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Ethics of Modern Recommendation Systems

Brandon Davis
Computer Science / Information Science & Technology

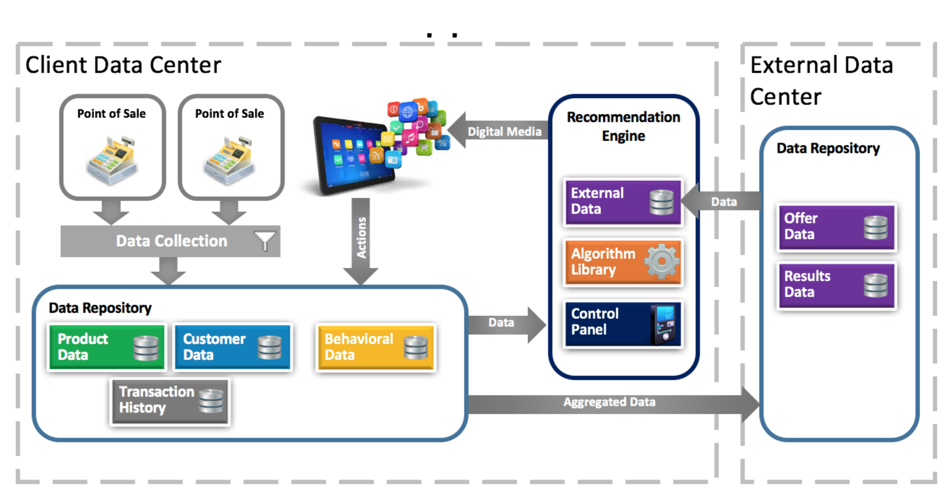
Introduction

The impact and influence of recommendations can be attributed to many of the decisions in which we make during our lifetime. Whether it be suggestions or sometimes advice, the way in which we as individuals choose to indulge in this council, is very much transformative to how we make decisions. Recommendation engines and systems have become a massive element of our digitally driven worlds. The right recommendations at the right time can have a huge influence on many actions in sequence throughout our lives. Whether it be Facebook, Google, Netflix, Amazon, LinkedIn, YouTube, or one of the many other platforms that utilize recommendation engines to anticipate as well as induce our decisions. These platforms use recommendation engines not only to algorithmically anticipate what people desire, they also nudge users to explore options and opportunities that might never have crossed their minds. As a society, we have built up our awareness to these recommendation systems. As they become more empowered and built into platforms that we use daily, there have been much more prominent concerns as to how these algorithmic recommenders are ethically used.

Discussion

The more recommendation engines are used, the more reliably they merge predictions and selection algorithm outcomes to generate powerful data insights. As I read in the book *Recommendation Engines*, Michael Schrage declares that "algorithms transform data into relevant recommendations by finding, calculating, and ranking the most interesting correlations and co-occurrences for users". Many of these recommendation systems not only know the information pertaining to the selected products, but also are able to predict its value for the individual user. Schrage pronounces that, "successful engines are not only digitally designed to get to know you better, but they're also built to learn and predict what you are most likely to like." An example of these recommendation systems is Netflix. The more data and metadata Netflix has about its videos, viewers, and views the more precise and persuasive their recommendations are likely to be. In many ways, these systems and algorithms are being used in more of a dark-side nature as they intrude into our more personal lives than ever before to gather insights for companies.

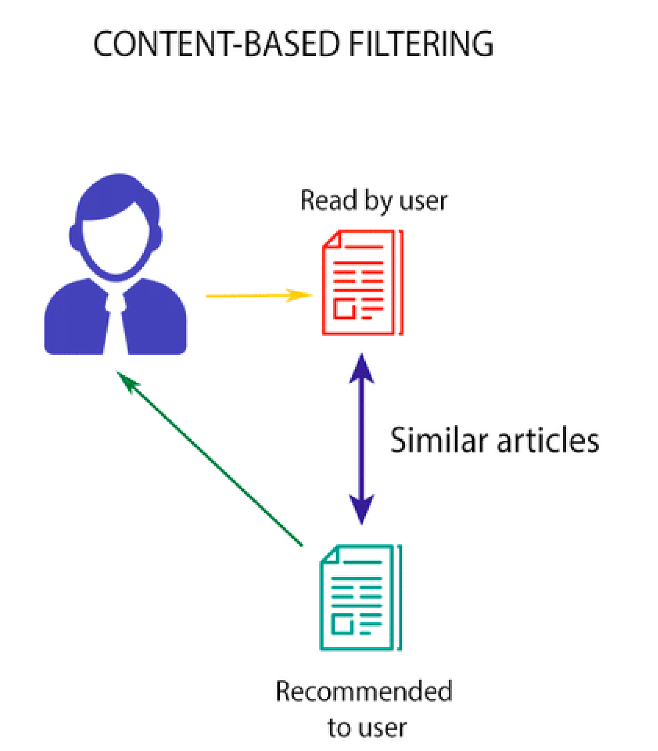
Users of a platform often submissively allow themselves to give up their digital habits and data. Based off a user's past behavior, predictions of future habits and future tendencies can be predicted. A helpful way to visualize this, is with a user on one side and things on the other, connected by graph lines. The idea is to fill out missing connections to best predict what they will "like" in the future. The answers to these questions are always in flux because people's tastes change overtime. But we can try to best calculate or estimate these preferences and values based off data we have in the present. Regardless the context, matrix calculations can be used to try to help mathematically create predictions. With user's and items being rows and columns and cells within the matrix maybe designating the level at which one visits a site or likes a particular movie for example, at a scale. There will be some set of data that is often incomplete, such as a movie that hasn't been seen. How to fill in these data points is one of the problems. So one way to do this is content filtering. Labeling or adding features to data hereby can help in content filtering. Mapping this information by labeling different factors to create a strength of connection estimation to predict. Gathering feature data to assess how one may like a particular thing. Matrix multiplication creates an estimated strength of connection based on the set scale. Content filtering can be overly simplistic and sometimes inaccurate. These calculations are then used to best present and induce users into further devoting their attention and time to the platform.

