Customer Segmentation using RFM Analysis and K-Means Clustering to enhance Marketing Strategies

(Technical Paper)

Analysis of Algorithmic Bias in Customer Segmentation Models

(STS Paper)

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Introduction

It is not possible for medium to large size businesses to have intuition about each and every buyer because they have a large, diversified customer base. At such a stage, along with attracting new customers, it is important to pay attention to the current customers. With the aim of identifying the high-value customer pool, for my technical project, I performed RFM analysis using a transactional dataset and built multiple clusters using k-means. I further analyzed and developed an understanding of the purchasing behavior of the existing customer base. Using the interpretations of each segment, I came up with recommendations for the marketing team. Actually, customer segmentation is something that businesses have been doing for years (Kolodko, 2019). However, these modern customer segmentation models have been created to allow businesses to quickly find and precisely reach specific profit-making customers, and to do so customers are required to be grouped together based on factors, such as demographic, psychographic, ethnographic, needs-based, and value-based. Although data scientists are trained in data handling, the bias can creep in at a number of stages of this process. So, for the STS portion of my project, I will research the efficiency of customer segmentation models such as these and how to prevent the bias that is associated with these models.

In order to gain a better understanding of their customer bases, businesses need detailed understanding about their customer characteristics, behaviors, and demographics. To achieve this, numerous techniques and models have been developed (Polovin, 2020). Many algorithms and mathematical models have been introduced to classify the shoppers. This is because it is easier for businesses to develop necessary marketing and technical strategies for their customers when they can understand the relation between their characteristics, needs, and behavior. As these models are increasingly becoming a part of our everyday lives, the dark side of it is left unchecked. It is important to question that side, as the bias is difficult to detect and fix. Fixing the discrimination and biases in the systems based on mathematical models and algorithms is a long, ongoing process, which is not going to end that easily. However, using this research project, I will explore how these models can be biased and try to find ways to prevent the bias associated with the models.

Technical Project

The introduction of AI based customer segmentation models has revolutionized the way people shop and how businesses work. It is essential for the businesses to detect similarities among their customer base, predict their behavior, and present better options to them. Customer Segmentation is the process by which the businesses divide their customer base into different segments based on common characteristics, such as demographics, common interests, and needs, so that they can target and market to the customers effectively. Talking about online businesses, they use a myriad of tools, consisting of mathematical algorithms, to closely align their marketing strategy and tactics with their targeted customer base (Gupta, 2020). To find the high-value customer pool for the online retail data set, which was taken from the UCI Machine Learning repository, for my technical project, I performed a cohort analysis to understand the purchasing behavior using RFM analysis and k-means clustering.

The dataset contains information about the transactions for a UK-based and registered online retail store. RFM analysis is used to generate and assign a score to each customer based on how recent their last transaction was (Recency), how many transactions they made in a given period of time (Frequency), and what the monetary value of their transactions (Monetary). This helps the business to answer questions like who were the most recent customers? How many times did they purchase from the store? And what was the total gain from the trade? This enables them to identify the best customers and targeted marketing campaigns that these customers require (Daoud et al., 2015). Besides, this data is purely calculated based on the invoice date, invoice number, and total sum. Next, I clustered the data using k-means. It is a well-known algorithm for unsupervised learning tasks that makes assumptions about the data. From my clustering process, I obtained four clusters that seem to be separated manifesting the heterogeneity of the clusters. Once this analysis was done, I was able to label the clusters and interpret each segment to generate reforms and strategy for that online retail store.

STS Research Project

My STS project analyzes the issue of algorithmic bias that comes with the modern customer segmentation models using the following STS frameworks: Actor Network Theory (Latour, 2007) and Social Construction of Technology (Bijker et al., 2012). As machine learning technologies are advancing at a great rate in today's world, the design errors in these algorithms and mathematical models leading to discrimination and biases are becoming more and more significant. Thus, to tackle my research question, I will be investigating in depth one of the customer segmentation models, as described in the technical section to reveal the issue of algorithmic bias with it and other similar models.

