Google News: News Recommendation System Redesign

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Introduction

The influx of information, derived from the digitalization of our modern world, has made it more difficult for individuals to make decisions and sift through information. To address this cognitive overload, news organizations integrated recommendation systems to help users make more efficient decisions by providing articles they would be inclined to read. There is a contradictory tension, however, between how these recommendation systems are designed for accuracy and the users' best and long-term interests. News Recommendation Systems (NRS) play a significant role in determining what news a reader will view and consume. The problem is that the news recommendation systems are not entirely aligned with positive outcomes. In other words, the algorithms tend to create adverse effects on the readers depending upon the factors that are accounted for and prioritized.

One of the main effects is the creation of a filter bubble—an ecosystem that provides the user with only information they want to see which is created by personalized searches and algorithms. By providing this limited type of news, a polarized culture emerges as individuals fail to encounter counter-attitudinal material and consider other perspectives (Zhang et al., 2023). Fortunately, the filter bubble can be disrupted by introducing other perspectives when recommending news articles. A balance needs to be struck between the exposure to counter-attitudinal news and the personalization that will engage and satisfy readers. This document will focus on redesigning a system that mitigates the algorithmic effect of filter bubbles. To do this, the design will consider how recommender systems may create these bubbles, provide users with more agency by giving them input, and center the users' long-term interests of consuming news that will allow them to make informed decisions while remaining stimulated by the type of content they read.

Recommender Systems' Relationship with Decision-Making and Learning

It's essential to understand the ways in which recommendation systems are replacing human cognition in order to address the gap between News Recommender Systems and users' desired outcome. There is a bidirectional relationship between human cognition and recommender systems, specifically the heuristics used to make decisions and reason and the expanded definition of the zone of proximal development.

The decision-making process of recommendation systems determines the content that will be presented to users, expediting the process of searching relevant and interesting information in respect to the reader. Recommendation systems integrate a number of cognitive psychology strategies into its infrastructure, developing algorithmically-driven heuristics that replace users' heuristics. They are oftentimes modeled on the individuals' inadvertent input–their interactions on the interface or demographics, for example. With a closer analysis, one can see the parallels between the algorithm models and the human heuristics. For instance, recommender systems similarly reflect representativeness heuristics, the calculation of an uncertain event based on its similarity to a specific population (Sternberg & Sternberg, 2012) when it makes inferences based on a specific demographic. The typical user modeling bases predictions based on a class–a characteristic of a population. There are also systems that draw inspiration from other cognitive phenomena like satisficing: the consideration of every option, in this case news article, until it finds one that satisfies the conditions set in the algorithm (Sternberg & Stergberg, 2012). There are many parallels between the recommendation system architectures and cognitive psychology heuristics.

Recommendation system algorithms and readers on news sites are learning from one another and ultimately changing the nature of news consumption. The two entities are learning from one another in a continuous feedback loop which creates a novel dynamic that requires us to reexamine traditional definitions in cognitive science. In one direction, recommender systems are processing human behaviors, preferences, and sociodemographics to enhance its accuracy (Ricci et al., 2011). In the bidirectional relationship, humans are engaging with the recommended items that have been presented to them by the algorithms. Thus, the recommended articles provide a bias and perspective that alters the readers' perception. In turn, the users' behaviors are also changing the algorithms as it tries to adapt their preferences. The nature of this relationship is changing both the technological infrastructure of recommender systems and the structure of our brains. According to a study conducted by Falikman (2020), our neural activity and brain structures are changing, supporting the concept of cultural neuroscience. The bidirectional relationship between human cognition and technology is established, but the implications differ depending upon the system.

This relationship compels us to consider how it has changed the way individuals gain knowledge and learn about new events, redefining the traditional definition of Zygotsky's zone of proximal development. According to Zygotsky's zone of proximal development, a gap exists between individuals' performance without help from others and their outcome when supported by a more experienced person (Falikman, 2020). With technology individuals don't need access to an experienced person, but rather they are now using devices to learn: "attention, memory, cognition, and activity are being shaped and organized by the interaction with the device itself" (Falikman, 2020). News Recommender Systems play a significant role in what readers will learn about current events, which also ultimately feeds into the opinions and belief systems that are formulated based on their readings. This cultural shift is not only altering the previous theoretical concept of the zone of proximal development, but the political landscape as individuals increasingly rely upon digital news.

