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IS 206: Introduction to Economics of Information

Final Brief: The Benefits and Detriments of Recommendation Systems

I. A Breakdown of the Recommendation System

A recommendation system is a software tool typically implemented by companies to suggest content or goods to users searching the web.[1] The suggestions recommendation systems generate are also called "items".[2] Recommendation systems utilize Artificial Intelligence (AI) by layering AI onto a company's website, allowing the system to collect and analyze user data and/or item data and then recommend additional content and products to users.[3] The user data that is analyzed to generate recommendations can include a user's "past purchases, demographic info, or their search history."[4] This data is turned into two types of information: char*acteristic information* and *user-item interactions*.[5] Characteristic information is generated by the user, such as searched key words, while user-item interaction information is drawn from user behavior, such as item ratings, number of purchases, and likes.[6] Recommendation systems are typically effective because they give users personalized suggestions through the collection and analysis of their corresponding data.[7]

1 Francesco Ricci, Lior Rokach, and Bracha Shapira, "Introduction to Recommender Systems Handbook," in *Recommender Systems Handbook*, ed. Francesco Ricci et al. (Boston, MA: Springer US, 2011), 1–35, https://doi.org/10.1007/978-0-387-85820-3_1.
2 Ibid.
3 "Recommendation Systems - How Companies Are Making Money," *Sigmoidal* (blog), September 27, 2017, https://sigmoidal.io/recommender-systems-recommendation-engine/.
4 Ibid.
5 "Introduction to Recommender Systems in 2019 | Tryolabs Blog," accessed June 8, 2019, https://tryolabs.com/blog/introduction-to-recommender-systems/.
6 Ibid.
7 Francesco Ricci, Lior Rokach, and Bracha Shapira, "Introduction to Recommender Systems Handbook," in *Recommender Systems Handbook*, ed. Francesco Ricci et al. (Boston, MA: Springer US, 2011), 1–35, https://doi.org/10.1007/978-0-387-85820-3_1.

II. Types of Recommendation System

There are several types of recommendation systems that collect characteristic information, user-item interaction data, or combination of both types of data. The two main types of recommendation systems currently in use are *collaborative filtering* and *content-based filtering*. While these systems are the most prevalent, an organization with a custom approach in recommending items to users may consider employing other recommendation systems. [8]

a. Collaborative Filtering Recommender System

Collaborative filtering recommends items based on users' past behaviors by utilizing two types of measurements.[9] The first is a user-based measurement: collecting and assessing the similarities between target users and other users.[10] The second is an item-based measurement: collecting and assessing the similarities between the items that target users interact with and rate.[11] Collaborative filtering assumes that users will both have similar interests and that their past and present preferences will remain in place for the future.[12] The issues with this system are its scalability; a site with more visitors is likely to not provide as accurate or personalized recommendations for a single user because of the need to categorize its many users, and the

[8] Stephanie Blanda, "Online Recommender Systems – How Does a Website Know What I Want?," *AMS Grad Blog* (blog), May 26, 2015, https://blogs.ams.org/mathgradblog/2015/05/25/online-recommender-systems-website-want/.
[9] "Introduction to Recommender System. Part 1 (Collaborative Filtering, Singular Value Decomposition)," accessed June 9, 2019, https://hackernoon.com/introduction-to-recommender-system-part-1-collaborative-filtering-singular-value-decomposition-44c9659c5e75.
[10] Ibid.
[11] Ibid.
[12] "Introduction to Recommender System. Part 1 (Collaborative Filtering, Singular Value Decomposition)," accessed June 9, 2019, https://hackernoon.com/introduction-to-recommender-system-part-1-collaborative-filtering-singular-value-decomposition-44c9659c5e75 and "Types of Recommender Systems | Machine Learning | Bluepi Blogs," *BluePi Blogging* (blog), November 14, 2015, https://www.bluepiit.com/blog/classifying-recommender-systems/.

assumption that human behaviors will not change minimizes the complexity of human behavior.[13]

b. Content-Based Filtering Recommender System

Content-based recommender systems are an extension of collaborative-filtering.[14] These systems analyze and learn a new user's interests based on discrete characteristics of the items the user selects; the item characteristics can include name, location, or description, in order to recommend additional items with similar properties.[15] Content-based recommender systems create a user profile " to provide information about the types of items that the user likes based on keywords used to describe the items."[16] An example of this system is Pandora Radio, which prompts users to enter an artist's name or genre to create a station based on the keyword they input into Pandora's search.[17] Though companies like Pandora have seen success with these systems, the issue with content-based filtering is its lack of dimensionality. These systems are unable to take one type of user preference and recommend a different type of item based on that preference; for example, if a system has profiled the user's music preference, that system cannot recommend books to that user, thus limiting the scope of the system's use.[18]

c. Demographic-Based Recommender System

[13] "Introduction to Recommender System. Part 1 (Collaborative Filtering, Singular Value Decomposition)," accessed June 9, 2019, https://hackernoon.com/introduction-to-recommender-system-part-1-collaborative-filtering-singular-value-decomposition-44c9659c5e75

