The Ex-Ante View of Recommender System Design

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ABSTRACT

Recommender systems (RS) are traditionally deployed in environments where users are uncertain about their preferences and thus face a problem of choice under uncertainty, but most popular design approaches ignore this fact. We argue that predicting and modeling consumer choice in these contexts can improve the usefulness of RS and reframe the RS problem as providing useful information to help reduce user uncertainty as opposed to simply predicting user preferences. Using a theoretical model, we show how this insight can be utilized to design RS that mitigate negative consequences such as filter bubble and user-homogenization effects as well as to better understand the role that RS play in contributing to these phenomena.

KEYWORDS

Recommender Systems, Beliefs, Decision Theory, Filter Bubbles

1 INTRODUCTION

Recommender Systems (RS) have been widely deployed in online platforms such as Netflix, Amazon, and YouTube. On these platforms the combination of most items being experience goods (i.e. valuation is only learned after consumption) and the number of choices available to users being incredibly large, results in users not knowing their true preference ordering over all of the items. For instance, on Netflix there are thousands of movies, Amazon millions of products, and YouTube billions of videos. As a result, RS have been useful in helping users make decisions on these platforms because they provide users with information to help them make their choices under uncertainty.

However, while acknowledging that this is why RS are useful, most of the literature on RS ignores this user uncertainty and takes what we call an *ex-post* viewpoint to preferences, focusing on the reported utility of users after they consume the item or inferring them via behavioral data [1, 17]. The RS problem traditionally is cast as solving the following prediction problem:

$$\arg\max_{x \in A} u(x)$$

where A is the set of possible items and $u(x)$ represents the utility a user gets to consume good x. Recently there has been a move away from metrics focused on maximizing the accuracy of this prediction problem and towards optimizing for metrics such as serendipity or discoverability [11, 16] due to the realization that accurate recommendations may not be the most useful recommendations for users. Furthermore, deployed RS have come under scrutiny for leading to “filter bubbles" [14] where users consume a less diverse set of content over time, as well as increased homogenization amongst users [3, 6].

In this paper we want to put forward the argument that one approach to make progress in tackling these problems is to make understanding about user item choice a first-order consideration when designing RS. In particular, we differentiate between the previous *ex-post* interpretation of the RS problem and what we define as the *ex-ante* viewpoint. Unlike the ex-post viewpoint, the ex-ante viewpoint simply states that users face uncertainty and so maximize their expected utility as is defined in economic decision theory under uncertainty [see e.g. 10]:

$$\arg\max_{x \in A} \mathbb{E}[u(x)]$$

Fundamentally, the move away from accuracy towards alternative metrics as well as tensions that have arisen from increased user homogenization and filter bubbles come from the *choices* that users make. This shift from thinking about true preferences after all uncertainty is resolved (the ex-post view) to user decisions under uncertainty (the ex-ante view) can serve as a theoretical tool to better frame and design recommendations as useful sources of information [2] as well as understanding what of the documented perverse effects of RS come from recommendation per-se and what effects come from inherent uncertainty in user decision-making.

2 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.[1]

[1]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

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[2] 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.[3]

Better understanding user beliefs is important for improving the performance of RS that optimize for metrics that move away from accuracy such as serendipity [8]. Serendipity-based RS attempt to provide recommendations that "have the quality of being both unexpected and useful" [9] but it is hard to know what items are both unexpected and useful [8]. 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. [7, 15] 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.[4]

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.

[2]This is a statement of *revealed preference* which has been studied heavily in economic decision theory (see e.g. [10]).

[3]There has been some work in this direction in understanding when recommendations are persuasive [4, 5] as well as the effect of their delivery on effectiveness [12].

[4]In particular, some results in [7, 15] 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.

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.

3 FILTER BUBBLES AND HOMOGENIZATION

In this section we further show that differentiating between the ex-ante and ex-post view allows us to not only design better RS but also better understand their consequences. To do so, we study a simple model where users have beliefs about how good each item is and can learn their valuation over the items by consuming them. However, drawing from the main idea behind content-based RS, similar items have similar valuations and consumers' beliefs about neighboring items update after consuming an item which influences future consumption decisions. For instance, in our model, if a user watches *The Matrix* and finds out that it is a good movie then they will update their beliefs positively about a similar movie such as *The Matrix Reloaded* (the sequel to *The Matrix*) but not update them much for a very different movie such as *La La Land*.

Viewing the goal of the RS as providing users with additional information they can utilize to update their beliefs, we first show that, without recommendation, users may get stuck in a "filter bubble" whereby they consume increasingly similar content and that, in this case, welfare will be negatively correlated with diversity. We show how providing information to users via recommendation can lead users out of this filter bubble. However, if recommendation does not properly take into account user beliefs, recommendations can lead to increasing homogenization among users and lower welfare and consumption diversity. Finally we then show that when the recommender does not know the user's beliefs about her valuation, recommendation becomes decreasingly useful as the user learns more about her own preferences.

Setup. Suppose that there is a group I of individuals and that each individual $i \in I$ can choose from the same finite set of N items $\mathcal{I} = \{0, 1, ..., N-1\}$. For simplicity, we assume that individuals only derive pleasure from a item $n \in \mathcal{I}$ the first time they consume it. We denote by u_{in} individual i's realized utility from consuming item n. We define the distance between two items as $d(n, m) := \min\{|m-n|, N-|m-n|\}$ where m and n are the index of the items in $\mathcal{I}$ so that, conceptually, the items are located in a ring of size N.

