Machine Learning-Based Customer Segmentation: A Comprehensive Investigation of Techniques, Challenges and Applications

Yazhi Zhang[a]

Steinhardt School of Culture, Education, and Human Development, New York University, New York, U.S.A.

Keywords: Customer Segmentation, Machine Learning, Deep Learning.

Abstract: Customer segmentation is vital for optimizing targeted marketing strategies, improving customer experiences, and driving profitability across various industries. This study proposes to provide a comprehensive analysis of how machine learning can improve segmentation accuracy and offer deeper insights into customer behaviours. To achieve this, this paper conducted a detailed examination of machine learning methods used in customer segmentation across banking, telecommunications, and healthcare industries. The methods reviewed include decision trees, random forests, k-means clustering, hierarchical clustering, auto machine learning (AutoML) tools like H2O, and deep learning models. The study also involved analyzing specific machine learning workflows, including problem definition, data collection, preprocessing with techniques like Local Outlier Factor (LOF) and Principal Component Analysis (PCA), model selection, training, evaluation, and deployment. Each industry-specific case study was scrutinized to emphasize the effectiveness and risks of these methods in real-world applications. The results demonstrate that while machine learning significantly enhances customer segmentation, it also introduces challenges related to model interpretability, domain applicability, and privacy concerns. The study supports the hypothesis that incorporating interpretability tools like SHAP and LIME, leveraging transfer learning, and adopting federated learning are crucial for overcoming these challenges.

1 INTRODUCTION

Customer segmentation entails categorizing a customer base into several different groups depended on common characteristics like reactions, requirements, and predilections. (Monil et al., 2020). In the context of machine learning, this process utilizes advanced algorithms to analyze vast datasets, uncovering patterns that traditional methods might miss. Employing machine learning techniques in customer segmentation helps to strengthen the advantages of targeted marketing strategies, upgrade customer experiences, optimize marketing efforts, and increase profitability for businesses across various sectors, particularly in the highly competitive landscape of modern commerce.

Machine learning can be generally divided into two main categories: supervised learning and unsupervised learning. Supervised learning is commonly utilized for addressing classification and regression problems, where the data includes an objective standard that the model aims to predict in future scenarios, such as estimating a student's grade or forecasting the number of current transactions (Narayana et al., 2022). In contrast, unsupervised learning does not involve predicting a specific label or target variable. Instead, it focuses on identifying patterns and grouping data based on similarities, such as categorizing students according to their purchasing behavior or learning patterns, without predefined labels (Narayana et al., 2022). Previous studies on customer segmentation in the industries have predominantly focused on traditional statistical methods, such as cluster analysis and regression models. These methods, while useful, often lack the ability to handle large and complex datasets effectively. Recent research has started to explore the use of machine learning techniques, including k-means clustering, auto machine learning, and neural networks, to enhance segmentation accuracy and provide deeper insights. For instance, Narayana and other researchers utilized methods of K-means,

[a] https://orcid.org/0009-0001-8080-1451

Agglomerative, and Mean Shift to identify possible customer segments in the mall, depended on their gender, age, yearly income, and consuming score (Narayana et al., 2022); Turkmen investigated k-means, Hierarchical clustering, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) for online retail industry (Turkmen, 2022); Yadegaridehkordi et al. scholars researched the k-means, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) , and Classification and Regression Trees (CART) method to analyze travelers for eco-friendly hotel (Yadegaridehkordi et al., 2021).

The primary aim of the article is to investigate the latest trends in customer segmentation in various industries using machine learning within the context of an omnichannel world. Initially, this paper examines the current state and innovations in customer segmentation. The methods utilized in different industries are then recapitulated. Subsequent sections discuss the advantages and disadvantages of implementing these models for customer segmentation, offering valuable insights for practitioners and researchers alike. The final part summarizes the theoretical and practical conclusions.

2 METHODS

2.1 Introduction of Machine Learning Workflow

The focus of machine learning is on developing algorithms that enable computers to learn and make decisions or predictions based on data, which is a branch of artificial intelligence. Figure 1 shows that machine learning can be divided into four categories: Supervised Learning, Unsupervised Learning, Semi-supervised Learning, and Reinforcement Learning (Taye, 2023). Supervised learning involves the progress of classification and regression, a traditional method of fitting the data into a pre-existing structure and types. It usually utilizes the knowledge of Linear Regression, Logistic Regression, Random Forest, and Network Neutral. Unsupervised learning, on the other hand, consists of clustering and association. It often includes K-means clustering, principal component analysis, t-distributed stochastic neighbor embedding, and association rule. Semi-supervised Learning contains the step of classification and clustering, with the algorithm of uClassify and GATE. And reinforcement learning requires classification and control, having the methods such as Q-learning, Monte Carlo Tree Search, Temporal Difference, and Asynchronous Actor-Critic Agents.

