

The Ex-Ante View of Recommender System Design

ABSTRACT

KEYWORDS

Recommender Systems, Beliefs, Decision Theory, Filter Bubbles

1 INTRODUCTION

Recommender Systems (RS) have become critical for assisting consumers in navigating the large choice sets that they face in many online markets. For instance, consumers have to select from thousands of movies on Netflix, millions of products on Amazon, and billions of videos on YouTube. Consumers in many cases are not aware of most items, let alone have full information about their preferences over them and, to make matters worse, the goods in these markets are usually experience goods whose true utility can only be learned after consumption. Furthermore, consumers interact with these systems routinely and watch more than one movie on Netflix, buy more than one product on Amazon, and listen to more than one video on YouTube.

Recommender systems have been influential in shaping consumer choice in these markets with 75% of movies watched on Netflix and 35% of page-views on Amazon coming from recommendations. While there are many positive effects from these systems, there is an increasing worry that there are unintended side-effects of recommendation systems. There have been claims that YouTube's recommendation algorithm unintentionally lead to the radicalization of many individuals¹, that personalized recommender systems lead consumers into *filter bubbles* where they get effectively isolated from a diversity of viewpoints or content [13], and that personalized recommender systems may also lead consumers to become increasingly homogenized at the same time [3, 4].

Our Model and Contributions In this paper, drawing from recent work in psychology and decision theory in economics, we first develop a model of consumer decision-making in the context of large choice sets faced by consumers in online markets. We then ask how a stylized model of recommendation can shape the behavior of long-lived consumers and finally ask how the insights from our model can be used to improve recommender system design and to better understand the consequences of these systems.

We focus on understanding the degree to which recommender systems can lead consumers into *filter bubbles*. Consistent with recent empirical work in the case of movie consumption [12], our

model shows that individual consumption behavior over time naturally exhibits patterns consistent with a filter bubble effect *without recommendation*. The key component of our model, drawn from the results of [15], is that the utilities of similar goods are correlated. This means that when consumers consume a good and learn its true utility this gives them information about similar goods. Crucially, this not only impacts the underlying belief about the average utility of the good, but also the amount of uncertainty. This learning spill-over induces consumers to consume goods “similar” to those they consumed before leading to an increasing narrowing of consumption patterns. This effect is further exemplified when consumers are *risk-averse*, a concept from economic decision theory where, all else being equal, consumers have a preference for goods with lower uncertainty to those with higher uncertainty.

We then consider a stylized model of user recommendation and explore how recommendation can affect consumption patterns. We suppose each good is a sum of a common value component and an idiosyncratic component, where the idiosyncratic component is inherently unpredictable given other individual's preferences. We model existing recommendation systems as providing consumers with information on the common-value component and denote as this as partial recommendation. We consider how consumer behavior varies as we move from no recommendation to partial recommendation to omniscient recommendation, which is the optimal consumption path for consumers if they knew the true utility of all the goods in their choice set.

Consistent with [12], we find that partial recommendation increases consumption diversity. However, we also find that partial recommendation increases homogeneity amongst consumers.

Related Work. Recommender Systems

2 OUR MODEL AND PRELIMINARIES

2.1 Preliminaries and Illustrative Example

[Duarte can do this]

Expected Utility Theory First, we review basic economic decision theory.

Illustrative Example

2.2 Model

Consumers We consider a set of consumers I where each individual $i \in I$ faces the same finite set of N items $\mathcal{N} = \{0, 1, \dots, N-1\}$. For simplicity, we assume that individuals only derive pleasure from item $n \in \mathcal{N}$ the first time they consume it.

We denote by u_{in} individual i 's realized utility from consuming item n . By realized utility we In particular, we consider that the realized utility derived from a given item can be decomposed in the following manner: $u_{in} = v_{in} + \beta v_n$, where v_{in} denotes an idiosyncratic component – i.e. consumer i 's idiosyncratic taste for good n – and v_n , a common-value component. One can interpret v_n as a measure of how much good n is valued in society in general and, in a sense, v_{in} denotes how i diverges from this overall ranking. The scalar $\beta \in [0, 1]$ denotes the degree to which utilities are

¹<https://www.theatlantic.com/politics/archive/2018/03/youtube-extremism-and-the-long-tail/555350/>

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idiosyncratic to each individual or common across individuals. If $\beta = 0$, it is impossible to generate meaningful predictions of any one's individual preferences based on others, while if $\beta \rightarrow \infty$, every individual has the same preferences.