There are numerous ways, such as segmenting factors, customer data, and mathematical models, through which the bias can enter into the customer segmentation models (Hao, 2019). Segmentation can lead to bias if the segments that are created are not representing the overall population, that is, the mathematical algorithm will include only those customers who have already purchased a certain product in the past and be biased against those who haven't by excluding them from the target customer base (Kirkpatrick, 2017). Customer data is another source that produces biases in the customer segmentation models. As the customer segmentation models need to work for various types of customers, rather than the ideal type of customers defined by the data used in training, the data used to develop the mathematical algorithm needs to be unbiased. Considering the Actor Network Theory (Latour, 2007), when looking for the solution to prevent the algorithmic bias associated with the customer segmentation models, we can start by adding new actors into the network who will control and direct the process by a set of rules. The purpose of these new actors would be to search for the possible source of biases and prevent potential biases. An advisory board should be introduced that can provide ethical knowledge to both engineers and businesses when framing the problem and creating the customer segmentation models. Besides, it is better to tackle the biases in the developing stage rather than the production stage (Amini et al., 2019). A new set of actors who test these models in the developing stage should be introduced, as they could prevent the biases from coming onto the market. This is because the companies that market these algorithms and models have less motivation to solve issues once the software is in production and widely accepted.

Furthermore, I also hope to use Social Construction of Technology to analyze the efficiency of current customer segmentation models and how it affects the user base. I think this will also allow me to better understand the user base of my technical project. As described in SCOT, a technical artifact is defined differently by different user bases and the involved social groups (Bijker et al., 2012). While inspecting the social effects of a customer segmentation model, I will be able to identify the social groups that are immediately affected by it and will also be able to analyze their demographics and how they are affected. Once the groups that are involved are recognized, I will be able to uncover who is at the greatest risk and most vulnerable to the biases caused by these models. Besides, the social groups related to the customer segmentation models will partially overlap with the social groups related to my technical project (Sweeney, 2013). Customer segmentation models like described in the technical project above, affect the buyers from minority social groups, such as men, workers, and parents as it will target the buyers that are rich or are high spenders, such as women and students. Moreover, after analyzing all the involved social groups, I will be able to explore the development and necessities of an algorithm that integrates debiasing capabilities into a mathematical model.

Conclusion

This proposal will ensure that the future customer segmentation models are more unbiased. My technical project and research paper analyzes the current customer segmentation model and provides a good foundation to what common mistakes are being made that lead to the biases in models. By the end of the school year, my project and research would have found an efficient way to perform segmentation that doesn’t contribute to the associated biases.

Timeline

The technical portion of the project will analyze a transactional dataset and generate strategy for that online retail store. The STS research project will interpret the efficiency of those customer segmentation models and research how to prevent the bias that is associated with models like the one talked about in the technical project. The case study of Amazon’s hiring algorithm is explored in the research project. The technical project will be further reformed and developed to generate more useful, profitable, and unbiased strategies. The STS research paper will be useful for identifying and resolving biases in the future customer segmentation models. Both the technical project and STS research paper will be finished in the Spring of 2023.

Key Texts

This is how AI bias really happens—and why it's so hard to fix (Hao, 2019). In this article, the author talks about the biases in AI and how these biases can be introduced in AI processes in multiple stages. The author explains how biases are generally introduced in three key stages: framing the problem, collecting the data, and cleaning the data. Further, the author also points out how mitigating bias is difficult to achieve even though we know the stages where it can be introduced. This article is useful for my study because it explores specific areas of machine learning algorithms and models where biases can be introduced. My project has similar stages and thus, this article provides structure and support to my claims.