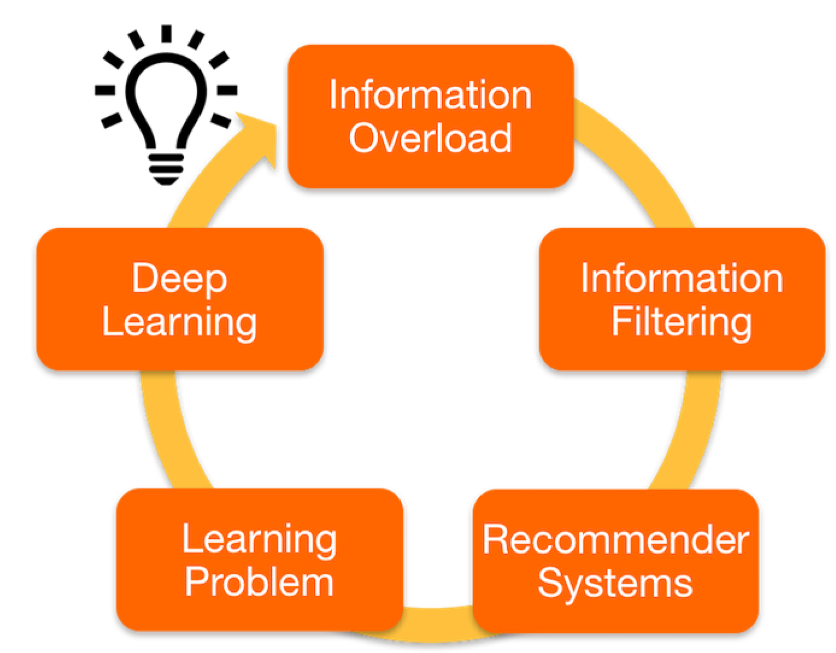


Nir Eyal's book *Hooked: How to Build Habit-Forming Products*, provides analytical insight to how our minds work and how to manipulate our desires, control our attention, and patterns of engagement. There are many ways where this seems to ethically intrude on our rights. Products that are meant to manipulate our human nature and deceive people into thinking one way or another intentionally. These ideas are not restricted to products per se, but also to the way we interact with different platforms that use recommendation systems. I read a book this winter by one of my favorite professors, Michael Kearns from Pennsylvania. The book is called The Ethical Algorithm: the science of socially aware algorithm design. Aaron Roth and Michael Kearns discuss issues with the current algorithm makeup and design for their implementation and uses within our society. Things like how if we specifically aim to create models for predictive accuracy, then they will do that, but they will defer important features that will bring for ethical balance. "We should want algorithms also to take into account privacy, fairness and other social values", claims Kearns. With algorithms, those values need to be specifically defined and specified within the design explicitly in order to accomplish this. The discussion of differential privacy, in the case of recommendation engines, with similar interactions and features, needs to be had. Collaborative and content-based recommenders can provide insight past the threshold that would be considered ethical privacy. These conversations need to be had at higher levels in order to allow for these systems to intrude on our important decision-making models. Kearns and Roth provide a number of real-world examples of the shortcomings of algorithms designed only to optimize for predictive accuracy. With privacy in recommenders there are several problems with the expansion of these systems into our every day lives. I would say that these recommendation engines and systems should be used as tools but need to be monitored as they become more prevalent in our platforms used going forward. As we have seen with Facebook and many other instances where these systems are abused for commercial gain.

Conclusions

Recommendation systems benefit us in many ways such as convenience, productivity, better understanding products, advancing society, and in many other minimally induced ways to create efficiency. But they way that these algorithms and recommendation engines are used, will be an increasingly crucial understanding for our society. How we use these advancements in algorithmic flexibility and capability for good is what is important. Collectively, awareness and information literacy will go a long way in helping us to better understand how recommendation systems are built into many of the systems we as users interact with as well as how influential they are.





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For further information

Brandon Davis
davisbm@uwm.edu
https://medium.com/@davis.brandonm8
Brandon Davis | LinkedIn