Stacking utilities in vector-form, we get $(u_{in})_{n \in \mathcal{N}} =: U_i = V_i + \beta V$, the vector of utilities associated with each good, where $V_i = (v_{in})_{n \in \mathcal{N}}$ and $V = (v_n)_{n \in \mathcal{N}}$.

Consumer Beliefs We assume that consumers do not know the realized utilities of the goods before consuming an item. We make this assumption as our model pertains to markets where the goods are experience goods and modeling consumers as being uncertain over their preferences in these environments is common in the economics literature [add citations]. Even though consumers have access to online reviews for goods in many of the markets where recommender systems are deployed, it is prohibitively costly for consumers to acquire information on all of the goods in their choice set. Even if they did so, this information would be helpful for reducing uncertainty on the common-value component of their utility and not the idiosyncratic component. While we do not explicitly incorporate this into our model, we use it to motivate that consumers make consumption decisions under some degree of uncertainty.

Formally, consumer i starts with some beliefs about U_i , namely that the idiosyncratic and common-value parts of the utilities are independent – $V_i \perp V$ – and that each is multivariate normal

Definition 2.1. The idiosyncratic utility and common-value utility are distributed as follows:

- (1) $V_i \sim \mathcal{N}(\bar{V}_i, \Sigma_i)$
- (2) $V \sim \mathcal{N}(\bar{V}, \Sigma)$ with $\bar{V} = 0$

We impose the normality assumption for two reasons. The first is that consumers update their beliefs using Bayesian updating and recall that the normal distribution forms a conjugate family, which allows for simple posterior updates. The second is that it allows us to incorporate an easily interpretable correlation structure between the items.

Keeping with the assumption that V_i represents idiosyncratic deviations from V , we assume that, on the population level, prior beliefs $\bar{V}_i = (\bar{v}_{in})_{n \in \mathcal{N}}$ are drawn independently from a jointly normal distribution, where $\bar{v}_{in} \sim \mathcal{N}(0, \sigma^2)$ are i.i.d. These \bar{v}_{in} denote the prior belief that i holds about the her valuation over good n . As people are exposed to different backgrounds, their beliefs about what is good for them also varies and \bar{v}_{in} denotes this idiosyncrasy at the level of prior beliefs.

Consumer Learning When a consumer consumes a good n they learn the realized utility for that good. In our model we incorporate the idea that learning the utility of good n gives a consumer information about similar items. This is drawn from recent empirical evidence in [15] that consumers learn how to navigate large choice sets using similarity-based generalization. We assume that learning about the utility of good n reveals more about the utility associated to items that are closer to it, which captures the idea that trying a product provides more information about similar products than about dissimilar ones.

In order to have a well-defined notion of similarity we need to define a distance function between goods, which we define as $d(n, m) := \min\{|m - n|, N - |m - n|\}$ where m and n are the index of the items in \mathcal{N} . We consider that the entry of n -th row and

the (m) -th column of Σ_i is given by $\sigma_i^2 \rho^{d(n, m)}$, and that of Σ is given by $\sigma^2 \rho^{d(n, m)}$. The scalar $\rho \in [0, 1]$ therefore impacts the covariance structure: a higher ρ implies that learning the utility of n is more informative about products nearby. Informativeness, for any $\rho \in (0, 1)$, is decreasing in distance. The particular distance function that we utilize leads to this covariance structure being simple, where the $(n, n + 1)$ -th entry in the covariance matrix is ρ , $(n, n + 2)$ -th entry is ρ^2 , etc. This spill-over process is represented in Figure [insert fig].

