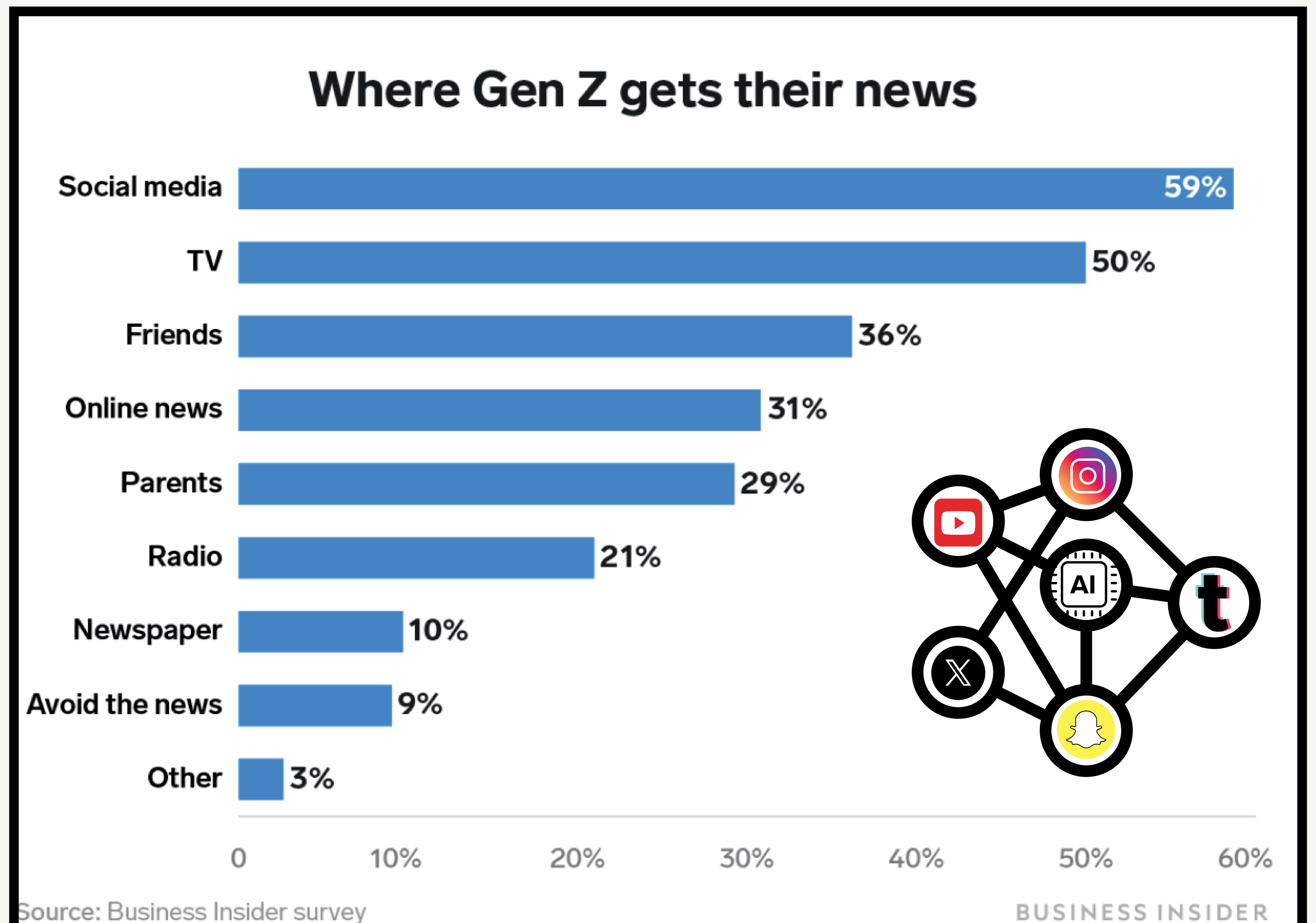
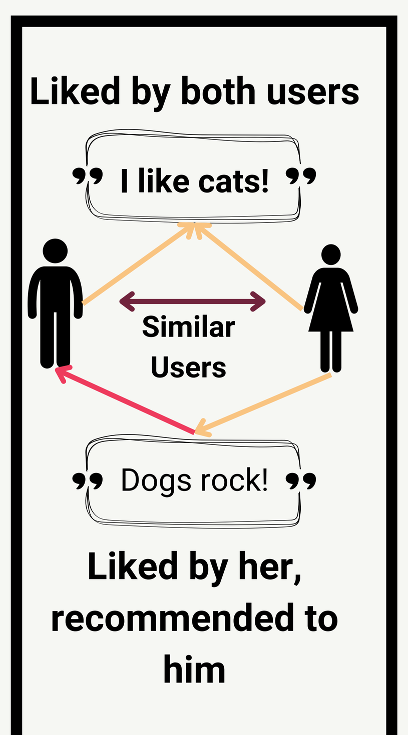
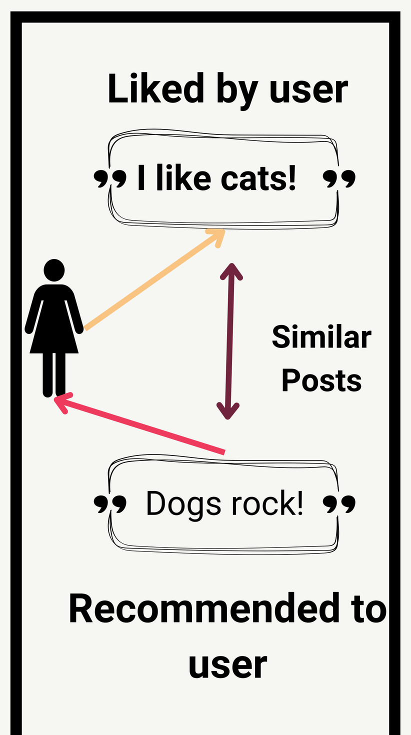
How Do Platforms Know What You Want?