A machine learning workflow shown in Figure 2 encompasses several key stages, each crucial for creating effective and reliable models. The first stage in the machine learning workflow is problem regression, or clustering. The second step is data preparation and preprocessing, which involves data cleaning, data transformation, and data splitting. The third step might be Model selection and training. The selection of appropriate machine learning algorithms is made during this phase according to the type of problem and the nature of the data. After training, the model's performance must be evaluated and validated. Visualizing the results and interpreting
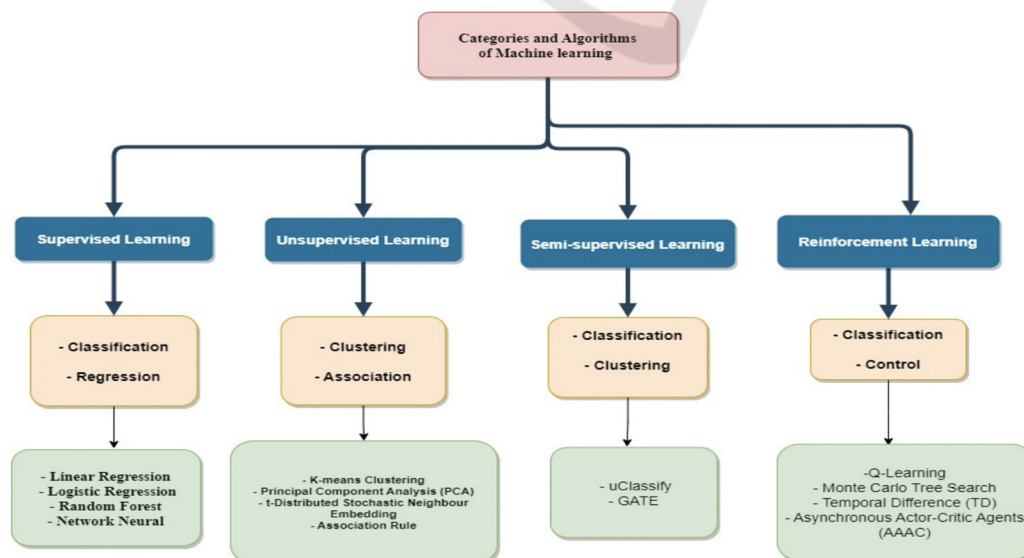

Figure 1: Different Categories and Algorithms of Machine Learning (Taye, 2023).
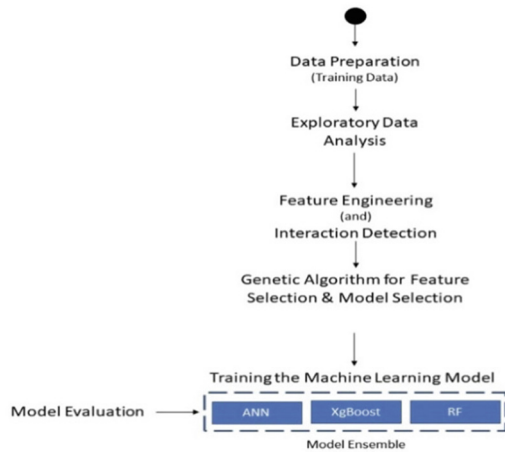
Figure 2: Workflow of the Machine Learning Procedure (Monge, 2021).

the mode's predictions are crucial for understanding the insights generated and communicating them to stakeholders. The final stage in the machine learning workflow is model deployment and monitoring, where it can be used for real-world applications. This often involves integrating the model into existing systems through APIs or user interfaces, making it accessible and functional. Detecting any degradation or drift over time requires continuous monitoring of the model's performance.

2.2 Customer Segmentation in Bank

Yuping et al. researchers explore the changing landscape of customer behavior and payment methods, especially in an omnichannel world where physical money is becoming obsolete (Yuping et al., 2020). Commercial banks face challenges when evaluating personal credit using traditional methods due to this shift. During the procedure of personal credit evaluation, the Local Outlier Factor (LOF) test method is used to identify and remove outliers from the sample data. Afterward, any missing values in the original sample data, as well as those that result from removing outliers, are filled in using a random forest model. This approach replaces the traditional statistical methods of filling in missing values with averages or most frequent values, thereby enhancing the accuracy of the predictions. The key variables that impact individual credit evaluation are identified using a gradient boosting decision tree model. Following this, utilizing either logistic regression or a Backpropagation (BP) neural network, a scorecard model is established to assess and forecast using the selected key variables, resulting in a personal credit score. This approach compensates for inaccuracies in

credit scoring that may arise from relying solely on credit data and the traditional model for generating the personal credit score.