Consumer Decision-Making We assume the user makes T choices and therefore can only consume up to T items, where T is but a small fraction of N . This captures the idea that users are faced with an immense choice set but that ultimately they end up experiencing (and learning) about just a small fraction of it. Since this is a sequential decision-making problem under uncertainty, in principle consumers face an exploration-exploitation trade-off. However, for tractability, we impose that consumers are myopic and every period consume the product that they have not yet tried (n_i^t) that gives them the highest expected utility given the information from past consumption offers ($C_i^{t-1} = (n_i^1, \dots, n_i^{t-1})$) and their initial beliefs. Any ties are broken uniformly at random. This assumption is critical not only for tractability but also in order to have easily defined benchmarks.

Recommendation Our model of recommendation is stylized in order to provide qualitative insights into how recommendation shapes behavior, instead of looking at realistic implementations of recommender systems. We model recommendation as giving consumers information about the utility of the goods.

We will consider three cases. The case of primary interest is *partial recommendation* where the recommender observes utilities accrued, but does not know consumer i 's starting beliefs \bar{U}_i . In this case, the recommender knows V but does not know neither V_i nor, crucially, users' beliefs \bar{V}_i . The recommendation will be that the consumer i chooses $r_{it} \in \arg \max_{n \in \mathcal{N} \setminus C_i^T} u_n$, but we assume the recommender provides full information about V . For instance, the recommender could display the whole distribution of utilities reported by other users or even its average, which is a good proxy for the common value component.² Note that with partial recommendation it is not necessarily optimal for the user to follow the recommendation, that is, to pick the item with the highest common-value component v_n . Consumer's beliefs about her valuation of each item become crucial in this case: knowing V may change the original ranking, but given this new information the consumer may find it best to pick an item other than the one recommended.

We further consider two cases that serve primarily as benchmarks. The first is *no recommendation*, where consumers get no additional information about utilities and make consumption choices based on their beliefs and consumption history. This gives us a benchmark as to how consumers in our model would behave *without* recommendation so that we can analyze what changes with the

² The best item that could be recommended with such information is the item with highest common value component. However, in that case, recommending only a single item generates costly Bayesian updating to the consumer and provides little guidance as to what she should indeed pick as the common value might be of little importance when compared to the idiosyncratic component. Therefore, we assume that the RS reports the whole V , which results in higher expected welfare in choices and is not costly to implement.

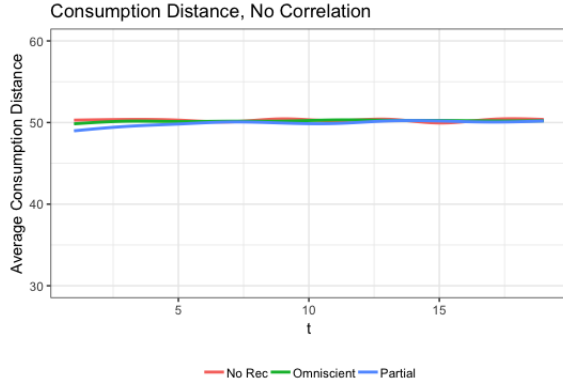


Figure 1: Consumption path with no correlation between utilities

introduction of recommendation. The second is *omniscient recommendation* where the recommender knows the true utility of each good for each consumer and can therefore recommend the best remaining good in every period. This gives us a full information benchmark, which is the optimal consumption path for a consumer if all uncertainty about their preferences was resolved. We compare this benchmark to the partial recommendation case and it allows us to understand how much this form of recommendation affects behavior relative to the ideal.

Simulation Details. We analyze our model using numerical simulation since the sequential decision-making component of our model paired with the rich covariance structure between the items make it difficult to characterize optimal consumer behavior analytically. We explore how consumption patterns differ as we consider different recommendation regimes and report representative results from our simulations. P populations of I users and compare their consumption choices under different recommendation system regimes. We simulate over 100 populations with 100 consumers. We average over the consumers in a population to get a representative consumer and then report results where a single data point is over the set of representative consumers.

3 USER BEHAVIOR

3.1 Local Consumption

We characterize “filter bubble” effects in our model as the degree to which consumers engage in *local consumption*. We define local consumption in terms of the average consumption distance between the items consumed by the representative consumer at time $t - 1$ and t . We compare the average movement within the product space across different recommendation regimes and associate lower average distance with more local consumption.