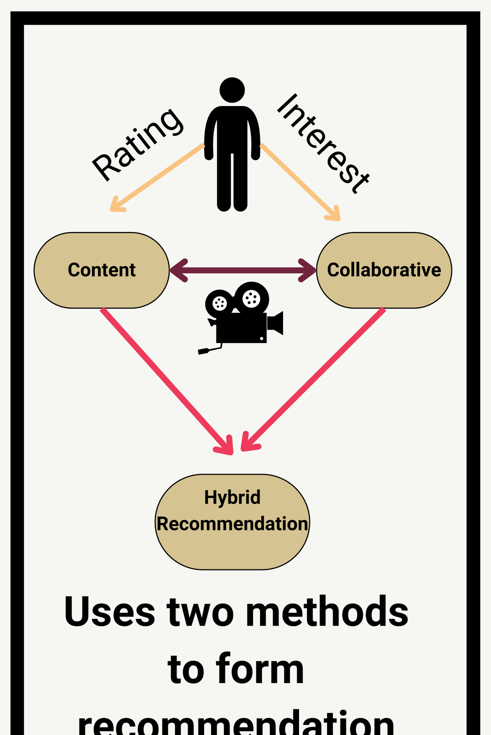
Every day, we interact with recommendation systems—whether it's YouTube suggesting a video, X recommending a tweet, or Spotify curating a playlist. But what shapes these predictions? This poster explores different ways to model the interaction between users and platforms in **recommender systems** through an analysis of a variety of literature.



What are Recommender Systems?







... And Why Do We Model Them?

Above are three examples of types of recommender systems, **Collaborative Filtering (Left), Content-Based Filtering (Center), and Hybrid Filtering (Right).** In real life, recommender systems are complex, often relying on intricate statistical methods to analyze vast amounts of data. To effectively understand and implement these systems, we must create simpler models that capture essential interactions.

