A User-Centric Approach to the Design and Consequences of Recommender Systems

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Recommender Systems

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  - millions of products on Amazon
  - billions of videos on YouTube

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  - thousands of movies on Netflix
  - millions of products on Amazon
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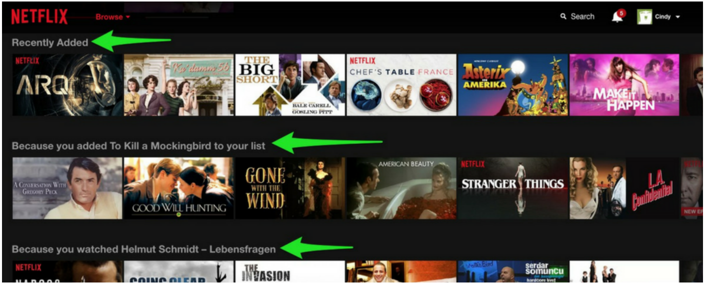
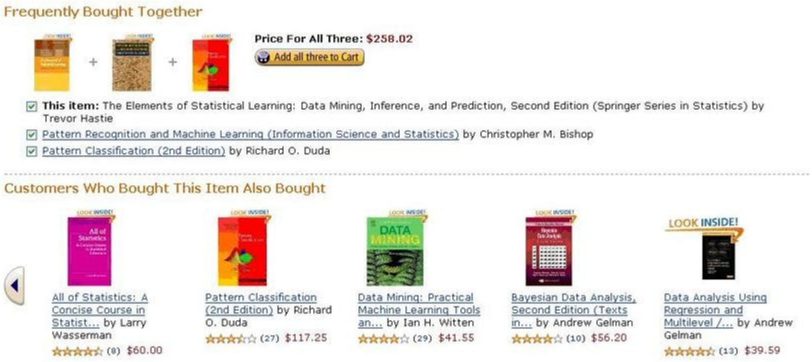
- The industry response has been the development of *recommender systems*



Another Example



Recommendation and Consumer Choice

- Recommender systems influence consideration and consumption choices of individuals
  - 75% of movies on Netflix
  - 35% of page-views on Amazon
  - Aguiar and Waldfogel (2018) show that inclusion in Spotify's public recommendation playlists dramatically affects a song's likelihood of success

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  - Aguiar and Waldfogel (2018) show that inclusion in Spotify's public recommendation playlists dramatically affects a song's likelihood of success
- But how does recommendation change how individuals make decisions?

Three Motivating Questions

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This paper: First-order concern is to understand how consumers make decisions in environments where recommender systems are deployed

Model Demonstration I

How to pick a movie on Netflix? a video on YouTube?

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Ingredient 1: Long-lived consumers that face large choice sets

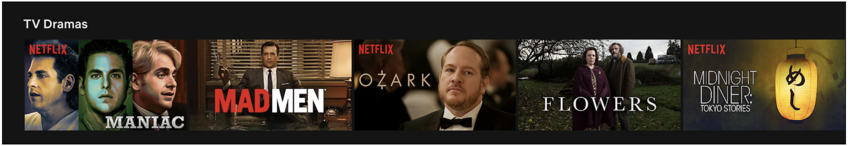
- Learn fast - learn true consumption utility after consuming once
- Challenge is that can only consume a small portion of the overall choice set

Model I - Setting

- Each individual faces a choice set $\mathcal{J} = \{1, ...N\}$ of N items
- Consumes $T << N$ of these items
- $u_{in} = v_{in} + \beta V_{in}$
  - v_{in} - idiosyncratic component of utility
  - V_{in} - common value component
  - β controls how "predictable" a user's preferences are given other's preferences
  - Users learn true u_{in} after consumption

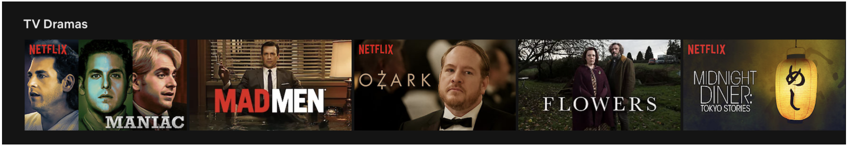
Model Demonstration II

Which would you pick?



Model Demonstration II

Which would you pick?