FINDING 1. *The impact of recommendation on local consumption:*

- (1) When $\rho = 0$, there is no difference in consumption distance between the three recommendation regimes.
- (2) When $\rho > 0$, no recommendation induces more local consumption than both partial and omniscient recommendation. This effect is amplified as ρ increases as well as when consumers are more risk averse (γ increases)

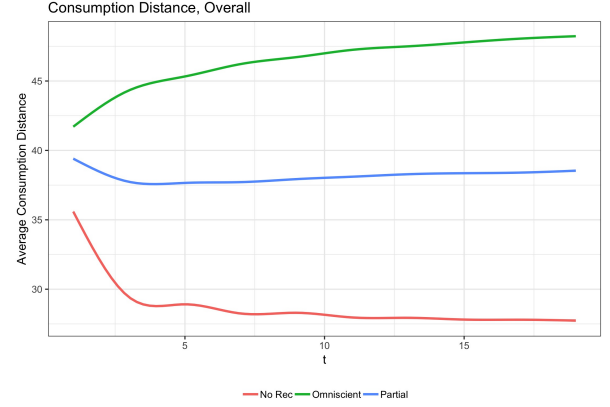


Figure 2: Consumption path between Recommendation Regimes

First, Figure 1 shows that, when $\rho = 0$, there is no difference in consumption distance between the three regimes. This is due to the fact that when $\rho = 0$, there is no reason that items that are close in the product space should have similar utilities and so the optimal consumption path does not depend on the similarity of the items. However this also means that consumers in the no recommendation regime do not learn anything about neighboring goods and so there is limited path-dependence in consumption.

Figure 2 shows that, when $\rho > 0$, both partial and no recommendation lead to increasingly local consumption compared to the benchmark omniscient case. Further, the average consumption path between periods is *decreasing* for the no recommendation case whereas it is *increasing* for the omniscient case. Partial recommendation decreases the degree of local consumption but not as much as the omniscient benchmark. Due to the correlation of utilities, the omniscient consumption path exploits this and leads to the consumption of more similar products than in the case when $\rho = 0$. However, since these spillovers also impact consumer learning in the no recommendation case, consumers *over-exploit* this and increasingly consume products similar to good products that they have consumed before. This is further illustrated by Figure 3 which shows how the consumption paths between omniscient and no recommendation vary as ρ increases.

Finally, this effect is further amplified as the level of risk aversion, γ , increases. Figure 4 shows how drastically the degree of local consumption increases as γ increases. This is due to the fact that the spillovers not only affect the mean expected belief about quality but also the degree of uncertainty. Local consumption therefore leads to consumers to have less uncertainty about certain areas of the product space and risk aversion may lead them to increasingly consume these products.

3.2 User Welfare and Product Diversity

In this section we primarily focus on the impact of recommendation on the welfare on consumers as well as the overall diversity of the items that they consume. Consumer’s *ex-post* welfare is the average of realized utilities, to control for the effect of T , and is defined as

