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 individuals[1], that personalized recommender systems lead consumers into *filter bubbles* where they get effectively isolated from a diversity of viewpoints or content [**?**], and that personalized recommender systems may also lead consumers to become increasingly homogenized at the same time [**? ?**].

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 [**?**], 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 [**?**], 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 spillover 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 [**?**], 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 $\mathcal{N} = \{0, 1, \ldots, N-1\}$. 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/

RecSys '19, September 16–20, 2019, Copenhagen, Denmark

ACM ISBN 978-1-4503-9999-9/18/06…$15.00

https://doi.org/10.1145/1122445.1122456

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 $\beta \longrightarrow \infty$, 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 – $V_i \perp\!\!\!\perp V$ – and that each is multivariate normal

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

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

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 $\overline{V}_i = (\overline{v}_{in})_{n \in \mathcal{N}}$ are drawn independently from a jointly normal distribution, where $\overline{v}_{in} \sim \mathcal{N}(0, \overline{\sigma}^2)$ are i.i.d. These $\overline{v}_{in}$ 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 $\overline{v}_{in}$ 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 [**?**] 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 $(C_i^{t-1} = (n_i^1, ..., n_i^{t-1}))$ 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 $\overline{U}_i$. In this case, the recommender knows V but does not know neither V_i nor, crucially, users' beliefs $\overline{V}_i$. 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 recommended with such information if 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.

Rec Policy	Welfare	Diversity	Homogeneity
No Rec	0.42 ± 0.002	0.19 ± 0.0003	0.001 ± 0
Partial Rec	1.25 ± 0.005	0.22 ± 0.0002	0.174 ± 0.004
Omniscient Rec	2.24 ± 0.006	0.24 ± 0.0001	0.035 ± 0.002

Table 1: Mean Welfare, Diversity, and Homogeneity for $N = 1000$, $T = 25$, $I = 50$, $S = 50$. Reported intervals are 95% confidence intervals.

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.

3 USER BEHAVIOR

3.1 Local Search

3.2 User Welfare

3.3 Diversity

3.4 Homogenization

3.5 Effectiveness of Recommendation

We are going to analyze three outcomes: how diverse consumer choices are, how similar are the choices that different individuals make and the resulting welfare. The first will be measured by $D_i = \frac{1}{N}\frac{1}{T(T-1)}\sum_{n,m\in C_i^T:n\neq m} d(n,m)$, the average normalized pairwise distance between the consumed products, a natural measure of diversity in this environment that is utilized in the literature [?]. The second will be measured by a consumer homogeneity index $H := \frac{1}{|I|(|I|-1)}\sum_{i,j\in I:i\neq j} d_J(C_i^T, C_j^T)$, where d_J denotes the Jaccard index and $H \in [0,1]$ which is similar to the approach to measuring homogeneity utilized in [?]. Note that a higher H indicates more homogeneity. Consumer i's welfare will just be the average of realized utilities, to control for the effect of T, $W_i = \frac{1}{T}\sum_{n\in C_i^T} u_{in}$.

Results. Table 1 shows aggregate results for welfare, diversity, and homogeneity. The omniscient recommendation case leads to the optimal consumption path for a consumer since she consumes the T items with the highest utility. Compared to this case, both partial recommendation and no recommendation not only lead to lower welfare but also have lower diversity. In fact, the no recommendation case leads to the lowest levels of consumption diversity since users do not explore the space of products sufficiently and do excessive amounts of local search as can be seen in Figure **??**. Figure **??** shows how "local" consumption choices are by looking at what fraction of consecutive consumption choices are close to each other with the definition of close being less than distance of 10. The partial recommendation case leads to higher consumption diversity and higher welfare, but also significantly higher homogeneity.

In our model, filter bubble effects occur simply because of the correlation structure between the utility and beliefs of products. It highlights the fact that the correlation structure induces users to consume increasingly narrow content when they get no guidance from recommendation whereas the "optimal" consumption path given by the omniscient policy does not exhibit this. The results of our model are consistent with the empirical results found in [?] who show that filter bubble effects can arise even amongst users who do not utilize recommendations.

Furthermore, [?] also find that recommendation can lead to an increase in consumption diversity. As Table 1 shows, our model is consistent with this effect but it depends on the nature of recommendation. If recommendations only provides information on the common-value component (partially informed recommender) then welfare and consumption diversity increase when contrasted to the no recommendation case, but homogenization increases dramatically. Knowing the common-value component leads users to have more information on where to explore in the product space. However, the fact that this information is about the common-value component and the same across all individuals leads them to explore the same sections of the product space and leads to substantially higher homogeneity among users. If recommendation takes into account user beliefs on the idiosyncratic component of utility (omniscient recommender), then welfare and consumption diversity can further increase and homogeneity will decrease.

Low consumption diversity is not necessarily bad by itself. Figure **??** shows that, in the no recommendation case, welfare and consumption diversity are negatively correlated. This is primarily because content diversity in the no recommendation case can arise from the fact that the user consumes a bad product and is forced to jump around the product space looking for "good" products. However, if a user finds a high utility product right away, then staying in this neighborhood may yield higher utility due to the correlation of utilities. The problem is that, even when the user finds a "good" product, this may only be "locally" good and the user will then excessively consume items around it due to having more information about these than more "different" ones, i.e. farther away.