Examining the machine learning methods in predicting bank crises, Buetel et al. highlight that neural networks, especially with a single hidden layer, can offer greater flexibility than traditional logit models (Buetel et al., 2019). However, they also note the risk of overfitting, particularly with more complex architectures like deep neural networks. The potential for neural networks to outperform simpler models like the logit model depends heavily on controlling this overfitting risk and effectively managing the network's complexity. However, authors consider that in some circumstances, machine learning methods can't perform better than the traditional methods.

2.3 Customer Segmentation in Telecommunication

The challenge of risk management within the telecommunications industry includes the need for efficient handling of large datasets, ensuring the scalability of the ML models, and enabling non-expert users to deploy and maintain these models (Ferreira et al., 2020). Specifically, it focuses on automating and scaling ML applications for tasks such as churn detection, event forecasting, and fraud detection. The AutoML tools, particularly H2O AutoML, were considered a robust solution for developing machine-learning models with minimal human intervention. This tool is noted for its ability to handle large datasets and integrate various machine learning algorithms, such as Gradient Boosting Machine (GBM), Generalized Linear Model (GLM), XGBoost, Random Forest, and Deep Learning models. The choice of H2O AutoML by the project's stakeholders suggests a strong endorsement of its capabilities in efficiently managing complex machine-learning tasks.

To deal with the problem of understanding and segmenting telecom customers based on their behavior and tailoring services more effectively, PCA was used to reduce the dimensionality of the dataset, and the elbow method helped to figure out the most favorable number of clusters before conducting clustering (Sharaf et al., 2022). K-means clustering was the primary approach emploted to segment telecom customers based on various attributes such as demographic, behavioral, and regional aspects. Subsequently, an interactive web-based dashboard called INSIGHT has been created to help telecom managers in obtaining a thorough comprehension of

their customers and creating more informed business decisions.

2.4 Customer Segmentation in Healthcare

K-means clustering and hierarchical clustering are identified as the most prevalent and useful techniques in addressing the issue of understanding healthcare consumer behaviors and attitudes, which is crucial in the shift towards patient-centered care (Swenson, 2018). While both machine learning methods are significant, K-means clustering is highlighted as particularly useful due to its ease of use, ability to handle large datasets, and widespread application in healthcare market segmentation, compared to hierarchical clustering. The method's capability to form well-defined clusters based on similarity measures makes it a preferred choice for segmenting healthcare data into actionable groups, which can inform targeted healthcare services and marketing strategies.

With the advent of big data in healthcare, customized segmentation can be utilized in web-based healthcare content (Guni et al., 2021). Deep learning used in advanced recommender systems like YouTube's processes a rich set of user and content features to generate and rank candidate items. It is highlighted for its ability to handle and integrate a wide variety of content features, both high-level (semantic features like tags, genre, and actors) and low-level (stylistic features like colors, texture, and lighting). And deep learning outperforms traditional methods by providing more accurate and personalized content recommendations, making it a powerful tool for processing large and complex datasets in healthcare industry.

3 DISCUSSIONS

3.1 Limitations and Challenges

Interpretability is a significant challenge in target marketing, particularly when complex machine learning models are used. These models often function as "black boxes", making it difficult to understand which factors are influencing the outcomes. In business contexts where trust and compliance depend on understanding the decision-making process, a lack of transparency can be problematic. For example, if a marketing model predicts customer behavior but doesn't provide clear reasoning behind these predictions, it may be difficult for marketers to explain or justify the strategies to

stakeholders, potentially leading to skepticism and reduced confidence in the model's results.

Another challenge is the limited applicability of specific models across different scenarios. Many models are tailored to specific datasets or marketing environments, which means they might not generalize well to other cases. This limitation is especially problematic in target marketing, where consumer behavior can vary significantly across different industries, regions, and time periods. The inability to generalize can reduce the effectiveness of the model when applied outside its initial context, requiring extensive retraining or adjustments that can be resource-intensive.

Privacy concerns are another significant limitation in target marketing, particularly with the increasing amount of customer data being used for personalized marketing strategies. The use of sensitive customer data raises the risk of privacy breaches, which can lead to significant legal and reputational consequences. If customer data is not handled securely, there is a high likelihood of privacy leaks, which can result in the loss of customer trust and, subsequently, customers themselves. This challenge underscores the need for rigorous data protection measures and accordance with privacy rules, such as GDPR, to mitigate the risks associated with customer data usage in marketing.

3.2 Future Prospects

To address the challenge of interpretability in target marketing models, future efforts could focus on integrating expert systems and advanced interpretability tools such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME). These methods offer knowledge about how different characteristics impact the model's predictions, providing a easier way to understand and explain the decisions made by complex models. SHAP, for instance, can supply a unified method of feature significance across different models, while LIME offers a way to understand individual predictions by approximating the model locally. By incorporating these tools, marketers can gain greater transparency and trust in the AI-driven decisions, ultimately leading to better-informed marketing strategies.