[14] "Types of Recommender Systems | Machine Learning | Bluepi Blogs," *BluePi Blogging* (blog), November 14, 2015, https://www.bluepiit.com/blog/classifying-recommender-systems/.

[15] Stephanie Bl and a, "Online Recommender Systems – How Does a Website Know What I Want?," *AMS Grad Blog* (blog), May 26, 2015, https://blogs.ams.org/mathgradblog/2015/05/25/online-recommender-systems-website-want/.

[16] Ibid.

[17] Ibid.

[18] Ibid.

The demographic-based system categorizes users into demographic classes.[19] To do so, companies conduct market research and use collaborative-based system relationship data, such as peer recommendations, to understand what items correlate to which particular demographic.[20]

d. Utility-Based Recommender System

Utility-based recommender systems use the multi-attribute utility theory to generate recommendations for users.[21] The utility theory is used to numerically scale preferences of users and "is a systematic approach for quantifying an individual's preferences."[22] In these systems, recommendations are based on the level of utility each item has to the user.[23] Cost is considered a utility attribute but each item can be associated with several utility attributes, such as "location information, available connectivity, performance and reliability requirements, and contractual aspects and costs."[24] With all of these attributes to consider, as well as how each attribute may be valued differently by different users, it is difficult to recommend an item that will be the best option for each user.[25]

e. Knowledge-Based Recommender System

Knowledge-based systems require greater interaction and agency from users to support decision making.[26] These systems incorporate machine learning to generate more accurate

19 "Types of Recommender Systems | Machine Learning | Bluepi Blogs," *BluePi Blogging* (blog), November 14, 2015, https://www.bluepiit.com/blog/classifying-recommender-systems/.
20 Ibid.
21 Alexander Felfernig et al., "An Overview of Recommender Systems in the Internet of Things," *Journal of Intelligent Information Systems* 52, no. 2 (April 1, 2019): 285–309, https://doi.org/10.1007/s10844-018-0530-7.
22 "HSOR.Org: What Is OR," accessed June 9, 2019, http://www.hsor.org/what_is_or.cfm?name=mutli-attribute_utility_theory.
23 "Types of Recommender Systems | Machine Learning | Bluepi Blogs," *BluePi Blogging* (blog), November 14, 2015, https://www.bluepiit.com/blog/classifying-recommender-systems/.
24 Francesco Ricci, Lior Rokach, and Bracha Shapira, "Introduction to Recommender Systems Handbook," in *Recommender Systems Handbook*, ed. Francesco Ricci et al. (Boston, MA: Springer US, 2011), 1–35, https://doi.org/10.1007/978-0-387-85820-3_1.
25 "Types of Recommender Systems | Machine Learning | Bluepi Blogs," *BluePi Blogging* (blog), November 14, 2015, https://www.bluepiit.com/blog/classifying-recommender-systems/.
26 "What Is Knowledge-Based Systems (KBS)? - Definition from WhatIs.Com," SearchCIO, accessed June 9, 2019, https://searchcio.techtarget.com/definition/knowledge-based-systems-KBS.

recommendations and improve performance based on experience and interactions.[27] The healthcare industry has utilized knowledge-based systems to "help healthcare providers make decisions and improve patient care… [by examining] a patient's medical history in conjunction with relevant clinical research. Such analysis can then help predict potential events, such as drug interactions, or flag disease symptoms."[28]

f. Hybrid Recommender System

Hybrid systems are the combination of two recommendation systems to best suit a particular industry.[29] This is the most sought-after system because it combines the strengths of multiple systems while compensating for the blind spots of a single system.[30] There are three types of hybrid systems:

i. Weighted Hybrid Recommender

Weighted hybrid systems give equal consideration of both collaborative-based and content-based filtering systems in the beginning stages of implementation.[31] Gradually, this equally weighted system adjusts to utilize the collaborative or content-based system to conform to the predictions of confirmed and unconfirmed user ratings.[32]

ii. Switching Hybrid Recommender

A switching hybrid system functions by deploying either a content-based system or collaborative-based system and then continually switching between systems. When one system is being utilized, the recommender engages the switch to the system that is not