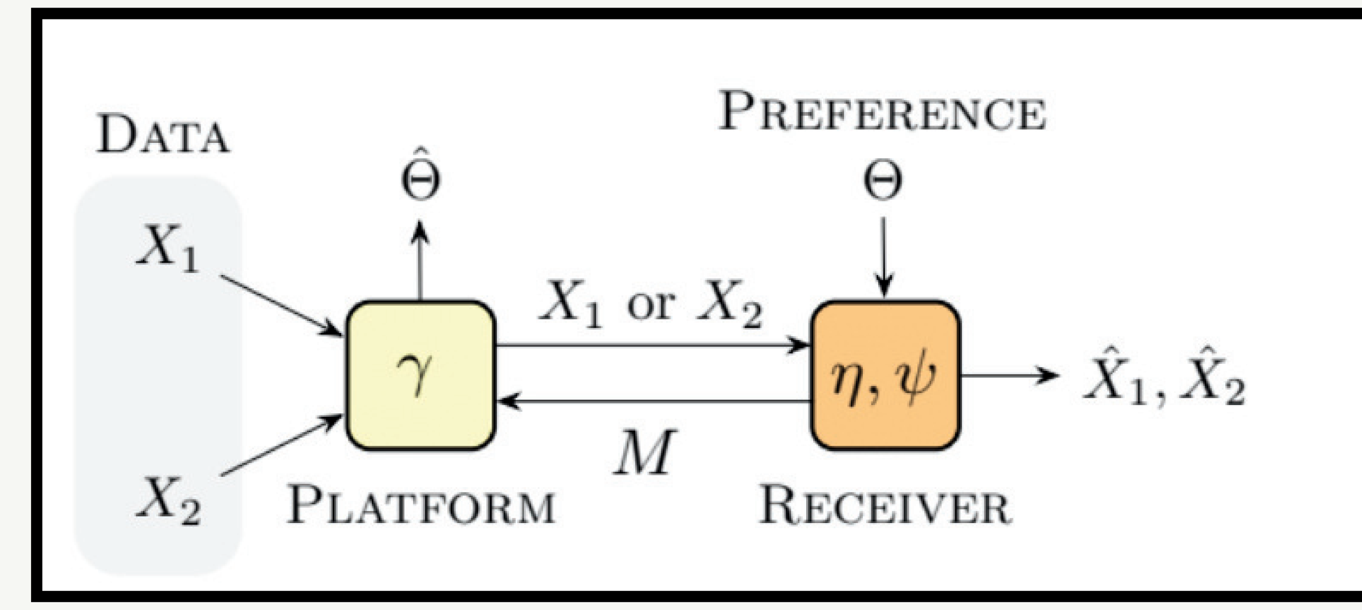
Different Models in the Literature

Models	Core Idea	Strengths	Weaknesses
Beta-Binomial Collaborative Filtering Model (Ribeiro et al., 2023)	-Employs a beta-binomial distribution to estimate utility for user-item interactions -Allows for both random and utility-informed item selection.	-Utilizes a flexible probability framework to accurately represent utility distribution across various topics such as political alignment and incorporates user preferences	-Assumes that items in the same topic have the same utility for users, which may not reflect real-world diversity in content. -Relies on cosine similarity, which may not capture deeper patterns in user behavior.
Information Inundation Model (Allon et al., 2021)	-Models how news platforms influence consumer beliefs by presenting K noisy versions of the truth, where each post has an unknown accuracy level.	-Captures the uncertainty in news accuracy and how consumers form beliefs in an information-rich environment.	-Assumes consumers lack external information to verify accuracy, potentially oversimplifying real-world decision-making.
Network-Based Opinion Formation Model (Dandekar et al., 2013)	-This model represents opinion dynamics on a social network, where individuals update their opinions over time based on weighted influences from their neighbors and their own prior beliefs.	-Captures social influence in a structured way, making it useful for studying echo chambers, polarization, and consensus formation	-Assumes individuals update opinions in a fixed manner without accounting for external shocks, learning, or strategic behavior
Deconvolving Feedback Loops (Sinha et al., 2017)	-Proposes a mathematical framework to separate true user preferences from recommender system-influenced ratings by modeling the iterative feedback process and using matrix factorization techniques	-Provides a structured approach to isolate recommendation biases, leverages a closed-form solution under reasonable assumptions, and offers insights into mitigating feedback loops in collaborative filtering models	-Relies on strong assumptions about user behavior and similarity metrics, requires accurate estimation of unknown probability parameters, and may struggle with real-world complexities like dynamic user preferences and external influences