Ingredient 2: Uncertainty over realized utility of items

Model II - User Beliefs

- Distributions of V and V_i
  - $V_i \perp\!\!\!\perp V$
  - $V_i \sim \mathcal{N}(\overline{V_i}, \Sigma_i)$
  - $V \sim \mathcal{N}(\overline{V}, \Sigma)$, $\overline{V} = 0$
  - Why Gaussian?
    - Recall Gaussian distributions form a conjugate prior - closed form Bayesian updating
    - Allows intuitive way to model correlation structure
- Prior beliefs for individual i are drawn $\overline{v}_{in} \sim \mathcal{N}(0, \overline{\sigma}^2)$
- CARA preferences - $\mathbb{E}[u_{in}] = \mu_n - \frac{1}{2}\gamma\Sigma_{nn}$

Model Demonstration II

Suppose you ended up watching *John Wick* and it was:

- Good?

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- Good? Watch *John Wick 2*?

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Ingredient 2: Learning spillovers - consumption gives information about similar items (e.g. similarity-based generalization)

Model III - Informational Spillovers

- Conceptually, products are evenly space on a circle
  - $d(n,m) = \min\{|m-n|, N - |m-n|\}$
- (n,m) entry in Σ_i is given by $\rho^{d(n,m)}\sigma_i^2$ (same with Σ)
- Combined with distance measure - $(n, n+1)$ entry is ρ, etc.
- higher $\rho \implies$ larger spill-overs
- higher $d(n,m) \implies$ smaller spill-overs

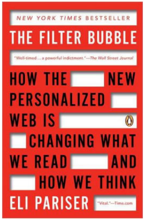
Model IV - Recommendation

- Model recommendation as providing information to users to reduce uncertainty
- Three recommendation regimes:
  1. No Recommendation: Users get no information
  2. Omniscient: Ex-post (full information) optimal consumption path
  3. Parital: Recommender knows true V + idiosyncratic beliefs = personalized recommendation

Model Evaluation

- Focus on numerical simulation of our model over P populations of I individuals
- For each population, average over consumers to get "representative" consumer from population
- Reported results are over a dataset of representative populations over a fine grid of parameter values

Question 1: Filter Bubbles

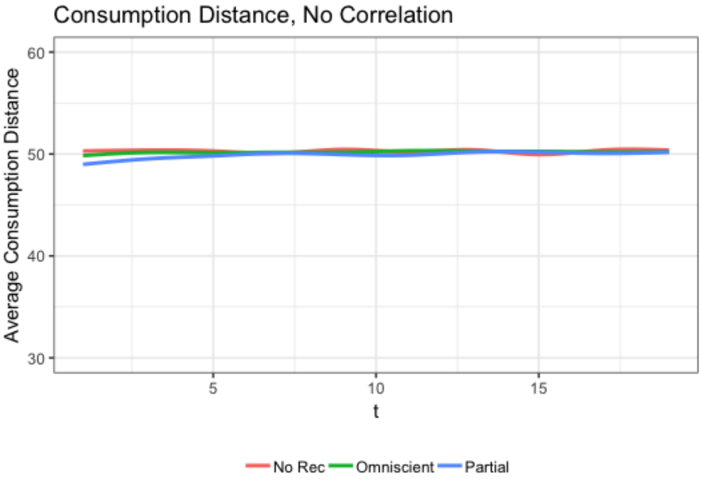


Do personalized recommender systems lead users into increasingly narrow portions of the product space?

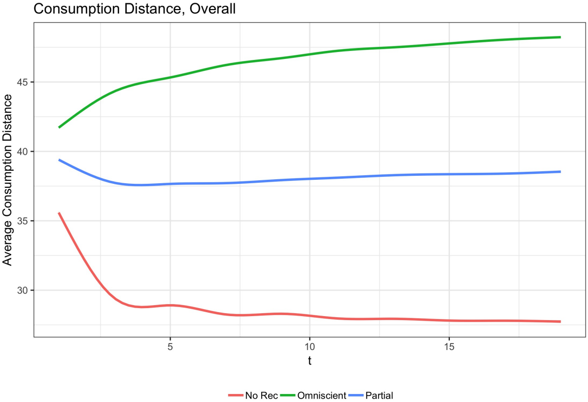
- Empirical studies find little evidence for this due to recommender systems in various domains (news, movie consumption)
- Find that this happens *without recommendation*

Our model: Learning spillovers induce over-consumption around "local maxima" (amplified when users are risk-averse)