Finally, the value of recommendation in the partial recommendation case decreases over time as users learn more about the idiosyncratic component of their own preferences (i.e. as t increases). Figure **??** shows that recommendation compliance decreases as t increases. Additionally, Figure **??** shows how homogeneity and welfare change as β increases. Most interestingly, when β is high so that the common-value component is small, recommendation can be harmful to users. The information from recommendation still leads to large user homogeneity even though the optimum would be for there to be almost none and leads to lower welfare than under no recommendation.

4 THE VALUE OF THE EX-ANTE VIEW

In this section we illustrate the differences between the ex-post and ex-ante view and show how it is useful for thinking about the design of RS. Our first point is trivial to state - since users do not know the true consumption values of the items, without any further information they may make *ex-post* sub-optimal consumption decisions, but *ex-ante* optimal given the information available to them at the moment of choice. Consider the following stylized example. The choice set of the individual is $\Omega = \{x_1, x_2, x_3\}$ and the ex-post utility values are given by $u(x_1) = 1$, $u(x_2) = 2$, $u(x_3) = 3$.

However, when users are making decisions they have unobservable *beliefs* about the ex-post utility value of the items and make decisions given these beliefs. As users obtain more information, their beliefs converge to the ex-post utility values but, generally, users do not have enough information and so have beliefs over the space of possible ex-post utility values. In this example we suppose these beliefs are simple so that users view each good as simple lotteries: for $n = 1, 2, 3$, $u(x_n) = n + \varepsilon_n$, $\varepsilon_1 \sim \mathcal{N}(2, 1)$, $\varepsilon_2 \sim \mathcal{N}(0, 1)$, $\varepsilon_3 \sim \mathcal{N}(-5, 2)$.

After uncertainty is unresolved, the user would consume x_3, but an expected utility maximizing consumer (without further information) would choose x_1.[3]

This observation, while seemingly trivial, has important implications. The fact that the user would choose C over A reveals that C prefers A given her current beliefs[4] and allows the system designer to get some information about a user's beliefs. Why are user beliefs important objects for designers of RS to understand and utilize?

Beliefs are useful for understanding how users interact and get value from RS. In particular, users use RS to get *information* about the set of items and update their beliefs about the value of the items. For instance, in the example, a RS could recommend to a user x_3 over x_2 and x_1 and that user will use this to update her beliefs about x_3. It is an empirical question that we leave for future work precisely how and to what extent users update their beliefs from recommendation and what factors of RS deisgn influence this.[5]

Better understanding user beliefs is important for improving the performance of RS that optimize for metrics that move away from accuracy such as serendipity [?]. Serendipity-based RS attempt to provide recommendations that "have the quality of being both unexpected and useful" [?] but it is hard to know what items are both unexpected and useful [?]. Understanding *why* a user has not consumed a good depends on the beliefs that the user has and this is important for designing serendipitious recommendations. For instance, in the example, the user does not consume x_3 because she expects the good to turn out worse than the other two. However, if given more information, she would prefer to consume it over x_1 and x_2. Moreover, when the user can use her known valuation of an item to make inferences on how good another item is, consumption is path-dependent, as beliefs guide consumption and consumption affects beliefs about other goods. For instance, learning the value of x_1 says something about how good x_2 is. As a result, understanding the beliefs of users helps us understand why users have not consumed certain items and, in particular, which items a user may find useful given more information about it. This poses an important problem: designing systems that elicit not only ex-post valuations but also ex-ante beliefs about valuations, as only by knowing these can RS be effective in steering users' choices. In particular, choice has to be perceived as guided by ex-ante utility, whereas ratings by the ex-post realized utility.

Understanding the choices that individuals will make in addition to what they will end up liking are complementary problems but require different viewpoints. [? ?] 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. We argue that the two problems should be considered separately – though they may interact in interesting and useful ways.[6]

RS are designed to give users *information* that is useful to help them make decisions. On the one hand, predicting a user's ex-post preferences is useful to know what items the user would like to consume. On the other hand, predicting what items a user will actually consume (without recommendation) can help reason about what information may actually be useful to give her. Furthermore, in designing RS to avoid filter bubble and homogenization effects, having accurate choice predictions allows mitigating such adverse effects to become a first-order component of design. In particular, by predicting both choice and ratings, RS can provide information to users that leads them to useful items but prevents them from falling into a filter bubble.

Solving this choice prediction problem requires data on the choices that individuals make and the sets that they choose them from in addition to the traditional ratings or behavioral data that is collected. In the example given previously the fact that the consumer chooses x_1 from the set $\{x_1, x_2, x_3\}$ would be the data that is useful for the choice prediction problem, as would the consumer's ex-ante beliefs about her valuation of the goods.

5 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.

[3]We ignore an important component of decision-making under uncertainty, risk attitudes, by focusing on risk-neutral consumers. A *risk-averse* user may choose to consume a good with lower expected *ex-post* payoff but lower ex-ante variance compared to another good. While risk-aversion is important for decision-making under uncertainty, especially in the context of RS, it is not our main focus here.

[4]This is a statement of *revealed preference* which has been studied heavily in economic decision theory (see e.g. [?]).

[5]There has been some work in this direction in understanding when recommendations are persuasive [? ?] as well as the effect of their delivery on effectiveness [?].

[6]In particular, some results in [? ?] may be driven by the fact that user choice embeds ratings 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 RS. 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.