To overcome the limitations of applicability, transfer learning and domain adaptation techniques could be employed. For instance, transfer learning enables models to transfer comprehension learned from one realm to another realm, lessening the requirement for substantial retraining when models

are applied to new datasets or scenarios. Domain adaptation, on the other hand, focuses on adjusting models to perform well in different but related domains. These techniques can significantly improve the generalizability of target marketing models, allowing them to be more flexible and effective across various contexts and industries. This would reduce the resource-intensive process of building new models from scratch for different applications.

Privacy concerns in target marketing can be addressed by adopting federated learning approaches. Federated learning makes it possible to train models on multiple decentralized devices or servers that contain local data samples, without having to exchange the data itself. This method ensures that customer data remains on their devices, reducing the risk of privacy breaches. Federated learning also complies with stringent data privacy regulations, such as GDPR, by enabling secure, decentralized learning processes. By implementing federated learning, organizations can enhance customer trust while still benefiting from personalized marketing strategies that leverage large-scale data insights.

4 CONCLUSIONS

The investigation into the latest trends in customer segmentation reaffirms the critical role that machine learning plays in enhancing targeted marketing strategies. As highlighted in the introduction, the transition from traditional methods to advanced algorithms offers businesses a competitive edge in understanding customer behavior and optimizing marketing efforts. This review's main contribution lies in synthesizing the current state of machine learning applications across various industries, providing a comprehensive analysis of their strengths and challenges. By examining case studies from banking, telecommunications, and healthcare, this paper demonstrates the effectiveness of machine learning models like k-means clustering, auto machine learning, decision trees, and neural networks in improving segmentation accuracy and customer insights. However, the review also identifies significant limitations, including the challenges of model interpretability, domain applicability, and privacy concerns. Addressing these issues will require future research focused on integrating interpretability tools like SHAP and LIME, exploring transfer learning and domain adaptation, and adopting federated learning to enhance privacy. These advancements are essential for ensuring that machine

learning continues to provide valuable and trustworthy insights in customer segmentation.

REFERENCES

Beutel, J., List, S., & von Schweinitz, G. 2019. Does machine learning help us predict banking crises?. *Journal of Financial Stability*, 45, 100693.

Ferreira, L., Pilastri, A. L., Martins, C., Santos, P., & Cortez, P. 2020. An Automated and Distributed Machine Learning Framework for Telecommunications Risk Management. In *ICAART (2)* (pp. 99-107).

Guni, A., Normahani, P., Davies, A., & Jaffer, U. 2021. Harnessing machine learning to personalize web-based health care content. *Journal of medical Internet research, 23*(10), e25497.

Monge, M., Quesada-López, C., Martínez, A., & Jenkins, M. 2021. Data mining and machine learning techniques for bank customers segmentation: A systematic mapping study. In *Intelligent Systems and Applications: Proceedings of the 2020 Intelligent Systems Conference (IntelliSys) Volume 2* (pp. 666-684). Springer International Publishing.

Monil, P., Darshan, P., Jecky, R., Vimarsh, C., & Bhatt, B. R. 2020. Customer segmentation using machine learning. *International Journal for Research in Applied Science and Engineering Technology (IJRASET), 8*(6), 2104-2108.

Narayana, V. L., Sirisha, S., Divya, G., Pooja, N. L. S., & Nouf, S. A. 2022. Mall customer segmentation using machine learning. In *2022 International Conference on Electronics and Renewable Systems (ICEARS)* (pp. 1280-1288). IEEE.

Sharaf Addin, E. H., Admodisastro, N., Mohd Ashri, S. N. S., Kamaruddin, A., & Chong, Y. C. 2022. Customer Mobile Behavioral Segmentation and Analysis in Telecom Using Machine Learning. *Applied Artificial Intelligence, 36*(1).

Swenson, E. R., Bastian, N. D., & Nembhard, H. B. 2018. Healthcare market segmentation and data mining: A systematic review. *Health Marketing Quarterly, 35*(3), 186-208.

Taye, M. M. 2023. Understanding of machine learning with deep learning: architectures, workflow, applications and future directions. *Computers, 12*(5), 91.

Turkmen, B. 2022. Customer Segmentation with machine learning for online retail industry. *The European Journal of Social & Behavioural Sciences*.

Yadegaridehkordi, E., Nilashi, M., Nasir, M. H. N. B. M., Momtazi, S., Samad, S., Supriyanto, E., & Ghabban, F. 2021. Customers segmentation in eco-friendly hotels using multi-criteria and machine learning techniques. *Technology in Society, 65*, 101528.

Yuping, Z., Jílková, P., Guanyu, C., & Weisl, D. 2020. New methods of customer segmentation and individual credit evaluation based on machine learning. In *"New Silk Road: Business Cooperation and Prospective of Economic Development" (NSRBCPED 2019)* (pp. 925-931) Atlantis Press.