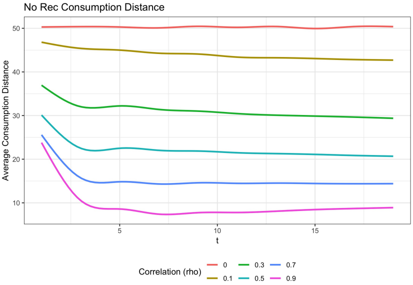
Filter Bubbles - No Correlation



Filter Bubbles - Overall



Filter Bubbles - Increasing ρ



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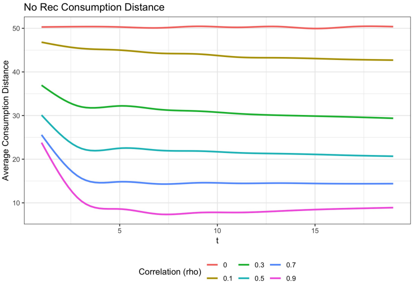
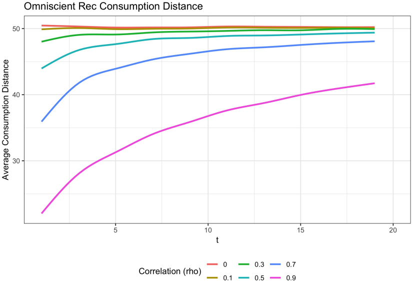




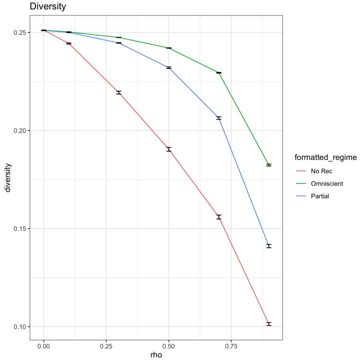
Question 2: Product Diversity

Is aiming for product diversity a good goal for recommender systems?

Our model: Without recommendation, diversity can be *negatively correlated* with consumer welfare

- Recall the John Wick example: high diversity can be induced by many bad experiences and lead users to jump all over the product space
- Strong risk-aversion weakens this, but leads to users being stuck in "bad" portions of the product space
- Recommendation weakens this since it coordinates users to consume in "good" parts of the product space

Diversity, Welfare vs ρ



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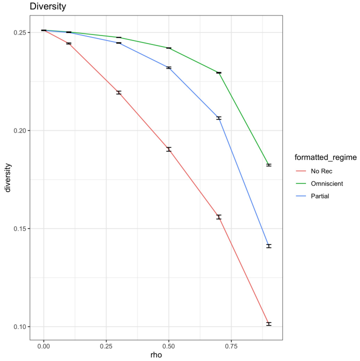
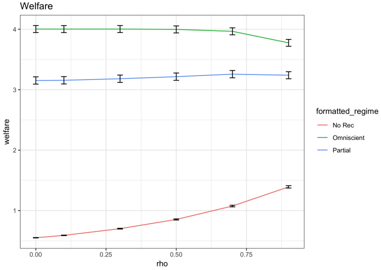
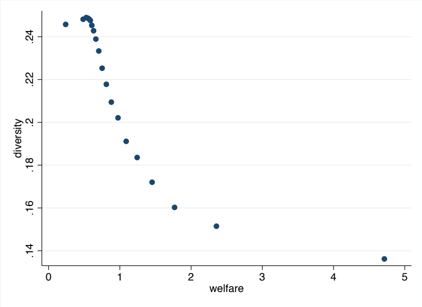




Diversity vs Welfare - No Recommendation



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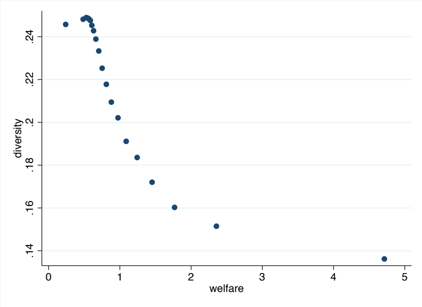
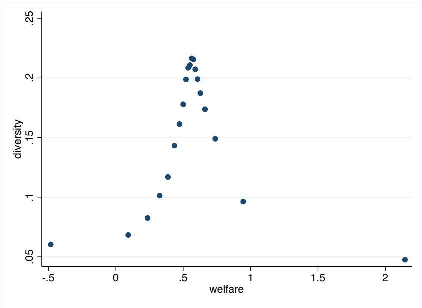