27 "What Is Expert System? - Definition from WhatIs.Com," SearchEnterpriseAI, accessed June 9, 2019, https://searchenterpriseai.techtarget.com/definition/expert-system.
28 "What Is Clinical Decision Support System (CDSS)? - Definition from WhatIs.Com," SearchHealthIT, accessed June 9, 2019, https://searchhealthit.techtarget.com/definition/clinical-decision-support-system-CDSS.
29 "Types of Recommender Systems | Machine Learning | Bluepi Blogs," *BluePi Blogging* (blog), November 14, 2015, https://www.bluepiit.com/blog/classifying-recommender-systems/.
30 Ibid.
31 Ibid.
32 Ibid.

being utilized.[33] The system will then switch recommenders and deploy the previously used recommender if one system is not effectively and accurately making recommendations.[34]

iii. Mixed Hybrid Recommender

Mixed hybrid systems are effective when making a large number of recommendations simultaneously.[35] The mixed system can introduce more than one technique from each system into a single system to offer a wide range of recommendations.[36]

III. The Economically Beneficial but Psychologically Damaging Nature of Recommendation Systems

American adults, on average, spend “six hours and 43 minutes a day looking at a screen, or 7,956 days of their life.”[37] Some of the highest trafficked sites worldwide are Amazon, YouTube, and Facebook, all of which utilize recommendation systems.[38] Recommendation systems offer website visitors a personalized experience, encouraging vistors to return to the site or remain on the site for a longer period.[39] Keeping users on a site increases the likelihood they will make a purchase, absorb content, and view advertisements; reasons companies want airtime on these sites. The model of implementing recommendation systems on corporate websites is profitable for several companies. Amazon’s revenue, for example, greatly increased when recommendation

33 Ibid.
34 Ibid.
35 Ibid.
36 Ibid.
37 “Screen Time Now Takes up Half Our Waking Hours,” accessed June 10, 2019, https://nypost.com/2018/08/13/americans-spend-half-their-lives-in-front-of-screens/.
38 Jerri Collins, “The Top 10 Most Popular Sites of 2019,” Lifewire, accessed June 10, 2019, https://www.lifewire.com/most-popular-sites-3483140.
39 “Recommender Systems | Their Impact on Customer Experience,” accessed June 10, 2019, https://theappsolutions.com/blog/development/recommender-systems-guide/.

systems were implemented on their site and via email: "[Amazon] reported a 29% sales increase to $12.83 billion during its second fiscal quarter, up from $9.9 billion during the same time last year. A significant portion of Amazon's growth can be attributed to Amazon's integration of recommendations into nearly every part of the purchasing process."[40] Netflix had similar success with recommendation systems with, "up to 75% of what consumers watch on Netflix… [generated] from the company's recommender system."[41]

Recommendation systems have proven to be economically beneficially for companies, but their impact on consumers has not been as positive. In order to retain a larger proportion of users, companies have resorted to implementing recommendation systems to hook users.[42] The almost addictive nature of these sites has led to a host of behavioral and psychological conditions, as well as a culture of screen dependence wherein over half of millennials feel anxious and irritated when they cannot check their phone.[43] The addictive nature and the lack of agency perpetuated by recommendation systems, should incline users to question a company's motives while they consume content and browse products on the web.

IV. The Effects of the Long Tail Economic Model

Recommendation systems allow companies to take advantage of the long-tail economic model to satisfy and reach more users. The long tail theory states that less popular goods with a lower demand can still increase a company's profitability:

[40] "Amazon's Recommendation Secret," Fortune, accessed June 13, 2019, http://fortune.com/2012/07/30/amazons-recommendation-secret/.
[41] "Recommendation Systems - How Companies Are Making Money," *Sigmoidal* (blog), September 27, 2017, https://sigmoidal.io/recommender-systems-recommendation-engine/.
[42] "Why The Brands We All Love Use Online Recommendation Systems," Zeta Global, September 22, 2016, https://zetaglobal.com/blog-posts/online-recommendation-systems-personalization/
[43] "Screen Time Now Takes up Half Our Waking Hours," accessed June 10, 2019, https://nypost.com/2018/08/13/americans-spend-half-their-lives-in-front-of-screens/.