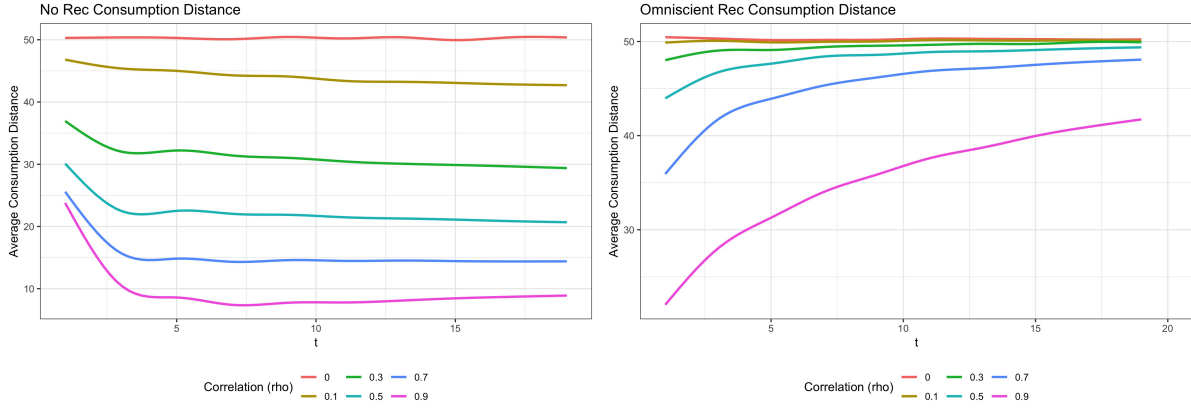


Figure 3: Extent of Local Consumption for No Recommendation (Left) and Omniscient Recommendation (Right)

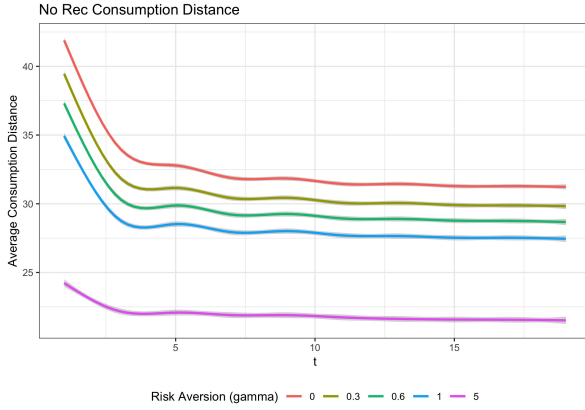


Figure 4: The Effect of Risk Aversion on Local Consumption

follows:

$$W_i = \frac{1}{T} \sum_{n \in C_i^T} u_{in}$$

While in the previous section we looked at the distance between consecutive goods, we also define a diversity measure that is defined over the entire consumed set. We utilize a diversity metric common in the literature (e.g. [17]) which is the average normalized pairwise distance between the consumed products:

$$D_i = \frac{1}{N} \frac{1}{T(T-1)} \sum_{n, m \in C_i^T: n \neq m} d(n, m)$$

FINDING 2. *The impact of recommendation on product diversity:*

- (1) When $\rho = 0$, product diversity is the same across all three recommendation regimes.
- (2) When $\rho > 0$, product diversity decreases across all recommendation regimes but decreases the most in the no recommendation regime. This effect is amplified as ρ increases as well as when consumers become more risk-averse.

As before, when there is no correlation between utilities product diversity is the same across different recommendation regimes.

The over-exploitation of the learning spillovers when $\rho > 0$ leads to product diversity being lowest in the no recommendation regime. Figure 6 shows how diversity varies across recommendation regimes and the level of ρ and Figure 5 shows how diversity varies as risk aversion levels change.

FINDING 3. *The welfare gap between no recommendation and partial recommendation as well as no recommendation and omniscient recommendation is decreasing in ρ .*

However, interestingly, the decrease in diversity is *not* associated with a decline in welfare. In fact, welfare stays roughly the same in the omniscient case and slightly increases for the partial recommendation case. The welfare gap between the no recommendation case and the other two cases *decreases* as the diversity gap increases.

FINDING 4. *Without recommendation, diversity and welfare are:*

- (1) *Negatively correlated when consumers have no risk-aversion*
- (2) *Uncorrelated when consumers have high levels of risk-aversion*

Figure 7 shows how diversity and welfare correlate for the no recommendation case. When there is no risk-aversion then there is a negative correlation between welfare and diversity. This is since, with no risk-aversion, in a given period a consumer will select the good that they currently believe has the highest expected value. High product diversity in this case can arise from a consumer who consumes a bad item and updates her beliefs about nearby items negatively. As a result, in the next period she will pick an item far away in the product space from the item that she consumed previously. If the item that she had consumed was “good”, then she is more likely to pick a nearby item. The learning spillovers therefore lead to high product diversity being negatively correlated with welfare.