News Recommender Systems Filter Bubbles

News Recommender Systems differ from other models due to the dynamic nature of the industry, and its personalization has inadvertently regurgitated news that adversely affects readers. There are a variety of techniques for user modeling that have been implemented in News Recommender Systems, but the stereotypical model is based on user profiles and interactions. The personalization creates undesirable filter bubbles–"intellectual isolation caused by personalized searches or algorithms" (Raza & Ding, 2022)--and epistemic bubbles in which relevant voices are left out. The NRSs are complex because they are trying to balance the users' interests with the unique challenges that the industry poses. For example, the recommended news articles have to be timely in delivering relevant news while also providing quality content that does not spread misinformation. That said, for the purposes of this document, we will disregard the other challenges and focus on how user modeling techniques have contributed to filter bubbles and the effect on users' behaviors.

Filter bubbles, while seemingly aligned with the users' satisfaction, are linked to undesired behavioral changes: boredom (Zheng et al, 2018), extreme opinions (Moller et al., 2018), misinterpreted facts (Moller et al., 2018), and polarization (Renick et al., 2018). The filter bubble is inadvertently driven by well-intentioned but misaligned algorithms that over personalize (Resnick et al., 2013; Zheng et al., 2018), foster ideological segregation (Flaxman et al., 2016), and hyper focus on accuracy-centric algorithms (Moller et al., 2018). The three algorithmic causes will expand upon the intentions of these practices and their unintentional effects on user behaviors:

I. <u>Personalization</u>

Personalization has the intent of providing articles that align with readers' preferences and interests, but this mechanism also incidentally excludes other perspectives. These preferences can be tracked implicitly by tracking user behaviors or accounting for their geographical location, but they can also be explicitly gathered by asking the user to provide their preferred news categories and interests. Unfortunately, this approach may incidentally exclude other voices. The exclusion of other views can facilitate erroneous reasoning by discouraging readers from considering other possibilities before coming to a conclusion–otherwise referred to as foreclosure effects–or reinforcing the belief that their behaviors and judgments are more appropriate than others, the false-consensus effect (Sternberg & Sternberg, 2012). These errors discourage critical thinking and the consideration of other perspectives when forming an opinion on the news. Many systems over personalize without considering the learning growth of readers and their interest in receiving diverse perspectives and novel information.

II. <u>Ideological segregation</u>

There's a misconception that people only want to see information that aligns with their views, but counter-evidence indicates that readers may seek out information that varies from their belief system in various circumstances. People tend to seek out information on opposing candidates during elections (Garret, 2009). These actions indicate a desire to make informed decisions, but these moments may be temporal and dependent on the news item. Regardless, it reveals a learning preference that may not be evident in their previous behaviors when selecting and reading the news or in their responses when explicitly asked what news they want to see.

The ideological segregation may exist, but it is only exacerbated by the recommendation system that has limited information and nuance. There may be a difference between the response individuals give when asked explicitly what they prefer compared to what their actual behaviors may be when unrestricted by recommendation systems. Currently, however, systems are set up in a manner that oftentimes segregates by political ideology.

III. Accuracy-centric algorithms

The measurement of success for recommendation systems have traditionally aimed for accuracy that fails to account for factors that will meet the users' long-term satisfaction. Accuracy for NRSs were measured by comparing the prediction against a known user rating of a news item (Herlocker et al., 2004). This approach did not account for users' satisfaction and ultimately introduces similar, repetitive content and perspectives. The data-centric evaluation systems do not necessarily line up with user-centric evaluation results (Fazeli et al, 2018). Raza & Ding (2022) introduce beyond-accuracy metrics that would puncture the filter bubble that is perpetuated by the current recommendation systems. These metrics include diversifying the content of recommended items, presenting more novel material, and integrating serendipity–a composition of relevant, new, but also unexpected information (Raza & Ding, 2022). The integration of these metrics into the evaluation system would create a NRS that better fits the needs of users.

Reader Agency to Disrupt Recommendation System Filter Bubble

Ideally, News Recommender Systems would align with the individuals' interests and foster their learning, not limit it, by encouraging the expansion of their zone of proximal development. A systematic review of studies that examine the relationship between learners' agency–the ability to set their learning goals– and recommender systems suggests that a majority of them had positive outcomes (Deschênes, 2020). The study also indicates that the intersection of agency and recommender systems can work synergistically and converge at the zone of proximal development by providing the individuals with information that will allow them to have control over their choices, permitting them to achieve their goals. Most of the studies analyzed in this review focused on systems applied to students and schools. However, these findings should be extended to the informal learning context of reading the news. Additionally, Vygotsky's standard pedagogical rule that encourages recommended learning sources to provide information that is slightly above the learner's current competence level should be accounted for by the NRS (Vygotsky & Cole, 1978). The combination of user agency and recommendations slightly outside of one's comfort zone could potentially address adverse effects of current News Recommender Systems that produce filter bubbles.