It's not the algorithm, it's the data (Kirkpatrick, 2017). This article talks about the use of artificial intelligence and machine learning in criminal justice and policing in the US. The author explores policing tools like recidivism risk-assessment algorithms and predictive policing. The recidivism risk-assessment algorithms predict the likelihood of a convicted criminal committing crime again, while predictive policing uses analytics to determine where and when a crime might occur. In the article, the critics argue how these algorithms and mathematical models used in the tools may produce biased results. Further, the author talks about how these tools will create more accurate predictions over time. This is an important article for my study because it explores the real-world application of machine learning that affects normal people directly and talks about how biases can appear in the models. It also explores and describes the causes of biases and the impact of those biases.

Discrimination in online ad delivery (Sweeney, 2013). This article talks about the racial discrimination found in online ad delivery through Google searches. The author performs a search on Google.com and Reuters.com, which uses a Google platform for searches, using black-identified and white-identified names, and the analyses show the patterns of ads that result. In this experiment, the author searched around 2000 names over the span of a month or so, and she elaborates her results and insights in this article. She points out how discrimination can be occurring due to the Google algorithm which basically learns over time depending on which ads get frequently clicked. This article is important for my study because it provides proof of the existing biases in commonly used technology which people are aware of.

Uncovering and mitigating algorithmic bias through learned latent structure (Amini et al., 2019). This article explores the development of an algorithm that integrates debiasing capabilities into a mathematical model and machine learning algorithms. The authors talk about the algorithms that learn the desired task along with learning the latent and hidden structure of training data. The article provides a reliable technique that tries to minimize the biases in the machine learning models and algorithms. In this article, the authors provide a test of facial recognition using this new model. This article is important for my study because it provides a reliable study and detailed explanation of an algorithm that is designed to recognize potential biases and correct while training.

References

Amini, A., Soleimany, A., Schwarting, W., Bhatia, S., & Rus, D. (2019). *Uncovering and mitigating algorithmic bias through learned latent structure.* Proceedings of the 2019 AAAI/ACM Conference on Artificial Intelligence, Ethics, and Society (AIES) (pp. 1-7). Honolulu, HI: Association for the Advancement of Artificial Intelligence/Association for Computing Machinery. Retrieved from http://hdl.handle.net/1721.1/121101

Bijker, Wiebe., et al. *The Social Construction of Technological Systems New Directions in the Sociology and History of Technology*. MIT Press, 2012.

Daoud, R.A., Amine, A., Bouikhalene, B., & Lbibb, R. (2015). *Combining RFM model and clustering techniques for customer value analysis of a company selling online*. *2015 IEEE/ACS 12th International Conference of Computer Systems and Applications (AICCSA)*, 1-6.

Gupta, S. (2020, July 9). *Is RFM still king? A data science evaluation*. ReSci. Retrieved December 16, 2022, from https://www.retentionscience.com/blog/rfm-king/

Hao, K. (2019, February 4). *This is how AI bias really happens—and why it's so hard to fix.* MIT Technology Review. Retrieved from https://www.technologyreview.com/s/612876/this-is-how-ai-bias-really-happensandwhy-

i

ts-so-hard-to-fix/

Kirkpatrick, K. (2017). *It's not the algorithm, it's the data*. Communications of the ACM, 60(2), 21–23. doi:10.1145/3022181

Kolodko, J. (2019, October 24). *Customer segmentation: "when and where" instead of "who" - blog*. Julia Kolodko. Retrieved December 16, 2022, from https://www.juliakolodko.com/segmentation

Latour, B. (2007). *Reassembling the social: An introduction to actor-network-theory*. Oup Oxford.

Polovin, G. (2020, December 15). *Market research bias and the customer experience*. Sogolytics Blog. Retrieved December 16, 2022, from https://www.sogolytics.com/blog/market-research-bias-and-the-customer-experience/

Sweeney, L. (2013). *Discrimination in online ad delivery.* ACM Queue, 11(3), 1-19. https://arxiv.org/abs/1301.6822