- **Models have three important characteristics**
  - How user behavior is shown (data driven vs. strategic interactions)
  - How platforms make decisions (fixed rules vs. adaptive strategies
  - What is emphasized (user preferences, platform control, strategic signaling, etc.)

References

Our Model

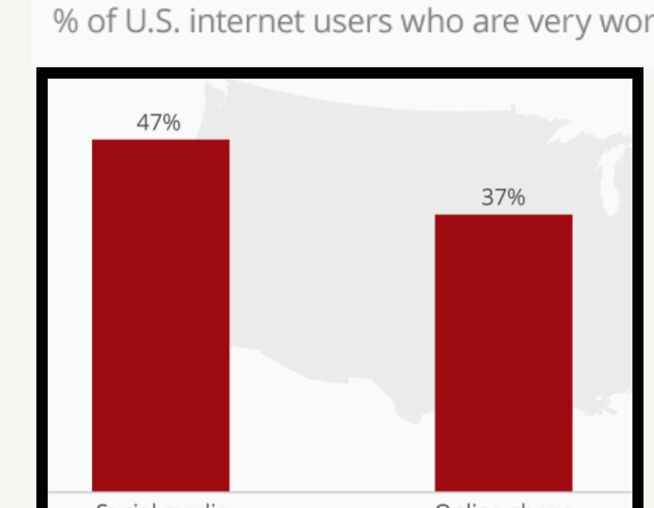


- **A signaling game between a Platform (Sender) and a User (Receiver).**
- **The platform has two pieces of content but can send only one.**
- **The user has a hidden bias (θ) for one content over the other.**
- **The user sends a limited message about their preference, and the platform then sends the most relevant content based on that message.**
- **The platform chooses which content to display based on the user's preference, using a decision rule based on the user's message.**
- **Both the platform and user try to minimize their losses (incorrect preferences), with the platform aiming to match the user's preferences as closely as possible.**

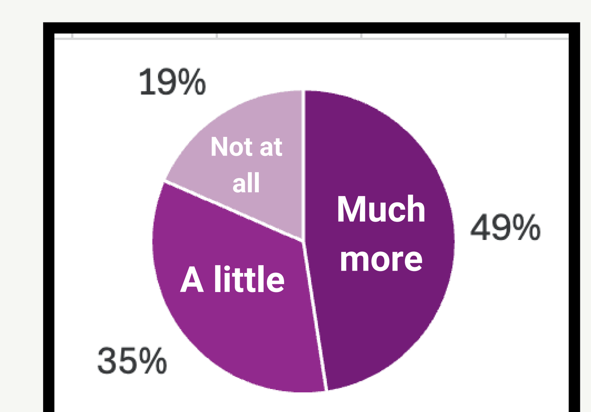
What comes next?

Americans Worried About Data Security on Social Media

% of U.S. internet users who are very worried about data security on following platforms



In 2022, when Americans were asked if they felt more concerned about privacy on social media now than the year before, 84% replied yes. Adapted from (Freer, 2022).



-Future research should explore models that incorporate differential privacy techniques or privacy-preserving federated learning to ensure user data is protected without sacrificing recommendation quality.

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