> With no shelf space to pay for and, in the case of purely digital services like iTunes, no manufacturing costs and hardly any distribution fees, a miss sold is just another sale, with the same margins as a hit. A hit and a miss are on equal economic footing, both just entries in a database called up on demand, both equally worthy of being carried. Suddenly, popularity no longer has a monopoly on profitability.[44]

Not only do large companies like Amazon generate higher revenues, but the user benefits from greater exposure to items, products, or services of which they may have been unaware of without recommendation systems.[45] Companies that ascribe to the long tail theory are giving small businesses a platform to which they previously did not have access; Amazon, for instance, has reportedly "helped more than 1.9 million U.S.-based small and medium-sized businesses (SBMs) generate more than $160 billion in 2018."[46] The long tail theory can also prove beneficial for companies that do not sell products, but instead offer free services, like Google. In this information economy, knowledge has become a commodity; as users seek out items outside of the mainstream, this fringe content distinguishes them from other consumers and thereby makes them easier to target. These fringe choices allow companies to create more specific user profiles, ultimately allowing for more effective targeting of users.

While the long tail model provides benefits to companies, users, and the marketplace, the personal information that users are giving to fuel recommendation systems is arguably not worth the benefits. Google has proven the value of collecting and selling user data at the expense of user privacy: "Upon the acquisition of user data as the raw material for proprietary analyses and

44 Chris Anderson, "The Long Tail," *Wired*, October 1, 2004, https://www.wired.com/2004/10/tail/.
45 https://dataconomy.com/2015/03/an-introduction-to-recommendation-engines/
46 "Amazon Says Small Business Owners Make $90,000 a Year from Selling in Its Stores," USA TODAY, accessed June 10, 2019, https://www.usatoday.com/story/tech/2019/05/07/small-businesses-selling-amazon-stores-create-1-6-m-jobs-report/1120026001/.

algorithm production [Google found] that [it] could sell and target advertising through a unique auction model with ever more precision and success. As Google's revenues rapidly grew, they motivated ever more comprehensive data collection"[47] Google's model has acquired the critical moniker of surveillance capitalism in reference to the monitoring of websites to collect data focused on market, social, physical, and biological behaviors.[48] Though companies like Google have commodified users' privacy to avoid the fees-for-service business model, they have put profit ahead of user privacy by selling data to third-party companies and taking advantage of the unregulated landscape.[49] Facebook similarly released user information, losing the trust of many users: "Mark Zuckerberg, who's expected to act as the trusted custodian of the personal information of more than 2 billion people, has allowed his company's partners — Netflix, Amazon and Spotify, among many others — access to users' most intimate communications."[50] Americans have trusted these companies with their personal information, in part because privacy is included in the Constitution and, as such, considered a hallmark of the country society. Companies like Google and Facebook have taken advantage of this trust by consistently prioritizing profit.

V. The Influence of the Network Effect over Recommendation Systems

Many recommendation systems, such as demographic-based or collaborative filtering systems, use aggregate data to make recommendations and rely heavily on the Network Effect to gather that data. The Network Effect "causes a good or service to have a value to a potential

47 Shoshana Zuboff, "Big Other: Surveillance Capitalism and the Prospects of an Information Civilization," *Journal of Information Technology* 30, no. 1 (March 2015): 75–89, https://doi.org/10.1057/jit.2015.5.
48 Ibid.
49 "Google Facing Legal Action in EVERY EU Country over 'data Goldmine' Collected about Users | Daily Mail Online," accessed June 10, 2019, https://www.dailymail.co.uk/sciencetech/article-2302870/Google-facing-legal-action-EVERY-EU-country-data-goldmine-collected-users.html.
50 "How Tracking And Selling Our Data Became A Business Model | On Point," accessed June 10, 2019, https://www.wbur.org/onpoint/2019/01/15/surveillance-capitalism-shoshana-zuboff-facebook-data.

customer which depends on the number of other customers who own the good or are users of the service."[51] Companies like Facebook have perfected the art of utilizing the Network Effect; as more users join Facebook, the more useful it becomes.[52] This culminates in a worldwide network that allows users to exchange and share information, Facebook can collect large amounts of personal information from users, create user profiles based on this information, and recommend new content that aligns with a user's interests. While users may benefit from the scale of this network, both in the quality and nature of the fringe recommendations, Facebook "makes plenty of money — millions daily — by selling access to users' data to advertisers."[53]

Social media platforms and companies with models similar to Facebook that recommending information via the Network Effect can wreak havoc with the spread of misinformation. The lack of information regulation, also referred to as disinformation or fake news, has promulgated conspiracy theories, spurred mass shootings, and advanced election tampering. The untraceable spread of information is problematic because"[d]etecting what's fake in images and video is only getting harder. Misinformation is part of an online economy that weaponizes social media to profit from our clicks and attention."[54] Companies like Facebook are trying to create solutions to battle misinformation, even going as far as considering crowdsourcing users as fact checkers.[55] While a solution may not be clear, it is evident that recommendation systems are increasing the misinformation epidemic.