NRS plays a pivotal role on how and what news individuals read about. This document will evaluate Google News and propose a redesign to mitigate the risk of producing filter bubbles by considering the relationship between readers' learning cognition and effects, news consumption, and the user interface and algorithmic design of Google's News Recommender System.

Evaluation of Google News & Redesign Recommendations to Mitigate Filter Bubble

The evaluation system will not be measured by accuracy, but instead will be based on the beyond-accuracy metrics posed by Raza & Ding (2022) and the principles from Zygotsky's zone of proximal development (Fazeli et al., 2018). The evaluation will consider the following four categories:

<u>Reader Agency and Initial Input Into Algorithms</u>

To converge at the individuals' zone of proximal development, the recommender system needs to incorporate a higher volume of input from the users. Google News gives users the option to select up to twelve news topics to populate their 'For You' section, but this does not sufficiently cover the decision-making process that a reader might make without using a technological tool. This also suggests that the recommender system might be making assumptions based on other classes (e.g. geography, clicked articles, time spent on an article, etc.). Thes reliance on user interactions and demographics create generalizations that limit the system's understanding of the long-term interest of readers. Deschenes (2020)'s findings, improving recommender systems by giving individuals more agency over their goals, should be applied to find the right balance of diversity and novelty in the news. The reasons why these two characteristics are important to incorporate will be further explored in the following sections.

Selective Exposure to Diverse News

Raza & Ding (2022) advocate for diversity-aware algorithms to mitigate the risk of filter bubbles. By implementing diversity into NRSs, readers will be presented with more diverse perspectives on news events which would, as mentioned earlier in the ideological segregation section, align with their interest in engaging with news that don't necessarily align with their views. According to Pew Research Center, 78% of U.S. adults claim to check the facts of news stories (Mitchell et al., 2019), and adding a variety of sources would ease this process. Currently, Google News incorporates diversity by offering two to three articles on the same news event for the top news. It also includes diversity in topics in the 'For You' section, but the visual intake is overwhelming with the number of options. The user experience shouldn't overload viewers cognitively, which is why the design should be asking for input on when and what type of news the user may want in respect to diversity. Some of the base questions may include collecting input from users on the frequency of viewing diverse news, categories that they might want to see a variety of perspectives, and the type of diversity they may want to encounter. This mechanism would give readers more agency over their news experience, and it would also be aligned with Raza & Ding's recommendation to provide selective exposure.

Novelty and Serendipity in News Topics

Both Raza & Ding (2022) and Zygotsky's zone of proximal development (Fazeli et al, 2018) encourages novelty and serendipity. From both the algorithmic evaluation and learning point of view, these two elements would benefit users. Individuals want to encounter new information which means that they will not be able to identify those topics explicitly when asked for their preferences, since by nature they are unknown. Thus, the algorithm will need to calculate novelty and serendipity by the online behaviors and by gathering feedback. Silviera et al. (2019) provides three dimensions of measurements for novelty: system level, life level, and recommendation level. At the system level, news items can be categorized with various tags. Based on the online behavior the NRS can identify the tags that have not been previously explored by the reader. Additionally, when presenting the 'novel' news recommendation, the interface can ask for feedback based on whether the user has heard of the item before and their level of familiarity (life level). Lastly, the system should also reduce the redundancy of items in the recommendation list. The incorporation of novelty layered on top of the diversity and accuracy dimension will also begin to address the element of serendipity, a degree of relevance, novelty, and unexpectedness combined (Ktkov et al., 2016). Further research will need to be done to identify interaction between these three components, but as a starting point a feature can be added for the user to give positive feedback when a novel recommended article pleasantly surprises them.

If one scrolls far enough into their 'For You' tab, Google News provides a section labeled 'Interesting Reads' which seems to suggest the system's recommendation of 'novel' news. That said, this category should be pulled out as a new section in the menu bar to encourage the exploration of new topics. The articles that are recommended should provide additional features that allow users to give feedback on the novelty dimension from their perspective.

Reader Input: News Consumption Alerts

Our limited attention can make it difficult to achieve our goals, so even as the NRS collects our preferences, and implicitly our goals, a more sophisticated nudge system should be integrated into the experience. The current 'Alert' system in Google News asks for users to indicate their preferences on the following: the frequency of notifications, the sources (e.g. news, blogs, web, videos, books, discussions, and finance). The nudge system should gather users' intentions on what they aim to learn from reading the news (e.g. I would like to learn more about {{insert topic}} over the next couple of months.). The nudge system should follow up accordingly based on the users' interactions with news related to the targeted topic. Lastly, this alert system was only discovered by an intentional Google Search, but this system should be visible on the Google News homepage.

FIGMA GOOGLE NEWS EVALUATION OVERVIEW AND PROTOTYPE RECOMMENDATIONS HERE.

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