This only happens since $\gamma = 0$ leads to consumers only caring about the expected value of the good. However, as we saw in Findings 1 and 2, increasing γ can lead to lower diversity and increasingly local consumption due to the fact that the degree of uncertainty now impacts consumers’ choices. This weakens the negative relationship between diversity and welfare since both negative and positive experiences with a good reduce uncertainty

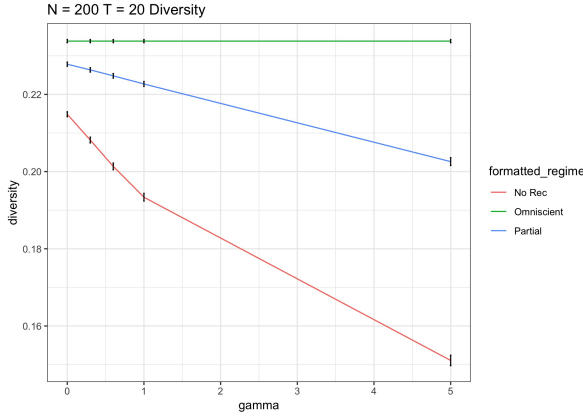


Figure 5: Risk Aversion and Diversity

about surrounding goods. This leads to the inverted-U shape found in Figure 7 when γ is relatively large (e.g. $\gamma = 5$).

3.3 User Homogenization

In this section we focus on across user comparisons and investigate how the consumed set of items across consumers varies across different recommendation regimes and parameter values. In particular we look at the degree of *homogenization* between consumers. Similar to [3] we use the Jaccard index between the consumption sets of consumers to measure homogeneity:

$$H := \frac{1}{|I|(|I| - 1)} \sum_{i,j \in I: i \neq j} d_J(C_i^T, C_j^T)$$

where d_J denotes the Jaccard index and $H \in [0, 1]$.

FINDING 5. *Homogeneity is:*

- (1) *Highest under partial recommendation and lowest under no recommendation*
- (2) *Increasing in β , or the weight of the common-value component*
- (3) *Decreasing in ρ for partial recommendation, but weakly increasing in ρ for no recommendation*

Figure 8 shows that as the weight of the common-value component, β , increases consumers consume increasingly similar sets of items. The homogenization effect is strongest under partial recommendation since the revelation of the common-value component induces consumers to consume products in similar areas of the product space. However, as β increases, some amount of homogenization is optimal as can be seen from the omniscient recommendation case. In the no recommendation case since consumers do not know the common-value component they engage in local consumption in different areas of the product space which leads to less than optimal homogeneity.

Figure 9 shows that the degree of homogeneity in the partial recommendation case however is *decreasing* as ρ increases. As was discussed in Findings 1 and 2, the degree of local consumption increases with ρ . Even though the revelation of the common-value component induces them to search in similar parts of the product space, their idiosyncratic components induce them to consume

products in a more localized area of the product space as ρ increases which leads to a decline in homogeneity.

4 RECOMMENDER SYSTEM EVALUATION

In this section we discuss how the insights from our model of user decision-making can be used to inform the evaluation and design of recommender systems.

The classic approach to recommender system evaluation is to predict user ratings for items and compare how accurate this prediction is to recorded ratings data, either explicitly given by users or inferred from behavioral data. Further, given this predicted rating, the recommender system should recommend to consumers the items with the highest predicted rating [2].

There has been a recent movement away from such evaluation measures due to the observation that accurate recommendations are not necessarily useful recommendations [11]. Our model illustrates why this could be the case. Consider the domain of movie recommendation and suppose a user has just watched the movie *John Wick* and rated it highly. A recommender system attempting to predict user ratings may then predict that this user is very likely to enjoy the sequel, *John Wick: Chapter Two*, as well. However, the user themselves may also have made this inference since the two movies are very similar to each other and, after enjoying *John Wick*, the user will update her beliefs about *John Wick: Chapter Two*. Thus, if the recommender system recommends this movie to the user then this recommendation is not useful since the recommendation gives the user little information that they did not already know. As a result, the user may watch *John Wick: Chapter Two* even without recommendation and the value of the recommendation was small.

To counteract this problem, alternative recommendation evaluation metrics have been proposed such as serendipity [8, 9]. Ideally, serendipitous recommendations “have the quality of being both unexpected and useful” [10]. [5] defines serendipitous recommendations as follows:

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.