51 Robert M. Metcalfe, "It's All In Your Head," Forbes, accessed June 11, 2019, forbes/2007/0507/052.
52 A. J. Chavar, "Why You Keep Using Facebook, Even If You Hate It," Vox, April 11, 2018, https://www.vox.com/videos/2018/4/11/17226430/facebook-network-effect-video-explainer.
53 Ibid.
54 "I Fell for Facebook Fake News. Here's Why Millions of You Did, Too. - The Washington Post," accessed June 11, 2019, https://www.washingtonpost.com/technology/2018/10/18/i-fell-facebook-fake-news-heres-why-millions-you-did-too/?noredirect=on&utm_term=.285f61272a2b.
55 Sam Levin and Julia Carrie Wong, "'He's Learned Nothing': Zuckerberg Floats Crowdsourcing Facebook Fact-Checks," *The Guardian*, February 20, 2019, sec. Technology, https://www.theguardian.com/technology/2019/feb/20/facebook-fact-checking-crowdsourced-mark-zuckerberg.

On December 1, 2016 Edgar Welch walked into a Washington, D.C. pizza shop with an AR-15 semiautomatic rifle, a .38 handgun, and a folding knife because he saw an Info-Wars report stating Hillary Clinton was sexually abusing children in the restaurant's basement.[56] The Info-Wars report was popularized by users and spread to users on Facebook's network through the recommendation systems. The recommendation system is meant to spread popular content that will generate clicks. The proliferation of this story gave it power, and without the ability to filter for misinformation through the recommendation system, Facebook's recommendation system played a role on Welch's actions on December 1st.[57] Though this may be considered an uncommon example of the effect of misinformation, company's like Facebook have received a great deal of backlash for ads and posts that have shown up on its site, including the implication that Facebook did not deter foreign meddling in the U.S. presidential election. Facebook is not alone; Amazon recommends products to users every time they enter the site; each product contains reviews allowing users to ask questions and garner a better understanding of the item. Amazon has even allowed reviews to be incentivized, which leads to bias through fake reviews, until this process was banned on the site in 2016.[58] To get around this ban, "[f]ake reviews… often appear as "verified purchases", just like real reviews, with no indication of a connection between the buyer and the seller… In reality, the purchase was funded by the seller using PayPal, an Amazon gift voucher, or other means."[59] The spread of misinformation through the use of recommendation systems in a network system is an incentive for users to distrust the information on those platforms. Until platforms that utilize the Network Effect through the use of

56 "Pizzagate: Anatomy of a Fake News Scandal – Rolling Stone," accessed June 11, 2019, https://www.rollingstone.com/politics/politics-news/anatomy-of-a-fake-news-scandal-125877/.
57 Ibid.
58 Chris McCabe, "Amazon's Fake Review Problem Is Worse Than Ever. Here's Why.," *Web Retailer* (blog), June 15, 2018, https://www.webretailer.com/lean-commerce/amazon-fake-reviews/.
59 Ibid.

recommendation systems can find a way to verify information sources, companies should be aware of the societal implications recommendation systems can have through the spread of misinformation.

VI. Conclusion

The benefits of recommendation systems must be weighed against the concerns for both individual privacy and widespread misinformation in an era of unlimited access to information. To strike an equitable balance, companies and users must broker an open and honest dialogue. Currently, companies such as Facebook are taking advantage of users' trust because, "Facebook knows that as long as your 2 billion friends are online, you're probably not going anywhere."[60] Recommendation systems are the driving force behind this dynamic, as they bridge the gap between users and companies through the collection of their users' personal data. Change can only come through regulation. Companies have little motivation to change as they continue to maximize profits using recommendation systems. Presently, antitrust laws are not established to regulate companies that are monopolizing the information economy, to establish oversight, legislators must prioritize regulation for companies using the recommendation system economic model.[61] Policy changes must be executed to protect users and prevent regulatory bodies from falling even further behind in the information economy.

60 A. J. Chavar, "Why You Keep Using Facebook, Even If You Hate It," Vox, April 11, 2018, https://www.vox.com/videos/2018/4/11/17226430/facebook-network-effect-video-explainer.
61 "Yale Law Journal - Amazon's Antitrust Paradox," accessed June 11, 2019, https://www.yalelawjournal.org/note/amazons-antitrust-paradox.

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