In particular, we consider that the utility derived from a given item can be decomposed in the following manner: $u_{in} = \beta v_{in} + (1-\beta)v_n$, 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 idiosyncratic to each individual or common across individuals. If $\beta = 1$, it is impossible to generate meaningful predictions of any one's individual preferences based on others, while if $\beta = 0$, every individual has the same preferences. Stacking utilities in vector-form, we get $(u_{in})_{n\in\mathcal{I}} =: U_i = \beta V_i + (1-\beta)V$, the vector of utilities associated with each good, where $V_i = (v_{in})_{n\in\mathcal{I}}$ and $V = (v_n)_{n\in\mathcal{I}}$.

We assume that user 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 $V_i \sim \mathcal{N}(\overline{V}_i, \Sigma_i)$ and $V \sim \mathcal{N}(\overline{V}, \Sigma)$, with $\overline{V} = 0$. Furthermore, we assume that learning about the utility of good n reveals more about the utility associated to items that are closer to it, i.e. $n \pm 1 \pmod N$), than about those farther away. This captures the idea that trying a product provides more information about similar products than about dissimilar ones. To this effect, 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 $\rho \in [0,1]$ 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.

Keeping with the assumption that V_i represents idiosyncratic deviations from V, we assume that, on the population level, prior beliefs $\overline{V}_i = (\overline{v}_{in})_{n\in\mathcal{I}}$ 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.

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. Each period $t = 1, ..., T$, the consumer chooses the best product that she has not yet tried (n_i^t) given the information that past consumption offers ($C_i^{t-1} = (n_i^1, ..., n_i^{t-1})$) and that that the RS offers (R), i.e. $n_i^t \in \arg\max_{n\in\mathcal{I}\setminus C_i^{t-1}} \mathbb{E}\left[u_{in} \mid C_i^{t-1}, R\right]$, with ties broken uniformly at random.

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 [18]. 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 [3]. 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, $W_i = \frac{1}{T}\sum_{n\in C_i^T} u_{in}$.

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.

Finally, we are going to study three different cases: (i) no recommendation, (ii) omniscient recommender and (iii) partially informed recommender where the recommender observes utilities accrued, but does not know consumer i's starting beliefs $\overline{U}_i$. In the first case, users choose their items myopically, that is, using a greedy algorithm, and pick the item that has maximum expected utility given beliefs at time t. Upon consuming that item and learning its value, the users update their beliefs about their valuation of other items and iterate this process T times. In the second case, the recommender knows exactly V_i and V and can therefore recommend the best item for each consumer. In the third 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 $r_{it} \in \arg\max_{n\in\mathcal{I}\setminus C_i^T} u_n$, 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.[5] Note that 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.

Simulation Details. We will simulate P populations of I users and compare their consumption choices under different recommendation system regimes. We simulate over a grid of parameter values for $\sigma, \sigma_i, \rho, \rho_i, \beta$ and report results for $P = 50, I = 50, N = 1000, T = 25$.[6]

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

[5] 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 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.

[6] Due to space constraints we omit simulations for different values of T but, unless otherwise noted, our results are robust to changes to T as long as T is not too large (close to N) or too small (close to 0).

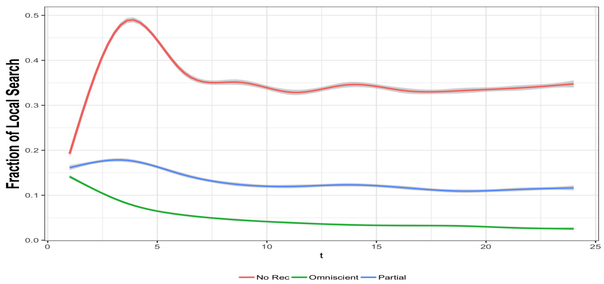

Figure 1: Extent of "Local" Consumption

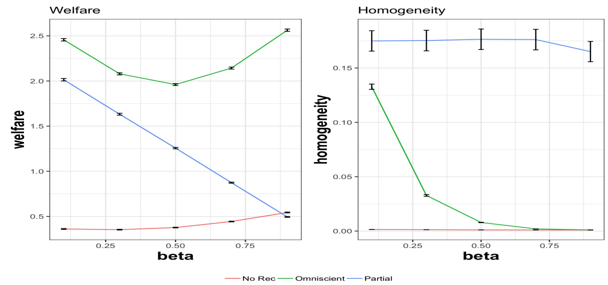

Figure 2: Welfare and Homogeneity

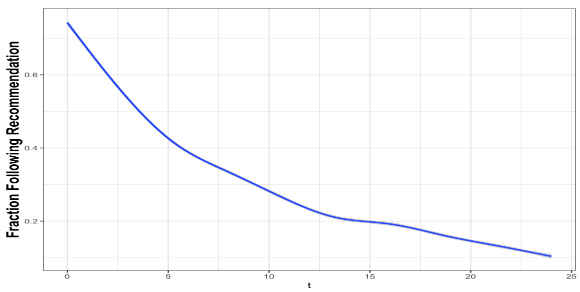

Figure 3: Recommendation Effectiveness

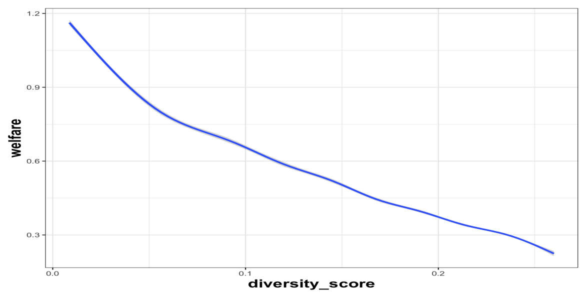

Figure 4: Diversity vs Welfare under No Recommendation

do excessive amounts of local search as can be seen in Figure 1. Figure 1 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 [13] who show that filter bubble effects can arise even amongst users who do not utilize recommendations.

Furthermore, [13] 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 4 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 3 shows that recommendation compliance decreases as t increases. Additionally, Figure 2 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 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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