All approaches to serendipity to our knowledge, however, do not take into account the *beliefs* that users have over the valuations for the items. For instance, [7, 16] propose unexpectedness metrics that look at the dissimilarity of the recommended items to what the recommender already knows the user likes either via a content-based approach or a collaborative-based approach. [1] use an expected utility approach but measure unexpectedness in terms of deviations from the “expected consideration set” of a user and do not explicitly incorporate user beliefs.

We propose a definition of serendipity based on *unexpectedness* and *usefulness* which have clear definitions in the context of our model of user decision-making. Users have *beliefs* over the valuations for the items and thus *unexpected* recommendations

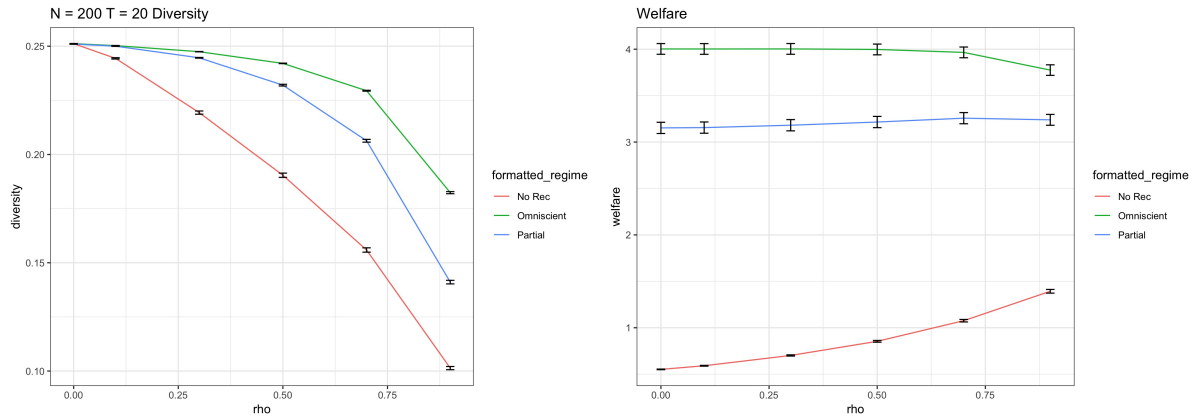


Figure 6: Welfare, Diversity, and Correlation

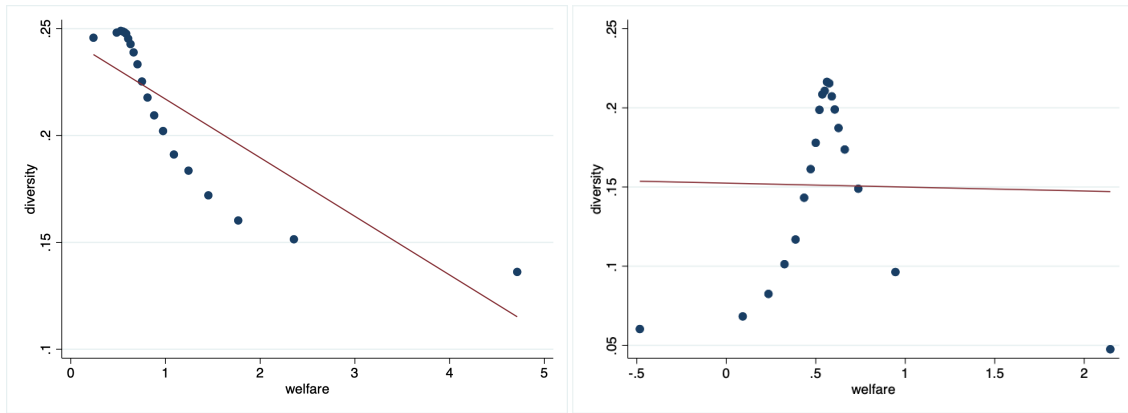


Figure 7: Diversity vs. Welfare, $\gamma = 0$ (Left), Diversity vs. Welfare, $\gamma = 5$ (Right)

