Defining the Role of User Input Bias in Personalized Platforms

Daniel Trielli and Nicholas Diakopoulos
Northwestern University, School of Communication
dtrielli@u.northwestern.edu, nad@northwestern.edu

Abstract

User input bias has relevant impact to algorithmic personalization and should be subject to further study. In this paper, we discuss ways in which that user input bias might manifest itself, and how it is dependent on the type of algorithmic platform. We also propose avenues of investigation to further study the effect, impact and mitigation of user input bias in algorithmic systems.

Defining input bias

Bias in information retrieval systems can be generated in many ways. First, the coverage of the data accessible to the system may be deficient, leading to limitations of possible outputs, an effect known as coverage bias. Second, the information retrieval system algorithm might be structured in a way that prioritizes, filters, classifies, and aggregates information in improper and/or unexpected way. And finally, the users themselves might inject biases into the systems by interacting with them in particularly predisposed ways.

User input and activity may be the cause of an important portion of bias in information retrieval systems. They also should be considered part of personalization, since these inputs reflect individual conditions of each user, and result in tailor-made outputs by automated systems. In other words, if personalized news is adapted to the user, don't we also need to understand how different users may themselves be systematically biased?

The idea of user input bias is not new. When discussing biases in computer systems in general, Friedman and Nissenbaum (1996) mention a particular type of emergent bias, one that (unlike preexisting or technical biases) appears after the systems are deployed and arises from user interaction with the system: "interfaces by design seek to reflect the capacities, character, and habits of prospective users. Thus, a shift in context of use may well create difficulties for a new set of users" (p. 335). With new digital platforms establishing more complex personalization algorithms, it is necessary to reevaluate how that human-computer interaction impacts information retrieval.

For this article, we are defining as user input bias any activity from the user that has an impact in how the algorithm retrieves information. In the next section we explore a few of those possible inputs and how they might be motivated.

Input bias across digital platforms

In this section, we describe how different platforms afford the user with different type of activities and, therefore, are open to different manifestations of input bias.

Search engines

Among all examples in this section, search engines are the one in which the power of the input of the user is most evident. Without a user query, there is no search, no results, and no bias. That is not to say that other factors do not come into play when search engines look for the most relevant results, such as user geographical location and demographic factors. And there is a wide array of possible investigations about how search algorithms determine relevancy, and the biases associated with that process. But the primary generator of search results – and, therefore, bias – are the queries that are defined by the user.

In that regard, investigations into search engine biases must take into account the construction of the query in a search. But a deeper understanding is needed of why users choose the search terms they use and how impactful those decisions are. For instance, what makes a user search for "gun rights" versus "gun control"? And what is the impact of those decisions?

It is important to note that in search there is another type of input bias, which is the bias in the corpus of relevant results for a query (Kulshrestha et al. 2017). In other words, results might be skewed because the websites relevant for that particular query are skewed. That is an important factor, but one that also highlights the weight that the query selection itself has in defining the corpus from which results will be extracted.

Another user input bias might be generated in the interaction of the users with results provided by the search engines. By clicking on specific results on Google, for instance, users generate data that allows engines to predict what type of website is most favored by the user and give preference to those in the next time the user makes a search. Therefore, the motivation of the user in selecting specific pages in the results is related to personalization as well.

Social media

Exposure to media in social media platforms is mostly done through a feed populated by user generated content (UGC) from accounts that the user follows. Algorithmic personalization impacts the ordering of that UGC, and a significant part of that personalization stems from user activities.

The primary input that the user generates to do that is selecting which accounts to follow. In some instances, platforms show content from accounts that the user does not follow; when that happens, it is usually paid content, though sometimes also the result of algorithmic curation from an extended social network. Thus, content selection begins with the user filtering in whatever source they want to follow.

What motivates a user in their selection of accounts to follow? That depends on the type of social media platform. On asymmetric social media platforms, the ones in which the connections between users are not necessarily mutual (e.g. Twitter and Instagram), research has shown that motivations for following are varied (Tanaka, Takemura & Tajima 2014). The decision to follow someone can be grounded on interest on specific people (celebrities and politicians, for instance), on interest in the expected content provided by that account (journalists that cover a topic the user is interested in) or on expected mutuality of connection (following and being followed back by peers).

On symmetric social media (e.g. Facebook, LinkedIn), connections are by definition mutual (some platforms such as Facebook have been allowing users to follow accounts, but these are not the majority of relationships in those platforms). Therefore, the motivations for that pre-selection of content are different. In many cases, the connection to other users replicate relationships of the physical world (families, coworkers). This variety on motivations on who to follow has implications in the mechanics of user input bias.

Another input is how users react to the content to which they are exposed. According to Twitter, for instance, "tweets you are likely to care about most will show up first in your timeline. We choose them based on accounts you interact with most, tweets you engage with, and much more." The ambiguity of "much more" notwithstanding, it means that liking and sharing tweets from certain accounts increase the likelihood of seeing content from those accounts more prominently.

Recommender systems

Recommender systems, which appear in search, social media, or regular websites, suggest items to users based on user personalization. While many of the inputs of these systems might be automated, user input is an essential aspect in their computation. And each instance of these systems has different user input biases that have to be accounted for.

Search engines might recommend specific search terms based on user personalization. Those can be generated from automated information about the user (geographical location, for instance), but history of previous search inputs is a strong factor in the elaboration of those suggestions.

Social media websites have recommender systems that suggest connections (friends or accounts to follow), based on signals that were discussed earlier (current social network that was selected by the user; content that the user liked or shared). For instance, Facebook suggests connections via its “People You May Know” features and Twitter also uses an account suggestion algorithm.

Other websites also recommend different items, according to their business. News websites suggest next articles to read; online stores propose similar products. These are the result of user input, either by selecting a topic or by searching a product.

Social media websites might also list trending topics, issues that a large proportion of users in the network are engaging with. These lists might be geographically defined, and while geolocation can be programmatically extracted by algorithms, in many cases it can be a result of the users adding that information to their profiles (e.g. self-reported geographic information rather than from a GPS sensor).

Investigating input bias

From this framework of variety of user input bias, a number of possible investigations can be imagined.

The first avenue of investigation is the origin of user input bias. In the previous section we alluded to foundations of input bias: what makes users choose to act the way they do and how that impacts their interaction with algorithms. Demographic, political, social, and economic profiles might be factors in those decisions of framing search terms, selecting friends and sources to follow. Exploration of that could be made through the use of surveys and crowdsourcing.

A second path is the effect of that user input bias. Much work is being done in algorithmic accountability to test biases in the overall process of algorithms. It is possible to look specifically into the impact of user input bias by using different but comparable user inputs to test variability of results from those systems.

Finally, another area worth exploring is the mitigation of input bias. Future research might test interventions in different steps of human-computer interaction to provide a lower level of bias or simply to increase transparency and self-awareness of that bias.

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