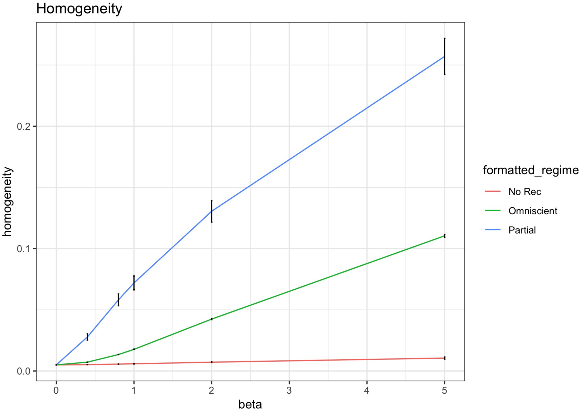
Question 3: User Homogeneity

Do recommender systems induce users to consume similar sets of items?

Our model:

- Omniscient recommendation has a small amount of homogeneity
- No recommendation has no homogeneity - random exploration around the product space
- Partial recommendation coordinates users around same goods - high homogeneity

Homogeneity - Varying β



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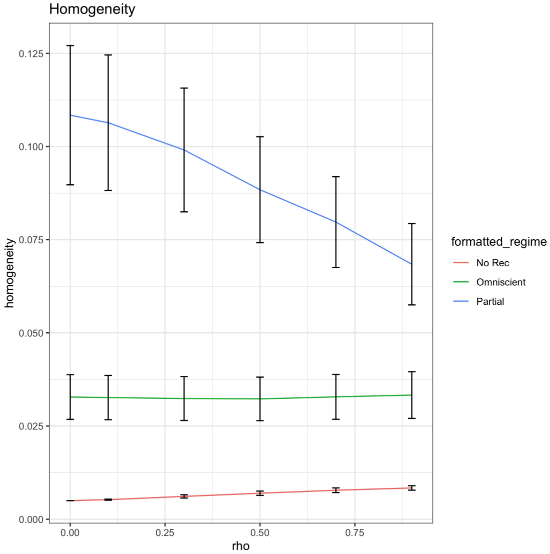

Towards Recommendation Design: Why are Accurate Recommendations not good?

Imagine you are using a travel recommender system. Suppose all of the recommendations it gives to you are for places you have already traveled to? Even if the system was very good at ranking all of the places you have visited in order of preference, this still would be a poor recommender system. Would you use such a system?

- McNee, Riedhl, Konstan (2006)

Towards Recommendation System Design: Why are Accurate Recommendations not good?

- Suppose the user liked *John Wick*, should you recommend *John Wick: Chapter Two*?

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- Suppose the user liked *John Wick*, should you recommend *John Wick: Chapter Two*?
- Recommender systems traditionally ignore inference users themselves make
  - Good news - not useful information for user
  - Bad news - useful information to users

Our approach: Understanding user beliefs + how these evolve is a first-order component of designing useful recommendations

Towards Recommendation System Design: Serendipitous Recommendations

One popular alternative design approach: **serendipity**

> *A serendipitous recommendation helps the user to find a surprisingly interesting item that she might not have otherwise discovered (or it would have been really hard to discover). [...] Serendipity cannot happen if the user already knows what is recommended to her, because a serendipitous happening is by definition something new. Thus the lower is the probability that user knows an item, the higher is the probability that a specific item could result in a serendipitous recommendation.*

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> *Serendipitious recommendations should be simultaneously unexpected and useful*

-Maksai, et. al (2015)

Towards Recommendation System Design: Serendipitious Recommendations

Two components of serendipitious recommendation:

1. **Unexpected**: Depends on user beliefs - items that have low *ex-ante* utility, given beliefs
2. **Useful**: Induces users to take an action *they wouldn't have taken without recommendation*

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Our approach: Prediction problem should be estimating the marginal expected utility gain of providing information about particular items

Conclusion

- Considered a model of long-lived users in the face of recommender systems
- Main takeaways:
  - Model implies a clear path-dependence in choice . important for understanding the effects of platform steering and recommendation bias
  - Understanding user beliefs and how users learn over time crucial for both understanding the consequences of recommender systems and their design
- Future directions:
  - Implications for regulatory policy for online platforms
  - Designing recommender systems for long-lived consumers instead of a sequence of static problems