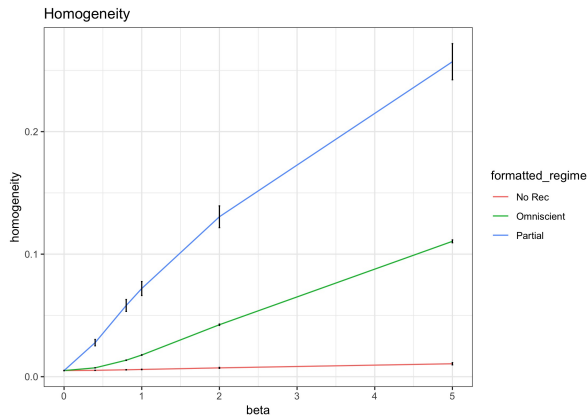


Figure 8: Strength of Recommendation and Homogeneity

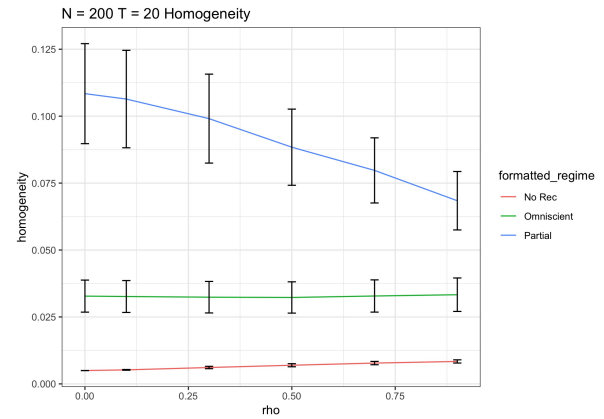


Figure 9: Correlation and Homogeneity

are given by items that consumers have low expected utility for, either due to the fact that their mean belief is low or the degree of uncertainty is high. Recall from Findings 1 and 4 that, particularly if users are risk-averse, they will consume content in increasingly

narrow portions of the product space and this may be detrimental to their realized welfare. As a result, identifying the portions of the product space where users may have significant uncertainty and utilizing recommendation to reduce this uncertainty can be

welfare-enhancing for consumers. This motivates a definition of *useful* recommendations as recommendations that give consumers information that would *change the item they consume relative to no recommendation*. Combining these, serendipitous recommendations are recommendations that provide users with information about *unexpected* items that end up being *useful* by changing consumption choices to increase the realized utility of a user.

Operationalizing this approach requires the collection of data that is not traditionally collected for recommender systems. In particular, it becomes important to understand what choices users would make *without recommendation* and to collect data on user beliefs, which can partially be inferred by observed choices. [6, 14] argue that choice-based approaches alone can help in designing better RS, though they argue for these approaches because they do a better job at providing more accurate recommendations. However, we argue that choice-based approaches are useful not as recommendations but as a baseline for what recommendations would be useful.³

Furthermore, our model shows the importance of understanding the underlying user preferences and the nature of the product space in the setting in which a recommender system is deployed since that will change the consumption patterns of consumers. For instance, understanding the degree of correlation of utilities and the level of risk-aversion become crucial in understanding how users will make consumption choices without recommendation and what kind of recommendation would be useful for users.

5 DISCUSSION

6 CONCLUSION

We have argued that incorporating user choice under uncertainty should be a first-order component of RS design. By collecting appropriate data about user choices and user beliefs, RS can be built to better understand what choices users are likely to make and thus what information would be useful to give them as opposed to simply predicting what items a user will like. This approach can not only aid in designing more useful RS, but can also be utilized to better understand and prevent recently documented adverse effects of RS such as filter bubbles and homogenization.

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³Furthermore, user beliefs and user choices contain information that may not have been observed by the recommender but is observed by the user. Ratings, reviews, friends, there are many sources of information affecting a person's beliefs and choices that are unobservable by recommender systems. Other consumption choices, e.g. movies seen in the cinema, change beliefs about for instance how good a director is, which affect beliefs about other movies and guide choices on a streaming platform that is unable to observe these data. However, this information can be inferred by the platform by collecting both beliefs and consumption choices.